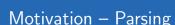
# Faster Parsing and Supertagging Model Estimation

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**ALTW 2009** 



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Syntactic information is crucial for many tasks in NLP, such as QA and MT, but parsers are slow:

- State-of-the-art, usually < 1 sentence / sec</li>
- Fastest state-of-the-art, < 50 sentences / sec</li>

Far too slow to process the data available:

Motivation

- > 1,000,000,000,000 words of English online
- More coming





Motivation

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# Tagging and Parsing

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One claims he is pro-choice





# Part of Speech Tagging

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One claims he is pro – choice NNVBZ PRP VBZ JJ





Motivation

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# Combinatory Categorial Grammar (CCG) - Supertagging

$$\frac{\text{One}}{N} \frac{\text{claims}}{(S \backslash NP)/S} \frac{\text{he}}{NP} \frac{\text{is}}{(S \backslash NP)/(S \backslash NP)} \frac{\text{pro-choice}}{S \backslash NP}$$





# Combinatory Categorial Grammar (CCG) – Parsing

Motivation

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$$\frac{N}{NP} \xrightarrow{\text{claims}} \frac{\text{he}}{NP} \xrightarrow{\text{is}} \frac{\text{pro-choice}}{S \backslash NP}$$

$$\frac{NP}{NP} \xrightarrow{S \backslash NP} \xrightarrow{S \backslash NP}$$

$$\frac{S \backslash NP}{S} \xrightarrow{S \backslash NP}$$





# Supertagging Ambiguity

Ι

ate pizza

pizza ate

with

with

anchovies

cutlery



# Supertagging Ambiguity

$$\frac{I}{NP} \underbrace{\frac{\text{ate}}{(S \backslash NP)/NP}}_{NP} \underbrace{\frac{\text{pizza}}{NP}}_{NP} \underbrace{\frac{((S \backslash NP) \backslash (S \backslash NP))/NP}{(S \backslash NP) \backslash (S \backslash NP)}}_{S \backslash NP} \underbrace{\frac{\text{cutlery}}{NP}}_{S}$$



# Supertagging Ambiguity

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Motivation

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# Motivation – Parsing

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The key idea behind the speed of the fastest parsers today is to shift work from parsing to tagging: For n words, each with k tags

- Tagging O(nk)
- Parsing  $O(n^3k^2)$





## Outline

#### Core Idea

 Provide fewer tags, but still include the tags the parser would have used anyway

#### Implementation

- Perceptron Algorithms
- Parallelisation

#### Results

- Modified rule usage
- Training data type and volume
- Algorithm comparison
- Feature extension





#### Ideal World

$$\frac{\text{One}}{N} \frac{\text{claims}}{(S \backslash NP)/S} \frac{\text{he}}{NP} \frac{\text{is}}{(S \backslash NP)/(S \backslash NP)} \frac{\text{pro-choice}}{S \backslash NP}$$



#### Current World – Problem

$$\frac{\text{One}}{N} \frac{\text{claims}}{(S \setminus NP)/NP} \frac{\text{he}}{NP} \frac{\text{is}}{(S \setminus NP)/(S \setminus NP)} \frac{\text{pro-choice}}{S \setminus NP}$$



4 D F 4 A F F 4 B F

## Current World - Solution

One	claims	he	is	pro-choice
$\overline{N/N}$	$(\overline{S \backslash NP)/NP}$	$\overline{NP}$	$(\overline{S \backslash NP)/(S \backslash NP)}$	$\overline{S \backslash NP}$
N	N		$(S \backslash NP)/NP$	$(S \backslash NP) \backslash (S \backslash NP)$
(S/S)/(S/S)			$(S \backslash NP)/(S \backslash NP)$	$(S \backslash NP)/S$
				N
				$(S \backslash NP)/PP$
				$(S \backslash NP)/NP$
				N/N
				$(S \backslash NP)/(S \backslash NP)$

# Adaptive Supertagging

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$$\frac{\text{One}}{N/N} \stackrel{\text{claims}}{\longrightarrow} \frac{\text{he}}{NP} \stackrel{\text{is}}{(S\backslash NP)/(S\backslash NP)} \frac{\text{pro-choice}}{S\backslash NP}$$

$$\frac{(S\backslash NP)/NP}{(S\backslash NP)/(S\backslash NP)} \frac{(S\backslash NP)/PP}{(S\backslash NP)/NP}$$

$$\frac{(S\backslash NP)/(S\backslash NP)}{N/N}$$

How do we teach the supertagger to produce these tags? Use the parser!







#### Outline

#### Core Idea

 Provide fewer tags, but still include the tags the parser would have used anyway

#### **Implementation**

- Perceptron Algorithms
- Parallelisation

#### Results

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- Feature extension





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# **Implementation**

Component	Initial System	Additions
Statistical Feature Extraction	3 Types	+9 Types
	Single thread	Parallel
Parameter Estimation	BFGS, GIS	AP, MIRA
	Single thread	Parallel

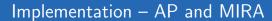


## Implementation – Extra Constraint

Added a constraint that only allows Backward Composition to occur if both children are type raised

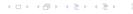






Algorithm	Training Time (sec)			
	40k	80k	440k	
GIS	7,200	14,000	*	
BFGS	6,300	13,000	*	
AP	76	160	950	
MIRA	96	200	1,200	





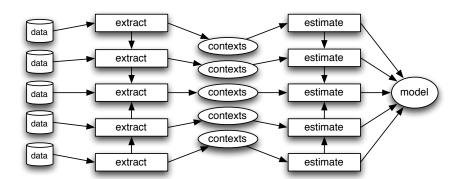
## Implementation – Initial System







## Implementation – Parallelised









# Implementation - Parallelised Weight Estimation

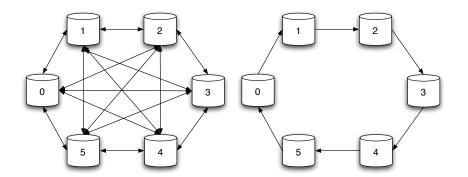


Figure: Information flow for parallel model estimation



Results



### Outline

#### Core Idea

 Provide fewer tags, but still include the tags the parser would have used anyway

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# Extra Constraint on Rule Application

	F-score	Speed
Parser	(%)	(sent / sec)
C&C 1.02	83.22	31.7
Modified	83.41	47.8







#### Plan

- Acquire a large set of unannotated data Wikipedia
- Parse the corpus
- Retrain the supertagger, using the parsed sentences

#### Variations

- Amount of data
- Estimation algorithms
- Feature set



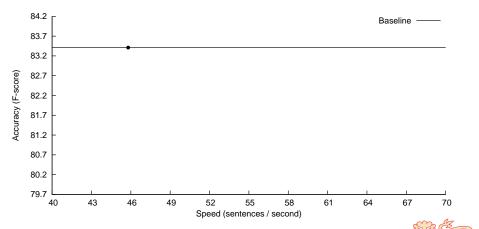


Results

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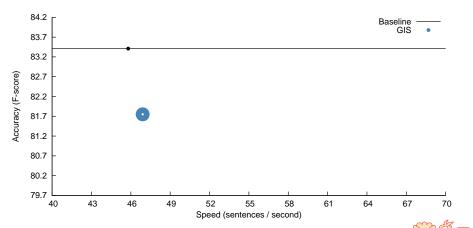
# Training Data Type and Volume

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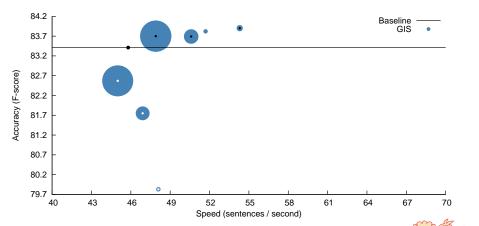


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The University of Sydney





Results

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# Training Data Type and Volume

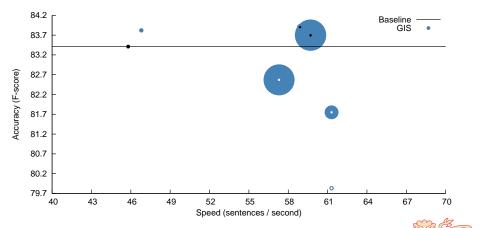
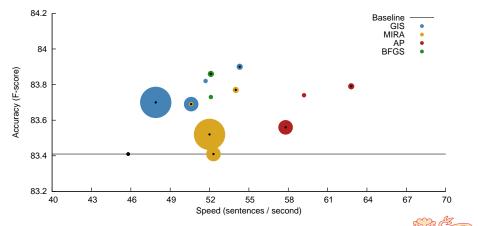


Figure: Evaluation on Wikipedia



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Results

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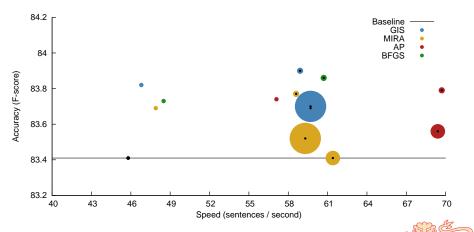


Figure: Evaluation on Wikipedia

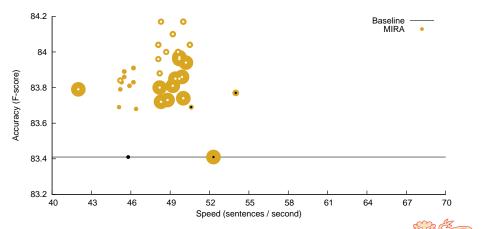


Results

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## Feature Extension

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## Feature Extension

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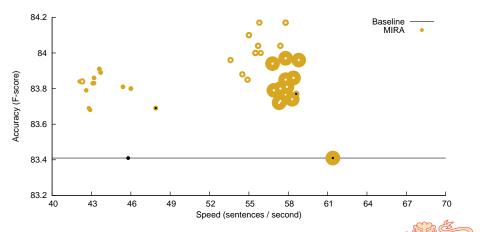


Figure: Evaluation on Wikipedia



## Future Work

- Other domains
- Expanded training sets
- Co-training
- Online learning







#### Conclusion

#### Improved training:

- Enabled access to more text
- Constructed an effective source of more text

#### Improved parsing speed:

- Added an extra constraint on rule usage
- Trained models that are adapted to the parser

#### Improved parsing accuracy:

- Constructed statistical models using more evidence
- Expanded the set of statistical features





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Metric	Initial	Final	Ratio
Training			
Sentences	40k	80k	2
Time (secs)	6,300	160	1/40
Accuracy			
F-score (%)	83.22	83.79	n/a
Speed			
WSJ (sents / sec)	31.7	62.8	2.0
Wikipedia (sents / sec)	30.8	69.7	2.3





# Acknowledgements

- Johns Hopkins University, CLSP Summer Workshop
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