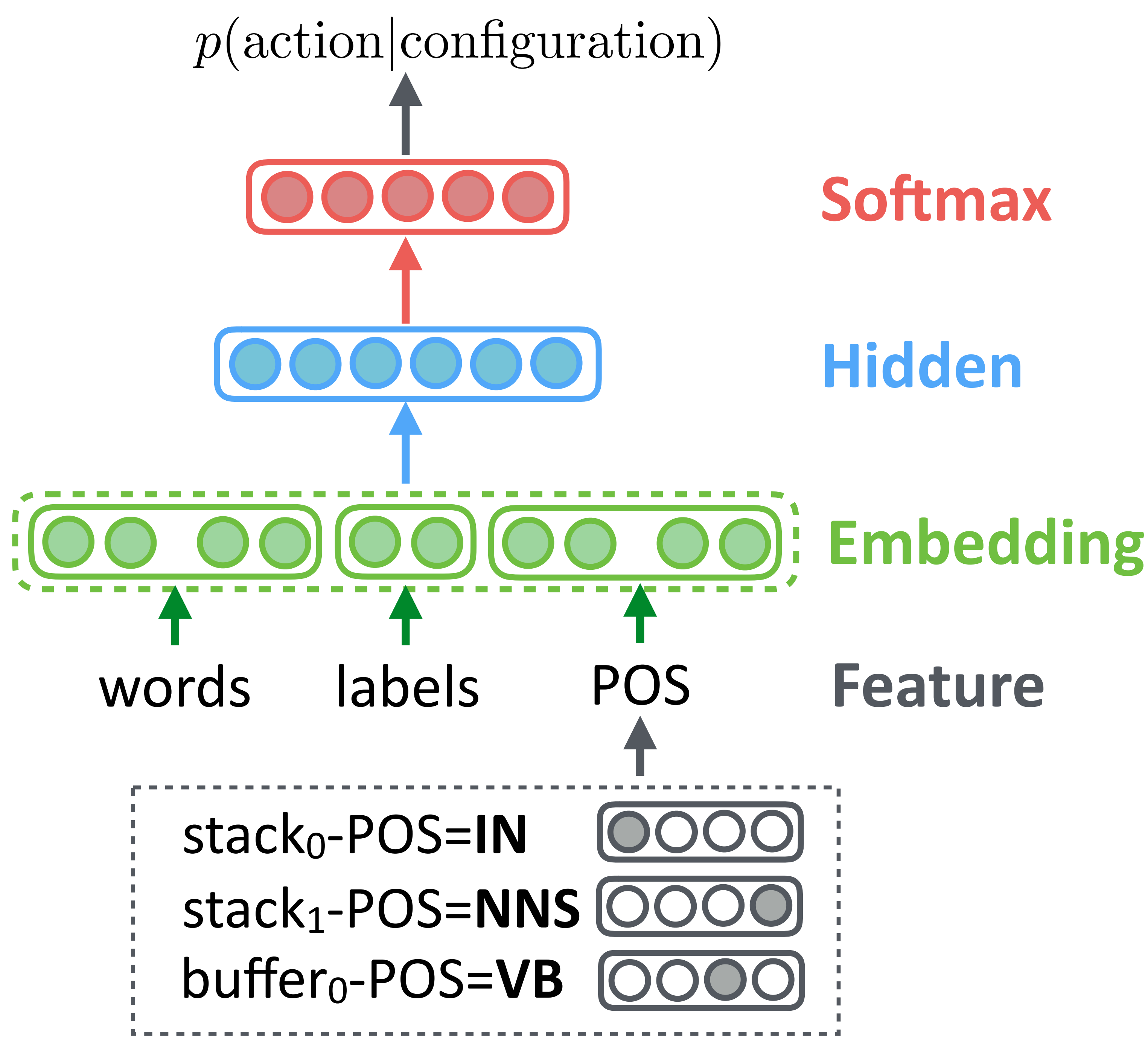
Stack-propagation: Improved Representation Learning for Syntax

Yuan Zhang, David Weiss

MIT, Google

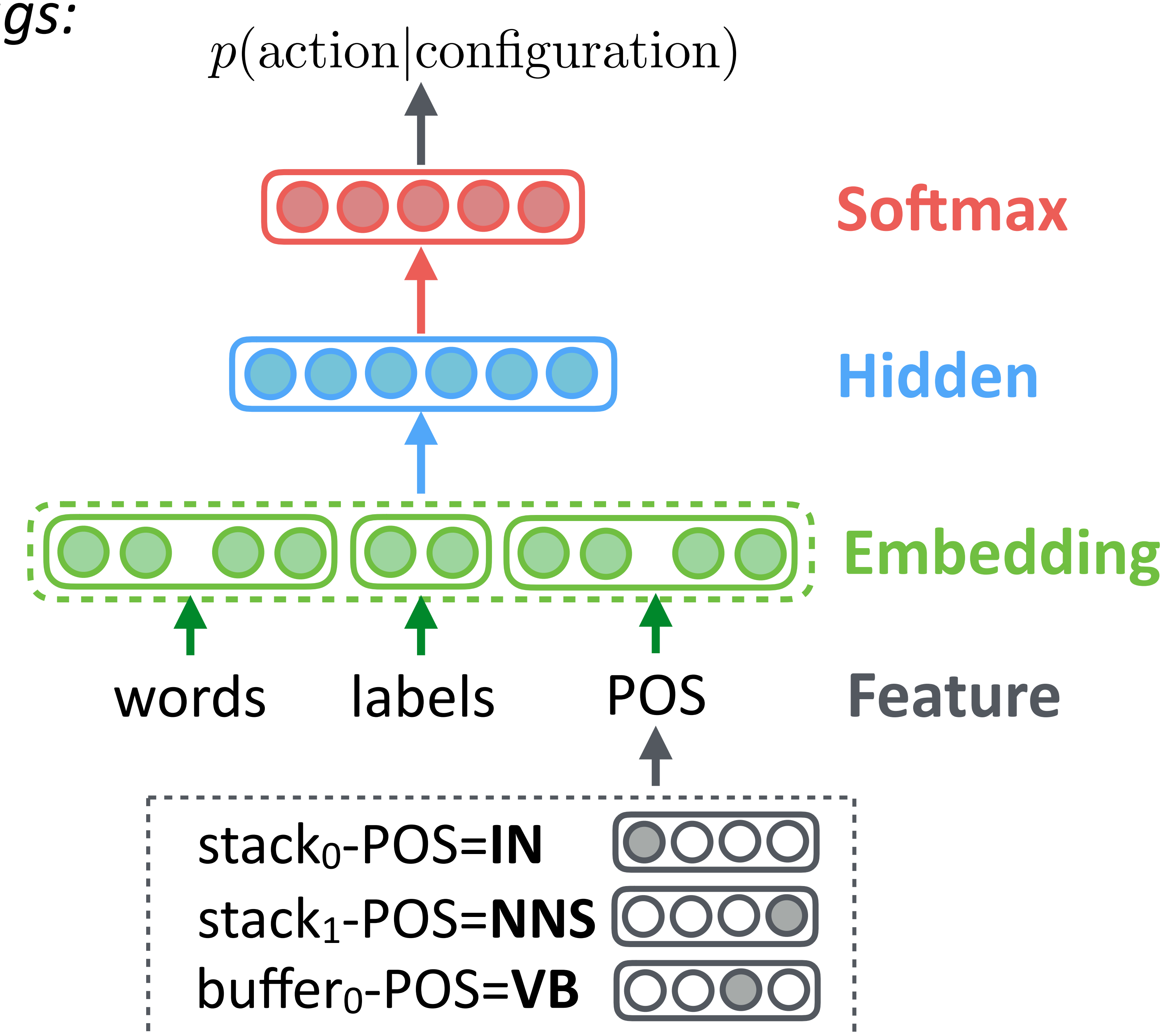
Transition-based Neural Network Parser



Transition-based Neural Network Parser

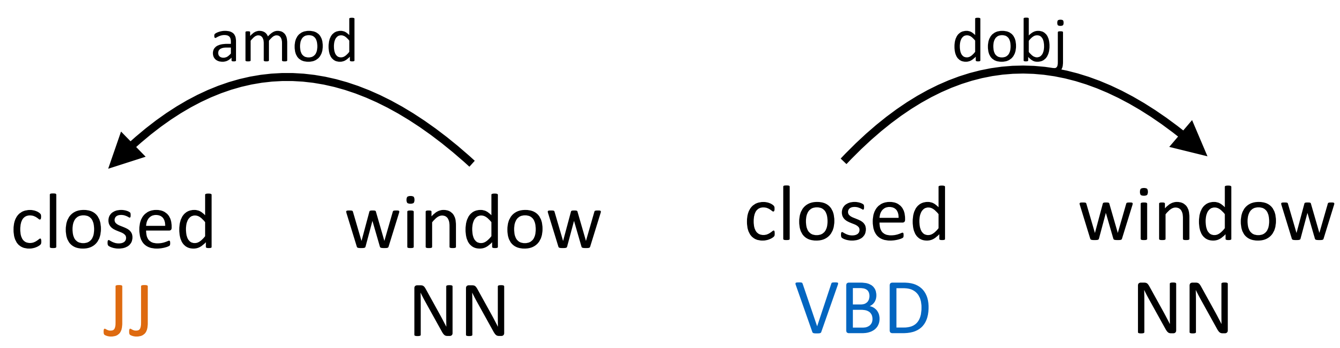
Prior methods on using POS tags:
Traditional stacking (Pipeline)
(Alberti'15, Weiss'15, Chen'14)

- Train an independent POS tagger
- Use predicted POS tags as sparse features



Issues of Traditional Stacking

- Error propagation from predicted POS tags
  - ✦ Predicted (■) vs. Gold (■)



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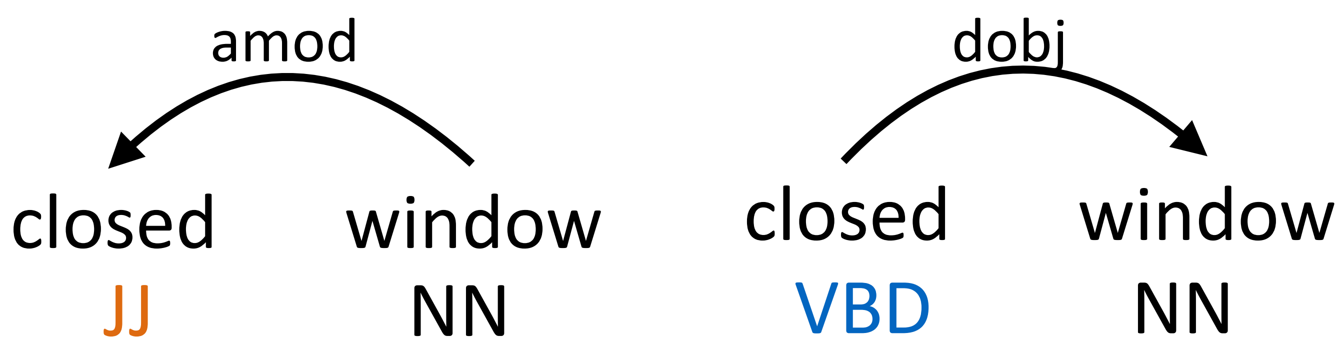
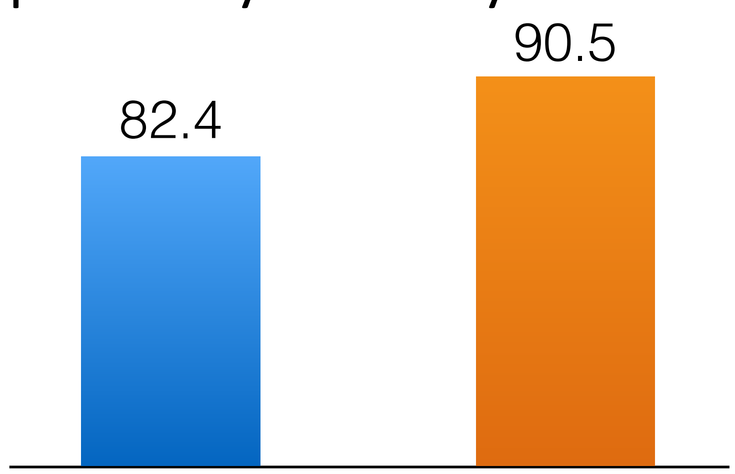


Dependency Accuracy on Arabic



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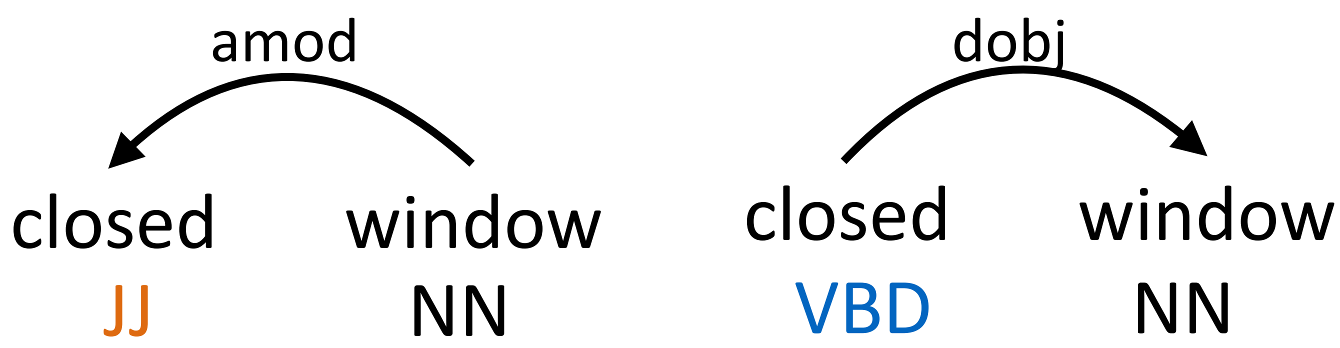
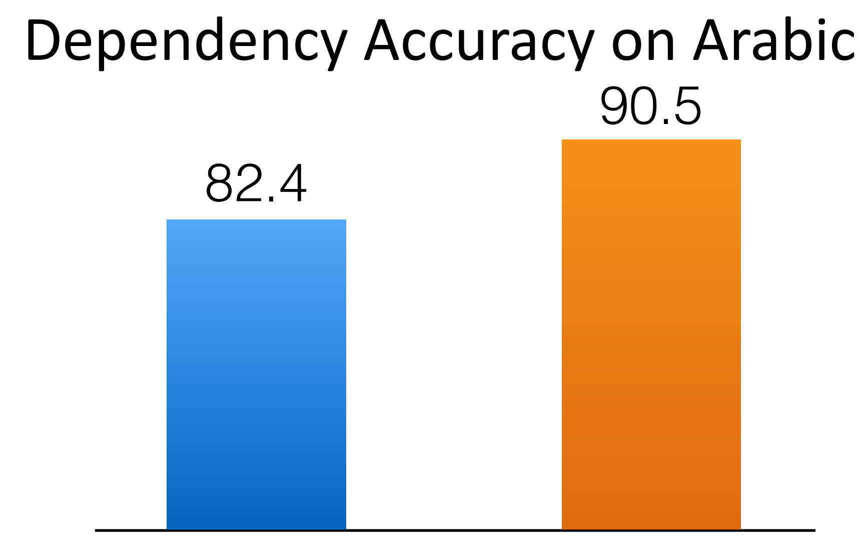
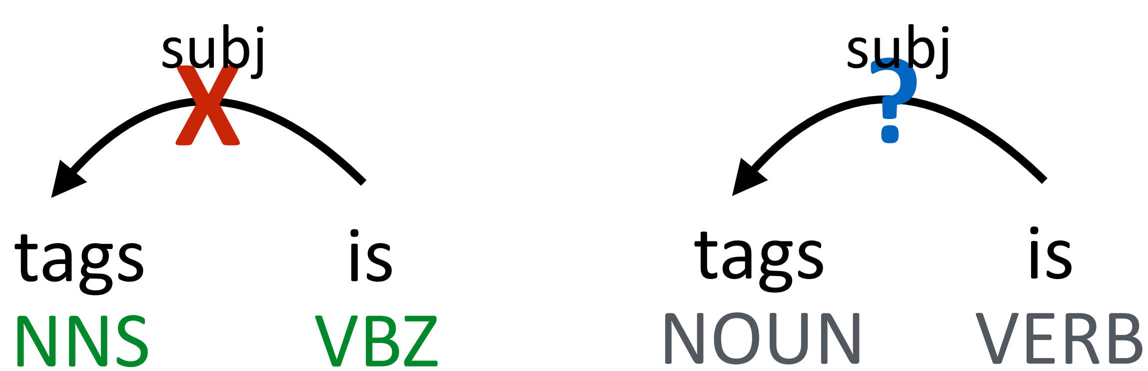




- Limitation of using discrete POS representation
  - ✦ Coarse (■ 12 tags) vs. Fine tagset (■ 45 tags)



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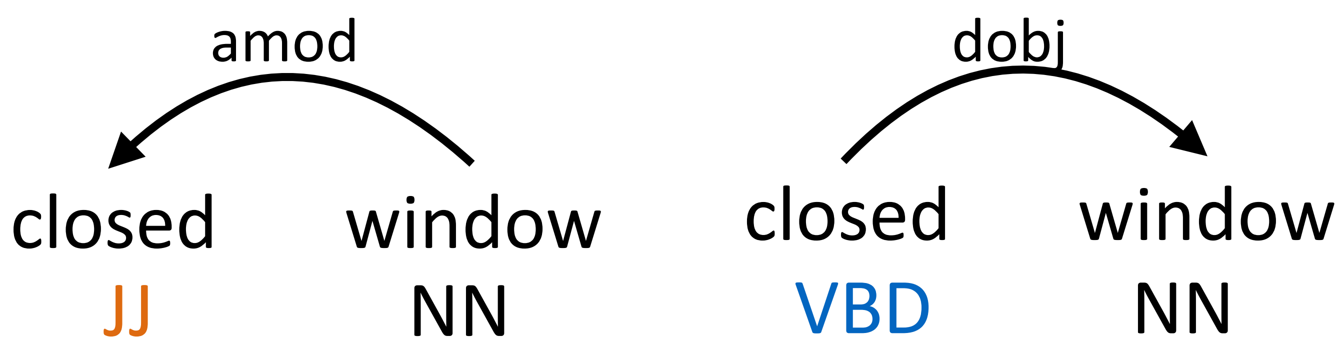

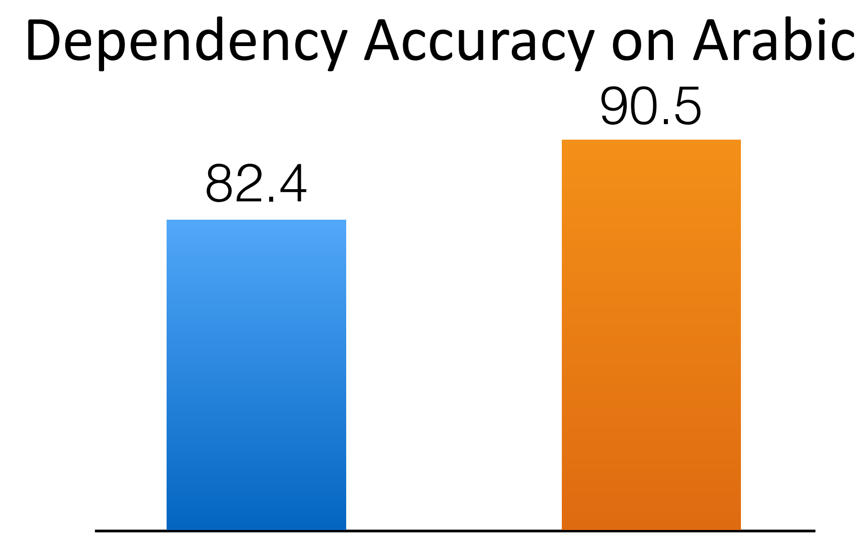

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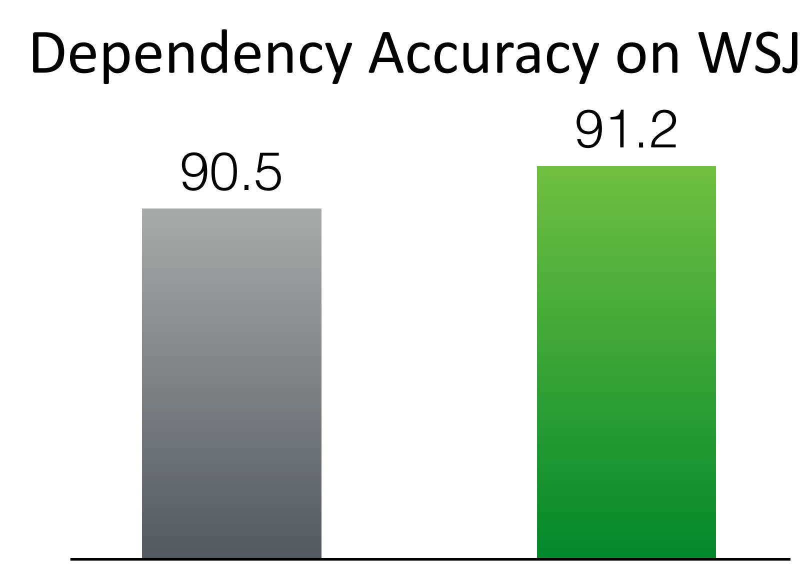
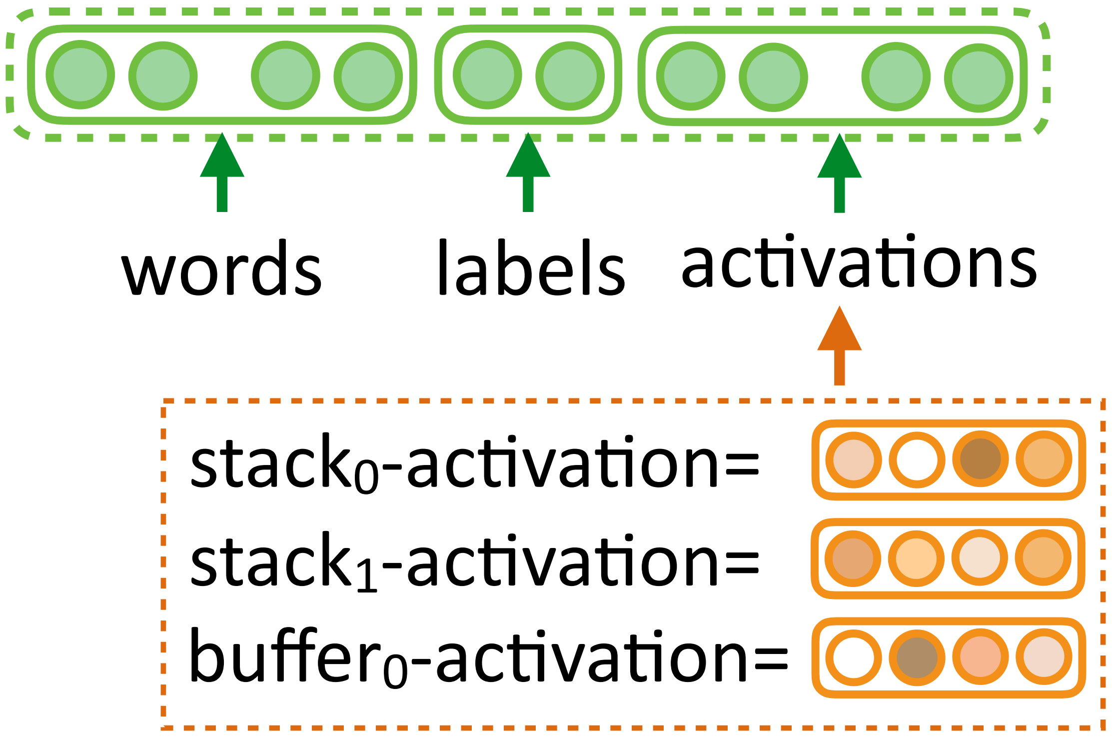


Core Idea of Our Stacking Methods

- Stack-propagation: Replace discrete POS features with hidden layer activations of a tagger



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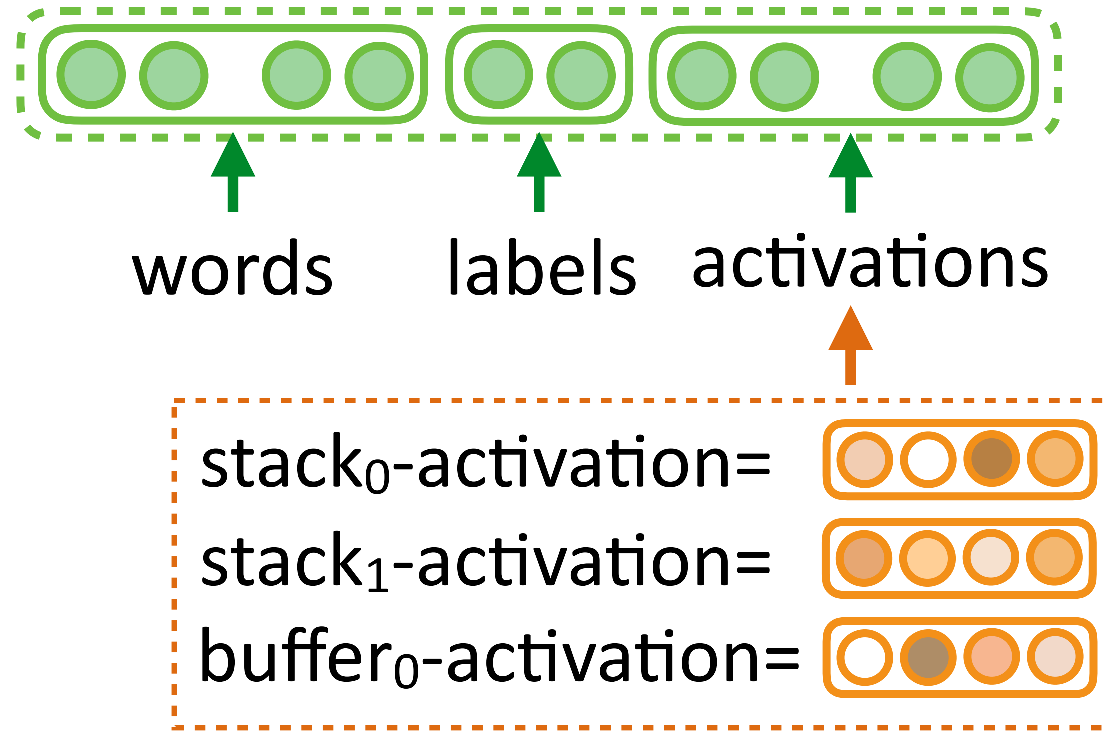
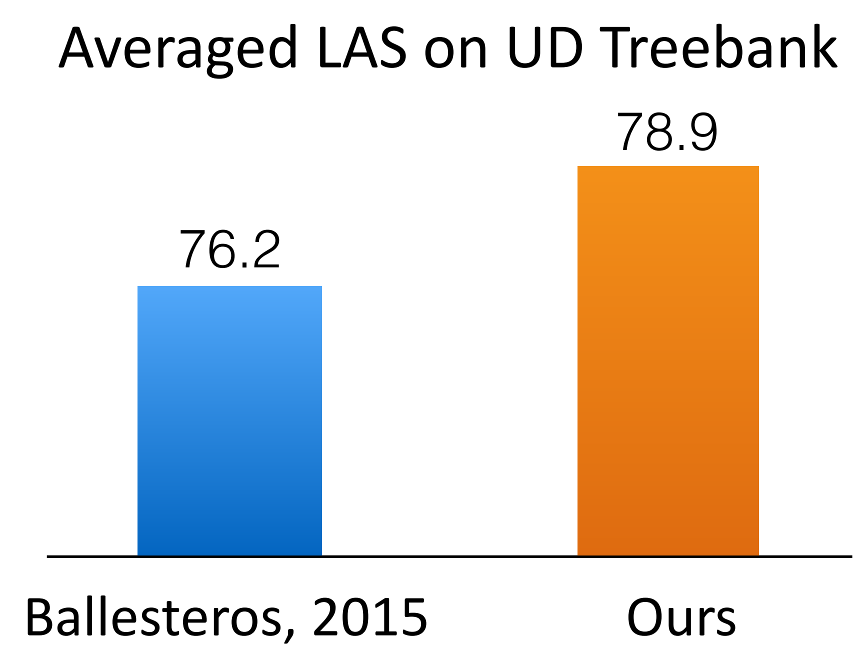
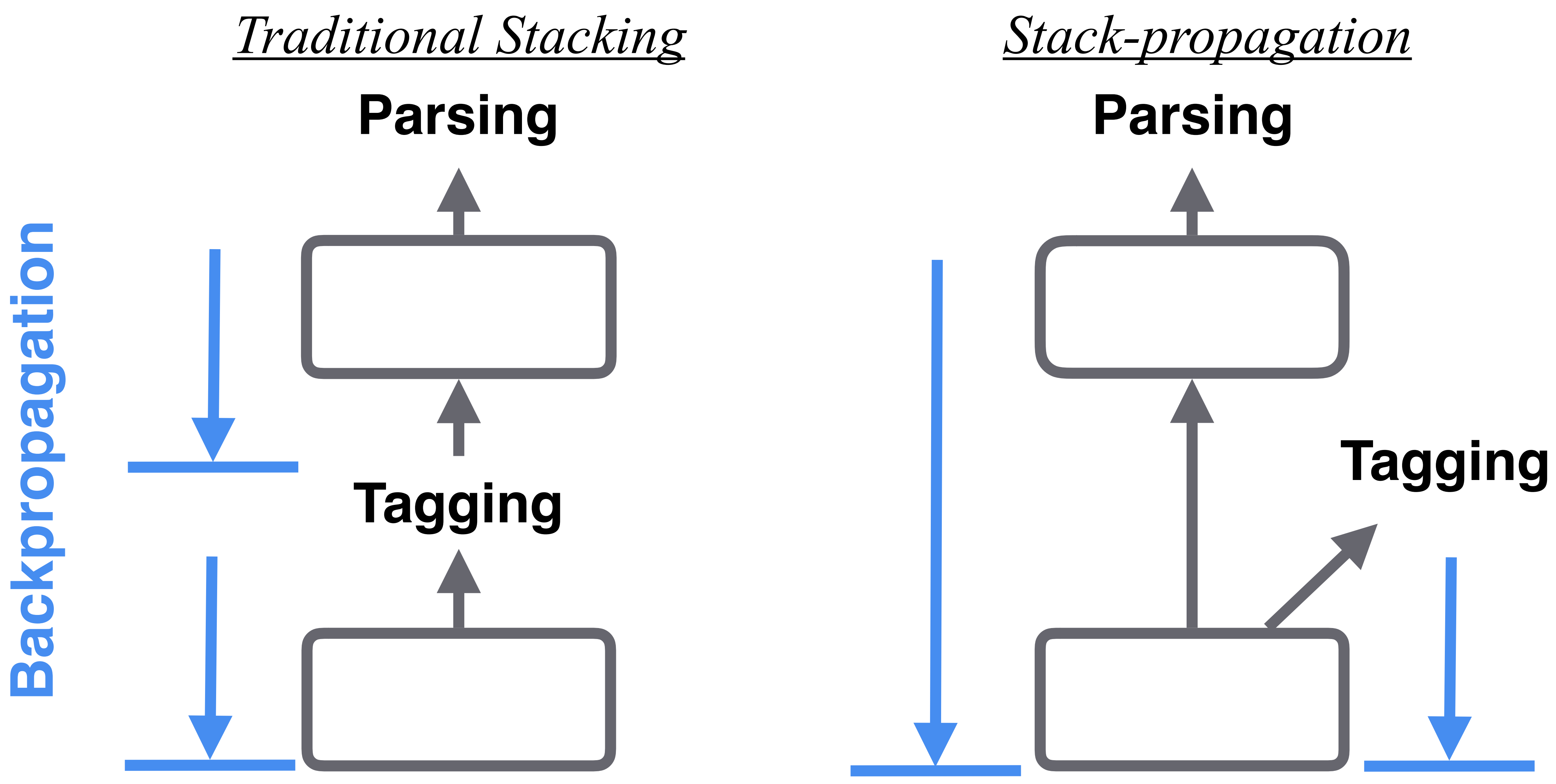


- Advantages:
  - ✦ Joint training for parsing and tagging
  - ✦ Robust to POS errors
  - ✦ Better feature representations than discrete POS features



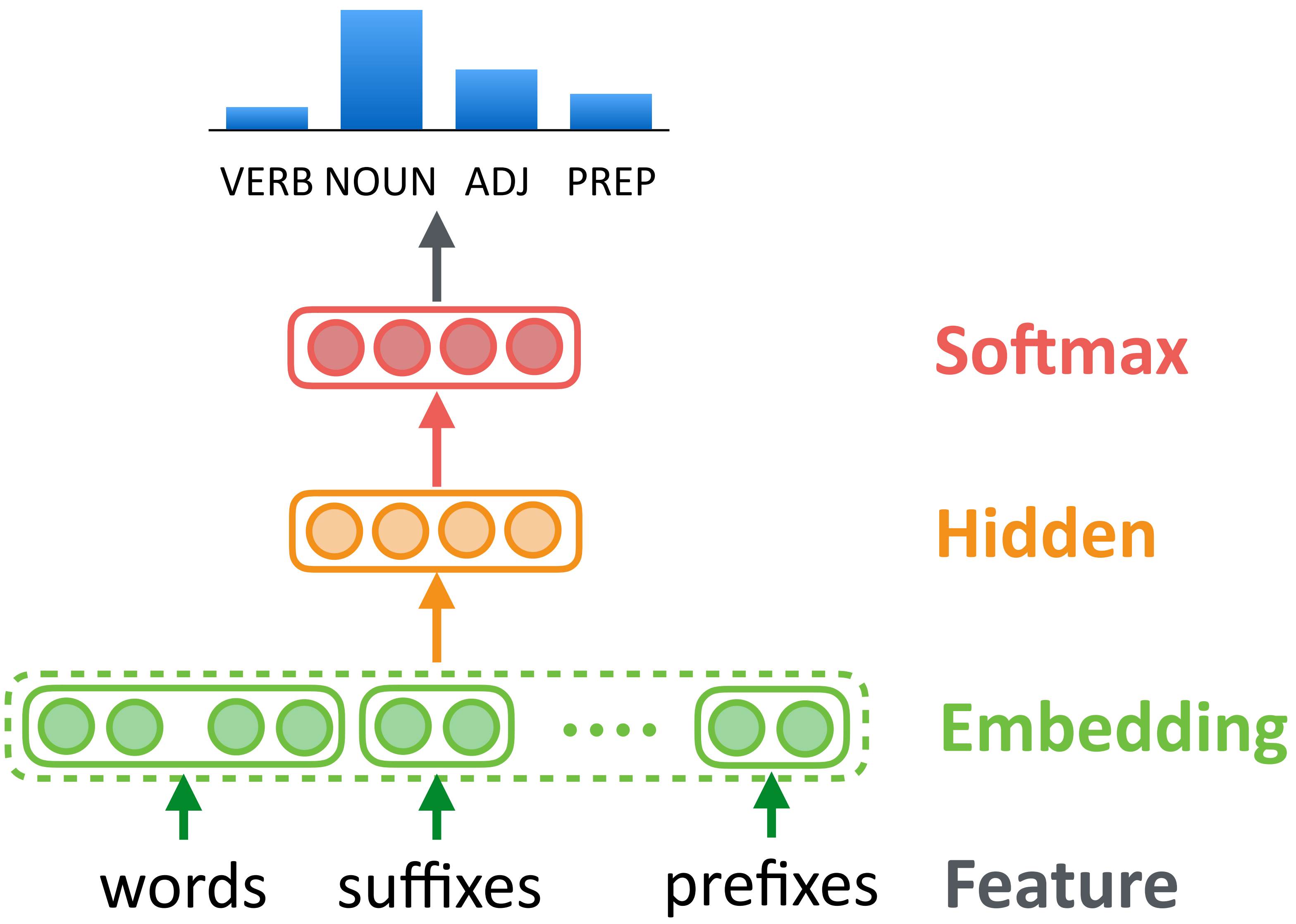
Overview of Network Architecture

- Two networks: a parser and a tagger
- Shared component: tagger except for softmax layers



Tagger Network

- Standard window-based NN classifier for tagging



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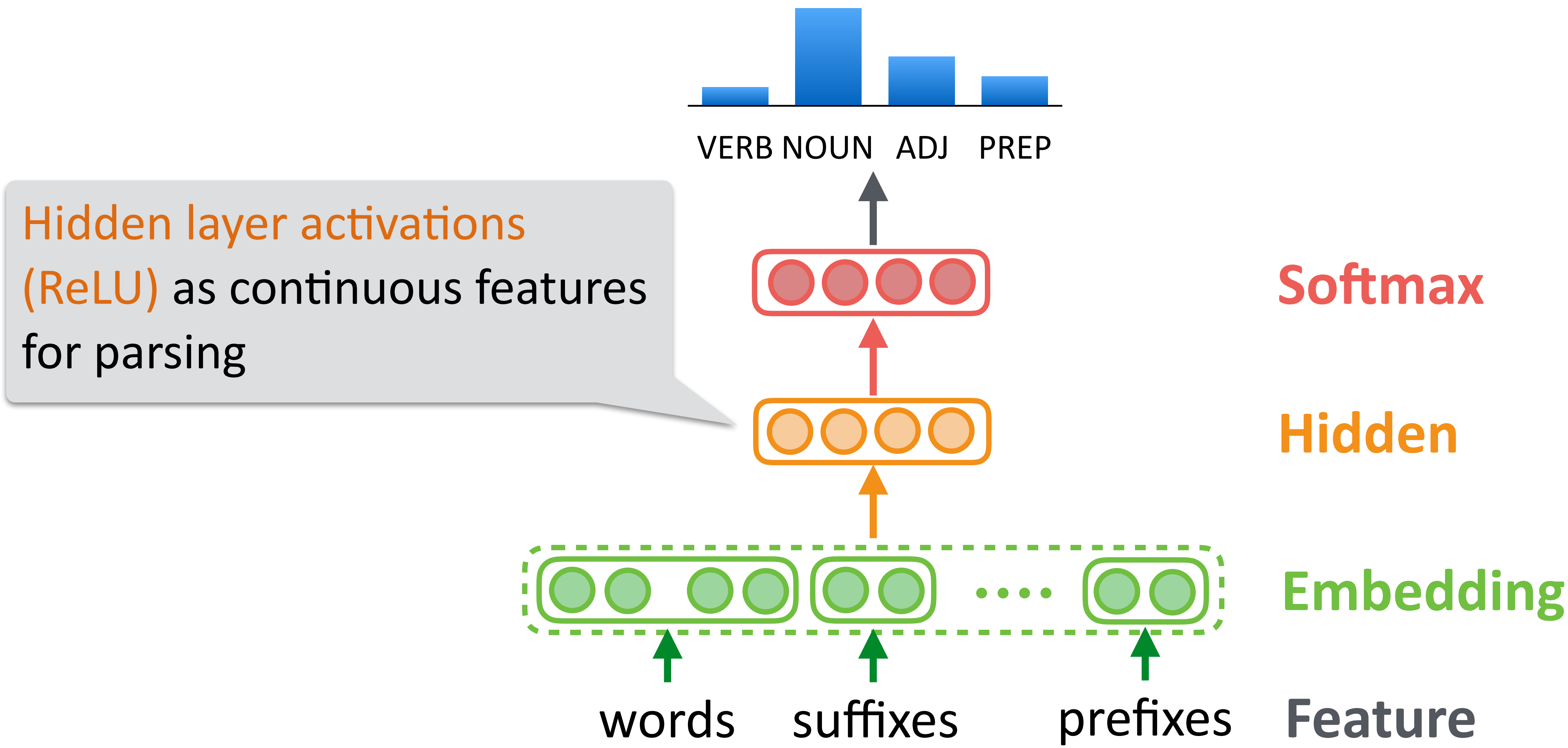
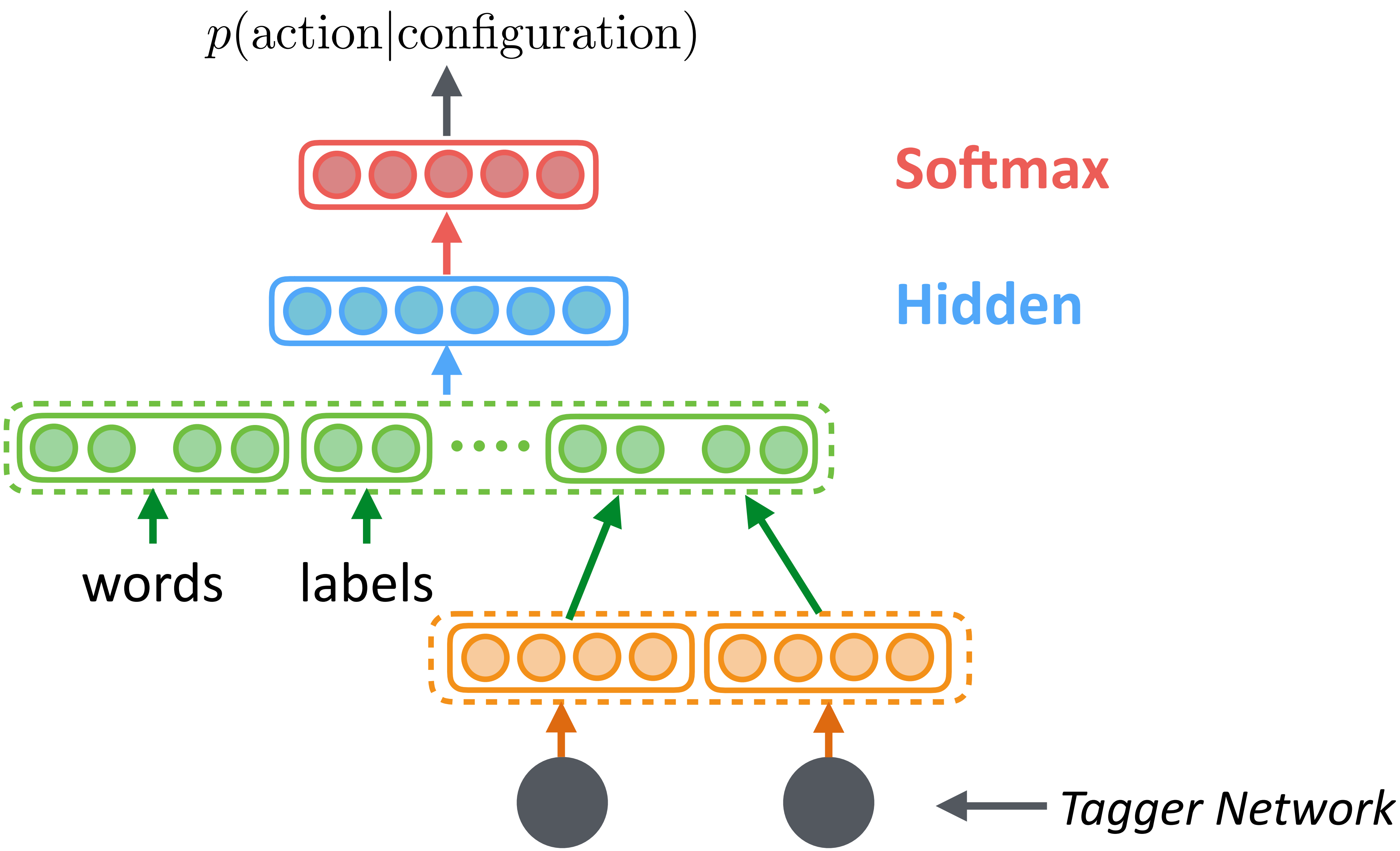


Parser Network

- Transition-based NN parser (Weiss'15, Chen'15) *stacked* on hidden layer activations of the tagger



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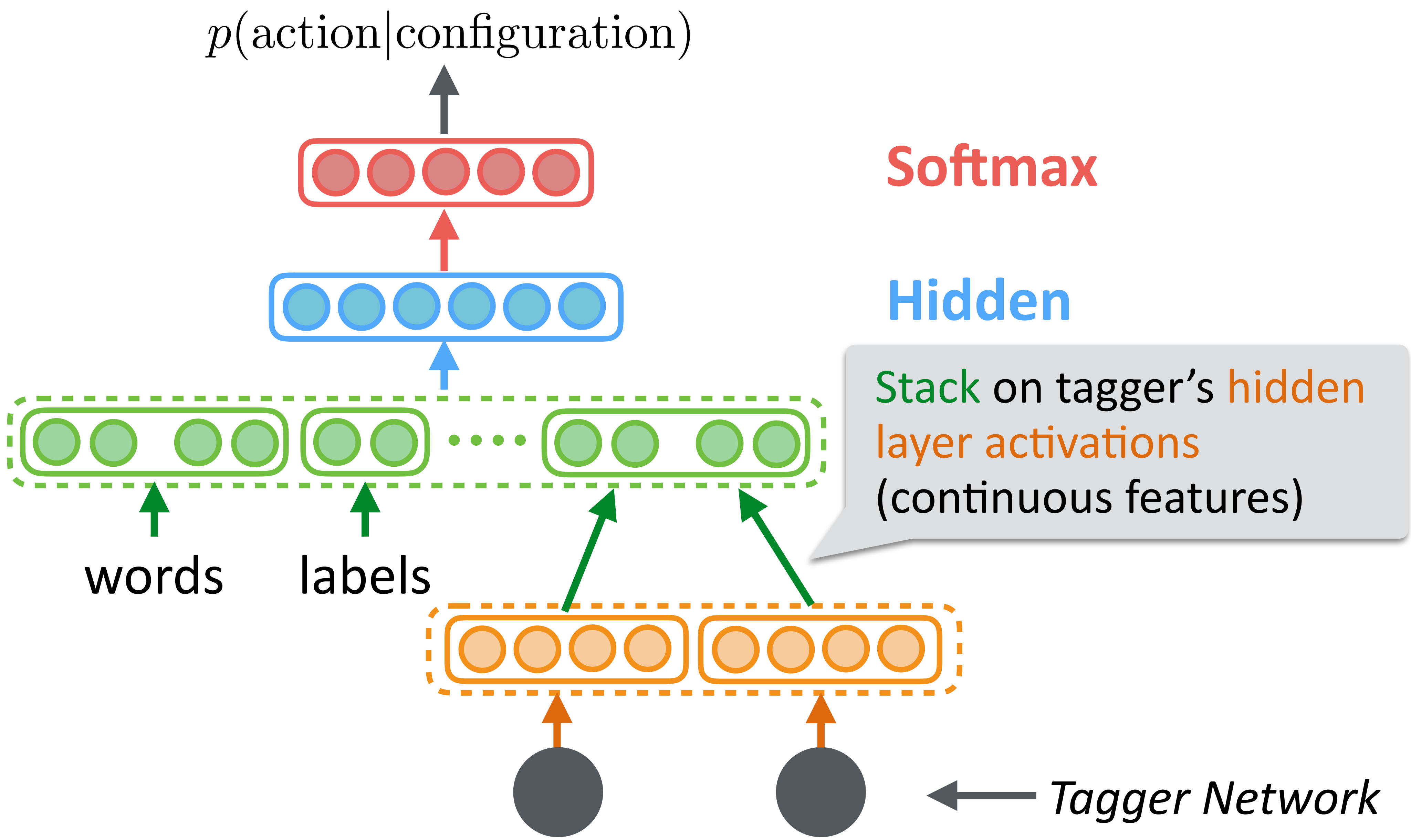

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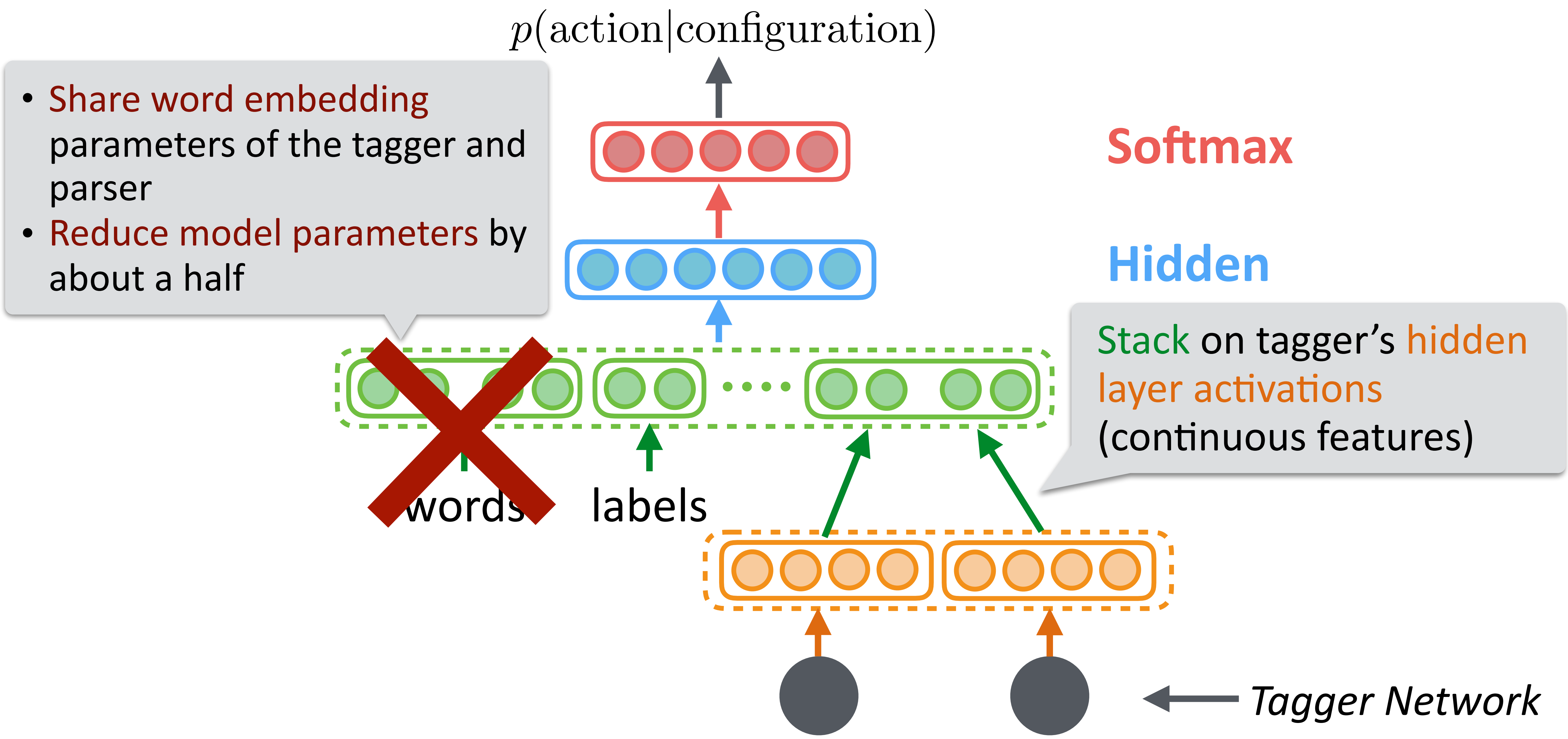

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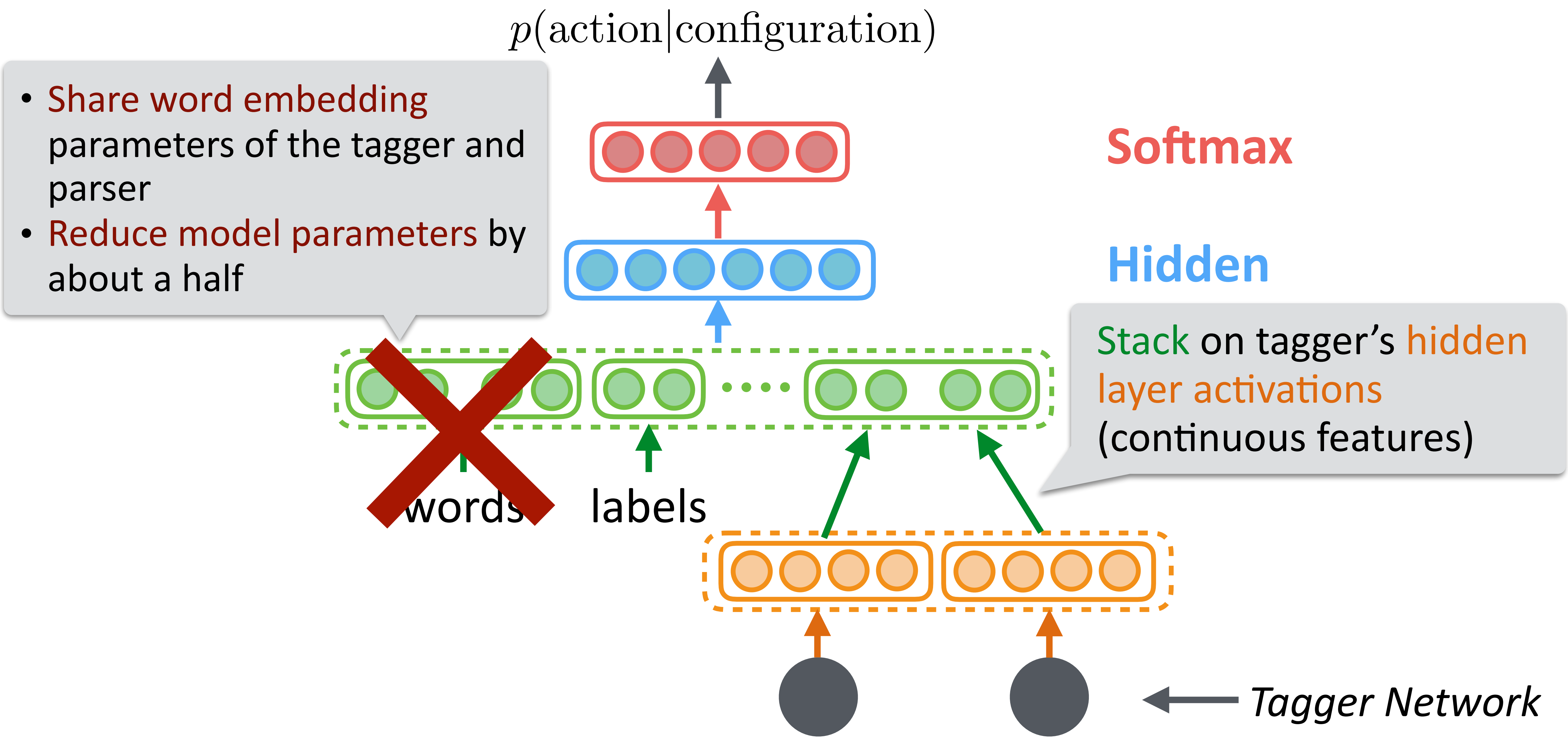
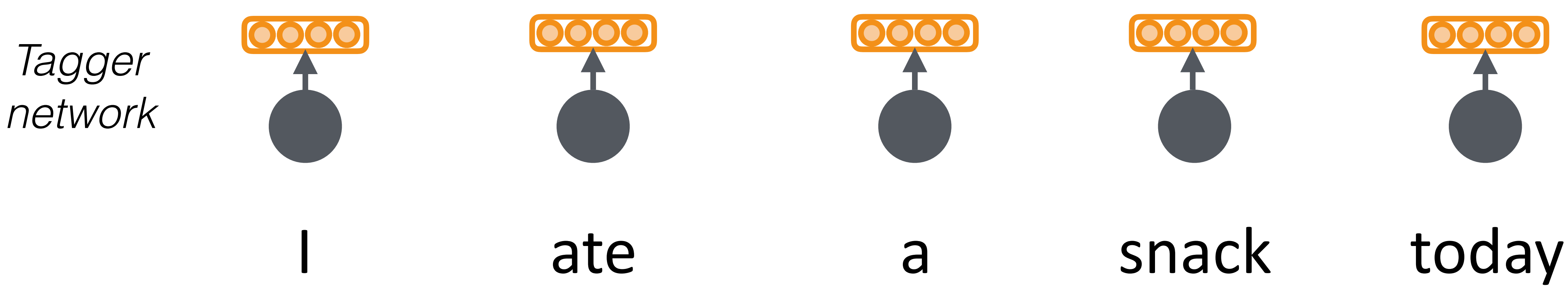


- More complex architecture after unrolling parser transitions

Unrolled NN Architecture (Inference)



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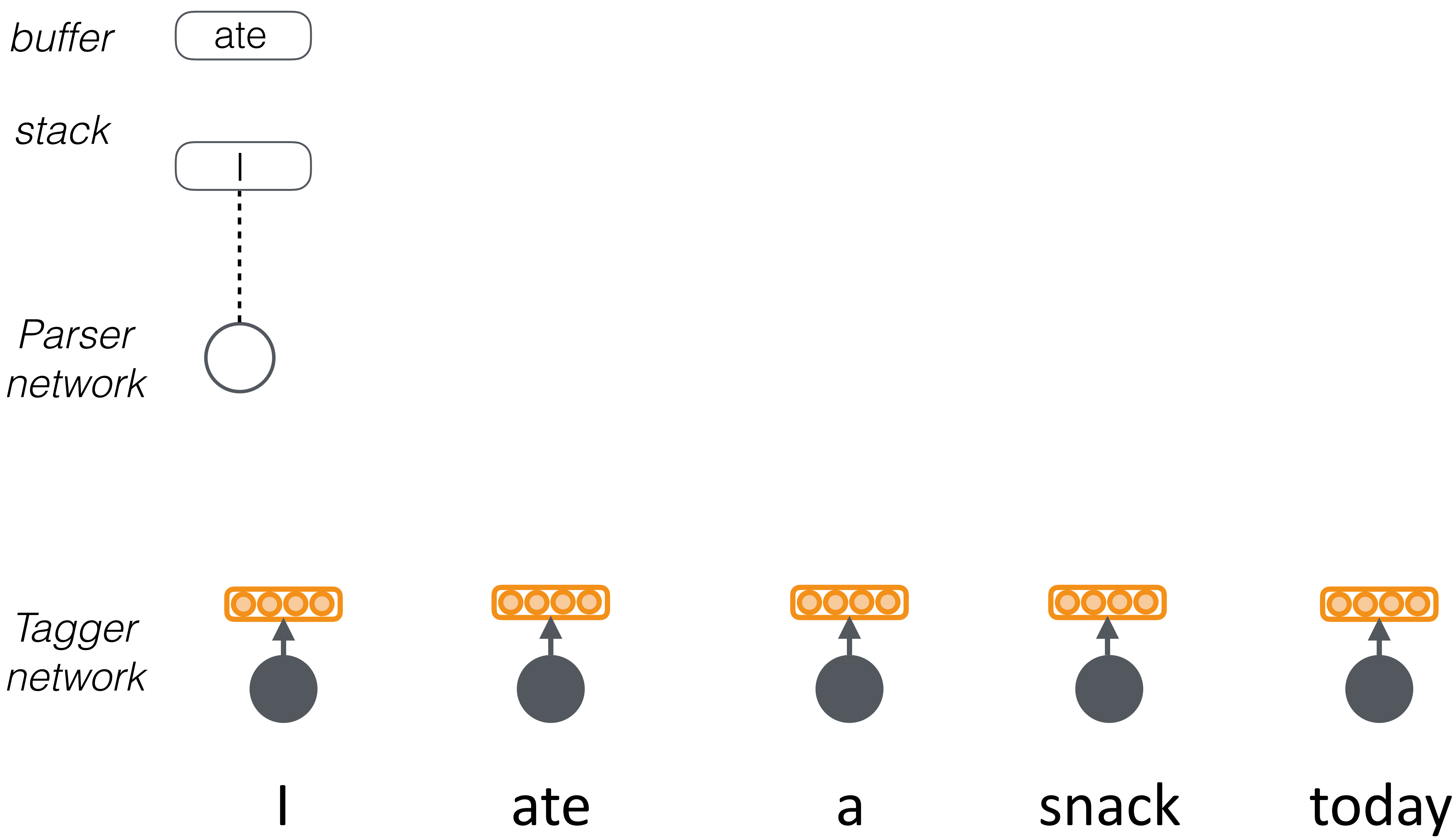

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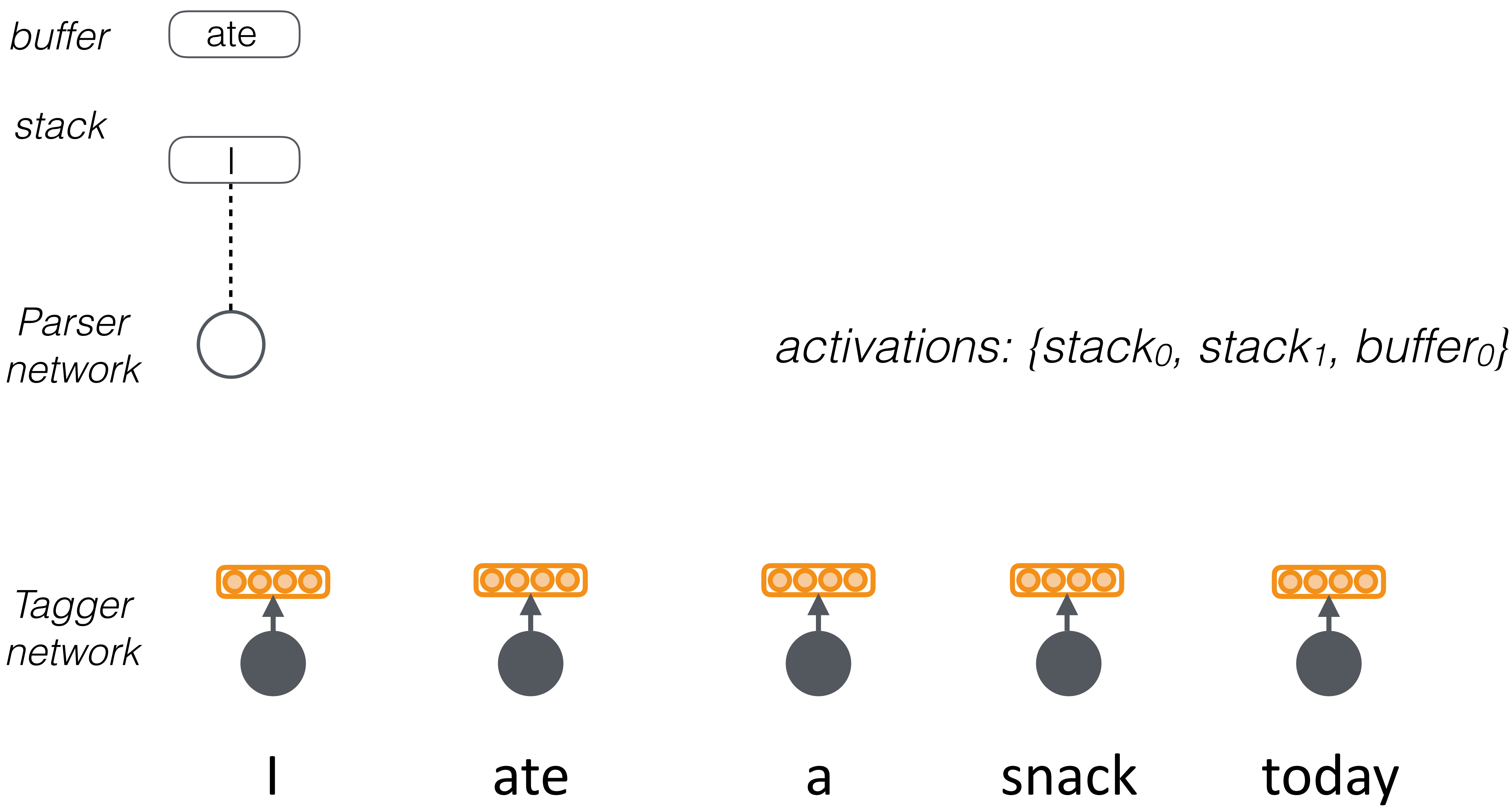

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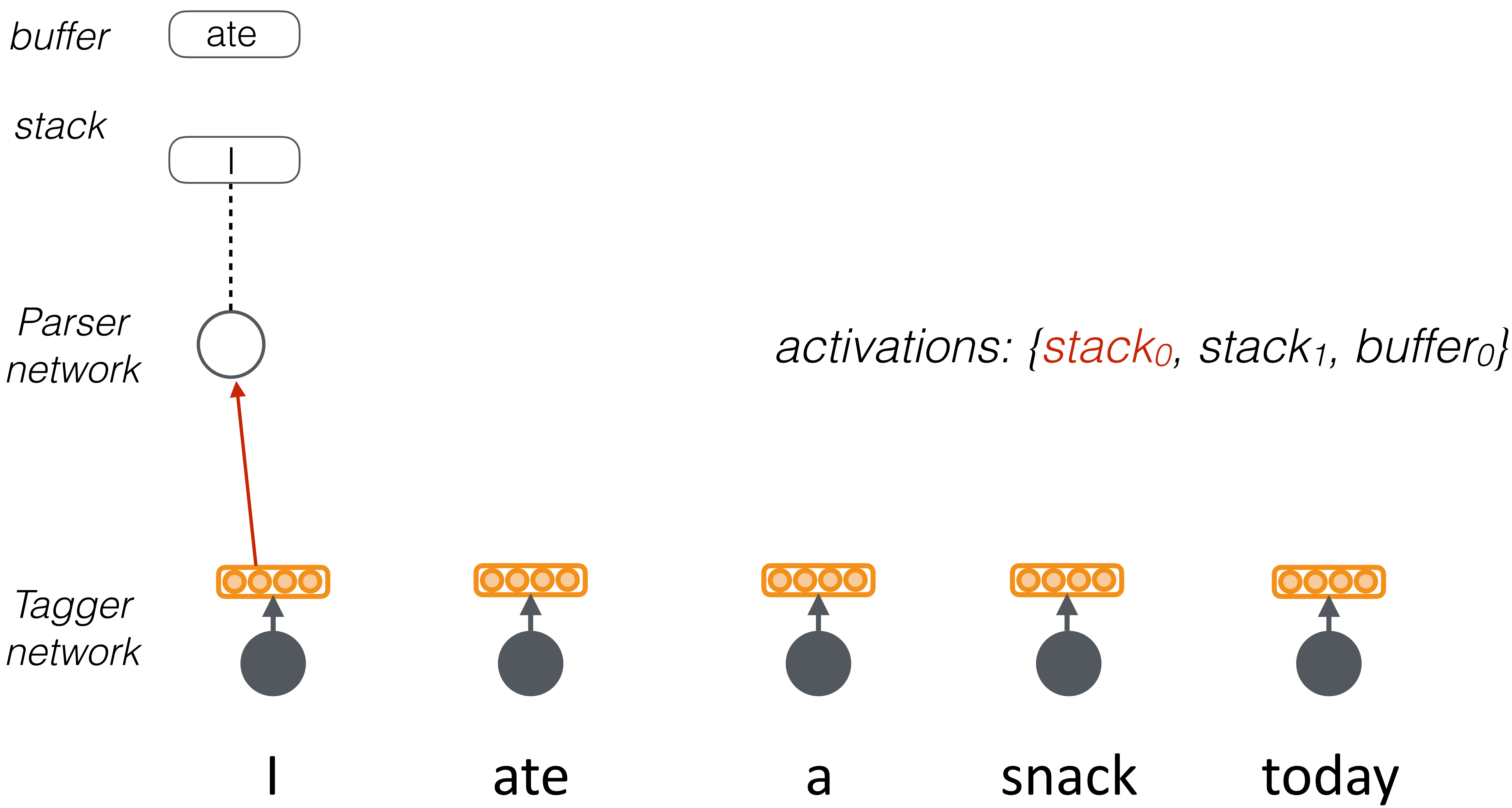

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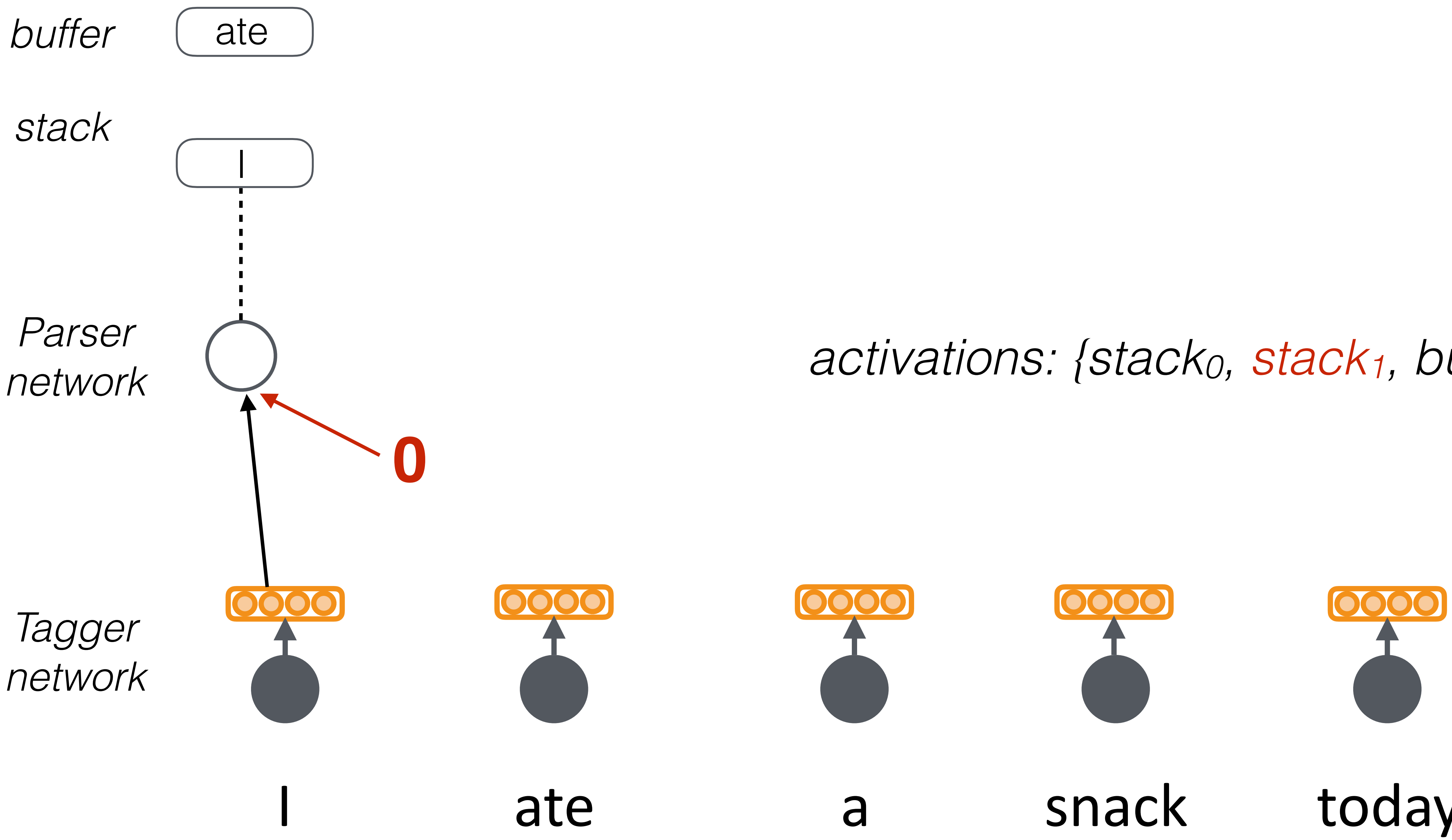

activations: {stack$_0$, stack$_1$, buffer$_0$}

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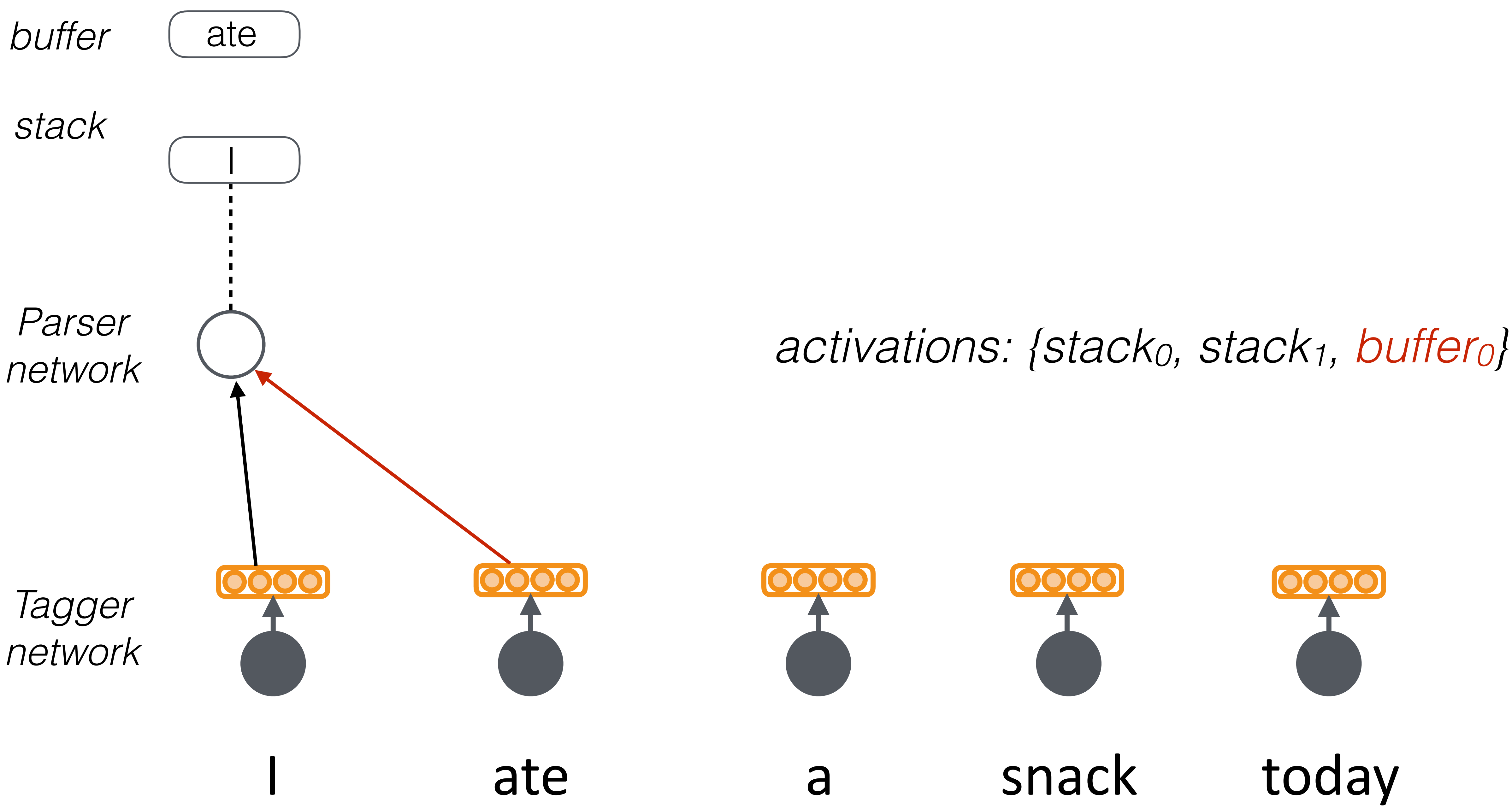

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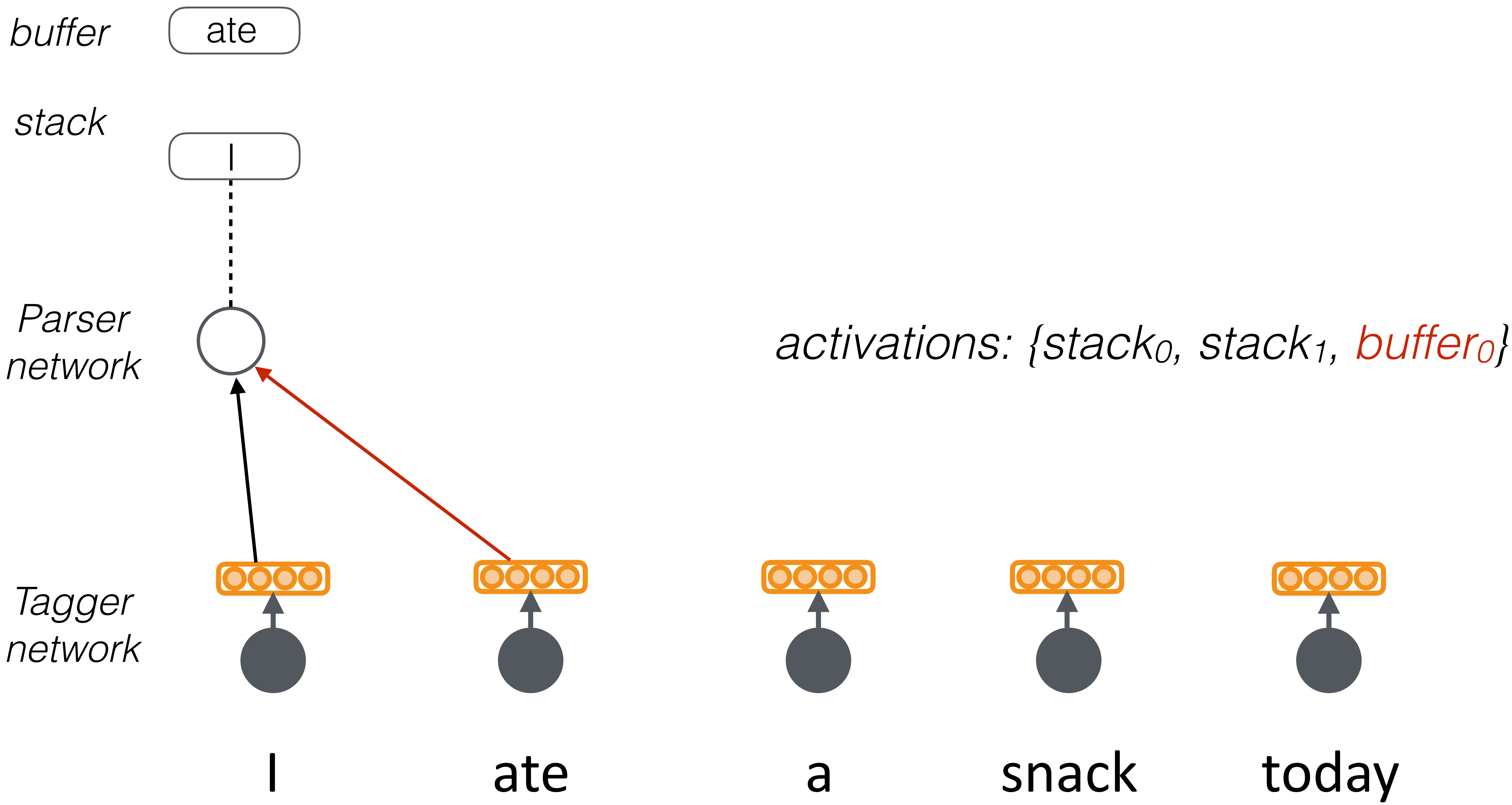

- In practice, the parser looks up activations from 20 locations
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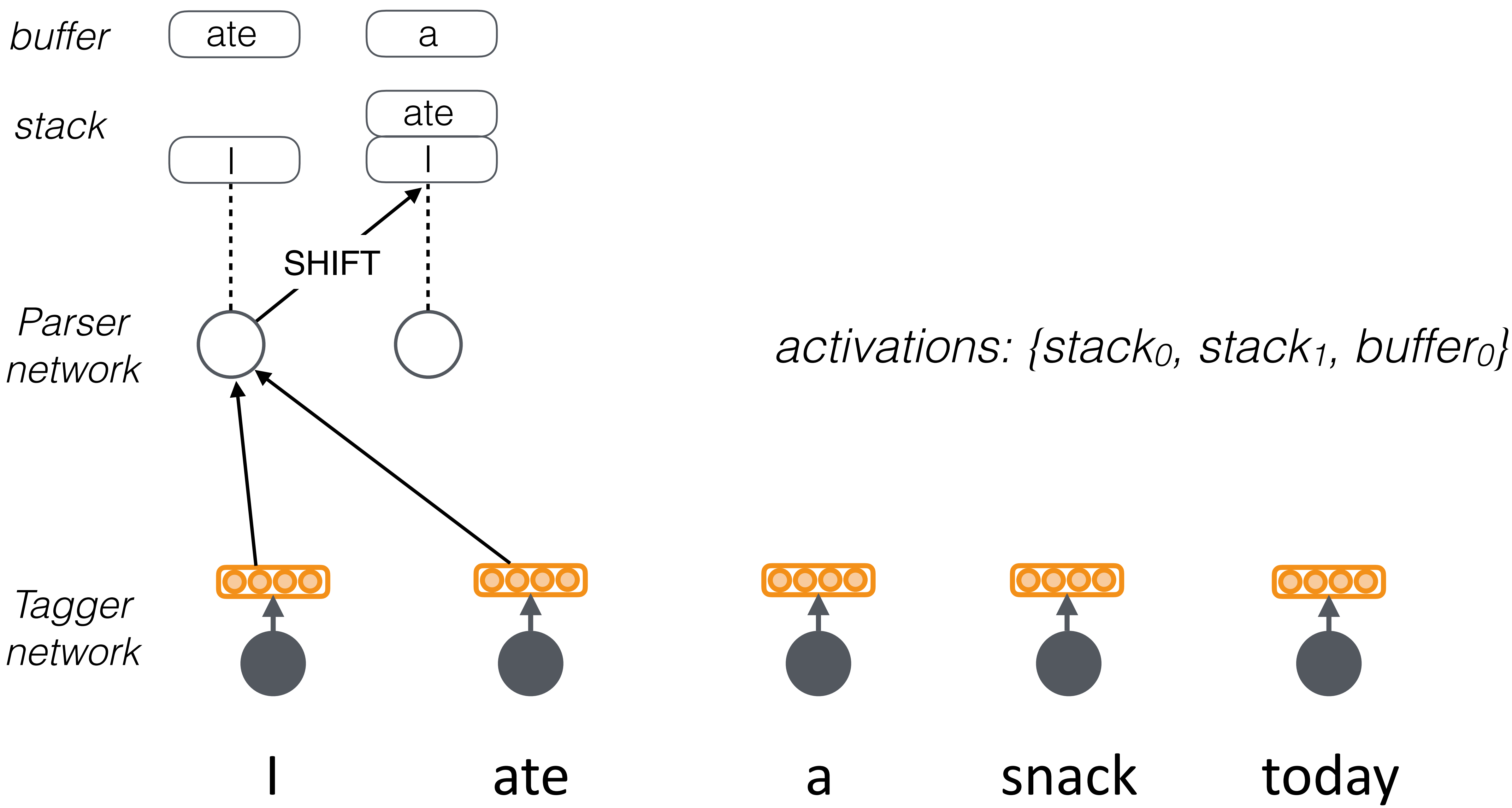

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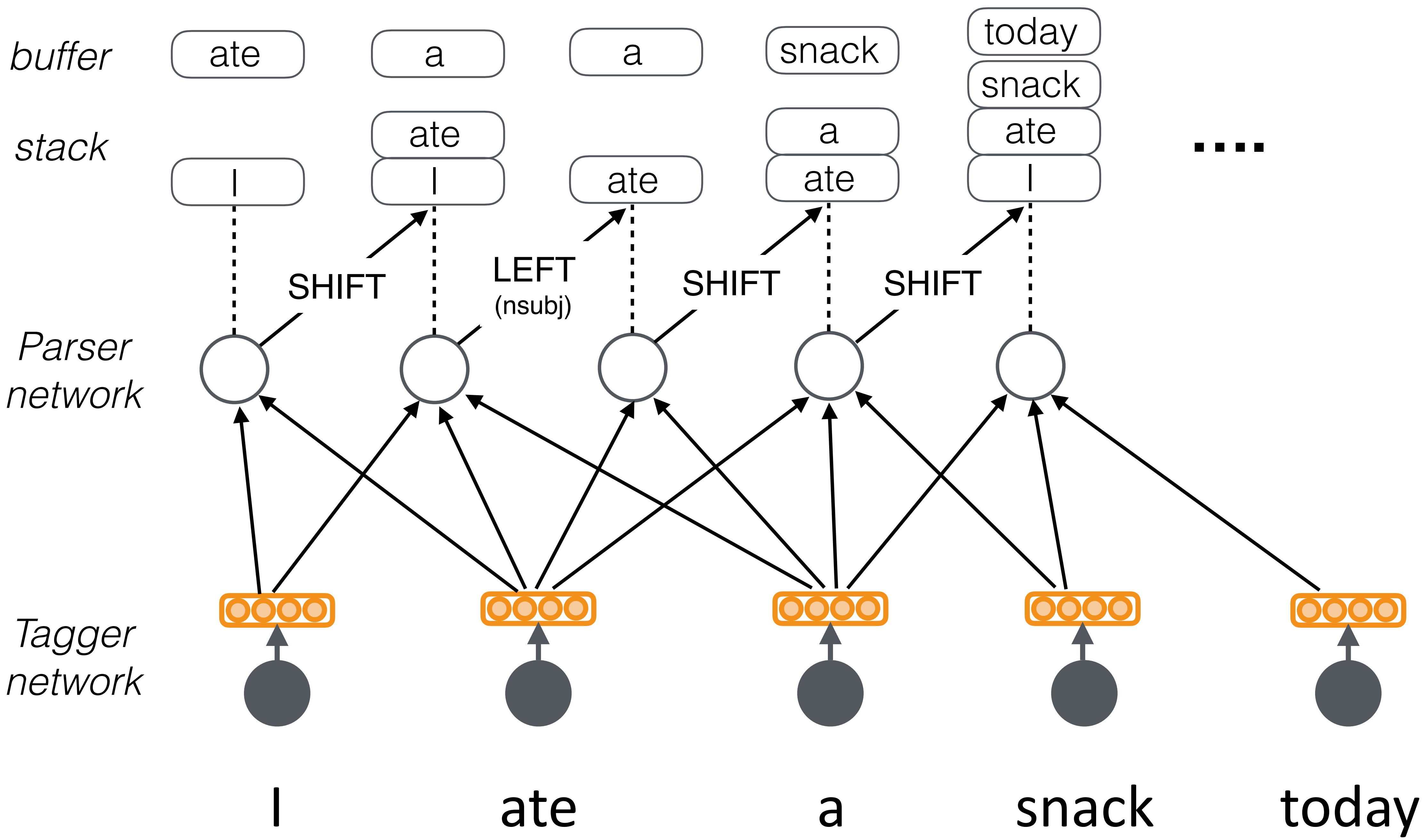

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Multi-task Style Learning

- Objective: maximize log-likelihood for parsing and tagging

$$\max_{\Theta} \boxed{\lambda \sum_{x,y \in \mathcal{T}} \log(P_\Theta(y|x))} + \boxed{\sum_{c,a \in \mathcal{P}} \log(P_\Theta(a|c))}$$

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  - ✦ Pre-train tagger for one epoch
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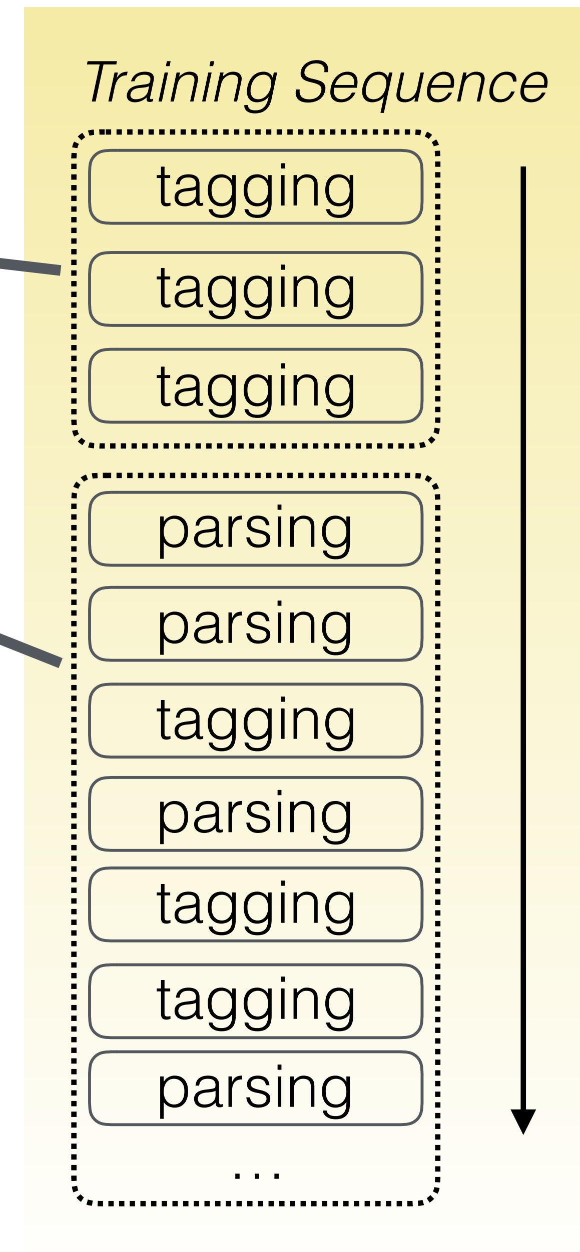

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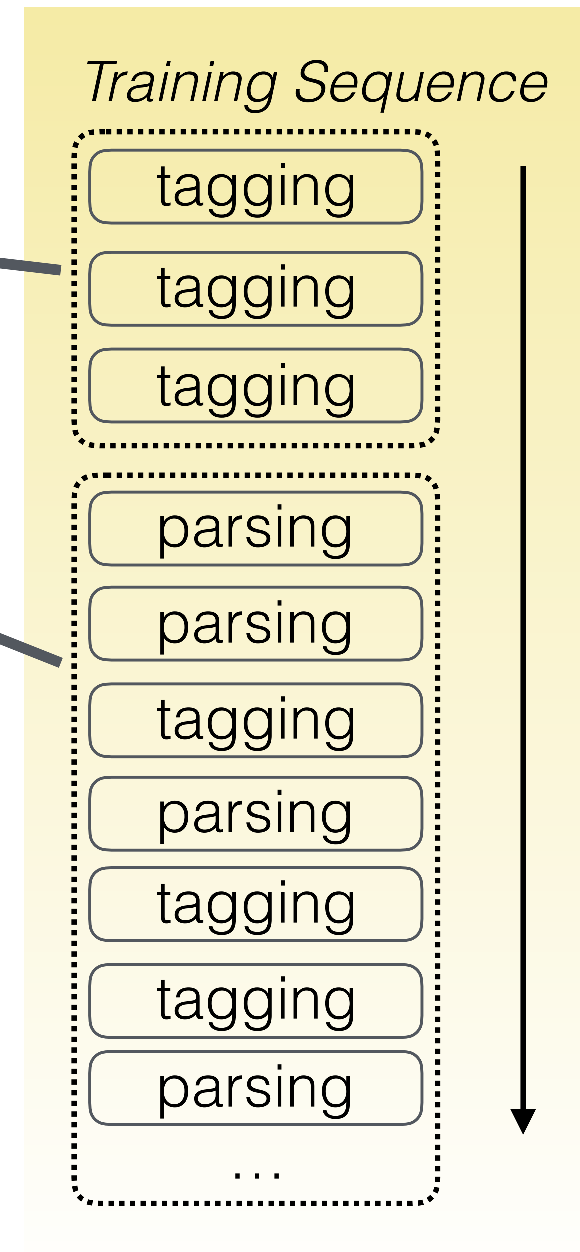
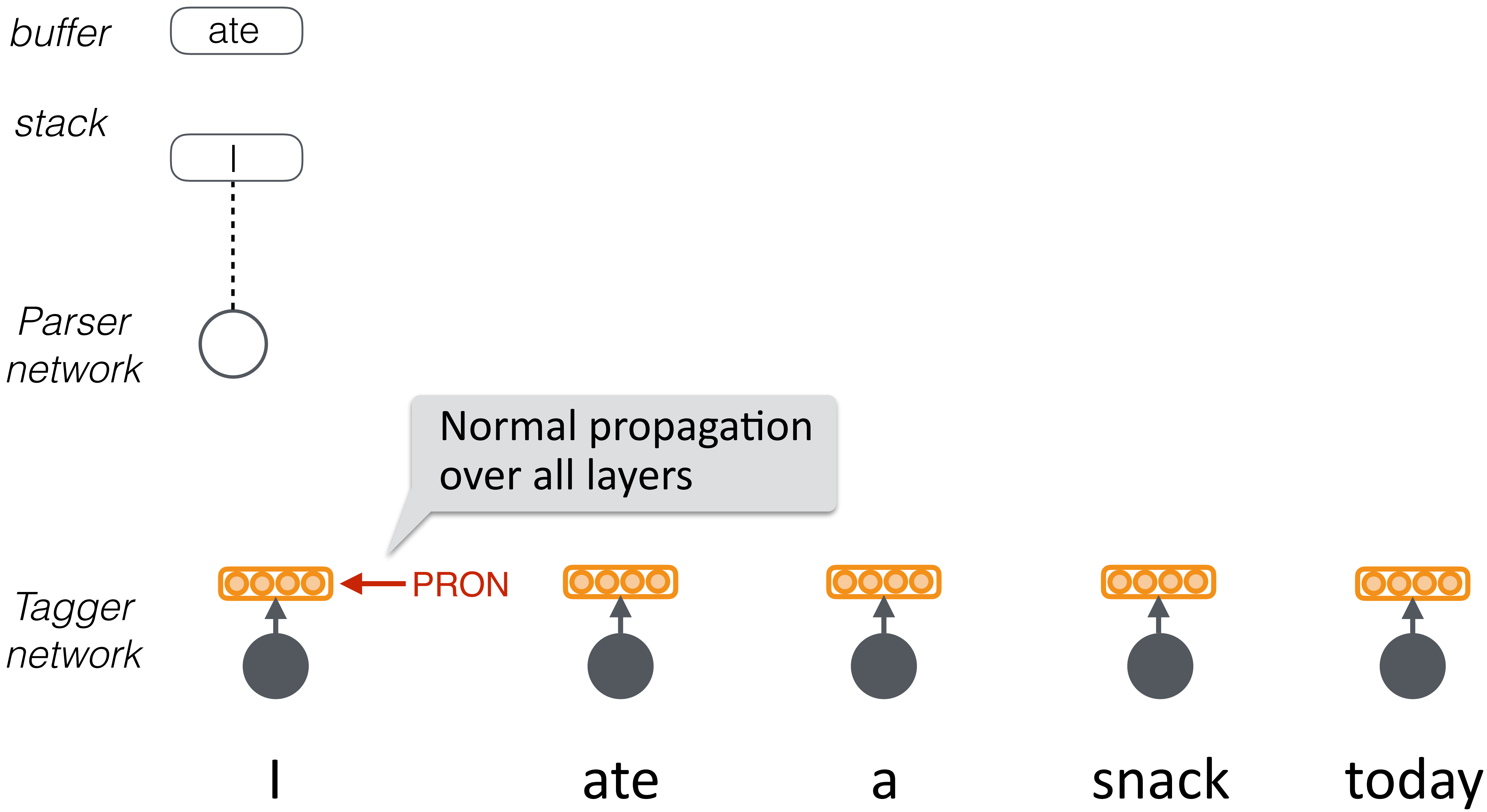


- Updating schema
  - ✦ Tagging: update tagger
  - ✦ Parsing: update parser & tagger except for softmax

Unrolled NN Architecture (Update Tagger)



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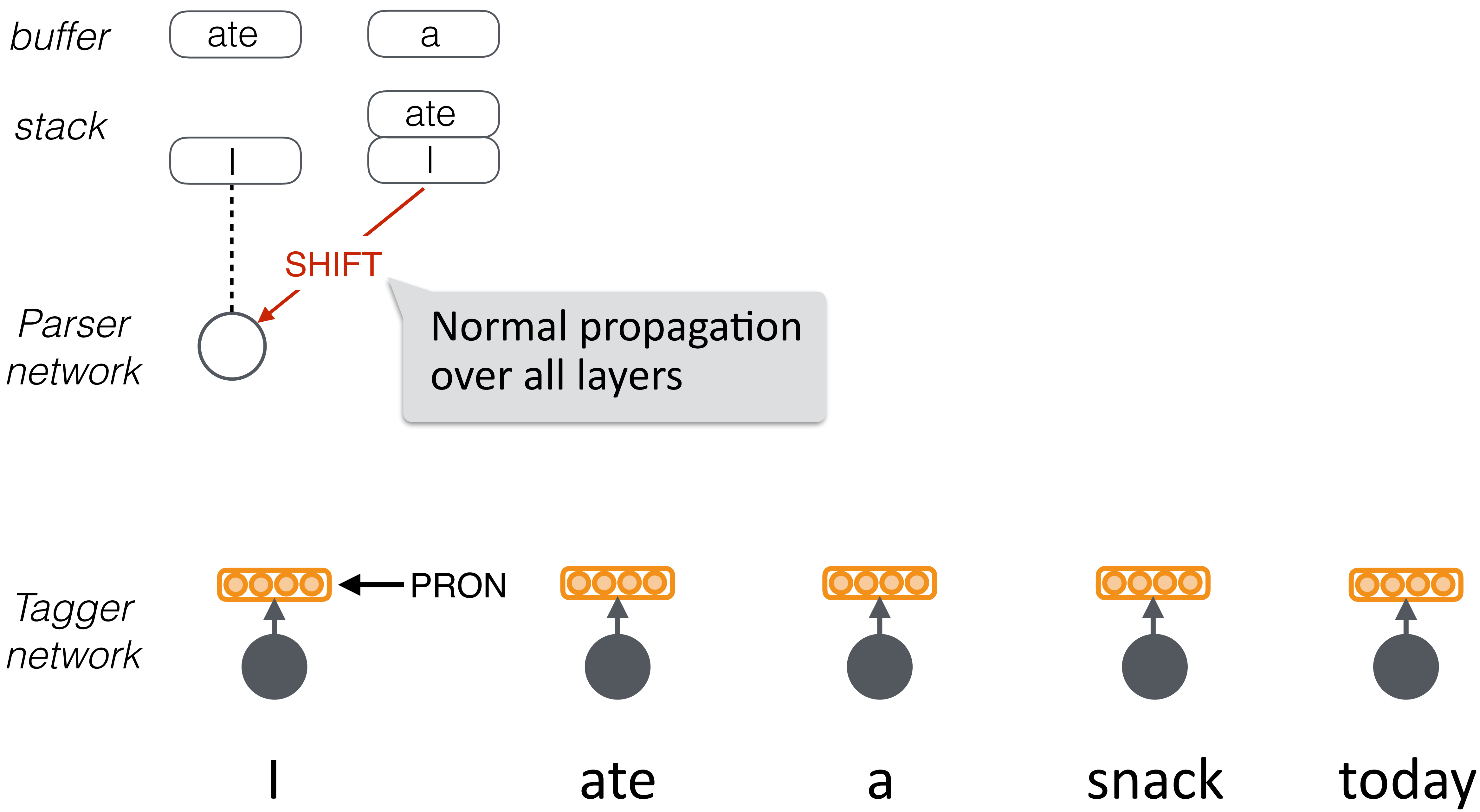

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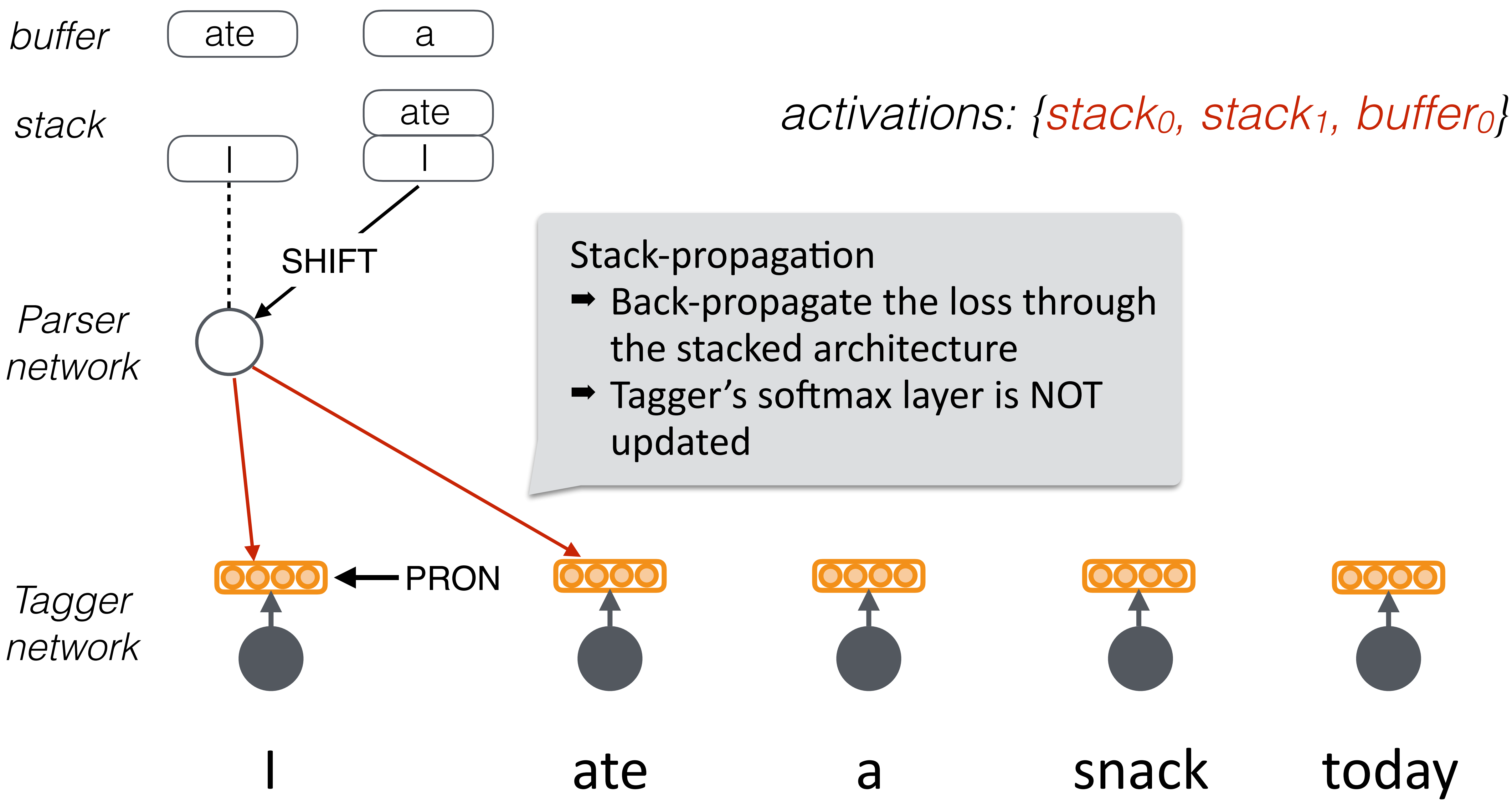

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➡ Back-propagate the loss through the stacked architecture
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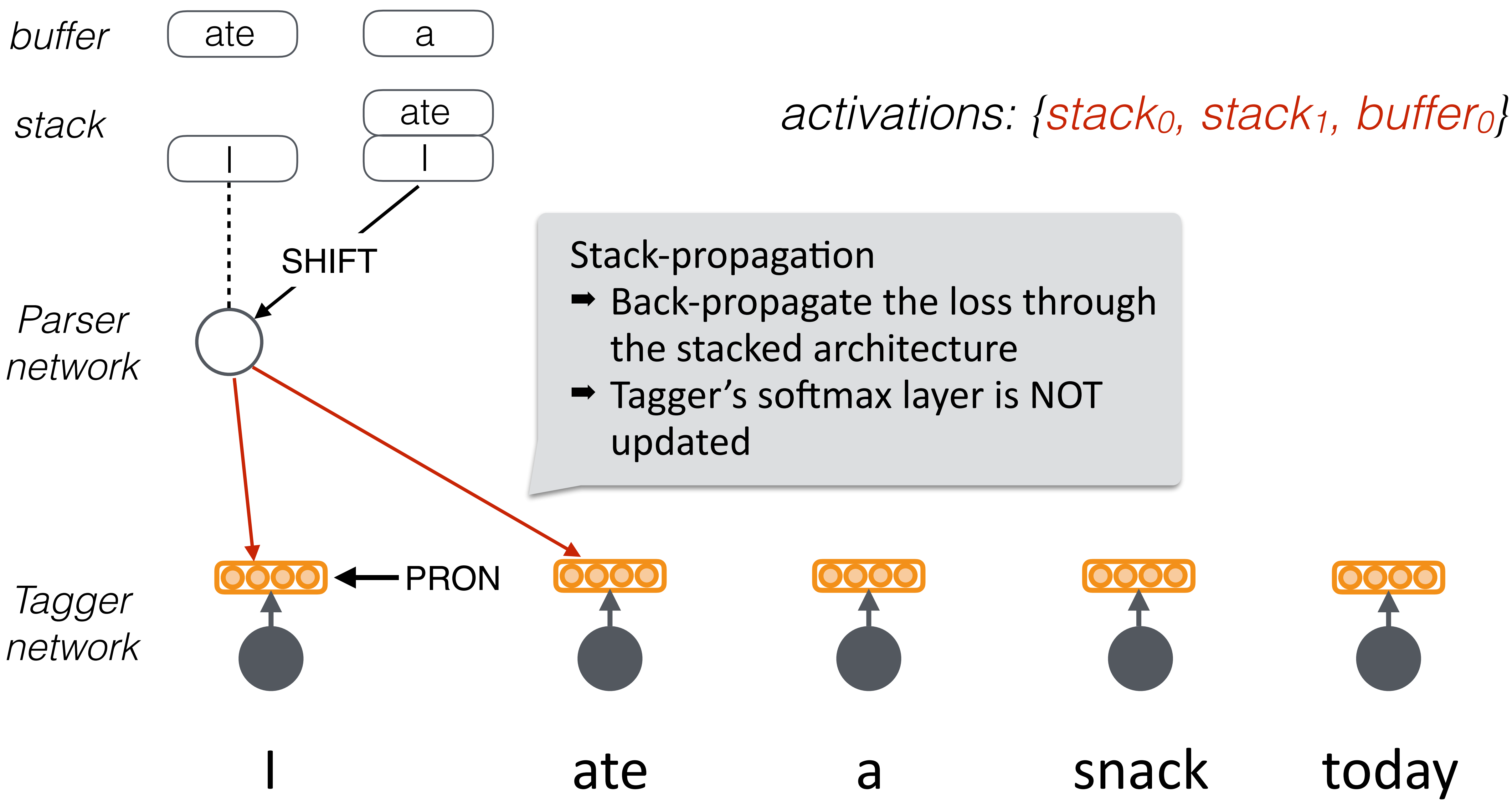

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- Other learning recipes borrowed from Weiss'15

Experimental Setup

- Dataset
    - ✦ 19 languages from the Universal Dependencies 1.2
    - ✦ Wall Street Journal (Stanford converter 3.3.0)

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- Word embeddings
  - ✦ No pre-trained embeddings for UD
  - ✦ Pre-trained embeddings for WSJ

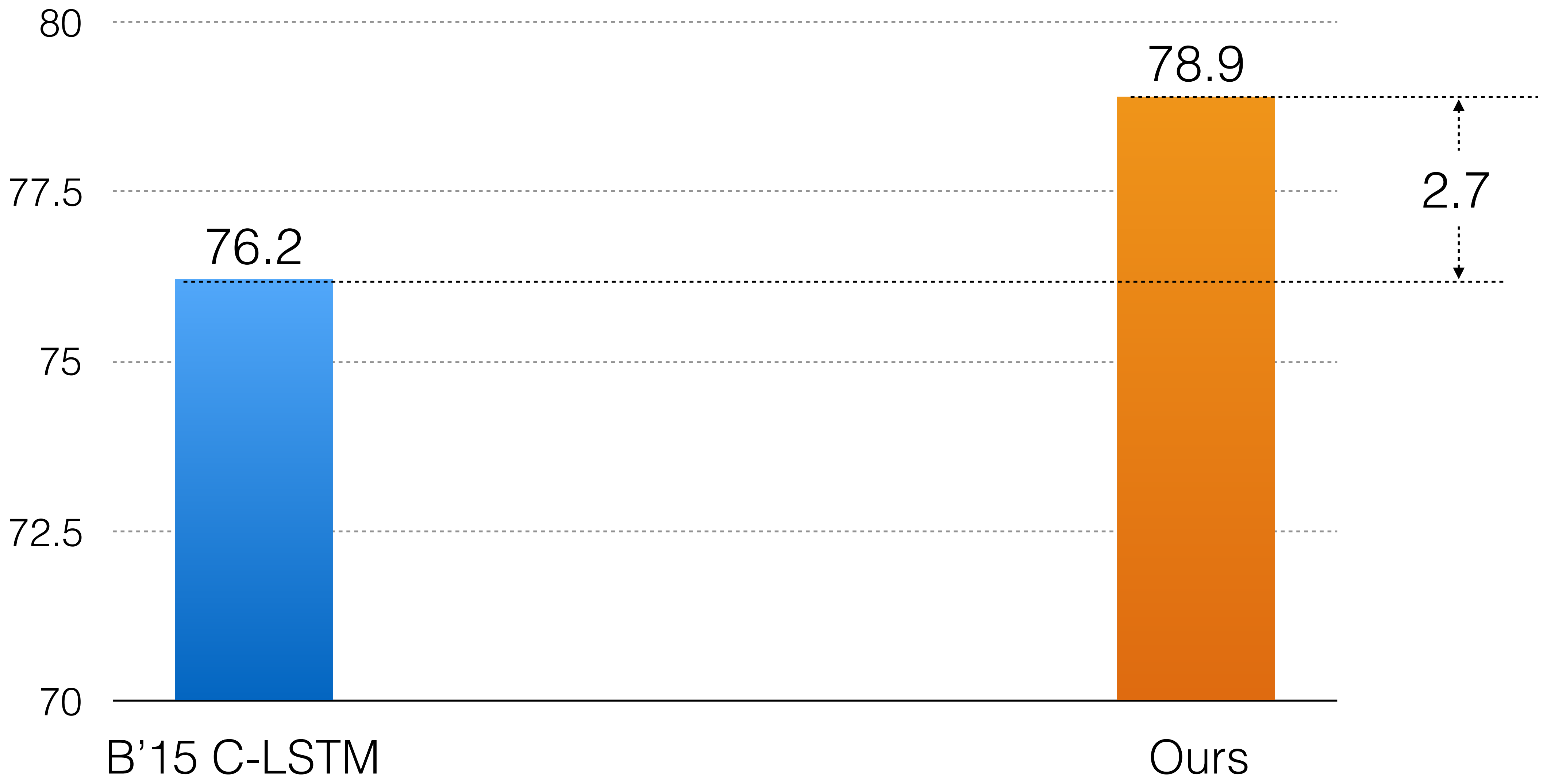
Baselines

- Transition-based NN system with greedy decoding
  - ✦ D'15 W-LSTM (Dyer'15): word-based LSTM
  - ✦ B'15 C-LSTM (Ballesteros'15): character-based LSTM
  - ✦ A'15 Joint (Alberti'15): joint parsing & tagging system

- Graph-based system
  - ✦ RBGParser (Lei'14, Zhang'14): state-of-the-art graph-based parser

Results on Universal Dependencies

Averaged Labeled Attachment Score (LAS) on 19 Languages



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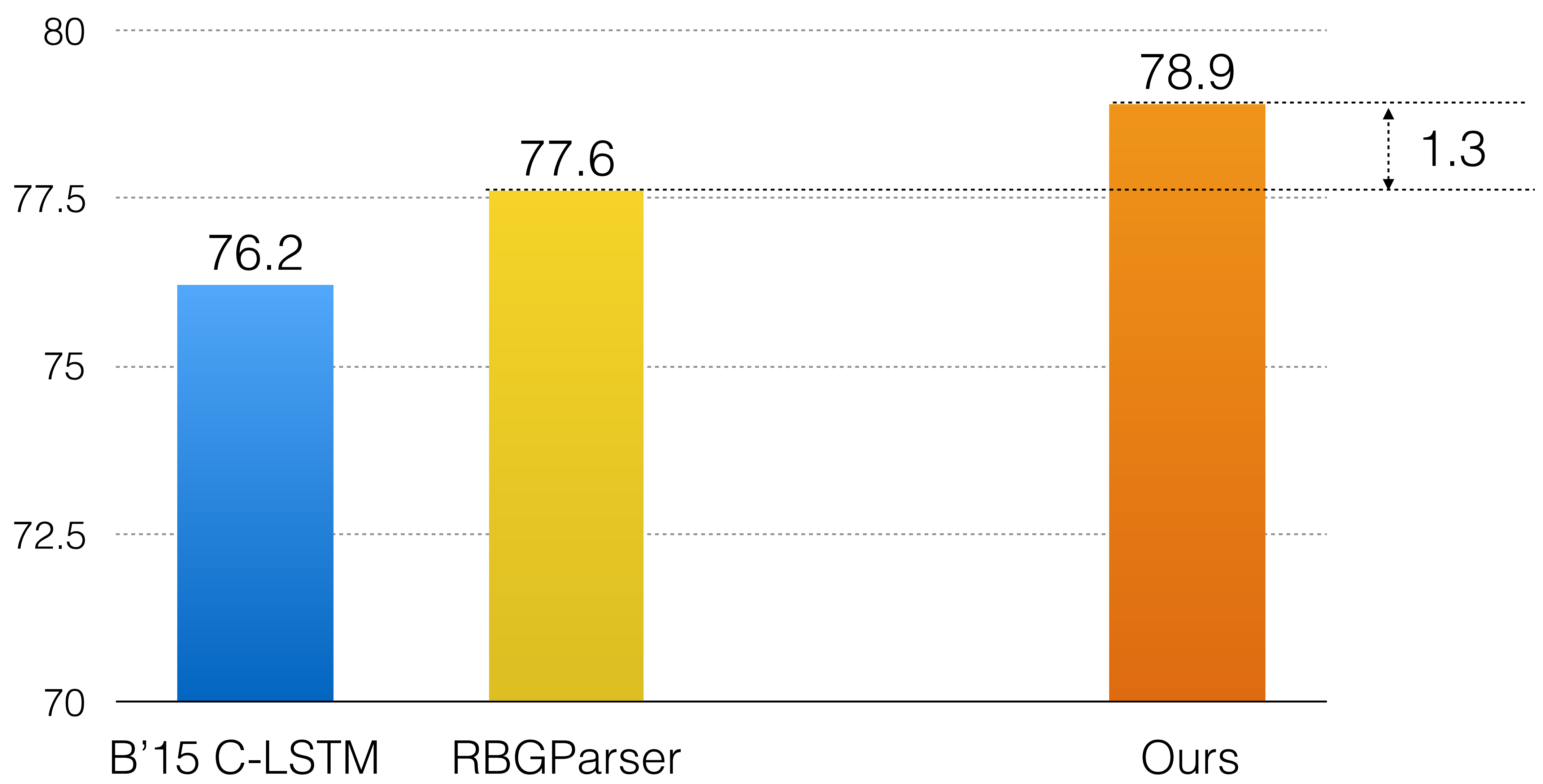

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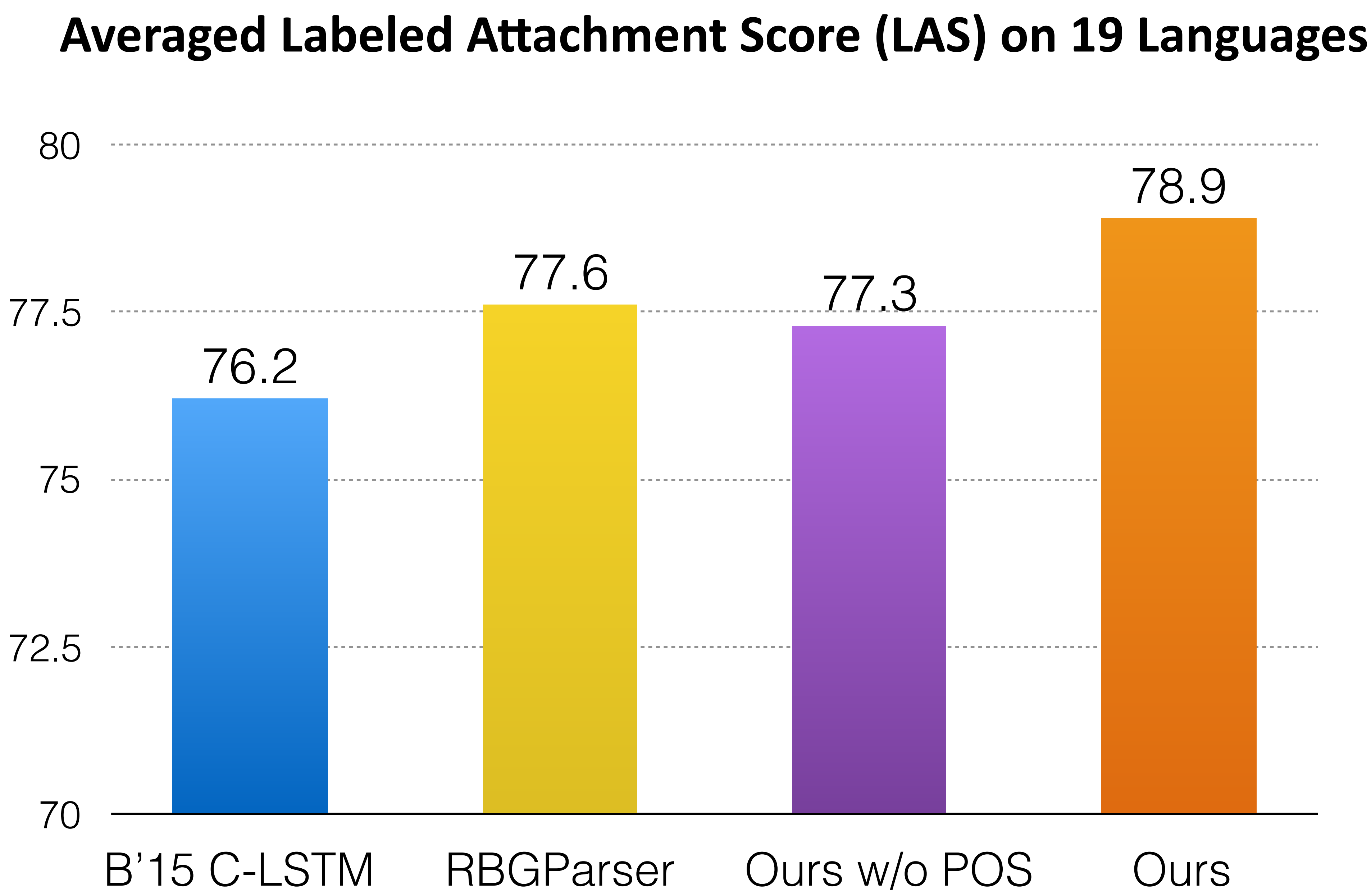
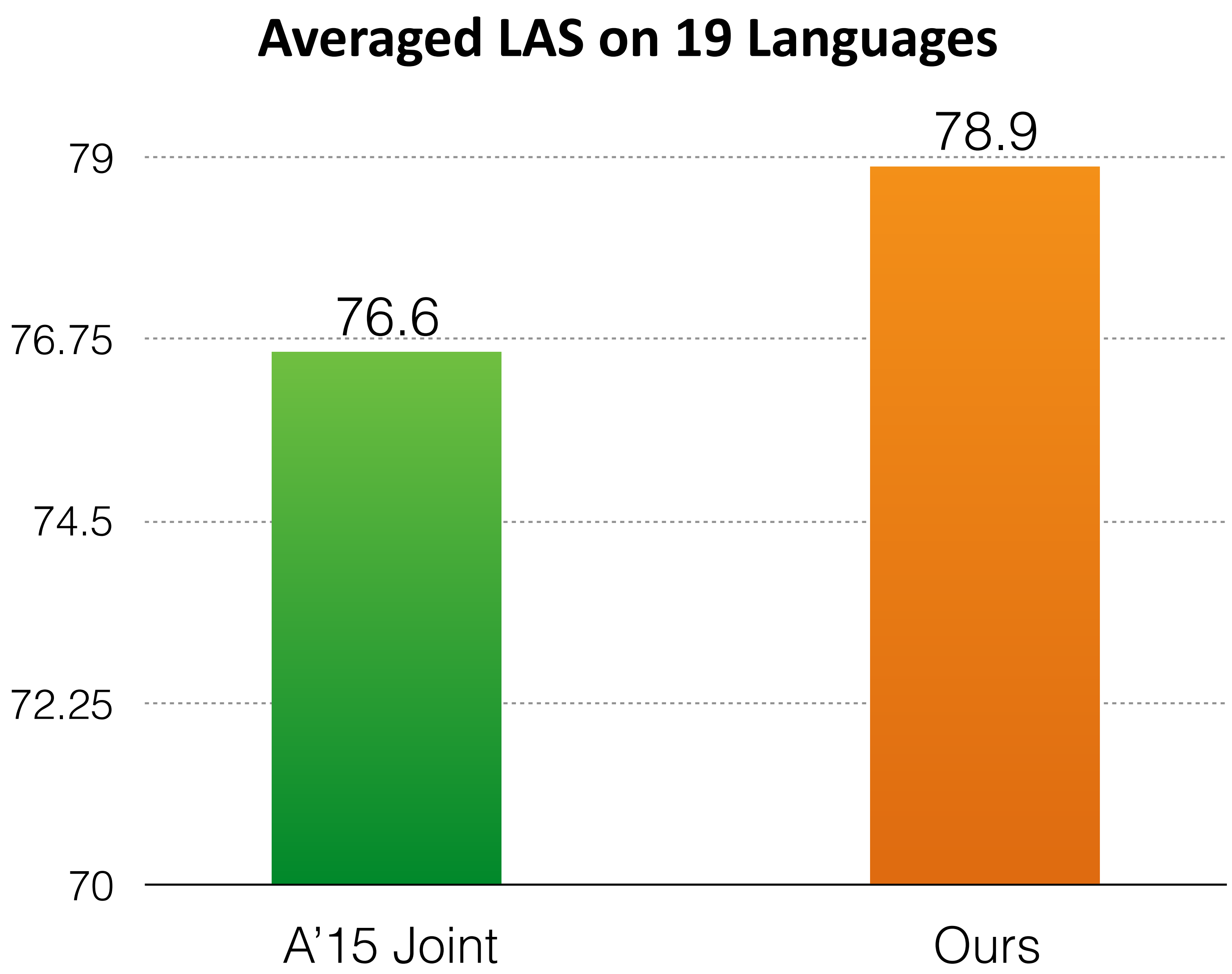


Stackprop vs. Joint Modeling



- Our learned representations are better than discrete feature vectors

Results on Wall Street Journal

Method	WSJ §23 UAS	LAS	
D'15 W-LSTM	93.10	90.90	
A'15 Joint	93.10	91.16	Beam=1
Ours	**93.43**	**91.41**	

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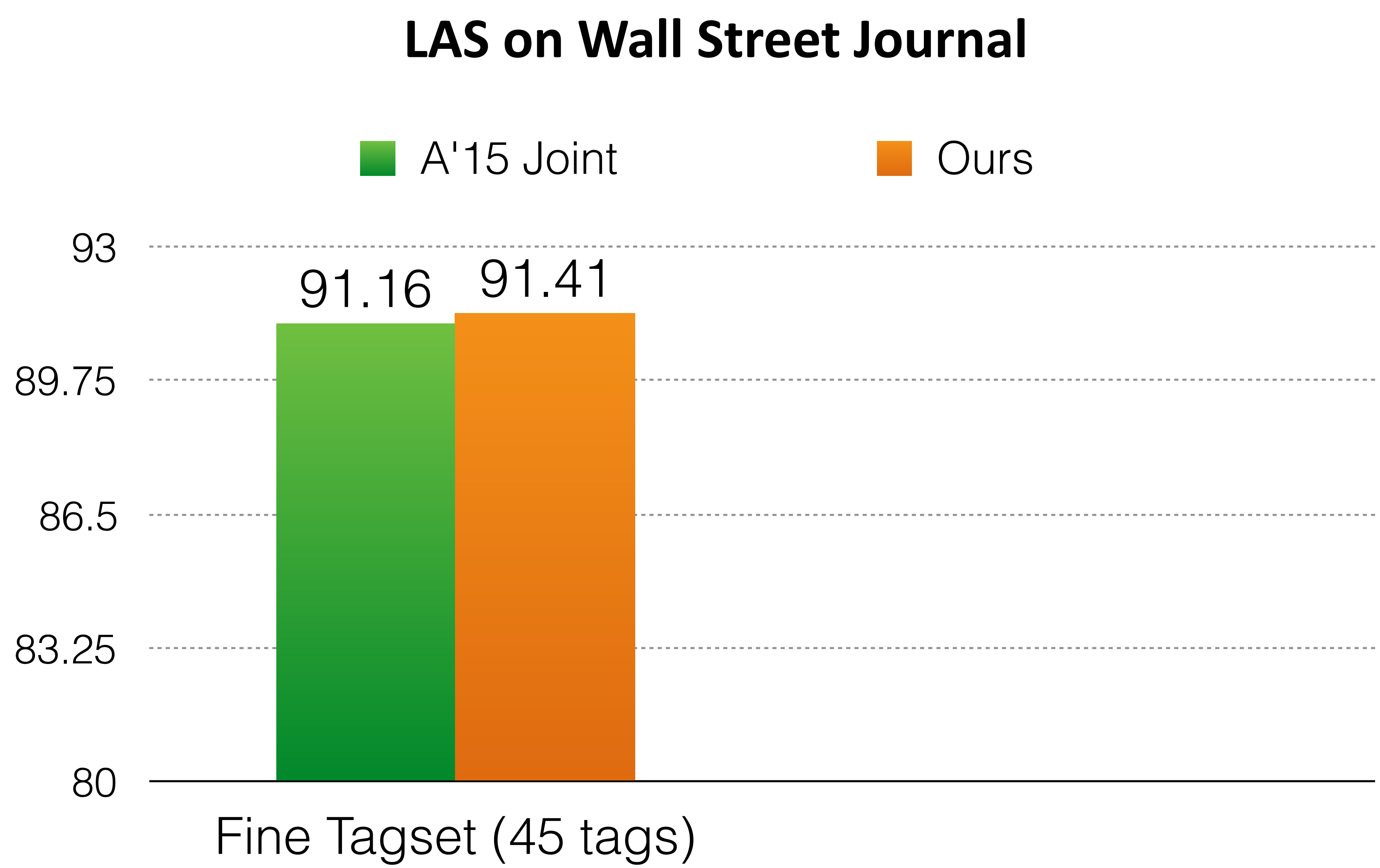
Weiss et al. (2015)	93.99	92.05	Beam=8
Alberti et al. (2015)	94.23	92.36	

Impact of Tagset Size



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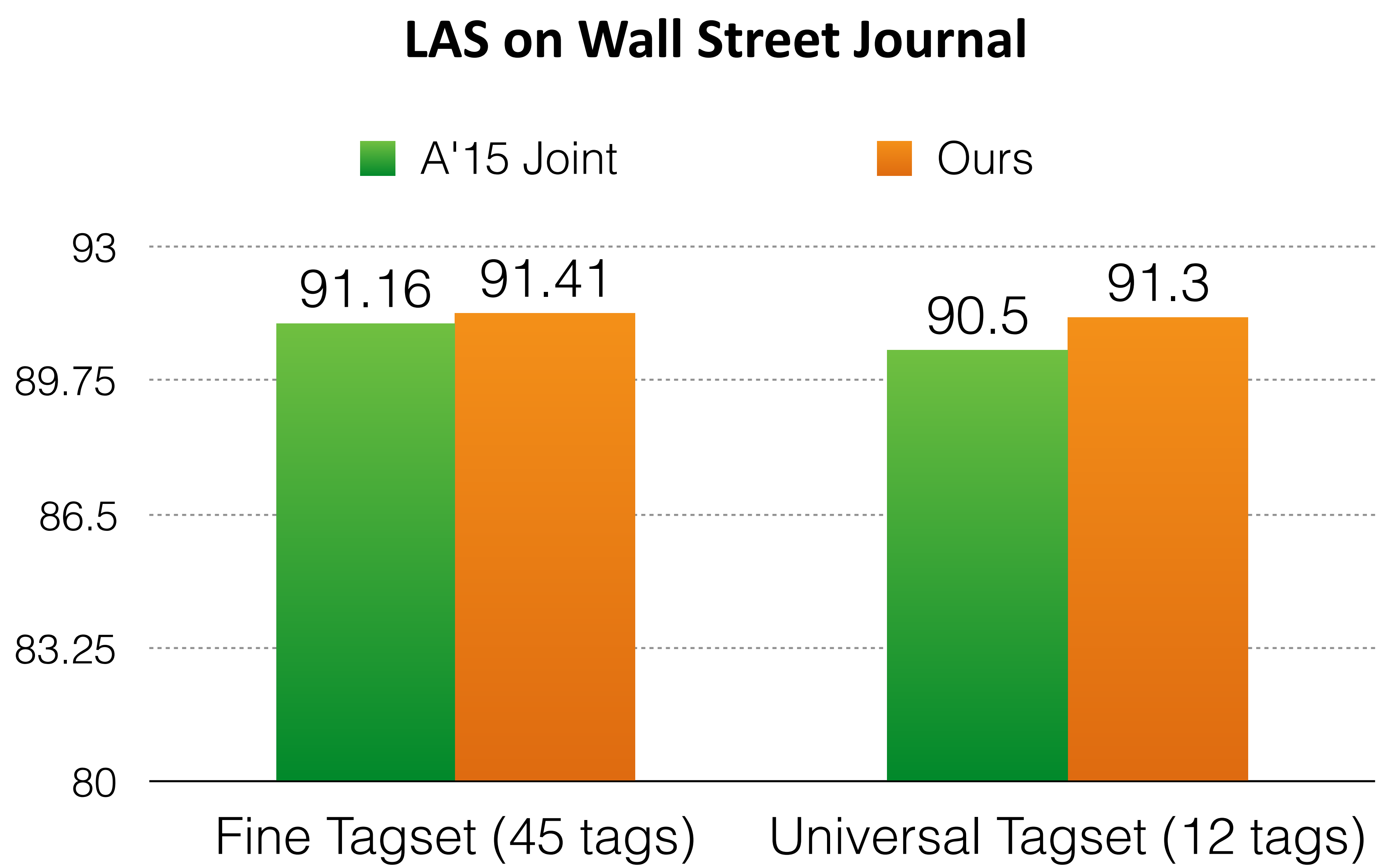
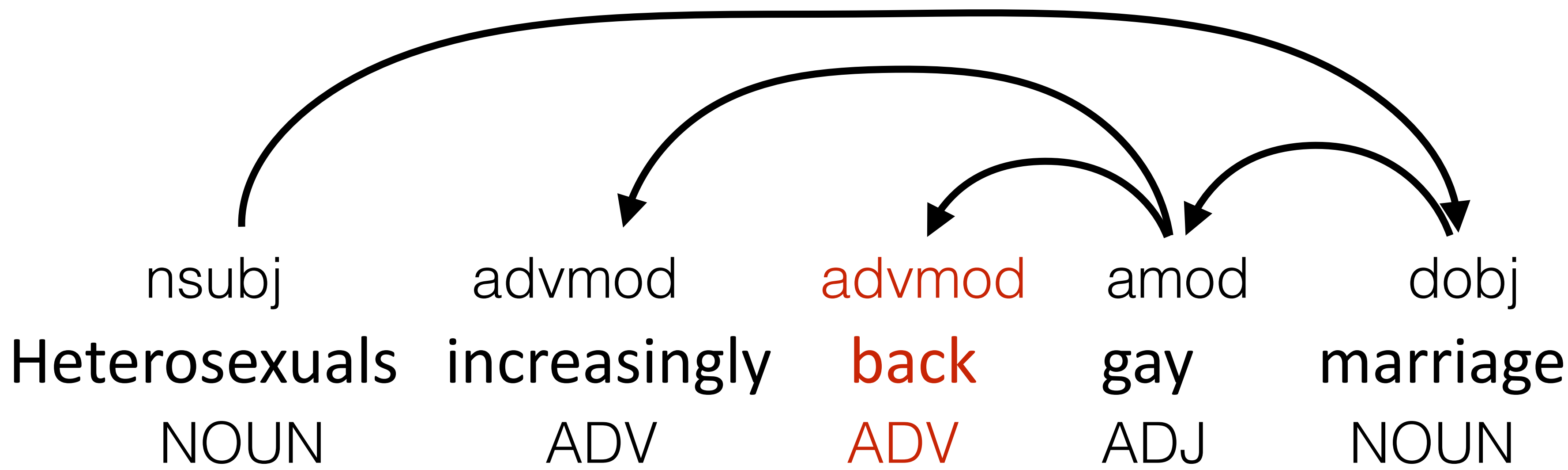
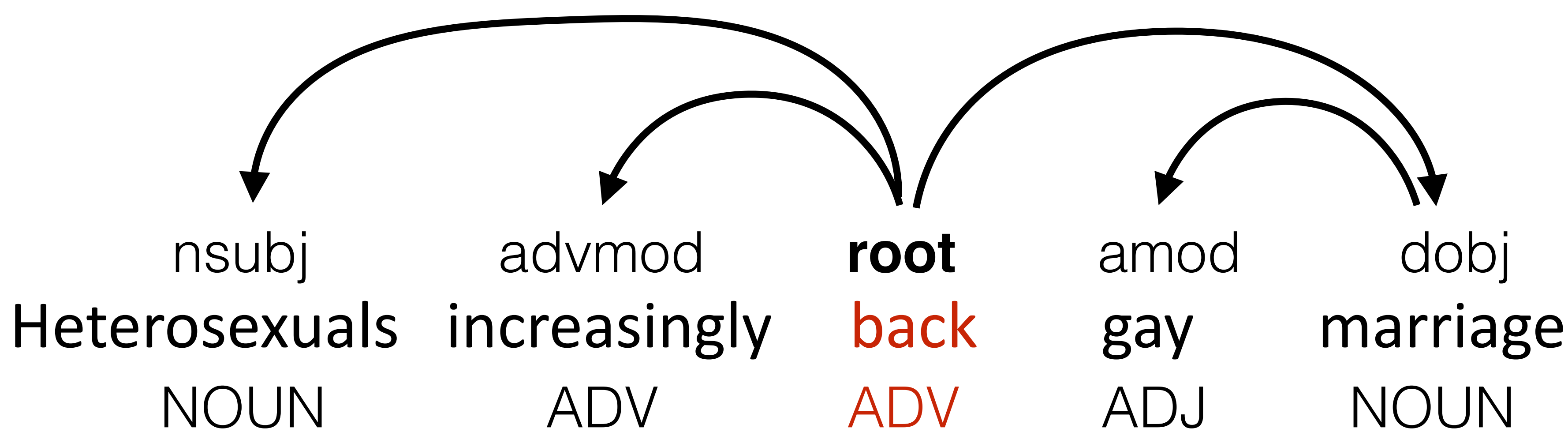


- More gains when only coarse tags are available

Reducing Error Propagations



Tree by a pipeline model



Tree by Stackprop model

- 10.9% LAS gain (34.1% vs 45.0%) on tokens with wrong POS tags

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- *Modeling:* we present a stacking neural network model for dependency parsing and tagging
- *Performance:* our model outperforms all baselines when evaluated on 19 languages of the UD treebank and outperforms other greedy models on the WSJ
- *Opportunities and Challenges:* we hope to apply this stacking idea to other structures and NLP problems.

Thank You!