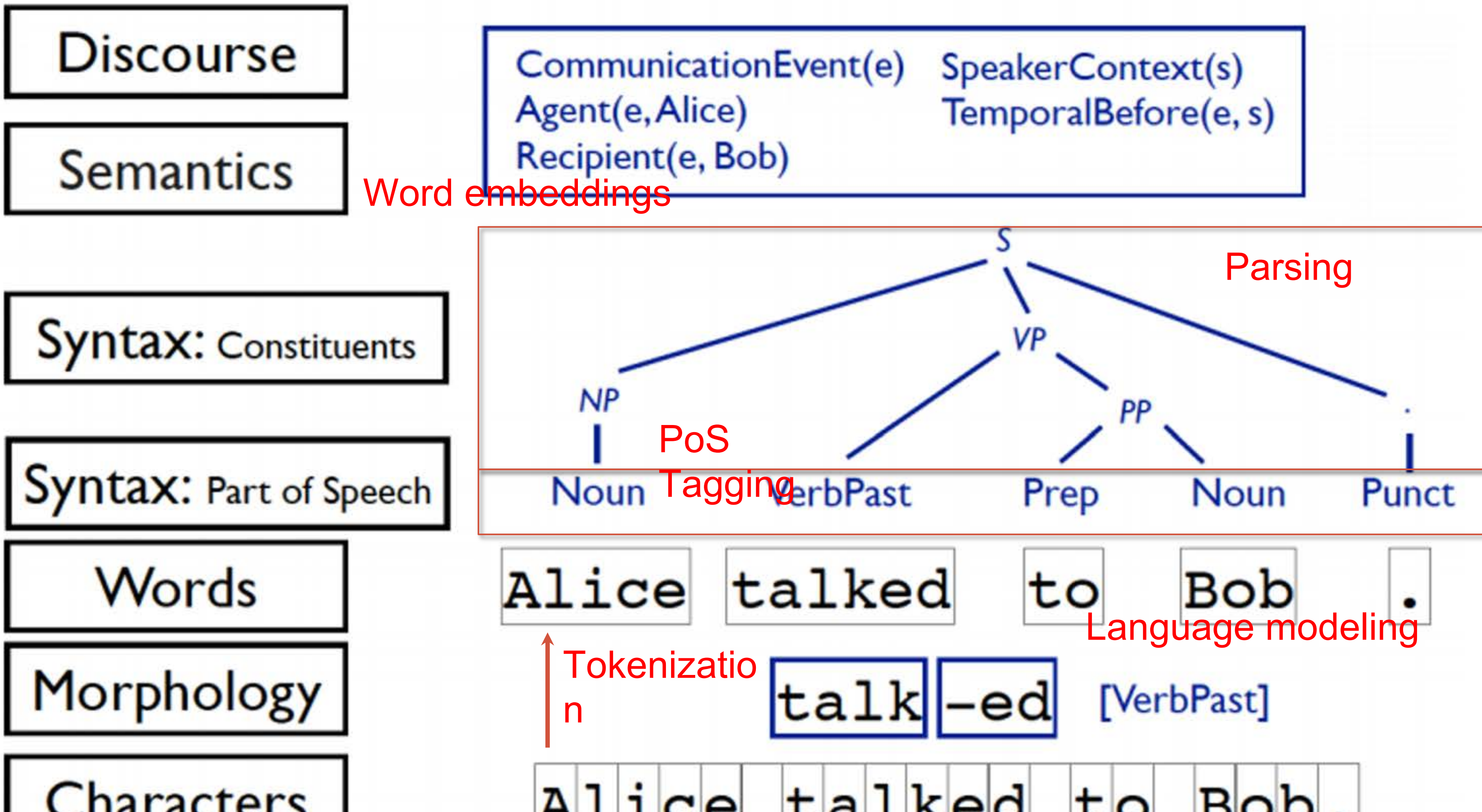
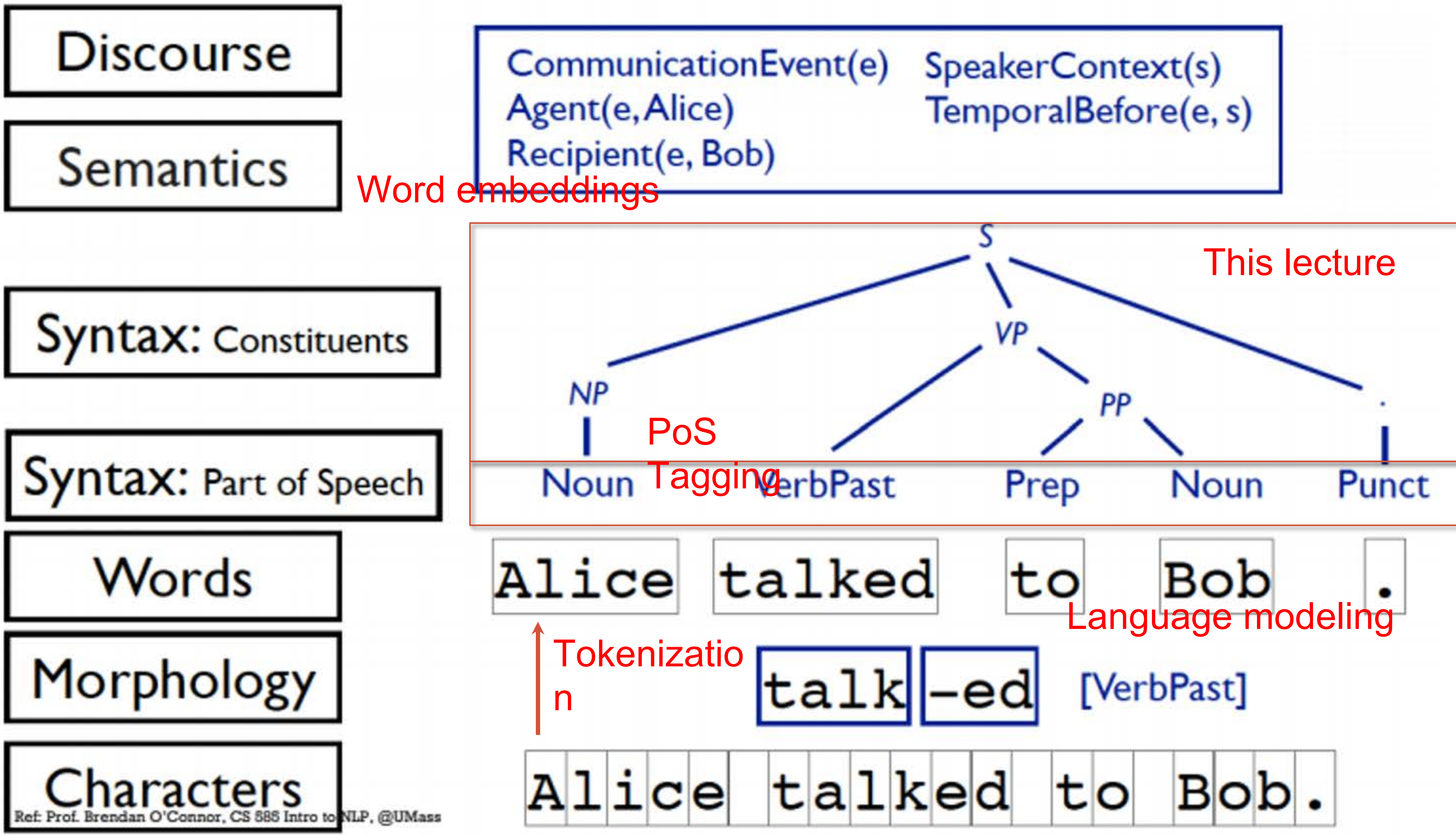
PARSING

PCFG, Recursive Neural Network

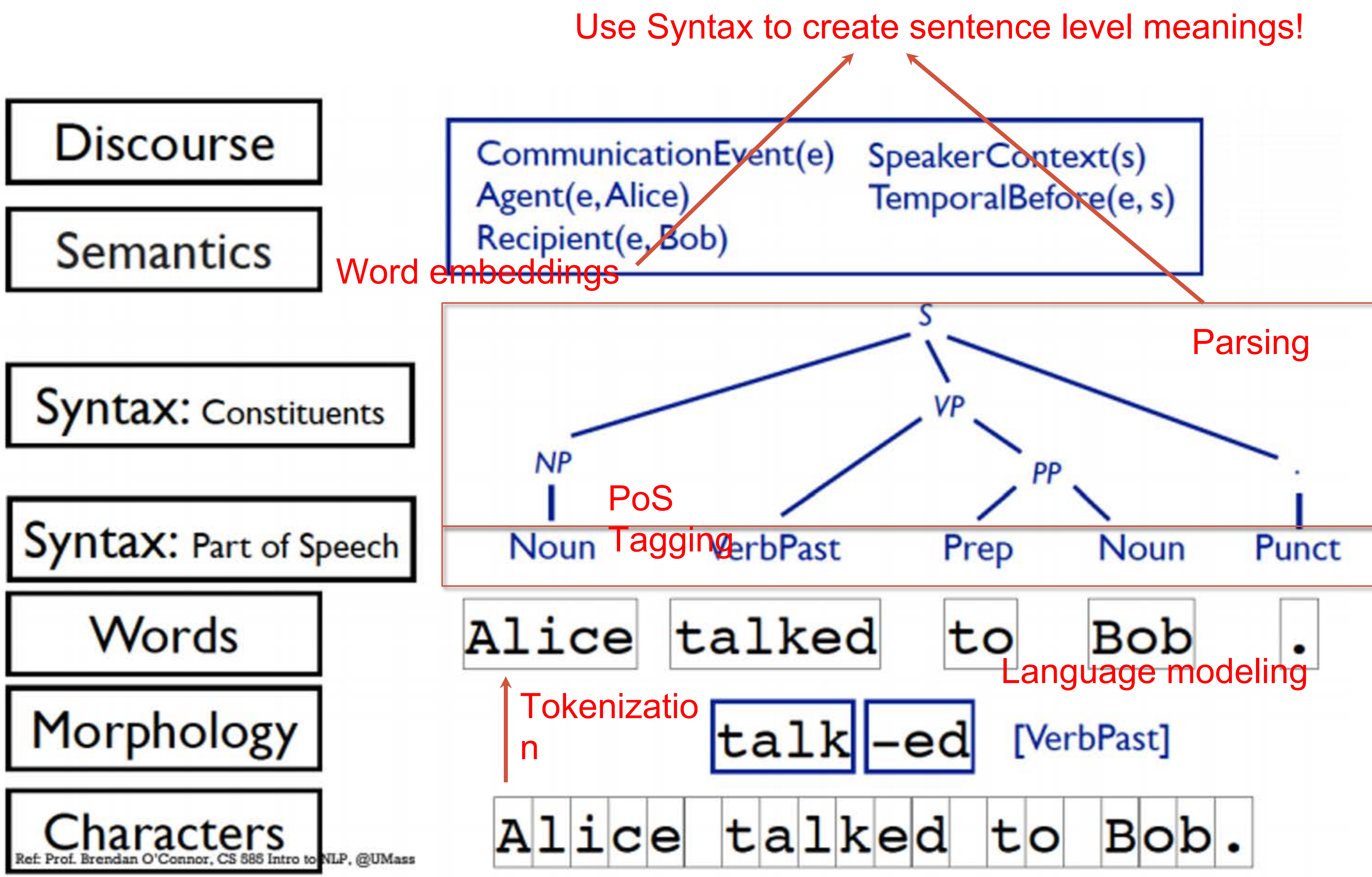
Document classification, sentiment analysis, QA, conversation agents, summarization, translation



Ref: Prof. Brendan O'Connor, CS 585 Intro to NLP, @UMass



Discourse
Semantics
Syntax: Constituents
Syntax: Part of Speech
Words
Morphology
Characters
CommunicationEvent(e)
Agent(e, Alice)
Recipient(e, Bob)
SpeakerContext(s)
TemporalBefore(e, s)
Word embeddings
S
VP
NP
PP
.
This lecture
PoS Tagging
Noun
VerbPast
Prep
Noun
Punct
Alice
talked
to
Bob
.
Language modeling
Tokenization
talk
-ed
[VerbPast]
Alice talked to Bob.
Ref: Prof. Brendan O'Connor, CS 585 Intro to NLP, @UMass


Use Syntax to create sentence level meanings!
Discourse
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Semantic embeddings of several words

- Compositionality
- We know how to create a dense vector representation for a word
  - What about larger linguistic units? (e.g. phrase, sentence)
- We can combine smaller units into a larger unit

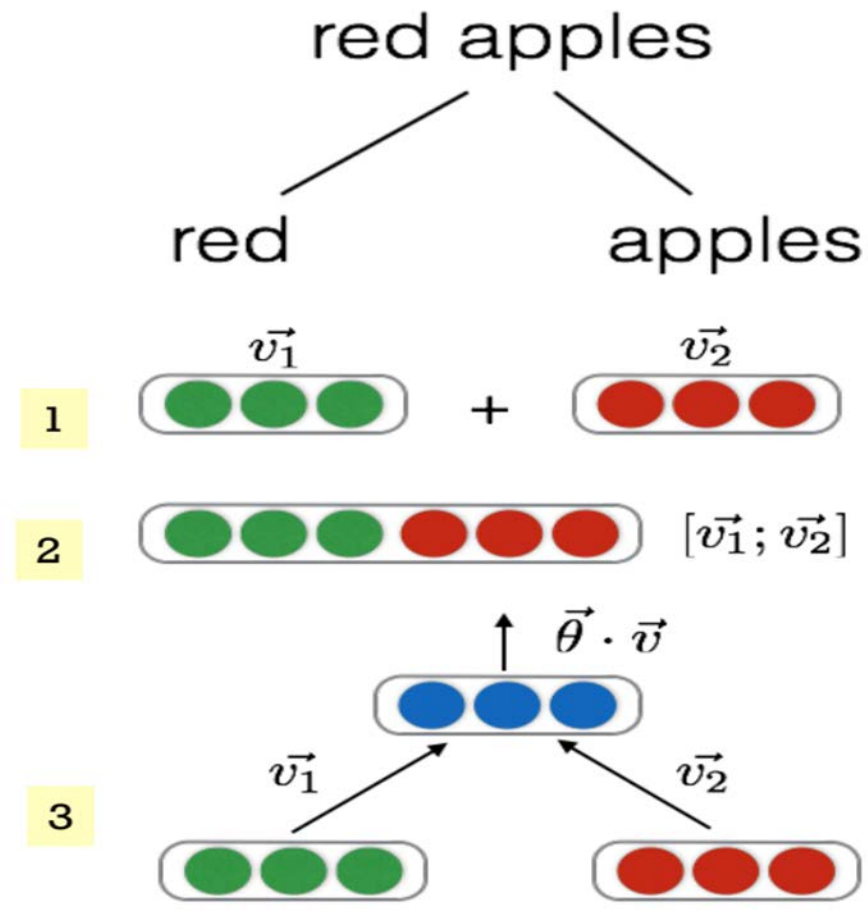


Image ref: Prof. Regina Barzilay , NLP@MIT

Semantic vectors overview

Discourse level

word phrase sentence paragraph document

- Word vectors
  - Co-occurrence
  - PPMI
  - TFIDF
  - Word2vec
    - CBoW
    - Skip-gram

- Doc vectors
  - Term-document
    - Bag of words model
  - Recurrent networks

Figure 15.3 A spatial visualization of the document vectors for the four Shakespeare play documents, showing just two of the dimensions, corresponding to the words *battle* and *fool*. The comedies have high values for the *fool* dimension and low values for the *battle* dimension.

Reference: Jurafsky, Dan, and James H. Martin. Speech and language processing. 3rd edition draft, https://web.stanford.edu/~jurafsky/slp3/, August 2017

Semantic vectors overview

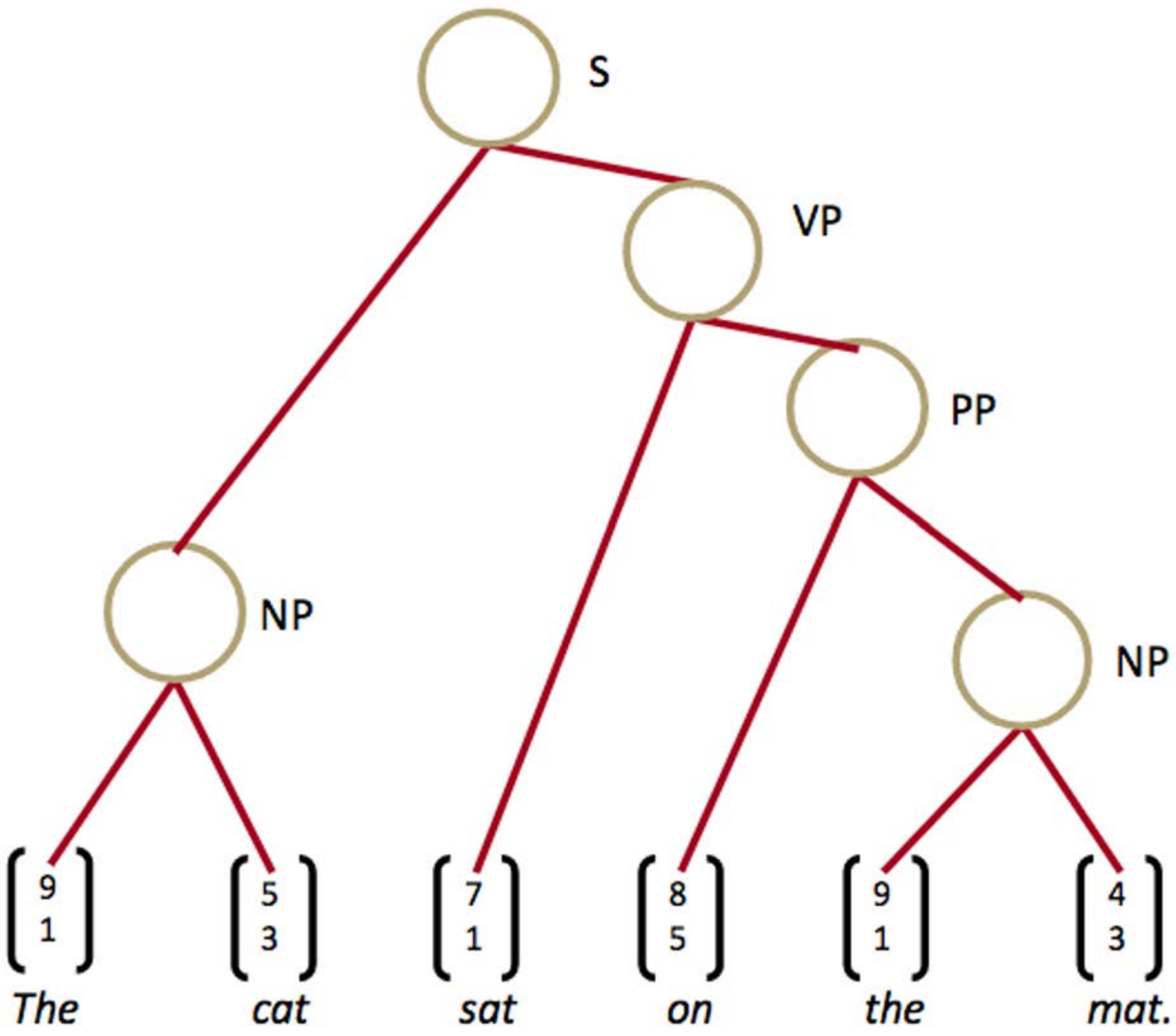
Discourse level

word phrase sentence paragraph document

How do we represent things in this level? Without ignoring word order (bag of words)

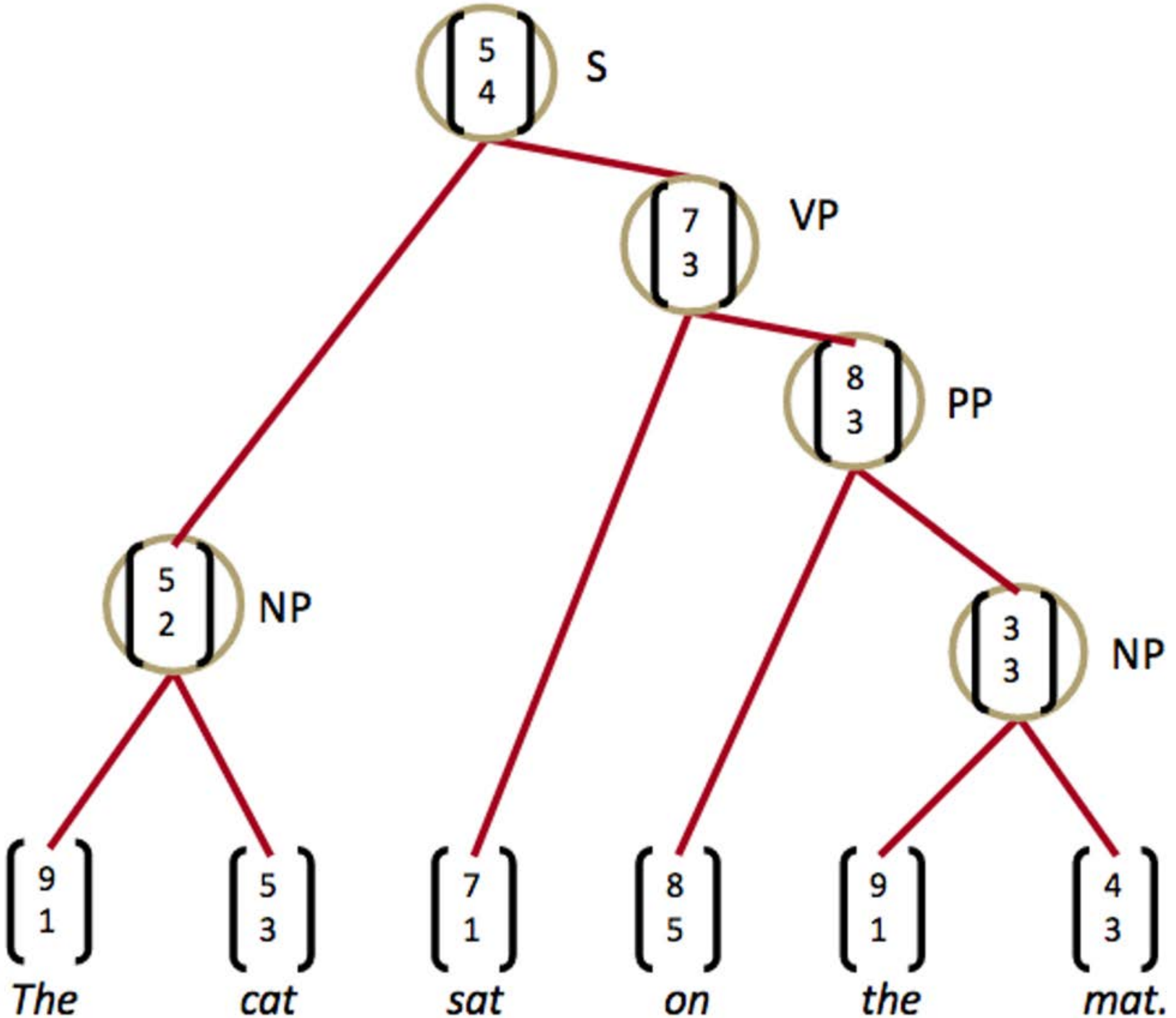
- Word vectors
  - Co-occurrence
  - PPMI
  - TFIDF
  - Word2vec
    - CBoW
    - Skip-gram
- Doc vectors
  - Term-document
    - Bag of words model
    - Doc2Vec
    - LDA2Vec
  - Recurrent networks

Parsing and representation big picture



http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf

Parsing and representation big picture



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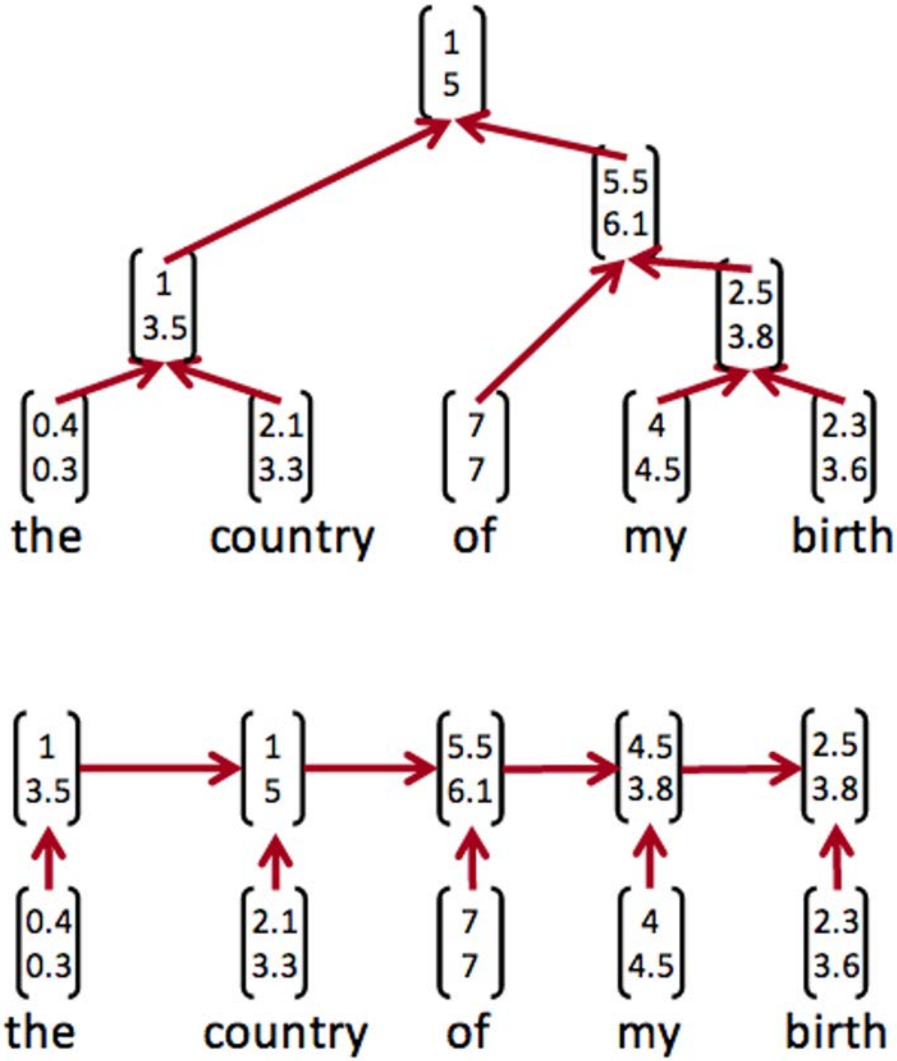
Recursive vs Recurrent representation



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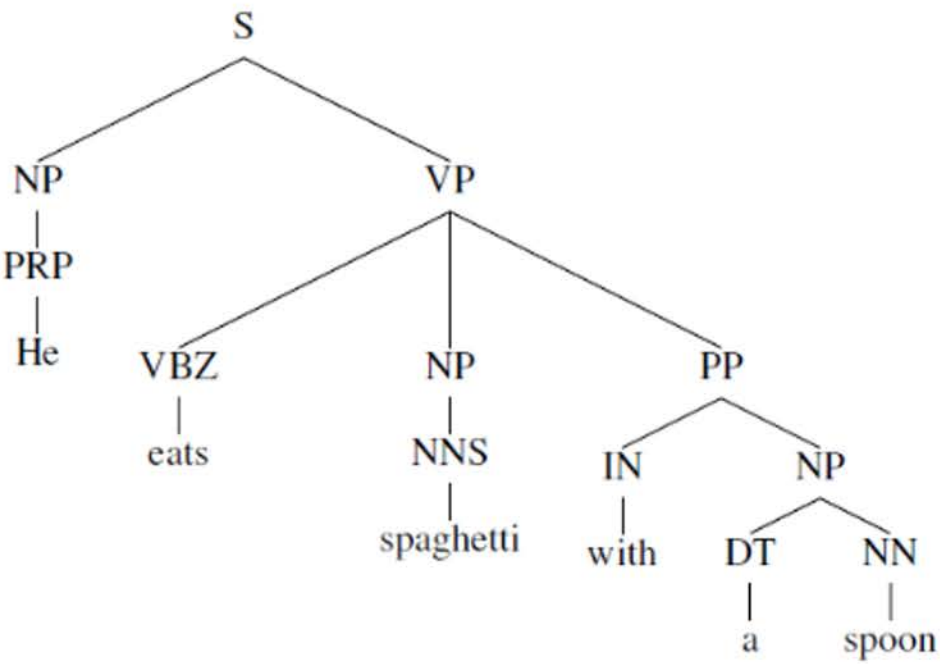
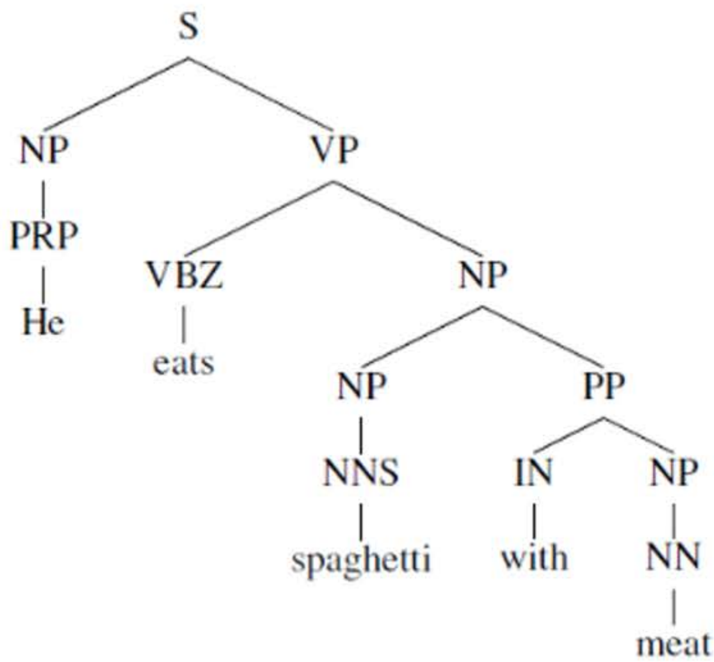
Cases where recursive might be better?



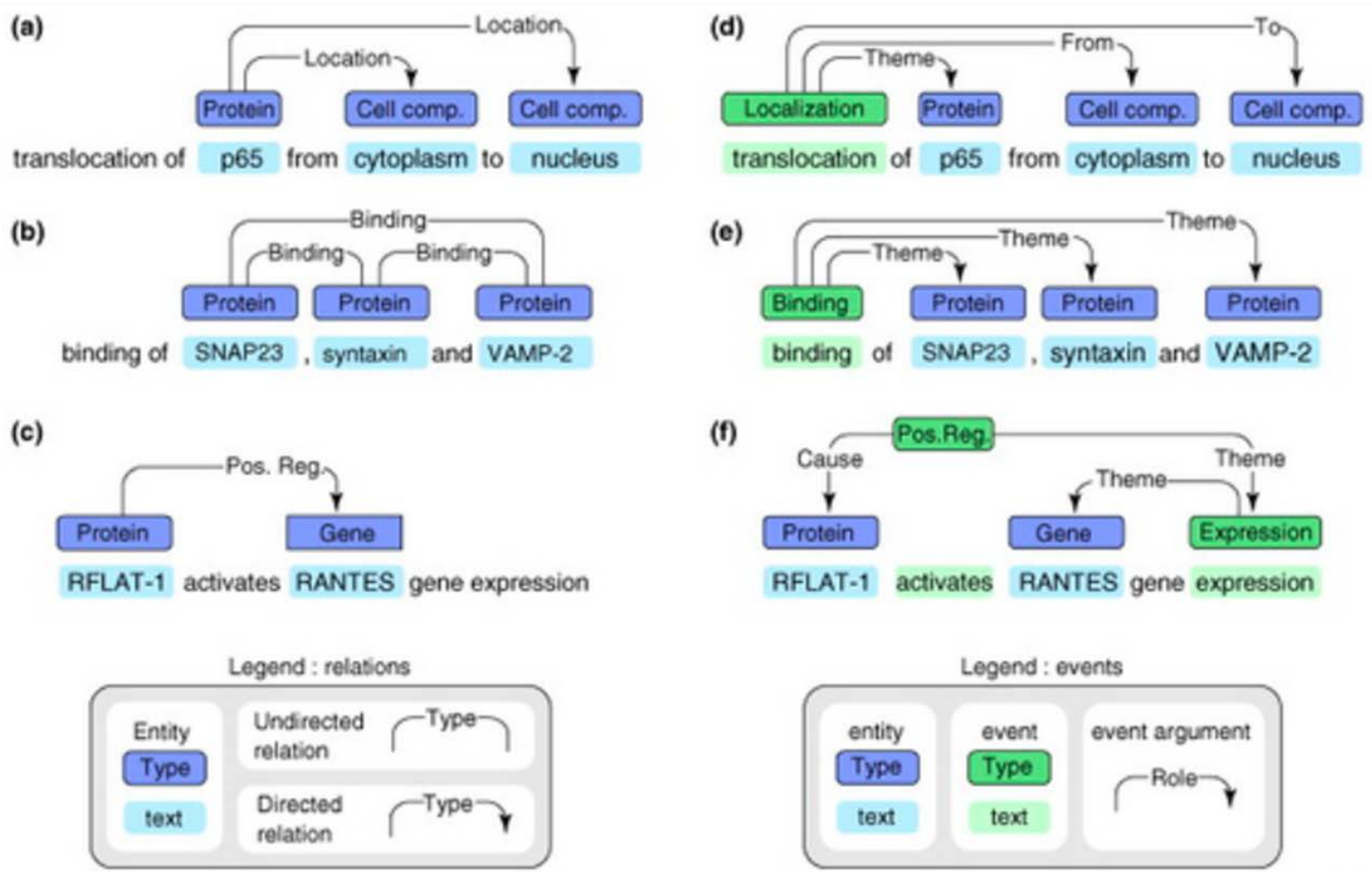


But recurrent structures might be able to learn this too…

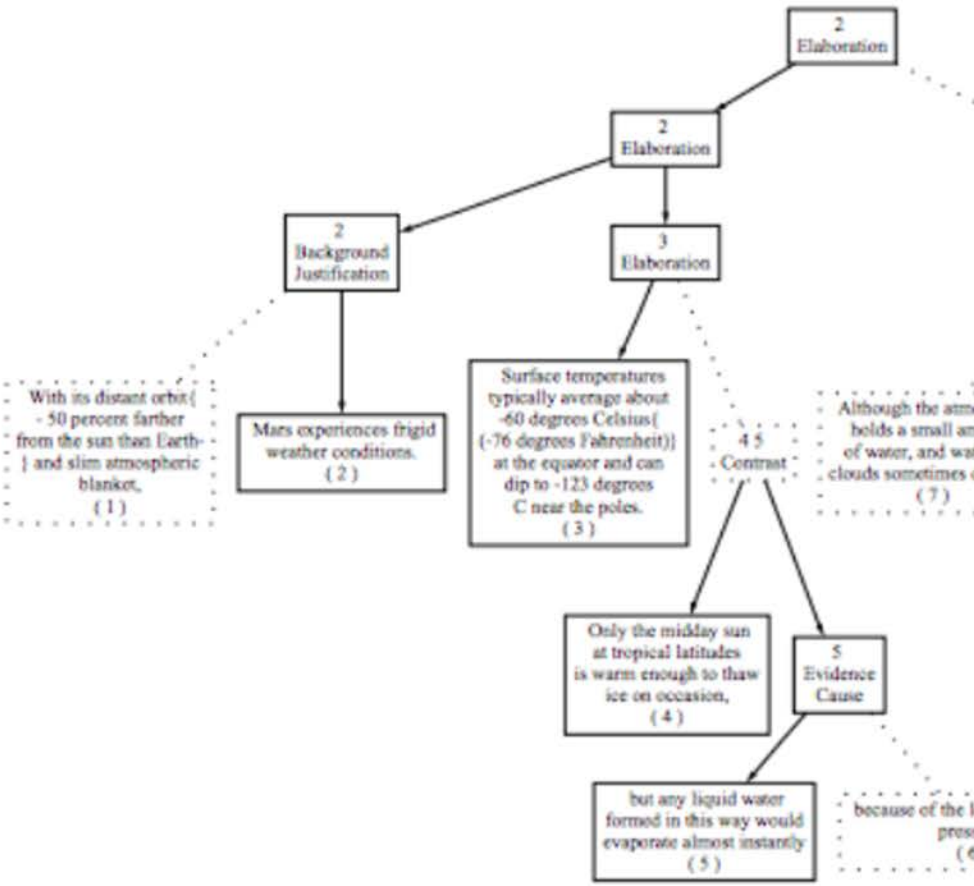
http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf

Application of parse trees: info extraction

parse tree + rule based extraction = more robust



A side note: discourse parsing



[*With* its distant orbit {— 50 percent farther from the sun than Earth —^{P1}} and slim atmospheric blanket,[1]] [Mars experiences frigid weather conditions.[2]] [Surface temperatures typically average about −60 degrees Celsius (−76 degrees Fahrenheit) at the equator and can dip to −123 degrees C near the poles.[3]] [Only the midday sun at tropical latitudes is warm enough to thaw ice

Image ref: Prof. Regina Barzilay , NLP@MIT

Overview

- Types of grammars
  - Context Free Grammar
  - Probabilistic Context Free Grammar
    - CYK parser
  - Dependency Grammar
    - Transition-based parsing
    - Recursive neural networks

Constituents

- Groups of words behaving as a single units
  - Ex: Noun phrase

  Harry the Horse

  The reason he comes into the house

  They

  A high-class spot such as Mindy's
- Checking for constituents
  - See if they can appear in similar syntactic environments

  They sit...

  The reason he comes into the house is…

http://web.stanford.edu/~jurafsky/slp3/11.pdf

Context-Free Grammar (CFG)

- A grammar specifies what kind of parse tree can be generated.
- CFG or Phrase-Structure Grammars assumes the grammar is context-free
  - Most forms of natural language are context-free
    - Thai and English are typically CFG languages
  - Used in many programming languages
- CFG is based on constituents structures

A context-free grammar example

A CFG is defined by
G = (N,S,Σ,R)

- N = {S, NP, VP, PP, DT, Vi, Vt, NN, IN} Nonterminals
- S = S Starting symbol
- Σ = {sleeps, saw, man, woman, telescope, the, with, in}

Terminals

R =

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

Vi	$\Rightarrow$	sleeps
Vt	$\Rightarrow$	saw
NN	$\Rightarrow$	man
NN	$\Rightarrow$	woman
NN	$\Rightarrow$	telescope
DT	$\Rightarrow$	the
IN	$\Rightarrow$	with
IN	$\Rightarrow$	in

Production rules
$X \rightarrow Y_1 \ldots Y_n$
Y_i can be terminal or nonterminal
The rule only relies on X (no context) (vs context-sensitive)

Note: S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition

Generation using left-most derivation strategy

- Recursive strategy

$R =$

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

Vi	$\Rightarrow$	sleeps
Vt	$\Rightarrow$	saw
NN	$\Rightarrow$	man
NN	$\Rightarrow$	woman
NN	$\Rightarrow$	telescope
DT	$\Rightarrow$	the
IN	$\Rightarrow$	with
IN	$\Rightarrow$	in

```
left_most_derivation(A):
     if terminal(A):
         return A          Return if terminal
     rule = choose (rules(A))
     rhs = right_hand_side(rule)
     return concatenate([left_most_derivation(A') for A' in rhs])
```

- To generate we call left_most_derivation(S) (top down)
- A string belongs to the language of a CFG if there exist a sequence of left-most derivation that can generate the string

$$L = \{s \in \Sigma^* | s = left\_most\_derivation(S)\}$$

Example

- The woman saw the man with the telescope

$R =$

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

Vi	$\Rightarrow$	sleeps
Vt	$\Rightarrow$	saw
NN	$\Rightarrow$	man
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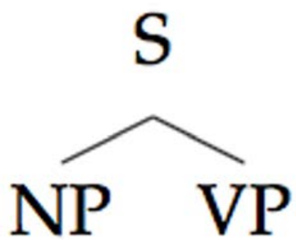
IN	$\Rightarrow$	with
IN	$\Rightarrow$	in

Example

- The woman saw the man with the telescope



$R =$

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

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Vt	$\Rightarrow$	saw
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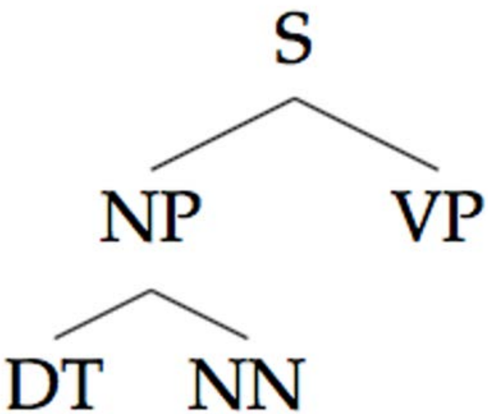
Example

- The woman saw the man with the telescope



$R =$

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
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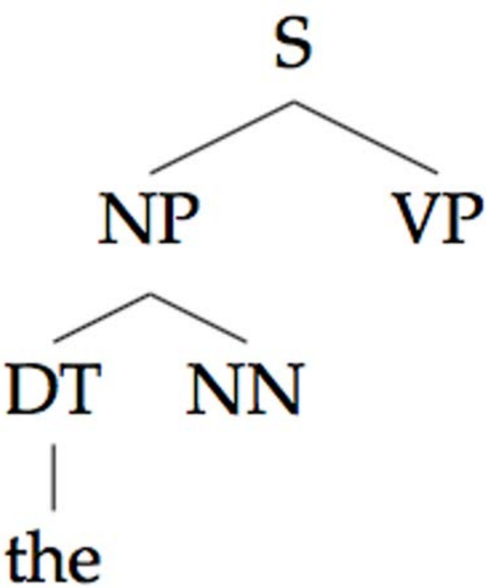

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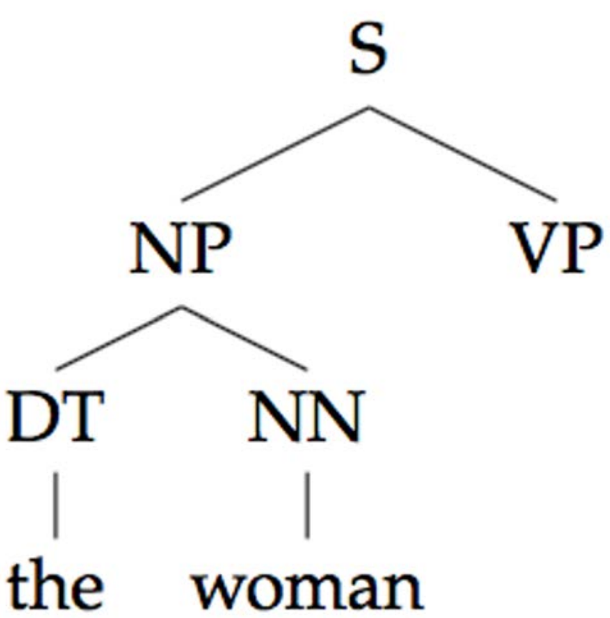
Example

- The woman saw the man with the telescope



$R =$

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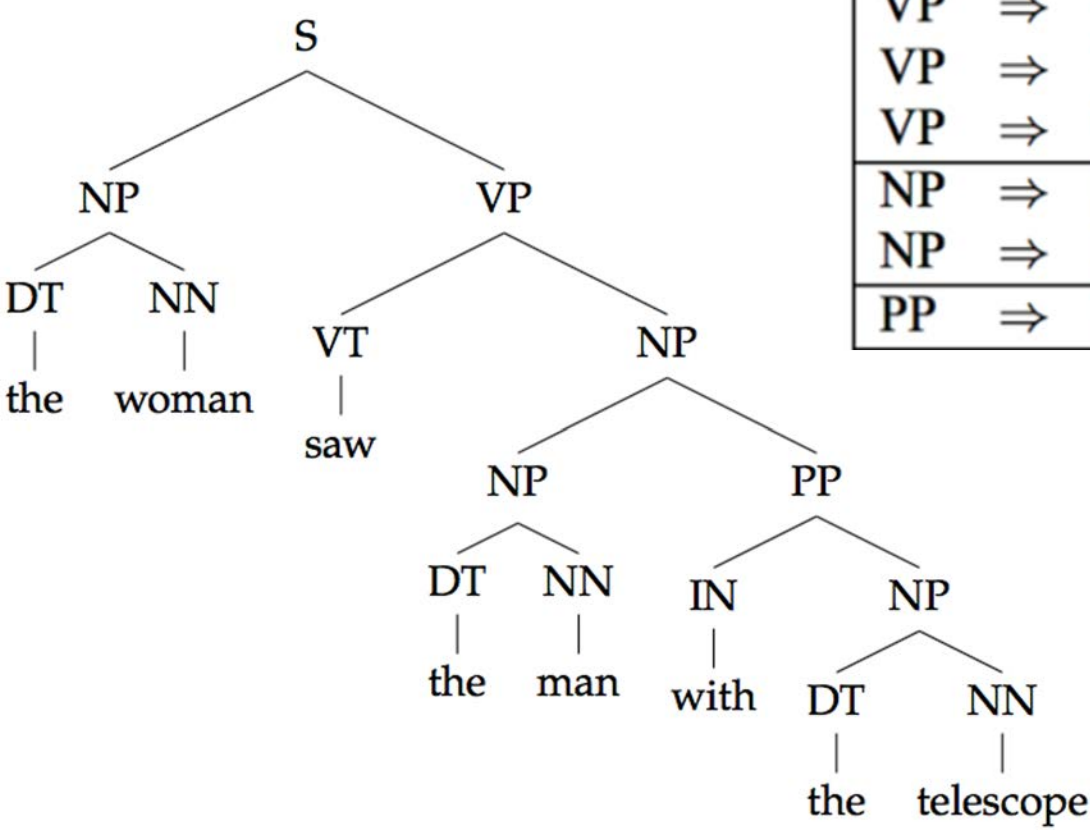
- The woman saw the man with the telescope



$R =$

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
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NN	$\Rightarrow$	telescope
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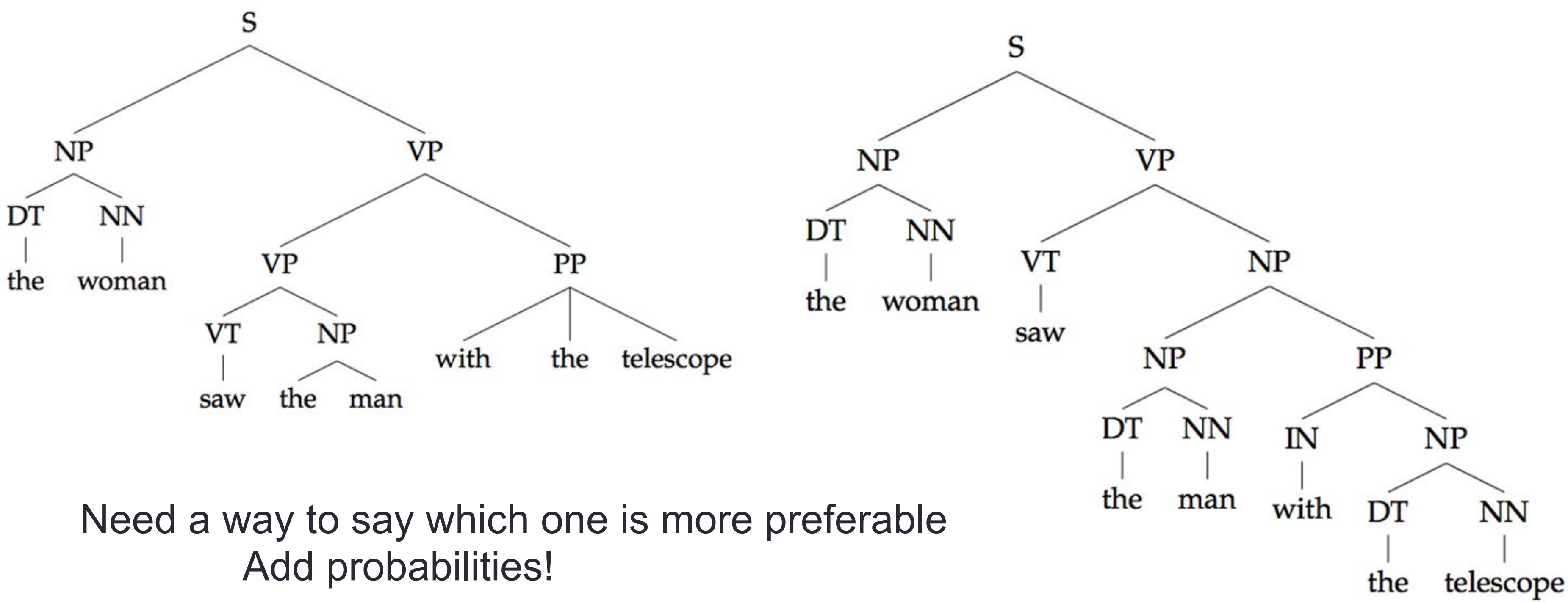
Ambiguities

- There can be multiple derivations for the same string
- These sentences are ambiguous as each parse represents a different meaning



Need a way to say which one is more preferable
Add probabilities!

Probabilistic Context-Free Grammar

- Production rules now have probabilities

S	⇒	NP	VP	1.0
VP	⇒	Vi		0.4
VP	⇒	Vt	NP	0.4
VP	⇒	VP	PP	0.2
NP	⇒	DT	NN	0.3
NP	⇒	NP	PP	0.7
PP	⇒	P	NP	1.0

Vi	⇒	sleeps	1.0
Vt	⇒	saw	1.0
NN	⇒	man	0.7
NN	⇒	woman	0.2
NN	⇒	telescope	0.1
DT	⇒	the	1.0
IN	⇒	with	0.5
IN	⇒	in	0.5

The probability of a (sentence, parse tree) pair is

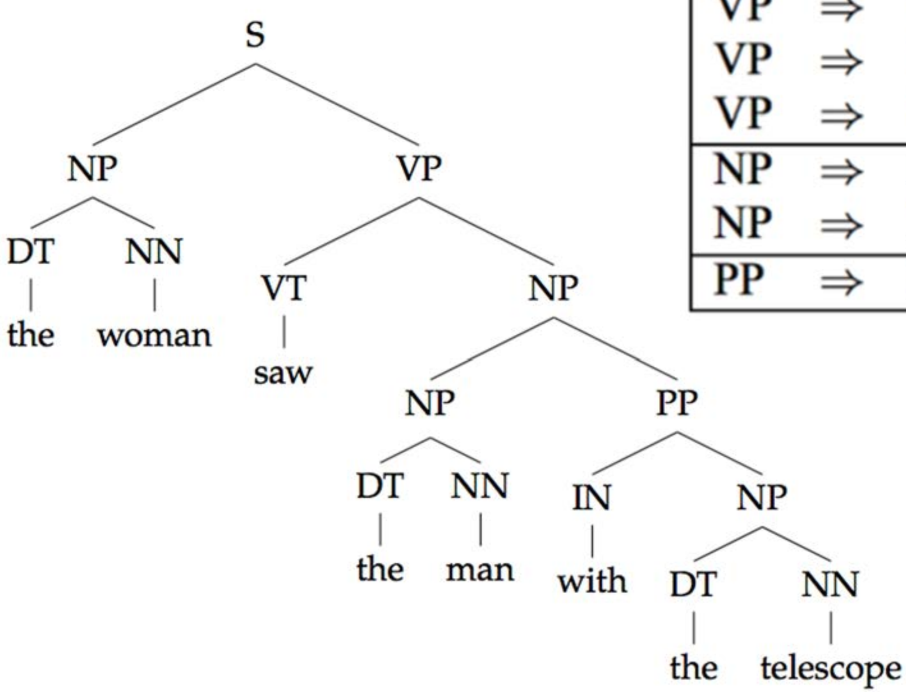
$$p(S,T) = \prod_{i=1}^{m} p(\alpha_i \rightarrow \beta_i | \alpha_i)$$

m is the number of transitions

P(NN -> man | NN) = 0.7

P(S,T)

- P(S,T) = [1.0 * 0.3 * 1.0 * 0.2] * [0.4 * 1.0 * 0.7 * (0.3 * 1.0 * 0.7) * (1.0 * 0.5 * 0.3 * 1.0 * 0.1)]



S	$\Rightarrow$	NP	VP	1.0
VP	$\Rightarrow$	Vi		0.4
VP	$\Rightarrow$	Vt	NP	0.4
VP	$\Rightarrow$	VP	PP	0.2
NP	$\Rightarrow$	DT	NN	0.3
NP	$\Rightarrow$	NP	PP	0.7
PP	$\Rightarrow$	P	NP	1.0

Vi	$\Rightarrow$	sleeps	1.0
Vt	$\Rightarrow$	saw	1.0
NN	$\Rightarrow$	man	0.7
NN	$\Rightarrow$	woman	0.2
NN	$\Rightarrow$	telescope	0.1
DT	$\Rightarrow$	the	1.0
IN	$\Rightarrow$	with	0.5
IN	$\Rightarrow$	in	0.5

Estimating transition probabilities

- Counts from training set!

$$P(S \rightarrow NP\ VP|S) = \frac{count(S \rightarrow NP\ VP)}{count(S)}$$

PCFG related questions

- What is the most likely parse? (parsing task)
  - $\text{argmax}_T\ P(T,S)$

- What is the probability of the sentence, P(S)? (Language modeling task)
  - $P(S) = \Sigma_T\ P(T,S)$

How?
Dynamic programming
(CYK algorithm –
Cocke–Younger–Kasami algorithm)


BRUTE FORCE
MAXIMAL MATCHING
VITERBI
CYK
imgflip.com

Chomsky Normal Form

- CYK can be used if the CFG is in Chomsky Normal Form
- A CFG is in Chomsky Normal Form if each rule either converts to two nonterminals or a single terminal.

$$X \rightarrow Y_1 Y_2$$

$$X \rightarrow y$$

Uppercase letters mean nonterminal
Lowercsae letters mean terminal

- Any CFG can be converted to CNF
  - For example NP -> DT, ADJ, NN
    - Turns into two rules
    - NP -> DT, ADJP
    - ADJP -> ADJ, NN

- N = {S, NP, VP, PP, DT, Vi, Vt, NN, IN} Nonterminals
- S = S Starting symbol
- Σ = {sleeps, saw, man, woman, telescope, the, with, in}

Terminals

R =

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
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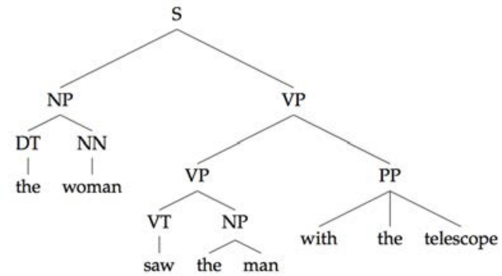
Production rules
$X \rightarrow Y_1 \ldots Y_n$
Y_i can be terminal or nonterminal
The rule only relies on X (no context)
(vs context-sensitive)

CYK algorithm for parsing

3 dimensional

- $\pi(i,j,N)$ probability that words i to j can be generated by nonterminal N

- Base case: $\pi(i,i,N) = P(N \rightarrow w_i|N)$



- Inductive case:

1 2 3 4 5 6 7 8

k is the index that splits the subsentence

$$\pi(i,j,N) = \max_{k,P,Q} Pr(N \rightarrow P\ Q|N) \cdot \pi(\underline{i,k},P) \cdot \pi(\underline{k+1,j},Q)$$

where $k \in \{i,\ldots,j-1\}$, $P \in \mathcal{N}$, and $Q \in \mathcal{N}$.

Saves the rule that gave max probability to backtrack

CYK algorithm for language modeling

- $\pi(i,j,N)$ probability that words i to j can be generated by nonterminal N
- Base case: $\pi(i,i,N) = P(N \rightarrow w_i|N)$
- Inductive case:

$$\pi(i,j,N) = \max_{k,P,Q} Pr(N \rightarrow P\ Q|N) \cdot \pi(i,k,P) \cdot \pi(k+1,j,Q)$$

argmax$_T$ P(T,S) vs P(S) = Σ_T P(T,S)

$$\pi(i,j,N) = \sum_{k,P,Q} P(N \rightarrow P\ Q|N) \cdot \pi(\underline{i,k},P) \cdot \pi(\underline{k+1,j},Q)$$

where $k \in \{i,\ldots,j-1\}$, $P \in \mathcal{N}$, and $Q \in \mathcal{N}$.

Language modeling example CYK with PCFG

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P("abc")

$A \rightarrow AB$	0.8
$A \rightarrow a$	0.2
$B \rightarrow BB$	0.7
$B \rightarrow b$	0.1
$B \rightarrow c$	0.2

$$\pi(i, j, N)$$

A

a			
b			
c			

B

a			
b			
c			

Base case

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P("abc")

$A \to AB$	0.8
$A \to a$	0.2
$B \to BB$	0.7
$B \to b$	0.1
$B \to c$	0.2

$$\pi(i, i, N) = P(N \to w_i | N)$$

A

a	0.2		
b		0	
c			0

B

a	0		
b		0.1	
c			0.2

1^{st} step

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P("abc")

$A \rightarrow AB$	0.8
$A \rightarrow a$	0.2
$B \rightarrow BB$	0.7
$B \rightarrow b$	0.1
$B \rightarrow c$	0.2

$$\pi(i,j,N) = \sum_{k,P,Q} P(N \rightarrow P\,Q|N) \cdot \pi(i,k,P) \cdot \pi(k+1,j,Q)$$

A

a	0.2		
b		0	
c			0

B

a	0		
b		0.1	
c			0.2

Only consider i, j where i < j

1st step

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P("abc")

$A \to AB$	0.8
$A \to a$	0.2
$B \to BB$	0.7
$B \to b$	0.1
$B \to c$	0.2

$$\pi(i,j,N) = \sum_{k,P,Q} P(N \to P\,Q|N) \cdot \pi(i,k,P) \cdot \pi(k+1,j,Q)$$

A

a	0.2	0.016	
b		0	
c			0

$$\begin{aligned}\pi[1,2,A] =& P(A \to AA) \cdot P(A \to a|A) \cdot P(A \to b|A)\\ &+P(A \to AB) \cdot P(A \to a|A) \cdot P(B \to b|B)\\ &+P(A \to BA) \cdot P(B \to a|B) \cdot P(A \to b|A)\\ &+P(A \to BB) \cdot P(B \to a|B) \cdot P(B \to b|B)\\ =& 0 + P(A \to AB) \cdot \pi[1,1,A] \cdot \pi[2,2,B] + 0 + 0\\ =& 0.8 \cdot 0.2 \cdot 0.1 = 0.016\end{aligned}$$

1st step

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P(“abc”)

$A \to AB$	0.8
$A \to a$	0.2
$B \to BB$	0.7
$B \to b$	0.1
$B \to c$	0.2

$$\pi(i,j,N) = \sum_{k,P,Q} P(N \to P\ Q|N) \cdot \pi(i,k,P) \cdot \pi(k+1,j,Q)$$

$\boldsymbol{\pi}$(1,2,B) = P(B -> BB)P(B->a|B)P(B->b|B)
= P(B -> B B)$\boldsymbol{\pi}$(1,1,B)$\boldsymbol{\pi}$(2,2,B)
= 0.7*0*0.1 = 0

B

a	0	0	
b		0.1	
c			0.2

2nd step

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P("abc")

$A \to AB$	0.8
$A \to a$	0.2
$B \to BB$	0.7
$B \to b$	0.1
$B \to c$	0.2

$$\pi(i,j,N) = \sum_{k,P,Q} P(N \to P\,Q|N) \cdot \pi(i,k,P) \cdot \pi(k+1,j,Q)$$

A

a	0.2	0.016	
b		0	0
c			0

B

a	0	0	
b		0.1	0.014
c			0.2

$\boldsymbol{\pi}(2,3,A) = P(A \to A\ B)\boldsymbol{\pi}(2,2,A)\boldsymbol{\pi}(3,3,B) = 0.8*0*0.2 = 0$

2^{nd} step

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P("abc")

$A \to AB$	0.8
$A \to a$	0.2
$B \to BB$	0.7
$B \to b$	0.1
$B \to c$	0.2

$$\pi(i,j,N) = \sum_{k,P,Q} P(N \to P\,Q|N) \cdot \pi(i,k,P) \cdot \pi(k+1,j,Q)$$

A

a	0.2	0.016	
b		0	0
c			0

B

a	0	0	
b		0.1	0.014
c			0.2

$\boldsymbol{\pi}$(2,3,B) = P(B -> B B)$\boldsymbol{\pi}$(2,2,B)$\boldsymbol{\pi}$(3,3,B) + 0 = 0.7*0.1*0.2 = 0.014

Finish

- N = {A, B}
- Σ = {a, b, c}
- S = {A}

Find P("abc")

$A \rightarrow AB$	0.8
$A \rightarrow a$	0.2
$B \rightarrow BB$	0.7
$B \rightarrow b$	0.1
$B \rightarrow c$	0.2

$$\pi(i,j,N) = \sum_{k,P,Q} P(N \rightarrow P\,Q|N) \cdot \pi(i,k,P) \cdot \pi(k+1,j,Q)$$

A

a	0.2	0.016	0.0048
b		0	0
c			0

B

a	0	0	0
b		0.1	0.014
c			0.2

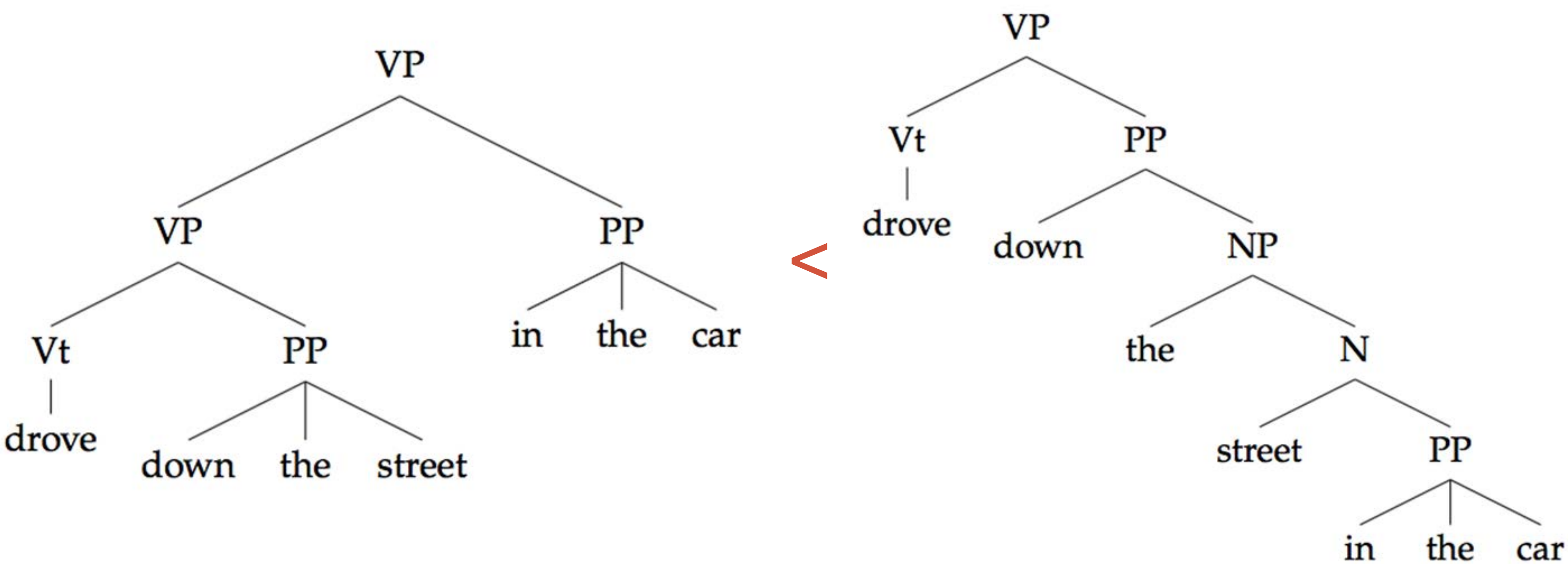
$\boldsymbol{\pi}$(1,3,A) = P(A -> A B)$\boldsymbol{\pi}$(1,2,A)$\boldsymbol{\pi}$(3,3,B) + P(A -> A B)$\boldsymbol{\pi}$(1,1,A)$\boldsymbol{\pi}$(2,3,B)
= 0.8 * 0.016 * 0.2 + 0.8 * 0.2 * 0.014 = 0.0048

PCFG weakness

- Lack of sensitivity to lexical info (does not consider semantics)
- Lack of sensitivity to structural frequency

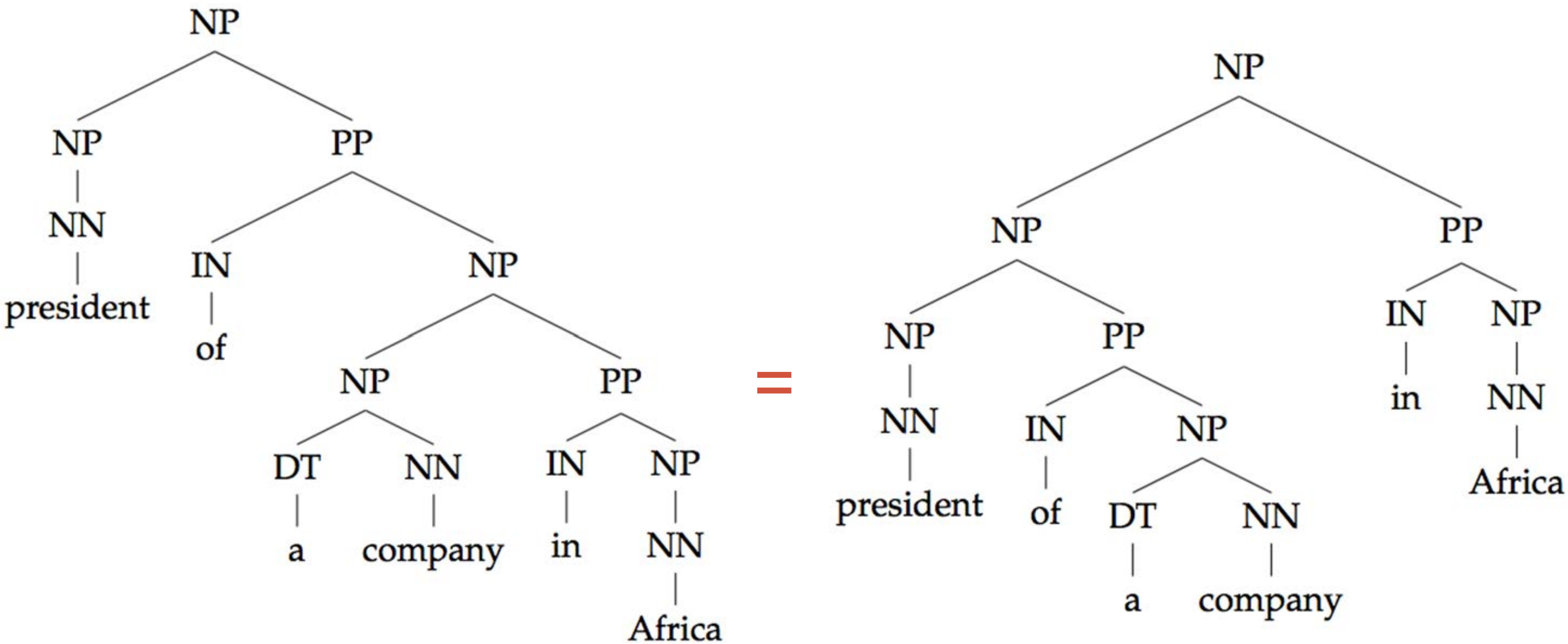
Lack of lexical info

The probabilities only see terminals and expansions



The street in the car

Lack of sensitivity to structural frequency



Both trees have same expansion and so same probability

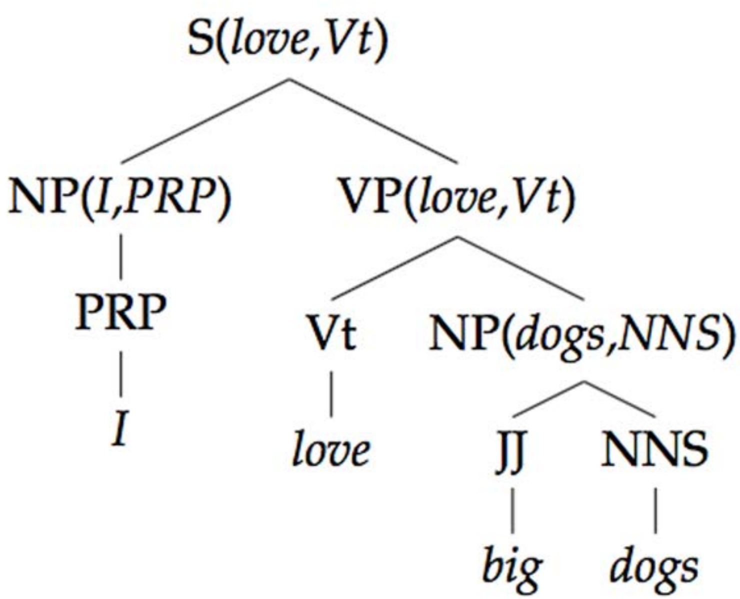
Turns out, left hand side structure appears more frequently in the training set

Methods to improve PCFG

- Add lexical information to the tree
  - Label each node with associate words
    - Lexicalized trees
    - Latent variable grammars
- Look at bigger portions of the tree at a time

S	⇒	NP	VP	1.0
VP	⇒	Vi		0.4
VP	⇒	Vt	NP	0.4
VP	⇒	VP	PP	0.2
NP	⇒	DT	NN	0.3
NP	⇒	NP	PP	0.7
PP	⇒	P	NP	1.0

Vi	⇒	sleeps	1.0
Vt	⇒	saw	1.0
NN	⇒	man	0.7
NN	⇒	woman	0.2
NN	⇒	telescope	0.1
DT	⇒	the	1.0
IN	⇒	with	0.5
IN	⇒	in	0.5



Lexicalized tree

Overview

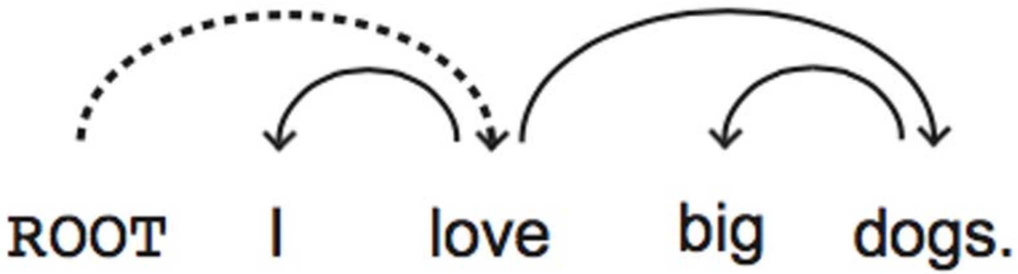
- Types of grammars
  - Context Free Grammar
  - Probabilistic Context Free Grammar
    - CYK parser
  - Dependency Grammar
    - Transition-based parsing
    - Recursive neural networks

Dependency grammar

- CFG is based on constituency relation
- In dependency grammar the structure is composed of lexical items (words) linked by edges to form a tree
- Assumptions
  - Each words in a sentence is related or modifies another word
  - All words have a direct or indirect relation to the main verb

Example

- Add ROOT node as the root of the tree
- The main verb always point to ROOT



A -> B means
A governs B or
B depends on A

A is the head of B

- Each arc can have a category for the relationship.
- Each word can have a PoS label

Constituency structures vs dependency structures

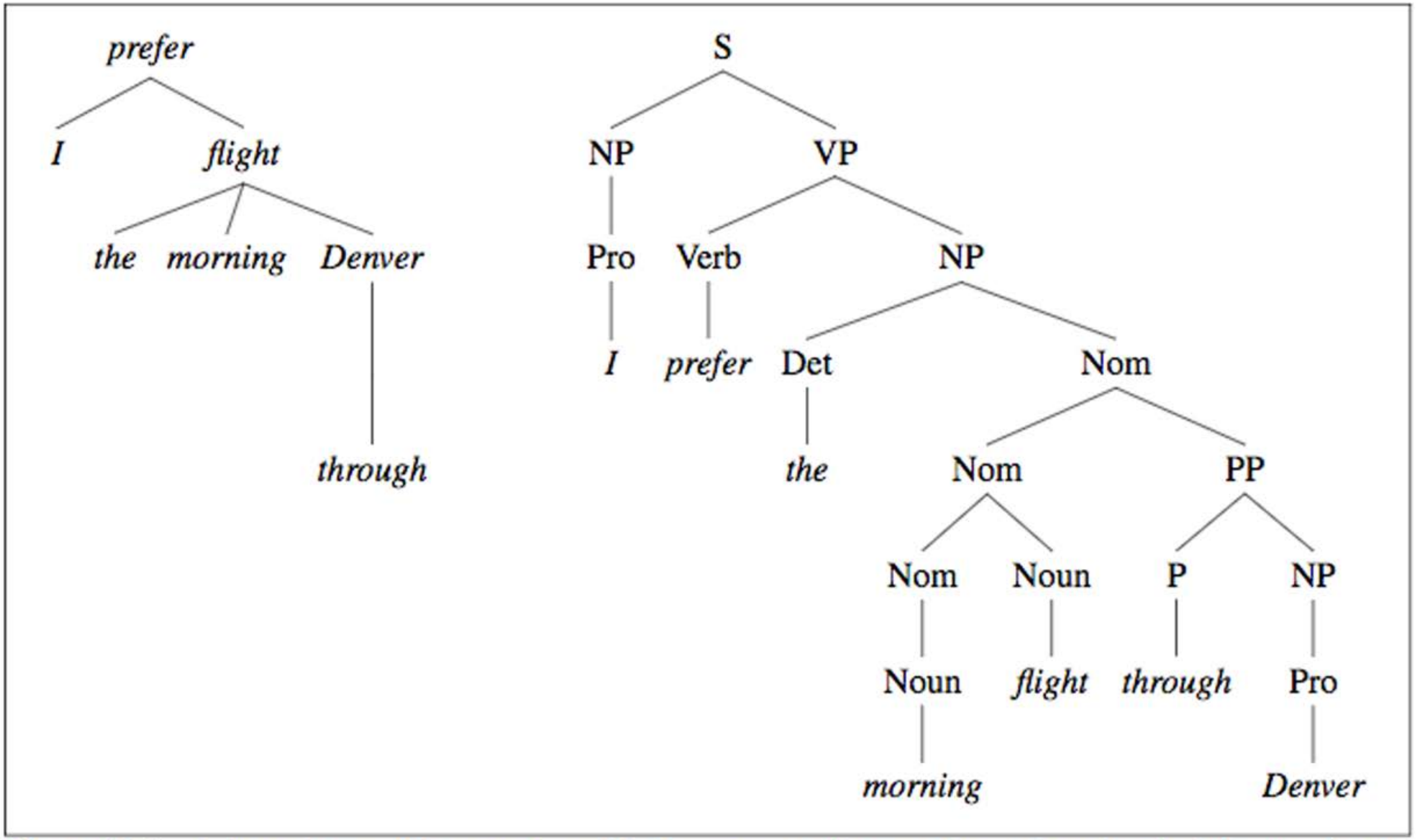


Figure 14.1 A dependency-style parse alongside the corresponding constituent-based analysis for *I prefer the morning flight through Denver.*

http://web.stanford.edu/~jurafsky/slp3/14.pdf

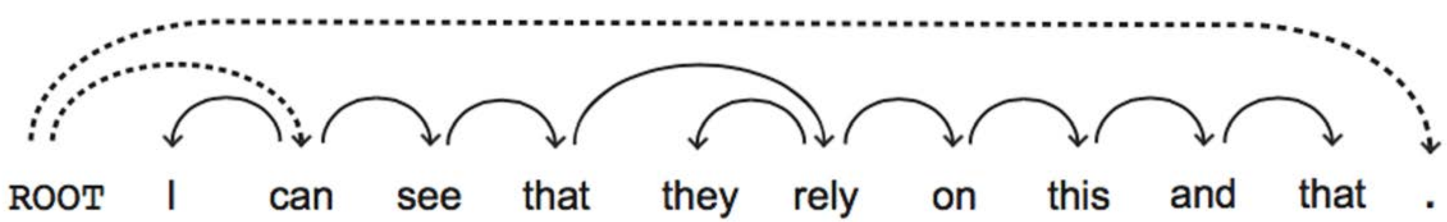
Constituency structures vs dependency structures

- Constituency structures use more nodes to represent sentences at different levels.
- Constituency structures explicitly label non-terminal nodes (NP vs VP)
- Constituency structures encode more info than dependency structures
- You can convert constituency structures to dependency structures
  - Dependency parsers trained on this is usually better than dependency parsers trained on original dependency structures

Criteria for heads (basics)

- Head, H. Dependent D
- D modifies H
  - Big (D) dogs (H), willow (D) tree (H)
- H can often replace D
  - I love big (D) dogs (H) -> I love dogs
- H is obligatory while D sometimes is optional
- H determines whether D is obligatory
  - Sarah sneezed (H) vs George kicks (H) the chair (D)
- More criterias! Mostly depends on corpus

Ex



Dependency and meaning

- Scientists study whales from space

- Scientists study whales from space

Dependency and meaning

- Scientists study whales from space
- Scientists study whales from space

Sample Thai sentences

- วัน หนึ่ง เกิด เหตุ ที่ ไม่ คาดคิด ขึ้น มา
- การ ที่ เรา จะ รู้ ถึง สิ่ง เหล่านั้น ได้ ก็ ต้อง อาศัย ปัจจัย หลาย ๆ อย่าง ประกอบ เข้า ด้วยกัน

Note these criteria depends on the corpus convention

Sample Thai sentences

- วัน หนึ่ง เกิด เหตุ ที่ ไม่ คาดคิด ขึ้น มา

Note these criteria depends on the corpus convention

Sample Thai sentences

- การ ที่ เรา จะ รู้ ถึง สิ่ง เหล่านั้น ได้ ก็ ต้อง อาศัย
  ปัจจัย หลาย ๆ อย่าง ประกอบ เข้า ด้วยกัน

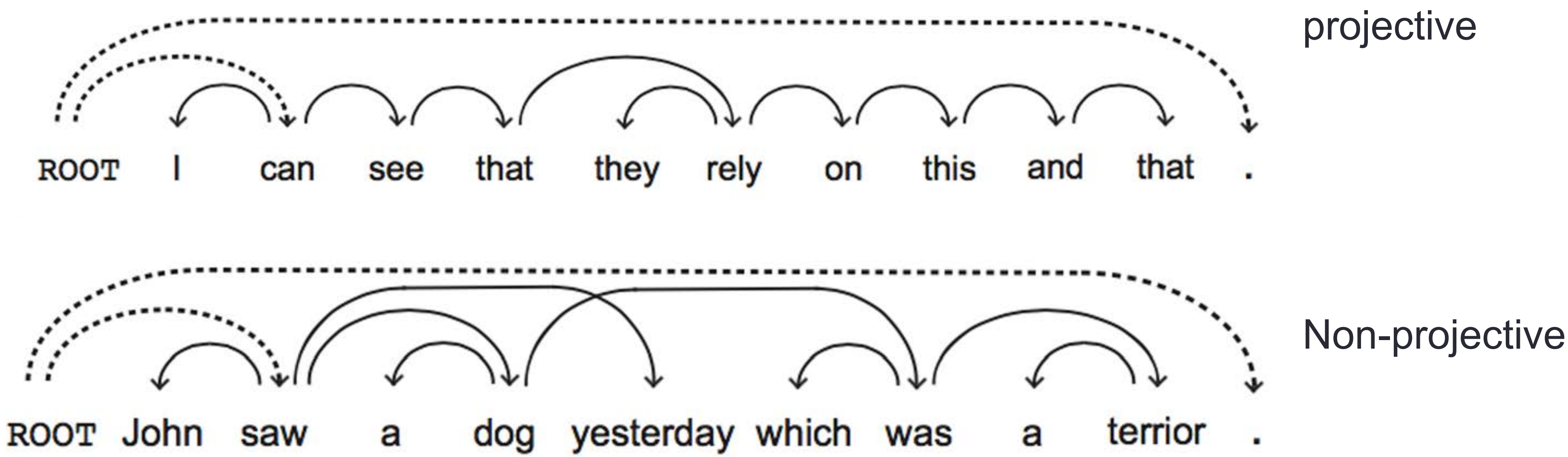
Note these criteria depends on the corpus convention

Dependency graph requirements

- Syntactic structure is complete (connectedness, spanning)
- Hierarchical (acyclic)
- Every word has a single head

Projectivity

- A dependency graph is projective if the arcs do not cross



English and Thai are mostly projective.
Some languages are more non-projective than others,
for example German, Dutch, Czech.

When picking a parser algo, check whether it assumes projectivity

Transition-based parsing (Nivre 2007)

- Use a stack and buffer data structure and sequentially add edges
- Characteristics
  - Greedy algo. Only goes left to right. No backtracking
    - Fast O(n)
  - Requires projectivity
  - The algo is closely related to how human parse sentences (left to right one word at a time instead of looking at the sentence as a whole)

Arc-standard Transition-based parsing

- A stack σ, written with top of the stack to the right
  - Starts with the ROOT symbol
- A buffer β, written with top to the left
  - Starts with the input sentence
- A set of dependency arcs A
  - Starts of empty
- A set of actions

$$\sigma = [\text{ROOT}],\ \beta = w_1, \ldots, w_n,\ A = \varnothing$$

1. Shift $\quad \sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$ Move buffer to stack
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$_r$ $\quad \sigma|w_i|w_j, \beta, A \rightarrow \sigma|w_i, \beta, A \cup \{r(w_i,w_j)\}$

- Finishes when β becomes empty

http://web.stanford.edu/class/cs224n/lectures/lecture7.pdf

I ate fish

Start

[root]

I ate fish

Shift

[root] I

ate fish

Shift

[root] I ate

fish

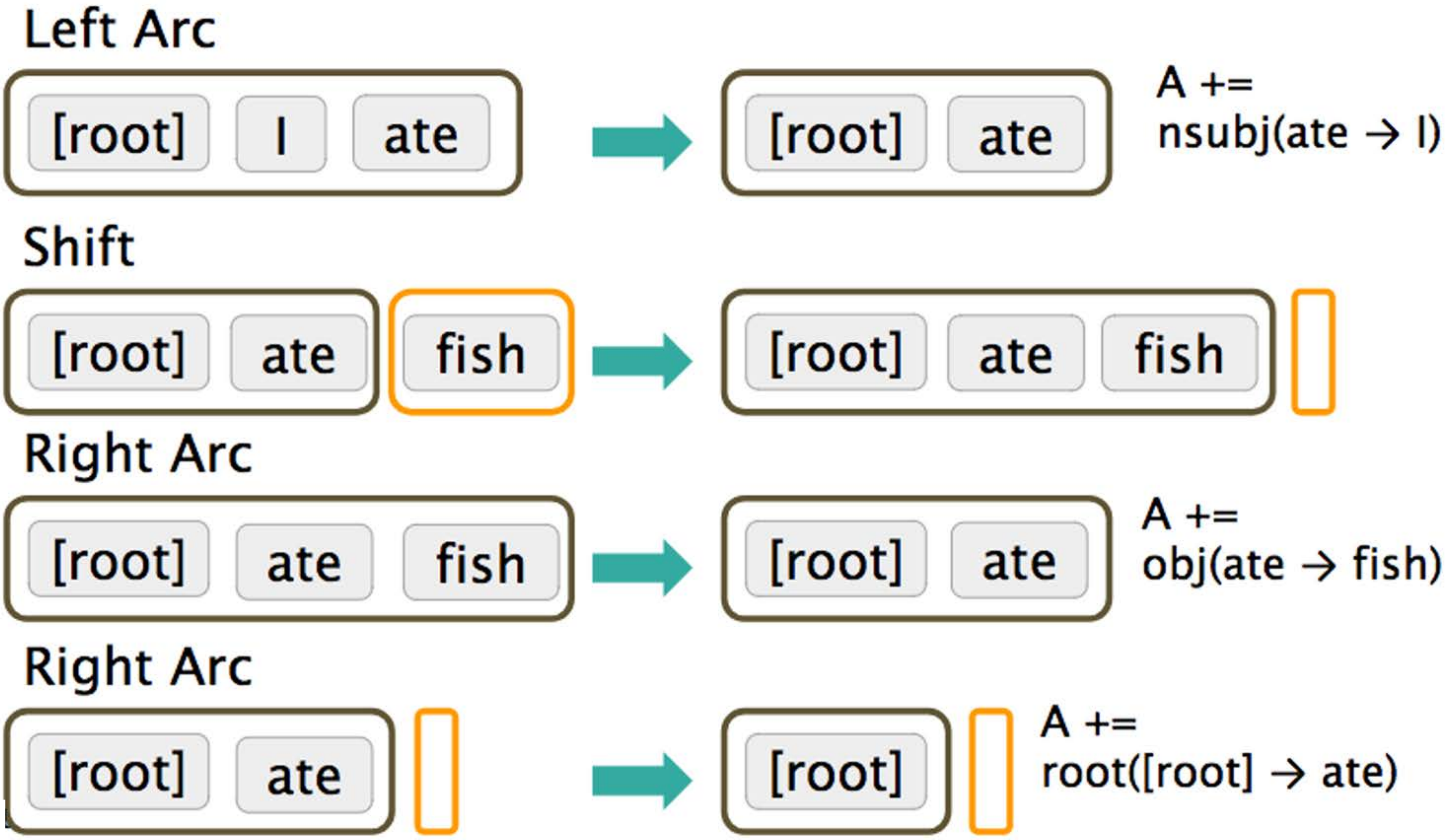
Start: $\sigma = [\text{ROOT}],\ \beta = w_1, \ldots, w_n,\ A = \varnothing$

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: $\beta = \varnothing$

http://web.stanford.edu/class/cs224n/lectures/lecture7.pdf

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)

Discriminative parsing

- How to choose an action?
  - Shift, left-arc, right-arc
- Each action is predicted by a discriminative classifier (SVM, logistic regression, Neural networks) over legal moves
  - Features: top two word from stack, POS, children info; first word in buffer, POS, children info; etc.
- Greedy and no beamsearch
  - But you can include beamsearch (modern parsers do)

https://cs.stanford.edu/people/danqi/papers/emnlp2014.pdf

Discriminative parsing with neural networks

Shift, left, right (in actual, left/right + type of dependency)
So 2N+1, where N = dependency types

Softmax layer:

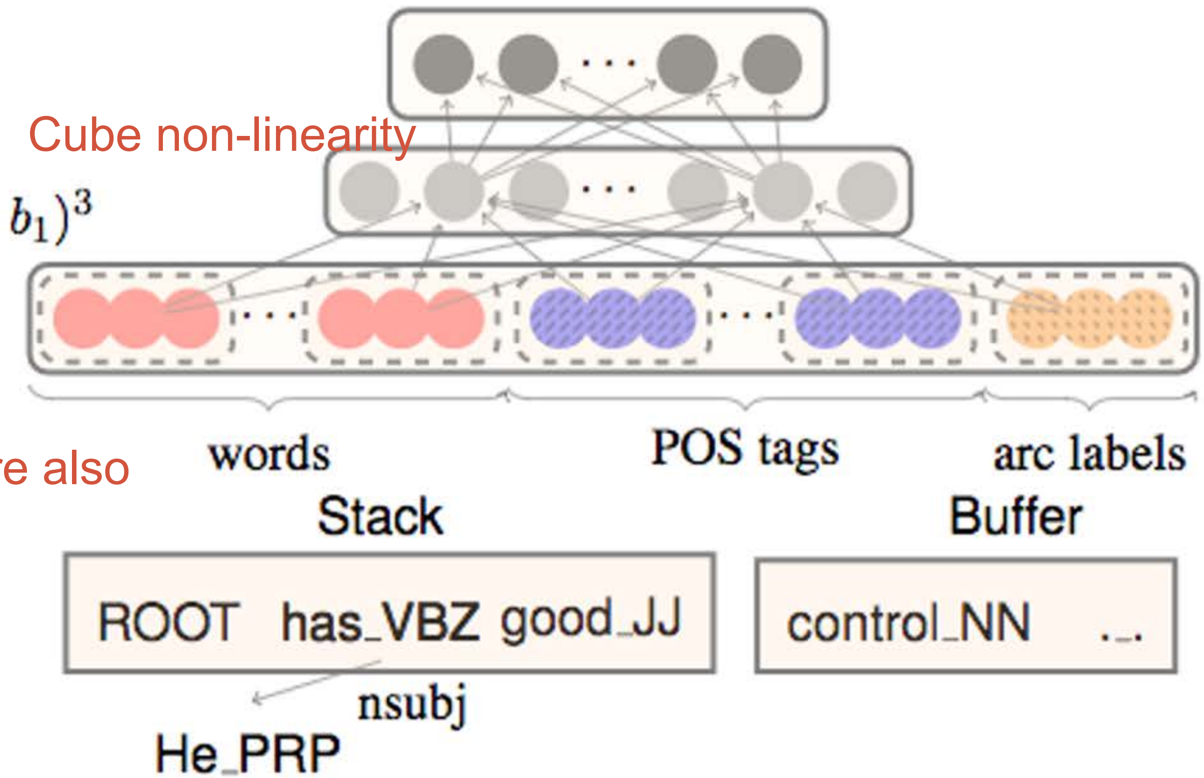
$$p = \mathtt{softmax}(W_2 h)$$

Hidden layer:

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

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

Cube non-linearity



POS and arc labels are also embeddings

Configuration

https://cs.stanford.edu/people/danqi/papers/emnlp2014.pdf

Improvements

- Bigger networks
- Beam search
- Global inference over the sequence (CRF style)

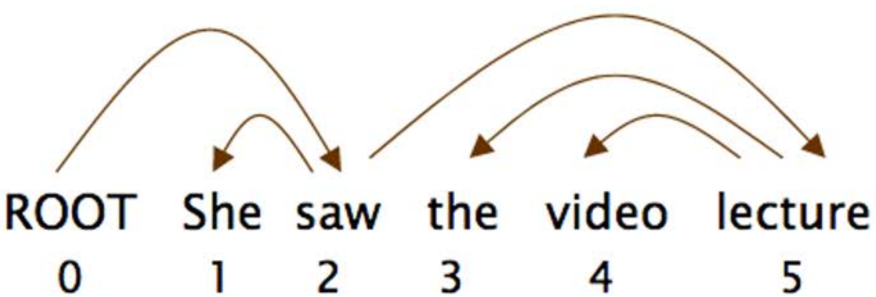
- Lead to SyntaxNet and Parsey McParseFace model

https://github.com/tensorflow/models/tree/master/research/syntaxnet

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

Parsing evaluation

- Labeled parsing accuracy (LAS)
- Unlabeled parsing accuracy (UAS)



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

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

http://web.stanford.edu/class/cs224n/lectures/lecture7.pdf

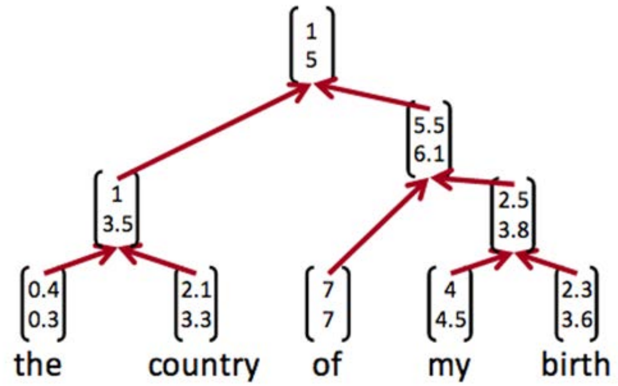
UAS of Parsey McParseFace

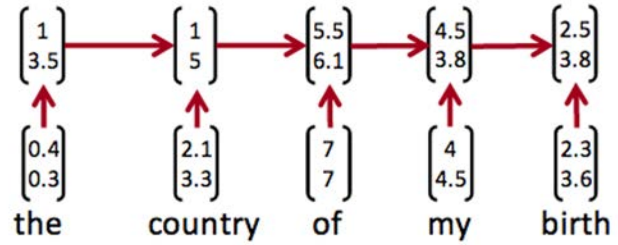
Model	News	Web	Questions
Martins et al. (2013)	93.10	88.23	94.21
Zhang and McDonald (2014)	93.32	88.65	93.37
Weiss et al. (2015)	93.91	89.29	94.17
Andor et al. (2016)*	94.44	90.17	95.40
Parsey McParseface	94.15	89.08	94.77

https://github.com/tensorflow/models/tree/master/research/syntaxnet

Recursive neural networks

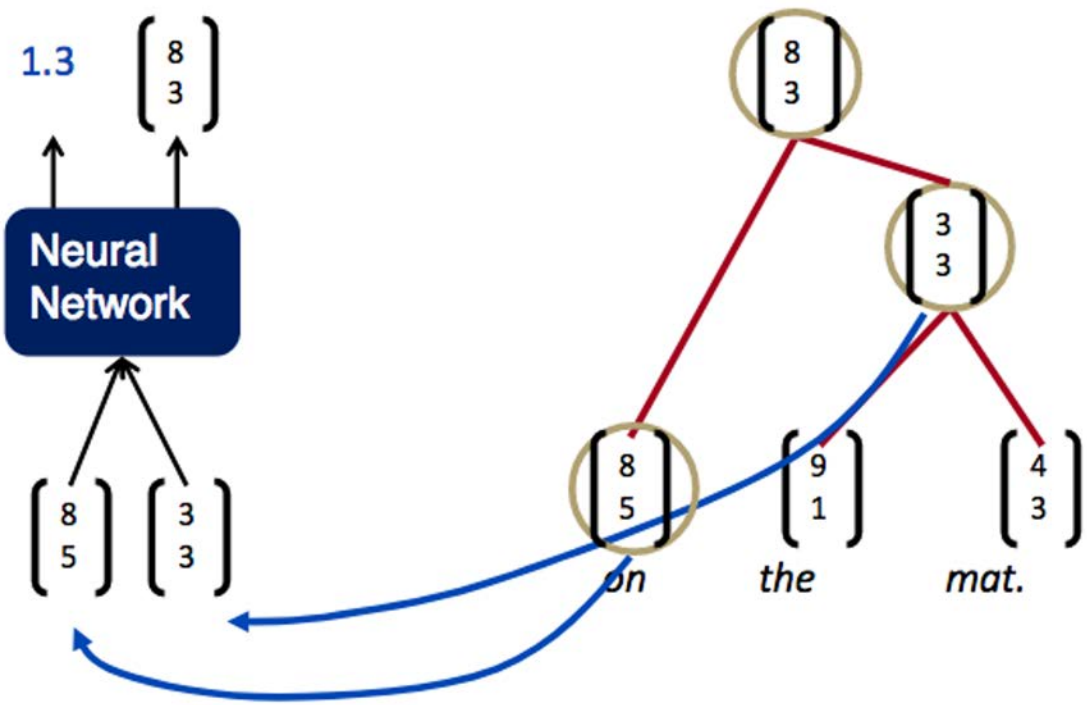
- Not really used in parsing anymore but interesting concept
- Recursive vs Recurrent



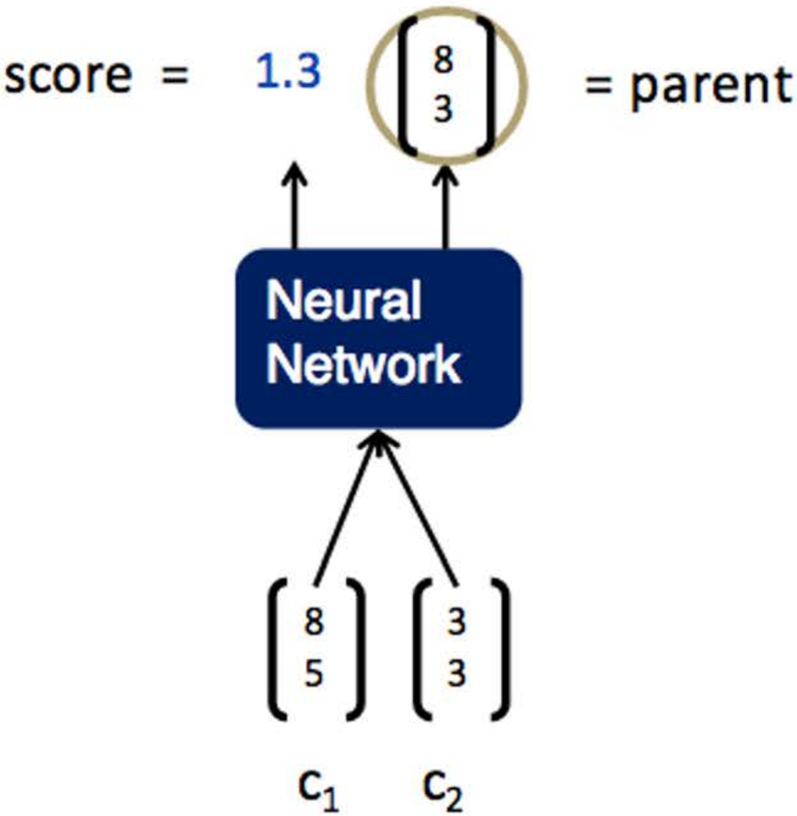


Recursive neural networks

- Concept: try different connections, see if which one gives the highest score (graph-based dependency parsers)
- Inputs: two candidate children representations
- Output:
  - Semantic representation of the parent
  - Score of new node



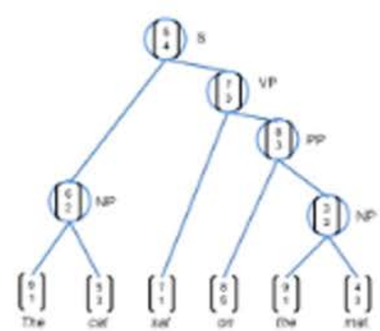
Shared recursive structure



score $= U^{\mathrm{T}}p$

$$\boxed{p = \tanh\left(W\begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right),}$$

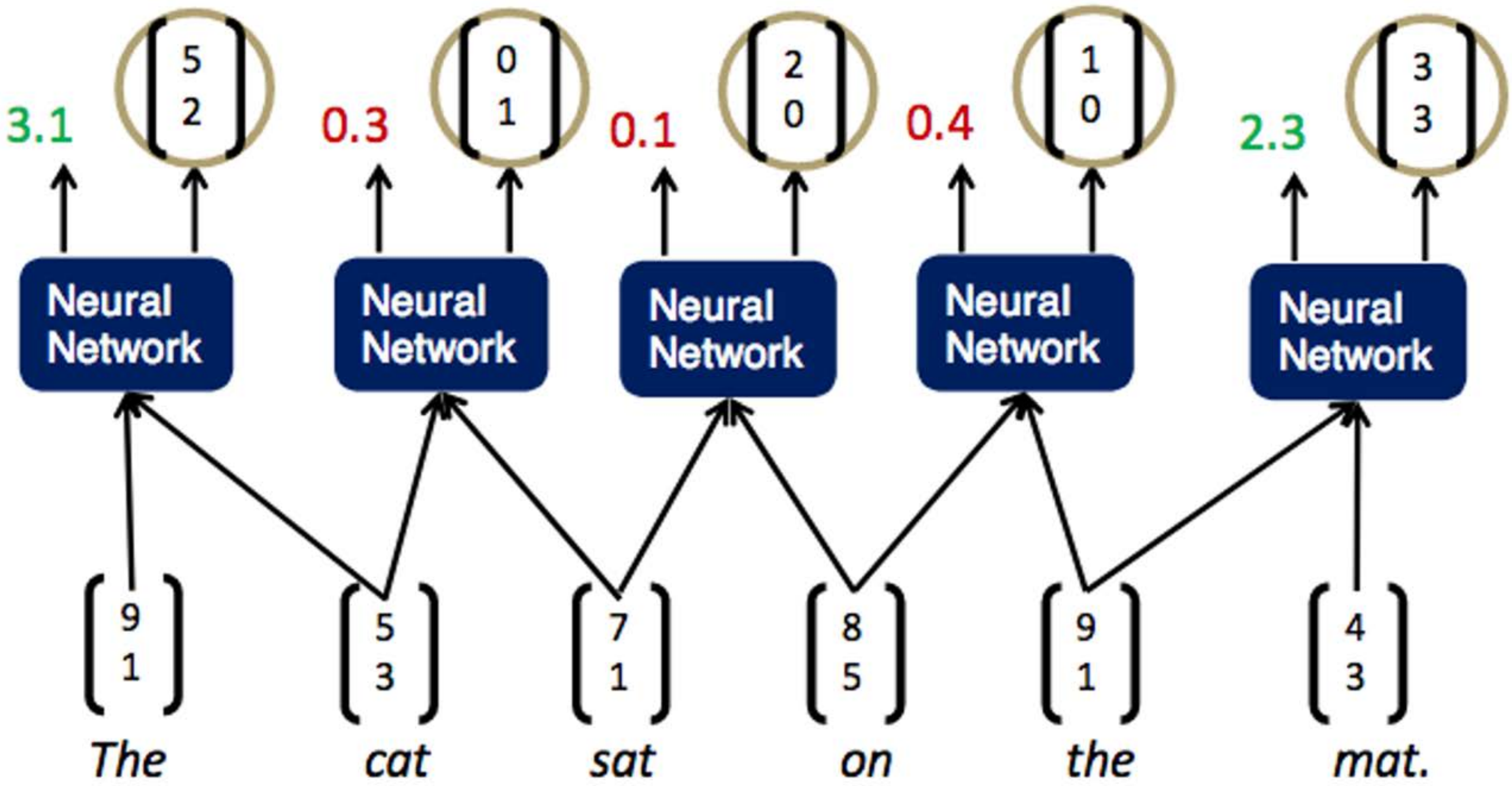
Same W **parameters at all nodes of the tree**

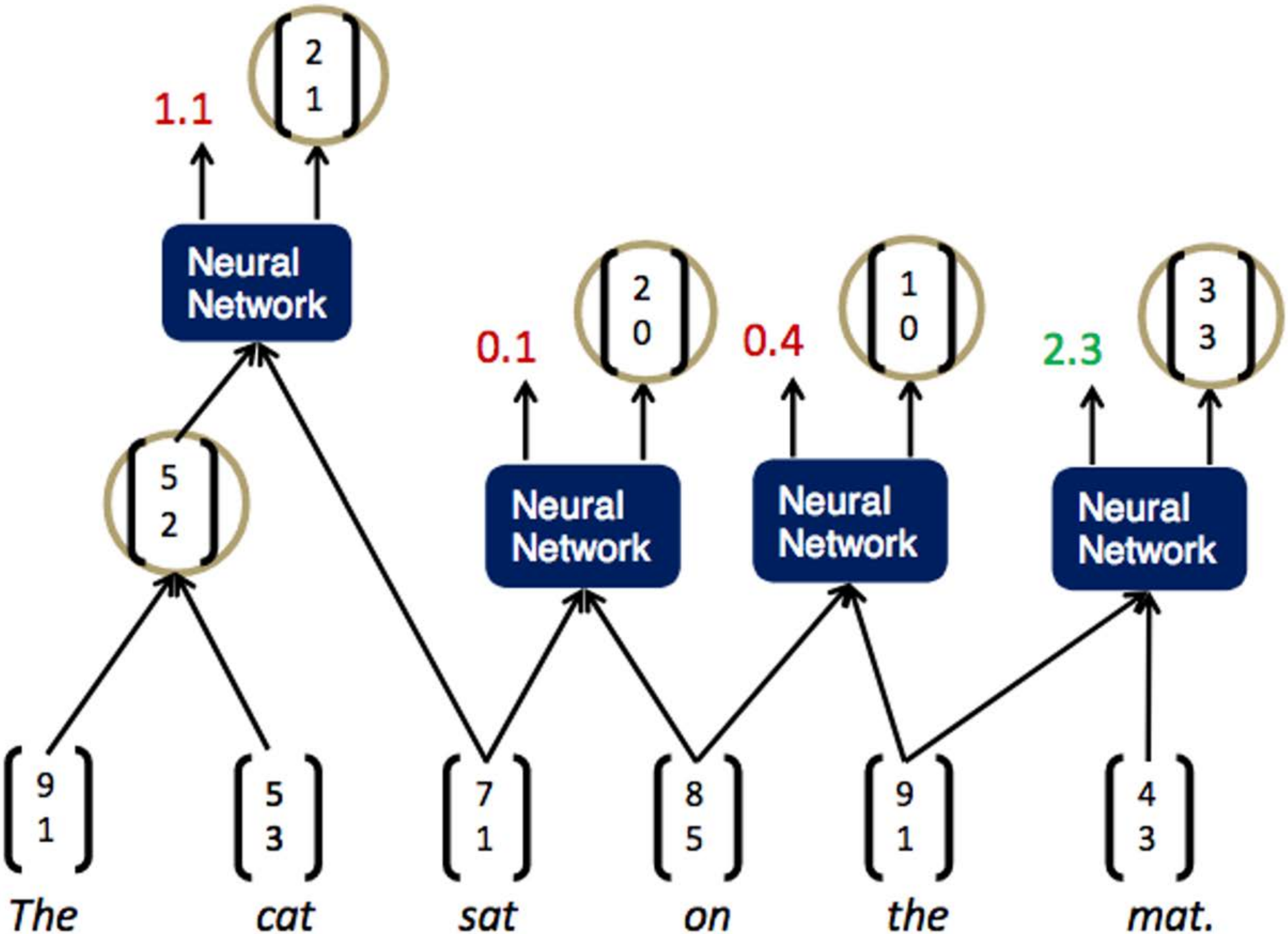


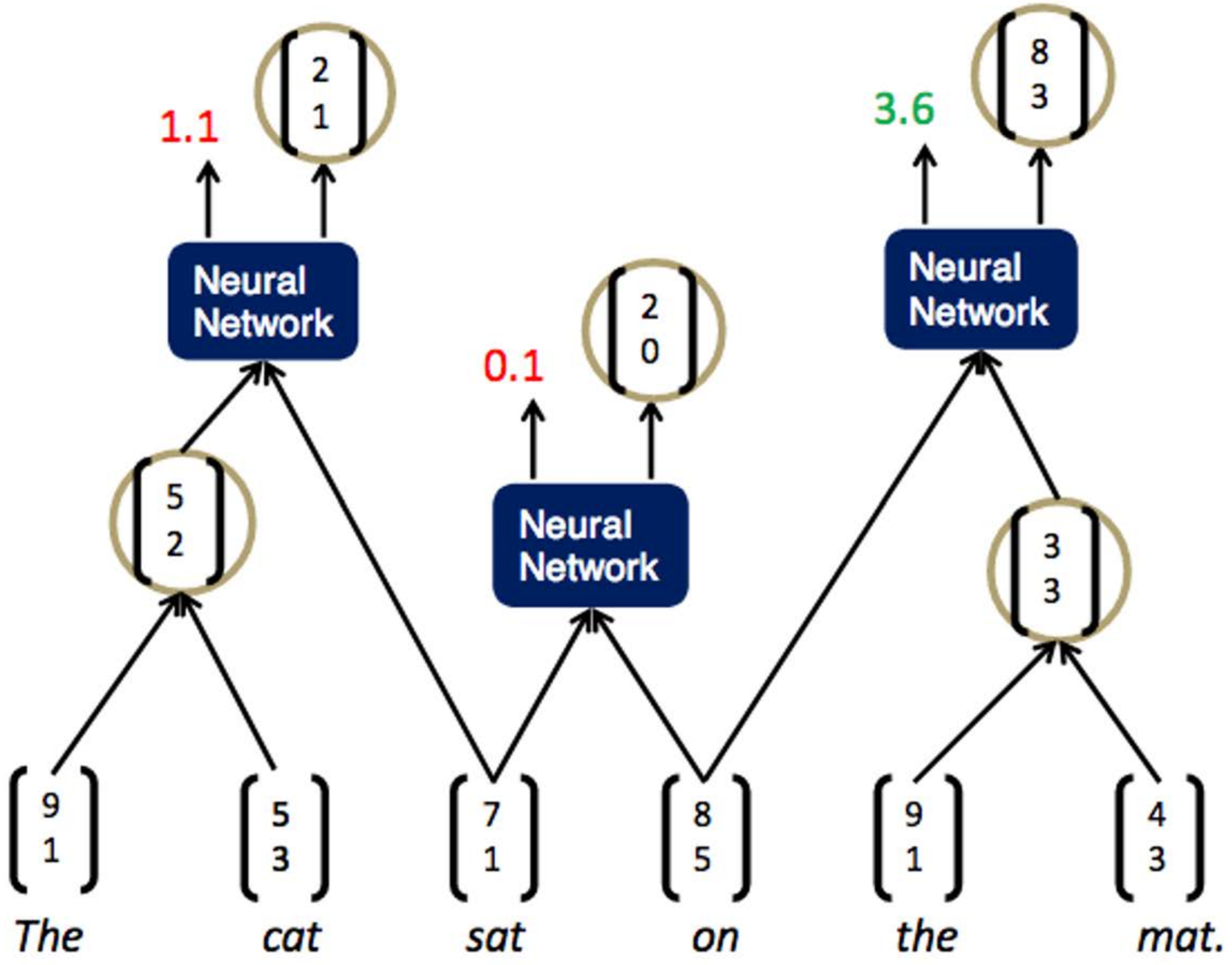
http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf

Parsing with recursive networks

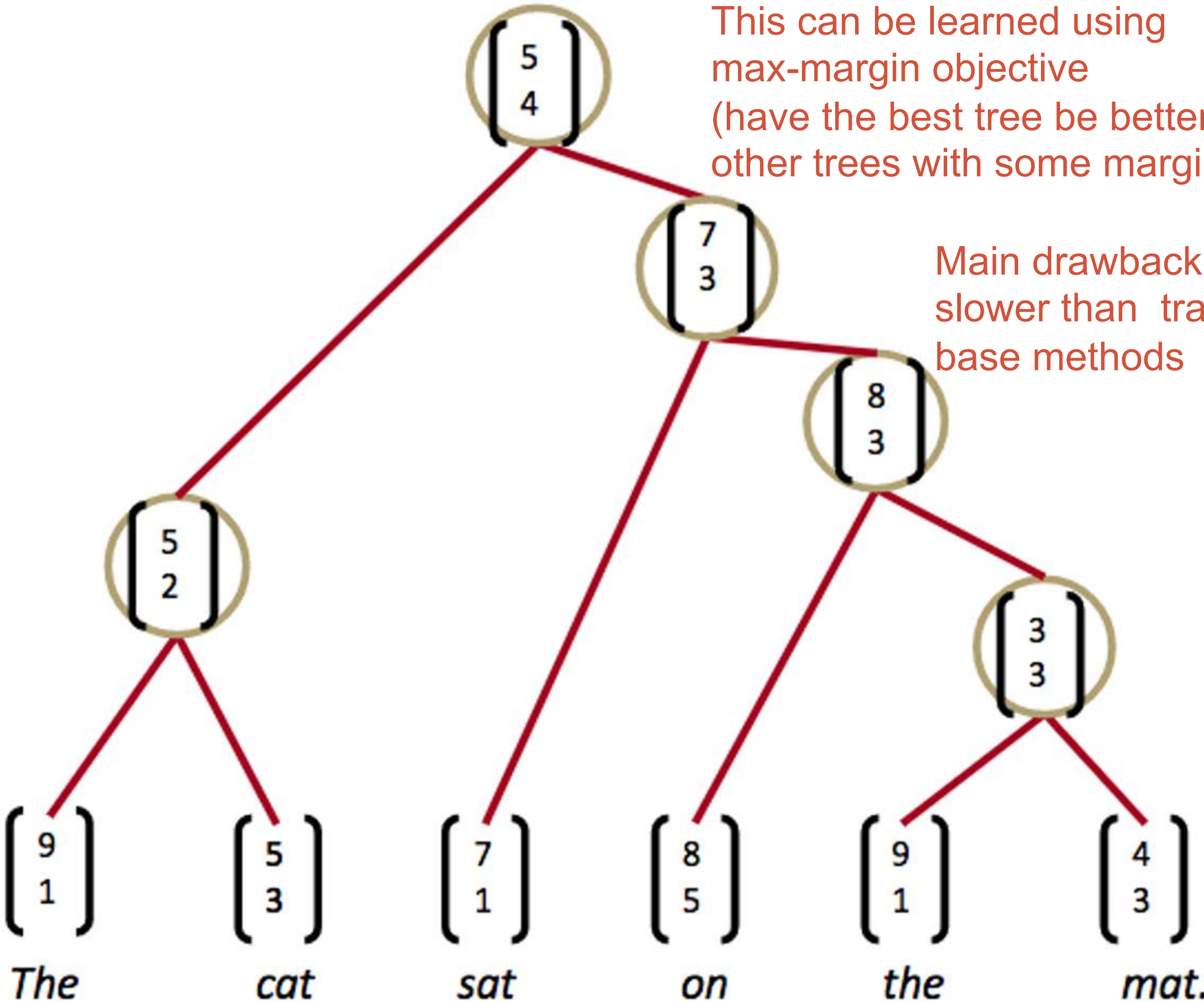
Follow the highest scoring pair




1.1
2
1
Neural Network
5
2
0.1
2
0
Neural Network
0.4
1
0
Neural Network
2.3
3
3
Neural Network
9
1
The
5
3
cat
7
1
sat
8
5
on
9
1
the
4
3
mat.



1.1
2
1
3.6
8
3
Neural Network
Neural Network
Neural Network
0.1
2
0
5
2
3
3
9
1
5
3
7
1
8
5
9
1
4
3
The
cat
sat
on
the
mat.

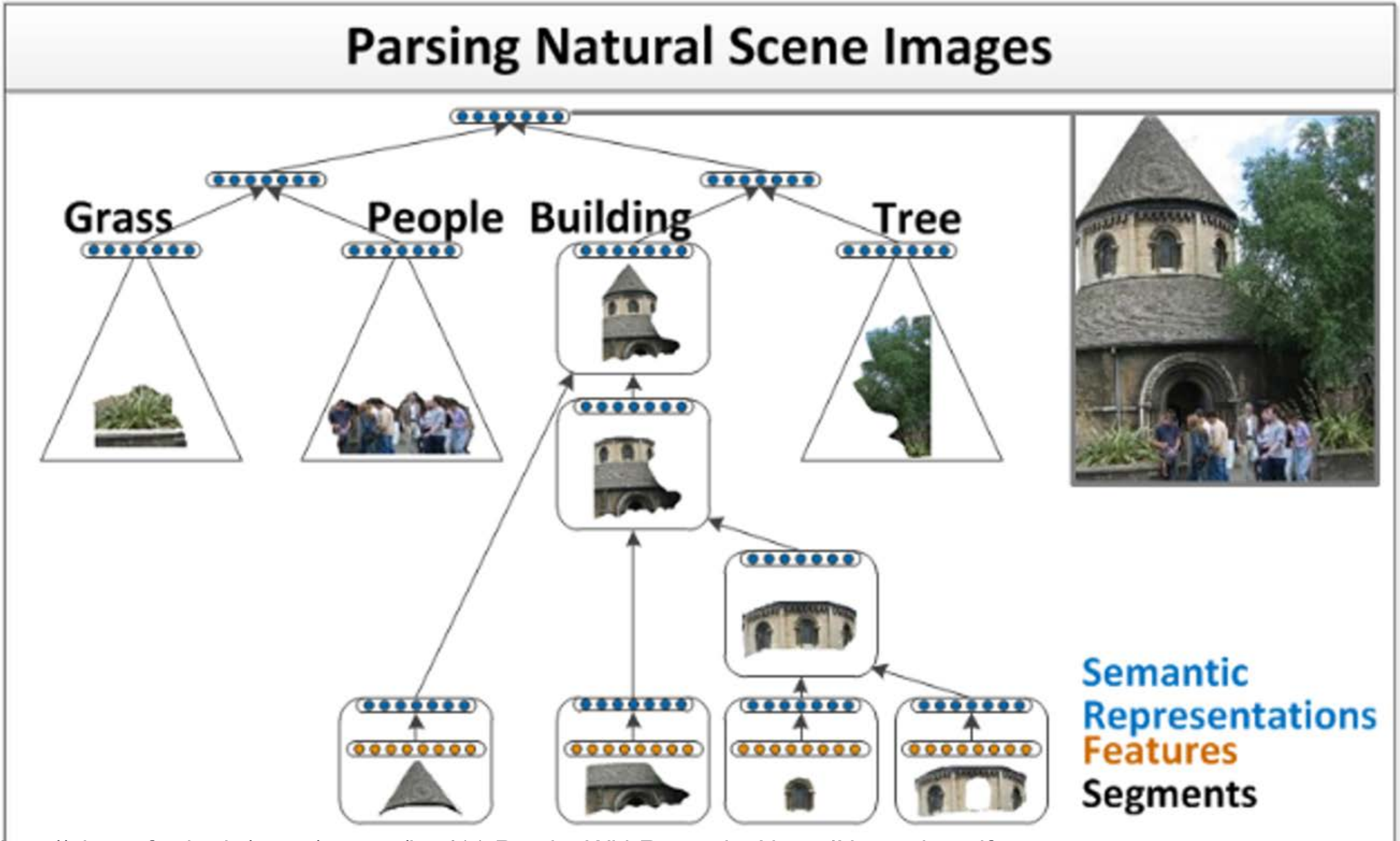


This can be learned using max-margin objective (have the best tree be better than other trees with some margin)

Main drawback, slower than transition-base methods

http://ai.stanford.edu/~ang/papers/icml11-ParsingWithRecursiveNeuralNetworks.pdf

Recursive neural networks for scene parsing



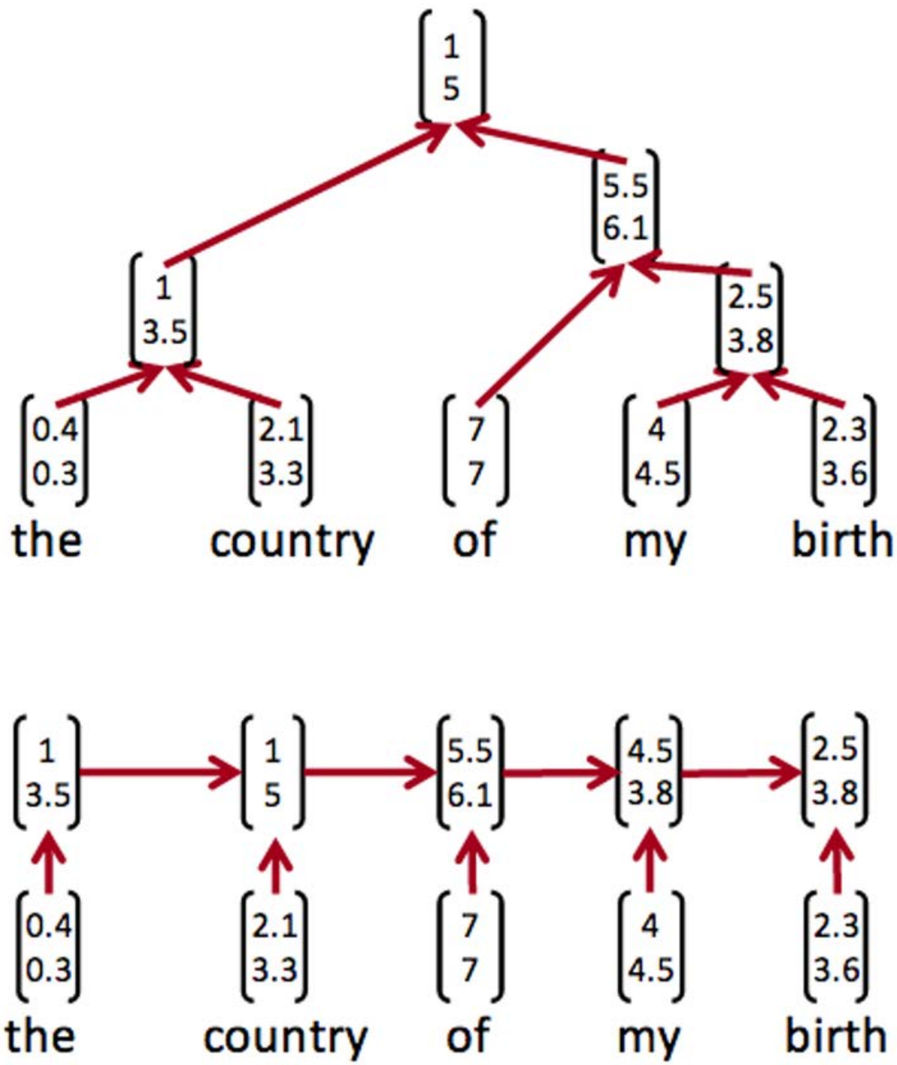
http://ai.stanford.edu/~ang/papers/icml11-ParsingWithRecursiveNeuralNetworks.pdf

Resources for parsing

- Orchid & some corpus in development by NECTEC
- http://universaldependencies.org/

Russian	3	1,226K	W	IE, Slavic
Sanskrit	1	1K		IE, Indic
Serbian	1	86K	W	IE, Slavic
Slovak	1	106K		IE, Slavic
Slovenian	2	170K		IE, Slavic
Spanish	3	1,004K	W	IE, Romance
Swedish	3	195K	W	IE, Germanic
Swedish Sign Language	1	1K		Sign Language
Tamil	1	9K		Dravidian, Southern
Telugu	1	6K		Dravidian, South Central
Thai	1	23K	W	Tai-Kadai
Turkish	2	74K	W	Turkic, Southwestern
Ukrainian	1	100K	W	IE, Slavic
Upper Sorbian	1	10K	W	IE, Slavic
Urdu	1	138K		IE, Indic
Uyghur	1	15K		Turkic, Southeastern
Vietnamese	1	43K		Austro-Asiatic

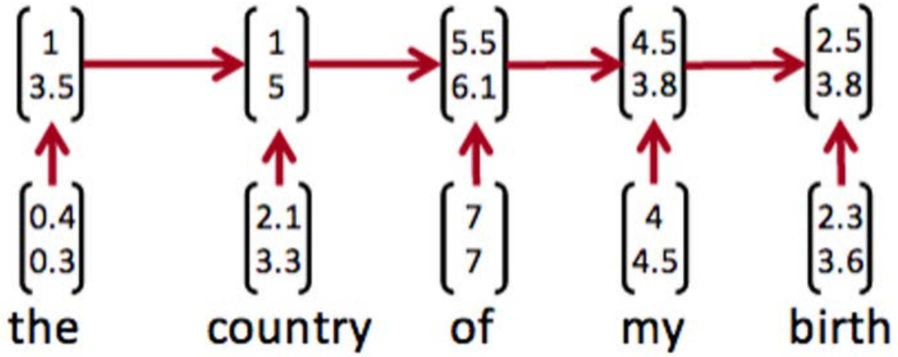
Recursive vs Recurrent representation



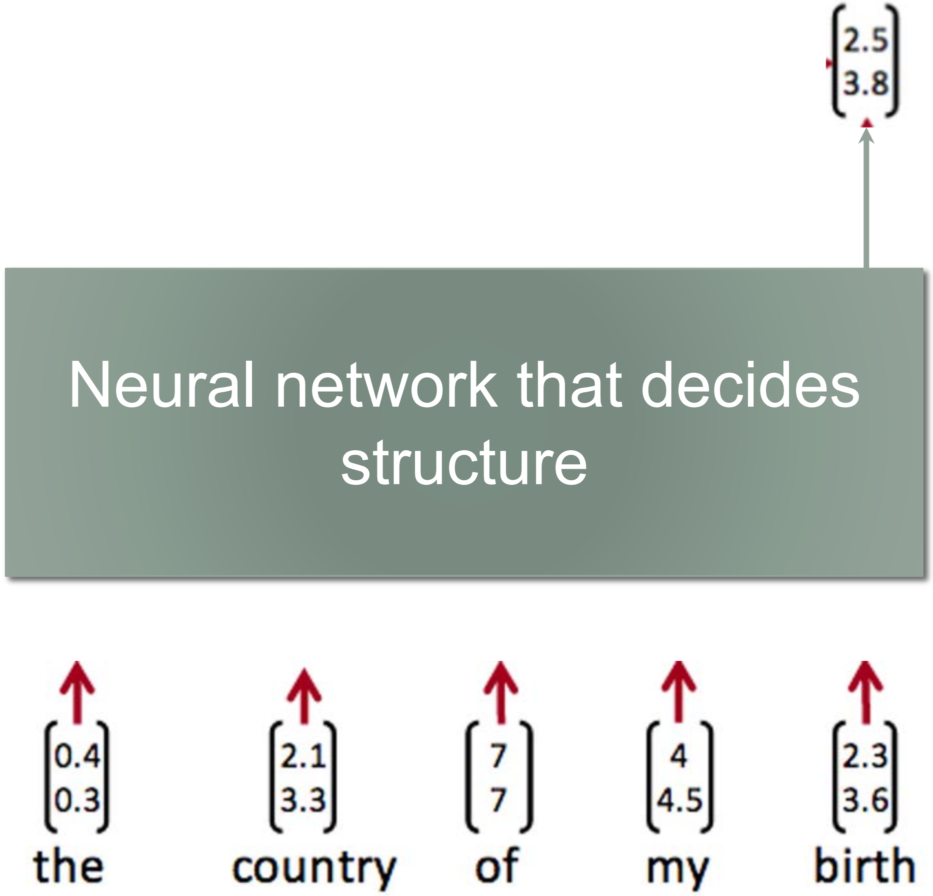
resurgence of recursive idea in newer BERTs

http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf

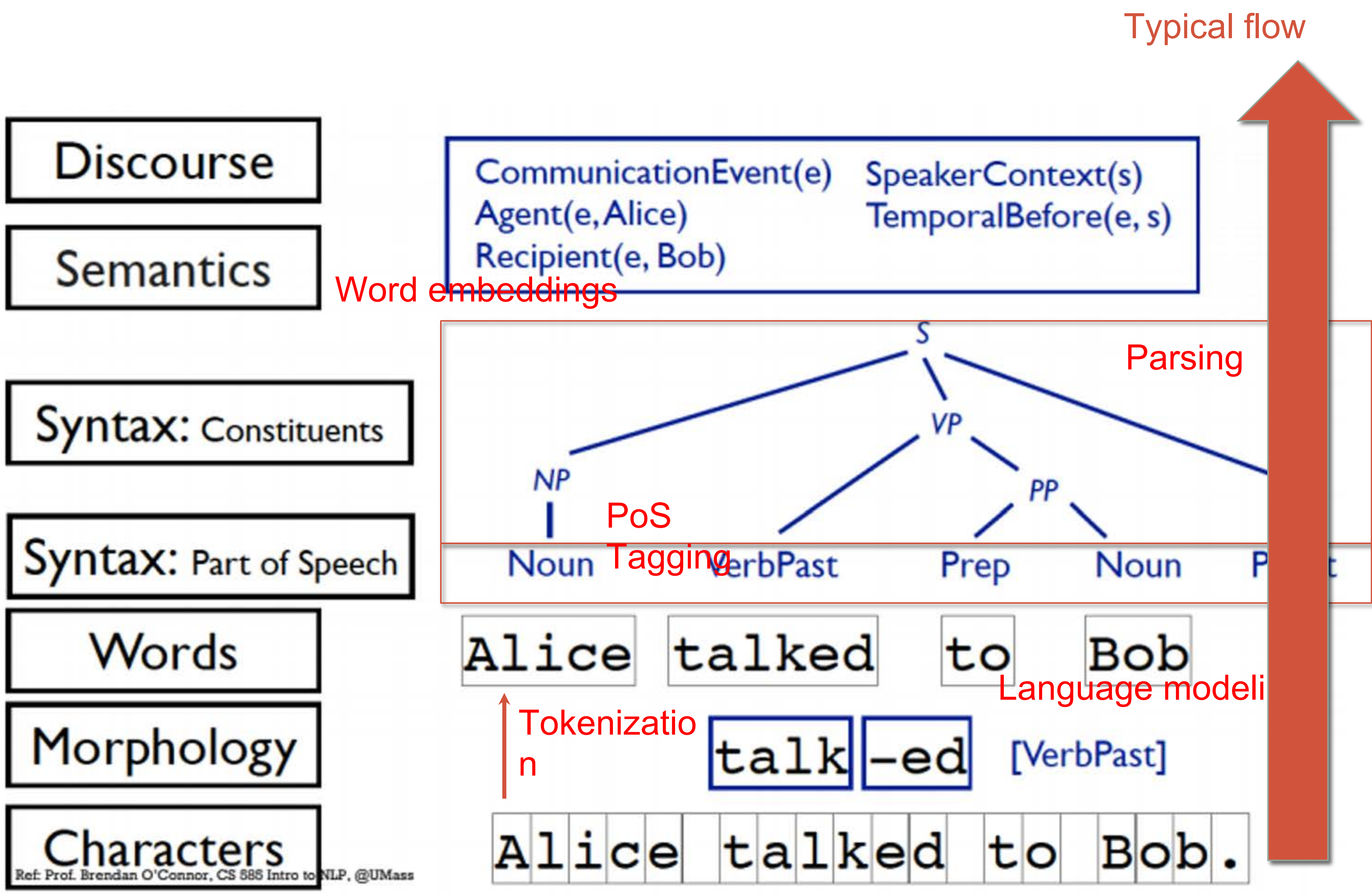
Towards unsupervised dependency parsing



Towards unsupervised dependency parsing



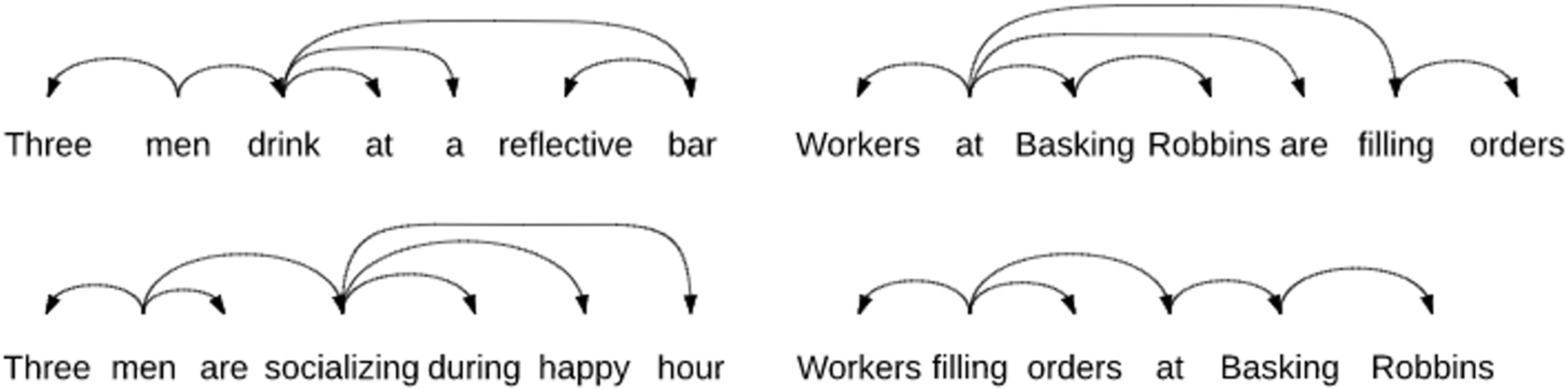
What is this piece? Next lecture! (attention modeling)


Typical flow
Discourse
Semantics
Syntax: Constituents
Syntax: Part of Speech
Words
Morphology
Characters
Ref: Prof. Brendan O'Connor, CS 585 Intro to NLP, @UMass
CommunicationEvent(e)
Agent(e, Alice)
Recipient(e, Bob)
SpeakerContext(s)
TemporalBefore(e, s)
Word embeddings
S
VP
NP
PP
Parsing
PoS Tagging
Noun
VerbPast
Prep
Noun
Alice
talked
to
Bob
Language modeli
Tokenizatio
n
talk
-ed
[VerbPast]
Alice talked to Bob.

An top down end-to-end approach

- Input: text
- Output: some task, sentiment analysis score
- Automatically gets parse tree (without any treebank corpus)

Example of generated parse tree



https://arxiv.org/pdf/1705.09207.pdf

Can also use recursive neural networks to learn unsupervised parse trees
Example https://arxiv.org/pdf/1707.02786.pdf

Summary

- Parsing
- Types of grammars
  - Context Free Grammar
  - Probabilistic Context Free Grammar (Constituency parsers)
    - CYK parser
  - Dependency Grammar (Dependency parsers)
    - Transition-based parsing
    - Recursive Neural networks