

Modeling Syntactic-Semantic Dependency Correlations in Semantic Role Labeling Using Mixture Models

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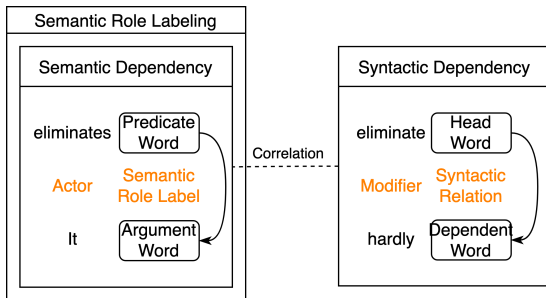
Introduction: Syntax-Aware Semantic Role Labeling

Semantic Role Labeling (SRL)

Extracting semantic dependencies (by modeling a distribution of semantic labels)

Syntactic-Semantic Dependency Correlation

Semantic dependencies are associated with some syntactic dependencies



It will hardly eliminate the pigeon



Introduction: Overview

Research Question

How to **interpret** and **utilize** the Syntactic-Semantic Dependency Correlation

Hypothesis for the Correlation

Semantic label distributions differ by hop patterns



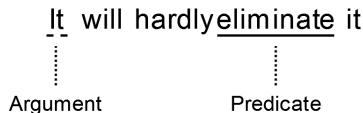
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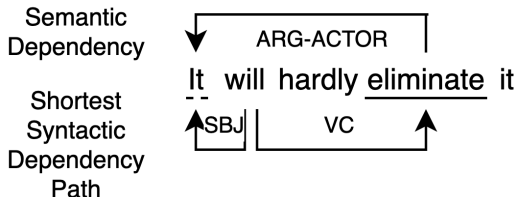
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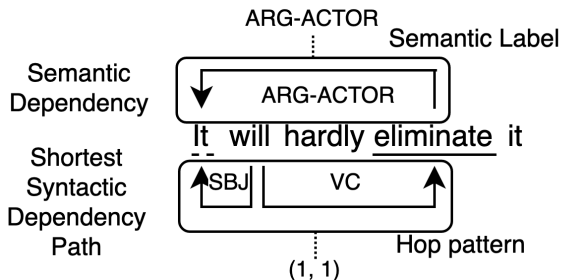
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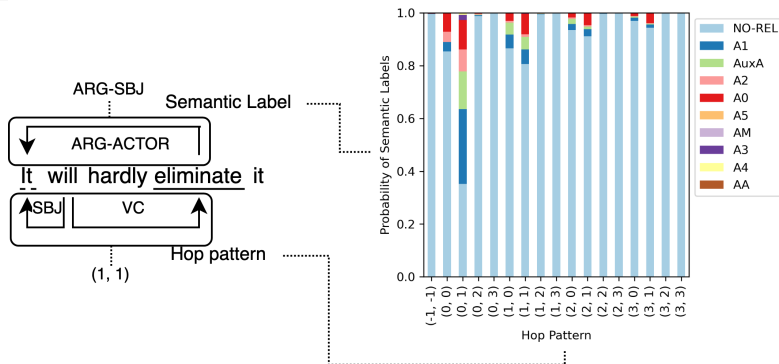
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Introduction: Shortest Syntactic Dependency Path and Hop Pattern

Shortest Syntactic Dependency Path (SSDP)

- The shortest path connecting predicates and arguments
- A salient feature for utilizing syntactic information in SRL [7]

Hop Pattern

- Tracks the transition from predicates to arguments
- Denoted as (α, β)
 - α : the number of dependent-to-head transitions
 - β : the number of head-to-dependent transitions

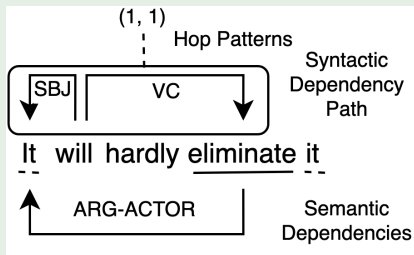


Figure: Example illustrating SSDP and hop patterns

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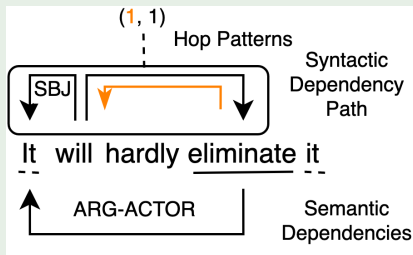


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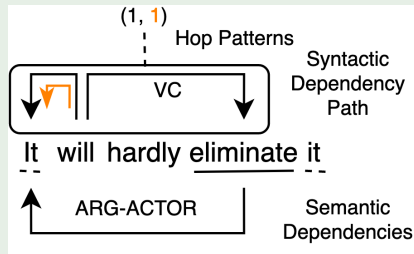


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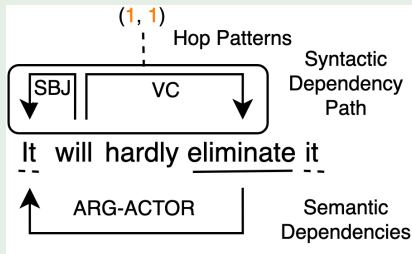


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Motivation

Variation in Semantic Label Distributions

Hop patterns have diverse mutual information gains with semantic label distributions

- ① $(0, 1)$ has the highest information gain
- ② short SSDPs have diverse non-zero information gains
- ③ long SSDPs have near-zero information gains

- 1 and 2 confirms the variation in semantic label distributions
- 3 confirms that long SSDPs have similar semantic label distributions

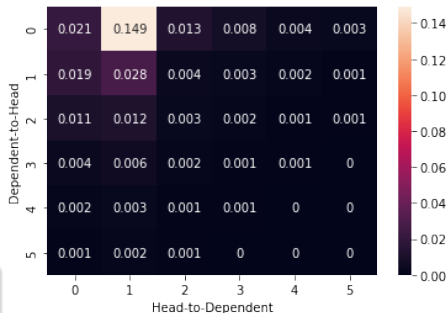


Figure: Mutual information gain of hop patterns up to (5,5)



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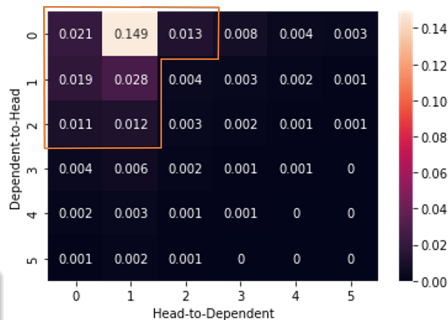


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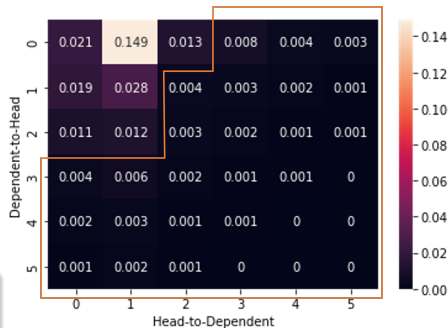


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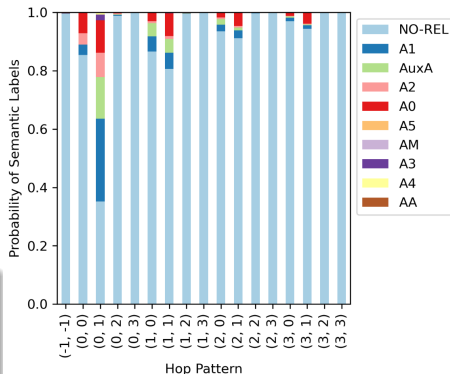


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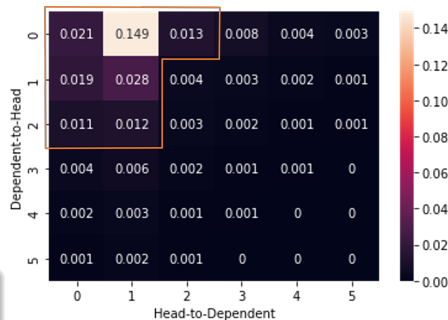


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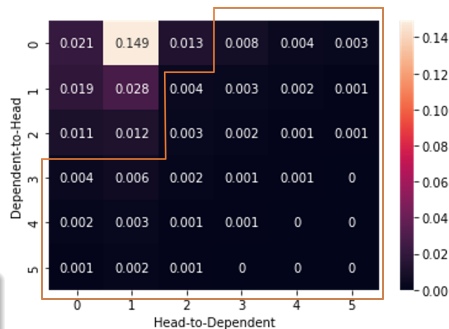


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Proposal: Separate Estimation for Different Semantic Label Distributions

We propose a mixture model-based semantic parser that

- Decouples semantic label distributions using component distributions
- Clusters hop patterns with similar semantic label distributions using mixture weights

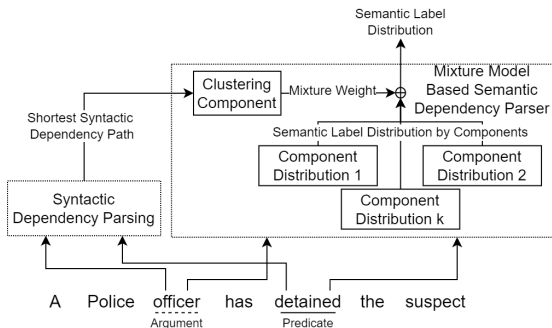


Figure: Overview of the mixture-model based semantic parser



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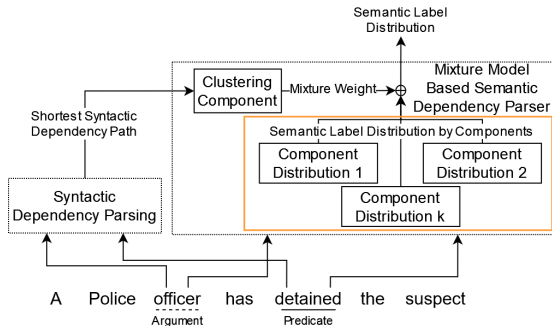


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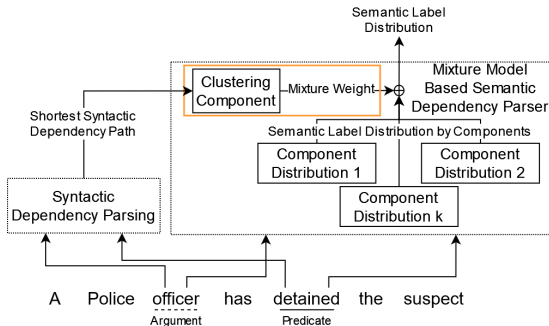


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Correlation as Co-occurrence Biases [4]

Semantic dependencies prefer short syntactic dependency paths over the long ones

Problems

- Modeling the correlation **regardless of** semantic labels
- Utilizing the correlation by **language-dependent** heuristics

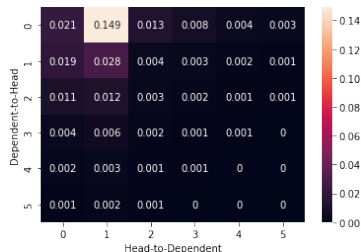
Our Contributions

- Modeling the correlation **with respect to** semantic labels
- The proposed approach is **language-independent**



Results: Syntactic-Semantic Dependency Correlation

Semantic label distributions of different hop patterns have unique properties



$\alpha \backslash \beta$	0	1	2	3
0	3	1	0	0
1	2	2	0	0
2	2	2	0	0
3	2	0	0	0
4	0	0	0	0
5	0	0	0	0

(a) FastText

$\alpha \backslash \beta$	0	1	2	3
0	2	0	4	4
1	2	1	4	4
2	3	3	4	4
3	4	4	4	4
4	4	4	4	4
5	4	4	4	4

(b) ELMo

$\alpha \backslash \beta$	0	1	2	3
0	4	0	2	2
1	4	3	2	2
2	4	3	2	2
3	4	4	2	2
4	2	2	2	2
5	2	2	2	2

(c) BERT

Table: Component assignments extracted from models



Results: Improvement over Baselines

Our Mixture-Model (MM) method outperforms baseline methods over input embeddings and languages in the CoNLL-2009 dataset [3]

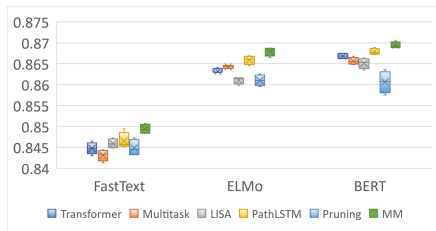


Figure: English LAS comparison on input embeddings

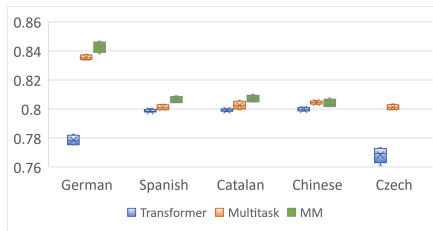


Figure: LAS comparison on five languages using FastText



Results: Improvement over Baselines

MM outperforms baseline methods on FastText, ELMo, and BERT embeddings

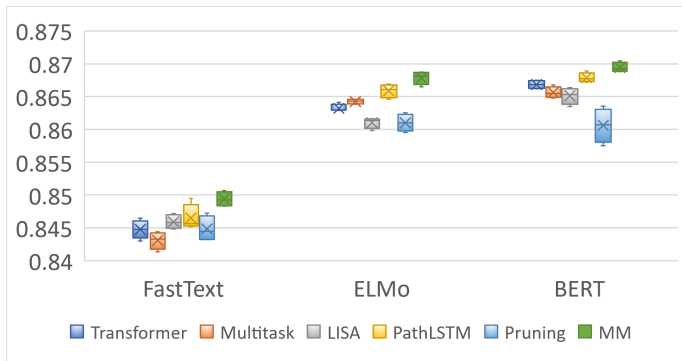


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Results: Improvement over Baselines

MM outperforms baseline methods in many languages

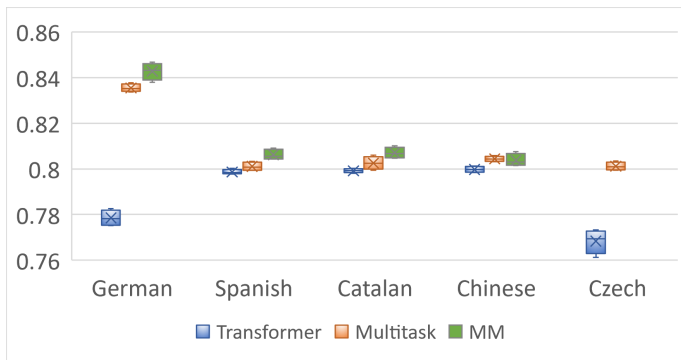


Figure: LAS comparison on five languages using FastText



Results: Improvement on Short-distance Semantic Dependencies

MM improves on short-distance semantic dependencies

- MM is the only method improving over Transformer on short-distance semantic dependencies (FastText and ELMo)
- MM retains the performance advantage of syntax-aware methods on long-distance semantic dependencies

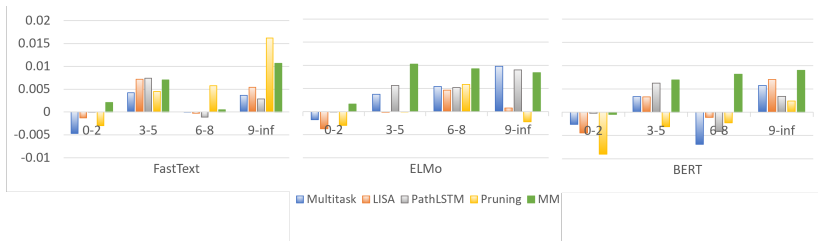


Figure: Relative LAS of MM and baselines to Transformer method



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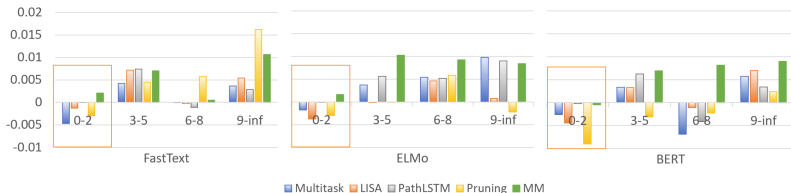


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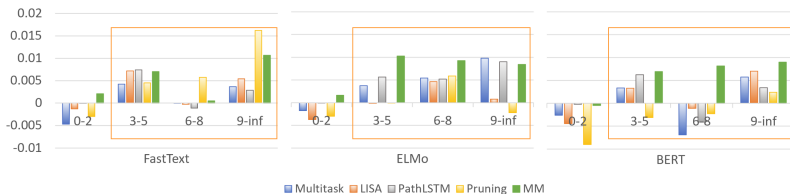


Figure: Relative LAS of MM and baselines to Transformer method



Results: Comparison with STOA

MM performs competitively with state-of-the-art methods

- MM is the best performant on the GloVe and the ELMo embeddings on the WSJ section
- MM performs best on the ELMo and the BERT embeddings on the Brown section

GloVe	WSJ			Brown		
	P	R	F1	P	R	F1
[9]	88.73	89.83	89.28	82.46	83.2	82.82
[5]	87.8	88	87.9	77	76.8	76.9
[4]	89.7	89.3	89.5	81.9	76.9	79.3
[7]	88.1	85.3	86.7	76.9	73.8	75.3
MM	91.03	90.13	90.58	80.59	79.21	79.83
MM (FastText)	91.16	90.19	90.71	83.93	82.64	83.28

ELMo	P	R	F1	P	R	F1
[5]	90.5	92.1	91.3	81.7	81.9	81.8
[1]	91.7	90.8	91.2	83.2	81.9	82.5
[6]	-	-	91	-	-	82.2
[2]	-	-	91.1	-	-	82.7
MM	92.21	91.45	91.82	86.51	85.30	85.90

BERT	P	R	F1	P	R	F1
[8](base)	92.1	91.9	92	85.6	84.7	85.1
[8](large)	92.4	92.3	92.4	85.7	85.8	85.7
[9]	91.21	91.19	91.2	85.65	86.09	85.87
MM	92.33	91.77	92.05	87.00	85.98	86.32



Conclusion

In this paper, we

- Interpreted the syntactic-semantic dependency correlation by **the variation in semantic label distributions**
- Learned the correlation with a mixture model-based semantic parser
- Produced a SRL method that
 - **excels in predicting short-distance semantic dependencies**
 - performs competitively with state-of-the-art methods



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