Natural Language Processing with Deep Learning

CS224N/Ling284

Christopher Manning and Richard Socher

Lecture 6: Dependency Parsing

Lecture Plan

1. Syntactic Structure: Consistency and Dependency
2. Dependency Grammar
3. Research highlight
4. Transition-based dependency parsing
5. Neural dependency parsing

Reminders/comments:

Assignment 1 due tonight ☺

Assignment 2 out today ☹

Final project discussion – come meet with us

Sorry that we've been kind of overloaded for office hours

1. Two views of linguistic structure: Constituency = phrase structure grammar = context-free grammars (CFGs)

Phrase structure organizes words into nested constituents.

the		cat	
a		dog	
	large		in a crate
	barking		on the table
	cuddly		by the door

1. Two views of linguistic structure: Constituency = phrase structure grammar = context-free grammars (CFGs)

Phrase structure organizes words into nested constituents.

the cat

a dog

large in a crate

barking on the table

cuddly by the door

large barking

talk to

look for

NP → Det N

NP → Det (A) N (PP)

PP → P NP

NP → Det A* N PP*

VP → V PP

Two views of linguistic structure: Dependency structure

- Dependency structure shows which words depend on (modify or are arguments of) which other words.

Look for the large barking dog by the door in a crate

Two views of linguistic structure: Dependency structure

- Dependency structure shows which words depend on (modify or are arguments of) which other words.

Ambiguity: PP attachments

Scientists study whales from space

Ambiguity: PP attachments

Scientists study whales from space

Scientists study whales from space

Attachment ambiguities

- A key parsing decision is how we ‘attach’ various constituents
  - PPs, adverbial or participial phrases, infinitives, coordinations,

The board approved [its acquisition] [by Royal Trustco Ltd.]

[of Toronto]

[for $27 a share]

[at its monthly meeting].

Attachment ambiguities

- A key parsing decision is how we 'attach' various constituents
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The board approved [its acquisition] [by Royal Trustco Ltd.]

[of Toronto]

[for $27 a share]

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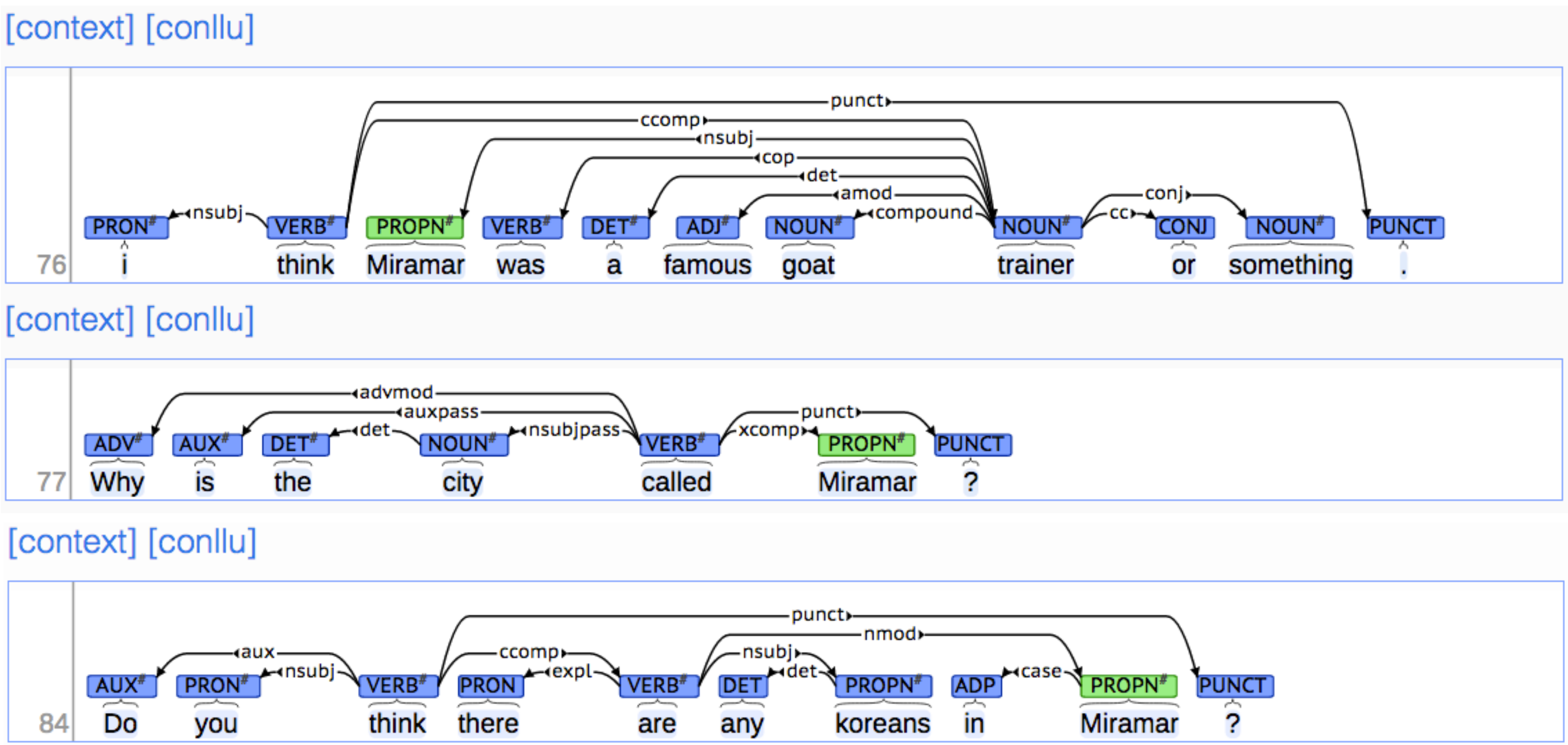
- Catalan numbers: $C_n = (2n)!/[(n+1)!n!]$
- An exponentially growing series, which arises in many tree-like contexts:
  - E.g., the number of possible triangulations of a polygon with n+2 sides
    - Turns up in triangulation of probabilistic graphical models….

The rise of annotated data: Universal Dependencies treebanks

[Universal Dependencies: http://universaldependencies.org/ ;
cf. Marcus et al. 1993, The Penn Treebank, *Computational Linguistics*]



The rise of annotated data

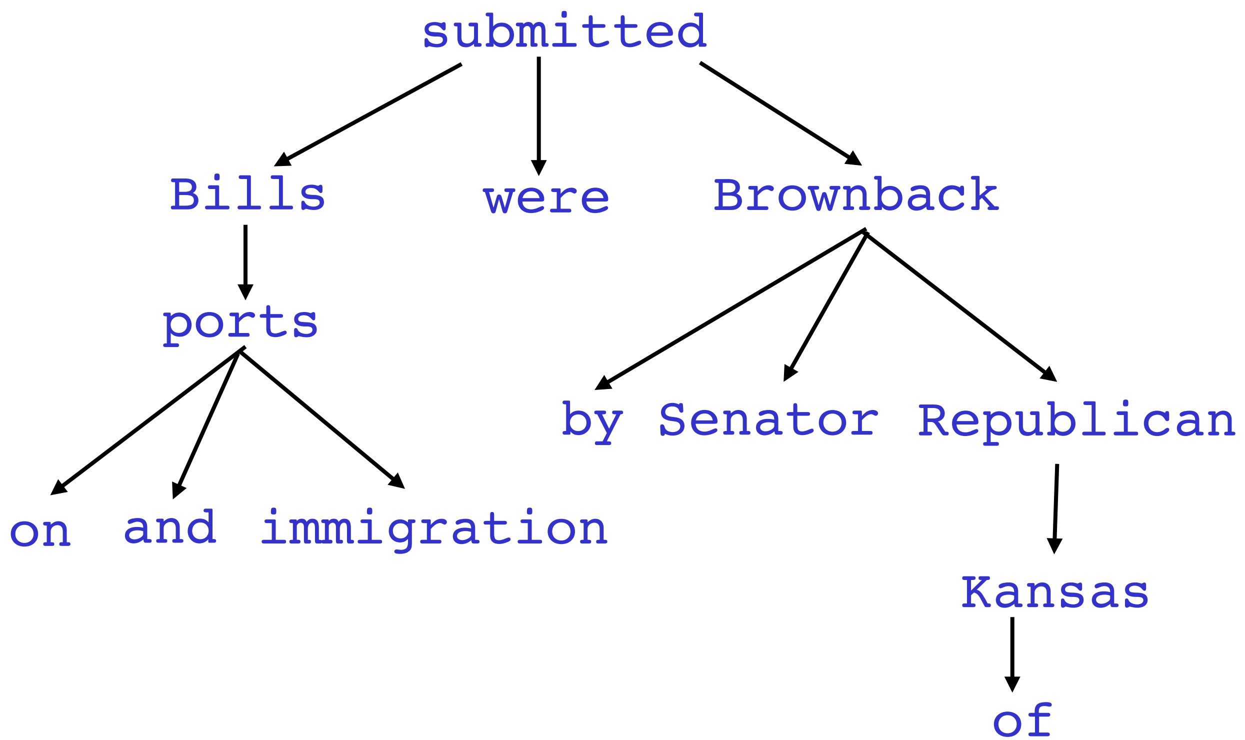
Starting off, building a treebank seems a lot slower and less useful than building a grammar

But a treebank gives us many things

- Reusability of the labor
  - Many parsers, part-of-speech taggers, etc. can be built on it
  - Valuable resource for linguistics
- Broad coverage, not just a few intuitions
- Frequencies and distributional information
- A way to evaluate systems

2. Dependency Grammar and Dependency Structure

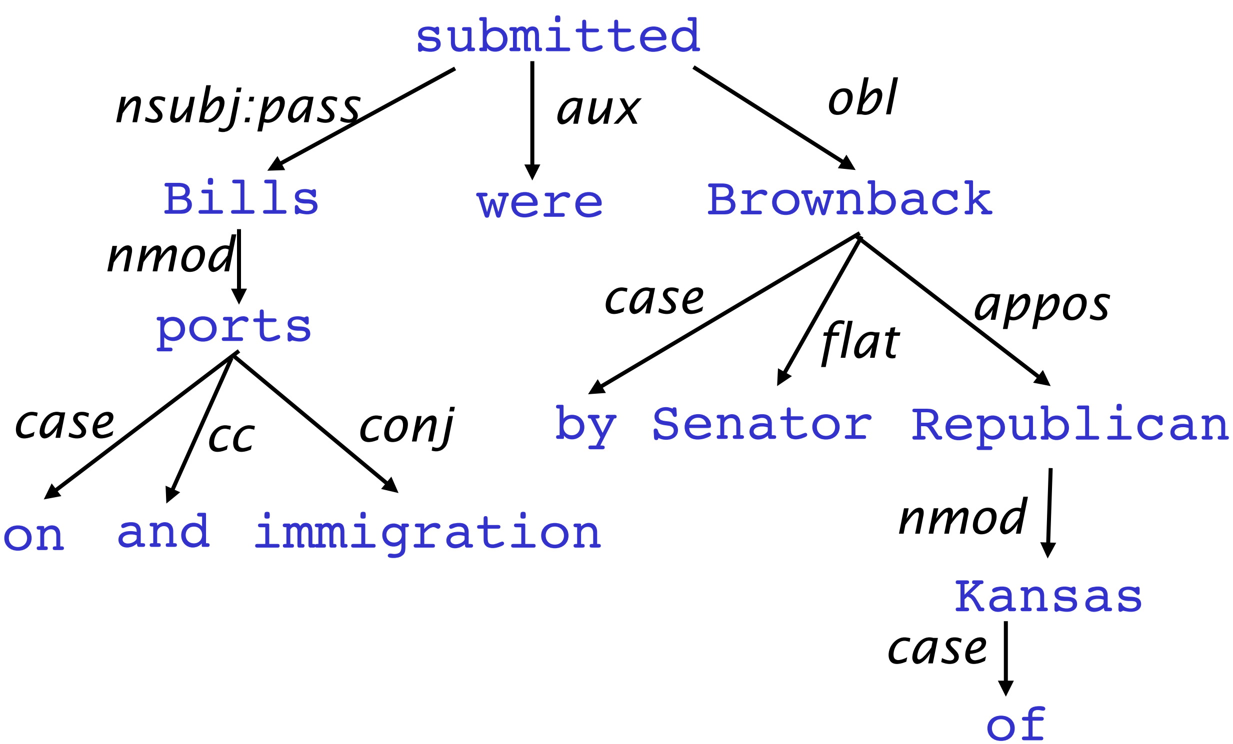
Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations ("arrows") called dependencies



Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations ("arrows") called dependencies

The arrows are commonly typed with the name of grammatical relations (subject, prepositional object, apposition, etc.)

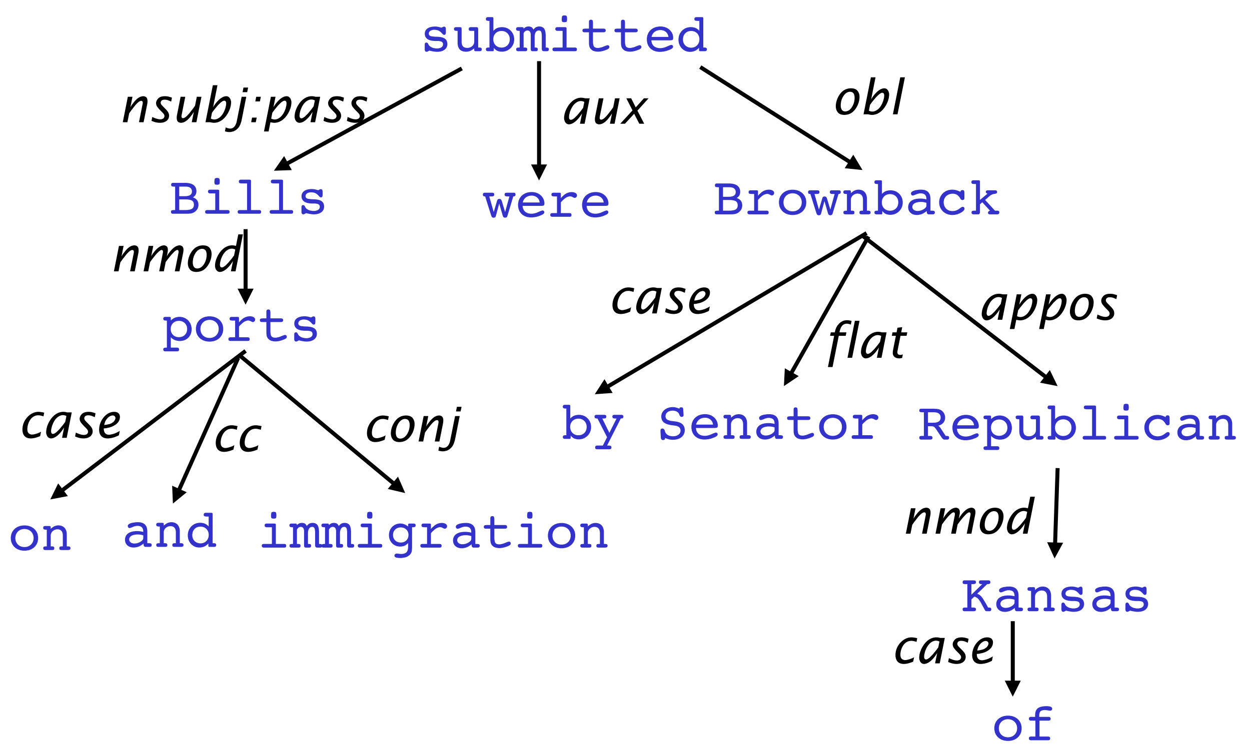


Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations ("arrows") called dependencies

The arrow connects a head (governor, superior, regent) with a dependent (modifier, inferior, subordinate)

Usually, dependencies form a tree (connected, acyclic, single-head)



Christopher Manning

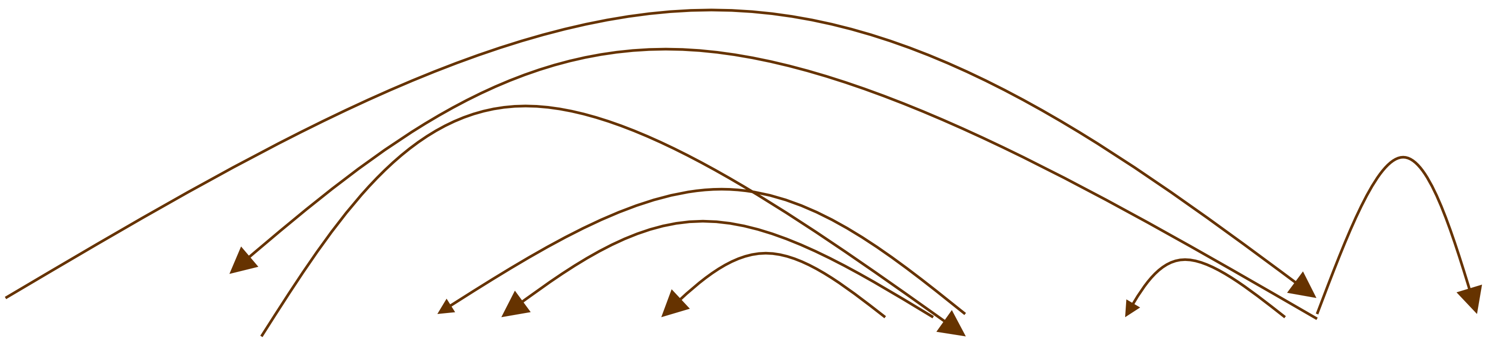
Pāṇini’s grammar (c. 5th century BCE)

Gallery: http://wellcomeimages.org/indexplus/image/L0032691.html

Dependency Grammar/Parsing History

- The idea of dependency structure goes back a long way
  - To Pāṇini's grammar (c. 5th century BCE)
  - Basic approach of 1st millennium Arabic grammarians
- Constituency/context-free grammars is a new-fangled invention
  - 20th century invention (R.S. Wells, 1947)
- Modern dependency work often linked to work of L. Tesnière (1959)
  - Was dominant approach in "East" (Russia, China, …)
    - Good for free-er word order languages
- Among the earliest kinds of parsers in NLP, even in the US:
  - David Hays, one of the founders of U.S. computational linguistics, built early (first?) dependency parser (Hays 1962)

Dependency Grammar and Dependency Structure



ROOT Discussion of the outstanding issues was completed .

- Some people draw the arrows one way; some the other way!
  - Tesnière had them point from head to dependent…
- Usually add a fake ROOT so every word is a dependent of precisely 1 other node

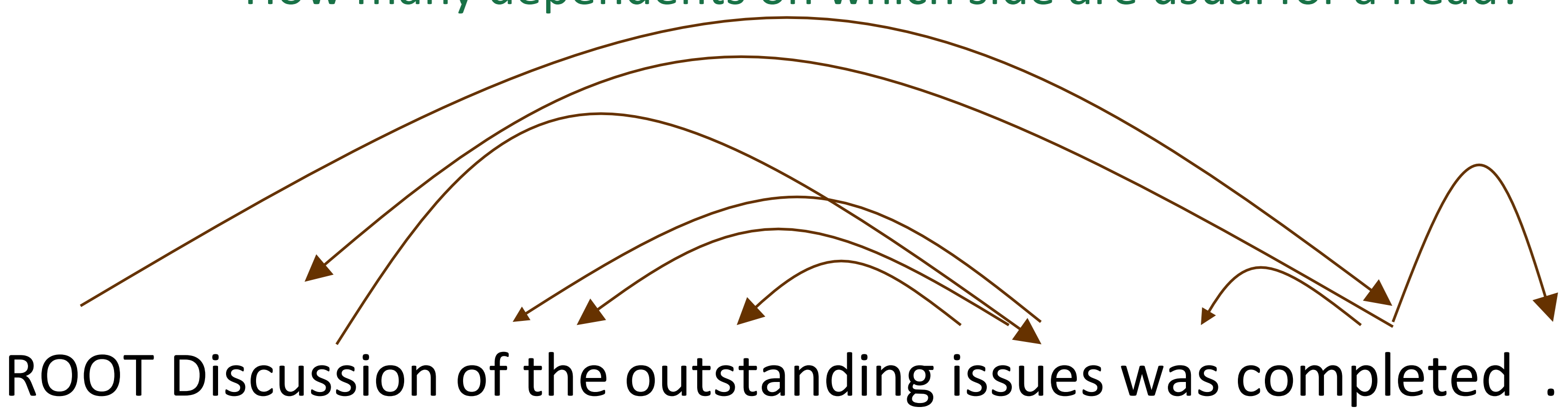
Dependency Conditioning Preferences

What are the sources of information for dependency parsing?

1. Bilexical affinities [discussion → issues] is plausible
2. Dependency distance mostly with nearby words
3. Intervening material

   Dependencies rarely span intervening verbs or punctuation
4. Valency of heads

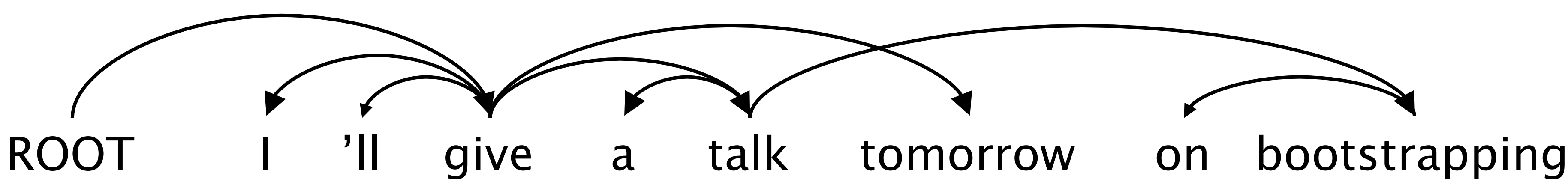
   How many dependents on which side are usual for a head?



Dependency Parsing

- A sentence is parsed by choosing for each word what other word (including ROOT) is it a dependent of

- Usually some constraints:
  - Only one word is a dependent of ROOT
  - Don’t want cycles A → B, B → A
- This makes the dependencies a tree
- Final issue is whether arrows can cross (non-projective) or not



Methods of Dependency Parsing

1. Dynamic programming

   Eisner (1996) gives a clever algorithm with complexity $O(n^3)$, by producing parse items with heads at the ends rather than in the middle

2. Graph algorithms

   You create a Minimum Spanning Tree for a sentence

   McDonald et al.'s (2005) MSTParser scores dependencies independently using an ML classifier (he uses MIRA, for online learning, but it can be something else)

3. Constraint Satisfaction

   Edges are eliminated that don't satisfy hard constraints. Karlsson (1990), etc.

4. "Transition-based parsing" or "deterministic dependency parsing"

   Greedy choice of attachments guided by good machine learning classifiers

   MaltParser (Nivre et al. 2008). Has proven highly effective.

Improving Distributional Similarity with Lessons Learned from Word Embeddings

Omer Levy, Yoav Goldberg, Ido Dagan

Presented by: **Ajay Sohmshetty**

Word Representation Methods

Count-based distributional models

Neural network-based models

Word Representation Methods

Count-based distributional models

- SVD (Singular Value Decomposition)
- PPMI (Positive Pointwise Mutual Information)

Neural network-based models

- SGNS (Skip-Gram Negative Sampling) / CBOW
- GloVe

Word Representation Methods

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- SVD (Singular Value Decomposition)
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Conventional wisdom:
Neural-network based models > Count-based models

Word Representation Methods

Count-based distributional models

- SVD (Singular Value Decomposition)
- PPMI (Positive Pointwise Mutual Information)

Neural network-based models

- SGNS (Skip-Gram Negative Sampling) / CBOW
- GloVe

Levy et. al.:

Hyperparameters and system design choices more important, not the embedding algorithms themselves.

Hyperparameters in Skip-Gram

of negative samples

$$J_t(\theta) = \log \sigma \left(u_o^T v_c\right) + \sum_{i=1}^{k} \mathbb{E}_{j \sim P(w)} \left[\log \sigma \left(-u_j^T v_c\right)\right]$$

$P(w)=U(w)^{3/4}/Z$

Unigram distribution smoothing exponent

→ These can be transferred over to the count-based variants.

Context Distribution Smoothing

$$PMI_{\alpha}(w,c) = \log \frac{\hat{P}(w,c)}{\hat{P}(w)\hat{P}_{\alpha}(c)}$$

$$\hat{P}_{\alpha}(c) = \frac{\#(c)^{\alpha}}{\sum_{c}\#(c)^{\alpha}}$$

Shifted PMI

$$SPPMI(w,c) = \max\left(PMI\left(w,c\right) - \log k, 0\right)$$

All Transferable Hyperparameters

	Hyperparameter	Explored Values	Applicable Methods
	Window	2, 5, 10	All
Preprocessing	Dynamic Context Window	None, with	All
	Subsampling	None, dirty, clean	All
	Deleting Rare Words	None, with	All
Association Metric	Shifted PMI	1, 5, 15	PPMI, SVD, SGNS
	Context Distribution Smoothing	1, 0.75	PPMI, SVD, SGNS
Postprocessing	Adding Context Vectors	Only w, w+c	SVD, SGNS, GloVe
	Eigenvalue Weighting	0, 0.5, 1	SVD
	Vector Normalization	None, row, col, both	All

Results

		Word Similarity Tasks						Analogy Tasks	
win	Method	WordSim Similarity	WordSim Relatedness	Bruni et al. MEN	Radinsky et al. M. Turk	Luong et al. Rare Words	Hill et al. SimLex	Google Add / Mul	MSR Add / Mul
2	PPMI	.732	**.699**	.744	.654	.457	.382	.552 / .677	.306 / .535
	SVD	.772	.671	**.777**	.647	**.508**	.425	.554 / .591	.408 / .468
	SGNS	**.789**	.675	.773	**.661**	.449	**.433**	.676 / **.689**	.617 / **.644**
	GloVe	.720	.605	.728	.606	.389	.388	.649 / .666	.540 / .591
5	PPMI	.732	**.706**	.738	**.668**	.442	.360	.518 / .649	.277 / .467
	SVD	.764	.679	**.776**	.639	**.499**	**.416**	.532 / .569	.369 / .424
	SGNS	**.772**	.690	.772	.663	.454	.403	.692 / **.714**	.605 / **.645**
	GloVe	.745	.617	.746	.631	.416	.389	.700 / .712	.541 / .599
10	PPMI	.735	**.701**	.741	.663	.235	.336	.532 / .605	.249 / .353
	SVD	.766	.681	.770	.628	**.312**	.419	.526 / .562	.356 / .406
	SGNS	**.794**	.700	**.775**	**.678**	.281	**.422**	.694 / .710	.520 / **.557**
	GloVe	.746	.643	.754	.616	.266	.375	.702 / **.712**	.463 / .519

Key Takeaways

- This paper challenges the conventional wisdom that neural network-based models are superior to count-based models.
- While model design is important, hyperparameters are also KEY for achieving reasonable results. Don’t discount their importance!
- Challenge the status quo!

4. Greedy transition-based parsing

[Nivre 2003]

- A simple form of greedy discriminative dependency parser
- The parser does a sequence of bottom up actions
  - Roughly like "shift" or "reduce" in a shift-reduce parser, but the "reduce" actions are specialized to create dependencies with head on left or right
- The parser has:
  - a stack σ, written with top to the right
    - which starts with the ROOT symbol
  - a buffer β, written with top to the left
    - which starts with the input sentence
  - a set of dependency arcs A
    - which starts off empty
  - a set of actions

Basic transition-based dependency parser

Start: σ = [ROOT], $\beta = w_1, \ldots, w_n$, $A = \varnothing$

1. Shift $\quad \sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$
2. Left-Arc$_r$ $\quad \sigma|w_i|w_j, \beta, A \rightarrow \sigma|w_j, \beta, A \cup \{r(w_j,w_i)\}$
3. Right-Arc$_r$ $\quad \sigma|w_i|w_j, \beta, A \rightarrow \sigma|w_i, \beta, A \cup \{r(w_i,w_j)\}$

Finish: $\sigma = [w]$, $\beta = \varnothing$

Arc-standard transition-based parser

(there are other transition schemes …)

Analysis of "I ate fish"

Start

[root] | I ate fish

Shift

[root] I | ate fish

Shift

[root] I ate | fish

Start: σ = [ROOT], $\beta = w_1, \ldots, w_n$, A = $\varnothing$

1. Shift $\quad \sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$
2. Left-Arc$_r$ $\quad \sigma|w_i|w_j, \beta, A \rightarrow \sigma|w_j, \beta, A \cup \{r(w_j,w_i)\}$
3. Right-Arc$_r$ $\quad \sigma|w_i|w_j, \beta, A \rightarrow \sigma|w_i, \beta, A \cup \{r(w_i,w_j)\}$

Finish: $\beta = \varnothing$

Arc-standard transition-based parser

Analysis of "I ate fish"

Left Arc

[root] I ate → [root] ate

A +=
nsubj(ate → I)

Shift

[root] ate | fish → [root] ate fish |

Right Arc

[root] ate fish → [root] ate

A +=
obj(ate → fish)

Right Arc

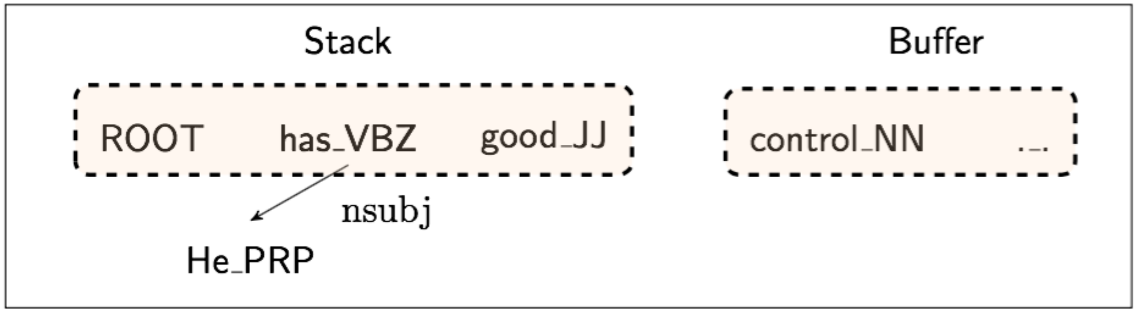
[root] ate | → [root] |

A +=
root([root] → ate)
Finish

MaltParser
[Nivre and Hall 2005]

- We have left to explain how we choose the next action
- Each action is predicted by a discriminative classifier (often SVM, can be perceptron, maxent classifier) over each legal move
  - Max of 3 untyped choices; max of $|R| \times 2 + 1$ when typed
  - Features: top of stack word, POS; first in buffer word, POS; etc.
- There is NO search (in the simplest form)
  - But you can profitably do a beam search if you wish (slower but better)
- It provides VERY fast linear time parsing
- The model's accuracy is *slightly* below the best dependency parsers, but
- It provides **fast**, close to state of the art parsing performance

Feature Representation



binary, sparse
dim $=10^6 \sim 10^7$

0	0	0	1	0	0	1	0	…	0	0	1	0

Feature templates: usually a combination of 1 ~ 3 elements from the configuration.

Indicator features

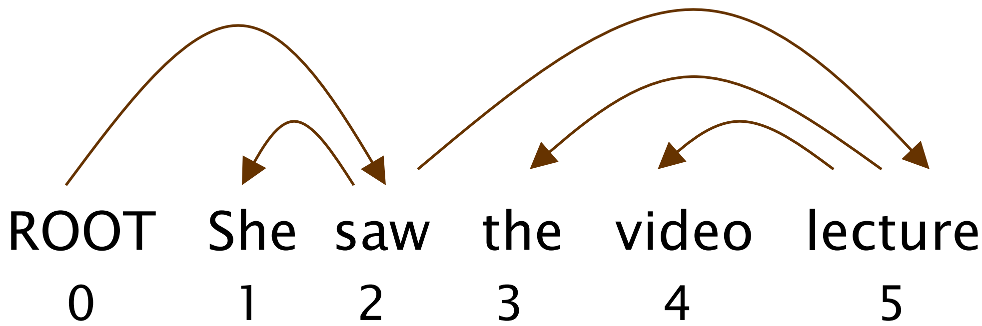
$$s1.w = \text{good} \wedge s1.t = \text{JJ}$$

$$s2.w = \text{has} \wedge s2.t = \text{VBZ} \wedge s1.w = \text{good}$$

$$lc(s_2).t = \text{PRP} \wedge s_2.t = \text{VBZ} \wedge s_1.t = \text{JJ}$$

$$lc(s_2).w = \text{He} \wedge lc(s_2).l = \text{nsubj} \wedge s_2.w = \text{has}$$

Evaluation of Dependency Parsing: (labeled) dependency accuracy



$$\text{Acc} = \frac{\text{\# correct deps}}{\text{\# of deps}}$$

UAS = 4 / 5 = 80%

LAS = 2 / 5 = 40%

Gold

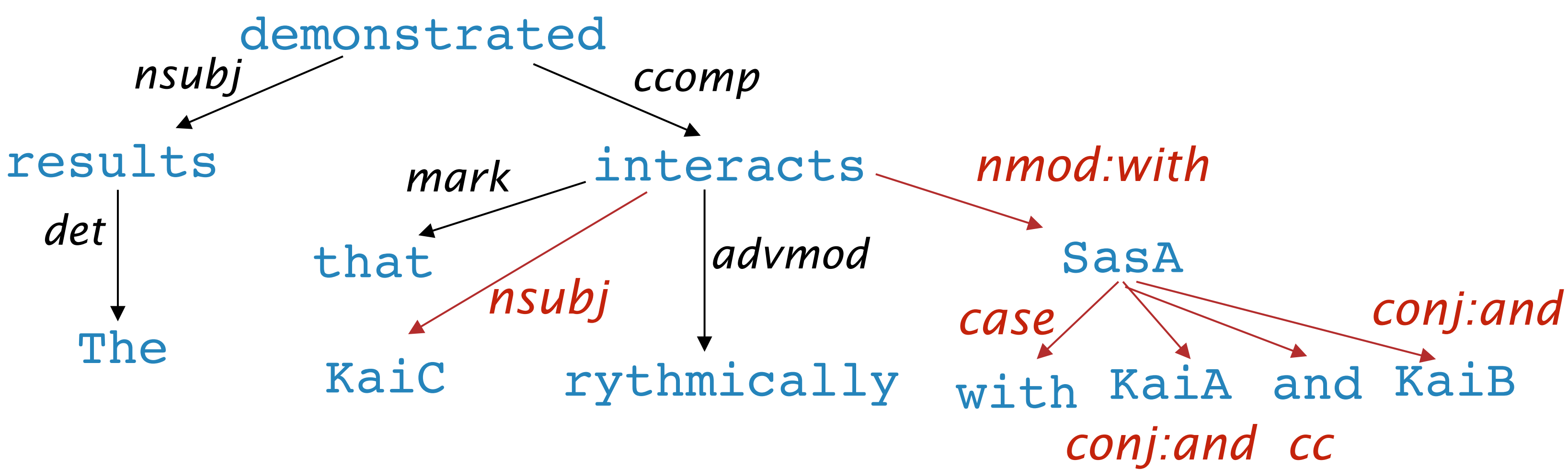
1	2	She	nsubj
2	0	saw	root
3	5	the	det
4	5	video	nn
5	2	lecture	obj

Parsed

1	2	She	nsubj
2	0	saw	root
3	4	the	det
4	5	video	nsubj
5	2	lecture	ccomp

Dependency paths identify semantic relations – e.g, for protein interaction

[Erkan et al. EMNLP 07, Fundel et al. 2007, etc.]



KaiC ←nsubj interacts nmod:with → SasA

KaiC ←nsubj interacts nmod:with → SasA conj:and→ KaiA

KaiC ←nsubj interacts prep_with→ SasA conj:and→ KaiB

Projectivity

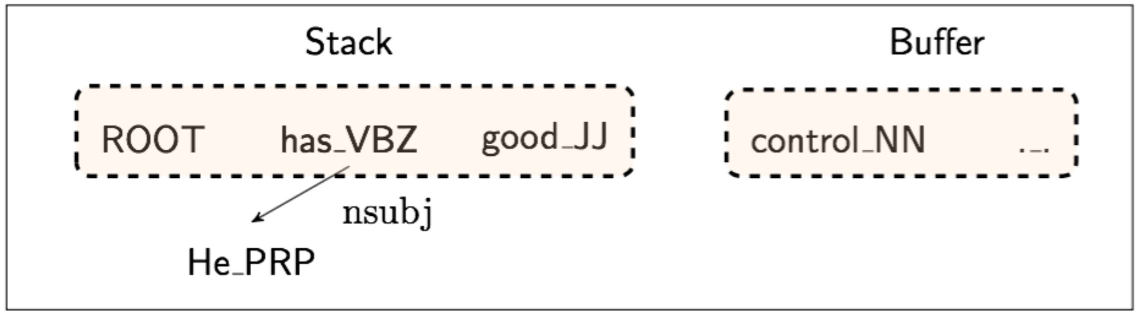
- Dependencies parallel to a CFG tree must be projective
  - There must not be any crossing dependency arcs when the words are laid out in their linear order, with all arcs above the words.
- But dependency theory normally does allow non-projective structures to account for displaced constituents
  - You can’t easily get the semantics of certain constructions right without these nonprojective dependencies

Handling non-projectivity

- The arc-standard algorithm we presented only builds projective dependency trees
- Possible directions to head:
  1. Just declare defeat on nonprojective arcs
  2. Use a dependency formalism which only admits projective representations (a CFG doesn't represent such structures…)
  3. Use a postprocessor to a projective dependency parsing algorithm to identify and resolve nonprojective links
  4. Add extra transitions that can model at least most non-projective structures (e.g., add an extra SWAP transition, cf. bubble sort)
  5. Move to a parsing mechanism that does not use or require any constraints on projectivity (e.g., the graph-based MSTParser)

5. Why train a neural dependency parser? Indicator Features Revisited

- Problem #1
- Problem #2
- Problem #3



0.1	0.9	-0.2	0.3	...	-0.1	-0.5

dense
dim = ~1000

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

Our Approach:

learn a dense and compact feature representation

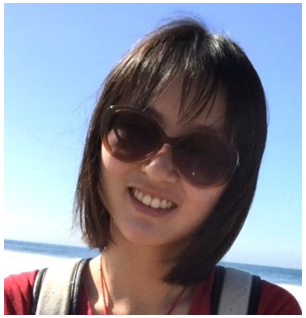
$$s1.w = \text{good} \wedge s1.t = \text{JJ}$$

$$s2.w = \text{has} \wedge s2.t = \text{VBZ} \wedge s1.w = \text{good}$$

$$lc(s_2).t = \text{PRP} \wedge s_2.t = \text{VBZ} \wedge s_1.t = \text{JJ}$$

$$lc(s_2).w = \text{He} \wedge lc(s_2).l = \text{nsubj} \wedge s_2.w = \text{has}$$

A neural dependency parser
[Chen and Manning 2014]



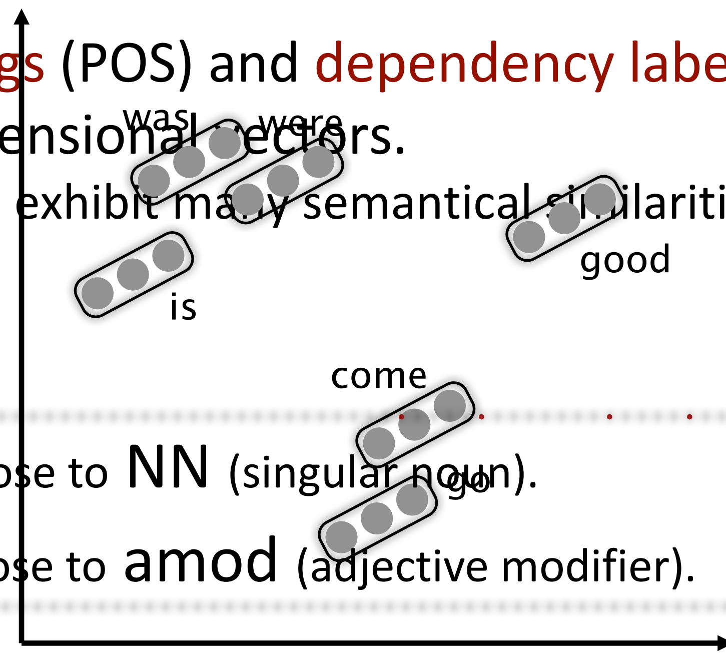
- English parsing to Stanford Dependencies:
  - Unlabeled attachment score (UAS) = head
  - Labeled attachment score (LAS) = head and label

Parser	UAS	LAS	sent. / s
MaltParser	89.8	87.2	469
MSTParser	91.4	88.1	10
TurboParser	**92.3***	89.6*	8
C & M 2014	92.0	**89.7**	**654**

Distributed Representations

- We represent each word as a *d*-dimensional dense vector (i.e., word embedding)
  - Similar words are expected to have close vectors.

- Meanwhile, part-of-speech tags (POS) and dependency labels are also represented as *d*-dimensional vectors.
  - The smaller discrete sets also exhibit many semantical similarities.

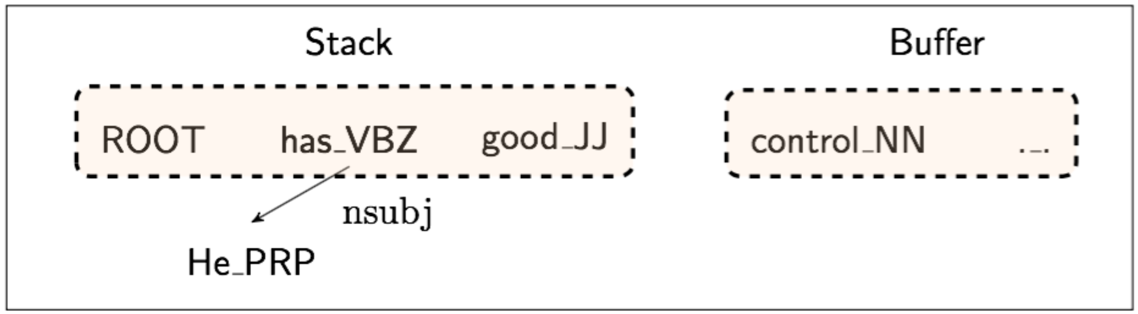


NNS (plural noun) should be close to NN (singular noun).

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

Extracting Tokens and then vector representations from configuration

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



	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
$rc(s_2)$	∅	∅	∅

- We convert them to vector embeddings and concatenate them

Model Architecture

Softmax probabilities

Output layer y

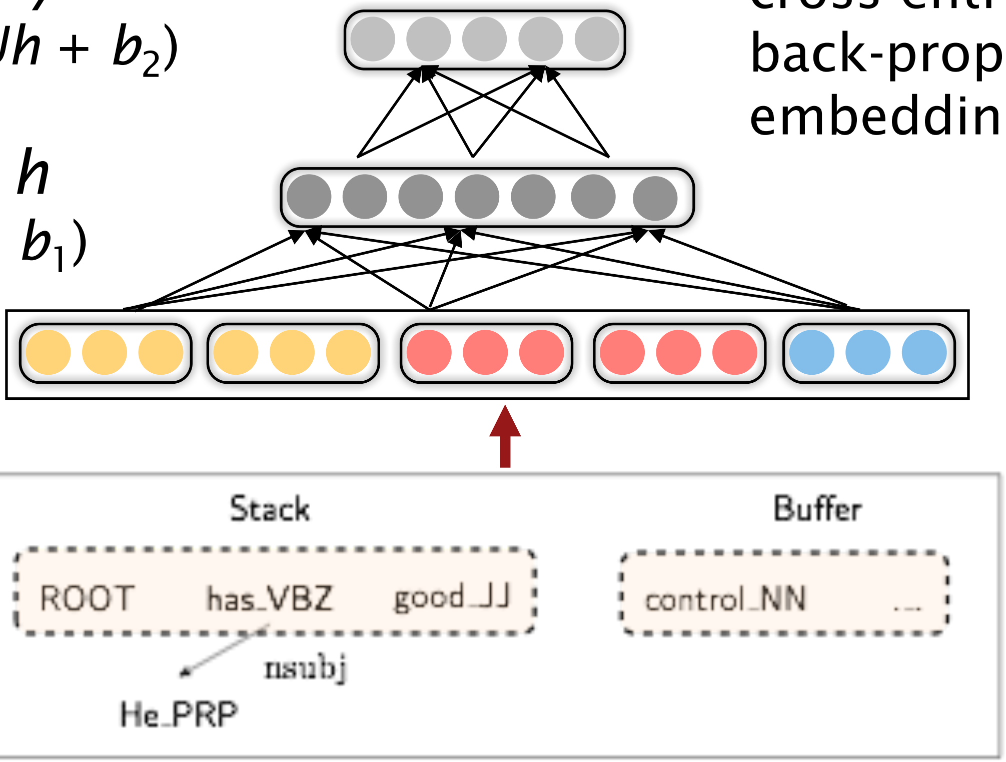
$y = \text{softmax}(Uh + b_2)$

Hidden layer h

$h = \text{ReLU}(Wx + b_1)$

Input layer x

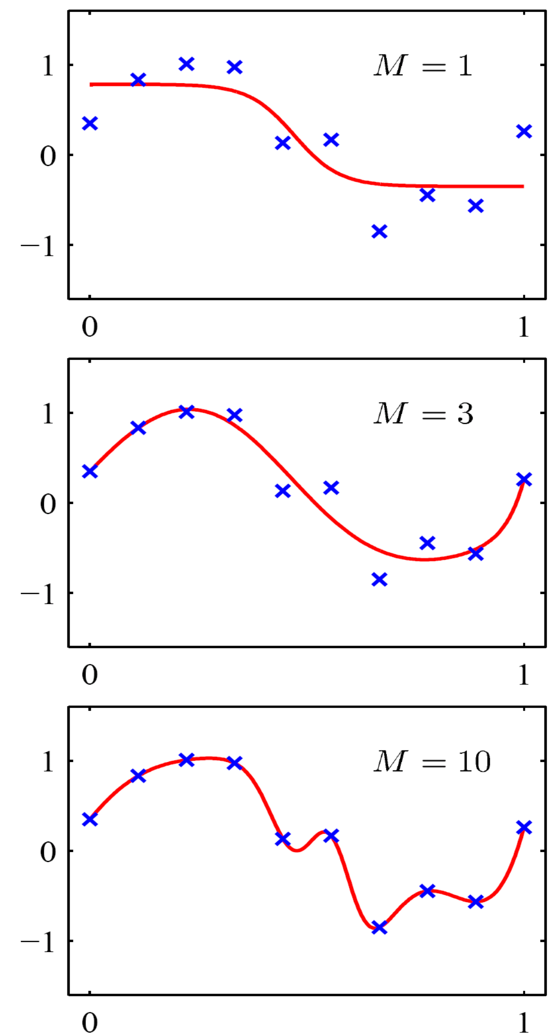
lookup + concat



cross-entropy error will be back-propagated to the embeddings.

Non-linearities between layers: Why they're needed

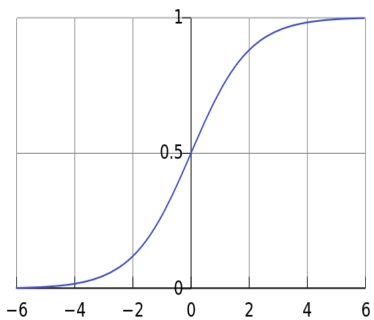
- For logistic regression: map to probabilities
- Here: function approximation, e.g., for regression or classification
  - Without non-linearities, deep neural networks can't do anything more than a linear transform
    - Extra layers could just be compiled down into a single linear transform
- People use various non-linearities



Non-linearities: What's used

logistic ("sigmoid")

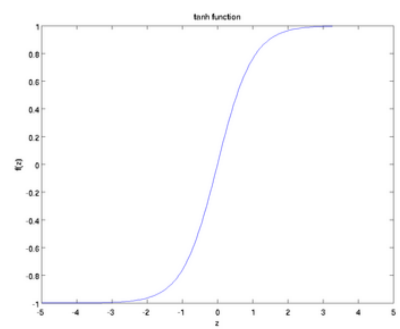
$$f(z) = \frac{1}{1 + \exp(-z)}.$$



$$f'(z) = f(z)(1 - f(z))$$

tanh

$$f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}},$$



$$f'(z) = 1 - f(z)^2$$

tanh is just a rescaled and shifted sigmoid $\tanh(z) = 2\text{logistic}(2z) - 1$

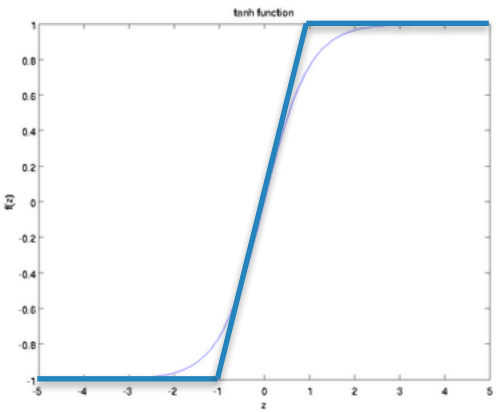
tanh is often used and often performs better for deep nets

- It's output is symmetric around 0

Non-linearities: What's used

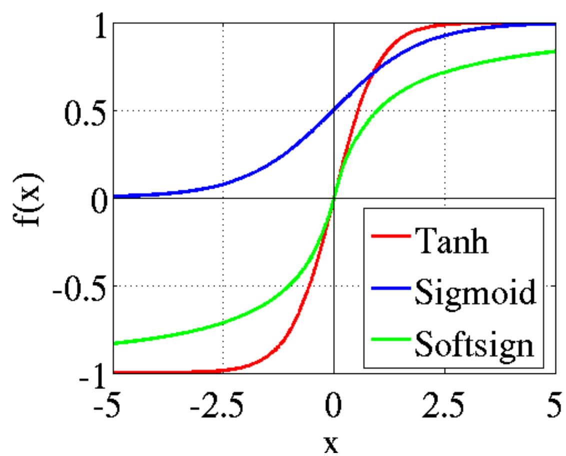
hard tanh

$$\mathrm{HardTanh}(x) = \begin{cases} -1 & \text{if } x < -1 \\ x & \text{if } -1 <= x <= 1 \\ 1 & \text{if } x > 1 \end{cases}$$



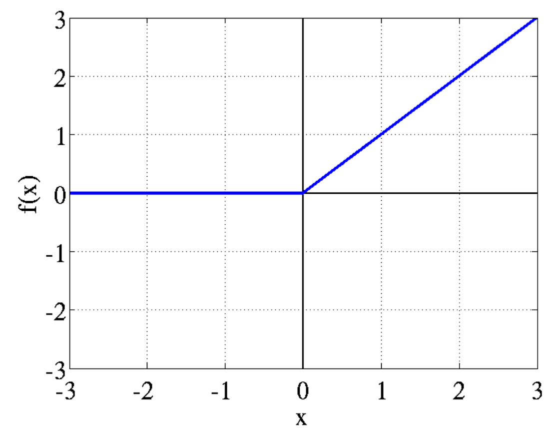
soft sign

$$\mathrm{softsign}(z) = \frac{a}{1+|a|}$$



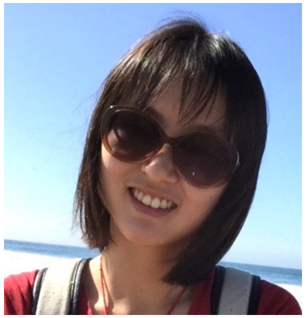
linear rectifier (ReLU)

$$\mathrm{rect}(z) = \max(z, 0)$$

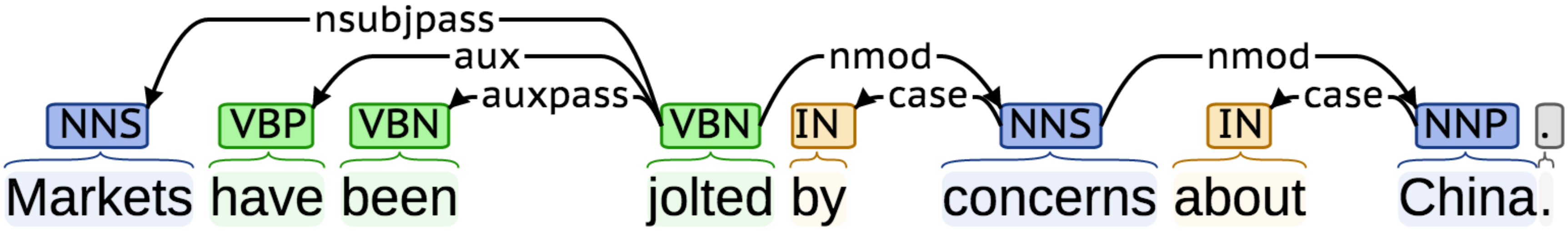


- hard tanh similar but computationally cheaper than tanh and saturates hard.
- [Glorot and Bengio *AISTATS* 2010, 2011] discuss softsign and rectifier
- **Rectified linear unit** is now mega common – transfers linear signal if active

Dependency parsing for sentence structure



Neural networks can accurately determine the structure of sentences, supporting interpretation



Chen and Manning (2014) was the first simple, successful neural dependency parser

The dense representations let it outperform other greedy parsers in both accuracy and speed

Further developments in transition-based neural dependency parsing

This work was further developed and improved by others, including in particular at Google

- Bigger, deeper networks with better tuned hyperparameters
- Beam search
- Global, conditional random field (CRF)-style inference over the decision sequence

Leading to SyntaxNet and the Parsey McParseFace model

https://research.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html

Method	UAS	LAS (PTB WSJ SD 3.3
Chen & Manning 2014	92.0	89.7
Weiss et al. 2015	93.99	92.05
Andor et al. 2016	94.61	92.79