Semantic Feature Engineering for Enhancing Disambiguation Performance in Deep Linguistic Processing

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Outline

1. **Motivation**
2. **Experiments**
   - Baseline
   - Deep semantic features
3. **Results**
4. **Conclusion**

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Motivation

Fine-grained deep grammars

- Wide and meaningful coverage.
- Many uses in NLP:
  - Machine Translation
  - Question Answering
  - ...

→ But: often license a vast number of structures that make the usage of those grammars difficult.

Solution: Parse disambiguation

Using statistical approaches to train a model in order to rank the different parses.

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Approaches

Generative methods

Probabilistic parsing; PCFG like derivations

- Early pruning.
- Difficult to integrate non-local features.
- Independence assumption between features.
- Inflexible: hard to integrate new features.

[Magerman, 1995], [Collins, 1997], [Charniak, 1997], [Roark, 2001], ..

Approaches (2)

Discriminative methods

Ranking parses; Log Linear models:

- Re-ranking of the parser's output.
- Easy integration of new features.
- No independence assumption.

[Charniak, 2000], [Riezler et al., 2002], [Toutanova et al., 2005], [Collins and Koo, 2005], [Fujita et al., 2007]

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The Setup

Delph-in Colloboration

Set of tools and Grammars for NLP.

- Available at http://www.delph-in.net.

Our Framework

- The Datasets: *LOGON* and *WeScience* Treebanks.
  - The Grammar: HPSG English Resource Grammar (Lingo ERG).
  - The Parser: PET parser for unification-based grammars.
  - Contains deep syntactic and semantic information.
- The Classifier: Maximum Entropy classifier
  - *TADM* - Toolkit for Advanced Discriminative Models.

Choosing the Baseline

Informative Baseline

- Should allow comparison with other approaches:
  - Common practice to choose syntactic features ([Toutanova et al., 2005], [Fujita et al., 2007], [Zhang et al., 2007]).
- Should provide a good testing measure for our approach:
  - We are testing the effects of adding semantic information.

→Using syntactic elements only, incorporating non-local features.

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Baseline: Results

In Domain Results:

	features	LOGON		WeScience	
		1-best	10-best	1-best	10-best
p0	233,982	49.2154	75.1783	40.2282	69.0442
p1	349,564	54.0656	78.8873	43.2239	71.6119
p2	1,008,198	54.3509	77.4607	46.7902	74.7503
p3	2,493,884	55.7774	79.7432	49.2154	75.1783

Domain Adaptation Results:

	features	WS-LO		LO-WS	
		1-best	10-best	1-best	10-best
p0	233,982	31,6690	62.9101	27.1041	56.4907
p1	349,564	32.6676	63.7660	29.5292	62.9201
p2	1,008,198	35.0927	67.0470	30.2442	59.7717
p3	2,493,884	34.0941	66.9044	31.5263	63.4807

Semantic Modules

Minimal Recursion Semantics

- Fully underspecified flat semantics.
- Captures ambiguities.
- Highly Expressive.
- Can be easily incorporated into the constraint based HPSG.

Elementary Dependency Structures

- Shallow Dependency structures
- Captures basic relations between words, particularly predicate-argument relations (similar to an MRS solved form).
- Can be automatically extracted from the MRS.

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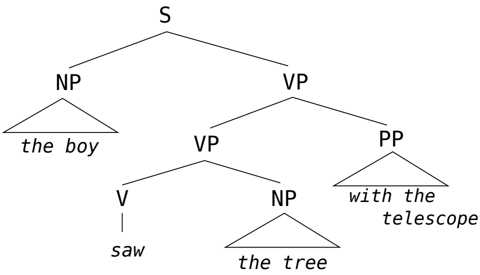
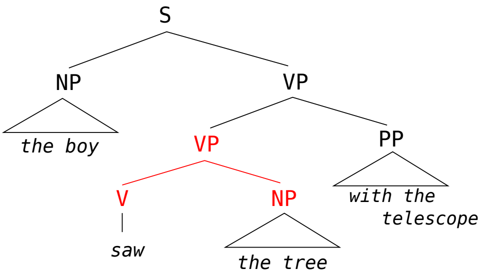
Example



Example

Syntactic Features:

Example



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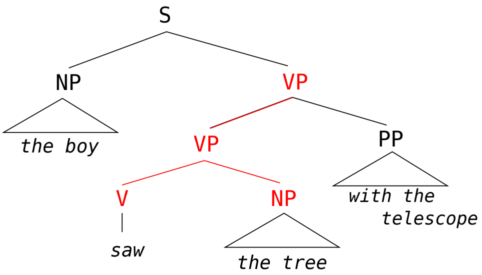
Syntactic Features:

<syn:p0>vp:v,np

Example

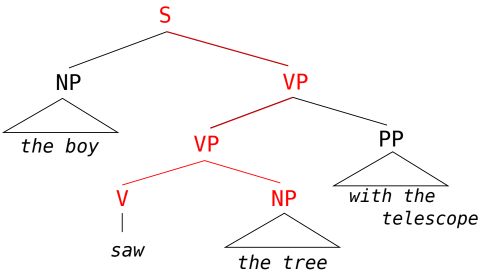


Example

Syntactic Features:

<syn:p0>vp:v,np
<syn:p1>vp,vp:v,np

Example



Example

Syntactic Features:

<syn:p0>vp:v,np
<syn:p1>vp,vp:v,np
<syn:p2>s,vp,vp:v,np
. . .

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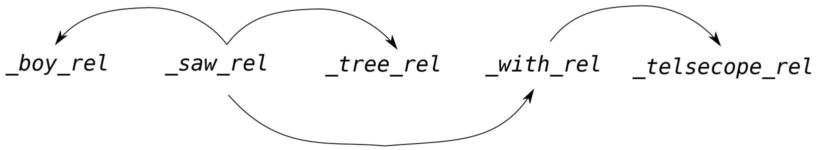

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Syntactic Features:

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Semantic Features:

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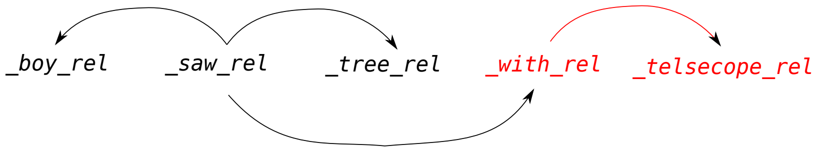


Example

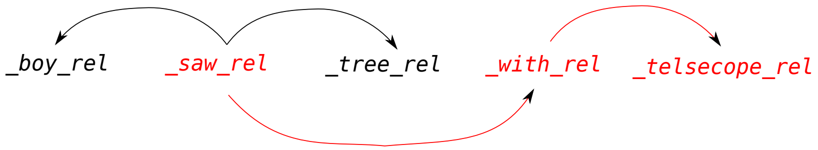
Syntactic Features:

<syn:p0>vp:v,np
<syn:p1>vp,vp:v,np
<syn:p2>s,vp,vp:v,np
. . .

Semantic Features:

<sem:d1>with:telescope

Example



Example

Syntactic Features:	Semantic Features:
<syn:p0>vp:v,np	<sem:d1>with:telescope
<syn:p1>vp,vp:v,np	<sem:d2>saw,with:telescope
<syn:p2>s,vp,vp:v,np	. . .
. . .	. . .

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Semantics Models

In Domain Results:

Model	# features	LOGON		WeScience	
		1-best	10-best	1-best	10-best
Random Pick		14.7113	37.0314	13.5550	35.0914
sem-eds	1,265,442	31.8116	67.4750	18.9728	50.9272
sem-mrs	159,420	37.8031	72.1825	25.3922	58.2025
sem-combined	1,424,862	42.5106	76.4621	28.1027	64.6219

Domain Adaptation Results:

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sem-mrs	159,420	21.2553	53.9229	17.4037	49.3580
sem-combined	1,424,862	25.2496	56.2054	18.5449	52.6390

Combined Models

In Domain Results:

	features	LOGON 1-best	LOGON 10-best	WeScience 1-best	WeScience 10-best
syn:p3	2,493,884	55.7774	79.7432	49.2154	75.1783
sem:mrs+eds	2,736,573	42.5106	76.4621	28.1027	64.6219
syn+sem	5,230,457	59.6291	82.0256	47.3609	75.3209

Domain Adaptation Results:

	features	WS-LO 1-best	WS-LO 10-best	LO-WS 1-best	LO-WS 10-best
syn:p3	2,493,884	33.3808	64.1949	31.5263	63.4807
sem:mrs+eds	2,736,573	25.2496	56.2054	18.2596	52.4964
syn+sem	5,230,457	36.9472	68.1883	29.6718	62.3395

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Conclusion

- Syntactic features have reached their limit:
  $\Rightarrow$ adding semantic information.
- MRS information performs very well with a small set of features.
- Using different data-sets might influence the results.

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