Speech and Language Processing: Statistical Parsing

Chapter 14

1

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.

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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.

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Simple PCFG for ATIS English

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

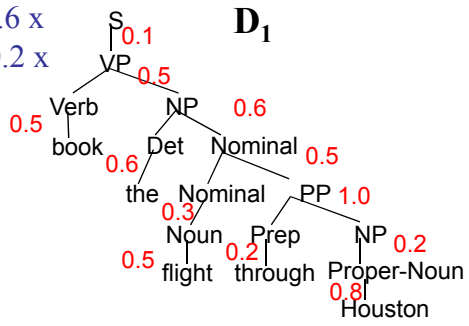
Aux → does
1.0

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 x 0.5 x 0.5 x 0.6 x 0.6 x 0.5 x 0.3 x 1.0 x 0.2 x 0.2 x 0.5 x 0.8
= 0.0000216



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Other Parses?

- book the flight through Houston

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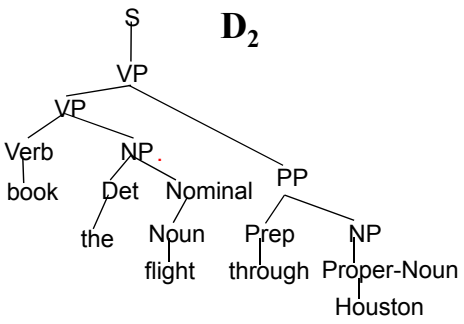
Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

$P(D_2)$ =



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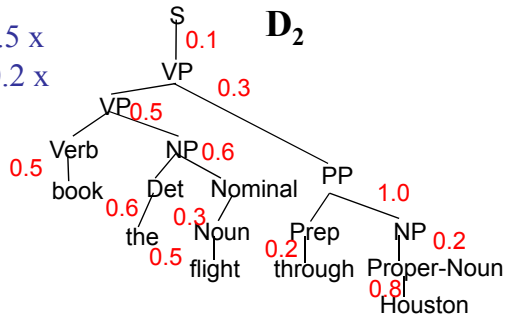
Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

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



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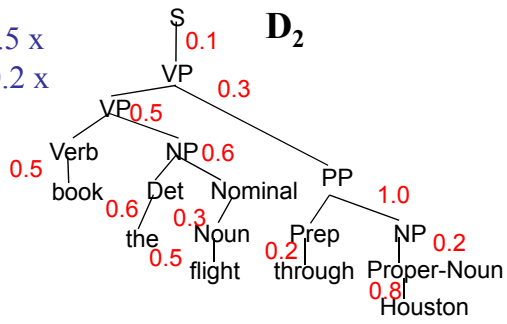
Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

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



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Disambiguation Result?

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Sentence Probability

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

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

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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.

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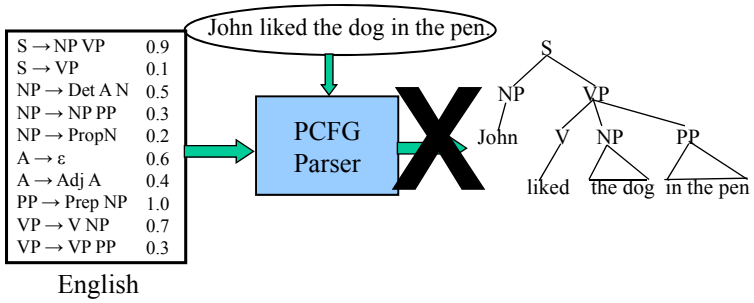
PCFG: Most Likely Derivation

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



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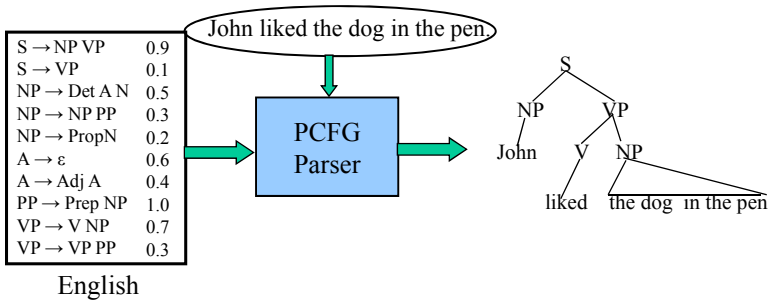

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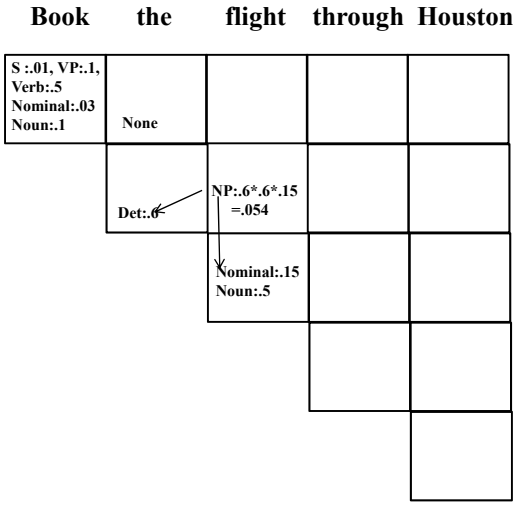
Probabilistic CKY

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

Probabilistic CKY Parser



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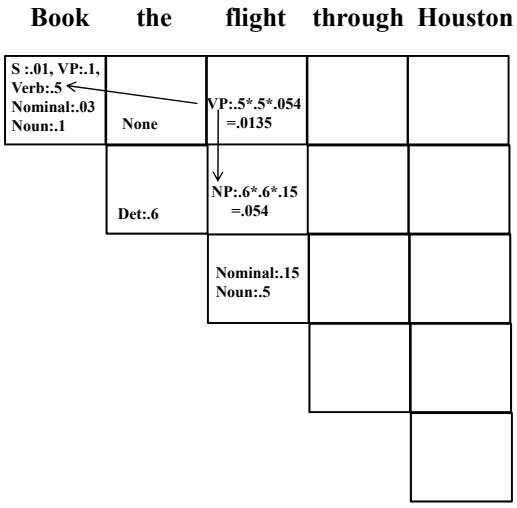
Probabilistic CKY Parser



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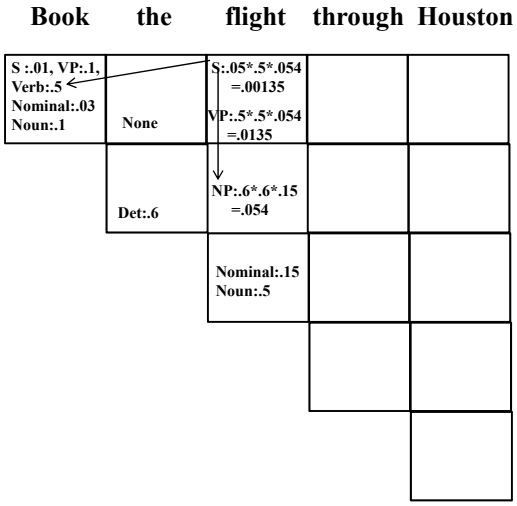
Probabilistic CKY Parser



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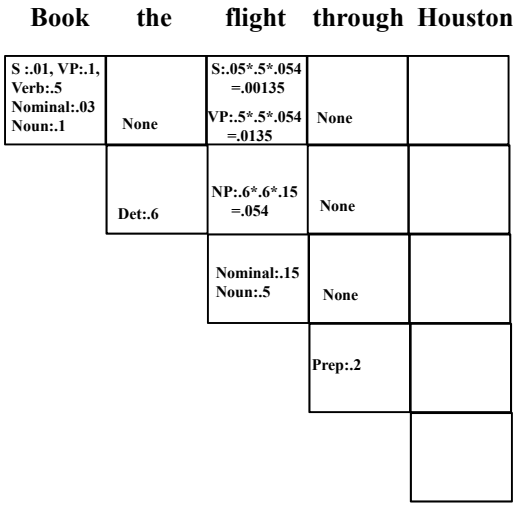
Probabilistic CKY Parser



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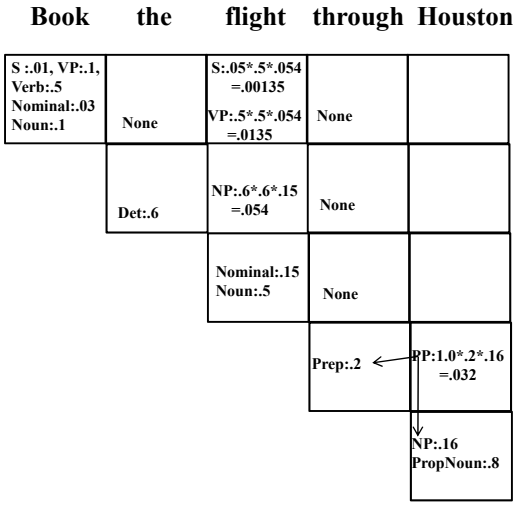
Probabilistic CKY Parser



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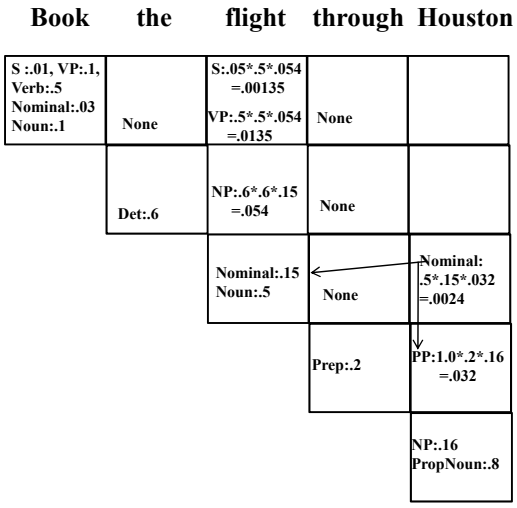
Probabilistic CKY Parser



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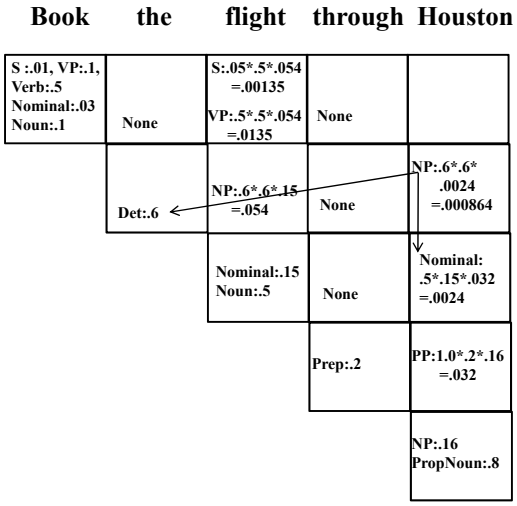
Probabilistic CKY Parser



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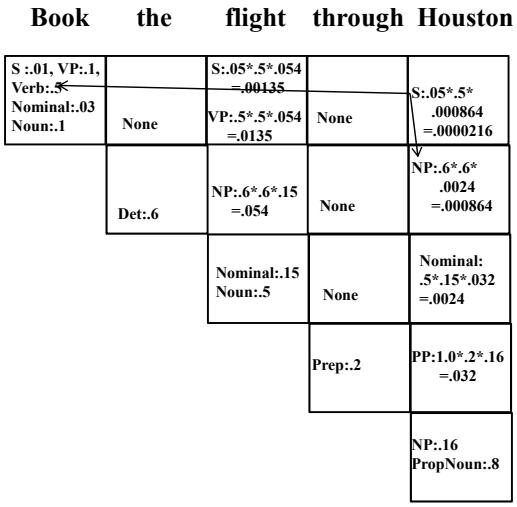
Probabilistic CKY Parser



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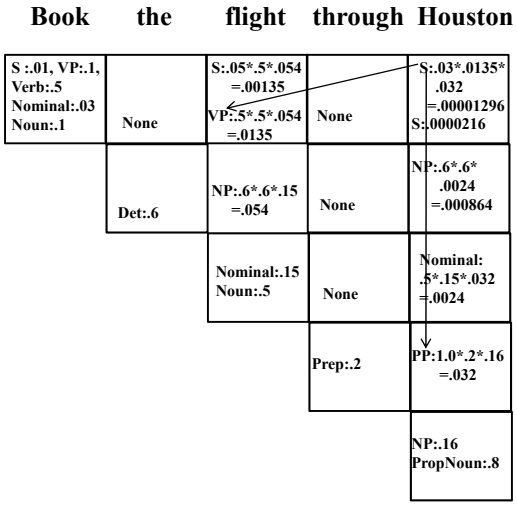
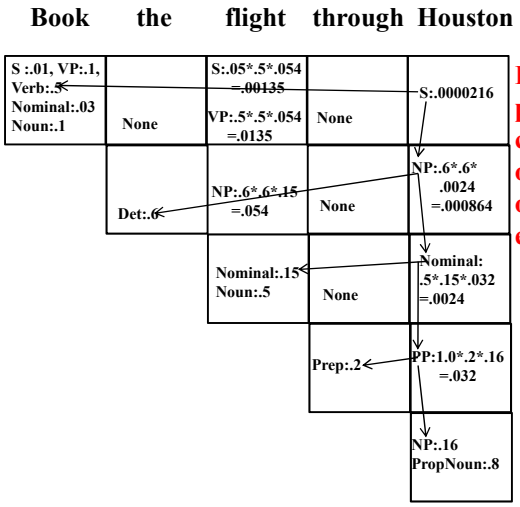
Probabilistic CKY Parser



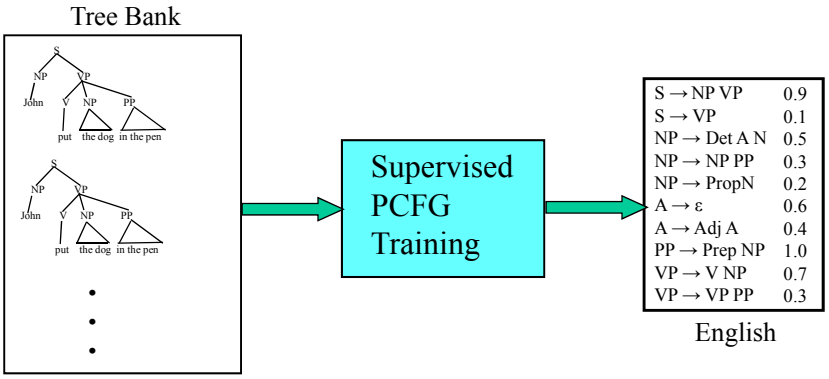
Probabilistic CKY Parser



Pick most probable parse, i.e. take max to combine 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).



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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.

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

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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).

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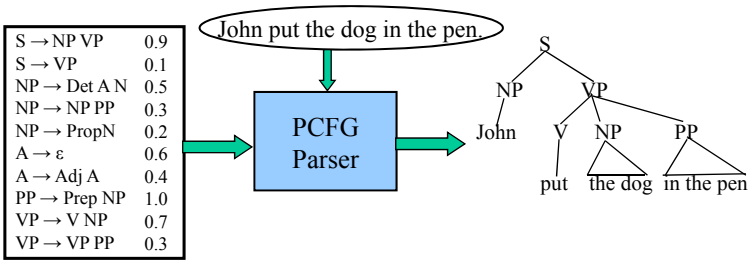
Example of Importance of Lexicalization

- 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.



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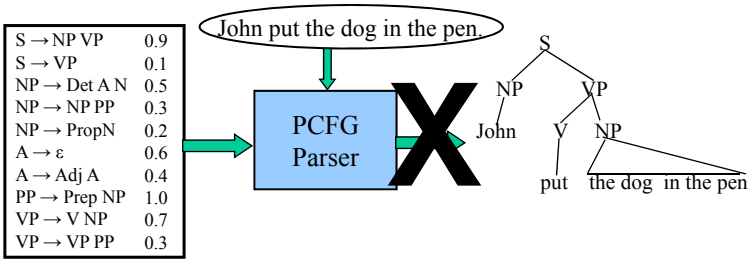

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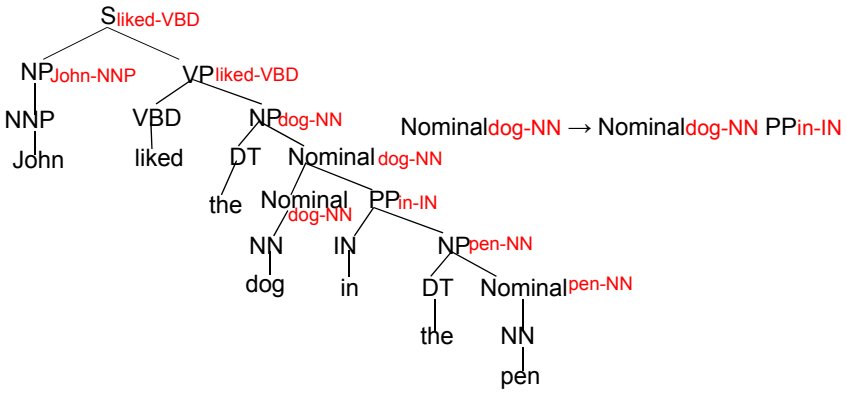
Head Words

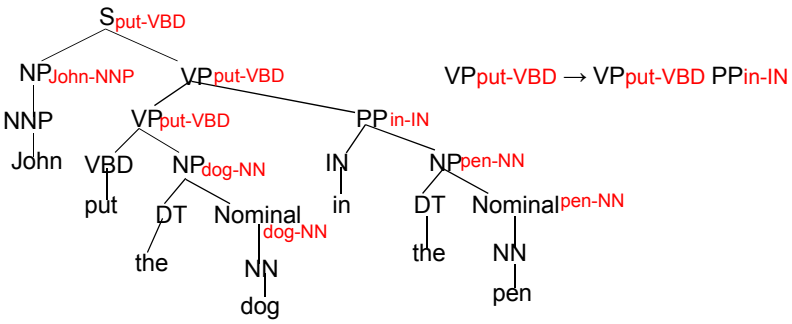
- Syntactic phrases usually have a word in them that is most "central" to the phrase.
- Linguists have defined the concept of a lexical **head** of a phrase.
- Simple rules can identify the head of any phrase by percolating head words up the parse tree.
  - Head of a VP is the main verb
  - Head of an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



Lexicalized Productions



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' Parser

- Collins' (1999) parser assumes a simple generative model of lexicalized productions.
- Models productions based on context to the left and the right of the head daughter.
  - LHS $\rightarrow L_n L_{n-1} \ldots L_1 H\ R_1 \ldots R_{m-1} R_m$
- First generate the head (H) and then repeatedly generate left (L_i) and right (R_i) context symbols until the symbol STOP is generated.

Sample Production Generation

VPput-VBD → VBDput-VBD NPdog-NN PPin-IN

Note: Penn treebank tends to have fairly flat parse trees that produce long productions.

VPput-VBD → STOP VBDput-VBD NPdog-NN PPin-IN STOP

L_1 H R_1 R_2 R_3

$P_L(\text{STOP} \mid \text{VPput-VBD}) * P_H(\text{VBD} \mid \text{Vpput-VBD}) *$
$P_R(\text{NPdog-NN} \mid \text{VPput-VBD}) *$
$P_R(\text{PPin-IN} \mid \text{VPput-VBD}) * P_R(\text{STOP} \mid \text{VPput-VBD})$

Estimating Production Generation Parameters

- Estimate P_H, P_L, and P_R parameters from treebank data.

$$P_R(\text{PPin-IN} \mid \text{VPput-VBD}) = \frac{\text{Count(PPin-IN right of head in a VPput-VBD production)}}{\text{Count(symbol right of head in a VPput-VBD)}}$$

$$P_R(\text{NPdog-NN} \mid \text{VPput-VBD}) = \frac{\text{Count(NPdog-NN right of head in a VPput-VBD production)}}{\text{Count(symbol right of head in a VPput-VBD)}}$$

- Smooth estimates by linearly interpolating with simpler models conditioned on just POS tag or no lexical info.

$$\text{sm}P_R(\text{PPin-IN} \mid \text{VPput-VBD}) = \lambda_1 P_R(\text{PPin-IN} \mid \text{VPput-VBD}) + (1-\lambda_1)(\lambda_2 P_R(\text{PPin-IN} \mid \text{VPVBD}) + (1-\lambda_2) P_R(\text{PPin-IN} \mid \text{VP}))$$

Missed Context Dependence

- Another problem with CFGs is that which production is used to expand a non-terminal is independent of its context.
- However, this independence is frequently violated for normal grammars.
  - NPs that are subjects are more likely to be pronouns than NPs that are objects.

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Splitting Non-Terminals

- To provide more contextual information, non-terminals can be split into multiple new non-terminals based on their parent in the parse tree using parent annotation.
  - A subject NP becomes NP^S since its parent node is an S.
  - An object NP becomes NP^VP since its parent node is a VP

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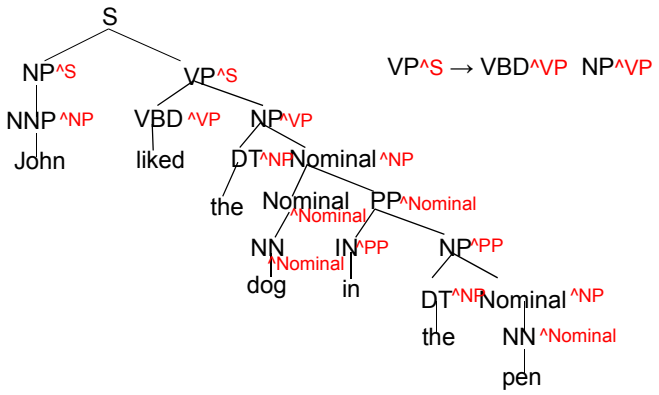
Parent Annotation Example



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Split and Merge

- Non-terminal splitting greatly increases the size of the grammar and the number of parameters that need to be learned from limited training data.
- Best approach is to only split non-terminals when it improves the accuracy of the grammar.
- May also help to merge some non-terminals to remove some un-helpful distinctions and learn more accurate parameters for the merged productions.
- Method: Heuristically search for a combination of splits and merges that produces a grammar that maximizes the likelihood of the training treebank.

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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.

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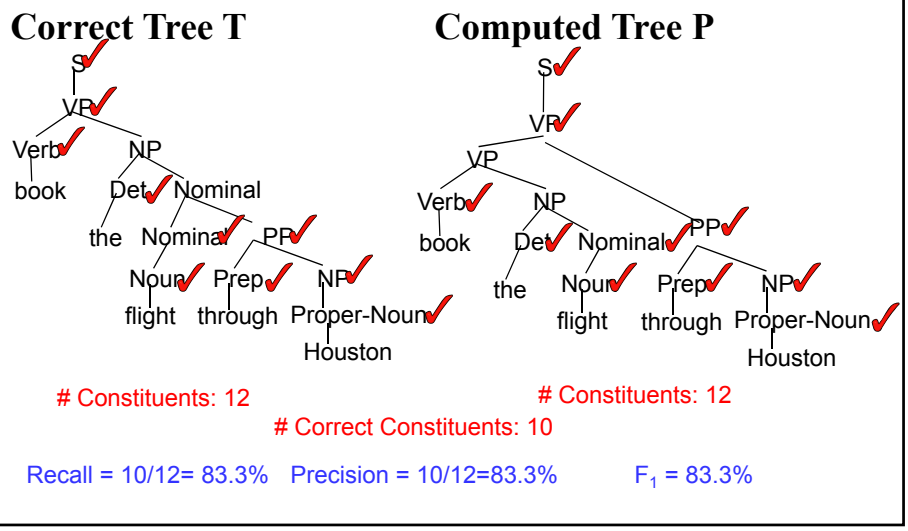
Computing Evaluation Metrics



Treebank Results

- Results of current state-of-the-art systems on the English Penn WSJ treebank are slightly greater than 90% labeled precision and recall.

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Discriminative Parse Reranking

- Motivation: Even when the top-ranked parse not correct, frequently the correct parse is one of those ranked highly by a statistical parser.
- Use a discriminative classifier that is trained to select the best parse from the N-best parses produced by the original parser.
- Reranker can exploit global features of the entire parse whereas a PCFG is restricted to making decisions based on local info.

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2-Stage Reranking Approach

- Adapt the PCFG parser to produce an ***N-best list*** of the most probable parses in addition to the most-likely one.
- Extract from each of these parses, a set of global features that help determine if it is a good parse tree.
- Train a discriminative classifier (e.g. logistic regression) using the best parse in each N-best list as positive and others as negative.

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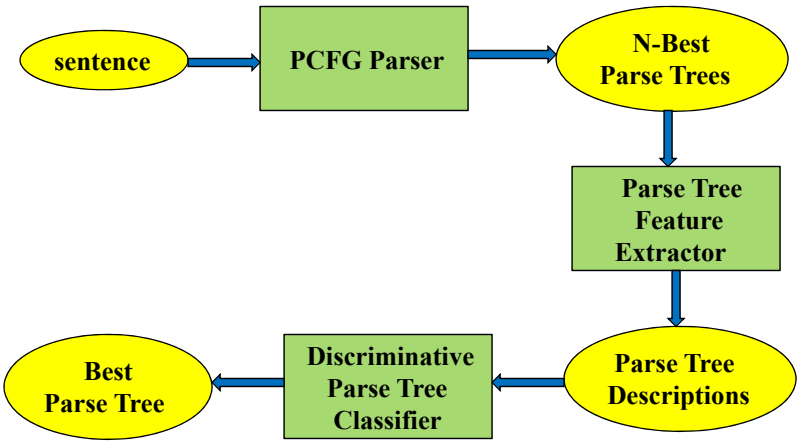
Parse Reranking



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Sample Parse Tree Features

- Probability of the parse from the PCFG.
- The number of parallel conjuncts.
  - "the bird in the tree and the squirrel on the ground"
  - "the bird and the squirrel in the tree"
- The degree to which the parse tree is right branching.
  - English parses tend to be right branching (cf. parse of "Book the flight through Houston")

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Evaluation of Reranking

- Reranking is limited by ***oracle accuracy***, i.e. the accuracy that results when an omniscient oracle picks the best parse from the N-best list.
- Typical current oracle accuracy is around F_1=97%
- Reranking can generally improve test accuracy of current PCFG models a percentage point or two.

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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.

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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.

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Unification Grammars (Ch 15)

- 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 – head driven phrase structure grammar) have been developed using this approach and have been partially integrated with modern statistical models of disambiguation.

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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.
- 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.

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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.

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