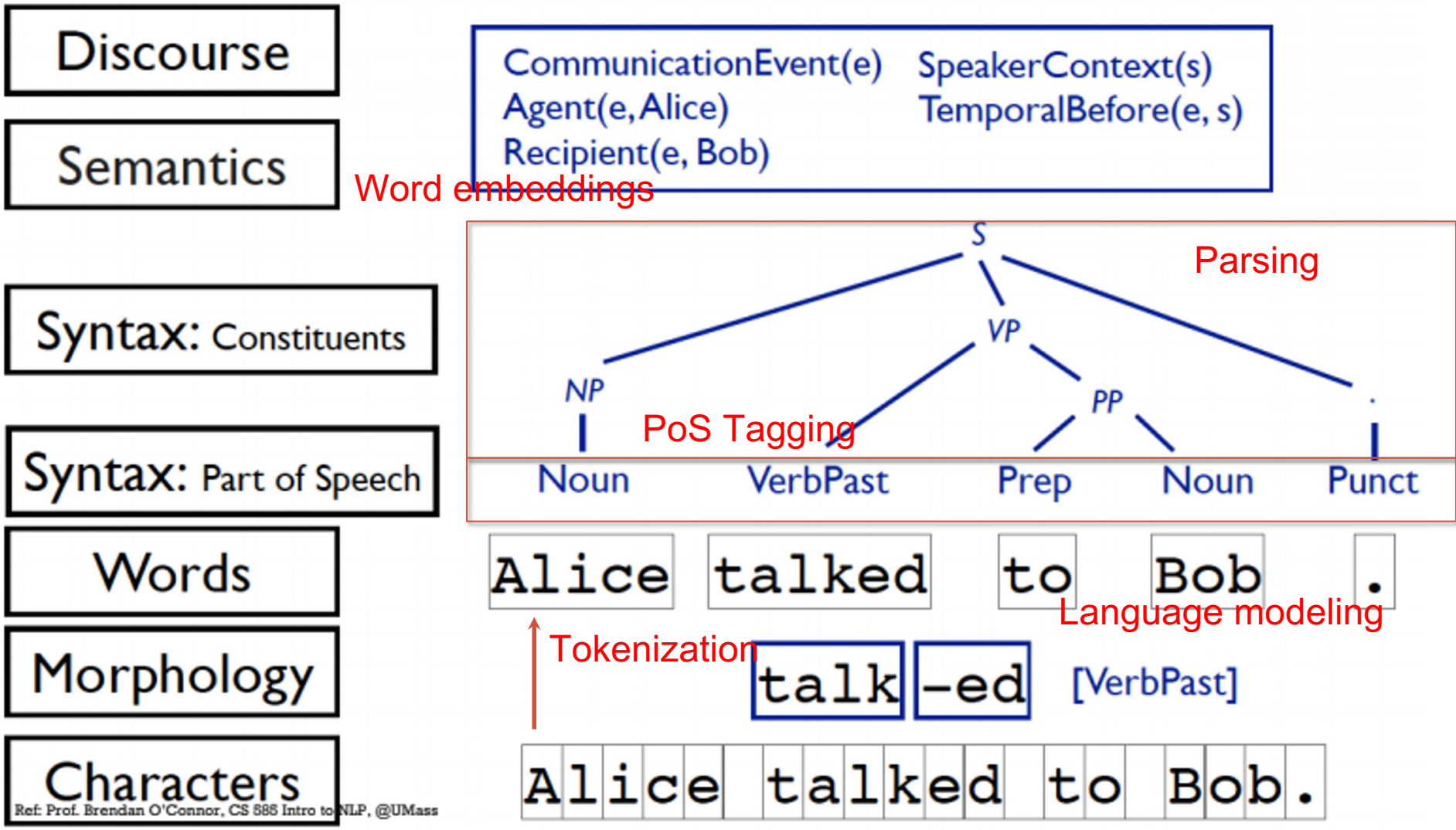
PARSING

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

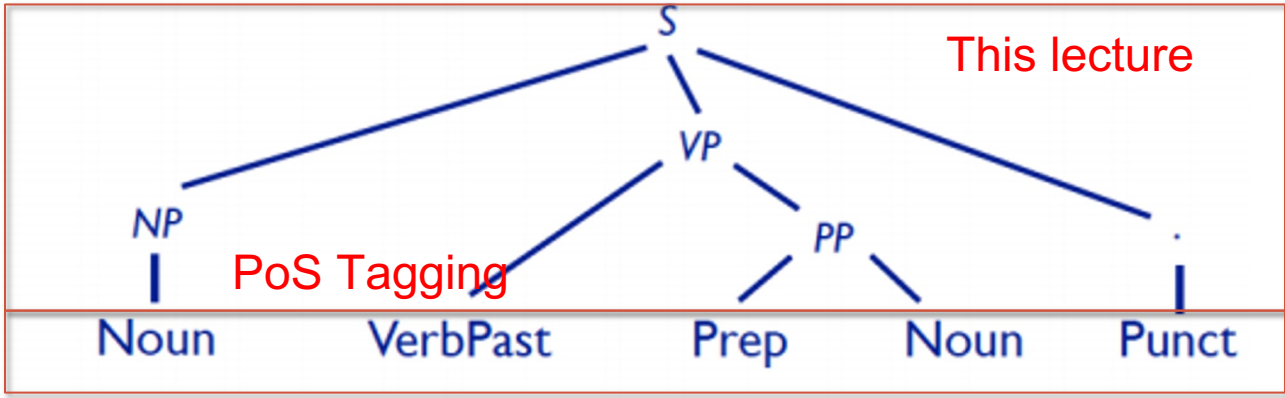
Words

Morphology

Characters

CommunicationEvent(e)
Agent(e, Alice)
Recipient(e, Bob)
SpeakerContext(s)
TemporalBefore(e, s)

Word embeddings



This lecture

PoS Tagging

Alice talked to Bob .

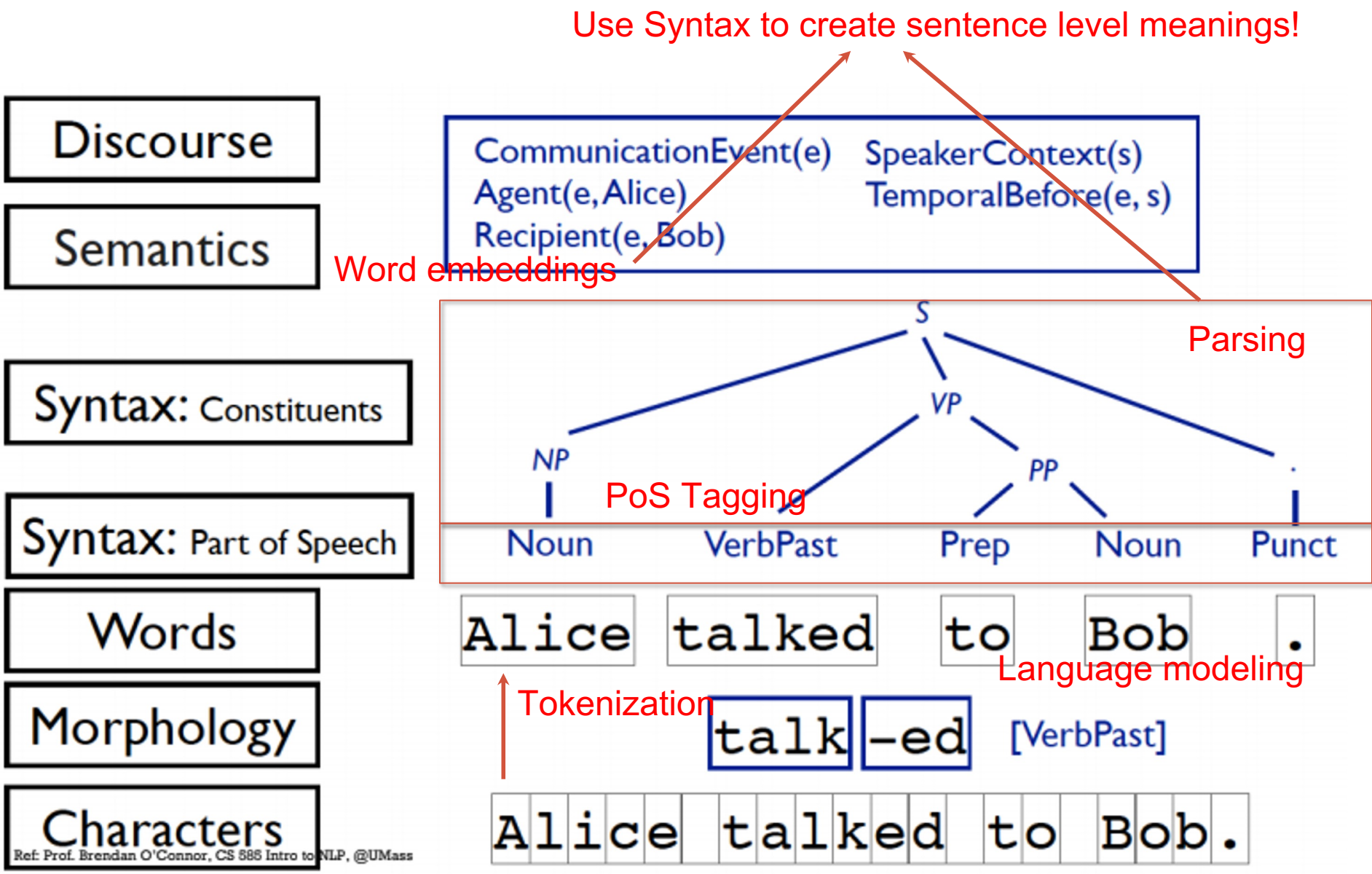
Language modeling

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
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
.
Parsing
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

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

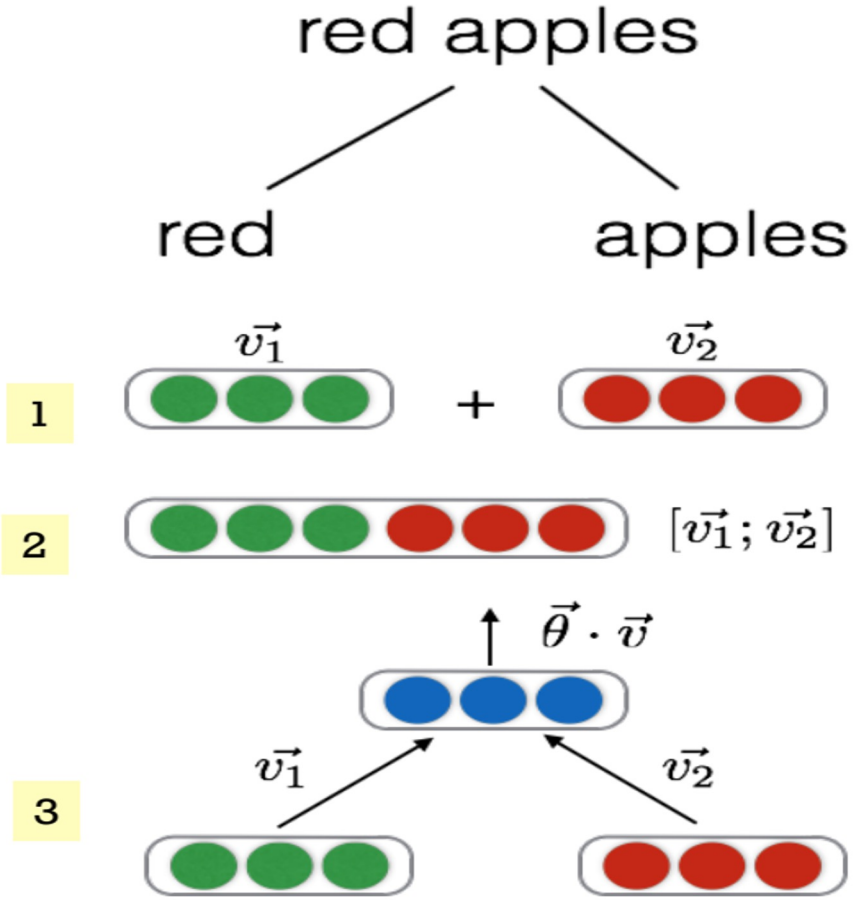


Image ref: Prof. Regina Barzilay , NLP@MIT

Semantic vectors overview

Discourse level

word phrase sentence paragraph document

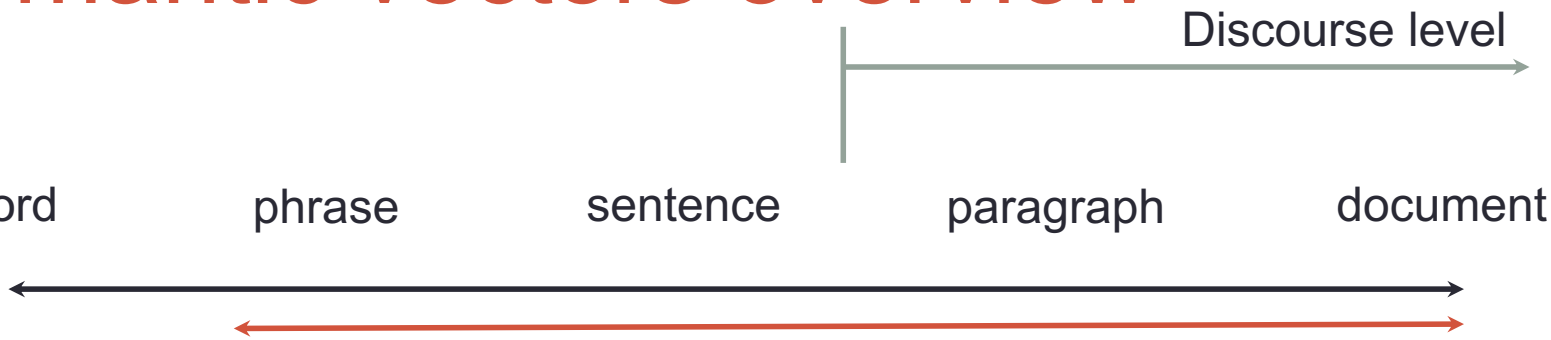
- Word vectors
  - Co-occurrence
  - PPMI
  - TFIDF
  - Word2vec
    - CBoW
    - Skip-gram

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.

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

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

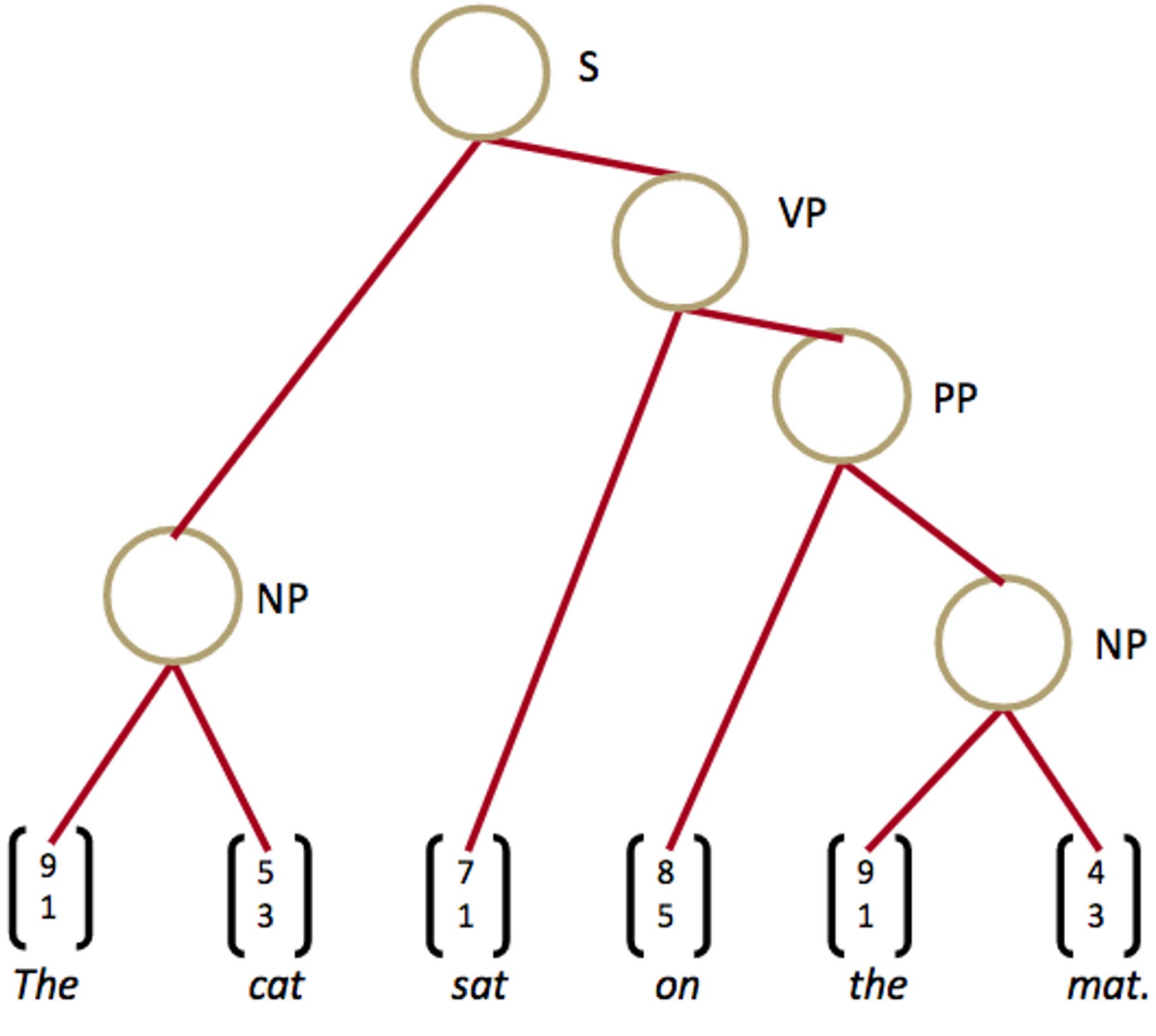
Semantic vectors overview



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

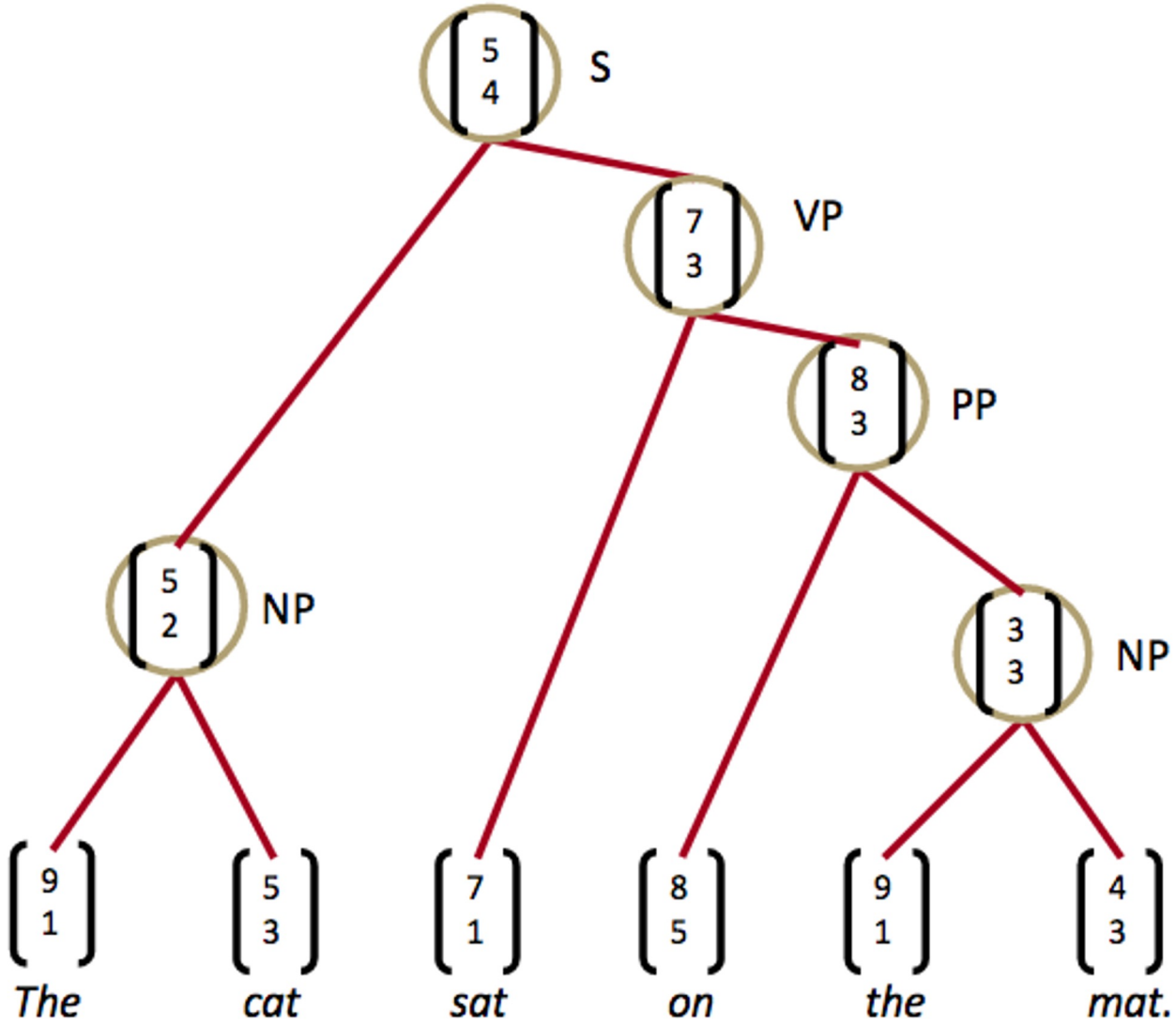
- Word vectors
  - Co-occurrence
  - PPMI
  - TFIDF
  - Word2vec
    - CBoW
    - Skip-gram
- Doc vectors
  - Term-document
    - Bag of words model
    - Doc2Vec
    - LDA2Vec
  - Recurrent networks

Parsing and representation big picture



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

Parsing and representation big picture



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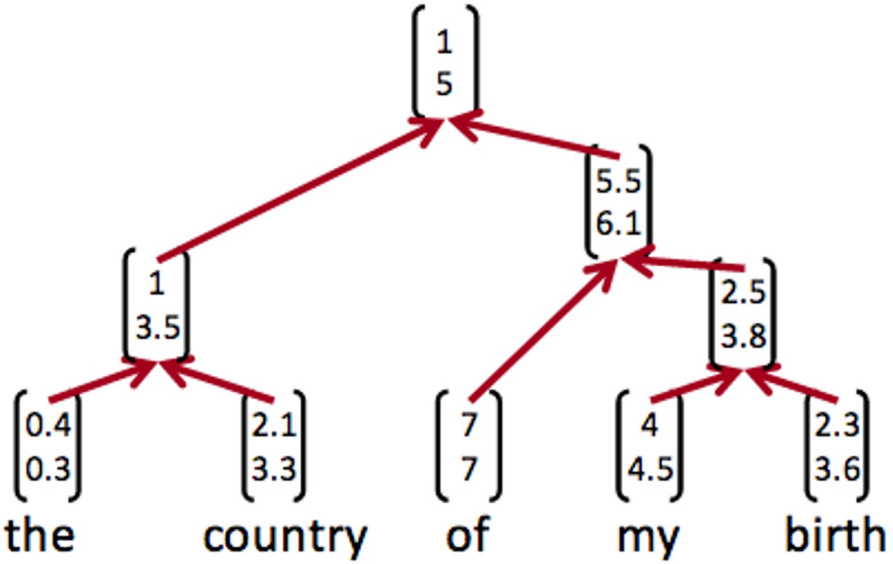
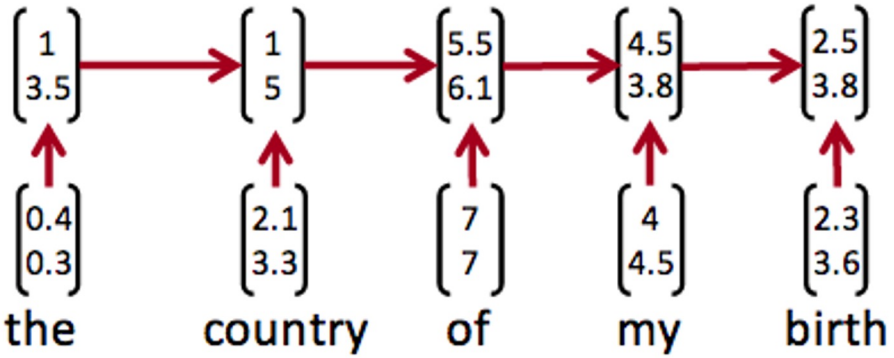
Recursive vs Recurrent representation





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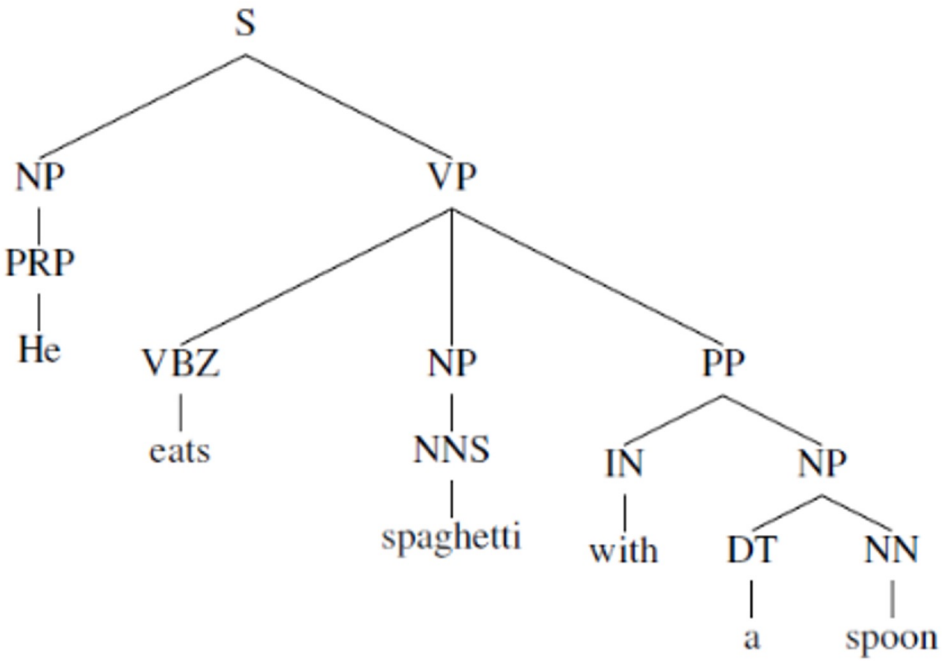
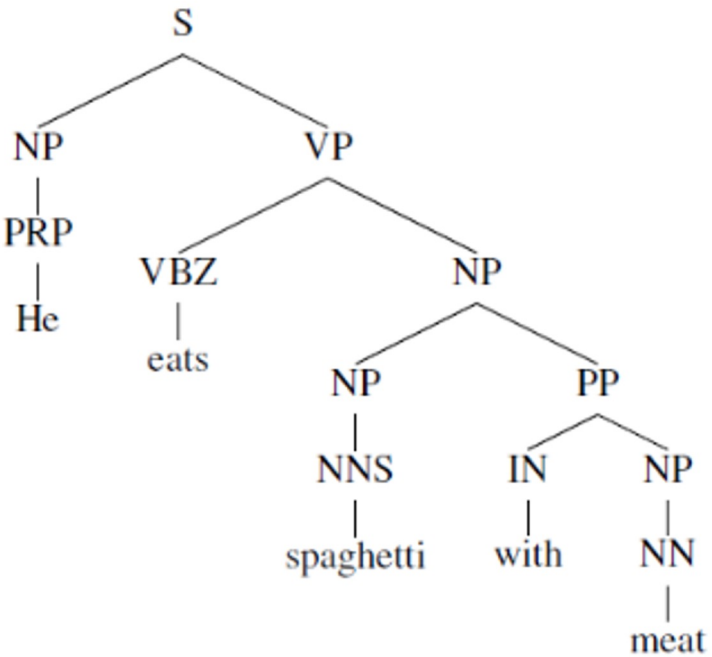
Cases where recursive might be better?



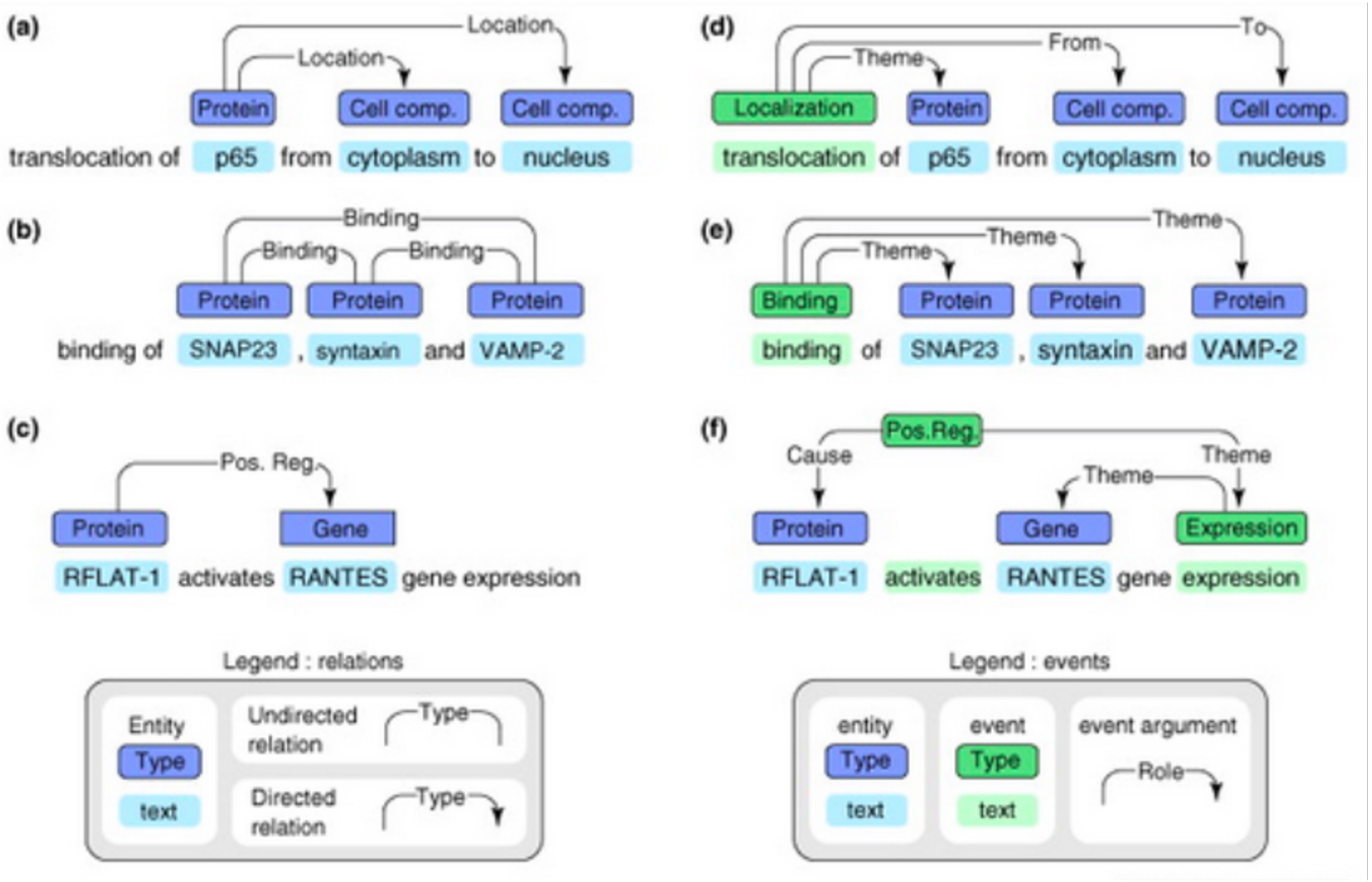


But recurrent structures might be able to learn this too…

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

Application of parse trees: info extraction

parse tree + rule based extraction = more robust



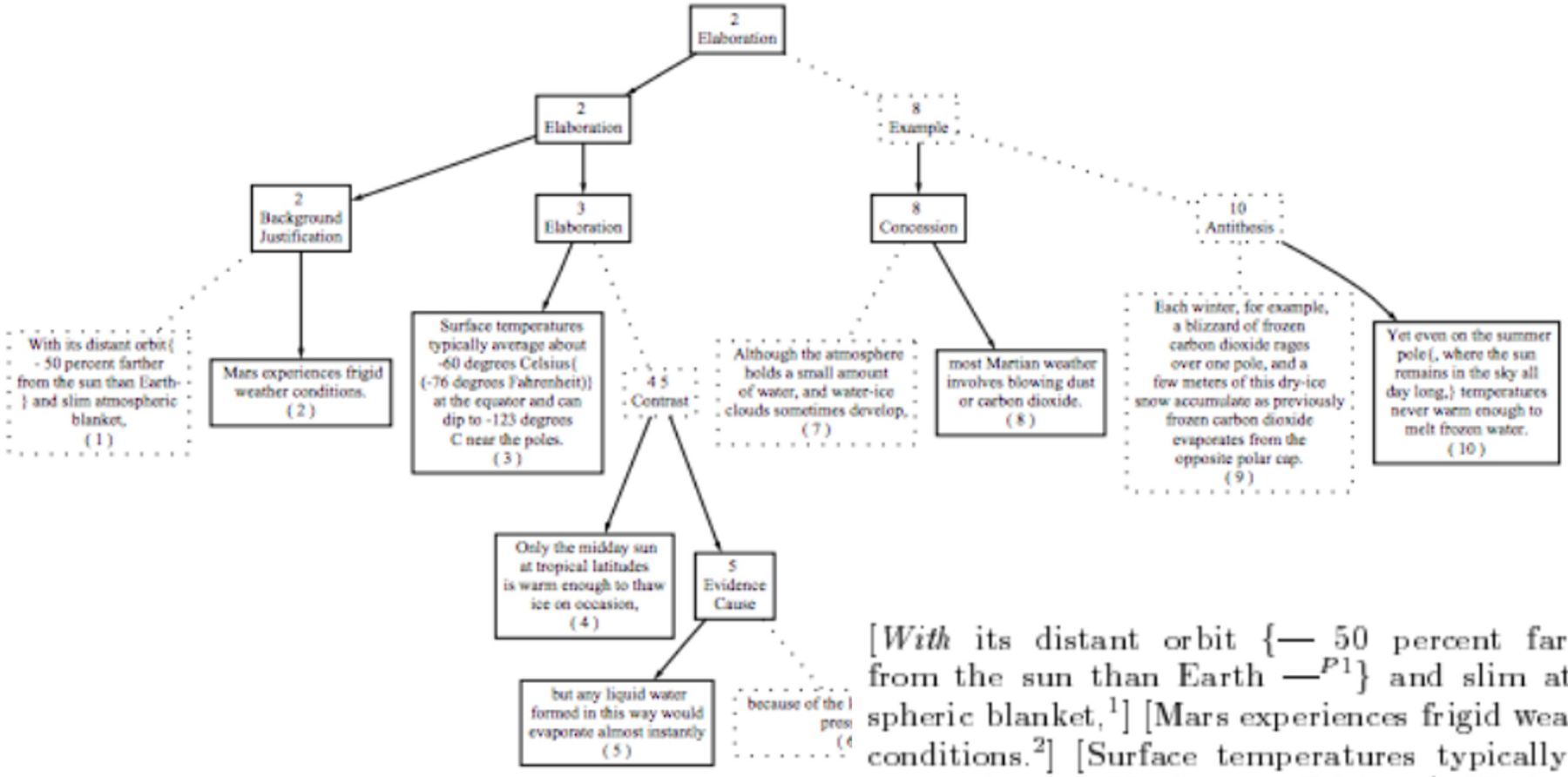
Application of parse trees: info extraction

parse tree + rule based extraction = more robust

EX ขอ สั่ง พิซซ่า หน้าฮาวายเอี้ยน
Rule: สั่ง + XXX

ขอ สั่ง พิซซ่า ให้ มา ส่ง ที่ บ้าน ขอ หน้าฮาวายเอี้ยน นะ ครับ
The rule will break

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 constituent structures

A context-free grammar example

A CFG is defined by
$G = (N, S, \Sigma, R)$

- 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	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
NP	⇒	NP	PP
PP	⇒	IN	NP

Vi	⇒	sleeps
Vt	⇒	saw
NN	⇒	man
NN	⇒	woman
NN	⇒	telescope
DT	⇒	the
IN	⇒	with
IN	⇒	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	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
NP	⇒	NP	PP
PP	⇒	IN	NP

Vi	⇒	sleeps
Vt	⇒	saw
NN	⇒	man
NN	⇒	woman
NN	⇒	telescope
DT	⇒	the
IN	⇒	with
IN	⇒	in

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

Return if terminal

- 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	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
NP	⇒	NP	PP
PP	⇒	IN	NP

Vi	⇒	sleeps
Vt	⇒	saw
NN	⇒	man
NN	⇒	woman
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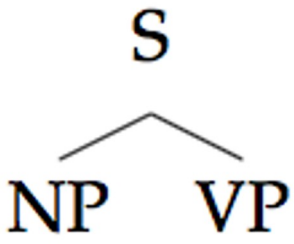
DT	⇒	the
IN	⇒	with
IN	⇒	in

Example

- The woman saw the man with the telescope



$R =$

S	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
NP	⇒	NP	PP
PP	⇒	IN	NP

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Example

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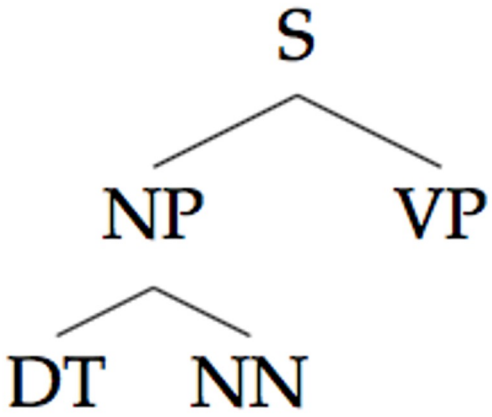

$R =$

S	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
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Example

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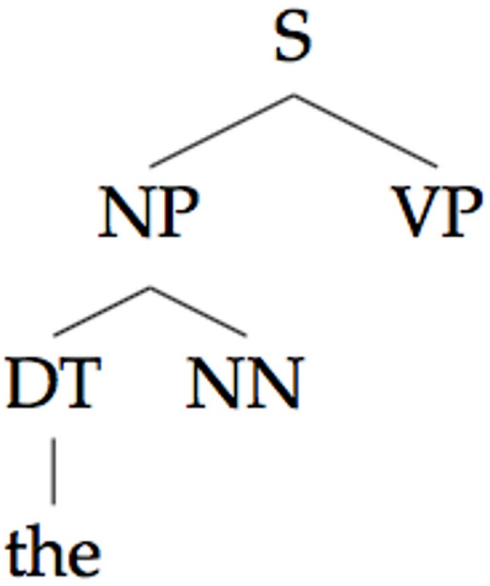

$R =$

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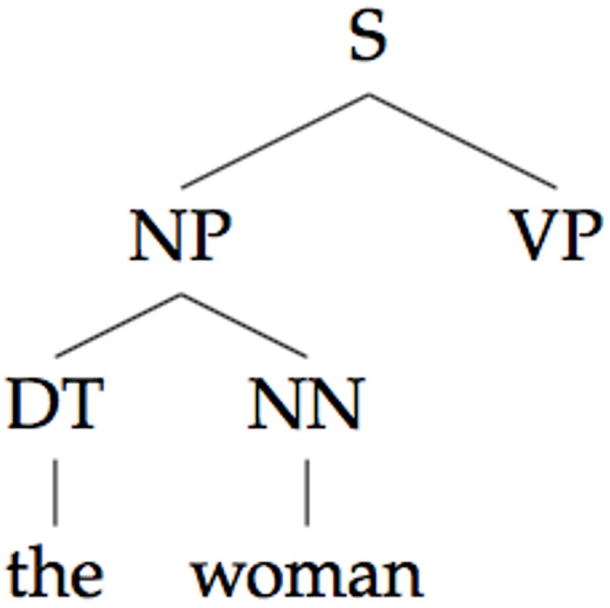
Example

- The woman saw the man with the telescope



$R =$

S	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
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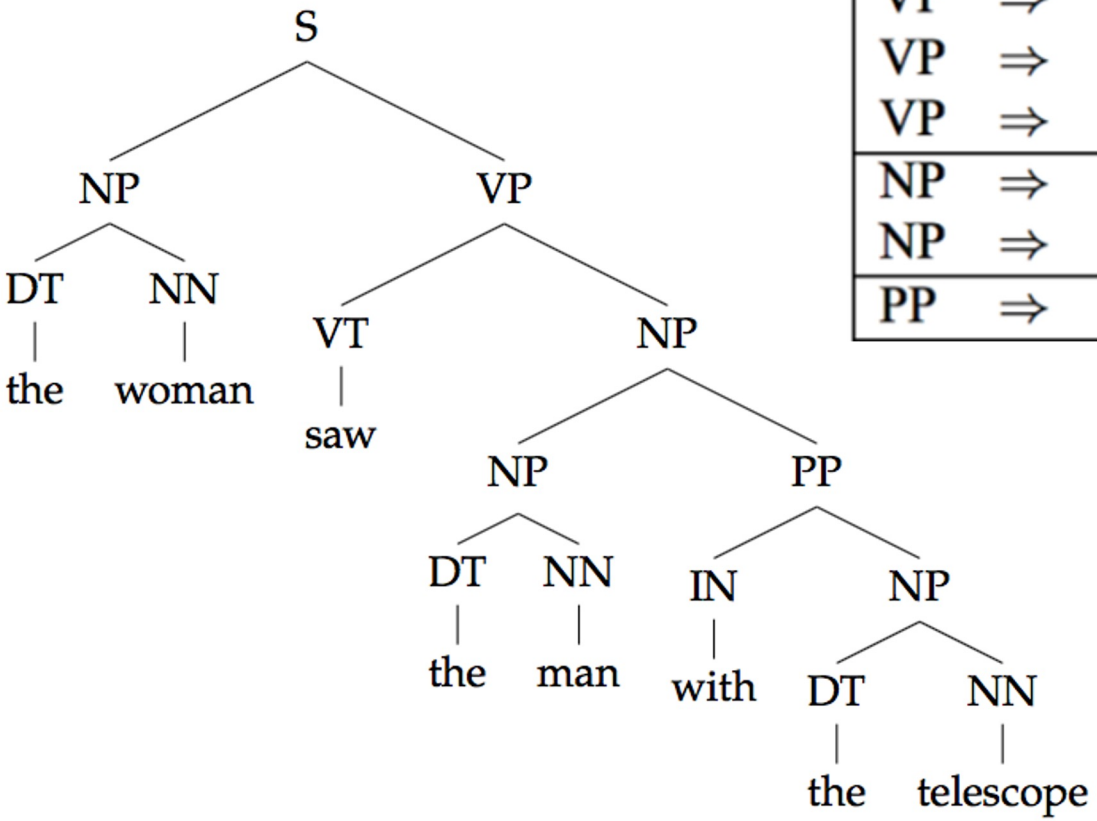
Example

- The woman saw the man with the telescope



$R =$

S	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
NP	⇒	NP	PP
PP	⇒	IN	NP

Vi	⇒	sleeps
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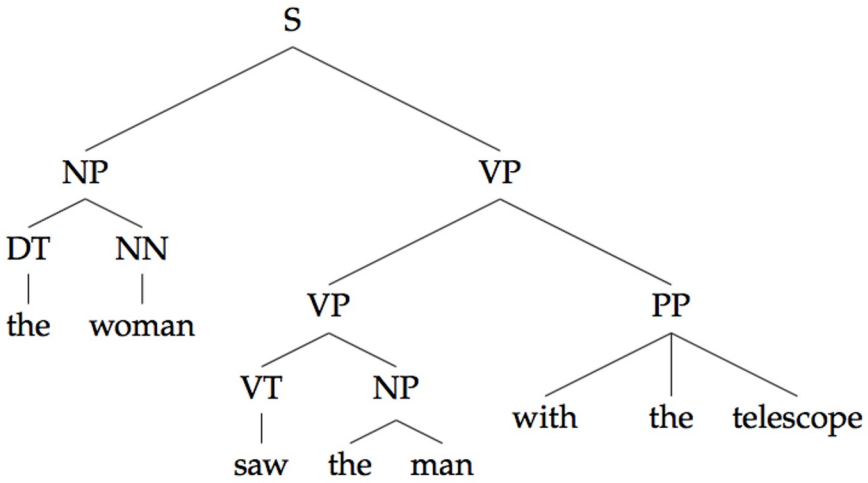
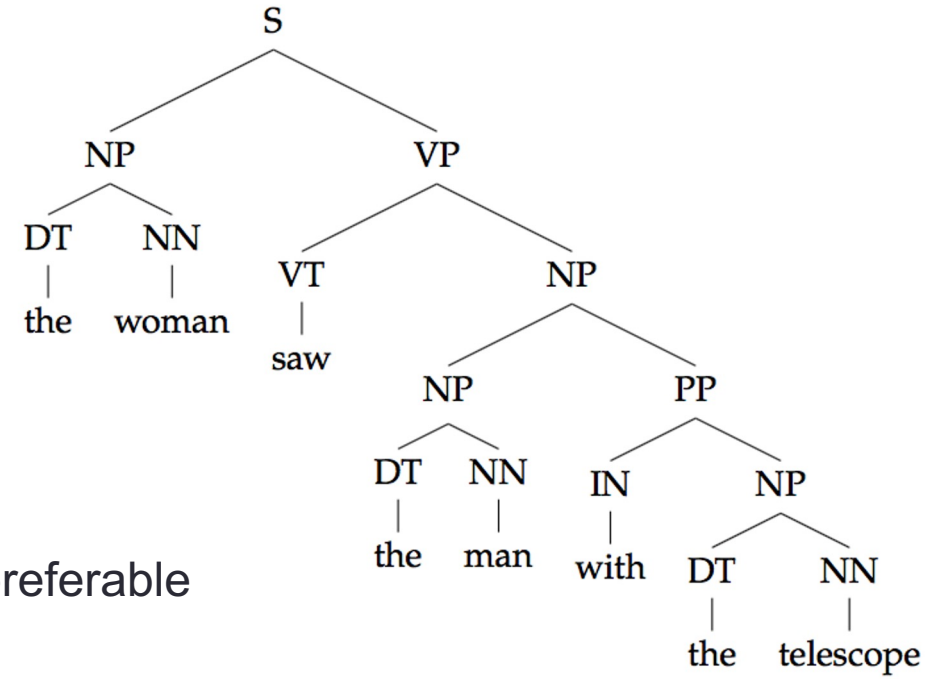
NN	⇒	man
NN	⇒	woman
NN	⇒	telescope
DT	⇒	the
IN	⇒	with
IN	⇒	in

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

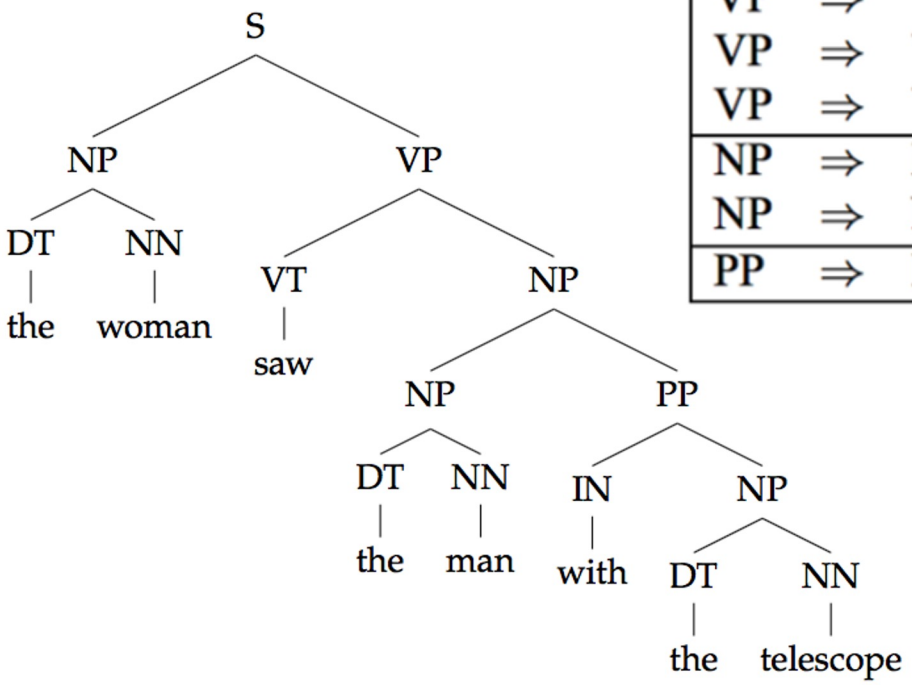
$$p(S,T) = \prod_{i=1}^{m} p(\alpha_i \rightarrow \beta_i | \alpha_i)$$

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	⇒	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

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)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VITERBI
CYK
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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	⇒	NP	VP
VP	⇒	Vi	
VP	⇒	Vt	NP
VP	⇒	VP	PP
NP	⇒	DT	NN
NP	⇒	NP	PP
PP	⇒	IN	NP

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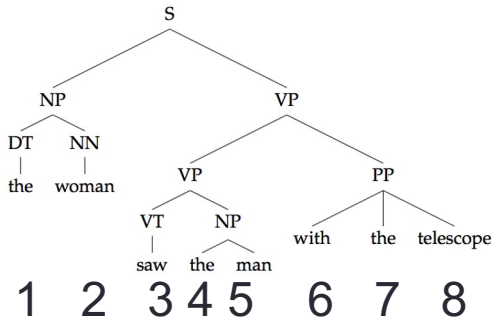
Production rules
$X \rightarrow Y_1 \ldots Y_n$
Y_i can be terminal or nonterminal
The rule only relies on X (no context)
(vs context-sensitive)

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:

k is the index that splits the subsentence

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

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)

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

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")

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

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

A

a	0.2		
b		0	
c			0

B

a	0		
b		0.1	
c			0.2

1st 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

Only consider i, j where i < j

B

a	0		
b		0.1	
c			0.2

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")

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

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

$\boldsymbol{\pi}$(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")

$A \rightarrow AB$	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	
b		0	0
c			0

B

a	0	0	
b		0.1	0.014
c			0.2

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

2nd 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	0.016	
b		0	0
c			0

B

a	0	0	
b		0.1	0.014
c			0.2

π(2,3,B) = P(B -> B B)π(2,2,B)π(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

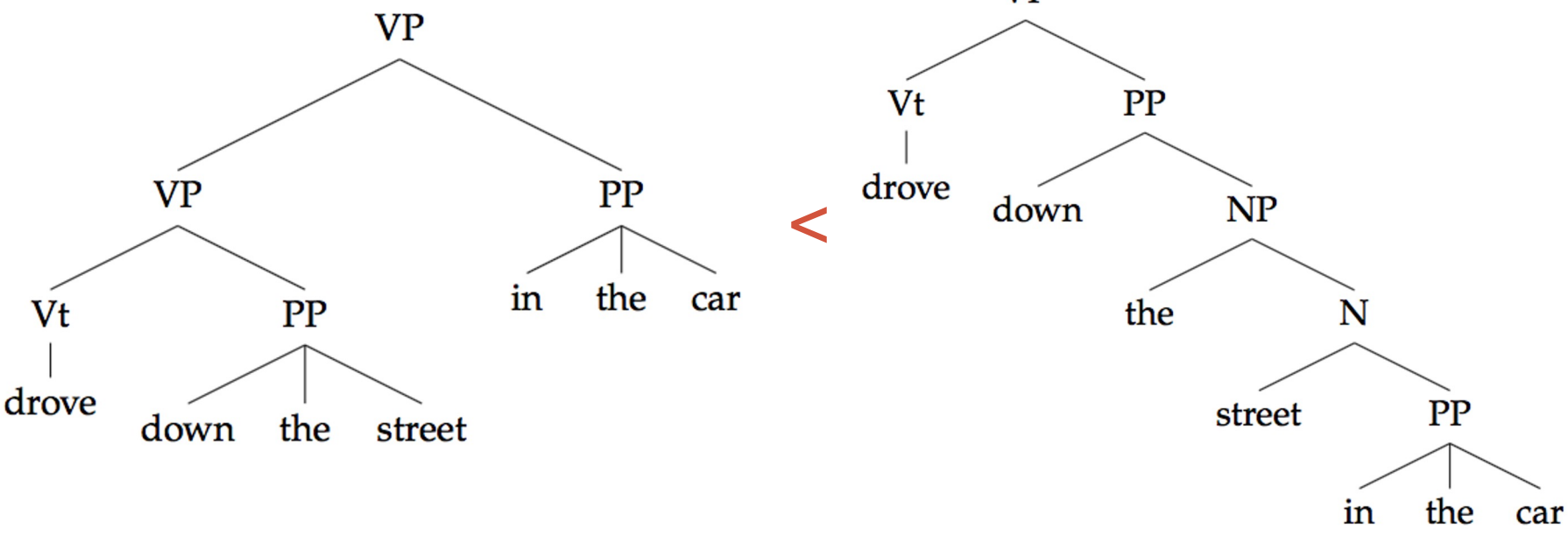
π(1,3,A) = P(A -> A B)π(1,2,A)π(3,3,B) + P(A -> A B)π(1,1,A)π(2,3,B)
= 0.8 * 0.016 * 0.2 + 0.8 * 0.2 * 0.014 = 0.0048

PCFG weakness

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

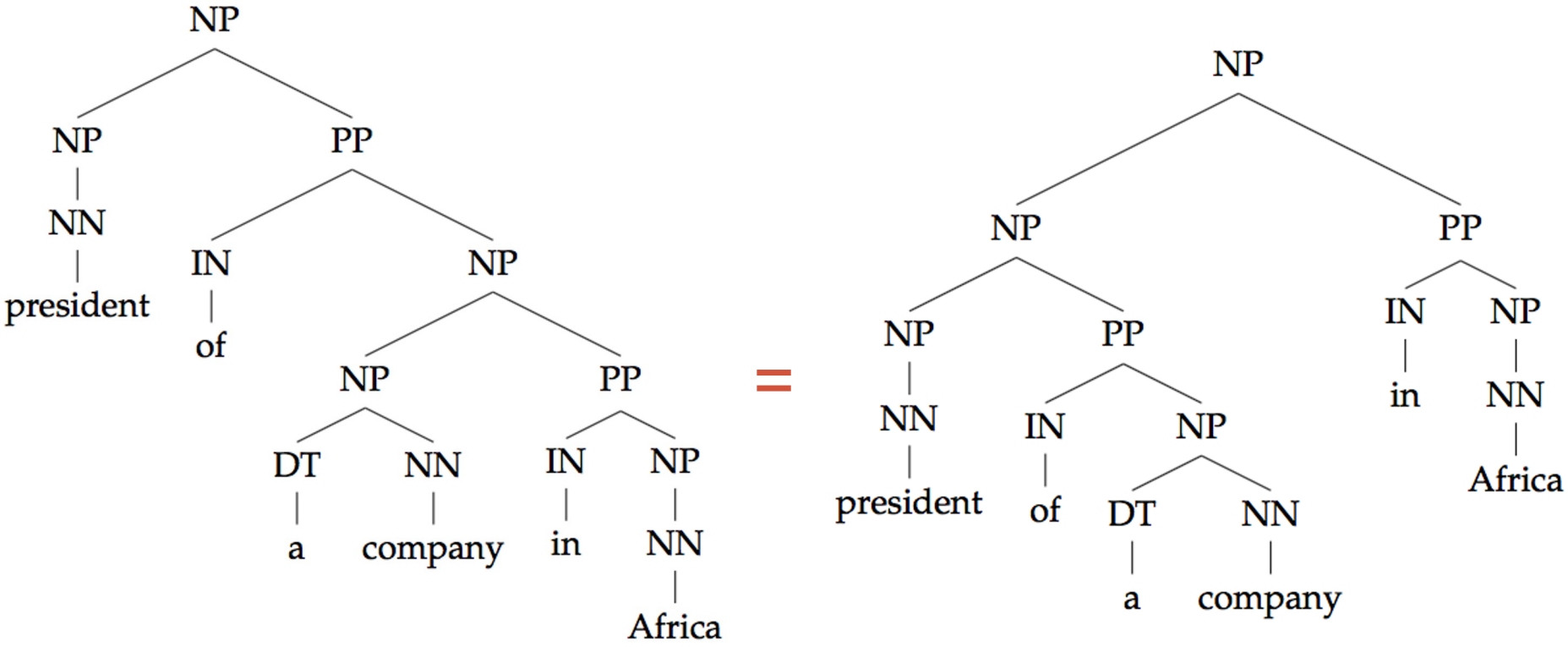
Lack of lexical info

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

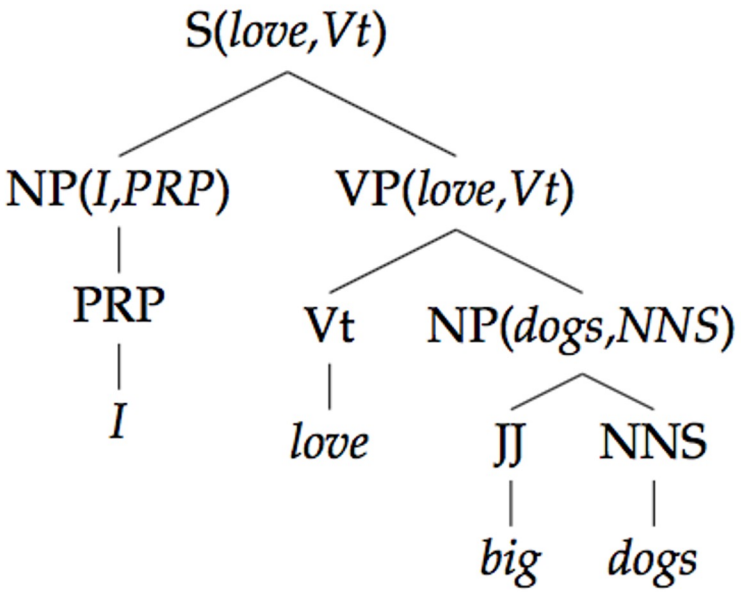
Turns out, left hand side structure appears more frequently in the training set

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

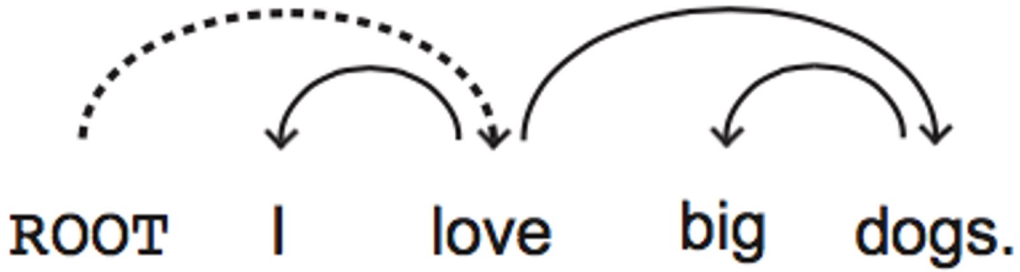
- Types of grammars
  - Context Free Grammar
  - Probabilistic Context Free Grammar
    - CYK parser
  - Dependency Grammar
    - Transition-based parsing
    - Recursive neural networks

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

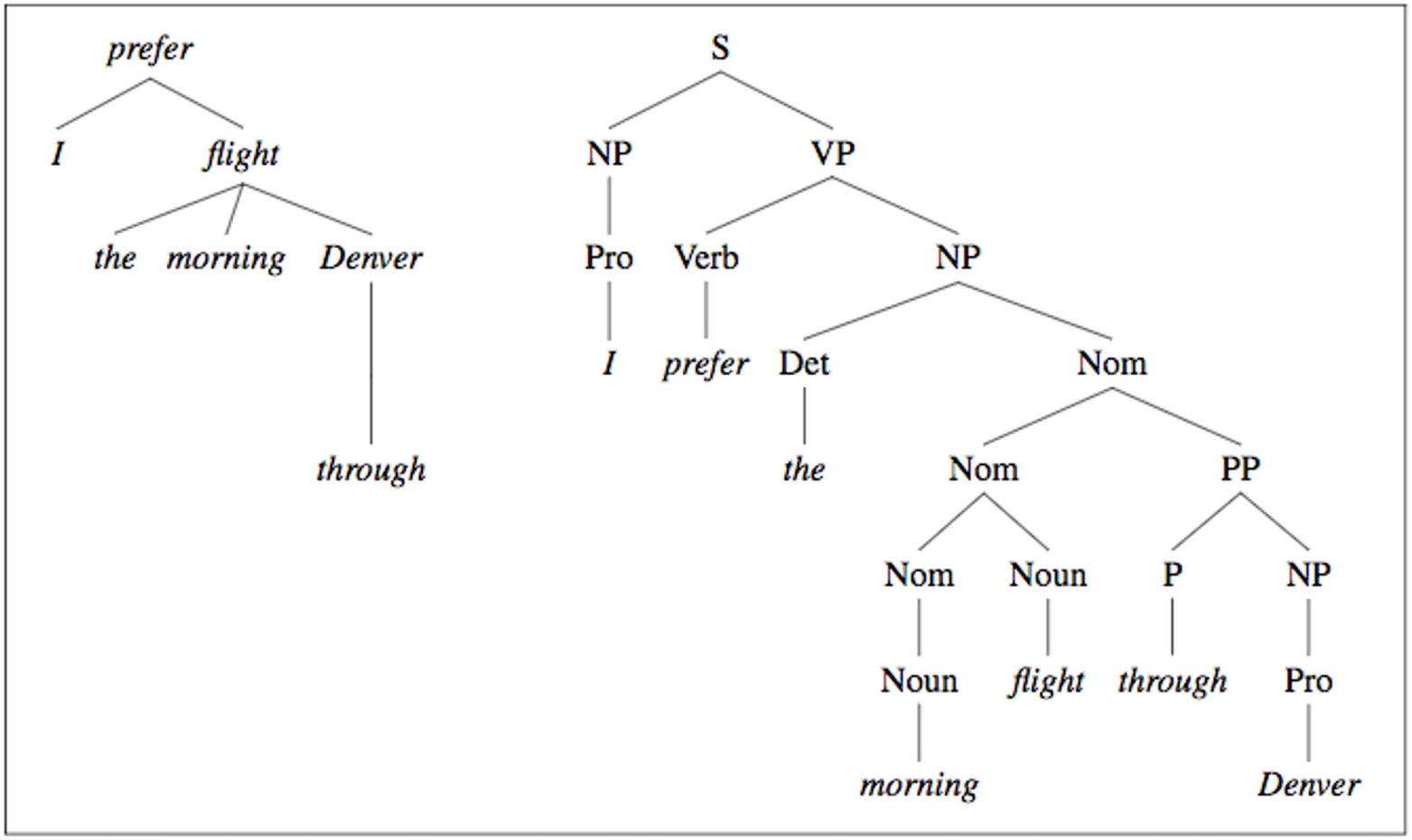


Figure 14.1 A dependency-style parse alongside the corresponding constituent-based analysis for *I prefer the morning flight through Denver.*

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

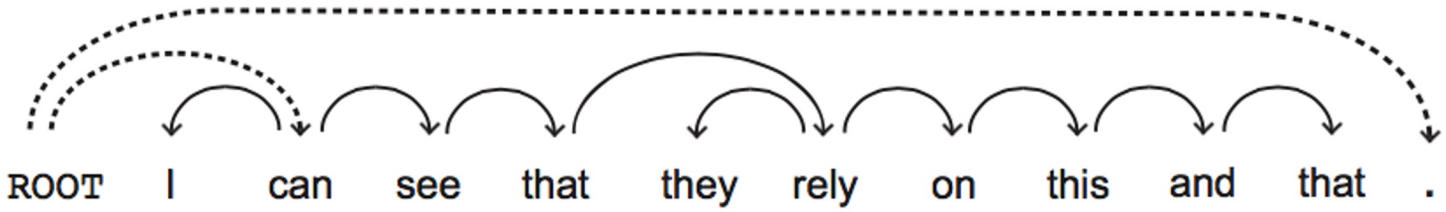
Constituency structures vs dependency structures

- 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 criteria! Mostly depends on corpus standard

Ex

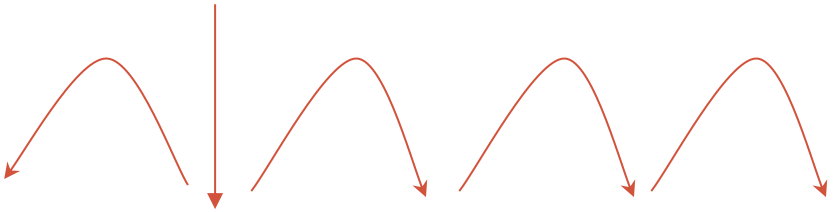


Dependency and meaning

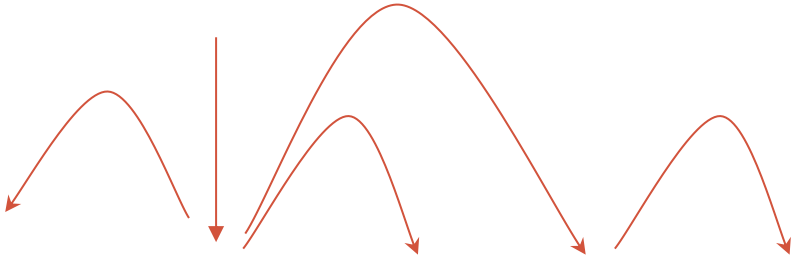
- Scientists study whales from space

- Scientists study whales from space

Dependency and meaning



- Scientists study whales from space



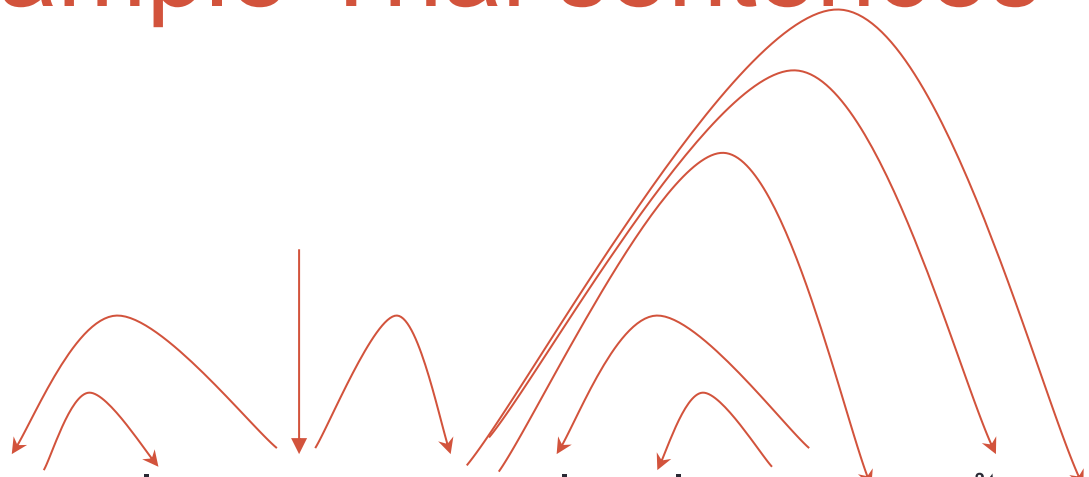
- Scientists study whales from space

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

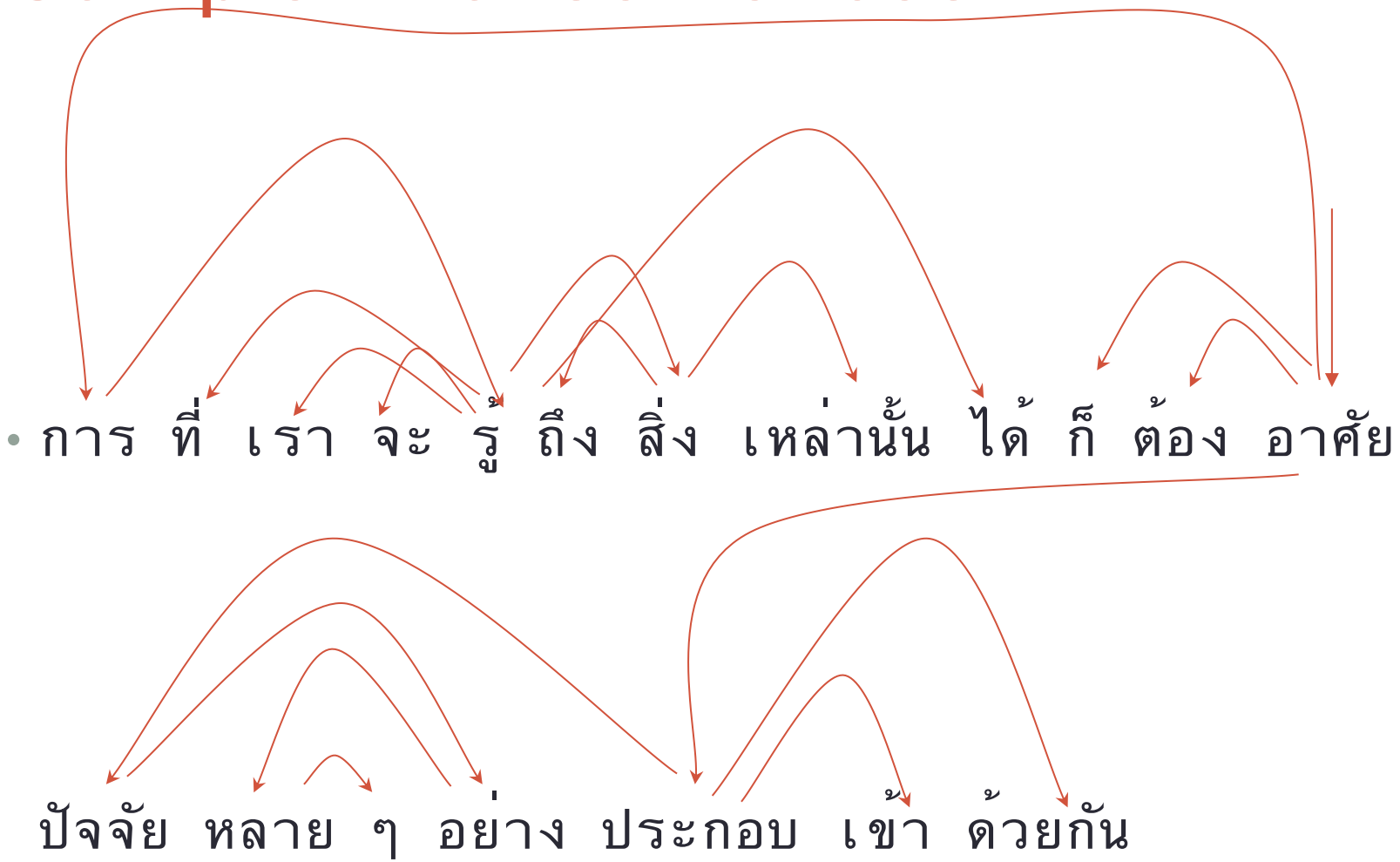
Sample Thai sentences



- วัน หนึ่ง เกิด เหตุ ที่ ไม่ คาดคิด ขึ้น มา

Note these criteria depends on the corpus convention

Sample Thai sentences



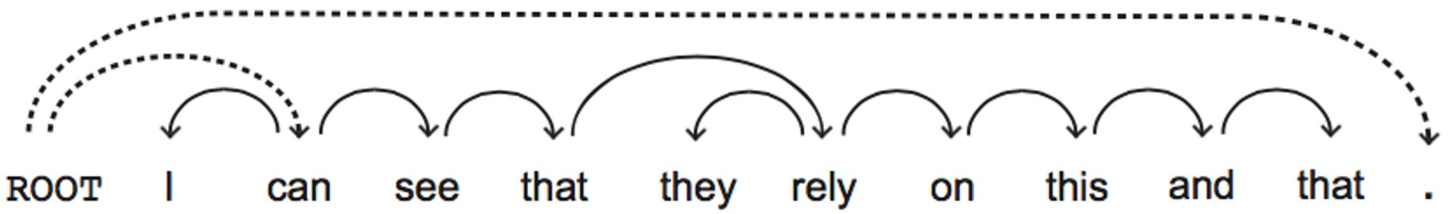
Note these criteria depends on the corpus convention

Dependency graph requirements

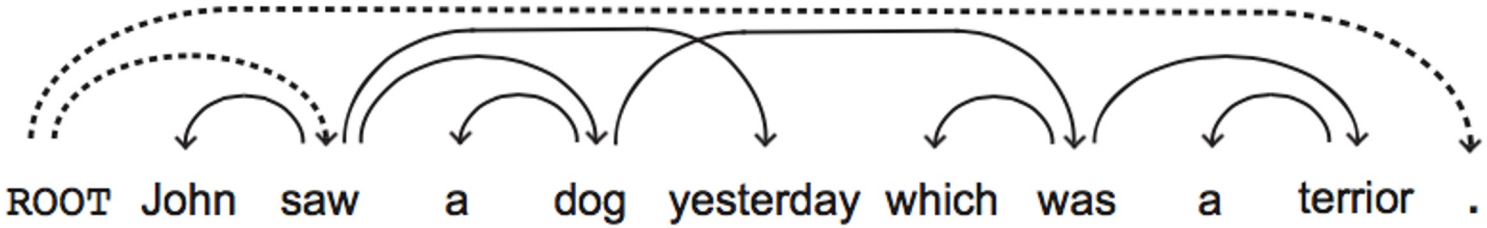
- Syntactic structure is complete (connectedness, spanning)
- Hierarchical (acyclic)
- Every word has a single head

Projectivity

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



projective



Non-projective

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

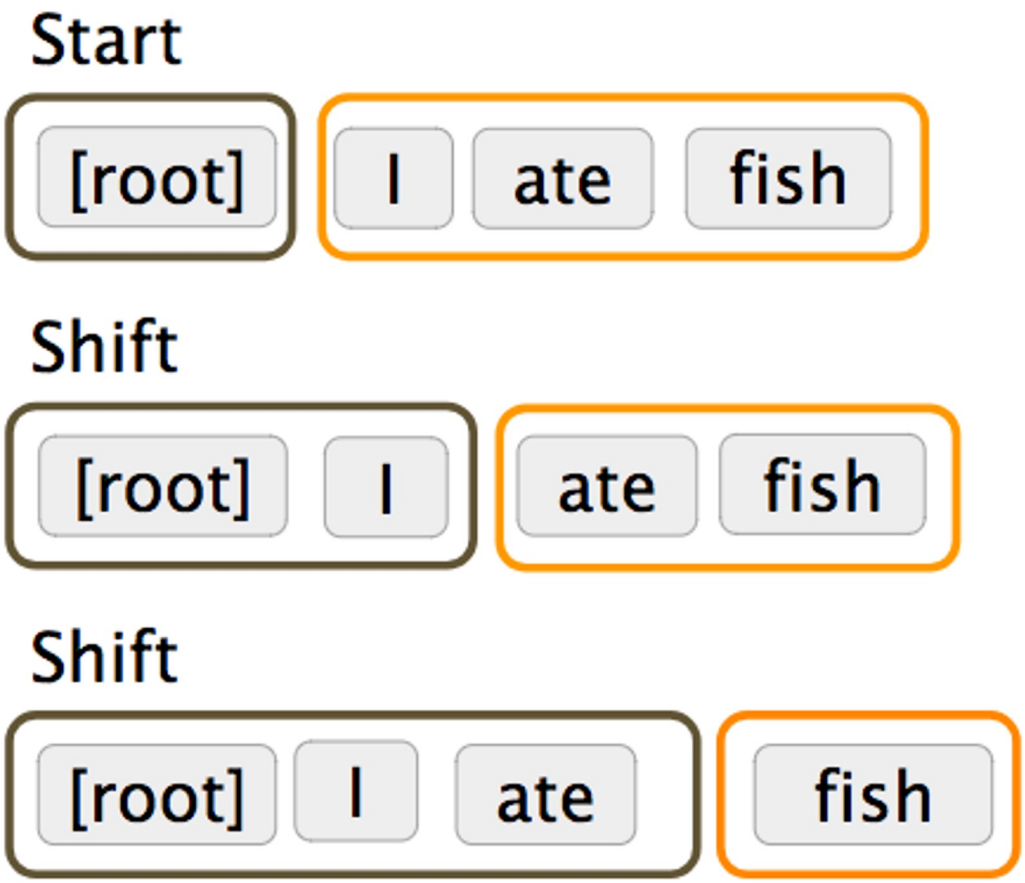
$$\sigma = [\text{ROOT}],\ \beta = w_1, \ldots, w_n,\ A = \varnothing$$

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



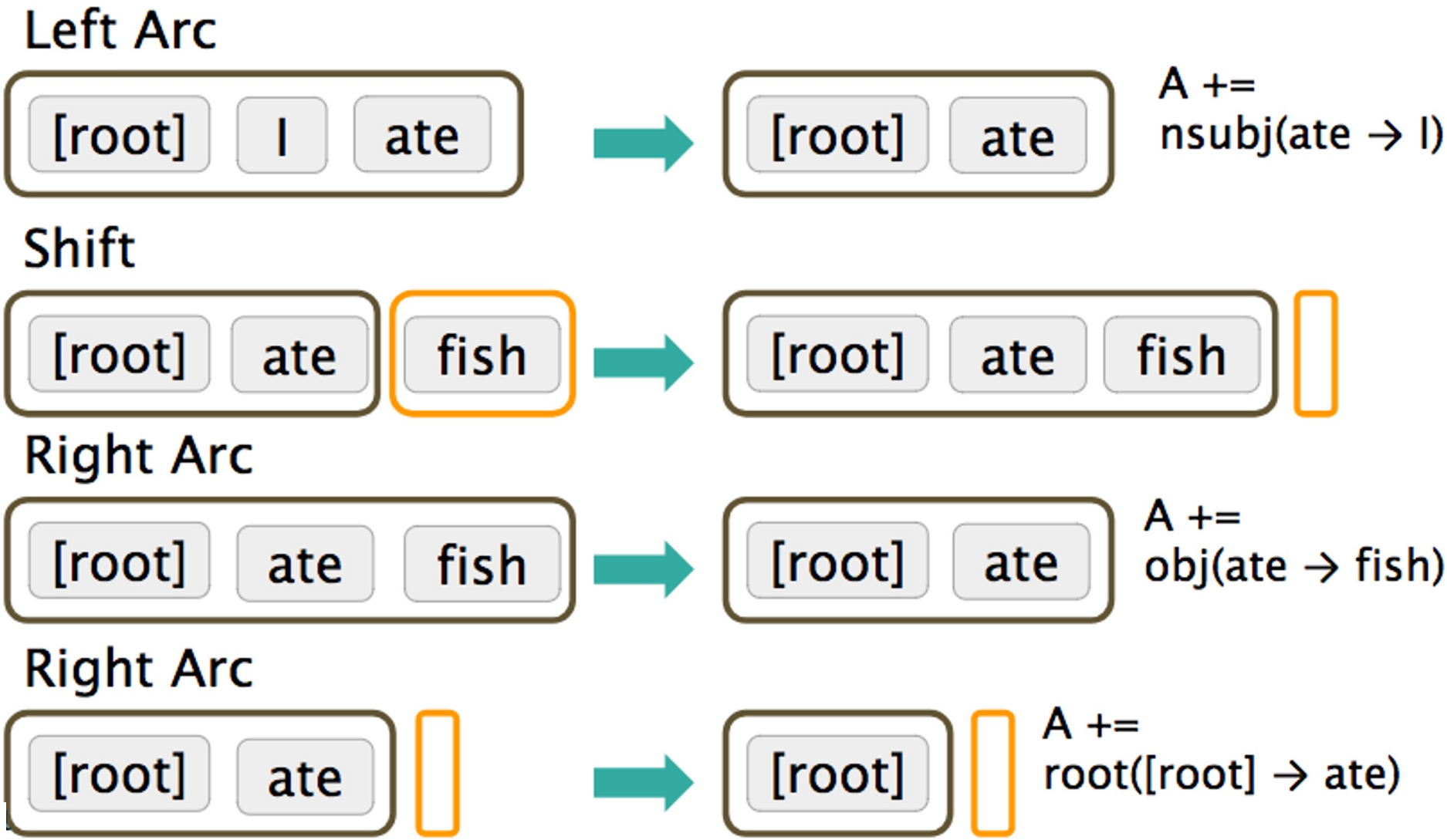
Start: $\sigma = [ROOT]$, $\beta = w_1, \ldots, w_n$, $A = \varnothing$

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:

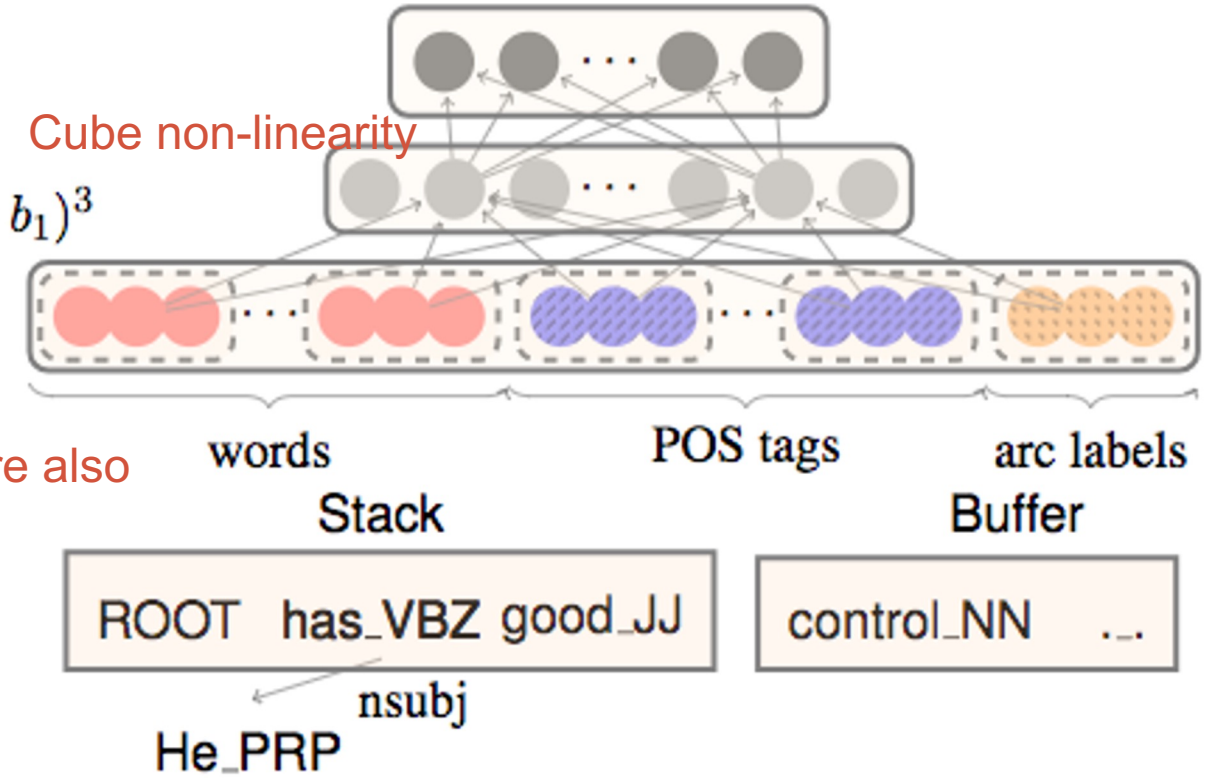
$$p = \texttt{softmax}(W_2 h)$$

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)

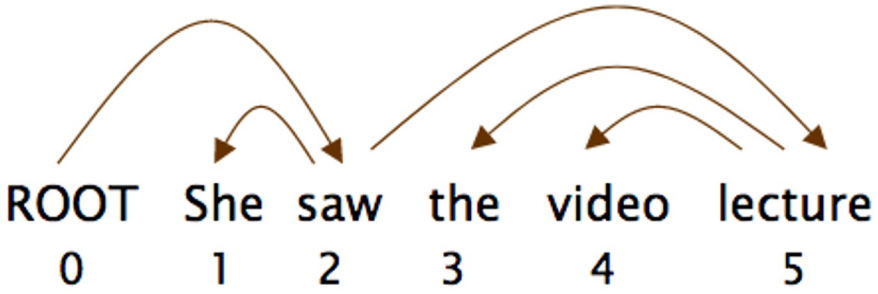
- Lead to SyntaxNet and Parsey McParseFace model

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

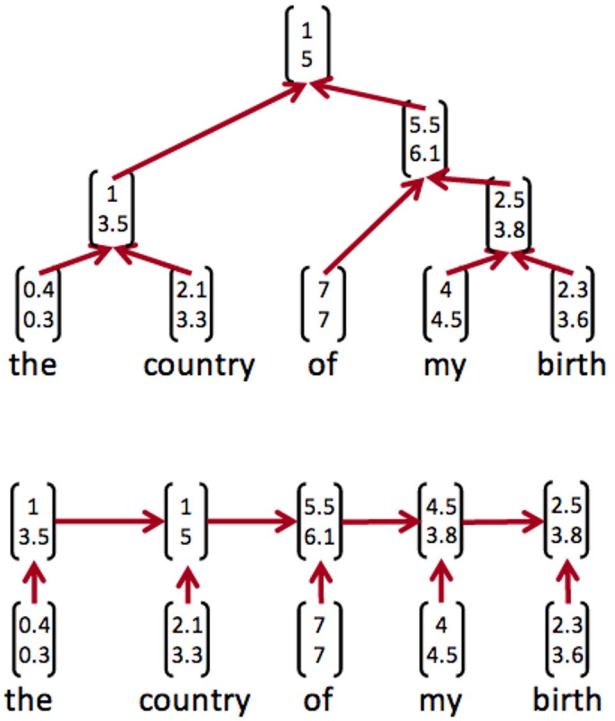
UAS of Parsey McParseFace

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

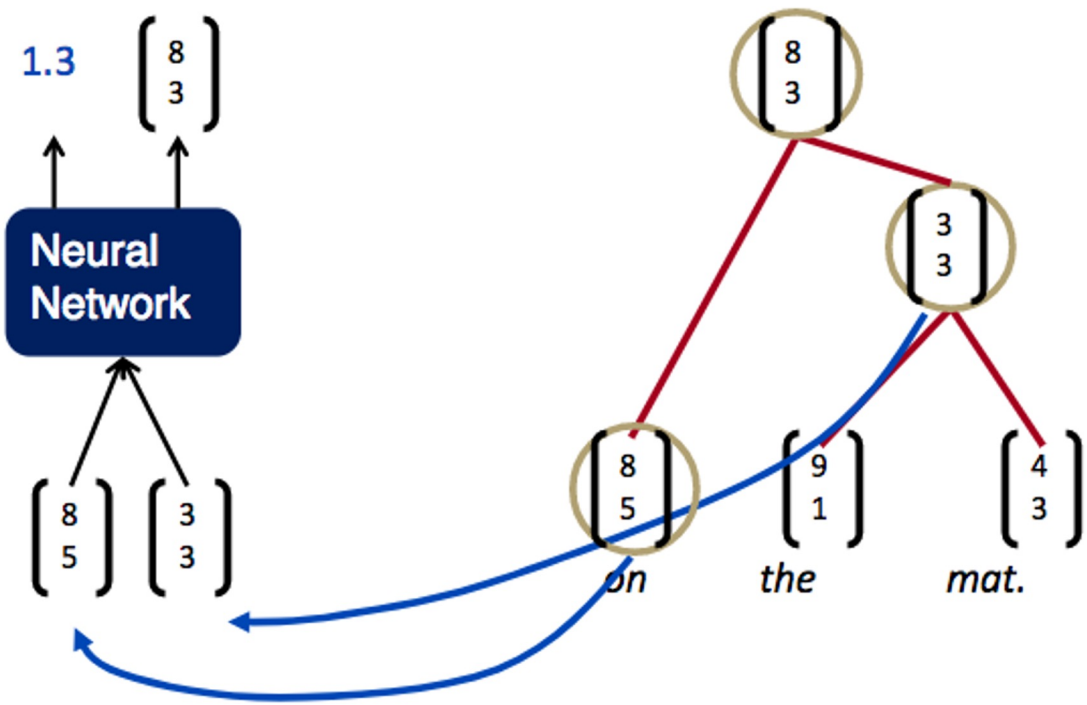
Recursive neural networks

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

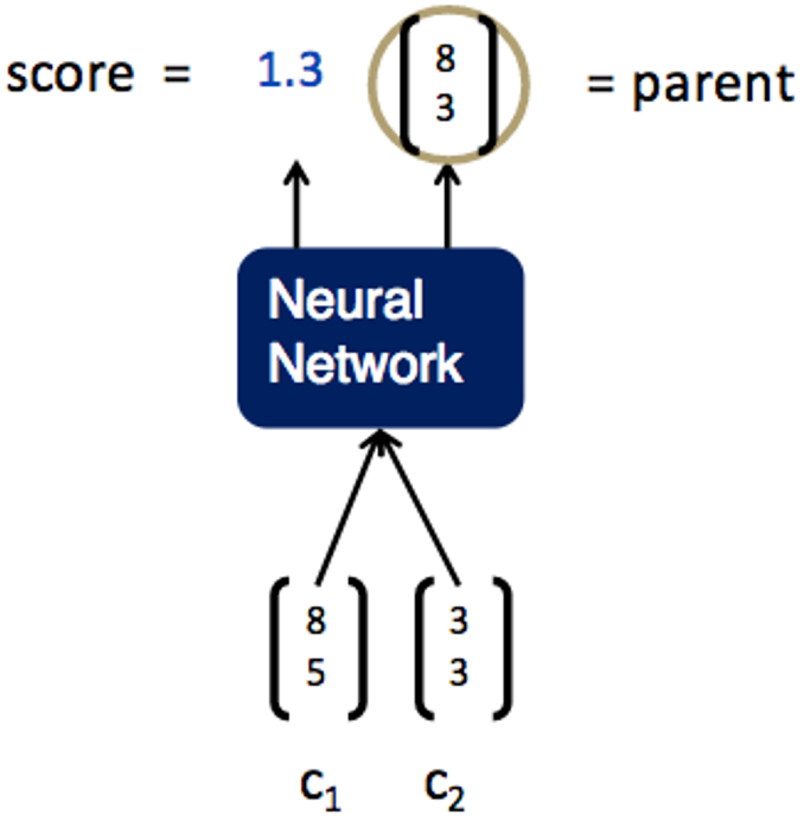


Recursive neural networks

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



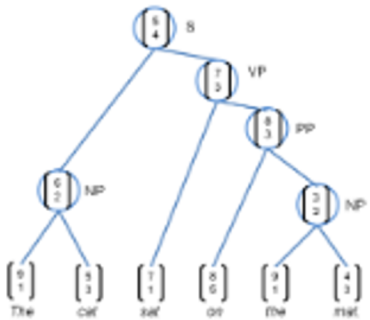
Shared recursive structure



score = $U^T p$

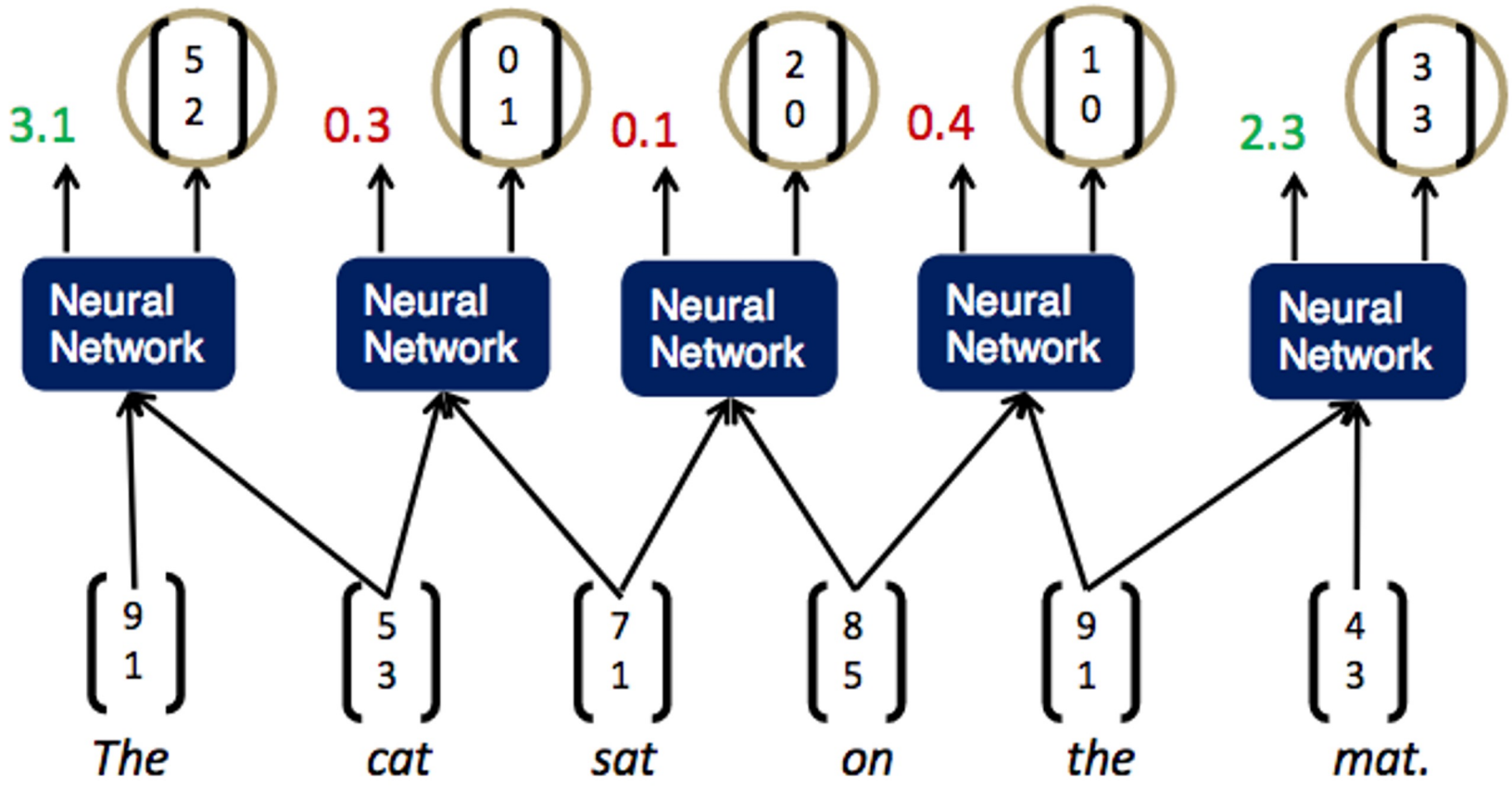
$$p = \tanh\left(W\begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right),$$

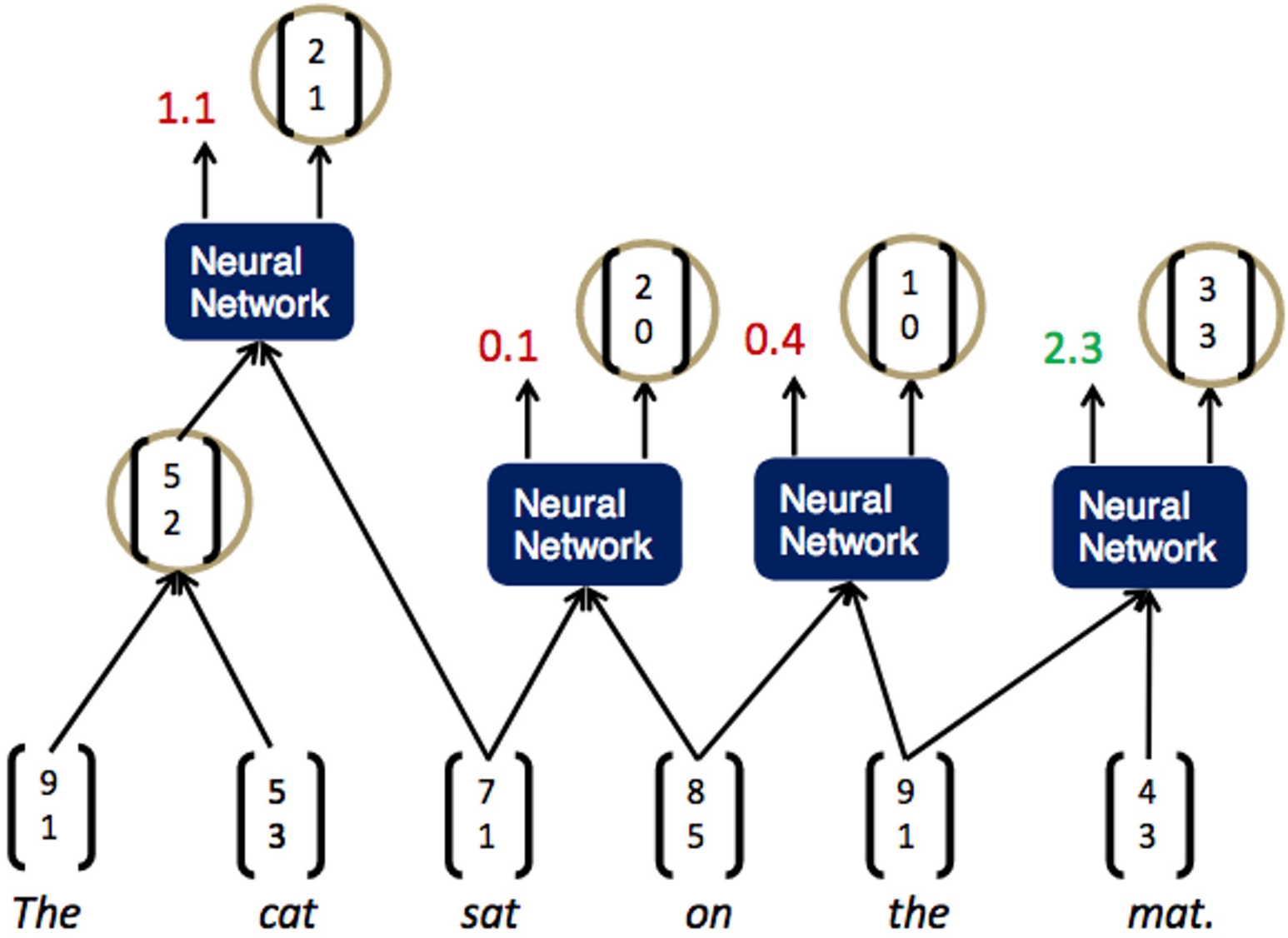
Same W parameters at all nodes of the tree

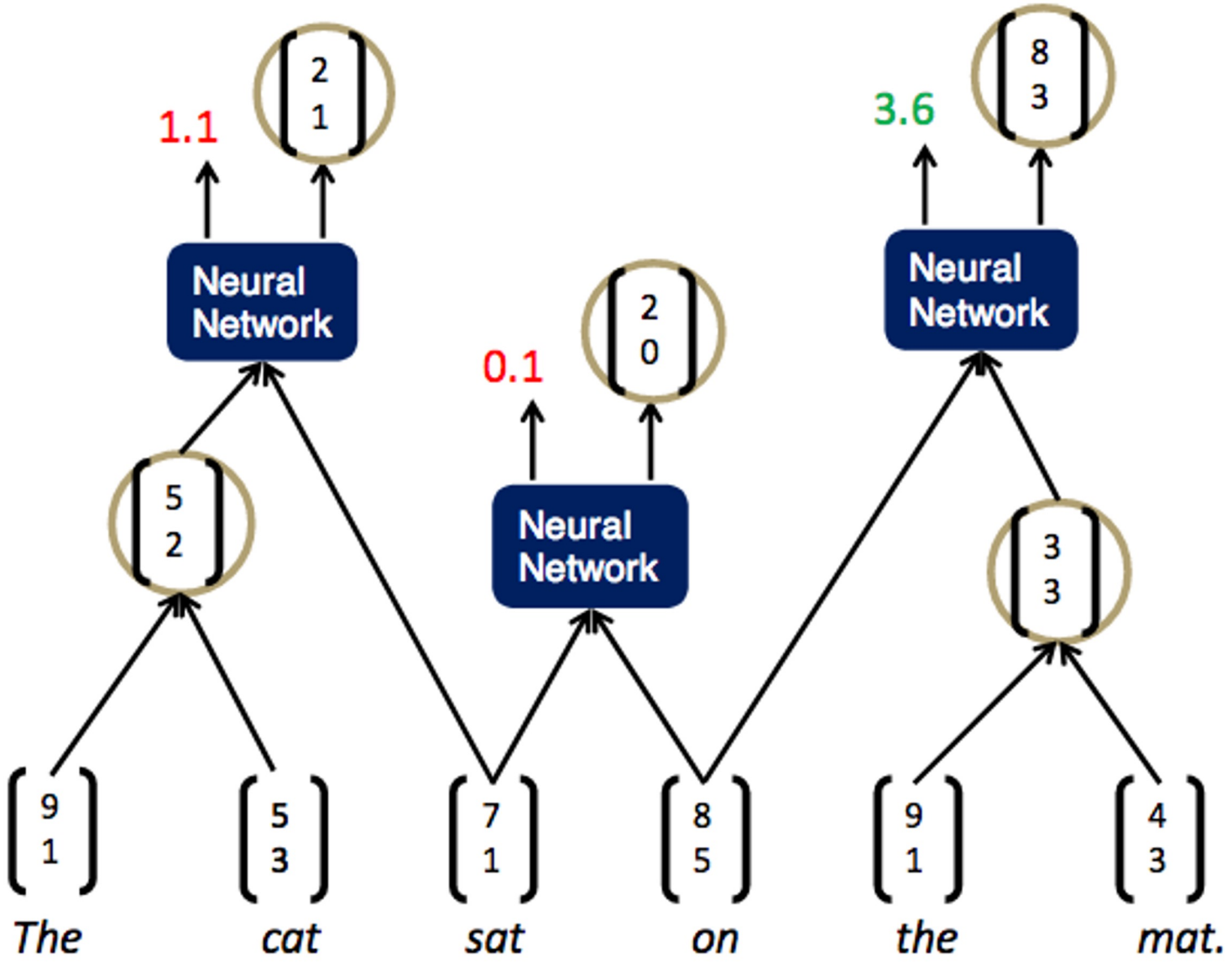


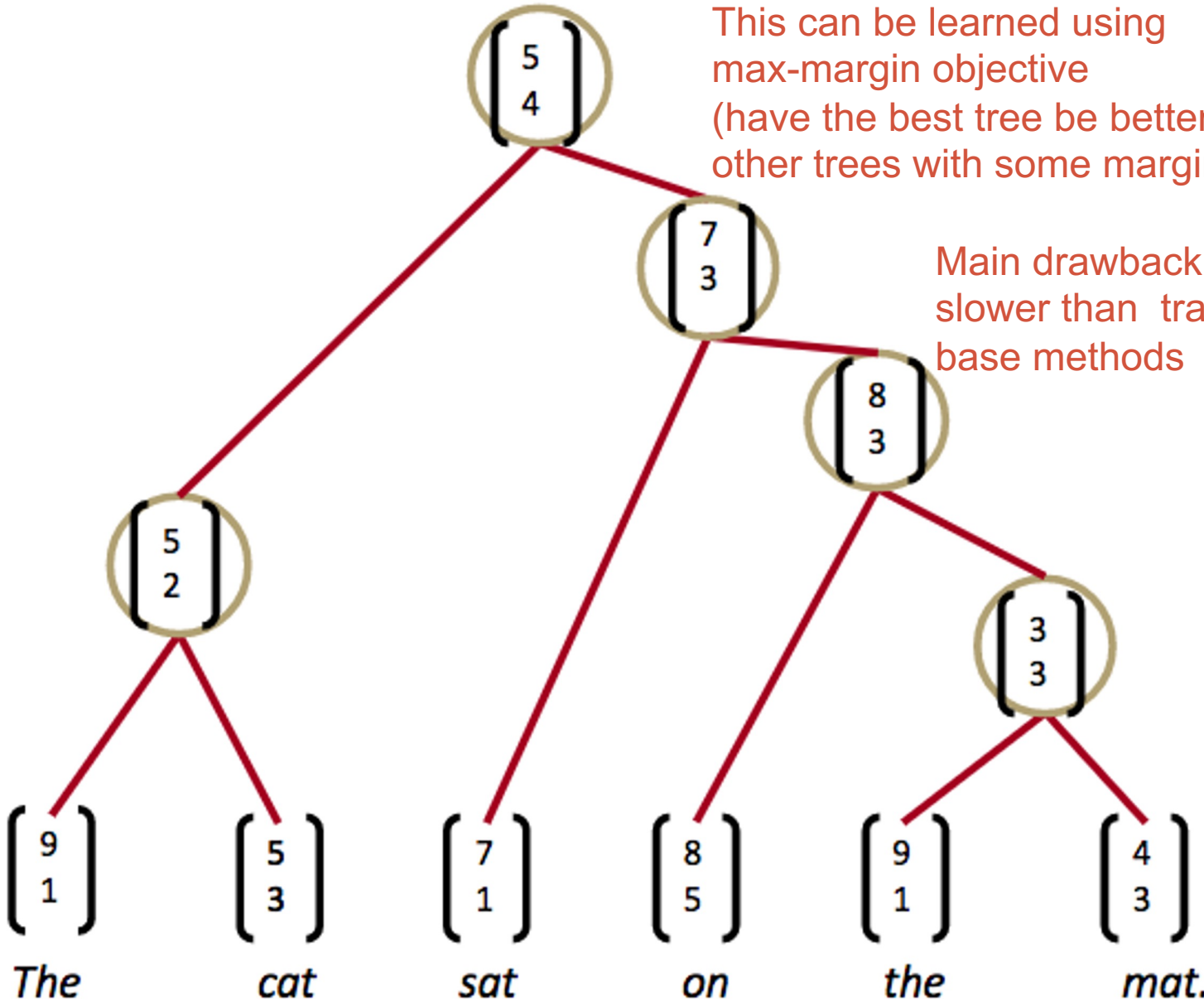
Parsing with recursive networks

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
5
3
7
1
8
5
9
1
4
3
The
cat
sat
on
the
mat.


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

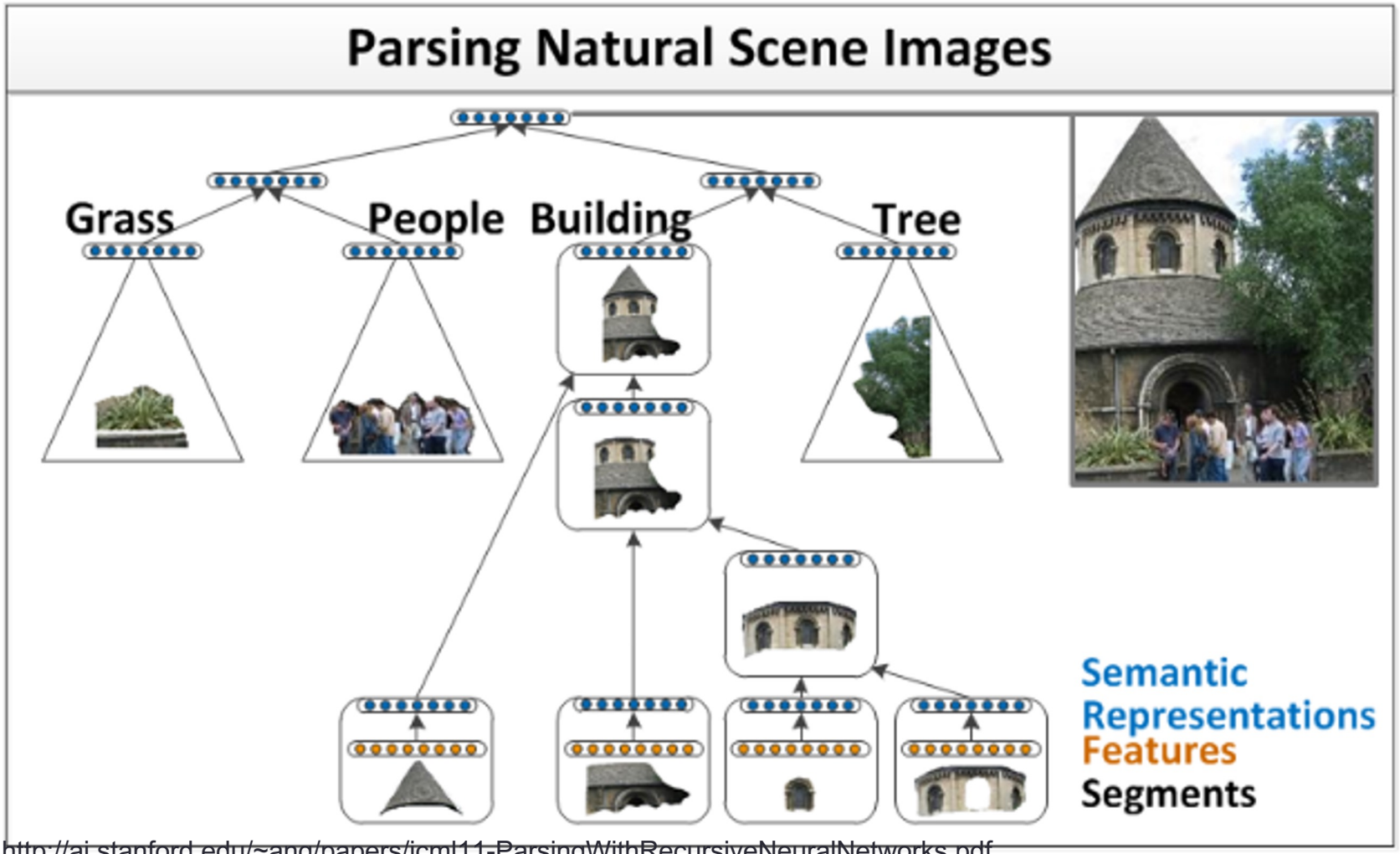


This can be learned using max-margin objective (have the best tree be better than other trees with some margin)

Main drawback, slower than transition-base methods

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

Recursive neural networks for scene parsing



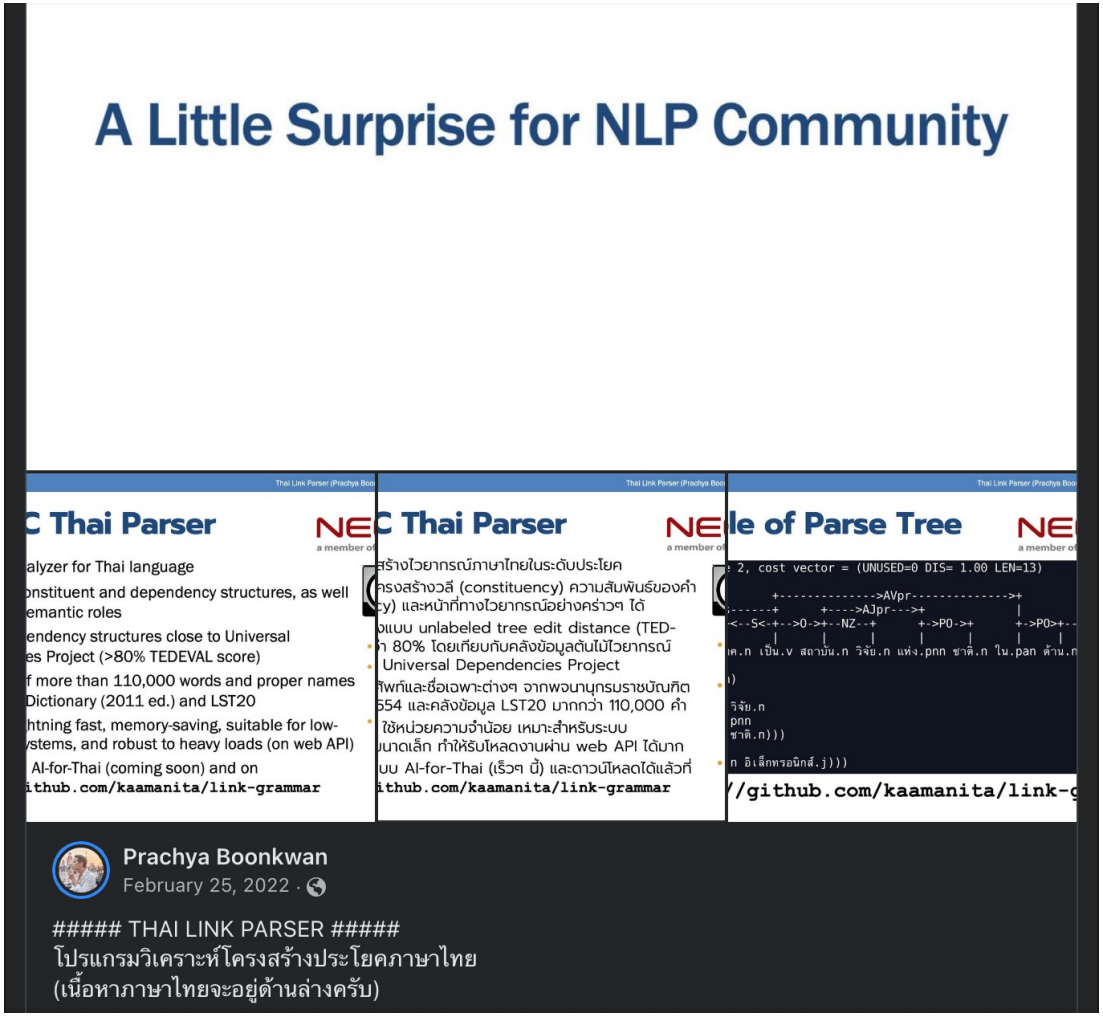
http://ai.stanford.edu/~ang/papers/icml11-ParsingWithRecursiveNeuralNetworks.pdf

Resources for parsing

- Orchid & corpuses by NECTEC
- http://universaldependencies.org/

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

Parsing corpus on LST20



https://web.facebook.com/dancearmy/posts/pfbid02GpMzUCgwgX3g87wVyioMYDGTVwnH8ZmFCVFRQKnC8erpgbbNgUps9AXFidVqA8cnl

NECTEC Thai Parser

NECTEC
a member of NSTDA

- Syntactic analyzer for Thai language
- Producing constituent and dependency structures, as well as general semantic roles
- Yielding dependency structures close to Universal Dependencies Project (>80% TEDEVAL score)
- Consisting of more than 110,000 words and proper names from ROYIN Dictionary (2011 ed.) and LST20
- Features: lightning fast, memory-saving, suitable for low-resourced systems, and robust to heavy loads (on web API)
- Available on AI-for-Thai (coming soon) and on **`https://github.com/kaamanita/link-grammar`**

- CC-BY License
- Easy-to-use interface with C/C++ and Python
- Full documentation for Thai Link Grammar coming soon

Example of Parse Tree

NECTEC
a member of NSTDA

```
        Linkage 2, cost vector = (UNUSED=0 DIS= 1.00 LEN=13)

                     +--------------->AVpr--------------->+
    +-------LWs------+       +---->AJpr--->+              |
    |         +<--S<-+-->O->+--NZ--+      +->PO->+      +->PO>+-->AJj-->+
    |         |      |      |      |      |      |      |     |          |
LEFT-WALL เนคเทค.n เป็น.v สถาบัน.n วิจัย.n แห่ง.pnn ชาติ.n ใน.pan ด้าน.n อิเล็กทรอนิกส์.j

(S (NP เนคเทค.n)
   เป็น.v
   (NP สถาบัน.n วิจัย.n
       (PP แห่ง.pnn
           (NP ชาติ.n)))
   (PP ใน.pan
       (NP ด้าน.n อิเล็กทรอนิกส์.j)))
```

https://github.com/kaamanita/link-grammar

Computer Science > Computation and Language

[Submitted on 12 Aug 2020]

The Annotation Guideline of LST20 Corpus

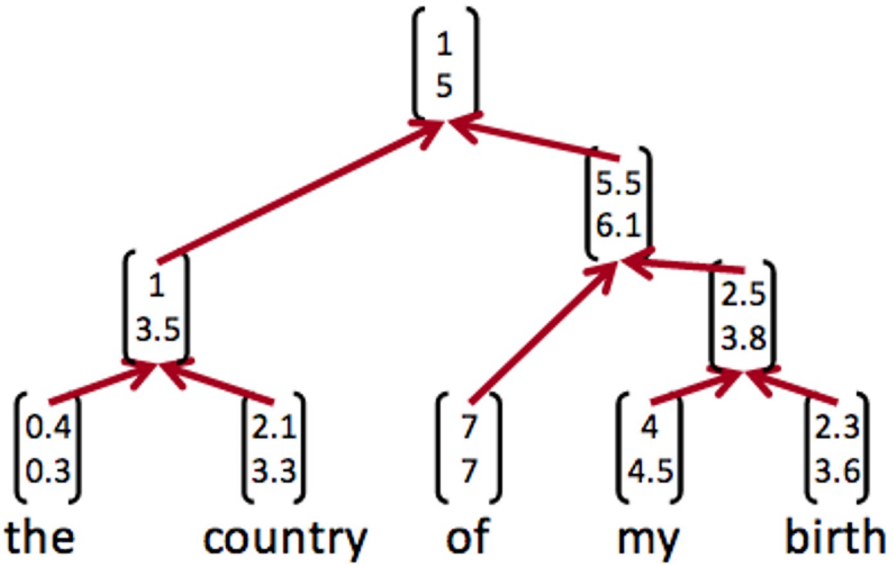
Prachya Boonkwan, Vorapon Luantangsrisuk, Sitthaa Phaholphinyo, Kanyanat Kriengket, Dhanon Leenoi, Charun Phrombut, Monthika Boriboon, Krit Kosawat, Thepchai Supnithi

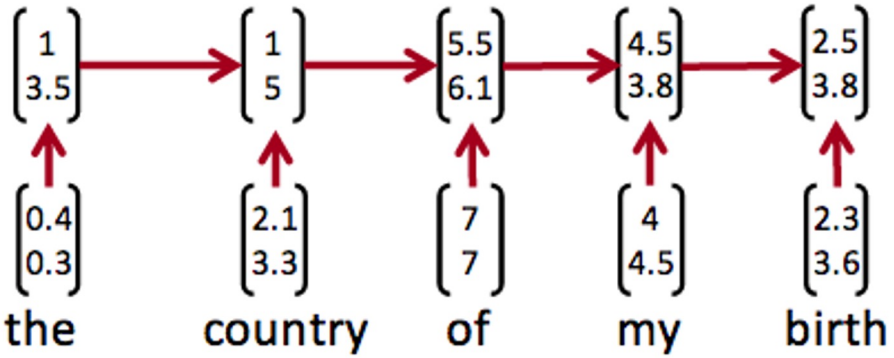
This report presents the annotation guideline for LST20, a large-scale corpus with multiple layers of linguistic annotation for Thai language processing. Our guideline consists of five layers of linguistic annotation: word segmentation, POS tagging, named entities, clause boundaries, and sentence boundaries. The dataset complies to the CoNLL-2003-style format for ease of use. LST20 Corpus offers five layers of linguistic annotation as aforementioned. At a large scale, it consists of 3,164,864 words, 288,020 named entities, 248,962 clauses, and 74,180 sentences, while it is annotated with 16 distinct POS tags. All 3,745 documents are also annotated with 15 news genres. Regarding its sheer size, this dataset is considered large enough for developing joint neural models for NLP. With the existence of this publicly available corpus, Thai has become a linguistically rich language for the first time.

Comments: 28 pages, 3 tables, 2 figures
Subjects: **Computation and Language (cs.CL)**
MSC classes: 68T50
ACM classes: I.2.7
Cite as: arXiv:2008.05055 **[cs.CL]**
(or arXiv:2008.05055v1 **[cs.CL]** for this version)
https://doi.org/10.48550/arXiv.2008.05055

https://arxiv.org/abs/2008.05055

Recursive vs Recurrent representation

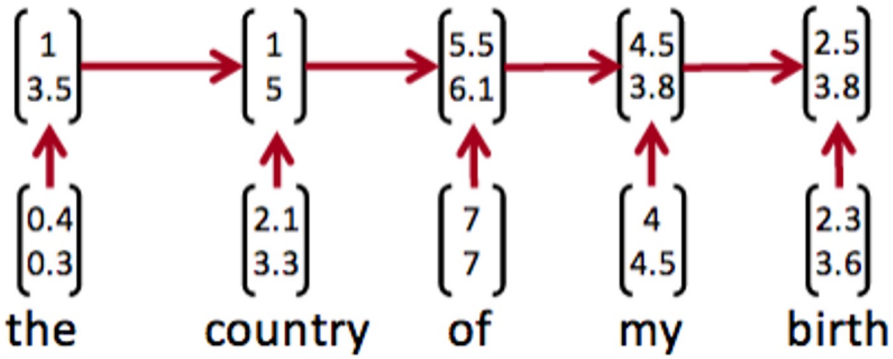




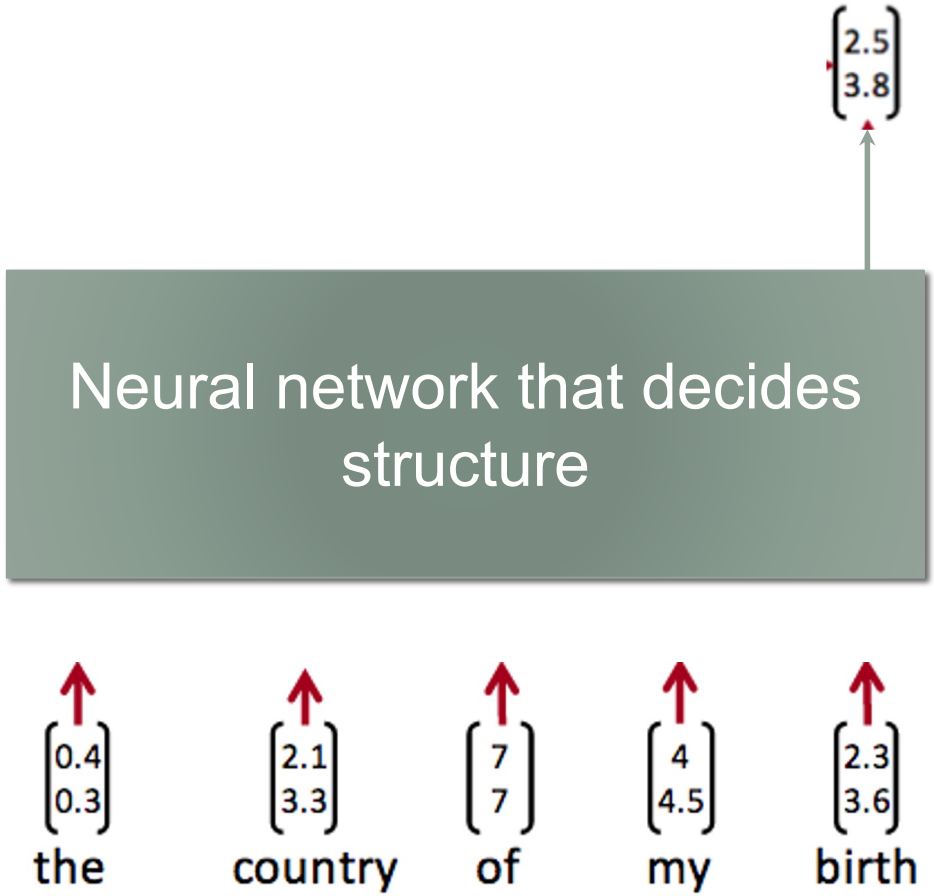
resurgence of recursive idea in newer BERTs

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

Towards unsupervised dependency parsing



Towards unsupervised dependency parsing

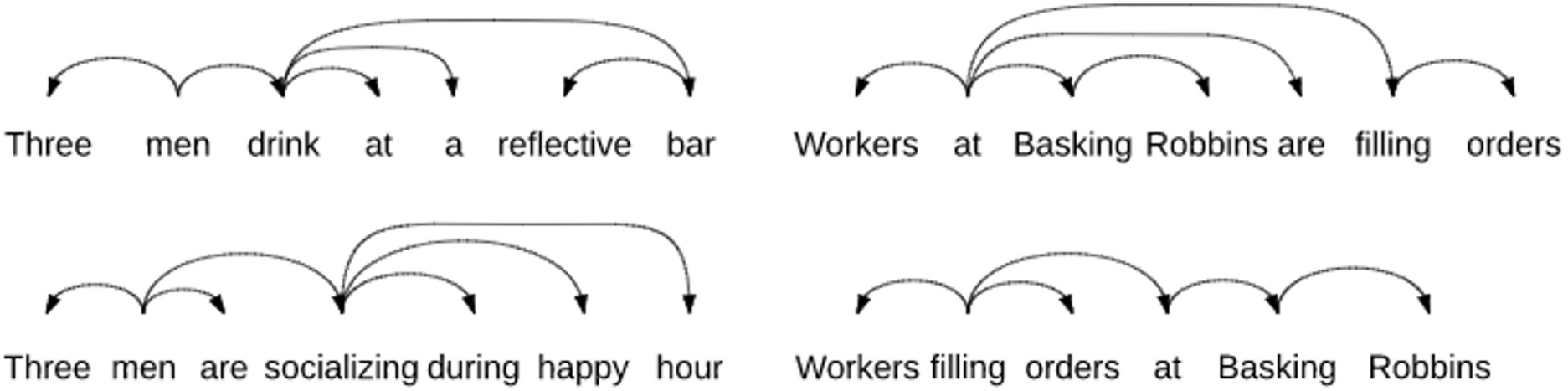


What is this piece? Next lecture! (attention modeling)

A top down end-to-end approach

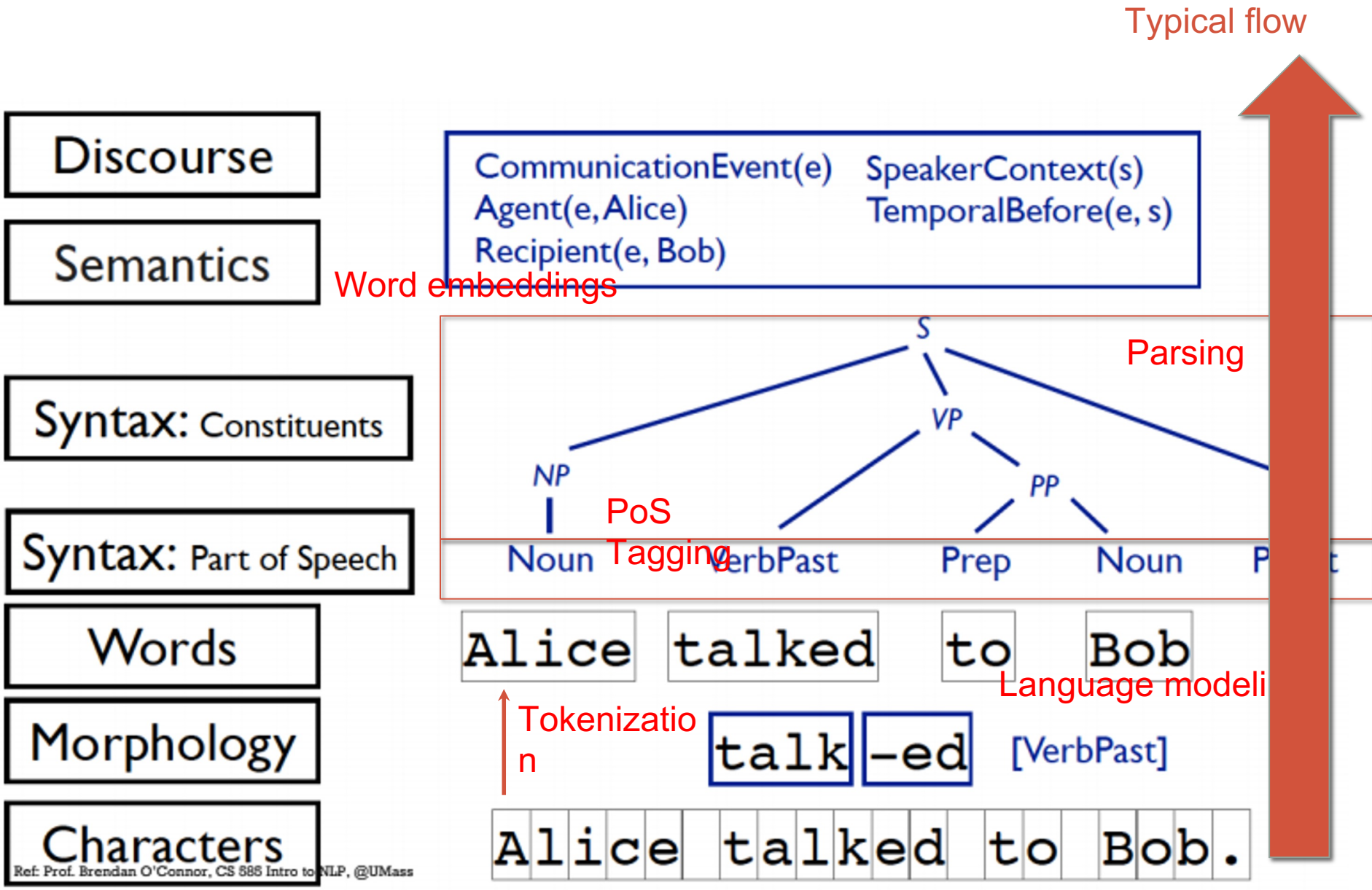
- Input: text
- Output: some task, sentiment analysis score
- Automatically gets parse tree (without any treebank corpus)

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


Typical flow
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
Parsing
Noun
VerbPast
Prep
Noun
PoS Tagging
Alice talked to Bob
Language modeli
Tokenizatio n
talk -ed
[VerbPast]
Alice talked to Bob.
Ref: Prof. Brendan O'Connor, CS 585 Intro to NLP, @UMass

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