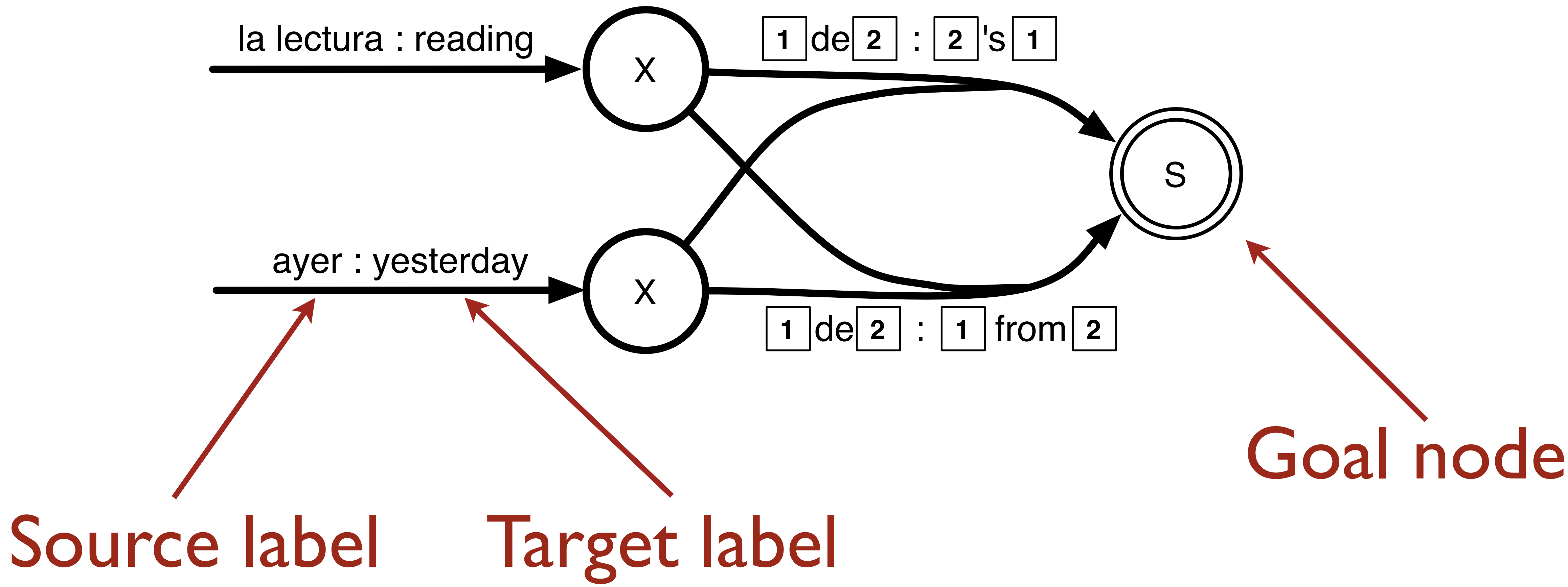
Using N-Gram LMs with SCFG TMs

March 20, 2013

Hypergraph review



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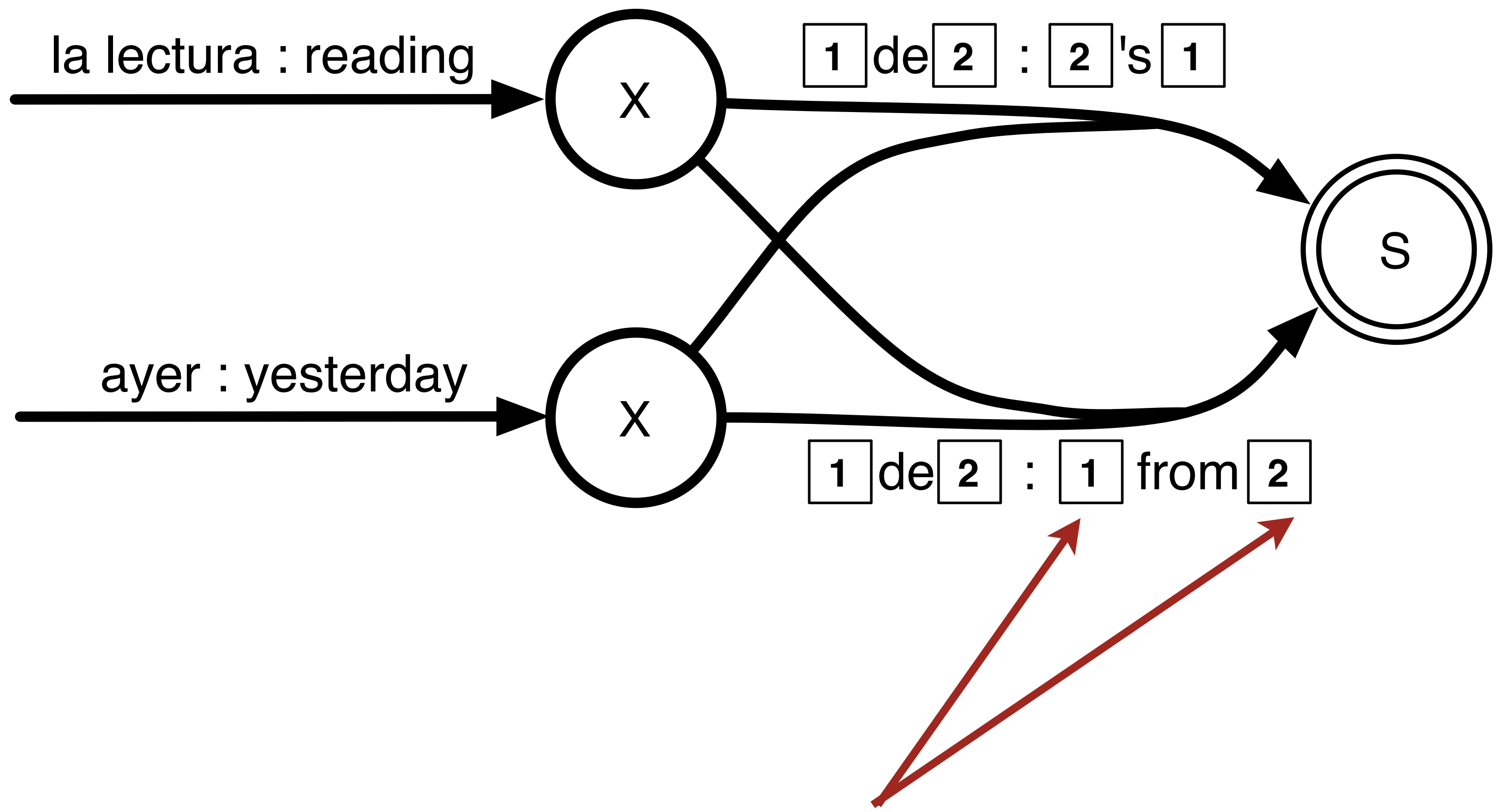
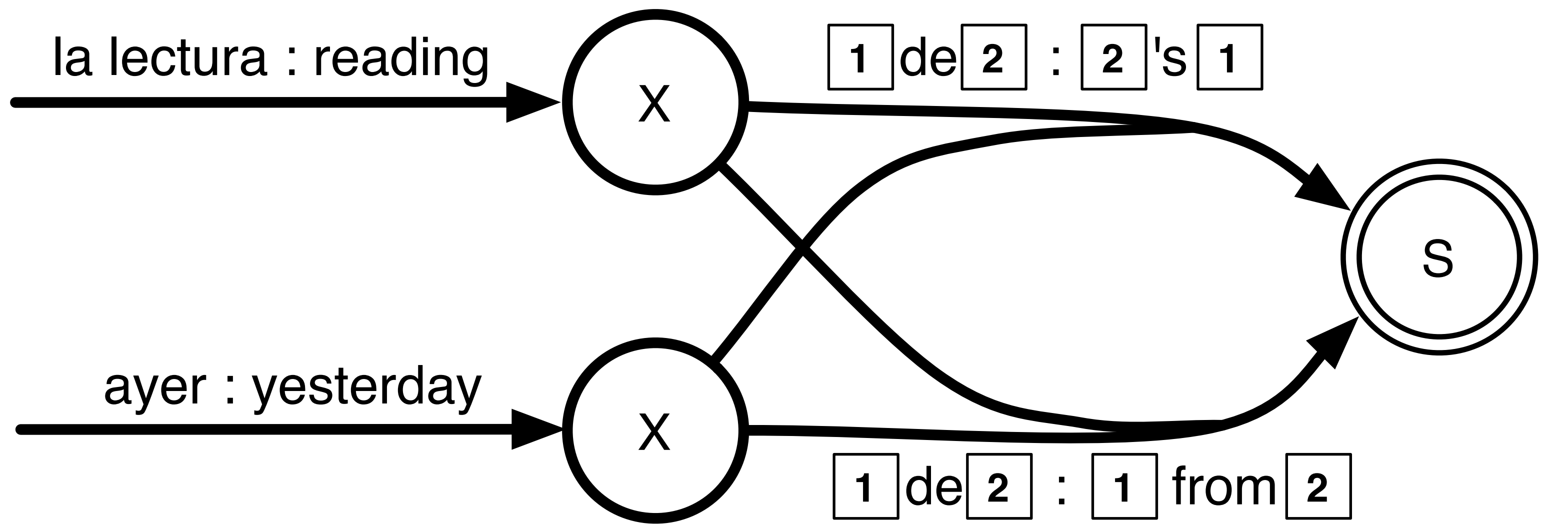


Substitution sites / variables / non-terminals

Hypergraph review



For LM integration, we ignore the source!

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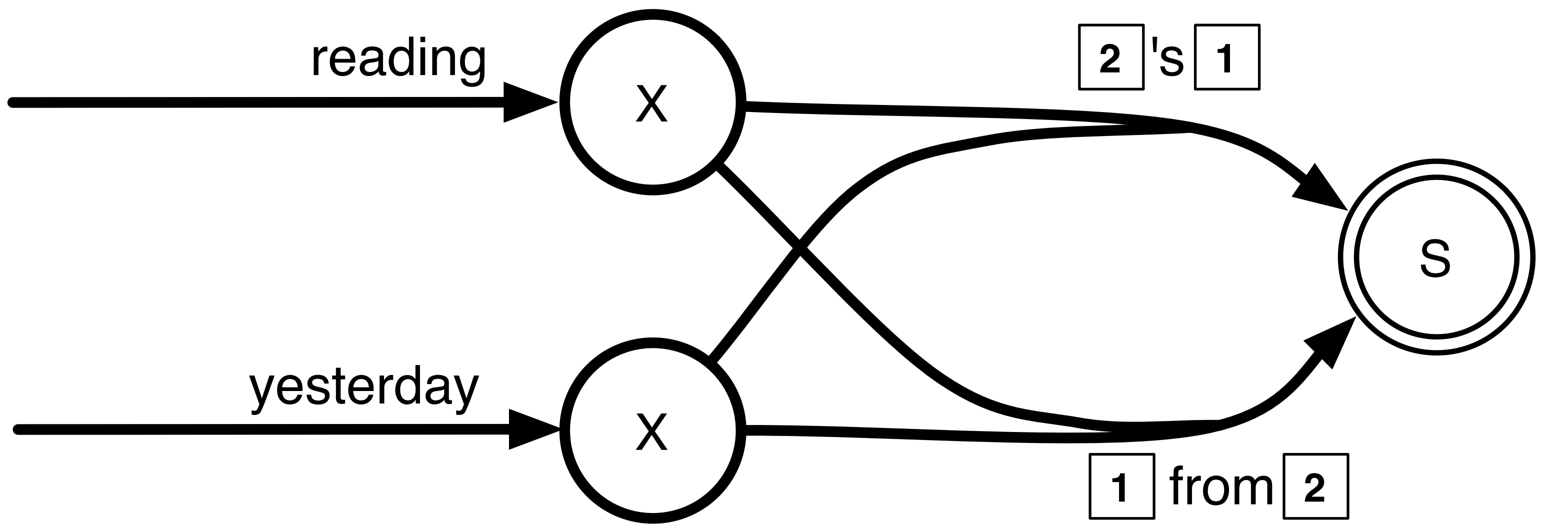

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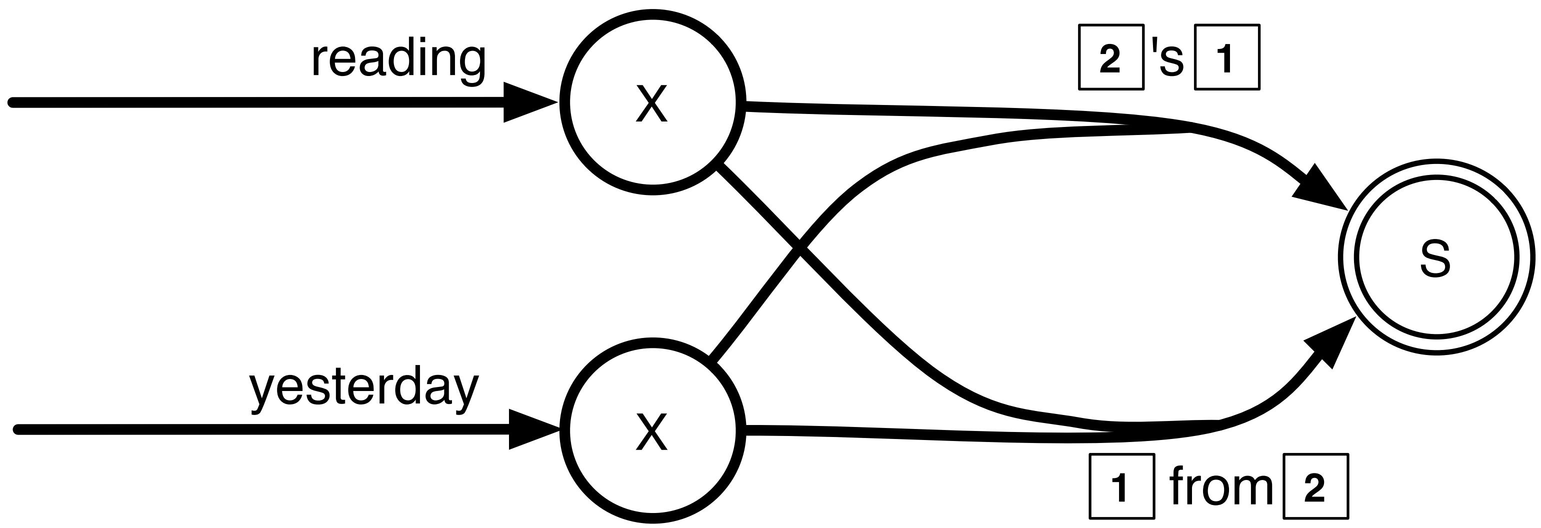


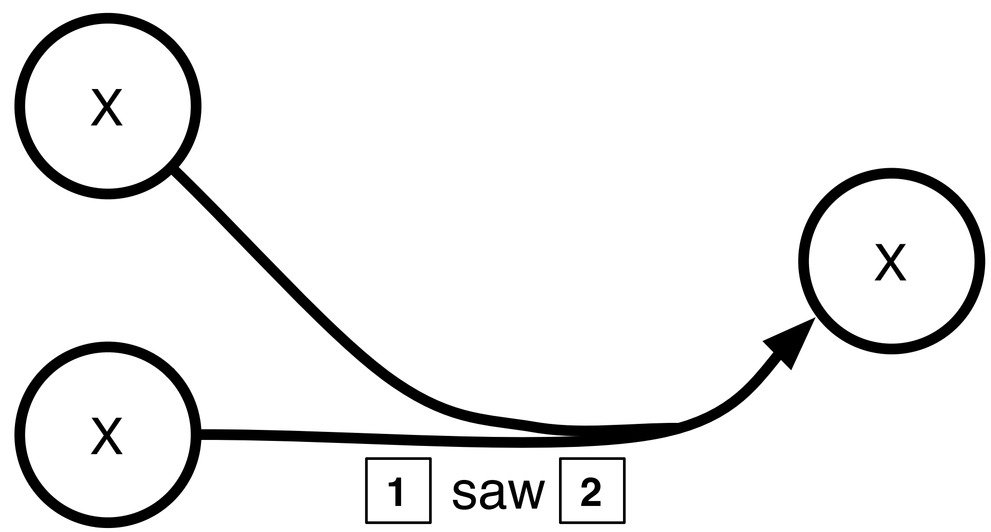
$\{$(*yesterday ’s reading*),
(*reading from yesterday*)$\}$

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

LM Integration

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

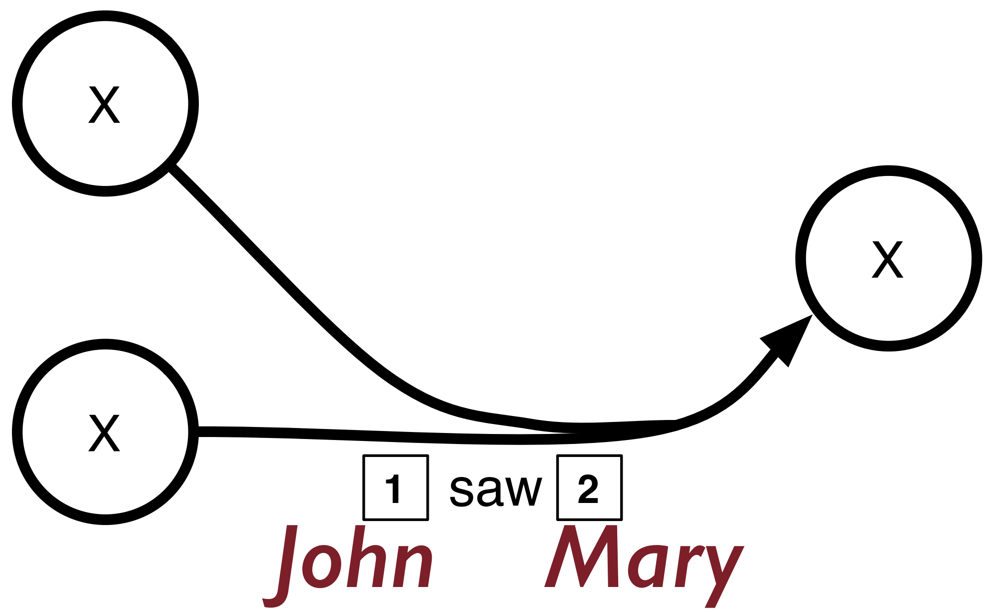
Why is it hard?



Two problems:

1. What is the content of the variables?

Why is it hard?



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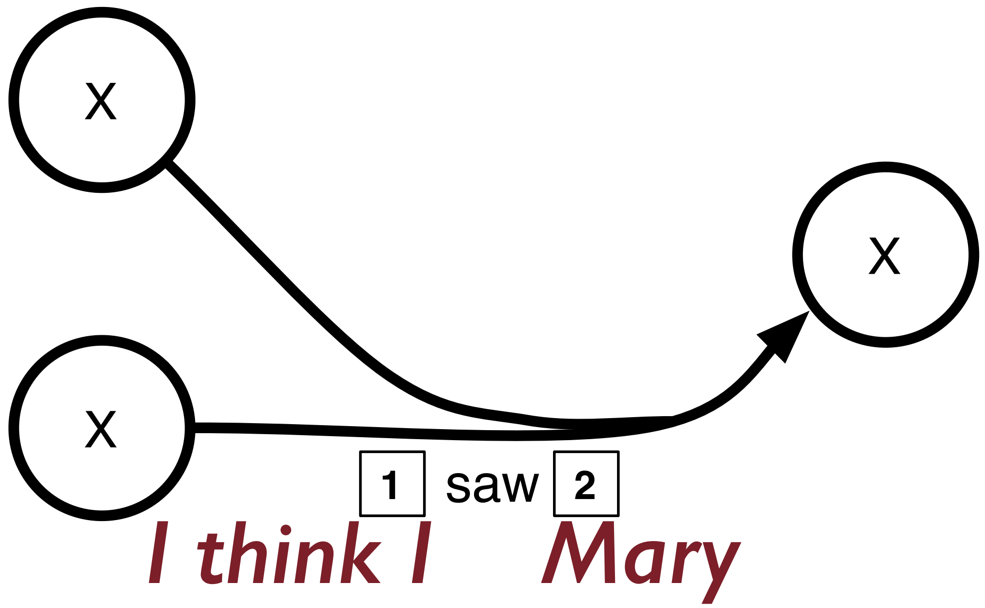

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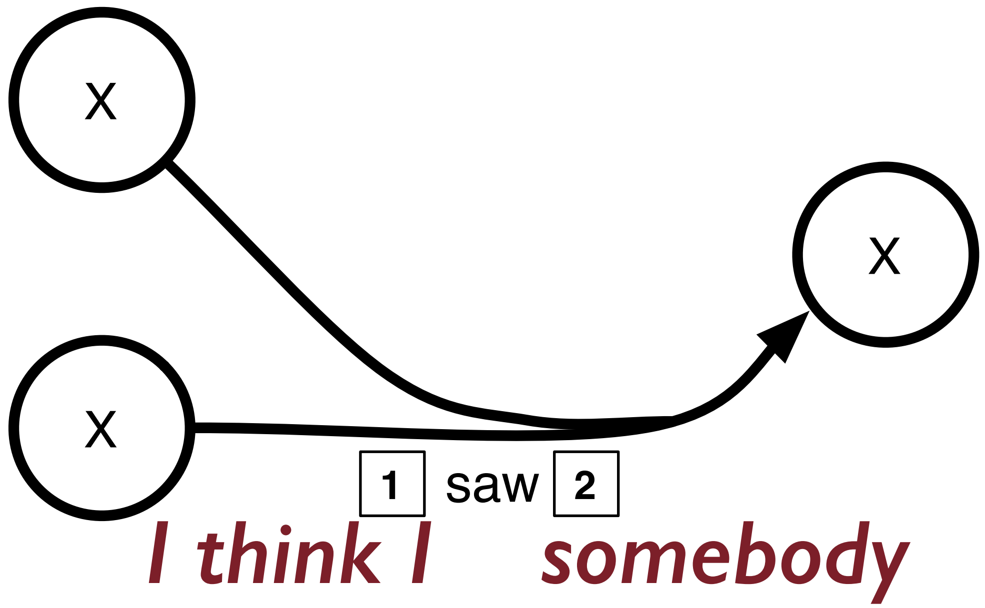

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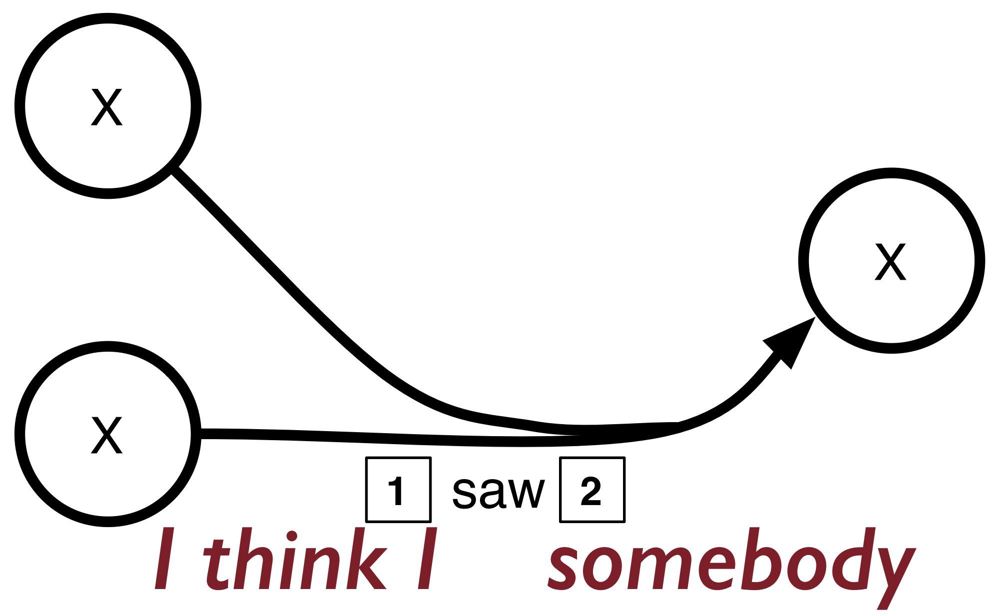

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2. What will be the **left context** when this string is substituted somewhere?

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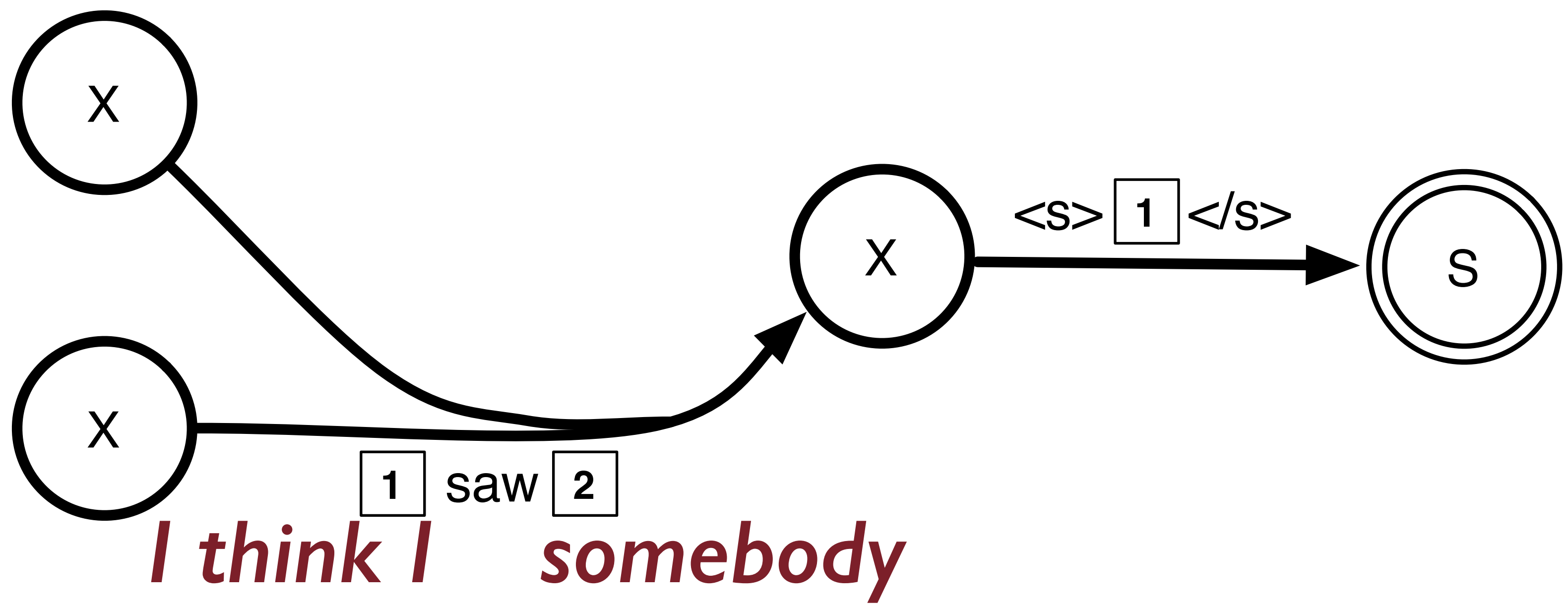

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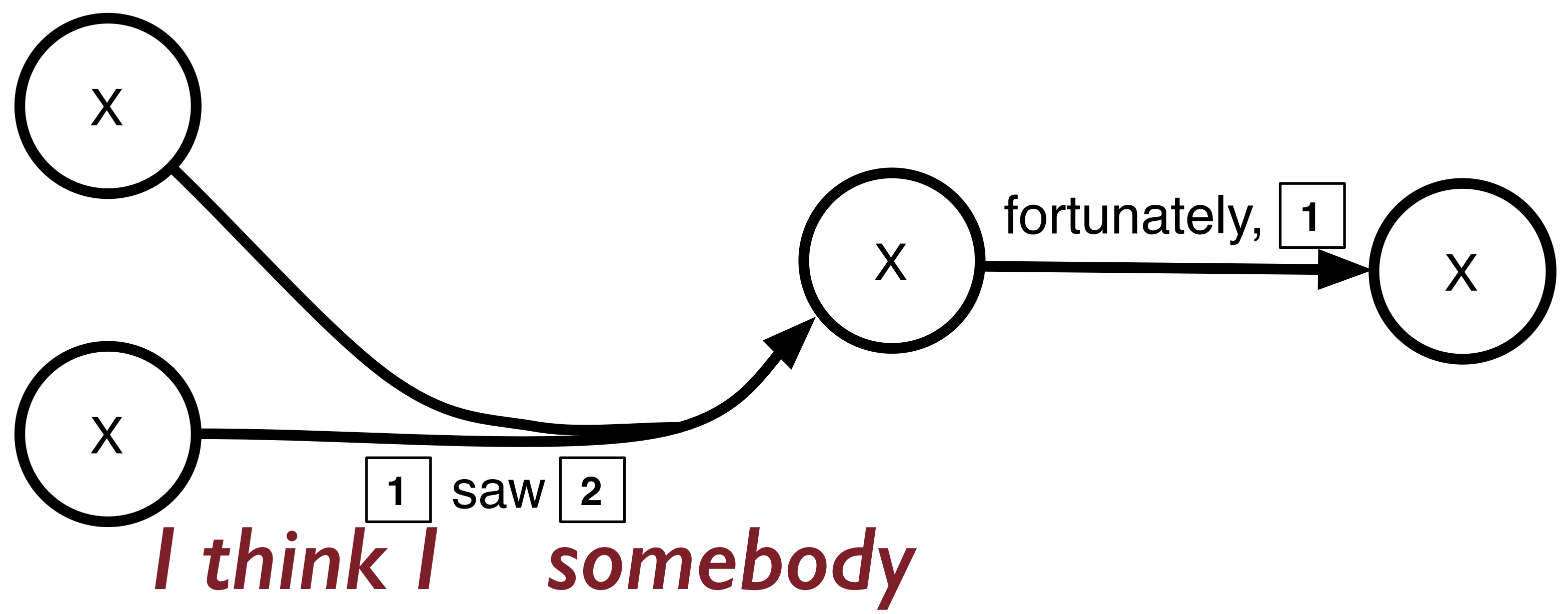

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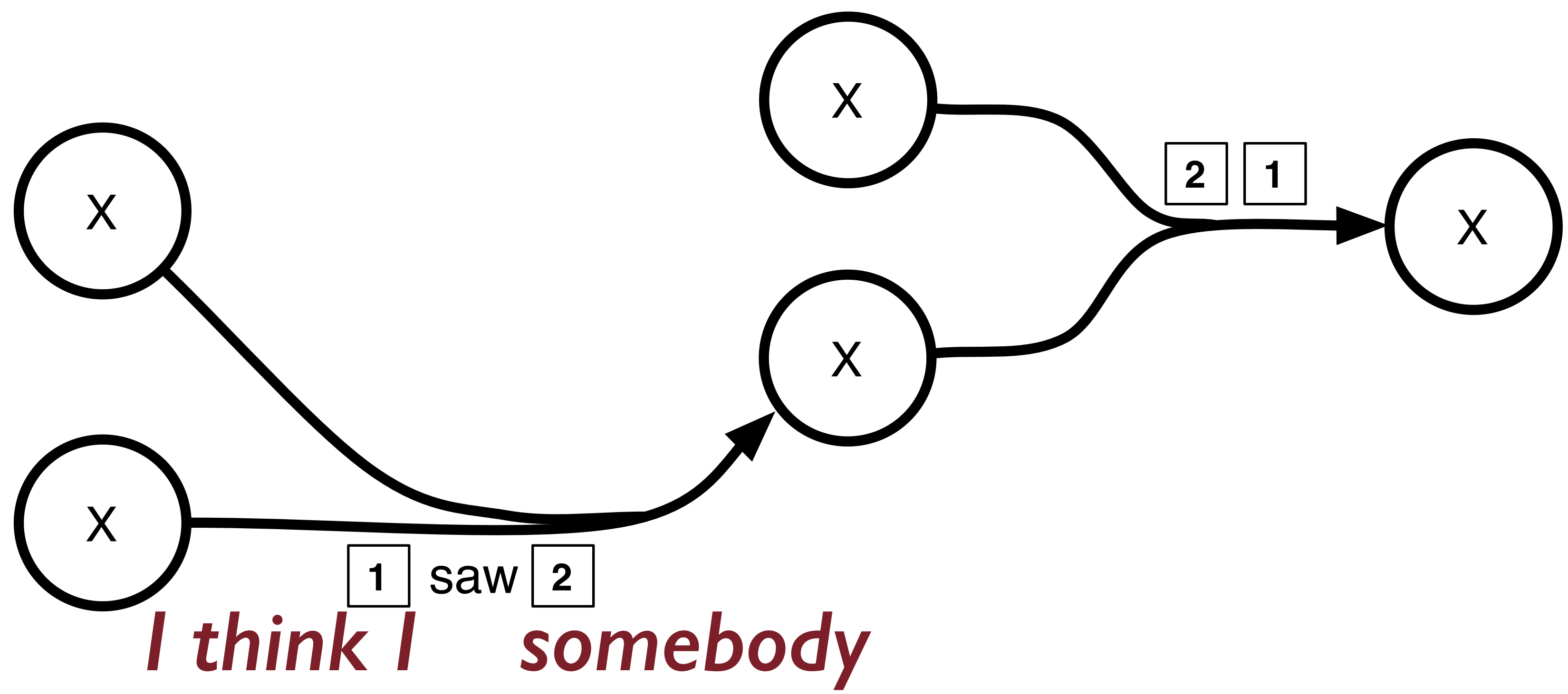

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Naive solution

- 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 nth, (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 nth, $(n+1)$th, ... words can be computed.

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

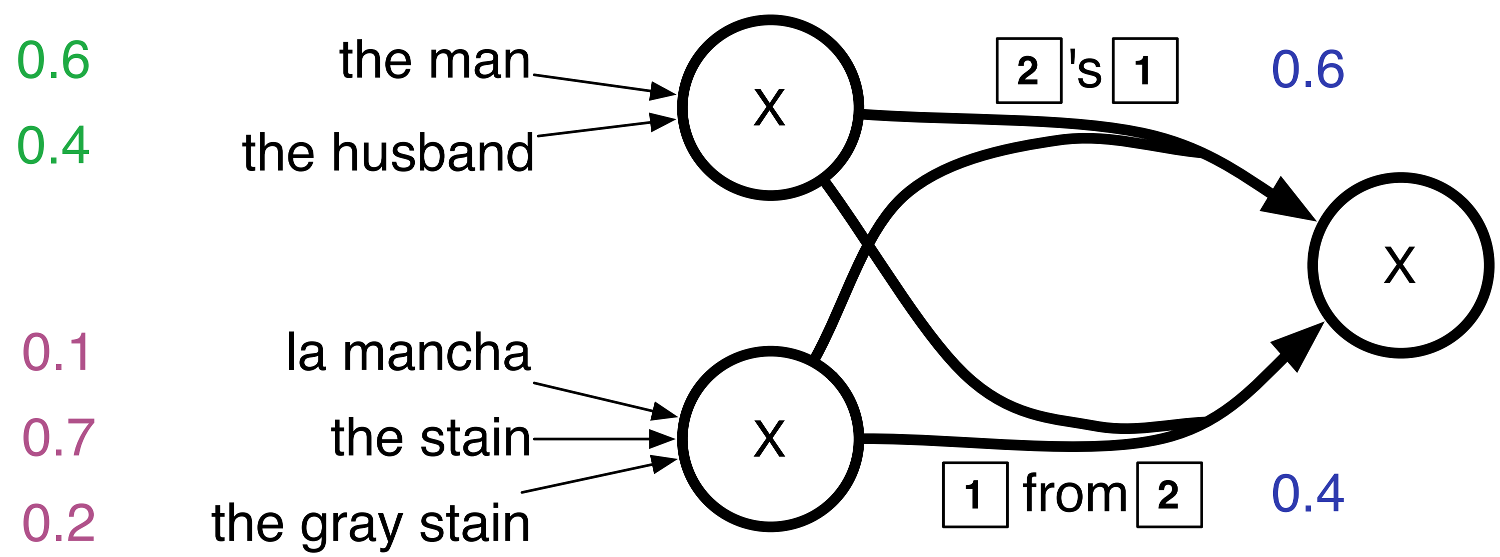
of

  - $(n\text{-}1)$ 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



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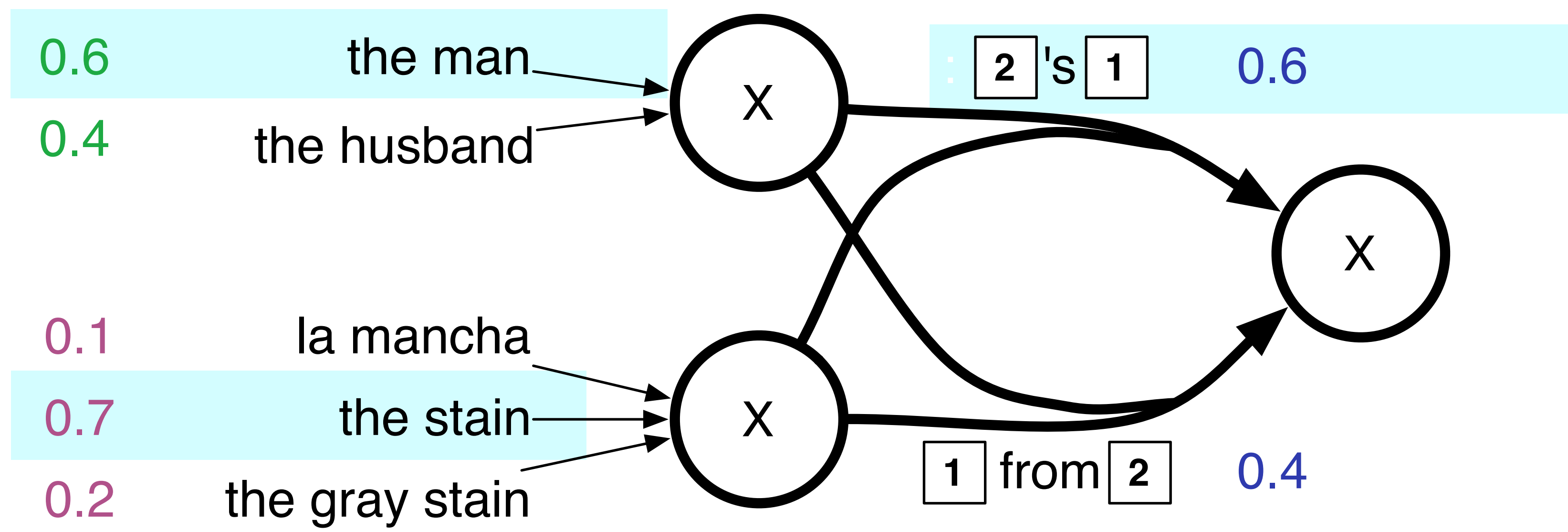
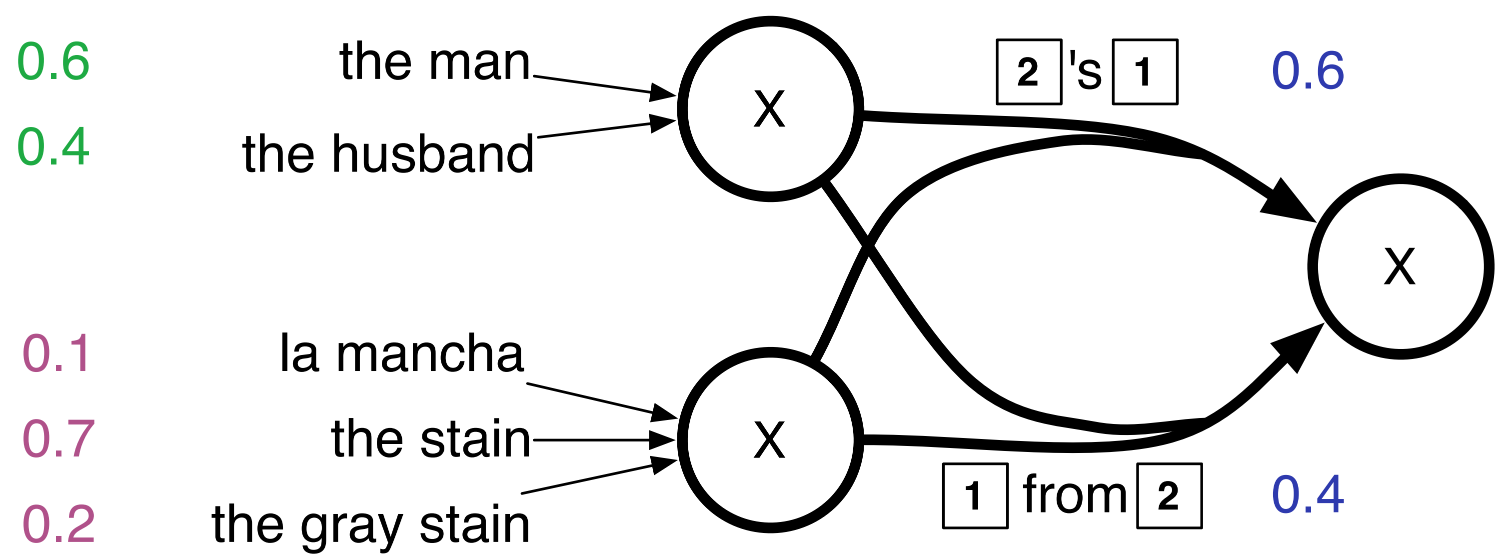


-LM Viterbi:

the stain's the man

Hypergraph restructuring

Let's add a bi-gram language model!



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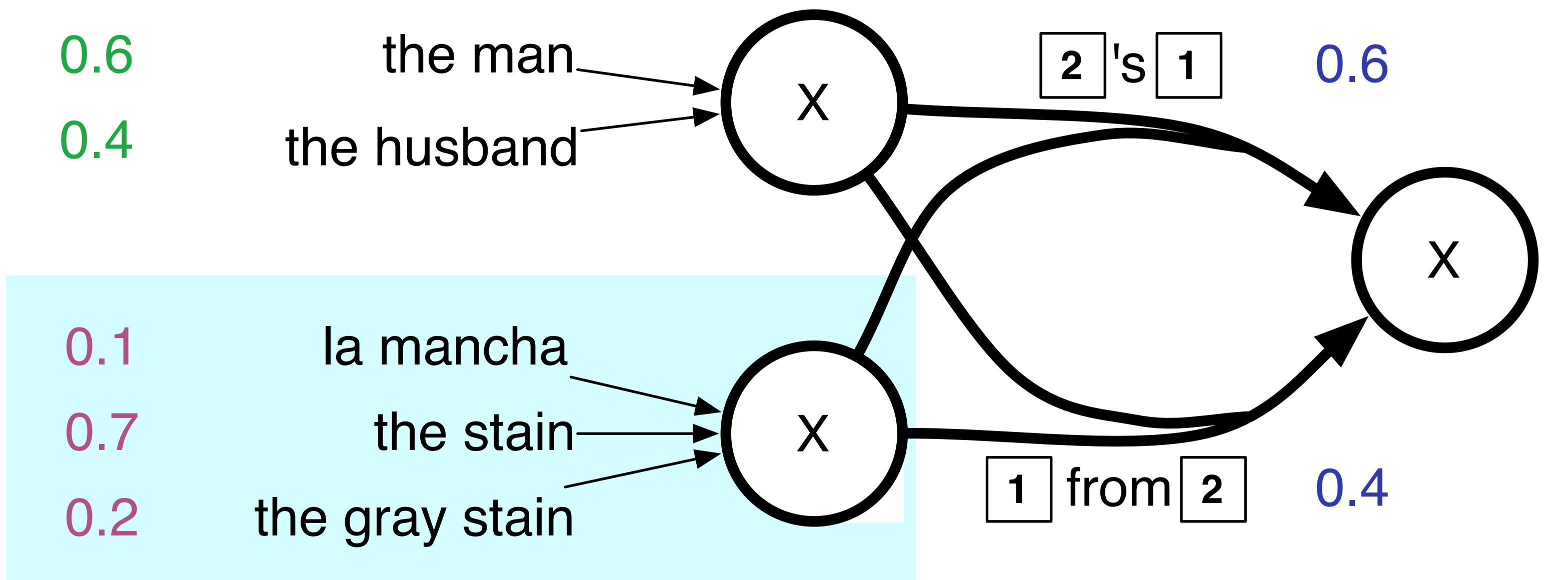

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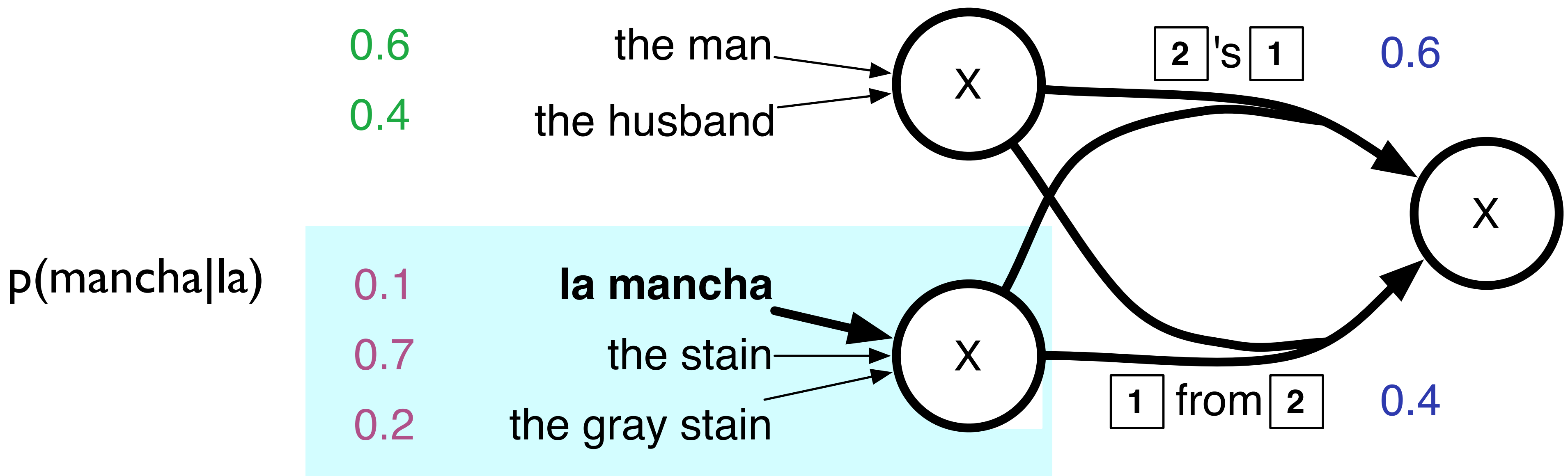

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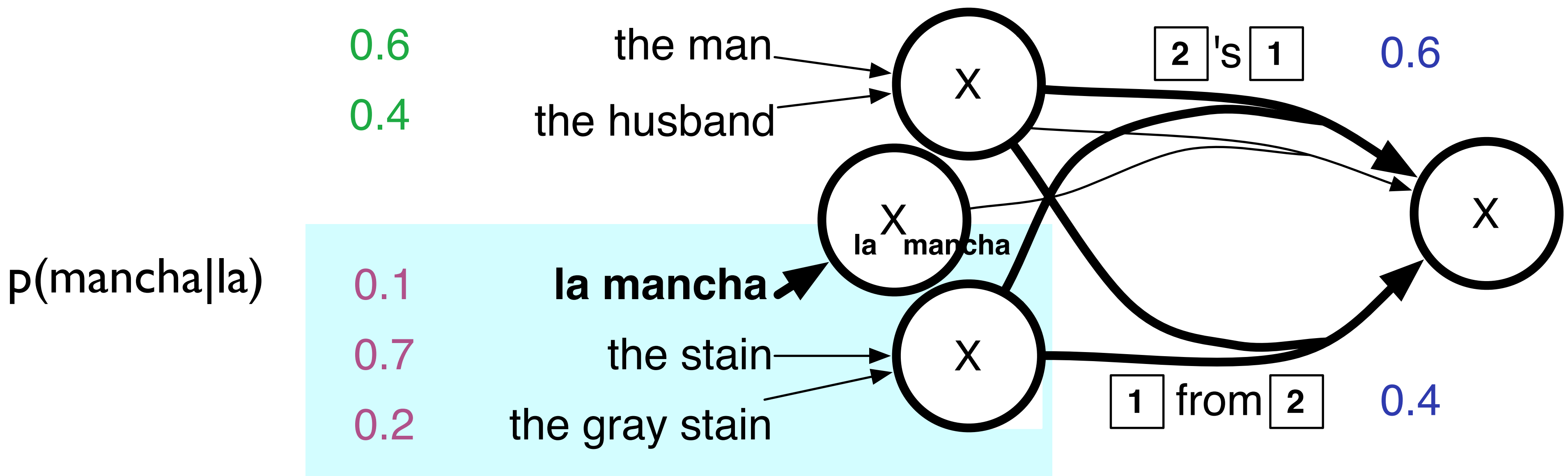

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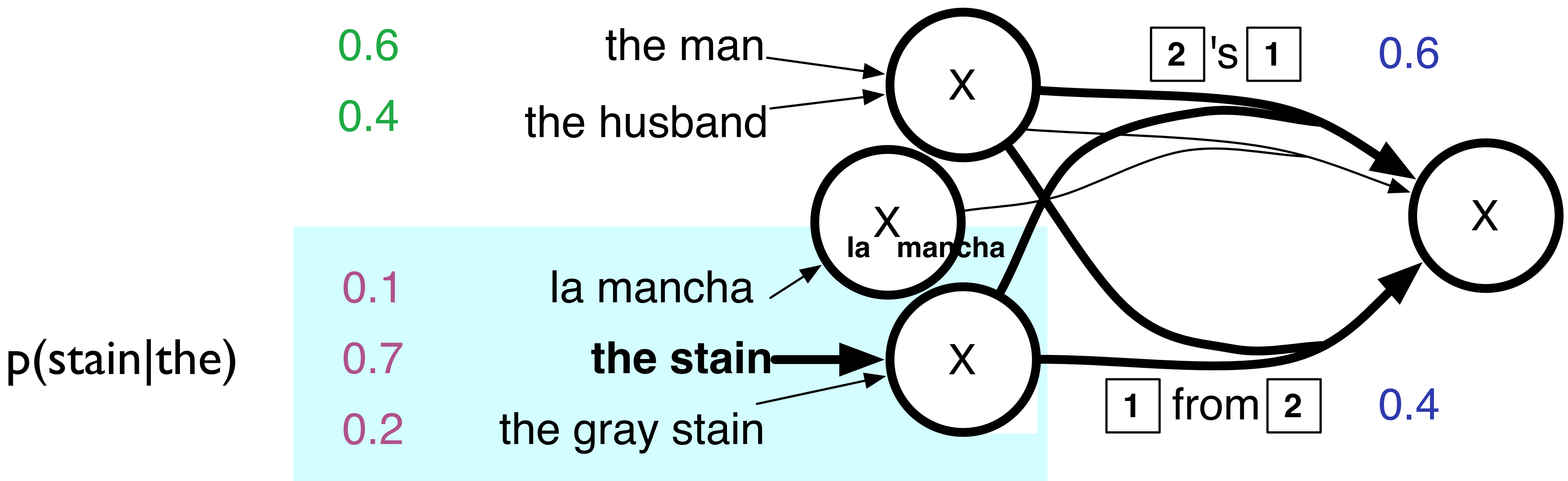

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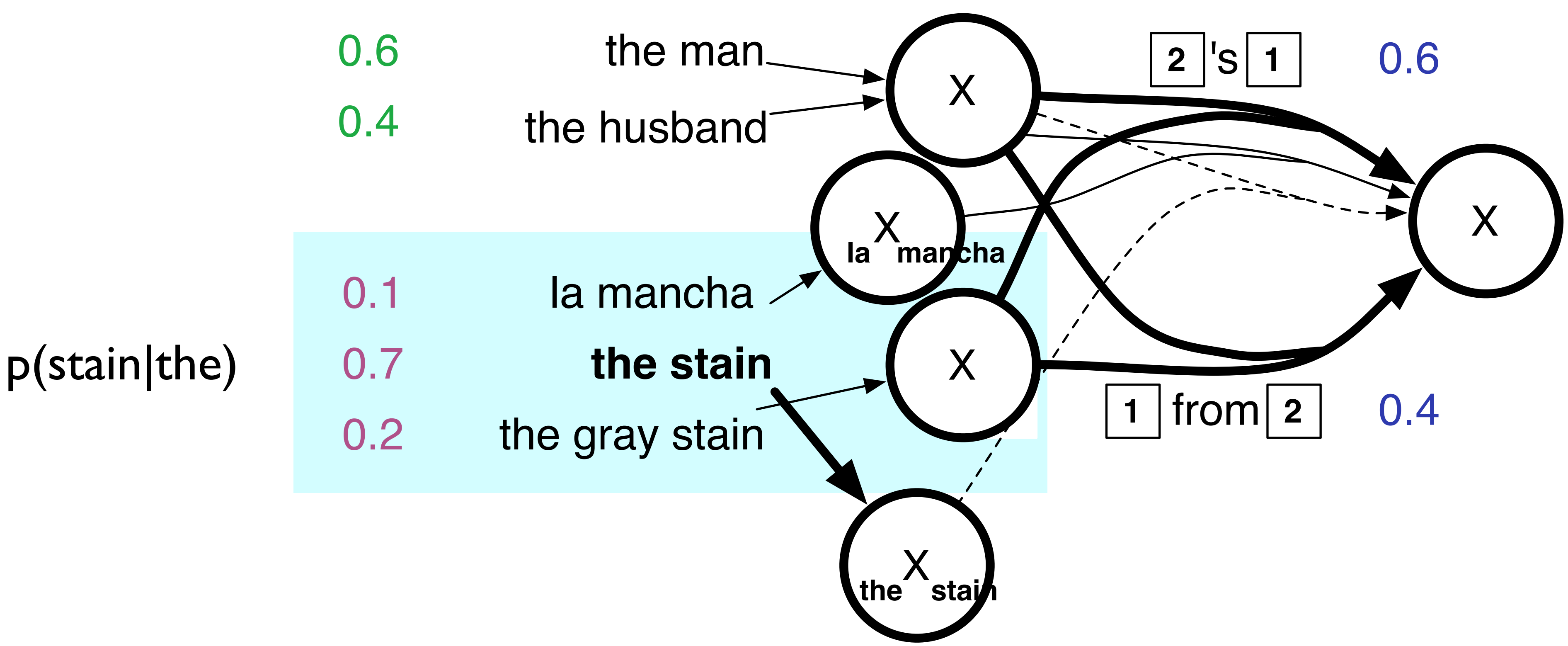

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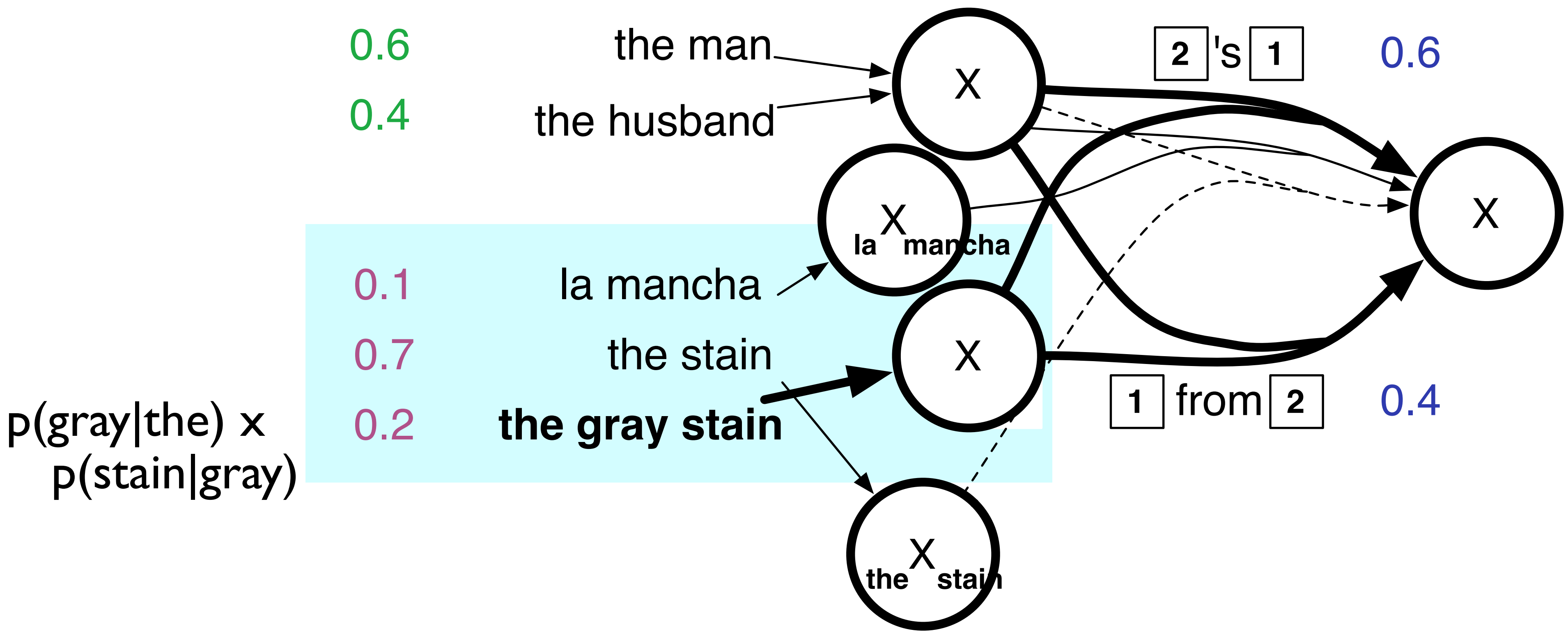

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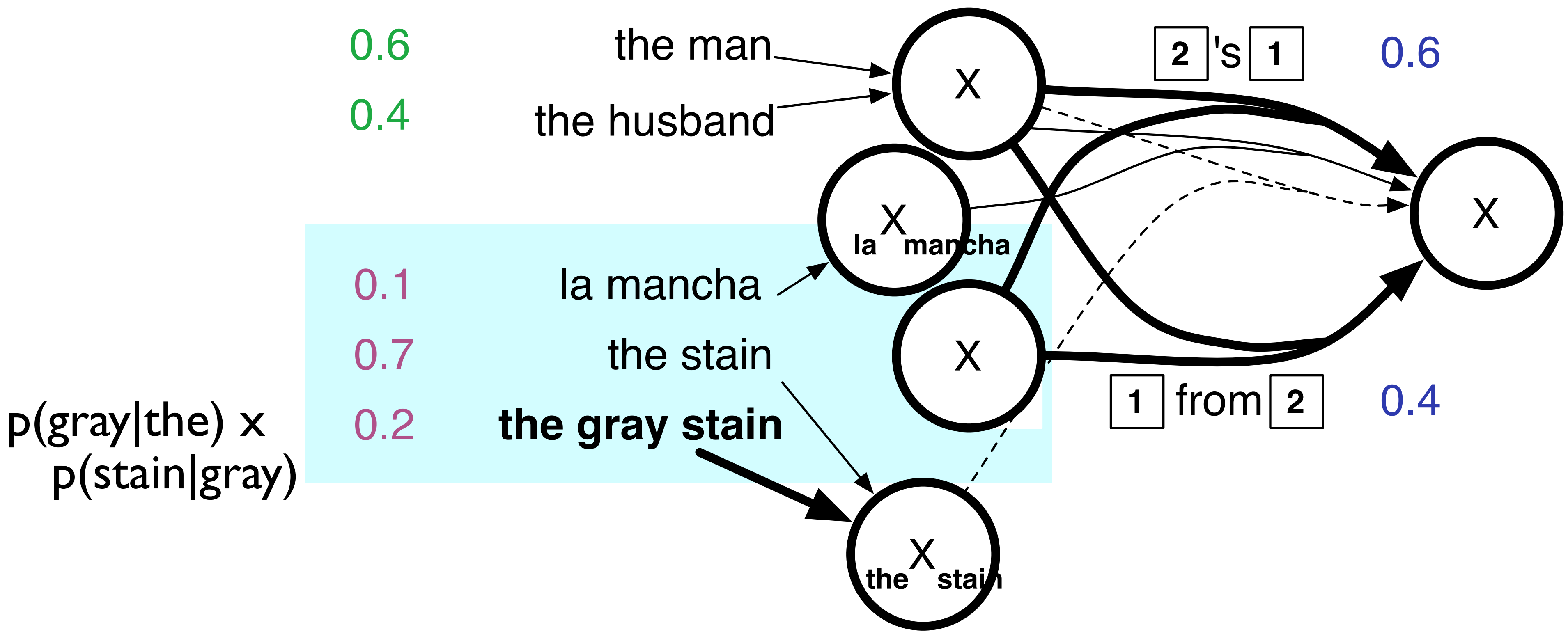

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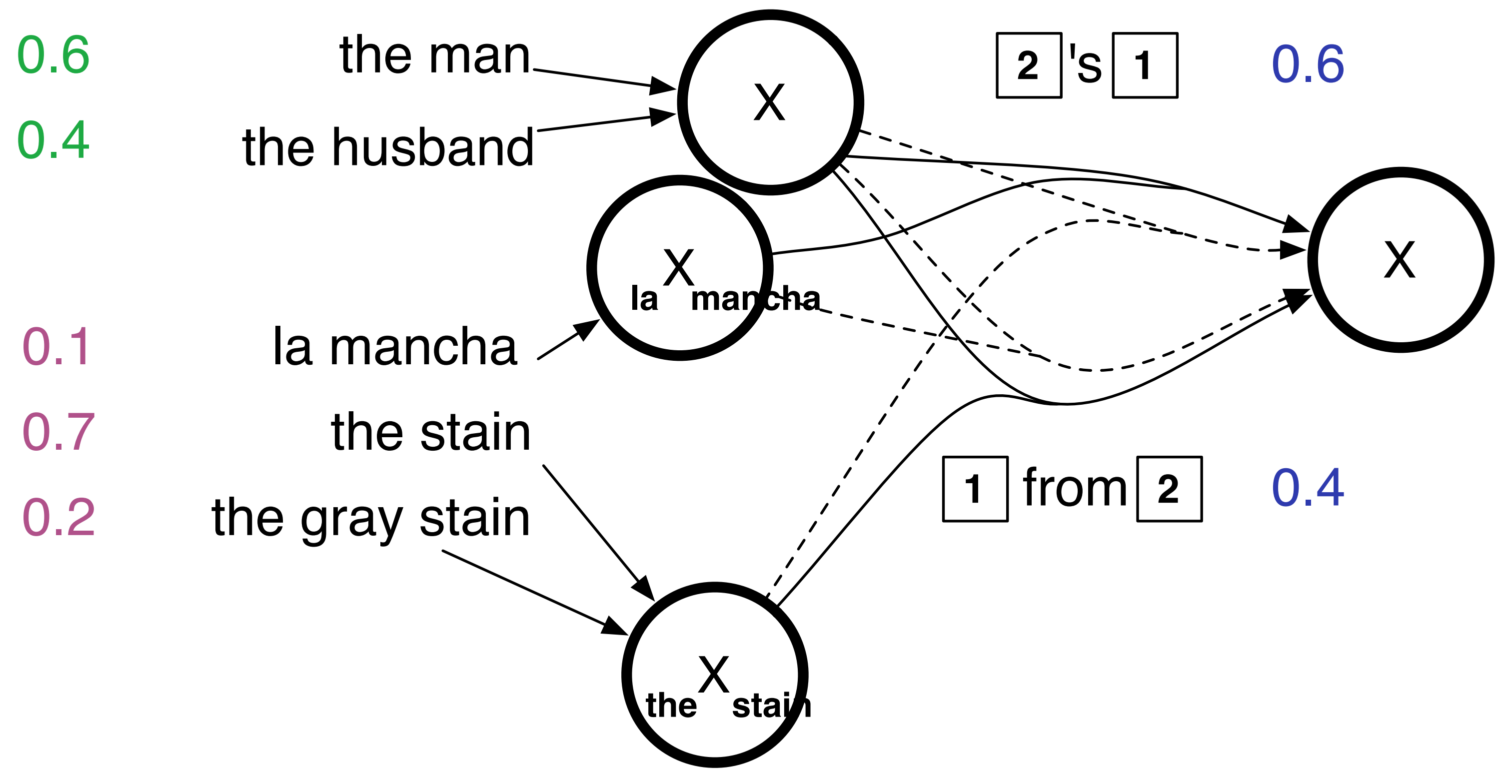

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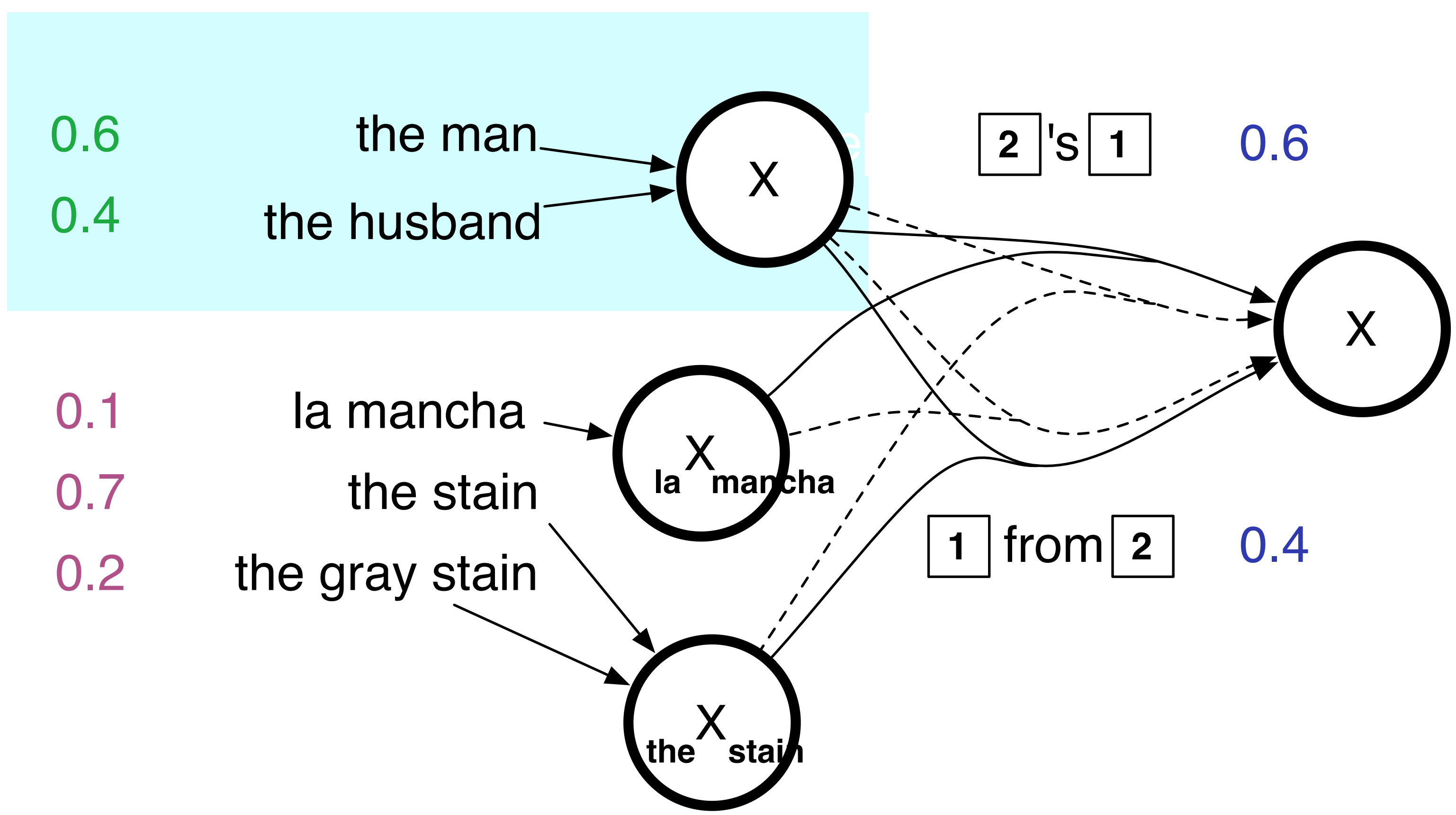

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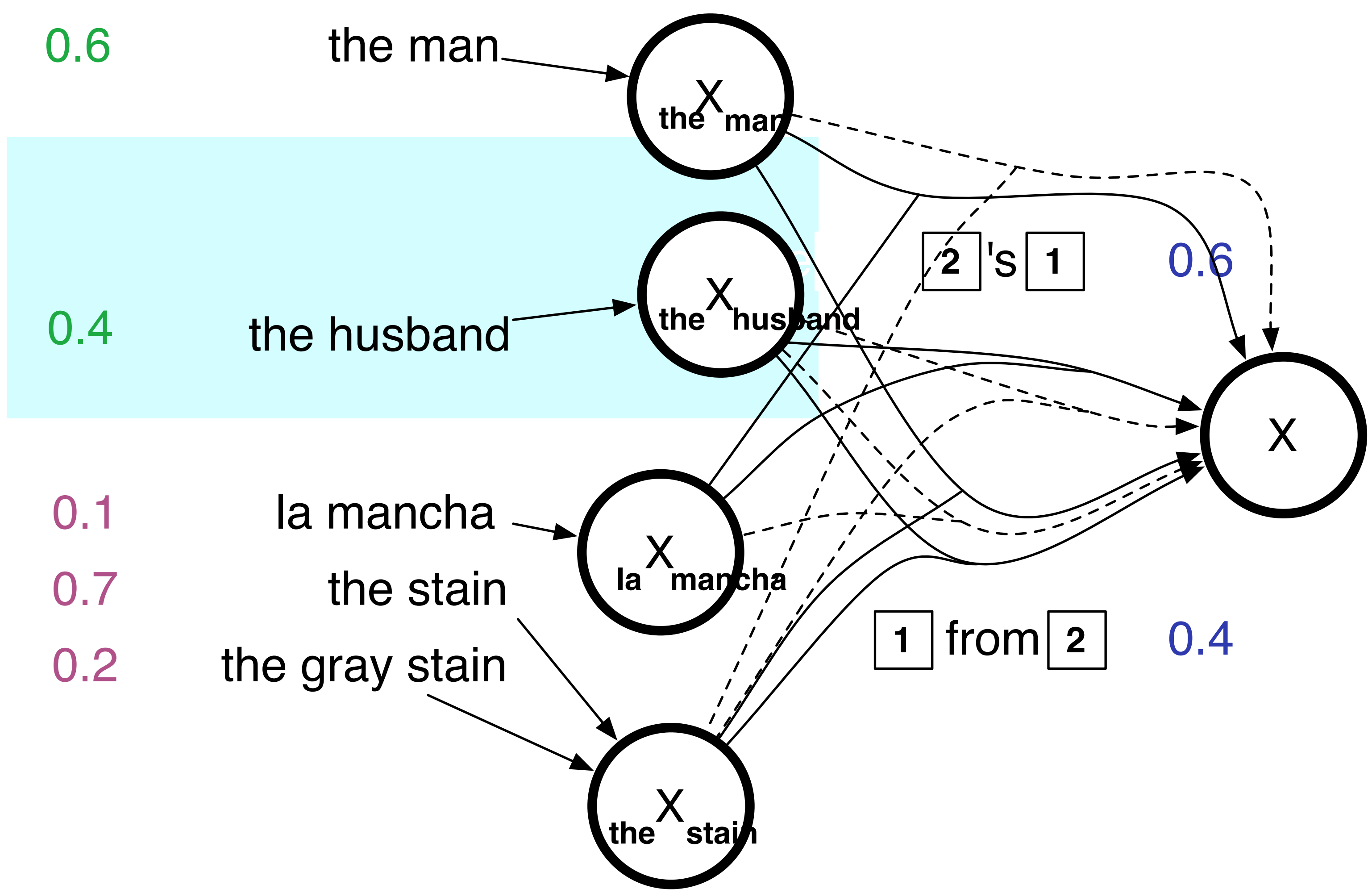

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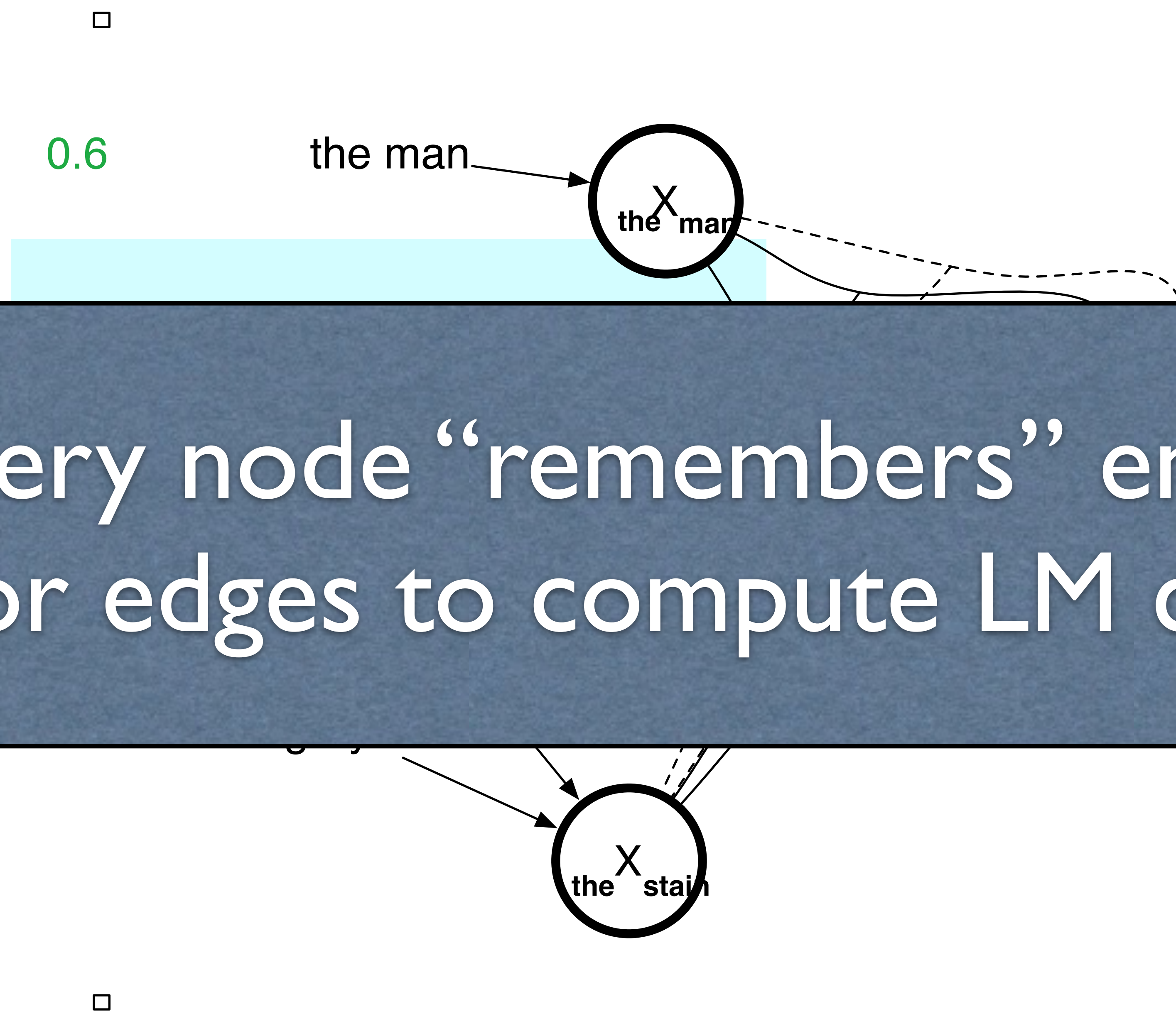

Every node "remembers" enough for edges to compute LM costs

Complexity

- What is the run-time of this algorithm?

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

Going to longer n-grams is exponentially expensive!

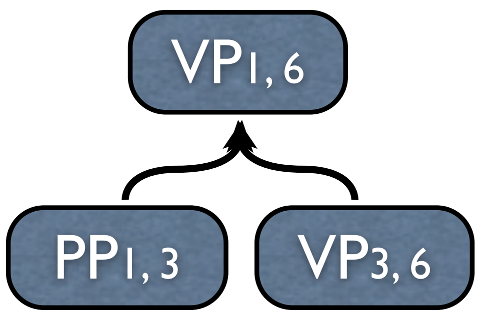
Cube pruning

- 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

- Why "cube" pruning?
  - Cube-pruning only involves a "cube" when arity-2 rules are used!
  - More appropriately called "square" pruning with arity-1
  - Or "hypercube" pruning with arity > 2!

Cube Pruning



monotonic grid?

		$(\mathrm{PP}^{\,\text{with} \,\star\, \text{Sharon}}_{1,3})$	$(\mathrm{PP}^{\,\text{along} \,\star\, \text{Sharon}}_{1,3})$	$(\mathrm{PP}^{\,\text{with} \,\star\, \text{Shalong}}_{1,3})$
		1.0	3.0	8.0
$(\mathrm{VP}^{\,\text{held} \,\star\, \text{meeting}}_{3,6})$	1.0	2.0	4.0	9.0
$(\mathrm{VP}^{\,\text{held} \,\star\, \text{talk}}_{3,6})$	1.1	2.1	4.1	9.1
$(\mathrm{VP}^{\,\text{hold} \,\star\, \text{conference}}_{3,6})$	3.5	4.5	6.5	11.5

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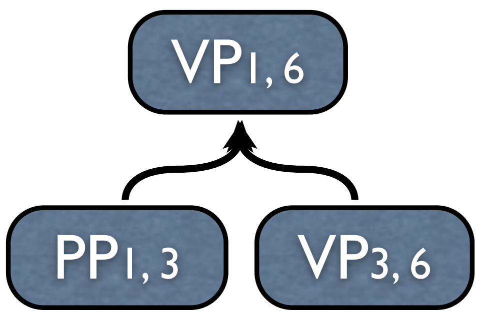

non-monotonic grid
due to LM combo costs

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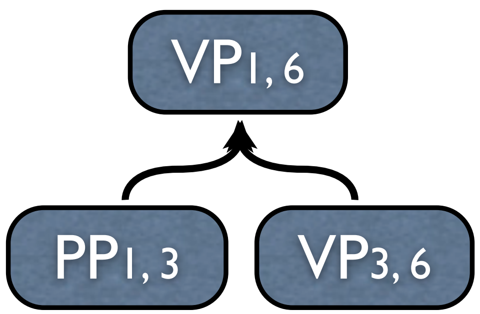

bigram (meeting, with)

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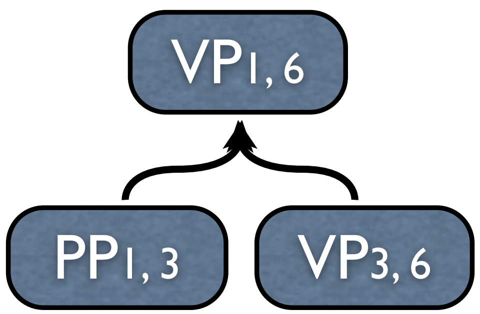

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Cube Pruning

k-best parsing
(Huang and Chiang, 2005)

- a priority queue of candidates
- extract the best candidate

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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

LM Integration

Method	Settings	Time	BLEU
rescore	$k = 10^4$	16	33.31
rescore	$k = 10^5$	139	33.33
intersect*		1455	37.09
cube prune	$\varepsilon = 0$	23	36.14
cube prune	$\varepsilon = 0.1$	35	36.77
cube prune	$\varepsilon = 0.2$	111	36.91