CS 388: Natural Language Processing: Statistical Parsing

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Statistical Parsing

- Statistical parsing uses a probabilistic model of syntax in order to assign probabilities to each parse tree.
- Provides principled approach to resolving syntactic ambiguity.
- Allows supervised learning of parsers from tree-banks of parse trees provided by human linguists.
- Also allows unsupervised learning of parsers from unannotated text, but the accuracy of such parsers has been limited.

Probabilistic Context Free Grammar (PCFG)

- A PCFG is a probabilistic version of a CFG where each production has a probability.
- Probabilities of all productions rewriting a given non-terminal must add to 1, defining a distribution for each non-terminal.
- String generation is now probabilistic where production probabilities are used to non-deterministically select a production for rewriting a given non-terminal.

Simple PCFG for ATIS English

Grammar	Prob	
S → NP VP	0.8	
S → Aux NP VP	0.1	+ 1.0
S → VP	0.1	
NP → Pronoun	0.2	
NP → Proper-Noun	0.2	+ 1.0
NP → Det Nominal	0.6	
Nominal → Noun	0.3	
Nominal → Nominal Noun	0.2	+ 1.0
Nominal → Nominal PP	0.5	
VP → Verb	0.2	
VP → Verb NP	0.5	+ 1.0
VP → VP PP	0.3	
PP → Prep NP	1.0	

Lexicon

Det → the | a | that | this
0.6 0.2 0.1 0.1

Noun → book | flight | meal | money
0.1 0.5 0.2 0.2

Verb → book | include | prefer
0.5 0.2 0.3

Pronoun → I | he | she | me
0.5 0.1 0.1 0.3

Proper-Noun → Houston | NWA
0.8 0.2

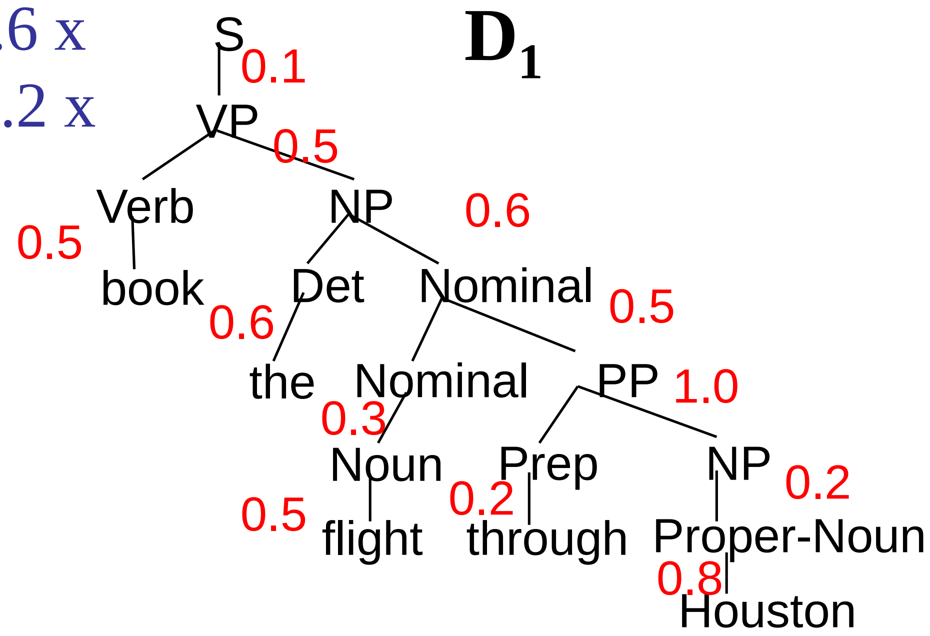
Aux → does
1.0

Prep → from | to | on | near | through
0.25 0.25 0.1 0.2 0.2

Sentence Probability

- Assume productions for each node are chosen independently.
- Probability of derivation is the product of the probabilities of its productions.

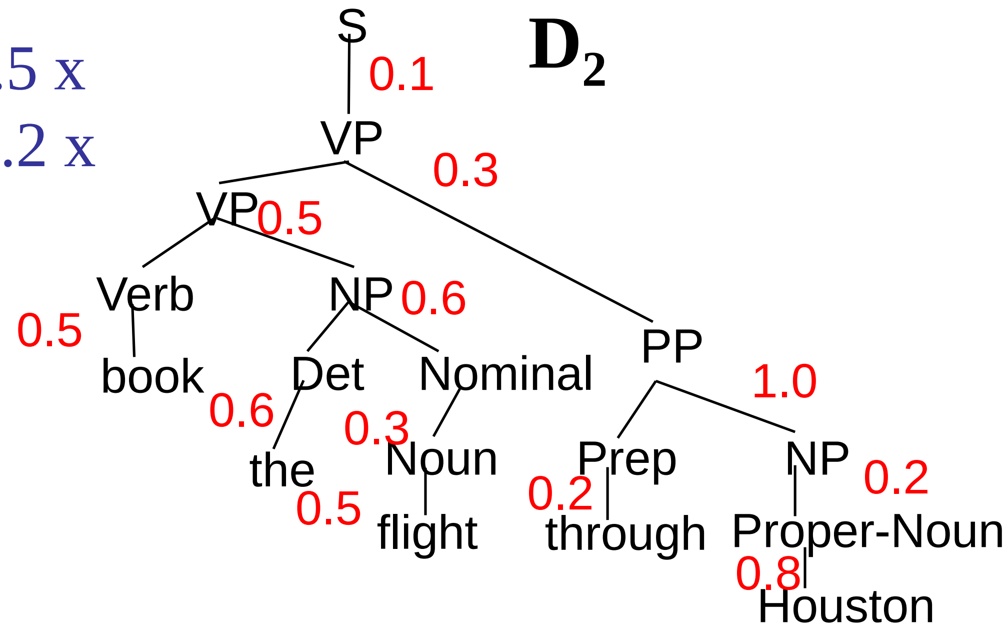
$$P(D_1) = 0.1 \times 0.5 \times 0.5 \times 0.6 \times 0.6 \times 0.5 \times 0.3 \times 1.0 \times 0.2 \times 0.2 \times 0.5 \times 0.8 = 0.0000216$$



Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

$$P(D_2) = 0.1 \times 0.3 \times 0.5 \times 0.6 \times 0.5 \times 0.6 \times 0.3 \times 1.0 \times 0.5 \times 0.2 \times 0.2 \times 0.8 = 0.00001296$$



Sentence Probability

- Probability of a sentence is the sum of the probabilities of all of its derivations.

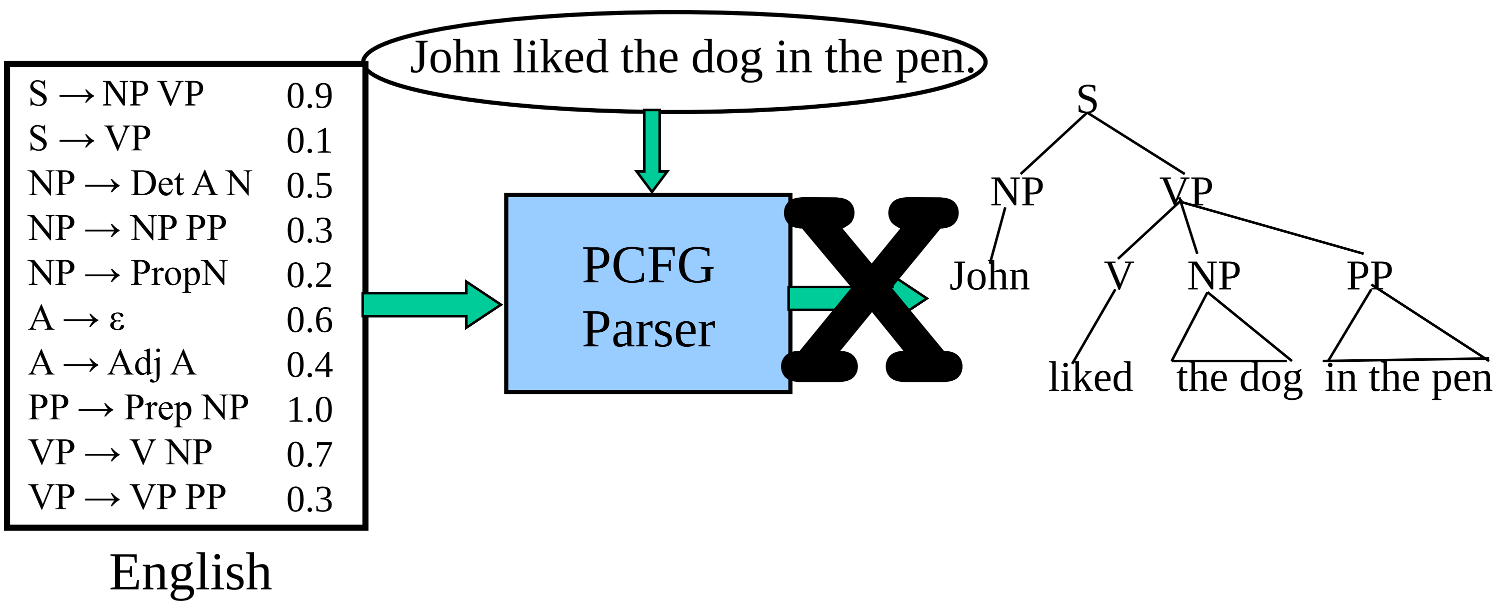
P("book the flight through Houston") =
$P(D_1) + P(D_2) = 0.0000216 + 0.00001296$
$= 0.00003456$

Three Useful PCFG Tasks

- Observation likelihood: To classify and order sentences.
- Most likely derivation: To determine the most likely parse tree for a sentence.
- Maximum likelihood training: To train a PCFG to fit empirical training data.

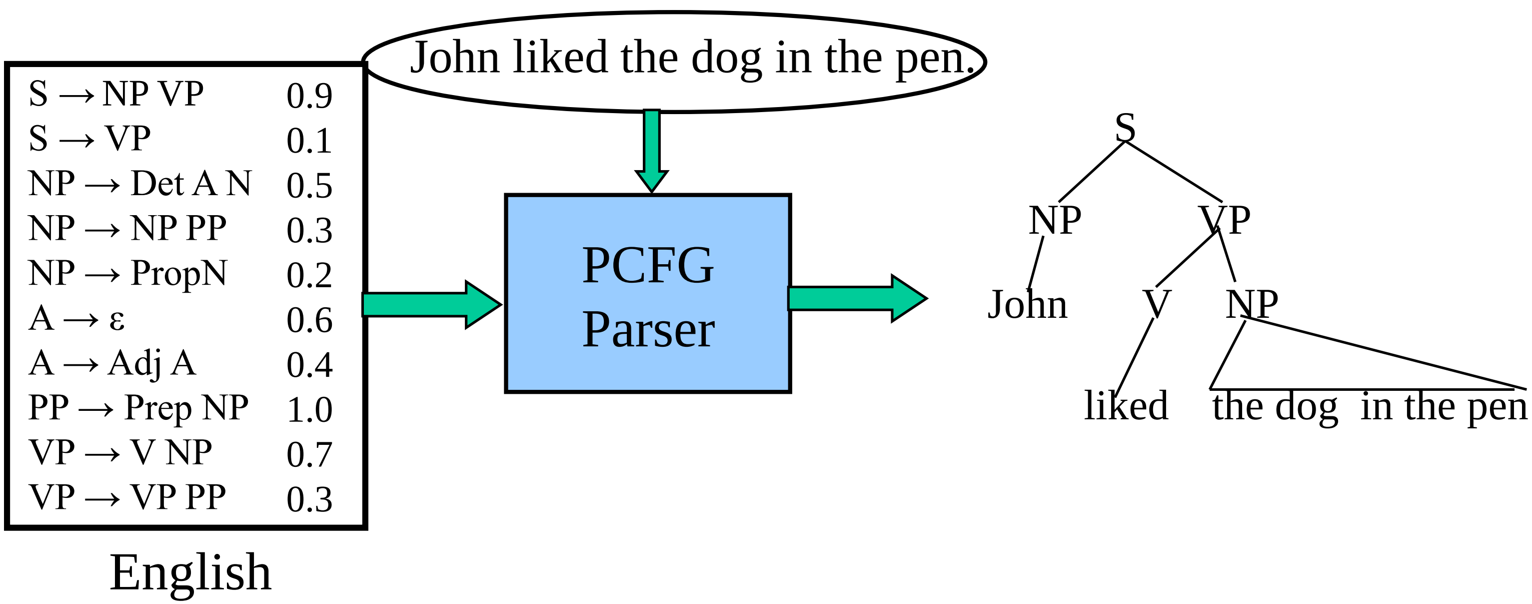
PCFG: Most Likely Derivation

- There is an analog to the Viterbi algorithm to efficiently determine the most probable derivation (parse tree) for a sentence.



PCFG: Most Likely Derivation

- There is an analog to the Viterbi algorithm to efficiently determine the most probable derivation (parse tree) for a sentence.



Probabilistic CKY

- CKY can be modified for PCFG parsing by including in each cell a probability for each non-terminal.
- Cell[i,j] must retain the *most probable* derivation of each constituent (non-terminal) covering words i +1 through j together with its associated probability.
- When transforming the grammar to CNF, must set production probabilities to preserve the probability of derivations.

Probabilistic Grammar Conversion

Original Grammar

S → NP VP 0.8
S → Aux NP VP 0.1
S → VP 0.1
NP → Pronoun 0.2
NP → Proper-Noun 0.2
NP → Det Nominal 0.6
Nominal → Noun 0.3
Nominal → Nominal Noun 0.2
Nominal → Nominal PP 0.5
VP → Verb 0.2
VP → Verb NP 0.5
VP → VP PP 0.3
PP → Prep NP 1.0

Chomsky Normal Form

S → NP VP 0.8
S → X1 VP 0.1
X1 → Aux NP 1.0
S → book | include | prefer
0.01 0.004 0.006
S → Verb NP 0.05
S → VP PP 0.03
NP → I | he | she | me
0.1 0.02 0.02 0.06
NP → Houston | NWA
0.16 .04
NP → Det Nominal 0.6
Nominal → book | flight | meal | money
0.03 0.15 0.06 0.06
Nominal → Nominal Noun 0.2
Nominal → Nominal PP 0.5
VP → book | include | prefer
0.1 0.04 0.06
VP → Verb NP 0.5
VP → VP PP 0.3
PP → Prep NP 1.0

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None			
	Det:.6	NP:.6*.6*.15 =.054		
		Nominal:.15 Noun:.5		

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	VP:.5*.5*.054 =.0135		
	Det:.6	NP:.6*.6*.15 =.054		
		Nominal:.15 Noun:.5		

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135		
	Det:.6	NP:.6*.6*.15 =.054		
		Nominal:.15 Noun:.5		

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	
		Nominal:.15 Noun:.5	None	
			Prep:.2	

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	
		Nominal:.15 Noun:.5	None	
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S:.05*.5* .000864 =.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S:.03*.0135* .032 =.00001296 S:.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S:.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

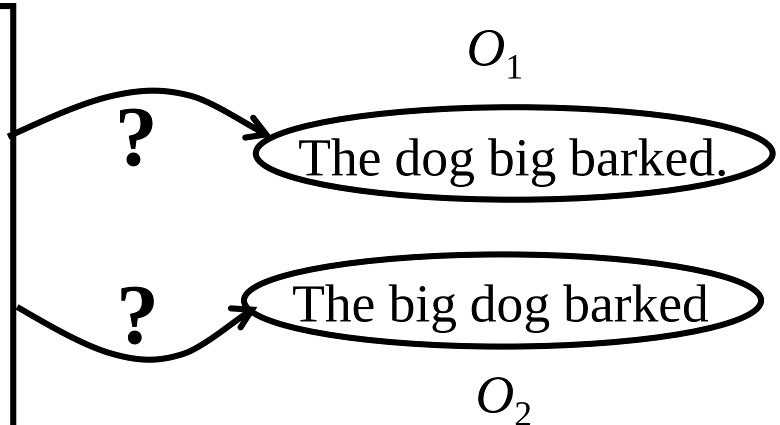
Pick most probable parse, i.e. take max to combine probabilities of multiple derivations of each constituent in each cell.

PCFG: Observation Likelihood

- There is an analog to Forward algorithm for HMMs called the Inside algorithm for efficiently determining how likely a string is to be produced by a PCFG.
- Can use a PCFG as a language model to choose between alternative sentences for speech recognition or machine translation.

S → NP VP	0.9
S → VP	0.1
NP → Det A N	0.5
NP → NP PP	0.3
NP → PropN	0.2
A → ε	0.6
A → Adj A	0.4
PP → Prep NP	1.0
VP → V NP	0.7
VP → VP PP	0.3

English



$P(O_2 \mid \text{English}) > P(O_1 \mid \text{English})$?

Inside Algorithm

- Use CKY probabilistic parsing algorithm but combine probabilities of multiple derivations of any constituent using **addition** instead of **max**.

Probabilistic CKY Parser for Inside Computation

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S:..00001296 S:.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Parser for Inside Computation

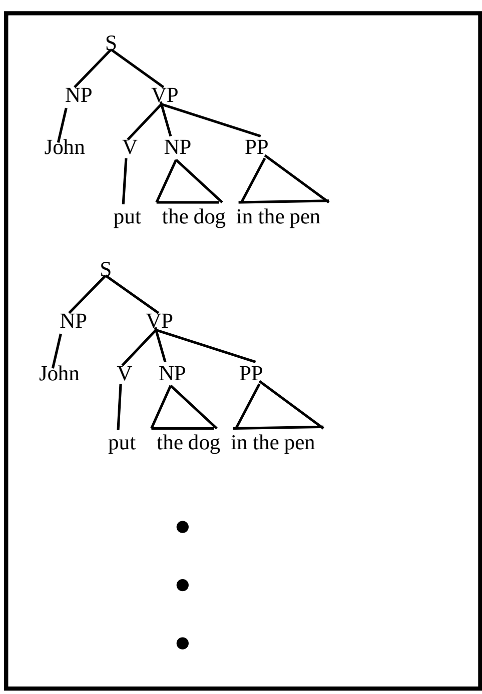
Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S: .00001296 +.0000216 =.00003456
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Sum probabilities of multiple derivations of each constituent in each cell.

PCFG: Supervised Training

- If parse trees are provided for training sentences, a grammar and its parameters can be can all be estimated directly from counts accumulated from the tree-bank (with appropriate smoothing).

Tree Bank



Supervised PCFG Training

S → NP VP	0.9
S → VP	0.1
NP → Det A N	0.5
NP → NP PP	0.3
NP → PropN	0.2
A → ε	0.6
A → Adj A	0.4
PP → Prep NP	1.0
VP → V NP	0.7
VP → VP PP	0.3

English

Estimating Production Probabilities

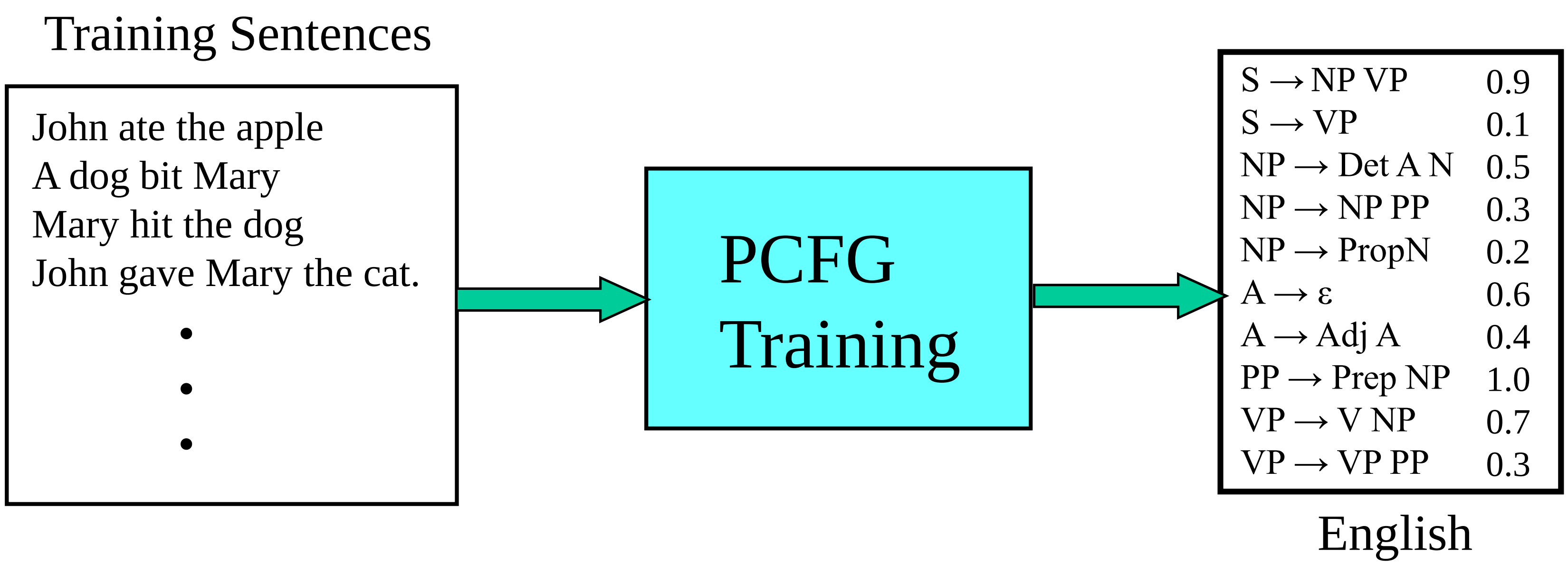
- Set of production rules can be taken directly from the set of rewrites in the treebank.
- Parameters can be directly estimated from frequency counts in the treebank.

$$P(\alpha \rightarrow \beta \mid \alpha) = \frac{\text{count}(\alpha \rightarrow \beta)}{\sum_{\gamma} \text{count}(\alpha \rightarrow \gamma)} = \frac{\text{count}(\alpha \rightarrow \beta)}{\text{count}(\alpha)}$$

PCFG: Maximum Likelihood Training

- Given a set of sentences, induce a grammar that maximizes the probability that this data was generated from this grammar.
- Assume the number of non-terminals in the grammar is specified.
- Only need to have an unannotated set of sequences generated from the model. Does not need correct parse trees for these sentences. In this sense, it is unsupervised.

PCFG: Maximum Likelihood Training



Inside-Outside

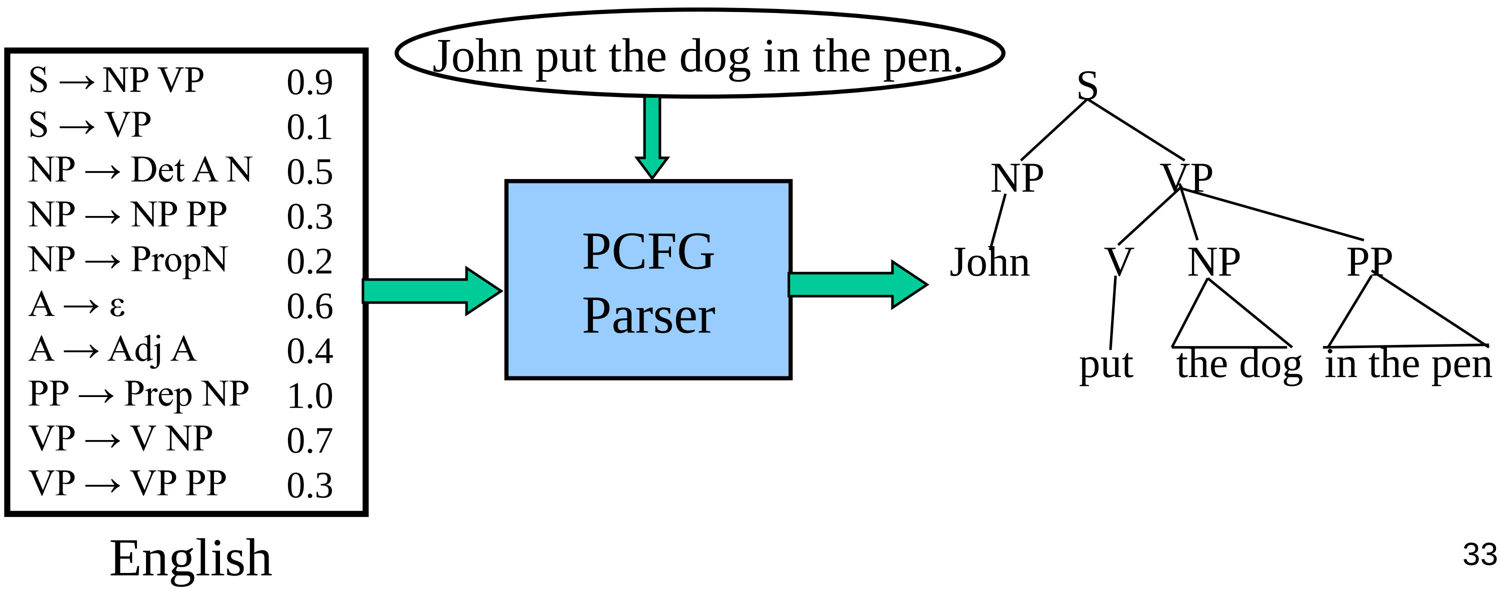
- The **Inside-Outside algorithm** is a version of EM for unsupervised learning of a PCFG.
  - Analogous to Baum-Welch (forward-backward) for HMMs
- Given the number of non-terminals, construct all possible CNF productions with these non-terminals and observed terminal symbols.
- Use EM to iteratively train the probabilities of these productions to locally maximize the likelihood of the data.
  - See Manning and Schütze text for details
- Experimental results are not impressive, but recent work imposes additional constraints to improve unsupervised grammar learning.

Vanilla PCFG Limitations

- Since probabilities of productions do not rely on specific words or concepts, only general structural disambiguation is possible (e.g. prefer to attach PPs to Nominals).
- Consequently, vanilla PCFGs cannot resolve syntactic ambiguities that require semantics to resolve, e.g. ate with fork vs. meatballs.
- In order to work well, PCFGs must be lexicalized, i.e. productions must be specialized to specific words by including their head-word in their LHS non-terminals (e.g. VP-ate).

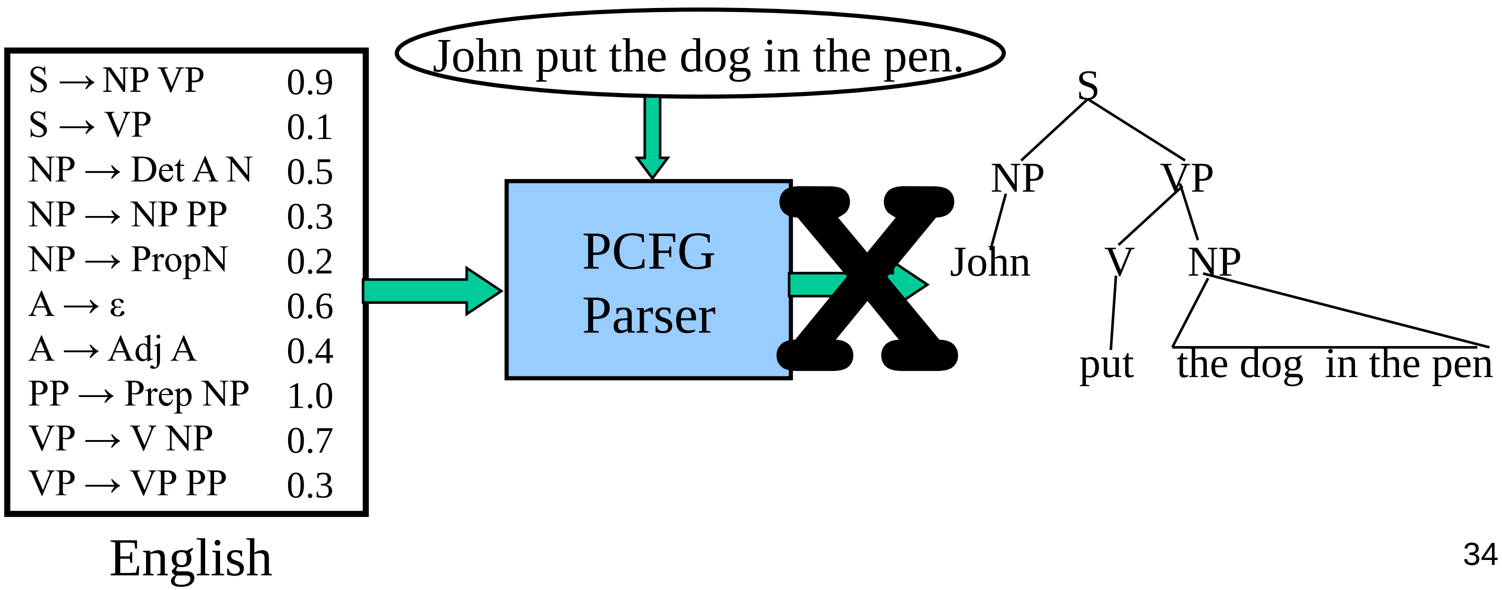
Example of Importance of Lexicalization

- A general preference for attaching PPs to NPs rather than VPs can be learned by a vanilla PCFG.
- But the desired preference can depend on specific words.



Example of Importance of Lexicalization

- A general preference for attaching PPs to NPs rather than VPs can be learned by a vanilla PCFG.
- But the desired preference can depend on specific words.

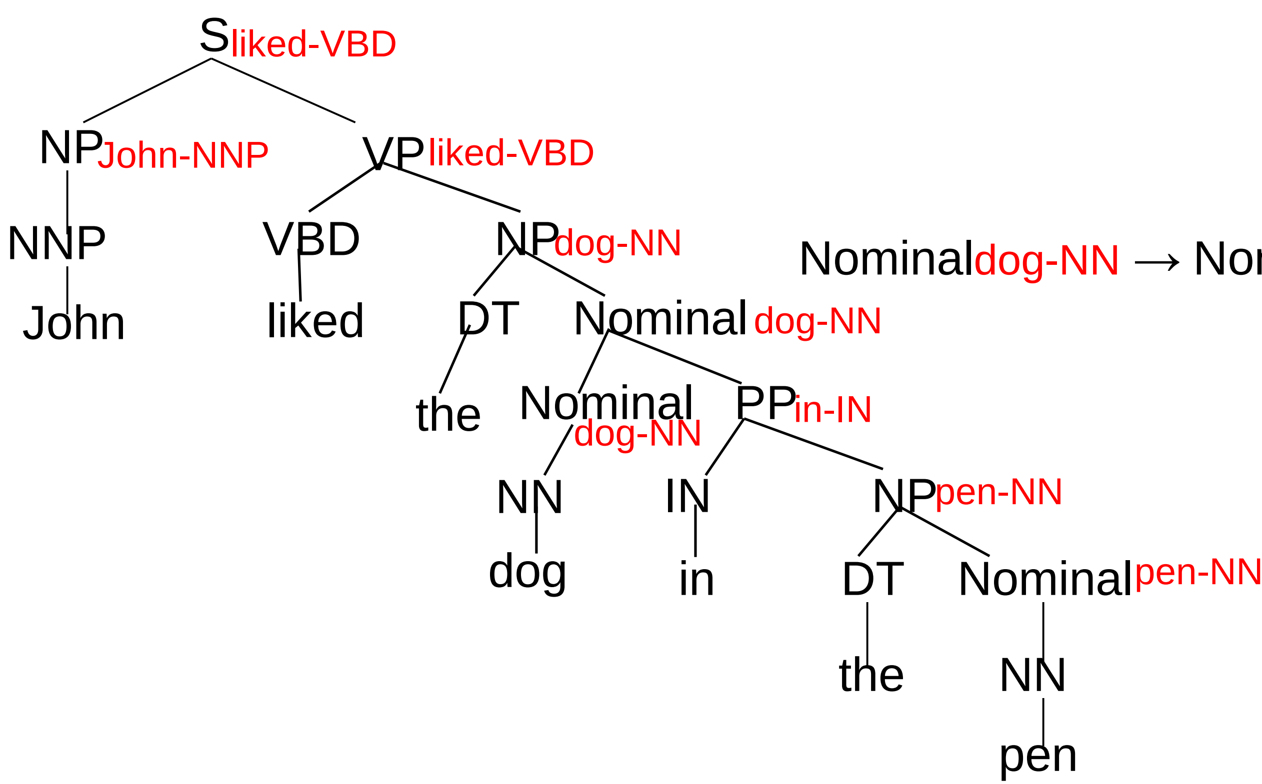


Head Words

- Syntactic phrases usually have a word in them that is most "central" to the phrase.
- Linguists have defined the concept of a lexical **head** of a phrase.
- Simple rules can identify the head of any phrase by percolating head words up the parse tree.
  - Head of a VP is the main verb
  - Head of an NP is the main noun
  - Head of a PP is the preposition
  - Head of a sentence is the head of its VP

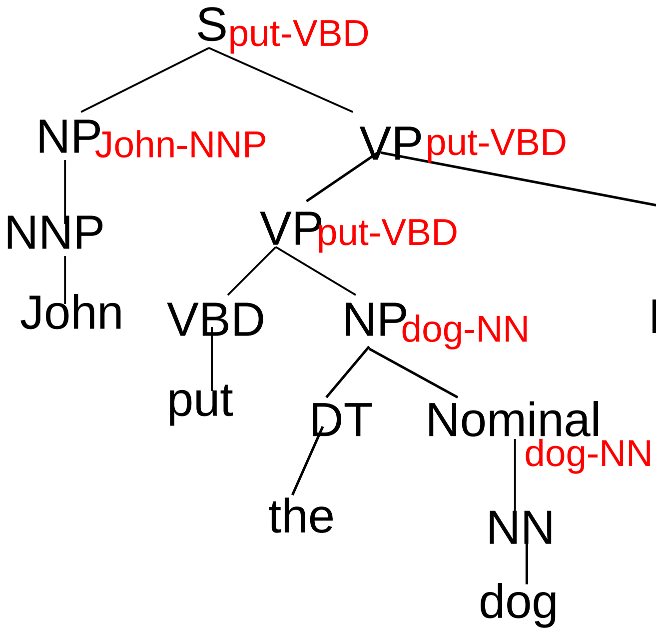
Lexicalized Productions

- Specialized productions can be generated by including the head word and its POS of each non-terminal as part of that non-terminal's symbol.



$\text{Nominal}_{\text{dog-NN}} \rightarrow \text{Nominal}_{\text{dog-NN}}\ \text{PP}_{\text{in-IN}}$

Lexicalized Productions



VPput-VBD → VPput-VBD PPin-IN

Parameterizing Lexicalized Productions

- Accurately estimating parameters on such a large number of very specialized productions could require enormous amounts of treebank data.
- Need some way of estimating parameters for lexicalized productions that makes reasonable independence assumptions so that accurate probabilities for very specific rules can be learned.
- Collins (1999) introduced one approach to learning effective parameters for a lexicalized grammar.

Treebanks

- English Penn Treebank: Standard corpus for testing syntactic parsing consists of 1.2 M words of text from the Wall Street Journal (WSJ).
- Typical to train on about 40,000 parsed sentences and test on an additional standard disjoint test set of 2,416 sentences.
- Chinese Penn Treebank: 100K words from the Xinhua news service.
- Other corpora existing in many languages, see the Wikipedia article "Treebank"

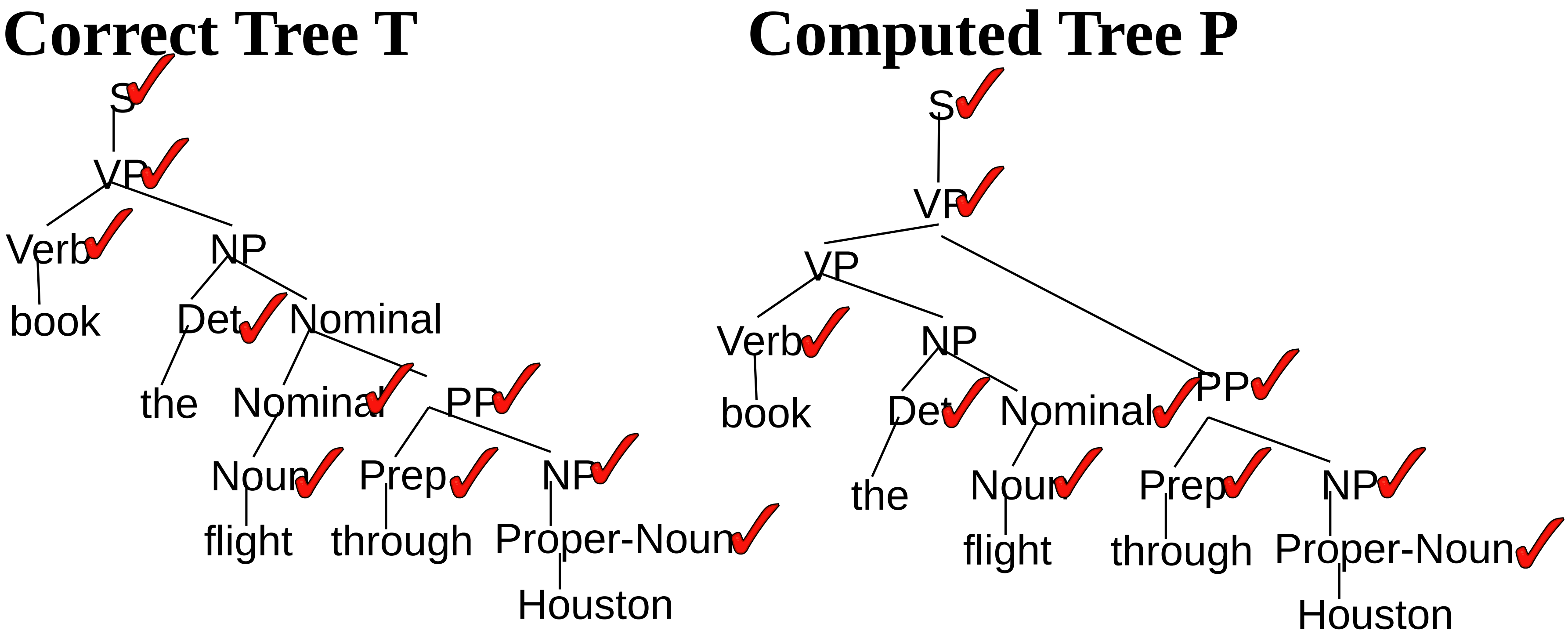
First WSJ Sentence

```
( (S
    (NP-SBJ
      (NP (NNP Pierre) (NNP Vinken) )
      (, ,)
      (ADJP
        (NP (CD 61) (NNS years) )
        (JJ old) )
      (, ,) )
    (VP (MD will)
      (VP (VB join)
        (NP (DT the) (NN board) )
        (PP-CLR (IN as)
          (NP (DT a) (JJ nonexecutive) (NN director) ))
        (NP-TMP (NNP Nov.) (CD 29) )))
    (. .) ))
```

Parsing Evaluation Metrics

- PARSEVAL metrics measure the fraction of the constituents that match between the computed and human parse trees. If *P* is the system's parse tree and *T* is the human parse tree (the "gold standard"):
  - ***Recall*** = (# correct constituents in *P*) / (# constituents in *T*)
  - ***Precision*** = (# correct constituents in *P*) / (# constituents in *P*)
- ***Labeled Precision*** and ***labeled recall*** require getting the non-terminal label on the constituent node correct to count as correct.
- F_1 is the harmonic mean of precision and recall.

Computing Evaluation Metrics



Constituents: 12

Constituents: 12

Correct Constituents: 10

Recall = 10/12= 83.3%   Precision = 10/12=83.3% F_1 = 83.3%

Treebank Results

- Results of current state-of-the-art systems on the English Penn WSJ treebank are 91-92% labeled F_1.

Human Parsing

- Computational parsers can be used to predict human reading time as measured by tracking the time taken to read each word in a sentence.
- Psycholinguistic studies show that words that are more probable given the preceding lexical and syntactic context are read faster.
  - John put the dog in the pen with a lock.
  - John put the dog in the pen with a bone in the car.
  - John liked the dog in the pen with a bone.
- Modeling these effects requires an ***incremental*** statistical parser that incorporates one word at a time into a continuously growing parse tree.

Garden Path Sentences

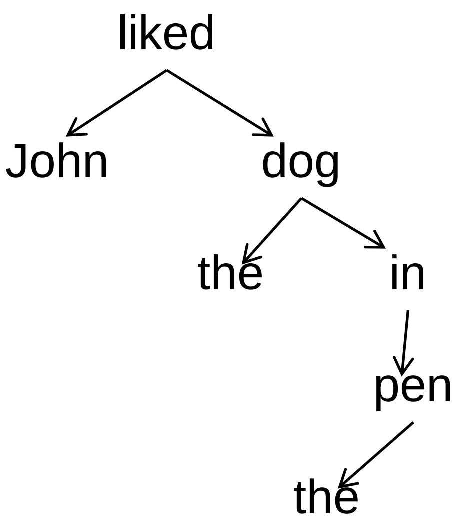
- People are confused by sentences that seem to have a particular syntactic structure but then suddenly violate this structure, so the listener is “lead down the garden path”.
  - The horse raced past the barn fell.
    - vs. The horse raced past the barn broke his leg.
  - The complex houses married students.
  - The old man the sea.
  - While Anna dressed the baby spit up on the bed.
- Incremental computational parsers can try to predict and explain the problems encountered parsing such sentences.

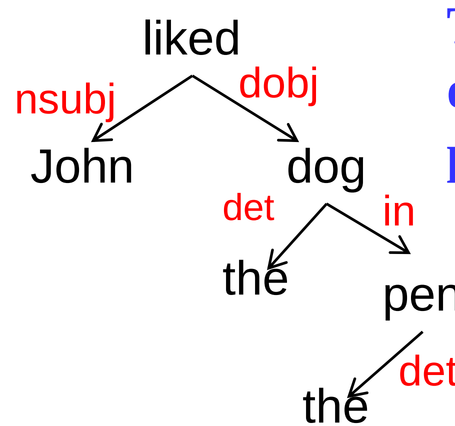
Center Embedding

- Nested expressions are hard for humans to process beyond 1 or 2 levels of nesting.
  - The rat the cat chased died.
  - The rat the cat the dog bit chased died.
  - The rat the cat the dog the boy owned bit chased died.
- Requires remembering and popping incomplete constituents from a stack and strains human short-term memory.
- Equivalent “tail embedded” (tail recursive) versions are easier to understand since no stack is required.
  - The boy owned a dog that bit a cat that chased a rat that died.

Dependency Grammars

- An alternative to phrase-structure grammar is to define a parse as a directed graph between the words of a sentence representing ***dependencies*** between the words.

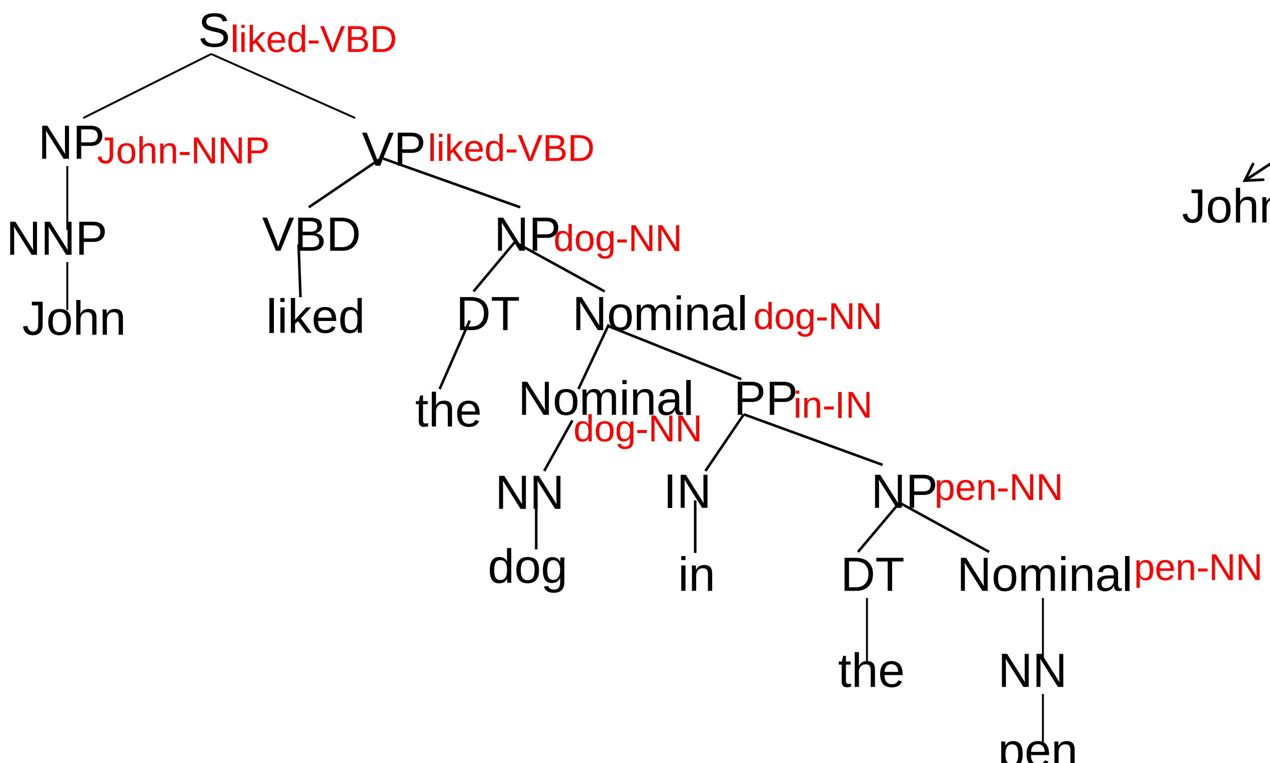


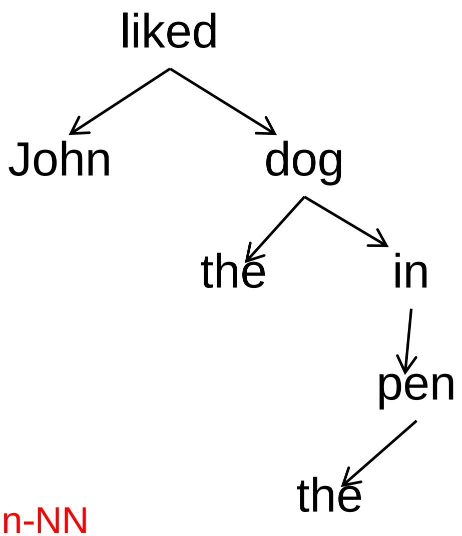


Typed dependency parse

Dependency Graph from Parse Tree

- Can convert a phrase structure parse to a dependency tree by making the head of each non-head child of a node depend on the head of the head child.





Unification Grammars

- In order to handle agreement issues more effectively, each constituent has a list of features such as number, person, gender, etc. which may or not be specified for a given constituent.
- In order for two constituents to combine to form a larger constituent, their features must ***unify***, i.e. consistently combine into a merged set of features.
- Expressive grammars and parsers (e.g. HPSG) have been developed using this approach and have been partially integrated with modern statistical models of disambiguation.

Mildly Context-Sensitive Grammars

- Some grammatical formalisms provide a degree of context-sensitivity that helps capture aspects of NL syntax that are not easily handled by CFGs.
- Tree Adjoining Grammar (TAG) is based on combining tree fragments rather than individual phrases.
- Combinatory Categorial Grammar (CCG) consists of:
  - Categorial Lexicon that associates a syntactic and semantic category with each word.
  - Combinatory Rules that define how categories combine to form other categories.

Statistical Parsing Conclusions

- Statistical models such as PCFGs allow for probabilistic resolution of ambiguities.
- PCFGs can be easily learned from treebanks.
- Lexicalization and non-terminal splitting are required to effectively resolve many ambiguities.
- Current statistical parsers are quite accurate but not yet at the level of human-expert agreement.