Natural Language Processing with Deep Learning

CS224N/Ling284

Christopher Manning

Lecture 5: Dependency Parsing

Hi!

Lecture Plan

Linguistic Structure: Dependency parsing

1. Syntactic Structure: Consistency and Dependency (25 mins)
2. Dependency Grammar and Treebanks (15 mins)
3. Transition-based dependency parsing (15 mins)
4. Neural dependency parsing (15 mins)

Reminders/comments:

Assignment 2 was due just before class ☺

Assignment 3 (dep parsing) is out today ☹

Start installing and learning PyTorch (Ass 3 has scaffolding)

Final project discussions – **come meet with us**; focus of week 5

Chris make-up office hour this week: Wed 1:00–2:20pm

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

Phrase structure organizes words into nested constituents

Starting unit: words

the, cat, cuddly, by, door

Words combine into phrases

the cuddly cat, by the door

Phrases can combine into bigger phrases

the cuddly cat by the door

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

Phrase structure organizes words into nested constituents

Can represent the grammar with CFG rules

Starting unit: words are given a category (part of speech = pos)

the,	cat,	cuddly,	by,	door
Det	N	Adj	P	N

Words combine into phrases with categories

the cuddly cat, by the door

$NP \rightarrow Det\ Adj\ N$ $PP \rightarrow P\ NP$

Phrases can combine into bigger phrases recursively

the cuddly cat by the door

$NP \rightarrow NP\ PP$

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

Phrase structure organizes words into nested constituents.

Det N

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

talk to
walked behind

NP → Det N
NP → Det (Adj) N
VP → V PP
NP → Det (Adj) N PP
PP → Prep NP

NP
Det N PP
P NP
Det Adj N
Prep PP
green

the cat by the large crate on the large table by the door

Two views of linguistic structure: Dependency structure

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

root

Look in the large crate in the kitchen by the door

V P Det Adj N

Why do we need sentence structure?

We need to understand sentence structure in order to be able to interpret language correctly

Humans communicate complex ideas by composing words together into bigger units to convey complex meanings

We need to know what is connected to what

Prepositional phrase attachment ambiguity

nmod

subj obj nmod

San Jose cops kill man with knife

Text Paper Close

Translate Listen

San Jose cops kill man with knife

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Science & Environment

Scientists count whales from space

By Jonathan Amos
BBC Science Correspondent

Prepositional phrase attachment ambiguity

nmod

subj obj

Scientists count whales from space

V N

✓

nmod

subj obj

Scientists count whales from space

NP → N PP

✗

PP attachment ambiguities multiply

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

subj obj

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

V N

[of Toronto]

[for $27 a share]

[at its monthly meeting].

- 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 (CS228)….

Coordination scope ambiguity

Shuttle veteran and longtime NASA executive Fred Gregory appointed to board

Shuttle veteran and longtime NASA executive Fred Gregory appointed to board

Coordination scope ambiguity

Adjectival Modifier Ambiguity

numbers, including some that featured a bucket and balls brigade of performers who beat rhythms on buckets and trash cans with drums sticks and hammer mallets. PHOTO BY JENNIFER STULTZ

MENTORING DAY

Students get first hand job experience

By Gale Rose
grose@pratttribune.com

Eager students invaded businesses all over Pratt Tuesday, October 24 as they looked for future job opportunities on Disability Mentoring Day.

The 97 students from 12 schools fanned out across Pratt and got first hand experience what it would be like to work at those 40 businesses. They asked questions and got some hands on experience with various operations.

Paola Luna of Pratt High School, Gina Patton of Kingman High School and America Fernandez of St. John chose the Main Street Small Animal Veterinarian Clinic for their business. Students got a tour of the facility, learned what happens in an examination, got to handle various animals and watched a snake eat a mouse.

Luna said she was interested in animal health and wanted to know more about caring for hurt animals. Patton likes all kinds of animals and said she learned a lot from the experience. Watching the snake eat the mouse impressed her the most.

Fernandez wants to become a veterinarian and enjoyed learning everything that veterinarians

SEE MENTORING, 6

Verb Phrase (VP) attachment ambiguity


theguardian

home › world › americas | asia | all

Rio de Janeiro

Mutilated body washes up on Rio beach to be used for Olympics beach volleyball

nmod

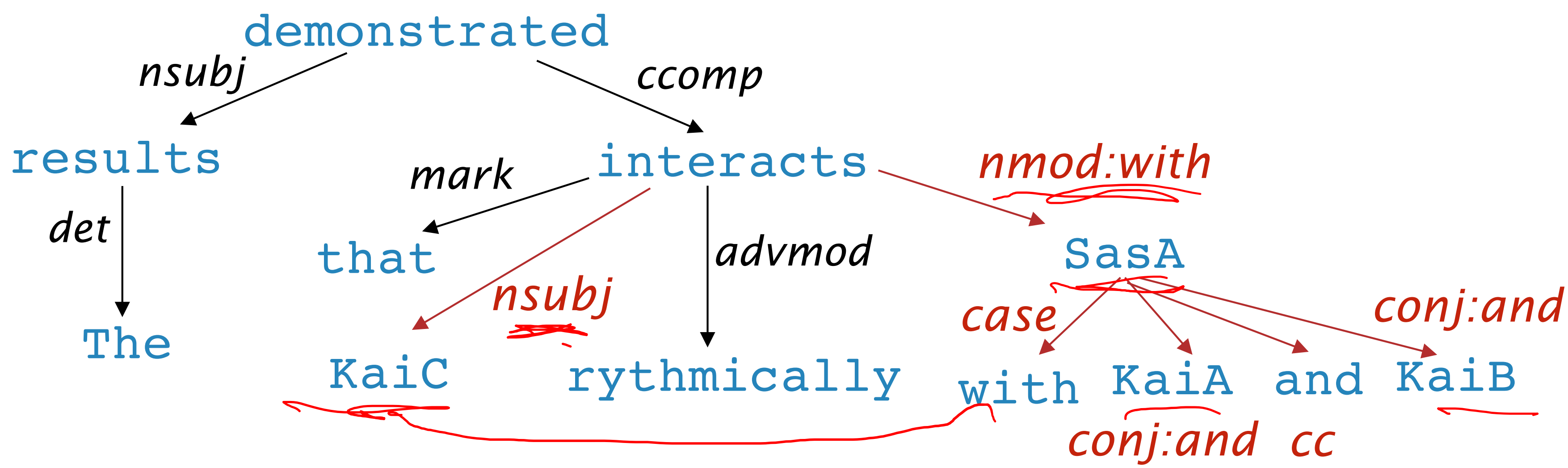
nmod

vp

6/29/16, 1:48 PM

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

nmod:with

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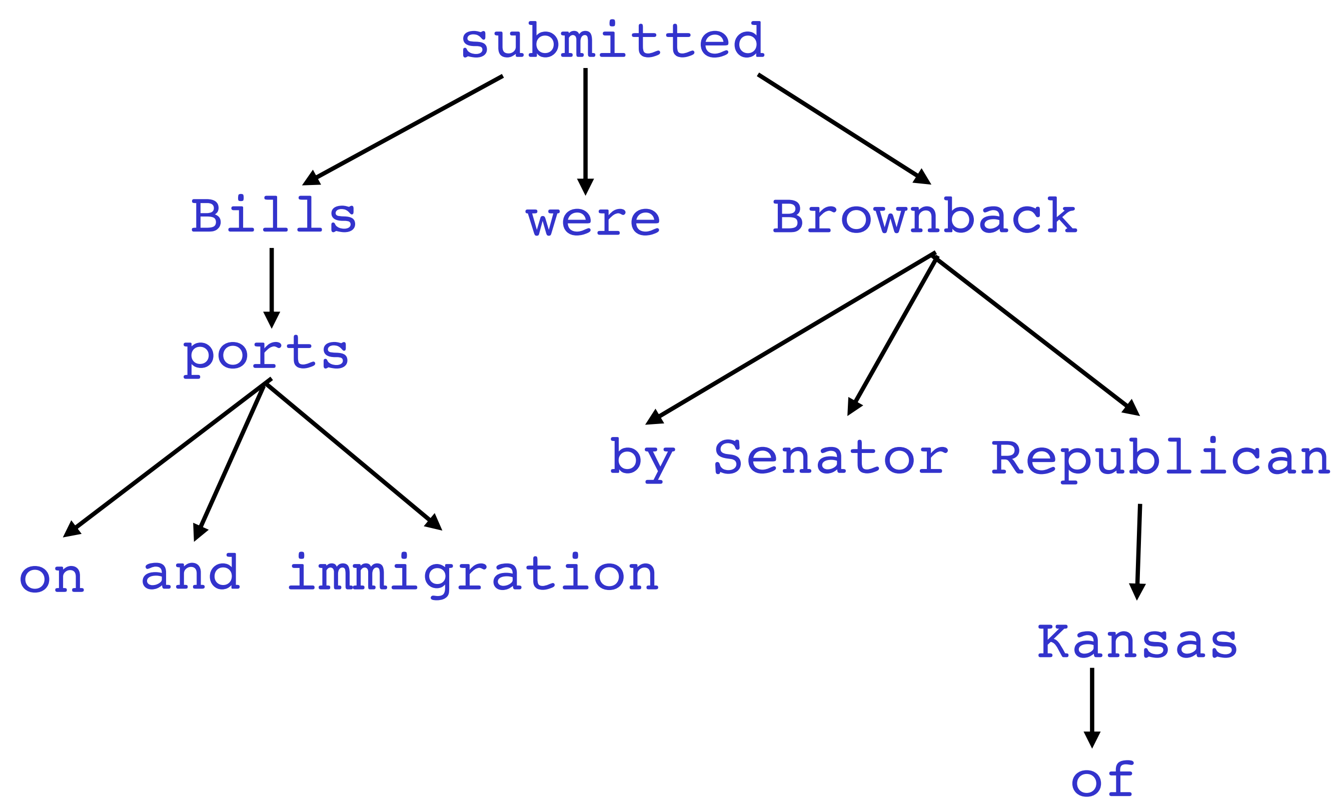
2. Dependency Grammar and Dependency Structure

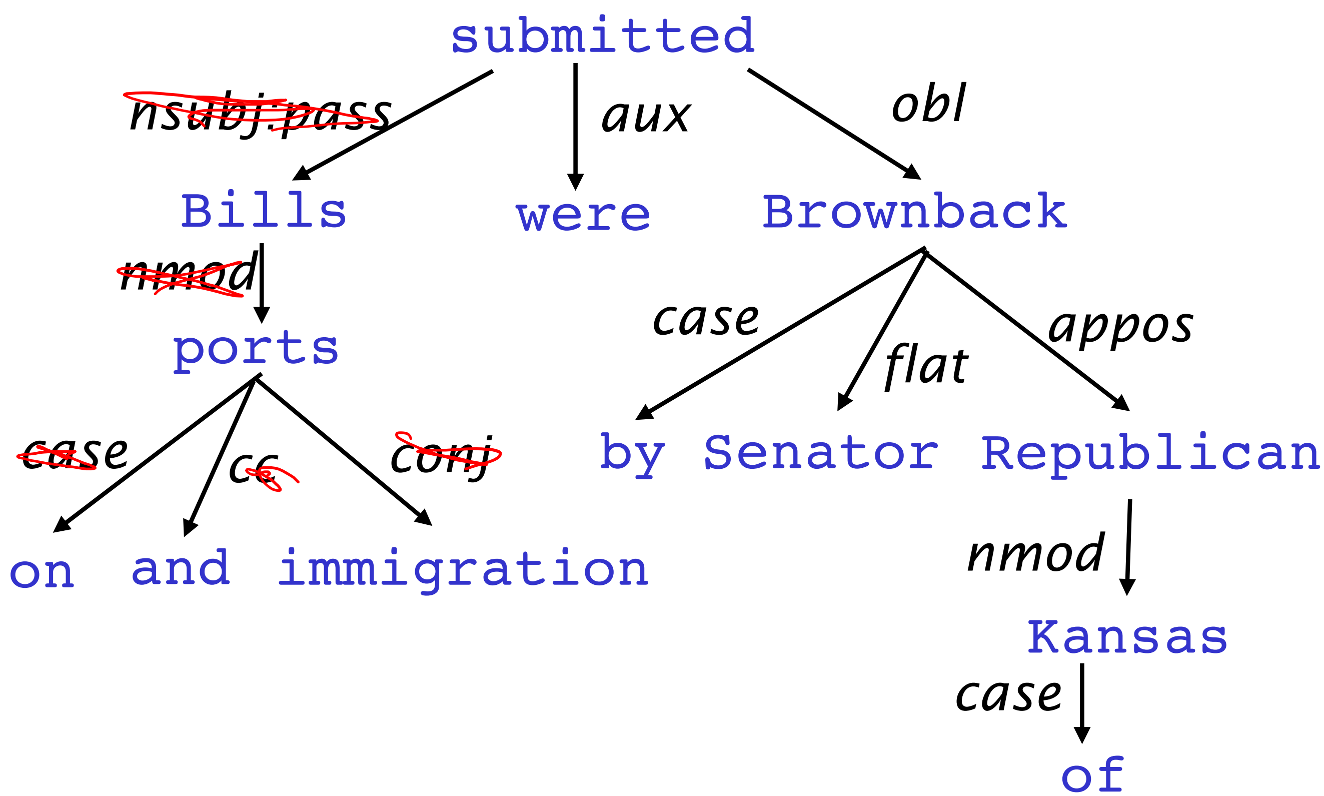
Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations ("arrows") called dependencies



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.)

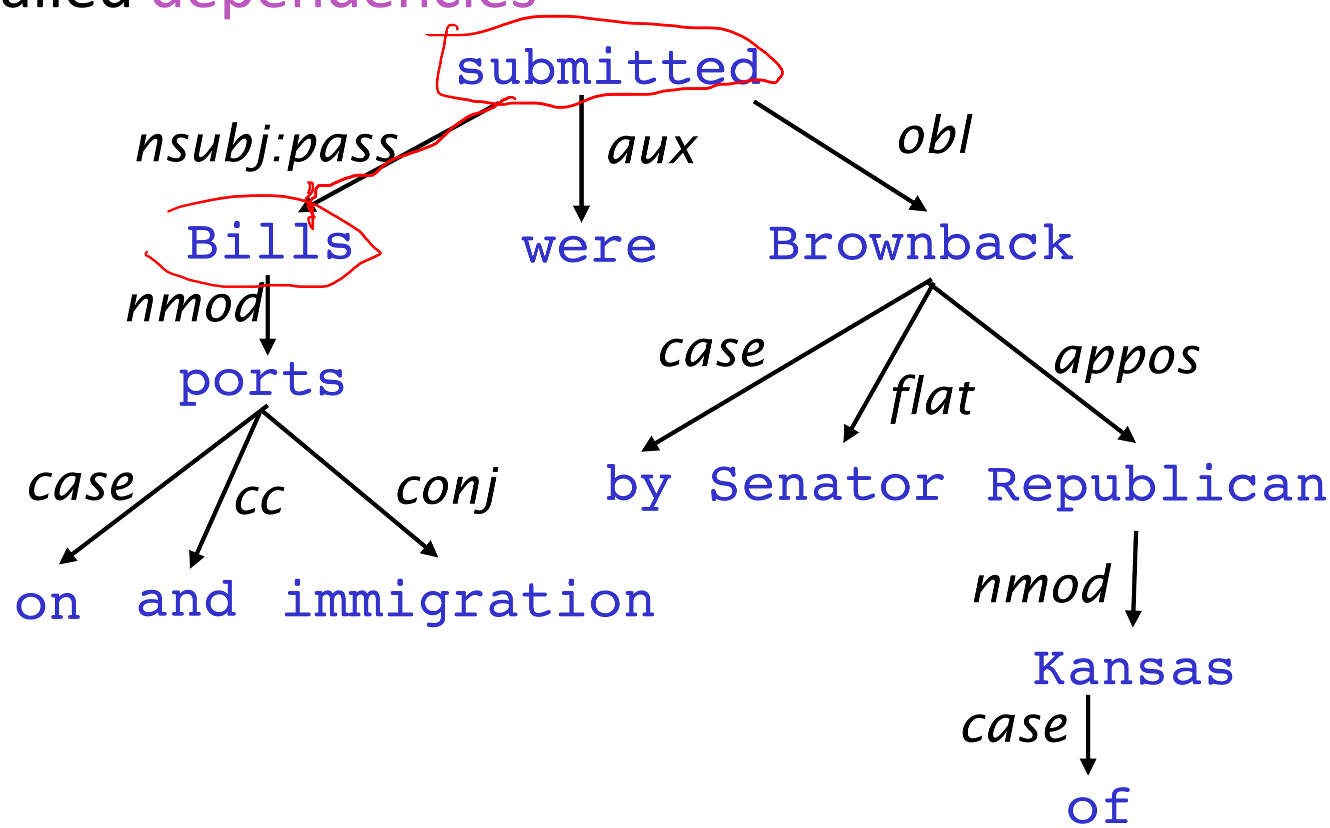


Dependency Grammar and Dependency Structure

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)



Pāṇini's grammar (c. 5th century BCE)

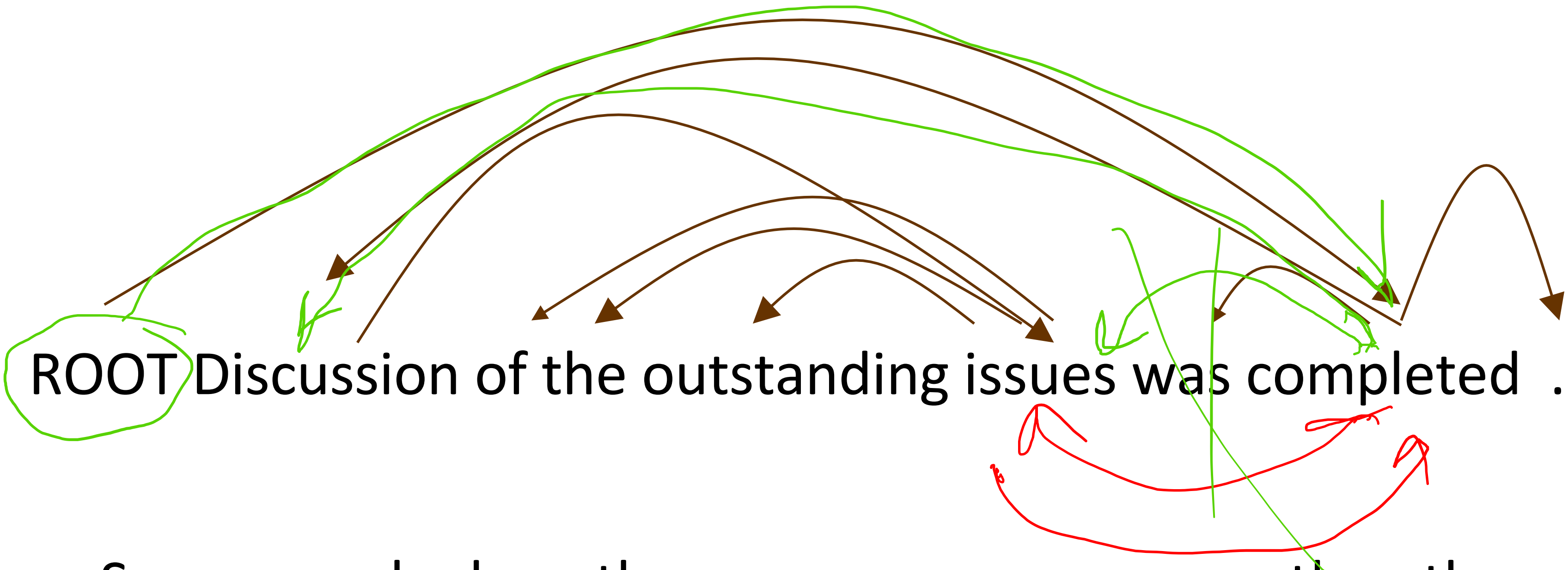
Gallery: http://wellcomeimages.org/indexplus/image/L0032691.html
[CC BY 4.0](CC BY 4.0) File:Birch bark MS from Kashmir of the Rupavatra Wellcome L0032691.jpg

NP → Det (Adj) N   N → goat

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; then Chomsky)
- Modern dependency work often sourced to L. Tesnière (1959)
  - Was dominant approach in "East" in 20th Century (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



- 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

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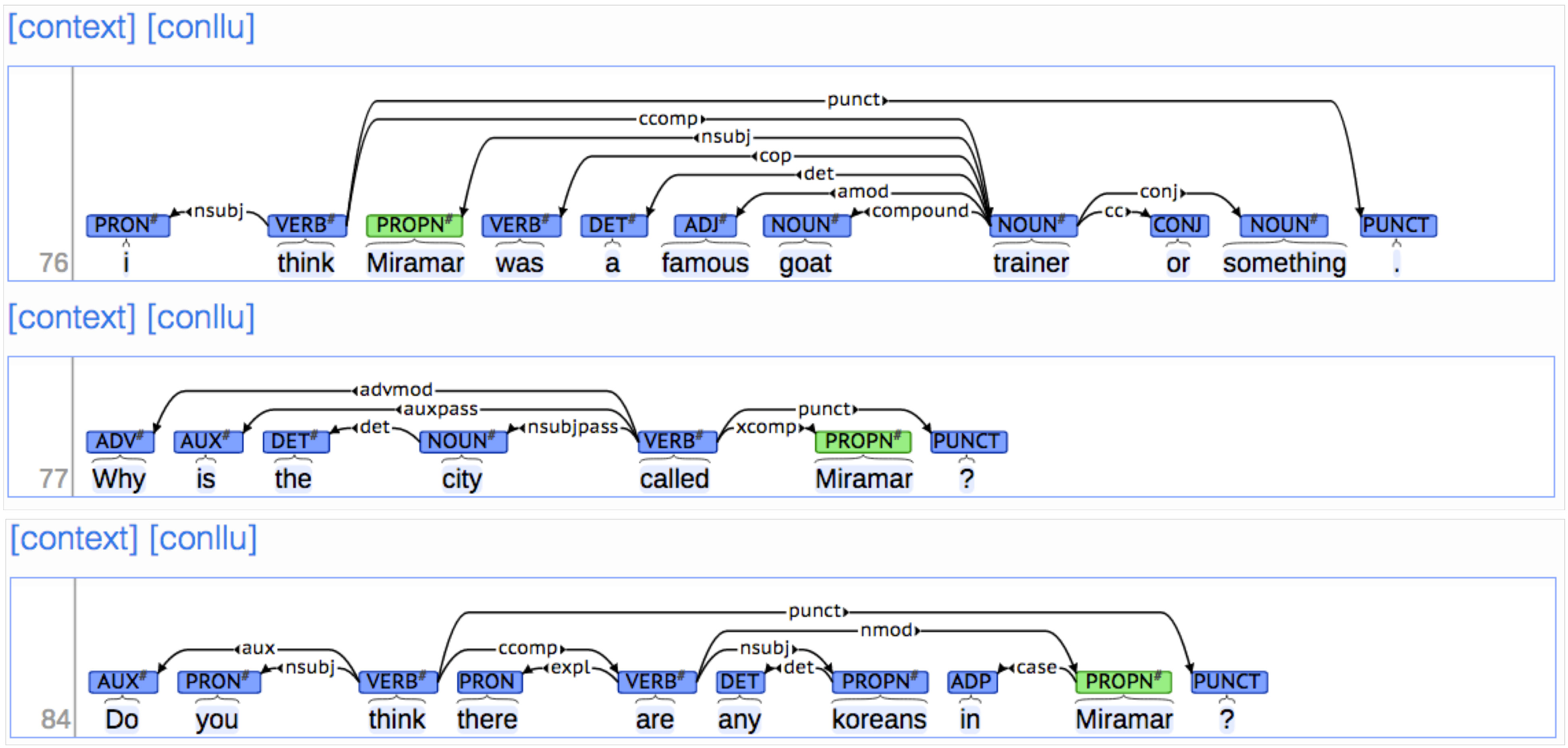
The rise of annotated data: Universal Dependencies treebanks

[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

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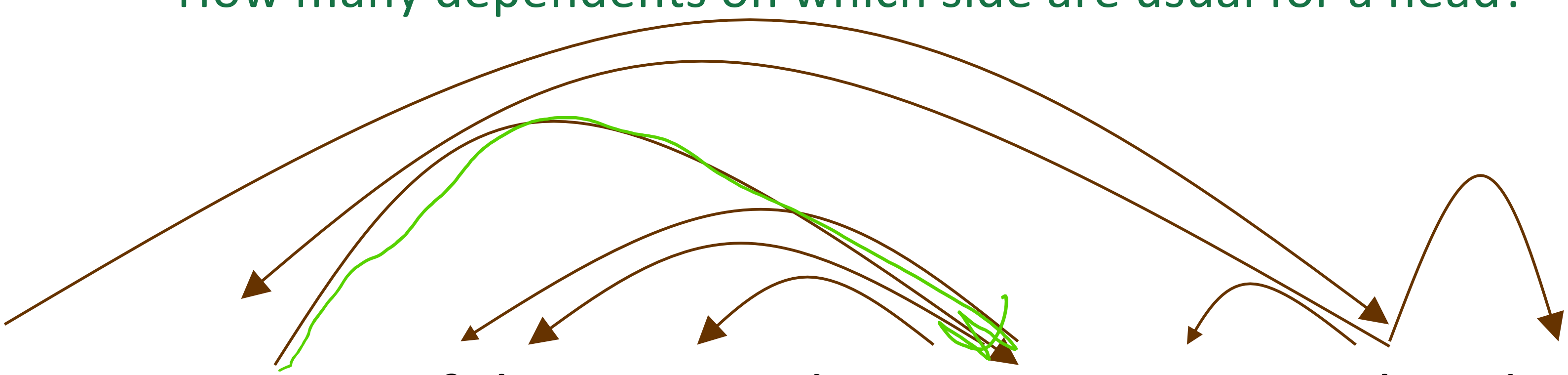
Dependency Conditioning Preferences

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

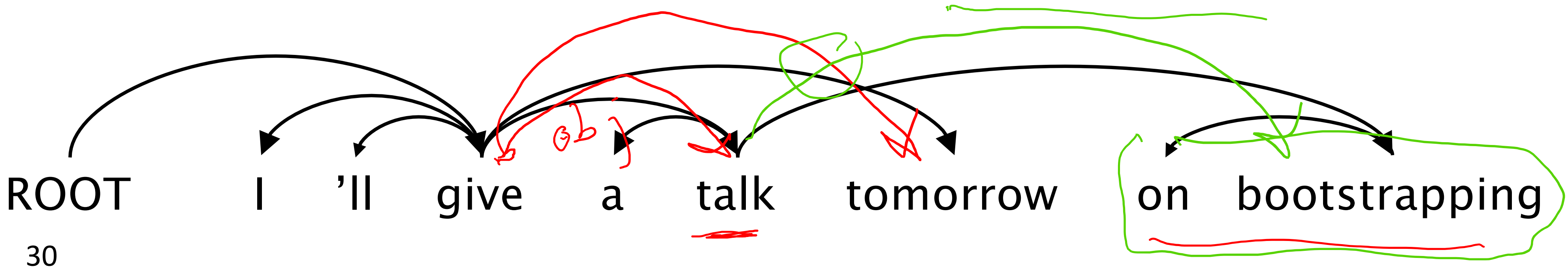
   How many dependents on which side are usual for a head?



ROOT Discussion of the outstanding issues was completed .

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



Projectivity

- Defn: There are no crossing dependency arcs when the words are laid out in their linear order, with all arcs above the words
- Dependencies parallel to a CFG tree must be projective
  - Forming dependencies by taking 1 child of each category as head
- 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

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.

3. 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: $\sigma = [\text{ROOT}], \beta = w_1, \ldots, w_n, A = \emptyset$

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

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

Arc-standard transition-based parser

(there are other transition schemes …)

Analysis of "I ate fish"

stack Buffer

Start

[root] | I ate fish

Shift

[root] I | ate fish

Shift

subj

[root] I ate | fish

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

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: $\beta = \emptyset$

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

root

A += obj(ate → fish)

Right Arc

[root] ate | → [root] |

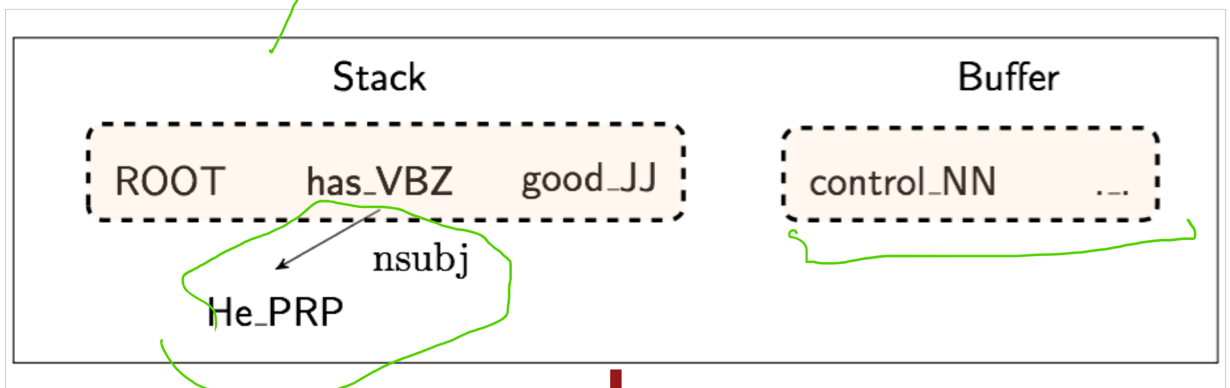
A += root([root] → ate)

Finish

MaltParser
[Nivre and Hall 2005]

- We have left to explain how we choose the next action
  - Answer: Stand back, I know machine learning!
- Each action is predicted by a discriminative classifier (e.g., softmax 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): You keep *k* good parse prefixes at each time step
- The model's accuracy is *fractionally* below the state of the art in dependency parsing, but
- It provides very **fast linear time parsing**, with great performance

Conventional 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

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

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

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

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

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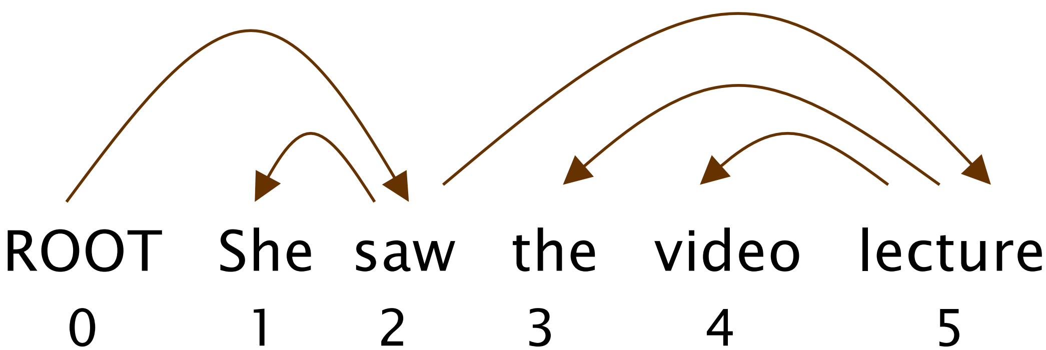
Evaluation of Dependency Parsing: (labeled) dependency accuracy



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

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

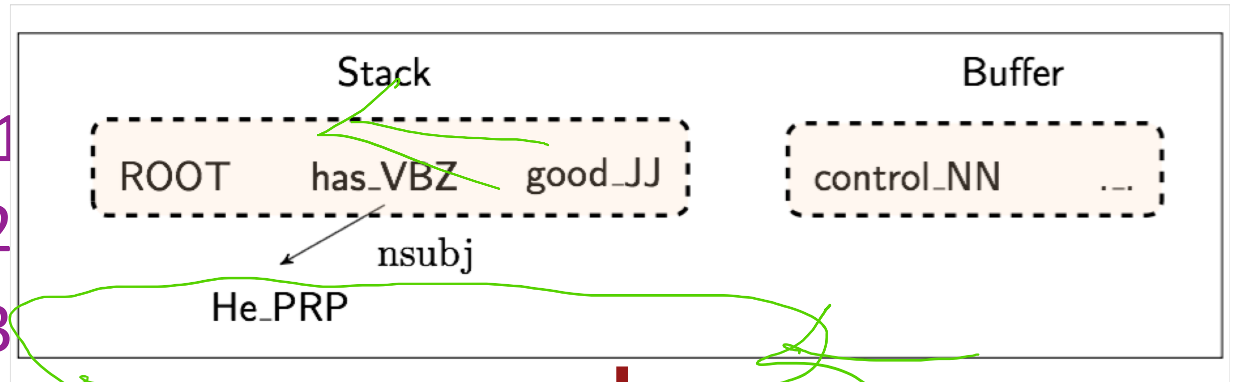
1	2	She	nsubj
2	0	saw	root
3	4	the	det
4	5	video	nsubj
5	2	lecture	ccomp

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 dependency formalism which only has projective representations
     - CFG only allows projective structures; you promote head of violations
  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)

4. 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

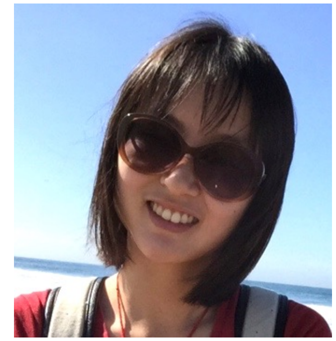
$$s1.w = \text{good} \wedge s1.t = \text{JJ}$$

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

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

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

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

Nivre

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**

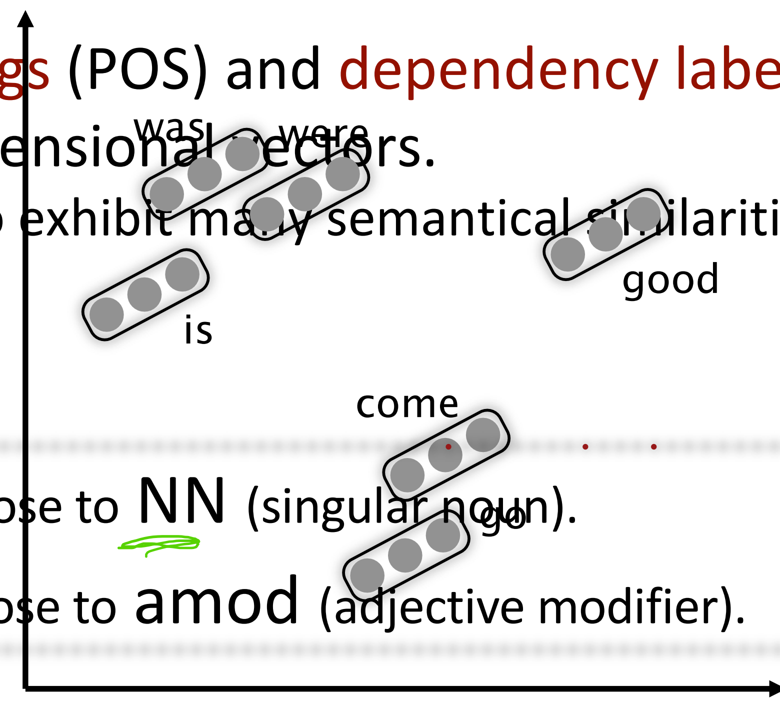
Distributed Representations

- 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.

work works working

VB VBZ VBZ

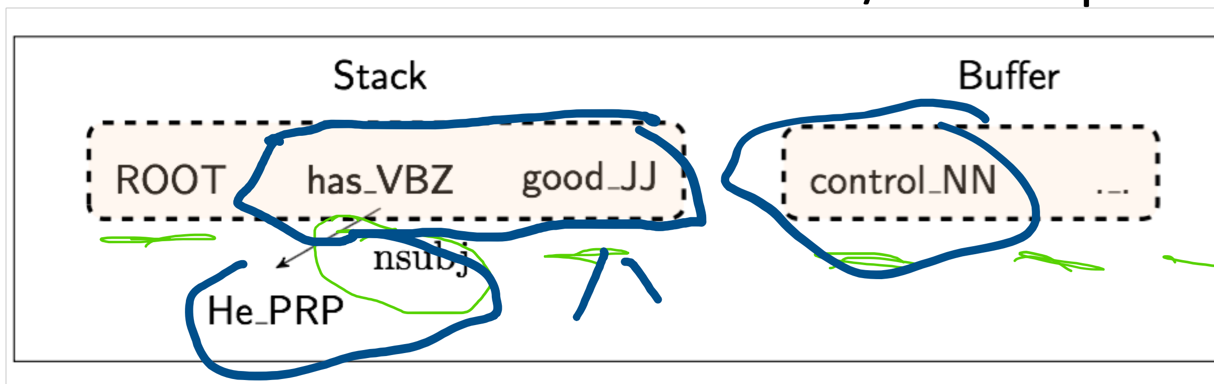


NNS (plural noun) should be close to NN (singular noun).

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

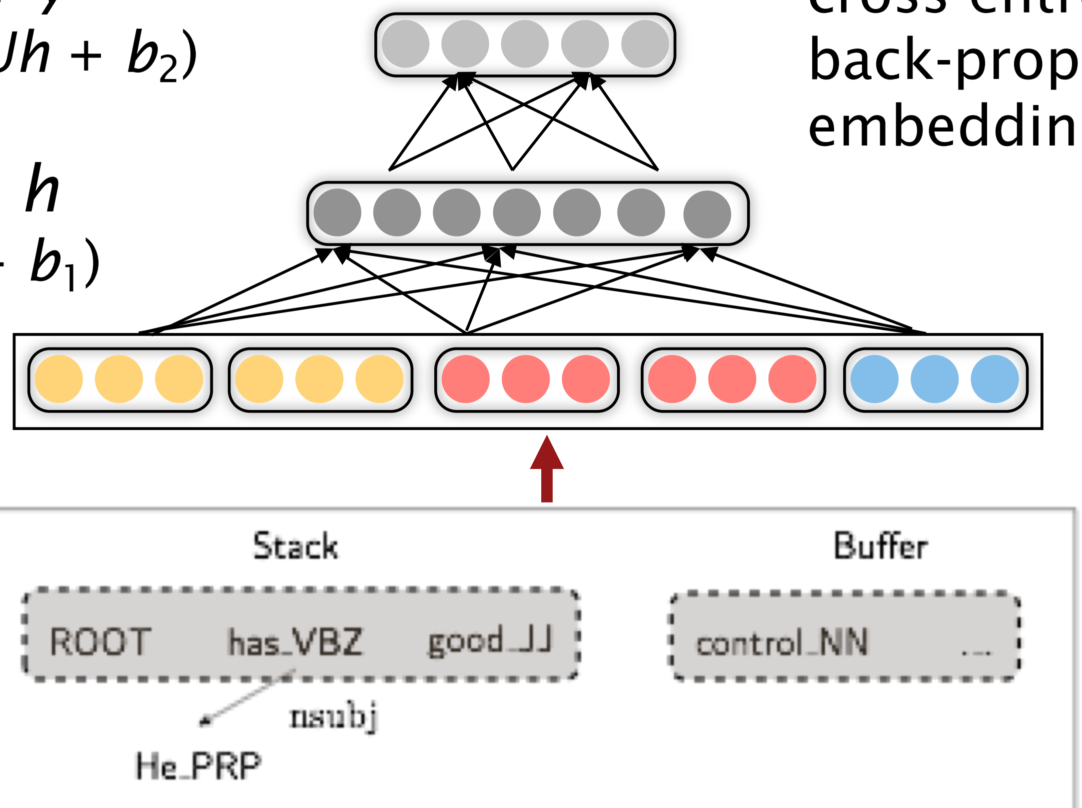
y = softmax($Uh + b_2$)

Hidden layer h

h = ReLU($Wx + b_1$)

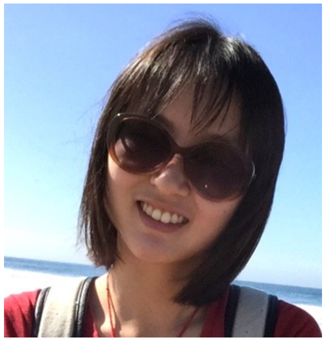
Input layer x

lookup + concat

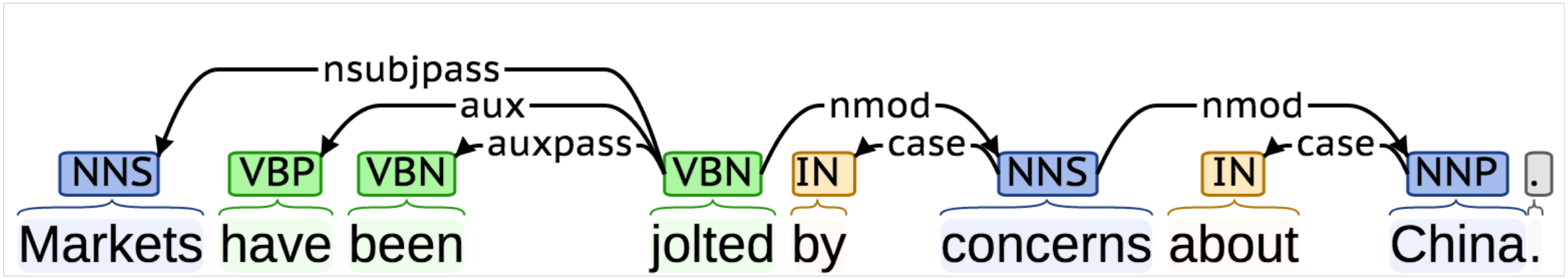


cross-entropy error will be back-propagated to the embeddings.

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

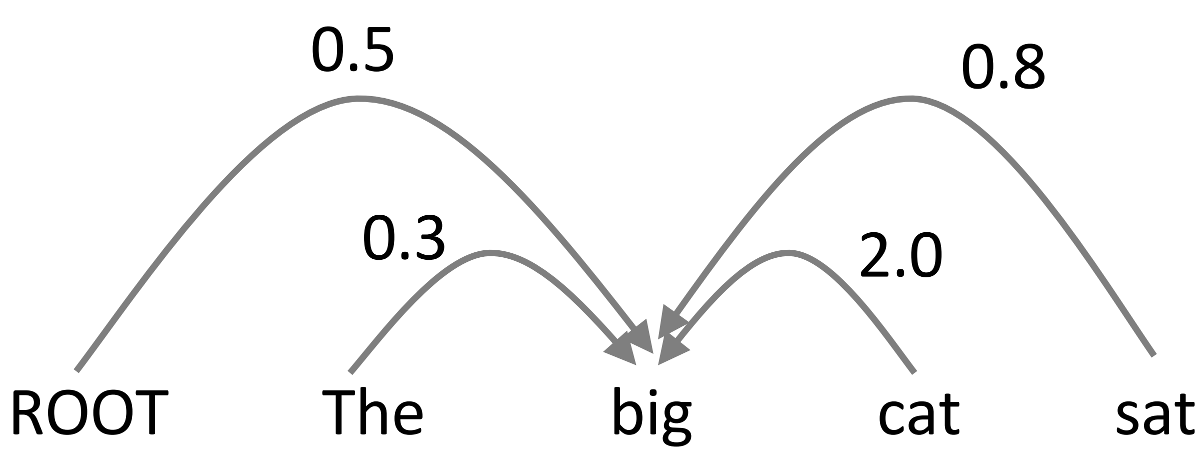
Leading to SyntaxNet and the Parsey McParseFace model

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

Graph-based dependency parsers

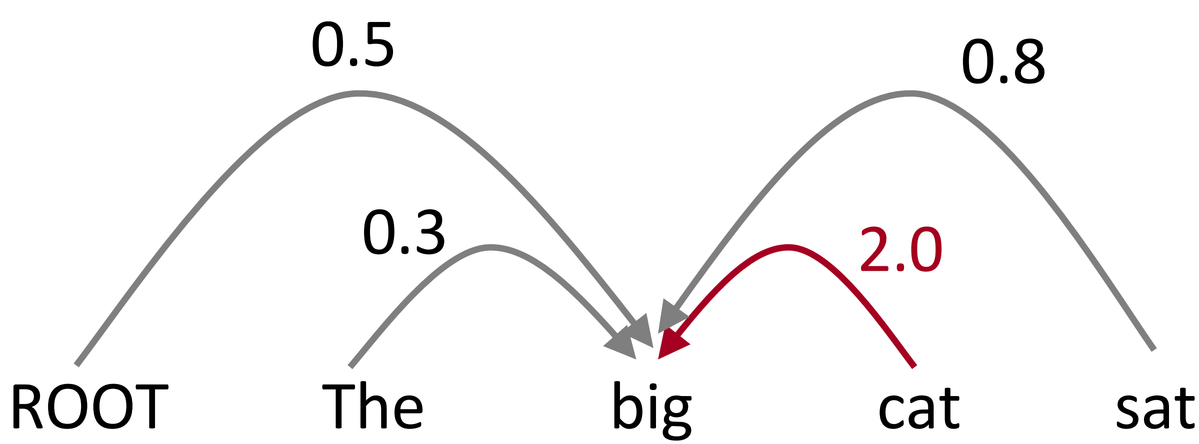
- Compute a score for every possible dependency for each edge



e.g., picking the head for “big”

Graph-based dependency parsers

- Compute a score for every possible dependency for each edge
  - Then add an edge from each word to its highest-scoring candidate head
  - And repeat the same process for each other word



e.g., picking the head for "big"

A Neural graph-based dependency parser

[Dozat and Manning 2017; Dozat, Qi, and Manning 2017]

- Revived graph-based dependency parsing in a neural world
  - Design a biaffine scoring model for neural dependency parsing
    - Also using a neural sequence model, as we discuss next week
- Really great results!
  - But slower than simple neural transition-based parsers
    - There are n^2 possible dependencies in a sentence of length n

Method	UAS	LAS (PTB WSJ SD 3.3
Chen & Manning 2014	92.0	89.7
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Andor et al. 2016	94.61	92.79
Dozat & Manning 2017	**95.74**	**94.08**