Statistical Parsing for Type-Logical Grammars

Richard Moot

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1 Overview

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(i) The Spoken Dutch Corpus (CGN)

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(ii) Type-Logical Proof Nets

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(iii) Extracting a Type-Logical Treebank

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(vi) Conclusions

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- POS tagging, phonetic transcription, ...
- 1 Million words syntactically annotated.

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  That is, we want to *derive* theory specific notions from the theory neutral export format.

CGN Annotation Graphs

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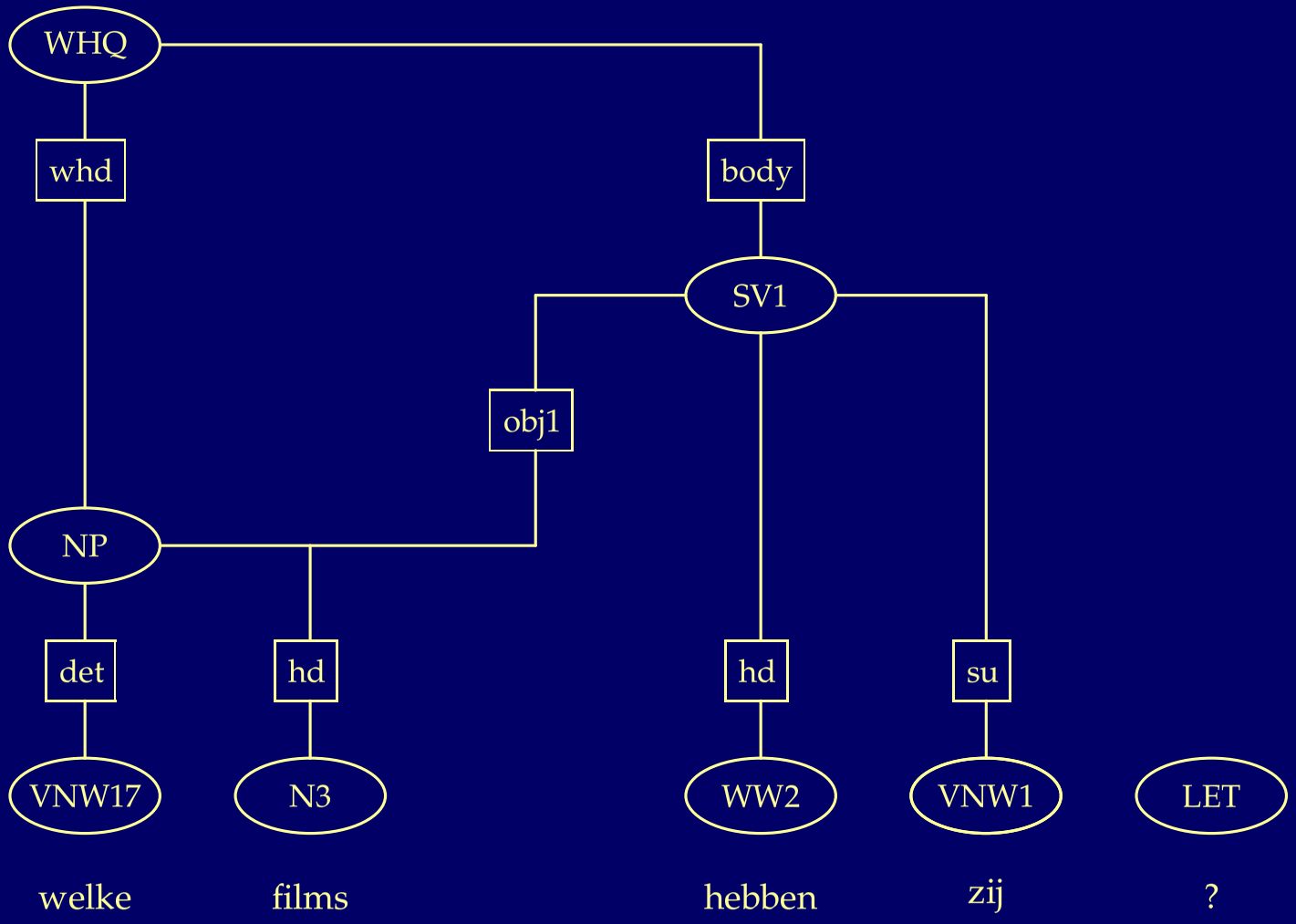
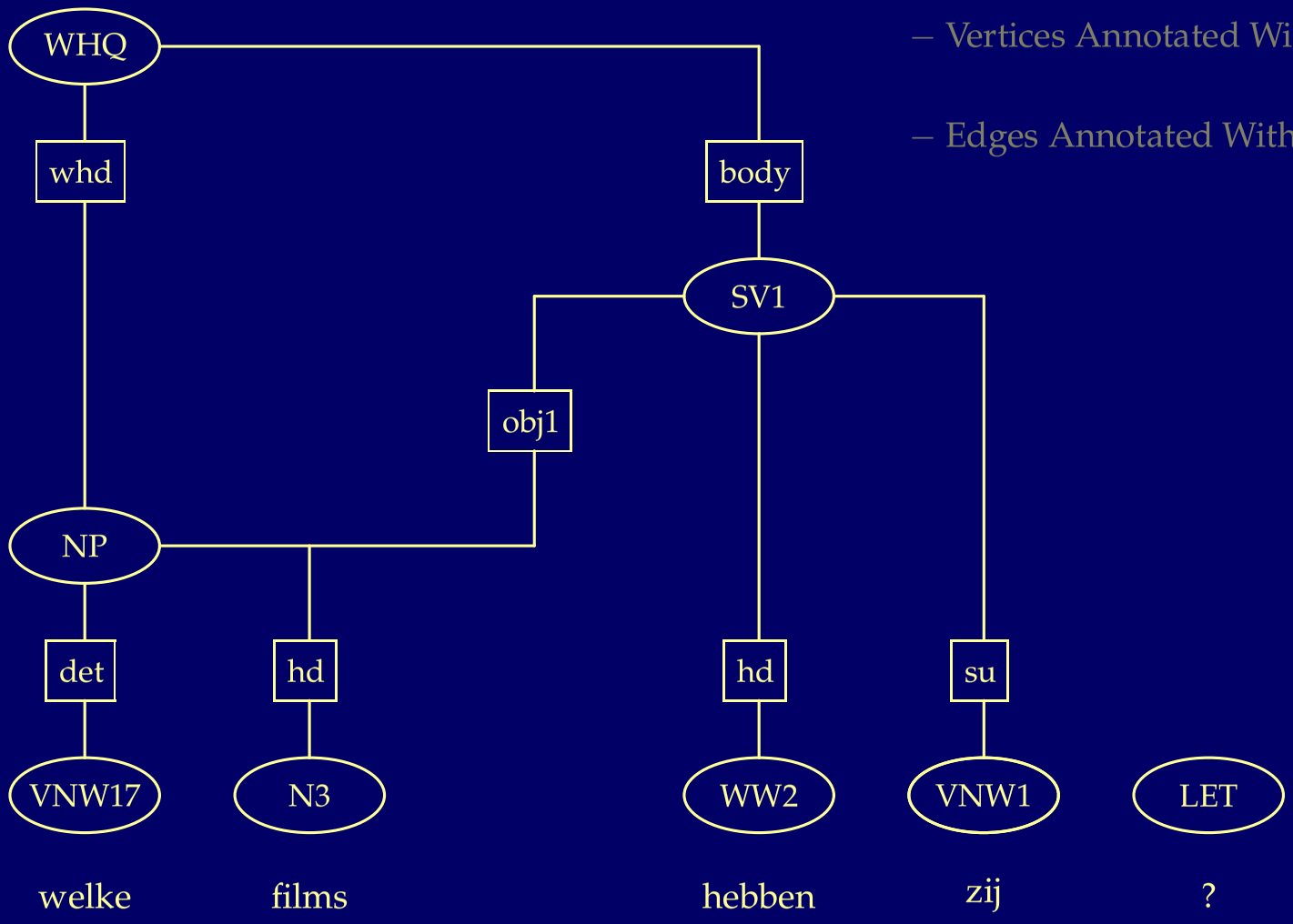


CGN Annotation Graphs

- Directect Acyclic Graph
- Vertices Annotated With Syntactic Categories
- Edges Annotated With Dependency Relations



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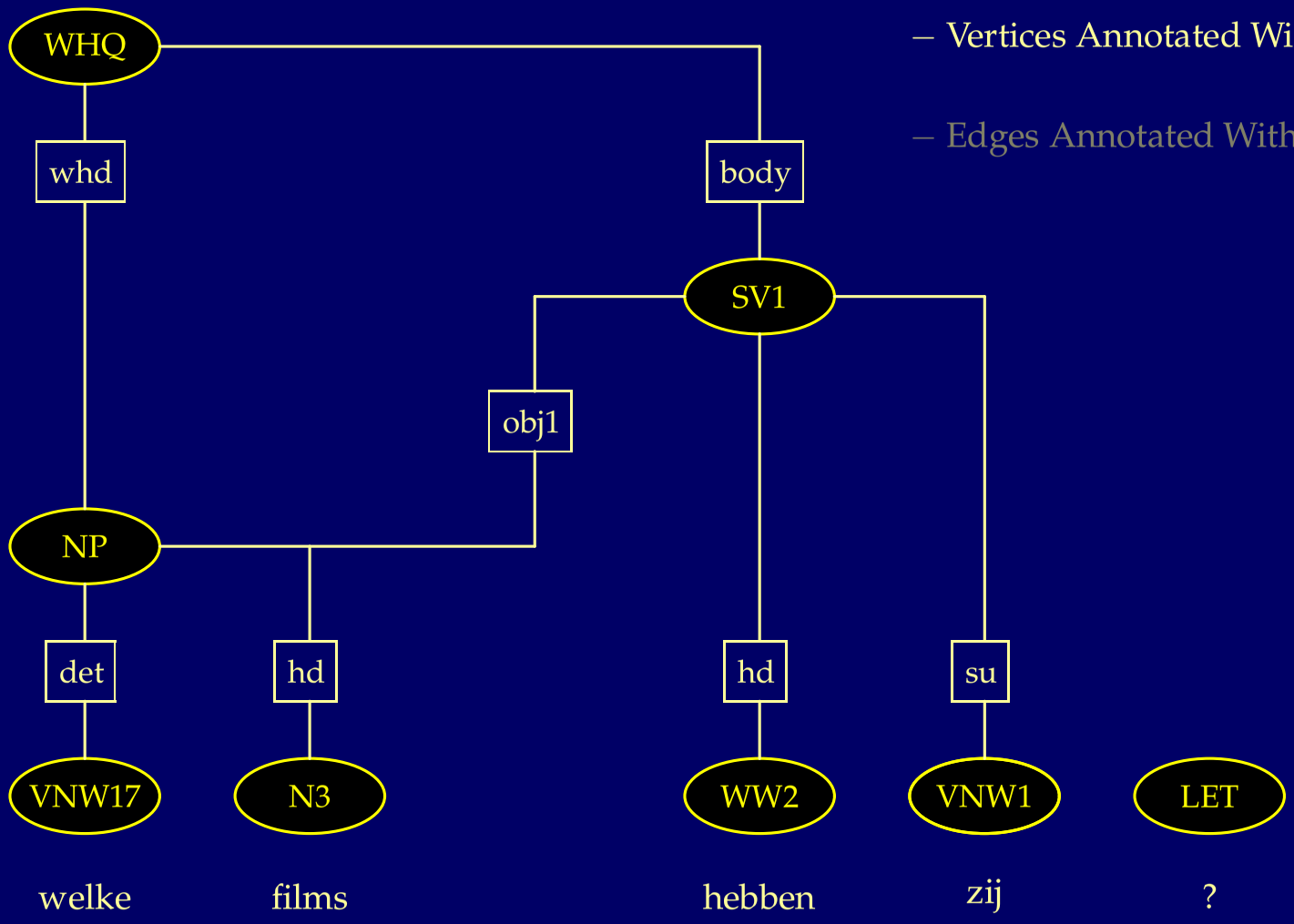

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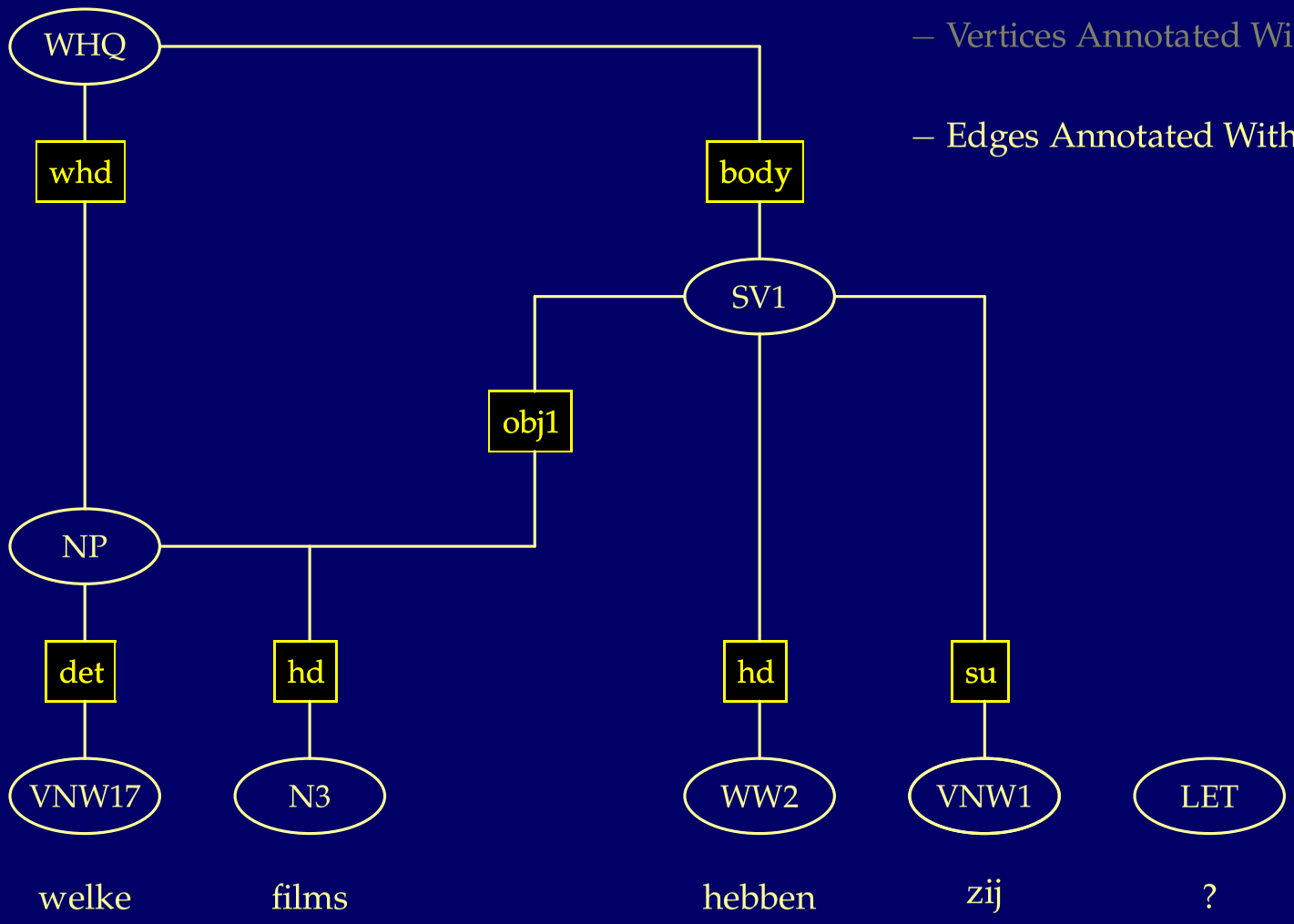

3 Type-Logical Proof Nets

Basic Elements

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Basic Elements

Terminals

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Terminals

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Basic Elements

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Nonterminals

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Nonterminals

$s, n, np, \ldots$

Constructors

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Main

Constructors

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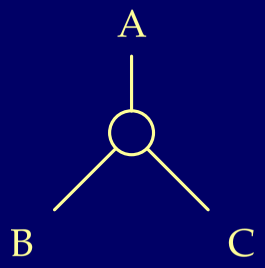

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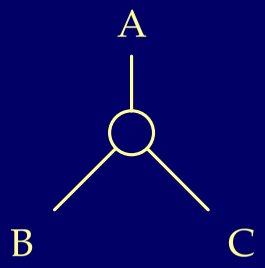

Auxiliary

Constructors

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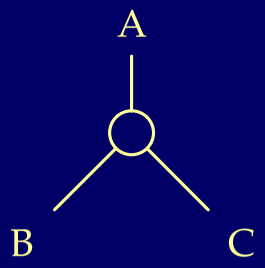

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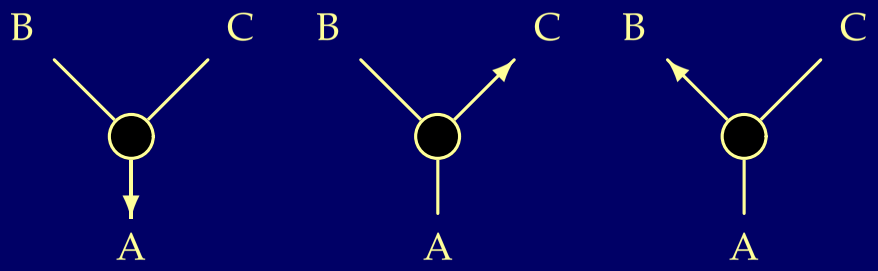

Graph Contractions

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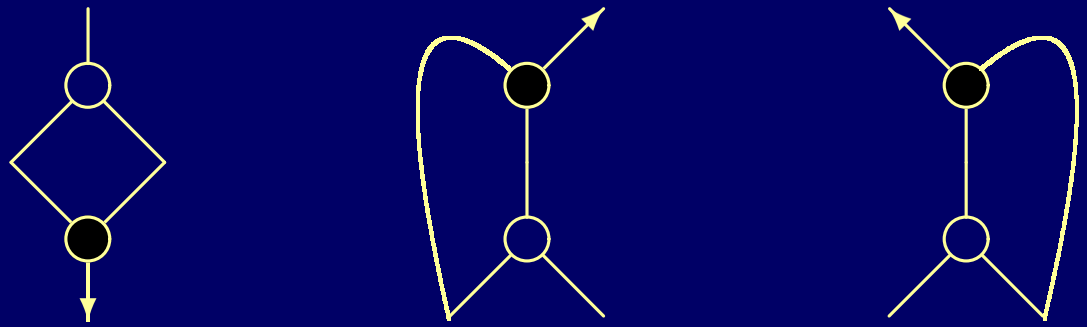

Example Lexicon

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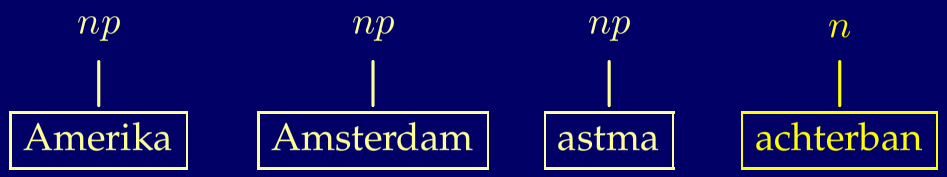

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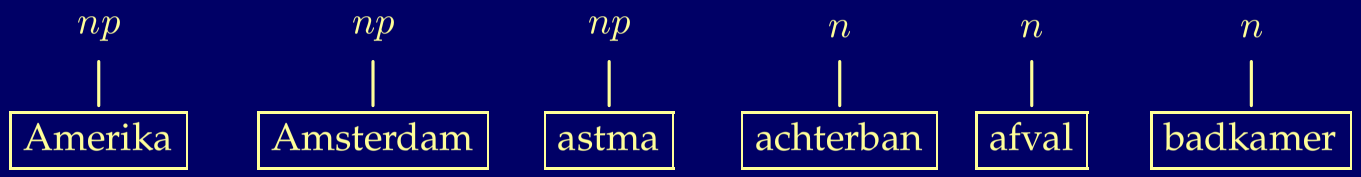

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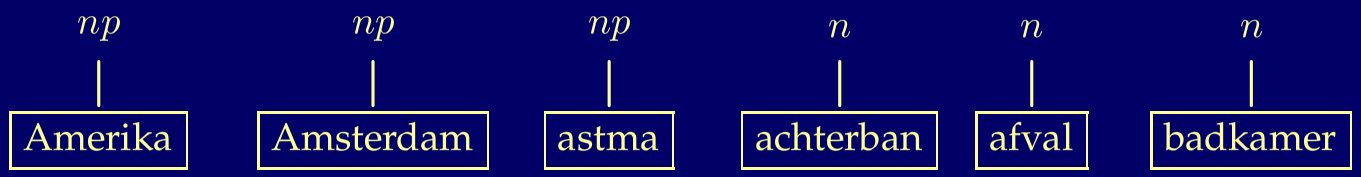

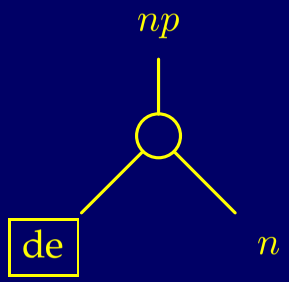

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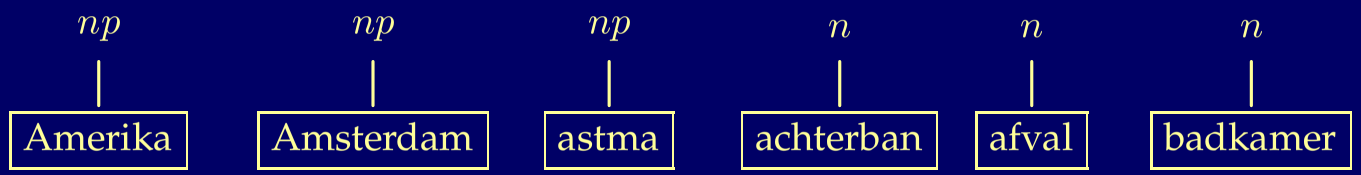

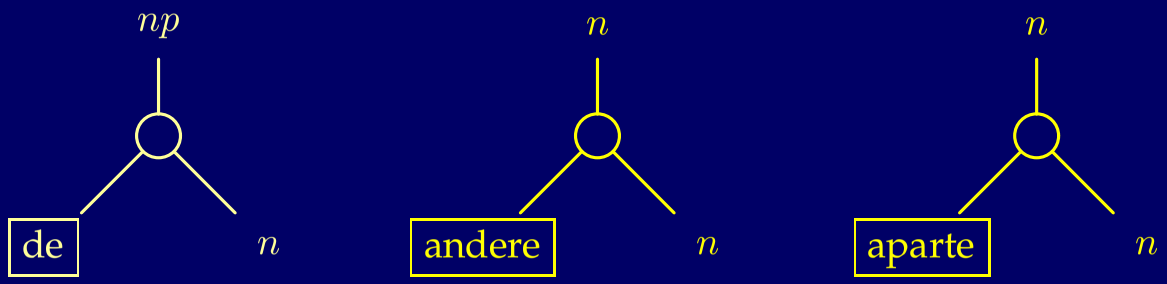

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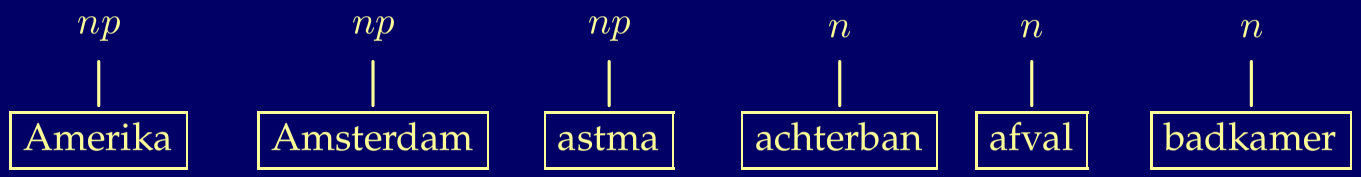

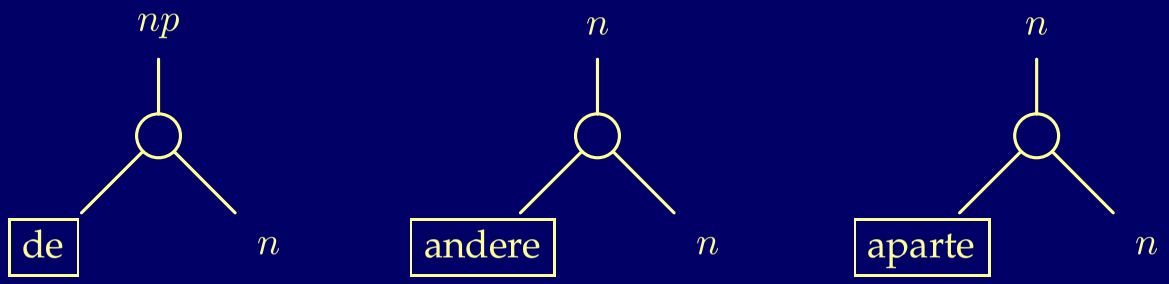

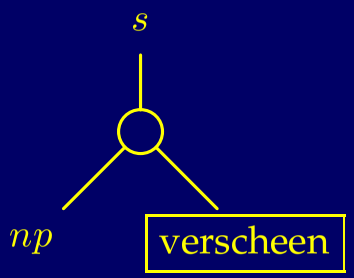

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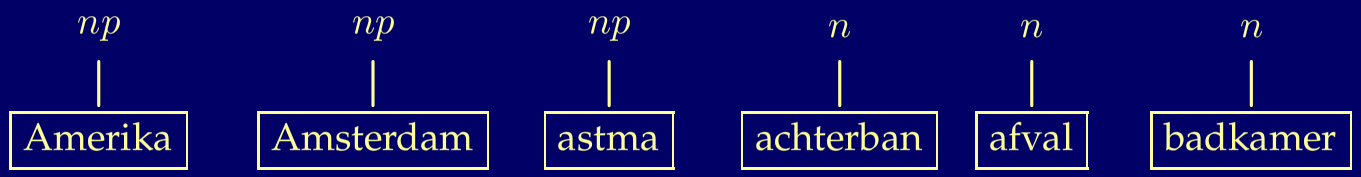
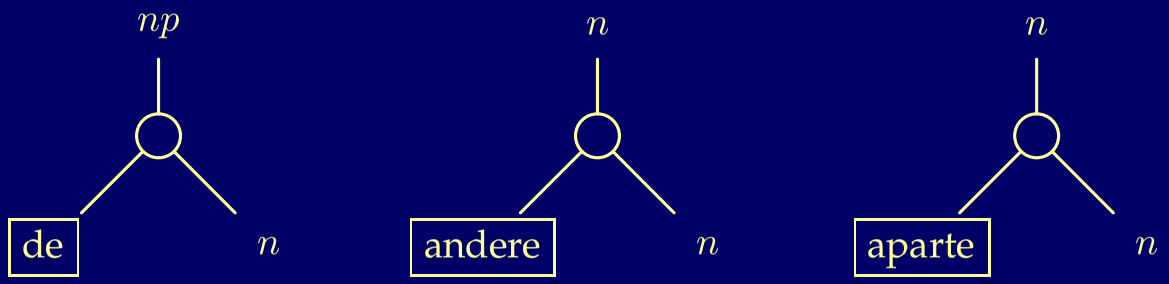
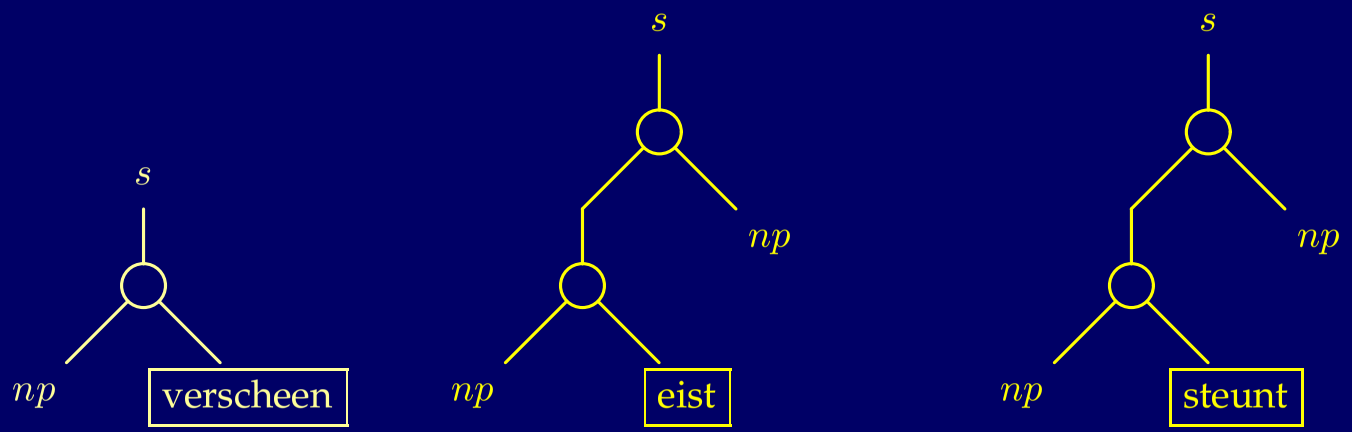
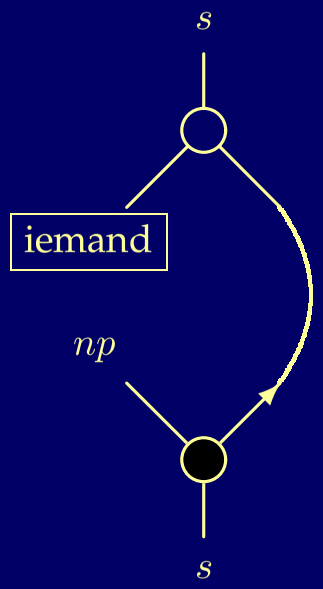


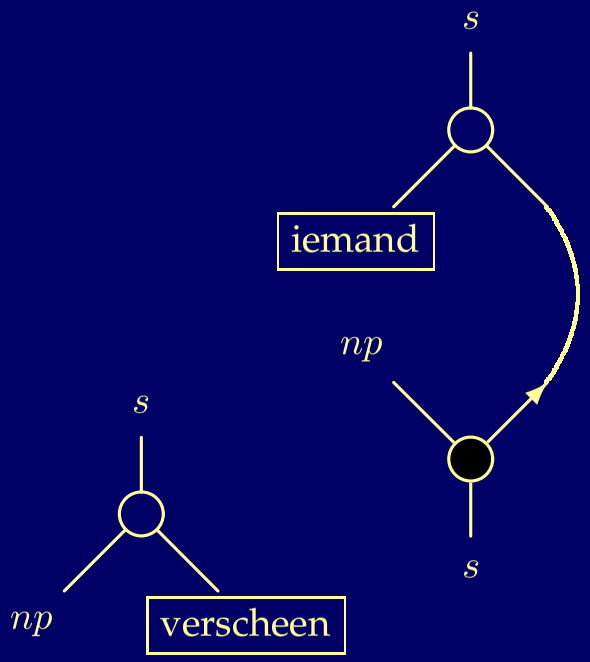




Example Lexical Entry



Example: Iemand verscheen



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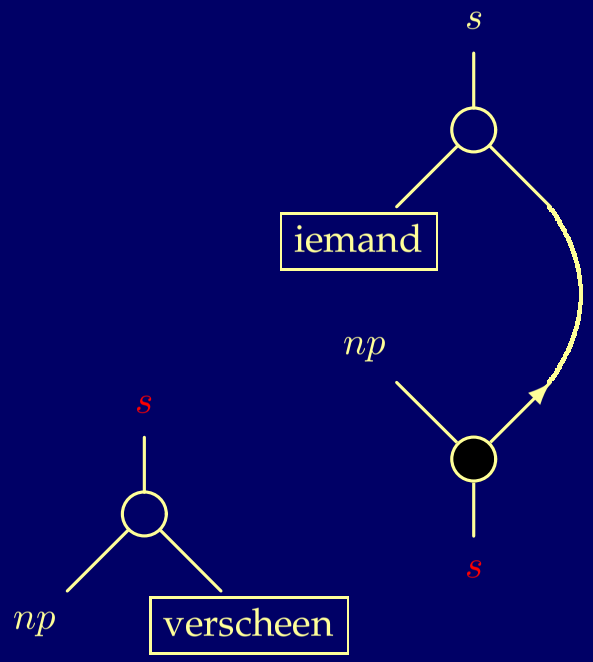

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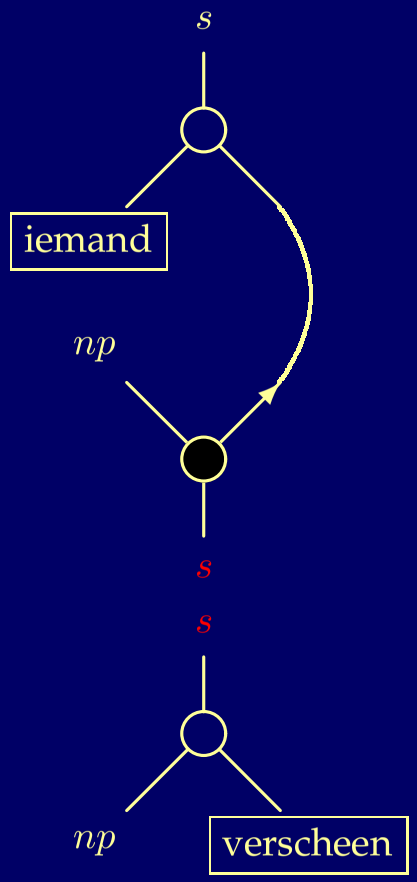

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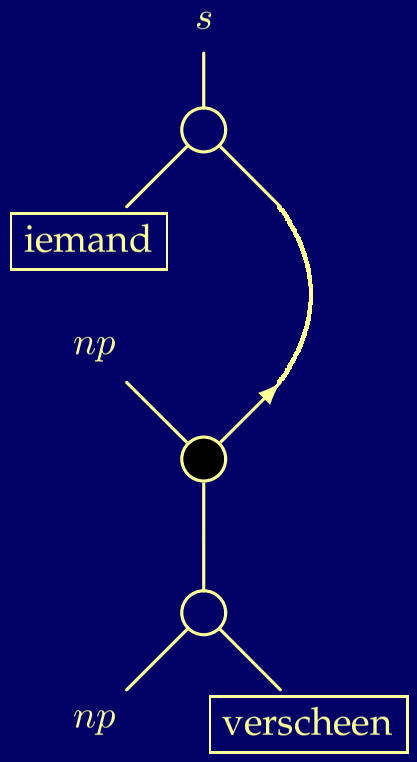

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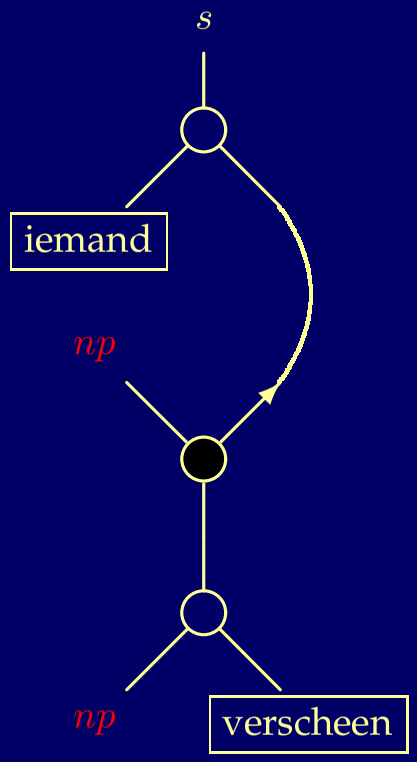

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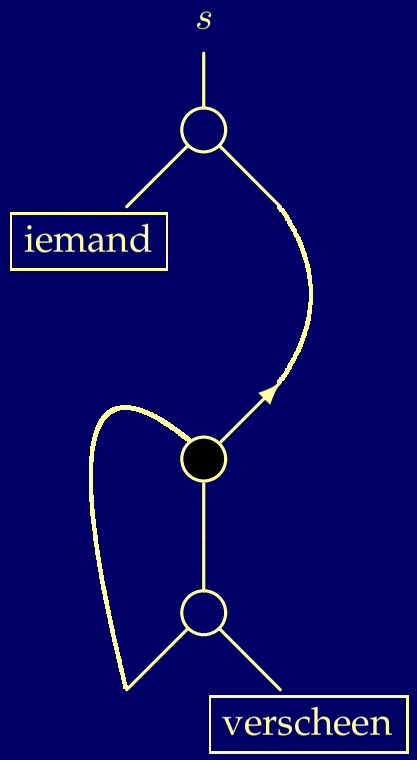

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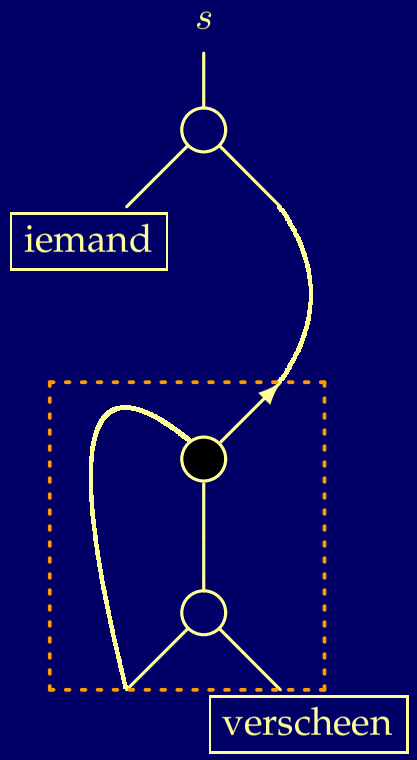

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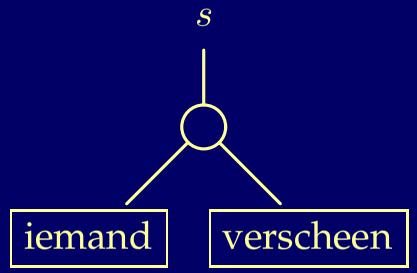

Algorithmic Aspects

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(iii) contract the resulting proof structure to a tree.

4 Extracting a Lexicon

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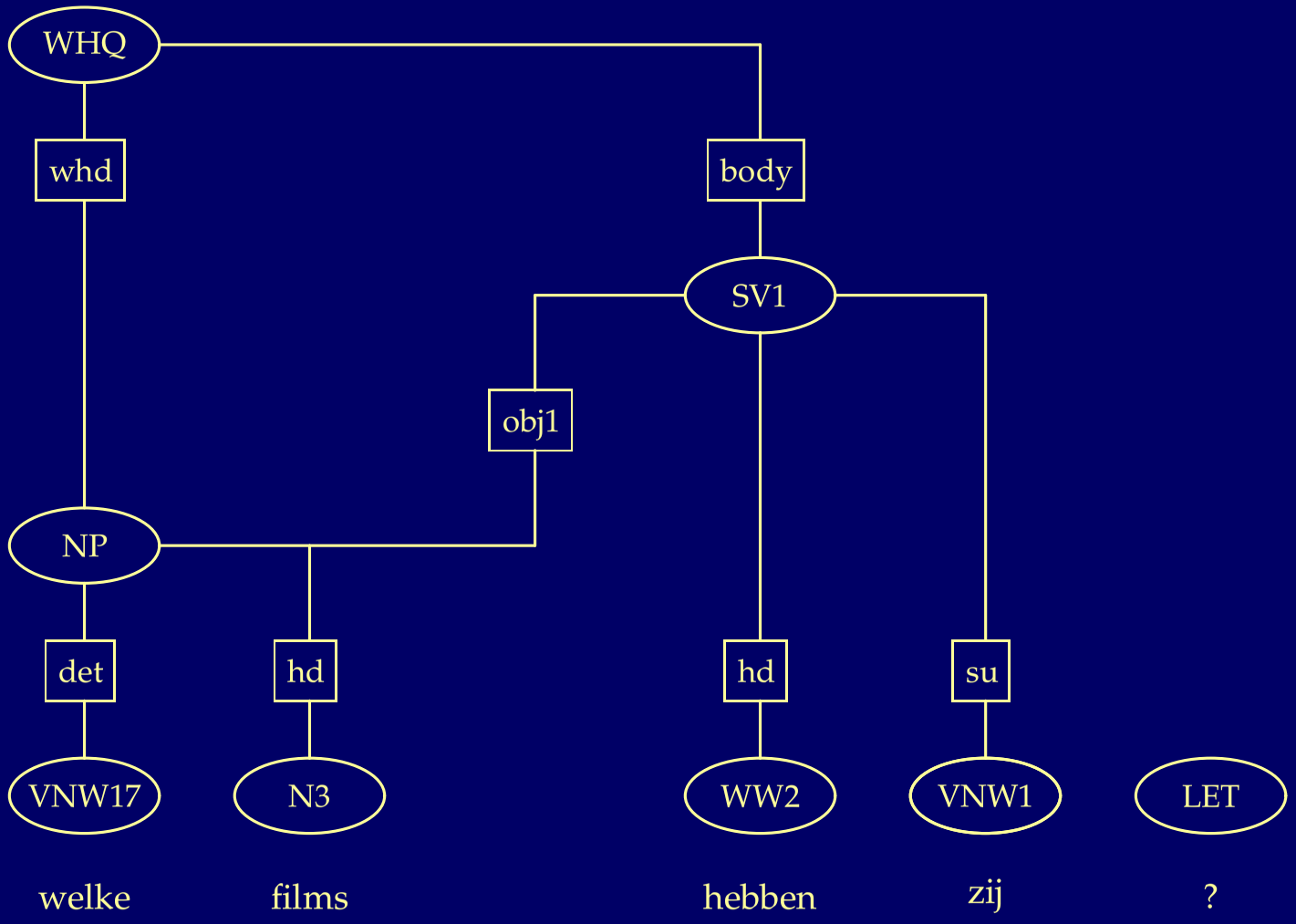
- Take a CGN annotation graphs.
- Identify the functor of every domain.
- Recursively disconnect all daughters which are not the functor.
- Translate the obtained graphs into lexical proof structures.

Identify Functors



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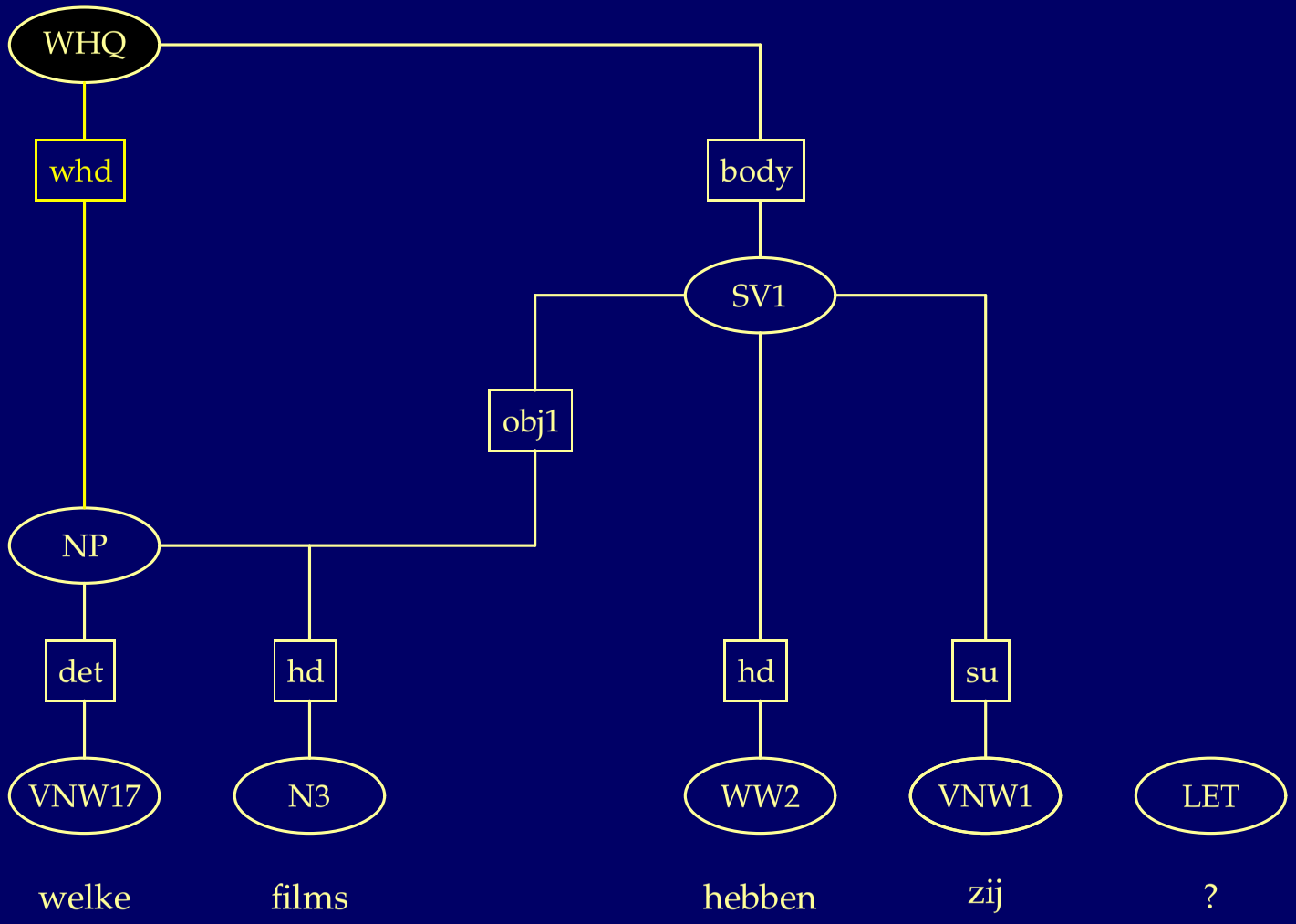

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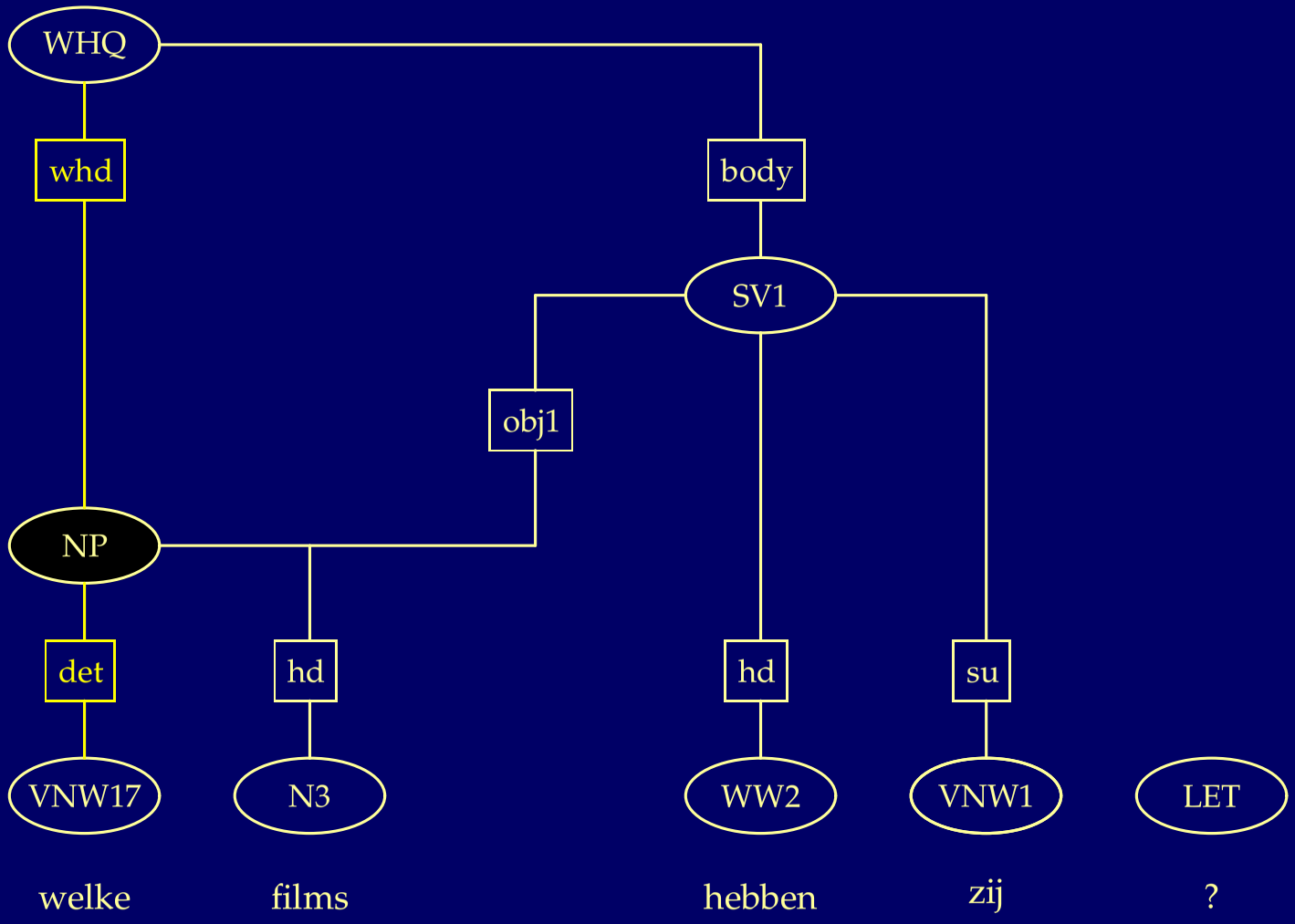

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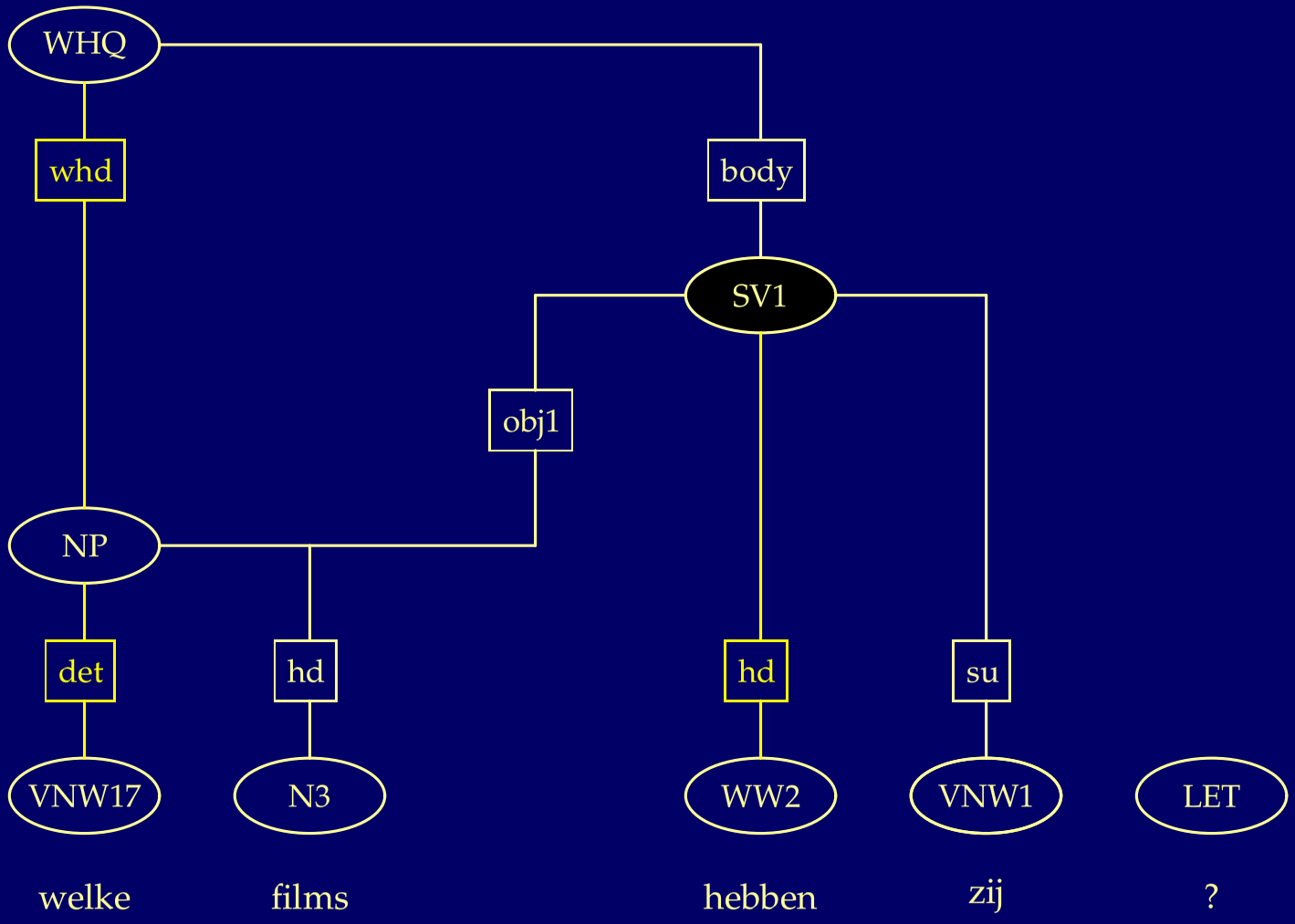
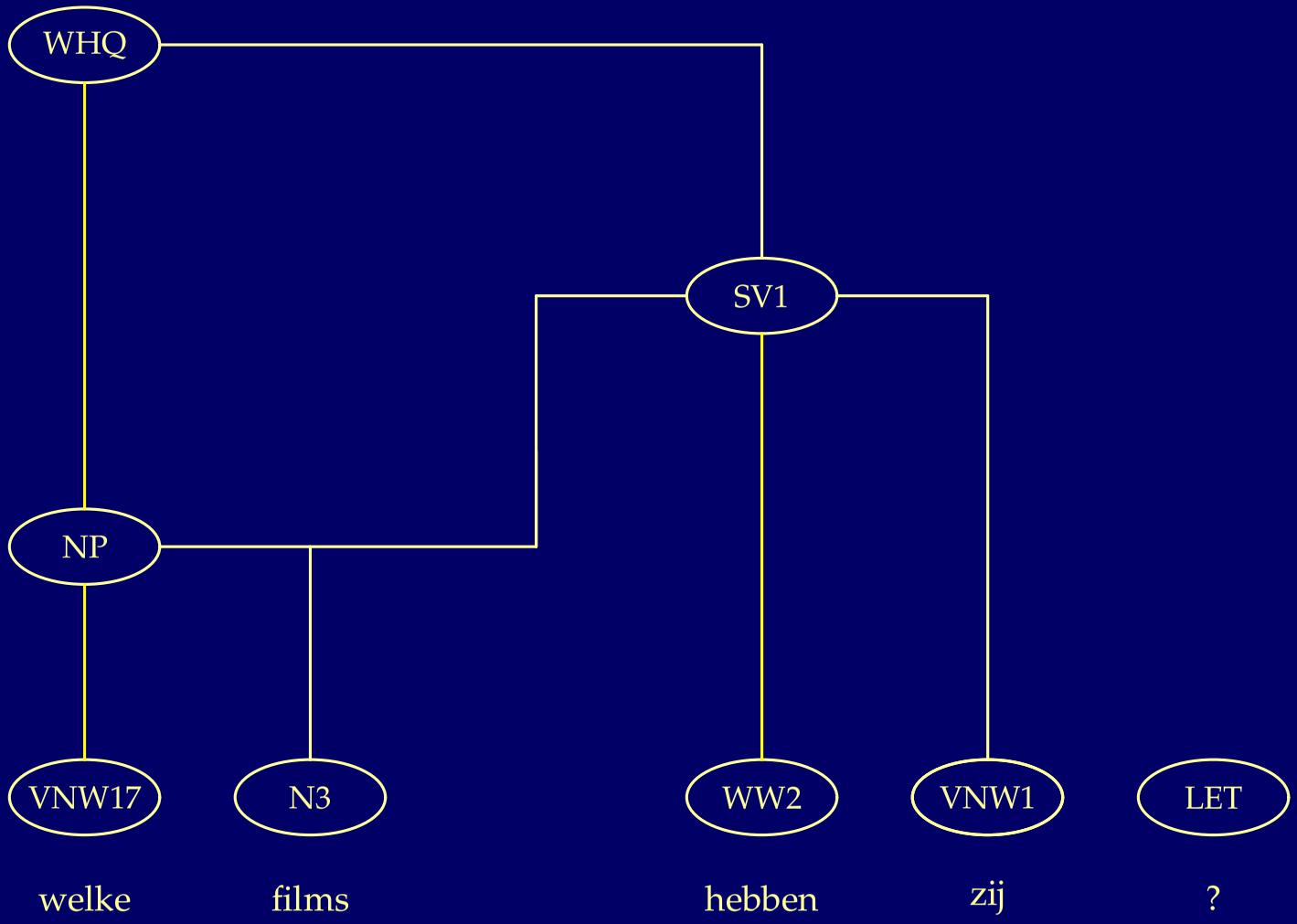


Remove Edge Labels



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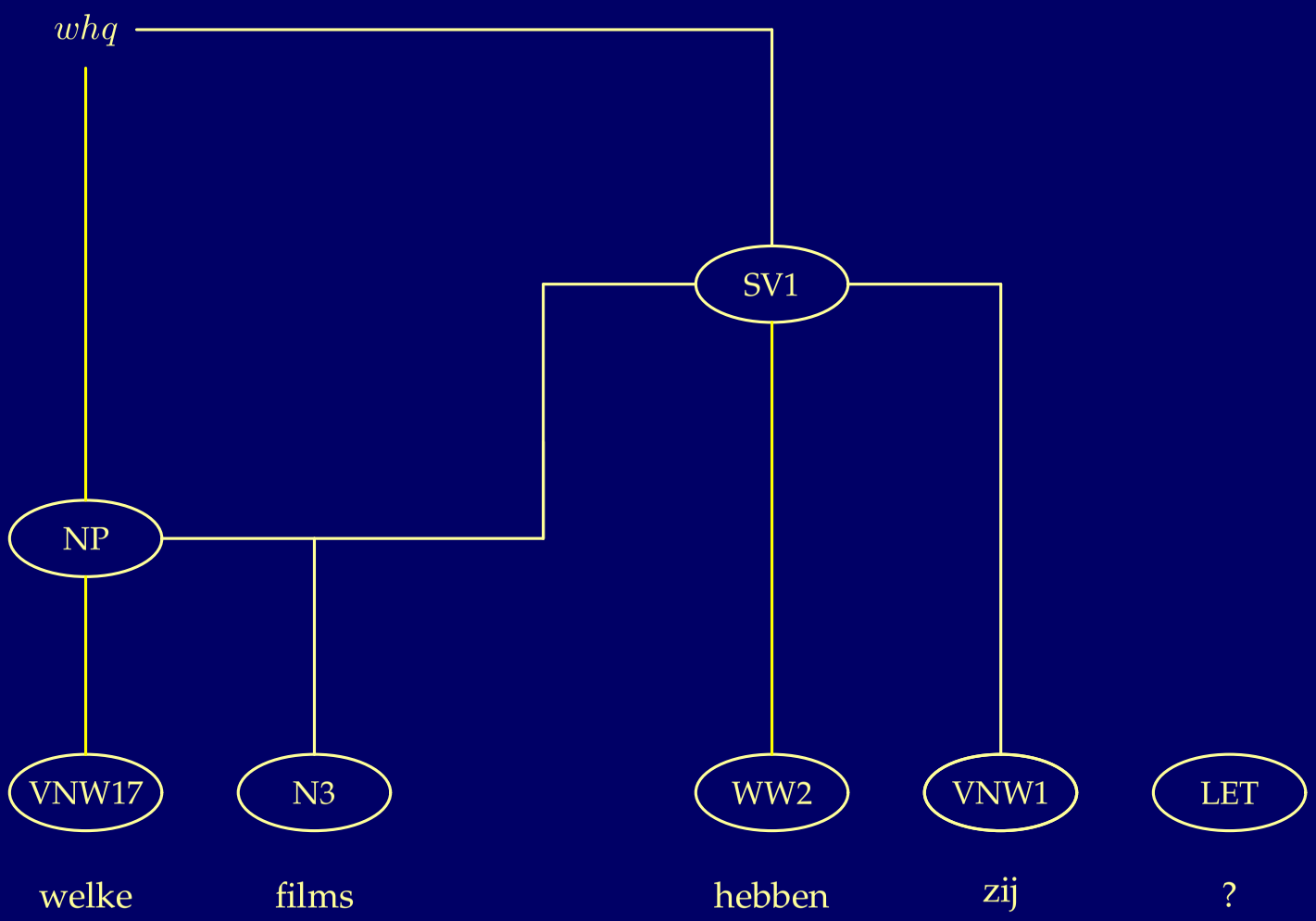

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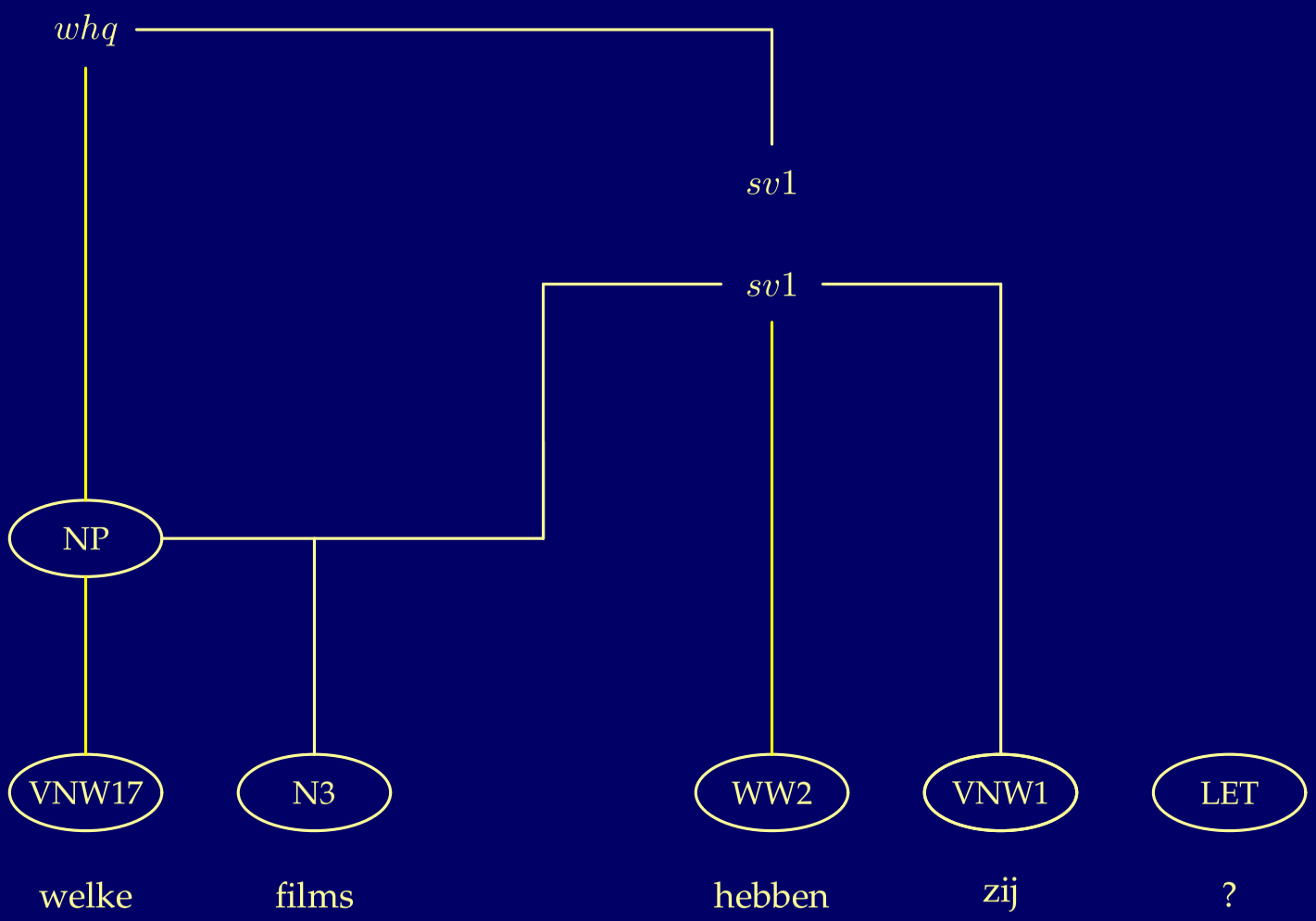

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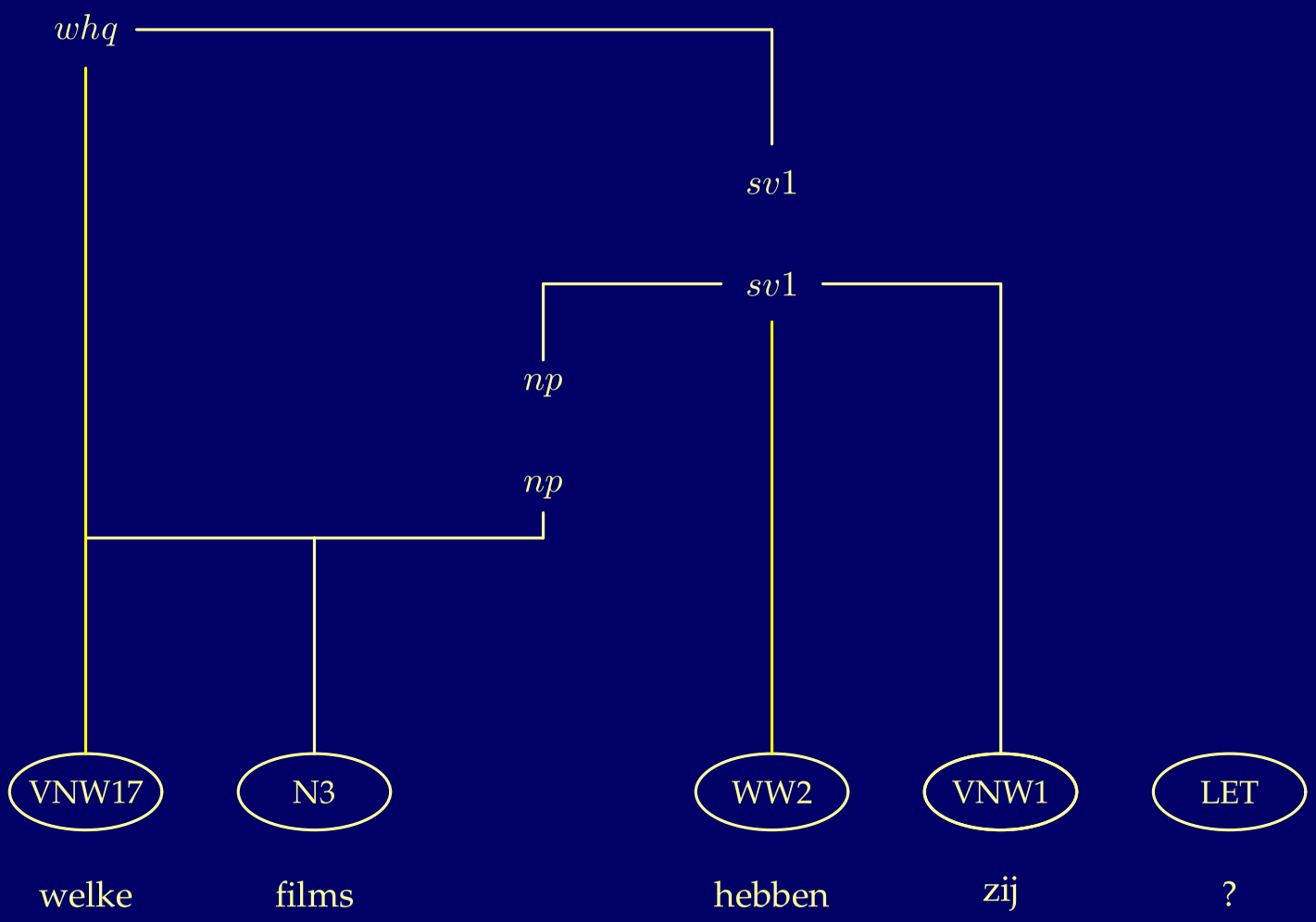

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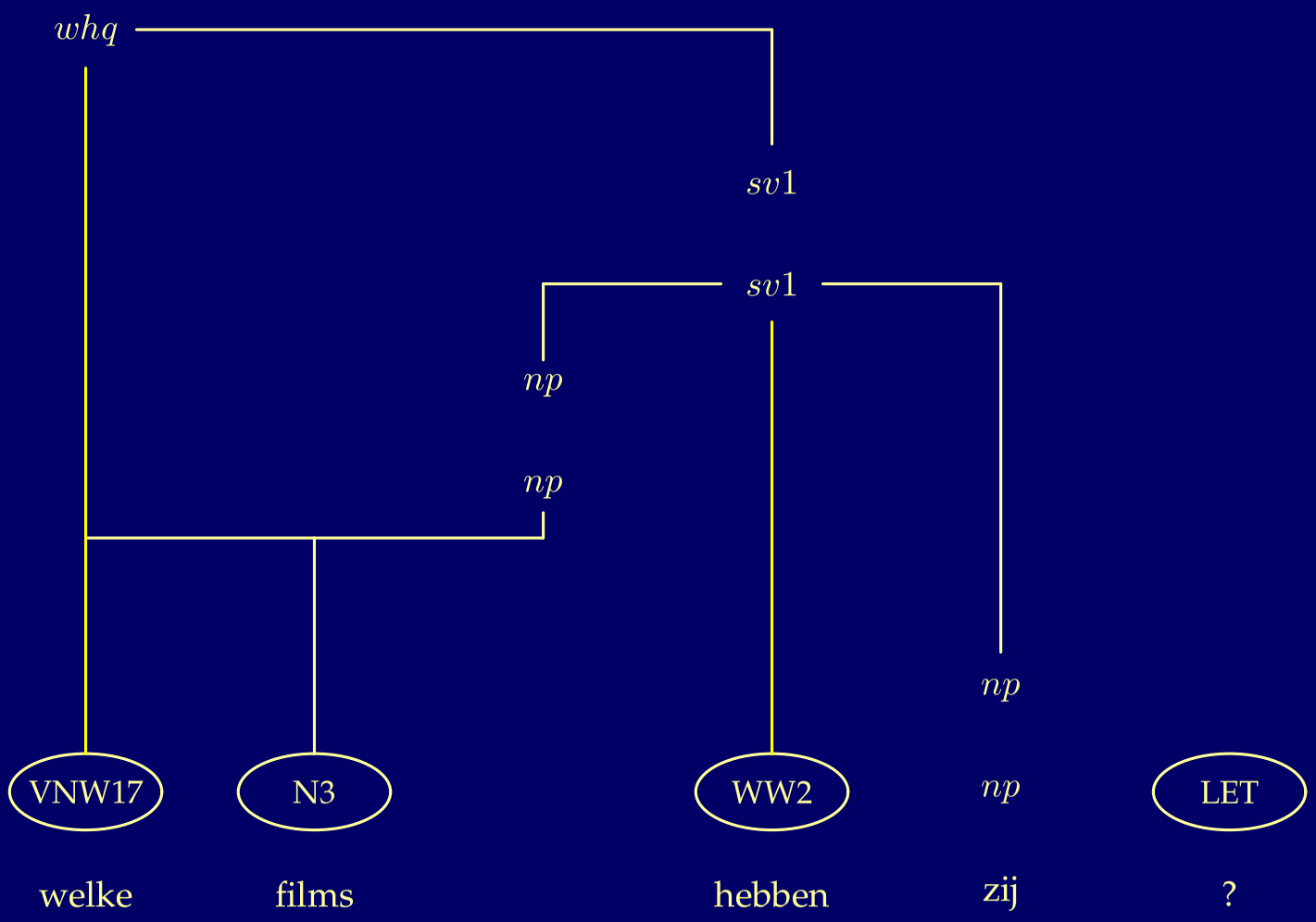

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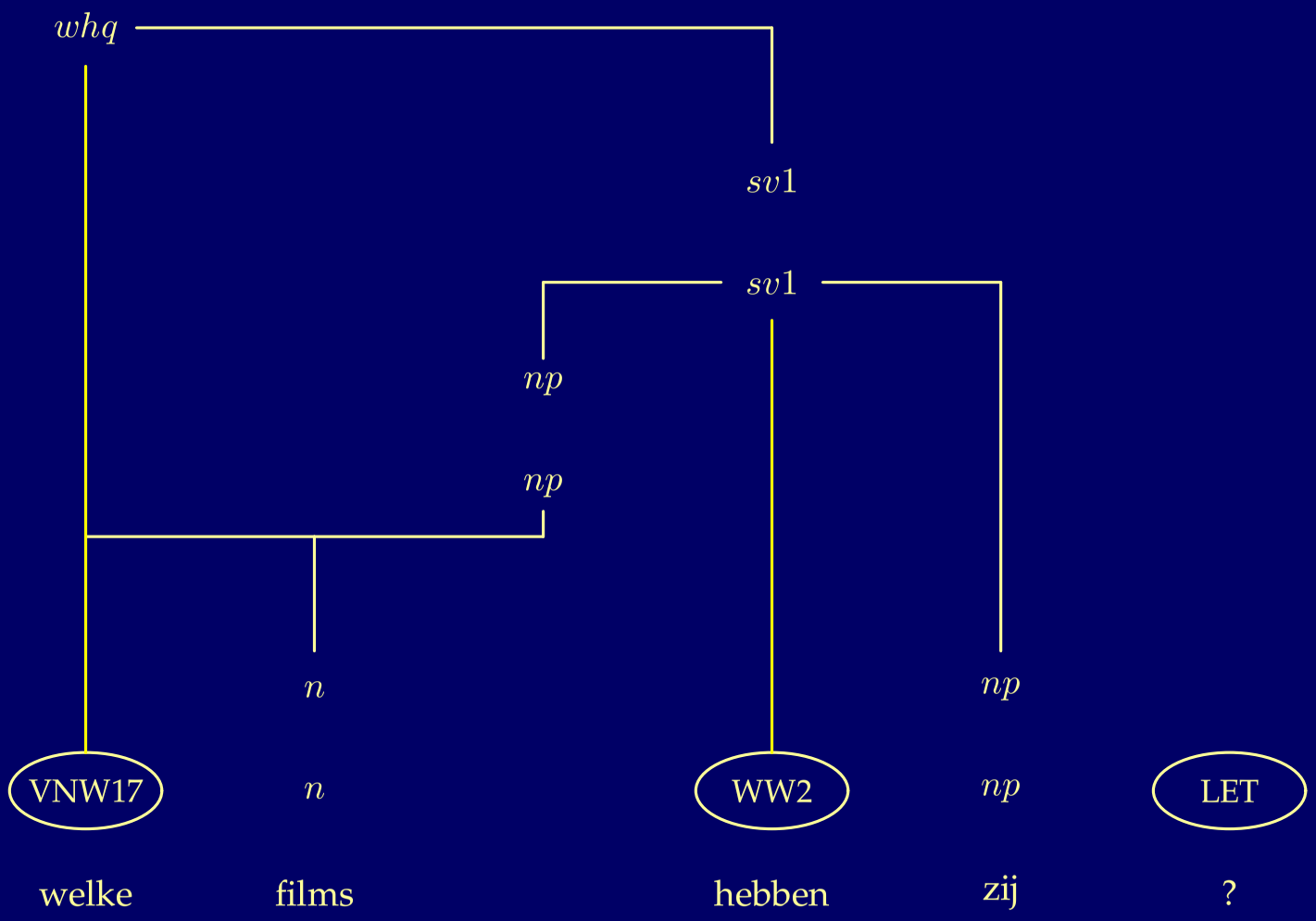

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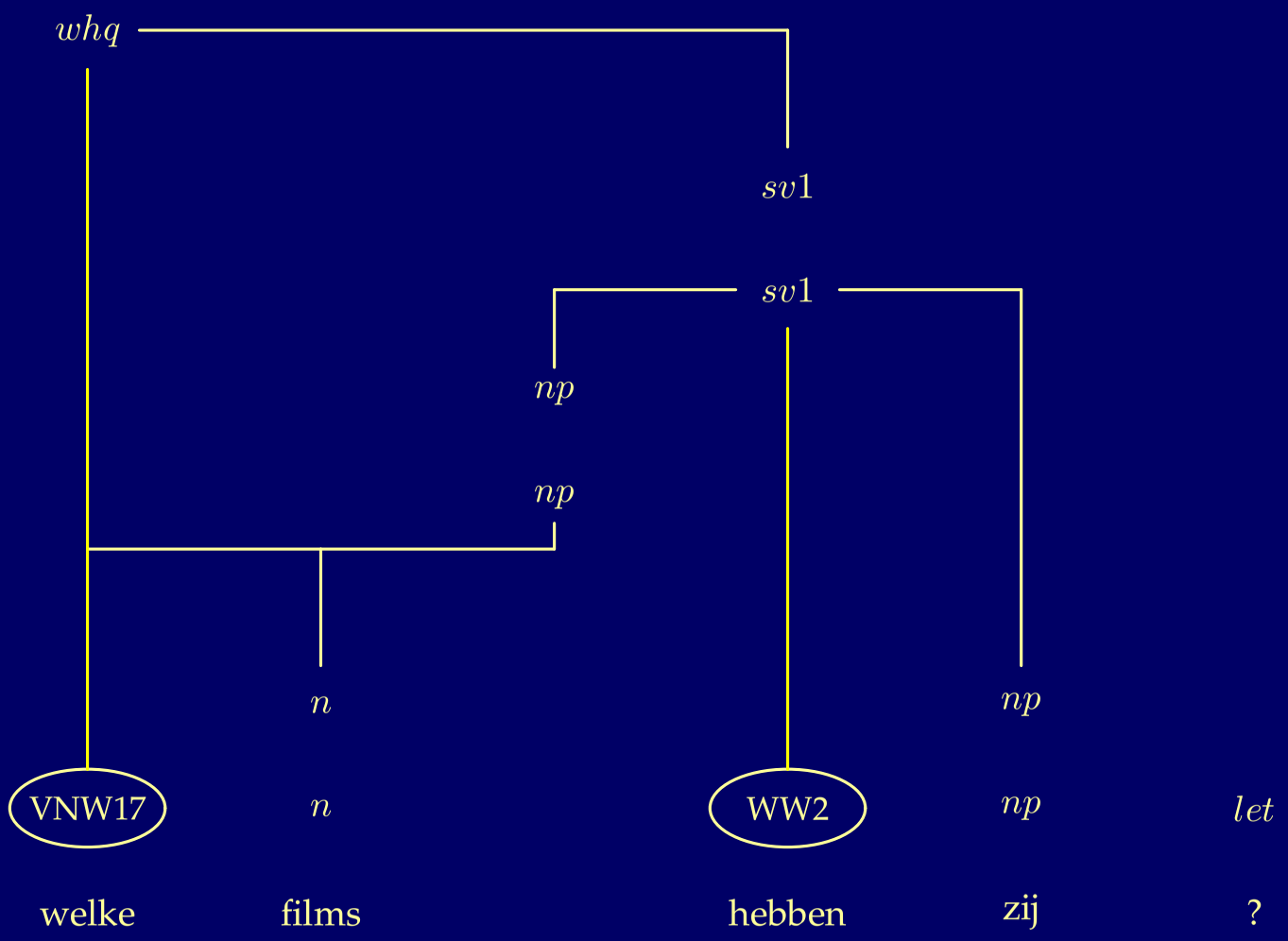

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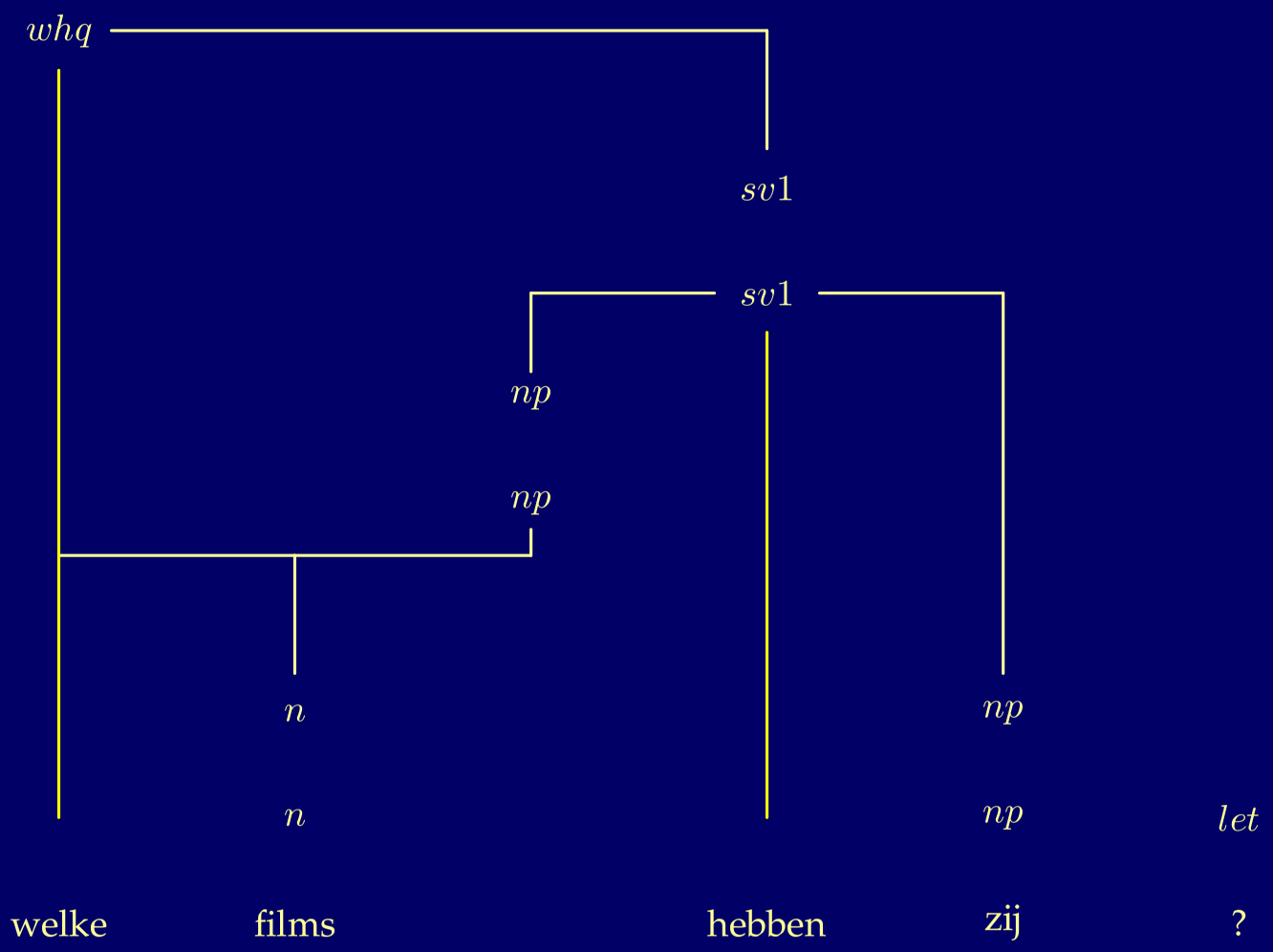

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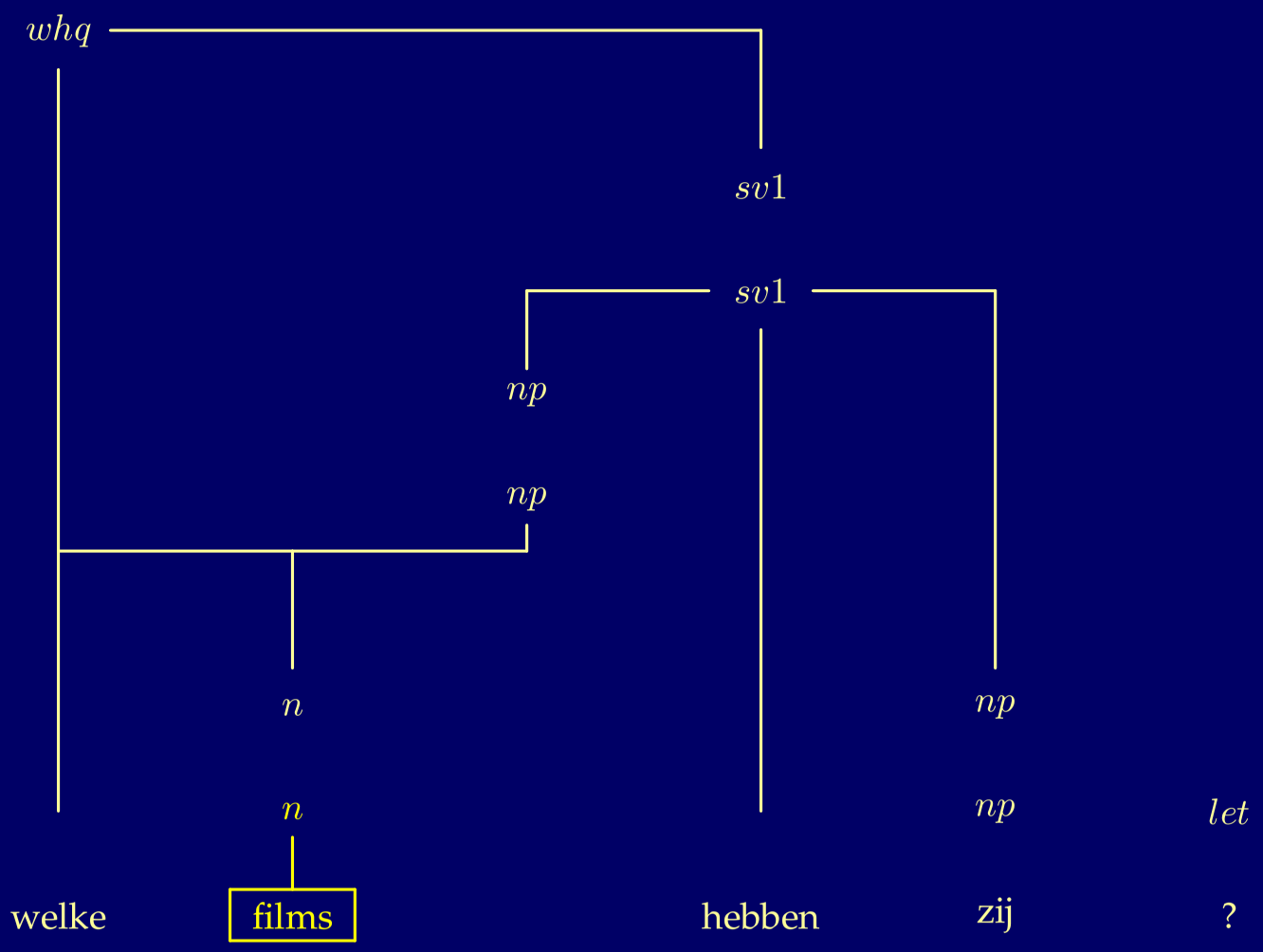

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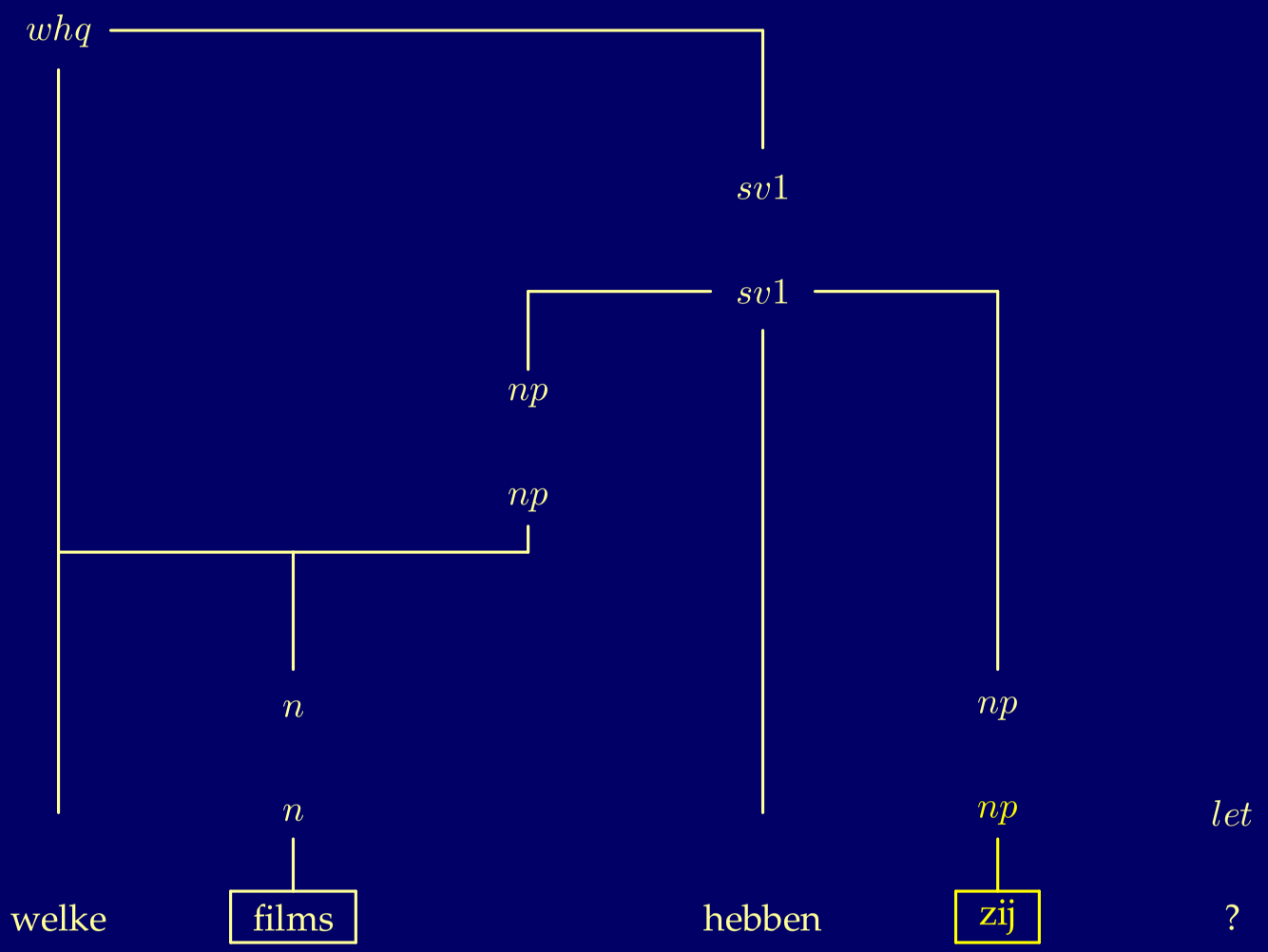

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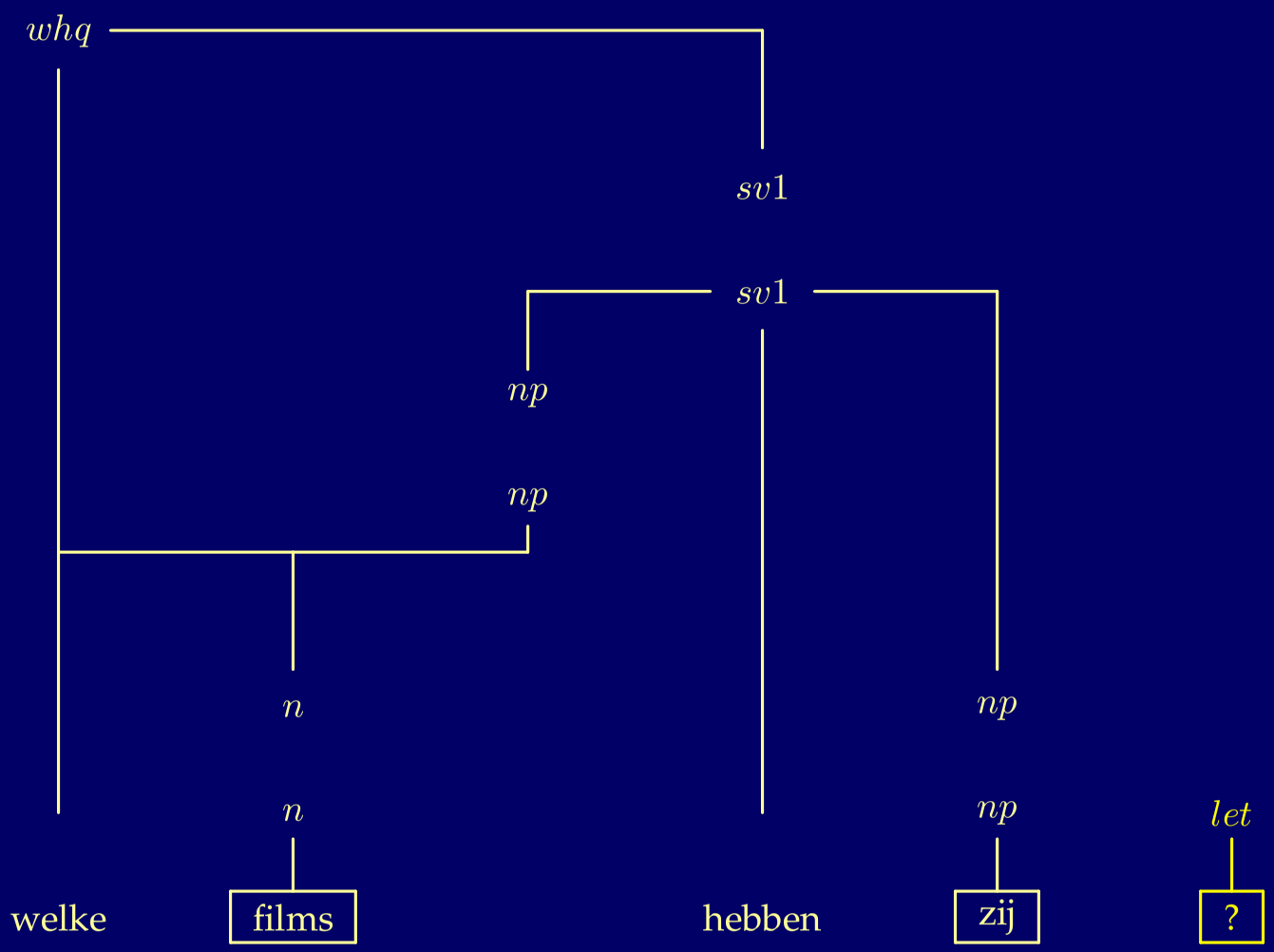

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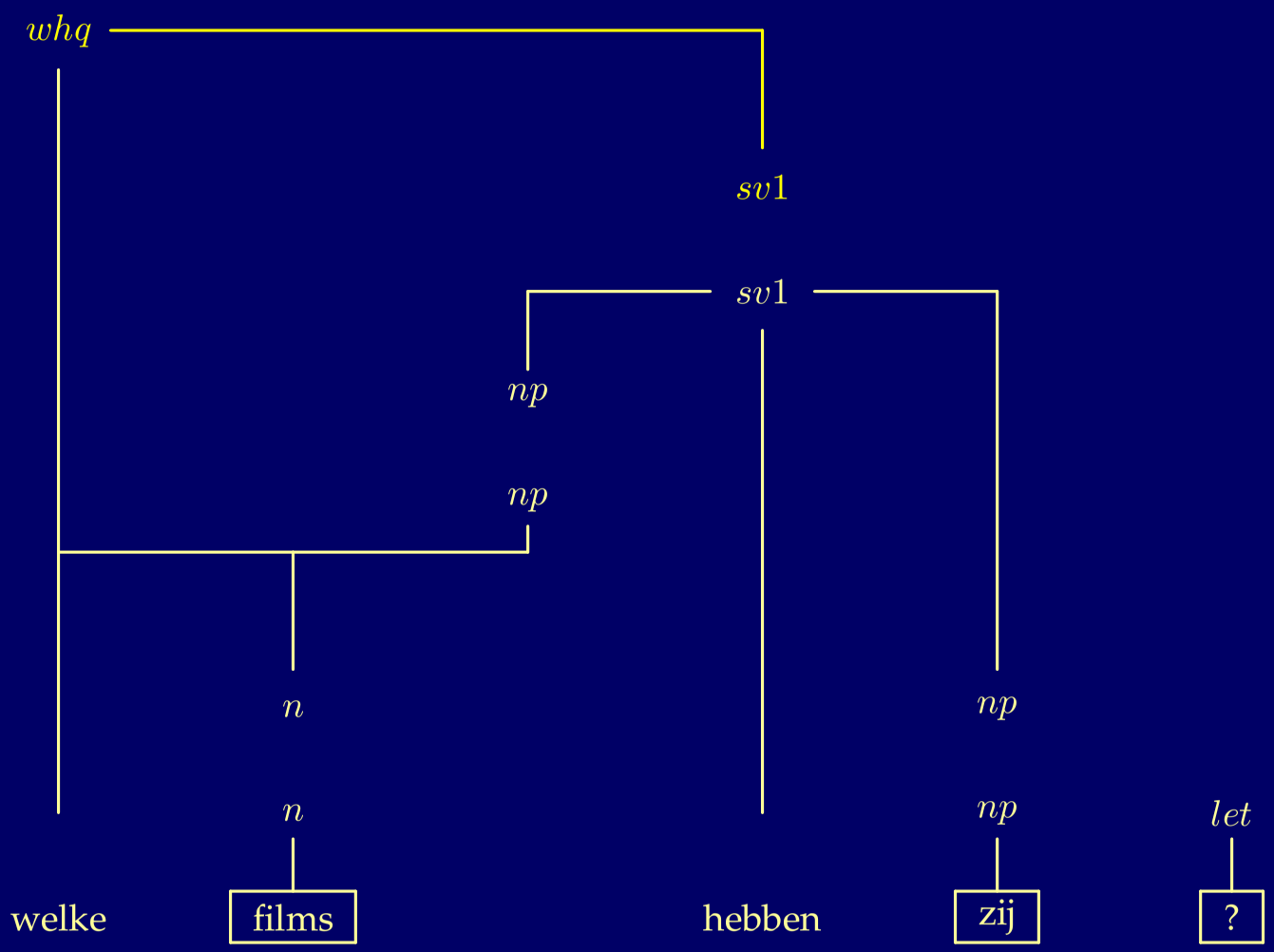

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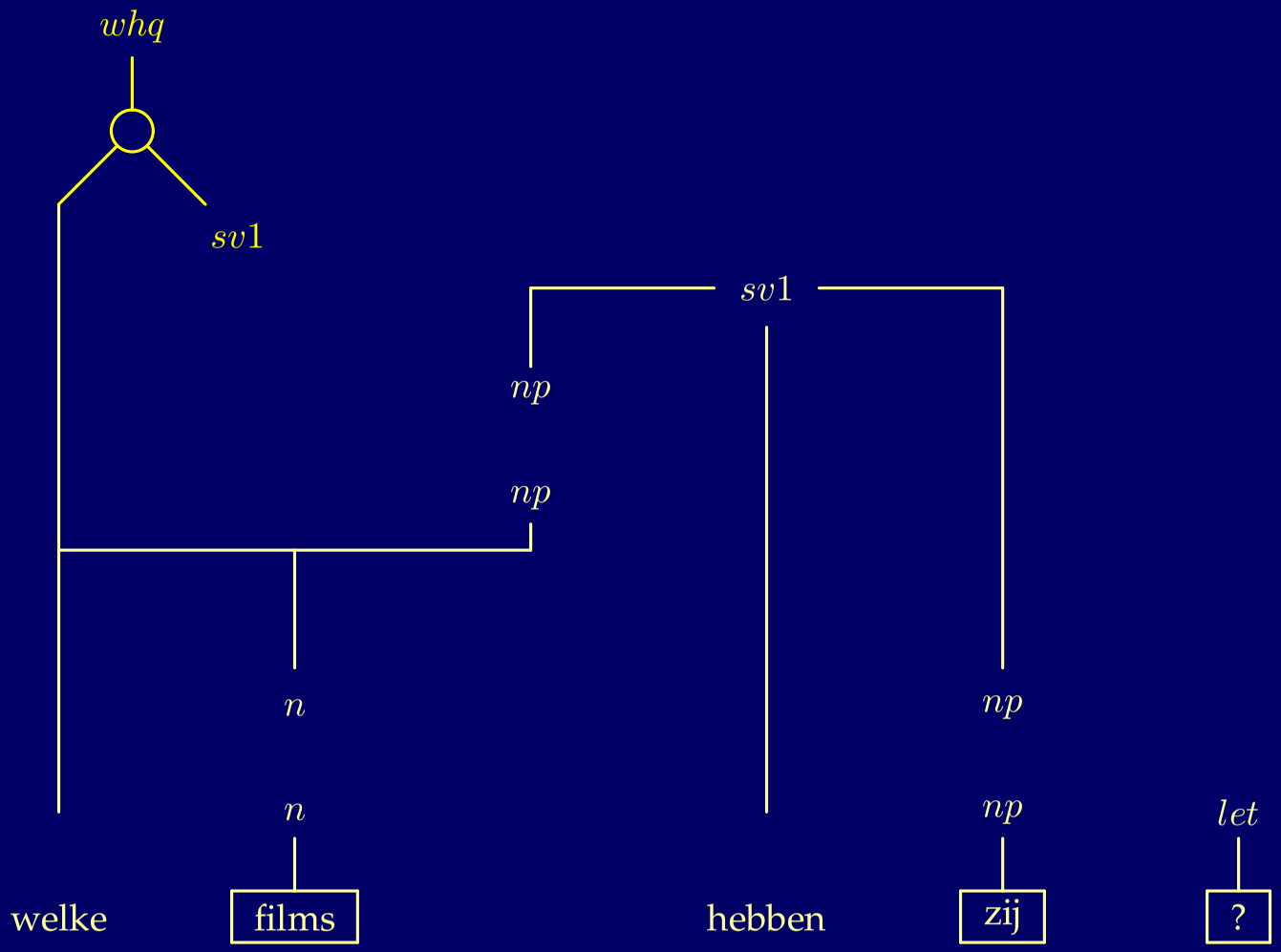

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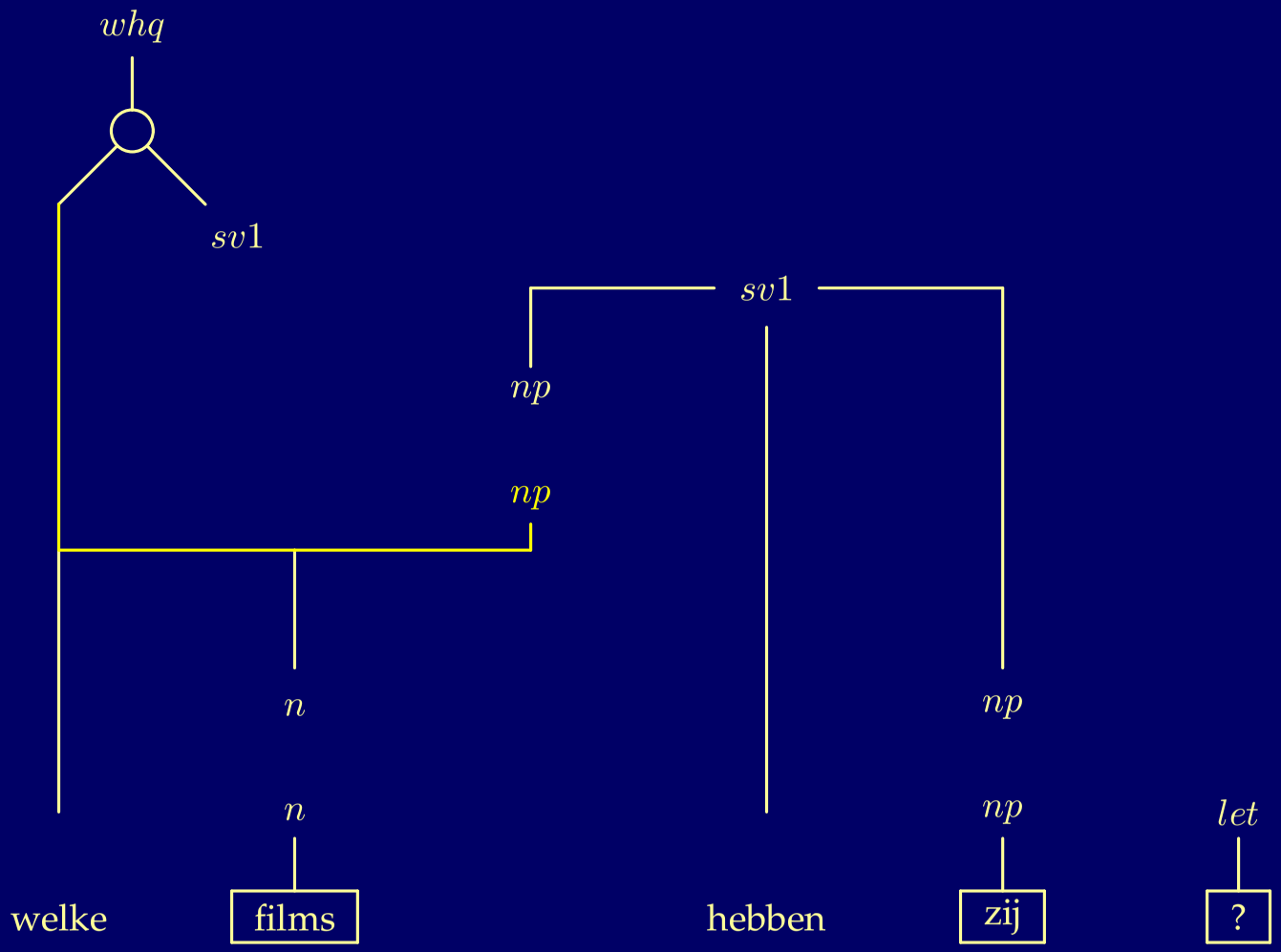

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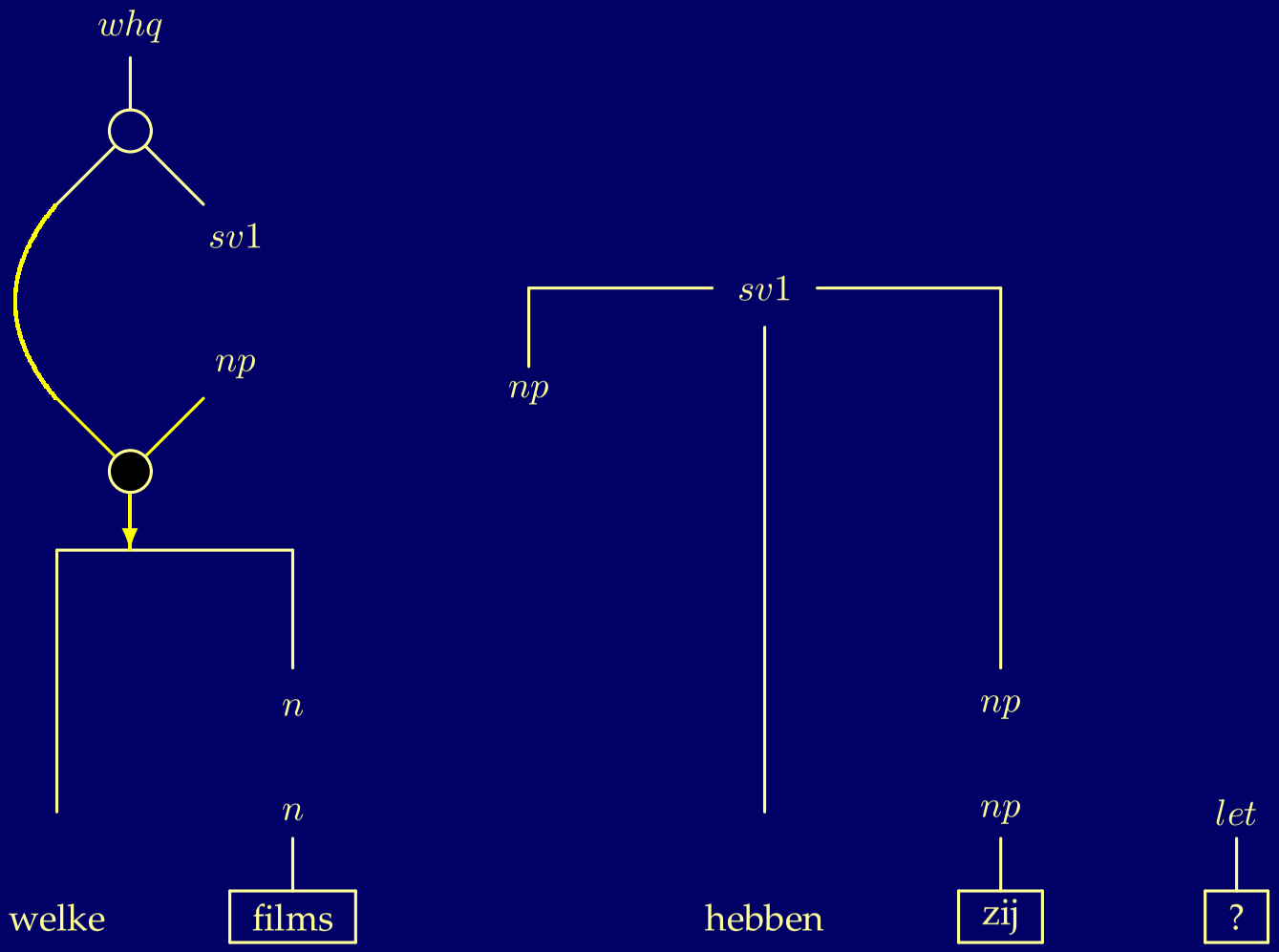

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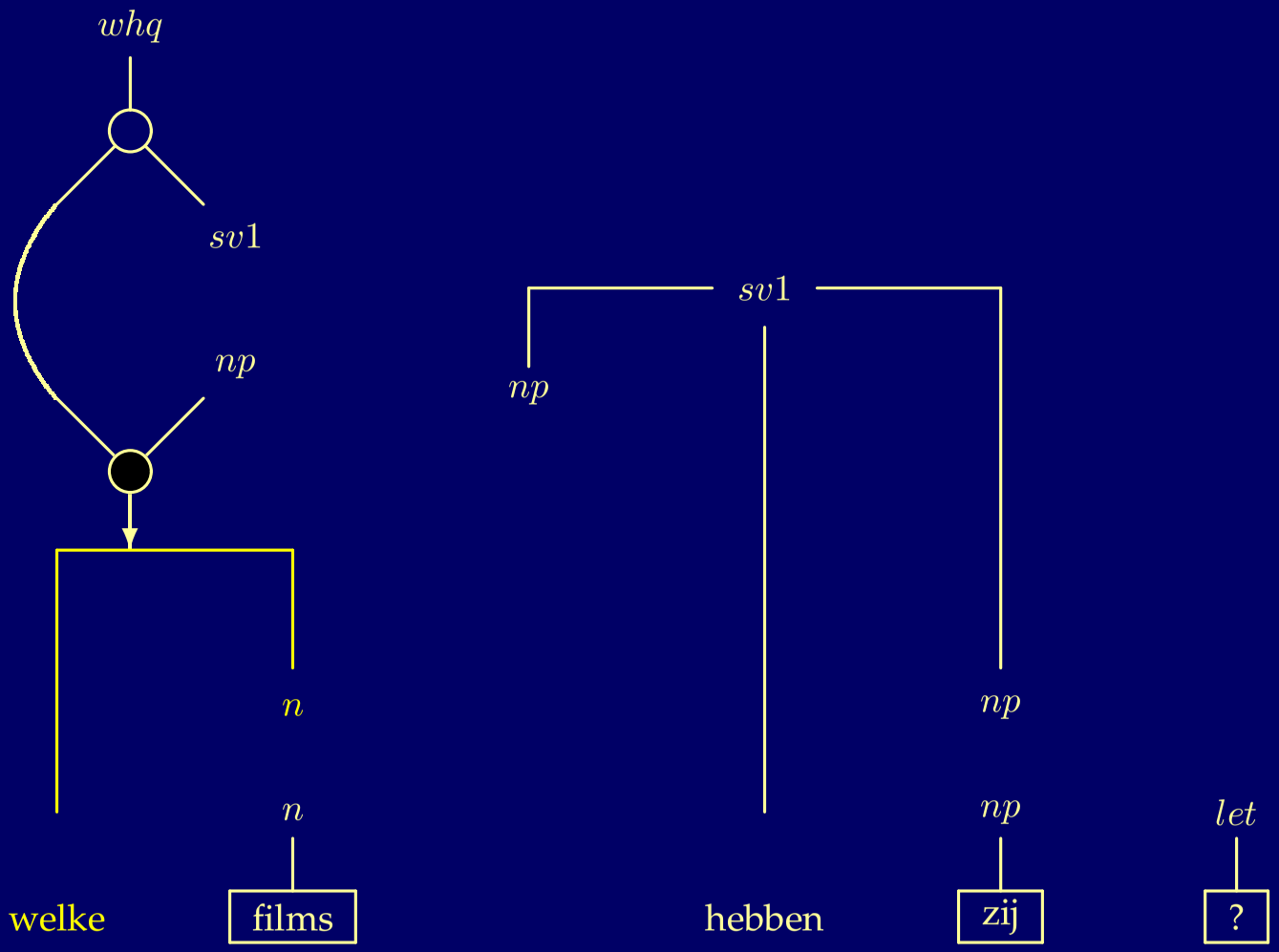

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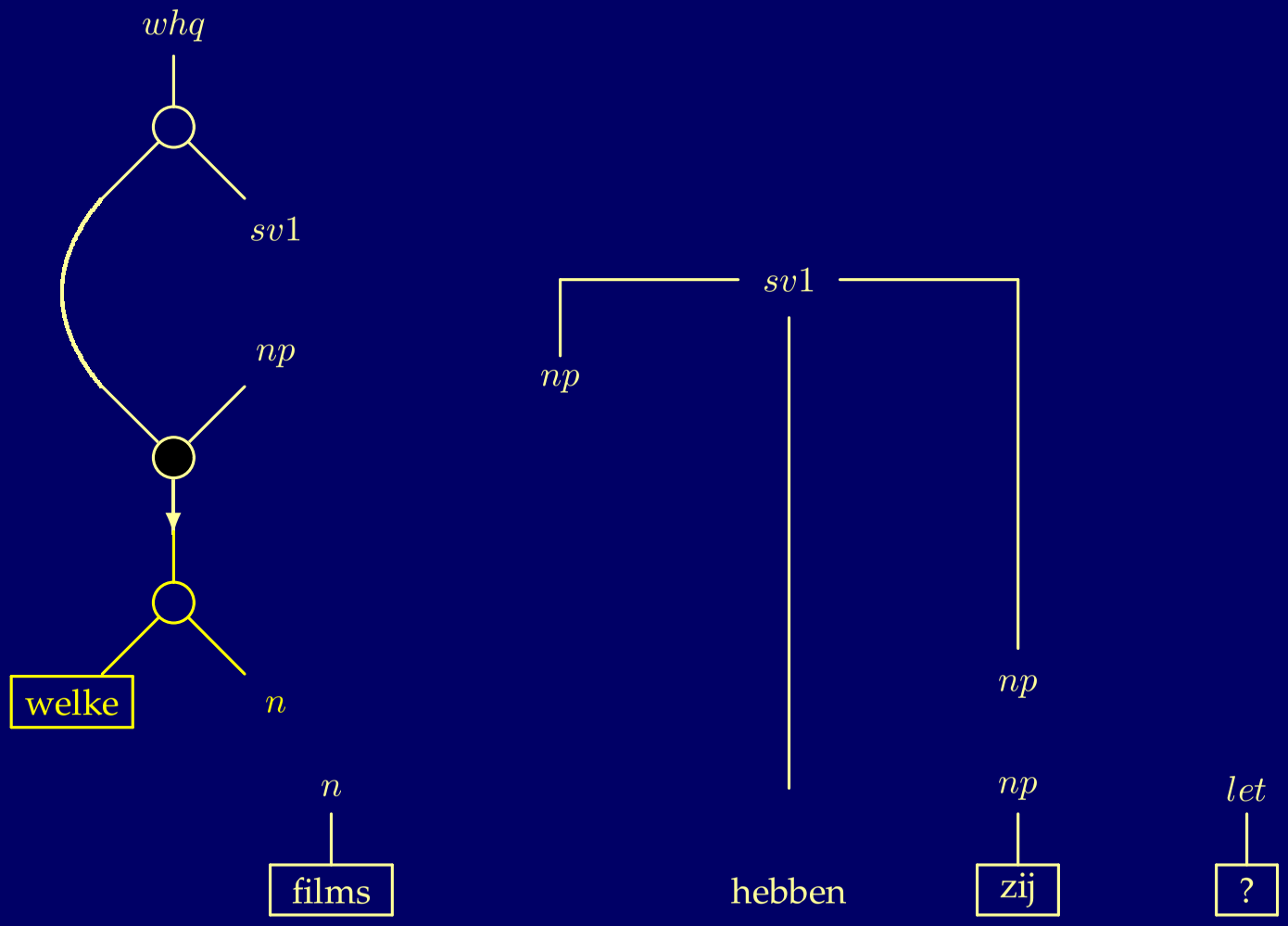

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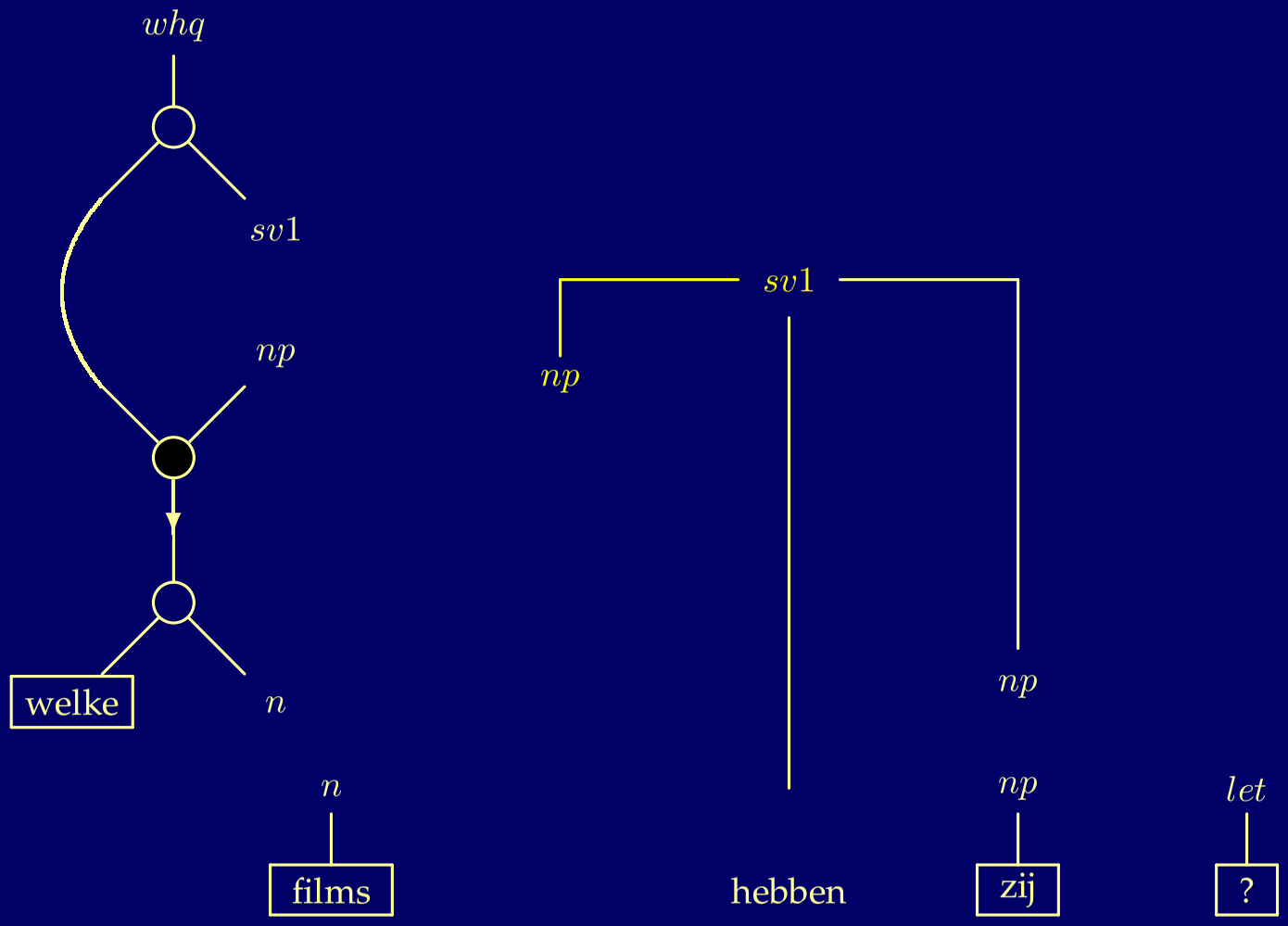

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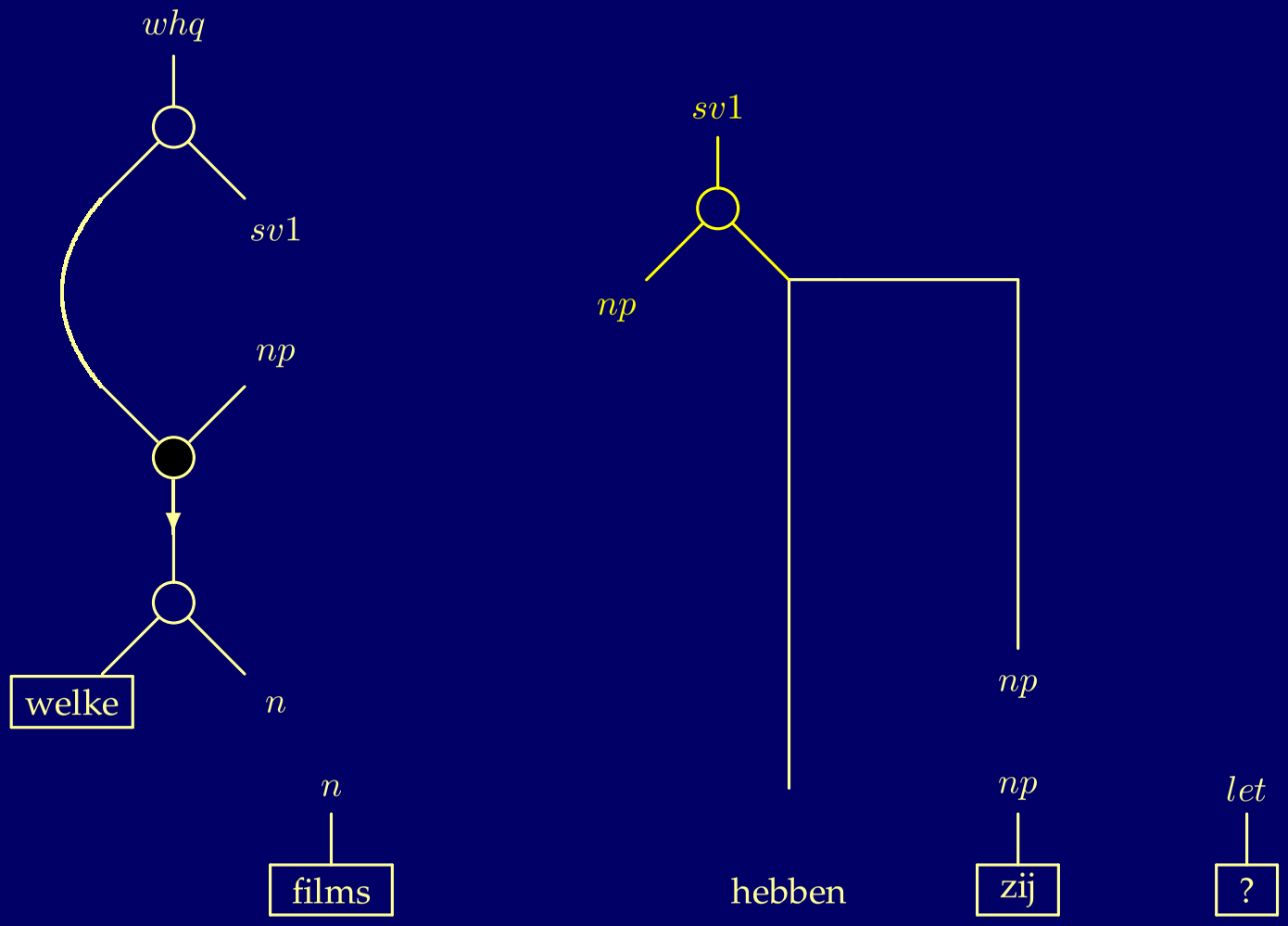

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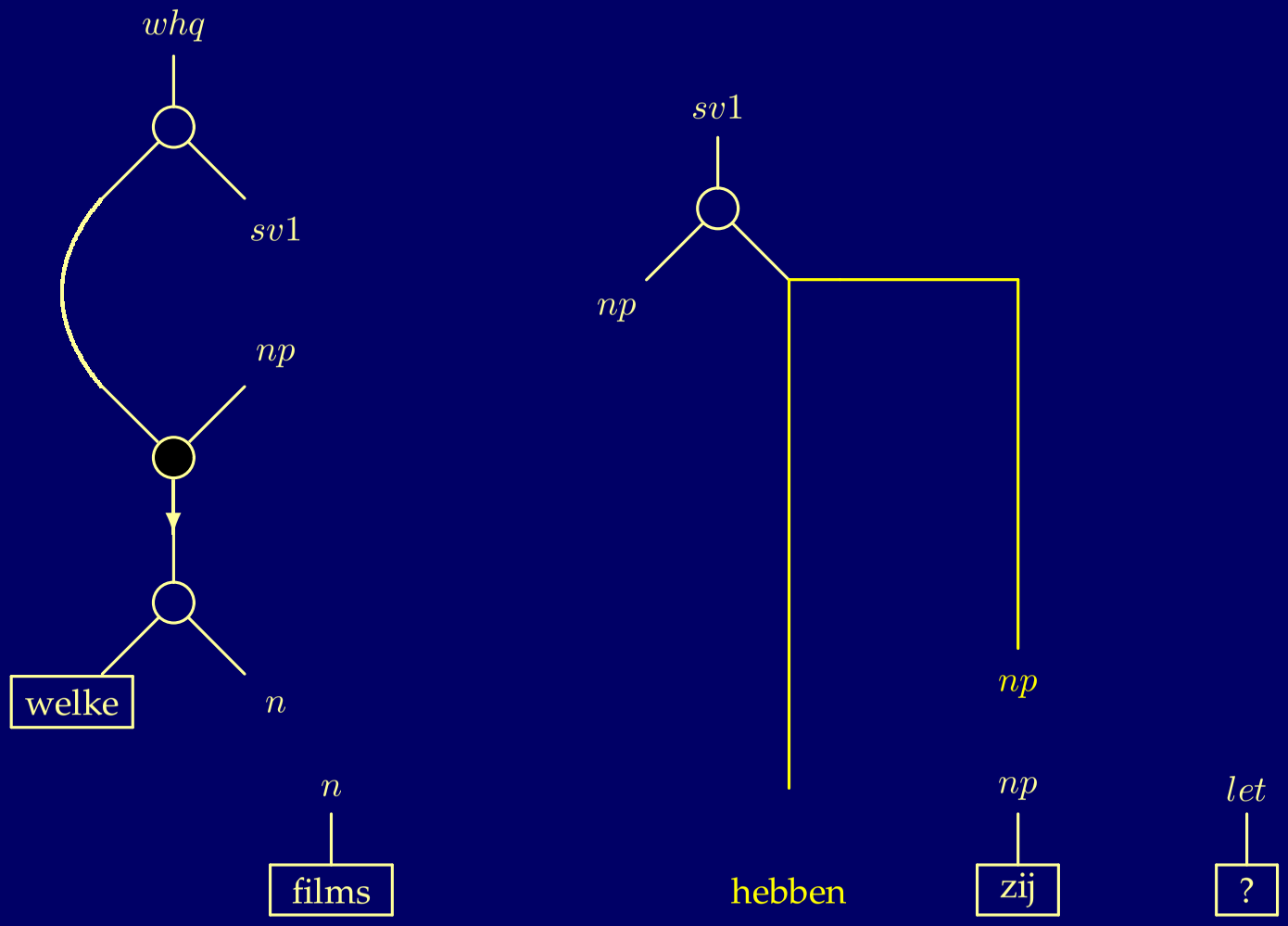

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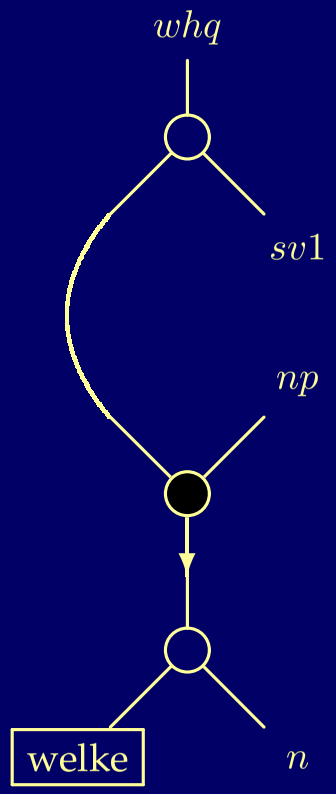

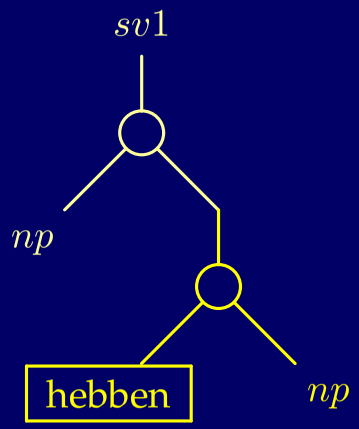

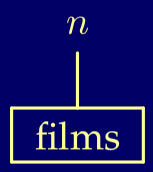

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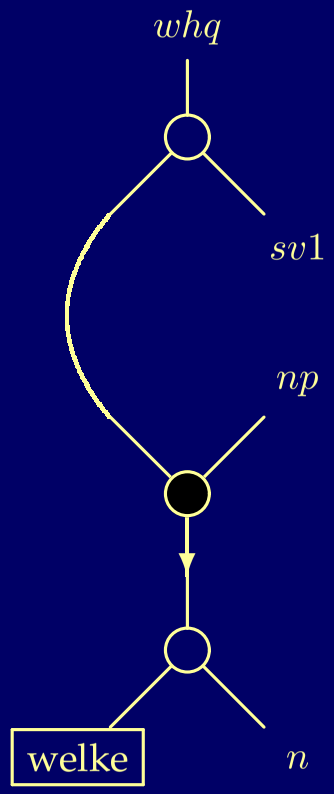

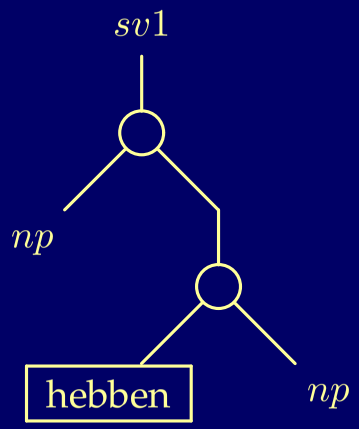

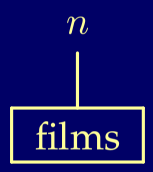

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- The formula assigned to 'hebben' has the constituents in OVS order.
- Our solution is to treat all sentences as verb final and select the constituents from left to right using an obliqueness ordering.

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- However, the formulas produces by the translation look a bit unfamiliar.
- For example, when we compute the formula assigned to 'welke' it is $((whq/sv1) \bullet np)/n$.
- A solution is to attach these dependencies at the argument category of which the second parent is a child.

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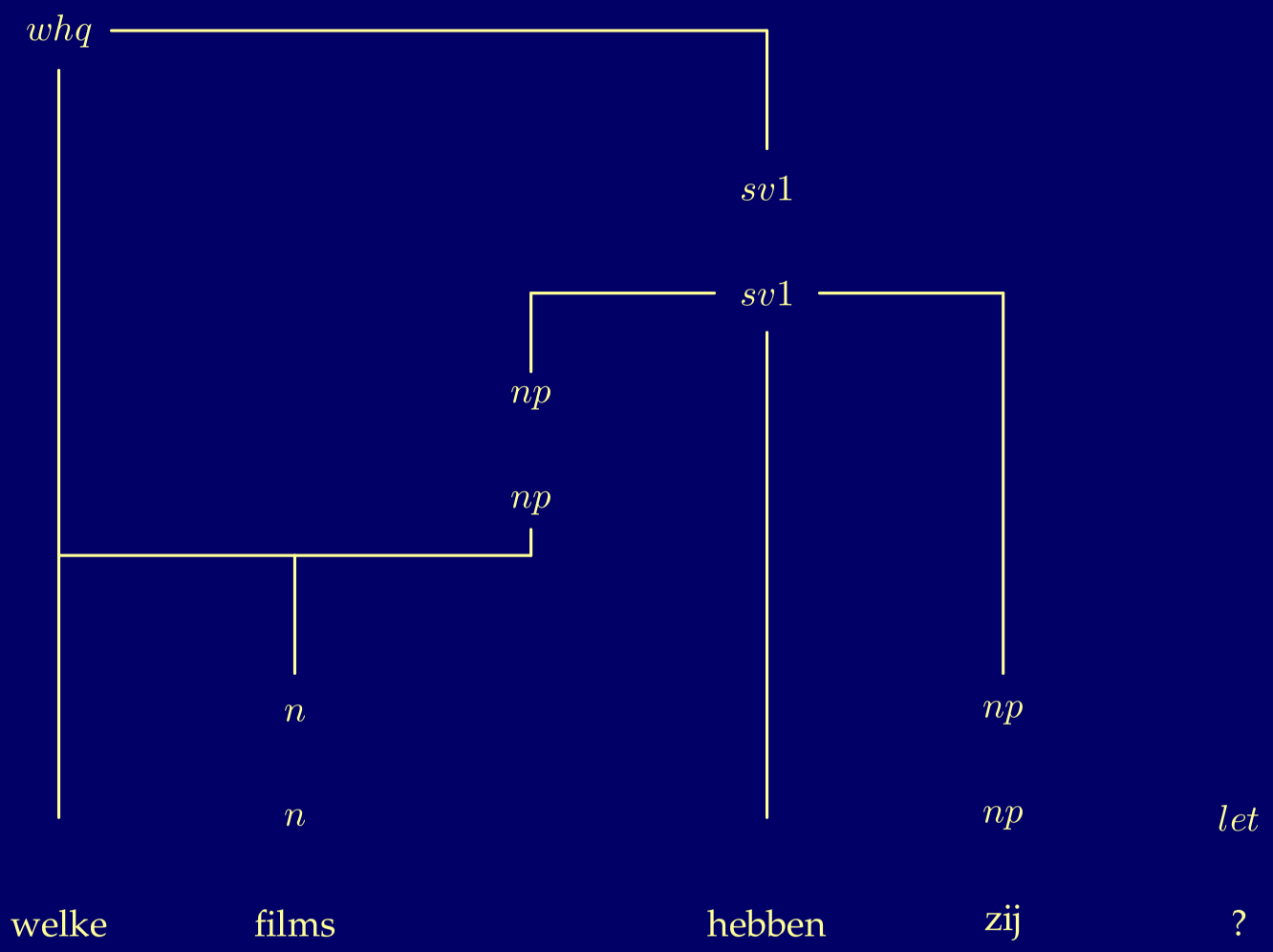

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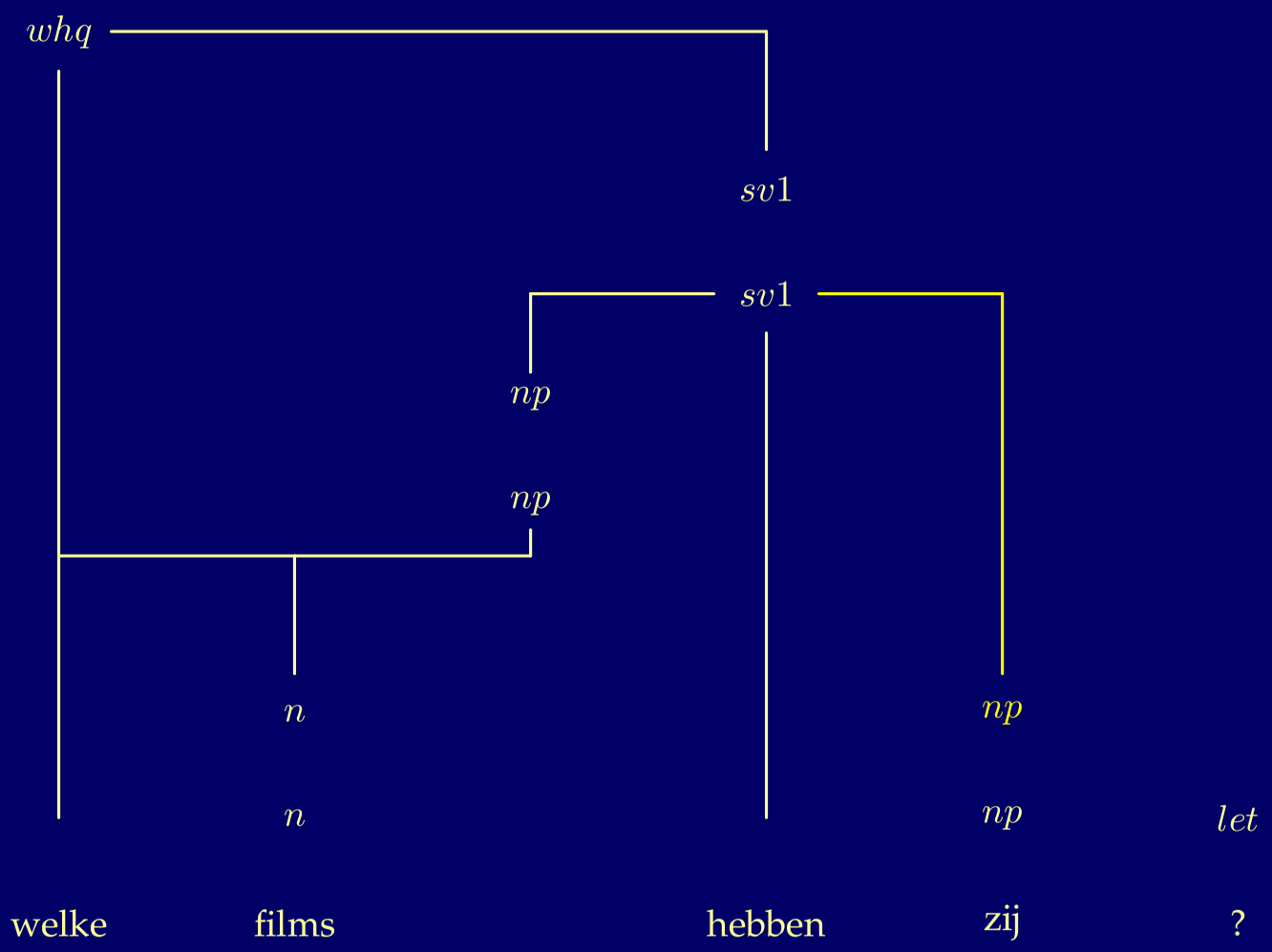

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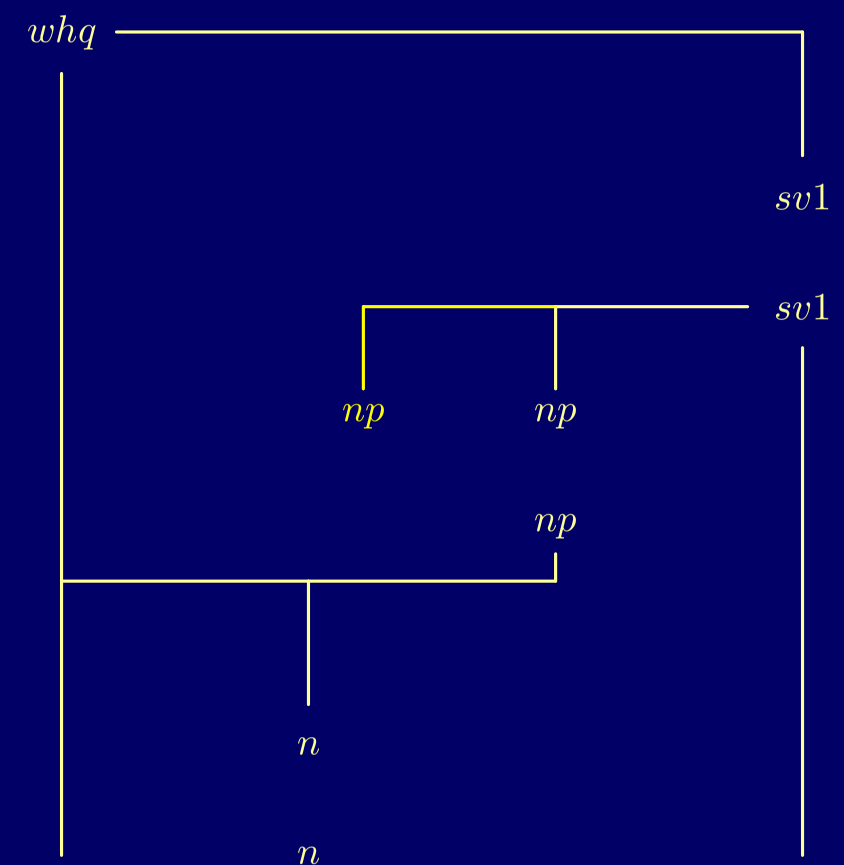

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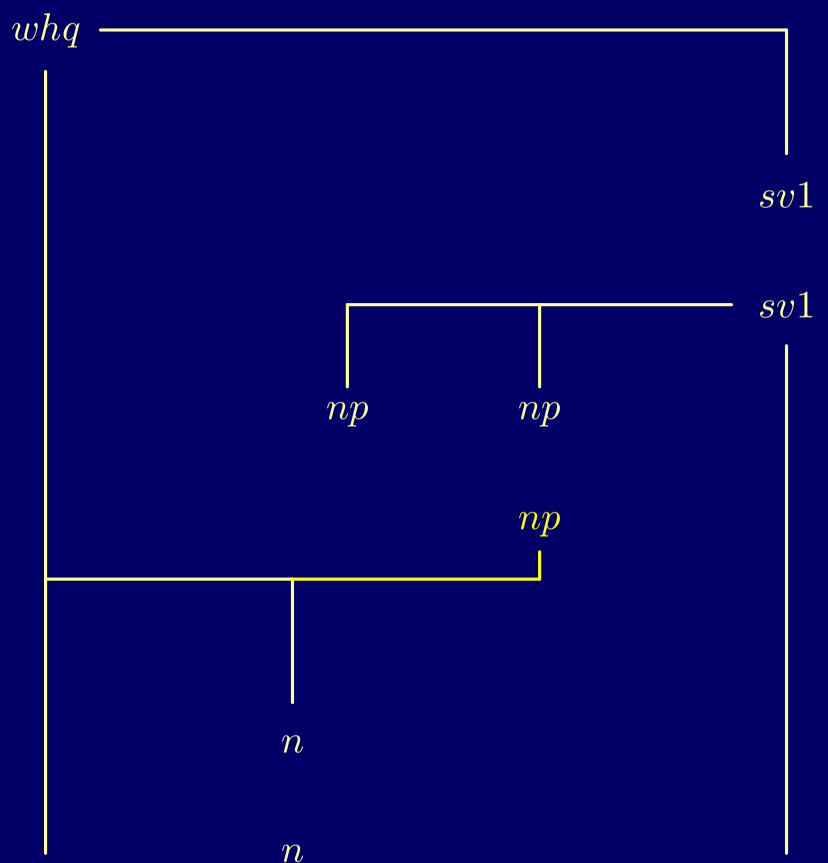

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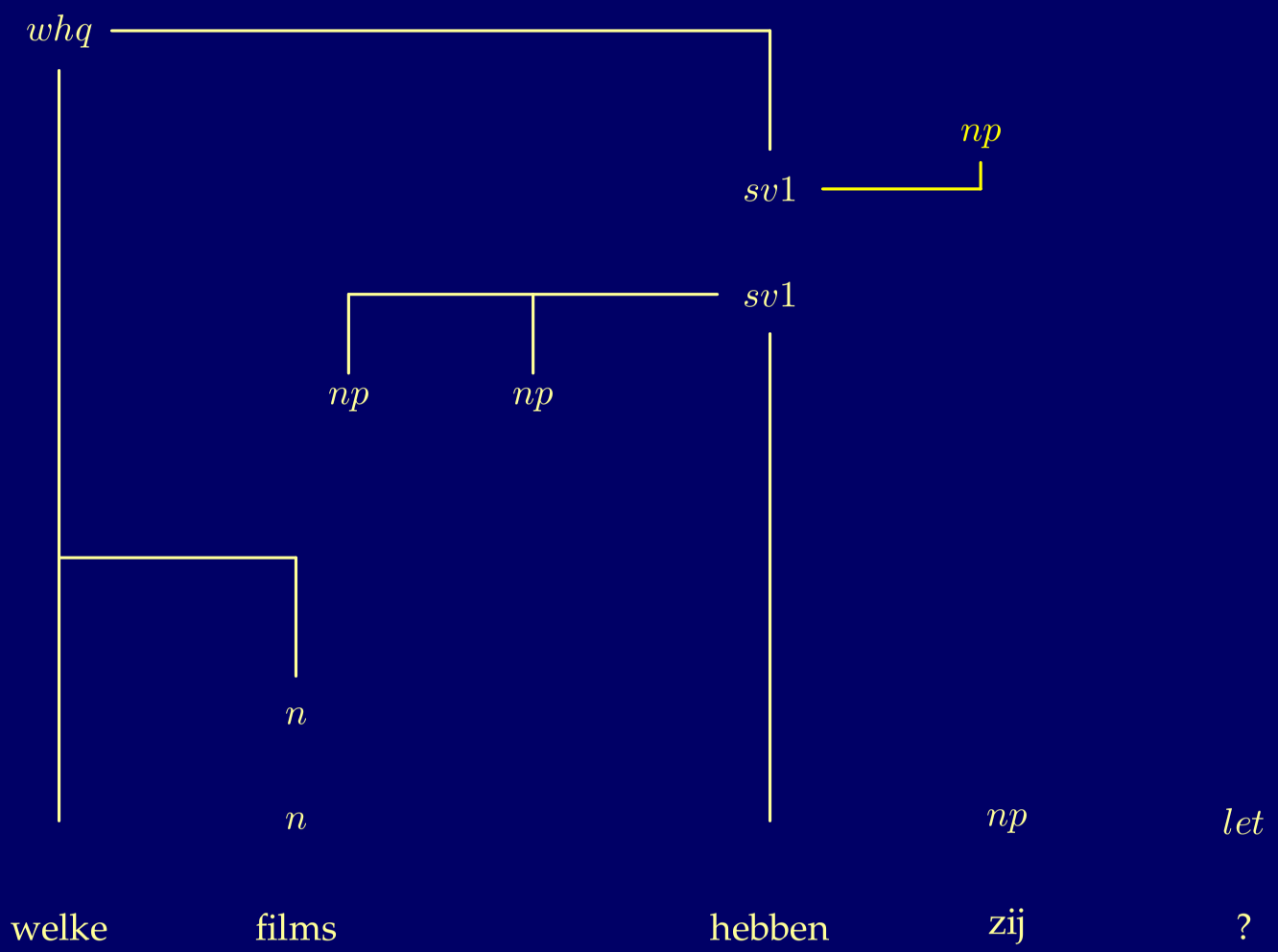

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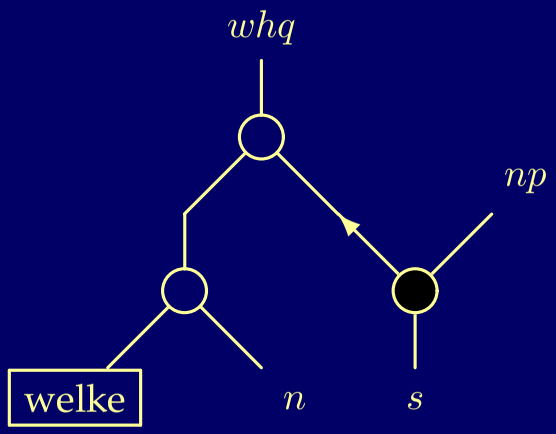

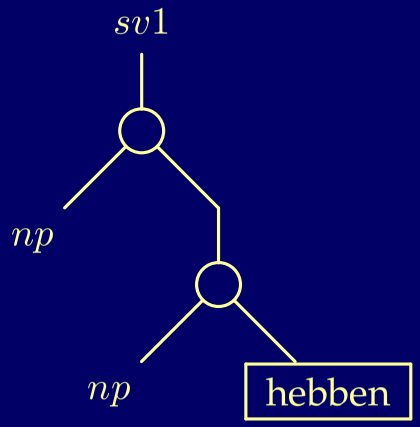

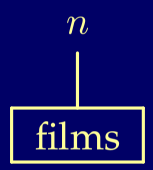

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- For large sentence, we have to consider many possible connections

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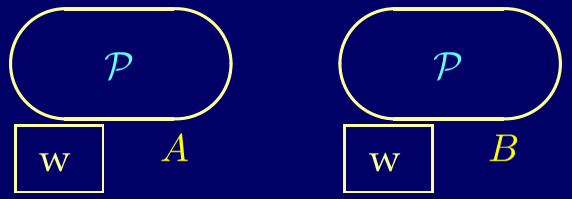

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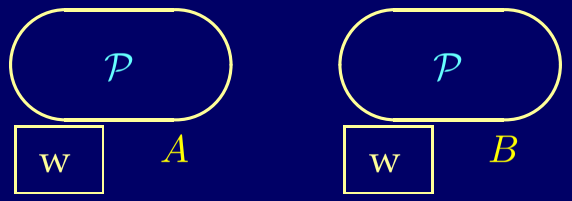

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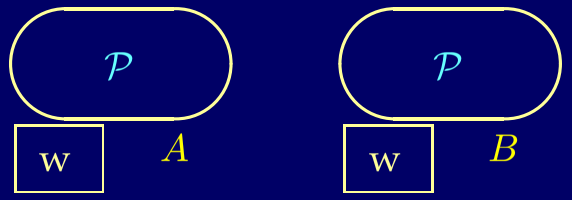

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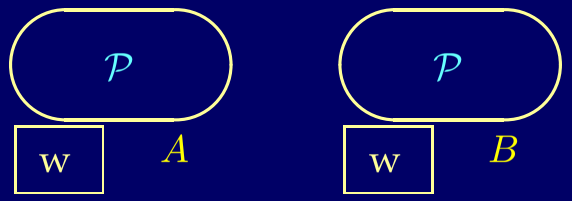

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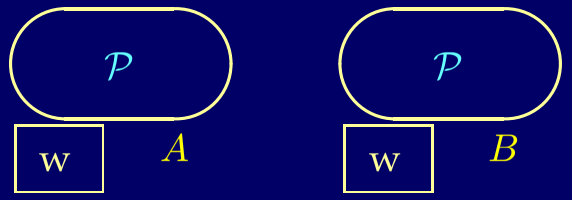

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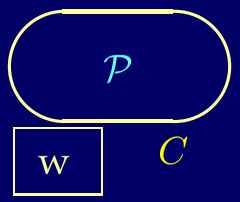

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$-$ identical influence on the complexity of performing the connections as the previous method.

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- Can be extended to other lexicalized grammar formalisms.

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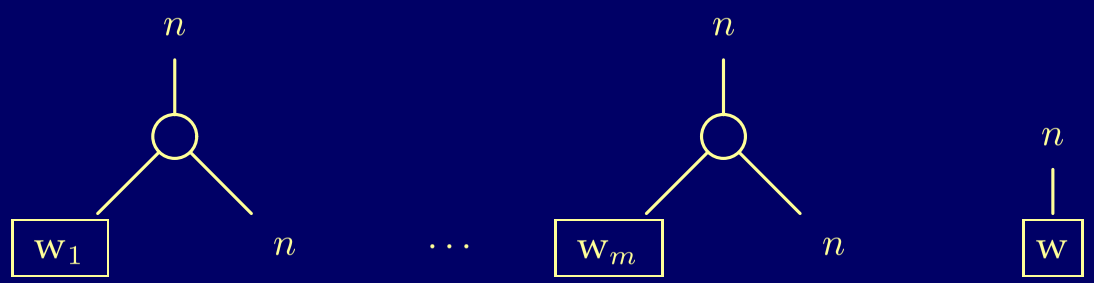

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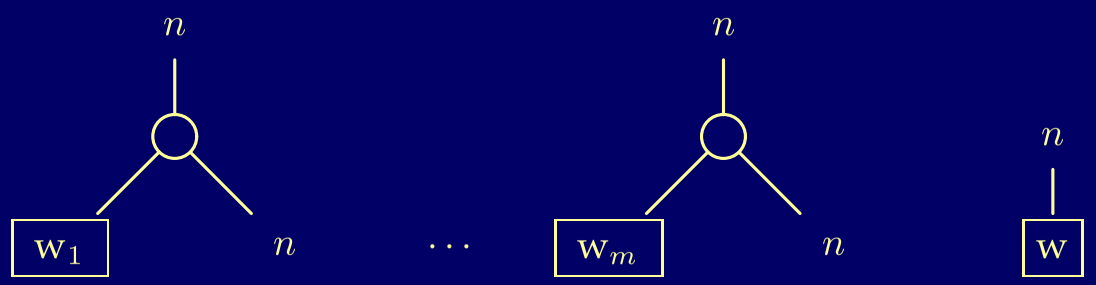

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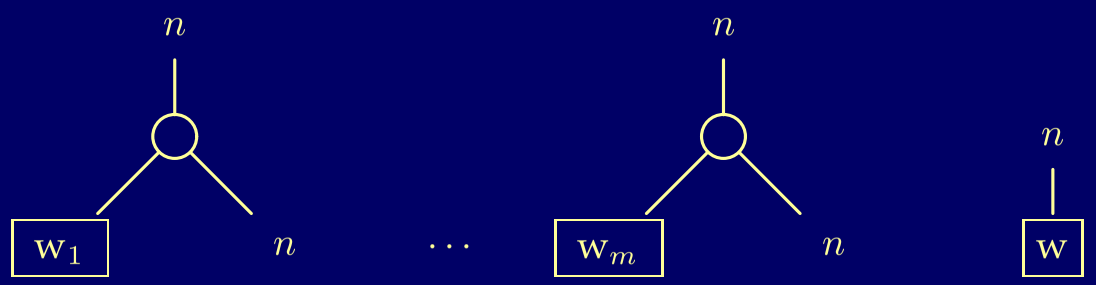

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Again, enumerating all possible solutions doesn't seem like a good strategy.

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- Other weight function are also possible.

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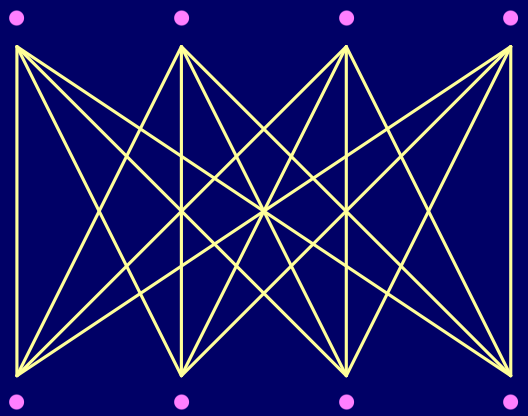

positive formulas

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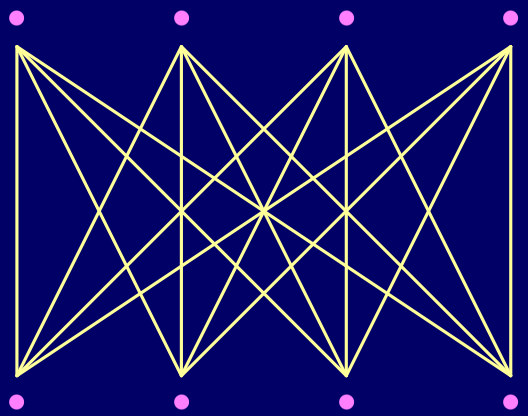

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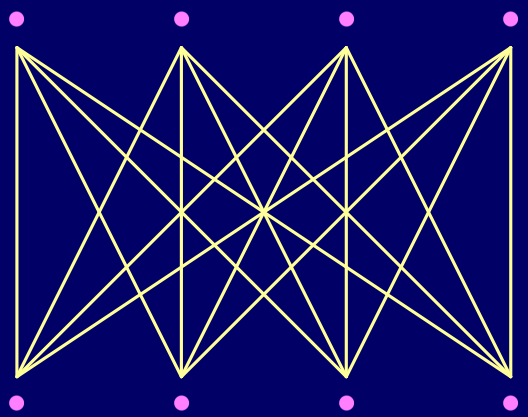

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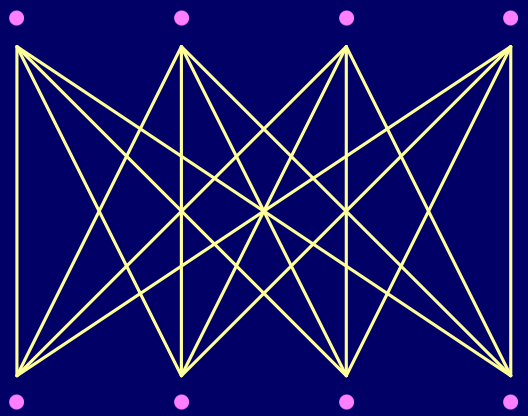

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- This produces rather unwieldy type-logical grammars:
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  - a prohibitive number of possible connections.
- We have sketched how statistical methods may help us solve both problems.

References

Chegireddy, C. R. & Hamacher, H. W. (1987), 'Algorithms for finding k-best perfect matchings', *Discrete Applied Mathematics* **18**, 155–165.

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Kuhn, H. W. (1955), 'The hungarian method for the assignment problem', *Naval Research Logistics Quarterly* **2**, 83–97.

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