Practical Parsing: Models and Algorithms

Introduction to Natural Language Processing
Computer Science 585—Fall 2009
University of Massachusetts Amherst

David Smith

including slides from Andrew McCallum, Chris Manning, and Jason Eisner

Overview

- Treebanks and evaluation
- Lexicalized parsing (with heads)
  - Examples: Collins
- Dependency Parsing
- Speeding up lexicalized parsing

Treebanks

- Pure Grammar Induction Approaches tend not to produce the parse trees that people want

- Solution
  - Give a some example of parse trees that we want
  - Make a learning tool learn a grammar

- Treebank
  - A collection of such example parses
  - PennTreebank is most widely used

Treebanks

- Penn Treebank
  - Trees are represented via bracketing
  - Fairly flat structures for Noun Phrases
    (NP Arizona real estate loans)
  - Tagged with grammatical and semantic functions
    (-SBJ , –LOC, …)
  - Use empty nodes(*) to indicate understood subjects and extraction gaps

```
(  ( S ( NP-SBJ  The move)
       ( VP  followed
             ( NP  ( NP a round )
                   ( PP  of
                         (NP  ( NP similar increases )
                              ( PP by
                                   ( NP other lenders ) )
                              ( PP against
                                   ( NP Arizona real estate loans )))))
             ,
             ( S-ADV ( NP-SBJ * )
                     ( VP  reflecting
                           ( NP a continuing decline )
                           ( PP-LOC  in
                                        (NP  that market ))))))
   . )
```

Treebanks

- Many people have argued that it is better to have linguists constructing treebanks than grammars

- Because it is easier
  - to work out the correct parse of sentences
- than
  - to try to determine what all possible manifestations of a certain rule or grammatical construct are

Parser Evaluation

Evaluation

Ultimate goal is to build system for IE, QA, MT

- People are rarely interested in syntactic analysis for its own sake
- Evaluate the system for evaluate the parser

For Simplicity and modularization, and Convenience

- Compare parses from a parser with the result of hand parsing of a sentence(gold standard)

What is objective criterion that we are trying to maximize?

Evaluation

Tree Accuracy (Exact match)

- It is a very tough standard!!!
- But in many ways it is a sensible one to use

PARSEVAL Measures

- For some purposes, partially correct parses can be useful
- Originally for non-statistical parsers
- Evaluate the component pieces of a parse
- Measures : Precision, Recall, Crossing brackets

Evaluation

(Labeled) Precision

How many brackets in the parse match those in the correct tree (Gold standard)?

(Labeled) Recall

How many of the brackets in the correct tree are in the parse?

Crossing brackets

Average of how many constituents in one tree cross over constituent boundaries in the other tree

B1					(								)			
B2			(						)							
B3	(														)	
B4											(				)	
		w1		w2		w3		w4		w5		w6		w7		w8

Problems with PARSEVAL

Even vanilla PCFG performs quite well

It measures success at the level of individual decisions

You must make many consecutive decisions correctly to be correct on the entire tree.

Problems with PARSEVAL (2)

Behind story

The structure of Penn Treebank

Flat → Few brackets → Low Crossing brackets

Troublesome brackets are avoided

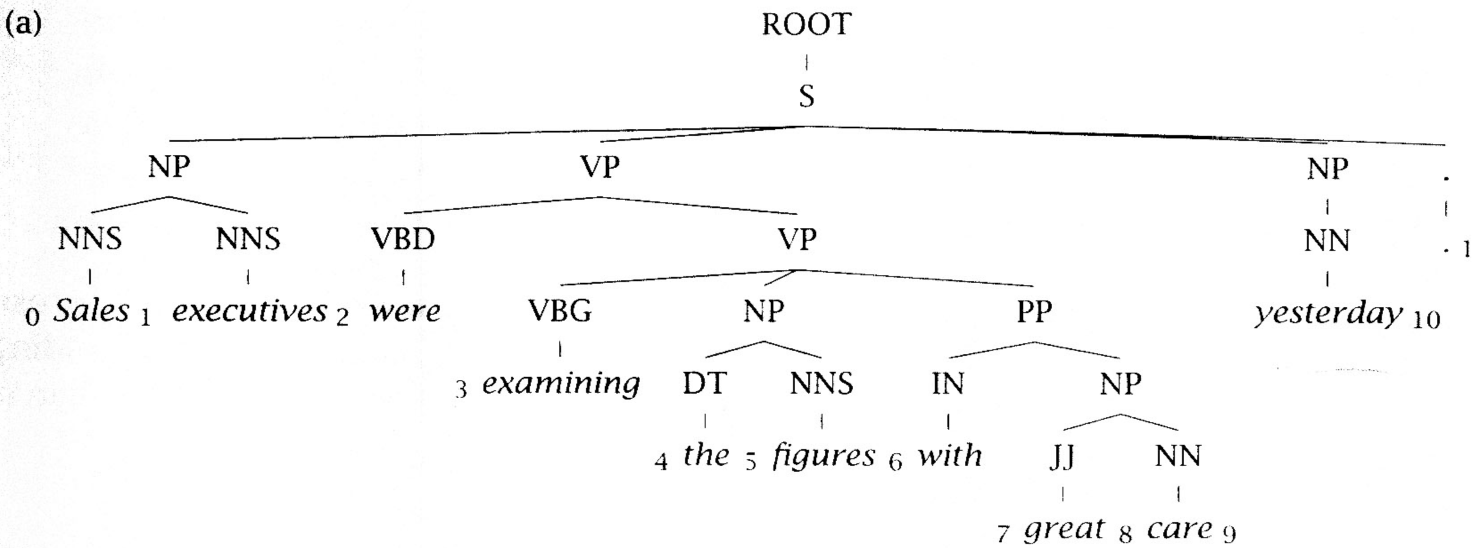
→ High Precision/Recall

The errors in precision and recall are minimal

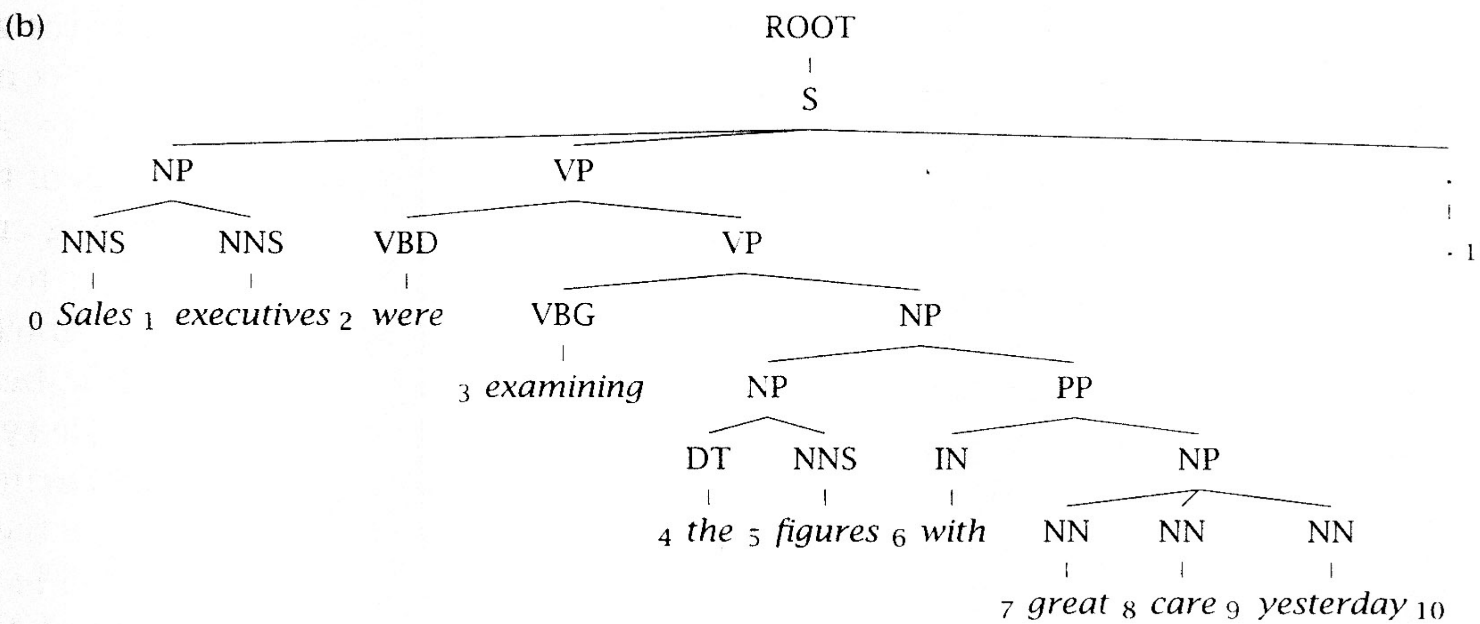
In some cases wrong PP attachment penalizes Precision, Recall and Crossing Bracket Accuracy minimally.

On the other hand, attaching low instead of high, then every node in the right-branching tree will be wrong: serious harm

(a)



(b)



(c) Brackets in gold standard tree (a.):
S-(0:11), NP-(0:2), $\boxed{\text{VP-(2:9)}}$, $\boxed{\text{VP-(3:9)}}$ **NP-(4:6),** PP-(6-9), NP-(7,9), *NP-(9:10)

(d) Brackets in candidate parse (b.):
S-(0:11), NP-(0:2), VP-(2:10), VP-(3:10), NP-(4:10), **NP-(4:6),** PP-(6-10), NP-(7,10)

(e)

Precision:	3/8 = 37.5%	Crossing Brackets:	3
Recall:	3/8 = 37.5%	Crossing Accuracy:	62%
Labeled Precision:	3/8 = 37.5%	Tagging Accuracy:	10/11 = 90.9%
Labeled Recall:	3/8 = 37.5%		

Evaluation

Do PARSEVAL measures succeed in real tasks?

- Many small parsing mistakes might not affect tasks of semantic interpretation
  - (Bonnema 1996,1997)
    - Tree Accuracy of the Parser : 62%
    - Correct Semantic Interpretations : 88%
  - (Hermajakob and Mooney 1997)
    - English to German translation

At the moment, people feel PARSEVAL measures are adequate for the comparing parsers

Lexicalized Parsing

Limitations of PCFGs

- PCFGs assume:
  - Place invariance
  - Context free: P(rule) independent of
    - words outside span
    - *also, words with overlapping derivation*
  - Ancestor free: P(rule) independent of
    - *Non-terminals above.*

- Lack of sensitivity to lexical information
- Lack of sensitivity to structural frequencies

Lack of Lexical Dependency

Means that

P(VP → V NP NP)

is independent of the particular verb involved!

... but much more likely with ditransitive verbs (like ***gave***).

He ***gave*** *the boy a ball.*

He ***ran*** *to the store.*

The Need for Lexical Dependency

Probabilities dependent on Lexical words

Problem 1 : Verb subcategorization

VP expansion is independent of the choice of verb

However …

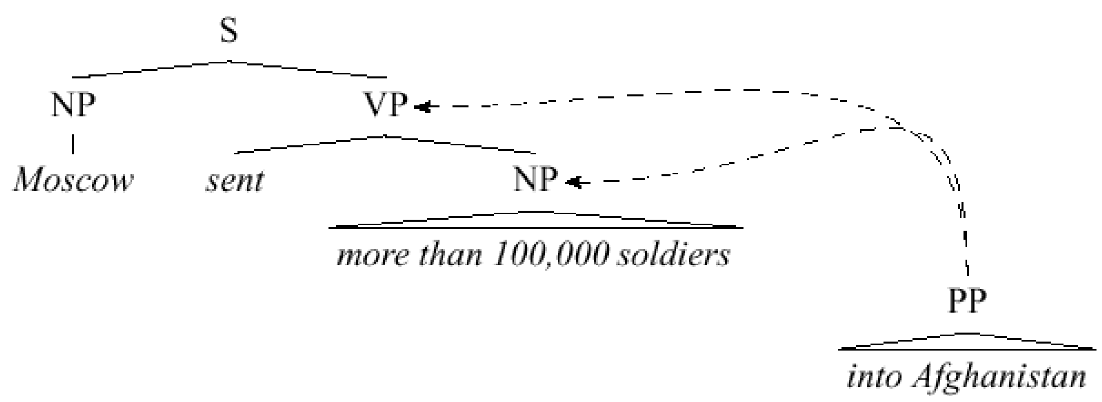
	verb			
	come	take	think	want
VP -> V	9.5%	2.6%	4.6%	5.7%
VP -> V NP	1.1%	32.1%	0.2%	13.9%
VP -> V PP	34.5%	3.1%	7.1%	0.3%
VP -> V SBAR	6.6%	0.3%	73.0%	0.2%
VP -> V S	2.2%	1.3%	4.8%	70.8%

Including actual words information when making decisions about tree structure is necessary

Weakening the independence assumption of PCFG

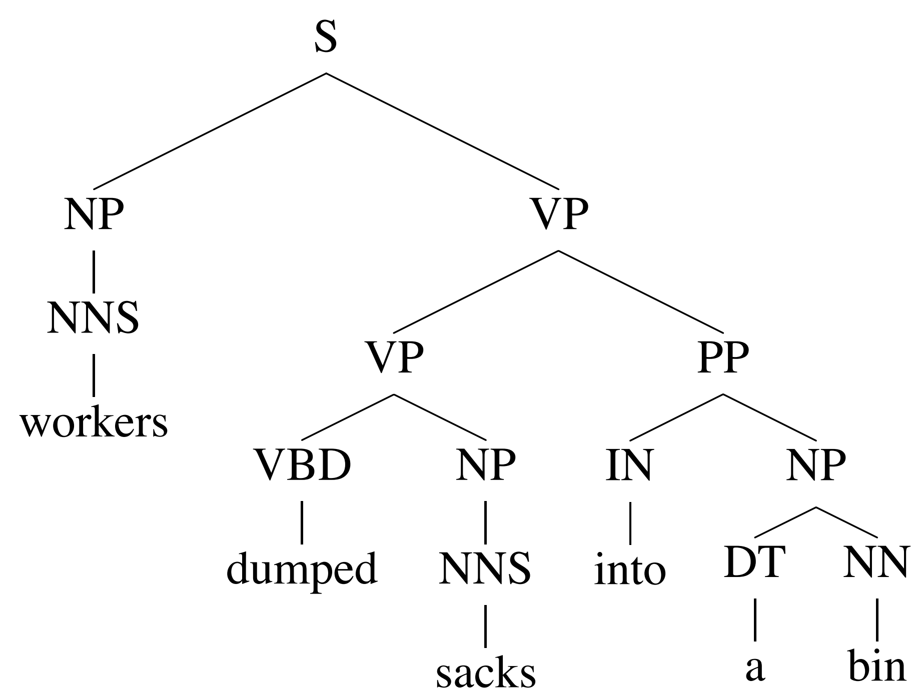
Probabilities dependent on Lexical words

- Problem 2 : Phrasal Attachment
    - Lexical content of phrases provide information for decision
    - Syntactic category of the phrases provide very little information
    - Standard PCFG is worse than n-gram models



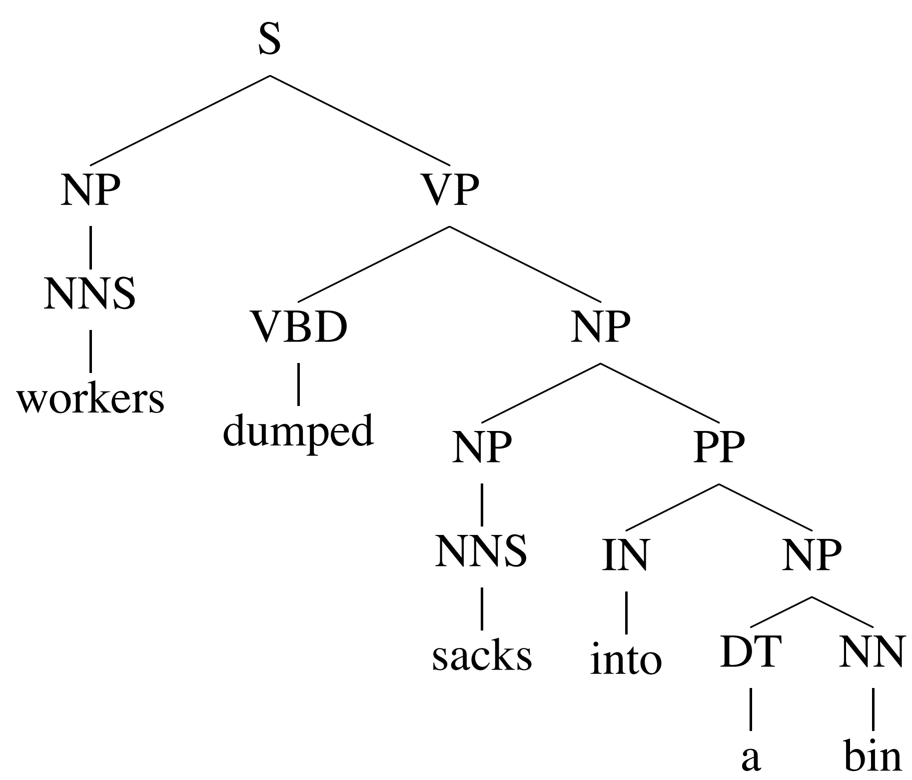
Another case of PP attachment ambiguity

(a)



Another case of PP attachment ambiguity

(b)



Another case of PP attachment ambiguity

(a)

Rules
S $\rightarrow$ NP VP
NP $\rightarrow$ NNS
VP $\rightarrow$ VP PP
VP $\rightarrow$ VBD NP
NP $\rightarrow$ NNS
PP $\rightarrow$ IN NP
NP $\rightarrow$ DT NN
NNS $\rightarrow$ workers
VBD $\rightarrow$ dumped
NNS $\rightarrow$ sacks
IN $\rightarrow$ into
DT $\rightarrow$ a
NN $\rightarrow$ bin

(b)

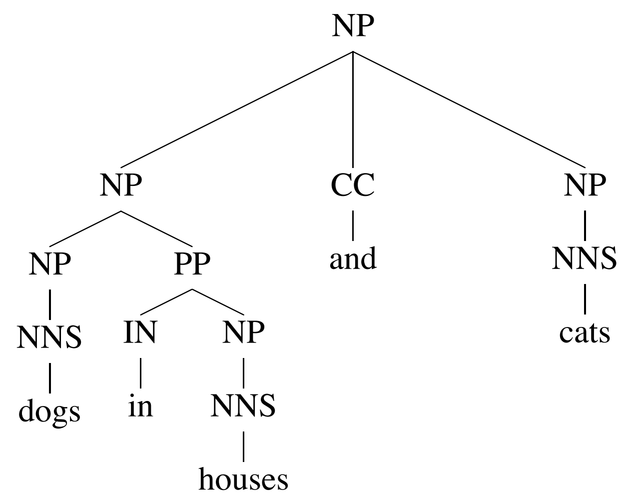
Rules
S $\rightarrow$ NP VP
NP $\rightarrow$ NNS
NP $\rightarrow$ NP PP
VP $\rightarrow$ VBD NP
NP $\rightarrow$ NNS
PP $\rightarrow$ IN NP
NP $\rightarrow$ DT NN
NNS $\rightarrow$ workers
VBD $\rightarrow$ dumped
NNS $\rightarrow$ sacks
IN $\rightarrow$ into
DT $\rightarrow$ a
NN $\rightarrow$ bin

If $P(\text{NP} \rightarrow \text{NP PP} \mid \text{NP}) > P(\text{VP} \rightarrow \text{VP PP} \mid \text{VP})$ then (b) is more probable, else (a) is more probable.

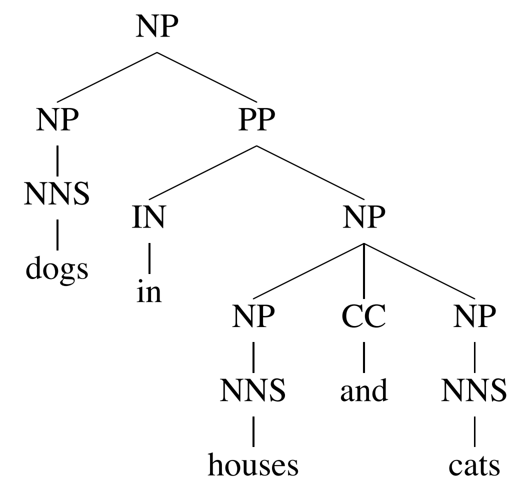
Attachment decision is completely independent of the words

A case of coordination ambiguity

(a)



(b)



(a)

Rules
NP → NP CC NP
NP → NP PP
NP → NNS
PP → IN NP
NP → NNS
NP → NNS
NNS → dogs
IN → in
NNS → houses
CC → and
NNS → cats

(b)

Rules
NP → NP CC NP
NP → NP PP
NP → NNS
PP → IN NP
NP → NNS
NP → NNS
NNS → dogs
IN → in
NNS → houses
CC → and
NNS → cats

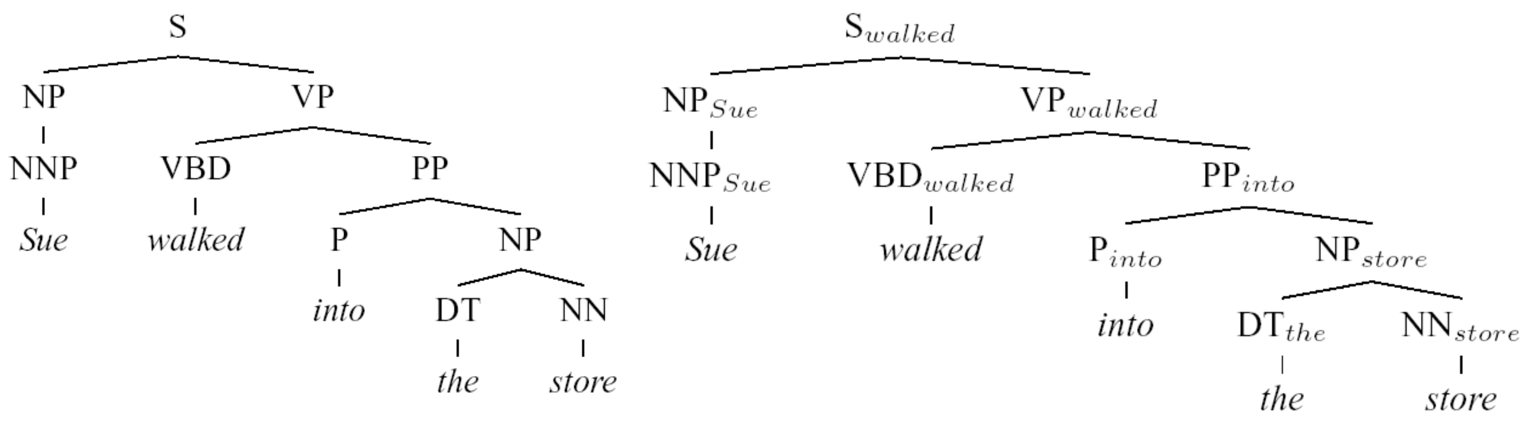
Here the two parses have identical rules, and therefore have identical probability under any assignment of PCFG rule probabilities

Weakening the independence assumption of PCFG

Probabilities dependent on Lexical words

Solution

Lexicalize CFG : Each phrasal node with its head word



Background idea

Strong lexical dependencies between heads and their dependents

Heads in Context-Free Rules

Add annotations specifying the "head" of each rule:

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

Vi	$\Rightarrow$	sleeps
Vt	$\Rightarrow$	saw
NN	$\Rightarrow$	man
NN	$\Rightarrow$	woman
NN	$\Rightarrow$	telescope
DT	$\Rightarrow$	the
IN	$\Rightarrow$	with
IN	$\Rightarrow$	in

Note: S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition

More about heads

- Each context-free rule has one "special" child that is the head of the rule. e.g.,

S	$\Rightarrow$	NP	VP		(VP is the head)
VP	$\Rightarrow$	Vt	NP		(Vt is the head)
NP	$\Rightarrow$	DT	NN	NN	(NN is the head)

- A core idea in linguistics
  (X-bar Theory, Head-Driven Phrase Structure Grammar)

- Some intuitions:
  - The central sub-constituent of each rule.
  - The semantic predicate in each rule.

Rules which recover heads: Example rules for NPs

If the rule contains NN, NNS, or NNP:
Choose the rightmost NN, NNS, or NNP

Else If the rule contains an NP: Choose the leftmost NP

Else If the rule contains a JJ: Choose the rightmost JJ

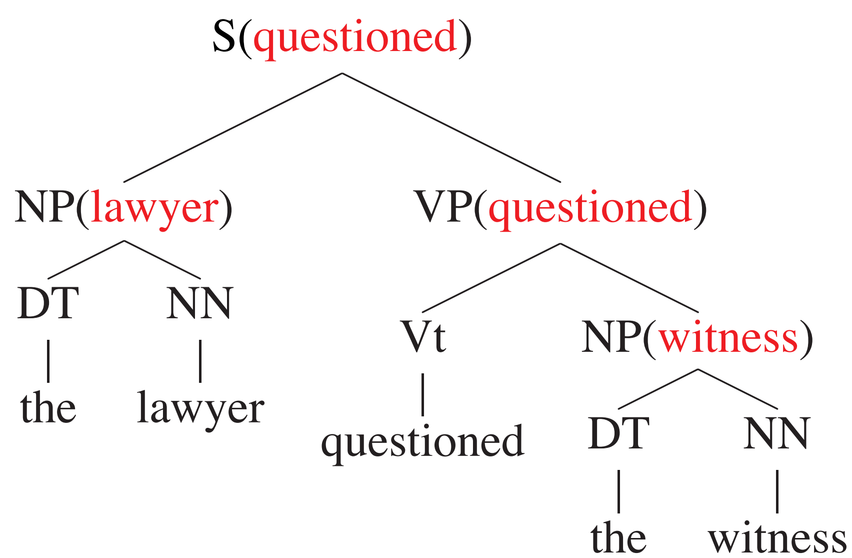
Else If the rule contains a CD: Choose the rightmost CD

Else Choose the rightmost child

e.g.,

NP	$\Rightarrow$	DT	NNP	NN
NP	$\Rightarrow$	DT	NN	NNP
NP	$\Rightarrow$	NP	PP	
NP	$\Rightarrow$	DT	JJ	
NP	$\Rightarrow$	DT		

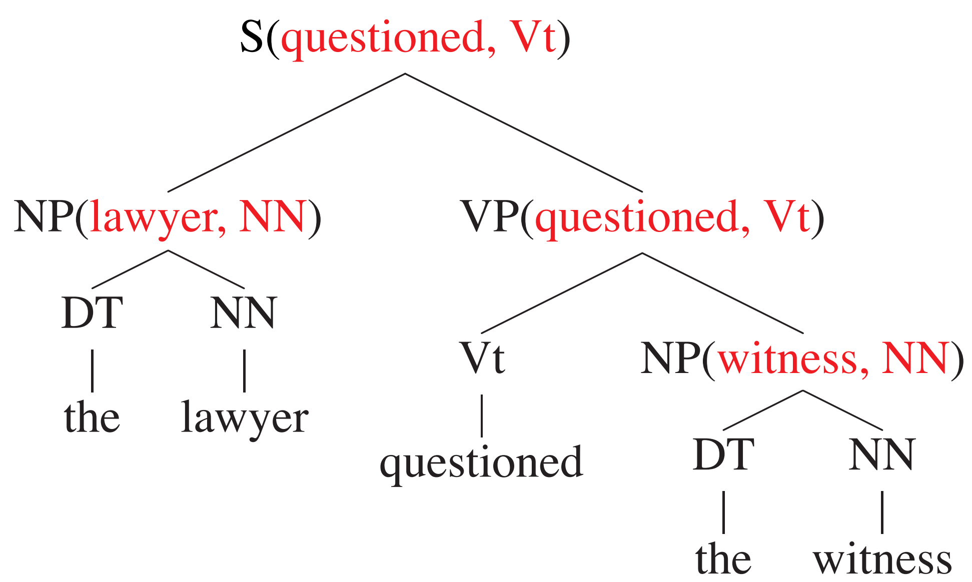
Adding Headwords to Trees



- A constituent receives its headword from its **head child**.

S	$\Rightarrow$	NP	VP		(S receives headword from VP)
VP	$\Rightarrow$	Vt	NP		(VP receives headword from Vt)
NP	$\Rightarrow$	DT		NN	(NP receives headword from NN)

Adding Headtags to Trees



- Also propogate **part-of-speech tags** up the trees

Explosion of number of rules

New rules might look like:

VP[gave] → V[gave] NP[man] NP[book]

But this would be a massive explosion in number of rules (and parameters)

Sparseness and the Penn Treebank

- The Penn Treebank – 1 million words of parsed English *WSJ* – has been a key resource (because of the widespread reliance on supervised learning)
- But 1 million words is like nothing:
  - 965,000 constituents, but only 66 WHADJP, of which only 6 aren't *how much* or *how many*, but there is an infinite space of these (*how clever/original/incompetent* (*at risk assessment and evaluation*))
- Most of the probabilities that you would like to compute, you can't compute

Sparseness and the Penn Treebank

- Most intelligent processing depends on bilexical statistics: likelihoods of relationships between pairs of words.
- Extremely sparse, even on topics central to the *WSJ*:
  - stocks plummeted 2 occurrences
  - stocks stabilized 1 occurrence
  - stocks skyrocketed 0 occurrences
  - #stocks discussed 0 occurrences
- So far there has been very modest success augmenting the Penn Treebank with extra unannotated materials or using semantic classes or clusters (cf. Charniak 1997, Charniak 2000) – as soon as there are more than tiny amounts of annotated training data.

Lexicalized, Markov out from head

Collins 1997: Markov model out from head

- Charniak (1997) expands each phrase structure tree in a single step.
- This is good for capturing dependencies between child nodes
- But it is bad because of data sparseness
- A pure dependency, one child at a time, model is worse
- But one can do better by in between models, such as generating the children as a Markov process on both sides of the head (Collins 1997; Charniak 2000)

Modeling Rule Productions as Markov Processes

- Step 1: generate category of head child

$$\text{S(told,V[6])}$$

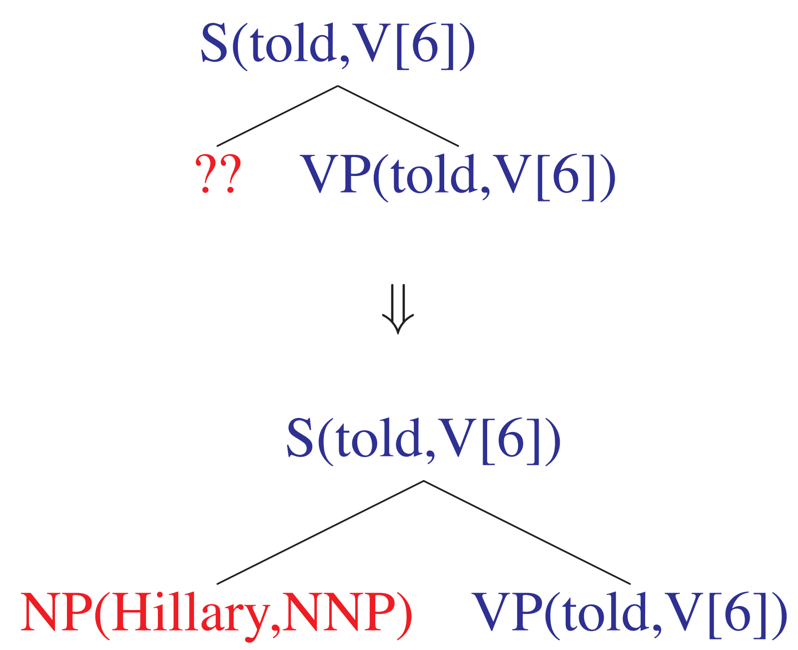
$$\Downarrow$$

$$\begin{array}{c}\text{S(told,V[6])}\\ |\\ \text{VP(told,V[6])}\end{array}$$

$P_h(\text{VP} \mid \text{S, told, V[6]})$

Modeling Rule Productions as Markov Processes

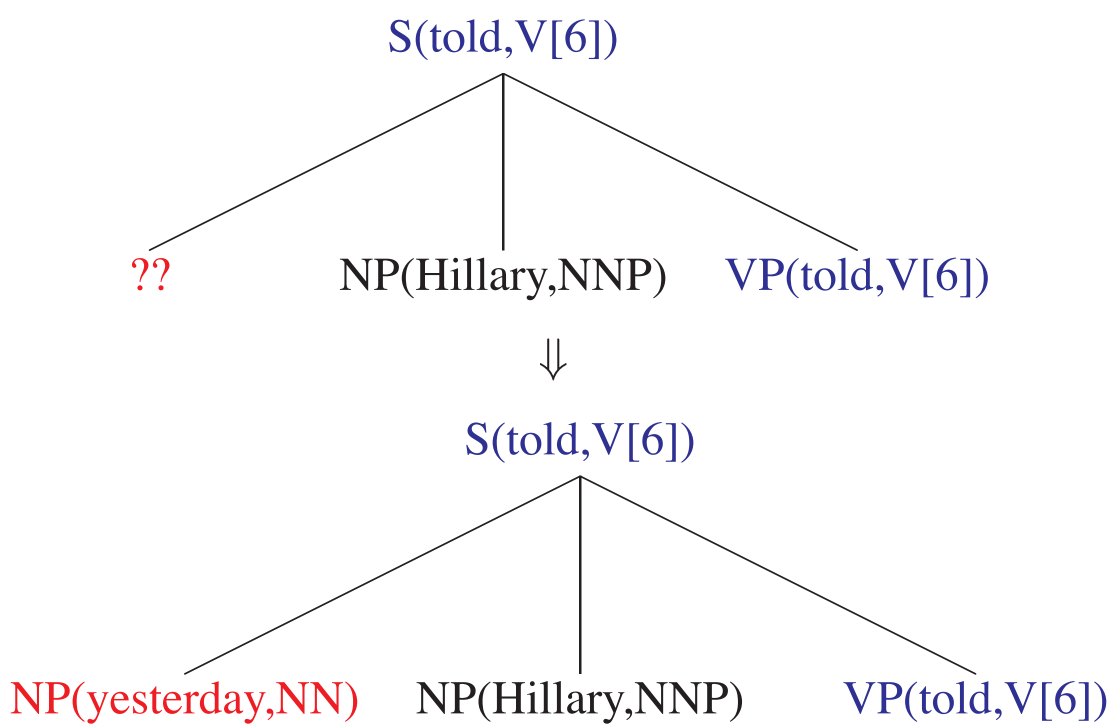
- Step 2: generate left modifiers in a Markov chain



$$P_h(\text{VP} \mid \text{S, told, V[6]}) \times P_d(\text{NP(Hillary,NNP)} \mid \text{S,VP,told,V[6],LEFT})$$

Modeling Rule Productions as Markov Processes

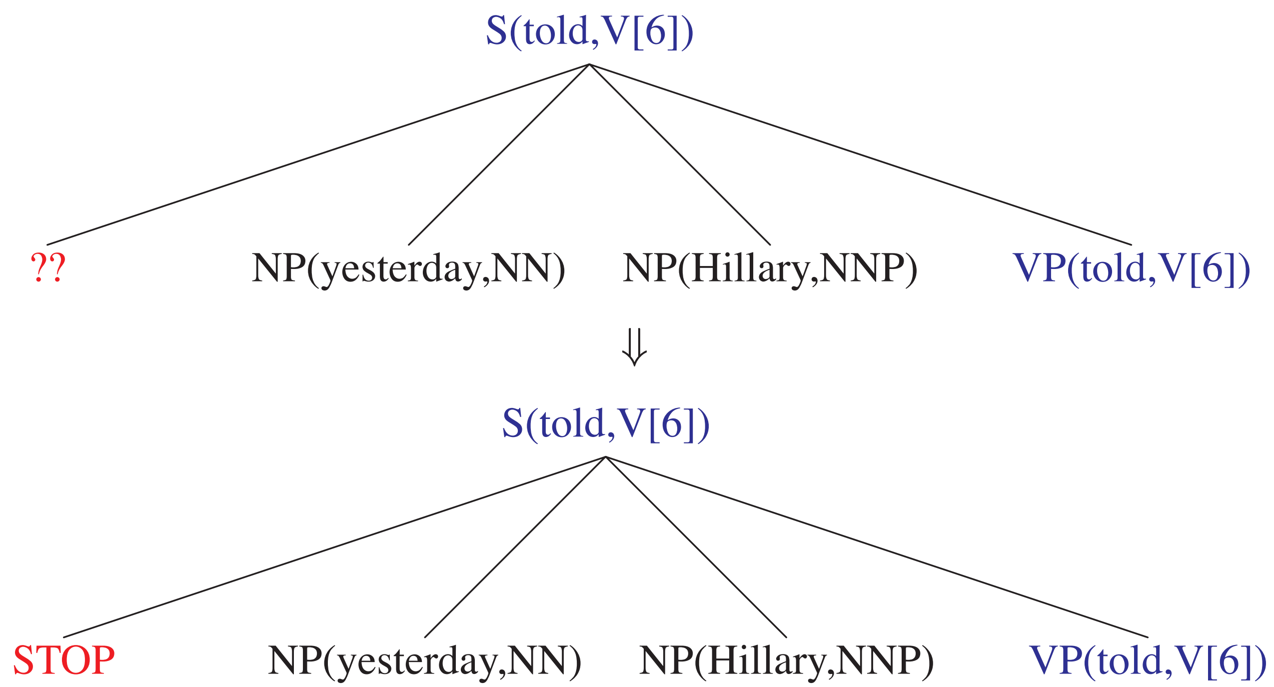
- Step 2: generate left modifiers in a Markov chain



$P_h(\text{VP} \mid \text{S, told, V[6]}) \times P_d(\text{NP(Hillary,NNP)} \mid \text{S,VP,told,V[6],LEFT}) \times$
$P_d(\text{NP(yesterday,NN)} \mid \text{S,VP,told,V[6],LEFT})$

Modeling Rule Productions as Markov Processes

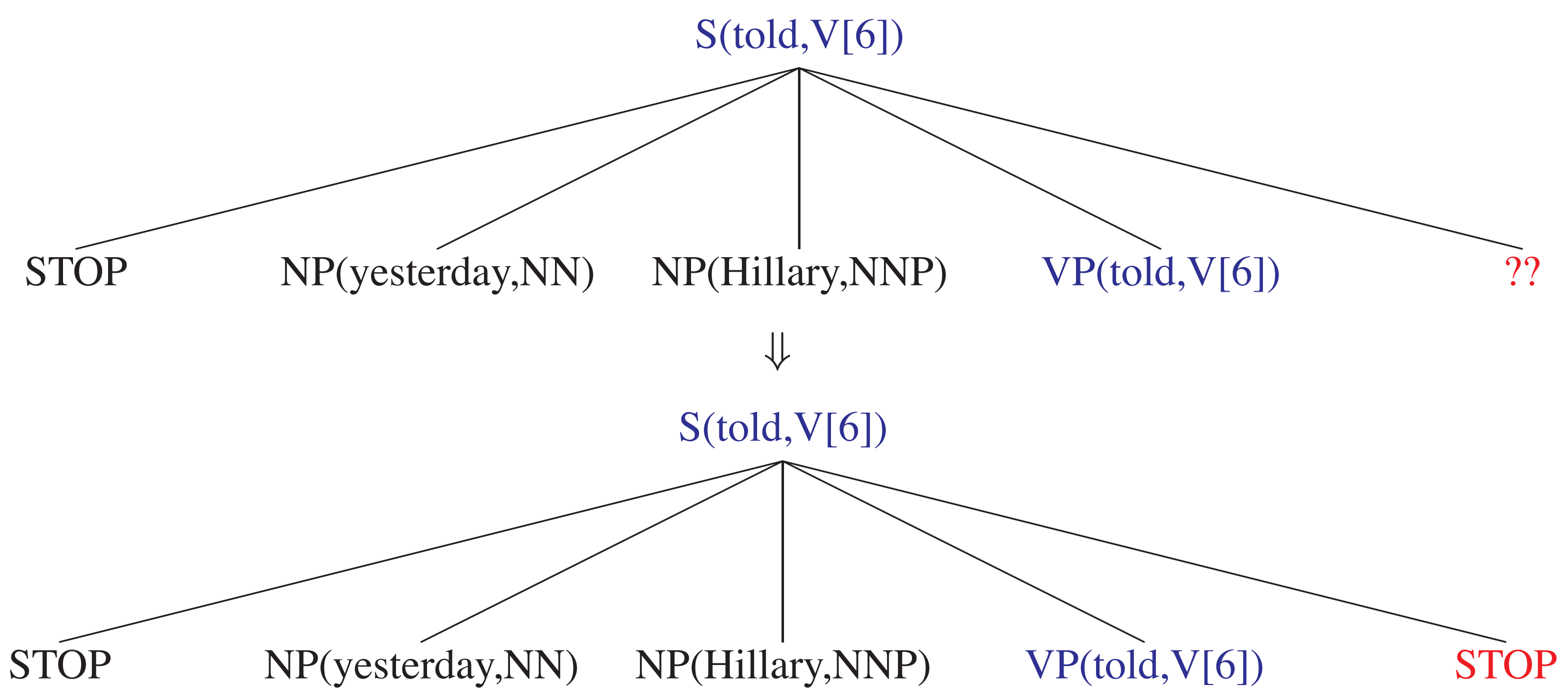
- Step 2: generate left modifiers in a Markov chain



P_h(VP | S, told, V[6]) $\times$ P_d(NP(Hillary,NNP) | S,VP,told,V[6],LEFT)$\times$
P_d(NP(yesterday,NN) | S,VP,told,V[6],LEFT) $\times$ P_d(STOP | S,VP,told,V[6],LEFT)

Modeling Rule Productions as Markov Processes

- Step 3: generate right modifiers in a Markov chain



P_h(VP | S, told, V[6]) $\times$ P_d(NP(Hillary,NNP) | S,VP,told,V[6],LEFT)$\times$
P_d(NP(yesterday,NN) | S,VP,told,V[6],LEFT) $\times$ P_d(STOP | S,VP,told,V[6],LEFT) $\times$
P_d(STOP | S,VP,told,V[6],RIGHT)

A Refinement: Adding a Distance Variable

- $\Delta = 1$ if position is adjacent to the head.

S(told,V[6])

?? VP(told,V[6])

$\Downarrow$

S(told,V[6])

NP(Hillary,NNP) VP(told,V[6])

$P_h(\text{VP} \mid \text{S, told, V[6]}) \times$
$P_d(\text{NP(Hillary,NNP)} \mid \text{S,VP,told,V[6],LEFT},\Delta = 1)$

Adding dependency on structure

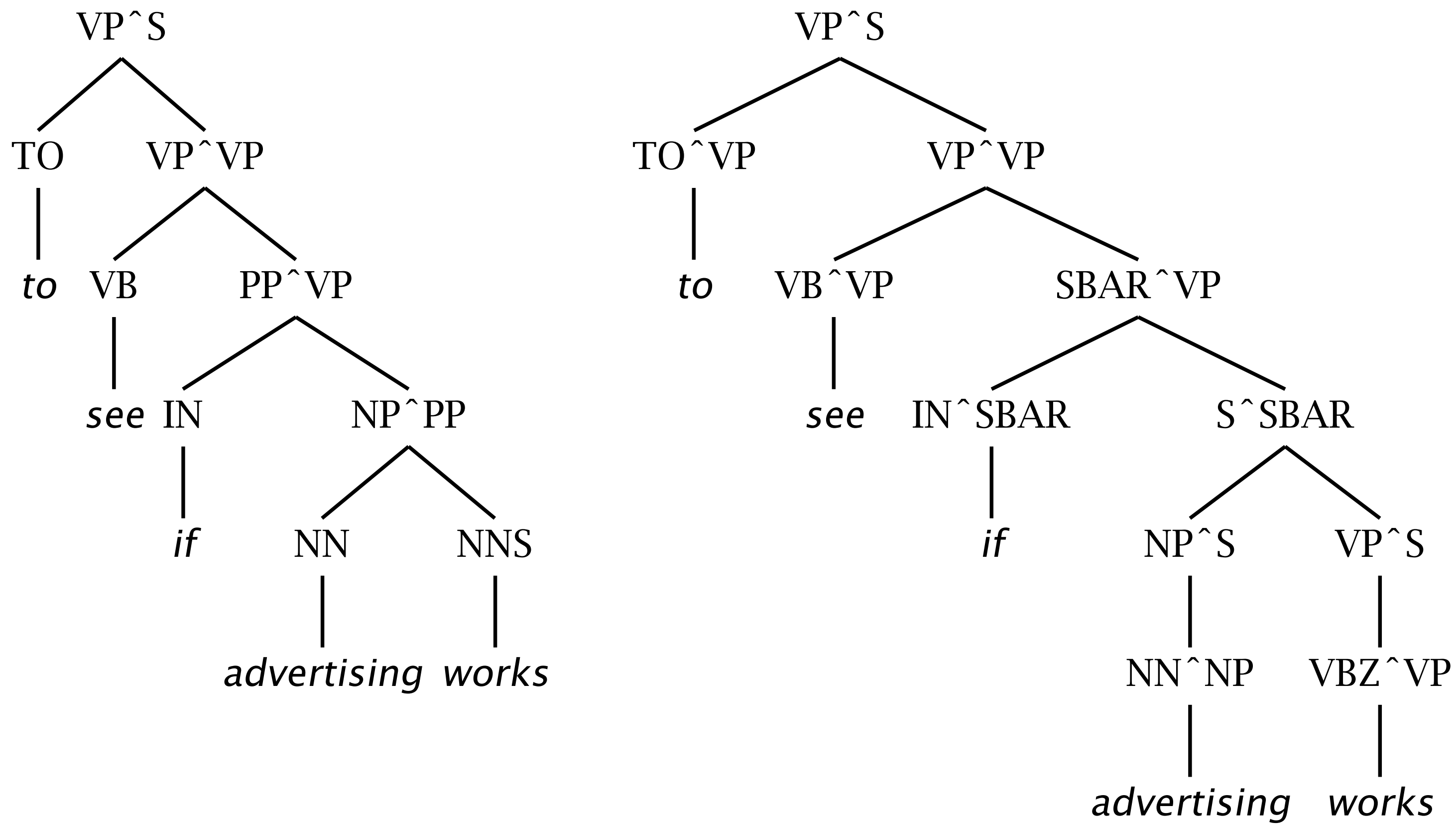
Weakening the independence assumption of PCFG

Probabilities dependent on structural context

- PCFGs are also deficient on purely structural grounds too
- Really context independent?

Expansion	% as Subj	% as Obj
NP → PRP	13.7%	2.1%
NP → NNP	3.5%	0.9%
NP → DT NN	5.6%	4.6%
NP → NN	1.4%	2.8%
NP → NP SBAR	0.5%	2.6%
NP → NP PP	5.6%	14.1%

Weakening the independence assumption of PCFG



(a) (b)

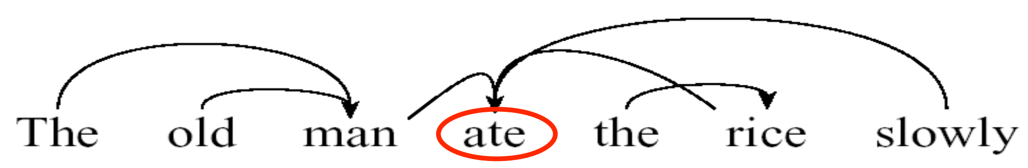
Dependency Parsing

Phrase Structure Grammars and Dependency Grammars

Phrase Structure Grammar describes the structure of sentences with phrase structure tree

Alternatively, a Dependency grammar describes the structure with dependencies between words

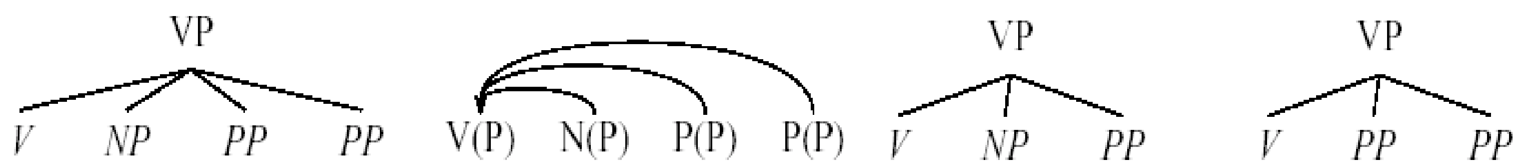
- One word is the head of a sentence and All other words are dependent on that word
- Dependent on some other word which connects to the headword through a sequence of dependencies



Phrase Structure Grammars and Dependency Grammars

Two key advantages of Dependency grammar are

- Easy to use lexical information
  - Disambiguation decisions are being made directly with words
  - No need to build a large superstructure
  - Not necessary to worry about how to lexicalize a PS tree
- Dependencies are one way of decomposing PS rules
  - Lots of rare flat trees in Penn Treebank → Sparse Data
  - Can get reasonable probabilistic estimate if we decompose it



Evaluation

Method	Recall	Precision
PCFGs (Charniak 97)	70.6%	74.8%
Decision trees (Magerman 95)	84.0%	84.3%
Lexicalized with backoff (Charniak 97)	86.7%	86.6%
Lexicalized with Markov (Collins 97 M1)	87.5%	87.7%
“ with subcategorization (Collins 97 M2)	88.1%	88.3%
MaxEnt-inspired (Charniak 2000)	90.1%	90.1%

Speeding Up Lexicalized Parsing

Bilexical CF grammars

Bilexical CF grammars

- Every rule has one of these forms:

`A[x] → B[x] C[y]`	so head of LHS
`A[x] → B[y] C[x]`	is inherited from
`A[x] → x`	a child on RHS.

Bilexical CF grammars

- Every rule has one of these forms:

`A[x] → B[x] C[y]`	so head of LHS
`A[x] → B[y] C[x]`	is inherited from
`A[x] → x`	a child on RHS.

(rules could also have probabilities)

Bilexical CF grammars

- Every rule has one of these forms:

A[x] → B[x] C[y]	so head of LHS
A[x] → B[y] C[x]	is inherited from
A[x] → x	a child on RHS.

(rules could also have probabilities)

B[x], B[y], C[x], C[y], … <u>many</u> nonterminals

Bilexical CF grammars

- Every rule has one of these forms:

A[x] → B[x] C[y]	so head of LHS
A[x] → B[y] C[x]	is inherited from
A[x] → x	a child on RHS.

(rules could also have probabilities)

B[x], B[y], C[x], C[y], … <u>many</u> nonterminals

A, B, C … are "traditional nonterminals"

Bilexical CF grammars

- Every rule has one of these forms:

`A[x]` → `B[x] C[y]`	so head of LHS
`A[x]` → `B[y] C[x]`	is inherited from
`A[x]` → `x`	a child on RHS.

(rules could also have probabilities)

`B[x]`, `B[y]`, `C[x]`, `C[y]`, ... <u>many</u> nonterminals

`A`, `B`, `C` ... are "traditional nonterminals"

`x`, `y` ... are words

How bad is bilex CF parsing?

How bad is bilex CF parsing?

$$\mathbf{A}[\mathbf{x}] \rightarrow \mathbf{B}[\mathbf{x}]\ \ \mathbf{C}[\mathbf{y}]$$

How bad is bilex CF parsing?

$$\mathbf{A[x]} \rightarrow \mathbf{B[x]}\ \ \mathbf{C[y]}$$

- Grammar size = $O(t^3\ V^2)$

How bad is bilex CF parsing?

$$\mathbf{A}[\mathbf{x}] \rightarrow \mathbf{B}[\mathbf{x}] \;\; \mathbf{C}[\mathbf{y}]$$

- Grammar size = $O(t^3 V^2)$

where $t = |\{\mathbf{A}, \mathbf{B}, \ldots\}|$ $\quad V = |\{\mathbf{x}, \mathbf{y} \ldots\}|$

How bad is bilex CF parsing?

$$\mathtt{A[x]} \rightarrow \mathtt{B[x]}\ \ \mathtt{C[y]}$$

- Grammar size = $O(t^3\ V^2)$

  where $t = |\{\mathtt{A}, \mathtt{B}, \ldots\}|$ $V = |\{\mathtt{x}, \mathtt{y}\ \ldots\}|$

- So CKY takes $\mathbf{O(t^3\ V^2\ n^3)}$

How bad is bilex CF parsing?

$$\mathtt{A[x]} \rightarrow \mathtt{B[x]}\ \ \mathtt{C[y]}$$

- Grammar size = $O(t^3\ V^2)$

    where $t = |\{\mathtt{A}, \mathtt{B}, \ldots\}|$ $\quad V = |\{\mathtt{x}, \mathtt{y} \ldots\}|$

- So CKY takes $\mathbf{O(t^3\ V^2\ n^3)}$
- Reduce to $\mathbf{O(t^3\ n^5)}$ since relevant $V = n$

How bad is bilex CF parsing?

$$\texttt{A[x]} \rightarrow \texttt{B[x]} \;\; \texttt{C[y]}$$

- Grammar size = $O(t^3 V^2)$

  where $t = |\{\texttt{A}, \texttt{B}, \ldots\}|$ $V = |\{\texttt{x}, \texttt{y} \ldots\}|$

- So CKY takes $\mathbf{O(t^3 V^2 n^3)}$
- Reduce to $\mathbf{O(t^3 n^5)}$ since relevant $V = n$

- This is terrible ... can we do better?

How bad is bilex CF parsing?

$$\mathtt{A[x]} \rightarrow \mathtt{B[x]}\ \ \mathtt{C[y]}$$

- Grammar size = $O(t^3\ V^2)$

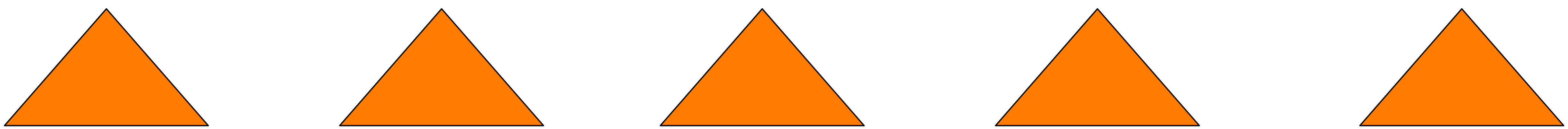
  where t = |{**A**, **B**, ...}| V = |{**x**, **y** ...}|

- So CKY takes $\mathbf{O(t^3\ V^2\ n^3)}$
- Reduce to $\mathbf{O(t^3\ n^5)}$ since relevant V = n

- This is terrible ... can we do better?
  - Recall: regular CKY is $O(t^3\ n^3)$

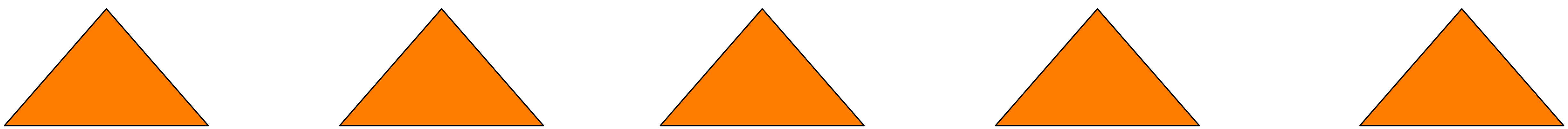
The CKY-style algorithm

Mary **loves** **the** **girl** **outdoors**



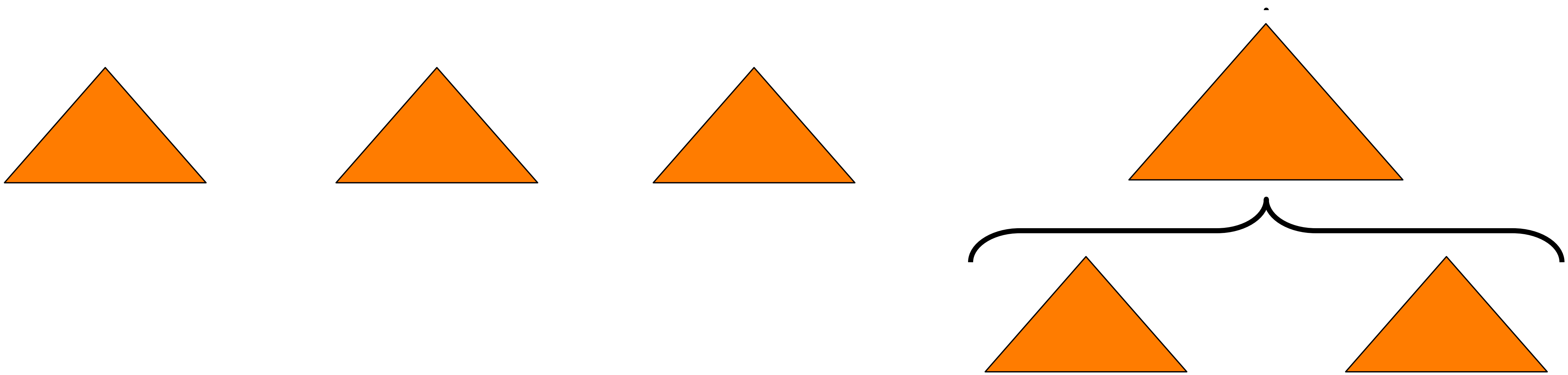
The CKY-style algorithm

Mary loves the girl ← [outdoors]

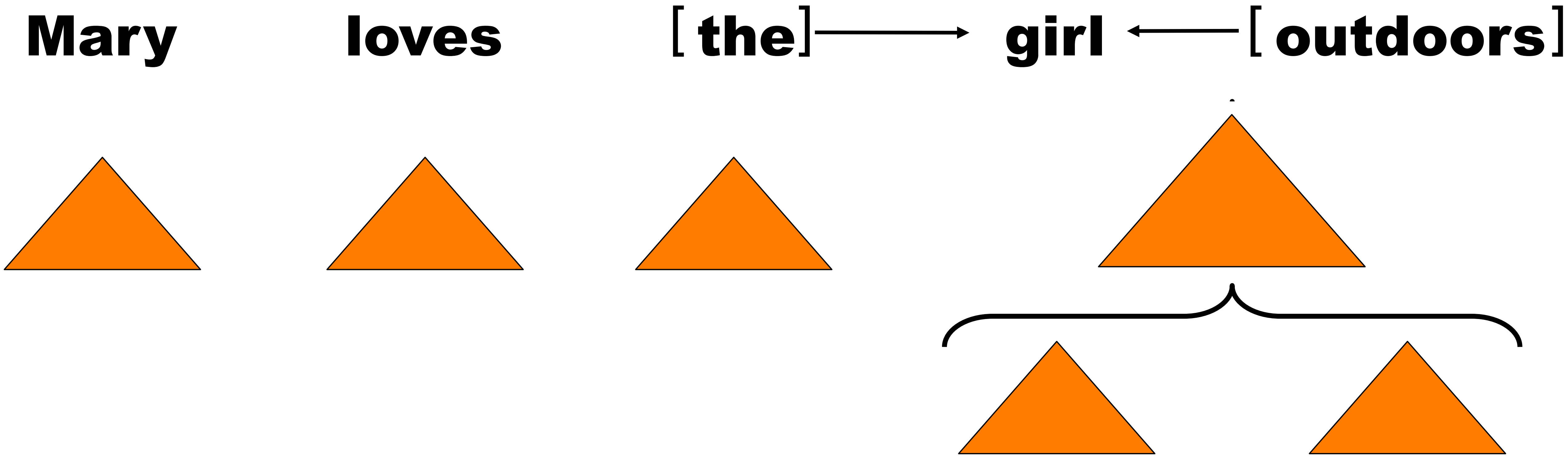


The CKY-style algorithm

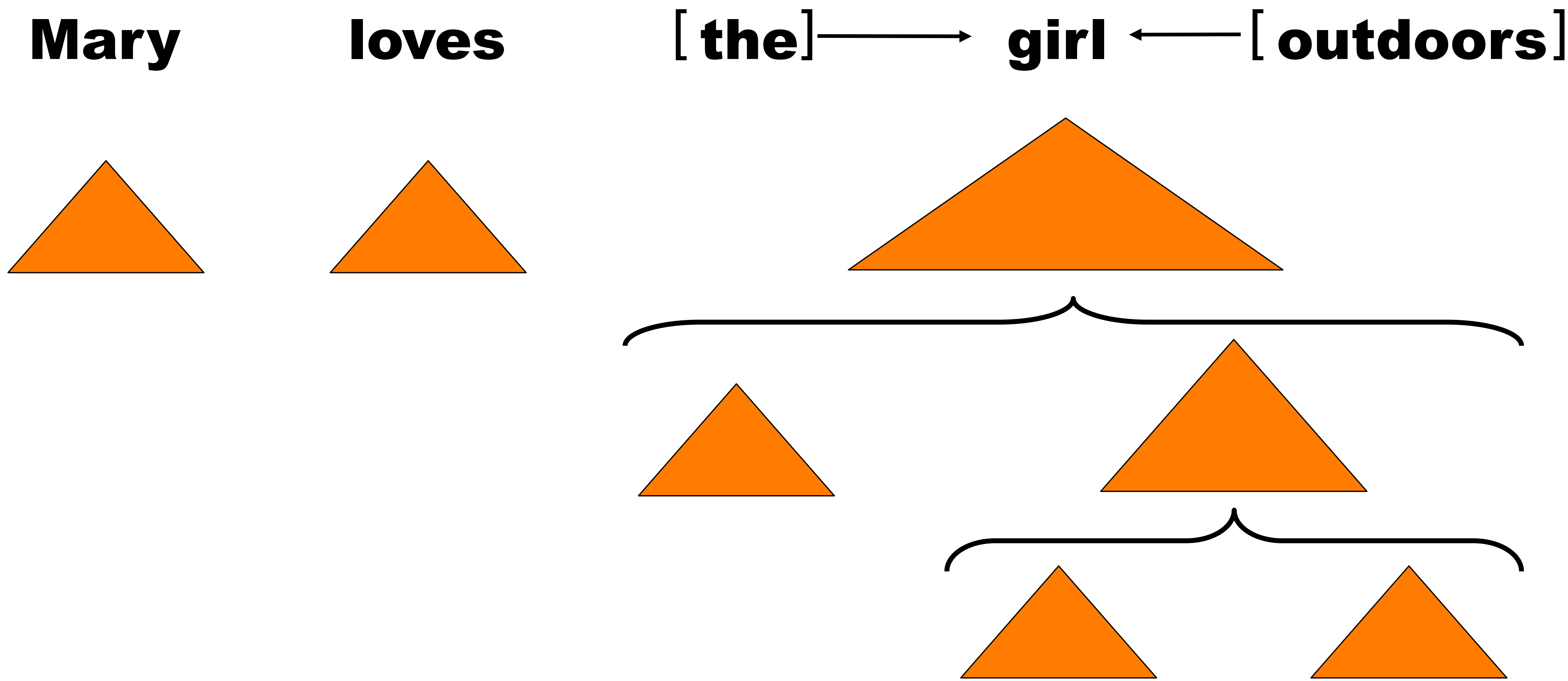
Mary loves the girl ⟵ [outdoors]



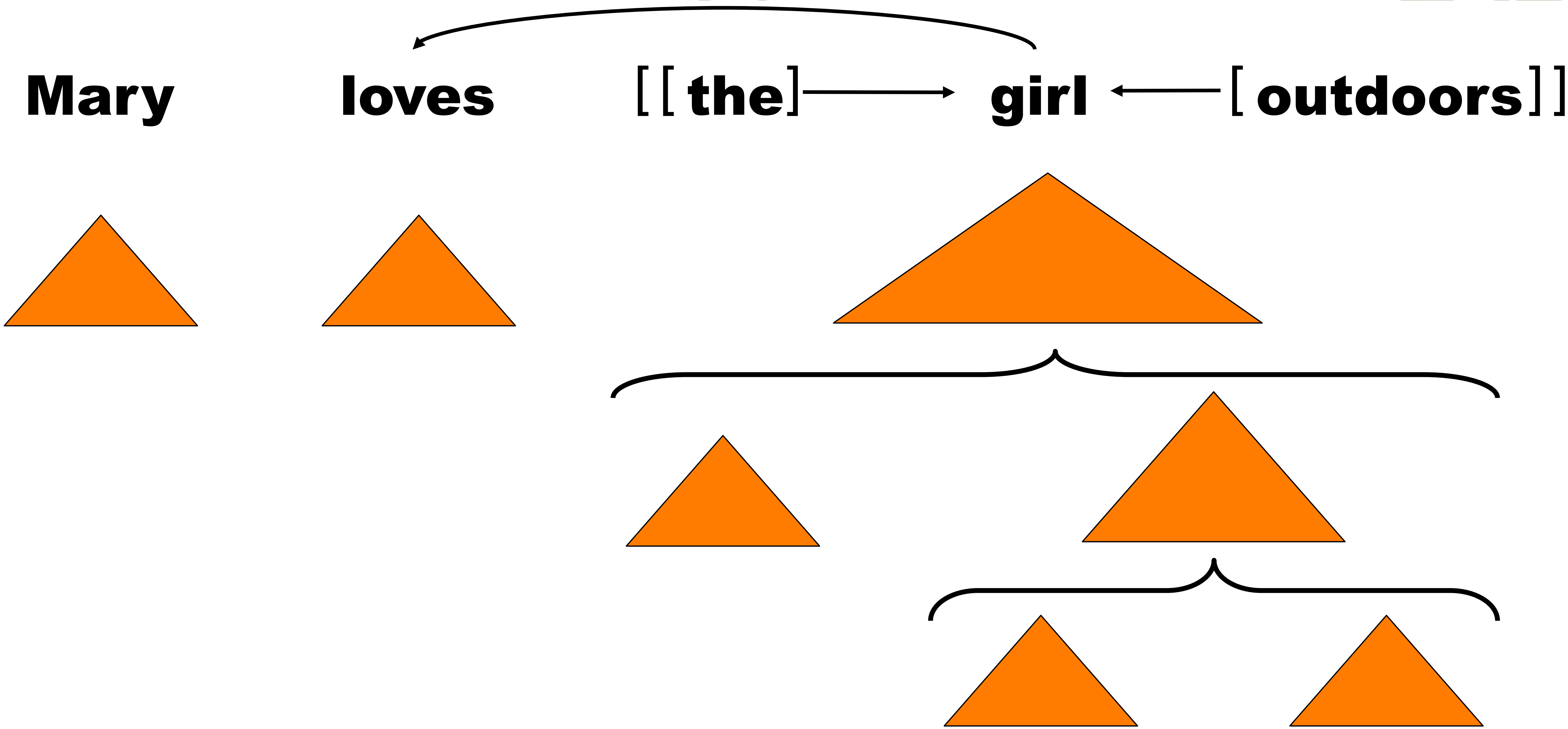
The CKY-style algorithm



The CKY-style algorithm

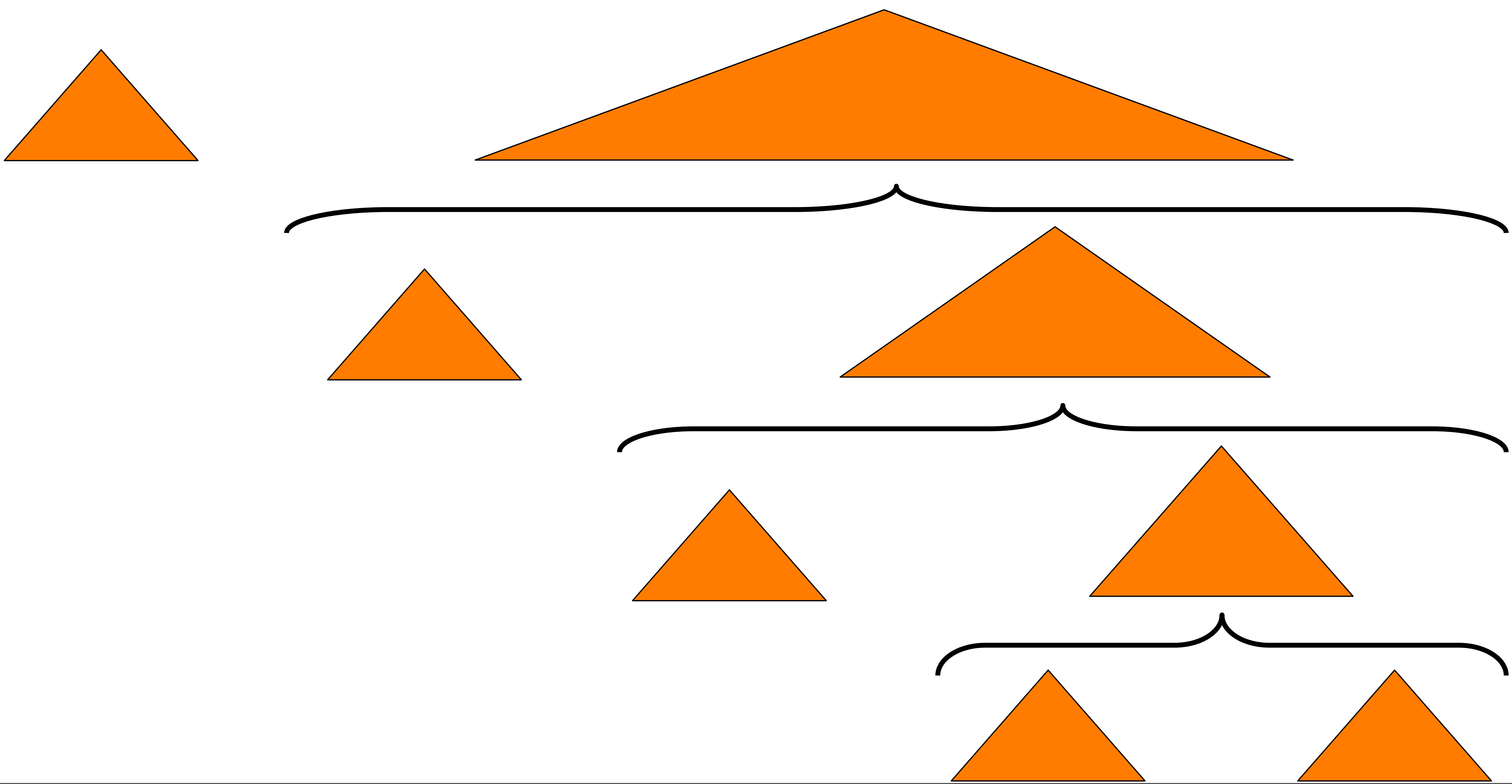


The CKY-style algorithm



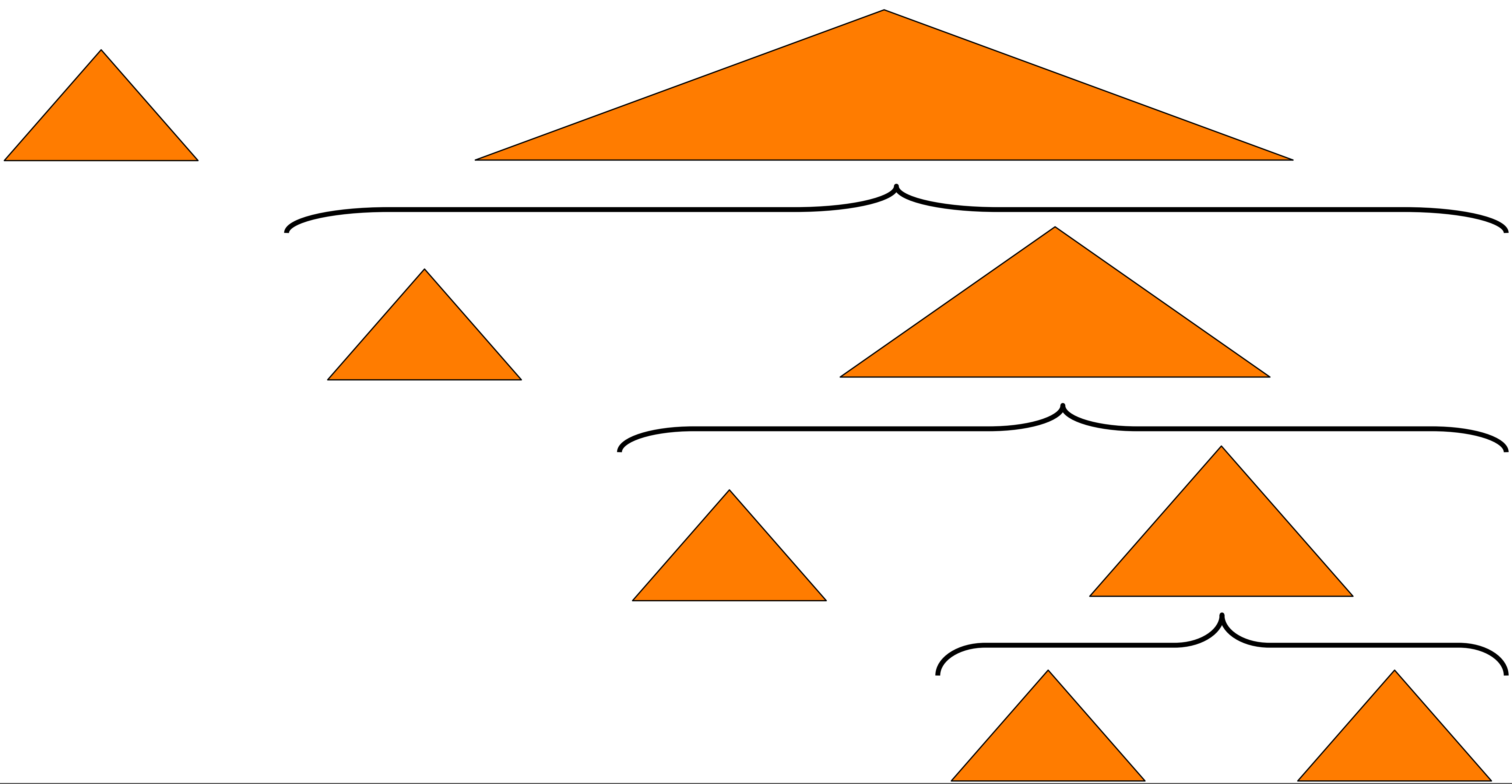
The CKY-style algorithm

Mary loves [[the] girl [outdoors]]

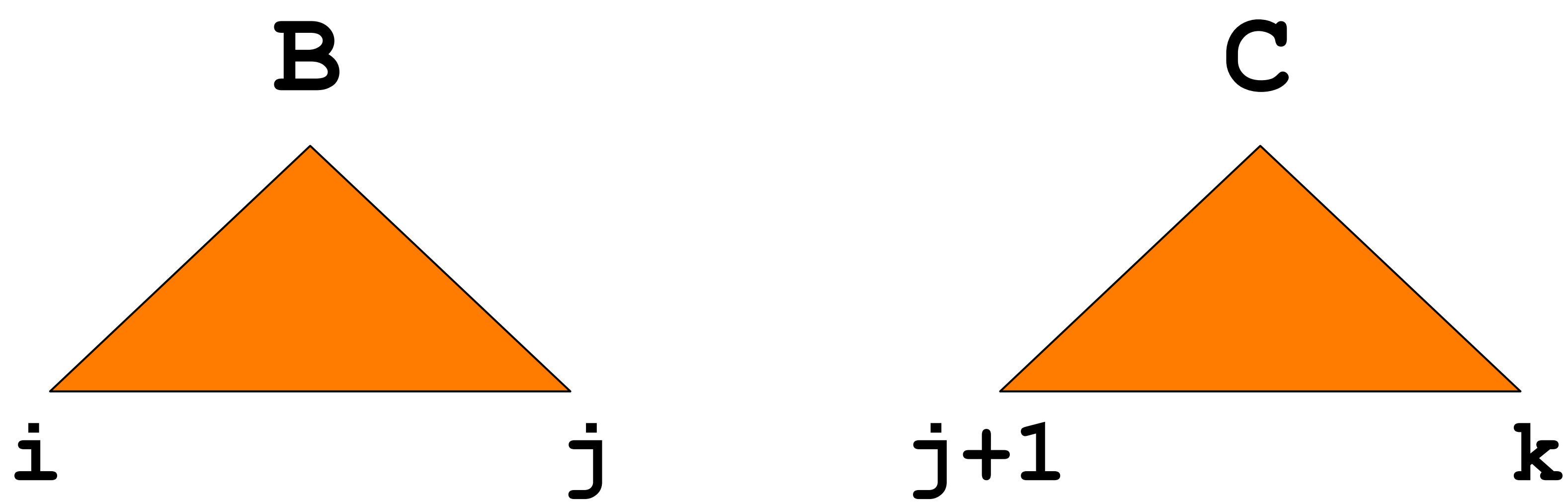


The CKY-style algorithm

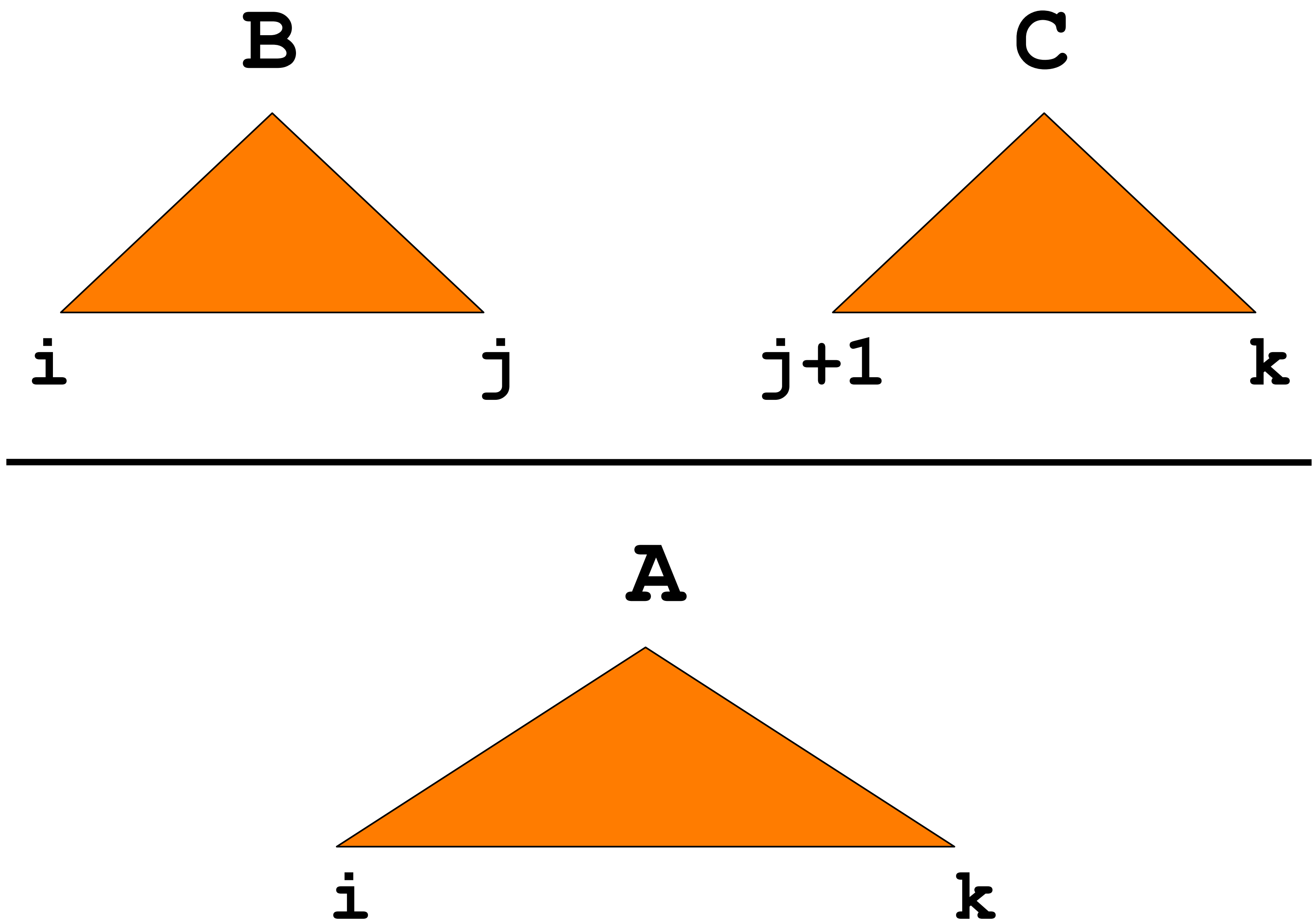
[Mary] loves [[the] girl [outdoors]]



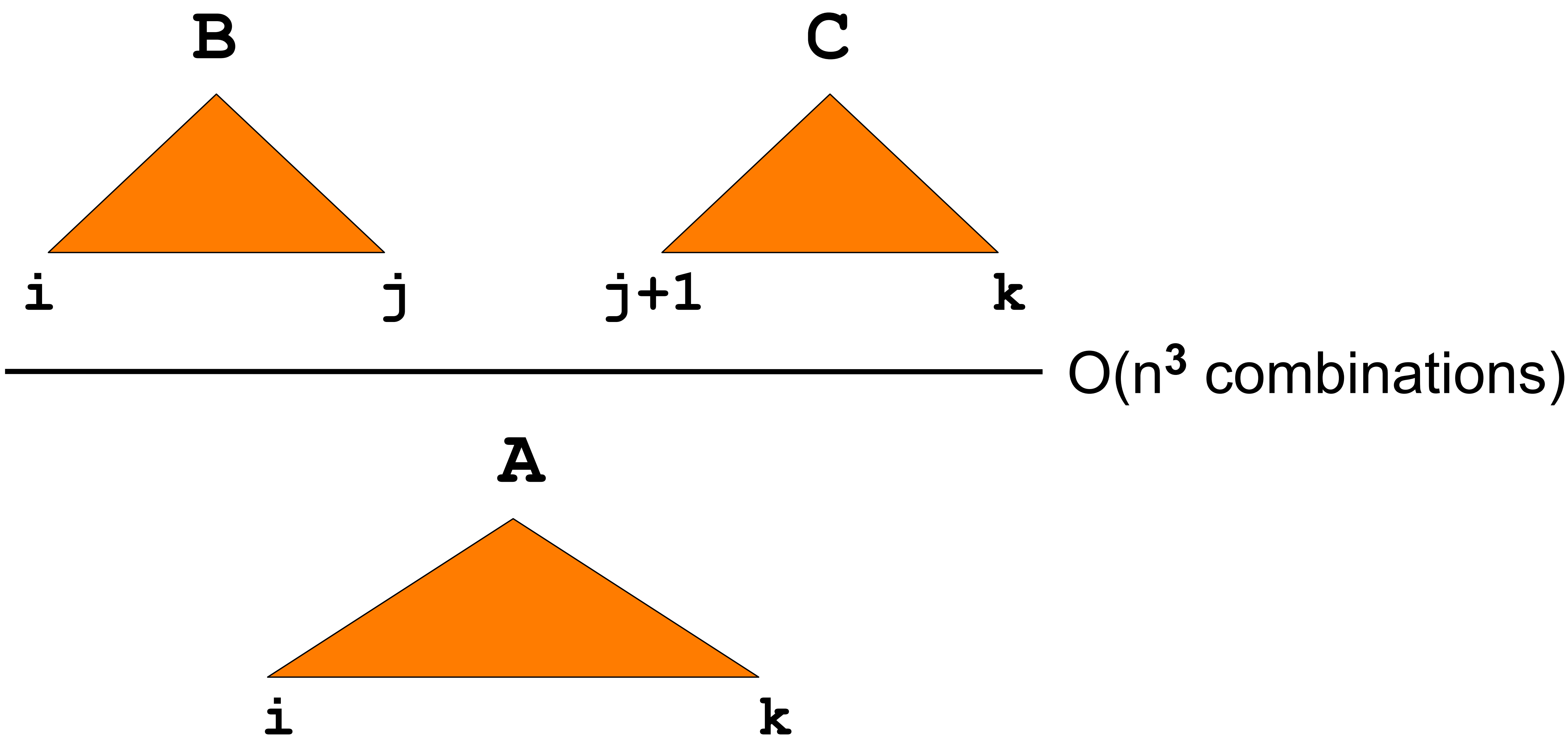
Why CKY is O(n^5) not O(n^3)



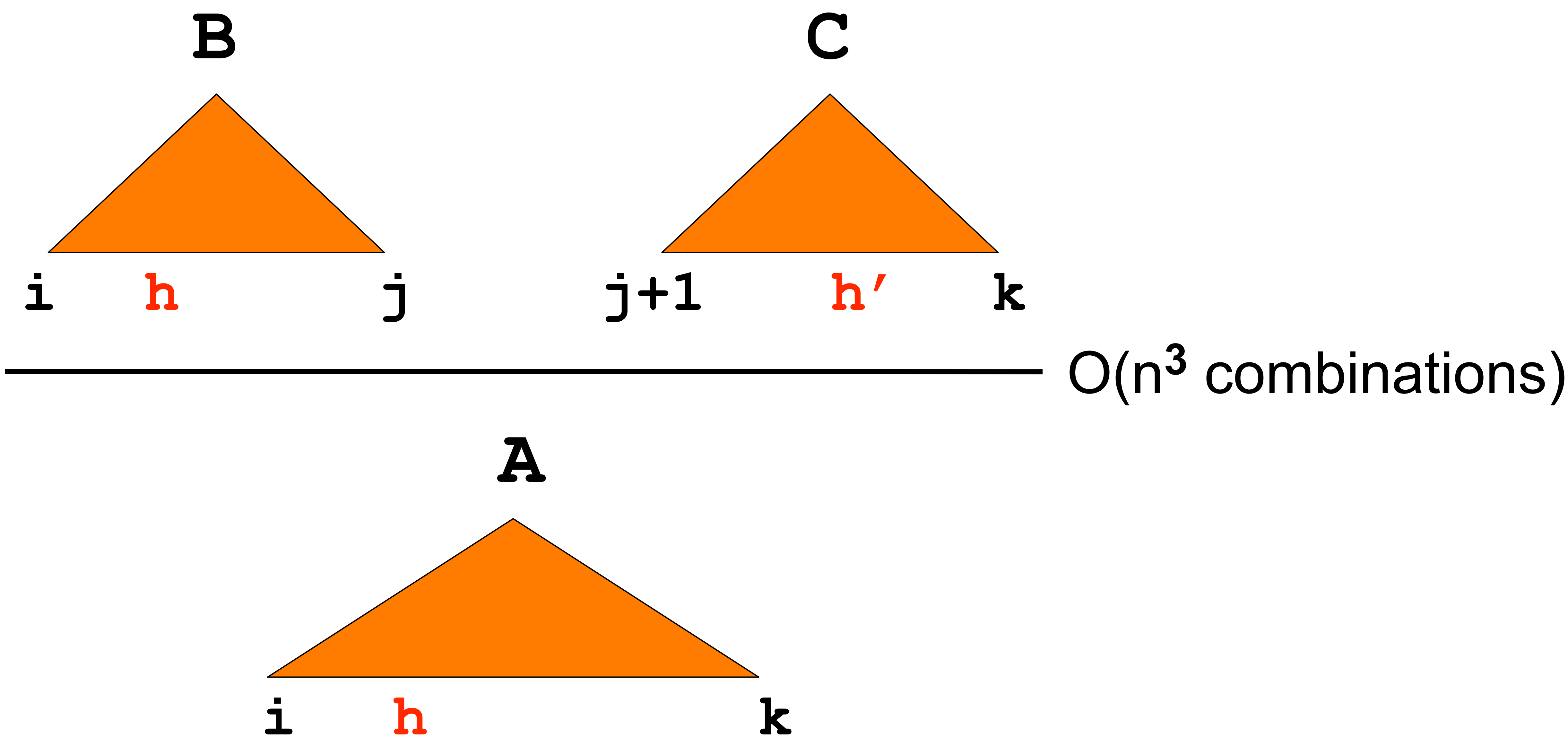
Why CKY is $O(n^5)$ not $O(n^3)$



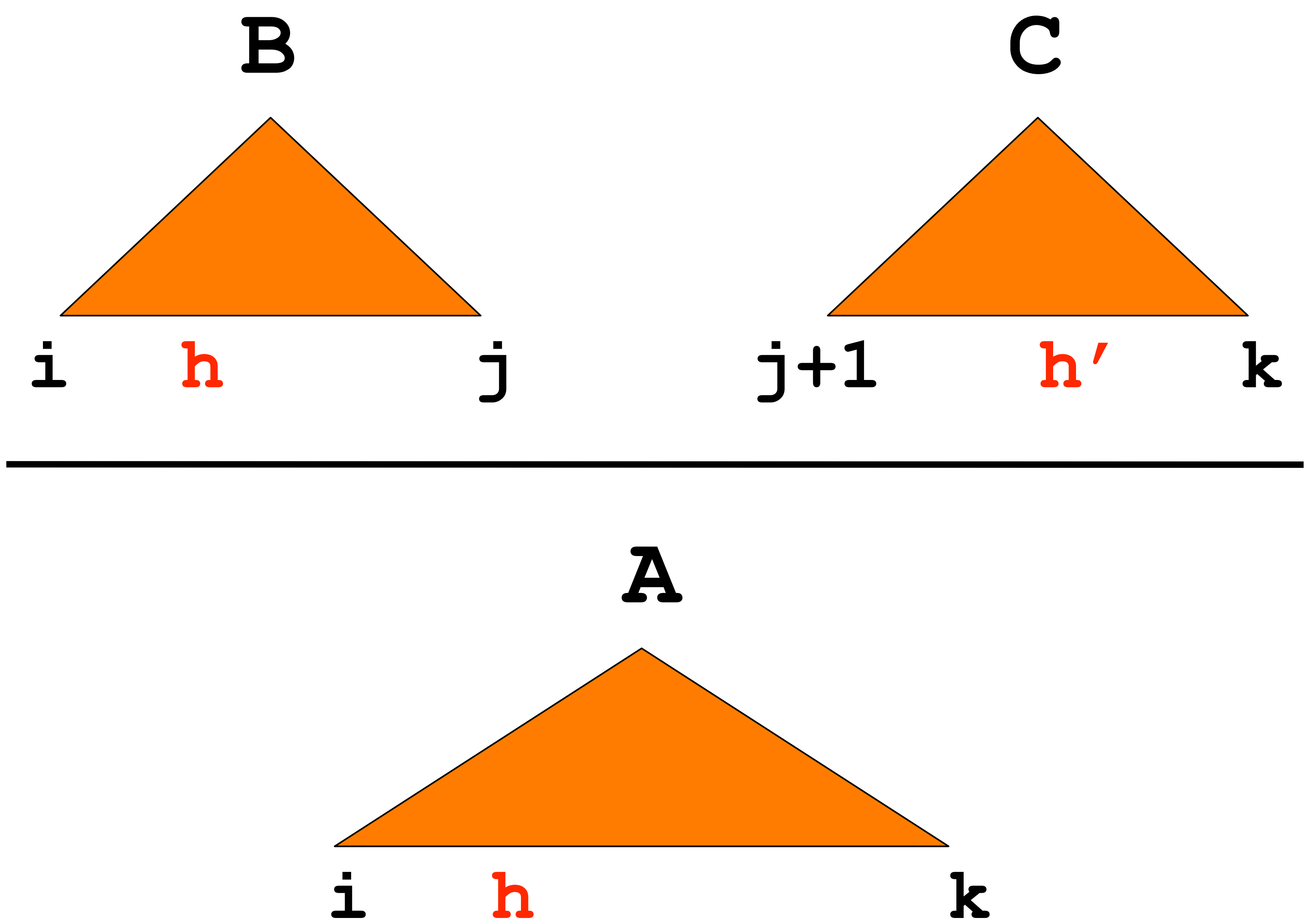
Why CKY is $O(n^5)$ not $O(n^3)$



Why CKY is $O(n^5)$ not $O(n^3)$



Why CKY is $O(n^5)$ not $O(n^3)$

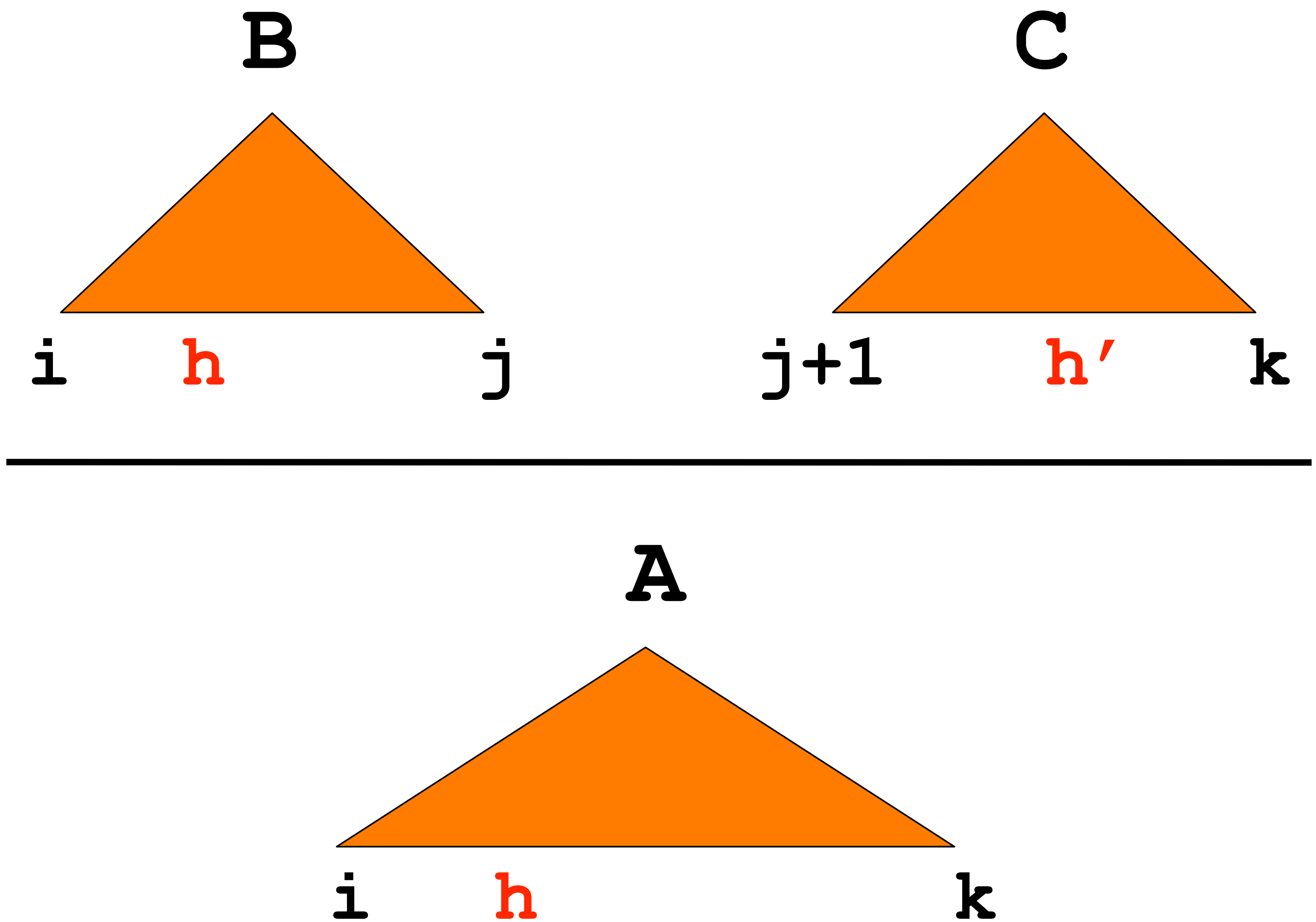


~~$O(n^3$ combinations)~~

$O(n^5$ combinations)

Why CKY is $O(n^5)$ not $O(n^3)$

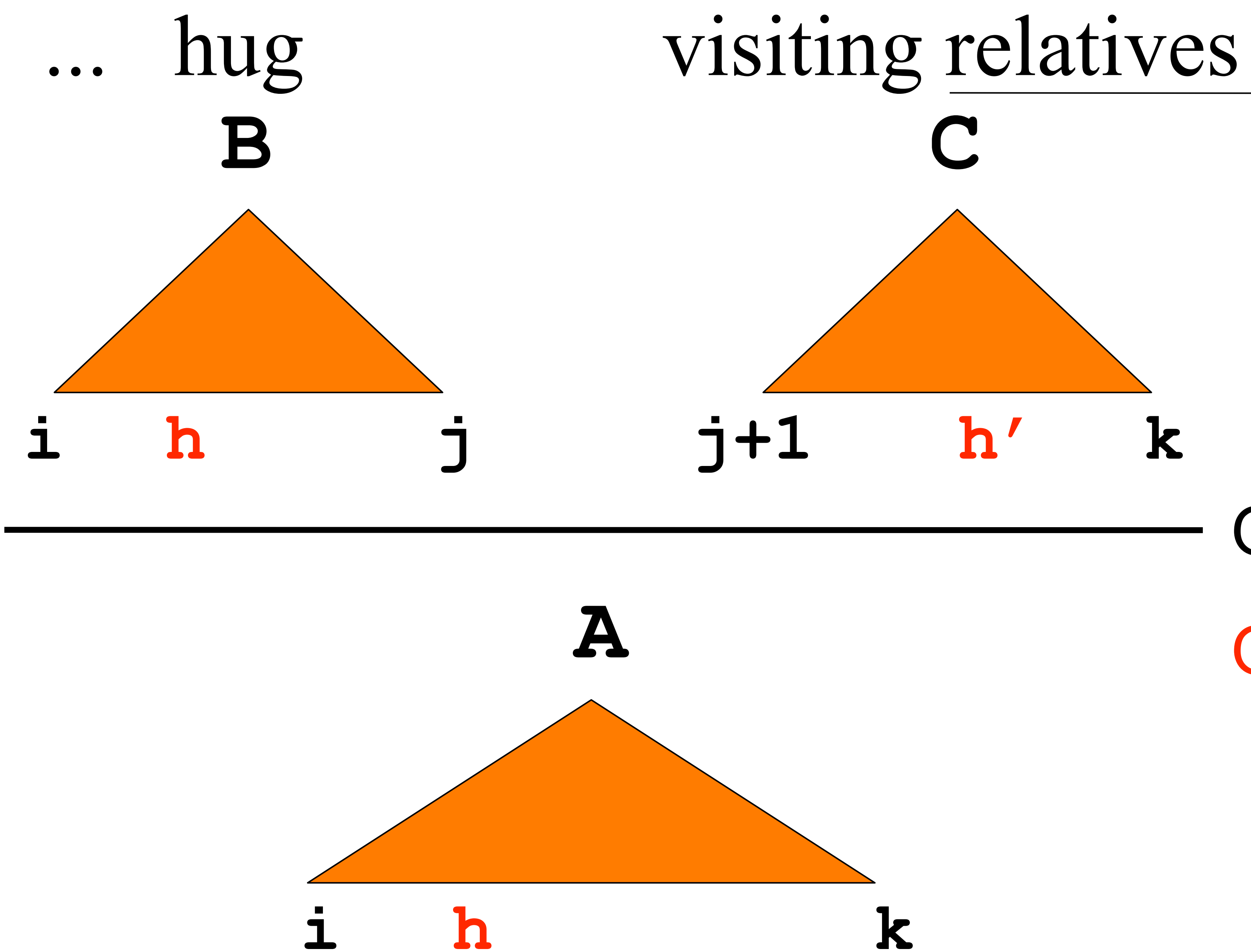
visiting relatives



~~$O(n^3$ combinations$)$~~

$O(n^5$ combinations$)$

Why CKY is $O(n^5)$ not $O(n^3)$

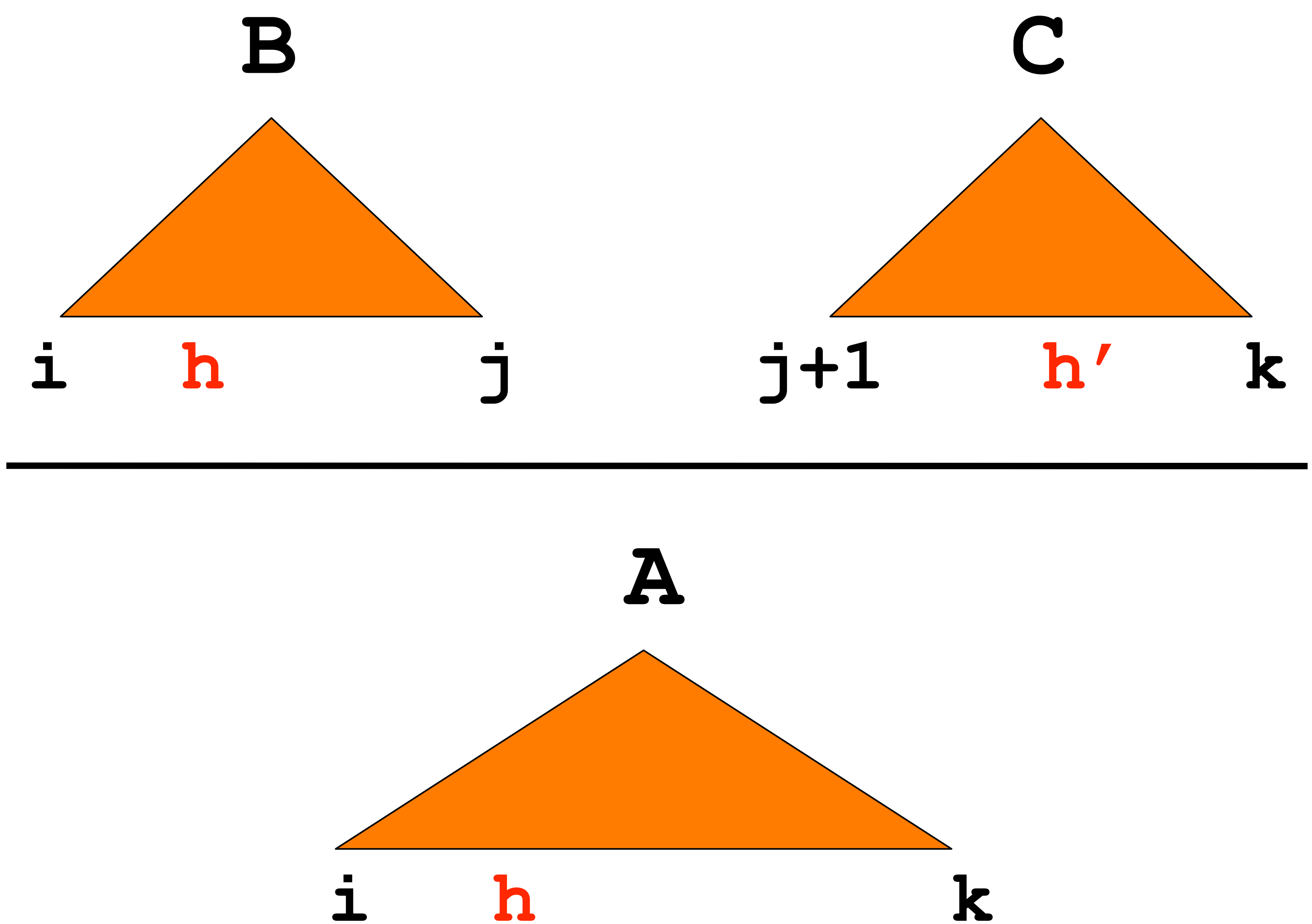


~~$O(n^3$ combinations)~~

$O(n^5$ combinations)

Why CKY is O(n^5) not O(n^3)

... advocate
... hug visiting relatives



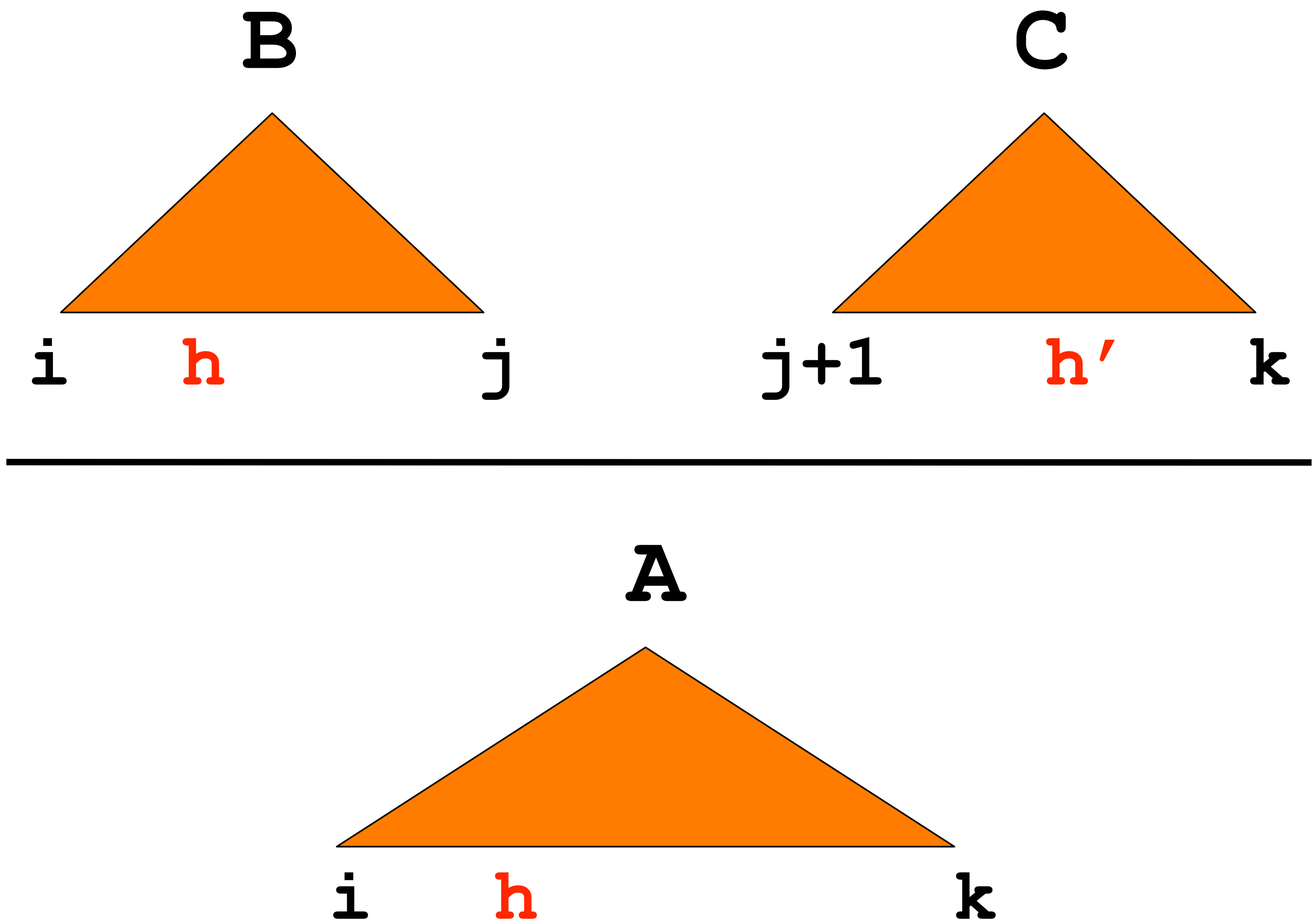
~~O(n^3 combinations)~~

O(n^5 combinations)

Why CKY is $O(n^5)$ not $O(n^3)$

... advocate visiting relatives

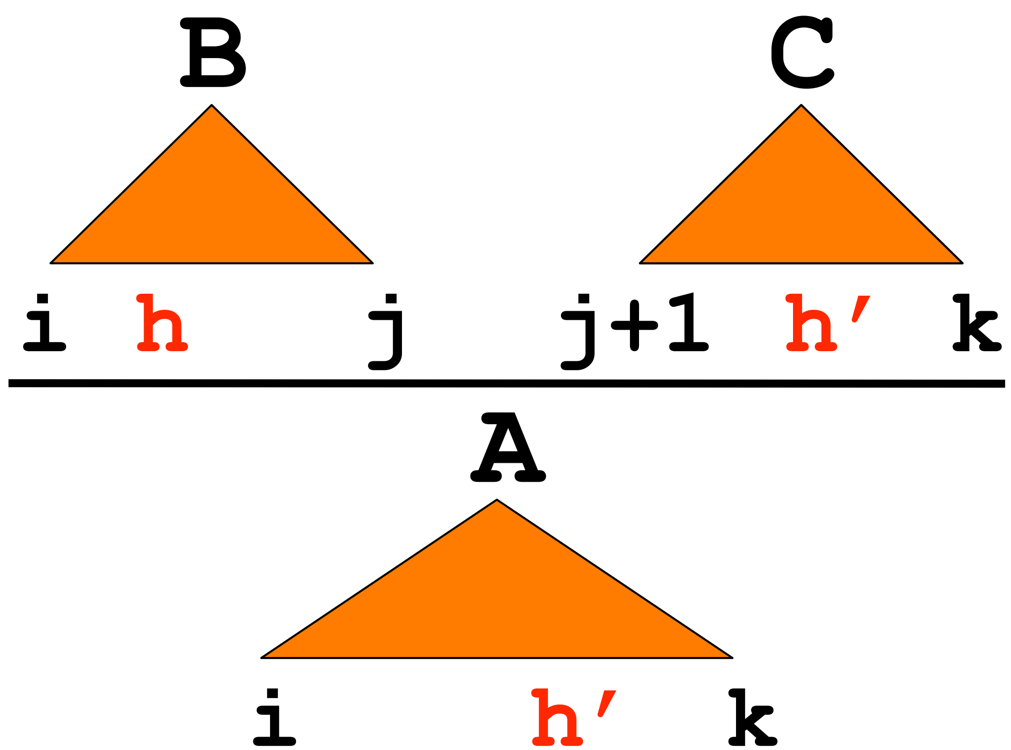
... hug visiting relatives



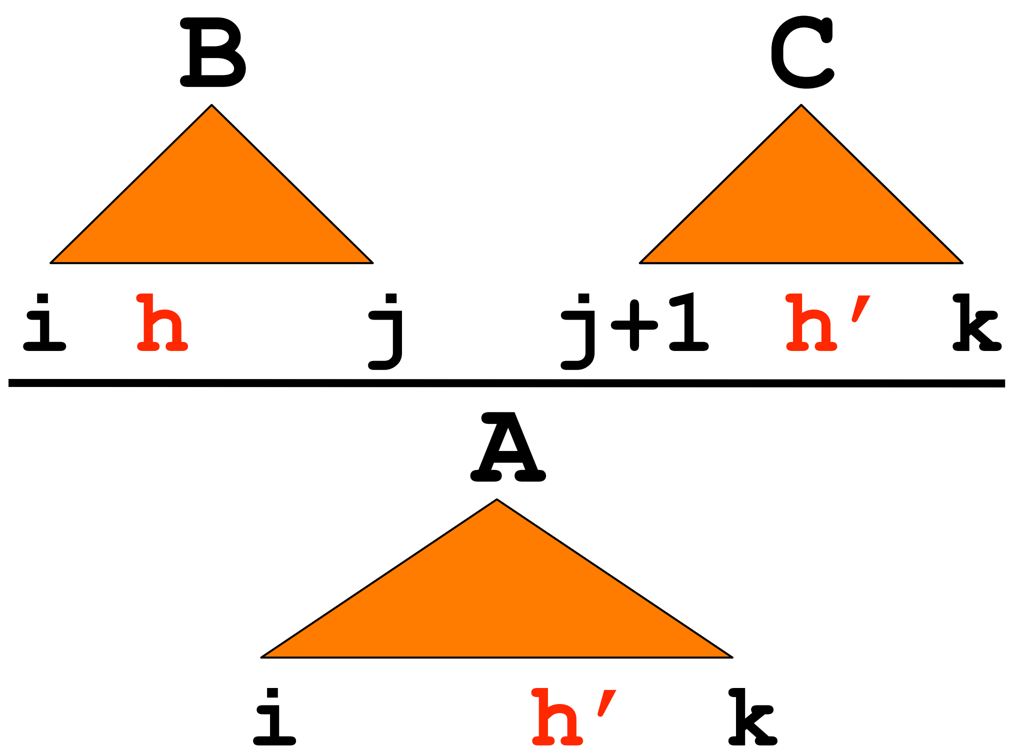
~~$O(n^3$ combinations)~~

$O(n^5$ combinations)

Idea #1

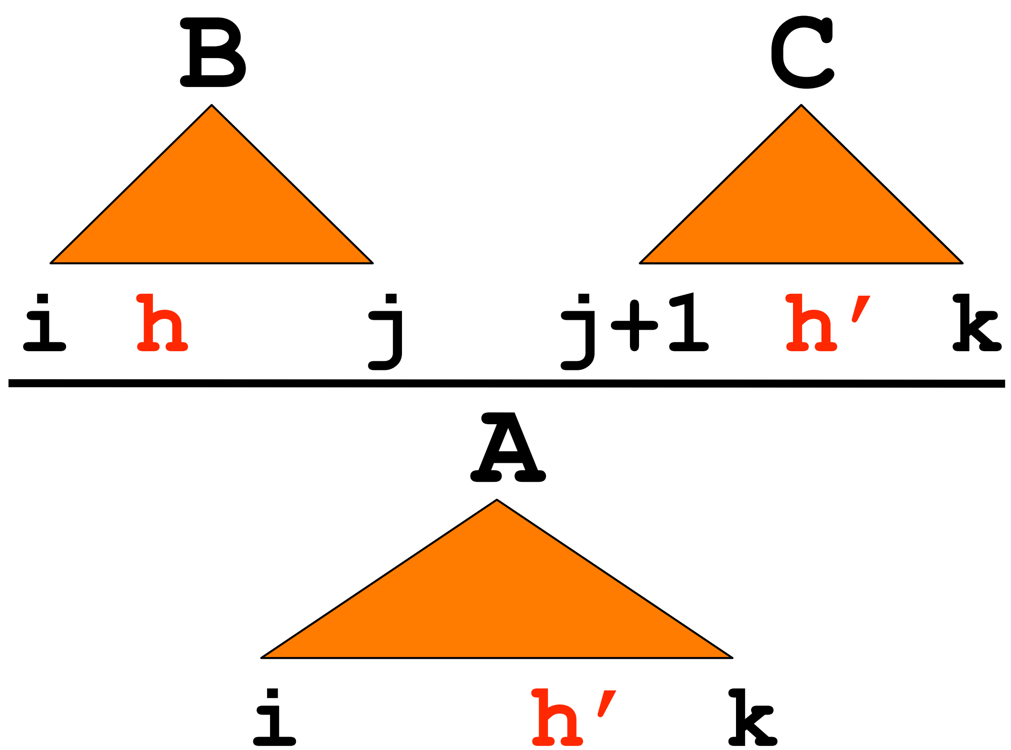


Idea #1



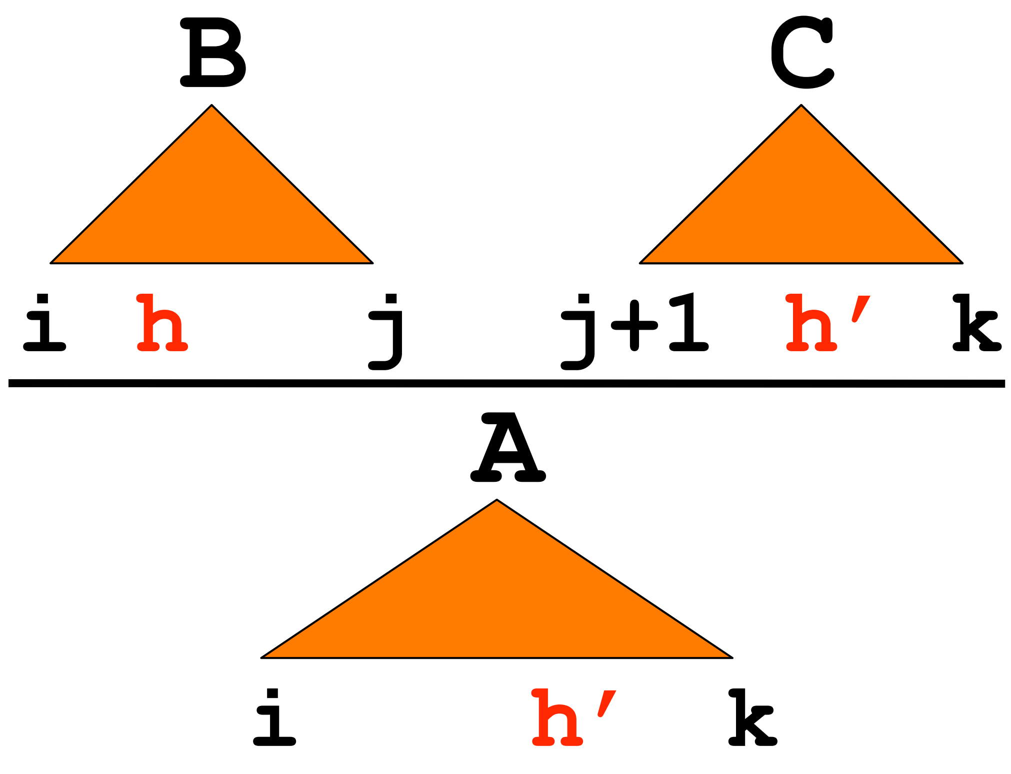
- Combine B with what C?

Idea #1



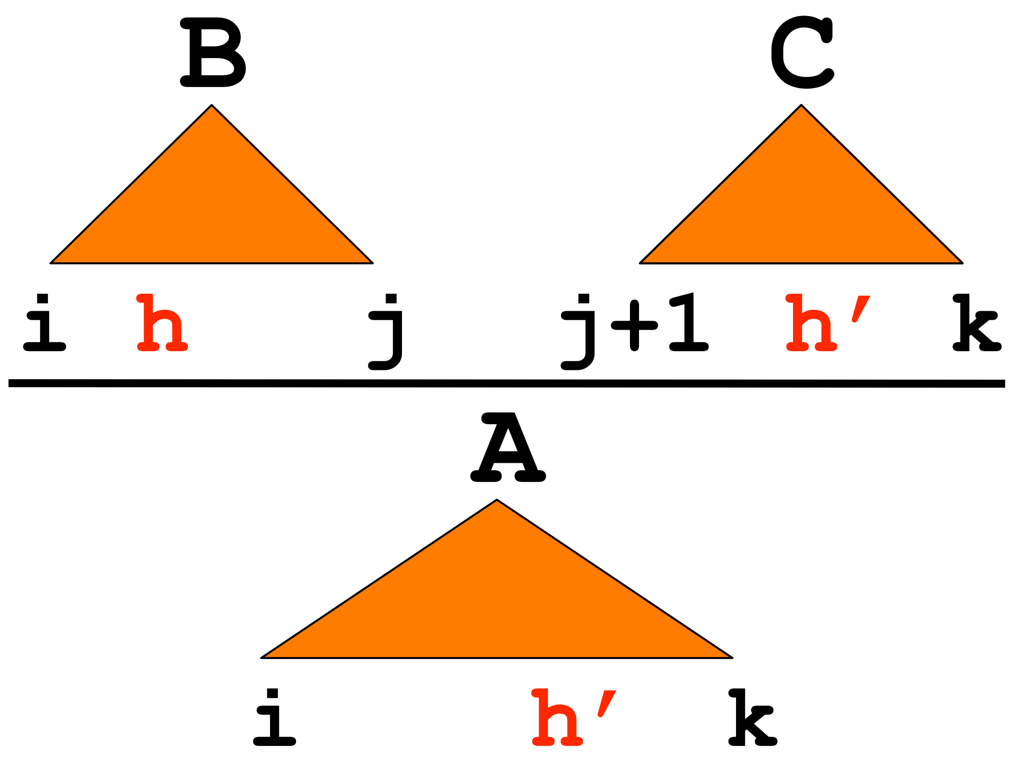
- Combine B with what C?
  - must try different-width C's (vary **k**)

Idea #1



- Combine B with what C?
  - must try different-width C's (vary **k**)
  - must try differently-headed C's (vary **h′**)

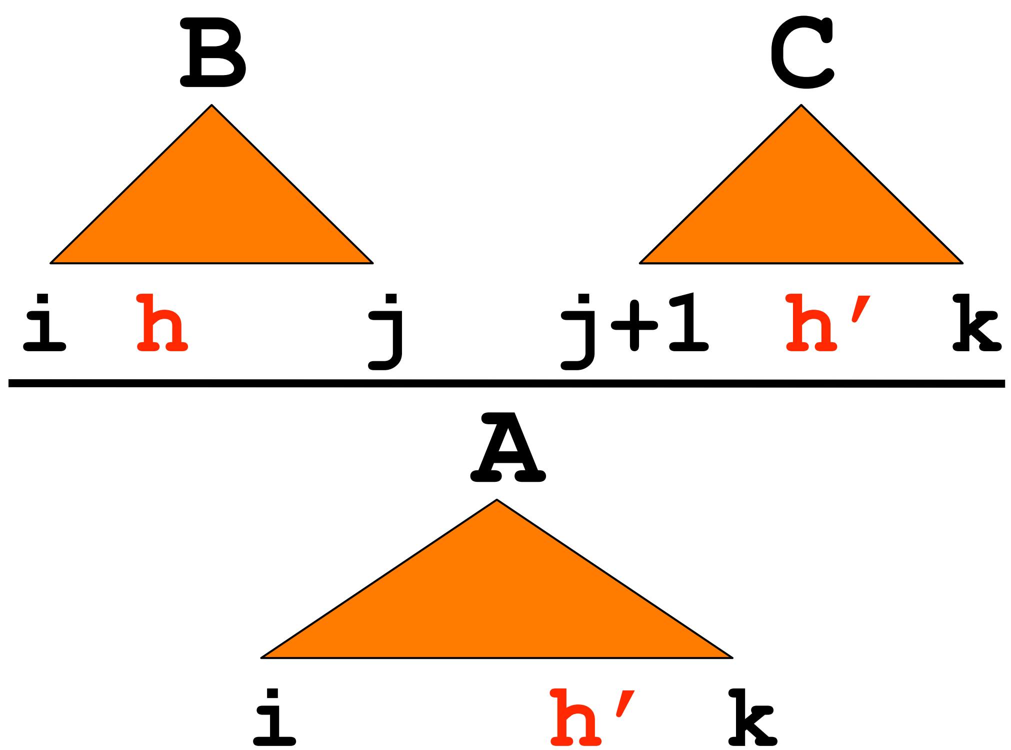
Idea #1

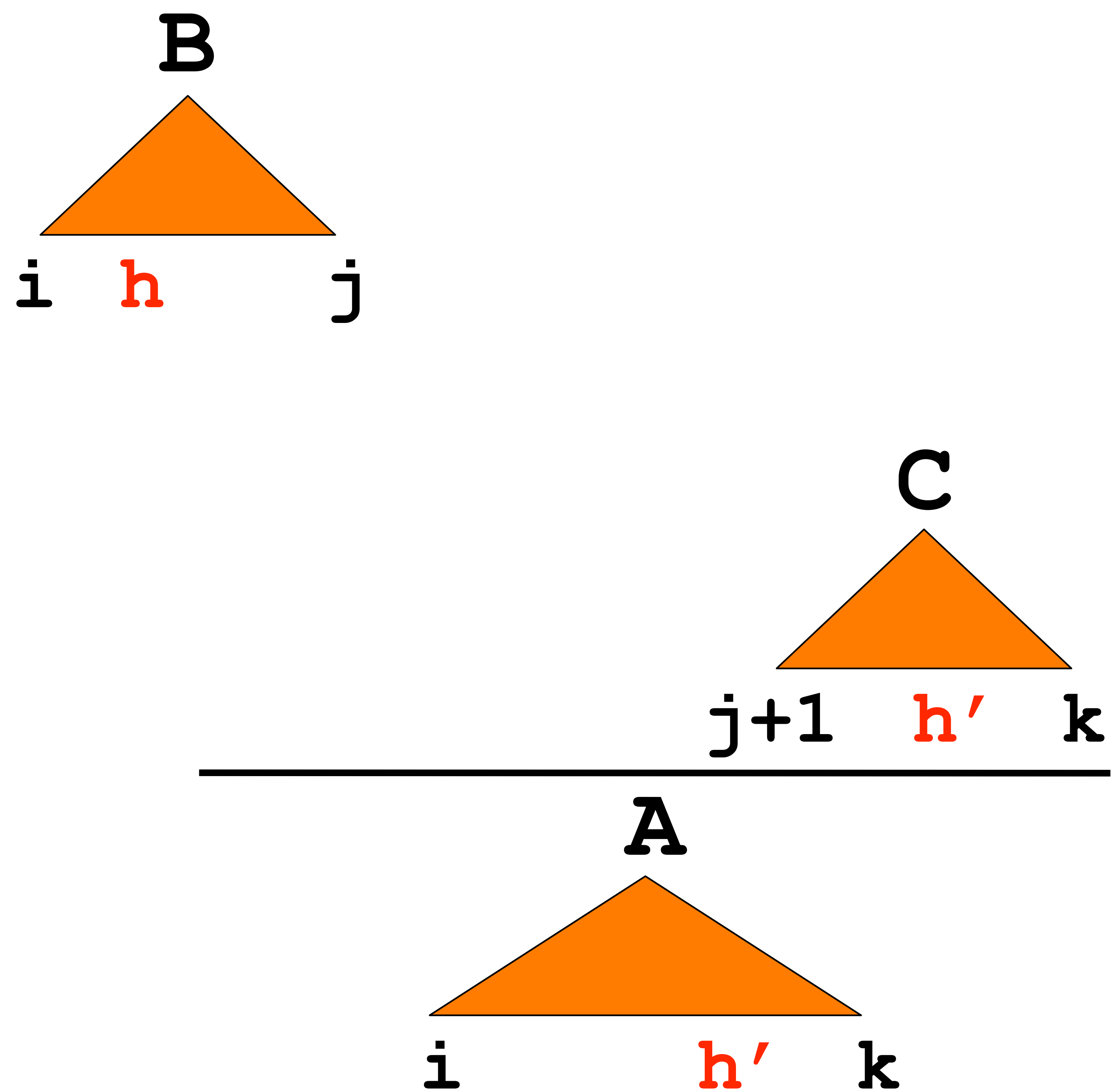


- Combine B with what C?
  - must try different-width C's (vary **k**)
  - must try differently-headed C's (vary **h'**)
  - Separate these!

Idea #1

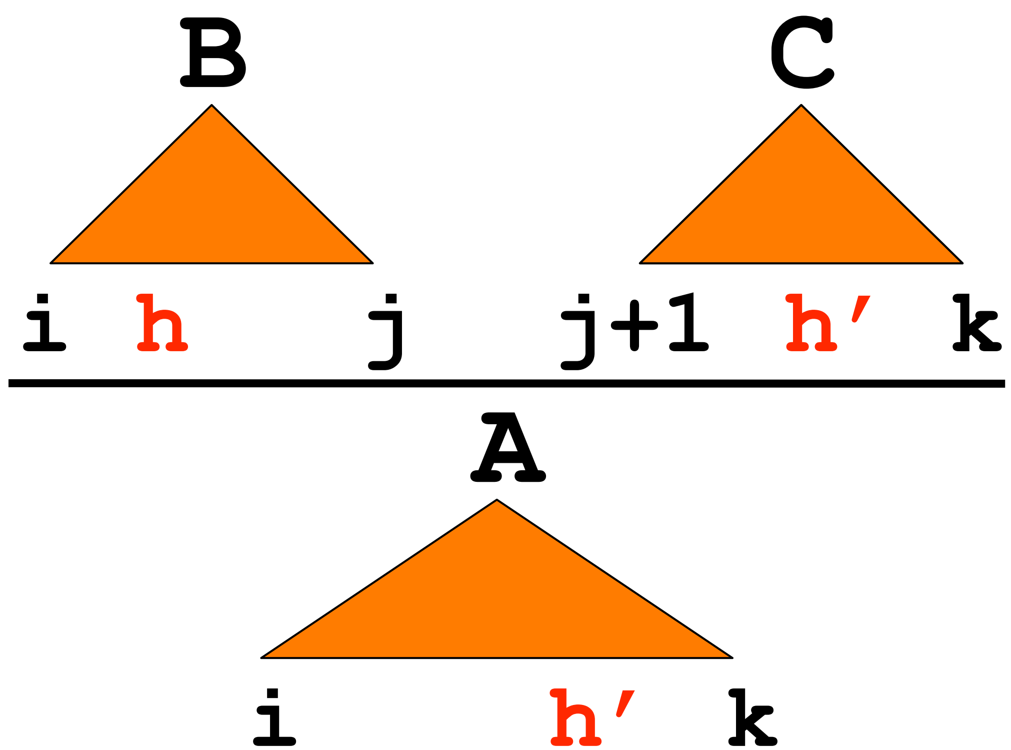
(the old CKY way)

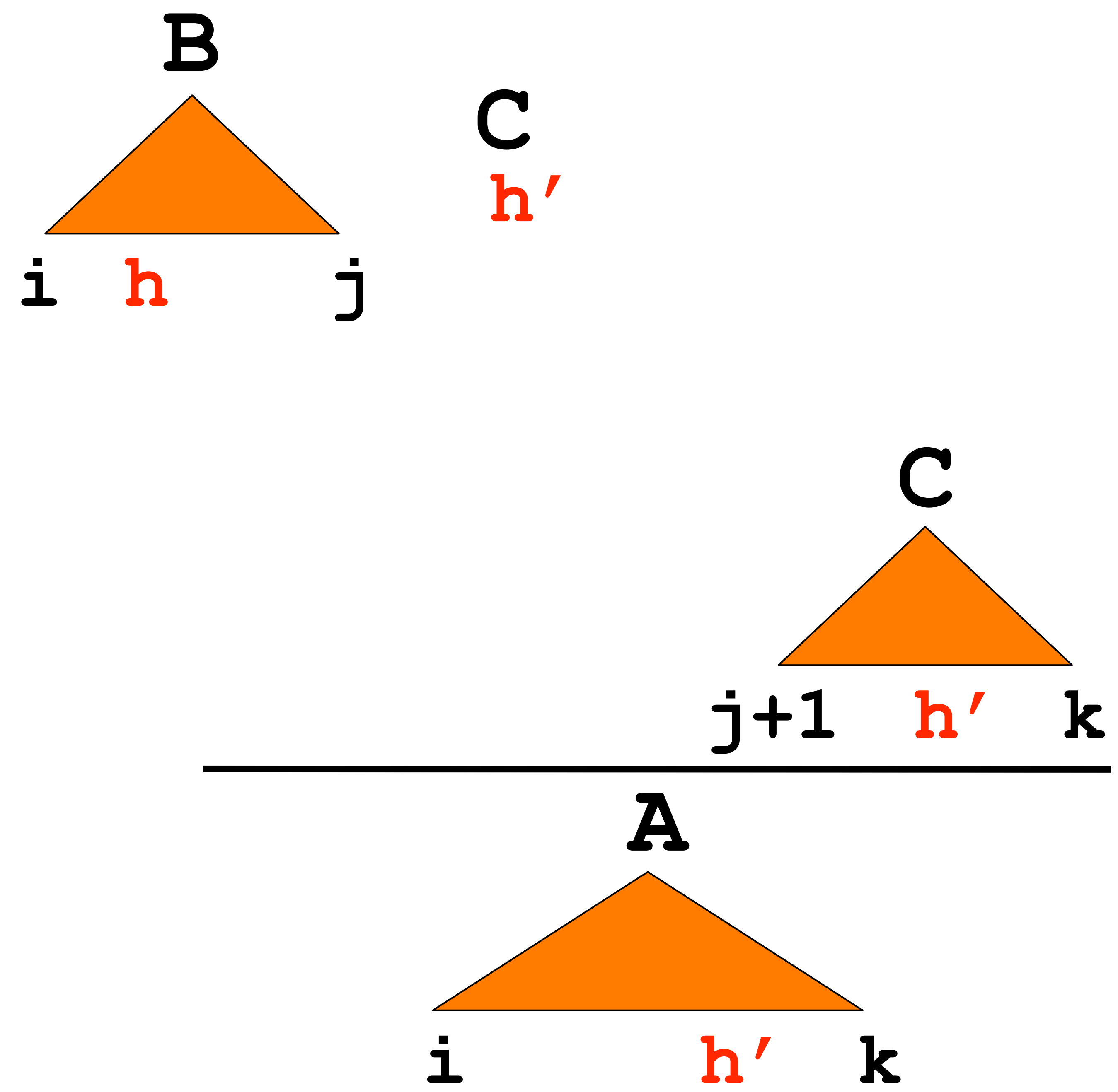




Idea #1

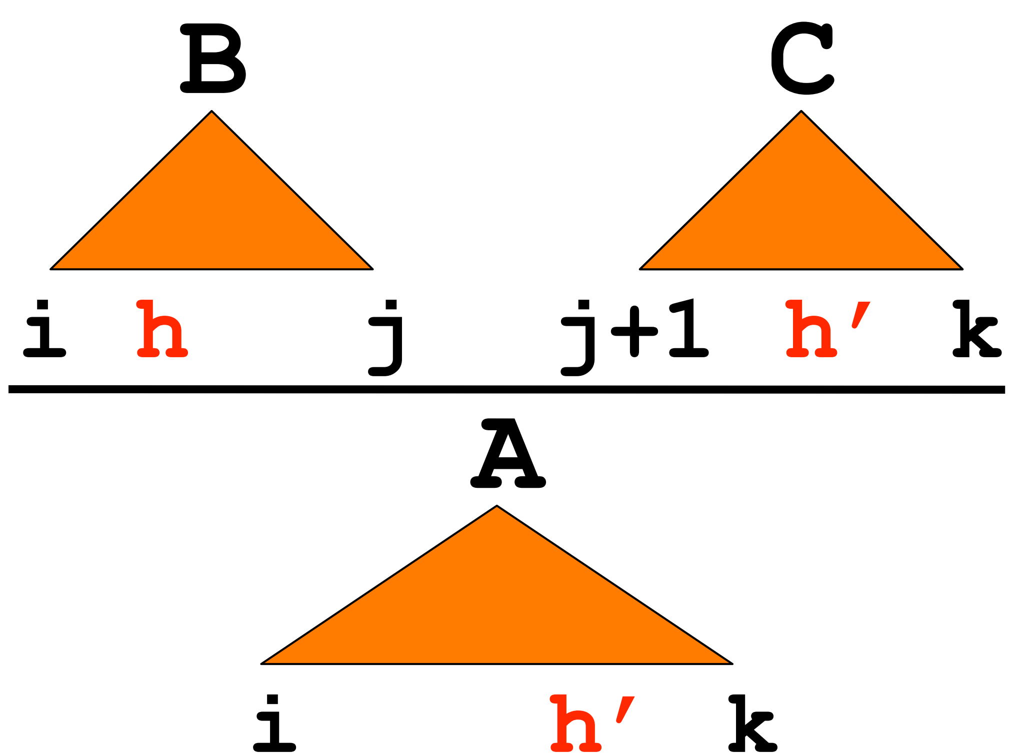
(the old CKY way)

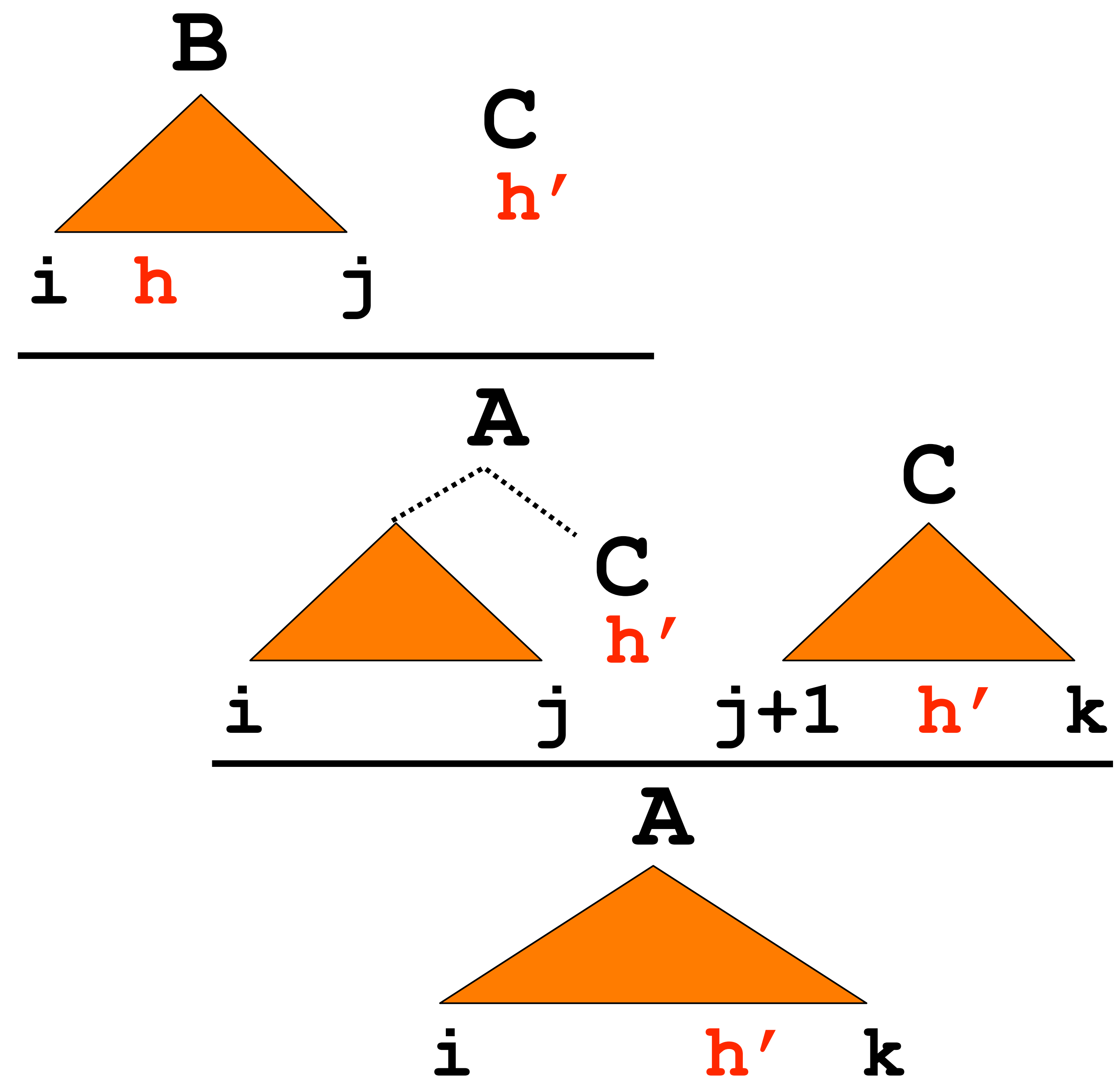




Idea #1

(the old CKY way)





Transform the grammar

Transform the grammar

- (Lossy?) Transformation to a “split grammar”:

Transform the grammar

- (Lossy?) Transformation to a "split grammar":
  - Each head eats all its right dependents first

Transform the grammar

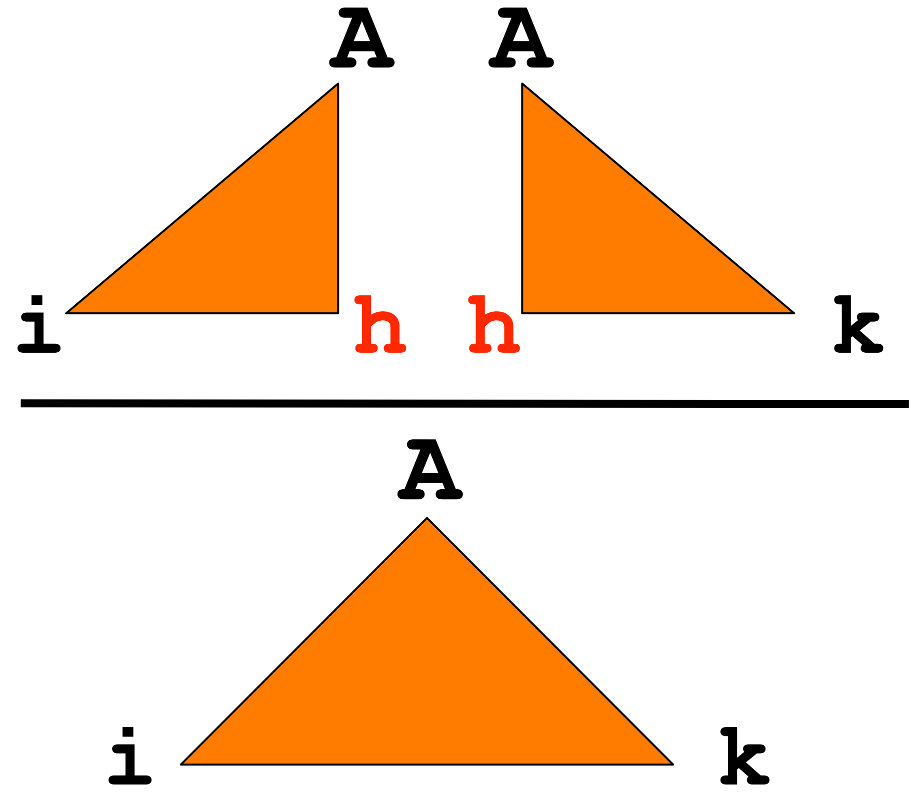
- (Lossy?) Transformation to a “split grammar”:
  - Each head eats all its right dependents first
  - I.e., left dependents are more oblique.

Transform the grammar

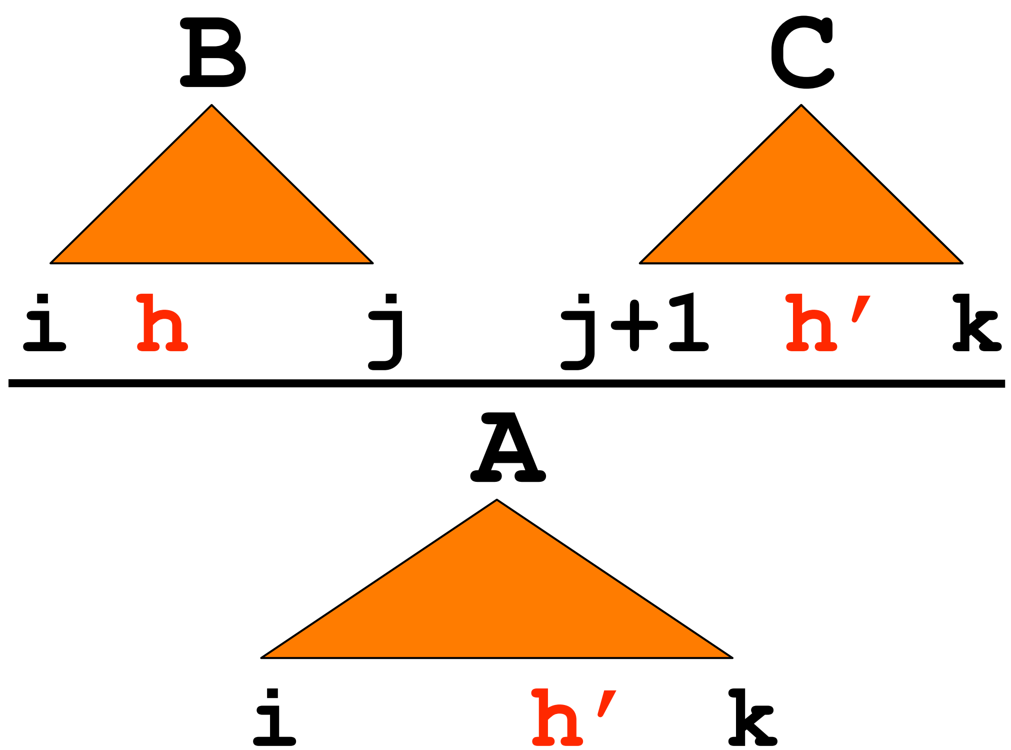
- (Lossy?) Transformation to a “split grammar”:
  - Each head eats all its right dependents first
  - I.e., left dependents are more oblique.

Transform the grammar

- (Lossy?) Transformation to a "split grammar":
  - Each head eats all its right dependents first
  - I.e., left dependents are more oblique.
- This allows



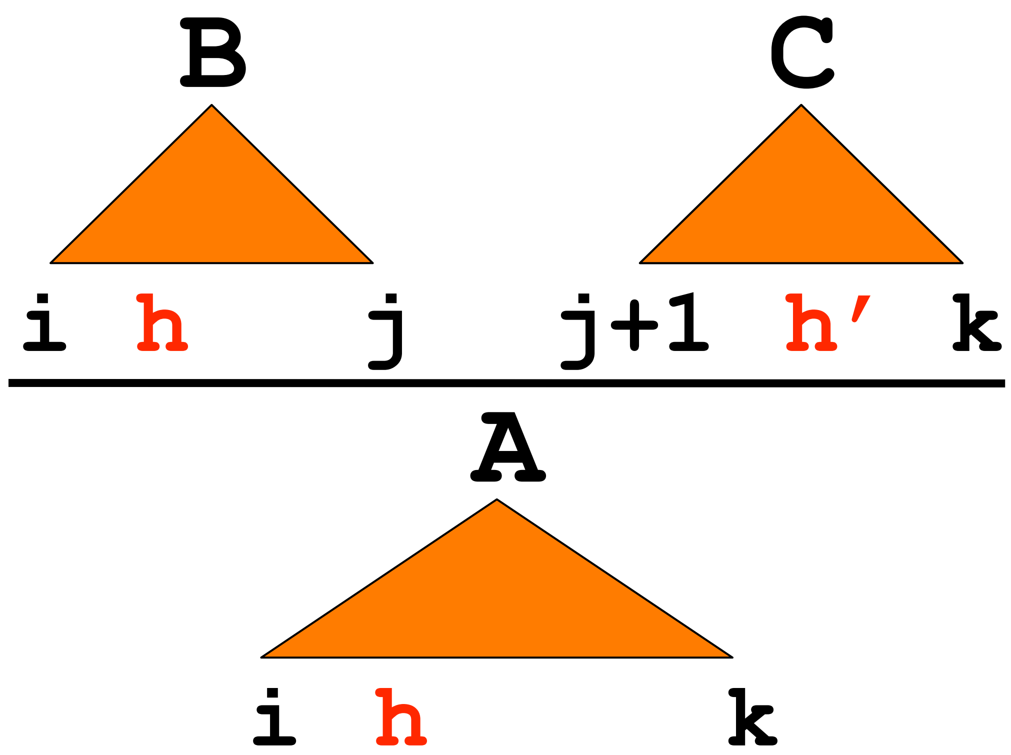
Idea #2

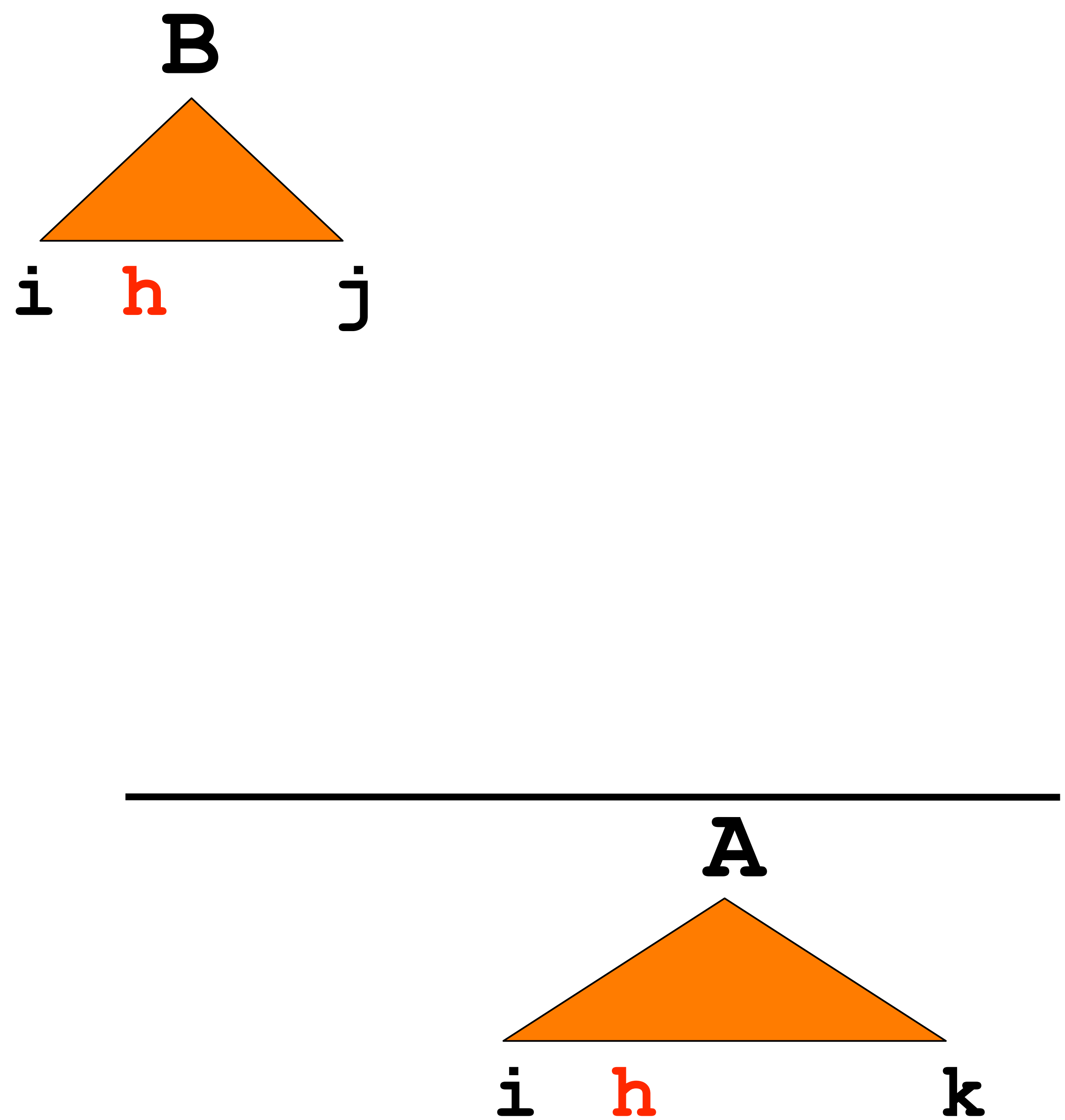


- Combine what B and C?
  - must try different-width C's (vary **k**)
  - must try different midpoints **j**
  - Separate these!

Idea #2

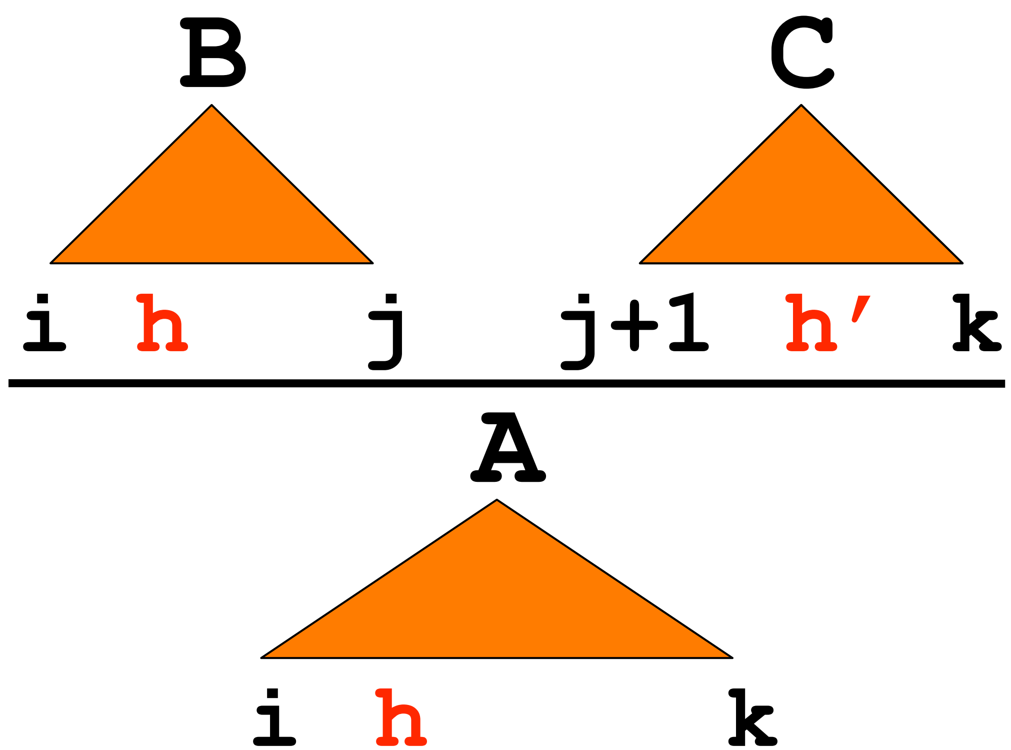
(the old CKY way)

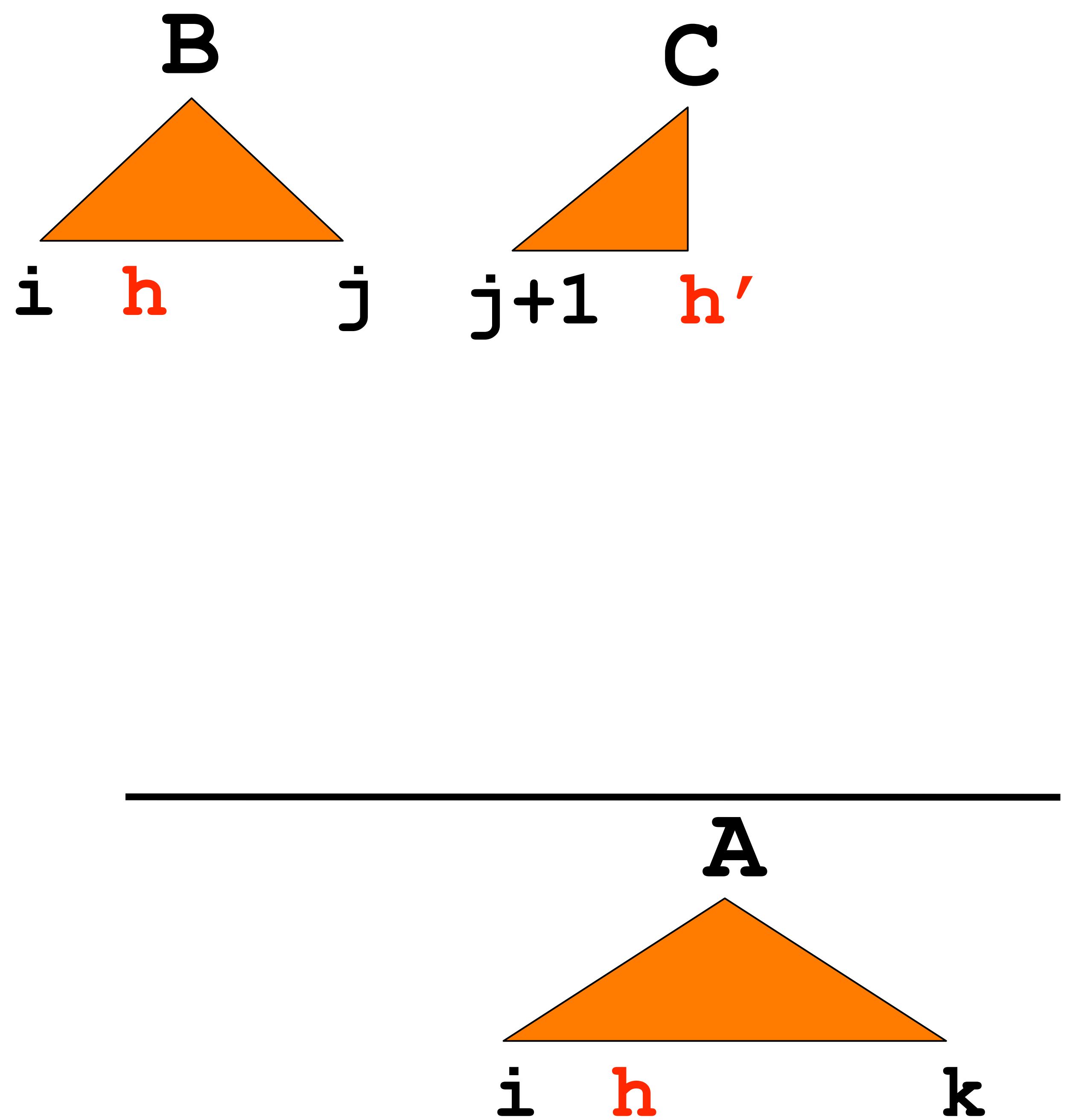




Idea #2

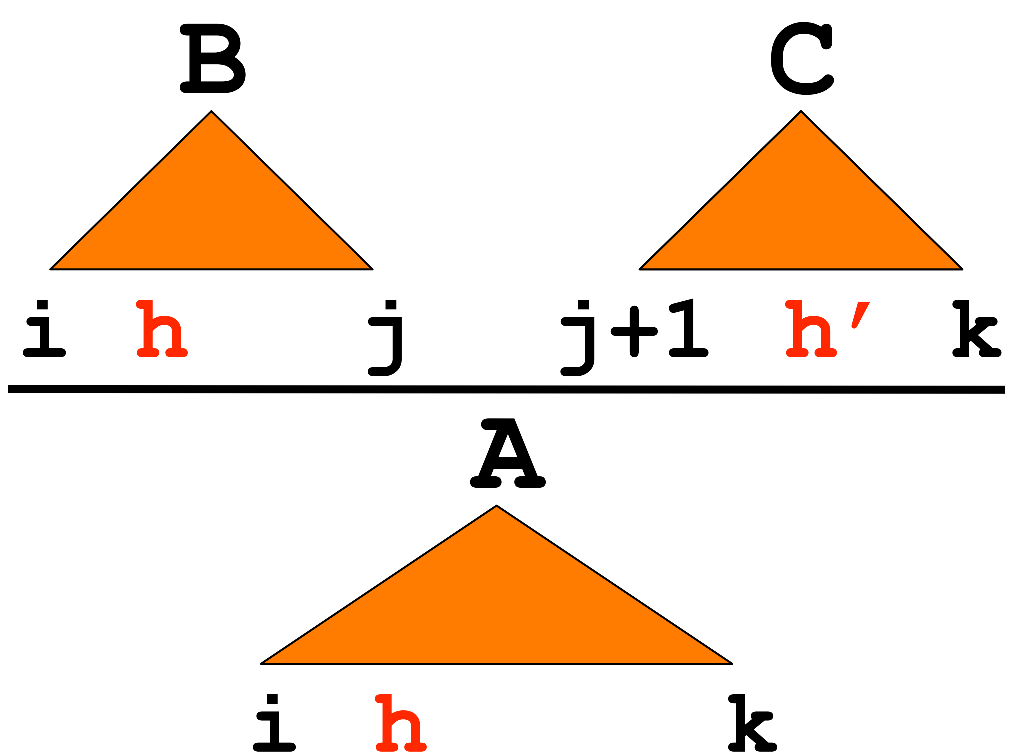
(the old CKY way)

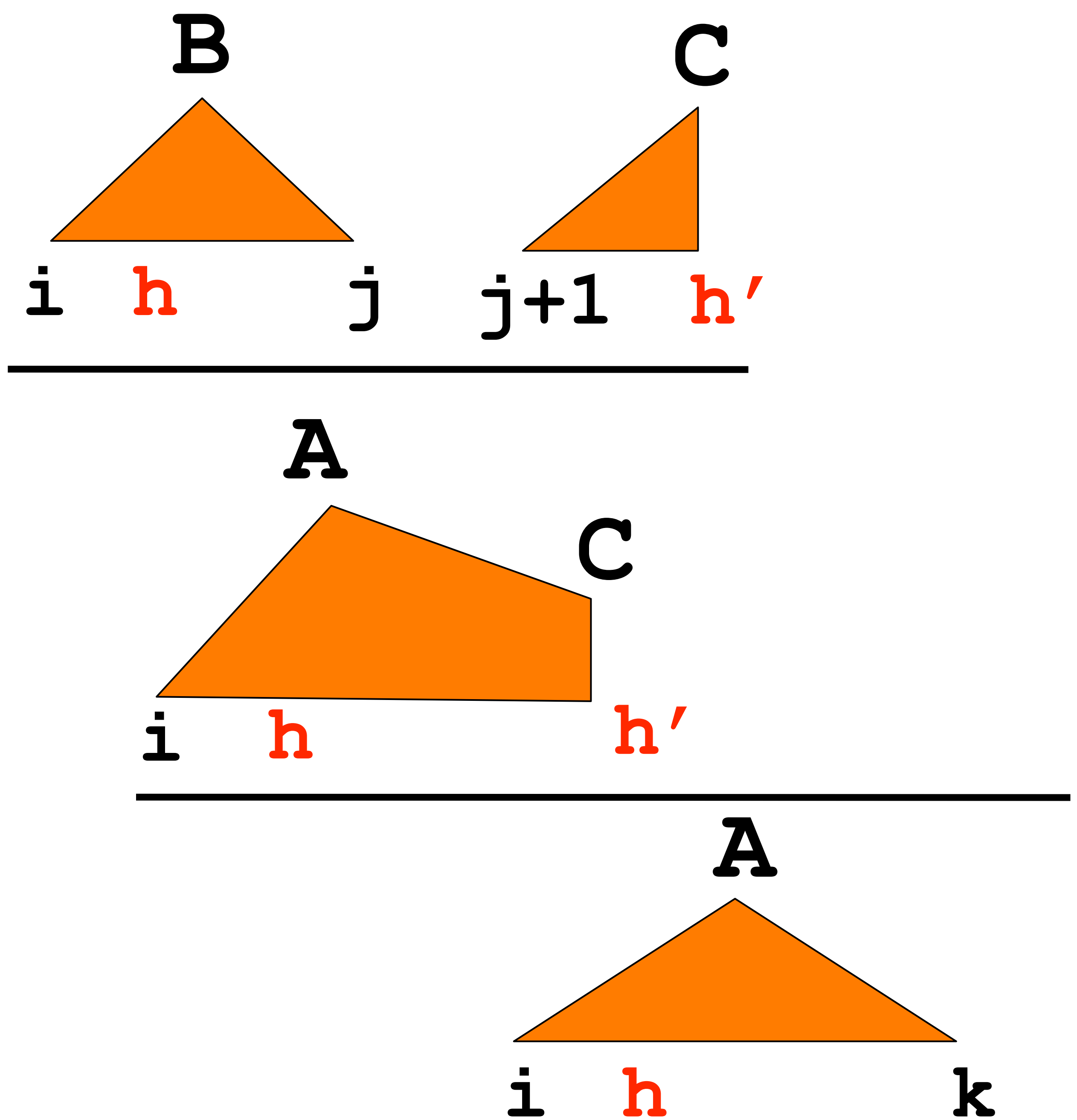




Idea #2

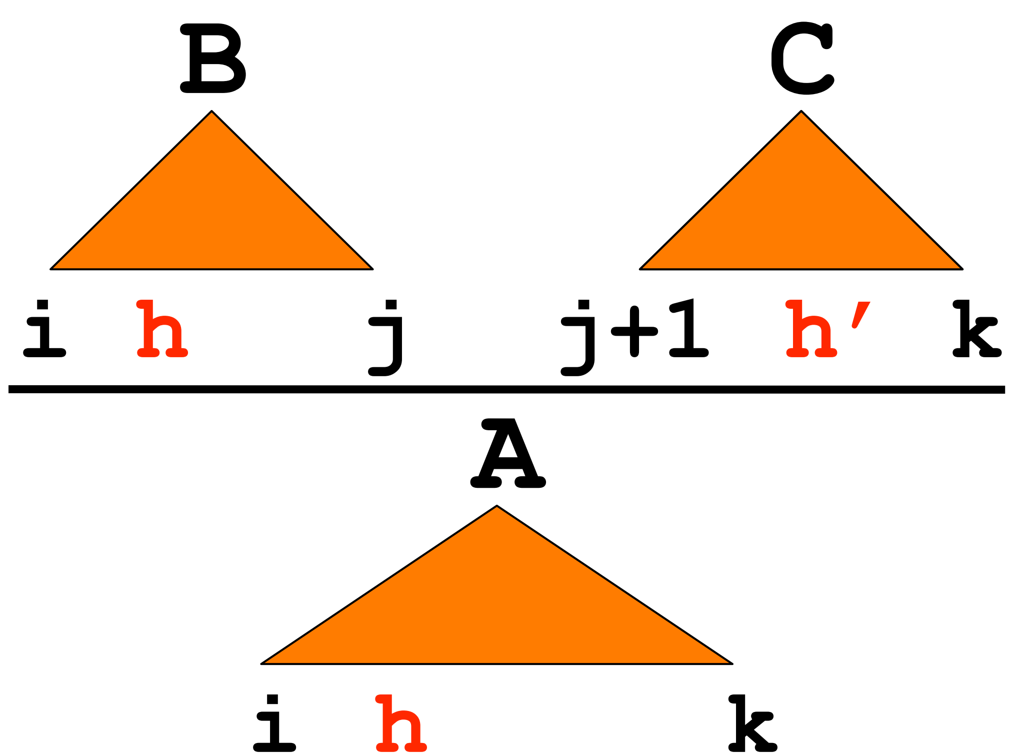
(the old CKY way)

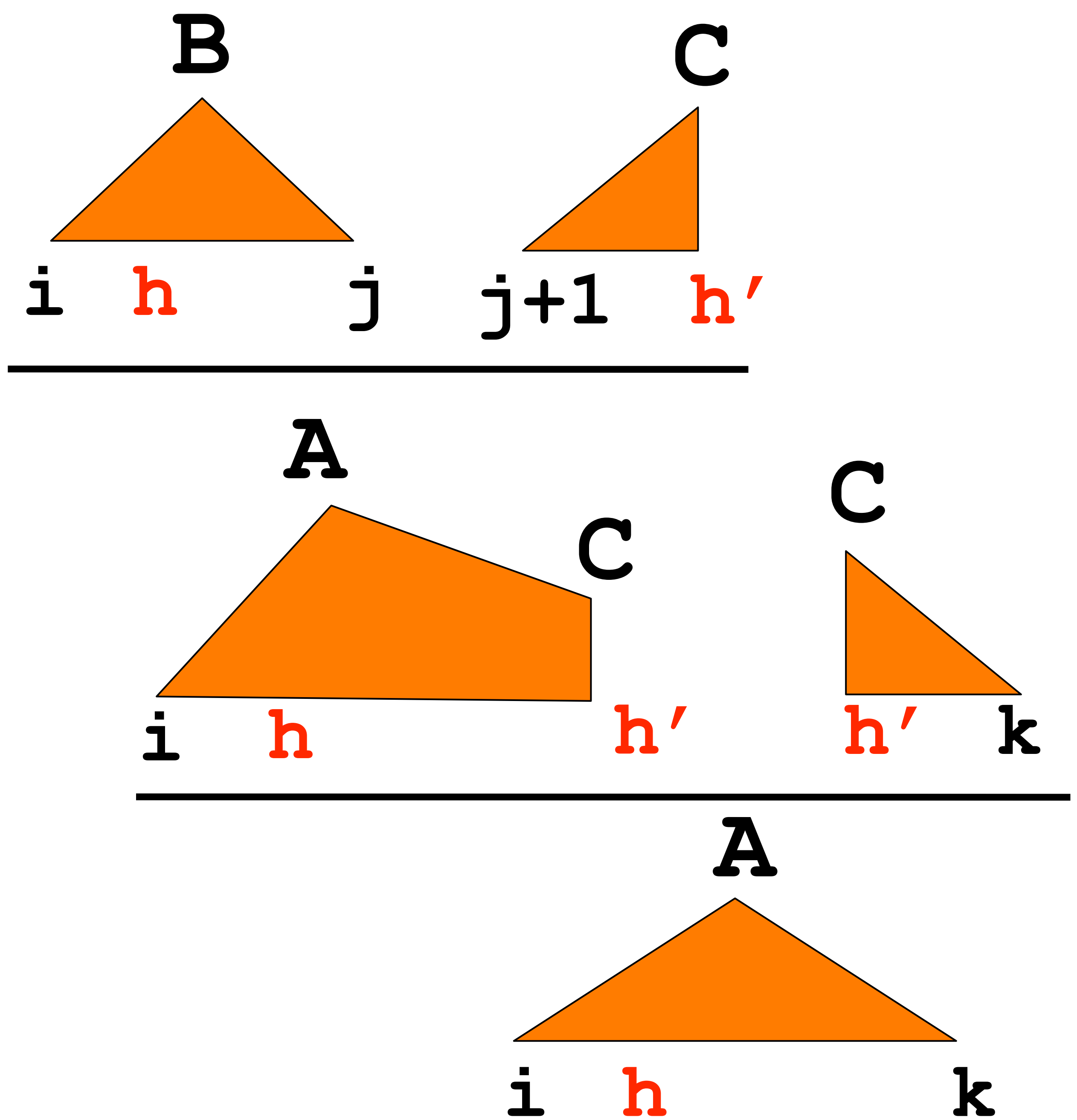




Idea #2

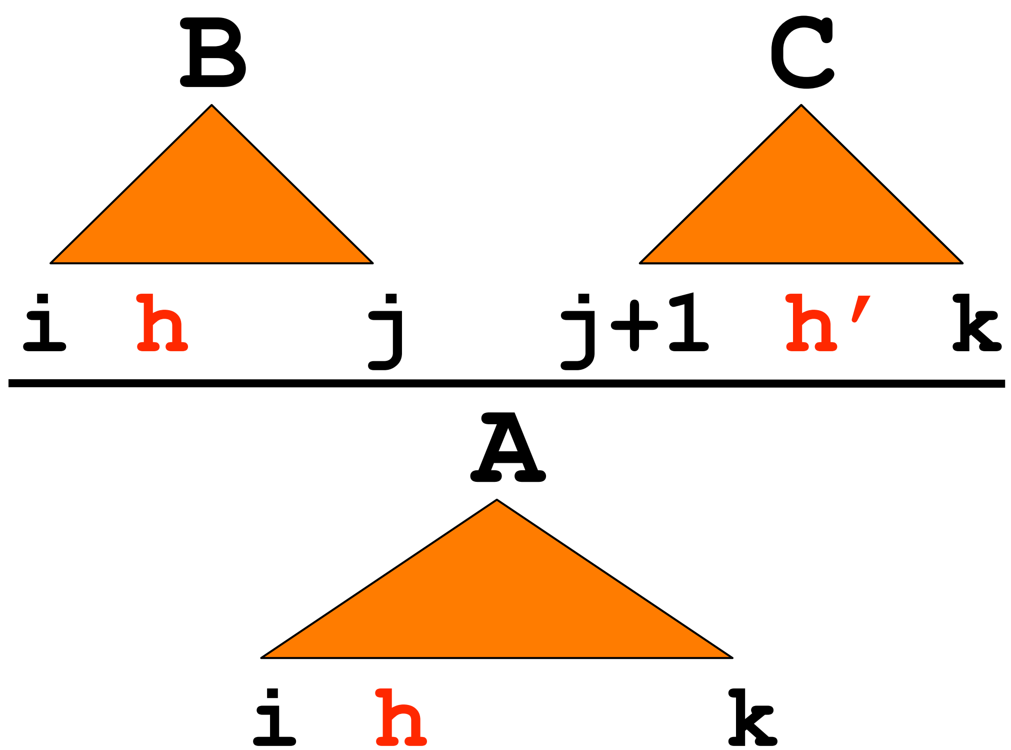
(the old CKY way)

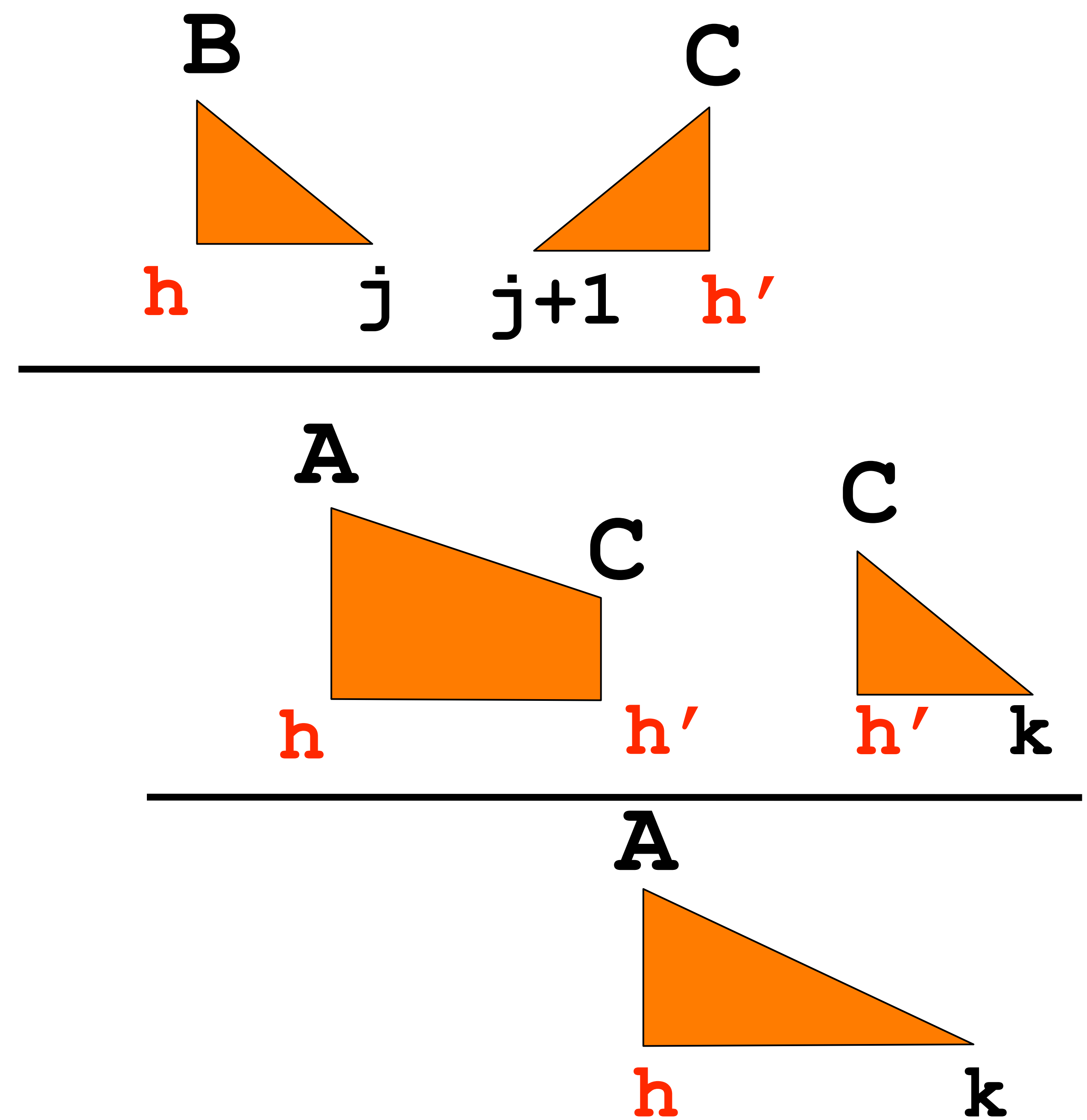




Idea #2

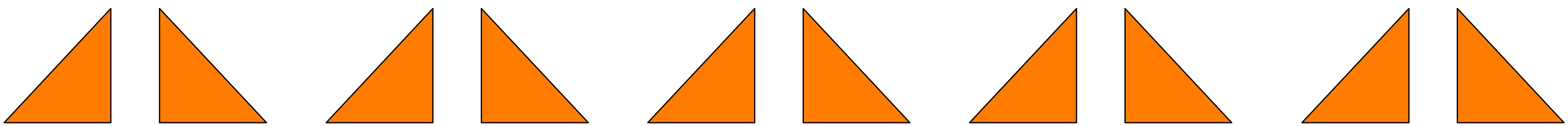
(the old CKY way)



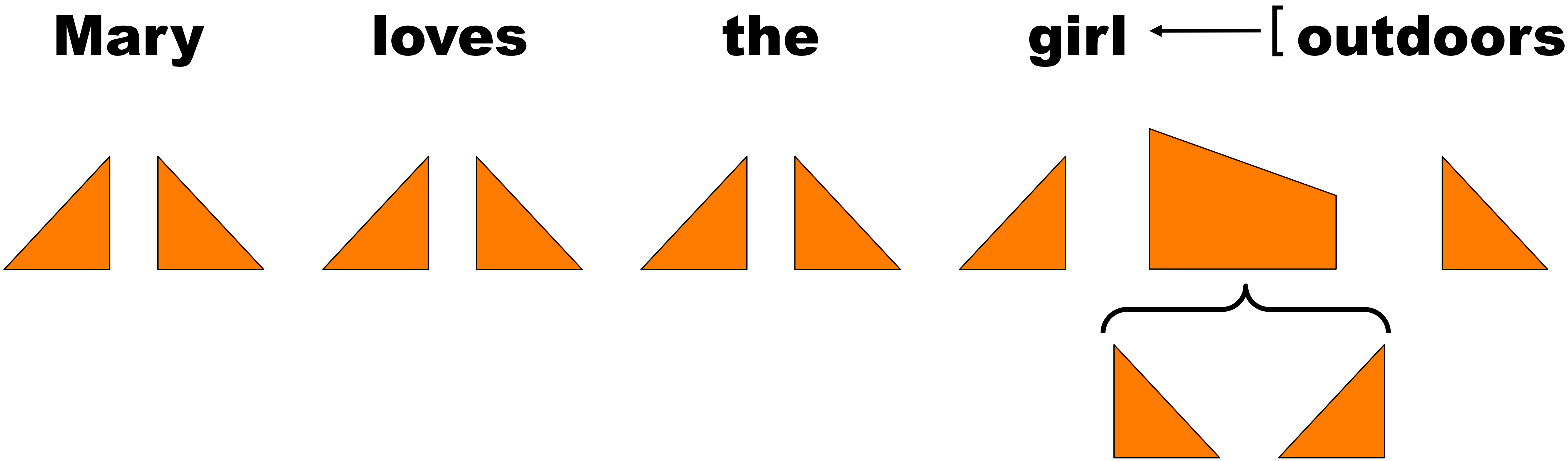


The $O(n^3)$ half-tree algorithm

Mary **loves** **the** **girl** **outdoors**

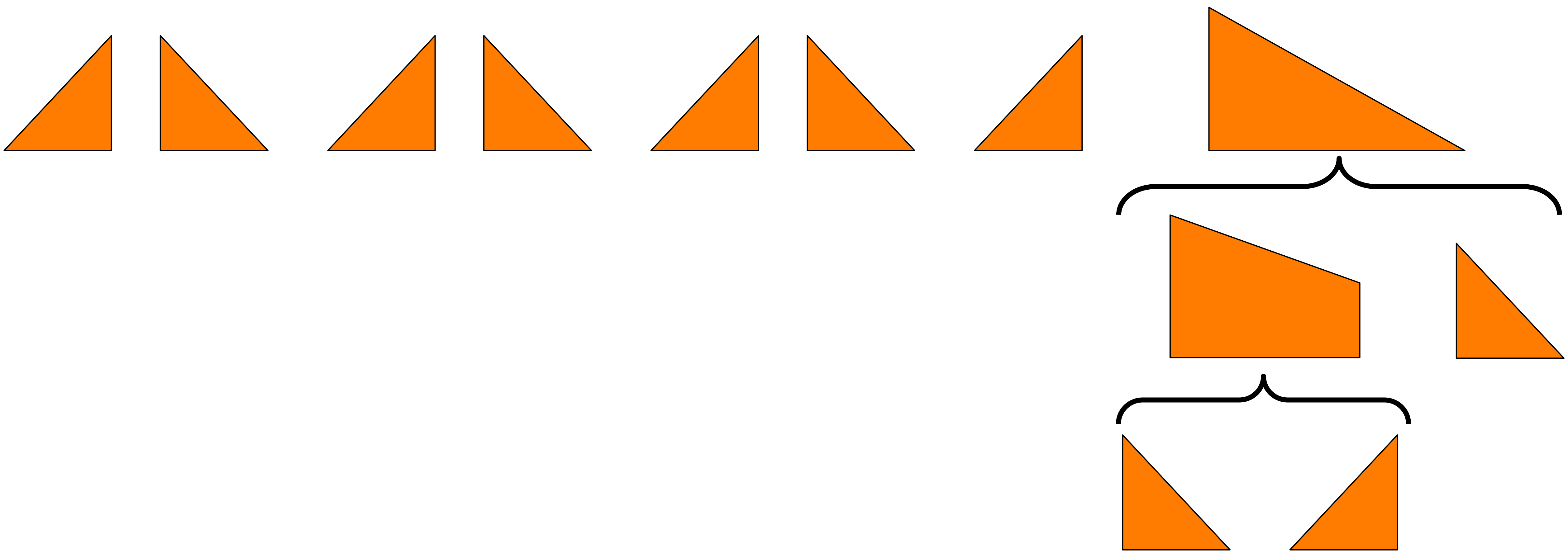


The $O(n^3)$ half-tree algorithm

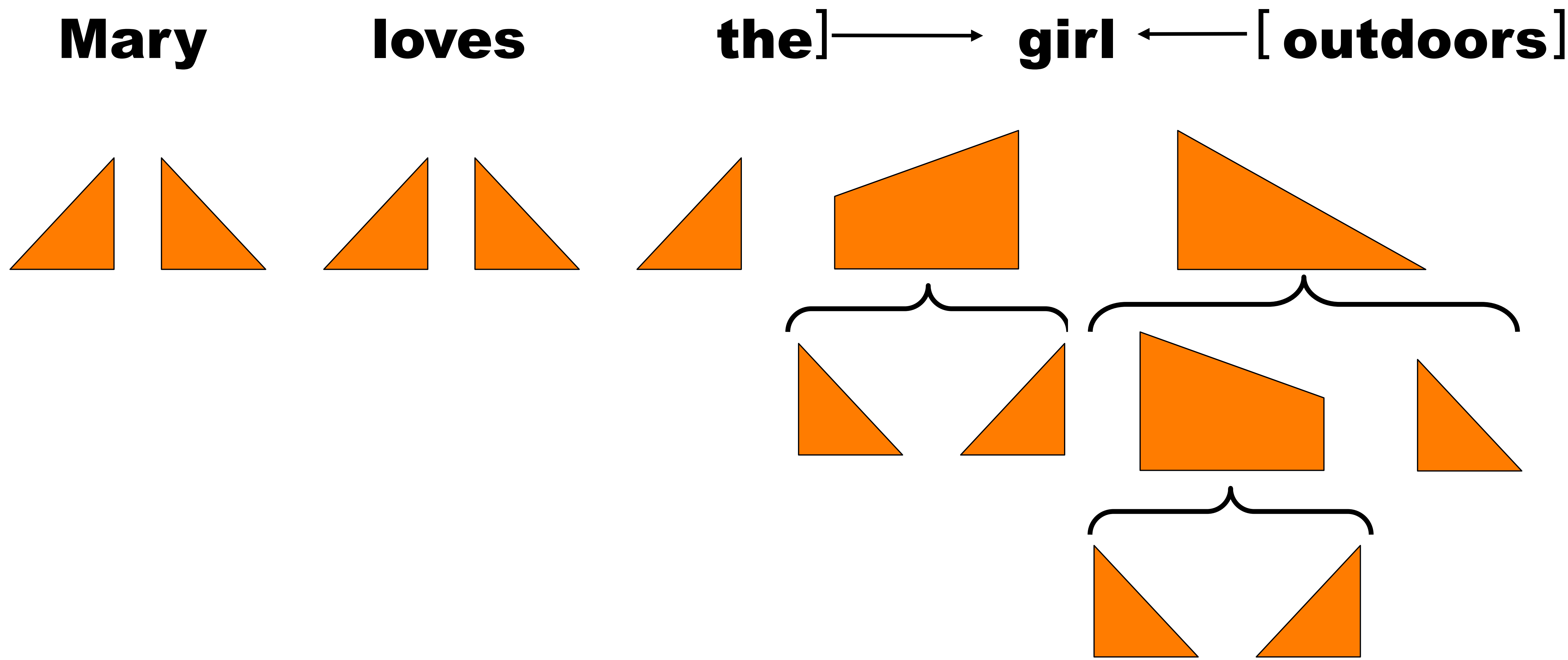


The O(n^3) half-tree algorithm

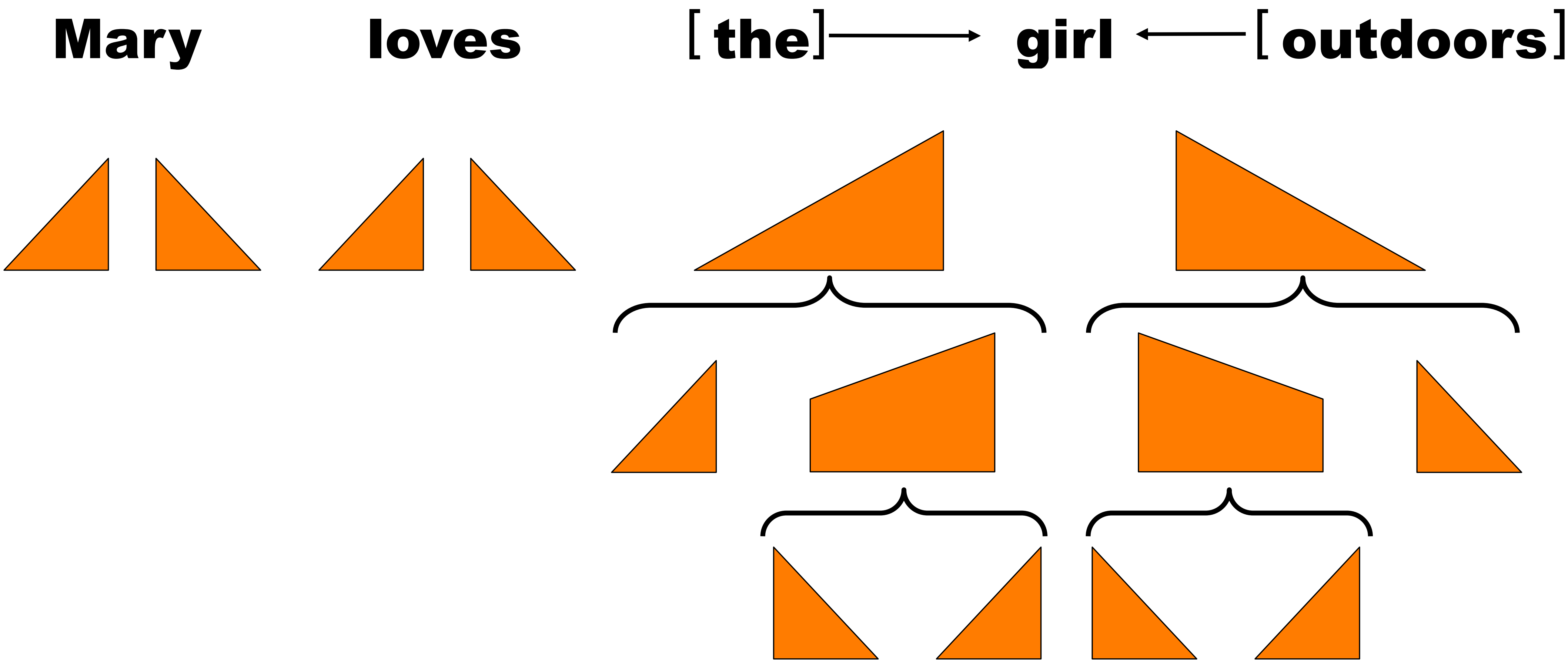
Mary loves the girl ⟵ [outdoors]



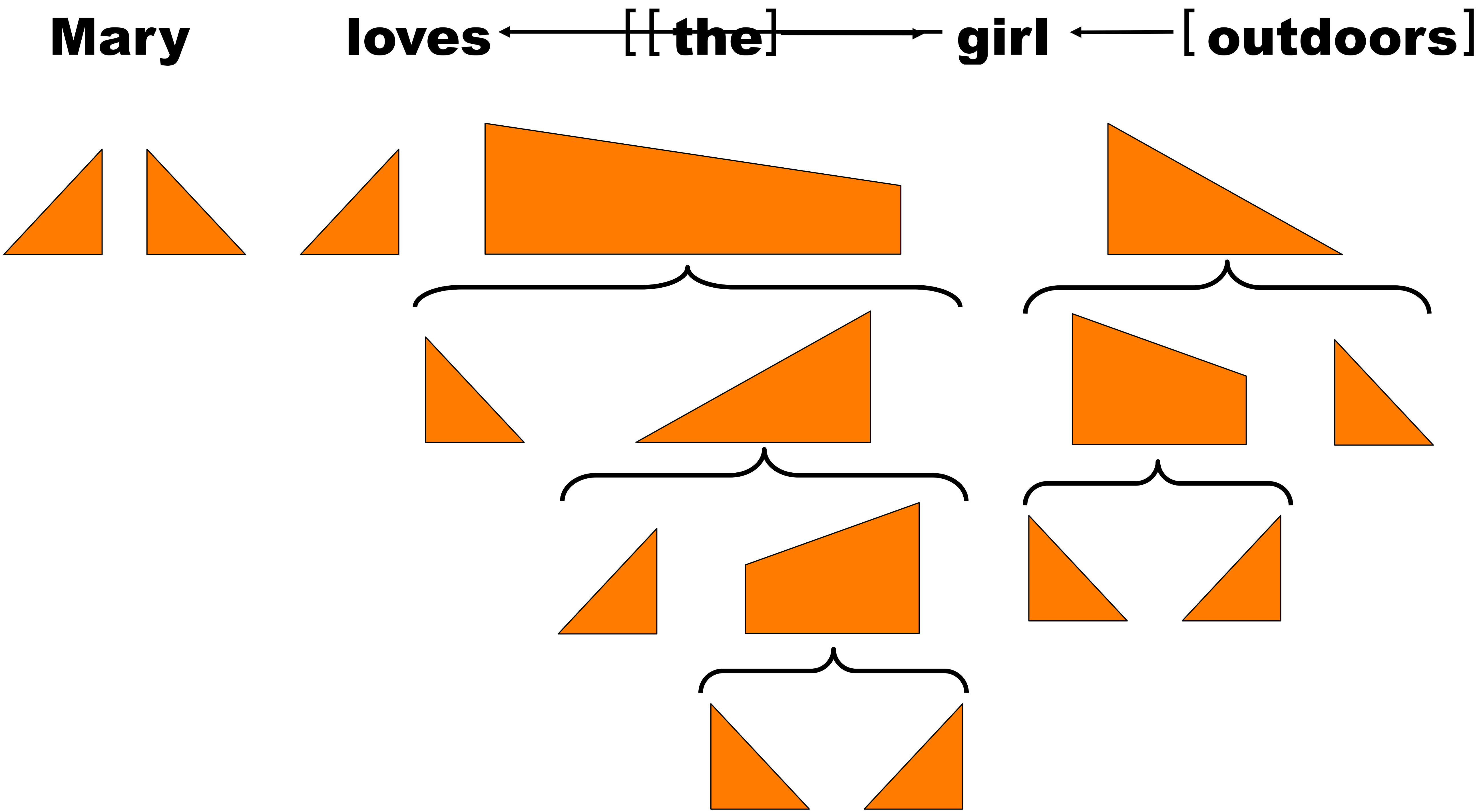
The $O(n^3)$ half-tree algorithm



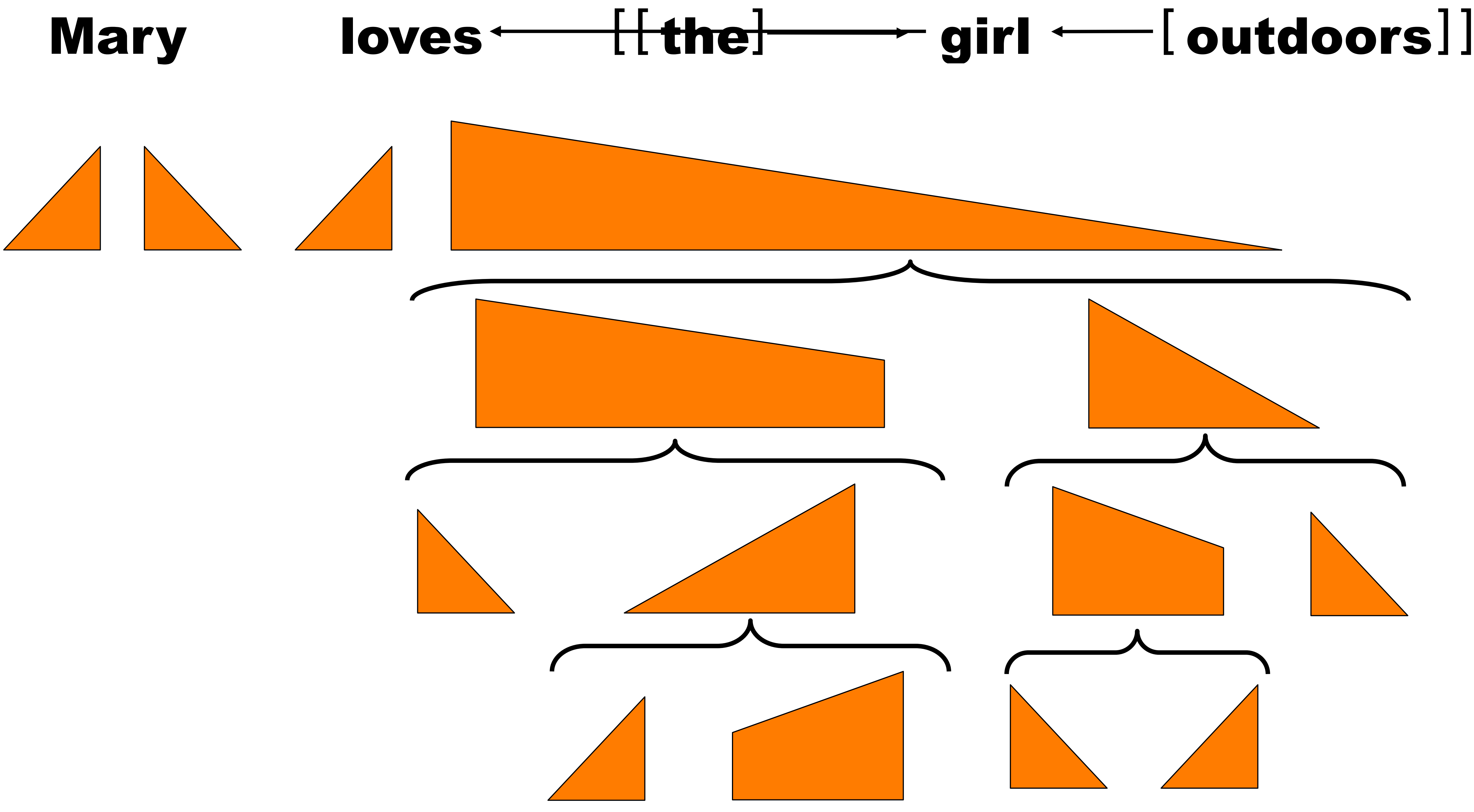
The $O(n^3)$ half-tree algorithm



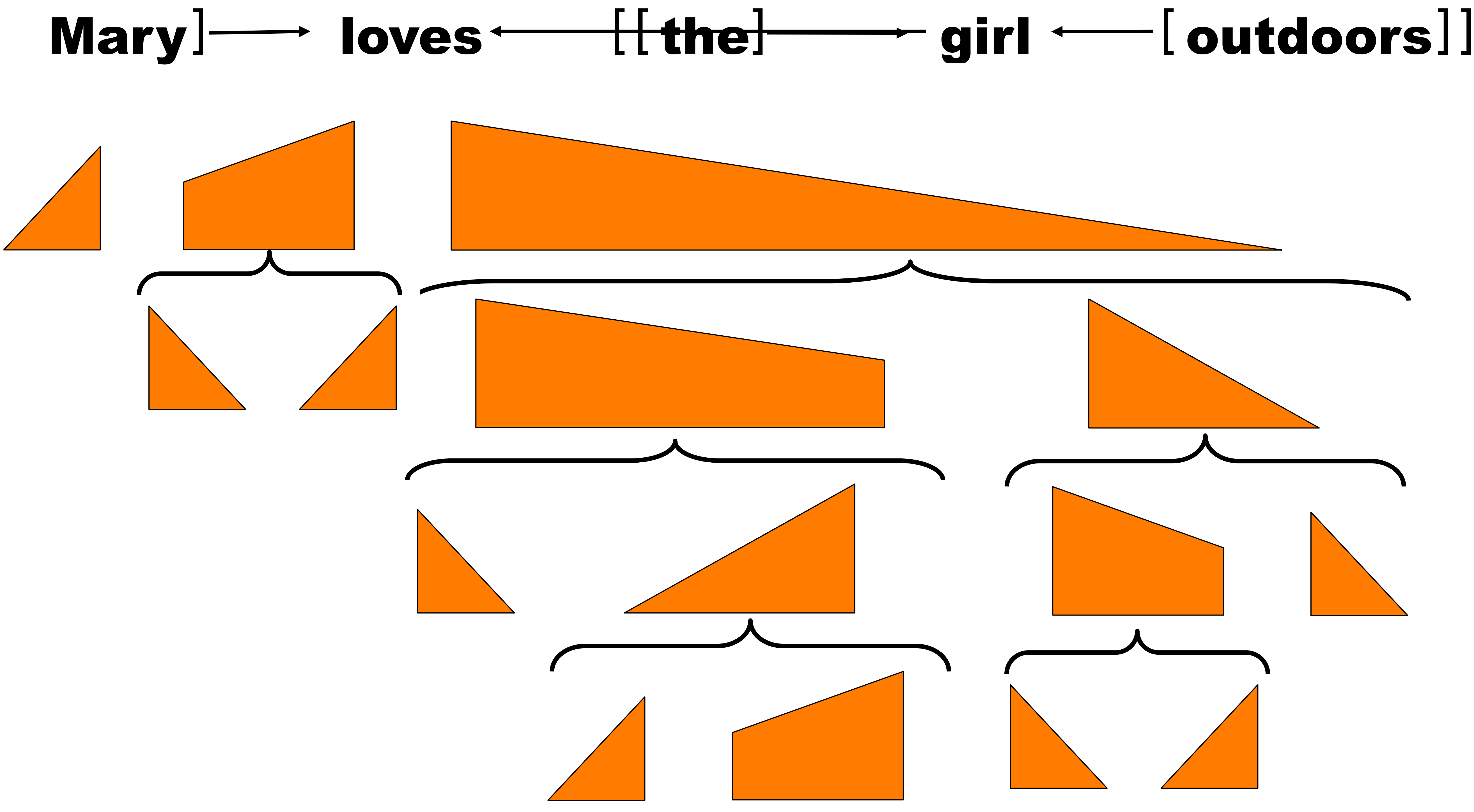
The $O(n^3)$ half-tree algorithm



The O(n^3) half-tree algorithm

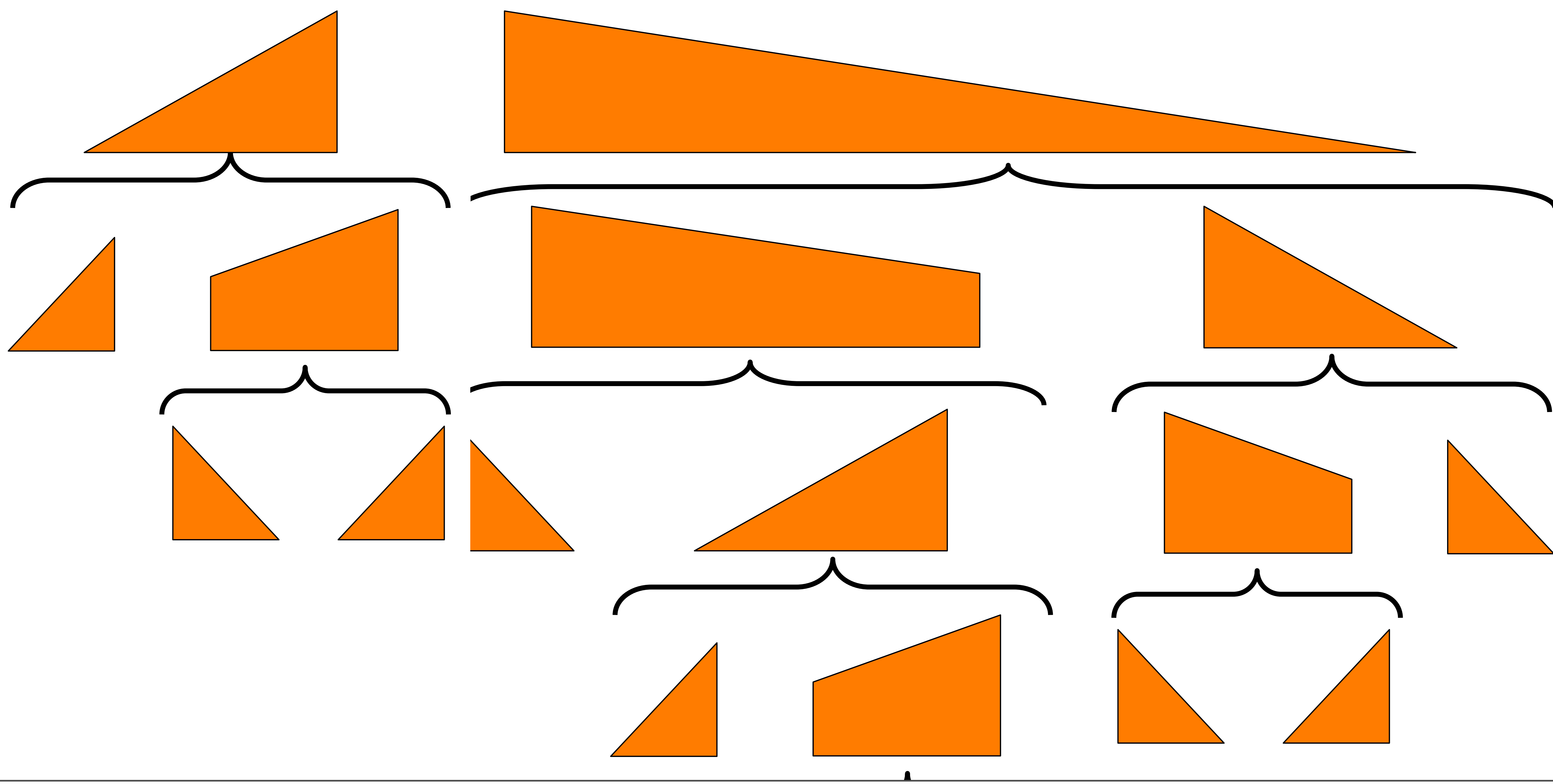


The O(n^3) half-tree algorithm



The O(n³) half-tree algorithm

[Mary] loves [[the] girl [outdoors]]



Theoretical Speedup

Theoretical Speedup

- **n** = input length **g** = polysemy

Theoretical Speedup

- **n** = input length   **g** = polysemy
- **t** = traditional nonterms or automaton states

Theoretical Speedup

- **n** = input length **g** = polysemy
- **t** = traditional nonterms or automaton states
- Naive: $\mathbf{O(n^5 g^2 t)}$

Theoretical Speedup

- **n** = input length **g** = polysemy
- **t** = traditional nonterms or automaton states
- Naive: $\mathbf{O(n^5 g^2 t)}$
- New: $\mathbf{O(n^4 g^2 t)}$

Theoretical Speedup

- **n** = input length **g** = polysemy
- **t** = traditional nonterms or automaton states
- Naive: $\mathbf{O(n^5 g^2 t)}$
- New: $\mathbf{O(n^4 g^2 t)}$
- Even better for split grammars:

Theoretical Speedup

- **n** = input length   **g** = polysemy
- **t** = traditional nonterms or automaton states
- Naive: $\mathbf{O(n^5 g^2 t)}$
- New: $\mathbf{O(n^4 g^2 t)}$
- Even better for split grammars:
  - Eisner (1997): $\mathbf{O(n^3 g^3 t^2)}$

Theoretical Speedup

- **n** = input length **g** = polysemy
- **t** = traditional nonterms or automaton states
- Naive: $\mathbf{O(n^5 g^2 t)}$
- New: $\mathbf{O(n^4 g^2 t)}$
- Even better for split grammars:
  - Eisner (1997): $\mathbf{O(n^3 g^3 t^2)}$
  - New: $\mathbf{O(n^3 g^2 t)}$

Theoretical Speedup

- **n** = input length **g** = polysemy
- **t** = traditional nonterms or automaton states
- Naive: $\mathbf{O(n^5 g^2 t)}$
- New: $\mathbf{O(n^4 g^2 t)}$
- Even better for split grammars:
  - Eisner (1997): $\mathbf{O(n^3 g^3 t^2)}$
  - New: $\mathbf{O(n^3 g^2 t)}$

all independent of vocabulary size!

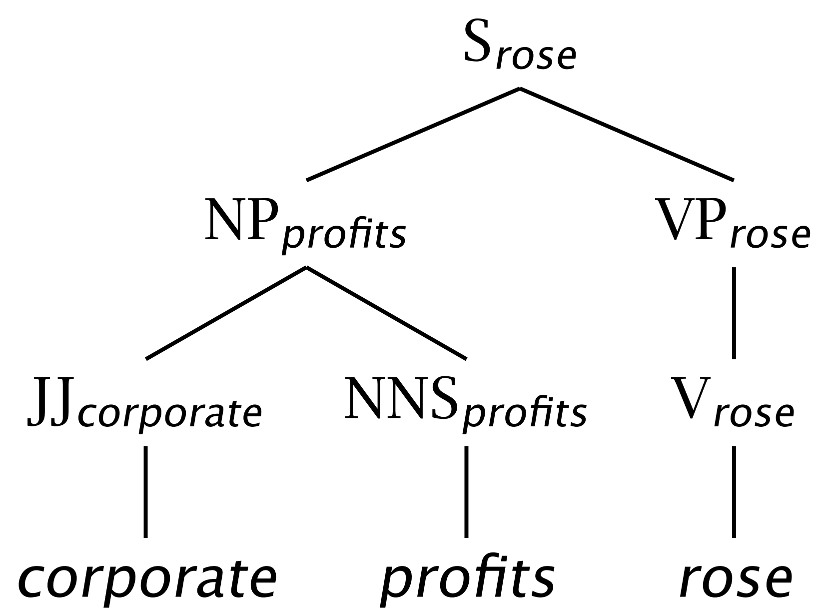
Midterm on Thursday

- 75 min. exam with one 8.5x11 cheat sheet
- Major topics:
  - Regular expressions
  - N-gram language models
  - Simple estimations and smoothing
  - HMMs: Viterbi and Forward-Backward
  - CFGs: CKY and Earley's algorithm

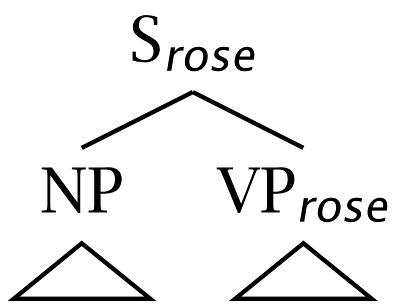
Lexicalized Parsing, with smoothing

Lexicalized parsing [Charniak 1997]

- A very simple, conservative model of lexicalized PCFG
- Probabilistic conditioning is “top-down” (but actual computation is bottom-up)



[Charniak 1997]
Generate head, then head constituent & rule

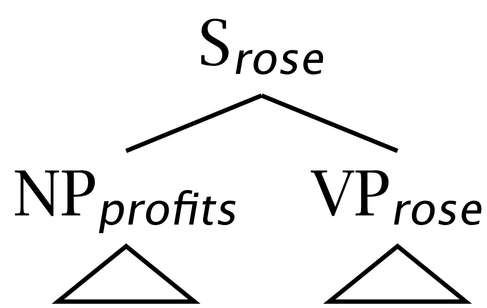


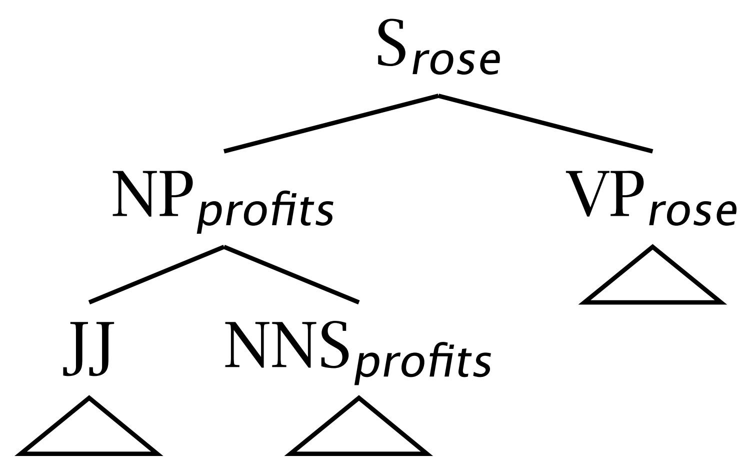
h = *profits*; c = NP

ph = *rose*; pc = S

$P(h|ph, c, pc)$

$P(r|h, c, pc)$





h=head word, c=head consituent
ph=parent head word, parent head constituent

Smoothing in [Charniak 1997]

$$\begin{aligned}\hat{P}(h|ph,c,pc) &= \lambda_1(e)P_{\mathrm{MLE}}(h|ph,c,pc)\\ &\quad +\lambda_2(e)P_{\mathrm{MLE}}(h|C(ph),c,pc)\\ &\quad +\lambda_3(e)P_{\mathrm{MLE}}(h|c,pc)+\lambda_4(e)P_{\mathrm{MLE}}(h|c)\end{aligned}$$

- $\lambda_i(e)$ is here a function of how much one would expect to see a certain occurrence, given the amount of training data, word counts, etc.
- $C(ph)$ is semantic class of parent headword
- Techniques like these for dealing with data sparseness are vital to successful model construction

[Charniak 1997] smoothing example

	$P(\text{prft}\mid\text{rose}, \text{NP}, \text{S})$	$P(\text{corp}\mid\text{prft}, \text{JJ}, \text{NP})$
$P(h\mid ph, c, pc)$	0	0.245
$P(h\mid C(ph), c, pc)$	0.00352	0.0150
$P(h\mid c, pc)$	0.000627	0.00533
$P(h\mid c)$	0.000557	0.00418

- Allows utilization of rich highly conditioned estimates, but smoothes when sufficient data is unavailable
- One can't just use MLEs: one commonly sees previously unseen events, which would have probability 0.

[Charniak 1997]
Rule probability with similar smoothing

$$
\begin{aligned}
P(r|h,hc,pc) = &\lambda_1(e)P(r|h,hc,pc)\\
&\lambda_2(e)P(r|h,hc)\\
&\lambda_3(e)P(r|\mathrm{C}(h),hc)\\
&\lambda_4(e)P(r|hc,pc)\\
&\lambda_5(e)P(r|hc)
\end{aligned}
$$