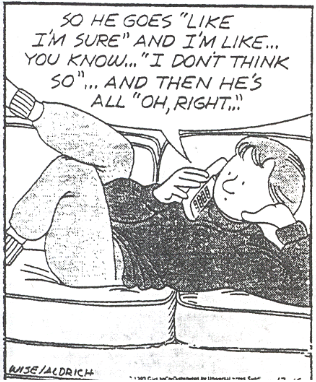
CS325 Artificial Intelligence
Natural Language Processing II (Ch. 23)

Dr. Cengiz Günay, Emory Univ.



So Probabilities Enough for Understanding Language?

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Today:

1. Using sentence structure in NLP
2. Machine translation
3. Speech recognition (no time, see textbook)

Entry/Exit Surveys

Exit survey: Natural Language Processing I

- What is a good method for identifying foreign languages?
- How do we improve bag of words to learn word sequences?

Entry survey: Natural Language Processing II (0.25 pts)

- Give some examples of why learning sentence structure may be useful.
- What was the most useful machine translation tool you ever used?

Uses of Sentence Structure in NLP

Can be useful for:

- Disambiguation of phrases

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- Disambiguation of phrases
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- Translation

Disambiguation

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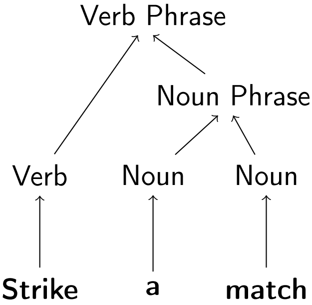

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Verb Phrase

Noun Phrase

Verb | Noun | Noun

Strike | **a** | **match**

Noun | Noun | Noun

Noun Phrase

Hint: 

Where Do the Trees Come From?

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From the forest?

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Seriously, from:

The grammar:

$S \rightarrow VP|NP$

$VP \rightarrow V\ NP|V$

$NP \rightarrow N|N\ N|N\ N\ N$

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VP → V NP|V
NP → N|N N|N N N
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Results in **multiple possible parses** of the same sentence.

Multiple Possible Parsleys

Parses, parsings, or parsleys
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1. Use probabilities
2. Use word associations
3. Unambiguous grammar

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context-free grammar: Words are expanded without context (e.g., $\mathrm{S} \rightarrow \mathrm{VP}|\mathrm{NP}$). Used with programming languages.

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It's called a **probabilistic context-free grammar (PCFG)**

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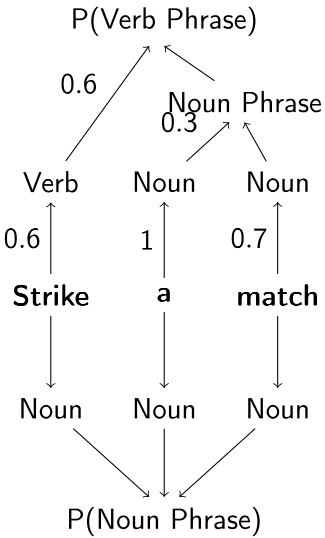

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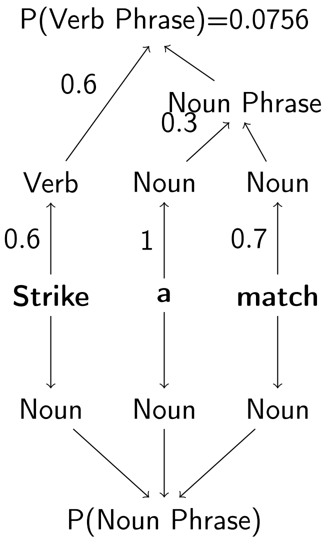

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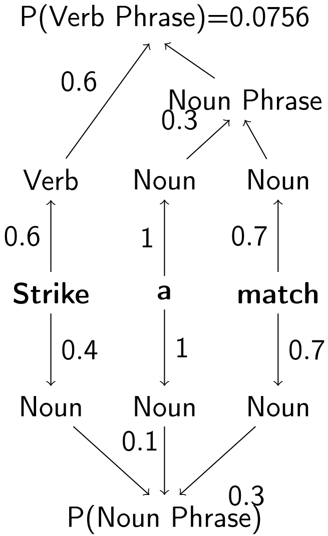

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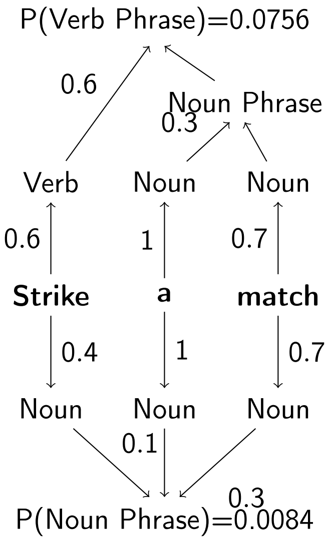

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Can we count them?

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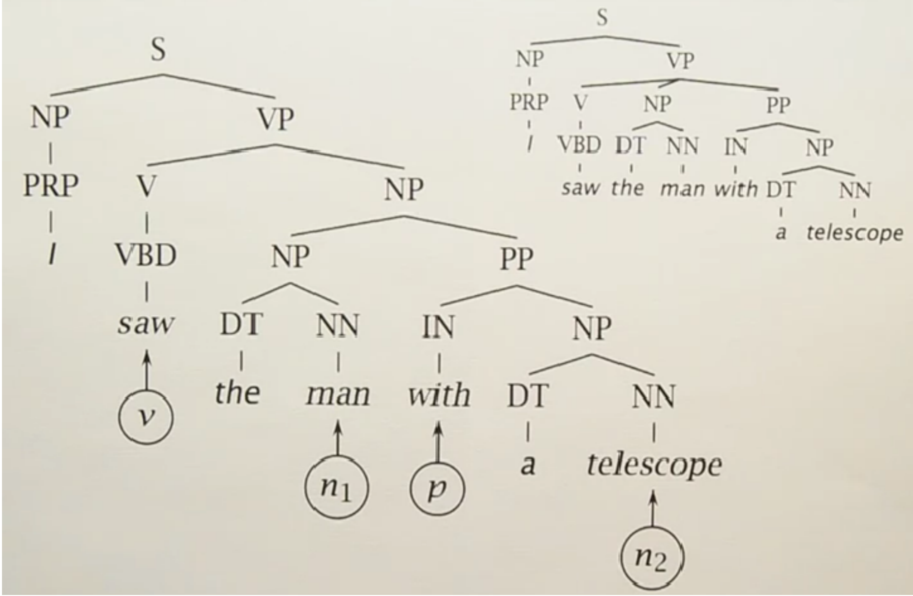
Can you think of a better solution?

- Understand context first?

Example Grammar

```
( (S
  (NP-SBJ (DT The) (NN move))
  (VP (VBD followed)
   (NP
    (NP (DT a) (NN round))
    (PP (IN of)
     (NP
      (NP (JJ similar) (NNS increases))
      (PP (IN by)
       (NP (JJ other) (NNS lenders)))
      (PP (IN against)
       (NP (NNP Arizona) (JJ real) (NN estate) (NNS loans))))))
   (, ,)
   (S-ADV
    (NP-SBJ (-NONE- *))
    (VP (VBG reflecting)
     (NP
      (NP (DT a) (VBG continuing) (NN decline))
      (PP-LOC (IN in)
```

Back to Disambiguation with Learned Grammar



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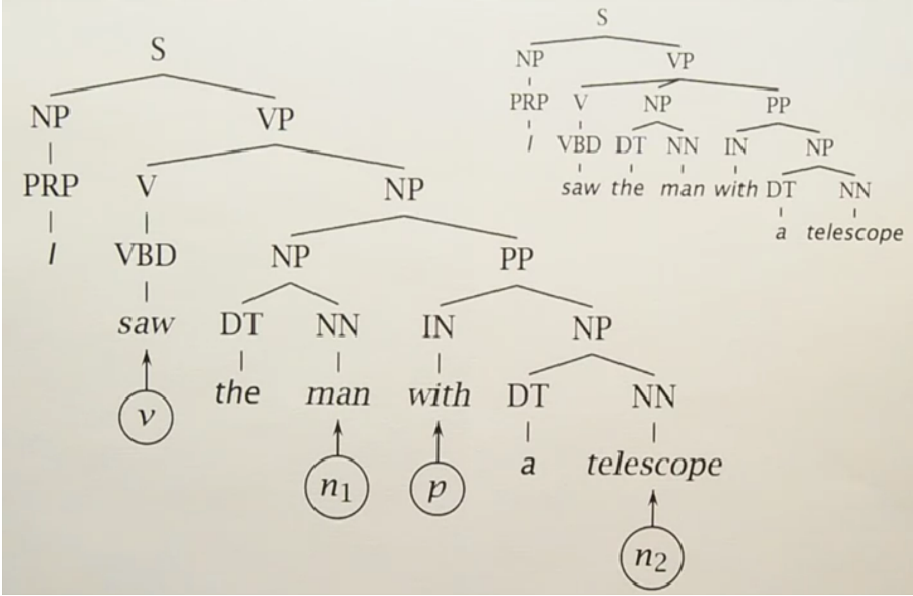

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Probabilities based on actual words:

$$
\begin{aligned}
P(\mathrm{VP} \rightarrow \mathrm{V\,NP\,NP} | \mathrm{V} = \mathrm{gave}) &= 0.8\,(\mathrm{common:\ gave\,me\,something}) \\
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But telescope example still hard to solve. But we can use:

- Smoothing
- Abstractions

Putting Them Together: Parsing Trees with LPCFGs

So we have all the information now. How to parse language into trees?

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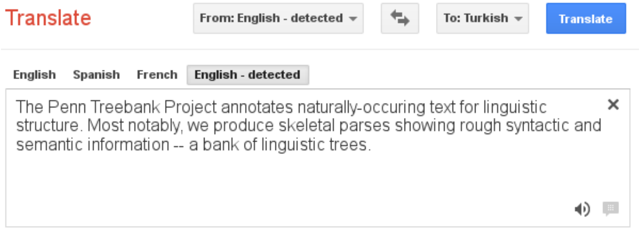
So it becomes like a regular tree search!

Note:

- Context-free grammars have advantage of parsing parts of the tree **independent** of the rest. That is, we can **divide and conquer**.

Machine Translation



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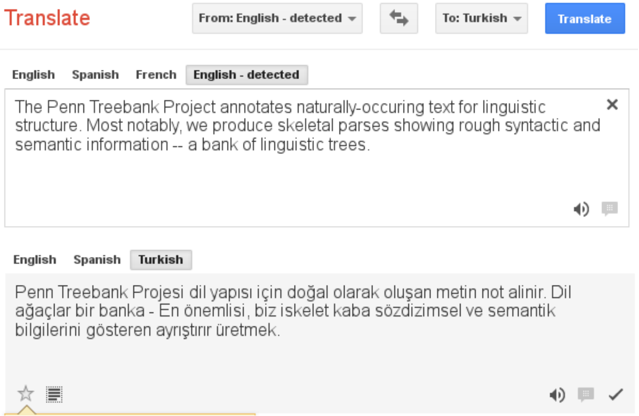

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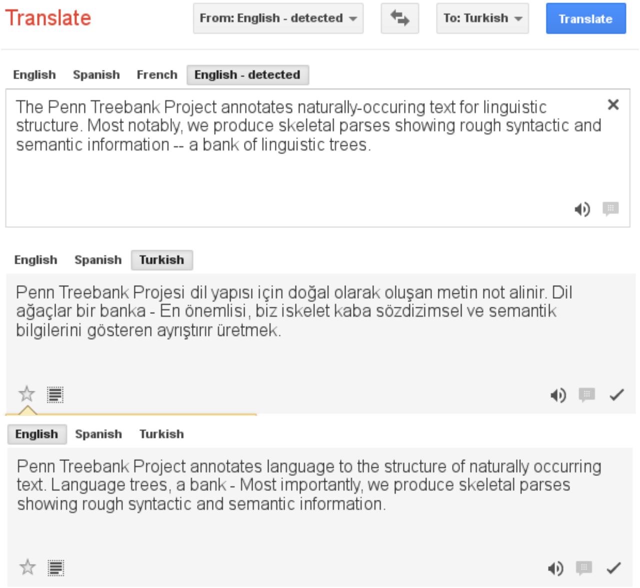

Machine Translation Levels

Multi-level pyramid of machine translation (by Vauquois):

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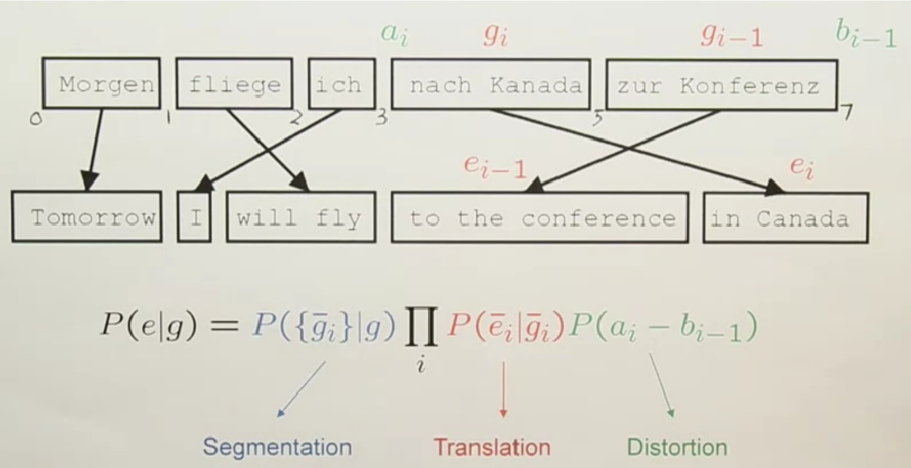
We'll concentrate on #2, but others are used on the field, too.

Phrase Translation



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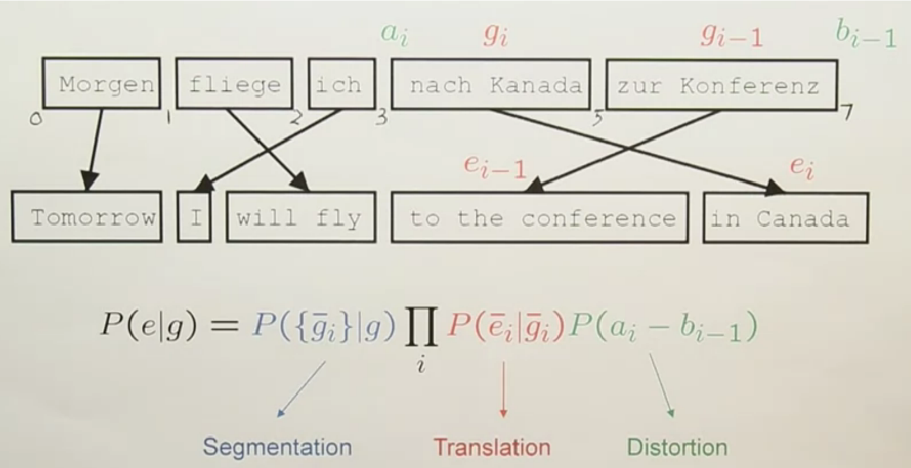

What else to improve?

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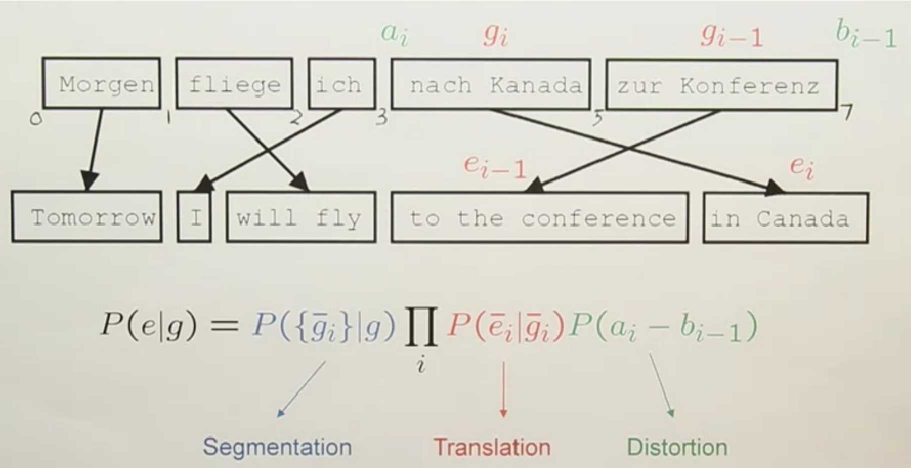

What else to improve?

- Calculate $p(e)$ from LPCFG and check if translated sentence is likely.