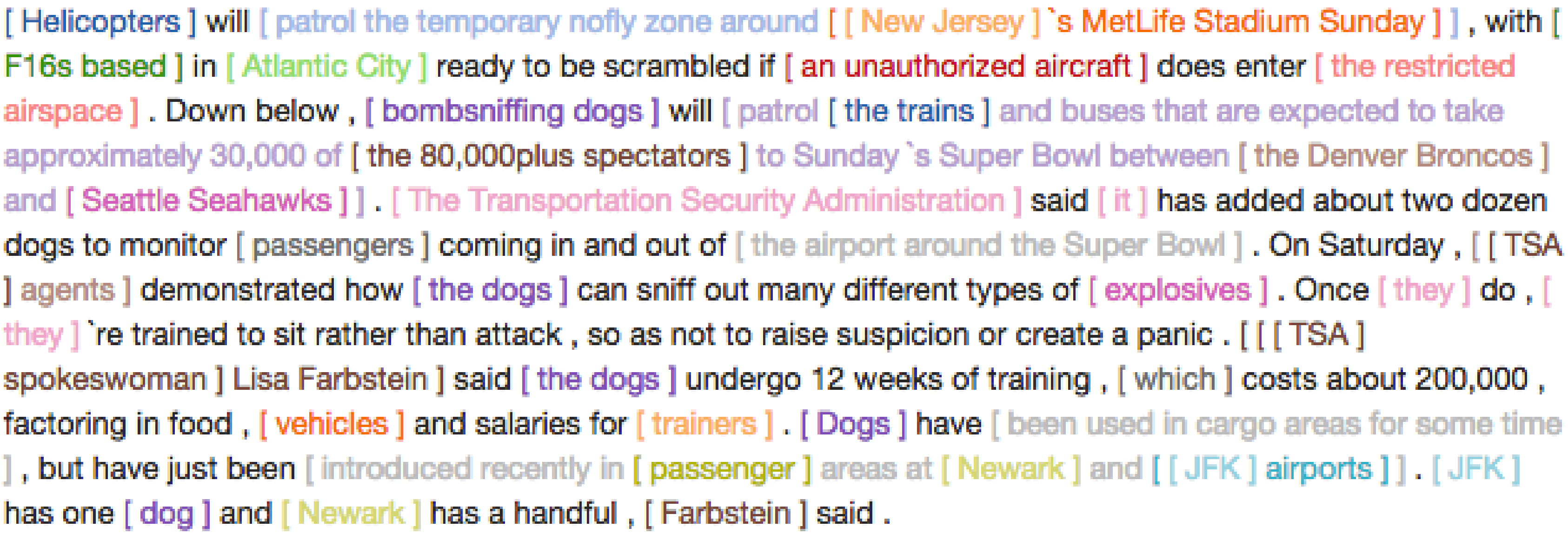
Coreference Resolution with Knowledge

Haoruo Peng

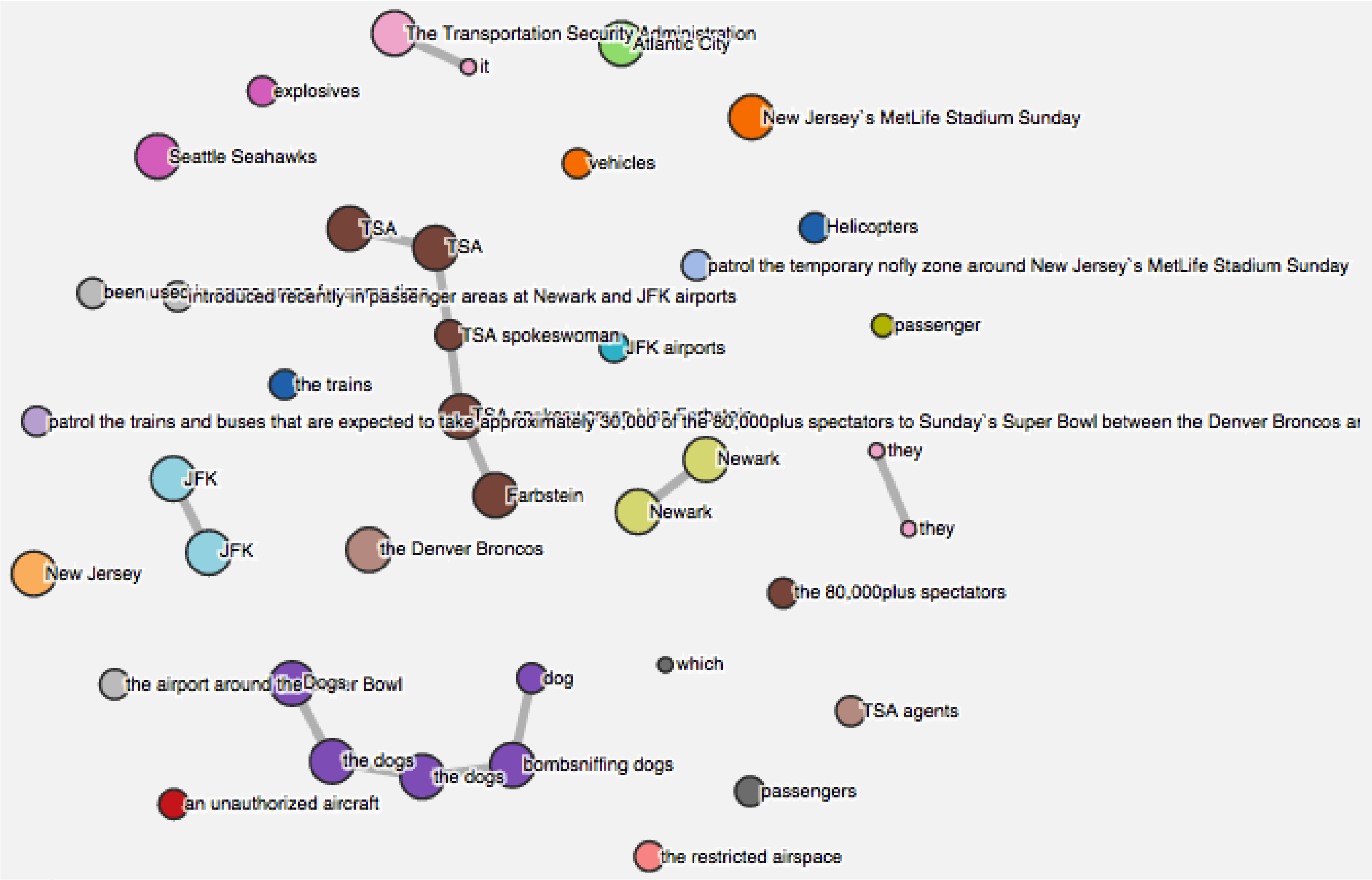
March 20, 2015

Coreference Problem



[Helicopters] will [patrol the temporary nofly zone around [[New Jersey] `s MetLife Stadium Sunday]] , with [F16s based] in [Atlantic City] ready to be scrambled if [an unauthorized aircraft] does enter [the restricted airspace] . Down below , [bombsniffing dogs] will [patrol [the trains] and buses that are expected to take approximately 30,000 of [the 80,000plus spectators] to Sunday `s Super Bowl between [the Denver Broncos] and [Seattle Seahawks]] . [The Transportation Security Administration] said [it] has added about two dozen dogs to monitor [passengers] coming in and out of [the airport around the Super Bowl] . On Saturday , [[TSA] agents] demonstrated how [the dogs] can sniff out many different types of [explosives] . Once [they] do , [they] `re trained to sit rather than attack , so as not to raise suspicion or create a panic . [[[TSA] spokeswoman] Lisa Farbstein] said [the dogs] undergo 12 weeks of training , [which] costs about 200,000 , factoring in food , [vehicles] and salaries for [trainers] . [Dogs] have [been used in cargo areas for some time] , but have just been [introduced recently in [passenger] areas at [Newark] and [[JFK] airports]] . [JFK] has one [dog] and [Newark] has a handful , [Farbstein] said .

Coreference Problem



Online Demo

- Please check outhttp://cogcomp.cs.illinois.edu/page/demo_view/Coref

General Framework

Jack threw the bags of Mary into the water since he is angry with her.

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Mention Detection

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Jack threw the bags of ***Mary*** into the water since ***he*** is angry with ***her***.

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Mention Detection

Pairwise Mention Scoring

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- Mention Detection
- Pairwise Mention Scoring
  - Goal: Coreferent Mentions have higher scores

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- Mention Detection
- Pairwise Mention Scoring
  - Goal: Coreferent Mentions have higher scores
- Inference (ILP)
  - Best-Link
  - All-Link

ILP formulation of CR

- Best-Link

$$\arg\max_y \sum_{u,v} w_{uv} y_{uv}$$

$$\text{s.t.} \quad \sum_{u<v} y_{uv} \leq 1, \ \forall v$$

$$y_{uv} \in \{0, 1\}$$

- All-Link

$$\arg\max_y \sum_{u,v} w_{uv} y_{uv}$$

$$\text{s.t.} \quad y_{um} \geq y_{uv} + y_{vm} - 1, \ \forall u, v, m$$

$$y_{uv} \in \{0, 1\}$$

General Framework

- Learning (for Pairwise Mention Scores)
  - Structural SVM
  - Features:
    - Mention Types, String Relations, Semantic, Relative Location, Anaphoricity(Learned), Aligned Modifiers, Memorization, etc.

General Framework

- Learning (for Pairwise Mention Scores)
  - ☐ Structural SVM
  - ☐ Features:
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Evaluation

MUC

BCUB

CEAF_e

General Framework

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Evaluation

MUC

BCUB

CEAF_e

IllinoisCoref

VS. Stanford Muti-pass Sieve System
VS. Berkeley CR System

Difficulties in CR

- Hard Coreference Problems
  - [A bird] perched on the [limb] and [it] bent.
  - [Robert] is robbed by [Kevin], and [he] is arrested by police.

  - Gender / Plurality information cannot help
  - -> Requires Knowledge

Part 1
Solving Hard Coreference Problems

Hard Coreference Problems

- Motivating Examples

Hard Coreference Problems

- Motivating Examples
  - Category 1
    - [A bird] perched on the [limb] and [it] bent.
    - [The bee] landed on [the flower] because [it] had pollen.

Hard Coreference Problems

- Motivating Examples

  Category 1

  [A bird] perched on the [limb] and [it] bent.

  [The bee] landed on [the flower] because [it] had pollen.

  Category 2

  [Jack] is robbed by [Kevin], and [he] is arrested by police.

  [Jim] was afraid of [Robert] because [he] gets scared around new people.

Hard Coreference Problems

- Motivating Examples

Category 1

[A bird] perched on the [limb] and [it] bent.

[The bee] landed on [the flower] because [it] had pollen.

Category 2

[Jack] is robbed by [Kevin], and [he] is arrested by police.

[Jim] was afraid of [Robert] because [he] gets scared around new people.

C

[Lakshman] asked [Vivan] to get him some ice cream because [he] was hot.

Predicate Schemas

- Type 1
  -
- Type 2
  -

Predicate Schemas

- Type 1
  - $pred_m(m, a)$
- Type 2
  -

Predicate Schemas

- Type 1
  - $pred_m(\overset{\text{Sub}}{\boxed{m}}, \overset{\text{Obj}}{\boxed{a}})$
- Type 2

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    (Cat1) [The bee] landed on [the flower] because [it] had pollen.
- Type 2

Predicate Schemas

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  - $pred_m(\overset{\text{Sub}}{\boxed{m}}, \overset{\text{Obj}}{\boxed{a}})$

    (Cat1) [The bee] landed on [the flower] because [it] had pollen.

    S(have(m=[the flower], a=[pollen])) >

    S(have(m=[the bee], a=[pollen]))
- Type 2

Predicate Schemas

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- Type 2
  - $pred_m(m, a)|\hat{pred}_m(m, \hat{a}), cn$

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Predicate Schemas

Sub Obj

- Type 1
  - $pred_m(\boxed{m}, \boxed{a})$

    (Cat1) [The bee] landed on [the flower] because [it] had pollen.

    S(have(m=[the flower], a=[pollen])) >

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Shared Mention

- Type 2
  - $pred_m(\boxed{m}, a) | \widehat{pred}_m(\boxed{m}, \hat{a}), cn$

Predicate Schemas

- Type 1

  Sub Obj

  - ☐ $pred_m(\boxed{m}, \boxed{a})$

    (Cat1) [The bee] landed on [the flower] because [it] had pollen.

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  Shared Mention

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  - ☐ $pred_m(\boxed{m}, a) | \widehat{pred}_m(\boxed{m}, \hat{a}), cn$

    (Cat2) [Jim] was afraid of [Robert] because [he] gets scared around new people.

Predicate Schemas

- Type 1
  - ☐ $pred_m(\underset{\text{Sub}}{\boxed{m}}, \underset{\text{Obj}}{\boxed{a}})$

    (Cat1) [The bee] landed on [the flower] because [it] had pollen.

    S(have(m=[the flower], a=[pollen])) >

    S(have(m=[the bee],   a=[pollen]))

- Type 2
  - ☐ $pred_m(\boxed{m}, a) | \widehat{pred}_m(\boxed{m}, \hat{a}), cn$ (Shared Mention)

    (Cat2) [Jim] was afraid of [Robert] because [he] gets scared around new people.

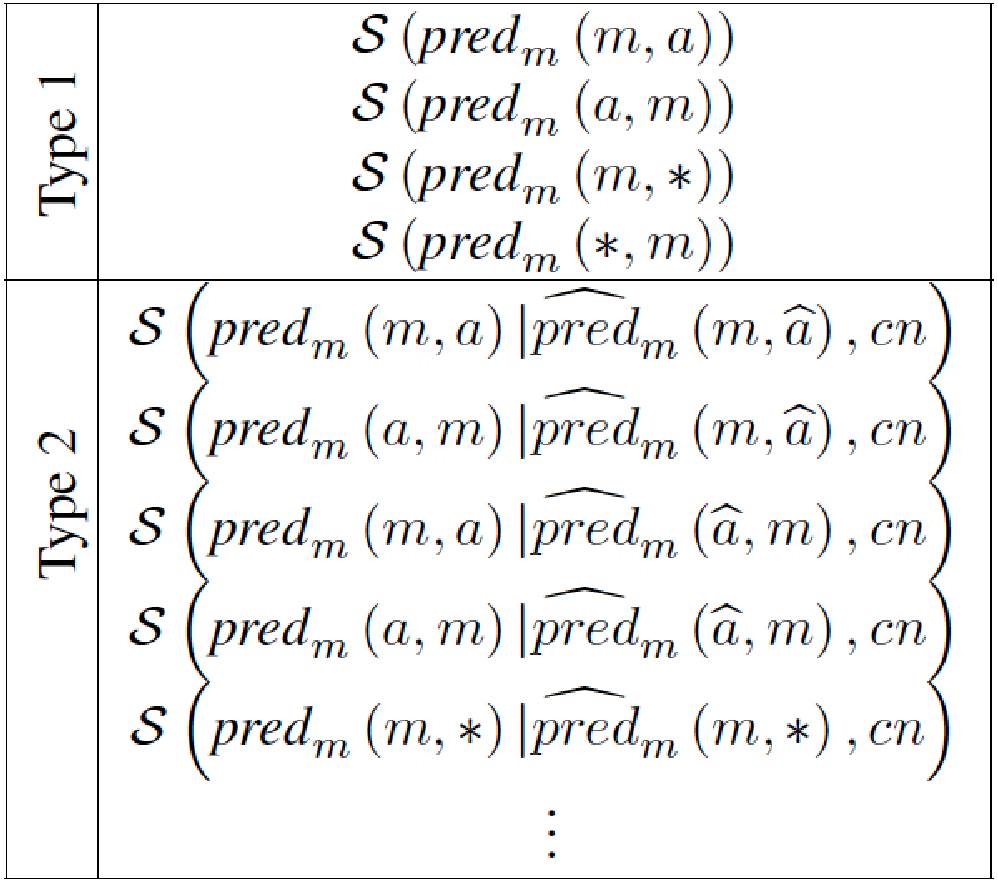
    ^

    S

    S(be afraid of(a=*, m=*) | get scared around(m=*, â=*), because)

Predicate Schemas

- Possible variations for scoring function statistics.



Type 1	$\mathcal{S}\left(pred_m\left(m,a\right)\right)$
	$\mathcal{S}\left(pred_m\left(a,m\right)\right)$
	$\mathcal{S}\left(pred_m\left(m,*\right)\right)$
	$\mathcal{S}\left(pred_m\left(*,m\right)\right)$
Type 2	$\mathcal{S}\left(pred_m\left(m,a\right) \mid \widehat{pred}_m\left(m,\hat{a}\right), cn\right)$
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	$\mathcal{S}\left(pred_m\left(m,*\right) \mid \widehat{pred}_m\left(m,*\right), cn\right)$
	$\vdots$

Predicate Schemas in Coreference

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Pairwise Mention Scoring Function

$$f_{u,v} = \mathbf{w}^\top \phi(u, v)$$

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Scoring Function for Predicate Schemas

$$\mathbf{s}(u, v)$$

Predicate Schemas in Coreference

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We can add scores of Predicate Schemas as **Features**

Ways of Using Knowledge

- Major Disadvantages of Using Knowledge as **Features**
  - Noise in Knowledge
  - Inexplicit Textual Inference

- Alternative way
  - Using Knowledge as **Constraints**

Using Knowledge as Constraints

Using Knowledge as Constraints

Generating Constraints

$$\begin{cases} \text{if } s_i(u,v) \geq \alpha_i s_i(w,v) \Rightarrow y_{u,v} \geq y_{w,v}, \\ \text{if } s_i(u,v) \geq s_i(w,v) + \beta_i \Rightarrow y_{u,v} \geq y_{w,v} \end{cases}$$

Using Knowledge as Constraints

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ILP inference (Best-Link)

$$\arg\max_y \sum_{u,v} w_{uv} y_{uv}$$

$$\text{s.t. } \sum_{u<v} y_{uv} \leq 1, \forall v \qquad y_{uv} \in \{0,1\}$$

$$\text{if } s_{uv} \geq t + s_{um} \text{ then } y_{uv} \geq y_{um}$$

$$\text{if } s_{uv} \geq t' \cdot s_{um} \text{ then } y_{uv} \geq y_{um}$$

Scores for Predicate Schemas

- Multiple Sources
  - Gigaword
  - Wikipedia
  - Web Search
  - Polarity Information

Scores for Predicate Schemas

- Gigaword
  - Chunking + Dependency Parsing

    => predicate(subject, object)

    => Type 1 Predicate Schema
  - Heuristic Coreference

    => Type 2 Predicate Schema

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Wikipedia

Entity Linking to ground on Wikipedia Entries (Disambiguation)

Gather Simple Statistics for 1) immediately after 2) immediately before 3) after 4) before

=> Type 1 Predicate Schema

) (approximation)

Scores for Predicate Schemas

- Web Search
  - Google Query with Quote (counts)
  - “m predicate”, “a m”, “a m”, “m predicate a”

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Polarity Information

Polarity on predicates => Polarity on mentions

Negate polarity if mention is object

Negate polarity for polarity-reversing connective

+1 if polarities for mentions are the same

-1 if polarities for mentions are different

=> Type 2 Predicate Schema

Recap

- Things to consider for using knowledge in NLP
  - Knowledge Representation
    - Predicate Schema
  - Knowledge Inference
    - Features VS. Inference
  - Knowledge Acquisition
    - Multiple Sources

Datasets

- Winograd dataset[1]
  - [The bee] landed on [the flower] because [it] *had* pollen.
    [The bee] landed on [the flower] because [it] *wanted* pollen.

---

[1] http://www.hlt.utdallas.edu/~vince/data/emnlp12/

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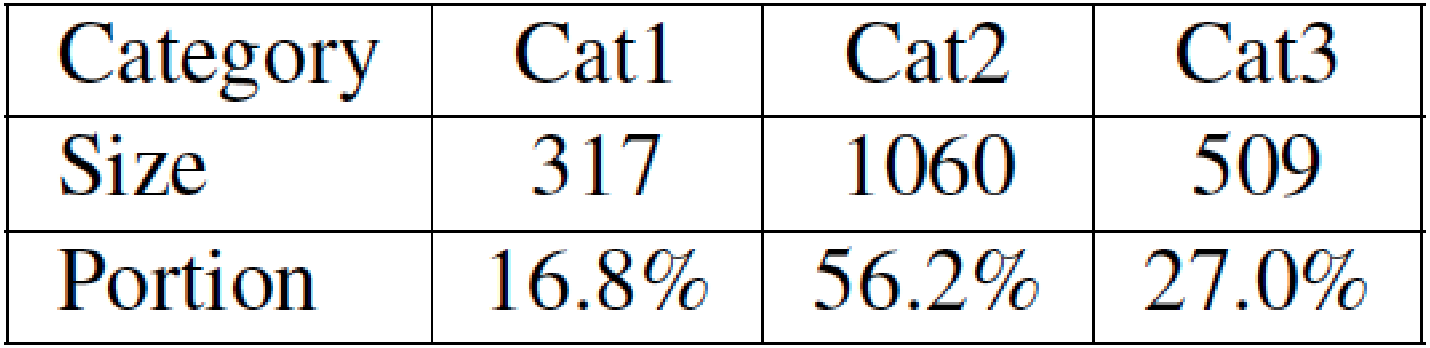
  - 

Category	Cat1	Cat2	Cat3
Size	317	1060	509
Portion	16.8%	56.2%	27.0%

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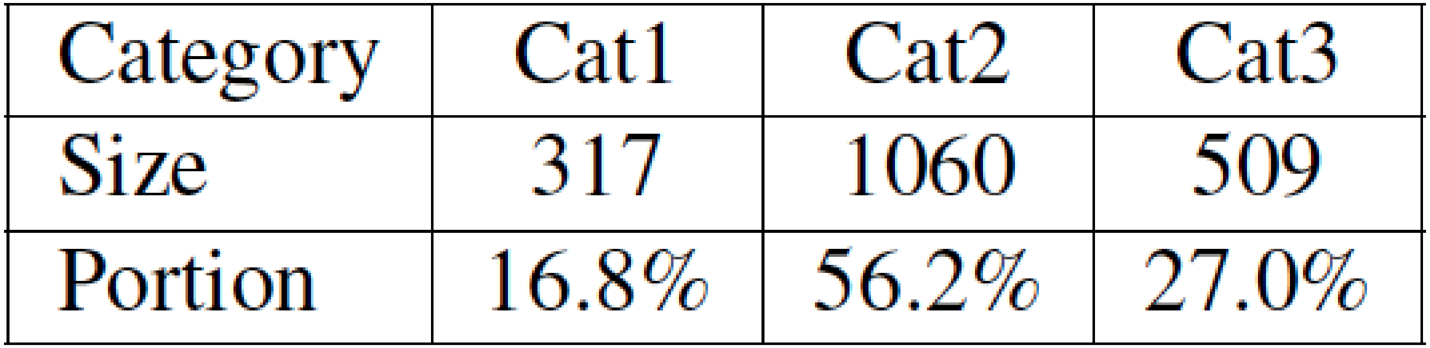
  - 

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    [Jack] threw the bags of [John] into the water since [he] mistakenly asked **him** to carry **his** bags.

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Datasets

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  - ☐ [The bee] landed on [the flower] because [it] *had* pollen.
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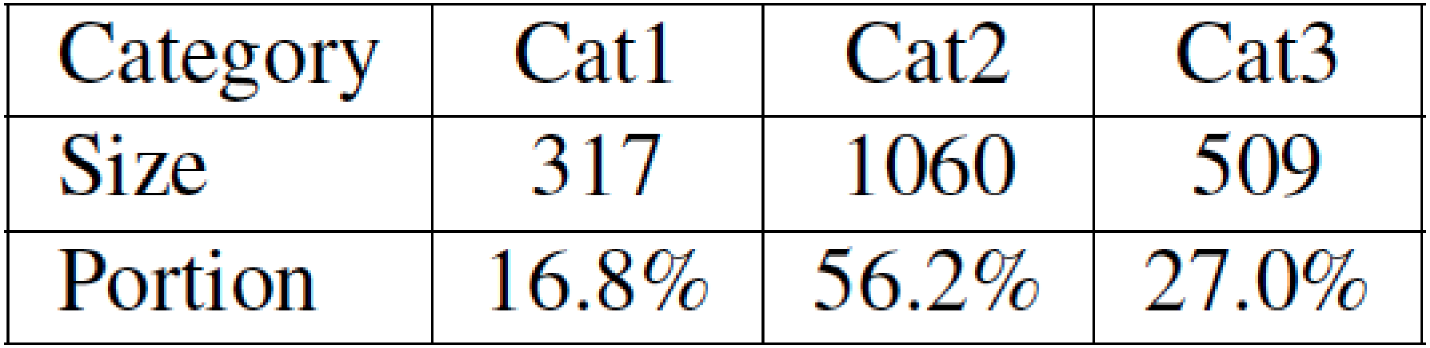
  - ☐



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- WinoCoref dataset

---

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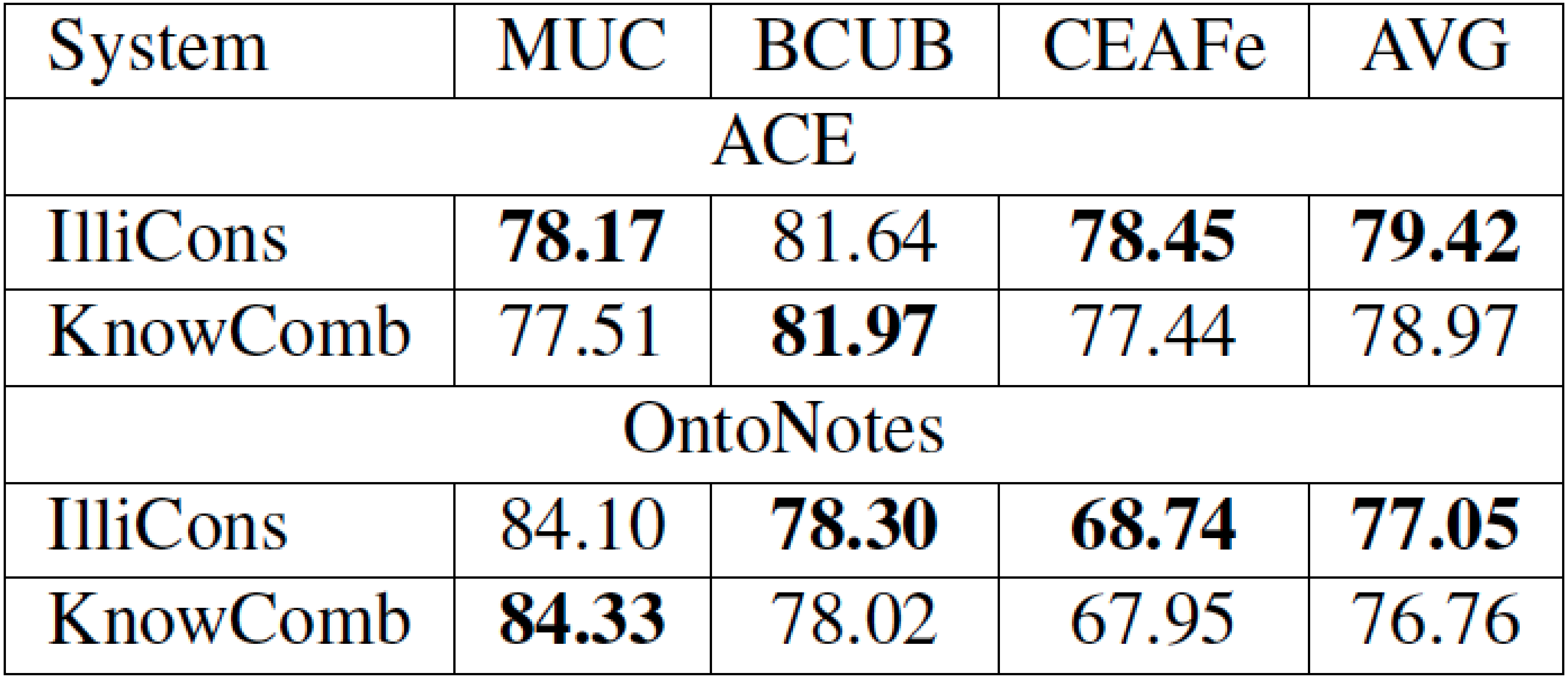
Evaluation on Hard Coreference

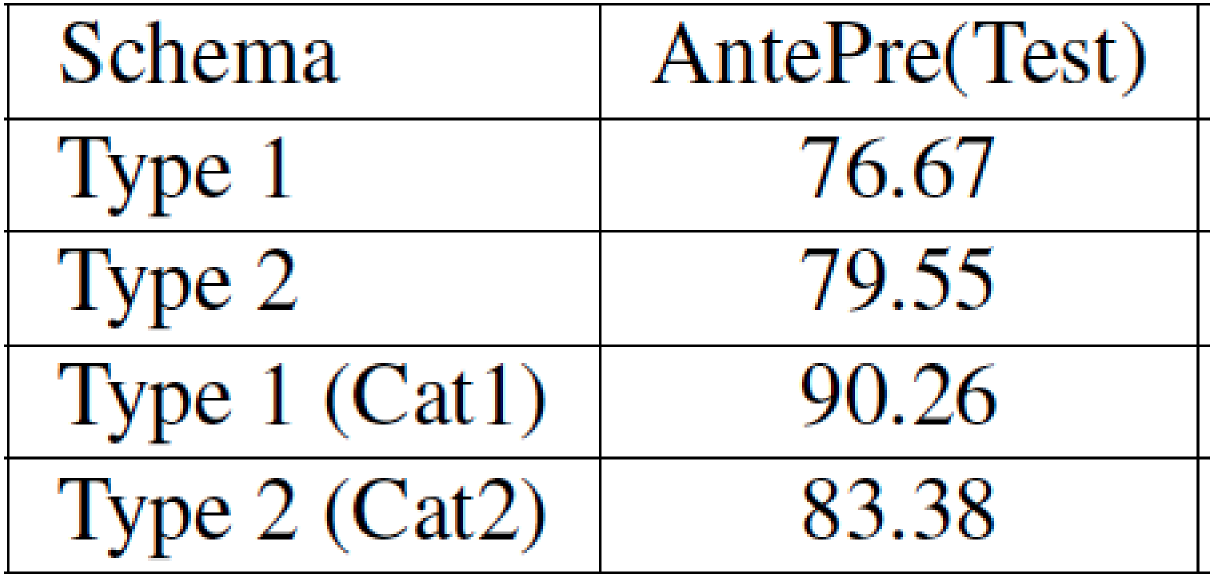
Dataset	Winograd	WinoCoref
Metric	Precision	AntePre
Illinois	51.48	68.37
IlliCons	53.26	74.32
Rahman and Ng (2012)	73.05	---
KnowFeat	71.81	88.48
KnowCons	74.93	88.95
KnowComb	**76.41**	**89.32**

Evaluation on Standard Coreference



System	MUC	BCUB	CEAFe	AVG
ACE				
IlliCons	**78.17**	81.64	**78.45**	**79.42**
KnowComb	77.51	**81.97**	77.44	78.97
OntoNotes				
IlliCons	84.10	**78.30**	**68.74**	**77.05**
KnowComb	**84.33**	78.02	67.95	76.76

Analysis on Effects of Schemas



Schema	AntePre(Test)
Type 1	76.67
Type 2	79.55
Type 1 (Cat1)	90.26
Type 2 (Cat2)	83.38

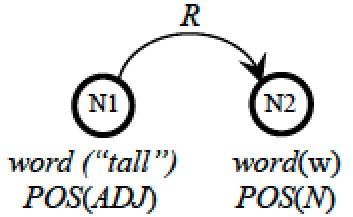
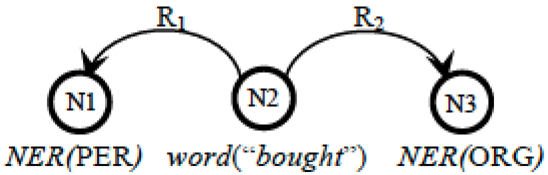
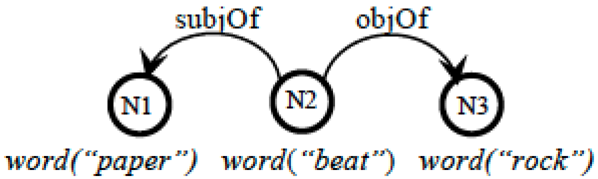
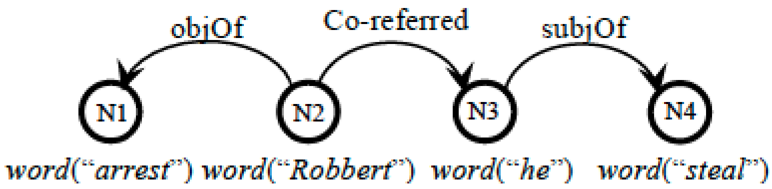
Part 2
Profiler: Knowledge Schemas at Scale

Goal

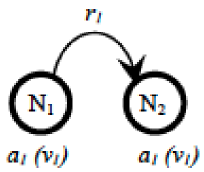
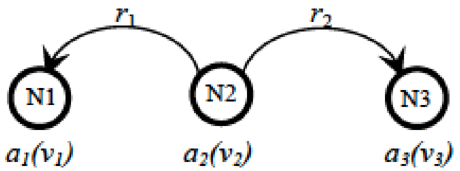
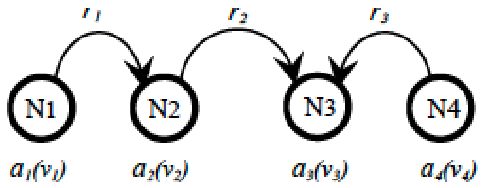
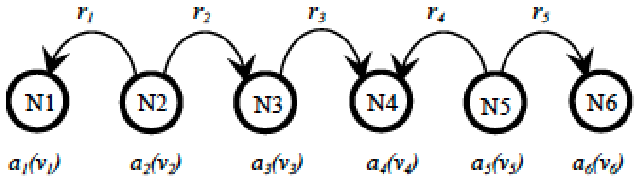
- How to enlarge the Knowledge acquired from text
  - Data Volume
  - Schema Richness

- Profiler
  - Demo: http://austen.cs.illinois.edu:60000/

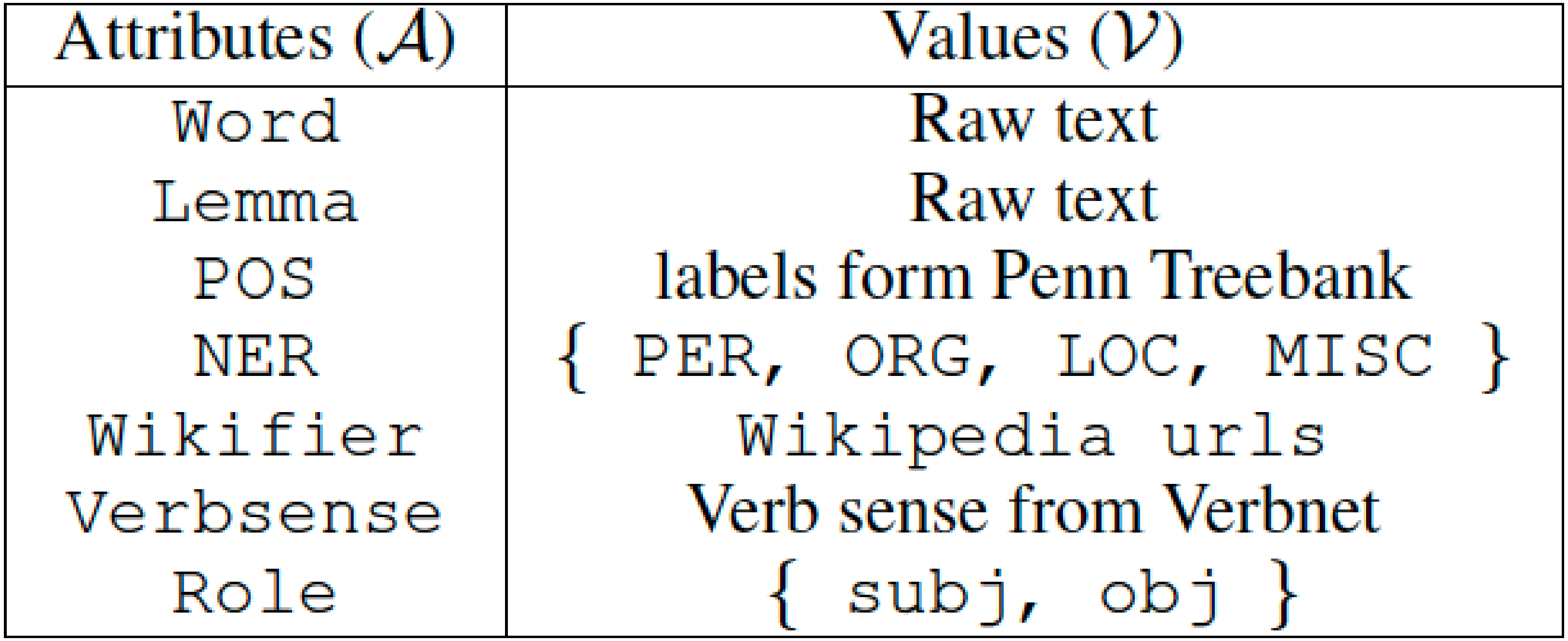
Motivation

#	Sentence	Schema Graph
1	"I chopped down [the tree] with my [axe] because [it] was tall."	
2	"[Larry Robbins], founder of Glenview Capital Management, bought shares of [Endo International Plc] ..."	
3	"Among [paper] and [rock] I chose rock, because [it] can beat scissors."	
4	"[Jimbo] attacked [Bobbert] because [he] stole an elephant from the zoo."	

Enriched Schemas

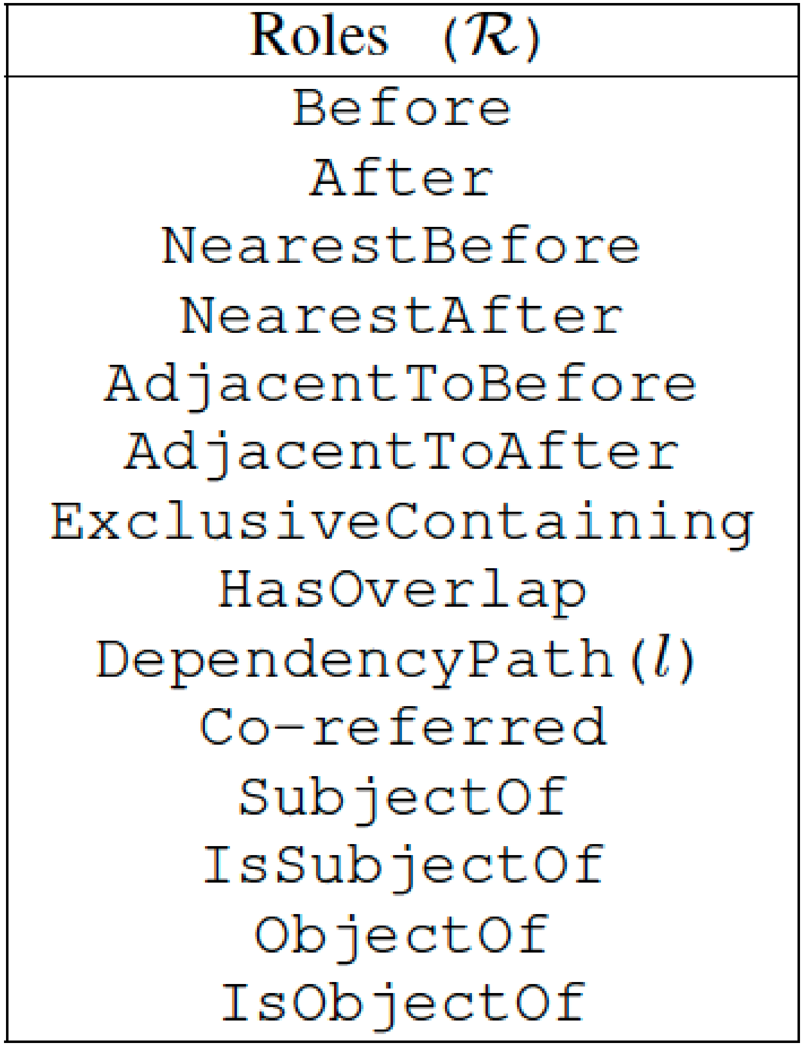
Concept Graph	Attributes = { Values }	Relations	Number of Schemas
	word = { set of words } POS = { Noun, Noun-Phrase, Verb, Verb-Phrase, Modifier } Wikifier = { URLS } Verbsense = { All verb senses }	Possible roles from Table 4 except Co-referred	24
	word = { set of words } POS = { Noun, Noun-Phrase, Verb, Verb-Phrase, Modifier } Verbsense ={ All verb senses }	Subj, ObjOf	2
	word = { All words } Verbsense = {All verb senses }	Subj, ObjOf, Co-referred	8
	word = { set of words } Verbsense = { All verb sense }	Subj, ObjOf, Co-referred	4

Enriched Schemas



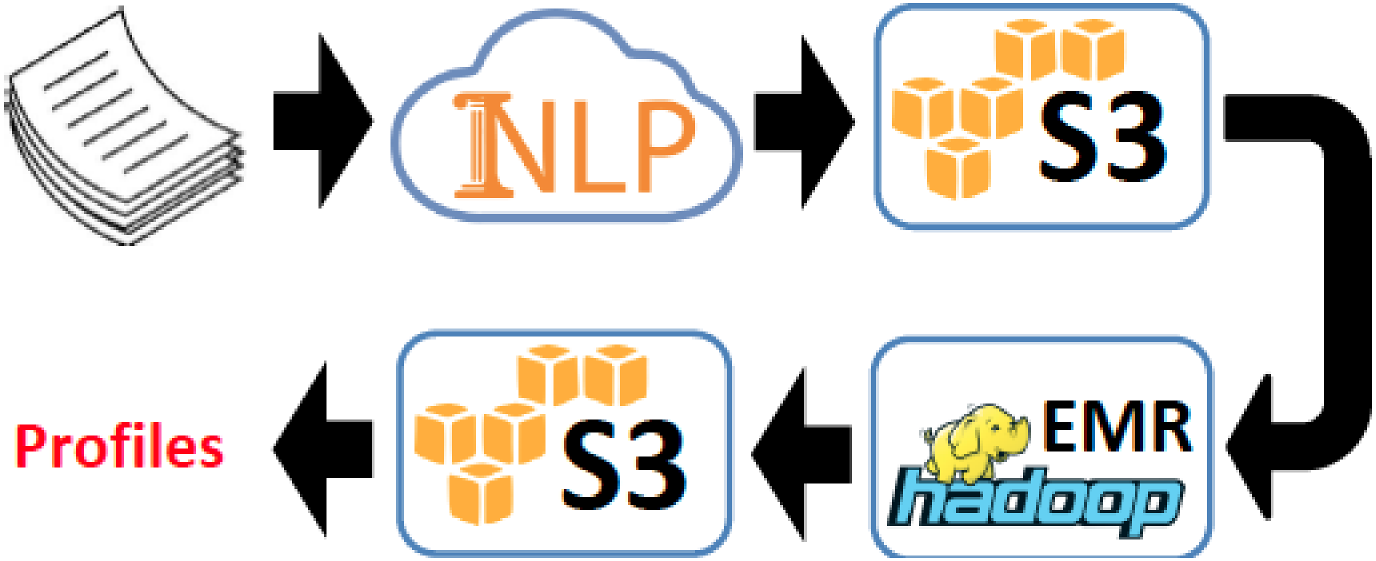
Attributes ($\mathcal{A}$)	Values ($\mathcal{V}$)
Word	Raw text
Lemma	Raw text
POS	labels form Penn Treebank
NER	{ PER, ORG, LOC, MISC }
Wikifier	Wikipedia urls
Verbsense	Verb sense from Verbnet
Role	{ subj, obj }

Enriched Schemas

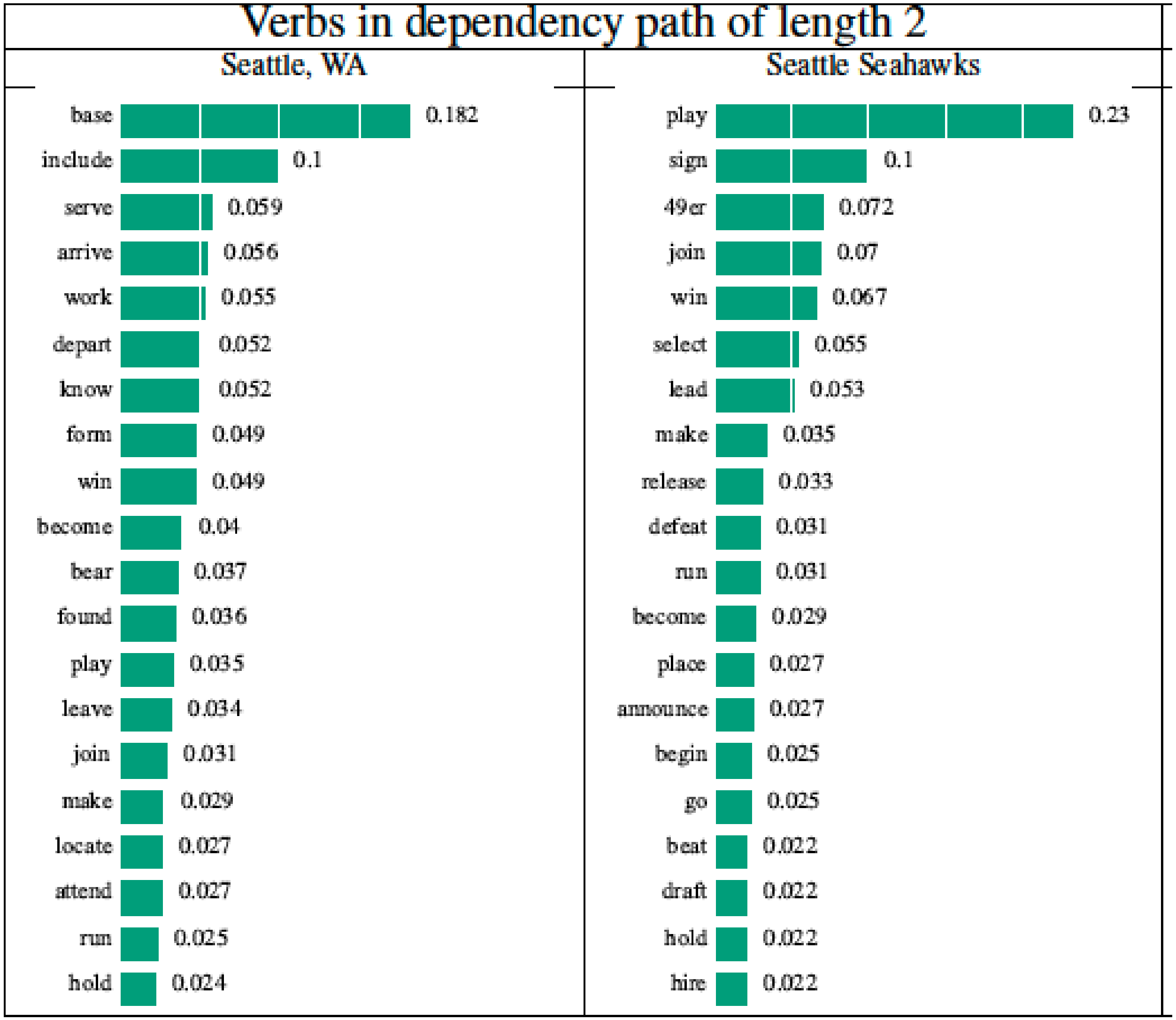


Roles ($\mathcal{R}$)
`Before`
`After`
`NearestBefore`
`NearestAfter`
`AdjacentToBefore`
`AdjacentToAfter`
`ExclusiveContaining`
`HasOverlap`
`DependencyPath`(l)
`Co-referred`
`SubjectOf`
`IsSubjectOf`
`ObjectOf`
`IsObjectOf`

Implementation



Effect of Wikification (Entity-Linking)



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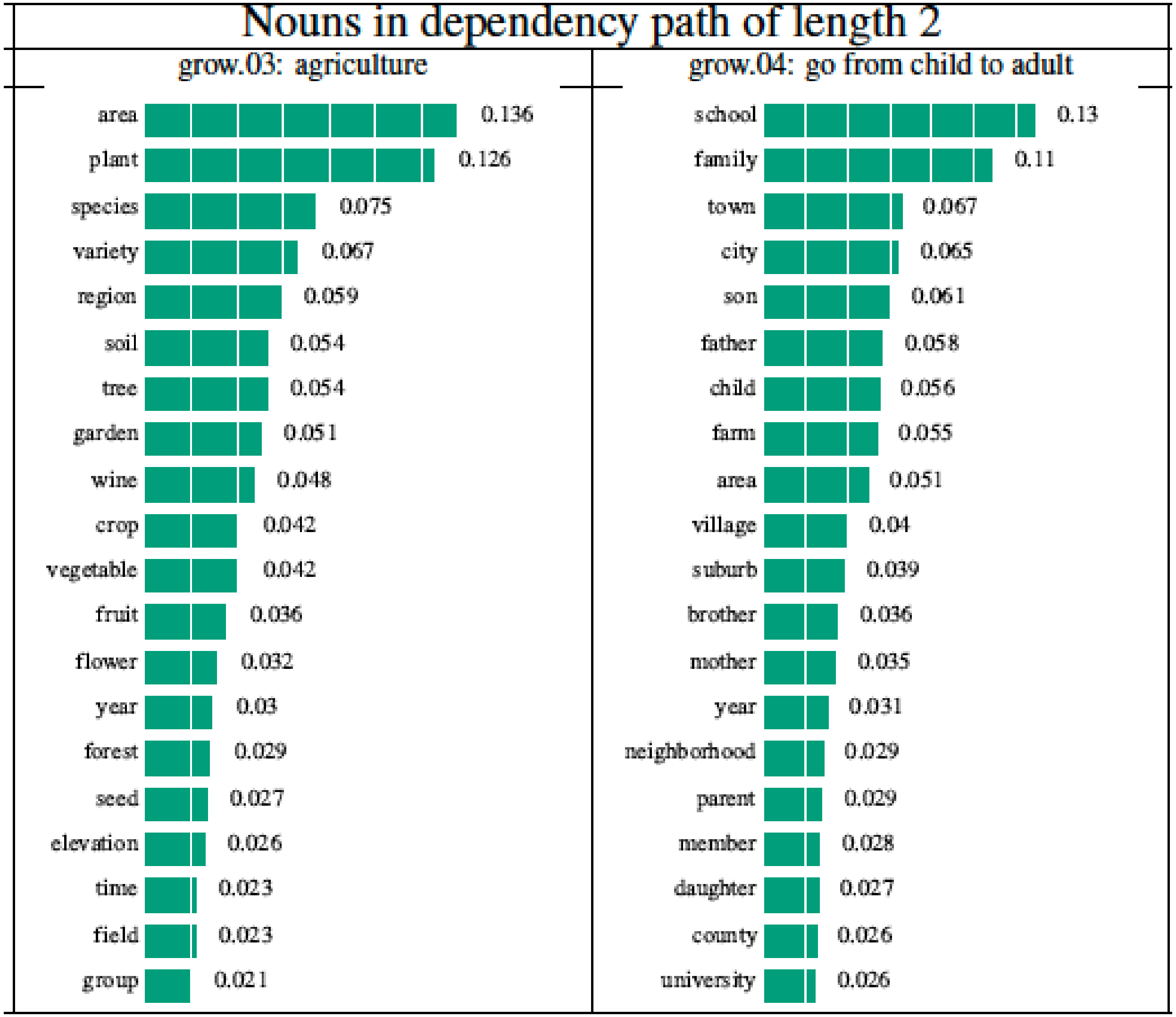
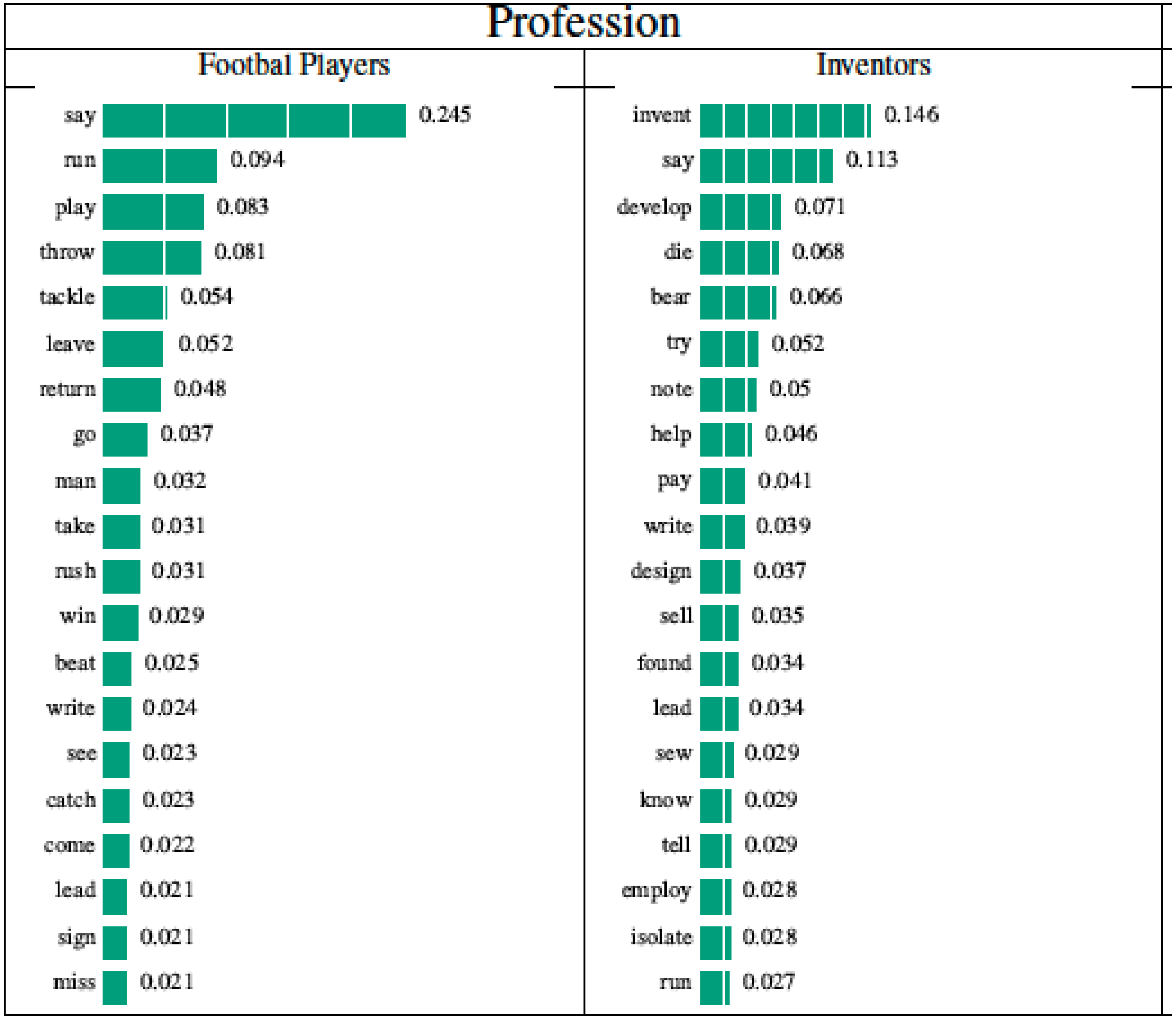


Knowledge Visualization



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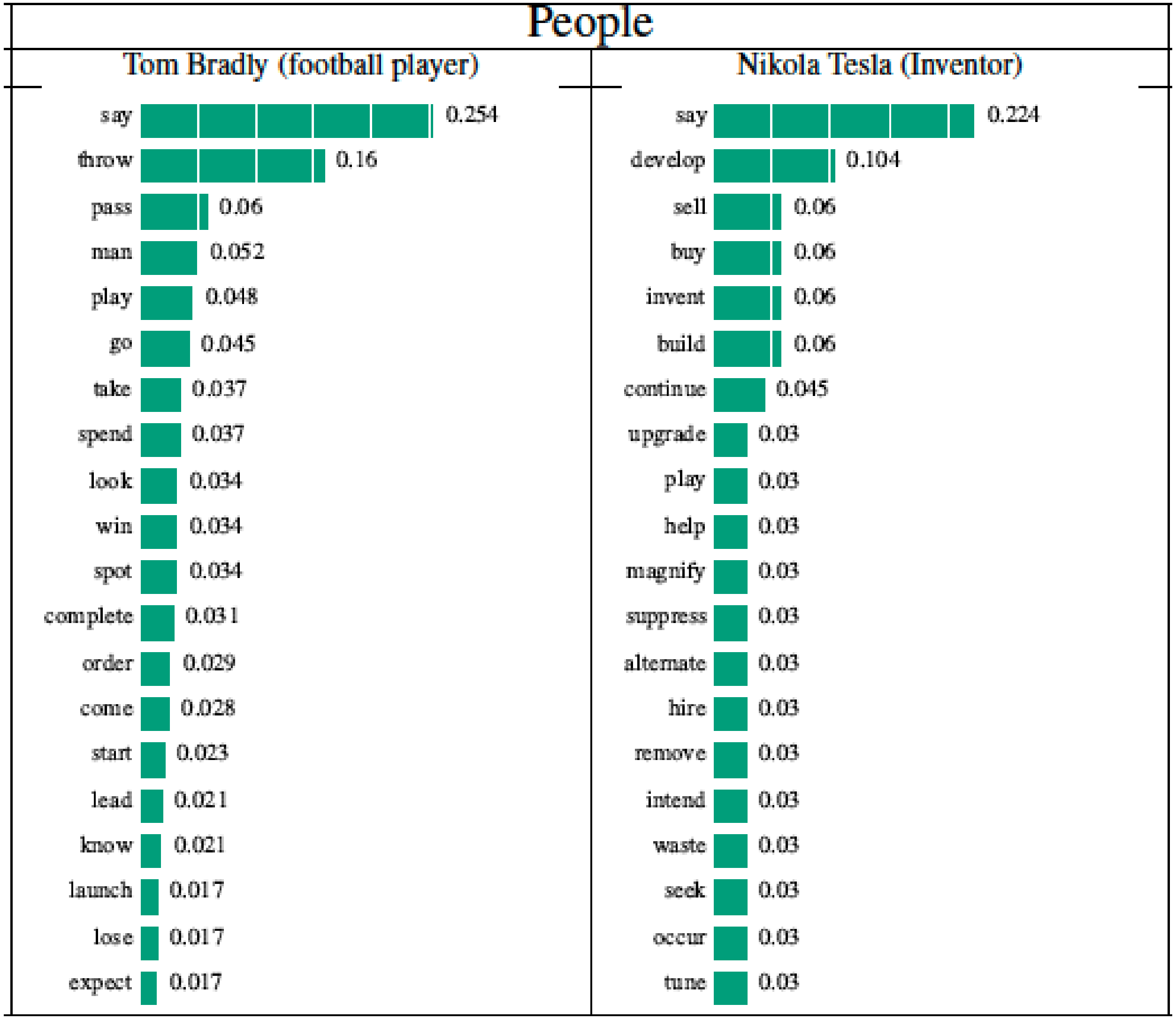


Publications

- [1] Solving Hard Coreference Problems. *Haoruo Peng****,** *Daniel Khashabi* and Dan Roth*. NAACL 2015.
- [2] A Joint Framework for Mention Head Detection and Coreference Resolution. Submitted to ACL 2015.
- [3] Profiler: Knowledge Schemas at Scale. Submitted to Transactions of ACL 2015 .

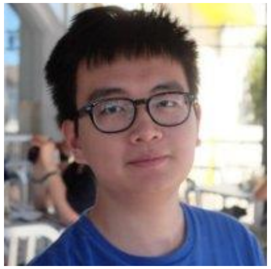
Future Directions

- The use of world knowledge in NLP tasks
  - Knowledge Representation (schemas)
    - Is co-occurrence information enough?
  - Knowledge Inference
    - Sparsity Issues
  - Knowledge Acquisition
    - Which sources to choose?
    - Interpolation /
  - Tasks beyond CR (CR can be seen as a subset of AI-complete problems)

- Outlier Detection for Singleton Mentions

Collaborators

Daniel Khashabi



Zhiye Fei

Kaiwei Chang

Prof. Dan Roth

Thank You !

Difficulties in CR

- Hard Coreference Problems
  - Ex.1 [A bird] perched on the [limb] and [it] bent.
  - Ex.2 [Robert] is robbed by [Kevin], and [he] is arrested by police.
  - Gender / Plurality information cannot help
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Performance Gaps

System	Dataset	Gold	Predicted	Gap
Illinois	CoNLL-12	77.05	60.00	17.05
Berkeley	CoNLL-11	76.68	60.42	16.26
Stanford	ACE-04	81.05	70.33	10.72

-> Requires Better Mention Detection

A Joint Framework for Mention Head Detection and Coreference Resolution

- Goal: Improve CR on predicted mentions (End-to-End)
- Solution:

[Multinational companies investing in [China]] had become so angry that [they] recently set up an ***anti-piracy league*** to pressure [the [Chinese] government] to take action. [Domestic manufacturers, [who] are also suffering], launched a similar body this month.

  - ☐ Traditional: MD -> Coref
  - ☐ Our paper: Mention Head -> Joint Coref -> Head to Mention
  - ☐ Joint Learning / Inference Step
    - Add decision variables to decide whether to choose a head or not
    - Joint Coref is able to reject some mention head candidates
- Results

Dataset	Illinois	Baseline	Our Paper
ACE-04	68.27	68.27	71.20
CoNLL-12	60.00	61.71	63.01

ILP formulation of CR

- Best-Link with Knowledge Constraints

$$\arg\max_y \sum_{u,v} w_{uv} y_{uv}$$

$$\text{s.t.} \quad \sum_{u<v} y_{uv} \leq 1, \; \forall v \qquad y_{uv} \in \{0,1\}$$

$$\text{if } s_{uv} \geq t + s_{um} \text{ then } y_{uv} \geq y_{um}$$

$$\text{if } s_{uv} \geq t' \cdot s_{um} \text{ then } y_{uv} \geq y_{um}$$

- Best-Link with Joint Mention Detection

$$\arg\max_y \sum_{u,v} w_{uv} y_{uv} + \sum_m \lambda_m y_m$$

$$\text{s.t.} \quad \sum_{u<v} y_{uv} \leq 1, \; \forall v \qquad y_{uv} \in \{0,1\}$$

$$\sum_u y_{uv} \leq y_v, \; \forall v \qquad y_v \in \{0,1\}$$