

PARSING

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CS159 – Fall 2014

Admin

Assignment 3

Quiz #1

- ▣ High: 36
- ▣ Average: 33 (92%)
- ▣ Median: 33.5 (93%)
- ▣ Next one will probably be a bit harder ☺

Parsing

Parsing is the field of NLP interested in automatically determining the syntactic structure of a sentence

parsing can also be thought of as determining what sentences are “valid” English sentences

Parsing

We have a grammar, determine the possible parse tree(s)

Let's start with parsing with a CFG (no probabilities)

S → NP VP
 NP → PRP
 NP → N PP
 VP → V NP
 VP → V NP PP
 PP → IN N
 PRP → I
 V → eat
 N → sushi
 N → tuna
 IN → with

I eat sushi with tuna

approaches?
 algorithms?

Parsing

Top-down parsing

- ▣ ends up doing a lot of repeated work
- ▣ doesn't take into account the words in the sentence until the end!


Bottom-up parsing

- ▣ constrain based on the words
- ▣ avoids repeated work (dynamic programming)
- ▣ CKY parser

Parsing


Top-down parsing

- ▣ start at the top (usually S) and apply rules
- ▣ matching left-hand sides and replacing with right-hand sides



Bottom-up parsing

- ▣ start at the bottom (i.e. words) and build the parse tree up from there
- ▣ matching right-hand sides and replacing with left-hand sides



Parsing Example

book that flight

→

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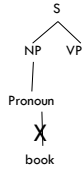
      S
      |
      VP
     /  \
  Verb  NP
  |     /  \
  book Det Nominal
        |   /  \
        that Noun
              |
              flight
          
```

Top Down Parsing

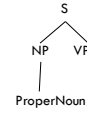
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      S
     /  \
    NP  VP
    |
  Pronoun
          
```

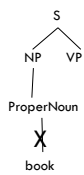
Top Down Parsing



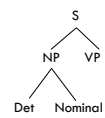
Top Down Parsing

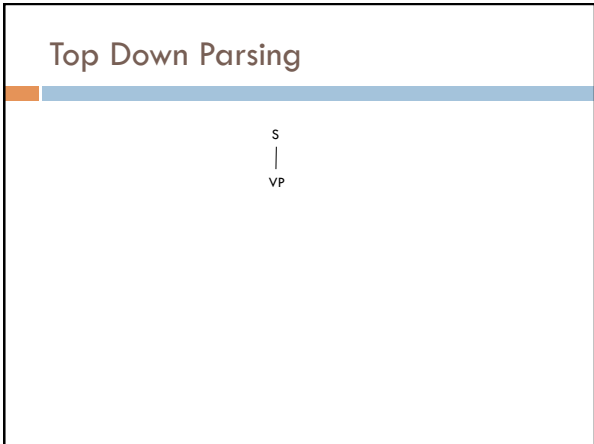
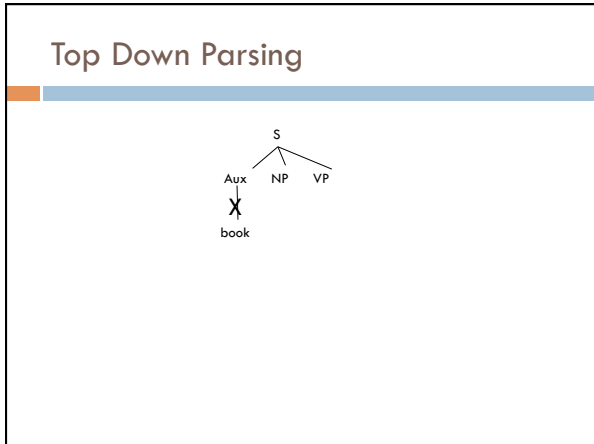
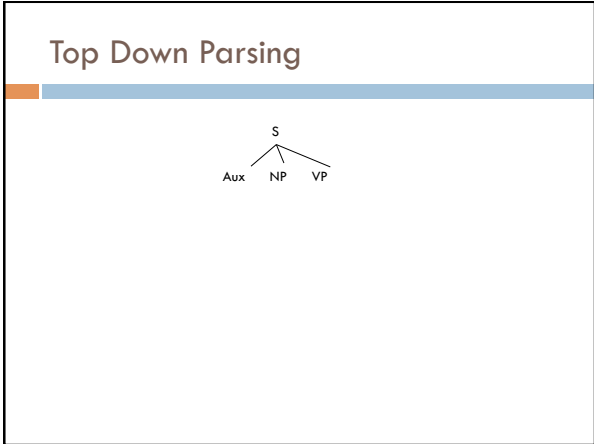
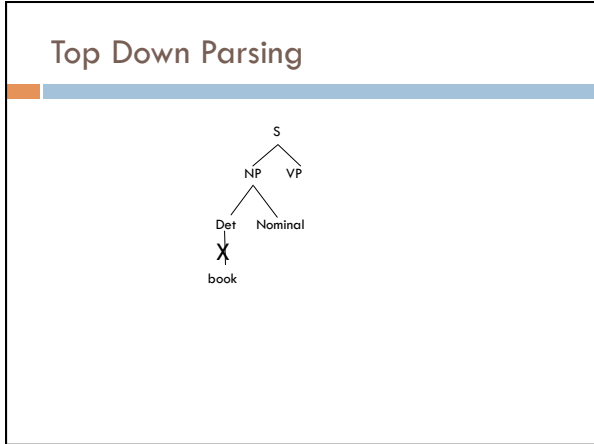


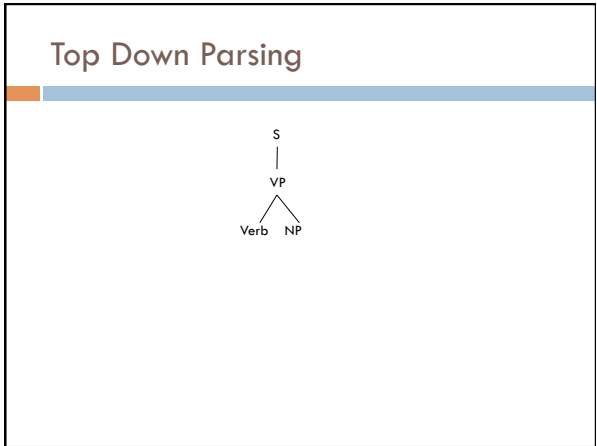
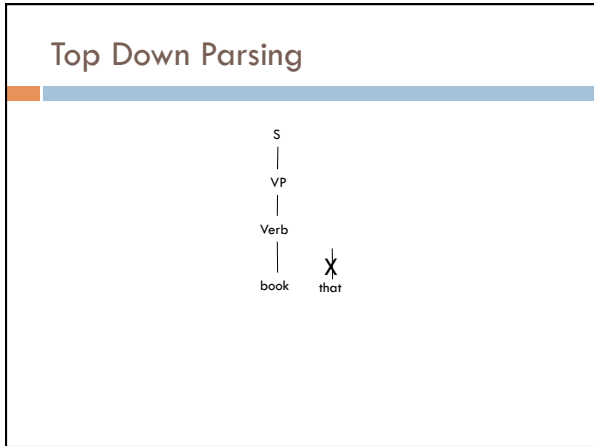
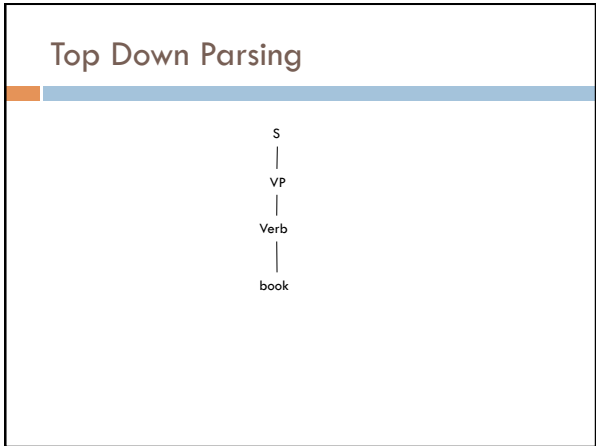
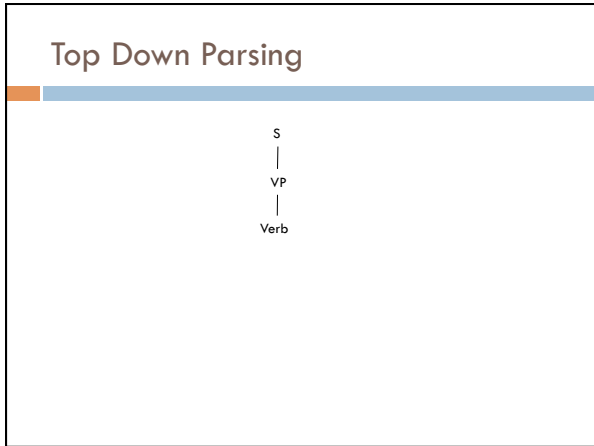
Top Down Parsing

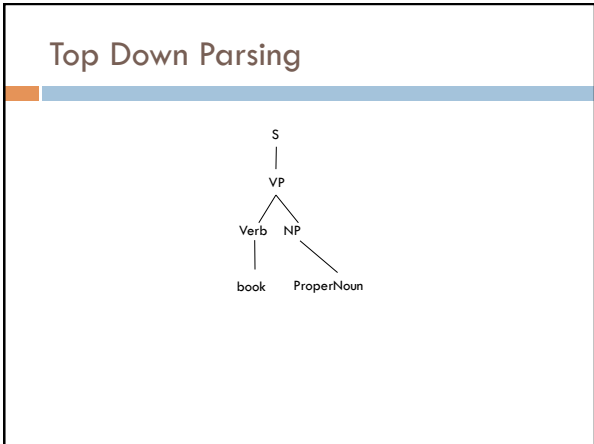
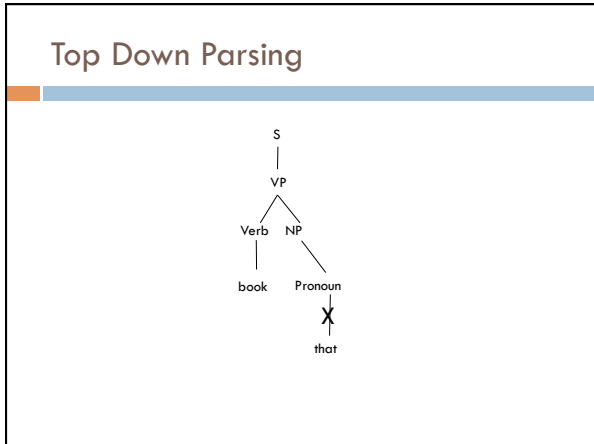
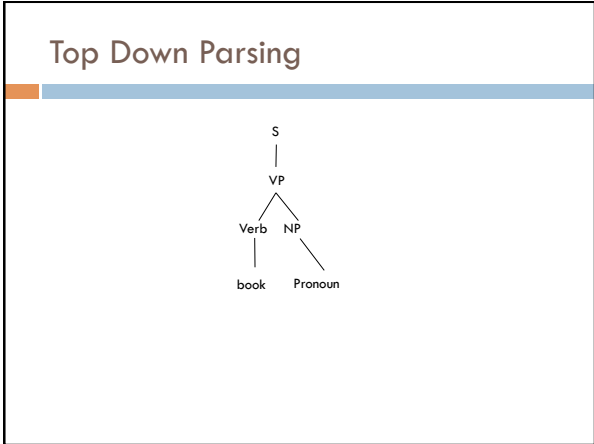
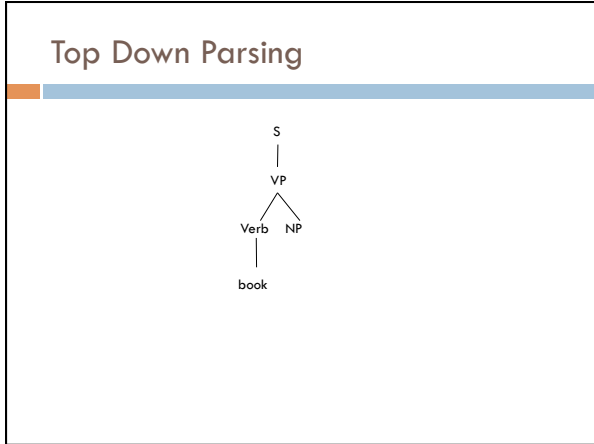


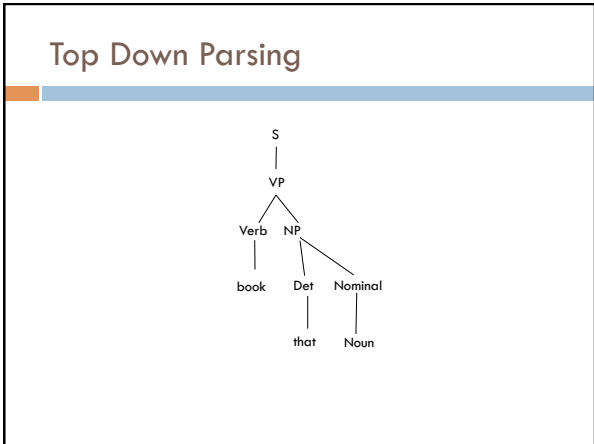
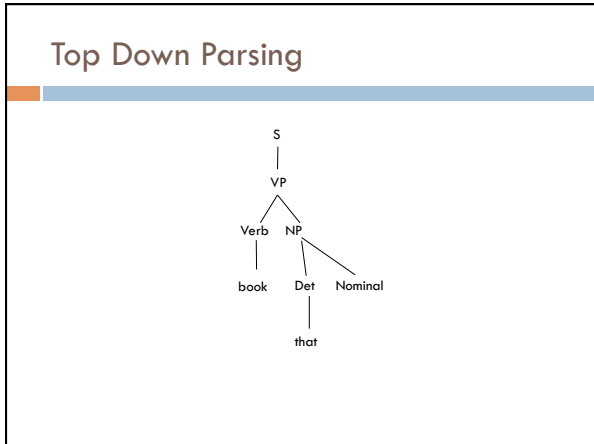
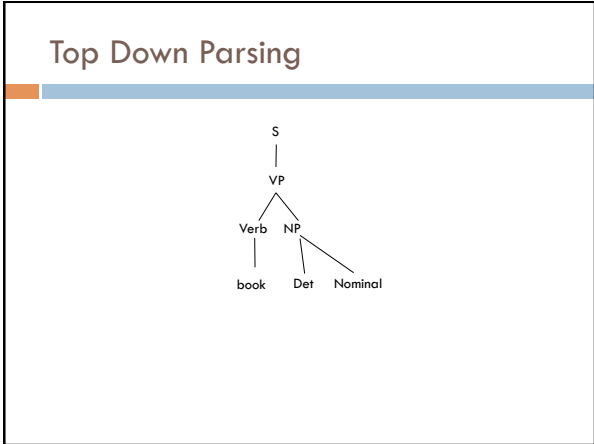
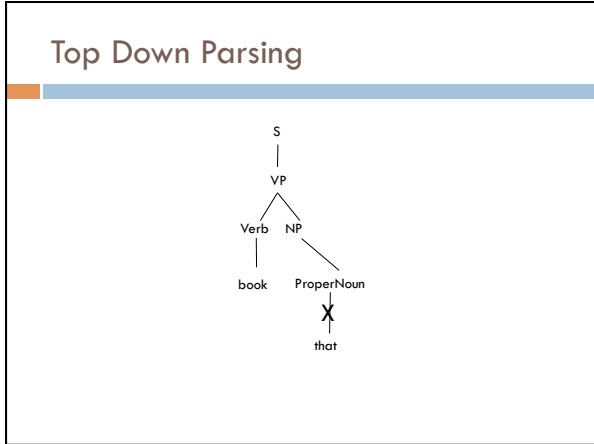
Top Down Parsing



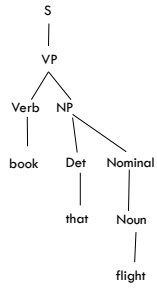








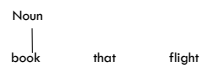
Top Down Parsing



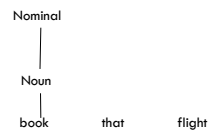
Bottom Up Parsing

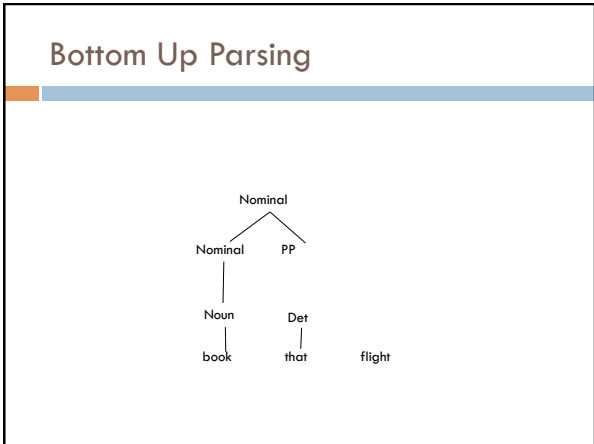
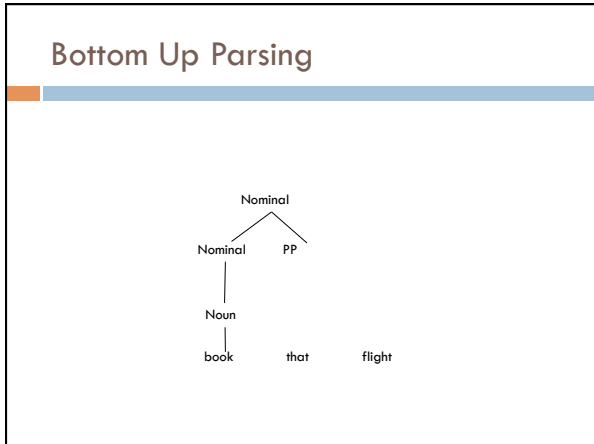
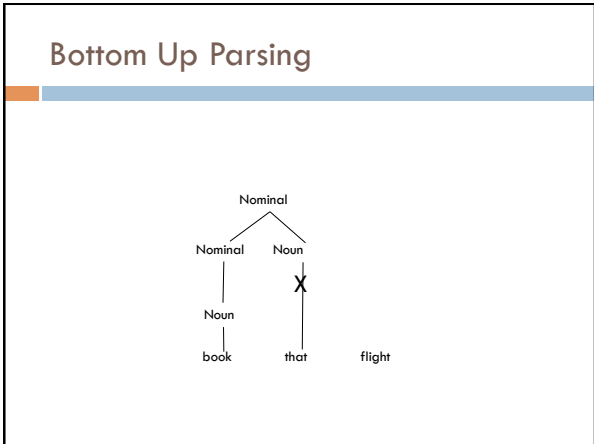
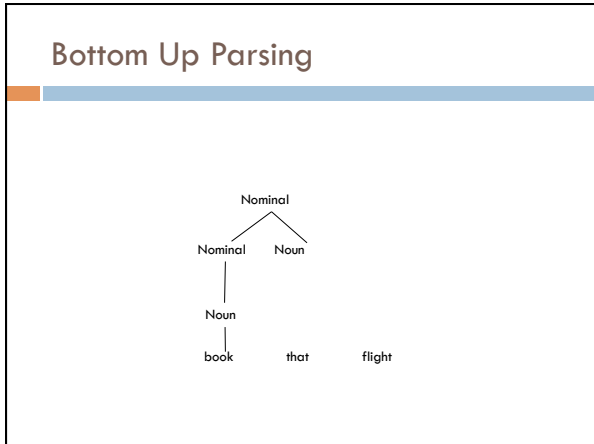
book that flight

Bottom Up Parsing

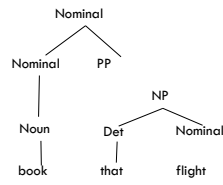


Bottom Up Parsing

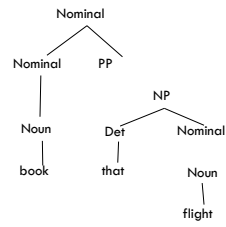




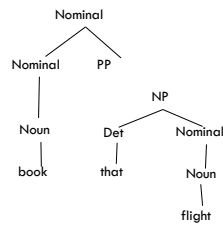
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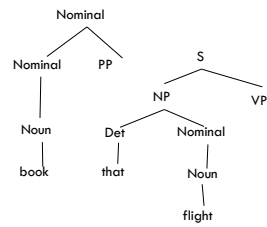
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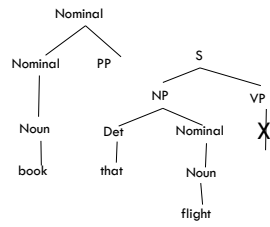
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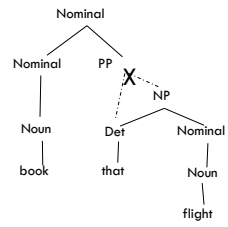
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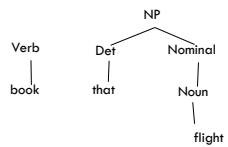
Bottom Up Parsing



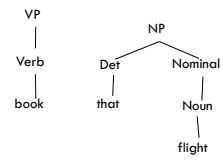
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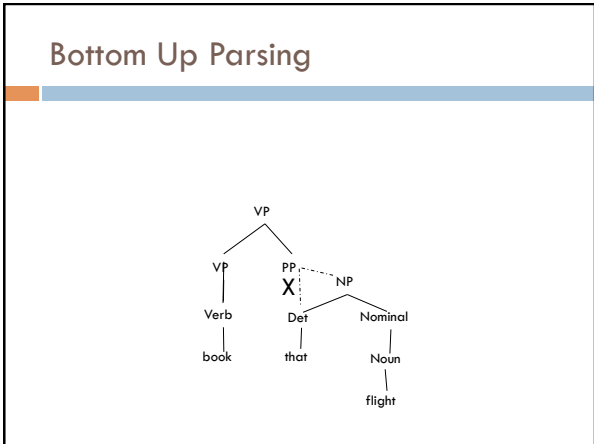
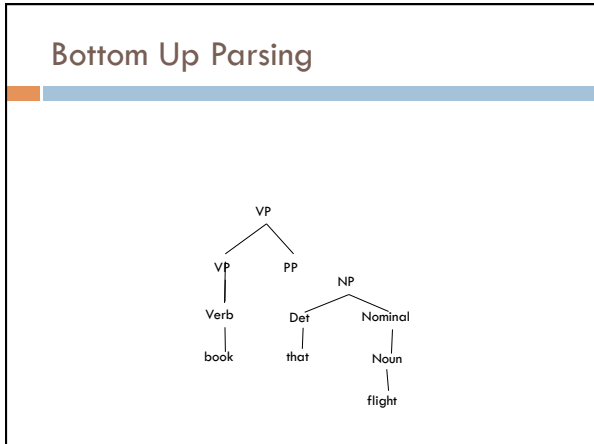
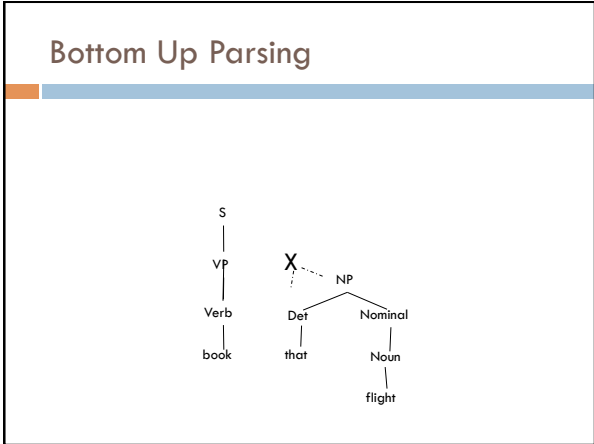
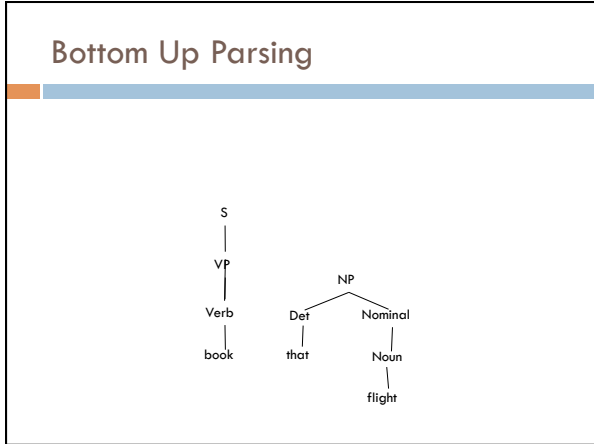


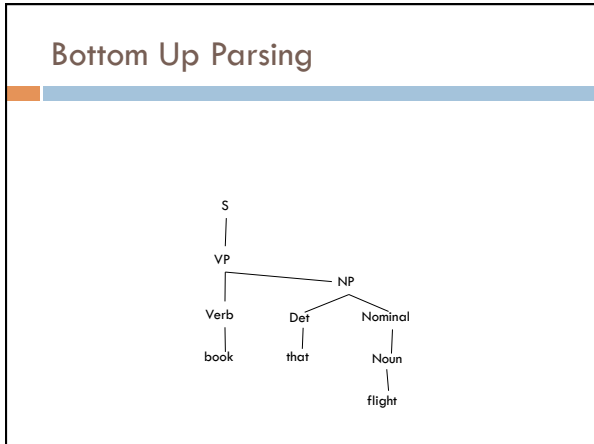
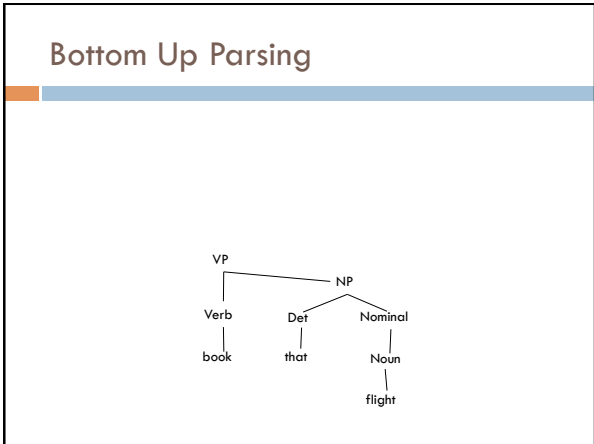
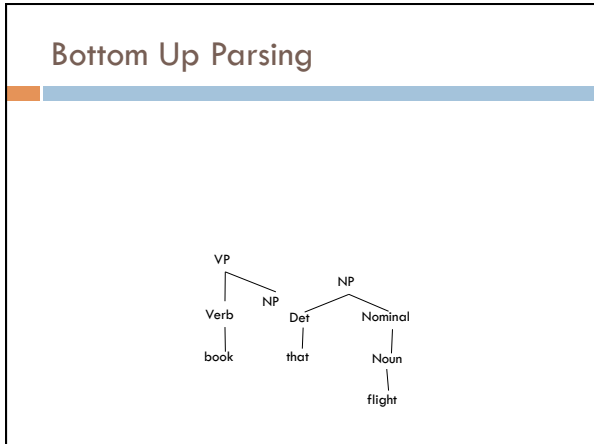
Bottom Up Parsing



Bottom Up Parsing







Parsing

Pros/Cons?

- ▣ **Top-down:**
 - Only examines parses that could be valid parses (i.e. with an S on top)
 - Doesn't take into account the actual words!
- ▣ **Bottom-up:**
 - Only examines structures that have the actual words as the leaves
 - Examines sub-parses that may NOT result in a valid parse!

Why is parsing hard?

Actual grammars are large

Lots of ambiguity!

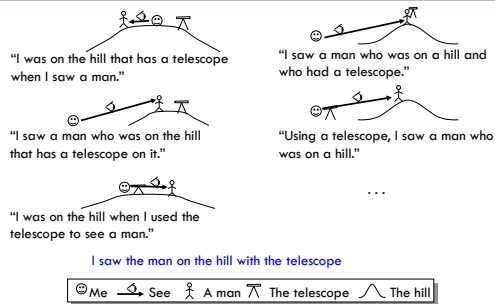
- ▣ Most sentences have many parses
- ▣ Some sentences have a lot of parses
- ▣ Even for sentences that are not ambiguous, there is often ambiguity for subtrees (i.e. multiple ways to parse a phrase)

Why is parsing hard?

I saw the man on the hill with the telescope

What are some interpretations?

Structural Ambiguity Can Give Exponential Parses



Dynamic Programming Parsing

To avoid extensive repeated work you must cache intermediate results, specifically found constituents

Caching (memoizing) is critical to obtaining a polynomial time parsing (recognition) algorithm for CFGs

Dynamic programming algorithms based on both top-down and bottom-up search can achieve $O(n^3)$ recognition time where n is the length of the input string.

Dynamic Programming Parsing Methods

CKY (Cocke-Kasami-Younger) algorithm based on bottom-up parsing and requires first normalizing the grammar.

Earley parser is based on top-down parsing and does not require normalizing grammar but is more complex.

These both fall under the general category of **chart parsers** which retain completed constituents in a chart

CKY parser: the chart

	Film	the	man	with	trust
j=	0	1	2	3	4
i=0					
1					
2					
3					
4					

Cell[i,j] contains all constituents covering words i through j

what does this cell represent?

CKY parser: the chart

	Film	the	man	with	trust
j=	0	1	2	3	4
i=0					
1					
2					
3					
4					

Cell[i,j] contains all constituents covering words i through j

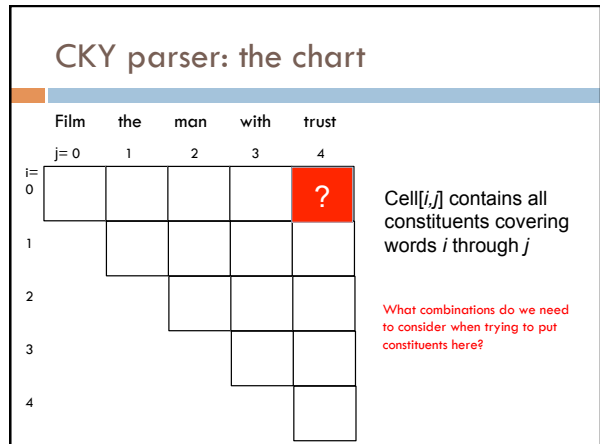
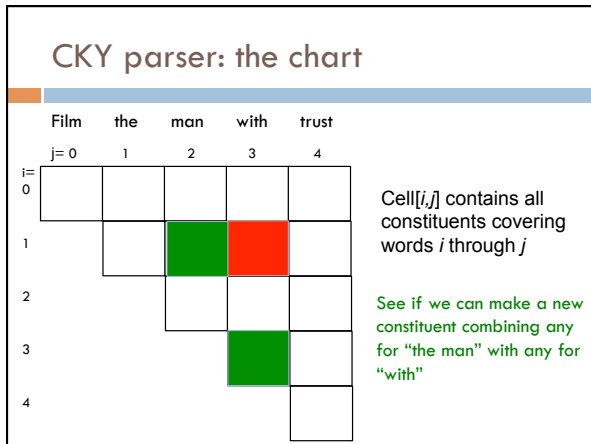
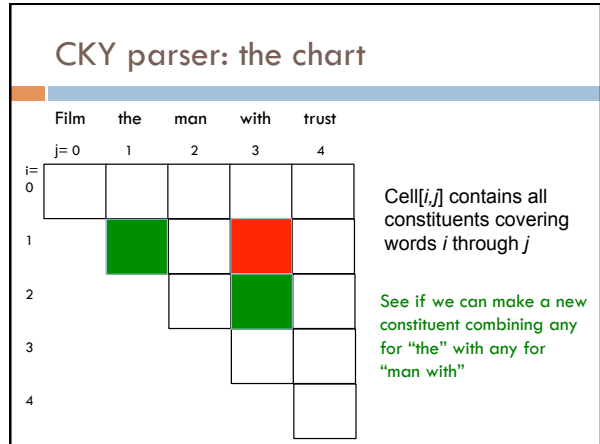
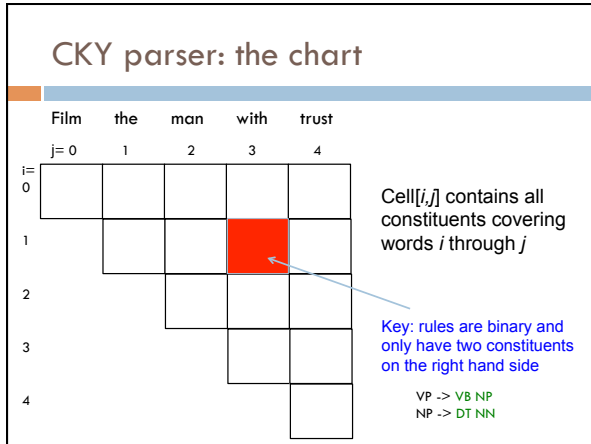
all constituents spanning 1-3 or "the man with"

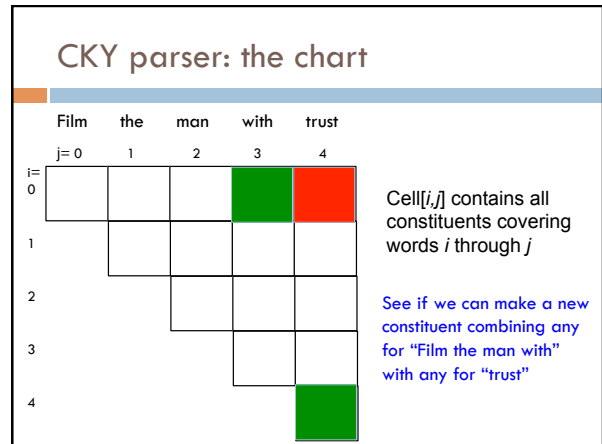
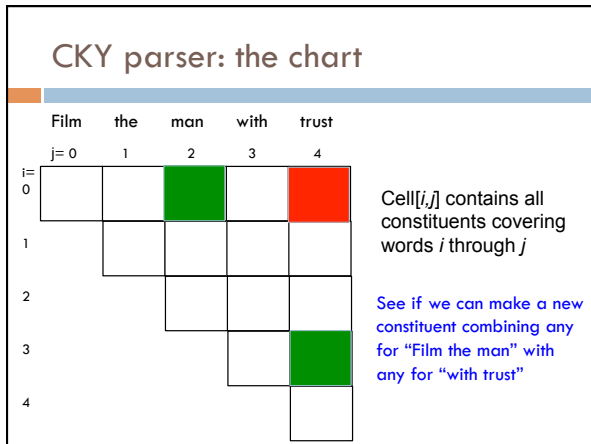
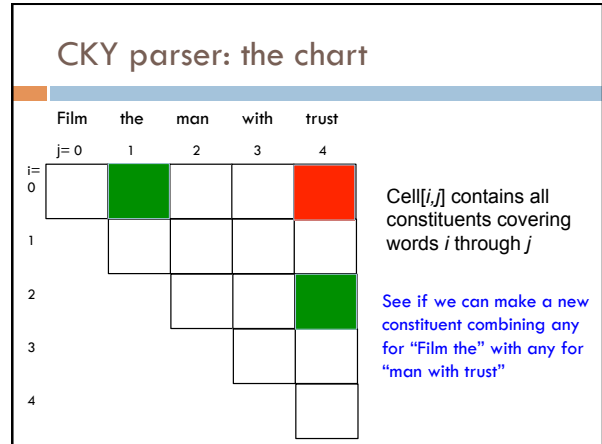
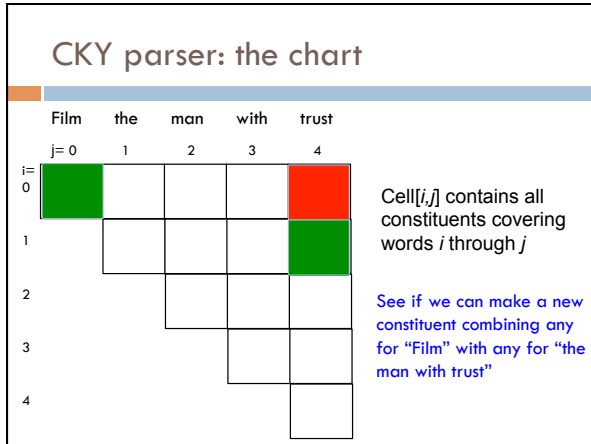
CKY parser: the chart

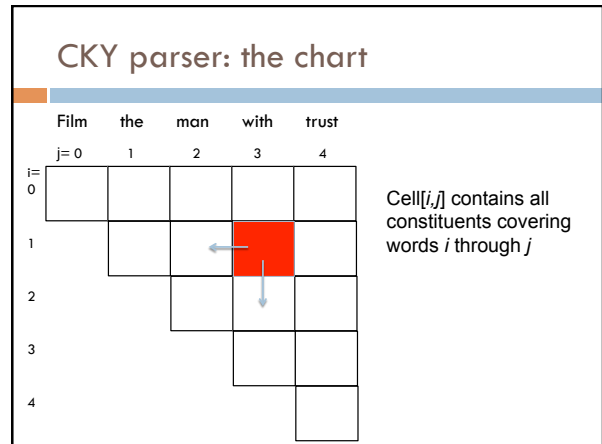
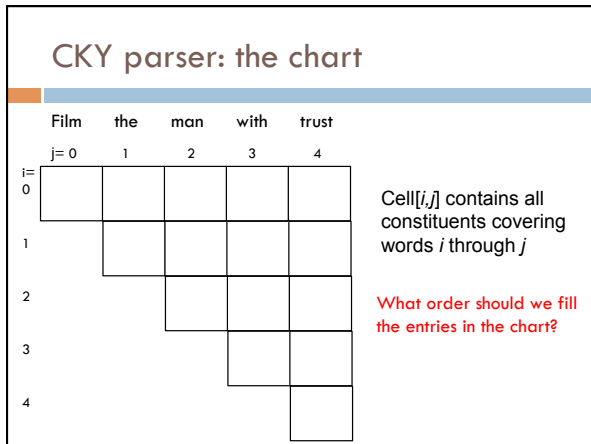
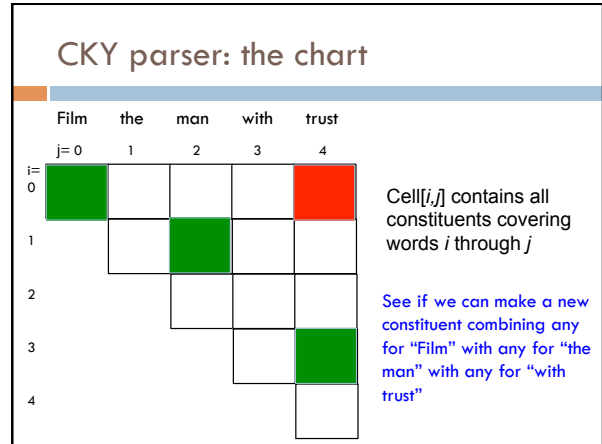
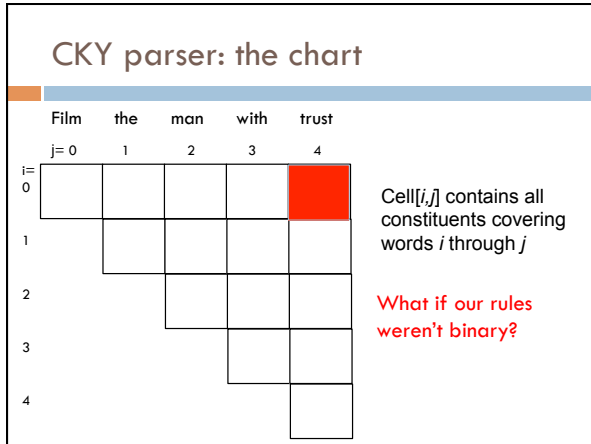
	Film	the	man	with	trust
j=	0	1	2	3	4
i=0					
1					
2					
3					
4					

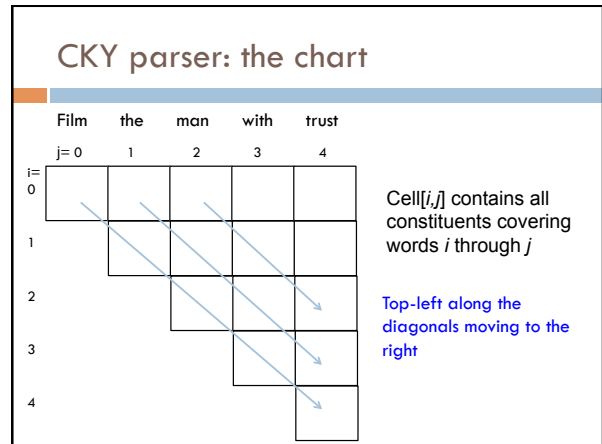
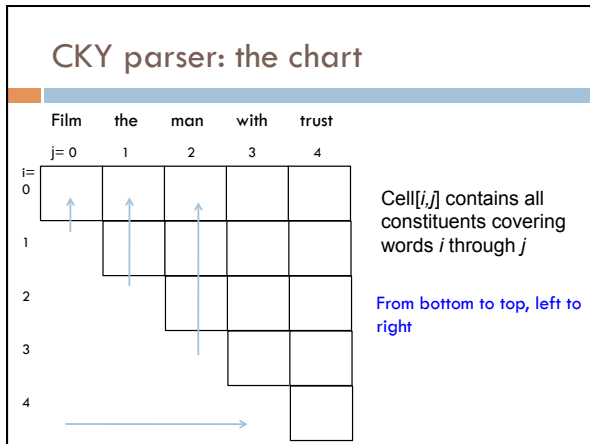
Cell[i,j] contains all constituents covering words i through j

how could we figure this out?









CKY parser: unary rules

S → VP
 VP → VB NP
 VP → VP2 PP
 VP2 → VB NP
 NP → DT NN
 NP → NN
 NP → NP PP
 PP → IN NP
 DT → the
 IN → with
 VB → film
 VB → trust
 NN → man
 NN → film
 NN → trust

Often, we will leave unary rules rather than converting to CNF

Do these complicate the algorithm?

Must check whenever we add a constituent to see if any unary rules apply

CKY parser: the chart

		Film	the	man	with	trust
	j=0	1	2	3	4	
i=0						
1						
2						
3						
4						

S	→	VP
VP	→	VB NP
VP	→	VP2 PP
VP2	→	VB NP
NP	→	DT NN
NP	→	NN
NP	→	NP PP
PP	→	IN NP
DT	→	the
IN	→	with
VB	→	film
VB	→	man
VB	→	trust
NN	→	man
NN	→	film
NN	→	trust

CKY parser: the chart

Film the man with trust					
	j=0	1	2	3	4
i=0	NN NP VB				
1		DT			
2			VB NN NP		
3				IN	
4					VB NN NP

S → VP
 VP → VB NP
 VP → VP2 PP
 VP2 → VB NP
 NP → DT NN
 NP → NN
 NP → NP PP
 PP → IN NP
 DT → the
 IN → with
 VB → film
 VB → man
 VB → trust
 NN → man
 NN → film
 NN → trust

CKY parser: the chart

Film the man with trust					
	j=0	1	2	3	4
i=0	NN NP VB	—			
1		DT	NP		
2			VB NN NP	—	
3				IN	PP
4					VB NN NP

S → VP
 VP → VB NP
 VP → VP2 PP
 VP2 → VB NP
 NP → DT NN
 NP → NN
 NP → NP PP
 PP → IN NP
 DT → the
 IN → with
 VB → film
 VB → man
 VB → trust
 NN → man
 NN → film
 NN → trust

CKY parser: the chart

Film the man with trust					
	j=0	1	2	3	4
i=0	NN NP VB	—	VP2 VP S		
1		DT	NP	—	
2			VB NN NP	—	NP
3				IN	PP
4					VB NN NP

S → VP
 VP → VB NP
 VP → VP2 PP
 VP2 → VB NP
 NP → DT NN
 NP → NN
 NP → NP PP
 PP → IN NP
 DT → the
 IN → with
 VB → film
 VB → man
 VB → trust
 NN → man
 NN → film
 NN → trust

CKY parser: the chart

Film the man with trust					
	j=0	1	2	3	4
i=0	NN NP VB	—	VP2 VP S	—	
1		DT	NP	—	NP
2			VB NN NP	—	NP
3				IN	PP
4					VB NN NP

S → VP
 VP → VB NP
 VP → VP2 PP
 VP2 → VB NP
 NP → DT NN
 NP → NN
 NP → NP PP
 PP → IN NP
 DT → the
 IN → with
 VB → film
 VB → man
 VB → trust
 NN → man
 NN → film
 NN → trust

CKY parser: the chart

		Film	the	man	with	trust
i=	j=	0	1	2	3	4
0	0	NN NP VB	—	VP2 VP S	—	S VP VP2
1	1		DT	NP	—	NP
2	2			VB NN NP	—	NP
3	3				IN	PP
4	4					VB NN NP

- S → VP
- VP → VB NP
- VP → VP2 PP
- VP2 → VB NP
- NP → DT NN
- NP → NN
- NP → NP PP
- PP → IN NP
- DT → the
- IN → with
- VB → film
- VB → man
- VB → trust
- NN → man
- NN → film
- NN → trust

CKY: some things to talk about

After we fill in the chart, how do we know if there is a parse?

- If there is an S in the upper right corner

What if we want an actual tree/parse?

		Film	the	man	with	trust
i=	j=	0	1	2	3	4
0	0	NN NP VB	—	VB2 VP S	—	S VP
1	1		DT	NP	—	NP
2	2			VB NN NP	—	NP
3	3				IN	PP
4	4					VB NN NP

CKY: retrieving the parse

		Film	the	man	with	trust
i=	j=	0	1	2	3	4
0	0	NN NP VB	—	VB2 VP S	—	S VP
1	1		DT	NP	—	NP
2	2			VB NN NP	—	NP
3	3				IN	PP
4	4					VB NN NP

```

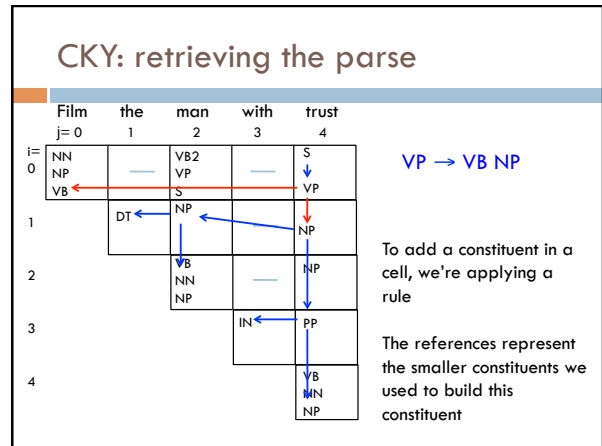
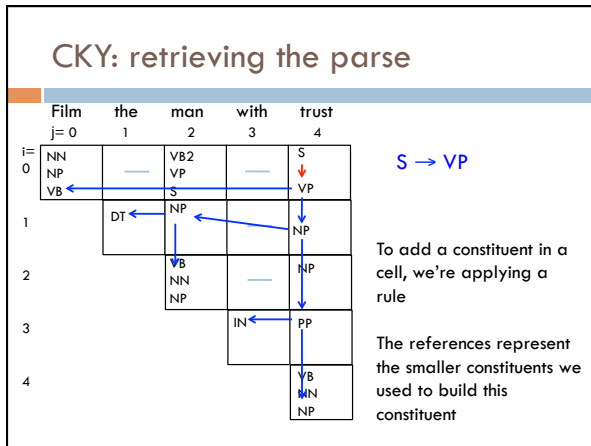
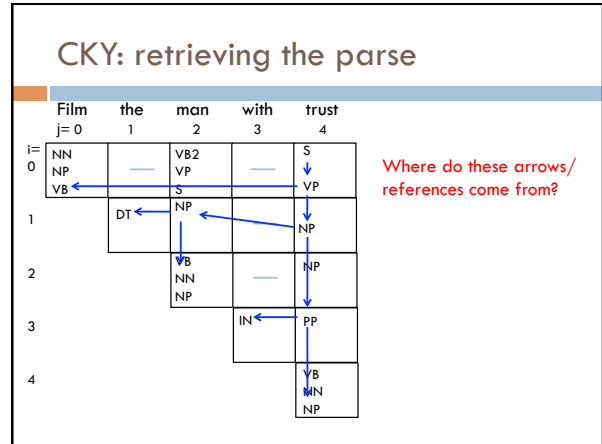
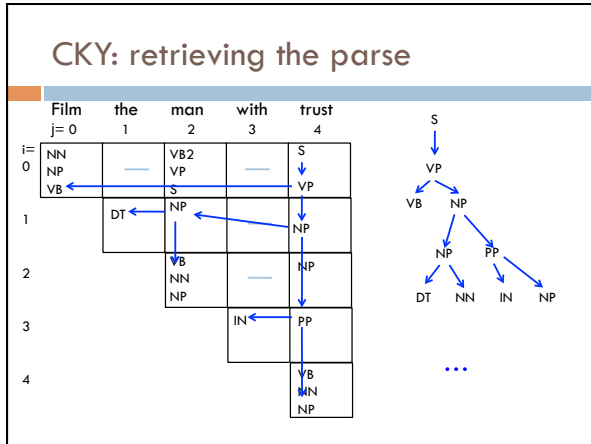
graph TD
    S --> VP
    VP --> VB
    VP --> NP
  
```

CKY: retrieving the parse

		Film	the	man	with	trust
i=	j=	0	1	2	3	4
0	0	NN NP VB	—	VB2 VP S	—	S VP
1	1		DT	NP	—	NP
2	2			VB NN NP	—	NP
3	3				IN	PP
4	4					VB NN NP

```

graph TD
    S --> VP
    VP --> VB
    VP --> NP
    NP --> NP
    NP --> PP
  
```



CKY: retrieving the parse

	Film	the	man	with	trust
j=0	1	2	3	4	
i=0	NN NP	—	VB2 VP	—	S VP
1	VB ←	DT	NP	—	NP
2	—	VB NN NP	—	NP	—
3	—	—	IN	PP	—
4	—	—	—	VB NN NP	—

What about ambiguous parses?

CKY: retrieving the parse

	Film	the	man	with	trust
j=0	1	2	3	4	
i=0	NN NP	—	VB2 VP	—	S VP
1	VB ←	DT	NP	—	NP
2	—	VB NN NP	—	NP	—
3	—	—	IN	PP	—
4	—	—	—	VB NN NP	—

We can store multiple derivations of each constituent

This representation is called a "parse forest"

It is often convenient to leave it in this form, rather than enumerate all possible parses. Why?

CKY: some things to think about

<p>CNF</p> <p>S → VP VP → VB NP VP → VP2 PP VP2 → VB NP NP → DT NN NP → NN ...</p>	<p>Actual grammar</p> <p>S → VP VP → VB NP VP → VB NP PP NP → DT NN NP → NN ...</p>
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We get a CNF parse tree but want one for the actual grammar

Ideas?

Parsing ambiguity

I eat sushi with tuna

I eat sushi with tuna

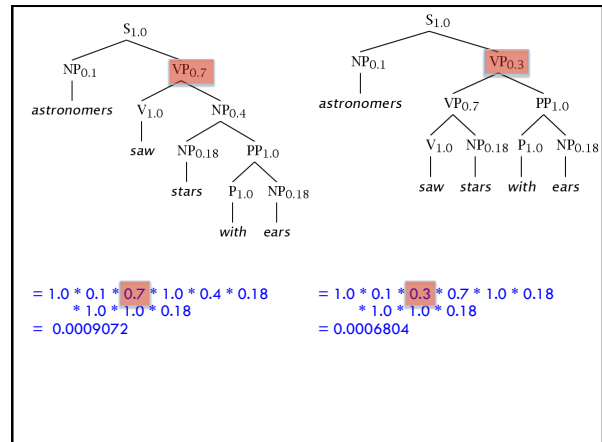
How can we decide between these?

- S → NP VP
- NP → PRP
- NP → N PP
- VP → V NP
- VP → V NP PP
- PP → IN N
- PP → I
- V → eat
- N → sushi
- N → tuna
- IN → with

A Simple PCFG

Probabilities!

S	→	NP VP	1.0	NP	→	NP PP	0.4
VP	→	V NP	0.7	NP	→	<i>astronomers</i>	0.1
VP	→	VP PP	0.3	NP	→	<i>ears</i>	0.18
PP	→	P NP	1.0	NP	→	<i>saw</i>	0.04
P	→	<i>with</i>	1.0	NP	→	<i>stars</i>	0.18
V	→	<i>saw</i>	1.0	NP	→	<i>telescope</i>	0.1



Parsing with PCFGs

How does this change our CKY algorithm?

- We need to keep track of the probability of a constituent

How do we calculate the probability of a constituent?

- Product of the PCFG rule times the product of the probabilities of the sub-constituents (right hand sides)
- Building up the product from the bottom-up

What if there are multiple ways of deriving a particular constituent?

- max: pick the most likely derivation of that constituent

Probabilistic CKY

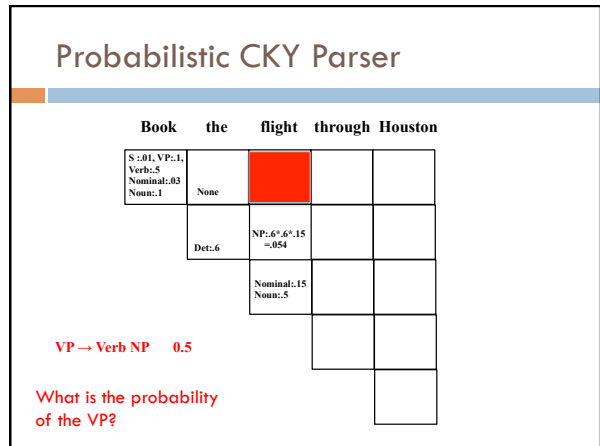
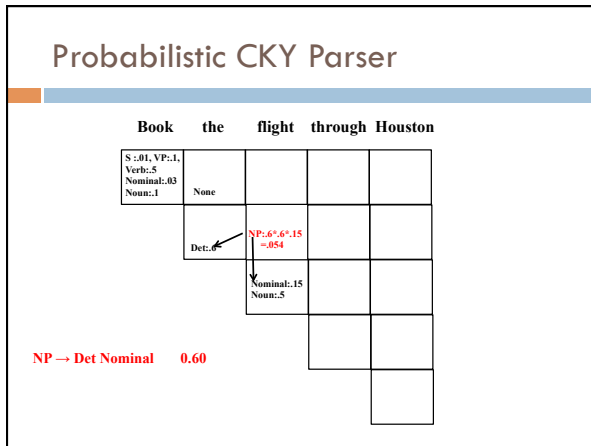
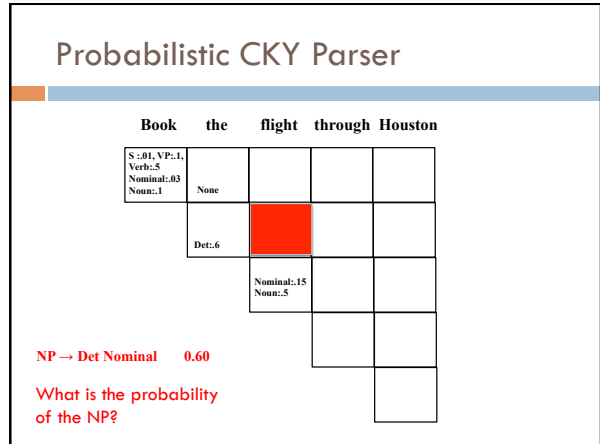
Include in each cell a probability for each non-terminal

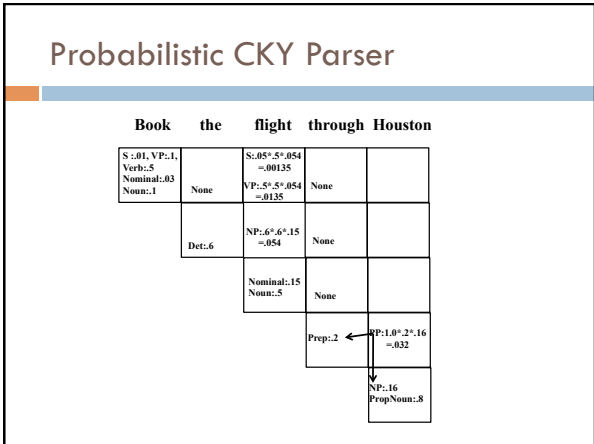
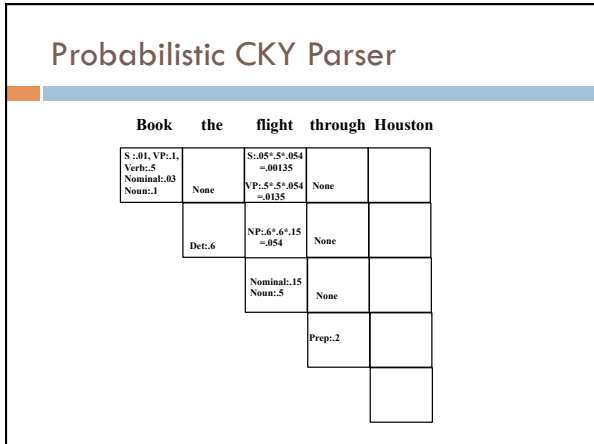
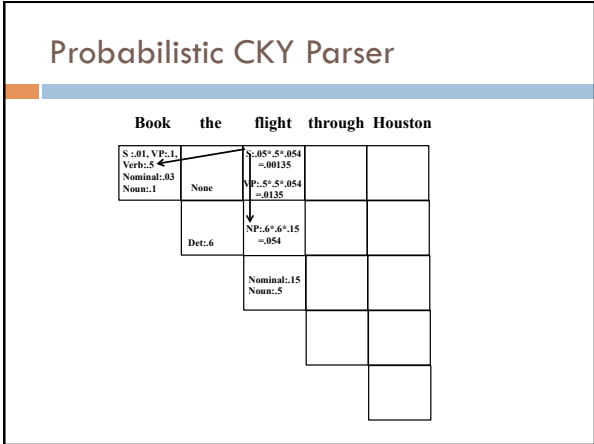
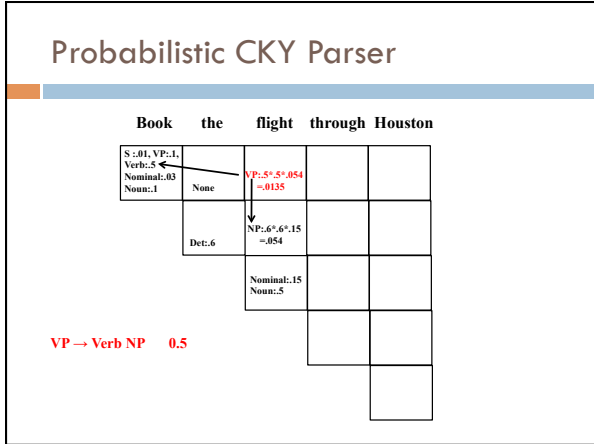
Cell $[i,j]$ must retain the *most probable* derivation of each constituent (non-terminal) covering words i through j

When transforming the grammar to CNF, must set production probabilities to preserve the probability of derivations

Probabilistic Grammar Conversion

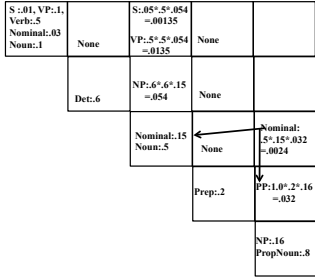
Original Grammar		Chomsky Normal Form	
$S \rightarrow NPVP$	0.8	$S \rightarrow NPVP$	0.8
$S \rightarrow Aux NPVP$	0.1	$S \rightarrow XI VP$	0.1
		$XI \rightarrow Aux NP$	1.0
$S \rightarrow VP$	0.1	$S \rightarrow book include prefer$	
		0.01 0.004 0.006	
		$S \rightarrow Verb NP$	0.05
		$S \rightarrow VP PP$	0.03
$NP \rightarrow Pronoun$	0.2	$NP \rightarrow I he she me$	
		0.1 0.02 0.02 0.06	
$NP \rightarrow Proper-Noun$	0.2	$NP \rightarrow Houston NWA$	
		0.16 .04	
$NP \rightarrow Det Nominal$	0.6	$NP \rightarrow Det Nominal$	0.6
$Nominal \rightarrow Noun$	0.3	$Nominal \rightarrow book flight meal money$	
		0.03 0.15 0.06 0.06	
$Nominal \rightarrow Nominal Noun$	0.2	$Nominal \rightarrow Nominal Noun$	0.2
$Nominal \rightarrow Nominal PP$	0.5	$Nominal \rightarrow Nominal PP$	0.5
$VP \rightarrow Verb$	0.2	$VP \rightarrow book include prefer$	
		0.1 0.04 0.06	
$VP \rightarrow Verb NP$	0.5	$VP \rightarrow Verb NP$	0.5
$VP \rightarrow VP PP$	0.3	$VP \rightarrow VP PP$	0.3
$PP \rightarrow Prep NP$	1.0	$PP \rightarrow Prep NP$	1.0





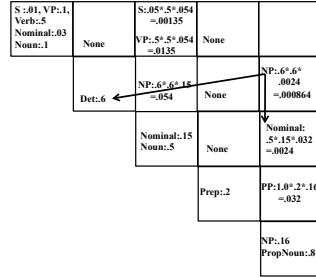
Probabilistic CKY Parser

Book the flight through Houston



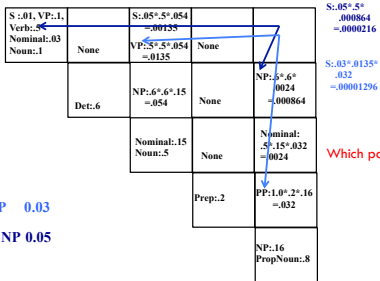
Probabilistic CKY Parser

Book the flight through Houston



Probabilistic CKY Parser

Book the flight through Houston

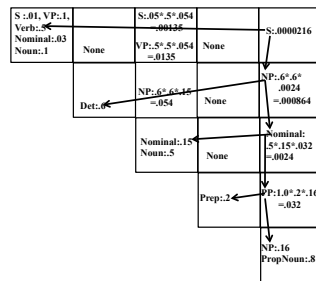


S → VP PP 0.03
S → Verb NP 0.05

Which parse do we pick?

Probabilistic CKY Parser

Book the flight through Houston



Pick most probable parse, i.e. take max to combine probabilities of multiple derivations of each constituent in each cell

Generic PCFG Limitations

PCFGs do not rely on specific words or concepts, only general structural disambiguation is possible (e.g. prefer to attach PPs to Nominals)

- ▣ Generic PCFGs cannot resolve syntactic ambiguities that require semantics to resolve, e.g. ate with fork vs. meatballs

Smoothing/dealing with out of vocabulary

MLE estimates are not always the best