CS388: Natural Language Processing

Lecture 11: Syntax I

credit: Imgflip

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Some slides adapted from Dan Klein, UC Berkeley

Administrivia

- Mini 2 due today
- Project 1 back soon
- Final project spec posted
  - Done in pairs or alone
  - Topic: see spec for suggestions
  - Proposals due before spring break, in-class presentations at the end of the semester, final report due later

This Lecture

- Constituency formalism
- Context-free grammars and the CKY algorithm
- Refining grammars
- Dependency grammar

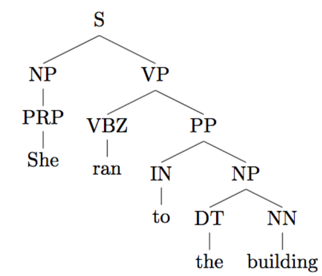
Constituency

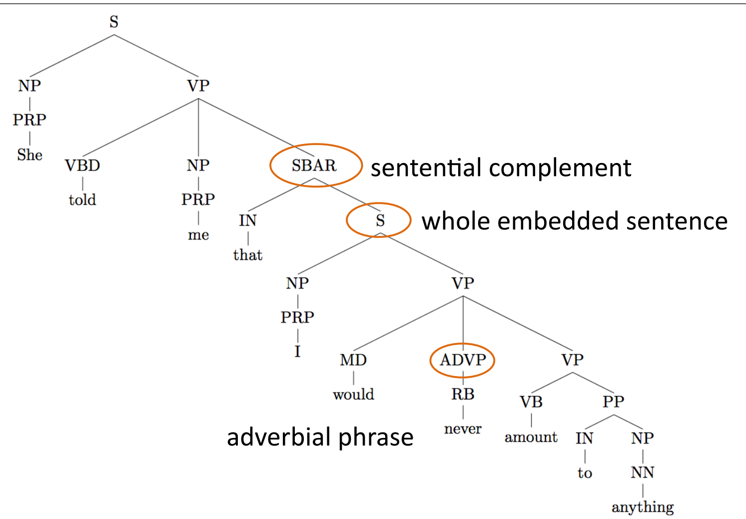
Syntax

- Study of word order and how words form sentences
- Why do we care about syntax?
  - Multiple interpretations of words (noun or verb?)
  - Recognize verb-argument structures (who is doing what to whom?)
  - Higher level of abstraction beyond words: some languages are SVO, some are VSO, some are SOV, parsing can canonicalize

Constituency Parsing

- Tree-structured syntactic analyses of sentences
- Common things: noun phrases, verb phrases, prepositional phrases
- Bottom layer is POS tags
- Examples will be in English. Constituency makes sense for a lot of languages but not all





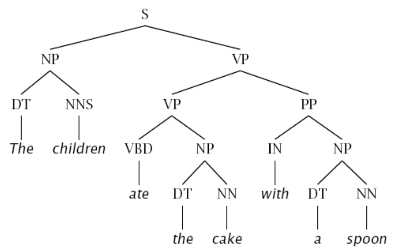
Constituency Parsing

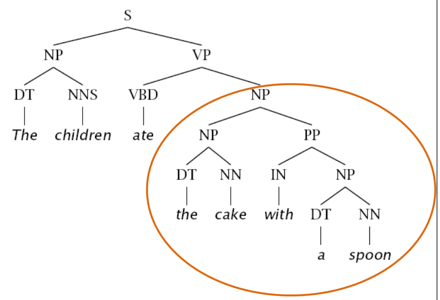
The rat the cat chased squeaked

I raced to Indianapolis , unimpeded by traffic

Challenges

- PP attachment

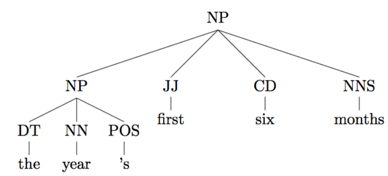


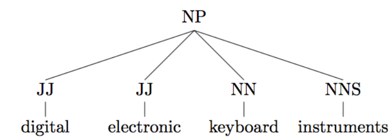


same parse as "the cake with some icing"

Challenges

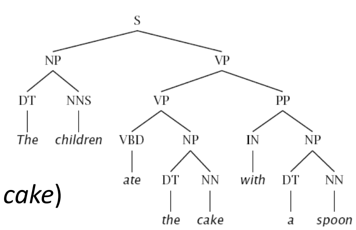
- NP internal structure: tags + depth of analysis





Constituency

- How do we know what the constituents are?
- Constituency tests:
  - Substitution by *proform* (e.g., pronoun)
  - Clefting (*It was with a spoon that…*)
  - Answer ellipsis (What did they eat? *the cake*)
    (How? *with a spoon*)



- Sometimes constituency is not clear, e.g., coordination: *she went to and bought food at the store*

Context-Free Grammars, CKY

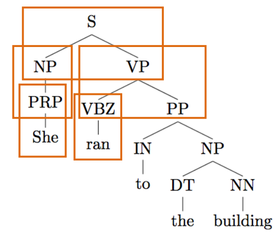
CFGs and PCFGs

Grammar (CFG)				Lexicon	
ROOT → S	1.0	NP → NP PP	0.3	NN → interest	1.0
S → NP VP	1.0	VP → VBP NP	0.7	NNS → raises	1.0
NP → DT NN	0.2	VP → VBP NP PP	0.3	VBP → interest	1.0
NP → NN NNS	0.5	PP → IN NP	1.0	VBZ → raises	1.0

- Context-free grammar: symbols which rewrite as one or more symbols
- Lexicon consists of "preterminals" (POS tags) rewriting as terminals (words)
- CFG is a tuple (N, T, S, R): N = nonterminals, T = terminals, S = start symbol (generally a special ROOT symbol), R = rules
- PCFG: probabilities associated with rewrites, normalize by source symbol

Estimating PCFGs

- Tree *T* is a series of rule applications *r*. $P(T) = \prod_{r \in T} P(r|\text{parent}(r))$



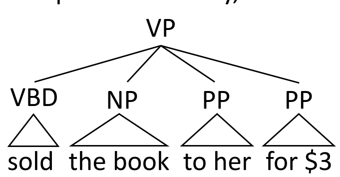
→

S → NP VP	1.0
NP → PRP	0.5
NP → DT NN	0.5
…	

- Maximum likelihood PCFG for a set of labeled trees: count and normalize! Same as HMMs / Naive Bayes

Binarization

- To parse efficiently, we need our PCFGs to be at most binary (not CNF)

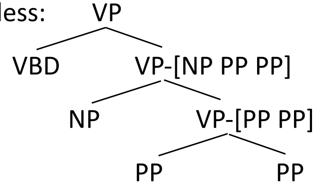


P(VP → VBD NP PP PP) = 0.2

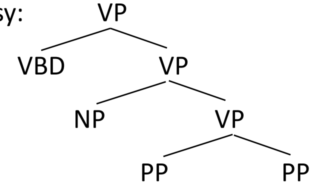
P(VP → VBZ PP) = 0.1

…

- Lossless:

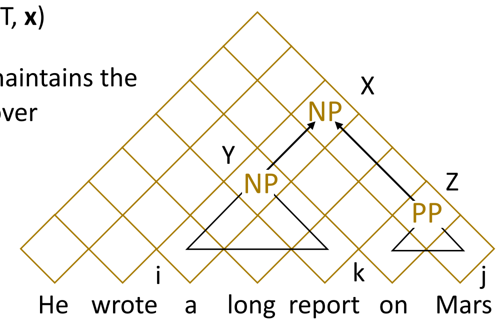


- Lossy:



CKY

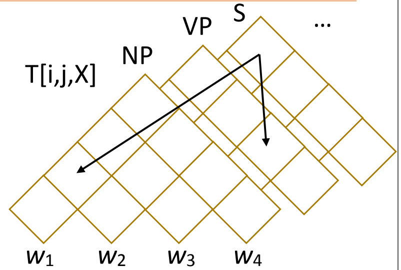
- Find argmax P(T|**x**) = argmax P(T, **x**)
- Dynamic programming: chart maintains the best way of building symbol X over span (i, j)
- CKY = Viterbi, there is also an algorithm called inside-outside = forward-backward



Cocke-Kasami-Younger

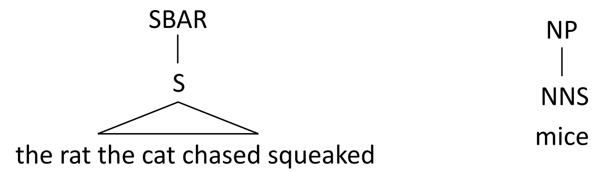
CKY

- Chart: T[i,j,X] = best score for X over (i, j)
- Base: T[i,i+1,X] = log P(X → w_i)
- Loop over all split points k, apply rules X -> Y Z to build X in every possible way
- Recurrence:
  $T[i,j,X] = \max_{k} \max_{r: X \to X1\ X2} T[i,k,X1] + T[k,j,X2] + \log P(X \to X1\ X2)$
- Runtime: O(n^3G) G = grammar constant



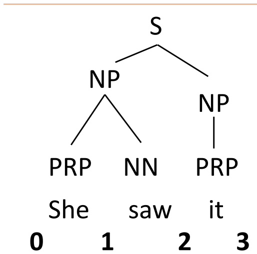
S[0,4] => NP[0,2] VP[2,4]

Unary Rules

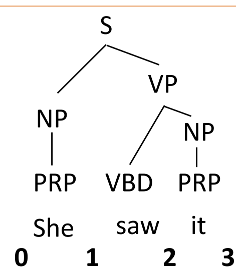


- Unary productions in treebank need to be dealt with by parsers
- Binary trees over n words have at most n-1 nodes, but you can have unlimited numbers of nodes with unaries (S → SBAR → NP → S → ...)
- In practice: enforce at most one unary over each span, modify CKY accordingly

Parser Evaluation



S(0,3),
NP(0,2),
NP(2,3),
~~PRP(0,1),~~
~~NN(1,2),~~
~~PRP(2,3)~~



S(0,3),
NP(0,1),
VP(1,3),
NP(2,3),
~~PRP(0,1),~~
~~VBD(1,2),~~
~~PRP(2,3)~~

- Precision: number of correct brackets / num pred brackets = 2/3
- Recall: number of correct brackets / num of gold brackets = 2/4
- F1: harmonic mean of precision and recall = $(1/2 * ((2/4)^{-1} + (2/3)^{-1}))^{-1}$

  = 0.57

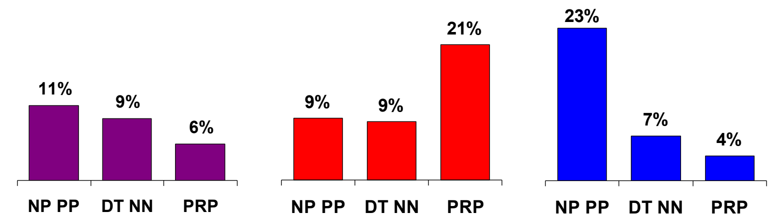
Results

- Standard dataset for English: Penn Treebank (Marcus et al., 1993)
  - Evaluation: F1 over labeled constituents of the sentence
- Vanilla PCFG: ~75 F1
- Best PCFGs for English: ~90 F1
- SOTA (discriminative models): 95 F1
- Other languages: results vary widely depending on annotation + complexity of the grammar

Klein and Manning (2003)

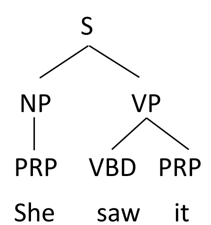
Refining Generative Grammars

PCFG Independence Assumptions

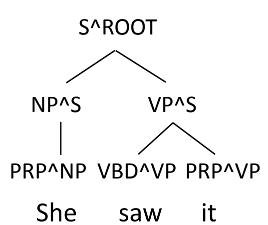


- Language is not context-free: NPs in different contexts rewrite differently
- Can we make the grammar "less context-free"?

Vertical Markovization



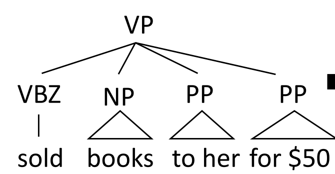
Basic tree (v = 0)

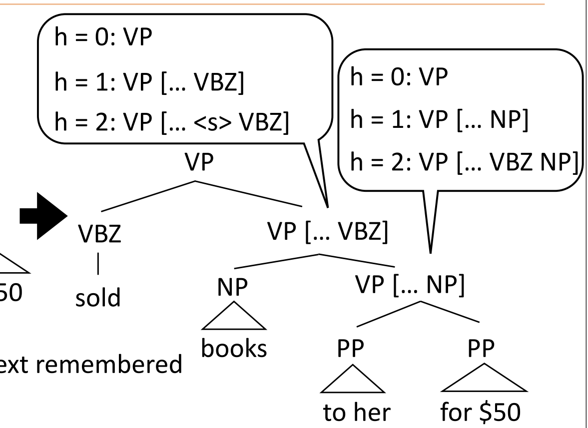


v = 1 Markovization

- Why is this a good idea?

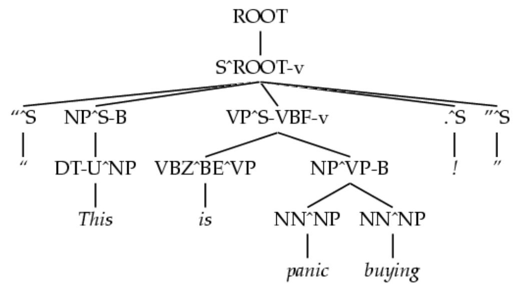
Horizontal Markovization





- Changes amount of context remembered in binarization process

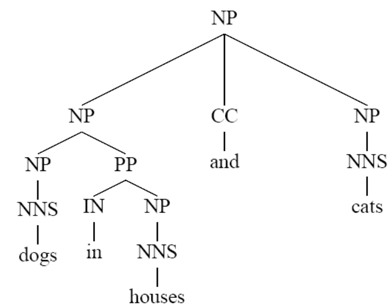
Annotated Tree

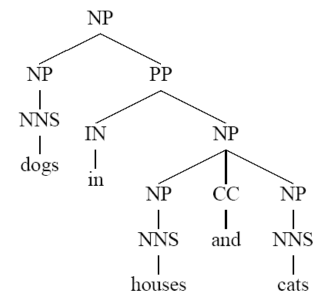


- 75 F1 with basic PCFG => 86.3 F1 with this highly customized PCFG, including other tweaks (SOTA was 90 F1 at the time, but with more complex methods)

Klein and Manning (2003)

Lexicalized Parsers

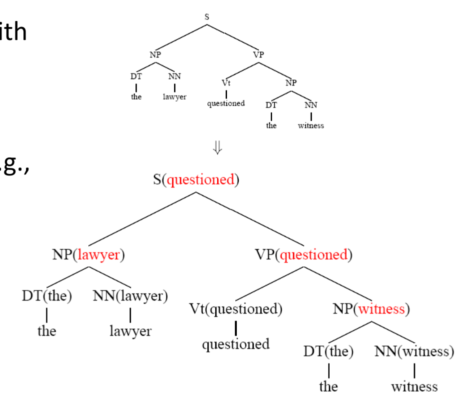




- Even with parent annotation, these trees have the same rules. Need to use the words

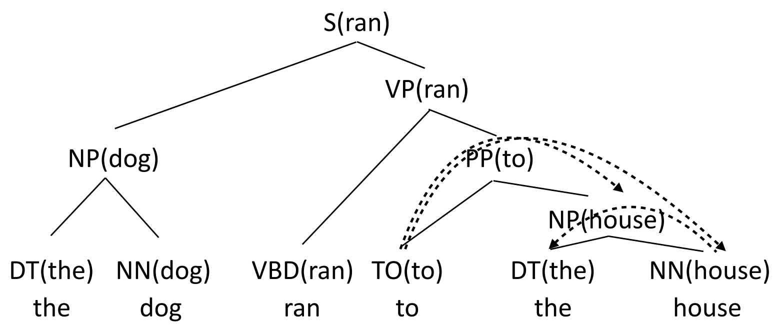
Lexicalized Parsers

- Annotate each grammar symbol with its “head word”: most important word of that constituent
- Rules for identifying headwords (e.g., the last word of an NP before a preposition is typically the head)
- Collins and Charniak (late 90s): ~89 F1 with these



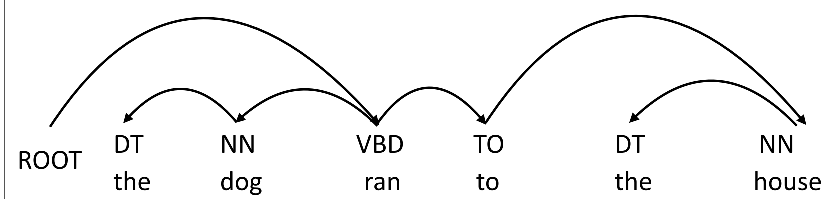
Dependency Syntax

Lexicalized Parsing



Dependency Parsing

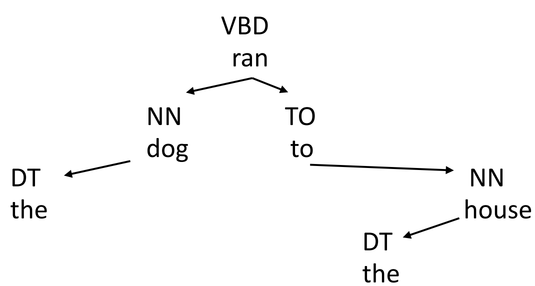
- Dependency syntax: syntactic structure is defined by these arcs
  - Head (parent, governor) connected to dependent (child, modifier)
  - Each word has exactly one parent except for the ROOT symbol, dependencies must form a directed acyclic graph



- POS tags same as before, usually run a tagger first as preprocessing

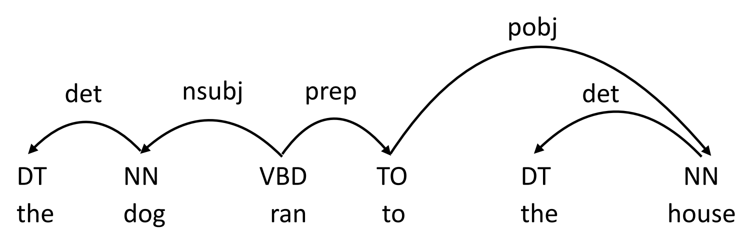
Dependency Parsing

- Still a notion of hierarchy! Subtrees often align with constituents



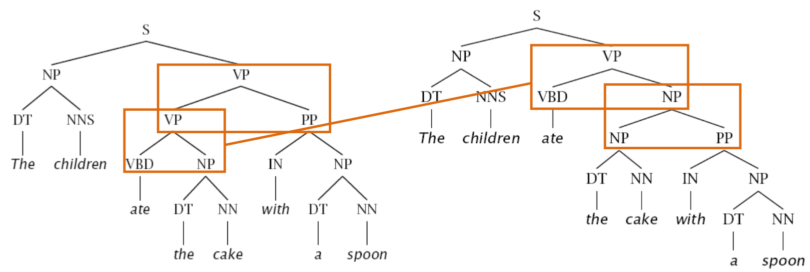
Dependency Parsing

- Can label dependencies according to syntactic function
- Major source of ambiguity is in the structure, so we focus on that more (labeling separately with a classifier works pretty well)



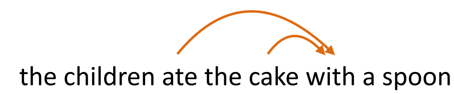
Dependency vs. Constituency: PP Attachment

- Constituency: several rule productions need to change



Dependency vs. Constituency: PP Attachment

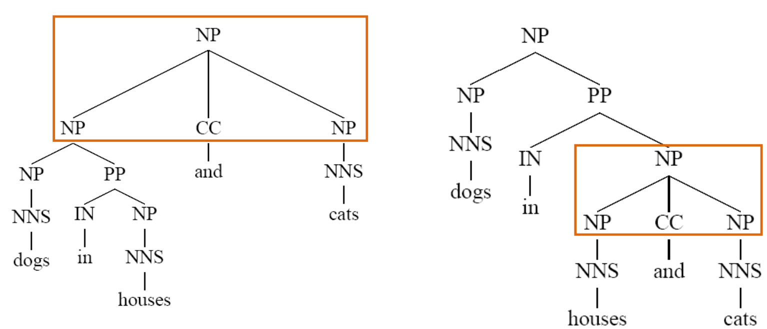
- Dependency: one word (with) assigned a different parent



- More predicate-argument focused view of syntax
- "What's the main verb of the sentence? What is its subject and object?" — easier to answer under dependency parsing

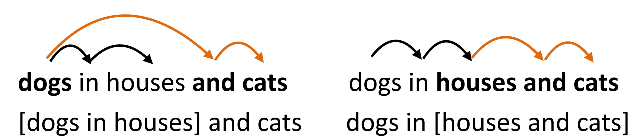
Dependency vs. Constituency: Coordination

- Constituency: ternary rule NP -> NP CC NP



Dependency vs. Constituency: Coordination

- Dependency: first item is the head



- Coordination is decomposed across a few arcs as opposed to being a single rule production as in constituency
- Can also choose *and* to be the head
- In both cases, headword doesn't really represent the phrase — constituency representation makes more sense

Takeaways

- PCFGs estimated generatively can perform well if sufficiently engineered
- Neural CRFs work well for constituency parsing
- Next time: revisit lexicalized parsing as *dependency parsing*