Syntax and Parsing

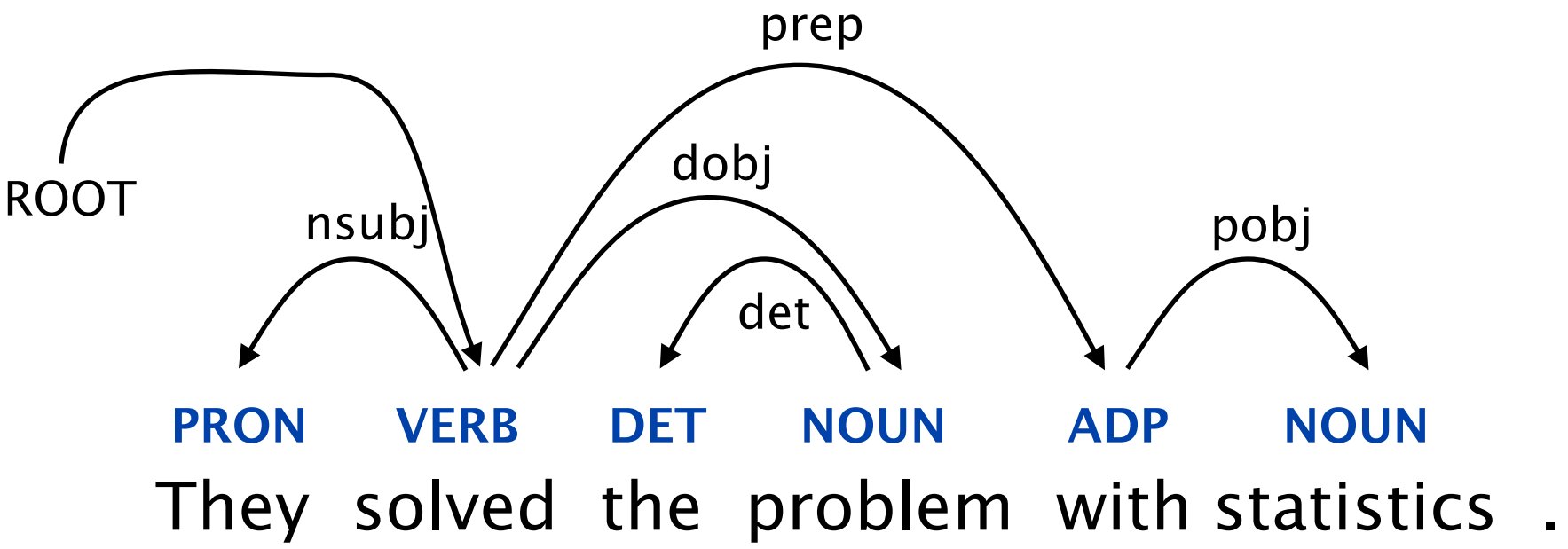
Slav Petrov – Google

Thanks to:

Dan Klein, Ryan McDonald, Alexander Rush, Joakim Nivre

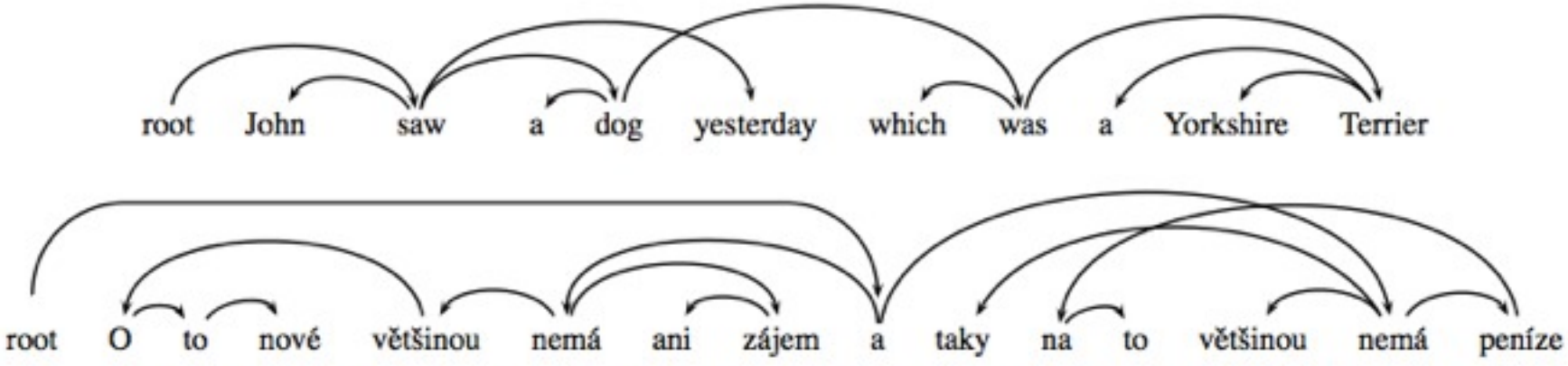
Lisbon Machine Learning School

Dependency Parsing



(Non-)Projectivity

- Crossing Arcs needed to account for non-projective constructions
- Fairly rare in English but can be common in other languages (e.g. Czech):



He is mostly not even interested in the new things and in most cases, he has no money for it either.

Formal Conditions

- For a dependency graph $G = (V, A)$
- With label set $L = \{l_1, \ldots, l_{|L|}\}$
- G is (weakly) connected:
  - If $i, j \in V$, $i \leftrightarrow^* j$.
- G is acyclic:
  - If $i \rightarrow j$, then not $j \rightarrow^* i$.
- G obeys the single-head constraint:
  - If $i \rightarrow j$, then not $i' \rightarrow j$, for any $i' \neq i$.
- G is projective:
  - If $i \rightarrow j$, then $i \rightarrow^* i'$, for any i' such that $i < i' < j$ or $j < i' < i$.

Styles of Dependency Parsing

- Transition-Based (tr)
  - Fast, greedy, linear time inference algorithms
  - Trained for greedy search
  - Beam search

[Nivre et al. ’03-’11]

- Graph-Based (gr)
  - Slower, exhaustive, dynamic programming inference algorithms
  - Higher-order factorizations

[McDonald et al. ’05-’06]

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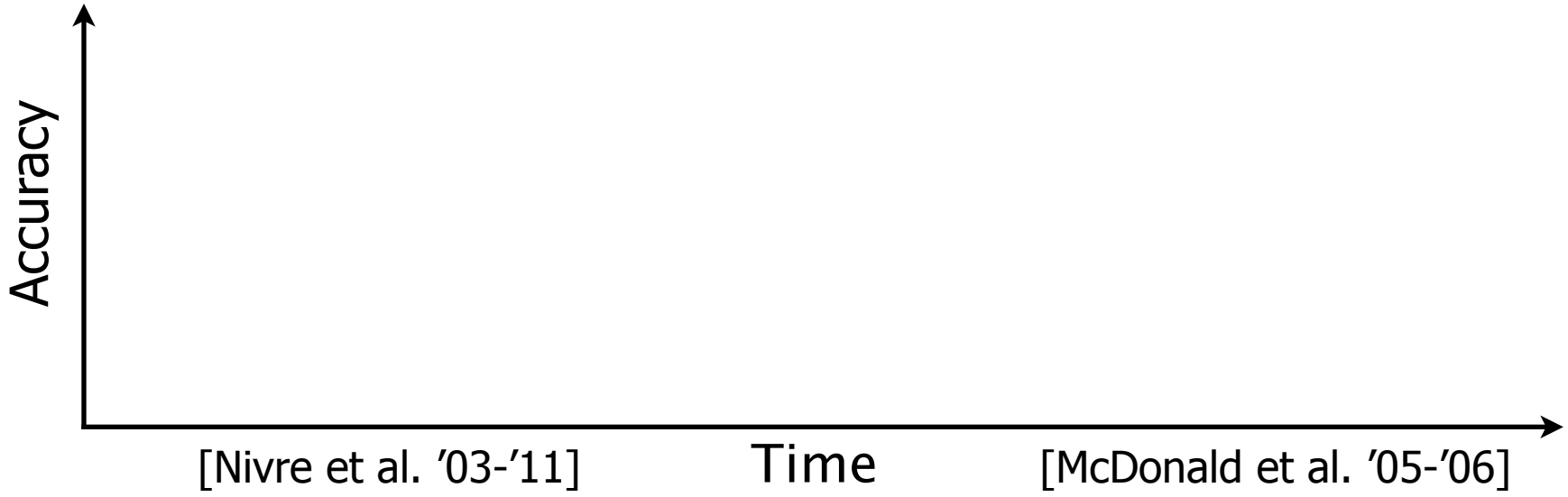

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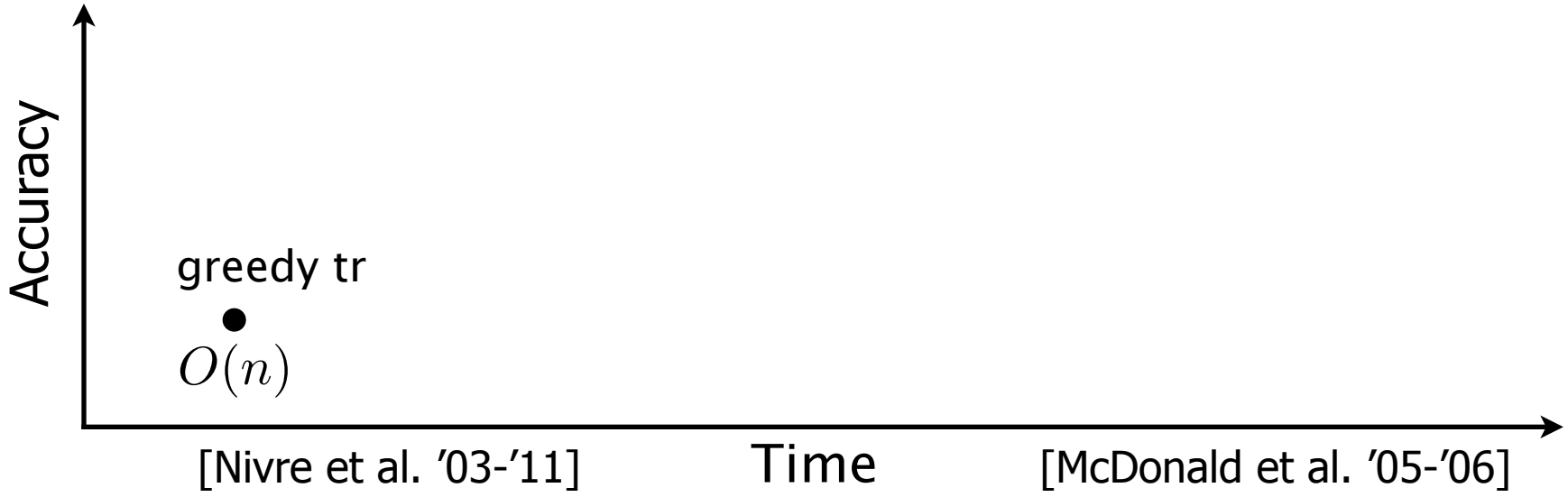

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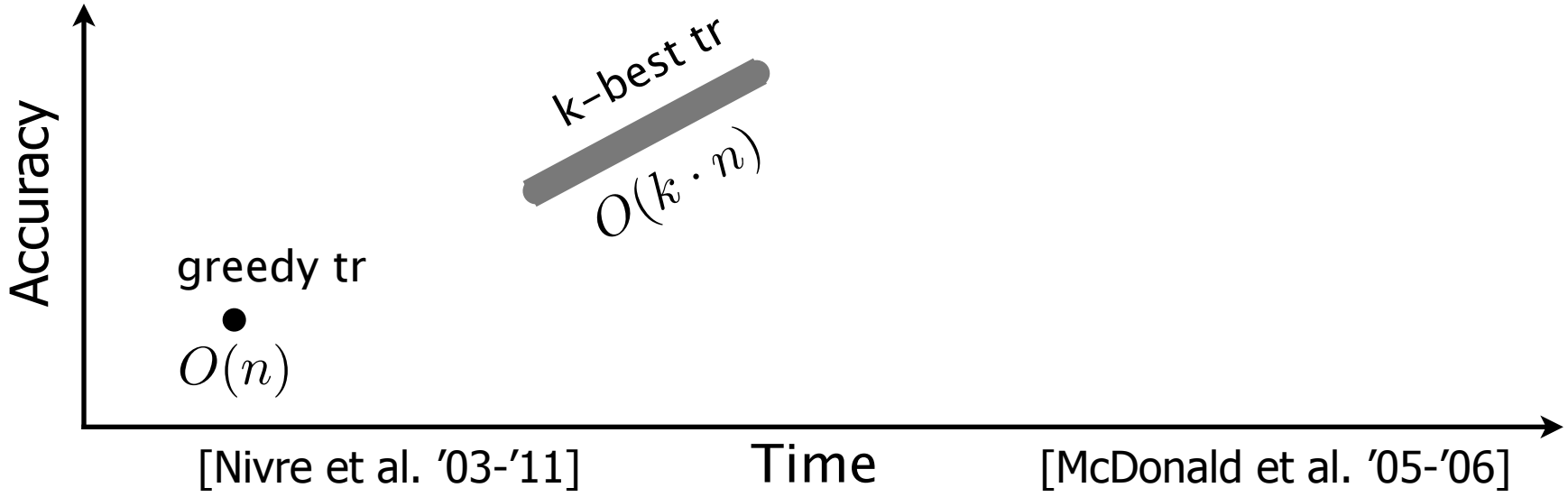

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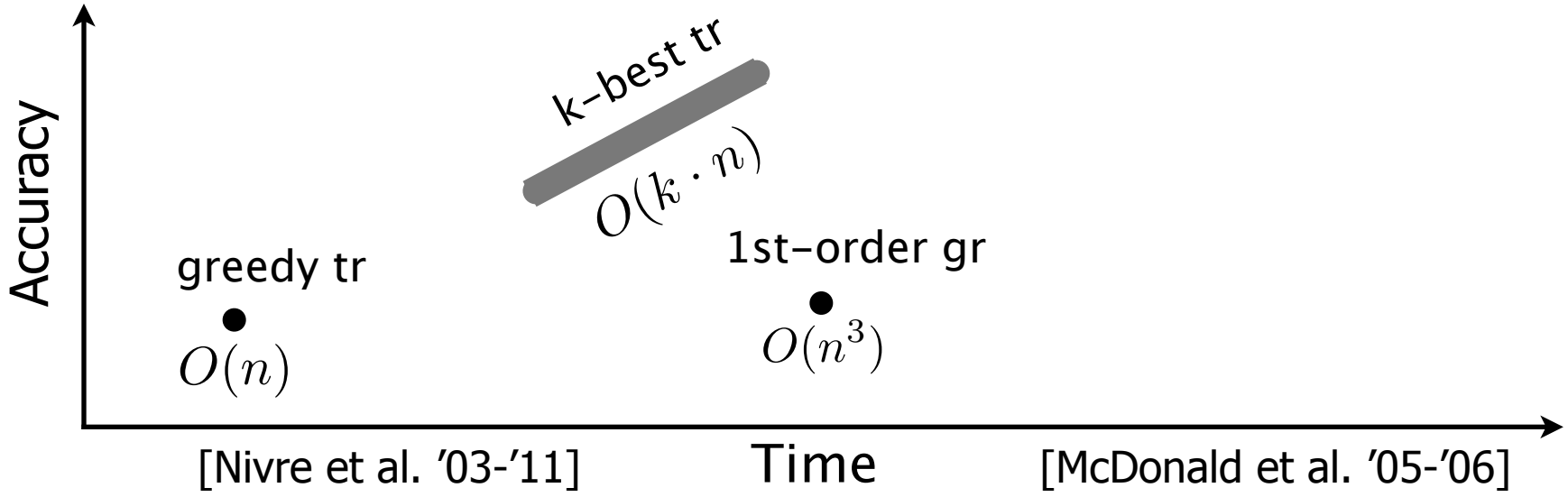

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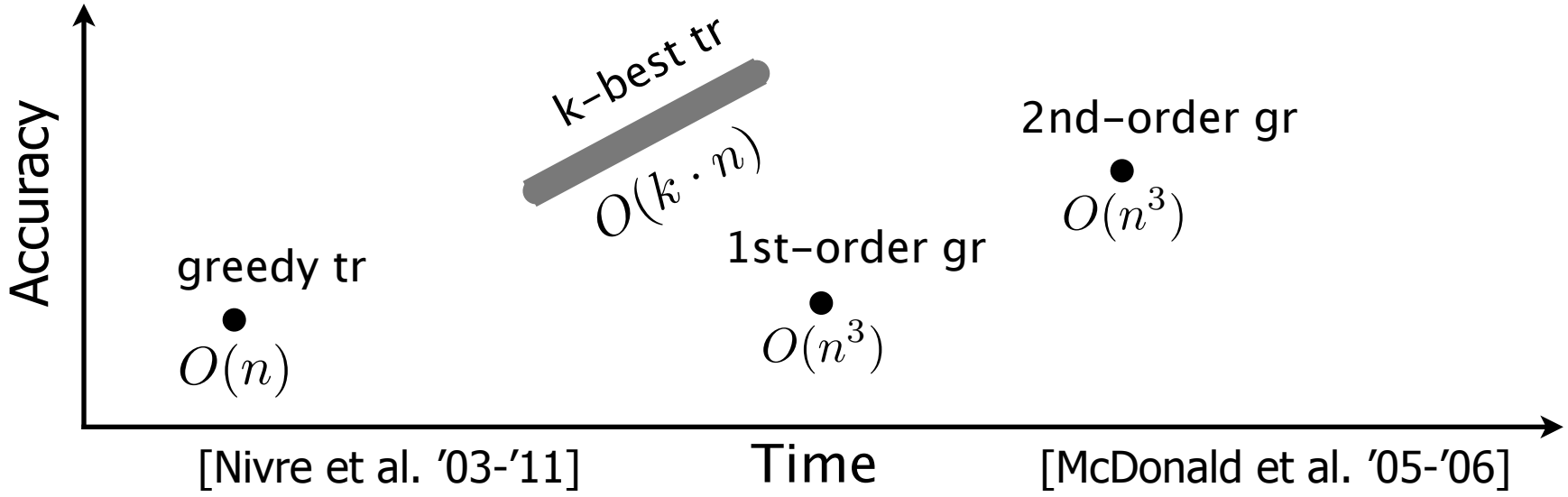

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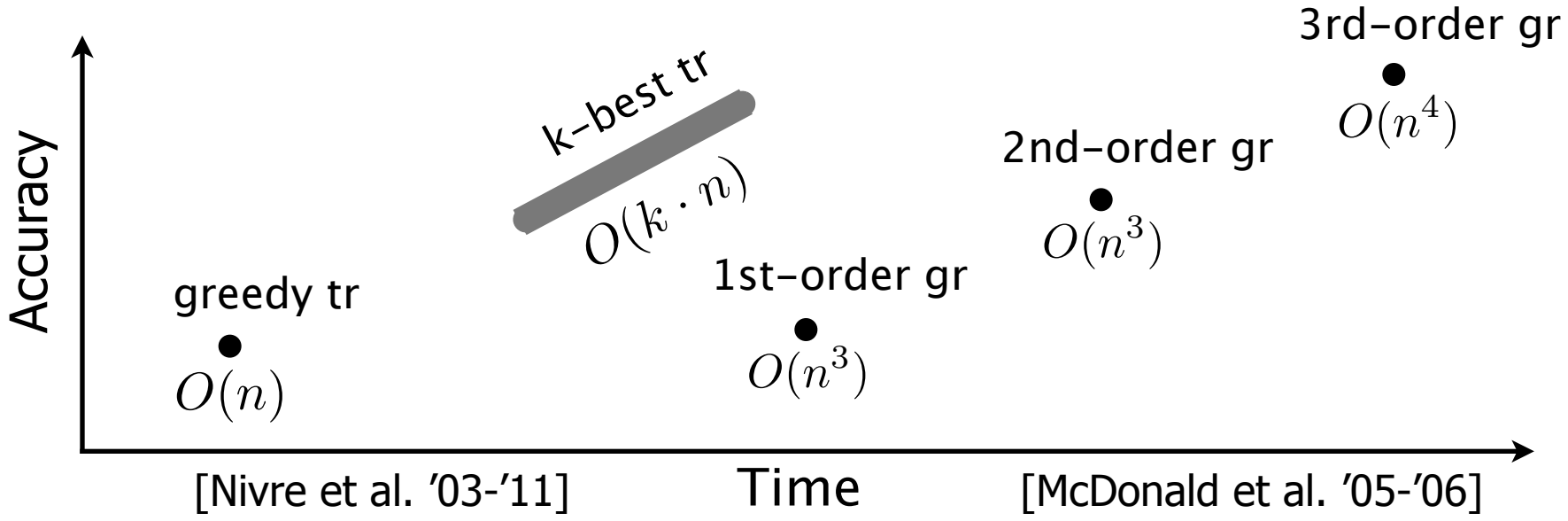


Arc-Factored Models

- Assumes that the score / probability / **weight** of a dependency graph factors by its arcs

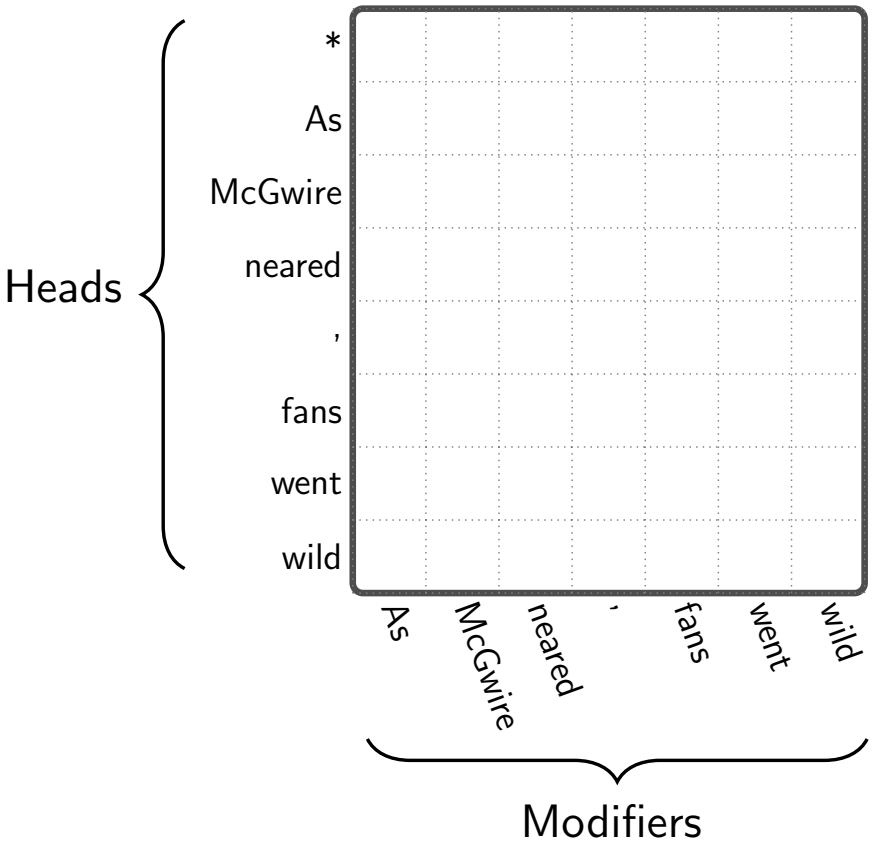
$$w(G) = \prod_{(i,j,k) \in G} w_{ij}^k$$

look familiar?

- w_{ij}^k is the weight of creating a dependency from word w_i to w_j with label l_k
- Thus there is an assumption that each dependency decision is independent
  - Strong assumption! Will address this later.

Dependency Representation

* As McGwire neared , fans went wild



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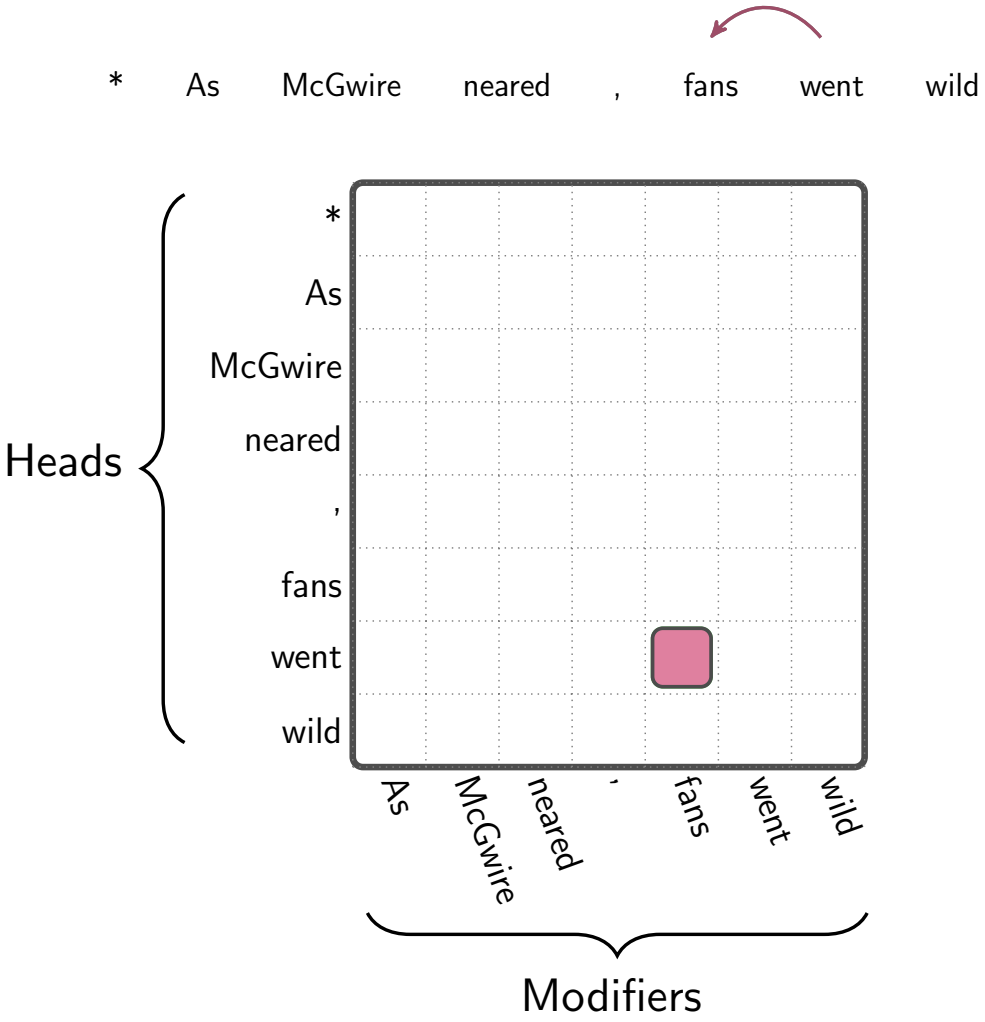

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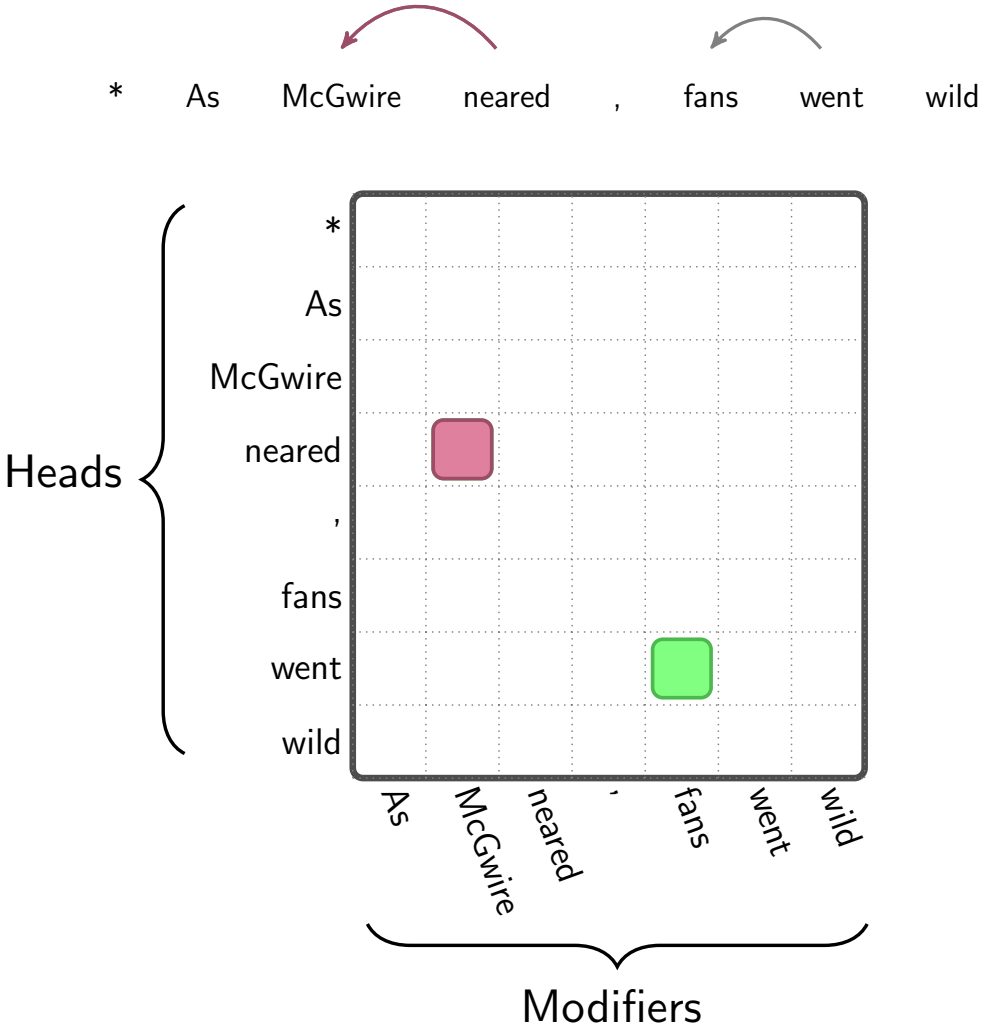

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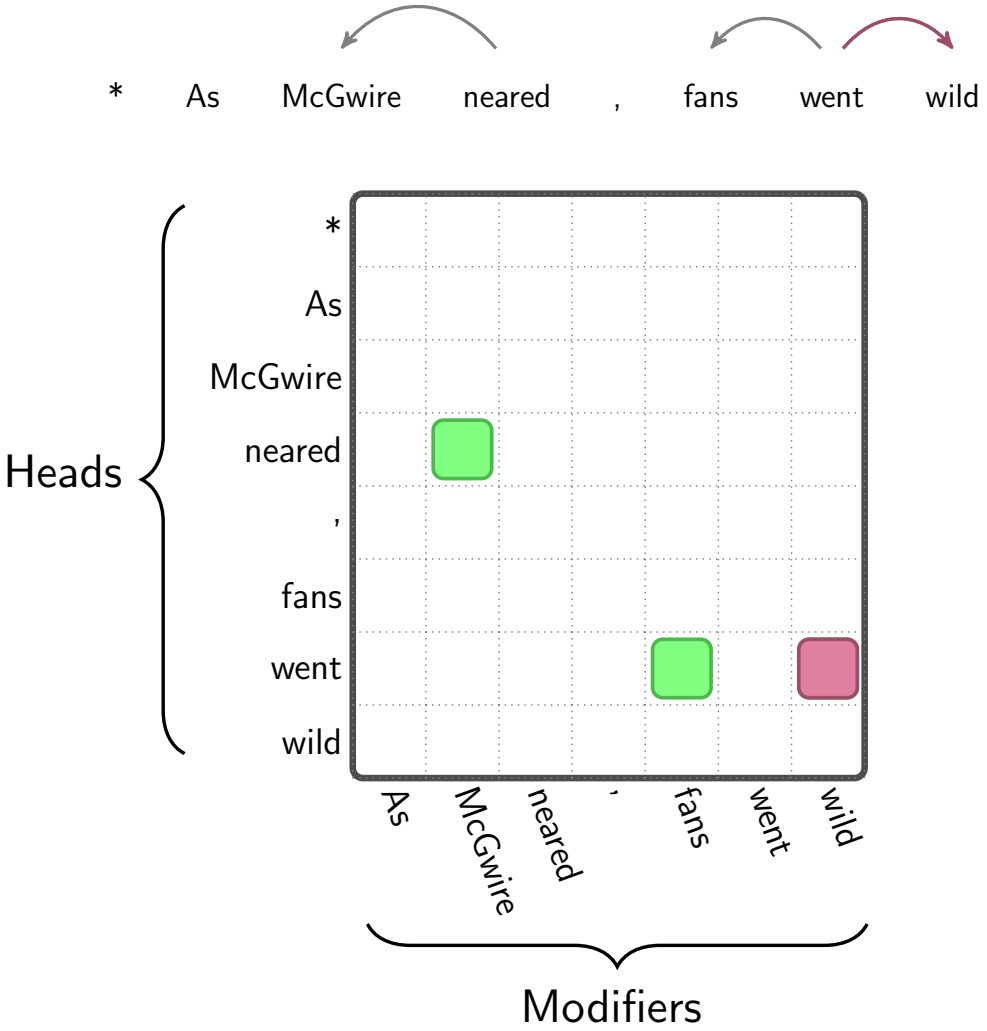

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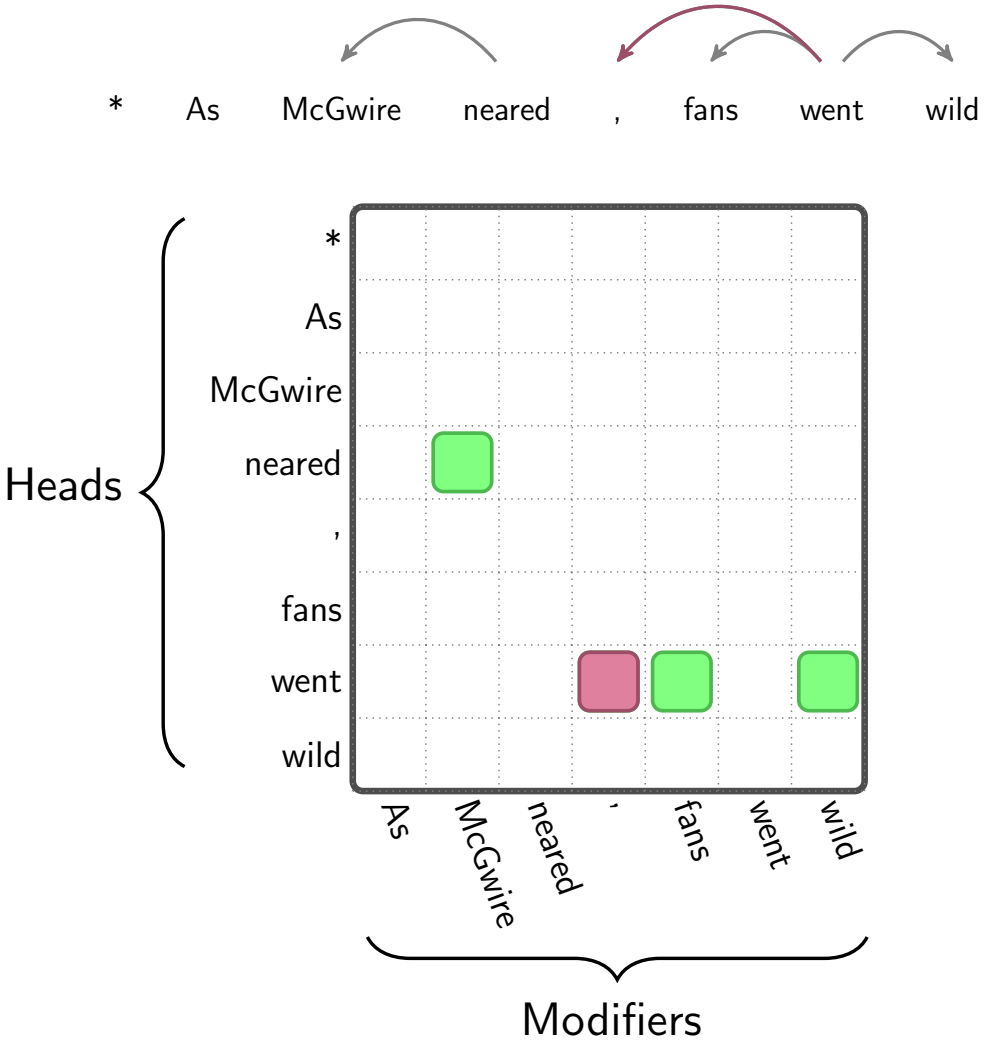

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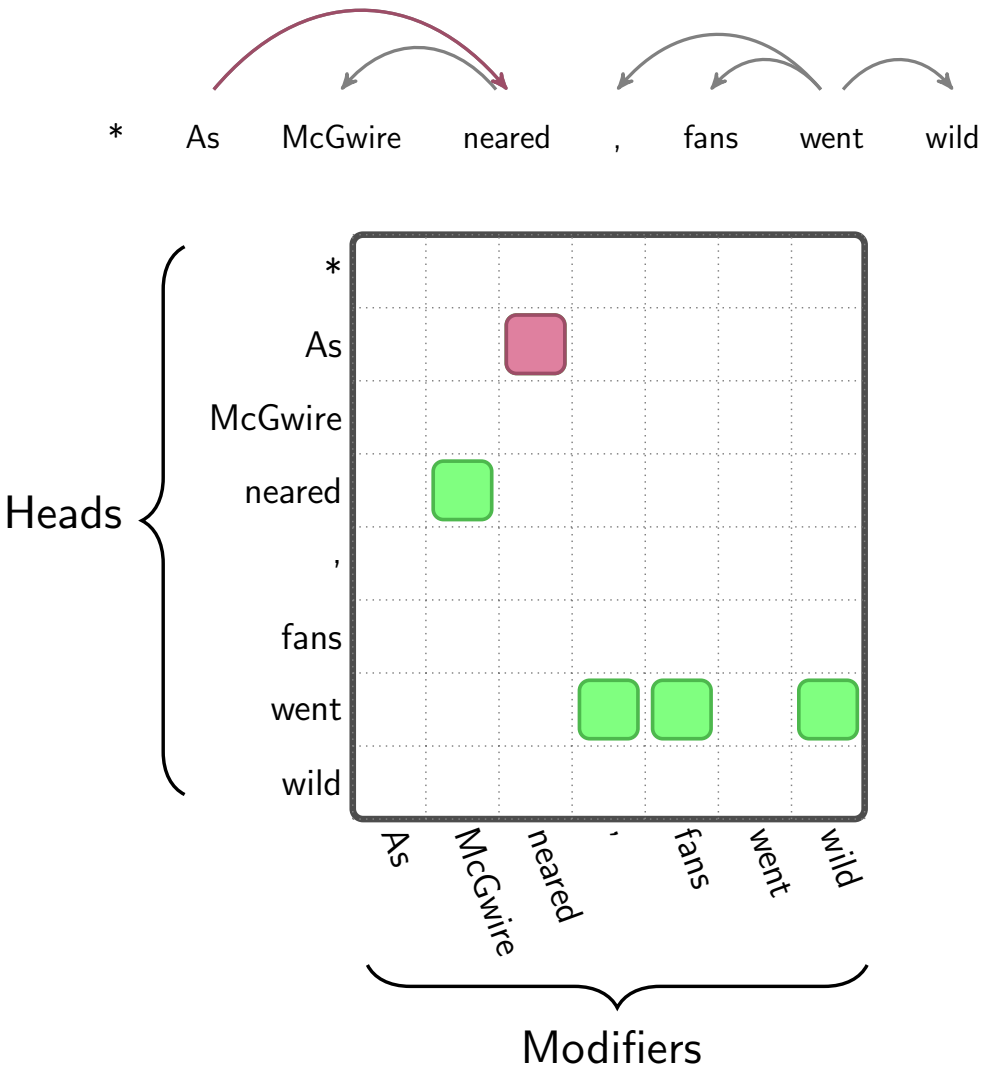

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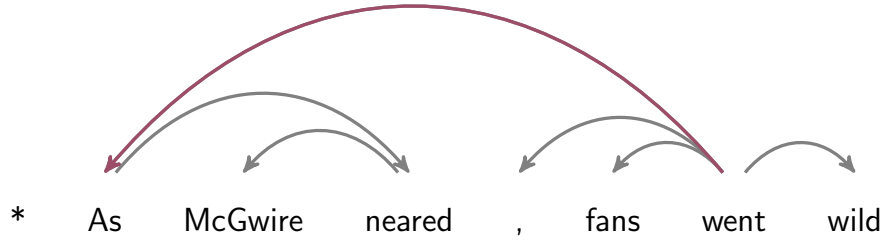

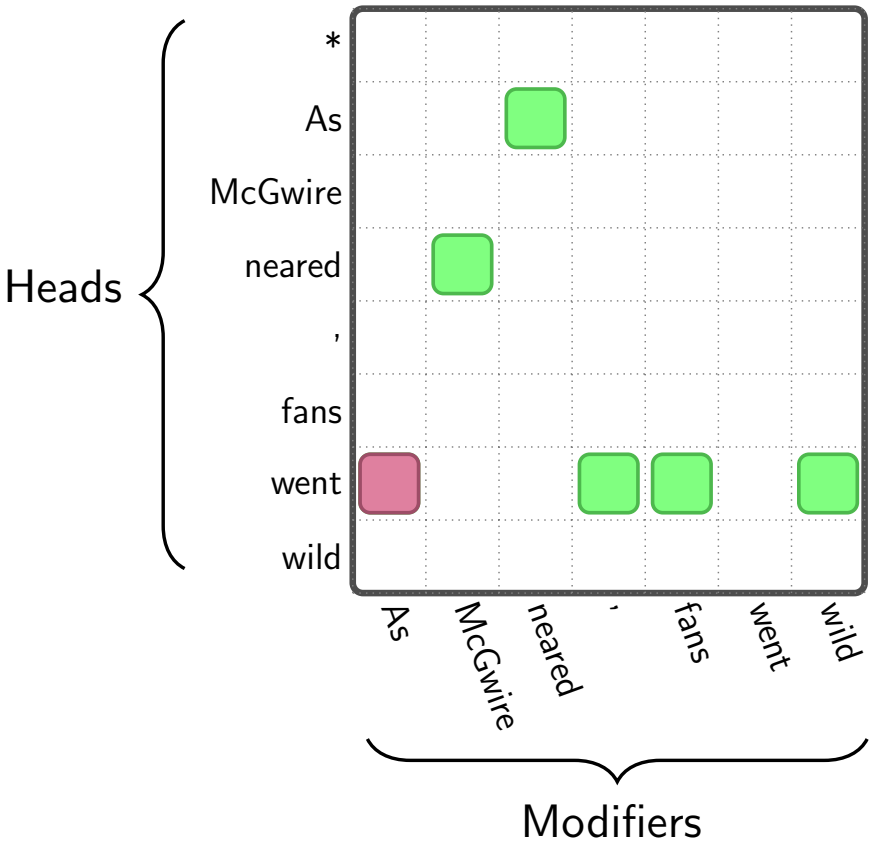

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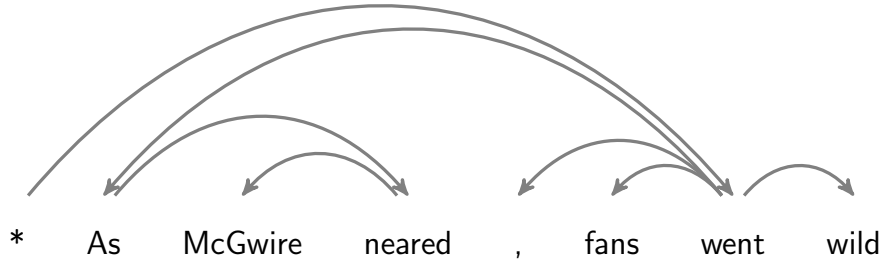
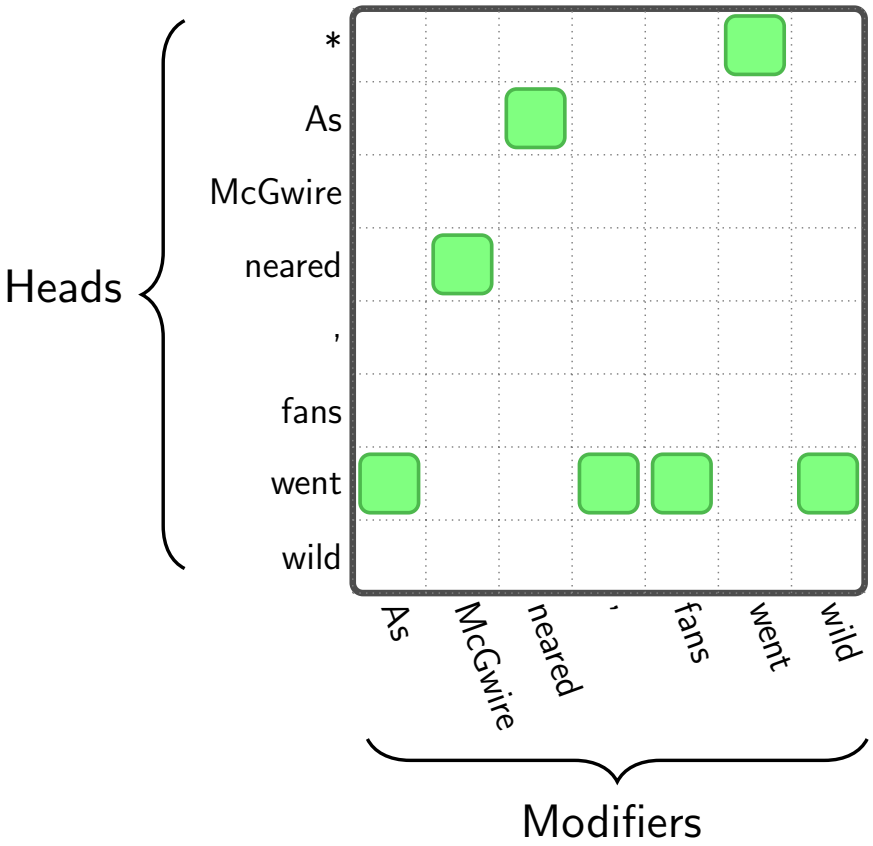
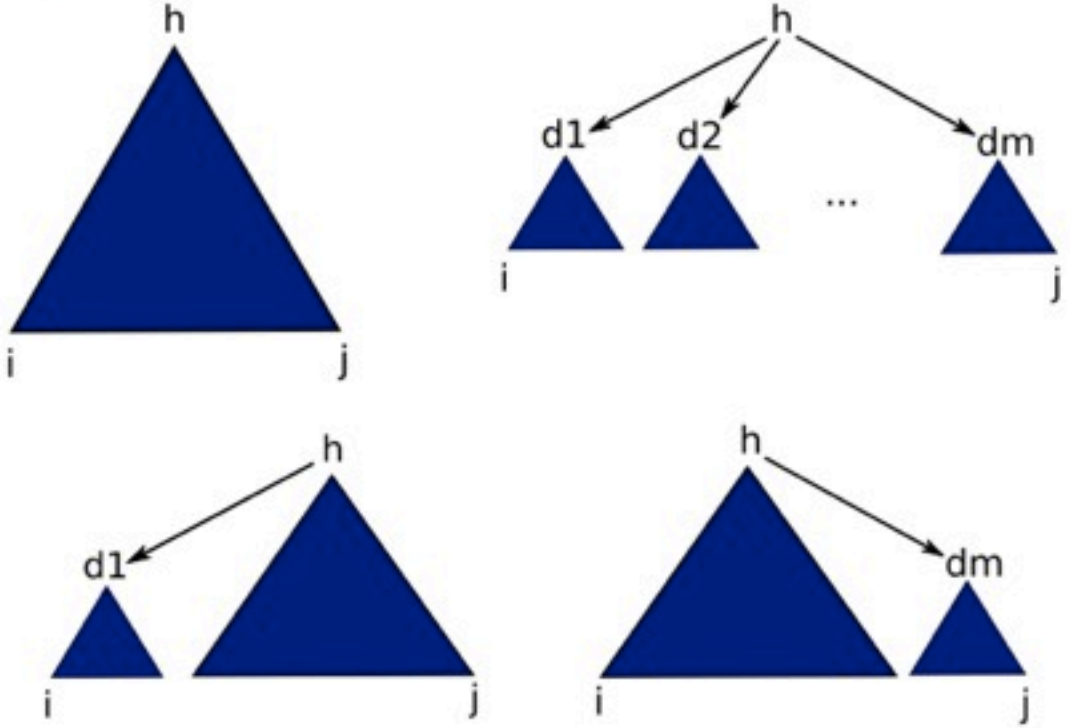




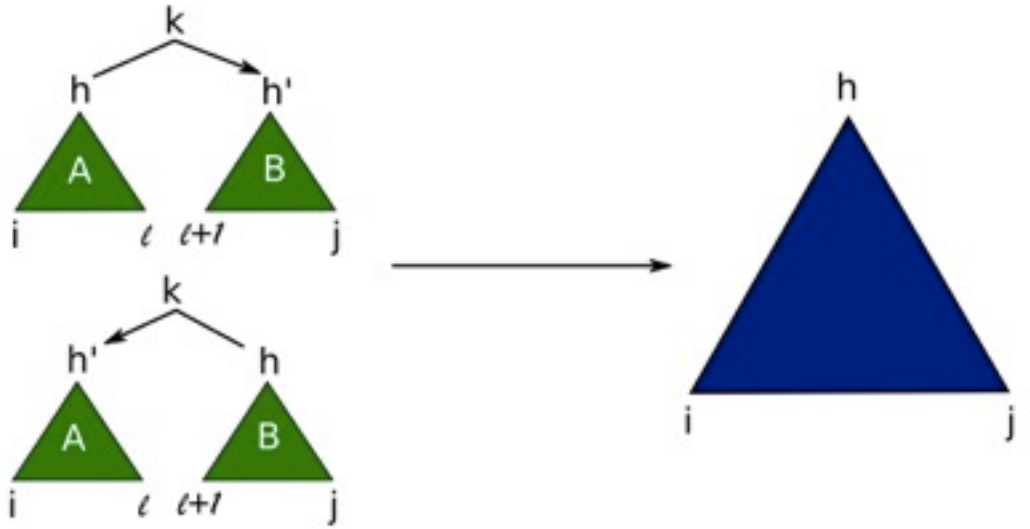
Arc-factored Projective Parsing

- All projective graphs can be written as the combination of two smaller adjacent graphs



Arc-factored Projective Parsing

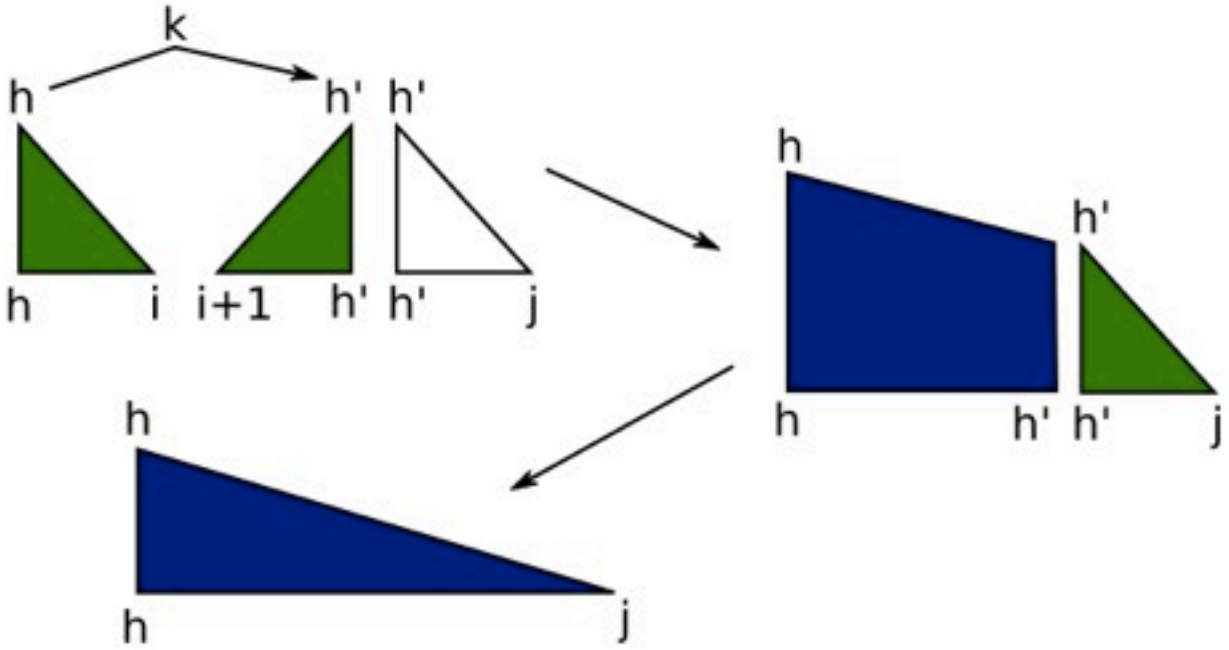
- Chart item filled in a bottom-up manner
  - First do all strings of length 1, then 2, etc. just like CKY



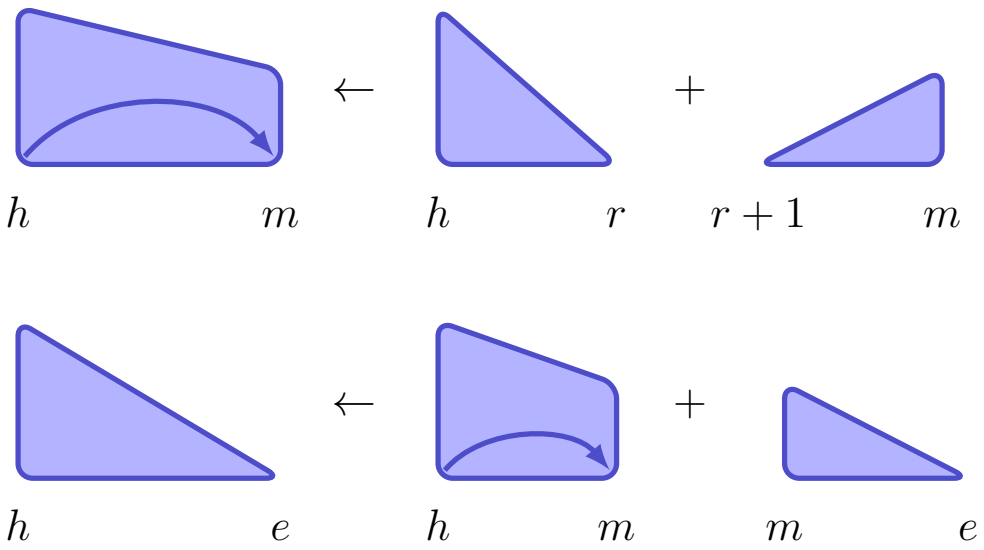
- Weight of new item: $\max_{l,j,k} \; w(A) \times w(B) \times w^k_{hh'}$
- Algorithm runs in $O(|L|n^5)$
- Use back-pointers to extract best parse (like CKY)

Eisner Algorithm

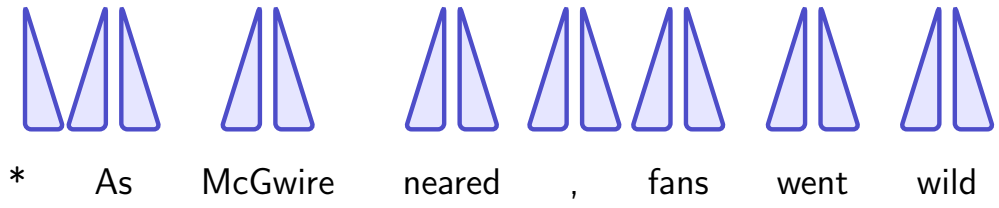
- $O(|L|n^5)$ is not that good
- [Eisner 1996] showed how this can be reduced to $O(|L|n^3)$
  - Key: split items so that sub-roots are always on periphery

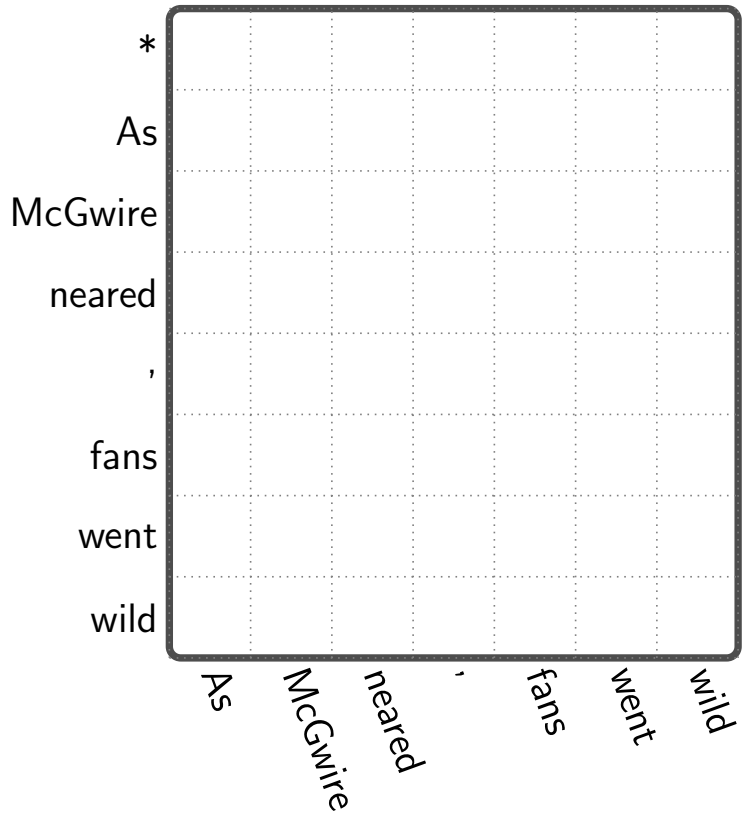


Eisner First-Order Parsing



Order Parsing





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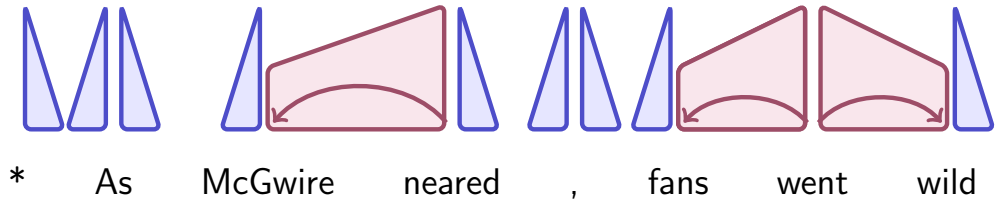

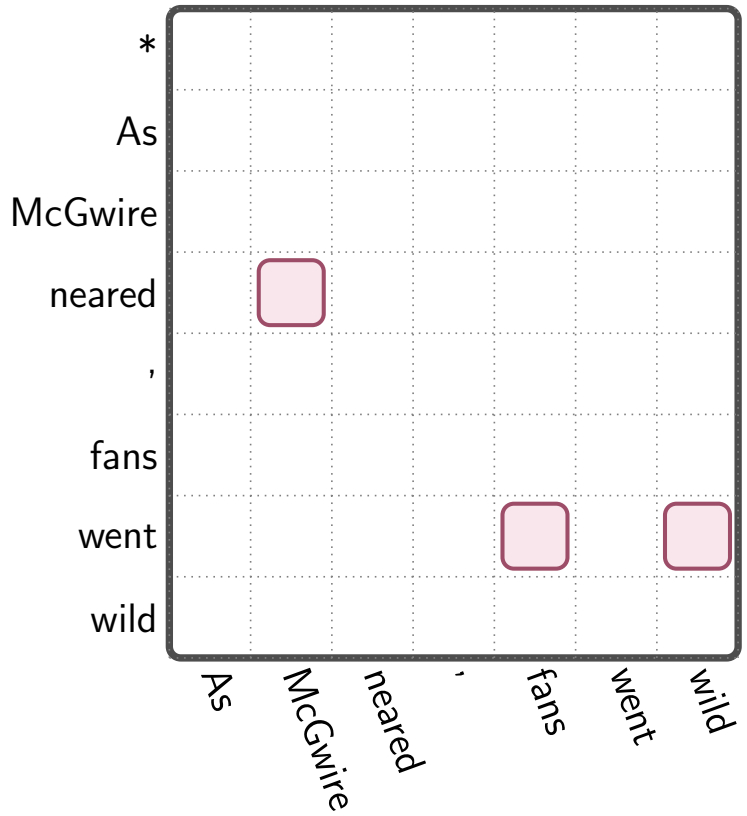

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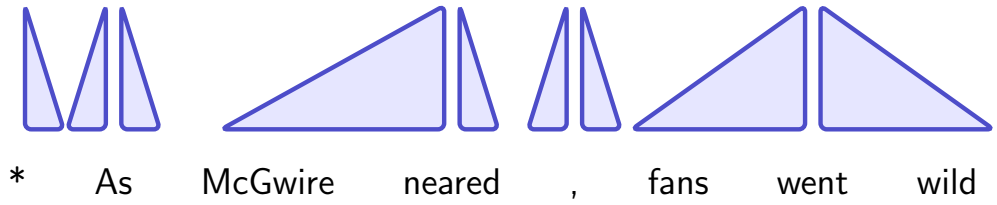

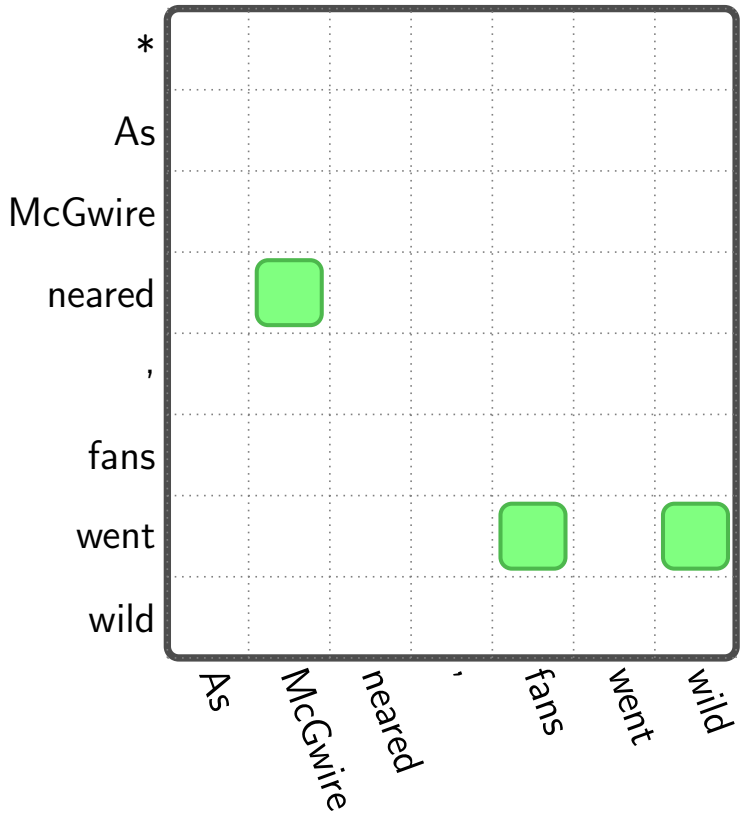

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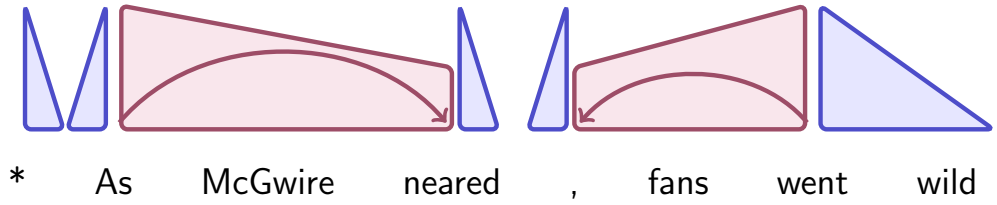

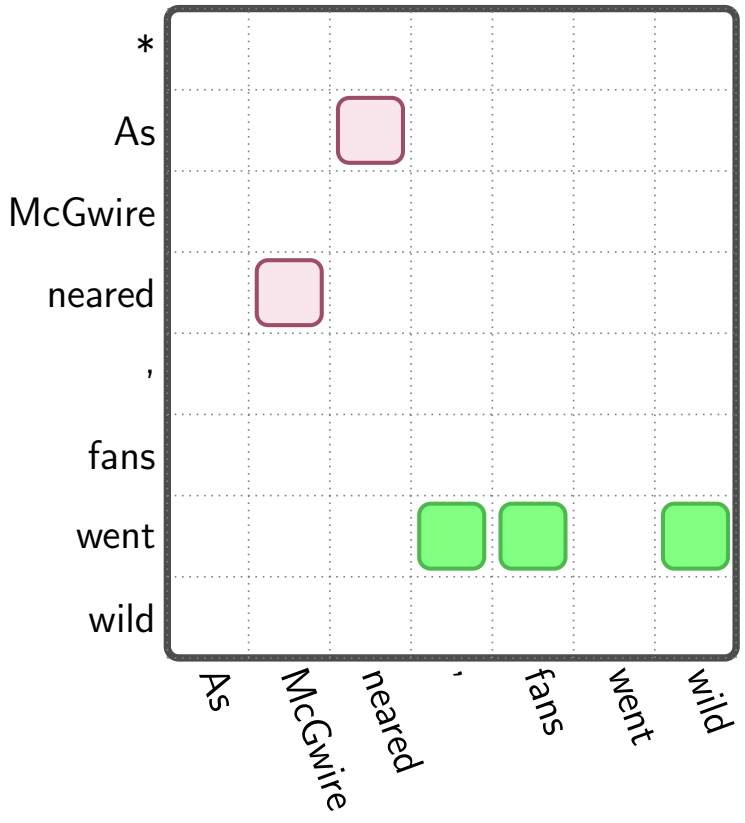

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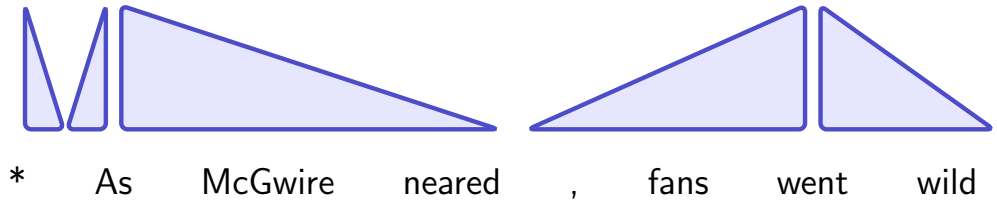

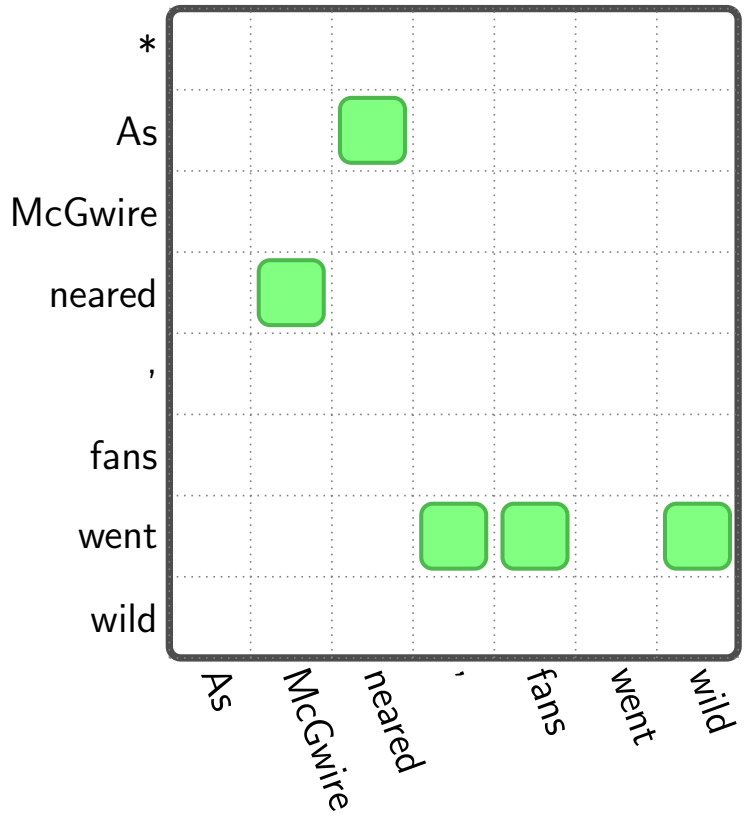

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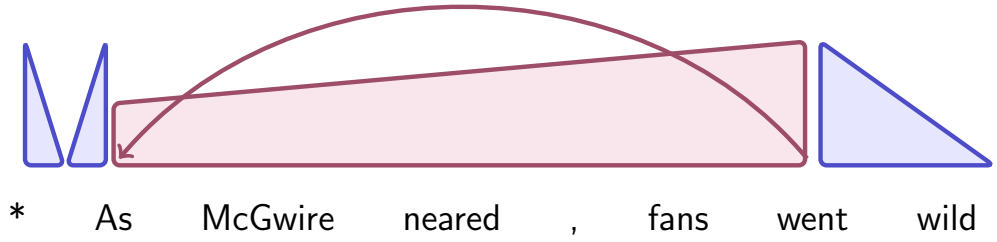

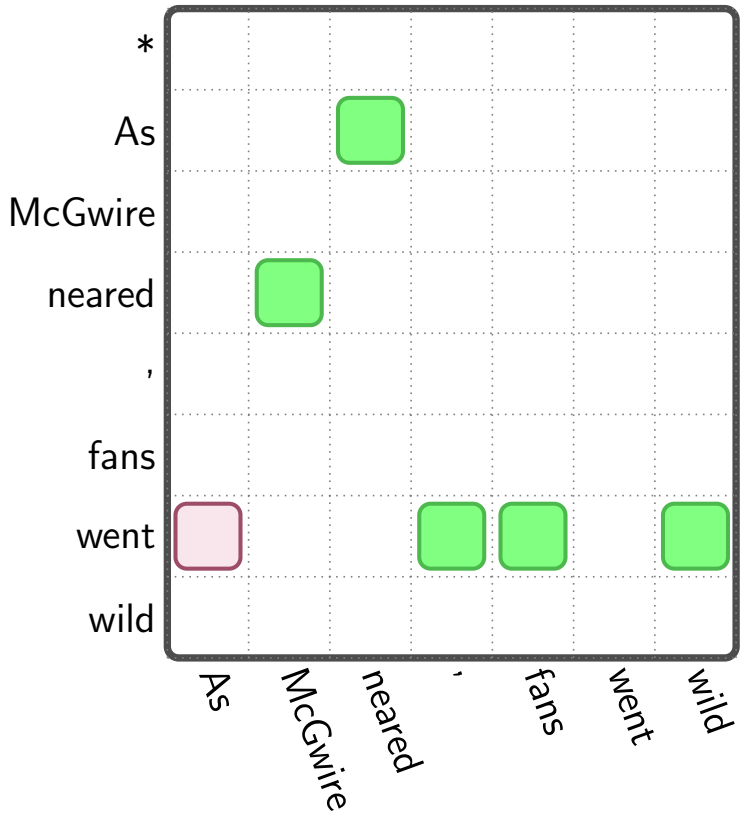

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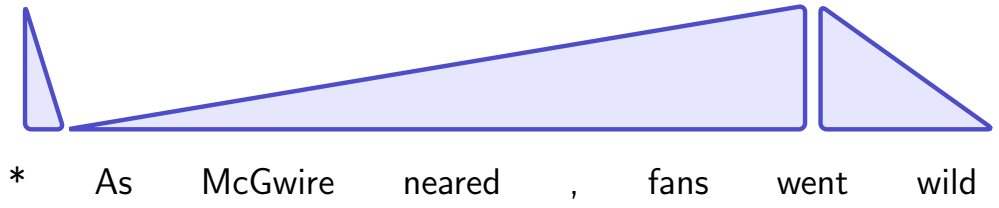

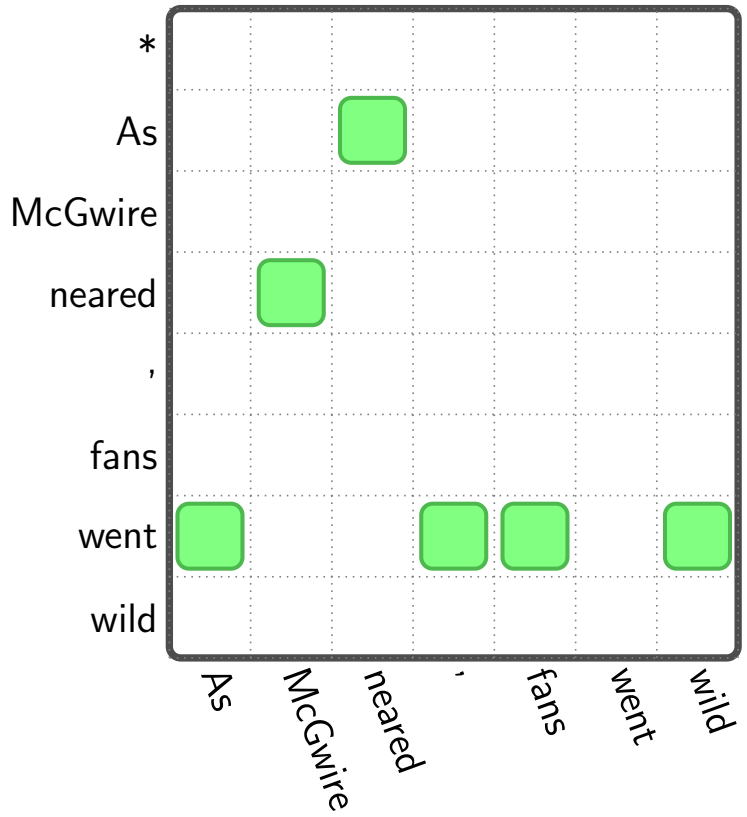

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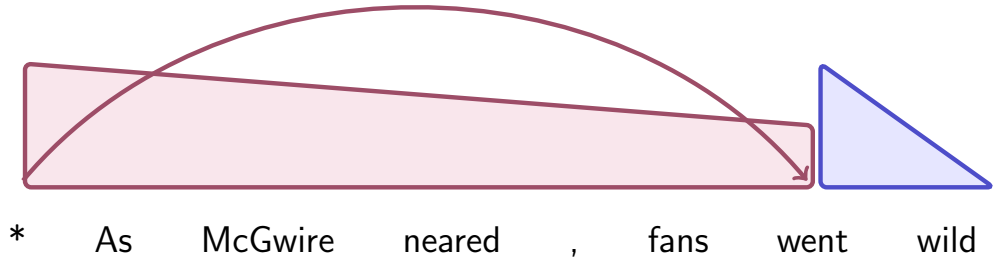

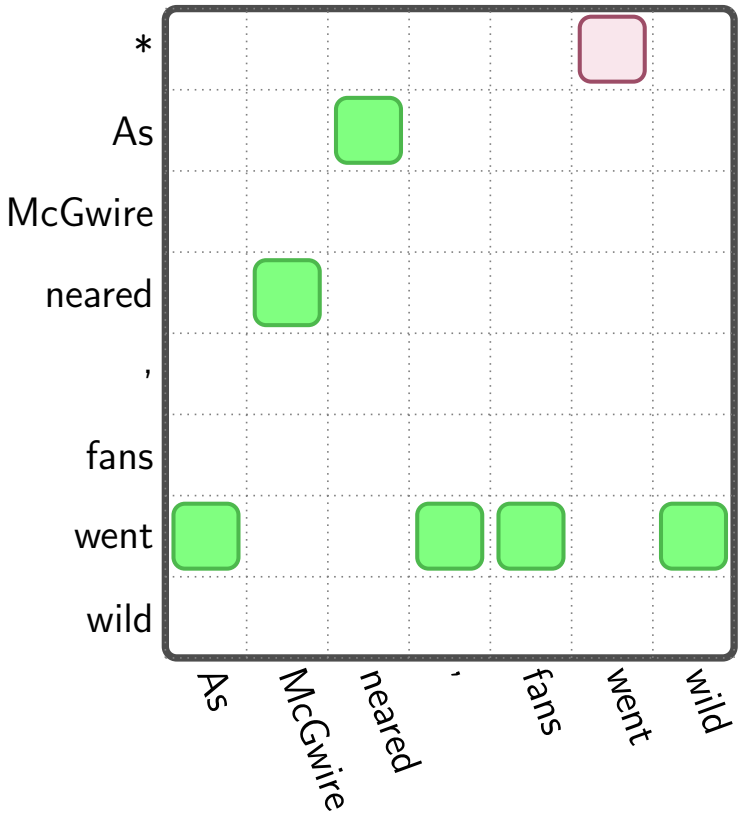

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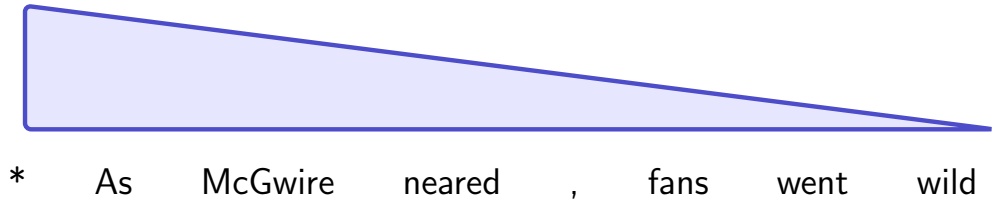
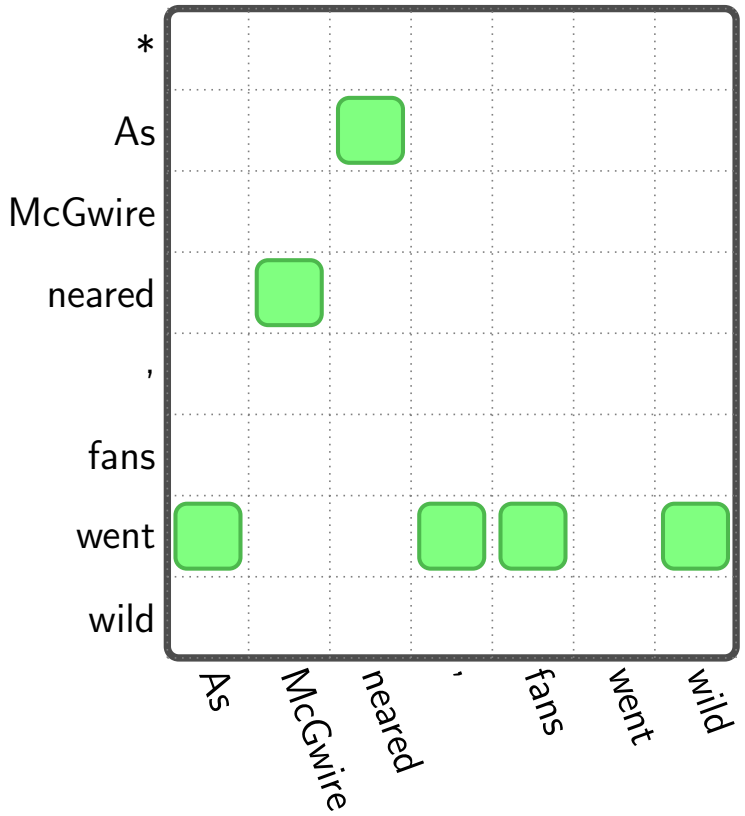




Eisner Algorithm Pseudo Code

Initialization: $C[s][s][d][c] = 0.0 \quad \forall s, d, c$

for $k : 1..n$

  for $s : 1..n$

    $t = s + k$

    if $t > n$ then break

    % First: create incomplete items

    $C[s][t][\leftarrow][0] = \max_{s \leq r < t} (C[s][r][\rightarrow][1] + C[r+1][t][\leftarrow][1] + s(t, s))$

    $C[s][t][\rightarrow][0] = \max_{s \leq r < t} (C[s][r][\rightarrow][1] + C[r+1][t][\leftarrow][1] + s(s, t))$

    % Second: create complete items

    $C[s][t][\leftarrow][1] = \max_{s \leq r < t} (C[s][r][\leftarrow][1] + C[r][t][\leftarrow][0])$

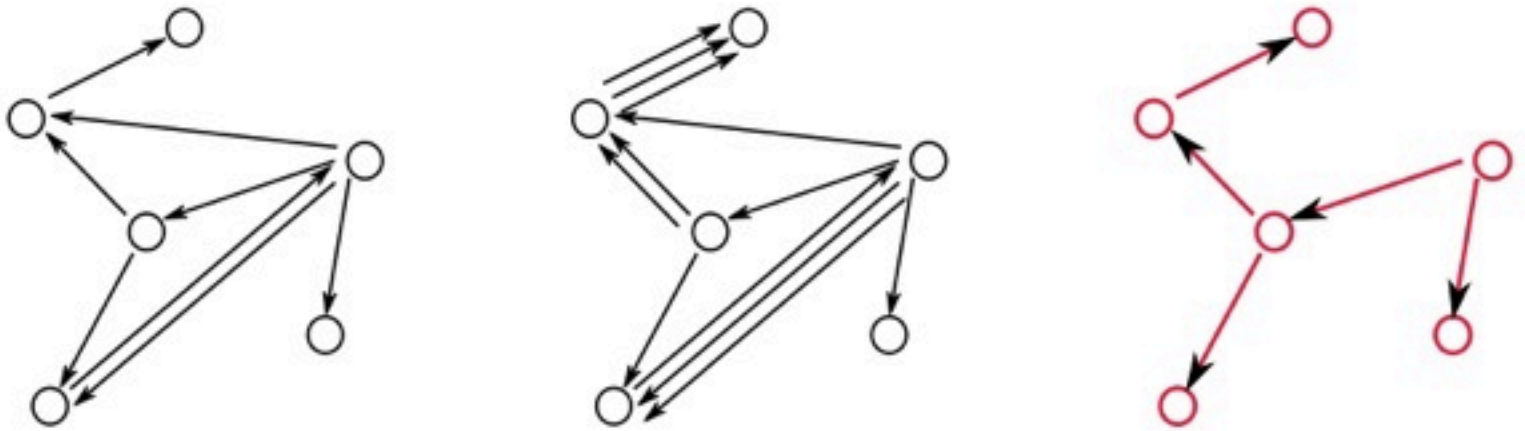
    $C[s][t][\rightarrow][1] = \max_{s < r \leq t} (C[s][r][\rightarrow][0] + C[r][t][\rightarrow][1])$

  end for

end for

Maximum Spanning Trees (MSTs)

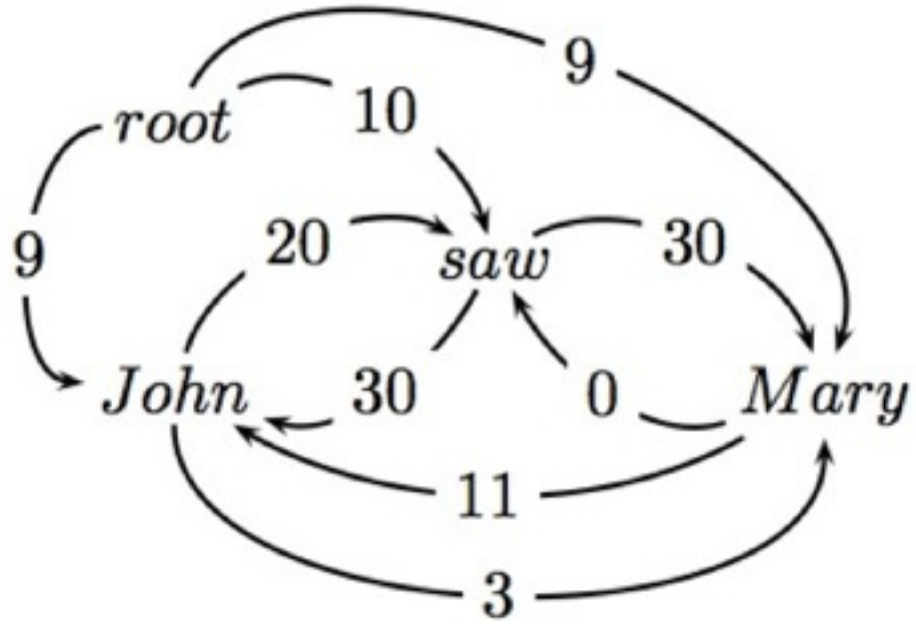
- A directed spanning tree of a (multi-)digraph $G = (V, A)$, is a subgraph $G' = (V', A')$ such that:
  - $V' = V$
  - $A' \subseteq A$, and $|A'| = |V'| - 1$
  - G' is a tree (acyclic)
- A spanning tree of the following (multi-)digraphs



Can use MST algorithms for nonprojective parsing!

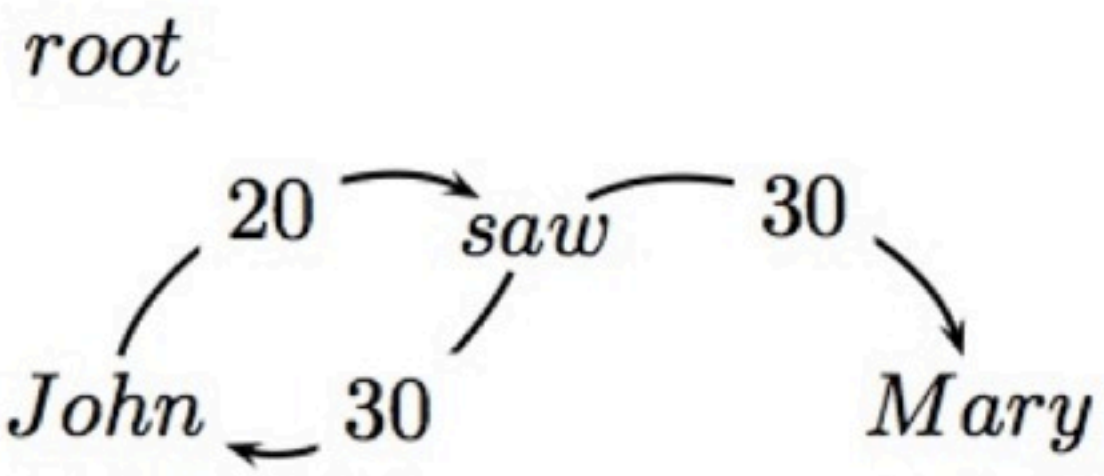
Chu-Liu-Edmonds

- x = root John saw Mary



Chu-Liu-Edmonds

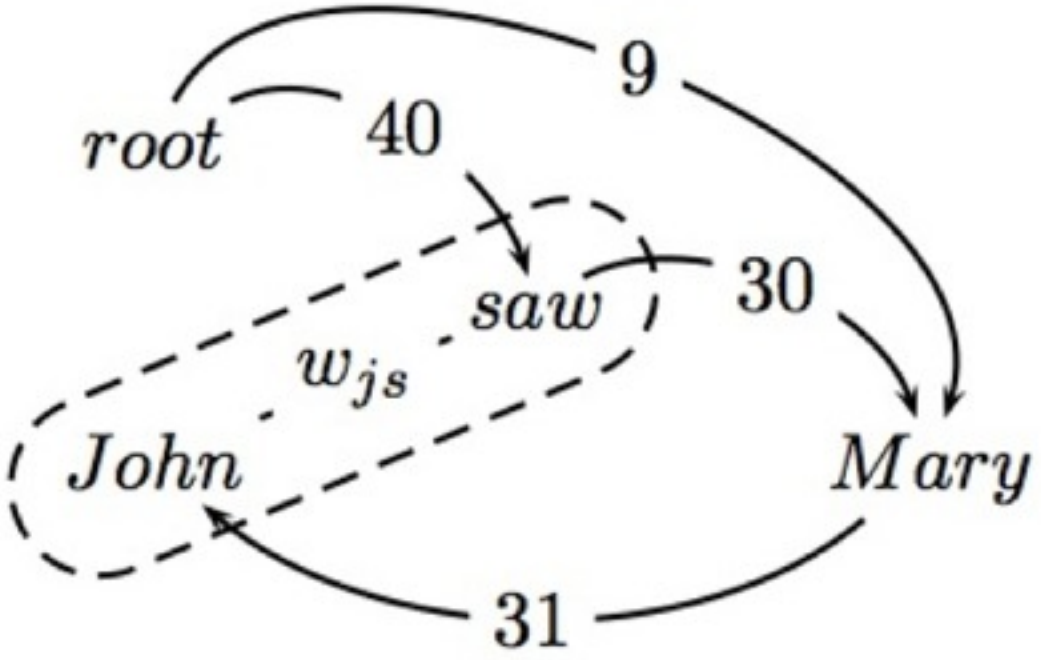
- Find highest scoring incoming arc for each vertex



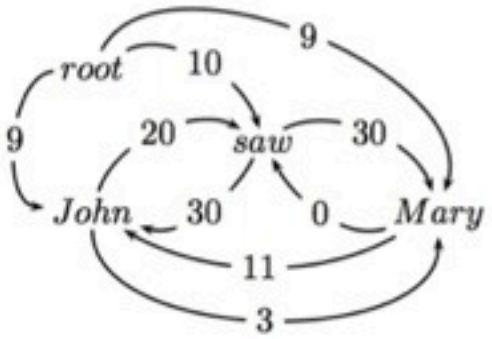
- If this is a tree, then we have found MST!!

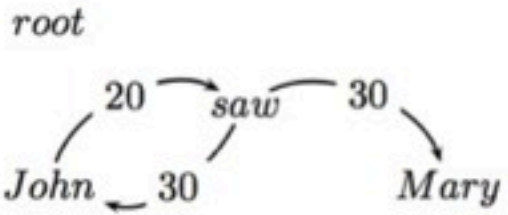
Find Cycle and Contract

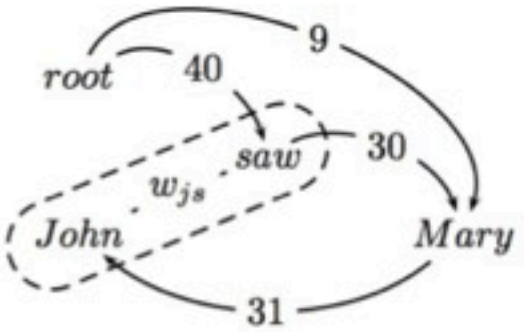
- If not a tree, identify cycle and contract
- Recalculate arc weights into and out-of cycle



Recalculate Edge Weights



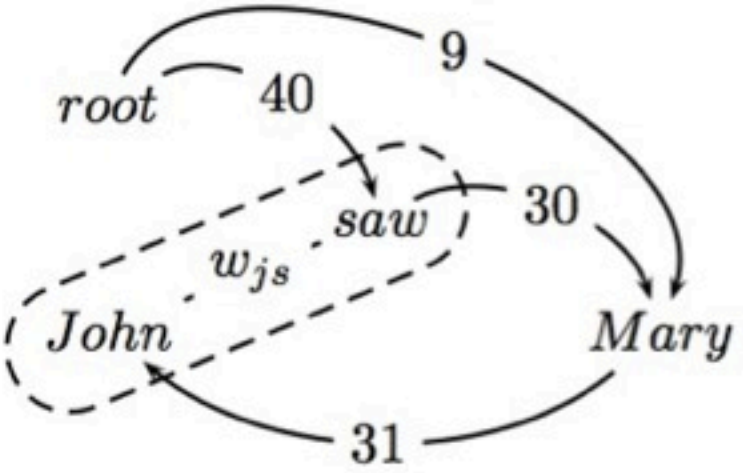




- Incoming arc weights
  - Equal to the weight of best spanning tree that includes head of incoming arc, and all nodes in cycle
  - root → saw → John is 40 (**)
  - root → John → saw is 29

Theorem

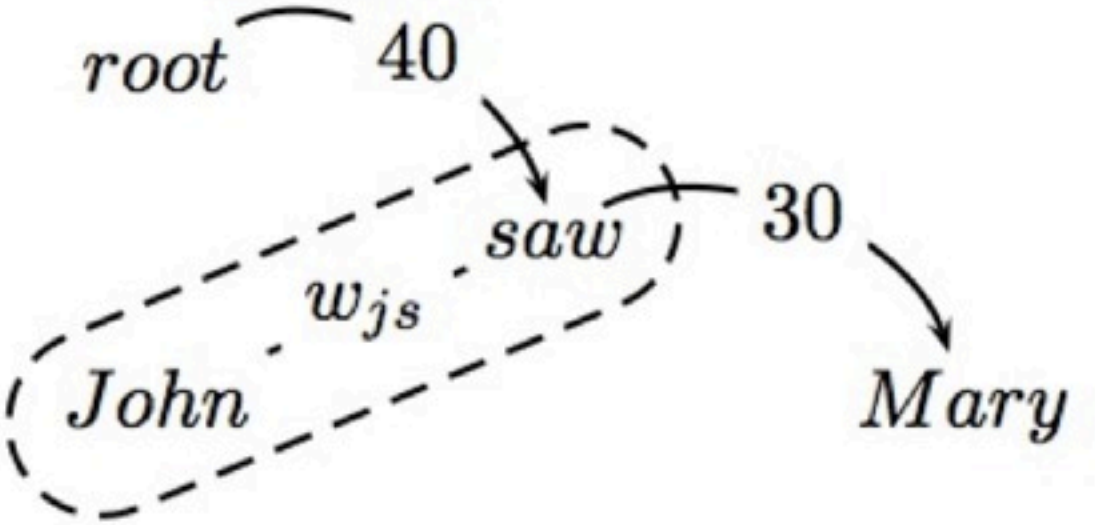
The weight of the MST of this contracted graph is equal to the weight of the MST for the original graph



- Therefore, recursively call algorithm on new graph

Final MST

- This is a tree and the MST for the contracted graph!!



- Go back up recursive call and reconstruct final graph

Chu-Liu-Edmonds PseudoCode

Chu-Liu-Edmonds(G_x, w)

1. Let $M = \{(i^*, j) : j \in V_x, i^* = \arg\max_{i'} w_{ij}\}$
2. Let $G_M = (V_x, M)$
3. If G_M has no cycles, then it is an MST: return G_M
4. Otherwise, find a cycle C in G_M
5. Let $< G_C, c, ma >=$ contract(G, C, w)
6. Let $G =$ Chu-Liu-Edmonds(G_C, w)
7. Find vertex $i \in C$ such that $(i', c) \in G$ and $ma(i', c) = i$
8. Find arc $(i'', i) \in C$
9. Find all arc $(c, i''') \in G$
10. $G = G \cup \{(ma(c, i'''), i''')\}_{\forall (c,i''') \in G} \cup C \cup \{(i', i)\} - \{(i'', i)\}$
11. Remove all vertices and arcs in G containing c
12. return G

- Reminder: $w_{ij} = \arg\max_k w_{ij}^k$

Chu-Liu-Edmonds PseudoCode

contract$(G = (V, A), C, w)$

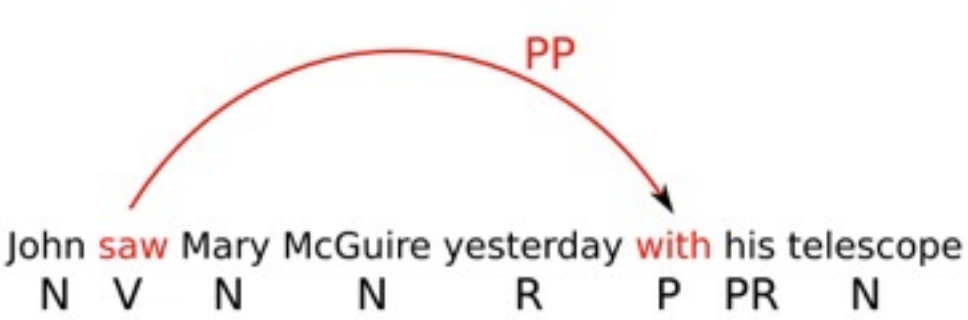
1. Let G_C be the subgraph of G excluding nodes in C
2. Add a node c to G_C representing cycle C
3. For $i \in V - C : \exists_{i' \in C}(i', i) \in A$
   Add arc (c, i) to G_C with
   $ma(c, i) = \arg\max_{i' \in C} score(i', i)$
   $i' = ma(c, i)$
   $score(c, i) = score(i', i)$
4. For $i \in V - C : \exists_{i' \in C}(i, i') \in A$
   Add edge (i, c) to G_C with
   $ma(i, c) = \arg\max_{i' \in C} [score(i, i') - score(a(i'), i')]$
   $i' = ma(i, c)$
   $score(i, c) = [score(i, i') - score(a(i'), i') + score(C)]$
   where $a(v)$ is the predecessor of v in C
   and $score(C) = \sum_{v \in C} score(a(v), v)$
5. return $< G_C, c, ma >$

Arc Weights

$$w_{ij}^{k} = e^{\mathbf{w} \cdot \mathbf{f}(i,j,k)}$$

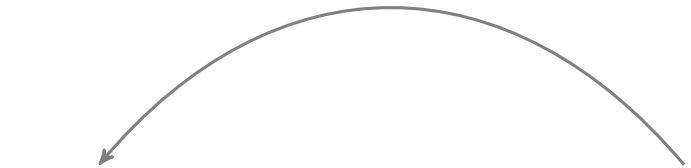
- Arc weights are a linear combination of features of the arc, **f**, and a corresponding weight vector **w**
- Raised to an exponent (simplifies some math ...)
- What arc features?
- [McDonald et al. 2005] discuss a number of binary features

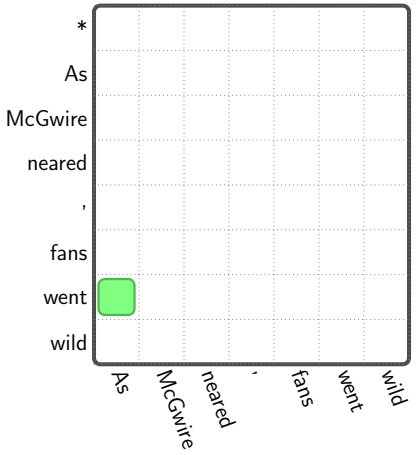
Arc Feature Ideas for f(i,j,k)



- Identities of the words wi and wj and the label lk
- Part-of-speech tags of the words wi and wj and the label lk
- Part-of-speech of words surrounding and between wi and wj
- Number of words between wi and wj , and their orientation
- Combinations of the above

First-Order Feature Computation





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[VERB]
[went, As]
[VERB, IN]
[ADJ, *, ADP]
[NNS, VBD, ADP]
[NNS, ADP, NNP]
[ADP, left, 5]
[JJ, *, IN]
[NOUN, VERB, IN]
[NOUN, IN, NOUN]
[IN, left, 5]
[NNS, VBD, ADP, NNP]
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[went, VERB, left, 5]
[went, As, ADP, left, 5]
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[ADJ, ADP, NNP, left, 5]
[VERB, As, IN, left, 5]
[VERB, *, IN, left, 5]

[VBD]
[As]
[VBD, ADP]
[VBD, As, ADP]
[VBD, *, ADP]
[NNS, VBD, *]
[NNS, VBD, NNP]
[VERB, As, IN]
[VERB, *, IN]
[NOUN, VERB, *]
[NOUN, VERB, NOUN]
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[As]
[IN]
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[VBD, ADJ, NNP, left, 5]
[went, VERB, IN, left, 5]
[VERB, JJ, *, left, 5]

[ADP]
[went, VBD]
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[went]
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[NNS, VBD, *, left, 5]
[NNS, VBD, NNP, left, 5]
[JJ, *, IN, left, 5]
[NOUN, VERB, IN, left, 5]

(Structured) Perceptron

Training data: $\mathcal{T} = \{(x_t, G_t)\}_{t=1}^{|\mathcal{T}|}$

1. $\mathbf{w}^{(0)} = 0;\ i = 0$
2. for $n : 1..N$
3. for $t : 1..T$
4. Let $G' = \arg\max_{G'} \mathbf{w}^{(i)} \cdot \mathbf{f}(G')$
5. if $G' \neq G_t$
6. $\mathbf{w}^{(i+1)} = \mathbf{w}^{(i)} + \mathbf{f}(G_t) - \mathbf{f}(G')$
7. $i = i + 1$
8. return $\mathbf{w}^i$

Partition Function

Partition Function: $Z_x = \sum_{G \in T(G_x)} w(G)$

- Lapacian Matrix Q for graph $G_x = (V_x, A_x)$

$$Q_{jj} = \sum_{i \neq j, (i,j,k) \in A_x} w_{ij}^k \quad \text{and} \quad Q_{ij} = \sum_{i \neq j, (i,j,k) \in A_x} -w_{ij}^k$$

- Cofactor Q^i is the matrix Q with the i^{th} row and column removed

The Matrix Tree Theorem [Tutte 1984]
The determinant of the cofactor Q^0 is equal to Z_x

- Thus $Z_x = |Q^0|$ – determinants can be calculated in $O(n^3)$
- Constructing Q takes $O(|L|n^2)$
- Therefore the whole process takes $O(n^3 + |L|n^2)$

Arc Expectations

$$\langle i,j,k \rangle_x = \sum_{G \in T(G_x)} w(G) \times \mathbb{1}[(i,j,k) \in A]$$

- Can easily be calculated, first reset some weights

$$w^{k'}_{i'j} = 0 \; \forall i' \neq i \text{ and } k' \neq k$$

- Now, $\langle i,j,k \rangle_x = Z_x$
- Why? All competing arc weights to zero, therefore every non-zero weighted graph must contain (i,j,k)
- Naively takes $O(n^5 + |L|n^2)$ to compute all expectations
- But can be calculated in $O(n^3 + |L|n^2)$ (see [McDonald and Satta 2007, Smith and Smith 2007, Koo et al. 2007])

Transition Based Dependency Parsing

- Process sentence left to right
  - Different transition strategies available
  - Delay decisions by pushing on stack

- Arc-Eager Transition Strategy [Nivre '03]

Start state: $([\,], [1, \ldots, n], \{\,\})$

Final state: $(S, [\,], A)$

Shift:	$(S, i\|B, A)$	$\Rightarrow$	$(S\|i, B, A)$
Reduce:	$(S\|i, B, A)$	$\Rightarrow$	$(S, \mathrm{B}, \mathrm{A})$
Right-Arc:	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S\|i\|j, B, A \cup \{i \rightarrow j\})$
Left-Arc:	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S, j\|B, A \cup \{i \leftarrow j\})$

Parsing Example

Parsing Example

Stack	Buffer

Parsing Example

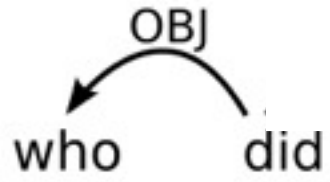
Stack	Buffer
[ ]	[who, did, you, see]

Parsing Example

Stack	Buffer
[ ]	[who, did, you, see]
[who]	[did, you, see]

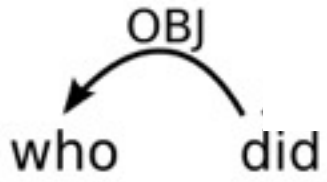
Parsing Example

Stack	Buffer
[ ]	[who, did, you, see]
[who]	[did, you, see]
[ ]	[did, you, see]



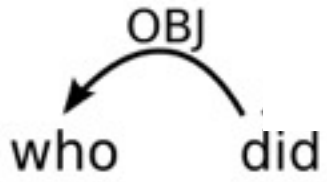
Parsing Example

Stack	Buffer
[ ]	[who, did, you, see]
[who]	[did, you, see]
[ ]	[did, you, see]
[did]	[you, see]



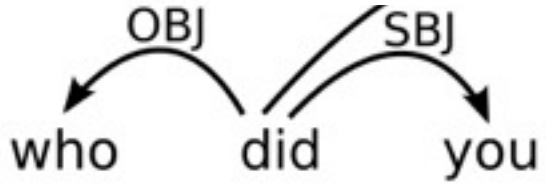
Parsing Example

Stack	Buffer
[ ]	[who, did, you, see]
[who]	[did, you, see]
[ ]	[did, you, see]
[did]	[you, see]
[did, you]	[see]



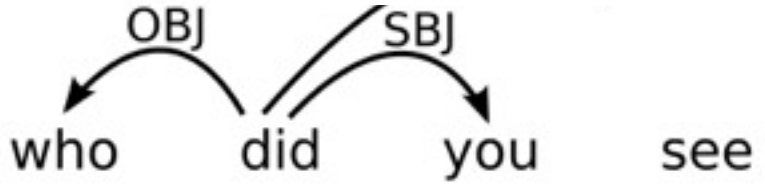
Parsing Example

Stack	Buffer
[ ]	[who, did, you, see]
[who]	[did, you, see]
[ ]	[did, you, see]
[did]	[you, see]
[did, you]	[see]
[did]	[see]



Parsing Example

Stack	Buffer
[ ]	[who, did, you, see]
[who]	[did, you, see]
[ ]	[did, you, see]
[did]	[you, see]
[did, you]	[see]
[did]	[see]
[did, see]	[ ]



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Stack	Buffer
[ ]	[who, did, you, see]
[who]	[did, you, see]
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[did, you]	[see]
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[did, see]	[ ]
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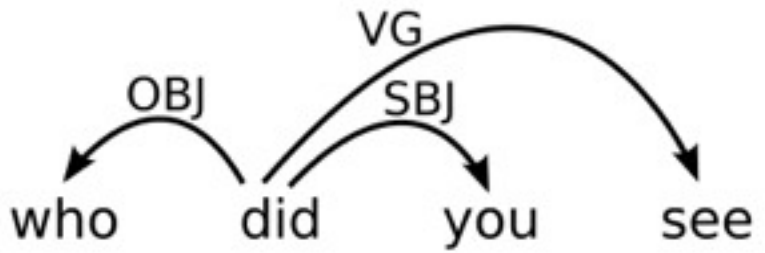

Styles of Dependency Parsing

- Transition-Based (tr)
  - Fast, greedy, linear time inference algorithms
  - Trained for greedy search
  - Beam search

[Nivre et al. ’03-’11]

- Graph-Based (gr)
  - Slower, exhaustive, dynamic programming inference algorithms
  - Higher-order factorizations

[McDonald et al. ’05-’06]

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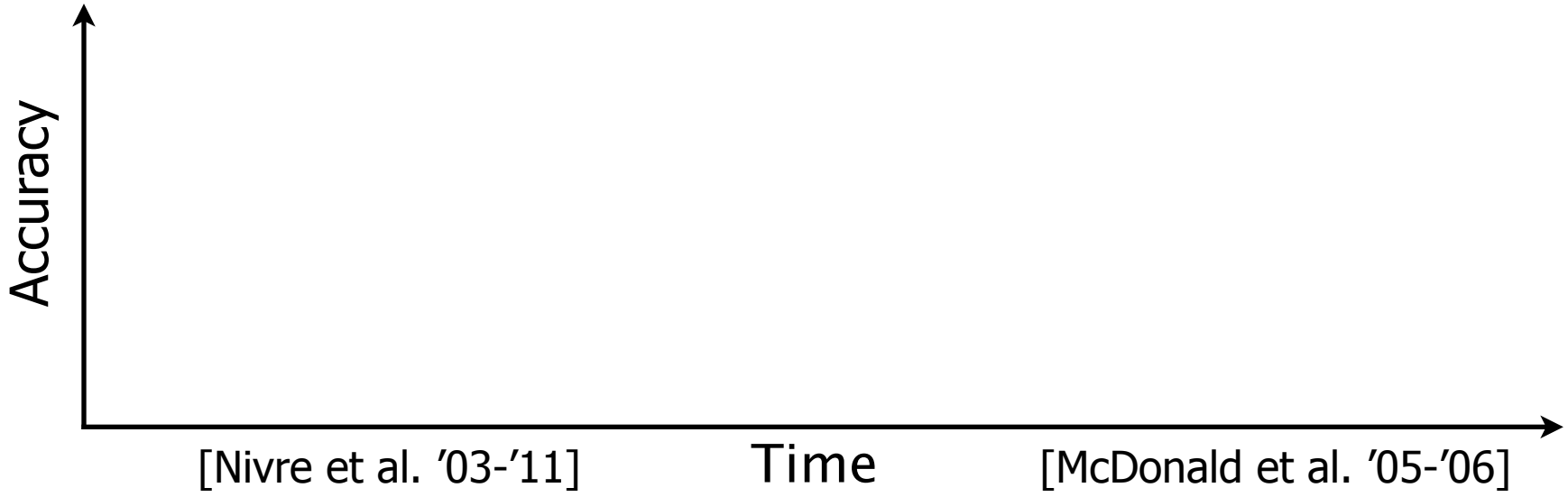

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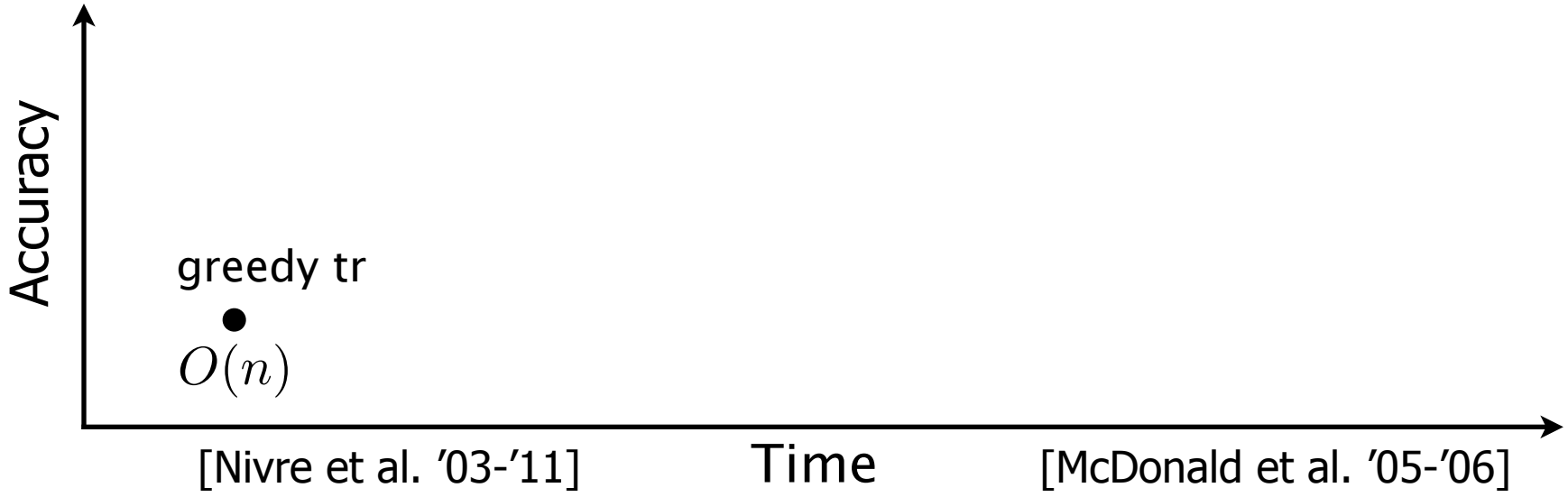

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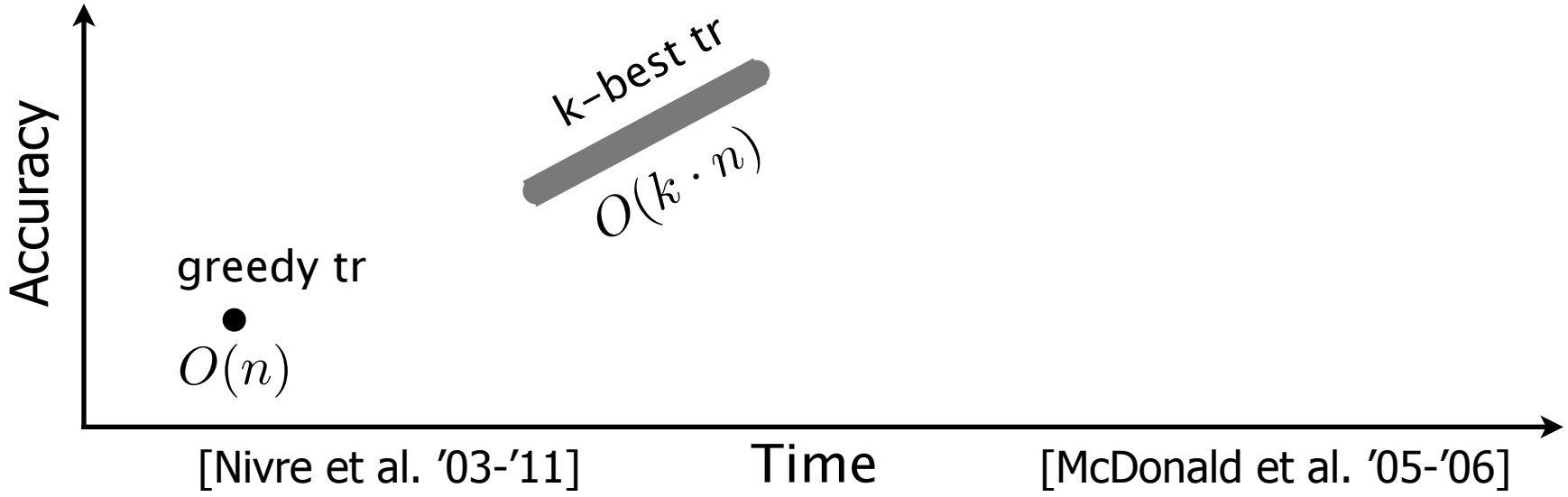

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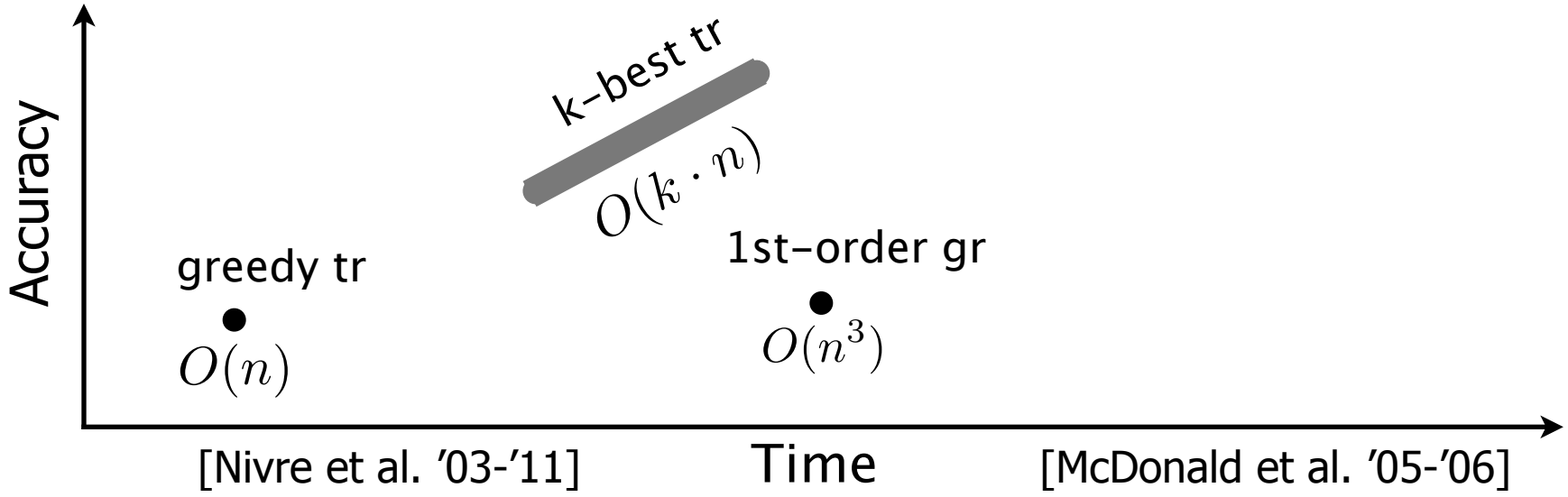

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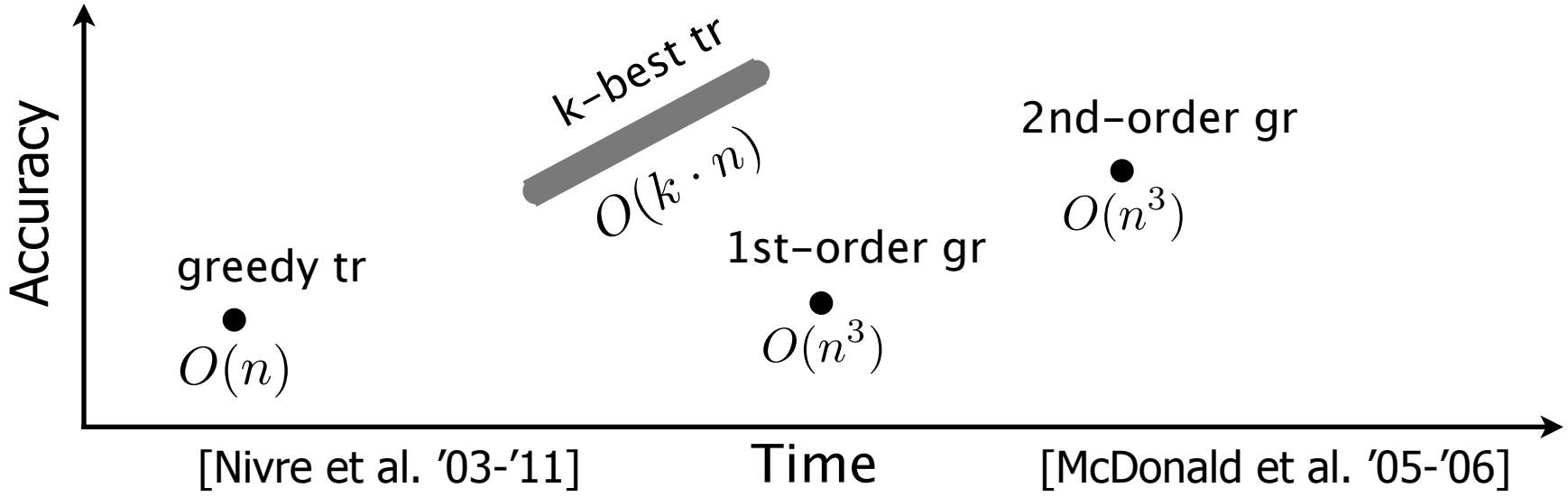

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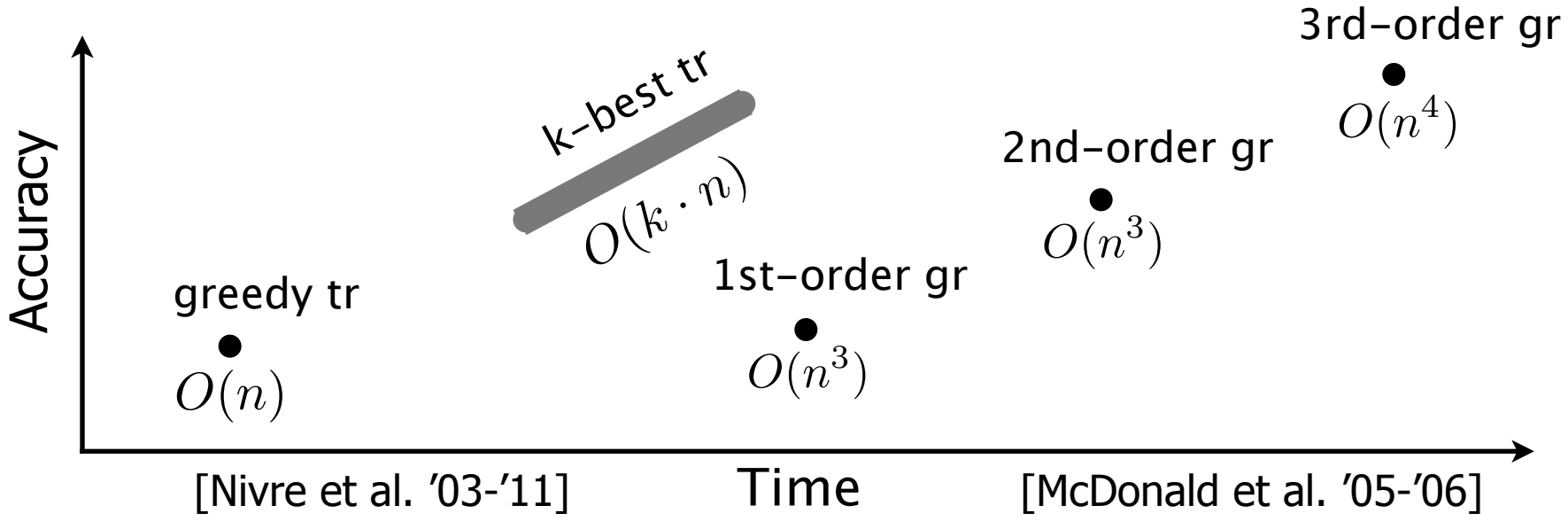
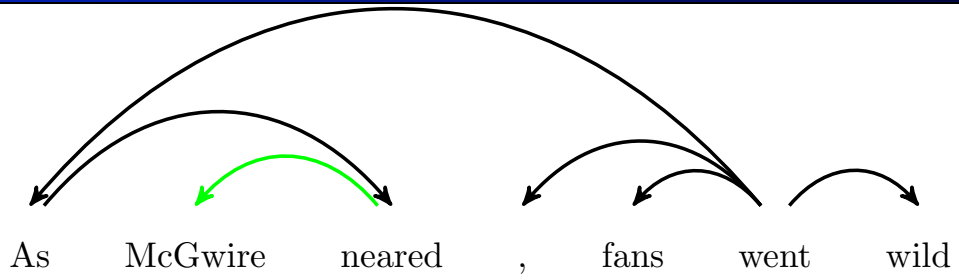
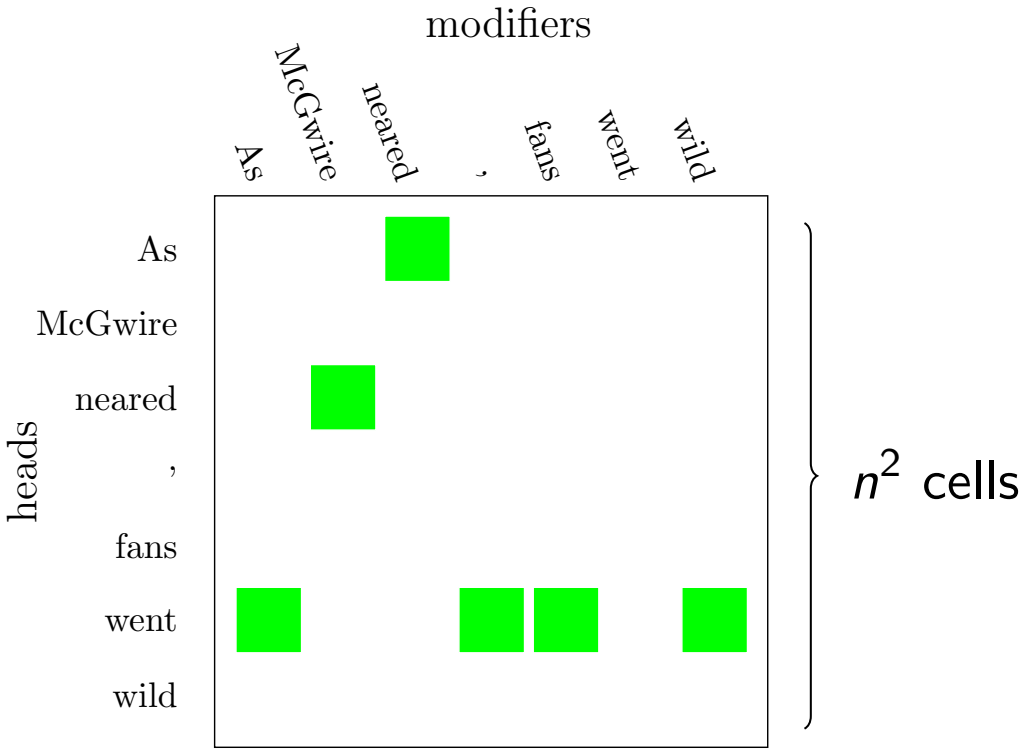


Dependency Representation





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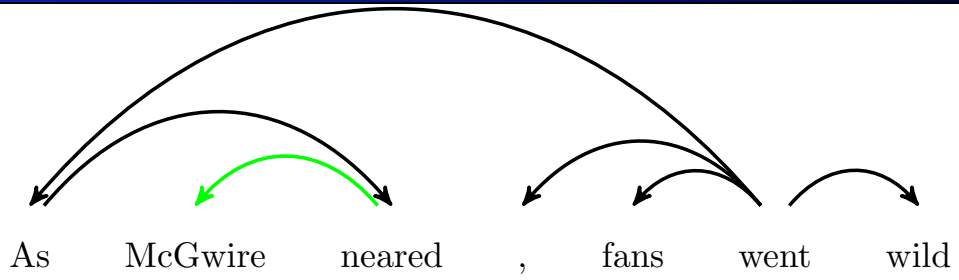
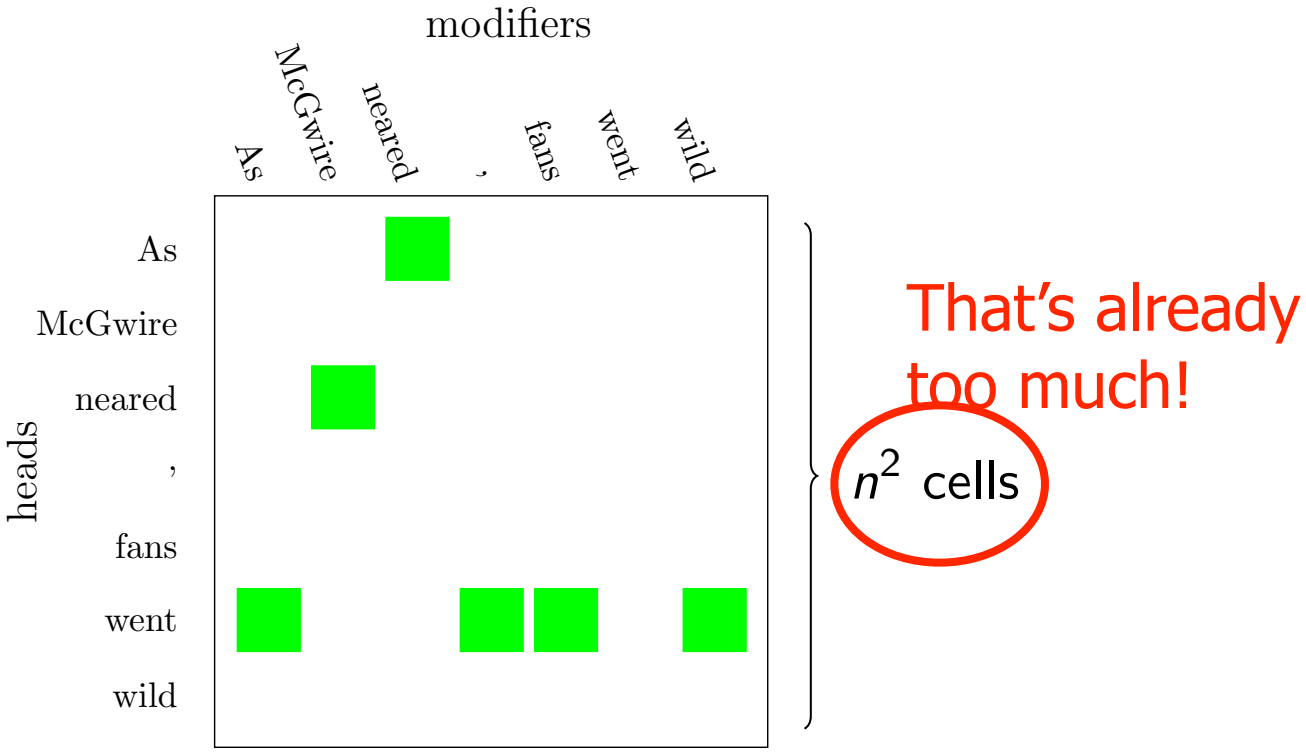
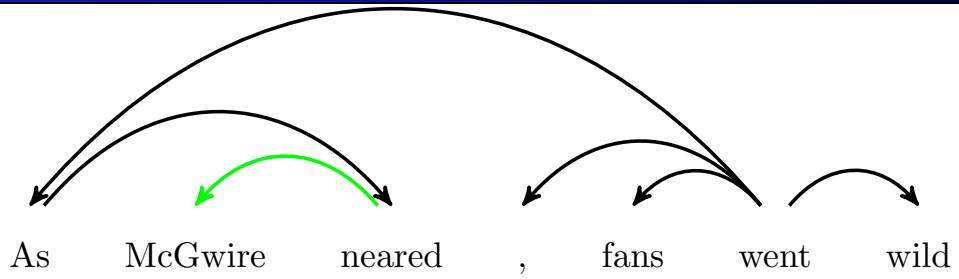
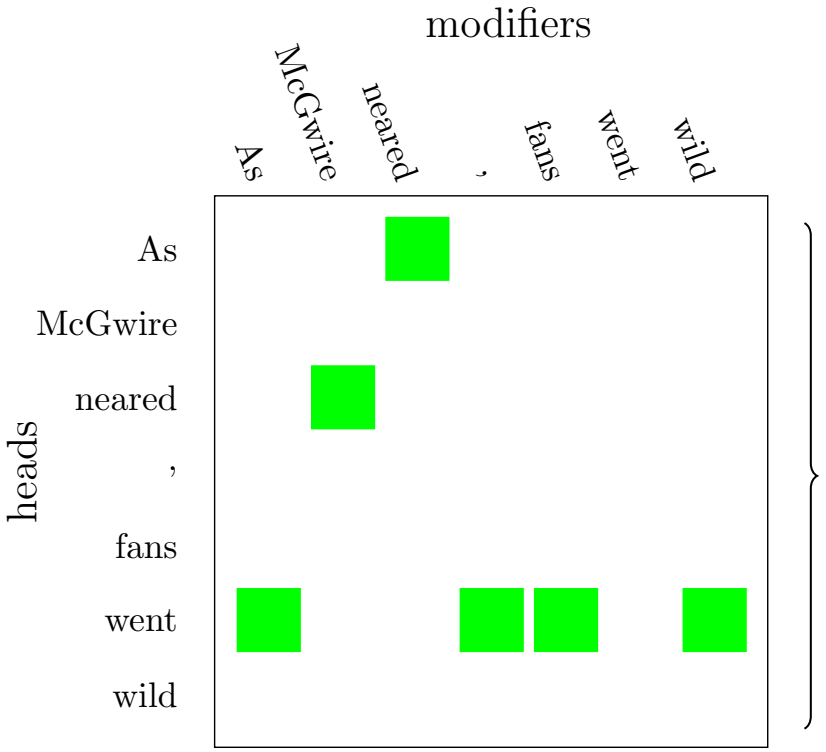




Dependency Representation



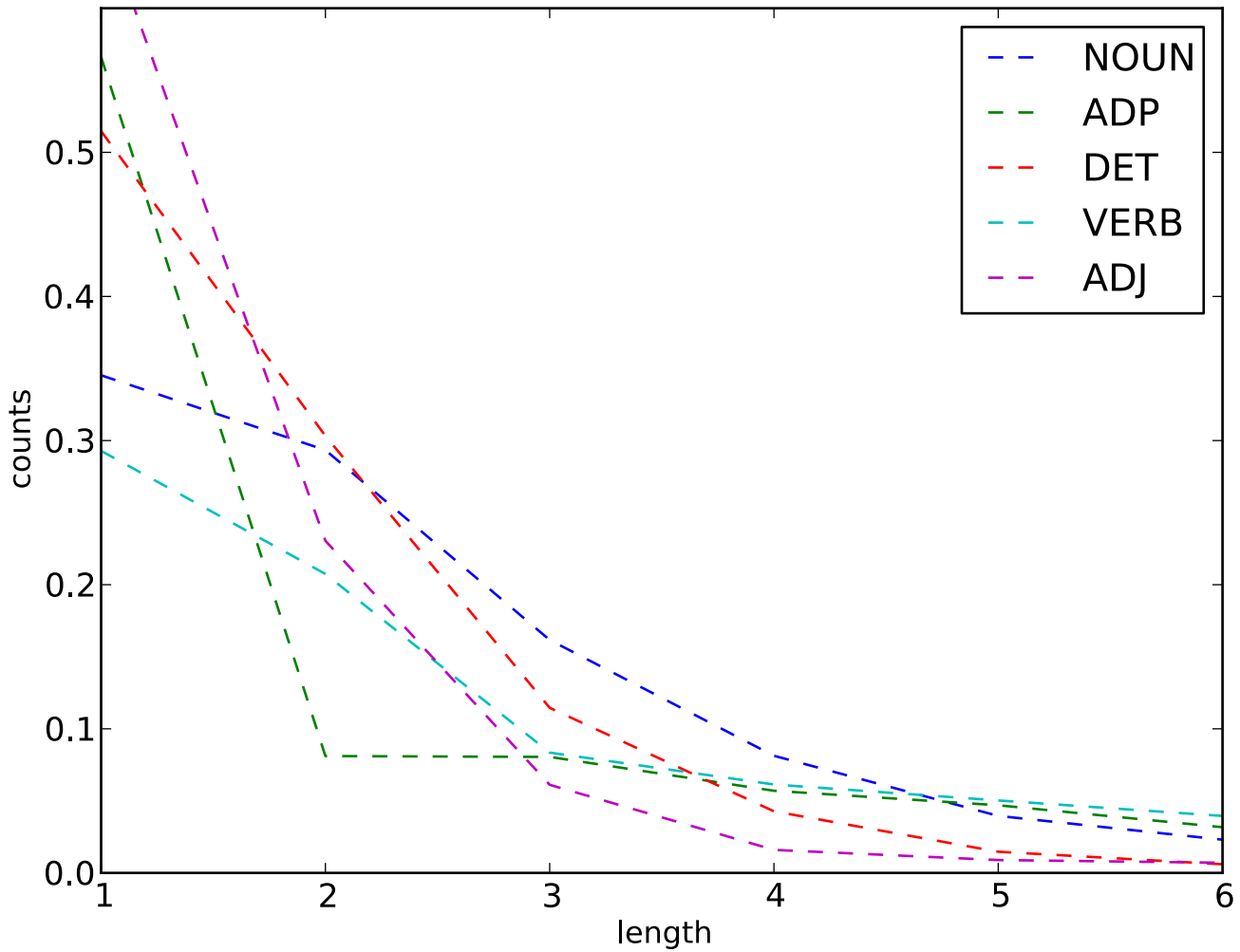


n^2 cells

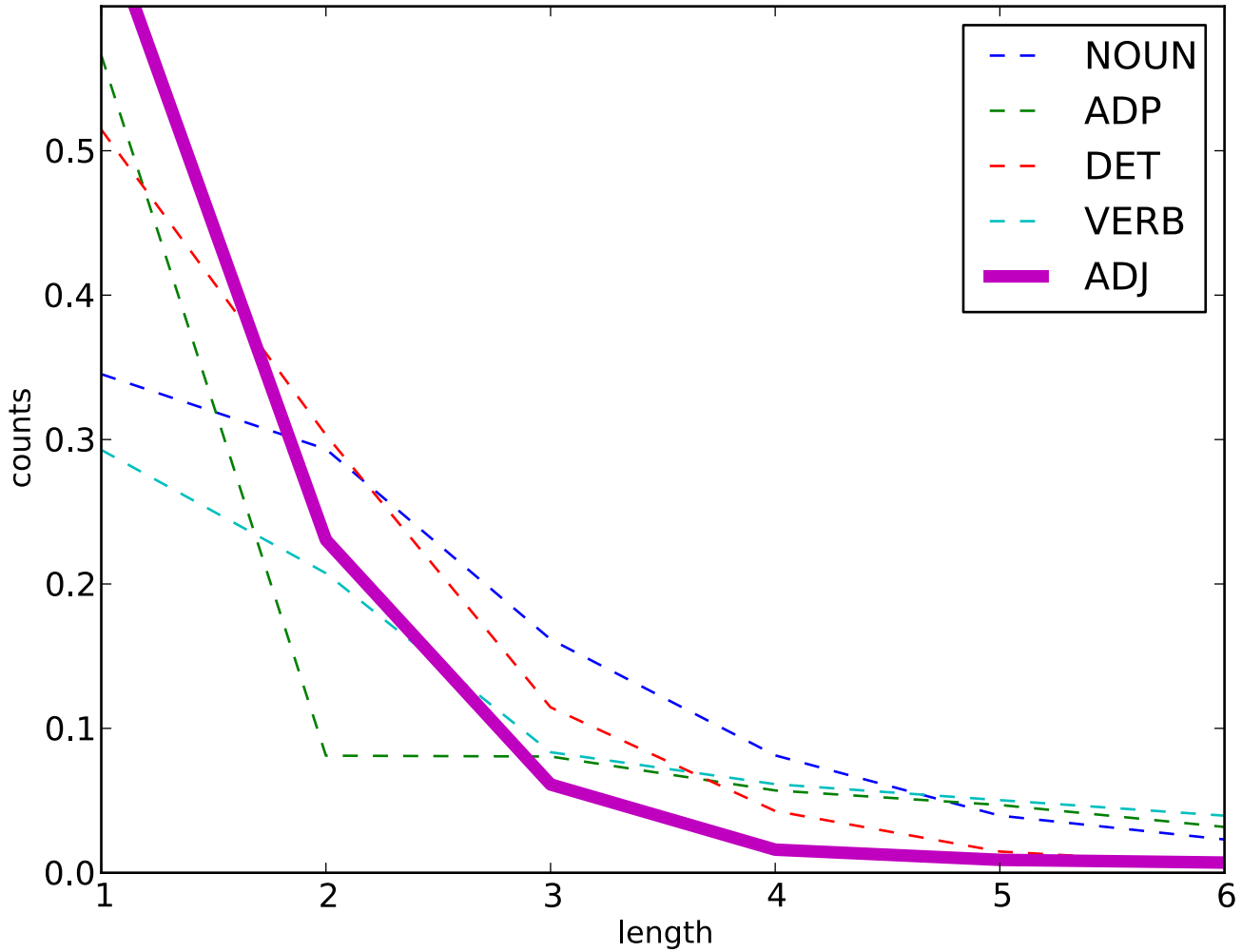
That's already too much!

Exploit problem structure!

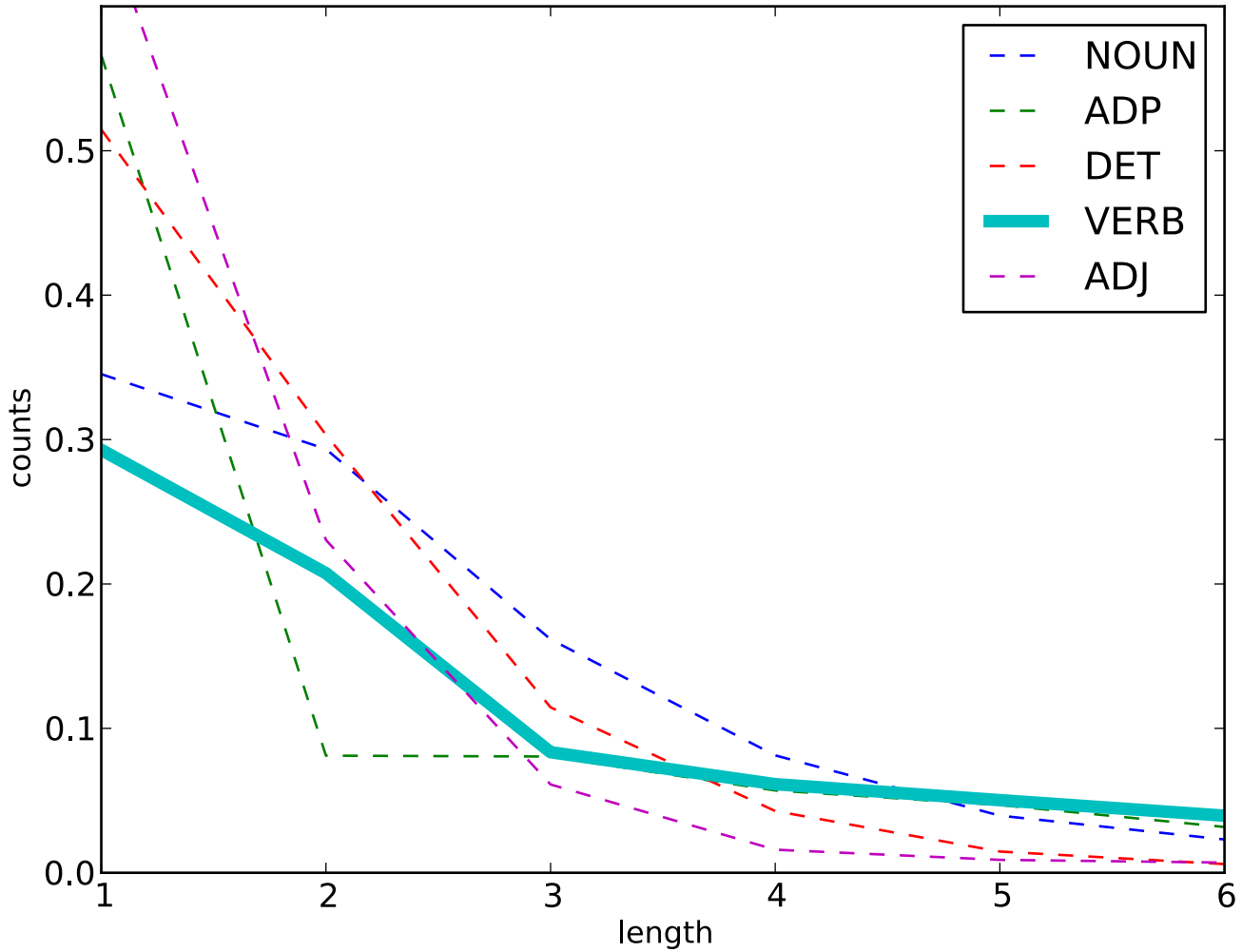
Modifier Length



Modifier Length



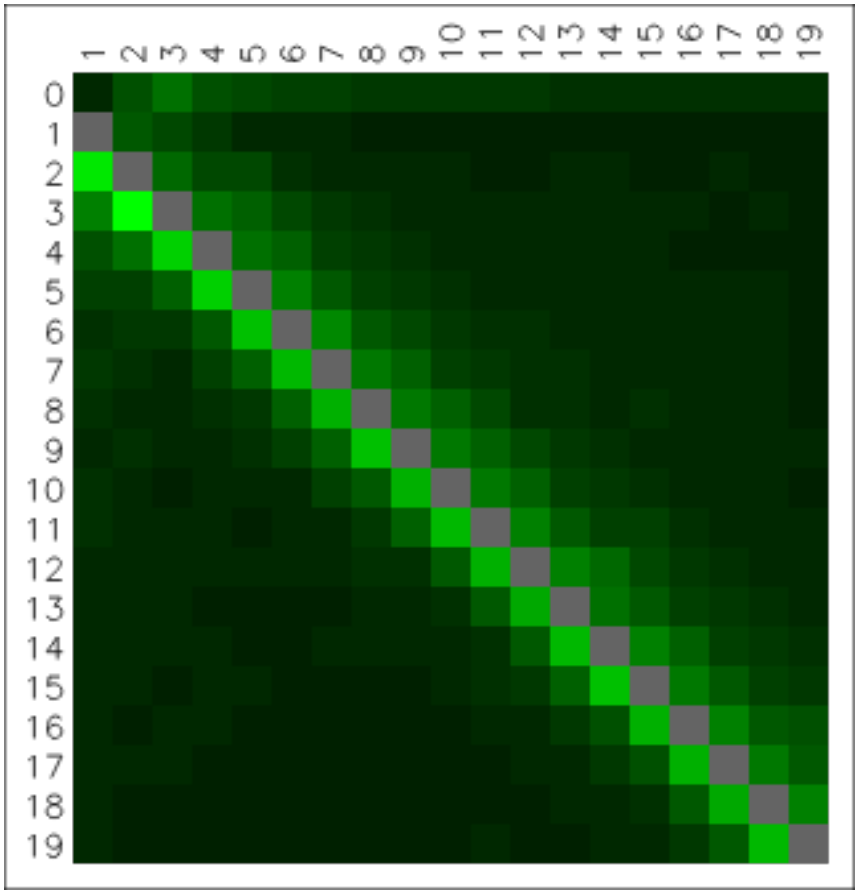
Modifier Length



Heat Map

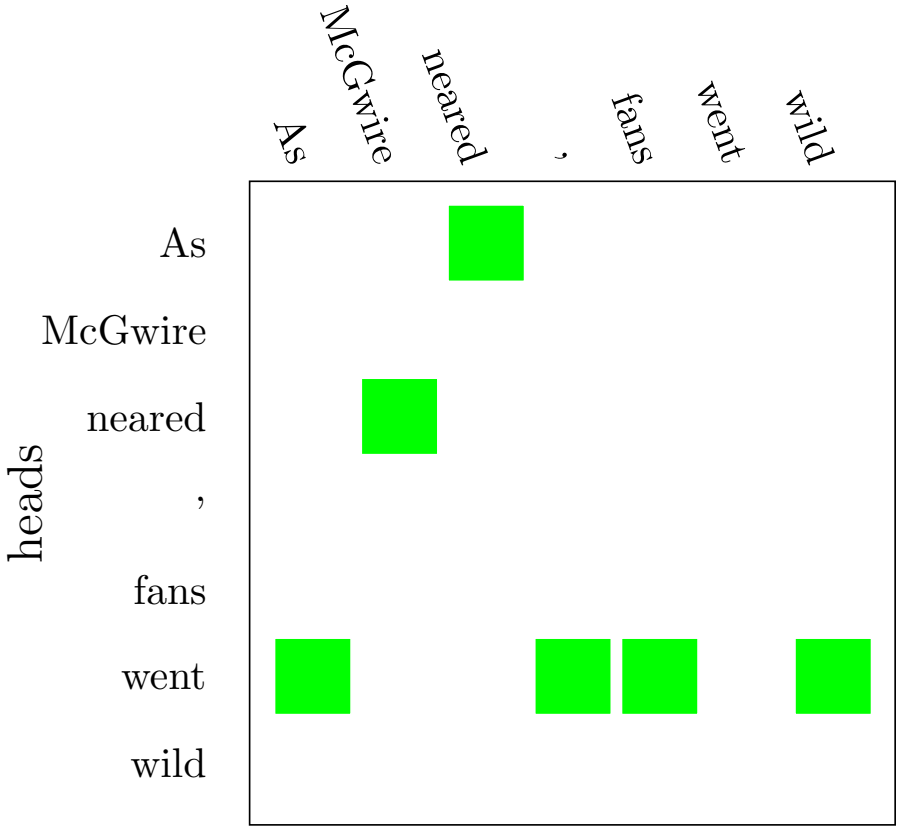
modifiers

heads



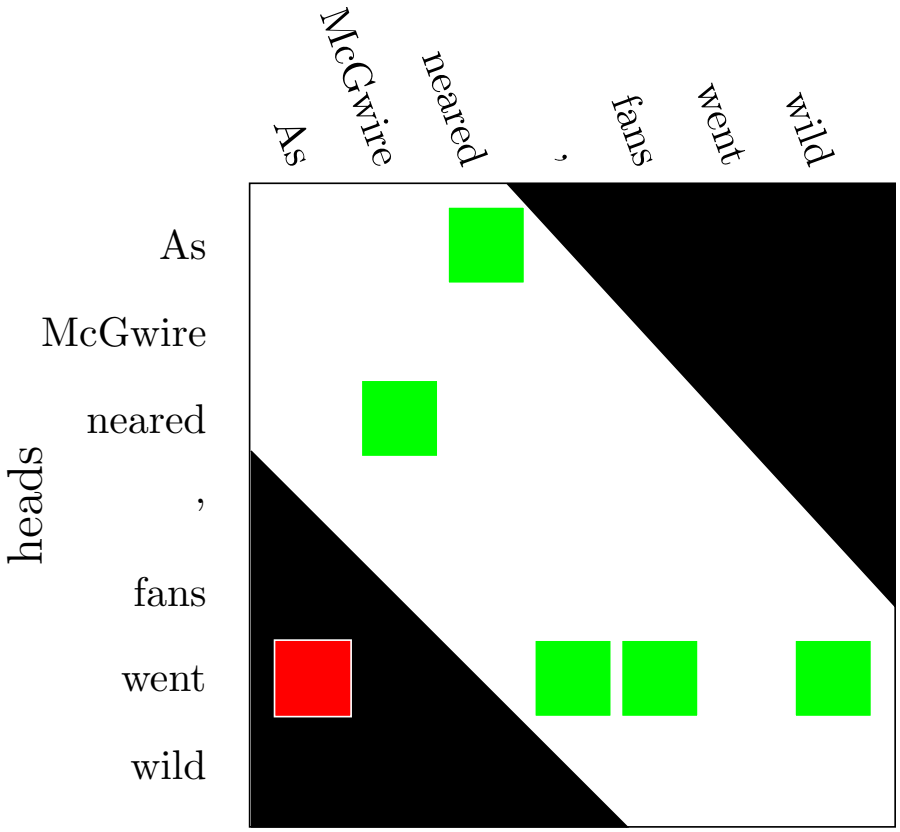
Linear Matrix

- Ignore arcs that are longer than fixed cutoff b



Linear Matrix

- Ignore arcs that are longer than fixed cutoff b



Linear Matrix

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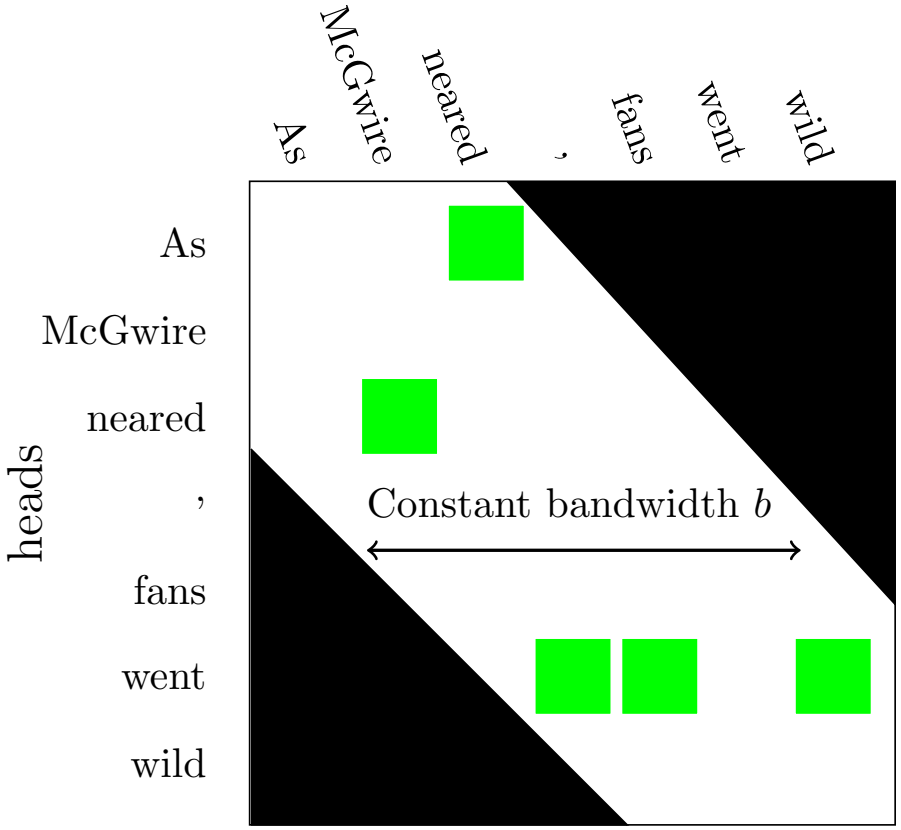
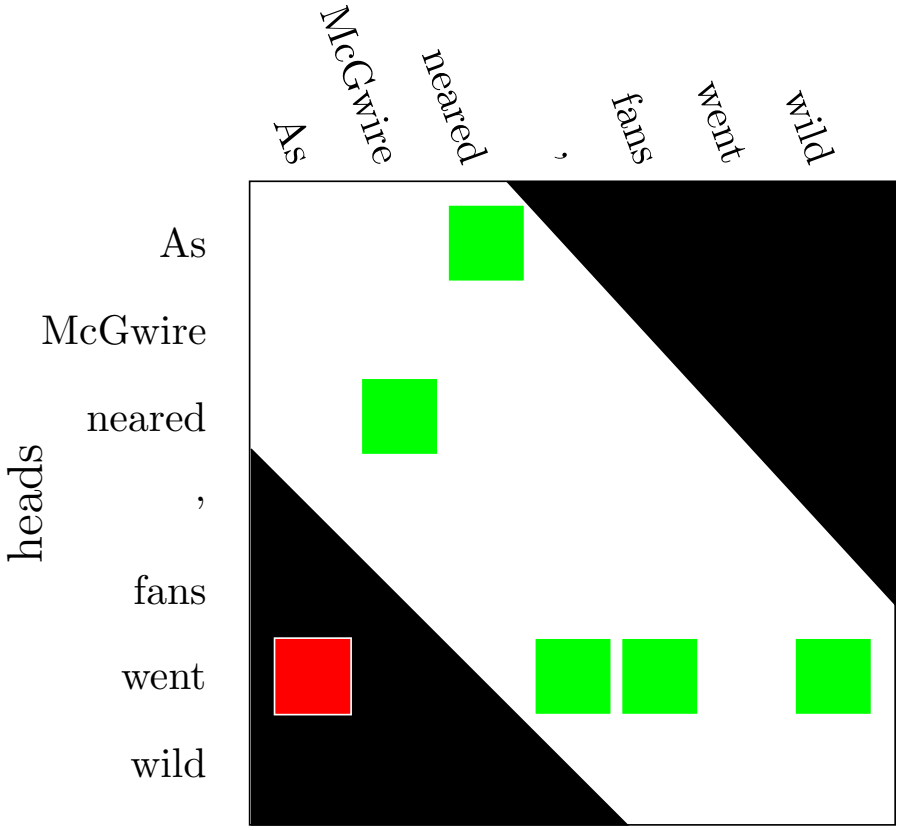


Vine Parsing

- Matrix has $O(nb)$ elements [Eisner & Smith '05]
- Can find best tree in $O(nb^2)$ time via vine parsing



Vine Parsing

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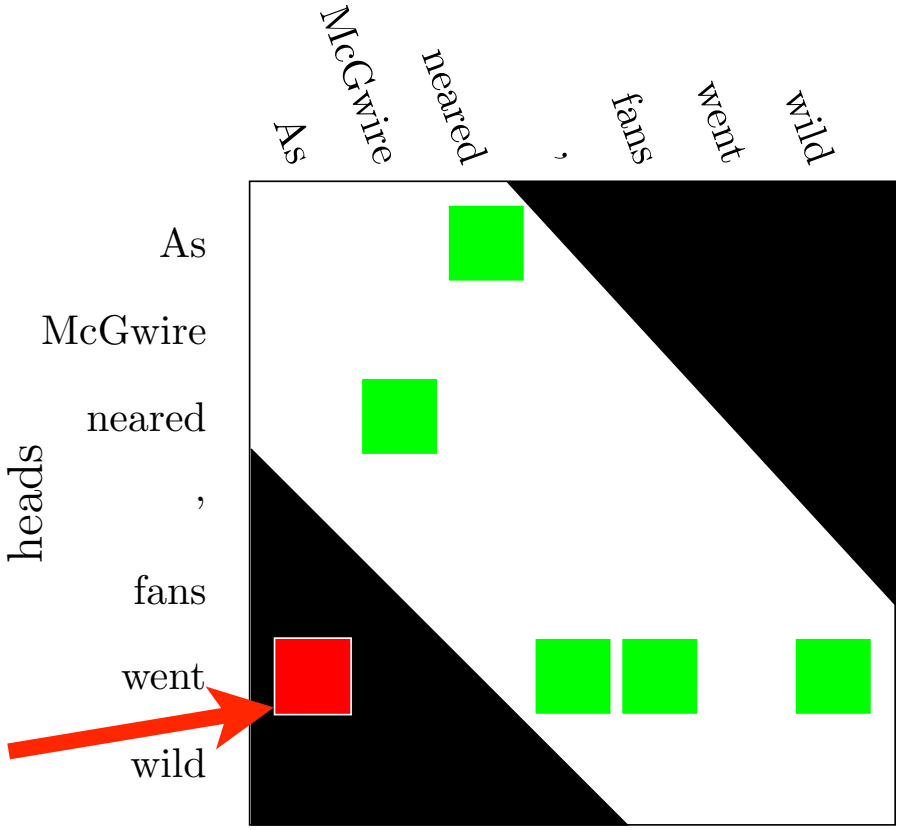
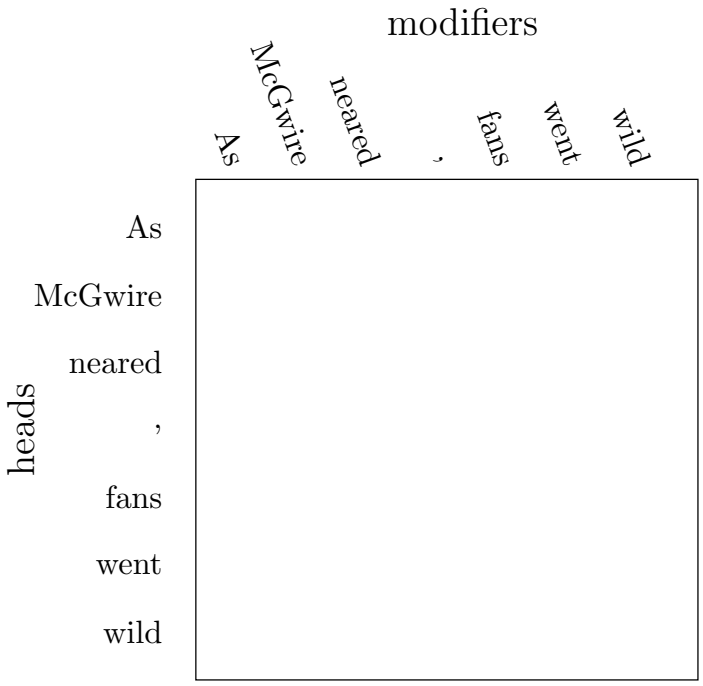


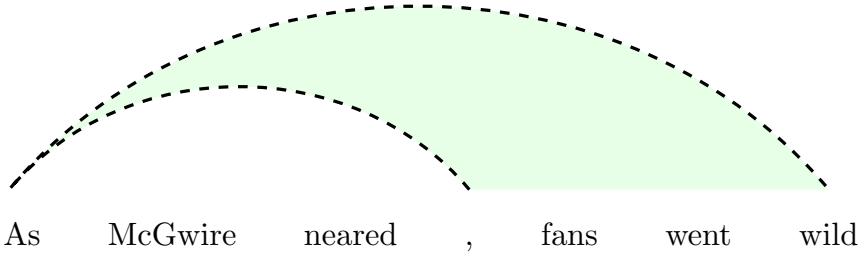
What about long arcs?

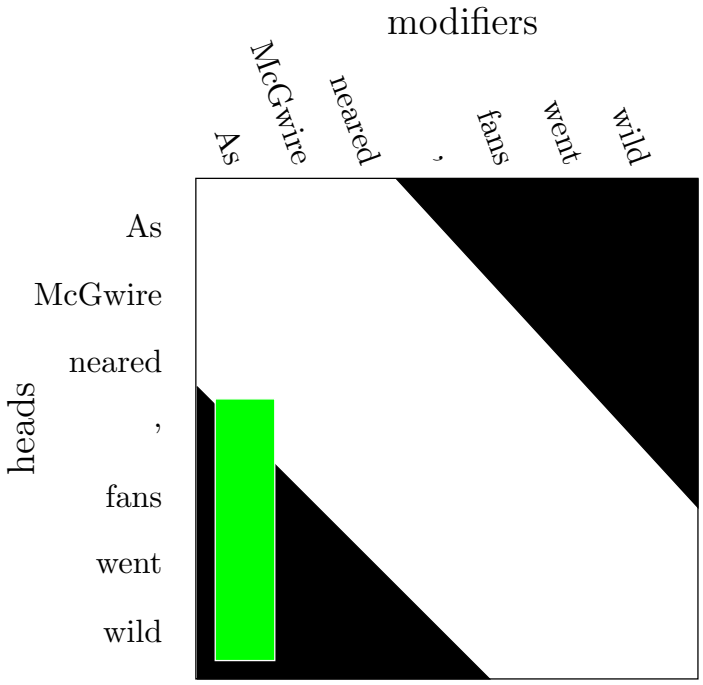
Outer Arcs

As McGwire neared , fans went wild



Outer Arcs


As
McGwire
neared
,
fans
went
wild


modifiers
As
McGwire
neared
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went
wild
heads
As
McGwire
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,
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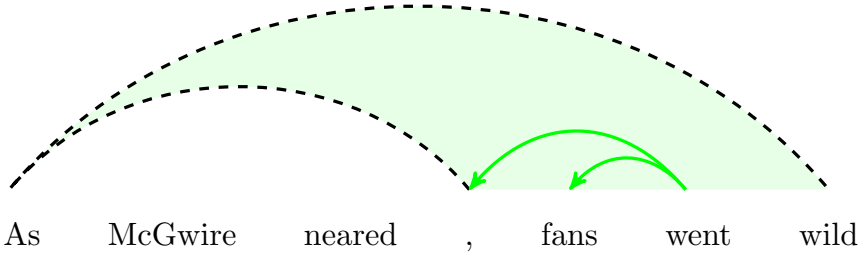
wild

Outer Arcs


As
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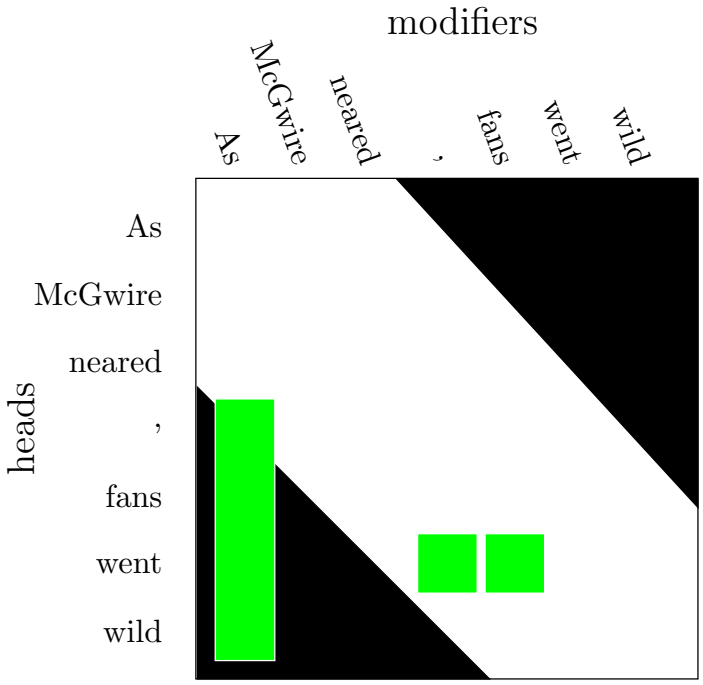
modifiers
As
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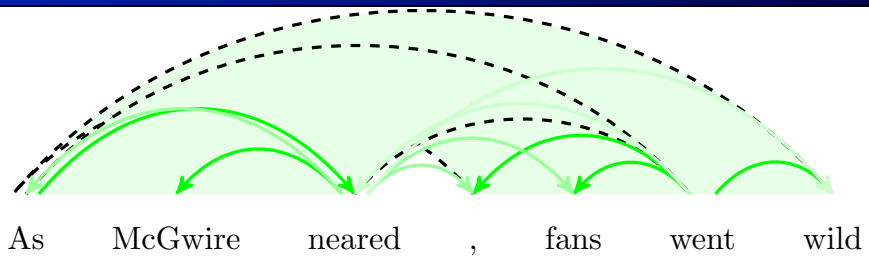
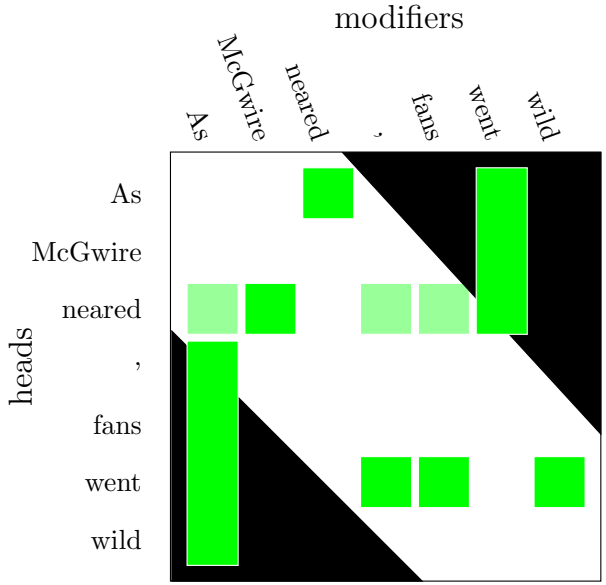
Vine Pruning

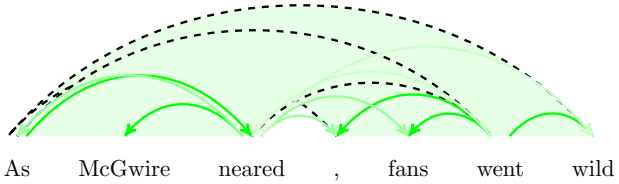
[Rush & Petrov '12]

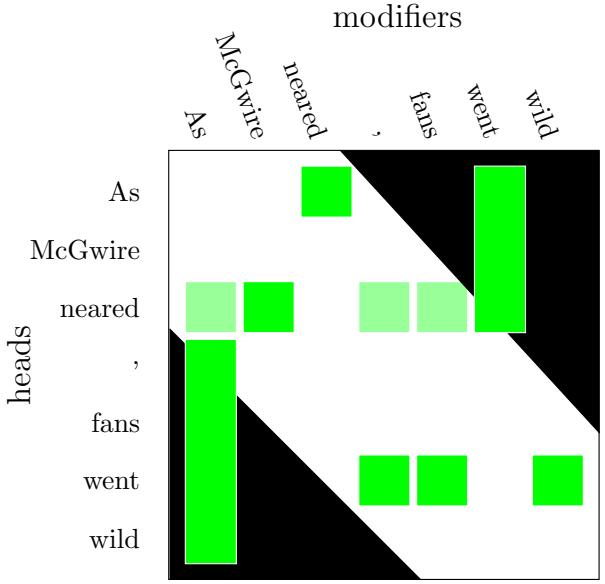




Coarse-to-Fine Cascades

[Rush & Petrov '12]

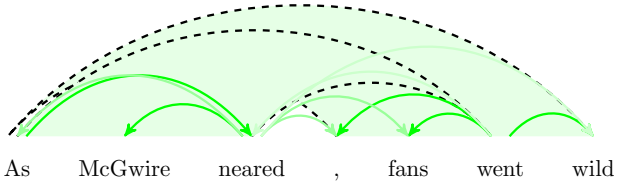


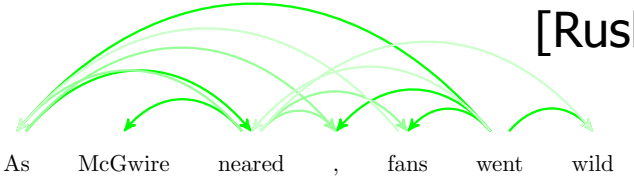


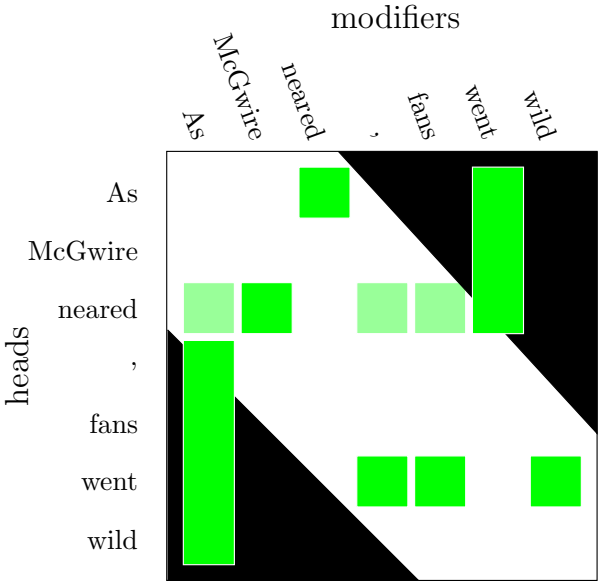
Vine

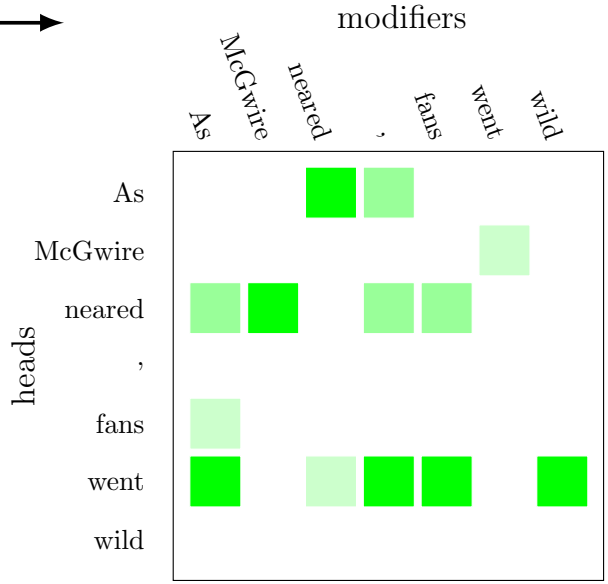
Coarse-to-Fine Cascades

[Rush & Petrov '12]







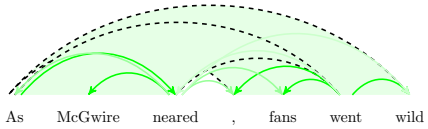


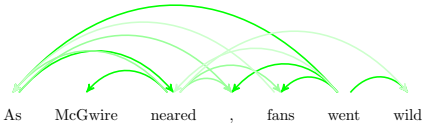
Vine

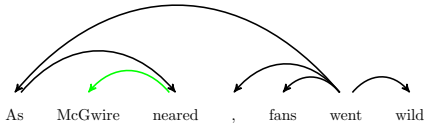
First-Order

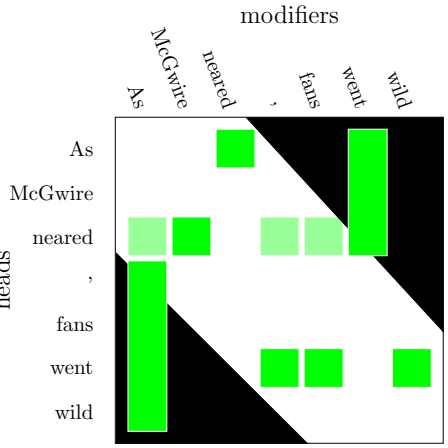
Coarse-to-Fine Cascades

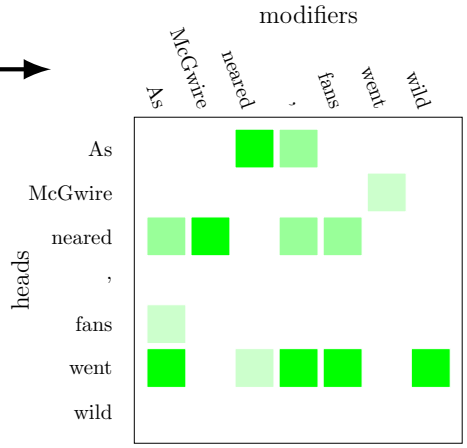
[Rush & Petrov '12]

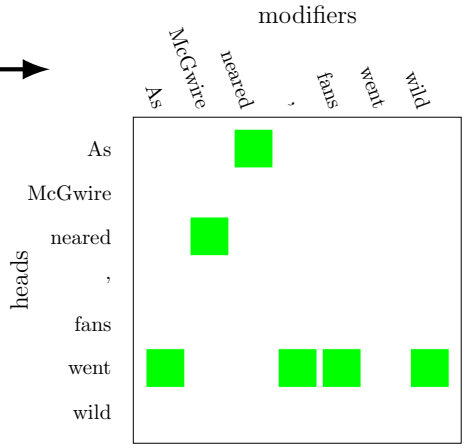










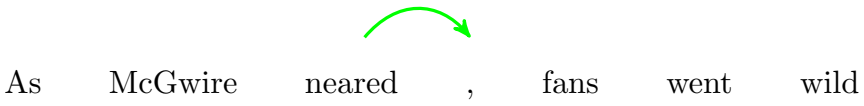


Vine

First-Order

Second-Order

Max-Marginals

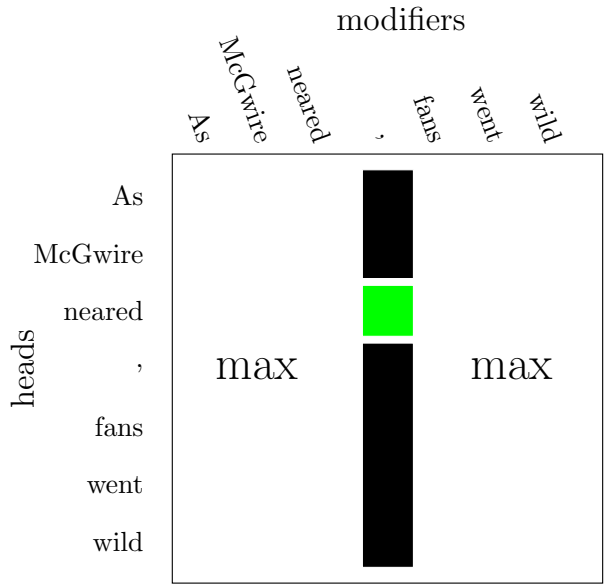


MAP Parse

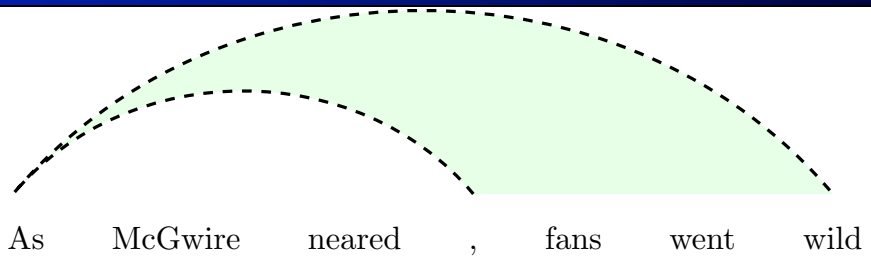
$$y^* = \arg\max_{y \in \mathcal{Y}} y \cdot w$$

Max-Marginal

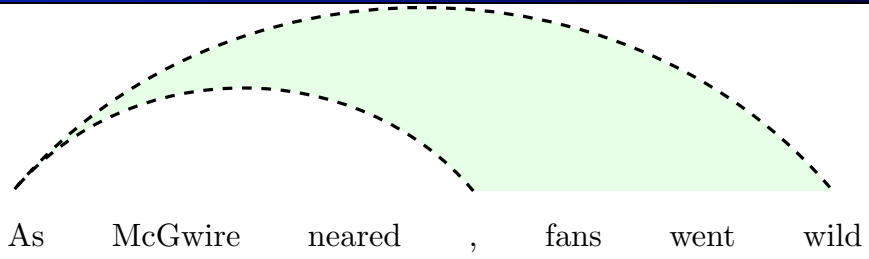
$$m(a) = \arg \max_{y \in \mathcal{Y}: a \in A} y \cdot w$$

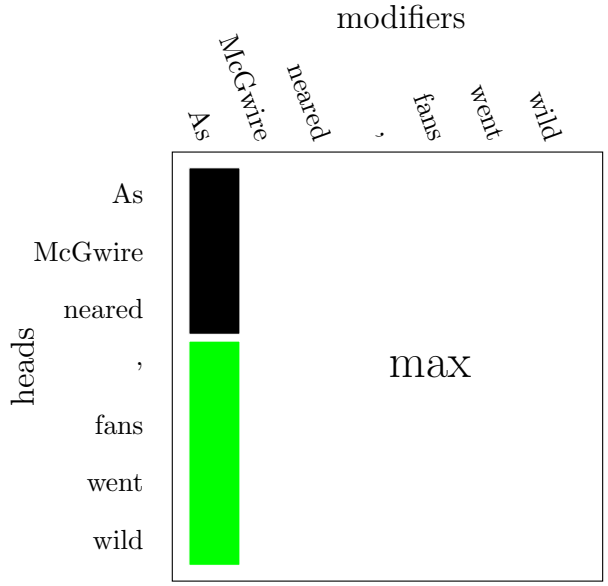


Max-Marginals



Max-Marginals





Structured Prediction Cascades Training

[Weiss & Taskar ’10]

Structured Prediction Cascades Training

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- Train to minimize pruning error (rather than 1-best)

Structured Prediction Cascades Training

[Weiss & Taskar '10]

- Train to minimize pruning error (rather than 1-best)
- Pruning threshold:

$$t_\alpha(w) = \alpha y^* \cdot w + (1-\alpha)\frac{1}{|A|}\sum_{a \in A} m(a) \cdot w$$

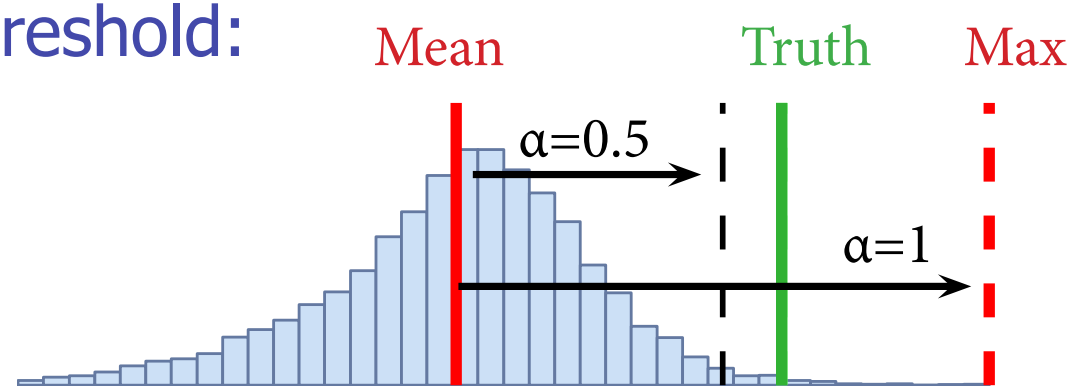
- Training objective:

$$\min_w \lambda \|w\|^2 + \frac{1}{M}\sum_{m=1}^{M} \max\{0, 1 + t_\alpha(w) - y^m \cdot w\}$$

Structured Prediction Cascades Training

[Weiss & Taskar '10]

- Train to minimize pruning error (rather than 1-best)
- Pruning threshold:



- Training objective:

Structured Prediction Cascades Training

[Weiss & Taskar '10]

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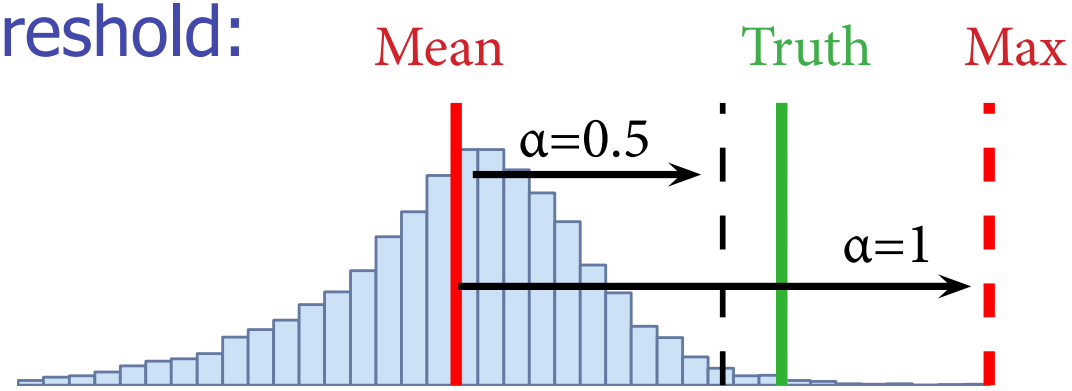
- Pruning threshold:



- Training objective:
  - Filter as many arcs as possible

Structured Prediction Cascades Training

[Weiss & Taskar '10]

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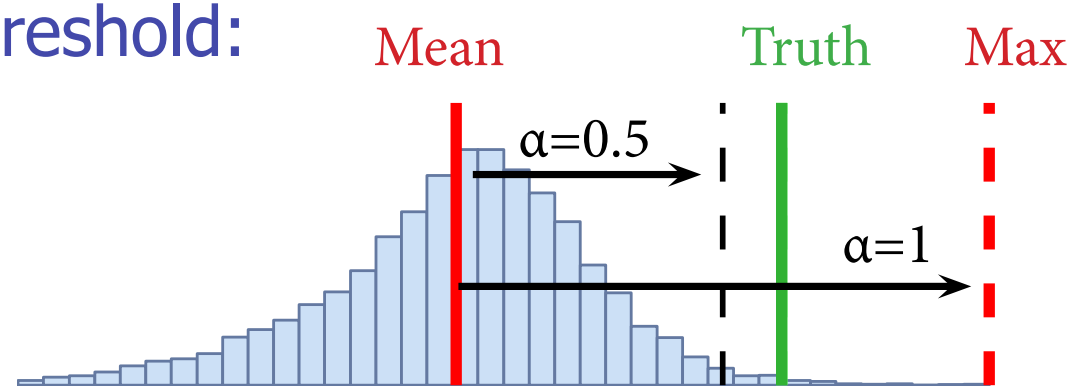
- Pruning threshold:

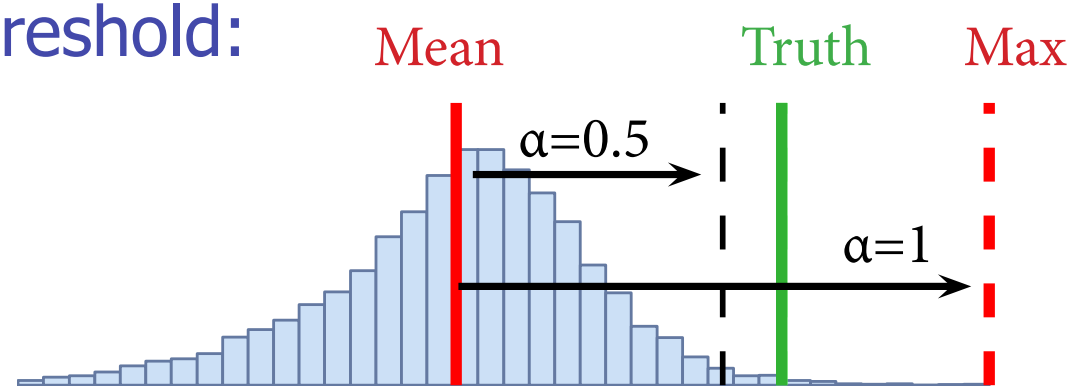


- Training objective:
  - Filter as many arcs as possible
  - While preserving gold arc

Structured Prediction Cascades Training

[Weiss & Taskar '10]

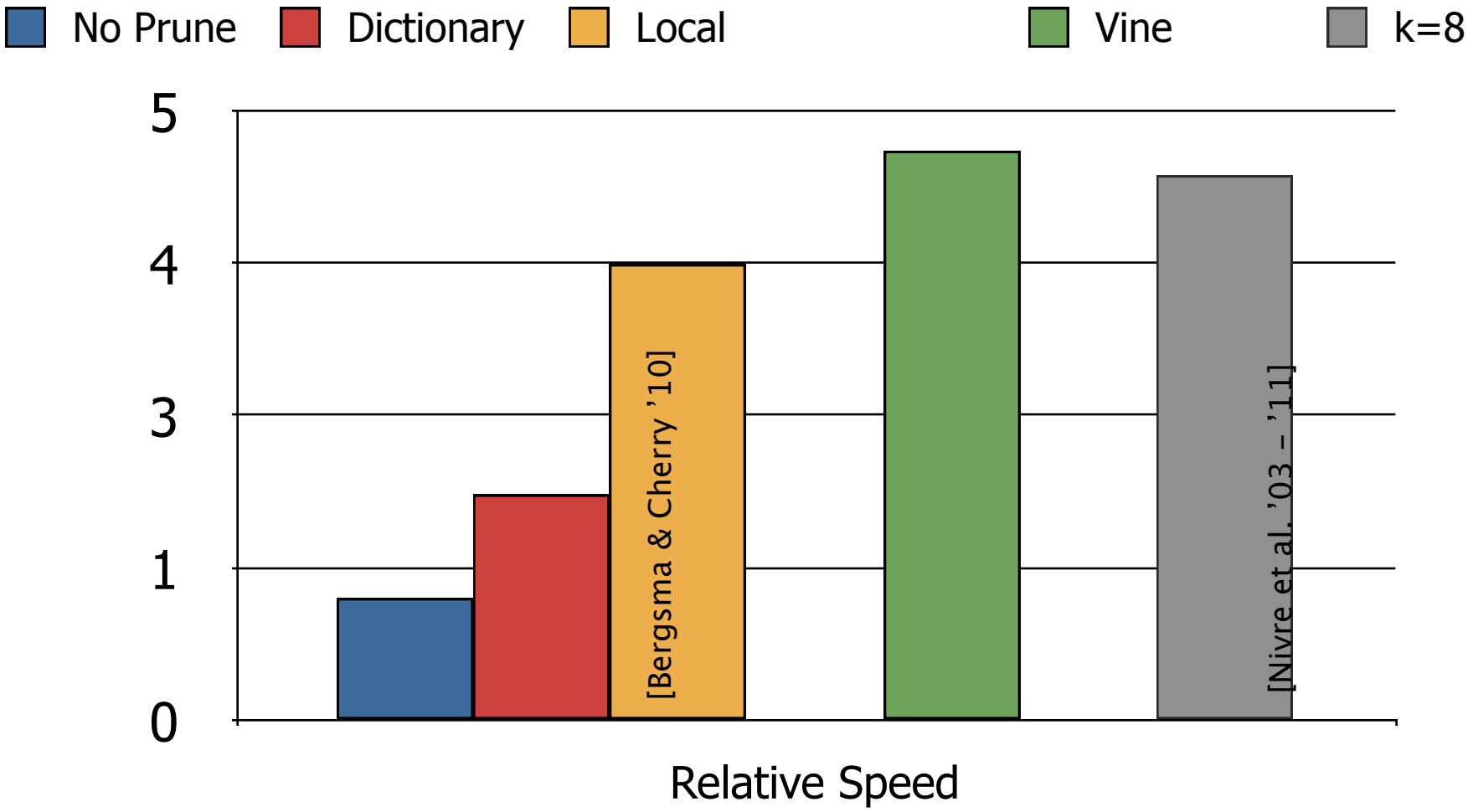
- Train to minimize pruning error (rather than 1-best)
- Pruning threshold:



- Training objective:
  - Filter as many arcs as possible
  - While preserving gold arc
  - Optimize with stochastic gradient decent (not so different from perceptron updates)

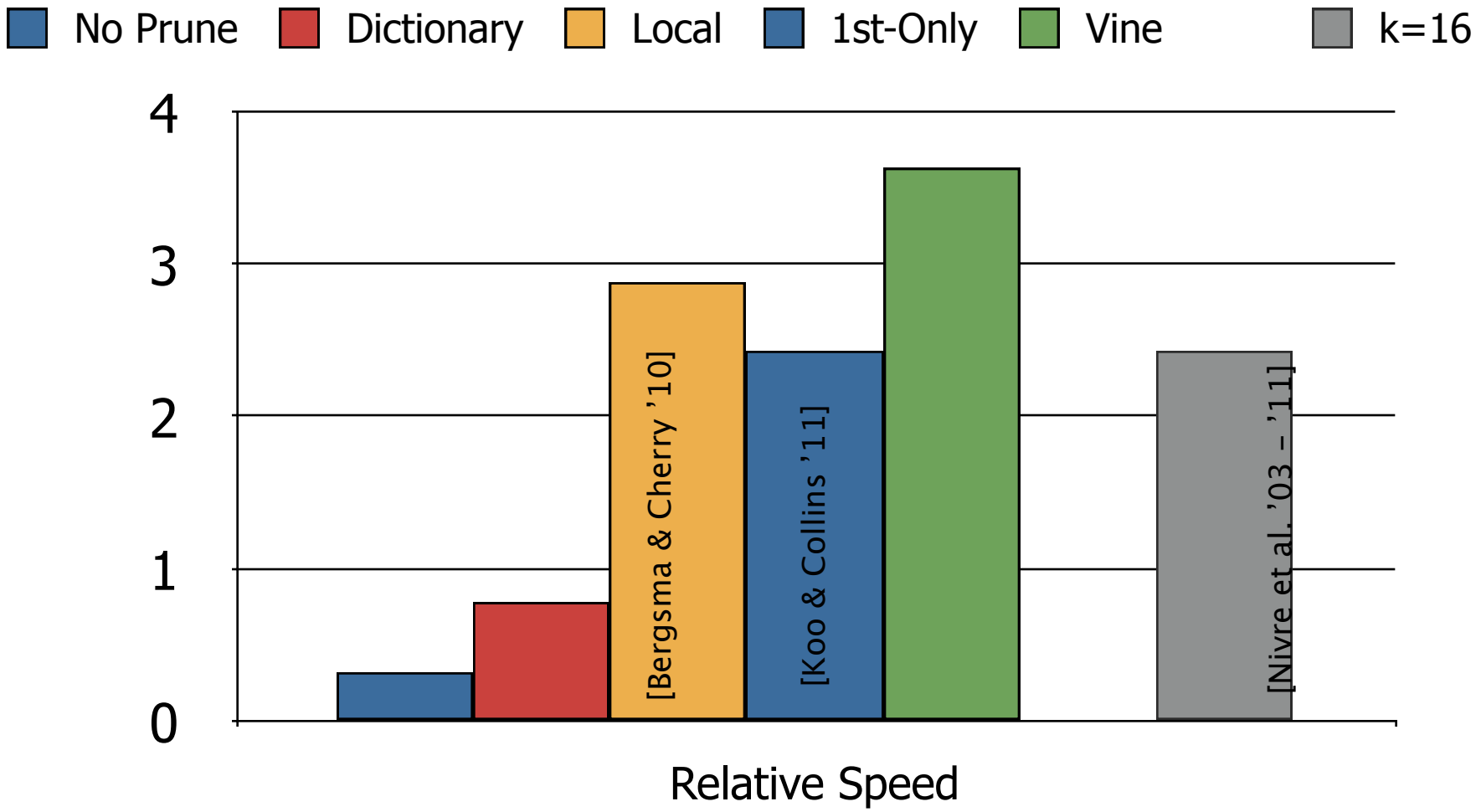
First-Order Parsing

UAS 91.0, Set pruning thresholds for no loss in accuracy



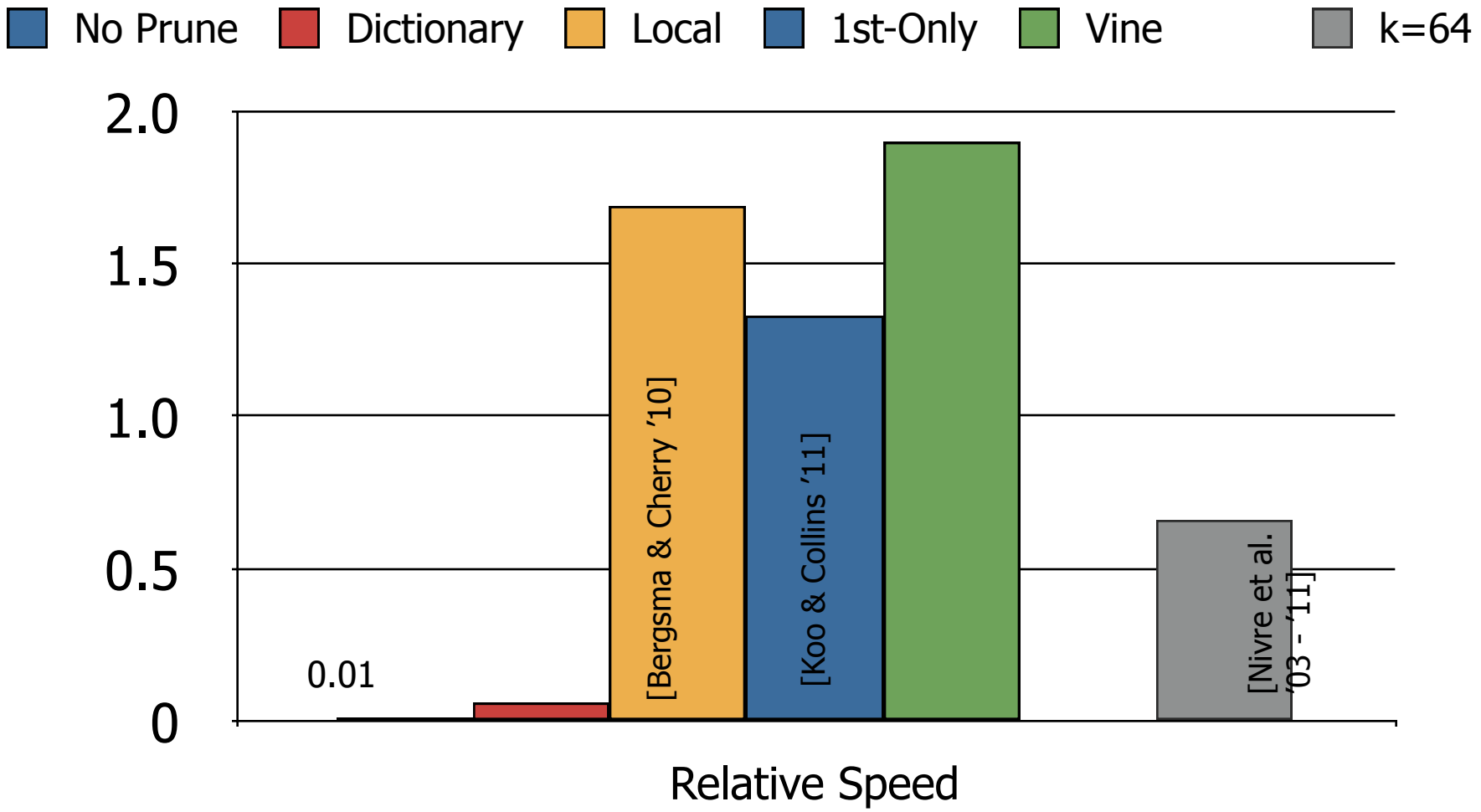
Second-Order Parsing

UAS 92.1, Set pruning thresholds for no loss in accuracy



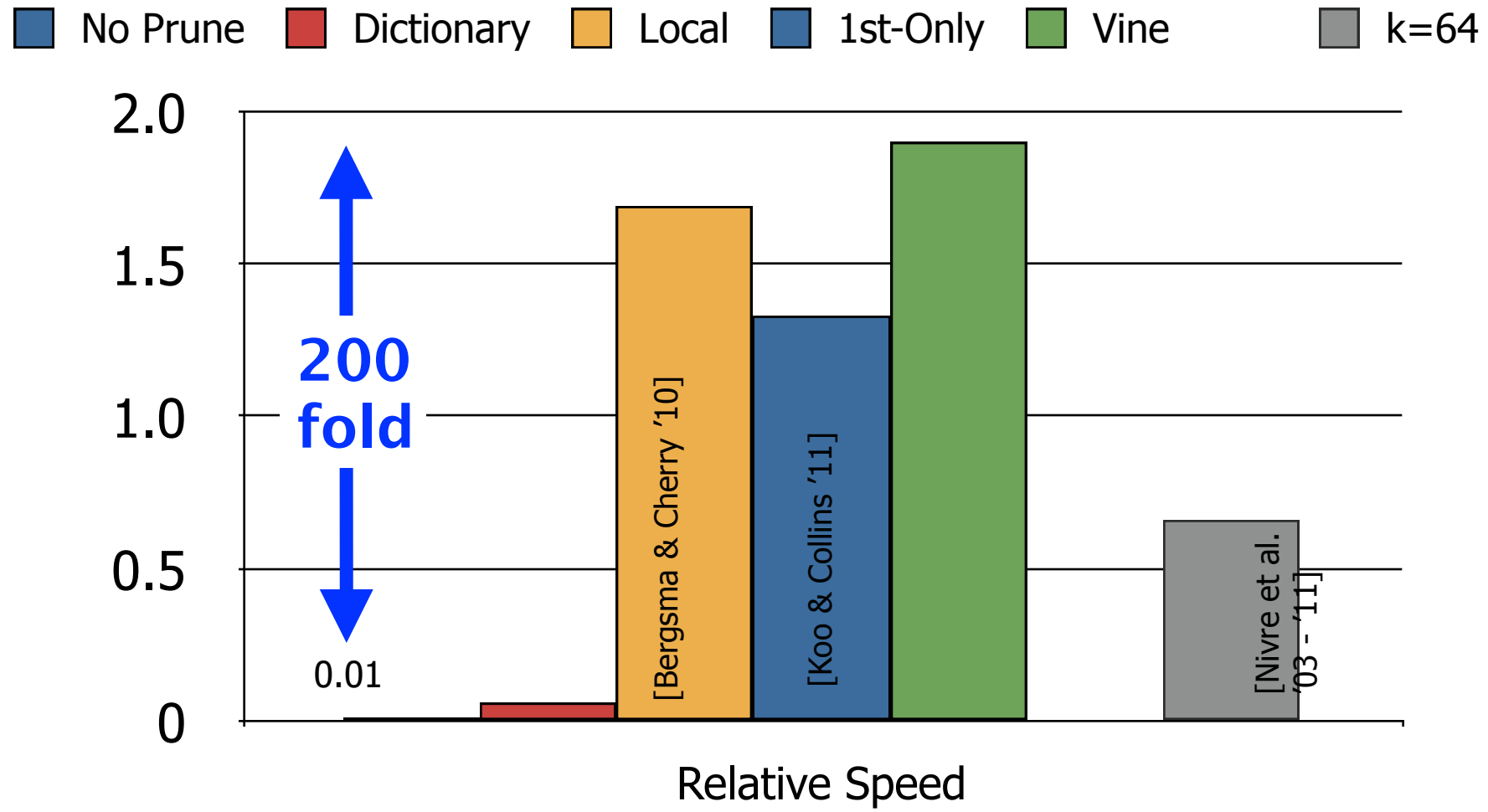
Third-Order Parsing

UAS 92.9, Set pruning thresholds for no loss in accuracy



Third-Order Parsing

UAS 92.9, Set pruning thresholds for no loss in accuracy



Google Web Treebanks

[Petrov & McDonald '12]

- Google Web Treebank
  - Funded by Google, annotated and released by LDC
  - 5 domains: Blogs, Newsgroups, Reviews, Emails, Q&A
  - ~2,000 manually annotated sentences (PTB-style)
  - >100,000 unlabeled sentences

- Shared Task at NAACL '12 Workshop
  - Constituency Trees or Stanford Dependencies
  - Train on WSJ + unlabeled data
  - 2 domains released for development
  - Test on remaining 3 domains

POS Accuracy (SANCL Shared Task)

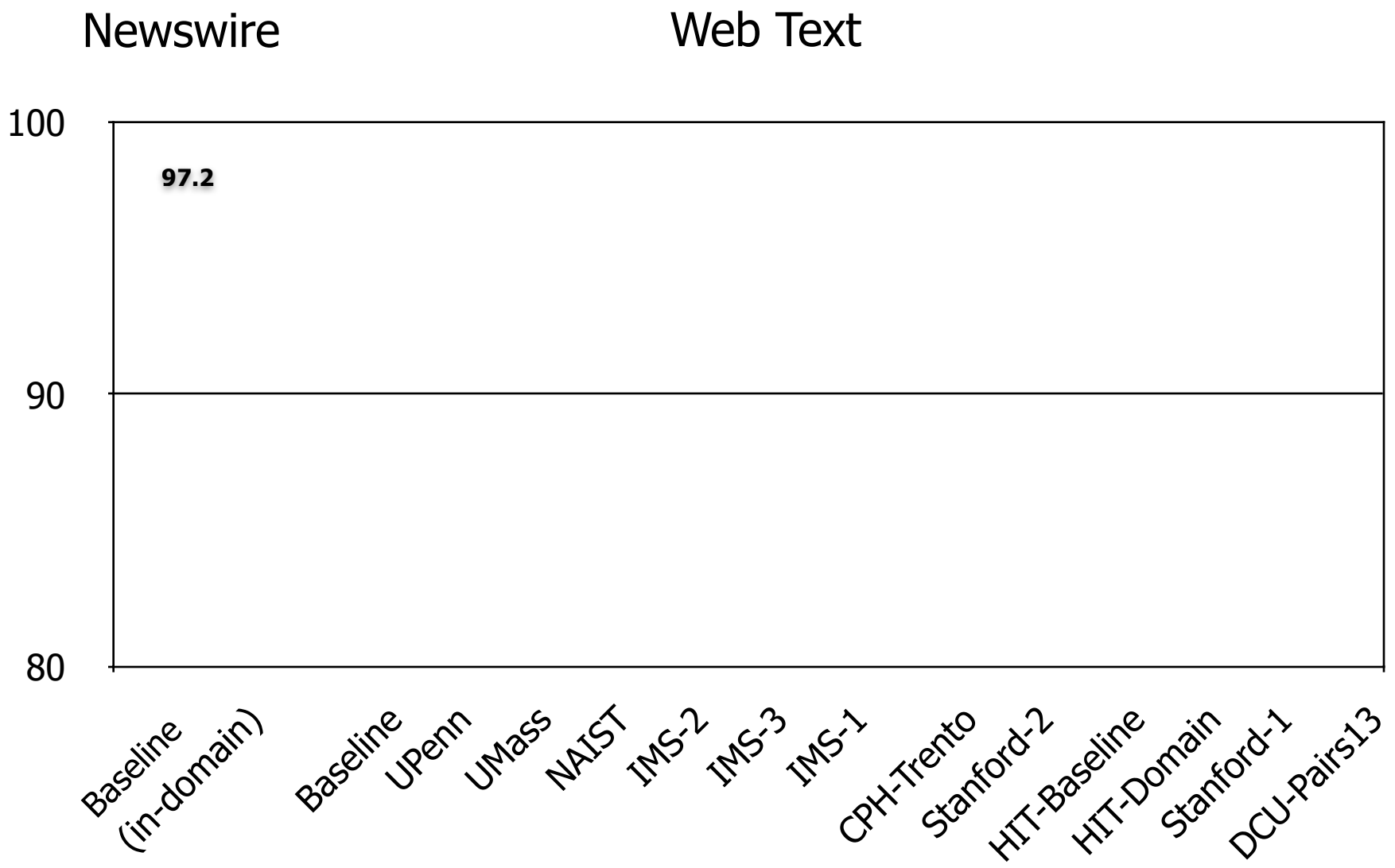
Newswire

Web Text

Baseline

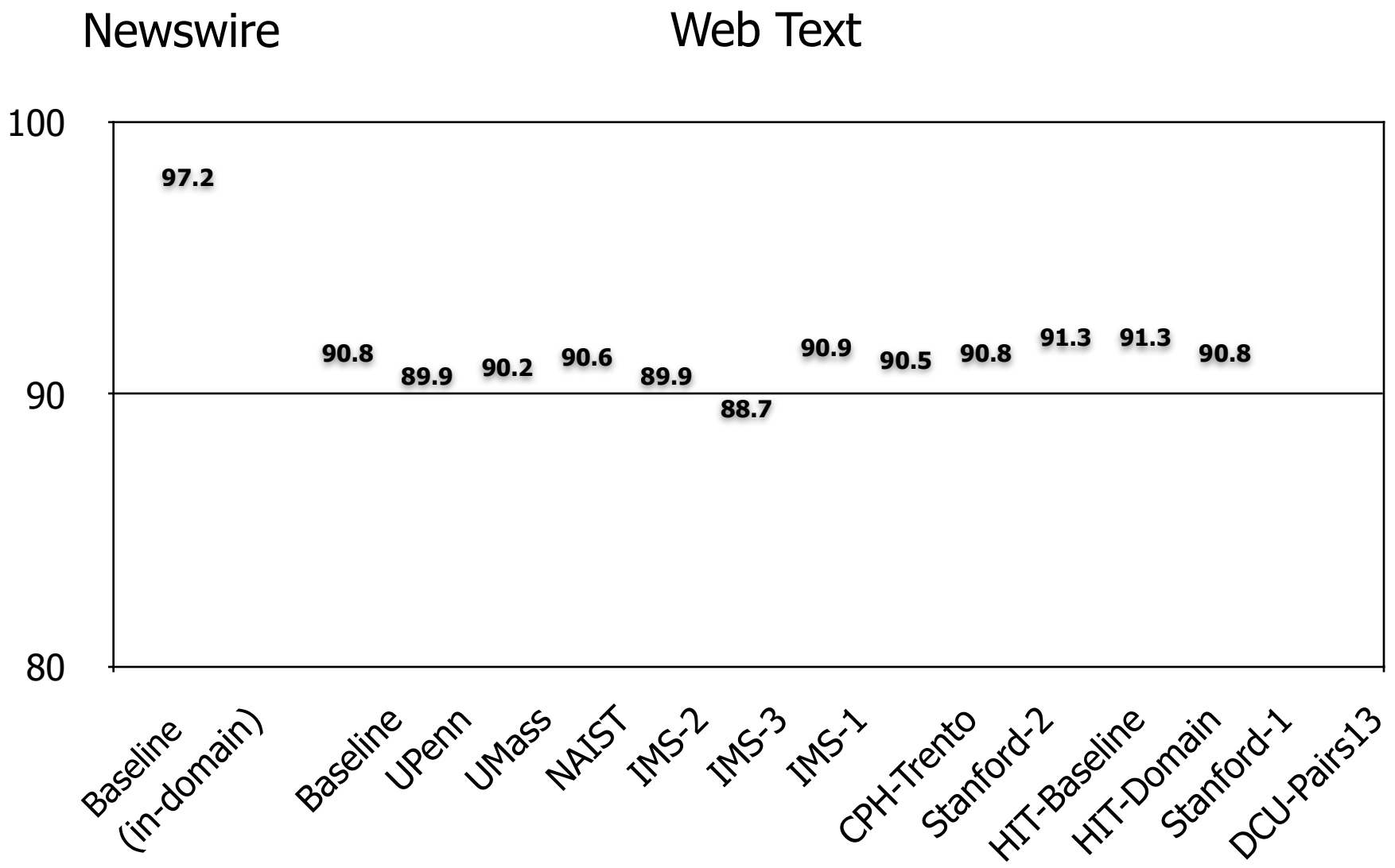
Baseline = StanfordTagger v2.0 [Manning '11]

POS Accuracy (SANCL Shared Task)



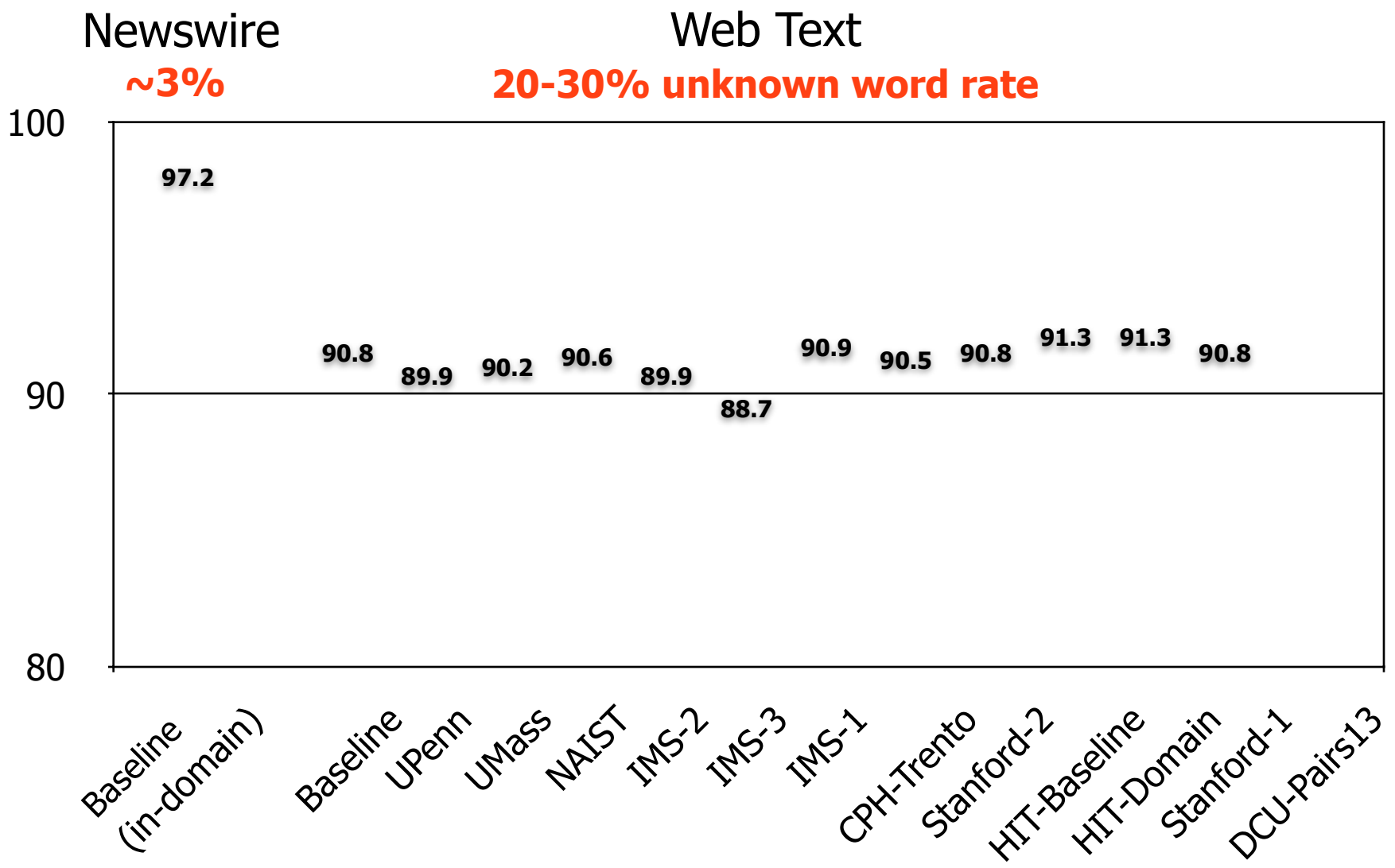
Baseline = StanfordTagger v2.0 [Manning '11]

POS Accuracy (SANCL Shared Task)



Baseline = StanfordTagger v2.0 [Manning '11]

POS Accuracy (SANCL Shared Task)



Baseline = StanfordTagger v2.0 [Manning '11]

POS Accuracy (SANCL Shared Task)

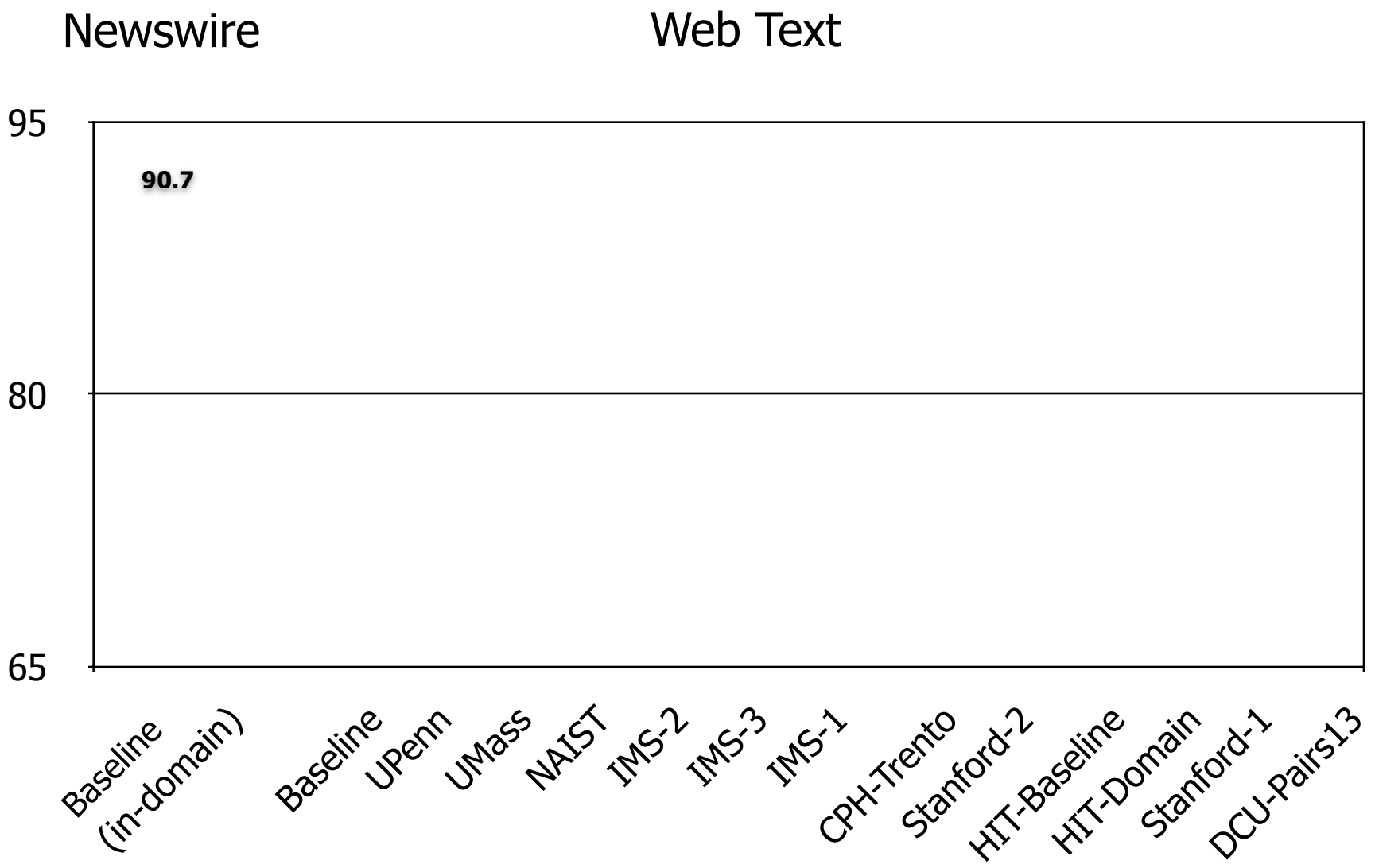
Newswire

Web Text

Baseline

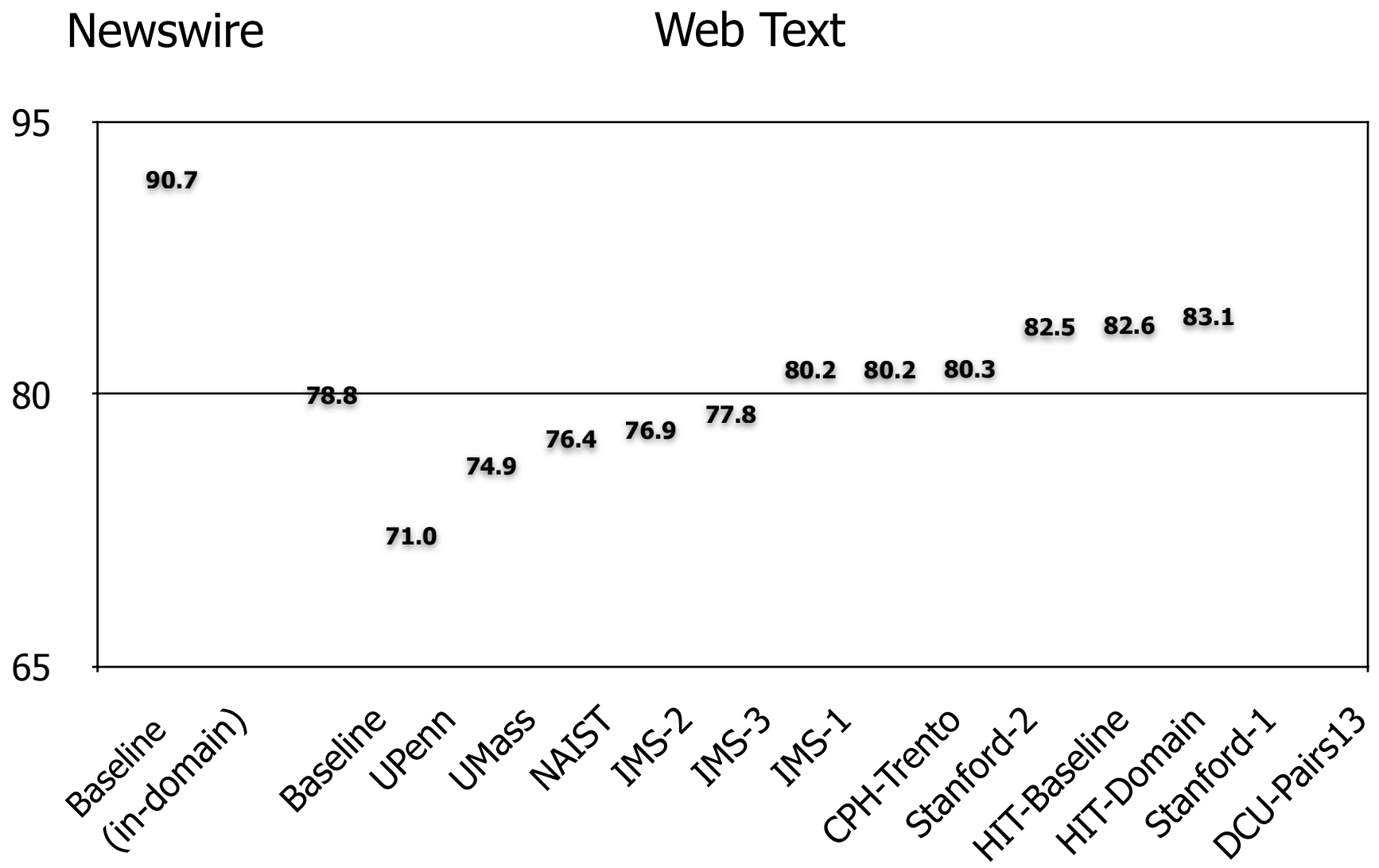
Baseline = StanfordTagger v2.0 [Manning '11]

POS Accuracy (SANCL Shared Task)



Baseline = StanfordTagger v2.0 [Manning '11]

POS Accuracy (SANCL Shared Task)



Baseline = StanfordTagger v2.0 [Manning '11]

Summary

- Constituency Parsing
  - CKY Algorithm
  - Lexicalized Grammars
  - Latent Variable Grammars
- Dependency Parsing
  - Eisner Algorithm
  - Maximum Spanning Tree Algorithm
  - Transition Based Parsing
  - Vine-Pruning and Coarse-to-Fine Parsing