

Microsoft Research Faculty Summit 2016



Machine Reading for Precision Medicine

Hoifung Poon





• Prior work

- Focused on Newswire / Web
- Popular entities and facts
- Redundancy \rightarrow Simple methods often suffice
- High-value verticals
 - Healthcare, finance, law, etc.
 - Little redundancy: Rare entities and facts
 - Novel challenges require sophisticated NLP





Orders of magnitude more extracted knowledge E.g., $10,000 \rightarrow 1.5$ million gene regulations

Cancer Precision Medicine



Literome doubles accuracy in cancer drug prediction

Growth of DNA Sequencing



The Information Within Ourselves, Coughlin, Forbes 2015

Panomics











Precision Medicine



Cancer

Caused by genetic mutations

- 22.5% deaths: Top killer for age under 85
- Expected in 2030:
 - Increase by 45%
 - 2.3 million new cases annually
 - No. 1 killer for all

Vemurafenib on BRAF-V600 Melanoma



Before Treatment

15 Weeks

Vemurafenib on BRAF-V600 Melanoma



Before Treatment

15 Weeks

23 Weeks

Precision Medicine



High-Throughput Measurements







Discovery

Bottleneck #1: Knowledge

Bottleneck #2: Reasoning

Example: Molecular Tumor Board



www.ucsf.edu/news/2014/11/120451/bridging-gap-precision-medicine

Example: Molecular Tumor Board

• Problem: Hard to scale

U.S. 2015: 1.6 million new cases, 600K deaths

- 902 cancer hospitals
- Memorial Sloan Kettering 2016:
 - Sequence ~ 60,000
 - Board can review ~ 200

Wanted: Decision support for cancer precision medicine

Network Knowledge

Genes work synergistically in pathways



Why Hard to Identify Drivers?

Complex diseases ← Perturb multiple pathways



Hanahan & Weinberg [Cell 2011]

Why Cancer Comes Back?

- Subtypes with alternative pathway profile
- Compensatory pathways can be activated



Why Cancer Comes Back?

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PubMed

- 24 millions abstracts
- Two new abstracts every minute
- Adds over one million every year







Long Tail of Variations

TP53 inhibits BCL2.

Tumor suppressor P53 down-regulates the activity of BCL-2 proteins. BCL2 transcription is suppressed by P53 expression. The inhibition of B-cell CLL/Lymphoma 2 expression by TP53 ...

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negative regulation

532 inhibited, 252 inhibition, 218 inhibit, 207 blocked, 175 inhibits, 157 decreased, 156 reduced, 112 suppressed, 108 decrease, 86 inhibitor, 81 Inhibition, 68 inhibitors, 67 abolished, 66 suppress, 65 block, 63 prevented, 48 suppression, 47 blocks, 44 inhibiting, 42 loss, 39 impaired, 38 reduction, 32 down-regulated, 29 abrogated, 27 prevents, 27 attenuated, 26 repression, 26 decreases, 26 down-regulation, 25 diminished, 25 downregulated, 25 suppresses, 22 interfere, 21 absence, 21 repress

Event Annotation



Bottleneck: Annotated Examples

- Challenge for supervised learning
- Hard to crowd-source
- Complex semantics
- Can we breach this bottleneck?

Free Lunch: Indirect Supervision

Poon & Domingos, "Unsupervised Semantic Parsing". *EMNLP-09*. **Best Paper Award**.

Poon, Toutanova, Quirk, "Distant Supervision for Cancer Pathway Extraction from Text". *PSB-15*.

Parikh, Poon, Toutanova. "Grounded Semantic Parsing for Complex Knowledge Extraction", *NAACL-15*.

. . .

Cause

FOX01

TP53

TP53

. . .

Regulation	Theme
Positive	A2M
Positive	ABCB1
Negative	BCL2

. . .

	Regulation	Theme	Cause
NCI-PID Pathway KB	Positive	A2M	FOX01
	Positive	ABCB1	TP53
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PubMed-Scale Extraction

- Preliminary pass:
 - 3 million instances
 - 15,000 genes, 1.5 million unique regulations
- Applications:
 - UCSC Genome Browser, MSR Interactions Track
 - Validate *de novo* pathway prediction
 - Breast cancer study
 - Etc.

Poon, Toutanova, Quirk, "Distant Supervision for Cancer Pathway Extraction from Text". *PSB-15*.

Extract Complex Knowledge

The activation of Bax by the tumor suppressor protein p53 is known to trigger the p53-mediated apoptosis ...

Outperform 19 out of 24 supervised participants in GENIA Shared Task



Parikh, Poon, Toutanova. "Grounded Semantic Parsing for Complex Knowledge Extraction", *NAACL-15*.

Tree HMM





BCL stimulates inhibition of RFLAT by IL-10.

Tree HMM



$$P_{\theta}(z,t) = \prod_{m} P_{\text{EMIT}}(t_m | z_m, \theta) \cdot P_{\text{TRANS}}(z_m | z_{\pi(m)}, \theta)$$

Expectation Maximization

$$\theta^* = \arg \max_{\theta} \quad \log P_{\theta}(T|K)$$
$$= \arg \max_{\theta} \quad \sum_{t \in T} \log \sum_{z} P_{\theta}(z,t) \cdot \phi_K(z)$$
$$\bigvee \text{Virtual Evidence}$$

Reasoning

- Extraction: Limited to explicitly stated facts
- Wanted: Reasoning
- Challenge: Inference is expensive

Neural Embedding

- Entity / Relation $\rightarrow (v_1, v_2, ..., v_k)$
- Relation candidate \langle subj, rel, obj $\rangle \rightarrow$ Score
- Distant sup.: Known relations score higher
- Increased recall by 20 points on held-out

Toutanova *et al.*, "Representing Text for Joint Embedding of Text and Knowledge Bases", *EMNLP-15*.

Toutanova *et al.*, "Compositional Learning of Embeddings for Relation Paths in Knowledge Bases and Text", *ACL-16*.

Drug-Gene Interaction

- Sensitivity or resistance to drugs
 - ALK (L1196M): Resistant to crizotinib
 - ALK (R1275Q): Sensitive to crizotinib
- State of the art: GDKD
 - Oncologists read reviews for years
 - 162 drug-gene interactions
- Can we automate extraction?

Drug-Gene Interaction

- Problem: Need discourse modeling
 - Usually appear in full text
 - Often span multiple sentences

We studied the effect of crizotinib on lung cancer cells.

Cells with ALK variant L1196M are not sensitive.

However, we observed a strong response on cells with variant R1275Q.

- Distant supervision w. discourse modeling
- Orders of magnitude increase: $162 \rightarrow 79,952$

Literome: Genomic KB on Azure

The Li	iterome F	Pro	ject		Welcome charlie change to user id	Research	
filter by	ABC*	į		Gene	s: ABCA1, ABCA2, ABCA3, ABCA4, ABCA5	(1 - 50 of 5498)	
genes	ABCA1		ABCA1	Abacavir	PMID: 15327972	of abacavir (ABC; 1 -(1S,4R)	^
snps	ABCA10				Improved antiviral activity of the	-4-[2-amino-6-(cyclopropylamino)-9H-purin-	
diseases	ABCA12				(APA) prodrug of abacavir (ABC) is due to	(details)	
drugs	ABCA13				the formation of markedly increased carbovir 5'-triphosphate metabolite levels.	A second count for	
	ABCA2			Abetalinonroteinemia	PMID: 16569910	of ABCA1 with	

Poon *et al.*, "Literome: PubMed-Scale Genomic Knowledge Base in the Cloud", *Bioinformatics-14*.

http://literome.azurewebsites.net

Cancer Precision Medicine



Personalized medicine approach to treating AML

The Leukemia & Lymphoma Society (LLS) and the Knight Cancer Institute at Oregon Health & Science University are leading a pioneering collaboration to develop a personalized medicine approach to improve outcomes for patients with acute myeloid leukemia (AML), a particularly devastating cancer of the blood and bone marrow. LLS provided \$8.2 million to fund Beat AML and here is how the collaboration will work:



2 Illumina will perform genetic sequencing to identify mutations in the patient samples collected.





will be first to test a

therapeutic.

S Intel will work with Knight Cancer's bioinformatics team to apply its technology to accelerate computational analysis of the mutation data collected.

LEUKEMIA & LYMPHOMA SOCIETY' fighting blood cancers





Vemurafenib on BRAF-V600 Melanoma



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15 Weeks

23 Weeks

Drug Combination

- Problem: What combos to try?
 - Cancer drug: 250+ approved, 1200+ developing
 - Pairwise: 719,400; three-way: 287,280,400
- Wanted: Prioritize drug combos in silico

Drug Combination

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Related Work

- Drug → Rank patients
- \bullet Drug / target / patient \rightarrow Find similar ones
- Our focus:
 - Patient \rightarrow Rank drugs
 - Target combination
 - Network knowledge

Machine Learning

Prediction: Classify top efficacy

Features

- Panomics: Gene expression, ...
- Pharmacology: Drug targets
- Network knowledge: TP53 inhibits BCL2, ...
- Start with single-drug experiments

Cancer Cell Line Encyclopedia

F1 (Drug Efficacy)



Cancer Cell Line Encyclopedia



Cancer Cell Line Encyclopedia

F1 (Drug Efficacy) 25 20 15 10 5 GALEN TIMMA GALEN [Tang et al. 2013] BASE + Literome

Next: BeatAML

- Goal: Identify promising drug combos
- Symbiosis: Oncologist + Computer
 - Interpretable model
 - Learn from feedback
 - Exploitation + Exploration



• 42-million program

- Reading, Assembly, Explanation
- Domain: Cancer signaling pathways
- We are in
 - PI: Andrey Rzhetsky
 - Co-PI w. James Evans, Ross King

Emerging Frontier: Electronic Medical Record (EMR)

Cost to develop a drug > \$2.5 billion

Virtual clinical trial: "EMR as a lab"

Disruption: Pay-by-quality

Patientomics

00000011 Age: 62; Gender: Female Week 27: 250.00, 272.4, 739.3 Week 32: 250.00, 715.90 Week 33: 250.00, 715.95

Patient was admitted with hypernatremia and acute mental status changes and right sided paralysis. Her corrected sodium on admission was about 170s and her free water deficit was 5.5L. She was volume repleted with normal saline. She also recieved D51/4 NS for free water repletion initially and this was changed to free water boluses through nasogastric tube. Her sodium gradually trended down with free water repletion. She also was in pre-renal renal failure and her creatinine trended down with hydration. With regards to the acute mental changes, this is partially explained by the hypernatrmic state.

Predict Progression

Machine Reading

Summary

- Genomics disruption: Precision medicine
- Challenge: Knowledge + Reasoning
- Machine reading: Literome
- Prioritize cancer drug combos

Collaborators

- Knight: Brian Drucker, Jeff Tyner
- U. Chicago: Andrey Rzhetsky
- Wisconsin: Mark Craven, Anthony Gitter
- UCSC: Max Haeussler, David Haussler
- Microsoft Research: Chris Quirk, Kristina Toutanova, David Heckerman, Scott Yih, Lucy Vanderwende, Bill Bolosky, Ravi Pandya
- Interns: Ankur Parikh, Maxim Grechkin, Victoria Lin, Sheng Wang, Stephen Mayhew