Proseminar: Deep learning for NLP

A Fast and Accurate Dependency Parser using Neural Networks

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Outline

What is Parsing?

- **Parsing** is the assignment of a **syntactical structure** to a string of symbols.

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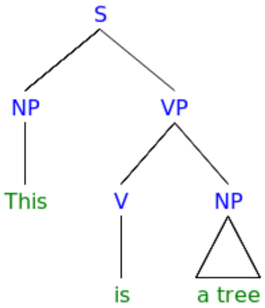
One morning I shot an elephant in my pajamas. How he got in my pajamas, I don't know.$_{GrouchoMarx}$

Two approaches to Parsing

1. **Constituency Parsing:**
   assigns a **deep nested** structure according to a **set of rules**



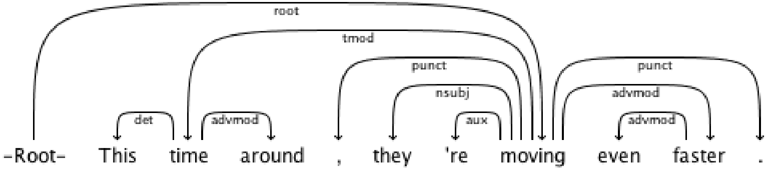
- S -> NP VP
- NP -> D NP
- VP -> V
- NP -> tree
- V -> is
- D -> a

2. **Dependency Parsing:**

Two approaches to Parsing

1. **Constituency Parsing:**
   assigns a **deep nested** structure according to a **set of rules**

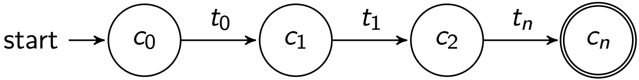
2. **Dependency Parsing:**
   assigns a **flat** structure that puts focus on binary relations (**head-dependent**) between words



https://nlp.stanford.edu/software/nndep.shtml

Transition dependency Parser

- is very similar to **bottom-up shift-reduce** parsers
- has a runtime of $\mathbf{O(n)}$
- tries to predict the **sequence of transitions** from the initial configuration c_0 to the final configuration c_n



Formalize it!

Configuration: c = (s, b, A):

- s = Stack
- b = Buffer (input)
- A = set of dependency arcs (labels)

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- s = [root]
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Actions in arc-standard system (Nivre, 2004):

1. LEFT-ARC(l):
   adds arc $s_1 -> s_2$ with label l to A and removes s_2
2. RIGHT-ARC(l):
   adds arc $s_2 -> s_1$ with label l to A and removes s_1
3. SHIFT:
   moves b_1 to the stack

Formalize it!

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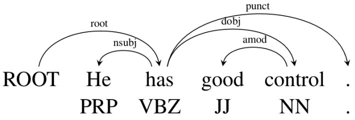
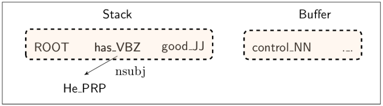
Final configuration:

- s = [root]
- b = $\emptyset$

Greedy transition dependency Parser



Correct transition: SHIFT



Transition	Stack	Buffer	A
	[ROOT]	[He has good control .]	$\emptyset$
`SHIFT`	[ROOT He]	[has good control .]	
`SHIFT`	[ROOT He has]	[good control .]	
`LEFT-ARC(nsubj)`	[ROOT has]	[good control .]	$A\cup$ nsubj(has,He)
`SHIFT`	[ROOT has good]	[control .]	
`SHIFT`	[ROOT has good control]	[.]	
`LEFT-ARC(amod)`	[ROOT has control]	[.]	$A\cup$amod(control,good)
`RIGHT-ARC(dobj)`	[ROOT has]	[.]	$A\cup$ dobj(has,control)
...	...	...	...
`RIGHT-ARC(root)`	[ROOT]	[]	$A\cup$ root(ROOT,has)

Chen and Manning, 2014

Finding the right transition

http://greekmythology.wikia.com

How does the parser learn the right transitions?

- the parser learns from an **Oracle**
- the Oracle extracts the **gold sequences** of transitions out of a treebank
- the Oracle is used to train a **multi-class classifier**

Finding the right transition

- How does the parser decide?
  1. extract all relevant words, their POS, their position on stack/buffer and any labels connecting them
  2. concatenate them together according to **feature templates**
  3. look up the vectors for these **indicator features**

Configuration:

Stack		Buffer				Arcs
was	riding	home	on	my	bicycle	nsubj (I <– was)
s_2	s_1	b_1	b_2	b_3	b_4	a_1

Features:

s_{1w} *riding* $\odot$ b_{1t} *verb*	s_{2t} *adj* $\odot$ s_{1t} *noun*	s_{1t} *verb* $\odot$ b_{1t} *noun*	$s1_w$ *riding*	s_{2l} *nsubj*	.....
0	0	1	1	1	.....

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  2. the **training data is incomplete**
  3. the feature templates are handcrafted
  4. the feature-concatenation and lookup is extremely time consuming

Chen and Mannings parser

1. Dense features through embeddings
2. The network
   - The input
   - The architecture
3. Training the network
4. Results

Dense features through embeddings

The Idea:

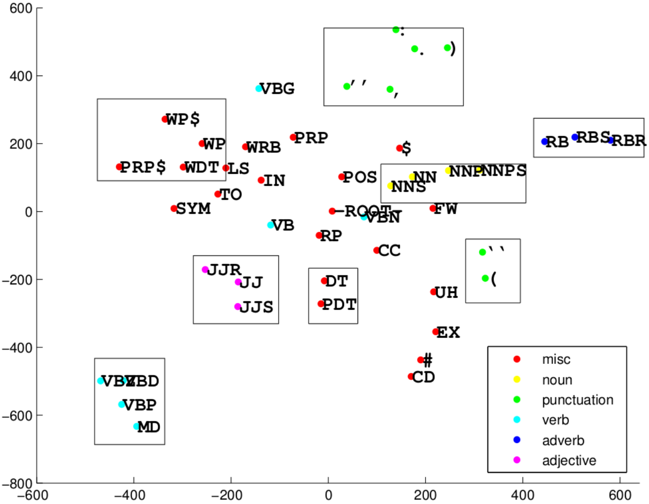
- words have semantic similarities and the word-vectors should reflect these
  - **king** should be similar to **queen** while being different from **airplane**

Dense features through embeddings

The Idea:

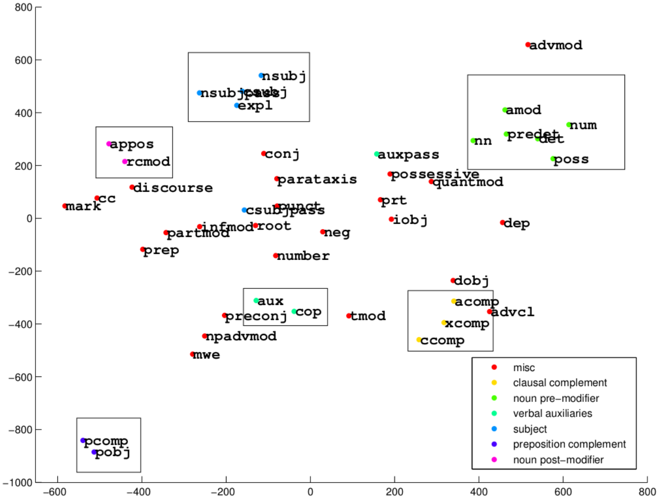
- words have semantic similarities and the word-vectors should reflect these
  - **king** should be similar to **queen** while being different from **airplane**
- POS tags and dependency labels also exhibit semantic similarity
  - **NNS** should be similar to **NN** while being different from **VB**
  - **acomp** should be similar to **xcomp** while being different from **nsubj**

Visualized POS embeddings



Chen and Manning, 2014

Visualized label embeddings



Chen and Manning, 2014

Dense features through embeddings

Word embeddings:

- each word is represented as a vector $e_i^w \in R^d$
- the word-embedding matrix is $E^w \in R^{d x N_w}$

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Label embeddings:

- each label is represented as a vector $e_i^l \in R^d$
- the label-embedding matrix is $E^l \in R^{dxN_l}$

where N_w, N_t, N_l are the number of words/pos-tags/labels

The Network

As **input** a rich set of elements is extracted from the stack, buffer and arc-labels.

- the sets are called $\mathbf{S^w}, \mathbf{S^l}, \mathbf{S^t}$
- $\mathbf{S^w}$ contains words, $\mathbf{S^l}$ labels and $\mathbf{S^t}$ POS
- the selected embedding vectors are then **concatenated**
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  - the **POS** for these words (18)
  - the **dependency labels** of the **non-stack/buffer** words (12)
  - for **non existent elements** a special **null** token is introduced

Feature example:

Configuration:

Stack		**Buffer**				**Arcs**
was	riding	home	on	my	bicycle	nsubj (I <– was)
s_2	s_1	b_1	b_2	b_3	b_4	a_1

Feature Sets:

S^w = {**riding**, null, null, null, null, **was**, **I**, null, ...}
S^t = {**VBG**, null, null, null, null, **VBP**, **PRP**, null, ...}
S^l = {null, null, null, null, null, null, **nsubj**, null, ...}

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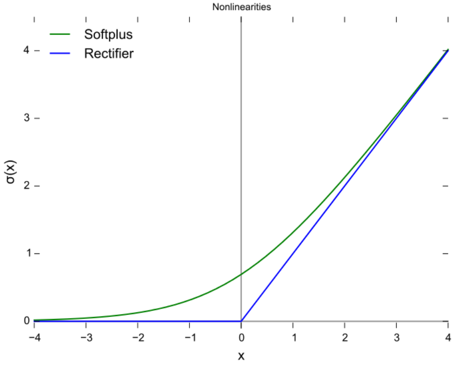

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- the output is produced by a **softmax layer** $P(y|\boldsymbol{x}) = \frac{e^{\boldsymbol{W}_y^\top \boldsymbol{x} + \boldsymbol{b}_y}}{\sum_{k \in Y} e^{\boldsymbol{W}_k^\top \boldsymbol{x} + b_k}}$

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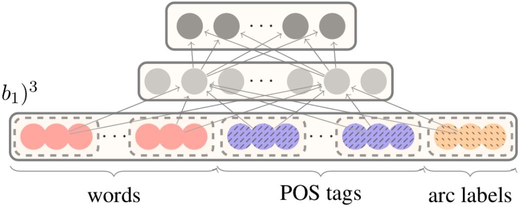
The full network is then:

Softmax layer:
$$p = \mathtt{softmax}(W_2 h)$$
Hidden layer:
$$h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3$$
Input layer: $[x^w, x^t, x^l]$



Chen and Manning 2014

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4. feed the configuration forward through the network
5. backpropagate the error, tune the weights using AdaGrad

The objective function

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

where

$$\theta = \{W_{1-n}, b_{1-n}, E^w, E^l, E^t\}$$

- usual **cross-entropy** loss function with a l2-regularization term
- l2-regularization **penalizes big parameters**

Results:

- the parser achieves **state-of-the-art accuracy** while being **significantly faster** than other state-of-the-art parsers

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**

PTB with CoNLL dependecies

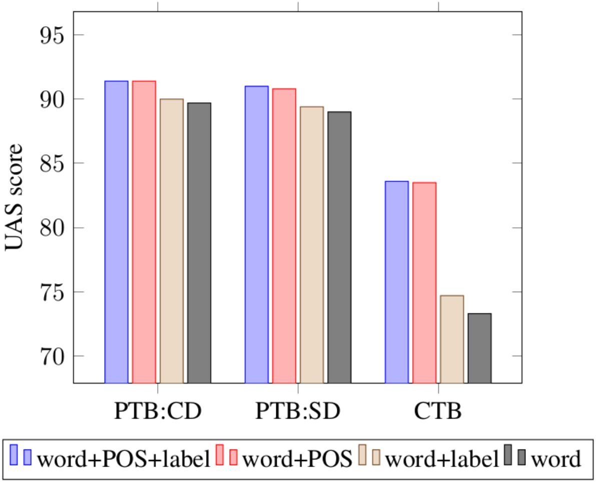
Parser	Dev		Test		Speed
	UAS	LAS	UAS	LAS	(sent/s)
standard	90.2	87.8	89.4	87.3	26
eager	89.8	87.4	89.6	87.4	34
Malt:sp	89.8	87.2	89.3	86.9	469
Malt:eager	89.6	86.9	89.4	86.8	448
MSTParser	91.4	88.1	90.7	87.6	10
Our parser	**92.0**	**89.7**	**91.8**	**89.6**	**654**

PTB with Stanford dependecies

Chen and Manning, 2014

Results:

- the POS and Label embeddings have proven to be useful



Chen and Manning, 2014

Results:

- the parser achieves **state-of-the-art accuracy** while being **significantly faster** than other state-of-the-art parsers
- the **POS and Label embeddings** have proven to be useful
- the network **learned complex features** from the single embedding representations

Recent Development

Newer approaches have included:

- **Beam search** instead of greedy search (Straka et al. 2015, SyntaxNet)
- use of **dynamic oracles** that make the parser more robust to recover from bad decisions (Straka et al. 2015, SyntaxNet)
- search for **global optima** instead of local config to config optima

The End

Thank you for listening!

Questions?

Sources:

Chen, Danqi and Christopher D Manning. 2014. A fast and accurate dependency parser using neural networks. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). pages 740–750.

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