Language Technologies Institute

Carnegie Mellon University

Algorithms for NLP

CS 11-711 · Fall 2020

Lecture 14: Graph-based dependency parsing

Emma Strubell

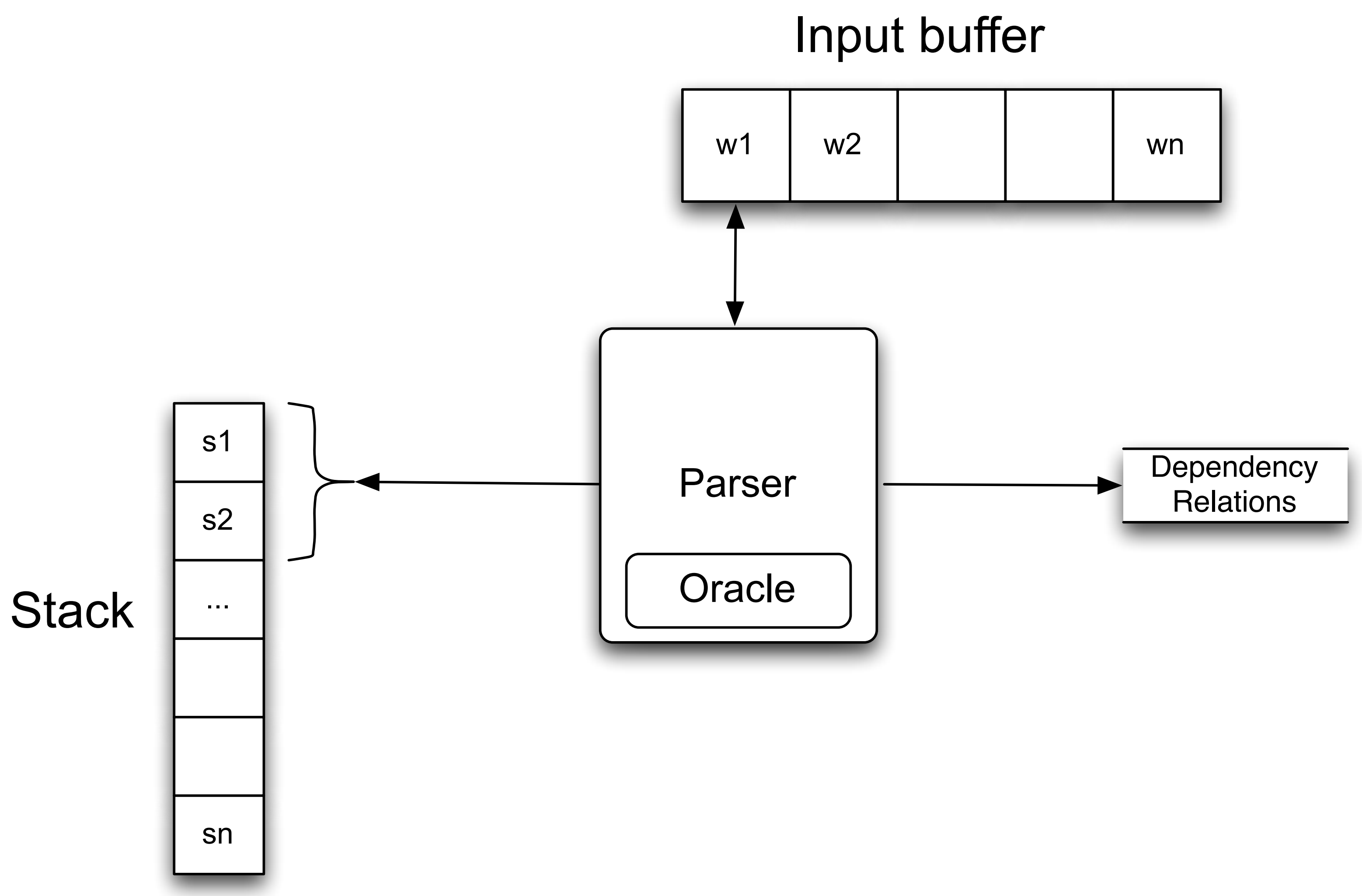
Announcements

- No recitation on Friday (Tartan Community Day).

Dependency parsing

Dependency parsing

- Transition-based (shift-reduce) parsing:



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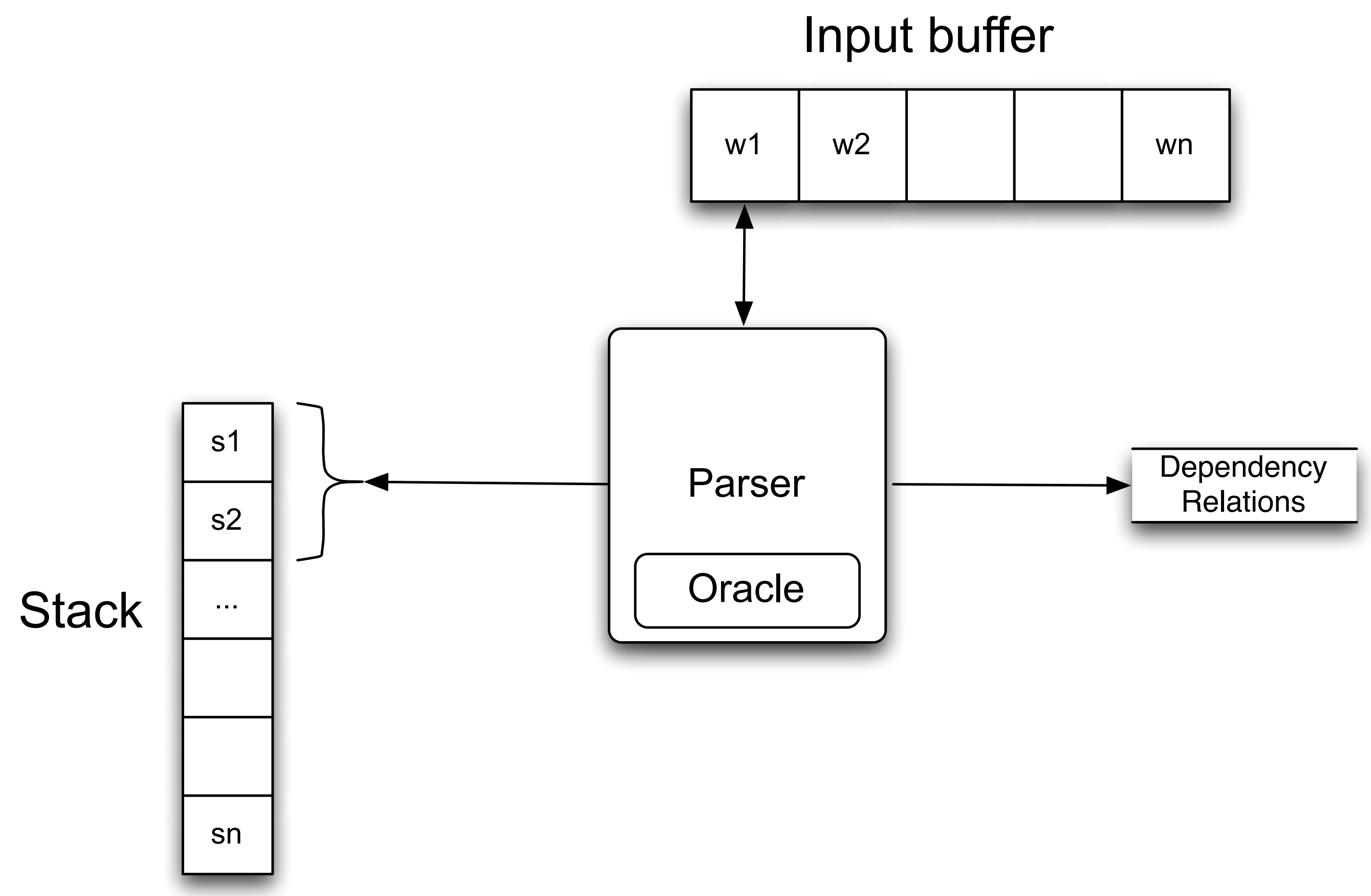
- Transition-based (shift-reduce) parsing:
  - Greedy choice of local transitions guided by a good classifier.



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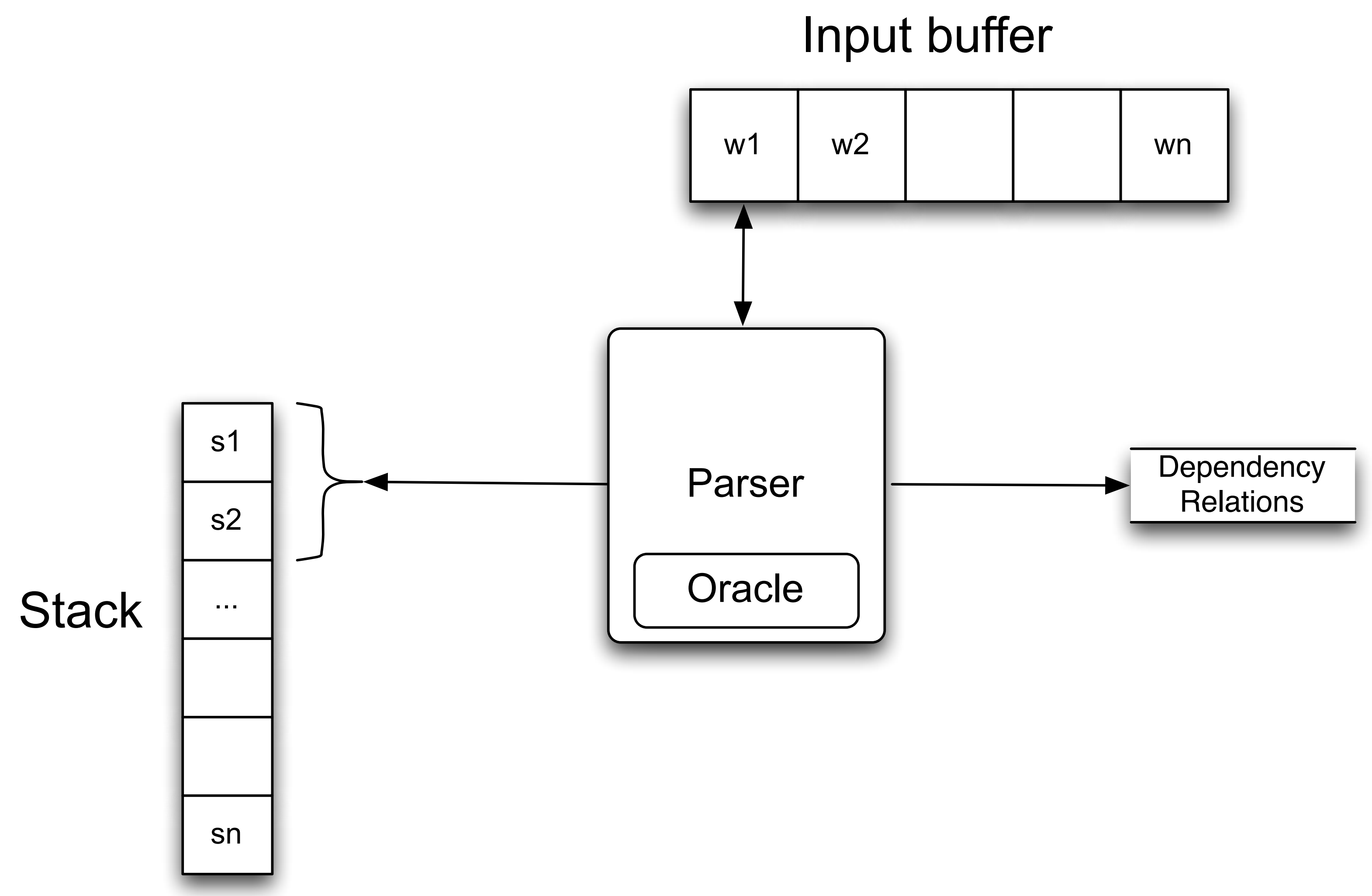
    - Examples: MaltParser [Nivre et al. 2008], Stack LSTM [Dyer et al. 2015]



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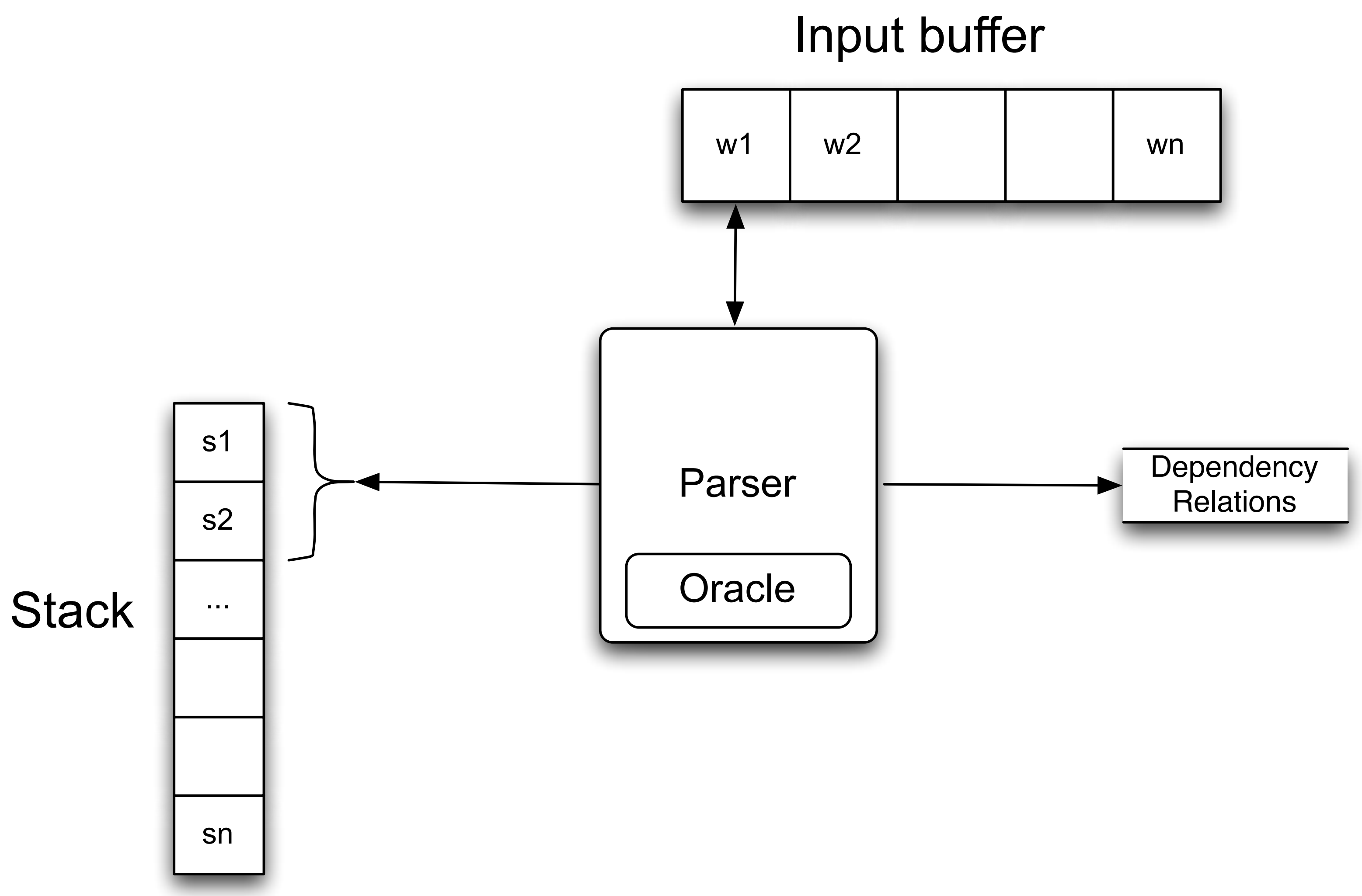

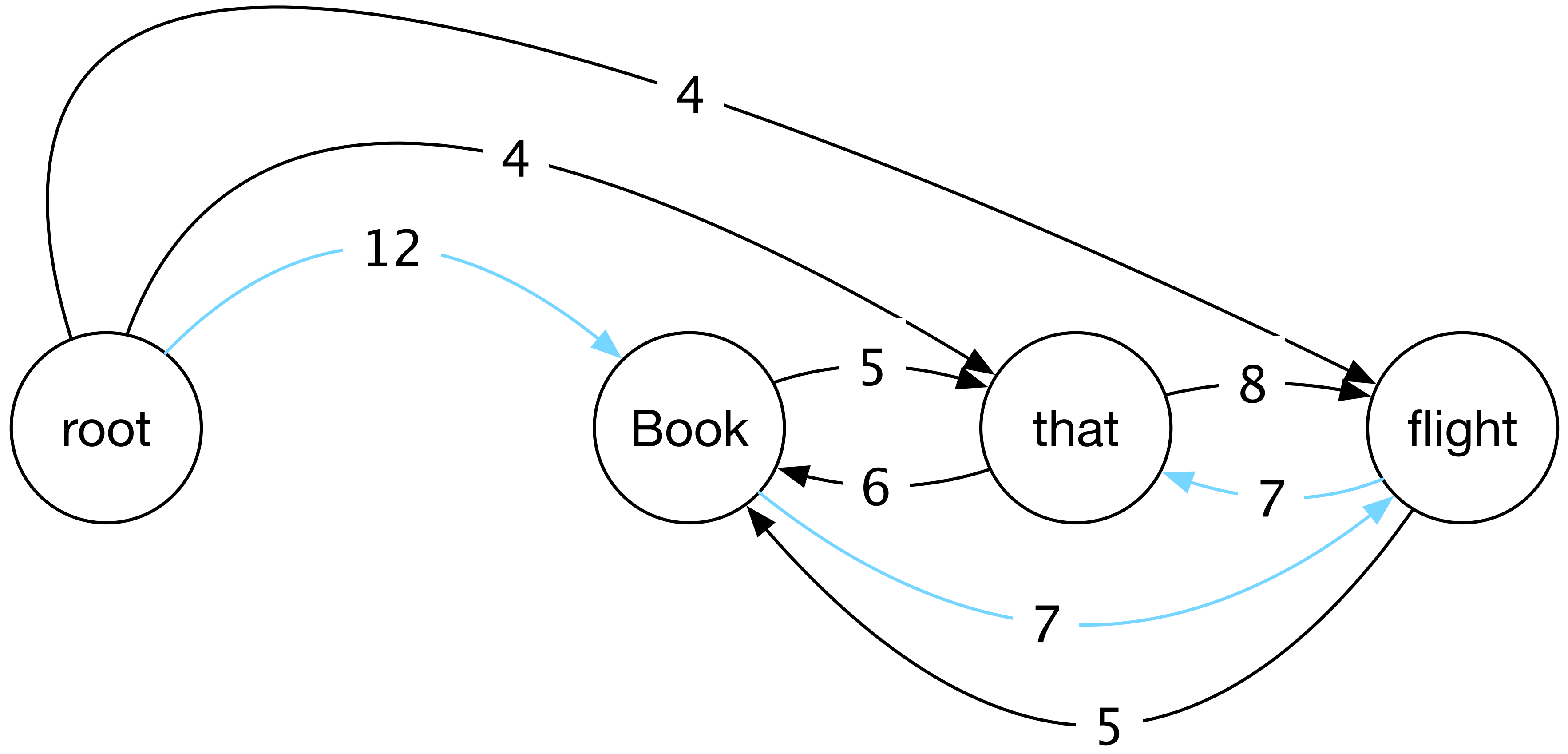

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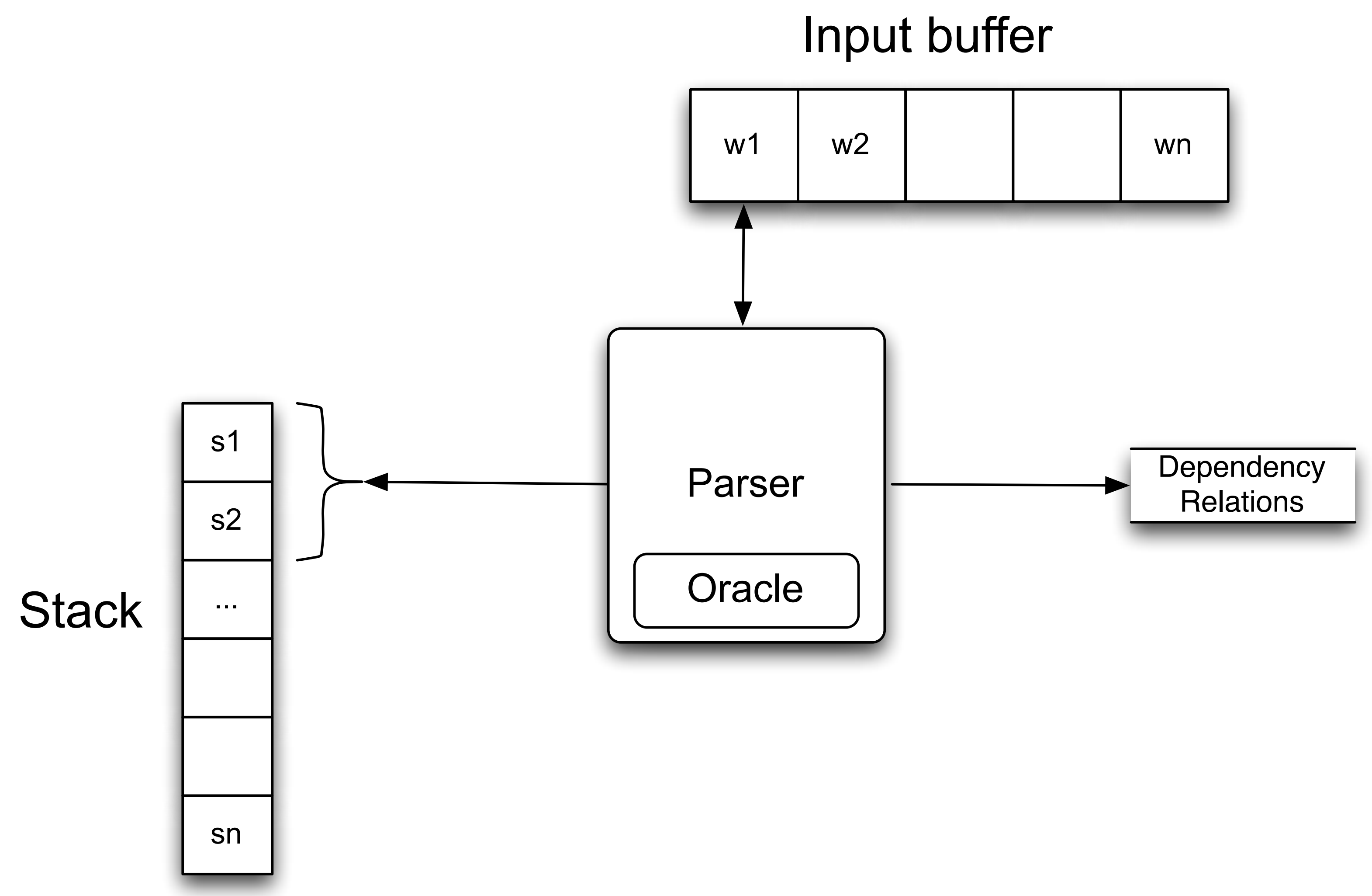

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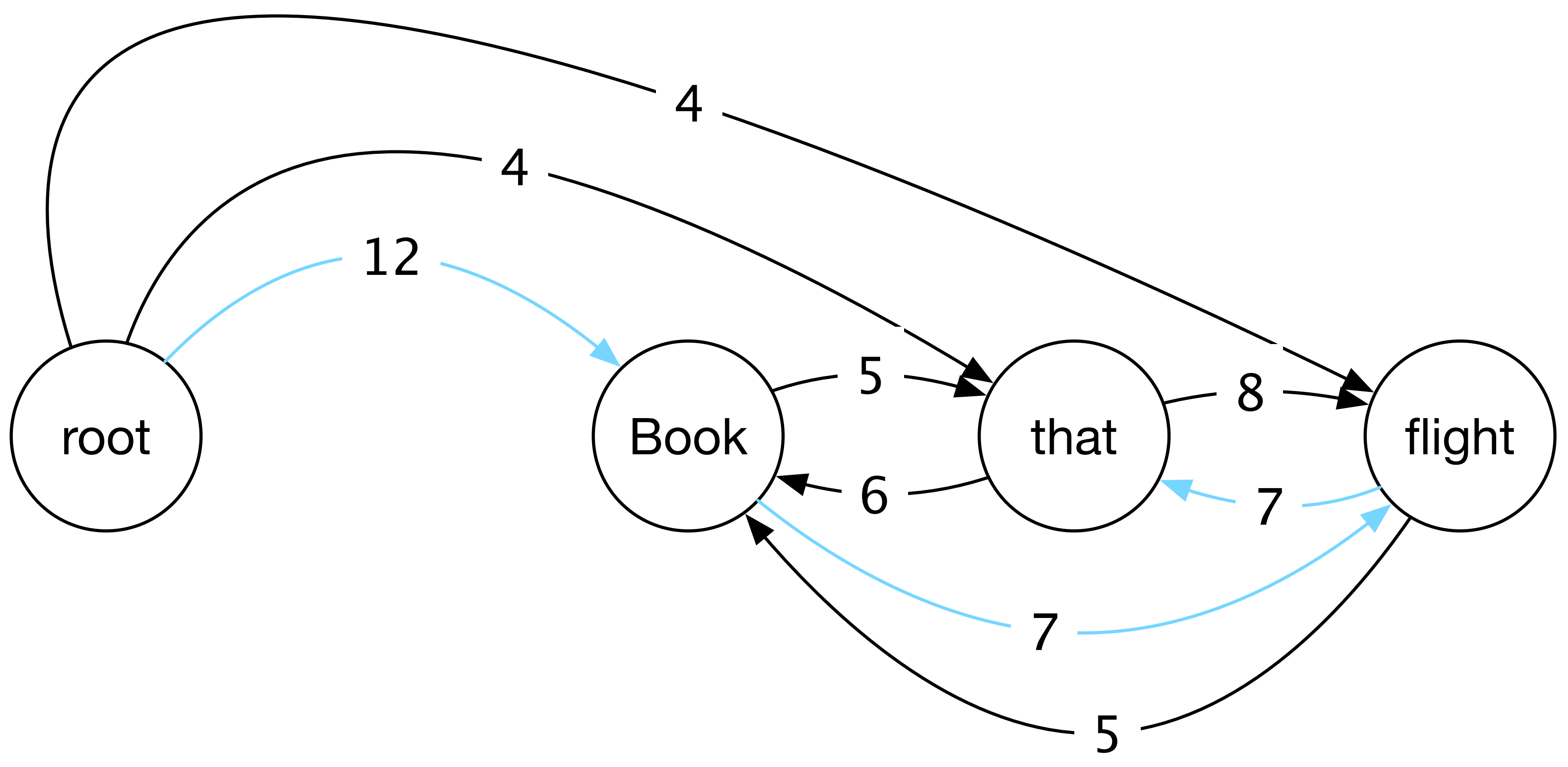
    - Given scores for every pair of words, find the (globally) highest scoring set of edges.



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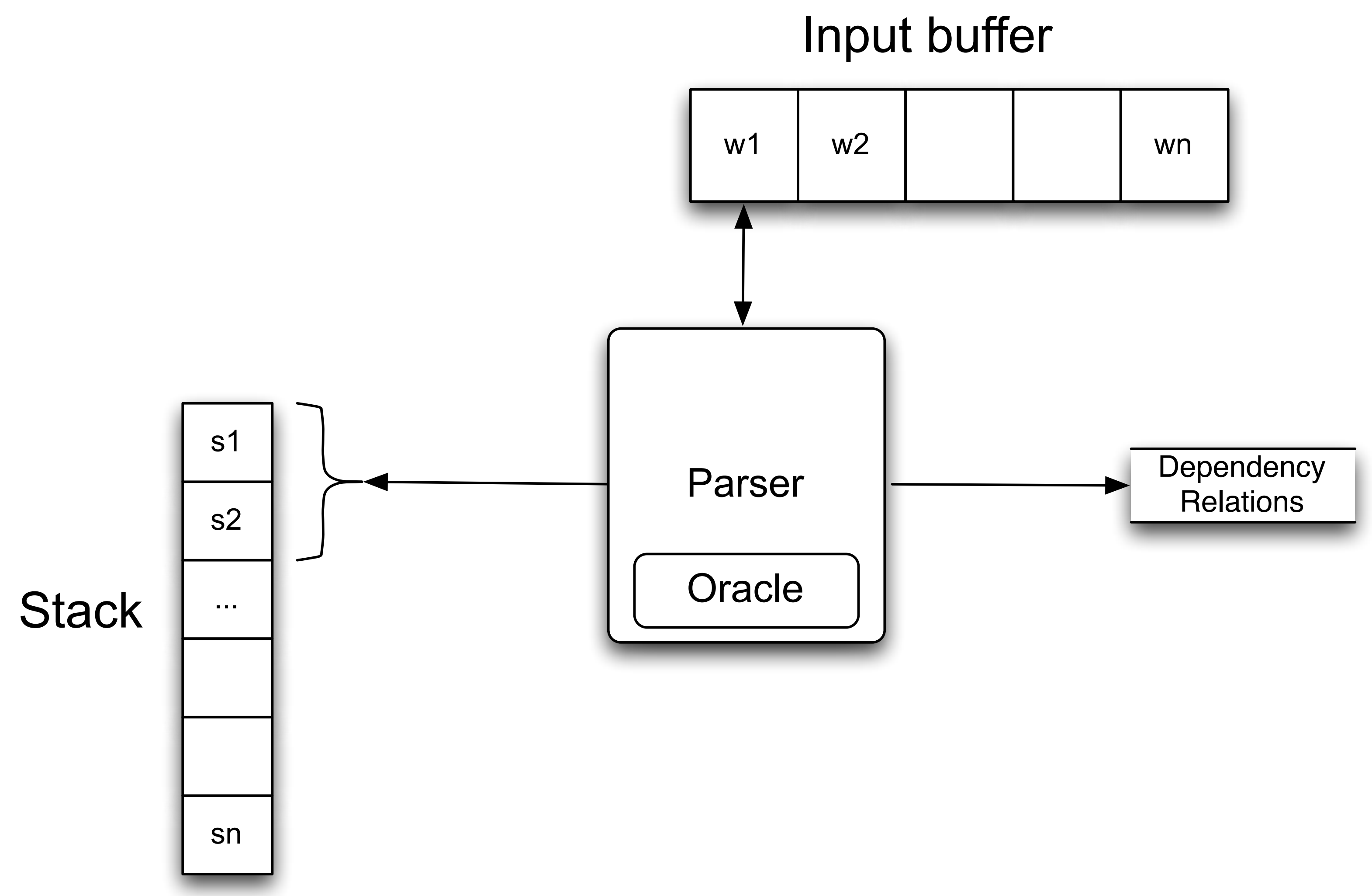

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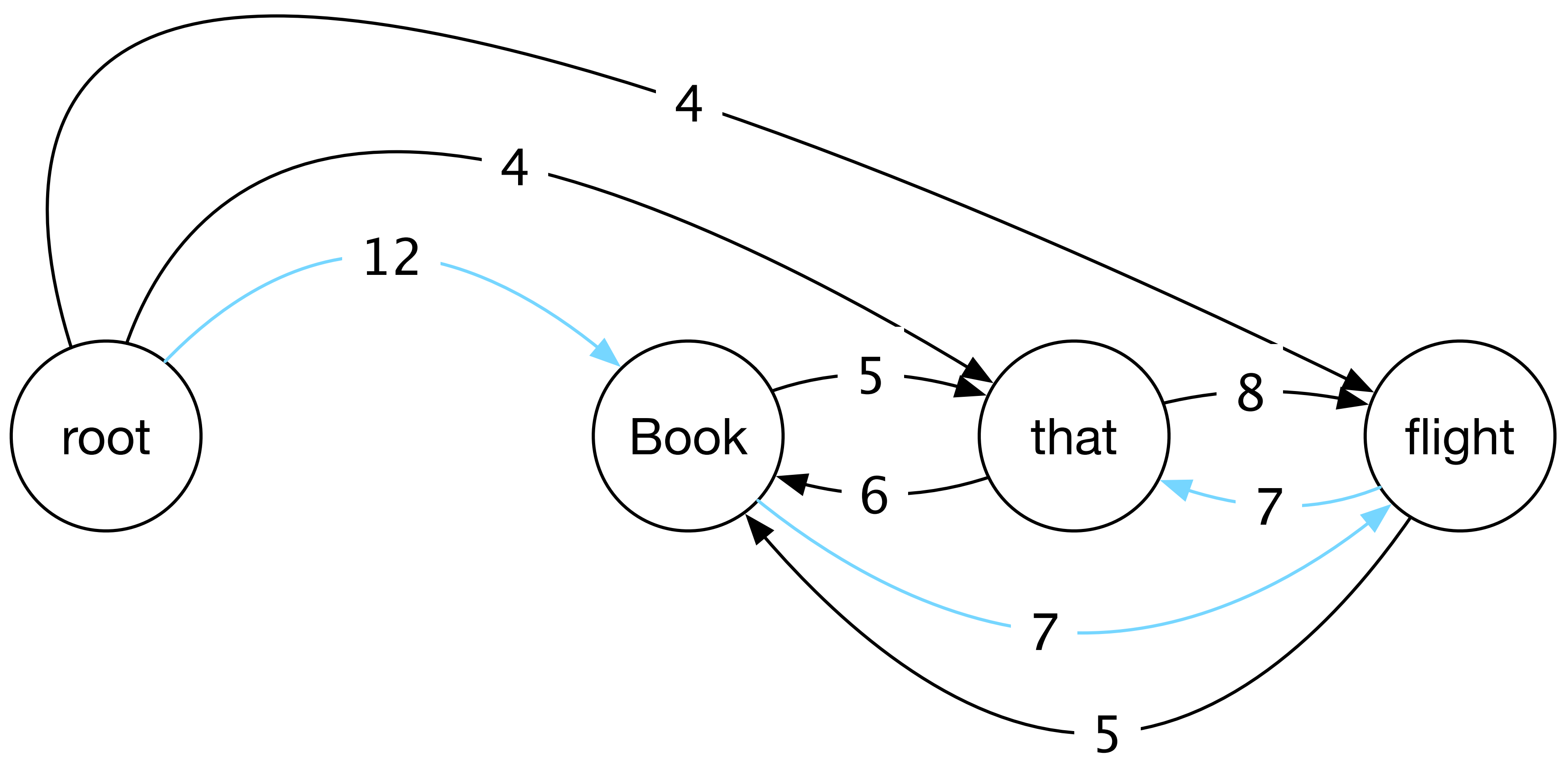

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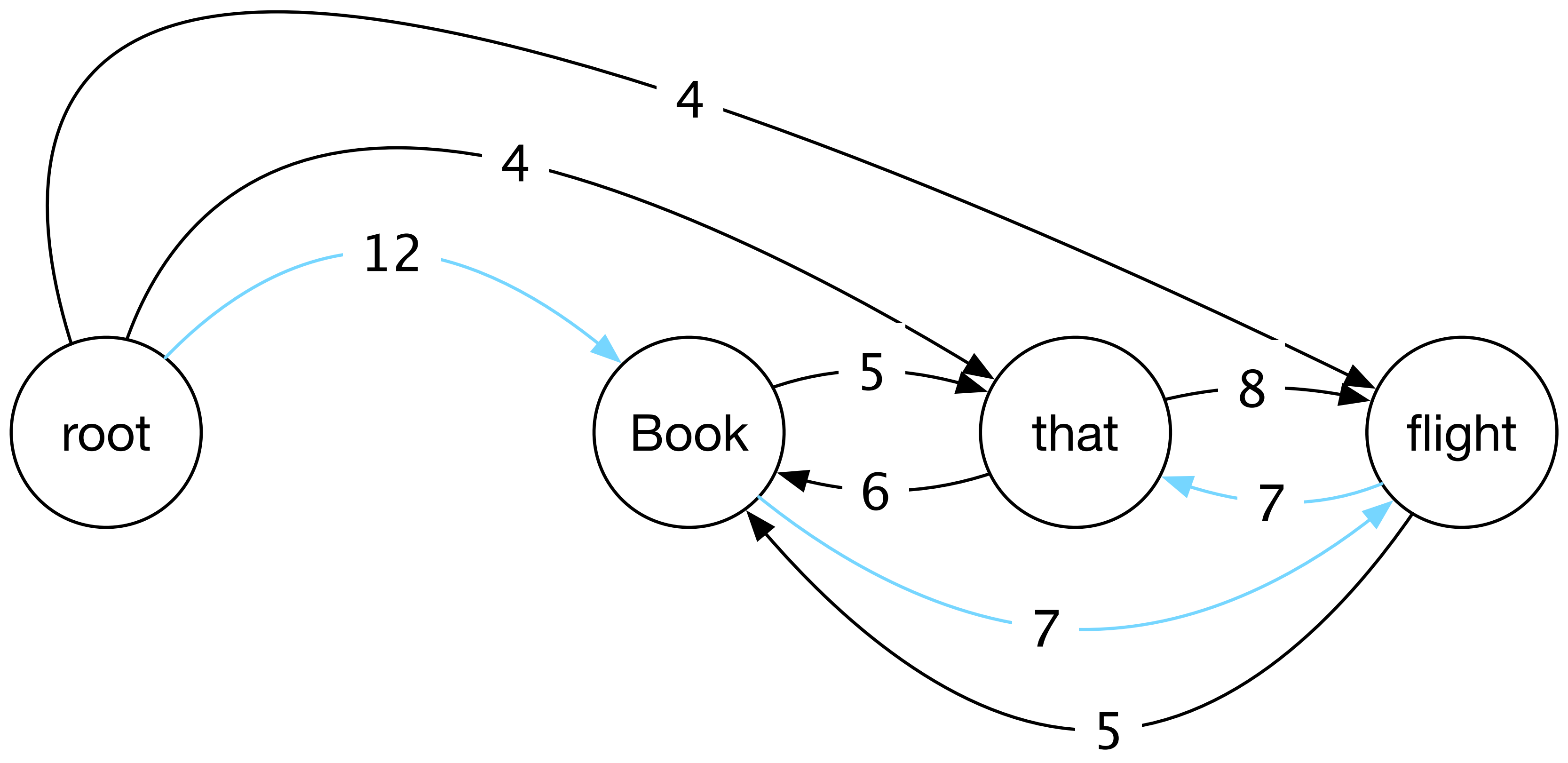
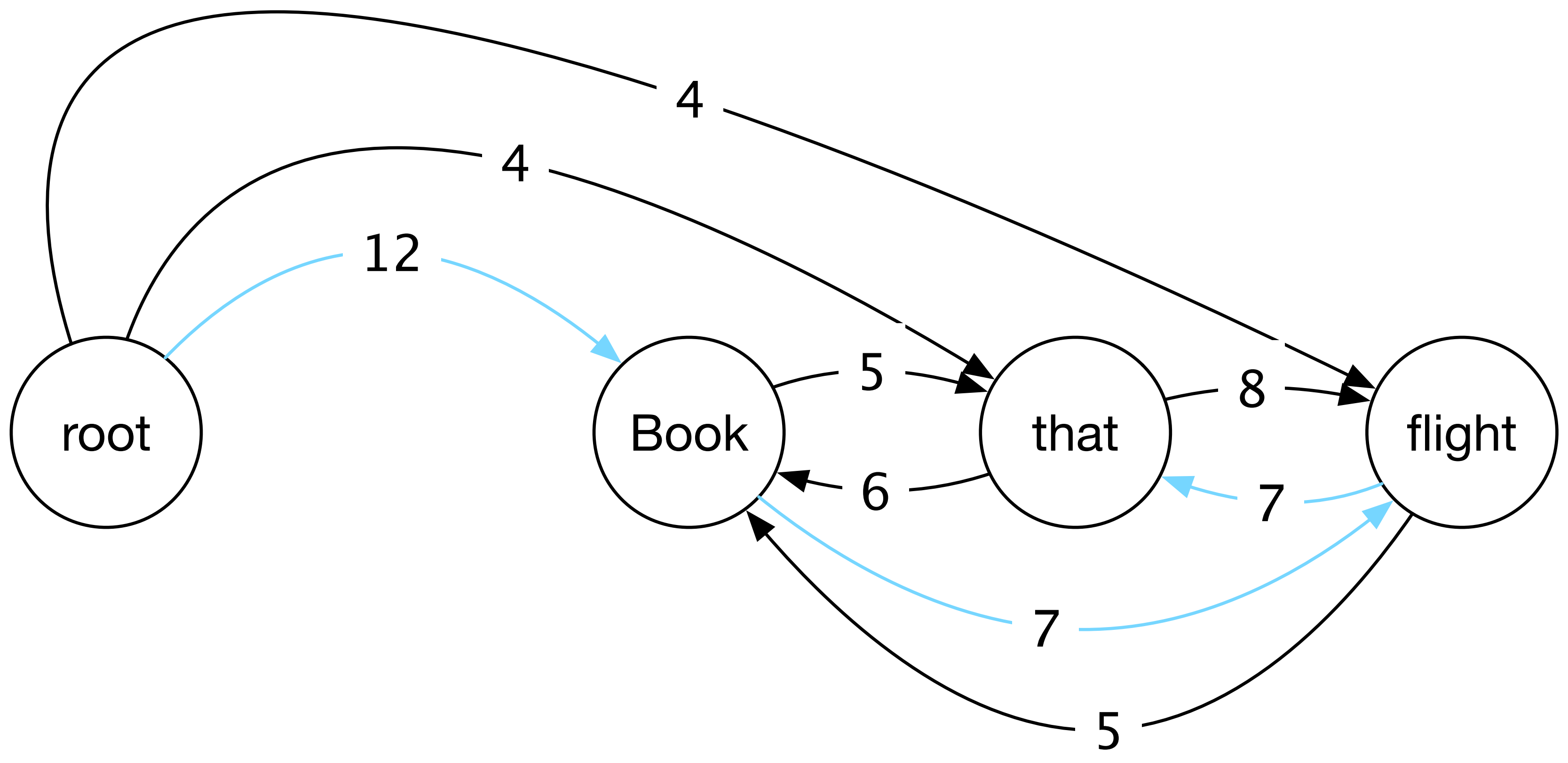


Graph-based dependency parsing

- **Edge-factored** (or **arc-factored**) approaches:



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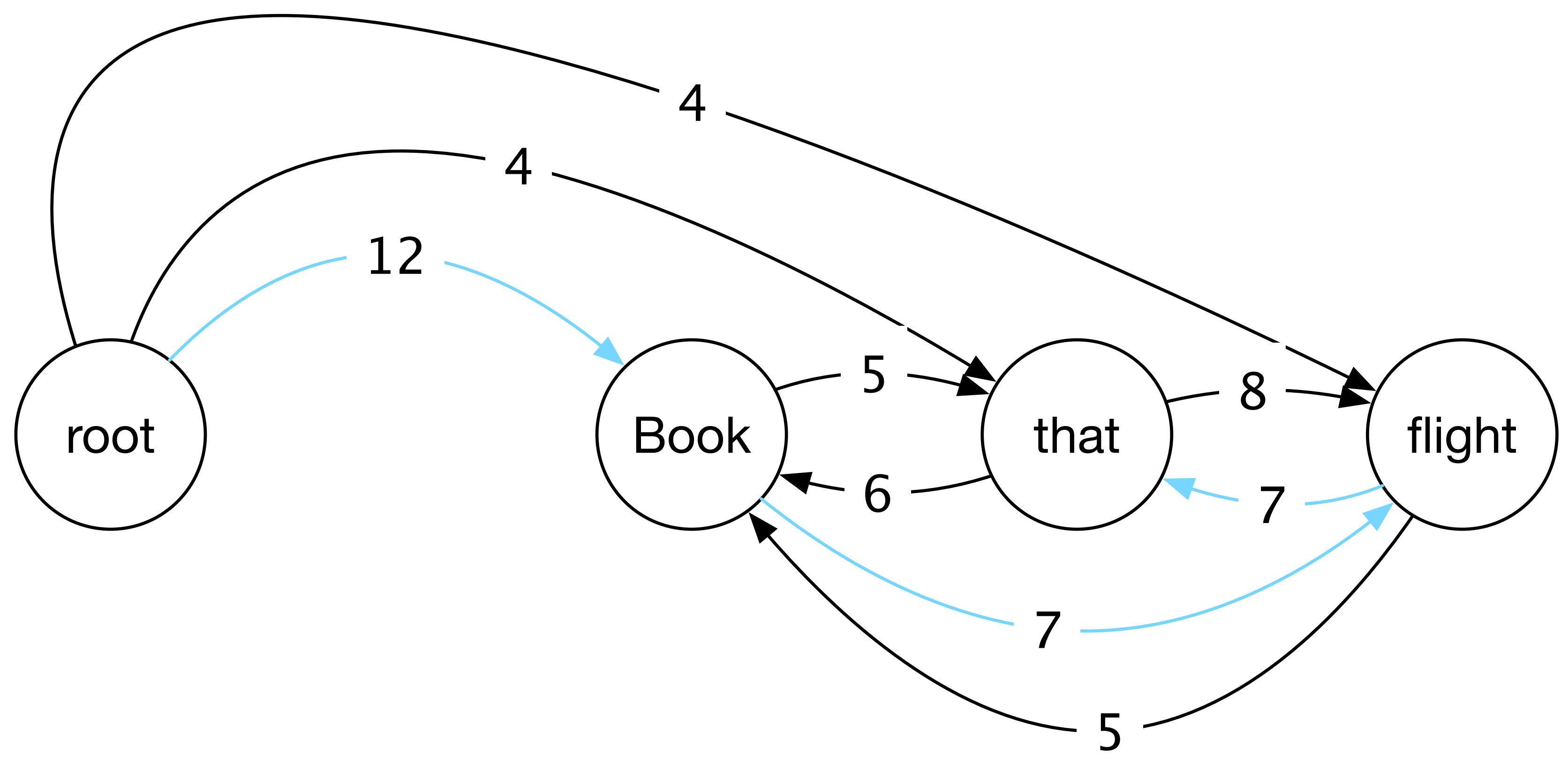

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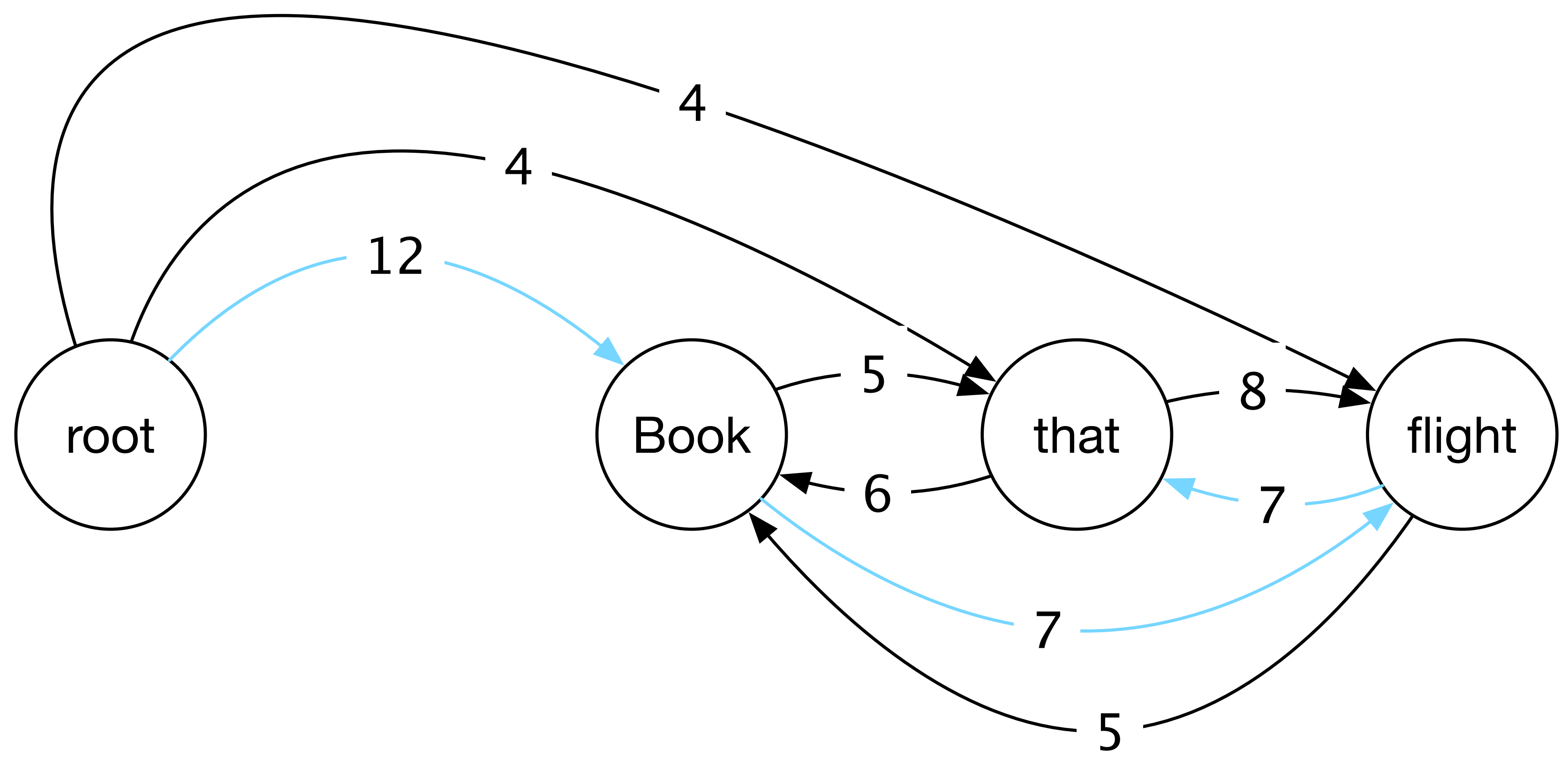
  - Start with a fully-connected directed graph



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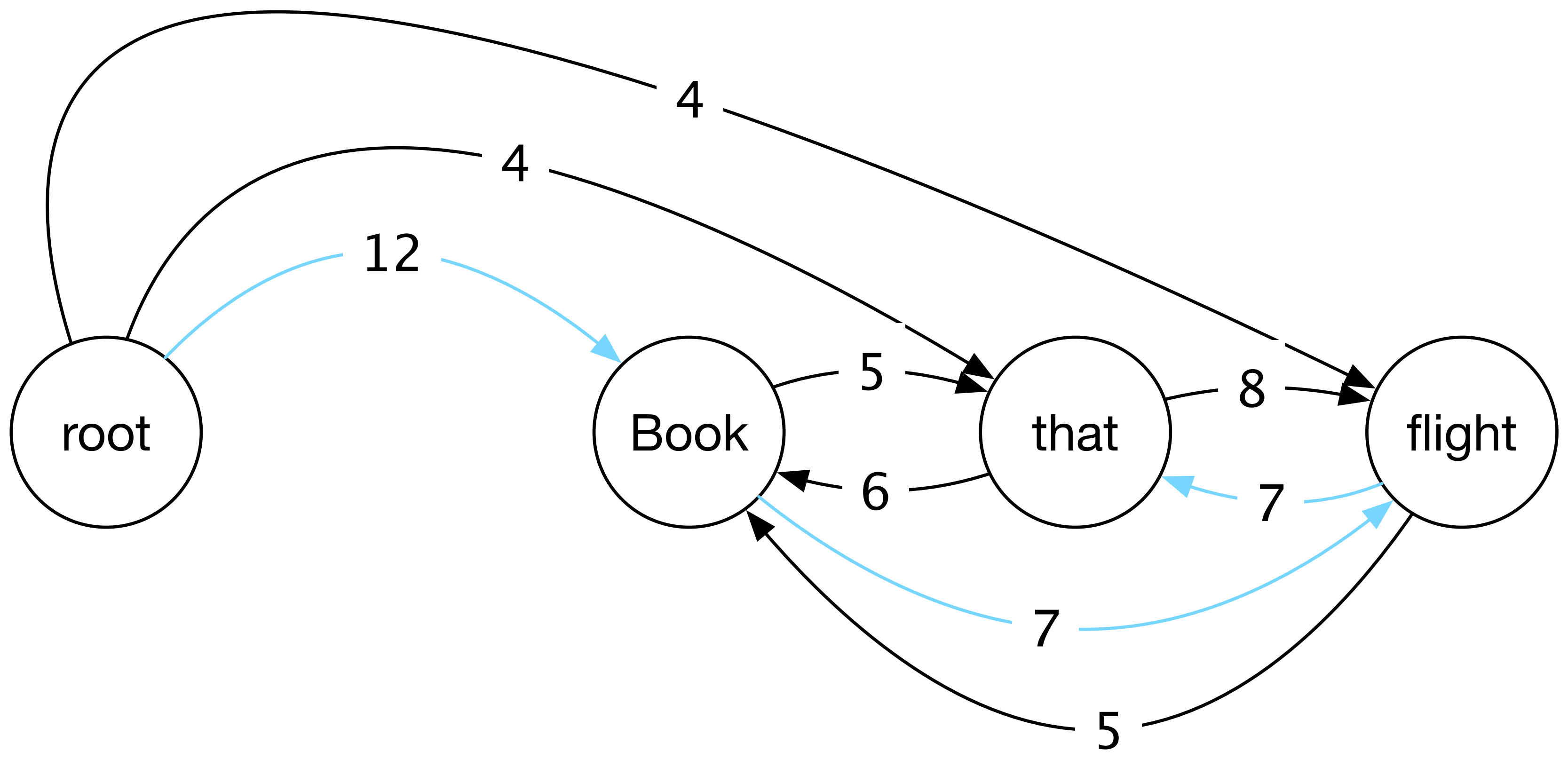

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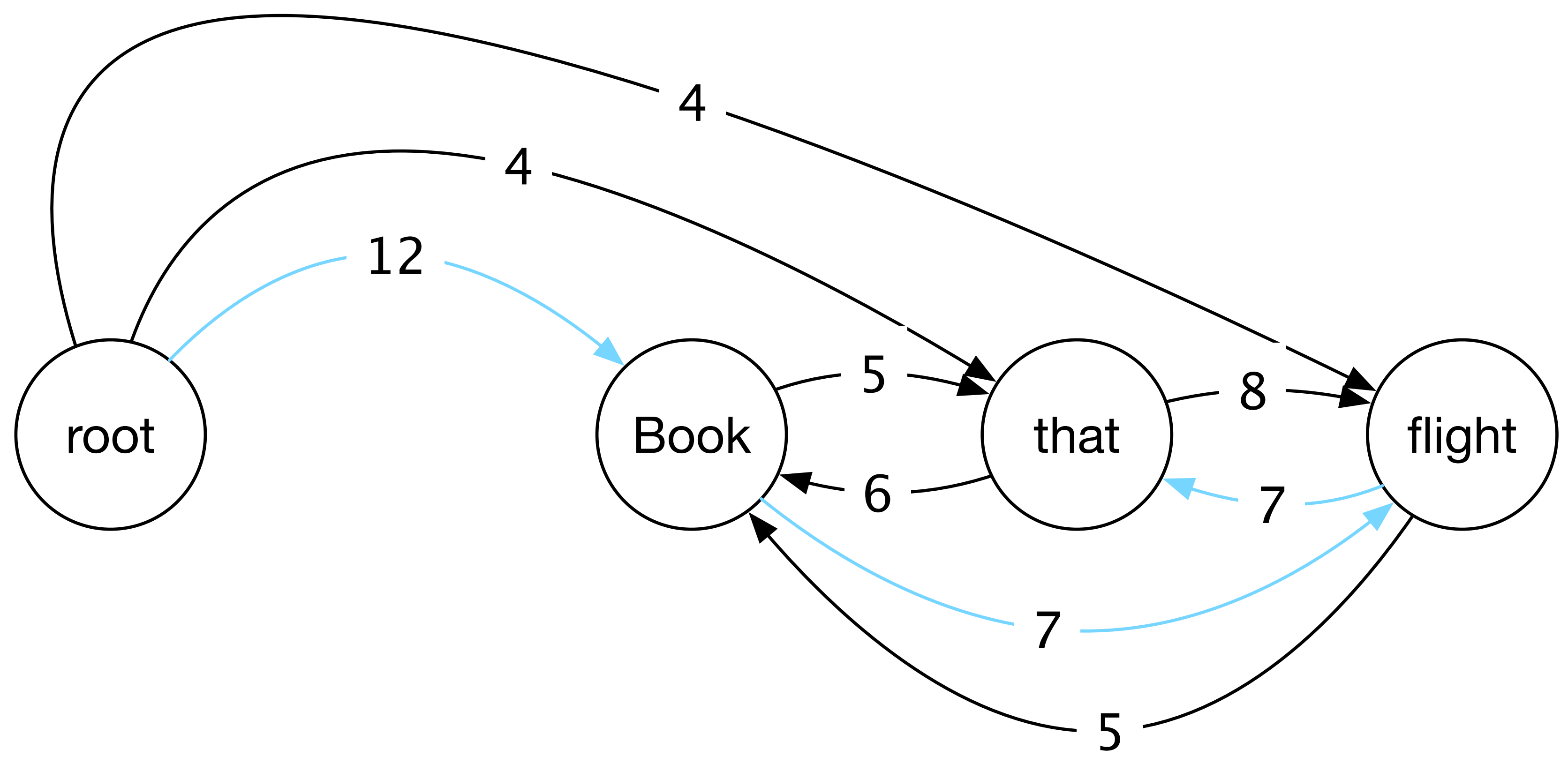
  - Find a **maximum directed spanning tree**:
    Chu and Liu (1965) and Edmonds (1967) algorithm



Chu-Liu-Edmonds algorithm

function MaxSpanningTree(G=(V,E), *root*, *score*) **returns** *spanning tree*

$F \leftarrow []$
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$score' \leftarrow []$
for each $v \in V$ **do**
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  if $T=(V,F)$ is a spanning tree **then return** it
  else
    $C \leftarrow$ a cycle in F
    $G' \leftarrow$ Contract(G, C)
    $T' \leftarrow$ MaxSpanningTree(G', *root*, *score'*)
    T $\leftarrow$ Expand(T', C)
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function Contract(G, C) **returns** *contracted graph*

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recursively compute MST

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    $T \leftarrow$ EXPAND(T', C) — expand contracted nodes
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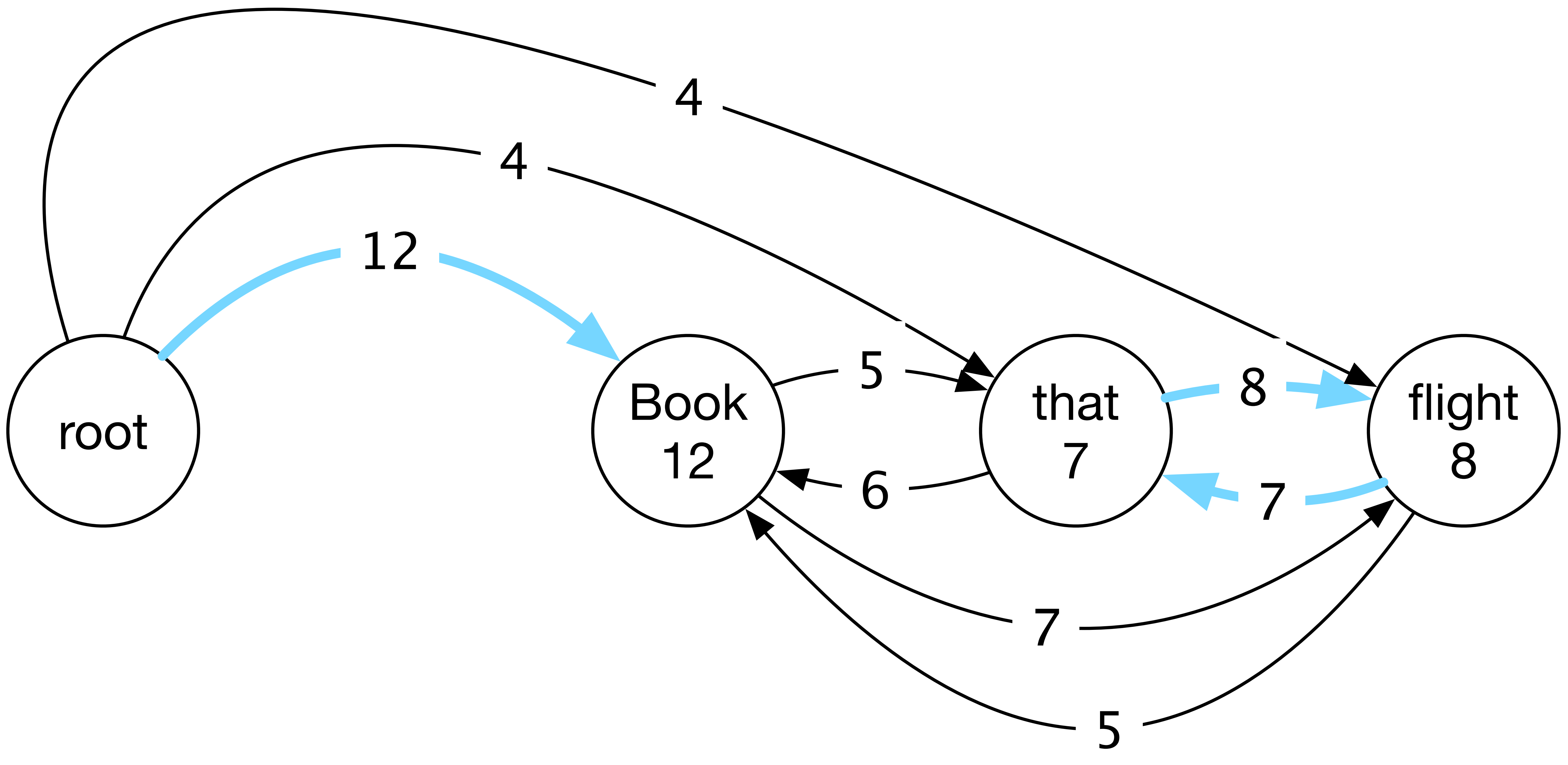
Chu-Liu-Edmonds algorithm

- Select best incoming edge for each node



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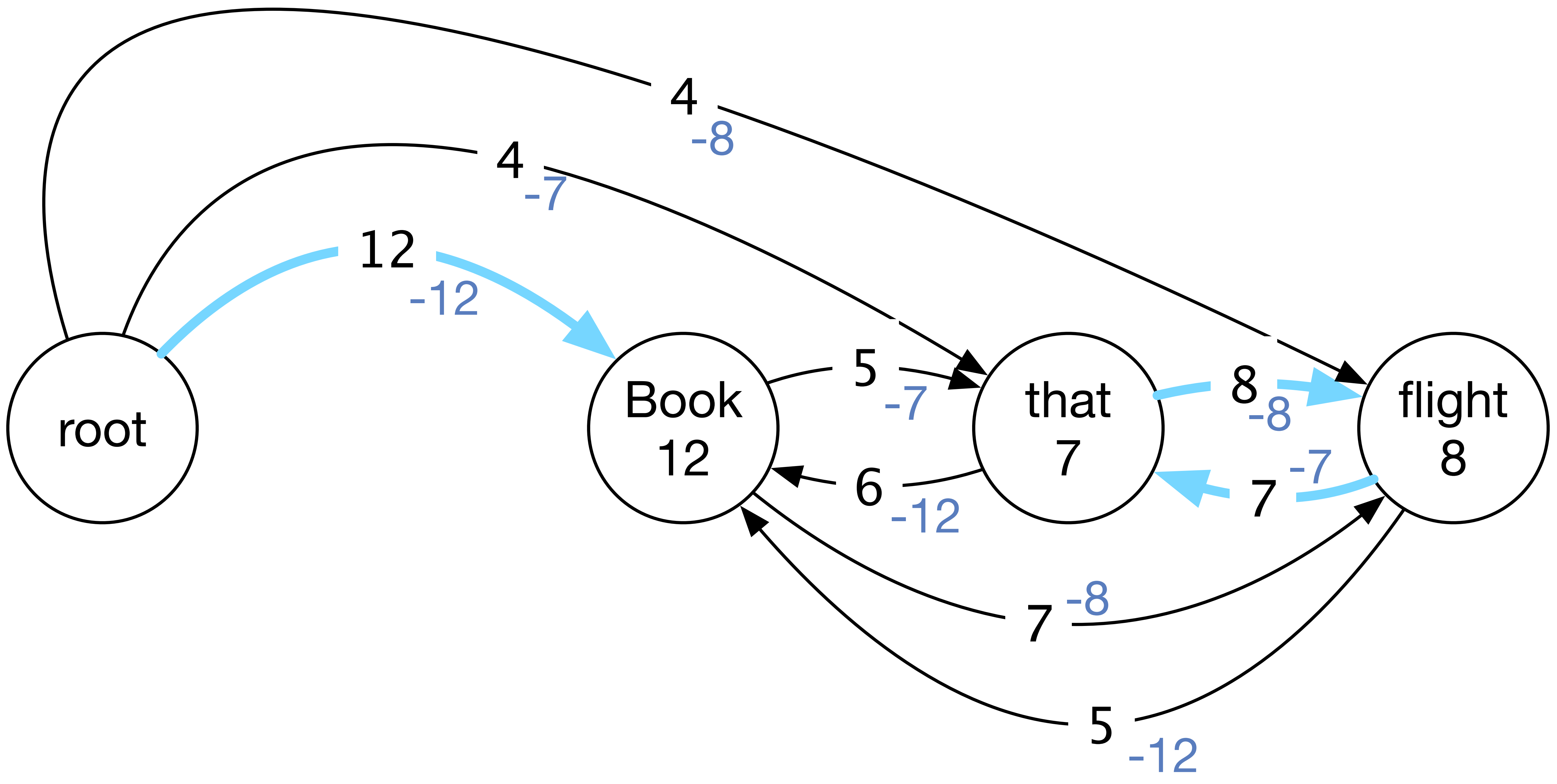

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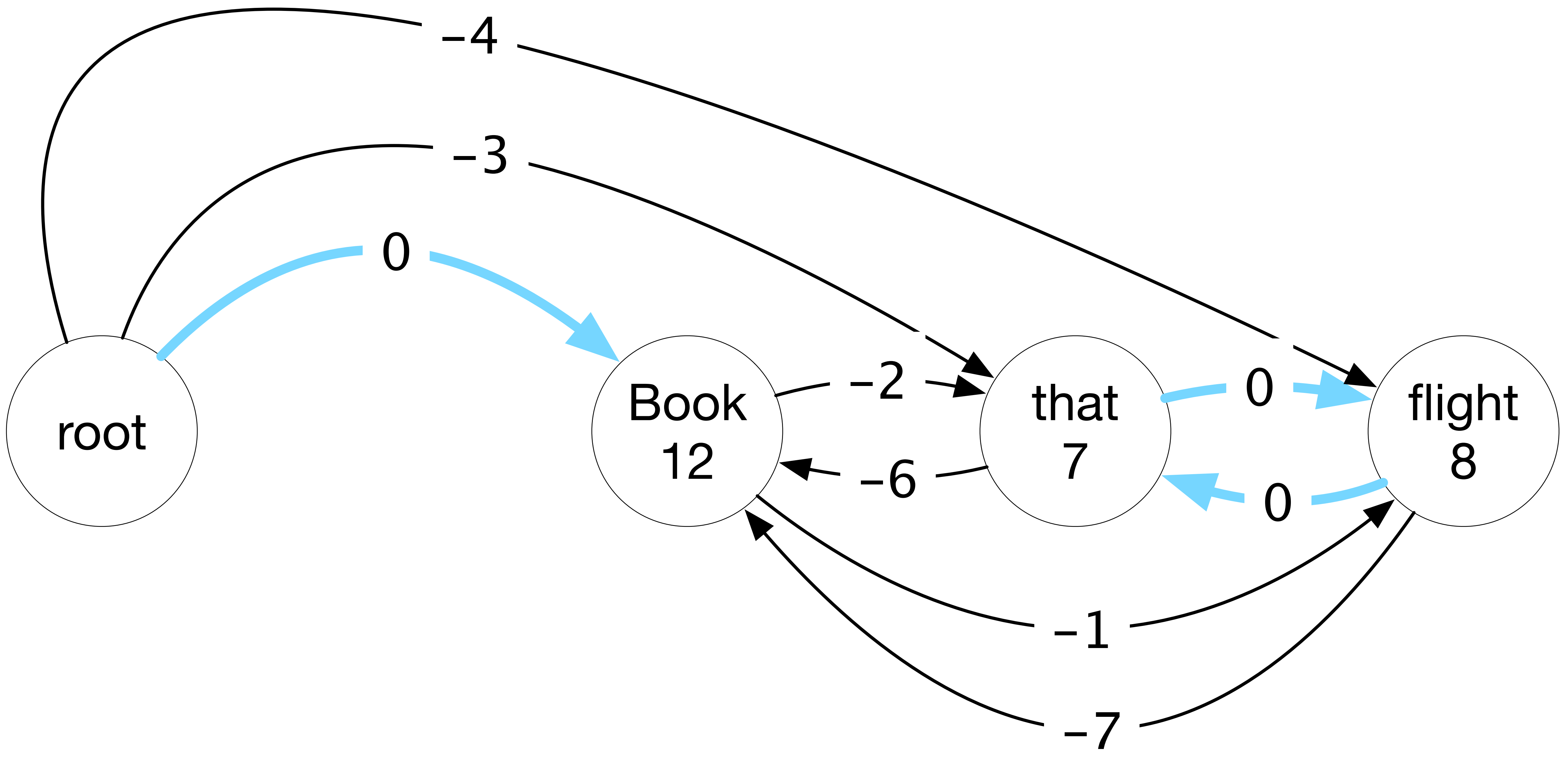

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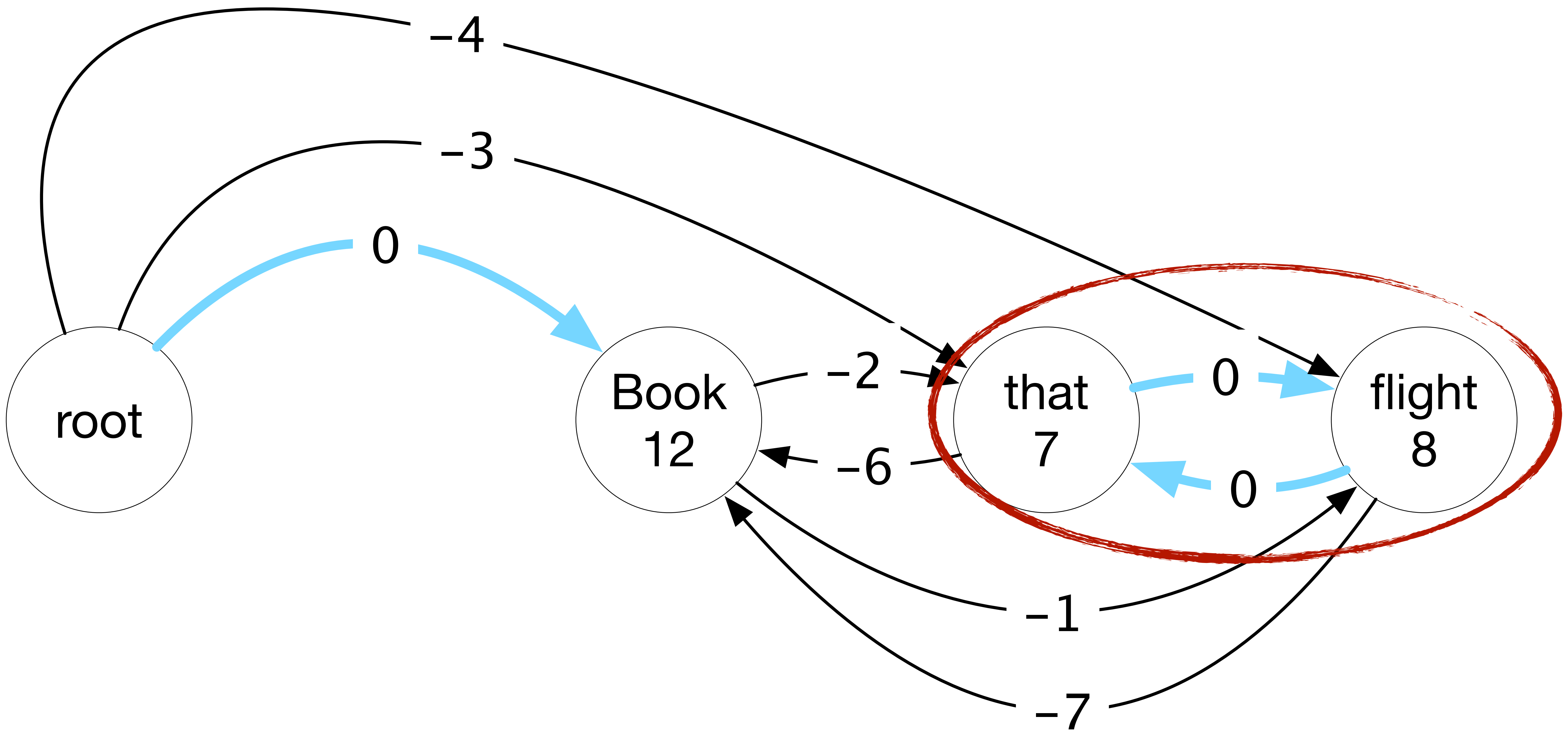

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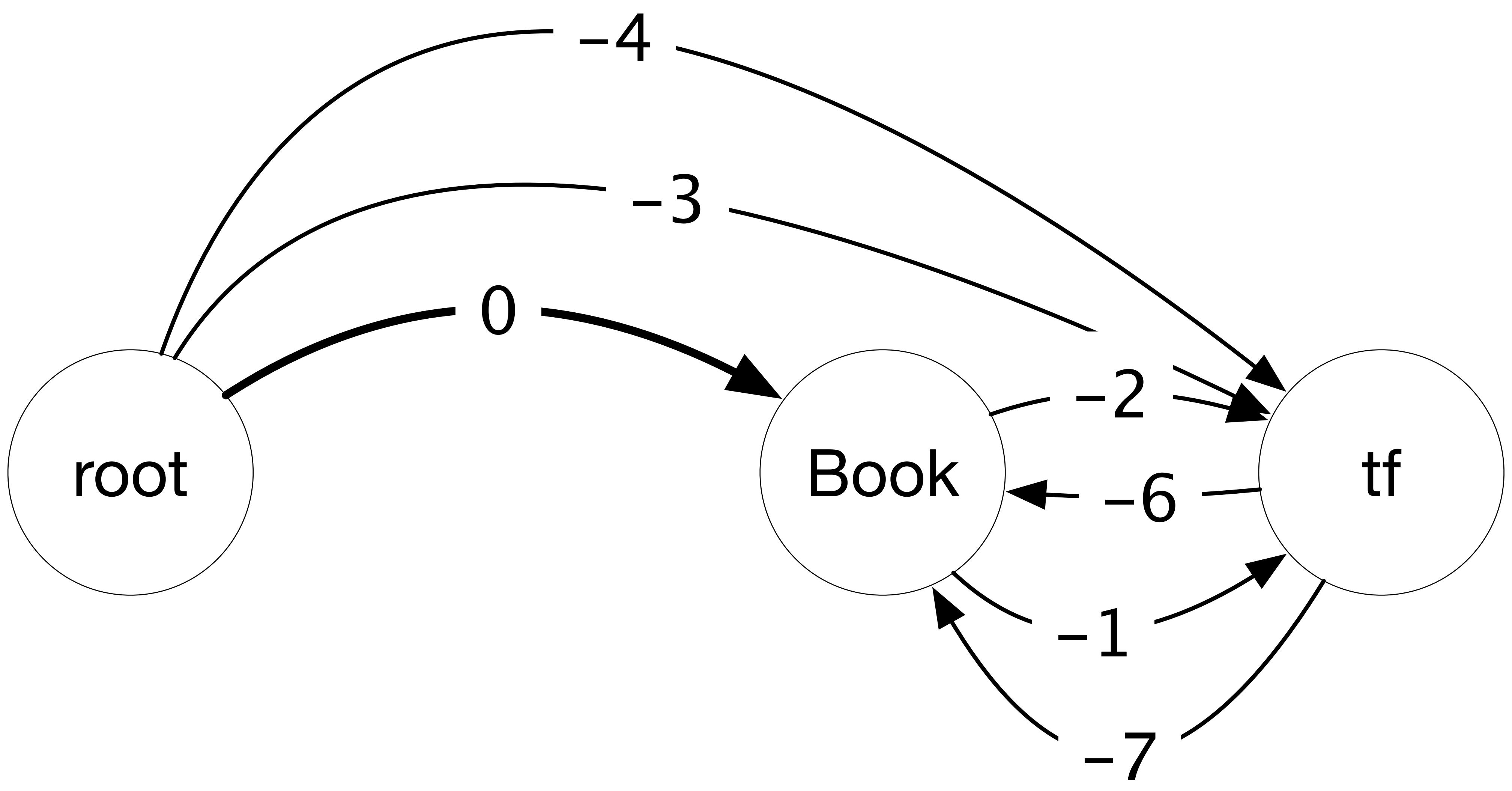
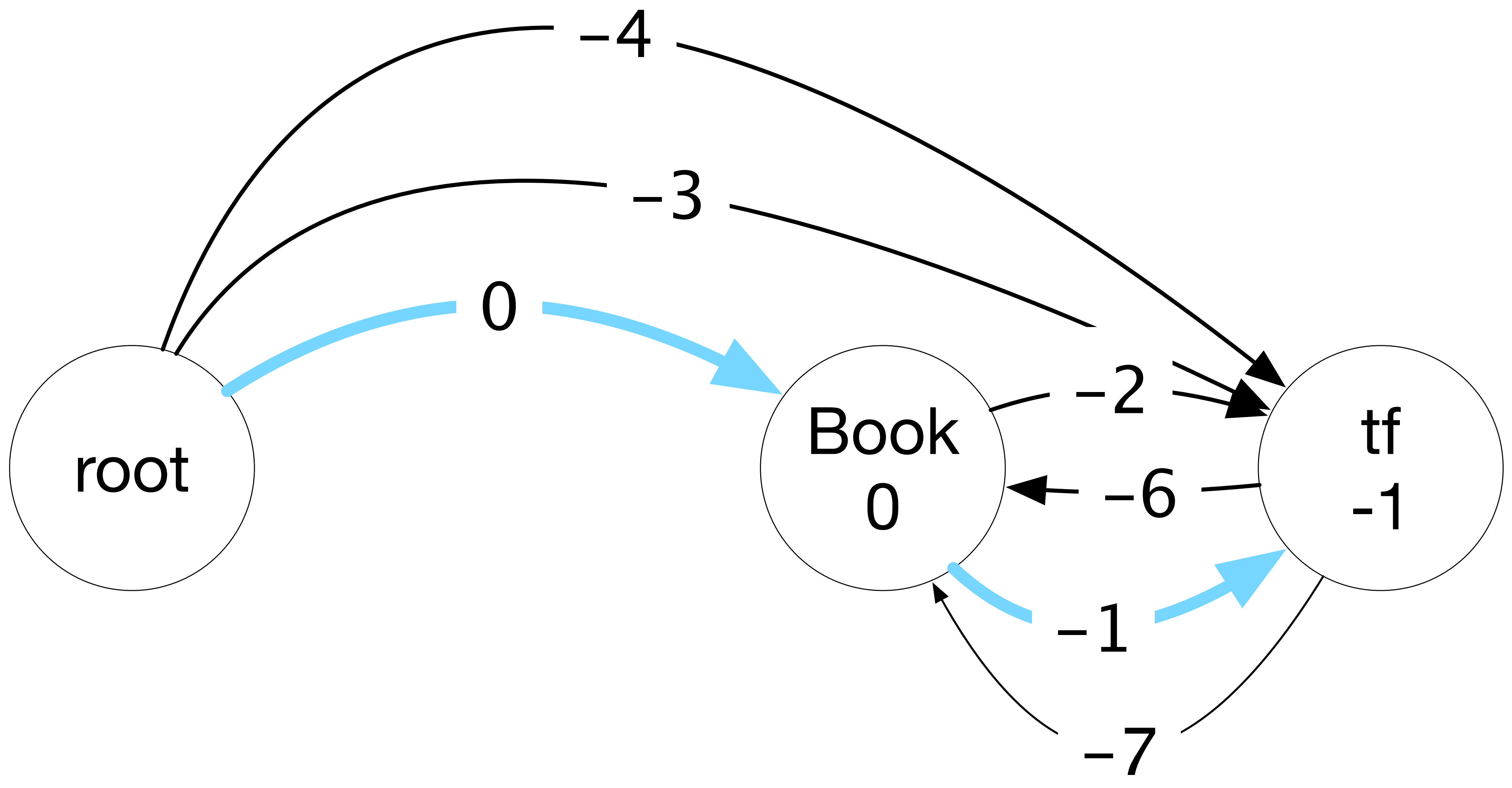


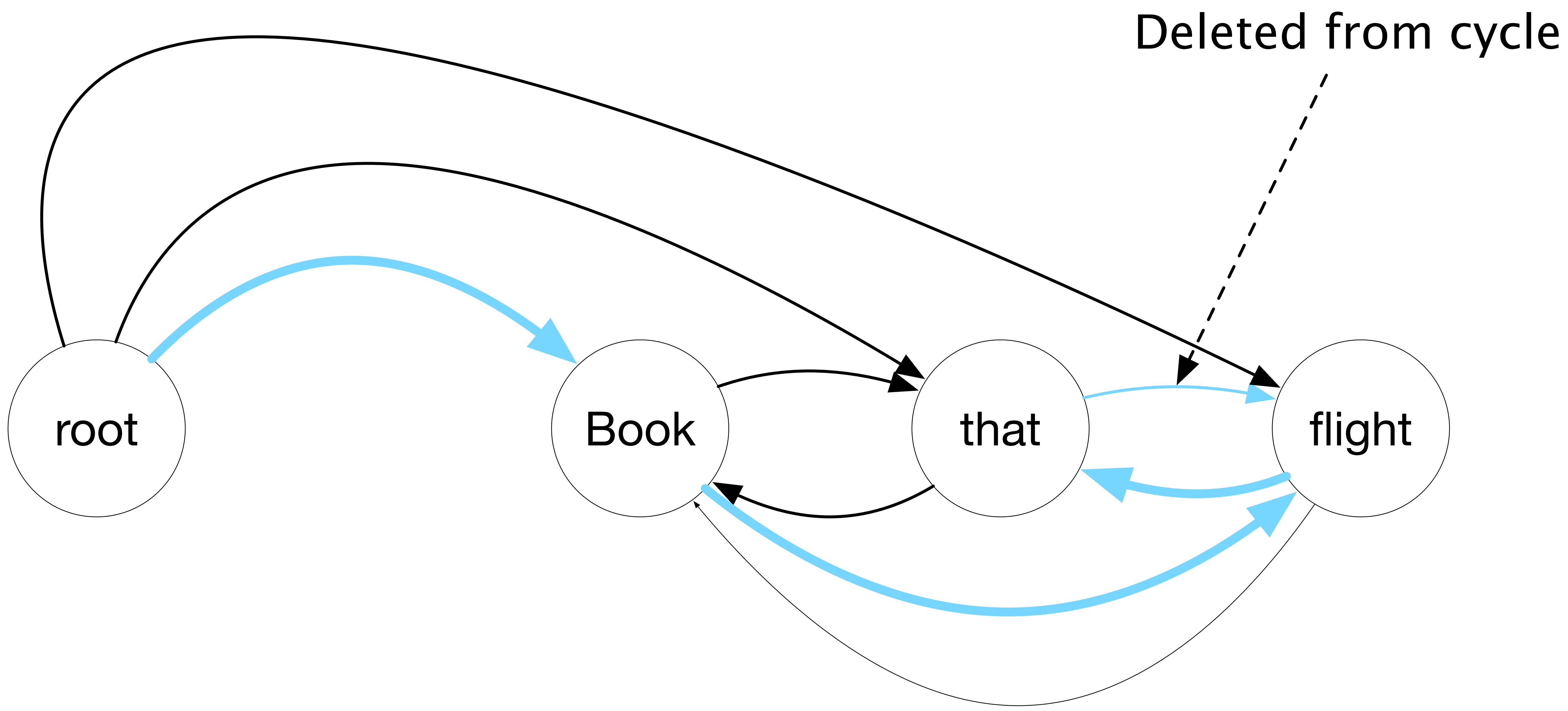
Chu-Liu-Edmonds algorithm

- Recursively compute MST



Chu-Liu-Edmonds algorithm

- Expand contracted nodes



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runtime?

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what about labeled parsing?

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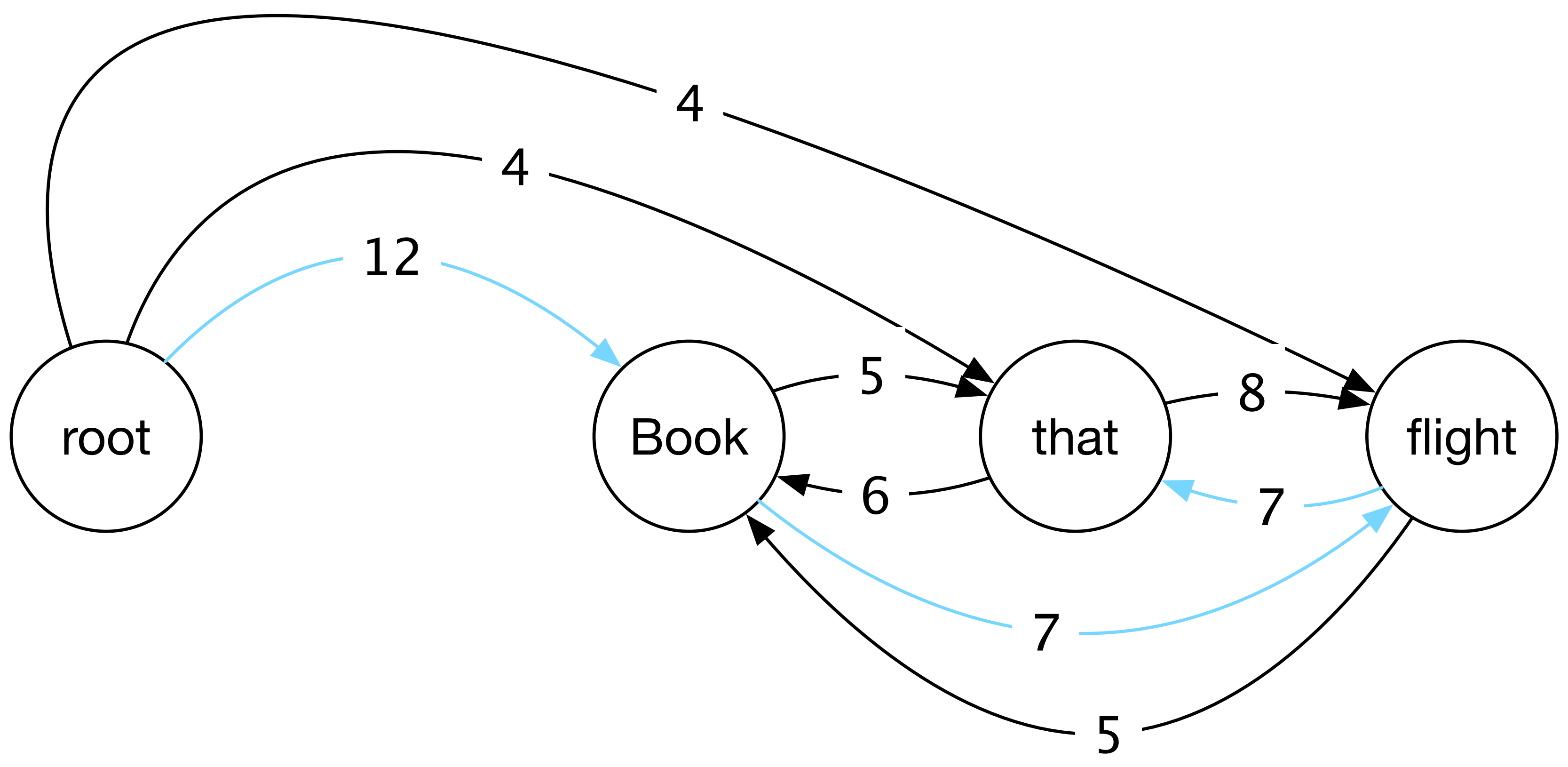
    Chu and Liu (1965) and Edmonds (1967) algorithm



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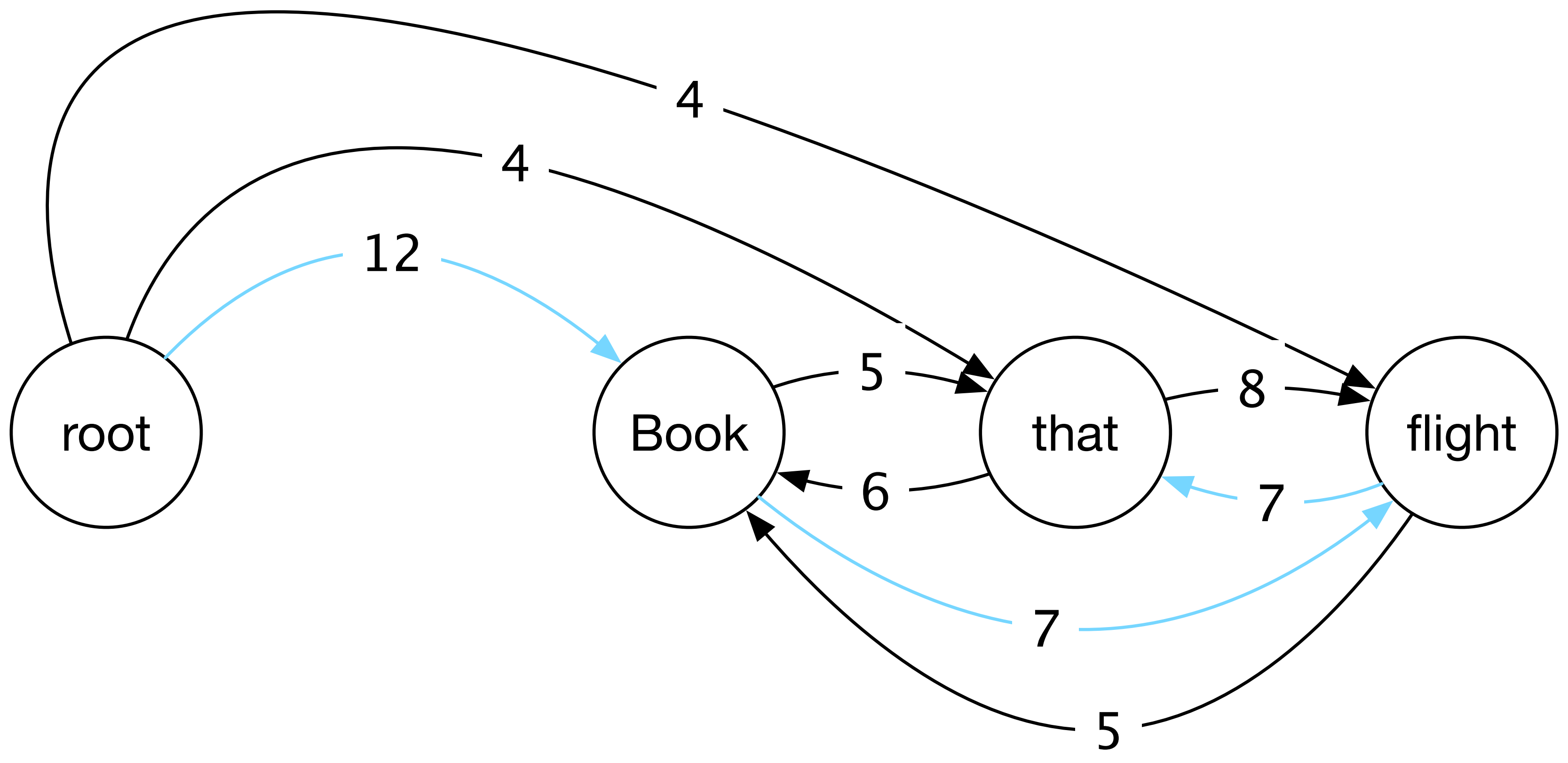
  - For projective trees: **Eisner's algorithm** [Eisner 1996]



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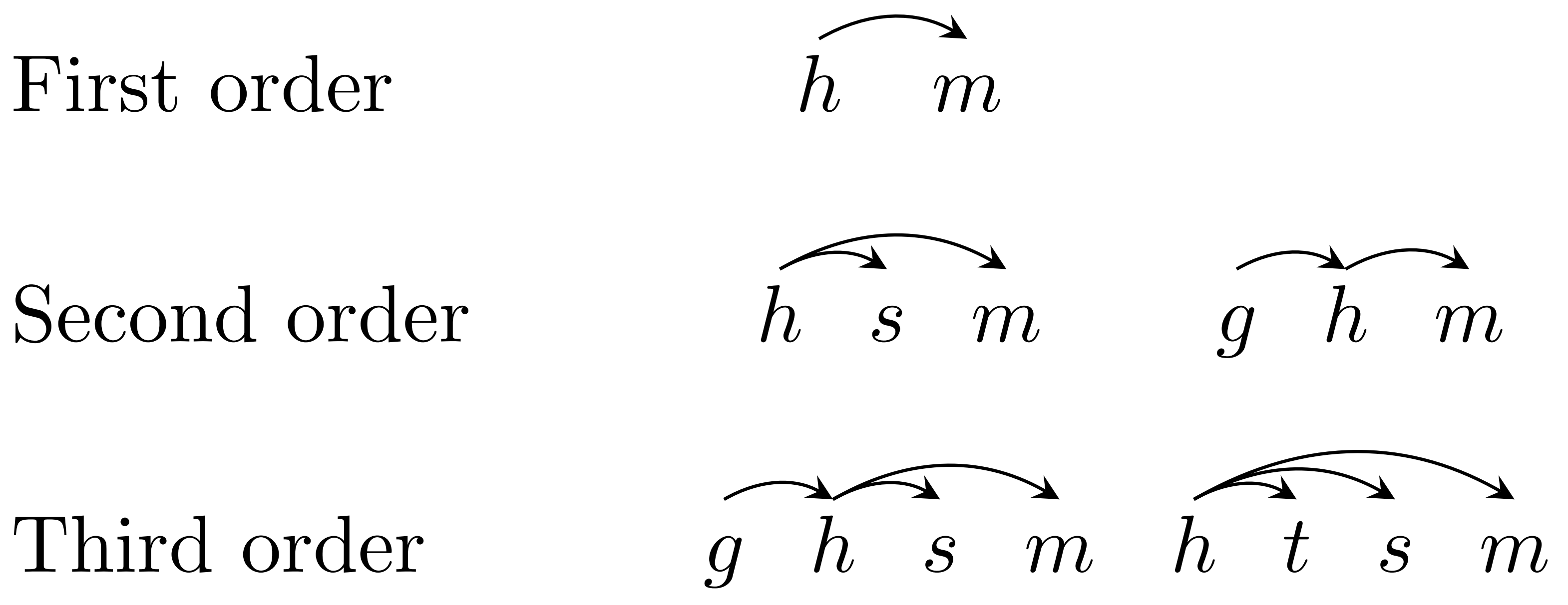
- Can also define **higher-order** models: score decomposes as a sum of scores of local subgraphs.



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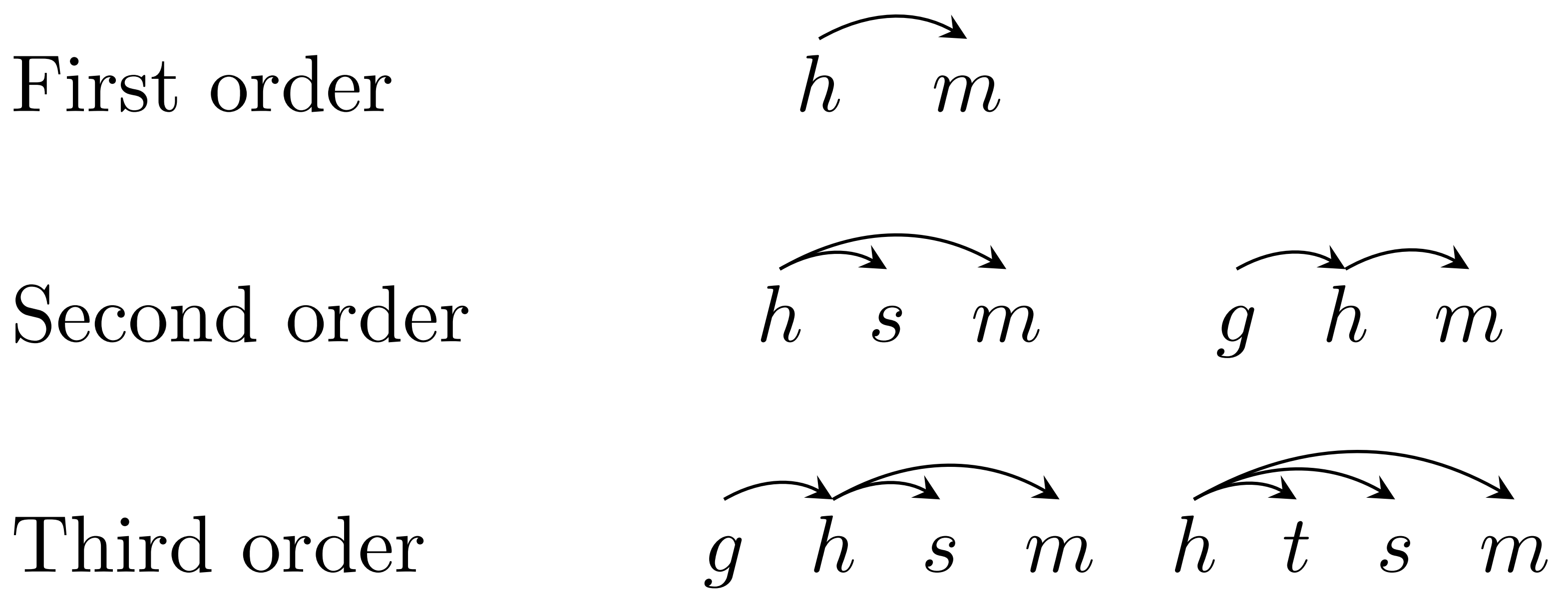

  - Have efficient (polynomial time) algorithms for second [Eisner 1996] and third order [Koo and Collins, 2010] *projective* dependency parsing.

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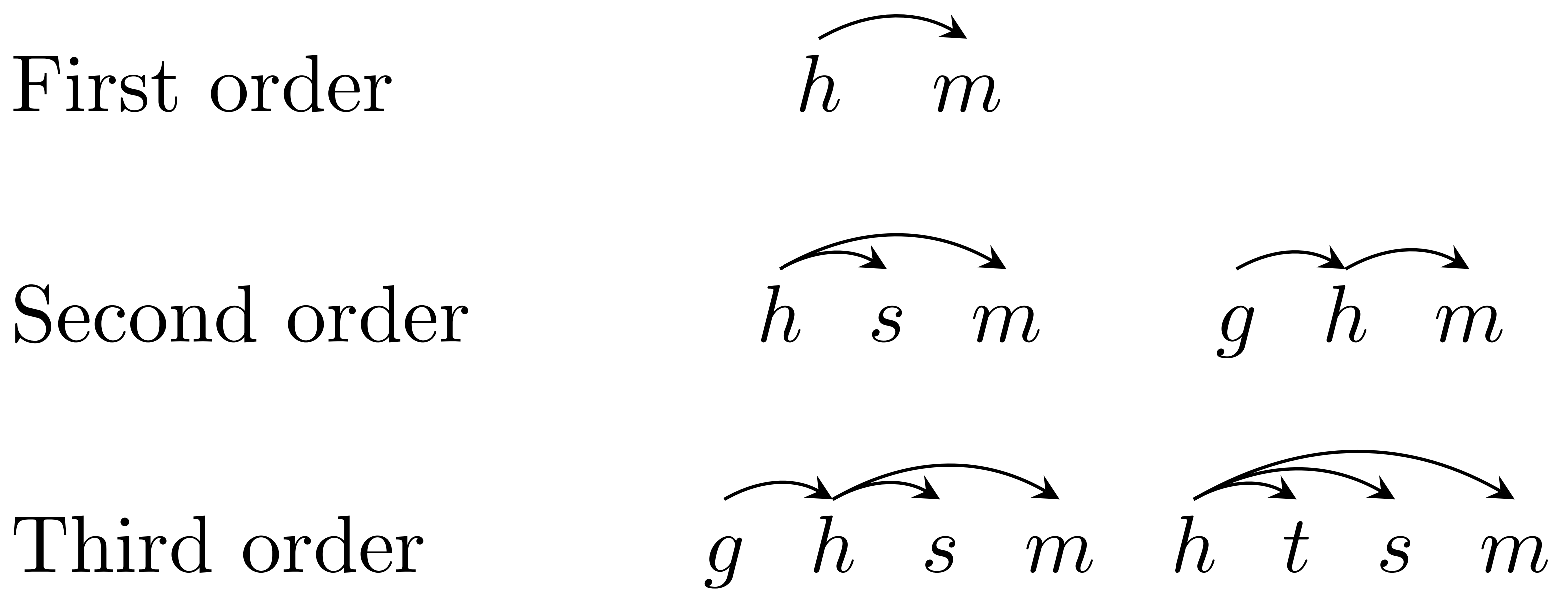
- Can also define **higher-order** models: score decomposes as a sum of scores of local subgraphs.



  - Have efficient (polynomial time) algorithms for second [Eisner 1996] and third order [Koo and Collins, 2010] *projective* dependency parsing.
  - Second order parsing is NP-hard for *non-projective* dependency graphs [McDonald and Pereira, 2006]!

Graph-based dependency parsing

- **Edge-factored** (or **arc-factored**) approaches: score of a tree decomposes as sum of edge scores.

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First order $\overset{\curvearrowright}{h \quad m}$

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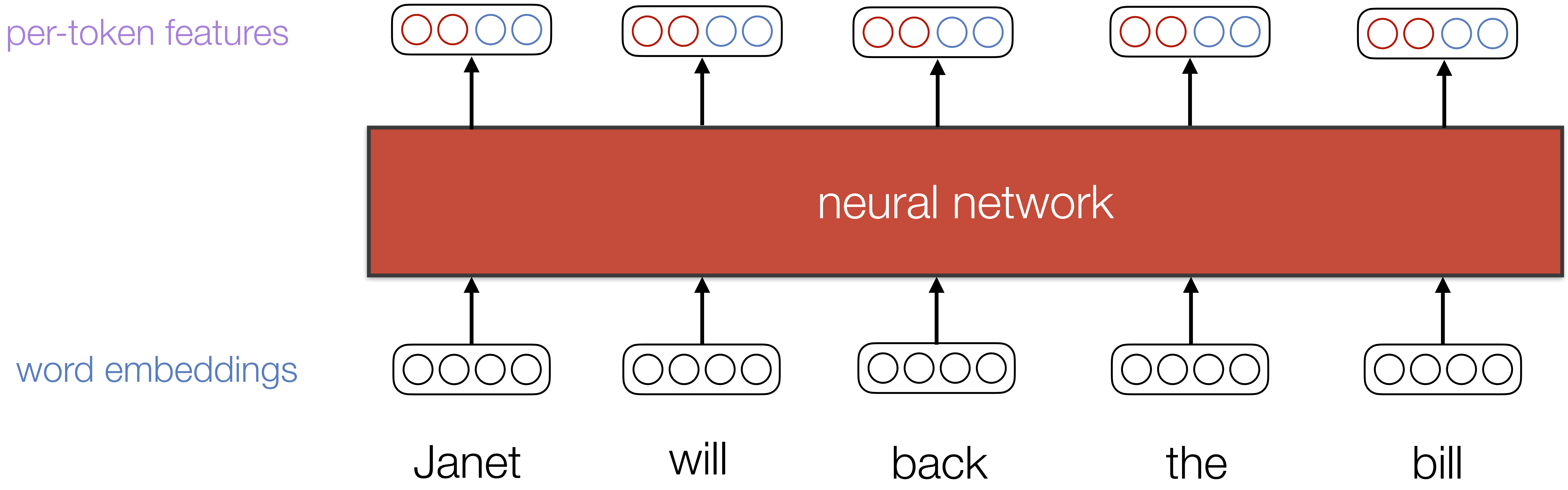
First order $h \qquad m$

- How to parameterize ψ ?

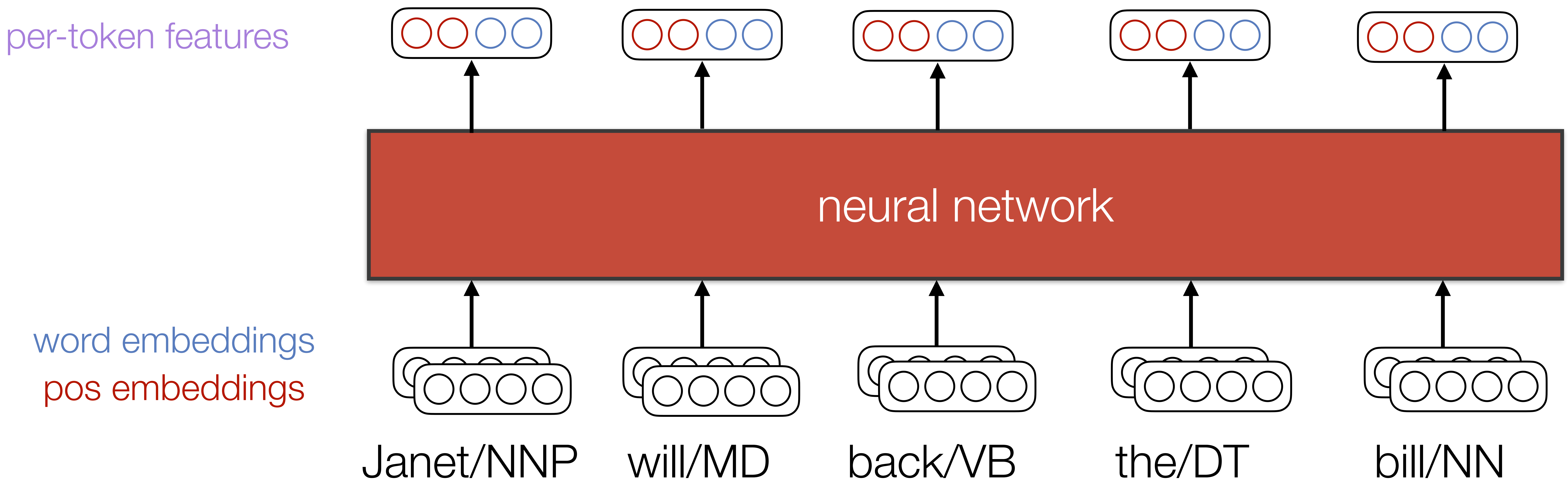
Classic graph-based parsing features

- Word forms, lemmas, parts of speech of the head word and its dependent
- Corresponding features derived from the contexts before, after, between words
- Word embeddings
- Dependency relation
- Direction of the relation (right or left)
- Distance from the head to the dependent
- Combinations of all of the above

Graph-based neural network parsers



Graph-based neural network parsers



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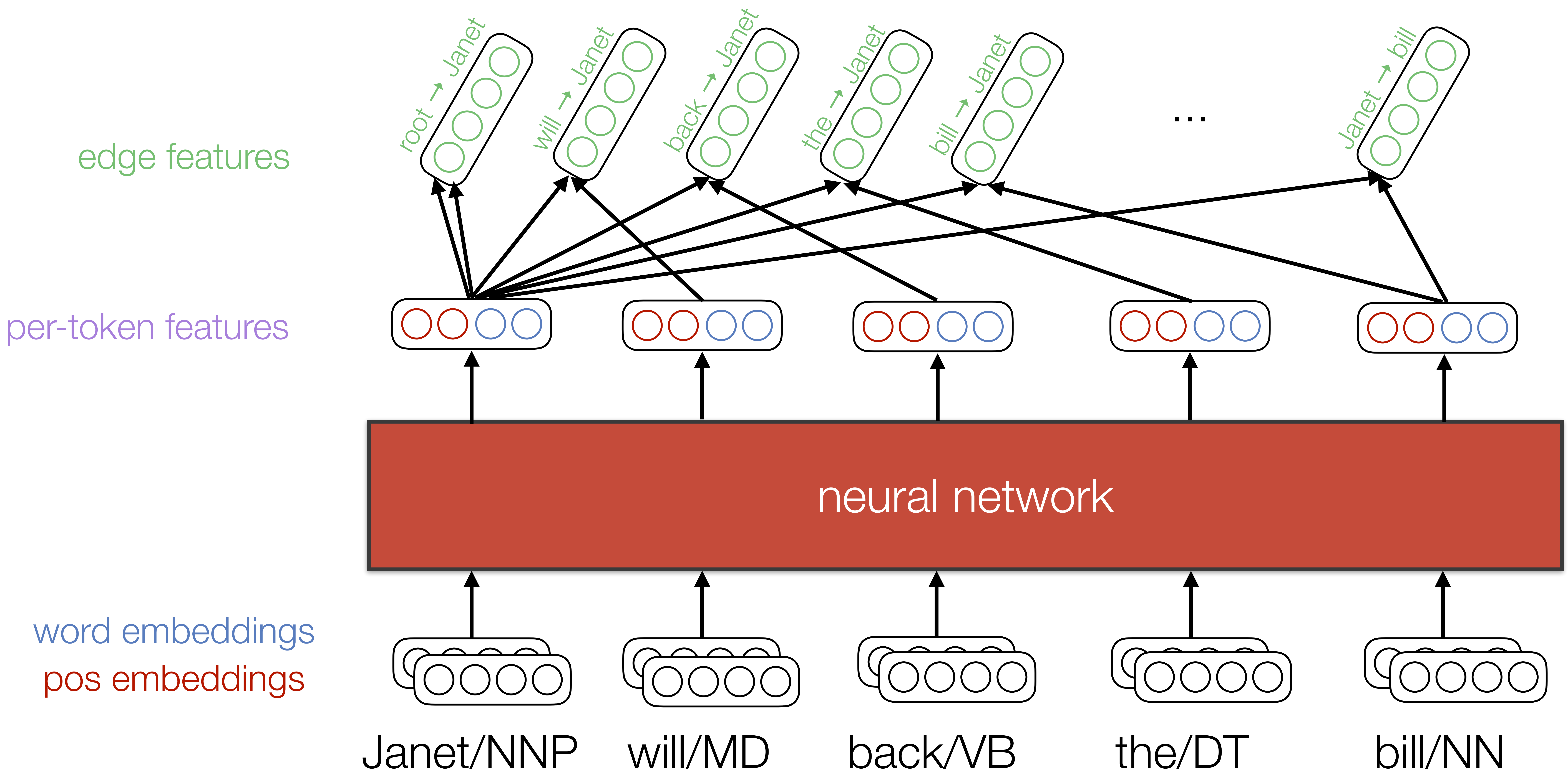

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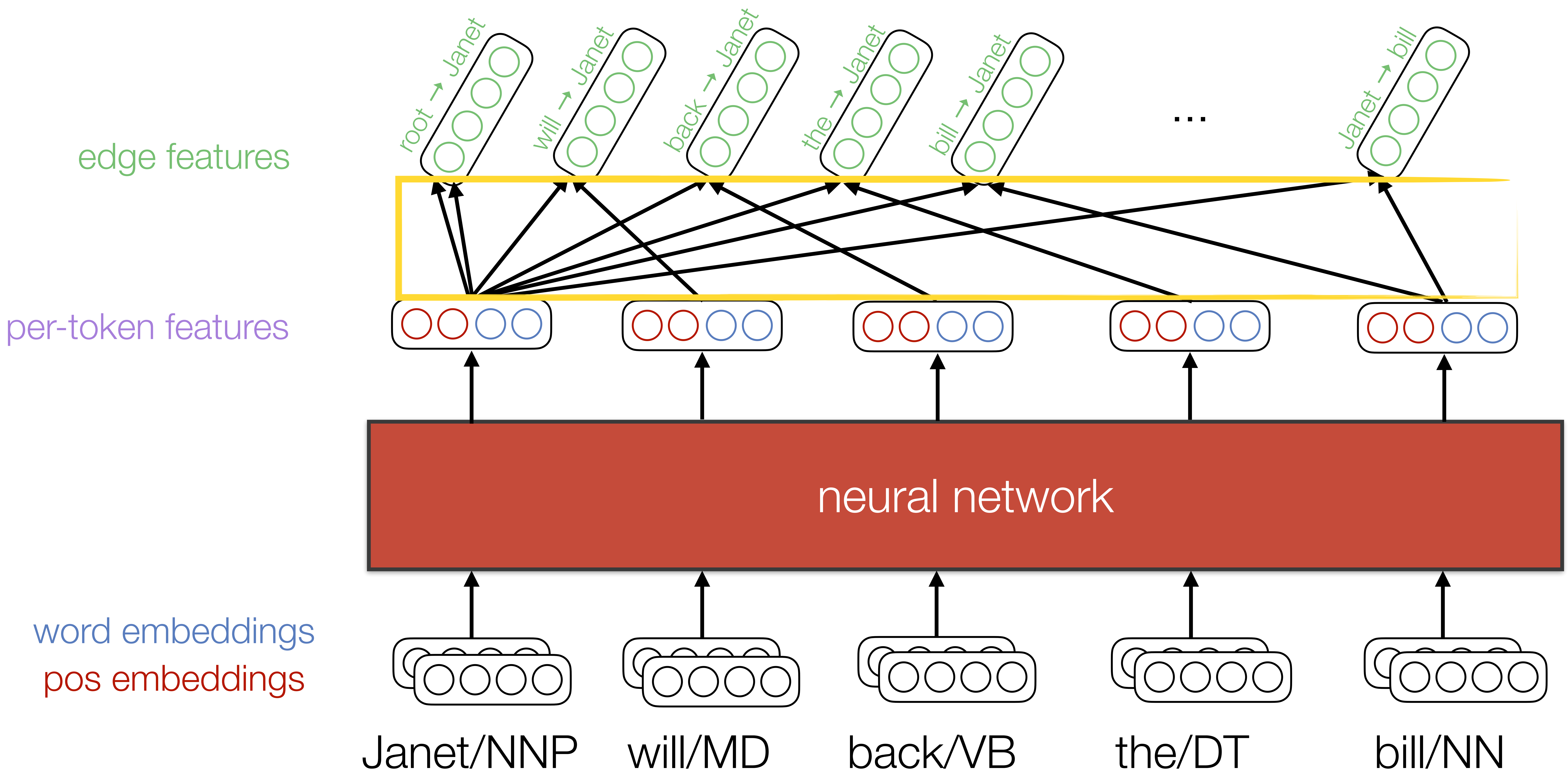
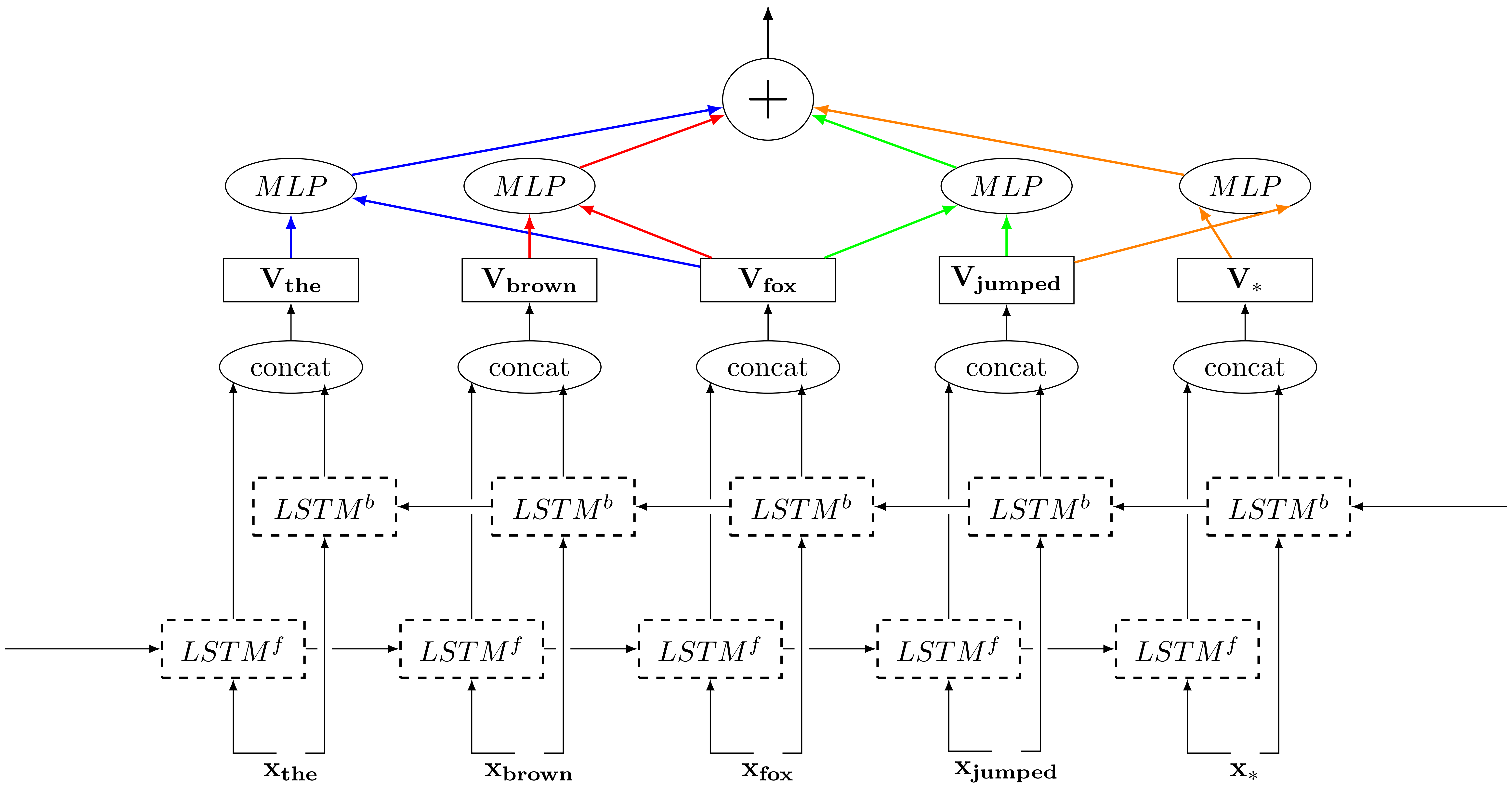


Graph-based neural network parsers

Graph-based neural network parsers

- Concat + feed-forward [Kiperwasser and Goldberg, 2016]



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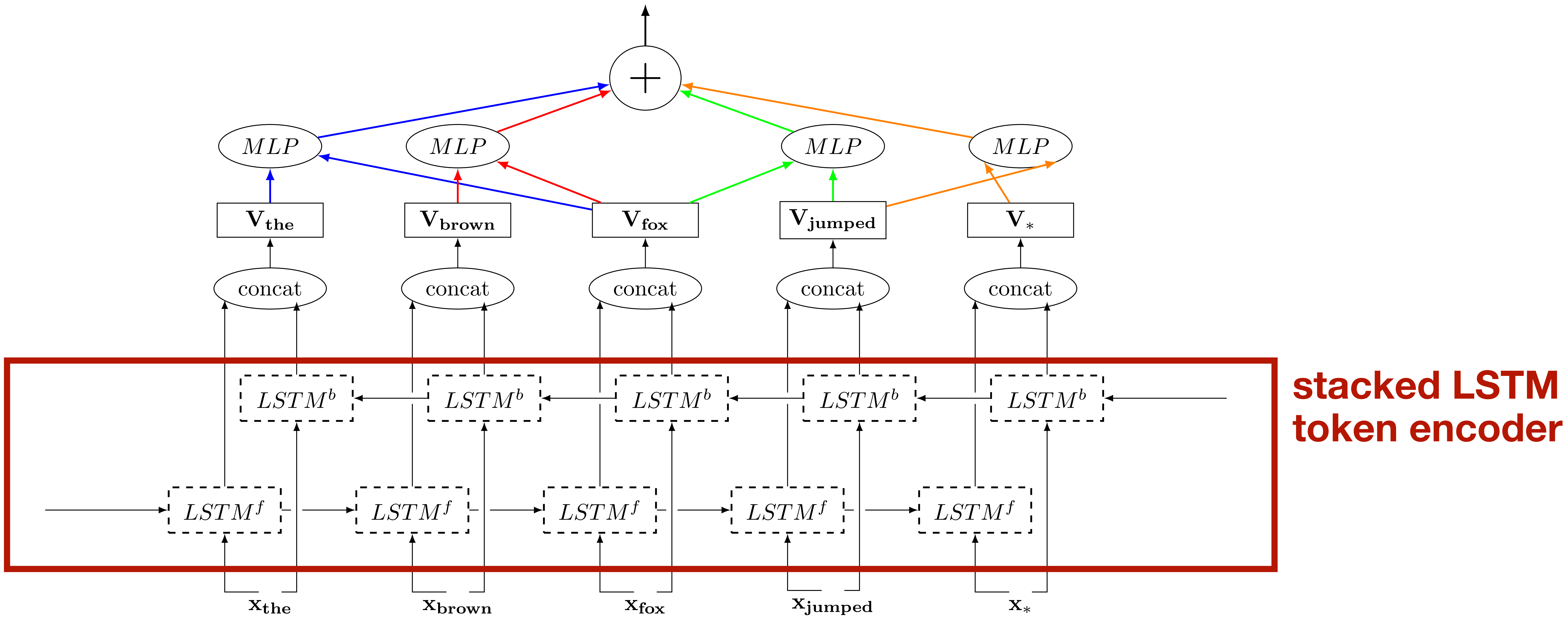

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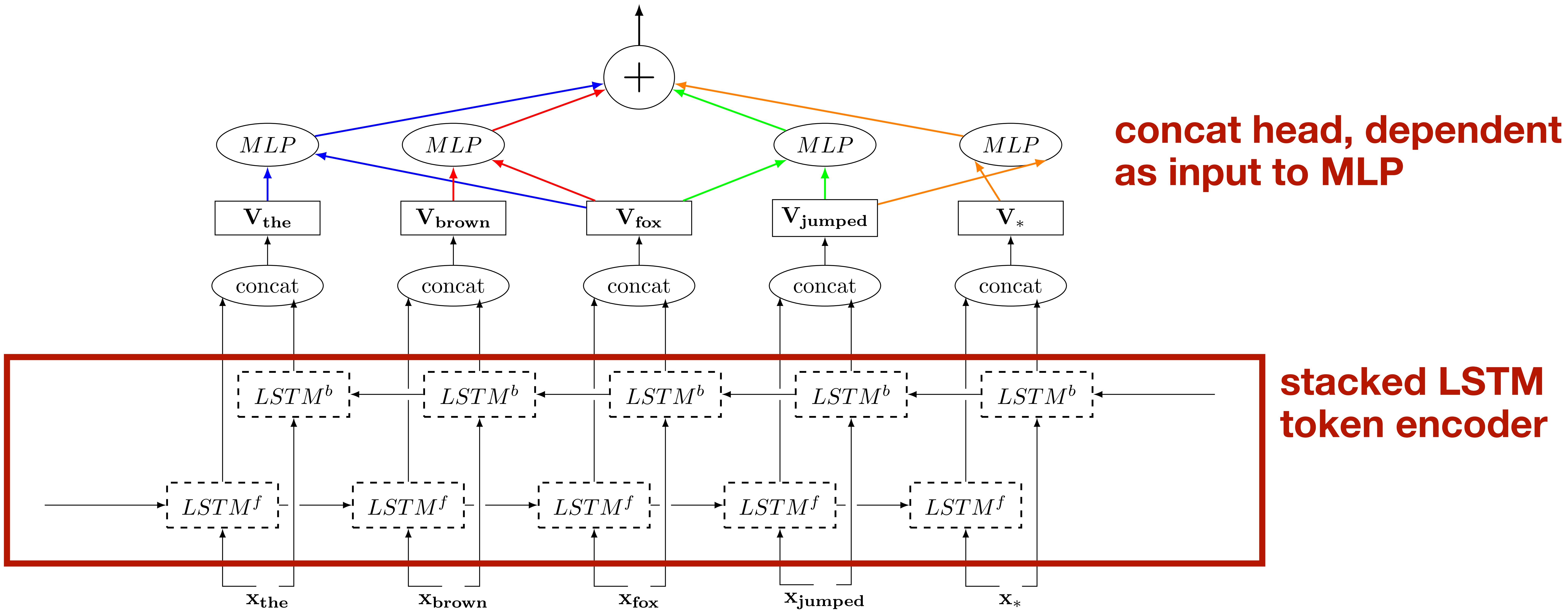
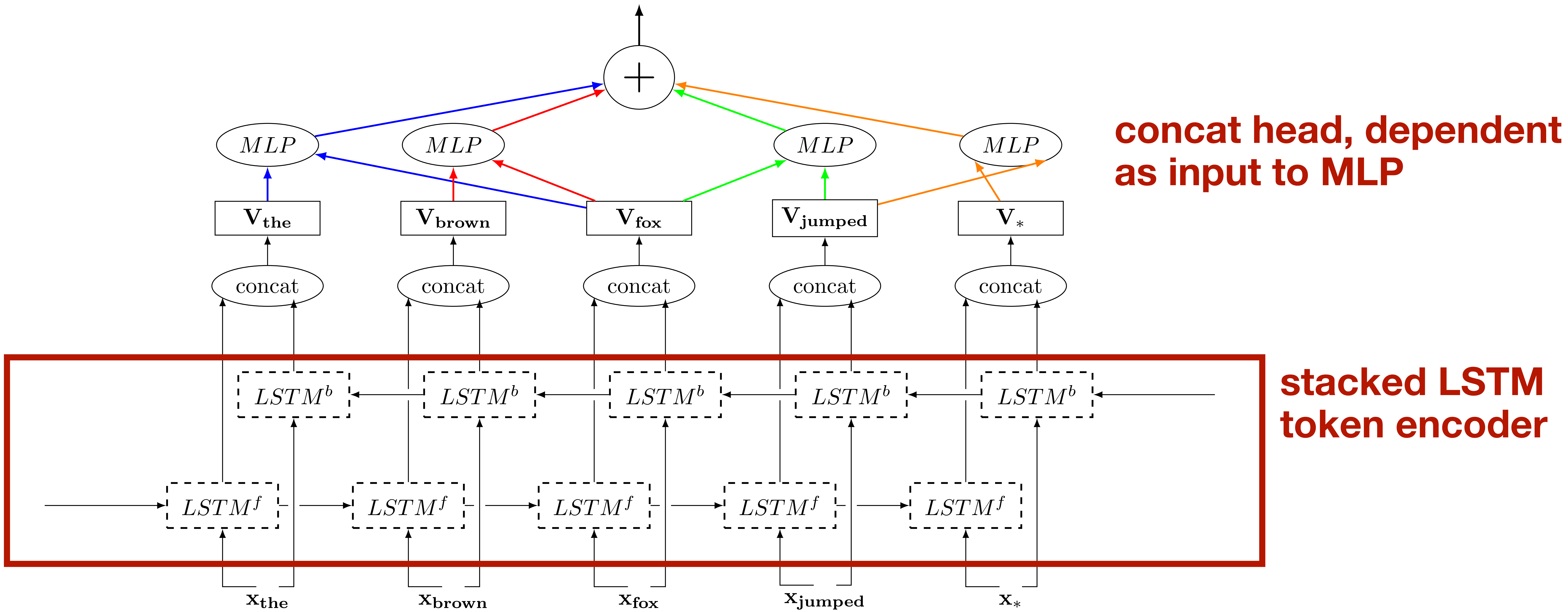


Graph-based neural network parsers

- Concat + feed-forward [Kiperwasser and Goldberg, 2016]
- Hinge loss: $max\Big(0, 1 - \max_{y' \neq y} \sum_{(h,m) \in y'} MLP(v_h \circ v_m) + \sum_{(h,m) \in y} MLP(v_h \circ v_m)\Big)$



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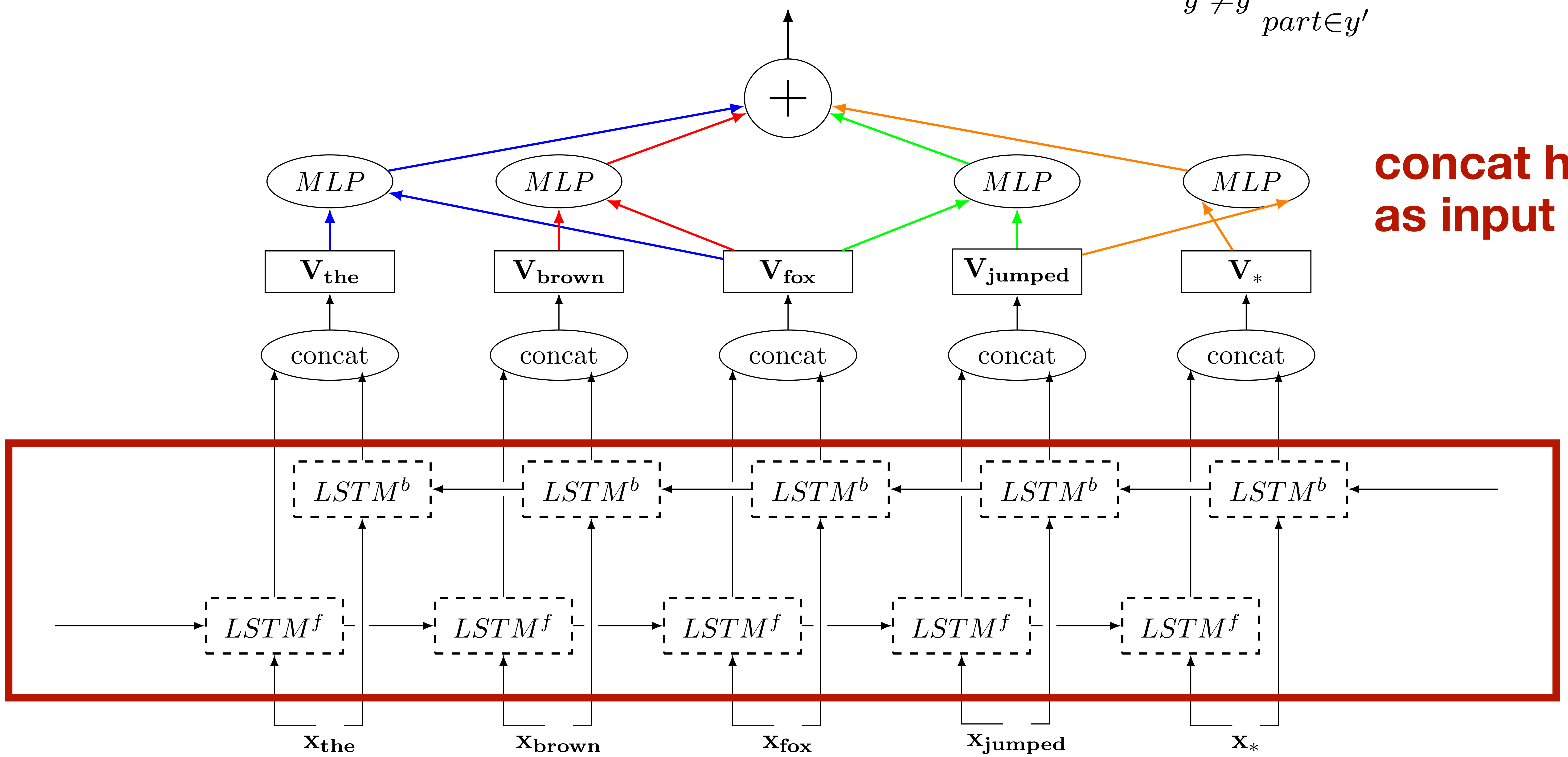
  - w/ loss augmented inference: $max(0, 1 + score(x,y) - \max_{y' \neq y} \sum_{part \in y'} (score_{local}(x, part) + \mathbb{1}_{part \notin y}))$



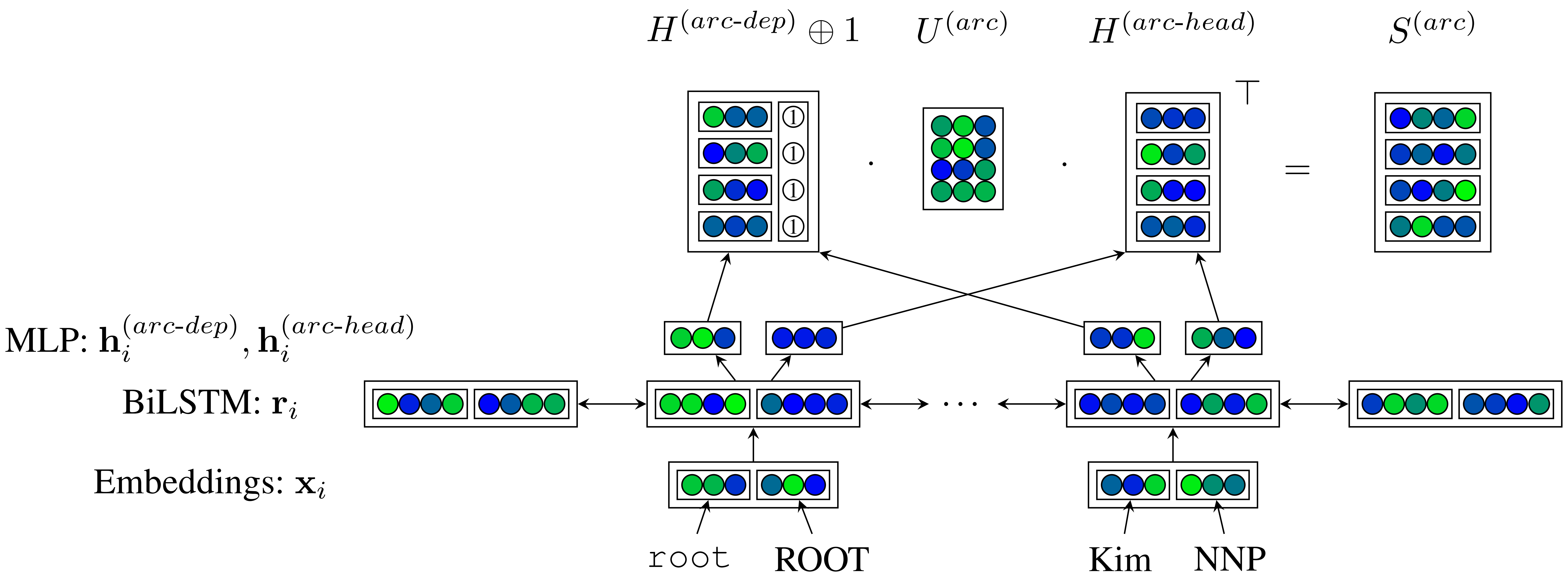
concat head, dependent as input to MLP

stacked LSTM token encoder

Graph-based neural network parsers

Graph-based neural network parsers

- Biaffine classifier [Dozat and Manning, 2017]



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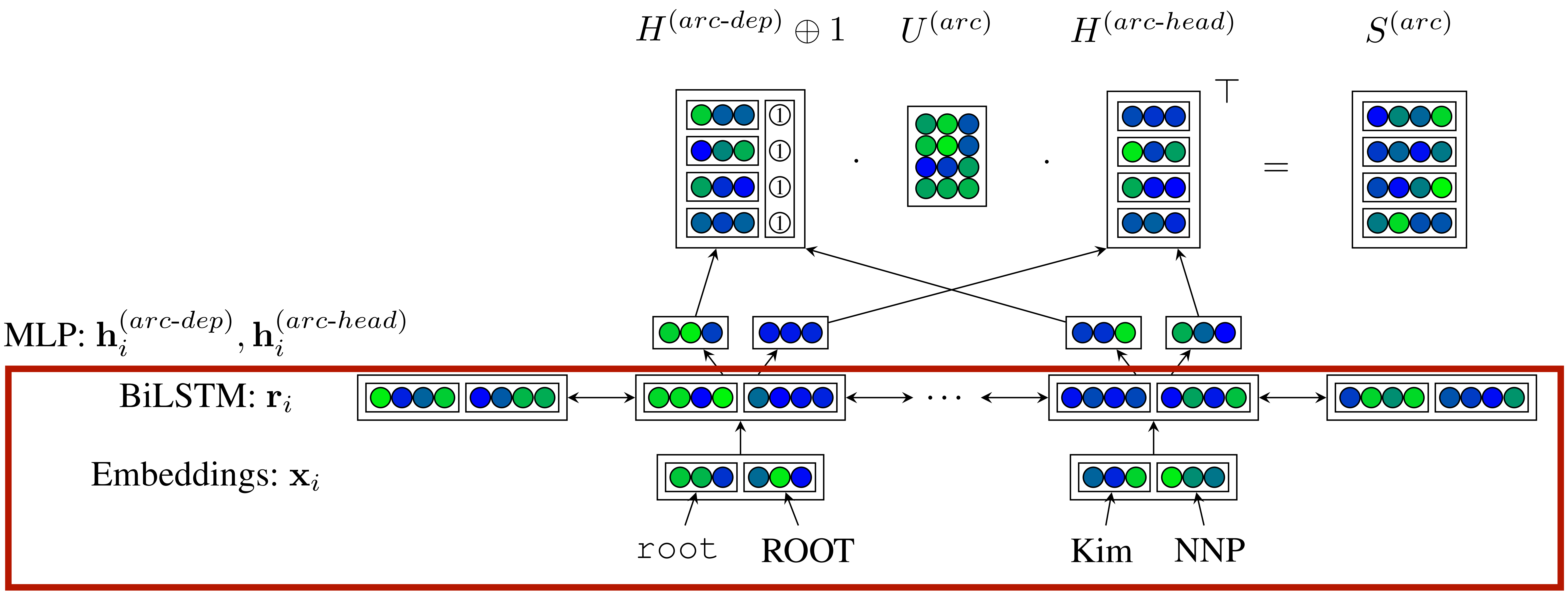

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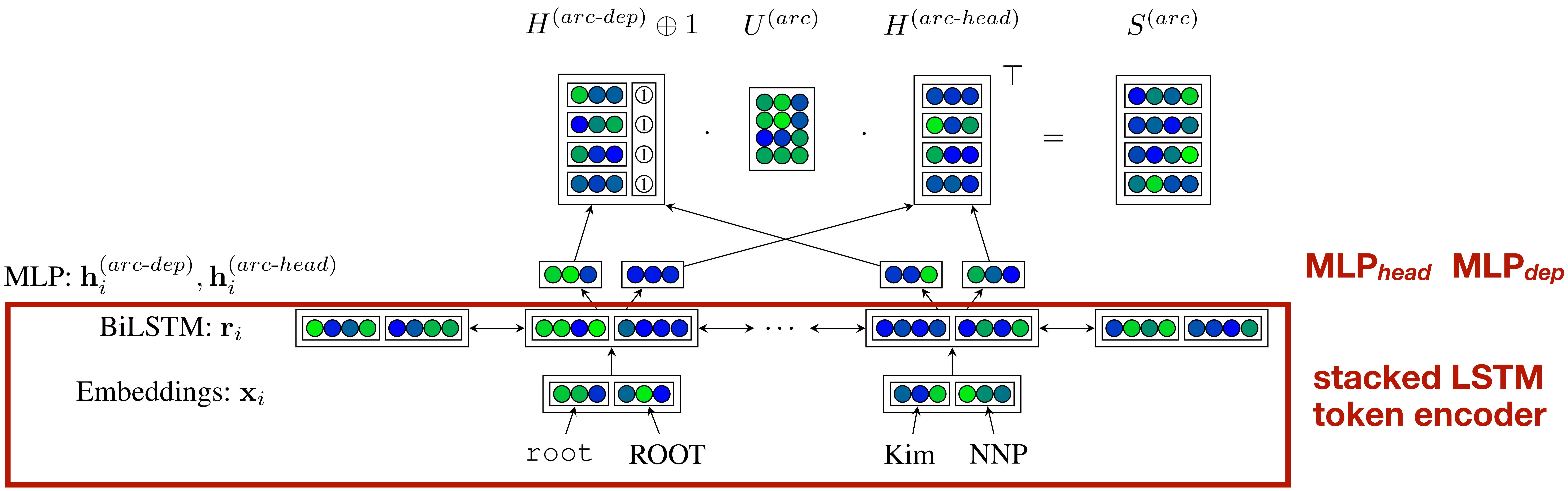

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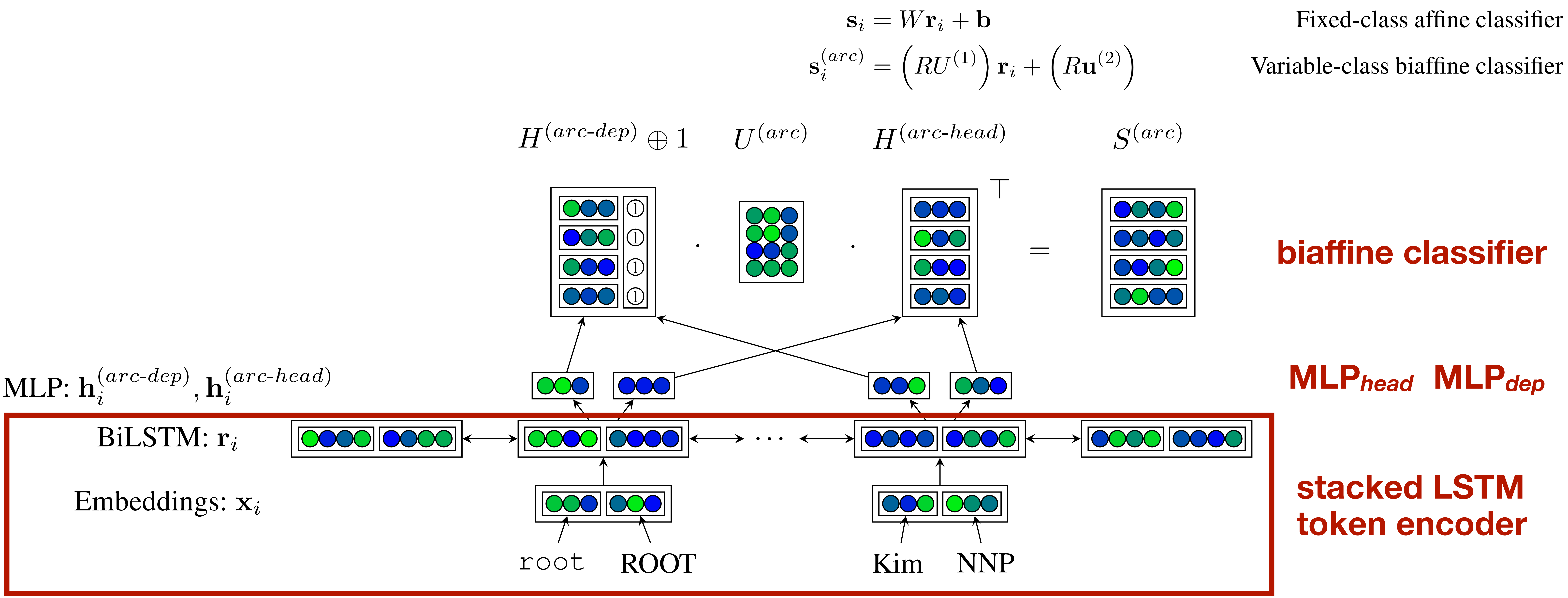
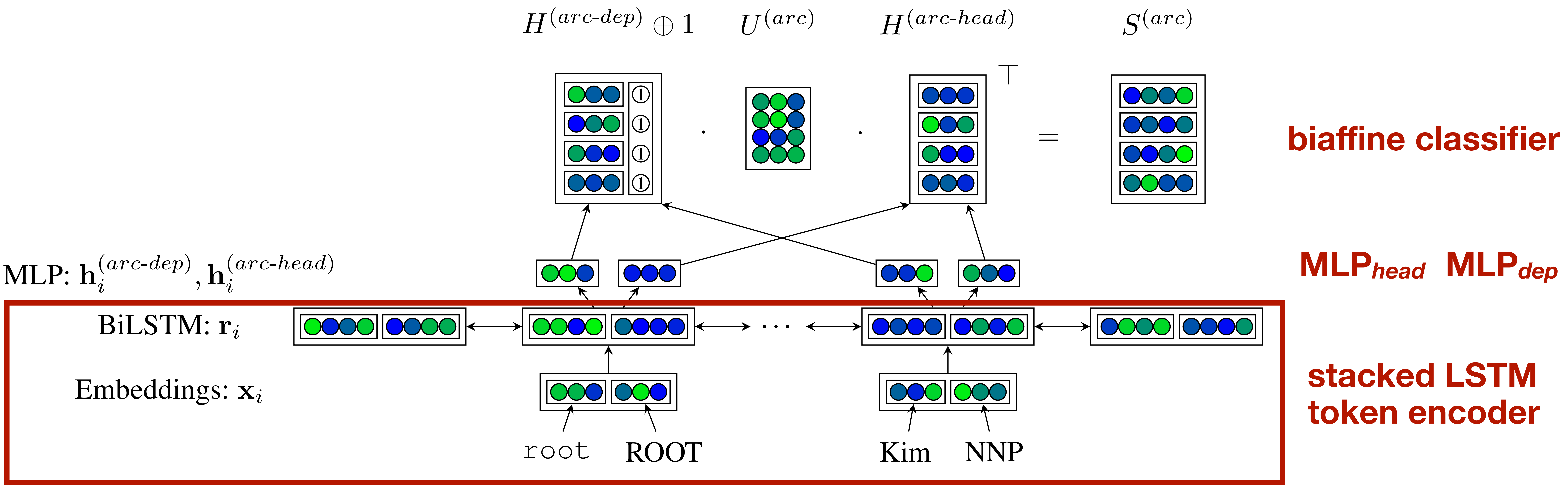


Graph-based neural network parsers

- Biaffine classifier [Dozat and Manning, 2017]
- Locally normalized log loss.

$$\mathbf{s}_i = W\mathbf{r}_i + \mathbf{b} \qquad \text{Fixed-class affine classifier}$$

$$\mathbf{s}_i^{(arc)} = \left(RU^{(1)}\right)\mathbf{r}_i + \left(R\mathbf{u}^{(2)}\right) \qquad \text{Variable-class biaffine classifier}$$



Graph-based dependency parsing

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First order $\overset{\frown}{h \quad m}$

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    - Locally normalized: predict each head and its label, softmax, log loss.

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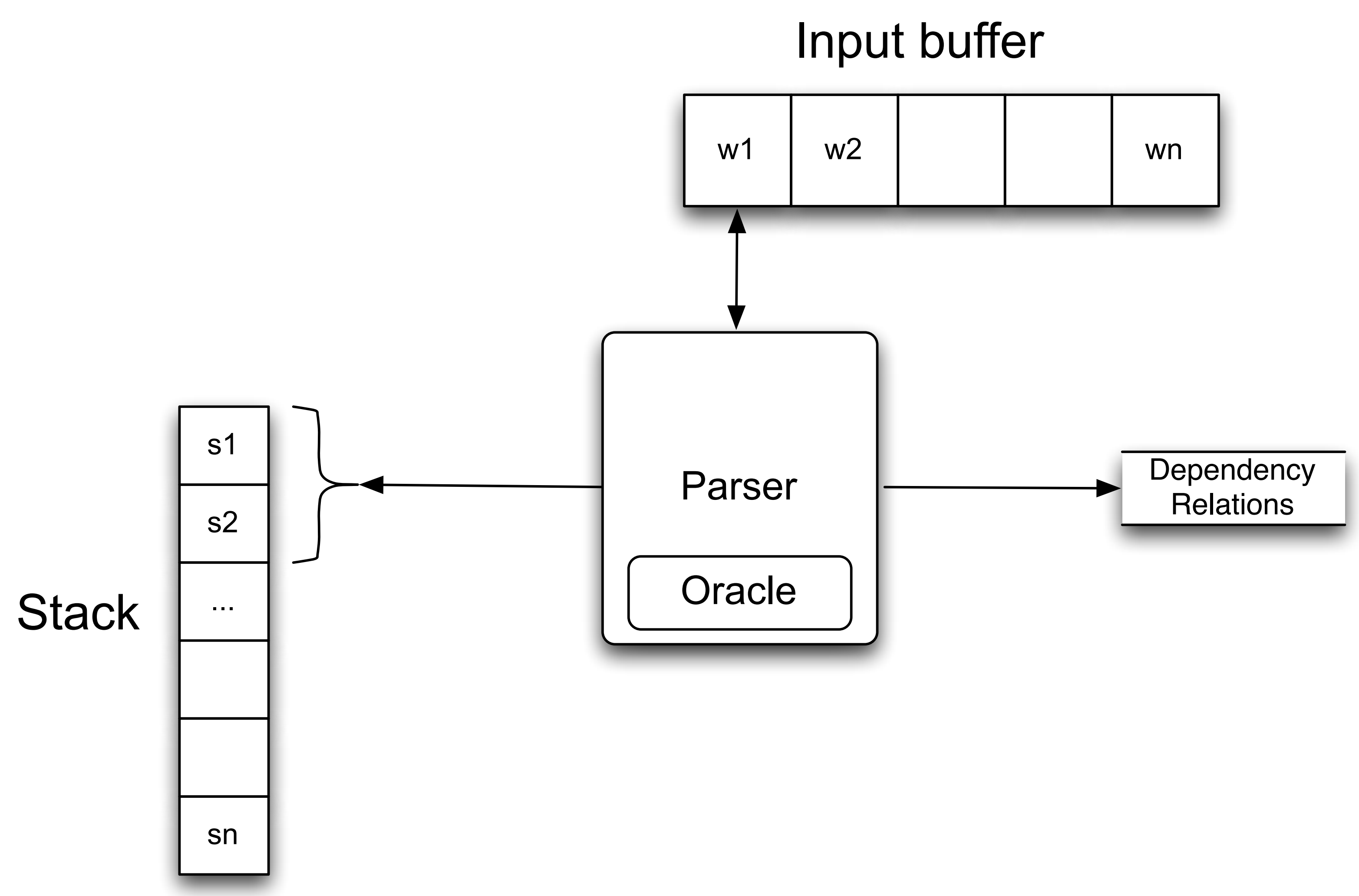
  - Locally normalized: predict each head and its label, softmax, log loss.
  - Hinge loss: Find the best scoring tree, and penalize edges not in the gold tree (with a margin).
  - Globally normalized CRF: can compute marginals/partition function using a variant of Kirchhoff's Matrix-Tree Theorem [Tutte, 1984; Koo et al. 2007].

Graph-based vs. transition-based parsing?

Graph-based vs. transition-based parsing?

- **Transition-based**
  - Fast
  - Greedy / local inference
  - Maybe closer to humans?



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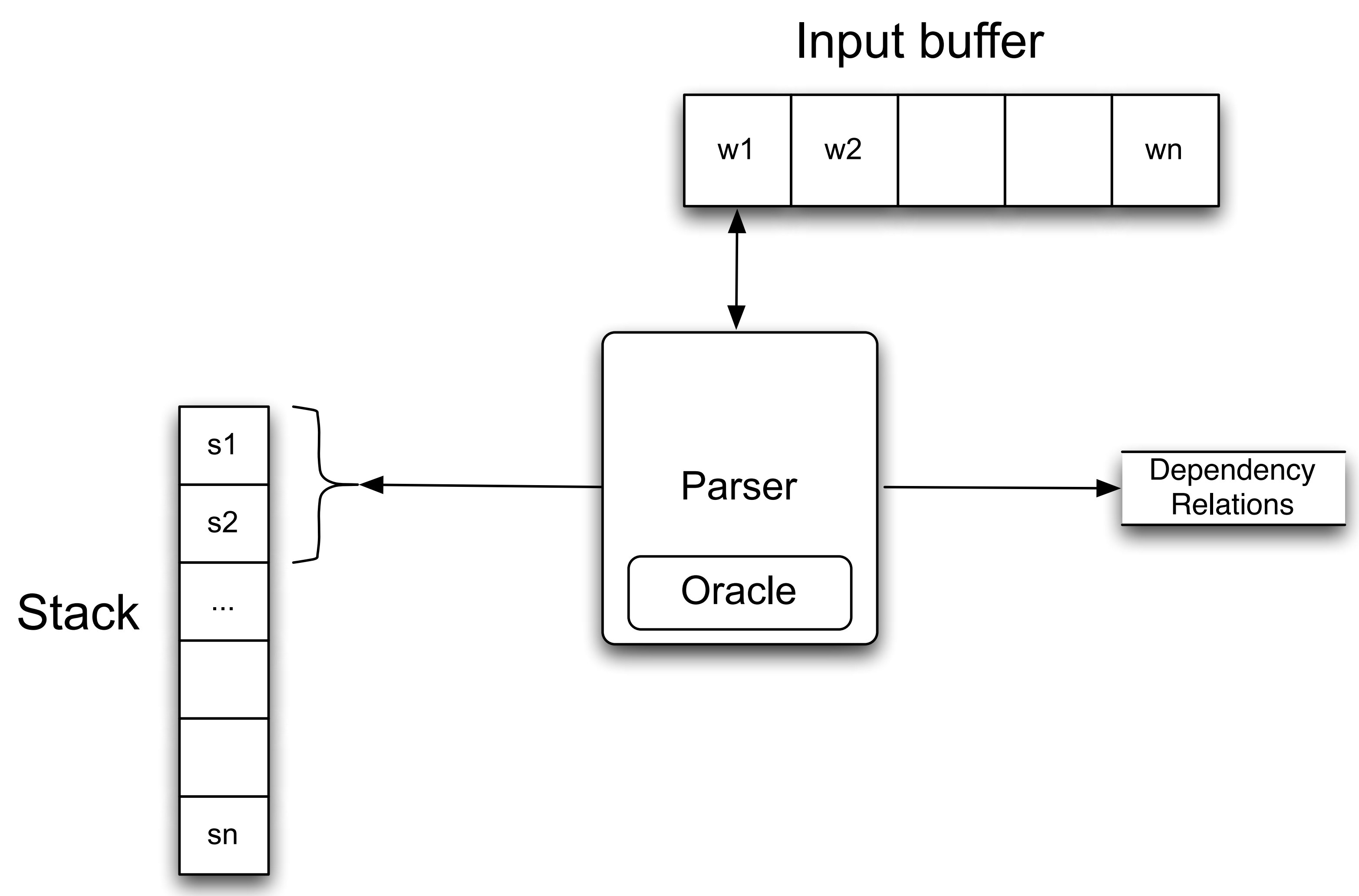
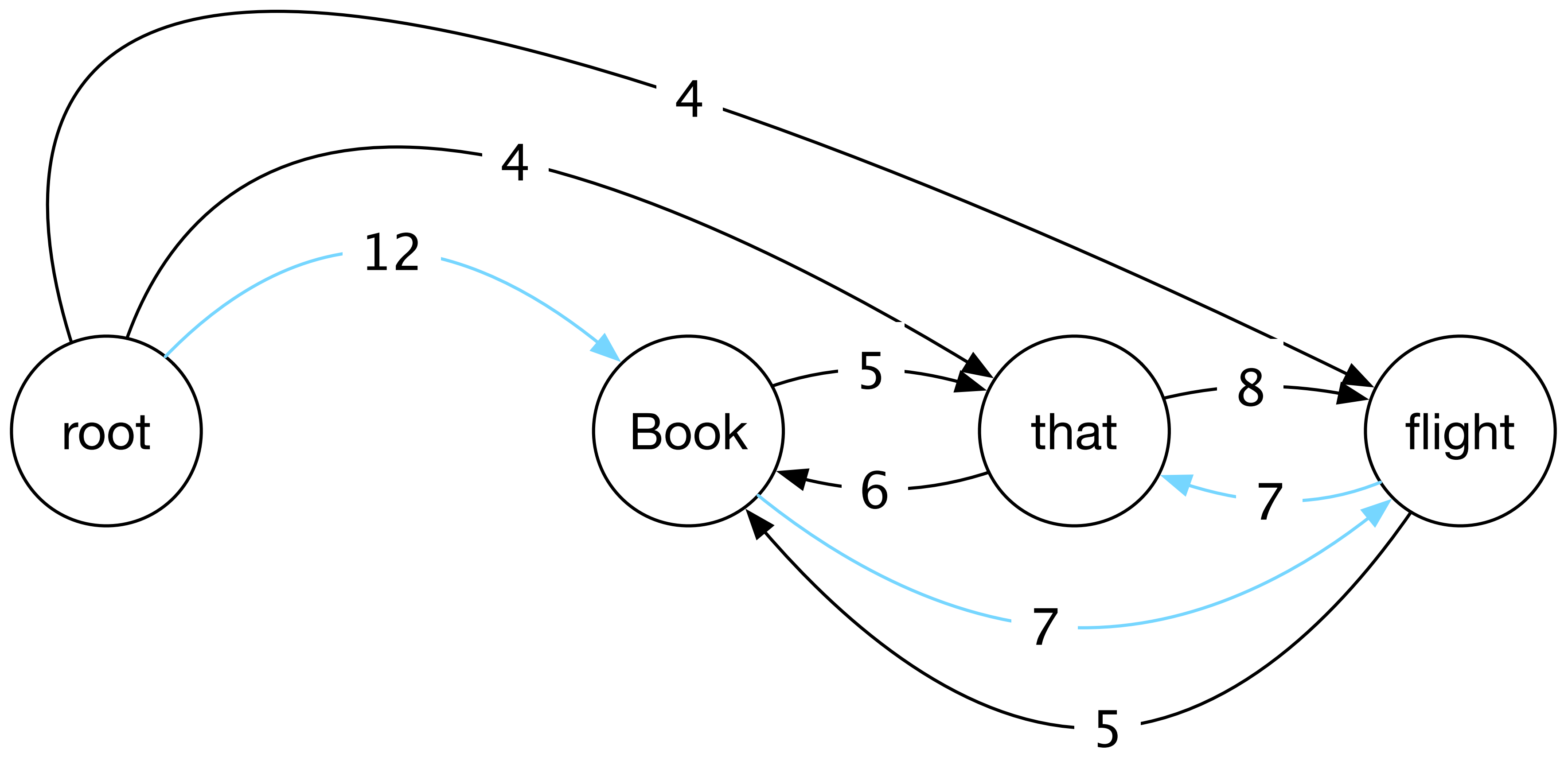
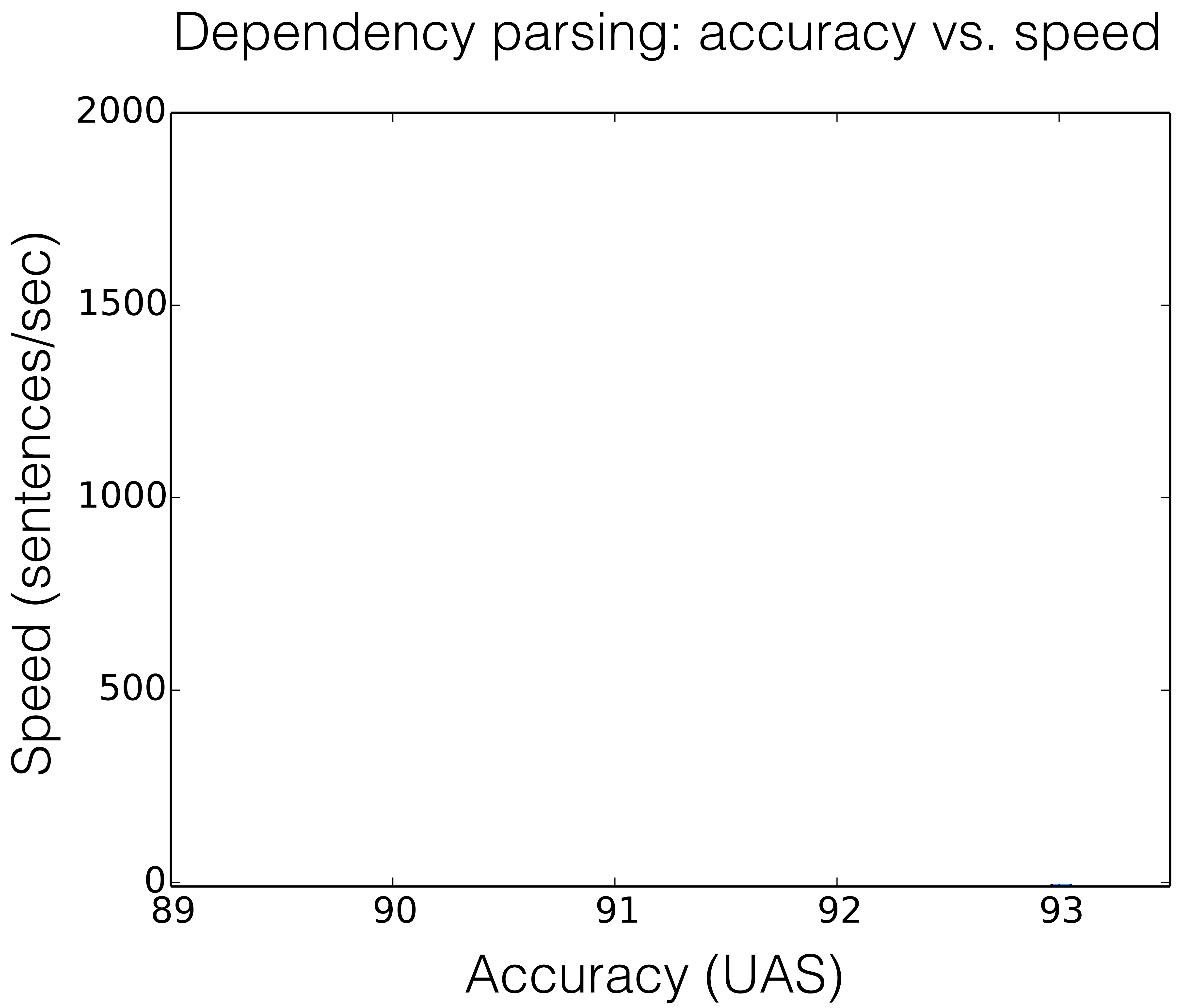


- **Graph-based**
  - Slow
  - Exact inference
  - More accurate



Graph-based vs. transition-based parsing?



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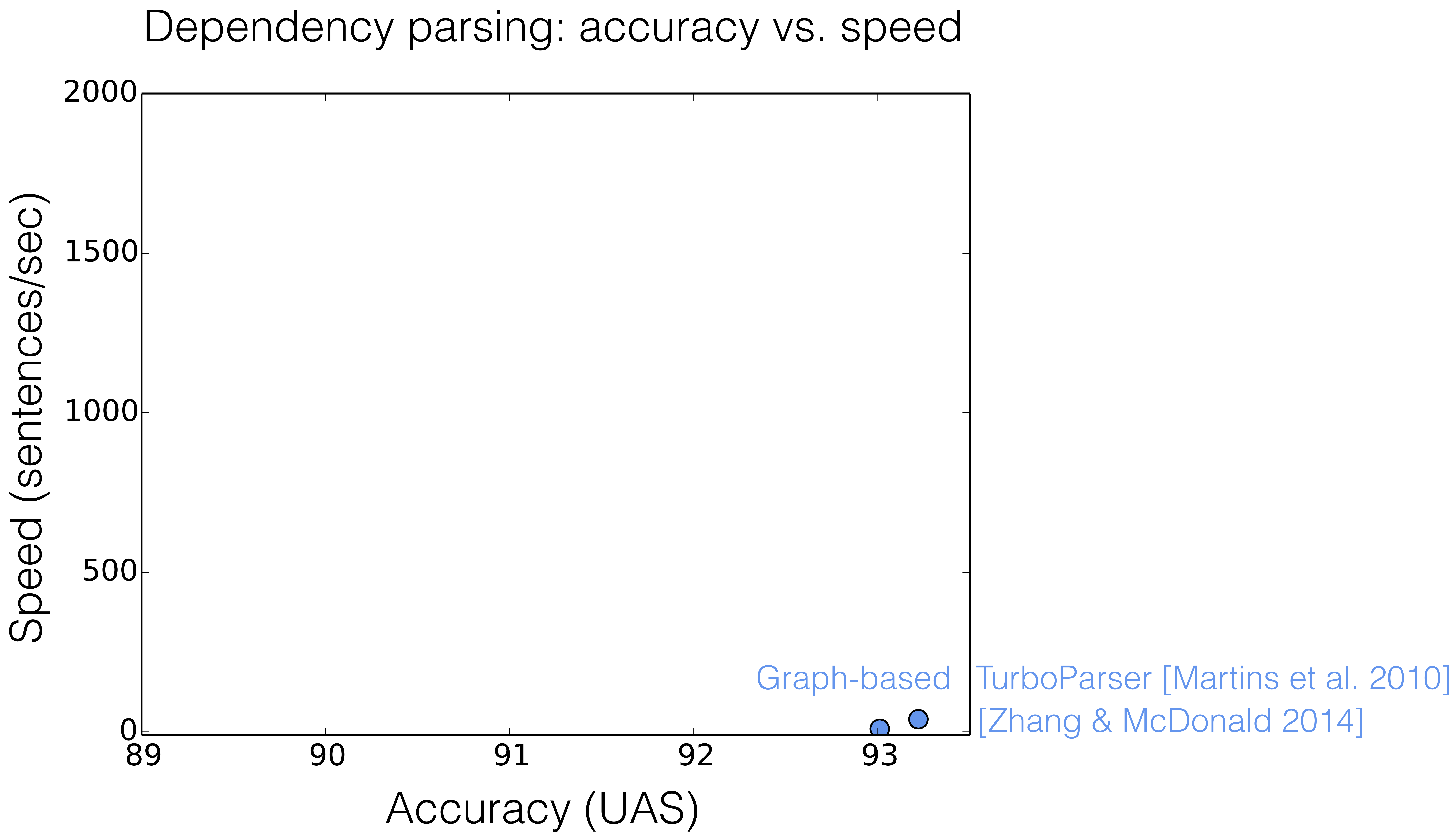
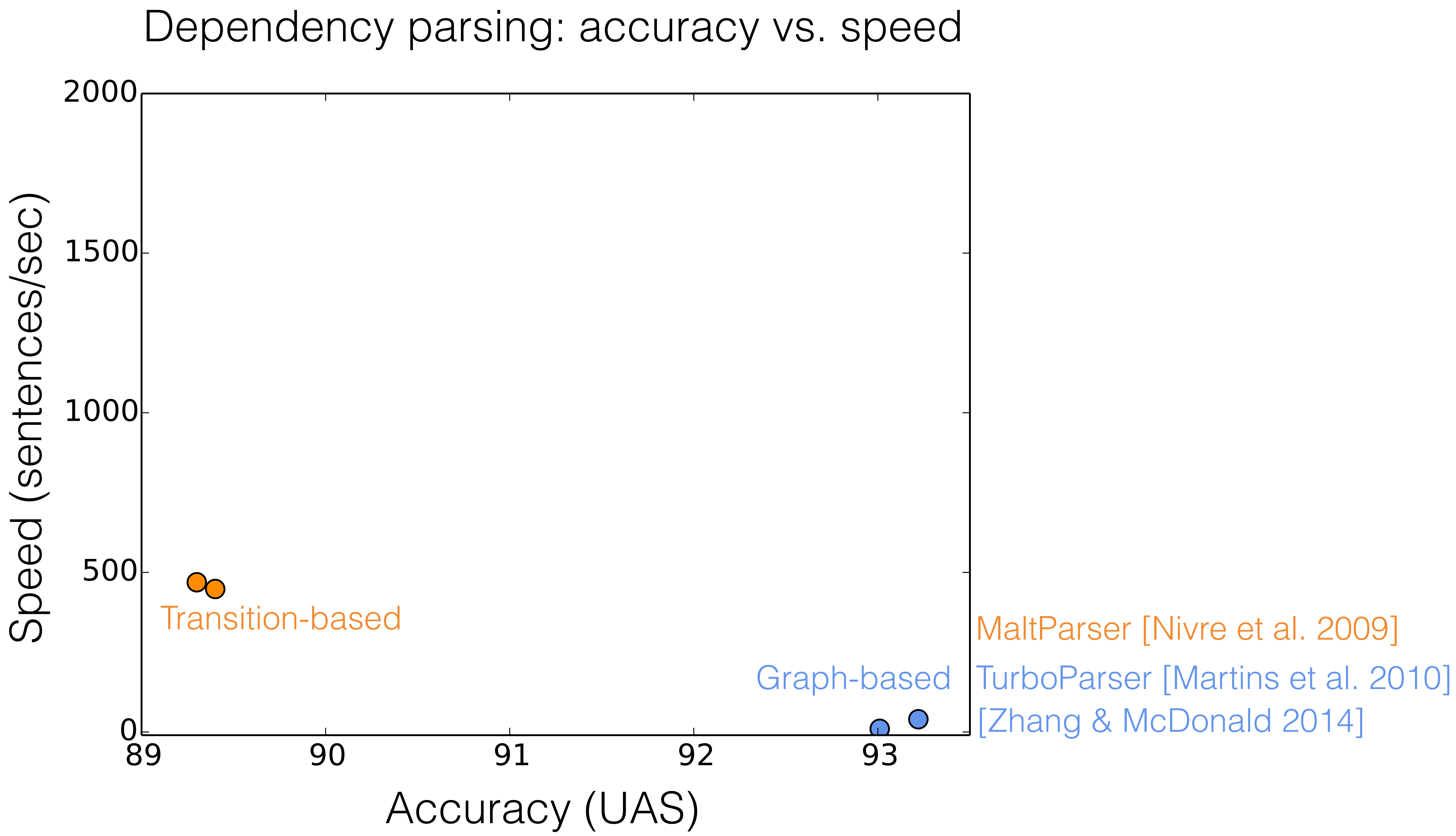


Graph-based vs. transition-based parsing?



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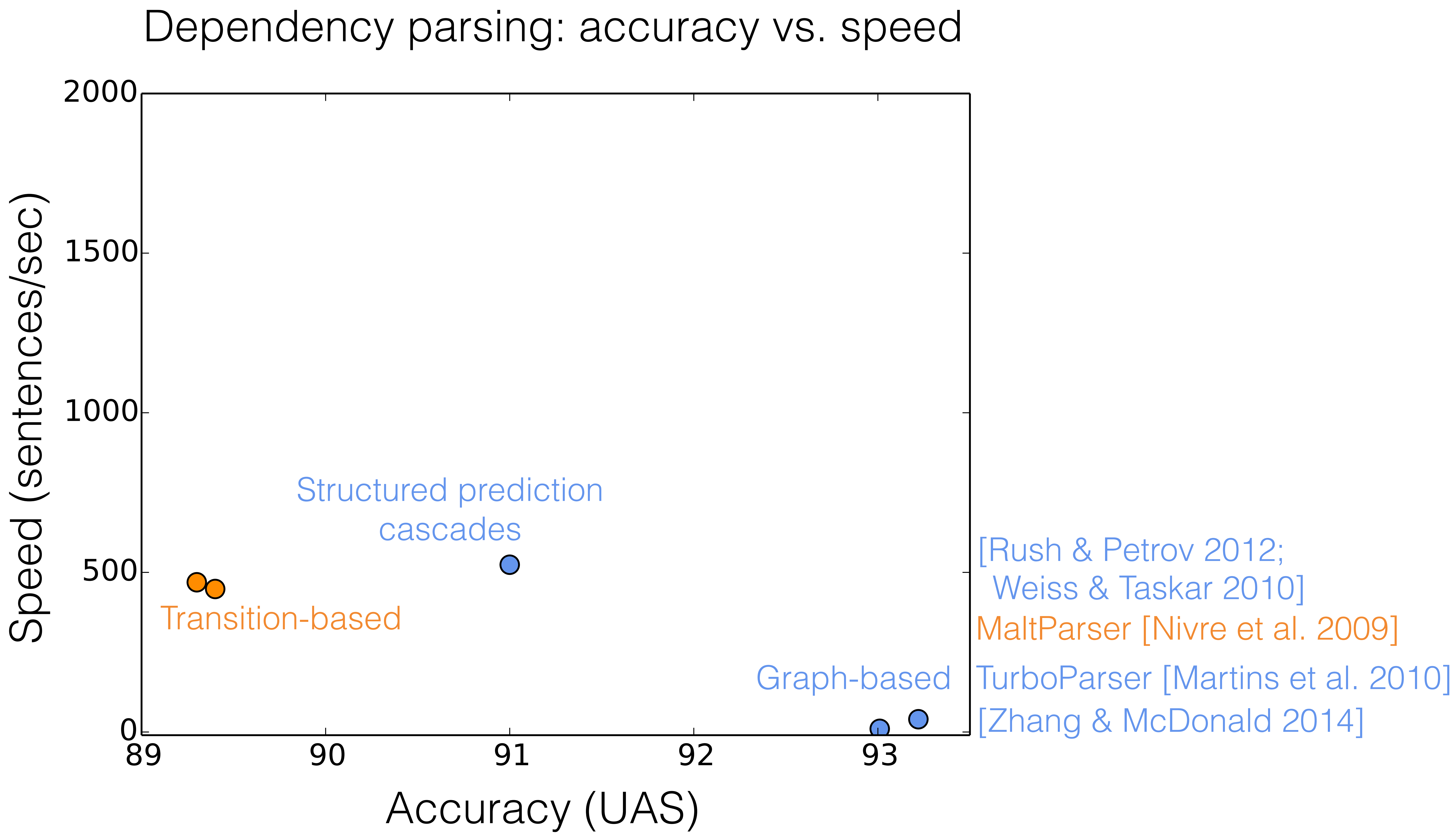

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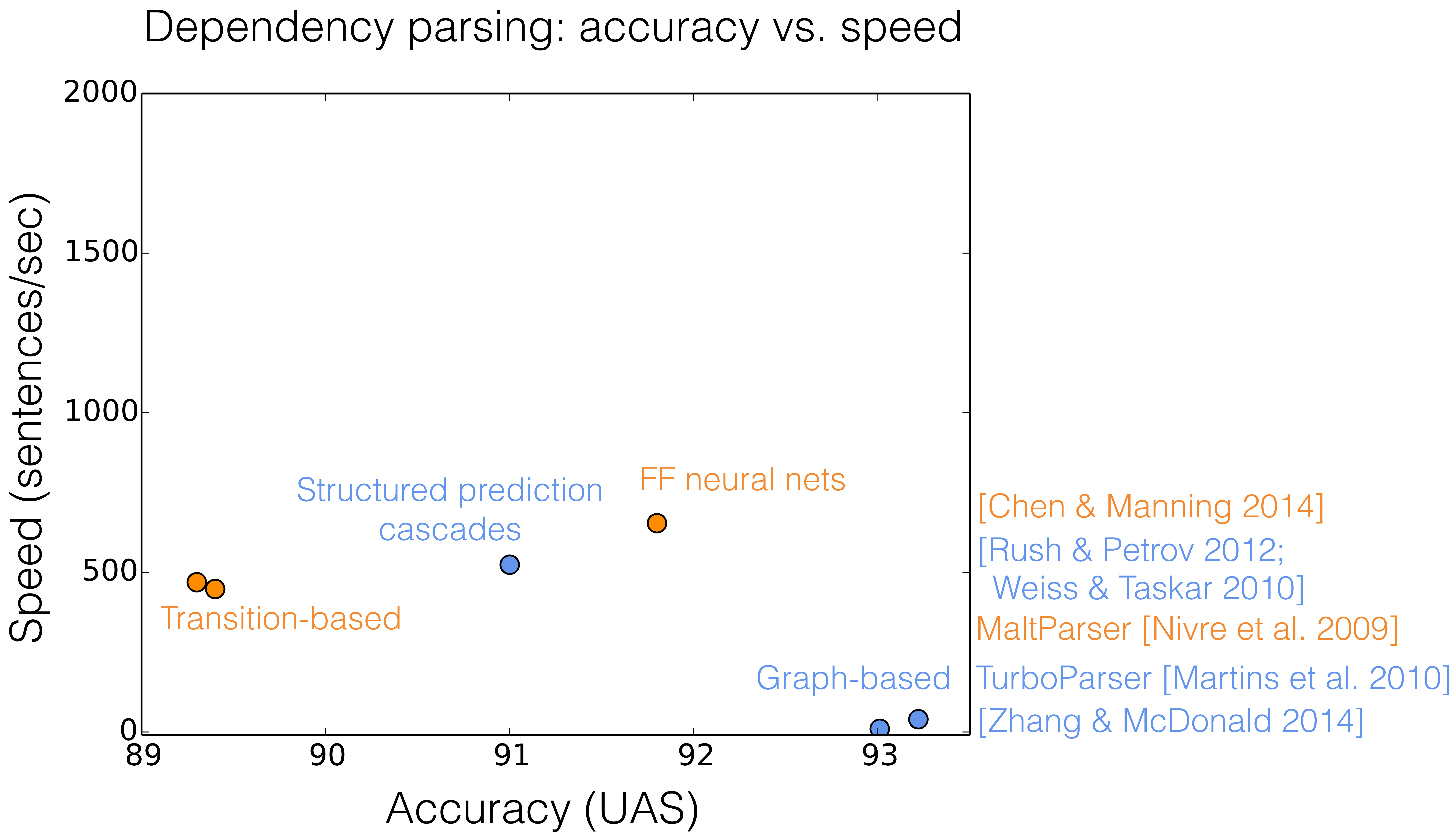

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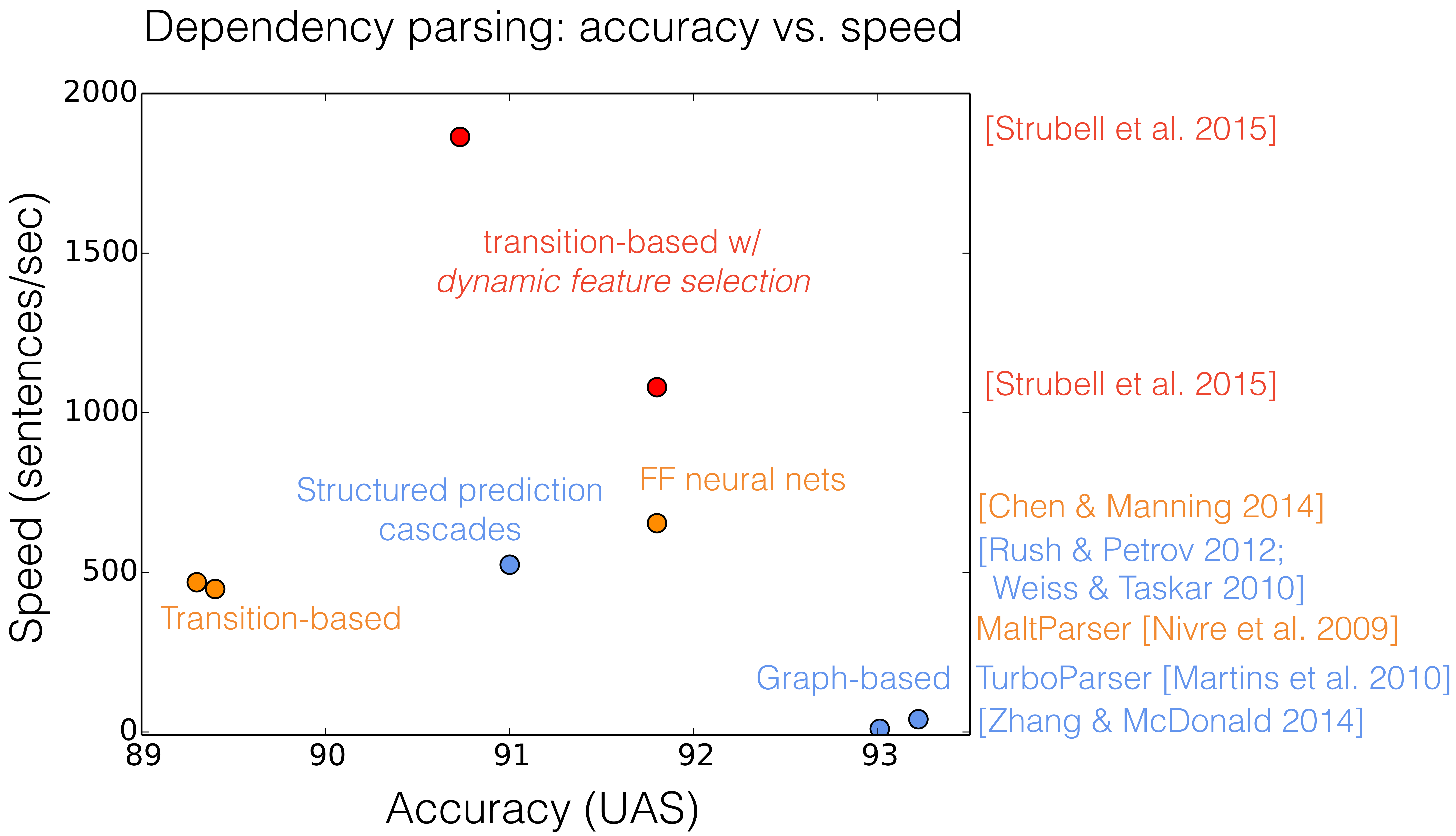

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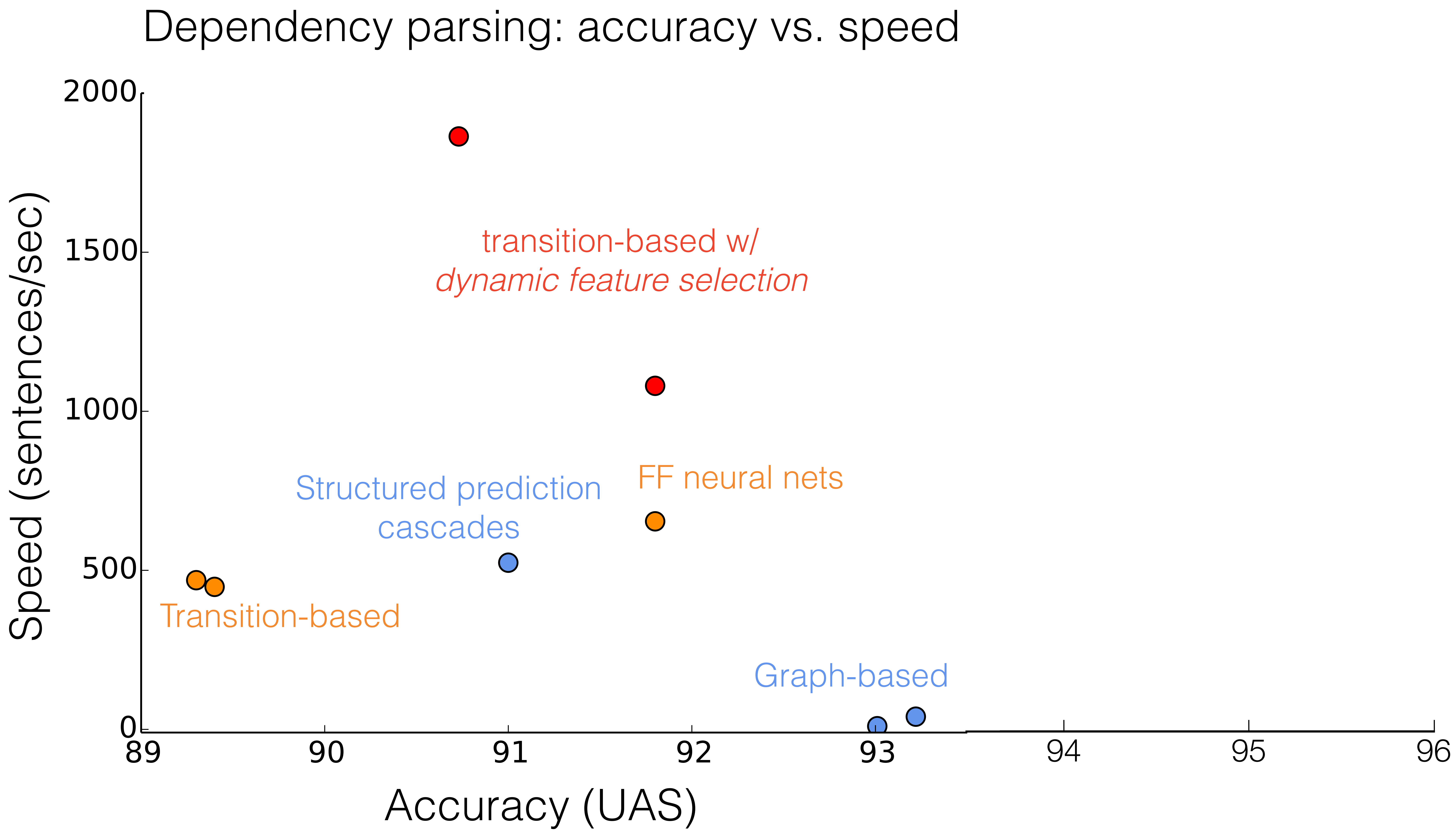

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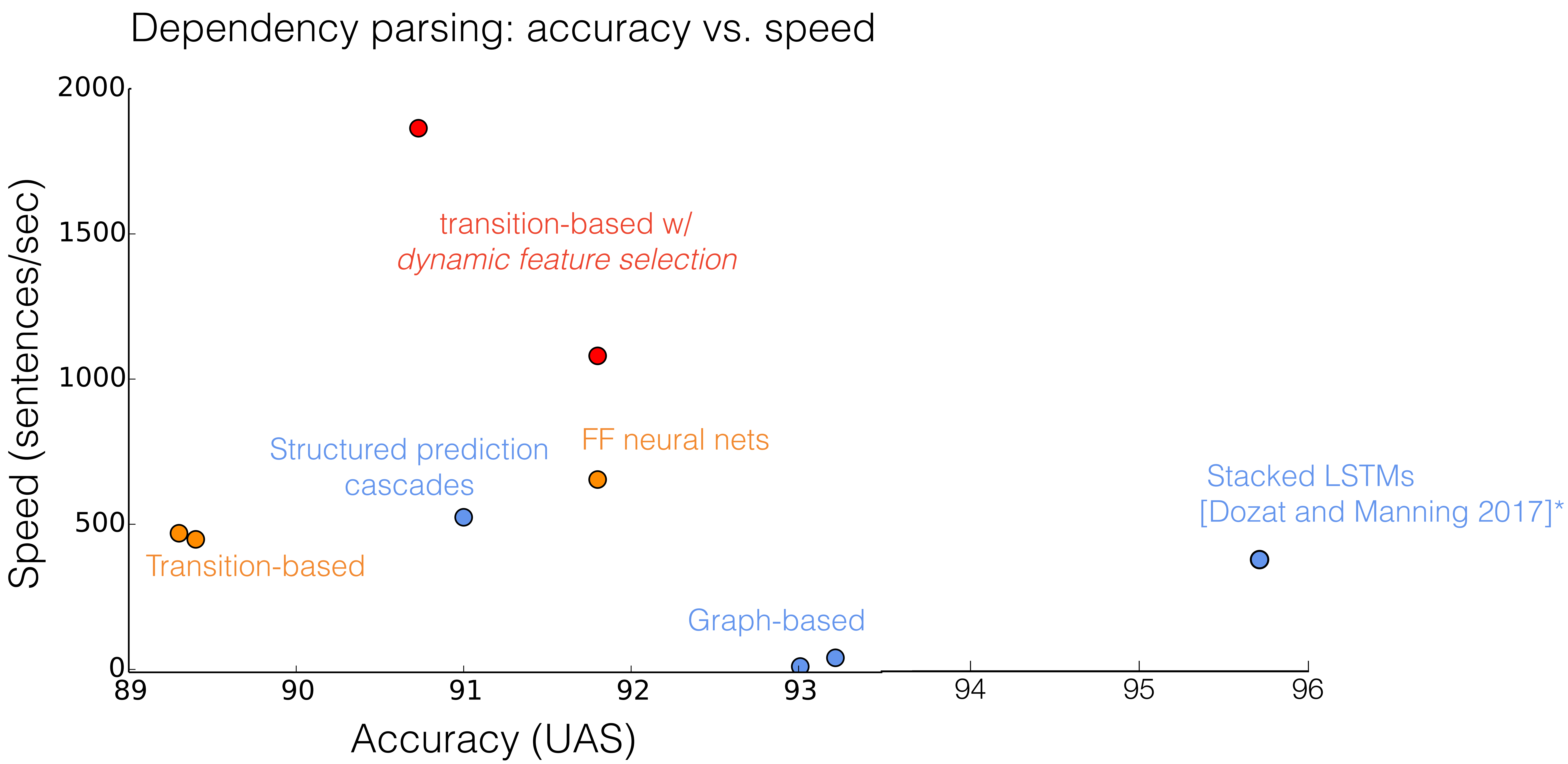

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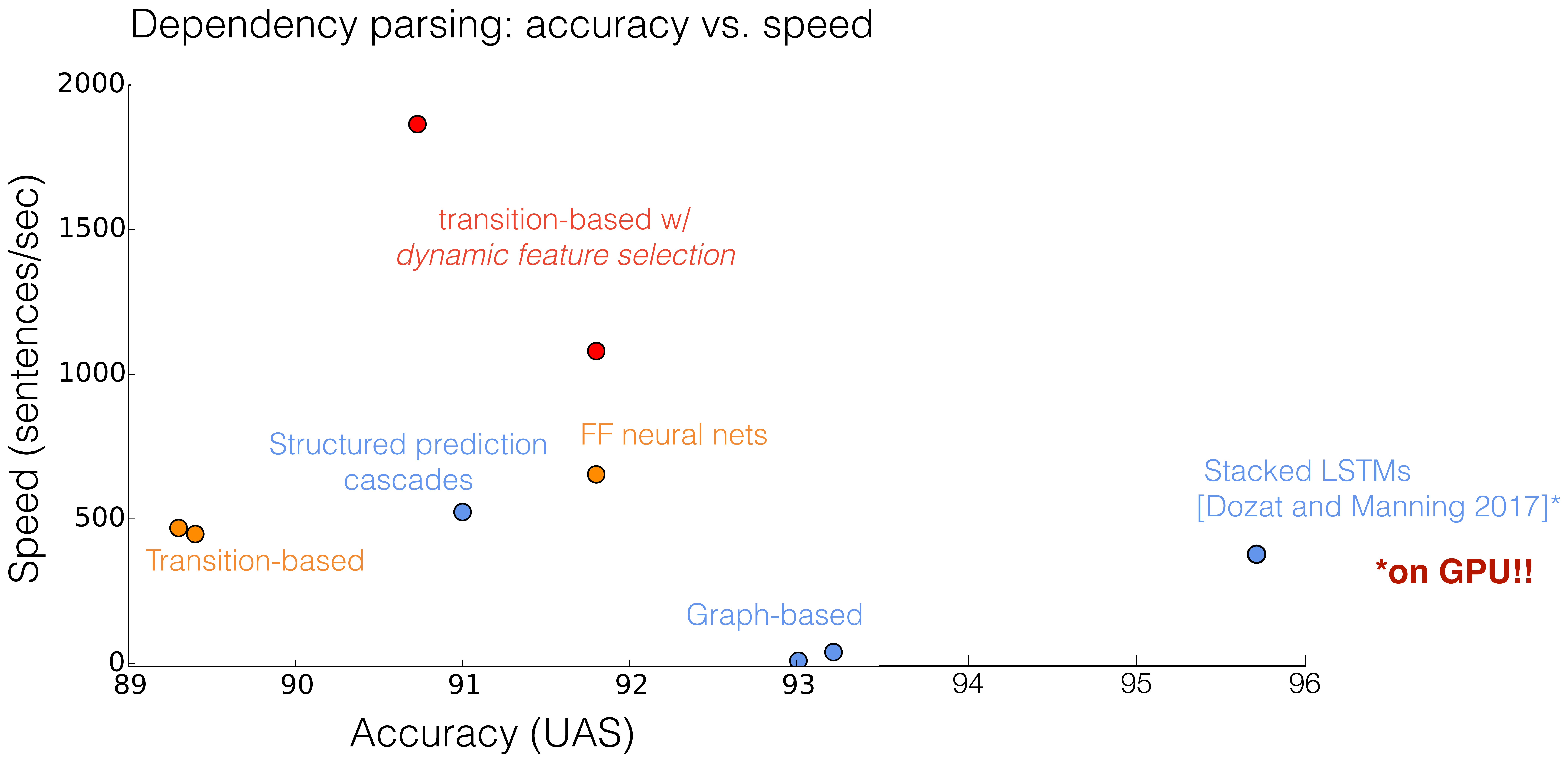

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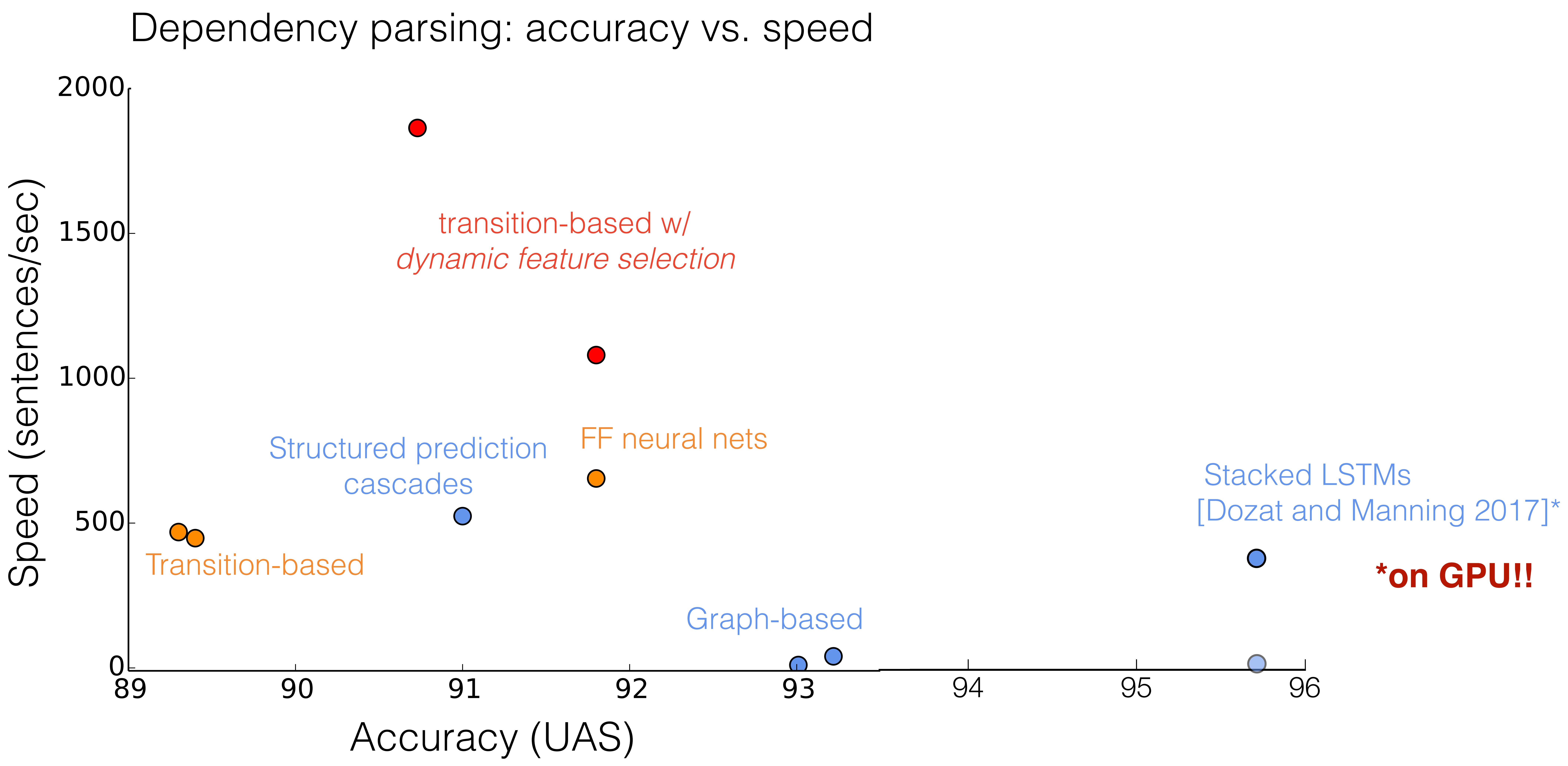

Announcements

- No recitation on Friday (Tartan Community Day).