Automated Data Extraction using Predictive Program Synthesis

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Abstract

In recent years there has been rising interest in the use of programming-by-example techniques to assist users in data manipulation tasks. Such techniques rely on an explicit input-output examples specification from the user to automatically synthesize programs. However, in a wide range of data extraction tasks it is easy for a human observer to predict the desired extraction by just observing the input data itself. Such *predictive* intelligence has not yet been explored in program synthesis research, and is what we address in this work. We describe a predictive program synthesis algorithm that infers programs in a general form of extraction DSLs (domain specific languages) given input-only examples. We describe concrete instantiations of such DSLs and the synthesis algorithm in the two practical application domains of text extraction and web extraction, and present an evaluation of our technique on a range of extraction tasks encountered in practice.

1 Introduction

With the ever-increasing growth of data in the world, recent years have seen rising interest from both academia and industry in the use of automatic programming techniques to address the problem of *data wrangling*: the challenge faced by data scientists to cope with data in a multitude of formats from different sources and to bring this raw data into a form that is amenable to their analysis tools. Such data preprocessing is a time-consuming activity (responsible for up to 80% of time in some cases (Kandel et al. 2011)) and most often requires programming skills in order to write robust extraction or transformation scripts.

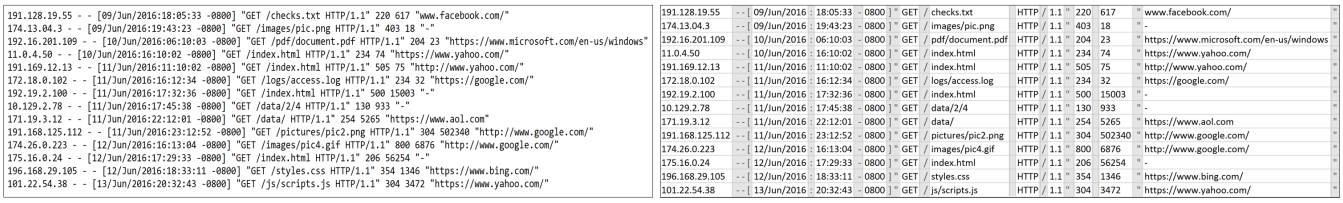
This is where automated generation of such programs can be extremely beneficial - both to speed up the wrangling process and also to make it accessible to a wide range of data analysts and knowledge workers who are not skilled programmers. In comparison to more opaque automated inference techniques for data processing where the user has little understanding of the inferred transformations, automatic program synthesis has the advantage of reusability (one-off learning of lightweight scripts that can be stored and applied to similar datasets in future), as well as transparency and editability: transformations are programs inspired from classical programming languages that can be manually edited if required.

Towards this goal, many recent works have explored various programming-by-example (PBE) approaches (Lieberman 2001; Gulwani, Harris, and Singh 2012; Raza, Gulwani, and Milic-Frayling 2014; Manshadi, Gildea, and Allen 2013; Lau et al. 2003). In PBE, users can specify their intended task by giving some input-output examples, from which the system attempts to automatically generate a program in some domain-specific language (DSL) that satisfies the given examples. A notable commercial success in this area is the *Flash Fill* feature in Microsoft Excel that is based on the PBE technique of (Gulwani 2011).

However, PBE approaches depend on an explicit intent specification from the user about the task that they want to perform, which often requires the user to correctly understand the examples that will help the system to infer the correct program, and can also require significant manual effort from the user in many kinds of tasks. In this work, we identify and address a wide range of data extraction tasks where the system can operate without explicit examples specifications and generate extraction scripts in a purely *predictive* manner, based on the properties of the input data alone. This can hence be seen as inference from *input-only* examples rather than input-output examples. We first illustrate such extraction scenarios in two concrete application domains that we investigate here, before discussing the predictive approach and its benefits in more detail.

Text extraction. Figure 1 shows a text extraction scenario, where the input data set (shown at the top) contains entries from a web server log. Each row is a text string that contains values such as the client IP address, date, etc, which are separated by various delimiting regions that are particular to this log format. The goal is to extract these values into separate columns as shown in the table at the bottom of the figure, where the columns representing the delimiting regions are highlighted.

In simple text-based formats such as CSV (Comma-Separated Values), such an extraction task is relatively easy as there is usually a fixed single-character delimiter used to separate data values. But in general, as shown in Figure 1, there can be any number of arbitrary string delimiters used in the same dataset, and a particular string may even be used



```
191.128.19.55 - - [09/Jun/2016:18:05:33 -0800] "GET /checks.txt HTTP/1.1" 220 617 "www.facebook.com/"
174.13.04.3 - - [09/Jun/2016:19:43:23 -0800] "GET /images/pic.png HTTP/1.1" 403 18 "-"
192.16.201.109 - - [10/Jun/2016:06:10:03 -0800] "GET /pdf/document.pdf HTTP/1.1" 204 23 "https://www.microsoft.com/en-us/windows"
11.0.4.50 - - [10/Jun/2016:16:10:02 -0800] "GET /index.html HTTP/1.1" 234 74 "https://www.yahoo.com/"
191.169.12.13 - - [11/Jun/2016:11:10:02 -0800] "GET /index.html HTTP/1.1" 505 75 "http://www.yahoo.com/"
172.18.0.102 - - [11/Jun/2016:16:12:34 -0800] "GET /logs/access.log HTTP/1.1" 234 32 "https://google.com/"
192.19.2.100 - - [11/Jun/2016:17:32:36 -0800] "GET /index.html HTTP/1.1" 500 15003 "-"
10.129.2.78 - - [11/Jun/2016:17:45:38 -0800] "GET /data/2/4 HTTP/1.1" 130 933 "-"
171.19.3.12 - - [11/Jun/2016:22:12:01 -0800] "GET /data/ HTTP/1.1" 254 5265 "https://www.aol.com"
191.168.125.112 - - [11/Jun/2016:23:12:52 -0800] "GET /pictures/pic2.png HTTP/1.1" 304 502340 "http://www.google.com/"
174.26.0.223 - - [12/Jun/2016:16:13:04 -0800] "GET /images/pic4.gif HTTP/1.1" 800 6876 "http://www.google.com/"
175.16.0.24 - - [12/Jun/2016:17:29:33 -0800] "GET /index.html HTTP/1.1" 206 56254 "-"
196.168.29.105 - - [12/Jun/2016:18:33:11 -0800] "GET /styles.css HTTP/1.1" 354 1346 "https://www.bing.com/"
101.22.54.38 - - [13/Jun/2016:20:32:43 -0800] "GET /js/scripts.js HTTP/1.1" 304 3472 "https://www.yahoo.com/"
```

191.128.19.55	- - [	09/Jun/2016	18:05:33	-0800] "	GET	/ checks.txt	HTTP/ 1.1 "	220	617	" www.facebook.com/ "
174.13.04.3	- - [	09/Jun/2016	19:43:23	-0800] "	GET	/ images/pic.png	HTTP/ 1.1 "	403	18	" - "
192.16.201.109	- - [	10/Jun/2016	06:10:03	-0800] "	GET	/ pdf/document.pdf	HTTP/ 1.1 "	204	23	" https://www.microsoft.com/en-us/windows "
11.0.4.50	- - [	10/Jun/2016	16:10:02	-0800] "	GET	/ index.html	HTTP/ 1.1 "	234	74	" https://www.yahoo.com/ "
191.169.12.13	- - [	11/Jun/2016	11:10:02	-0800] "	GET	/ index.html	HTTP/ 1.1 "	505	75	" http://www.yahoo.com/ "
172.18.0.102	- - [	11/Jun/2016	16:12:34	-0800] "	GET	/ logs/access.log	HTTP/ 1.1 "	234	32	" https://google.com/ "
192.19.2.100	- - [	11/Jun/2016	17:32:36	-0800] "	GET	/ index.html	HTTP/ 1.1 "	500	15003	" - "
10.129.2.78	- - [	11/Jun/2016	17:45:38	-0800] "	GET	/ data/2/4	HTTP/ 1.1 "	130	933	" - "
171.19.3.12	- - [	11/Jun/2016	22:12:01	-0800] "	GET	/ data/	HTTP/ 1.1 "	254	5265	" https://www.aol.com "
191.168.125.112	- - [	11/Jun/2016	23:12:52	-0800] "	GET	/ pictures/pic2.png	HTTP/ 1.1 "	304	502340	" http://www.google.com/ "
174.26.0.223	- - [	12/Jun/2016	16:13:04	-0800] "	GET	/ images/pic4.gif	HTTP/ 1.1 "	800	6876	" http://www.google.com/ "
175.16.0.24	- - [	12/Jun/2016	17:29:33	-0800] "	GET	/ index.html	HTTP/ 1.1 "	206	56254	" - "
196.168.29.105	- - [	12/Jun/2016	18:33:11	-0800] "	GET	/ styles.css	HTTP/ 1.1 "	354	1346	" https://www.bing.com/ "
101.22.54.38	- - [	13/Jun/2016	20:32:43	-0800] "	GET	/ js/scripts.js	HTTP/ 1.1 "	304	3472	" https://www.yahoo.com/ "

Figure 1: A sample text extraction from a server log (left) into a tabular representation (right)

"I have a column that looks like the below however consistently changes in number of characters and letter. I need to be able to separate the numbers from the letters as they are the unit of measurement. I believe the mid or right function would work together however I just can't figure it out. Any help would be greatly appreciated. I would love to be able to isolate both the numbers and letters into their own cells."

http://www.mrexcel.com/forum/excel-questions/830653-separate-letters-numbers.html

Input data	Target extraction	
2.27KG	2.27	KG
1L	1	L
2.5KG	2.5	KG
2KG	2	KG
1.7KGA	1.7	KGA
3KG	3	KG
2KG	2	KG
.650GA	.650	GA
125G	125	G

Figure 2: A text extraction task faced by an Excel user

as a delimiter in some places but not in others. For example, in Figure 1 the "/" character is a delimiter separating the HTTP protocol version, but should not act as a delimiter inside the URLs. Hence it is not possible to simply split by all occurrences of a particular string. In fact, in many cases there is actually no delimiting string between two data values. For example, Figure 2 shows the extraction task from a user in an Excel help forum who is struggling to separate numeric values from units of measurement in a dataset with a lot of variability. In this case there are obviously no delimiting characters, so the goal is actually to find the *zero-length* delimiting regions which are single points in the string defined by the context of having a number on the left and a letter on the right side.

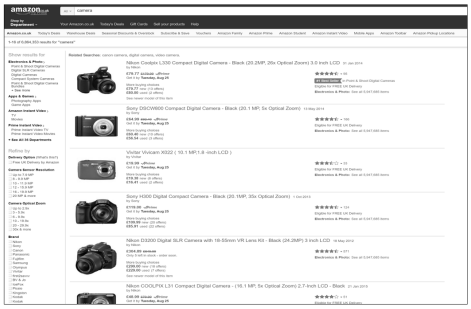
Web extraction. Another automated data extraction domain is the extraction of tabular information from web pages, especially in cases where there is no explicit visual (row by column) table present in the web page. For example, Figure 3 shows the task of extracting the results of an Amazon product search, where each result item has numerous fields such as title, date, various prices, etc that are not laid out in an explicit row by column table. These fields, some of which are missing for some items, are represented in the DOM (Document Object Model) tree structure of the web page using different formatting properties rather than simple HTML table tags. And some fields, such as "new" and "used" prices, actually have no difference in formatting and can only be distinguished by examining the text content.

Hence, as every such website uses different representations of tabular information, dedicated extraction scripts are required in each case. Although there has been much work on automatically detecting tables based on particular tags or visual properties (Krüpl, Herzog, and Gatterbauer 2005; Gatterbauer and Bohunsky 2006; Chu et al. 2015), extraction of arbitrary non-visual tables has mostly been explored with the help of user-provided examples, such as (Tengli, Yang, and Ma 2004) and the *Flash Extract* system (Le and Gulwani 2014).

Predictive program synthesis. The extraction scenarios described above have been addressed by the various PBE approaches that require the user to specify their intention through explicit examples of the desired extraction. However, in all of these scenarios it is easy for a human to predict the desired extraction by just observing the input data itself, without any need to be told what to extract. Such *predictive* intelligence has not yet been explored in program synthesis research, and is what we address in this work: automatic learning of extraction programs from input-only examples. The predictive approach we propose here has a number of advantages over previous PBE-based techniques:

- *Reducing user effort in giving examples*. In the scenarios in Figures 1 and 3 there are more than 10 extracted fields, and in practice it is normal for some log files to have around 50 fields. PBE systems such as Flash Fill and Flash Extract can normally require 2 or 3 examples per field, which can therefore lead to significant manual effort on the part of the user to complete an extraction task.
- *Less reliance on user understanding of system requirements*. In PBE approaches users are not aware of which examples would be most useful to the learning system, given all the variability in the data. For example, in Flash Fill users usually give examples on the top few rows, from which the system can often learn a program that is overspecific to the given examples, and therefore fails at a later row somewhere in the dataset.
- *Using all of the input data for learning*. PBE approaches work from a very small number of input-output examples to reduce the manual effort for users. In contrast, the predictive approach we describe here can utilise the many more inputs available in the data to infer the common patterns as well as the variability present in the data.
- *Allowing batch processing*. The need for manual intervention from the user in PBE approaches prevents the possibility of large scale automation of data processing tasks. For example, if the user has to process a large collection of datasets in different formats or pages from different websites, then they would need to manually provide examples for every new kind of format that is encountered.

In the next section, we begin by defining a general form of DSLs for performing data extraction, in which programs are structured as a combination of independent sub-programs



Nikon Coolpix L330 Compact Digital Camera - Black	31-Jan-14	Nikon	£79.77	£179.99	£79.77 new (13 offers)	£80.00 used (2 offers)	4.5 out of 5 stars	95	# 1 Best Seller		
Sony DSCW800 Compact Digital Camera - Black (20	13-May-14	Sony	£64.99	£92.40	£60.40 new (10 offers)	£56.54 used (3 offers)	4.3 out of 5 stars	166			
Vivitar Vivicam X022 (10.1 MP,1.8 -inch LCD)		Vivitar	£19.99		£19.38 new (6 offers)	£16.41 used (2 offers)	3.5 out of 5 stars	33			
Sony H300 Digital Compact Camera - Black (20.1MI	1-Oct-13	Sony	£119.00		£109.99 new (20 offers)	£85.91 used (22 offers)	4.3 out of 5 stars	124			
Nikon D3200 Digital SLR Camera with 18-55mm VR	18-May-12	Nikon	£304.89	£649.99	£299.00 new (18 offers)	£229.00 used (7 offers)	4.6 out of 5 stars	571		Only 5 left in stock	
Nikon COOLPIX L31 Compact Digital Camera - (16.1	21-Jan-15	Nikon	£48.99	£79.99	£48.99 new (11 offers)	£44.10 used (4 offers)	4.2 out of 5 stars	51			
Bundle Fuji S4800 Black Digital Camera +Case +San		Ehome	£109.98	£149.98			4.7 out of 5 stars	43			
Sony H200 Bridge Camera (20.1MP with Optical Sta	14-Jan-13	Sony	£99.00	£180.00	£99.00 new (7 offers)	£69.99 used (4 offers)	4.3 out of 5 stars	71		Only 6 left in stock	
Canon EOS 300 / EOS Rebel 2000 35mm Film Came		Canon				£67.50 used (5 offers)	4.6 out of 5 stars	16			
Sony DSCHX50 Compact Digital Camera - Black (20.	15-May-13	Sony	£157.49	£350.00	£157.49 new (9 offers)	£124.99 used (6 offers)	4.4 out of 5 stars	205			
Canon EOS 350D Digital SLR Camera (18-55mm Ler	10-Feb-05	Canon				£149.99 used (6 offers)	4.5 out of 5 stars	72			
Case Bag for CANON POWERSHOT SX500 IS SX510 I		BV & Jo	£9.98		£7.98 new (2 offers)		4.4 out of 5 stars	81			
Fujifilm FinePix S2950 Digital Camera - (14MP, 18x	28-Jan-11	Fujifilm				£79.95 used (6 offers)	4.3 out of 5 stars	155			
Fujifilm Instax Mini 8 Instant Camera - Blue	1-Aug-13	Fujifilm	£52.80	£64.99	£52.80 new (12 offers)	£48.05 used (2 offers)	4.7 out of 5 stars	114			
myCamera HD : Kindle Fire Camera	5-Dec-12	NextIn	Free				3.2 out of 5 stars	213			
MaxRam 32GB Class 10 SD SDHC Memory Card	5-May-14	MaxRam	£14.98	£19.98			4.7 out of 5 stars	328	# 1 Best Seller		
Polaroid Bumper Case for Cube Action Camera - Re	6-Feb-15	Polaroid	£17.99	£20.00			2.8 out of 5 stars	4			Sponsored
BenQ DC E600 Digital camera - 6.0 Mpix - optical zo		BenQ					4.4 out of 5 stars	7			Sponsored

Figure 3: A non-visual table extraction from a webpage of shopping results (left) into a tabular representation (right)

for different data fields. We illustrate this with the concrete DSLs that we have designed for the text and web extraction domains, which are based on classical languages such as regular expressions and CSS (Cascading Style Sheets) selectors and can express the range of transformations illustrated in the scenarios above. We then describe our novel predictive synthesis algorithm for inferring programs in an extraction DSL given an input dataset. This is a domain-agnostic algorithm which operates by generating programs up to semantic equivalence in an efficient bottom-up fashion, and uses the notion of a correspondence relation between sub-programs as the central ranking principle. We describe concrete instantiations of the algorithm and ranking relations for the text and web domains, and in the following section we describe the evaluation of our technique on practical test scenarios obtained from log files, real users and the web. We end with a discussion of conclusions and future work.

2 Data Extraction DSLs

The design of the domain specific language (DSL) is an important component of any program synthesis approach, as there is always a delicate trade-off between expressivity (ability to address a range of practical use cases) and tractability (efficiently generating correct programs). In this section we describe a general form of DSLs for performing data extraction tasks, and then illustrate this with the concrete DSLs that we have designed for the text and web extraction domains. An extraction DSL is defined as a context-free grammar of the form

$$(\tilde{\psi}_N, \tilde{\psi}_T, \psi_{start}, \mathcal{R})$$

where $\tilde{\psi}_N$ is a set of non-terminal symbols, $\tilde{\psi}_T$ is the set of terminal symbols, ψ_{start} is the start symbol and $\mathcal{R}$ is the set of non-terminal production rules of the grammar. Every symbol ψ is semantically interpreted as ranging over a set of values $[\![\psi]\!]$, which can be standard types such as integers, strings, arrays, etc. Each production rule $r \in \mathcal{R}$ represents an operator in the programming language, and is of the form

$$\psi_h := Op(\psi_1, \ldots, \psi_n)$$

where Op is the name of the operator, which takes parameter types given by the body symbols $\psi_i \in \tilde{\psi}_N \cup \tilde{\psi}_T$ and returns a value of type given by the head symbol $\psi_h \in \tilde{\psi}_N$. Hence the formal semantics of the DSL is given by an interpretation of each rule r as a function

$$[\![r]\!] : [\![\psi_1]\!] \times, \ldots, \times [\![\psi_n]\!] \rightarrow [\![\psi_h]\!]$$

where ψ_h is the head symbol and $\psi_1, ..., \psi_n$ are the body symbols of the rule operator. A program P of type ψ is any concrete syntax tree defined by the DSL grammar with root symbol ψ. A *complete program* has the root symbol ψ_{start}. Any derivation from a non-root symbol is a *sub-program*.

We impose two structural constraints on extraction DSLs that are oriented towards the data extraction task. Firstly, there exists a global variable that is available to the semantics of all operators in the programming language, which holds the input data on which the extraction task is being performed. This input variable has a fixed type $\mathcal{I}$. For instance, this type can be a text string in the text extraction domain or the DOM tree of a webpage in web extraction. The semantics of each rule r in an extraction DSL with head symbol ψ_h and body symbols $\psi_1, ..., \psi_n$ is defined with respect to the input variable:

$$[\![r]\!] : [\![\mathcal{I}]\!] \times [\![\psi_1]\!] \times, \ldots, \times [\![\psi_n]\!] \rightarrow [\![\psi_h]\!]$$

Secondly, we require that there is a unique top-level rule in the DSL that has the start symbol as the head, and that this rule is of the form

$$\psi_{start} := Op_t(\psi_f, \ldots, \psi_f)$$

for some Op_t and ψ_f. This models an extraction task as a program that consists of a top-level operator Op_t that combines the results of different *field-level* sub-programs that work at the level of individual fields in the input data. For example, in the text extraction task, the field-level programs identify the logic for detecting particular delimiters between data values, while the top-level operator combines these different delimiters to produce the list of extracted values. In the case of web extraction, the field-level sub-programs identify the selection logic for particular fields in the webpage, and the top-level operator combines these individual selection lists into an aligned table of values. We next illustrate these concepts with the concrete extraction DSLs we have designed for text and web extraction.

Text Extraction DSL

Figure 4 shows the DSL $\mathcal{L}_t$ for text extraction, which is based on delimiters and regular expressions for detecting extraction patterns. The symbols of the grammar are shown

```
@start string[] spl   := SplitByDelimiters(d, ..., d)
    Pair⟨int, int⟩[] d := c | LookAround(r, c, r)
    Pair⟨int, int⟩[] c := Str(s) | StrWs(s)
    Pair⟨int, int⟩[] r := Empty() | Tok(t) | Concat(r, r)
                string s
             RegexToken t
@input string
```

Figure 4: The DSL $\mathcal{L}_t$ for text extraction

with their associated semantic types and the start symbol is explicitly marked. The input is a text string containing values possibly separated by delimiting regions, and the output (start symbol) of a program is an array of the extracted substrings. The top-level operator in this case is the SplitByDelimiters function which uses a number of different delimiter programs to produce the final splitting of the string. Each delimiter program computes a sequence of delimiting regions represented as a pair of start and end positions in the input string.

A delimiter program is either a match of a constant string (exact matches with Str or matches including surrounding whitespace with StrWs) or a *contextual* delimiter LookAround(r_1, c, r_2) that matches occurrences of a constant string when it occurs between regular expression matches r_1 and r_2. For example, a program that splits by ";" and any occurrences of "," including the surrounding whitespace is given as

$$\text{SplitByDelimiters}(\text{Str}(\text{";"}), \text{StrWs}(\text{","}))$$

On an input string "a;b, c;d, e;f" this will produce the output ["a", ";", "b", ", ", "c", ";", "d", ", ", "e", ";", "f"]. A contextual delimiter with an empty string can address zero-length delimiter scenarios such as in Figure 2, where the desired extraction task can be accomplished with the following delimiter program that detects the boundaries between numbers and letters:

$$\text{LookAround}(\text{Tok}(\text{[0-9]}), \text{Str}(\text{""}), \text{Tok}(\text{[A-Za-z]}))$$

Web Extraction DSL

Figure 5 shows the DSL $\mathcal{L}_w$ for extracting tabular data from web pages, which is inspired by the CSS selector language. In this case the input is the DOM tree of a webpage, and the output is table of text values that are extracted, such as the table illustrated in Figure 3. Each field-level sub-program selects all the nodes for a particular field in the webpage (a column of the desired table), and the top level operator ExtractTable aligns each of these selections into the final table.

The selection logic for fields is based on CSS selectors, and includes operators for getting descendant nodes, right siblings, and filtering nodes by tag type, class name, ID, text content and child node positions. Note that the DSL does not bias towards any particular tag types such as table or list elements. For example, the selector for the first column in

```
@start string[][] tbl  := ExtractTable(c, ..., c)
      DomNode[] c      := AllNodes() | Descendants(c) |
                          RightSiblings(c) | filter
   DomNode[] filter    := Tag(tg,c) | Class(cl,c) | ID(id,c)
                          | Text(t, c) | NthChild(n, c) |
                          NthLastChild(n, c)
  string tg, cl, id, t
                 int n
@input DomTree
```

Figure 5: The DSL $\mathcal{L}_w$ for web extraction

the extracted table in Figure 3 is a simple class name filter

$$\text{Class}(\text{"s-access-detail-page"}, \text{AllNodes}())$$

while the selector for the ratings (column 8) requires a deeper tree search:

$$\text{Class}(\text{"a-icon-alt"}, \text{Descendants}(\text{Class}(\text{"a-row"}, \text{AllNodes}())))$$

3 Predictive Synthesis Algorithm

In this section we describe the predictive program synthesis algorithm that generates an extraction program from input-only examples. The general algorithm is parametric in a number of domain-specific properties (including the DSL) which can be provided as configuration parameters for particular domain instantiations.

In summary, for a given DSL and a set of input examples, the algorithm performs a systematic search to compute the semantically distinct values that can be generated by field-level programs in the DSL up to a certain size bound. This search is similar to previous bottom-up synthesis approaches such as (Katayama 2007; Raza, Gulwani, and Milic-Frayling 2015), but unlike previous approaches it utilizes certain operator-specific functions to gain orders of magnitude improvement in complexity, thereby making the synthesis tractable for practical DSLs such as $\mathcal{L}_t$ and $\mathcal{L}_w$. After this semantic state space exploration, the final step is to perform a ranking to obtain the collection of field-level programs that will be used by the top-level DSL operator. Unlike previous program synthesis approaches, this ranking of field programs is not based solely on the properties of individual programs, but on correspondences that hold between different programs. Intuitively, in the absence of any output specification, the main ranking criterion is to prefer programs that identify maximal structure in the input data. We do this by finding the largest collection of field-level extractions that align well with one another, for some notion of alignment that is relevant to the data domain.

The general algorithm is shown in Figure 6. The parameter $\bar{I}$ holds the m input examples I_1,..., I_m. For instance, in the text domain each input example may be a string in a spreadsheet row, while in the web domain each example would be the DOM tree of a single webpage. The other parameter C is the configuration parameter, which defines five

```
1:  function PredictiveSynthesis(Ī, C)
2:      let Ī = (I_1, ..., I_m)
3:      let C.DSL = (ψ̃_N, ψ̃_T, ψ_start, R)
4:      let r_t ∈ R be the top rule ψ_start := Op_t(ψ_f, ..., ψ_f)
5:      let M : ψ̃_N ∪ ψ̃_T → P(Σ) map symbols to sets of states
6:      for each ψ ∈ ψ̃_T do
7:          M[ψ] ← {((v)^m, v) | v ∈ C.ExtractLiterals(Ī, ψ̃_T)}
8:      for (iter = 0; iter < C.MaxDepth; iter++) do
9:          for each r ∈ R\{r_t} do
10:             let r be ψ_h := Op(ψ_1, ..., ψ_n)
11:             if C.LiftFuncs[r] ≠ null then
12:                 σ̃ ← C.LiftFuncs[r](Ī, M[ψ_1], ..., M[ψ_n])
13:             else
14:                 σ̃ ← LiftGeneric(Ī, M, r)
15:             σ̃_new ← {(v̄, P) ∈ σ̃ | ¬∃P'.(v̄, P') ∈ M[ψ_h]}
16:             M[ψ_h] ← M[ψ_h] ∪ σ̃_new
17:     ((v̄_1, P_1), ..., (v̄_k, P_k)) ← C.Rank(M[ψ_f])
18:     return Op_t(P_1, ..., P_k)
```

Figure 6: Program synthesis algorithm

configuration properties for the algorithm: DSL, MaxDepth, ExtractLiterals, LiftFuncs and Rank, which we shall describe in turn.

The DSL is the domain-specific language (as defined in section 2) in which programs will be synthesized. The top-level rule and the field programs symbol ψ_f is determined at line 4. Line 5 initializes a map M from symbols to a set of *states* which will be used to maintain the values generated by different programs on the given inputs. A state $\sigma \in \Sigma$ of type ψ is of the form $(\bar{v}, P)$, representing a tuple of values $\bar{v} = (v_1,...,v_m)$, where each $v_i \in [\![\psi]\!]$ is the value generated on input I_i by program P of type ψ. We use $\tilde{\sigma}$ to denote a set of states and denote all states of type ψ by $\Sigma(\psi)$. We now describe the algorithm in three phases: state space initialization, search and ranking.

Initialization

The state map is initialized with literal values for each of the terminal symbols of the DSL (lines 6 and 7). This is done using the ExtractLiterals function, which computes literal values for each terminal type from the given input data. For instance, for the web DSL $\mathcal{L}_w$, the literals for tg, cl, id and t are respectively determined by all the tag types, class names, ids and text content of all the nodes in all of the input webpages, and numeric values for n are determined by the maximum number of child nodes of any node.

For the text DSL $\mathcal{L}_t$, constant string values for s can be determined as any substrings of the inputs, but in practice it is more effective to restrict these to special character strings as these are normally used as delimiters. The regular expression tokens t we consider are standard regex patterns for numbers, lower or upper case letters, special characters, date/time, etc. At line 7, the states for each terminal symbol are initialised with the extracted literal values (where $(v)^m$ represents a value tuple of m occurrences of the same value v, since a literal has the same value on any input).

```
1:  function LiftGeneric(Ī, M, r)
2:      let Ī = (I_1, ..., I_m)
3:      let r be ψ_h := Op(ψ_1, ..., ψ_n)
4:      let result = ∅
5:      for each ((v̄_1, P_1), ..., (v̄_n, P_n)) ∈ M[ψ_1] × ... × M[ψ_n] do
6:          for k = 1 ... m do
7:              v_k ← [[r]](I_k, v̄_1[k], ..., v̄_n[k])
8:          result ← result ∪ {((v_1, ..., v_m), Op(P_1, ..., P_n))}
9:      return result
```

Figure 7: Generic lifting function for operator rules

Search

At line 8 we begin the bottom-up exploration of the state space. This is bounded by the MaxDepth configuration parameter, which imposes a bound on the depth of the syntax tree of the programs we consider. We determine the value used for the MaxDepth parameter in a particular domain based on an empirical evaluation, taking the maximum depth that yields sufficiently expressive programs in the given DSL in practical running time. Given the existing set of states at each iteration, for each rule r other than the top rule, at line 15 we compute the set $\tilde{\sigma}_{new}$ representing the new distinct values created by application of the rule over the existing values. This rule application is hence a *lifting* of the rule operator semantics function $[\![r]\!]$ to sets of states, that is, a function with signature:

$$[\![\mathcal{I}]\!]^m \times \mathcal{P}(\Sigma(\psi_1)) \times \ldots \times \mathcal{P}(\Sigma(\psi_n)) \rightarrow \mathcal{P}(\Sigma(\psi_h))$$

where $\mathcal{I}$ is the input type of the DSL. A generic way of implementing this lifting function for an arbitrary rule is with the procedure LiftGeneric defined in Figure 7, which simply computes the cross product over all the parameter sets and applies the rule semantics over all combinations of value tuples. Although it is rule-agnostic, this naive combinatorial approach can be prohibitively expensive in practice. Significant complexity reduction can be gained by using specific lifting functions for certain kinds of operators, which can be specified using the configuration parameter LiftFuncs mapping certain rules to their lifting functions. The algorithm uses the lifting function if one exists (line 12), or else defaults to the generic function (line 14).

Examples of lifting functions exist in both the text and web domains. Most of the filter operators in the web DSL $\mathcal{L}_w$ benefit from specific lifting functions, and an example for the ID operator is shown in Figure 8. In this case, given a set of ID values and a set of node sets, the naive approach would be to filter every node set by every ID. However, the only useful results will be for IDs that actually exist in any of the nodes. This is achieved by the method in Figure 8 by traversing each node set only once, and maintaining a map from all ID values encountered to the nodes that have that ID. Hence formally we go from complexity that is quadratic in the sizes of $\tilde{\sigma}_1$ and $\tilde{\sigma}_2$ to linear in these sizes. Similar complexity reductions can be made for other filter operators in $\mathcal{L}_w$.

In the text domain, lifting functions play a vital role for the Concat and LookAround operators in $\mathcal{L}_t$. For example,

for Concat we have an existing set of regexes that match on the input strings, and would like to find all concatenations of these regexes that also match on the input strings. While the naive approach is to simply check all pairs, the optimal lifting function traverses the set of regex matches and builds a map from end positions to the regexes matching on those end positions. A second linear traversal can then check for all regexes that start at these end positions, so that only pairs of regexes that actually have adjacent matches on the input strings are ever considered. A similar technique is used in the case of LookAround, where triples instead of pairs of matches are considered.

Ranking

The ranking function Rank is the final configuration parameter, which selects the field-level programs that the algorithm uses to construct the final extraction program with the top-level operator (line 18). The general principle behind our ranking functions is the notion of *inter-subprogram correspondence*. Unlike previous ranking approaches that examine properties of individual programs, the idea behind the correspondence relations for extraction DSLs is to detect maximal structure in the input data by finding the largest collection of field-level extractions that align well with one another. The ranking function finds such maximal collections of states.

In the web domain, the main correspondence relation that we use is based on an *interleaving* relationship between the sequence of DOM nodes that are extracted by different field-level programs. Formally, states $(\bar{v}_1, P_1)$ and $(\bar{v}_2, P_2)$ satisfy the interleaving relation if we have $\bar{v}_1 = (s_1,..., s_m)$ and $\bar{v}_2 = (s'_1,..., s'_m)$ and $\texttt{Interleave}(s_i, s'_i)$ holds for all i. Each s_i and s'_i is an array of nodes DomNode[] that is the result of the field extraction programs P_1 and P_2 on the ith input, and $\texttt{Interleave}(s, s')$ holds iff

- $\exists N.\ |s| = |s'| = N$ and
- node $s[j]$ is before $s'[j]$ in document order, for $0 \leq j < N$
- node $s'[j]$ is before $s[j+1]$, for $0 \leq j < N-1$

This interleaving relation captures the common pattern on web pages with structured information where a sequence of records occurs in document order, and each record contains nodes for particular fields that are similarly formatted. We note that this strategy assumes that the document order in the DOM tree corresponds to the visual rendering of information on the web page, which is an assumption that holds in a large majority of web pages but not always (in our evaluation we found a single example of such a webpage where the document order did not correspond to the visual order). Also, in addition to the interleaving relationship, we also impose preferences on more structured patterns where the nodes of all the fields share a common ancestor node. This prefers common patterns in webpages where records are grouped under separate DOM nodes, such as DIV of TR tags. Although we give preference to these more structured patterns, we do not depend on them as in many cases such common ancestor nodes do not exist.

In the text domain, the main correspondence relation we use is based on consistent disjoint alignment of delimiters

```
1: function LiftFuncs[r_id](I, σ̃1, σ̃2)
2:     idSet ← {v | (v̄, v) ∈ σ̃1}
3:     result ← ∅
4:     for each ((s1, ..., sm), P) ∈ σ̃2 do
5:         let M : [[id]] → (DomNode[])^m
6:         for k = 1 ... m do
7:             for each node ∈ s_k do
8:                 if node.ID ∈ idSet then
9:                     add node to M[node.ID][k]
10:        for each v ∈ domain(M) do
11:            result ← result ∪ {(M[v], ID(v, P))}
12:        return result
```

Figure 8: Lifting function for the ID filter operator in $\mathcal{L}_w$

across all inputs. Formally, states $(\bar{v}_1, P_1)$ and $(\bar{v}_2, P_2)$ satisfy the relation if we have $\bar{v}_1 = (d_1,..., d_m)$ and $\bar{v}_2 = (d'_1,..., d'_m)$ and

$$\texttt{Ordering}(d_1, d'_1) = \ldots = \texttt{Ordering}(d_m, d'_m) \neq null$$

Each d_i and d'_i is an array of integer pairs $\mathsf{Pair}\langle\mathsf{int}, \mathsf{int}\rangle[]$ determined by delimiter programs P_1 and P_2 on the ith input, where each pair represents a region in the input string that is an occurrence of the delimiter. We define $\texttt{Ordering}(d_1, d_2) = \ell$, where $\ell = null$ if any delimiter regions in d_1 and d_2 overlap, and otherwise $\ell \in \{0,1\}^{|d_1|+|d_2|}$ is a list of binary numbers representing the left-to-right ordering of all of the delimiter regions from d_1 and d_2. For example,

$$\texttt{Ordering}([(1,4)], [(3,7)]) = null$$

because the two delimiter regions overlap, while

$$\texttt{Ordering}([(2,3),(7,9)], [(4,6),(13,15)]) = (0,1,0,1)$$

because the two delimiters occur disjointly in an alternating fashion.

In the maximal alignment analysis, we also give preference to non-zero-length delimiters by only considering zero-length delimiter programs if consistently occurring non-empty delimiters cannot be found. This is to avoid *over-splitting* of data in cases where actual delimiting strings are present. In practice, the desired extraction can also be controlled by the user through iterative splitting and merging, as we describe in the next section.

4 Implementation and Evaluation

We have implemented our generic predictive synthesis algorithm as a new learning strategy in the PROSE framework (Polozov and Gulwani 2015), which is a library of program synthesis algorithms that allows the user to simply provide a DSL and other domain-specific parameters to get a PBE tool for free. We implemented our particular systems for both the text and web extraction domains in this way, with a user interface implemented in a Microsoft Excel add-in.

The text extraction feature implemented for Excel is called ColumnSplit. Using this feature, the user can select a column of textual data in the spreadsheet, and then click a "Split" button, at which point the system learns a program in

Number of extracted fields (primary)	10.3
Number of extracted fields (secondary)	3.45
Number of non-extracted fields	0.2
Execution time, full system (seconds)	4.20
Execution time, without lifting functions (seconds)	210.73

Figure 9: Text extraction average performance results

Number of extracted fields (individually)	5.85
Number of extracted fields (subsumed)	0.9
Number of non-extracted fields	0.25
Execution time, full system (seconds)	6.41
Execution time, without lifting functions (seconds)	27.04

Figure 10: Web extraction average performance results

the text extraction DSL to perform a splitting of the column data into different field columns (as shown in Figures 1 and 2). However, different users may have different preferences for the degree of splitting they would like (e.g., whether or not to split a date into day, month, year). If data has not been split enough, the user can select an output field column and split it further. On the other hand, the user can highlight any number of adjacent columns and click a "Merge" button to simply merge the columns and undo the unwanted splits.

For web extraction tasks, we implemented a similar Excel add-in called WebExtract. Using this feature, the user can specify the URL of a webpage, and then click an "Extract" button, at which point the system learns an extraction program in the web DSL and displays the extracted table in the spreadsheet (as in Figure 3). WebExtract can be used together with ColumnSplit to perform further text-based splitting on columns that have been extracted by WebExtract.

Evaluation of ColumnSplit

For evaluation in the text domain, we collected a set of 20 benchmark cases from product teams, help forums, as well as real users in our organization who provided us with data sets on which they would like to perform extraction. A lot of these datasets come from various log files such as from web servers, but also include other text-based datasets. The goal of our evaluation was to measure the maximum number of fields our system can extract.

The average performance results of our system on these benchmarks are shown in Figure 9. There were an average of 13.95 fields per dataset, of which 10.3 were detected on the first attempt (primary), 3.45 were extracted by further splitting on some of the columns (not more than three levels of splitting required in any test case), and 0.2 could not be extracted at all. All the non-extracted fields were in a single test case, which was a task involving different numbers of fields on different inputs. With such possibly-missing fields it is in general not possible to determine the desired alignment of fields as there are different alternatives, so such tasks may be better handled by some kind of output specification from the user such as examples. The average execution time per task was 4.2 seconds, although 16 tasks were completed in under 2 seconds. Memory usage was observed to approximately double at each iteration of the synthesis algorithm, which remained under tractable limits as the algorithm maintains the state space of programs up only up to semantic equivalence over the given input states.

For comparison, we also evaluated our system without using the operator-specific lifting functions as described in Section 3, and observed the drastic increase in execution time to an average of 210 seconds per task. We also investigated the dependence of our system on the presence of the standard data type tokens supplied to the DSL $\mathcal{L}_t$. Reconducting our experiment with just five basic regular expression tokens (numbers, lower case letters, upper case letters, alphanumeric and special characters), we found all fields were extracted in 14 of the 20 test cases, and most fields in the other cases as well.

Evaluation of WebExtract

In the case of web extraction, we evaluated our system on a collection of 20 webpages that contain tabular data not represented using explicit HTML table tags. The evaluation results are shown in Figure 10. Our system extracted 5.85 fields per page on average. However, some (0.9) of the fields on the page were not extracted as individual fields but "subsumed" into other fields (e.g. a parent node containing two child nodes for different fields was extracted as one field). An average of 0.25 fields were not extracted at all, which happened only in 4 webpages. The average execution time was 6.41 seconds per task, although 15 tasks completed in under 2 seconds. Execution time increased to 27 seconds without the use of lifting functions for the filter operators, again showing significant performance degradation and why previous bottom-up synthesis approaches cannot be used in our predictive setting for either the text or web domains.

All of our evaluation cases involved extraction from a single webpage (learning the extraction program from a single input), although our algorithm can work with multiple inputs as in the case of text extraction. Providing multiple webpages as inputs may be helpful in cases where websites have a large number of similarly formatted pages that often have slight variations in formats. Our algorithm can take them as multiple inputs to learn generalized programs applicable across all pages, but we have not explored such scenarios in this work.

5 Conclusion

We have described a novel predictive program synthesis technique for data extraction tasks. This includes a general form of extraction DSLs, a synthesis algorithm designed in a domain-parametric fashion, as well as concrete DSLs and algorithm instantiations in the practical application domains of text and web extraction. Our evaluation shows the effectiveness of our approach in practical extraction scenarios, and its benefits over previous PBE approaches which require manual effort in providing examples as well as correct understanding of system requirements from the user.

Apart from PBE techniques, various natural interaction paradigms have been explored in recent work, such as programming by natural language (PBNL) systems (Kushman

and Barzilay 2013; Manshadi, Gildea, and Allen 2013; Gulwani and Marron 2014) and various mixed-initiative approaches (Allen et al. 2007; Kandel et al. 2011; Raza, Gulwani, and Milic-Frayling 2015). However, all of these approaches depend on some kind of explicit intent specification from the user e.g. PBNL approaches often suffer from inaccurate or ambiguous user descriptions and vocabulary mismatch. The key difference in the predictive approach we present here is to not rely on explicit intent specification from the user, which works well for extraction tasks. In this respect the predictive approach can be seen as one part of a broad spectrum of approaches for different kinds of tasks: predictive approaches may be effective for extraction, while examples may be useful for transformation tasks and natural language interfaces may be useful for querying.

In another respect, we have yet to explore the combination of the predictive approach together with output examples given by the user. This would be analogous to semi-supervised learning in the PBE setting, as opposed to the fully supervised learning of traditional PBE systems and the purely unsupervised learning we have proposed in this work. PBE techniques, although capable of addressing transformations that go beyond extraction, have generally relied on the small number of input-output examples provided by the user, without making use of all the additional inputs available in the dataset. Only in recent work (Singh 2016) have signals from additional inputs been shown to improve the ranking of a PBE system. However, it is unclear how strong these additional input signals are by themselves, especially in comparison to our predictive approach which can function in a purely unsupervised manner without the need for any output examples. It will therefore be interesting to explore the use of our predictive analysis to infer global alignments and variability in the input data, and use this information to improve the ranking of previous PBE systems. For example, if the predictive analysis yields that a certain delimiter occurs regularly throughout all inputs, then programs utilizing that delimiter may be ranked higher by the PBE system, even if the user has only provided a single output example which does not disambiguate between different candidate delimiters to use.

A different direction for future work is to explore the applicability of our generic framework for predictive synthesis to other practical application domains. Richly formatted documents such as XML-based formats (DOCX, ODF, PPTX, etc) may be addressed using DSLs similar to the X-Path language, perhaps following the technique of least general generalizations over input states as in (Raza, Gulwani, and Milic-Frayling 2014). Extraction from PDF documents may be explored with DSLs that include geometrical co-ordinate constructs. It will also be interesting to investigate the case of plain unstructured text files where record boundaries are not predetermined, as previously addressed by non-predictive PBE approaches such as (Le and Gulwani 2014). While the DSL $\mathcal{L}_t$ we presented for text extraction addresses the case of structured log files where row boundaries are given, we may potentially address the case of undetermined row boundaries with a generalization of $\mathcal{L}_t$. in which records are inferred using an interleaving-style relation similar to the one we used for web extraction with $\mathcal{L}_w$. Semantically-based extractions (Singh and Gulwani 2012a; 2012b) are yet another domain where input data alone may yield useful extraction patterns. In general, it will be interesting to explore the applicability of the predictive approach to most extraction domains previously addressed by PBE techniques.

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