NLP in practice, an example: Semantic Role Labeling

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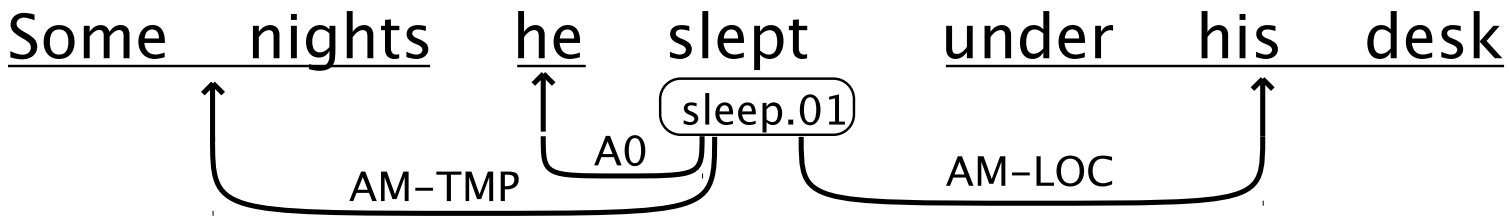
Semantic Role Labeling at LTH

- Work started by Richard Johansson (Uni Trento)
  - Carsim (2006)
  - SemEval 2007 Task
  - CoNLL 2008 Shared Task
- Continued by Björkelund & Hafdell in 2009
  - CoNLL 2009 Shared Task
  - Complete pipeline implementation, COLING 2010

Introduction to SRL

- Capture events and participants in text,

  who? what? where? when?



Semantic Roles

- Invariant under paraphrasing (as opposed to syntax), e.g.

  He slept under his desk some nights

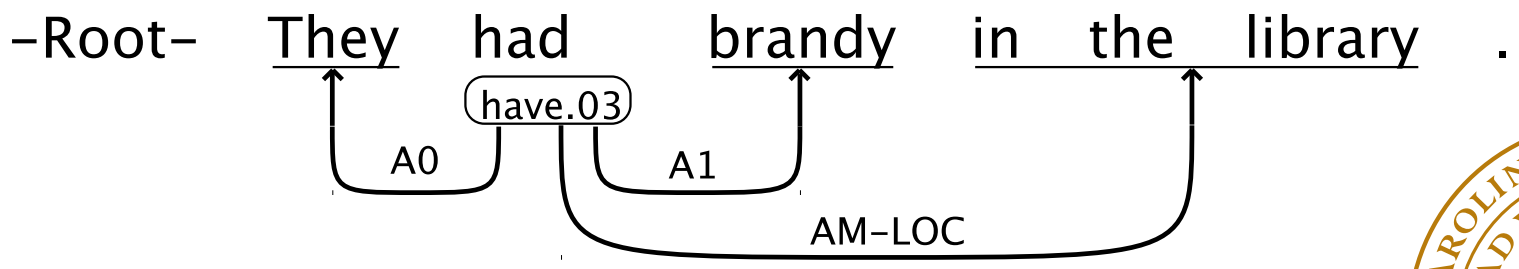
  Some nights he slept under his desk

- SRL is not an end-user application
- Intermediate step towards solving other problems
  - Information extraction
  - Document categorization
  - Automatic machine translation
  - Speech recognition

Semantic Dependencies

- Events are denoted by *predicates*
- Predicates define a set of participants, *roles*
- Participants and adjuncts are called *arguments*
- Relation to predicate logic, e.g.

```
have(They,brandy,in the library)
```



Semantic Frames

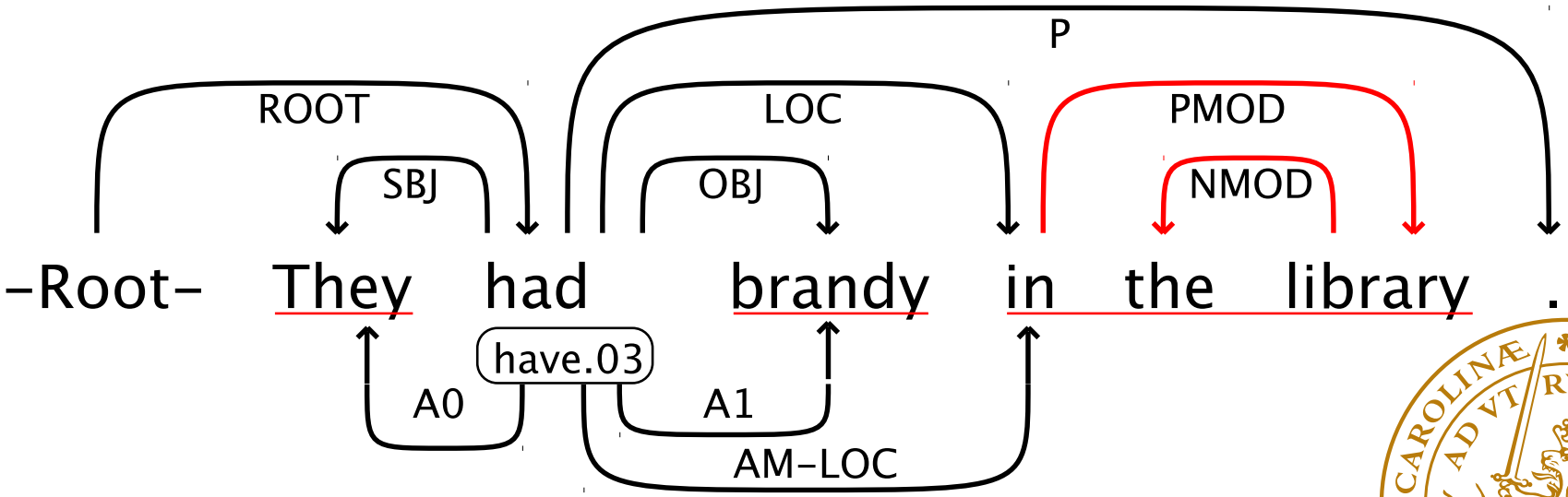
- Frames are defined in a lexicon
- Example from PropBank

```
<roleset id="have.03" vncls="-" name="own, possess">
<roles>
  <role n="0"  descr="owner"/>
  <role n="1"  descr="possession"/>
</roles>
</roleset>
```

- Lexicons are specific to each language, creation requires lots of human effort

Semantics and Dependency Grammar

- Semantic dependencies are also binary
- The *yield* (i.e. subtree) of the argument node specifies the argument phrase



The CoNLL 2009 Shared Task

- Extension of the monolingual CoNLL 2008 task
- Multilingual setting, 7 languages
- Provided annotated corpora in common format
  - Annotation included lemmata, POS-tags, dependency trees, semantic dependencies
  - 5,000 - 40,000 sentences, different across languages
  - Collected from various newspapers (El Periódico, WSJ, etc.)
  - Semantic annotation according to language-specific semantic lexicons

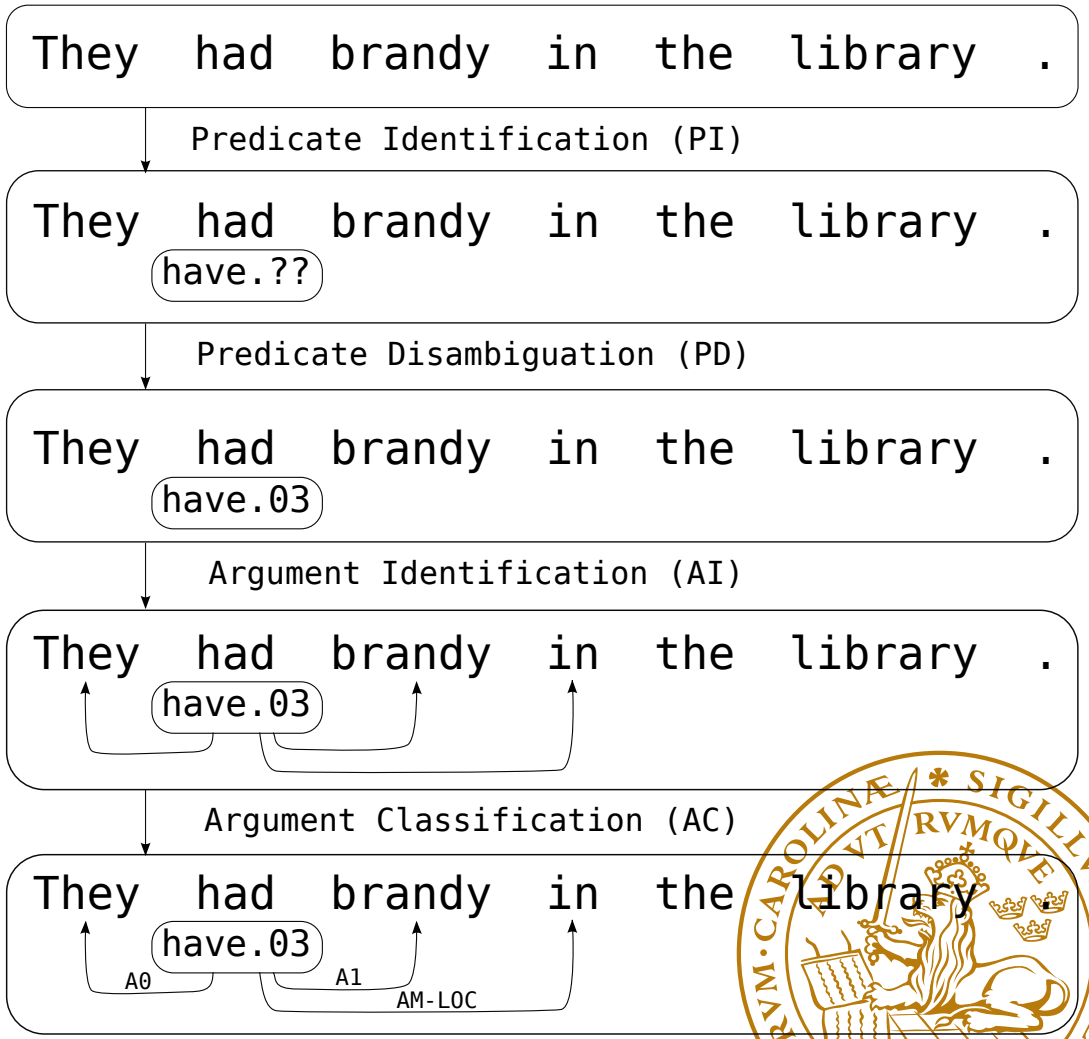
Corpus example

ID	Form	Lemma	PLemma	POS	PPOS	Feats	PFeats	Head	PHead	Deprel	PDeprel	FillPred	Sense	APred1
1	Some	some	some	DT	DT	_	_	2	2	NMOD	NMOD	_	_	_
2	nights	night	night	NNS	NNS	_	_	4	0	TMP	ROOT	_	_	AM-TMP
3	he	he	he	PRP	PRP	_	_	4	4	SBJ	SBJ	_	_	A0
4	slept	sleep	sleep	VBD	VBD	_	_	0	2	ROOT	NMOD	Y	sleep.01	_
5	under	under	under	IN	IN	_	_	4	4	LOC	LOC	_	_	AM-LOC
6	his	his	his	PRP$	PRP$	_	_	7	7	NMOD	NMOD	_	_	_
7	desk	desk	desk	NN	NN	_	_	5	5	PMOD	PMOD	_	_	_
8	.	.	.	.	.	_	_	4	2	P	P	_	_	_

P-columns denote predicted values

The Baseline System

- Pipeline of classifiers
  - Predicate Identification
  - Predicate Disambiguation
  - Argument Identification
  - Argument Classification
- Requires annotated input
  - Lemma
  - Part of speech
  - Syntactic dependencies
  - Semantic dependencies (training only)
- Language-independent



Predicate Identification (PI)

- Binary classifier that considers every word of a sentence
- Yields a set of predicates, for subsequent processing

	They	had	brandy	in	the	library	.
P(Pred)	0.182	0.921	0.232	0.091	0.057	0.286	0.002
P(¬Pred)	0.818	0.079	0.768	0.909	0.943	0.714	0.998

Probability that each word is a predicate

Predicate Disambiguation (PD)

- Predicate frames grouped by lemma
- One classifier for each lemma

	They	had	brandy	in	the	library	.
P(have.03)		0.852					
P(have.04)		0.108					
P(have.02)		0.0230					
P(have.01)		0.0170					

Probability for all frames for the predicate `have`

Argument Identification (AI)

- Binary classifier that considers each word in a sentence
- Generates an unlabeled proposition

	They	had	brandy	in	the	library	.
P(Arg)	0.979	0.00087	0.950	0.861	0.00006	0.0076	0.00009
P(¬Arg)	0.021	0.999	0.050	0.139	0.999	0.992	0.999

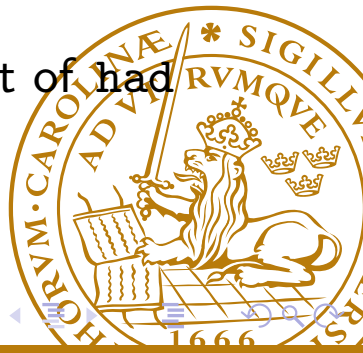
Probability that each word is an argument of `had`

Argument Classification (AC)

- Multiclass classifier, one class for each label

They		had	brandy		in		the	library	.
A0	0.999	-	A1	0.993	AM-TMP	0.471	-	-	-
A1	0.000487	-	C-A1	0.00362	AM-LOC	0.420	-	-	-
AM-DIS	0.000126	-	AM-ADV	0.000796	AM-MNR	0.0484	-	-	-
AM-ADV	0.000101	-	A0	0.000722	C-A1	0.00423	-	-	-

Probability of top four labels from the AC module for each argument of had

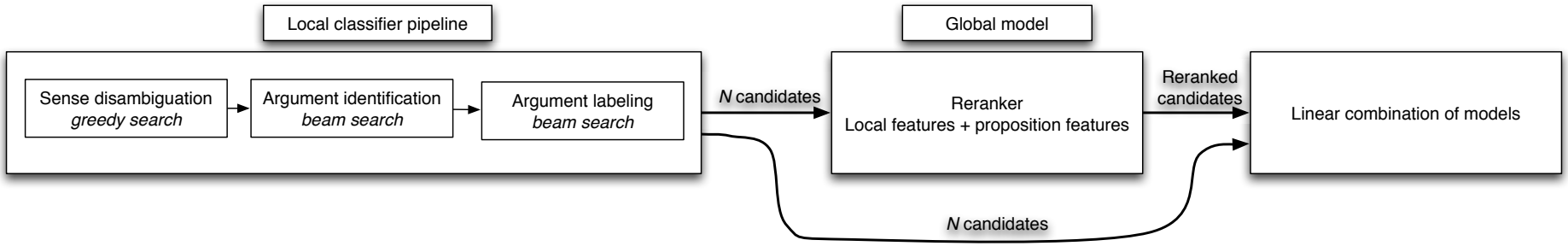


Shortcomings of the Pipeline

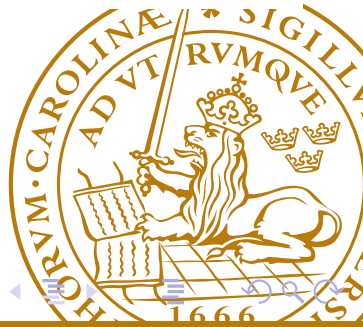
- Steps are executed sequentially
  - Error propagation
- Arguments are considered independently
  - Fails to catch the whole predicate argument structure

Beam Search Extension

- Generation of N candidate propositions
- Reranker scores each candidate
- Pipeline and reranker are combined for final choice



N.B. old architecture image, PI step missing



Generation of Candidates (AI)

- AI module generates the top k unlabeled propositions

	They	had	brandy	in	the	library	.
P(Arg)	0.979	0.00087	0.950	0.861	0.00006	0.0076	0.00009
P(¬Arg)	0.021	0.999	0.050	0.139	0.999	0.992	0.999

- P_{AI} := the product of the probabilities of all choices

Example

- Using $k = 4$, we get the following unlabeled propositions

Proposition	P_{AI}
[They] had [brandy] [in] the library.	0.792
[They] had [brandy] in the library.	0.128
[They] had brandy [in] the library.	0.0417
They had [brandy] [in] the library.	0.0170

Generation of Candidates (AC)

- AC module generates the top *l* labellings of each proposition

They		had	brandy		in		the	library	.
A0	0.999	-	A1	0.993	AM-TMP	0.471	-	-	-
A1	0.000487	-	C-A1	0.00362	AM-LOC	0.420	-	-	-
AM-DIS	0.000126	-	AM-ADV	0.000796	AM-MNR	0.0484	-	-	-
AM-ADV	0.000101	-	A0	0.000722	C-A1	0.00423	-	-	-

- P_{AC} := the product of the probabilities of all labels

Example

- Using $l = 4$ and the most likely unlabeled proposition from last step, we get

Proposition	P_{AC}
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-TMP}}$ the library.	0.467
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-LOC}}$ the library.	0.417
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-MNR}}$ the library.	0.0480
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{C-A1}}$ the library.	0.0421

Generation of Candidates

- AC probabilities are normalized by taking the geometric mean

$$P'_{AC} := (P_{AC})^{(1/a)}$$

  a denotes the number of arguments in the proposition

- The probability of a labeled proposition is defined as

$$P_{Local} := P_{AI} \times P'_{AC}$$

The Reranker

- Binary classifier that considers complete propositions
- Features
  - All local AI features
  - All local AC features
  - Complete proposition features
- The reranker outputs a probability, $P_{Reranker}$
- Final candidate is selected to maximize

$$P_{Final} := P_{Local} \times P_{Reranker}$$

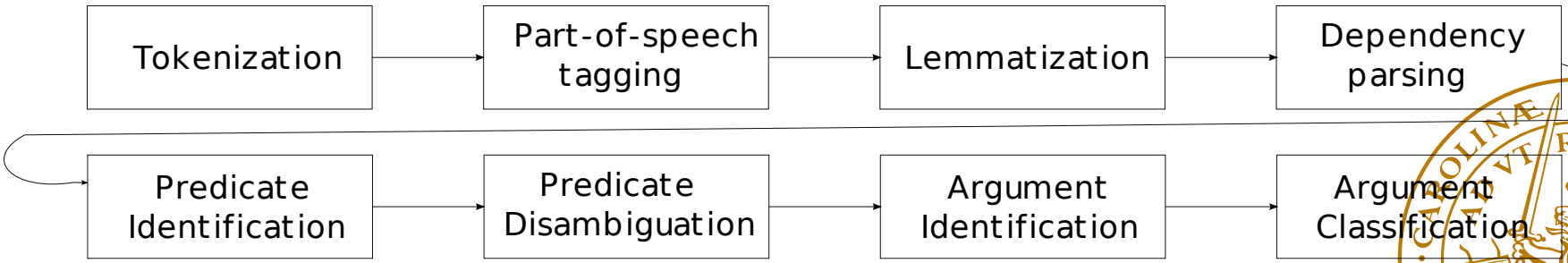
Selecting Final Candidate

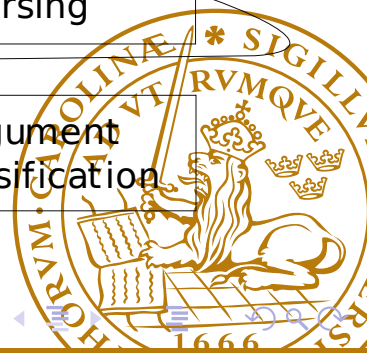
Proposition	P_{Local}	$P_{Reranker}$	P_{Final}
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-TMP}}$ the library.	0.306	0.359	0.110
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-LOC}}$ the library.	0.295	0.246	0.0726
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ in the library.	0.0636	0.451	0.0287
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-MNR}}$ the library.	0.143	0.0890	0.0128
[They]$_{\text{A0}}$ had [brandy]$_{\text{A1}}$ [in]$_{\text{C-A1}}$ the library.	0.137	0.0622	0.00854
[They]$_{\text{A0}}$ had brandy [in]$_{\text{AM-TMP}}$ the library.	0.0139	0.0206	$2.86 \cdot 10^{-4}$
[They]$_{\text{A0}}$ had brandy [in]$_{\text{AM-LOC}}$ the library.	0.0131	0.0121	$1.58 \cdot 10^{-4}$
They had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-TMP}}$ the library.	0.00452	0.0226	$1.02 \cdot 10^{-4}$
They had [brandy]$_{\text{A1}}$ [in]$_{\text{AM-LOC}}$ the library.	0.00427	0.0133	$5.68 \cdot 10^{-5}$
[They]$_{\text{A0}}$ had brandy [in]$_{\text{AM-MNR}}$ the library.	0.00445	0.00364	$1.62 \cdot 10^{-5}$

Top ten propositions sorted by final score

Complete sentence processing

- Annotation required - need preprocessing
- Extend pipeline by modules to perform
  - Tokenization
  - POS-tagging
  - Lemmatization
  - Dependency Parsing
  - Currently only Chinese, English, and German



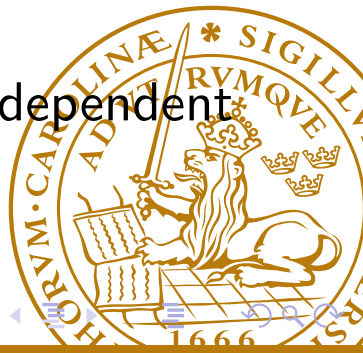


Initial extensions

- OpenNLP Tokenizer
- Lemma lookup table by Richard Johansson
- OpenNLP POS-tagger
- Dependency Parser by Bernd Bohnet (Uni Stuttgart)
- Poor performance - salvaged by better lemmatizer and tagger from Bernd Bohnet

Technical details

- Java Implementation, ca 8k LOC (SRL system only)
- Training time
  - SRL: ca 1 hour (10 hours reranker)
  - Full pipeline: ca 20 hours (excluding tokenizer)
- Parsing time
  - SRL: only a few ms
  - Full pipeline: ca 200-500ms
- Memory requirements for parsing
  - SRL: ca 1gb (2gb reranker)
  - Full pipeline: 3gb (4gb reranker), though rather language dependent.



Evaluation Measures

- Labeled attachment score (LAS) – Syntax accuracy (input)
- Semantic F_1 ($SemF_1$) – Overall system accuracy
- Predicate F_1 ($PredF_1$) – PD accuracy
- Argument F_1 ($ArgF_1$) – AI and AC accuracy
- Scores range from 0 (bad) to 100 (good)

N.B. all figures in following slides from spring 2009, i.e. not the latest

Baseline Results

- Evaluation figures on test sets

	LAS	PredF$_1$	ArgF$_1$	SemF$_1$
Catalan	86.13	87.20	76.13	79.54
Chinese	78.46	94.92	69.83	77.84
Czech	78.46	94.20	74.24	84.99
English	85.50	95.59	79.29	84.44
German	85.93	81.45	77.44	79.01
Japanese	91.12	99.07	60.26	75.61
Spanish	86.20	85.43	76.56	79.28
Average	84.54	91.12	73.39	80.10

Reranker Results

- Results and improvement by reranker ($SemF_1$ scores)

	Baseline	Reranker	Gain
Catalan	79.54	80.01	0.47
Chinese	77.84	78.60	0.76
Czech	84.99	85.41	0.42
English	84.44	85.63	1.19
German	79.01	79.71	0.70
Japanese	75.61	76.30	0.69
Spanish	79.28	79.91	0.63
Average	80.10	80.80	0.70

Contribution to CoNLL Shared Task

- Results in CoNLL 2009 Shared Task ($SemF_1$ scores)

	Team	Average	Catalan	Chinese	Czech	English	German	Japanese	Spanish
1	Hong Kong	80.47	**80.32**	77.72	85.19	85.44	75.99	78.15	**80.46**
2	Lund†	80.31	80.01	**78.60**	85.41	85.63	**79.71**	76.30	76.52
3	Hong Kong	79.96	80.10	76.77	82.04	**86.15**	76.19	78.17	80.29
4	Harbin	79.94	77.10	77.15	**86.51**	85.51	78.61	**78.26**	76.47
5	Geneva	78.42	77.44	76.05	86.02	83.24	71.78	77.23	77.19
6	Edinburgh	77.46	78.00	77.73	75.75	83.34	73.52	76.00	77.91
7	Berkeley	76.00	74.53	75.29	79.02	80.39	75.72	72.76	74.31
8	NIST	75.65	72.35	74.17	84.69	84.26	63.66	77.93	72.50
9	Brown	72.85	72.18	72.43	78.02	80.43	73.40	61.57	71.95
10	Hefei	70.78	66.34	71.57	75.50	78.93	67.43	71.02	64.64
11	DFKI	70.31	67.34	73.20	78.28	77.85	62.95	64.71	67.81
12	Harbin	69.72	66.95	67.06	79.08	77.17	61.98	69.58	66.23
...									

Summary

- Dependency-based automatic SRL system
- Pipeline of linear classifiers
- Further extended with reranker
- State-of-the-art performance in seven languages
- Plenty of room for improvements

Reranker Potential

- Upper bound on reranker when using oracle for proposition selection

	Baseline	Reranker	Upper Bound
Catalan	79.54	80.01	90.11
Chinese	77.84	78.60	88.70
Czech	84.99	85.41	92.55
English	84.44	85.63	93.80
German	79.01	79.71	88.78
Japanese	75.61	76.30	90.04
Spanish	79.28	79.91	89.12
Average	80.10	80.80	90.44

Using beam widths $k = l = 4$

Further work

- Unsupervised Tokenization (Helmut Schmid, Uni Stuttgart)
- Try other learning algorithms
- Try other preprocessing modules
- Multi-threading
- Extending for more languages
- Reranker improvements
  - Feature sets for the reranker
  - Review combination of pipeline and reranker
  - Dynamic beam width

Links

- Source code download
  `http://code.google.com/p/mate-tools/`
- Online demo
  `http://barbar.cs.lth.se:8081/`
- OpenNLP Tools
  `http://opennlp.sourceforge.net/`
- PropBank
  `http://verbs.colorado.edu/propbank/framesets-english/`
- SRL demo from CCG at Univeristy of Illinois
  `http://cogcomp.cs.illinois.edu/demo/srl/`

References

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- **Multilingual semantic role labeling**, Björkelund et al.
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- **A high-performance syntactic and semantic dependency parser**, Björkelund et al.
  In Coling 2010: Demonstration Volume
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  The 23rd International Conference on Computational Linguistics (COLING 2010)