A Relation-Centric View of Semantic Representation Learning

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To the women in my life.
My mother and my wife.

Abstract

Much of NLP can be described as mapping of a message from one sequence of symbols to another. Examples include word surface forms, POS-tags, parse trees, vocabularies of different languages, etc. Machine learning has been applied successfully to many NLP problems by adopting the symbol mapping view. No knowledge of the sets of symbols is required: only a rich feature representation to map between them.

The task of coming up with expressive features is typically a knowledge-intensive and time-consuming endeavor of human creativity. However the representation learning paradigm (Bengio et al., 2013) offers an alternative solution, where an optimal set of features are automatically learned from data for a target application. It has been successfully used in many applied fields of machine learning including speech recognition (Dahl et al., 2010), vision and object recognition (Krizhevsky et al., 2012), and NLP (Socher et al., 2010; Schwenk et al., 2012).

One particular area of NLP that has received a lot of interest, from the perspective of representation learning, is lexical semantics. Many efforts have focussed on attempting to learn high-dimensional numerical vector representations for units of meaning (most often words) in a vocabulary. While the current slew of research uses neural network techniques (Collobert and Weston, 2008; Mikolov et al., 2013a), word-embeddings have been around much longer in the form of distributional vector space models (Turney and Pantel, 2010). We use the term semantic representation learning to encompass all these views and techniques.

Semantic representations learned automatically from data have proven to be useful for many downstream applications such as question answering (Weston et al., 2015), word-sense discrimination and disambiguation (McCarthy et al., 2004; Schütze, 1998), and selectional preference modeling (Erk, 2007). The successes of representation learning, along with its unsupervised and data-driven nature make it a compelling modelling solution for semantics.

However, unlike manual feature engineering, it remains difficult to inject linguistic or world knowledge into the process of learning semantic representations automatically. This has led many models to still fail to account for many basic properties of human languages, such as antonymy, polysemy, semantic composition, and negation, among others. We attempt to outline solutions to some of these shortcomings in this thesis.

When considering semantic representation learning models, two questions may be asked: firstly, *how* is the model learned; and secondly; *what* does the model represent? The research community has largely focussed on the first of the two questions – the *how* – proposing many different machine learning solutions that yield semantic vector representations. In this thesis, we instead focus on the second of the two questions – the *what* – namely gaining insight into the underlying semantic information that is actually captured by models.

To explain this information we introduce the two connected notions of *semantic*

relations and *contextual relations*. Semantic relations are properties of language that we generally wish to capture with semantic models, such as similarity and relatedness. However, given some data, unsupervised representation learning techniques have no way of directly optimizing and learning these semantic relations.

At the same time, a crucial component of every representation learning model, is the notion of a *context*. This is the basis upon which models extract count statistics to process and produce representations. It is, effectively a model's view of the world and one of the few ways of biasing the unsupervised learner's perception of semantics, with data. A contextual relation is the operationalization that yields the contexts, upon which a semantic model can be trained.

Therefore, to understand *what* information a model represents one must understand and articulate the key contextual relation that defines its learning process. In other words, being able to specify what is being counted leads to insights into what is being represented. Conversely, if we wish to learn a model that captures a specific semantic relation it is important to define a contextual relation that captures the intuition of the semantic relation through contextual views of data. The connection between semantic and corresponding contextual relation may not always be easy or evident, but in this thesis we present some examples where we can make such a connection and also provide a framework for thinking about future solutions.

To clarify the idea of semantic and contextual relations let us consider the example of learning a model of semantic similarity. In this case the semantic relation that we wish to learn is similarity, but how do we bias the learner to capture a specific relation in an unsupervised way from unannotated data? We need to start with an intuition about semantic similarity, and make it concrete with a contextual relation. Harris (1954) and Firth (1957) intuited that words that appear in similar contexts tend to have similar meaning; this is known as the distributional hypothesis. This hypothesis is often operationalized to yield contexts over word window neighborhoods, and many existing word vector learning techniques (Collobert and Weston, 2008; Mnih and Teh, 2012; Mikolov et al., 2013a) use just such contexts. The *word-neighborhood-word* contextual relation thus produces models that capture similarity.

From this point of view the distributional hypothesis is first and foremost a contextual relational, only one among many possible contextual relations. It becomes clear why models that use this relation to extract counts and process information are incapable of capturing all of semantics. The contextual relation based on the distributional hypothesis is simply not the right or most expressive one for many linguistic phenomena or semantic problems – for example composition, negation, antonymy etc.

Turney and Pantel (2010) describe other contextual relations that define and yield contexts such as entire documents or patterns. Models that use these contextual relations capture different information (i.e. semantic relations) because they define views of the data via *contexts* differently. This thesis hypothesizes that relations and structure play a primary role in creating meaning in language, and that each linguistic phenomenon has its own set of relations and characteristic structure. We further hypothesize that by understanding and articulating the principal contextual relations

relevant to a particular problem, one can leverage them to build more expressive and empirically superior models of semantic representations.

We begin by introducing the problem of semantic representation learning, and by defining semantic and contextual relations. We then outline a framework within which to think about and implement solutions that bias learners of semantic representations towards capturing specific relational information. The framework is example-based, in the sense that we draw from concrete instances in this thesis to illustrate five sequential themes that need to be considered.

The rest of the thesis provides concrete instantiations of these sequential themes. The problems we tackle in the four subsequent chapters (Chapters 3– 6) are broad, both from the perspective of the target learning problem as well as the nature of the relations and structure that we use. We thus show that by focussing on relations, we can learn models of word meaning that are semantically and linguistically more expressive while also being empirically superior.

In the first of these chapters, we outline a general methodology to learn sense-specific representations for polysemous words by using the relational links in an ontological graph to tease apart the different senses of words. In the next chapter, we show how the relational structure of tables can be used to produce high-quality annotated data for question answering, as well as build models that leverage this data and structure to perform question answering. The third of the four chapters deals with the problem of inducing an embedded semantic lexicon using minimal annotation. In this chapter we jointly leverage local token-level and global type-level relations between predicate-argument pairs to yield representations for words in the vocabulary, as well as a codebook for a set of latent relational argument slots. Finally, in the last content chapter we show how tensor-based structured distributional semantic models can be learned for tackling the problems of contextual variability and facetted comparison; we give examples of both syntactic and latent semantic relational integration into the model.

This thesis provides a step towards better understanding computational semantic modelling with representation learning. It presents a way of connecting what knowledge or semantic information a model captures with its contextual view of the data. Moreover it provides a framework and examples of how this connection can be made to learn better and more expressive models of semantics, which can potentially benefit many downstream NLP applications that rely on features of semantic units.

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Chapter 1

Introduction

Most of NLP can be viewed as a mapping from one sequence of symbols to another. For example, translation is mapping between sequences of symbols in two different languages. Similarly, part-of-speech tagging is mapping between words' surface forms and their hypothesized underlying part-of-speech tags. Even complex structured prediction tasks such as parsing or simple tasks like text categorization labelling are mappings: only between sequences of symbols of different granularities. These sequences may or may not interact with one another in complex ways.

From a computational perspective, this is a powerful and appealing framework. There is no need to know anything about linguistics or language: only that it can be represented as sequences of symbols. Using this symbol mapping perspective, machine learning has been applied with great success to practically every NLP problem.

Driven by better learning techniques, more capable machines and vastly larger amounts of data, useable natural language applications are finally in the hands of millions of users. People can now translate text between many languages via services like Google Translate[1], or interact with virtual personal assistants such as Siri[2] from Apple, Cortana[3] from Microsoft or Alexa[4] from Amazon.

However, while these applications work well for certain common use cases, such as translating between linguistically and structurally close language pairs or asking about the weather, they continue to be embarrassingly poor for processing and understanding the vast majority of human language.

For example, asking Siri "I think I have alcohol poisoning. What do I do?" led one user to receive the darkly humorous failed response "I found 7 liquor stores fairly close to you." with a list of map locations to the liquor stores. Many instances of NLP systems failing occur because language is complex, nuanced and very often highly ambiguous (although the example above is not). And despite recent efforts, such as Google's Knowledge Graph project[5] to build repositories of world and linguistic knowledge – models for semantics continue to be incomplete,

[1] `https://translate.google.com/`
[2] `https://en.wikipedia.org/wiki/Siri`
[3] `https://en.wikipedia.org/wiki/Cortana_(software)`
[4] `https://en.wikipedia.org/wiki/Amazon_Alexa`
[5] `https://en.wikipedia.org/wiki/Knowledge_Graph`

rudimentary, and extremely knowledge-intensive to build.

From the symbol transformation perspective, a typical NLP pipeline involves taking an input A in symbol vocabulary $\mathcal{A}$, featurizing this input by some function F to express the important dimensions of distinction, learning or applying a model M to the featurized input and finally performing a transformation to a sequence B in symbol vocabulary $\mathcal{B}$.

To concretize this notional pipeline, consider the example of part-of-speech-tagging:

- Sequence A is typically text in a source language – say English, which contains a vocabulary of English tokens $\mathcal{A}$.
- The function F may consist of features like lexical-to-tag mapping probabilities that are estimated from some training data, or induced in an unsupervised fashion. In machine learning terms this process is known as featurization.
- The model M concerns the definition and learning of a mathematical function that is able to map featurized input to output. In the case of part-of-speech tagging this could be, for example, a Hidden Markov Model (HMM) (Rabiner and Juang, 1986) or a Conditional Random Field (CRF) (Lafferty et al., 2001).
- Finally the transformation via model M to output is known as decoding or inference. The output symbols obtained in the case of part-of-speech tagging would be a sequence of tags B from a vocabulary consisting of some tagset $\mathcal{B}$, such as the Penn Treebank tagset[6].

A similar sort of abstract pipeline can be envisaged for almost any NLP problem.

A symbol mapping pipeline of this kind systematizes and separates the different steps involved in the transformation. Thus, the machine learning model M does not really need to know anything beyond the denotation of the sets of symbols $\mathcal{A}$ and $\mathcal{B}$. Rather, a much more important requirement is an expressive featurization F that characterizes the two symbol vocabularies, the example sequences A and B and their relationships to one another. These features provide the basis upon which a symbol mapping model can be learned to generalize from known to unseen examples.

This thesis is centrally concerned with the *featurization* component of the pipeline, namely F.

Until recently, the work of thinking up and engineering expressive features for machine learning models was still, for the most part, the responsibility of the researcher or engineer. It was up to the researcher or engineer to think up clever ways of featurizing the input, and in the case of NLP often applying her insight into linguistics and knowledge about the world to do this effectively.

However, the **representation learning** paradigm (Bengio et al., 2013) was proposed as an alternative that eliminated the need for manual feature engineering of data. In general, representation learning allows a system to automatically learn a set of optimal features given a target application and training data. In the context of the pipeline described above, the featurization step F is no longer a separate stage in the pipeline but rather a sub-component of the model M.

In the running example of part-of-speech tagging above, the model M might now be a sequential neural network such as a Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber,

[6] `https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html`

1997) that only requires examples of aligned inputs A and B. The features or *representations* of the input A are no longer required to be coded manually via F. Rather, F might now be an embedding matrix that maps words in the input vocabulary to some high dimensional vector representation. This embedding matrix is induced automatically through the process of training the network M.

An important point to note is that, while representation learning integrates features with the model, it does not mean that *featurization* as a research practise is no longer required. Rather, the process of featurization is abstracted away from the raw data in two important ways. Specifically manual engineering of features on data is replaced with engineering of model architecture and learning, and engineering of data itself.

The first abstraction deals with feature engineering of model architecture. For example, in the context of neural networks – which integrate representation learning models – feature engineering goes into defining network structure for particular tasks and problems. Recurrent Neural Networks (RNNs) are *featurized* to learn and represent sequences of data, while Long Short-term Memory networks (LSTMs) are *featurized* to capture long-range dependencies in sequences. Similarly, Convolutional Neural Networks (CNNs) are *featurized* to represent local neighborhood structure. In this way, featurization is abstracted away from functions of the data, and the responsibility of the researcher or engineer is to define features over model components and architecture.

In conjunction with this first abstraction, featurization has also moved away from manual engineering of features *on* data, to featurization *of* the data itself. In terms of representation learning, the model no longer requires features on the data as input, but rather *views* of the data to bias its learning of features. For example, an RNN that is fed with words and another that is fed with characters will not only learn different units of representations but will have a different model of language altogether. Thus featurization is also abstracted over data, where the responsibility of the researcher or the engineer is to define views of the data that the representation learning model can consume.

In this thesis, we will be primarily dealing with the second kind of abstraction in the practise of featurization. Namely, we will be thinking about ways to present novel, structured views of data in order to bias existing representation learning techniques to learn representations.

In any case, representation learning has been successfully used in several applied research areas of machine learning including speech recognition (Dahl et al., 2010; Deng et al., 2010), vision and object recognition (Ciresan et al., 2012; Krizhevsky et al., 2012), and NLP Socher et al. (2010); Schwenk et al. (2012); Glorot et al. (2011). In particular for NLP, Collobert et al. (2011) showed how a single architecture could be applied in an unsupervised fashion to many NLP problems, while achieving state-of-the-art results (at the time) for many of them.

There have since been a number of efforts to extend and improve the use of representation learning for NLP. One particular area that has received a lot of recent interest in the research community is semantics.

In semantics, representation learning is commonly referred to in the literature as the so-called word-embedding problem. Typically, the aim is to learn features (or *embeddings*) for words in a vocabulary – which are often the units of lexical semantics – automatically from a corpus of text. However in this thesis, we adopt a broader view of lexical semantics where the *lexicon* can consist of other semantic units for which we may wish to learn representations. Therefore, where

appropriate we will talk about word embeddings, but otherwise deal with the general problem of representation learning for semantics.

There are two principal reasons that representation learning for semantics is an attractive proposition: it is unsupervised (thus requiring no human effort to build), and data-driven (thus letting the data effectively bias the learning process). However, in contrast to manual feature engineering it is significantly more difficult to introduce coded linguistic or world knowledge.

This is where featurization over views of the data comes into play. We hypothesize that, for certain kinds of problems, a richer or different view of data can be used to bias learners of representations to capture deeper linguistic or structural knowledge. In what follows we shall motivate and outline a possible solution.

1.1 The Two Basic Questions of Representation Learning

To understand the variety of different approaches to representation learning for semantics, one can examine the following two questions:

1. How is a model learned?
2. What does the model represent?

Each of these questions is closely linked to one of the two abstractions of featurization that we previously mentioned: one with featurization of model component and architecture, and the other with featurization of views of data.

The first question attempts to classify the general class of methods or models used to learn the representations in question. The currently dominant approach is the **neural embedding** class of models which use neural networks to maximize some objective function over the data and learn word vectors in the process. The LSTM, mentioned in the context of the part-of-speech tagging example above, is one such model. Some notable papers that learn semantic representations on the basis of neural networks are Collobert et al. (2011), Mikolov et al. (2010), Mikolov et al. (2013a) and Pennington et al. (2014).

Earlier work on **count statistics** over windows and transformations thereof are other ways to automatically learn representations of some semantic units from data. These include heuristic methods such as Term Frequency Inverse Document Frequency (TF-IDF) and Point-wise Mutual Information (PMI) weighting, and mathematically motivated **matrix factorization** techniques such as Latent Semantic Analysis (Deerwester et al., 1990). Turney and Pantel (2010) provide an overview of these diverse approaches. More recently, Levy and Goldberg (2014) show an inherent mathematical link between older matrix factorization work and current neural embedding techniques.

Addressing the second – and, for this thesis, the more interesting – question specifies the underlying view of the data that is given as input to the model. In other words, how is the data presented to the model so that raw statistics can be converted into meaningful information and used to bias semantic representations? Moreover what semantic properties are captured and maintained by this transformation?

Every semantic representation learning model operates on the notion of a *context*. The context specifically defines what information is available during training, and consequently what

statistics can be computed and converted into representations. Different kinds of contexts, naturally lead to models that capture different information. This is – crucially – the operational *view* of a semantic representation learning model, and is central to the rest of this thesis.

Consider the example of perhaps the most commonly used semantic hypothesis: the **distributional hypothesis** (Harris, 1954). Articulated by Firth (1957) in the popular dictum "You shall know a word by the company it keeps", the hypothesis claims that words that have similar meaning tend to occur in similar contexts.

The example below illustrates how the distributional hypothesis works. For example, the words "stadium" and "arena" may have been found to occur in a corpus with the following contexts:

- People crowded the *stadium* to watch the game.
- The *arena* was crowded with people eager to see the match.
- The *stadium* was host to the biggest match of the year.
- The most important game of season was held at the *arena*.

From these sentences it may be reasonably inferred (without knowing anything about them a priori) that the words "stadium" and "arena" in fact have similar meanings.

Notice that the *context*, in this case, is simply the neighboring words – perhaps parametrized by a window size. This is, in fact, the *view* of the data: it is the input to the representation learning model, which has access to nothing else but this information. Extending the reasoning above to extract *neighborhood* statistics from a corpus of millions of words, which contain many hundreds of occurrences of the words "stadium" and "arena" the learner will build reasonably good and robust representations of the two words. That is, the resulting feature representations of the two words will be close together in semantic space.

This is a very simple yet extremely powerful insight and the contributions of the distributional hypothesis on representation learning in semantics remain profound. Operationalized in practise, most word embedding models use the insight of the distributional hypothesis to essentially count statistics over a word's neighborhood contexts across a corpus and represent all those statistics in a compact form as a vector representation for that word. The result is a vector space model (VSM), where every word is represented by a point in some high-dimensional space. We refer to any model that automatically produces such a VSM as a semantic representation learning model, regardless of what underlying machine learning technique is used to learn it.

While much effort in the research community has been devoted towards improving *how* models learn word vectors, most work gives little consideration to *what* the model represents. They simply uses the standard distributional hypothesis, because of its simplicity and wide empirical success to learning representations that are useful for a host of downstream NLP tasks. They essentially use the same kind of *context* to extract and process count statistics, therefore biasing their learners with the same kind of semantic knowledge. So while word-embedding models may be learned differently, many of them continue to represent the same underlying information.

It should be noted that the distributional hypothesis is not the only way of converting raw text statistics into semantic representations. Turney and Pantel (2010) lists several other examples of hypotheses. These include the **bag-of-words hypothesis** (Salton et al., 1975), which conjectures that documents can be characterized by the frequency of words in it; the **latent relation**

hypothesis (Turney, 2008a), which proposes that pairs of words that occur in similar patterns tend to have similar relations between them; and the **extended distributional hypothesis** which specifies that patterns that occur in similar contexts have similar meaning. This is by no means a comprehensive list though, and there are others who have experimented with contexts in different ways as well (Baroni and Lenci, 2010; Xu et al., 2010).

In the terminology of Turney and Pantel (2010), each of these hypotheses yields a different representation matrix. These are, for example, a Term-Document matrix in the case of the bag-of-words hypothesis, or a Pair-Pattern matrix in the case of the latent relation hypothesis. The columns of these matrices are tied to our idea of *contexts*: they define the view of the data that can be leveraged to extract and process count statistics, and the values in these columns are the count statistics themselves.

An interesting question, in relation to this thesis, is whether there is any underlying connection between the different semantic hypotheses and their related contexts. We do not claim that this will necessarily be true for every different kind of semantic problem or context. However, we will show in what follows, that such a connection does exist, and that it can provide useful insight into a number of interesting semantic problems.

Semantic vectors in continuous space representations can be used for meaningful semantic operations such as computing word similarity (Turney, 2006), performing analogical reasoning (Turney, 2013) and discovering lexical relationships (Mikolov et al., 2013b).

These models have also been used for a wide variety of NLP applications including question answering (Tellex et al., 2003), semantic similarity computation (Wong and Raghavan, 1984; McCarthy and Carroll, 2003), automated dictionary building (Curran, 2004), automated essay grading (Landauer and Dumais, 1997), word-sense discrimination and disambiguation (McCarthy et al., 2004; Schütze, 1998), selectional preference modeling (Erk, 2007) and identification of translation equivalents (Hjelm, 2007).

Nevertheless, while they have been widely successful, representation learning models for semantics often fail at capturing many common linguistic phenomena. Semantic *compositionality* and *antonymy* are just two examples of phenomena that are stumbling blocks to many common vector learning approaches.

And this failure stems, not from *how* the representations are learned, but rather *what* semantic information is captured by them. In other words, the problem lies with the contexts that are used to bias the representation learner, and tell it what semantic units should have similar representations to one another. Most often the distributional hypothesis (i.e. the word-neighborhood context) is used. And while it continues to be very influential for its simplicity and effectiveness, it remains an incomplete explanation for the diversity of possible expressions and linguistic phenomena in all of natural language.

For example, compositionality is a basic property of language where unit segments of meaning combine to form more complex meaning. The words "big", "brown" and "cow" all have unique meanings, and when put together produce a precise semantic meaning – a "big brown cow" – that is more than just big-ness, brown-ness or cow-ness. But in a VSM, where the unit segments are words, it remains unclear – and according to previous work non-trivial (Mitchell and Lapata, 2008) – how the vectors for words should be combined to form their compositional embedding. From the perspective of the distributional hypothesis, there is no signal in the neigh-

borhood context of "big" or "brown" that says precisely how these words should modify the representation of "cow".

Another example of a language phenomenon that is difficult to capture is antonymy. Words such as "good" and "bad" are semantic inverses, but are often contextually interchangeable. You can have a "good day" or a "bad day", eat a "good meal" or a "bad meal" and watch a "good TV show" or a "bad TV show". Thus, based on the distributional hypothesis, which relies on the contextual neighborhood of words, the vectors assigned to "good" and "bad" would be very close in the resulting semantic space. Again, the neighborhood context of words is not ideal for differentiating between synonyms and antonyms.

Yet another property of language that standard representation learning techniques are incapable of handling is polysemy, where an identical surface form has more than one meaning. For example, the word "bank" may refer to a financial institution or the shore of a river. Because representation learning techniques are unsupervised and operate on large unannotated corpora, the string "bank" is treated as a single semantic unit, despite the fact that it has more than one sense. From the perspective of context, the neighborhoods of the different senses are conflated and only a single representation is learned.

Of course, there are ways of making the standard word-neighborhood template work for these problematic linguistic phenomena. For example, Turney (2008b) and Turney (2011) make modifications to the distributional hypothesis in order to be able to distinguish synonyms from antonyms. Meanwhile, Pantel and Lin (2002), Reisinger and Mooney (2010) and Neelakantan et al. (2014) also make changes to the same template to get it to work for representation learning of word sense. Other simplistic ways may exist too: for example, pre-annotating a corpus with senses before learning sense embeddings directly from the data[7].

In any case, with these modifications, the word-neighborhood context is no longer the same. We may be representing word-windows, but over neighborhood contexts of different kinds. Thus the relation between a word and its context is, from the perspective of representation learning, different.

To summarize, the word-neighborhood context is useful, but does not capture the varied semantic phenomena in natural language. While modifications to this template can be made, in order to account for some kinds of problems, other richer contexts may provide deeper insight into the problems we deal with. In this thesis, we will attempt to provide precisely these kinds of richer, more structured contexts in order to help bias representation learners to capture problematic semantic phenomena.

But this naturally begs the question: what is the right (or at least better) context for any given specific semantic phenomenon? In the next section we formalize and outline some ideas on how to tackle this problem. Note that defining the right context is a non-trivial problem. This thesis only hopes to provide examples of how to use better contexts for learning better representations for specific use cases, and a framework within which to think of possible future solutions. It does not claim to present a solution to every possible natural language semantic problem. Nor does it hypothesize an over-arching view of all of semantics.

[7]Although we show that this is not the best approach, and leads to poor empirical results. See Chapter 3.4 for details.

1.2 Semantic and Contextual Relations

Consider a semantic property such as similarity, and assume that we are interested in training learners of semantic representations that capture the notion of similarity. What is similarity?

We propose that similarity is an instance of a **semantic relation**. Semantic relations are, broadly speaking, properties of language or our data that we care about and wish to represent. So, for example, other properties like relatedness, antonymy and polysemy are also semantic relations. Semantic relations can also be properties that do not have a specific name – such as the connection between cells in a table – but that we still want to capture with our representations.

In short, we refer to semantic relations in the context of representation learning as any property that we expect to compute from a comparison of representation units. They are, essentially, the desired outputs of our representation learning models. For example, suppose that we have a semantic vector space model that we think has captured the *similarity* relation. We can test our assumption by comparing the representations of "cat" and "feline", and "cat" and "violin". A good model of similarity will assign a higher score to the first pair than the second, while a bad model might do the opposite or be unable to clearly differentiate between the two.

Let us thus define a semantic relation as the following.

Definition 1. *Consider one set of target object types* $\Omega^A = \{o_1^A, ..., o_N^A\}$ *and another set of target object types* $\Omega^B = \{o_1^B, ..., o_M^B\}$*. A semantic relation* $\mathcal{R}_s$ *capturing a property* $\mathcal{P}_s$ *is a mapping of the ordered cross-product of the two sets into the set of real numbers* $\Omega^A \times \Omega^b \implies \mathbb{R}$*.*

Here, and in what follows we will use the word "object" in its broadest sense to mean any cognitive atom. This could be a word, a word sense, a phrase, a sentence, or any textual or even non-textual phenomenon such a visual thing, etc. Moreover, note that we qualify the object types in the definition above by specifying them as *targets*. This distinction will become important when we introduce our next definition, but in general the *target* objects are those for which we wish to learn representations.

For the sake of simplicity, we shall only consider binary relations in this thesis – and in fact, binary relations are adequate to capture many semantic phenomena that NLP researchers care about. Besides, in representation space, comparison functions (such as dot-products or cosines) are typically defined between two objects (typically vectors) anyway. It should be noted, however, that certain semantic phenomena (e.g. buying and selling), are more naturally captured by higher-order relations. The definition above is not limited to binary relations and can be extended to encompass semantic relations with more than two objects.

Notice, that by this definition the only difference between models that have identical object sets, but whose goal is to capture different semantic relations, is the mapping to the set of reals. This intuitively makes sense because we expect, for example, a model of synonymy to score comparisons between words differently than a model of relatedness.

Broadly speaking, the goal of semantic representation learning then is to find representations whose comparison accurately reflects a semantic relation we care about. But how do we train our representation learners to capture specific semantic relations of interest? In other words, what should we give our models as input, in order for them to learn and compute the specific outputs we desire?

Semantic relations, such as similarity and relatedness, aren't self-evident in natural language text and obtaining annotated data that encodes these relations defeats the purpose of the representation learning paradigm in the first place. Thus we can't simply learn a semantic relation directly from data.

Recall from the previous section that with the generally unsupervised paradigm of representation learning, there are only two ways of controlling the end result. Namely they are defining *how* our models are learnt, and *what* semantic property they capture. These correspond to specifying our model, learning process or architecture, and articulating the *contexts* that represent the model's view of the data. While both these factors control the mapping of pairs of objects in semantic space to the set of real numbers, in this thesis we shall focus on the latter in order to control the inputs to our models, and consequently bias them. It may be argued that, in fact, the input *view* may be even more important than the model in order to gain insight into a representation learner's ability to learn distinctly different semantic relations. This is because contexts are our means of biasing learners of representations to capture specific semantic relations.

Given that contexts are the inputs to our models, we propose that articulating different or richer contexts is the only way of learning models that fundamentally encode different semantic relations. But how do we operationalize our intuitions about semantic relations into specific types of context on which models can count, process and learn representations? Namely, how do we define and make counts over our inputs (i.e. contexts) so that they produce the outputs (i.e. semantic relations) we care about? We propose that **contextual relations** are the key to bridging this gap. They are a compact way of specifying the inputs to our model.

Very generally, contextual relations are functions of the data that define inputs, which have some common shared property. The inputs are of the form "(target, context)", where the target is what we *want* to learn representations for (see Definition 1), and the context is its corresponding *view* of the data. Moreover, contextual relations map these target-context pairs to some statistical measure of association.

We will clarify this with a few examples before providing a formal definition.

Consider the similarity relation, which has been conveniently operationalized in Firth (1957) by the intuition that words that tend to occur in similar neighborhood contexts tend to have similar meaning. This operationalization has been encoded in previous semantic representation learning literature as the *word-neighbor-word* contextual relation. We can summarize this relation by the following:

- **Targets** are words in a corpus.
- **Contexts** are other words in the neighborhood of targets.
- **Measure of association**, or weight, is some function of frequency – for example, co-occurrence probabilities, PPMI values (Bullinaria and Levy, 2007) or vector dot-products as is the case with a model like Skip-gram (Mikolov et al., 2013a).

Contextual relations can also be defined over static lexicons, such as WordNet, where types rather than tokens are the units of representation. Consider the synonym relation from WordNet. We can summarize this relation by the following:

- **Targets** are word senses in WordNet.
- **Contexts** are other word senses that belong to the same synsets as targets.

- **Measure of association**, or weight, is – in the simplest case – 1.0, which indicates the existence of a synonym relationship between target and context and 0.0 otherwise.

Other examples from Turney and Pantel (2010) can be similarly encoded as contextual relations: the bag-of-words hypothesis is in fact a *belong-to-same-document* contextual relation, and the latent relational hypothesis is in fact a *word-neighbor-pattern* contextual relation, with various models (e.g. TF-IDF, PMI) designed to assign the numerical measure of association to target-context pairs. Note that these are just informal relation names that we have assigned to illustrate as examples. We will now formalize this.

We define a contextual relation in the following way:

Definition 2. *Consider one set of target object types $\Omega^A = \{o_1^A, ..., o_N^A\}$ and another set of context object types $\Omega^C = \{o_1^C, ..., o_M^C\}$. A contextual relation $\mathcal{R}_c$ that associates targets and contexts with a shared property $\mathcal{P}_c$ is a mapping of the ordered cross-product of the two sets into the set of real numbers $\Omega^A \times \Omega^C \implies \mathbb{R}$.*

Again, we use "object" in its broadest sense here as in Definition 1.

Note that it is important to explicitly tie target-context pairs to measures of associations, or weights (i.e. the mapping to the set of reals). Turney and Pantel (2010) explicitly tie *frequency* to all the different hypotheses (i.e. contextual relations) and the corresponding representation matrices they describe. And this is certainly true: frequency is inalienable from meaning when attempting to learn representations from a corpus. Every semantic representation learning model is *always* learned by performing some counting or processing over contexts. Even in the case of a model that simply mimics a static lexicon such as WordNet, the counts are binary values indicating the presence or absence of a relational edge.

Definitions 1 and 2 – dealing with semantic and contextual relations respectively – seem very similar, but they are subtly different in three important ways. First, semantic relations specify the desiderata of our models, while contextual relations specify how these desiderata are fulfilled. Therefore, when we talk about the property $\mathcal{P}_s$ of Definition 1, it is a desired output, while when we talk about the property $\mathcal{P}_c$ of Definition 2, it is an engineered input. Second, semantic relations are mappings between pairs of target objects to reals, while contextual relations are mappings of target and context object pairs to reals. Finally, the mappings to the reals is directly computed from the data (or specified heuristically) in the case of contextual relations, while it is a result of the model in the case of semantic relations.

Let us return to models that learn representations of words based on the distributional hypothesis. The following summarizes the inputs to this class of models and their mapping to the reals, in terms of a contextual relation:

- Ω^A are word types in a corpus.
- Ω^C are also word types in a corpus.
- $\mathcal{P}_c$ is defined by $|i(o_n^A) - i(o_m^C)| \leq k$, where $i(\cdot)$ is a function that returns the index of a word token, and k is the *neighborhood* parameter.
- The mapping between target-context pairs and the reals – $f(o_n^A, o_m^C) \implies \mathbb{R}$ – is specified by the function f. f, in the case of distributional models, is typically some function of frequency obtained by sampling from a corpus.

This contextual relation view of semantic representation learning also allows us to explain the failures of existing models. A model that is learned with the distributional hypothesis does not accurately capture antonymy simply because antonymy require a different relation than the *word-neighbor-word* relation. In other words, the property $\mathcal{P}_c$ of Definition 2 is (or should be) different for synonyms and antonyms. More generally, some structural or relational information has been ignored or misrepresented by using the *word-neighbor-word* relation, and therefore the resulting model has not been properly biased to recognize antonymy.

Expanding on the definition of a contextual relation we define structure over relations as the following.

Definition 3. *Consider the set of contextual relations $\mathcal{R}_{c1}, ..., \mathcal{R}_{cK}$ defined over the object set pairs $(\Omega_{A1}, \Omega_{C1}), ..., (\Omega_{AK}, \Omega_{CK})$ with corresponding properties $\mathcal{P}_{c1}, ..., \mathcal{P}_{cK}$ and mappings to the reals $(\Omega_{A1}, \Omega_{C1}) \implies \mathbb{R}, ..., (\Omega_{AK}, \Omega_{CK}) \implies \mathbb{R}$. A structure over contextual relations $\mathcal{S}_c$ is a mapping $(\Omega_{A1}, \Omega_{C1}), ..., (\Omega_{AK}, \Omega_{CK}) \implies \mathbb{R}^K$.*

This is a very natural extension to contextual relations that allows us to conceive of and use more complex structure. Consider the example of an ontology such as WordNet. We can summarize its structure in terms of Definition 3 by the following:

- $\Omega_{A1}, ..., \Omega_{AK}$ are all word sense types in WordNet.
- $\Omega_{C1}, ..., \Omega_{CK}$ are also all word sense types in WordNet.
- $\mathcal{P}_{c1}, ..., \mathcal{P}_{cK}$ are the different edge types in WordNet, such as synonym, hypernym, hyponym etc.
- Finally, the mapping $(\Omega_{A,1}, \Omega_{B,1}), ..., (\Omega_{A,K}, \Omega_{B,K}) \implies \mathbb{R}^K$ is simply the vectorized form of the different individual mappings of the relations $(\Omega_{A1}, \Omega_{C1}) \implies \mathbb{R}, ..., (\Omega_{AK}, \Omega_{CK}) \implies \mathbb{R}$. Each of these individual mappings is, in the simplest case, a binary value indicating the existence of a specific edge type (e.g. synonym, hypernym, hyponym etc.) between word sense pairs.

By considering the two definitions of relation and structure together, we obtain the following corollary.

Corollary 1. *Structure is decomposable into a set of objects and relations.*

With these definitions and corollary, we note that contextual relations and structure are in fact two inherently interconnected phenomena. In this thesis we will often deal with some linguistic structure and attempt to break it down into contextual relations upon which our models can operate and learn representations.

Figure 1.1 visually encapsulates the cycle from defining semantic relations, to learning representations that capture these relations. It also presents a convenient summary of our approach to relation-centric semantic representation learning.

The cycle begins with articulating a semantic relation of interest, that is to say the goal output of our model. It then intuits about what contexts may be useful for capturing and encoding this semantic relation. The next step then proceeds to operationalize this intuition by defining contexts in terms of contextual relations with a common shared property. Finally, some definition,

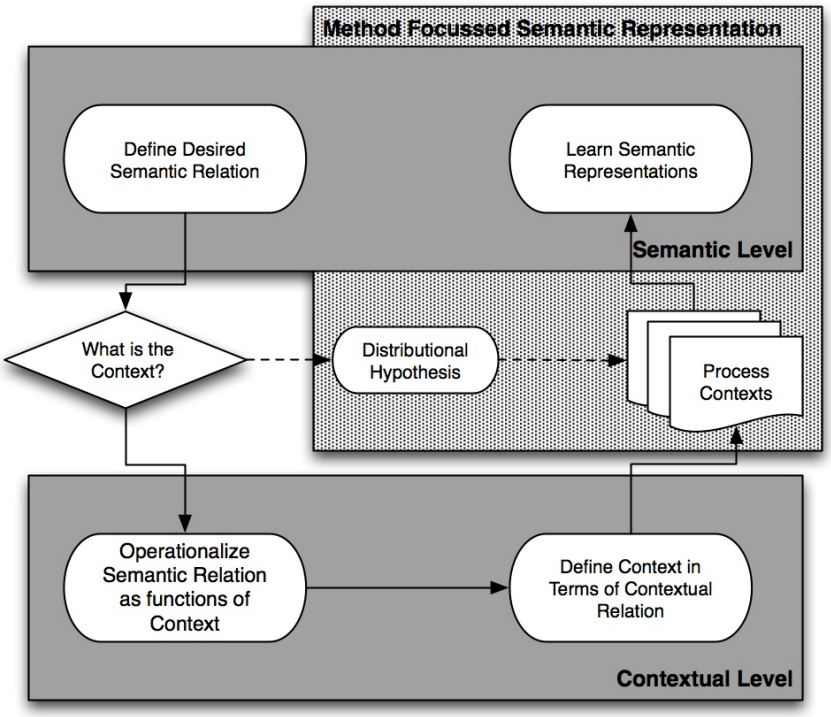


Figure 1.1: A summary of our approach to relation-centric representation learning and how it differs from models that simply use the distributional hypothesis as a base for operationalizing contexts.

counting or processing associates weights to the contextual relations and thus biases the learner to capture the semantic relation we care about (ideally).

The figure also illustrates, in contrast, a very commonly used pipeline (the dotted grey area) that simply operationalizes the distributional hypothesis and learns representations from word-neighbor-word contexts.

Of course this view does not represent a comprehensive solution to all of representation learning. Therefore, what we present in this thesis is not a recommendation of how all semantic representation learning research should progress in the future. Nor is it a panacea for every learning problem in semantics.

One of the major challenges with our relation-centric approach is to creatively think about contexts that can capture a desired semantic relation, and to operationalize these via some structure or contextual relations. This may not always be easy, or even possible. Consider the example where we set ourselves the goal of learning the specific set of PropBank relations[8]; these are effectively the semantic relations we wish to learn. Short of furnishing the model with a few million examples of predicates and arguments, annotated PropBank style, there is no way of ensuring that the model will learn exactly what we want it to learn. This, of course, defeats the purpose of using the representation learning paradigm in the first place, since we would require vast amounts of annotated data. In general, the more specific or restricted the requirements of a desired semantic relation the harder it is to operationalize via a contextual relation.

Nevertheless, our relation-centric approach brings a way of coding knowledge and featurization into the representation learning paradigm. Therefore, we believe that this is a useful framework for thinking about the kinds of information and knowledge that are captured by semantic models, and providing solutions to certain challenging semantic learning problems. And the applied examples of this framework that we provide in the rest of thesis are broad-ranging and diverse enough that they substantiate this belief.

Relations and structure in language are ubiquitous. Turney (2007a) makes the point that relations are primary to producing meaning in language. He argues that even an attributive adjective like the color "red" is in fact a relation, a property that is "redder" than something else. Relations can even be defined over other relations. Such meta-relations can capture complex linguistic phenomena like describing the inherently linked acts of buying and selling, and the repercussions on ownership of goods and money.

Figure 1.2 illustrates just some of the sources of information where we discover and use structure and operationalize contextual relations to learn representations of semantic relations that we care about in this thesis.

In summary, putting relations at the center of our investigation allows us to come up with a common theme that bridges the gap between what semantic property we wish to learn (i.e. semantic relation) and how we learn it from data (i.e. contextual relation).

Answers to the question "What does the model represent?" are simply instances of different semantic relations. At the same time, different problems require access to different linguistic information, or views of the data, to be properly encoded. Thus, understanding, defining and

[8]We learn a set of semantic argument slots in Chapter 5, but we do not impose any restrictions on the slots a priori – like making them map exactly to PropBank slots.

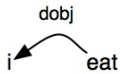
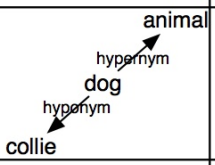
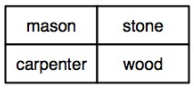
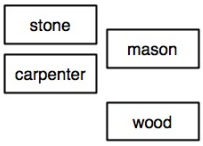
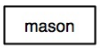
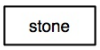
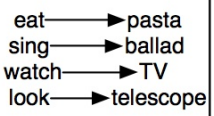
SOURCE	STRUCTURE	OBJECTS	RELATIONS	CONTEXT
DEPENDENCY RELATIONS		i, eat	dobj	**Target:** eat **Context:** i
ONTOLOGIES		collie, dog, animal	hypernym, hyponym	**Target:** dog **Context:** animal
TABLES			Latent but enumerable, e.g. (belong to same row) (belong to same col)	**Target:**  **Context:** 
PATTERNS	X causes Y Y caused by X	X, Y	Latent and un-enumerable	**Target:** eat, pasta **Context:** i [...] with fork
PREDICATE ARGUMENT PAIRS		PREDS, ARGS	Latent and un-enumerable	**Target:** sing **Context:** ballad

Figure 1.2: Examples illustrating various sources of information exhibiting the dual nature of structure and relations. Note how Definitions 2 and 3, as well as Corollary 1 apply to each of these examples. All these sources of relations and structure are used in this thesis.

leveraging the correct (or at least more expressive) contextual relation and structure are crucial in learning better representations of semantic relations.

1.3 Contributions of this Thesis

Formally, we propose the central conjectures of this thesis:

1. Relations are central to producing and understanding meaning in language.
2. Semantic representation learning models essentially capture semantic relations.
3. Context is one of the few ways of biasing an unsupervised representation learning model to capture a specific semantic relation. Correctly operationalizing context is crucial in learning good semantic representations.
4. Different linguistic phenomena require different contextual relations and structure, in order to be optimally represented.
5. Articulating the right (or at least) better contextual relation and structure for a particular problem often leads to more expressive and empirically superior models of semantic representation learning.

This thesis substantiates these conjectures with evidence for several different semantic problems. The problems are selected to represent a broad range of linguistic phenomena and sources of contextual relations and structural knowledge. So while our framework may not capture all of semantics, our examples still demonstrate the applicability of our hypotheses to fairly broad-ranging and diverse problems. The problems also provide an example-based narrative which we study to suggest a framework for relation-centric representation learning. This framework suggests a way to think about and implement solutions for integrating relations and structure in semantic representation learning.

In Chapter 2 we introduce our framework as a series of five research questions, each tackling a sequential set of themes related to relational modelling in representation learning. We suggest possible answers to these research questions by citing instances from this thesis as well as analyzing the different aspects related to each theme. In summary the five themes deal with:

1. Formulating a representation learning problem centered around the question "What should be represented?", and defining a semantic relation of interest.
2. Finding a source of information that encodes knowledge about the learning problem.
3. Decomposing the information into a set manageable structural units and defining contextual relations over these units.
4. Formulating an objective or model for the learning problem, that biases the learner with the contextual relations and associates weights to target-context pairs.
5. Characterizing the nature of the learned model and evaluating it to see if it actually captures the semantic relation we set out to learn. The goal of the evaluation is to justify the central claims of this thesis – namely that using relations and structure in representation learning leads to more expressive and empirically superior models of semantics.

The rest of the thesis is organized as instantiations of this high level framework for several different semantic problems. While all these chapters fall into the broader theme of this thesis, we can divide them organizationally into two distinct parts.

The first part, consisting of Chapters 3 and 4 deal with leveraging existing structural and relational data to improve representation learning models for different problems. In the second part, which contains Chapters 5 and 6, we will investigate problems where there is no existing structure or relational data. Rather we will attempt to induce structure and relations and embed representation learning models with them. Nevertheless, all four chapters can be formulated in terms of a target semantic relation, and it's operationalization in learning via some contextual relations. The contributions of each of the main chapters are summarized in what follows.

Chapter 3 introduces work published in Jauhar et al. (2015). It deals with the problem of polysemy in semantic representation learning. In particular it introduces two models that learn vectors for polysemous words grounded in an ontology. The structure of the ontology is the source of contextual relations that we use to guide our techniques. The first model acts as a simple post-processing step that teases apart the different sense vectors from a single sense vector. It is computationally efficient and can be applied to any existing technique for learning word vectors from unannotated corpora. The second builds on the first and introduces a way of modifying maximum likelihood representation learning models to also account for senses grounded in an ontology. We show results on a battery of semantic tasks, including two additional sets of results not published in Jauhar et al. (2015) – one of which shows that our model can be applied to deal with antonymy as well.

In Chapter 4 we deal with the semi-structured representation of knowledge tables for the task of question answering. Our paper, Jauhar et al. (2016a), places relations at the center of our investigation. First, we leverage the contextual relations between cells in tables to guide non-expert annotators to create a large dataset of high quality Multiple-Choice Questions (MCQs) with minimal effort (Jauhar et al., 2016b). Because of the set-up of our task, we obtain fine-grained alignments between MCQs and table elements as a by-product. We also introduce two different models that solve multiple-choice questions by using tables as a source of background knowledge. Crucially, both solutions leverage the structure and contextual relations present within tables to solve MCQs. The first solution is a manually engineered feature-rich model, whose features are based on the structural properties of tables. The second solution extends the intuition of the feature-rich model with a neural network that automatically learns representations over cells.

We look at the problem of relation induction in Chapter 5, within the context of embedded semantic lexicons. This work is published in Jauhar and Hovy (2017). It represents a novel integration between a predictive maximum likelihood model and an Indian Buffet Process to induce an embedded semantic lexicon that contain a set of latent, automatically generated relation slots. A key contribution of this model is that it requires no high-level annotations – such as dependency information – and can learn slots by only accessing a corpus of predicate-argument pairs. Our proposed solutions jointly leverages two types of contextual relations: local token level affinities as well as global type level affinities between predicates and arguments to arrive at an understanding of the latent slot structure. Quantitatively as well as qualitatively, we show that the induced latent slots produce an embedded lexicon that is semantically expressive and that captures several interesting properties of known, manually defined semantic relations.

Chapter 6 deals with the problems of contextual variability of word meaning, and facetted comparison in semantics. We introduce two solutions for these problems, both bound by a common modelling paradigm: tensor based representation. In a tensor representation the semantic signature of a standard word vector is decomposed into distinct relation dimensions. We instantiate this modelling paradigm with two kinds of relations: syntactic and latent semantic relations, each leading to a solution for the two central problems of this chapter. The models we develop are published in Goyal et al. (2013a), Goyal et al. (2013b) and Jauhar and Hovy (2014).

Finally, in Chapter 7, we conclude with a look back at the contributions of this thesis and suggest avenues for future research that merit investigation.

Chapter 2

Relational Representation Learning

A Framework for Using Semantic Relations in Lexical Representation Learning

Given our definitions of relations and structure in Definition 2 and 3, many linguistic properties, knowledge resources and computational phenomena can be said to exhibit relational and structural attributes. Moreover, there are many different ways that these phenomena can be used to bias existing methods of representation learning.

Hence, within the scope of our goal of proving a relation-centric view of semantic representation learning, it is difficult to come up with a single mathematical framework through which all semantic representation learning techniques may be viewed. Even if we were to propose such a framework, it isn't clear whether it would simplify an understanding of the models we deal with, nor the contexts that they rely on.

Instead, we propose an example-based scheme to illustrate our use of relations in learning semantic models. The scheme sequentially highlights a number of recurring themes that we encountered in our research, and we structure our illustration as a series of questions that address these themes. The question-theme structure allows us to focus on observationally important information while also proposing an outline for how to apply our example-based framework to a new domain. The examples we cite from this thesis for each theme will illustrate the diverse range and flexibility of using contextual relations in representation learning.

In summary, the five research questions we address, along with the themes that they expose are:

1. What is the semantic representation learning problem we are trying to solve?

   Identify a target representation learning problem that focusses on what (linguistic) property needs to be modelled. That is, specify the semantic relation to be learned.

2. What linguistic information or resource can we use to solve this problem?

   Find a corpus-based or knowledge-based resource that contains information relevant to solving the problem in item 1.

3. How do we operationalize the desired semantic relation with contextual relations in the resource?

   Discover useful structure that is present in the linguistic annotation or knowledge resource.

Furthermore, operationalize any intuitions about the semantic relation from item 1 via contextual relations. Define and generate actual contexts with the common shared property of contextual relations.

4. How do we use the contextual relations in representation learning?

   Think about an objective or model that maps target-context pairs into the set of reals, in order to fully specify the contextual relations from item 3.

5. What is the result of biasing the learner with contextual relations in learning the semantic model?

   Evaluate the learned model to see if the influence of contextual relations has measurably affected the learning of the semantic relation in item 1. Possibly characterize the nature of the learned model to gain insight on what evaluation might be appropriate.

We should stress that the set of questions and themes we describe is by no means complete and absolute. While useful as guidelines to addressing a new problem, they should be complemented by in-domain knowledge of the problem in question.

This chapter should be viewed as a summary of the thesis as well as a framework for applying our ideas to future work. The framework is outlined by the research agenda listed above. In the rest of this chapter we delve further into each of the five questions of our research agenda.

In the section detailing each of the five research questions, the final paragraph – which is formatted as a quotation block, for visual clarity – summarizes the high-level findings of this thesis as they relate to the respective questions. If only interested in these high-level findings the reader should feel free to skip over the examples from the thesis that we list in order to flesh out the findings. Skipping over those parts of this chapter will not affect the comprehensibility of the rest of the thesis.

Additionally, at the end of each chapter in the rest of the thesis, we will return to this five-point theme. This will not only serve as a summary of each chapter, but will tie the contents of that chapter back to our central goal of relation-centric representation learning.

What is the semantic representation learning problem we are trying to solve?

As detailed in our introduction this is a thesis about representation learning that focusses more on the question of *what* is being learned, rather than *how* it is being learned. Hence, the first and most fundamental question needs to address the issue of what semantic representation learning problem is being tackled. We have named this desiderata as the *semantic relation* to be learned (see Section 1.2).

Many existing methods for semantic representation learning operate on the intuition of the distributional hypothesis (Firth, 1957). Namely, that words that occur in similar contexts tend to have similar meanings. But as we have argued in Chapter 1, this hypothesis – while extremely useful – does not cover the the entire spectrum of natural language semantics. In fact, every different semantic understanding problem requires a specific relation and corresponding *context* to properly express and represent it.

In this thesis, for example, we tackle several different problems that do not fit into the mould of the word-neighborhood context that is engendered by the distributional hypothesis. We ad-

dress the problem of contextual variability (Blank, 2003) in Chapter 6.2, where the meaning of a word varies and stretches based on the neighborhood context in which it occurs[1]. Another problem with semantic vector space models is the facetedness in semantic comparison (Jauhar and Hovy, 2014), whereby concepts cannot be compared along different facets of meaning (e.g. color, material, shape, size, etc.). We tackle this problem in Chapter 6.3. Yet another issue with distributional semantic models is their incapacity to learn polysemy from un-annotated data, or to learn abstract types that are grounded in known word senses. We propose a joint solution to both problems in Chapter 3.

Not all problems are necessarily linguistic shortcomings. For example, our work in Chapter 5 is motivated as a shortcoming of data and linguistic resources in learning a semantic lexicon, not of the representation problems themselves.

Another example is our work in Chapter 4, which tackles a representational issue, not a linguistic one: namely the trade-off between the expressive power of a representation and the ease of its creation or annotation. Hence our research focusses on semi-structured representations (Soderland, 1999) and the ability to learn models over and perform structured reasoning with these representations. In similar fashion, the models we propose in Chapter 6 – while tackling specific linguistic issues – are also concerned with schemas: moving from vectors to tensors as the unit of representation Baroni and Lenci (2010).

> In summary, the first step in our sequence of research questions is to address the central issue of what is being represented. We need to articulate the semantic relation that we want our model to capture. Any problem is legitimate as long as it focusses on this central research question. In our experience, generally problems will stem from issues or shortcomings in existing models to represent complex linguistic phenomena, but they could also concern (sometimes by consequence) the form of the representation itself.

What linguistic information or resource can we use to solve this problem?

Once a representation learning problem has been identified, the next item on the research agenda is to find a source of knowledge that can be applied to the problem. Naturally this source of knowledge should introduce information that helps to solve the central problem.

In our experience, there seem to be two broad categories of such sources of knowledge. First there is corpus-based information that is easily and abundantly available as naturally occurring free text, or some level of linguistic annotation thereof. For example, this category would cover free text from Wikipedia, it's part-of-speech tags, parse trees, coreference chains, to name only a few. Second are knowledge-based resources that are compiled in some form to encapsulate some information of interest. For example, these could be ontologies, tables, gazetteer lists, lexicons, etc.

The two categories are, of course, not mutually exclusive: for example a treebank could be reasonably assumed to belong to both categories. Moreover there is no restriction on using a

[1]Not to be confused with polysemy, which Blank (2003) contrasts with contextual variability in terms of a lexicon. The former is characterized by different lexicon entries (e.g. "human arm" vs "arm of a sofa"), while the latter is the extension of a single lexicon entry (e.g. "human arm" vs "robot arm"). Naturally, the distinction is a continuum that depends on the granularity of the lexicon.

single source of knowledge. Any number of each category can be combined to bring richer information to the model.

Examples of the first category of sources of information in this thesis are dependency information (Nivre, 2005) (Chapter 6.2 and Chapter 5), textual patterns (Ravichandran and Hovy, 2002) (Chapter 6.3), and predicate-argument pairs (Marcus et al., 1994) (Chapter 5). Similarly, examples of the second category of sources of knowledge include ontologies (Miller, 1995) (Chapter 3) and tables (Chapter 4).

In each of these cases we selected these sources of knowledge to bring novel and useful information to the problem we were trying to resolve. For example, ontologies contain word sense inventories that are useful to solving the problem of polysemy in representation learning. Similarly dependency arcs define relational neighborhoods that are useful for creating structured distributional semantic models or yielding features that can be used to find the principal relational arguments of predicates. Predicate-argument structures provide weak, latent cues that can be aggregated to arrive at an understanding of semantic frames.

> To sum up, the goal of the second research question is to identify a resource or resources that can be used to resolve the central representation learning problem proposed in response to the first research question. In our experience resources fall into two broad (possibly overlapping) categories: corpus-based and knowledge-based.

How do we operationalize the desired semantic relation with contextual relations in the resource?

This item in the research agenda is perhaps the most important and often the most difficult. It deals with making the connection between the desired semantic relation to be learned (i.e. item 1) and the best way of consuming the data or resource (i.e. item 2). In other words, it requires specifying some contextual relations with contexts that share some common property over the resource.

There is no systematic way of engineering contextual relations. Rather they require creativity and domain knowledge, much like machine learning models that require manually coded and engineered features. This should not be surprising since we propose that it is contextual relations that provide a way of injecting linguistic, domain or world knowledge into the class of unsupervised representation learning techniques.

In our experience, defining a set of useful contextual relations stems from an intuition about the original semantic relation to be learned. But in addition to this vague guideline, there is often something concrete that can be done to make the connection between semantic and contextual relations easier. This is done by recognizing the existing structure in the knowledge resource and articulating the relations within this structure. This systematic decomposition of the resource can lead to insights about the semantic relation and suggest ways of defining contextual relations over the data.

At face value, identifying the structure and relations within a resource may seem like a simple exercise of listing items. And this is, in fact, the simplest use case for well-defined and carefully crafted resources.

In this thesis, the most direct uses of structure and relations involves our work on ontologies (Chapter 3). Here the ontology is a carefully conceived graph structure with typed edges that

relate word senses to one another. Our work on tables (Chapter 4) also largely falls into this category, where the structure is constant and well-defined. However, the structure itself is not typed or even explicit. Rather, it stems from the inherent relations between table cells, which interact with one another in a number of interesting ways (see Chapter 4.2.1). Analogies (Turney, 2013), for example, are one type of semantic property that is naturally embedded in tables, and comes directly from the relations between table cells.

However, in the absence of such well-defined structure, there are several challenges to identifying and using the relations in a resource.

When the relations are latent rather than explicit, the goal of the model may be to discover or characterize these contextual relations in some fashion. This is not the case with our work on tables, where relational properties between table cells are only leveraged but are not required to be directly encoded in the model. In contrast our work on latent tensor models (Chapter 6.3) and event argument induction (Chapter 5) both require the latent relations to be explicitly learned as parts of the resulting representations.

There is also the problem of resources that do not specify a closed class of definite relations at all. This is the case with our work on Structured Distributional Semantics (Chapter 6.3), for example, when we attempt to extract relational patterns from free text. There is simply no way of enumerating all possible patterns beforehand, and even the patterns that are harvested number in the many millions and are consequently very difficult to manage. Similarly, in our work on Lexicon Induction (Chapter 5), the set of relations between predicate-argument types cannot be enumerated beforehand.

However, identifying properties of the relations and structure can lead to insight that makes the space of un-enumerable relations more manageable. For example, the pattern relations or predicate-argument relations are likely to follow a Zipfian distribution. This insight can be used to select and only use the most frequent relation that occur in the data. Similarly when one is considering relations in a dependency parse tree (Chapter 6.2), it may be useful – for example – to note that the tree is projective (Nivre, 2003). In general, insights into these facets can lead to computationally desirable models or algorithms, as we will note in the our next research question.

There is, of course, an inherent trade-off between the linguistic complexity or abstractness of a contextual relation, and its ability to be harvested or leveraged for learning word vectors. The distributional hypothesis, for example, encodes a simple relation that can be abundantly harvested from unannotated text. More complex relations, such as those defined over ontologies (Chapter 3) or tables (Chapter 4) are fewer and harder to directly leverage. In this thesis we sometimes supplement the distributional hypothesis with other forms of relational information (such as ontological relations), while at others, completely replacing it with some other form of more structured data (such as tables). We show that the inherent tension between complexity and availability in the data is resolved because even small amounts of structured data provide a great amount of valuable information.

> In conclusion, making the connection between a semantic relation and expressive contexts that can bias learners to capture this semantic relation is hard. Defining contextual relations often stems from operationalizing some intuition about the desired semantic relation. However, a more concrete step can also be taken to aid in this creative process. This involves analyzing and articulating the structure and

relations that can be extracted from the resources.

Specific kinds of structure, such as graphs or trees for example, have well-defined relational structure. These can lead to computational models or algorithms that can leverage the structural properties through principled approaches specifically designed for them. More generally, the wealth of research in structured prediction (Smith, 2011) is applicable to the scope of our problems since it deals with learning and inference over complex structure that is often decomposable into more manageable constituents, – which is exactly how we define the link between contextual relations and structure in Definitions 2 and 3, and Corollary 1.

Finally, when the relations and their resulting structure are latent or un-enumerable, it may be required to induce representations that encode and consolidate the latent or un-enumerable relations into the model. In these cases, too, insights into the properties of the relations and underlying structure can help in developing models or learning solutions that are more computationally attractive and practical.

How do we use the contextual relations in representation learning?

The next research question on the agenda deals with the actual modelling problem of assigning a real valued score to pairs of target and context objects. This is an important step in order to convert raw contexts into some summary statistic and thereby fully specify the contextual relation defined in item 3.

Here there is considerable flexibility, since there is no single correct way of integrating intuitions and observations about the target domain into a model – and no guarantee that once one does, that it will function as expected.

Nevertheless, we draw a distinction here between defining an objective and a model. The former attempts to encode some mathematical loss function or transformation (such as maximum likelihood, or singular value decomposition) that captures the desiderata of a problem, while the latter specifies a model that will numerically compute and optimize this loss function (for example a recursive neural network or a log-linear model). The two are sometimes connected, and the definition of one may lead to the characterization of the other.

We note that our purpose for drawing this distinction is merely for the sake of illustrating our example-based framework. Hence, we will discuss the objective or model, as appropriate, when either one or the other more intuitively captures the use of relations or structure in the representation learning problem.

In this thesis we work with several kinds of transformations and objectives. An example of transformation based representation learning is singular value decomposition (Golub and Reinsch, 1970), which we use to reduce sparsity and noise in learning latent relations for our tensor model (Chapter 6.3).

Many existing semantic representation learning models are formulated as maximum likelihood estimation problems over corpora (Collobert et al., 2011; Mikolov et al., 2010). In our work with ontologies we propose a way to modify these objectives minimally with structured regularizers, thereby integrating knowledge from the ontological graph (Chapter 3). A very similar formulation is also applied to our work on semantic lexicon induction (Chapter 5), where we

maximize the likelihood of a corpus of predicate-argument pairs, while accounting for a structured regularizer that is defined over predicate embedding representations.

Also in our work with ontologies, post-processing is another method that we use to modify word vectors and derive sense representations. In this case, a maximum a-posteriori estimation over smoothness properties of the graph (Corduneanu and Jaakkola, 2002; Zhu et al., 2003; Subramanya and Bilmes, 2009) is more appropriate. Specifically we have a prior (the existing word vectors) which we'd like to modify with data (the ontological graph) to produce a posterior (the final sense vectors).

In the case of tables, we are dealing with a countable set of predictable relations over table cells. Featurizing these relations is the most direct way of encoding them into learning our model. Consequently we use a log-linear model (Chapter 4.5) which conveniently captures features (Smith, 2004). We can also leverage these relations to automatically induce features, which we do with a neural network model over table cells (Chapter 4.6. For both kinds of models, we use a cross-entropy loss.

In characterizing the argument structure of predicates in a semantic lexicon (Chapter 5), we wish to allow for a potentially infinite set of relations, while letting the data decide what a really meaningful set of relations should be. Hence we use the Indian Buffet process (Griffiths and Ghahramani, 2005), which is a Bayesian non-parametric model (Hjort et al., 2010) to precisely model feature learning in such a setting.

> Summarizing the theme of this part of the research agenda, we seek to concretize a specific model that efficiently and meaningfully assigns weights to target-context pairs in terms of contextual relations. The goal remains to solve the representation learning problem we originally defined, and capture the desired semantic relation. While there is a lot of flexibility in how this may be done, it can be useful to think about two aspects of the problem: the objective function and the actual model. Often one or the other presents an intuitive way of characterizing how relations or structure should be integrated, and the other follows directly or is left to empirical validation.

What is the result of biasing the learner with contextual relations in learning the semantic model?

Our final research item deals with the model after it has been learned. In short, we wish to characterize the quality of the learned model with respect to the semantic relation that it set out to capture. Moreover, we wish to measure the influence of the contextual relations on this quality. In this context, we discuss some differences in the models we learn in this thesis in an attempt to characterize them, and we also list how we evaluate them.

With regards to the learned model, there are several distinction. The most salient distinction, however, is between the case where contextual relations have simply been leveraged as an external influencer on learning models, versus cases where relations become part of the resulting model. In this thesis examples of the first case can be found in Chapters 3 and 4, while examples of the second case are Chapter 5 and Chapter 6.

In terms of evaluation, when specifically dealing with the latter of the two cases it is useful to evaluate the relations in the model in addition to the representations for vocabulary elements (which should be evaluated anyway). We do this in this thesis with a relation classification

task (Zhang, 2004) in Chapter 6.3 and two different evaluations on local token-level and global type-level relations between predicates and arguments in Chapter 5. Additionally, we qualitatively evaluate the relations in both relevant chapters by mapping them to know, manually-defined semantic relations to better understand how they represent information.

For the sake of completeness of our summary of the work in this thesis, we also list some less important distinctions about the models we learn. These need not be considered, in general when characterizing a learned model or thinking about how it will be evaluated. Most often semantic representation learning yields vectors, which is the case for our work on ontologies, tables and semantic lexicons (in Chapters 3, 4, and 5 respectively). But we also introduce tensor based semantic models (Chapter 6). In both kinds of objects, the numerical values that comprise them are most often abstract real numbers, as is the case with our models from Chapters 6.3, 3 and 4. But we also have models that are probabilistically normalized (Chapter 6.2) and binary (Chapter 5).

On the evaluation side, depending on the nature of the model and it's connection to the problem that it is attempting to solve, it is also useful to consider an intrinsic or an extrinsic evaluation. For general purpose semantic word vector (or tensor) models, such as the ones learned in Chapters 3 and 6 popular intrinsic evaluation tasks such as *word similarity judgement* (Finkelstein et al., 2002) and *most appropriate synonym selection* (Rubenstein and Goodenough, 1965) are adequate. For targeted models such as the one we learn over tables specifically created for question answering (Chapter 4), an extrinsic task evaluation is more appropriate. This is also the case for the evaluations that we conduct for our work on predicate-argument structure (Chapter 5).

> In summary, most importantly, – as with any good empirical task – the evaluation should directly gauge whether there was a measurable influence of using targeted contextual relations towards improving the quality of the representations in capturing the desired semantic relation. Sometimes, characterizing the nature of the learned model can lead to insights of what might be an appropriate evaluation.

In the rest of this thesis we detail instances of the application of this research agenda to several research problems and proposed future work. At the end of each chapter we will return to this agenda to summarize our findings and tie them back to our theme of relation-centric semantic representation learning.

Chapter 3

Ontologies and Polysemy

Using Ontological Relation Links to Learn Sense-specific Word Representations of Polysemy

Most approaches to representation learning for lexical semantics assign a single vector to every surface word type. This is a problem we encounter in Chapter 6.3 with respect to the issue of the multiple facets or relational arguments of concepts.

In this chapter we tackle a different problem, which however has its roots in the same representational issue with the vector space model. Namely, that words – across all human languages – are polysemous.

Models that assign a single representation to a unique surface form (such as vector space models) ignore the possibility that words may have more than one meaning. For example, the word "bank" can either denote a financial institution or the shore of a river.

The ability to model multiple meanings is an important component of any NLP system, given how common polysemy is in language. For example, knowing which of the senses of a word needs to be used in a Machine Translation system (Carpuat and Wu, 2007) to translate into another language can make the difference between a correct translation and a nonsensical one.

Much of the attractiveness of vector space models of semantics are their ability to be learned in an unsupervised fashion from vast amounts of unannotated data. Thus it is difficult for them to capture the different senses of words, when these senses are not annotated to begin with.

The lack of sense annotated corpora large enough to robustly train VSMs, and the absence of fast, high quality word sense disambiguation (WSD) systems makes handling polysemy difficult in the representation learning of semantics.

Meanwhile, lexical ontologies, such as WordNet (Miller, 1995) specifically catalog sense inventories and provide typologies that link these senses to one another. These ontologies typically encode structure and connectedness between concepts through relations, such as synonymy, hypernymy and hyponymy. Data in this form provides a complementary source of information to distributional statistics. Its relation-induced semantic structure also falls into the over-arching theme of this thesis as a potential source of structured knowledge that can be leveraged to learn more expressive models of semantics.

Recent research tries to leverage ontological information to train better VSMs (Yu and Dredze, 2014; Faruqui et al., 2014), but does not tackle the problem of polysemy. Parallely, work on polysemy for VSMs revolves primarily around techniques that cluster contexts to distinguish between different word senses (Reisinger and Mooney, 2010; Huang et al., 2012), but does not integrate ontologies in any way.

In this chapter we present two novel approaches to integrating ontological and distributional sources of information. Our focus is on allowing already existing, proven techniques to be adapted to produce ontologically grounded word sense embeddings.

Our first technique is applicable to any sense-agnostic VSM as a post-processing step that performs graph propagation on the structure of the ontology. The second is applicable to the wide range of current techniques that learn word embeddings from predictive models that maximize the likelihood of a corpus (Collobert and Weston, 2008; Mnih and Teh, 2012; Mikolov et al., 2013a). Our technique adds a latent variable representing the word sense to each token in the corpus, and uses EM to find parameters. Using a structured regularizer based on the ontological graph, we learn grounded sense-specific vectors.

Both techniques crucially rely on the structure of the underlying ontology, and the relations that bind related word senses to one another.

There are several reasons to prefer ontologies as distant sources of supervision for learning sense-aware VSMs over previously proposed unsupervised context clustering techniques. Clustering approaches must often parametrize the number of clusters (senses), which is neither known a priori nor constant across words (Kilgarriff, 1997). Also the resulting vectors remain abstract and un-interpretable. With ontologies, interpretable sense vectors can be used in downstream applications such as WSD, or for better human error analysis. Moreover, clustering techniques operate on distributional similarity only whereas ontologies support other kinds of relationships between senses. Finally, the existence of cross-lingual ontologies would permit learning multilingual vectors, without compounded errors from word alignment and context clustering.

We evaluate our methods on 4 lexical semantic tasks across 9 datasets and 2 languages, and show that our sense-specific VSMs effectively integrate knowledge from the ontology with distributional statistics. Empirically, this results in consistently and significantly better performance over baselines in most cases. We discuss and compare our two different approaches to learning sense representations from the perspectives of performance, generalizability, flexibility and computational efficiency. Finally, we qualitatively analyze the vectors and show that they indeed capture sense-specific semantics.

3.1 Related Work

Since Reisinger and Mooney (2010) first proposed a simple context clustering technique to generate multi-prototype VSMs, a number of related efforts have worked on adaptations and improvements relying on the same clustering principle. Huang et al. (2012) train their vectors with a neural network and additionally take global context into account. Neelakantan et al. (2014) extend the popular skip-gram model (Mikolov et al., 2013a) in a non-parametric fashion to allow for different number of senses for words. Guo et al. (2014) exploit bilingual alignments to perform better context clustering during training. Tian et al. (2014) propose a probabilistic ex-

tension to skip-gram that treats the different prototypes as latent variables. This is similar to our second EM training framework, and turns out to be a special case of our general model. In all these papers, however, the multiple senses remain abstract and are not grounded in an ontology.

Conceptually, our work is also similar to Yu and Dredze (2014) and Faruqui et al. (2014), who treat lexicons such as the Paraphrase Database (PPDB) (Ganitkevitch et al., 2013) or WordNet (Miller, 1995) as an auxiliary thesaurus to improve VSMs. However, they do not model senses in any way. Pilehvar et al. (2013) do model senses from an ontology by performing random-walks on the WordNet graph, however their approach does not take distributional information from VSMs into account.

Thus, to the best of our knowledge, our work presents the first attempt at producing sense grounded VSMs that are symbolically tied to lexical ontologies. From a modelling point of view, it is also the first to outline a unified, principled and extensible framework that effectively combines the symbolic and distributional paradigms of semantics by specifically paying attention to relational structure.

Both our models leverage the graph structure of and relational links in ontologies to effectively ground the senses of a VSM. This ties into previous research (Das and Smith, 2011; Das and Petrov, 2011) that propagates information through a factor graph to perform tasks such as frame-semantic parsing and POS-tagging across languages. More generally, this approach can be viewed from the perspective of semi-supervised learning, with an optimization over a graph loss function defined on smoothness properties (Corduneanu and Jaakkola, 2002; Zhu et al., 2003; Subramanya and Bilmes, 2009).

Related to the problem of polysemy is the issue of different shades of meaning a word assumes based on context. The space of research on this topic can be divided into three broad categories: models for computing contextual lexical semantics based on composition (Mitchell and Lapata, 2008; Erk and Padó, 2008; Thater et al., 2011), models that use fuzzy exemplar-based contexts without composing them (Erk and Padó, 2010; Reddy et al., 2011), and models that propose latent variable techniques (Dinu and Lapata, 2010; Séaghdha and Korhonen, 2011; Van de Cruys et al., 2011). Chapter 6 addresses the first of the three categories with a Structured Distributional Semantic Model that takes relational context into account. The current chapter, however, tackles the stronger form of lexical ambiguity in polysemy and falls into the latter two of three categories.

3.2 Unified Symbolic and Distributional Semantics

In this section, we present our two techniques for inferring sense-specific vectors grounded in an ontology. We begin with notation and define the following symbols for our data:

- $W = \{w_1, ..., w_n\}$ is a set of word types of interest. These are the surface forms that you would typically encounter in an unnannotated corpus; so for example, words like "cat", "dog", "feline", "canine" etc.
- $W_s = \{s_{ij} \mid \forall w_i \in W \ , \ 1 \leq j \leq k_i\}$ is a set of word sense types, where k_i the number of senses of the word type w_i. This set contains elements such as "cat(1)" (the animal), and "cat(2)" (the Linux command).

- $\Omega = (T_\Omega, E_\Omega)$ is an ontology, with:
  - $T_\Omega = \{t_{ij} | \forall\ s_{ij} \in W_s\}$ is a set of nodes, one for each of word sense types in W_s
  - $E_\Omega = \{e^r_{ij-i'j'} | \forall\ r \in \mathcal{R}\}$ is a set of undirected edges connecting some subset of word sense $(s_{ij}, s_{i'j'})$ by semantic relation r. So for example, "cat(1)" might be connected to "feline(1)" by a "synonym" edge.

Our goal, in both the models that we present is to learn some vector representation for the word sense types in W_s. Furthermore, we want to enforce that these representations are somehow influence by, and grounded in the ontology Ω.

3.2.1 Retrofitting Vectors to an Ontology

Our first technique assumes that we already have a vector space embedding representation of a vocabulary of *surface forms* $\hat{U} = \{\hat{u}_i | \forall\ w_i \in W\}$. We wish to infer vectors $V = \{v_{ij} | \forall\ s_{ij} \in W_s\}$ for *word senses* that are maximally consistent with both $\hat{U}$ and Ω, by some notion of consistency. We formalize this notion as MAP inference in a Markov network (MN).

The MN we propose contains variables for every vector in $\hat{U}$ and V. These variables are connected to one another by dependencies as follows. Variables for vectors v_{ij} and $v_{i'j'}$ are connected iff there exists an edge $e^r_{ij-i'j'} \in E_\Omega$ connecting their respective word senses in the ontology. That is, we create edges between the vectors of word senses like "cat(1)" and "feline(1)", for example.

Furthermore, the vector $\hat{u}_i$ for the word type w_i is connected to all the vectors v_{ij} of the different senses s_{ij} of w_i. So, for example, the vector for "cat" is connected to both "cat(1)" and "cat(2)". If w_i is not contained in the ontology, we assume it has a single unconnected sense and set it's only sense vector v_{i1} to it's empirical estimate $\hat{u}_i$. Let us define these new set of edges between nodes in the ontology and their sense-agnostic word types as $e_{i-ij} \in E_\omega$. These are edges between word types w_i and the sense types s_{ij}.

The structure of this MN is illustrated in Figure 3.1. Here, the neighborhood of the ambiguous word "bank" is presented, as a factor graph. Note that the neighborhood is fabricated for purposes of illustration, and is not the actual neighborhood of "bank" from WordNet or some other ontology.

The energy of a Markov Network is defined by a set of clique potentials, or functions defined over cliques in the resulting graphical model. We set each pairwise clique potential to be of the form $\exp(a\|u - v\|^2)$ between neighboring nodes. Here u and v are the vectors corresponding to these nodes, and a is a weight controlling the strength of the relation between them. We use the Euclidean norm instead of a distance based on cosine similarity because it is more convenient from an optimization perspective.[1]

We can take the log of these pairwise clique potentials, and the minimization problem over the Markov Network remains the same. Thus our inference problem becomes one of finding the MAP estimate of the vectors V, given $\hat{U}$, which may be stated as follows:

[1]It can be shown, in fact, that using the Euclidean norm turns out to be a special case of the constrained problem with cosine log factors. Moreover, vectors that are spatially close – in the Euclidean sense – also have small cosine distances (and high cosine similarity) between them, anyway.

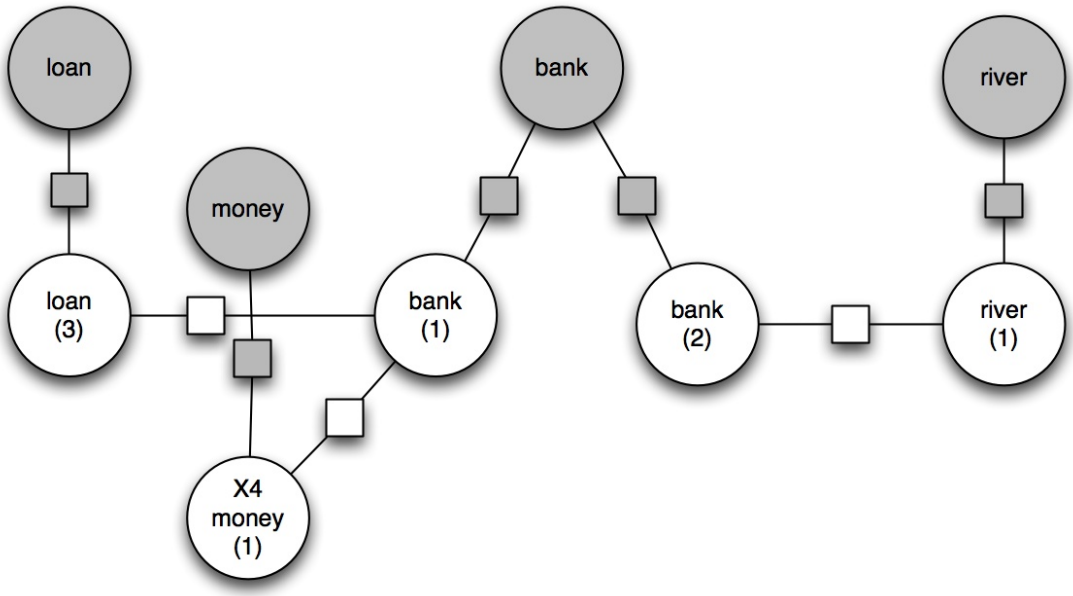


Figure 3.1: A factor graph depicting the retrofitting model in the neighborhood of the word "bank". Observed variables corresponding to word types are shaded in grey, while latent variables for word senses are in white.

$$C(V) = \arg\min_{V} \sum_{e_{i-ij} \in E_\omega} \alpha \|\hat{u}_i - v_{ij}\|^2 + \sum_{e^r_{ij-i'j'} \in E_\Omega} \beta_r \|v_{ij} - v_{i'j'}\|^2 \tag{3.1}$$

Here α is the sense-agnostic weight (that is the weight we apply to neighbors like "cat" and "cat(1)") and β_r are relation-specific weights for different semantic relations (that is the weights we apply to neighbors like "cat(1)" and "feline(1)", based on their "synonym" relation). This objective encourages vectors of neighboring nodes in the MN to pull closer together, leveraging the tension between sense-agnostic neighbors (the first summation term) and ontological neighbors (the second summation term). This allows the different neighborhoods of each sense-specific vector to tease it apart from its sense-agnostic vector.

Taking the partial derivative of the objective in equation 3.1 with respect to vector v_{ij} and setting to zero gives the following solution:

$$v_{ij} = \frac{\alpha \hat{u_i} + \sum_{e^r_{ij-i'j'} \in \mathcal{N}_{ij}} \beta_r v_{i'j'}}{\alpha + \sum_{e^r_{ij-i'j'} \in \mathcal{N}_{ij}} \beta_r} \tag{3.2}$$

where $\mathcal{N}_{ij}$ denotes the set of neighbors of s_{ij} based solely on the edge set $e^r_{ij-i'j'} \in E_\Omega$ of the ontology. Thus, the MAP sense-specific vector is an α-weighted combination of its sense-agnostic vector and the β_r-weighted sense-specific vectors in its ontological neighborhood.

Algorithm 1 Outputs a sense-specific VSM, given a sense-agnostic VSM and ontology

function RETROFIT($\hat{U}, \Omega$)
  $V^{(0)} \leftarrow \{v_{ij}^{(0)} = \hat{u}_i \mid \forall s_{ij} \in W_s\}$
  while $\|v_{ij}^{(t)} - v_{ij}^{(t-1)}\| \geq \epsilon \; \forall s_{ij}$ **do**
    for $t_{ij} \in T_\Omega$ **do**
      $v_{ij}^{(t+1)} \leftarrow$ update using equation 3.2
    end for
  end while
  return $V^{(t)}$
end function

We use coordinate descent to iteratively update the variables V using equation 3.2. The optimization problem in equation 3.1 is convex, and we normally converge to a numerically satisfactory stationary point within 10 to 15 iterations. This procedure is summarized in Algorithm 1. The generality of this algorithm allows it to be applicable to any VSM as a computationally attractive post-processing step.

An implementation of this technique is available at `https://github.com/sjauhar/SenseRetrofit`.

3.2.2 Adapting Predictive Models with Latent Variables and Structured Regularizers

Many successful techniques for semantic representation learning are formulated as models where the desired embeddings are parameters that are learned to maximize the likelihood of a corpus (Collobert and Weston, 2008; Mnih and Teh, 2012; Mikolov et al., 2013a). In our second approach we formulate a method to extend existing maximum likelihood models to also accommodate word senses grounded in an ontology.

Broadly, the inutition of our approach relies on adding latent variables representing the senses and then marginalizing over them. And furthermore, we use a structured prior based on the structure of the ontology to ground the sense embeddings.

Formally, we assume input of the following form:

- $D = \{(w_1, c_1), \ldots, (w_N, c_N)\}$ is a corpus of pairs of target and context words. While these pairs can represnt any relationship, for the purposes of this chapter we assume a standard distributional neighborhood. So for example, we expect to see word pairs such as "(eat, pasta)", "(spaghetti, fork)" etc.
- $\Omega = (T_\Omega, E_\Omega)$ is an ontology, and is defined as in the beginning of Section 3.2.

Our goal is to infer sense-specific vectors $V = \{v_{ij} | \; \forall \; s_{ij} \in W_s\}$, as before, but now additionally using the data of word-context pairs in D.

Consider a model with parameters θ that factorizes the probability over the corpus as $\prod_{(w_i,c_i)\in D} p(w_i, c_i; \theta)$. We propose to extend such a model to learn ontologically grounded sense vectors by presenting a general class of objectives of the following form:

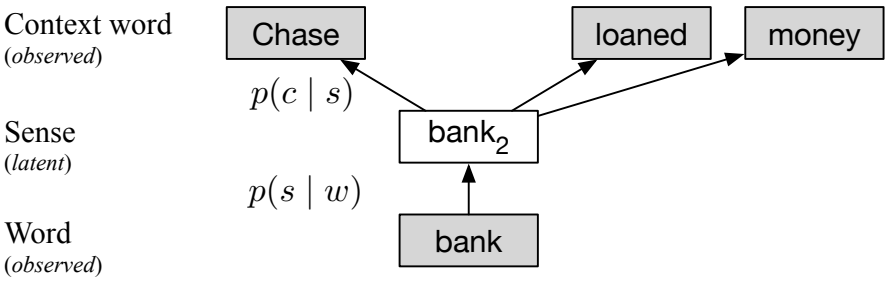


Figure 3.2: The generative process associated with the skip-gram model, modified to account for latent senses. Here, the context of the ambiguous word "bank" is generated from the selection of a specific latent sense.

$$C(\theta) = \arg\max_{\theta} \sum_{(w_i,c_i)\in D} \log \left(\sum_{s_{ij}} p(w_i, c_i, s_{ij}; \theta) \right) + \log p_\Omega(\theta) \tag{3.3}$$

This objective introduces latent variables s_{ij} for senses and adds a structured regularizer $p_\Omega(\theta)$ that grounds the vectors V in an ontology. This form permits flexibility in the definition of both $p(w_i, c_i, s_{ij}; \theta)$ and $p_\Omega(\theta)$ allowing for a general yet powerful framework for adapting MLE models.

In what follows we show that the popular skip-gram model (Mikolov et al., 2013a) can be adapted to generate ontologically grounded sense vectors. The classic skip-gram model uses a set of parameters $\theta = (U, V)$, with $U = \{u_i \mid \forall c_i \in W\}$ and $V = \{v_i \mid \forall w_i \in W\}$ being sets of vectors for context and target words respectively. The generative story of the skip-gram model involves generating the context word c_i conditioned on an observed word w_i. The conditional probability is defined to be $p(c_i \mid w_i; \theta) = \dfrac{\exp(u_i \cdot v_i)}{\sum_{c_{i'} \in W} \exp(u_{i'} \cdot v_i)}$.

We modify the generative story of the skip-gram model to account for latent sense variables by first selecting a latent word sense s_{ij} conditional on the observed word w_i, then generating the context word c_i from the sense distinguished word s_{ij}. This process is illustrated in Figure 3.2. The factorization $p(c_i \mid w_i; \theta) = \sum_{s_{ij}} p(c_i \mid s_{ij}; \theta) \times p(s_{ij} \mid w_i; \theta)$ follows from the chain rule since senses are word-specific.

To parameterize this distribution, we define a new set of model parameters $\theta = (U, V, \Pi)$, where U remains identical to the original skip-gram as vectors for context words (i.e. sense agnostic types), $V = \{v_{ij} \mid \forall s_{ij} \in W_s\}$ are a set of vectors for word senses (rather than word surface forms), and Π are the context-independent sense proportions $\pi_{ij} = p(s_{ij} \mid w_i)$. We use a Dirichlet prior over the multinomial distributions π_i for every w_i, with a shared concentration parameter λ.

This is a standard maximum likelihood learning problem with latent variables, so the natural solution is to use Expectation Maximization (Dempster et al., 1977), or EM. However,

there is nothing to identify the representations that we learn to the senses in the ontology Ω. We address this by formulating priors. We define the ontological prior on vectors as $p_\Omega(\theta) \propto \exp(-\gamma \sum_{e^r_{ij-i'j'} \in E_\Omega} \beta_r \|v_{ij} - v_{i'j'}\|^2)$, where γ controls the strength of the prior. We note the similarity to the retrofitting objective in equation 3.1, except with $\alpha = 0$. This leads to the following realization of the objective in equation 3.3:

$$C(\theta) = \arg\max_\theta \sum_{(w_i,c_i) \in D} \log \Big(\sum_{s_{ij}} p(c_i \mid s_{ij}; \theta) \times p(s_{ij} \mid w_i; \theta) \Big) - \gamma \sum_{e^r_{ij-i'j'} \in E_\Omega} \beta_r \|v_{ij} - v_{i'j'}\|^2 \tag{3.4}$$

This objective can be optimized using EM, for the latent variables, and with lazy updates (Carpenter, 2008) every k words to account for the prior regularizer. However, since we are primarily interested in learning good vector representations for word senses, and we want to learn efficiently from large datasets, we make the following simplifications.

First, we perform "hard" EM, selecting the most likely sense at each position rather than using the full posterior over senses. Also, given that the structured regularizer $p_\Omega(\theta)$ is essentially the retrofitting objective in equation 3.1, we run retrofitting periodically every k words (with $\alpha = 0$ in equation 3.2) instead of lazy updates.[2]

The following decision rule is used in the "hard" E-step:

$$s_{ij} = \arg\max_{s_{ij}} p(c_i \mid s_{ij}; \theta^{(t)}) \pi^{(t)}_{ij} \tag{3.5}$$

In the M-step we use Variational Bayes to update Π with:

$$\pi^{(t+1)}_{ij} \propto \frac{\exp\left(\psi\left(\tilde{c}(w_i, s_{ij}) + \lambda \pi^{(0)}_{ij}\right)\right)}{\exp\left(\psi\left(\tilde{c}(w_i) + \lambda\right)\right)} \tag{3.6}$$

where $\tilde{c}(\cdot)$ is the online expected count and $\psi(\cdot)$ is the digamma function. This approach is motivated by Johnson (2007) who found that naive EM leads to poor results, while Variational Bayes is consistently better and promotes faster convergence of the likelihood function.

To update the parameters U and V, we use negative sampling (Mikolov et al., 2013a) which is an efficient approximation to the original skip-gram objective. Negative sampling attempts to distinguish between true word pairs in the data, relative to noise. Stochastic gradient descent on the following equation is used to update the model parameters U and V:

$$\mathcal{L} = \log \sigma(u_i \cdot v_{ij}) + \sum_{\substack{j' \\ j' \neq j}} \log \sigma(-u_i \cdot v_{ij'}) + \sum_m \mathbb{E}_{c_{i'} \sim P_n(c)} \left[\log \sigma(-u_{i'} \cdot v_{ij})\right] \tag{3.7}$$

Here $\sigma(\cdot)$ is the sigmoid function, $P_n(c)$ is a noise distribution computed over unigrams and m is the negative sampling parameter. This is almost exactly the same as negative sampling

[2]We find this gives slightly better performance.

proposed for the original skip-gram model (Mikolov et al., 2013a). The only change is that we additionally take a negative gradient step with respect to all the senses that were *not* selected in the hard E-step (the second term in the loss function above). We summarize the training procedure for the adapted skip-gram model in Algorithm 2.

Algorithm 2 Outputs a sense-specific VSM, given a corpus and an ontology

function SENSEEM(D, Ω)
  $\theta^{(0)} \leftarrow$ initialize
  for $(w_i, c_i) \in D$ **do**
    if period $> k$ **then**
      RETROFIT($\theta^{(t)}, \Omega$)
    end if
    (Hard) E-step:
    $s_{ij} \leftarrow$ find argmax using equation 3.5
    M-step:
    $\Pi^{(t+1)} \leftarrow$ update using equation 3.6
    $U^{(t+1)}, V^{(t+1)} \leftarrow$ update using equation 3.7
  end for
  return $\theta^{(t)}$
end function

3.3 Resources, Data and Training

We detail the training and setup for our experiments in this section.

We use WordNet (Miller, 1995) as the sense repository and ontology in all our experiments. WordNet is a large, hand-annotated ontology of English composed of 117,000 clusters of senses, or "synsets" that are related to one another through semantic relations such as hypernymy and hyponymy. Each synset additionally comprises a list of sense specific lemmas which we use to form the nodes in our graph. There are 206,949 such sense specific lemmas, which we connect with synonym, hypernym and hyponym[3] relations for a total of 488,432 edges.

To show the applicability of our techniques to different VSMs we experiment with two different kinds of base vectors.

Global Context Vectors (GC) (Huang et al., 2012): These word vectors were trained using a neural network which not only uses local context but also defines global features at the document level to further enhance the VSM. We distinguish three variants: the original single-sense vectors (SINGLE), a multi-prototype variant (MULTI), – both are available as pre-trained vectors for download[4] – and a sense-based version obtained by running retrofitting on the original vectors (RETRO).

Skip-gram Vectors (SG) (Mikolov et al., 2013a): We use the word vector tool `Word2Vec`[5]

[3]We treat edges as undirected, so hypernymy and hyponymy are collapsed and unified in our representation schema.

[4]`http://nlp.stanford.edu/~socherr/ACL2012_wordVectorsTextFile.zip`

[5]`https://code.google.com/p/word2vec/`

to train skip-gram vectors. We define 6 variants: a single-sense version (SINGLE), two multi-sense variants that were trained by first sense disambiguating the entire corpus using WSD tools, – one unsupervised (Pedersen and Kolhatkar, 2009) (WSD) and the other supervised (Zhong and Ng, 2010) (IMS) – a retrofitted version obtained from the single-sense vectors (RETRO), an EM implementation of the skip-gram model with the structured regularizer as described in section 3.2.2 (EM+RETRO), and the same EM technique but ignoring the ontology (EM). All models were trained on publicly available WMT-2011[6] English monolingual data. This corpus of 355 million words, although adequate in size, is smaller than typically used billion word corpora. We use this corpus because the WSD baseline involves preprocessing the corpus with sense disambiguation, which is slow enough that running it on corpora orders of magnitude larger was infeasible.

Retrofitted variants of vectors (RETRO) are trained using the procedure described in algorithm 1. We set the convergence criteria to $\epsilon = 0.01$ with a maximum number of iterations of 10. The weights in the update equation 3.2 are set heuristically: the sense agnostic weight α is 1.0, and relations-specific weights β_r are 1.0 for synonyms and 0.5 for hypernyms and hyponyms. EM+RETRO vectors are the exception where we use a weight of $\alpha = 0.0$ instead, as required by the derivation in section 3.2.2.

We did not tune the sense agnostic and relation-specific weights of our model to our evaluation suite. We did experiment with tweaking the weights heuristically but this did not provide consistent and statistically significant improvements across our benchmark datasets. This is likely because each target problem or dataset requires a different set of weights – and perhaps even a different set of ontological relations to begin with. This is certainly in keeping with the overall theme of this thesis which stresses that different problems in fact require different contextual relations to better learn and represent the underlying semantic relations.

This suggests that a more integral optimization in future work will likely benefit our technique, given different problem desiderata. A completely unsupervised approach might consider factors such as sense frequency (which is available in WordNet), or the in- and out-degrees of sense nodes as indicators on setting the weights. These factors might be used to compute the distribution and polysemy of word surface forms and senses in order to make a more informed decision on when to rely more on corpus statistics (possibly for more frequent and popular senses) and when to rely more on the knowledge derived from the ontological graph (possibly for infrequent, uncommon senses). Using a more supervised approach, when a target problem has some development data, this data can of course be used to perform grid search on the relation weights that yield the highest evaluation scores on the development data.

For skip-gram vectors (SG) we use the following standard settings, and do not tune any of the values. We filter all words with frequency < 5, and pre-normalize the corpus to replace all numeric tokens with a placeholder. We set the dimensionality of the vectors to 80, and the window size to 10 (5 context words to either side of a target). The learning rate is set to an initial value of 0.025 and diminished linearly throughout training. The negative sampling parameter is set to 5.

Additionally for the EM variants (section 3.2.2) we set the Dirichlet concentration parameter λ to 1000. We use 5 abstract senses for the EM vectors, and initialize the priors uniformly.

[6] `http://www.statmt.org/wmt11/`

Model	Variant	Word Similarity (ρ)				Synonym Selection (%)		
		WS-353	RG-65	MC-30	MEN-3K	ESL-50	RD-300	TOEFL-80
GC	Single	**0.623**	0.629	0.657	0.314	47.73	45.07	60.87
	Multi	0.535	0.510	0.309	0.359	27.27	47.89	52.17
	Retro	0.543	**0.661**	**0.714**	**0.528**	**63.64**	**66.20**	**71.01**
SG	Single	**0.639**	0.546	0.627	**0.646**	52.08	55.66	66.67
	EM	0.194	0.278	0.167	0.228	27.08	33.96	40.00
	WSD	0.481	0.298	0.396	0.175	16.67	49.06	42.67
	IMS	0.549	0.579	0.606	0.591	41.67	53.77	66.67
	Retro	0.552	0.673	0.705	0.560	56.25	65.09	**73.33**
	Retro+EM	0.321	**0.734**	**0.758**	0.428	**62.22**	**66.67**	68.63

Table 3.1: Similarity scoring and synonym selection in English across several datasets involving different VSMs. Higher scores are better; best scores within each category are in bold. In most cases our models consistently and significantly outperform the other VSMs.

For EM+RETRO, WordNet dictates the number of senses; also when available WordNet lemma counts are used to initialize the priors. Finally, we set the retrofitting period k to 50 million words.

3.4 Evaluation

In this section we detail experimental results on 4 lexical semantics tasks across 9 different datasets and 2 languages.

3.4.1 Experimental Results

We evaluate our models on 3 kinds of lexical semantic tasks: similarity scoring, synonym selection, and similarity scoring in context.

Similarity Scoring: This task involves using a semantic model to assign a score to pairs of words. We use the following 4 standard datasets in this evaluation: WS-353 (Finkelstein et al., 2002), RG-65 (Rubenstein and Goodenough, 1965), MC-30 (Miller and Charles, 1991) and MEN-3k (Bruni et al., 2014). Each dataset consists of pairs of words along with an averaged similarity score obtained from several human annotators. For example an item in the WS-353 dataset is "book, paper $\rightarrow$ 7.46". We use standard cosine similarity to assign a score to word pairs in single-sense VSMs, and the following average similarity score to multi-sense variants, as proposed by Reisinger and Mooney (2010):

$$avgSim(w_i, w_{i'}) = \frac{1}{k_i k_j} \sum_{j,j'} cos(v_{ij}, v_{i'j'}) \tag{3.8}$$

The output of systems is evaluated against the gold standard using Spearman's rank correlation coefficient.

Synonym Selection: In this task, VSMs are used to select the semantically closest word to a target from a list of candidates. We use the following 3 standard datasets in this evaluation: ESL-50 (Turney, 2002), RD-300 (Jarmasz and Szpakowicz, 2004) and TOEFL-80 (Landauer and Dumais, 1997). These datasets consist of a list of target words that appear with several candidate lexical items. An example from the TOEFL dataset is "rug $\rightarrow$ sofa, ottoman, carpet, hallway", with "carpet" being the most synonym-like candidate to the target. We begin by scoring all pairs composed of the target and one of the candidates. We use cosine similarity for single-sense VSMs, and max similarity for multi-sense models[7]:

$$maxSim(w_i, w_{i'}) = \max_{j,j'} cos(v_{ij}, v_{i'j'}) \tag{3.9}$$

These scores are then sorted in descending order, with the top-ranking score yielding the semantically closest candidate to the target. Systems are evaluated on the basis of their accuracy at discriminating the top-ranked candidate.

The results for similarity scoring and synonym selection are presented in table 3.1. On both tasks and on all datasets, with the partial exception of WS-353 and MEN-3k, our vectors (RETRO & EM+RETRO) consistently yield better results than other VSMs. Notably, both our techniques perform better than preprocessing a corpus with WSD information in unsupervised or supervised fashion (SG-WSD & SG-IMS). Simple EM without an ontological prior to ground the vectors (SG-EM) also performs poorly.

We investigated the observed drop in performance on WS-353 and found that this dataset consists of two parts: a set of *similar* word pairs (e.g. "tiger" and "cat") and another set of *related* word pairs (e.g. "weather" and "forecast"). The synonym, hypernym and hyponym relations we use tend to encourage *similarity* to the detriment of *relatedness*.

We ran an auxiliary experiment to show this. SG-EM+RETRO training also learns vectors for context words – which can be thought of as a proxy for relatedness. Using this VSM we scored a word pair by the average similarity of all the sense vectors of one word to the context vector of the other word, averaged over both words. For example, given the pair "bank" and "money" (which are related, not similar), we would take the different sense vectors of "bank" from the sense vector space and compare it to the single vector of "money" from the context space.

Using this scoring strategy the correlation ρ jumped from 0.321 to 0.493. While still not as good as some of the other VSMs, it should be noted that this scoring function, while improving *related* words, negatively influences the *similar* word pairs in the dataset.

A possible solution to this problem could be to learn representations from contexts derived from corpus-based statistics and ontological relations separately and maintain disparate *corpus* and *ontology* vector spaces. The results from the experiment above indicate, in fact, that there is some orthogonality in the information derived from the two sources of knowledge and that maintaining such disparate spaces might be beneficial.

This idea is similar, in spirit, to the *domain* and *function* vector spaces from Turney (2012). The vectors from the two different spaces can be used jointly to compute a measure of comparsion between terms, which should ideally reflect a balance between their similarity as well and their relatedness. Moreover, the reliance on one space versus another, when computing this

[7]Here we are specifically looking for synonyms, so the max makes more sense than taking an average.

Model	Variant	SCWS (ρ)
GC	Multi	**0.657**
	Retro	0.420
SG	EM	**0.613**
	WSD	0.343
	IMS	0.528
	Retro	0.417
	Retro+EM	0.587

Table 3.2: Contextual word similarity in English. Higher scores are better.

quantity can be data driven – preferring corpus statistics for problems that require a measure of relatedness, while preferring ontological knowledge for problems that need a measure of similarity instead.

We also sometimes have lower scores on the MEN-3k dataset, which is crowd-sourced and contains much diversity, with word pairs evidencing similarity as well as relatedness. However, we aren't sure why the performance for GC-RETRO improves greatly over GC-SINGLE for this dataset, while that of SG-RETRO and SG-RETRO+EM drops in relation to SG-SINGLE. The idea of maintaining disparate vector spaces for *corpus* and *ontology* are likely to produce better results on this dataset as well.

Similarity Scoring in Context: As outlined by Reisinger and Mooney (2010), multi-sense VSMs can be used to consider context when computing similarity between words. We use the SCWS dataset (Huang et al., 2012) in these experiments. This dataset is similar to the similarity scoring datasets, except that they additionally are presented in context. For example an item involving the words "bank" and "money", gives the words in their respective contexts, "along the east **bank** of the Des Moines River" and "the basis of all **money** laundering" with a low averaged similarity score of 2.5 (on a scale of 1.0 to 10.0). Following Reisinger and Mooney (2010) we use the following function to assign a score to word pairs in their respective contexts, given a multi-sense VSM:

$$avgSimC(w_i, c_i, w_{i'}, c_{i'}) = \sum_{j,j'} p(s_{ij}|c_i, w_i)p(s_{i'j'}|c_{i'}, w_{i'})cos(v_{ij}, v_{i'j'}) \tag{3.10}$$

As with similarity scoring, the output of systems is evaluated against gold standard using Spearman's rank correlation coefficient.

The results are presented in table 3.2. Pre-processing a corpus with WSD information in an unsupervised fashion (SG-WSD) yields poor results. In comparison, the retrofitted vectors (SG-RETRO & GC-RETRO) already perform better, even though they do not have access to context vectors, and thus do not take contextual information into account. Supervised sense vectors (SG-IMS) are also competent, scoring better than both retrofitting techniques. Our EM vectors (SG-EM & SG-EM+RETRO) yield even better results and are able to capitalize on contextual information, however they still fall short of the pre-trained GC-MULTI vectors. We were

surprised that SG-EM+RETRO actually performed worse than SG-EM, given how poorly SG-EM performed in the other evaluations. However, an analysis again revealed that this was due to the kind of similarity encouraged by WordNet rather than an inability of the model to learn useful vectors. The SCWS dataset, in addition to containing related words – which we showed, hurt our performance on WS-353 – also contains word pairs with different POS tags. WordNet synonymy, hypernymy and hyponymy relations are exclusively defined between lemmas of the same POS tag, which adversely affects performance further.

3.4.2 Generalization to Another Language

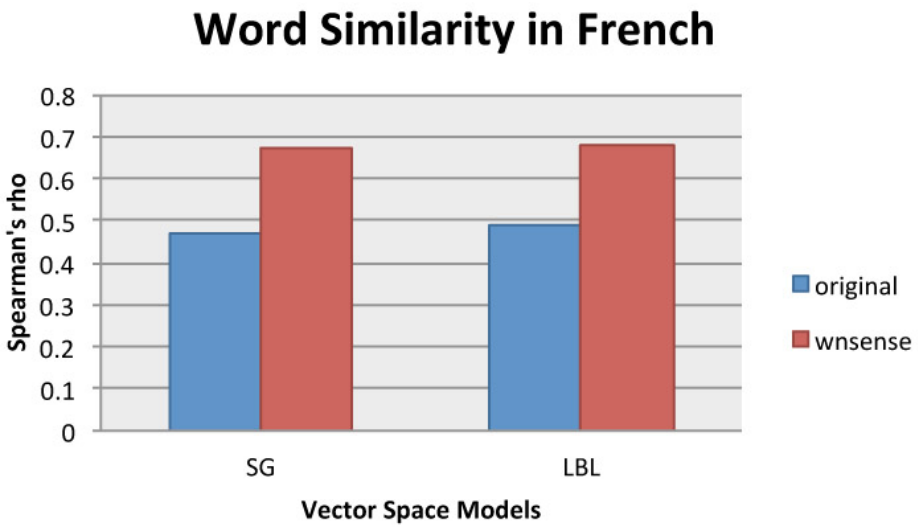


Figure 3.3: Performance of sense specific vectors (wnsense) compared with single sense vectors (original) on similarity scoring in French. Higher bars are better. *wnsense* outperforms *original* across 2 different VSMs on this task.

Our method only depends on a sense inventory to improve and disambiguate VSMs. We thus experiment with extending the technique to another language. In particular, we run the retrofitting procedure in algorithm 1 on VSMs trained on French monolingual data from the WMT-2011 corpus. The ontological base for our algorithm is obtained from a semi-automatically created version of WordNet in French (Pradet et al., 2013).

We compare the resulting VSMs against the "original" vectors on a French translation of the RG-65 word similarity dataset (Joubarne and Inkpen, 2011). GC vectors cannot be retrained and are thus not used in this evaluation. We do not include WSD or IMS results for this task since we were unable to find a reasonable WSD system in French to sense tag the training corpus. As with previous experiments involving similarity scoring we use the $avgSim$ function to assign similarity scores to word pairs, and system outputs are evaluated against gold standard on Spearman's rank correlation coefficient.

Results of the experiment are presented in figure 3.3, and again show that our sense disambiguated VSMs outperform their single-sense counterparts on the evaluation task. We conclude

that the technique we propose not only generalizes to any VSM but to any language, as long as a reasonable sense inventory for that language exists.

3.4.3 Antonym Selection

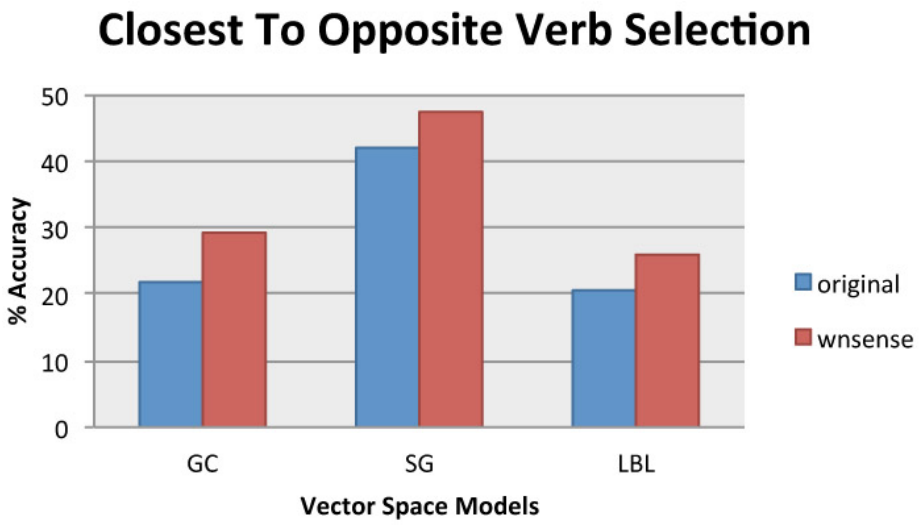


Figure 3.4: Performance of sense specific vectors (wnsense) compared with single sense vectors (original) on closest to opposite selection of target verbs. Higher bars are better. *wnsense* outperforms *original* across 3 different VSMs on this task.

The general formulation of our model allows us to incorporate knowledge from more than just the similarity neighborhood (i.e. the synonyms, the hypernyms and the hyponyms) of word senses in an ontology. The power of the model lies in leveraging the relational structure of the ontology, and the flexibility to use different kinds of relations in different ways.

For example, it may be useful to also know the antonyms of a word sense to tease its vector apart from the empirical surface form embedding more effectively.

Corpus-based methods struggle to learn good representations for antonyms, because antonym pairs often occur in very similar contexts. For example the words "hot" and "cold" are equally appropriate to describe a number of things – food, the weather, or someone's mood. Thus, based on the distributional hypothesis, their associated vectors tend to be very similar.

However, antonym pairs should ideally have low similarity (i.e. large distance) between them. In our model, it is thus appropriate to set a negative relation weight to these terms in the model parameters in equation 3.2 to force the respective vectors further apart.

Mathematically, in certain cases this causes the objective to diverge, and thus produces unpredictable behavior. This happens, in particular when some variables in the model form an "antonym clique". That is, when the nodes associated which each of the concepts in this "clique" are all connected to one another (and *only* to one another) via an antonym relation.

Thus we test our model on the subset of WordNet consisting only of verb lemmas, which contain very few antonym cliques[8]. We run exactly the same procedure of algorithm 1 to create

[8]For comparison, 45% of all adjective lemmas appear in such cliques, while only 0.1% of verbs do.

Method	CPU Time
Retro	˜20 secs
Retro+EM	˜4 hours
IMS	˜3 days
WSD	˜1 year

Table 3.3: Training time associated with different methods of generating sense-specific VSMs.

sense disambiguated vectors as before, except that we additionally expand word sense neighborhoods with antonyms, and set the antonym specific relation weight γ_r to be -1.0 in equation 3.2 for the model parameters. In the few cases that do evidence divergent behavior, we heuristically overcome the problem by ceasing to update the problematic vectors if their norm increases beyond some threshold (in our experiments we set this to be the norm of the longest vector before any update iterations).

We evaluate the resulting VSMs on the task of closest-to-opposite verb selection. This is very similar in format to the synonym selection task, except that the candidate with the most antonym-like meaning with respect to a target needs to be selected. The dataset we use in our experiments is from Mohammad et al. (2008). The data contains 226 closest-to-opposite verb selection questions such as the following: "inflate $\rightarrow$ overstating, understating, deflate, misrepresenting, exaggerating" where "deflate" is the correct answer.

We use the $minSim$ function to score similarity between words since we are interested in discovering the least synonymous word sense pairs. These scores are then sorted in descending order, with the lowest-ranking score yielding the closest-to-opposite candidate to the target. Systems are evaluated on the basis of their accuracy at discriminating the correct candidate.

Results on this task are shown in figure 3.4. The baseline vectors show typical behavior of models that are based on the distributional hypothesis. Antonyms are treated much like synonyms, and thus the baselines perform poorly on this task. In contrast, our sense specific vectors are forced to be further apart if they are antonyms and thus perform better on the evaluation task consistently across all three VSMs.

3.5 Discussion

While both our approaches are capable of integrating ontological information into VSMs, an important question is which one should be preferred? From an empirical point of view, the EM+RETRO framework yields better performance than RETRO across most of our semantic evaluations. Additionally EM+RETRO is more powerful, allowing to adapt more expressive models that can jointly learn other useful parameters – such as context vectors in the case of skip-gram. However, RETRO is far more generalizable, allowing it to be used for *any* VSM, not just predictive MLE models, and is also empirically competitive. Another consideration is computational efficiency, which is summarized in table 3.3.

Not only is RETRO much faster, but it scales linearly with respect to the vocabulary size, unlike EM+RETRO, WSD, and IMS which are dependent on the input training corpus. Nevertheless, both our techniques are empirically superior as well as computationally more efficient

Word or Sense	Top 3 Most Similar
hanging	hung, dangled, hangs
hanging (suspending)	shoring, support, suspension
hanging (decoration)	tapestry, braid, smock
climber	climbers, skier, Loretan
climber (sportsman)	lifter, swinger, sharpshooter
climber (vine)	woodbine, brier, kiwi

Table 3.4: The top 3 most similar words for two polysemous types. Single sense VSMs capture the most frequent sense. Our techniques effectively separates out the different senses of words, and are grounded in WordNet.

than both unsupervised and supervised word-sense disambiguation paradigms.

Both our approaches are sensitive to the structure of the ontology. Therefore, an important consideration is the relations we use and the weights we associate with them. In our experiments we selected the simplest set of relations and assigned weights heuristically, showing that our methods can effectively integrate ontological information into VSMs. A more exhaustive selection procedure with weight tuning on held-out data would almost certainly lead to better performance on our evaluation suite.

3.5.1 Qualitative Analysis

We qualitatively attempt to address the question of whether the vectors are truly sense specific. In table 3.4 we present the three most similar words of an ambiguous lexical item in a standard VSM (SG-SINGLE) in comparison with the three most similar words of different lemma senses of the same lexical item in grounded sense VSMs (SG-RETRO & SG-EM+RETRO).

The sense-agnostic VSMs tend to capture only the most frequent sense of a lexical item. On the other hand, the disambiguated vectors capture sense specificity of even less frequent senses successfully. This is probably due to the nature of WordNet where the nearest neighbors of the words in question are in fact these rare words. A careful tuning of weights will likely optimize the trade-off between ontologically rare neighbors and distributionally common words.

In our analyses, we noticed that lemma senses that had many neighbors (i.e. synonyms, hypernyms and hyponyms), tended to have more clearly sense specific vectors. This is expected, since it is these neighborhoods that disambiguate and help to distinguish the vectors from their single sense embeddings.

3.6 Conclusion

We have presented two general and flexible approaches to producing sense-specific VSMs grounded in an ontology. The first technique is applicable to any VSM as an efficient post-processing step, which we call retrofitting. The second provides a framework to integrate ontological information by adapting existing MLE-based predictive models. We evaluated our models on a battery of

tasks and the results show that our proposed methods are effectively able to capture the different senses in an ontology. In most cases this results in significant improvements over baselines. We thus re-affirm the central claim of our thesis: namely that integrating relational structure into learning semantic models results in representations that are more expressive and empirically superior than their relation agnostic counterparts.

We also discussed the trade-offs between the two techniques from several different perspectives. In summary, while the adaptive MLE technique seems to be empirically superior, retrofitting is much more computationally friendly. Crucially, however, both models significantly surpass word-sense disambiguating a training corpus from both computational and empirical perspectives. Finally, we also presented a qualitative analysis investigating the nature of the sense-specific vectors, and showed that they do indeed capture the semantics of different senses.

3.6.1 Five Point Thematic Summary

What was the semantic representation learning problem that we tried to solve?

We attempted to learn a model of similarity over word senses instead of word tokens. We were seeking to resolve the problem of polysemy. Based on Definition 1 of Chapter 1.2 our goal was to learn a semantic relation with a mapping from pairs of word senses to the set of real numbers. Our expectation was that a good model would reflect the property that word sense pairs that have similar meaning would have higher scores than word sense pairs that are unrelated.

What linguistic information or resource did we use to solve this problem?

We set up our solution to use ontologies as the external resource to help solve the problem. In particular we envisaged WordNet (Miller, 1995) would be particularly beneficial, since it not only contains an inventory of word sense, but a structure that connects these senses to one another via several typed relations.

How did we operationalize the desired semantic relation with contextual relations in the resource?

We began with the intuition that the ontology provides additional information to what knowledge can be obtained from a corpus. Furthermore, with the goal of learning semantic similarity between word senses, we intuited that ontological neighbors connected by certain kinds of relations (synonym, hypernym and hyponym edges) will be similar.

We operationalized these intuitions by defining contextual relations in terms of ontological neighborhoods. In particular we decomposed the structure of WordNet (see Definition 3) into contextual relations – one for each type of relation we cared about (see Definition 2), and we assigned weights to these relations based on our intuition about their importance in capturing similarity. The contexts we thus obtained were word senses and all their ontological neighbors, as well as their surface form representation obtained from corpus statistics.

How did we use the contextual relations in representation learning?

We defined a Markov Network over the graph structure of the ontology, which was optimized by a MAP objective (see Equation 3.1). In the objective, we tried to leverage the tension of similarity between ontological neighbors and the similarity of a word sense representation with its sense agnostic representation obtained from corpus statistics.

What was the result of biasing the learner with contextual relations in learning the semantic model?

By biasing the learner with contextual relations defined over the structure of an ontology, we were able to learn representations that not only outperformed representations trained purely on data (see Section 3.4) but did so efficiently, and produced representations that were grounded in the ontology (see Section 3.5). We concluded that the contextual relations we defined were a successful operationalization of the semantic relation we set out to learn.

Chapter 4

Tables for Question Answering

Leveraging Structural Relations in Tables for Question Answering

Question answering (QA) has emerged as a practical research problem for pushing the boundaries of artificial intelligence (AI). Dedicated projects and open challenges to the research community include examples such as Facebook AI Research's challenge problems for AI-complete QA (Weston et al., 2015) and the Allen Institute for AI's (AI2) Aristo project (Clark, 2015) along with its recently completed Kaggle competition[1]. The reason for this emergence is the diversity of core language and reasoning problems that a complex, integrated task like QA exposes: information extraction (Srihari and Li, 1999), semantic modelling (Shen and Lapata, 2007; Narayanan and Harabagiu, 2004), logic and reasoning (Moldovan et al., 2003), and inference (Lin and Pantel, 2001).

Complex tasks such as QA require some form of knowledge base to store facts about the world and reason over them. Consider the example question: "In which country is Texas?". A system truly capable of understanding and then answering this question must know – or infer – that Texas is the name of a place and that it is contained within a geo-political entity called the United States of America. But even the simplest system must be able to search for a relevant passage in a background corpus to answer this question.

Thus by knowledge base, we mean any form of knowledge: structured (e.g., tables, ontologies, rules) or unstructured (e.g., natural language text). For QA, knowledge has been harvested and used in a number of different modes and formalisms: large-scale extracted and curated knowledge bases (Fader et al., 2014), structured models such as Markov Logic Networks (Khot et al., 2015), and simple text corpora in information retrieval approaches (Tellex et al., 2003).

When considered in the context of this thesis, an important question concerns the semantic relations that structure the source of background knowledge for a problem like QA.

For example, the relations structuring a large-scale ontology such as Yago (Suchanek et al., 2007) or DBpedia (Lehmann et al., 2015) are very different from the relations in a triple store such as the PropStore (see Chapter 6.2). These in turn are very different from the set of relations in a collection of tables, which are for example, implicit membership relations such as "in_same_row" or "in_same_column".

[1] `https://www.kaggle.com/c/the-allen-ai-science-challenge`

The schema of the relations in the underlying knowledge base have direct implications on the QA system that is built on top of it. What relations are usable? Which ones capture important properties relating questions to answers?

There is a fundamental trade-off in the structure and regularity of the knowledge schema and its ability to be curated, modelled or reasoned with easily. The degree of structure can be thought of as falling on a spectrum.

At one end of this spectrum is, for example, a simple text corpus. It contains no structure, and is therefore hard to reason with in a principled manner. Nevertheless, vast amounts of unstructured text data are easily and abundantly available. At the other end of the spectrum is, for example, a Markov Logic Networks. This sort of knowledge formalism comes with a wealth of theoretical knowledge connected with its usage in principled inference. However, it is difficult to induce automatically from text or to build manually.

In this chapter we explore a knowledge formalism that falls somewhere in the middle of this spectrum of structured knowledge. Specifically we investigate tables as semi-structured knowledge for multiple-choice question (MCQ) answering.

In particular, we focus on tables that represent general knowledge facts, with cells that contain free-form text (Section 4.2.1 details the nature and semantics of these tables). The structural properties of tables, along with their free-form text content represents a semi-structured balanced compromise in the trade-off between degree of structure and ubiquity.

Crucially, in the context of this thesis, the role of semantic relations in these tables is threefold. First, the way the tables are structured leads to a formalism that is easy enough to build by non-expert annotators, while being flexible enough to be used for the complex reasoning required in QA. Second, the relations governing tables define a greater connection with QA; specifically, they can be used as constraints to generate high quality QA data via crowd-sourcing for our target domain. Thirdly, the same structure in tables and its connection to the QA data we generate can be leveraged to build QA solvers that are capable of performing reasoning over tables.

The two main contributions of this chapter are centered around the role that relations play in the structure of tables. First, we crowd-source a collection of over 9000 MCQs with alignment annotations to table elements, using the structural properties of tables as guidelines in efficient data harvesting. Second, we develop feature-driven models that use these MCQs to perform QA, while fact-checking and reasoning over tables.

Additionally, in the latter contribution we explore two model paradigms. In the first, the structure and relations of tables are used to inspire manual feature-engineering. While in the second, those same relations are used in a neural network to automatically induce features for the task.

The use of tables in the context of QA is not new; others have explored this avenue of research as well. Question bank creation for tables has been investigated (Pasupat and Liang, 2015), but without structural guidelines or the alignment information that we propose. Similarly, tables have been used in QA reasoning (Yin et al., 2015b; Neelakantan et al., 2015; Sun et al., 2016) but have not explicitly attempted to encode all the semantics of table structure (see Section 4.2.1). To the best of our knowledge, no previous work uses tables for both creation and reasoning in a connected framework.

We evaluate our manually feature-engineered model on MCQ answering for three benchmark datasets. Our results consistently and significantly outperform a strong retrieval baseline as well

as a Markov Logic network model (Khot et al., 2015). We thus show the benefits of semi-structured data and models over unstructured or highly-structured counterparts. We also validate our curated MCQ dataset and its annotations as an effective tool for training QA models. Finally, we find that our model learns generalizations that permit inference when exact answers may not even be contained in the knowledge base.

Our evaluations of the neural network model show that the architecture we define is able to capture the relational and structural properties of tables. It shows promising results when we evaluate on a held-out portion of our training set. The model is however, much more sensitive to the content in training than the manually feature-engineered model. The representations over MCQ and table elements we learn do not port to the largest of our benchmark test sets, which has a very different profile to our crowd-sourced training set. Our analyses indicate the need for a larger and more diverse training set to accommodate the power of the neural network model.

But both sets of results re-affirm the central claims of this thesis. That structure and relations are key to producing meaning in language. Moreover, leveraging the correct set of relations to yield feature representations (in this chapter, both manually and automatically) lead to richer and more capable models.

4.1 Related Work

Our work with tables, semi-structured knowledge bases and QA relates to several parallel lines of research. In terms of dataset creation via crowd-sourcing, Aydin et al. (2014) harvest MCQs via a gamified app, although their work does not involve tables. Pasupat and Liang (2015) use tables from Wikipedia to construct a set of QA pairs. However their annotation setup does not impose structural constraints from tables, and does not collect fine-grained alignment to table elements.

The construction of knowledge bases in structured format relates more broadly to work on open information extraction (Etzioni et al., 2008; Wu and Weld, 2010; Fader et al., 2011) and knowledge base population (Ji and Grishman, 2011). While the set of tables we currently work with are hand-built, there are efforts to at least partially automate this process (Dalvi et al., 2016).

On the inference side Pasupat and Liang (2015) also reason over tables to answer questions. Unlike our approach, they do not require alignments to table cells. However, they assume knowledge of the table that contains the answer, a priori – which we do not. Yin et al. (2015b) and Neelakantan et al. (2015) also use tables in the context of QA, but deal with synthetically generated query data. Sun et al. (2016) perform cell search over web tables via relational chains, but are more generally interested in web queries. Clark et al. (2016) combine different levels of knowledge for QA, including an integer-linear program for searching over table cells. None of these other efforts leverage tables for generation of data.

Our research more generally pertains to natural language interfaces for databases. Cafarella et al. (2008) parse the web to create a large-scale collection of HTML tables. They compute statistics about co-occurring attributes, inferring schemas and reasoning about likely table relational structure. Venetis et al. (2011) are more specifically concerned with recovering table schema, and their insight into column semantics is related to our own structural decomposition and analysis of tables. Other research connected with relational schema induction for database

Phase Change		Initial State		Final State		Form of Energy Transfer
Melting	causes a	solid	to change into a	liquid	by	adding heat
Vaporization	causes a	liquid	to change into a	gas	by	adding heat
Condensation	causes a	gas	to change into a	liquid	by	removing heat
Sublimation	causes a	solid	to change into a	gas	by	adding heat

Table 4.1: Example part of table concerning phase state changes.

tables is by Syed et al. (2010) and Limaye et al. (2010).

A closely related line of study is connected with executing queries over tables represented as relational databases. This applies more directly to the problem of QA with tables. Cafarella et al. (2008), besides building tables and inferring schemas, also perform queries against these tables. But unlike the natural language questions normally associated with QA, these queries are more IR style lists of keywords. The work of Pimplikar and Sarawagi (2012) is another effort that relies on column semantics to reason better about search requests. Yin et al. (2015a) consider databases where information is stored in n-tuples, which are essentially tables.

4.2 Tables as Semi-structured Knowledge Representation

Tables can be found on the web containing a wide range of heterogenous data. To focus and facilitate our work on QA we select a collection of tables that were specifically designed for the task. Specifically we use AI2's Aristo Tablestore[2]. However, it should be noted that the contributions of this work are not tied to specific tables, as we provide a general methodology that could equally be applied to a different set of tables.

In this section we present the set of tables of curated natural language facts. In the context of this thesis, we discuss their semi-structured form and the semantic relations that make up their structural components. We also discuss the utility of these relations in knowledge representation for the domain. Finally we give details of the data we deal with.

4.2.1 Table Semantics and Relations

Part of a table from the Aristo Tablestore is given as an example in Table 4.1. The format is semi-structured: the rows of the table (with the exception of the header) are a list of sentences, but with well-defined recurring filler patterns. Together with the header, these patterns divide the rows into meaningful columns. This semi-structured data format is flexible. Since facts are presented as sentences, the tables can act as a text corpus for information retrieval. At the same time the structure can be used – as we do – to focus on specific nuggets of information. The flexibility of these tables allows us to compare our table-based system to an information retrieval baseline.

Such tables have some interesting structural semantics, which we will leverage throughout the paper. A row in a table corresponds to a *fact*[3]. For example, the sentence "Melting causes a

[2] `http://allenai.org/content/data/AristoTablestore-Nov2015Snapshot.zip`

[3] Also predicates, or more generally frames with typed arguments.

solid to change into a liquid by adding heat" is ostensibly a fact.

The cells in a row correspond to concepts, entities, or processes that participate in this fact. In the example sentence above, "melting" "solid", "liquid" etc. are all related processes or concepts that participate in the corresponding fact. They are bound to one another by the prototype relation defined by *types and effects of energy addition*.

A content column – which we differentiate from filler columns that only contain a recurring pattern, and no information in their header cells – corresponds to a group of concepts, entities, or processes that are the same *type*. For example, the column containing the processes "melting", "vaporization", "condensation" etc. is a content column, while the column containing the identical pattern "to change into" in every row is a filler column.

The header cell of the column is an abstract description of the *type*. We may view the head as a hypernym and the cells in the column below as co-hyponyms of the head. The header row defines a generalization of which the rows in the table are specific instances. For example, "phase change" is an abstract descriptor, or hypernym of the processes "melting", "vaporization", "condensation" etc.

These tables also encode implicit analogical relations. Let row_1 and row_2 be any two rows in a table. Let col_1 and col_2 be any two *content* columns in a table. The four cells where the rows and columns intersect form an analogy: $cell_{1,1}$ is to $cell_{1,2}$ as $cell_{2,1}$ is to $cell_{2,2}$. That is, the relation between $cell_{1,1}$ and $cell_{1,2}$ is highly similar to the relation between $cell_{2,1}$ and $cell_{2,2}$. As an example, one might be able to derive the following analogy from the intersection of rows and columns in the tables: "melting is to solid" as "freezing is to liquid". The table is thus essentially a compact representation of a large number of scientific analogies.

The semi-structured nature of this data is flexible. Since facts are presented as sentences, the tables can simply act as a text corpus for information retrieval. Depending on the end application, more complex models can rely on the inherent structure in tables. They can be used as is for information extraction tasks that seek to zero in on specific nuggets of information, or they can be converted to logical expressions using rules defined over neighboring cells. Regarding construction, the recurring filler patterns can be used as templates to extend the tables semi-automatically by searching over large corpora for similar facts (Ravichandran and Hovy, 2002; Dalvi et al., 2016).

Finally, this structure is directly relevant to multiple-choice QA. Facts (rows) form the basis for creating or answering questions, while instances of a type (columns) act as the choices of an MCQ. We use these observations both for crowd-sourcing MCQ creation as well as for designing models to answer MCQs with tables.

4.2.2 Table Data

The Aristo Tablestore consists of 65 hand-crafted tables organized by topic. Some of the topics are bounded, containing only a fixed number of facts, such as the possible phase changes of matter (see Table 4.1). Other topics are unbounded, containing a very large or even infinite number of facts, such as the kind of energy used in performing an action (the corresponding tables can only contain a sample subset of these facts). A total of 3851 facts (one fact per row) are present in the manually constructed tables. An individual table has between 2 and 5 *content* columns.

The target domain for these tables is two 4th grade science exam datasets. The majority of the tables were constructed to contain topics and facts from the publicly available Regents dataset[4]. The rest were targeted at an unreleased dataset called Monarch. In both cases only the training partition of each dataset was used to formulate and hand-craft tables. However, for unbounded topics, additional facts were added to each table, using science education text books and web searches.

4.3 Answering Multiple-choice Questions using Tables

In this section we detail how tables can be used to answer MCQs. Importantly, the method we describe relies of fine grained alignments between MCQs and the relational components of tables.

Consider the table give in Table 4.1, and the MCQ "What is the process by which water is changed from a liquid to a gas?" with choices "melting, sublimation, vaporization, condensation". The problem of finding the correct answer amounts to finding a cell (or cells) in the table that is most relevant to a candidate Question-Answer pair. In other words, a relevant cell should confirm the assertion made by a particular Question-Answer pair.

It turns out that relevant cells can be defined (as shown in the example below) as a function of row and column intersections. Fortunately, there are clues in the table and the MCQ that help in locating such intersections and relevant cells.

If one can parse the question correctly one might learn that the question is seeking a "process". Parallely one might learn that the choices "melting, sublimation, vaporization, condensation" are all phase changes, and therefore processes. Then, by the hypernym-hyponym relationship between a header-cell and its corresponding column, one might be able to say – with some degree of certainty – that the relevant cell is contained in the column headed by the cell "Phase Change".

Solving the MCQ also requires locating a correct row. This can be done by matching the words "liquid" and "gas" to entries of a single row, and hypothetically using the "from" and "to" indicators to further distinguish between initial and final states of a phase change (thus potentially avoiding ambiguity between evaporation and condensation).

If we follow this line of reasoning, we find that the intersection of the correct row and column is the cell "vaporization", which correctly answers the MCQ.

Figure 4.1 illustrates this with color for row and color alignments to the example MCQ presented above. The intersection of the blue row and the yellow column is the red cell, which contains the correct answer.

Of course, the ability to find these fine grained alignments is hypothetical. Lexical variation, word ordering, syntactic diversity all contribute to making the discovery of these alignments a non-trivial problem. We require training data in order to train a model to align table elements to parts of MCQs properly. And in the next section we will see exactly how these alignments can be obtained cheaply by non-expert annotators through a Mechanical Turk task that leverages the structural and relational properties of tables.

[4] `http://allenai.org/content/data/Regents.zip`

PHASE CHANGE		INITIAL PHASE		FINAL PHASE		HEAT TRANSFER
Melting	causes a	solid	to change into a	liquid	by	adding heat
Vaporization	causes a	liquid	to change into a	gas	by	adding heat
Sublimation	causes a	solid	to change into a	gas	by	adding heat
Freezing	causes a	liquid	to change into a	solid	by	removing heat
Deposition	causes a	gas	to change into a	solid	by	removing heat
Condensation	causes a	gas	to change into a	liquid	by	removing heat

Figure 4.1: Example table from MTurk annotation task illustrating constraints. We ask Turkers to construct questions from blue cells, such that the red cell is the correct answer, and distracters must be selected from yellow cells.

4.4 Crowd-sourcing Multiple-choice Questions and Table Alignments

Since this thesis is focussed on feature representation learning, we are interested in developing models that leverage features that rely on the structural and relational properties of tables, MCQs and the alignments between them.

In this section we outline the MCQs generated from tables. We first describe the annotation task and argue for constraints imposed by table structure and relations. We then describe the data generated from this annotation task.

4.4.1 MCQ Annotation Task

We use Amazon's Mechanical Turk (MTurk) service to generate MCQs by imposing constraints derived from the structure of the tables. These constraints help annotators create questions with scaffolding information, and lead to consistent quality in the generated output. An additional benefit of this format is the alignment information, linking cells in the tables to the MCQs generated by the Turkers. The alignment information is generated as a by-product of making the MCQs and is crucial in developing our models that answer MCQs (see Section 4.3).

We present Turkers with a table such as the one in Figure 4.1. Given this table, we choose a target cell to be the correct answer for a new MCQ; for example, the red cell in Figure 4.1. First, Turkers create a question by using information from the rest of the row containing the target (i.e., the blue cells in Figure 4.1), such that the target is its correct answer. Then they select the cells in the row that they used to construct the question. Following this, they construct four succinct choices for the question, one of which is the correct answer and the other three are distractors. Distractors are formed from other cells in the column containing the target (i.e. yellow cells in Figure 4.1). If there are insufficient unique cells in the column Turkers create their own. Annotators can rephrase and shuffle the contents of cells as required to create the question, answer or any of the distractors.

In addition to an MCQ, we obtain alignment information with no extra effort from annotators.

Task	Avg. Time (s)	$/hour	% Reject
Rewrite	345	2.61	48
Paraphrase	662	1.36	49
Add choice	291	2.47	24
Write new	187	**5.78**	38
TabMCQ	**72**	5.00	**2**

Table 4.2: Comparison of different ways of generating MCQs with MTurk.

What is the orbital event with the longest day and the shortest night?
A) **Summer solstice**
B) Winter solstice
C) Spring equinox
D) Fall equinox
Steel is a/an _____ of electricity
A) Separator
B) Isolator
C) Insulator
D) Conductor

Table 4.3: Examples of MCQs generated by MTurk. Correct answer choices are in bold.

We know which table, row, and column contains the answer, and thus we know which header cells might be relevant to the question. We also know the cells of a row that were used to construct a question. This is precisely the alignment information that we need to be able to train a model to replicate these alignments and thus answer MCQs by finding intersections between maximally aligned rows and columns.

It is worth noting, in the context of this thesis, that both the constraints of the annotation task and the alignment information we obtain as a by-product are centered around the relational properties of tables. The row and column structure play an important role in framing the annotation task for Turkers, while alignment information links into these same structural components.

4.4.1.1 The TabMCQ Dataset

We created a HIT (the MTurk acronym for Human Intelligence Task) for every *content* cell (i.e. non-filler cell; see Section 4.2) from each one of the 65 manually constructed tables of the Aristo Tablestore. We paid annotators 10 cents per MCQ, and asked for 1 annotation per HIT for most tables. For an initial set of four tables which we used in a pilot study, we asked for three annotations per HIT[5]. We required Turkers to have a HIT approval rating of 95% or higher, with a minimum of at least 500 HITs approved. We restricted the demographics of our workers to the US.

Table 4.2 compares our method with other studies conducted at AI2 to generate MCQs. These

[5]The goal was to obtain diversity in the MCQs created for a target cell. The results were not sufficiently conclusive to warrant a threefold increase in the cost of creation.

methods attempt to generate new MCQs from existing ones, or write them from scratch, but do not involve tables in any way. Our annotation procedure leads to faster data creation, with consistent output quality that resulted in the lowest percentage of rejected HITs. Manual inspection of the generated output also revealed that questions are of consistently good quality. They are good enough for training machine learning models and many are good enough as evaluation data for QA. A sample of generated MCQs is presented in Table 4.3.

We implemented some simple checks to evaluate the data before approving HITs. These included things like checking whether an MCQ has at least three choices and whether choices are repeated. We had to further prune our data to discard some MCQs due to corrupted data or badly constructed MCQs. A total of 159 MCQs were lost through the cleanup. In the end our complete data consists of 9092 MCQs, which is – to the best of our knowledge – orders of magnitude larger than any existing collection of science exam style MCQs available for research. These MCQs also come with alignment information to tables, rows, columns and cells. The dataset, bundled together with the Aristo Tablestore, can be freely downloaded at `http://ai2-website.s3.amazonaws.com/data/TabMCQ_v_1.0.zip`.

4.5 Feature Rich Table Embedding Solver

In this section we detail the first of our two system that leverages MCQs, tables and alignment information between them. Specifically we develop a feature rich solver of multiple-choice questions, where the features are manually engineered. Crucially, these features rely on the relational information in tables for inspiration.

We begin by outlining the model and the objective against which it is trained. We then describe our feature set, and show evaluation results in a number of different settings on three different benchmark datasets. Our results consistently and significantly outperform two baselines: a strong retrieval model and a highly structured Markov Logic Network model (Khot et al., 2015).

We demonstrate the advantages of semi-structured data and models over unstructured or highly-structured counterparts. We also find that our manually feature engineered model learns generalizations that permit inference when exact answers may not even be contained in the knowledge base, – thus effectively learning a model that abstracts over the content *and* structure of tables.

4.5.1 Model and Training Objective

Recall from Section 4.3 that a table may be used to answer a question by finding and focussing on a small set of relevant cells. Moreover, these cells are are found by creating an intersection between rows and columns of interest, by a combination of leveraging the structure of a table as well as its contents.

By applying the reasoning used to create MCQs (see Section 4.4) in the inverse direction, finding these relevant cells becomes the task of finding an intersection between rows and columns of interest.

Consider the MCQ "What is the process by which water is changed from a liquid to a gas?" with choices "melting, sublimation, vaporization, condensation", and the table given in Fig-

ure 4.1. Assuming we have some way of aligning a question to a row (blue cells) and choices to a column (yellow cells), then the relevant cell is at the intersection of the two (the red cell). This alignment is precisely what we get as a by-product of the annotation task we setup in Section 4.2.1 to harvest MCQs.

We can thus featurize connections between MCQs and elements of tables and use the alignment data to train a model over the features. This is exactly the intuition that our Feature Rich Table Embedding Solver (FRETS) seeks to model.

We begin by defining symbols for our data:

- $\mathcal{Q} = \{q_1, ..., q_N\}$ denote a set of MCQs. Note that each question q_n is typically a sequence of tokens.
- $\mathcal{A}_n = \{a_n^1, ..., a_n^K\}$ denotes a set of candidate answer choices for a given question q_n. Again, note that while answer choice a_n^k may sometimes be a single token, more generally it will consist of a sequence of tokens.
- $\mathcal{T} = \{T_1, ..., T_M\}$ is a set of tables with text entries. Given a table T_m, let t_m^{ij} be the cell in that table corresponding to the ith row and jth column. Note that each cell t_m^{ij} is a sequence of tokens.

We then define a log-linear model that scores every cell t_m^{ij} of every table in our collection, according to a set of discrete weighted features, for a given QA pair. We have the following:

$$\log p(t_m^{ij} | q_n, a_n^k; \mathcal{A}_n, \mathcal{T}) = \sum_d \lambda_d f_d(q_n, a_n^k, t_m^{ij}; \mathcal{A}_n, \mathcal{T}) - \log Z \tag{4.1}$$

Here λ_d are weights and $f_d(q_n, a_n^k, t_m^{ij}; \mathcal{A}_n, \mathcal{T})$ are features. These features should ideally leverage both structure and content of tables to assign high scores to relevant cells, while assigning low scores to irrelevant cells. Z is the partition function, defined as follows:

$$Z = \sum_{m,i,j} \exp\left(\sum_d \lambda_d f_d(q_n, a_n^k, t_m^{ij}; \mathcal{A}_n, \mathcal{T})\right) \tag{4.2}$$

Z normalizes the scores associated with every cell over all the cells in all the tables to yield a probability distribution. During inference the partition term $\log Z$ can be ignored, making scoring cells of every table for a given QA pair efficient. However, Z must be taken into account when training.

These scores can be used to find a solution for an MCQ. Every QA pair produces a hypothetical fact, and as noted in Section 4.2.1, the row of a table is in essence a fact. Relevant cells (if they exist) should confirm the hypothetical fact asserted by a given QA pair. During inference, we assign the score of the highest scoring row (or the most likely fact) to a hypothetical QA pair. Then the correct solution to the MCQ is simply the answer choice associated with the QA pair that was assigned the highest score. Mathematically, this is expressed as follows:

$$a_n^* = \arg\max_{a_n^k} \max_{m,i} \sum_j \sum_d \lambda_d f_d(q_n, a_n^k, t_m^{ij}; \mathcal{A}_n, \mathcal{T}) \tag{4.3}$$

4.5.1.1 Training

Since FRETS is a log-linear model, training involves optimizing a set of weights λ_d. As training data, we use alignment information between MCQs and table elements (see Section 4.2.2). The predictor value that we try to maximize with our model is an alignment score that is closest to the true alignments in the training data. True alignments to table cells for a given QA pair are essentially indicator values but we convert them to numerical scores as follows[6].

- If the answer in a QA pair is the right answer, we assign:
  - a score of 1.0 to cells whose row and column values are both relevant (i.e. contains exactly the information needed to answer the question).
  - a score of 0.5 to cells whose row but not column values are relevant (i.e. is related to the fact asserted by the QA pair, but not exactly the relevant information).
  - a score of 0.0 otherwise (i.e. is not related to the QA pair)
- If the answer in a QA pair is not the right answer, we assign:
  - a score of 0.1 to random cells from irrelevant tables, with a probability of 1%.
  - a score of 0.0 otherwise.

The intuition behind this scoring scheme is to guide the model to pick relevant cells for correct answers, while encouraging it to pick faulty evidence with low scores for incorrect answers.

Given these scores assigned to all cells of all tables for all QA pairs in the training set, suitably normalized to a probability distribution over tables for a given QA pair, we can then proceed to train our model. We use cross-entropy, which minimizes the following loss:

$$L(\vec{\lambda}) = \sum_{\substack{q_n \\ a_n^k \in \mathcal{A}_n}} \sum_{m,i,j} p(t_m^{*ij} | q_n, a_n^k; \mathcal{T}) \cdot \log p(t_m^{ij} | q_n, a_n^k; \mathcal{A}_n, \mathcal{T}) \tag{4.4}$$

Here $p(t_m^{*ij} | q_n, a_n^k; \mathcal{T})$ is the normalized probability of the true alignment scores.

While this is an indirect way to train our model to pick the best answer, in our pilot experiments it worked better than direct maximum likelihood or ranking with hinge loss, achieving a training accuracy of almost 85%. Our experimental results on the test suite, presented in the next section, also support the empirical effectiveness of this approach.

4.5.2 Features

The features we implement are summarized in Table 4.4. In the context of this thesis, it should be noted that almost all of these features leverage some structural or relational property of the tables as described in Section 4.2. The features in our model compute statistics between question-answer pairs and different structural components of tables.

Even though they are manually engineered, thinking about the semantic relations as a basis for knowledge representation can facilitate the process of feature engineering. They can also

[6]On training data, we experimented with a few different scoring heuristics and found that these ones worked well.

Level	Feature	Description	Intuition	S-Var	Cmpct
Table	Table score	Ratio of words in **t** to **q+a**	Topical consistency	◊	
	†TF-IDF table score	Same but TF-IDF weights	Topical consistency	◊	●
Row	Row-question score	Ratio of words in **r** to **q**	Question align	◊	●
	Row-question w/o focus score	Ratio of words in **r** to **q-($\mathbf{a_f}$+$\mathbf{q_f}$)**	Question align	◊	
	Header-question score	Ratio of words in **h** to **q**	Prototype align	◊	
Column	Column overlap	Ratio of elements in **c** and **A**	Choices align	◊	●
	Header answer-type match	Ratio of words in $\mathbf{c_h}$ to $\mathbf{a_f}$	Choices hypernym align	◊	●
	Header question-type match	Ratio of words in $\mathbf{c_h}$ to $\mathbf{q_f}$	Question hypernym align	◊	
Cell	†Cell salience	Salience of **s** to **q+a**	QA hypothesis assert	◊	●
	†Cell answer-type entailment	Entailment score between **s** and $\mathbf{a_f}$	Hypernym-hyponym align		●
	Cell answer-type similarity	Avg. vector sim between **s** and $\mathbf{a_f}$	Hypernym-hyponym sim.		

Table 4.4: Summary of features. For a question (**q**) and answer (**a**) we compute scores for elements of tables: whole tables (**t**), rows (**r**), header rows (**h**), columns (**c**), column headers ($\mathbf{c_h}$) and cells (**s**). Answer-focus ($\mathbf{a_f}$) and question-focus ($\mathbf{q_f}$) terms added where appropriate. Features marked ◊ denote soft-matching variants, marked with while those marked with a † are described in further detail in Section 4.5.2. Finally, ● features denote those that received high weights during training with all features, and were subsequently selected to form a compact FRETS model.

lead to a model that replicates this process by automating the process of feature generation (see Section 4.6).

While the features in Table 4.4 are weighted and summed for each cell individually, they can capture more global properties such as scores associated with tables, rows or columns in which the specific cell is contained. Features are divided into four broad categories based on the level of granularity at which they operate. In what follows we give some details of Table 4.4 that require further elaboration.

4.5.2.1 Soft matching

Many of the features that we implement are based on string overlap between bags of words. However, since the tables are defined statically in terms of a fixed vocabulary (which may not necessarily match words contained in an MCQ), these overlap features will often fail. We therefore soften the constraint imposed by hard word overlap by a more forgiving soft variant. More specifically we introduce a word-embedding based soft matching overlap variant for every feature in the table marked with $\diamondsuit$. The soft variant targets high recall while the hard variant aims at providing high precision. We thus effectively have almost twice the number of features listed.

Mathematically, let a hard overlap feature define a score $|S_1 \cap S_2| \ / \ |S_1|$ between two bags of words S_1 and S_2. We can define the denominator S_1 here, without loss of generality. Then, a corresponding word-embedding soft overlap feature is given by this formula:

$$\frac{1}{|S_1|} \sum_{w_i \in S_1} \max_{w_j \in S_2} sim(\vec{w_i}, \vec{w_j}) \tag{4.5}$$

Intuitively, rather than matching a word to its exact string match in another set, we instead match it to its most similar word, discounted by the score of that similarity.

4.5.2.2 Question parsing

We parse questions to find the desired answer-type and, in rarer cases, question-type words. For example, in the question "What form of energy is required to convert water from a liquid to a gas?", the type of the answer we are expecting is a "form of energy". Generally, this answer-type corresponds to a hypernym of the answer choices, and can help find relevant information in the table, specifically related to column headers.

By carefully studying the kinds of question patterns in our data, we implemented a rule-based parser that finds answer-types from queries. This parser uses a set of hand-coded regular expressions over phrasal chunks. The parser is designed to have high accuracy, so that we only produce an output for answer-types in high confidence situations. In addition to producing answer-types, in some rarer cases we also detect hypernyms for parts of the questions. We call this set of words question-type words. Together, the question-type and answer-type words are denoted as focus words in the question.

4.5.2.3 TF-IDF weighting

TF-IDF scores for weighting terms are pre-computed for all words in all the tables. We do this by treating every table as a unique document. At run-time we discount scores by table length as well as length of the QA pair under consideration to avoid disproportionately assigning high scores to large tables or long MCQs.

4.5.2.4 Salience

The salience of a string for a particular QA pair is an estimate of how relevant it is to the hypothesis formed from that QA pair. It is computed by taking words in the question, pairing them with words in an answer choice and then computing PMI statistics between these pairs from a large corpus. A high salience score indicates words that are particularly relevant for a given QA pair hypothesis.

4.5.2.5 Entailment

To calculate the entailment score between two strings, we use several features, such as overlap, paraphrase probability, lexical entailment likelihood, and ontological relatedness, computed with n-grams of varying lengths.

4.5.2.6 Normalization

All the features in Table 4.4 produce numerical scores, but the range of these scores vary to some extent. To make our final model more robust, we normalize all feature scores to have a range between 0.0 and 1.0. We do this by finding the maximum and minimum values for any given feature on a training set. Subsequently, instead of using the raw feature value of a feature f_d, we instead replace it with $(f_d - \min f_d) \,/\, (\max f_d - \min f_d)$.

4.5.3 Experimental Results

We train FRETS (Section 4.5.1.1) on the TabMCQ dataset (Section 4.4.1.1) using adaptive gradient descent with an L2 penalty of 1.0 and a mini-batch size of 500 training instances. We train two variants: one consisting of all the features from Table 4.4, the other – a compact model – consisting of the most important features (above a threshold) from the first model by feature-weight. These features are noted by ● in the final column of Table 4.4.

We run experiments on three 4th grade science exam MCQ datasets: the publicly available Regents dataset, the larger but unreleased dataset called Monarch, and a third even larger public dataset of Elementary School Science Questions (ESSQ)[7]. For the first two datasets we use the test splits only, since the training sets were directly studied to construct the Aristo Tablestore, which was in turn used to generate our TabMCQ training data. On ESSQ we use all the questions since they are independent of the tables. The Regents test set consists of 129 MCQs, the Monarch test set of 250 MCQs, and ESSQ of 855 MCQs.

[7] `http://aristo-public-data.s3.amazonaws.com/AI2-Elementary-NDMC-Feb2016.zip`

Model	Data	Regents Test	Monarch Test	ESSQ
Lucene	Regents Tables	37.5	32.6	36.9
	Monarch Tables	28.4	27.3	27.7
	Regents+Monarch Tables	34.8	35.3	37.3
	Waterloo Corpus	55.4	51.8	54.4
MLN (Khot et al., 2015)	-	47.5	-	-
FRETS (Compact)	Regents Tables	**60.7**	47.2	51.0
	Monarch Tables	56.0	45.6	48.4
	Regents+Monarch Tables	59.9	47.6	50.7
FRETS	Regents Tables	59.1	**52.8**	54.4
	Monarch Tables	52.9	49.8	49.5
	Regents+Monarch Tables	59.1	52.4	**54.9**

Table 4.5: Evaluation results on three benchmark datasets using different sets of tables as knowledge bases. Best results on a dataset are highlighted in bold.

Since we are investigating semi-structured models, we compare against two baselines. The first is an unstructured information retrieval method, which uses the Lucene search engine. To apply Lucene to the tables, we ignore their structure and simply use rows as plain-text sentences. The score for top retrieved hits are used to rank the different choices of MCQs. The second baseline is the highly-structured Markov-logic Network (MLN) model from Khot et al. (2015) as reported in Clark et al. (2016), who use the model as a baseline[8]. Note that Clark et al. (2016) achieve a score of 71.3 on Regents Test, which is higher than FRETS' scores (see Table 4.5), but their results are not comparable to ours because they use an ensemble of algorithms. In contrast, we use a single algorithm with a much smaller collection of knowledge. FRETS rivals the best individual algorithm from their work.

We primarily use the tables from the Aristo Tablestore as knowledge base data in three different settings: with only tables constructed for Regents (40 tables), with only supplementary tables constructed for Monarch (25 tables), and with all tables together (all 65 tables; see Section 4.2.2). For the Lucene baseline we also experiment with several orders of magnitude more data by indexing over the 5×10^{10} words Waterloo corpus compiled by Charles Clarke at the University of Waterloo. Data is not a variable for MLN, since we directly cite results from Clark et al. (2016).

The word vectors we used in soft matching feature variants (i.e., $\Diamond$ features from Table 4.4) for all our experiments were trained on 300 million words of Newswire English from the monolingual section of the WMT-2011 shared task data. These vectors were improved post-training by retrofitting (Faruqui et al., 2014) them to PPDB (Ganitkevitch et al., 2013).

The results of these experiments is presented in Table 4.5. All numbers are reported in percentage accuracy. We perform statistical significance testing on these results using Fisher's exact test with a p-value of 0.05 and report them in our discussions.

First, FRETS – in both full and compact form – consistently outperforms the baselines, often by large margins. For Lucene, the improvements over all but the Waterloo corpus baseline

[8]We do not re-implement the MLN, and therefore only cite results from previous work on part of our test suite.

Model	REG	MON	ESSQ
FRETS	59.1	**52.4**	**54.9**
w/o tab features	59.1	47.6	52.8
w/o row features	49.0	40.4	44.3
w/o col features	59.9	47.2	53.1
w/o cell features	25.7	25.0	24.9
w/o $\Diamond$ features	**62.2**	47.5	53.3

Table 4.6: Ablation study on FRETS, removing groups of features based on level of granularity. $\Diamond$ refers to the soft matching features from Table 4.4. Best results on a dataset are highlighted in bold.

are statistically significant. Thus FRETS is able to capitalize on data more effectively and rival an unstructured model with access to orders of magnitude more data. For MLN, the improvements are statistically significant in the case of *Regents* and *Regents+Monarch* tables. FRETS is thus performing better than a highly structured model while making use of a much simpler data formalism.

Our models are able to effectively generalize. With Monarch tables, the Lucene baseline is little better than random (25%). But with the same knowledge base data, FRETS is competitive and sometimes scores higher than the best Lucene or MLN models (although this difference is statistically insignificant). These results indicate that our models are able to effectively capture both content and structure, reasoning approximately (and effectively) when the knowledge base may not even contain the relevant information to answer a question. The Monarch tables themselves seem to add little value, since results for Regents tables by themselves are just as good or better than Regents+Monarch tables. This is not a problem with FRETS, since the same phenomenon is witnessed with the Lucene baseline. It is noteworthy, however, that our models do not suffer from the addition of more tables, showing that our search procedure over table cells is robust.

Finally, dropping some features in the compact model doesn't always hurt performance, in comparison with the full model. This indicates that potentially higher scores are possible by a principled and detailed feature selection process. In these experiments the difference between the two FRETS models on equivalent data is statistically insignificant.

4.5.3.1 Ablation Study

To evaluate the contribution of different features we perform an ablation study, by individually removing groups of features from the full FRETS model, and re-training. Evaluation of these partial models is given in Table 4.6. In this experiment we use all tables as knowledge base data.

Judging by relative score differential, cell features are by far the most important group, followed by row features. In both cases the drops in score are statistically significant. Intuitively, these results make sense, since row features are crucial in alignment to questions, while cell features capture the most fine-grained properties. It is less clear which among the other three feature groups is dominant, since the differences are not statistically significant. It is possible that cell features replicate information of other feature groups. For example, the cell answer-type entail-

ment feature indirectly captures the same information as the header answer-type match feature (a column feature). Similarly, salience captures weighted statistics that are roughly equivalent to the coarse-grained table features. Interestingly, the success of these fine-grained features would explain our improvements over the Lucene baseline in Table 4.5, which is incapable of such fine-grained search.

The results of this ablation study also provide insight into some of our assumptions about the learning model with respect to specific features. For example, the column based features make some fairly strong assumptions about the MCQs. They assume, in general, that the different choices of an MCQ are semantically connected by a single hypernym type – in the current context that they belong to a single table column. This is of course true of our TabMCQ dataset, where the choices are in fact generated from a single column. However, this may not be true of our test sets, where there is no restriction placed on the distractors for an MCQ. Moreover, the tables are constructed by manually inspecting MCQ training data; there is no reason to imagine that the columns of tables constructed from training will accurately reflect the classification of choices into types on the test set.

In general, a more detailed feature analysis in future work will likely highlight other assumptions of our model and indicate ways of improving current features or suggesting new ones altogether. For example, our note above on the column-based features suggests that a reliance on the Wh- word in the question, instead of column-header matching might be a better indicator of the expected answer type of a question. This would also enable our system to work on QA without multiple choices, where column matching might not be possible to begin with.

4.6 TabNN: QA over Tables with Neural Networks

We have shown that tables can be effectively used as a source of semi-structured background knowledge in Question Answering. In particular, we demonstrated that the implicit relations in tables can be leveraged as insight into developing a feature rich model for QA.

However, the FRETS MCQ solver that we implemented and evaluated in Section 4.5 uses a set of manually engineered features to find relevant cells in tables for answering questions. In keeping with the over-arching goal of this thesis, we'd like to also explore the replacement of manual feature engineering with automatic representation learning, while still leveraging the relational properties of tables.

Some important question must be asked, in this context. Does such a replacement in fact result in a model that is as effective or better at solving MCQs? What are the trade-offs between manually engineering features versus inducing them automatically via representation learning, – while continuing to leverage structural and relational information. What are the repercussions in terms of performance, generality and dependence on data?

To answer these questions we develop a neural network model that mimics some of the relational features we developed for FRETS. This model requires no feature engineering. Instead it leverages the structural components of tables (i.e. rows and columns) and their relations to MCQ elements to learn representations that reproduce the alignment signal from our TabMCQ dataset.

4.6.1 The Model

Recall the discussion about the relational structure in tables and its semantics from Section 4.2.1, and the translation of these semantics into manually engineered features in Section 4.5.2. At a high level, one can think about a question as being *mapped* to a specific row, while its choices are *mapped* to a specific column and the correct answer is *mapped* to the cell at the intersection of these specific row and column. In fact this is the process of thinking through which we guide our annotators in crowd-sourcing MCQs, as described in Section 4.4.1.

Hence, from a representation learning point of view, it makes sense to develop a neural network model that learns each of these mappings in a joint framework. This is precisely what we do with TabNN. We compute affinity scores between question and rows, choices and columns and answer and cells with three distinct loss functions. Each of these affinities are much like the feature score computed by FRETS for a particular cell given an MCQ. Jointly, they capture how likely the cell at the intersection of a row and column is to containing information relevant to asserting a QA pair.

In what follows, we describe the parametrization of each of these three mappings, but we begin by describing shared components of the model.

4.6.1.1 Shared Model Components

Shared components of the model describe elements that are reused across the three mappings that we attempt to learn. They represent smaller units of representation, across which we attempt to share statistical strength, reduce the parameter space of our model and increase overall robustness. The shared representations are also what tie the three different objectives together.

Cell Embedding

These embedding parameters take the input words of cell elements in tables and map them into dense vectorial representations. Assuming a sequence of words $w_1, ..., w_n$ in a specific cell, this layer converts it into a sequence of vectors $v_1, ..., v_n$, each with dimension d_1.

The vector space of embeddings V can be learnable, or may be pre-trained and fixed.

Cell LSTM

These parameters convert the sequence of vector representations $v_1, ..., v_n$ that we generated from the embeddings into a single vector V_c that captures the *meaning* of the entire sequence. The LSTM that we use to perform this encoding makes this conversion with the sequence of following gated operations. A hidden state and cell state (not to be confused with the cell of a table), h_t and C_t are maintained throughout the sequence at every time step t.

The first step is to compute a forget gate to decide how much of the information from the previous state must actually be carried forward. This is done by:

$$f_t = \sigma(W_f \cdot [h_{t-1}, v_t] + b_f) \tag{4.6}$$

Parallely we can also compute what new information must be stored in the current cell state. This involves two related parts. The first is the "input gate layer" which decides what values must be

updated. The second is a new candidate for the current state. Equations for these two parts are given below:

$$i_t = \sigma(W_i \cdot [h_{t-1}, v_t] + b_i) \tag{4.7}$$

$$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, v_t] + b_C) \tag{4.8}$$

The forget and input vectors are then used to weight the previous cell state and current candidate state to produce the new current cell state:

$$C_t = f_t \odot C_{t-1} + i_t * \widetilde{C}_t \tag{4.9}$$

where $\odot$ is the element-wise multiplication operation between vectors.

Finally, we compute the new hidden state. This is done by an intermediate "output gate layer" that is then combined with the new current cell state:

$$o_t = \sigma(W_o \cdot [h_{t-1}, v_t] + b_o) \tag{4.10}$$

$$h_t = o_t \odot \tanh(C_t) \tag{4.11}$$

By repeatedly applying these series of gated operations with each input vector at every time step t we obtain a final hidden state h_n. This hidden state is the single vector V_c that we are seeking, and is a representation of the entire cell.

The set of parameters W_i, b_i, W_C, b_C, W_o and b_o must all be trained.

Choice Embedding

These embeddings are very similar to the cell embeddings, except that they convert words in the different choices of the MCQ into sequences of vectors. As with the Cell Embeddings, this vector space of embeddings can be learned or pre-trained and fixed.

Choice LSTM

Again, these parameters convert the sequence of choice embeddings into a single vector representing the entire choice. The architecture of the LSTM network used to do this is identical to the one described above. Also as before, the set of parameters of the LSTM must all be trained, and are different from the LSTM parameters of the Cell LSTM.

4.6.1.2 Question-Row Objective

The question-row objective attempts to learn a set of discriminative representations that can distinguish when a question is in fact aligned to a row, and when it is not. The architecture of this model component is depicted in Figure 4.2. It comprises several parts that we describe below.

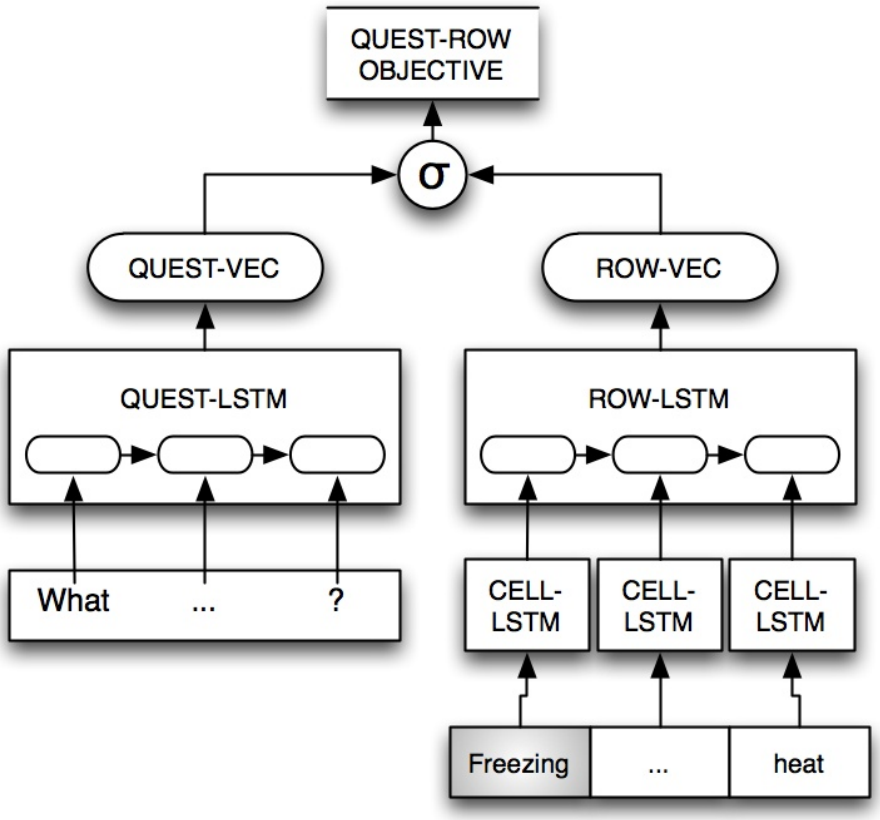


Figure 4.2: The component of the TabNN model that embeds question and row in a joint space and predicts an alignment score between the two. Embedding layers are omitted for visual compactness.

Question Embedding & LSTM

This part of the model performs the same function for questions as the shared components in Section 4.6.1.1 do for table cells and answer choices. We essentially take a sequence of words in the question as input and produce a single vector that encodes the question as an output. This is done with an LSTM on top of an embedding layer.

Row Encoding

The input to this component of the model is different from others, because it is already a sequence of vectors and not words. We take the sequence of vectors produced by the *Cell LSTM* for each cell in the row and feed it into another LSTM that combines them. This is effectively a stacked LSTM, which combines a sequence of sequences to produce a single vector that is a representation of the entire row.

Question-Row Prediction

We concatenate the question and row vectors and feed the resulting vector through a sigmoid activation to produce a response variable. The signal we seek to imitate with this response is the row-alignment score as described in Section 4.5.1.1.

4.6.1.3 Choices-Column Objective

The choices-column objective computes the affinity between the column of a table and the set of choices of the MCQ under consideration. The architecture of this model component is depicted in Figure 4.3. It comprises several parts that we describe below.

Choices Encoding

This model component uses the shared Choice Embedding and LSTM parameters to convert the four different choices into four distinct vectors. It then computes the centroid of these four choices by averaging their four corresponding vectors.

Column Encoding

This model component performs a similar operation on columns. It uses the shared Cell Embedding and LSTM parameters to generate individual vectors for each cell in a column and then computes a centroid vector that is the average of all these cells.

Choices-Column Prediction

We concatenate the two centroid vectors of the choices and column and pass the resulting vector through a sigmoid activation. The response variable seeks to imitate the signal obtained from the alignment of columns to choices as described in Section 4.5.1.1.

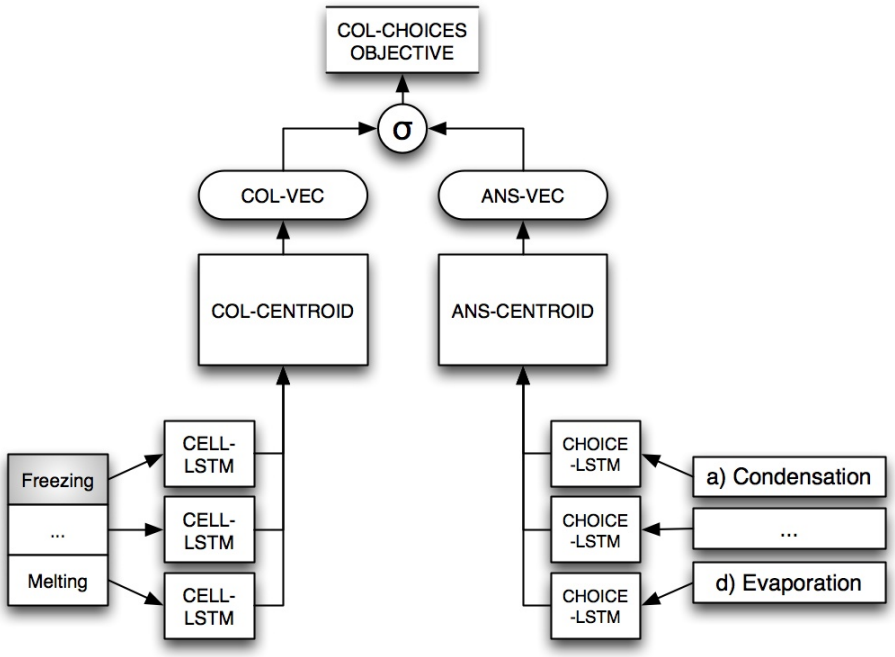


Figure 4.3: The component of the TabNN model that embeds choices and column in a joint space and predicts an alignment score between the two. Embedding layers are omitted for visual compactness.

4.6.1.4 Answer-Cell Objective

Finally, the answer-cell objective predicts whether a cell contains the answer to a question or not. This is done by concatenating cell and answer vectors obtained through the shared embedding and LSTM components of the model and passing the resulting vector through a sigmoid activation. The response variable here is imitating the signal obtained from the alignment of a cell to a particular answer as described in Section 4.5.1.1.

This model objective is pictorially represented in Figure 4.4

Intuitively our model is thus capturing three distinct relational affinities. They are, namely, between questions and rows, the multiple choices and a column, and a specific answer and a particular cell in the tables. These affinities are defined over the structural properties and are thus inspired from the same properties we use to engineer our features manually in the FRETS model (Chapter 4.5).

At test time, it should be clear that for our model to predict a high score for a particular answer pair based on some evidence from the tables, the score associated with each of the three different objectives must also be high.

4.6.2 Training

Since our proposed TabNN model follows the same design template as FRETS, namely by scoring individual rows, columns and cells for relevance to QA pairs, we can use the same training

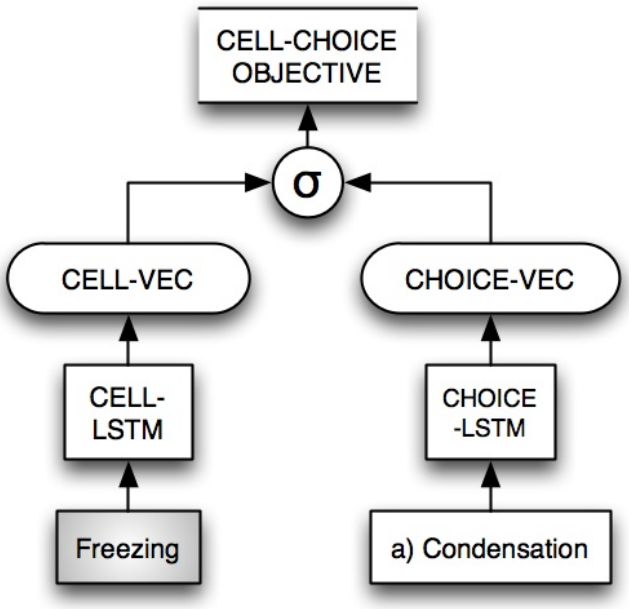


Figure 4.4: The component of the TabNN model that embeds a single choice and table cell in a joint space and predicts an alignment score between the two. Embedding layers are omitted for visual compactness.

schema as before (see Section 4.5.1.1). In summary this objective is the cross-entropy loss between a hypothesized distribution and the true one in training.

The hypothesized distributions are obtained from the scores we assign to the three objectives of Section 4.6.1 with our model. The true distribution are obtained in the same way as with FRETS: by converting alignments annotations between MCQs and table entries into numerical scores. By considering the discrepancy between the hypothesized and true distributions thus defined, we back-propagate the error to update all the model parameters.

An important distinction from the model in FRETS is that we do not consider representations over entire tables. Neither do we search over every row and column of all the tables. These choices are based on the computational complexities that are introduced by considering a model that either directly, or through some combination of smaller components, represents an entire table.

Instead, we use the following criteria to decide which tables we search over and featurize, for every QA pair:

- At training time
  - 1 correct table
  - 2 randomly chosen tables
- At test time
  - 3 top tables from TF-IDF ranking

The TF-IDF ranking we refer to is the same as the TF-IDF table feature defined in our FRETS

model (see Table 4.4 in Section 4.5.2). On a section of the training set that we used to develop our FRETS features, this ranker selected the correct table for a particular MCQ with over 90% accuracy.

4.6.3 Experiments and Evaluation

We now turn to the task of evaluating the TabNN model. We experiment on the publicly available and largest of the three datasets that we used to evaluate FRETS (the ESSQ dataset) and compare the results to the manually feature engineered model. We also discuss differences between the two models and attempt to explain the discrepancy between the results in the context of these differences.

We begin by providing some implementational details.

4.6.3.1 Implementational Details

The training data is obtained by converting the TabMCQ dataset and its corresponding alignment data into response variables as described in Section 4.5.1.1. To normalize the data for input to our neural network architecture we use padding, truncation and masking.

Padding and truncation ensure that the size of each input is constant. So, for example, if a question is too short it is *padded* to be of the constant size and if it is too long it is *truncated* to be of the same size. We set a maximum size of 20 tokens for answer choices and table cells, a maximum of 8 cells in a column, a maximum of 5 cells in a row, and a maximum of 30 tokens in a question.

We also apply masking to the fixed length input sequences. This process indicates time-steps in a sequence that need to be skipped. This works in combination with padding, where the additional time-steps introduced for maintaining constant size are to be skipped when performing LSTM computations.

We implement a total of four distinct models, which are formed from the cross-product of two dimensions of distinction. The first dimension consists of two variants in the types of embeddings we use: learned and pre-trained.

The learned embeddings variant – as the name suggests – randomly initializes the embedding matrices and updates the parameters through training. In this variant the embedding layers used in different parts of the model are correspondingly different.

But the vocabulary sets in training and testing might be different. In this case the learned embeddings, which are obtained from training, will not cover the words encountered at test time. To account for this discrepancy we also experiment with a set of pre-trained embeddings that cover a large vocabulary.

The pre-trained embeddings are obtained by training regular Skip-gram word vectors (Mikolov et al., 2013a) over Wikipedia, then retrofitting (Faruqui et al., 2014) them for enhanced quality. We use this single set of embeddings for all components of the model that require an embedding layer, and we do not update the parameters during training. This significantly reduces the size of the model in terms of the number of parameters.

In both cases we maintain a constant embedding size of 80 for all embedding layers.

Embeddings	LSTM Size	Number of Parameters
Learned	160	4,377,603
	320	7,147,843
Pre-trained	160	1,131,843
	320	3,902,083

Table 4.7: A summary of the different TabNN model variants we train along with the number of parameters learned with each model.

Model	Embeddings	LSTM Size	Training Accuracy	ESSQ Test Accuracy
TabNN	Learned	160	66.5%	25.3%
		320	68.2%	24.3%
	Pre-trained	160	42.2%	26.2%
		320	42.6%	26.1%
FRETS	-	-	-	**54.9%**

Table 4.8: Evaluation of the TabNN model. Training results are provided to gain insight into the models and should not be taken to represent goodness of the models in any way. The best FRETS model's test results are given as a comparison.

The second dimension of distinction, which deals with the size of the LSTM encoding, also yields two variants. We experiment with 160 and 320 for compact and complex LSTM models respectively.

These 4 models are summarized in Table 4.7 along with the number of parameters that they contain.

To avoid overfitting, we apply regularization throughout our model architecture. While training we use a dropout factor of 0.5, which is the recommended standard value (Srivastava et al., 2014), to regularize the different LSTMs. We also use L-2 regularization, with a parameter value of 0.5, applied to all the embedding matrices.

To maximize the joint objective of the model, we perform stochastic gradient descent on batch sizes of 512 and train for a total of 10 epochs over the entire training set.

4.6.3.2 Results

The results of the TabNN model are presented in Table 4.8. We present training values to gain insights into the model, but it should be stressed that high values are by no means an indication of a good model.

In fact we see this in the results, since evaluation on the ESSQ test set show that all variants of the TabNN model perform no better than random guessing (at 25%). The high training values, coupled with the poor test results seem to indicate that the TabNN architecture is massively overfitting to the training set, and is incapable of generalizing to test.

But is this true, considering that we use regularization throughout our model, both with dropout and with L-2 penalties? To test whether this is indeed the case, we run a second batch of experiments where we hold out a randomly selected 10% of training questions from TabMCQ

Model	Embeddings	LSTM Size	Training Acc.	10% TabMCQ Test Acc.	ESSQ Test Acc.
TabNN	Learned	160	68.0%	**56.8**%	24.4%
		320	71.1%	50.8%	24.8%
	Pre-trained	160	42.2%	31.9%	27.1%
		320	43.7%	30.9%	**28.4**%

Table 4.9: Evaluation of the TabNN model, trained on only 90% of the TabMCQ dataset. Test results on the 10% held out portion of TabMCQ show that the model itself is capable of learning, and that it's architecture is sound. There is, however, a severe domain mismatch between TabMCQ and the ESSQ test set.

as a secondary test set. We then train TabNN only on the remaining 90% of TabMCQ and then evaluate the results.

These results are presented in Table 4.9. While the test results on ESSQ are still no different than random, the test results on the 10% held out portion of TabMCQ are much better, with the best model achieving a score of 56.8%. This demonstrates that our model itself is capable of learning effectively, but there is a severe mismatch between the TabMCQ and ESSQ datasets that the TabNN model is incapable of overcoming – and the FRETS model is.

There are some other things to note, across both Tables 4.8 and 4.9. Firstly, as expected, having a more complex model, with an LSTM embed dimension of 320 leads to better training results. But this does not transfer to test, where the simpler models perform better (on 10% TabMCQ test) or at least no worse (on ESSQ test).

Secondly, using pre-trained embeddings does not seem to be justified. While the test results for corresponding models on ESSQ are *marginally* better than learning embeddings from scratch, they are a *lot* worse when tested on 10% TabMCQ data. Thus not much power is gained by having access to pre-trained embeddings with a larger vocabulary.

Which leads to the third insight: that more training data, in this case, would not help. Instead, *different* and more *diverse* training data is required. This insight is also confirmed by the fact that TabNN, whether trained on the full TabMCQ dataset or only 90% has similar accuracies on training and ESSQ test.

4.6.3.3 Discussion on Differences with FRETS

The results from Section 4.6.3.2 have demonstrated a significant difference between the FRETS and TabNN model. In summary, while they are both capable of leveraging the relations and structure within tables to solve MCQs, FRETS does so by abstracting over both content *and* structure, while TabNN can only abstract over structure and is much more dependent on content.

This finding is in keeping with general expectations of neural network models. While they have potentially infinite capacity to approximate arbitrarily complex functions, they require vast amounts of diverse training data in order to be able to generalize from training to test.

In our case, the TabMCQ (training) dataset is not sufficiently diverse to accommodate the very different ESSQ (test) dataset. For example, the average length of questions in ESSQ is 24.4 words, with some questions containing lengthy explanatory paragraphs before the actual

question. In contrast, the crowd-sourced TabMCQ dataset only has an average of only 11 words, with Turkers only creating direct MCQs.

The TabNN model must deal with these discrepancies by automatic means such as truncation and padding. There is no guarantee that truncation maintains all the information in the question relevant to finding an answer. In contrast, the feature-rich FRETS model relies on sentence splitting and manually crafted regular expression patterns over phrase chunks to extract relevant parts of the question.

Another issue is the content of tables. While FRETS demonstrated itself capable of answering questions that may not even be contained in tables, TabNN did not. In fact, TabNN only performed well on the 10% held out portion of the TabMCQ dataset, when the answers were guaranteed to be found in tables. Unfortunately, our proposed solution of using pre-trained embeddings to counter the mismatch in tables between training and test did not work because learning power is gained by learning the embeddings on in-domain data.

Again, this indicates the need for TabNN to have access to more diverse training data – this time in the form of tables.

In conclusion, the TabNN model is architecturally sound and capable of leveraging the relations within tables to learn representations over table elements for solving MCQs. We thus, re-iterate the central claim of this thesis: that representation learning can benefit from a relation-centric view of semantics. Finding and leveraging the correct relations for a particular domain, specifically, can lead to better models.

However, in comparison with FRETS, TabNN is much more reliant on content and less able to adapt to significantly different test sets. This is in keeping with the general understanding of neural network models which require very large and diverse training sets to properly generalize to unseen examples.

4.7 Conclusion

Tables represent a unique and interesting domain for the study of relational structure in representation learning, with interesting semantic properties emerging from relationships between row and column elements. These properties lead to two separate contributions in this chapter.

Firstly, we leveraged the semi-structured formalism of tables with text entries to create a dataset of MCQs. The semantics of this structure were used as scaffolding information to guide non-expert crowd-sourcing annotators to easily create a high-quality MCQ dataset. The relation-centric annotation setup also led us to harvest rich alignment information of these MCQs table elements, with no additional effort to annotators.

We have released our dataset of more than 9000 MCQs and their alignment information to the research community. To the best of our knowledge, it is the largest elementary school science MCQ dataset of its kind, containing a unique set of alignments to tables. We believe it offers interesting challenges that go beyond the scope of this chapter – such as question parsing, or textual entailment – and are exciting avenues for future research.

Secondly, we developed two kinds of feature-driven models that predicted the previously generated alignment information to answer new unseen MCQs. The first used manually engineered features, while the second automatically induced features within a neural network model.

Crucially however, both kinds of models leveraged the relational and structural properties of tables and thus fit into the broader scope of this thesis.

We evaluated our models on the task of answering MCQs.

On three benchmark sets the manually engineered model, that relied on semi-structured tables, consistently and significantly outperformed an unstructured and a highly-structured baseline. We also showed that this model was able to generalize over content and structure, thus reasoning about questions whose answer was not even contained in the tables that we used as a knowledge repository. This demonstrated that the rich relational structure inherent in tables can in fact be usefully featurized to perform QA.

The neural network model also demonstrated the ability to leverage the relations within tables for learning representations jointly over table elements and MCQs. It showed, that with no feature engineering whatsoever, we were able to obtain promising results on a held-out portion of the training data that we used as a test set. However, it was much more dependent on content than the FRETS model, performing poorly on a test set that had a distinctly different profile to the training data. These findings were in keeping with the general understanding of neural network models, that require large and diverse training sets to learn optimally. Our training set was simply not diverse enough.

The mixed results from the neural network model do not, however, counter the central claims of this thesis. This is because we still demonstrated that we benefitted from a relation-centric view of our domain – solving MCQs with tables. The only difference, in this case, was that in our test setup a manually feature-engineered model (which, it should be noted, centers around the relations and structure of tables) was better than a model that learned feature representations automatically. Our analyses indicate, though, that with a larger and (especially) more diverse training set, the neural network model is likely to perform much better.

4.7.1 Five Point Thematic Summary

What was the semantic representation learning problem that we tried to solve?

We were interested in exploring tables as a medium for storing background knowledge for the task of question answering. Specifically, we were hoping to validate the semi-structured nature of text tables as being a balanced compromise that offered the convenience of fuzzy matching over text with some degree of structure for principled reasoning.

From the perspective of representation learning, we were interested in learning features over elements of tables that maximized our ability to answer questions correctly. Phrased in terms of Definition 1, we were attempting to learn several different semantic relations over pairs that consist of table elements and parts of an MCQ. These relations corresponded to the semantic properties of the tables (see Section 4.2.1) and their connections to MCQs. They were defined over table elements such as rows and columns, as well as questions and the different answer choices.

Since we were interested in learning representations for an extrinsic task – question answering, specifically – we expected the mapping from paired table and MCQ elements to the set of real numbers (according to Definition 1 for a semantic relation) to reflect the requirements of the task. We expected that a good model would score table elements that accurately contained

information to answer an MCQ higher than irrelevant or spurious information.

What linguistic information or resource did we use to solve this problem?

Our task was premised on exploring tables as a source of semi-structured knowledge for question answering. Therefore we used a set of knowledge tables that were designed and constructed to contain an inventory of facts for our domain of choice: fourth-grade science exam MCQs. Section 4.2.2 outlines the resource.

How did we operationalize the desired semantic relation with contextual relations in the resource?

Our operationalization of the desired semantic relation stemmed from the intuition and observation that answers to MCQs can be found by aligning question and answer choices to table rows and columns respectively. Specifically, we observed that with a good alignment, the answer is often found at the intersection of an aligned row and column (see Section 4.3).

Thus, we reversed this intuition to reduce our task to finding an alignment between MCQs and table elements. We created a large dataset of MCQs generated from the tables (see Section 4.4), so that we obtained alignments that would concretize the operationalization of the semantic relations we set out to learn.

Then, we defined contextual relations that had the shared property of explicitly tying questions to rows of a table and columns to a set of answer choices over the training set. In terms of Definition 2, our object sets consisted of structured objects such as questions and entire rows, etc. and the corresponding properties were defined in terms of existing alignments between these structured objects in the training data.

How did we use the contextual relations in representation learning?

We experimented with two separate learning paradigms for solving the MCQs: with a log-linear model consisting of manually engineered features, and a neural network model that automatically induced a set of features for the task. However, in both instances, the contextual relations we defined in the previous item of the five point agenda were used to bias the learners along the same intuitions and principles.

In particular we used the alignment scores between questions and rows, and answer choices and cells as response variables to assign the weights to contextual relations. In the log-linear model we attempted to code features that captured the intuition of these alignments (see Section 4.5.2). Meanwhile we tried to replicate these intuitions in the neural network model with a network architecture that also captured these alignments (see Section 4.6.1).

What was the result of biasing the learner with contextual relations in learning the semantic model?

We concluded from our experiments with both model paradigms that our contextual relations were effectively able to bias the learners with features that were useful for solving multiple-choice question-answering. In particular, we found that the semi-structured nature of the tables

afforded a compromise that allowed us to leverage both their content and structure to answer unseen questions.

However, we found that while our log-linear model was capable of abstracting over both content and structure, our neural network model was only able to abstract over structure while being more tied to the content. Our analyses revealed the need for a larger and more diverse training set (including tables) to properly train the neural network model.

Our overall results indicated that the contextual relations we defined over table elements and MCQs did, in fact, at least partially operationalize our intuitions about the semantic relations we cared about.

Chapter 5

Embedded Frame Lexicons

Learning Event Structure through Unsupervised Lexicon Induction

This thesis is concerned with using semantic relations to learn more expressive models of semantics. Relations encompass a very broad range of phenomena in language and data formalisms, and in Chapter 2 we have attempted to provide a taxonomy of these occurrences of relations as it pertains to our work. This taxonomy serves, both as a technical summary of this thesis, as well as a high-level guideline on how to think about using relations in representation learning of a new domain or problem.

However, an important research issue when dealing with relations for representation learning is the relations themselves. In particular, for a given language phenomenon or data formalism, what happens when the relations are ill-defined, or no annotated data exists?

More generally, what happens when we must induce rather than use a pre-existing set of relations? This is an important question, in the context of this thesis because a comprehensive treatment of semantic relations requires dealing with such scenarios as well.

For example, a low-resource language may simply not have annotated data containing rich structure – such as an ontology – or even partial structure – such as tables. Or consider the example of semantic roles: it is a disputed matter what the exact set of relations to encode all possible semantic roles should be (Kingsbury and Palmer, 2002; Baker et al., 1998).

This and a major part of Chapter 6 will thus be concerned with developing representation learning models that do not leverage or embed a pre-defined annotated set of relations. Our models will rather work on inducing relations as part of the learning process.

Because we are inducing an unknown set of relations, we will also attempt to tackle some general questions about the nature of these relations. How many are there? What are they? How do they organize the elements in the domain to one another? Although, it may be noted that finding answers to these questions does not preclude the *usage* of the induced relations for practical and effective representation learning, since even if the relations are not interpretable they may still produce good results in downstream applications.

In this chapter we turn to the problem of providing a representation learning solution to the relations in a frame lexicon. This is an apt domain, since verbs undoubtedly have relational arguments, as supported by the body of linguistic literature devoted to studying argument re-

alization (Jackendoff, 1987; Moens and Steedman, 1988; Levin and Rappaport Hovav, 2005). However, the specific number and nature of these arguments remains contested (Fillmore, 1967; Sowa, 1991), with solutions ranging from a few prototypical PropBank style relations (Kingsbury and Palmer, 2002) to an effectively open-ended set of highly specific and fine-grained roles in FrameNet (Baker et al., 1998).

These semantic lexicons contain information about predicate-argument frame structure. These frames encode relations that capture knowledge about the affinity of predicates for certain types of arguments. They also specify their number and their semantic nature, regardless of syntactic realization.

For example, PropBank specifies frames in the following manner:

- eat $\rightarrow$ $[\text{agent}]_0, [\text{patient}]_1$
- give $\rightarrow$ $[\text{agent}]_0, [\text{theme}]_1, [\text{recipient}]_2$

These frames provide semantic information such as the fact that "eat" is transitive, while "give" is di-transitive, or that the beneficiary of one action is a "patient", while the other is a "recipient".

This structural knowledge is crucial for a number of NLP applications. Information about frames has been successfully used to drive and improve diverse tasks such as information extraction (Surdeanu et al., 2003), semantic parsing (Das et al., 2010) and question answering (Shen and Lapata, 2007), among others.

However, building these frame lexicons is very expensive and time consuming. Thus, it remains difficult to port applications from resource-rich languages or domains to data impoverished ones. The NLP community has tackled this issue along two different lines of unsupervised work.

At the local level, researchers have attempted to model frame structure by the selectional preference of predicates for certain arguments (Resnik, 1997; Séaghdha, 2010). This can be categorized as token level affinity of predicates for their relational arguments. For example, on this problem a good model might assign a high probability to the word "pasta" occurring as an argument of the word "eat".

Contrastingly, at the global level, work has focussed on inducing frames by clustering predicates and arguments in a joint framework (Lang and Lapata, 2011a; Titov and Klementiev, 2012b). This can be categorized as the type level affinity between predicates and their semantically linked arguments. So for example, one might be interested in associating predicates such as "eat", "consume", "devour", with a joint clustering of arguments such as "pasta", "chicken", "burger".

While these two classes of solutions have been useful for several problems, they also have shortcomings. Selectional preference modelling only captures local predicate-argument affinities, but does not aggregate these associations to arrive at a structural understanding of frames.

Meanwhile, frame induction performs clustering at a global level. But most approaches tend to be algorithmic methods (or some extension thereof) that focus on semantic role labelling. Their lack of portable features or model parameters unfortunately means they cannot be used to solve other applications or problems that require lexicon-level information – such as information extraction or machine translation. Another limitation is that they always depend on high-level linguistic annotation, such as syntactic dependencies, which may not exist in resource-poor settings.

Thus, in this chapter we propose to combine the two approaches to induce a frame semantic lexicon in a minimally supervised fashion, using nothing more than unlabeled predicate-argument word pairs as input data. Additionally, we will learn an embedded lexicon that jointly produces embeddings for predicates, arguments and an automatically induced collection of latent slots. These slots are the induced relations that we learn and investigate in this chapter.

Because of the productivity of argument realization, the embedded lexicon we propose, provides flexibility for usage in downstream applications, where predicate-argument affinities can be computed at will.

To jointly capture the local and global streams of knowledge we propose a novel integration between a predictive embedding model and the posterior of an Indian Buffet Process. The embedding model maximizes the predictive accuracy of predicate-argument selectional preference at the local token level, while the posterior of the Indian Buffet process induces an optimal set of latent slots at the global type level that capture the regularities in the learned predicate embeddings. In the context of this thesis, it should be noted that both components of our models are centered on the relational properties between predicates and arguments and attempt to capture these properties in a latent fashion.

We evaluate our approach and show that our models are able to outperform baselines on both the local token and global type level of frame knowledge. At the local level we score higher than a standard predictive embedding model on selectional preference, while at the global level we outperform a syntactic baseline on lexicon overlap with PropBank. Finally, our analysis on the induced latent slots yields insight into some interesting generalities that we are able to capture from unlabeled predicate-argument pairs.

5.1 Related Work

The work in this chapter relates to research on identifying predicate-argument structure in both local and global contexts. These related areas of research correspond to the NLP community's work respectively on selectional preference modelling and semantic frame induction (which is also known variously as unsupervised semantic role labelling or role induction).

Selectional preference modelling seeks to capture the semantic preference of predicates for certain arguments in local contexts. These preferences are useful for many tasks, including unsupervised semantic role labelling (Gildea and Jurafsky, 2002) among others.

Previous work has sought to acquire these preferences using various means, including ontological resources such as WordNet (Resnik, 1997; Ciaramita and Johnson, 2000), latent variable models (Rooth et al., 1999; Séaghdha, 2010; Ritter et al., 2010) and distributional similarity metrics (Erk, 2007). Most closely related to our contribution is the work by Van de Cruys (2014) who use a predictive neural network to capture predicate-argument associations.

To the best of our knowledge, our research is the first to attempt using selectional preference as a basis for directly inducing semantic frames.

At the global level, frame induction subsumes selectional preference by attempting to group arguments of predicates into coherent and cohesive clusters. While work in this area has included diverse approaches, such as leveraging example-based representations (Kawahara et al., 2014) and cross-lingual resources (Fung and Chen, 2004; Titov and Klementiev, 2012b), most attempts

have focussed on two broad categories. These are latent variable driven models (Grenager and Manning, 2006; Cheung et al., 2013) and similarity driven clustering models (Lang and Lapata, 2011a,b).

Our work includes elements of both major categories, since we use latent slots to represent arguments, but an Indian Buffet process induces these latent slots in the first place. The work of Titov and Klementiev (2012a) and Woodsend and Lapata (2015) are particularly relevant to our research. The former use another non-parametric Bayesian model (a Chinese Restaurant process) in their work, while the latter embed predicate-argument structures before performing clustering.

Crucially, however all these previous efforts induce frames that are not easily portable to applications other than semantic role labelling (for which they are devised). Moreover, they rely on syntactic cues to featurize and help cluster argument instances. To the best of our knowledge, ours is the first attempt to go from unlabeled bag-of-arguments to induced frame embeddings without any reliance on annotated data.

5.2 Joint Local and Global Frame Lexicon Induction

In this section we present our approach to induce a frame lexicon with latent slots. The intuition is to jointly capture local token level and global type level associations between predicates and arguments to arrive at a representation that best explains the input data.

Following prior work on frame induction (Lang and Lapata, 2011a; Titov and Klementiev, 2012a), the procedural pipeline can be split into two distinct phases: argument identification and argument clustering.

As with previous work, we focus on the latter stage, and assume that we have unlabeled predicate-argument structure pairs. These could be obtained from gold standard annotation or through heuristic means (Lang and Lapata, 2014), although the model we describe is agnostic to this choice.

Notably we do not require a full dependency parser to find and annotate predicate-argument relations, which previous work does. Although, it should be noted that predicate-argument pairs – linguistically speaking – do represent part of a dependency parse. However, from a computational perspective our requirements are simpler (and therefore easier to satisfy) because we do not require access to phrasal heads, nor do we require labelled dependency arcs of any kinds. Our only requirement is a list of unlabelled predicate argument pairs (or predicate-argument-preposition triples, in an extension that we describe in what follows) given to us as input.

We now begin with preliminary notation, by defining the input data as:

- $P = \{p_1, ..., p_n\}$ is a vocabulary of predicates types.
- $A = \{a_1, ..., a_m\}$ is a vocabulary of argument types.
- $C = \{(p_1, a_1), ..., (p_N, a_N)\}$ is a corpus of predicate-argument word token pairs.

In this work, we will only consider verbal predicates; so, for examples “eat”, “drink”, “work”, “play” etc. Additionally, we consider entire argument chunks rather than only the argument head. It should be noted, though, that in this work, we assume argument chunks are broken down into individual words, – to increase training data size – but the model remains agnostic to this decision.

For example, consider sentence fragments such as "eat pasta with a fork" or "take bath in a tub". Since we split argument chunks to increase training data size, our corpus would essentially consist of pairs of words such as "eat, pasta", "eat, fork" "take, bath", "take, tub" etc. Given a large corpus of this form, we will attempt to learn an optimal set of model parameters θ that maximizes a regularized likelihood over the corpus. That is, we will learn a model that best explains the data, subject to some regularization constraints.

The model parameters include $V = \{v_i \mid \forall p_i \in P\}$ an $n \times d$ embedding matrix for the predicates and $U = \{u_i \mid \forall a_i \in A\}$ an $m \times d$ embedding matrix for the arguments. V and U are basically the word vectors, in two distinct vector spaces, of the predicates and arguments respectively.

Additionally, assuming K latent frame slots we define $Z = \{z_{ik}\}$ as an $n \times k$ binary matrix that represents the presence or absence of the slot k for the predicate i. Intuitively, K defines the number of the relational arguments we are going to induce and Z is the template of the lexicon that says which predicates take on which relational arguments.

We also define a latent $K \times d$ weight matrix $S = \{s_k \mid 1 \leq k \leq K\}$ that associates a weight vector to each latent slot. This matrix S, intuitively, captures the semantic *signature* of each of the latent relational slots.

Given the corpus $C = \{(p_1, a_1), ..., (p_N, a_N)\}$, a standard maximum likelihood model factorizes the probability of the corpus as $\prod_{(p_i,a_i)\in C} Pr(p_i, a_i; \theta)$. Given our set of parameters, we extend such a model to obtain the following generalized objective.

$$\hat{\theta} = \arg\max_{\theta} \sum_{(p_i,a_i)\in C} \log \left(\sum_{z_{ik}, s_k} Pr(a_i | p_i, z_{ik}, s_k; \theta) \right) + \log Pr_\theta(Z|V) \tag{5.1}$$

This objective has two parts: a likelihood term, and a posterior regularizer. Thus, Equation 5.1 doesn't define a single model, but rather a family of models that can be parametrized by the choice of the likelihood and regularizer components. Notice, the similarity to the form of Equation 3.3 in Chapter 3.2.2. In that case, just as in the present one, we are attempting to reconcile two streams of information jointly.

In this chapter, we instantiate this objective in a way that accounts for both token and type level associations between predicates and arguments. The first part of the objective (the likelihood term) will be responsible for modelling the predictive accuracy of selectional-preference at a local level, while the second part of the objective (the posterior regularizer) will capture global consistencies for an optimal set of latent relational slots.

We detail the parametrization of each of these components separately in what follows.

5.2.1 Local Predicate-Argument Likelihood

The likelihood term of our model is based on the popular Skip-gram model from Mikolov et al. (2013a) but suitably extended to incorporate the latent frame slots and their associated weights.

Recall that the original skip grams would model our data as the conditional probability of an

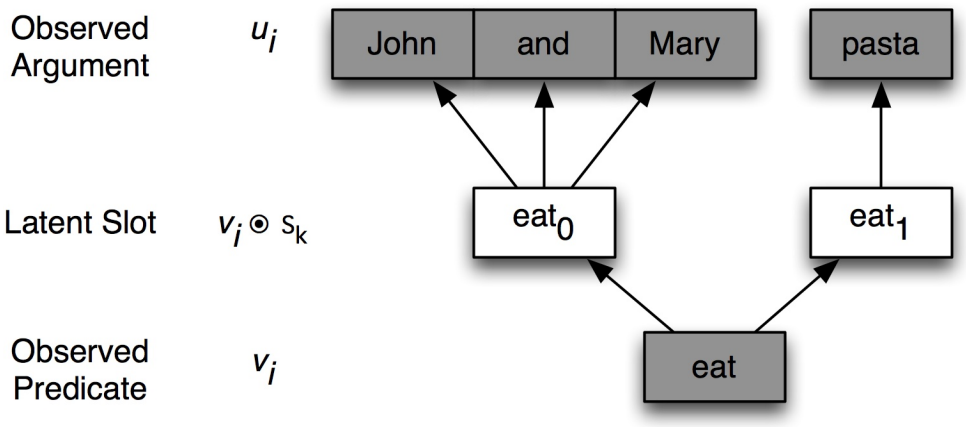


Figure 5.1: The generative story depicting the realization of an argument from a predicate. Argument words are generated from latent argument slots. Observed variables are shaded in grey, while latent variables are in white.

argument, given a predicate as follows: $Pr(a_i|p_i;\theta) = \dfrac{\exp(v_i \cdot u_i)}{\sum\limits_{a_{i'} \in W} \exp(v_i \cdot u_{i'})}$.

We modify this to now also account for the presence or absence of an argument slot, and the weight associated with that slot. Specifically, we marginalize over the latent slot variables:

$$Pr(a_i|p_i;\theta) = \sum_{z_{ik}, s_k} Pr(a_i|p_i, z_{ik}, s_k;\theta) \propto \sum_k z_{ik} \frac{\exp((v_i \odot s_k) \cdot u_i)}{\sum_{a_{i'}} \exp((v_i \odot s_k) \cdot u_{i'})} \tag{5.2}$$

where $\odot$ represents the element-wise multiplication operator. Intuitively, in the likelihood term we weight a general predicate embedding v_i with a slot-specific representations s_k, which then predicts a specific argument u_i. The generative story of this intuition is graphically represented in Figure 5.1.

5.2.2 Global Latent Slot Regularization

The posterior regularization term in equation 5.1 seeks to balance the likelihood term by yielding an optimal set of latent slots, given the embedding matrix of predicates.

The choice of the number and specific nature of the slots is a contentious issue. In the NLP community proposed solutions have dealt with this problem with different assumptions about the relationships between predicates and arguments. For example, the PropBank lexicon (Kingsbury and Palmer, 2002) categorizes arguments into a finite number of broad, prototypical slots. Meanwhile, the FrameNet lexicon (Baker et al., 1998) takes an altogether different approach by allowing different predicates to take on an arbitrary number of highly specialized slots. The debate extends to Linguistics as well. For example, Dowty (1991) proposes proto-roles which subsume commonly used thematic roles based on a set of properties exhibited by arguments, while Levin (1993) attempts to organize predicates into classes according to which argument syntax and alternations are manifested.

Rather than commit to a particular representational schema, we instead choose to let the data guide the process of learning the number and nature of the argument slots. A natural way to allow this to happen is to subscribe to a class of methods known as Bayesian nonparametric models. These models assume infinite priors, and combined with a suitable likelihood term permits the data to dictate the complexity of the learned model. The modelling assumption applied to our problem means that we accept a potentially arbitrary number of argument slots, but our data specifies a selection of only a finite subset of these slots. The advantage of letting the data specify our model does come with a caveat, though: the learned slots are latent and are not easily interpretable as manually defined thematic roles.

Nevertheless, in this work we choose the posterior of an Indian Buffet process (IBP) (Griffiths and Ghahramani, 2005) in this step to induce an optimal latent binary matrix Z. Recall that, in Bayesian learning, the posterior is a product of a prior and likelihood function.

In the present case, the IBP itself places a prior on equivalence classes of infinite dimensional sparse binary matrices. It defines a culinary analogy on how matrices Z can be incrementally built, such that they are legitimate draws from the underlying distribution.

P customers (predicates) enter a restaurant one after another. The restaurant has a buffet consisting of an infinite number of dishes (relational arguments). When the first customer p_1 enters, she takes a serving from the first Poisson(α) dishes until her plate is full. Every subsequent customer p_i samples previously tasted dishes (previously selected relational arguments) with a probability $\frac{m_k}{i}$ that is proportional to its popularity (m_k is the number of predicates that already selected the ith relational argument). The new customers also serves themselves Poisson($\frac{\alpha}{i}$) new dishes.

The elements z_{ik} of the matrix are 1 if customer v_i sampled dish k, and 0 otherwise – that is if predicate i selected argument k or not. In the limit of the number of features $K \to \infty$, it can be shown that the probability of a matrix being produced by this process is:

$$P(Z) = \frac{\alpha^{K_+}}{\prod_{i=1}^{N} K^i!} \exp\left(-\alpha H_N\right) \prod_{k=1}^{K_+} \frac{(N - m_k!)(m_k - 1)}{N!} \tag{5.3}$$

Here K_+ denotes the non-zero columns of the infinite feature matrix,i.e. those whose $m_k > 0$. Also K^i is the number of new dishes sampled by the ith customer to enter the restaurant. Finally, H_N is the Nth harmonic number – which can be computed as $\sum_{j=1}^{N} \frac{1}{j}$.

This is the form of the prior distribution that we will use to compute our actual feature matrices for verb argument structure induction. Given a suitable likelihood function and some data, inference in an IBP computes a posterior that yields an optimal *finite* binary matrix with respect to regularities in the data.

Setting the *data*, in our case, to be the embedding matrix of predicates V, this gives us precisely what we are seeking. It allows us to find regularities in the embeddings, while factorizing them according to these consistencies. The model also automatically optimizes the number of and relationship between latent slots, rather than setting these a priori.

For example, Figure 5.2 illustrates the kind of binary matrix Z that might be produced as a result of running IBP inference over our data.

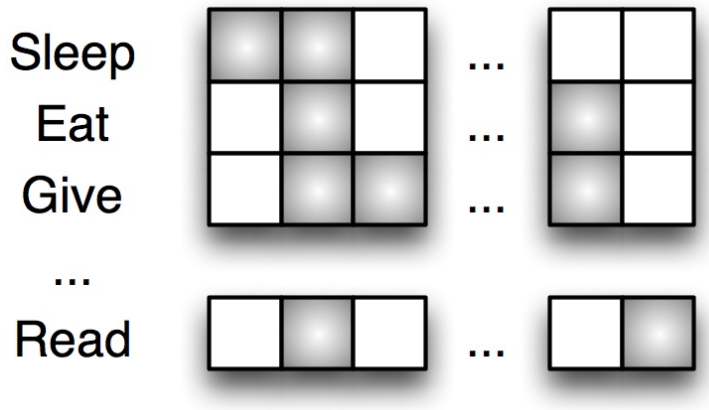


Figure 5.2: Illustration of a potential binary feature matrix (1s colored, 0s blank) learned by IBP. Rows represent verbs from a fixed vocabulary, while columns are of a fixed but arbitrary number and represent latent arguments.

The IBP encodes other desiderata as well. These include the fact that the matrix Z remains sparse, while the frequency of slots follows a power-law distribution proportional to Poisson(α). In practise, this captures the power-law distribution of relational slots in real-world semantic lexicons such as PropBank (Palmer et al., 2005). All of these properties stem directly from the choice of prior, and are a natural consequence of using an IBP.

As mentioned above, the second part of computing the posterior is the choice of the likelihood function. In this chapter, we use a linear-Gaussian model as the likelihood function. This is a popular model that has been applied to several problems, and for which different approximate inference strategies have been developed (Doshi-Velez et al., 2009a; Doshi-Velez and Ghahramani, 2009). According to this model, the predicate embeddings are distributed as:

$$v_i \sim Gaussian(z_i W, \sigma_V^2 \mathbf{I}) \tag{5.4}$$

where W is a $K \times d$ matrix of weights and σ_V is a hyperparameter.

A detailed derivation of the posterior of an IBP prior with a linear-Gaussian likelihood is beyond the scope of this work. We point the reader to Griffiths and Ghahramani (2011), who provide a meticulous summary.

5.2.3 Optimization

Since our objective in equation 5.1 contains two distinct components, we can optimize using alternating maximization. Although guaranteed convergence for this technique only exist for convex functions, it has proven successful even for non-convex problems (Jain et al., 2013; Netrapalli et al., 2013).

We thus alternate between keeping Z fixed and optimizing the parameters V, U, S in the likelihood component of section 5.2.1, and keeping V fixed and optimizing the parameters Z in the posterior regularization component of section 5.2.2.

Intuitively, what we are doing is alternating between optimizing the local token level and global type level relations between predicates and their arguments. In particular, in one stage we are given a fixed template for our frame lexicon and we attempt to learn the best representations for predicates and their arguments. Then, in the next stage, we are given fixed representations for predicates and we attempt to learn the best template for the frame lexicon that captures regularities in these embeddings. We continue to alternate between these stages until some criteria are met.

In practise, the likelihood component is optimized using negative sampling with EM for the latent slots. In particular we use *hard* EM, to select a single slot before taking gradient steps with respect to the model parameters. This was shown to work well for Skip-gram style models with latent variables by Jauhar et al. (2015) – see Chapter 3.

In the E-Step we find the best latent slot for a particular predicate-argument pair:

$$\hat{k} = \arg\max_{k} Pr(a_i|p_i, z_{ik}, s_k; \theta) \tag{5.5}$$

We follow this by making stochastic gradient updates to the model parameters U, V, S in the M-Step using the negative sampling objective:

$$\mathcal{L} = \log z_{i\hat{k}} \cdot \sigma\left((v_i \odot s_{\hat{k}}) \cdot u_i\right) + \sum_{l} \mathbb{E}_{a_{i'} \sim Pr_n(a)} \left[\log z_{i\hat{k}} \cdot \sigma\left((v_i \odot s_{\hat{k}}) \cdot u_{i'}\right)\right] \tag{5.6}$$

where $\sigma(\cdot)$ is the sigmoid function, $Pr_n(a)$ is a unigram noise distribution over argument types and l is the negative sampling parameter. The resulting objective is thus very similar to the original negative sampling objective of Skip-gram, as detailed in Mikolov et al. (2013a). The only differences is that we modify the target word representations (the predicates) with a weight vector (the slot-specific weights).

As for optimizing the posterior regularization component, it is computationally intractable to perform IBP inference exactly. Therefore, an approximate inference technique such as Gibbs sampling must be used. In Gibbs sampling we iteratively sample individual z_{ik} terms from the posterior:

$$Pr(z_{ik}|X, Z_{-ik}) \propto Pr(X|Z) \cdot Pr(z_{ik}|Z_{-ik}) \tag{5.7}$$

where Z_{-ik} is the Markov blanket of z_{ik} in Z. The prior and likelihood terms are respectively those of equations 5.3 and 5.4. Doshi-Velez and Ghahramani (2009) present an accelerated version of Gibbs sampling for this model, that computes the likelihood and prior terms efficiently. We use this approach in our work since it has the benefits of mixing like a collapsed sampler, while maintaining the running time of an uncollapsed sampler.

In conclusion, the optimization steps iteratively refine the parameters V, U, S to be better predictors of the corpus, while Z is updated to best factorize the regularities in the predicate embeddings V, thereby capturing better relational slots. We thus jointly capture both the local and global levels of relational association between predicates and arguments.

5.2.4 Relational Variant

In addition to the standard model introduced above, we also experiment with an extension where the input corpus consists of predicate-argument-relation triples instead of just predicate-argument pairs. These relations are observed relations, and should not be confused with the latent slots of the model.

So, for example, instead of having a simple predicate-argument pair such as "eat, fork" we might have the predicate-argument-relation triple "eat, fork, R-with" indicating that the argument "fork" appears to the right of the predicate, connected by a preposition "with".

To accommodate this change we modify the argument embedding matrix U to be of dimensions $m \times \frac{d}{2}$ and introduce a new $q \times \frac{d}{2}$ embedding matrix $R = \{r_i \mid 1 \leq i \leq q\}$ for the q observed relation types.

Then, wherever the original model calls for an argument vector u_i (which had dimensionality d) we instead replace it with a concatenated argument-relation vector $[u_i; r_j]$ (which now also has dimensionality d). During training, we must make gradient updates to R in addition to all the other model parameters as usual.

While this relation indicator can be used to capture arbitrary relational information, in this paper we set it to a combination of the directionality of the argument with respect to the predicate (L or R), and the preposition immediately preceding the argument phrase (or *None* if there isn't one). Thus, for example, we have relational indicators such as "L-on", "R-before", "L-because", "R-None", etc. We obtain a total of 146 such relations.

Note, that in keeping with the goals of this work, these relation indicators still require no tools to annotate (prepositions are closed-class words than can be enumerated).

5.3 Experiments and Evaluation

The task of evaluating the learned binary representations Z of predicates over latent relational arguments (see Figure 5.2), as well as the vector embeddings for predicates and arguments is a complicated one. The difficulty arises from the fact that there is no single gold standard of what the true set of relations should be.

In what follows, we detail experimental results on two quantitative evaluation tasks: at the local token and global type levels of predicate-argument structure. In particular we evaluate on pseudo disambiguation of selectional preference, and semantic frame lexicon overlap. We also qualitatively inspect the learned latent relations against hand-annotated roles. We first specify the implementational details.

5.3.1 Implementational Details

We begin by pre-training standard skip-gram vectors (Mikolov et al., 2013a) on the NY-Times section of the Gigaword corpus, which consists of approximately 1.67 billion word tokens. These vectors are used as initialization for the embedding matrices V and U, before our iterative optimization. Specifically we use the *target* word space of the skip-gram model to initialize the

predicate embeddings and the *context* word space of the model to initialize the argument embeddings.

While this step is not strictly required, we found that it leads to generally better results than random initialization given the relatively small size of our predicate-argument training corpus. Initialization helps because the two embedding matrices V and U are already somewhat semantically *consistent* with one another before training begins.

Note that in keeping with the aims of this chapter, this pre-training step requires no annotation or access to higher-level linguistic information whatsoever.

For training our models, we use a combination of the training data released for the CoNLL 2008 shared task (Surdeanu et al., 2008) and the extended PropBank release which covers annotations of the Ontonotes (Hovy et al., 2006) and English Web Treebank (Bies et al., 2012) corpora. We reserve the test portion of the CoNLL 2008 shared task data for one of our evaluations.

In this work, we only focus on verbal predicates. Our training data gives us a vocabulary of 4449 predicates, after pruning verbs that occur fewer than 5 times.

Then, from the training data we extract all predicate-argument pairs using gold standard argument annotations, for the sake of simplicity. Note that previous unsupervised frame induction work also uses gold argument mentions (Lang and Lapata, 2011a; Titov and Klementiev, 2012b). Our method, however, does not depend on this, or any other annotation, and we could as easily use the output from an automated system such as Abend et al. (2009) instead. However, to test the efficacy of our approach in a more controlled environment we use gold argument mentions as done in previous work.

In this manner, we obtain a total of approximately 3.35 million predicate-argument word pairs on which to train.

Using this data we train a total of 4 distinct models: a base model and a relational variant (see Section 5.2.4), both of which are trained with two different IBP hyperparameters of $\alpha = 0.35$ and $\alpha = 0.7$. The hyperparameter controls the avidity of the model for latent slots (a higher α implies a greater number of induced slots).

We set our embedding size to $d = 100$. The result of training with these parameters results in the learned number of slots ranging from 17 to 30. The conservative model averaging about 4 latent slots per word, while the permissive model averaging about 6 latent slots per word.

Since our objective is non-convex we record the training likelihood at each power iteration (which includes a single optimization step that alternates over both the predictive and IBP components of our objective), and save the model with the highest training likelihood.

5.3.2 Pseudo Disambiguation of Selection Preference

The pseudo disambiguation task aims to evaluate our models' ability to capture predicate-argument knowledge at the local level. In this task, systems are presented with a set of triples: a predicate, a true argument and a fake argument. The systems are evaluated on the percentage of true arguments they are able to select.

For example, given a triple:

resign, post, liquidation

a successful model should rate the pair "resign-post" higher than "resign-liquidation".

Model	α	Variant	k slots	% Acc
Skip-gram	-	-	-	0.77
pa2IBPVec	0.35	Standard	17	0.81
		Relational	15	**0.84**
	0.7	Standard	27	0.81
		Relational	30	0.81

Table 5.1: Results on pseudo disambiguation of selectional preference. Numbers are in % accuracy of distinguishing true arguments from false ones. Our models all outperform the skip-gram baseline.

This task has often been used in the selectional preference modelling literature as a benchmark task (Rooth et al., 1999; Van de Cruys, 2014).

To obtain the triples for this task we use the test set of the CoNLL 2008 shared task data. In particular, for every verbal predicate mention in the data we select a random nominal word from each of its arguments phrase chunks to obtain a true predicate-argument word pair. Then, to introduce distractors, we sample a random nominal from a unigram noise distribution. In this way we obtain 9859 pseudo disambiguation triples as our test set.

Note that while the term "selectional preference" is used to describe this task, it is different from what is traditionally understood in linguistics as the selectional preference of a predicate for the *head* of an argument.

Rather, it is the selectional preference of a predicate for *any* noun in the governed argument. Linguistically speaking this may seem astonishing, even bizarre. However, from the computational perspective of the models we evaluate this is not only natural, but is actually based on the way they are trained. For example, the local predicate-argument affinity of our model (see Section 5.2.1), breaks argument chunks into individual words, and attempts to maximize the likelihood of a predicate predicting any of these words. The standard skip-gram model (which is our baseline), on which our local likelihood component is based, does much the same thing.

From a linguistic perspective of selectional preference, the *predictive* capability of our models is simply their ability to distinguish predicate-argument word pairs that *should* be associated from randomly generated pairs that *should not*.

Thus our task setup still works for purposes of our evaluation because the way our models and the baseline (see below) are trained, they should be capable of distinguishing the affinity between the predicate and *any* governed word – not simply the head word.

We use our models to score a word pair by taking the probability of the pair under our model, using the best latent slot:

$$\max_k z_{ik} \cdot \sigma\left((v_i \odot s_k) \cdot u_i\right) \tag{5.8}$$

where v_i and u_i are predicate and argument embeddings respectively, z_{ik} is the binary indicator of the k'th slot for the i'th predicate, and s_k is the slot specific weight vector. The argument in the higher scoring pair is selected as the correct one.

In the relational variant, instead of the single argument vector u_i we also take a max over the relation indicators – since the exact indicator is not observed at test time.

Model	α	Variant	Coarse			Fine		
			PU	CO	F1	PU	CO	F1
Syntax	-	-	0.71	0.87	0.78	0.70	0.91	0.79
pa2IBPVec	0.35	Standard	0.76	0.89	0.82	0.76	0.97	0.85
		Relational	0.73	0.90	0.81	0.73	0.97	0.83
	0.7	Standard	0.79	0.91	**0.85**	0.79	**0.98**	0.87
		Relational	**0.80**	**0.92**	**0.85**	**0.80**	**0.98**	**0.88**

Table 5.2: Results on the lexicon overlap task. Our models outperform the syntactic baseline on all the metrics.

We compare our models against a standard skip-gram model (Mikolov et al., 2013a) trained on the same data. Word pairs in this model are scored using the dot product between their associated skip-gram vectors.

This is a fair comparison since our models as well as the skip-gram model have access to the same data – namely predicates and their neighboring argument words. They are trained on their ability to discriminate true argument words from randomly sampled noise.

The evaluation then, is whether the additionally learned slot structure helps in differentiating true arguments from noise. That is, if the set of induced semantic relations that give our frame lexicon its template structure actually help in defining the local token level of frame knowledge.

The results of this evaluation are presented in Table 5.1.

The results show that all our models outperform the skip-gram baseline. This demonstrates that the added structural information gained from latent slots in fact help our models to better capture predicate-argument affinities in local contexts.

The impact of latent slots or additional relation information does not seem to impact basic performance, however. Both the addition of the relational indicator and the increase in the hyper-parameter of the model α do not produce any significant difference in the overall score.

This could be because of the trade-off that occurs when a more complex model is learned from the same amount of limited data.

5.3.3 Frame Lexicon Overlap

Next, we evaluate our models at their ability to capture global type predicate-argument structure. Previous work on frame induction has focussed on evaluating instance-based argument overlap with gold standard annotations in the context of semantic role labelling (SRL). Unfortunately, because our models operate on individual predicate-argument words rather than argument spans, a fair comparison becomes problematic.

But unlike previous work, which clusters argument instances, our approach produces a model as a result of training. Specifically we produce the latent binary matrix Z (see Figure 5.2), which captures the presence or absence of individual relational arguments for each predicate in our vocabulary.

A hand-crafted lexicon such as PropBank gives us very similar information. It defines a set of (hand-crafted) relational arguments and then tells us for every predicate in the vocabulary, which

of the relational arguments are accepted by that predicate.

We can thus directly evaluate our models' latent slot factors against a gold standard frame lexicon. Our evaluation framework is, in many ways based on the metrics used in unsupervised SRL, except applied at the "type" lexicon level rather than the corpus-based "token" cluster level.

In particular, given a gold frame lexicon Ω with K^* real argument slots (i.e. the total number of possible humanly assigned arguments in the lexicon), we evaluate our models' latent slot matrix Z in terms of its overlap with the gold lexicon.

Intuitively, consider Ω to be a different binary matrix than the one pictured for Z in Figure 5.2. This different matrix has the same number of rows (we consider the intersection of the vocabularies of our model and the gold standard, in practise), but may have a different number of columns.

The columns in each of the matrices can be thought of as different, possibly overlapping clusters over predicates. They effectively define which relations (gold or induced) are accepted by which predicates. The idea, then is to measure, the degree of overlap between the gold clusters and the IBP induced ones.

To do this, we use the cluster *purity* and *collocation* metrics often used to evaluate clustering quality.

We define *purity* as the average proportion of overlap between predicted latent slots and their maximally similar gold lexicon slots:

$$PU = \frac{1}{K} \sum_{k} \max_{k'} \frac{1}{n} \sum_{i} \delta(\omega_{ik'}, z_{ik}) \tag{5.9}$$

where $\delta(\cdot)$ is an indicator function. Given that the ω's and z's we compare are binary values, this indicator function is effectively an "XNOR" gate.

Intuitively, the purity metric takes every column in the induced matrix Z, looks for it's most similar column in the gold matrix Ω and measures the overlap between the two. Similarity is itself defined as the sum of identical terms (essentially overlap) between the two column vectors under consideration. These overlap scores are then averaged over all the columns in Z.

Similarly we define *collocation* as the average proportion of overlap between gold standard slots and their maximally similar predicted latent slots:

$$CO = \frac{1}{K^*} \sum_{k'} \max_{k} \frac{1}{n} \sum_{i} \delta(\omega_{ik'}, z_{ik}) \tag{5.10}$$

Intuitively, the collocation metric is the same as purity, except applied in the reverse direction. That is, we take every column in the gold matrix Ω, look for it's most similar column in the induced matrix Z and measure the overlap between the two. The overlap scores are then averaged over all the columns in Ω.

Note that the purity and collocation metrics are different because the number of columns in Z and Ω are (likely) different, as well as the fact that the mapping between maximally similar columns is not one-to-one.

Given, the *purity* and *collocation* metrics we can also define the $F1$ score as the harmonic mean of the two:

$$F1 = \frac{2 \cdot CO \cdot PU}{CO + PU} \tag{5.11}$$

In our experiments we use the frame files provided with the PropBank corpus (Palmer et al., 2005) as gold standard. We derive two variants from the frame files.

The first is a coarse-grained lexicon. In this case, we extract only the functional arguments of verbs in our vocabulary as gold standard slots. There are 16 such gold slots and include types such as "prototypical agent", "prototypical patient", "instrument", "benefactive", etc. Each of these 16 gold slots are mapped to indices. For every verb the corresponding binary ω vector marks the existence or not of the different functional arguments according to the gold frame files.

The second variant is a fine-grained lexicon. Here, in addition to functional arguments we also consider the numerical argument with which it is associated, such as "ARG0", "ARG1" etc. So for example we might have slots such as "prototypical agent ARG0", "prototypical patient ARG1" etc. Note that a single functional argument may appear with more than one numerical slot with different verbs over the entire lexicon. So, for example, we may additionally also have the "prototypical agent ARG1" slot type. The fine-grained lexicon yields 72 gold slots.

We compare our models against a baseline inspired from the syntactic baseline often used for evaluating unsupervised SRL models. For unsupervised SRL, syntax has proven to be a difficult-to-outperform baseline (Lang and Lapata, 2014).

This baseline is constructed by taking the 21 most frequent syntactic labels in the training data and associating them each with a slot. All other syntactic labels are associated with a 22nd generic slot. Given these slots, we associate a verbal predicate with a specific slot if it takes on the corresponding syntactic argument in the training data.

This process also yields a binary matrix with rows that correspond to predicates and columns that correspond to 22 syntactic slots. We can then evaluate this binary matrix against the gold standard Ω in the same way as our own matrices on the purity and collocation metrics described above.

The results on the lexicon overlap task are presented in Table 5.2.

They show that our models consistently outperform the syntactic baseline on all metrics in both the coarse-grained and fine-grained settings. We conclude that our models are better able to capture predicate-argument structure at a global type level.

Specifically, the semantic relations we induce to govern the template for our frame lexicon yields more semantically meaningful slots than those obtained by using syntax as a surrogate for semantics.

Inspecting and comparing the results of our different models seems to indicate that we perform better when our IBP posterior allows for a greater number of latent slots. This happens when the hyperparameter $\alpha = 0.7$.

Additionally our models consistently perform better on the fine-grained lexicon than on the coarse-grained one. The former itself does not necessarily represent an easier benchmark, since there is hardly any difference in the $F1$ score of the syntactic baseline on the two lexicons.

Overall it would seem that allowing for a greater number of latent slots does help capture global predicate-argument structure better. This makes sense, if we consider the fact that we are effectively trying to factorize a dense representation (the predicate embeddings) with IBP

Predicate	Latent Slot							
	1	2	3	5	6	8	10	12
provide	A0			A1	A2			A2
enter	A0	A1						AM-ADV
praise	A0	A1				A2		
travel	A0	A0				AM-PNC	AM-TMP	
distract	A0		A1	A2				
overcome	AM-TMP		A0	A0				

Table 5.3: Examples for several predicates with mappings of latent slots to the majority class of the closest argument vector in the shared embedded space.

inference. Thus allowing for a greater number of latent factors permits the discovery of greater structural consistency within these embeddings.

This finding does have some problematic implications, however. Increasing the IBP hyperparameter α arbitrarily represents a computational bottleneck since inference scales quadratically with the number of latent slots K. There is also the problem of splitting argument slots too finely, which may result in optimizing purity at the expense of collocation. A solution to this trade-off between performance and inference time remains for future work.

5.3.4 Qualitative Analysis of Latent Slots

To better understand the nature of the latent slots induced by our model we conduct an additional qualitative analysis. The goal of this analysis is to inspect the kinds of generalities about semantic roles that our model is able to capture from completely unannotated data.

Table 5.3 lists some examples of predicates and their associated latent slots. The latent slots are sorted according to their frequency (i.e. column sum in the binary slot matrix Z). We map each latent slot to the majority semantic role type – from training data – of the closest argument word to the predicate vector in the shared embedding space.

The model for which we perform this qualitative analysis is the standard variant with the IBP hyperparameter set to $\alpha = 0.35$; this model has 17 latent slots. Note that slots that do not feature for any of the verbs in the table are omitted for visual compactness.

There are several interesting trends to notice here. Firstly, the basic argument structure of predicates is often correctly identified, when matched against gold PropBank frame files. For example, the core roles of "enter" identify it as a transitive verb, while "praise", "provide" and "distract" are correctly shown as di-transitive verbs. Obviously the structure isn't always perfectly identified, as with the verb "travel" where we are missing both an "ARG1" and an "ARG2".

In certain cases a single argument type spans multiple slots – as with "A2" for "provide" and "A0" for "travel". This is not surprising, since there is no binding factor on the model to produce one-to-one mappings with hand-crafted semantic roles. Generally speaking, the slots represent distributions over hand-crafted roles rather than strict mappings. In fact, to expect a one-to-one mapping is unreasonable considering we use no annotations whatsoever.

Nevertheless, there is still some consistency in the mappings. The core arguments of verbs

– such as “ARG0” and “ARG1” are typically mapped to the most frequent latent slots. This can be explained by the fact that the more frequent arguments tend to be the ones that are core to a predicate’s frame. This is quite a surprising outcome of the model, considering that it is given no annotation about argument types. Of course, we do not always get this right as can be seen with the case of “overcome”, where a non-core argument occurs in the most frequent slot.

Since this is a data driven approach, we identify non-core roles as well, if they occur with predicates often enough in the data. For example we have the general purpose “AM-ADV” argument of “enter”, and the “ARG-PNC” and “ARG-TMP” (purpose and time arguments) of the verb “travel”. In future work we hope to explore methods that might be able to automatically distinguish core slots from non-core ones.

In conclusion, our models show promise in that they are able to capture some interesting generalities with respect to predicates and their hand-crafted roles, without the need for any annotated data.

5.4 Conclusion and Future Work

In this chapter, we have focussed on a general problem of semantic representation learning where we *induced* a new set of relations rather than simply *leverage* an existing set of relations.

Specifically we have have presented a first attempt at learning an embedded frame lexicon from data, using minimal annotated information. Our approach revolved around jointly capturing local predicate-argument affinities with global slot-level consistencies. We modeled this approach with a novel integration between a predictive embedding model and the posterior of an Indian Buffet Process.

The result of this process is a fully embedded semantic lexicon that is able to compute expected affinities between predicates and arguments. Crucially, the template structure of this lexicon – that is, the set of relations that define the frames therein – are induced automatically from data.

We experimented with our model on two quantitative tasks, each designed to evaluate performance on capturing local token and global type predicate-argument structure respectively. On both tasks we demonstrated that our models are able to outperform baselines, thus indicating our ability to jointly model the local and global level information of predicate-argument structure.

Additionally, we qualitatively inspected our induced latent slots and showed that we are able to capture some interesting generalities with respect to hand-crafted semantic role labels.

In the context of this thesis, this is an important contribution because we demonstrated that we can learn rich models of semantic representation, not only when we have a set of well-defined relations to work with, but also now in the more ambiguous case when relational information does not exist or annotated data with relations is not easily accessible.

There are several avenues of future work that are open to exploration. Rather than depend on gold argument mentions in training, an important future step would be to fully automate the pipeline to leverage much larger amounts of data. With this greater data size, one would likely no longer need to break down argument spans into individual words. Instead, entire argument spans can be modeled as chunks using an LSTM.

Currently the Indian Buffet Process inference remains a bottleneck of our current effort’s

ability to explore the model space. Parallelizing the IBP inference and speeding up this process will allow us to explore more complex (and potentially better) models. For example Doshi-Velez et al. (2009b), Campbell et al. (2015) and Zhang et al. (2017) all suggest approaches to perform distributed computations in the IBP inference.

These are all natural extensions of the current preliminary work to improve the overall robustness and expressive power of the model.

With this additional modeling power we hope to evaluate on downstream applications such as semantic role labelling, and semantic parsing.

An important test for our work is its application to learning embedded lexicons in low-resource languages. There are two potential settings to explore. The first deals with a language or domain where there is sufficient data, but few or rudimentary tools to process this data (for example, the lack of a high quality dependency parser). In this situation we expect the results we found in our English evaluations to transfer to the low resource language, since our model is equipped to deal with precisely such a scenario. Namely where a large amount of data with minimal annotations can be processed to learn an embedded lexicon.

If, however, there is insufficient data to begin with, our approach will be less directly applicable. While the results from this chapter indicate that our models do capture some interesting semantic trends beyond syntax, an embedded lexicon trained on a high-resource language are unlikely to directly port to a new domain or language. In this case domain adaptation or transfer learning will become an interesting avenue of future work to explore in order to make our proposed model feasible. In particular, pre-training our embeddings on a high-resource language and then *tweaking* them to fit the relations and structure of the low-resource language might be a first logical step.

Another potential interesting, complex and challenging application for future exploration is the Winograd Schema (Levesque et al., 2011). This challenge presents a system with a pair of sentences containing some referential ambiguity, with a very minimal difference representing the means for disambiguation. For example:

1. The city council refused the demonstrators a permit because they *feared* violence.
2. The city council refused the demonstrators a permit because they *advocated* violence.

Here the change of the word *feared* to *advocated* changes the likely referent of the ambiguous pronoun they from "the city council" to "the demonstrators".

While our embedded frame lexicon is currently incapable of handling such a complex task – being unable to represent argument chunks as well as being fairly noisy – one can imagine that a more robust future frame lexicon would help in a task like Winograd Schemas. In particular the affinity between predicate and argument (span) embeddings might be used to compute preference scores of *feared* and *city council* versus *feared* and *demonstrators* (viz. *advocated* and *city council* versus *advocated* and *demonstrators*) to disambiguate the most likely referent of the pronominal agent of the predicate.

In any case, embedded frame lexicons represent a useful tool for many downstream applications and merit future exploration to improve their expressive power.

5.4.1 Five Point Thematic Summary

What was the semantic representation learning problem that we tried to solve?

We attempted to induce an embedded representation of a semantic lexicon. Rather than place restrictions with a pre-defined set of manually crafted argument slot on our lexicon, we allowed these to be induced and represented latently.

From the point of view of Definition 1 of Chapter 1.2, we set ourself the goal of learning multiple semantic relations, one each corresponding to the latent argument slots of the model. Specifically, the mapping between predicate-argument pairs to the set of reals was modulated and different for each of the argument slots. Our expectation was that these mappings would capture the relationships between predicates and arguments based on the different semantic roles they fulfill.

Notice that in this case the semantic relations we defined as the goals of our model are not explicit or humanly interpretable. But that's perfectly acceptable from the point of view of our relation-centric representation learning framework. What's important is that the relations can still be defined in terms of Definition 1 as mappings between object pairs (predicates and arguments) and the set of real numbers, and the assumption of a semantic property – in this case, the role specific relations between predicates and arguments.

What linguistic information or resource did we use to solve this problem?

Since our goal was to learn the embedded semantic lexicon from minimally annotated data, we only assumed a corpus of predicate-argument pairs as input. In a variant of our model we also experiment with predicate-argument-preposition triples, but still did not require additional annotated data.

In this work, we used gold-standard SRL parses to extract the predicate-argument pairs (or predicate-argument-preposition triples). However, our approach did not depend on gold-standard data at all; instead, predicate-argument pairs extracted by some automatic means would be just as suitable for our models.

How did we operationalize the desired semantic relation with contextual relations in the resource?

Our operationalization of the semantic slot relations was based on two assumptions. Firstly, we intuited that local predicate-argument structure can be captured by instance (i.e. token) based affinity of predicates for their arguments. Meanwhile, global predicate-argument structure can be captured by corpus aggregated (i.e. type) affinities of predicates for their arguments.

The training data consisting of predicate-argument pairs already captures these intuitions. Recall that Definition 2 defines contextual relations as mappings to real numbers, over sets of target and context objects. For the local token-level context, our sets of target and context objects were predicates and arguments respectively. The shared property of this contextual relation was simply existance in the training data. In other words, our contexts were simply predicate-argument pairs.

Meanwhile, the global predicate-argument structure was an aggregation of these local contexts, and therefore did not require the definition of a separate contextual relation.

How did we use the contextual relations in representation learning?

We modeled our intuitions about the local token-level and global type-level predicate-argument affinities by a regularized maximum-likelihood model. We used this model to assign weights to target-context pairs generated by the contextual relation defined above. This model consisted of two parts: a maximum-likelihood component that we designated to capture the local token-level affinities, and a regularizer that we designated to capture the global type-level affinities. Section 5.2 detailed the two parts of our model.

The contextual relation previously defined was used to bias the local maximum-likelihood component. In particular we learned representations of predicates and arguments that were likely to predict one another if they appeared together in training, while being unlikely to do the same if they didn't.

Our regularizer aggregated the contexts from the local component to induce the type-level semantic argument slots. However, the aggregation was indirect in the sense that the regularizer only dealt with the predicate embeddings – which we assume have aggregated and encoded the affinities from all the local contexts.

What was the result of biasing the learner with contextual relations in learning the semantic model?

We ran experiments to test our embedded lexicons abilities to evaluate predicate-argument affinities at both the local token-level and the global type-level. In particular we evaluated on the tasks of pseudo-disambiguation of selectional preference and lexicon overlap. We showed the results of these experiments in Section 5.3.2 and 5.3.3.

Our findings revealed that in both cases, the semantic relations consisting of the latent role slots in the lexicon, measurably improved over baselines that did not contain this sort of information. Thus, we concluded that biasing our learner with contextual relations defined over predicate-argument pairs does in fact lead to representations that are able to capture useful latent role slots. Moreover, in an auxiliary qualitative analysis (see Section 5.3.4) we found that the slots do capture some interesting generalities, when compared with manually defined, humanly interpretable slots.

Chapter 6

Structured Distributional Semantics

Syntactic and Latent Semantic Tensor Models for Non-constant and Non-unique Representation Learning

Most current methods for lexical representation learning yield a vector space model (Turney and Pantel, 2010) in which words are represented as distinct, discrete and static points in some high dimensional space. The most fundamental operation in such semantic vector spaces is comparison of meaning, in which the distance of two points is measured according to a distance metric.

However, the meaning of a word is neither constant nor unique.

Meaning depends on the context in which it occurs; in other words it depends on the relations that bind it to its compositional neighborhood. Consider the following fragment containing the predicate "killed":

- Example: [**Ag** Booth] [**Pred** killed] [**Pat** Lincoln]

In this fragment, relational attachment matters and specifies that Booth was the one doing the killing while Lincoln was the sufferer of these actions. It is not equivalent to the fragment "Lincoln killed Booth".

However, in a vector space model the word "killed" is learned beforehand. It is fixed to a single point in vector space, typically capturing the bag-of-word statistics of "killed". It does not have the power to change or accommodate an *Agent* or *Patient* argument, for example.

Meaning is also not unique. It depends on what it's compared to for proximity of meaning, and more specifically along what relational facet the comparison is being made. Take the following disambiguation triple:

- Example: shoe $\rightarrow$ tuxedo, football

Is the word "shoe" more similiar to "tuxedo" or "football"? The answer, in fact, really depends on the *facet* along which we are making the comparison. Specifically, if we wish to know similarity along the *article_of_clothing* facet, we would say "shoe" and "tuxedo" are more sim-

ilar. Similarly, if what we cared about instead was the *sports* facet, we would say "shoe" and "football" were more similar.

Again, a single point in vector space cannot typically be de-composed into its relational facets to capture finer grained semantics along specific dimensions of interest.

These two problems, context-sensitivity and facetedness in semantics, are the representation problems that we tackle in this chapter. We introduce two different models that tackle one of the two problems, each.

However, both problems are defined by semantic relations: the one to neighborhood structure, the other to comparative concepts. Thus the solutions that we present are also very related. Their approaches fall into an umbrella paradigm we call *Structured Distributional Semantics*. This paradigm is similar to the work on *Distributional Memory* proposed by Baroni and Lenci (2010).

Structured Distributional Semantics aims to improve upon simple vector space models of semantics by hypothesizing that the meaning of a word is captured more effectively through its relational — rather than its raw distributional — signature.

In accordance, it extends the vector space paradigm by structuring elements with relational information that decompose distributional signatures over discrete relation dimensions. The resulting representation for a word is a semantic tensor (or matrix) rather than a semantic vector.

The easiest way to think of these representations are to associate them with semantic frames. Each word is represented by a frame tensor, with each frame element being captured by a specific row in the learned semantic matrix.

The move from simple Vector Space Models (VSMs) to Structured Distributional Semantic Models (SDSM) represents a perspective on semantic representation learning that aligns with the theme of this thesis. Specifically, that relations drive and give meaning to concepts. This view is not new and has gained much popularity with the field of frame semantics (Baker et al., 1998).

In this chapter we will show that decomposing a single word vector into distinct relation dimensions results in more expressive and empirically superior models for several tasks.

An important choice, with an SDSM is the nature of the discrete relation dimensions, or the frame elements of the semantic tensors – in practise the rows of the matrix. Nominally, this choice not only determines the process by which an SDSM is learned, but also what information is represented and the resulting strengths and weaknesses of the model. Our two models differ in this choice.

The first model is a Syntactic SDSM that represents meaning as distributions over relations in syntactic neighborhoods. This model tackles the problem of contextual sensitivity, with a dynamic SDSM that constructs semantic tensors for words and their relational arguments. We argue that our model approximates meaning in compositional configurations more effectively than standard distributional vectors or bag-of-words models. We test our hypothesis on the problem of judging event coreferentiality, which involves compositional interactions in the predicate-argument structure of sentences, and demonstrate that our model outperforms both state-of-the-art window-based word embeddings as well as simple approaches to compositional semantics previously shown in the literature.

The second model is a Latent Semantic SDSM whose relational dimensions are learned over neighborhood patterns using Latent Relational Analysis (LRA). In comparison to the dynamic SDSM of syntax, this model is static due to its latent nature and therefore does not model compositional structures. However, it frees the model from its reliance on syntax (or any other set

of pre-defined relations for that matter), and allows the data to dictate an optimal set of (albeit latent) relations. The result is a model that is much more effective at representing single word units and tackling the problem of facetedness in the comparison of relational facets. Evaluation of our model yields results that significantly outperform several other distributional approaches (including the Syntactic SDSM) on two semantic tasks and performs competitively on a third relation classification task.

Through both models we re-affirm the central claim of this thesis, namely that by integrating structured relational information, we can learn more expressive and empirically superior models of semantics.

6.1 Distributional Versus Structured Distributional Semantics

We begin by formalizing the notion of a Distributional Semantic Model (DSM) as a vector space, and it's connections and extension to a tensor space in a Structured Distributional Semantic Model (SDSM).

Consider a vocabulary Σ that contains k distinct word types $\Sigma = \{w_1, w_2, ..., w_k\}$. The goal of both DSM and SDSM is to represent words of this vocabulary, so that element pairs that are semantically similar – by some notion of similarity – are *close* together. The only difference between the two model paradigms is that while the former represents elements as vectors, the latter extends the representation space to tensors.

Formally, a DSM is a vector space V that contains $|\Sigma|$ elements in $\mathbb{R}^n$. Every vocabulary word w_i has an associated semantic vector $\vec{v_i}$ representing its distributional signature. Each of the n elements of $\vec{v_i}$ is associated with a single dimension of its distribution. This dimension may correspond to another word — that may or may not belong to Σ — or a latent dimension as might be obtained from an SVD projection or an embedding learned via a deep neural network. Additionally, each element in $\vec{v_i}$ is typically a normalized co-occurrence frequency count, a PMI score, or a number obtained from an SVD or RNN transformation. The semantic similarity between two words w_i and w_j in a DSM is the vector distance defined in terms of their associated distributional vectors:

$$sim(\vec{v_i}, \vec{v_j}) = \vec{v_i} \cdot \vec{v_j} \tag{6.1}$$

Often, a cosine distance is used as well (which is essentially a normalized dot-product).

An SDSM is an extension of DSM. Formally, it is a space U that contains $|\Sigma|$ elements in $\mathbb{R}^{d \times n}$. Every vocabulary word w_i has an associated semantic tensor $\vec{\vec{u_i}}$, which is itself composed of d vectors $\vec{u_i^1}, \vec{u_i^2}, ..., \vec{u_i^d}$ each having n dimensions. Every vector $\vec{u_i^l} \in \vec{\vec{u_i}}$ represents the distributional signature of the word w_i in a relation (or along a facet) r_l. The d relations of the SDSM may be syntactic, semantic, or latent. The n dimensional relational vector $\vec{u_i^l}$ is configurationally the same as a vector $\vec{v_i}$ of a DSM. This definition of an SDSM closely relates to an alternate view of Distributional Memories (DMs) (Baroni and Lenci, 2010) where the semantic space is a third-order tensor, whose modes are Word $\times$ Link $\times$ Word.

The semantic similarity between two words w_i and w_j in an SDSM is the similarity function defined by $sim(\vec{u_i}, \vec{u_j})$ on their associated semantic tensors. We use the following decomposition of the similarity function:

$$sim(\vec{u_i}, \vec{u_j}) = \frac{1}{d} \sum_{l=1}^{d} \vec{u_i^l} \cdot \vec{u_j^l} \tag{6.2}$$

Mathematically, this corresponds to the ratio of the normalized Frobenius product of the two matrices representing $\vec{u_i}$ and $\vec{u_j}$ to the number of rows in both matrices. Intuitively it is simply the average relation-wise similarity between the two words w_i and w_j.

6.2 Syntactic Structured Distributional Semantics

We begin by describing our first SDSM, which tackles the problem of contextual variability in semantics by a representation over syntactic relational dimensions.

Systems that use window-based DSMs implicitly make a bag of words assumption: that the meaning of a phrase can be reasonably estimated from the meaning of its constituents, agnostic of ordering. However, semantics in natural language is a compositional phenomenon, encompassing interactions between syntactic structures, and the meaning of lexical constituents.

It follows that the DSM formalism lends itself poorly to composition since it implicitly disregards syntactic structure. For instance, returning to the example presented in the introduction to this chapter, the representation for "Lincoln", "Booth", and "killed" when merged produce the same result regardless of whether the input is "Booth killed Lincoln" or "Lincoln killed Booth". As suggested by Pantel and Lin (2000) and others, modeling the distribution over preferential attachments for each syntactic relation separately can yield greater expressive power.

Attempts have been made to model linguistic composition of individual word vectors (Mitchell and Lapata, 2009), as well as remedy the inherent failings of the standard distributional approach (Erk and Padó, 2008). The results show varying degrees of efficacy, and have been only partially successful in modelling deeper lexical semantics or compositional expectations of words and word combinations.

The Syntactic SDSM we propose is an extension of traditional DSMs. This extension explicitly preserves structural information and permits the approximation of distributional expectation over distinct dependency relations. It is also a dynamic model, meaning that statistics are stored in decomposed form as dependency triples, only to be composed to form representations for arbitrary compositional structures as and when desired.

This is in contrast to a standard VSM which learns its representations once and is then used in fixed form for all downstream semantic computations.

In the new model the tensor representing a word is a distribution over relation-specific syntactic neighborhoods. In other words, the SDSM representation of a word or phrase is several vectors defined over the same vocabulary, each vector representing the word or phrase's selectional preferences for a different syntactic argument.

We show that this representation is comparable to a single-vector window-based DSM at capturing the semantics of individual word, but significantly better at representing the semantics

of composed units. Our experiments on individual word semantics are conducted on the two tasks of similarity scoring and synonym selection. For evaluating compositional units, we turn to the problem of event coreference and the representation of predicate-argument structures. We use two different event coreference corpora and show that our Syntactic SDSM achieves greater predictive accuracy than simplistic compositional approaches as well as a strong baseline that uses window based word embeddings trained via deep neural-networks.

6.2.1 Related Work

Recently, a number of studies have tried to model a stronger form of semantics by phrasing the problem of DSM compositionality as one of vector composition. These techniques derive the meaning of the combination of two words a and b by a single vector $c = f(a, b)$. Mitchell and Lapata (2008) propose a framework to define the composition $c = f(a, b, r, K)$ where r is the relation between a and b, and K is some additional knowledge used to define composition.

While the framework is quite general, most models in the literature tend to disregard K and r and are generally restricted to component-wise addition and multiplication on the vectors to be composed, with slight variations. Dinu and Lapata (2010) and Séaghdha and Korhonen (2011) introduced a probabilistic model to represent word meanings by a latent variable model. Subsequently, other high-dimensional extensions by Rudolph and Giesbrecht (2010), Baroni and Zamparelli (2010) and Grefenstette et al. (2011), regression models by Guevara (2010), and recursive neural network based solutions by Socher et al. (2012) and Collobert et al. (2011) have been proposed.

Pantel and Lin (2000) and Erk and Padó (2008) attempted to include syntactic context in distributional models. However, their approaches do not explicitly construct phrase-level meaning from words which limits their applicability to modelling compositional structures. A quasi-compositional approach was also attempted in Thater et al. (2010) by a systematic combination of first and second order context vectors. Perhaps the most similar work to our own is Baroni and Lenci (2010) who propose a *Distributional Memory* that stores syntactic contexts to dynamically construct semantic representations. However, to the best of our knowledge the formulation of composition we propose is the first to account for K and r within the general framework of composition $c = f(a, b, r, K)$, as proposed by Mitchell and Lapata (2008).

6.2.2 The Model

In this section, we describe our Structured Distributional Semantic framework in detail. We first build a large knowledge base from sample english texts and use it to represent basic lexical units. Next, we describe a technique to obtain the representation for larger units by composing their constituents.

6.2.2.1 The PropStore

To build a lexicon of SDSM representations for a given vocabulary we construct a proposition knowledge base (the PropStore) by processing the text of Simple English Wikipedia through a dependency parser. Dependency arcs are stored as 3-tuples of the form $\langle w_1, r, w_2 \rangle$, denoting

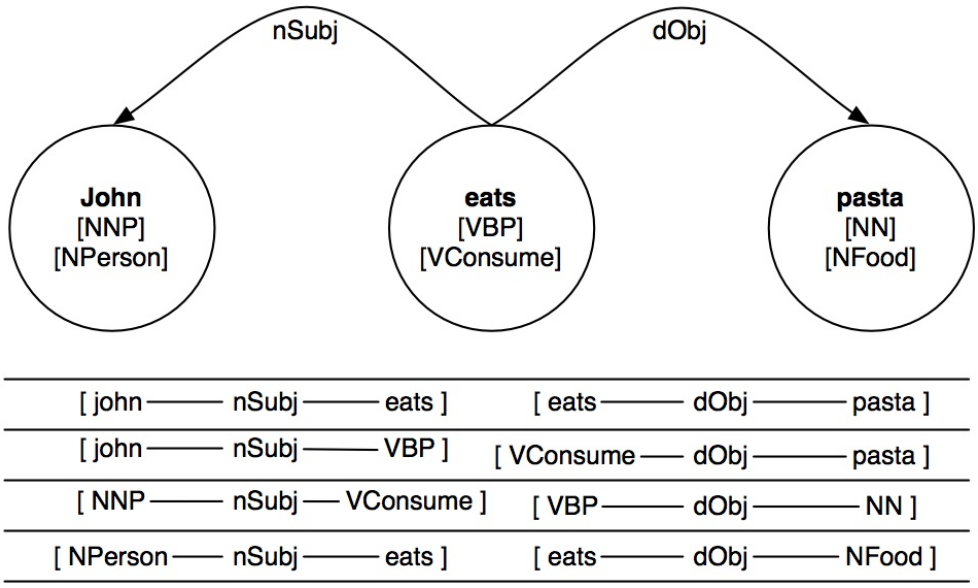


Figure 6.1: A sample parse fragment and some examples of triples that we extract from it. Triples are generated from each dependency arc by taking the cross-product of the annotations that the nodes connected to the arc contain.

occurrences of words w_1 and word w_2 related by the syntactic dependency relation r. We also store sentence identifiers for each triple for reasons described later. In addition to the words' surface-forms, the PropStore also stores their POS tags, lemmas, and WordNet super-senses.

The PropStore can be used to query for preferred expectations of words, super-senses, relations, etc., around a given word. In the example in Figure 6.1, the query (SST(W_1) = verb.consumption, ?, dobj) i.e., "what is consumed", might return expectations [pasta:1, spaghetti:1, mice:1 ...]. In our implementation, the relations and POS tags are obtained using the Fanseparser (Tratz and Hovy, 2011), super-sense tags using sst-light (Ciaramita and Altun, 2006), and lemmas are obtained from WordNet (Miller, 1995).

6.2.2.2 Building the Representation

Next, we describe a method to represent lexical entries as structured distributional matrices using the PropStore.

Recall from Section 6.1, that the representation of a concept w_i (word, phrase, etc.) in the SDSM framework is a matrix $\vec{u_i}$.

In the Syntactic SDSM, we differentiate between two forms of representation: the canonical form, and the representational form. In the canonical form, the elements u_i^{lj} of the SDSM matrix are a list of sentence identifiers obtained by querying the PropStore. Specifically these identifiers are obtained by looking for syntactic contexts in which the word w_i appears with the word w_j linked by a dependency relation l. The canonical form, as we shall see in what follows, allows us to mimick compositionality by intersecting sentence identifier sets and finding expected counts of composed units.

In the representational form, the elements u_i^{lj} of the SDSM matrix are counts. Specifically,

the counts are obtained from the cardinality of the canonical form of the SDSM. This cardinality is thus the content of every cell of the representational matrix and denotes the frequency of co-occurrence of a concept and word under the given relational constraint.

This representational matrix form can be interpreted in several different ways. Each interpretation is based on a different normalization scheme.

1. **Row Norm**: each row of the matrix is interpreted as a distribution over words that attach to the target concept with the given dependency relation. The elements of the matrix become:

$$u_i^{lj} = \frac{u_i^{lj}}{\sum_{j' \in \vec{u_i^l}} u_i^{lj'}} \qquad \forall i, j, l$$

2. **Full Norm**: The entire matrix is interpreted as a distribution over the word-relation pairs which can attach to the target concept. The elements of the matrix become:

$$u_i^{lj} = \frac{u_i^{lj}}{\sum_{l', j' \in \vec{u_i}} u_i^{l'j'}} \qquad \forall i, j, l$$

3. **Collapsed Vector Norm**: The columns of the matrix are collapsed to form a standard normalized distributional vector trained on dependency relations rather than sliding windows. The elements of the matrix become:

$$u_i^{j} = \frac{\sum_{l', j' \in \vec{u_i}} u_i^{l'j'} \delta(j = j')}{\sum_{l', j' \in \vec{u_i}} u_i^{l'j'}} \qquad \forall i, j, l$$

   where δ is the indicator function.

Note that these normalization schemes only apply to the representational SDSMs and cannot be applied to their corresponding canonical form (which contain sentence identifiers, instead of counts).

6.2.3 Mimicking Compositionality

For representing intermediate multi-word phrases, we extend the above word-relation matrix symbolism in a bottom-up fashion. The combination hinges on the intuition that when lexical units combine to form a larger syntactically connected phrase, the representation of the phrase is given by its own distributional neighborhood within the embedded parse tree. The distributional neighborhood of the net phrase can be computed using the PropStore given syntactic relations anchored on its parts. For the example in Figure 6.1, we can compose SST(w_1) = Noun.person and Lemma(w_2) = eat with relation 'nsubj' to obtain expectations around "people eat" yielding [pasta:1, spaghetti:1 . . .] for the *object* relation ([dining room:2, restaurant:1 . . .] for the *location*

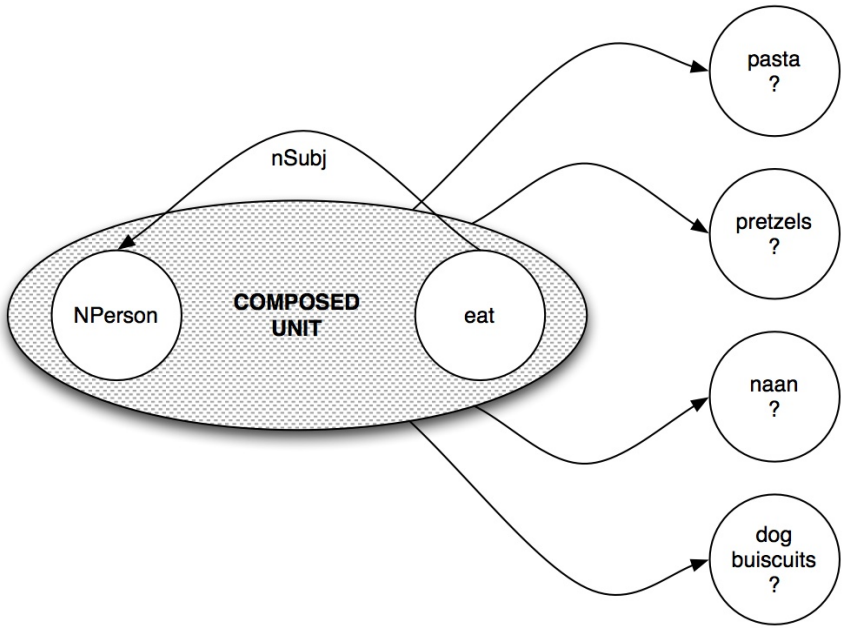


Figure 6.2: A depiction of the composition of two words. After composition the joint unit is treated as a single node, and the expectations of that combined node are then computed from the PropStore.

relation, etc.) (See Figure 6.2). Larger phrasal queries can be built to answer questions like "What do people in China eat with?", "What do cows do?", etc. All of this helps us to account for both relation r and knowledge K obtained from the PropStore within the compositional framework $c = f(a, b, r, K)$.

The general outline to obtain a composition of two words is given in Algorithm 3. Here, we first determine the sentence indices where the two words w_1 and w_2 occur with relation r_l. Then, we return the expectations around the two words within these sentences. Note that the entire algorithm can conveniently be written in the form of database queries to our PropStore.

Algorithm 3 ComposePair(w_1, r_l, w_2)

Canonical $\vec{u_1} \leftarrow$ queryMatrix(w_1)
Canonical $\vec{u_2} \leftarrow$ queryMatrix(w_2)
SentIDs $\leftarrow \vec{u_1^l} \cap \vec{u_2^l}$
return Representational ($(\vec{u_1} \cap$ SentIDs) $\cup$ $(\vec{u_2} \cap$ SentIDs))

Similar to the two-word composition process, given a parse subtree T of a phrase, we can obtain its matrix representation of empirical counts over word-relation contexts. Let $E = \{e_1 \dots e_n\}$ be the set of edges in T, and specifically $e_i = (w_{i,1}, r_l, w_{i,2})\ \forall i = 1 \dots n$. The procedure for obtaining the compositional representation of T is given in Algorithm 4.

Algorithm 4 ComposePhrase(T)

SentIDs $\leftarrow \{i \mid \forall\ i$ s.t. $i =$ SentIDs $\in$ Corpus$\}$
for $e_i \in E$ **do**
  Canonical $\vec{u_{i,1}} \leftarrow$ queryMatrix($w_{i,1}$)
  Canonical $\vec{u_{i,2}} \leftarrow$ queryMatrix($w_{i,2}$)
  SentIDs $\leftarrow$ SentIDs $\cap(\vec{u_{i,1}^{l}} \cap \vec{u_{i,2}^{l}})$
end for
return Representational $((\vec{u_{1,1}} \cap$ SentIDs$) \cup (\vec{u_{1,2}} \cap$ SentIDs$) \cdots \cup (\vec{u_{n,1}} \cap$ SentIDs$) \cup (\vec{u_{n,2}} \cap$ SentIDs$))$

6.2.3.1 Tackling Sparsity

The SDSM model reflects syntactic properties of language through preferential filler constraints. But by distributing counts over a set of relations the resultant SDSM representation is comparatively much sparser than the DSM representation for the same word. In this section we present some ways to address this problem.

Sparse Back-off

The first technique to tackle sparsity is to back off to progressively more general levels of linguistic granularity when sparse matrix representations for words or compositional units are encountered or when the word or unit is not in the lexicon. For example, the composition "Balthazar eats" cannot be directly computed if the named entity "Balthazar" does not occur in the PropStore's knowledge base. In this case, a query for a super-sense substitute – "Noun.person eat" – can be issued instead. When super-senses themselves fail to provide numerically significant counts for words or word combinations, a second back-off step involves querying for POS tags. With coarser levels of linguistic representation, the expressive power of the distributions becomes diluted. But this is often necessary to handle rare words. Note that this is an issue with DSMs too.

Densification

In addition to the back-off method, we also propose a secondary method for "densifying" distributions. A concept's distribution is modified by using words encountered in its syntactic neighborhood to infer counts for other semantically similar words. In other terms, given the matrix representation of a concept, densification seeks to populate its null columns (which each represent a word-dimension in the structured distributional context) with values weighted by their scaled similarities to words (or effectively word-dimensions) that actually occur in the syntactic neighborhood.

For example, suppose the word "play" had an "nsubj" preferential vector that contained the following counts: [cat:4 ; Jane:2]. One might then populate the column for "dog" in this vector with a count proportional to its similarity to the word cat (say 0.8), thus resulting in the vector [cat:4 ; Jane:2 ; dog:3.2]. These counts could just as well be probability values or PMI associa-

tions (suitably normalized). In this manner, the k most similar word-dimensions can be densified for each word that actually occurs in a syntactic context. As with sparse back-off, there is an inherent trade-off between the degree of densification k and the expressive power of the resulting representation.

Dimensionality Reduction

The final method tackles the problem of sparsity by reducing the representation to a dense low-dimensional word embedding using singular value decomposition (SVD). In a typical term-document matrix, SVD finds a low-dimensional approximation of the original matrix where columns become latent concepts while similarity structure between rows are preserved. The PropStore, as described in Section 6.2.2.1, is an order-3 tensor with w_1, w_2 and rel as its three axes. We explore the following two possibilities to perform dimensionality reduction using SVD.

Word-word matrix SVD: In this method, we preserve the axes w_1 and w_2 and ignore the relational information. Following the SVD regime ($W = U\Sigma V^T$) where Σ is a square diagonal matrix of the k largest singular values, and U and V are matrices with dimensionality $m \times k$ and $n \times k$ respectively. We adopt matrix U as the compacted concept representation.

Tensor SVD: To remedy the relation-agnostic nature of the word-word SVD matrix representation, we use tensor SVD (Vasilescu and Terzopoulos, 2002) to preserve relational structure information. The mode-n vectors of an order-N tensor $\mathcal{A} \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N}$ are the I_n-dimensional vectors obtained from $\mathcal{A}$ by varying index i_n while keeping other indices fixed. The matrix formed by all the mode-n vectors is a mode-n flattening of the tensor. To obtain the compact representations of concepts we thus first apply mode w_1 flattening and then perform SVD on the resulting tensor.

6.2.4 Single Word Evaluation

In this section we describe experiments and results for judging the expressive power of the structured distributional representation for individual words. We use a similarity scoring task and a synonym selection task for the purpose of this evaluation. We compare the SDSM representation to standard window-based distributional vectors trained on the same corpus (Simple English Wikipedia). We also experiment with different normalization techniques outlined in Section 3.2, which effectively lead to structured distributional representations with distinct interpretations.

We experimented with various similarity metrics and found that the normalized city-block distance metric provides the most stable results.

$$\text{City-block}(X, Y) = \frac{ArcTan(d(X, Y))}{d(X, Y)} \tag{6.3}$$

$$d(X, Y) = \frac{1}{|R|} \sum_{r \in R} d(X_r, Y_r) \tag{6.4}$$

Results in the rest of this section are thus reported using the normalized city-block metric. We also report experimental results for the two methods of alleviating sparsity discussed in Section 3.4, namely, densification and SVD.

Model	Finklestein (ρ Correlation)	ESL (% Accuracy)
DSM	**0.283**	24.7
Collapsed	0.260	17.8
Full Norm	0.282	19.2
Row Norm	0.236	26.4
Densified Row Norm	0.259	**26.7**

Table 6.1: Single word evaluations on similarity scoring and synonym selections. SDSM does not clearly outperform DSM, likely due to issues of sparsity.

Model	Finklestein (ρ Correlation)
DSM	0.283
Matrix SVD 100	0.207
Matrix SVD 500	0.221
Tensor SVD 100	0.267
Tensor SVD 500	**0.315**

Table 6.2: Effects of SVD methods on SDSM representations. With higher order tensor SVD, SDSM outperforms DSM baseline.

6.2.4.1 Similarity Scoring

On this task, the different semantic representations are used to compute similarity scores between two (out of context) words. We used the dataset from Finkelstein et al. (2002) for our experiments. It consists of 353 pairs of words along with an averaged similarity score on a scale of 1.0 to 10.0 obtained from 13–16 human judges.

For example, an item in the dataset is "book, paper $\rightarrow$ 7.46". Systems are evaluated on the degree of correlation between the similarity scores they assign to pairs of words and those obtained from the gold standard reference scores.

6.2.4.2 Synonym Selection

In the second task, the same set of semantic representations are used to produce a similarity ranking on the Turney (2002) ESL dataset. This dataset comprises 50 words that appear in a context (we discarded the context in this experiment), along with 4 candidate lexical substitutions. Only one of the four candidates is an apt substitute.

For example, the dataset contains items of the form "rug $\rightarrow$ sofa, ottoman, carpet, hallway" (with carpet being the correct synonym). We evaluate the semantic representations on the basis of their ability to discriminate the top-ranked candidate.

6.2.4.3 Results and Discussion

Table 6.1 summarizes the results for the window-based baseline and each of the structured distributional representations on both tasks. It shows that our representations for single words are

competitive with window based distributional vectors. Densification in certain conditions improves our results, but no consistent pattern is discernible. This can be attributed to the trade-off between the gain from generalization and the noise introduced by surrogate neighboring words.

We also explor dimensionality reduction as an additional means of reducing sparsity. Table 6.2 gives correlation scores on the Finkelstein et al. (2002) dataset when SVD is performed on the representations, as described in Section 6.2.3.1. We give results when 100 and 500 principal components are preserved for both matrix as well as tensor SVD techniques.

These experiments suggest that though afflicted by sparsity, the proposed Structured Distributional paradigm is competitive with window-based distributional vectors. In the following sections we show that that the framework provides considerably greater power for modeling composition when dealing with units consisting of more than one word.

6.2.5 Event Coreference Judgment

Given the SDSM formulation and assuming no sparsity constraints, it is possible to calculate SDSM matrices for composed concepts. However, are these correct? Intuitively, if they truly capture semantics, the two SDSM matrix representations for "Booth assassinated Lincoln" and "Booth shot Lincoln with a gun" should be (almost) the same. To test this hypothesis we turn to the task of predicting whether two event mentions are coreferent or not, even if their surface forms differ.

While automated resolution of entity coreference has been an actively researched area (Haghighi and Klein, 2009; Stoyanov et al., 2009; Raghunathan et al., 2010), there has been relatively little work on event coreference resolution. Lee et al. (2012) perform joint cross-document entity and event coreference resolution using the two-way feedback between events and their arguments.

In this paper, however, we only consider coreferentiality between pairs of events. Formally, two event mentions generally refer to the same event when their respective actions, agents, patients, locations, and times are (almost) the same. Given the non-compositional nature of determining equality of locations and times, we represent each event mention by a triple $\mathbf{E} = (e, a, p)$ for the event, agent, and patient.

While linguistic theory of argument realization is a debated research area (Levin and Rappaport Hovav, 2005; Goldberg, 2005), it is commonly believed that event structure (Moens and Steedman, 1988) centralizes on the predicate, which governs and selects its role arguments (Jackendoff, 1987). In the corpora we use for our experiments, most event mentions are verbs. However, when nominalized events are encountered, we replace them by their verbal forms. We use Semantic Role Labelling (SRL) Collobert et al. (2011) to determine the agent and patient arguments of an event mention. When SRL fails to determine either role, its empirical substitutes are obtained by querying the PropStore for the most likely word expectations for the role. The triple (e, a, p) is the composition of the triples (a, rel_{agent}, e) and $(p, rel_{patient}, e)$, and hence a complex object. To determine equality of this complex composed representation we generate three levels of progressively simplified event constituents for comparison:

- **Level 1**: Full Composition:
  $M_{full} = \textit{ComposePhrase}(e, a, p)$.

	IC Corpus				ECB Corpus			
Model	Prec	Rec	F-1	Acc	Prec	Rec	F-1	Acc
DSM	0.743	0.843	0.790	74.0	0.854	0.378	0.524	83.0
Senna	0.850	0.881	0.865	83.5	0.616	**0.408**	0.505	79.1
Senna+AVC	0.753	0.941	0.837	77.7	0.901	0.373	0.528	83.4
Senna+MVC	0.756	**0.961**	0.846	78.7	**0.914**	0.353	0.510	83.1
SDSM	**0.916**	0.929	**0.922**	**90.6**	0.901	0.401	**0.564**	**84.3**

Table 6.3: Cross-validation performance of Event Coreference Judgement on IC and ECB datasets. SDSM outperforms the other models on F-1 and accuracy on both datasets.

- **Level 2**: Partial Composition:
  $M_{part:EA} = \textit{ComposePair}(e, r_{ag}, a)$
  $M_{part:EP} = \textit{ComposePair}(e, r_{pat}, p)$.
- **Level 3**: No Composition:
  $M_E = queryMatrix(e)$
  $M_A = queryMatrix(a)$
  $M_P = queryMatrix(p)$.

where each M is a Structured Distributional Semantic matrix representing a single word or a multiword unit.

To judge coreference between events $\mathbf{E1}$ and $\mathbf{E2}$, we compute pairwise similarities such as, Sim$(M1_{full}, M2_{full})$, Sim$(M1_{part:EA}, M2_{part:EA})$, etc. We do this for each level of the composed triple representation. Furthermore, we vary the computation of similarity by considering different levels of granularity (lemma, SST), various choices of distance metric (Euclidean, city-block, cosine), and score normalization techniques (Row-wise, Full, Column collapsed). This results in 159 similarity-based features for every pair of events, which are used to train a classifier to make a binary decision for coreferentiality.

6.2.5.1 Datasets

We evaluate our method on two datasets and compare it against four baselines, two of which use window based distributional vectors and two that use simple forms of vector composition previously suggested in the literature.

IC Event Coreference Corpus: The dataset, drawn from 100 news articles about violent events, contains manually created annotations for 2214 pairs of co-referent and non-coreferent events each. Where available, events' semantic role-fillers for *agent* and *patient* are annotated as well. When missing, empirical substitutes were obtained by querying the PropStore for the preferred word attachments.

EventCorefBank (ECB) Corpus: This corpus (Bejan and Harabagiu, 2010) of 482 documents from Google News is clustered into 45 topics, with event coreference chains annotated over each topic. The event mentions are enriched with semantic roles to obtain the canoni-

cal event structure described above. Positive instances are obtained by taking pairwise event mentions within each chain, and negative instances are generated from pairwise event mentions across chains, but within the same topic. This results in 11039 positive instances and 33459 negative instances.

6.2.5.2 Baselines

To establish the efficacy of our model, we compare SDSM against a purely window-based baseline (DSM) trained on the same corpus. In our experiments we set a window size of three words to either side of the target.

We also compare SDSM against the window-based embeddings trained using a neural network (SENNA) (Collobert et al., 2011) on both datasets. The SENNA pre-trained embeddings are state-of-the-art for many NLP tasks. This baseline uses SENNA to generate level 3 similarity features for events' individual words (agent, patient and action), since no compositionality between words in a fixed VSM is possible.

As our final set of baselines, we extend two simple techniques proposed by Mitchell and Lapata (2008) that use element-wise addition and multiplication operators to perform composition. The two baselines thus obtained are Senna+AVC (element-wise addition) and Senna+MVC (element-wise multiplication).

6.2.5.3 Results and Discussion

We experimented with a number of common classifiers, and selected decision-trees (J48) as they gave the best classification accuracy across models. Table 6.3 summarizes our results on both datasets.

The results reveal that the SDSM model consistently outperforms DSM, SENNA embeddings, and the MVC and AVC models, both in terms of F-1 score and accuracy. The IC corpus comprises of domain specific texts, resulting in high lexical overlap between event mentions. Hence, the scores on the IC corpus are consistently higher than those on the ECB corpus.

The improvements over DSM and SENNA embeddings, support our hypothesis that syntax lends greater expressive power to distributional semantics in compositional configurations. Furthermore, the increase in predictive accuracy over MVC and AVC shows that our formulation of composition of two words based on the relation binding them yields a stronger form of composition than simple additive and multiplicative models.

We also performed an ablation study to determine the most predictive features for the task of determining event coreferentiality. The forward selection procedure revealed that the most informative attributes are the level 2 compositional features involving the agent and the action, as well as their individual level 3 features. This corresponds to the intuition that the agent and the action are the principal determiners for identifying events. Features involving the patient and level 1 representations are least useful. The latter involve full composition, resulting in very sparse representations and hence have low predictive power.

6.3 Latent Structured Distributional Semantics

We now turn to our second SDSM, which represents its relational dimensions as latent embeddings obtained from matrix factorization. This SDSM tackles the problem of relational facets in meaning comparison by moving away from syntax to a data-driven approach of choosing a set of relational dimensions.

One short-coming of DSMs derives from the fundamental nature of the vector space model, which characterizes the semantics of a word by a single vector in a high dimensional space (or some lower dimensional embedding thereof).

However, the semantics of a word is not unique. Rather, it is composed of many facets of meaning, and similarity (or dissimilarity) to other words is an outcome of the aggregate harmony (or dissonance) between the individual facets under consideration. For example, a shirt may be similar along one facet to a balloon in that they are both colored blue, at the same time being similar to a shoe along another facet for both being articles of clothing, while being dissimilar along yet another facet to a t-shirt because one is stitched from linen while the other is made from polyester.

Of course, in this example the facets of comparison are sensitive to a particular context instance. But at an aggregate level one would be inclined to say that a shirt is most synonymous to a t-shirt because it evidences a high similarity along the principal facet of relevance, or relation between the two words. It is our belief, as a result, that the semantics of a word may be captured more effectively by considering its *relations* to other words and their composite distributional signature, rather than straightforwardly by co-occurrence statistics.

SDSMs in general provide a natural way of capturing the multiple facets of meaning of a concept by decomposing distributional signatures over discrete relation dimensions, or facets. This leads to a representation that characterizes the semantics of a word by a distributional tensor, whose constituent vectors each represent the semantic signature of a word along one particular relational facet of meaning.

In Section 6.2 we introduced one such SDSM. However it uses syntactic relational facets from a dependency parser as surrogates for semantic ones. Other similar previous approaches include work by Padó and Lapata (2007) and Baroni and Lenci (2010).

There are limiting factors to this approximation. Most importantly, the set of syntactic relations, while relatively uncontroversial, is unable to capture the full extent of semantic nuance encountered in natural language text. Often, syntax is ambiguous and leads to multiple semantic interpretations. Conversely, passivization and dative shift are common examples of semantic invariance in which multiple syntactic realizations are manifested. Additionally, syntax falls short in explaining more complex phenomena – such as the description of buying and selling – in which complex interactions between multiple participants must be represented.

Section 6.2 also revealed another very practical problem with a dynamic syntax-driven SDSM: that of sparsity.

While it is useful to consider relations that draw their origins from semantic roles such as Agent, Patient and Recipient, it remains unclear what the complete set of such semantic roles should be. This problem is one that has long troubled linguists (Fillmore, 1967; Sowa, 1991), and has been previously noted by researchers in NLP as well (Màrquez et al., 2008). Proposed

solutions range from a small set of generic Agent-like or Patient-like roles in PropBank (Kingsbury and Palmer, 2002) to an effectively open-ended set of highly specific and fine-grained roles in FrameNet (Baker et al., 1998). In addition to the theoretic uncertainty of the set of semantic relations there is the very real problem of the lack of high-performance, robust semantic parsers to annotate corpora. These issues effectively make the use of pre-defined, linguistically ordained semantic relations intractable for use in SDSM.

In this section we introduce our second novel approach to structuring distributional semantic models, this time with *latent* relations that are automatically discovered from corpora. This approach solves the conceptual dilemma of selecting the most expressive set of semantic relations. It also solves the problems of sparsity plaguing the Syntactic SDSM, albeit at the expense of a dynamic model of composition. To the best of our knowledge this is the first work to propose latent relation dimensions for SDSM-type models. The intuition for generating these latent relation dimensions leads to a generic framework, which — in this paper — is instantiated with embeddings obtained from latent relational analysis (Turney, 2005).

We conduct experiments on three different semantic tasks to evaluate our model. On a similarity scoring task and another synonym ranking task the model significantly outperforms other distributional semantic models, including a standard window-based model, the previously described Syntactic SDSM, and a state-of-the-art semantic model trained using recursive neural-networks. On a relation classification task, our model performs competitively, outperforming all but one of the models it is compared against.

Additionally, our analyses reveal that the learned SDSM captures semantic relations that broadly conform to intuitions of humanly interpretable relations. Optimal results for the first two semantic tasks are reached when the number of latent dimensions vary in the proposed range of known fine-grained semantic relations (O'Hara and Wiebe, 2009). Moreover, a correlation analysis of the models trained on the relation classification task show that their respective weights distinguish fairly well between different semantic relations.

6.3.1 Related Work

Insensitivity to the multi-faceted nature of semantics has been one of the focal points of several papers. Earlier work in this regard is a paper by Turney (2012), who proposes that the semantics of a word is not obtained along a single distributional axis but simultaneously in two different spaces. He proposes a DSM in which co-occurrence statistics are computed for neighboring nouns and verbs separately to yield independent domain and function spaces of semantics.

This intuition is taken further by a stance which proposes that a word's semantics is distributionally decomposed over *many* independent spaces – each of which is a unique relation dimension. Authors who have endorsed this perspective are Erk and Padó (2008), Goyal et al. (2013a), Reisinger and Mooney (2010) and Baroni and Lenci (2010). Our second model relates to these papers in that we subscribe to the multiple space semantics view.

However, this work differs from them by structuring the semantic space with information obtained from latent semantic relations rather than from a syntactic parser. In this section the instantiation of the SDSM with latent relation dimensions is obtained using LRA (Turney, 2005), which is an extension of LSA (Deerwester et al., 1990) to induce relational embeddings for pairs of words.

From a modelling perspective, SDSMs characterize the semantics of a word by a distributional tensor. Other notable papers on tensor based semantics or semantics of compositional structures are the simple additive and multiplicative models of Mitchell and Lapata (2009), the matrix-vector neural network approach of Socher et al. (2012), the physics inspired quantum view of semantic composition of Grefenstette and Sadrzadeh (2011) and the tensor-factorization model of Van de Cruys et al. (2013).

A different, partially overlapping line of research attempts to induce word embeddings using methods from deep learning, yielding state-of-the-art results on a number of different tasks. Notable research papers on this topic are the ones by Collobert et al. (2011), Turian et al. (2010) and Socher et al. (2010).

Other related work to note is the body of research concerned with semantic relation classification, which is one of our evaluation tasks. Research-community-wide efforts in the SemEval-2007 task 4 (Girju et al., 2007), the SemEval-2010 task 8 (Hendrickx et al., 2009) and the SemEval-2012 task 2 (Jurgens et al., 2012) are notable examples. However, different from our work, most previous attempts at semantic relation classification operate on the basis of feature engineering and contextual cues (Bethard and Martin, 2007). In this section the features for the task are induced automatically from word representations.

6.3.2 Latent Semantic Relation Induction

Recall from Section 6.1 the definition and notation of DSMs and SDSMs, and the relationship between the two.

6.3.2.1 Latent Relation Induction for SDSM

The intuition behind our approach for inducing latent relation dimensions revolves around the simple observation that SDSMs, while representing semantics as distributional signatures over relation dimensions, also effectively encode relational vectors between pairs of words. Our method thus works backwards from this observation — beginning with a relational embedding for pairs of words, that are subsequently transformed to yield an SDSM.

Concretely, given a vocabulary $\Gamma = \{w_1, w_2, ..., w_k\}$ and a list of word pairs of interest from the vocabulary $\Sigma_V \subseteq \Gamma \times \Gamma$, we assume that we have some method for inducing a DSM V' that has a vector representation $\vec{v'_{ij}}$ of length d for every word pair $w_i, w_j \in \Sigma_V$, which intuitively embeds the distributional signature of the relation binding the two words in d latent dimensions. So, for example, if we have some words such as "eat", "pasta", "table", "river", "fish" etc., we will want to learn some representation for word pairs such as "(eat, pasta)", "(table, fish)" and "(river, fish)" etc.

Notice that a vector representing "(table, fish)" can effectively be used as one of the columns of the SDSM representing "table" – specifically the column corresponding to the vocabulary word "fish". Similarly, every relational vector can be transformed to become a column vector in the SDSM representation.

Therefore, formally we construct an SDSM U where $\Sigma_U = \Gamma$ is the vocabulary of the model. For every word $w_i \in \Gamma$ a tensor $\vec{u_i} \in \mathbb{R}^{d \times k}$ is generated. The tensor $\vec{u_i}$ has d unique k dimensional vectors $\vec{u_i^1}, \vec{u_i^2}, ..., \vec{u_i^d}$. For a given relational vector $\vec{u_i^l}$, the value of the jth element is taken from

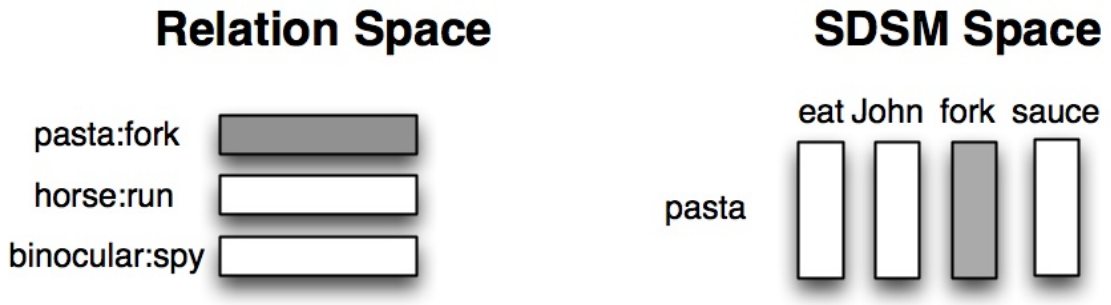


Figure 6.3: Visual representation of the intuition behind the Latent Relational SDSM. The idea revolves around inducing a relation space from which a row vector is transformed to a column vector in SDSM space.

the lth element of the vector $\vec{v'_{ij}}$ belonging to the DSM V'. Intuitively what we are doing, is taking the transpose of the relational row vector (i.e. "(table, fish)") and converting it into a column vector in SDSM space (i.e. "fish" column of the SDSM representation of "table").

If the vector $\vec{v'_{ij}}$ does not exist in V' – as is the case where the pair $w_i, w_j \notin \Sigma_V$ – the value of the jth element of $\vec{u'_i}$ is set to 0. By applying this mapping to generate semantic tensors for every word in Γ, we are left with an SDSM U that effectively embeds latent relation dimensions. From the perspective of DMs we convert the third-order tensor into a two-dimensional matrix and perform truncated SVD, before restoring the resulting matrix to a third-order tensor.

This intuition is visually represented in Figure 6.3. The grey highlighted row vector is transposed from the "relation space" into a column vector of the representation for the word "pasta" in SDSM space.

Latent Relational Analysis

In what follows, we present our instantiation of this model with an implementation that is based on Latent Relational Analysis (LRA) (Turney, 2005) to generate the DSM V'. While other methods (such as RNNs) are equally applicable in this scenario, we use LRA for its operational simplicity as well as proven efficacy on semantic tasks such as analogy detection (which also relies on relational information between word-pairs). The parameter values we chose in our experiments are not fine-tuned and are guided by recommended values from Turney (2005), or scaled suitably to accommodate the size of Σ_V.

The input to LRA is a vocabulary $\Gamma = \{w_1, w_2, ..., w_k\}$ and a list of word pairs of interest from the vocabulary $\Sigma_V \subseteq \Gamma \times \Gamma$. While one might theoretically consider a large vocabulary with all possible pairs, for computational reasons we restrict our vocabulary to approximately 4500 frequent English words and only consider about 2.5% word pairs with high PMI (as computed on the whole of English Wikipedia) in $\Gamma \times \Gamma$. For each of the word pairs $w_i, w_j \in \Sigma_V$ we extract a list of contexts by querying a search engine indexed over the combined texts of the whole of English Wikipedia and Gigaword corpora (approximately 5.8×10^9 tokens). Suitable query expansion is performed by taking the top 4 synonyms of w_i and w_j using Lin's thesaurus (Lin, 1998). Each of these contexts must contain both w_i, w_j (or appropriate synonyms) and optionally

some intervening words, and some words to either side.

Given such contexts, patterns for every word pair are generated by replacing the two target words w_i and w_j with placeholder characters X and Y, and replacing none, some or all of the other words by their associated part-of-speech tag or a wildcard symbol "*".

For example, consider the case when w_i and w_j are "eat" and "pasta" respectively, and the queried context is "I eat a bowl of pasta with a fork". One would then generate all possible patterns, with the words "eat" and "pasta" substituted by the symbols X and Y, and the other words either being replaced by the part-of-speech tags, the wildcard symbol "*", or not replaced at all. Here are some of the examples of patterns one might generate:

- * X * NN * Y IN a *
- * X DT bowl IN Y with DT *
- I X a NN of Y * * fork

For every word pair, only the 5000 most frequent patterns are stored.

Once the set of all relevant patterns $P = p_1, p_2, ..., p_n$ have been computed a DSM V is constructed. In particular, the DSM constitutes a Σ_V based on the list of word pairs of interest, and every word pair w_i, w_j of interest has an associated vector $\vec{v_{ij}}$. Each element m of the vector $\vec{v_{ij}}$ is a count pertaining to the number of times that the pattern p_m was generated by the word pair w_i, w_j.

SVD Transformation

The resulting DSM V is noisy and very sparse. Two transformations are thus applied to V. Firstly all co-occurrence counts between word pairs and patterns are transformed to PPMI scores (Bullinaria and Levy, 2007). Then given the matrix representation of V — where rows correspond to word pairs and columns correspond to patterns — SVD is applied to yield $V = M\Delta N$. Here M and N are matrices that have unit-length orthogonal columns and Δ is a matrix of singular values. By selecting the d top singular values, we approximate V with a lower dimension projection matrix that reduces noise and compensates for sparseness: $V' = M_d\Delta_d$. This DSM V' in d latent dimensions is precisely the one we then use to construct an SDSM, using the transformation described above.

Since the large number of patterns renders it effectively impossible to store the entire matrix V in memory we use a memory friendly implementation[1] of a multi-pass stochastic algorithm to directly approximate the projection matrix (Halko et al., 2011; Rehurek, 2010). A detailed analysis to see how change in the parameter d effects the quality of the model is presented in section 6.3.3.

The optimal SDSM embeddings we trained and used in the experiments detailed below are available for download at `http://www.cs.cmu.edu/~sjauhar/Software_files/LR-SDSM.tar.gz`. This SDSM contains a vocabulary of 4546 frequent English words with 130 latent relation dimensions.

[1] `http://radimrehurek.com/gensim/`

Note on 3-Mode Tensor Extension

We use Latent Relational Analysis as prescribed by Turney (2005) because it has proven to be successful for learning representations for word pairs. However, a natural extension is to altogether avoid the transformation from the SDSM representation to a pair-pattern matrix and directly operate on a 3-mode tensor. This 3-mode tensor would essentially be a *Word* $\times$ *Word* $\times$ *Pattern* matrix, rather than the slices of the same matrix that we stack to obtain a 2-mode pair-pattern matrix.

Once this 3-Mode tensor is populated with pair-pattern counts in much the same manner as we populate its 2-dimensional counterpart, we can directly use a tensor decomposition algorithm (Vasilescu and Terzopoulos, 2002; Kolda and Bader, 2009) to find a dense, lower-dimensional embedding of the original semantic space. This is the approach that Baroni and Lenci (2010) adopt in their treatment of distributional memory, which is similar to our idea of SDSM.

The motivation to maintain a 3-mode tensor is to preserve the structure of the representation space, which is lost when decomposing the same elements into a 2-mode matrix. Turney (2007b) compares different tensor decomposition algorithms and concludes that 3-mode decomposition works better than SVD on a 2-mode corresponding matrix.

The difference can also be clearly interpreted by visualizing the resultant representations. With 2-mode SVD applied to a pair-pattern matrix, we obtain an SDSM representation that contains some non-zero columns and many all zero columns. This is because the zero columns represent pairs of words that were filtered out and hence were never captured in the original pair-pattern matrix. On the other hand, a 3-mode tensor captures a strictly greater amount of structure. Here decomposition yields a fully dense representation, thus allowing us to extend the pattern counts for some pairs of words to capture a dense representation between all pairs of words.

3-mode dimensionality represents a natural extension to our work on Latent SDSM, and we leave this to future work.

6.3.3 Evaluation

Section 6.3.2 described a method for embedding latent relation dimensions in SDSMs. We now turn to the problem of evaluating these relations within the scope of the distributional paradigm in order to address two research questions:

1. Are latent relation dimensions a viable and empirically competitive solution for SDSM?
2. Does structuring lead to a semantically more expressive model than a non-structured DSM?

In order to answer these questions we evaluate our model on two generic semantic tasks and present comparative results against other structured and non-structured distributional models. We show that we outperform all of them significantly, thus answering both research questions affirmatively.

While other research efforts have produced better results on these tasks (Jarmasz and Szpakowicz, 2004; Gabrilovich and Markovitch, 2007; Hassan and Mihalcea, 2011), they are either lexicon or knowledge based, or are driven by corpus statistics that tie into auxiliary resources such as multi-lingual information and structured ontologies like Wikipedia. Hence they are not relevant to our experimental validation, and are consequently ignored in our comparative evaluation.

Model	WS-353 (Spearman's rho)	ESL (% Accuracy)
Random	0.000	25.0
DSM	0.179	28.0
Syntactic SDSM	0.315	26.7
Senna	0.510	38.0
LR SDSM (300)	0.567	46.9
LR SDSM (130)	**0.586**	**51.0**

Table 6.4: Results on the WS-353 similarity scoring task and the ESL synonym selection task. LRA-SDSM significantly outperforms other structured and non-structured distributional semantic models.

6.3.3.1 Word-Pair Similarity Scoring Task

The first task consists in using a semantic model to assign similarity scores to pairs of words. The dataset used in this evaluation setting is the WS-353 dataset from Finkelstein et al. (2002). It consists of 353 pairs of words along with an averaged similarity score on a scale of 1.0 to 10.0 obtained from 13–16 human judges. Word pairs are presented as-is, without any context. For example, an item in this dataset might be "book, paper $\rightarrow$ 7.46".

System scores are obtained by using the standard cosine similarity measure between distributional vectors in a non-structured DSM. In the case of a variant of SDSM, these scores can be found by using the cosine-based similarity functions in Equation 6.2 of the previous section. System generated output scores are evaluated against the gold standard using Spearman's rank correlation coefficient.

6.3.3.2 Synonym Selection Task

In the second task, the same set of semantic space representations is used to select the semantically closest word to a target from a list of candidates. The ESL dataset from Turney (2002) is used for this task, and was selected over the slightly larger TOEFL dataset (Landauer and Dumais, 1997). The reason for this choice was because the latter contained more complex vocabulary words — several of which were not present in our simple vocabulary model. The ESL dataset consists of 50 target words that appear with 4 candidate lexical substitutes each. While disambiguating context is also given in this dataset, we discard it in our experiments. An example item in this dataset might be "rug $\rightarrow$ sofa, ottoman, carpet, hallway", with "carpet" being the most synonym-like candidate to the target.

Similarity scores — which are obtained in the same manner as for the previous evaluation task — are extracted between the target and each of the candidates in turn. These scores are then sorted in descending order, with the top-ranking score yielding the semantically closest candidate to the target. Systems are evaluated on the basis of their accuracy at discriminating the top-ranked candidate.

6.3.3.3 Results

We compare our model (LR-SDSM) to several other distributional models in these experiments. These include a standard distributional vector space model (DSM) trained on the combined text of English Wikipedia and Gigaword with a window-size of 3 words to either side of a target, the Syntactic SDSM from Chapter 6.2 (synSDSM) trained on the same corpus parsed with a dependency parser (Tratz and Hovy, 2011) and the state-of-the-art neural network embeddings from Collobert et al. (2011) (SENNA). We also give the expected evaluation scores from a random baseline, for comparison.

An important factor to consider when constructing an SDSM using LRA is the number of latent dimensions selected in the SVD projection. In Figure 6.4 we investigate the effects of selecting different number of latent relation dimensions on both semantic evaluation tasks, starting with 10 dimensions up to a maximum of 800 (which was the maximum that was computationally feasible), in increments of 10. We note that optimal results on both datasets are obtained at 130 latent dimensions. In addition to the SDSM obtained in this setting we also give results for an SDSM with 300 latent dimensions (which has been a recommended value for SVD projections in the literature (Landauer and Dumais, 1997)) in our comparisons against other models. Comparative results on the Finkelstein WS-353 similarity scoring task and ESL synonym selection task are given in Table 6.4.

6.3.3.4 Discussion

The results in Table 6.4 show that LR-SDSM outperforms the other distributional models by a considerable and statistically significant margin (p-value < 0.05) on both types of semantic evaluation tasks. It should be noted that we do not tune to the test sets. While the 130 latent dimension SDSM yields the best results, 300 latent dimensions also gives comparable performance and moreover outperforms all the other baselines. In fact, it is worth noting that the evaluation results in figure 6.4 are almost all better than the results of the other models on either datasets.

We conclude that structuring of a semantic model with latent relational information in fact leads to performance gains over non-structured variants. Also, the latent relation dimensions we propose offer a viable and empirically competitive alternative to syntactic relations for SDSMs.

Figure 6.4 shows the evaluation results on both semantic tasks as a function of the number of latent dimensions. The general trend of both curves on the figure indicate that the expressive power of the model quickly increases with the number of dimensions until it peaks in the range of 100–150, and then decreases or evens out after that. Interestingly, this falls roughly in the range of the 166 frequent (those that appear 50 times or more) frame elements, or fine-grained relations, from FrameNet that O'Hara and Wiebe (2009) find in their taxonomization and mapping of a number of lexical resources that contain semantic relations.

6.3.4 Semantic Relation Classification and Analysis of the Latent Structure of Dimensions

In this section we conduct experiments on the task of semantic relation classification. We also perform a more detailed analysis of the induced latent relation dimensions in order to gain insight

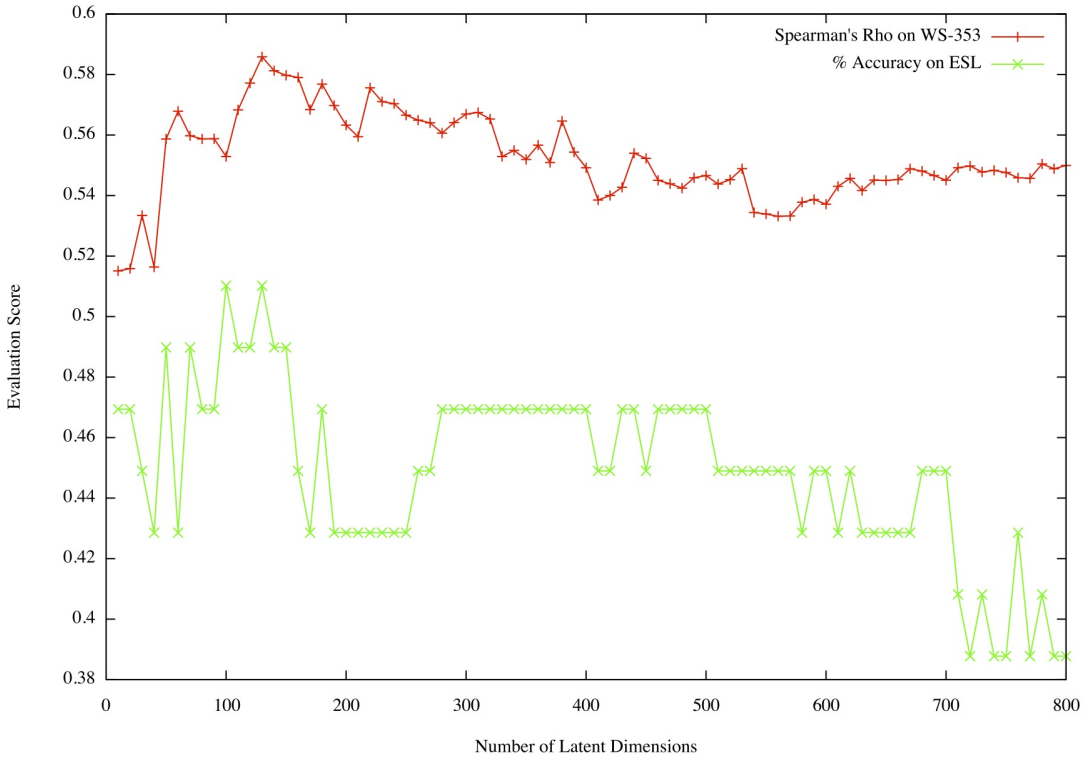


Figure 6.4: Evaluation results on WS-353 and ESL with varying number of latent dimensions. Generally high scores are obtained in the range of 100-150 latent dimensions, with optimal results on both datasets at 130 latent dimensions.

	Relation Classification			
Model	Precision	Recall	F-1	% Accuracy
Random	0.111	0.110	0.110	11.03
Senna (Mik)	0.273	0.343	0.288	34.30
DSM+AVC	0.419	0.449	0.426	44.91
DSM+MVC	0.382	0.443	0.383	44.26
Senna+AVC	**0.489**	**0.516**	**0.499**	**51.55**
Senna+MVC	0.416	0.457	0.429	45.65
LR SDSM	0.431	0.475	0.444	47.48

Table 6.5: Results on Relation Classification Task. LR-SDSM scores competitively, outperforming all but the SENNA-AVC model.

into our model's perception of semantic relations.

6.3.4.1 Semantic Relation Classification

In this task, a relational embedding is used as a feature vector to train a classifier for predicting the semantic relation between previously unseen word pairs. The dataset used in this experiment is from the SemEval-2012 task 2 on measuring the degree of relational similarity (Jurgens et al., 2012), since it characterizes a number of very distinct and interesting semantic relations. In particular it consists of an aggregated set of 3464 word pairs evidencing 10 kinds of semantic relations. We prune this set to discard pairs that don't contain words in the vocabularies of the models we consider in our experiments. This leaves us with a dataset containing 933 word pairs in 9 classes (1 class was discarded altogether because it contained too few instances). The 9 semantic relation classes are: "Class Inclusion", "Part-Whole", "Similar", "Contrast", "Attribute", "Non-Attribute", "Case Relation", "Cause-Purpose" and "Space-Time". For example, an instance of a word pair that exemplifies the "Part-Whole" relationship is "engine:car". Note that, as with previous experiments, word pairs are given without any context.

6.3.4.2 Results

We compare LR-SDSM on the semantic relation classification task to several different models. These include the additive vector composition (AVC) and multiplicative vector composition methods (MVC) proposed by Mitchell and Lapata (2009); we present both DSM and SENNA based variants of these models. We also compare against the vector difference method of Mikolov et al. (2013b) (SENNA-Mik) which sees semantic relations as a meaning preserving vector translation in an RNN embedded vector space. Finally, we note the performance of random classification as a baseline, for reference. We attempted to produce results of a syntactic SDSM on the task; however, the hard constraint imposed by syntactic adjacency meant that effectively all the word pairs in the dataset yielded zero feature vectors.

To avoid overfitting on all 130 original dimensions in our optimal SDSM, and also to render results comparable, we reduce the number of latent relation dimensions of LR-SDSM to 50. We similarly reduce the feature vector dimension of DSM-AVC and DSM-MVC to 50 by feature

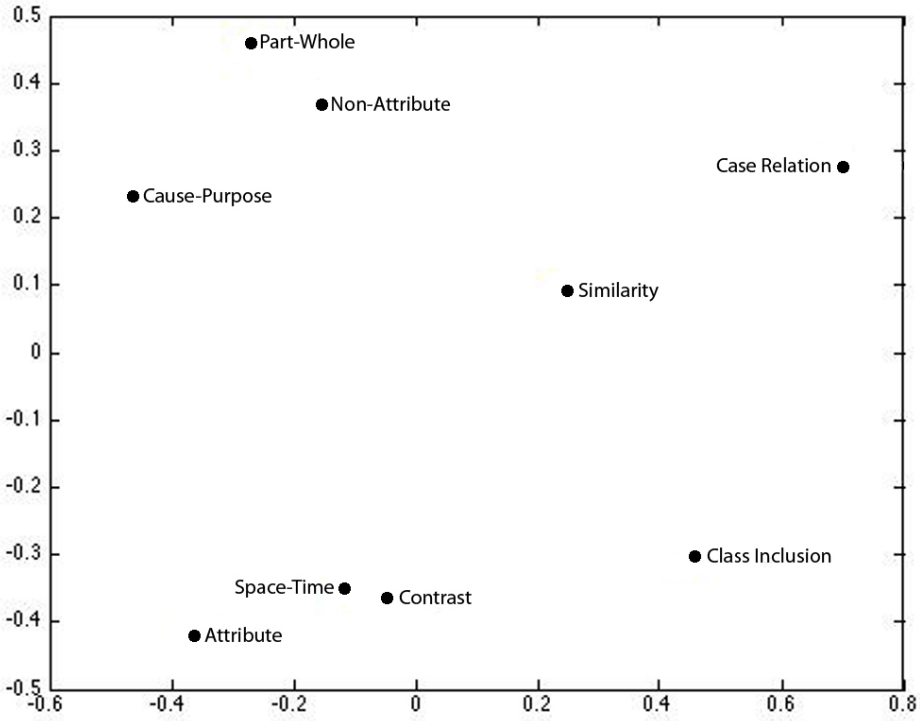


Figure 6.5: Correlation distances between semantic relations' classifier weights. The plot shows how our latent relations seem to perceive humanly interpretable semantic relations. Most points are fairly well spaced out, with opposites such as "Attribute" and "Non-Attribute" as well as "Similar" and "Contrast" being relatively further apart.

selection. The dimensions of SENNA-AVC, SENNA-MVC and SENNA-Mik are already 50, and are not reduced further.

For each of the methods we train a logistic regression classifier. We don't perform any tuning of parameters and set a constant ridge regression value of 0.2, which seemed to yield roughly the best results for all models. The performance on the semantic relation classification task in terms of averaged precision, recall, F-measure and percentage accuracy using 10-fold cross-validation is given in Table 6.5.

Additionally, to gain further insight into the LR-SDSM's understanding of semantic relations, we conduct a secondary analysis. We begin by training 9 one-vs-all logistic regression classifiers for each of the 9 semantic relations under consideration. Then pairwise correlation distances are measured between all pairs of weight vectors of the 9 models. Finally, the distance adjacency matrix is projected into 2-d space using multidimensional scaling. The result of this analysis is presented in Figure 6.5.

6.3.4.3 Discussion

Table 6.5 shows that LR-SDSM performs competitively on the relation classification task and outperforms all but one of the other models. The performance differences are statistically significant with a p-value < 0.5. We believe that some of the expressive power of the model is lost by compressing to 50 latent relation dimensions, and that a greater number of dimensions might improve performance. However, testing a model with a 130-length dense feature vector on a dataset containing 933 instances would likely lead to overfitting and also not be comparable to the SENNA-based models that operate on 50-length feature vectors.

Other points to note from Table 6.5 are that the AVC variants of the the DSM and SENNA composition models tend to perform better than their MVC counterparts. Also, SENNA-Mik performs surprisingly poorly. It is worth noting, however, that Mikolov et al. (2013b) report results on fairly simple lexico-syntactic relations between words – such as plural forms, possessives and gender – while the semantic relations under consideration in the SemEval-2012 dataset are relatively more complex.

In the analysis of the latent structure of dimensions presented in Figure 6.5, there are few interesting points to note. To begin with, all the points (with the exception of one pair) are fairly well spaced out. At the weight vector level, this implies that different latent dimensions need to fire in different combinations to characterize distinct semantic relations, thus resulting in low correlation between their corresponding weight vectors. This indicates the fact that the latent relation dimensions seem to capture the intuition that each of the classes encodes a distinctly different semantic relation. The notable exception is "Space-Time", which is very close to "Contrast". This is probably due to the fact that distributional models are ineffective at capturing spatio-temporal semantics. Moreover, it is interesting to note that "Attribute" and "Non-Attribute" as well as "Similar" and "Contrast", which are intuitively semantic inverses of each other are also (relatively) distant from each other in the plot.

These general findings indicate an interesting avenue for future research, which involves mapping the empirically learned latent relations to hand-built semantic lexicons or frameworks. This could help to validate the empirical models at various levels of linguistic granularity, as well as establish correspondences between different views of semantic representation.

6.4 Conclusion

In this chapter we outlined a general framework of representing semantics with a more expressive Structured Distributional formalism. This formalism tackled the problem of context-sensitivity and facetedness in semantics by a model that decomposes a vector representation into several discrete relation dimensions. We proposed two novel models that each instantiated these relation dimensions in a different way.

The first used dependency syntax and introduced a dynamic model that was capable of composing units into complex structure by taking relational context into account. By doing so it effectively tackled the problem of context-sensitivity in semantics. The Syntactic SDSM we introduced showed promising results on event coreference judgment, a task that specifically brings the problem of contextual variability into focus.

Our second instantiation of relation dimensions was a model that learned a set of latent relations from contextual pattern occurrences. This approach was better suited to resolve the issue of facetedness in semantics, or the facets along which a word may be represented or compared. Its data-driven approach allowed the SDSM to move away from syntax (and any set schema of relations for that matter), while also tackling the problem of sparsity that plagued the Syntactic SDSM. Experimental results of the model supported our claim that the Latent SDSM captures the semantics of words more effectively than a number of other semantic models, and presents a viable — and empirically competitive — alternative to Syntactic SDSMs. Finally, our analyses to investigate the structure of, and interactions between, the latent relation dimensions revealed some interesting tendencies on how they represented and differentiated between known, humanly-interpretable relations.

6.4.1 Five Point Thematic Summary

What was the semantic representation learning problem that we tried to solve?

We tackled two different but related semantic representation learning problems in this chapter. The first problem was that of context-sensitivity (see Section 6.2), which is the property of a representation to be modified by its contextual neighbors so as to alter its meaning. The second problem we dealt with was that of semantic facetedness (see Section 6.3), which had the modelling goal to represent the different attributes of objects as separate dimensions of representation.

We envisaged a modelling paradigm that was capable of solving both kinds of problems. Namely we moved from representing units of semantics as vectors, to representing them as two-dimensional tensors, and called these representations Structured Distributional Semantic Models (SDSMs). Specifically, we hypothesized that a semantic tensor was effectively a decomposed representation of a vector — and that the rows of the tensor were essentially the semantic signatures of the object along a particular semantic dimension (or facet, in our terminology).

In terms of Definition 1 in Chapter 1.2, the two-dimensional tensor modelling paradigm defined a different semantic relation for each of the rows of the tensor. These relations were framed as mappings from pairs of co-occurring words in the corpus to the set of real numbers. Each of the mappings had the goal of capturing the affinity for co-occurrence of pairs of words, along a particular relation dimension.

Based on this interpretation, an intuitive way of describing SDSMs is that they are nothing more than simultaneously co-existing vector space models, represented together in compact form. We have one vector space model each for the different semantic relations we are interested in capturing. The relations themselves, and therefore their corresponding mappings into the set of reals, depends – of course – on the target problem we care about.

What linguistic information or resource did we use to solve this problem?

We used different linguistic information for each of the two problems we tackled. For the problem of context-sensitivity we used vast amounts of syntactically parsed text that we then decomposed and stored in a database called the PropStore. Our intuition was that the decomposed

dependency triples (consisting of pairs of words connected by typed arcs) would provide us with the building blocks to compute the expected representations of composed units.

Meanwhile, for the problem of semantic facetdness, we set ourselves the goal of moving from syntax as the rows of the tensor representation, to having latent semantic rows. Accordingly, we only relied on raw un-annotated text under the assumption that the semantic relations we cared about were latent in the text and could be uncovered by our model.

How did we operationalize the desired semantic relation with contextual relations in the resource?

Recall that we made the analogy that an SDSM is essentially a compact representation of multiple co-existing vector space models. Each of these vector space models captures a single semantic relation, and this relation corresponds to a single row in the two-dimension SDSM tensor. We operationalized these semantic relations differently according to the two different target problems we were attempting to solve.

For the SDSM designed to tackle context-sensitivity, we defined contextual relations over dependency trees. The different relations (and thereby different rows of the tensor) were the types of dependency arcs produced by the syntactic parser. Thus, from the perspective of Definition 2, we defined the shared property of a particular contextual relations as target-context word pairs in the vocabulary that were found to have been connected by a dependency arc of that type, in the data.

Meanwhile, for the SDSM that had the goal of tackling facetedness, we defined contextual relations over patterns in raw text. Our operationalization of the semantic relations in the latent tensor model were based on the intuition that pairs of words that occur with similar patterns around them have a similar relation between them (Turney, 2008a).

How did we use the contextual relations in representation learning?

Differently to the rest of the thesis, neither of our two instantiations of SDSM were learning models. However, as with all representation learning models, we still had to make counts over contexts. That is, we still assigned weights to pairs of target-context objects by some summary of count statistics over contexts.

In the case of the first SDSM, we developed a dynamic model that counted co-occurrence statistics on the fly for composed representations. These counts were made from queries to the PropStore, but were essentially counts over the syntactic neighborhood of words. The contextual relations specified by the different syntactic relations, as a result, biased the representations of the rows of the two-dimensional SDSM tensor. We explored different ways of normalizing these counts, but all our normalization schemes had probabilistic interpretations (see Section 6.2.2.2).

The second SDSM operationalized the semantic relations as contextual relations over neighborhood patterns. Thus we computed co-occurrence statistics between pairs of words and their neighboring patterns. In this case, to account for the vast number of patterns and their relative sparsity we normalized the counts in two ways. We first transformed the counts with positive point-wise mutual information and furthermore performed singular-value decomposition to reduce the pair-pattern count matrix (see Section 6.3.2.1). The columns of the resulting matrix

became the latent semantic relations of the SDSM.

What was the result of biasing the learner with contextual relations in learning the semantic model?

We evaluated the context-sensitive SDSM on the task of semantic similarity of words (which really does not require modelling of context-sensitivity), but found the results to be fairly mediocre (see Section 6.2.4). However, on the task of event coreference judgment (which, in contrast, does require modelling of context-sensitivity), we found our syntactic SDSM capable and indeed outperforming several baselines (see Section 6.2.5). We concluded that biasing our model with syntactic contexts, and embedding those syntactic relations as the rows of the model enabled us to effectively capture how words are modified by their context. At the same time, these factors did not benefit the model's ability to capture the semantics of individual words.

The latent semantic SDSM, in contrast, was much better at capturing the semantics of individual words. It not only outperformed the syntactic SDSM, but other competent baselines – including a neural network model. Section 6.3.3 contains all the details of our evaluation. Additionally we also measured the second SDSM instantiation on the task of relation classification and attempted to visualize the model's perception of known, humanly interpretable semantic relations. We found that it was able to differentiate between these relations fairly well. Thus we were able to capture latent semantic relations that not only benefitted the representation of individual words, but were also good discriminators of known relations. We thus concluded that the bias obtained from our contextual relations over word pairs and their neighboring patterns did, in fact, help us capture latent semantic relations that effectively represented the relational dimensions of our SDSM.

Chapter 7

Conclusion

We now conclude this thesis by summarizing our contributions and looking forward to avenues for future exploration.

7.1 Summary of Contributions

This thesis has presented a relation-centric view to the problem of representation learning in semantics.

- We have argued for this relation-centric view by positing that relations and structure are a core component of producing meaning in language. This led us in an attempt to characterize the nature of the information captured by semantic representation learning models. We argued that the goal of every model is to capture some semantic relation but that these relations are almost never annotated in data, and therefore cannot be directly learned from data as such. Instead, the only way to bias an unsupervised learner of semantic representations is to rework its input, – its context or view of the data. We introduced the idea of a contextual relation as the operationalization of a semantic relation that we wish to learn from data. We argued that this connection between semantic and contextual relations provides a way of injecting knowledge into the unsupervised paradigm of representation learning. Moreover relations and structure represented a way of consolidating and understanding semantic models and their associated contexts. They also suggested that different problems require different semantic and contextual relations, and that articulating and then leveraging the right (or at least more expressive) relations for these problems can lead to better models.

- We then developed a set of five key research questions that presented a framework in which to think about and implement solutions that adopt the relation-centric view of semantic representation learning. The rest of our thesis is organized as an example-based instantiation of this high-level framework. Each of the questions dealt with one of five sequential themes. The first begins by identifying a representation learning problem that can be articulated in terms of a linguistic or structural phenomenon in natural language data – that is, specifying the desired semantic relation to be learned. Second, the framework

suggests identifying a corpus or knowledge resource that contains information relevant to solving the problem. The third then seeks to articulate the principal contextual relations in the resource, by drawing inspiration from intuitions of the desired semantic relation. After this, the fourth deals with specifying a mathematical model that processes contexts and subsequently assigns weights, or association strengths to pairs of target and concept objects. Fifth and finally, the framework requires an evaluation of the learned model in order to see if the inclusion of contextual relations measurably improved its ability to represent the desired semantic relation.

- In Chapter 3 we looked at the problem of polysemy from the perspective of representation learning models. We suggested that ontologies contain a complimentary source of knowledge to distributional statistics, and that their structure can be used to tease apart representations for different senses of words that share a unique surface forms. To this end we developed two general and flexible solutions that integrates this structure into the process of learning sense representations that are grounded in an ontology. The first was an easy and computationally attractive post-processing step, called retrofitting, that split representations of word vectors into different sense vectors. The second built on the first method by also introducing a corpus into the learning process. Crucially, both methods leveraged the structure and relations within an ontology to define smoothness properties over the underlying graph, and used the neighborhoods of senses to tease them apart from other senses with which they shared a word surface form.

- Chapter 4 tackled the problem of QA in the context of the question, "What is the right level of structure for background knowledge"? In particular, we looked at background knowledge in the form of semi-structured tables with text entries. These tables represented interesting semantics over relations defined in terms of rows and columns, that we leveraged in two important ways. First, we used table relations to guide non-expert annotators to create a large bank of multiple-choice questions. As a benefit of the annotation setup we also obtained fine-grained alignments from these multiple-choice questions to table elements, with no added cost or effort to annotators. Second, we used this newly created dataset of questions and table alignments to implement two question answering solutions. Crucially, both solutions leveraged the inherent structure of tables to find and use information relevant to answering questions. The first solution modelled table structure with a rich-set of hand-crafted features, while the second mimicked these features with a neural network model that automatically generated representations for table elements. The manually engineered model proved to be very successful, capable of abstracting over both the content and structure of tables to find answers in unseen test cases. The neural network model was also successful, but only at abstracting over structure and was more tied to content – understandably since its representations were learned over the content of tables.

- We explored the task of learning a semantic lexicon in Chapter 5. Specifically, we attempted to induce embeddings for a set of predicates and arguments, as well a set of latent relational argument slots associated with predicates – all while using minimal annotation. In fact, to the best of our knowledge, our work was the first to induce latent semantic role information without requiring high-level annotations such as dependency parses. Our solu-

tion revolved around the insight that the relations between predicates and arguments occur both at token and type level. To put this insight into practise we developed a novel integration between a predictive embedding model and the posterior of an Indian Buffet Process. By jointly leveraging the local (token) and global (type) levels of information over a corpus of predicate-argument pairs we were able to learn lexicon embeddings and latent relation slots that were maximally able to account for both types of relational information. We evaluated our model at both the local (token) level and the global (type) level and demonstrated that the relational structure that we learn from latent slots in fact benefits the expressive power of the semantic lexicon. Finally, we also qualitatively showed that our solution was capable of capturing some interesting generalities of known, humanly-interpretable relations while having no access or supervision to guide it towards this understanding.

- Finally, in Chapter 6 we tackled the two related problems of context-sensitivity and facetedness in learning distributional semantic models. We outlined a framework that we called Structured Distributional Semantics to address these problems. The core idea behind Structured Distributional Semantics echoes the overall theme of this thesis, namely that relations play a key role in giving rise to semantics. Consequently the model decomposes the representation of a concept from a single vector into a relational tensor. The rows of this tensor define relations, and these relations are the principle dimensions of representations in the resulting semantic space. We instantiated the relations of the tensor in two different ways that were devised to tackle the problems of context-sensitivity and facetedness. The first instantiation used syntactic relations and relied on a large store of syntactic triples in order to build compositional and context-sensitive representations on the fly. The second instantiation directly induced a set of latent semantic relations and used them to approach the problem of semantic facetedness. Both kinds of models produced empirically competitive results on relevant evaluations. And in the case of the latent relational model we again discovered (as in Chapter 5) some interesting tendencies of the latent relations to capture and differentiate between known, humanly-interpretable relations.

7.2 Future Directions

Each of the problems we have summarized above, and their respective solutions open up future avenues of research, such as performance improvements, extensions or scaling-up. The papers published from each of the corresponding chapters detail these future directions.

However, to conclude this thesis we mention some of the bigger trends that merit exploration. In particular we list three major themes.

Digging Deeper

From the five research questions and their corresponding topics, introduced in Chapter 2, we can deepen and generalize our approach to at least three of them. The first and the last of the themes concern defining and evaluating a problem and are necessarily task dependent, but the others are high-level generalizations that could encompass more than one problem.

The first and the second of the remaining three themes concerns the selection of the data source and the articulation of the principle relations within it. These two themes are deeply connected both in terms of this thesis as well as our envisaged outline of their future exploration.

In particular, the examples in this thesis have been split roughly into two major categories. The first used existing, at least partially manually created structured data that influenced the way we learn relations (such as ontologies in Chapters 3 and tables in 4), while the second attempted to use latent relations in data to induce a set of relations for our models (such as predicate-argument pairs in Chapters 5 and text patterns in 6). In other words, we explored research use cases where we selected a structured resource that had a pre-defined set of well articulated contextual relations, and other use cases where we were only given plain text (or some variant thereof) and were required to define the set of contextual relations in terms of the raw text.

The latter use case, of course is a more general approach, but using latent relations is often more difficult and produces models that are less interpretable and not as empirically effective. Exploring these themes further would require characterizing and numerically evaluating the differences between models that leverage structured and unstructured resources, or that learn from manually defined and latent contextual relations. For example, our approach in Chapter 3 uses an ontology for sense representation and grounding, but there are approaches (Reisinger and Mooney, 2010; Neelakantan et al., 2014) that induce the senses in a latent way directly from plain text data. How do the senses learned by each of these methods differ from one another? Which ones are "better"? In general, can we do away with structured resources altogether and do all our learning from plain text corpora? This would provide us with a great deal of modelling power and flexibility to tackle the problems we chose.

The third research theme we wanted to broach, in terms of deeper and more general future work, concerns the models we define to learn representations. Most of the models detailed during the course of this thesis have been (perhaps necessarily) task specific. However, is it possible to frame relation-centric representation learning problems in terms of a unified mathematical framework? We believe probably not. But it would still be helpful if several different problems were capable of being captured by a single framework. This would indicate a deeper connection between different semantic relation learning problems, but also provide a very concrete and definite first indication on how to apply the ideas in this thesis to new domains.

The general idea behind the model introduced in Equation 3.3 of Chapter 3.2 represents one possible unification for several semantic relation learning problems. This is an idea that we return to again in Equation 5.1 of Chapter 5.2. The general form of this idea is a regularized maximum-likelihood model, in which the likelihood and regularization components can be instantiated in different task-specific ways. This represents a powerful framework that fits into the overarching goals of this thesis: learning representations from data with the influence of relations and structure.

In the two examples we showed in this thesis, we tackled two very different problems showing that this framework is in fact quite flexible. The first example dealt with maximizing the likelihood of a corpus with latent senses, while accounting for a posterior regularizer over an ontology. The second dealt with the very different problem of maximizing the likelihood of local token predicate-argument affinities with latent relation slots, while accounting for a posterior regularizer that captured global type-level affinities between them. In both cases, the Skip-gram model of Word2Vec Mikolov et al. (2013a) – which learns representations from maximizing the

likelihood of a corpus – was modified minimally to account for the generative story of the likelihood component of the framework. Meanwhile, the regularizer component was very different – necessarily accounting for the contextual relations that were relevant to the two very different problems: in the one case ontological structure, in the other aggregated predicate-argument structure.

One can imagine several problems that attempt to integrate relations or structure into the learning process would want to accommodate both a component that learns from data as well as a component that accounts for the contextual relations or structure. The regularized maximum-likelihood framework presents a theme that is capable of assimilating these two components, and could be an interesting avenue to explore as a general model for tackling several different relation-centric semantic representation learning problems.

Putting it All Together

The holy grail of semantics is a model that is capable of processing and understanding all of human language, with all its richness, variation and ambiguity. How do we move the research introduced in this thesis towards that holy grail? Currently our models represent disparate attempts at tackling different nugget problems within the larger semantic space.

While we are not arguing for or against an approach that attempts to solve a vast problem like semantics in bits and pieces, an important question arises when you do have solutions to these bits and pieces: how do you put them all together? One could envisage a joint approach that pools all the different model outputs into a single semantic representation. Something similar is done by Yao et al. (2012) and Riedel et al. (2013), who use a so-called Universal Schema that is simply the union of different knowledge base schemas and representations in one gigantic whole.

But putting different semantic representations together, learned with different target problems in mind raises the natural follow-up question: how do you use the representations together, or how do you decide when to use which relation? We believe that resolving this problem requires an important future step in relation-centric learning.

We have introduced the relation-centric view of semantics as one of different kinds of contexts. Specifically, every relation gives rise to a different kind of context. We have, up to this point, only defined relations and used their corresponding contexts to learn representations. But what if we were to reverse the direction of influence? Namely, can we look a context and identify the specific relation that we need to focus on for a particular problem. This would enable us to select from potential candidates in an integrated representation model to select precisely the one we require to use for a particular problem.

An exploration of relation identification also would require a deeper understanding of the connection between different problems and their corresponding relations. Up until this point, we have defined and used these relations in a fairly ad-hoc fashion, intuiting on what might or might not be useful for a particular problem. In the future, a deeper understanding of the connection might lead to a more informed understanding and choice of relations for different problems.

What is a Relation?

This thesis was concerned with using relations to learn more expressive models of semantics. Relations encompass a very broad range of phenomenon in language and data formalisms, and in Chapter 2 we attempted to provide a taxonomy of these occurrences of relations as it pertains to our work. This taxonomy served, both as a technical summary of this thesis, as well as a high-level guideline on how to think about using relations in representation learning of a new domain or problem.

However, an important research issue when dealing with relations for representation learning is the relations themselves. In particular, for a particular language phenomenon or data formalism, how many relations are there? What are they? How do they organize the elements in the domain to one another? Is the existing structure ideal?

In Definition 1 of Chapter 1.2, we stated that relations are characterized by their mapping between pairs of vocabulary objects to the set of real numbers. This means that there are a potentially infinite number of semantic relations that can be learned by models. But which ones are meaningful? More importantly, which ones are useful?

It may be noted that finding answers to these questions does not necessarily affect the problem of *using* these relations for learning representations. However, these questions are crucial to providing a comprehensive account of relation-centric semantic representation learning. More importantly, when existing structured data in the form of annotated language resources are non-existent (say for a new domain or low resource language), these questions are no longer theoretical. They become practical precursor to using relations to learn more expressive models of semantics.

These questions became especially relevant, for example, when dealing with latent relations and relation induction, as we did in the second part of this thesis (Chapters 5 and 6). And finding answers to these questions become all the harder *because* of the fact that we are dealing with latent relations. Except for the simplest count-and-normalize word vector models that represent contexts as vocabulary counts or probabilities in an explicit manner, most representation learning models are dense and opaque. Naturally, understanding and articulating relations that are learned from latent contexts and represented in dense vectors or tensors is challenging.

We attempted to map induced relations to known, humanly-interpretable ones to gain insight into how our models are organized, both in Chapter 5 and 6. But we believe this understanding is only scratching the surface. Hence, an important avenue for future research involves attempting to understand and characterize learned relations in dense embedded spaces as they pertain to a particular domain of interest. For example, Li et al. (2015) propose a way of visualizing representations in the context of semantic compositionality to better understand what properties are being captured by the un-interpretable representations of neural models.

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