INF4820: Algorithms for Artificial Intelligence and Natural Language Processing

Context-Free Grammars & Parsing

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Overview

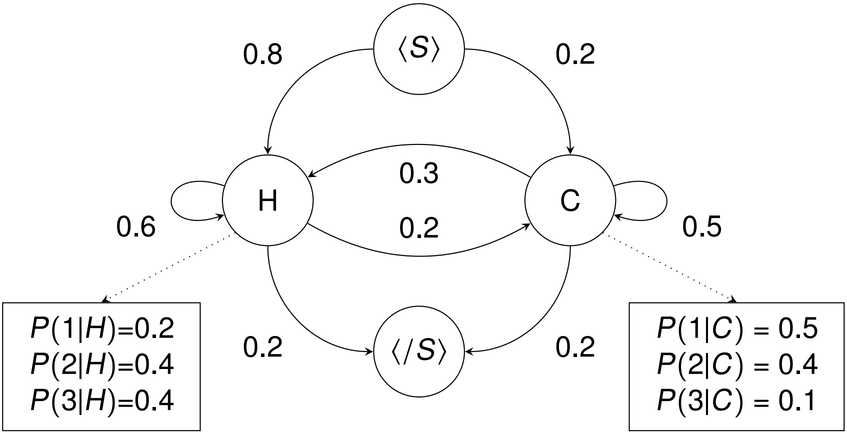
Last Time

- Sequence Labeling
- Dynamic programming
- Viterbi algorithm
- Forward algorithm

Today

- Grammatical structure
- Context-free grammar
- Treebanks
- Probabilistic CFGs

Recall: Ice Cream and Global Warming



Recall: Viterbi Algorithm

- To find the best state sequence, maximize:
  $P(s_1 \dots s_n | o_1 \dots o_n) = P(s_1|s_0)P(o_1|s_1)P(s_2|s_1)P(o_2|s_2)\dots$
- The value we cache at each step:

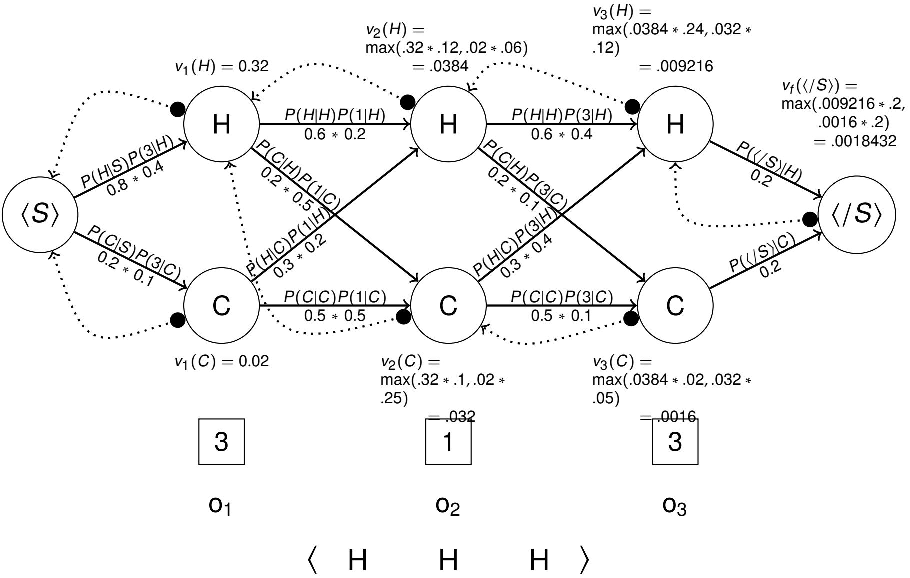
$$v_i(s) = \max_{k=1}^{L} [v_{i-1}(k) \cdot P(s|k) \cdot P(o_i|s)]$$

- The variable $v_i(s)$ represents the maximum probability that the i-th state is s, given that we have seen O_1^i.
- At each step, we record backpointers showing which previous state led to the maximum probability.

Recall: Dynamic Programming

- Dynamic programming algorithms
  - solve large problems by compounding answers from smaller sub-problems
  - record sub-problem solutions for repeated use
- They are used for complex problems that
  - can be described recursively
  - require the same calculations over and over again
- Examples:
  - Dijkstra's shortest path
  - minimum edit distance
  - longest common subsequence
  - Viterbi decoding

Recall: An Example of the Viterbi Algorithmn



Recall: Using HMMs

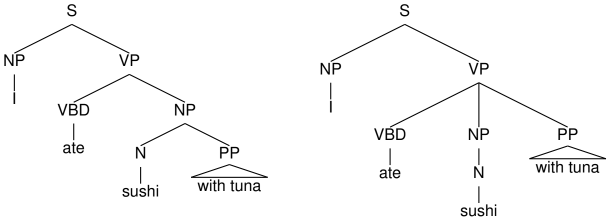
The HMM models the process of generating the labelled sequence. We can use this model for a number of tasks:

- $P(S, O)$ given S and O
- $P(O)$ given O
- S that maximizes $P(S|O)$ given O
- $P(s_x|O)$ given O
- We learn model parameters from a set of observations.

Moving Onwards

Determining

- which string is most likely: ✓
  - *How to recognize speech* vs. *How to wreck a nice beach*
- which tag sequence is most likely for *flies like flowers*: ✓
  - **NNS VB NNS** vs. **VBZ P NNS**
- which syntactic structure is most likely:



From Linear Order to Hierarchical Structure

- The models we have looked at so far:
  - *n*-gram models (Markov chains).
    - Purely linear (sequential) and surface-oriented.
  - sequence labeling: HMMs.
    - Adds one layer of abstraction: PoS as hidden variables.
    - Still only sequential in nature.
- Formal grammar adds hierarchical structure.
  - In NLP, being a sub-discipline of AI, we want our programs to *'understand'* natural language (on some level).
  - Finding the grammatical structure of sentences is an important step towards 'understanding'.
  - Shift focus from *sequences* to *grammatical structures*.

Why We Need Structure (1/3)

Constituency

- Words tends to lump together into groups that behave like single units: we call them *constituents*.
- *Constituency tests* give evidence for constituent structure:
  - interchangeable in similar syntactic environments.
  - can be co-ordinated
  - can be moved within a sentence as a unit

(1) Kim read [a very interesting book about grammar]$_{NP}$.
Kim read [it]$_{NP}$.

(2) Kim [read a book]$_{VP}$, [gave it to Sandy]$_{VP}$, and [left]$_{VP}$.

(3) [Read the book]$_{VP}$ I really meant to this week.

Examples from *Linguistic Fundamentals for NLP: 100 Essentials from Morphology and Syntax*. Bender (2013)

Why We Need Structure (2/3)

Constituency

- Constituents are theory-dependent, and are not absolute or language-independent.
- A constituent usually has a *head* element, and is often named according to the type of its head:
  - A noun phrase (NP) has a nominal (noun-type) head:

    (4) [a very interesting <u>book</u> about grammar $]_{\mathrm{NP}}$

  - A verb phrase (VP) has a verbal head:

    (5) [<u>gives</u> books to students $]_{\mathrm{VP}}$

Why We Need Structure (3/3)

Grammatical functions

- Terms such as *subject* and *object* describe the grammatical function of a constituent in a sentence.
- *Agreement* establishes a symmetric relationship between grammatical features.

  The *decision* of the Nobel committee member*s* surprise*s* most of us.

- Why would a purely linear model have problems predicting this phenomenon?
- Verb agreement reflects the grammatical structure of the sentence, not just the sequential order of words.

Grammars: A Tool to Aid Understanding

Formal grammars describe a language, giving us a way to:

- judge or predict well-formedness

  Kim was happy because __________ passed the exam.

  Kim was happy because __________ final grade was an A.

- make explicit structural ambiguities

  Have her report on my desk by Friday!

  I like to eat sushi with { chopsticks | tuna }.

- derive abstract representations of meaning

  Kim gave Sandy a book.

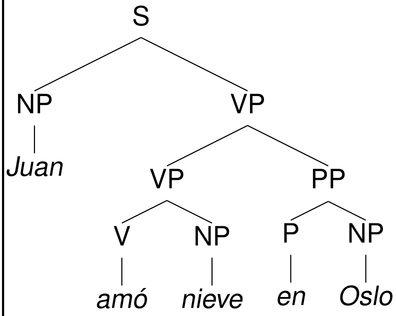
  Kim gave a book to Sandy.

  Sandy was given a book by Kim.

A Grossly Simplified Example

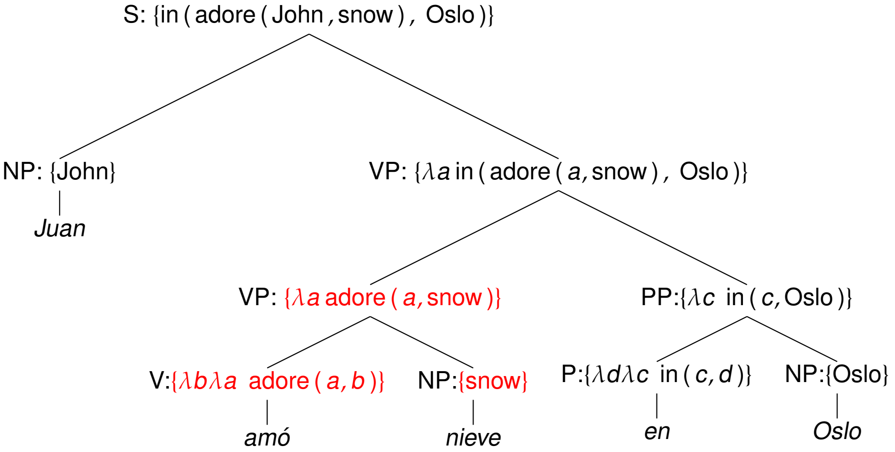
The Grammar of Spanish

$S \rightarrow NP\ VP$	$\{ VP(NP) \}$
$VP \rightarrow V\ NP$	$\{ V(NP) \}$
$VP \rightarrow VP\ PP$	$\{ PP(VP) \}$
$PP \rightarrow P\ NP$	$\{ P(NP) \}$
NP → “nieve”	{ snow }
NP → “Juan”	{ John }
NP → “Oslo”	{ Oslo }
V → “amó”	$\{ \lambda b \lambda a\ \mathrm{adore}(a, b) \}$
P → “en”	$\{ \lambda d \lambda c\ \mathrm{in}(c, d) \}$



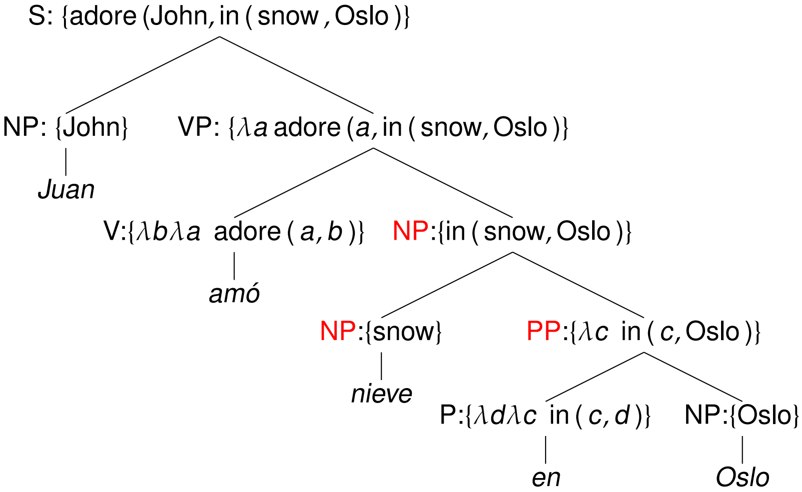
Juan amó nieve en Oslo

Meaning Composition (Still Very Simplified)



VP $\rightarrow$ V NP { V (NP) }

Another Interpretation



NP → NP PP { PP (NP) }

Context Free Grammars (CFGs)

- Formal system for modeling constituent structure.
- Defined in terms of a lexicon and a set of rules
- Formal models of ‘language’ in a broad sense
  - natural languages, programming languages, communication protocols, . . .
- Can be expressed in the ‘meta-syntax’ of the Backus-Naur Form (BNF) formalism.
  - When looking up concepts and syntax in the Common Lisp HyperSpec, you have been reading (extended) BNF.
- Powerful enough to express sophisticated relations among words, yet in a computationally tractable way.

CFGs (Formally, this Time)

Formally, a CFG is a quadruple: $G = \langle C, \Sigma, P, S \rangle$

- C is the set of categories (aka *non-terminals*),
  - $\{\mathrm{S}, \mathrm{NP}, \mathrm{VP}, \mathrm{V}\}$
- Σ is the vocabulary (aka *terminals*),
  - $\{\mathrm{Kim}, \mathrm{snow}, \mathrm{adores}, \mathrm{in}\}$
- P is a set of category rewrite rules (aka *productions*)

S → NP VP	NP → Kim
VP → V NP	NP → snow
	V → adores

- $S \in C$ is the *start symbol*, a filter on complete results;
- for each rule $\alpha \to \beta_1, \beta_2, ..., \beta_n \in P$: $\alpha \in C$ and $\beta_i \in C \cup \Sigma$

Generative Grammar

Top-down view of generative grammars:

- For a grammar G, the language $\mathcal{L}_G$ is defined as the set of strings that can be derived from S.
- To derive w_1^n from S, we use the rules in P to recursively rewrite S into the sequence w_1^n where each $w_i \in \Sigma$
- The grammar is seen as generating strings.
- *Grammatical* strings are defined as strings that can be generated by the grammar.
- The ‘context-freeness’ of CFGs refers to the fact that we rewrite non-terminals without regard to the overall context in which they occur.

Treebanks

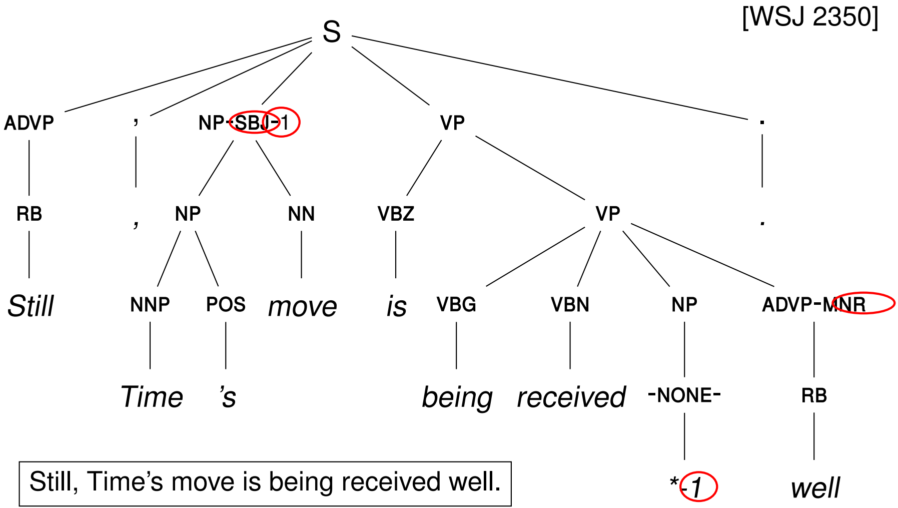
Generally

- A *treebank* is a corpus paired with ‘gold-standard’ (syntactico-semantic) analyses
- Can be created by manual annotation or selection among outputs from automated processing (plus correction).

Penn Treebank (Marcus et al., 1993)

- About one million tokens of Wall Street Journal text
- Hand-corrected PoS annotation using 45 word classes
- Manual annotation with (somewhat) coarse constituent structure

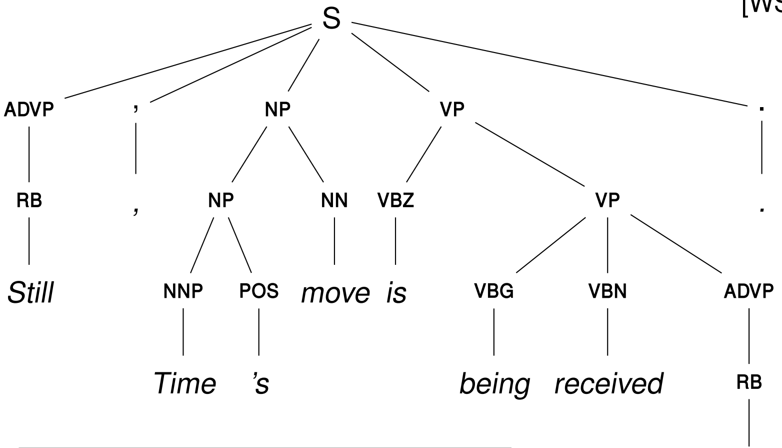
One Example from the Penn Treebank



Still, Time's move is being received well.

Elimination of Traces and Functions

[WSJ 2350]



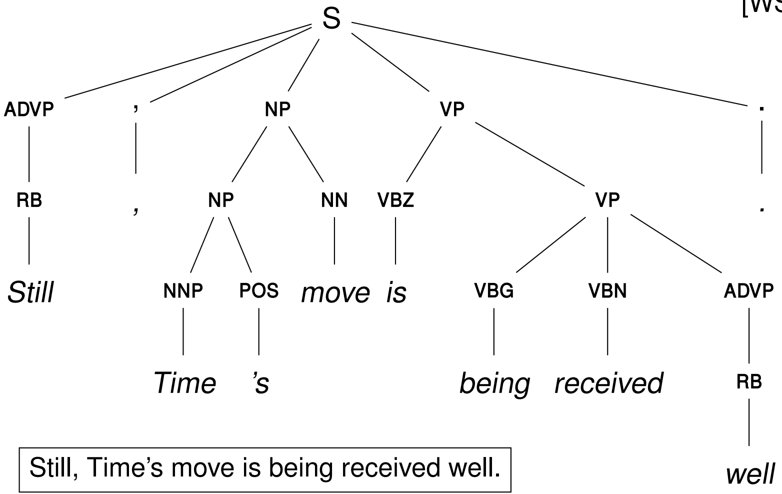
Still, Time's move is being received well.

Probabilitic Context-Free Grammars

- We are interested, not just in which trees apply to a sentence, but also to which tree is most likely.
- Probabilistic context-free grammars (PCFGs) augment CFGs by adding probabilities to each production, e.g.
  - S → NP VP 0.6
  - S → NP VP PP 0.4
- These are conditional probabilities — the probability of the right hand side (RHS) given the left hand side (LHS)
  - $P(S \rightarrow NP\ VP) = P(NP\ VP|S)$
- We can learn these probabilities from a treebank, again using Maximum Likelihood Estimation.

Estimating PCFGs (1/3)

[WSJ 2350]



Still, Time's move is being received well.

Estimating PCFGs (2/3)

```
(S
   (ADVP (RB "Still"))
   (|,| ",")
   (NP
      (NP (NNP "Time") (POS "'s"))
      (NN "move"))
    (VP
      (VBZ "is")
      (VP
         (VBG "being")
         (VP
           (VBN "received")
           (ADVP (RB "well")))))
   (\. "."))
```

RB → Still	1
ADVP → RB	2
|,| → ,	1
NNP → Time	1
POS → 's	1
NP → NNP POS	1
NN → move	1
NP → NP NN	1
VBZ → is	1
VBG → being	1
VBN → received	1
RB → well	1
VP → VBN ADVP	1
VP → VBG VP	1
\. → .	1
S → ADVP |,| NP VP \.	1
START → S	1

Estimating PCFGs (3/3)

Once we have counts of all the rules, we turn them into probabilities.

S → ADVP |,| NP VP \\.	50	S → NP VP \\.	400
S → NP VP PP \\.	350	S → VP !	100
S → NP VP S \\.	200	S → NP VP	50

$$
\begin{aligned}
P(S \rightarrow ADVP\ |,|\ NP\ VP\ \backslash.) &\approx \frac{C(S \rightarrow ADVP\ |,|\ NP\ VP\ \backslash.)}{C(S)} \\
&= \frac{50}{1150} \\
&= 0.0435
\end{aligned}
$$