Ensembles of Diverse Cluster-based Discriminative Dependency Parsers

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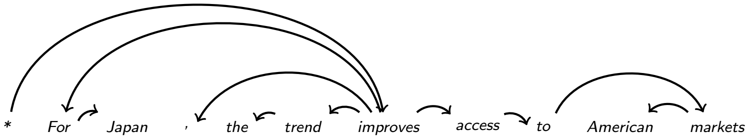
Simon Fraser University

16 August 2012

Discriminative Dependency Parsing



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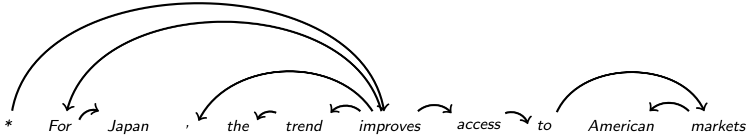
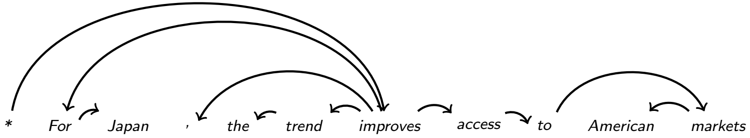


- Structured Linear Model



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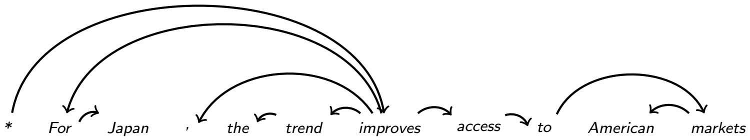

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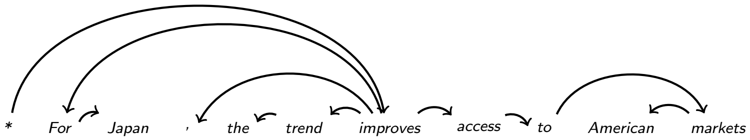

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Discriminative Dependency Parsing

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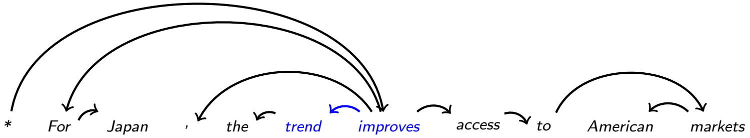

- Individual parts (h, m)

Discriminative Dependency Parsing

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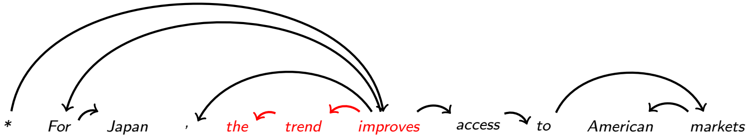

- grandchild parts (h, m, c)

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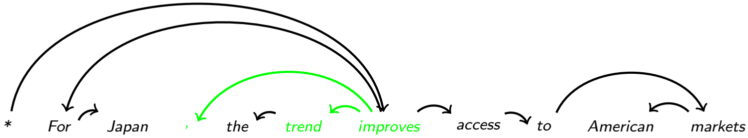

- sibling parts (h, m, si)

Discriminative Dependency Parsing

- Flexible feature vector representation
  - Lexical information (e.g. improves, trend)
  - POS tags (e.g. VBZ, NN)

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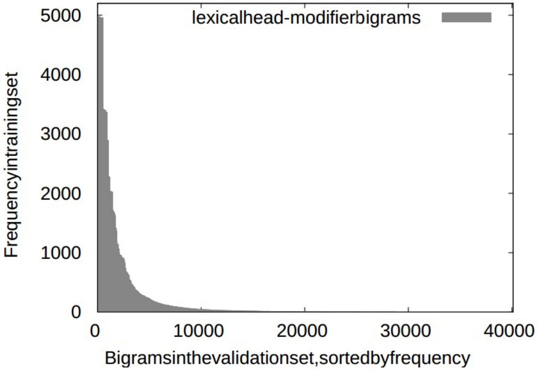

Cluster-based Discriminative Dependency Parsing

- (Koo, Carreras, and Collins, 2008):
  - A simple semi-supervised method
  - Use unlabeled data to extract **word clusters**
  - (Brown et al., 1992) clustering algorithm
  - Incorporate word clusters as features

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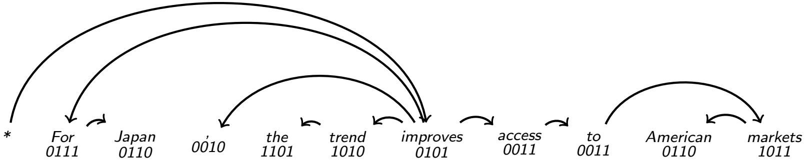

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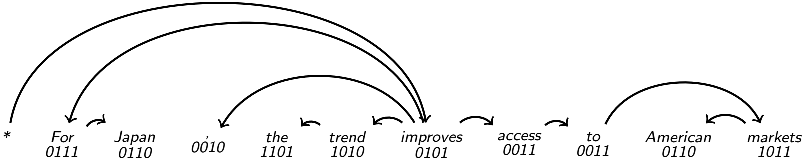


- Can inform the parser about **unknown words** in test data that are clustered with known words

Contribution

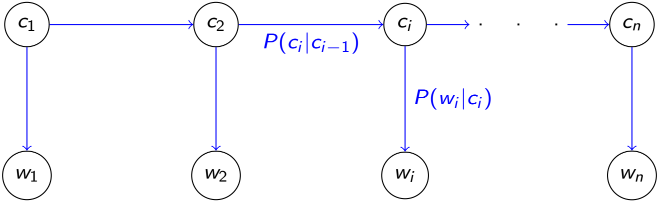
- **Extend** the framework of (Koo, Carreras, and Collins, 2008): use **multiple diverse** clustering methods
- **Ensemble model**: **exact inference** on the **shared hypothesis** space of base models
- **Improving** unlabeled dependency accuracy from 90.82% to 92.46% on Sec. 23 of PTB
- Significant improvements in **domain adaptation** to the Switchboard and Brown corpora

Multiple Clustering Methods

Multiple Clustering Methods

Brown Algorithm:

- Bottom-up Algorithm
- Repeatedly merges the two clusters that maximize the likelihood of the input according to class-based bigram language model:



- By tracing the merges we can obtain a binary tree

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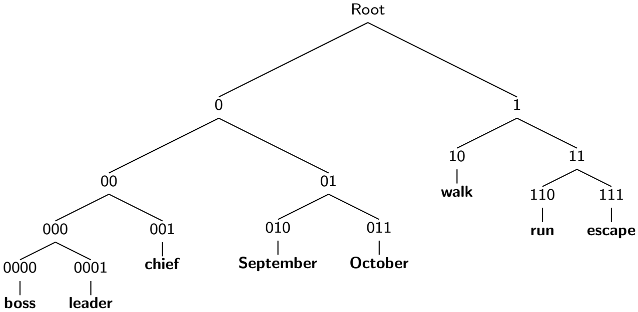

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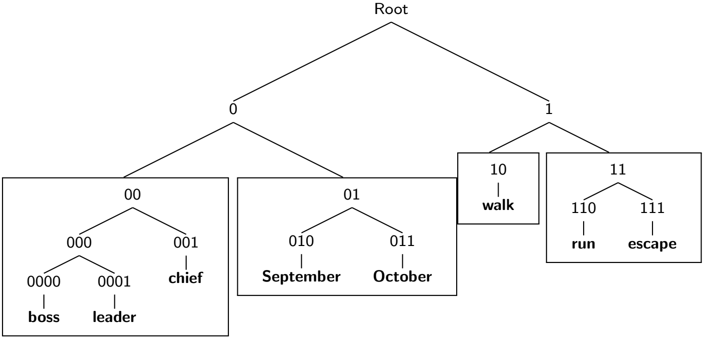

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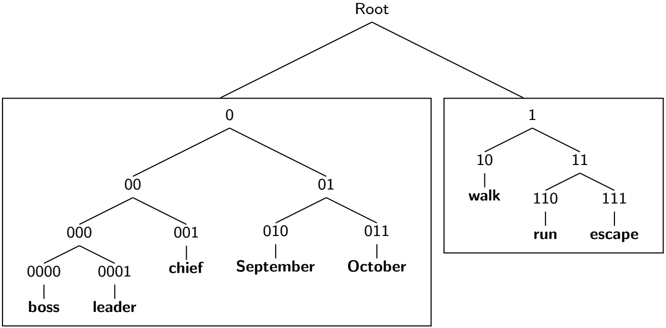

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Multiple Clustering Methods

HMM State Splitting

- The clusters can be viewed as hidden states in HMM
- Brown Algorithm : **Hard** clustering of words
- Maximize the likelihood function using EM: **Soft** clustering of words
- Hierarchical Split-Merge Technique:

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C_1

C_2

.
.
.

C_i

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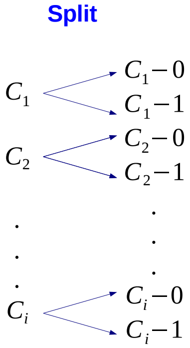

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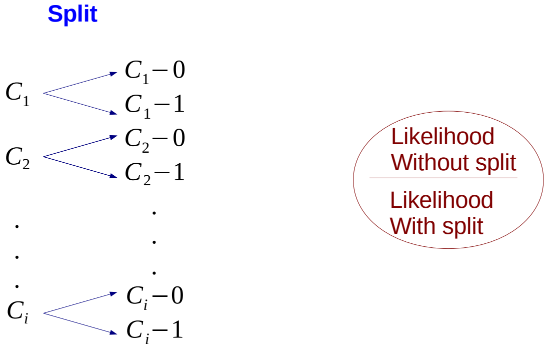

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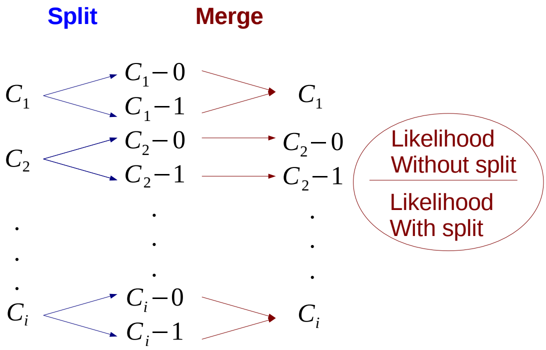

Multiple Clustering Methods

- Context specific clustering of HMM vs. hard clustering of Brown:
- Brown Clustering :

1010
milk
pick up
juice
drink
...

- HMM Clustering:

10101111111 **milk (v)** service transport fuel ...	**1010**011111 **milk (n)** cheese fruit water ...

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State splitting in PCFGs

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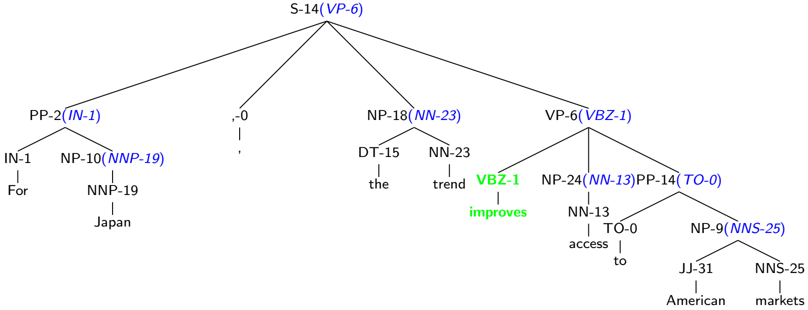

- Syn-Low: Split POS tag from Berkeley parser
  - e.g., improves : VBZ-1

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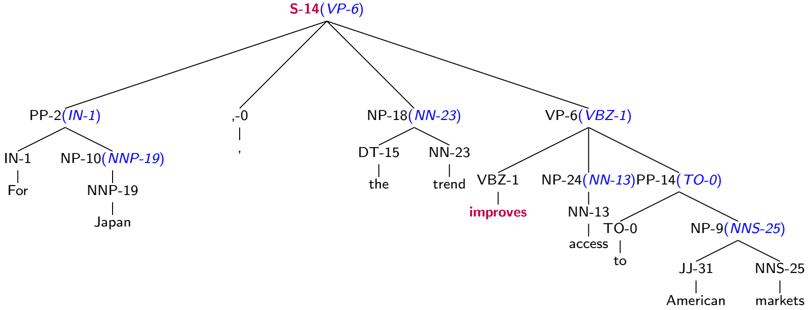

- Syn-High: Split non-terminals from Berkeley parser
  - e.g., improves : S-14

Diversity Among Clustering Annotations

- different HMM Clustering with various randomization seeds:

HMM1	HMM2	HMM3	HMM4	HMM5
stuff	mess	problem	idea	story
list	impression	stuff	stuff	stuff
mess	problem	chore	limitation	limitation
pool	stuff	triangle	argument	mentality

- Diversity of the words clustered with *stuff* in each model
- Intuition: Ensemble of HMMs can lead to a better model
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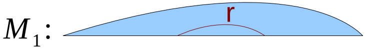

$$sc_1(s,r) = w_1 . f_1(s,r)$$

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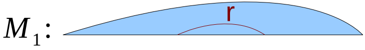

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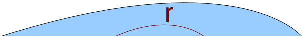

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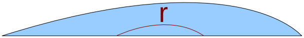
...

M_K:



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Ensemble Model

Related Works on ensemble learning:

- Combine **different** dependency parsing systems
- Combining base parsers at parsing time using **voting** (Sagae and Lavie, 2006)
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Our Approach:

- Combine various **graph-based** models
- **Online** combination of clustering-based models

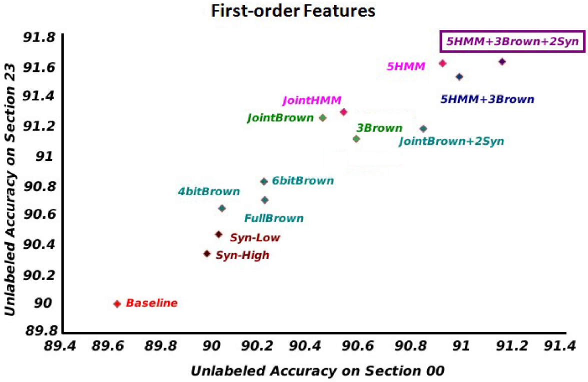
Experiments

In-domain Experimental Set-up

- MSTParser framework (McDonald, Crammer, and Pereira, 2005)
  - Inference : (Eisner, 1996)
  - Extend the feature set to incorporate cluster based features from (Koo, Carreras, and Collins, 2008)
  - Implementation of the ensemble and joint model
- Data : English Penn Treebank
  - Training set : Section 2-21
  - Dev set : section 22
  - Test set : Section 0, 1, 23, 24
  - POS tags : MXPOST (Ratnaparkhi, 1996)
    - Training data created by "leave one section out" method
- Clusters
  - Brown Clustering: Liang's implementation [1] on BLLIP Corpus
  - HMM Clustering: On-House implementation on BLLIP corpus
  - Syntactic Clustering: Berkeley Parser [2]

[1] *cs.stanford.edu/∼pliang/software/brown-cluster-1.2.zip*
[2] *code.google.com/p/berkeleyparser*

1^{st} Order Results: Consistent Improvement in Accuracy



- The ensemble outperforms the baseline and the individual models in all cases
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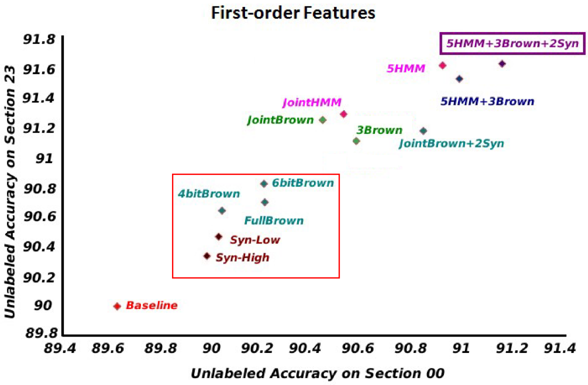

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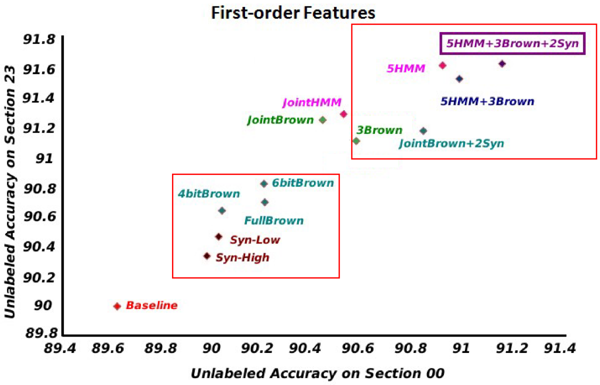

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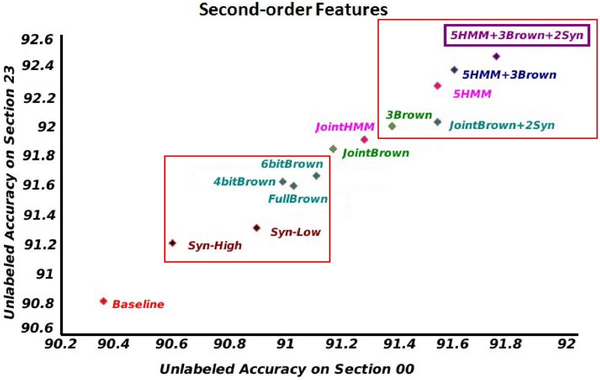

- Incrementally adding number of models
  - Further improvement in accuracy

Out-of-domain Experiments

Set-up:

- Brown Corpora : Press reviews
- SwitchBoard Corpora : Phone conversations
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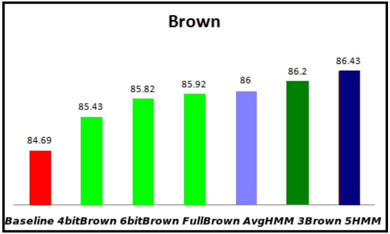

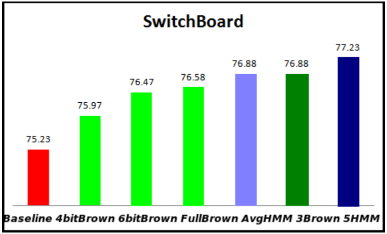

- the ensemble performance improvement for the SwitchBoard is more than that for the Brown corpus

Error Analysis

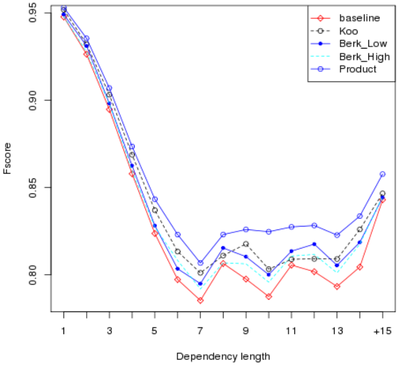

Figure : F-score for each dependency length for in-domain setting.

- Ensemble combines each model's expertise and does best at each dependency length

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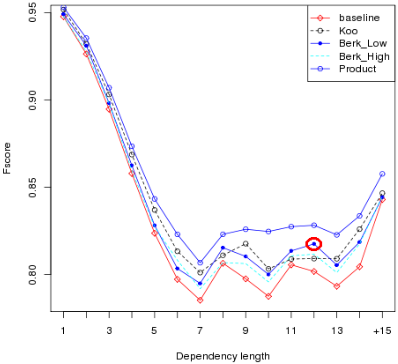

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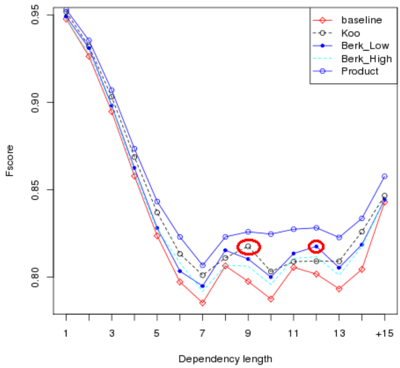

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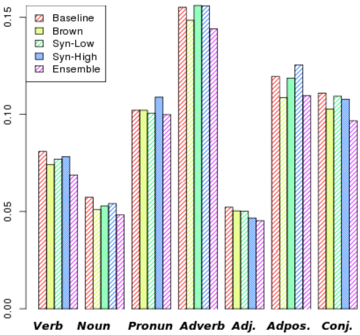

Figure : Error rate of the head attachment for different types of modifier categories for in-domain setting.

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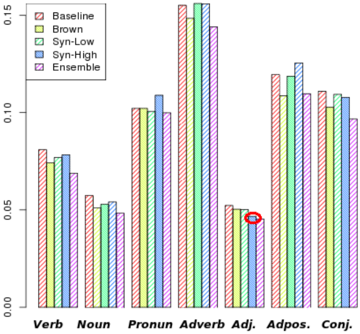

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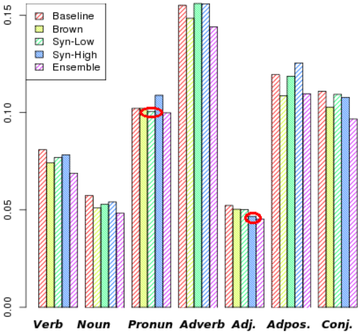

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- **Set-up**
  - Modified-MIRA: update the weights based on a specific dependency type
  - dev set : Section 0
  - test set : Section 22, 23
- **Experimental Results:**
  - Verb and Pronoun : Effective in improving the accuracy (5.6% error reduction)

sec	uniform	Verb
22	91.31	**91.33**
	40.55	**40.96**

sec	uniform	Pronoun
23	91.12	**91.14**
	38.73	**38.77**

  - Learning the model weights can lead to improvements in some cases,but it does not have an important contribution to the overall accuracy

Conclusion and Future directions

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- Ensemble of different parsing models:
  - More Powerful model : improving unlabeled accuracy from 90.82% to 92.46% on Sec. 23 of PTB
  - Strength in Domain Adaptation Scenario : from 75.23% to 77.23% on SwitchBoard data
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Future directions:

- Experimenting Ensemble on other languages
  - word clusters are shown to be useful for a diverse set of languages (Täckström, McDonald, and Uszkoreit, 2012)
- Using other word representations
  - distributed word representations (Turian, Ratinov, and Bengio, 2010)

Questions?

Bibliography I

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