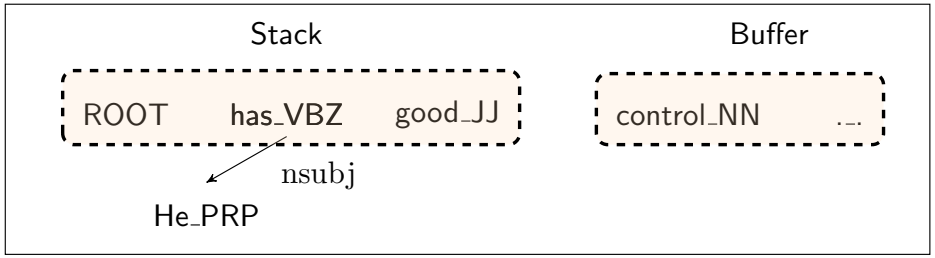
Traditional Features



binary, sparse
dim =10^6 ~ 10^7

Indicator features

$$s_2.w = \text{has} \wedge s_2.t = \text{VBZ}$$
$$s_1.w = \text{good} \wedge s_1.t = \text{JJ} \wedge b_1.w = \text{control}$$
$$lc(s_2).t = \text{PRP} \wedge s_2.t = \text{VBZ} \wedge s_1.t = \text{JJ}$$
$$lc(s_2).w = \text{He} \wedge lc(s_2).l = \text{nsubj} \wedge s_2.w = \text{has}$$

leftmost child

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Indicator Features Revisited

$$s_2.w = \text{has} \wedge s_2.t = \text{VBZ}$$
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Indicator Features Revisited

- Problem #1: sparse
  - lexicalized features
  - high-order interaction features

$$s_2.w = \text{has} \wedge s_2.t = \text{VBZ}$$
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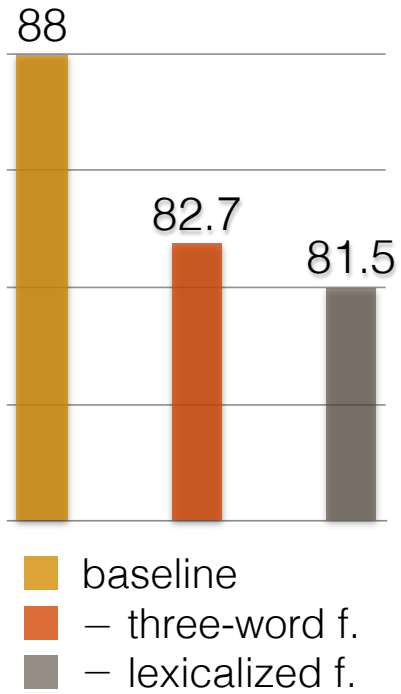

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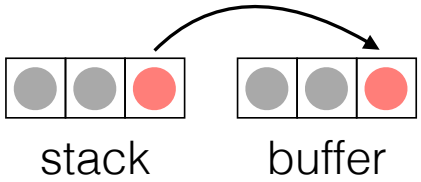
Indicator Features Revisited

- Problem #1: sparse
- Problem #2: incomplete

Unavoidable in hand-crafted feature templates.



~~RIGHT-ARC~~

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Indicator Features Revisited

- Problem #1: sparse
- Problem #2: incomplete
- Problem #3: computationally expensive

More than 95% of parsing time is consumed by feature computation.

$$s_2.w = \text{has} \wedge s_2.t = \text{VBZ}$$
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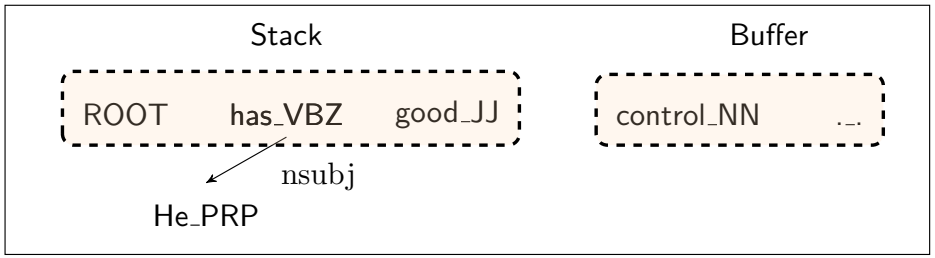
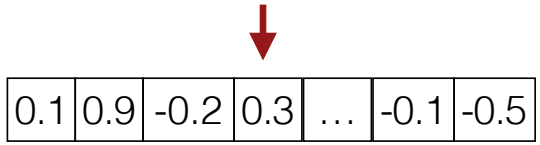
Indicator Features Revisited



dense
dim = 200



Our Solution: Neural Networks!

Learn a **dense** and **compact** feature representation

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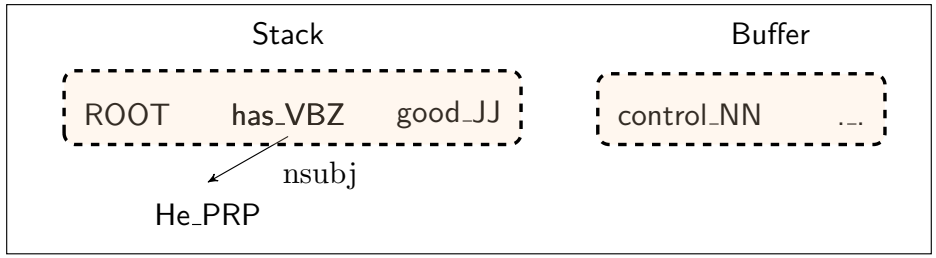
The Challenge



dense
dim = 200

- How to encode all the available information?
- How to model high-order features?

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Distributed Representations

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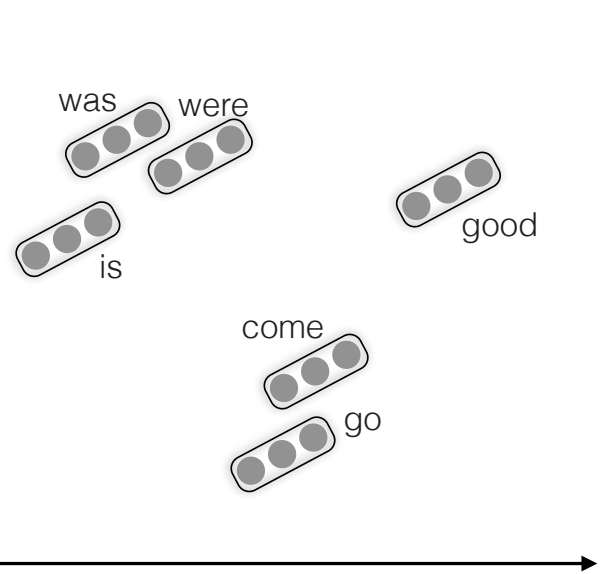
Distributed Representations

- We represent each word as a d-dimensional dense vector (i.e., word embeddings).
  - Similar words expect to have close vectors.



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Distributed Representations

- We represent each word as a d-dimensional dense vector (i.e., word embeddings).
  - Similar words expect to have close vectors.
- Meanwhile, part-of-speech tags and dependency labels are also represented as d-dimensional vectors.
  - POS and dependency embeddings.
  - The smaller discrete sets also exhibit many semantical similarities.

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  - The smaller discrete sets also exhibit many semantical similarities.

NNS (plural noun) should be close to NN (singular noun).

num (numerical modifier) should be close to amod (adjective modifier).

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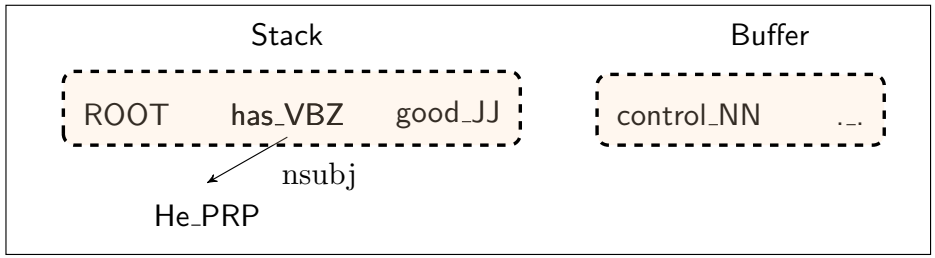
Extracting Tokens from Configuration

- We extract a set of tokens based on the positions:



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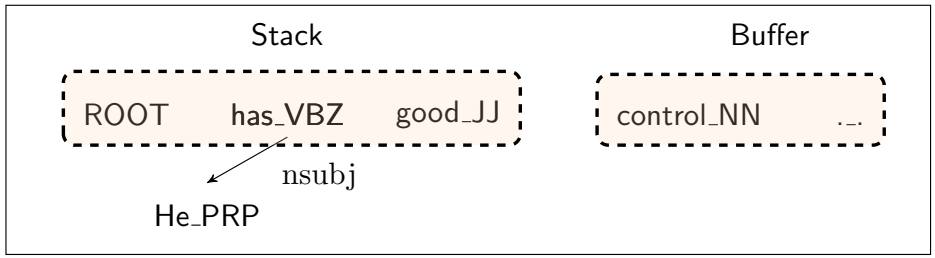

s_1
s_2
b_1
$lc(s_1)$
$rc(s_1)$
$lc(s_2)$
$rc(s_2)$
...

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Extracting Tokens from Configuration

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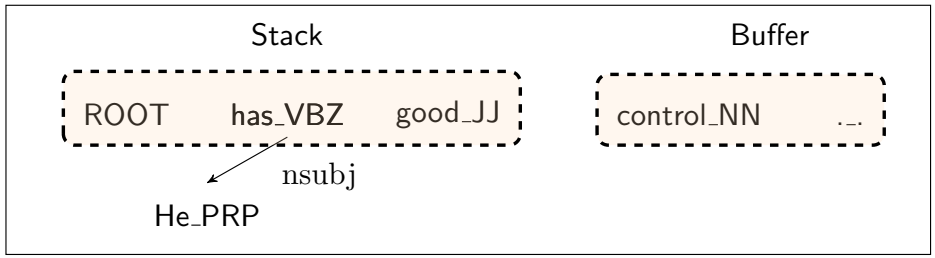

	word	POS	dep.
s_1	good	JJ	
s_2	has	VBZ	
b_1	control	NN	
$lc(s_1)$	∅	∅	∅
$rc(s_1)$	∅	∅	∅
$lc(s_2)$	He	PRP	nsubj
$rc(s_2)$	∅	∅	∅
…	…	…	…

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Model Architecture

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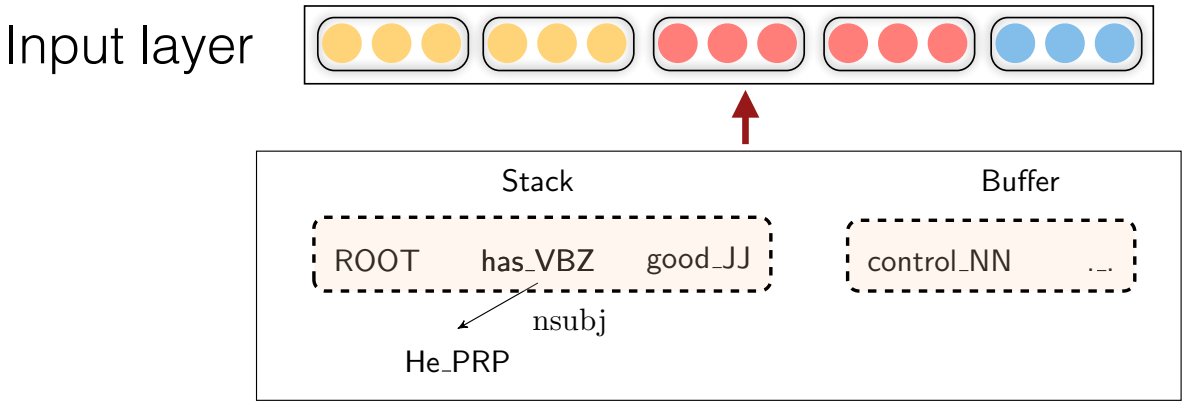
Model Architecture



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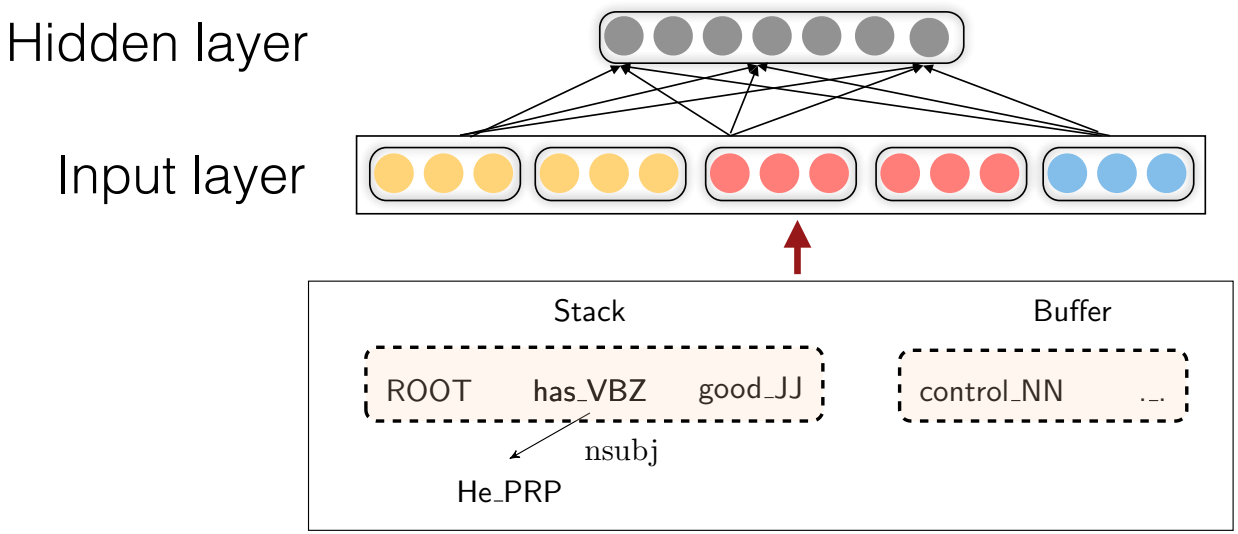
Model Architecture



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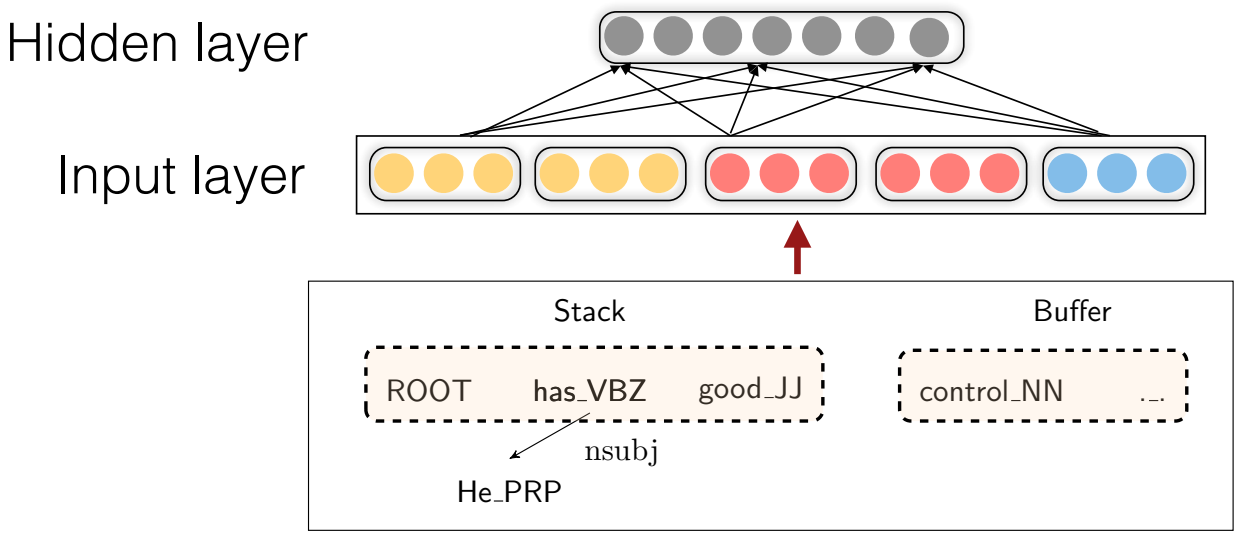
Model Architecture

Cube activation function: $g(x) = x^3$



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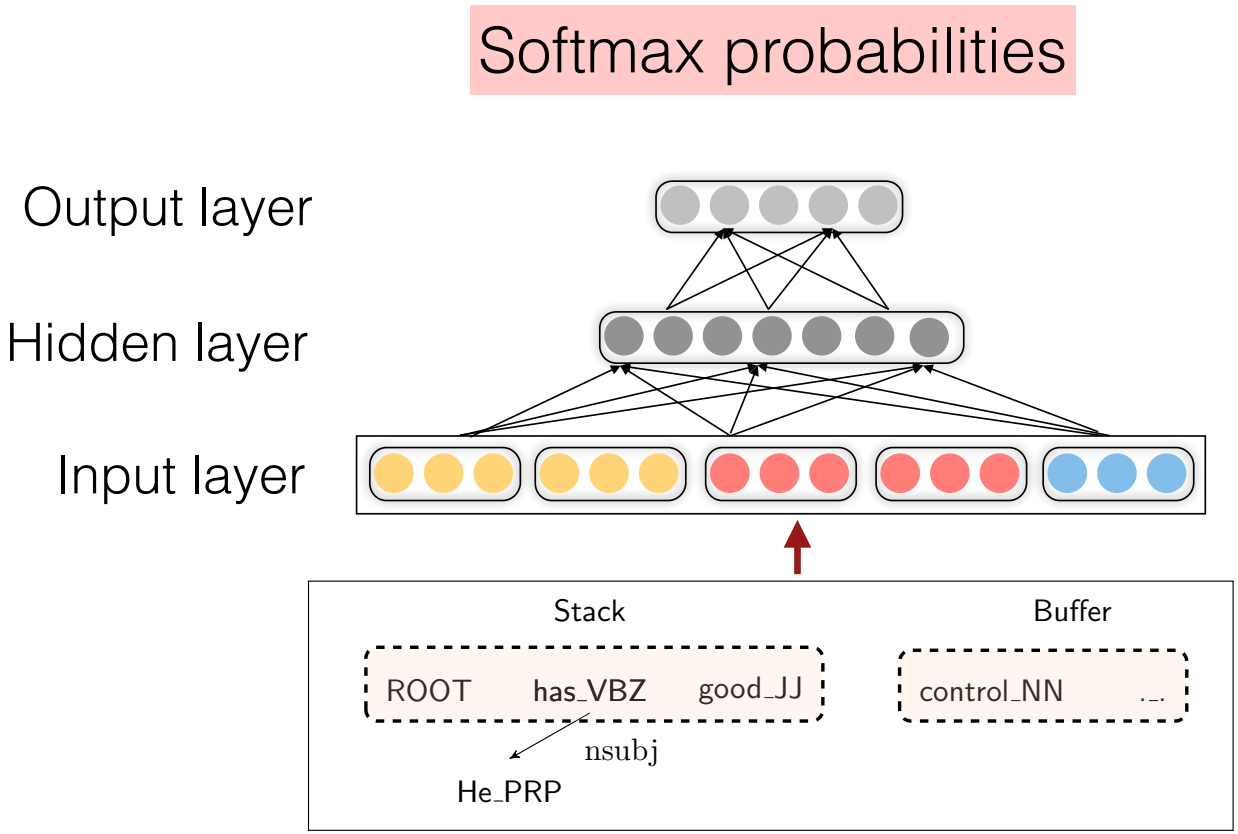

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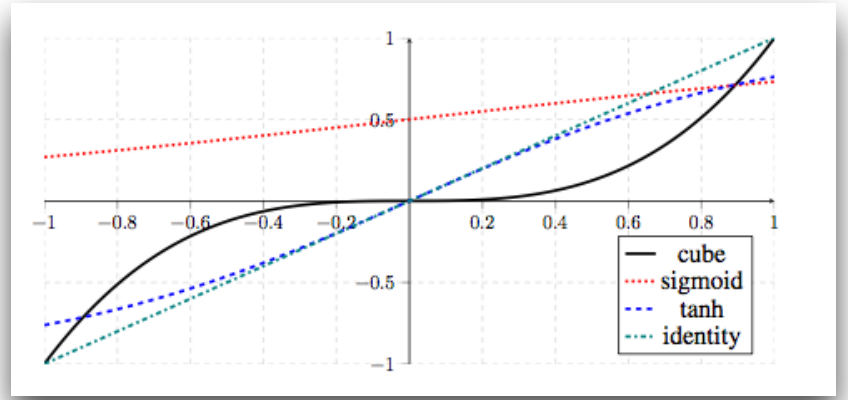
Cube Activation Function



$$g(w_1x_1 + \ldots + w_mx_m + b) =$$
$$\sum_{i,j,k}(w_iw_jw_k)x_ix_jx_k + \sum_{i,j} b(w_iw_j)x_ix_j \ldots$$

Better capture the **interaction** terms!

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Training

- Generating training examples using a fixed oracle.
- **Training objective**: cross entropy loss
- Back-propagation to all embeddings.
- **Initialization**:
  - Word embeddings from pre-trained word vectors.
  - Random initialization for others.

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Indicator vs. Dense Features

- Problem #1: sparse

  Distributed representations can capture similarities.

- Problem #2: incomplete

  We don't need to enumerate the combinations.
  Cube non-linearity can learn combinations automatically.

- Problem #3: computationally expensive

  String concatenation + look-up in a big table $\Longrightarrow$ matrix operations. Pre-computation trick can speed up.

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Experimental Setup

- **Datasets**
  - English Penn Treebank (PTB)
  - Chinese Penn Treebank (CTB)
- **Representations**
  - CoNLL representations (CD) for PTB and CTB
  - Stanford Dependencies V3.3.0 (SD) for PTB
- **Part-of-speech tags**:
  - Stanford POS tagger for PTB (97.3% accuracy)
  - Gold tags for CTB

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Details

- Embedding size = 50
- Hidden size = 200
- Use mini-batched AdaGrad for optimization ($\alpha = 0.01$)
- Use 0.5 dropout on hidden layer.

- Pre-trained word vectors:
  - C & W for English
  - Word2vec for Chinese

- We use a rich set of 18 tokens from the configuration.

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(Nivre et al 2006, McDonald and Pereira 2006)

Baselines

- **Standard / eager**: our own implemented perceptron-based greedy parsers using arc-standard or arc-eager system, with a rich feature set from (Zhang and Nivre, 2011).
- **MaltParser**
  - two algorithms **stackproj** and **nivreeager**.
- **MSTParser**

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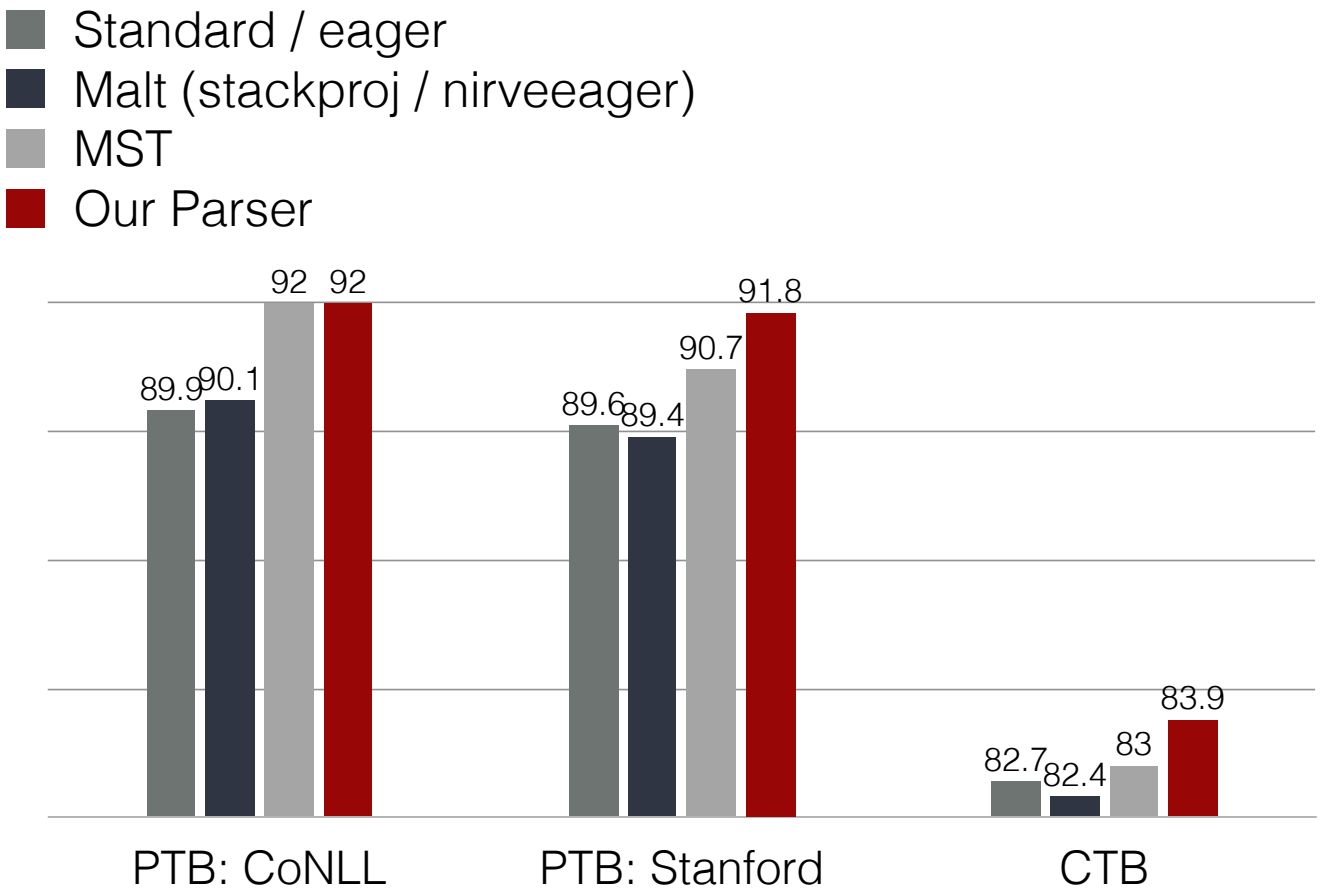
Unlabeled Attachment Score (UAS)



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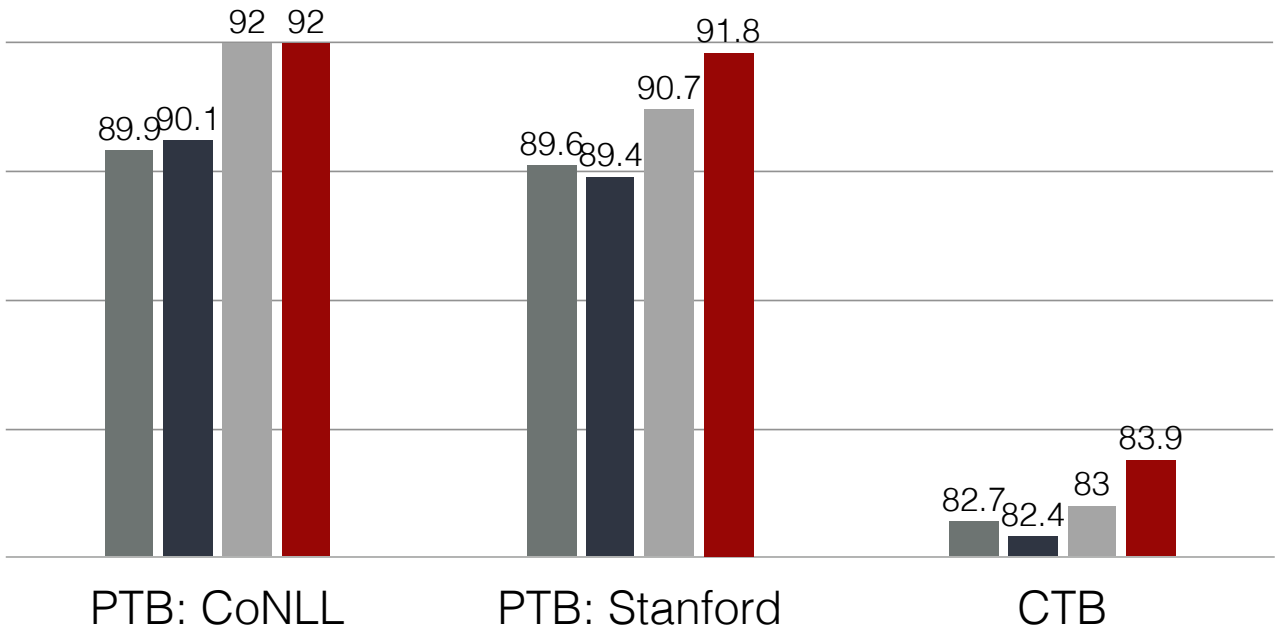
Unlabeled Attachment Score (UAS)

- Standard / eager
- Malt (stackproj / nirveeager)
- MST
- Our Parser

Compared with greedy parsers,
PTB: > 2.0%
CTB: >1.2%



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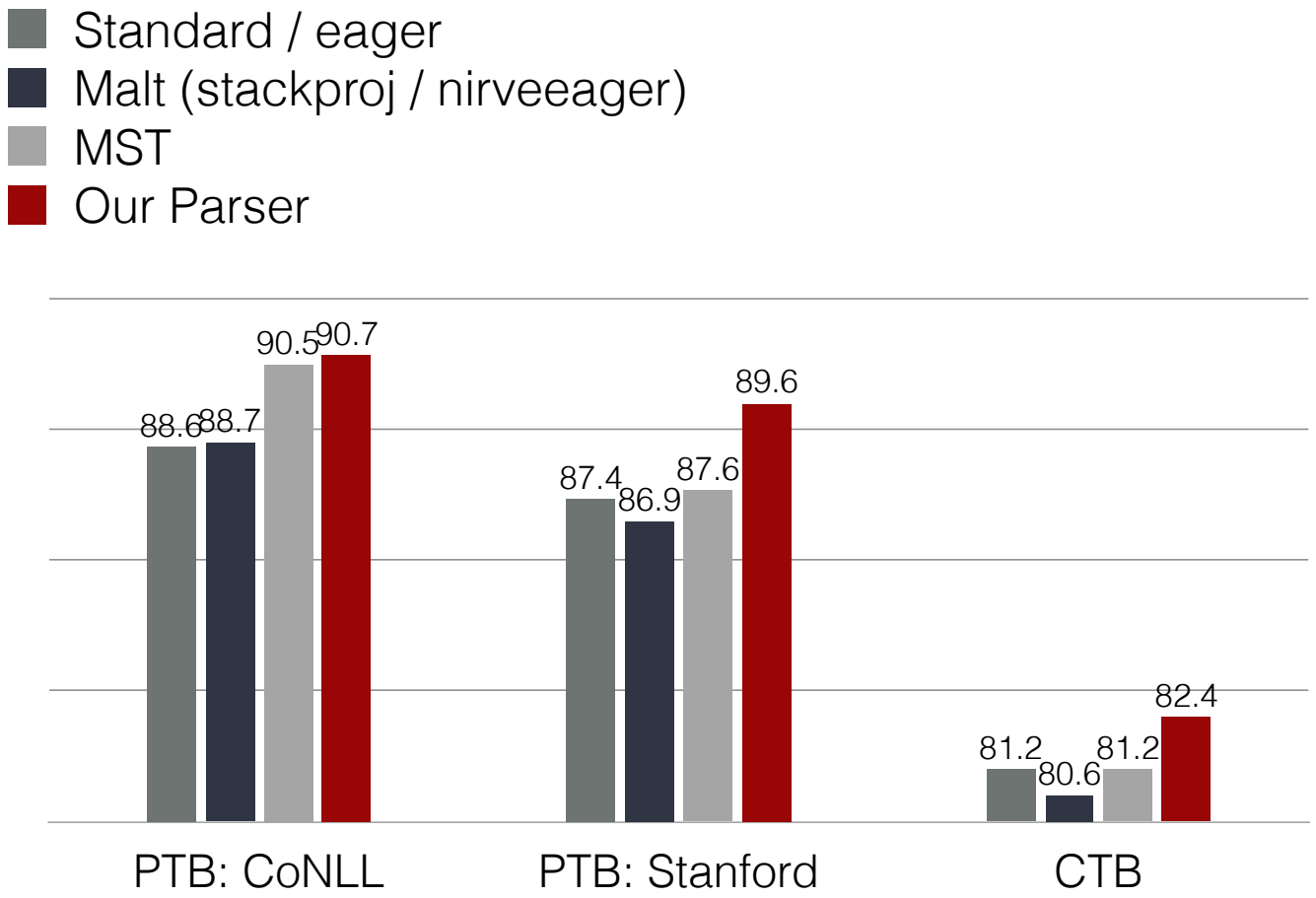
Labeled Attachment Score (LAS)



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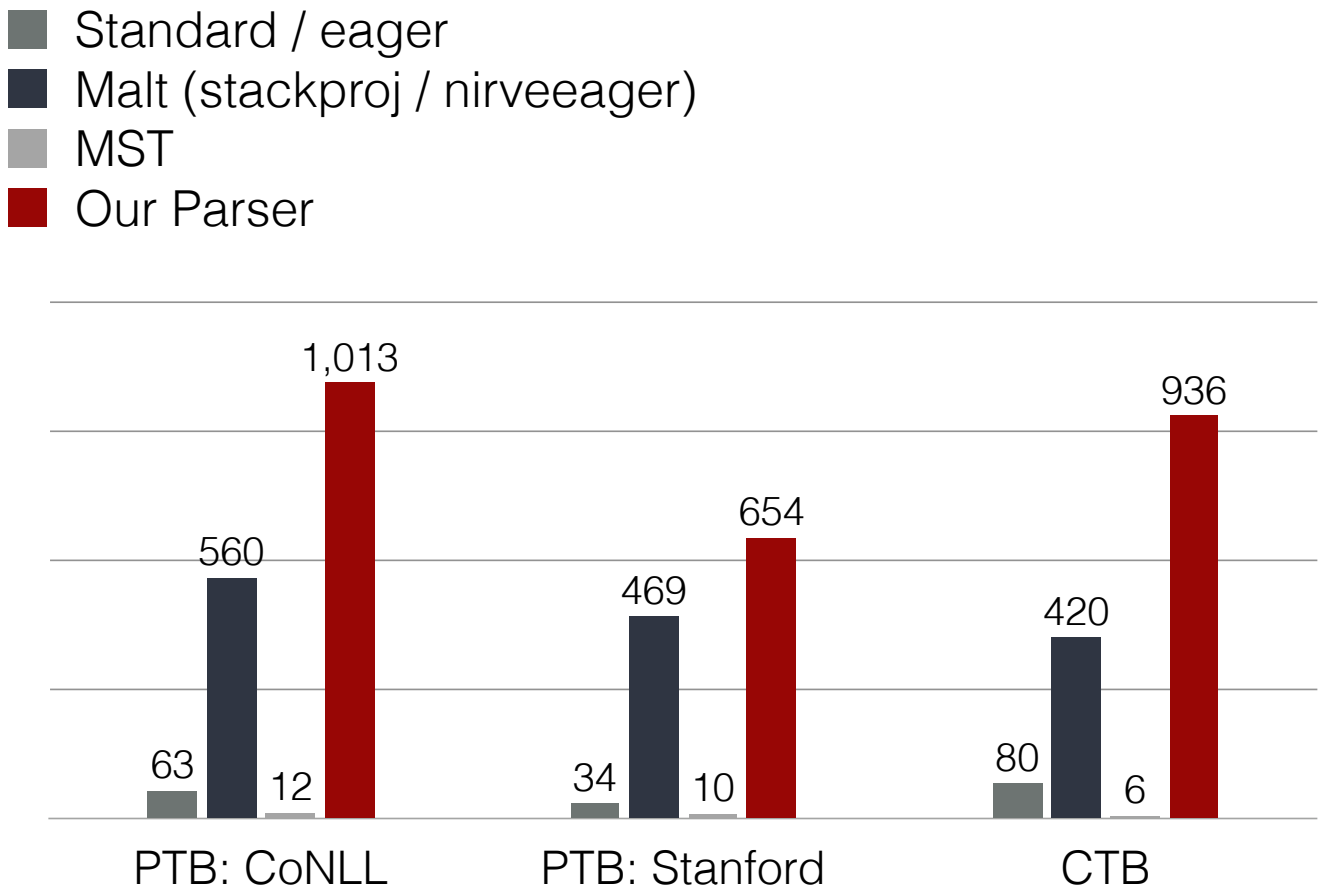
Parsing Speed (sent/s)



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(Zhang and Nirve 2011, Martins et al 2013)

Our Work

- A neural network based dependency parser!

Parsing on English Penn Treebank (§23):

		Unlabeled attachment score (UAS)	sent / s
Transition -based	MaltParser (greedy)	89.9	560
	Our Parser (greedy)	92.0 (+2.1)	1013 (×1.8)
	Zpar: beam = 64	92.9*	29*
Graph -based	MSTParser	92.0	12
	TurboParser	93.1*	31*

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Content

1. Grammars and syntax parsing
2. Parsing with context free grammars
3. Parsing with probabilistic context free grammars
4. Dependency parsing
5. Parsing with neural networks