Last Class: Question-Answering Systems

Today: Probabilistic Parsing

1. Parsing with PCFGs
2. Problems
3. Probabilistic lexicalized CFGs

CFG's

A context free grammar consists of:

1. a set of non-terminal symbols N
2. a set of terminal symbols Σ (disjoint from N)
3. a set of productions, P, each of the form $A \rightarrow \alpha$, where A is a non-terminal and α is a string of symbols from the infinite set of strings $(\Sigma \cup N)$
4. a designated start symbol S

Probabilistic CFGs

Augments each rule in P with a conditional probability:

$A \rightarrow \beta\ [p]$

where p is the probability that the non-terminal A will be expanded to the sequence β. Often referred to as

$P(A \rightarrow \beta)$ or

$P(A \rightarrow \beta | A)$.

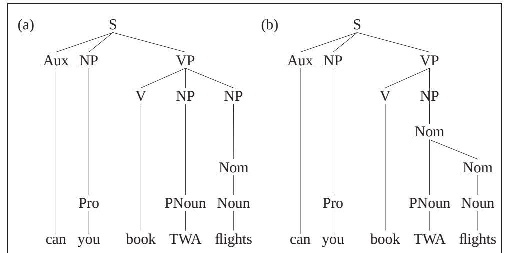
Example

S → *NP VP*	[.80]	*Det* → *that* [.05] | *the* [.80] | *a* [.15]	
S → *Aux NP VP*	[.15]	*Noun* → *book*	[.10]
S → *VP*	[.05]	*Noun* → *flights*	[.50]
NP → *Det Nom*	[.20]	*Noun* → *meal*	[.40]
NP → *Proper-Noun*	[.35]	*Verb* → *book*	[.30]
NP → *Nom*	[.05]	*Verb* → *include*	[.30]
NP → *Pronoun*	[.40]	*Verb* → *want*	[.40]
Nom → *Noun*	[.75]	*Aux* → *can*	[.40]
Nom → *Noun Nom*	[.20]	*Aux* → *does*	[.30]
Nom → *Proper-Noun Nom*	[.05]	*Aux* → *do*	[.30]
VP → *Verb*	[.55]	*Proper-Noun* → *TWA*	[.40]
VP → *Verb NP*	[.40]	*Proper-Noun* → *Denver*	[.40]
VP → *Verb NP NP*	[.05]	*Pronoun* → *you* [.40] | *I* [.60]	

Why are PCFGs useful?

- Useful in **disambiguation**
  - Choose the most likely parse
  - Computing the probability of a parse
    If we make independence assumptions, $P(T) = \prod_{n \in T} p(r(n))$.
- Useful in **language modeling** tasks

Example



Rules			P
S	→	Aux NP VP	.15
NP	→	Pro	.40
VP	→	V NP NP	.05
NP	→	Nom	.05
NP	→	PNoun	.35
Nom	→	Noun	.75
Aux	→	Can	.40
NP	→	Pro	.40
Pro	→	you	.40
Verb	→	book	.30
PNoun	→	TWA	.40
Noun	→	flights	.50

Rules			P
S	→	Aux NP VP	.15
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NP	→	Nom	.05
Nom	→	PNoun Nom	.05
Nom	→	Noun	.75
Aux	→	Can	.40
NP	→	Pro	.40
Pro	→	you	.40
Verb	→	book	.30
Pnoun	→	TWA	.40
Noun	→	flights	.50

Where do the probabilities come from?

1. from a **treebank**:

$$P(\alpha \to \beta | \alpha) = Count(\alpha \to \beta)/Count(\alpha)$$

2. use EM (forward-backward algorithm, inside-outside algorithm)

Parsing with PCFGs

Produce the most likely parse for a given sentence:

$$\hat{T}(S) = argmax_{T \in \tau(S)} P(T)$$

where $\tau(S)$ is the set of possible parse trees for S.

- Augment the Earley algorithm to compute the probability of each of its parses.
  When adding an entry E of category C to the chart using rule i with n subconstituents, $E_1, \ldots, E_n$:
  $P(E) = P(rule\ i \mid C) * P(E_1) * \ldots * P(E_n)$
- probabilistic CYK (Cocke-Younger-Kasami) algorithm

Problems with PCFGs

Do not model *structural dependencies*.

Often the choice of how a non-terminal expands depends on the location of the node in the parse tree.

E.g. Strong tendency in English for the syntactic subject of a spoken sentence to be a pronoun.

- 91% of declarative sentences in the Switchboard corpus are pronouns (vs. lexical).
- In contrast, 34% of direct objects in Switchboard are pronouns.

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Problems with PCFGs

Do not adequately model *lexical dependencies*.

Moscow sent more than 100,000 soldiers into Afghanistan...

PP can attach to either the NP or the VP:
NP $\rightarrow$ NP PP or VP $\rightarrow$ V NP PP?

Attachment choice depends (in part) on the verb: *send* subcategorizes for a destination (e.g. expressed via a PP that begins with *into*).

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Probabilistic lexicalized CFGs

- Each non-terminal is associated with its head.
- Each PCFG rule needs to be augmented to identify one rhs constituent to be the head daughter.
- Headword for a node in the parse tree is set to the headword of its head daughter.

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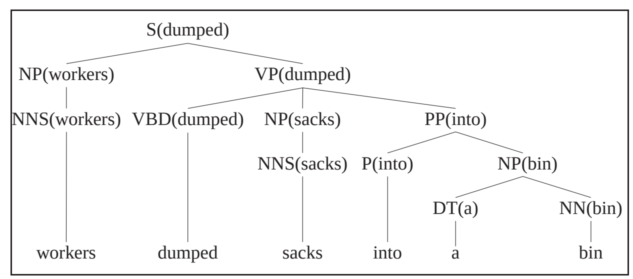
Example



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Probabilistic lexicalized CFGs

View a lexicalized (P)CFG as a simple (P)CFG with a lot more rules.

VP(dumped) $\rightarrow$ VBD(dumped) NP(sacks) PP(into) [3x10^{-10}]
VP(dumped) $\rightarrow$ VBD(dumped) NP(cats) PP(into) [8x10^{-10}]
VP(dumped) $\rightarrow$ VBD(dumped) NP(sacks) PP(above) [1x10^{-12}]
...

Problem?

Incorporating lexical dependency information

Incorporates lexical dependency information by:

1. relating the heads of phrases to the heads of their constituents;
2. including syntactic subcategorization information.

Syntactic subcategorization dependencies:

Probability of a rule r of syntactic category n:
p(r(n) | n, h(n)).

Example: probability of expanding VP as VP $\rightarrow$ VBD NP PP will be p (r | VP, dumped).

Incorporating lexical dependency information

Condition the probability of a node n having a head h on two factors:

1. the syntactic category of the node n
2. the head of the node's mother $h(m(n))$

p(h(n) = word_i | n, h(m(n)))

Computing the proability of a parse

Producing the most likely parse for a given sentence changes from:

P(T) = $\prod_{n \in T}$ p(r(n))

to

P(T) = $\prod_{n \in T}$ p(r(n)|n,h(n)) * p(h(n)|n,h(m(n)))

Evaluation Measures and State of the Art

- labeled recall: # correct constituents in candidate parse of s / # correct constituents in treebank parse of s
- labeled precision: # correct constituents in candidate parse of s / total # of constituents in candidate parse of s
- crossing brackets: the number of crossed brackets

State of the art: 90% recall, 90% precision, 1% crossed bracketed constituents per sentence (WSJ treebank)