

# Unifying Linguistic, Musical and Visual Processing

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# What do Language, Music and Image have in common?

E.g.:

Language:

"List the sales of products in 2003"

Music:

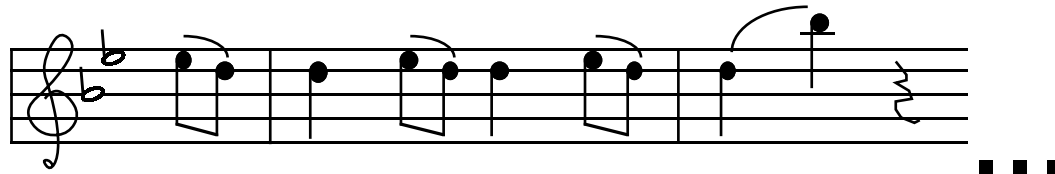
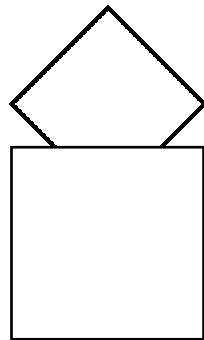


Image:



At first sight very little...

# How do we perceive Language, Music and Image?

Inherent to all forms of perception:

*A structuring process in groups, subgroups, sub-subgroups, etc.*

It is virtually impossible *not* to perceive structure

(People even assign structure to noise...)

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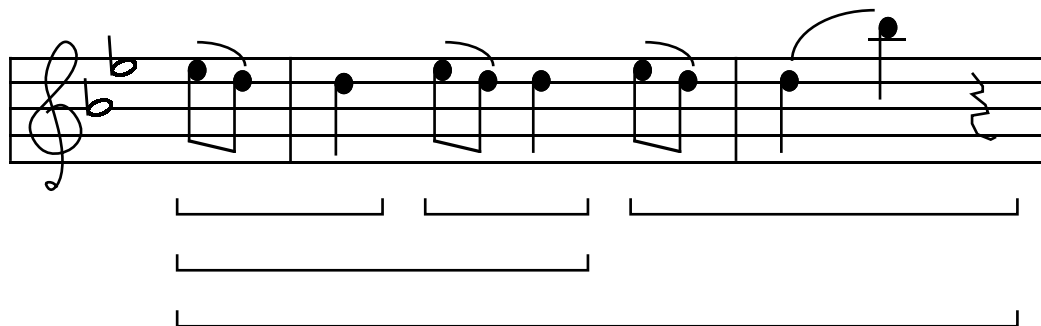
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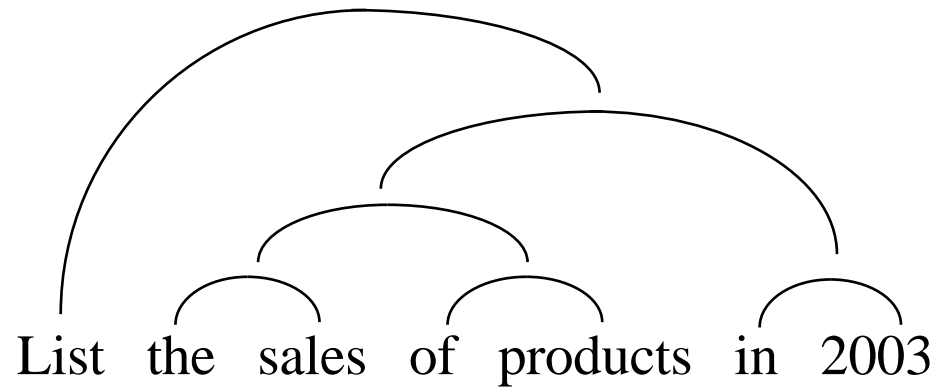
In music, grouping structure is typically represented as:





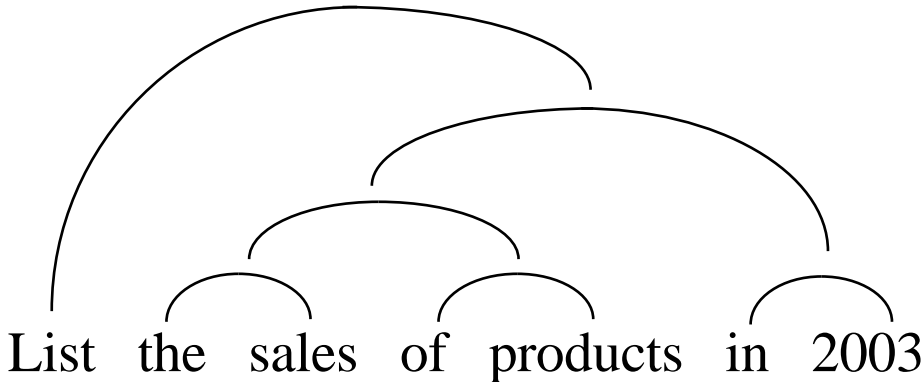
# Grouping Structure in Language

Groups in language form a *tree structure* (Wundt 1880):

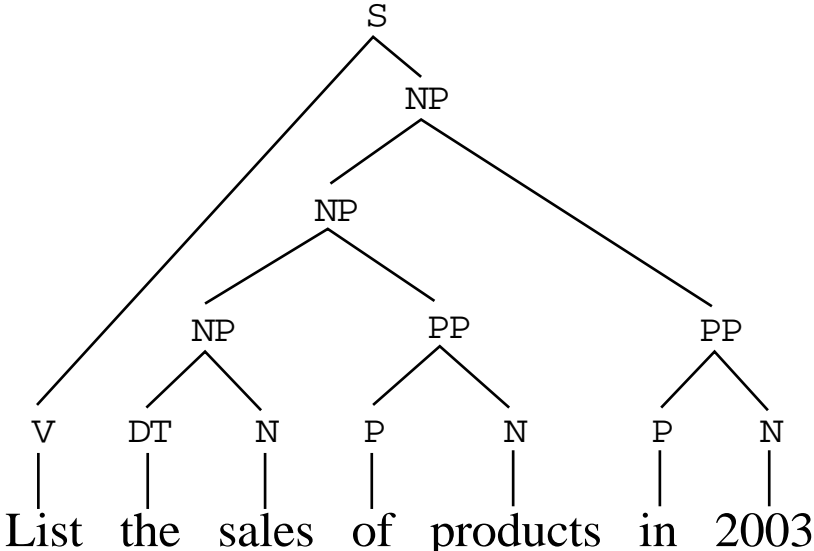
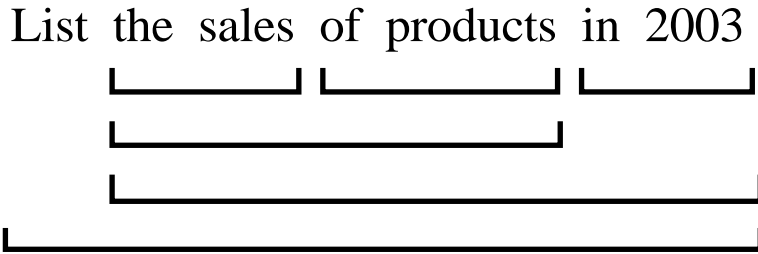


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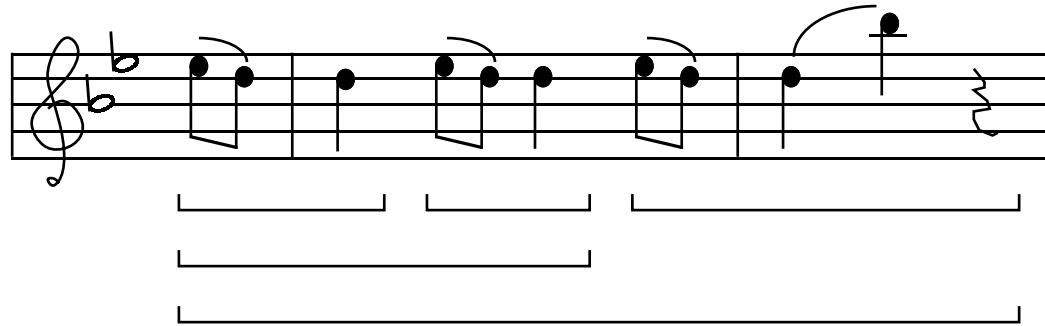
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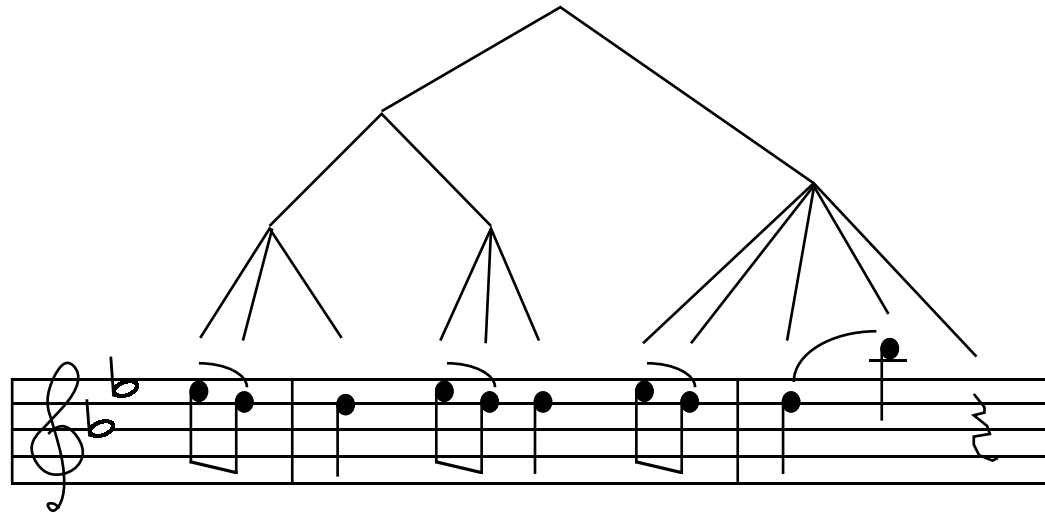
Grouping structure in different representations (Chomsky 1956):



# Grouping Structure = Tree Structure

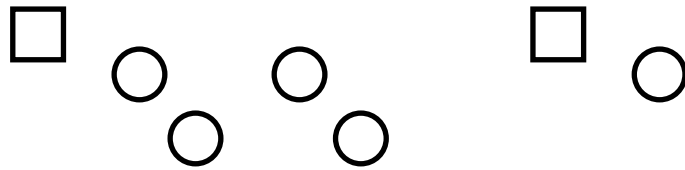


is equivalent (isomorphic) with:

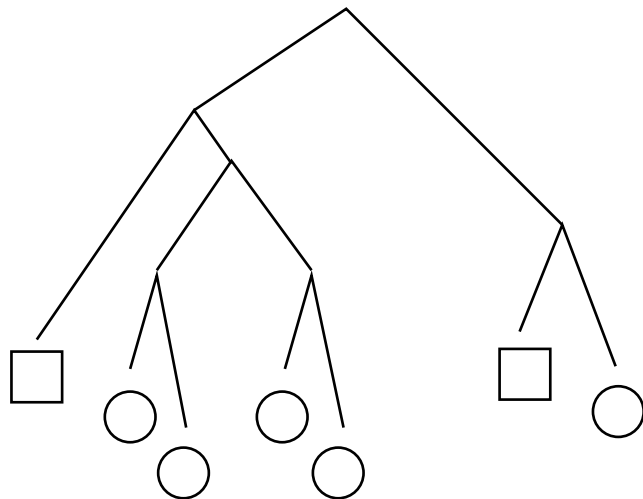


# Also Visual Groups form a Tree Structure

According to Wertheimer (1923) the visual input

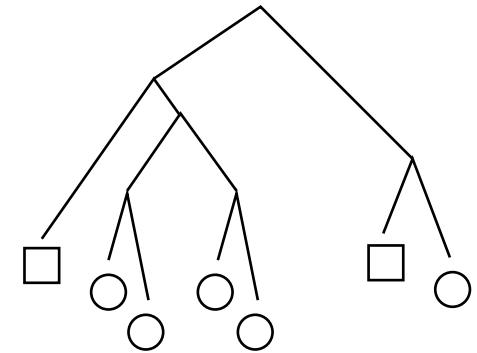
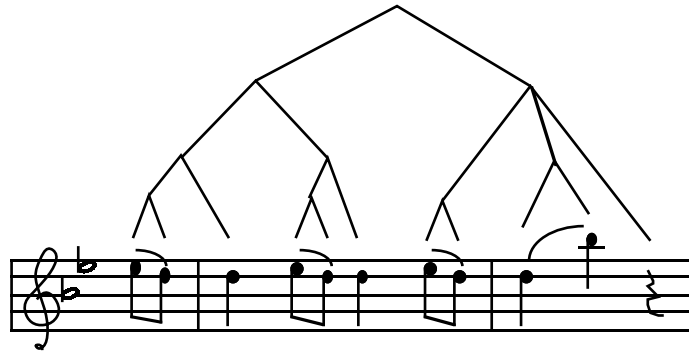
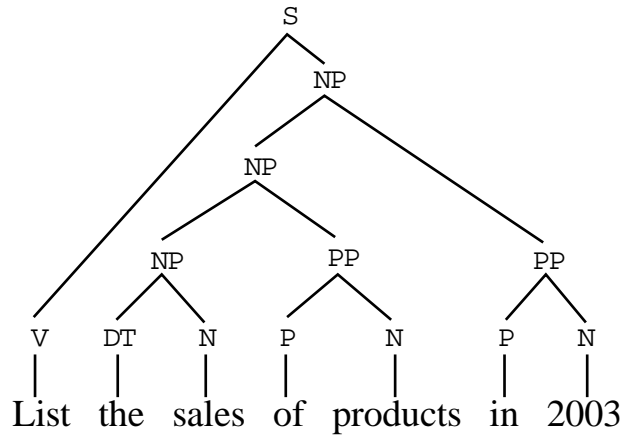


is assigned the following structure:



Perceptual structuring forms the link between low-level segmentation and higher-level interpretation algorithms

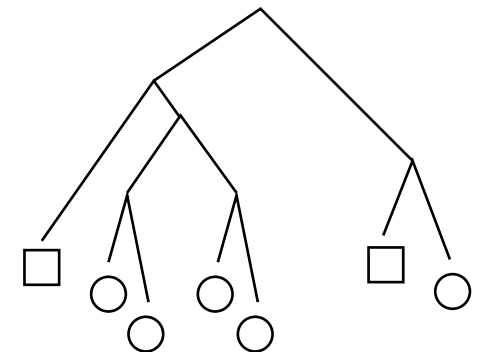
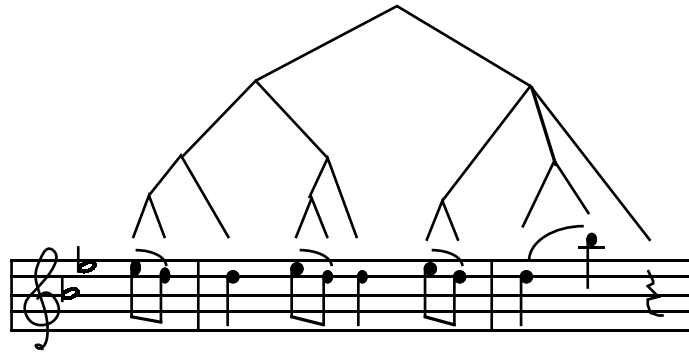
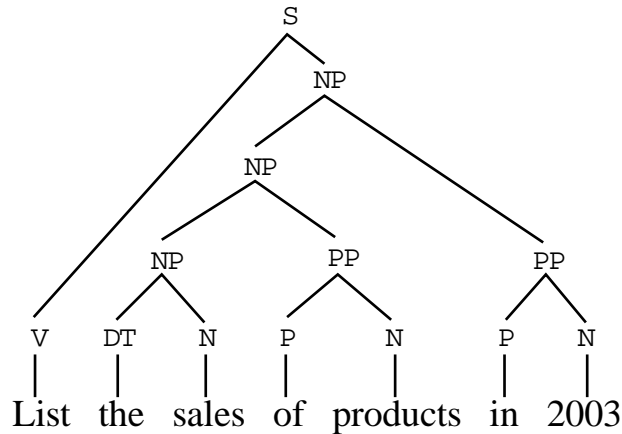
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## Relatively Uncontroversial:

There exists *one representation* for structural perception for all modalities

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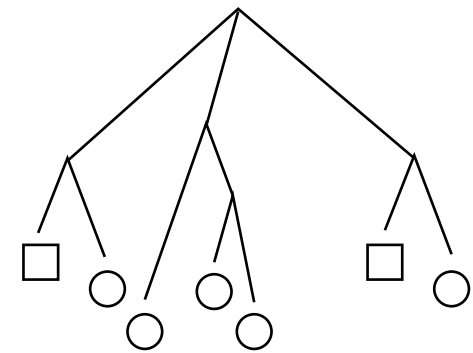
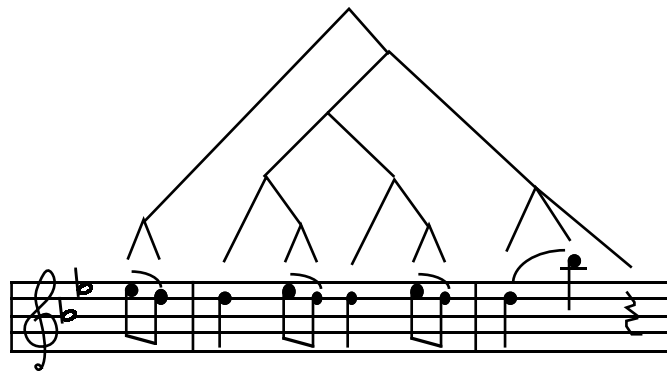
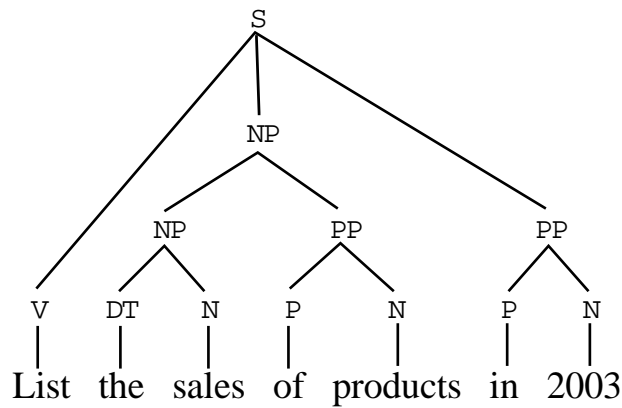
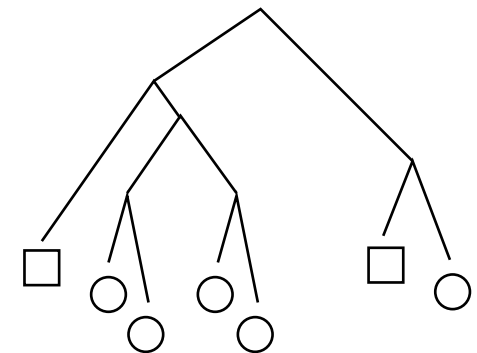
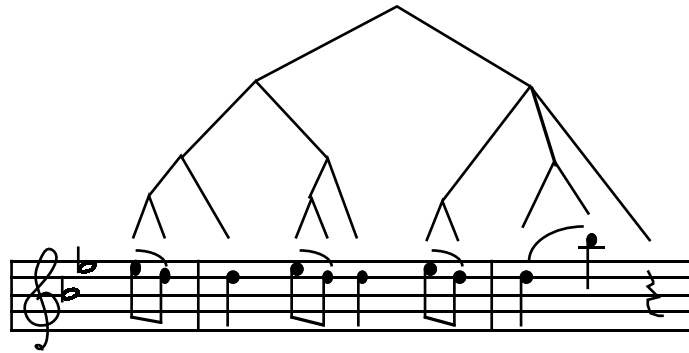
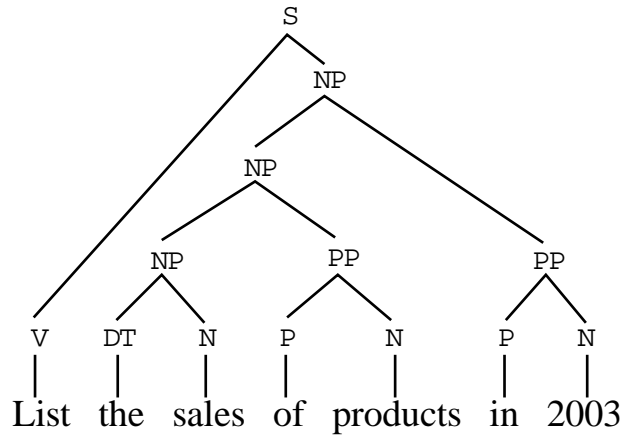
## Relatively Uncontroversial:

There exists *one representation* for structural perception for all modalities

## Very Controversial:

There exists *one model* that predicts the perceived structure in *language, music en vision*

# Additional Problem: Perception is Ambiguous



The same input can be assigned several structures: ambiguity

# Ambiguity is not just a problem

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"Any given sequence of notes is infinitely ambiguous, but this ambiguity is seldom apparent to the listener" (Longuet-Higgins 1987)

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> 96% agreement among subjects (language users)

<b>Language:</b>	<i>Penn Treebank</i>
<b>Music:</b>	<i>Essen Folksong Collection</i>
<b>Vision:</b>	<i>Nijmegen Visual Database</i>

# Historically, two competing principles for solving ambiguity in perception

## 1. **Simplicity Principle** (Wertheimer 1923...Leeuwenberg 2001, Chater 2003)

Preference for the *simplest* structure

## 2. **Likelihood Principle** (Helmholtz 1910...Suppes 1984, Charniak 2001)

Preference for the *most likely* structure

Can these principles still inspire us?

# The Dual Nature of Perception

These principles each play a *different* role in perception:

**Simplicity:** general preference for "economy", "least effort", "shortest derivation"

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**Hypothesis:** perceptual system strives for the *simplest* structure but in doing so it is influenced by the *likelihood* of previous structures

# Possible Measures for Simplicity and Likelihood

**Simplicity:** *number* of "steps" to generate a tree structure

**Likelihood:** joint *probability* of the steps to generate a tree structure

We can compute this if we have a large, representative collection of tree structures for each modality (a "corpus")

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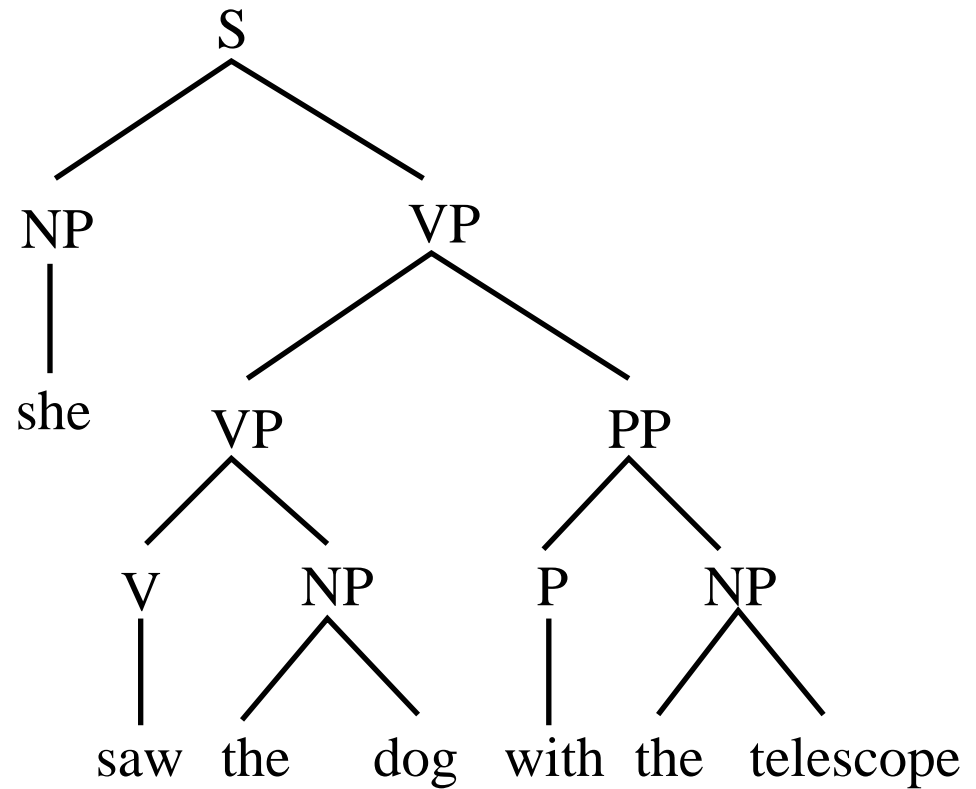
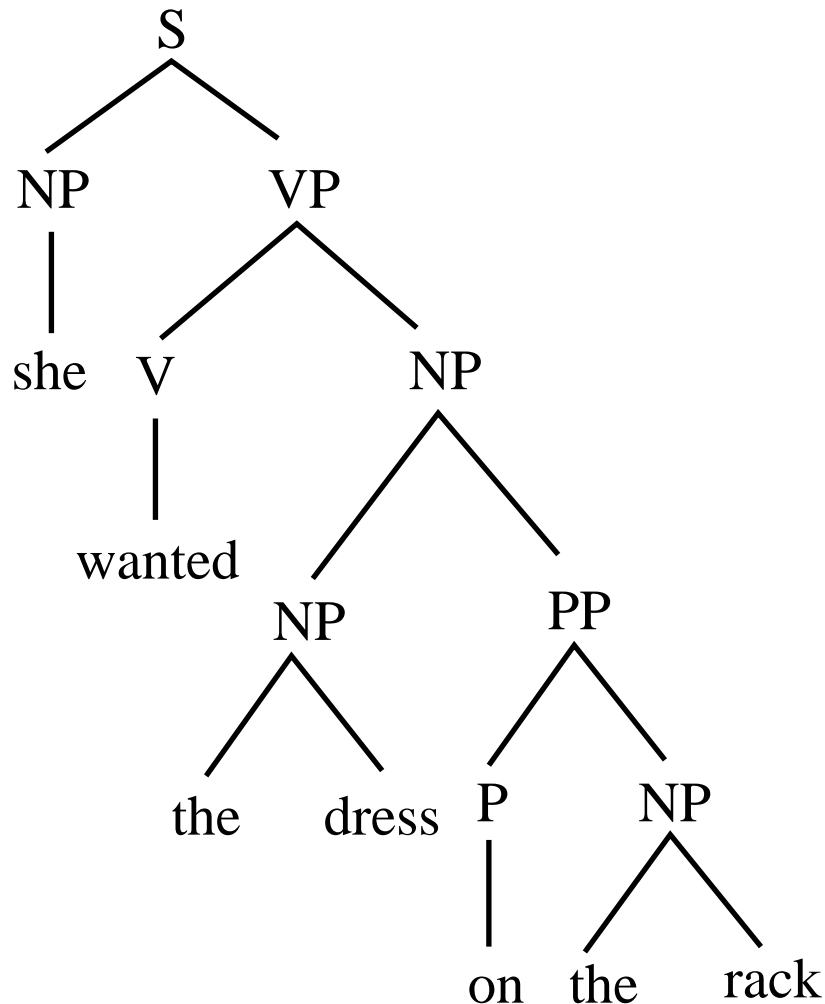
## ***Data-Oriented Parsing model (DOP):***

*New input is analyzed and interpreted out of parts of previously perceived input*

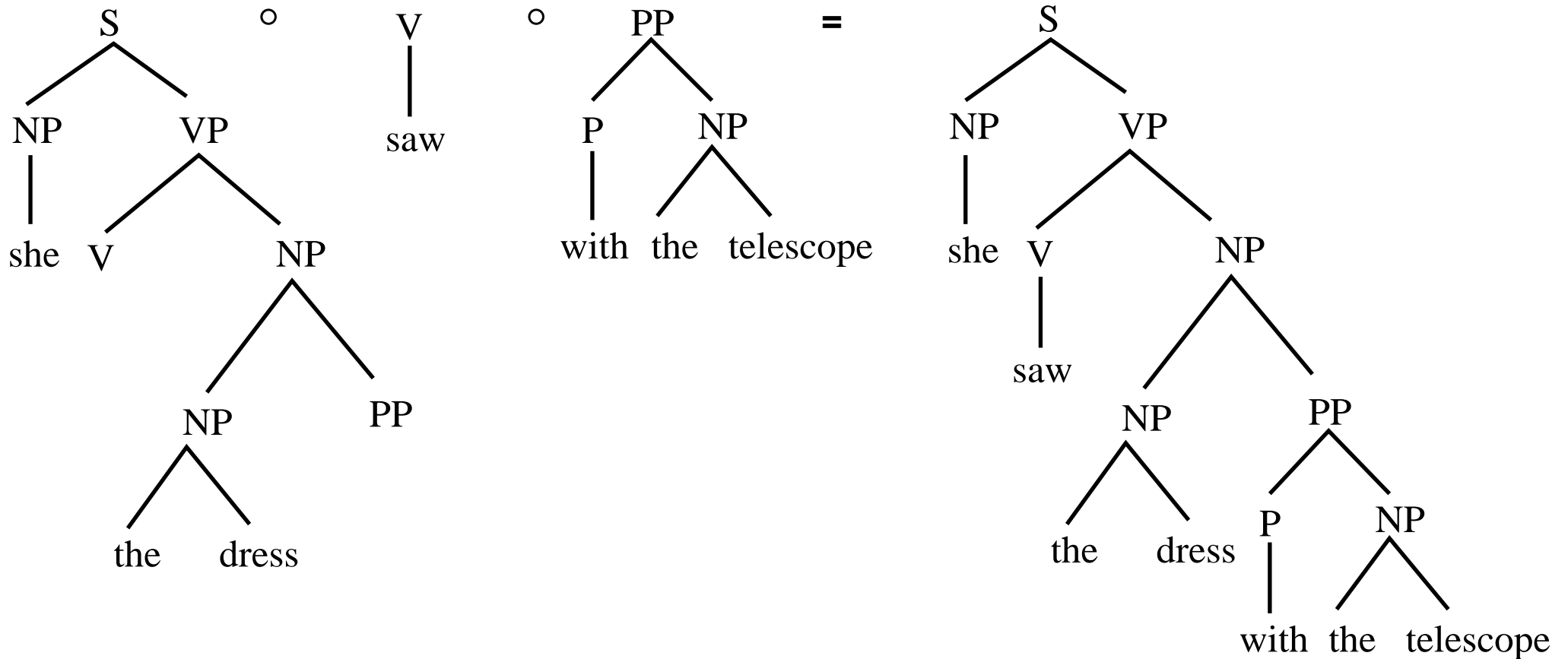
(cf. CBR, Corpus-based NLP, EBL, ...)

# Example of a DOP model for Language

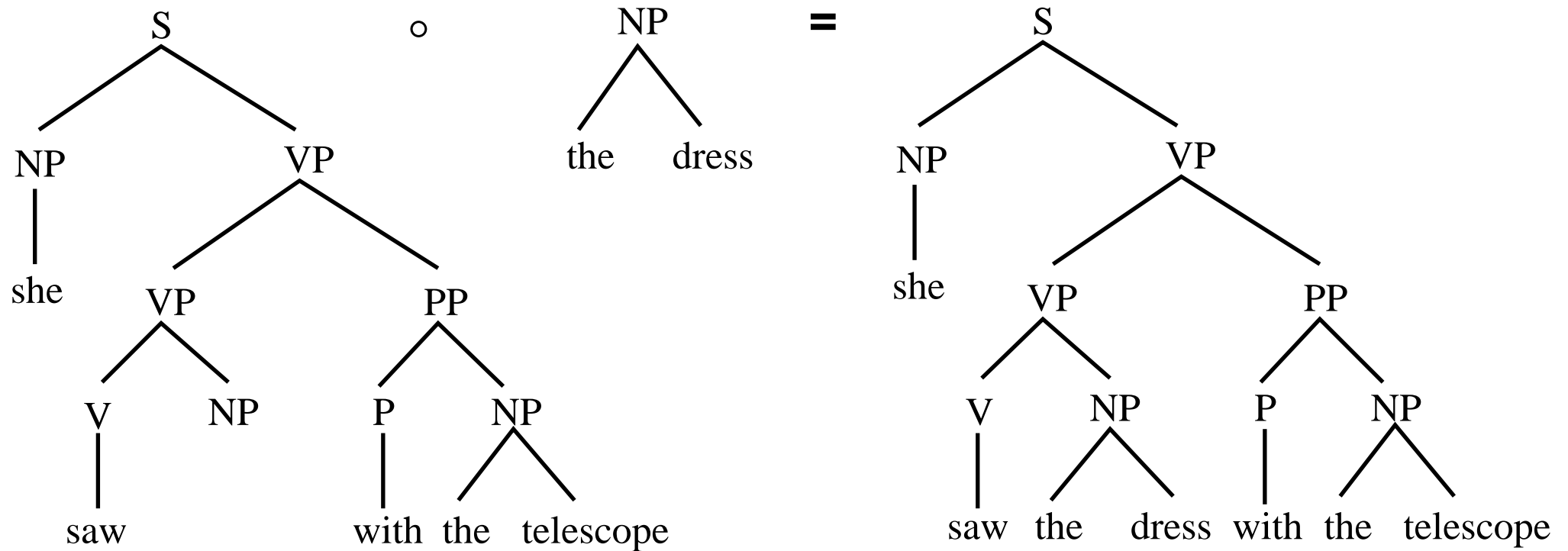
Let's start with an extremely simple corpus:



A new sentence such as "*She saw the dress with the telescope*" is analyzed by **combining subtrees from the corpus**



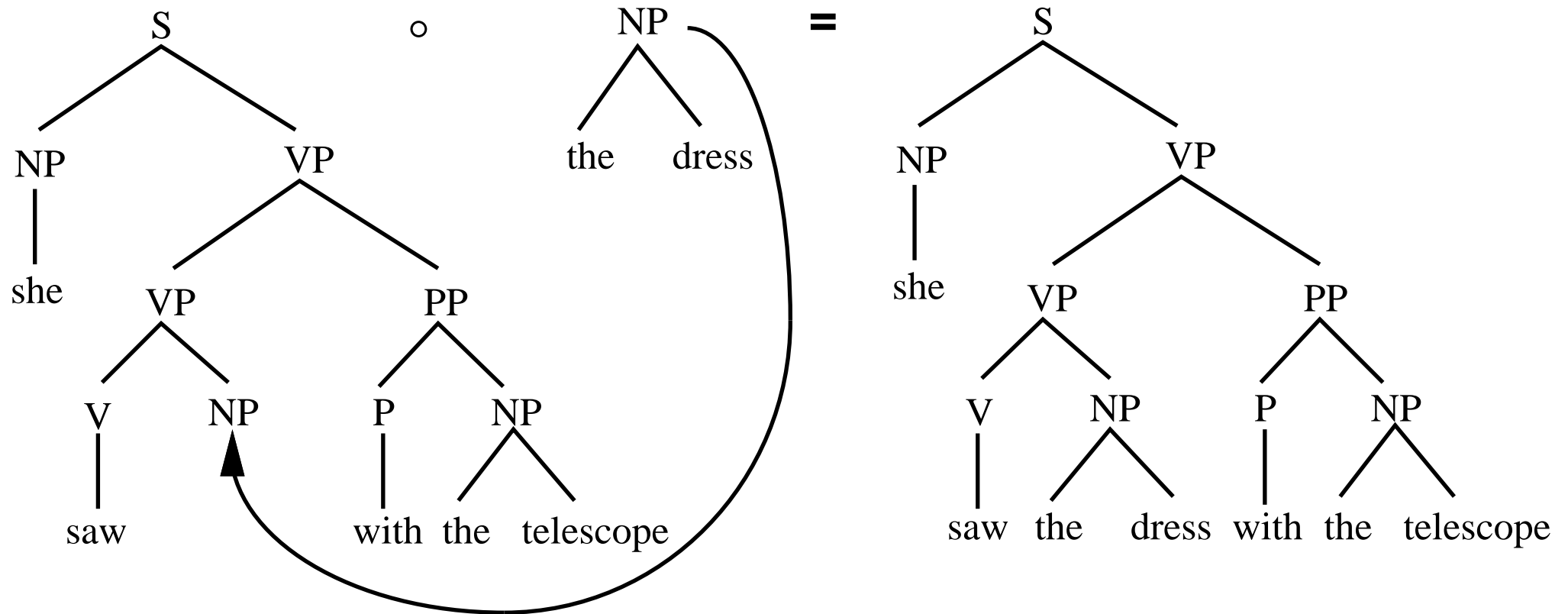
But there is also a "competing" analysis:



This analysis consists of two steps, and is therefore preferred according to the *simplicity principle*: **maximal similarity** with corpus.

But it is **not** preferred according to the *likelihood principle*!

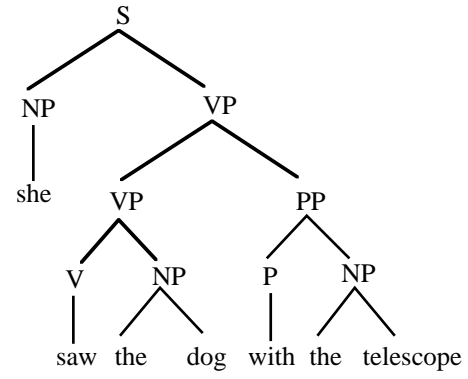
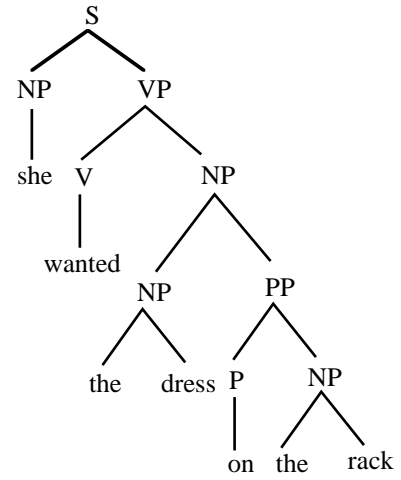
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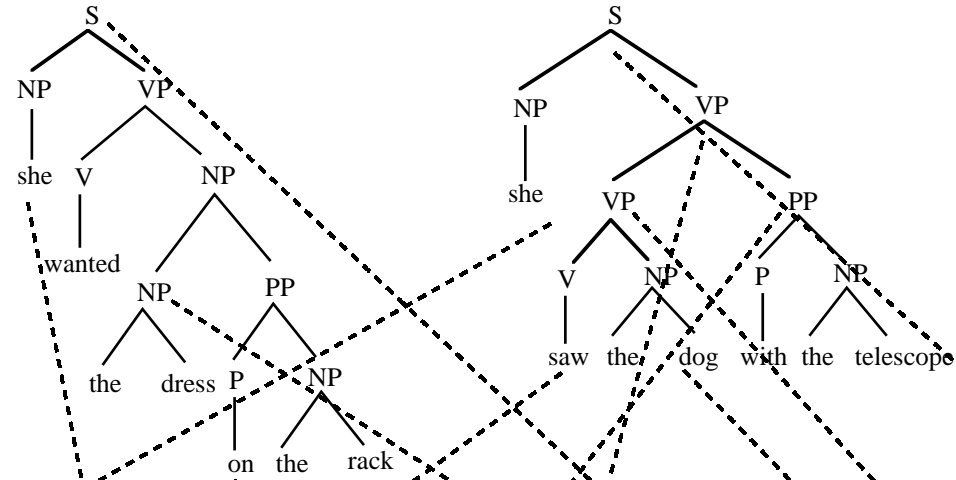
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Corpus

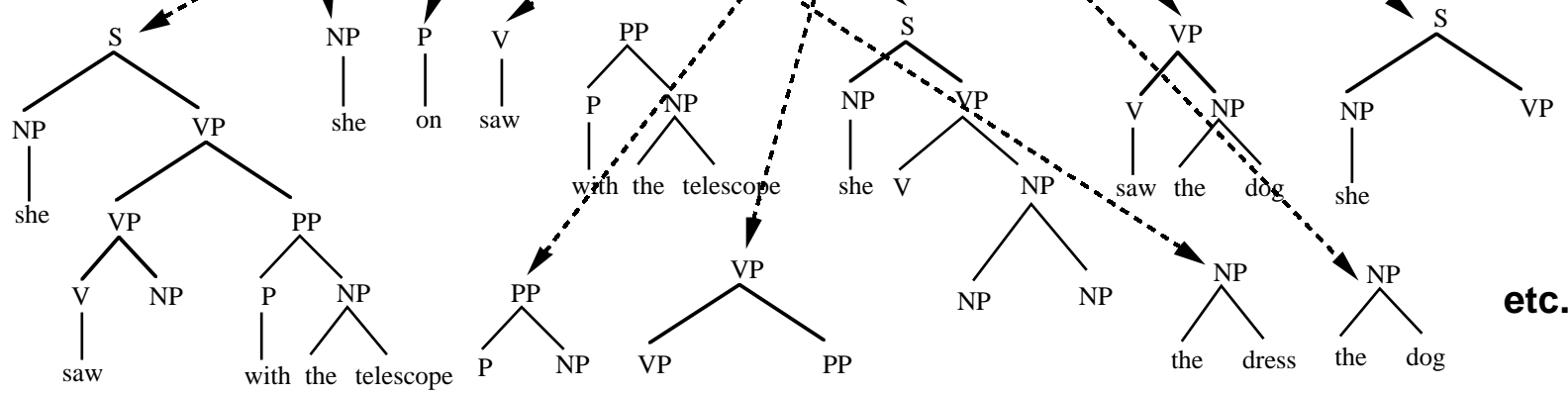




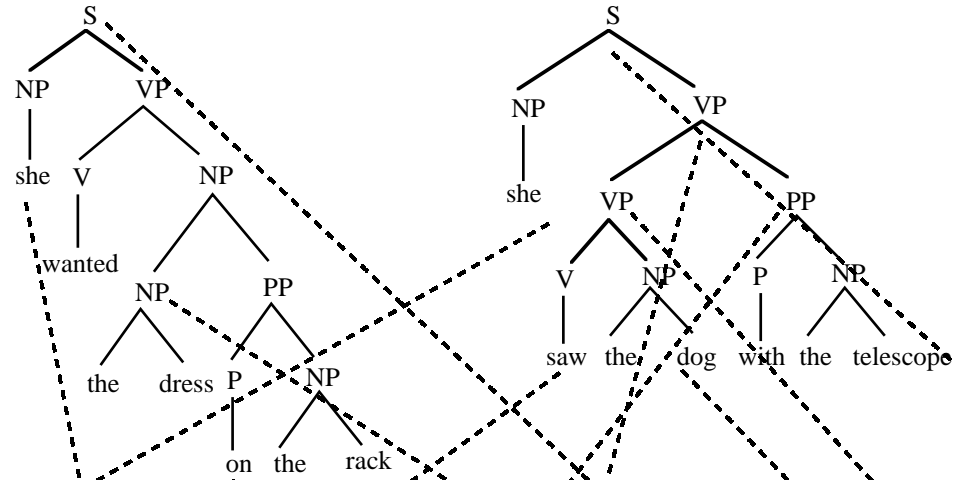
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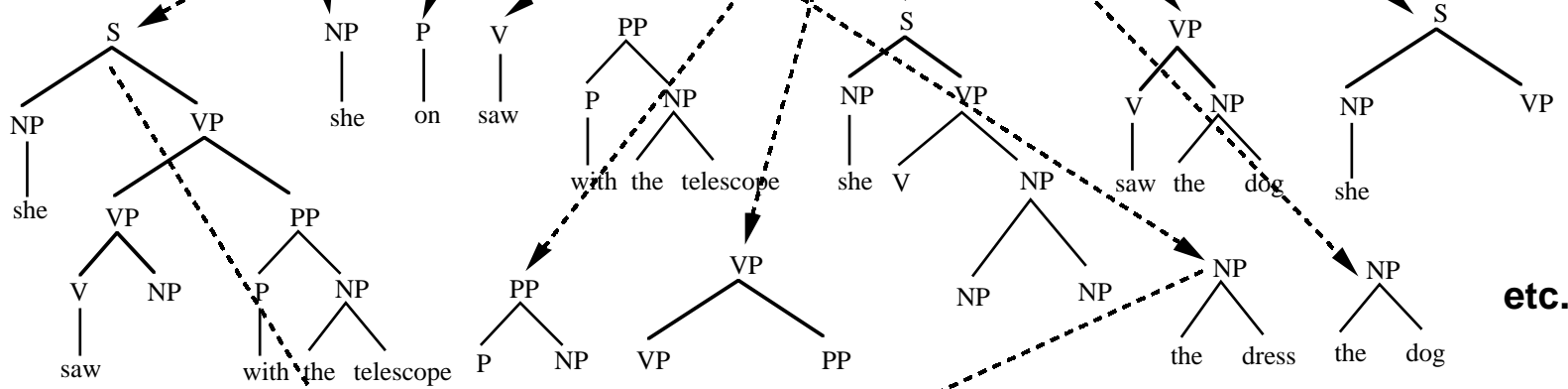
Decompositie



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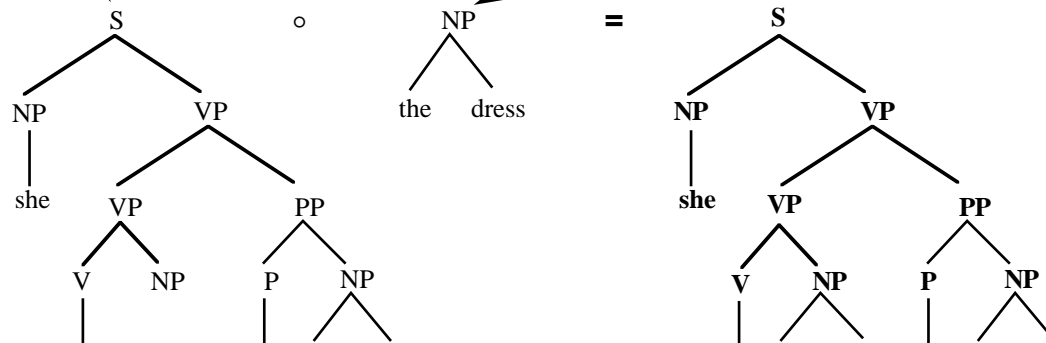


Decompositie



etc.

Recompositie



# DOP models are Stochastic Tree Grammars

By putting various constraints on STGs, we can instantiate:

- stochastic context-free grammars
  - stochastic head-lexicalized grammars
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- etc...

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However, we have also developed DOP models for richer structures, such as *LFG*, *HPSG*, *Logical-Semantic* and *Discourse annotations*

(e.g. Bod & Kaplan 1998, 2003; Way 2003; Neumann 2003; Bod et al. 1996; Bod 1998)

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## **Our best hypothesis so far:**

The perceptual system selects the *simplest* structure from the top of the distribution of *most probable* structures

# The probability of:

a subtree  $t$  :

$$P(t) = \frac{|t|}{\sum_{t' : \text{root}(t') = \text{root}(t)} |t'|}$$

a derivation  $d = t_1 \circ \dots \circ t_n$  :

$$P(t_1 \circ \dots \circ t_n) = \prod_i P(t_i)$$

a parse tree  $T$  :

$$P(T) = \sum_d \prod_i P(t_{id})$$

where  $t_{id}$  is the  $i$ -th subtree in derivation  $d$  that produces  $T$

# Computational Aspects of DOP

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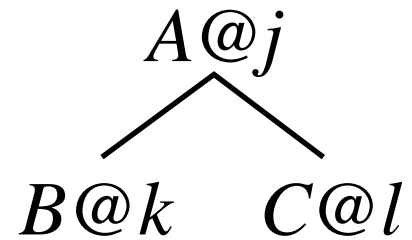
Every node in every tree in corpus is assigned a unique number:

$A@k$  denotes node at address  $k$  where  $A$  is nonterminal of that node

A new nonterminal is created for each node in the training data:  $A_k$

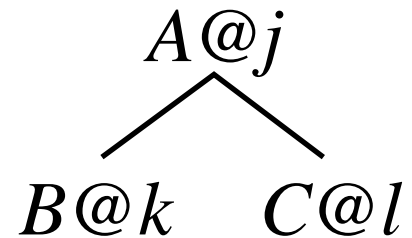
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Consider a node  $A@j$  of the following form in STSG/DOP:



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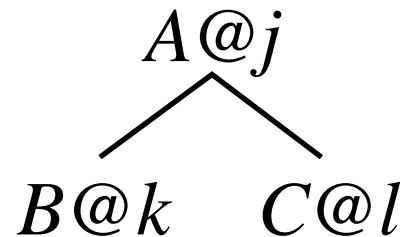
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Thus  $b_k + 1$  different possibilities on the left branch

Similarly,  $c_l + 1$  possibilities on the right branch

Thus,  $a_j = (b_k + 1)(c_l + 1)$  possible subtrees headed by  $A@j$

# Sketch of PCFG reduction of DOP (2)

There is a PCFG with the following property (Bod 2003; Goodman 2003):

for every subtree in training corpus headed by  $A$ , the PCFG will generate an isomorphic subderivation with probability  $1/a$

$A_j \rightarrow BC$	$(1/a_j)$	$A \rightarrow BC$	$(1/a)$
$A_j \rightarrow B_k C$	$(b_k/a_j)$	$A \rightarrow B_k C$	$(b_k/a)$
$A_j \rightarrow BC_l$	$(c_l/a_j)$	$A \rightarrow BC_l$	$(c_l/a)$
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Rather than using all subtrees, we can use a "compact" PCFG !

# Sketch of PCFG reduction of DOP (3)

- Dynamic programming algorithm known as *Viterbi bottom-up search* computes *most probable derivation* for input string
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- Other work has proposed different computational solutions:  
*Voted Perceptron* (Collins), *Tree Kernels* (Bod, Duffy), *MaxEnt* (Sima'an), *MDL* (Bonnema), *E-M* (Prescher)...

# Test Domains

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Essen Folksong Collection (EFC): 20.150 melodically  
analyzed western folksongs:

- *Pitches*: numbers from 1 to 7
- *Duration indicators*: underscore (\_) or a period (.) *after* the numbers
- *Octave position*: plus and minus signs (+,-) *before* the numbers
- *Chromatic alterations*: "#" or "b" *after* the numbers
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- ***Visual test domain:*** see later

# Example from Essen Folksong Collection

#4551: *Schneckhaus Schneckhaus stecke deine Hörner aus*

(German children song)

5\_3\_5\_3\_1234553\_1234553\_12345\_3\_12345\_3\_553\_553\_553\_65432\_1\_

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Grouping structure according to Essen Folksong collection:

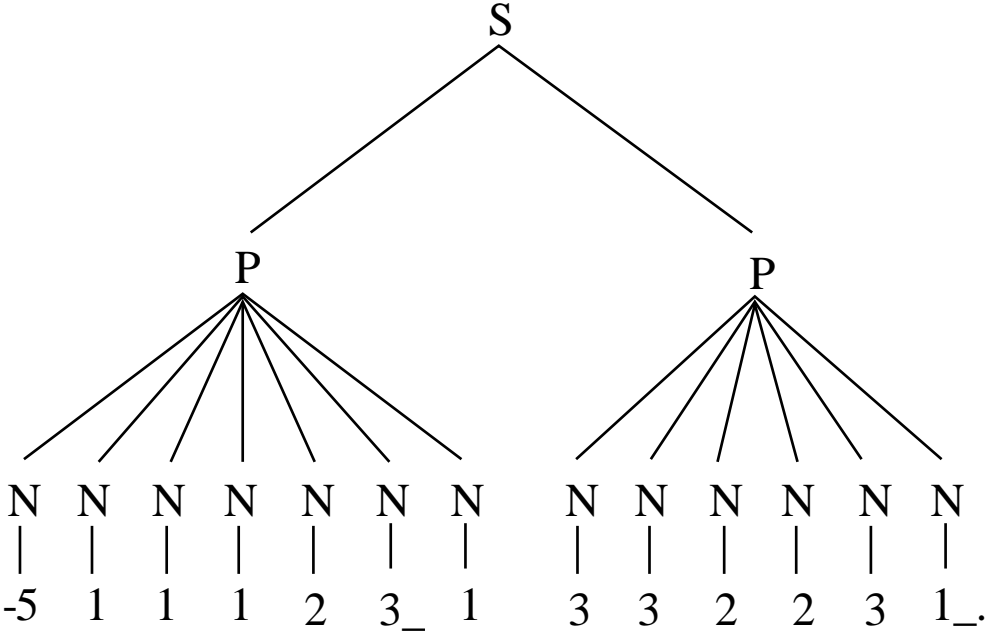
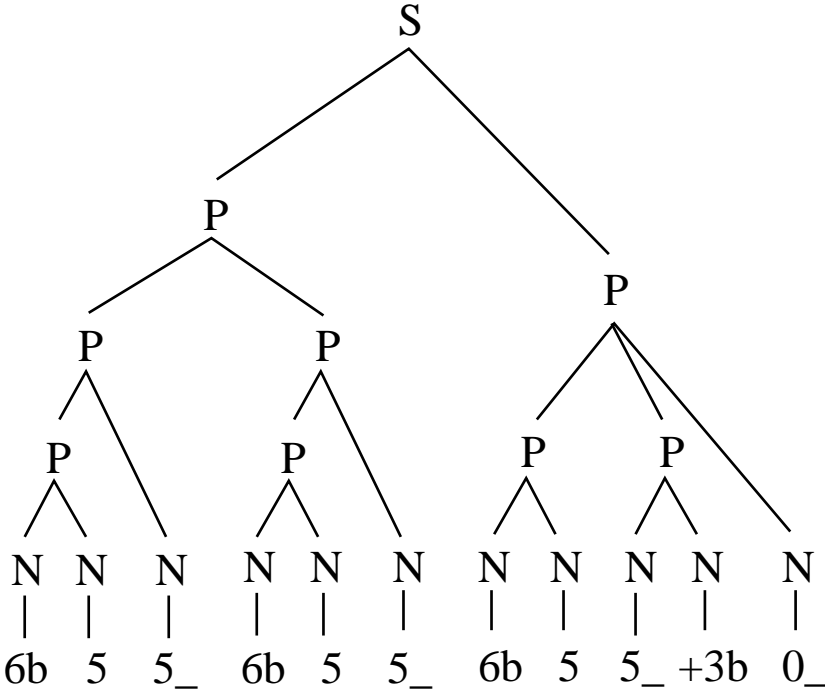
((5\_3\_5\_3\_) (1234553\_) (1234553\_) (12345\_3\_) ( 12345\_3\_) (553\_553\_)  
(553\_65432\_1\_))

NB: linguistic phrase structure does not predict musical phrase structure!

# Preprocessing the Essen Folksong Annotations

- We automatically added three basic labels to the phrase structures:
  - "S" to each whole song
  - "P" to each phrase
  - "N" to each note
- In this way, we obtain conventional tree structures that can be used by DOP/STSG, or its isomorphic PCFG

# Examples of some simple musical trees



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## **Test 1: Simplicity-Likelihood-DOP (SL-DOP)**

*Selects simplest structure from among  $n$  likeliest structures*

## **Test 2: Likelihood-Simplicity-DOP (LS-DOP)**

*Selects likeliest structure from among  $n$  simplest structures*

# Scores of SL-DOP & LS-DOP

<i>n</i>	SL-DOP (simplest among <i>n</i> likeliest)		LS-DOP (likeliest among <i>n</i> simplest)	
	Language	Music	Language	Music
1	87.9%	86.0%	85.6%	84.3%
5	89.3%	86.8%	86.1%	85.5%
10	90.2%	87.2%	87.0%	85.7%
<b>11</b>	<b>90.2%</b>	<b>87.3%</b>	87.0%	85.7%
<b>12</b>	<b>90.2%</b>	<b>87.3%</b>	87.0%	85.7%
<b>13</b>	<b>90.2%</b>	<b>87.3%</b>	87.0%	85.7%
14	90.2%	87.2%	87.0%	85.7%
15	90.2%	87.2%	87.0%	85.7%
20	90.0%	86.9%	87.1%	85.7%
50	88.7%	85.6%	87.4%	86.0%
100	86.8%	84.3%	87.9%	86.0%
1,000	85.6%	84.3%	87.9%	86.0%

# Scores of SL-DOP & LS-DOP

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**Same** model obtains **maximal** scores for **both** language and music

Perceptual system strives for **simplest** analysis, but "searches" only among the **most likely** analyses (see Schaefer et al. 2004 for psychological experiments)

# Comparison with other work

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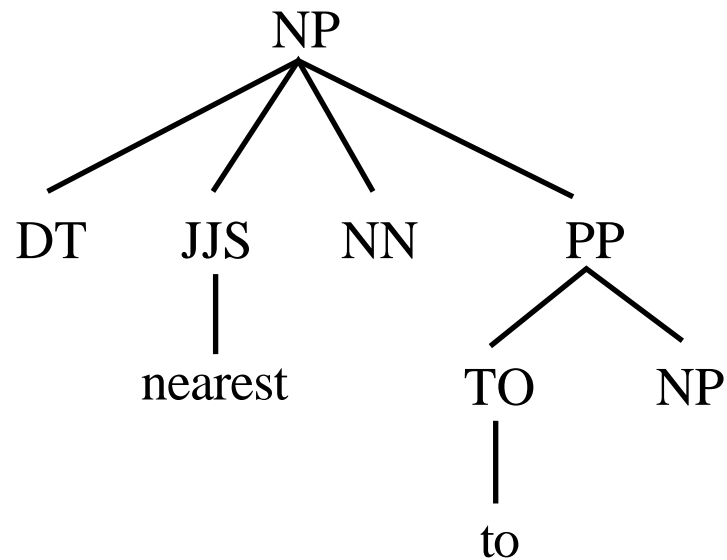
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**Music:** DOP outperforms Temperley, Thom, Chang on EFC

→ many phrases that include large intervals are not captured by harmonic, metrical or melodic "rules"

By using largest possible subtrees (simplest analysis) which occur most frequently, DOP takes into account more dependencies

## Example of non-headword dependency (ATIS corpus)



E.g.: *Show the nearest airport to Denver*

- non-head modifier *nearest* predicts the correct PP-attachment
- Example from WSJ: *BA carried more people than cargo in 1988*

## Example of "jump phrase" (EFC)

Folksong K0690:

**(3\_2\_11-5) (-5332211-5) (-512314\_2) (...)**

- Gestalt principles predict "wrong" phrases on large intervals:

**(3\_2\_11-5-5) (332211-5-5) (12314\_2) (...)**

- Parallelism, meter & harmony reinforce same "wrong" predictions!
- Many phrases reflect idiom-dependent pitch contours which cannot be predicted by rules, but only by "patterns" (Cf. Huron 1996)

# The importance of large subtrees

- Large subtrees may be statistically significant though they are linguistically and musically redundant
- Continuum between "regular phrases" (*rules*) and "idiomatic phrases" (*patterns*) both in language and music
- DOP can capture the full gradience between *rules* and *patterns*

# How can we apply this to Visual Structures?

Structured visual databases are still too small (<300) to get statistically significant results

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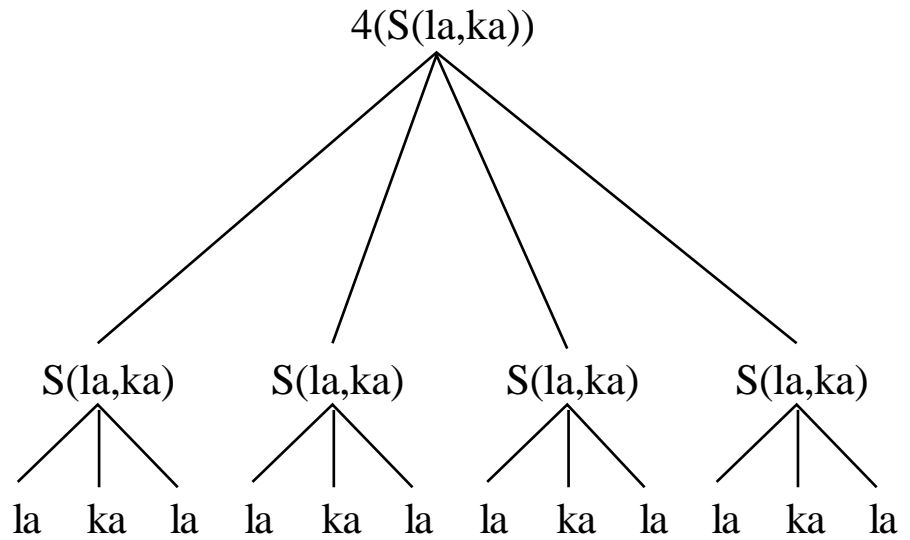
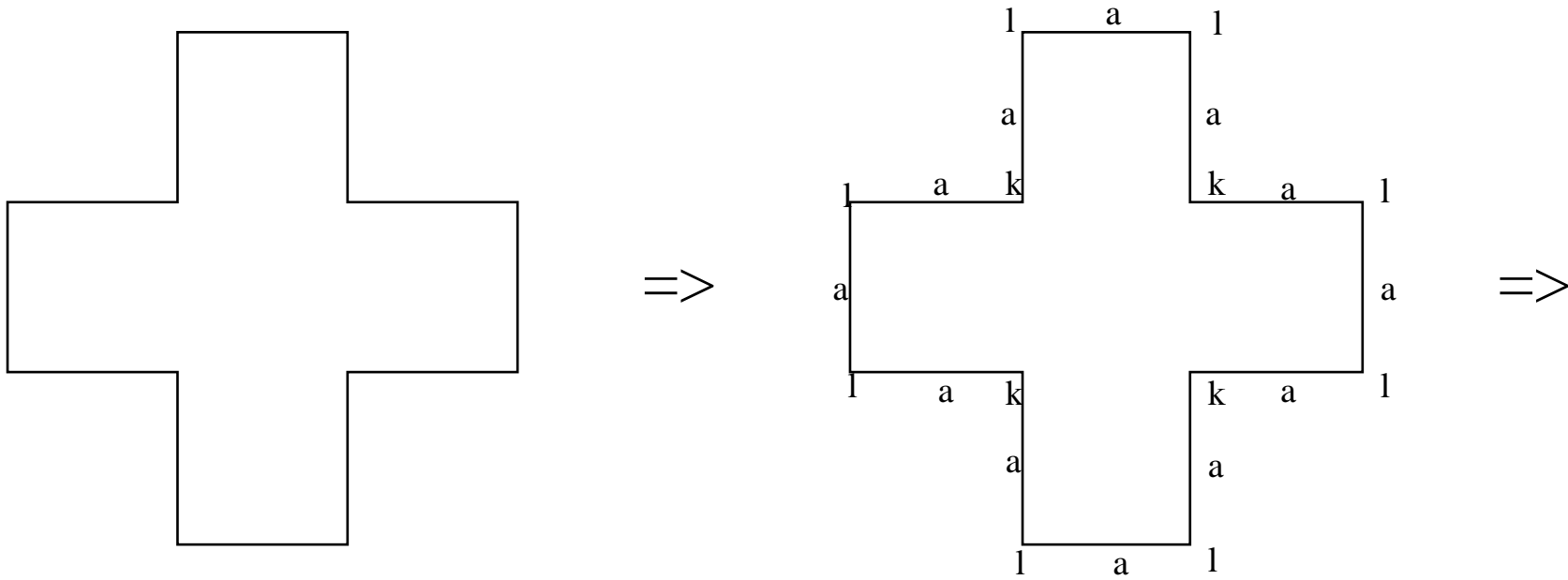
Structured visual databases are still too small (<300) to get statistically significant results

What are the primitive elements in visual perception?

In Nijmegen Visual Database: *line segments, angles, a.o.*

"Syntactic" categories: *symmetry (S), alternation (A), iteration (I).*

Of course, we only deal with medium-level computer vision in this way



Experiments support SL-DOP, but not statistically significant

# DOP is used in various AI applications

- Structural language models for speech (Bod 1998, 2000; Chelba 1998)

$$\operatorname{argmax}_W P(W | A) = \operatorname{argmax}_W \sum_T P(W, T | A)$$

- Statistical machine translation (Hearne & Way 2004; Poutsma & Bod 2003)

$$\operatorname{argmax} P(\text{Translated sentence} | \text{Source sentence})$$

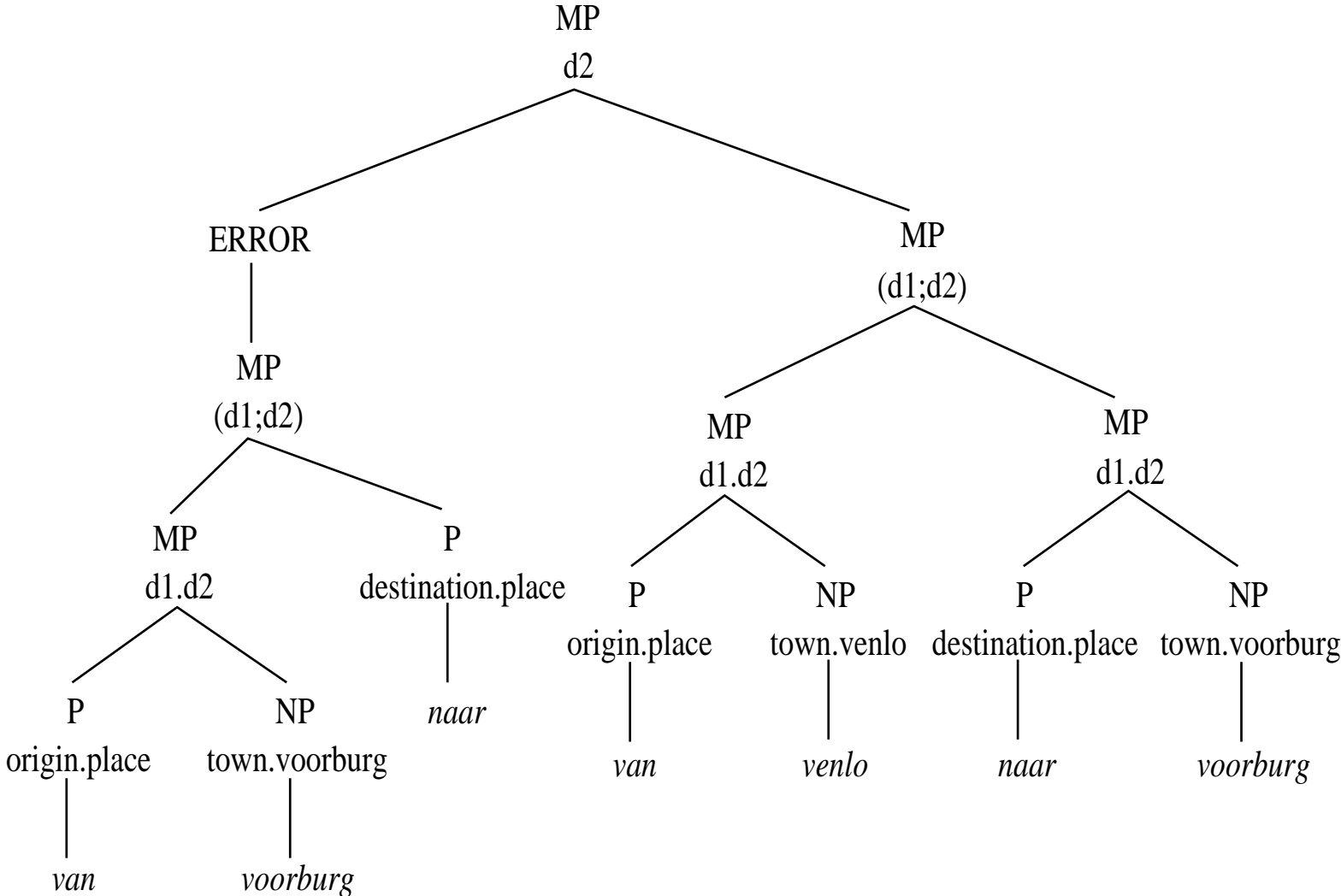
- Musical tempo tracking systems (Zaanen, Honing & Bod 2004)

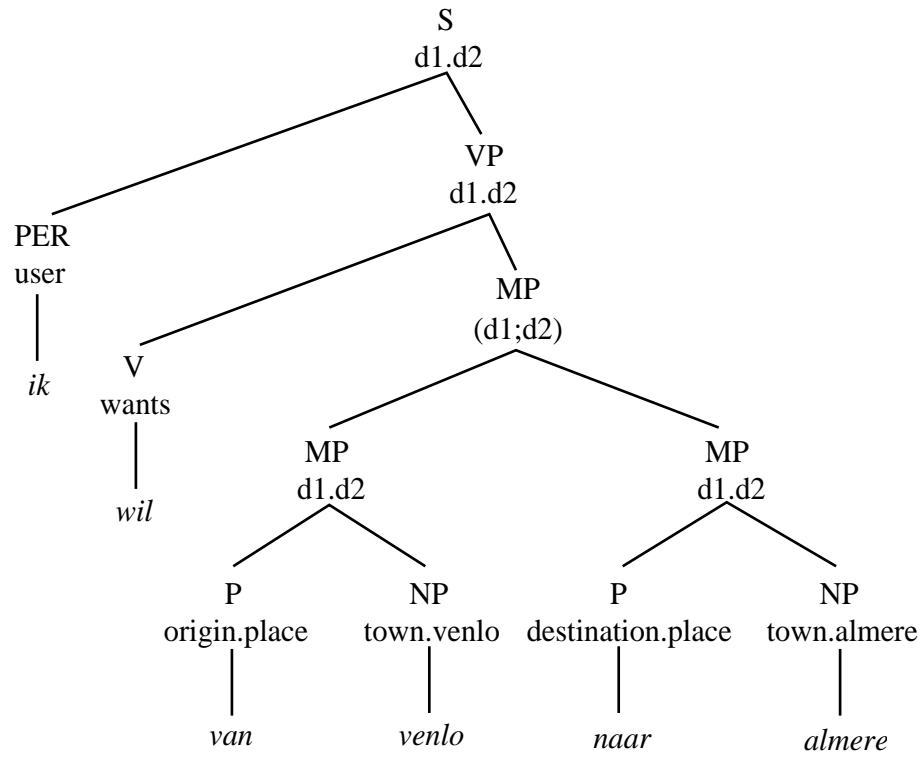
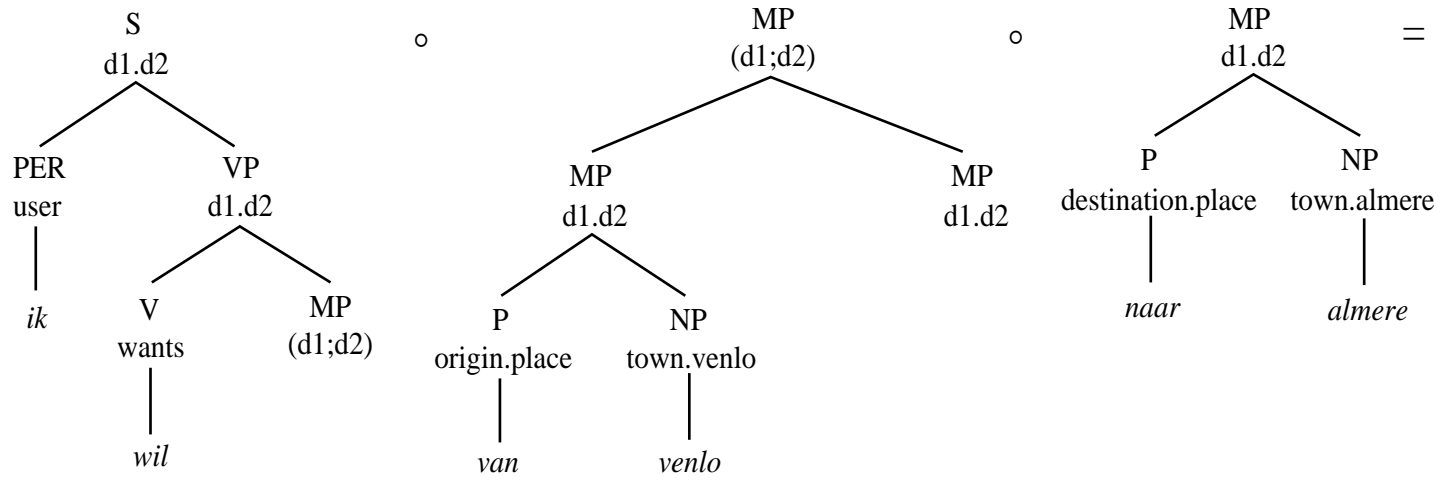
$$\operatorname{argmax} P(\text{Temporal structure} | \text{Acoustic input})$$

- Interactive spoken dialog systems (Bod 1999; Scha et al. 1999), used by OVIS

$$\operatorname{argmax} P(\text{Interpretation, Word string} | \text{Acoustic signal})$$

# Example of OVIS annotation used in spoken dialog





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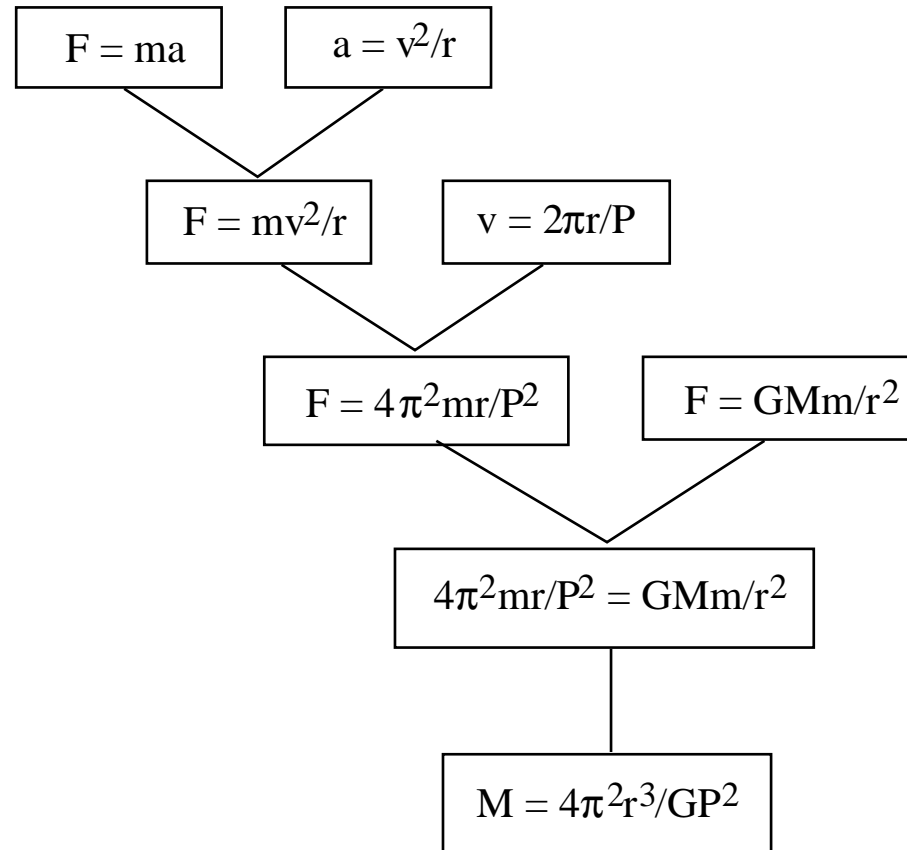
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- Problem-solutions in physics can be represented by derivation trees -- though they do not represent grouping structure

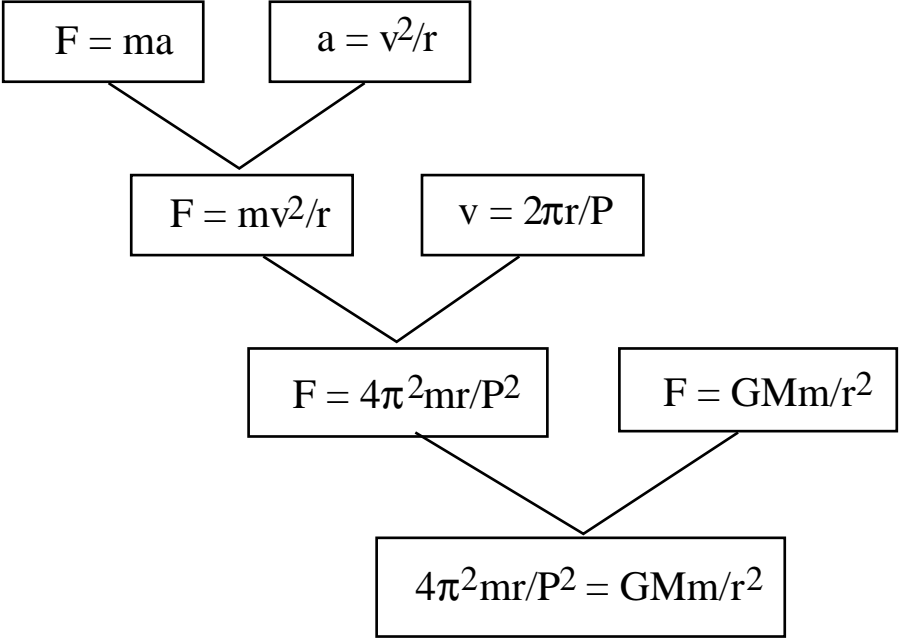
# Example of derivation tree in classical mechanics

Derivation of planet's mass from a satellite's orbit using Newton's laws

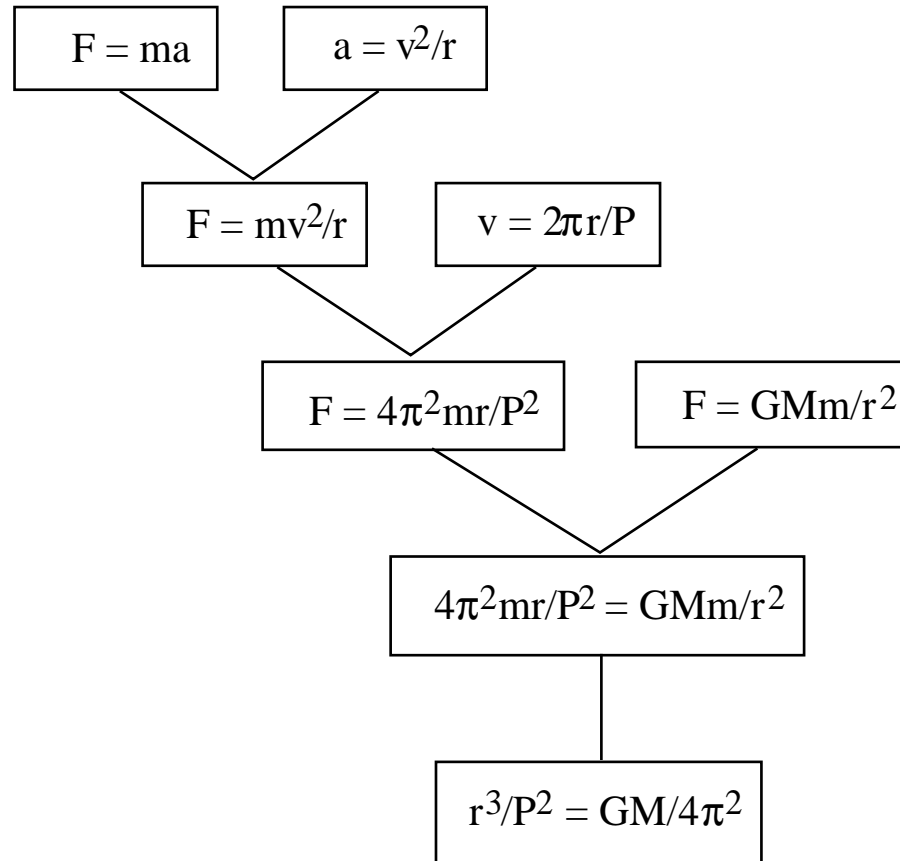


A tree describes the steps from higher-level laws to the solution (formula)

# Subtrees can be reused to solve new problems

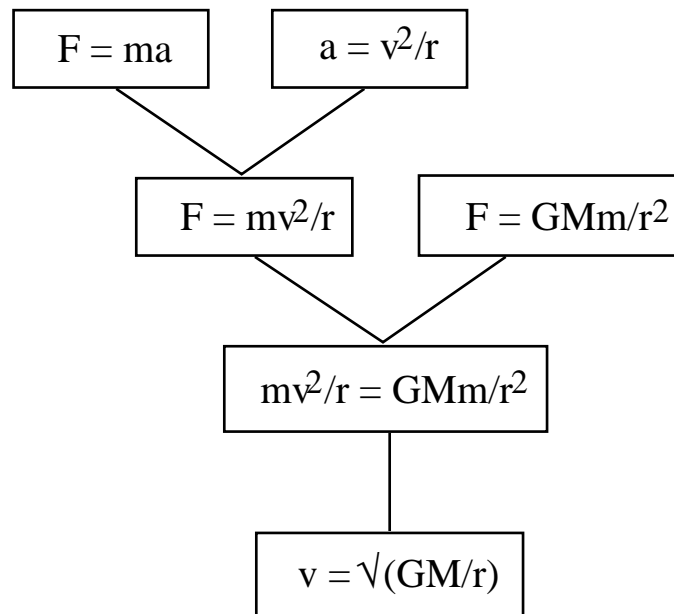
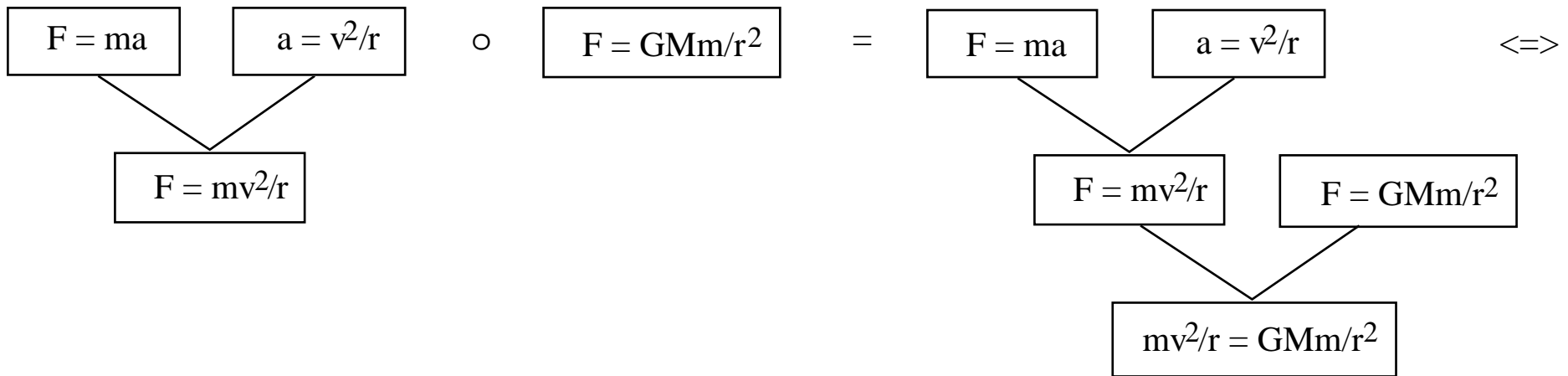


# Deriving Kepler's third law by this subtree



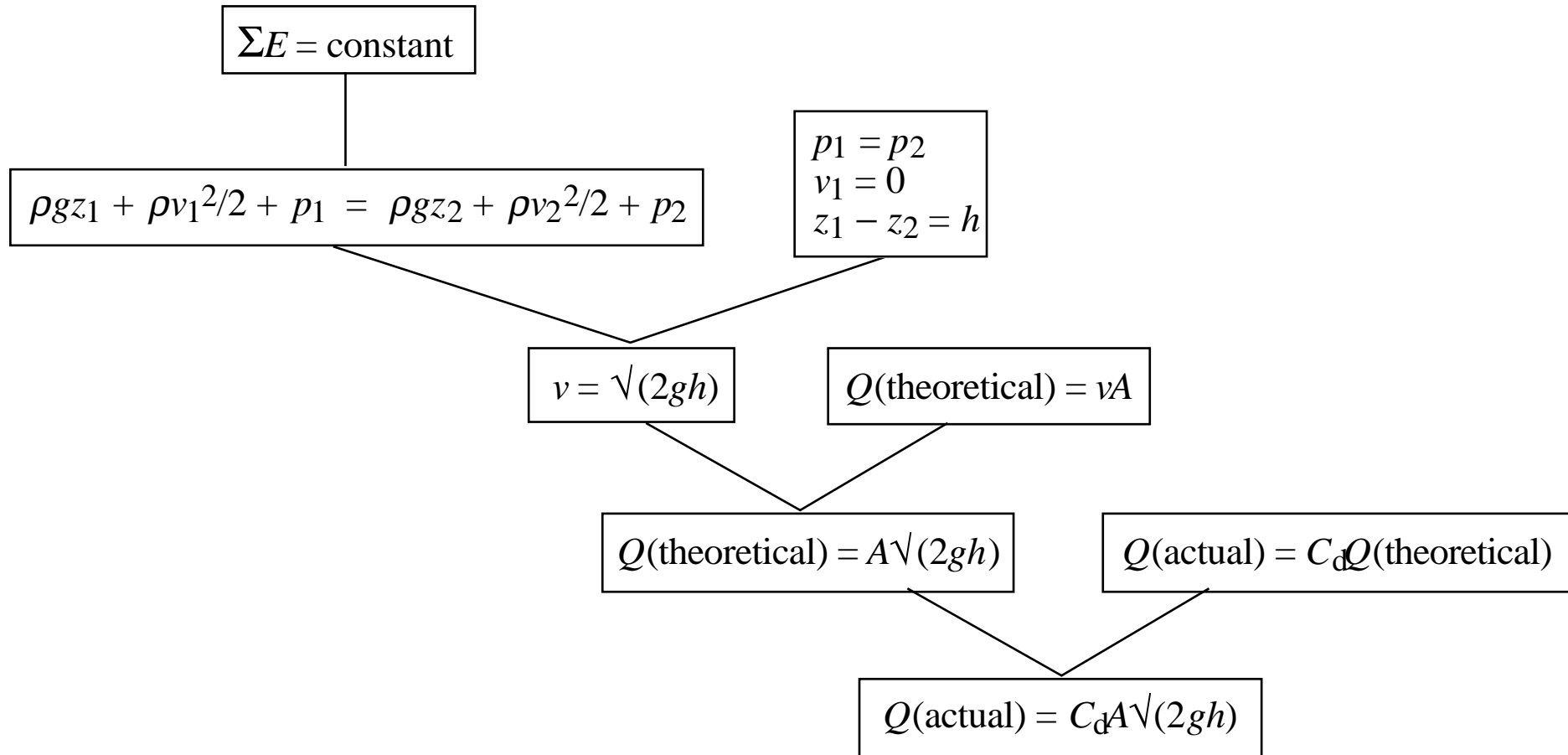
We only need to solve the last equation of the previous subtree for  $r^3/P^2$

Often we need to combine two or more subtrees (by term rewriting)

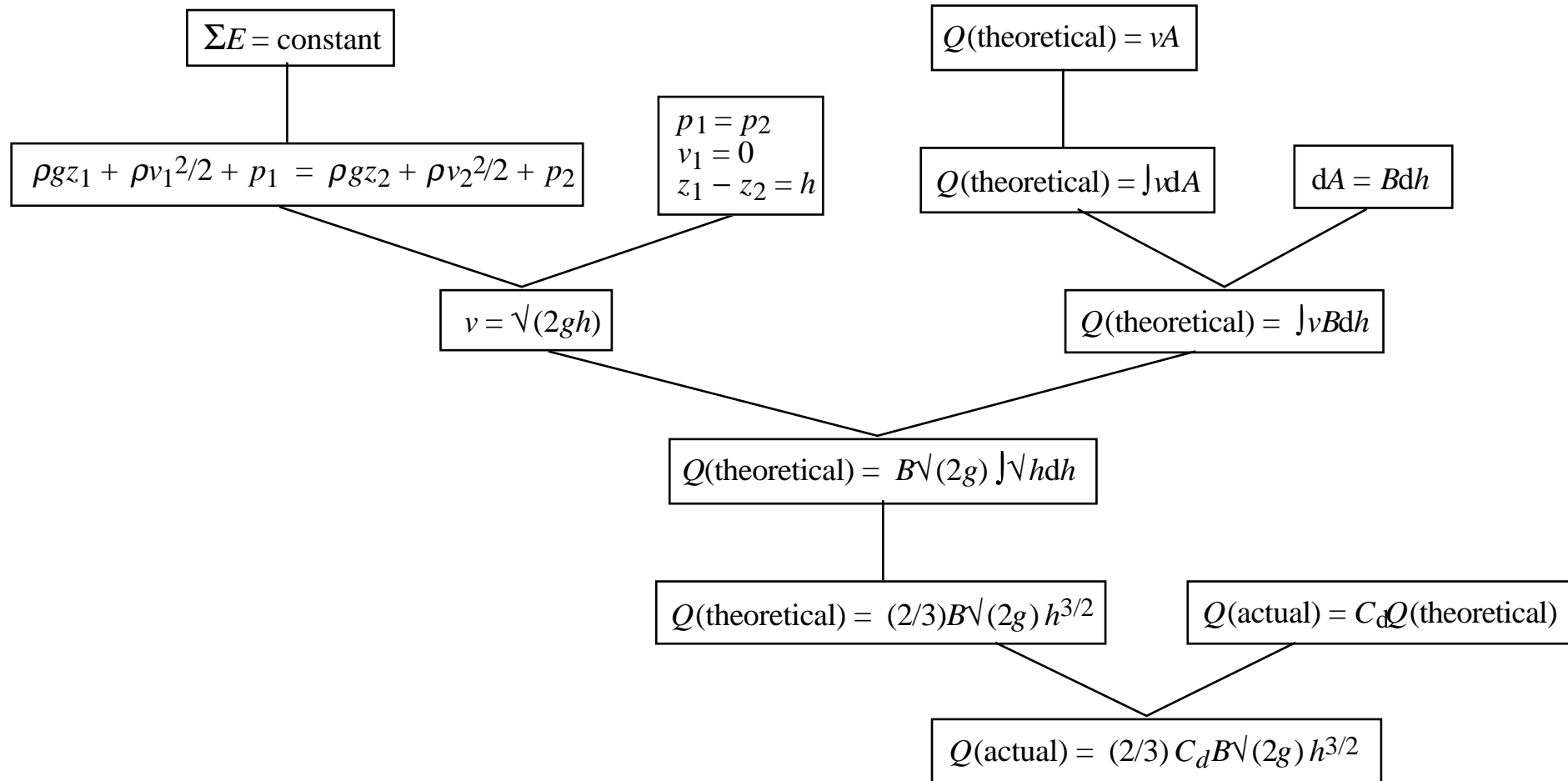


# Derivation trees in fluid mechanics

E.g. derivation of *orifice system* from Bernoulli involves an ad hoc correction coefficient ( $C_d$ )



Derivation tree for a *weir (dam)* can still be derived by subtrees from orifice system that include the ad hoc correction



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- Prefer largest possible derivational chunks, such that minimal recourse to additional derivational steps is needed
- Prefer more frequently occurring chunks: reflects usefulness
- $P(\textit{Derivation-tree} \mid \textit{Phenomenon})$  can be computed in a Bayesian way as in language and music, given a corpus of "exemplars"

We have just received an NWO grant for "Exemplar-Based Explanation" (one postdoc and one phd student)

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- DOP provides a general framework for stochastic grammar models
- Same model achieves highest accuracy for both music and language on resp. EFC and WSJ
- The model can also be used for vision, problem solving and reasoning -- as long as we can create a corpus of prior structures
- **AI** should aim at developing general models for (each level of) cognition rather than particularist models for each cognitive task separately

there are autonomous levels of explanation, but without striving for underlying models AI becomes a plethora of disparate algorithms