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## Distant Supervision for Cancer Pathway Extraction from Text

Presented by Gus Hahn-Powell

Hoifung Poon<sup>1</sup> hoifung@microsoft.com

Kristina Toutanova<sup>1</sup> Chris Quirk<sup>1</sup>

<sup>1</sup>Microsoft Research, Redmond, WA

October 2, 2015

### How do we keep up with the literature?

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- Over a million publications a year!
- Cancer pathways require a systemic understanding
- Need to bring together findings scattered across the literature

### What's Distant Supervision?

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### Train a classifier from a weakly labeled training set

- This usually means noisy data (i.e. annotations that we cannot always trust)
- supervision comes from a knowledge base resource

### Challenge

- Knowledge base is incomplete
- How to handle the noise?
- How to handle overlapping relations?

### Why Distant Supervision?

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- leverage existing resources (knowledge base)
- mitigate annotation sparsity

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# Simulated distance supervision

### BioNLP 2009 Event Extraction

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Entity annotations are provided

■ training: 800 instances

development: 150 instances

Only considering regulations involving proteins

### Building a knowledge base from BioNLP 2009

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```
R ={
  positive regulation,
  regulation,
  negative regulation,
  NULL
}
```

- Extract triples from training data sentences
  - (Protein1:Theme, Relation, Protein2:Cause)
  - Relation is conservatively labelled
    - Path to Theme may not have intervening Cause
    - When in doubt about directionality, assume regulation

### Training the distant supervision classifier

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For each sentence in training . . .

- For each pair of proteins . . .
  - Extract features and predict relation label
- For  $r \in R$ , r can only be assigned to a triple iff the triple exists in the database
  - A triple's existence in the kb does not mean it must be assigned the label r (could be NULL)

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### **Features**

### Directionality

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$$E_1$$
 = theme  $E_2$  = cause

score	criteria
0	$E_1 \& E_2$ overlap
1	$E_1$ precedes $E_2$
-1	$E_2$ precedes $E_1$

### Distance

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When  $E_1$  follows  $E_2$ , count the distance in tokens . . .

- if (k > 5) 1 else 0
- if (k > 10) 1 else 0
- if (k > 15) 1 else 0
- if (k > 20) 1 else 0

### Lexical

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For tokens between  $E_1 \& E_2 \dots$ 

- Direction + words
- Direction + lemma
- Direction + each word
- Direction + each lemma

### Syntactic

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For the dependency path connecting  $E_1 \& E_2 \dots$ 

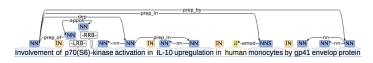


Figure: A visualization of the dependency parse for the sentence referenced in Poon et al. (2014) on page 4.

- Unlexicalized
- Lexicalized (with lemmas)
- Direction + each word
- Direction + each lemma
- lacktriangle path of (trigger ightarrow arg) + trigger's lemma



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- Uses MultiR system of Hoffmann et al. (2011)
- online learning with perceptron
- 1:3 ratio for positive:negative

### Choose most common label

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 $\blacksquare$  For all entity pairs, assign the label positive\\_regulation

### Supervised system

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Some feature selection

• filtered out features  $\leq$  3 occurrences in positive examples

### Rules I

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### Data available at

literome.azurewebsites.net/papers/psb15

### Negative Regulation

```
(ability prep_of: (CAUSE) infmod: (inhibit dobj: (THEME))) (attenuated nsubj: (CAUSE) dobj: (production nn: (THEME)))
```

### Positive Regulation

```
(CAUSE appos: (factor rcmod: (activates dobj: (THEME))))
(CAUSE partmod: (enhanced iobj: (expression prep_of: (THEME))))
```

### Rules II

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### Skipped elements

```
walk("gene", "nn")
walk("genes", "nn")
walk("gene", "appos")
```

### Comparing systems

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#### Table 2. Test results on GENIA binary-relation classification comparing distant supervision with two baseline systems, supervised learning, and MSR11, a state-of-the-art system training on full event structures.

System	Precision	Recall	F1
Most-Frequent	3.4	69.7	6.5
Rule-Based	45.8	5.2	9.4
Distant Supervision	39.2	19.0	25.6
Supervised	37.5	29.9	33.2
MSR11	55.1	28.0	37.1

Figure: Comparing performance of different models<sup>1</sup>.

Poon et al. (2014) doesn't attempt to capture ...

- unary events
- "recursive events"



<sup>&</sup>lt;sup>1</sup>Poon et al. (2014)

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■ Look at relationship between cancer types and genes

- Use subset of Pathway Interaction Database (PID) to populate KB
- Extracted 1.5 million pathways
  - 800*K* were unique!
  - Estimated 372K are correct extractions

### Challenges

Much noisier



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References

Hoffmann, R., Zhang, C., Ling, X., Zettlemoyer, L., and Weld, D. S. 2011. Knowledge-based weak supervision for information extraction of overlapping relations. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1*, pages 541–550. Association for Computational Linguistics.

Poon, H., Toutanova, K., and Quirk, C. 2014. Distant supervision for cancer pathway extraction from text. In *Pacific Symposium on Biocomputing*. *Pacific Symposium on Biocomputing*, volume 20, pages 120–131. World Scientific.