Natural Language Processing with Deep Learning

CS224N/Ling284

Christopher Manning

Lecture 4: Dependency Parsing

Lecture Plan

Syntactic Structure and 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 (20 mins)

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

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

walked behind

Two views of linguistic structure: Dependency structure

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

Look in the large crate in the kitchen by the door

Why do we need sentence structure?

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

Listeners need to work out what modifies [attaches to] what

A model needs to understand sentence structure in order to be able to interpret language correctly

Prepositional phrase attachment ambiguity


San Jose cops kill man with knife

Close

Text Paper Translate Listen

San Jose cops kill man with knife


BBC Sign in News Sport Weather Shop Reel Travel

NEWS

Home Video World US & Canada UK Business Tech Science Stories

Science & Environment

Scientists count whales from space

By Jonathan Amos
BBC Science Correspondent

Prepositional phrase attachment ambiguity

Scientists count whales from space

Scientists count whales from space

PP attachment ambiguities multiply

- 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].

- 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/Adverbial Modifier Ambiguity

numbers, including some that featured a bucket and bells 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

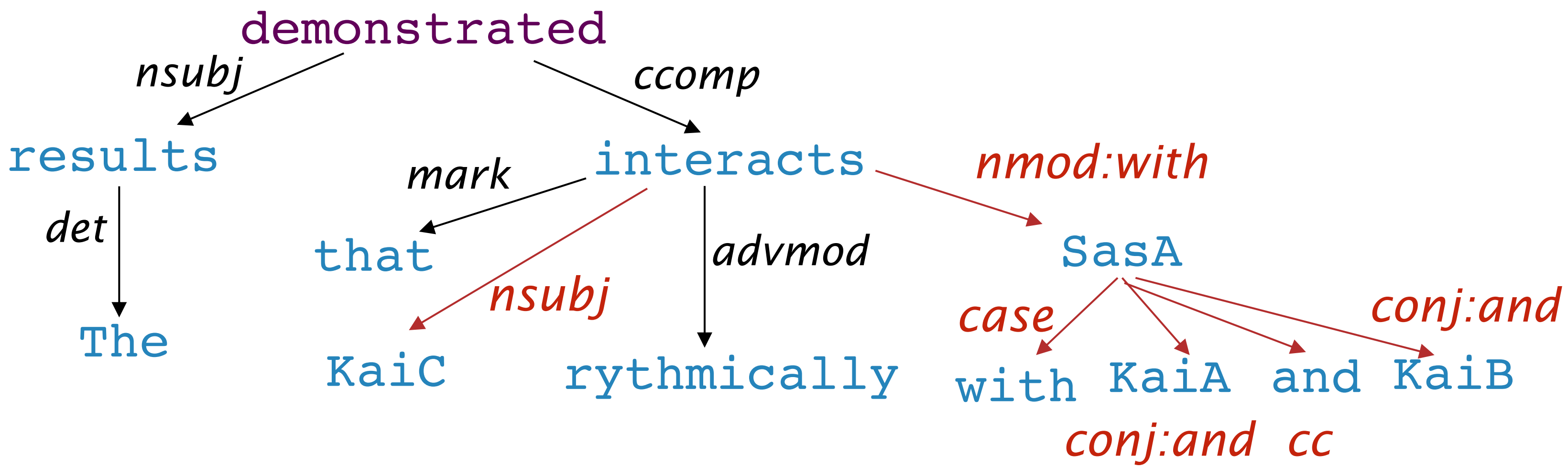
home › world › americas | asia | all

Rio de Janeiro

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

6/29/16, 1:48 PM

Dependency paths help extract semantic interpretation – simple practical example: extracting protein-protein interaction



KaiC ←nsubj interacts nmod:with → SasA

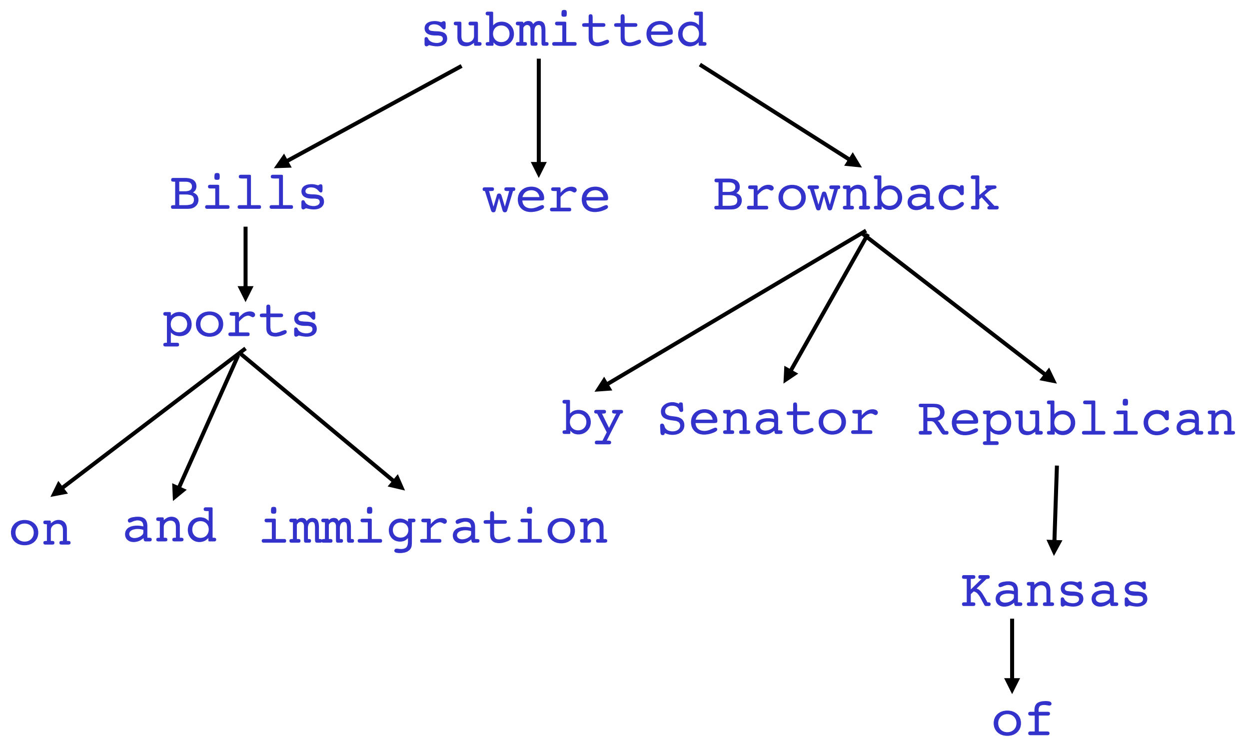
KaiC ←nsubj interacts nmod:with → SasA conj:and→ KaiA

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

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

2. Dependency Grammar and Dependency Structure

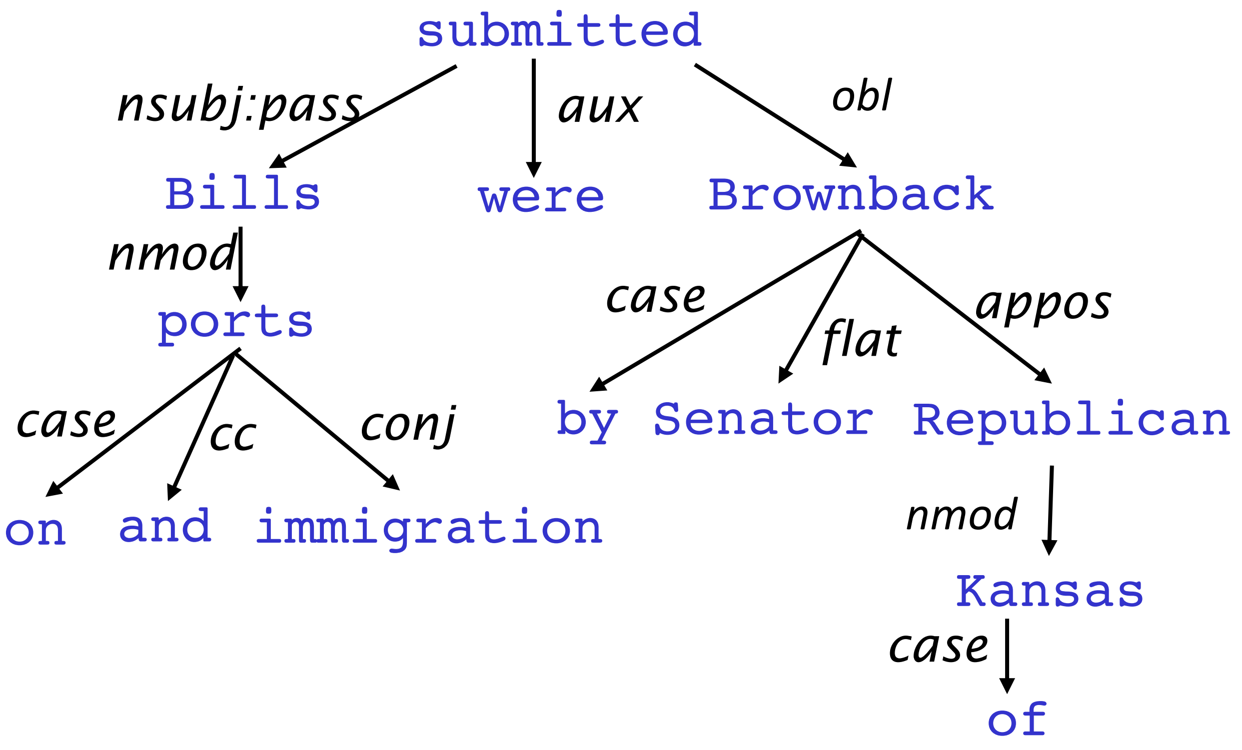
Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations (“arrows”) called dependencies



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.)

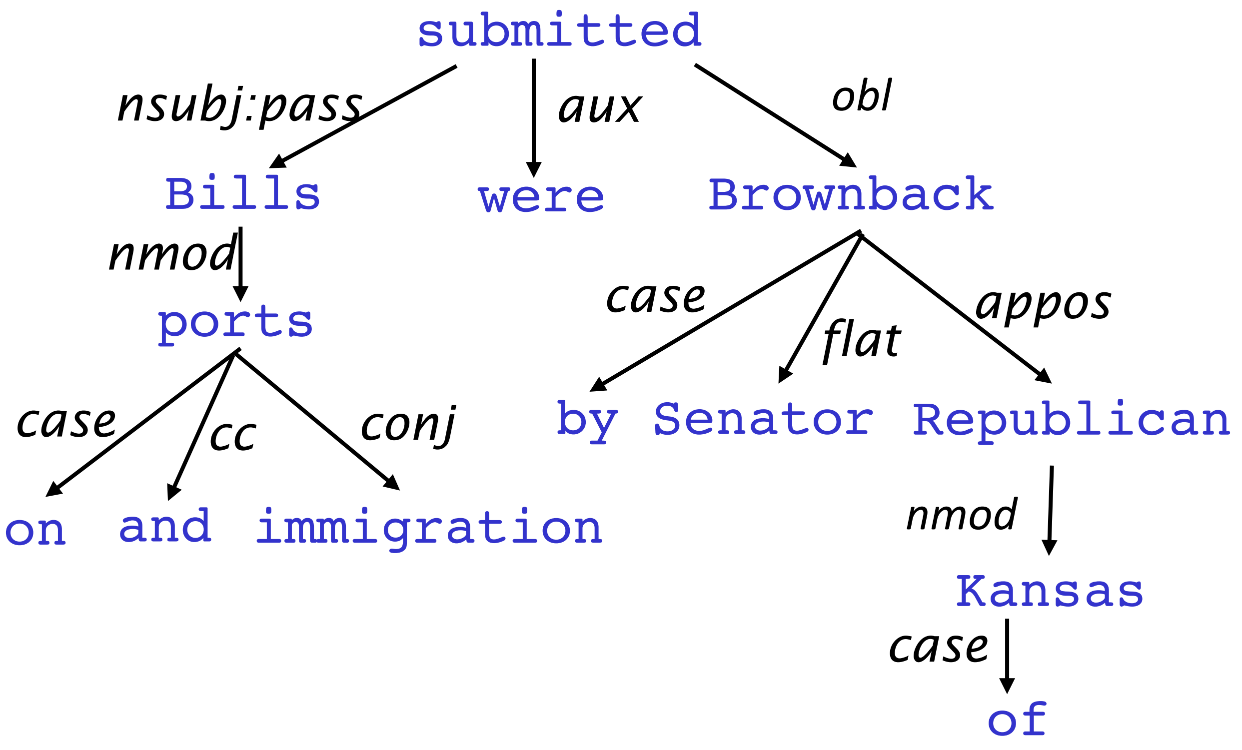


Dependency Grammar and Dependency Structure

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

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

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



Pāṇini’s grammar (c. 5th century BCE)

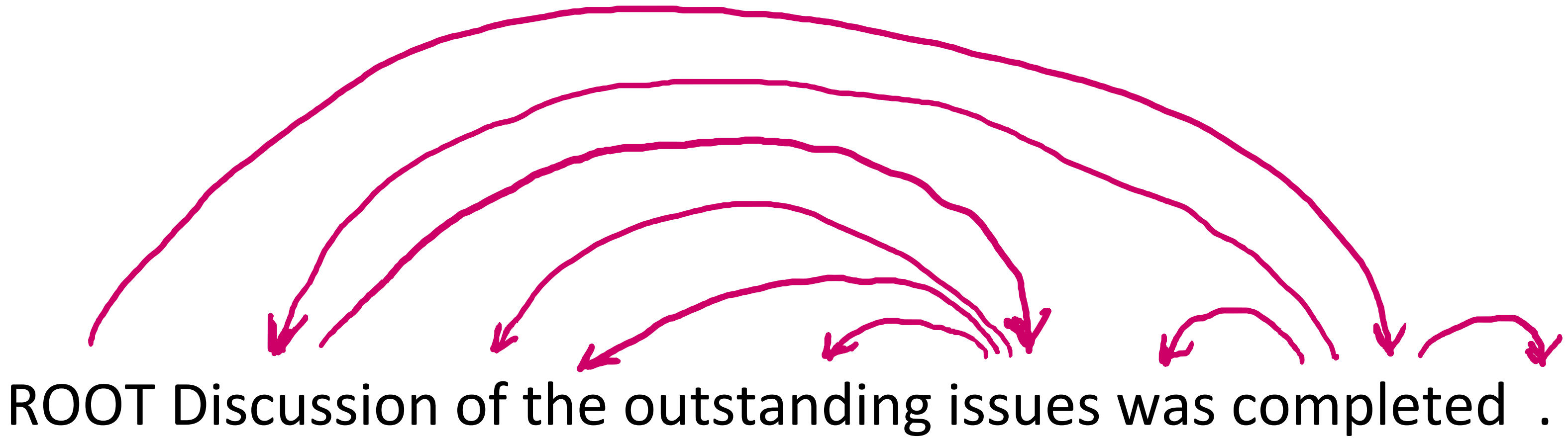
Gallery: http://wellcomeimages.org/indexplus/image/L0032691.html

 File:Birch bark MS from Kashmir of the Rupavatra Wellcome L0032691.jpg

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 grammar is a new-fangled invention
  - 20th century invention (R.S. Wells, 1947; then Chomsky 1953, etc.)
- Modern dependency work is often sourced to Lucien Tesnière (1959)
  - Was dominant approach in "East" in 20th Century (Russia, China, …)
    - Good for free-er word order, inflected languages like Russian (or Latin!)
- Used in some of the earliest 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) and published on dependency grammar in *Language*

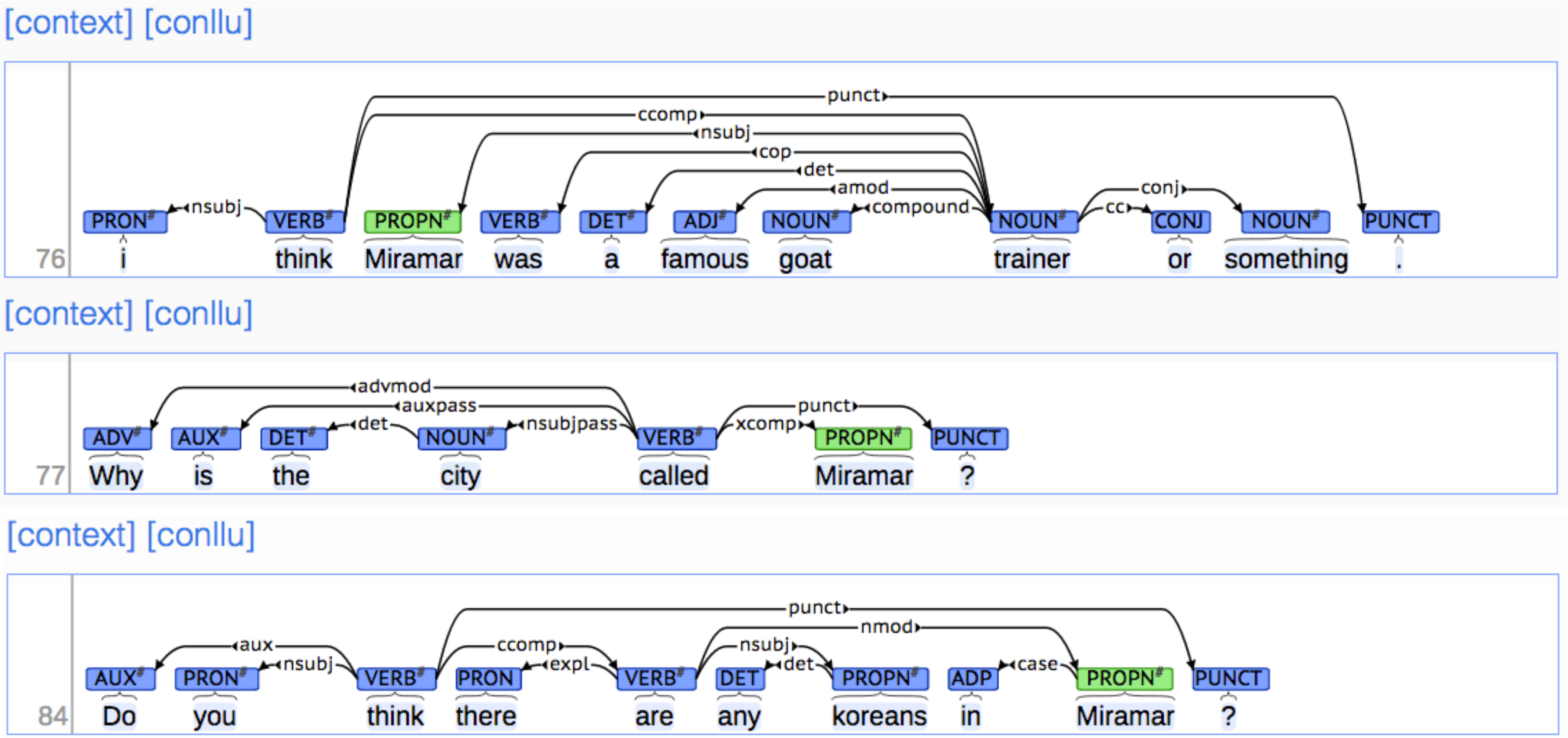
Dependency Grammar and Dependency Structure



- Some people draw the arrows one way; some the other way!
  - Tesnière had them point from head to dependent – we follow that convention
- We usually add a fake ROOT so every word is a dependent of precisely 1 other node

The rise of annotated data & Universal Dependencies treebanks

Brown corpus (1967; PoS tagged 1979); Lancaster-IBM Treebank (starting late 1980s);
Marcus et al. 1993, The Penn Treebank, *Computational Linguistics;*
Universal Dependencies: http://universaldependencies.org/



The rise of annotated data

Starting off, building a treebank seems a lot slower and less useful than writing a grammar (by hand)

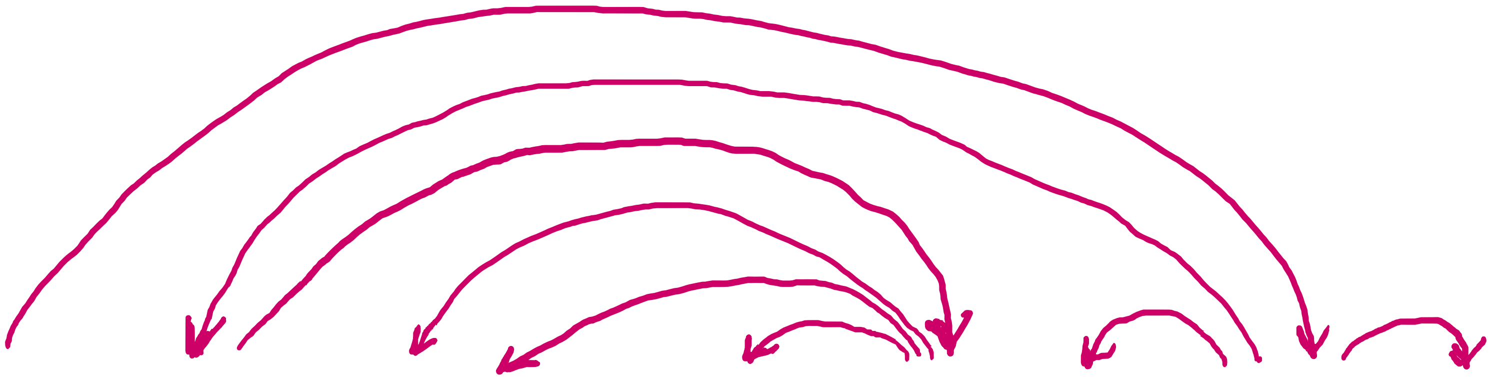
But a treebank gives us many things

- 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 NLP systems

Dependency Conditioning Preferences

What are the sources of information for dependency parsing?

1. Bilexical affinities — The dependency [discussion → issues] is plausible
2. Dependency distance — Most dependencies are between 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?

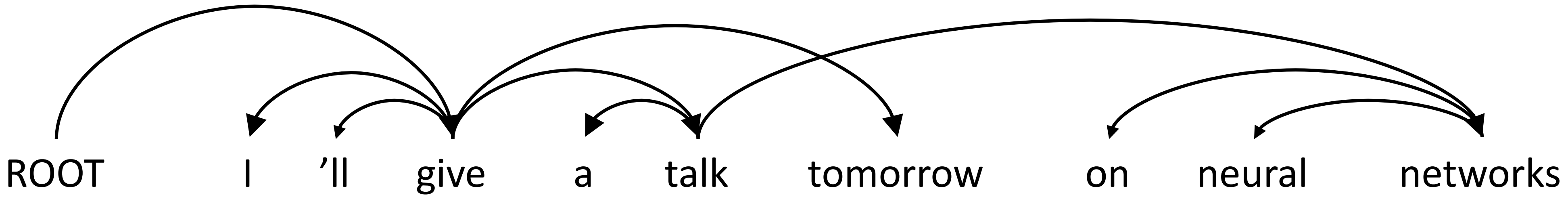


ROOT Discussion of the outstanding issues was completed .

Dependency Parsing

- A sentence is parsed by choosing for each word what other word (including ROOT) it is 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 (be non-projective) or not



Projectivity

- Definition of a projective parse: There are no crossing dependency arcs when the words are laid out in their linear order, with all arcs above the words
- Dependencies corresponding to a CFG tree must be projective
  - I.e., by forming dependencies by taking 1 child of each category as head
- Most syntactic structure is projective like this, 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

3. 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)

   Neural graph-based parser: Dozat and Manning (2017) et seq. – very successful!

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

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

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 = $\emptyset$

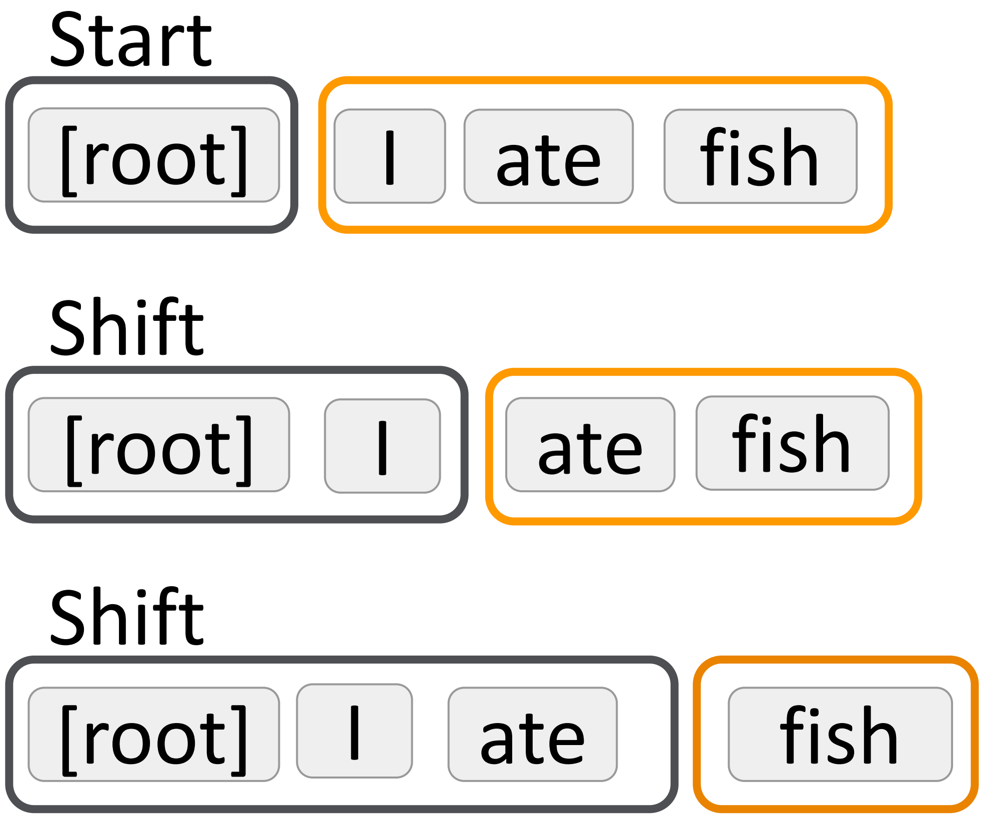
1. Shift $\sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$
2. Left-Arc$_r$ $\sigma|w_i|w_j, \beta, A \rightarrow \sigma|w_j, \beta, A \cup \{r(w_j,w_i)\}$
3. Right-Arc$_r$ $\sigma|w_i|w_j, \beta, A \rightarrow \sigma|w_i, \beta, A \cup \{r(w_i,w_j)\}$

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

Arc-standard transition-based parser

(there are other transition schemes …)

Analysis of "I ate fish"



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

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

A += obj(ate → fish)

Right Arc

[root] ate | → [root] |

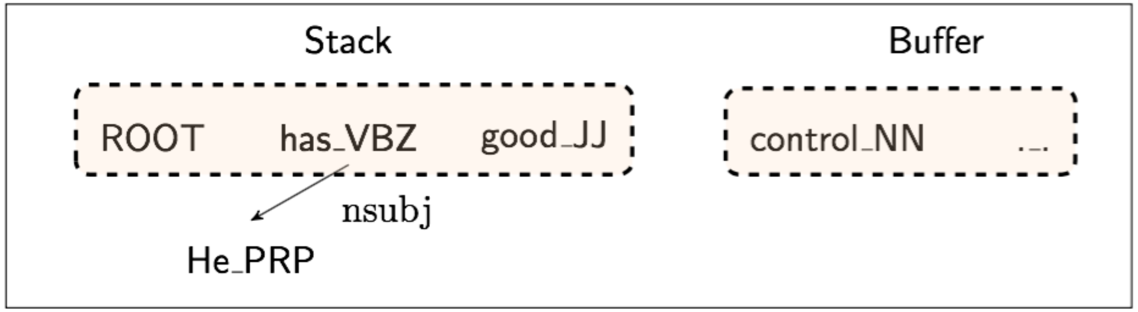
A += root([root] → ate)

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 high accuracy – great for parsing the web

Conventional Feature Representation



binary, sparse
dim $=10^6 – 10^7$

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

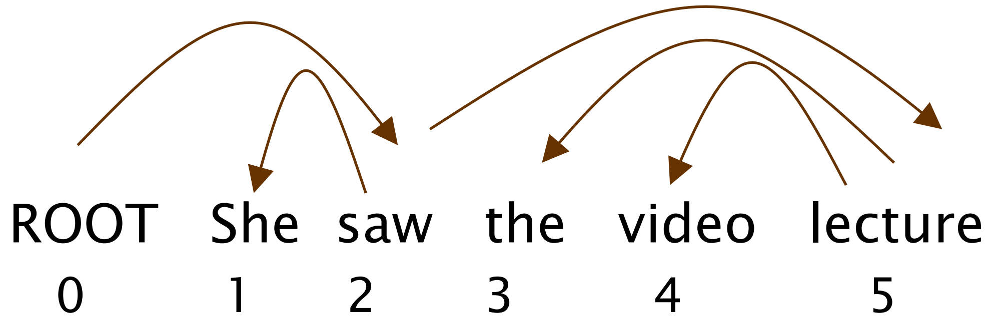
$$s1.w = \text{good} \wedge s1.t = \text{JJ}$$

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

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

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

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

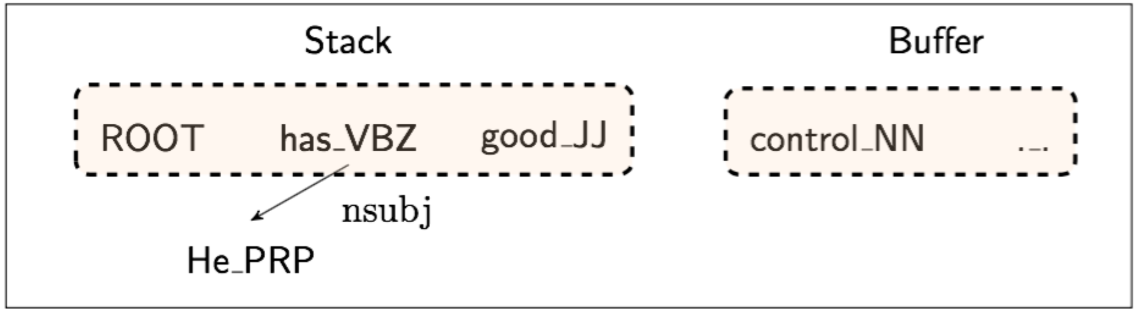
1	2	She	nsubj
2	0	saw	root
3	4	the	det
4	5	video	nsubj
5	2	lecture	ccomp

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
     - A CFG only allows projective structures; you promote head of projectivity 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 or Dozat and Manning (2017))

4. Why do we gain from a neural dependency parser?
Indicator Features Revisited

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



dense
dim = ~1000

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

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

Neural 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]

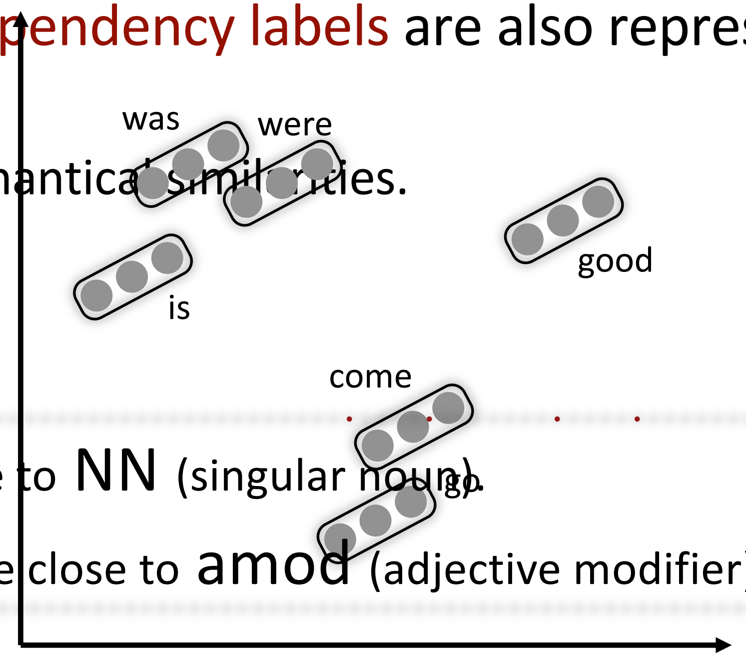
- Results on English parsing to Stanford Dependencies:
  - Unlabeled attachment score (UAS) = head
  - Labeled attachment score (LAS) = head and label

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**

First win: 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.

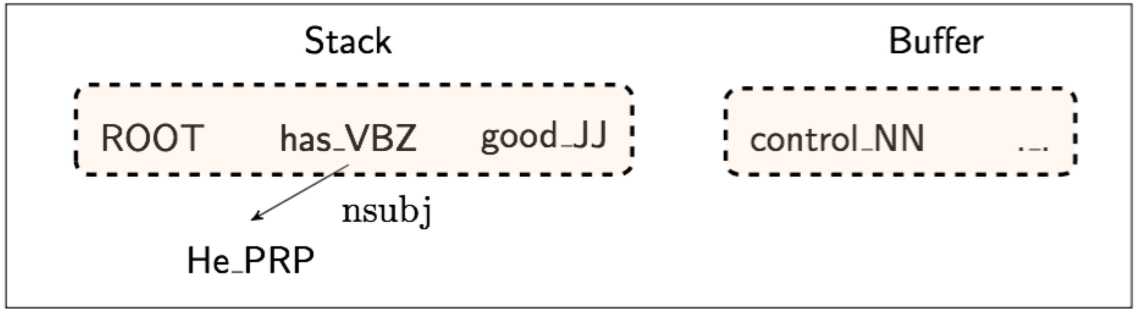


NNS (plural noun) should be close to NN (singular noun).

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

Extracting Tokens & vector representations from configuration

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



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

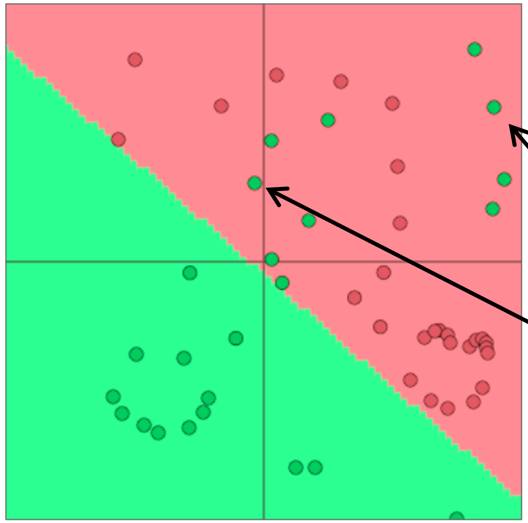
A concatenation of the vector representation of all these is the neural representation of a configuration

Second win: Deep Learning classifiers are non-linear classifiers

- A softmax classifier assigns classes $y \in C$ based on inputs $x \in \mathbb{R}^d$ via the probability:

$$p(y|x) = \frac{\exp(W_y.x)}{\sum_{c=1}^{C} \exp(W_c.x)}$$

- We train the weight matrix $W \in \mathbb{R}^{C \times d}$ to minimize the neg. log loss : $\sum_i -\log p(y_i|x_i)$
- Traditional ML classifiers (including Naïve Bayes, SVMs, logistic regression and softmax classifier) are not very powerful classifiers: they only give linear decision boundaries



This can be quite limiting

→ Unhelpful when a problem is complex

Wouldn't it be cool to get these correct?

Neural Networks are more powerful

- Neural networks can learn much more complex functions with nonlinear decision boundaries!
    - Non-linear in the original space, linear for the softmax at the top of the neural network

Visualizations with ConvNetJS by Andrej Karpathy!

http://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html

Simple feed-forward neural network multi-class classifier

Softmax probabilities

Log loss (cross-entropy error) will be back-propagated to the embeddings

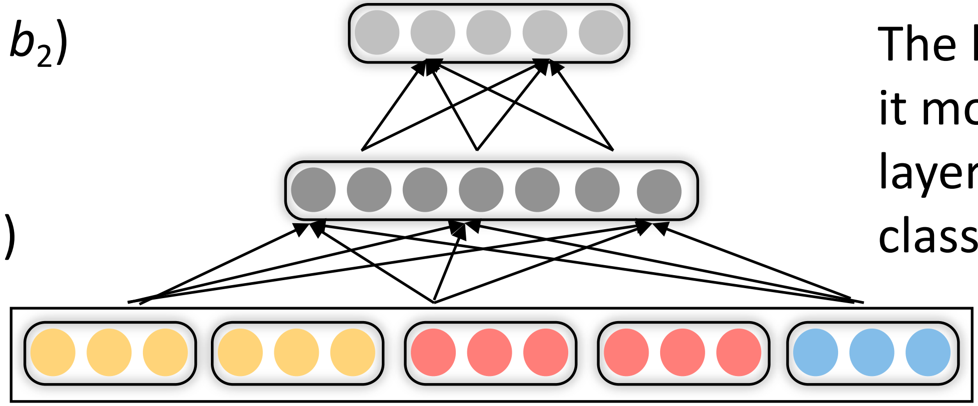
Output layer y

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

Hidden layer h

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

Input layer x



The hidden layer re-represents the input — it moves inputs around in an intermediate layer vector space—so it can be easily classified with a (linear) softmax

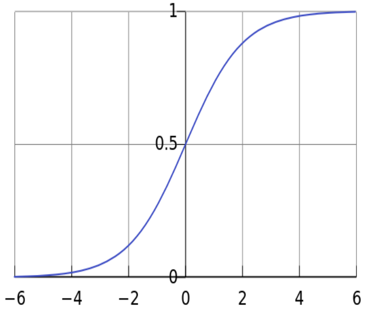
x is result of lookup

$x_{(i,\ldots,i+d)} = Le$

lookup + concat

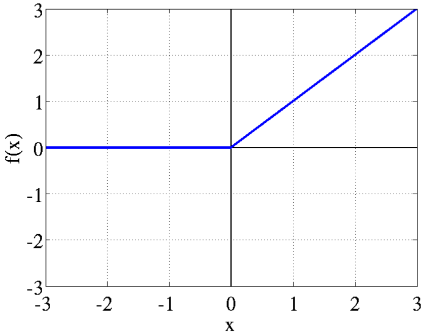
logistic = “sigmoid”

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



ReLU = Rectified Linear Unit

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



Neural Dependency Parser Model Architecture

Softmax probabilities

Output layer y

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

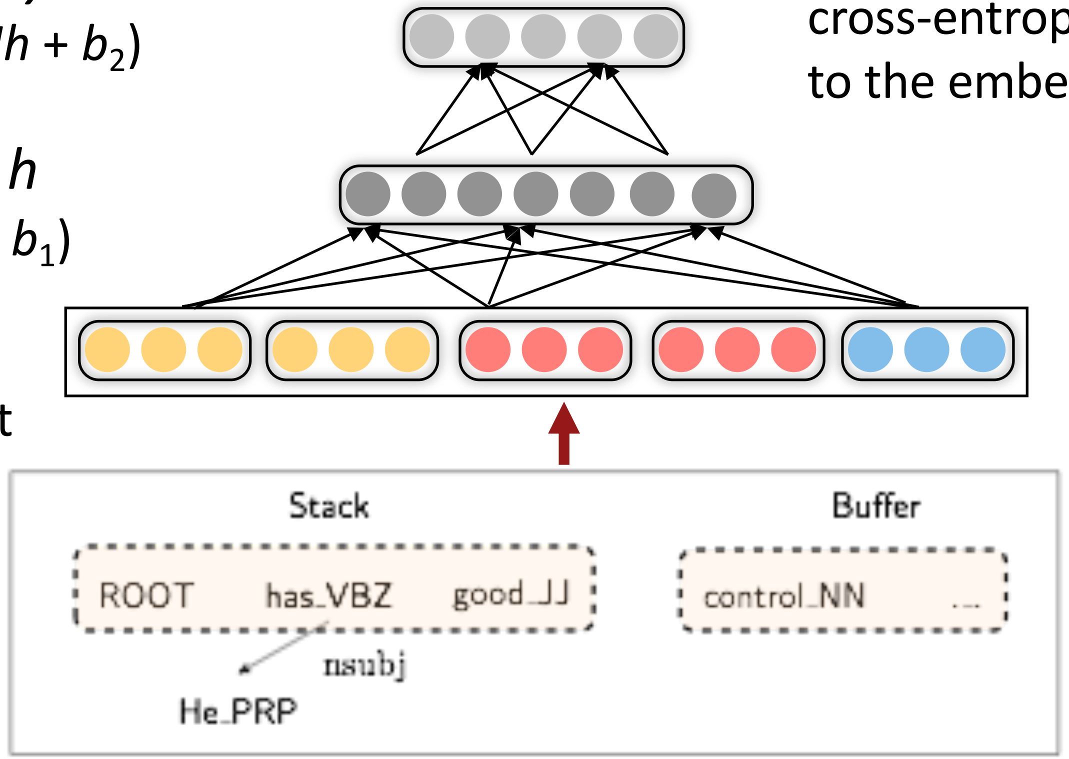
cross-entropy error will be back-propagated to the embeddings

Hidden layer h

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

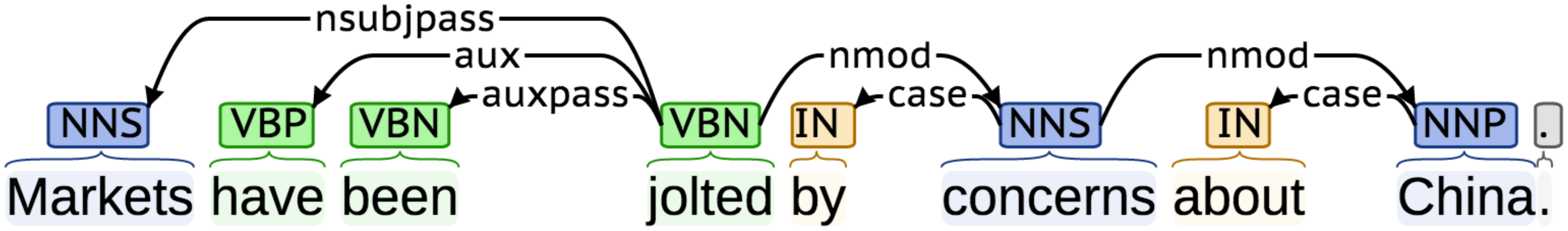
Input layer x

lookup + concat



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 (and non-linear classifier) 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 (2016):

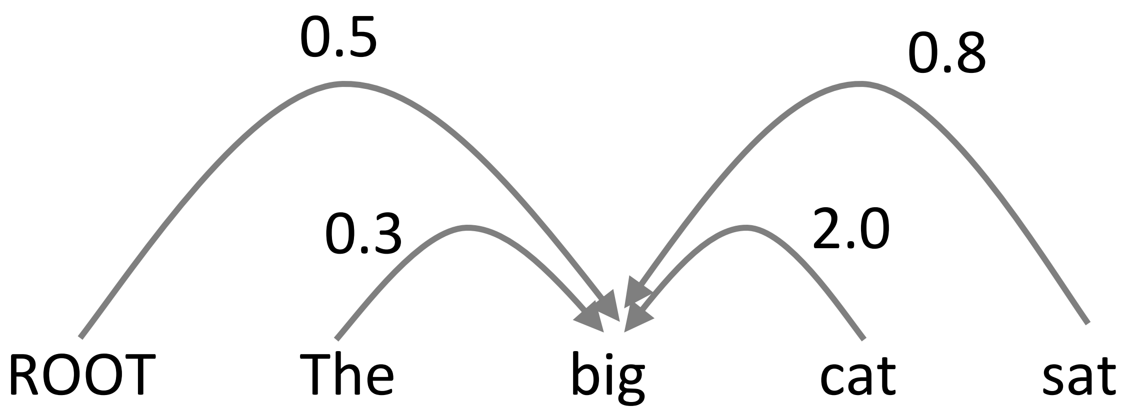
"The World's Most Accurate Parser"

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

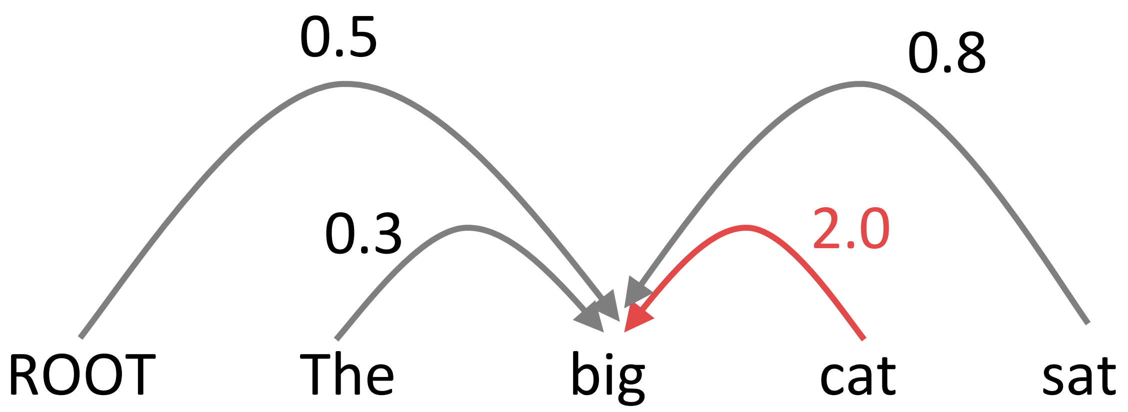
- Compute a score for every possible dependency for each word
  - Doing this well requires good "contextual" representations of each word token, which we will develop in coming lectures



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

Graph-based dependency parsers

- Compute a score for every possible dependency for each word
  - Doing this well requires good "contextual" representations of each word token, which we will develop in coming lectures
  - 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]

- This paper revived interest in graph-based dependency parsing in a neural world
  - Designed a biaffine scoring model for neural dependency parsing
    - Also crucially uses a neural sequence model, something we discuss next week
- Really great results!
  - **But slower than the 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
Weiss et al. 2015	93.99	92.05
Andor et al. 2016	94.61	92.79
Dozat & Manning 2017	**95.74**	**94.08**

Lecture Plan

1. Neural dependency parsing (20 mins)
2. A bit more about neural networks (15 mins)
3. Language modeling + RNNs (45 mins)
    - A new NLP task: **Language Modeling**

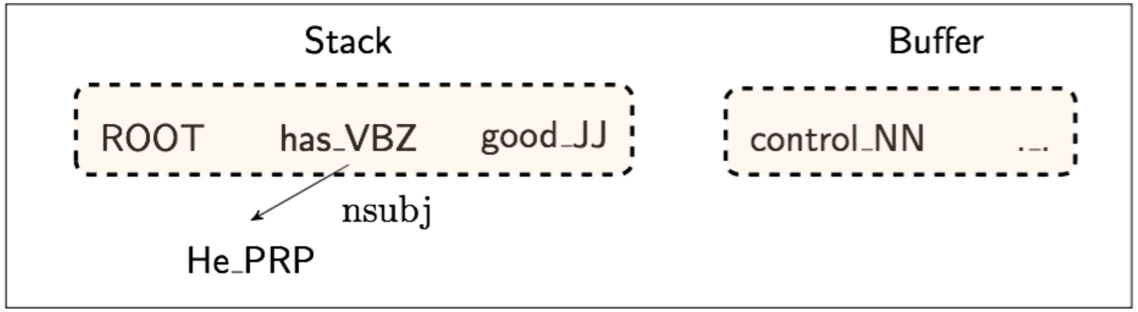
      motivates

    - A new family of neural networks: **Recurrent Neural Networks (RNNs)**

These are two of the most important concepts for the rest of the class!

1. How do we gain from a neural dependency parser?
Indicator Features Revisited

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



dense
dim = ~1000

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

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

Neural 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]

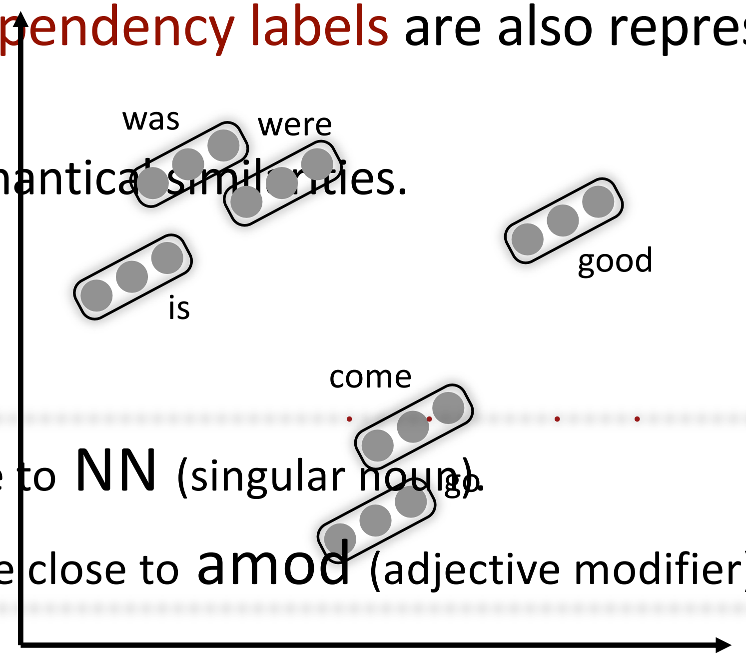
- Results on English parsing to Stanford Dependencies:
  - Unlabeled attachment score (UAS) = head
  - Labeled attachment score (LAS) = head and label

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**

First win: 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.

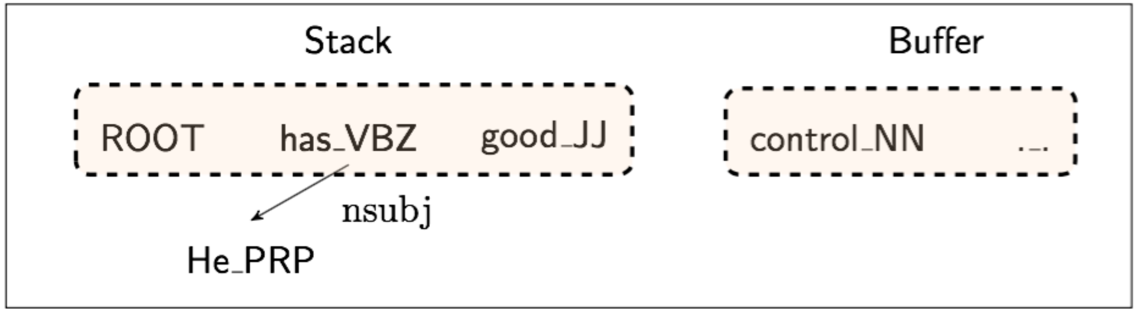


NNS (plural noun) should be close to NN (singular noun).

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

Extracting Tokens & vector representations from configuration

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



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

A concatenation of the vector representation of all these is the neural representation of a configuration

Second win: Deep Learning classifiers are non-linear classifiers

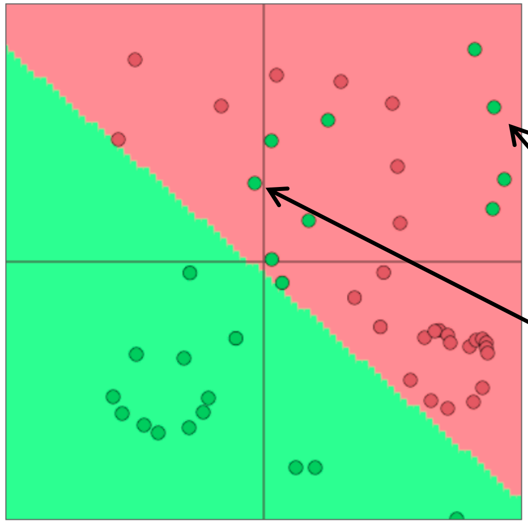
- A softmax classifier assigns classes $y \in C$ based on inputs $x \in \mathbb{R}^d$ via the probability:

$$p(y|x) = \frac{\exp(W_y.x)}{\sum_{c=1}^{C} \exp(W_c.x)}$$

a.k.a. “cross entropy loss”

- We train the weight matrix $W \in \mathbb{R}^{C \times d}$ to minimize the neg. log loss : $\sum_i -\log p(y_i|x_i)$

- Traditional ML classifiers (including Naïve Bayes, SVMs, logistic regression and softmax classifier) are not very powerful classifiers: they only give linear decision boundaries



This can be quite limiting

→ Unhelpful when a problem is complex

Wouldn’t it be cool to get these correct?

Neural Networks are more powerful

- Neural networks can learn much more complex functions with nonlinear decision boundaries!
  - Non-linear in the original space, linear for the softmax at the top of the neural network

Visualizations with ConvNetJS by Andrej Karpathy!

http://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html

Simple feed-forward neural network multi-class classifier

Softmax probabilities

Log loss (cross-entropy error) will be back-propagated to the embeddings

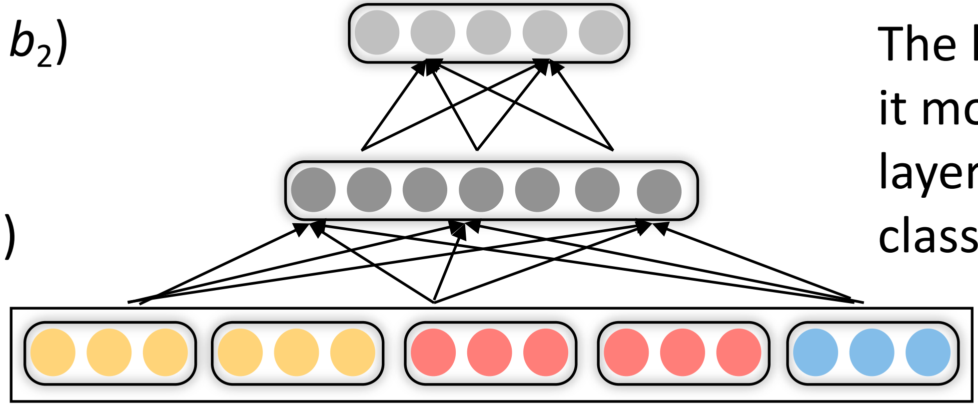
Output layer y

y = softmax($Uh + b_2$)

Hidden layer h

h = ReLU($Wx + b_1$)

Input layer x



The hidden layer re-represents the input — it moves inputs around in an intermediate layer vector space—so it can be easily classified with a (linear) softmax

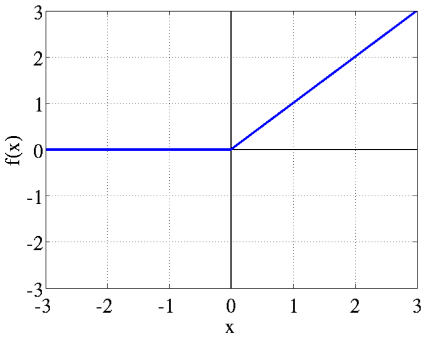
x is result of lookup

$x_{(i,\ldots,i+d)} = Le$

lookup + concat

ReLU = Rectified Linear Unit

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



Neural Dependency Parser Model Architecture

Softmax probabilities → { Shift , Left-Arc$_r$, Right-Arc$_r$ }

Output layer y

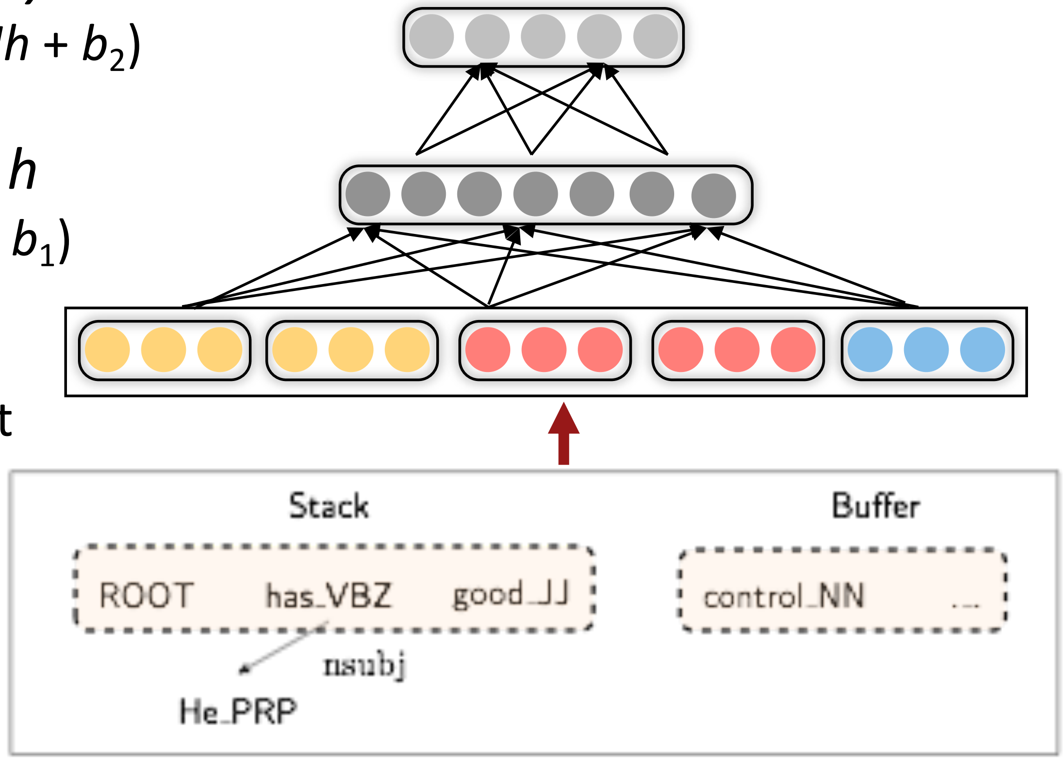
y = softmax($Uh + b_2$)

Hidden layer h

h = ReLU($Wx + b_1$)

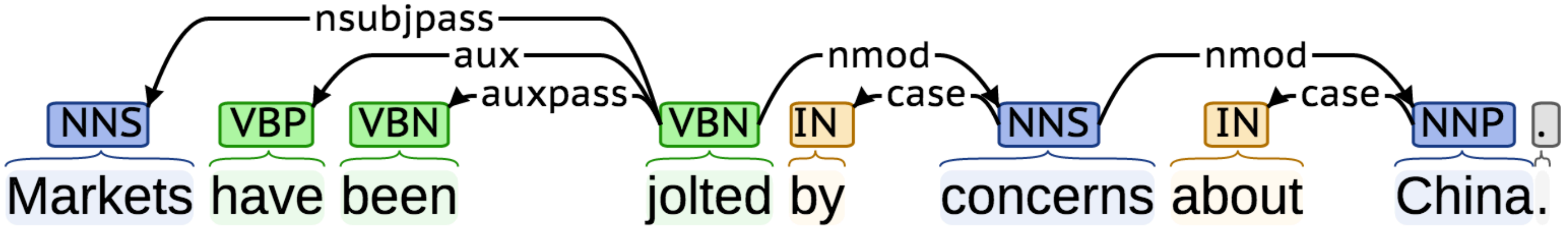
Input layer x

lookup + concat



Dependency parsing for sentence structure

Chen and Manning (2014) showed that neural networks can accurately determine the structure of sentences, supporting meaning interpretation



It was the first simple, successful neural dependency parser

The dense representations (and non-linear classifier) 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 (2016):

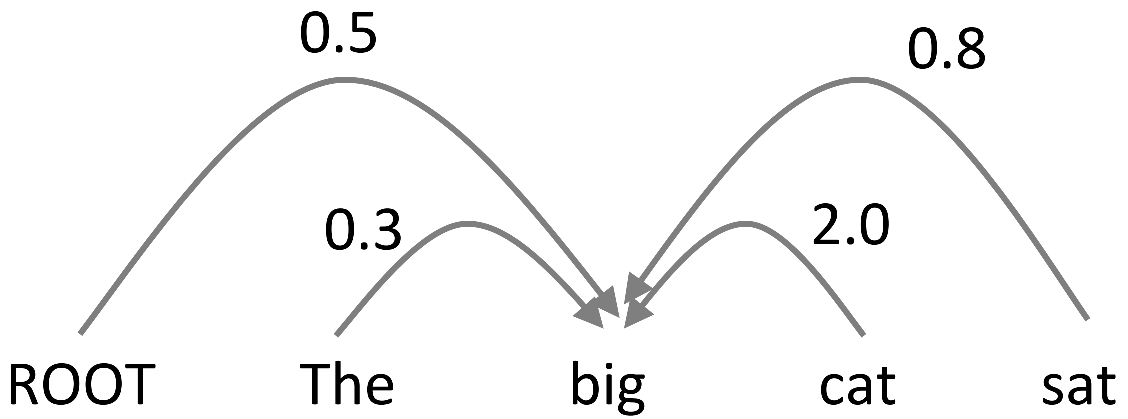
“The World’s Most Accurate Parser”

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

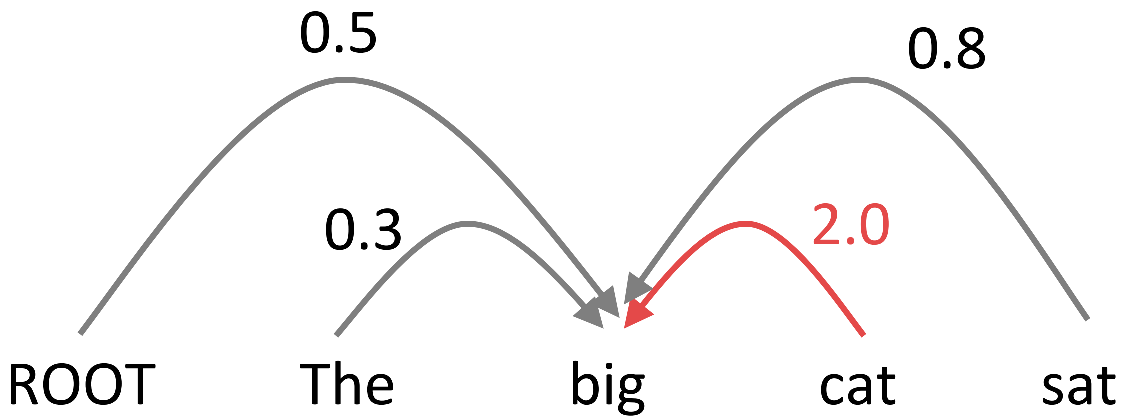
- Compute a score for every possible dependency (choice of head) for each word
  - Doing this well requires more than just knowing the two words
  - We need good "contextual" representations of each word token, which we will develop in the coming lectures
- Repeat the same process for each other word; find the best parse (MST algorithm)



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

Graph-based dependency parsers

- Compute a score for every possible dependency (choice of head) for each word
  - Doing this well requires more than just knowing the two words
  - We need good “contextual” representations of each word token, which we will develop in the coming lectures
- Repeat the same process for each other word; find the best parse (MST algorithm)



e.g., picking the head for “big”

A Neural graph-based dependency parser

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

- This paper revived interest in graph-based dependency parsing in a neural world
  - Designed a biaffine scoring model for neural dependency parsing
    - Also crucially uses a neural sequence model, something we discuss next week
- Really great results!
  - **But slower than the 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
Weiss et al. 2015	93.99	92.05
Andor et al. 2016	94.61	92.79
Dozat & Manning 2017	**95.74**	**94.08**