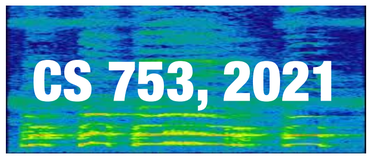
Search and Decoding

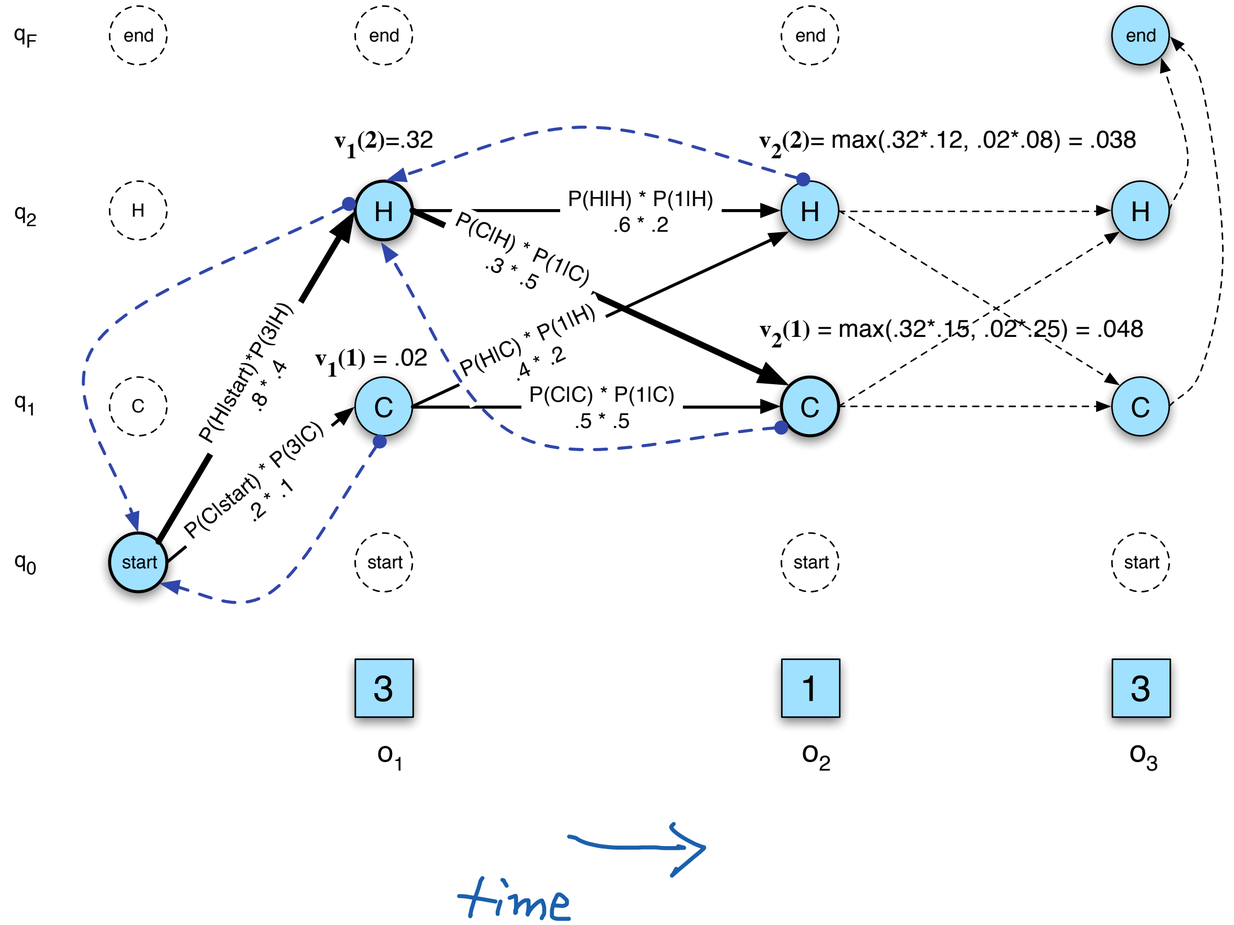
Lecture 11a



Instructor: Preethi Jyothi, IITB

Recall Viterbi search

- Viterbi search finds the most probable path through a trellis of time on the X-axis and states on the Y-axis



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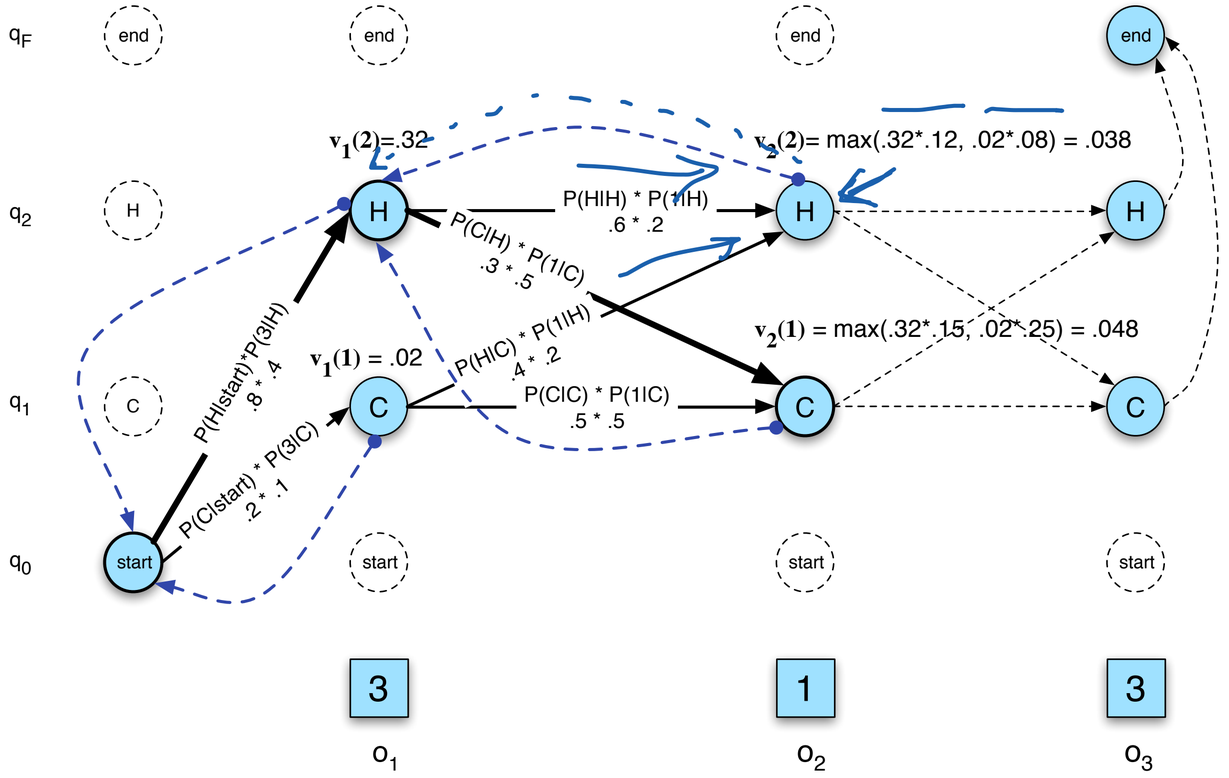
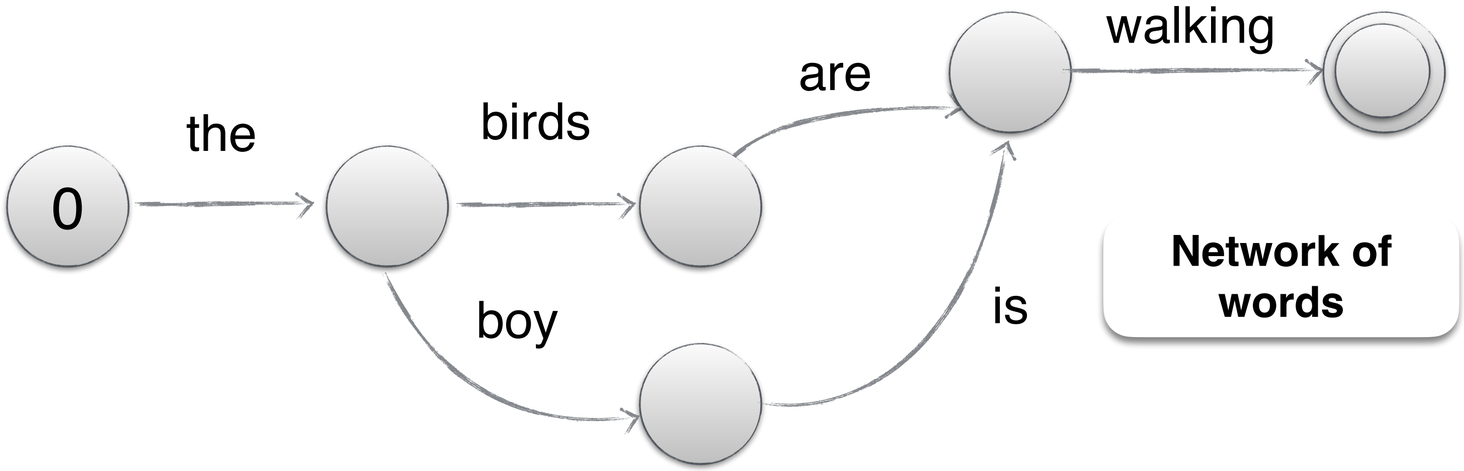


- Viterbi algorithm: Only needs to maintain information about the most probable path at each state

Image from [JM]: Jurafsky & Martin, 3rd edition, Chapter 9

ASR Search Network



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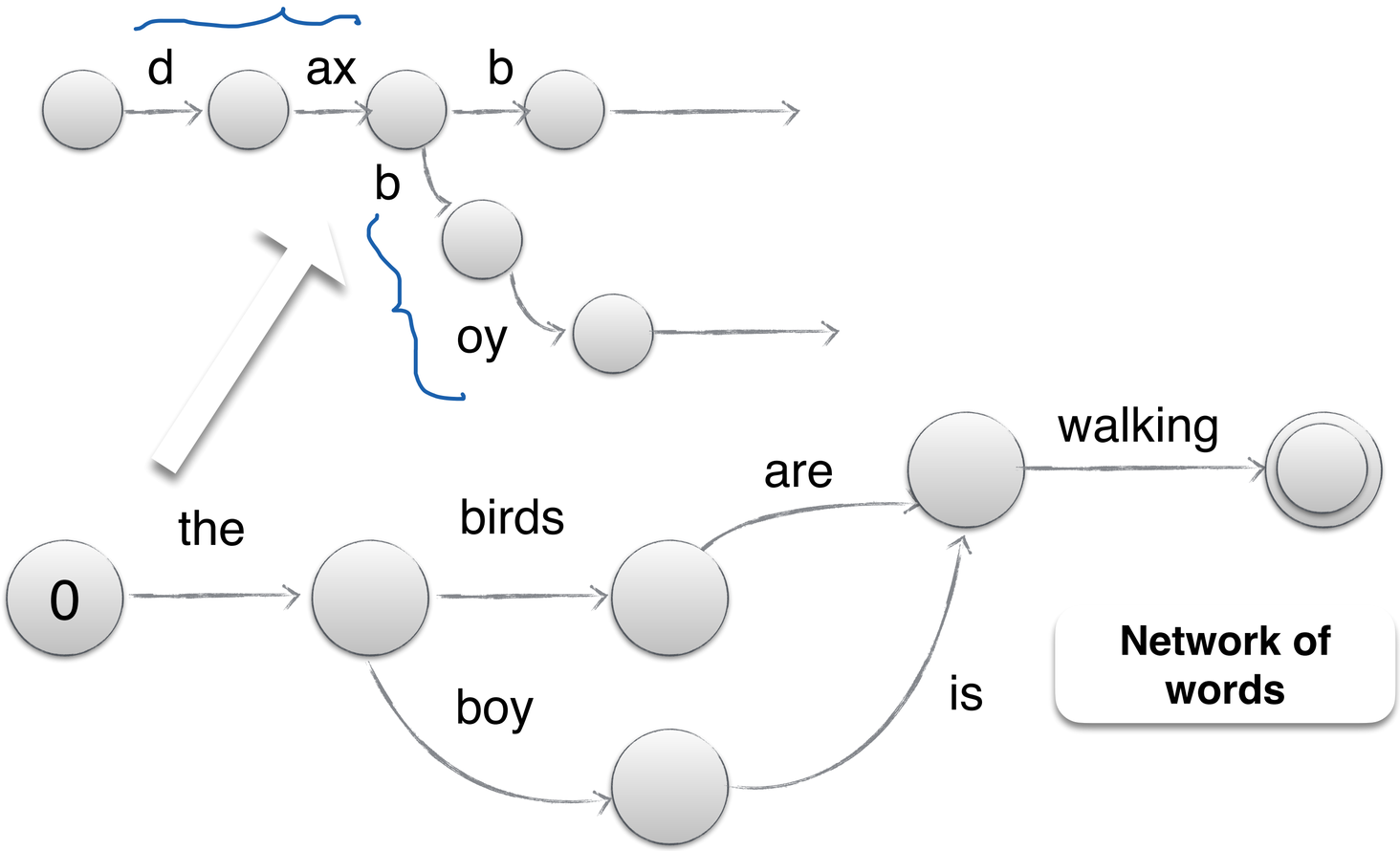

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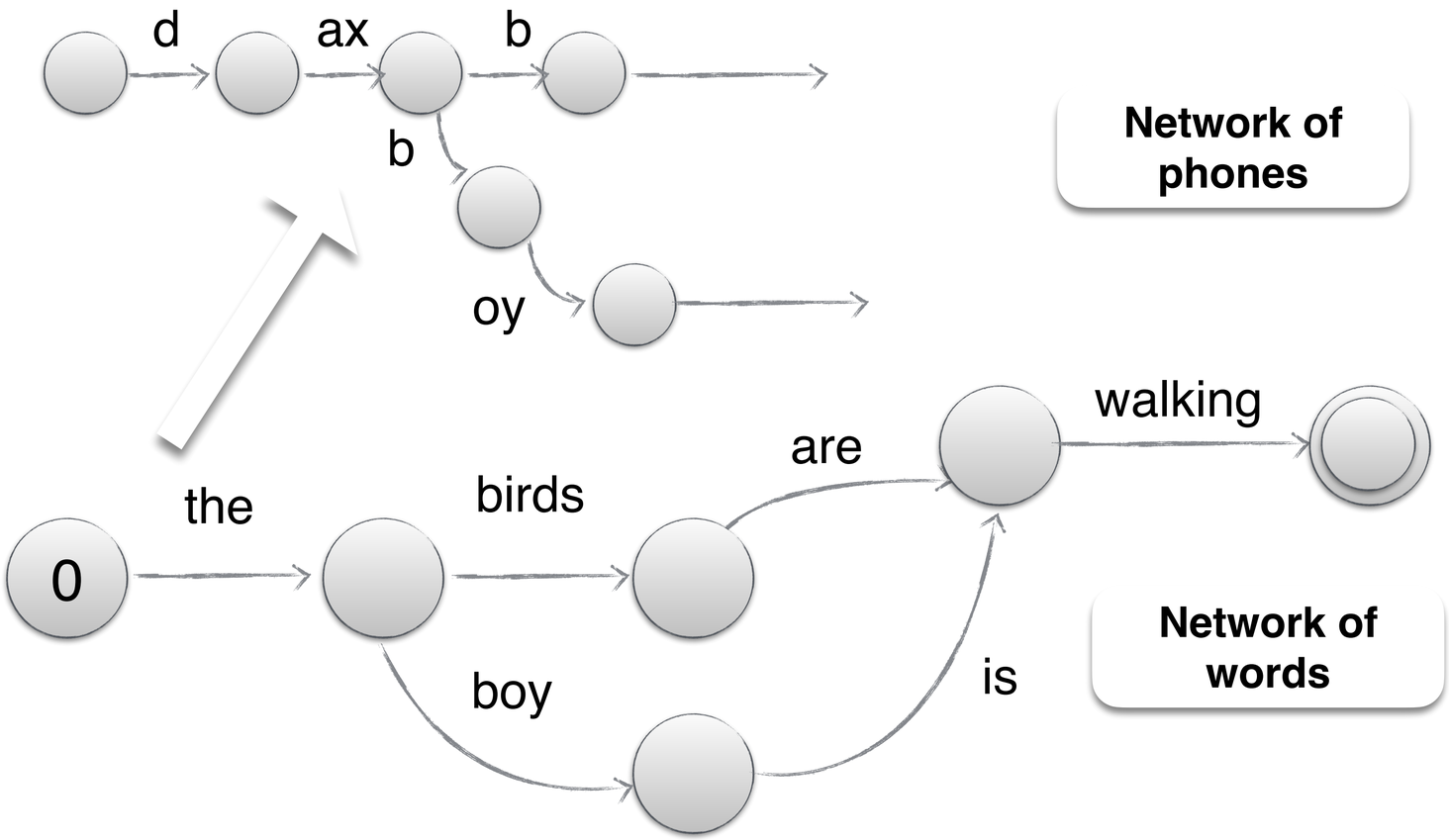

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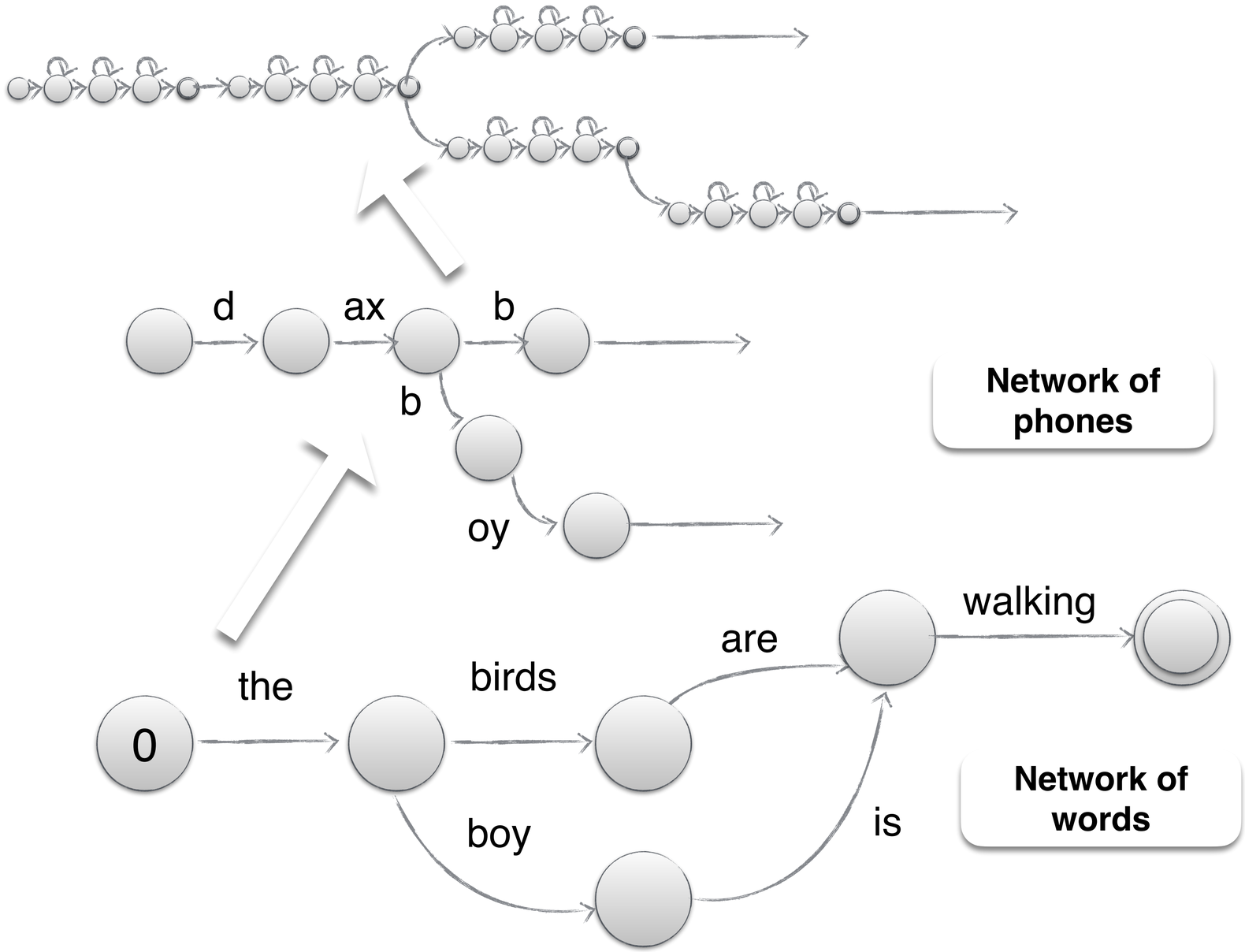

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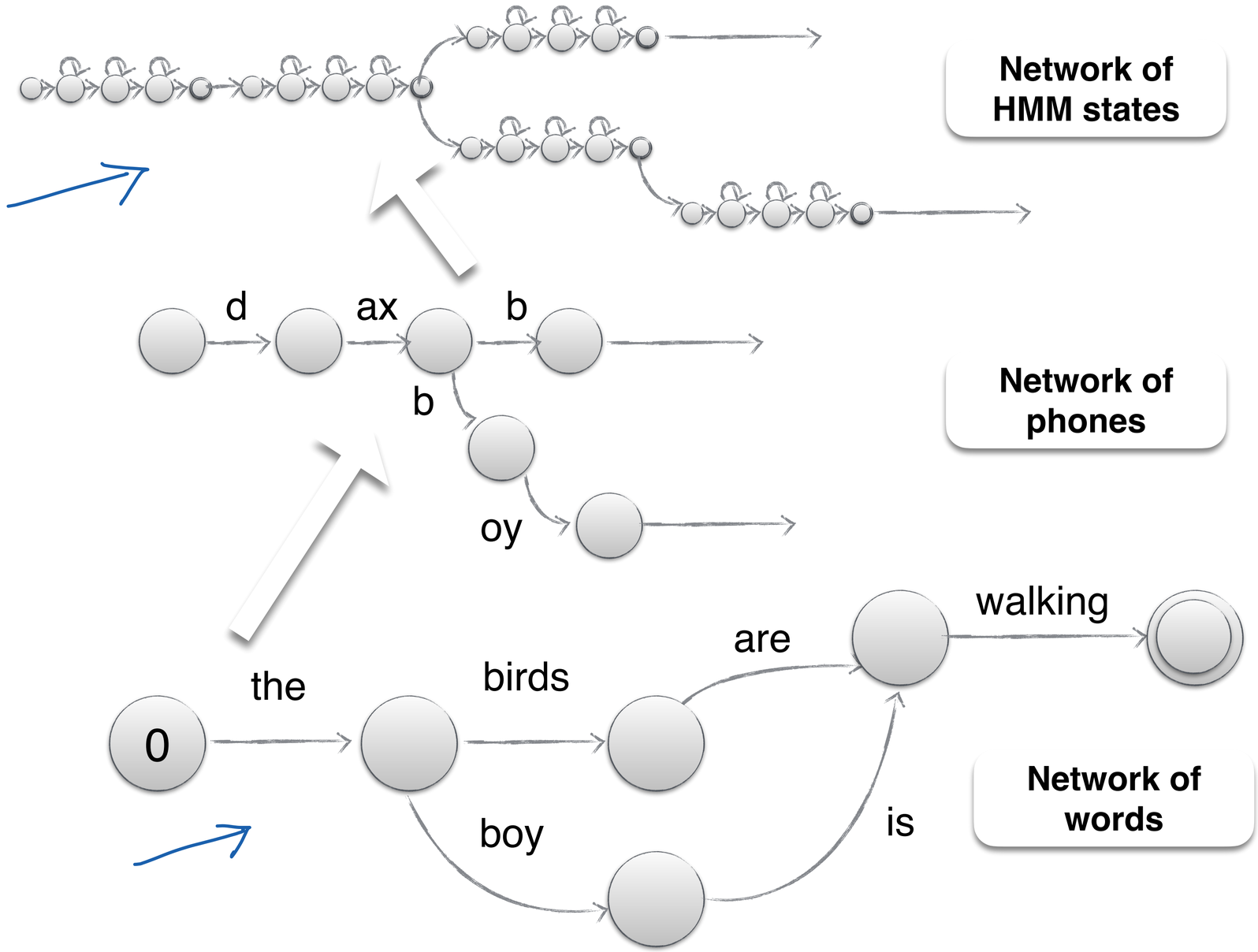
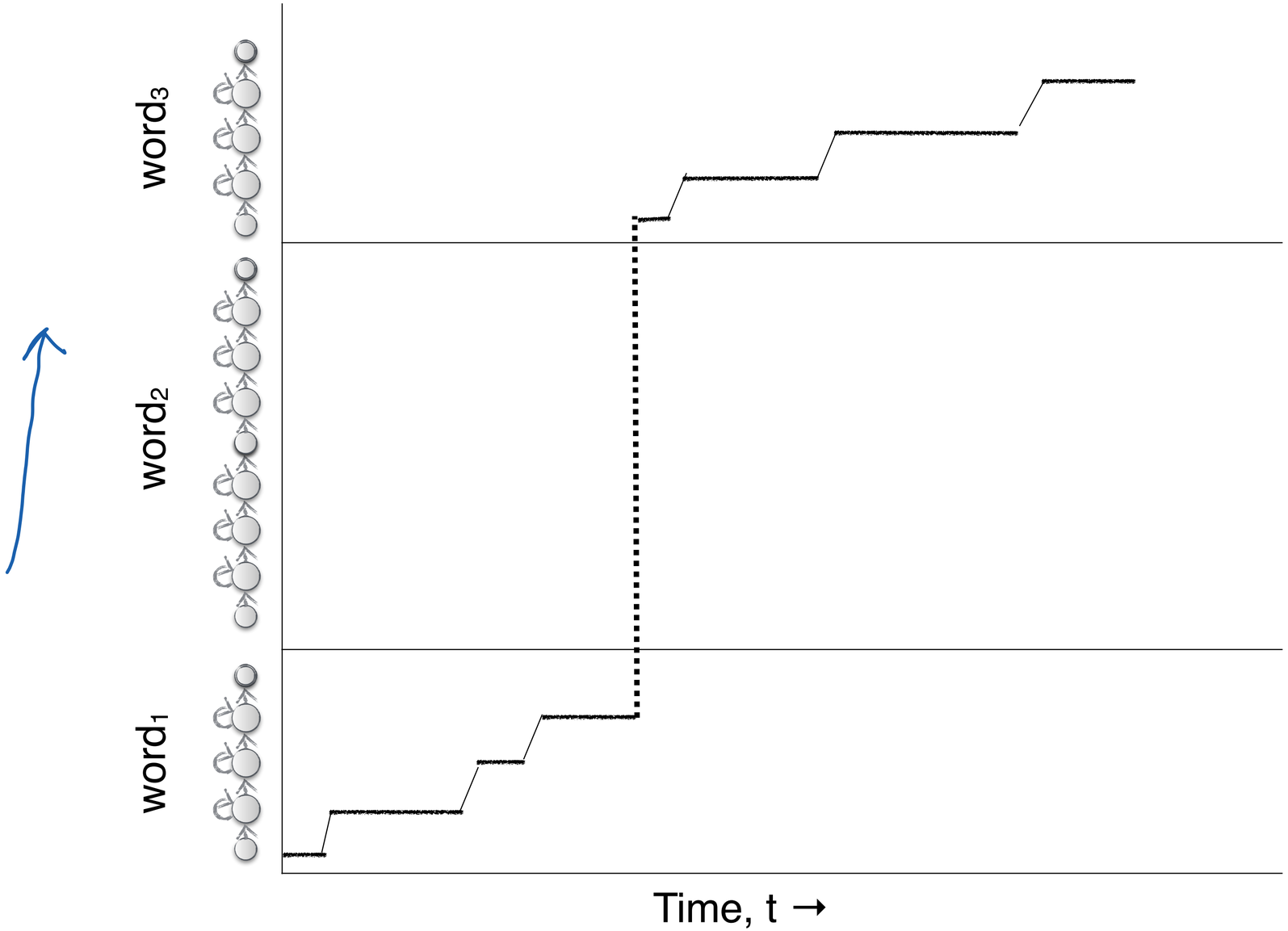


Time-state trellis



Viterbi search over the large trellis

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  - Unknown word boundaries
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Recall not all weighted transducers are determinizable

To ensure determinizability of L ○ G, introduce disambiguation symbols in L to deal with homophones in the lexicon

read : r eh d #1
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$H \circ C \circ L \circ G$

Propagate the disambiguation symbols as self-loops back to C and H. Resulting machines are $\tilde{H}$, $\tilde{C}$, $\tilde{L}$

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Replaces disambiguation symbols in input alphabet of $\tilde{H}$ with ε

1st pass recognition networks (40K vocab)

transducer	x real-time
$C \circ L \circ G$	12.5
$C \circ det(L \circ G)$	1.2
$det(H \circ C \circ L \circ G)$	1.0

Recognition speeds for systems with an accuracy of 83%

Static and dynamic networks

- What we've seen so far: *Static* decoding graph
  - H ○ C ○ L ○ G
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  - H ○ C ○ L ○ G
  - Determinize/minimize to make this graph more compact
- Another approach: *Dynamic* graph expansion
  - Dynamically build the graph with active states on the fly
  - Do on-the-fly composition with the language model G
    - (H ○ C ○ L) ○ G

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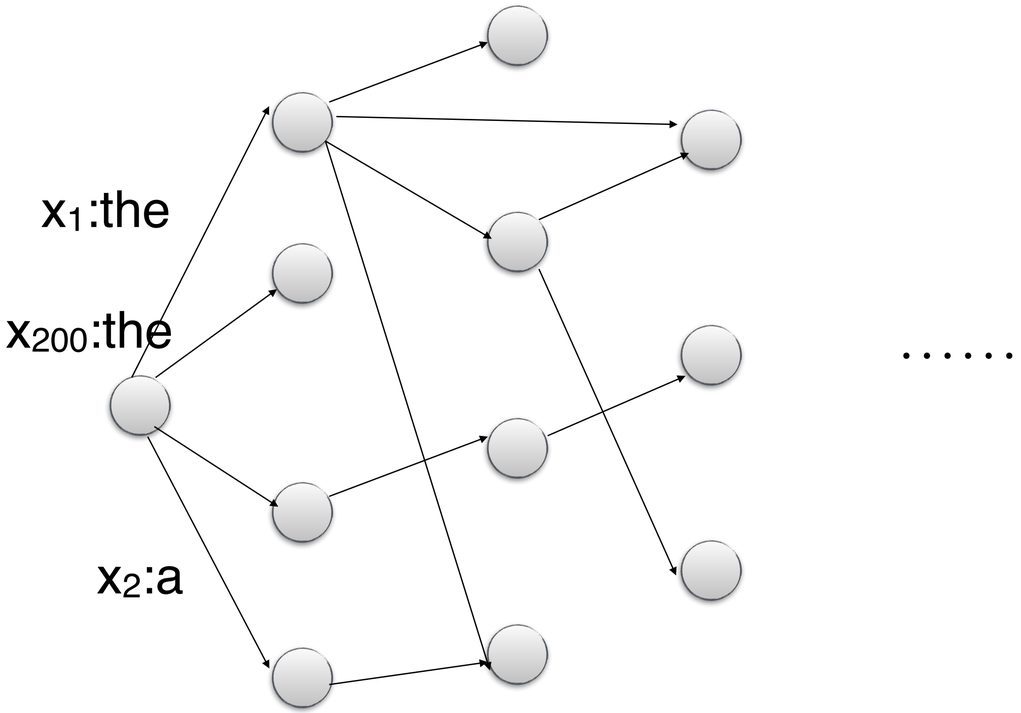
Beam search algorithm

Initialization: c*urrent states* := *initial state*

while (*current states* do not contain the *goal state*) do:

> *successor states* := NEXT(*current states*)
>
> where NEXT is next state function
>
> score the *successor states*
>
> set *current states* to a pruned set of *successor states* using beam width δ
>
> only retain those *successor states* that are within a fixed δ of the score of the best path

Beam search over the decoding graph



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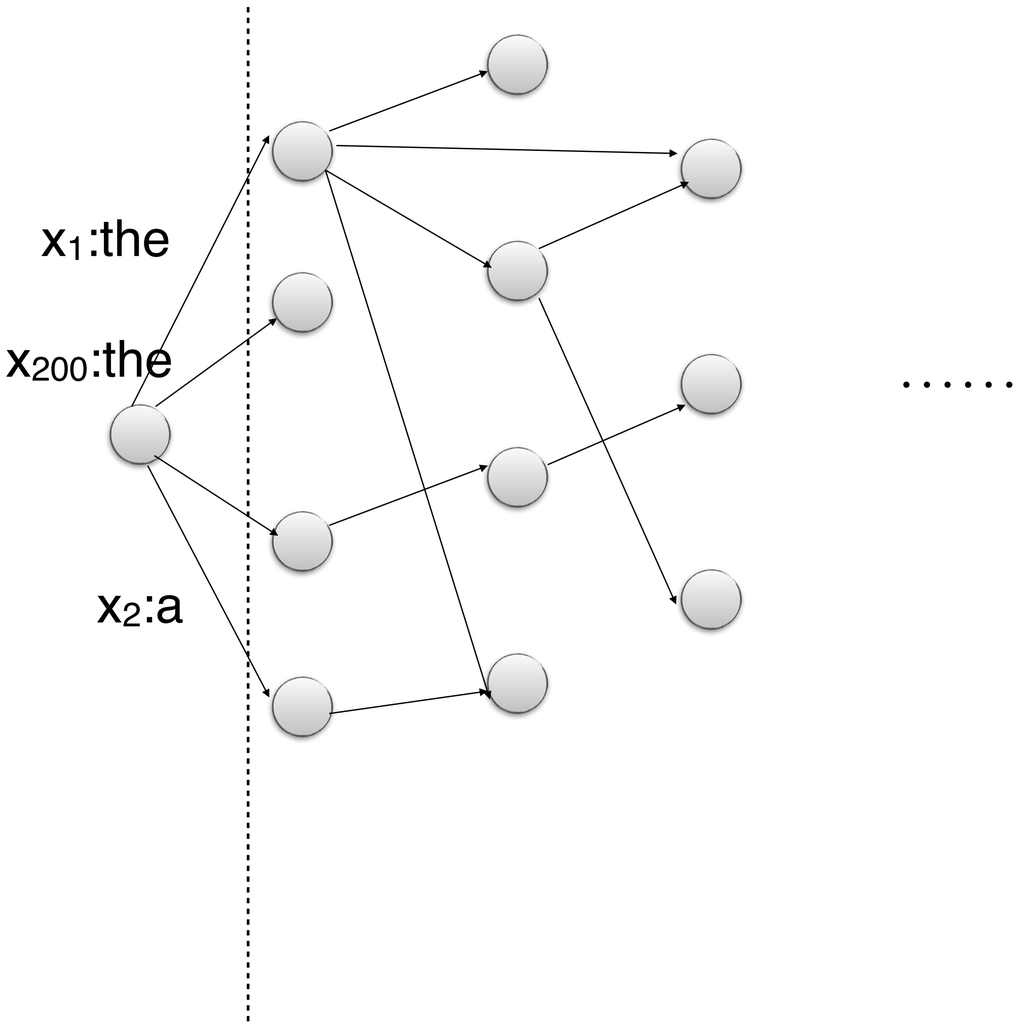

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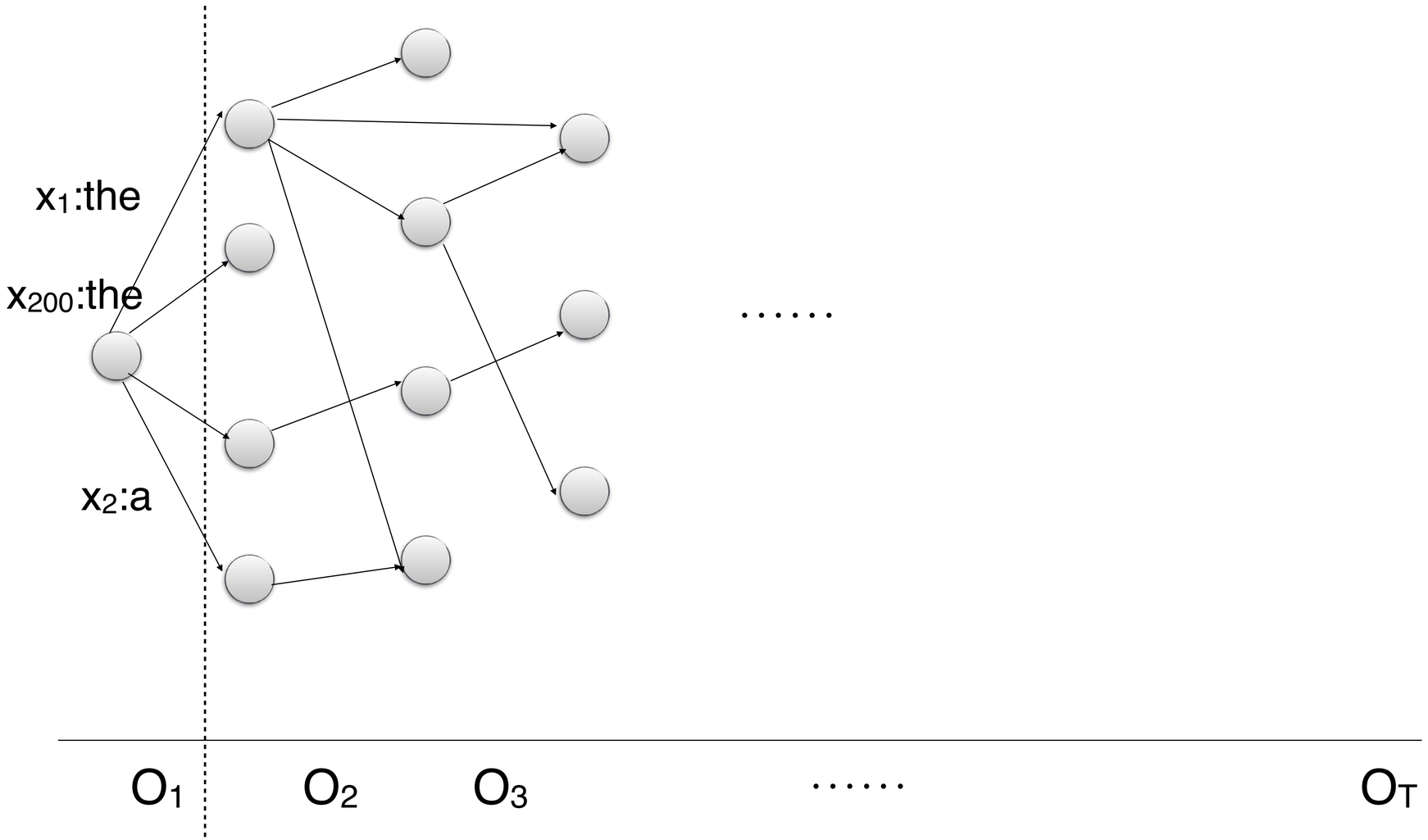

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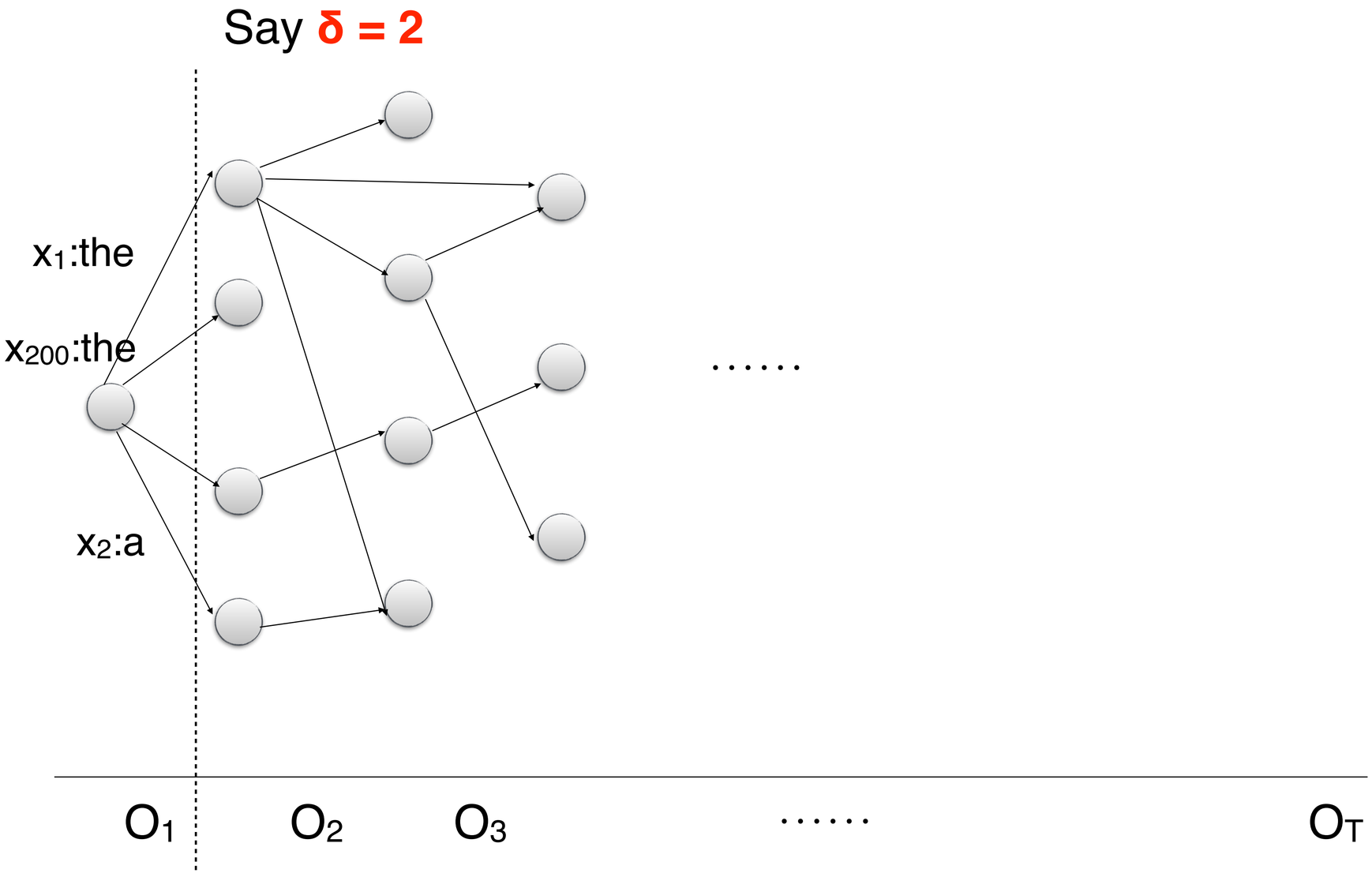

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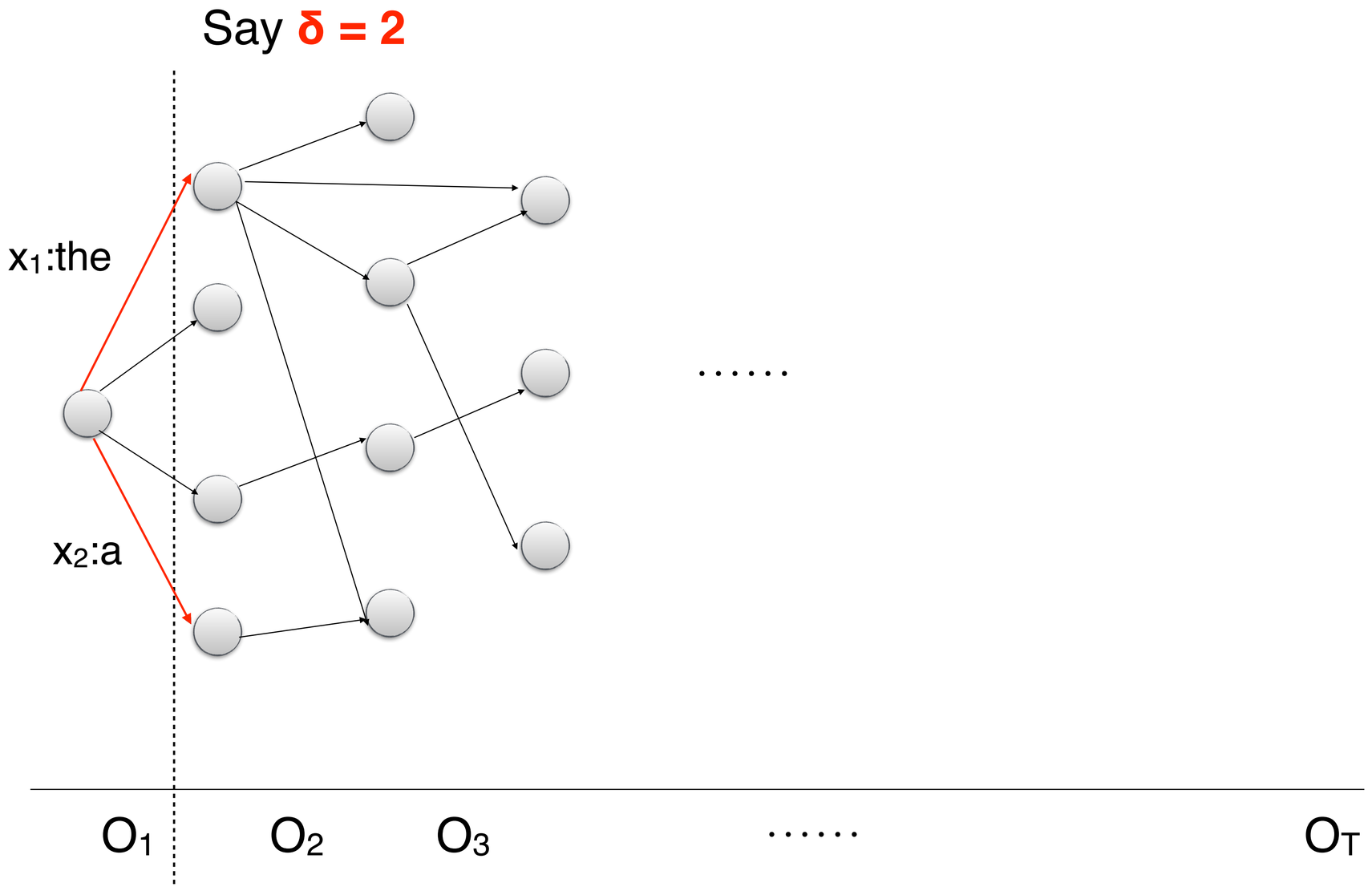
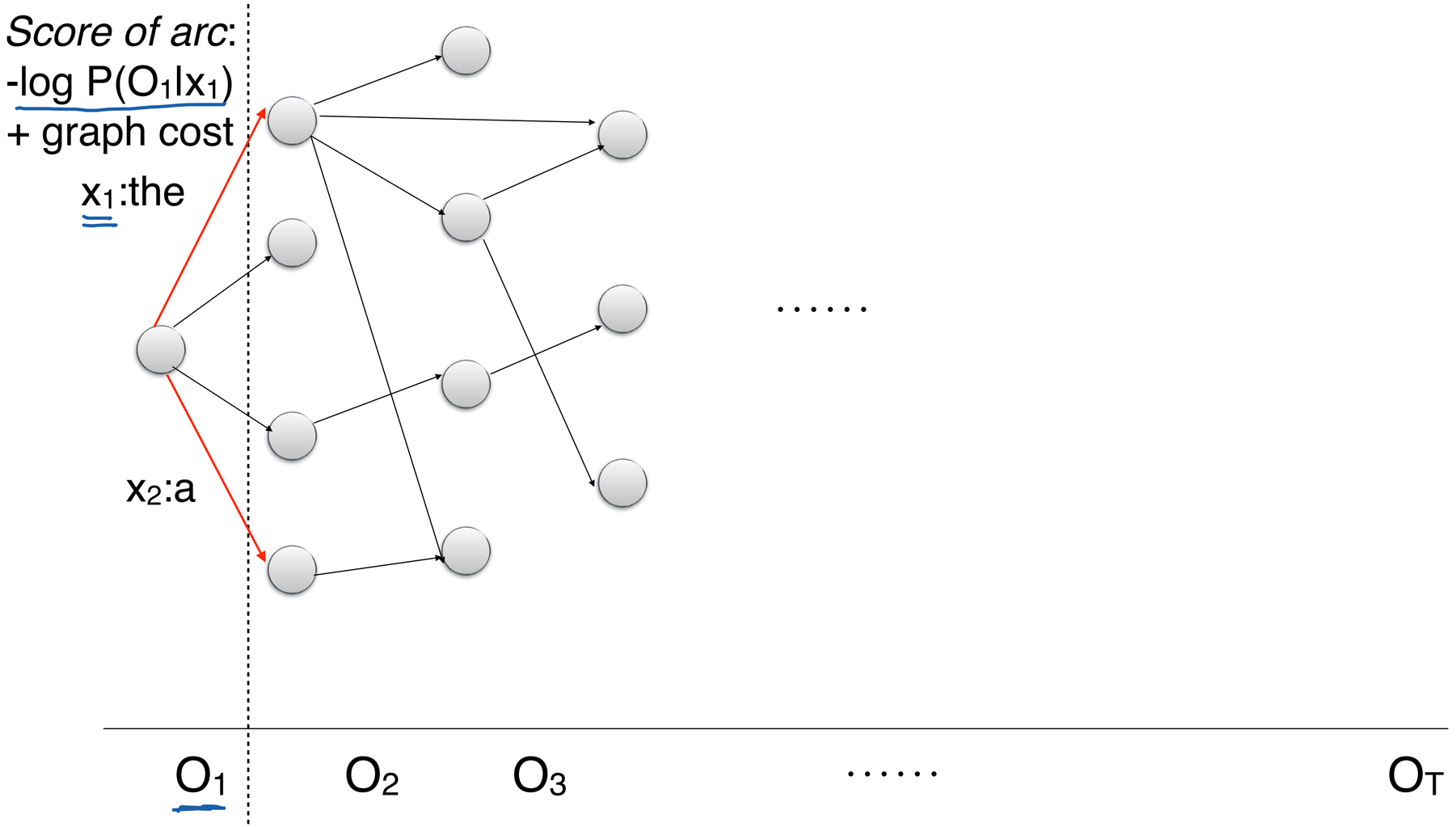


Beam search over the decoding graph

$H \circ C \circ L \circ G$

Say **δ = 2**



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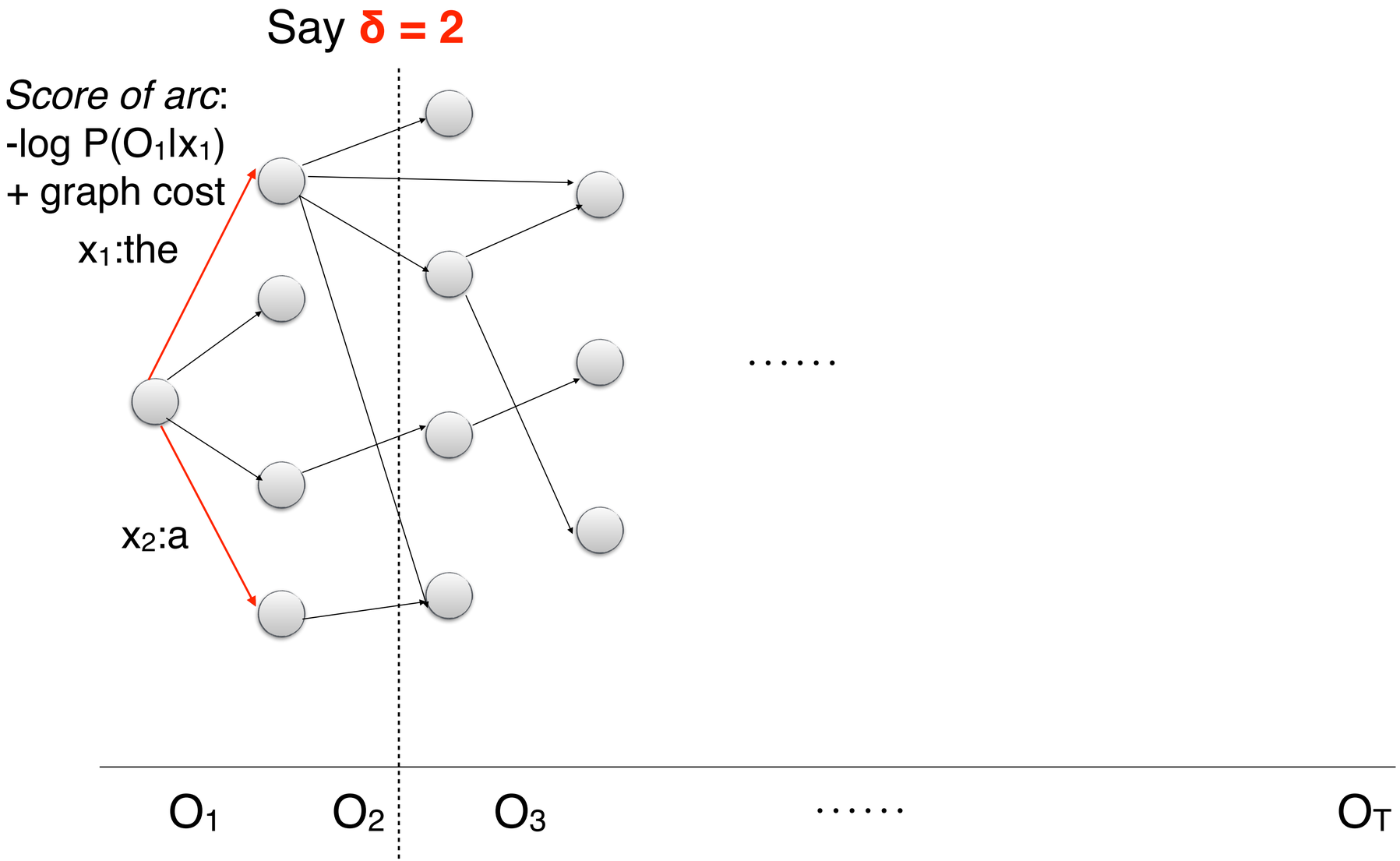

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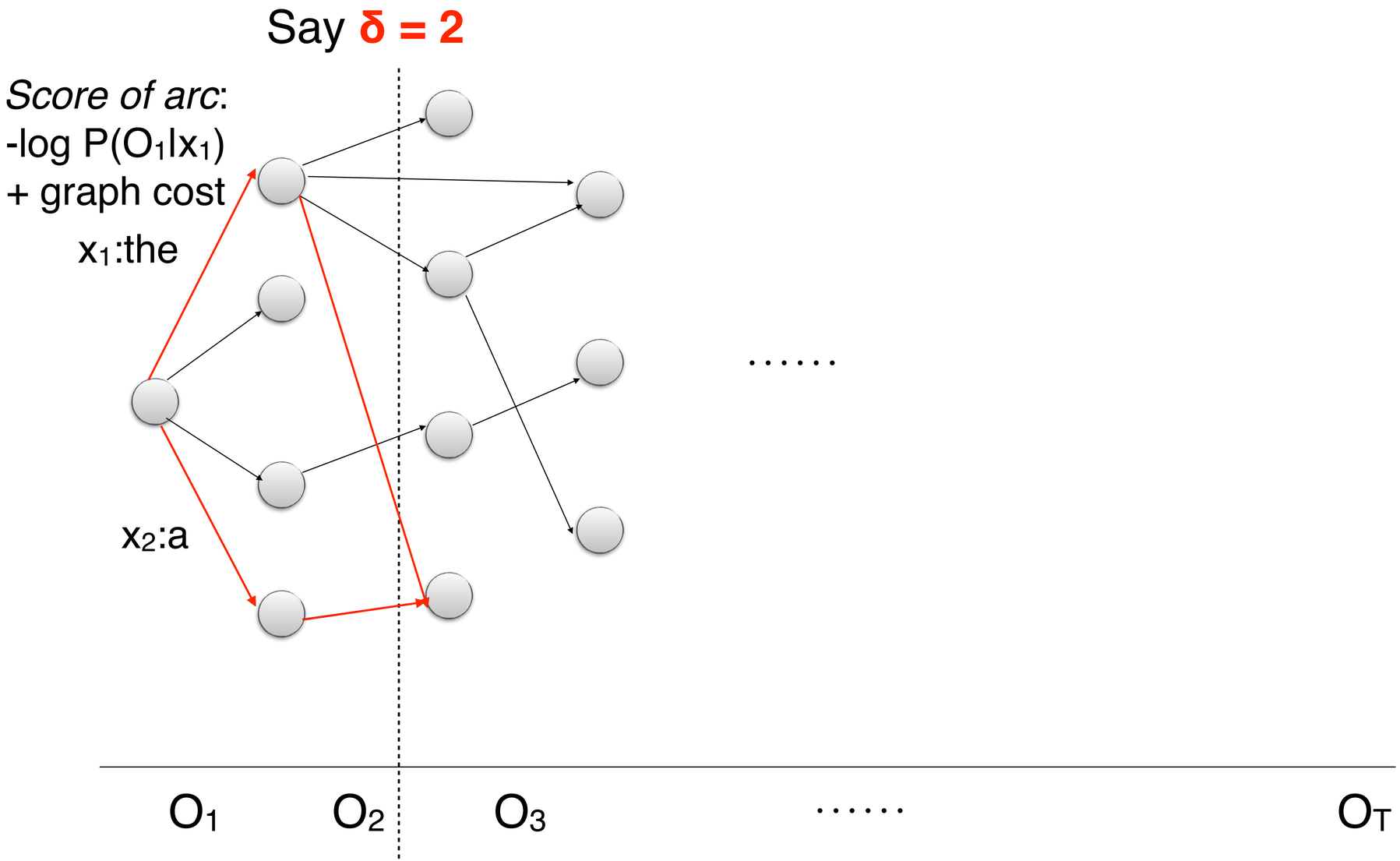

Beam pruning

- At each time-step t, only retain those nodes in the time-state trellis that are within a fixed threshold δ (beam width) of the best path

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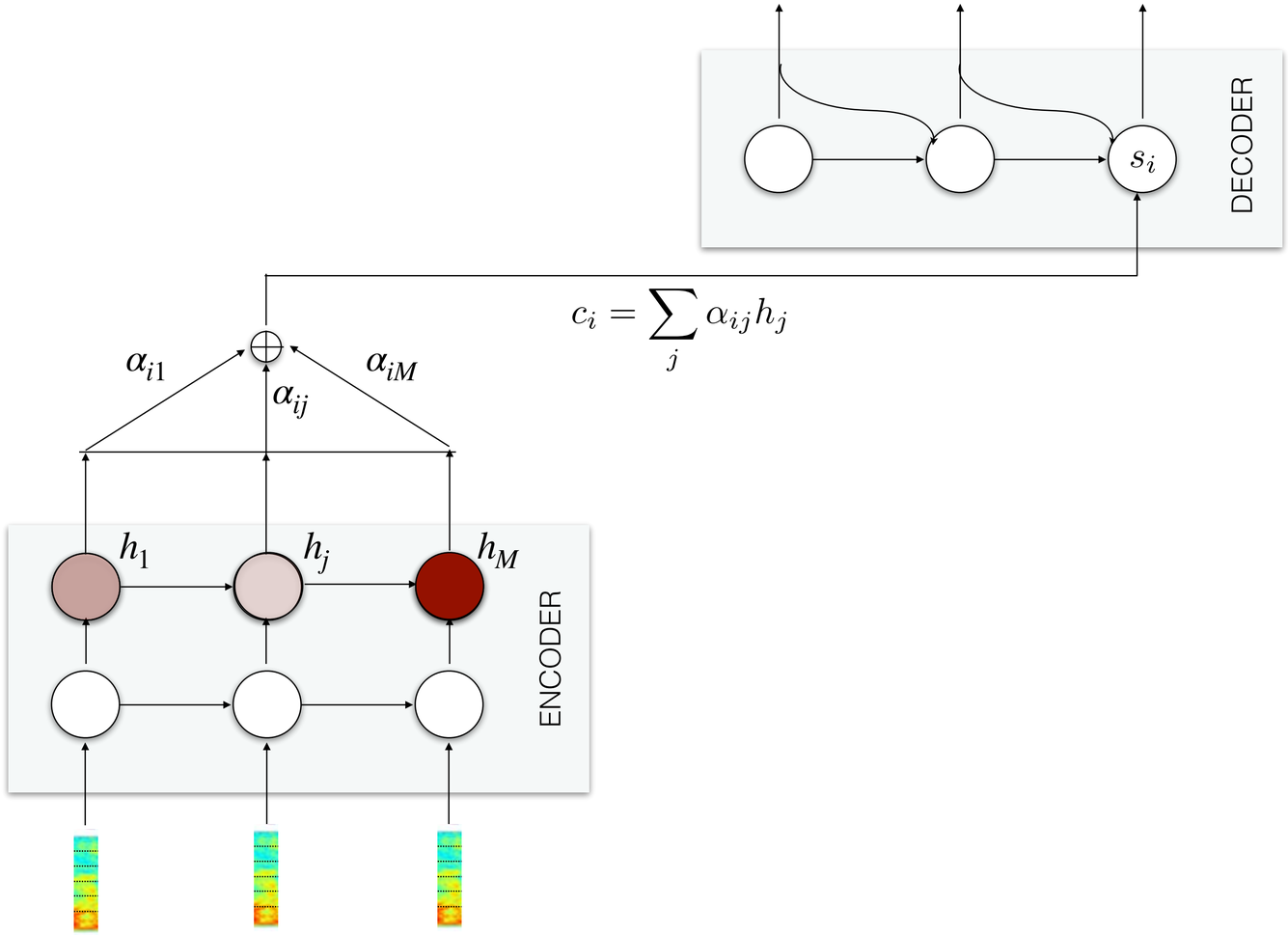
- At each time-step t, only retain those nodes in the time-state trellis that are within a fixed threshold δ (beam width) of the best path
- Given active nodes from the last time-step:
  - Examine nodes in the current time-step …
  - … that are reachable from active nodes in the previous time-step
  - Get active nodes for the current time-step by only retaining nodes with hypotheses that score close to the score of the best hypothesis

Beam search in a seq2seq model



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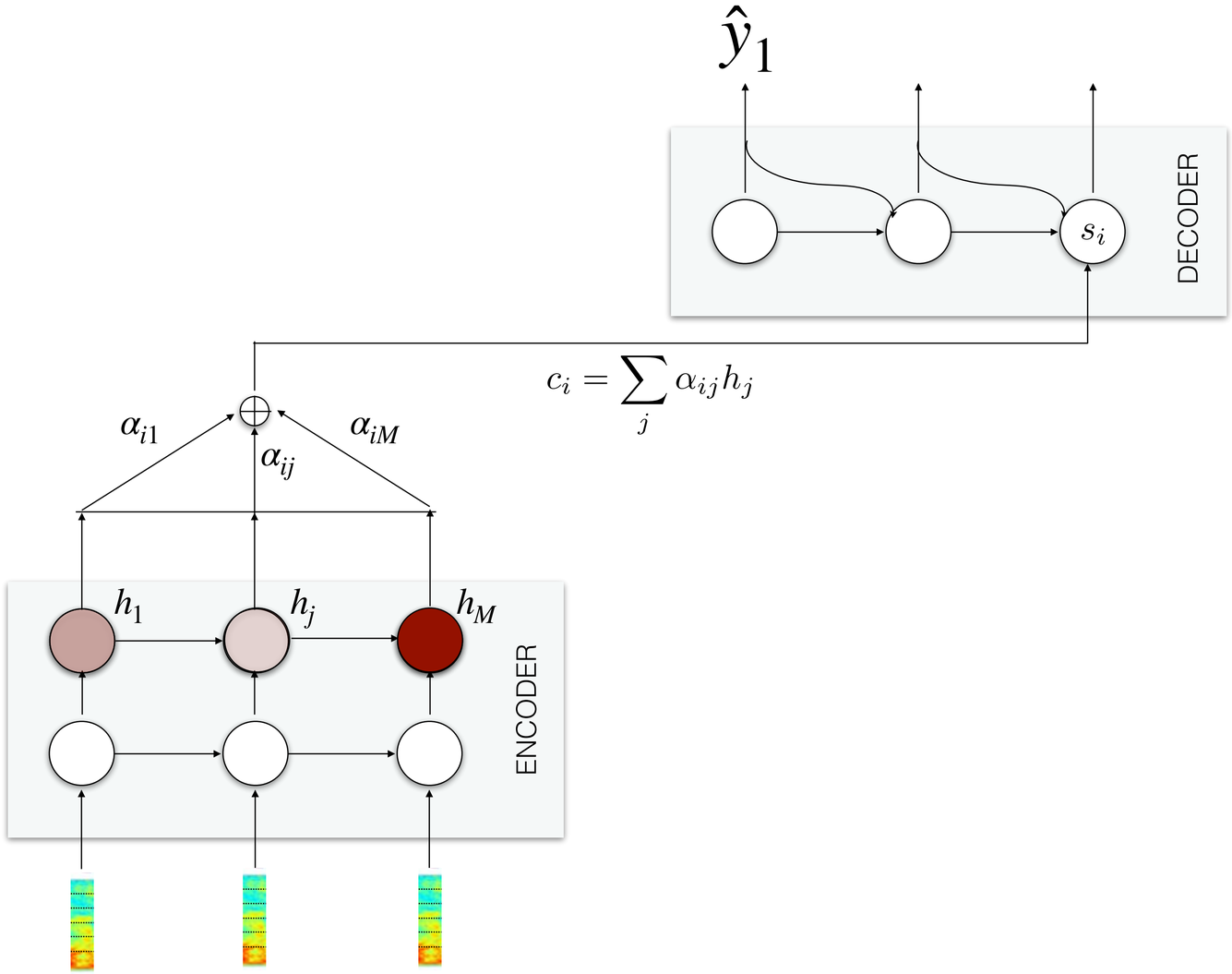
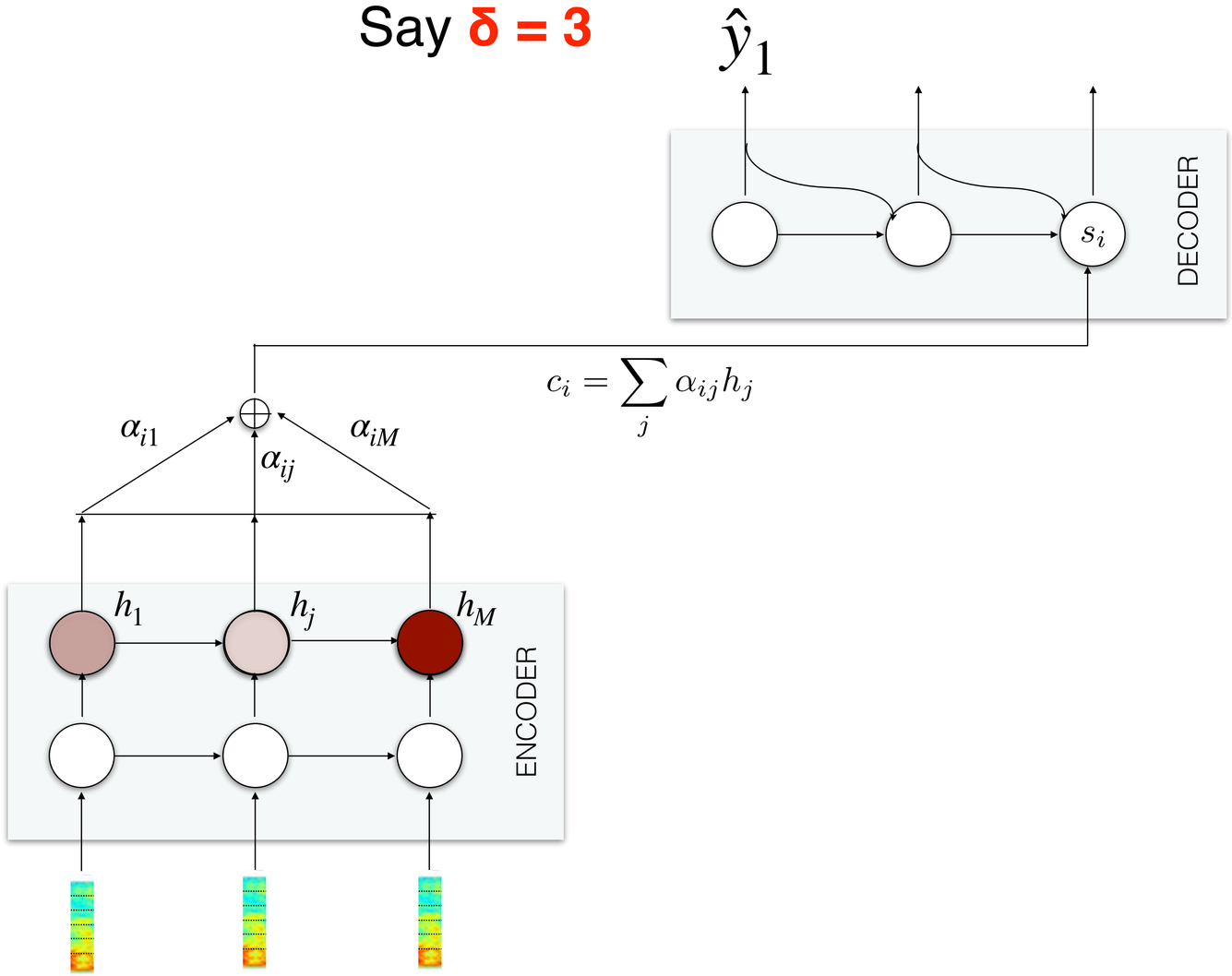


Beam search in a seq2seq model

Say **δ = 3**



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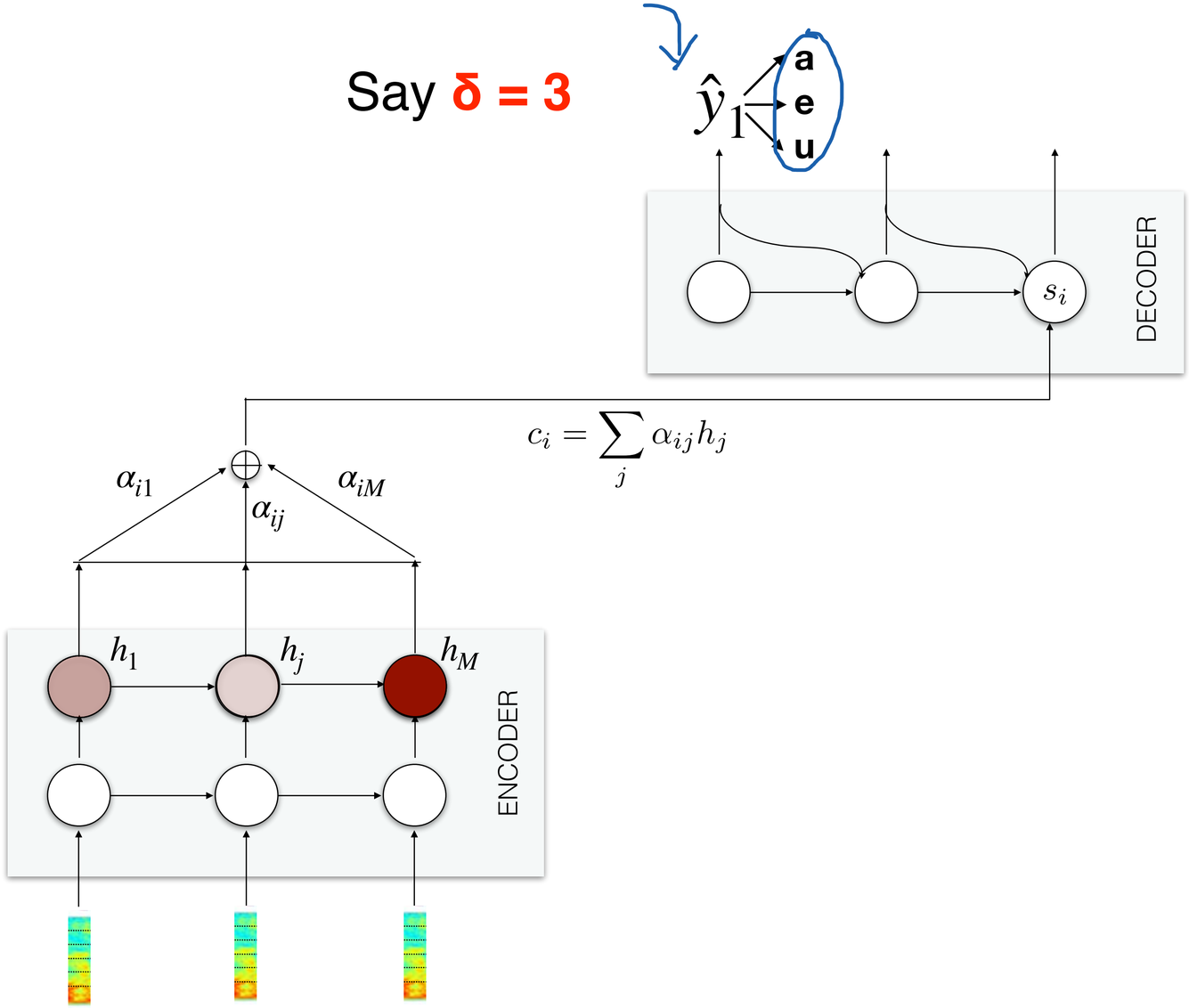

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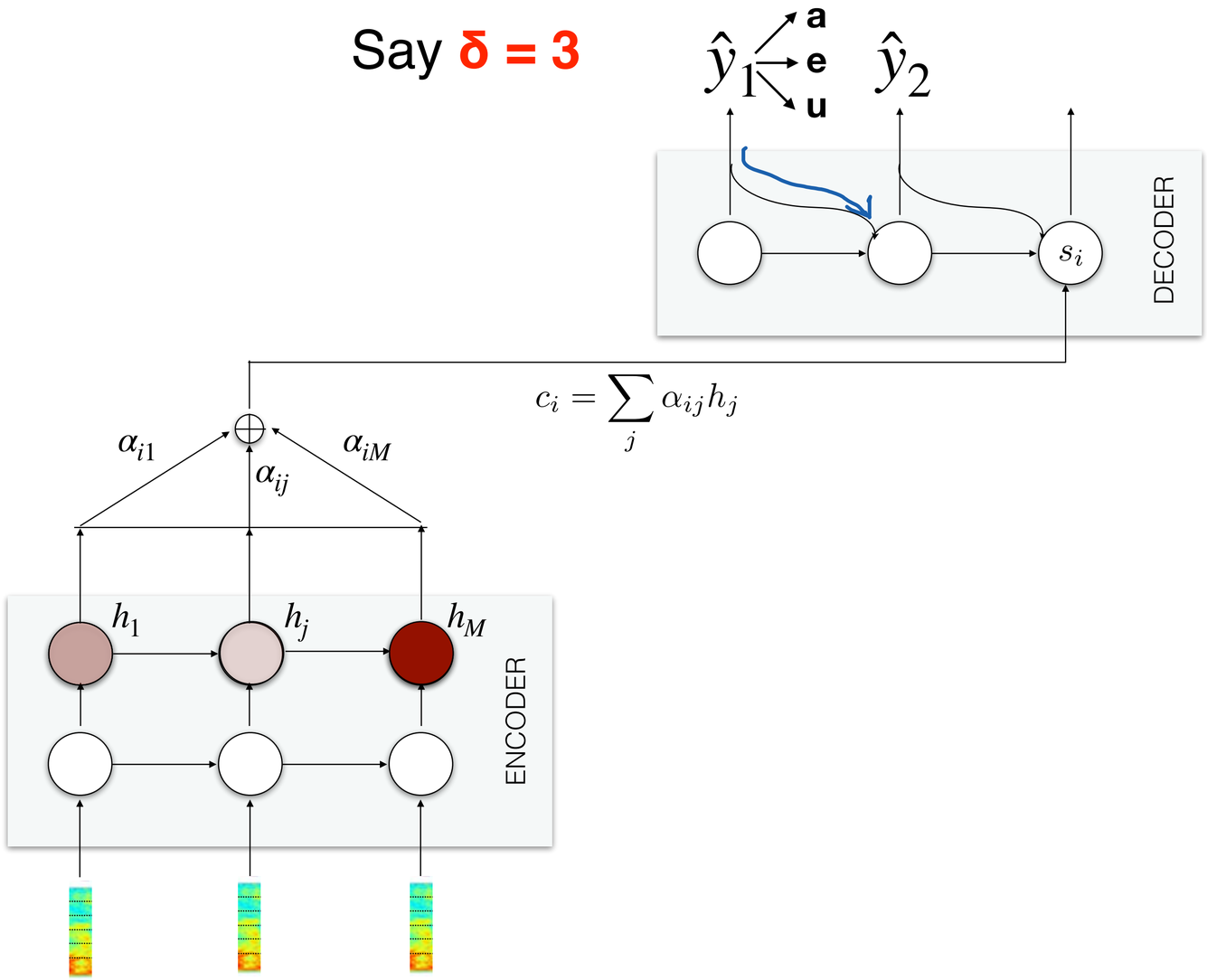

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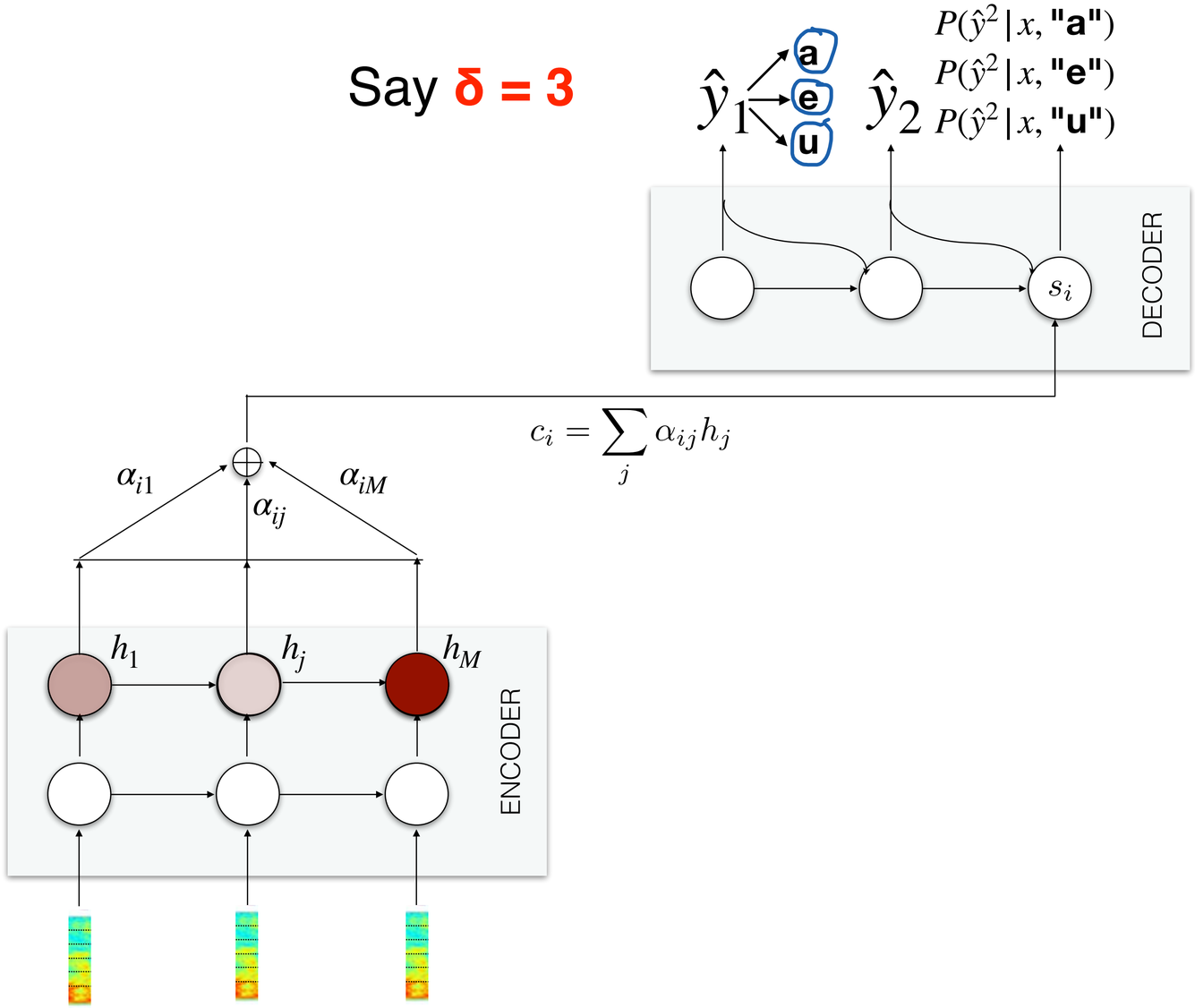

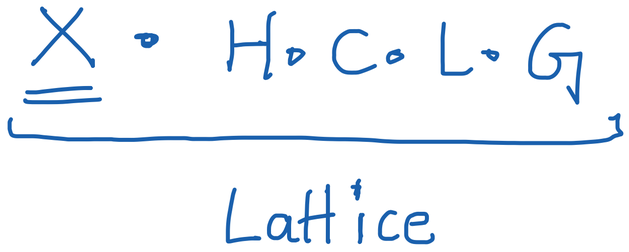

$$w^* = \arg\max_w p(o|w)p(w)$$

Lattices

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- A lattice is a weighted, directed acyclic graph which encodes a large number of ASR hypotheses weighted by acoustic model +language model scores specific to a given utterance

Lattice Generation

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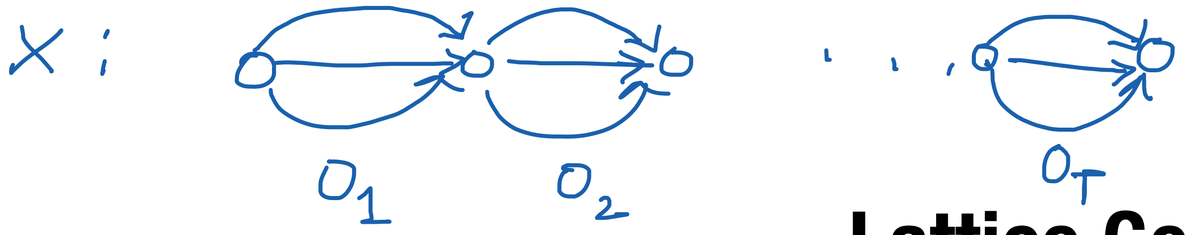

Lattice Generation

- Say we want to decode an utterance, U, of T frames.
- Construct a sausage acceptor for this utterance, X, with T+1 states and arcs for each context-dependent HMM state at each time-step
- Search the following composed machine for the best word sequence corresponding to U:

$$D = X \circ HCLG$$

Lattice construction using lattice-beam

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- To produce a lattice, prune the decoding graph using “lattice-beam” width (s.t. only arcs or states on paths that are within cutoff cost = best_path_cost + lattice-beam will be retained) and then determinize s.t. there’s a single path for every word sequence

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- Naive algorithm
  - Maintain a list of active tokens and links during decoding
  - Turn this structure into an FST, L.
  - When we reach the end of the utterance, prune L using lattice-beam.

Moving on to multi-pass decoding

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  - Rescore first-pass hypotheses using complex model to find the best word sequence

Multi-pass decoding with N-best lists

- Simple algorithm: Modify the Viterbi algorithm to return the N-best word sequences for a given speech input

Rank	Path	AM logprob	LM logprob
1.	it's an area that's naturally sort of mysterious	-7193.53	-20.25
2.	that's an area that's naturally sort of mysterious	-7192.28	-21.11
3.	it's an area that's not really sort of mysterious	-7221.68	-18.91
4.	that scenario that's naturally sort of mysterious	-7189.19	-22.08
5.	there's an area that's naturally sort of mysterious	-7198.35	-21.34
6.	that's an area that's not really sort of mysterious	-7220.44	-19.77
7.	the scenario that's naturally sort of mysterious	-7205.42	-21.50
8.	so it's an area that's naturally sort of mysterious	-7195.92	-21.71
9.	that scenario that's not really sort of mysterious	-7217.34	-20.70
10.	there's an area that's not really sort of mysterious	-7226.51	-20.01

Image from [JM]: Jurafsky & Martin, SLP 2nd edition, Chapter 10

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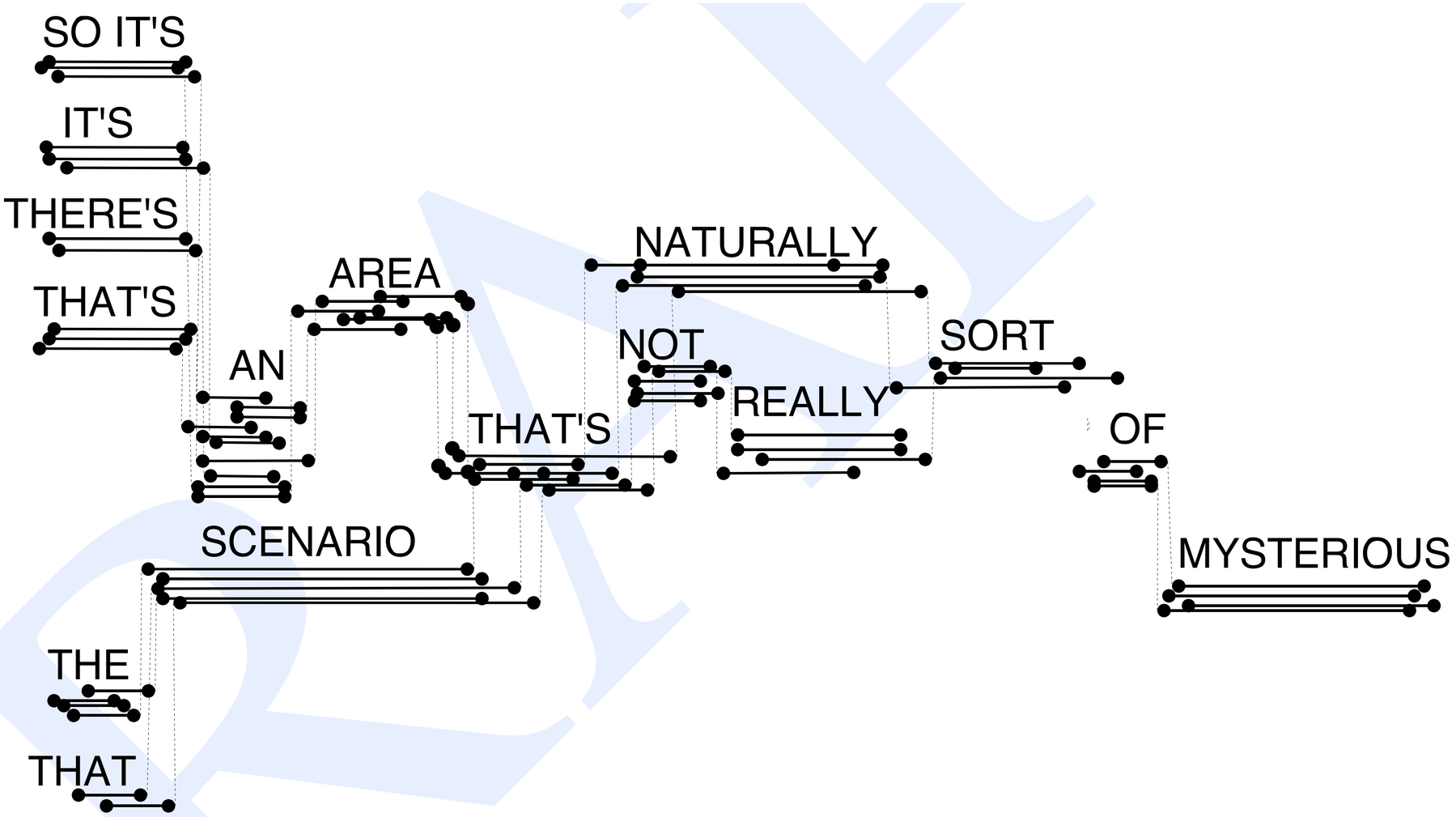
- Problem: N-best lists aren't as diverse as we'd like. And, not enough information in N-best lists to effectively use other knowledge sources

Image from [JM]: Jurafsky & Martin, SLP 2nd edition, Chapter 10

Multi-pass decoding with lattices



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