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• Screencasts: [http://www.youtube.com/view_play_list?p=-XXv-cvA_iCIEwJhyDVdyLMCiimv6Tup](http://www.youtube.com/view_play_list?p=-XXv-cvA_iCIEwJhyDVdyLMCiimv6Tup)
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  ▪ See http://inst.eecs.berkeley.edu/~cs61a/fa13/exams/final.html for the schedule.
Natural Language Processing
Ambiguity in Natural Language

Unlike programming languages, natural languages are ambiguous.
Ambiguity in Natural Language

Unlike programming languages, natural languages are ambiguous.

Syntactic ambiguity:
Ambiguity in Natural Language

Unlike programming languages, natural languages are ambiguous.

**Syntactic ambiguity:** TEACHER STRIKES IDLE KIDS
Ambiguity in Natural Language

Unlike programming languages, natural languages are ambiguous.

Syntactic ambiguity: TEACHER STRIKES IDLE KIDS  HOSPITALS ARE SUED BY 7 FOOT DOCTORS
Ambiguity in Natural Language

Unlike programming languages, natural languages are ambiguous.

**Syntactic ambiguity:**
- TEACHER STRIKES IDLE KIDS
- HOSPITALS ARE SUED BY 7 FOOT DOCTORS

**Semantic ambiguity:**
Ambiguity in Natural Language

Unlike programming languages, natural languages are ambiguous.

**Syntactic ambiguity:**   TEACHER STRIKES IDLE KIDS   HOSPITALS ARE SUED BY 7 FOOT DOCTORS

**Semantic ambiguity:**   IRAQI HEAD SEeks ARMS
Ambiguity in Natural Language

Unlike programming languages, natural languages are ambiguous.

**Syntactic ambiguity:**  TEACHER STRIKES IDLE KIDS  HOSPITALS ARE SUED BY 7 FOOT DOCTORS

**Semantic ambiguity:**  IRAQI HEAD SEEKS ARMS  STOLEN PAINTING FOUND BY TREE
Tasks in Natural Language Processing
Tasks in Natural Language Processing

Research in natural language processing (NLP) focuses on tasks that involve language:
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**Question answering.** "Harriet Boyd Hawes was the first woman to discover and excavate a Minoan settlement on this island." Watson says, "What is Crete?"
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Much attention is given to more focused language analysis problems:
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**Coreference Resolution:** Do the phrases "Barack Obama" and "the president" co-refer?  
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**Syntactic Parsing:** In "I saw the man with the telescope," who has the telescope?

**Word Sense Disambiguation:** Does the "bank of the Seine" have an ATM?

**Named-Entity Recognition:** What names are in "Did van Gogh paint the Bank of the Seine?"
Machine Translation
Machine Translation
Target language corpus gives examples of well-formed sentences

I will get to it later  See you later  He will do it
Machine Translation

Target language corpus gives examples of well-formed sentences

I will get to it later  See you later  He will do it

Parallel corpus gives translation examples

I will do it gladly  You will see later
Yo lo haré de muy buen grado  Después lo veras
Machine Translation

*Target language corpus gives examples of well-formed sentences*

I will get to it later  See you later  He will do it

*Parallel corpus gives translation examples*

I will do it gladly
Yo lo haré de muy buen grado

You will see later
Después lo veras

*Machine translation system:*
Machine Translation

Target language corpus gives examples of well-formed sentences
- I will get to it later
- See you later
- He will do it

Parallel corpus gives translation examples
- I will do it gladly
- Yo lo haré de muy buen grado
- You will see later
- Después lo veras

Machine translation system:

Model of translation
Machine Translation

Target language corpus gives examples of well-formed sentences

<table>
<thead>
<tr>
<th>English</th>
<th>Spanish</th>
</tr>
</thead>
<tbody>
<tr>
<td>I will get to it later</td>
<td>Yo lo haré de muy buen grado</td>
</tr>
<tr>
<td>See you later</td>
<td>Después lo veras</td>
</tr>
<tr>
<td>He will do it</td>
<td></td>
</tr>
</tbody>
</table>

Parallel corpus gives translation examples

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>I will do it gladly</td>
<td></td>
</tr>
<tr>
<td>You will see later</td>
<td></td>
</tr>
<tr>
<td>Después lo veras</td>
<td></td>
</tr>
</tbody>
</table>

Machine translation system:

Source language: Yo lo haré después

Model of translation

Target language: I will do it later
Syntactic Agreement in Translation

Yo lo haré de muy buen grado
I will do it gladly

Después lo verás
You will see later

Yo lo haré después
I will do it later

Machine translation system:
Syntactic Agreement in Translation

I will do it gladly

You will see later

Yo lo haré de muy buen grado

Después lo veras

Machine translation system:

Yo lo haré **después**

**Model of translation**

I will do it **later**
Syntactic Agreement in Translation

Machine translation system:

Yo lo haré de muy buen grado

Después lo verás

I will do it gladly

You will see later

Model of translation

Yo lo haré después

I will do it later
Syntactic Agreement in Translation

Machine translation system:
Syntactic Reordering in Translation

pair added to the lexicon
Syntactic Reordering in Translation

pair added to the lexicon
Syntactic Reordering in Translation

S
  VP
    PP
      NP
        NN
        VBD
        TO
        DT
        NN

pair added to the lexicon pair

S
  NP
    NN

arrow

arrow
Syntactic Reordering in Translation

```
pair added to the lexicon
```

```
pair added
```
Syntactic Reordering in Translation

pair added to the lexicon

pair to added
Syntactic Reordering in Translation

pair added to the lexicon

pair the lexicon to added
Syntactic Reordering in Translation

pair added to the lexicon

pair the lexicon to added
Syntactic Reordering in Translation

pair added to the lexicon

pair the lexicon to added
Syntactic Reordering in Translation

```
NP  VBD  TO  DT  NN
  |       |     |
  pair  added  to  the  lexicon

NP  PP  NP
  |     |     |
  NP  VP
  |     |
  NN

S  VP
  |
  PP

S  VP
  |
  PP

pair  the  lexicon  to  added
```
Syntactic Reordering in Translation

Pair added to the lexicon

Pair the lexicon to added
Syntactic Reordering in Translation

```
pair added to the lexicon
```

```
/grpc pair the lexicon to added
```
Syntactic Reordering in Translation

- **English:**
  - The tree diagrams illustrate syntactic reordering in translation.
  - Words are reorganized within the tree structure, and new word order is represented.

- **Japanese:**
  - The tree diagrams are labeled with Japanese text, indicating the reorganization of phrases and word order.
  - The reordering process is visually demonstrated through the arrows between nodes in the trees.
Syntactic Reordering in Translation

```
pair added to the lexicon
```

```
(pair added to the lexicon)
```

```
(pair) the lexicon to added
```

```
(pair) list to added
```

```
(one pair) added
```

```
(one pair) list to added
```

Syntactic Reordering in Translation

pair added to the lexicon

一対が 目録 に 追加されました

pair list to add was
Context-Free Grammars
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.
A context-free grammar models language generation.

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

\[ S \]
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

Grammar Rules

S \rightarrow \text{NP VP}
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

Grammar Rules

\[ S \rightarrow NP \text{ VP} \]
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

Grammar Rules

\[
S \rightarrow NP \ VP \\
NP \rightarrow PRP
\]
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

Grammar Rules

\[
\begin{align*}
S & \rightarrow NP \ VP \\
NP & \rightarrow PRP
\end{align*}
\]
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

```
Grammar Rules
S  ->  NP  VP
NP  ->  PRP
```

Lexicon

```
S
   NP
     PRP
   VP
```
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

Grammar Rules

- $S \rightarrow NP \ VP$
- $NP \rightarrow PRP$

Lexicon

- $PRP \rightarrow I$
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

Grammar Rules

\[
S \rightarrow NP \ VP \\
NP \rightarrow PRP \\
\]

Lexicon

\[
PRP \rightarrow I \\
\]
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

```
Grammar Rules
S  ->  NP  VP
NP  ->  PRP
VP  ->  VB

Lexicon
PRP  ->  I
```
A grammar contains rules that hierarchically generate word sequences using syntactic tags.

\[
S \rightarrow NP \ VP \\
NP \rightarrow PRP \\
VP \rightarrow VB \\
VP \rightarrow VB \ NP
\]

Lexicon

\[
PRP \rightarrow I
\]
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

Grammar Rules

S → NP VP

NP → PRP

VP → VB

VP → VB NP

Lexicon

PRP → I
A grammar contains rules that hierarchically generate word sequences using syntactic tags.

**Grammar Rules**
- $S \rightarrow NP \ VP$
- $NP \rightarrow PRP$
- $VP \rightarrow VB$
- $VP \rightarrow VB \ NP$

**Lexicon**
- $PRP \rightarrow I$
- $VB \rightarrow know$
- $VB \rightarrow help$
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

```
S -> NP VP
NP -> PRP
VP -> VB
VP -> VB NP
VB -> know
VB -> help
```

Grammar Rules

```
S → NP VP
NP → PRP
VP → VB
VP → VB NP
```

Lexicon

```
PRP → I
VB → know
VB → help
```
A grammar contains rules that hierarchically generate word sequences using syntactic tags.

**Grammar Rules**
- $S \rightarrow NP \ VP$
- $NP \rightarrow PRP$
- $VP \rightarrow VB\ NP$

**Lexicon**
- $PRP \rightarrow I$
- $VB \rightarrow know$
- $VB \rightarrow help$
A grammar contains rules that hierarchically generate word sequences using syntactic tags.

**Grammar Rules**

- **S**: NP VP
- **NP**: PRP
- **VP**: VB, VB NP
- **PRP**: you
- **VB**: know

**Lexicon**

- **PRP**: I, you
- **VB**: know, help
A Context-Free Grammar Models Language Generation

A grammar contains rules that hierarchically generate word sequences using syntactic tags.

**Grammar Rules**

- $S \rightarrow NP \; VP$
- $NP \rightarrow PRP$
- $VP \rightarrow VB$
- $VP \rightarrow VB \; NP$

**Lexicon**

- $PRP \rightarrow I$
- $PRP \rightarrow you$
- $VB \rightarrow know$
- $VB \rightarrow help$
Probabilistic Context-Free Grammars

Grammar Rules

- S → NP VP
- NP → PRP
- VP → VB
- VP → VB NP

Lexicon

- PRP → I
- PRP → you
- VB → know
- VB → help
Probabilistic Context-Free Grammars

Grammar Rules
- $S \rightarrow NP \ VP$
- $NP \rightarrow PRP$
- $VP \rightarrow VB$
- $VP \rightarrow VB \ NP$

Lexicon
- $PRP \rightarrow I$
- $PRP \rightarrow you$
- $VB \rightarrow know$
- $VB \rightarrow help$
Probabilistic Context-Free Grammars

**Grammar Rules**

- S → NP VP
- NP → PRP
- VP → VB
- VP → VB NP
- VP → MD VP

**Lexicon**

- PRP → I
- PRP → you
- VB → know
- VB → help
Probabilistic Context-Free Grammars

Grammar Rules

\[ S \rightarrow NP \ VP \]
\[ NP \rightarrow PRP \]
\[ PRP \rightarrow I \]
\[ VP \rightarrow VB \]
\[ VP \rightarrow VB \ NP \]
\[ VP \rightarrow MD \ VP \]

Lexicon

\[ PRP \rightarrow I \]
\[ PRP \rightarrow you \]
\[ VB \rightarrow know \]
\[ VB \rightarrow help \]
Probabilistic Context-Free Grammars

Grammar Rules

S → NP VP
NP → PRP
PRP → I
VP → VB
VP → VB NP
VP → MD VP

Lexicon

PRP → I
PRP → you
VB → know
VB → help
Probabilistic Context-Free Grammars

```
S  ->  NP  VP
NP  ->  PRP
PRP  ->  I
VP  ->  VB
  |  ->  VB  NP
  |  ->  MD  VP
PRP  ->  you
VP  ->  MD  VP
```

**Lexicon**

- PRP  ->  I
- PRP  ->  you
- VB  ->  know
- VB  ->  help
Probabilistic Context-Free Grammars

Grammar Rules

S → NP VP
NP → PRP
PRP → I
VP → VB
VP → VB NP
MD → can

Lexicon

PRP → I
PRP → you
VB → know
VB → help
MD → can
Probabilistic Context-Free Grammars

Grammar Rules

- S → NP VP
- NP → PRP
- VP → VB
- VP → VB NP
- VP → MD VP

Lexicon

- PRP → I
- PRP → you
- VB → know
- VB → help
- MD → can
Probabilistic Context-Free Grammars

Grammar Rules

S -> NP VP
NP -> PRP
VP -> VB
VP -> VB NP
PRP -> you
VP -> MD VP
VB -> know
VB -> help
MD -> can

Lexicon

PRP -> I
PRP -> you
VB -> know
VB -> help
MD -> can
Probabilistic Context-Free Grammars

Grammar Rules

S \rightarrow \text{NP } \text{VP}

\text{NP } \rightarrow \text{PRP}

\text{PRP } \rightarrow \text{I}

\text{VP } \rightarrow \text{VB}

\text{VP } \rightarrow \text{VB } \text{NP}

\text{MD } \rightarrow \text{can}

\text{VB } \rightarrow \text{know}

\text{VB } \rightarrow \text{help}

Lexicon

\text{PRP } \rightarrow \text{I}

\text{PRP } \rightarrow \text{you}

\text{VB } \rightarrow \text{know}

\text{VB } \rightarrow \text{help}

\text{MD } \rightarrow \text{can}
Probabilistic Context-Free Grammars

Grammar Rules

S → NP VP
NP → PRP
VP → VB
VP → VB NP
MD → can
PRP → you
VP → MD VP

Lexicon

PRP → I
PRP → you
VB → know
VB → help
MD → can
Probabilistic Context-Free Grammars

Grammar Rules

- S → NP VP
- NP → PRP
- VP → VB
- VP → VB NP
- PRP → you
- VP → MD VP
- VB → know
- VB → help
- MD → can

Lexicon

- PRP → I
- PRP → you
- VB → know
- VB → help
- MD → can
Learning Probabilistic Context-Free Grammars

(Demo)
Parsing with Probabilistic Context-Free Grammars
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

time flies like an arrow
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

\[
time \text{flies like an arrow}
\]
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

time flies like an arrow
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

time flies like an arrow
fruit flies like bananas
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

- time flies like an arrow
- fruit flies like bananas
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

\[
\text{time flies like an arrow} \quad \text{fruit flies like bananas}
\]
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

- time flies like an arrow
- fruit flies like bananas

Parse by finding the tree with the highest total probability that yields the sentence.
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

\[
\text{time \ flies \ like \ an \ arrow} \quad \text{fruit \ flies \ like \ bananas}
\]

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

```
time  flies  like  an  arrow
fruit  flies  like  bananas
```

Parse by finding the tree with the highest total probability that yields the sentence.

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```
time  flies  like  an  arrow
fruit  flies  like  bananas
```

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.

```
S  ->  NP  VP
```

```
time  flies  like  an  arrow
0  1  2  3  4  5
```
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

```
time    flies    like    an    arrow
```
```
fruit    flies    like    bananas
```

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.

```
S -> NP VP
```
```
NP -> NN
```

```
time  flies  like  an  arrow
```
```
0      1      2      3      4      5
```
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

```
time  flies  like  an  arrow
fruit  flies  like  bananas
```

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.

```
S  ->  NP  VP
NP  ->  NN
NN  ->  time
```

```
time  flies  like  an  arrow
0    1    2    3    4    5
```
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

```
time  flies  like  an  arrow
fruit  flies  like  bananas
```

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.

```
n	 0  
n	 1  
n	 2  
n	 3  
n	 4  
n	 5  
S  ->  NP  VP
NP  ->  NN
VP  ->  VBZ  PP
NN  ->  time
time  flies  like  an  arrow
```

```
S  ->  NP  VP
NP  ->  NN
VP  ->  VBZ  PP
NN  ->  time
```

```
time  flies  like  an  arrow
```
A probabilistic context-free grammar can be used to select a parse for a sentence.

Parse by finding the tree with the highest total probability that yields the sentence.

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Parsing is Maximizing Likelihood

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Algorithm: Try every rule over every span. Match the lexicon to each word.
A probabilistic context-free grammar can be used to select a parse for a sentence.

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Algorithm: Try every rule over every span. Match the lexicon to each word.
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

```
time flies like an arrow
fruit flies like bananas
```

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.

```
S → NP VP
NP → NN
VP → VBZ PP
PP → IN NP
NP → DT NN
NN → time
VBZ → flies
IN → like
```

```
time flies like an arrow
0 1 2 3 4 5
```
Parsing is Maximizing Likelihood

A probabilistic context–free grammar can be used to select a parse for a sentence.

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.
Parsing is Maximizing Likelihood

A probabilistic context-free grammar can be used to select a parse for a sentence.

time flies like an arrow
fruit flies like bananas

Parse by finding the tree with the highest total probability that yields the sentence.

Algorithm: Try every rule over every span. Match the lexicon to each word.
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Tree Transformations
Reordering Modal Arguments
Reordering Modal Arguments

English
Reordering Modal Arguments

English → Yoda-English
Reordering Modal Arguments

English  →  Yoda-English

Help you, I can!
Yes! Mm!
Reordering Modal Arguments

English  Yoda-English

Help you, I can!
Yes! Mm!

When 900 years old you reach, look as good, you will not. Hm.
Help you, I can! Yes! Mm!

When 900 years old you reach, look as good, you will not. Hm.
Reordering Modal Arguments

Help you, I can! Yes! Mm!

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Reordering Modal Arguments

English  Yoda-English

S

VP          NP          VP

VB          PRP          PRP          MD

help         you           I           can

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Reordering Modal Arguments

English ➔ Yoda-English

S
  VP
    VB  PRP
      help  you
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      I
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