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Natural Language Processing
DSECL ZG565

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Session 10 -Statistical Constituency Parsing
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These slides are prepared by the instructor, with grateful acknowledgement of Prof. Jurafsky and Prof. Martin and many others who made their course materials freely available online.

Session Content

(Ref: Chapter 14 Jurafsky and Martin)

- CKY Parsing
- Probabilistic Context-Free Grammars
- PCFG for disambiguation
- Probabilistic CKY Parsing of PCFGs
- Ways to Learn PCFG Rule Probabilities
- Probabilistic Lexicalized CFGs
- Evaluating Parsers
- Problems with PCFGs

Some funny examples

– Policeman to little boy: “We are looking for a thief with a bicycle.” Little boy: “Wouldn’t you be better using your eyes.”
– Why is the teacher wearing sun-glasses. Because the class is so bright.

Ambiguity is Explosive

- "I saw the man with the telescope": 2 parses
- "I saw the man on the hill with the telescope.": 5 parses
- "I saw the man on the hill in Texas with the telescope": 14 parses
- "I saw the man on the hill in Texas with the telescope at noon.": 42 parses
- "I saw the man on the hill in Texas with the telescope at noon on Monday" 132 parses

CKY parsing

Classic, bottom-up dynamic programming algorithm (Cocke-Kasami-Younger).

Requires input grammar based on Chomsky Normal Form

- A CNF grammar is a Context-Free Grammar in which:
  - Every rule LHS is a non-terminal
  - Every rule RHS consists of either a single terminal or two non-terminals.
  - Examples:
    - A → B C
    - NP → N PP
    - A → a
    - Noun → man
  - But not:
    - NP → the N
    - S → VP

Chomsky Normal Form

- Any CFG can be re-written in CNF, without any loss of expressiveness.
  - That is, for any CFG, there is a corresponding CNF grammar which accepts exactly the same set of strings as the original CFG.
  - Normal forms give us more structure to work with, resulting in easier parsing algorithms.
  - CNF provides an upper bound for parsing **complexity**

Converting a CFG to CNF

- To convert a CFG to CNF, we need to deal with three issues:

1. Rules that mix terminals and non-terminals on the RHS
   - E.g. NP → *the* Nominal
2. Rules with a single non-terminal on the RHS (called unit productions)
   - E.g. NP → Nominal
3. Rules which have more than two items on the RHS
   - E.g. NP → Det Noun PP

*Nominal definition is a noun, noun phrase, or any word or word group that functions as a noun. The term comes from the Latin, meaning "name."

Converting a CFG to CNF

1. Rules that mix terminals and non-terminals on the RHS
   - E.g. NP → *the* Nominal

   - Solution:
     - Introduce a dummy non-terminal to cover the original terminal
       - E.g. Det → the
     - Re-write the original rule:
       - NP → Det Nominal
       - Det → the

Converting a CFG to CNF

2. Rules with a single non-terminal on the RHS (called unit productions)
   - E.g. NP → Nominal
   - Solution:
     - Find all rules that have the form Nominal → ...
       - Nominal → Noun PP
       - Nominal → Det Noun
     - Re-write the above rule several times to eliminate the intermediate non-terminal:
       - NP → Noun PP
       - NP → Det Noun
   - Note that this makes our grammar "flatter"

Converting a CFG to CNF

3. Rules which have more than two items on the RHS
   - E.g. NP → Det Noun PP

- Solution:
  - Introduce new non-terminals to spread the sequence on the RHS over more than 1 rule.
    - Nominal → Noun PP
    - NP → Det Nominal

CNF Grammar

- If we parse a sentence with a CNF grammar, we know that:
  – Every phrase-level non-terminal (above the part of speech level) will have exactly 2 daughters.
    - NP → Det N
  – Every part-of-speech level non-terminal will have exactly 1 daughter, and that daughter is a terminal:
    - N → lady

Recognising strings with CKY

Example input: The flight includes a meal.

The CKY algorithm proceeds by:

1. Splitting the input into words and indexing each position.

   (0) the (1) flight (2) includes (3) a (4) meal (5)

2. Setting up a table. For a sentence of length n, we need (n+1) rows and (n+1) columns.

3. Traversing the input sentence left-to-right

4. Use the table to store constituents and their span.

CKY example

- S → NP VP
- NP → Det N
- VP → V NP
- V → includes
- Det → the
- Det → a
- N → meal
- N → flight

CKY example

Rule: Det → *the*

[0,1] for "the"

	1	2	3	4	5
0	**Det**				S
1					
2					
3					
4					
	the	flight	includes	a	meal

CKY example

Rule1: Det → *the*
Rule 2: N → flight

[0,1] for "the"   [1,2] for "flight"

	1	2	3	4	5
0	**Det**				S
1		**N**			
2					
3					
4					
	the	flight	includes	a	meal

CKY example

[0,2] for "the flight"

[0,1] for "the"

[1,2] for "flight"

Rule1: Det → *the*
Rule 2: N → flight
Rule 3: NP → Det N

	1	2	3	4	5
0	**Det**	**NP**			S
1		**N**			
2					
3					
4					
	the	flight	includes	a	meal

CKY: lexical step (j = 1)

- *The flight includes a meal.*

Lexical lookup
- Matches Det → the

	1	2	3	4	5
0	Det				
1					
2					
3					
4					
5					

CKY: lexical step (j = 2)

- *The flight includes a meal.*

Lexical lookup
- Matches N → flight

	1	2	3	4	5
0	Det				
1		N			
2					
3					
4					
5					

CKY: syntactic step (j = 2)

- *The flight includes a meal.*

Syntactic lookup:
• look backwards and see if there is any rule that will cover what we've done so far.

	1	2	3	4	5
0	Det	NP			
1		N			
2					
3					
4					
5					

CKY: lexical step (j = 3)

- *The flight includes a meal.*

Lexical lookup
- Matches V → includes

	1	2	3	4	5
0	Det	NP			
1		N			
2			V		
3					
4					
5					

CKY: lexical step (j = 3)

- *The flight includes a meal.*

Syntactic lookup
• There are no rules in our grammar that will cover Det, NP, V

	1	2	3	4	5
0	Det	NP			
1		N			
2			V		
3					
4					
5					

CKY: lexical step (j = 4)

- *The flight includes a meal.*

Lexical lookup
• Matches Det → a

	1	2	3	4	5
0	Det	NP			
1		N			
2			V		
3				Det	
4					
5					

CKY: lexical step (j = 5)

- *The flight includes a meal.*

Lexical lookup
- Matches N → meal

	1	2	3	4	5
0	Det	NP			
1		N			
2			V		
3				Det	
4					N

CKY: syntactic step (j = 5)

- *The flight includes a meal.*

Syntactic lookup
• We find that we have
NP → Det N

	1	2	3	4	5
0	Det	NP			
1		N			
2			V		
3				Det	NP
4					N

CKY: syntactic step (j = 5)

- *The flight includes a meal.*

Syntactic lookup
• We find that we have
VP → V NP

	1	2	3	4	5
0	Det	NP			
1		N			
2			V		VP
3				Det	NP
4					N

CKY: syntactic step (j = 5)

- *The flight includes a meal*.

Syntactic lookup

• We find that we have

S → NP VP

	1	2	3	4	5
0	Det	NP			S
1		N			
2			V		VP
3				Det	NP
4					N

From recognition to parsing

- The procedure so far will recognise a string as a legal sentence in English.
- But we'd like to get a parse tree back!
- Solution:
  - We can work our way back through the table and collect all the partial solutions into one parse tree.
  - Cells will need to be augmented with "backpointers", i.e. With a pointer to the cells that the current cell covers.

From recognition to parsing

	1	2	3	4	5
0	Det	NP			S
1		N			
2			V		VP
3				Det	NP
4					N

From recognition to parsing

	1	2	3	4	5
0	Det	NP			S
1		N			
2			V		VP
3				Det	NP
4					N

NB: This algorithm always fills the top “triangle” of the table!

What about ambiguity?

- The algorithm does not assume that there is only one parse tree for a sentence.
  - (Our simple grammar did not admit of any ambiguity, but this isn't realistic of course).

- There is nothing to stop it returning several parse trees.

- If there are multiple local solutions, then more than one non-terminal will be stored in a cell of the table.

CFG definition (reminder)

- A CFG is a 4-tuple: (N,Σ,R,S):
  - N = a set of non-terminal symbols (e.g. NP, VP)
  - Σ = a set of terminals (e.g. words)
    - N and Σ are disjoint (no element of N is also an element of Σ)
  - R = a set of rules of the form $A \rightarrow \beta$ where:
    - A is a non-terminal (a member of N)
    - β is any string of terminals and non-terminals
  - S = a designated start symbol (usually, “sentence”)

Motivation

- Context-free grammars can be generalized to include probabilistic information by adding it to CFG rule
- Probabilistic Context Free Grammars (PCFGs) are the simplest and most natural probabilistic model for tree structures and the algorithms for them are closely related to those for HMMs.
- PCFG are also known as Stochastic Context-Free Grammar (SCFG)

Formal Definition of a PCFG

- A PCFG consists of:
  - A set of terminals, $\{w^k\}$, $k= 1,\ldots,V$
  - A set of nonterminals, N^i, $i= 1,\ldots, n$
  - A designated start symbol N^1
  - A set of rules, $\{N^i \rightarrow \xi^j\}$, (where ξ^j is a sequence of terminals and nonterminals)
  - A corresponding set of probabilities on rules such that: $\forall i \quad \sum_j P(N^i \rightarrow \xi^j) = 1$

Probability of a Derivation Tree and a String

- The probability of a derivation (i.e. parse) tree:

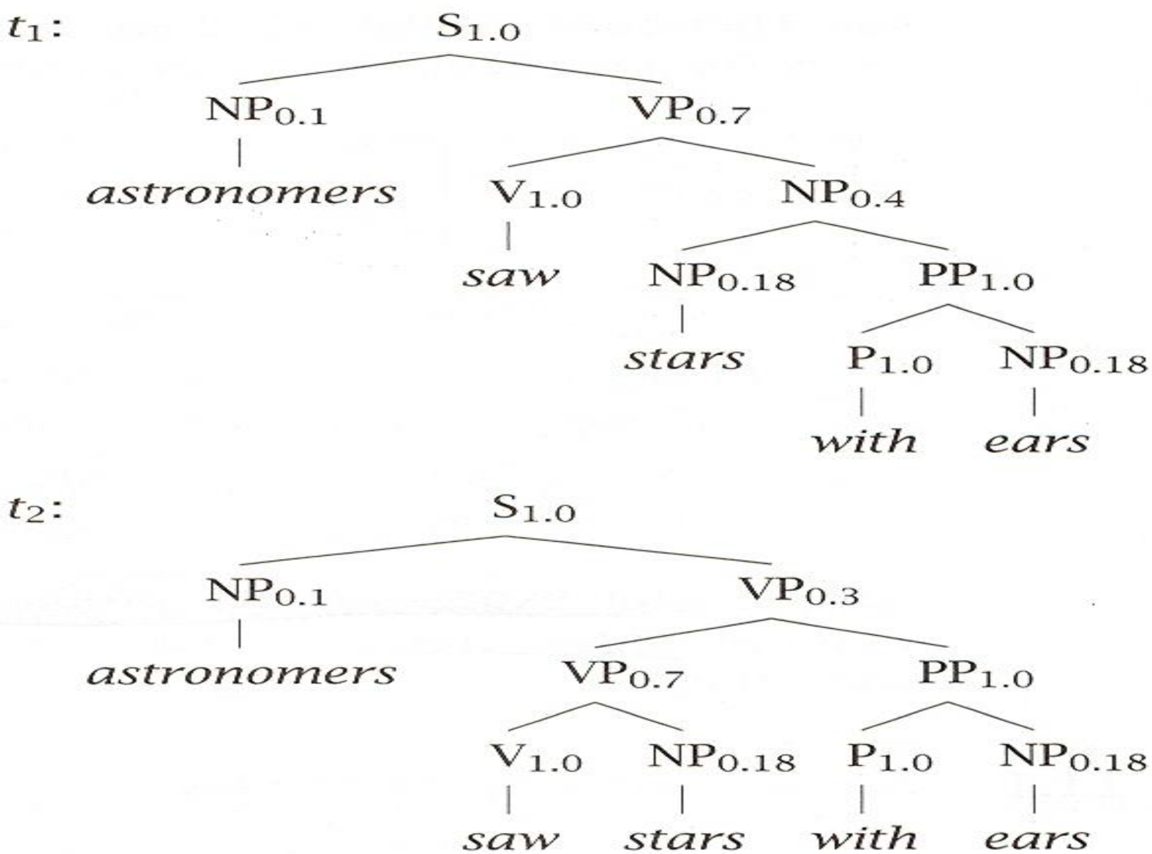
  $$P(T) = \Pi_{i=1..k}\ p(r(i))$$

  where r(1), …, r(k) are the rules of the CFG used to generate the sentence $\mathbf{w_{1m}}$ of which T is a parse.
- The probability of a sentence (according to grammar G) is given by:

  $$P(w_{1m}) = \Sigma_t\ P(w_{1m},t) = \Sigma_{\{t:\ yield(t)=w_{1m}\}}\ P(t)$$

  where t is a parse tree of the sentence. Need dynamic programming to make this efficient!

Example: Probability of a Derivation Tree



S → NP VP	1.0	NP → NP PP	0.4
PP → P NP	1.0	NP → *astronomers*	0.1
VP → V NP	0.7	NP → *ears*	0.18
VP → VP PP	0.3	NP → *saw*	0.04
P → *with*	1.0	NP → *stars*	0.18
V → *saw*	1.0	NP → *telescopes*	0.1

Some Features of PCFGs

- A PCFG gives some idea of the plausibility of different parses; however, the probabilities are based on structural factors and not lexical ones.
- PCFGs are good for grammar induction.
- PCFGs are robust.
- PCFGs give a probabilistic language model for English.
- The predictive power of a PCFG tends to be greater than for an HMM.
- PCFGs are not good models alone but they can be combined with a trigram model.

Properties of PCFGs

- Assigns a probability to each *left-most derivation*, or parse-tree, allowed by the underlying CFG
- Say we have a sentence s, set of derivations for that sentence is $\mathcal{T}(s)$. Then a PCFG assigns a probability $p(t)$ to each member of $\mathcal{T}(s)$. i.e., *we now have a ranking in order of probability*.
- The most likely parse tree for a sentence s is

$$\arg\max_{t \in \mathcal{T}(s)} p(t)$$

PCFG based Grammar

- PCFGs augments CFGs by including a probability for each rule in the grammar.

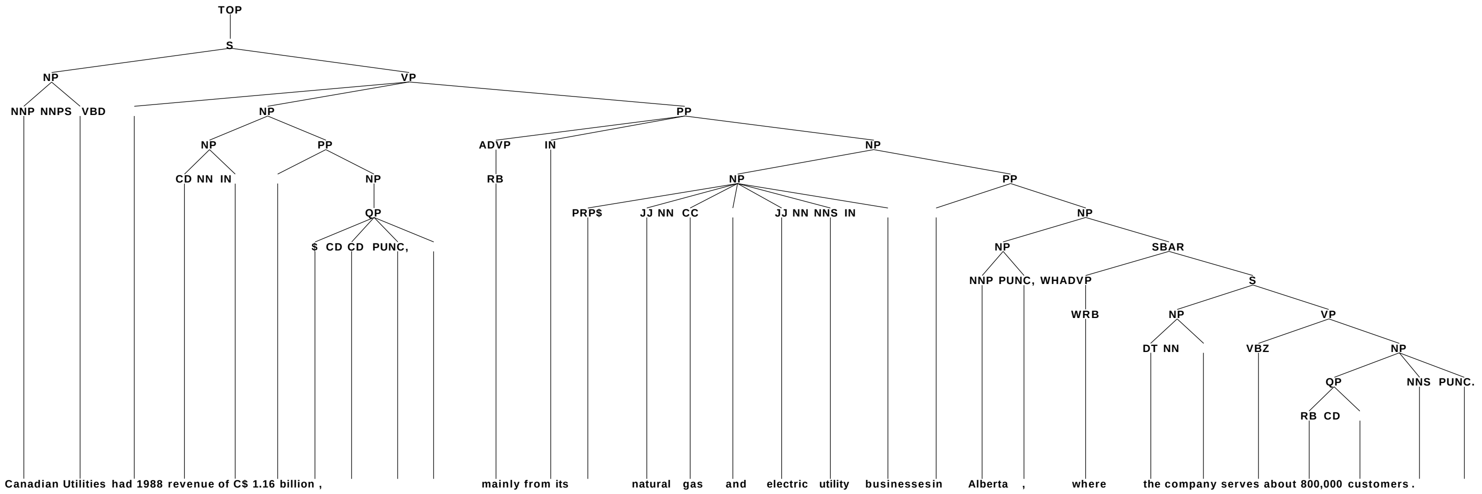
- The probability for a parse tree is the product of probabilities for the rules in the tree

- To build a PCFG-parsed parser:
  1. Learn a PCFG from a treebank
  2. Given a test data sentence, use the CKY algorithm to compute the highest probability tree for the sentence under the PCFG

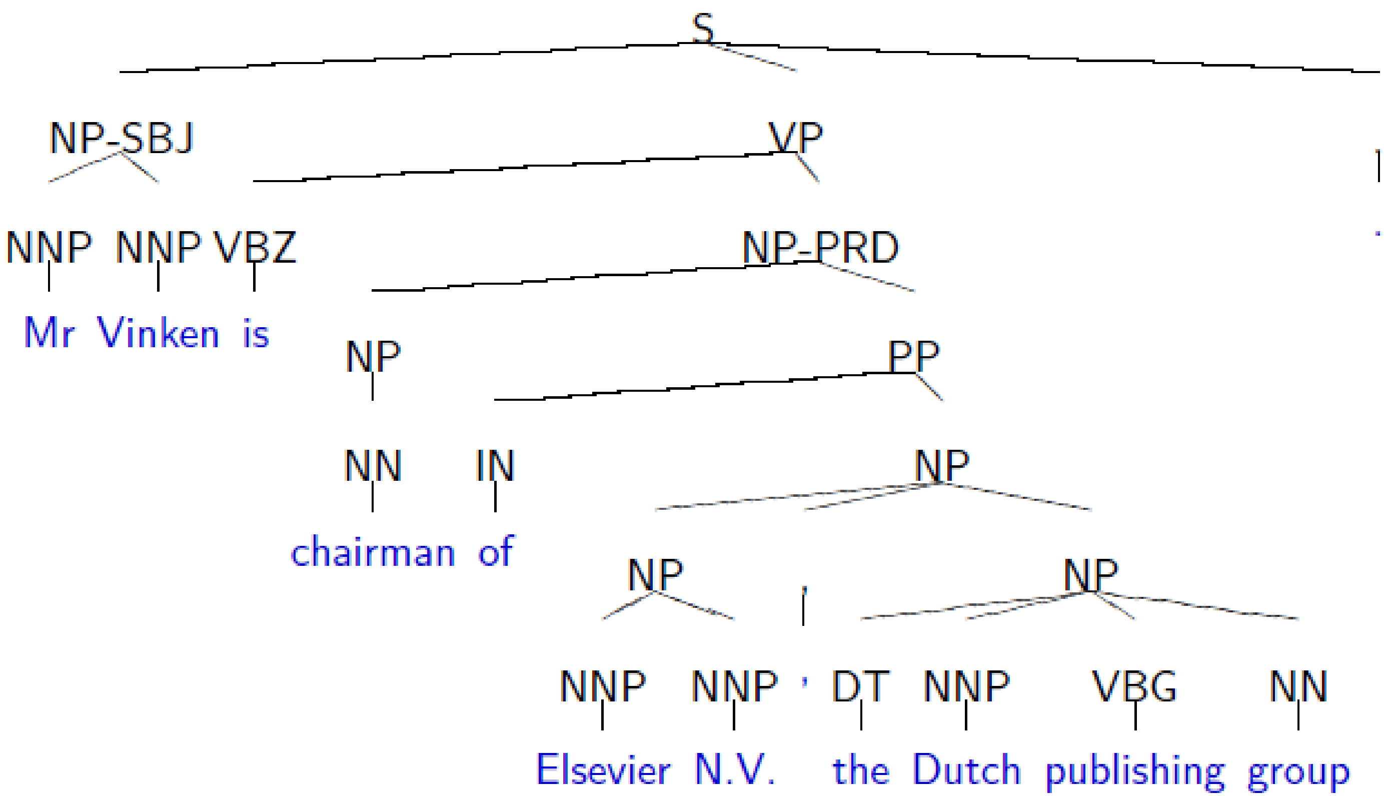
Data for Parsing Experiments: Treebanks

- Penn WSJ Treebank = 50,000 sentences with associated trees
- Usual set-up: 40,000 training sentences, 2400 test sentences

An example tree:



Example tree



Characteristics of PCFGs

- In a PCFG, the probability $P(A \rightarrow \beta)$ expresses the likelihood that the non-terminal A will expand as β.
  - e.g. the likelihood that $S \rightarrow NP\ VP$
    - (as opposed to $S \rightarrow VP$, or $S \rightarrow NP\ VP\ PP$, or…)

- can be interpreted as a conditional probability:
  - probability of the expansion, given the LHS non-terminal
  - $P(A \rightarrow \beta) = P(A \rightarrow \beta | A)$

- Therefore, for any non-terminal A, probabilities of every rule of the form $A \rightarrow \beta$ must sum to 1
  - in this case, we say the PCFG is consistent

Word/Tag Counts

	N	V	ARI	P	TOTAL
flies	21	23	0	0	44
fruit	49	5	1	0	55
like	10	30	0	21	61
a	1	0	201	0	202
the	1	0	300	2	303
flower	53	15	0	0	68
flowers	42	16	0	0	58
birds	64	1	0	0	65
others	592	210	56	284	1142
TOTAL	833	300	558	307	1998

Lexical Probability Estimates

P(the|ART)=300 /558 = 0.54

P(the|ART)	.54	P(a|ART)	.360
P(flies|N)	.025	P(a|N)	.001
P(flies|V)	.076	P(flower|N)	.063
P(like|V)	.1	P(flower|V)	.05
P(like|P)	.068	P(birds|N)	.076
P(like|N)	.012		

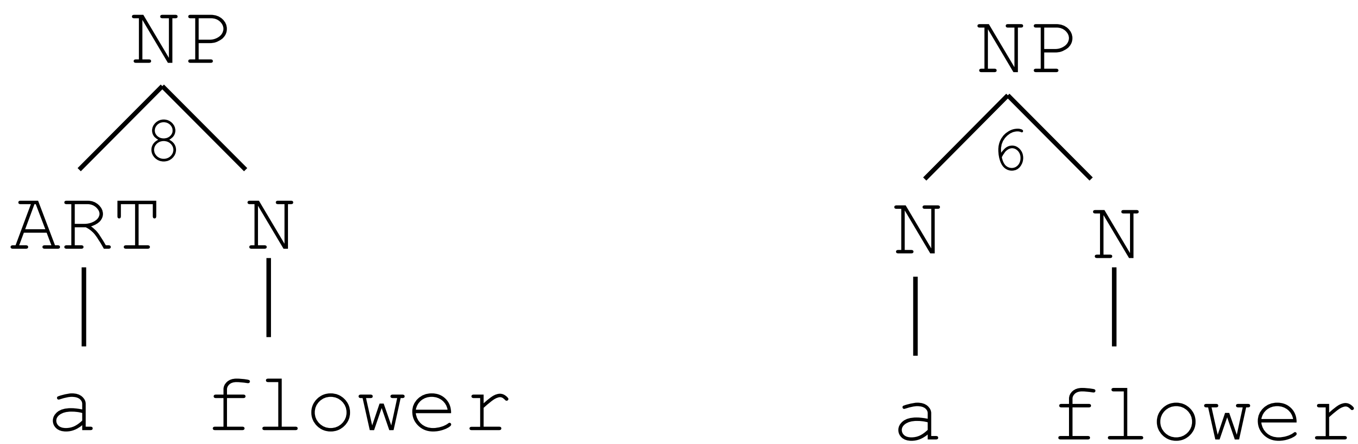
The PCFG

- Below is a probabilistic CFG (PCFG) with probabilities derived from analyzing a parsed version of Allen's corpus.

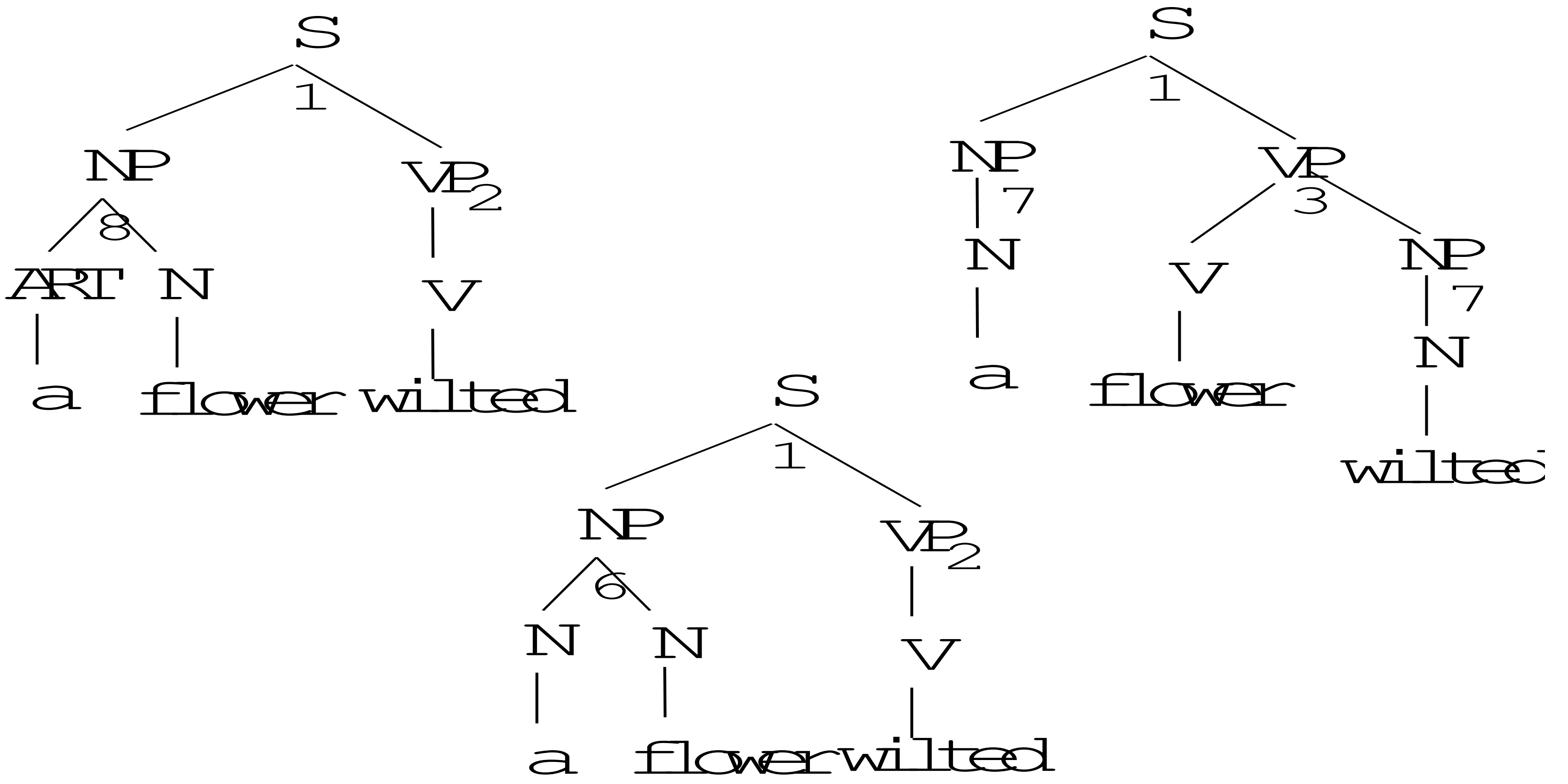
Rule	Count for LHS	Count for Rule	PROB
1. S → NP VP	300	300	1
2. VP → V	300	116	.386
3. VP → V NP	300	118	.393
4. VP → V NP PP	300	66	.22
5. NP → NP PP	1032	241	.23
6. NP → N N	1032	92	.09
7. NP → N	1032	141	.14
8. NP → ART N	1032	558	.54
9. PP → P NP	307	307	1

Parsing with a PCFG

- Using the lexical probabilities, we can derive probabilities that the constituent NP generates a sequence like *a flower*. Two rules could generate the string of words:



Three Possible Trees for an S



Parsing with a PCFG

- The probability of a sentence generating *A flower wilted*:

$$P(\textit{a flower wilted} \mid S) = P(R_1 \mid S) \times P(\textit{a flower} \mid NP) \times P(\textit{wilted} \mid VP) + P(R_1 \mid S) \times P(\textit{a} \mid NP) \times P(\textit{flower wilted} \mid VP)$$

- Using this approach, the probability that a given sentence will be generated by the grammar can be efficiently computed.
- It only requires some way of recording the value of each constituent between each two possible positions. The requirement can be filled by a packed chart structure.

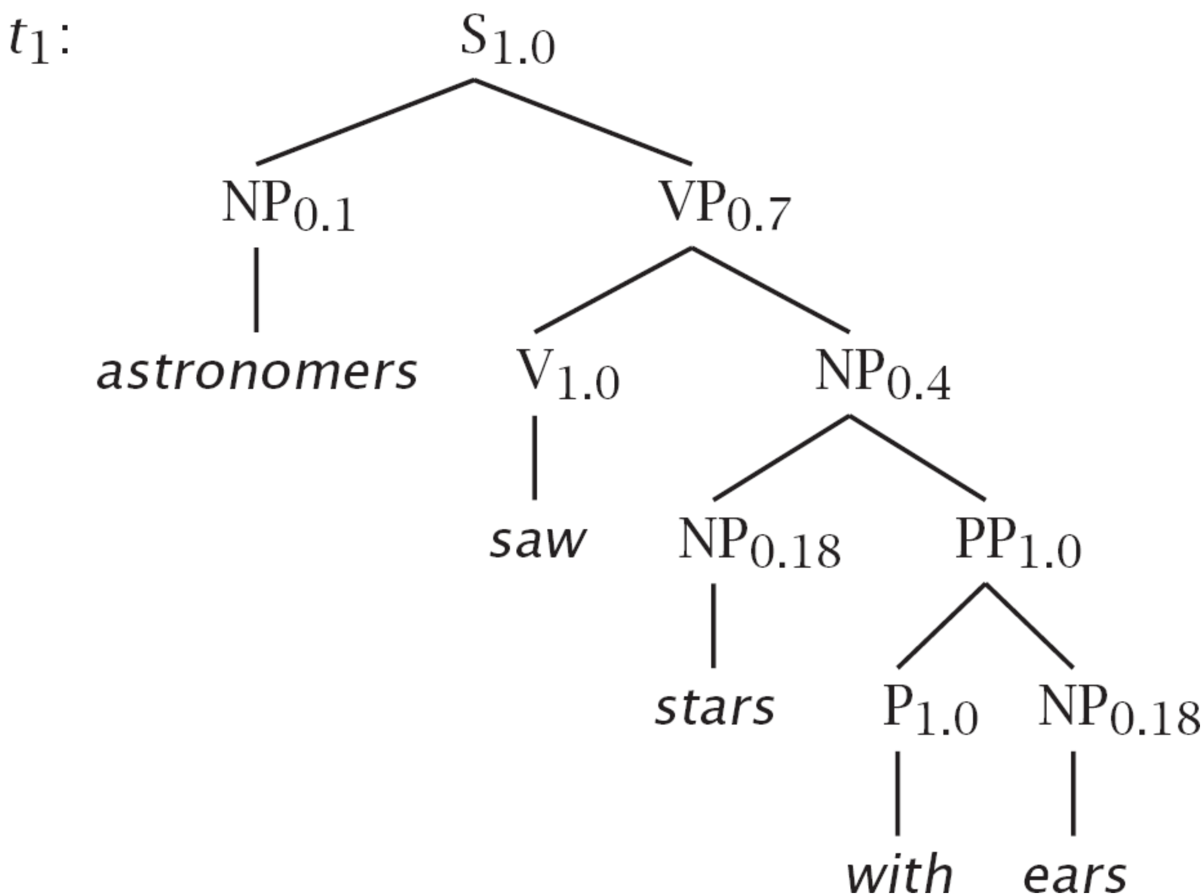
Example

S → NP VP	1.0	NP → NP PP	0.4
PP → P NP	1.0	NP → *astronomers*	0.1
VP → V NP	0.7	NP → *ears*	0.18
VP → VP PP	0.3	NP → *saw*	0.04
P → *with*	1.0	NP → *stars*	0.18
V → *saw*	1.0	NP → *telescopes*	0.1

- Terminals with, saw, astronomers,ears, stars, telescopes
- Nonterminals S, PP, P, NP, VP, V
- Start symbol S

Slide based on "Foundations of Statistical Natural Language Processing" by Christopher Manning and Hinrich Schütze

astronomers saw stars with ears



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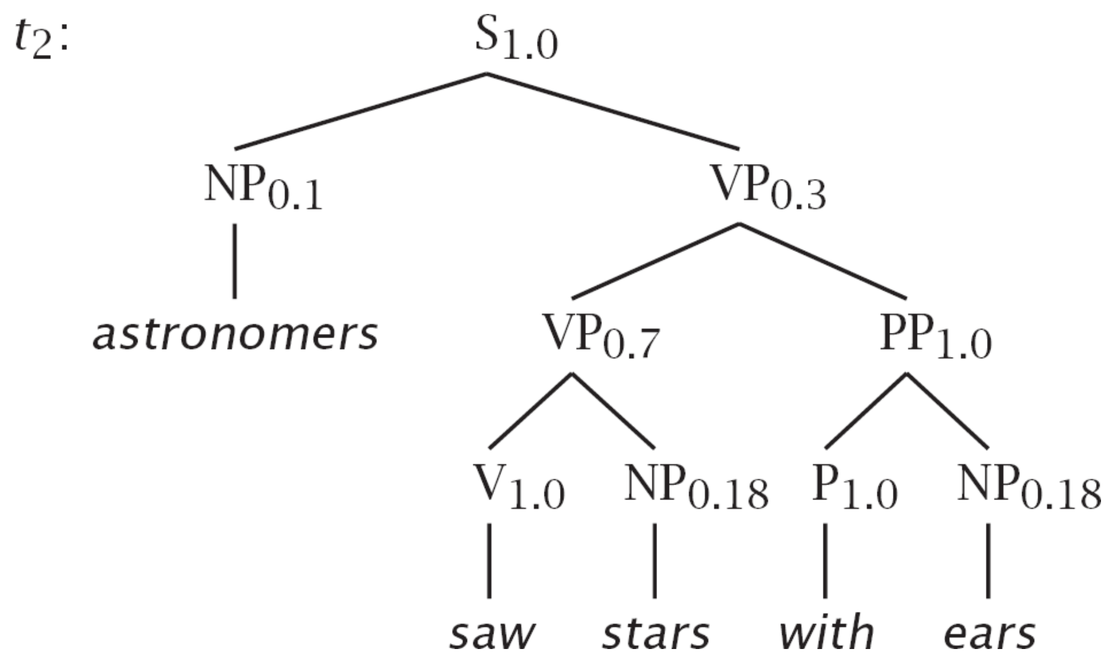
astronomers saw stars with ears



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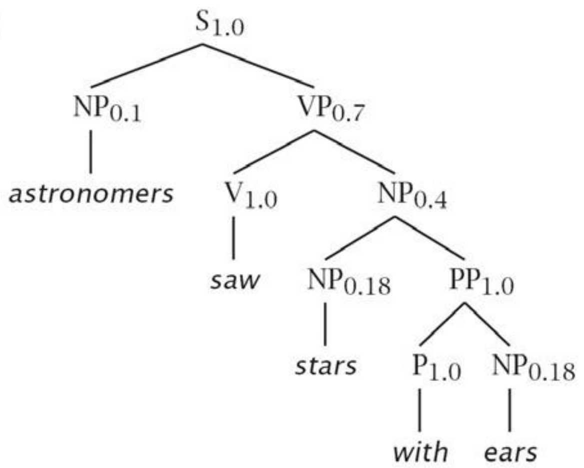
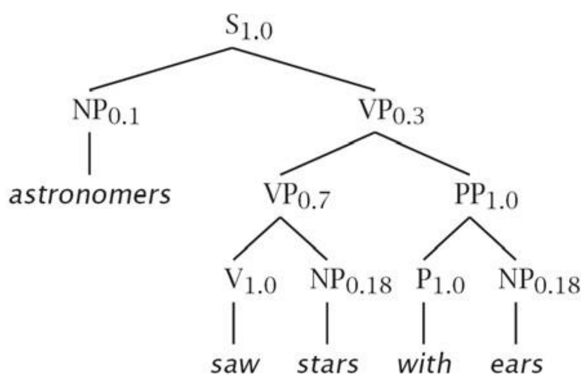
Probabilities

t_1:



t_2:



$$
\begin{aligned}
P(t_1) &= 1.0 \times 0.1 \times 0.7 \times 1.0 \times 0.4 \\
&\quad \times 0.18 \times 1.0 \times 1.0 \times 0.18 \\
&= 0.0009072 \\
P(t_2) &= 1.0 \times 0.1 \times 0.3 \times 0.7 \times 1.0 \\
&\quad \times 0.18 \times 1.0 \times 1.0 \times 0.18 \\
&= 0.0006804 \\
P(w_{15}) &= P(t_1) + P(t_2) = 0.0015876
\end{aligned}
$$

Slide based on "Foundations of Statistical Natural Language Processing" by Christopher Manning and Hinrich Schütze

Uses of probabilities in parsing

- Disambiguation: given *n* legal parses of a string, which is the most likely?
  - e.g. PP-attachment ambiguity can be resolved this way
- Speed: we've defined parsing as a search problem
  - search through space of possible applicable derivations
  - search space can be pruned by focusing on the most likely sub-parses of a parse
- Parser can be used as a model to determine the probability of a sentence, given a parse
  - typical use in speech recognition, where input utterance can be "heard" as several possible sentences

Using PCFG probabilities

- PCFG assigns a probability to every parse-tree t of a string W
  - e.g. every possible parse (derivation) of a sentence recognised by the grammar

- Notation:
  - G = a PCFG
  - s = a sentence
  - t = a particular tree under our grammar
    - t consists of several nodes *n*
    - each node is generated by applying some rule *r*

Probability of a tree vs. a sentence

- We work out the probability of a parse tree t by multiplying the probability of every rule (node) that gives rise to t (i.e. the derivation of t).

- Note that:
  - A tree can have multiple derivations
    - (different sequences of rule applications could give rise to the same tree)
  - But the probability of the tree remains the same
    - (it's the same probabilities being multiplied)
  - We usually speak as if a tree has only one derivation, called the **canonical derivation**

Picking the best parse in a PCFG

- A sentence will usually have several parses
  - we usually want them ranked, or only want the *n* best parses
  - we need to focus on P(t|s,G)
    - probability of a parse, given our sentence and our grammar
  - definition of the best parse for s:
    - The tree for which P(t|s,G) is highest

Probability of a sentence

- Given a probabilistic context-free grammar G, we can the probability of a sentence (as opposed to a tree).

- Observe that:
  - As far as our grammar is concerned, a sentence is only a sentence if it can be recognised by the grammar (it is "legal")
  - There can be multiple parse trees for a sentence.
    - Many trees whose **yield** is the sentence
  - The probability of the sentence is the sum of all the probabilities of the various trees that yield the sentence.

Using CKY to parse with a PCFG

- The basic CKY algorithm remains unchanged.
- However, rather than only keeping partial solutions in our table cells (i.e. The rules that match some input), we also keep their probabilities.

Probabilistic CKY: example PCFG

- S → NP VP [.80]
- NP → Det N [.30]
- VP → V NP [.20]
- V → includes [.05]
- Det → the [.4]
- Det → a [.4]
- N → meal [.01]
- N → flight [.02]

Probabilistic CYK: initialisation

- *The flight includes a meal.*
  - S → NP VP [.80]
  - NP → Det N [.30]
  - VP → V NP [.20]
  - V → includes [.05]
  - Det → the [.4]
  - Det → a [.4]
  - N → meal [.01]
  - N → flight [.02]

	1	2	3	4	5
0					
1					
2					
3					
4					
5					

Probabilistic CYK: lexical step

- *The flight includes a meal.*
- S → NP VP [.80]
- NP → Det N [.30]
- VP → V NP [.20]
- V → includes [.05]
- Det → the [.4]
- Det → a [.4]
- N → meal [.01]
- N → flight [.02]

	1	2	3	4	5
0	Det (.4)				
1					
2					
3					
4					
5					

Probabilistic CYK: lexical step

- *The flight includes a meal.*
  - S → NP VP [.80]
  - NP → Det N [.30]
  - VP → V NP [.20]
  - V → includes [.05]
  - Det → the [.4]
  - Det → a [.4]
  - N → meal [.01]
  - N → flight [.02]

	1	2	3	4	5
0	Det (.4)				
1		N .02			
2					
3					
4					
5					

Probabilistic CYK: syntactic step

- *The flight includes a meal.*
  - S → NP VP [.80]
  - NP → Det N [.30]
  - VP → V NP [.20]
  - V → includes [.05]
  - Det → the [.4]
  - Det → a [.4]
  - N → meal [.01]
  - N → flight [.02]

	1	2	3	4	5
0	Det (.4)	NP .3			
1		N .02			
2					
3					
4					
5					

Note: probability of NP in [0,2]
P(Det → the) * P(N → meal) * P(NP → Det N)

Probabilistic CYK: lexical step

- *The flight includes a meal.*
  - S → NP VP [.80]
  - NP → Det N [.30]
  - VP → V NP [.20]
  - V → includes [.05]
  - Det → the [.4]
  - Det → a [.4]
  - N → meal [.01]
  - N → flight [.02]

	1	2	3	4	5
0	Det (.4)	NP .3			
1		N .02			
2			V .05		
3					
4					
5					

Probabilistic CYK: lexical step

- *The flight includes a meal.*

- S → NP VP [.80]
- NP → Det N [.30]
- VP → V NP [.20]
- V → includes [.05]
- Det → the [.4]
- Det → a [.4]
- N → meal [.01]
- N → flight [.02]

	1	2	3	4	5
0	Det (.4)	NP .3			
1		N .02			
2			V .05		
3				Det .4	
4					
5					

Probabilistic CYK: syntactic step

- *The flight includes a meal.*

- S → NP VP [.80]
- NP → Det N [.30]
- VP → V NP [.20]
- V → includes [.05]
- Det → the [.4]
- Det → a [.4]
- N → meal [.01]
- N → flight [.02]

	1	2	3	4	5
0	Det (.4)	NP .3			
1		N .02			
2			V .05		
3				Det .4	
4					N .01

Probabilistic CYK: syntactic step

- *The flight includes a meal.*
  - S → NP VP [.80]
  - NP → Det N [.30]
  - VP → V NP [.20]
  - V → includes [.05]
  - Det → the [.4]
  - Det → a [.4]
  - N → meal [.01]
  - N → flight [.02]

	1	**2**	**3**	**4**	**5**
0	Det (.4)	NP .3			
1		N .02			
2			V .05		
3				Det .4	NP .3
4					N .01

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  - Det → a [.4]
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  - N → flight [.02]

	1	2	3	4	5
0	Det (.4)	NP .3			
1		N .02			
2			V .05		VP 0.2
3				Det .4	NP .3
4					N .01

Probabilistic CYK: syntactic step

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- Det → a [.4]
- N → meal [.01]
- N → flight [.02]

	1	2	3	4	5
0	Det .4	NP .3			S (.8*.3*.4*.02 *.2*.05*.3*.4*.01)
1		N .02			
2			V .05		VP .2
3				Det .4	NP .3
4					N .01

Probabilistic CYK: summary

- Cells in chart hold probabilities
- Bottom-up procedure computes probability of a parse incrementally.
- To obtain parse trees, we traverse the table "backwards" as before.
  - Cells need to be augmented with backpointers.

Probabilistic Parsing Implementation Demo

Problems with PCFGs

- No Context
  - (immediate prior context, speaker, ...)
- No Lexicalization
  - "VP NP NP" more likely if verb is "hand" or "tell"
  - fail to capture lexical dependencies (n-grams do)
- No Structural Context
  - How NP expands depends on position

Slide based on "Foundations of Statistical Natural Language Processing" by Christopher Manning and Hinrich Schütze

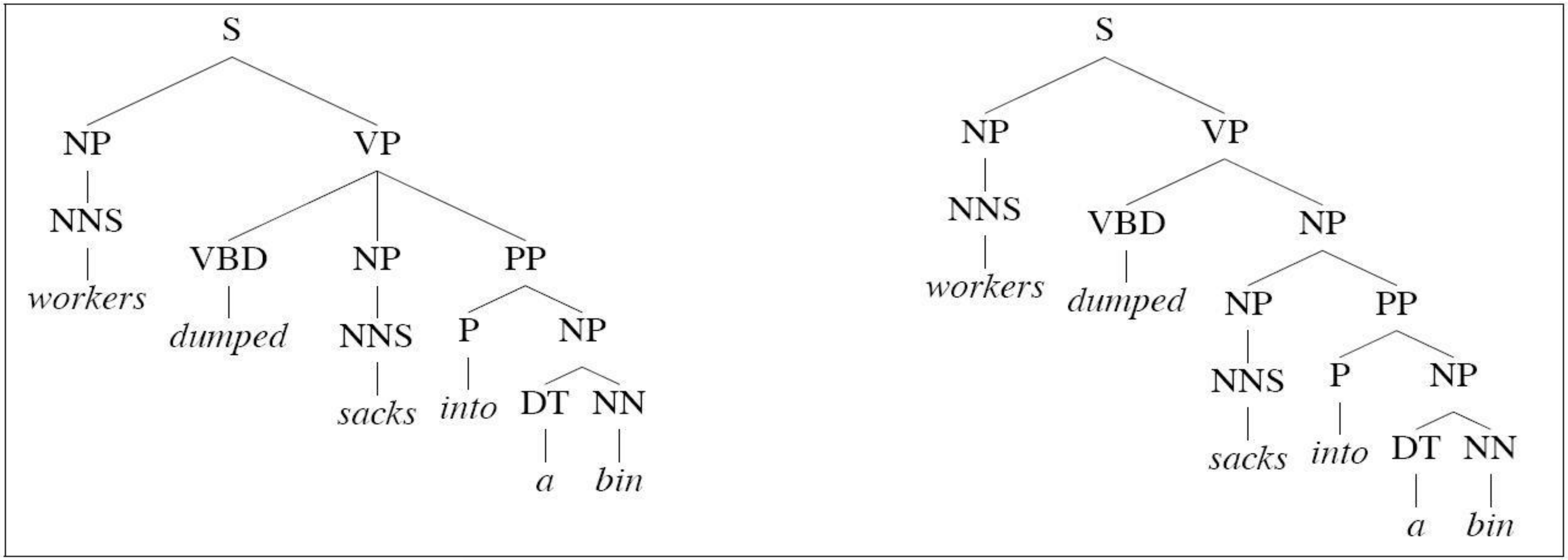
Flaws I: Structural independence

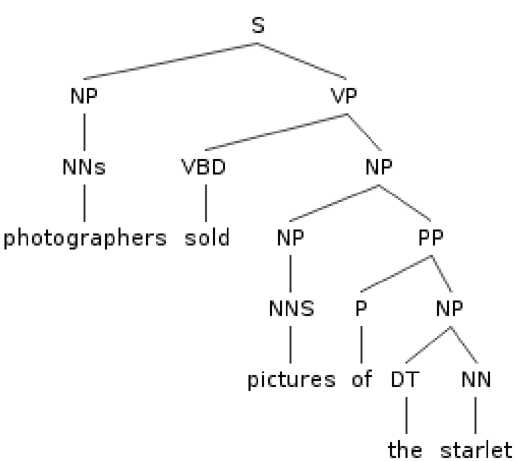
- Probability of a rule r expanding node n depends only on n.
- Independent of other non-terminals

- Example:
  - P(NP → Pro) is independent of where the NP is in the sentence
  - but we know that NP→Pro is much more likely in subject position
  - Francis et al (1999) using the Switchboard corpus:
    - 91% of subjects are pronouns;
    - only 34% of objects are pronouns

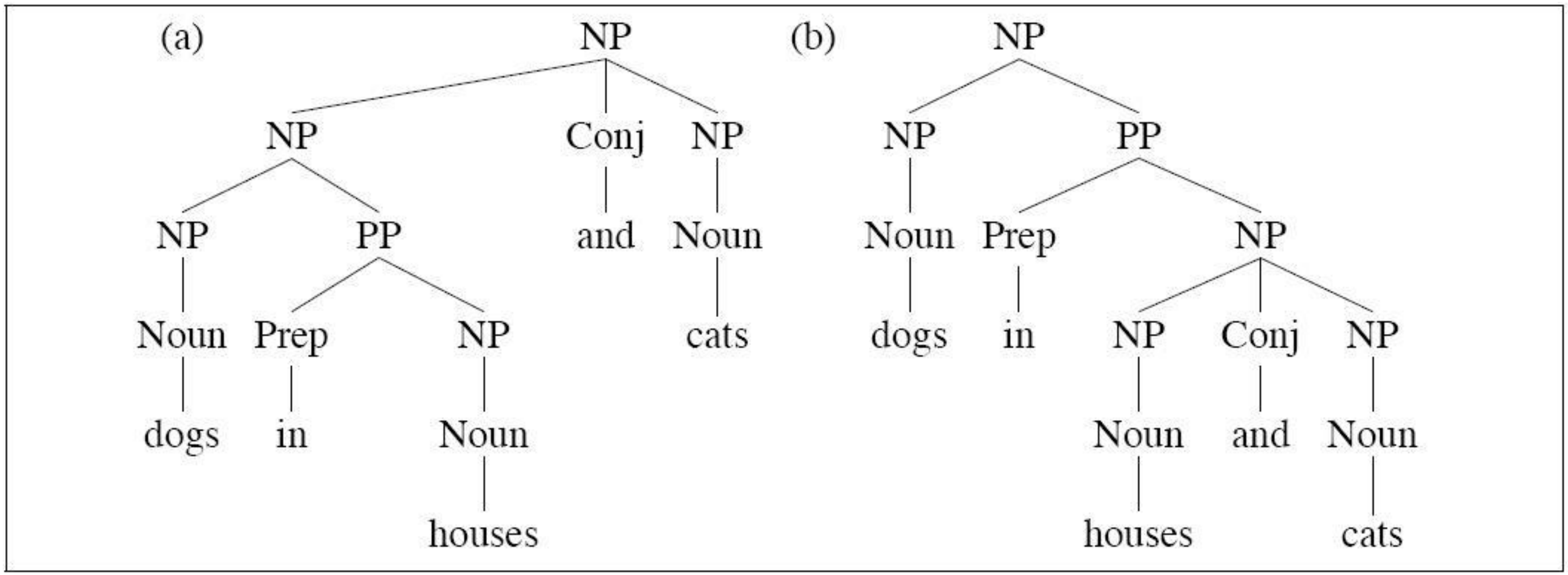
Flaws II: lexical independence

- vanilla PCFGs ignore lexical material
  - e.g. P(VP → V NP PP) independent of the head of NP or PP or lexical head V
- Examples:
  - prepositional phrase attachment preferences depend on lexical items; cf:
    - Workers dumped [sacks into a bin]
    - Workers dumped [sacks] [into a bin] (preferred parse)
  - coordination ambiguity:
    - [dogs in houses] and [cats]
    - [dogs] [in houses and cats]


S
NP VP
NNS VBD NP PP
workers dumped NNS P NP
sacks into DT NN
a bin
S
NP VP
NNS VBD NP
workers dumped NP PP
NNS P NP
sacks into DT NN
a bin


S
NP VP
NNs VBD NP
photographers sold NP PP
NNS P NP
pictures of DT NN
the starlet

Conjunction attachment



Lexicalised PCFGs

- Attempt to weaken the lexical independence assumption.
- Most common technique:
  - mark each phrasal head (N,V, etc) with the lexical material
  - this is based on the idea that the most crucial lexical dependencies are between head and dependent
  - E.g.: Charniak 1997, Collins 1999

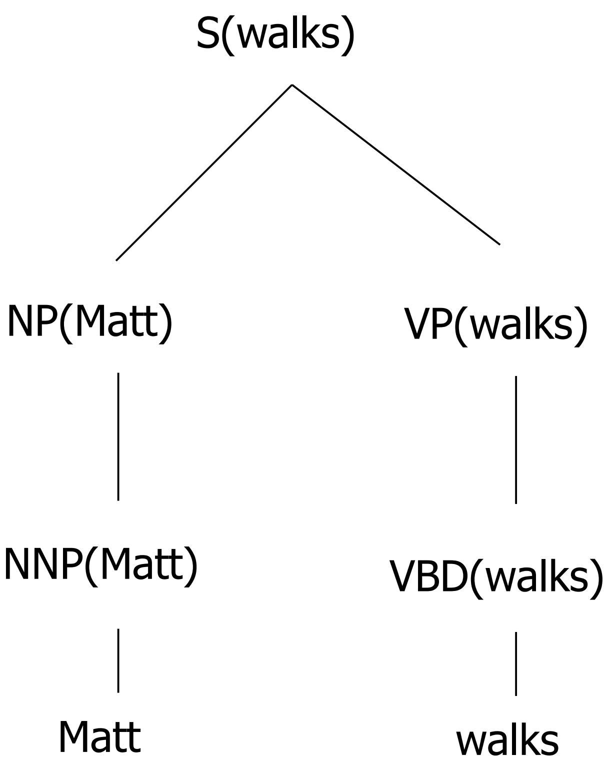
Lexicalised PCFGs: *Matt walks*

- Makes probabilities partly dependent on lexical content.

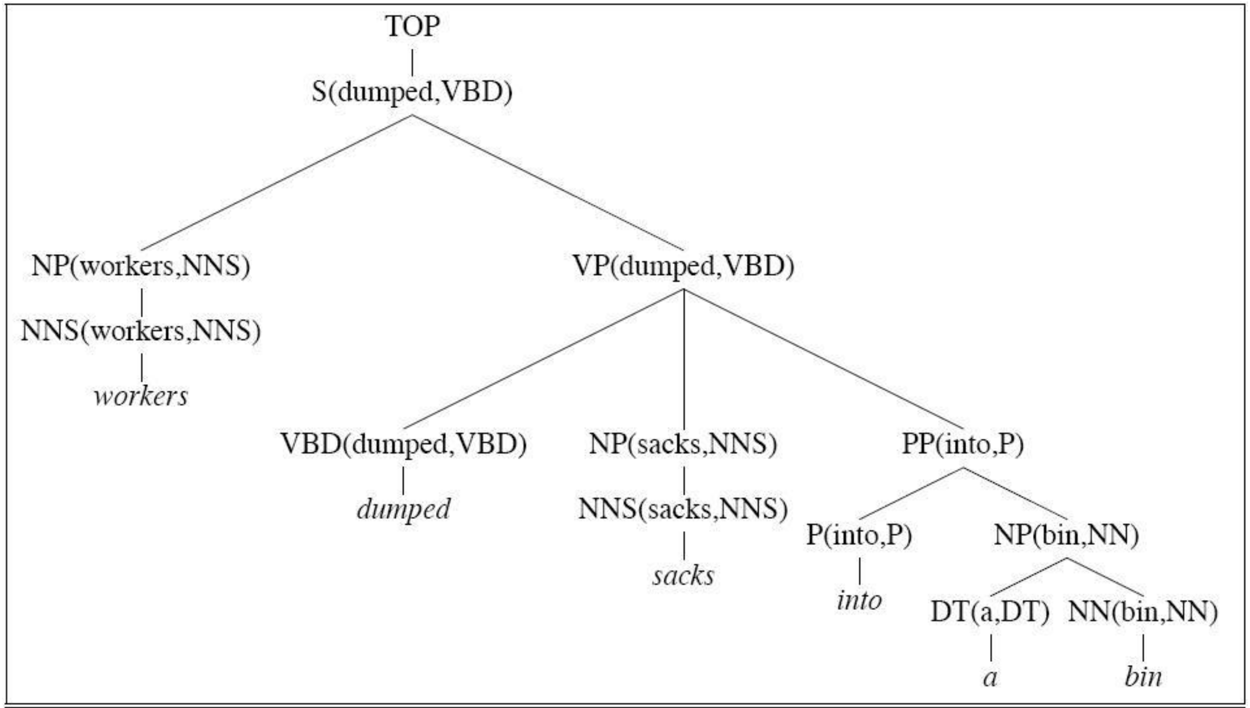
- P(VP→VBD|VP) becomes:

  P(VP→VBD|VP,h(VP)=walks)

- NB: normally, we can't assume that all heads of a phrase of category C are equally probable.



Lexical attachment



Internal Rules					**Lexical Rules**		
TOP	→	S(dumped,VBD)			NNS(workers,NNS)	→	workers
S(dumped,VBD)	→	NP(workers,NNS)	VP(dumped,VBD)		VBD(dumped,VBD)	→	dumped
NP(workers,NNS)	→	NNS(workers,NNS)			NNS(sacks,NNS)	→	sacks
VP(dumped,VBD)	→	VBD(dumped, VBD)	NP(sacks,NNS)	PP(into,P)	P(into,P)	→	into
PP(into,P)	→	P(into,P)	NP(bin,NN)		DT(a,DT)	→	a
NP(bin,NN)	→	DT(a,DT)	NN(bin,NN)		NN(bin,NN)	→	bin

Practical problems for lexicalised PCFGs

- Data sparseness: we don't necessarily see all heads of all phrasal categories often enough in the training data

- Flawed assumptions: lexical dependencies occur elsewhere, not just between head and complement
    - *I got the easier problem of the two to solve*
    - *of the two* and *to solve* are very likely because of the prehead modifier *easier*

Evaluating Parsers

- We need a measure to evaluate parser performance against gold standard
  - ratio of fully correct sentences parses too coarse

→ ratio of correct constituents

- Does *correct* mean *precision*?

$$\text{precision} = \frac{\text{count(matching constituents)}}{\text{count(predicted constituents)}}$$

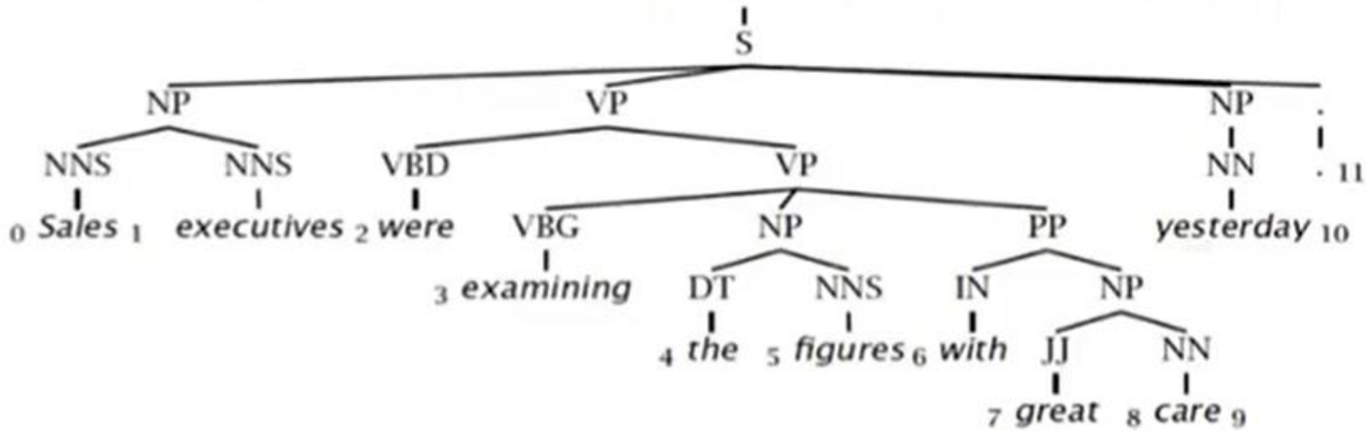
- Does *correct* mean *recall*?

$$\text{Recall} = \frac{\text{count(matching constituents)}}{\text{count(gold standard constituents)}}$$

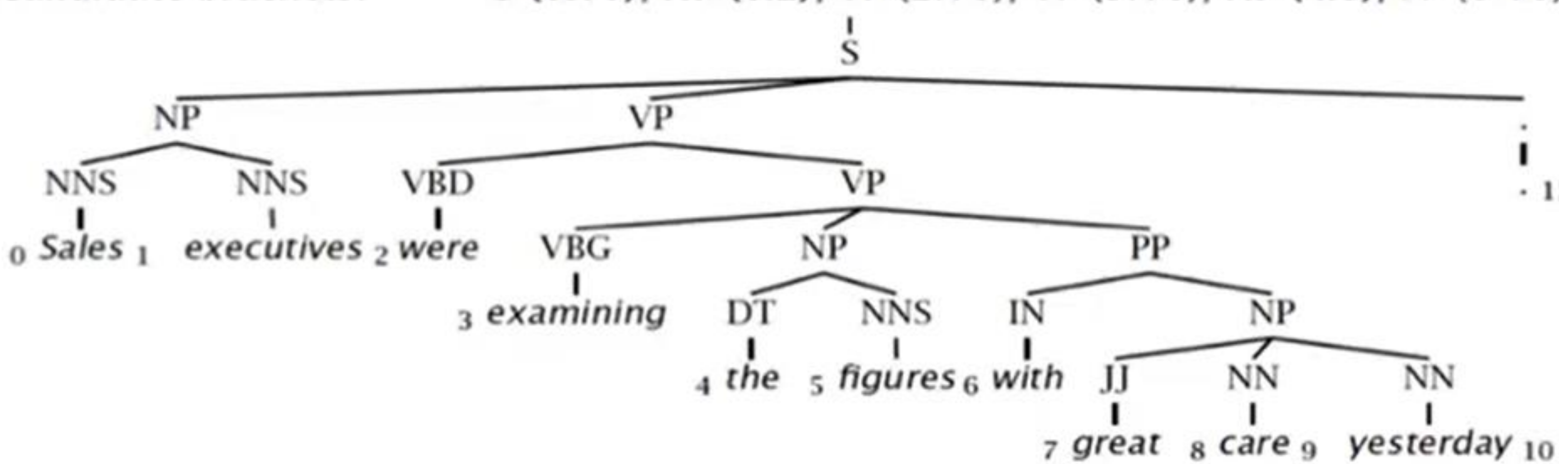
Credits: Philipp Koehn

Evaluating Parsers

Gold standard brackets: **S-(0:11)**, **NP-(0:2)**, VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), NP-(9:10)



Candidate brackets: **S-(0:11)**, **NP-(0:2)**, VP-(2:10), VP-(3:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)



Evaluating Parsers

- **Gold standard brackets: 8**

S-(0:11), NP-(0:2), VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), NP-(9:10)

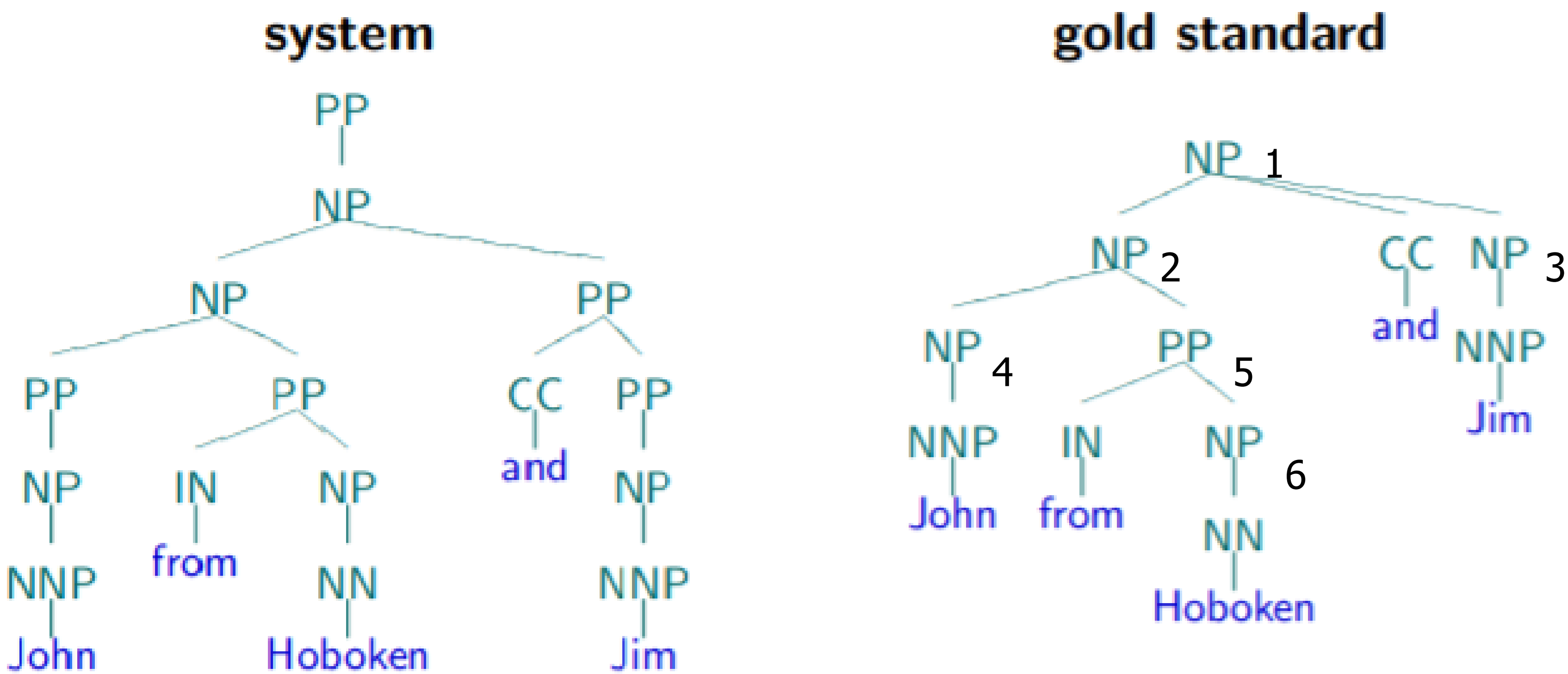
Candidate brackets: 7

S-(0:11), **NP-(0:2)**, VP-(2:10), VP-(3:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)

Labeled Precision	3/7 = 42.9%
Labeled Recall	3/8 = 37.5%
LP/LR F1	40.0%
Tagging Accuracy	11/11 = 100.0%

Evaluating Parsers

Low Precision, High Recall



all gold standard constituents are predicted (recall 6/6)
... but we are predicting many more (precision 6/10)

Credits: Philipp Koehn

Evaluating Parsers

- F-measure: balance of precision and recall

$$F_1 = \frac{\text{precision} \times \text{recall}}{(\text{precision} + \text{recall})/2}$$

- F-measure is used in many other NLP tasks and may be adjusted to give more emphasis to either precision or recall

Credits: Philipp Koehn

Extra Reading

- https://www.youtube.com/watch?v=Z6GsoBA-09k&list=PLQiyVNMpDLKnZYBTUOlSI9mi9wAErFtFm&index=62
- https://lost-contact.mit.edu/afs/cs.pitt.edu/projects/nltk/docs/tutorial/pcfg/nochunks.html
- http://www.nltk.org/howto/grammar.html
- https://www.tutorialspoint.com/natural_language_toolkit/natural_language_toolkit_parsing.htm
- https://lost-contact.mit.edu/afs/cs.pitt.edu/projects/nltk/docs/tutorial/pcfg/nochunks.html
- http://courses.washington.edu/ling571/ling571_WIN2017/slides/ling571_class6_pcfg_impr_flat.pdf
- http://www.cs.columbia.edu/~mcollins/courses/nlp2011/notes/lexpcfgs.pdf

Thank you for your time!!