# Natural Language Processing

Anoop Sarkar
anoopsarkar.github.io/nlp-class

Simon Fraser University

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Part 1: Ambiguity

# Context Free Grammars and Ambiguity

$$
\begin{array}{ccc}
S & \rightarrow & NP\ VP \\
VP & \rightarrow & V\ NP \\
VP & \rightarrow & VP\ PP \\
PP & \rightarrow & P\ NP \\
NP & \rightarrow & NP\ PP \\
NP & \rightarrow & Calvin \\
NP & \rightarrow & monsters \\
NP & \rightarrow & school \\
V & \rightarrow & imagined \\
P & \rightarrow & in
\end{array}
$$

What is the analysis using the above grammar for:
*Calvin imagined monsters in school*

# Context Free Grammars and Ambiguity

*Calvin imagined monsters in school*

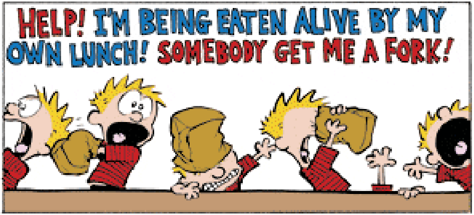
```
(S (NP Calvin)
   (VP (V imagined)
       (NP (NP monsters)
           (PP (P in)
               (NP school)))))
```

```
(S (NP Calvin)
   (VP (VP (V imagined)
           (NP monsters))
       (PP (P in)
           (NP school))))
```

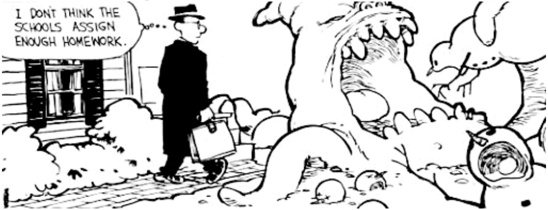
Which one is more plausible?

# Context Free Grammars and Ambiguity

Calvin imagined monsters in school




Calvin imagined monsters in school



# Ambiguity Kills (your parser)

*natural language learning course*
(run demos/parsing-ambiguity.py)

```
((natural language) (learning course))
(((natural language) learning) course)
((natural (language learning)) course)
(natural (language (learning course)))
(natural ((language learning) course))
```

- Some difficult issues:
  - Which one is more plausible?
  - How many analyses for a given input?
  - Computational complexity of parsing language

# Treebanks

- What is the CFG that can be extracted from this single tree:

```
(S   (NP (Det the) (NP man))
     (VP (VP (V played)
             (NP (Det a) (NP game)))
         (PP (P with)
             (NP (Det the) (NP dog)))))
```

# PCFG

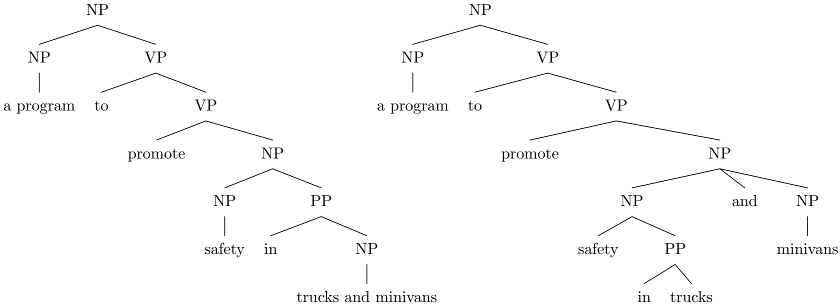
$$
\begin{array}{ccccc}
S & \rightarrow & NP\ VP & c = 1 \\
NP & \rightarrow & Det\ NP & c = 3 \\
NP & \rightarrow & man & c = 1 \\
NP & \rightarrow & game & c = 1 \\
NP & \rightarrow & dog & c = 1 \\
VP & \rightarrow & VP\ PP & c = 1 \\
VP & \rightarrow & V\ NP & c = 1 \\
PP & \rightarrow & P\ NP & c = 1 \\
Det & \rightarrow & the & c = 2 \\
Det & \rightarrow & a & c = 1 \\
V & \rightarrow & played & c = 1 \\
P & \rightarrow & with & c = 1
\end{array}
$$

- We can do this with multiple trees. Simply count occurrences of CFG rules over all the trees.
- A repository of such trees labelled by a human is called a TreeBank.

# Ambiguity

- Part of Speech ambiguity
  `saw` → noun
  `saw` → verb
- Structural ambiguity: Prepositional Phrases
  `I saw (the man) with the telescope`
  `I saw (the man with the telescope)`
- Structural ambiguity: Coordination
  `a program to promote safety in ((trucks) and (minivans))`
  `a program to promote ((safety in trucks) and (minivans))`
  `((a program to promote safety in trucks) and (minivans))`

# Ambiguity ← attachment choice in alternative parses



# Ambiguity in Prepositional Phrases

- noun attach: *I bought the shirt with pockets*
- verb attach: *I washed the shirt with soap*
- As in the case of other attachment decisions in parsing: it depends on the meaning of the entire sentence – needs world knowledge, etc.
- Maybe there is a simpler solution: we can attempt to solve it using heuristics or associations between words

# Structure Based Ambiguity Resolution

- Right association: a constituent (NP or PP) tends to attach to another constituent immediately to its right (Kimball 1973)
- Minimal attachment: a constituent tends to attach to an existing non-terminal using the fewest additional syntactic nodes (Frazier 1978)
- These two principles make opposite predictions for prepositional phrase attachment
- Consider the grammar:

$$VP \rightarrow V\ NP\ PP \quad (1)$$
$$NP \rightarrow NP\ PP \quad (2)$$

for input: *I* $[_{VP}$ *saw* $[_{NP}$ *the man* ... $[_{PP}$ *with the telescope* $]$, RA predicts that the PP attaches to the NP, i.e. use rule (2), and MA predicts V attachment, i.e. use rule (1)

# Structure Based Ambiguity Resolution

- Garden-paths look structural:
  *The emergency crews hate most is domestic violence*
- Neither MA or RA account for more than 55% of the cases in real text
- Psycholinguistic experiments using eyetracking show that humans resolve ambiguities as soon as possible in the left to right sequence using the words to disambiguate
- Garden-paths are caused by a combination of lexical and structural effects:
  *The flowers delivered for the patient arrived*

# Ambiguity Resolution: Prepositional Phrases in English

- Learning Prepositional Phrase Attachment: Annotated Data

| v | n1 | p | n2 | Attachment |
|---|---|---|---|---|
| join | board | as | director | V |
| is | chairman | of | N.V. | N |
| using | crocidolite | in | filters | V |
| bring | attention | to | problem | V |
| is | asbestos | in | products | N |
| making | paper | for | filters | N |
| including | three | with | cancer | N |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

# Prepositional Phrase Attachment

| Method | Accuracy |
| --- | --- |
| Always noun attachment | 59.0 |
| Most likely for each preposition | 72.2 |
| Average Human (4 head words only) | 88.2 |
| Average Human (whole sentence) | 93.2 |

# Some other studies

- **Toutanova, Manning, and Ng, 2004**: 87.54% using some external knowledge (word classes)
- **Merlo, Crocker and Berthouzoz, 1997**: test on multiple PPs
  - generalize disambiguation of 1 PP to 2-3 PPs
  - 14 structures possible for 3PPs assuming a single verb
  - all 14 are attested in the Penn WSJ Treebank
  - 1PP: 84.3%   2PP: 69.6%   3PP: 43.6%
- **Belinkov+ TACL 2014**: Neural networks for PP attachment (multiple candidate heads)
  - NN model (no extra data): 86.6%
  - NN model (lots of raw data for word vectors): 88.7%
  - NN model with parser and lots of raw data: 90.1%
- **This experiment is still only part of the real problem faced in parsing English**. Plus other sources of ambiguity in other languages

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Part 2: Context Free Grammars

# Context-Free Grammars

- A CFG is a 4-tuple: $(N, T, P, S)$, where
  - $N$ is a set of non-terminal symbols,
  - $T$ is a set of terminal symbols which can include the empty string $\epsilon$. $T$ is analogous to $\Sigma$ the alphabet in FSAs.
  - $P$ is a set of rules of the form $A \to \alpha$, where $A \in N$ and $\alpha \in \{N \cup T\}^*$
  - $S$ is a set of start symbols, $S \in N$

# Context-Free Grammars

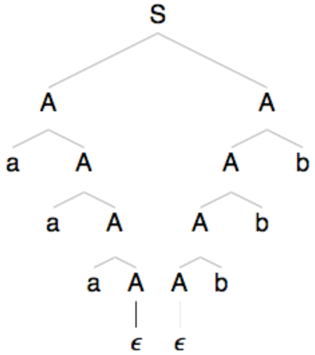
- Here's an example of a CFG, let's call this one $G$:
  1. $S \rightarrow a\ S\ b$
  2. $S \rightarrow \epsilon$
- What is the language of this grammar, which we will call $L(G)$, the set of strings *generated* by this grammar How? Notice that there cannot be any FSA that corresponds exactly to this set of strings $L(G)$ Why?
- What is the *tree set* or derivations produced by this grammar?

# Context-Free Grammars

- This notion of generating both the strings and the trees is an important one for Computational Linguistics
- Consider the trees for the grammar $G'$:
  $P = \{S \rightarrow A\ A, A \rightarrow aA, A \rightarrow A\ b, A \rightarrow \epsilon\}$,
  $\Sigma = \{a, b\}, N = \{S, A\}, T = \{a, b, \epsilon\}, S = \{S\}$
- Why is it called *context-free* grammar?

# Context-Free Grammars

- Can the grammar $G'$ produce only trees with equal height subtrees on the left and right?

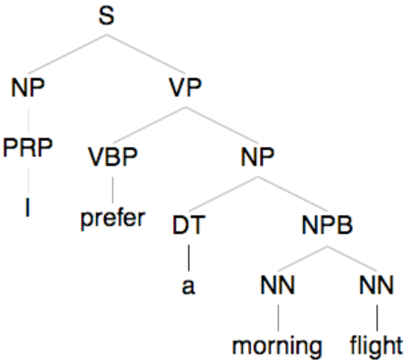


# Parse Trees

Consider the grammar with rules:

$$
\begin{array}{rcl}
S & \rightarrow & NP\ VP \\
NP & \rightarrow & PRP \\
NP & \rightarrow & DT\ NPB \\
VP & \rightarrow & VBP\ NP \\
NPB & \rightarrow & NN\ NN \\
PRP & \rightarrow & I \\
VBP & \rightarrow & prefer \\
DT & \rightarrow & a \\
NN & \rightarrow & morning \\
NN & \rightarrow & flight
\end{array}
$$

# Parse Trees



# Parse Trees: Equivalent Representations

- (S (NP (PRP I) ) (VP (VBP prefer) (NP (DT a) (NPB (NN morning) (NN flight)))))
- [$_S$ [$_{NP}$ [$_{PRP}$ I ] ] [$_{VP}$ [$_{VBP}$ prefer ] [$_{NP}$ [$_{DT}$ a ] [$_{NPB}$ [$_{NN}$ morning ] [$_{NN}$ flight ] ] ] ] ]

# Ambiguous Grammars

- $S \rightarrow S\ S$
- $S \rightarrow a$
- Given the above rules, consider the input *aaa*, what are the valid parse trees?
- Now consider the input *aaaa*

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Part 3: Probabilistic Context Free Grammars

# Probabilistic CFG (PCFG)

$$
\begin{array}{ccccc}
S & \rightarrow & NP \ VP & 1 \\
VP & \rightarrow & V \ NP & 0.9 \\
VP & \rightarrow & VP \ PP & 0.1 \\
PP & \rightarrow & P \ NP & 1 \\
NP & \rightarrow & NP \ PP & 0.25 \\
NP & \rightarrow & Calvin & 0.25 \\
NP & \rightarrow & monsters & 0.25 \\
NP & \rightarrow & school & 0.25 \\
V & \rightarrow & imagined & 1 \\
P & \rightarrow & in & 1
\end{array}
$$

$$P(input) = \sum_{tree} P(tree \mid input)$$

$$P(Calvin\ imagined\ monsters\ in\ school) = ?$$

Notice that $P(VP \rightarrow V \ NP) + P(VP \rightarrow VP \ PP) = 1.0$

# Probabilistic CFG (PCFG)

$$P(\textit{Calvin imagined monsters in school}) = ?$$

```
(S (NP Calvin)
   (VP (V imagined)
       (NP (NP monsters)
           (PP (P in)
               (NP school)))))

(S (NP Calvin)
   (VP (VP (V imagined)
           (NP monsters))
       (PP (P in)
           (NP school))))
```

# Probabilistic CFG (PCFG)

```
(S (NP Calvin)
   (VP (V imagined)
       (NP (NP monsters)
           (PP (P in)
               (NP school)))))
```

$$
\begin{aligned}
P(tree_1) &= P(S \rightarrow NP\ VP) \times P(NP \rightarrow Calvin) \times P(VP \rightarrow V\ NP) \times \\
&\quad P(V \rightarrow imagined) \times P(NP \rightarrow NP\ PP) \times P(NP \rightarrow monsters) \times \\
&\quad P(PP \rightarrow P\ NP) \times P(P \rightarrow in) \times P(NP \rightarrow school) \\
&= 1 \times 0.25 \times 0.9 \times 1 \times 0.25 \times 0.25 \times 1 \times 1 \times 0.25 = .003515625
\end{aligned}
$$

# Probabilistic CFG (PCFG)

```
(S (NP Calvin)
   (VP (VP (V imagined)
           (NP monsters))
       (PP (P in)
           (NP school))))
```

$$
\begin{aligned}
P(tree_2) &= P(S \rightarrow NP\ VP) \times P(NP \rightarrow Calvin) \times P(VP \rightarrow VP\ PP) \times \\
&\quad P(VP \rightarrow V\ NP) \times P(V \rightarrow imagined) \times P(NP \rightarrow monsters) \times \\
&\quad P(PP \rightarrow P\ NP) \times P(P \rightarrow in) \times P(NP \rightarrow school) \\
&= 1 \times 0.25 \times 0.1 \times 0.9 \times 1 \times 0.25 \times 1 \times 1 \times 0.25 = .00140625
\end{aligned}
$$

# Probabilistic CFG (PCFG)

$$
\begin{aligned}
P(\textit{Calvin imagined monsters in school}) &= P(\textit{tree}_1) + P(\textit{tree}_2) \\
&= .003515625 + .00140625 \\
&= .004921875 \\
\text{Most likely tree is } \textit{tree}_1 &= \underset{\textit{tree}}{\arg\max}\ P(\textit{tree} \mid \textit{input})
\end{aligned}
$$

```
(S (NP Calvin)
   (VP (V imagined)
       (NP (NP monsters)
           (PP (P in)
               (NP school)))))
```

```
(S (NP Calvin)
   (VP (VP (V imagined)
           (NP monsters))
       (PP (P in)
           (NP school))))
```

# PCFG

- Central condition: $\sum_{\alpha} P(A \rightarrow \alpha) = 1$
- Called a *proper* PCFG if this condition holds
- Note that this means $P(A \rightarrow \alpha) = P(\alpha \mid A) = \frac{f(A,\alpha)}{f(A)}$
- $P(T \mid S) = \frac{P(T,S)}{P(S)} = P(T,S) = \prod_i P(RHS_i \mid LHS_i)$

# PCFG

- What is the PCFG that can be extracted from this single tree:

```
(S   (NP (Det the) (NP man))
     (VP (VP (V played)
             (NP (Det a) (NP game)))
         (PP (P with)
             (NP (Det the) (NP dog)))))
```

- How many different rhs $\alpha$ exist for $A \rightarrow \alpha$ where $A$ can be $S$, $NP$, $VP$, $PP$, $Det$, $N$, $V$, $P$

# PCFG

$$
\begin{array}{llllll}
S & \rightarrow & NP\ VP & c=1 & p=1/1 & =1.0 \\
NP & \rightarrow & Det\ NP & c=3 & p=3/6 & =0.5 \\
NP & \rightarrow & man & c=1 & p=1/6 & =0.1667 \\
NP & \rightarrow & game & c=1 & p=1/6 & =0.1667 \\
NP & \rightarrow & dog & c=1 & p=1/6 & =0.1667 \\
VP & \rightarrow & VP\ PP & c=1 & p=1/2 & =0.5 \\
VP & \rightarrow & V\ NP & c=1 & p=1/2 & =0.5 \\
PP & \rightarrow & P\ NP & c=1 & p=1/1 & =1.0 \\
Det & \rightarrow & the & c=2 & p=2/3 & =0.67 \\
Det & \rightarrow & a & c=1 & p=1/3 & =0.33 \\
V & \rightarrow & played & c=1 & p=1/1 & =1.0 \\
P & \rightarrow & with & c=1 & p=1/1 & =1.0
\end{array}
$$

- We can do this with multiple trees. Simply count occurrences of CFG rules over all the trees.
- A repository of such trees labelled by a human is called a TreeBank.

# Ambiguity

- Part of Speech ambiguity
  `saw` → noun
  `saw` → verb
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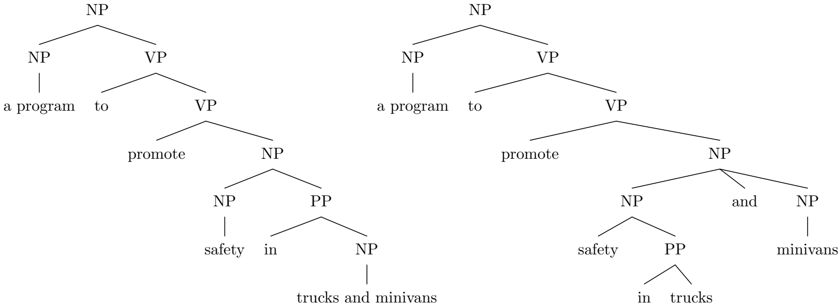
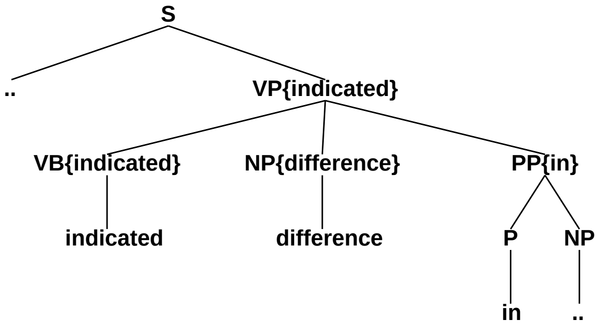
# Ambiguity ← attachment choice in alternative parses



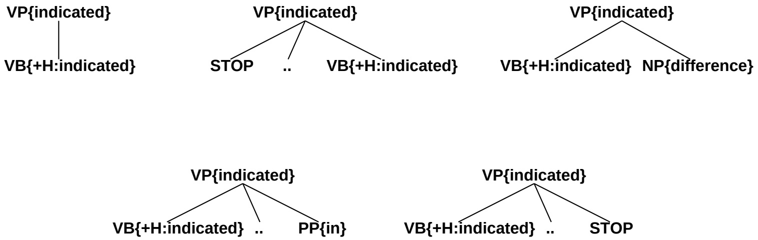
# Parsing as a machine learning problem

- $S$ = a sentence
  $T$ = a parse tree
  A statistical parsing model defines $P(T \mid S)$
- Find best parse: $\underset{T}{\arg\max}\ P(T \mid S)$
- $P(T \mid S) = \frac{P(T,S)}{P(S)} = P(T,S)$
- Best parse: $\underset{T}{\arg\max}\ P(T,S)$
- e.g. for PCFGs: $P(T,S) = \prod_{i=1\ldots n} P(\mathrm{RHS}_i \mid \mathrm{LHS}_i)$

# Adding Lexical Information to PCFG



# Adding Lexical Information to PCFG (Collins 99, Charniak 00)




$$
\begin{aligned}
&P_h(\texttt{VB} \mid \texttt{VP}, \texttt{indicated}) \times P_l(\texttt{STOP} \mid \texttt{VP}, \texttt{VB}, \texttt{indicated}) \times \\
&P_r(\texttt{NP(difference)} \mid \texttt{VP}, \texttt{VB}, \texttt{indicated}) \times \\
&P_r(\texttt{PP(in)} \mid \texttt{VP}, \texttt{VB}, \texttt{indicated}) \times \\
&P_r(\texttt{STOP} \mid \texttt{VP}, \texttt{VB}, \texttt{indicated})
\end{aligned}
$$

# Evaluation of Parsing

- Consider a candidate parse to be evaluated against the truth (or gold-standard parse):

```
candidate: (S (A (P this) (Q is)) (A (R a) (T test)))
gold:      (S (A (P this)) (B (Q is) (A (R a) (T test))))
```

- In order to evaluate this, we list all the constituents

| Candidate | Gold |
|---|---|
| (0,4,S) | (0,4,S) |
| (0,2,A) | (0,1,A) |
| (2,4,A) | (1,4,B) |
| | (2,4,A) |

- Skip spans of length 1 which would be equivalent to part of speech tagging accuracy.
- Precision is defined as $\frac{\#correct}{\#proposed} = \frac{2}{3}$ and recall as $\frac{\#correct}{\#in\ gold} = \frac{2}{4}$.
- Another measure: crossing brackets,

```
candidate: [ an [incredibly expensive] coat ] (1 CB)
gold:      [ an [incredibly [expensive coat]]
```

# Evaluation of Parsing

$$\text{Bracketing recall } R = \frac{\text{num of correct constituents}}{\text{num of constituents in the goldfile}}$$

$$\text{Bracketing precision } P = \frac{\text{num of correct constituents}}{\text{num of constituents in the parsed file}}$$

$$\text{Complete match} = \text{\% of sents where recall \& precision are both 100\%}$$

$$\text{Average crossing} = \frac{\text{num of constituents crossing a goldfile constituent}}{\text{num of sents}}$$

$$\text{No crossing} = \text{\% of sents which have 0 crossing brackets}$$

$$\text{2 or less crossing} = \text{\% of sents which have} \leq 2 \text{ crossing brackets}$$

# Statistical Parsing Results

$$\text{F1-score} = 2\frac{\mathit{precision} \cdot \mathit{recall}}{\mathit{precision} + \mathit{recall}}$$

| System | $\leq 100\mathit{wds}$ F1-score |
|---|---|
| Shift-Reduce (Magerman, 1995) | 84.14 |
| PCFG with Lexical Features (Charniak, 1999) | 89.54 |
| Unlexicalized Berkeley parser (Petrov et al, 2007) | 90.10 |
| *n*-best Re-ranking (Charniak and Johnson, 2005) | 91.02 |
| Tree-insertion grammars (Carreras, Collins, Koo, 2008) | 91.10 |
| Ensemble *n*-best Re-ranking (Johnson and Ural, 2010) | 91.49 |
| Forest Re-ranking (Huang, 2010) | 91.70 |
| Unlabeled Data with Self-Training (McCloskey et al, 2006) | 92.10 |
| Self-Attention (Kitaev and Klein, 2018) | 93.55 |
| Self-Attention with unlabeled data (Kitaev and Klein, 2018) | 95.13 |

# Practical Issues: Beam Thresholding and Priors

- Probability of nonterminal $X$ spanning $j \ldots k$: $N[X, j, k]$
- Beam Thresholding compares $N[X, j, k]$ with every other $Y$ where $N[Y, j, k]$
- But what should be compared?
- Just the *inside probability*: $P(X \stackrel{*}{\Rightarrow} t_j \ldots t_k)$? written as $\beta(X, j, k)$
- Perhaps $\beta(\texttt{FRAG}, 0, 3) > \beta(\texttt{NP}, 0, 3)$, but NPs are much more likely than FRAGs in general

# Practical Issues: Beam Thresholding and Priors

- The correct estimate is the *outside probability*:

$$P(S \stackrel{*}{\Rightarrow} t_1 \ldots t_{j-1}\ X\ t_{k+1} \ldots t_n)$$

  written as $\alpha(X, j, k)$
- Unfortunately, you can only compute $\alpha(X, j, k)$ efficiently after you finish parsing and reach $(S, 0, n)$

# Practical Issues: Beam Thresholding and Priors

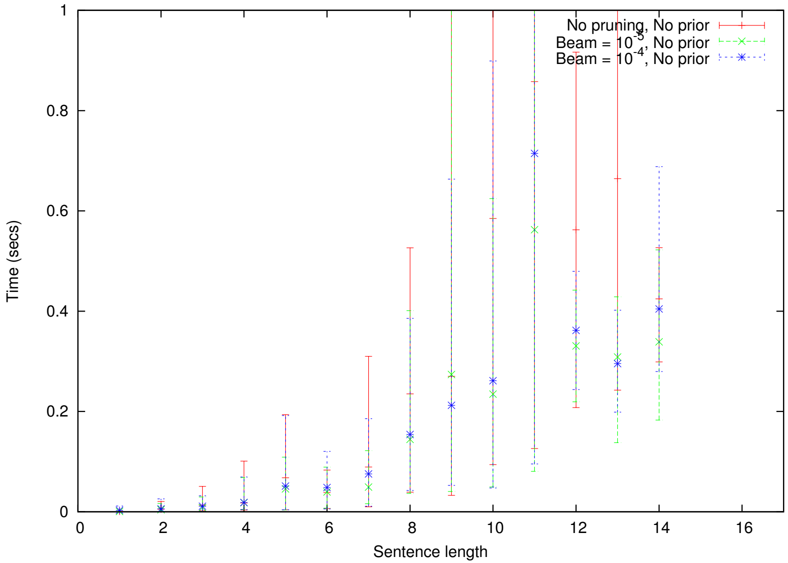
- To make things easier we multiply the prior probability $P(X)$ with the inside probability
- In beam Thresholding we compare every new insertion of $X$ for span $j, k$ as follows:
  Compare $P(X) \cdot \beta(X, j, k)$ with the most probable $Y$ $P(Y) \cdot \beta(Y, j, k)$
- Assume $Y$ is the most probable entry in $j, k$, then we compare

$$\text{beam} \cdot P(Y) \cdot \beta(Y, j, k) \tag{3}$$

$$P(X) \cdot \beta(X, j, k) \tag{4}$$

- If $(4) < (3)$ then we prune $X$ for this span $j, k$
- beam is set to a small value, say 0.001 or even 0.01.
- As the beam value increases, the parser speed increases (since more entries are pruned).
- A simpler (but not as effective) alternative to using the beam is to keep only the top $K$ entries for each span $j, k$

# Experiments with Beam Thresholding



# Experiments with Beam Thresholding