Learning a Part-of-Speech Tagger from Minimal Annotation

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Low-Resource Languages

Supervised training is not an option.

We do semi-supervised training.

→ Annotate some data by hand

... cheaply

Semi-Supervised Training

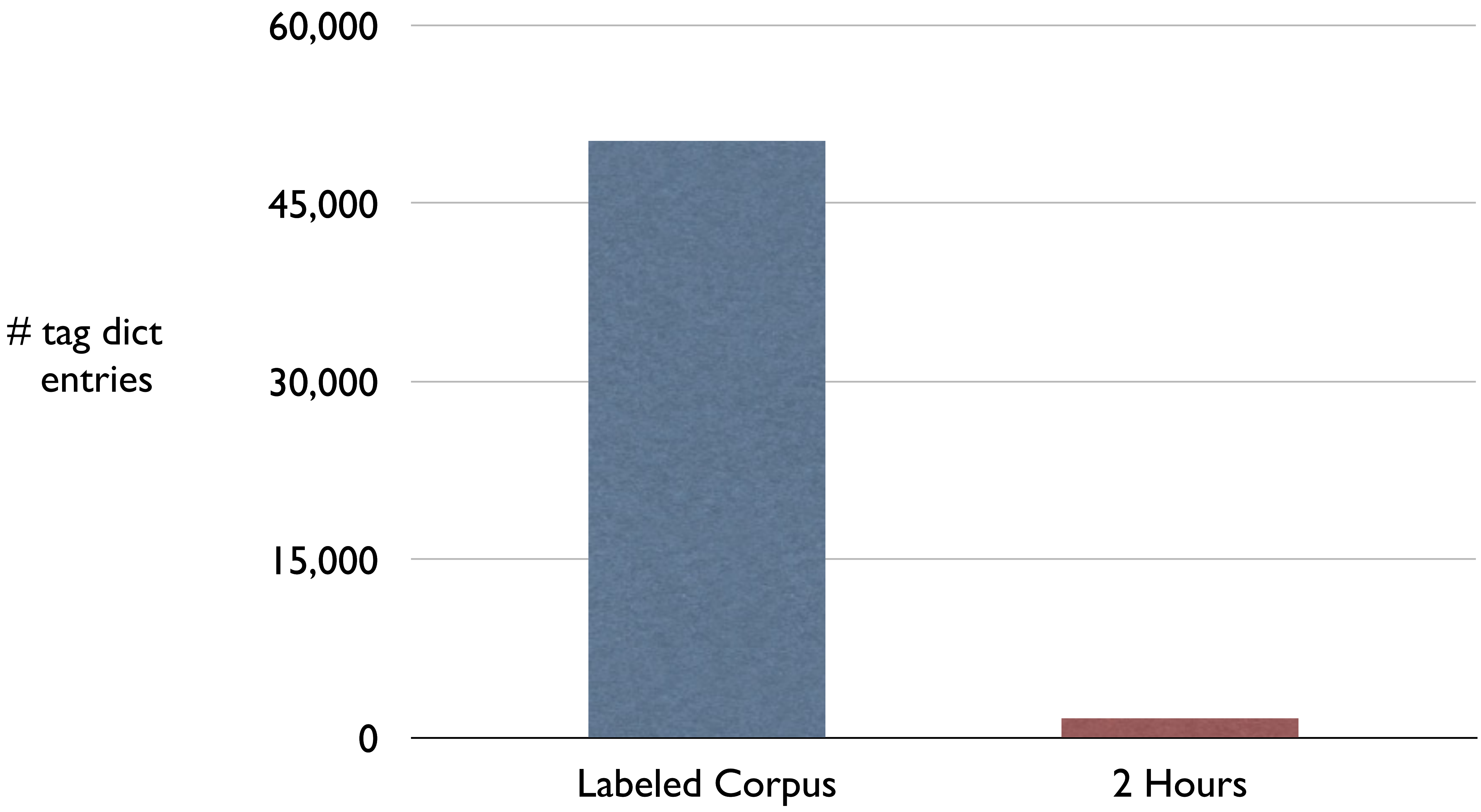
HMM with Expectation-Maximization (EM)

Need:

- Large **raw** corpus ← know how to get this
- Tag dictionary ← where is this from?

[Kupiec, 1992]
[Merialdo, 1994]

A **Real** Tag Dictionary

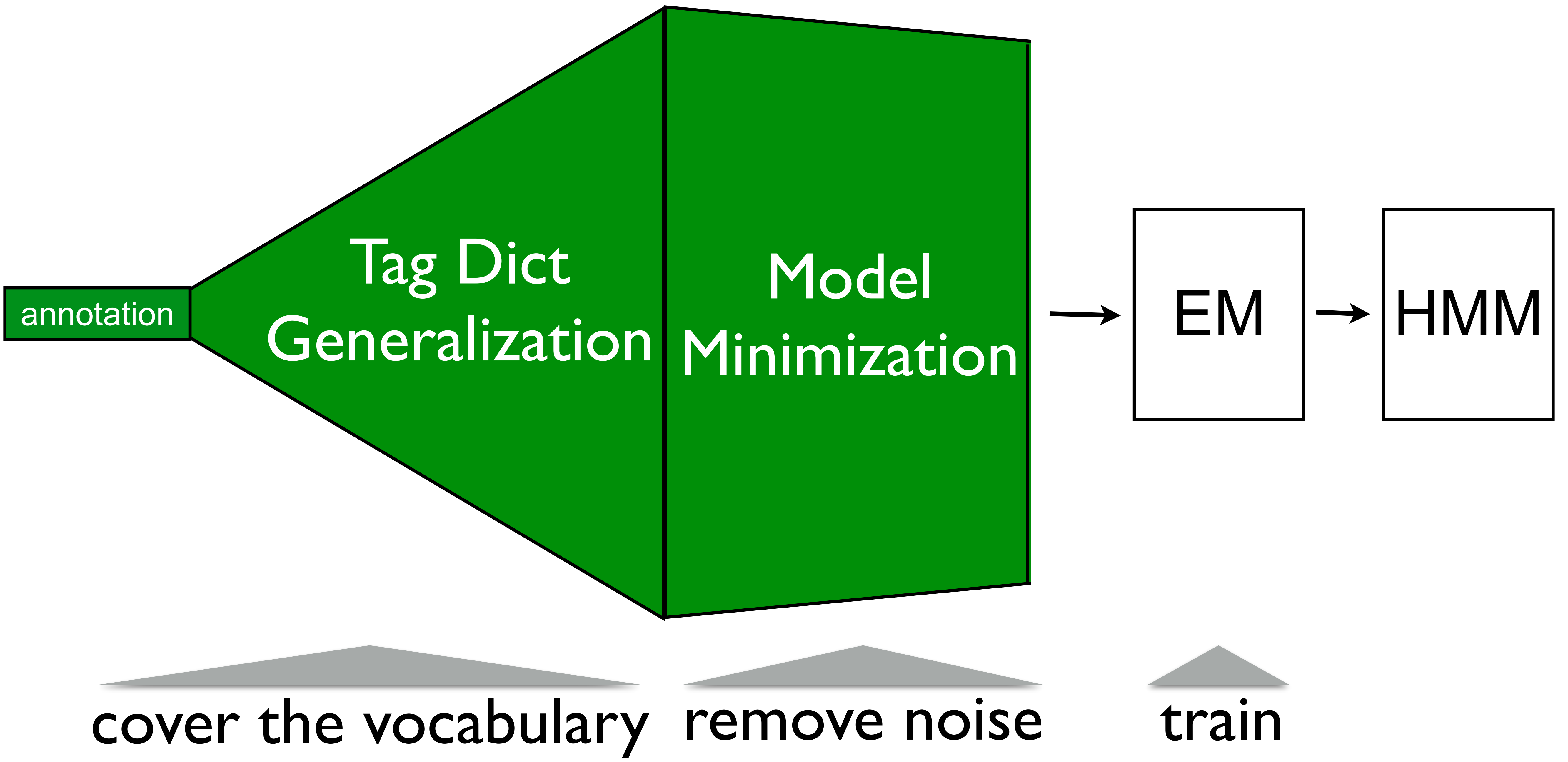


A **Real** Tag Dictionary

Extremely low coverage means **most** words are **unknown**

⇒ **Bad for learning** (poorly constrained)

Our Approach



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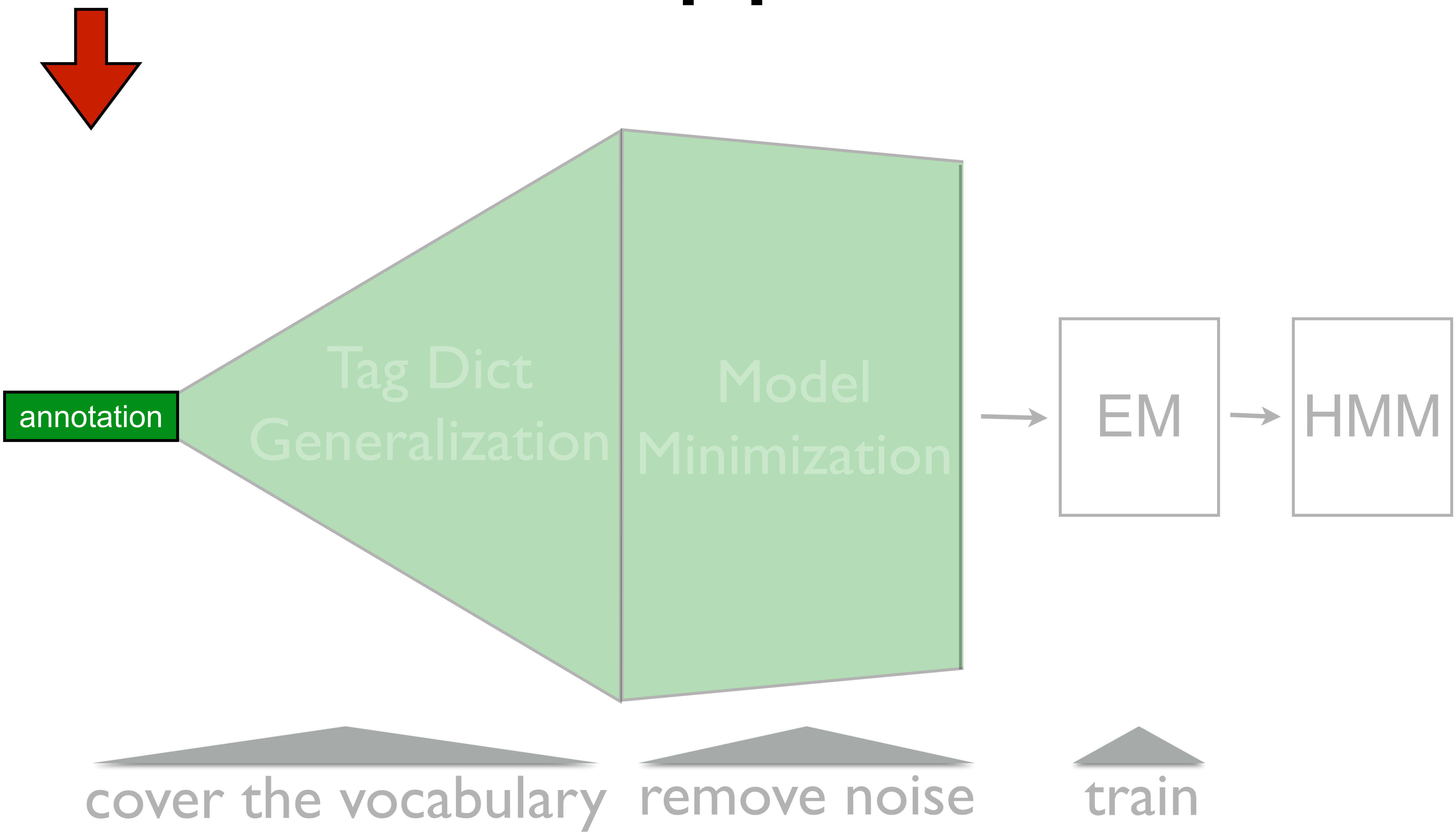


Collecting Annotations

Task #1

Up to 4 hours to create a **tag dictionary**

ordered by frequency

,	,		
the	DT		
.	.		
of	IN	RP	
to	TO	RP	
a	DT		
and	CC		
⋮	⋮		
only	RB		
can	VB	VBP	MD
York	NNP		
into	IN	RP	
after	IN	RP	
president	NN		
⋮	⋮		

Collecting Annotations

Task #2

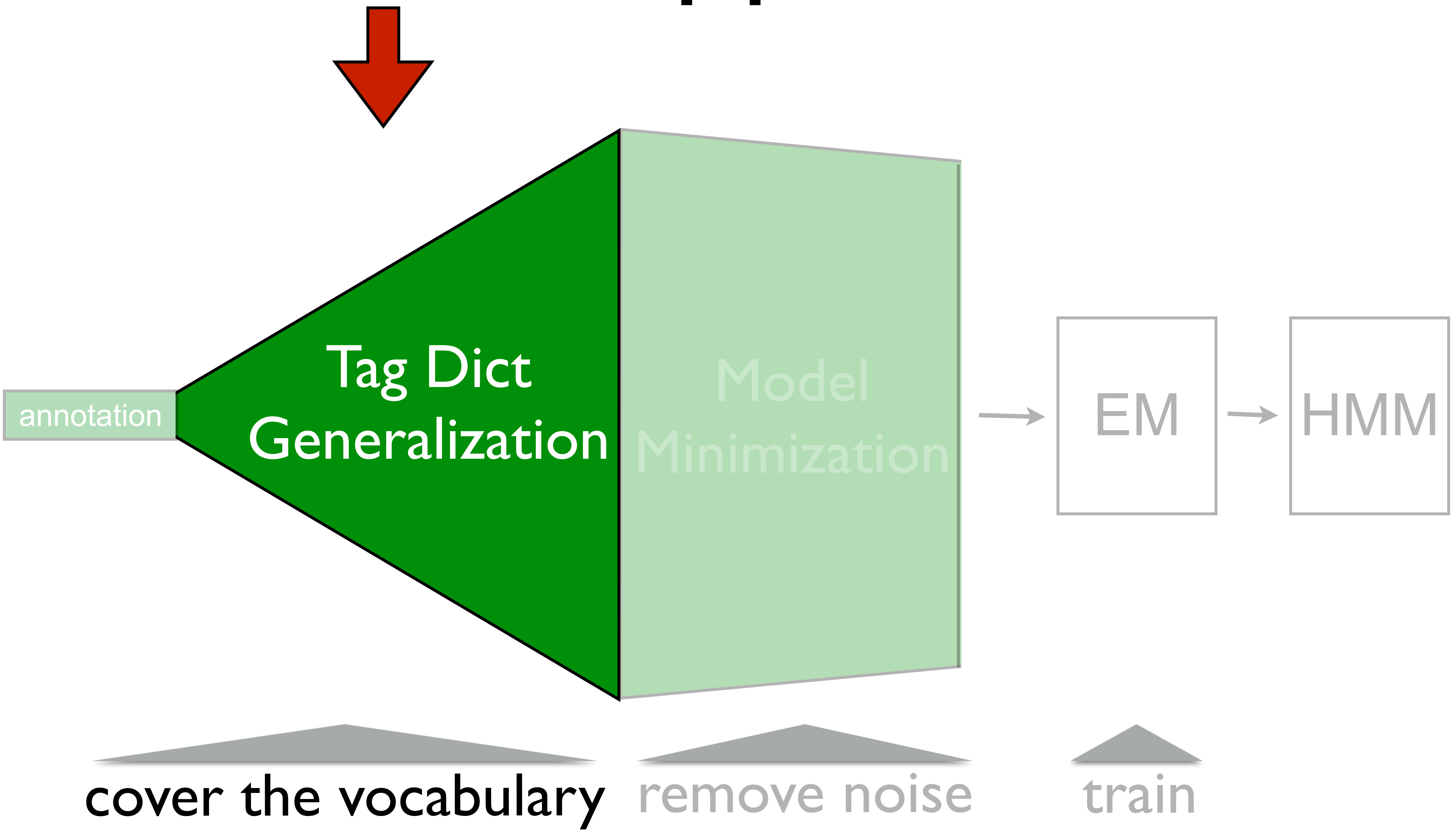
Up to 4 hours to annotate **full sentences**

Pierre	Vinken	,	61	years	old	,	will	join	the	board	as	a	nonexecutive	director	Nov.	29	.
NNP	NNP	,	CD	NNS	JJ	,	MD	VB	DT	NN	IN	DT	JJ	NN	NNP	CD	.

Mr.	Vinken	is	chairman	of	Elsevier	N.V.	,	the	Dutch	publishing	group	.
NNP	NNP	VB	NN	IN	NNP	NNP	,	DT	JJ	JJ	NN	.

⋮

Our Approach



Tag Dict Generalization

These annotations are too sparse!

→ Generalize to the entire vocabulary

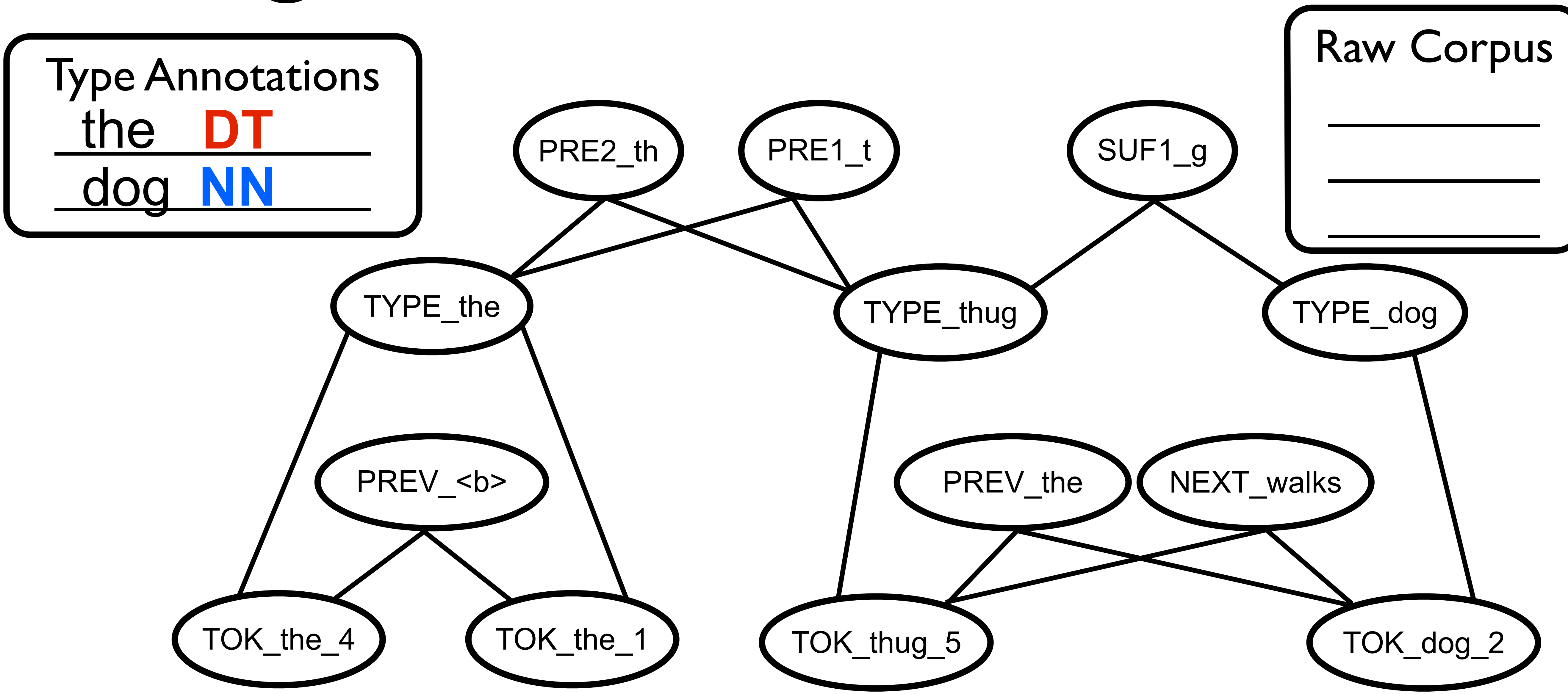
Tag Dict Generalization

Our strategy: Label Propagation

- **Connect** annotations to raw corpus tokens
- Push tag labels to **entire corpus**

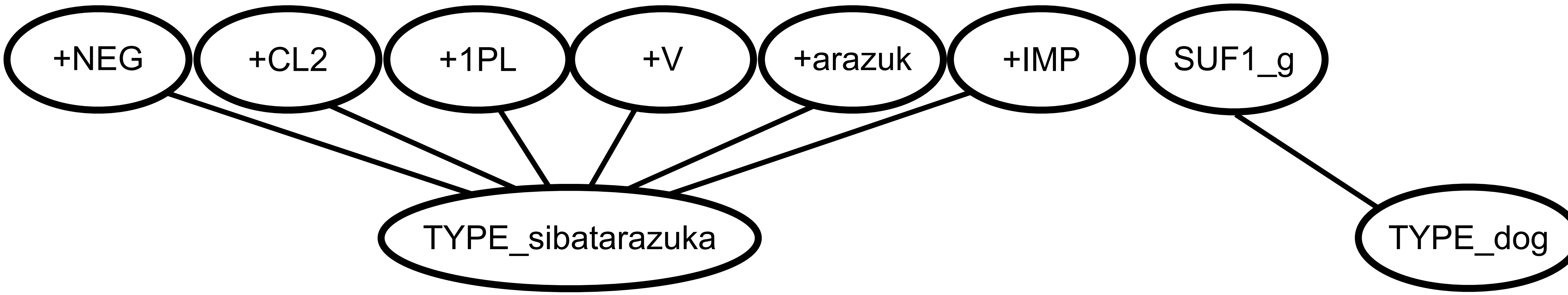
[Talukdar and Crammer. 2009]

Tag Dict Generalization



Any arbitrary features could be used

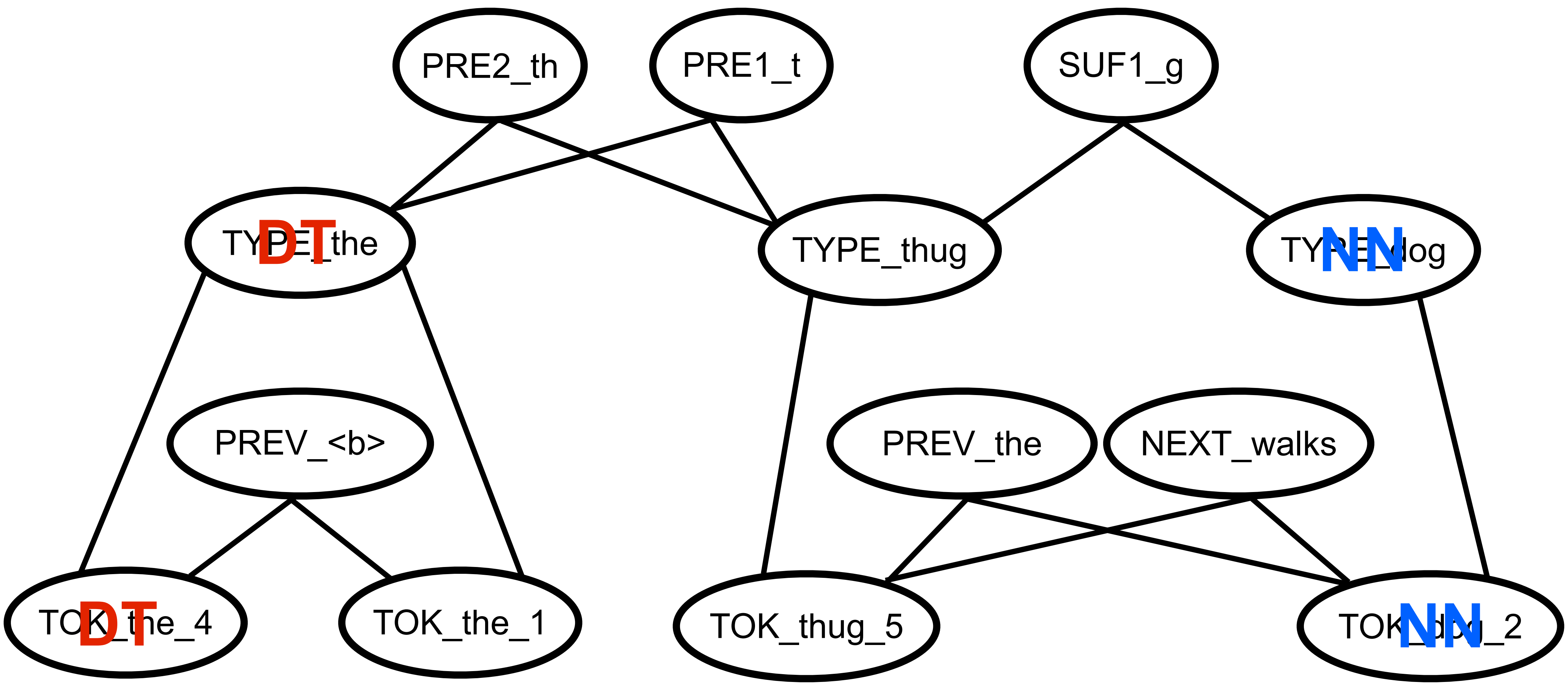
Tag Dict Generalization



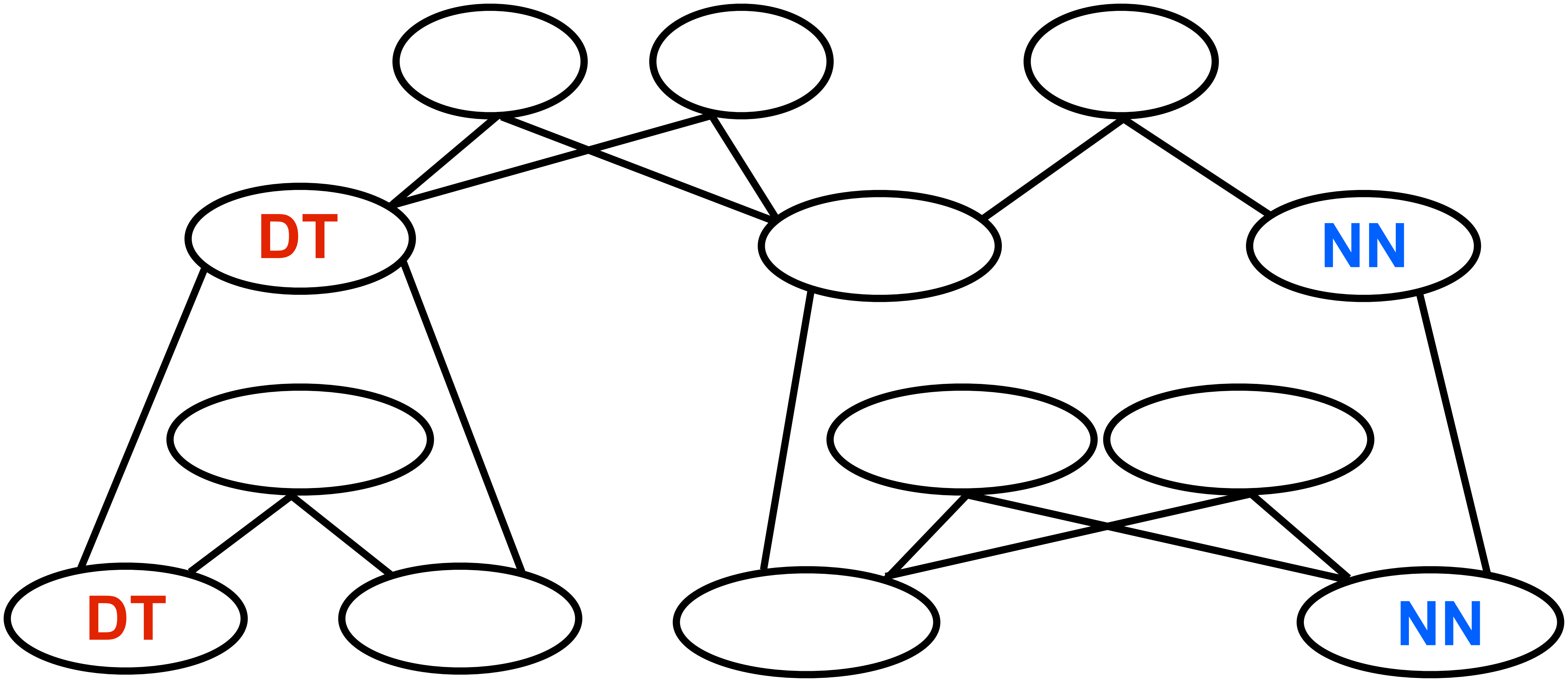
Finite-State Transducer (FST)

- Generates morphological analysis
- Hand-built by a linguist in 10 hours

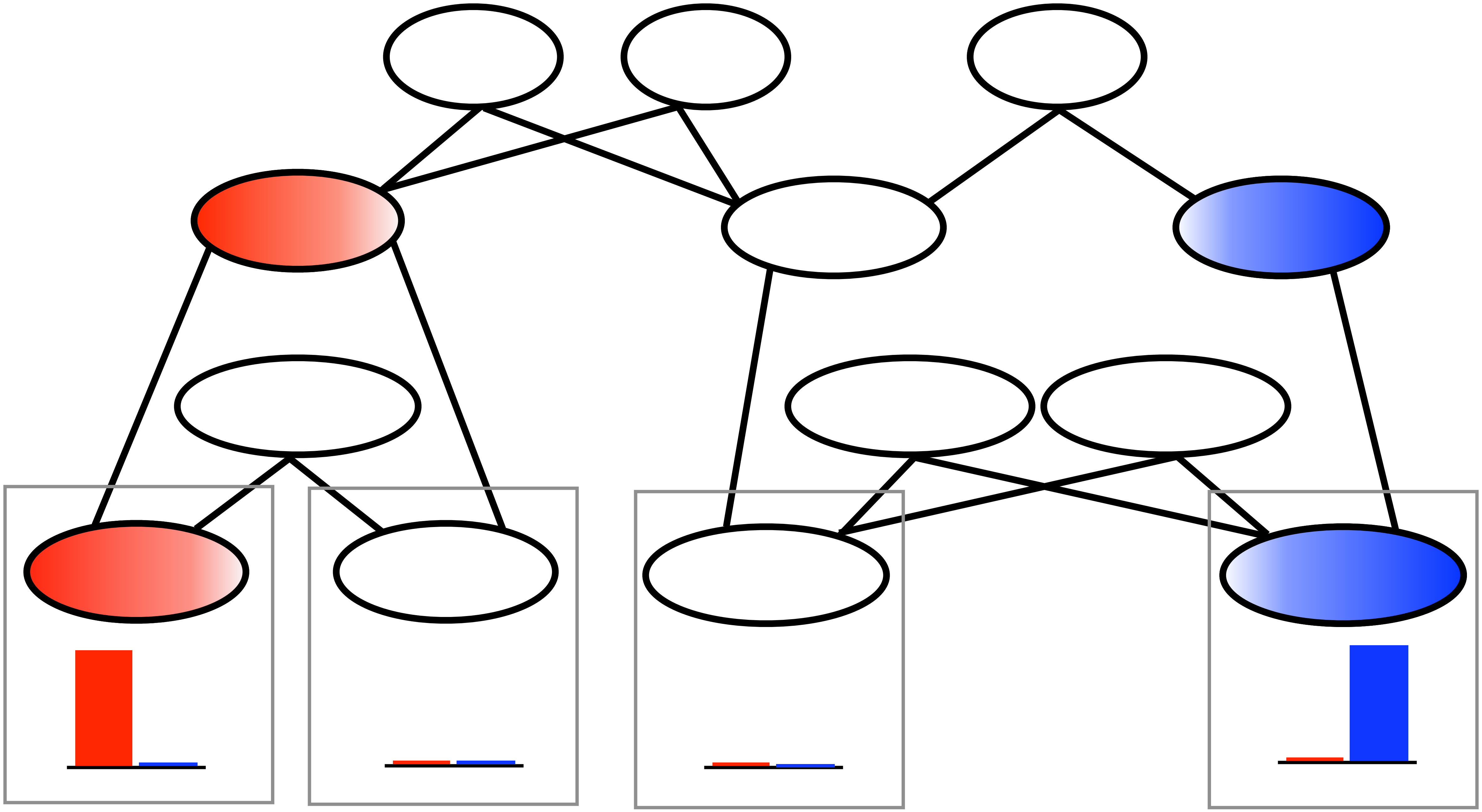
Tag Dict Generalization



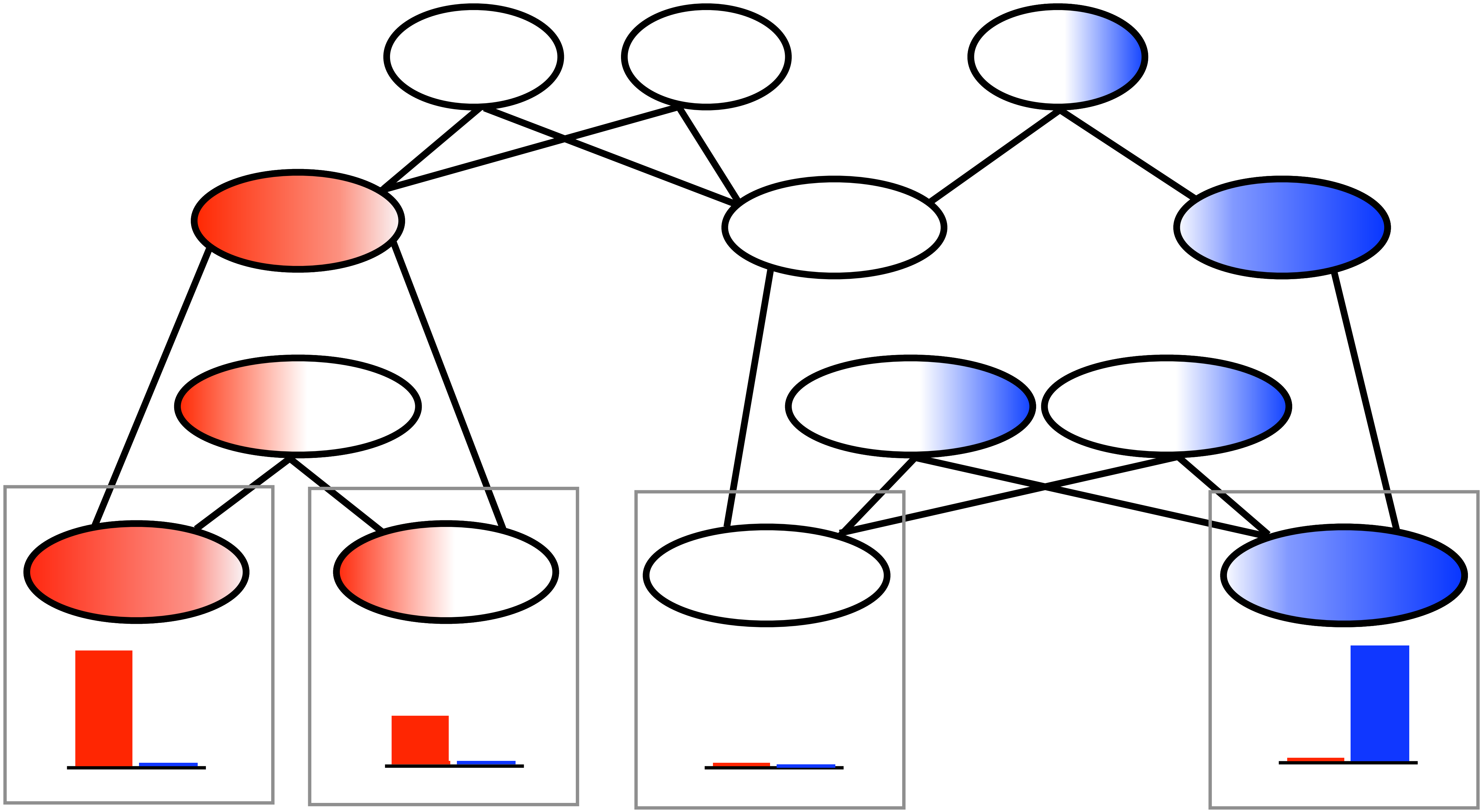
Tag Dict Generalization



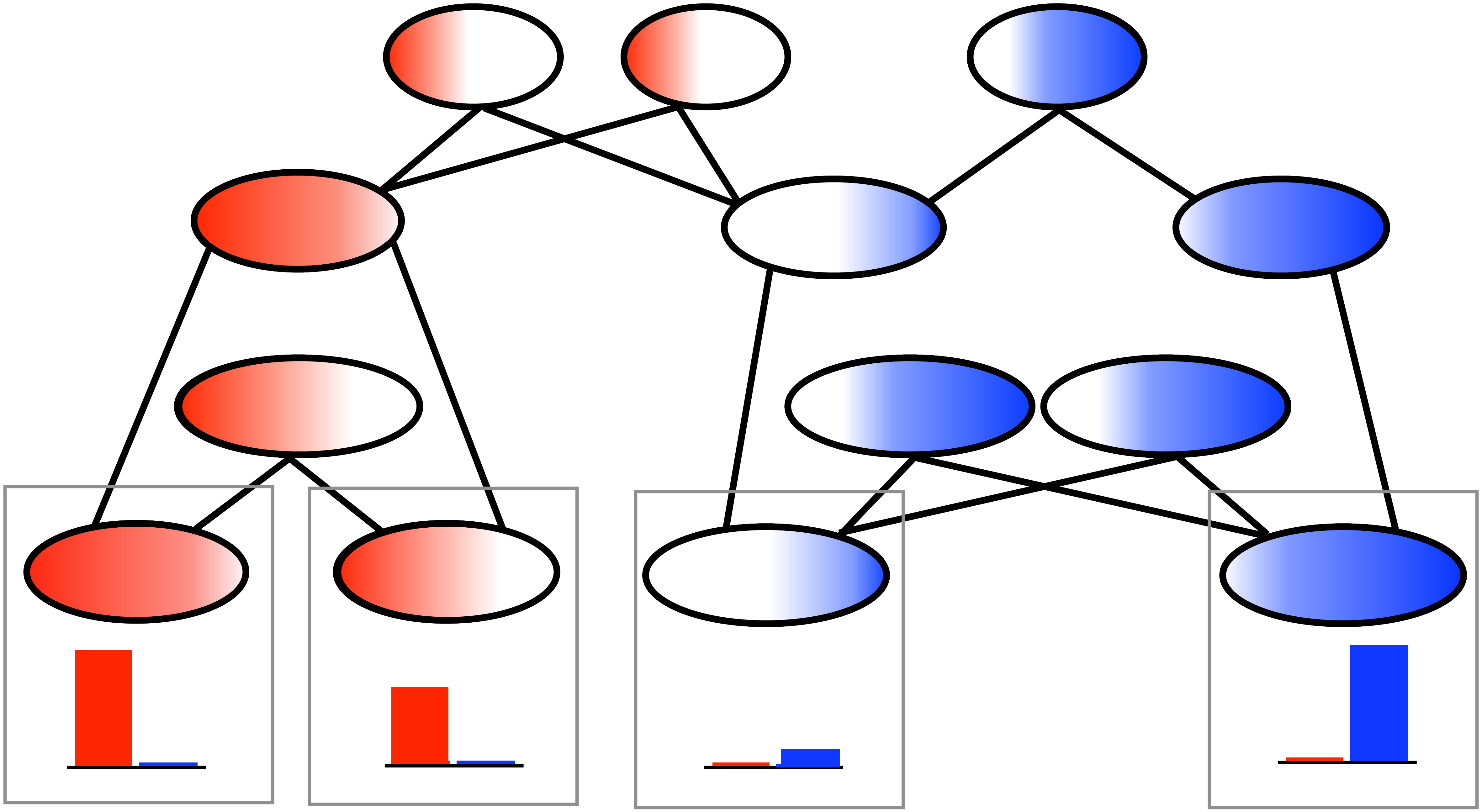
Tag Dict Generalization



Tag Dict Generalization



Tag Dict Generalization



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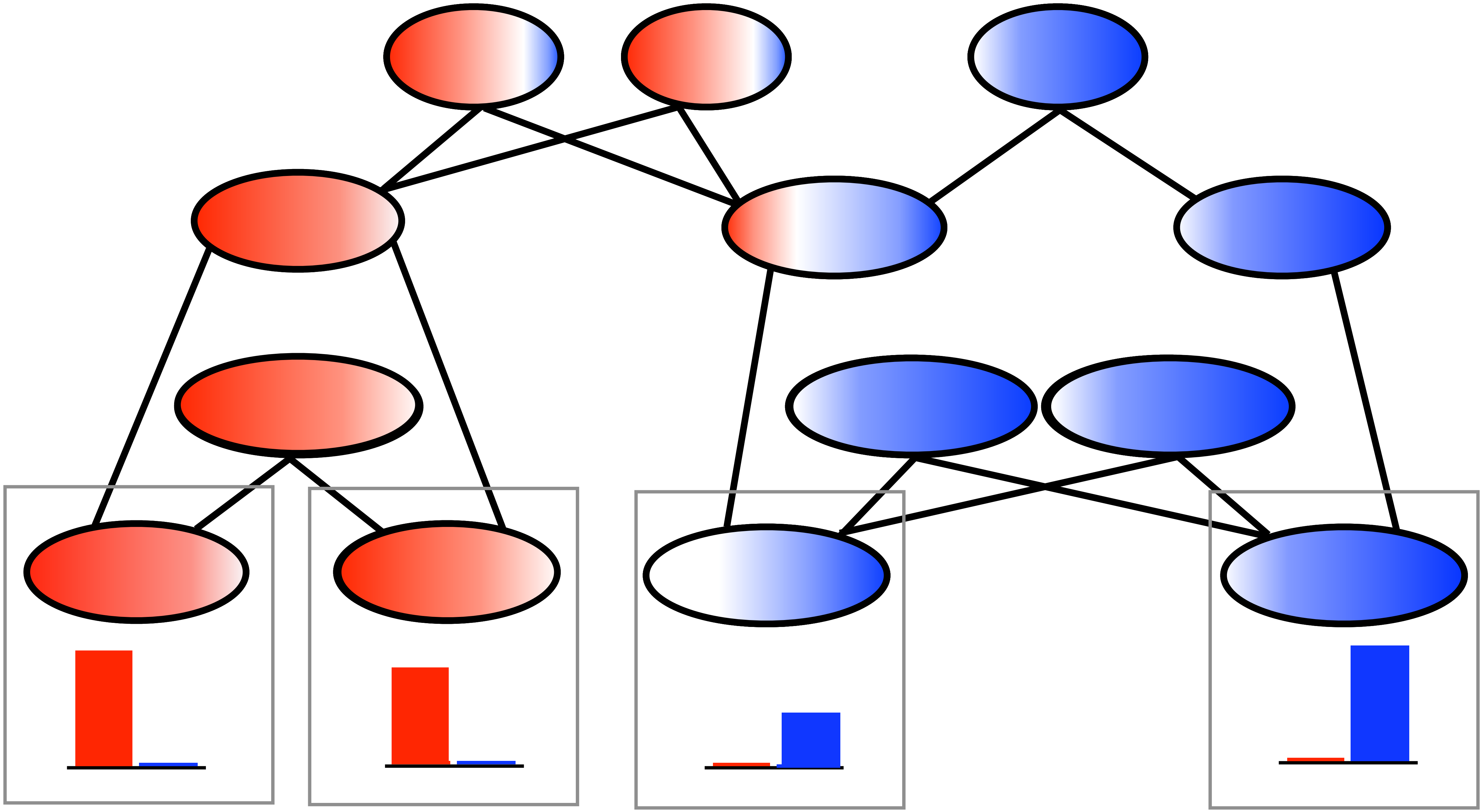

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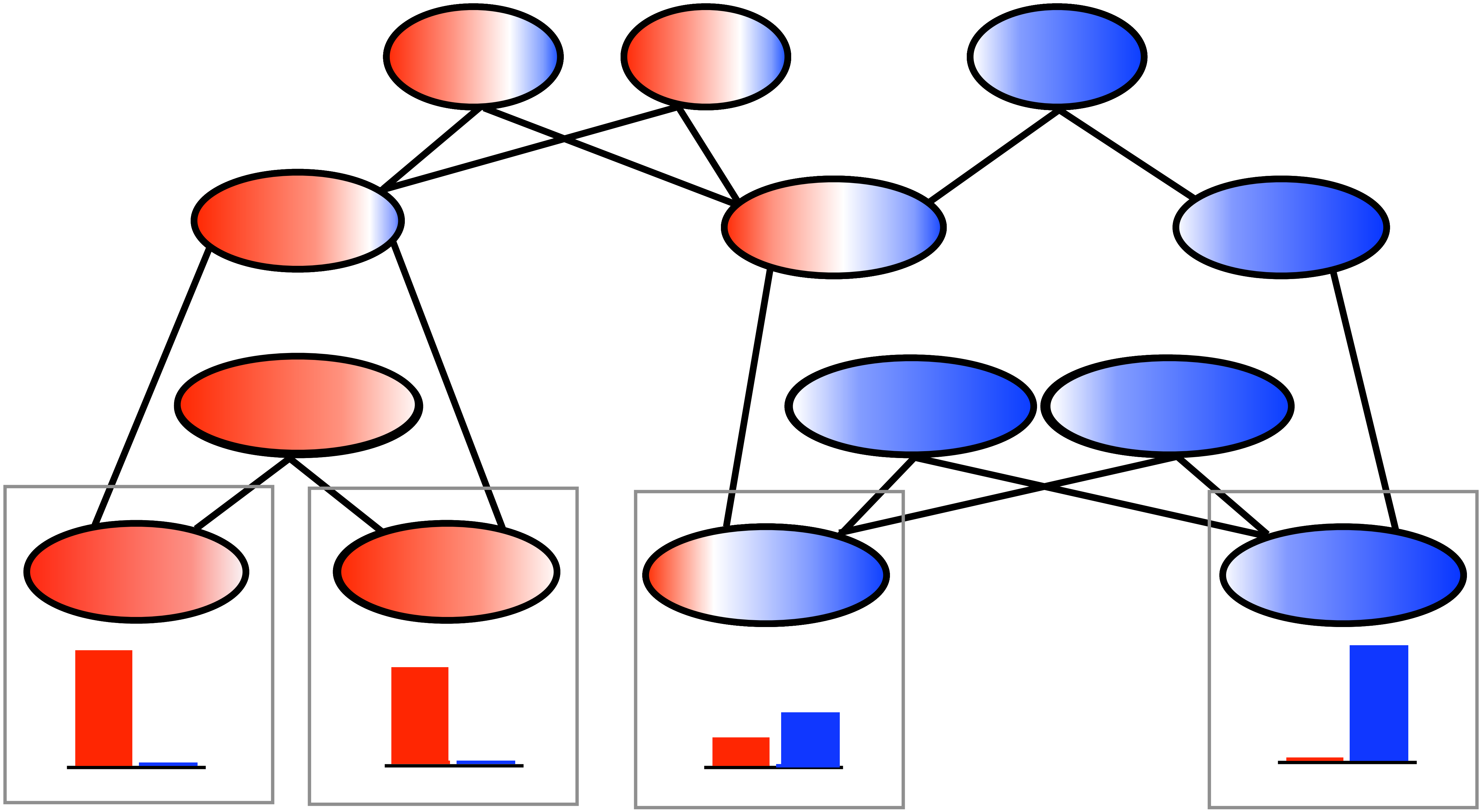
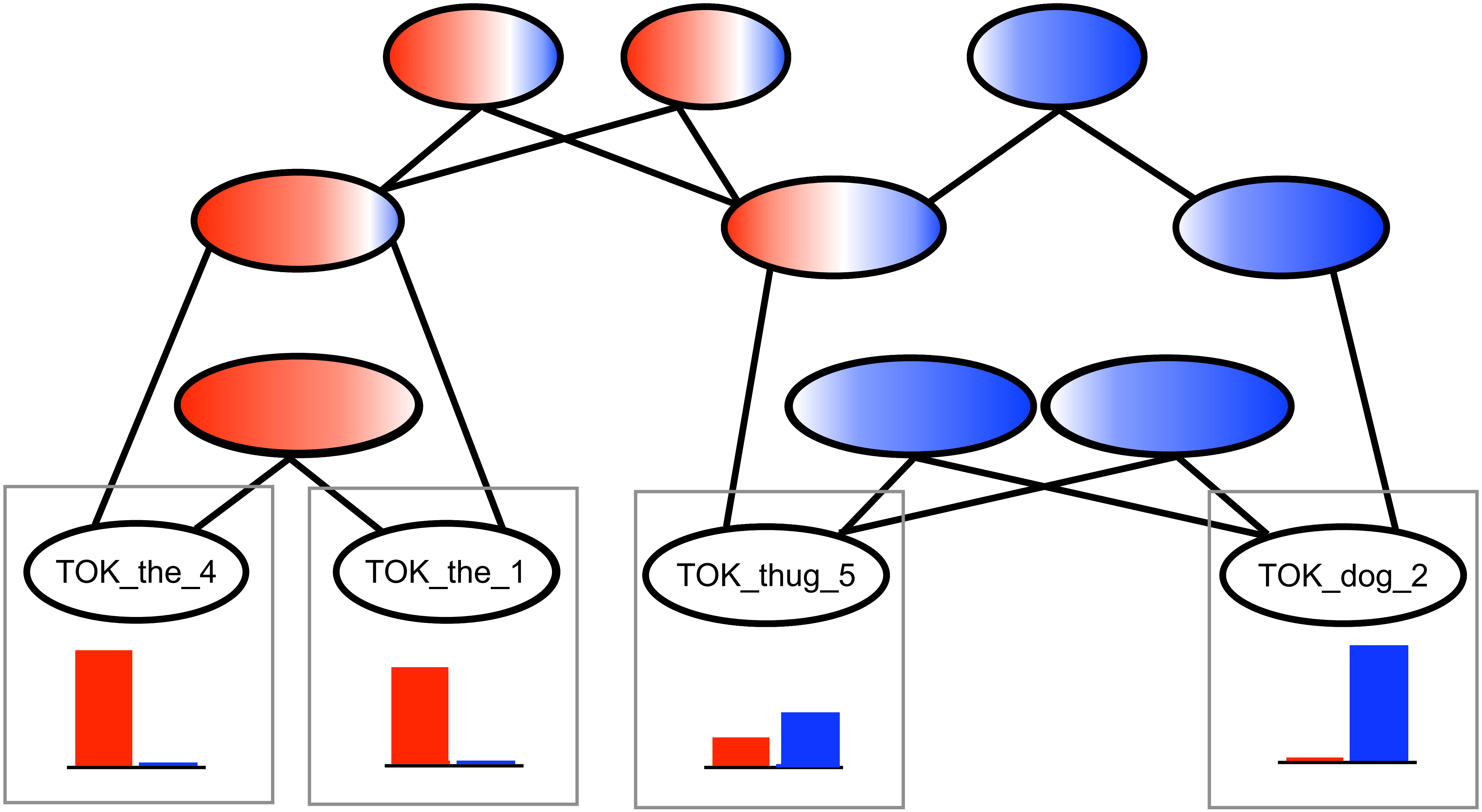


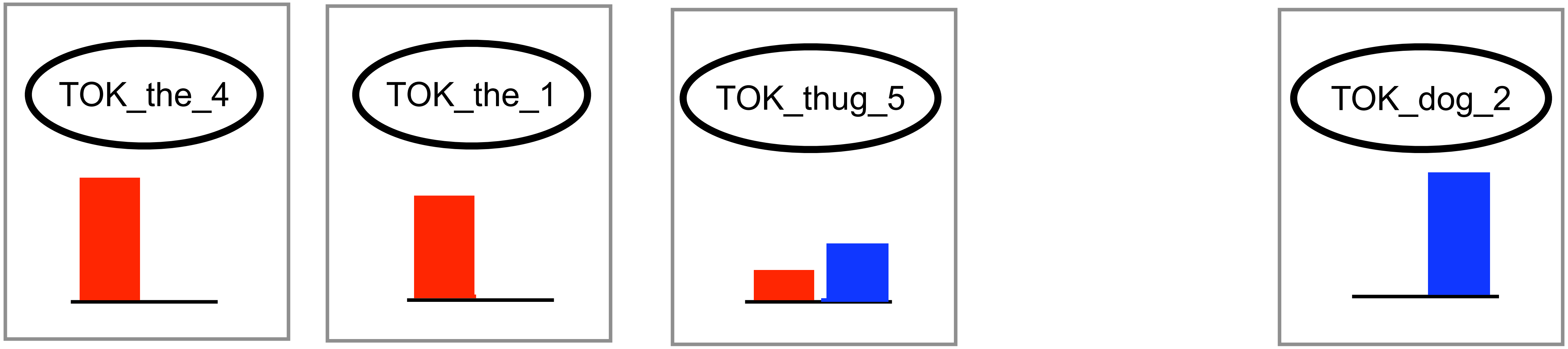
Tag Dict Generalization



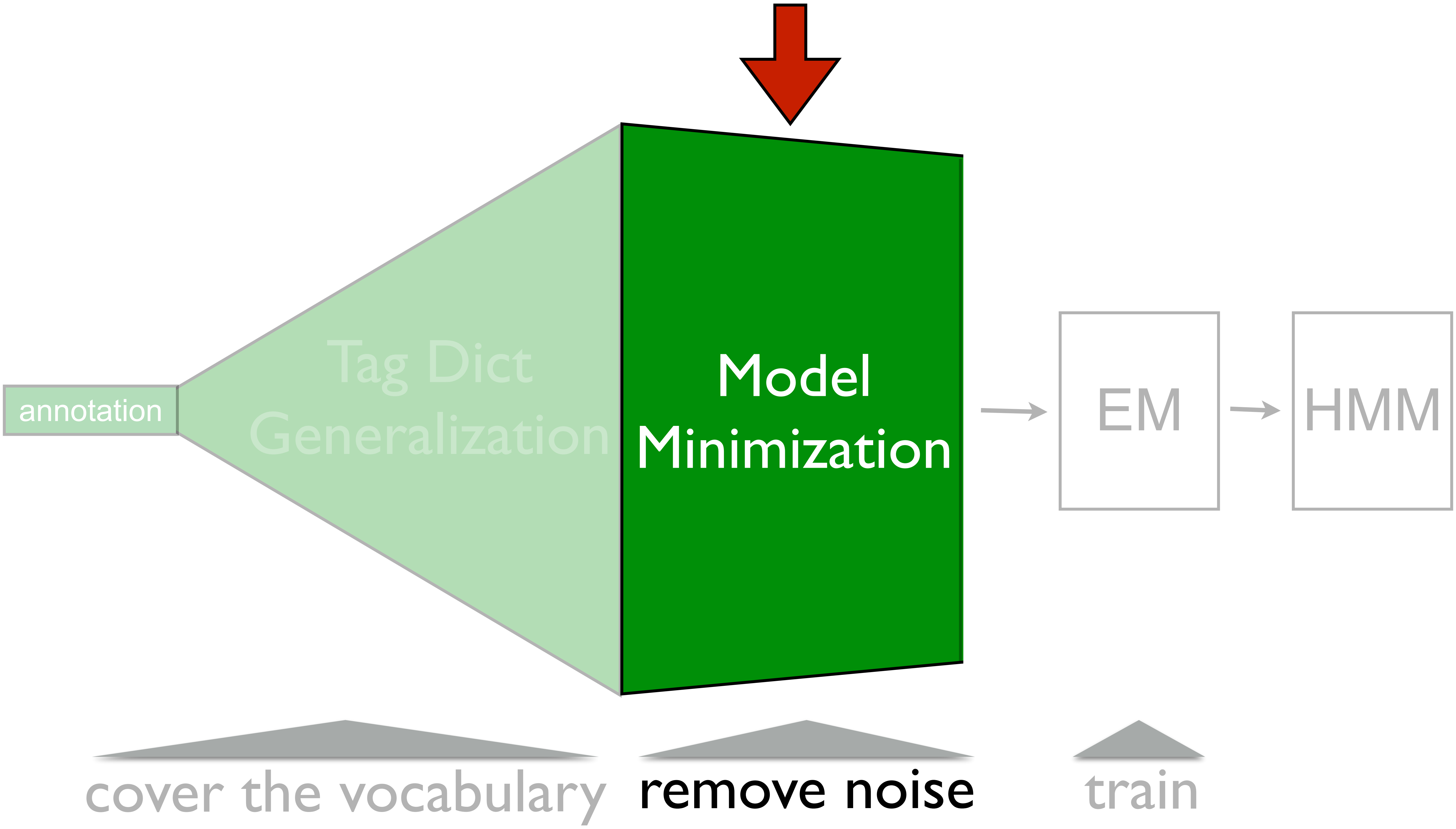
Tag Dict Generalization

Result:

- a tag distribution on every token (soft tagging)
- an expanded tag dictionary (non-zero tags)



Our Approach

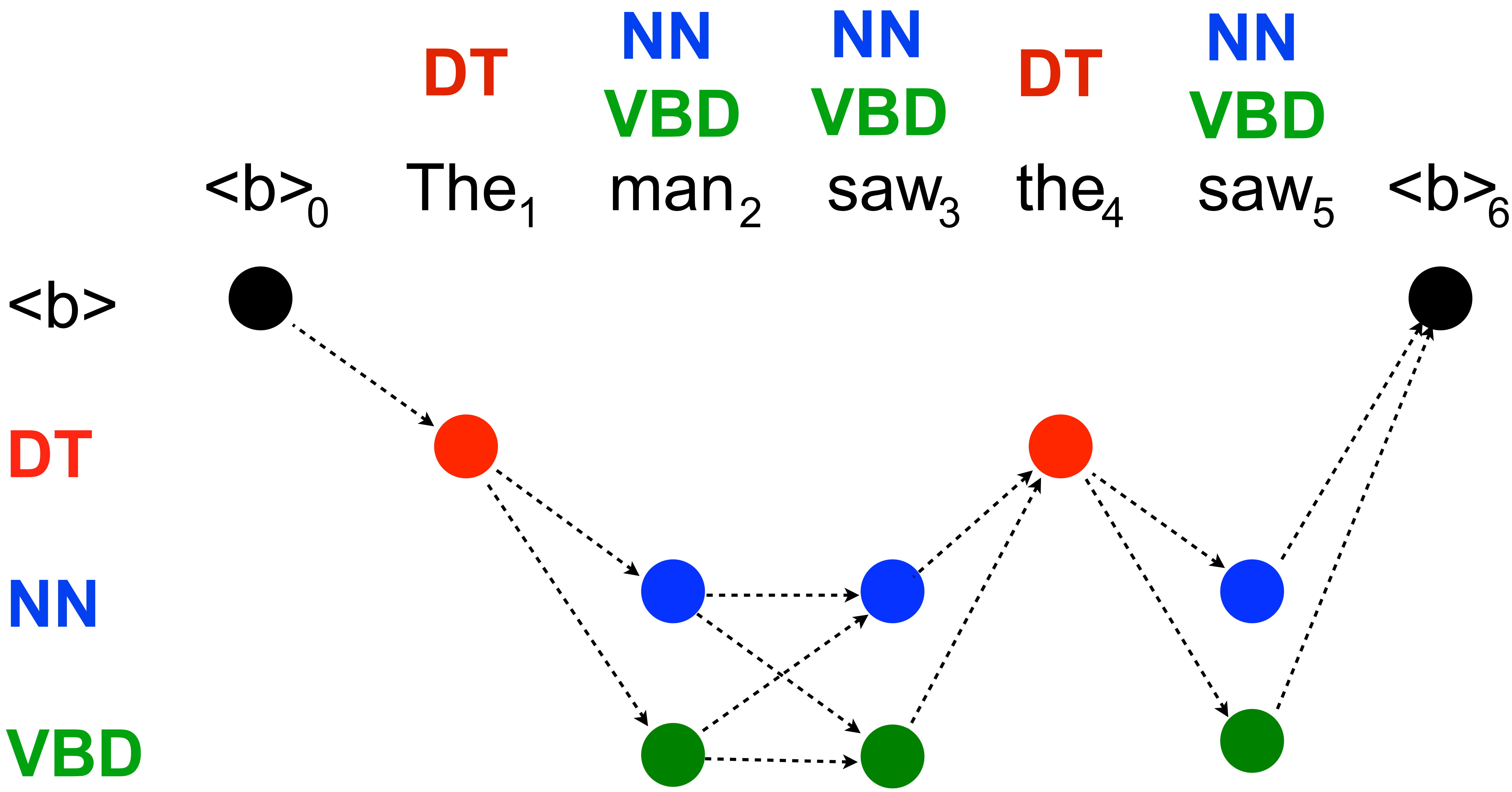


Model Minimization

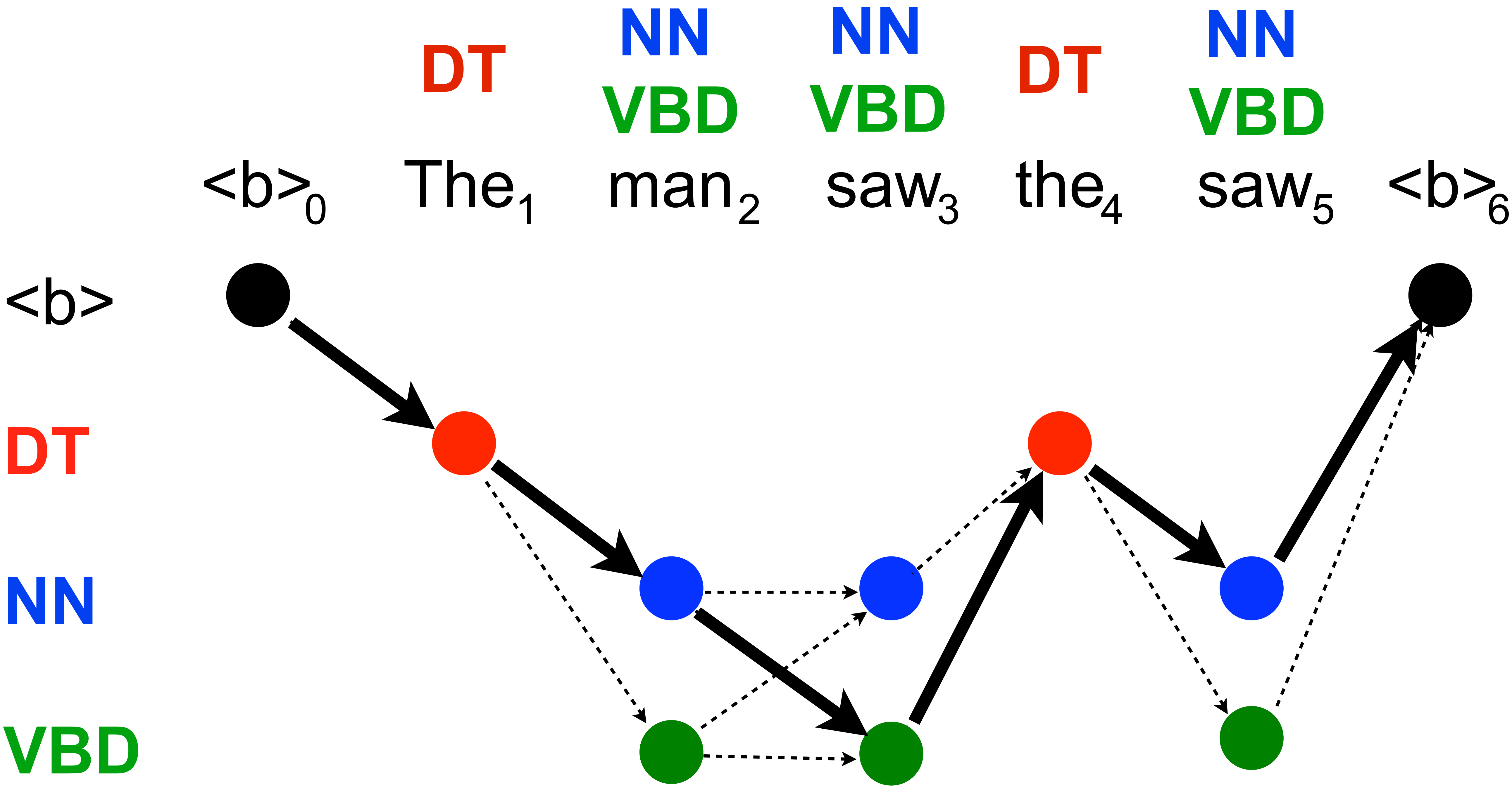
- Induce a cleaner hard tagging from a noisy soft tagging.
- Approach based on work by Sujith Ravi and Kevin Knight (ISI)

[Ravi et al., 2010; Garrette and Baldridge, 2012]

Model Minimization



Model Minimization



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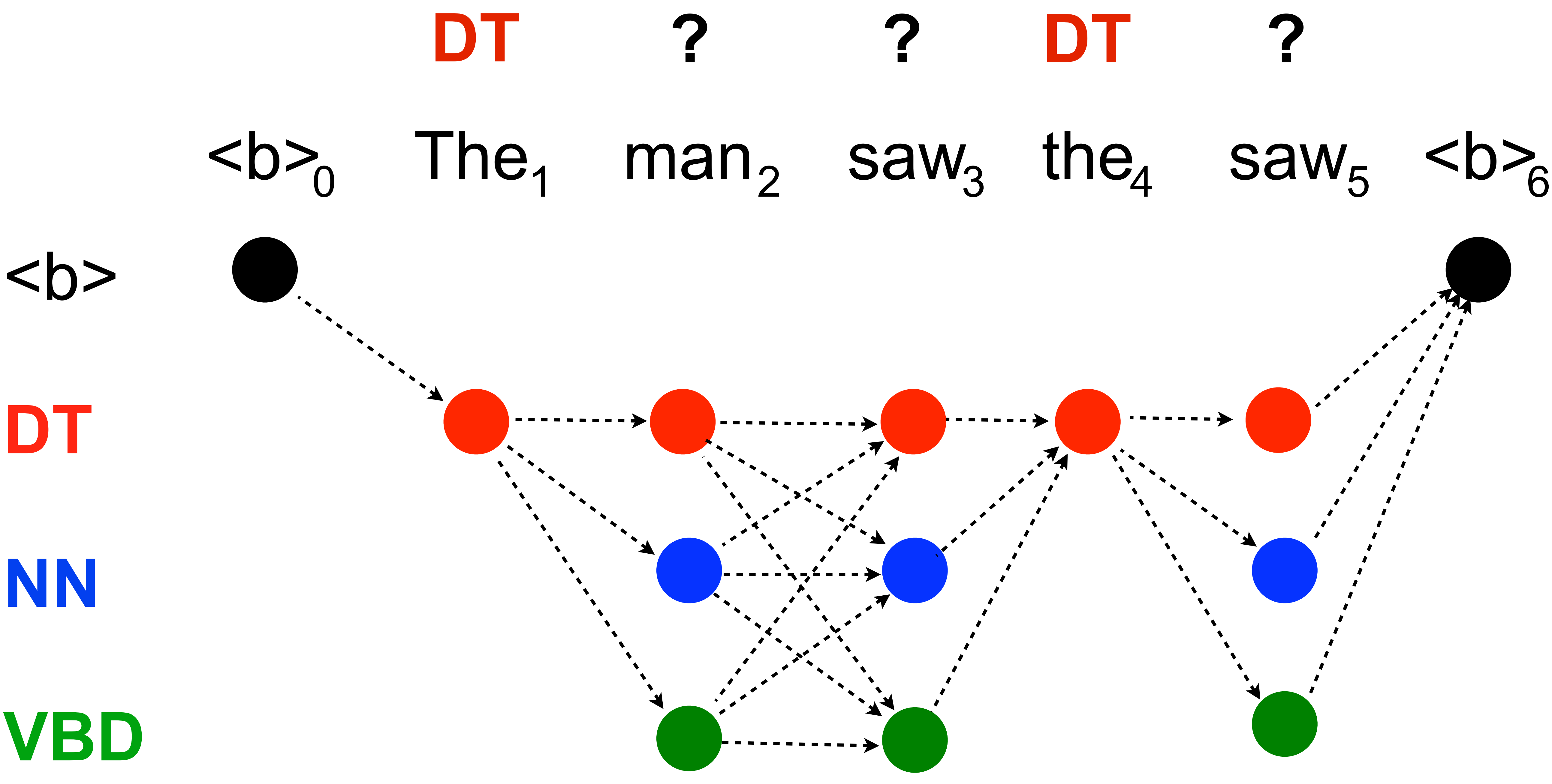

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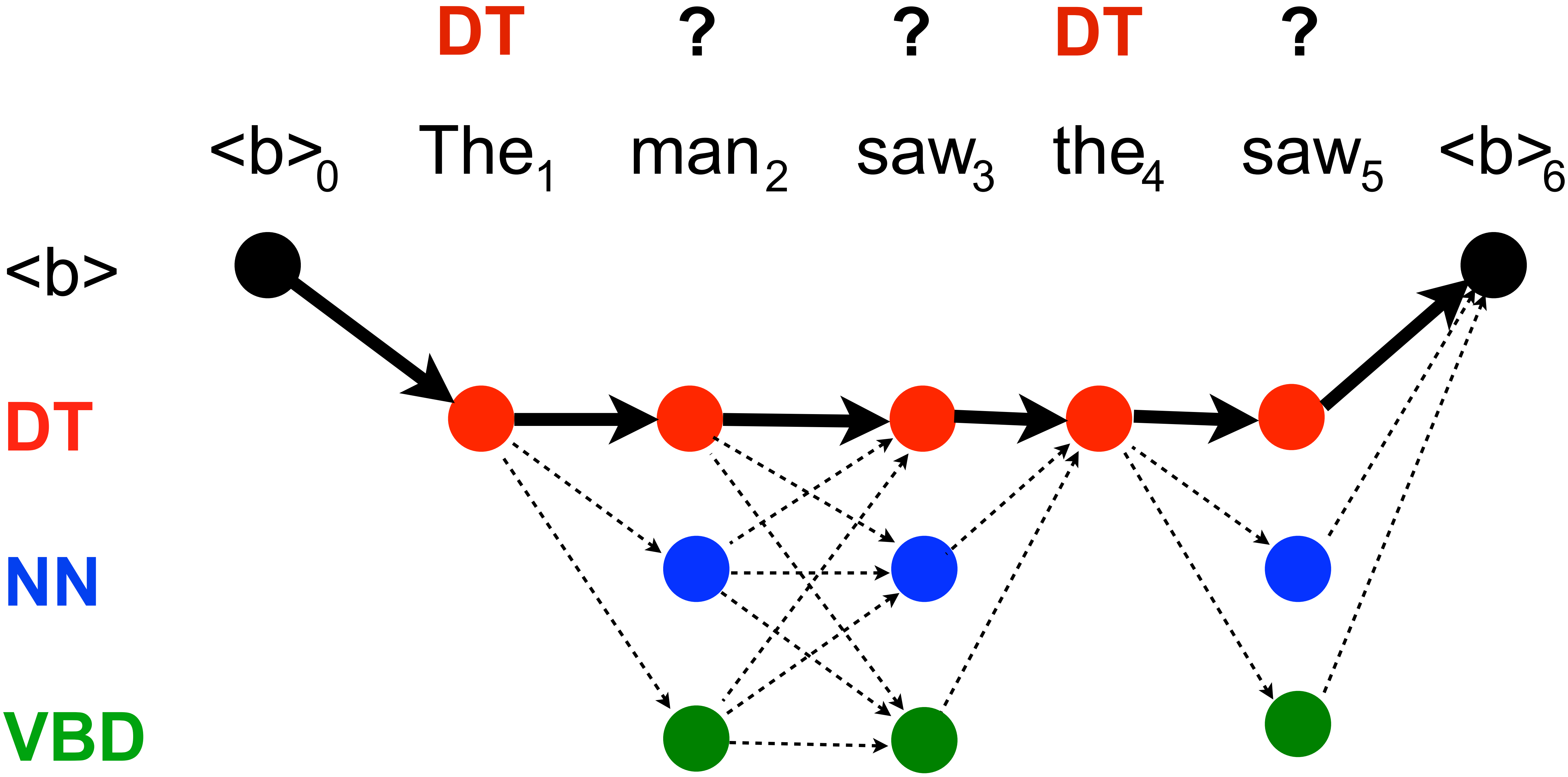

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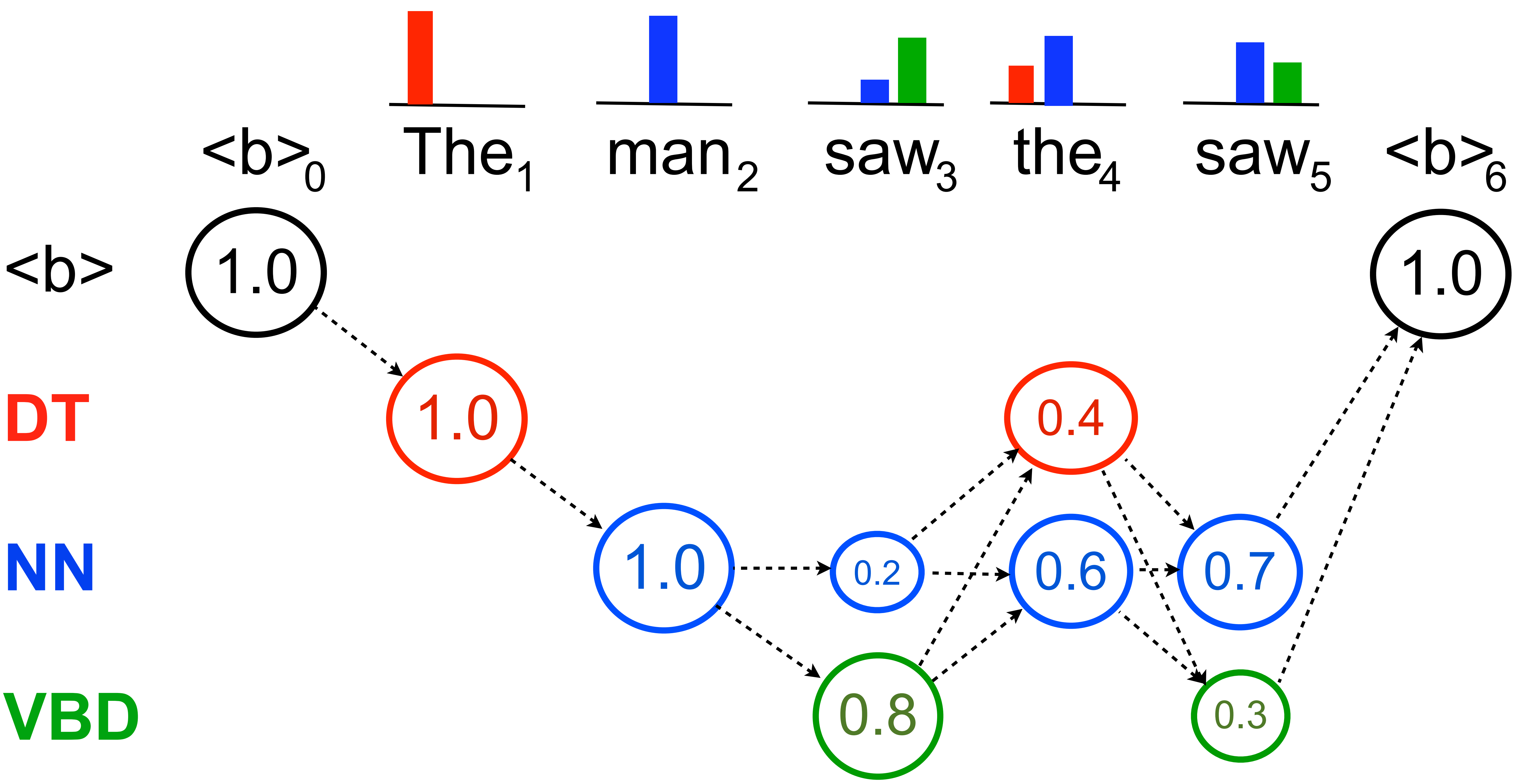

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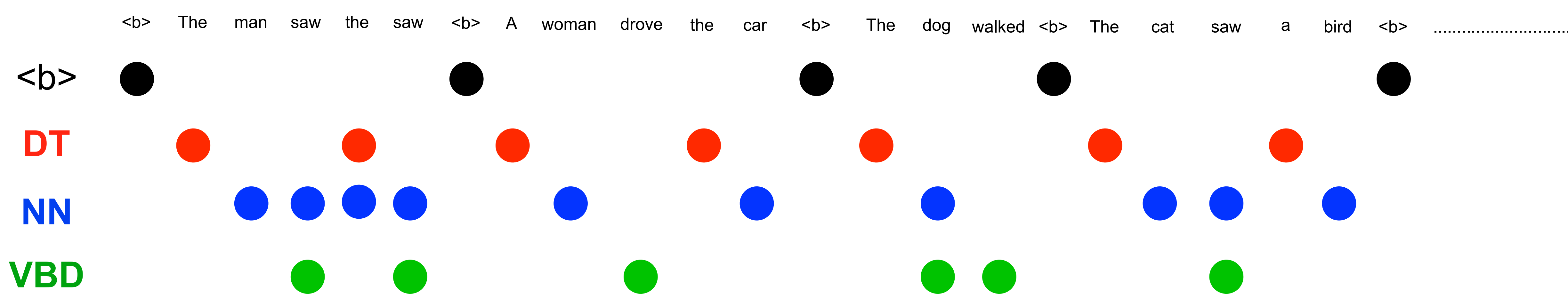
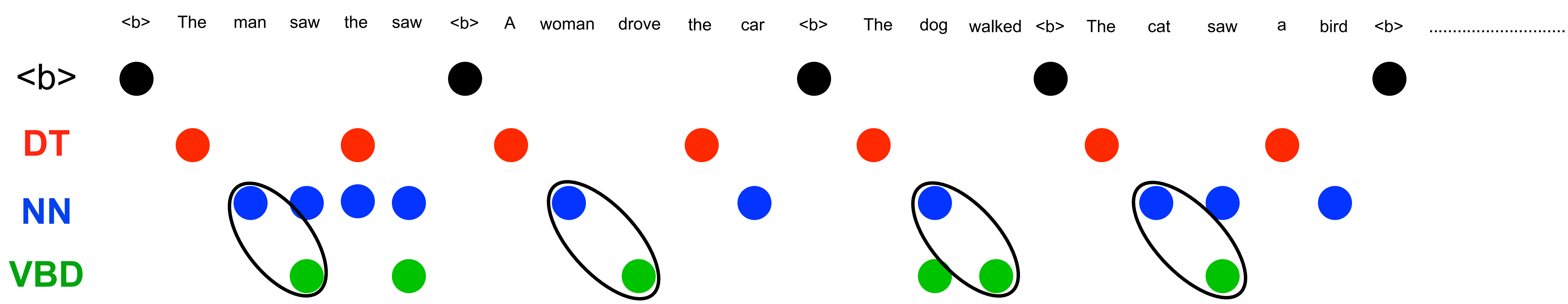
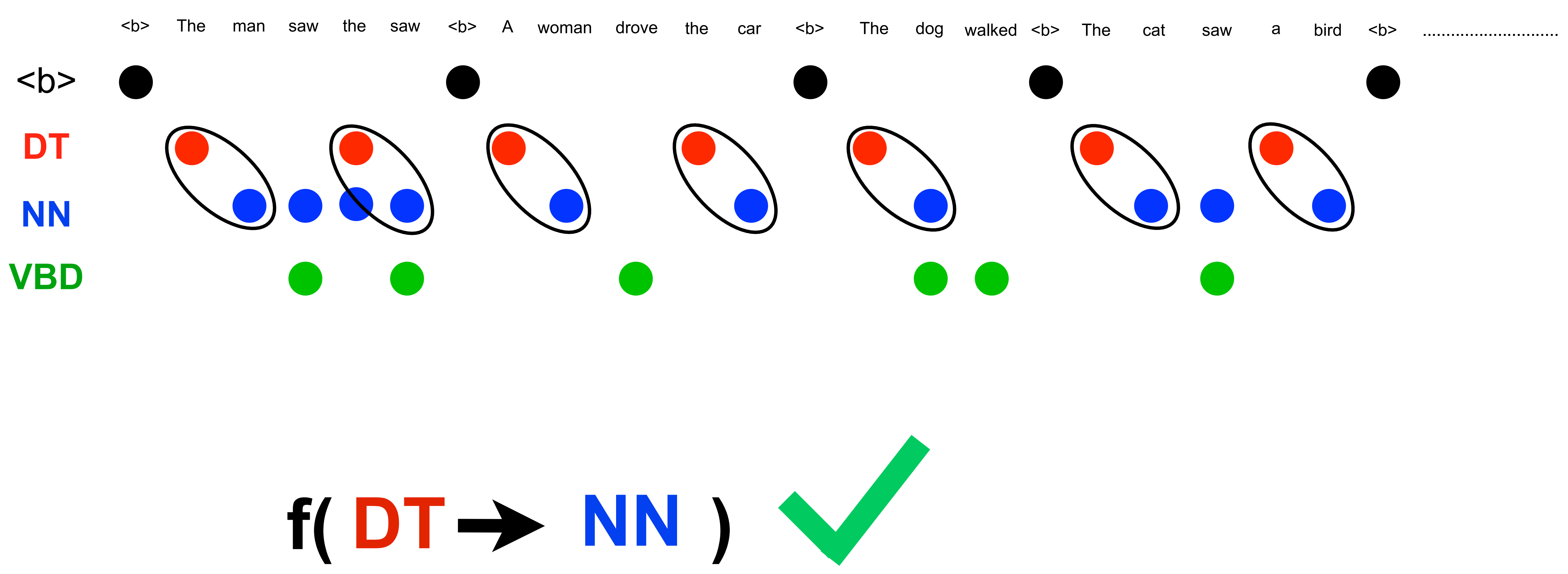


Model Minimization



$$f(\mathrm{NN} \rightarrow \mathrm{VBD}) \begin{cases} \text{tag bigram occurrences} \\ \text{weights on their nodes} \end{cases}$$

Model Minimization



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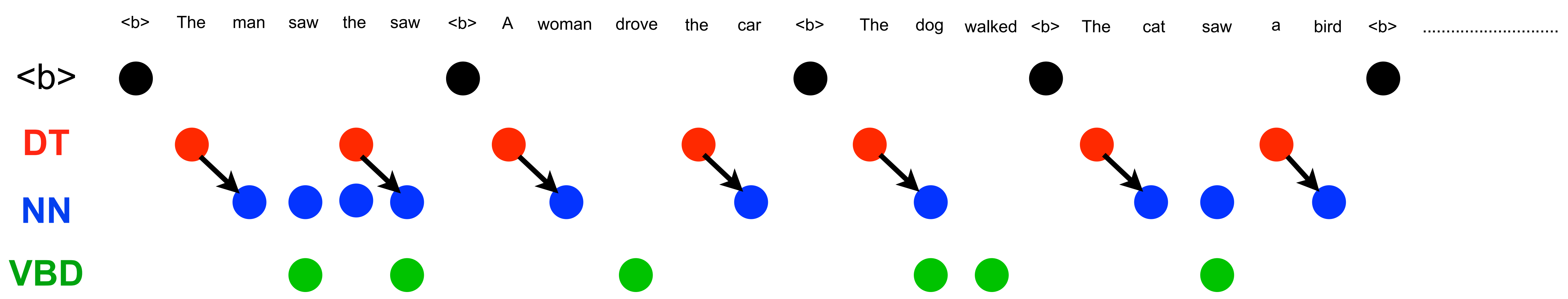

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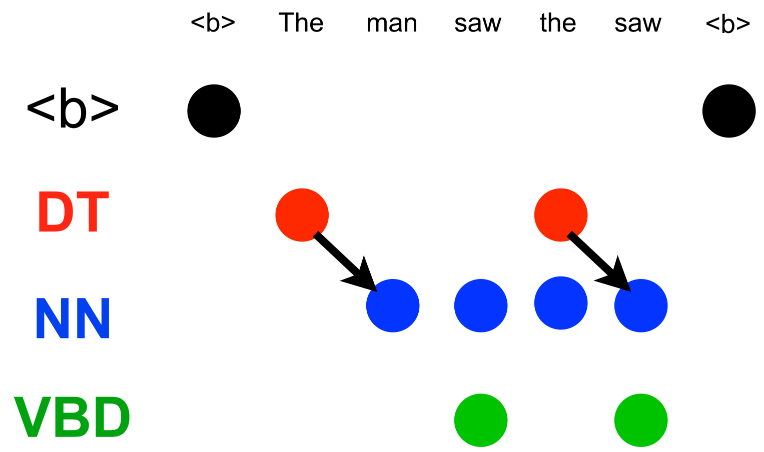

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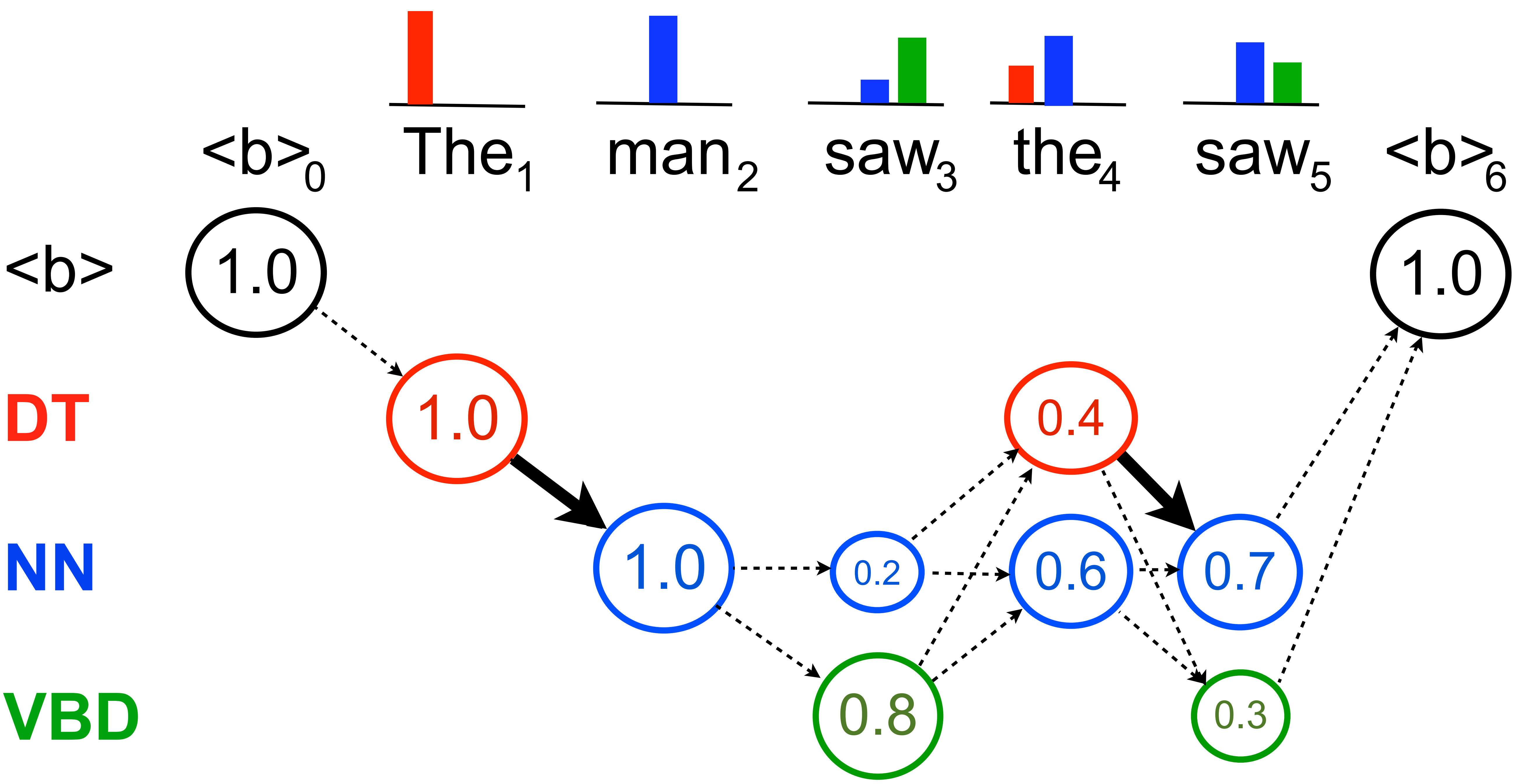

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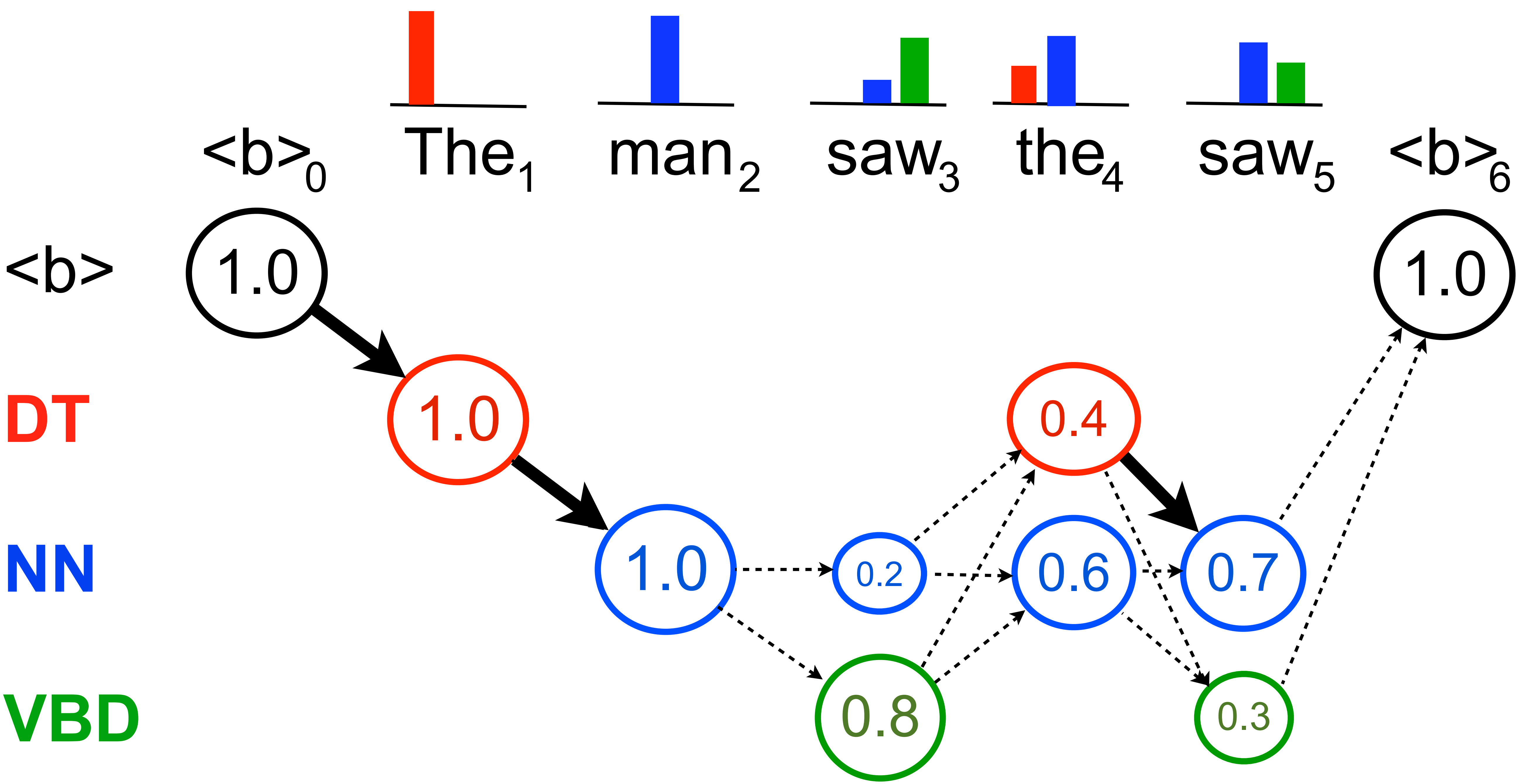

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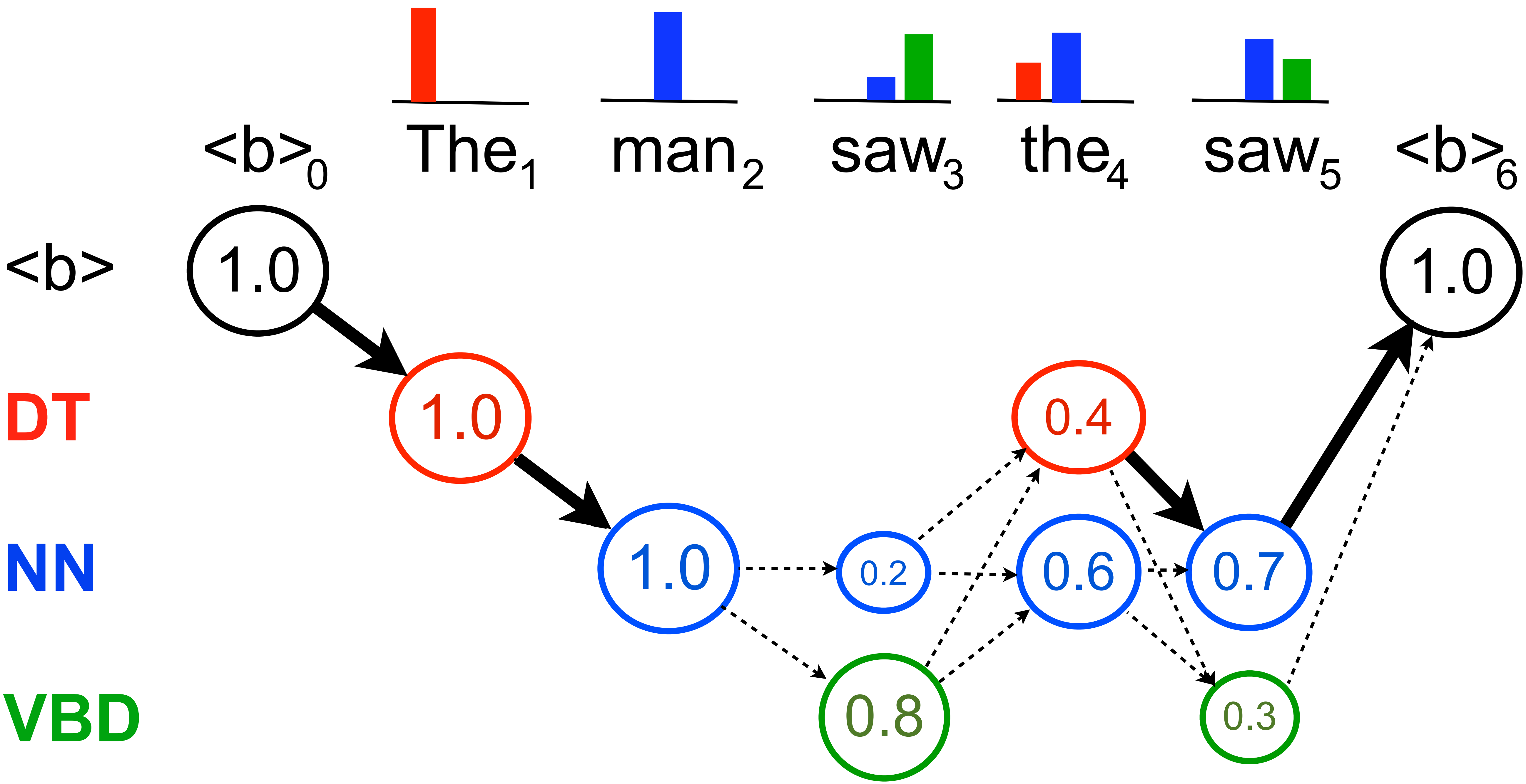

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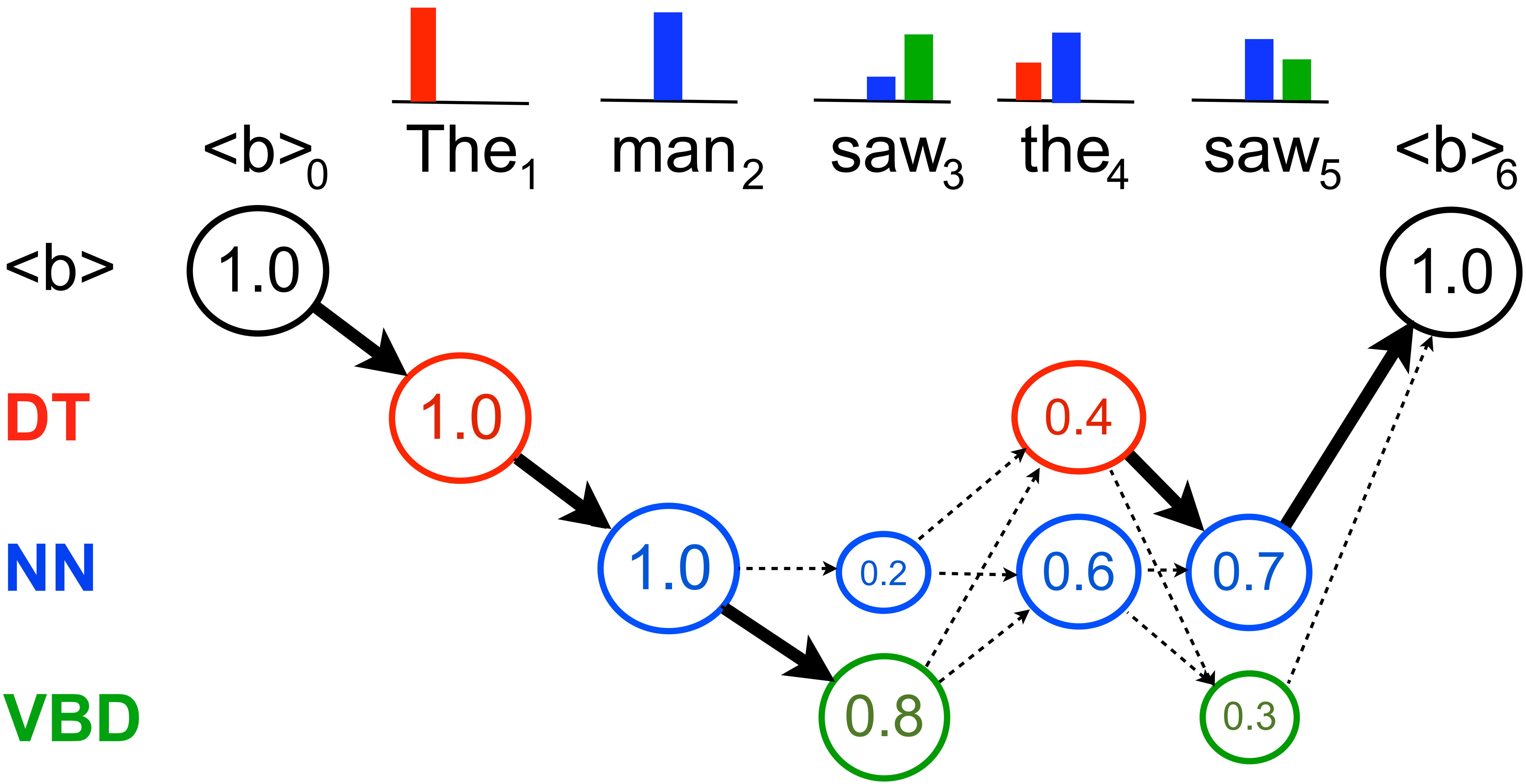

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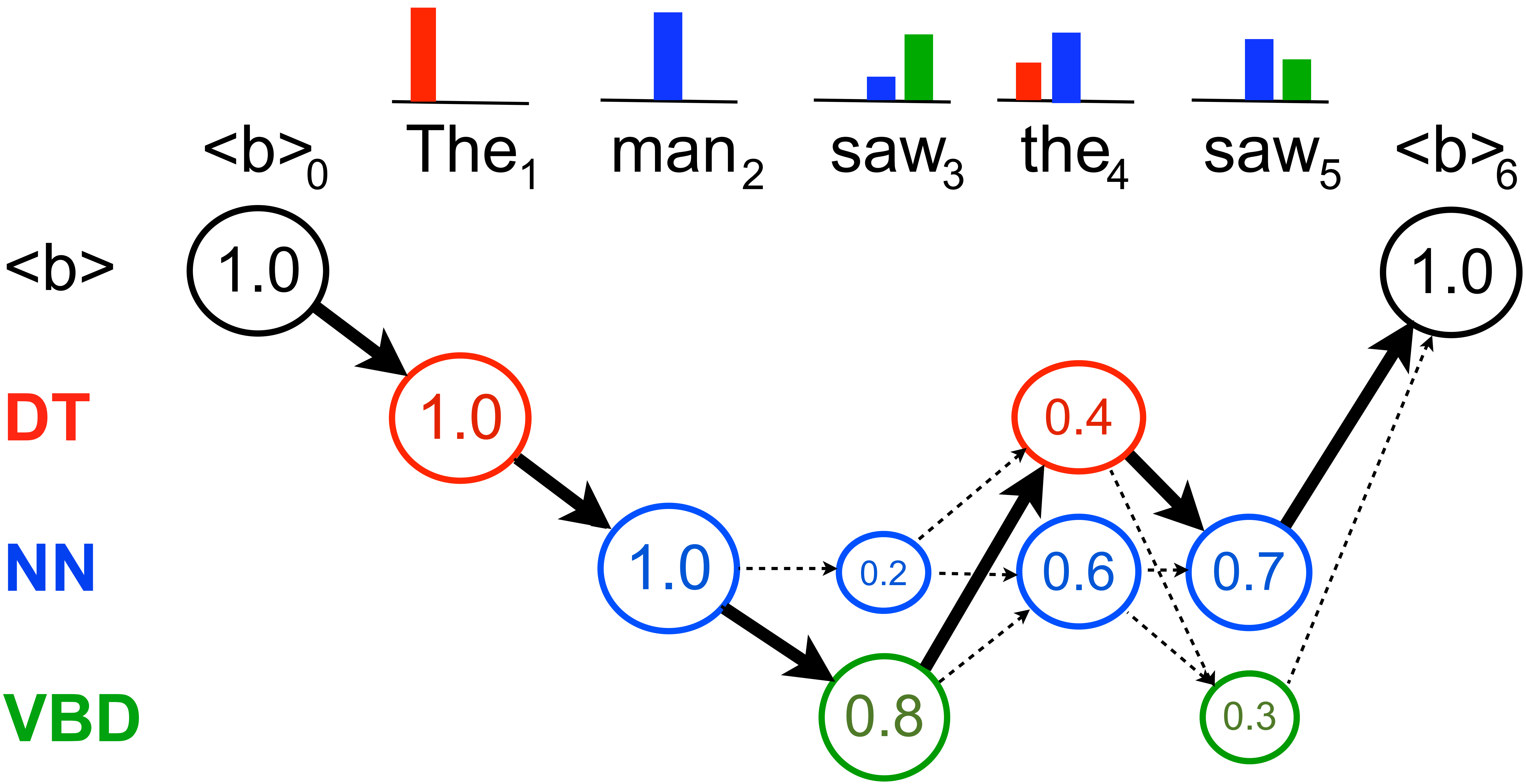

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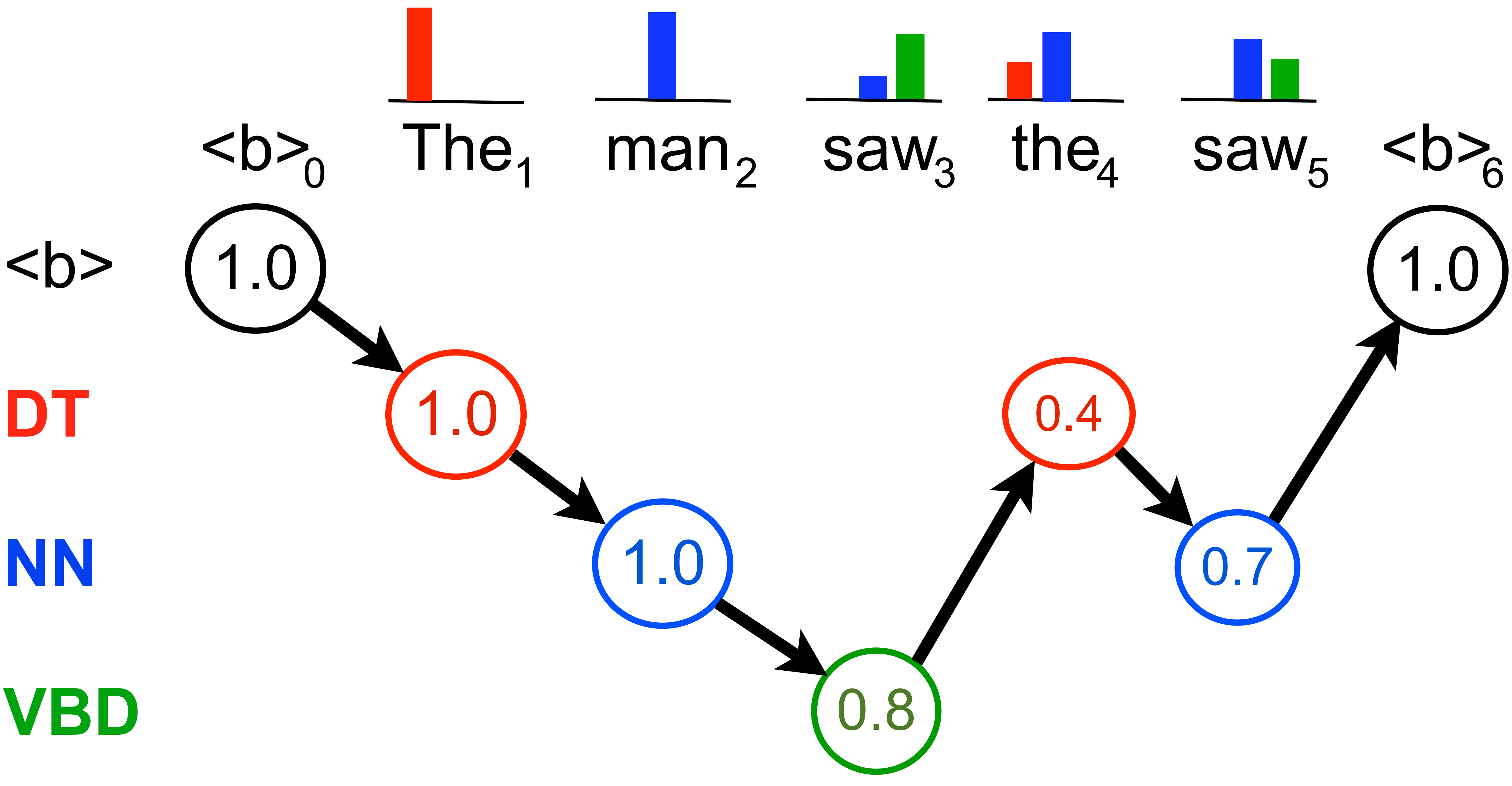

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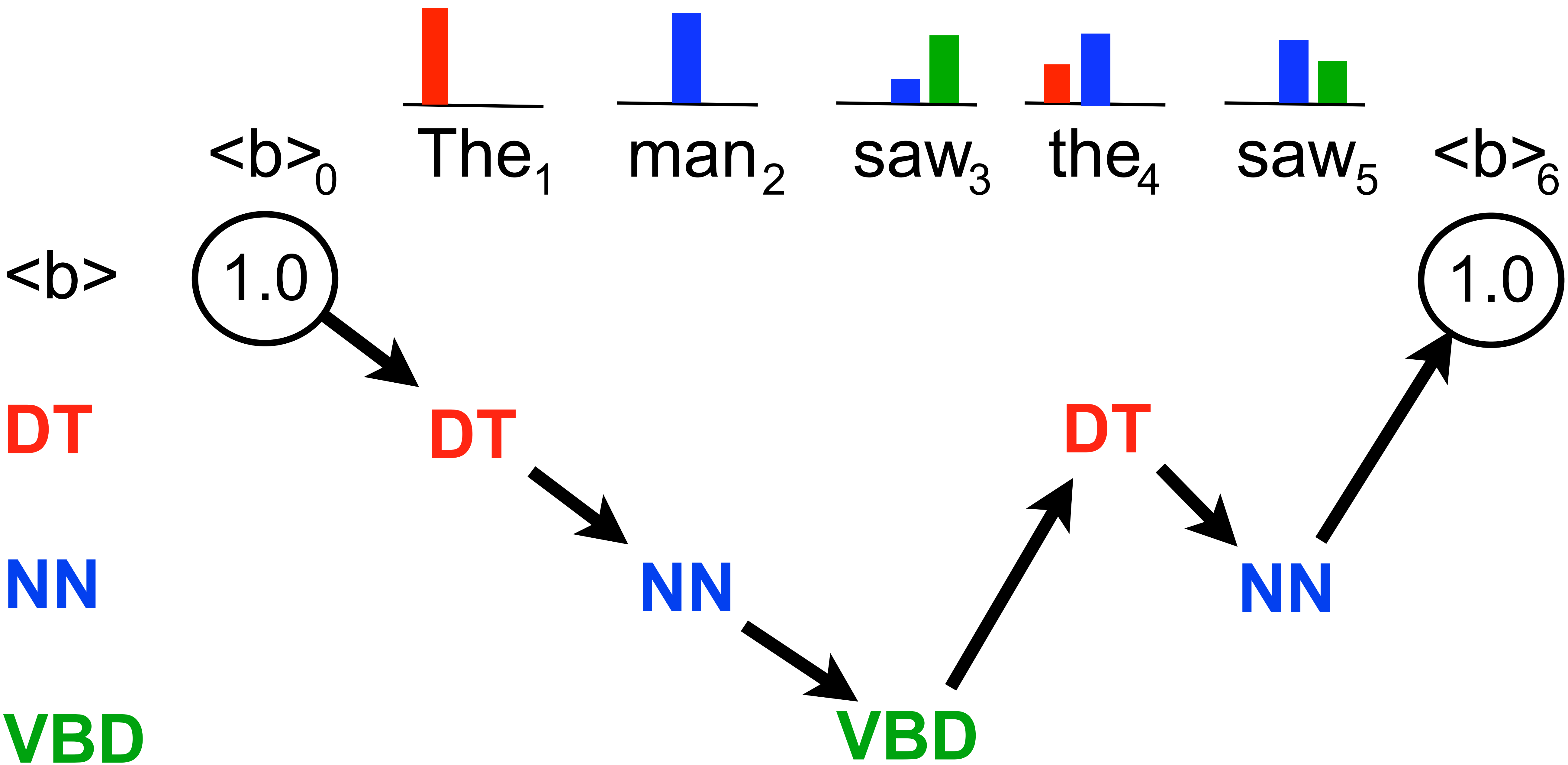
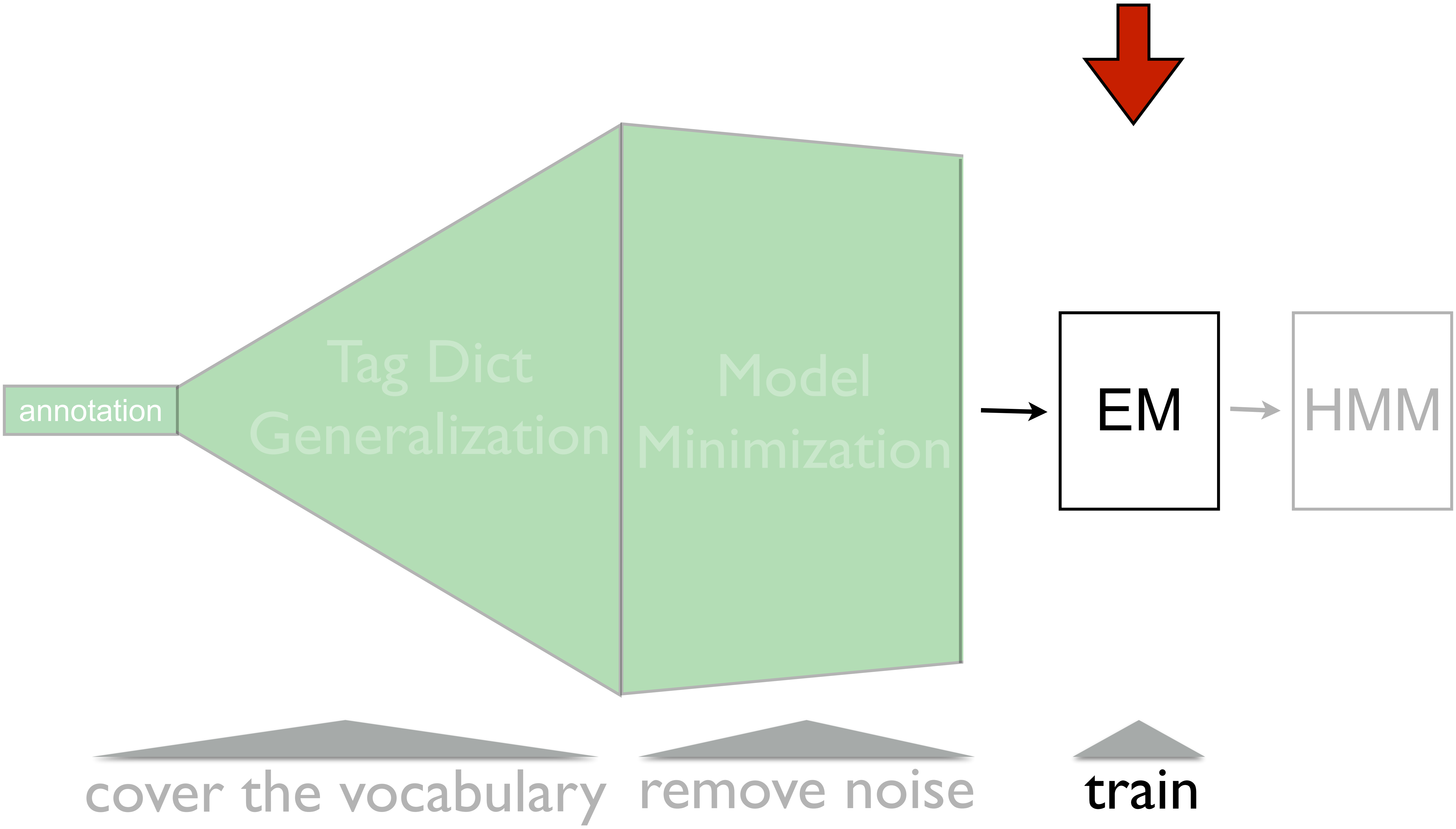


Model Minimization

<b>$_0$	The$_1$	man$_2$	saw$_3$	the$_4$	saw$_5$	<b>$_6$
	DT	**NN**	**VBD**	**DT**	**NN**	

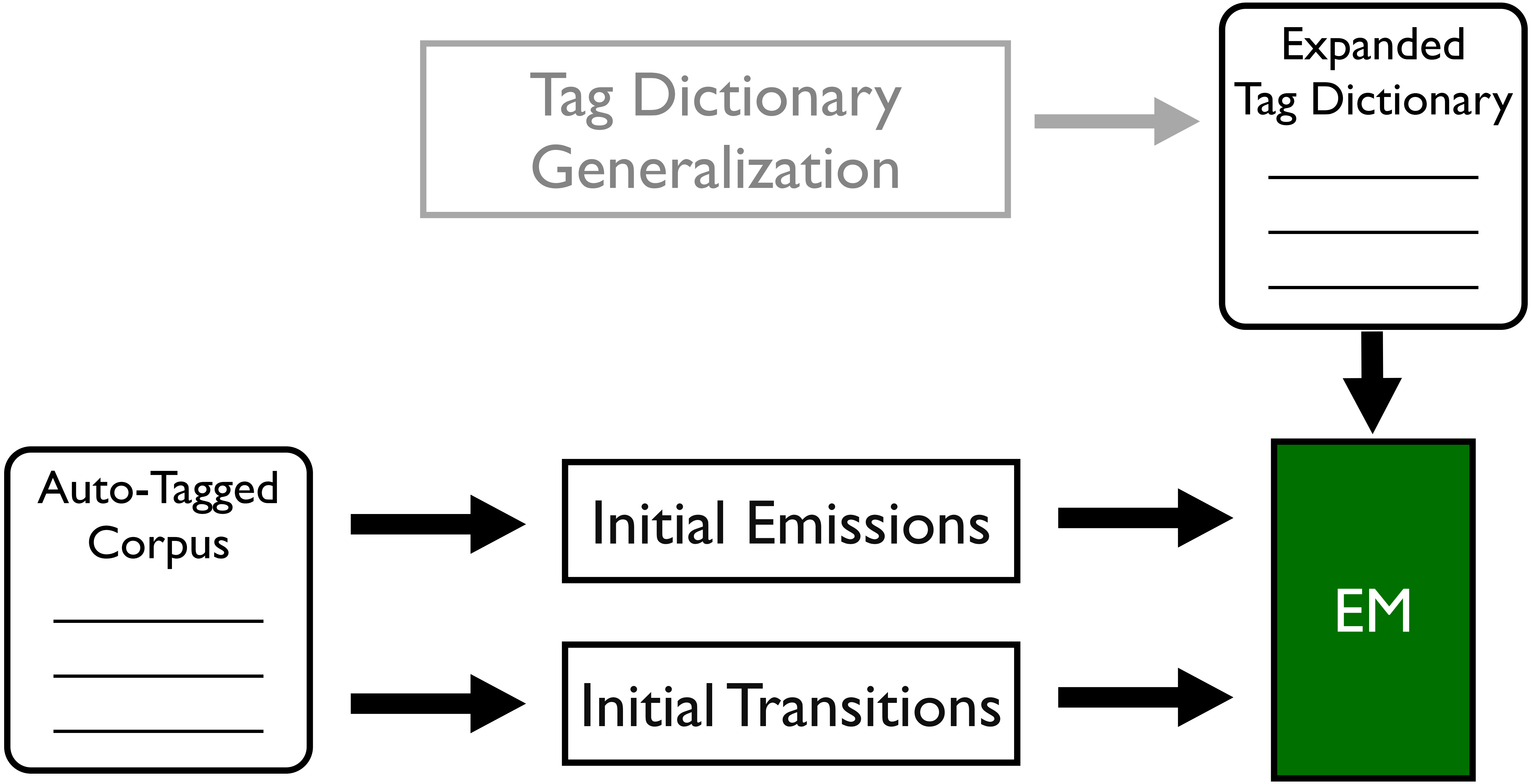
Our Approach



EM Training

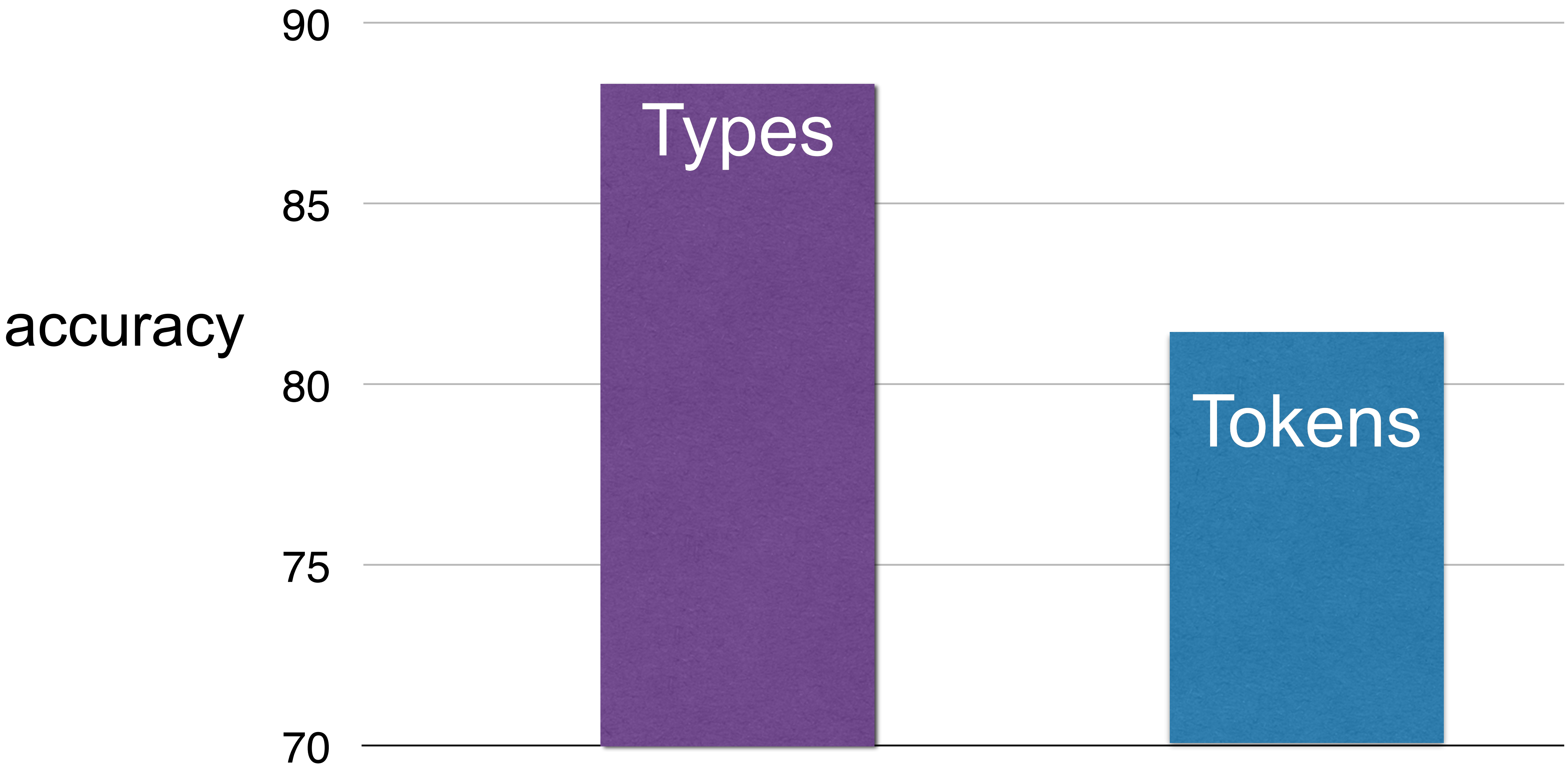
<b>$_0$	The$_1$	man$_2$	saw$_3$	the$_4$	saw$_5$	<b>$_6$
	DT	**NN**	**VBD**	**DT**	**NN**	

EM Training


Tag Dictionary Generalization
Expanded Tag Dictionary
Auto-Tagged Corpus
Initial Emissions
Initial Transitions
EM

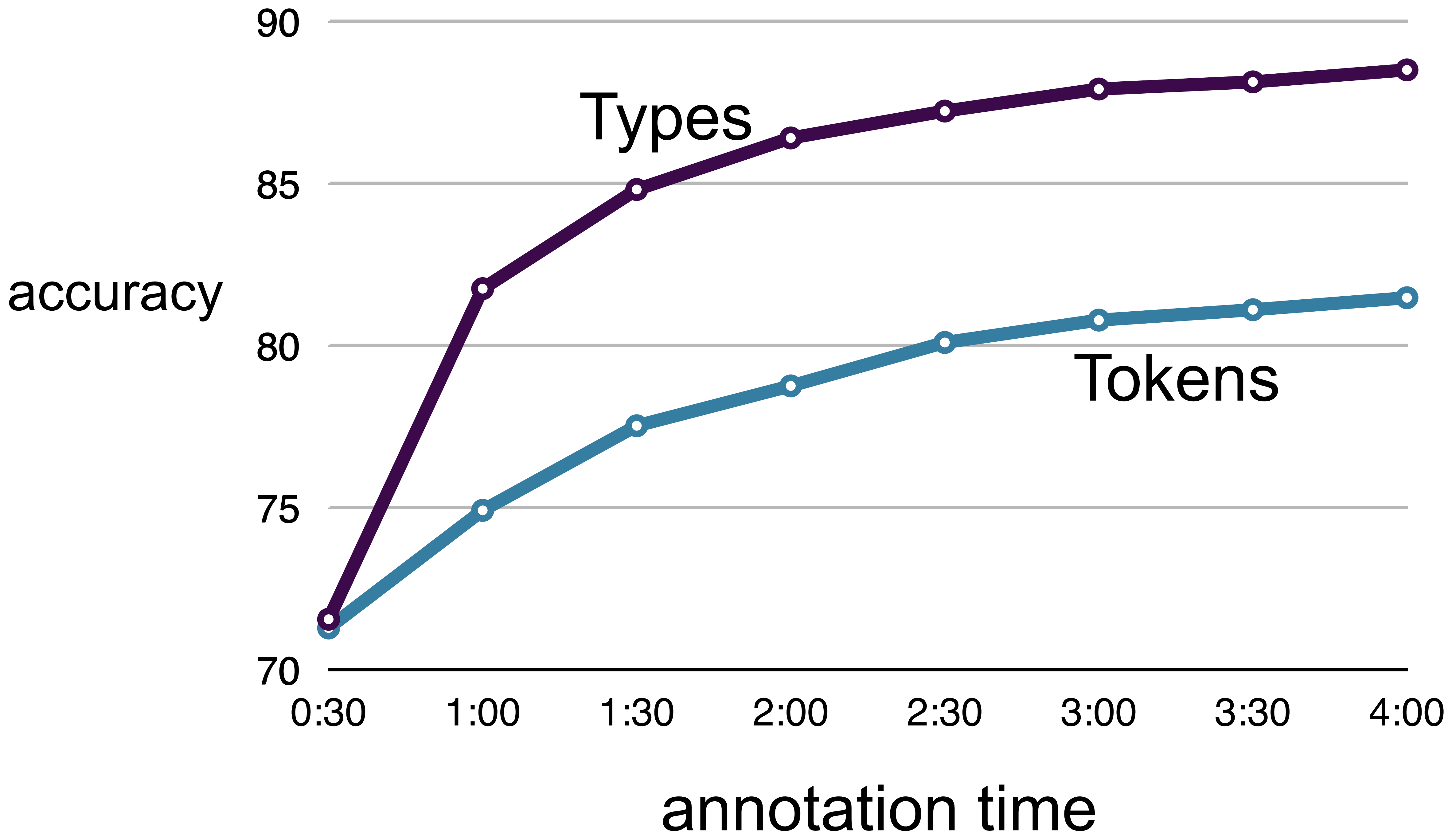
Results

Types vs. Tokens



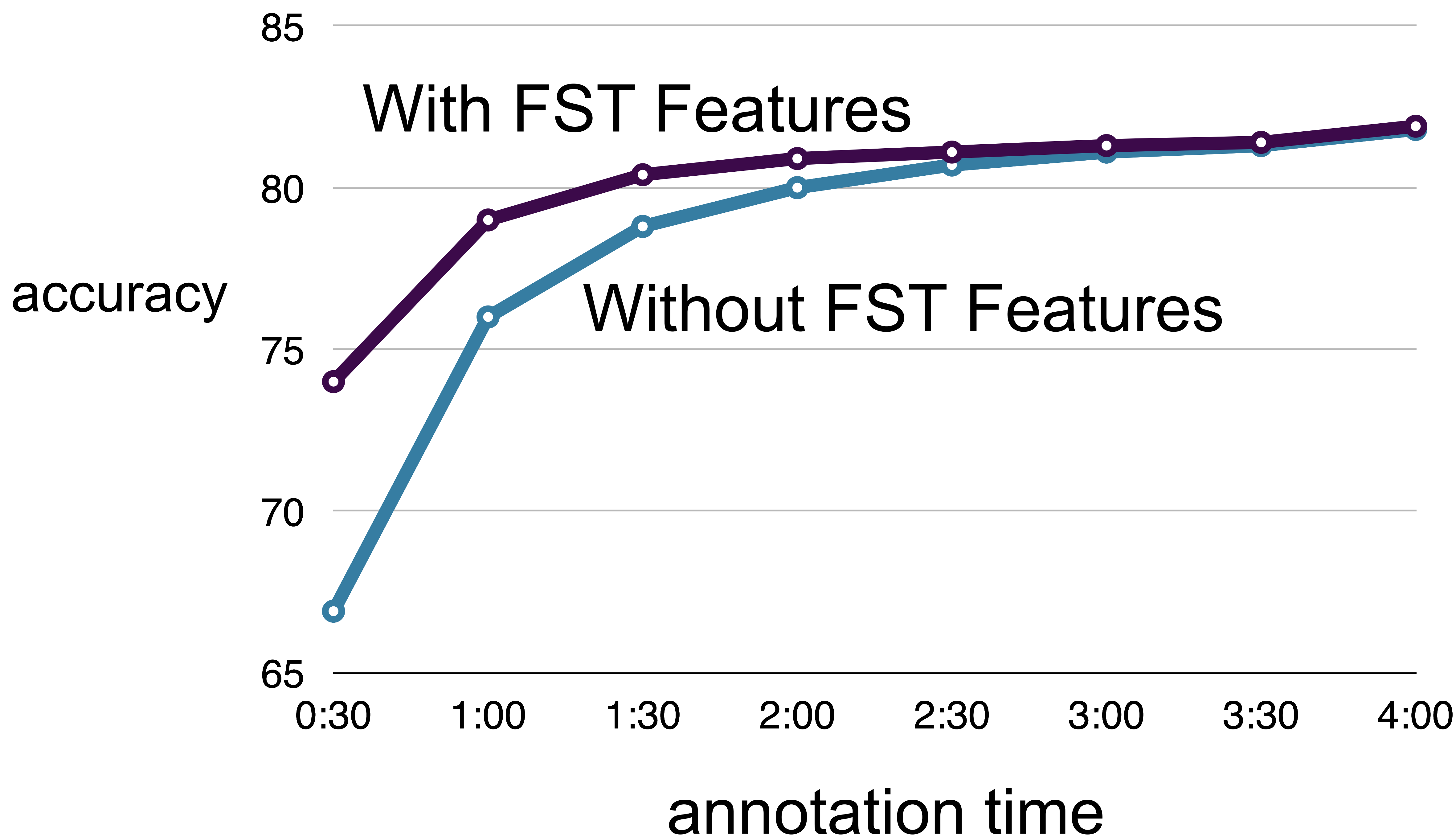
[English]

Types vs. Tokens



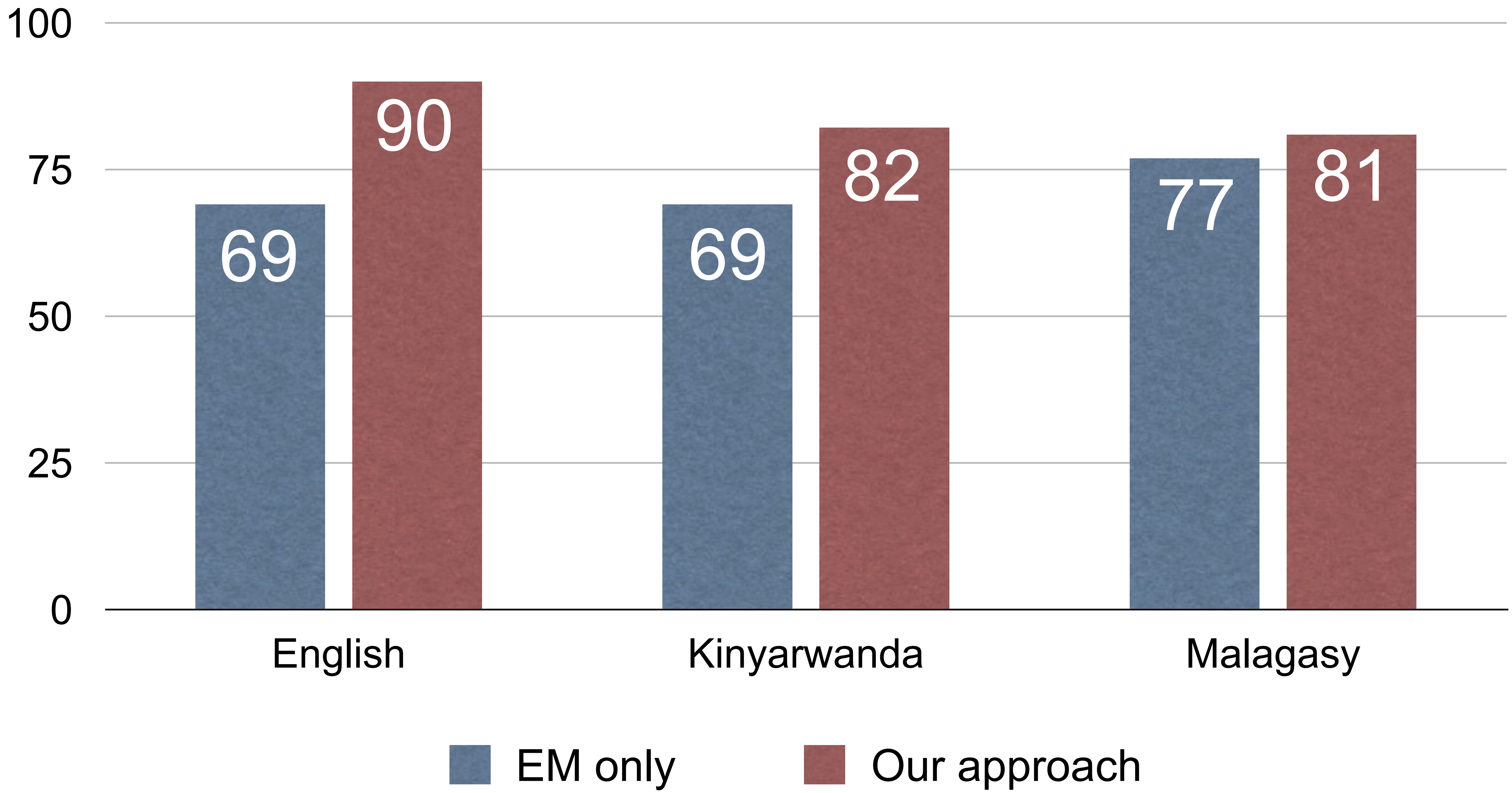
[English]

Morphological Analysis



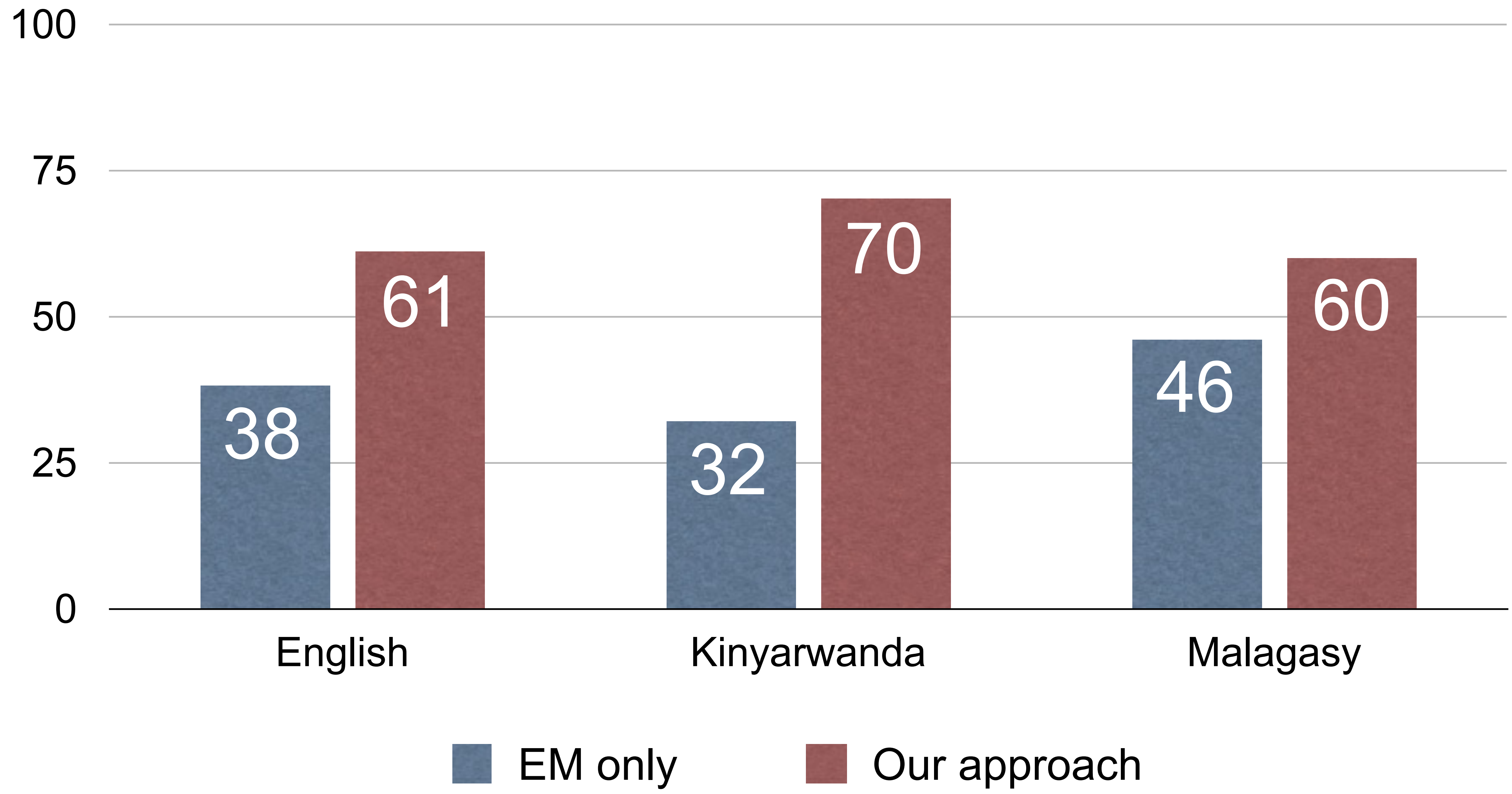
[Kinyarwanda]

Total Accuracy



[4 hours of type annotation]

Unknown Word Accuracy



[2 hours of type annotation]

English Results

12 tags	All of **Wiktionary** (Li et al., 2012)	87%
	Parallel Corpus (Täckström et al., 2013)	89%
45 tags	**4-hours** (Garrette et al., 2013)	**90%**

Rich Morphology

Parallel Corpus (Täckström et al., 2013)

Turkish	65%

4-hours (Garrette et al., 2013)

Kinyarwanda	**82%**

Current Work

- Minimally supervised CCG supertagging and parsing
- Human-provided GFL annotations

Conclusion

- Our approach is able to achieve results better that or comparable to others, but given significantly less input.
- Our annotations are available to others.
- Software available as well.