# Decoding and Inference with Syntactic Translation Models

**Machine Translation**
**Lecture 15**

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**TAs: Mitchell Stern, Justin Chiu**

**Website: mt-class.org/penn**

# CFGs

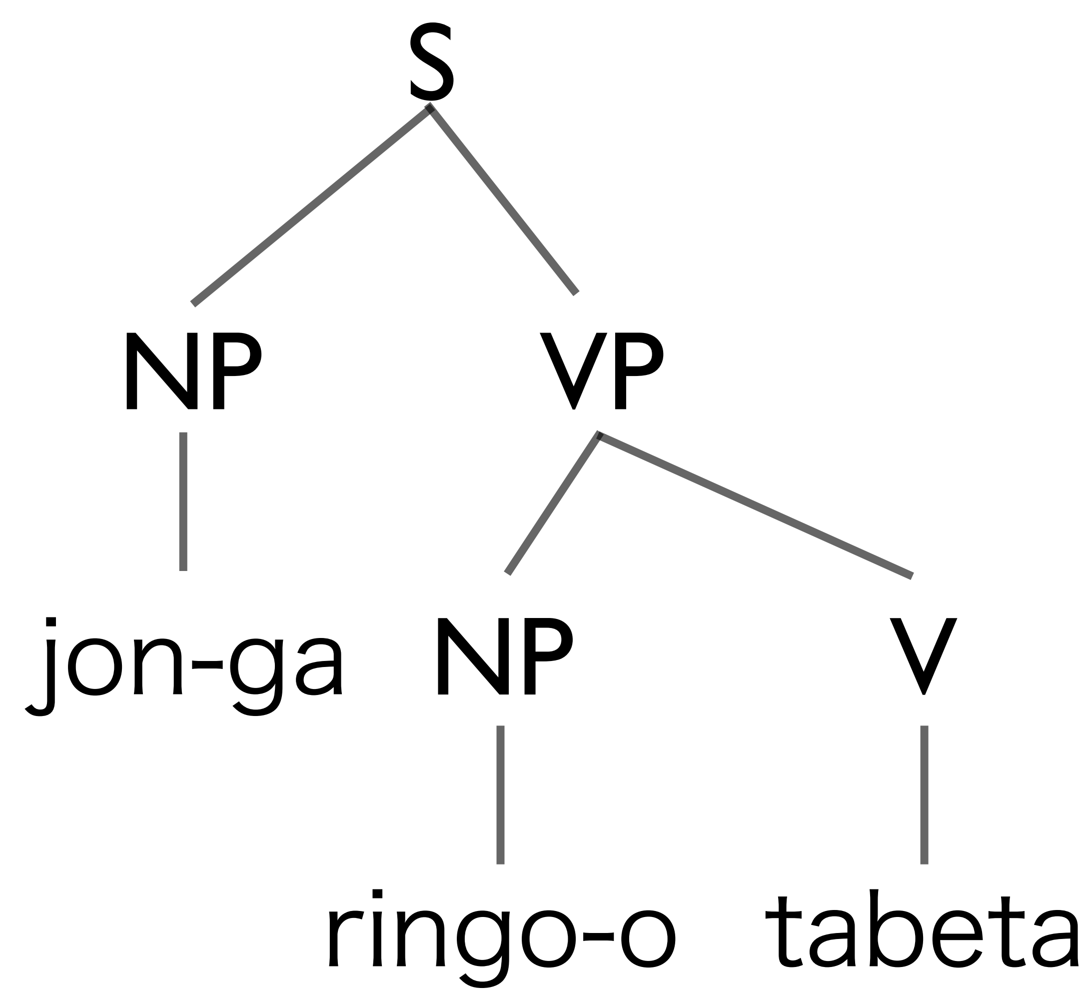
S → NP VP

VP → NP V

V → tabeta

NP → jon-ga

NP → ringo-o




**Output:** jon-ga ringo-o tabeta

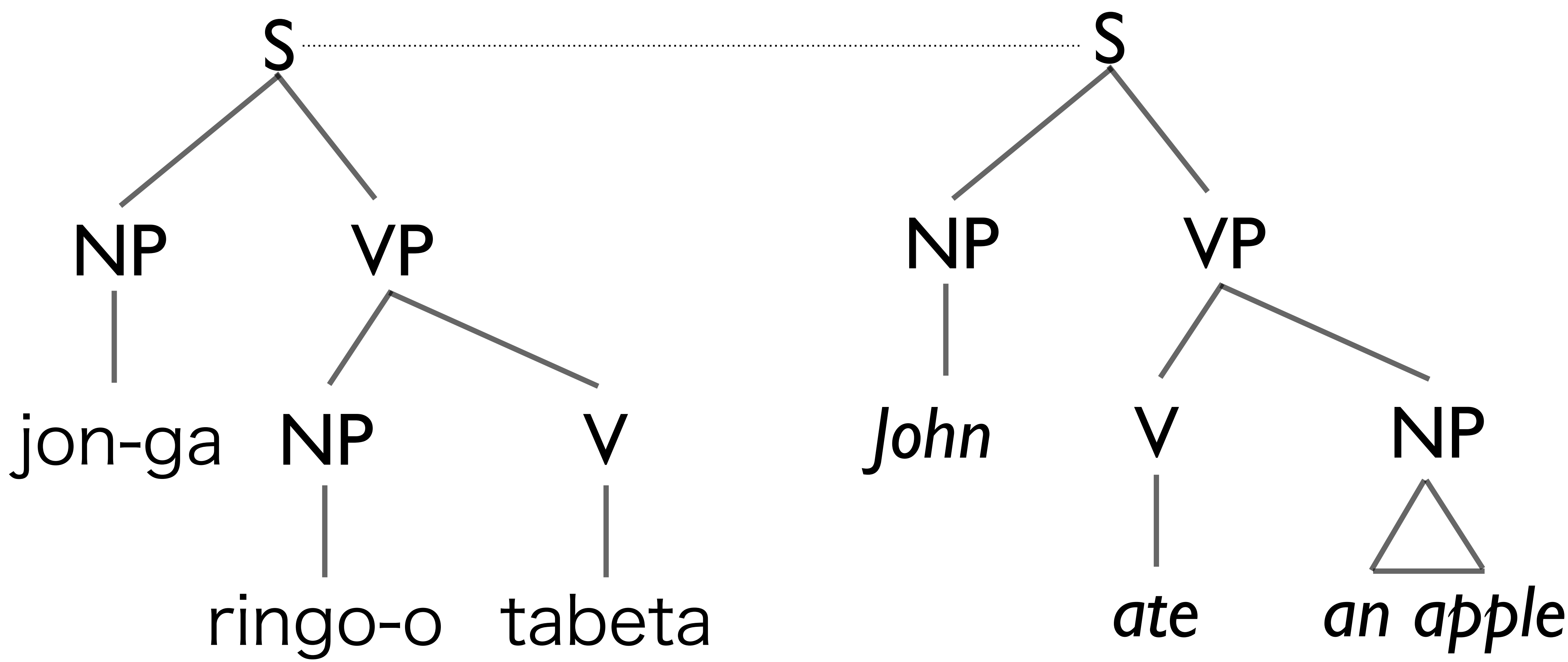
# Synchronous CFGs

| | | |
|---|---|---|
| S | → | NP VP |
| VP | → | NP V |
| | | |
| V | → | tabeta |
| NP | → | jon-ga |
| NP | → | ringo-o |

# Synchronous CFGs

| | | | | | |
|---|---|---|---|---|---|
| S | $\rightarrow$ | NP VP | : | $\boxed{1}$ $\boxed{2}$ | (monotonic) |
| VP | $\rightarrow$ | NP V | : | $\boxed{2}$ $\boxed{1}$ | (inverted) |
| V | $\rightarrow$ | tabeta | : | *ate* | |
| NP | $\rightarrow$ | jon-ga | : | *John* | |
| NP | $\rightarrow$ | ringo-o | : | *an apple* | |

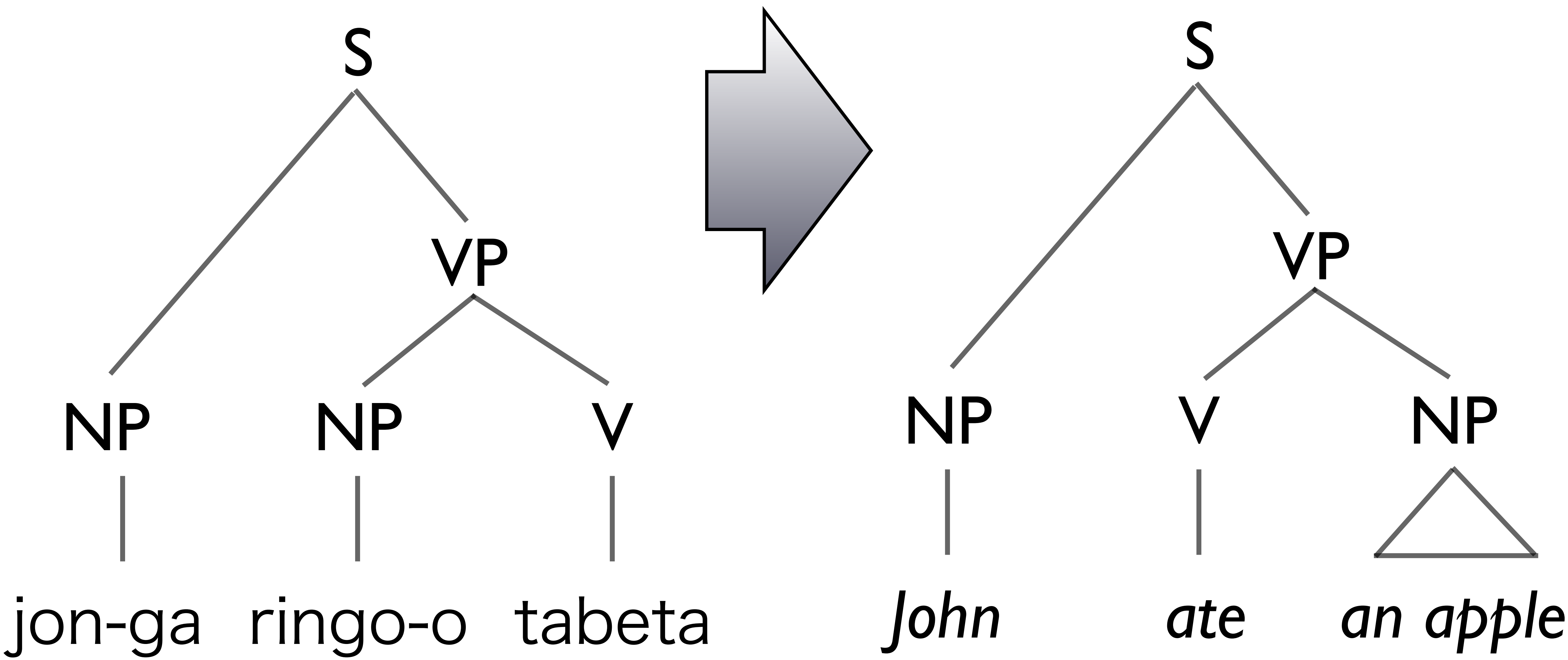
# Synchronous generation




**Output:** (jon-ga ringo-o tabeta : *John ate an apple*)

# Translation as parsing

**Parse source** **Project to target**



# A closer look at parsing

- Parsing is usually done with dynamic programming
  - **Share common computations and structure**
  - Represent exponential number of alternatives in polynomial space
  - With SCFGs there are two kinds of ambiguity
    - source parse ambiguity
    - translation ambiguity
    - parse forests can represent both!

# A closer look at parsing

- Any monolingual parser can be used (most often: CKY or variants on the CKY algorithm)
- Parsing complexity is $O(|n^3|)$
  - cubic in the length of the sentence ($n^3$)
  - cubic in the number of non-terminals ($|G|^3$)
    - adding nonterminal types increases parsing complexity substantially!
    - With few NTs, exhaustive parsing is tractable

# Parsing as deduction

Antecedents

Side conditions

$$\frac{A : u \quad B : v}{C : w} \quad \phi$$

Consequent

"If $A$ and $B$ are true with weights $u$ and $v$, and phi is also true, then $C$ is true with weight $w$."

# Example: CKY

Inputs:

$$\mathbf{f} = \langle f_1, f_2, \ldots, f_\ell \rangle$$

$G$ Context-free grammar in Chomsky normal form.

Item form:

$[X, i, j]$ A subtree rooted with NT type $X$ spanning $i$ to $j$ has been recognized.

# Example: CKY

Goal:

$$[S, 0, \ell]$$

Axioms:

$$\frac{}{[X, i-1, i] : w} \quad (X \xrightarrow{w} f_i) \in G$$

Inference rules:

$$\frac{[X, i, k] : u \quad [Y, k, j] : v}{[Z, i, j] : u \times v \times w} \quad (Z \xrightarrow{w} XY) \in G$$

S → PRP VP

VP → V NP

VP → V SBAR

SBAR → PRP V

NP → PRP NN

V → saw

NN → duck

V → duck

PRP → I

PRP → her

**I saw her duck**

0 1 2 3 4

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PRP,0,1

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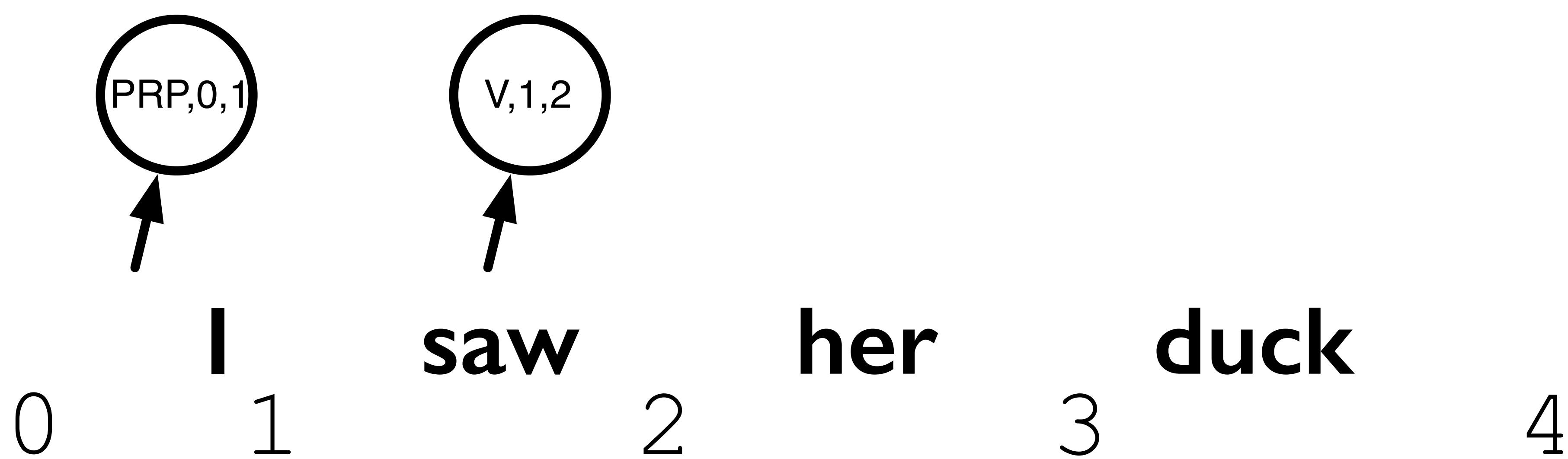

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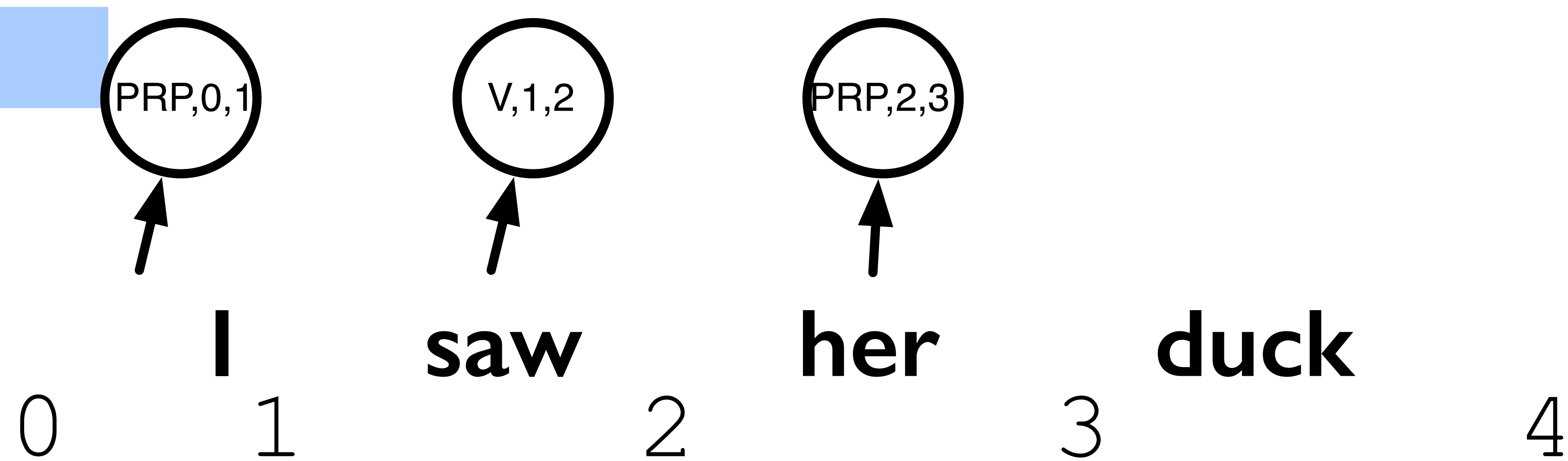

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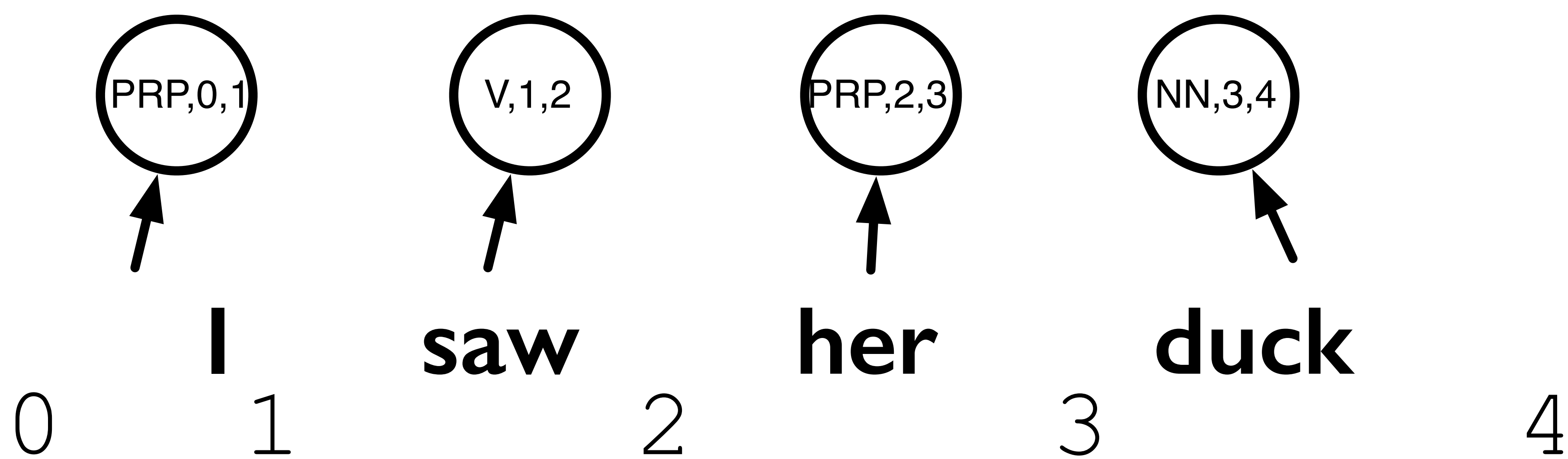

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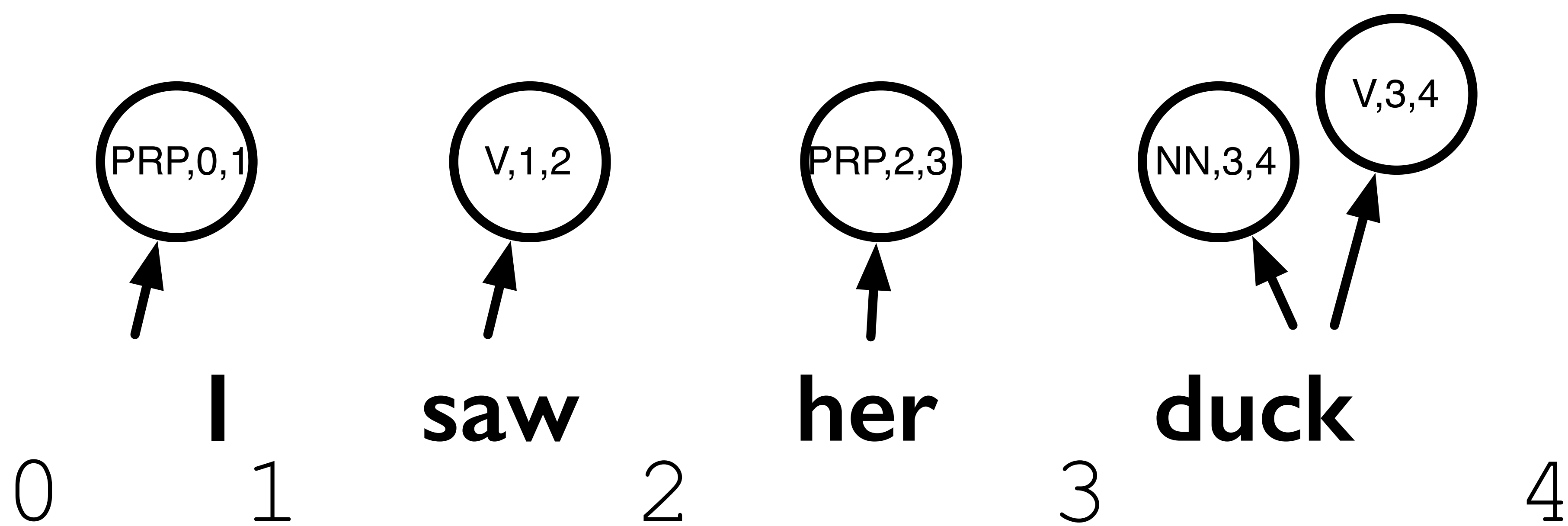

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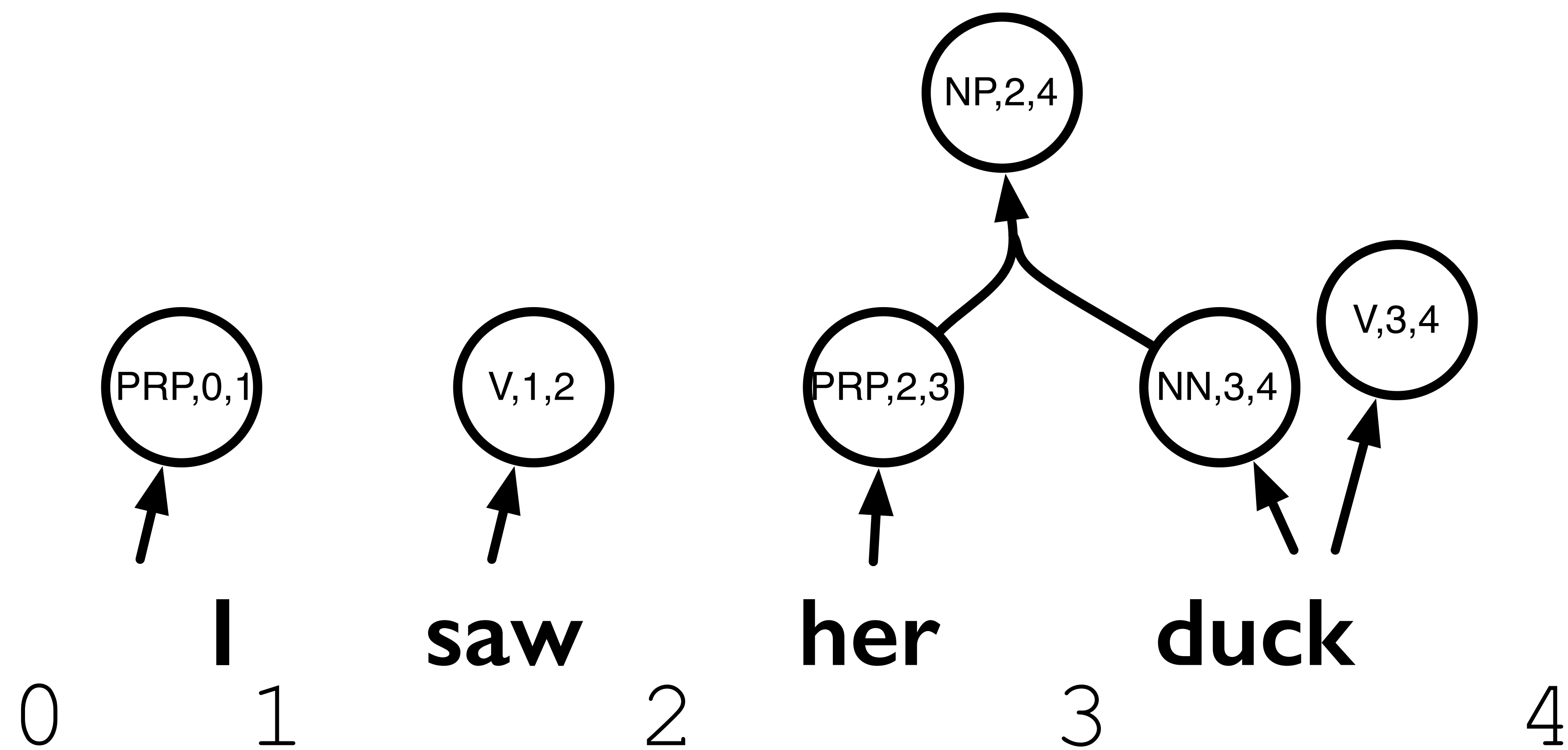

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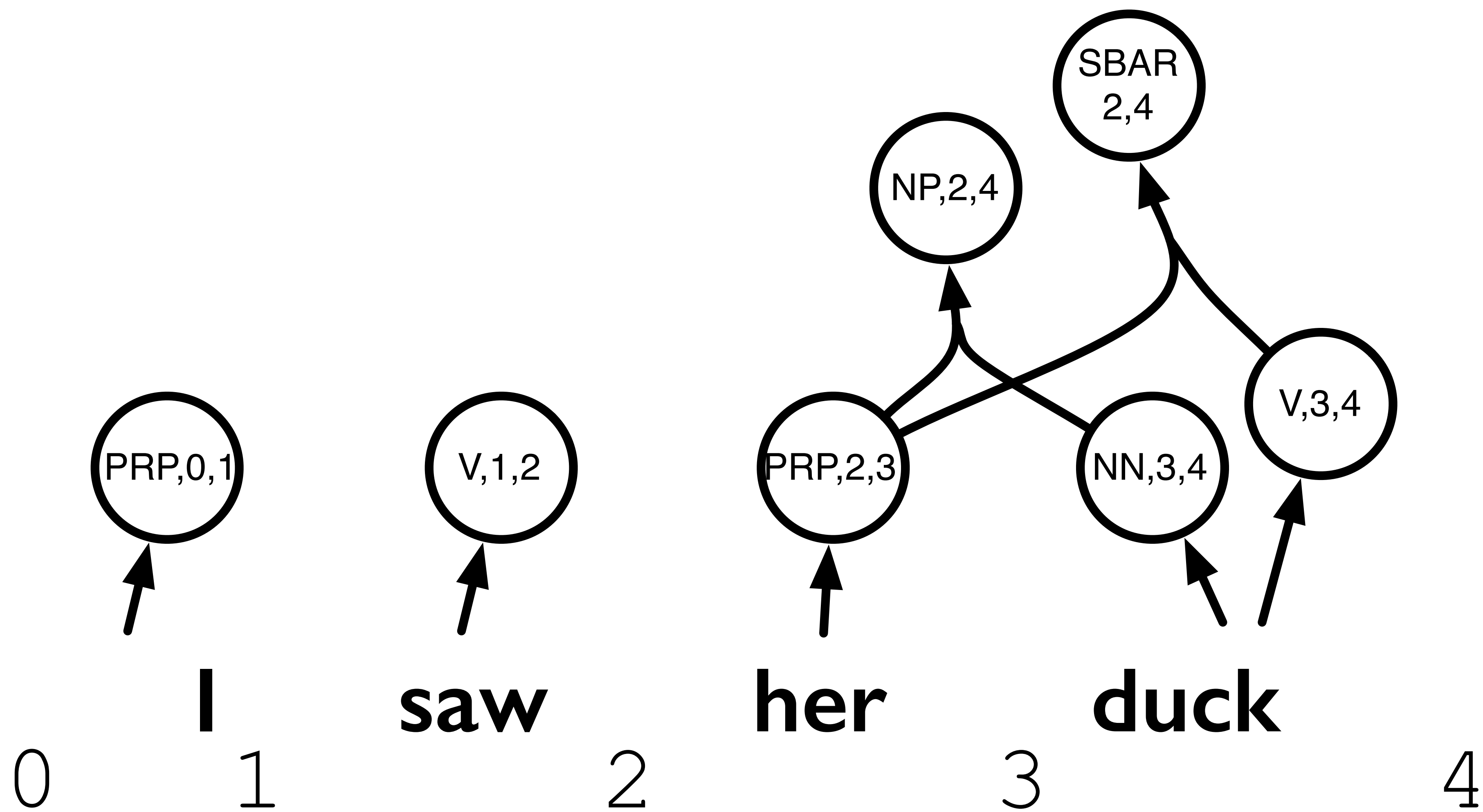

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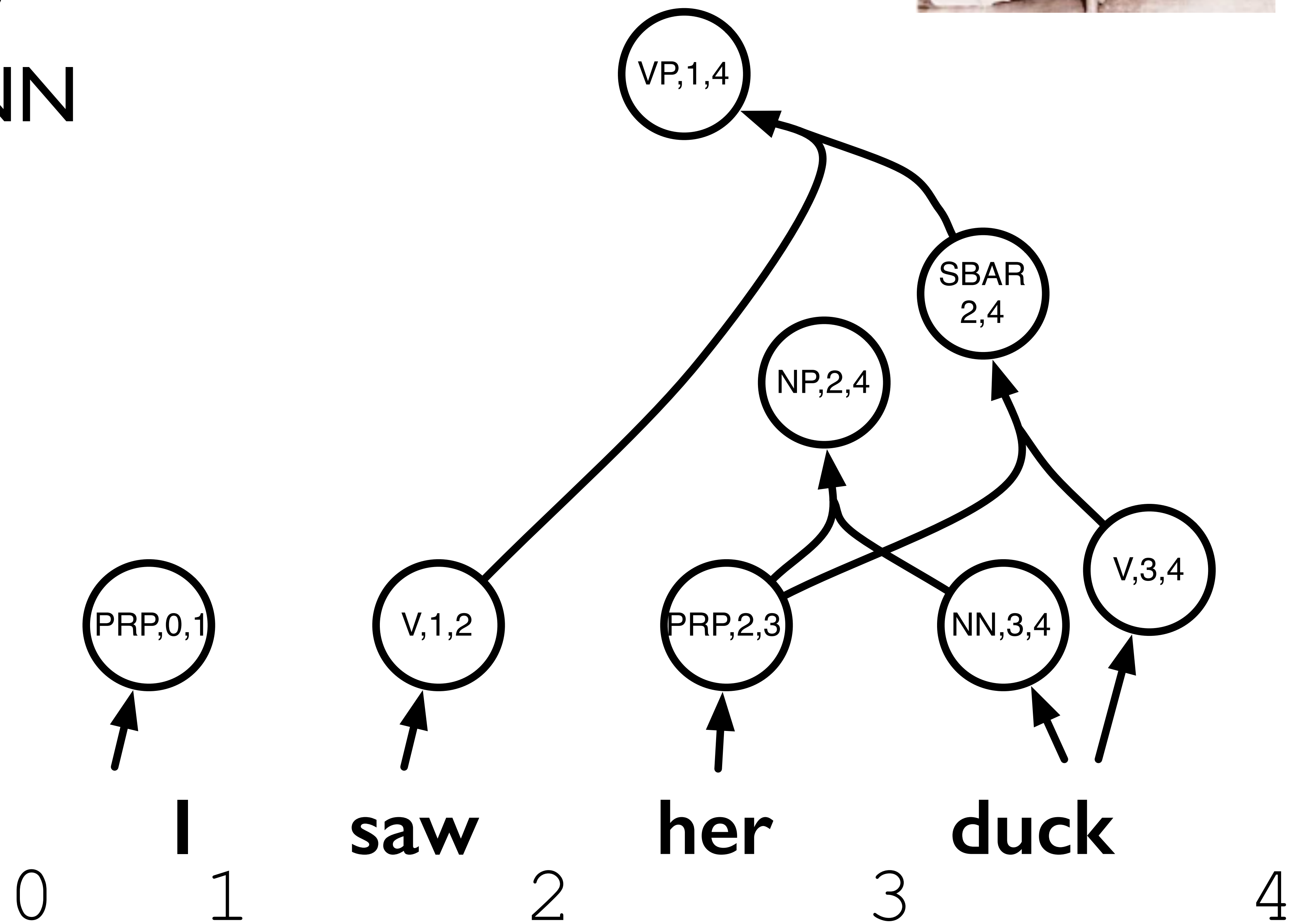


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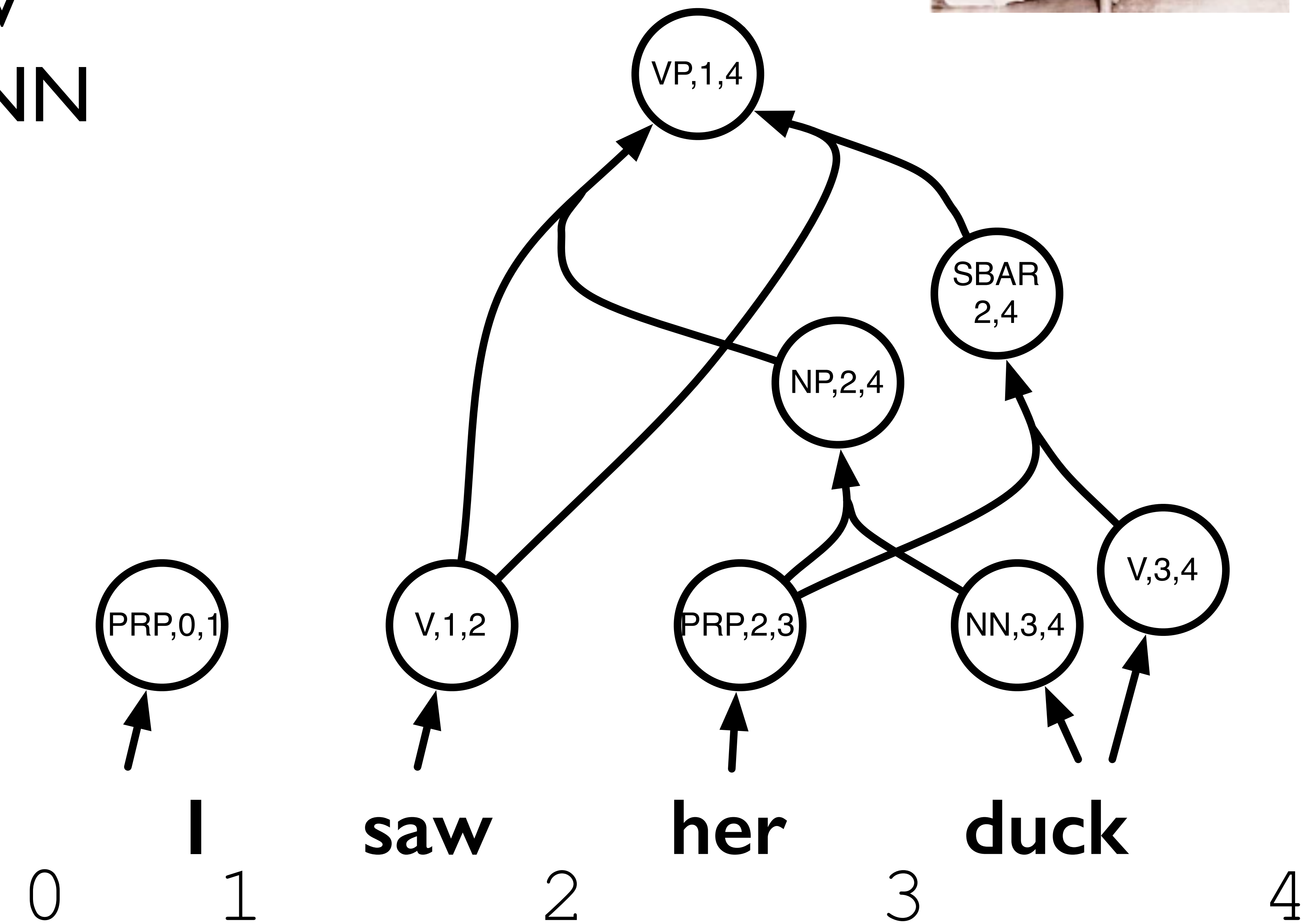


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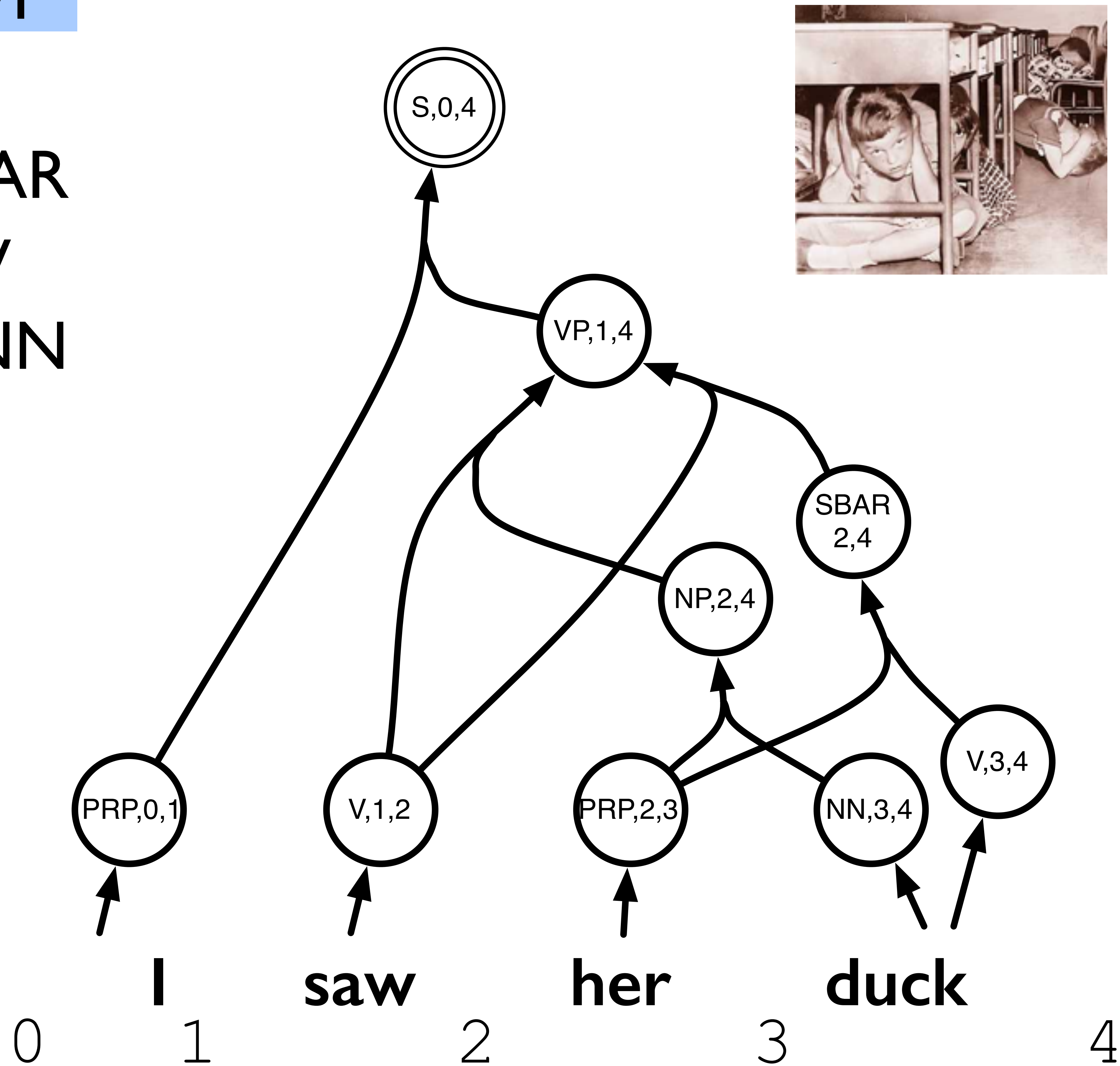
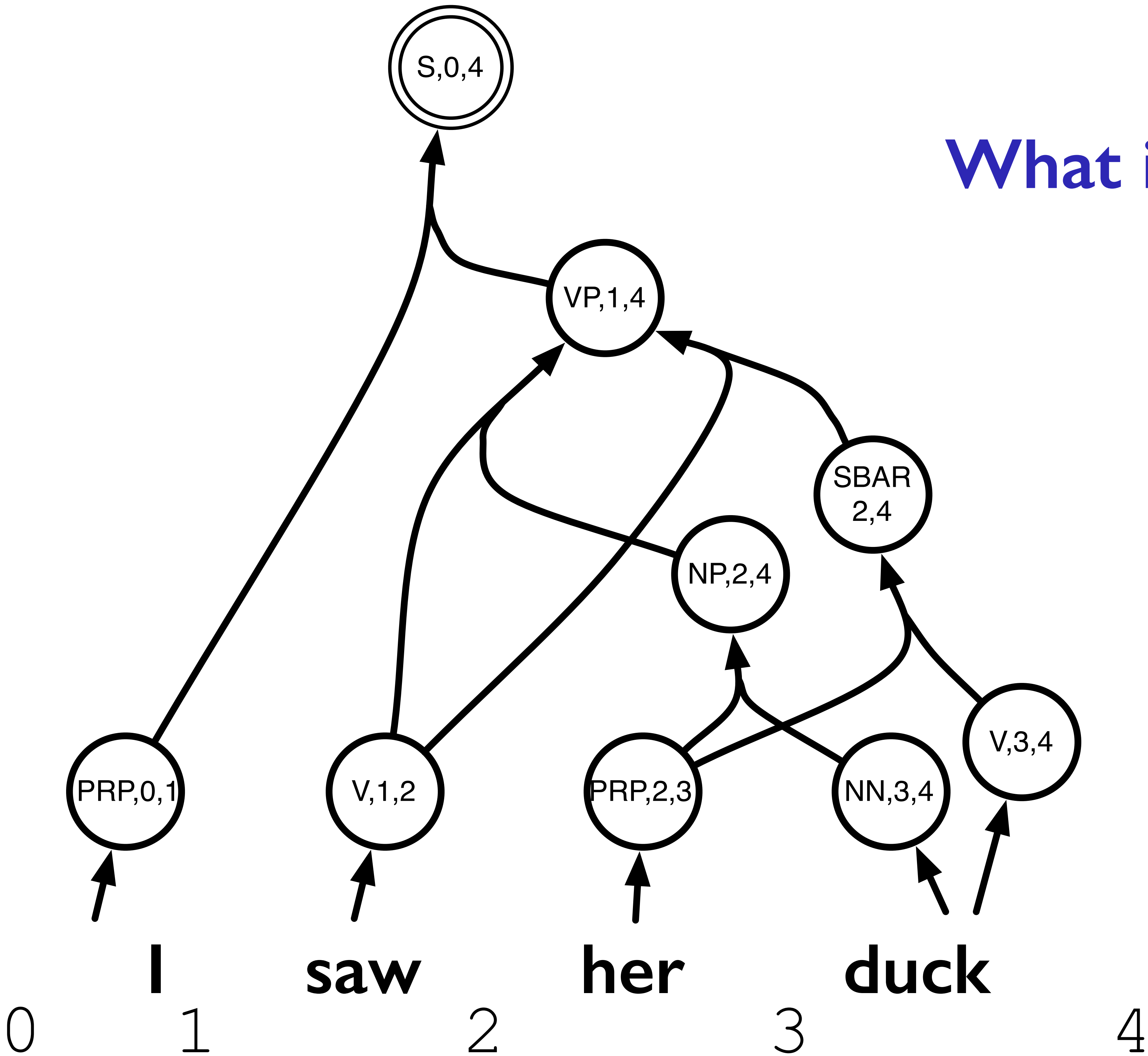



## What is this object?



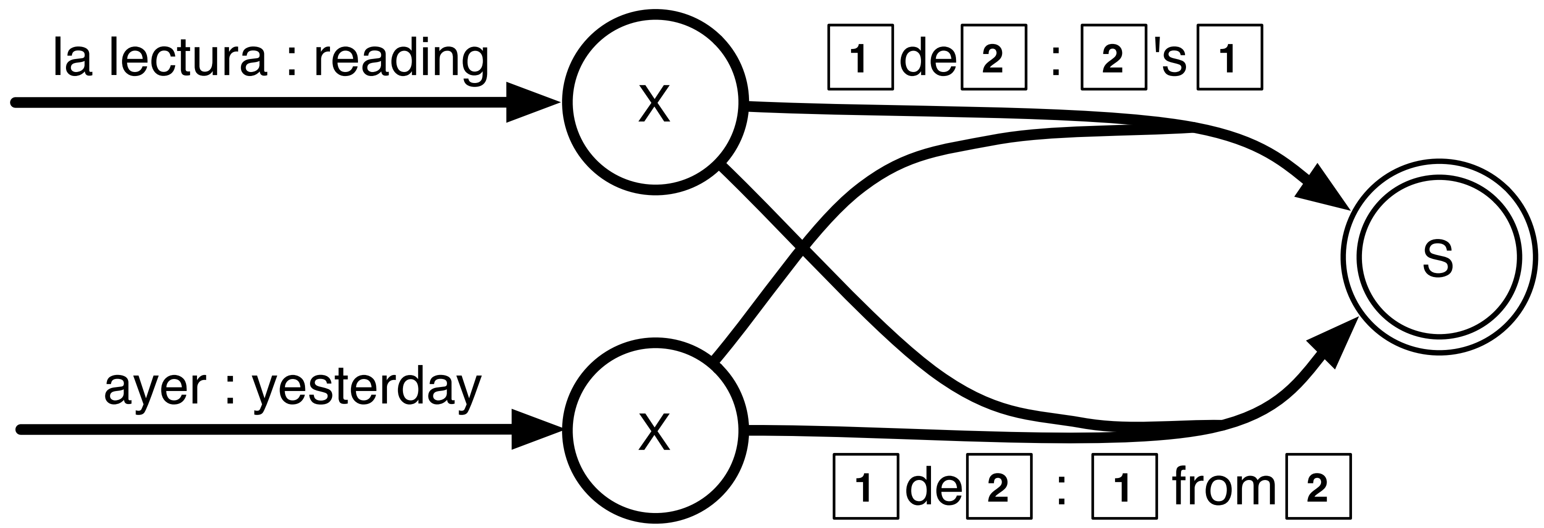
# Semantics of hypergraphs

- Generalization of directed graphs
- Special node designated the “goal”
- Every edge has a single head and 0 or more tails (the **arity** of the edge is the number of tails)
- Node labels correspond to LHS’s of CFG rules
- A **derivation** is the generalization of the graph concept of **path** to hypergraphs
- Weights multiply along edges in the derivation, and add at nodes (cf. **semiring parsing**)

# Edge labels

- Edge labels may be a mix of terminals and substitution sites (non-terminals)
- In translation hypergraphs, edges are labeled in both the source and target languages
- The number of substitution sites must be equal to the arity of the edge and must be the same in both languages
- The two languages may have different orders of the substitution sites
- There is no restriction on the number of terminal symbols

# Edge labels




{( la lectura de ayer : *yesterday 's reading* ),
( la lectura de ayer : *reading from yesterday* )}

# Inference algorithms

- Viterbi $O(|E| + |V|)$
  - Find the maximum weighted derivation
  - Requires a partial ordering of weights
- Inside - outside $O(|E| + |V|)$
  - Compute the marginal (sum) weight of all derivations passing through each edge/node
- $\mathrm{k}$-best derivations $O(|E| + |D_{max}|k \log k)$
  - Enumerate the $\mathrm{k}$-best derivations in the hypergraph
  - See IWPT paper by Huang and Chiang (2005)

# Things to keep in mind

Bound on the number of edges:

$$|E| \in O(n^3|G|^3)$$

Bound on the number of nodes:

$$|V| \in O(n^2|G|)$$

# Decoding Again

- Translation hypergraphs are a "lingua franca" for translation search spaces
  - Note that FST lattices are a special case
- **Decoding problem: how do I build a translation hypergraph?**

# Representational limits

Consider this very simple SCFG translation model:

“Glue” rules:

$$S \rightarrow S\ S : \boxed{1}\ \boxed{2}$$

$$S \rightarrow S\ S : \boxed{2}\ \boxed{1}$$

# Representational limits

Consider this very simple SCFG translation model:

"Glue" rules:

$$S \rightarrow S \quad S : \boxed{1} \; \boxed{2}$$

$$S \rightarrow S \quad S : \boxed{2} \; \boxed{1}$$

"Lexical" rules:

$$S \rightarrow \text{tabeta} : \textit{ate}$$

$$S \rightarrow \text{jon-ga} : \textit{John}$$

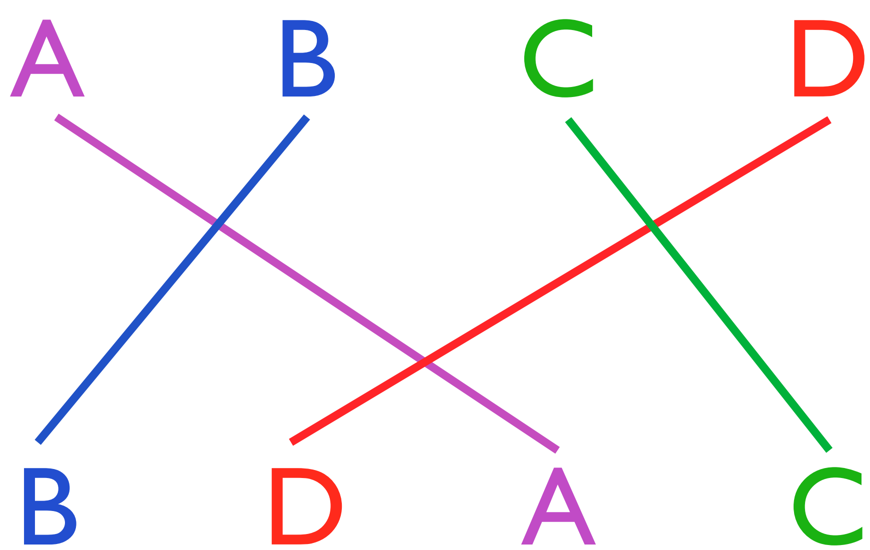
$$S \rightarrow \text{ringo-o} : \textit{an apple}$$

# Representational limits

- Phrase-based decoding runs in exponential time
  - All permutations of the source are modeled (traveling salesman problem!)
  - Typically distortion limits are used to mitigate this
- But parsing is polynomial...what’s going on?

# Representational limits

Binary SCFGs cannot model this
(however, ternary SCFGs can):



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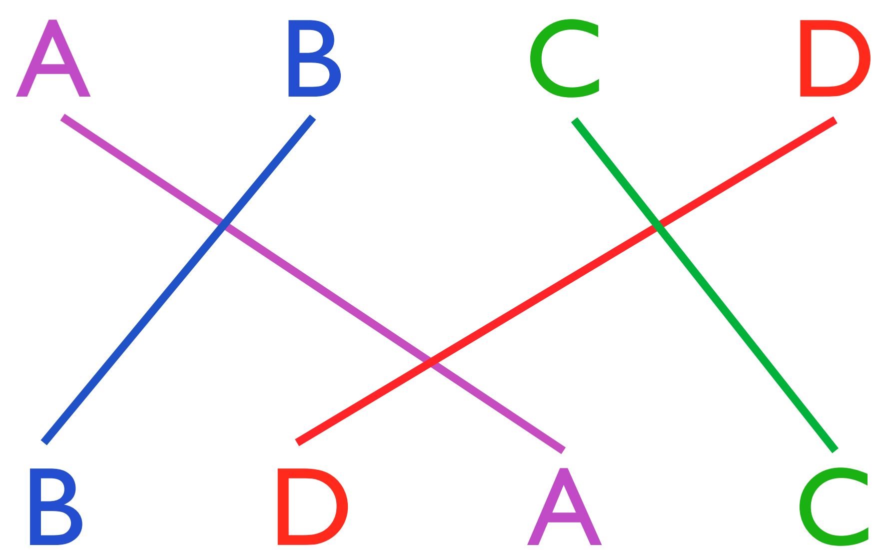


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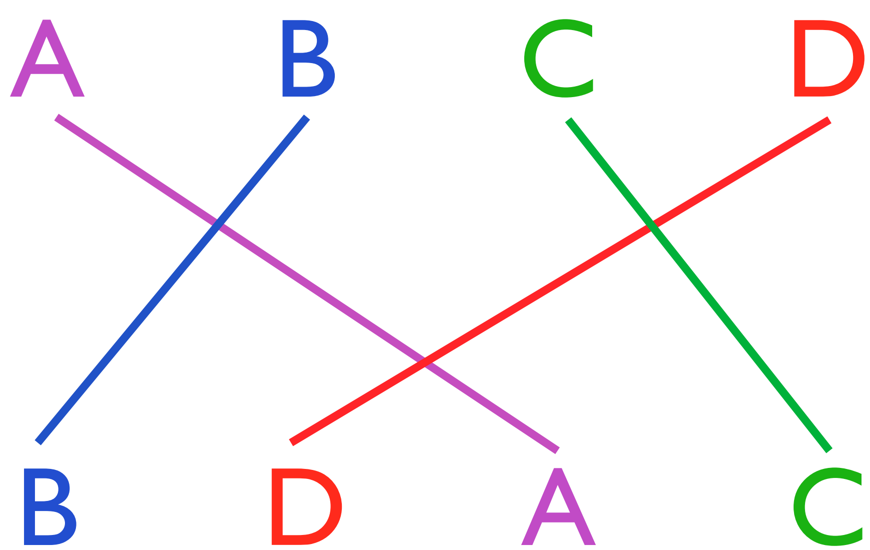


But can't we binarize *any* grammar?

**No.** Synchronous CFGs cannot generally be binarized!

# Does this matter?

- The "forbidden" pattern **is** observed in real data (Melamed, 2003)
- Does this matter?
  - Learning
    - Phrasal units and higher rank grammars can account for the pattern
    - Sentences can be simplified or ignored
  - Translation
    - The pattern does exist, but how often **must** it exist (i.e., is there a good translation that doesn't violate the SCFG matching property)?

# Tree-to-string

- How do we generate a hypergraph for a tree-to-string translation model?
  - Simple linear-time (given a fixed translation model) top-down matching algorithm
    - Recursively cover "uncovered" sites in tree
  - Each node in the input tree becomes a node in the translation forest
  - For details, Huang et al. (AMTA, 2006) and Huang et al. (EMNLP, 2010)

$$\mathrm{S}(x_1{:}\mathrm{NP}\ x_2{:}\mathrm{VP}) \rightarrow x_1\ x_2$$

$$\mathrm{VP}(x_1{:}\mathrm{NP}\ x_2{:}\mathrm{V}) \rightarrow x_2\ x_1$$

$$tabeta \rightarrow ate$$

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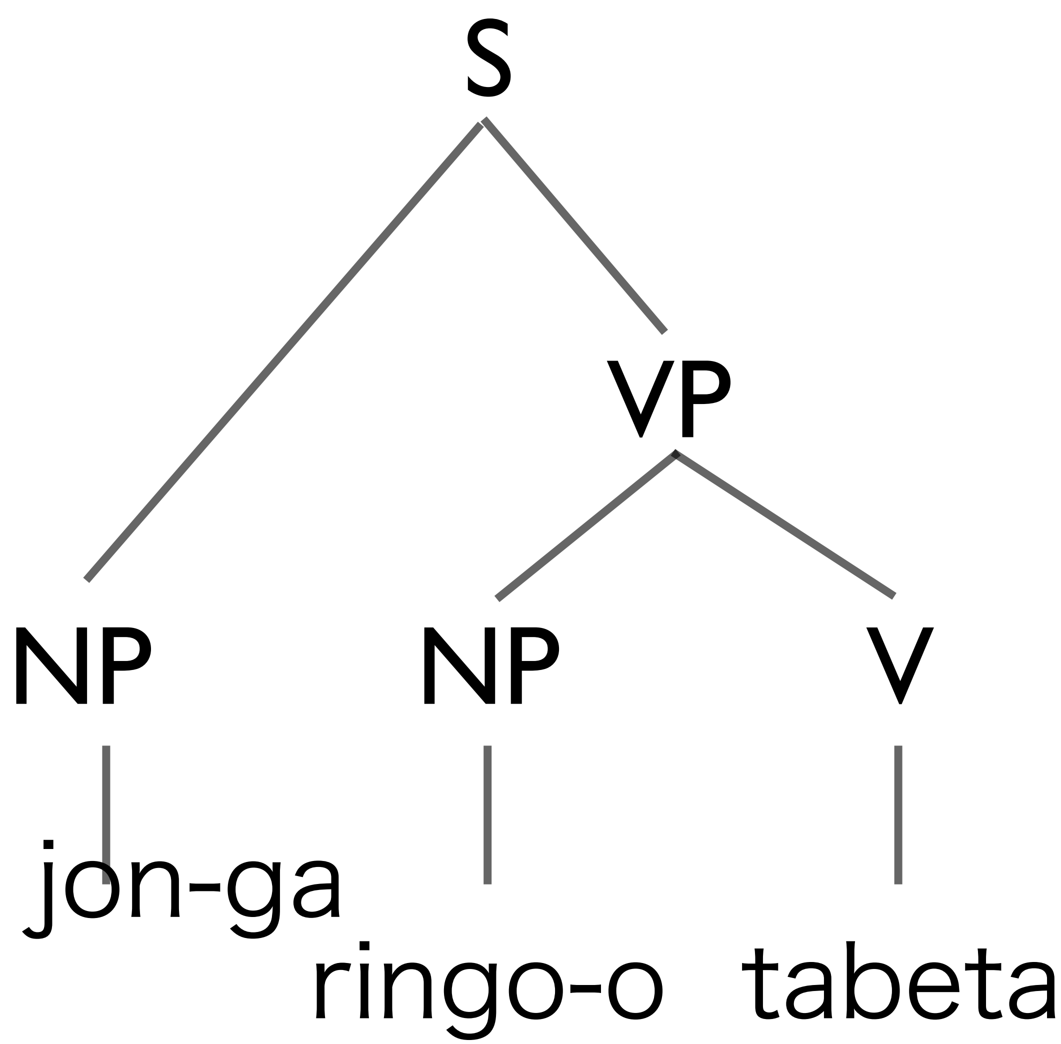
$$jon\text{-}ga \rightarrow John$$

Tree-to-string grammar

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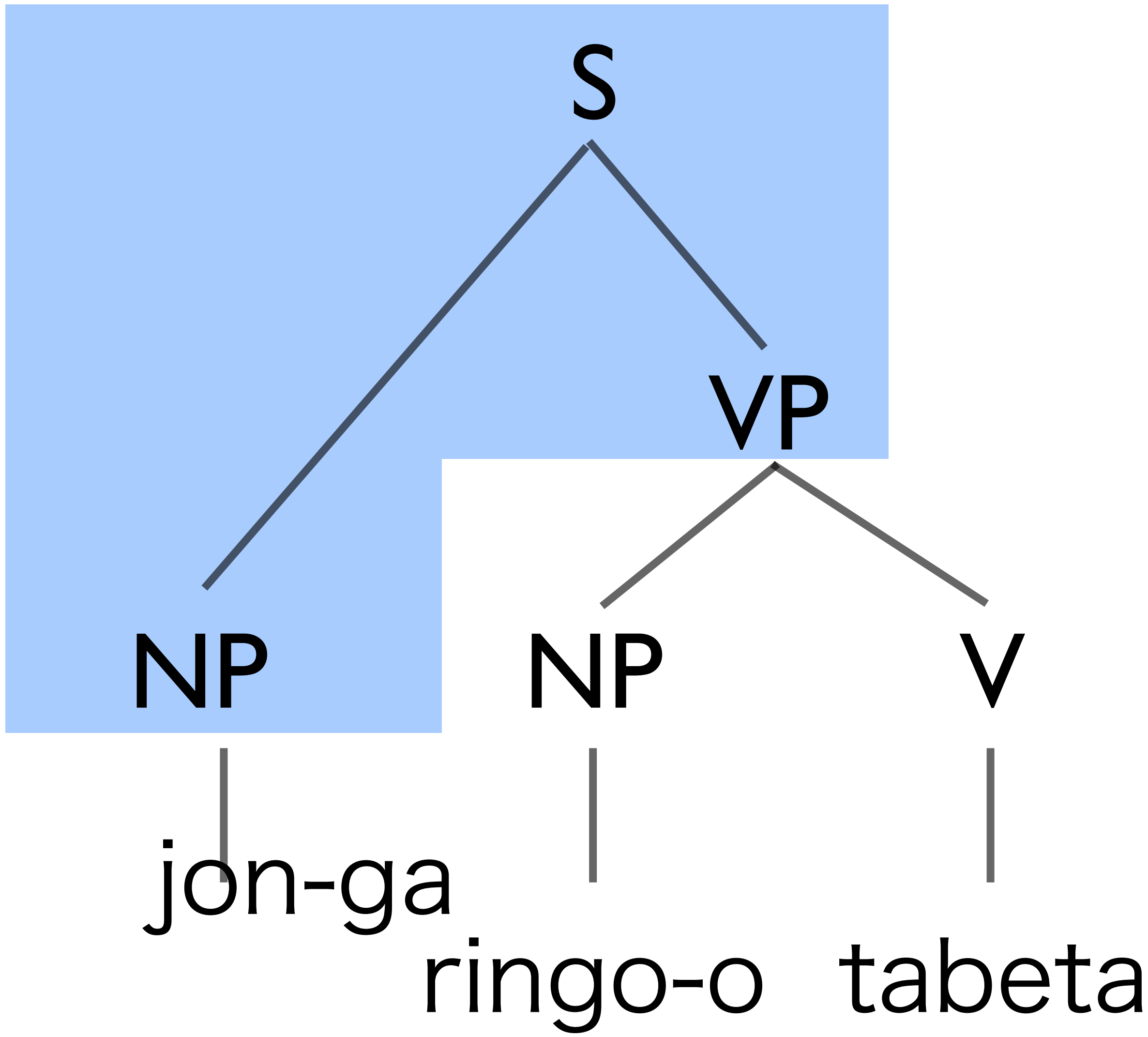


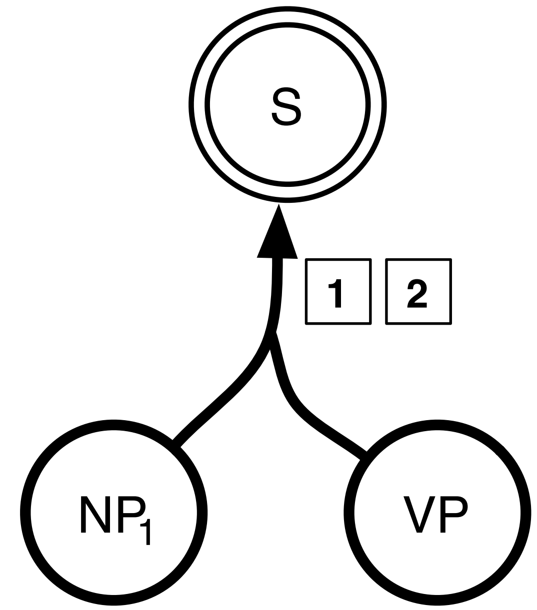


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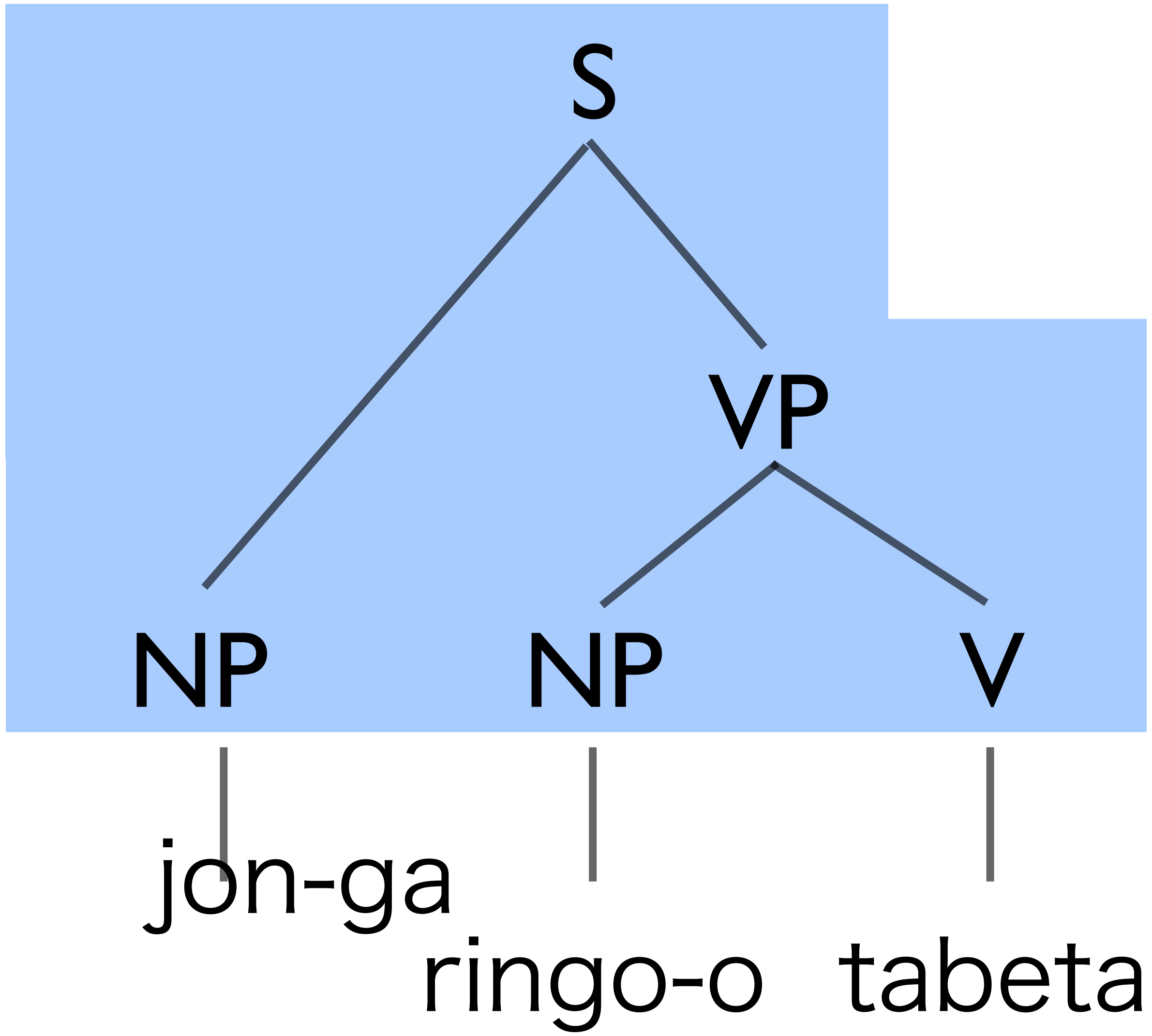


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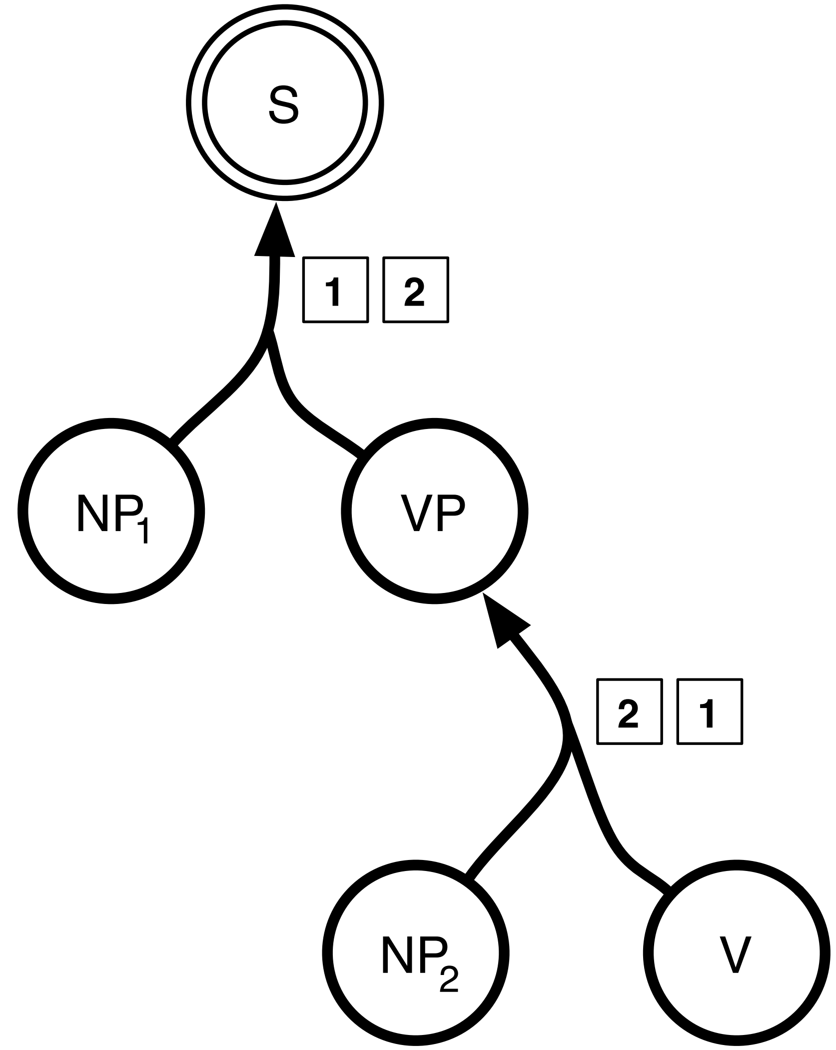

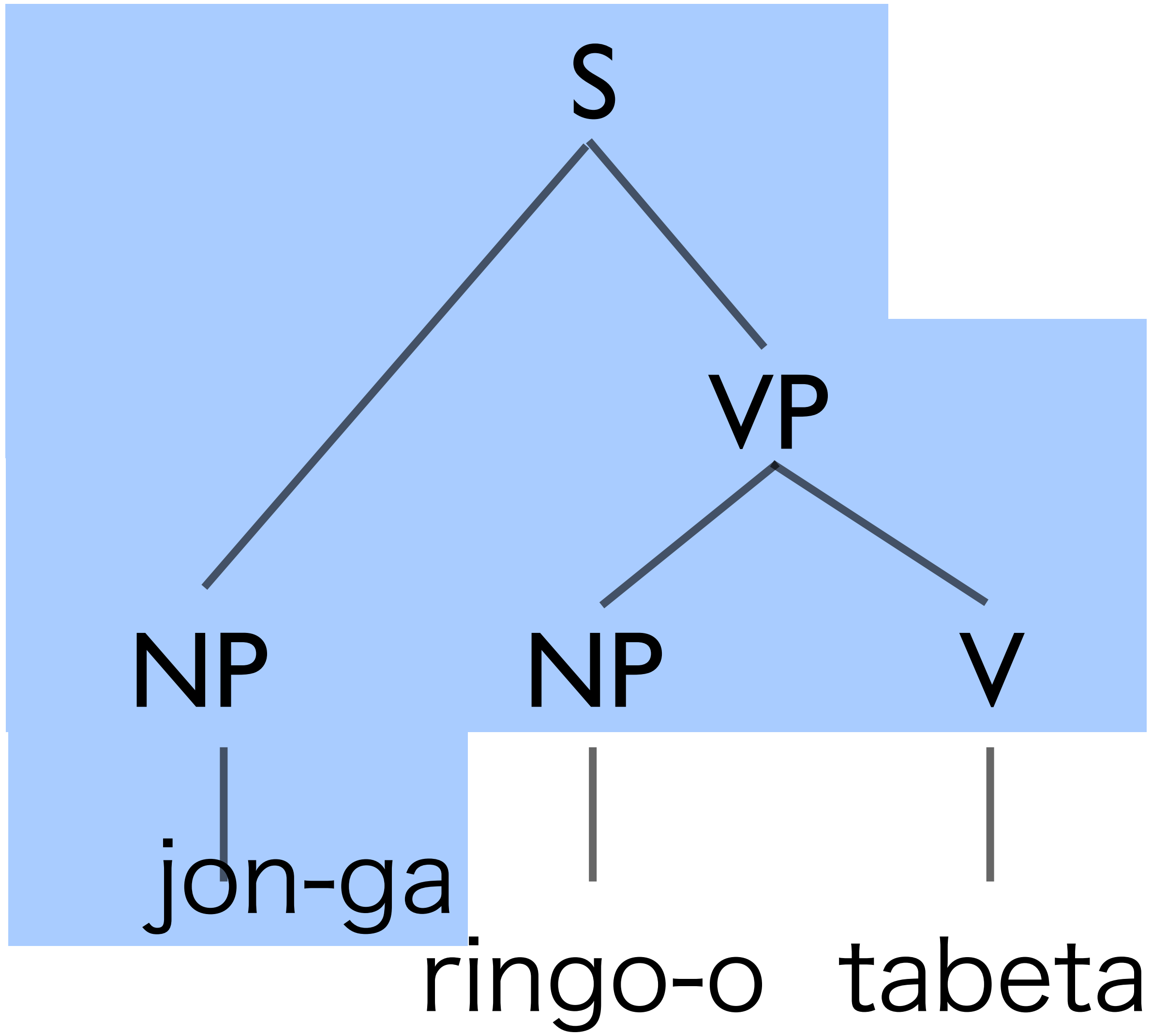


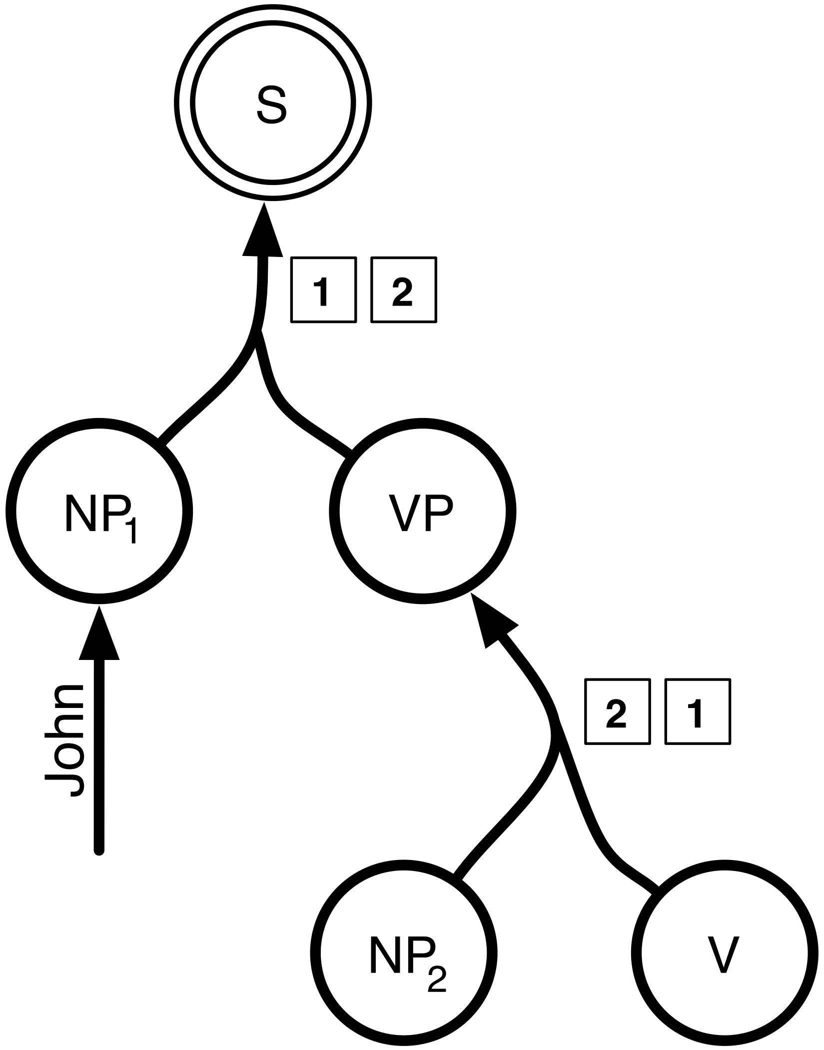


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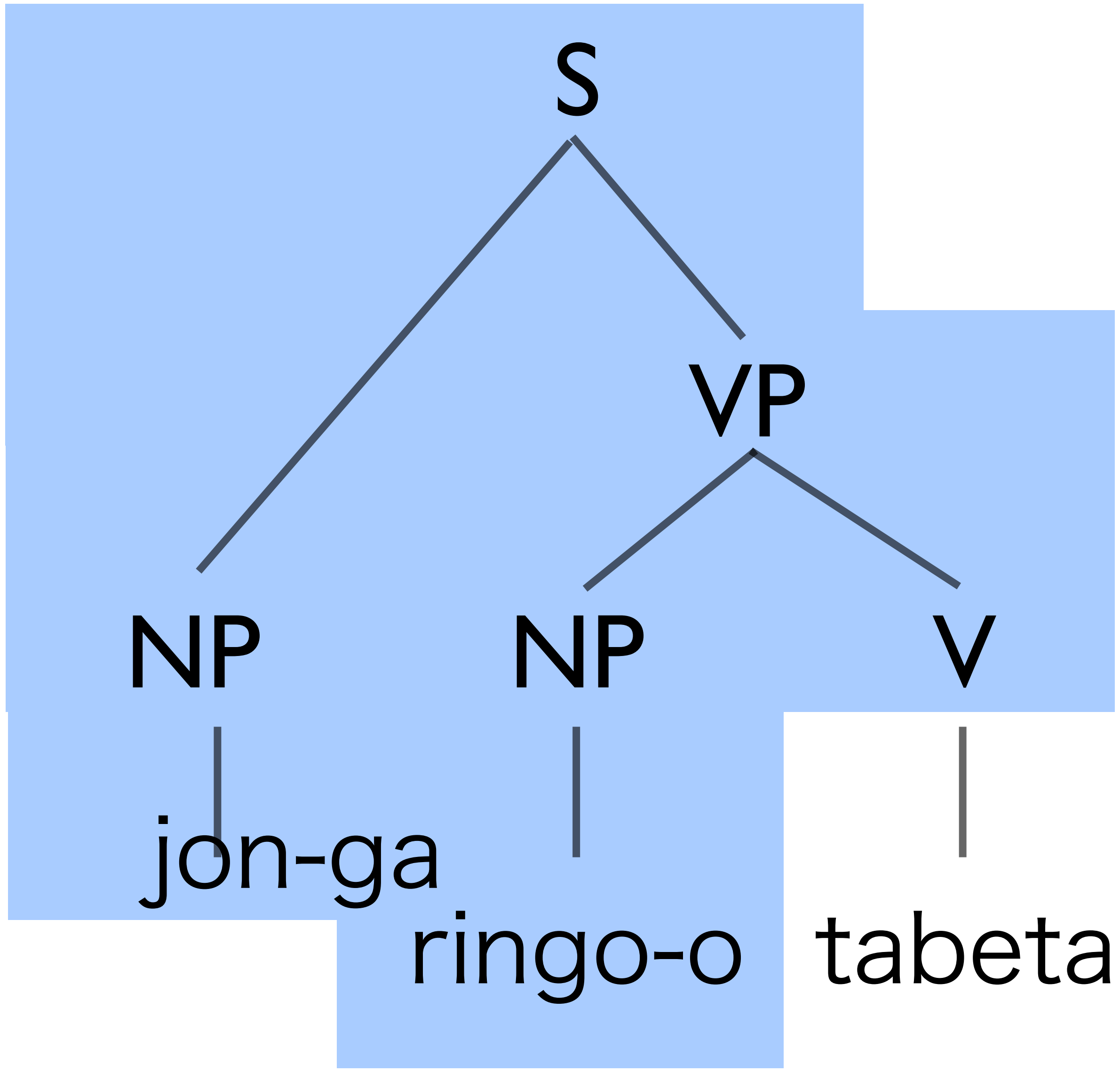


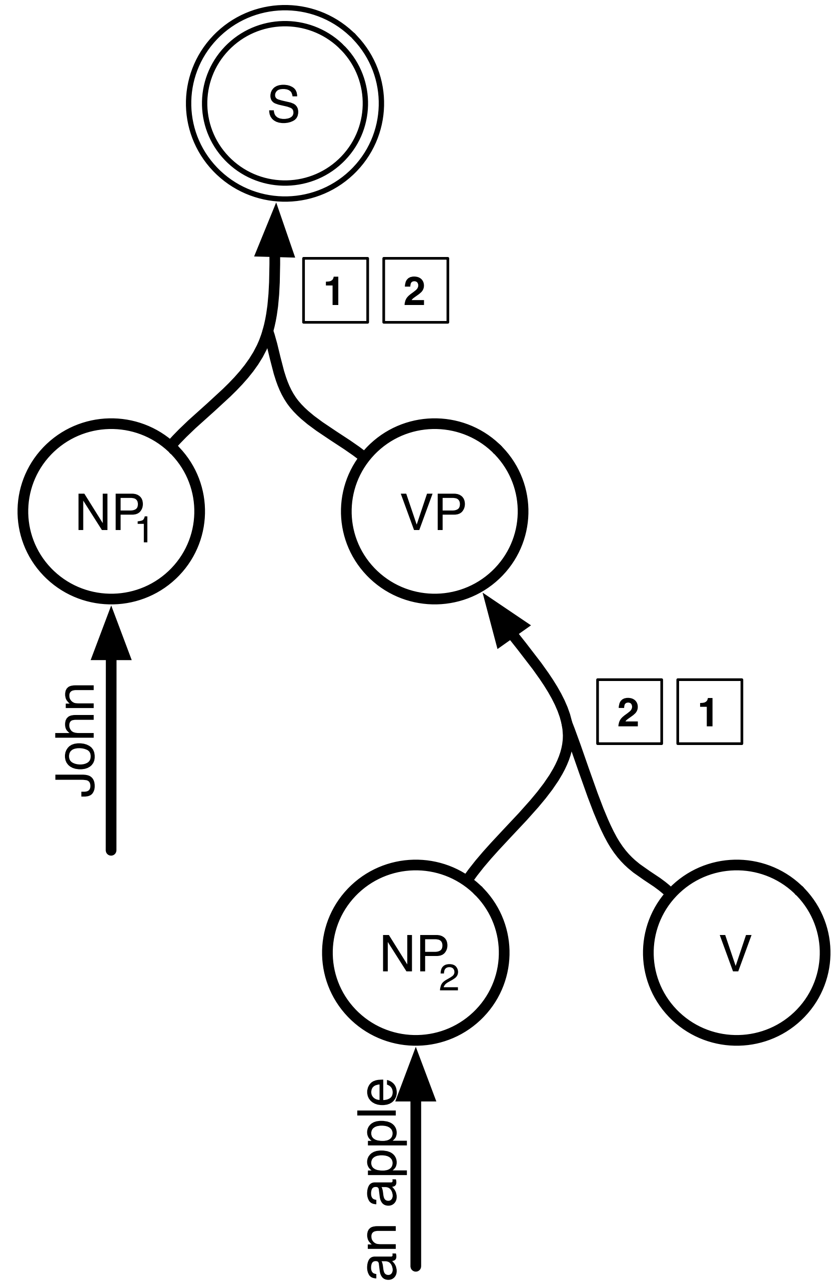


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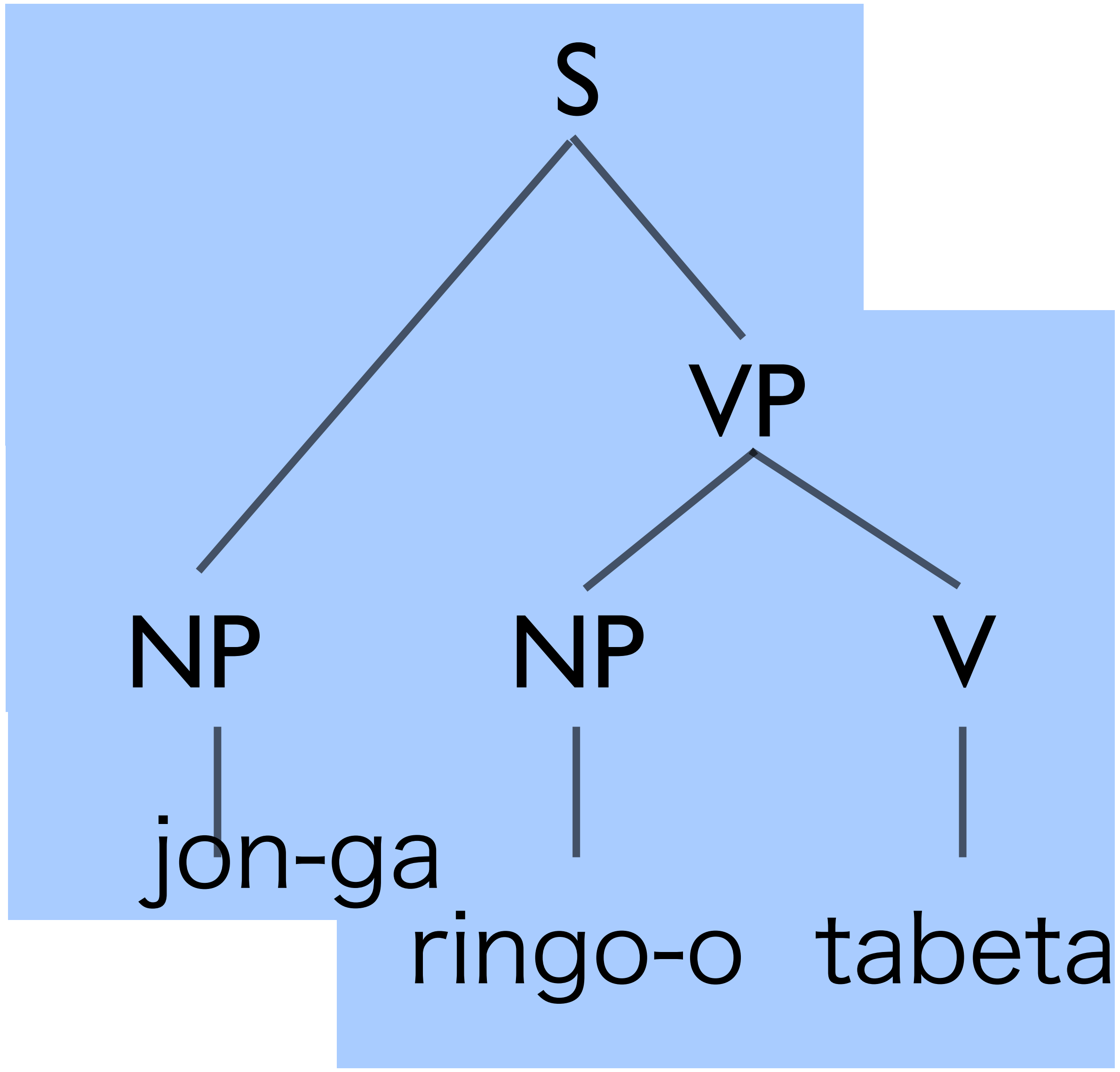


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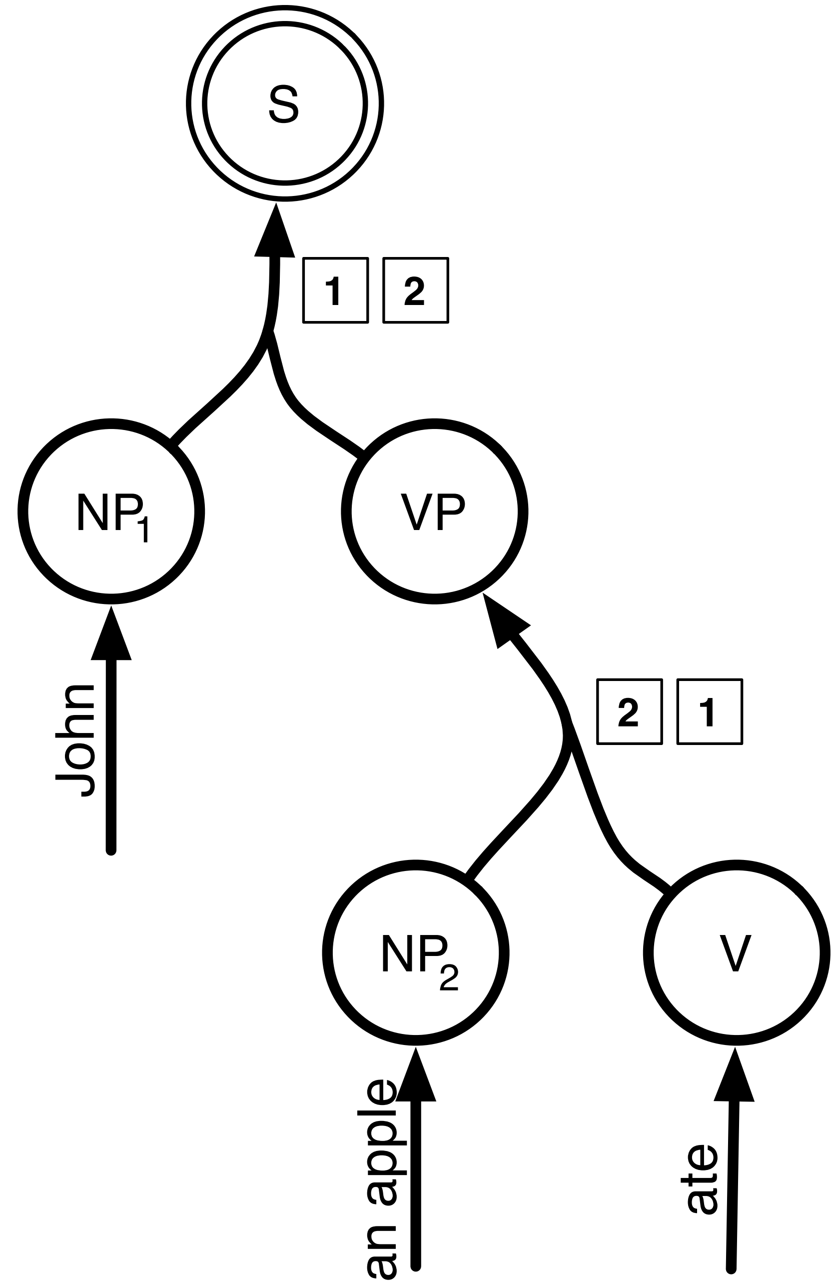
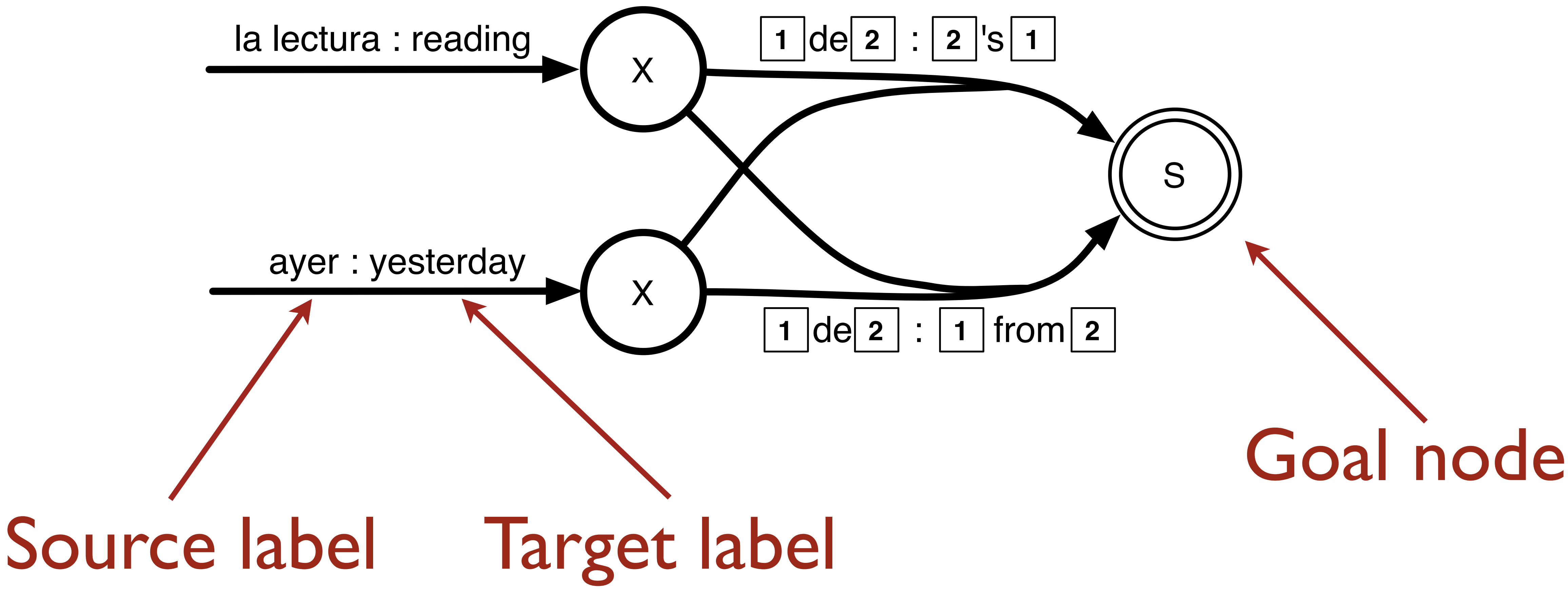


# Language Models

# Hypergraph review



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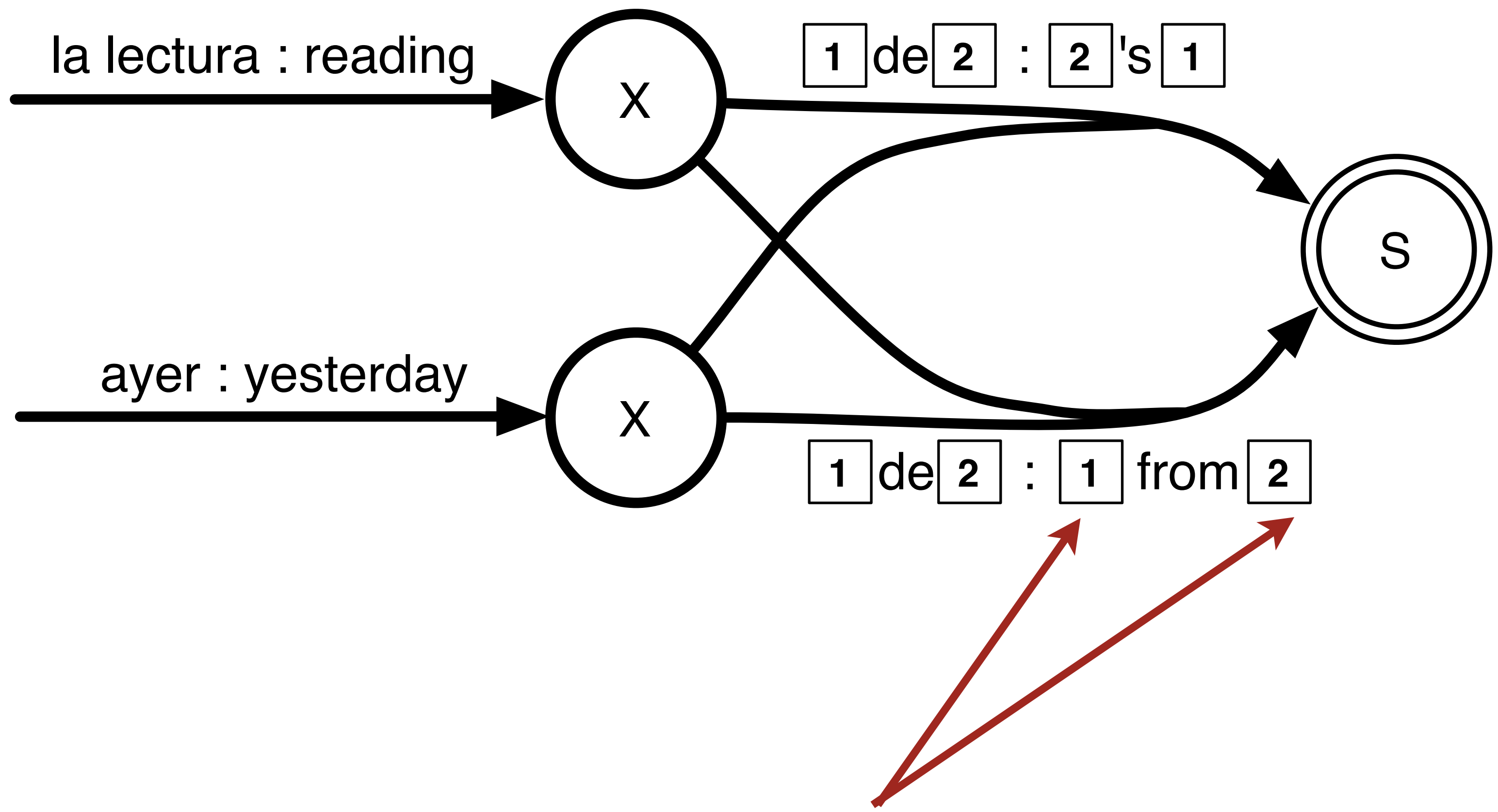
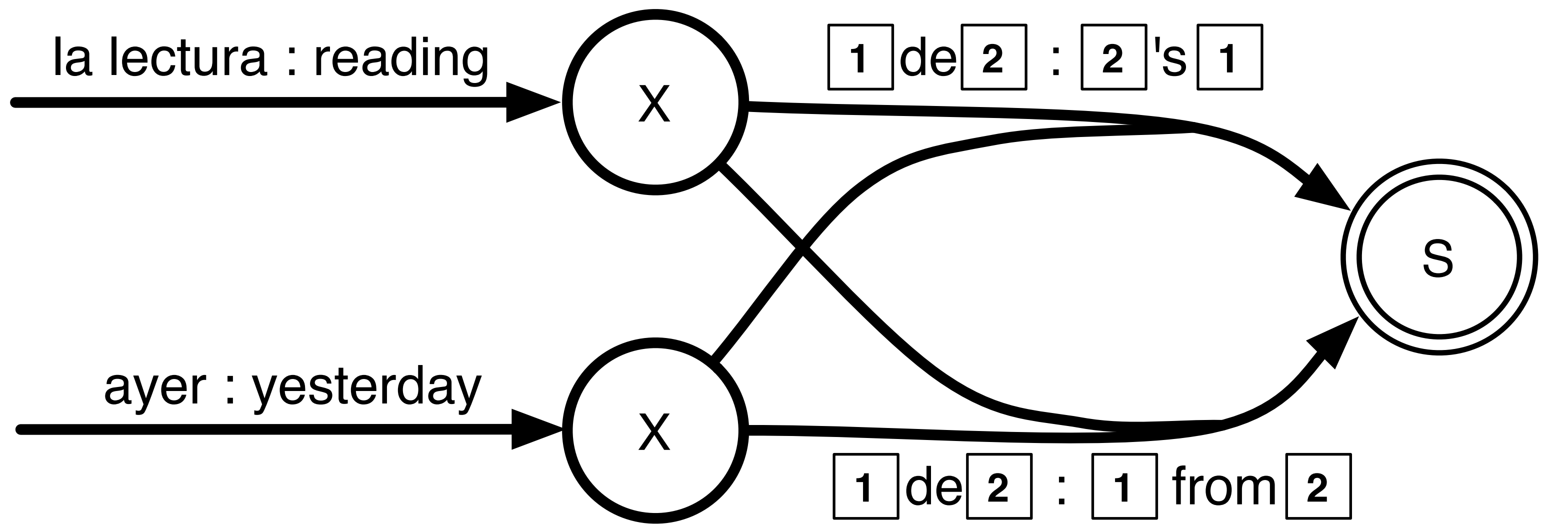



Substitution sites / variables / non-terminals

# Hypergraph review




**For LM integration, we ignore the source!**

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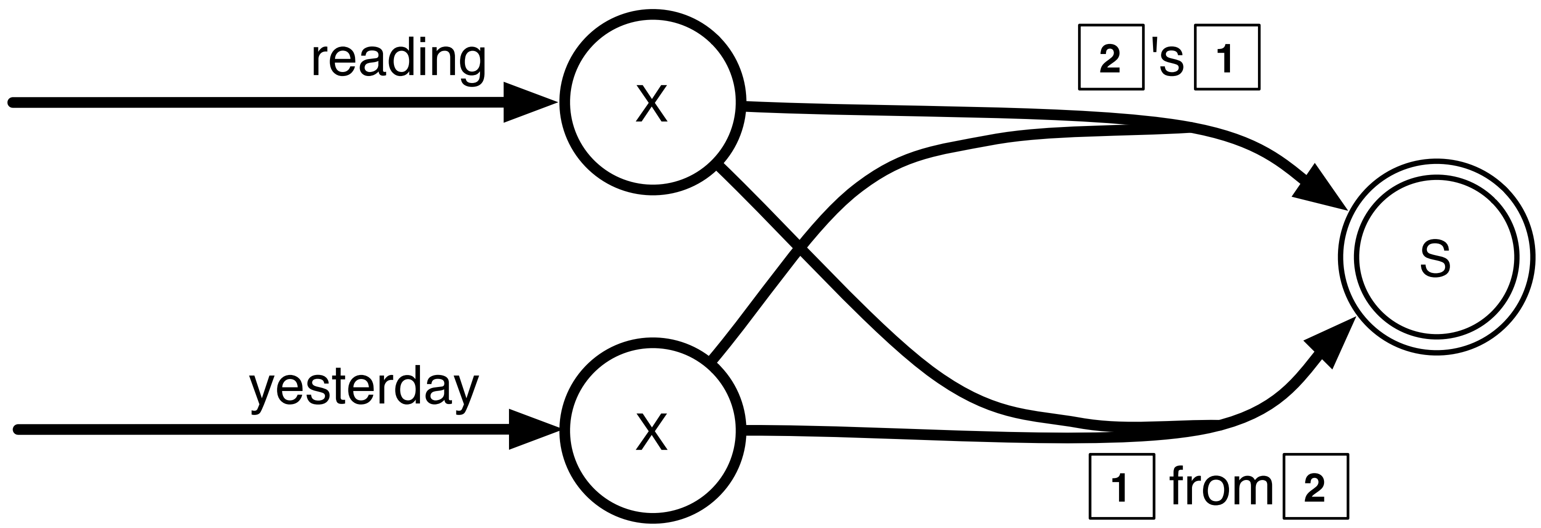


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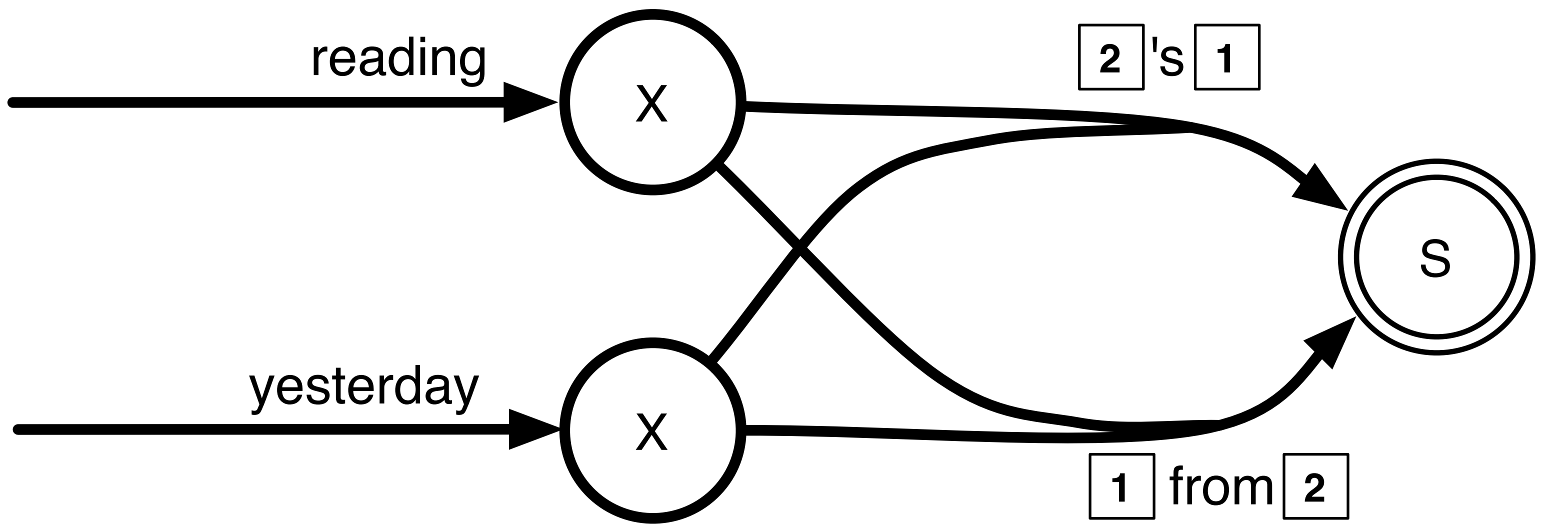


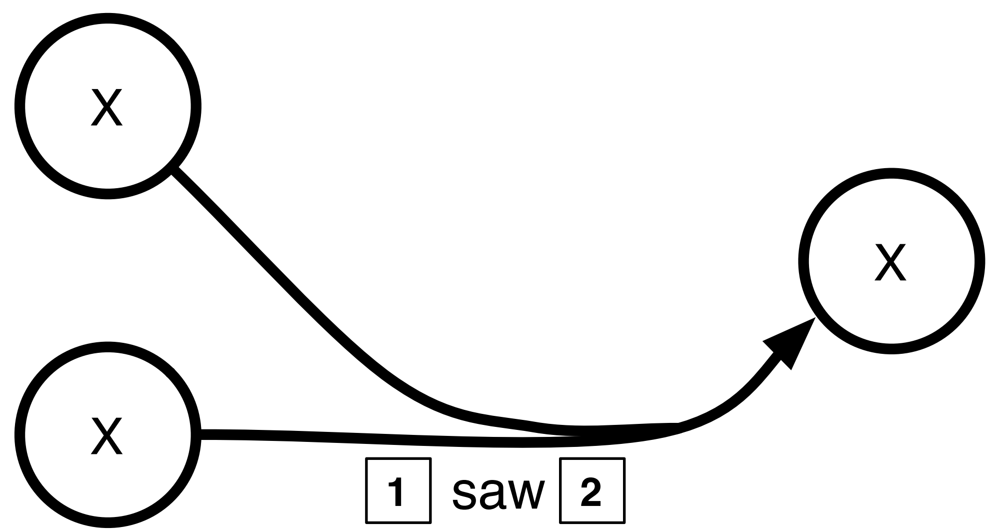

$\{$(*yesterday 's reading*), (*reading from yesterday*)$\}$

**How can we add the LM score to each string derived by the hypergraph?**

# LM Integration

- If LM features were purely local ...
  - “Unigram” model
- ... integration would be a breeze
  - Add an “LM feature” to every edge
- But, LM features are non-local!

# Why is it hard?




Two problems:

1. What is the content of the variables?

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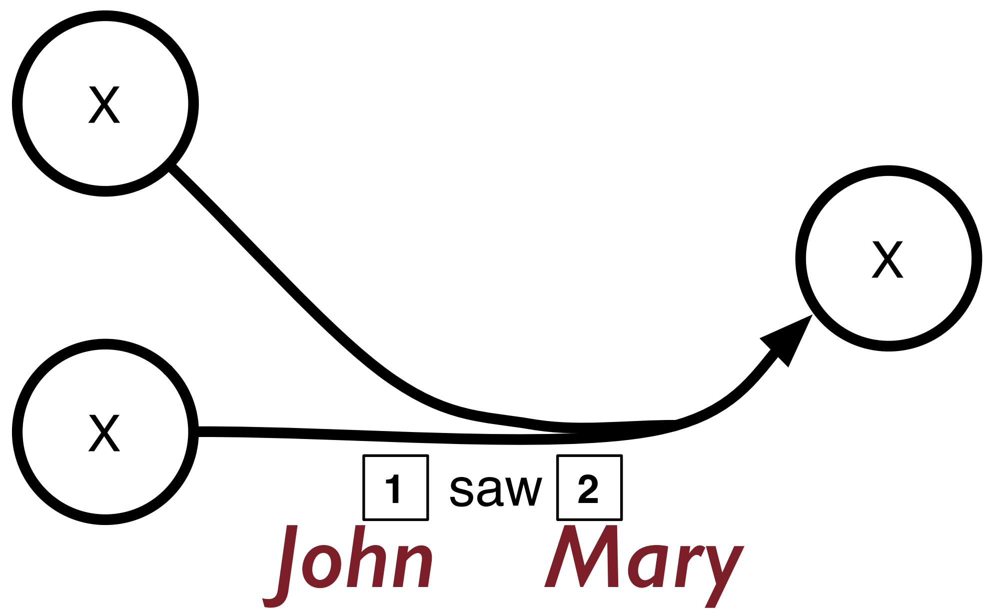


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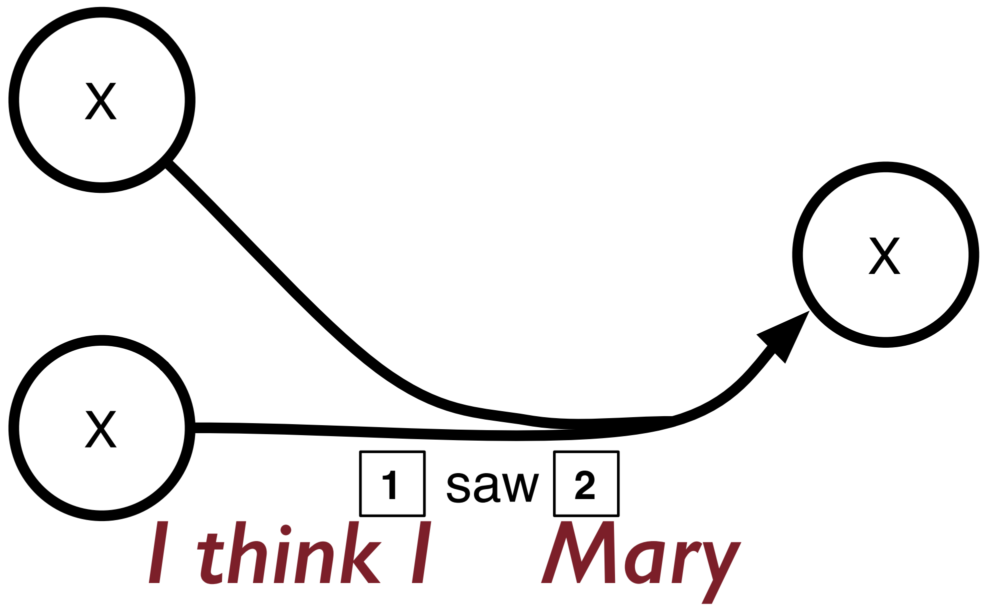


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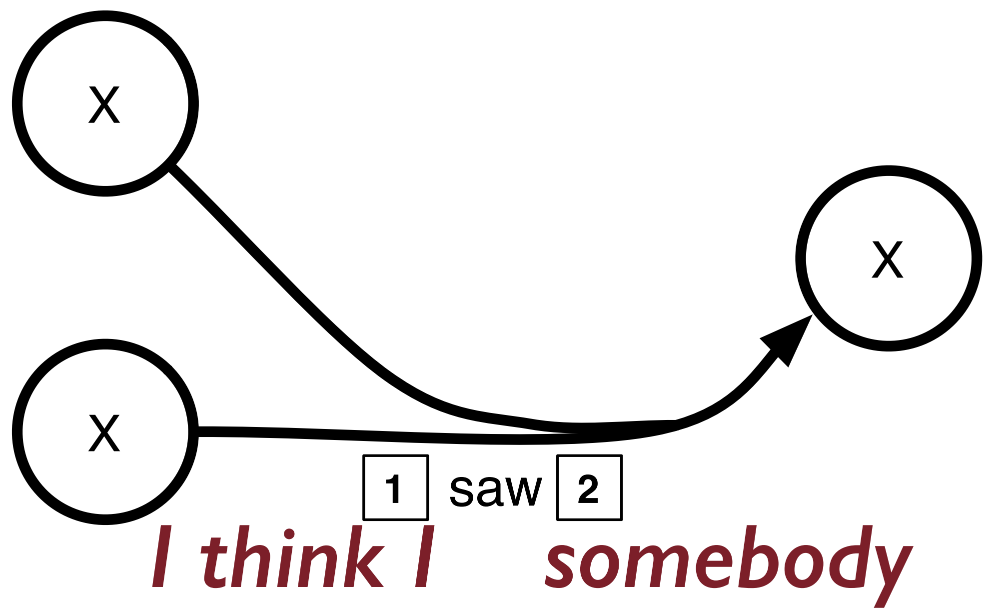


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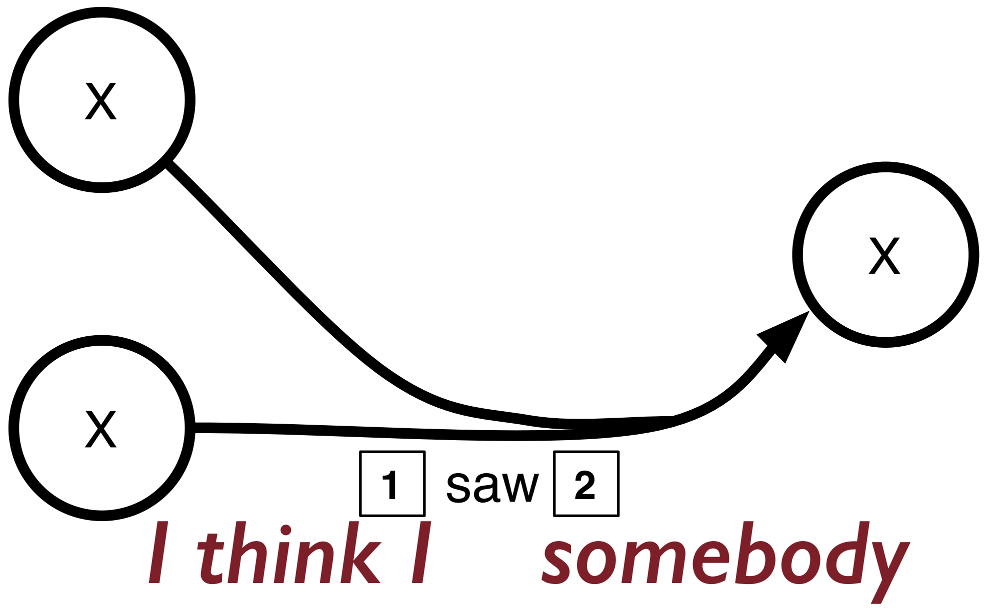


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2. What will be the **left context** when this string is substituted somewhere?

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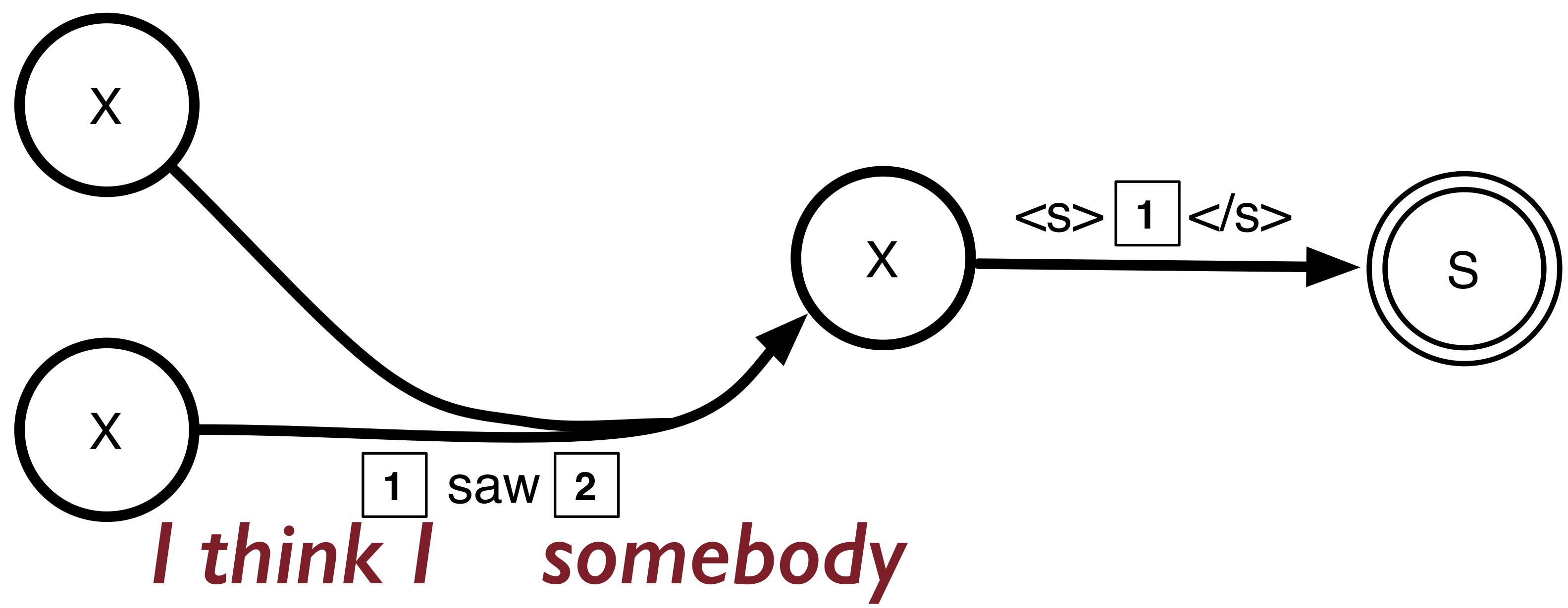


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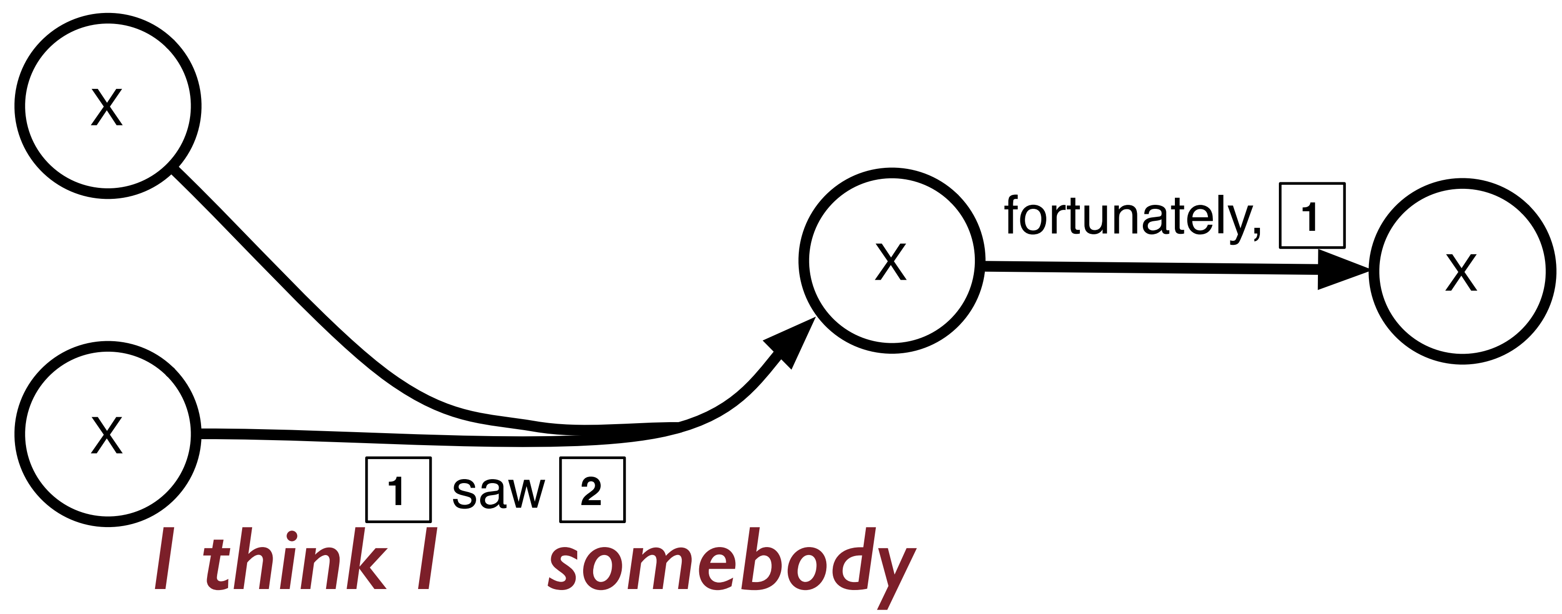


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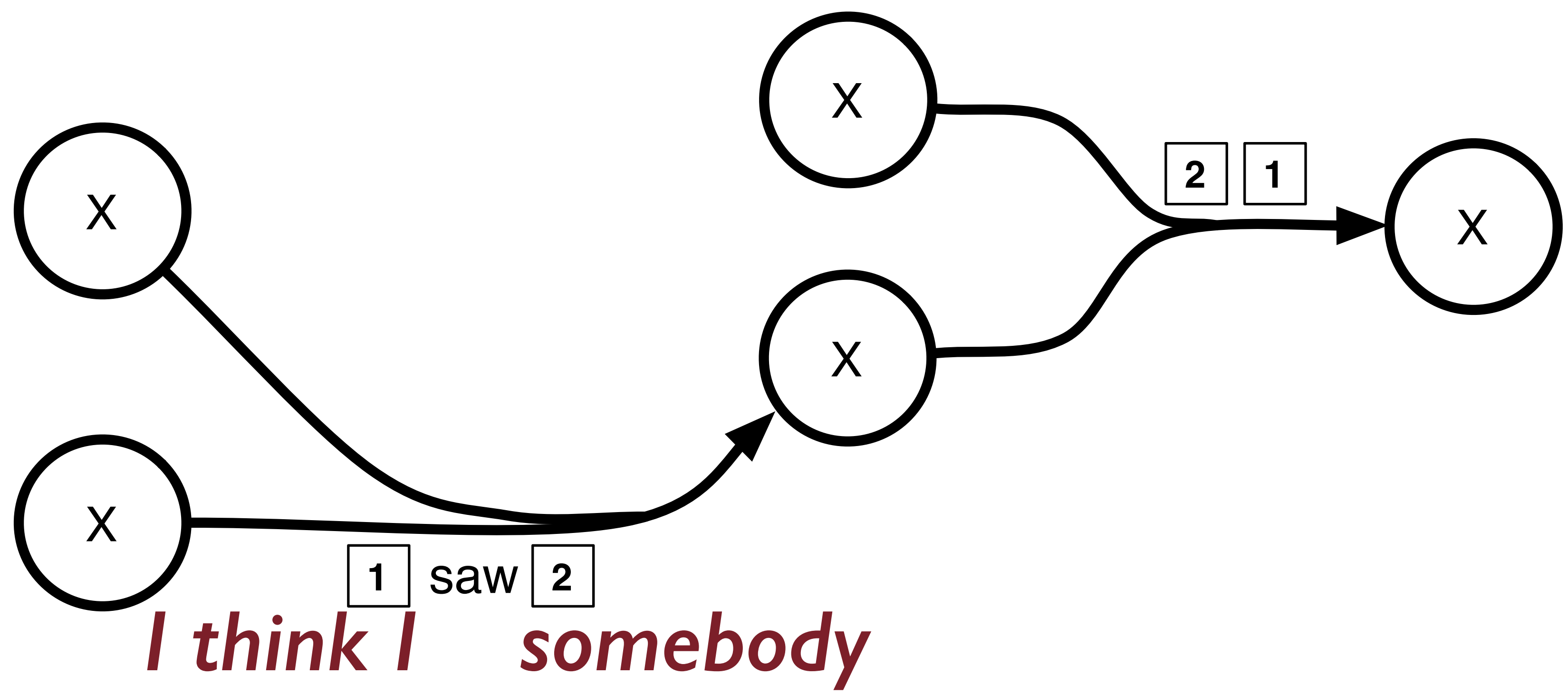
# Why is it hard?




Two problems:

1. What is the content of the variables?

2. What will be the **left context** when this string is substituted somewhere?

# Naive solution

- Extract the all (k-best?) translations from the translation model
- Score them with an LM
- What's the problem with this?

# Outline of DP solution

- Use $n$-order Markov assumption to help us
  - In an $n$-gram LM, words more than $n$ words away will not affect the local (conditional) probability of a word in context
  - **This is not generally true, just the Markov assumption!**
- General approach
  - Restructure the hypergraph so that LM probabilities decompose along edges.
  - Solves both "problems"
    - we will not know the full value of variables, but we will know "enough".
    - defer scoring of left context until the context is established.

# Hypergraph restructuring

- Note the following three facts:
  - If you know $n$ or more consecutive words, the conditional probabilities of the $n$th, ($n$+1)th, ... words can be computed.
    - Therefore: add a feature weight to the edge for words.
  - ($n$-1) words of context to the **left** is enough to determine the probability of any word
    - Therefore: split nodes based on the ($n$-1) words on the **right** side of the span dominated by every node
  - ($n$-1) words on the **left** side of a span cannot be scored with certainty because the context is not known
    - Therefore: split nodes based on the ($n$-1) words on the **left** side of the span dominated by every node

# Hypergraph restructuring

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  - If you know $n$ or more consecutive words, the conditional probabilities of the $n$th, $(n+1)$th, ... words can be computed.
    - 
  - ($n$ ... he pr

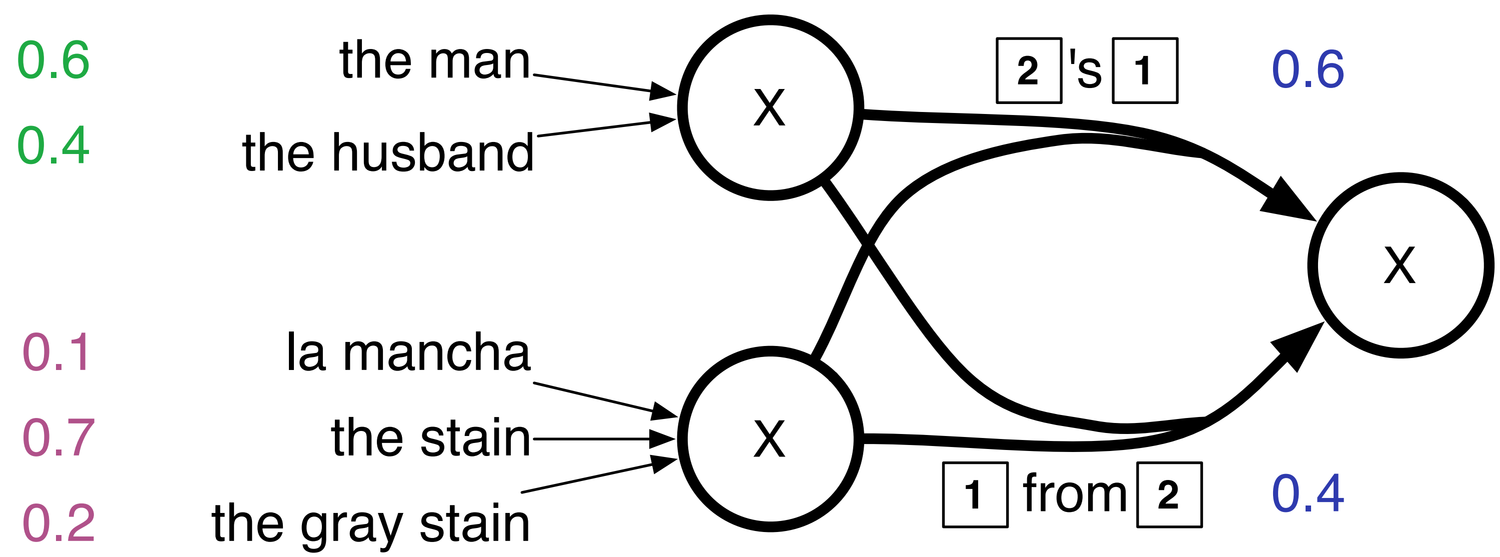
Split nodes by the (n-1) words on both sides of the convergent edges.

    - ... **ight** side of the span dominated by every node
  - $(n\text{-}1)$ words on the **left** side of a span cannot be scored with certainty because the context is not known
    - Therefore: split nodes based on the $(n\text{-}1)$ words on the **left** side of the span dominated by every node

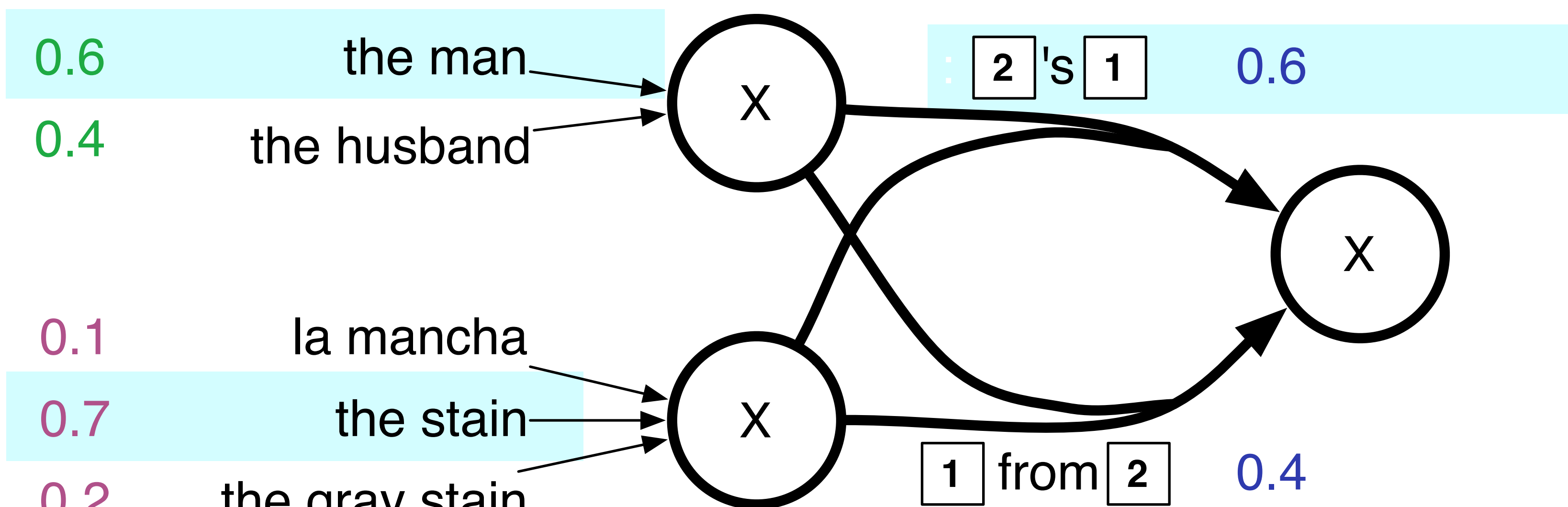
# Hypergraph restructuring

- Algorithm ("cube intersection"):
  - For each node $v$ (proceeding in **topological order** through the nodes)
    - For each edge $e$ with head-node $v$, compute the ($n$-1) words on the left and right; call this $q_e$
      - Do this by substituting the ($n$-1)x2 word string from the tail node corresponding to the substitution variable
      - If node $vq_e$ does not exist, create it, duplicating all outgoing edges from $v$ so that they also proceed from $vq_e$
      - Disconnect $e$ from $v$ and attach it to $vq_e$
  - Delete $v$

# Hypergraph restructuring



# Hypergraph restructuring

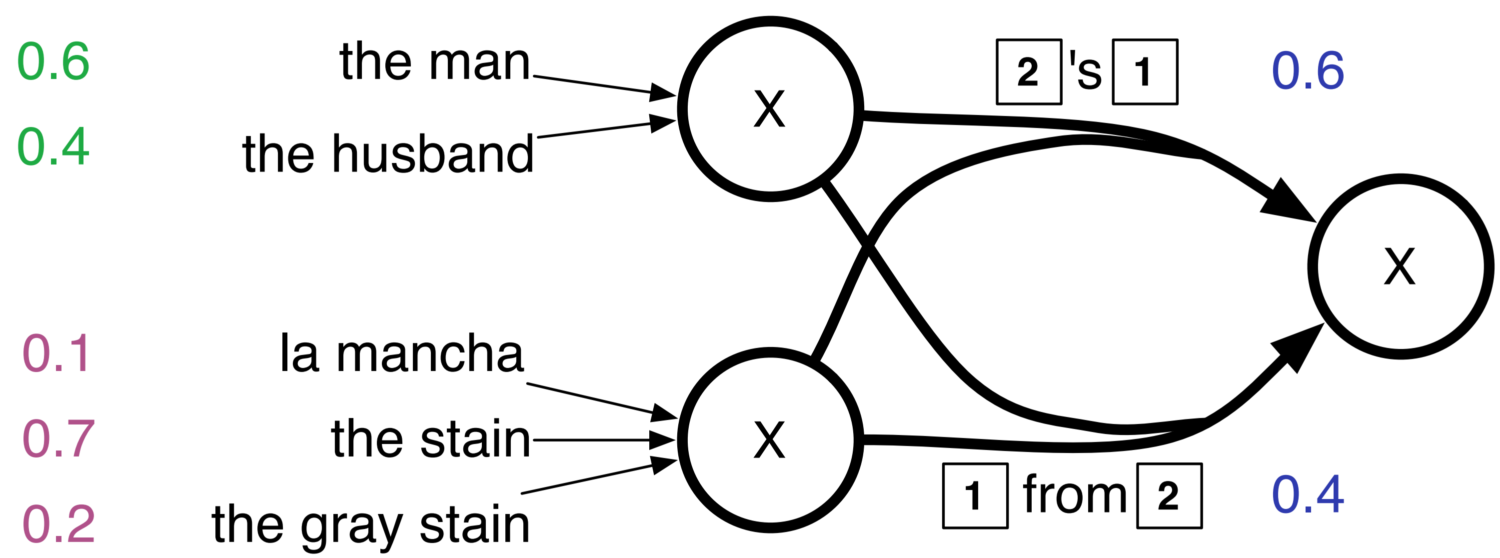



-LM Viterbi:

the stain's the man

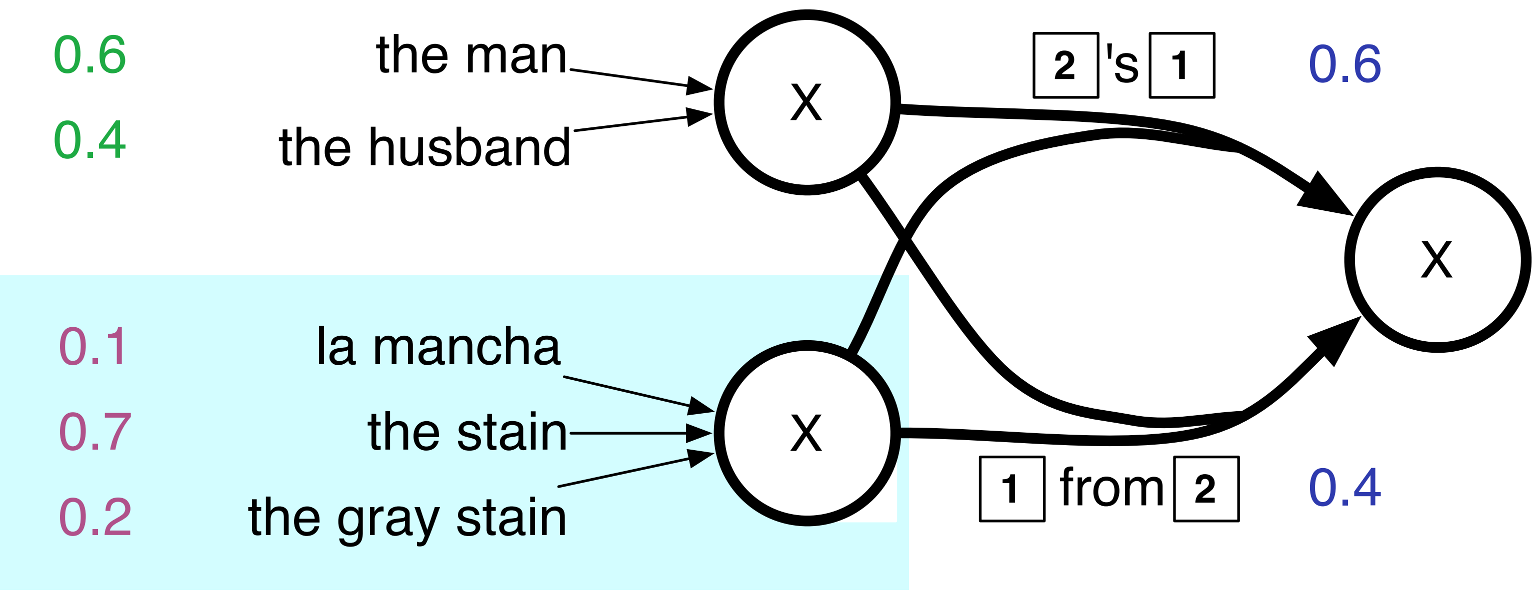
# Hypergraph restructuring

## Let's add a bi-gram language model!

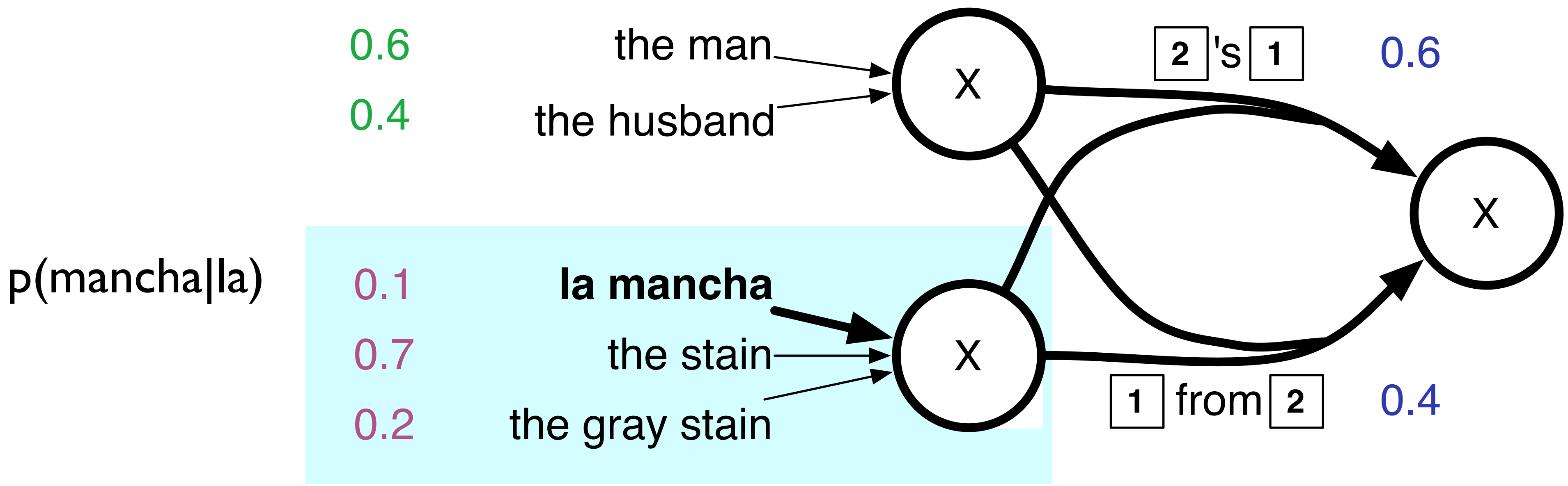


# Hypergraph restructuring

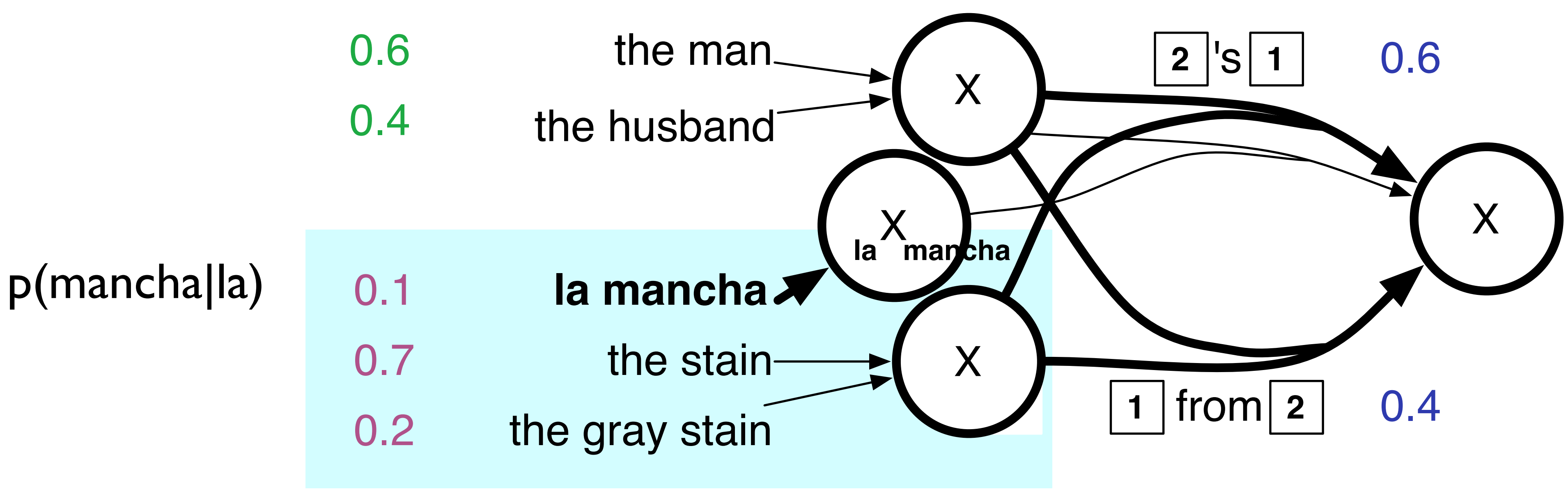
Let's add a bi-gram language model!



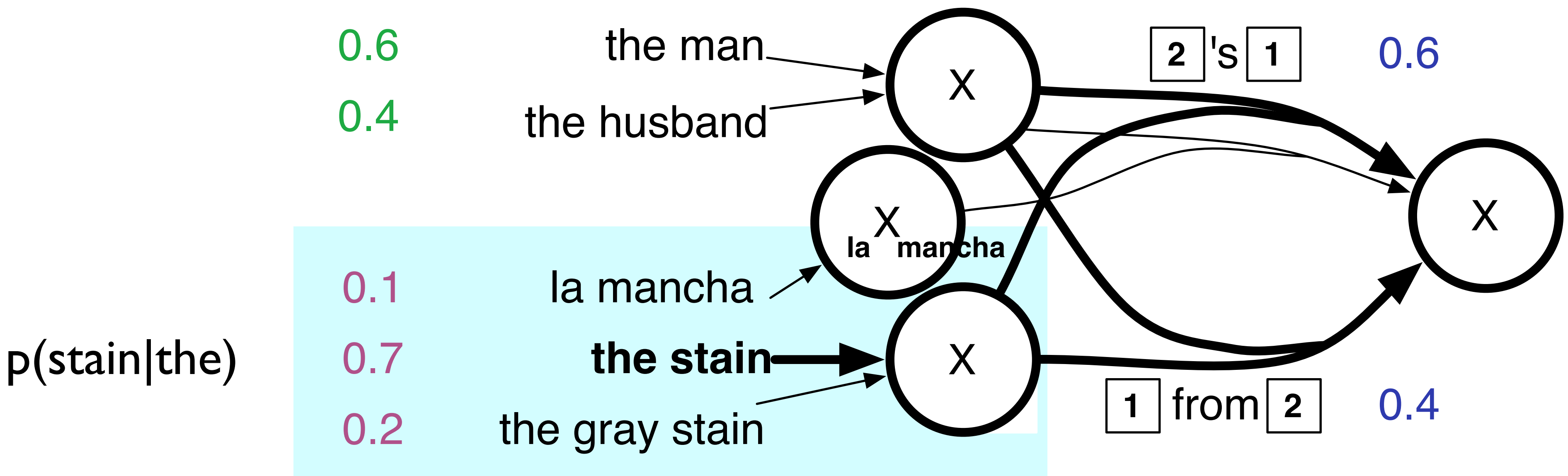
# Hypergraph restructuring



# Hypergraph restructuring



# Hypergraph restructuring



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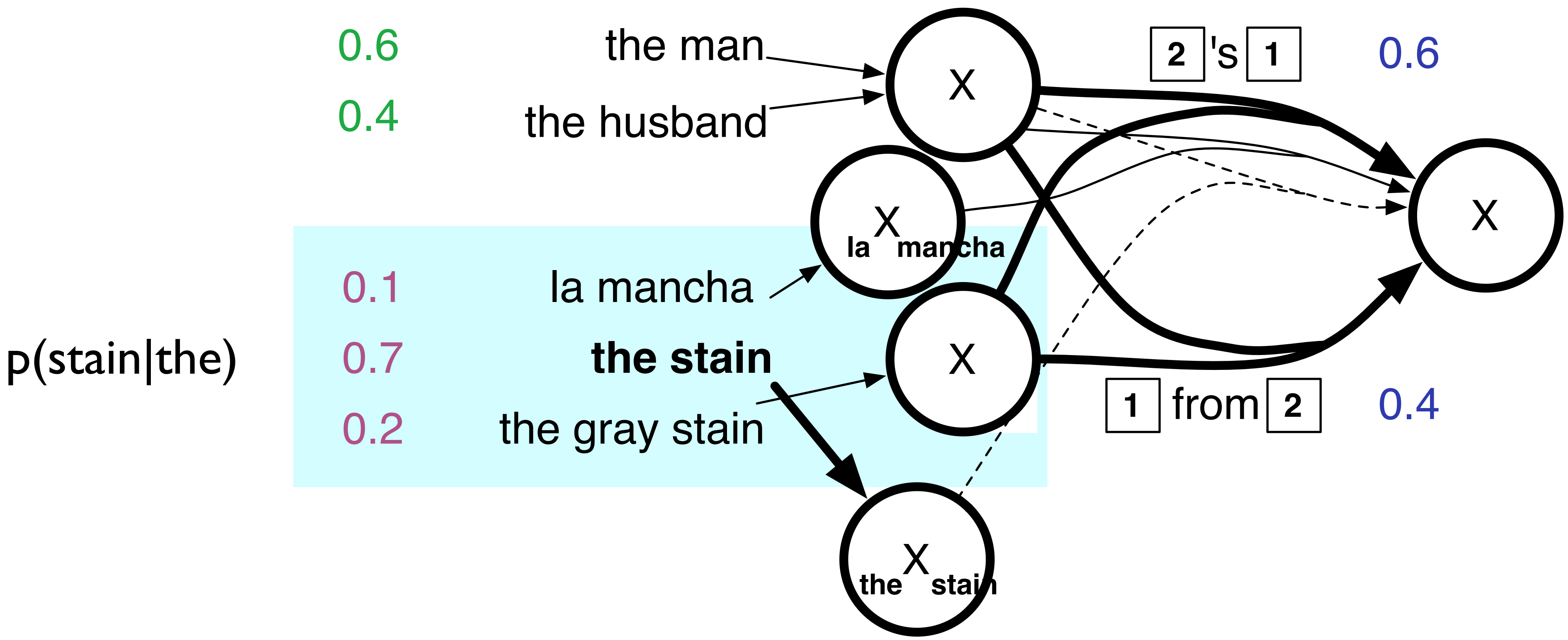

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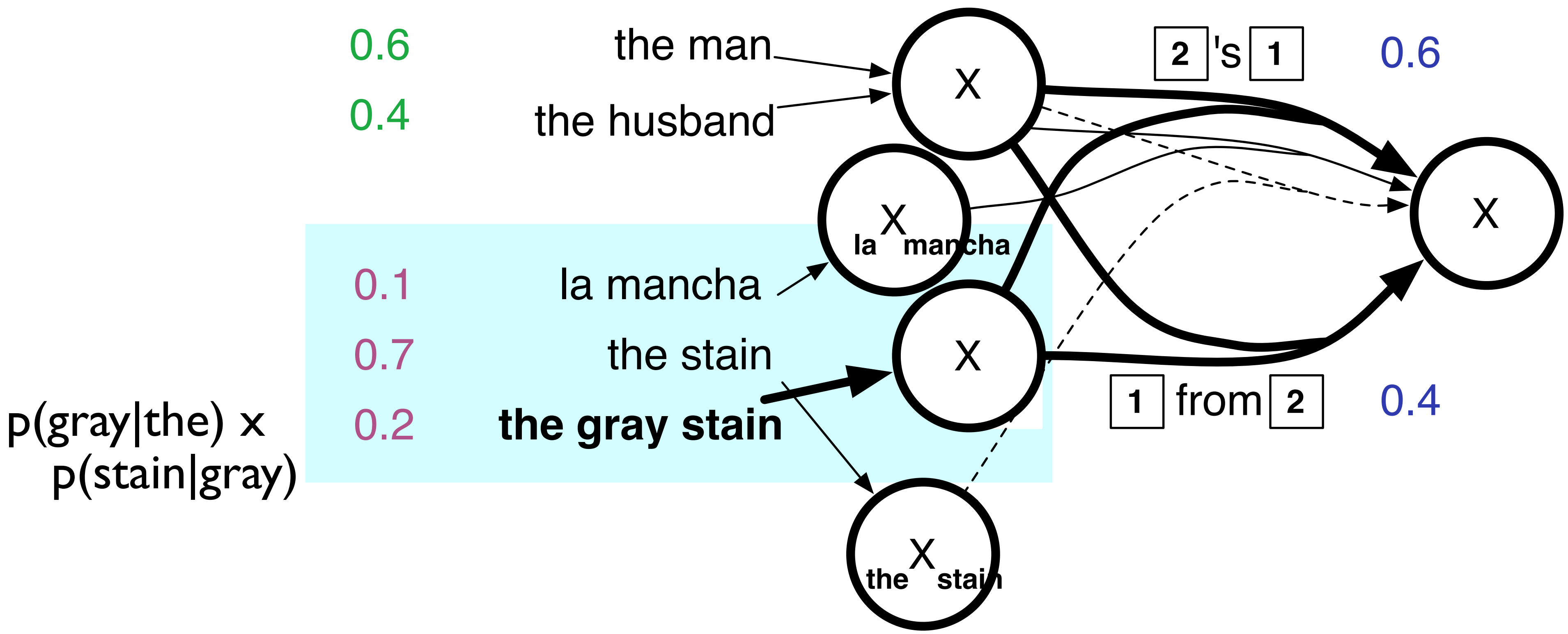

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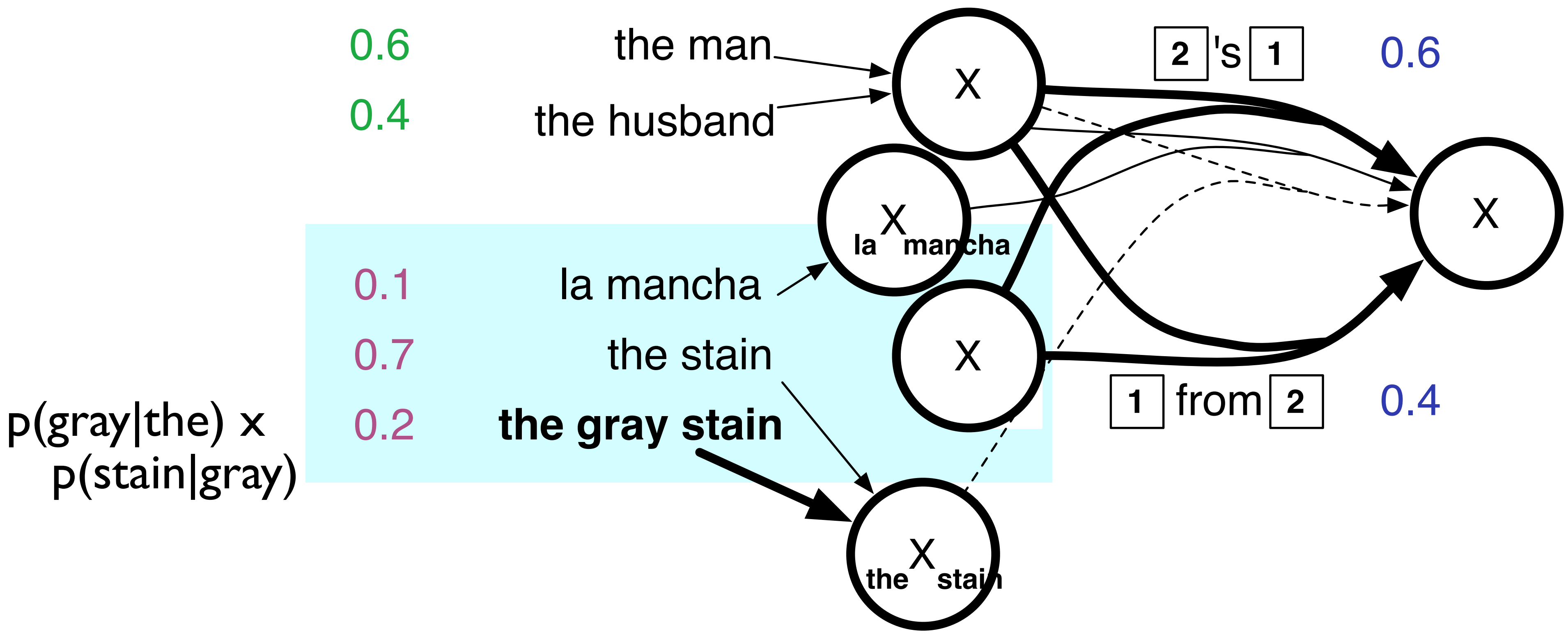

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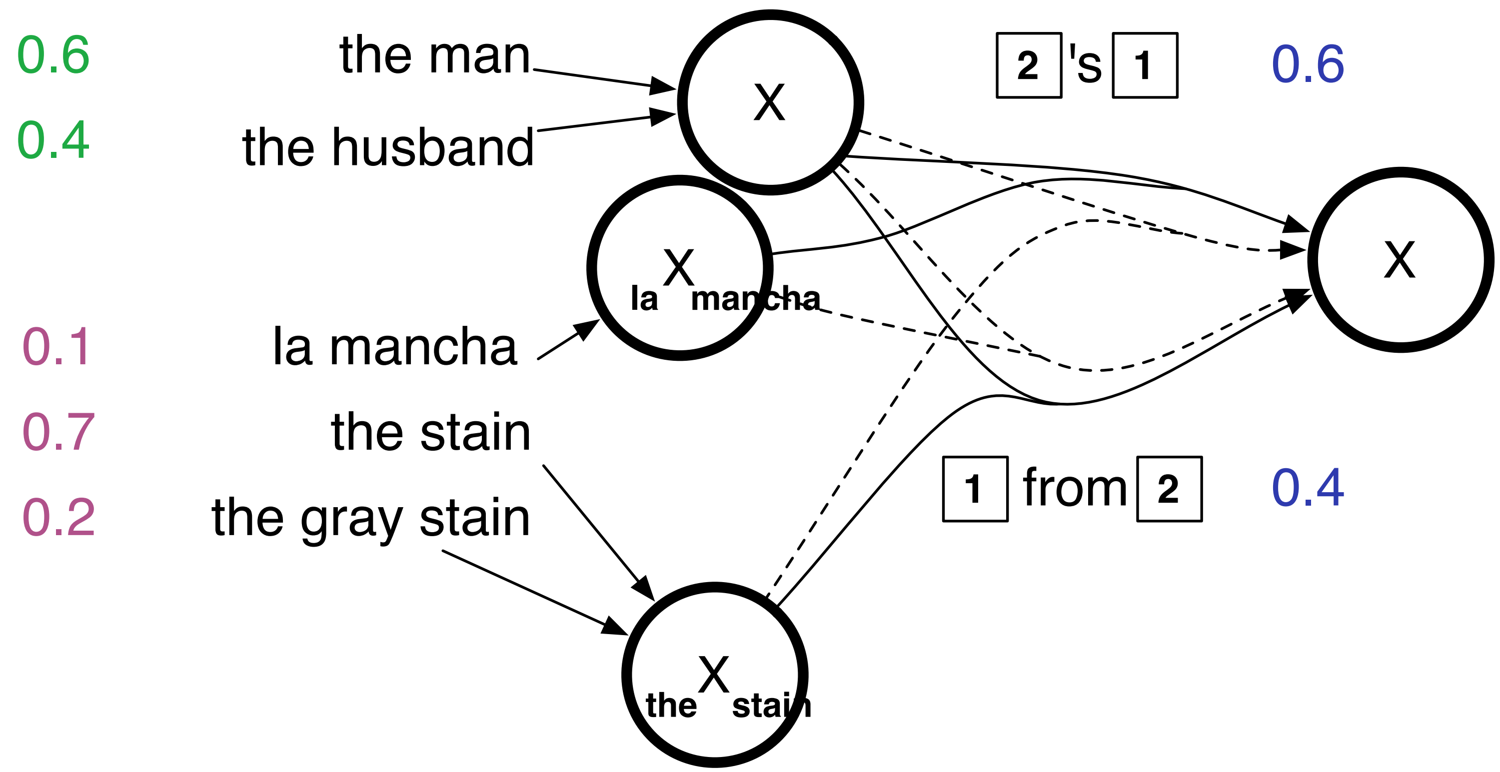

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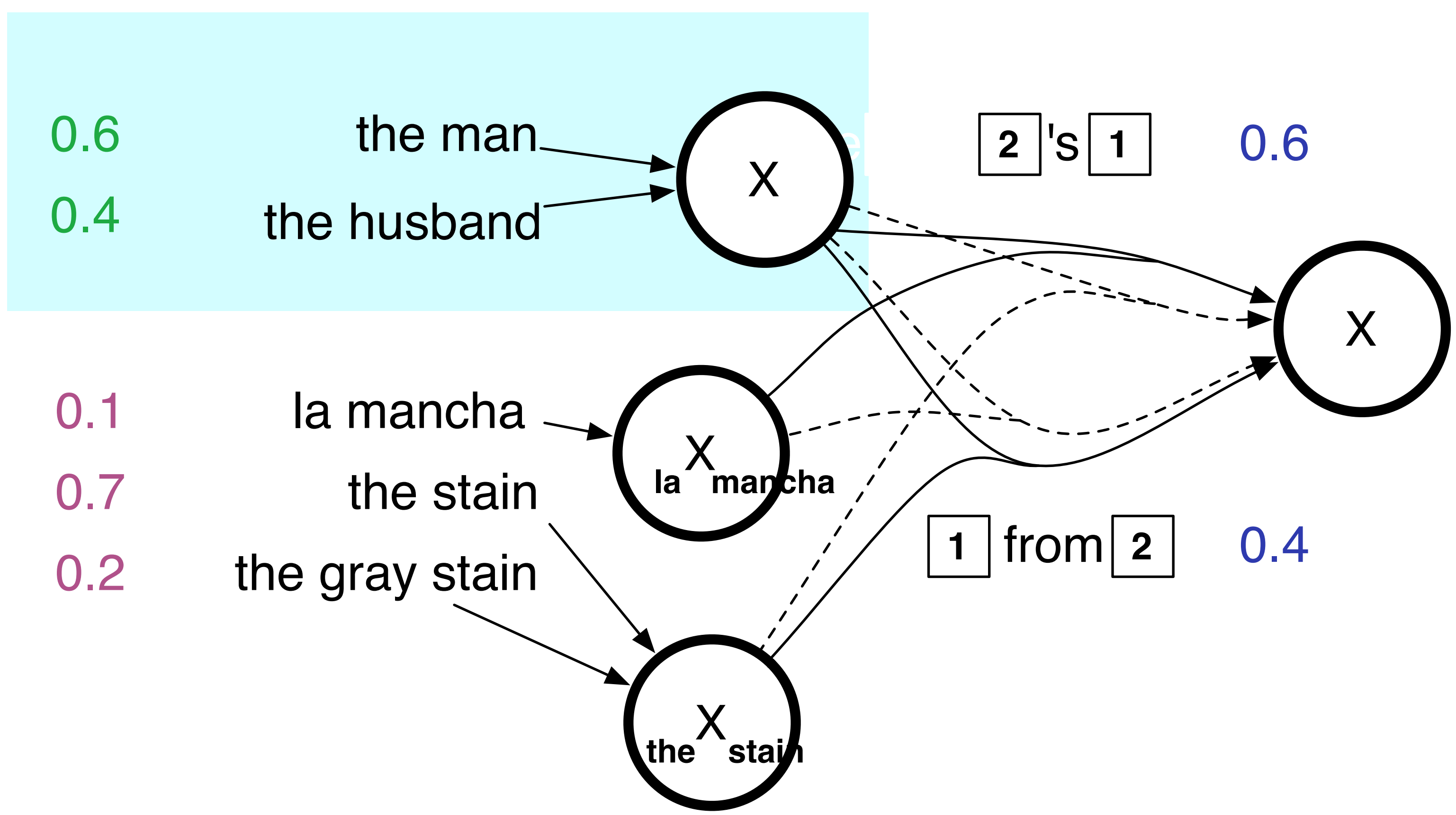

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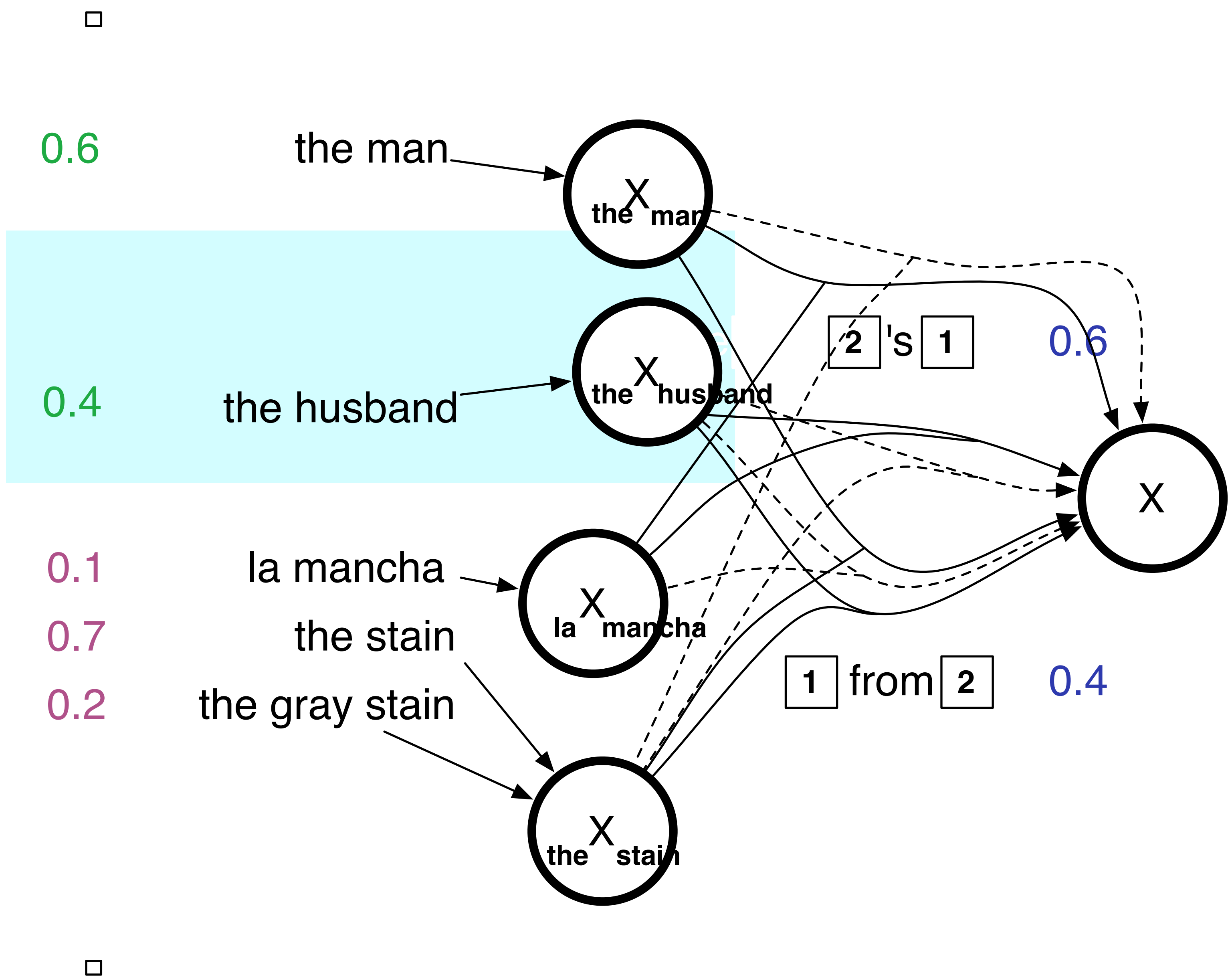

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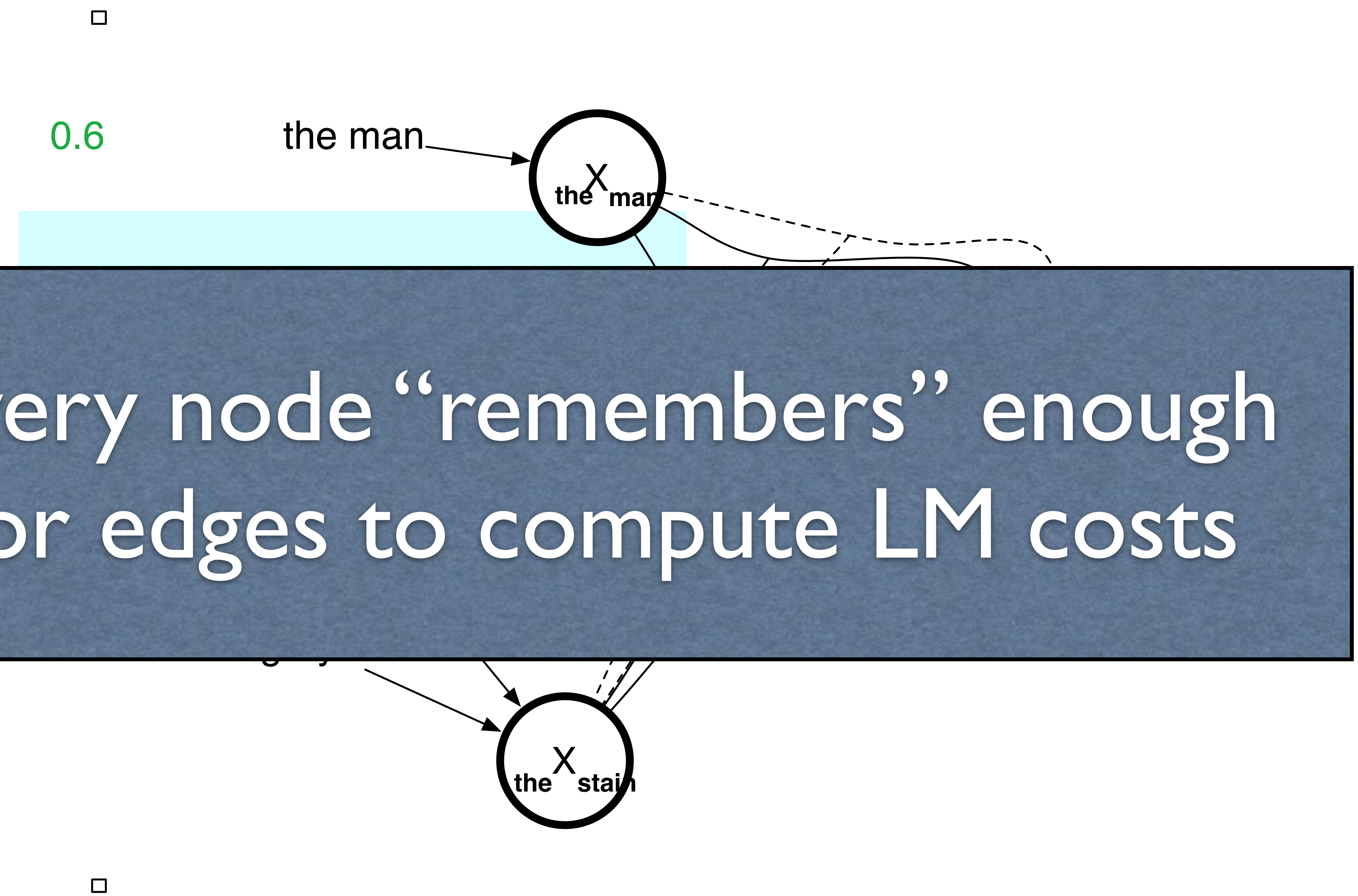


Every node “remembers” enough for edges to compute LM costs

# Complexity

- What is the run-time of this algorithm?

# Complexity

- What is the run-time of this algorithm?

$$O(|V||E||\Sigma|^{2(n-1)})$$

Going to longer n-grams is exponentially expensive!

# Cube pruning

- Expanding every node like this exhaustively is impractical
  - Polynomial time, but really, really big!
- Cube pruning: minor tweak on the above algorithm
  - Compute the k-best expansions at each node
  - Use an **estimate** (usually a unigram probability) of the unscored left-edge to rank the nodes

# Cube pruning

- Widely used for phrase-based and syntax-based MT
- May be applied in conjunction with a bottom-up decoder, or as a second “rescoring” pass
  - Nodes may also be grouped together (for example, all nodes corresponding to a certain source span)
- Requirement for topological ordering means translation hypergraph may not have cycles

# Reading

- Chapter 11 from the textbook
- Research papers listed in the syllabus