Greed is Good if Randomized: New Inference for Dependency Parsing

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Joint work with Tao Lei,
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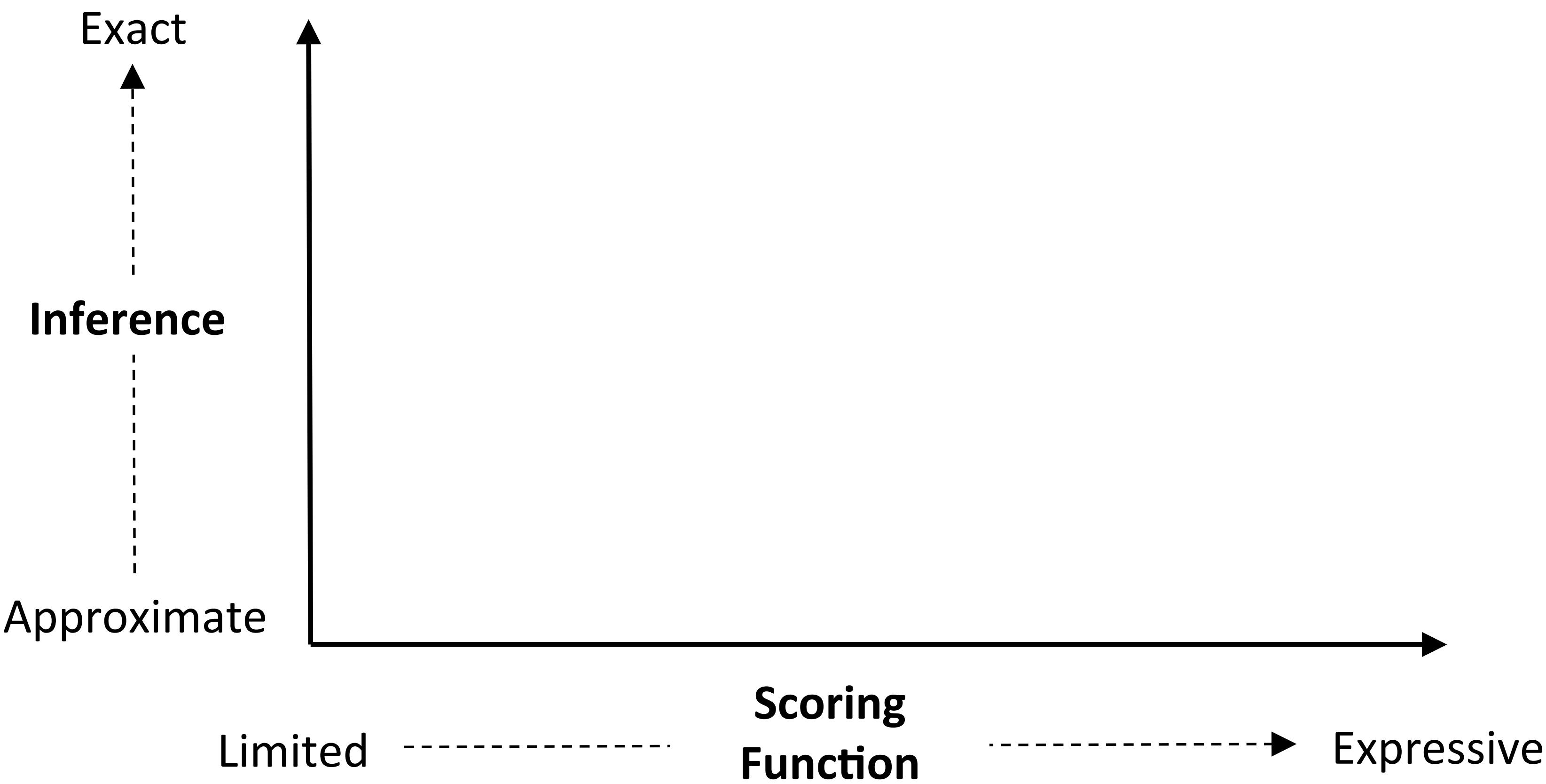
Inference vs. Scoring



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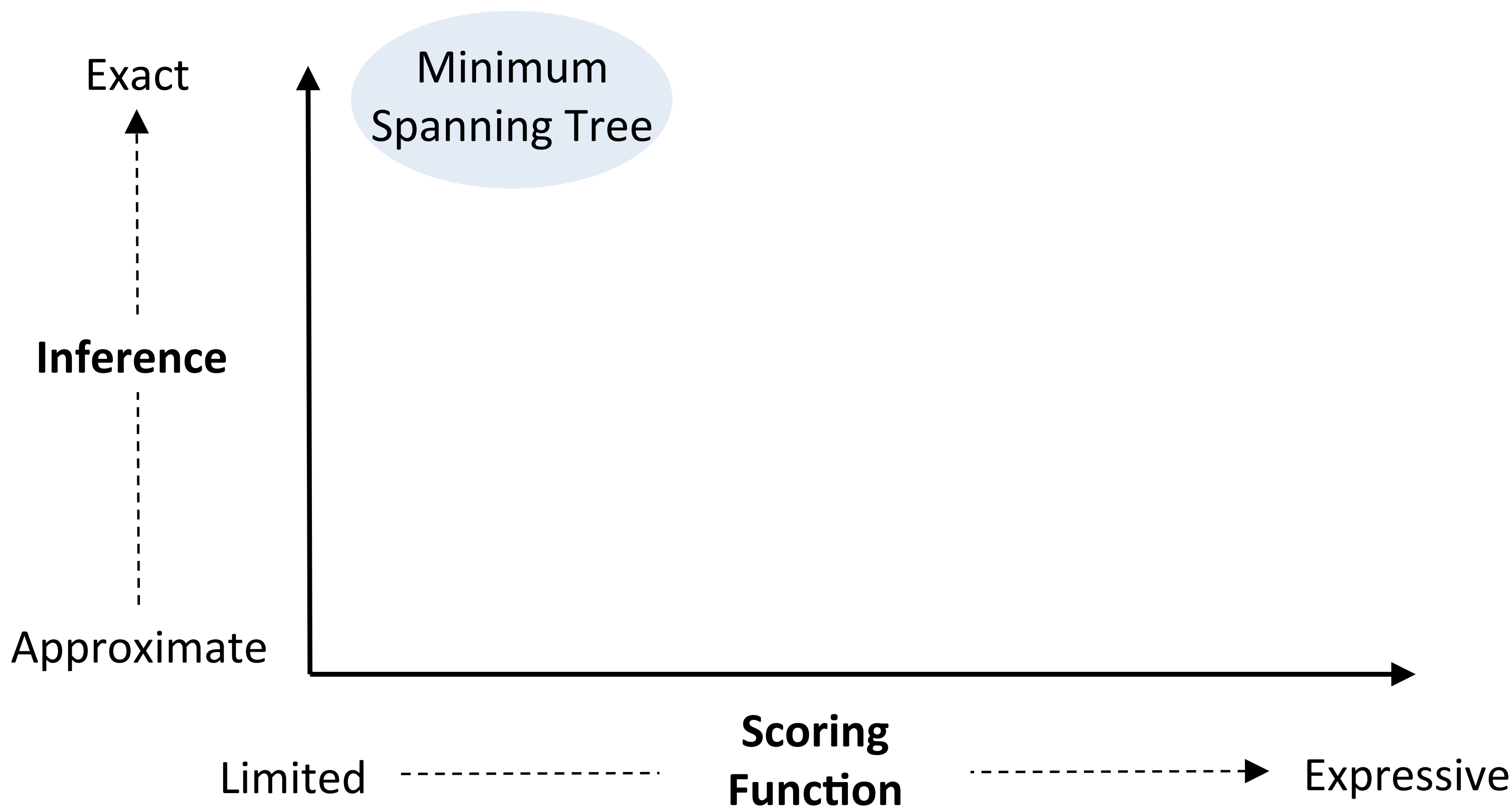

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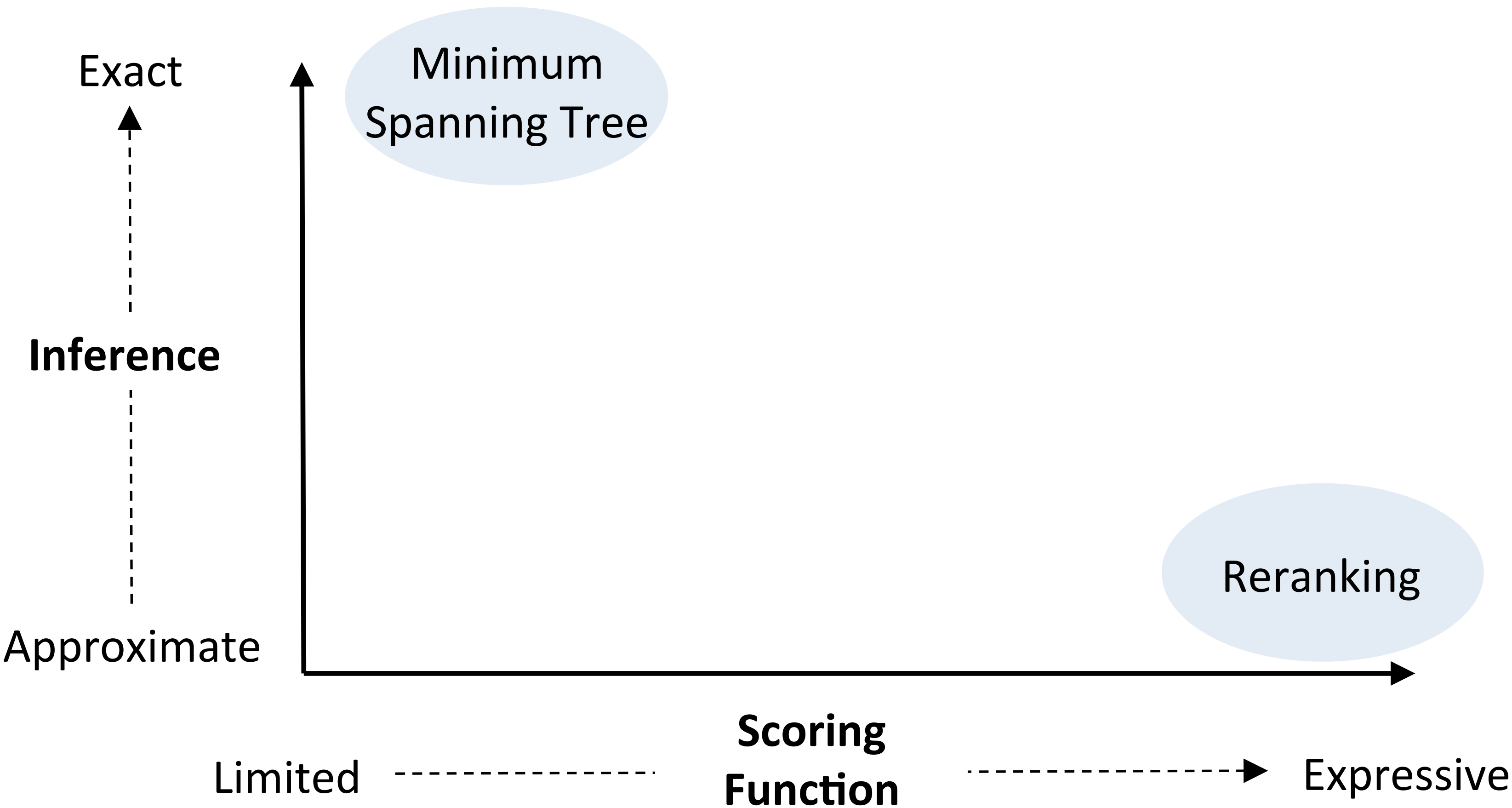

- Reranking: incorporate arbitrary features

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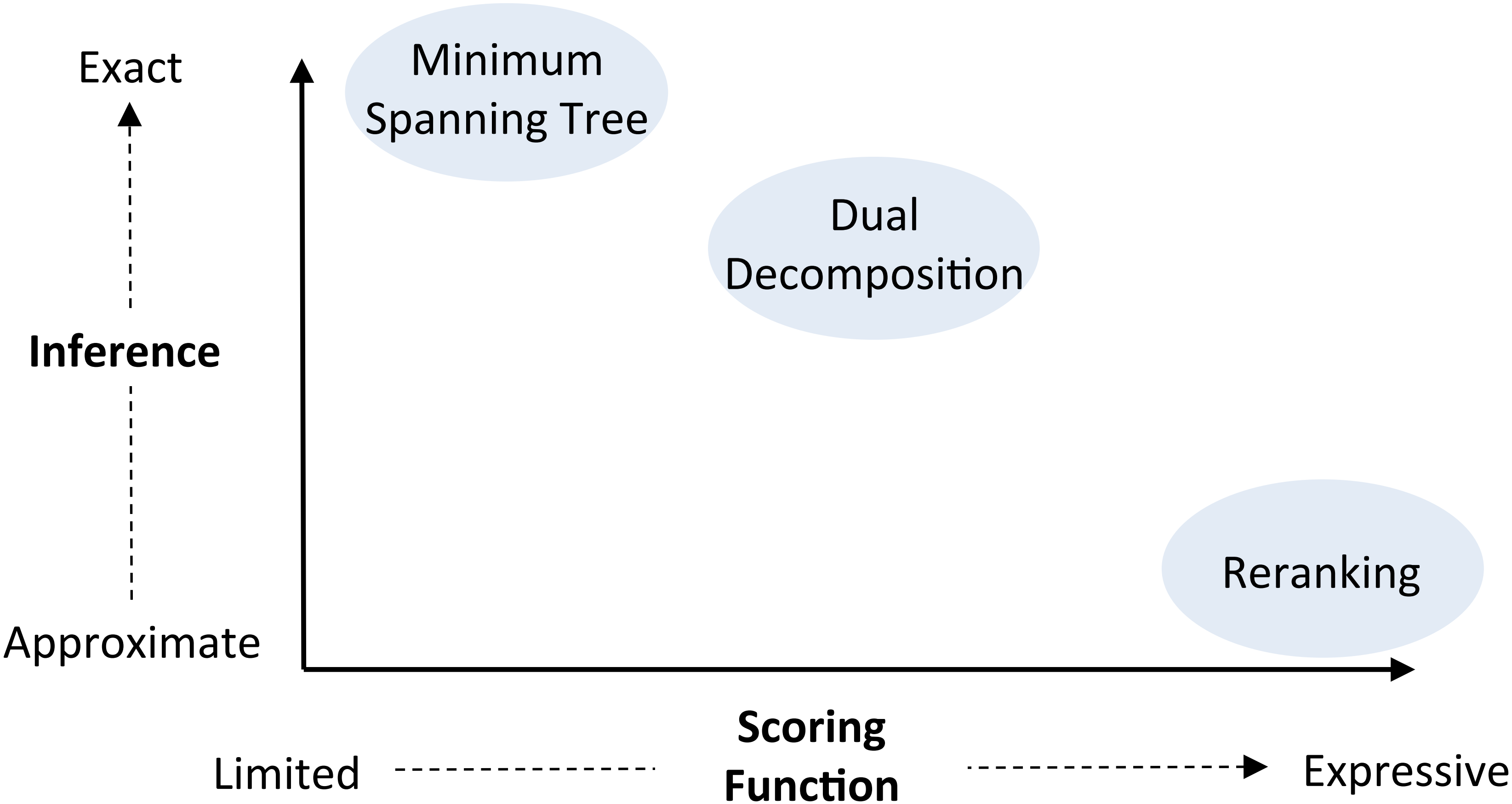

- Reranking: incorporate arbitrary features
- Dual Decomposition: search in full space

Parsing Complexity

- High-order parsing is NP-hard (McDonald et al., 2006)
- Hypothesis: parsing is easy on average
- Many NP-hard problems are easy on average
  - MAX-SAT (Resende et al., 1997)
  - Set cover (Hochbaum, 1982)

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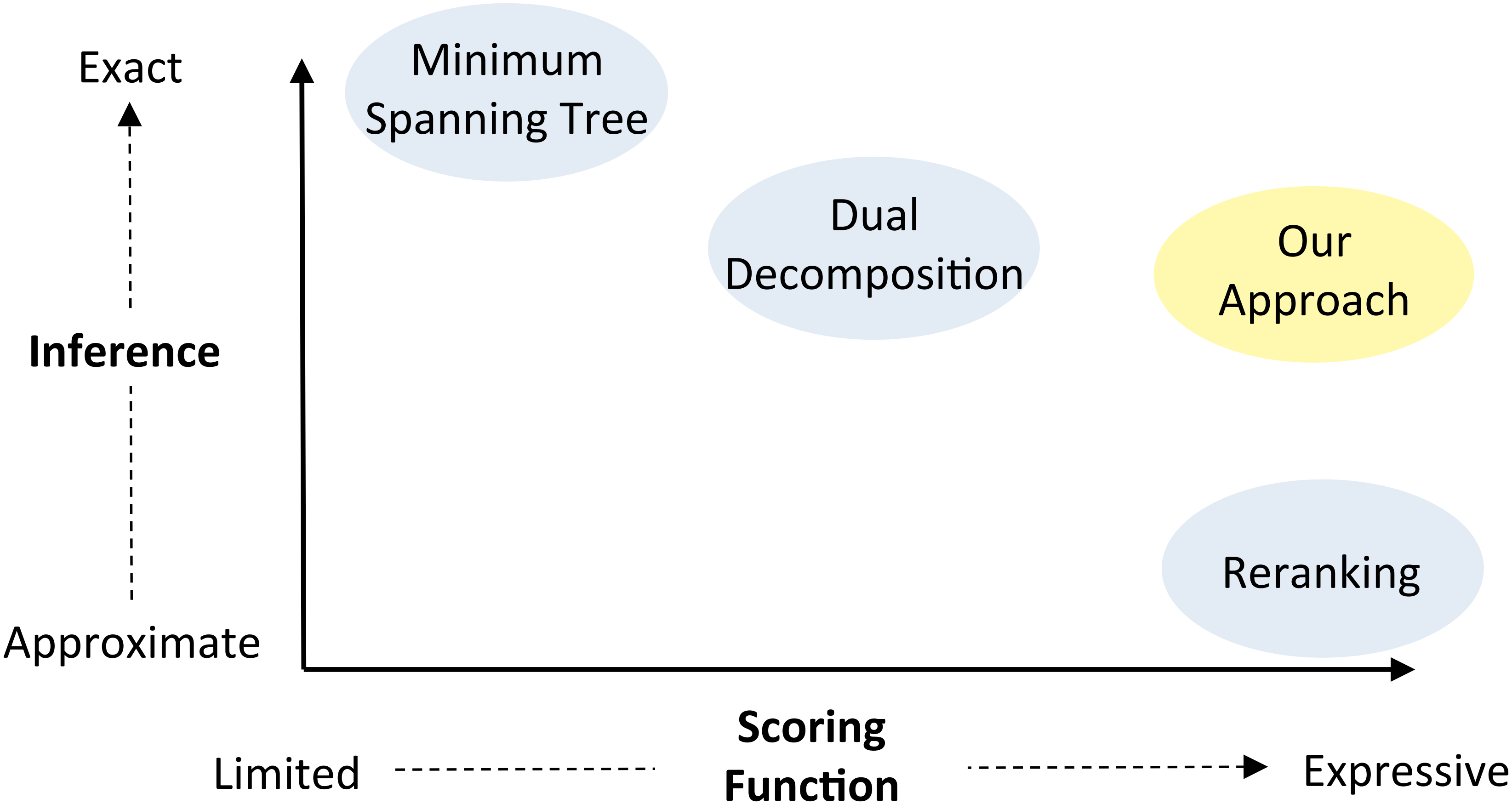
We show

- Analysis on average parsing complexity
- A simple inference algorithm based on the analysis

Our Approach



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Core Idea

- Climb to the optimal tree in a few small greedy steps

Randomized Hill-climbing

For k = 1 to K

1) Randomly sample a dependency tree
2) Greedily improve the tree one edge at a time
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Select the tree with the highest score

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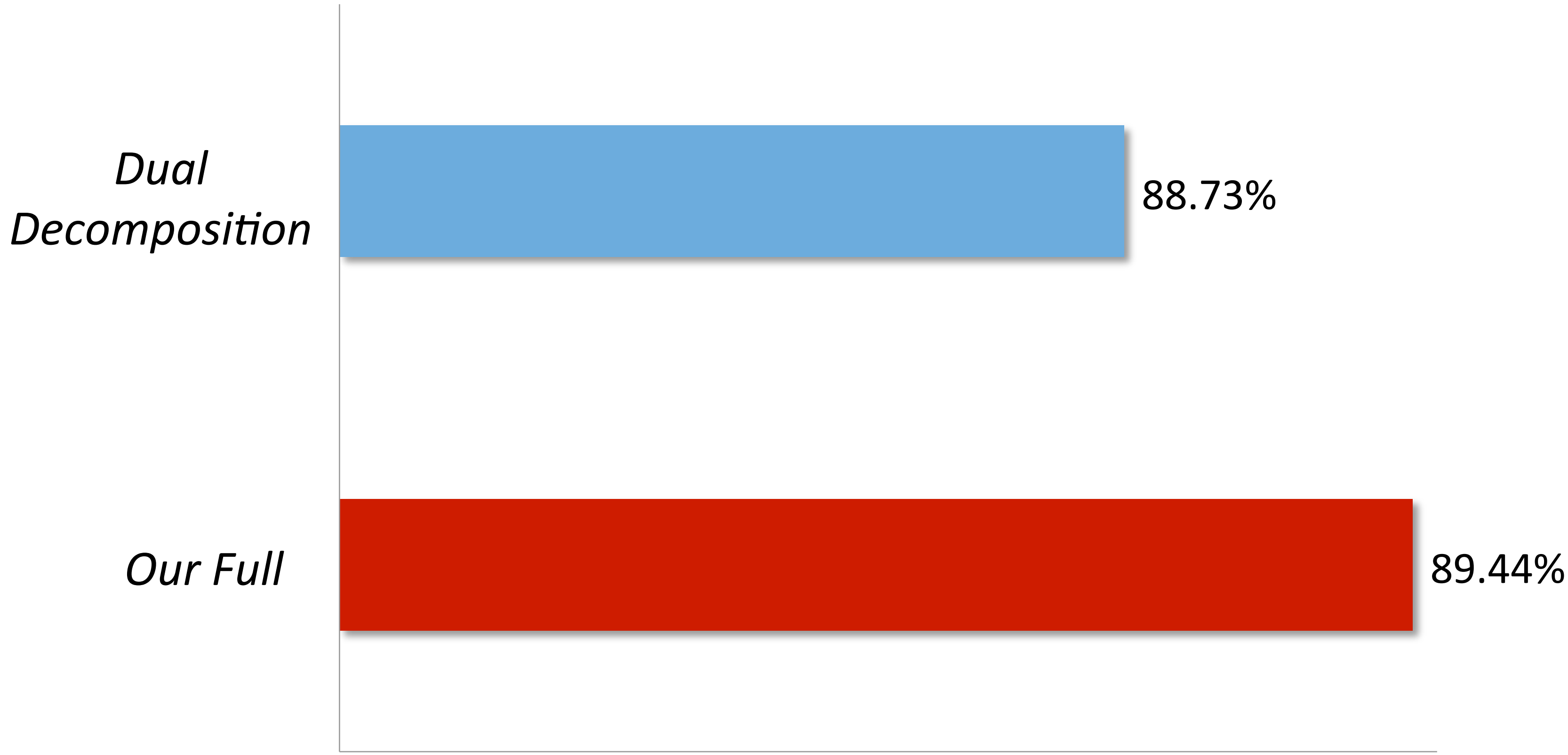
That's it!

It Works!



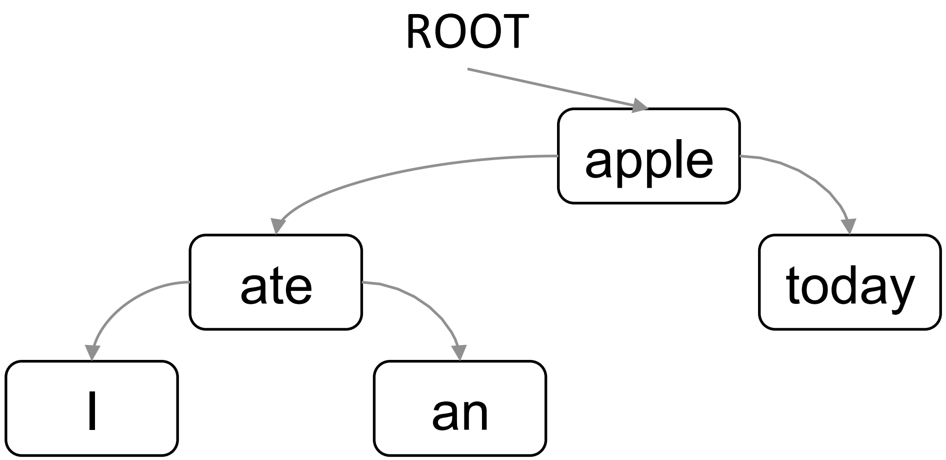
Parsing Performance on CoNLL Dataset

Example

" I ate an apple today"

Example

Initial tree



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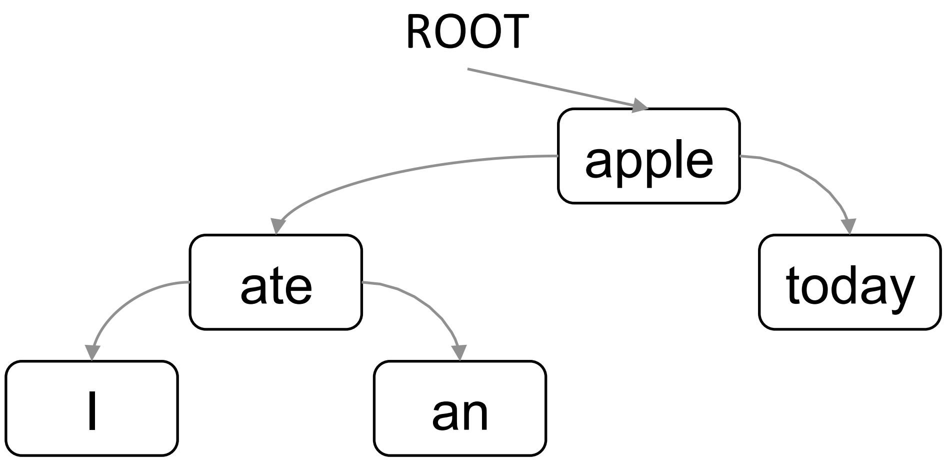

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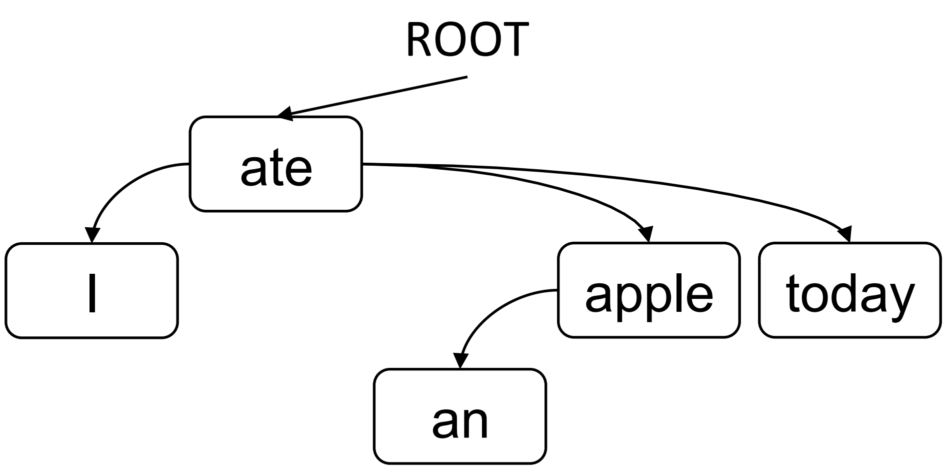

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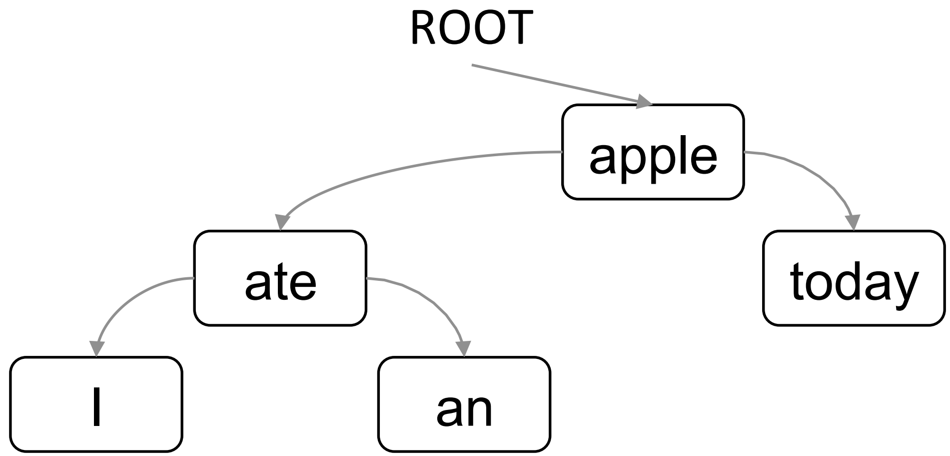

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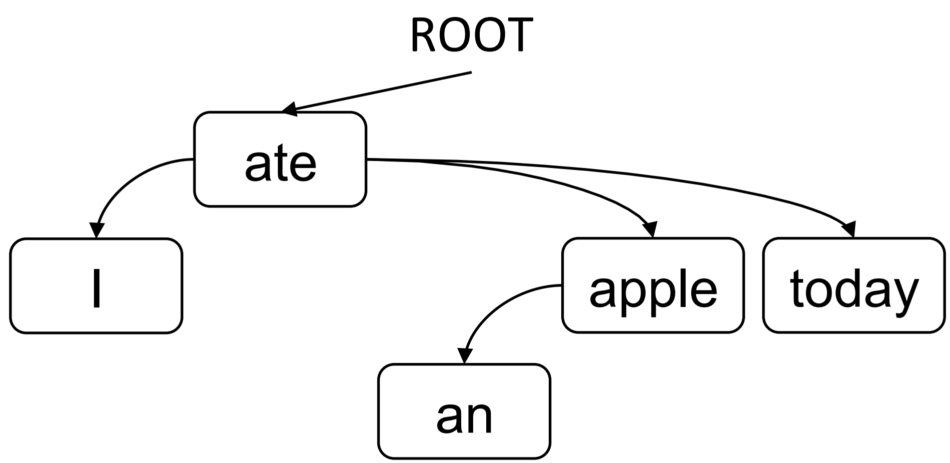

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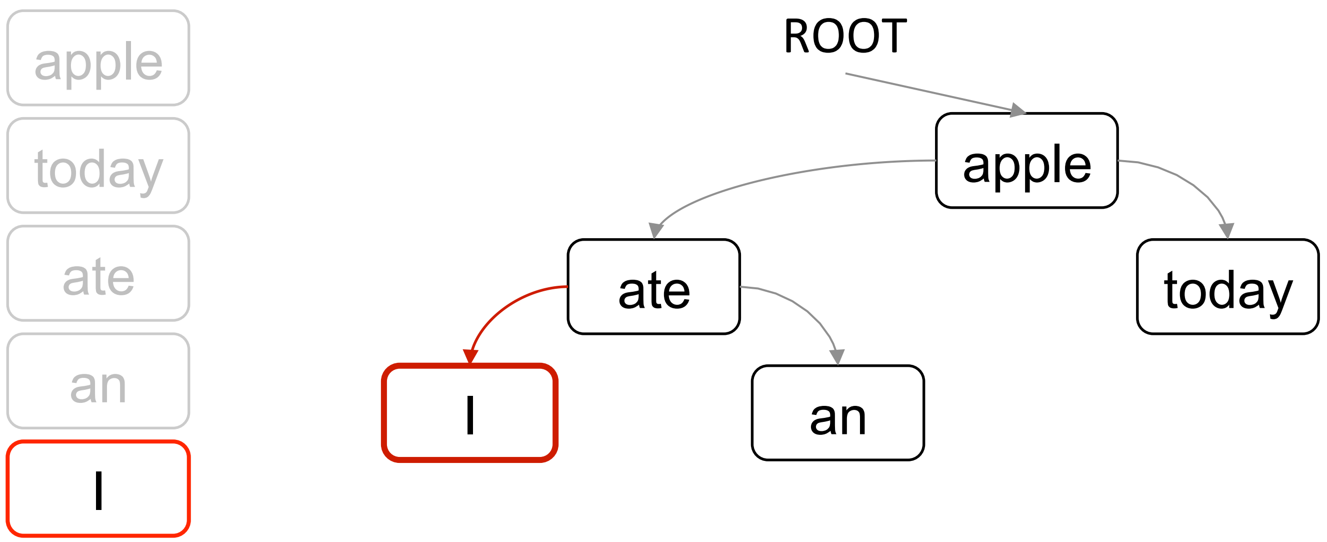

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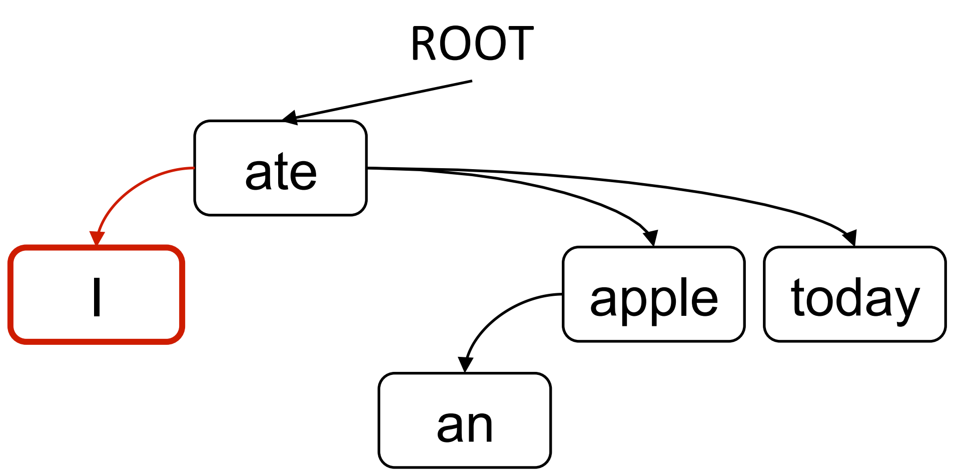

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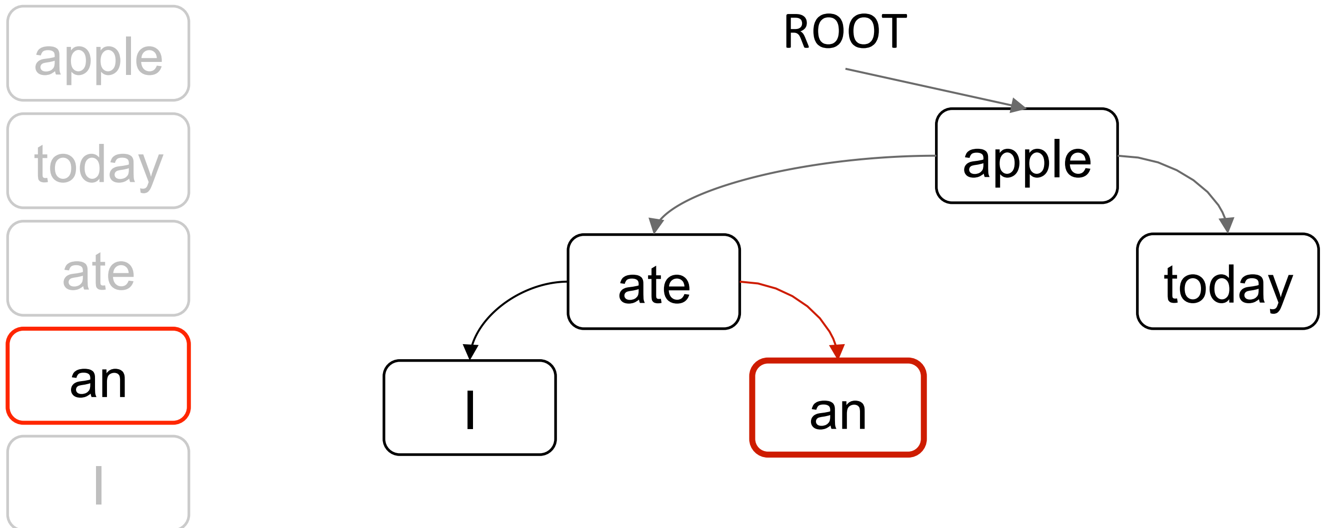

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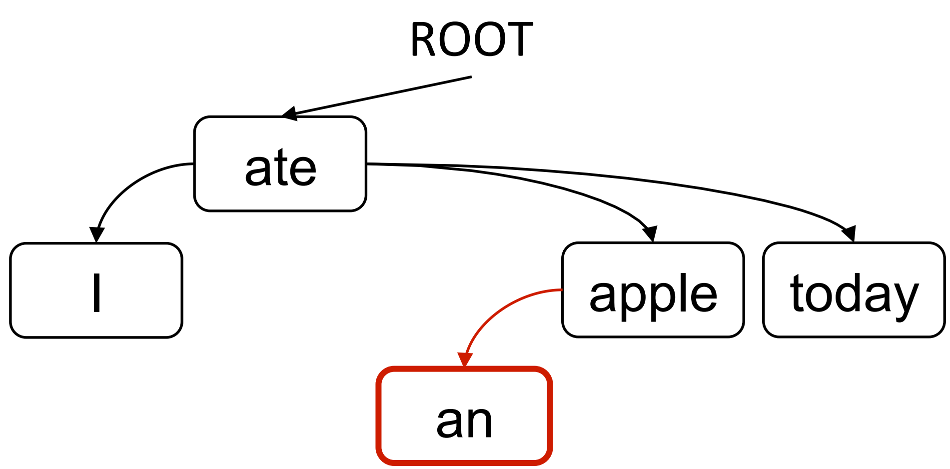

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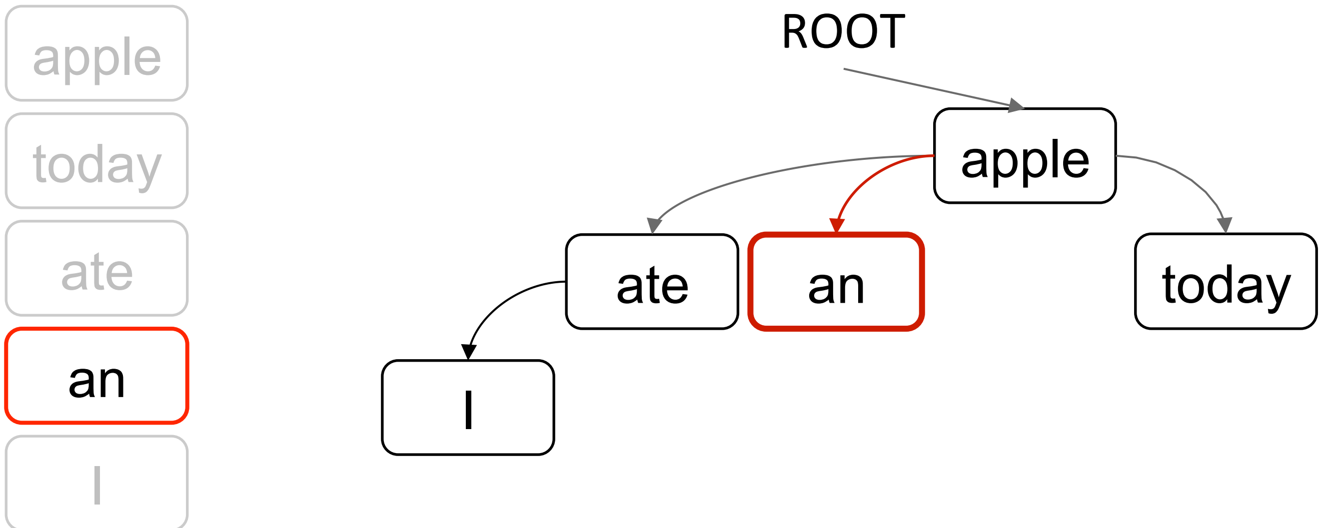

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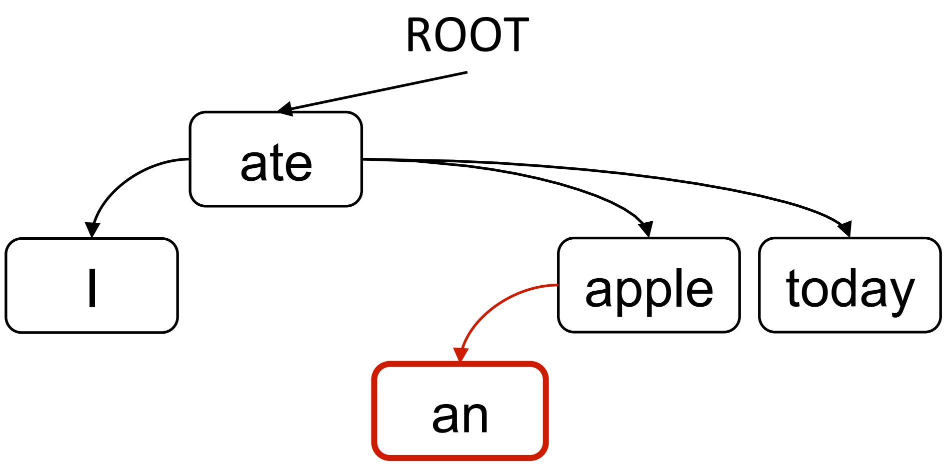

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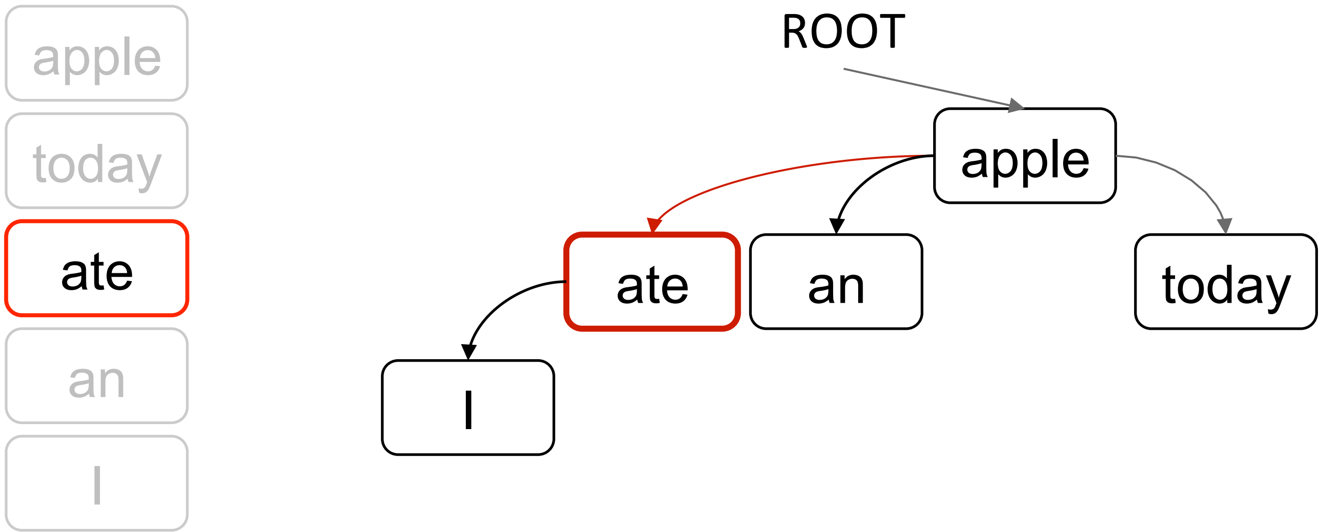

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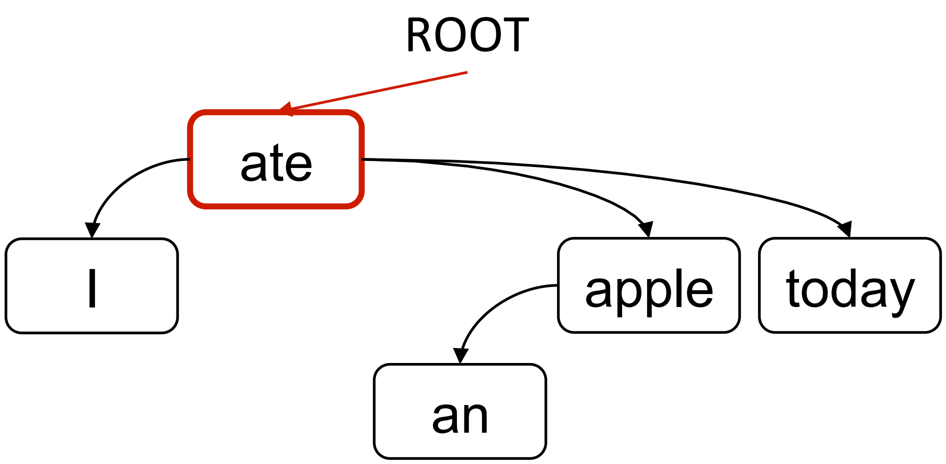

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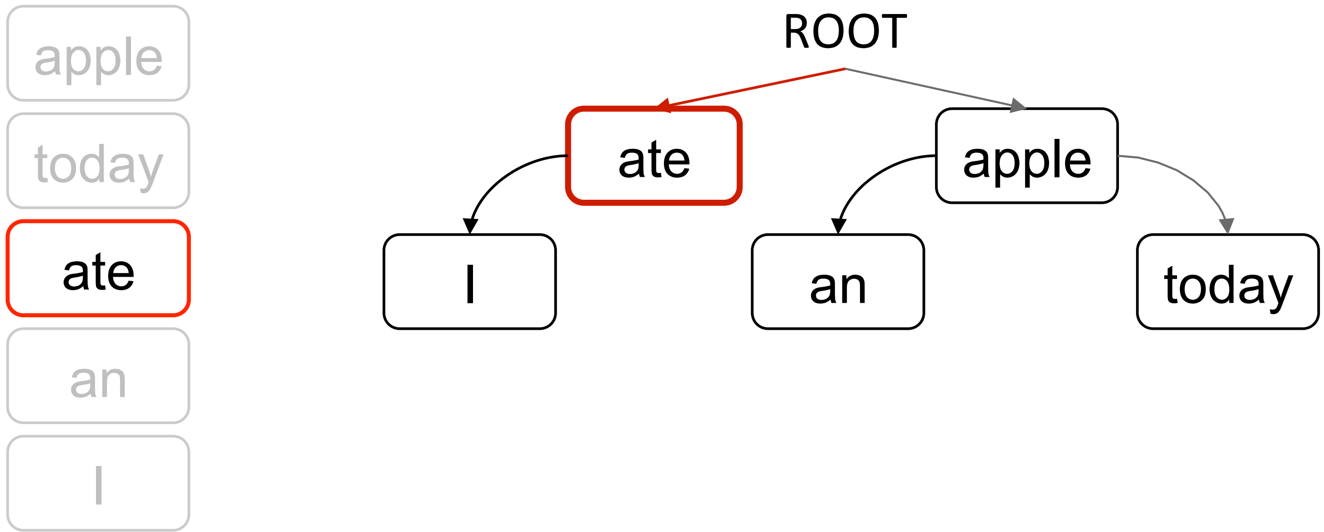

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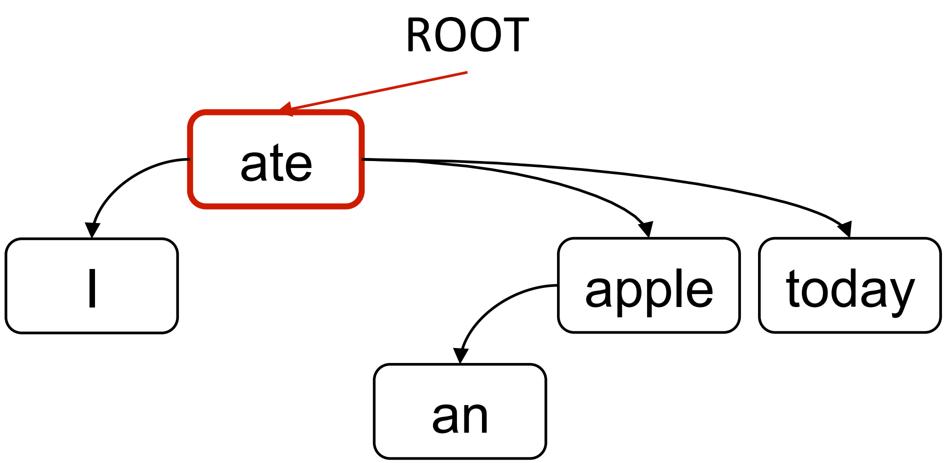

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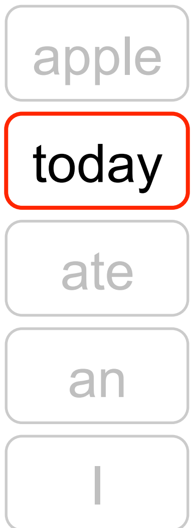

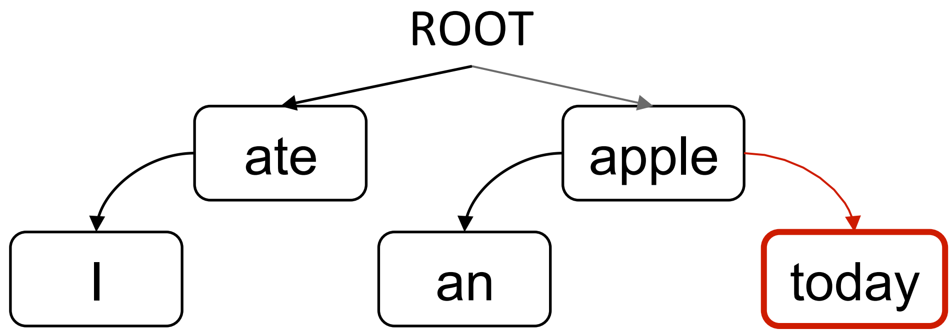

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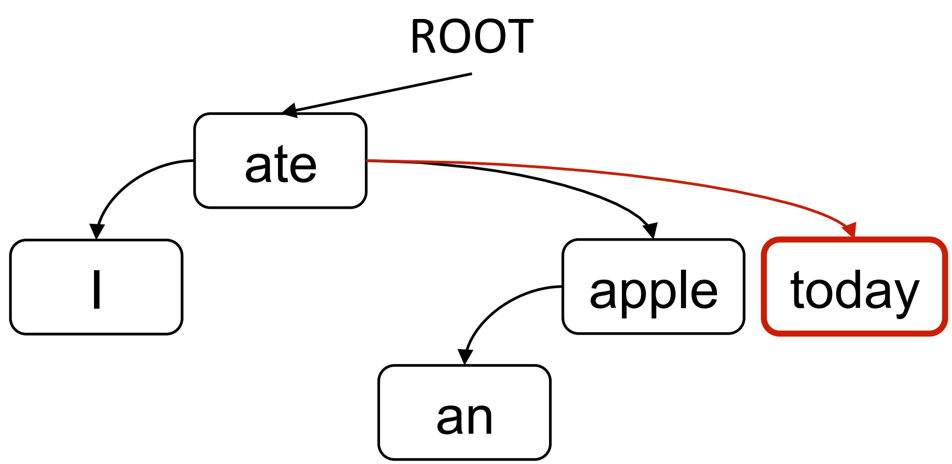

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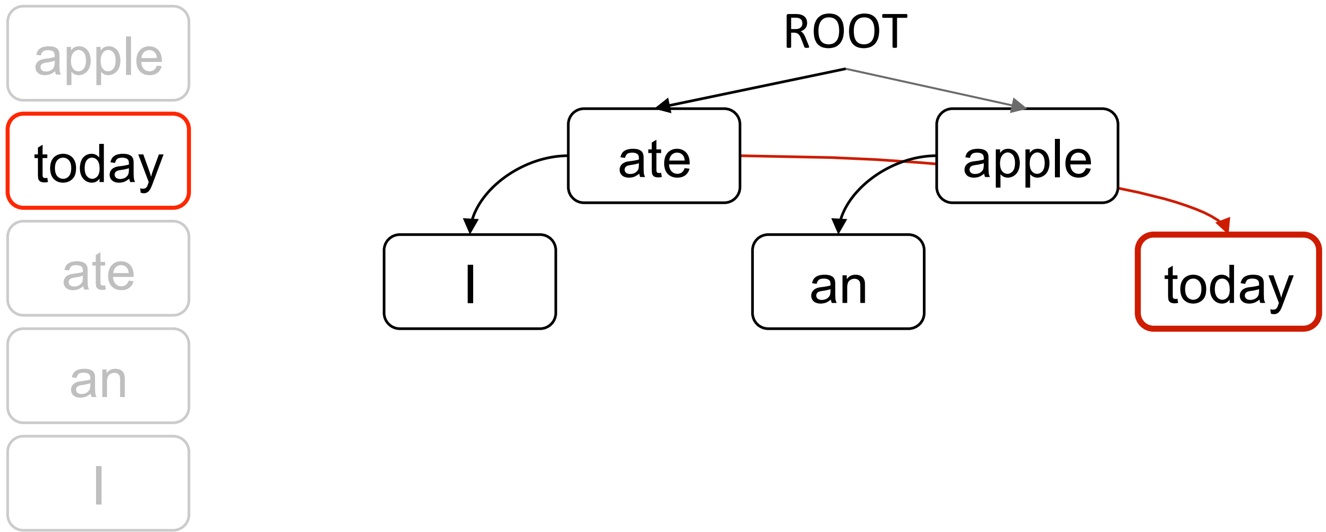

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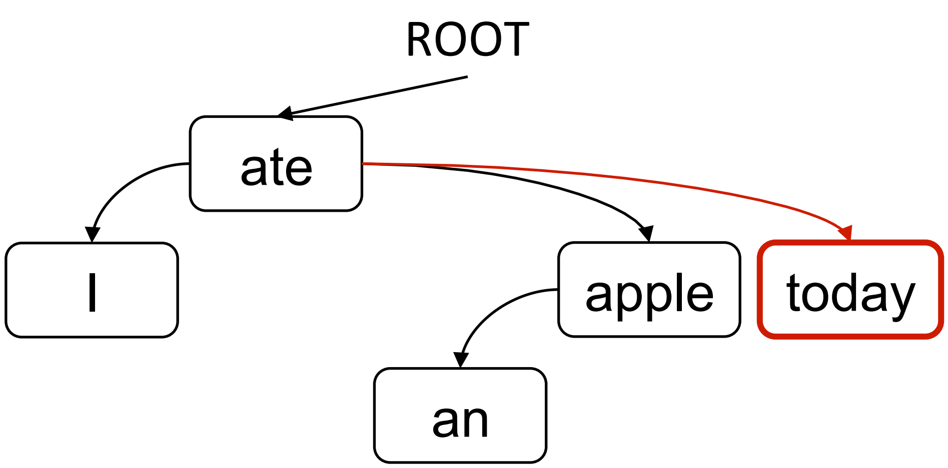

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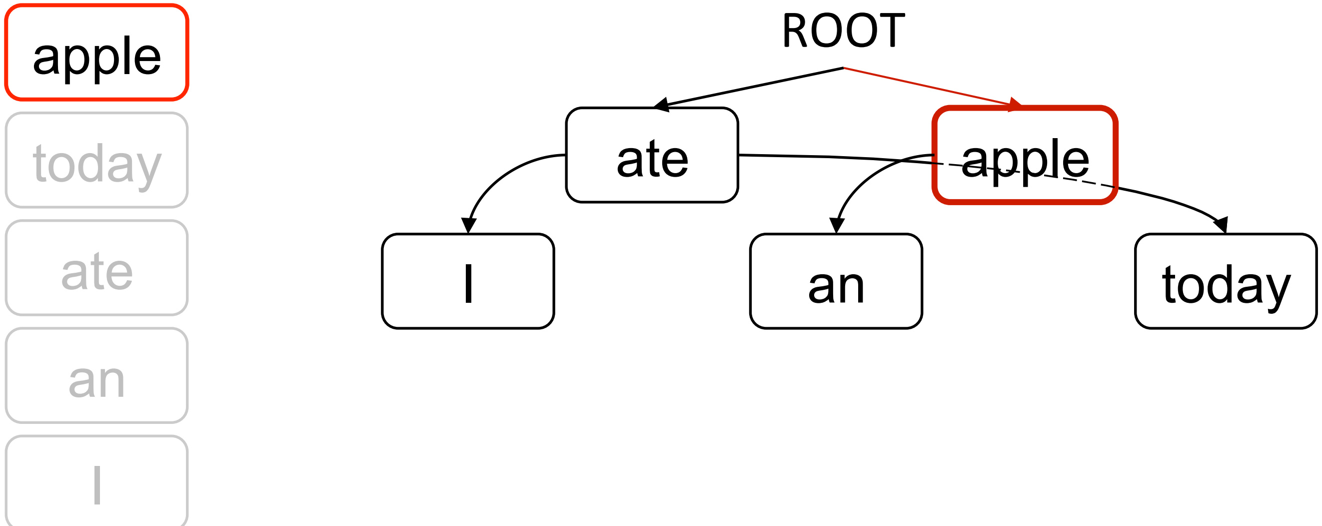

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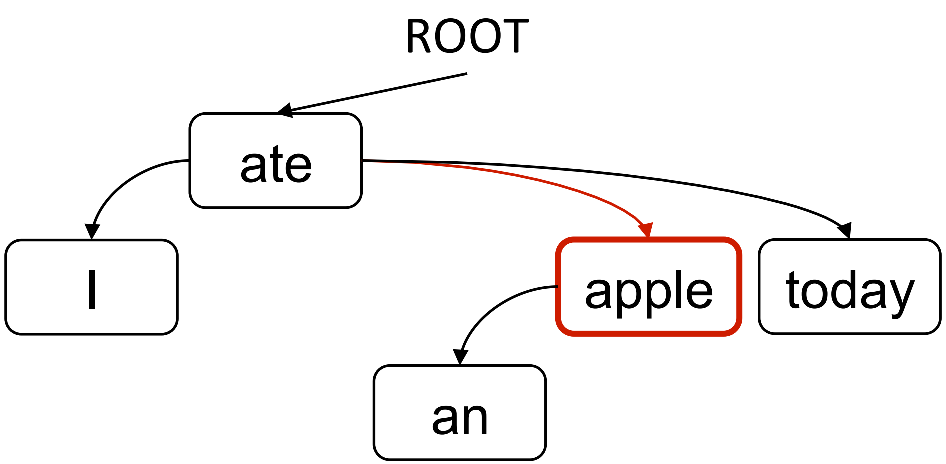

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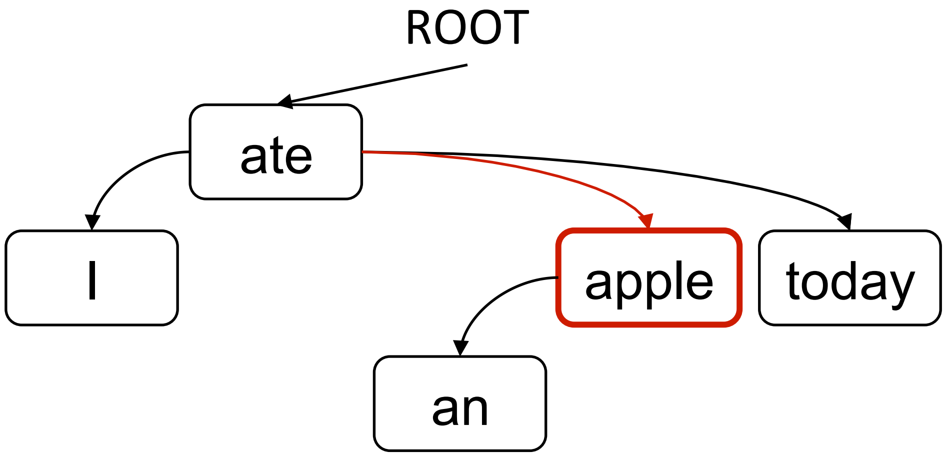

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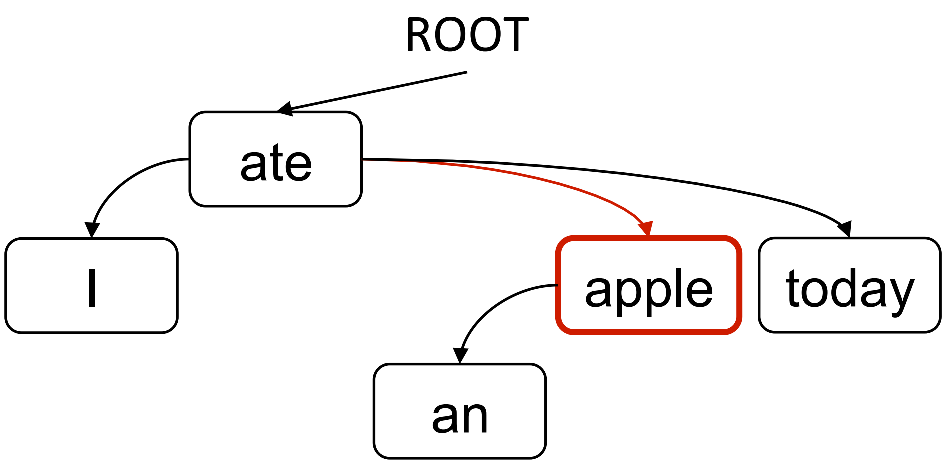

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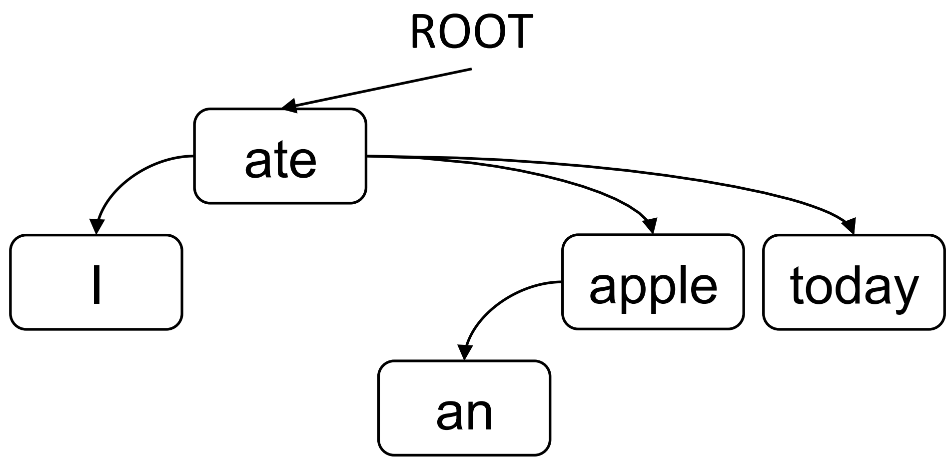

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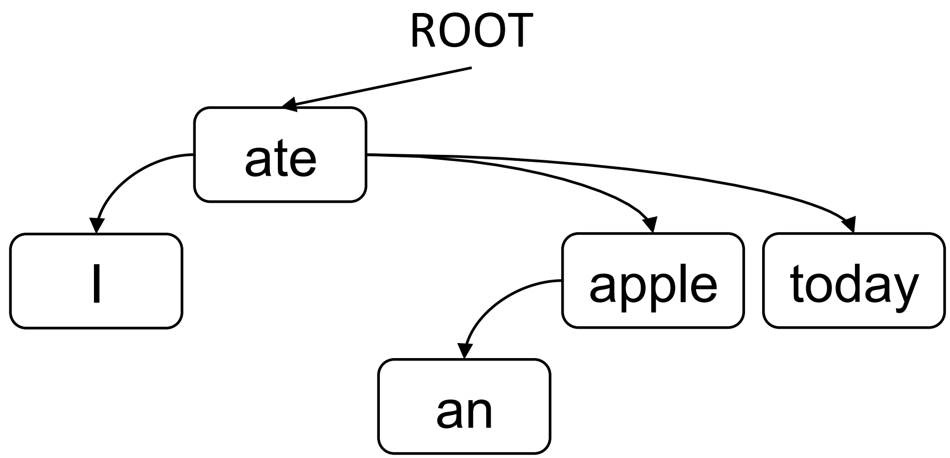
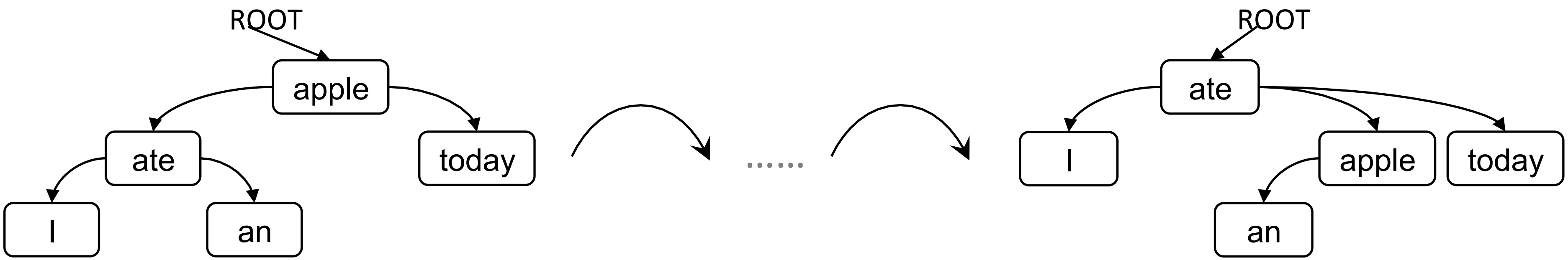


Why Greedy Has a Chance to Work

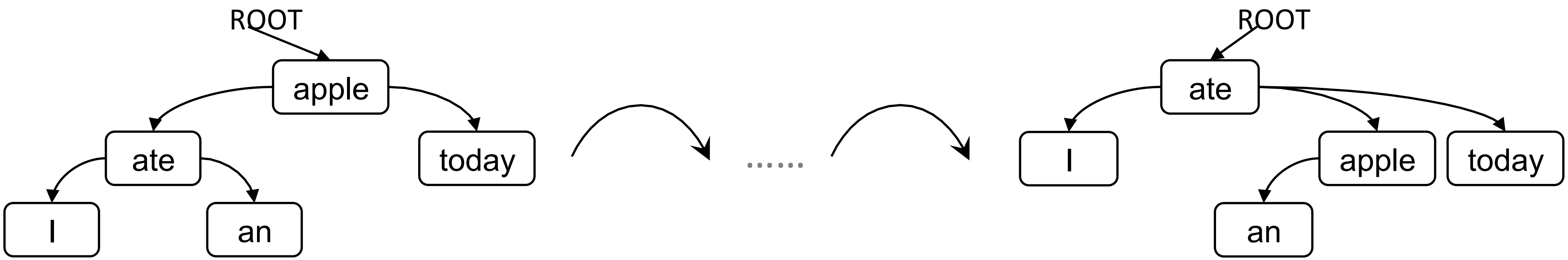


$$y^{(0)} \dashrightarrow y^{(T)}$$

Reachability: transforming any tree to any other tree

- maintaining the structure a valid tree at any point
- using as few as *d* steps (*d* : head differences/hamming distance)

Greedy Hill-climbing



$y^{(0)}$ ------ increase $S(x, y^{(t)})$ ------> $y^{(T)}$

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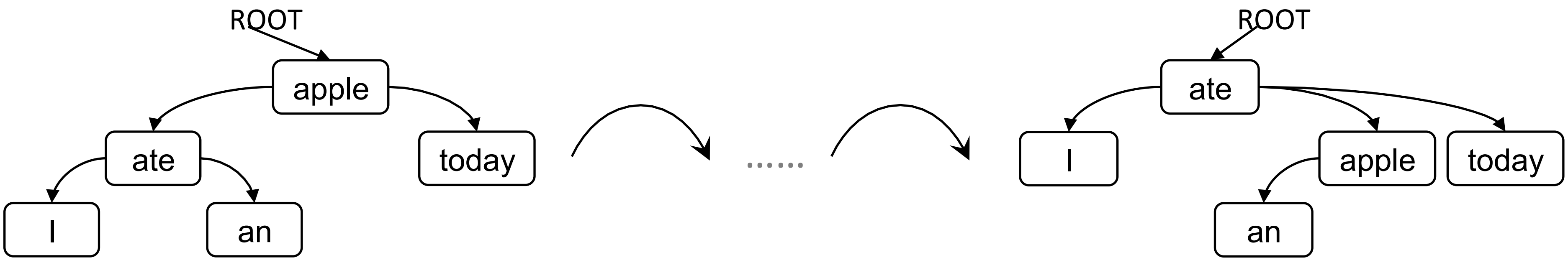
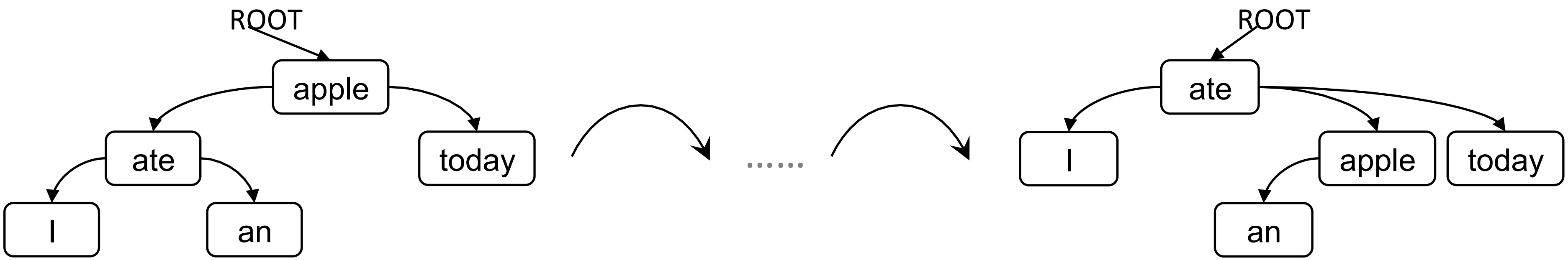


$y^{(0)}$ - - - - - increase $S(x, y^{(t)})$ - - - - - → $y^{(T)}$

Arbitrary features in the scoring function

Challenge: Local Optimum



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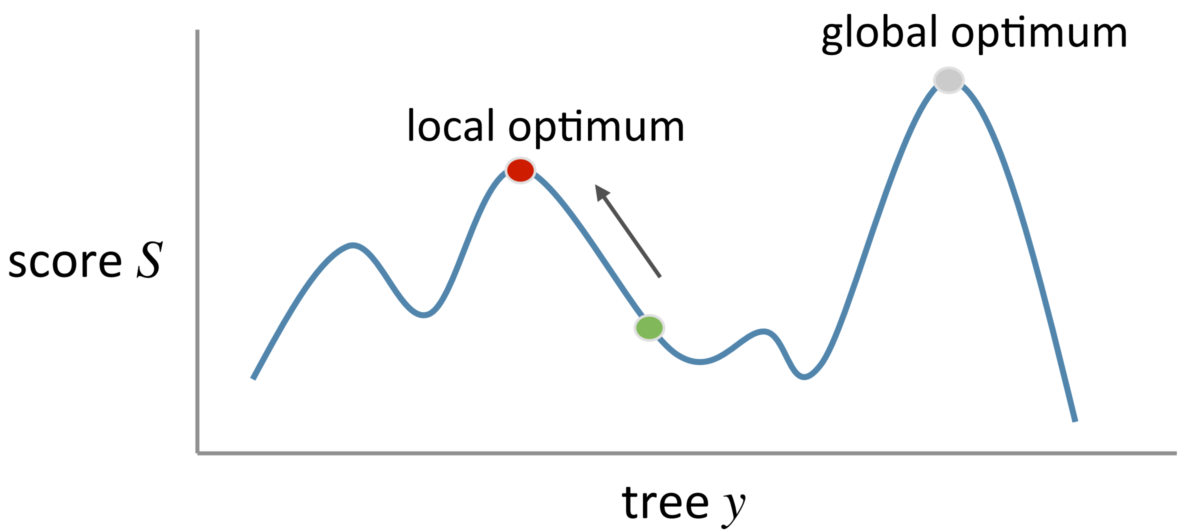
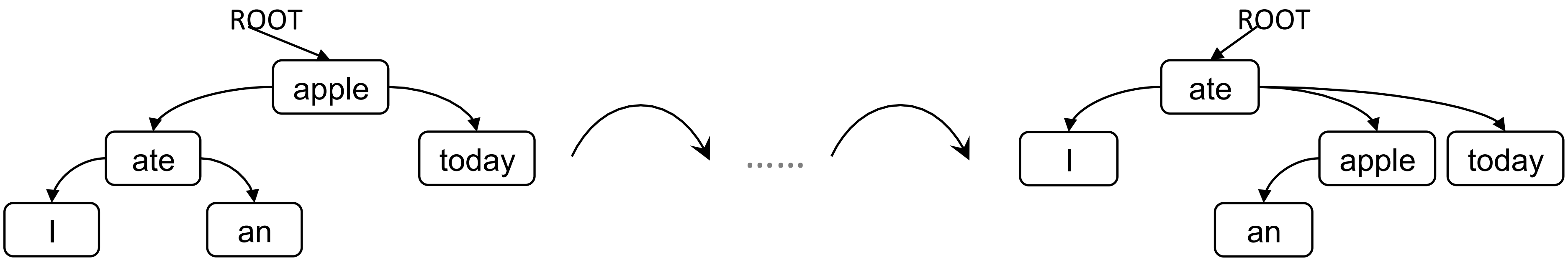
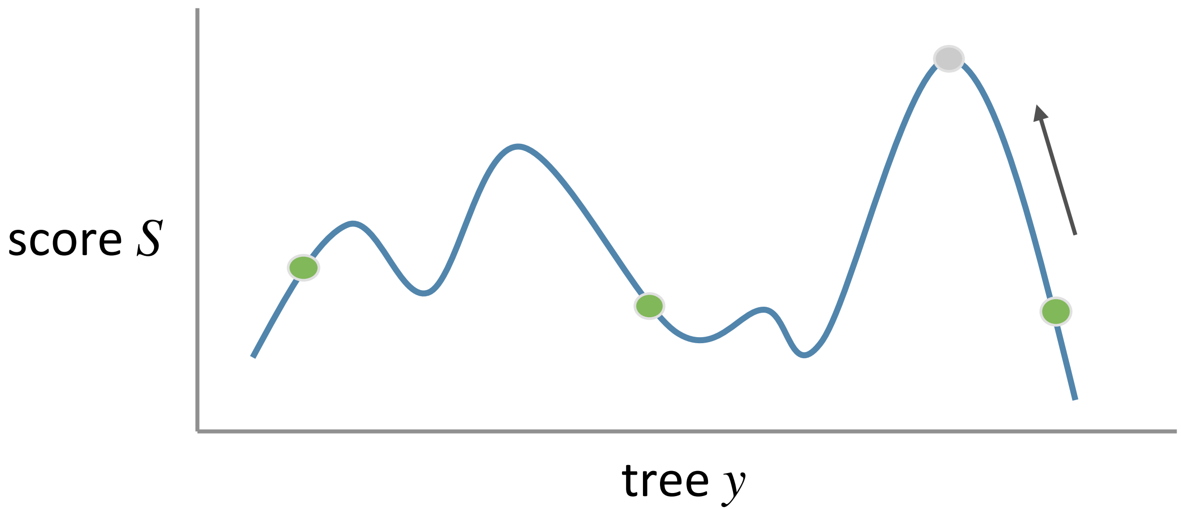


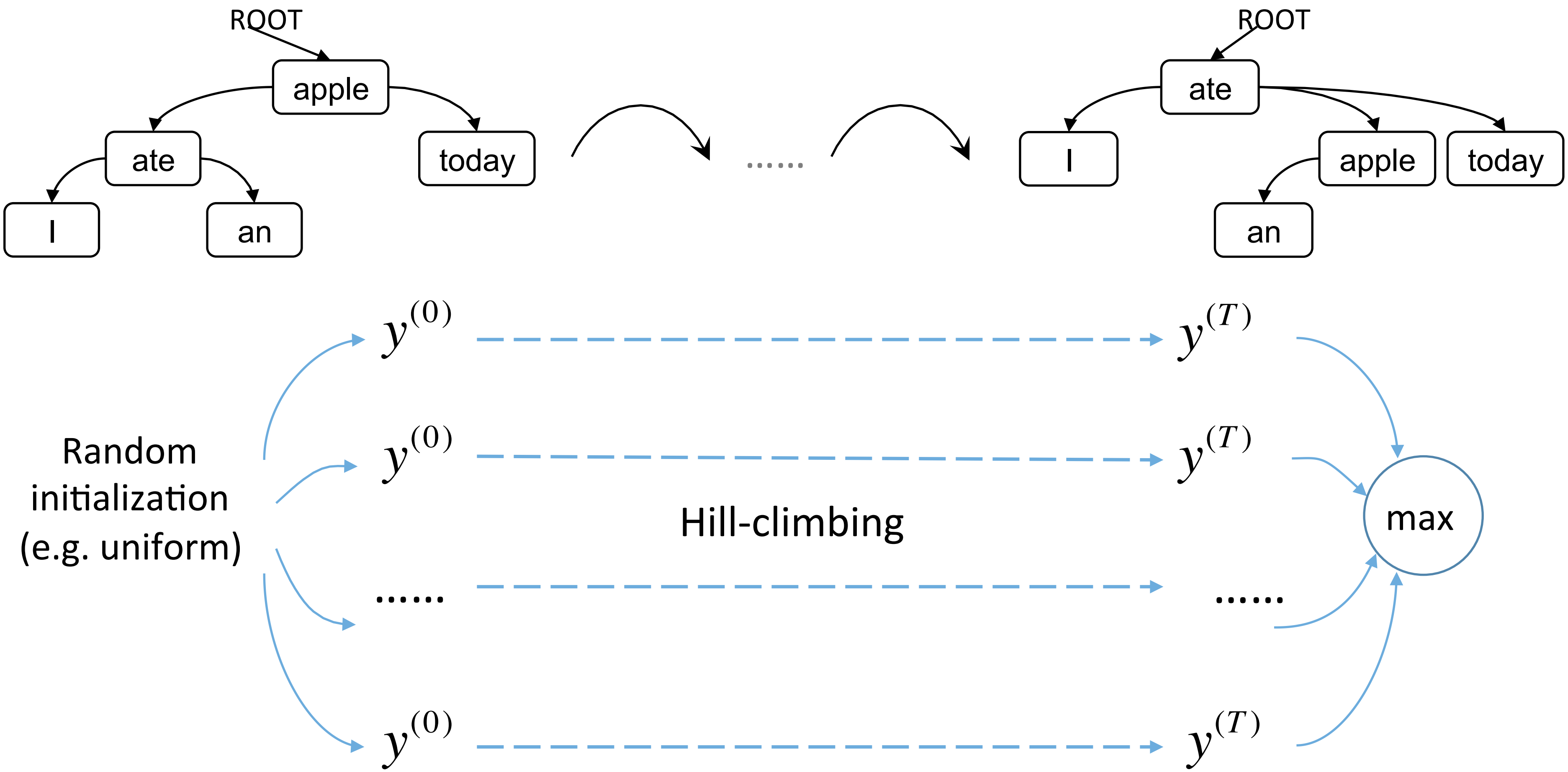
Hill-climbing with Restarts





Overcome local optima via restarts

Hill-climbing with Restarts



Overcome local optima via restarts

Learning Algorithm

- Follow common max-margin framework

$$\forall y \in T(x) \qquad S(x,\hat{y}) \geq S(x,y) + |\hat{y} - y| - \xi$$

  - $\hat{y}$ is the gold tree

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  - $\hat{y}$ is the gold tree

- Adopt passive-aggressive online learning framework (Crammer et al. 2006)

- Decode with our randomized greedy algorithm

Analysis

Analysis

	Theoretical	Empirical
First-order	✓	✓

Analysis

	Theoretical	Empirical
First-order	✓	✓
High-order	?	✓

Analysis

	Theoretical	Empirical
First-order	✓	✓
High-order	?	✓

Search Space Complexity: First-order

10 words

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≈ 2 billion trees

10 words

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< 512 local optima

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Theorem: For any first-order scoring function:

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Theorem: For any first-order scoring function:

- there are at most 2^{n-1} locally optimal trees
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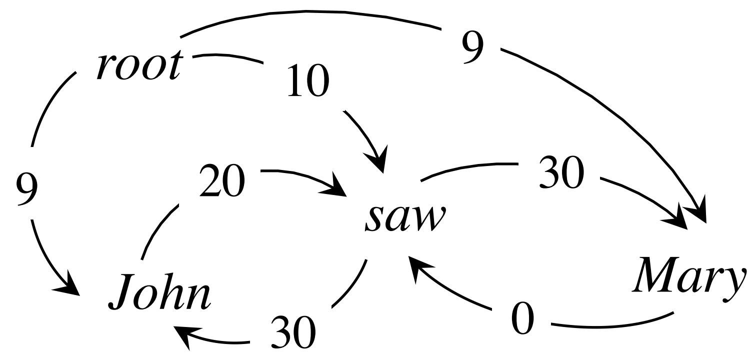
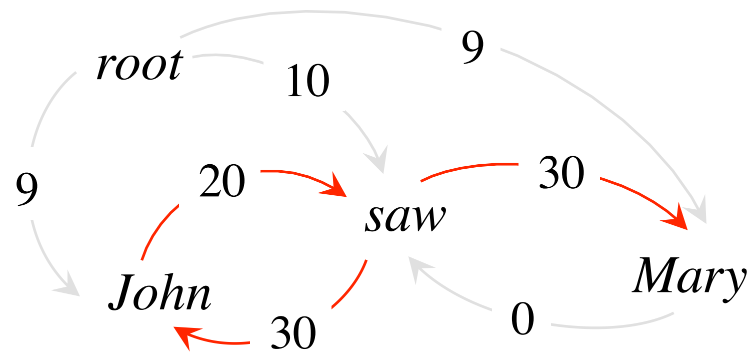
What about the average case?

Algorithm for Counting Local Optima



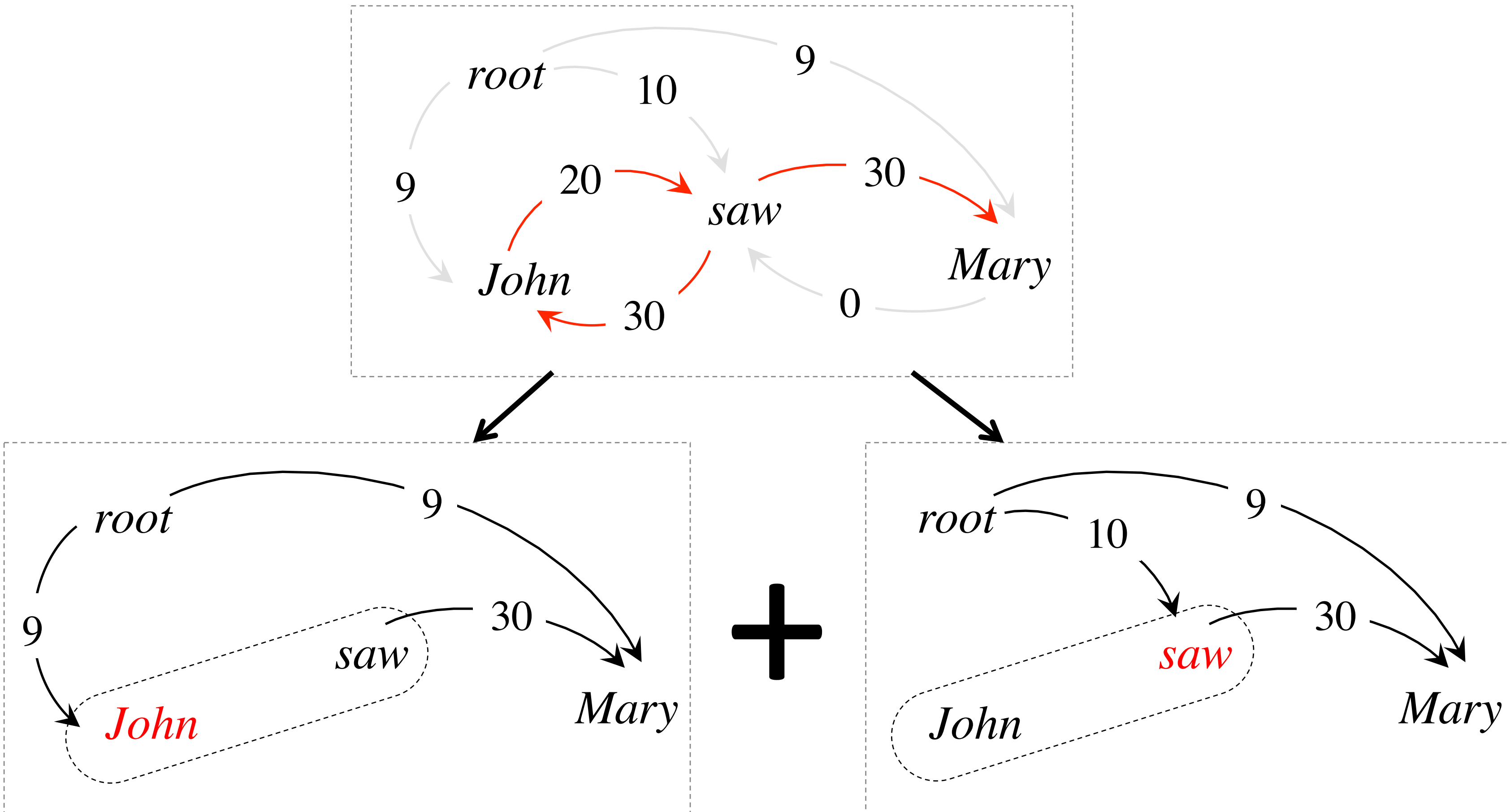
Algorithm for Counting Local Optima

The method is based on Chu-Liu-Edmonds algorithm



- Select the best heads independently

Algorithm for Counting Local Optima

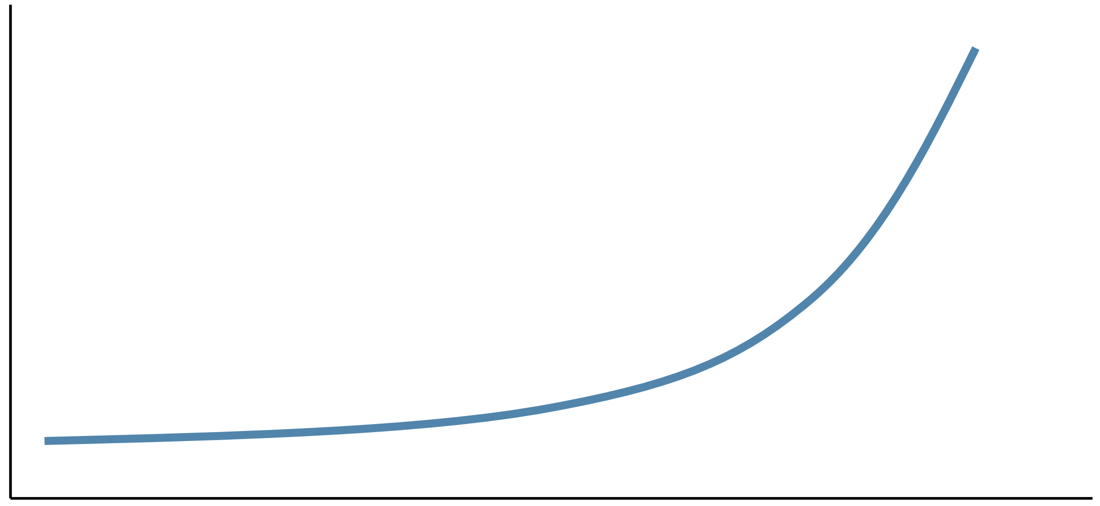


- Contract the cycle and recursively count the local optima
  - ➢ Any local optimum exactly reassigns one edge in the cycle

Empirical Results: First-order

How many local optima in real data?

 # Optima on English Dataset



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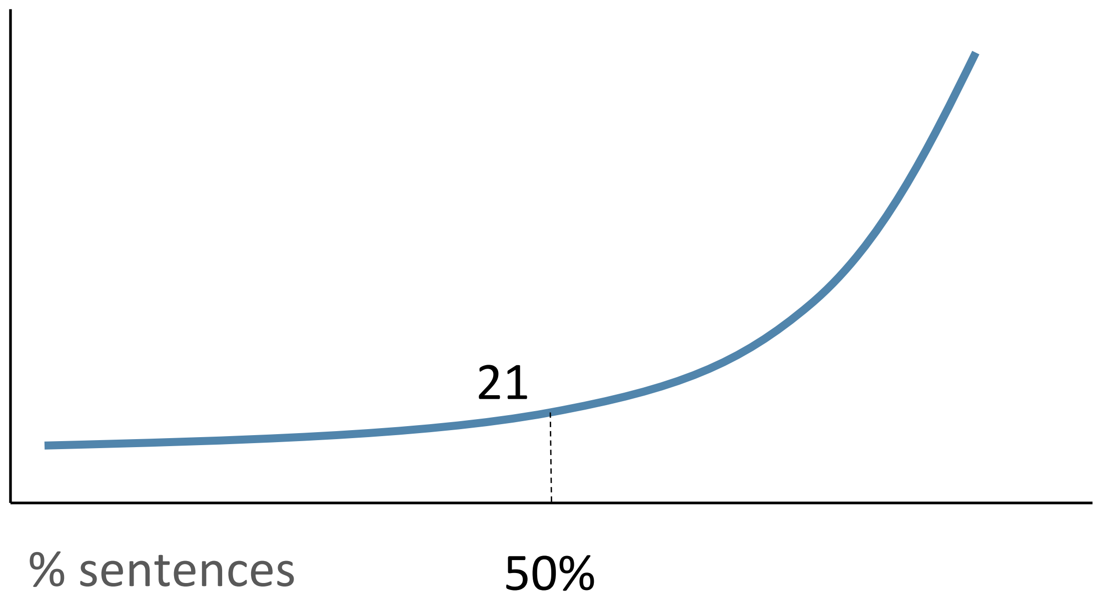

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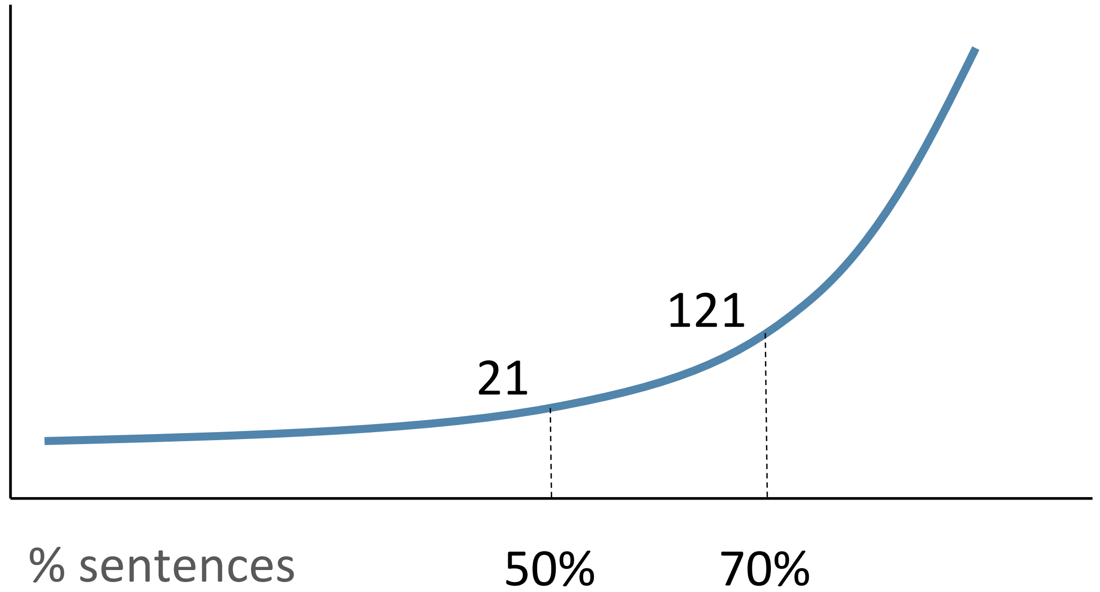

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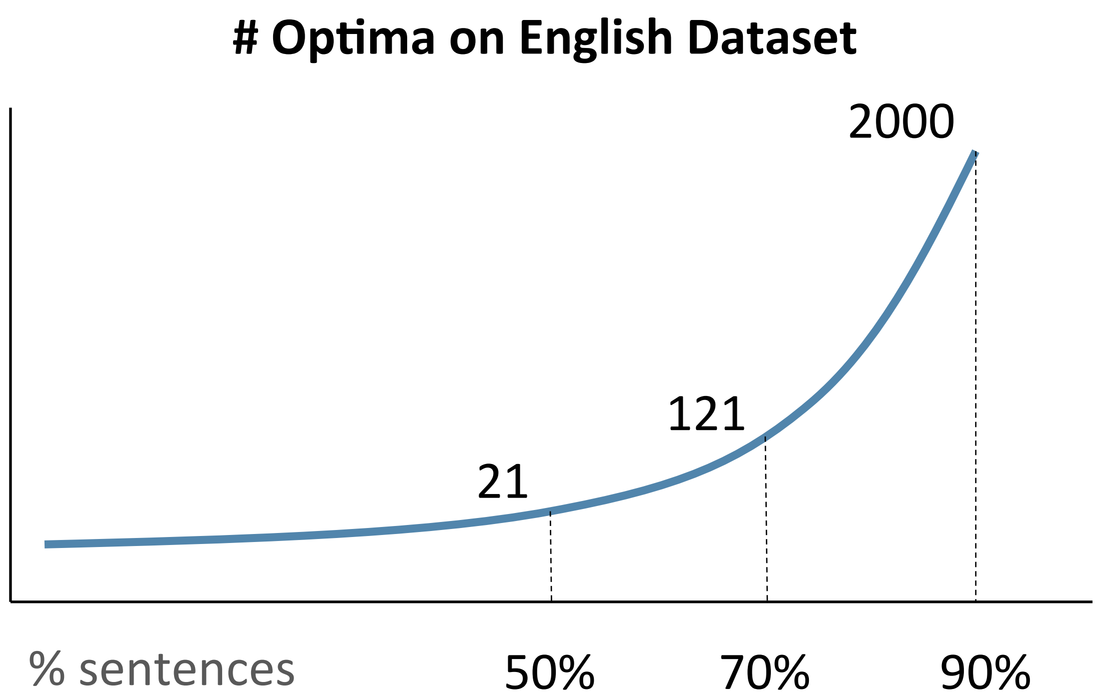


Empirical Results: First-order

Does the hill-climbing find the argmax?

Finding Global Optimum on English

Empirical Results: First-order

Does the hill-climbing find the argmax?

Finding Global Optimum on English

Len. ≤ 15
100%

Len. > 15
99.3%

Easy search space leads to successful decoding

Empirical Results: High-order

Does the hill-climbing find the argmax?

Comparison on English Given DD Cert.

	% Certificate
Dual decomposition (Koo et al., 2010)	94.5%

	$S_{DD} = S_{HC}$
Given a certificate by DD	99.8%

Empirical Results: High-order

Does the hill-climbing find the argmax?

Overall Comparison on English

Empirical Results: High-order

Does the hill-climbing find the argmax?

Overall Comparison on English

$S_{DD} = S_{HC}$
98.7%

Empirical Results: High-order

Does the hill-climbing find the argmax?

Overall Comparison on English

$S_{DD} = S_{HC}$
98.7%

$S_{DD} < S_{HC}$
1.0%

$S_{DD} > S_{HC}$
0.3%

Experimental Setup

Datasets

- 14 languages in CoNLL 2006 & 2008 shared tasks

Features

- Up to 3rd-order (three arcs) features used in MST/Turbo parsers
- Global features used in re-ranking

Implementation

- Adaptive restarting strategy with $K = 300$

Baselines and Evaluation Measure

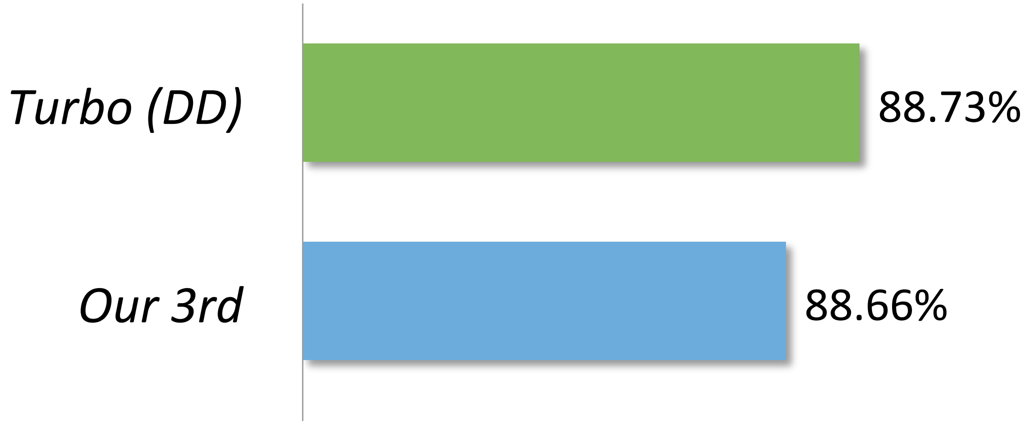
Baselines:

- Turbo Parser: Dual Decomposition with 3rd-order features (Martins et al., 2013)
- Sampling-based Parser: MCMC sampling with global features (Zhang et al., 2014)

Evaluation Measure:

- Unlabeled Attachment Score (UAS), without punctuations

Comparing with Baselines



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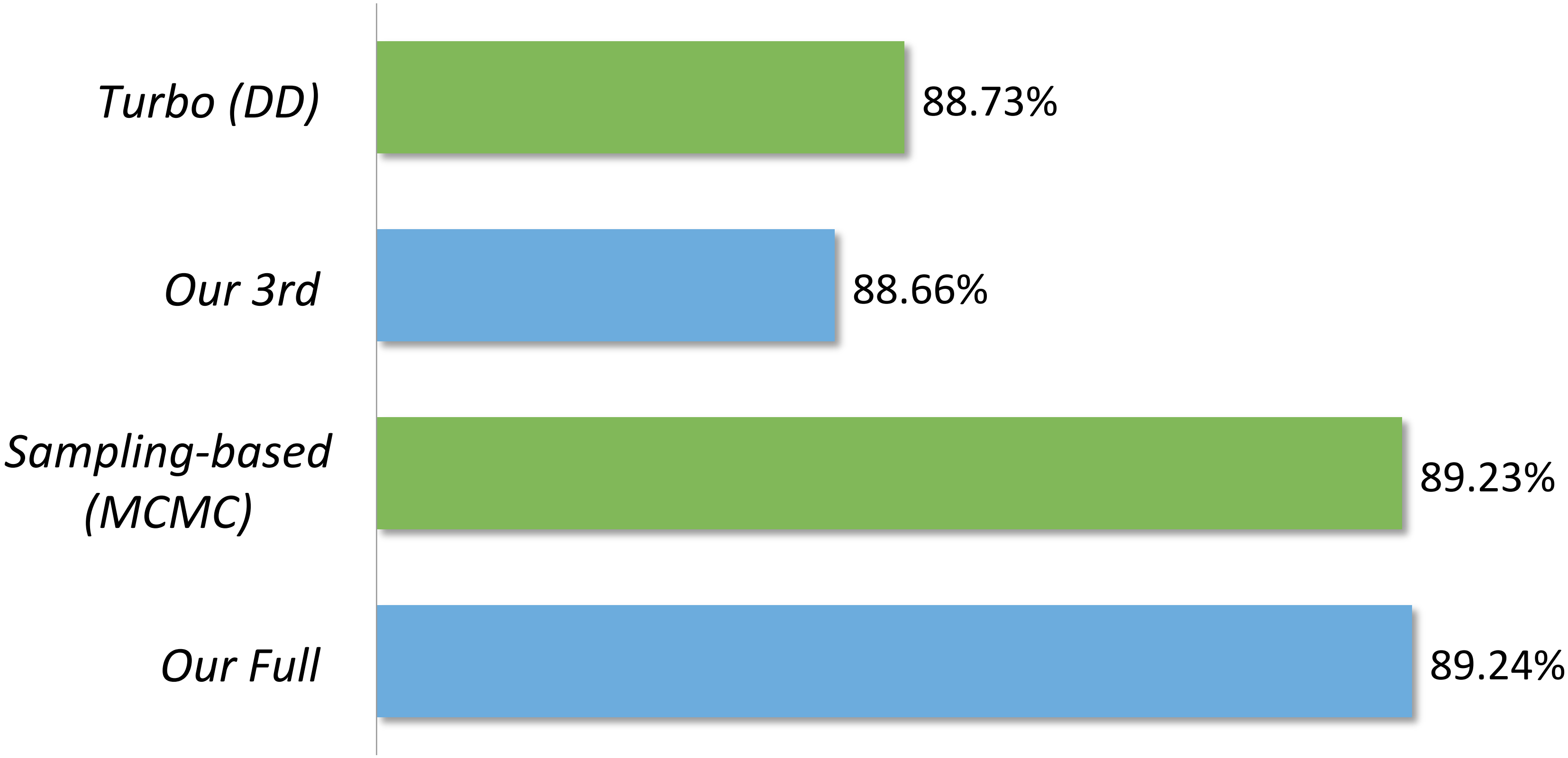

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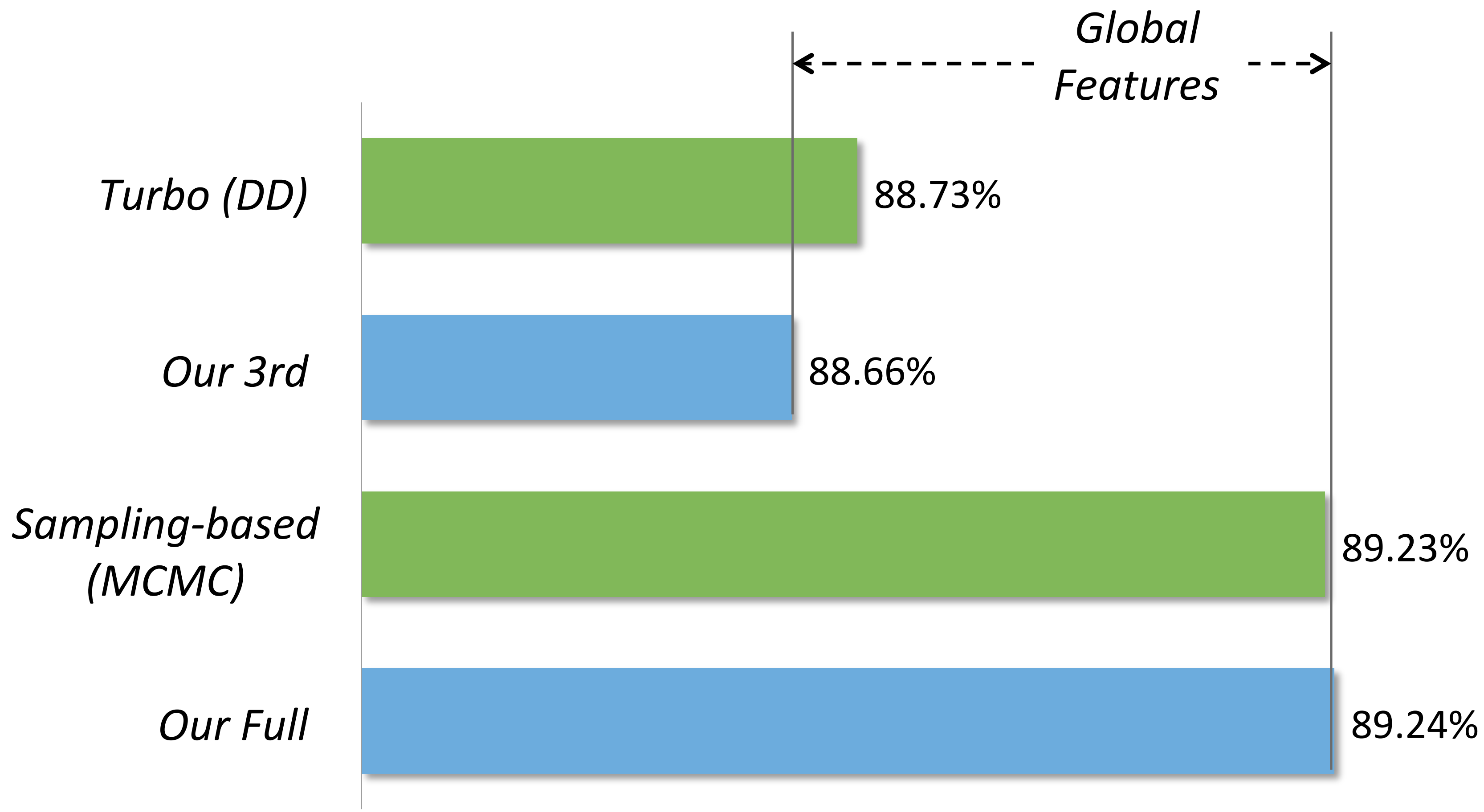
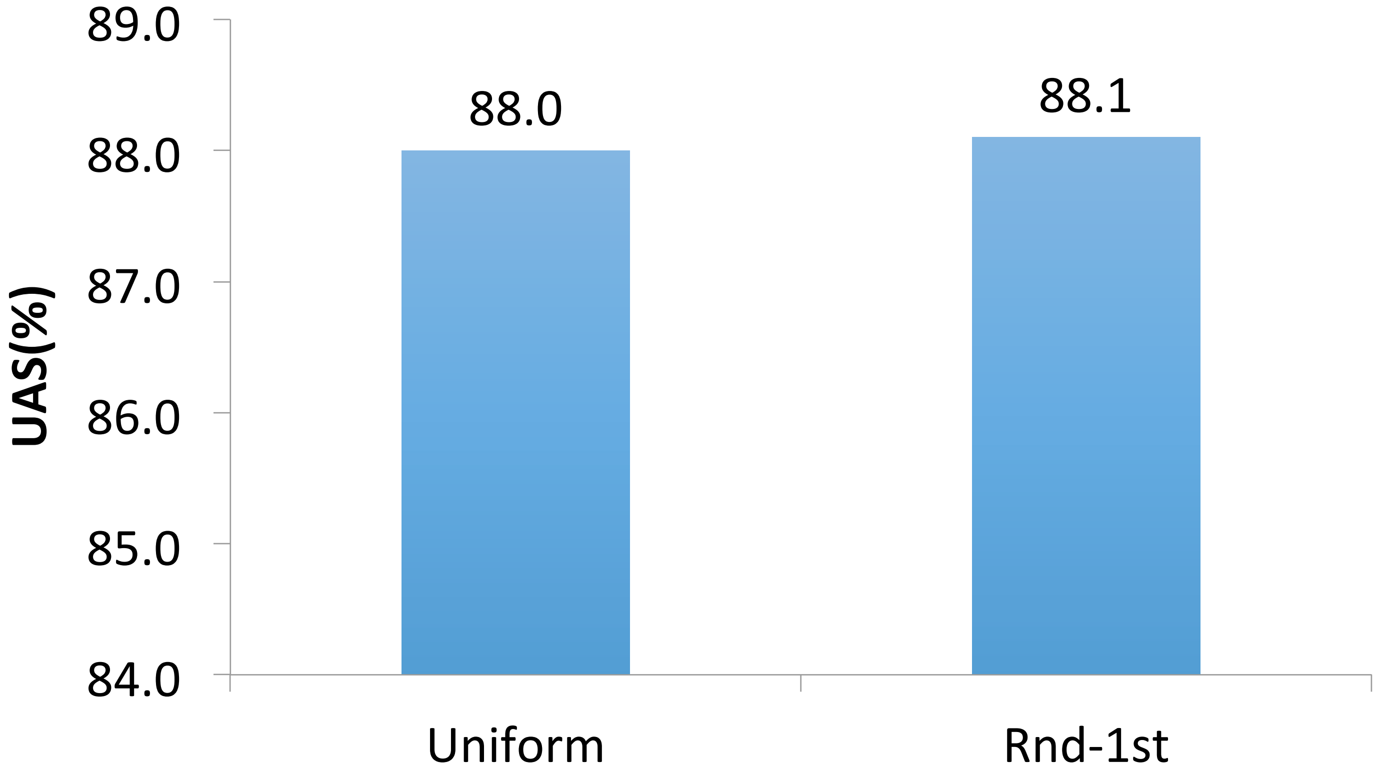
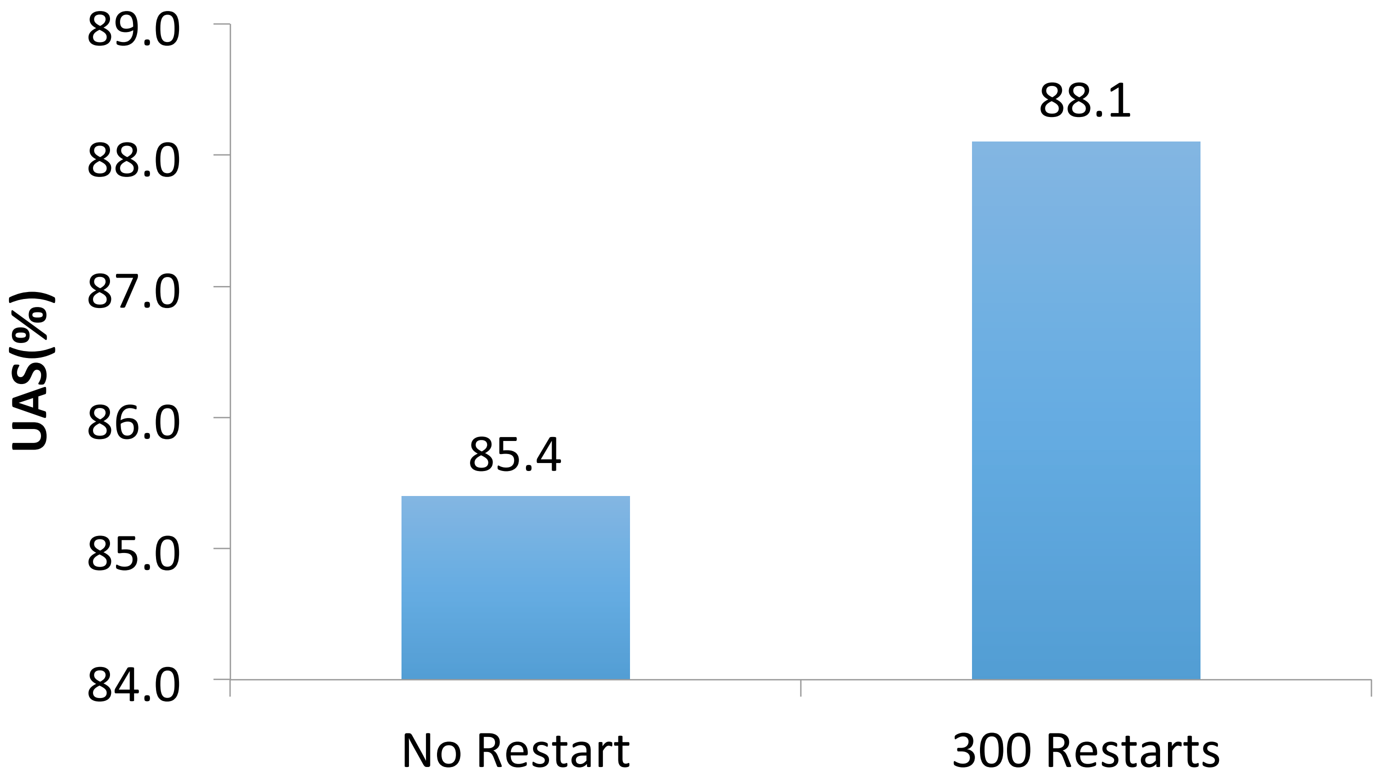


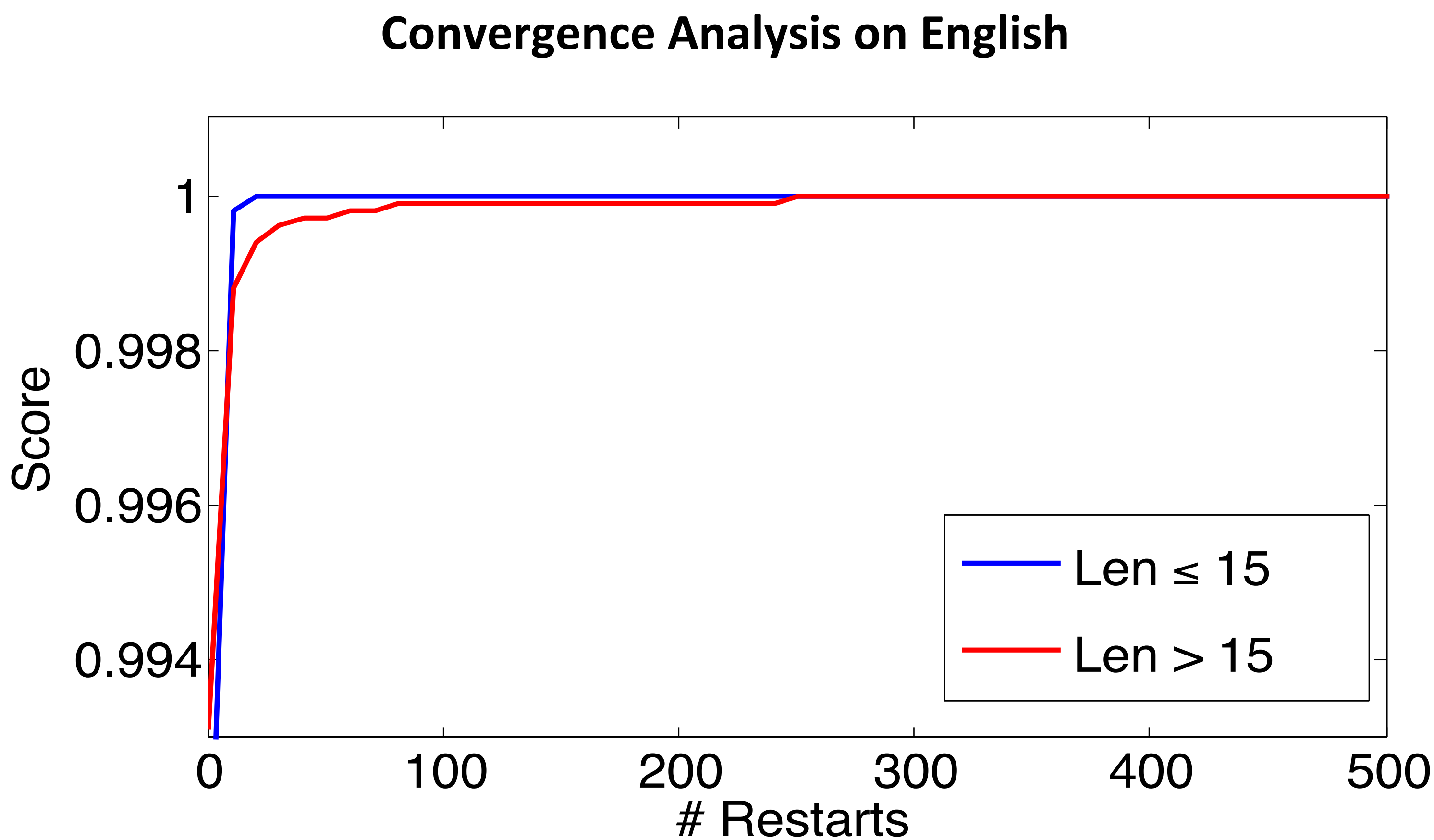
Impact of Initialization



Impact of Restarts

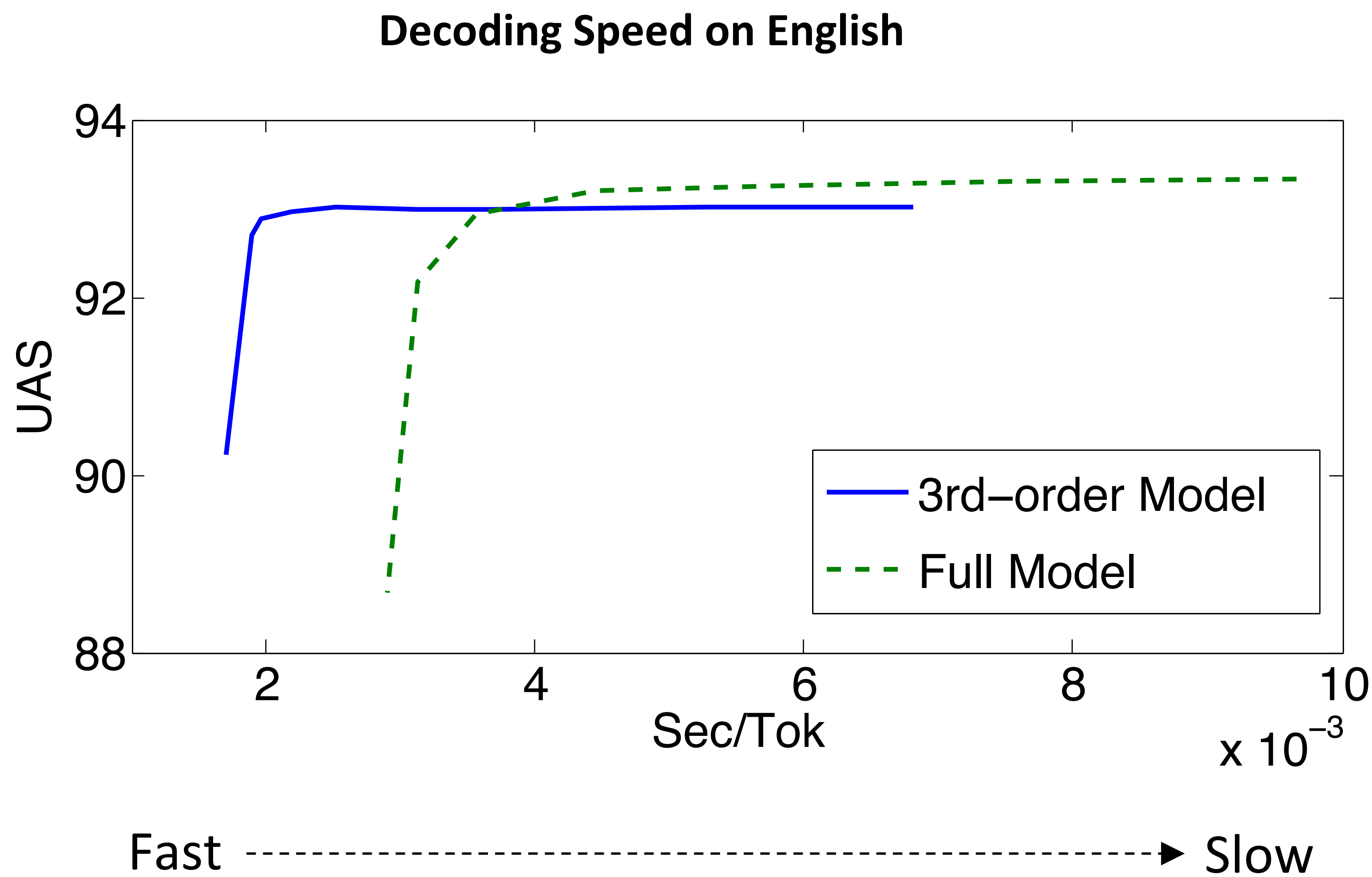


Convergence Property



- Score normalized by the highest score in 3000 restarts

Trade-off between Speed and Performance



Conclusion

- *Analysis:* we investigate average case complexity of parsing
- *Algorithm:* we introduce a simple randomized greedy inference algorithm

Source code available at:

https://github.com/taolei87/RBGParser

Thank You!