Natural Language Understanding

Lecture 9: Dependency Parsing with Neural Networks

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Reading: Chen and Manning (2014).

Dependency Parsing

Traditional dependency parsing (Nivre 2003):

- simple shift-reduce parser (see last lecture);
- classifier chooses which transition (parser action) to take for each word in the input sentence;
- features for classifier similar to MALT parser (last lecture):
  - word/PoS unigrams, bigrams, trigrams;
  - state of the parser;
  - dependency tree built so far.

Problems:

- feature templates need to be handcrafted;
- results in millions of features
- feature are sparse and slow to extract.

Dependency Parsing

Chen and Manning (2014) propose:

- keep the simple shift-reduce parser;
- replace the classifier for transitions with a neural net;
- use dense features (embeddings) instead of sparse, handcrafted features.

Results:

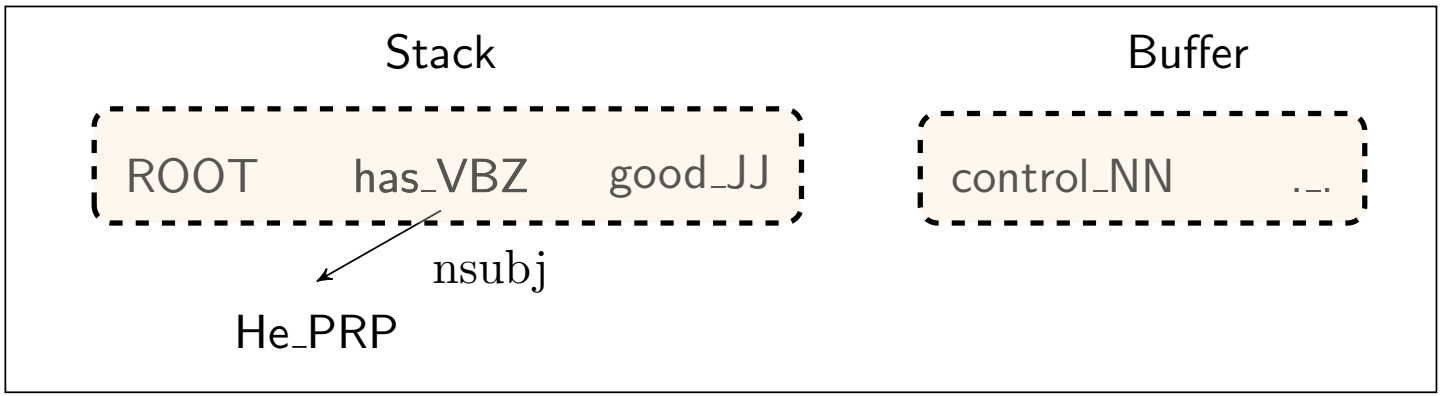
- efficient parser (up to twice as fast as standard MALT parser);
- good performance (about 2% higher precision than MALT).

Network Architecture

Goal of the network: predict correct transition $t \in \mathcal{T}$, based on configuration c. Relevant information:

1. words and PoS tags (e.g., has/VBZ);
2. head of words with dependency label (e.g., `nsubj`, `dobj`);
3. position of words on stack and buffer.

Correct transition: `SHIFT`



Network Architecture

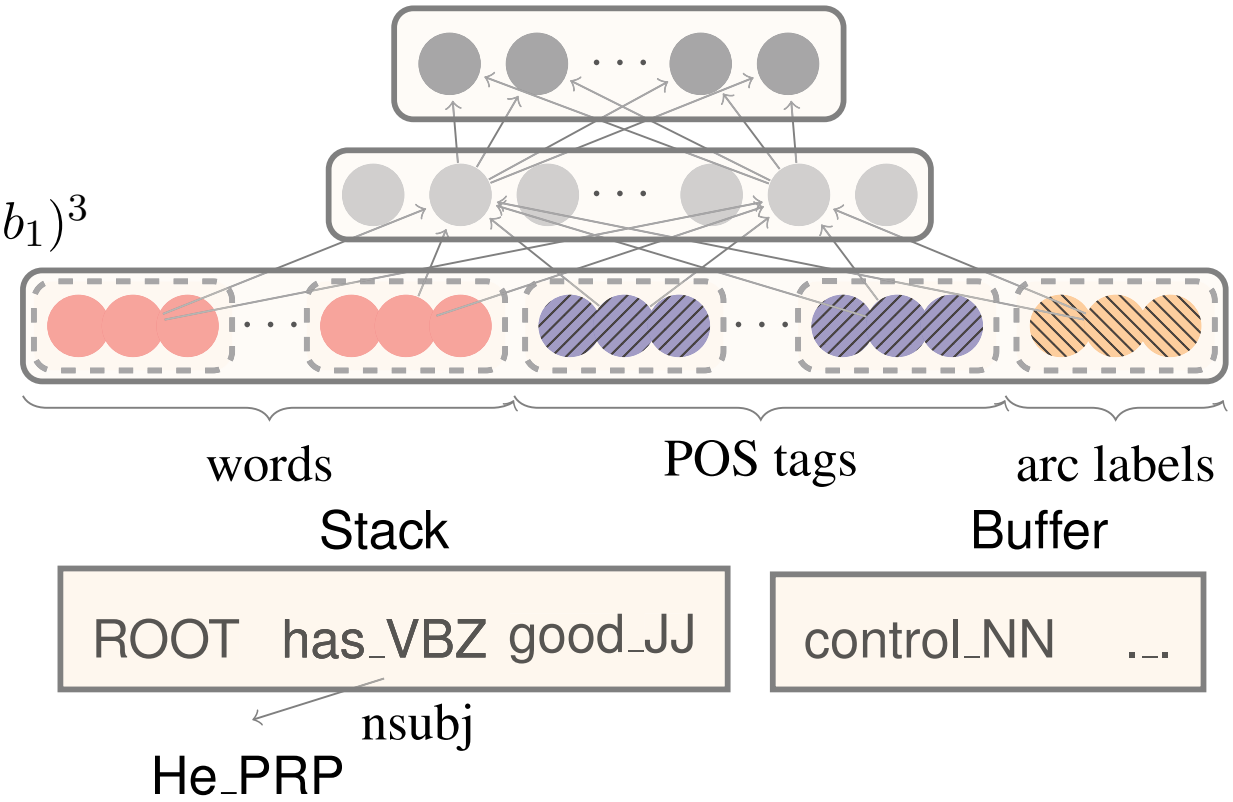
Softmax layer:

$$p = \texttt{softmax}(W_2 h)$$

Hidden layer:

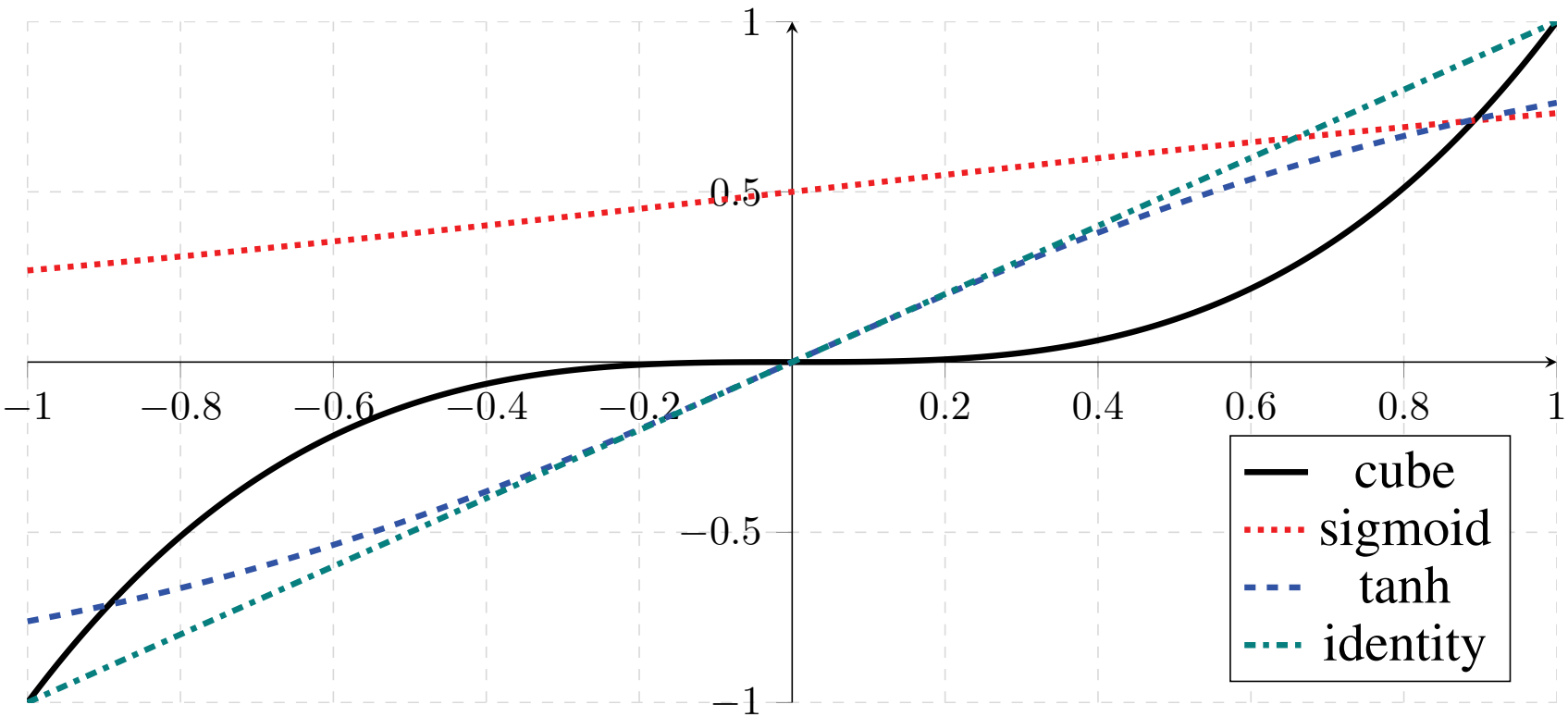
$$h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3$$

Input layer: $[x^w, x^t, x^l]$

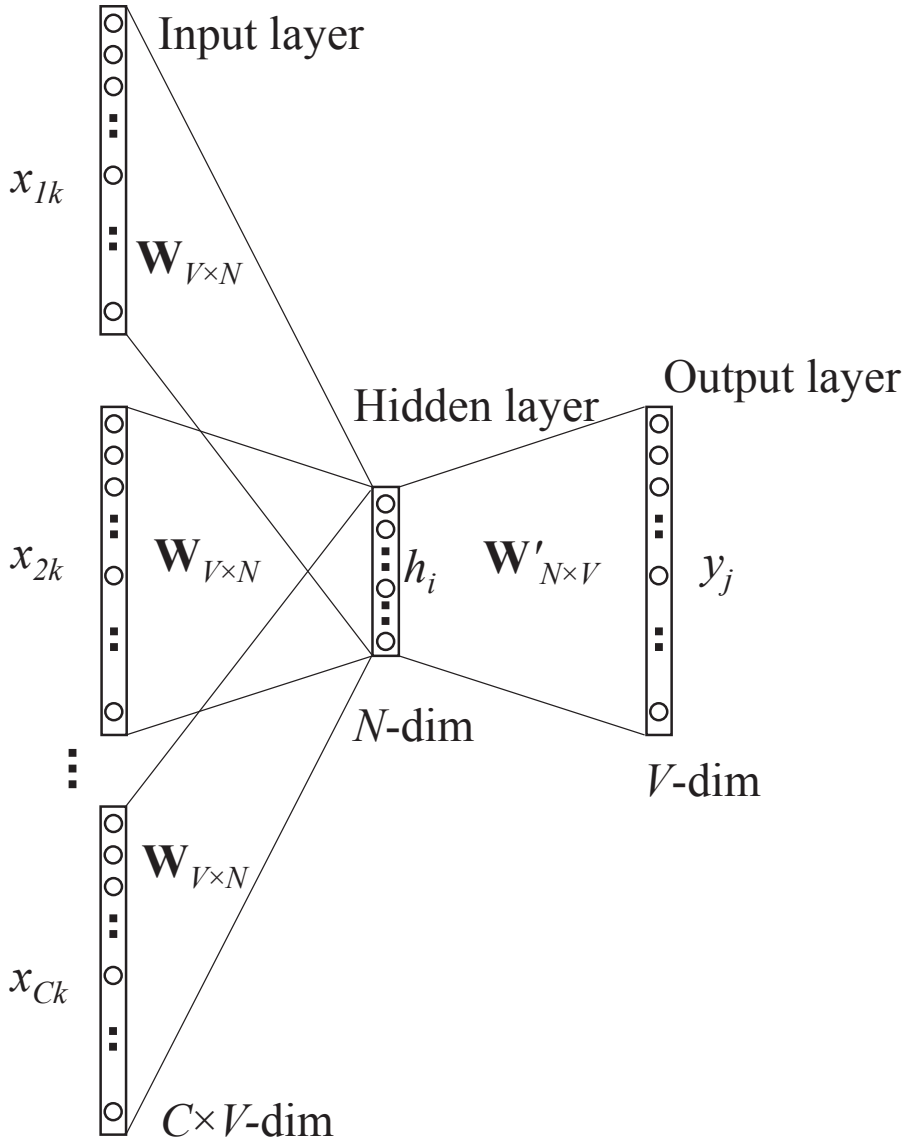


Configuration

Activation Function



Revision: Embeddings

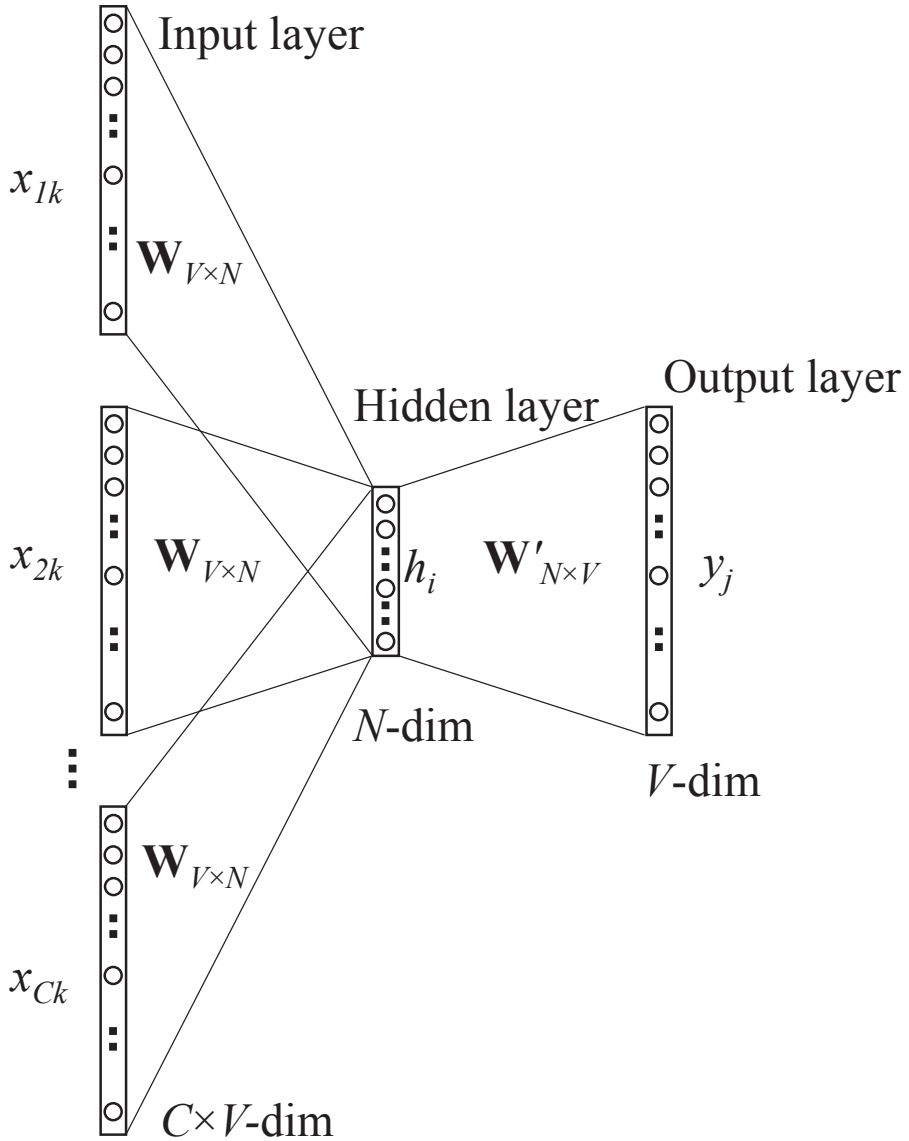


CBOW (Mikolov et al. 2013):

x_{ik}	context words (one-hot)
h_i	hidden units
y_j	output units (one-hot)
$\mathbf{W}$, $\mathbf{W}'$	weight matrices
V	vocabulary size
N	size of hidden layer
C	number of context words

[Figure from Rong (2014).]

Revision: Embeddings



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By *embedding* we mean the hidden layer **h**!

[Figure from Rong (2014).]

Embeddings

Chen and Manning (2014) use the following word embeddings S^w (18 elements):

1. top three words on stack and buffer: s_1, s_2, s_3, b_1, b_2, b_3;
2. first and second leftmost/rightmost children of top two words on stack: $lc_1(s_i)$, $rc_1(s_i)$, $lc_2(s_i)$, $rc_2(s_i)$, $i = 1, 2$;
3. leftmost of leftmost/rightmost of rightmost children of top two words on the stack: $lc_1(lc_1(s_i))$, $rc_1(rc_1(s_i))$, $i = 1, 2$.

Tag embeddings S^t (18 elements): same as word embeddings.

Arc label embeddings S^l (12 elements): same as word embeddings, excluding those the six words on the stack/buffer.

Training

Generate examples $\{(c_i, t_i)\}_{i=1}^{m}$ from sentences with gold parse trees using *shortest stack* oracle (always prefers LEFT-ARC(l) over SHIFT), where c_i is a configuration, $t_i \in \mathcal{T}$ a transition.

Objective: minimize cross-entropy loss with l_2-regularization:

$$L(\theta) = -\sum_i \log p_{t_i} + \frac{\lambda}{2}||\theta||^2$$

where p_{t_i} is the probability of transition t_i (from softmax layer), and θ is set of all parameters $\{W_1^w, W_1^t, W_1^l, b_1, W_2, E^w, E^t, E^l\}$.

Training

Use pre-trained word embeddings to initialize E^w; use random initialization within $(-0.01, 0.01)$ for E^t and E^l.

Word embeddings (Collobert et al. 2011) for English; 50-dimensional word2vec embeddings (Mikolov et al. 2013) for Chinese; compare with random initialization of E_w.

Mini-batched AdaGrad for optimization, dropout with 0.5 rate. Tune parameters on development set based UAS.

Hyper-parameters: embedding size $d = 50$, hidden layer size $h = 200$, regularization parameter $\lambda = 10^{-8}$, initial learning rate of AdaGrad $\alpha = 0.01$.

Decoding

The parser performs greedy decoding:

- for each parsing step, extract all word, PoS, and label embeddings from current configuration c;
- compute the hidden layer $h(c)$;
- pick transition with the highest score: $t = \text{argmax}_t\, W_2(t, \cdot)h(c)$;
- execute transition $c \rightarrow t(c)$.

Results: English with CoNLL Dependencies

Parser	Dev		Test		Speed
	UAS	LAS	UAS	LAS	(sent/s)
standard	89.9	88.7	89.7	88.3	51
eager	90.3	89.2	89.9	88.6	63
Malt:sp	90.0	88.8	89.9	88.5	560
Malt:eager	90.1	88.9	90.1	88.7	535
MSTParser	92.1	90.8	92.0	90.5	12
Our parser	92.2	91.0	92.0	90.7	1013

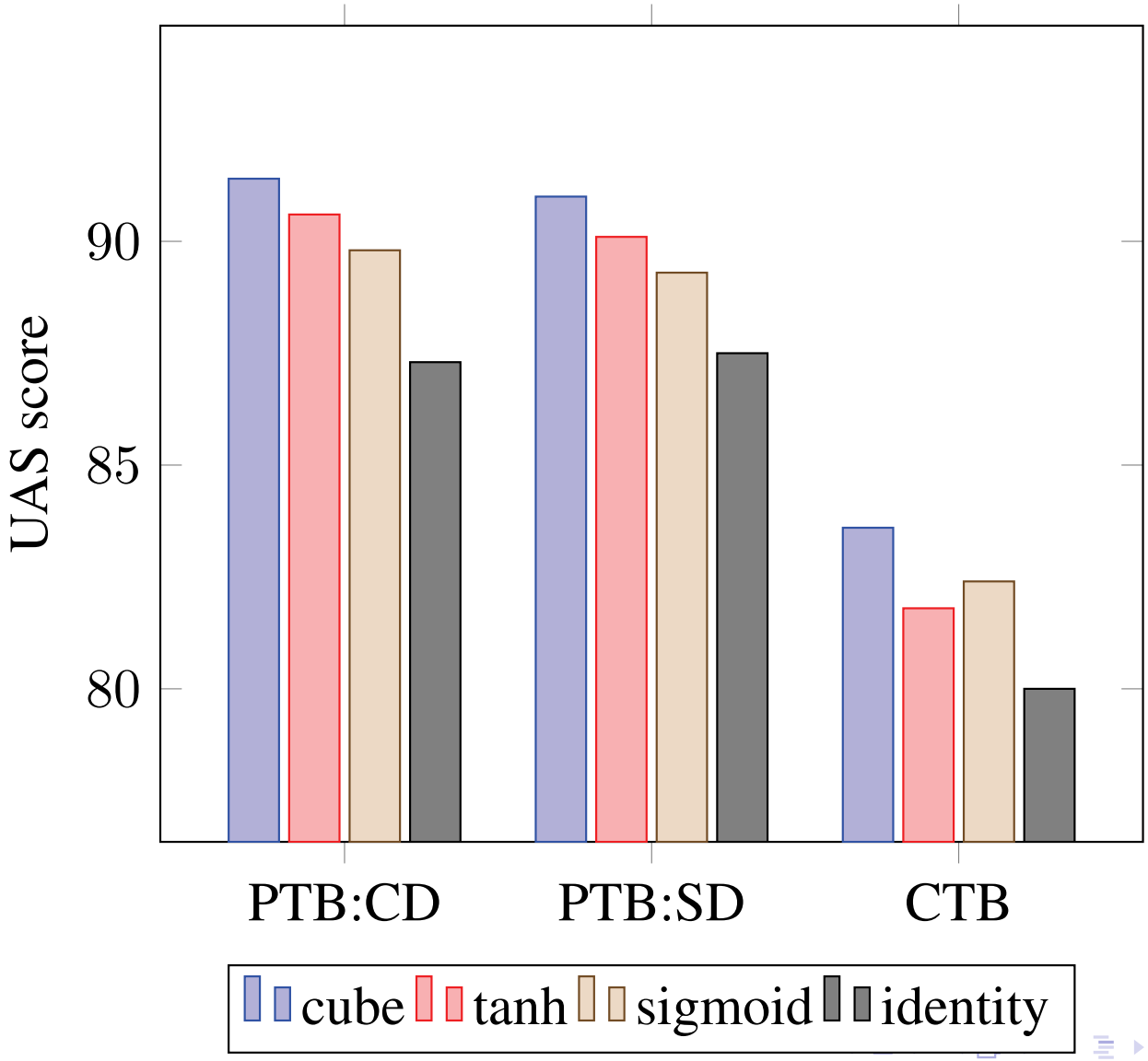
Results: English with Stanford Dependencies

Parser	Dev		Test		Speed
	UAS	LAS	UAS	LAS	(sent/s)
standard	90.2	87.8	89.4	87.3	26
eager	89.8	87.4	89.6	87.4	34
Malt:sp	89.8	87.2	89.3	86.9	469
Malt:eager	89.6	86.9	89.4	86.8	448
MSTParser	91.4	88.1	90.7	87.6	10
Our parser	92.0	89.7	91.8	89.6	654

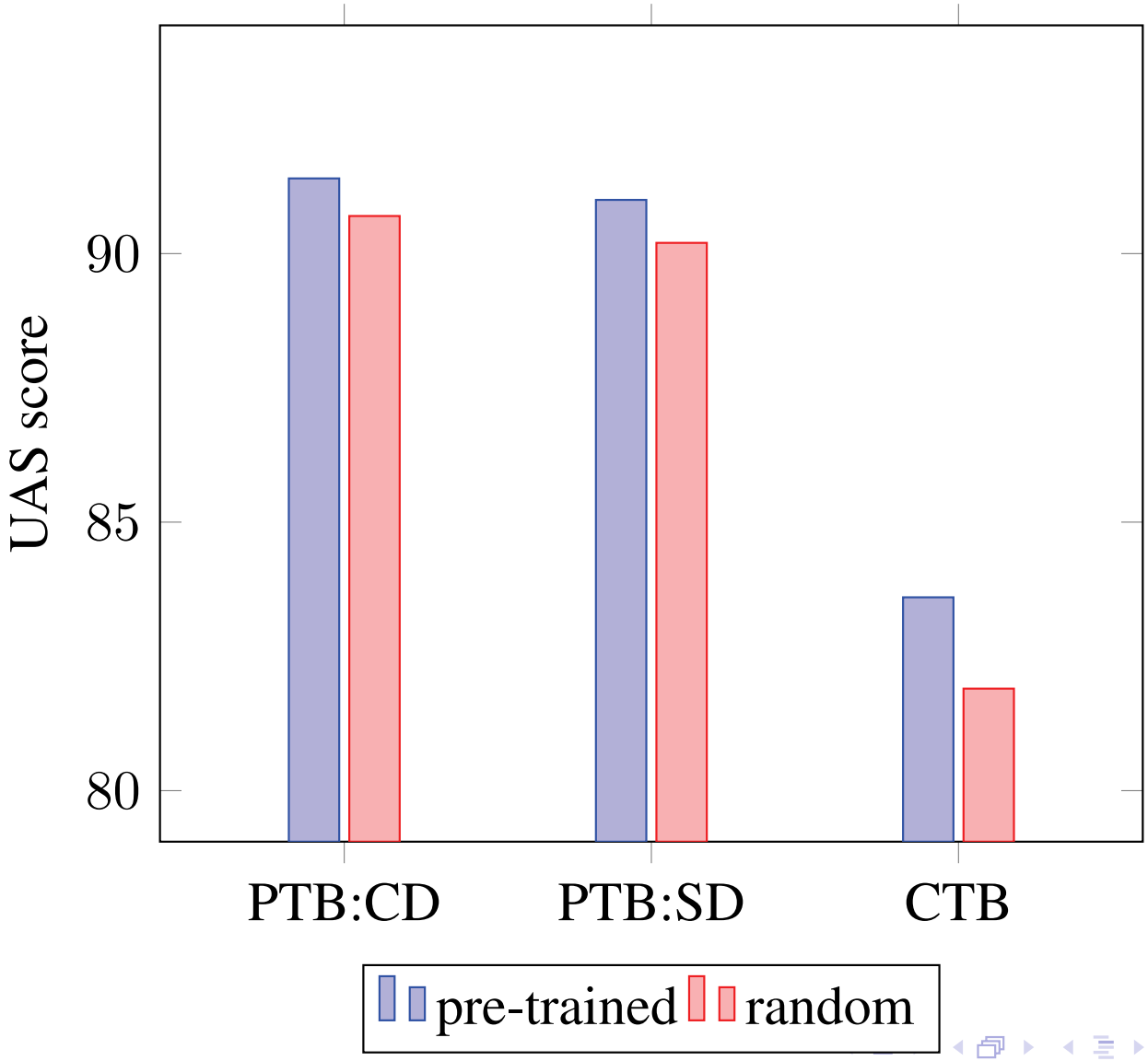
Results: Chinese

Parser	Dev		Test		Speed
	UAS	LAS	UAS	LAS	(sent/s)
standard	82.4	80.9	82.7	81.2	72
eager	81.1	79.7	80.3	78.7	80
Malt:sp	82.4	80.5	82.4	80.6	420
Malt:eager	81.2	79.3	80.2	78.4	393
MSTParser	84.0	82.1	83.0	81.2	6
Our parser	84.0	82.4	83.9	82.4	936

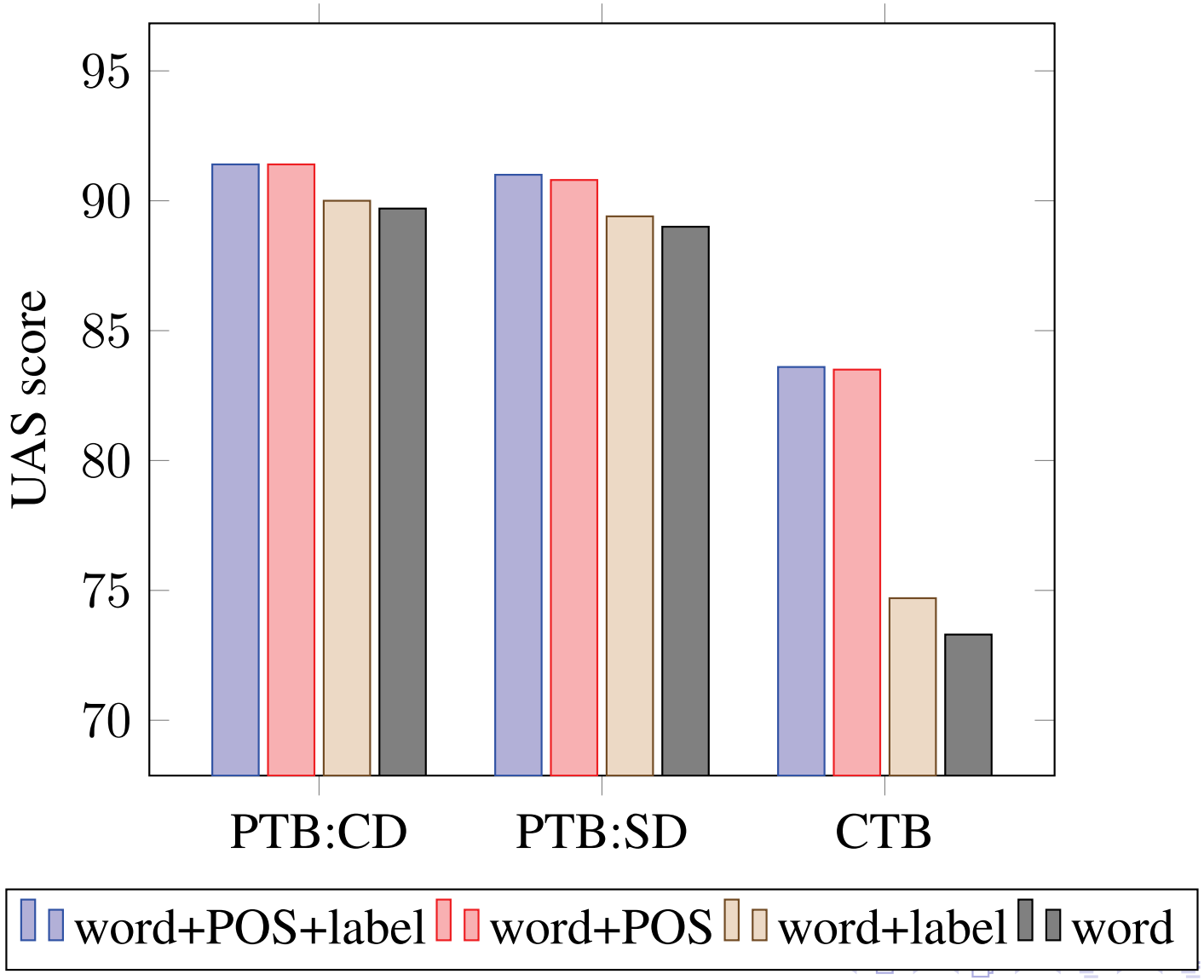
Effect of Activation Function



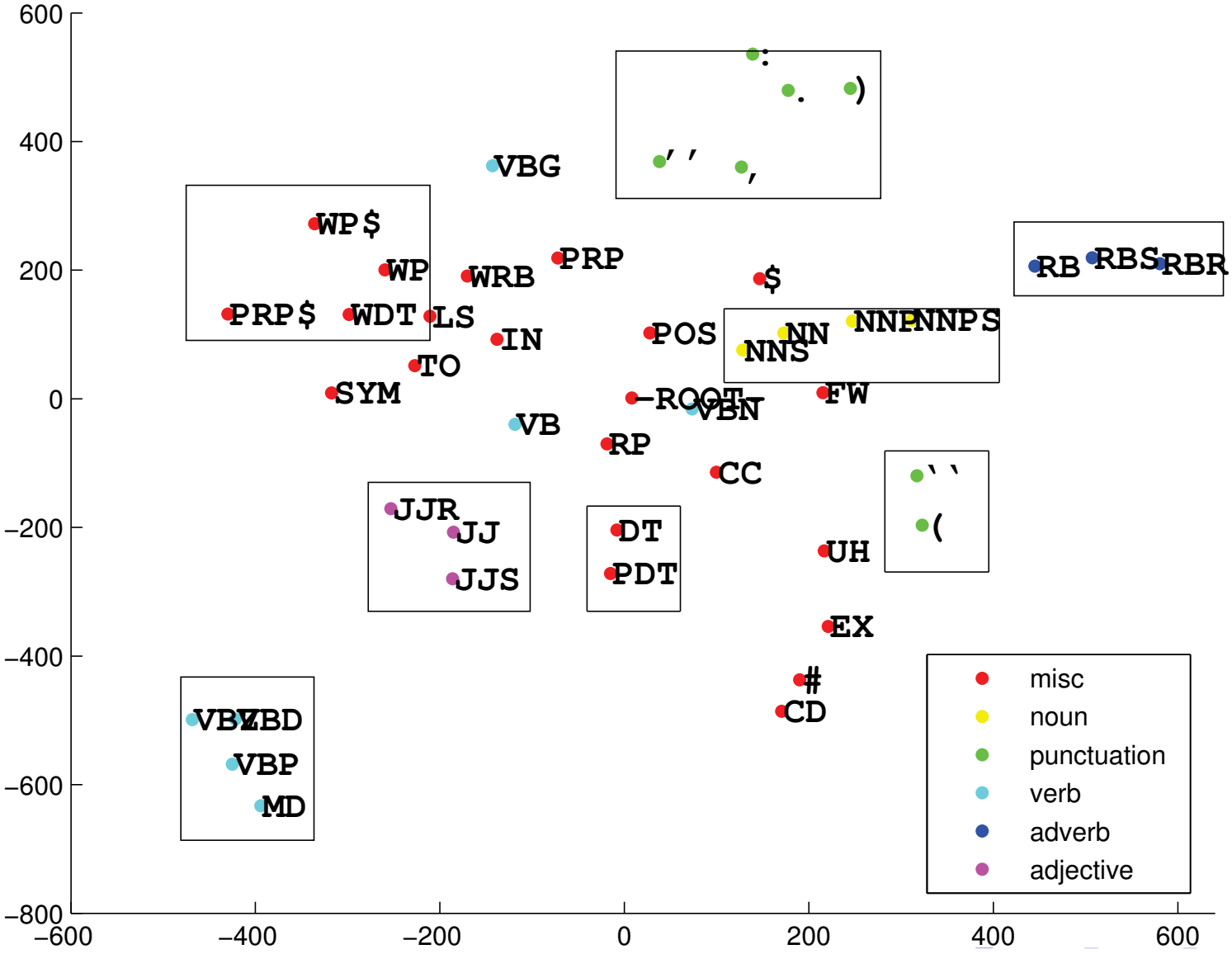
Pre-trained Embeddings vs. Random Initialization



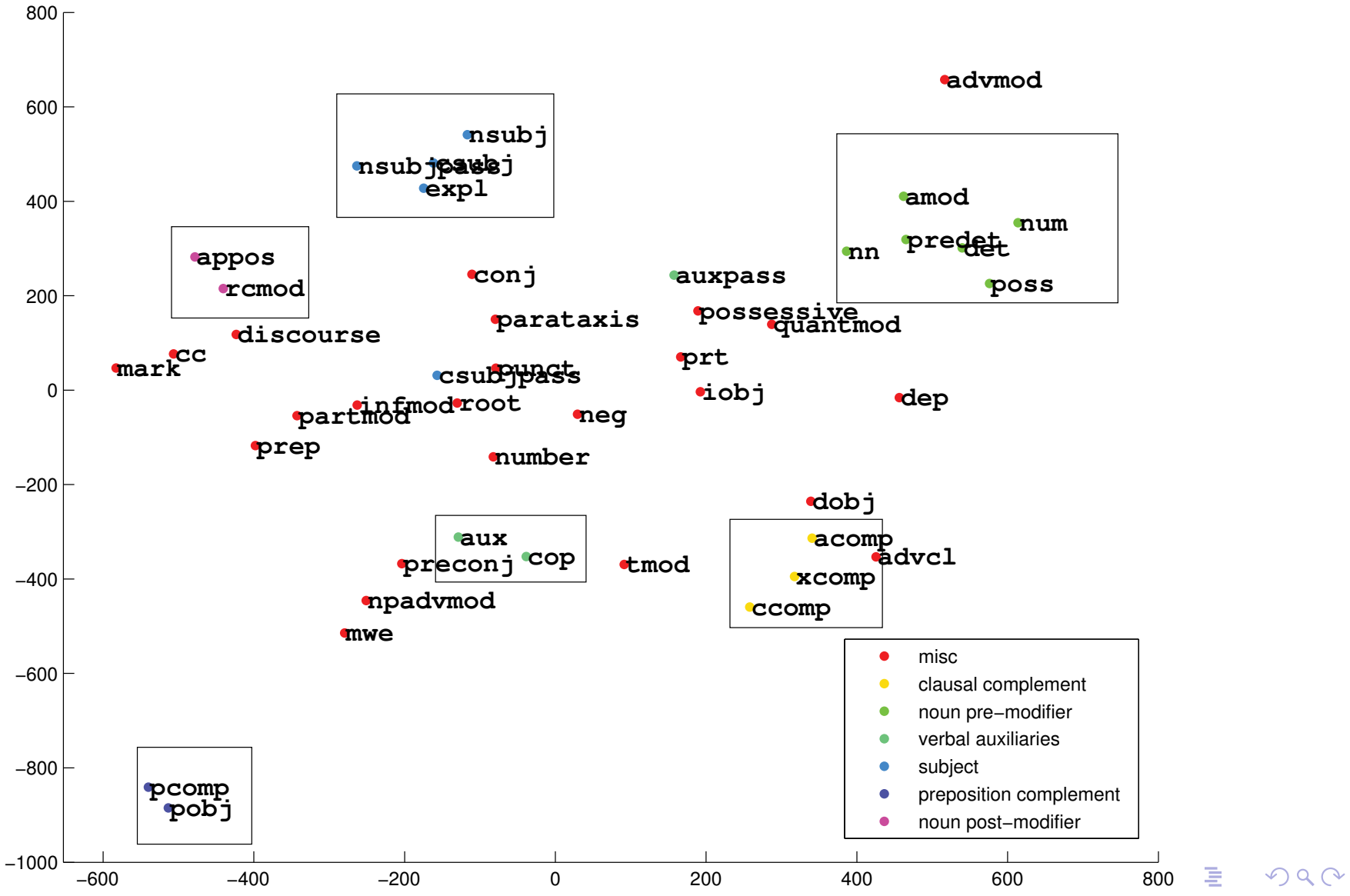
Effect of PoS and Label Embeddings



Visualization of PoS Embeddings



Visualization Label Embeddings



Summary

- Chen and Manning's (2014) model builds on standard transition-based dependency parsing;
- uses neural net to select transitions;
- uses dense features (embeddings) instead of sparse, handcrafted features;
- embeddings over words, PoS, and arc labels;
- new cube activation function;
- good accuracy for English and Chinese dependency parsing;
- substantial improvement in speed.

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