

Weighted Parsing, Probabilistic Parsing



Our bane: Ambiguity



- John saw Mary
 - Typhoid Mary
 - Phillips screwdriver Mary

note how rare rules interact
- I see a bird
 - is this 4 nouns – parsed like “city park scavenger bird”?

rare parts of speech, plus systematic ambiguity in noun sequences
- Time flies like an arrow
 - Fruit flies like a banana
 - Time reactions like this one
 - Time reactions like a chemist
 - or is it just an NP?

Our bane: Ambiguity

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 - Typhoid Mary
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- I see a bird
 - is this 4 nouns – parsed like “city park scavenger bird”?

rare parts of speech, plus systematic ambiguity in noun sequences
- Time | flies like an arrow NP VP
 - Fruit flies | like a banana NP VP
 - Time | reactions like this one V[stem] NP
 - Time reactions | like a chemist S PP
 - or is it just an NP?

How to solve this combinatorial explosion of ambiguity?



1. First try parsing without any weird rules, throwing them in only if needed.
2. Better: every rule has a weight.
A tree's weight is total weight of all its rules.
Pick the overall lightest parse of sentence.
3. Can we pick the weights automatically?
We'll get to this later ...

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3				
1		NP 4 VP 4			
2			P 2 V 5		
3				Det 1	
4					N 8

- 1 S → NP VP
- 6 S → Vst NP
- 2 S → S PP
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- 2 VP → VP PP
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time 1 flies 2 like 3 an 4 arrow 5

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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10			
1		NP 4 VP 4			
2			P 2 V 5		
3				Det 1	
4					N 8

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time 1 flies 2 like 3 an 4 arrow 5

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1		NP 4 VP 4			
2			P 2 V 5		
3				Det 1	
4					N 8

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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			
1		NP 4 VP 4			
2			P 2 V 5		
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time 1 flies 2 like 3 an 4 arrow 5

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1		NP 4 VP 4			
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1		NP 4 VP 4			
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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			
1		NP 4 VP 4			
2			P 2 V 5		PP 12
3				Det 1	NP 10
4					N 8

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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			
1		NP 4 VP 4			
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
4					N 8

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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			
1		NP 4 VP 4			NP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
4					N 8

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1		NP 4 VP 4			NP 18 S 21
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
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1		NP 4 VP 4			NP 18 S 21 VP 18
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1		NP 4 VP 4			NP 18 S 21 VP 18
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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
4					N 8

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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
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2			P 2 V 5		PP 12 VP 16
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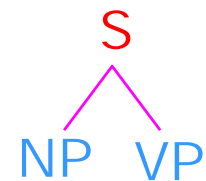
Follow backpointers ... S

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3	NP 10			NP 24
	Vst 3	S 8			S 22
		S 13			S 27
					NP 24
					S 27
1		NP 4			NP 18
		VP 4			S 21
2			P 2		VP 18
			V 5		PP 12
3				Det 1	VP 16
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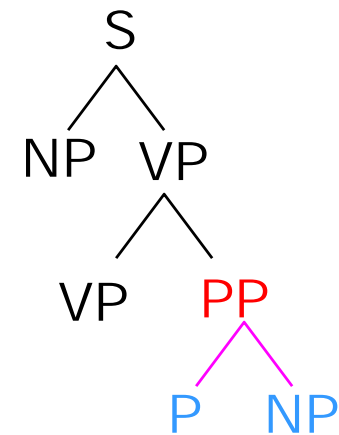


0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 22 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
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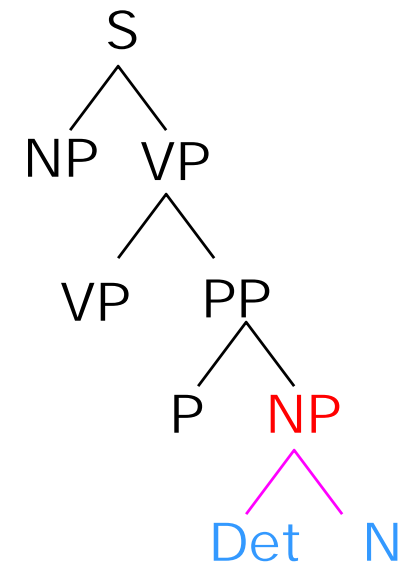
0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 22 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
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Which entries do we need?

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 22 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
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time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 22 S 27
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Not worth keeping ...

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 22 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
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... since it just breeds worse options

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 22 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
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Keep only best-in-class!

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 22 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
4					N 8

inferior stock

- 1 S → NP VP
- 6 S → Vst NP
- 2 S → S PP
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- 2 VP → VP PP
- 1 NP → Det N
- 2 NP → NP PP
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Keep only best-in-class!

(and its backpointers so you can recover best parse)

	time	1	flies	2	like	3	an	4	arrow	5
0		NP 3		NP 10						NP 24
		Vst 3		S 8						S 22
1				NP 4						NP 18
				VP 4						S 21
										VP 18
2						P 2				PP 12
						V 5				VP 16
3							Det 1			NP 10
4										N 8

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Chart Parsing

```
phrase(X,I,J) :- rewrite(X,W), word(W,I,J).
```

```
phrase(X,I,J) :- rewrite(X,Y,Z), phrase(Y,I,Mid), phrase(Z,Mid,J).
```

```
goal      :- phrase(start_symbol, 0, sentence_length).
```

Weighted Chart Parsing (“min cost”)

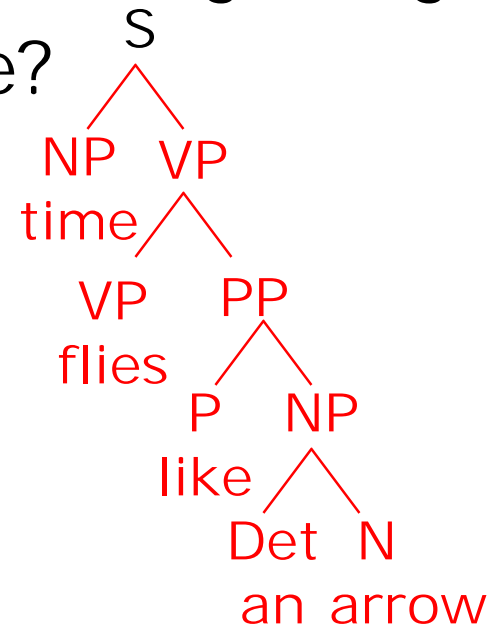
phrase(X,I,J) min= rewrite(X,W) + word(W,I,J).

phrase(X,I,J) min= rewrite(X,Y,Z) + phrase(Y,I,Mid) + phrase(Z,Mid,J).

goal min= phrase(start_symbol, 0, sentence_length).

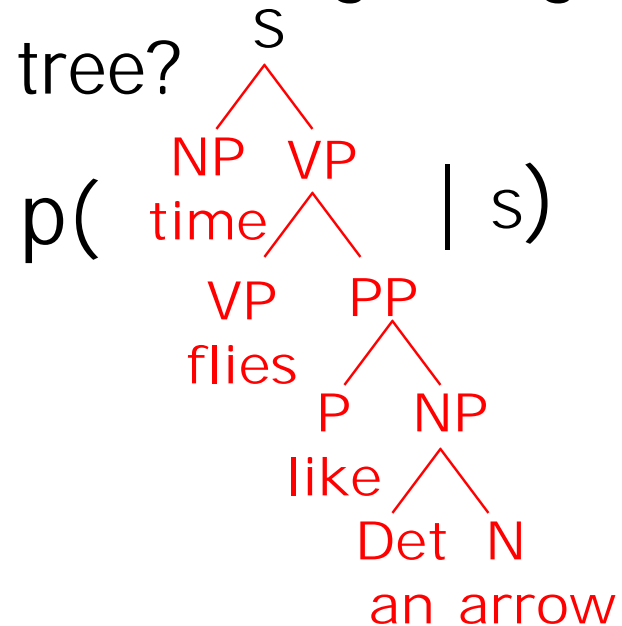
Probabilistic Trees

- Instead of lightest weight tree, take highest probability tree
- Given any tree, your assignment 1 generator would have some probability of producing it!
- Just like using n-grams to choose among strings ...
- What is the probability of this tree?



Probabilistic Trees

- Instead of lightest weight tree, take highest probability tree
- Given any tree, your assignment 1 generator would have some probability of producing it!
- Just like using n-grams to choose among strings ...
- What is the probability of this tree?
- You rolled a lot of independent dice ...



Chain rule: One word at a time



$$\begin{aligned} & p(\text{time flies like an arrow}) \\ &= p(\text{time}) \\ &\quad * p(\text{flies} \mid \text{time}) \\ &\quad * p(\text{like} \mid \text{time flies}) \\ &\quad * p(\text{an} \mid \text{time flies like}) \\ &\quad * p(\text{arrow} \mid \text{time flies like an}) \end{aligned}$$

Chain rule + backoff (to get trigram model)



$$\begin{aligned} & p(\text{time flies like an arrow}) \\ &= p(\text{time}) \\ &\quad * p(\text{flies} \mid \text{time}) \\ &\quad * p(\text{like} \mid \text{time flies}) \\ &\quad * p(\text{an} \mid \text{time flies like}) \\ &\quad * p(\text{arrow} \mid \text{time flies like an}) \end{aligned}$$

Chain rule – written differently

$p(\text{time flies like an arrow})$

= $p(\text{time})$

* $p(\text{time flies} \mid \text{time})$

* $p(\text{time flies like} \mid \text{time flies})$

* $p(\text{time flies like an} \mid \text{time flies like})$

* $p(\text{time flies like an arrow} \mid \text{time flies like an})$

Proof: $p(x, y \mid x) = p(x \mid x) * p(y \mid x, x) = 1 * p(y \mid x)$

Chain rule + backoff

$p(\text{time flies like an arrow})$

= $p(\text{time})$

* $p(\text{time flies} \mid \text{time})$

* $p(\text{time flies like} \mid \text{time flies})$

* $p(\text{time flies like an} \mid \text{time flies like})$

* $p(\text{time flies like an arrow} \mid \text{time flies like an})$

Proof: $p(x, y \mid x) = p(x \mid x) * p(y \mid x, x) = 1 * p(y \mid x)$

Chain rule: One node at a time

$$\begin{aligned}
 p(& \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad \quad VP \quad PP \\ \quad \quad \text{flies} \quad \swarrow \quad \searrow \\ \quad \quad \quad \quad P \quad NP \\ \quad \quad \quad \quad \text{like} \quad \swarrow \quad \searrow \\ \quad \quad \quad \quad \quad \quad Det \quad N \\ \quad \quad \quad \quad \quad \quad \text{an} \quad \text{arrow} \end{array} \mid s) = p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \end{array} \mid s) * p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \end{array} \mid \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \end{array}) \\
 & * p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad \quad VP \quad PP \end{array} \mid \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \end{array}) \\
 & * p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad \quad VP \quad PP \\ \text{flies} \end{array} \mid \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad \quad VP \quad PP \end{array}) * \dots
 \end{aligned}$$

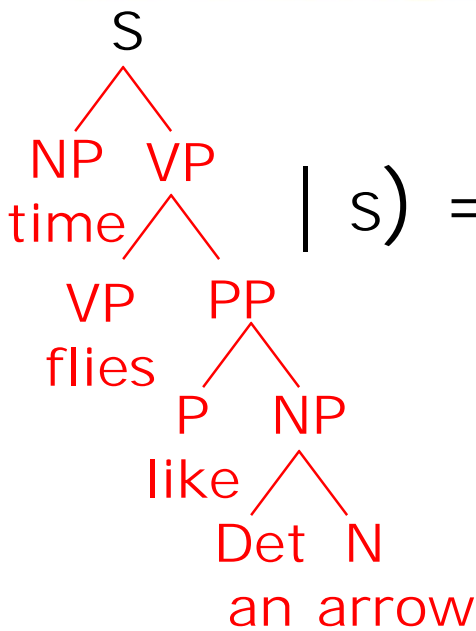
Chain rule + backoff

*model you used
in homework 1!
(called “PCFG”)*

$$\begin{aligned}
 p(& \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad VP \quad PP \\ \quad \text{flies} \quad \swarrow \quad \searrow \\ \quad \quad P \quad NP \\ \quad \quad \text{like} \quad \swarrow \quad \searrow \\ \quad \quad \quad Det \quad N \\ \quad \quad \quad \text{an} \quad \text{arrow} \end{array} \mid s) = p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \end{array} \mid s) * p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \end{array} \mid \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \end{array}) \\
 & * p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad VP \quad PP \end{array} \mid \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \end{array}) \\
 & * p(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad VP \quad PP \\ \text{flies} \end{array} \mid \begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ \text{time} \quad \swarrow \quad \searrow \\ \quad VP \quad PP \end{array}) * \dots
 \end{aligned}$$

Simplified notation

*model you used
in homework 1!
(called “PCFG”)*


$$p(\text{time flies like an arrow} \mid s) = p(s \dot{\leftarrow} \text{NP VP} \mid s) * p(\text{NP} \dot{\leftarrow} \text{time} \mid \text{NP})$$
$$* p(\text{VP} \dot{\leftarrow} \text{VP NP} \mid \text{VP})$$
$$* p(\text{VP} \dot{\leftarrow} \text{flies} \mid \text{VP}) * \dots$$

Already have a CKY alg for weights ...

$$\begin{array}{c}
 \text{S} \\
 \swarrow \quad \searrow \\
 \text{NP} \quad \text{VP} \\
 \text{time} \quad \swarrow \quad \searrow \\
 \quad \text{VP} \quad \text{PP} \\
 \quad \text{flies} \quad \swarrow \quad \searrow \\
 \quad \quad \text{P} \quad \text{NP} \\
 \quad \quad \text{like} \quad \swarrow \quad \searrow \\
 \quad \quad \quad \text{Det} \quad \text{N} \\
 \quad \quad \quad \text{an} \quad \text{arrow}
 \end{array}
 \quad | \quad \text{s) = } W(\text{S} \dot{\leftarrow} \text{NP VP}) \quad + \quad W(\text{NP} \dot{\leftarrow} \text{time})$$

$$\quad + \quad W(\text{VP} \dot{\leftarrow} \text{VP NP})$$

$$\quad + \quad W(\text{VP} \dot{\leftarrow} \text{flies}) \quad + \quad \dots$$

Just let $w(x \dot{\leftarrow} YZ) = -\log p(x \dot{\leftarrow} YZ | x)$

Then lightest tree has highest prob

Weighted Chart Parsing (“min cost”)

phrase(X,I,J) min= rewrite(X,W) + word(W,I,J).

phrase(X,I,J) min= rewrite(X,Y,Z) + phrase(Y,I,Mid) + phrase(Z,Mid,J).

goal min= phrase(start_symbol, 0, sentence_length).

Probabilistic Chart Parsing (“max prob”)

phrase(X,I,J) max= rewrite(X,W) * word(W,I,J).

phrase(X,I,J) max= rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).

goal max= phrase(start_symbol, 0, sentence_length).

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
4					N 8

2^{-8}

multiply to get 2^{-22}

2^{-12}

- 1 $S \rightarrow NP VP$
- 6 $S \rightarrow Vst NP$
- 2 $S \rightarrow S PP$
- 1 $VP \rightarrow V NP$
- 2 $VP \rightarrow VP PP$
- 1 $NP \rightarrow Det N$
- 2 $NP \rightarrow NP PP$
- 3 $NP \rightarrow NP NP$
- 0 $PP \rightarrow P NP$



Need only best-in-class to get best parse

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 8 S 13			NP 24 S 22 S 27 NP 24 S 27 S 27
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 12 VP 16
3				Det 1	NP 10
4					N 8

- 1 S → NP VP
- 6 S → Vst NP
- 2 S → S PP
- 1 VP → V NP
- 2 VP → VP PP
- 1 NP → Det N
- 2 NP → NP PP
- 3 NP → NP NP
- 0 PP → P NP

2⁻¹³

2⁻⁸

multiply to get 2⁻²²

2⁻¹²

2⁻²

Why probabilities not weights?

- We just saw probabilities are really just a special case of weights ...
- ... but we can estimate them from training data by counting and smoothing! Yay!
 - Warning: What kind of training corpus do we need (if we want to estimate rule probabilities simply by counting and smoothing)?
- Probabilities tell us how likely our best parse actually is:
 - Might improve user interface (e.g. ask for clarification if not sure)
 - Might help when learning the rule probabilities (later in course)
 - Should help combination with other systems
 - Text understanding: Even if the 3rd-best parse is 40x less probable syntactically, might still use it if it's > 40x more probable semantically
 - Ambiguity-preserving translation: If the top 3 parses are all probable, try to find a translation that would be ok regardless of which is correct

A slightly different task

- Been asking: What is probability of generating a given tree with your homework 1 generator?
 - To pick tree with highest prob: useful in parsing.
- But could also ask: What is probability of generating a given string with the generator?
(i.e., with the `-t` option turned off)
 - To pick string with highest prob: useful in speech recognition, as substitute for an n-gram model.
 - (“Put the file in the folder” vs. “Put the file and the folder”)
 - To get prob of generating string, must add up probabilities of all trees for the string ...

Could just add up the parse probabilities

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3	NP 10			NP 24
	Vst 3	S 8			S 22
		S 13			S 27
					NP 24
					S 27
					S 22
1		NP 4			S 27
		VP 4			NP 18
					S 21
2			P 2		VP 18
			V 5		PP 12
3				Det 1	VP 16
4					NP 10
					N 8

oops, back to finding exponentially many parses

- 1 S → NP VP
- 6 S → Vst NP
- 2 S → S PP
- 1 VP → V NP
- 2 VP → VP PP
- 1 NP → Det N
- 2 NP → NP PP
- 3 NP → NP NP
- 0 PP → P NP

Any more efficient way?

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S 2 ⁻⁸ S 2 ⁻¹³			NP 24 S 22 S 27 NP 24 S 27 S 2 ⁻²² S 2 ⁻²⁷
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 2 ⁻¹² VP 16
3				Det 1	NP 10
4					N 8

- 1 S → NP VP
- 6 S → Vst NP
- 2⁻² S → S PP
- 1 VP → V NP
- 2 VP → VP PP
- 1 NP → Det N
- 2 NP → NP PP
- 3 NP → NP NP
- 0 PP → P NP

Add as we go ... (the "inside algorithm")

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S $2^{-8} + 2^{-13}$			NP 24 S 22 S 27 NP 24 S 27 S 2^{-22} $+ 2^{-27}$
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 2^{-12} VP 16
3				Det 1	NP 10
4					N 8

- 1 S → NP VP
- 6 S → Vst NP
- 2^{-2} S → S PP
- 1 VP → V NP
- 2 VP → VP PP
- 1 NP → Det N
- 2 NP → NP PP
- 3 NP → NP NP
- 0 PP → P NP

Add as we go ... (the "inside algorithm")

time 1 flies 2 like 3 an 4 arrow 5

0	NP 3 Vst 3	NP 10 S $2^{-8} + 2^{-13}$			NP 2^{-22} + 2^{-27} S 2^{-22} + 2^{-27} + 2^{-27} + $(2^{-22} + 2^{-27})$
1		NP 4 VP 4			NP 18 S 21 VP 18
2			P 2 V 5		PP 2^{-12} VP 16
3				Det 1	NP 10
4					N 8

- 1 S → NP VP
- 6 S → Vst NP
- 2^{-2} S → S PP
- 1 VP → V NP
- 2 VP → VP PP
- 1 NP → Det N
- 2 NP → NP PP
- 3 NP → NP NP
- 0 PP → P NP

Probabilistic Chart Parsing (“max prob”)

phrase(X,I,J) max= rewrite(X,W) * word(W,I,J).

phrase(X,I,J) max= rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).

goal max= phrase(start_symbol, 0, sentence_length).

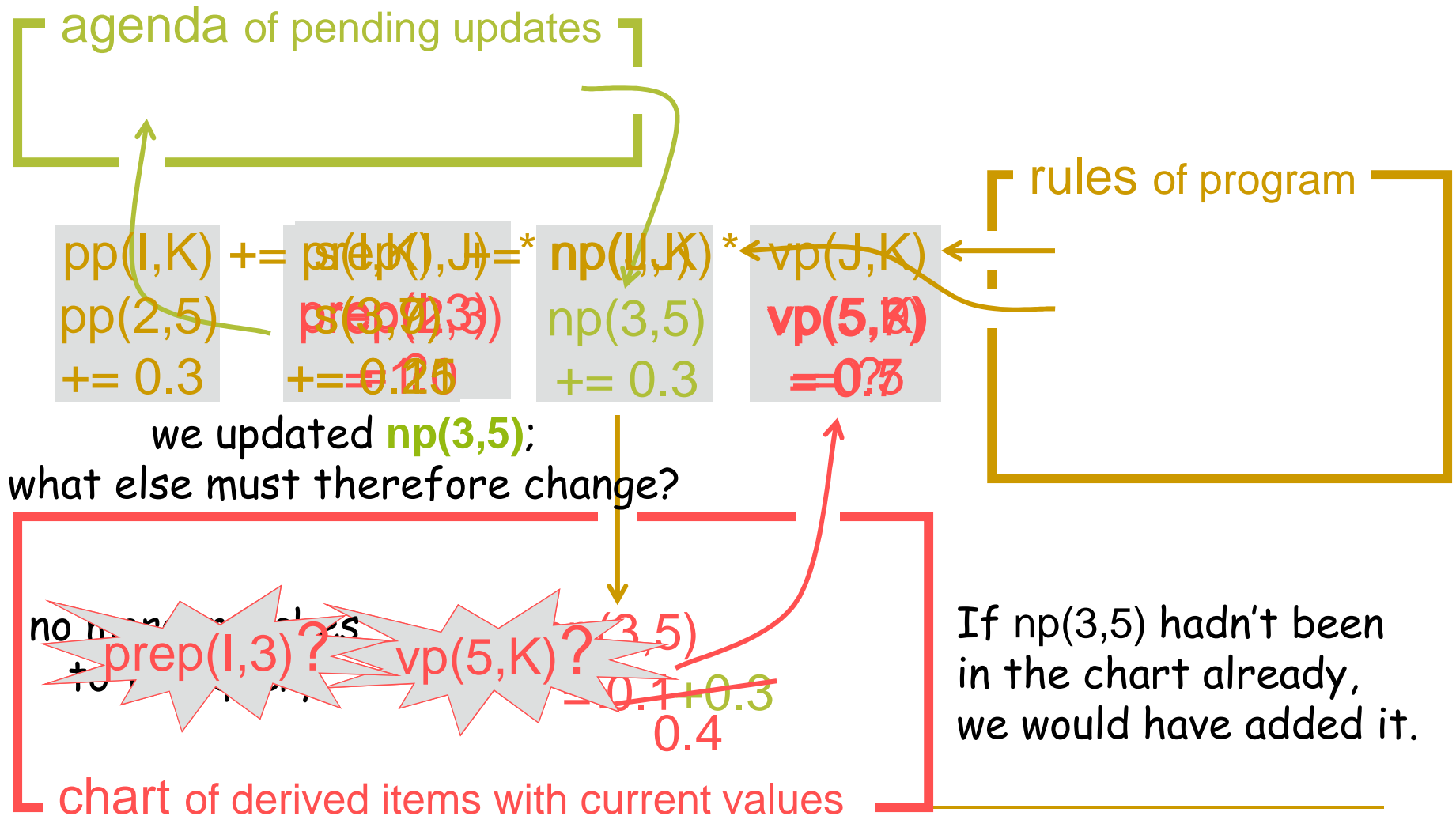
The “Inside Algorithm”

phrase(X,I,J) += rewrite(X,W) * word(W,I,J).

phrase(X,I,J) += rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).

goal += phrase(start_symbol, 0, sentence_length).

Bottom-up inference



Parameterization ...

```
phrase(X,I,J) += rewrite(X,W) * word(W,I,J).  
phrase(X,I,J) += rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).  
goal          += phrase(start_symbol, 0, sentence_length).
```

- `rewrite(X,Y,Z)`'s value represents the rule probability $p(Y Z | X)$.
- This could be defined by a formula instead of a number.
- Simple conditional log-linear model (each rule has 4 features):
 - `urewrite(X,Y,Z) *= exp(weight_xy(X,Y)).` % $\exp \theta_{xy,x,y}$
 - `urewrite(X,Y,Z) *= exp(weight_xz(X,Z)).`
 - `urewrite(X,Y,Z) *= exp(weight_yz(Y,Z)).`
 - `urewrite(Same,Same,Z) *= exp(weight_adjunction).` % $\exp \theta_{adjunction}$
 - `urewrite(X) += urewrite(X,Y,Z).` % normalizing constant
 - `rewrite(X,Y,Z) = urewrite(X,Y,Z) / urewrite(X).` % $p(X \rightarrow Y Z | X)$

Parameterization ...

```
phrase(X,I,J) += rewrite(X,W) * word(W,I,J).
```

```
phrase(X,I,J) += rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).
```

```
goal += phrase(start_symbol, 0, sentence_length).
```

- `rewrite(X,Y,Z)`'s value represents the rule probability $p(Y Z | X)$.
- Simple conditional log-linear model ...
- What if the program uses the unnormalized probability `urewrite` instead of `rewrite`?
- Different model! Each parse has an overall unnormalized prob:
$$\text{uprob}(\text{Parse}) = \exp(\text{total weight of all features in the parse})$$
- Can still normalize at the end:
$$p(\text{Parse} | \text{sentence}) = \text{uprob}(\text{parse}) / Z$$

where Z is the sum of all $\text{uprob}(\text{Parse})$: given by `goal!`

Chart Parsing: Recognition algorithm

```
phrase(X,I,J) :- rewrite(X,W), word(W,I,J).
```

```
phrase(X,I,J) :- rewrite(X,Y,Z), phrase(Y,I,Mid), phrase(Z,Mid,J).
```

```
goal      :- phrase(start_symbol, 0, sentence_length).
```

Chart Parsing: Viterbi algorithm (min-

cost)

phrase(X,I,J) min= rewrite(X,W) + word(W,I,J).

phrase(X,I,J) min= rewrite(X,Y,Z) + phrase(Y,I,Mid) + phrase(Z,Mid,J).

goal min= phrase(start_symbol, 0, sentence_length).

Chart Parsing: Viterbi algorithm (max-prob)

phrase(X,I,J) max= rewrite(X,W) * word(W,I,J).

phrase(X,I,J) max= rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).

goal max= phrase(start_symbol, 0, sentence_length).

Chart Parsing: Inside algorithm

phrase(X,I,J) += rewrite(X,W) * word(W,I,J).

phrase(X,I,J) += rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).

goal += phrase(start_symbol, 0, sentence_length).

Generalization: Semiring-Weighted Chart Parsing

phrase(X,I,J) $\beta = \text{rewrite}(X,W) \triangleright \text{word}(W,I,J)$.

phrase(X,I,J) $\beta = \text{rewrite}(X,Y,Z) \triangleright \text{phrase}(Y,I, \text{Mid}) \triangleright \text{phrase}(Z, \text{Mid}, J)$.

goal $\beta = \text{phrase}(\text{start_symbol}, 0, \text{sentence_length})$.

Unweighted CKY: Recognition algorithm

- initialize all entries of chart to false
- for $i := 1$ to n
 - for each rule R of the form $X \rightarrow \text{word}[i]$
 - $\text{chart}[X, i-1, i] \ || = \text{in_grammar}(R)$
- for width $:= 2$ to n
 - for start $:= 0$ to n -width
 - Define end $:= \text{start} + \text{width}$
 - for mid $:= \text{start}+1$ to end-1
 - for each rule R of the form $X \rightarrow Y Z$
 - $\text{chart}[X, \text{start}, \text{end}] \ || = \text{in_grammar}(R) \ \&\&$
 $\text{chart}[Y, \text{start}, \text{mid}] \ \&\& \ \text{chart}[Z, \text{mid}, \text{end}]$
- return $\text{chart}[\text{ROOT}, 0, n]$

Pay attention to the orange code ...

Weighted CKY: Viterbi algorithm (min-cost)

- initialize all entries of chart to ∞
- for $i := 1$ to n
 - for each rule R of the form $X \rightarrow \text{word}[i]$
 - $\text{chart}[X, i-1, i] \min = \text{weight}(R)$
 - for width $:= 2$ to n
 - for start $:= 0$ to n -width
 - Define end $:= \text{start} + \text{width}$
 - for mid $:= \text{start}+1$ to $\text{end}-1$
 - for each rule R of the form $X \rightarrow Y Z$
 - $\text{chart}[X, \text{start}, \text{end}] \min = \text{weight}(R) + \text{chart}[Y, \text{start}, \text{mid}] + \text{chart}[Z, \text{mid}, \text{end}]$
- return $\text{chart}[\text{ROOT}, 0, n]$

Pay attention to the orange code ...

Probabilistic CKY: Inside algorithm

- initialize all entries of chart to 0
- for $i := 1$ to n
 - for each rule R of the form $X \rightarrow \text{word}[i]$
 - $\text{chart}[X, i-1, i] += \text{prob}(R)$
- for width $:= 2$ to n
 - for start $:= 0$ to n -width
 - Define end $:= \text{start} + \text{width}$
 - for mid $:= \text{start}+1$ to end-1
 - for each rule R of the form $X \rightarrow Y Z$
 - $\text{chart}[X, \text{start}, \text{end}] += \text{prob}(R) * \text{chart}[Y, \text{start}, \text{mid}] * \text{chart}[Z, \text{mid}, \text{end}]$
- return $\text{chart}[\text{ROOT}, 0, n]$

Pay attention to the orange code ...

Semiring-weighted CKY: General algorithm!

- initialize all entries of chart to \emptyset
- for $i := 1$ to n
 - for each rule R of the form $X \rightarrow \text{word}[i]$
 - $\text{chart}[X, i-1, i] \beta = \text{semiring_weight}(R)$
- for width $:= 2$ to n
 - for start $:= 0$ to n -width
 - Define end $:= \text{start} + \text{width}$
 - for mid $:= \text{start}+1$ to end-1
 - for each rule R of the form $X \rightarrow Y Z$
 - $\text{chart}[X, \text{start}, \text{end}] \beta = \text{semiring_weight}(R) \triangleright$
 $\text{chart}[Y, \text{start}, \text{mid}] \triangleright \text{chart}[Z, \text{mid}, \text{end}]$
- return $\text{chart}[\text{ROOT}, 0, n]$

\triangleright is like "and"/ \forall :
combines all of several
pieces into an X

β is like "or"/ \exists :
considers the alternative
ways to build the X

Semiring-weighted CKY: General algorithm!

- initialize all entries of chart to $\textcircled{0}$
- for $i := 1$ to n
 - for each rule R of the form $X \rightarrow \text{word}[i]$
 - $\text{chart}[X, i-1, i] \oplus = \text{semiring_weight}(R)$
- for width $:= 2$ to n
 - for start $:= 0$ to $n - \text{width}$
 - Define end $:= \text{start} + \text{width}$
 - for mid $:= \text{start} + 1$ to end - 1
 - for each rule R of the form $X \rightarrow Y Z$
 - $\text{chart}[X, \text{start}, \text{end}] \oplus = \text{semiring_weight}(R) \otimes \text{chart}[Y, \text{start}, \text{mid}] \otimes \text{chart}[Z, \text{mid}, \text{end}]$
- return $\text{chart}[\text{ROOT}, 0, n]$

Weighted CKY, general version

- initialize all entries of chart to $\textcircled{0}$
- for $i := 1$ to n
 - for each rule R of the form $X \rightarrow \text{word}[i]$
 - $\text{chart}[X, i-1, i] \oplus = \text{semiring_weight}(R)$

	weights	\oplus	\otimes	$\textcircled{0}$
total prob (inside)	$[0, 1]$	+	\times	0
min weight	$[0, \infty]$	min	+	∞
recognizer	{true, false}	or	and	false

- $\text{chart}[X, \text{start}, \text{end}] \oplus = \text{semiring_weight}(R) \otimes \text{chart}[Y, \text{start}, \text{mid}] \otimes \text{chart}[Z, \text{mid}, \text{end}]$
- return $\text{chart}[\text{ROOT}, 0, n]$

Other Uses of Semirings

- The semiring weight of a constituent, $\text{Chart}[X,i,k]$, is a flexible bookkeeping device.
- If you want to build up information about larger constituents from smaller ones, design a semiring:
 - Probability of best parse, or its log
 - Number of parses
 - Total probability of all parses, or its log
 - The gradient of the total log-probability with respect to the parameters (use this to optimize the grammar weights)
 - The entropy of the probability distribution over parses
 - The 5 most probable parses
 - Possible translations of the constituent (this is how MT is done!)
- We'll see semirings again later with finite-state machines.

Some Weight Semirings

	weights	\oplus	\otimes	\ominus	$\mathbb{1}$
total prob (inside)	$[0, 1]$	+	\times	0	1
max prob	$[0, 1]$	max	\times	0	1
min weight = $-\log(\text{max prob})$	$[0, \infty]$	min	+	∞	0
$\log(\text{total prob})$	$[-\infty, 0]$	$\log+$	+	$-\infty$	0
recognizer	{true, false}	or	and	false	true

Semiring elements are log-probabilities l_p, l_q ; helps prevent underflow

$$l_p \otimes l_q = \log(\exp(l_p) \times \exp(l_q)) = l_p + l_q$$

$$l_p \oplus l_q = \log(\exp(l_p) + \exp(l_q)), \text{ denoted } \log+(l_p, l_q)$$

The Semiring Interface

```
public interface Semiring<K extends Semiring> {
    public K oplus(K k);    //  $\oplus$ 
    public K otimes(K k);  //  $\otimes$ 
    public K zero();      //  $\mathbb{0}$ 
    public K one();       //  $\mathbb{1}$ 
}

public class Minweight implements Semiring<Minweight> {
    protected float f;
    public Minweight(float f) { this.f = f; }
    public float toFloat() { return f; }
    public Minweight oplus(Minweight k) {
        return (f <= k.toFloat()) ? this : k; }
    public Minweight otimes(Minweight k) {
        return new Minweight(f + k.toFloat()); }
    static Minweight ZERO = new Minweight(Float.POSITIVE_INFINITY);
    static Minweight ONE = new Minweight(0);
    public Minweight zero() { return ZERO; }
    public Minweight one() { return ONE; } }
```

A Generic Parser for Any Semiring K

```
public interface Semiring<K extends Semiring> {
    public K oplus(K k);    //  $\oplus$ 
    public K otimes(K k);  //  $\otimes$ 
    public K zero();       //  $\mathbb{0}$ 
    public K one();        //  $\mathbb{1}$ 
}

public class ContextFreeGrammar<K extends Semiring<K>> {
    ... // CFG with rule weights in K
}

public class CKYParser<K extends Semiring<K>> {
    ... // parser for a CFG whose rule weights are in K
    K parse(Vector<String> input) { ... }
    // returns "total" weight (using  $\oplus$ ) of all parses
}

g = new ContextFreeGrammar<Minweight>(...);
p = new CKYParser<Minweight>(g);
minweight = p.parse(input); // returns min weight of any parse
```


The Semiring Axioms

```
public interface Semiring<K extends Semiring> {  
    public K oplus(K k);    //  $\oplus$   
    public K otimes(K k);  //  $\otimes$   
    public K zero();       //  $\ominus$   
    public K one();        //  $\odot$   
}
```

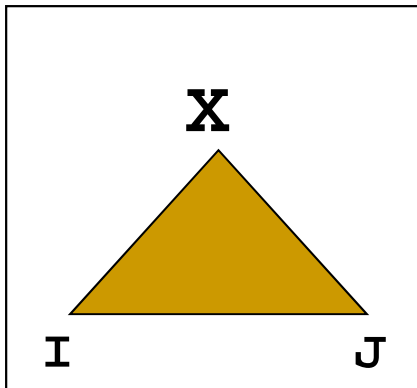
An implementation of **Semiring** must satisfy the semiring axioms:

- **Commutativity of \oplus** : $a \oplus b = b \oplus a$
- **Associativity**: $(a \oplus b) \oplus c = a \oplus (b \oplus c)$,
 $(a \otimes b) \otimes c = a \otimes (b \otimes c)$
- **Distributivity**: $a \otimes (b \oplus c) = (a \otimes b) \oplus (a \otimes c)$,
 $(b \oplus c) \otimes a = (b \otimes a) \oplus (c \otimes a)$
- **Identities**: $a \oplus \ominus = \ominus \oplus a = a$, $a \otimes \odot = \odot \otimes a = a$
- **Annihilation**: $a \otimes \ominus = \ominus$

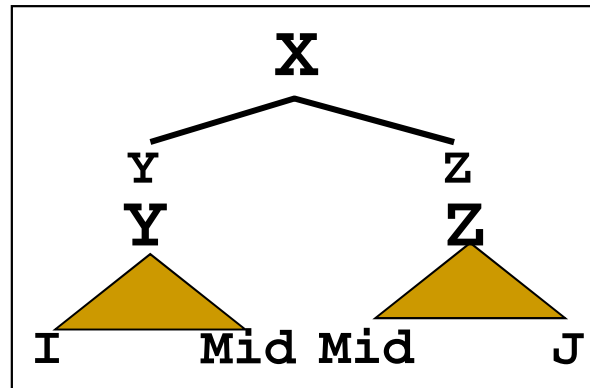
Otherwise the parser won't work correctly. Why not? (Look back at it.)

Rule binarization can speed up program

$\text{phrase}(X,I,J) += \text{rewrite}(X,Y,Z) * \text{phrase}(Y,I,\text{Mid}) * \text{phrase}(Z,\text{Mid},J).$



$+=$

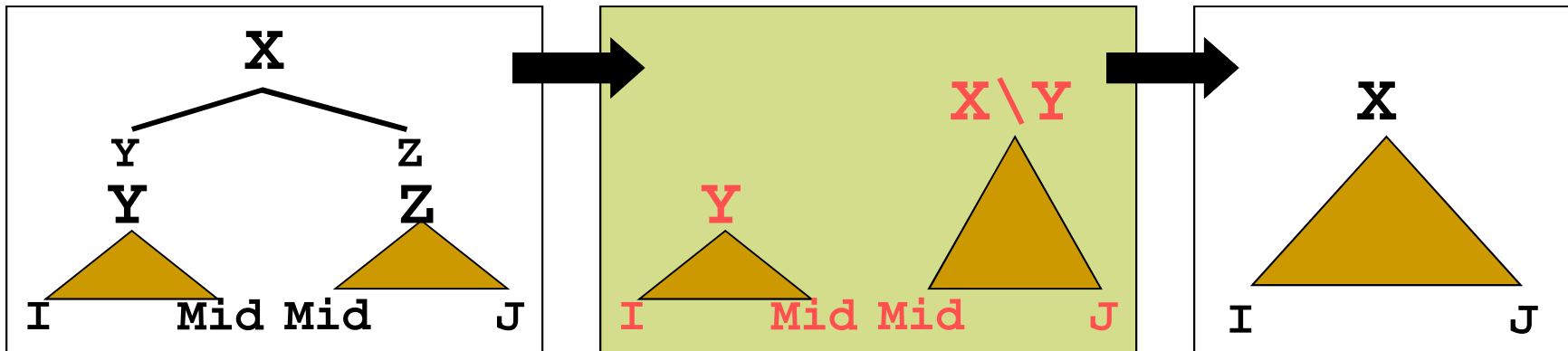


Rule binarization can speed up program

$\text{phrase}(X,I,J) \ += \ \text{phrase}(Y,I,\text{Mid}) * \text{phrase}(Z,\text{Mid},J) * \text{rewrite}(X,Y,Z).$

↓ folding transformation: asymp. speedup!

$\text{temp}(X\backslash Y,\text{Mid},J) \ += \ \text{phrase}(Z,\text{Mid},J) * \text{rewrite}(X,Y,Z).$
 $\text{phrase}(X,I,J) \ += \ \text{phrase}(Y,I,\text{Mid}) * \text{temp}(X\backslash Y,\text{Mid},J).$



Rule binarization can speed up program

$\text{phrase}(X,I,J) \ += \ \text{phrase}(Y,I,\text{Mid}) * \text{phrase}(Z,\text{Mid},J) * \text{rewrite}(X,Y,Z).$

folding transformation: asymp. speedup!

$\text{temp}(X\backslash Y,\text{Mid},J) \ += \ \text{phrase}(Z,\text{Mid},J) * \text{rewrite}(X,Y,Z).$
 $\text{phrase}(X,I,J) \ += \ \text{phrase}(Y,I,\text{Mid}) * \text{temp}(X\backslash Y,\text{Mid},J).$

$\sum_{Y,Z,\text{Mid}} \text{phrase}(Y,I,\text{Mid}) * \text{phrase}(Z,\text{Mid},J) * \text{rewrite}(X,Y,Z)$


**graphical models
constraint programming
multi-way database join**

$\sum_{Y,\text{Mid}} \text{phrase}(Y,I,\text{Mid}) \sum_Z \text{phrase}(Z,\text{Mid},J) * \text{rewrite}(X,Y,Z)$

Earley's algorithm in Dyna

```
phrase(X,I,J) += rewrite(X,W) * word(W,I,J).  
phrase(X,I,J) += rewrite(X,Y,Z) * phrase(Y,I,Mid) * phrase(Z,Mid,J).  
goal += phrase(start_symbol, 0, sentence_length).
```

magic templates transformation
(as noted by Minnen 1996)



```
need(start_symbol,0) = true.  
need(Nonterm,J) :- phrase(_/[Nonterm|_],_,J).  
phrase(Nonterm/Needed,I,I)  
    += need(Nonterm,I), rewrite(Nonterm,Needed).  
phrase(Nonterm/Needed,I,K)  
    += phrase(Nonterm/[W|Needed],I,J) * word(W,J,K).  
phrase(Nonterm/Needed,I,K)  
    += phrase(Nonterm/[X|Needed],I,J) * phrase(X/[],J,K).  
goal += phrase(start_symbol/[],0,sentence_length).
```