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

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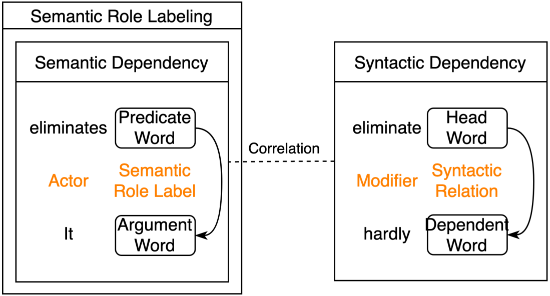
Introduction: Syntax-Aware Semantic Role Labeling

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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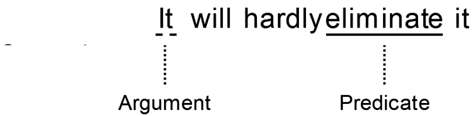

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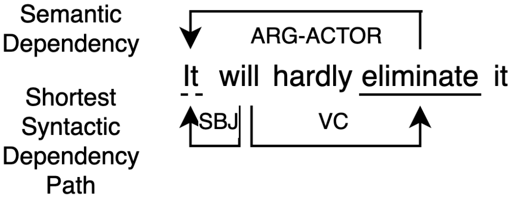

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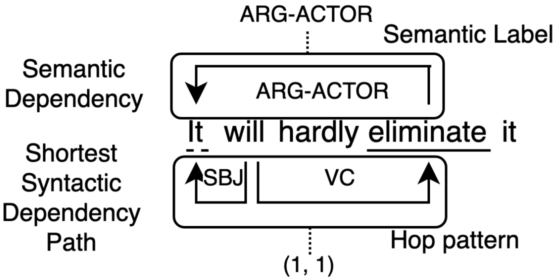

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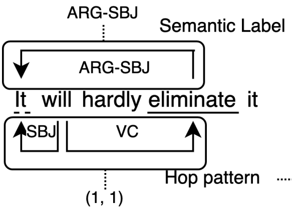

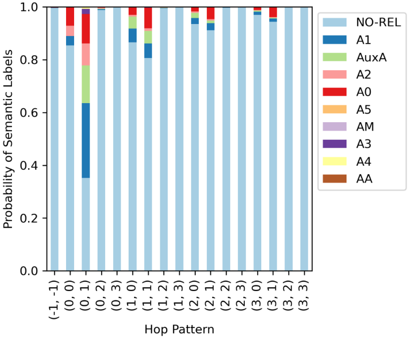

Introduction: Shortest Syntactic Dependency Path and Hop Pattern

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

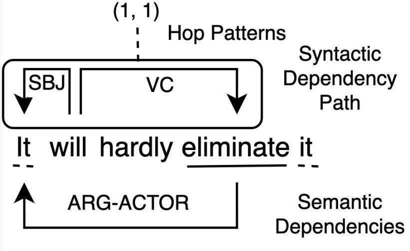

Figure: Example illustrating SSDP and hop patterns

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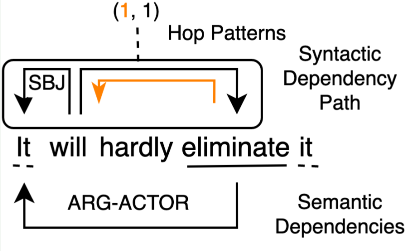

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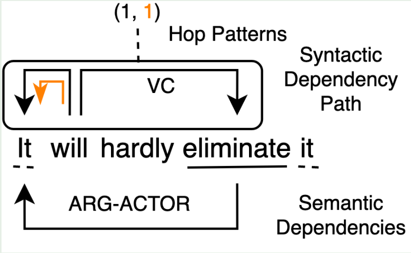

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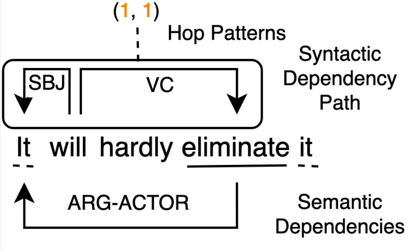

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Motivation

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**

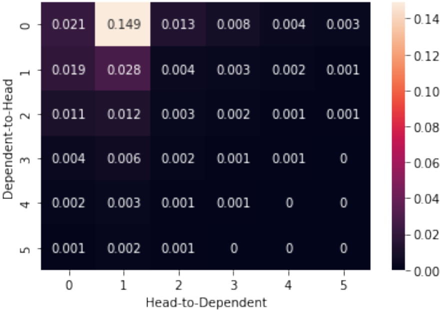

Figure: Mutual information gain of hop patterns up to (5,5)

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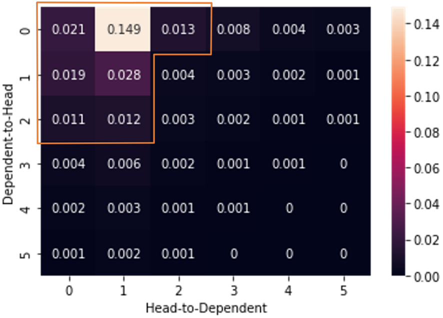

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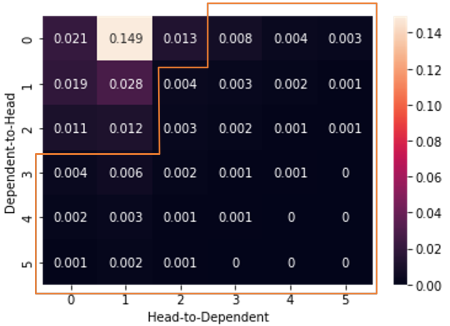

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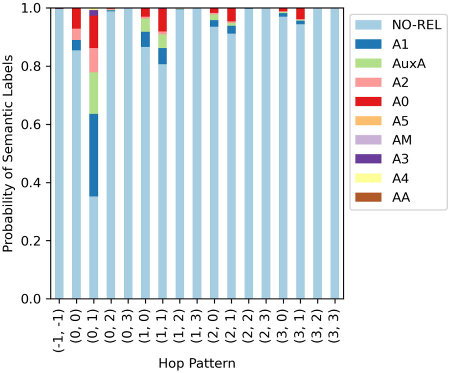

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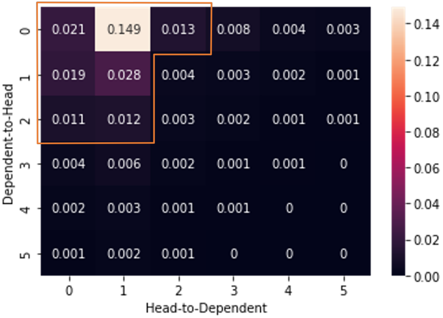

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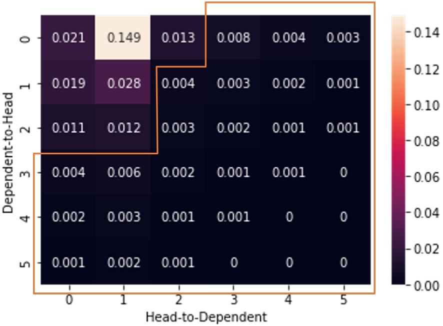

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Proposal: Separate Estimation for Different Semantic Label Distributions

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

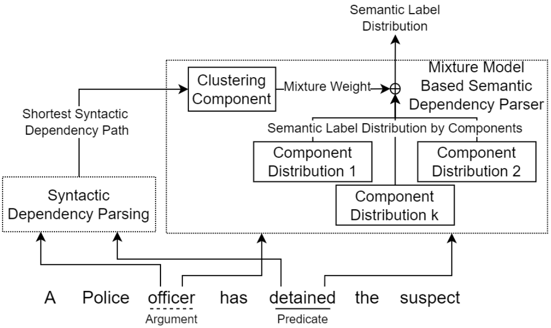

Figure: Overview of the mixture-model based semantic parser

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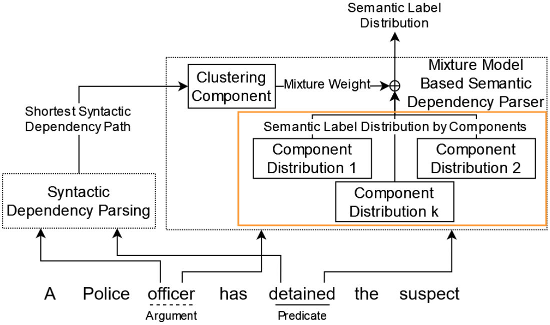

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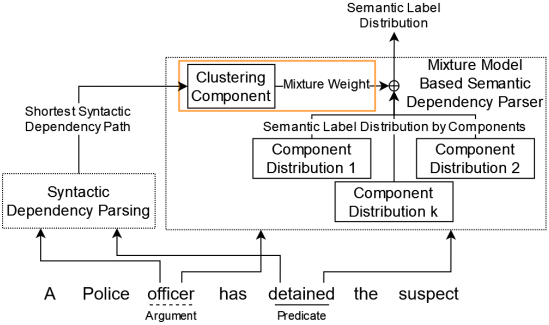

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Related Works

Correlation as Co-occurrence Biases [4]

Semantic dependencies prefer short syntactic dependency paths over the long ones

Problems

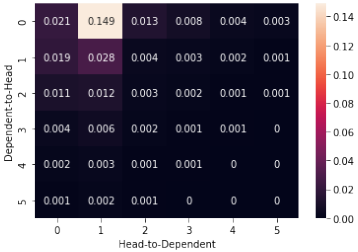
- Modeling the correlation **regardless of** semantic labels
- Utilizing the correlation by **language-dependent** heuristics

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 diffrent hop patterns have unique properties



α \ β	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

α \ β	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

α \ β	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]

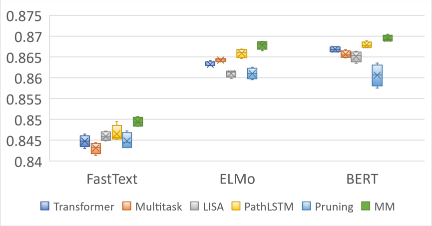


Figure: English LAS comparison on input embeddings

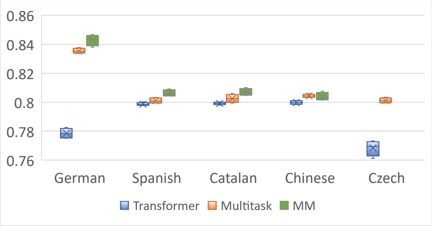


Figure: LAS comparison on five languages using FastText

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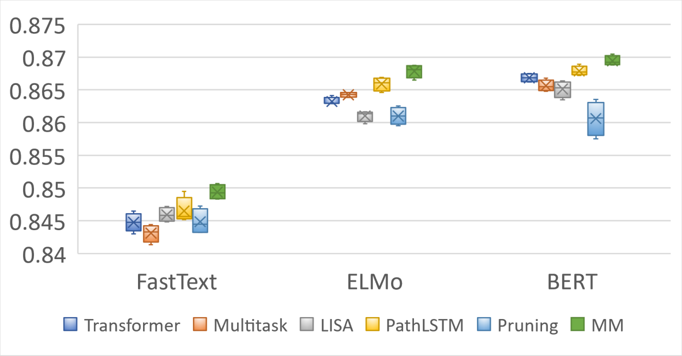

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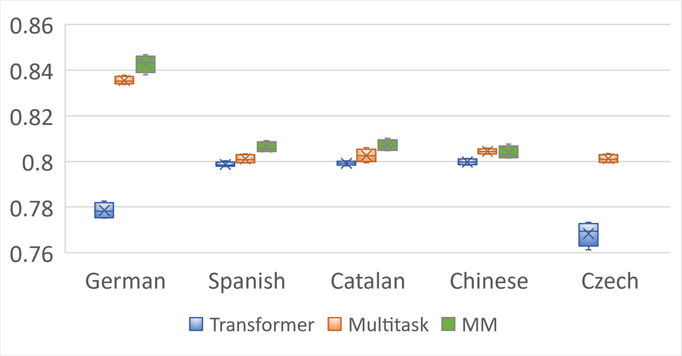

Figure: LAS comparison on five languages using FastText

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

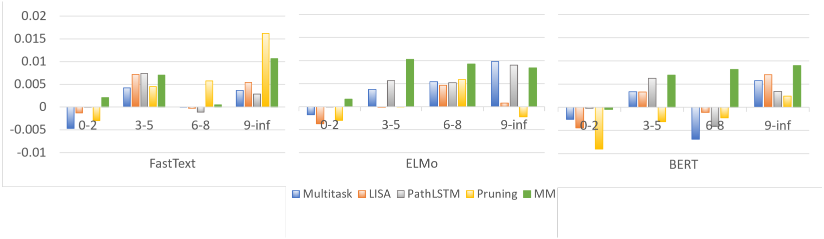

Figure: Relative LAS of MM and baselines to Transformer method

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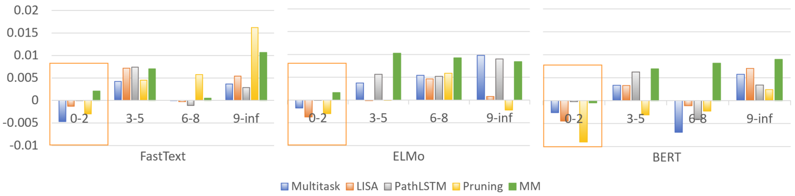

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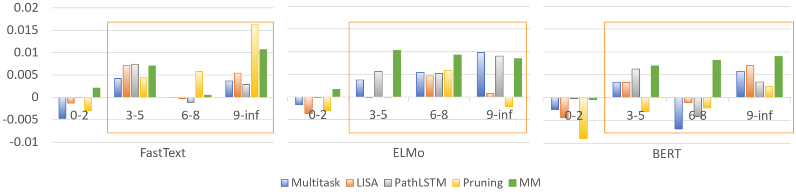

Figure: Relative LAS of MM and baselines to Transformer method

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

	WSJ			Brown		
GloVe	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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