Syntax and Parsing II

Dependency Parsing

Slav Petrov – Google

Thanks to:

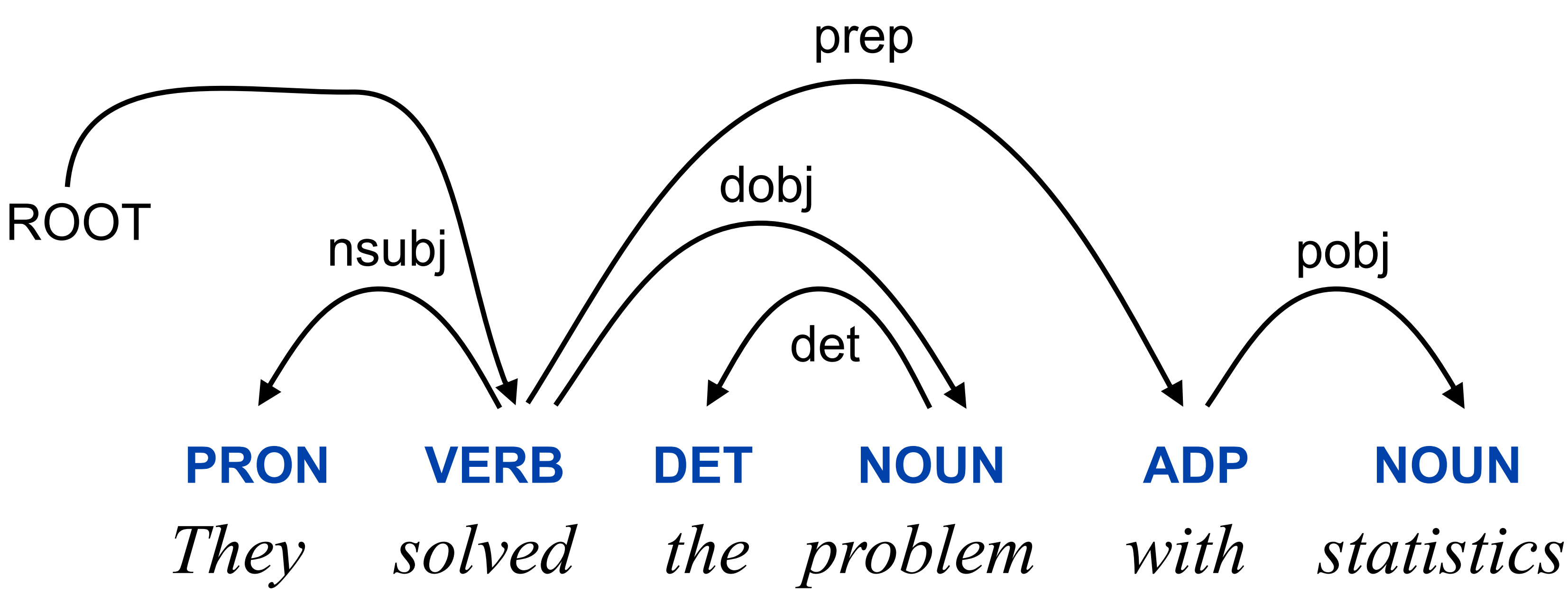
Dan Klein, Ryan McDonald, Alexander Rush, Joakim Nivre,
Greg Durrett, David Weiss

Lisbon Machine Learning School 2015

Notes for 2016

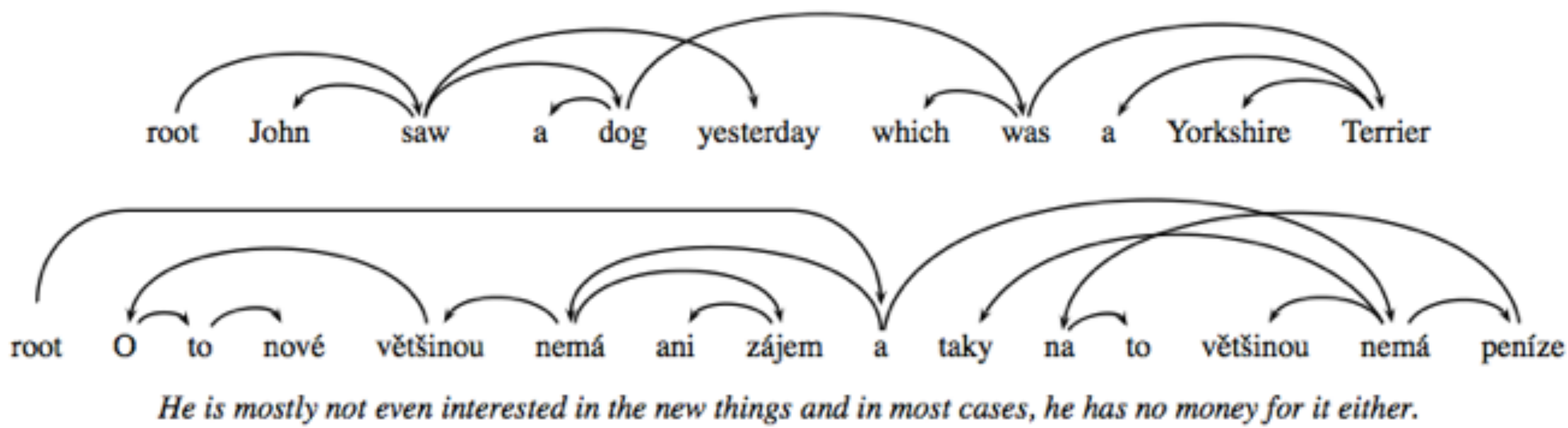
- Can add 10min of material

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):



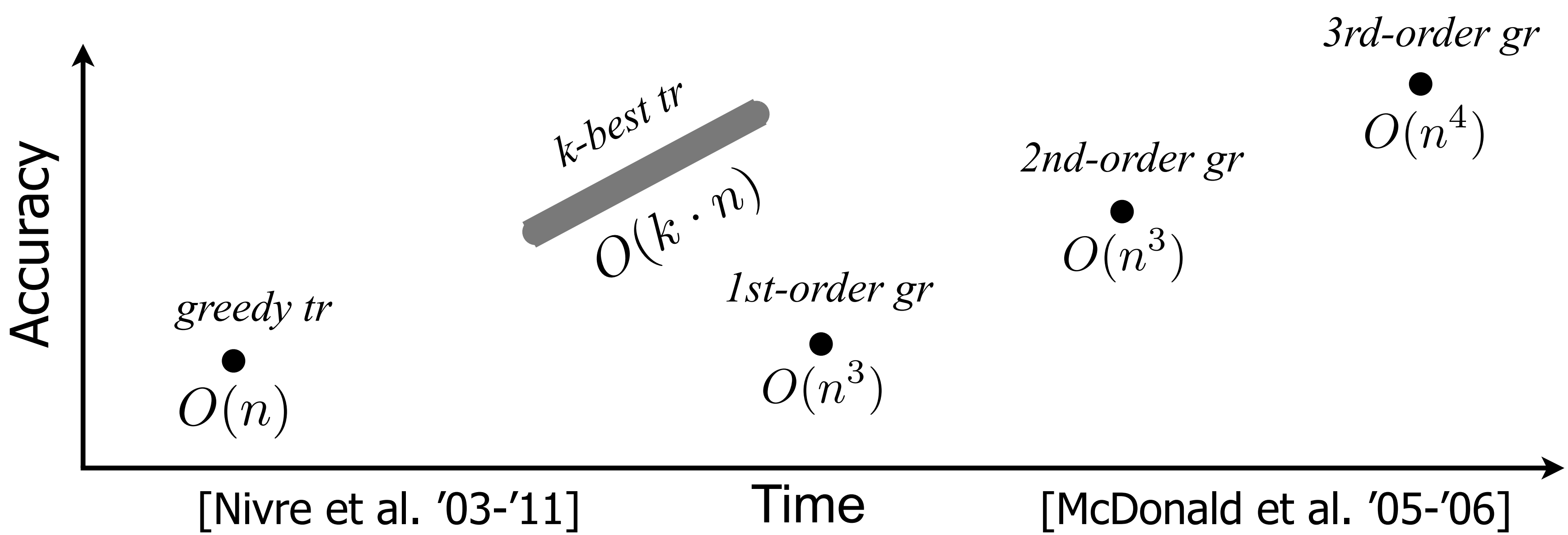
Formal Conditions

- 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 $i \to j$, then not $j \to^* i$.
- G obeys the single-head constraint:
  - If $i \to j$, then not $i' \to j$, for any $i' \neq i$.
- G is projective:
  - If $i \to j$, then $i \to^* i'$, 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
- Graph-Based (gr)
  - Slower, exhaustive, dynamic programming inference algorithms
  - Higher-order factorizations



Arc-Factored Models

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

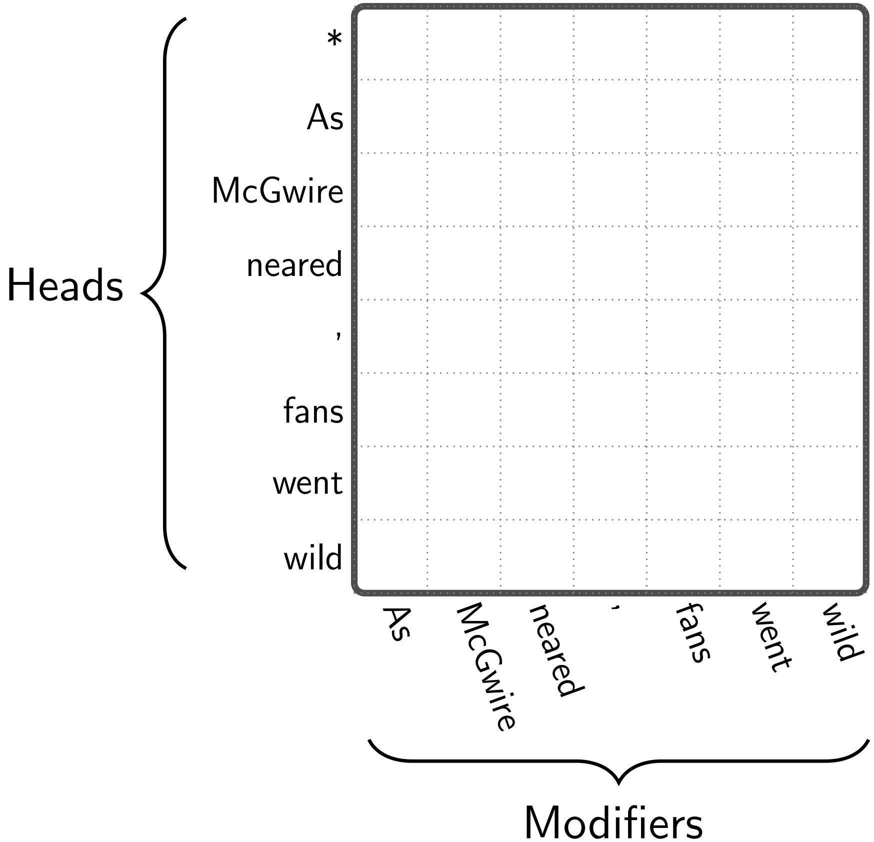
$$w(G) = \prod_{(i,j,k)\in G} w_{ij}^{k}$$

look familiar?

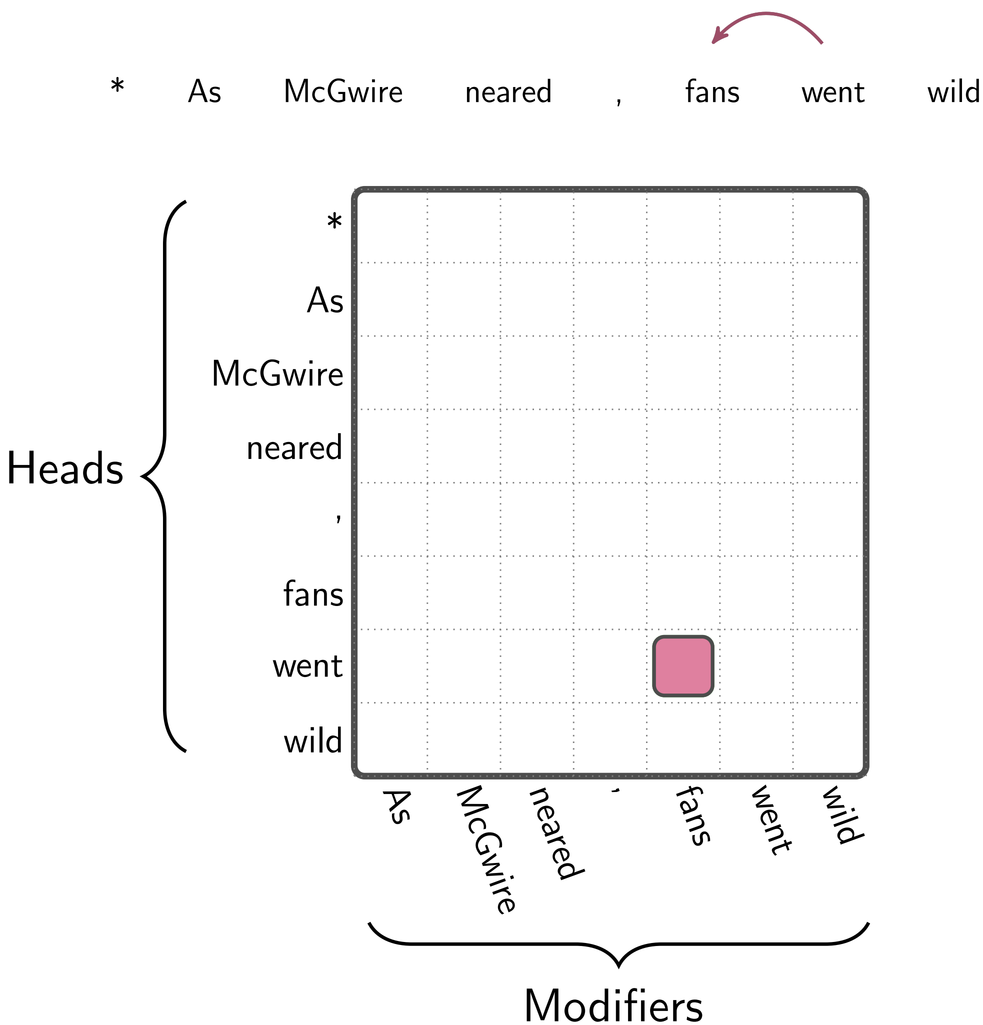
- w_{ij}^{k} is the weight of creating a dependency from word w_i to w_j with label l_k
- Thus there is an assumption that each dependency decision is independent
  - Strong assumption! Will address this later.

Dependency Representation

* As McGwire neared , fans went wild

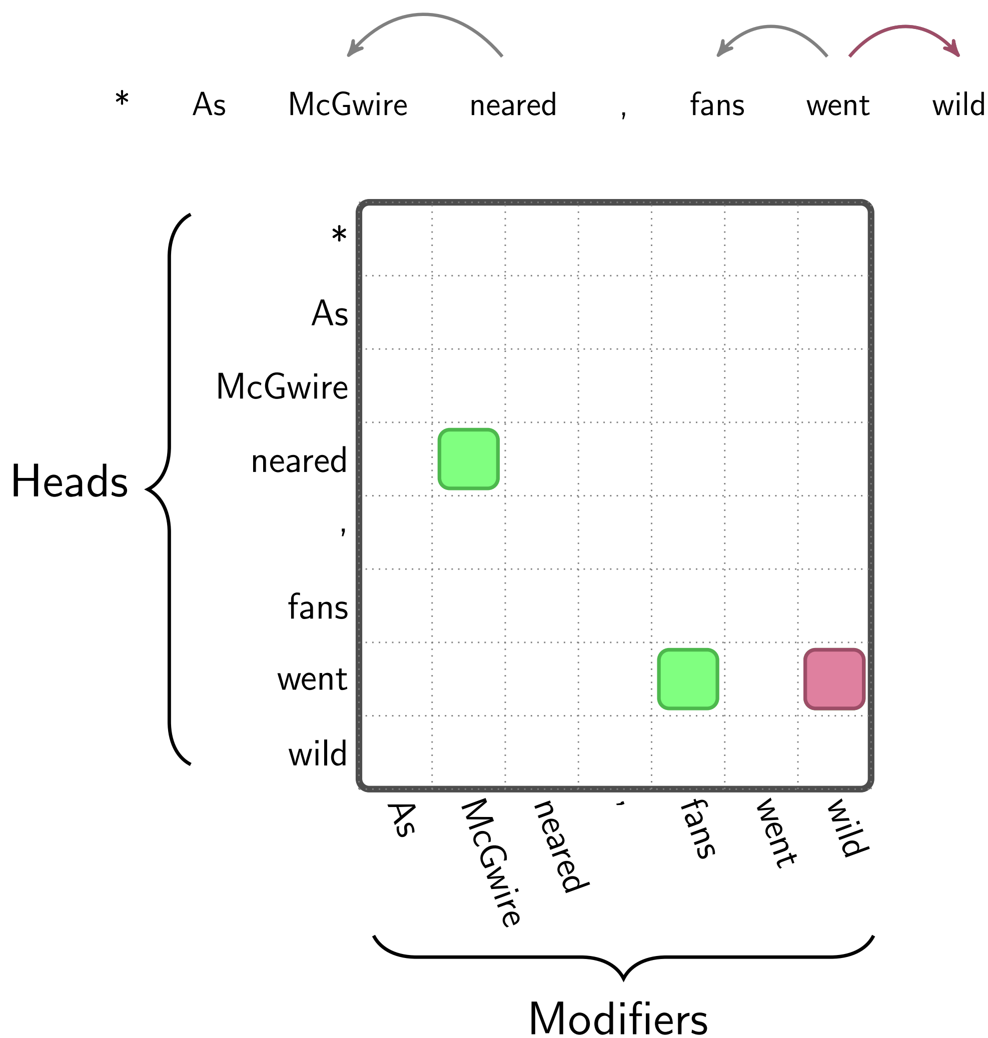


Dependency Representation

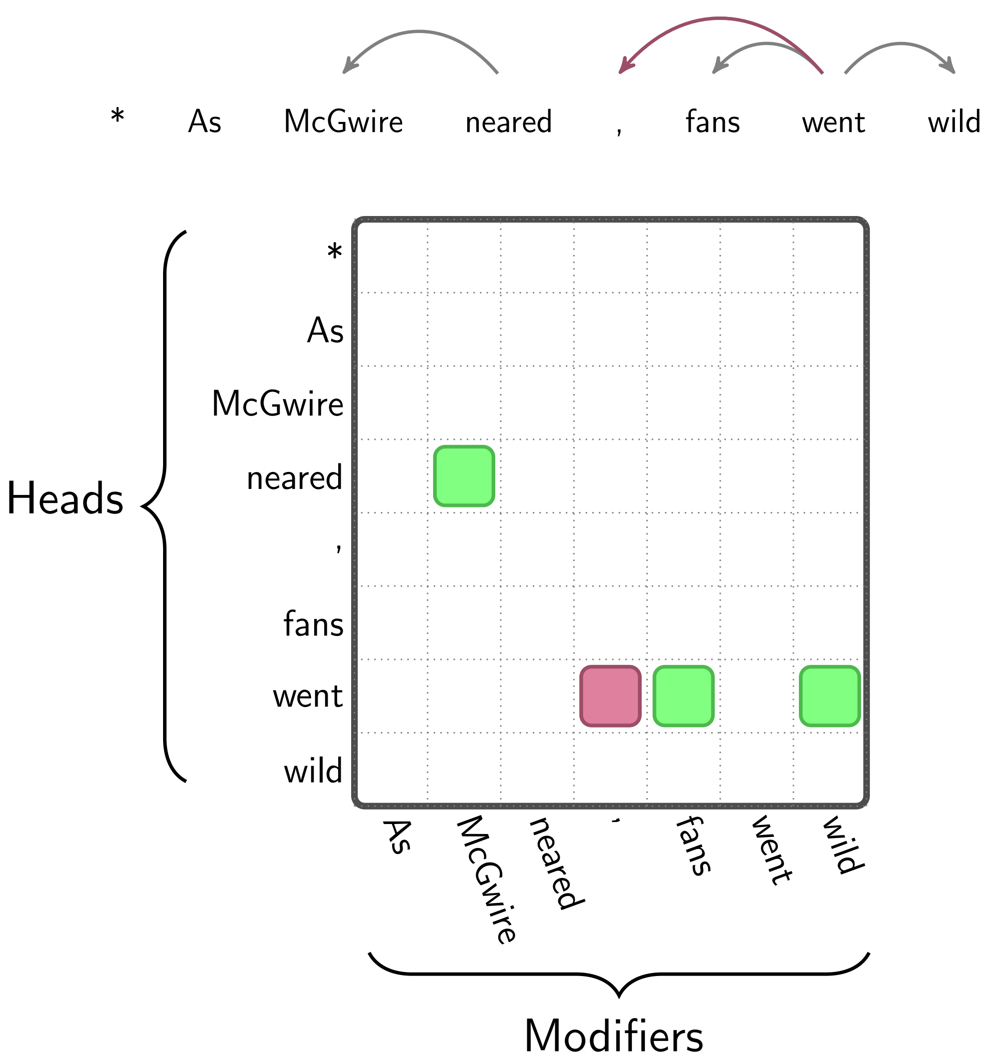


Dependency Representation

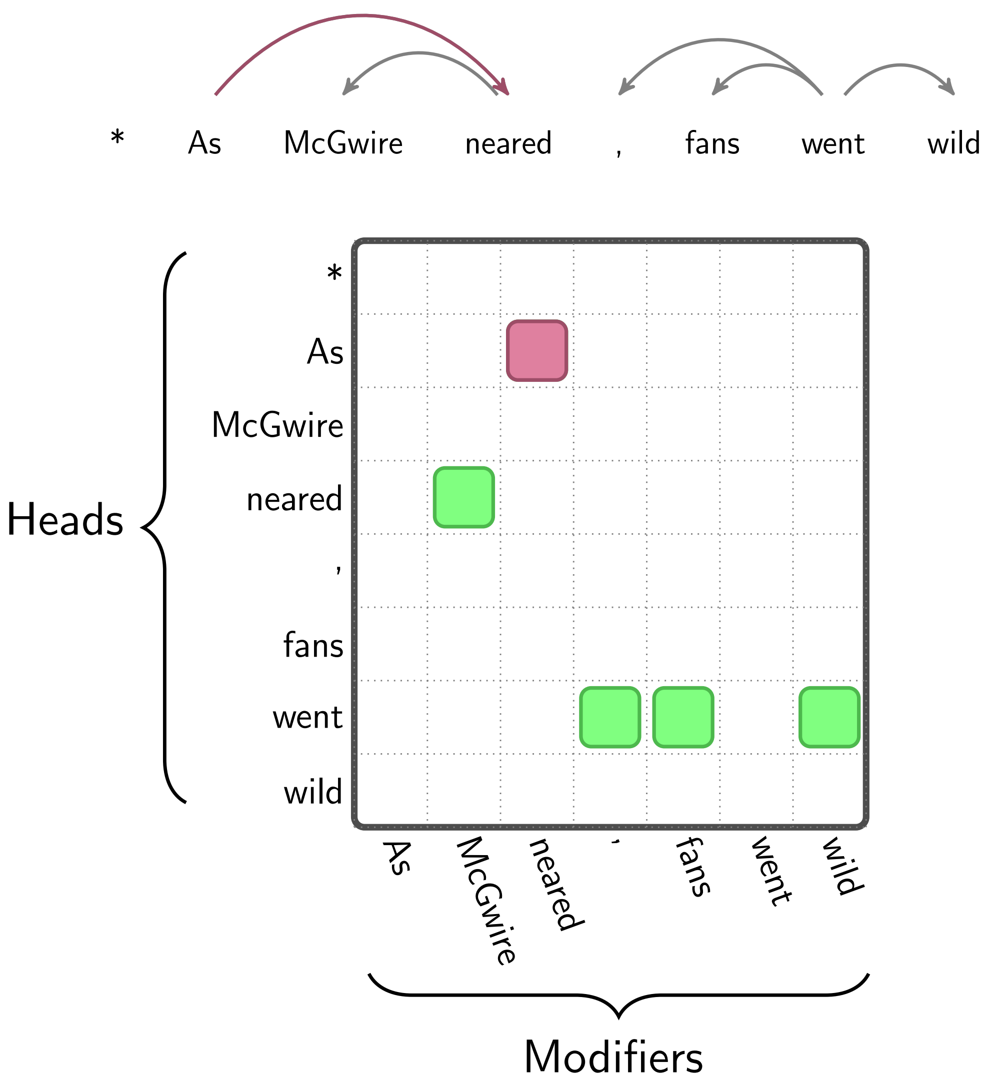
Dependency Representation



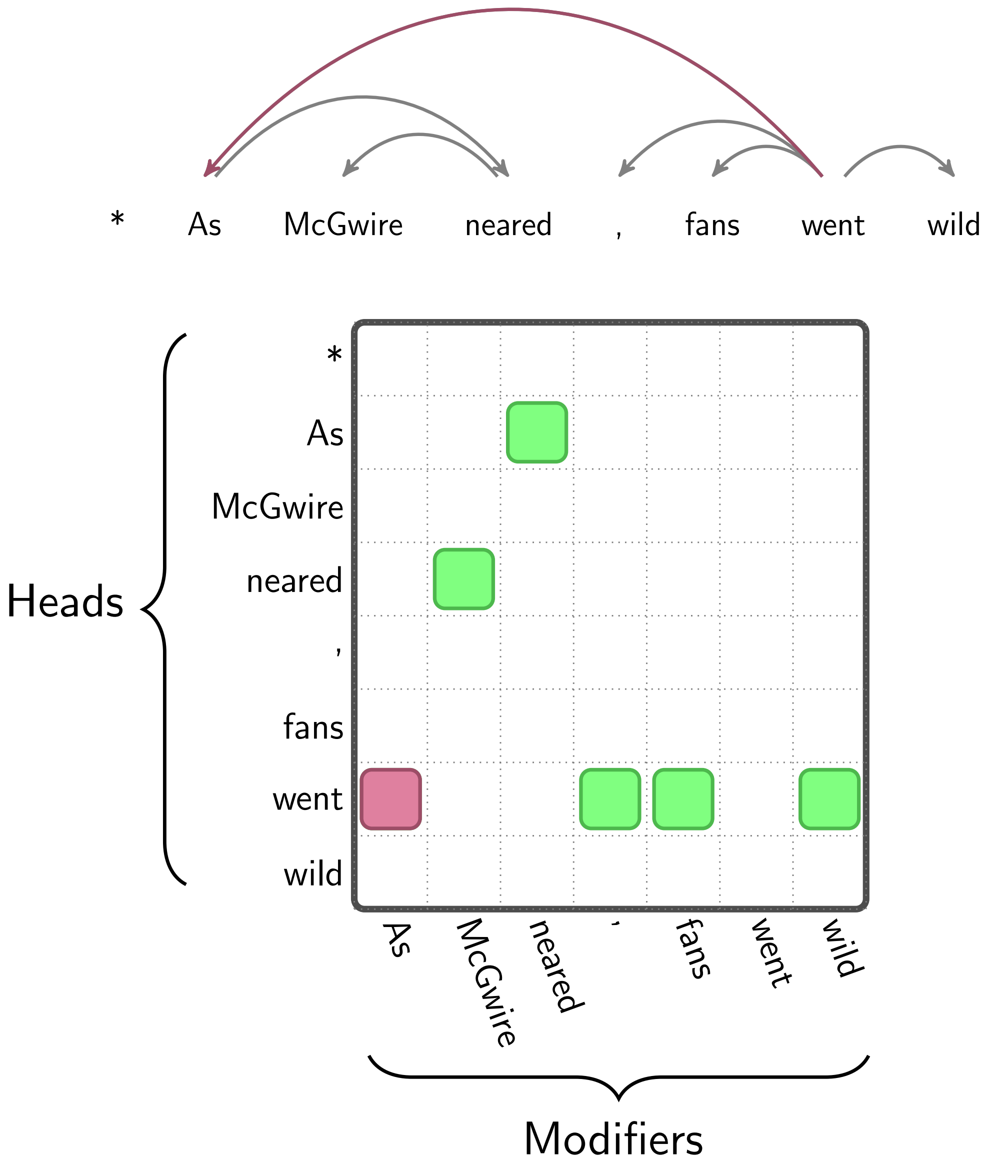
Dependency Representation



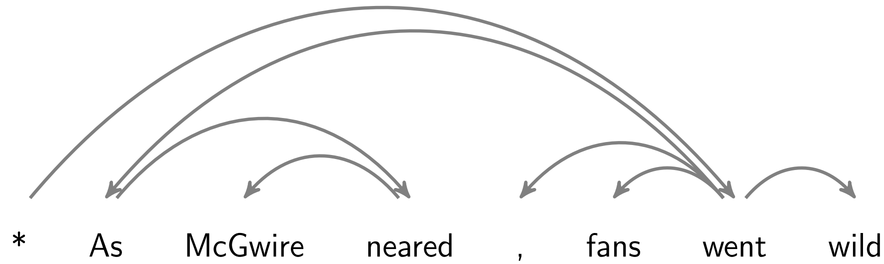
Dependency Representation

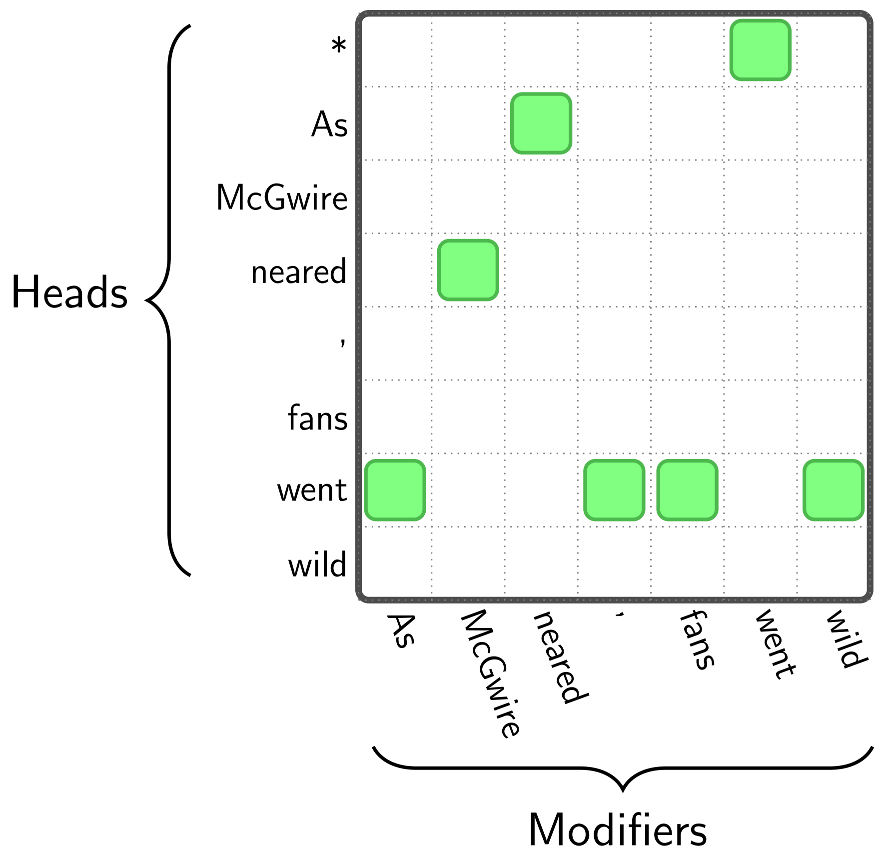


Dependency Representation



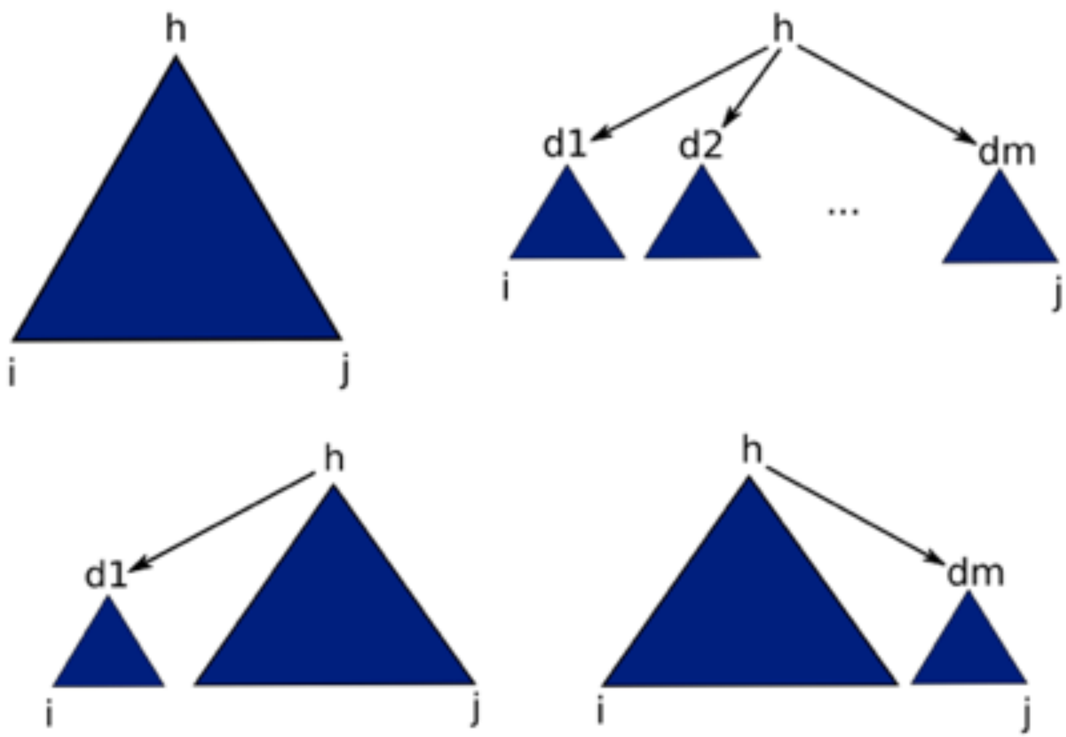
Dependency Representation





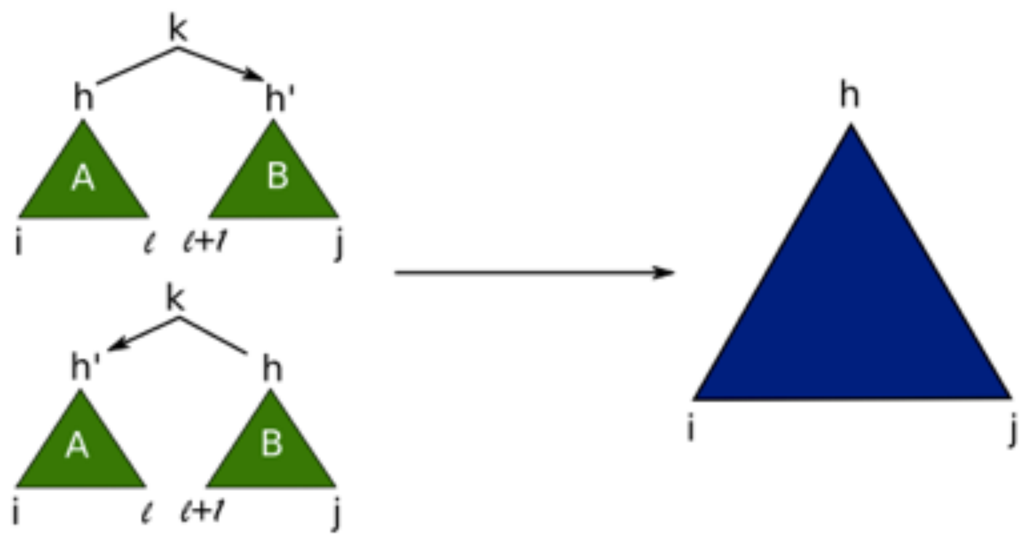
Arc-factored Projective Parsing

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



Arc-factored Projective Parsing

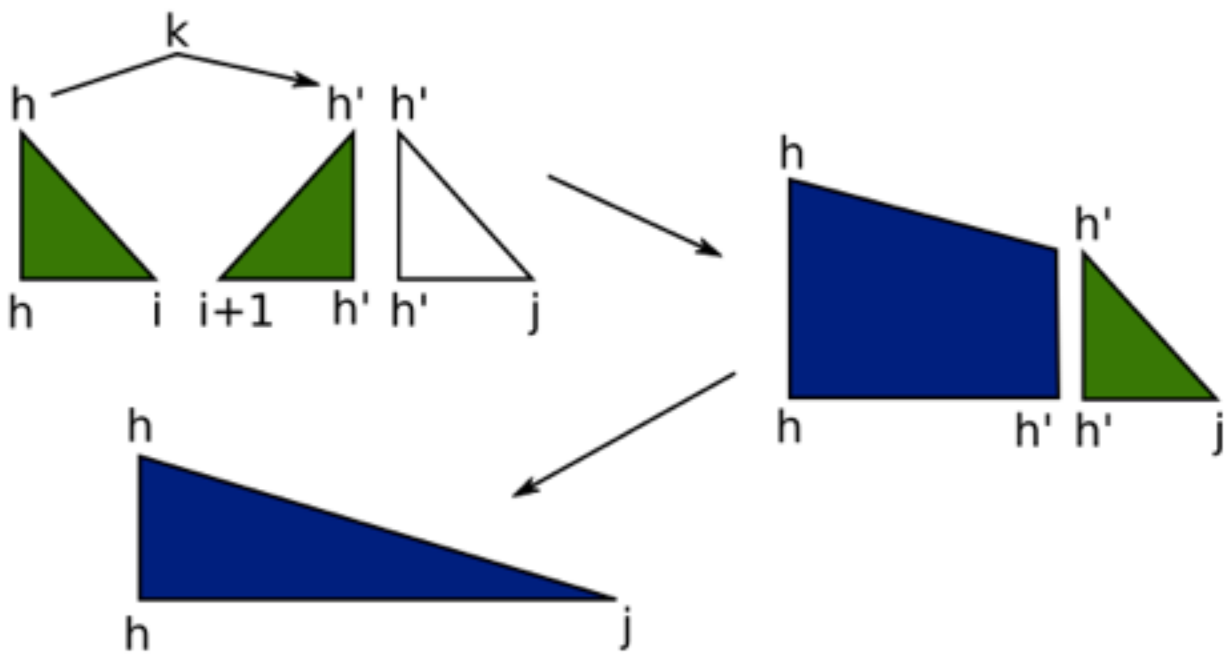
- Chart item filled in a bottom-up manner
  - First do all strings of length 1, then 2, etc. just like CKY



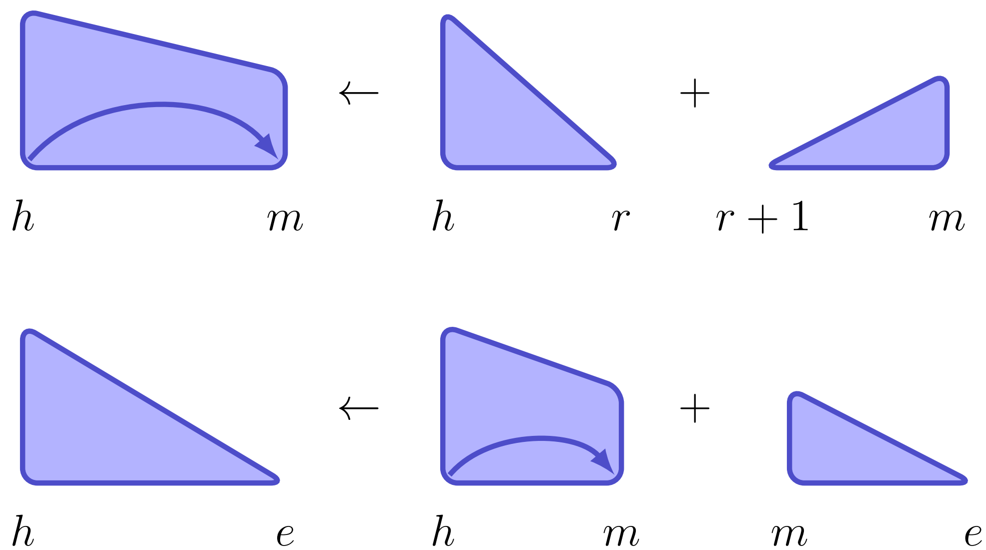
- Weight of new item: $\max_{l,j,k} \; w(A) \times w(B) \times w^{k}_{hh'}$
- Algorithm runs in $O(|L|n^5)$
- Use back-pointers to extract best parse (like CKY)

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

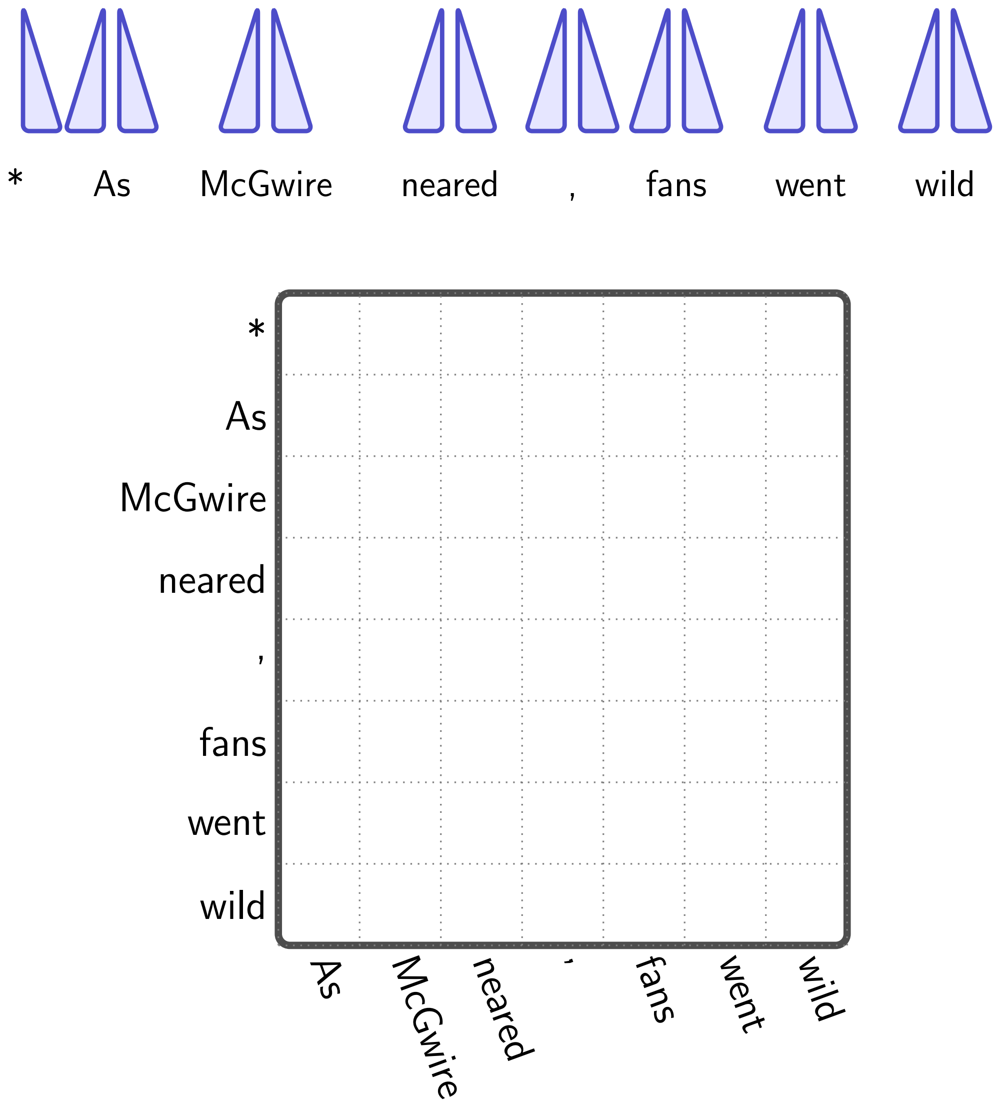


Eisner First-Order Parsing



In practice also left arc version

Eisner First-Order Parsing



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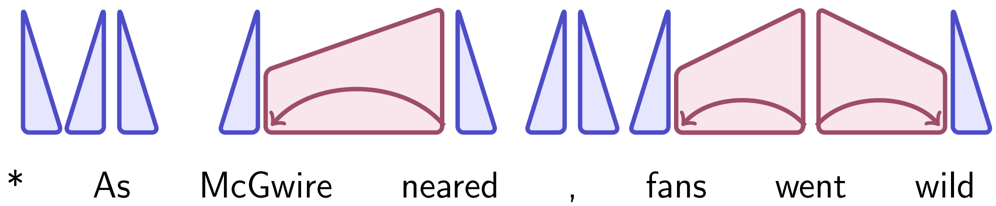

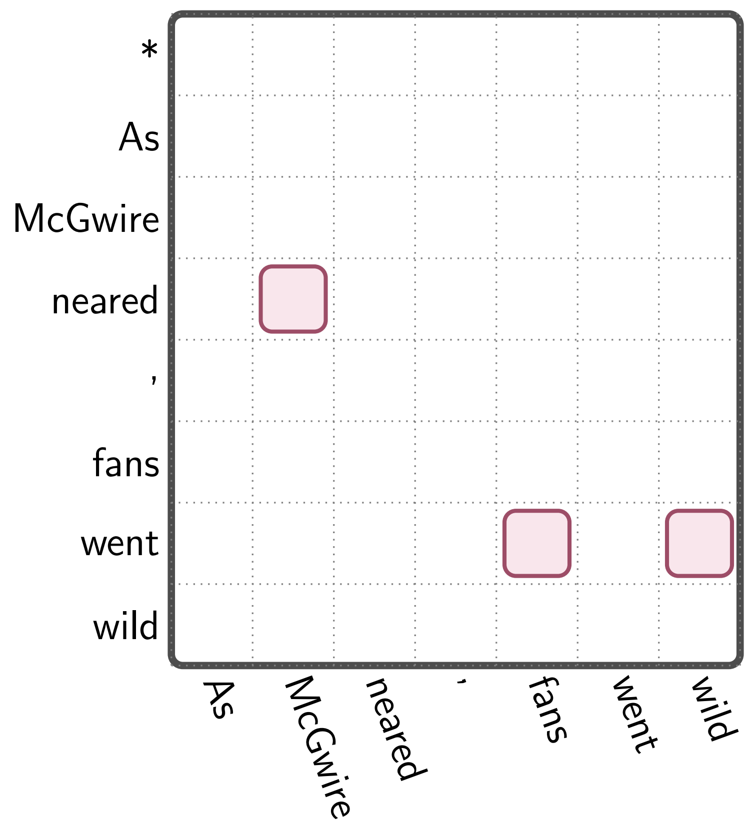

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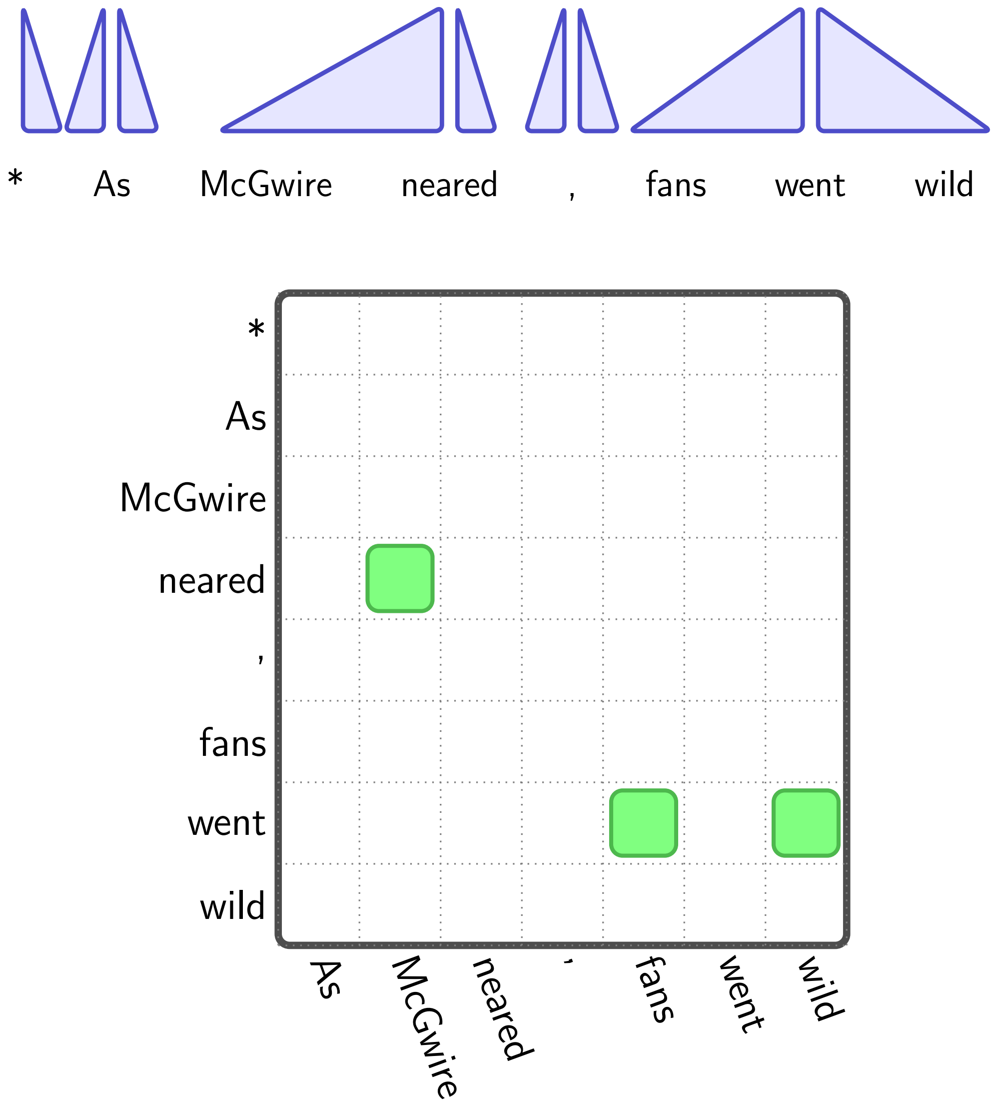

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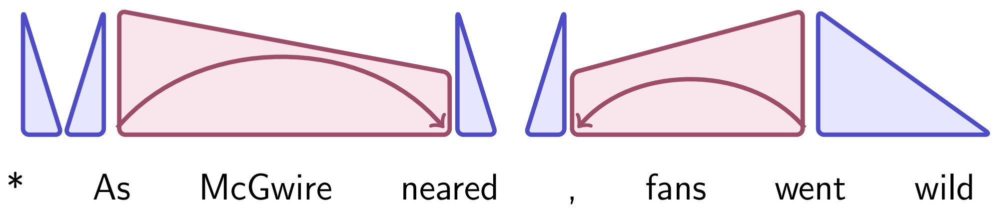
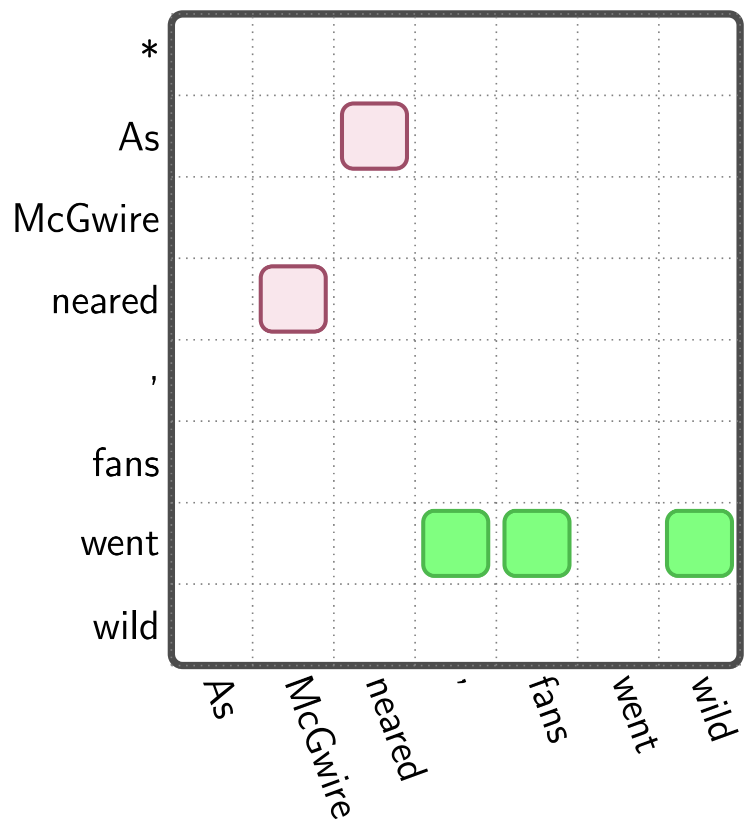
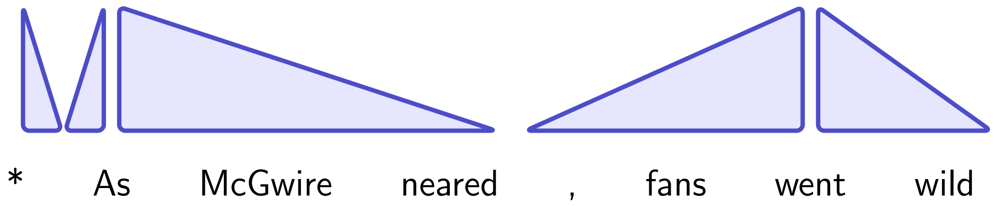
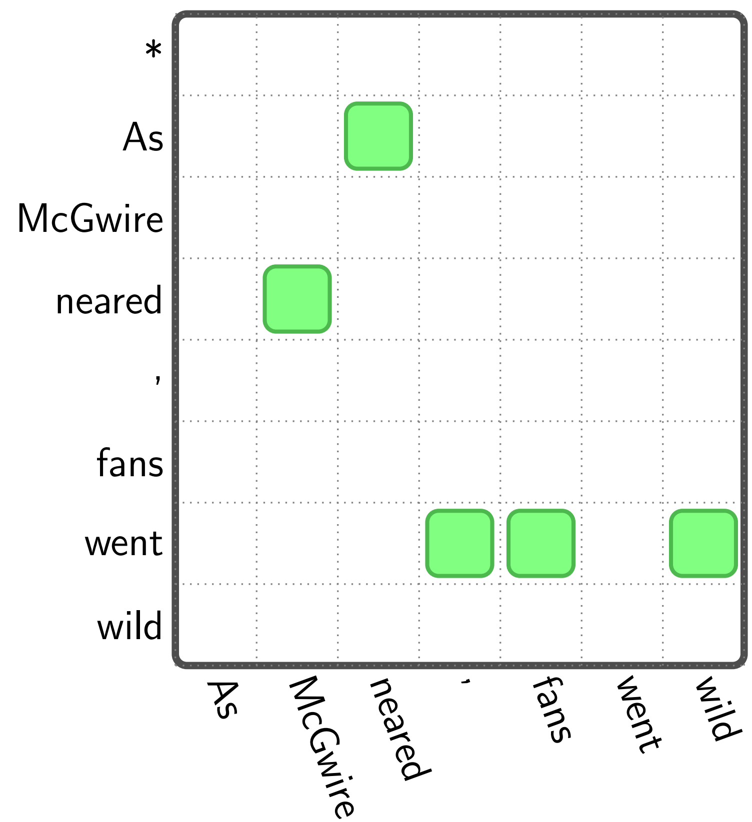




Eisner First-Order Parsing





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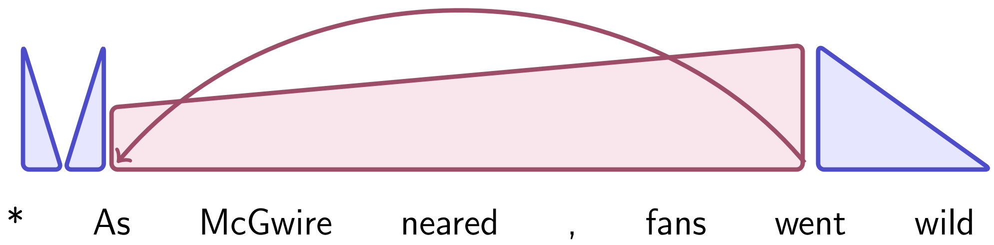
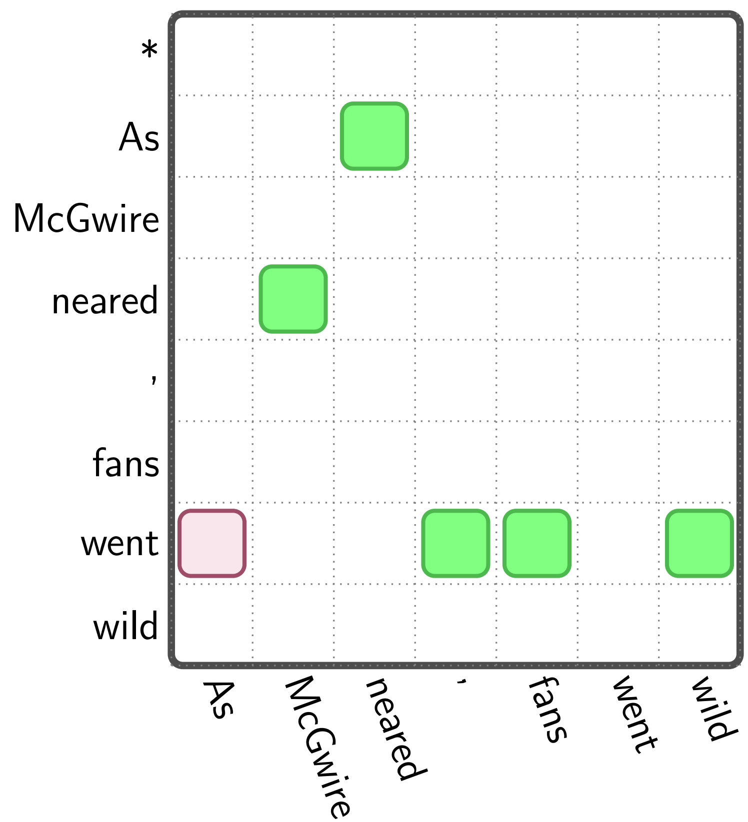
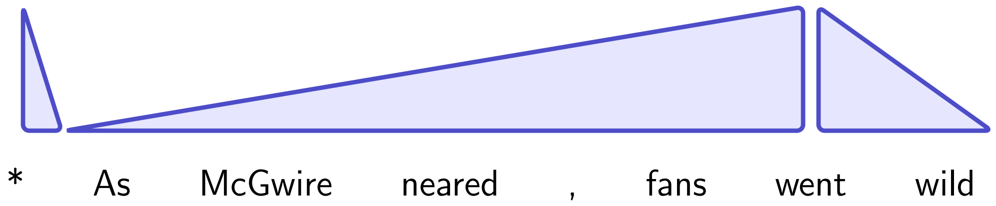
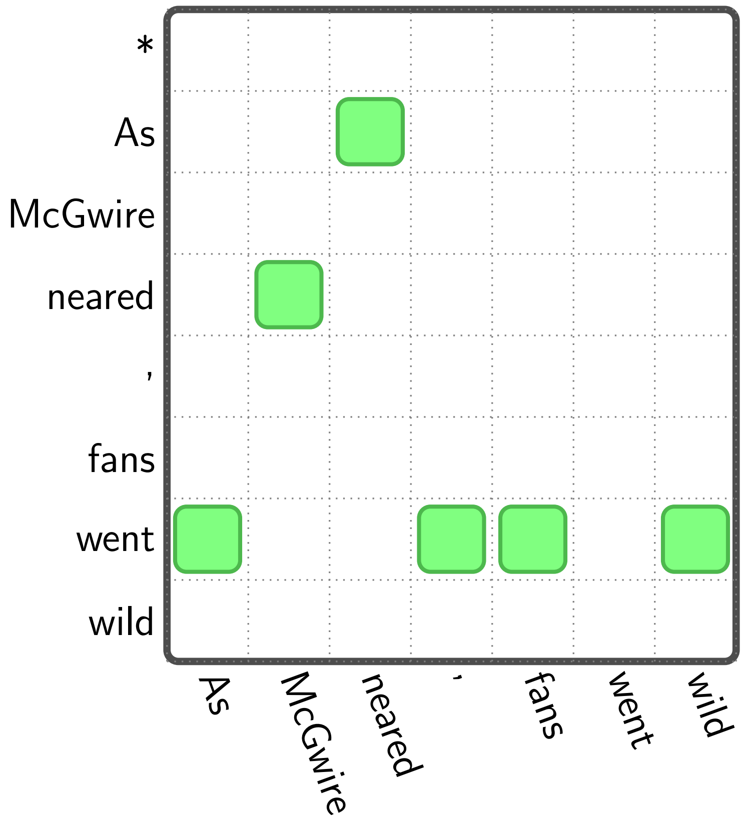


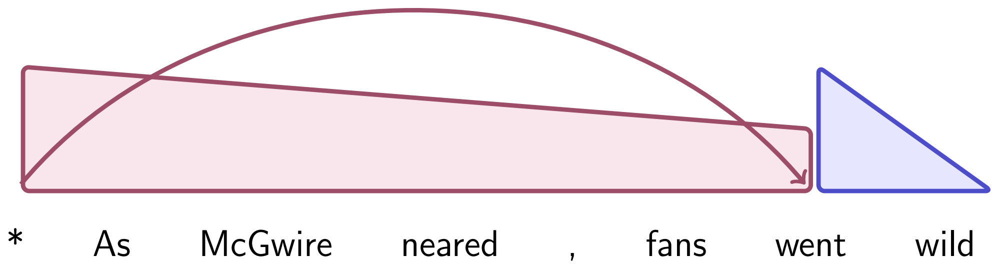


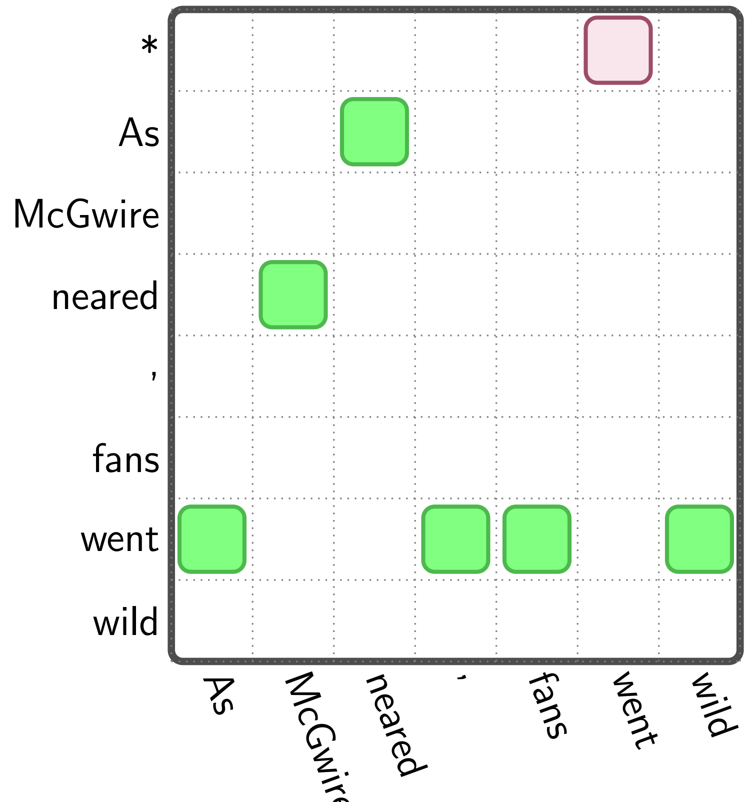
Eisner First-Order Parsing





Eisner First-Order Parsing





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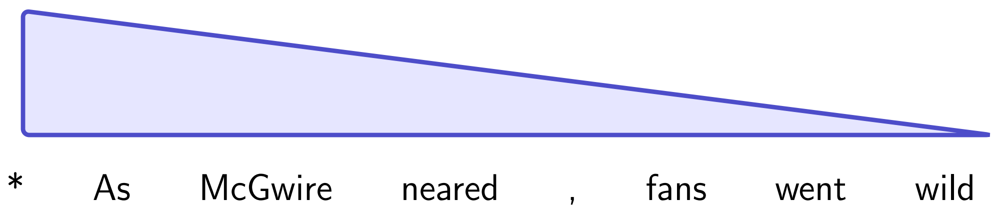
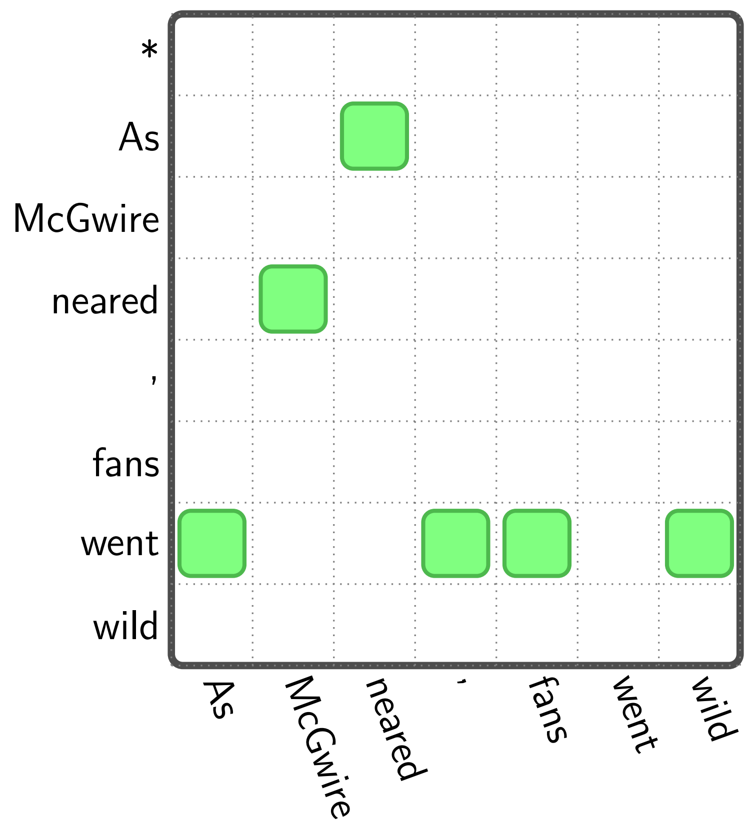




Eisner Algorithm Pseudo Code

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

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

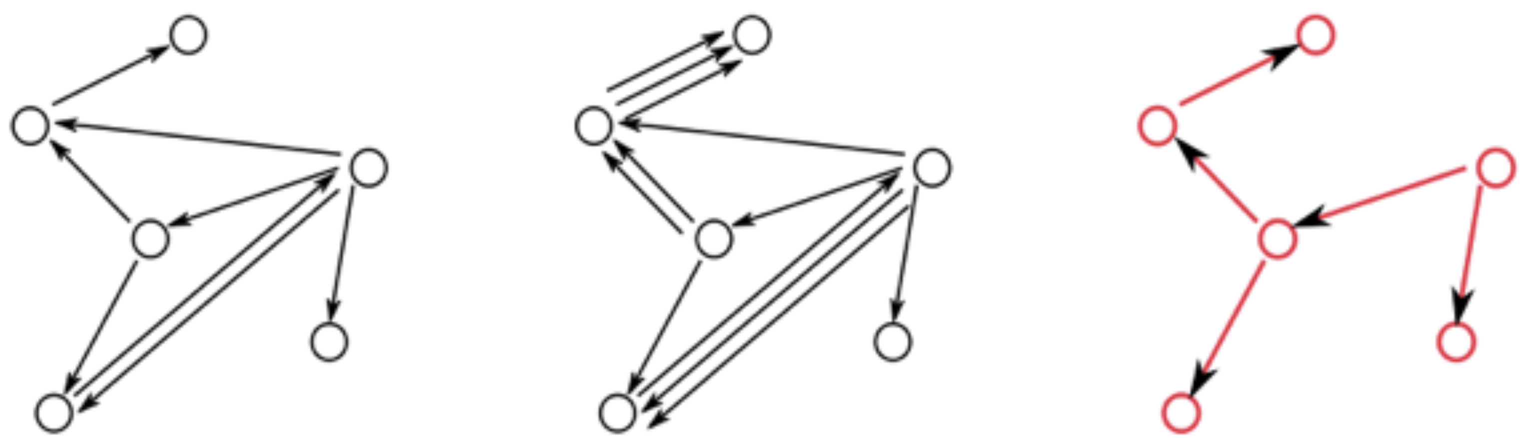
    $C[s][t][\rightarrow][1] = \max_{s < r \leq t} \; (C[s][r][\rightarrow][0] + C[r][t][\rightarrow][1])$

  end for

end for

Maximum Spanning Trees (MSTs)

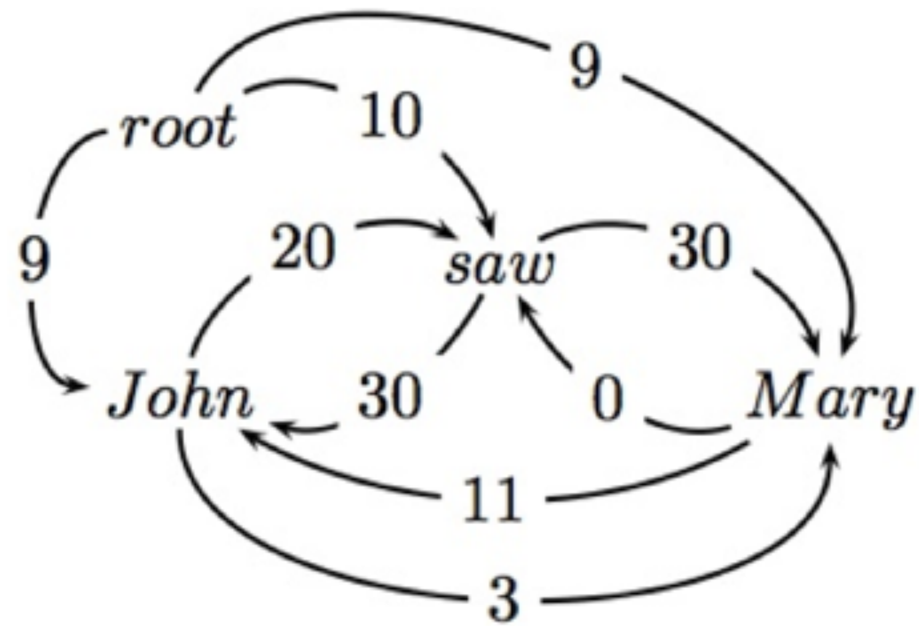
- A directed spanning tree of a (multi-)digraph $G = (V, A)$, is a subgraph $G' = (V', A')$ such that:
  - $V' = V$
  - $A' \subseteq A$, and $|A'| = |V'| - 1$
  - G' is a tree (acyclic)
- A spanning tree of the following (multi-)digraphs



Can use MST algorithms for nonprojective parsing!

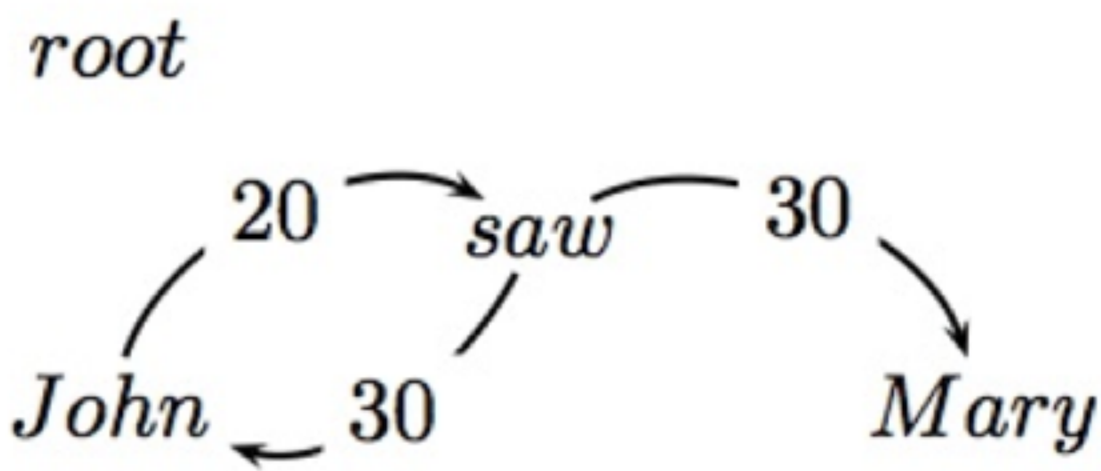
Chu-Liu-Edmonds

- x = root John saw Mary



Chu-Liu-Edmonds

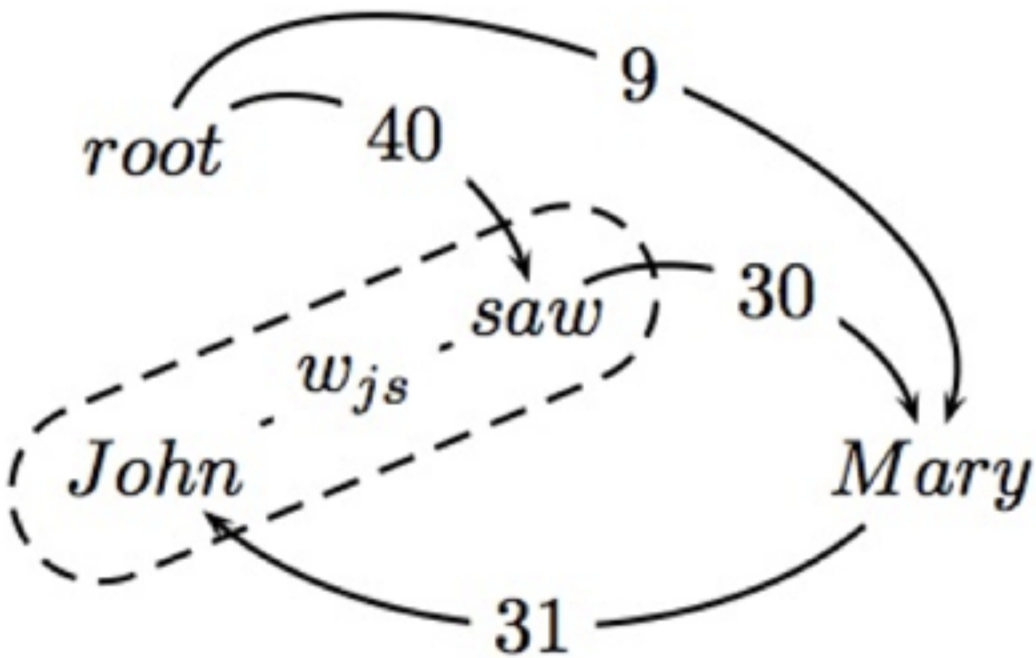
- Find highest scoring incoming arc for each vertex



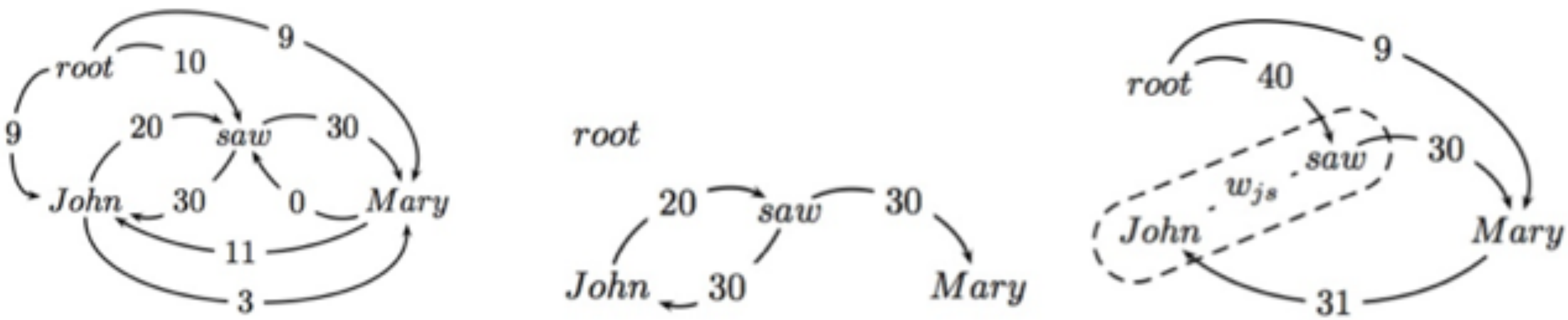
- If this is a tree, then we have found MST!!

Find Cycle and Contract

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



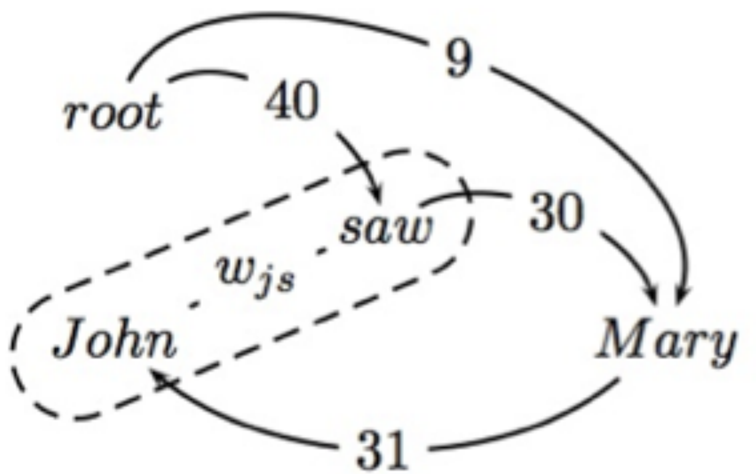
Recalculate Edge Weights



- 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

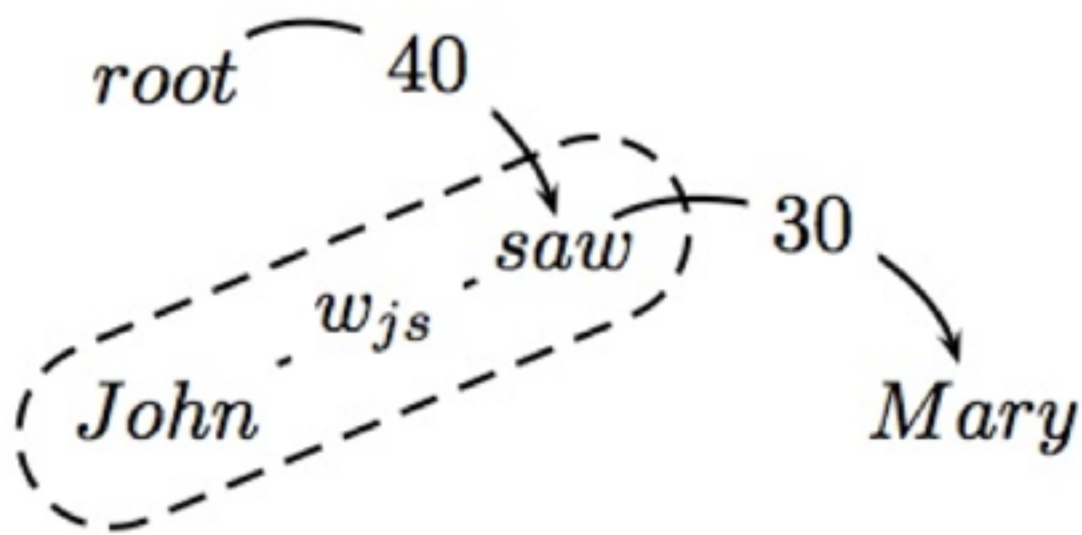
The weight of the MST of this contracted graph is equal to the weight of the MST for the original graph



- 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)

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

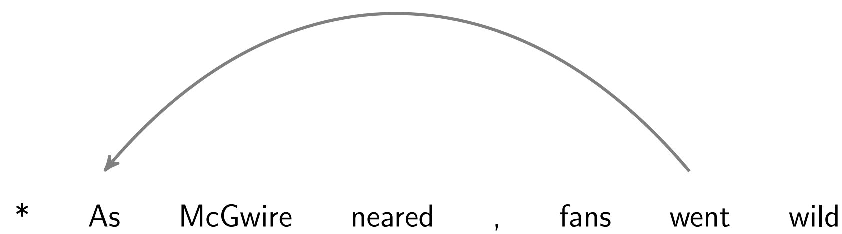
$$w_{ij}^{k} = e^{\mathbf{w} \cdot \mathbf{f}(i,j,k)}$$

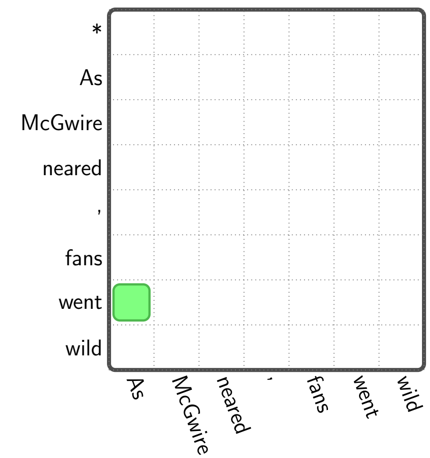
- Arc weights are a linear combination of features of the arc, **f**, and a corresponding weight vector **w**
- Raised to an exponent (simplifies some math ...)
- What arc features?
- [McDonald et al. 2005] discuss a number of binary features

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





[went]	[VBD]	[As]	[ADP]	[went]
[VERB]	[As]	[IN]	[went, VBD]	[As, ADP]
[went, As]	[VBD, ADP]	[went, VERB]	[As, IN]	[went, As]
[VERB, IN]	[VBD, As, ADP]	[went, As, ADP]	[went, VBD, ADP]	[went, VBD, As]
[ADJ, *, ADP]	[VBD, *, ADP]	[VBD, ADJ, ADP]	[VBD, ADJ, *]	[NNS, *, ADP]
[NNS, VBD, ADP]	[NNS, VBD, *]	[ADJ, ADP, NNP]	[VBD, ADP, NNP]	[VBD, ADJ, NNP]
[NNS, ADP, NNP]	[NNS, VBD, NNP]	[went, left, 5]	[VBD, left, 5]	[As, left, 5]
[ADP, left, 5]	[VERB, As, IN]	[went, As, IN]	[went, VERB, IN]	[went, VERB, As]
[JJ, *, IN]	[VERB, *, IN]	[VERB, JJ, IN]	[VERB, JJ, *]	[NOUN, *, IN]
[NOUN, VERB, IN]	[NOUN, VERB, *]	[JJ, IN, NOUN]	[VERB, IN, NOUN]	[VERB, JJ, NOUN]
[NOUN, IN, NOUN]	[NOUN, VERB, NOUN]	[went, left, 5]	[VERB, left, 5]	[As, left, 5]
[IN, left, 5]	[went, VBD, As, ADP]	[VBD, ADJ, *, ADP]	[NNS, VBD, *, ADP]	[VBD, ADJ, ADP, NNP]
[NNS, VBD, ADP, NNP]	[went, VBD, left, 5]	[As, ADP, left, 5]	[went, As, left, 5]	[VBD, ADP, left, 5]
[went, VERB, As, IN]	[VERB, JJ, *, IN]	[NOUN, VERB, *, IN]	[VERB, JJ, IN, NOUN]	[NOUN, VERB, IN, NOUN]
[went, VERB, left, 5]	[As, IN, left, 5]	[went, As, left, 5]	[VERB, IN, left, 5]	[VBD, As, ADP, left, 5]
[went, As, ADP, left, 5]	[went, VBD, ADP, left, 5]	[went, VBD, As, left, 5]	[ADJ, *, ADP, left, 5]	[VBD, *, ADP, left, 5]
[VBD, ADJ, ADP, left, 5]	[VBD, ADJ, *, left, 5]	[NNS, *, ADP, left, 5]	[NNS, VBD, ADP, left, 5]	[NNS, VBD, *, left, 5]
[ADJ, ADP, NNP, left, 5]	[VBD, ADP, NNP, left, 5]	[VBD, ADJ, NNP, left, 5]	[NNS, ADP, NNP, left, 5]	[NNS, VBD, NNP, left, 5]
[VERB, As, IN, left, 5]	[went, As, IN, left, 5]	[went, VERB, IN, left, 5]	[went, VERB, As, left, 5]	[JJ, *, IN, left, 5]
[VERB, *, IN, left, 5]	[VERB, JJ, IN, left, 5]	[VERB, JJ, *, left, 5]	[NOUN, *, 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 $\mathbf{w}^{i}$

Transition Based Dependency Parsing

- Process sentence left to right
  - Different transition strategies available
  - Delay decisions by pushing on stack
- Arc-Standard Transition Strategy [Nivre ’03]

Initial configuration: $([],[0,\ldots,n],[])$
Terminal configuration: $([0],[],A)$

shift: $(\sigma,[i|\beta],A) \Rightarrow ([\sigma|i],\beta,A)$

left-arc (label): $([\sigma|i|j],B,A) \Rightarrow ([\sigma|j],B,A\cup\{j,l,i\})$

right-arc (label): $([\sigma|i|j],B,A) \Rightarrow ([\sigma|i],B,A\cup\{i,l,j\})$

Arc-Standard Example

↑ Stack

← Buffer

I	*booked*	*a*	*flight*	*to*	*Lisbon*

SHIFT

I booked a flight to Lisbon

Arc-Standard Example

↑ Stack

I

← Buffer

booked | *a* | *flight* | *to* | *Lisbon*

SHIFT

I *booked* *a* *flight* *to* *Lisbon*

Arc-Standard Example

↑ Stack

booked

I

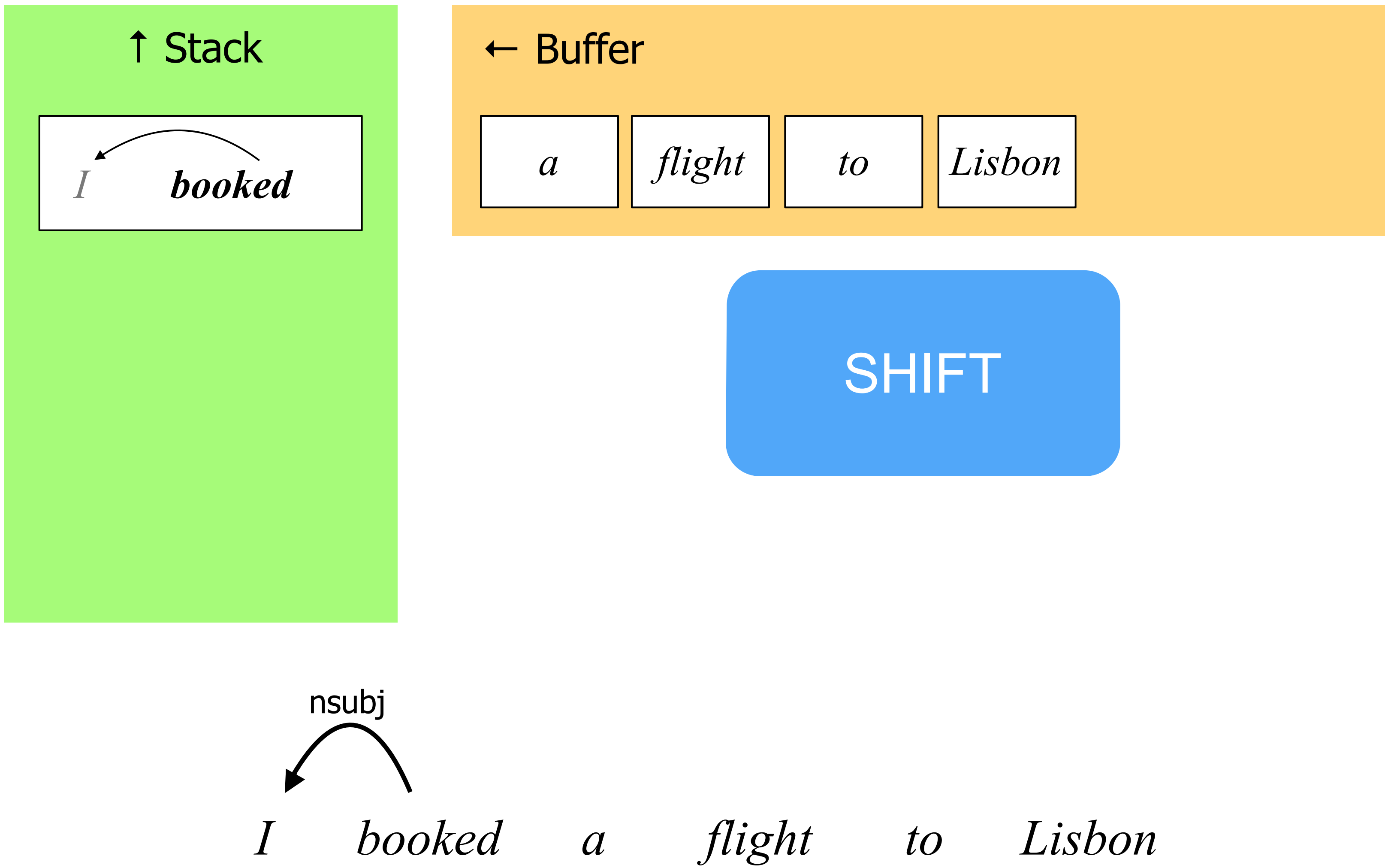
← Buffer

a | *flight* | *to* | *Lisbon*

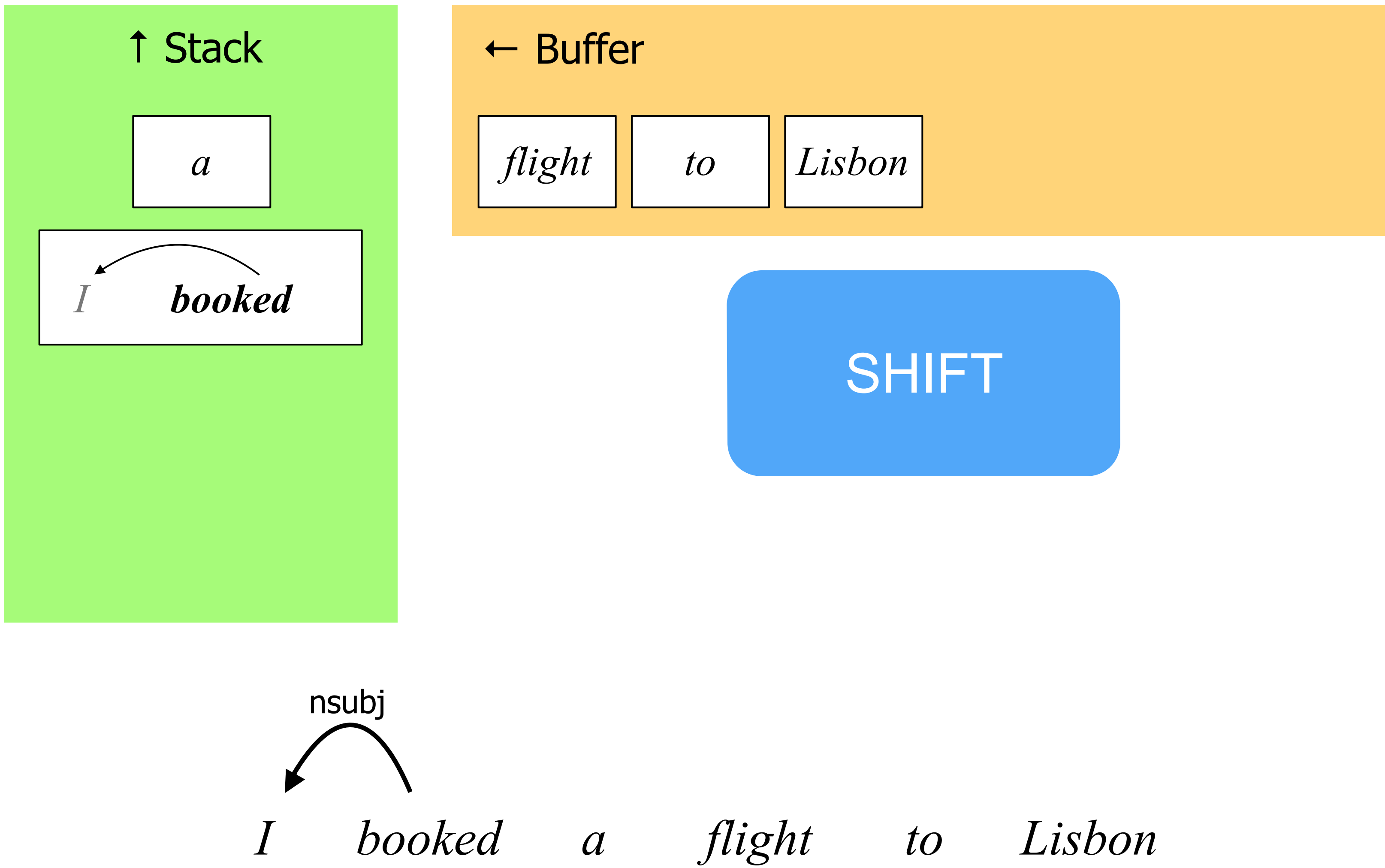
LEFT-ARC
nsubj

I *booked* *a* *flight* *to* *Lisbon*

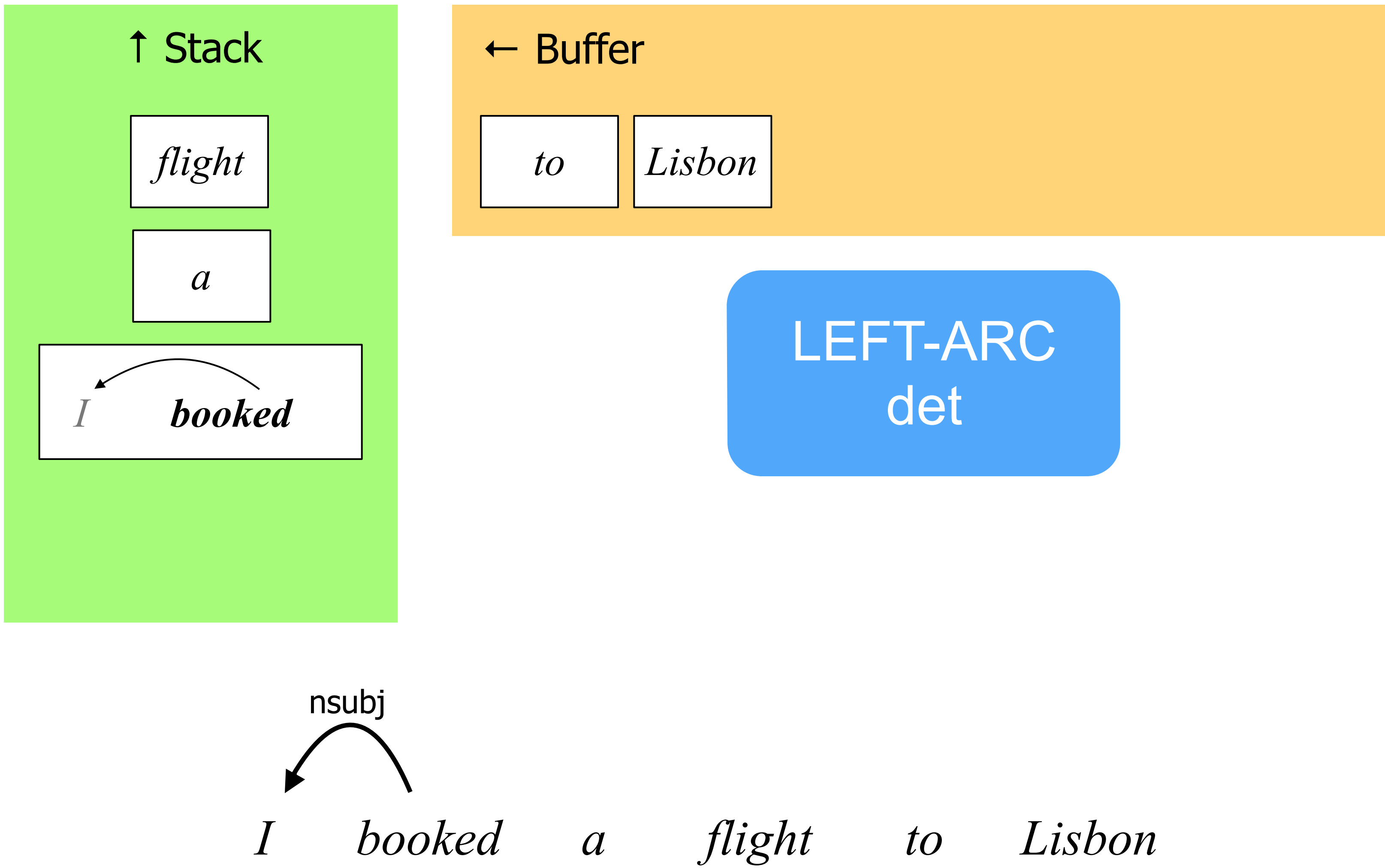
Arc-Standard Example



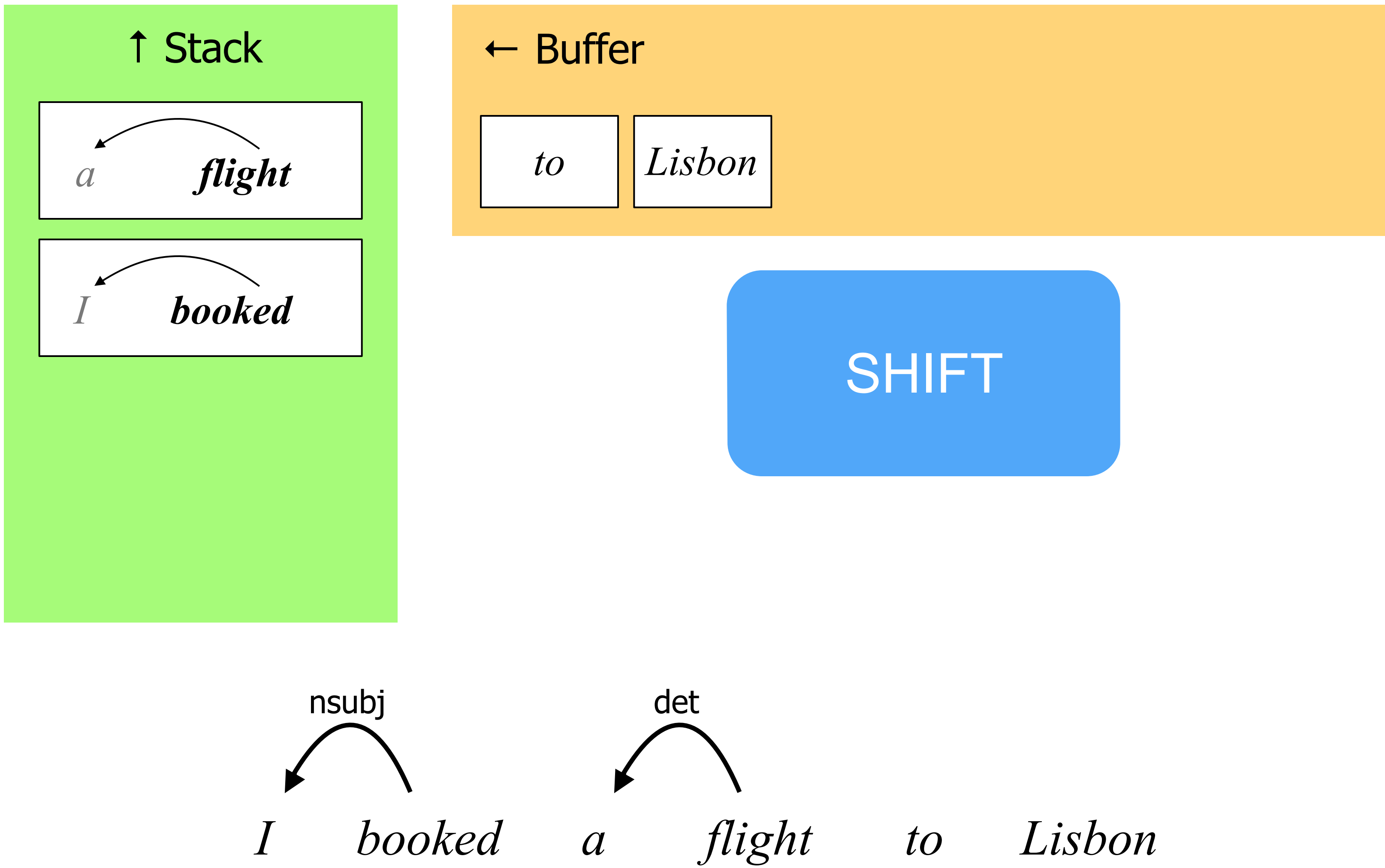
Arc-Standard Example



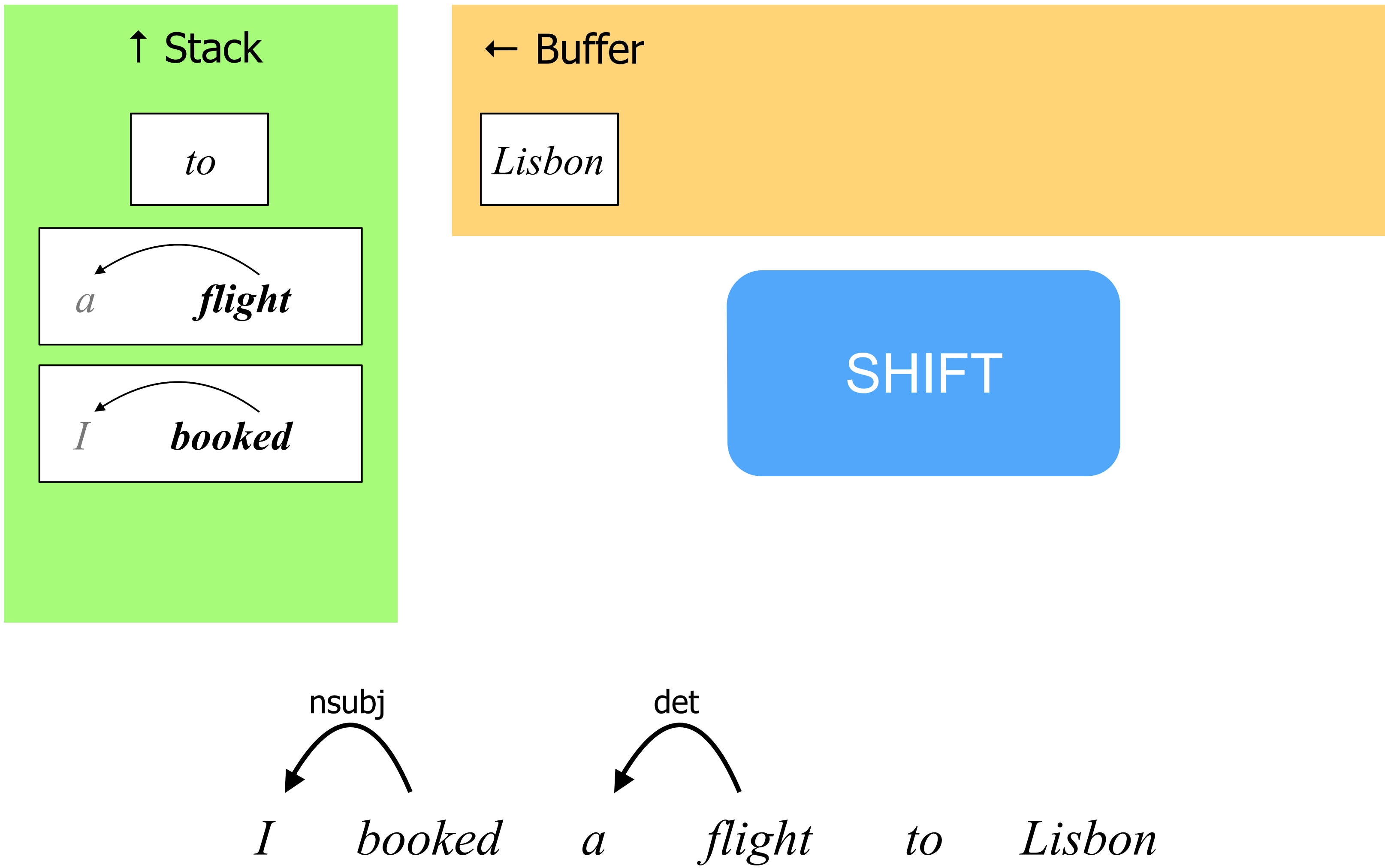
Arc-Standard Example



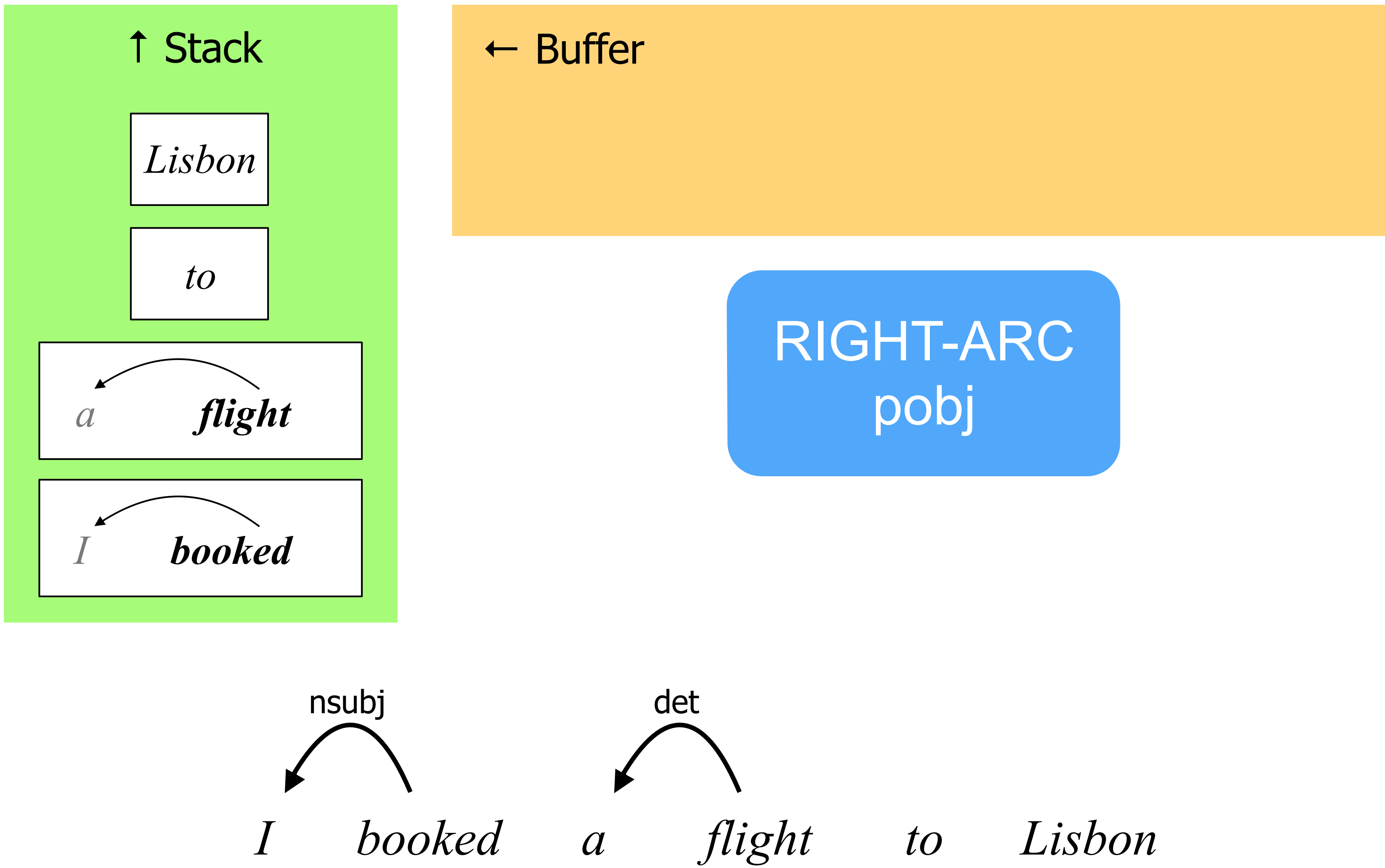
Arc-Standard Example



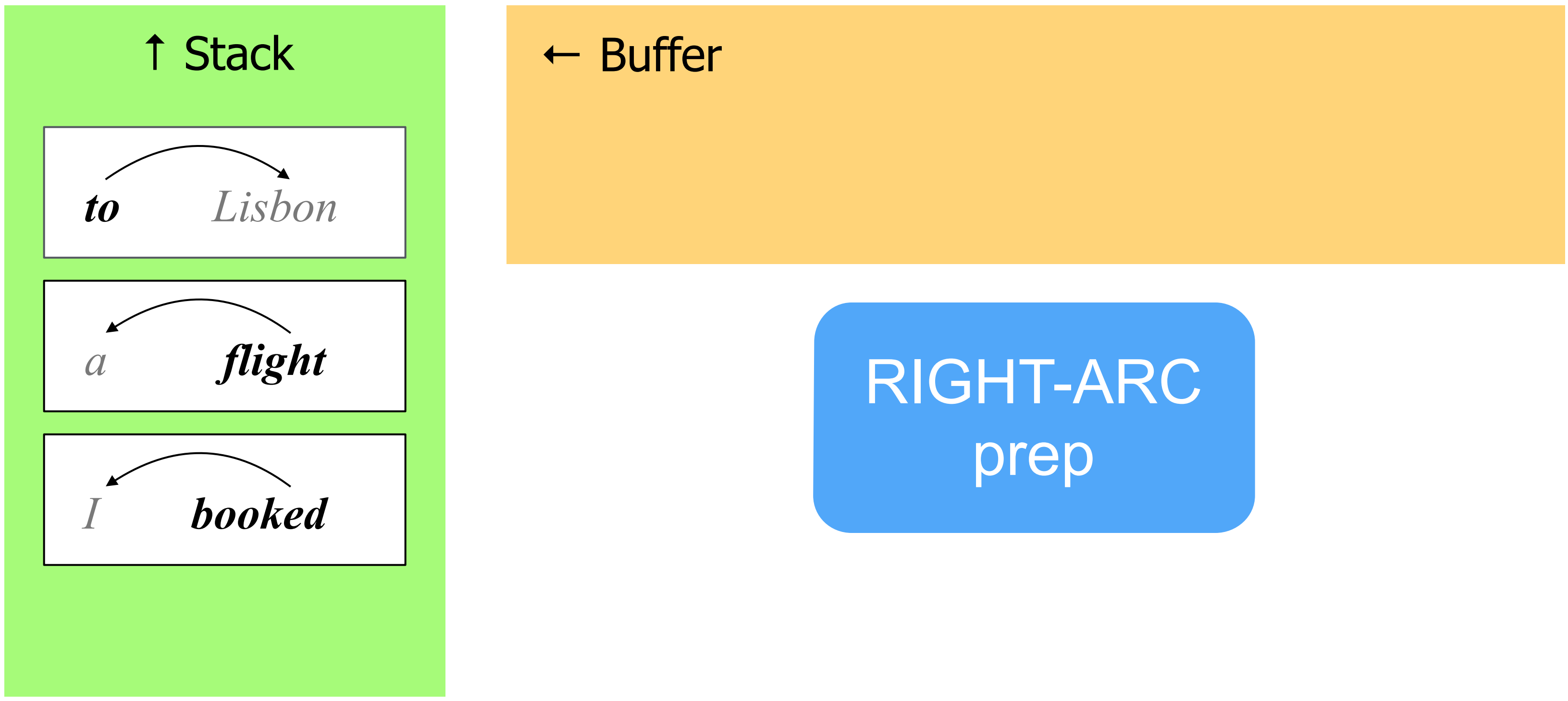
Arc-Standard Example

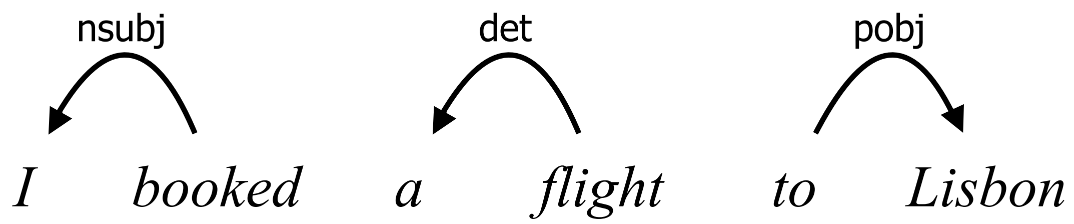


Arc-Standard Example

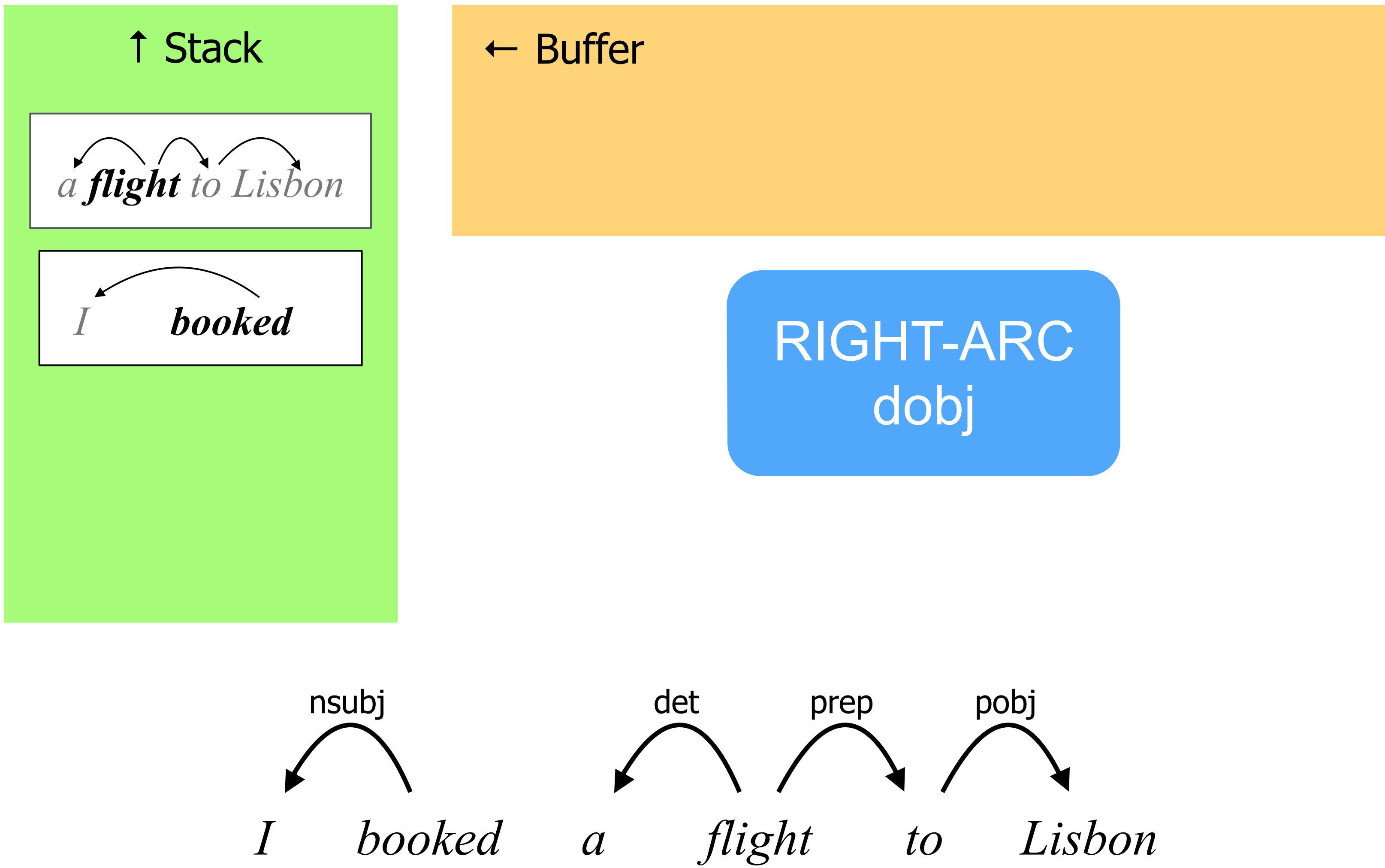


Arc-Standard Example



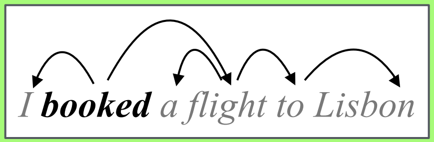


Arc-Standard Example

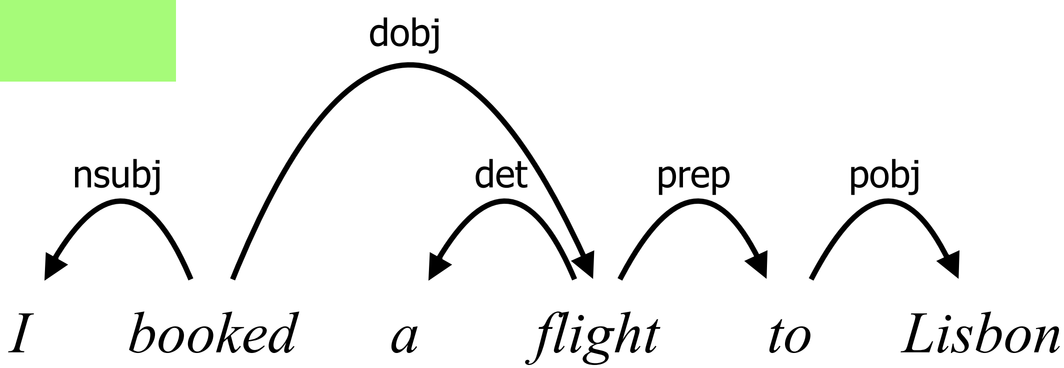


Arc-Standard Example

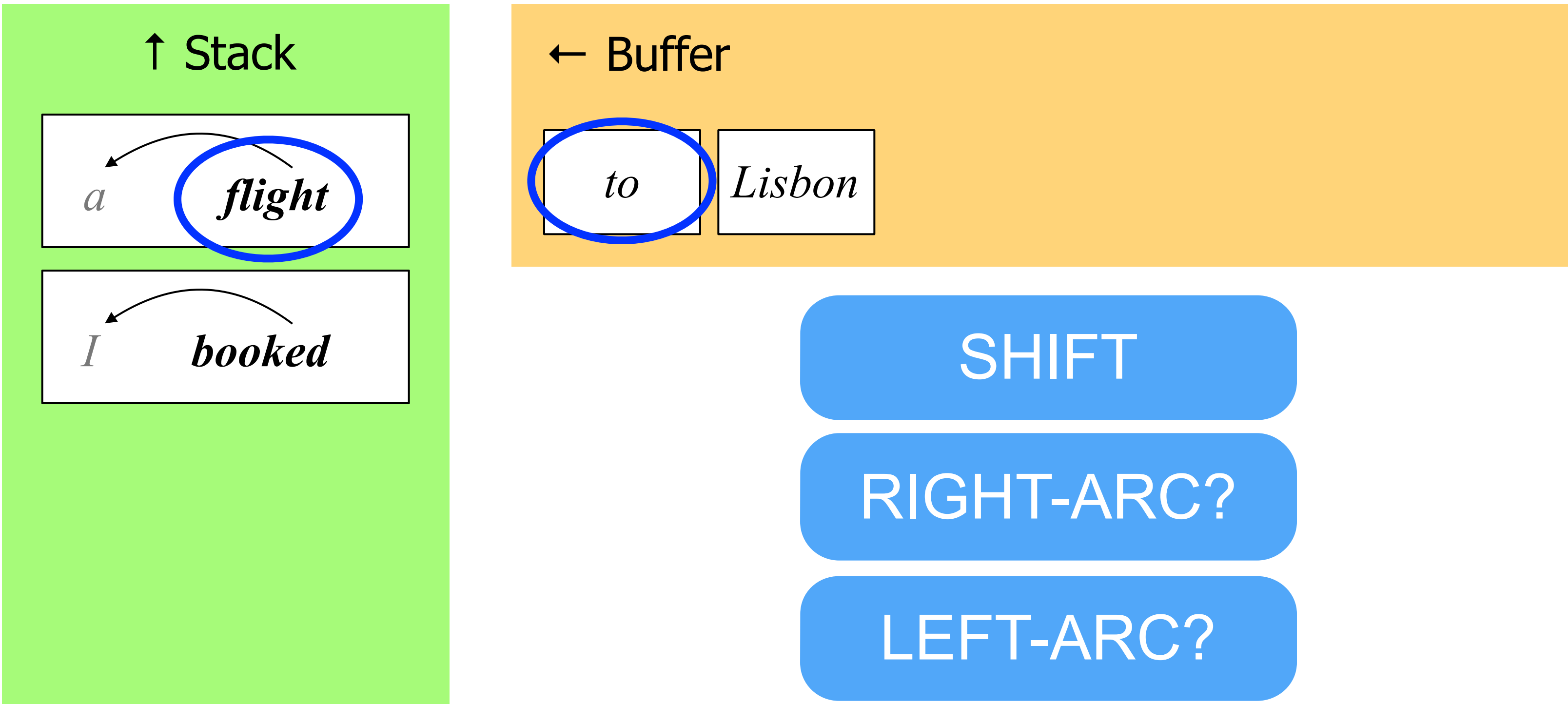
↑ Stack



← Buffer



Features



Stack top word = “flight”
Stack top POS tag = “NOUN”
Buffer front word = “to”
Child of stack top word = “a”
....

SVM / Structured Perceptron Hyperparameters

- Regularization
- Loss function
- **Hand-crafted features**

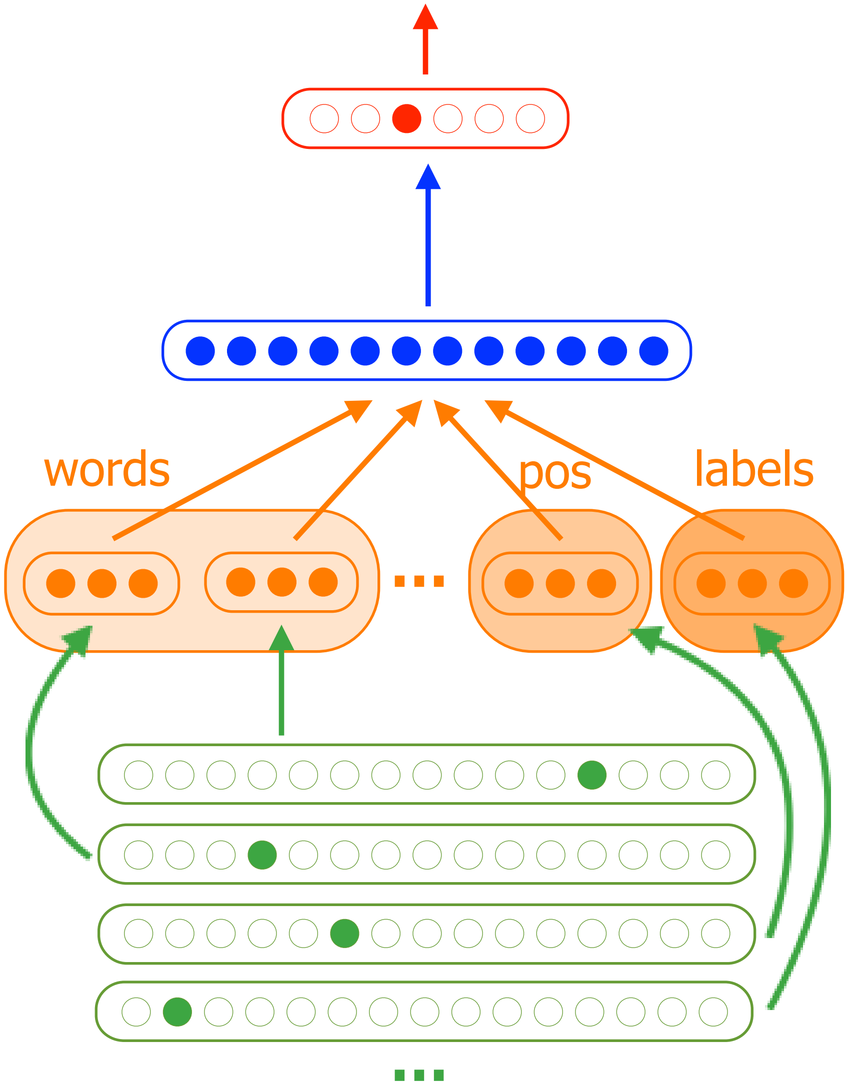
Features ZPar Parser

```
# From Single Words
pair { stack.tag stack.word }
stack { word tag }
pair { input.tag input.word }
input { word tag }
pair { input(1).tag input(1).word }
input(1) { word tag }
pair { input(2).tag input(2).word }
input(2) { word tag }

# From word pairs
quad { stack.tag stack.word input.tag input.word }
triple { stack.tag stack.word input.word }
triple { stack.word input.tag input.word }
triple { stack.tag stack.word input.tag }
triple { stack.tag input.tag input.word }
pair { stack.word input.word }
pair { stack.tag input.tag }
pair { input.tag input(1).tag }

# From word triples
triple { input.tag input(1).tag input(2).tag }
triple { stack.tag input.tag input(1).tag }
triple { stack.head(1).tag stack.tag input.tag }
triple { stack.tag stack.child(-1).tag input.tag }
triple { stack.tag stack.child(1).tag input.tag }
triple { stack.tag input.tag input.child(-1).tag }

# Distance
pair { stack.distance stack.word }
pair { stack.distance stack.tag }
pair { stack.distance input.word }
pair { stack.distance input.tag }
triple { stack.distance stack.word input.word }
triple { stack.distance stack.tag input.tag }
```

```
# valency
pair { stack.word stack.valence(-1) }
pair { stack.word stack.valence(1) }
pair { stack.tag stack.valence(-1) }
pair { stack.tag stack.valence(1) }
pair { input.word input.valence(-1) }
pair { input.tag input.valence(-1) }

# unigrams
stack.head(1) {word tag}
stack.label
stack.child(-1) {word tag label}
stack.child(1) {word tag label}
input.child(-1) {word tag label}

# third order
stack.head(1).head(1) {word tag}
stack.head(1).label
stack.child(-1).sibling(1) {word tag label}
stack.child(1).sibling(-1) {word tag label}
input.child(-1).sibling(1) {word tag label}
triple { stack.tag stack.child(-1).tag stack.child(-1).sibling(1).tag }
triple { stack.tag stack.child(1).tag stack.child(1).sibling(-1).tag }
triple { stack.tag stack.head(1).tag stack.head(1).head(1).tag }
triple { input.tag input.child(-1).tag input.child(-1).sibling(1).tag }

# label set
pair { stack.tag stack.child(-1).label }
triple { stack.tag stack.child(-1).label stack.child(-1).sibling(1).lab
quad { stack.tag stack.child(-1).label stack.child(-1).sibling(1).label
pair { stack.tag stack.child(1).label }
triple { stack.tag stack.child(1).label stack.child(1).sibling(-1).labe
quad { stack.tag stack.child(1).label stack.child(1).sibling(-1).label
pair { input.tag input.child(-1).label }
triple { input.tag input.child(-1).label input.child(-1).sibling(1).lab
quad { input.tag input.child(-1).label input.child(-1).sibling(1).label
```

Neural Network Transition Based Parser

[Chen & Manning '14] and [Weiss et al. '15]



Softmax

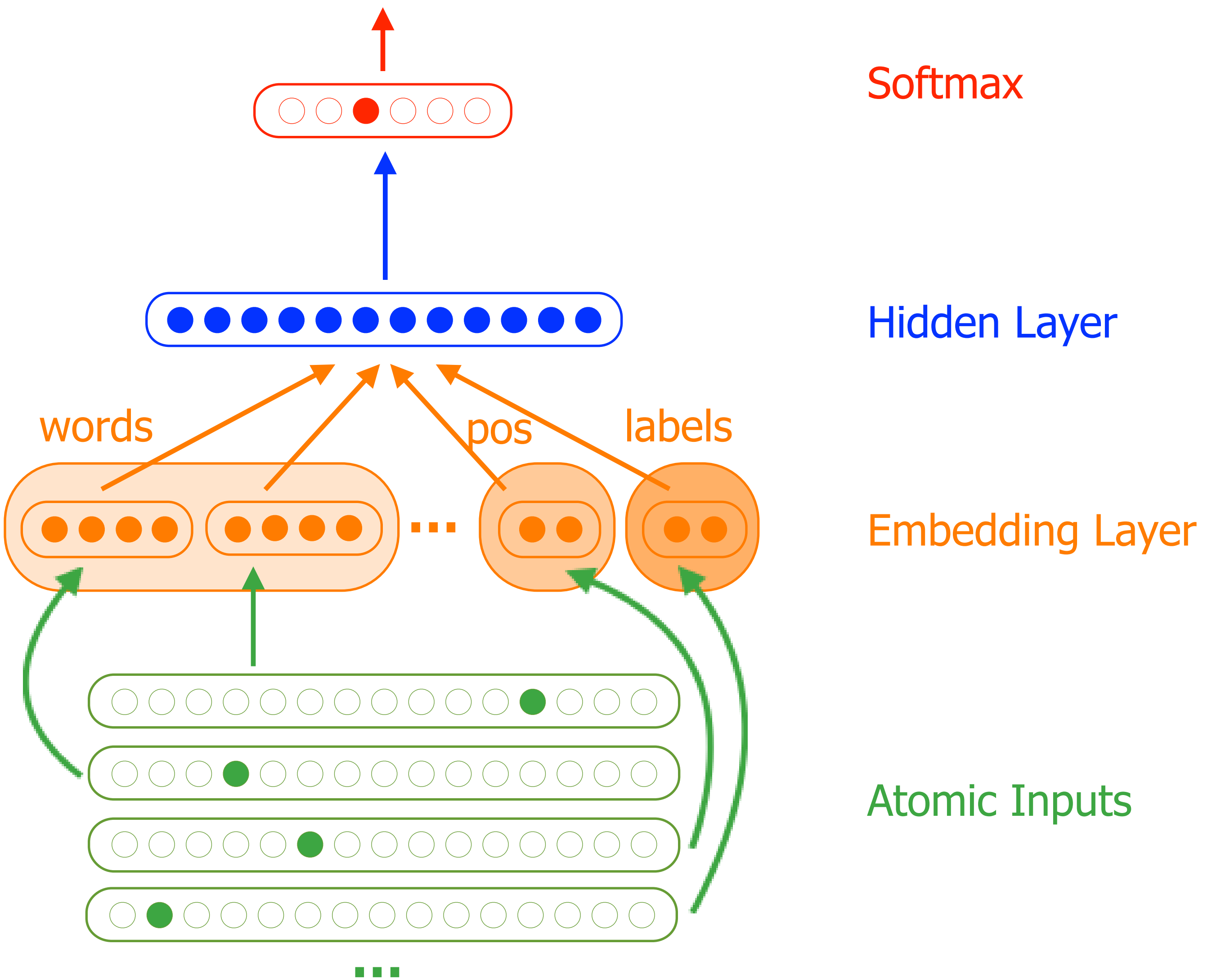
Hidden Layer

Embedding Layer

Atomic Inputs

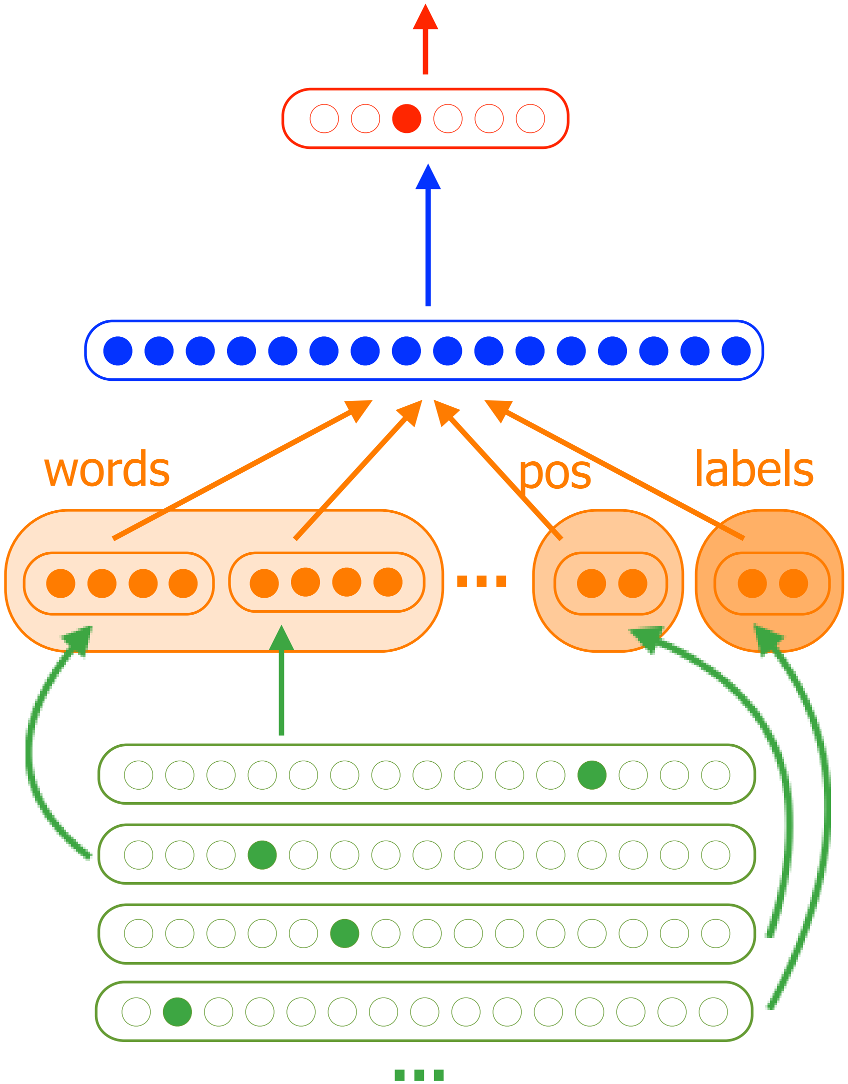
Neural Network Transition Based Parser

[Weiss et al. '15]



Neural Network Transition Based Parser

[Weiss et al. '15]



Softmax

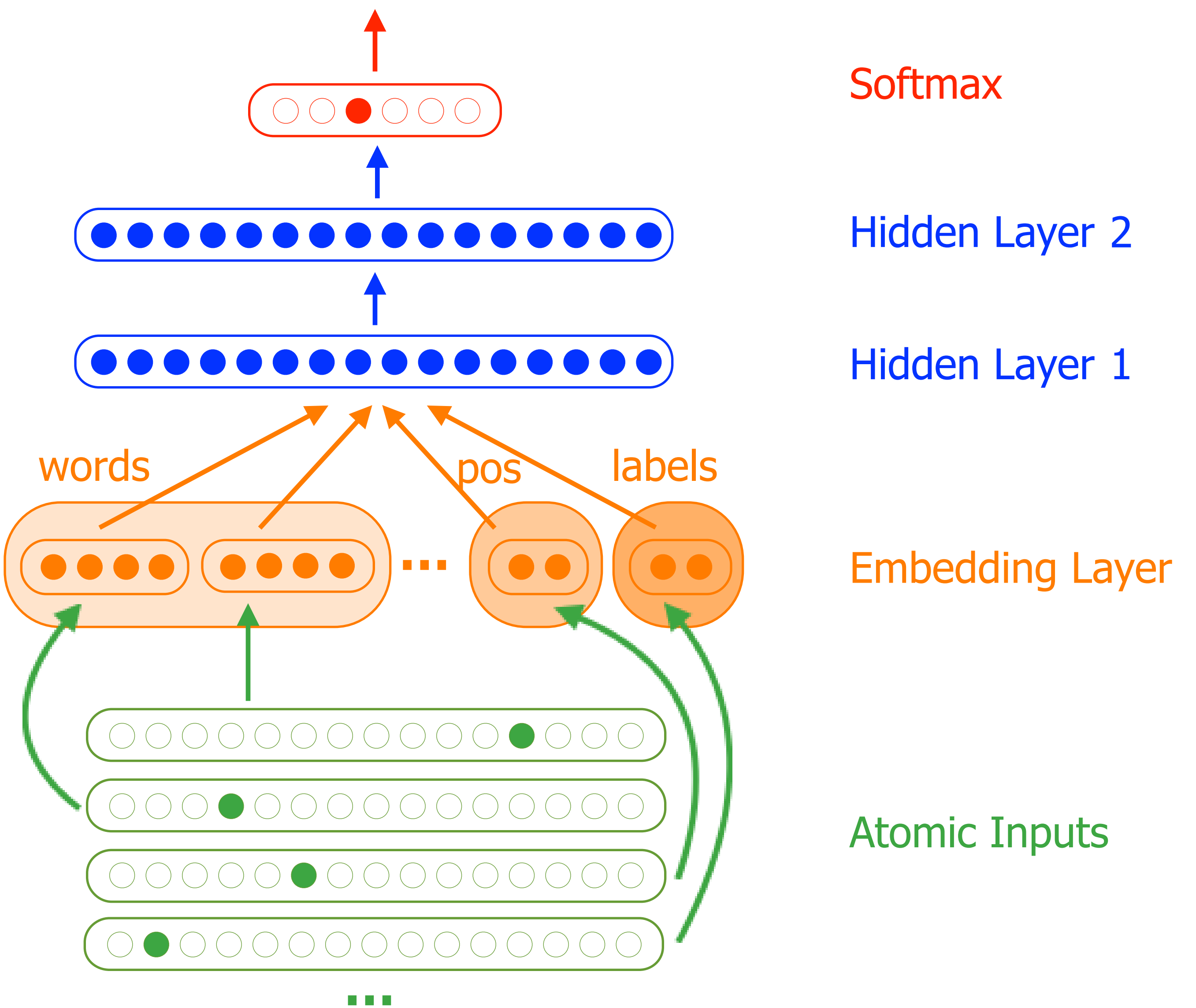
Hidden Layer

Embedding Layer

Atomic Inputs

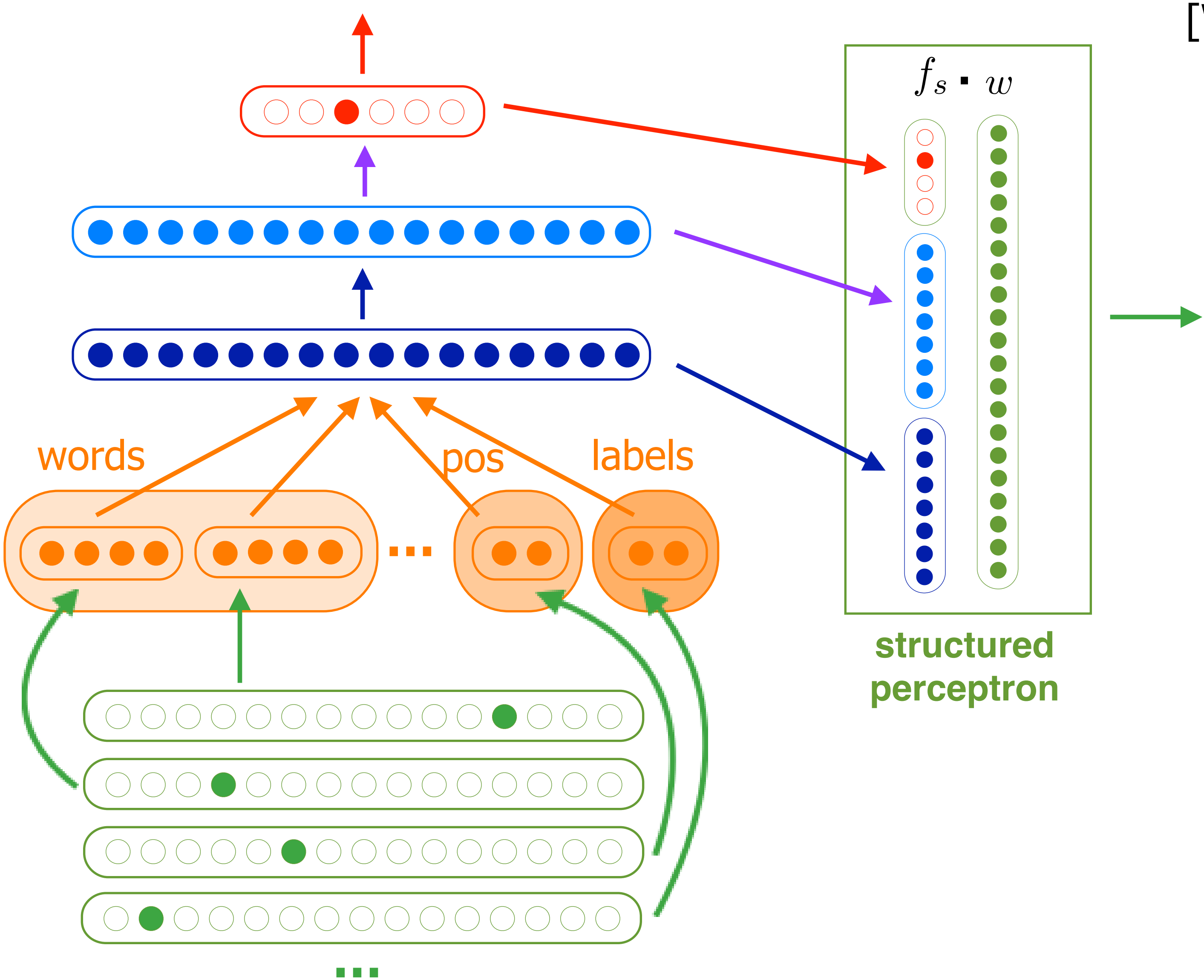
Neural Network Transition Based Parser

[Weiss et al. '15]



Neural Network Transition Based Parser

[Weiss et al. '15]



NN Hyperparameters

- Regularization
- Loss function

NN Hyperparameters

- Regularization
- Loss function

- Dimensions
- Activation function
- Initialization
- Adagrad
- Dropout

NN Hyperparameters

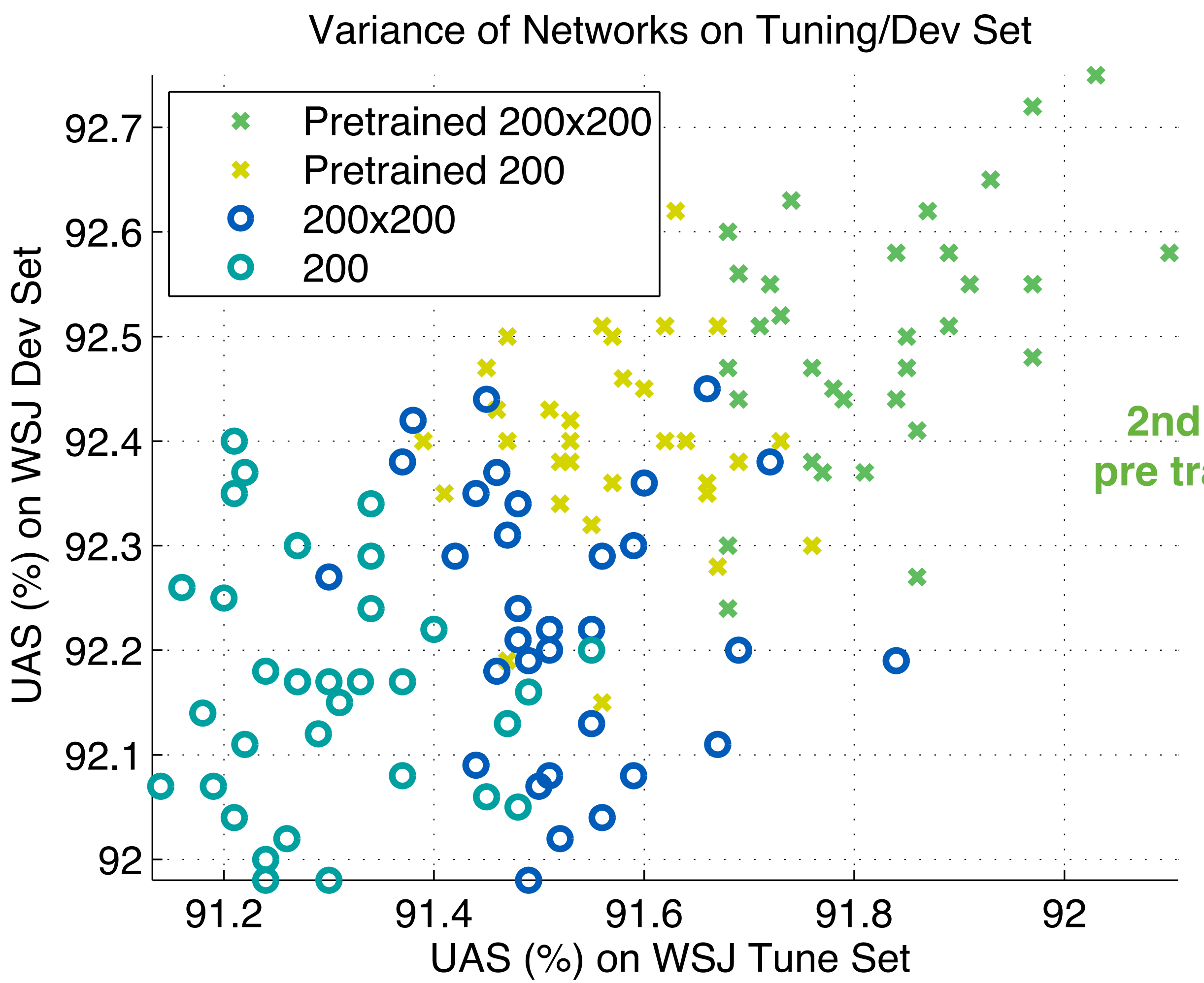
- Regularization
- Loss function
- Dimensions
- Activation function
- Initialization
- Adagrad
- Dropout
- Mini-batch size
- Initial learning rate
- Learning rate schedule
- Momentum
- Stopping time
- Parameter averaging

NN Hyperparameters

Optimization matters!
Use random restarts, grid
Pick best using holdout data

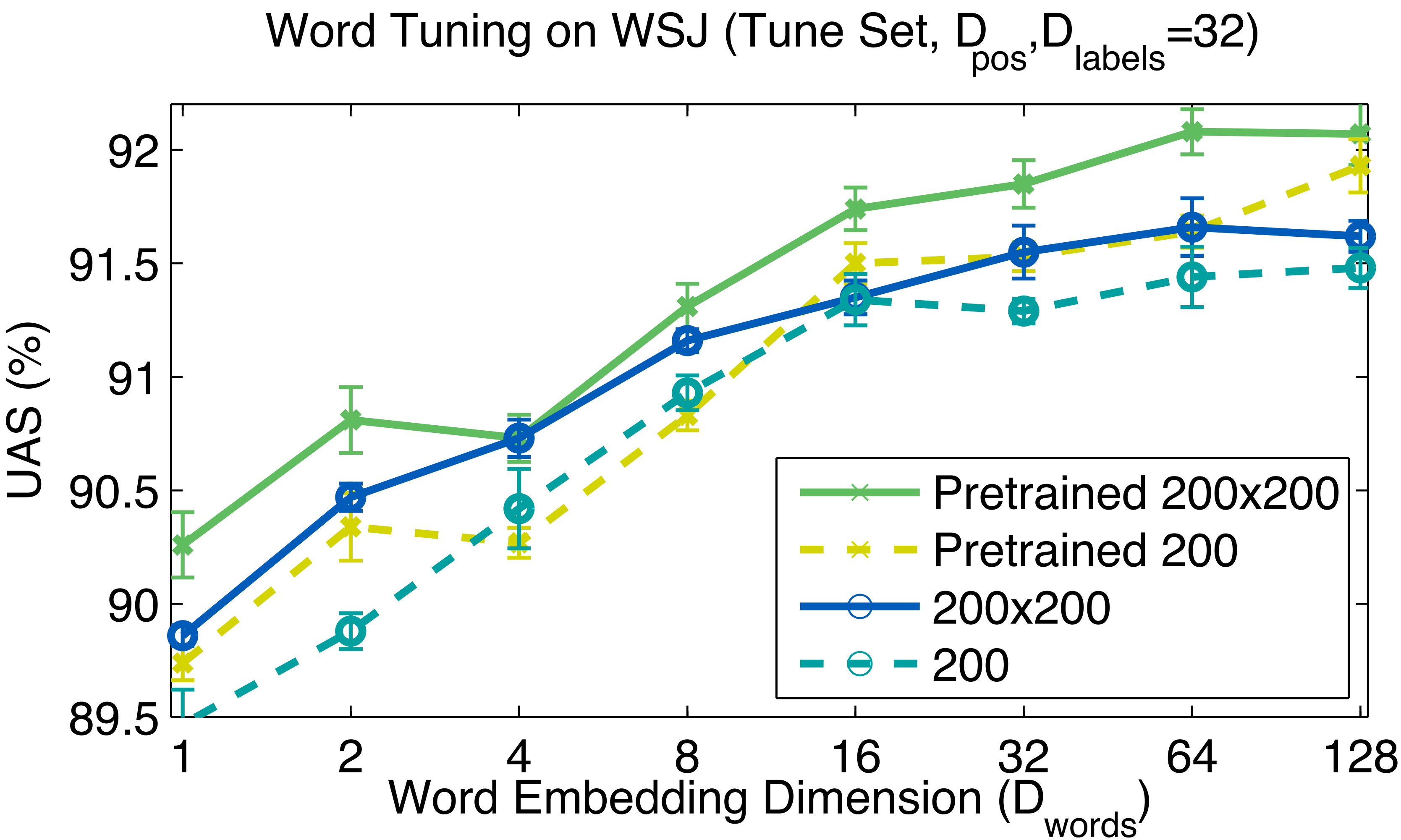
Tune: WSJ S24
Dev: WSJ S22
Test: WSJ S23

Random Restarts: How much Variance?

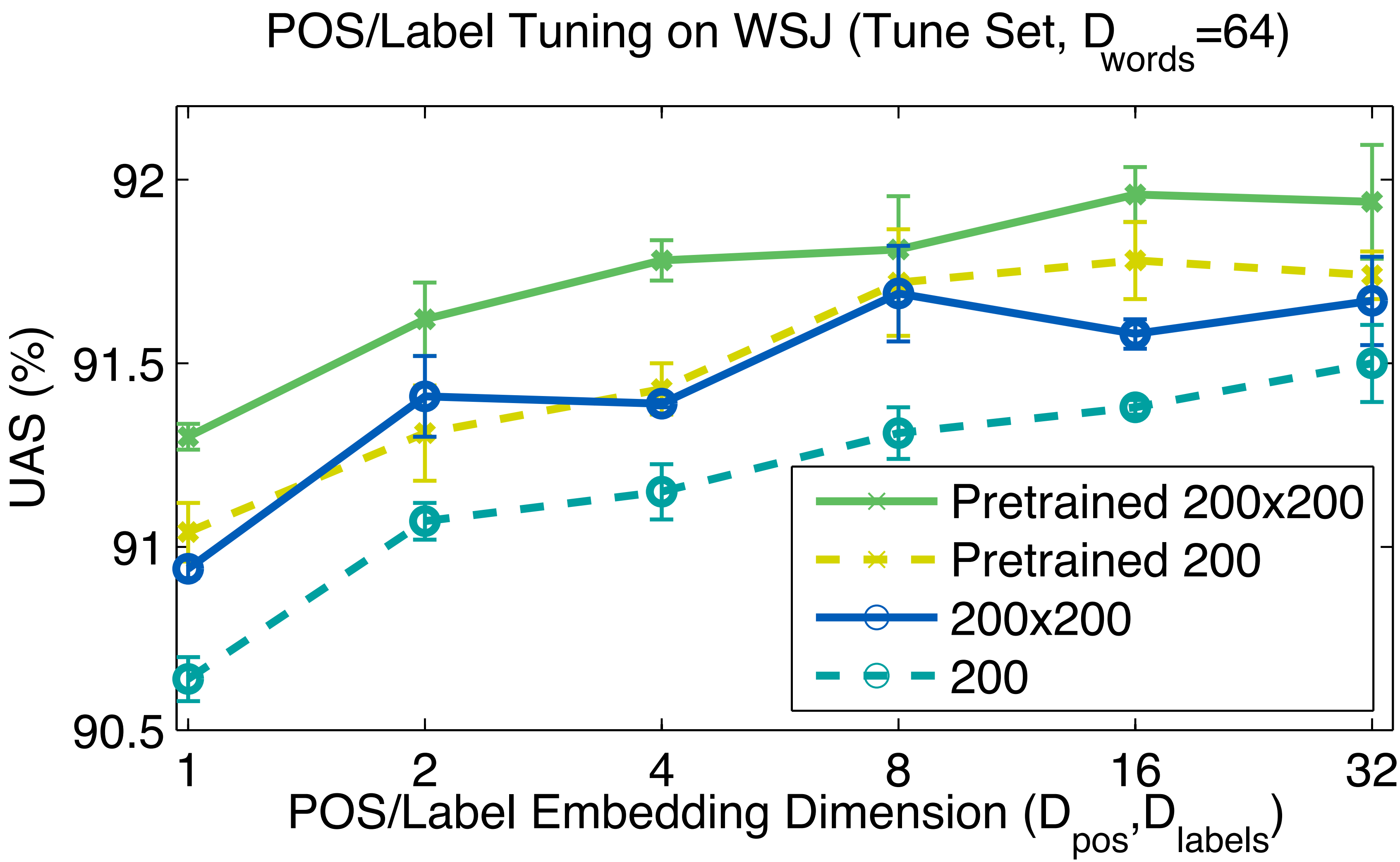


2nd hidden layer + pre training increases correlation

Effect of Embedding Dimensions

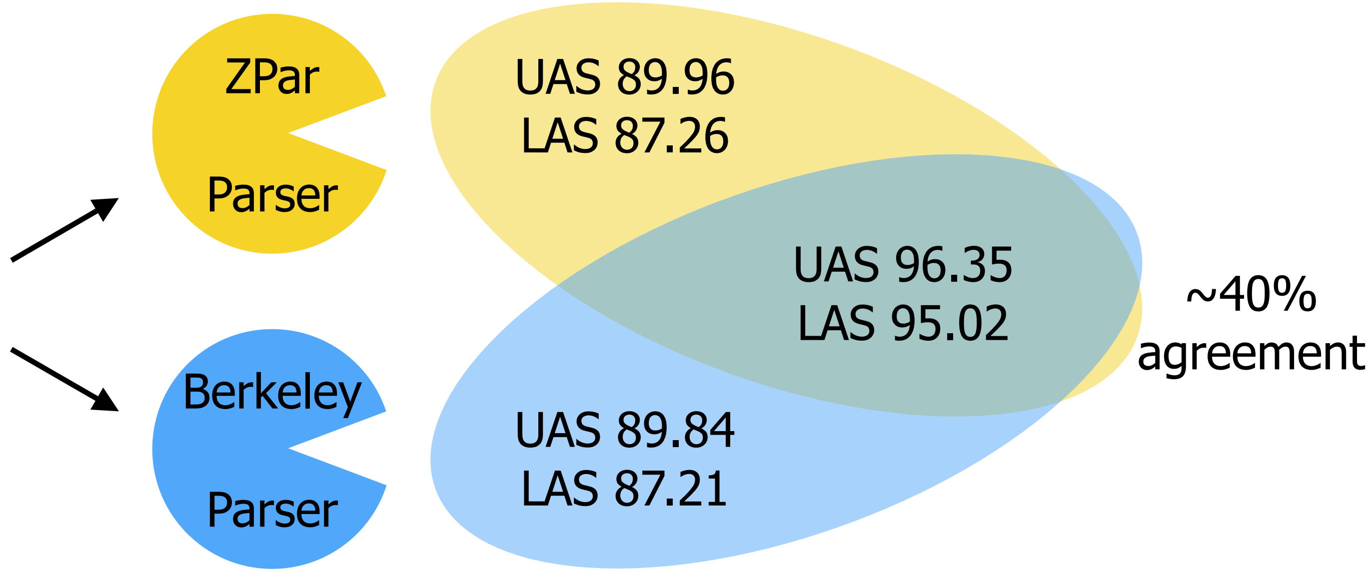


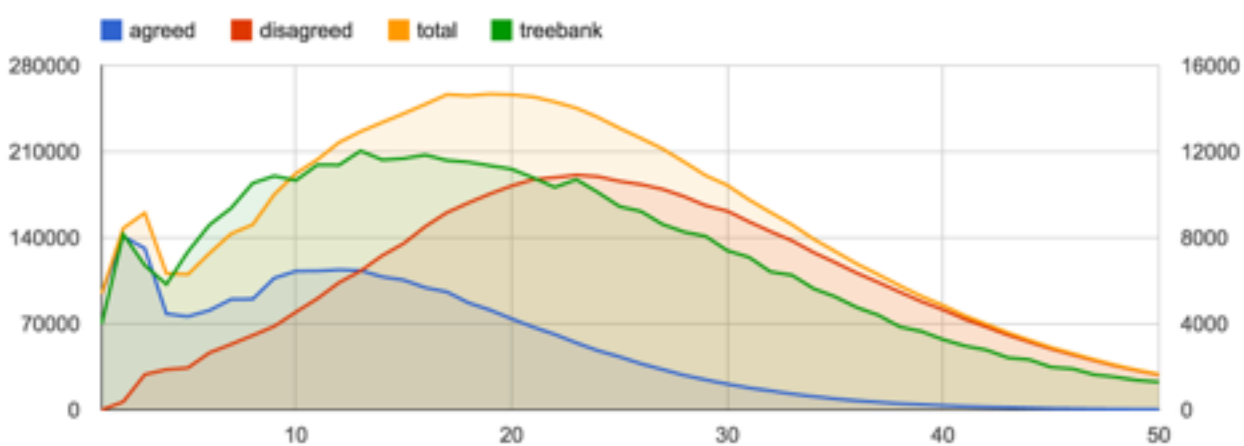
Effect of Embedding Dimensions



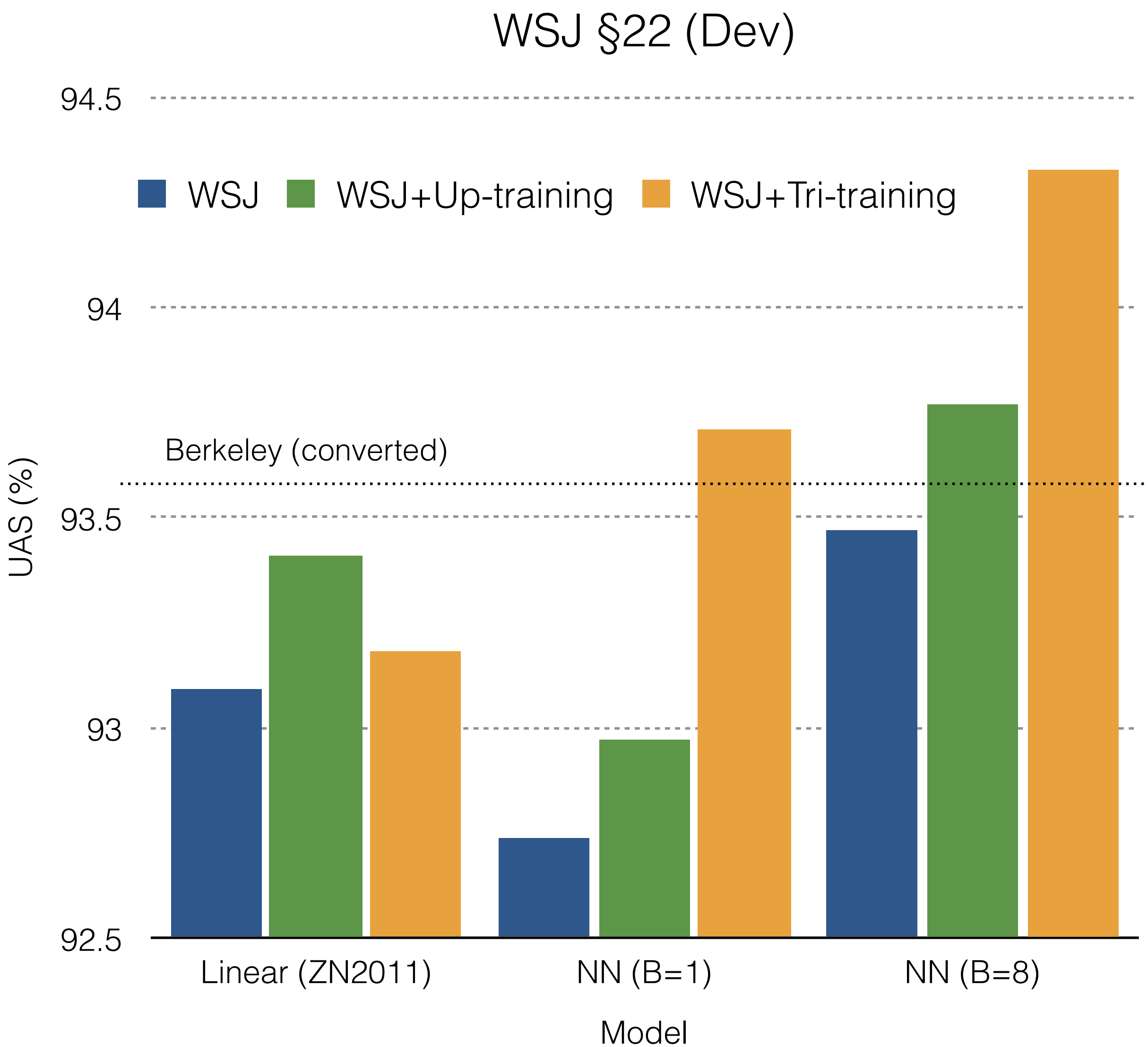
Tri-Training

[Zhou et al. '05, Li et al. '14]





Tri-Training Impact



NN model benefits more from additional data

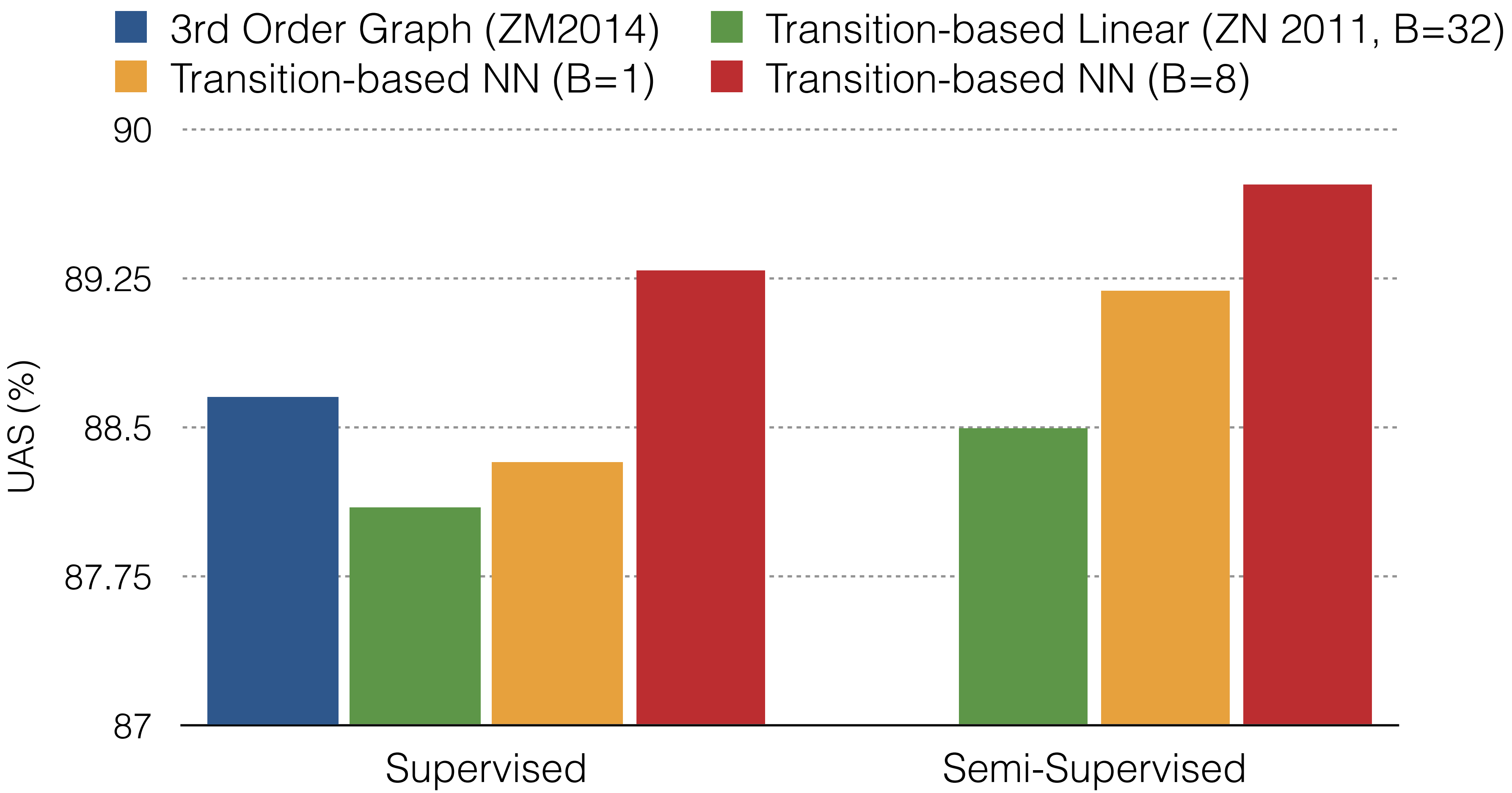
ZN does not improve even when using an alternative hyper graph model for Tri-training

English Results (WSJ 23)

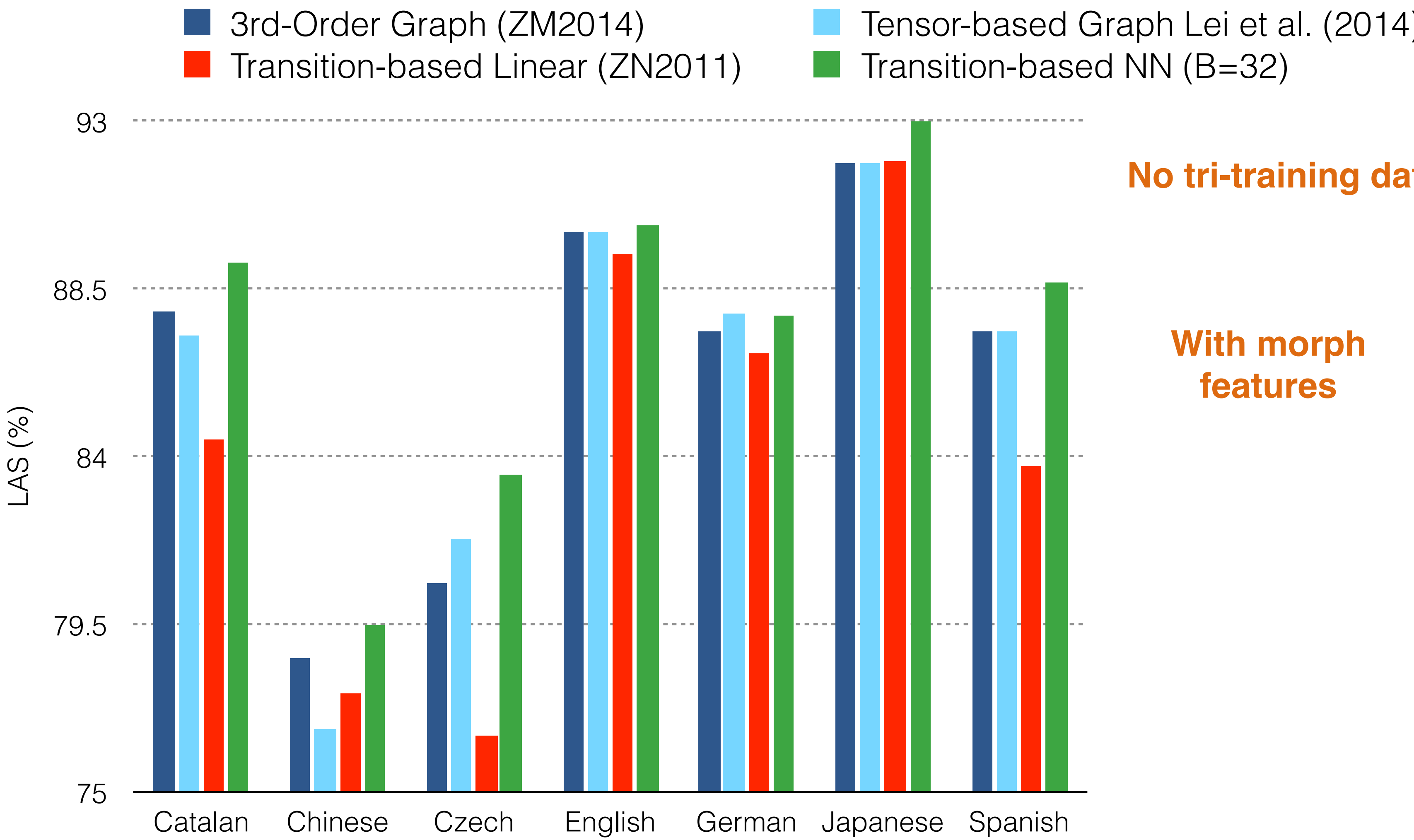
Method	UAS	LAS	Beam
3rd-order Graph-based (ZM2014)	93.22	91.02	-
Transition-based Linear (ZN2011)	93.00	90.95	32
NN Baseline (Chen & Manning, 2014)	91.80	89.60	1
NN Better SGD (Weiss et al., 2015)	92.58	90.54	1
NN Deeper Network (Weiss et al., 2015)	93.19	91.18	1
NN Perceptron (Weiss et al., 2015)	93.99	92.05	8
NN Semi-supervised (Weiss et al., 2015)	94.26	92.41	8
S-LSTM (Dyer et al., 2015)	93.20	90.90	1
Contrastive NN (Zhou et al., 2015)	92.83	—	100

English Out-of-Domain Results

- Train on WSJ + Web Treebank + QuestionBank
- Evaluate on Web



Multilingual Results



No tri-training data

With morph features

[Alberti et al., in submission]

Summary

- Constituency Parsing
  - CKY Algorithm
  - Lexicalized Grammars
  - Latent Variable Grammars
  - Conditional Random Field Parsing
  - Neural Network Representations
- Dependency Parsing
  - Eisner Algorithm
  - Maximum Spanning Tree Algorithm
  - Transition Based Parsing
  - Neural Network Representations