Large vocabulary language modeling

Essential epistemology

	Exact sciences
Deals with	Axioms & theorems
Truth is	Forever
Examples	Mathematics C.S. theory **F.L. theory**

Essential epistemology

	Exact sciences	Empirical sciences
Deals with	Axioms & theorems	Facts & theories
Truth is	Forever	Temporary
Examples	Mathematics C.S. theory **F.L. theory**	Physics Biology **Linguistics**

Essential epistemology

	Exact sciences	Empirical sciences	Engineering
Deals with	Axioms & theorems	Facts & theories	Artifacts
Truth is	Forever	Temporary	It works
Examples	Mathematics C.S. theory **F.L. theory**	Physics Biology **Linguistics**	Many, including applied C.S. e.g. **NLP**

Essential epistemology

Exact sciences	Empirical sciences	Engineering
	morphological properties of words (facts)	

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	morphological properties of words (facts) optimality theory	

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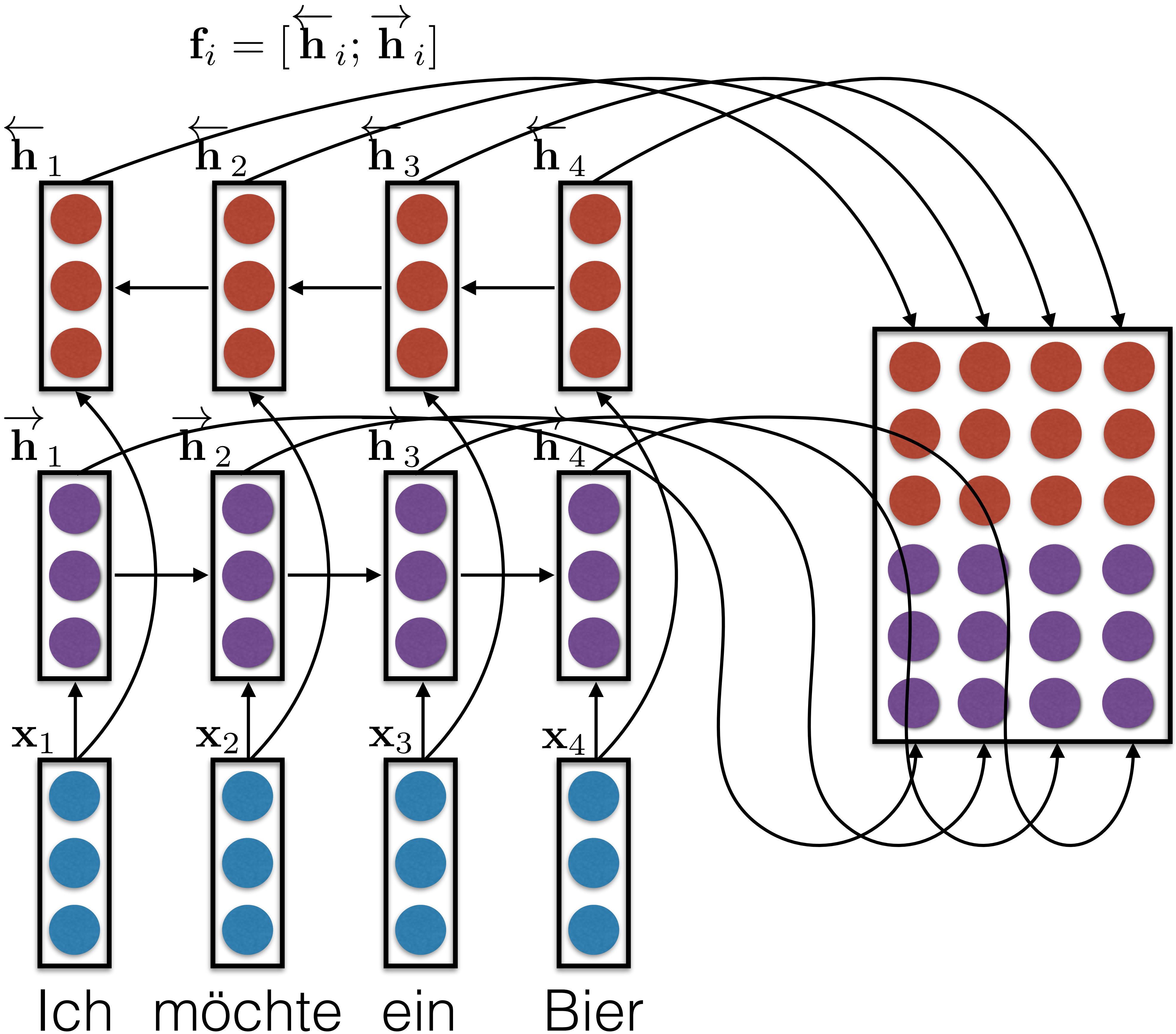
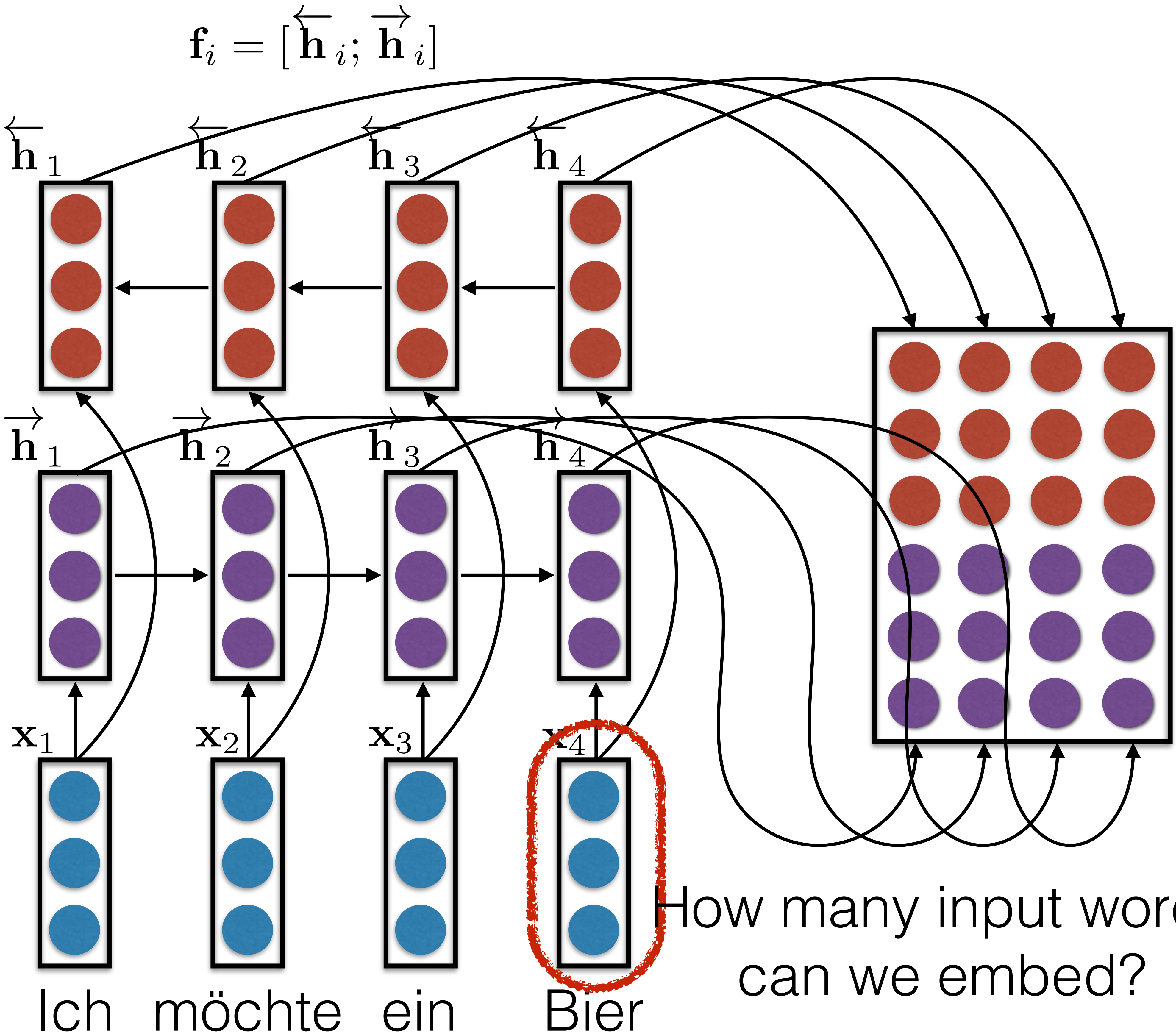
Essential epistemology

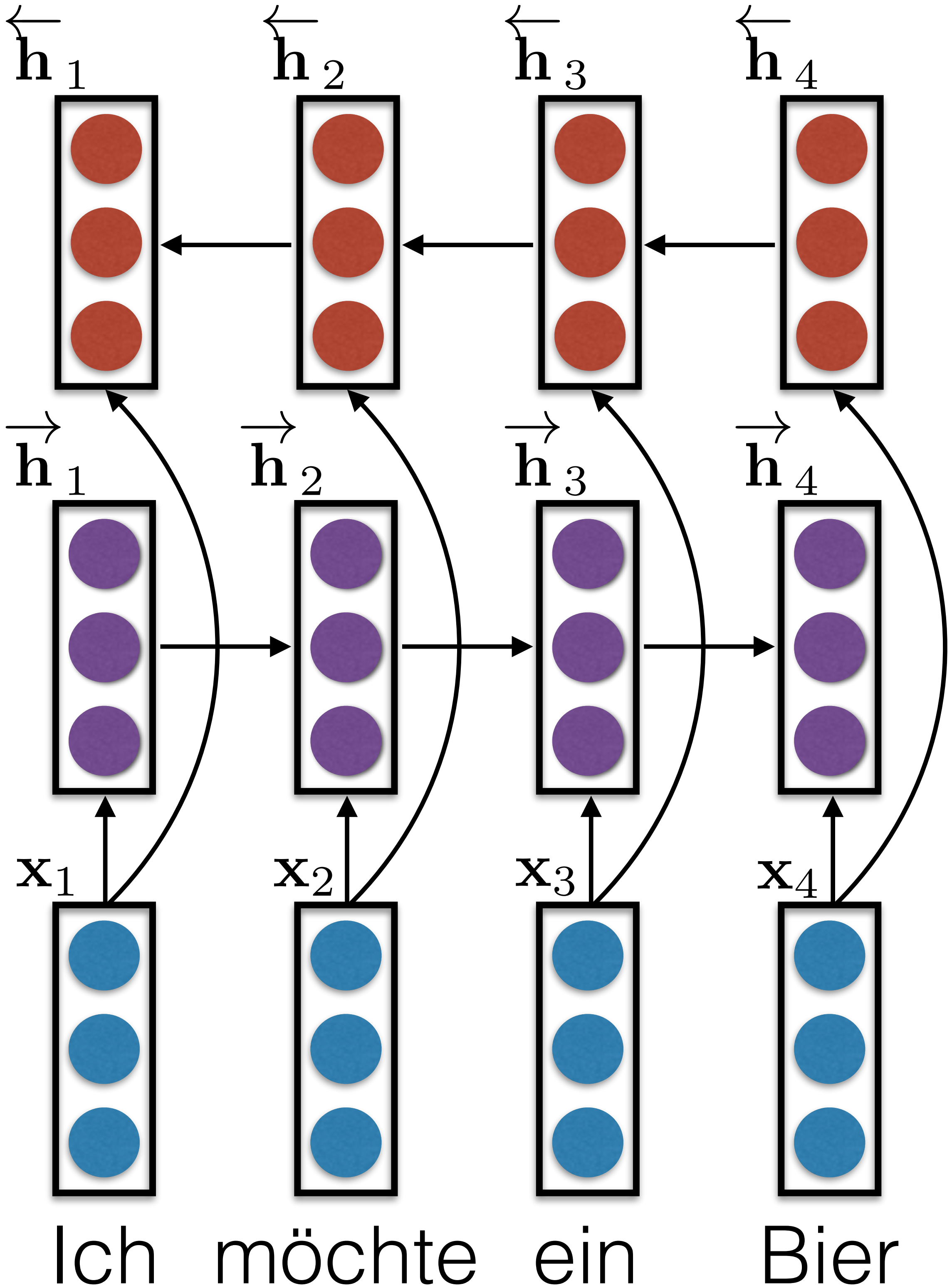
Exact sciences	Empirical sciences	Engineering
optimality theory is finite-state	morphological properties of words (facts)	we can represent words using finite-state machines (or *continuous*-state machines, i.e. NNs)
	optimality theory	


$\mathbf{f}_i = [\overleftarrow{\mathbf{h}}_i; \overrightarrow{\mathbf{h}}_i]$
$\overleftarrow{\mathbf{h}}_1$
$\overleftarrow{\mathbf{h}}_2$
$\overleftarrow{\mathbf{h}}_3$
$\overleftarrow{\mathbf{h}}_4$
$\overrightarrow{\mathbf{h}}_1$
$\overrightarrow{\mathbf{h}}_2$
$\overrightarrow{\mathbf{h}}_3$
$\overrightarrow{\mathbf{h}}_4$
$\mathbf{x}_1$
$\mathbf{x}_2$
$\mathbf{x}_3$
$\mathbf{x}_4$
Ich
möchte
ein
Bier

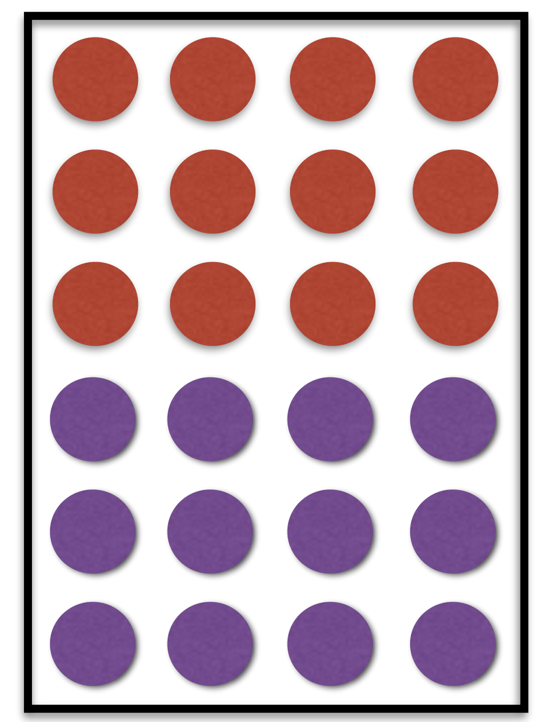


How many input words can we embed?

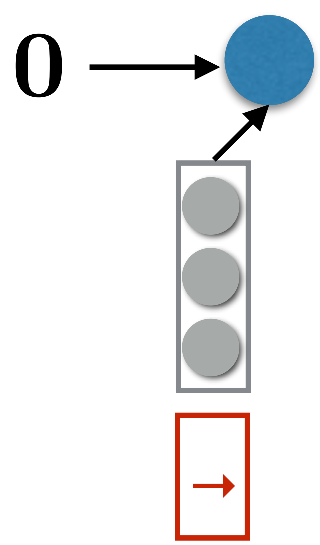
$$\mathbf{f}_i = [\overleftarrow{\mathbf{h}}_i; \overrightarrow{\mathbf{h}}_i]$$

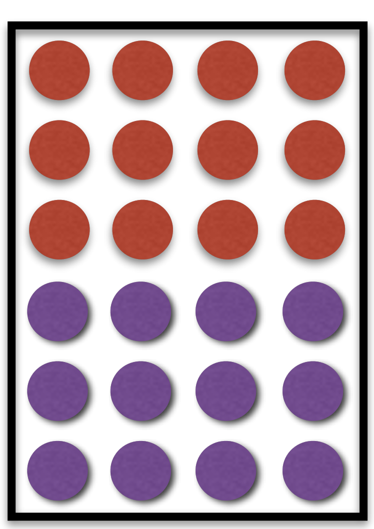


$\mathbf{F} \in \mathbb{R}^{2n \times |\boldsymbol{f}|}$



Ich möchte ein Bier





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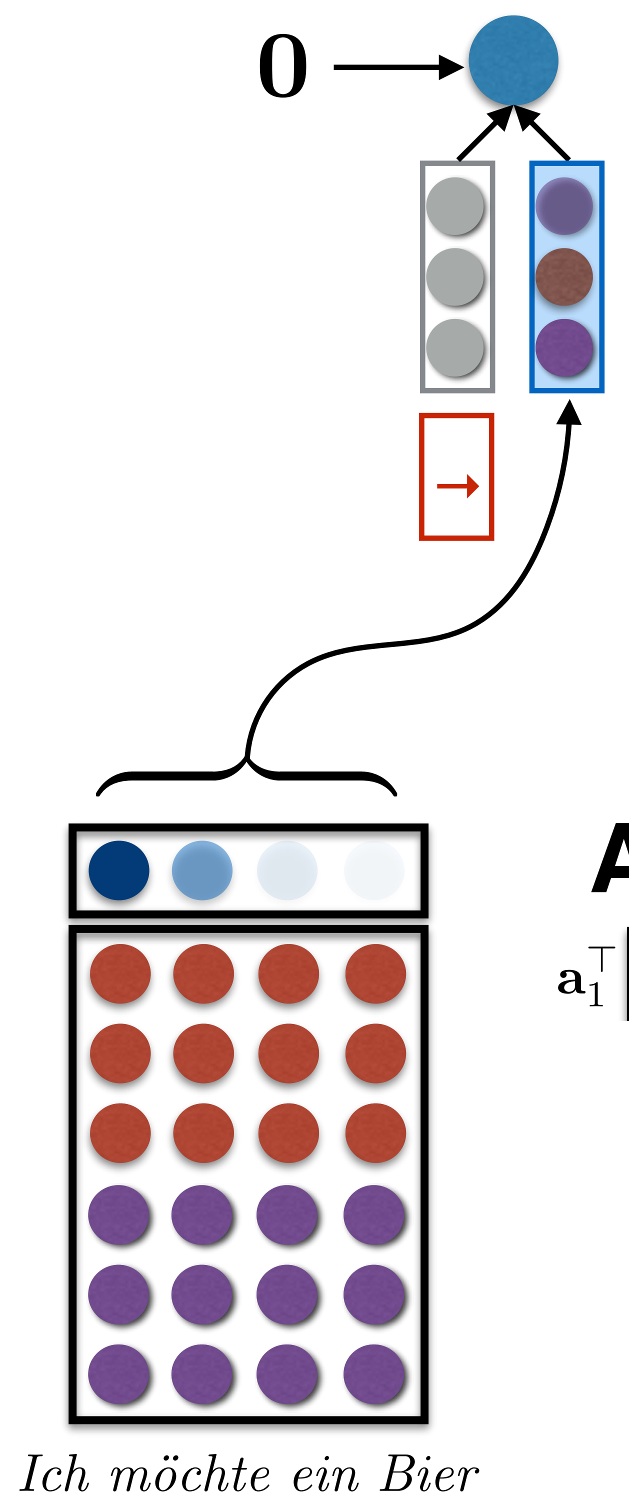

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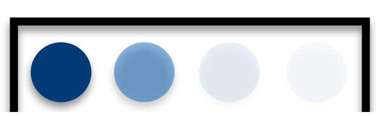
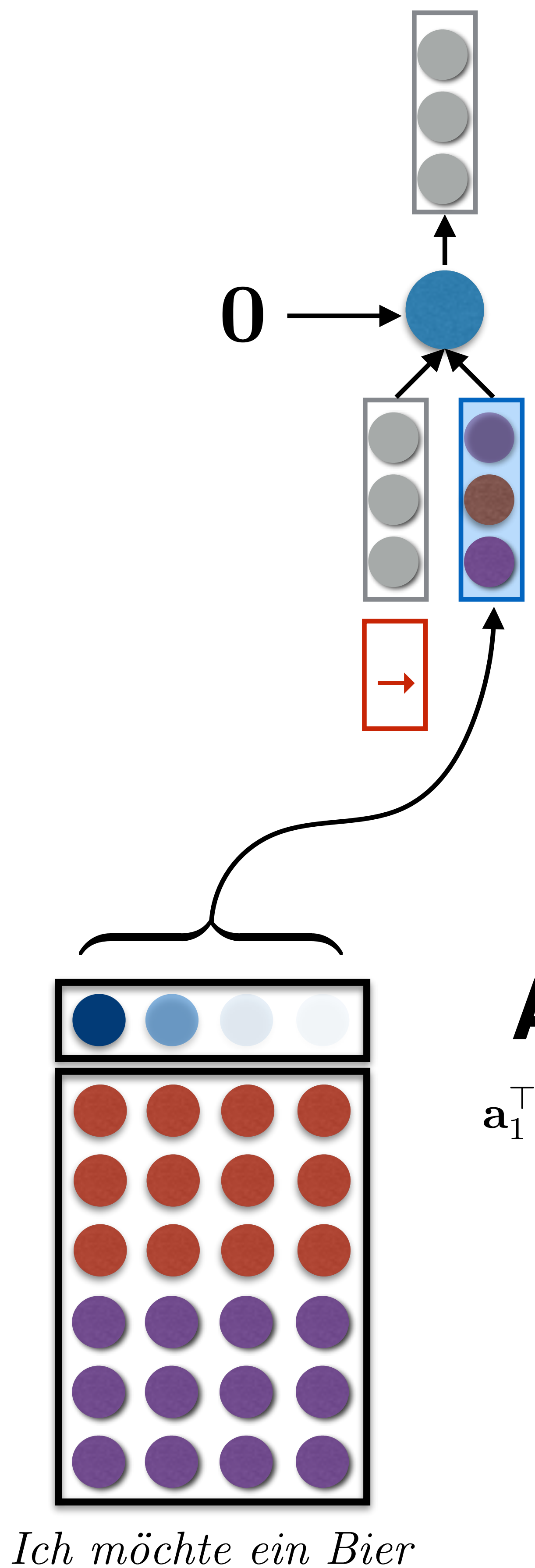
$\mathbf{a}_1^\top$ 



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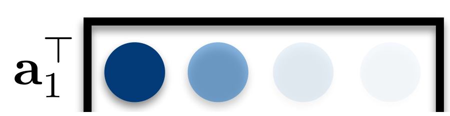

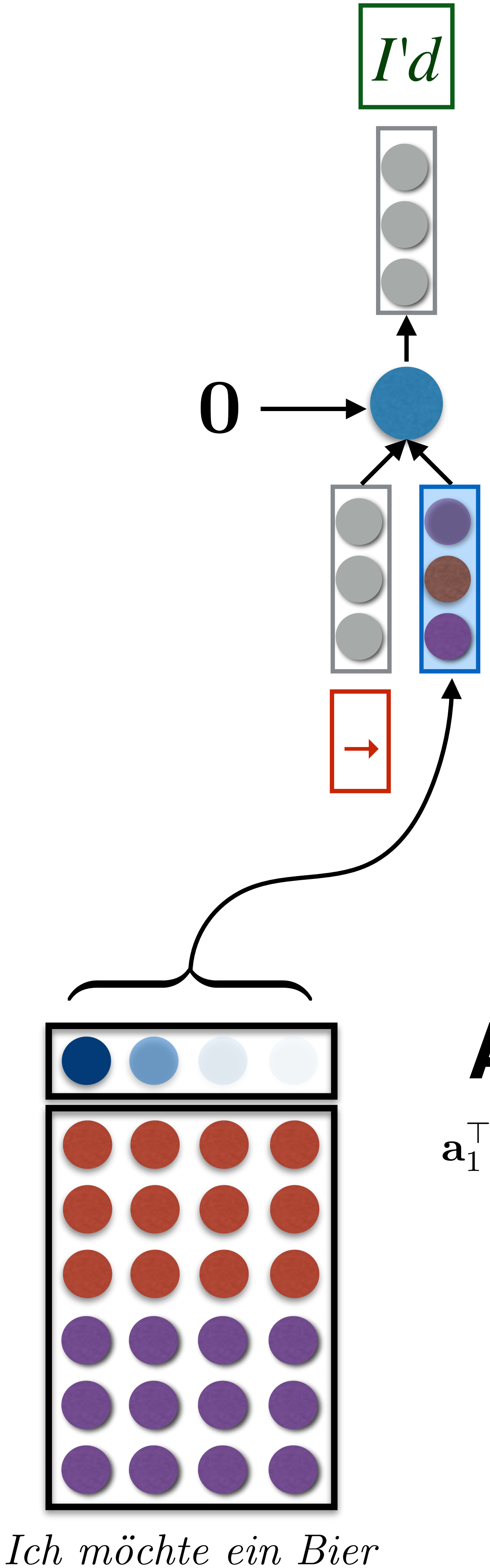

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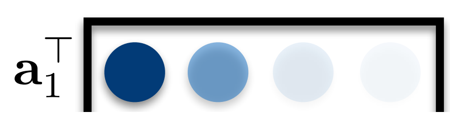

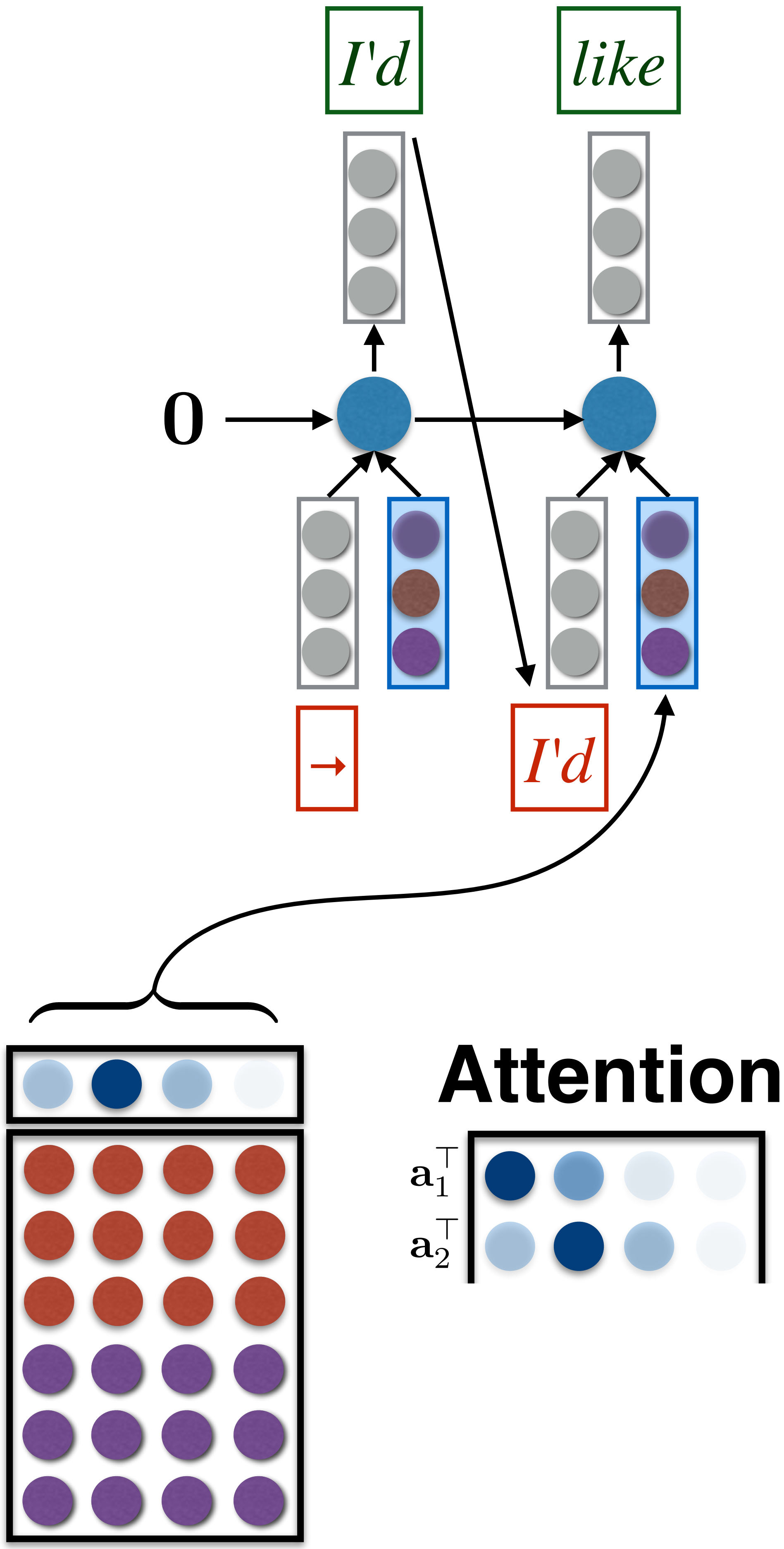

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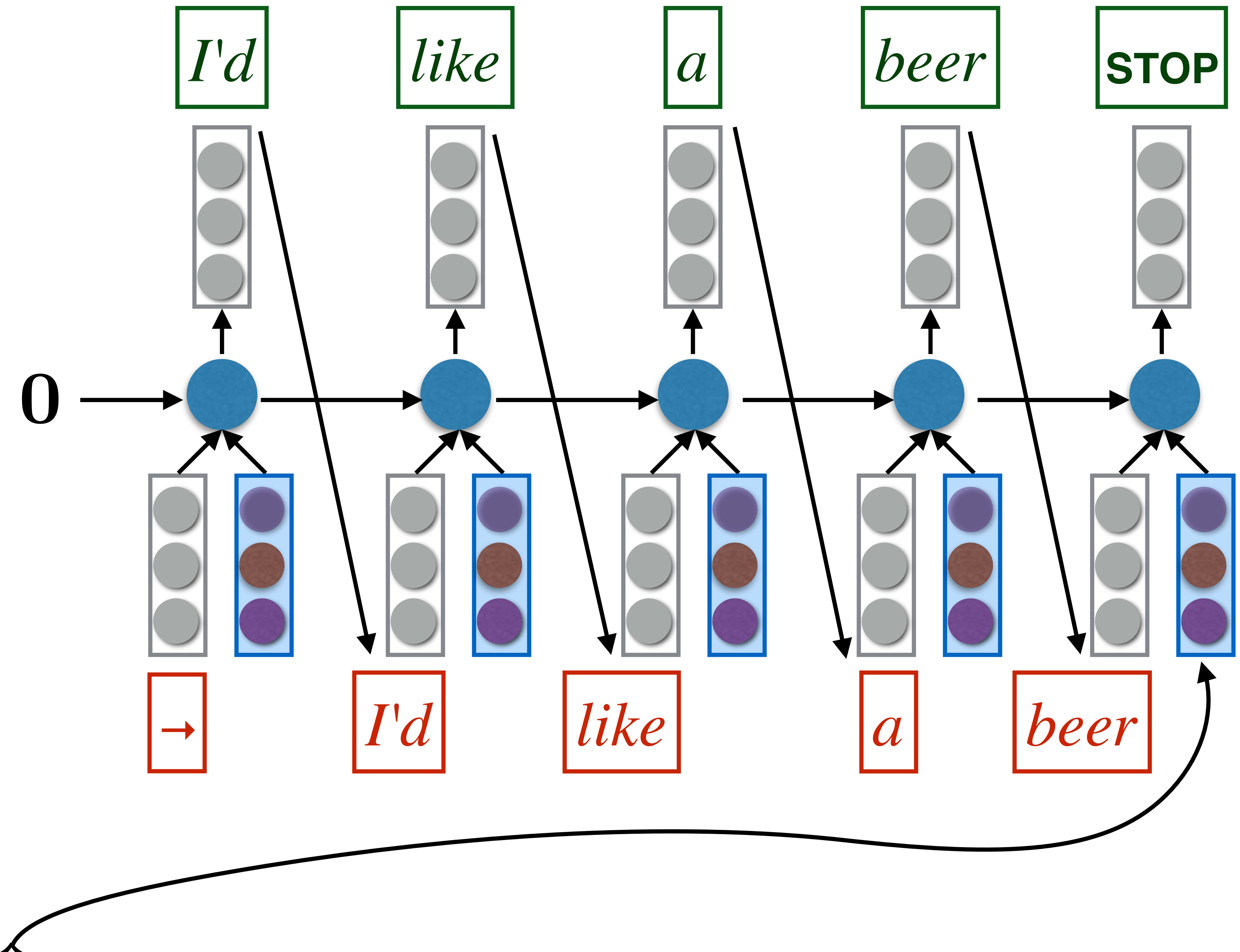

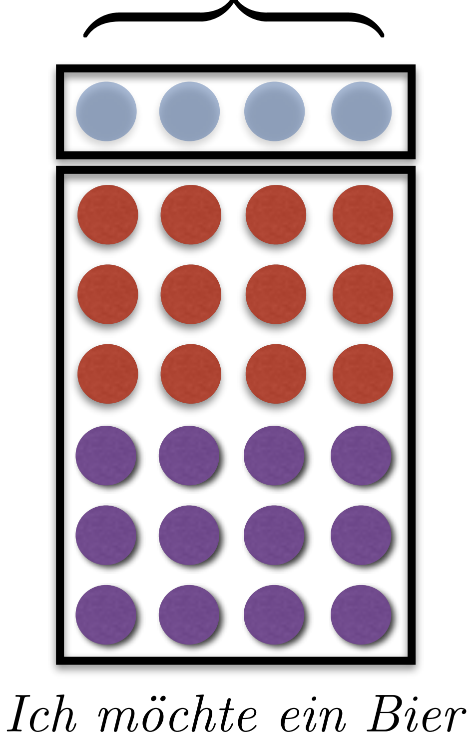

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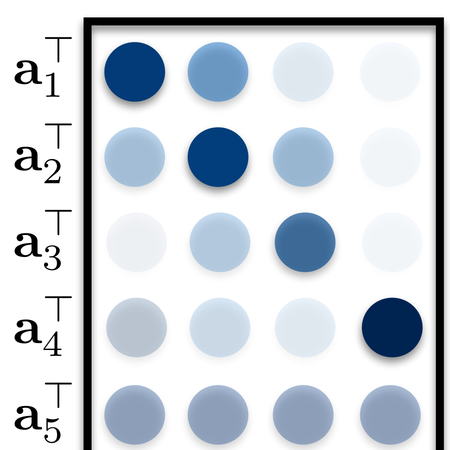
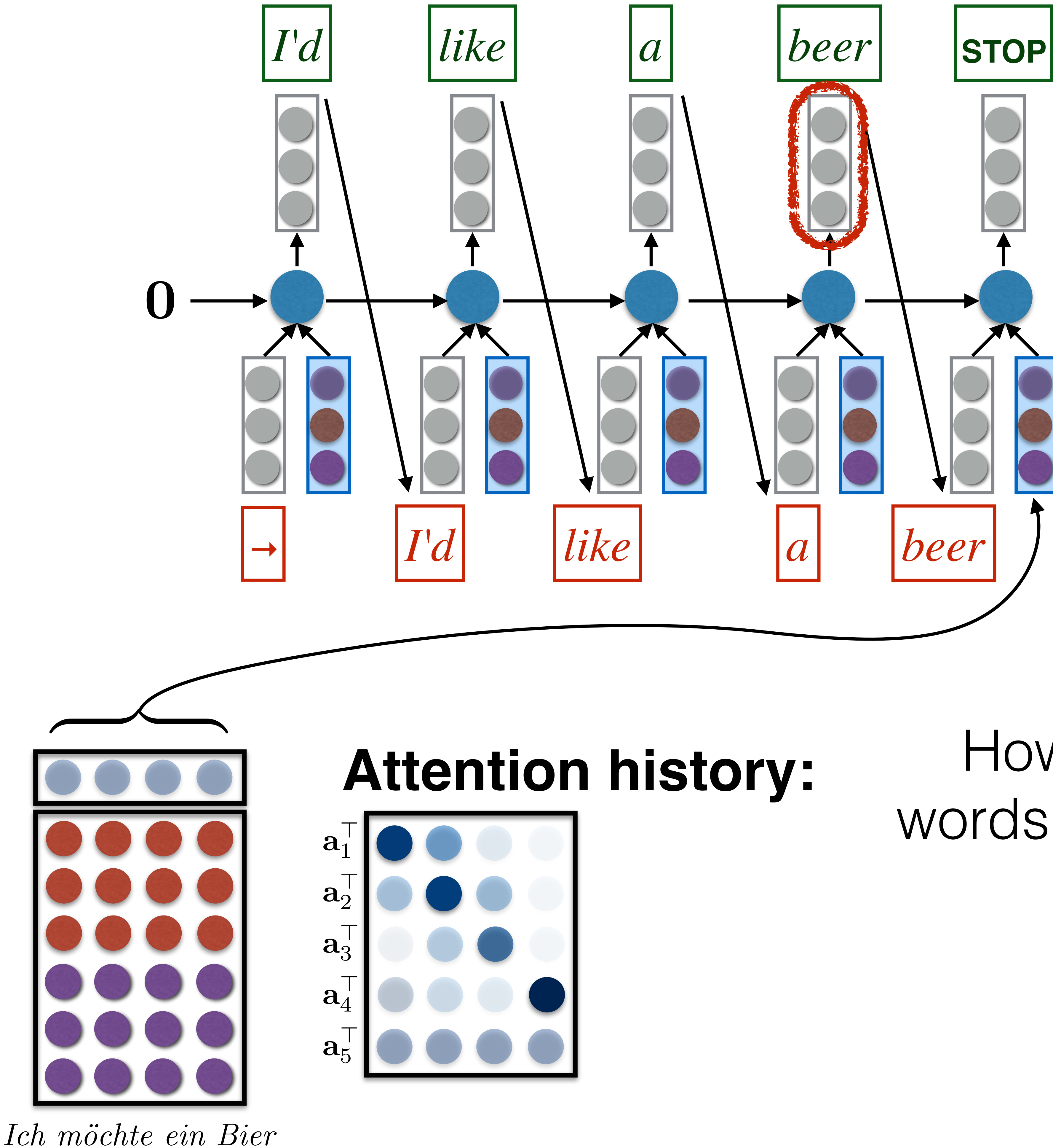


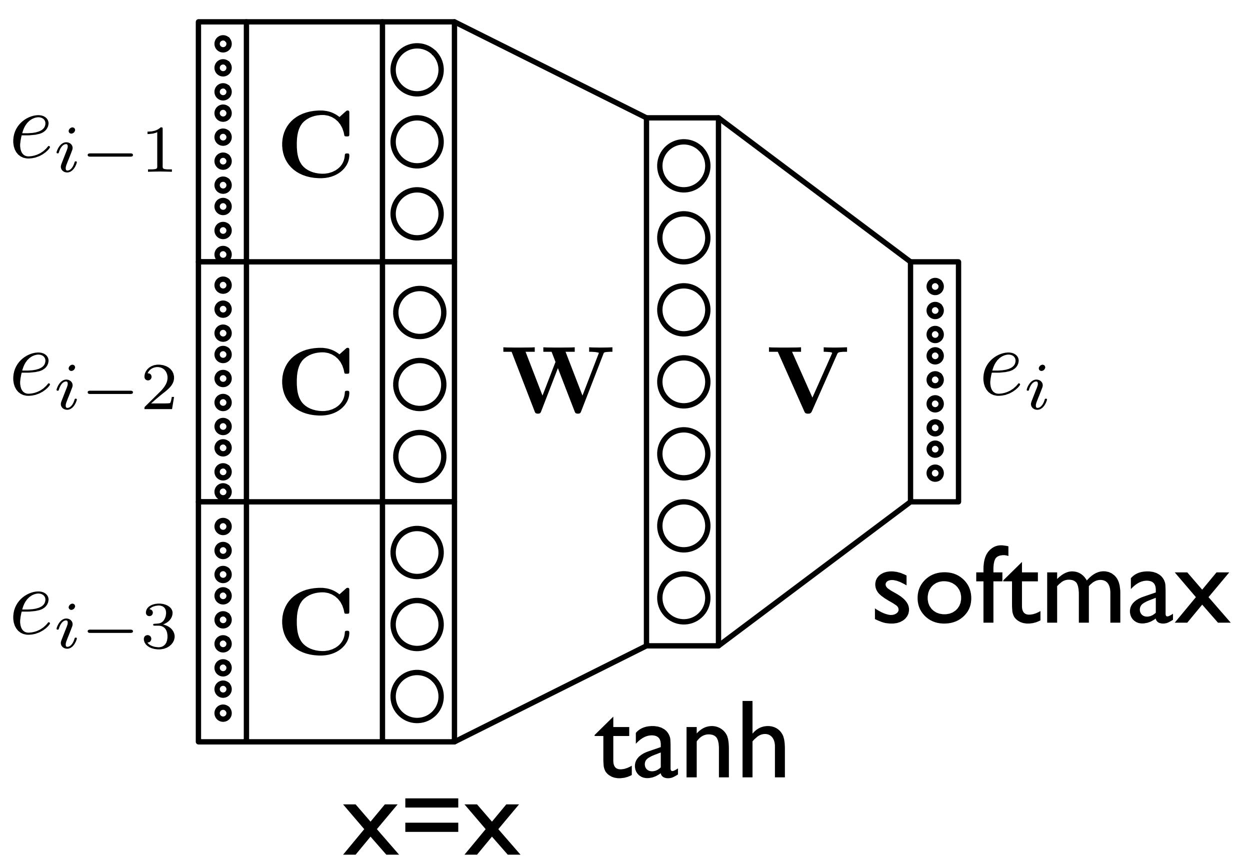


How many output words can we predict?

Bengio et al. (2003)

$$p(\mathbf{e}) = \prod_{i=1}^{|\mathbf{e}|} p(e_i \mid e_{i-n+1}, \ldots, e_{i-1})$$

$$p(e_i \mid e_{i-n+1}, \ldots, e_{i-1}) =$$



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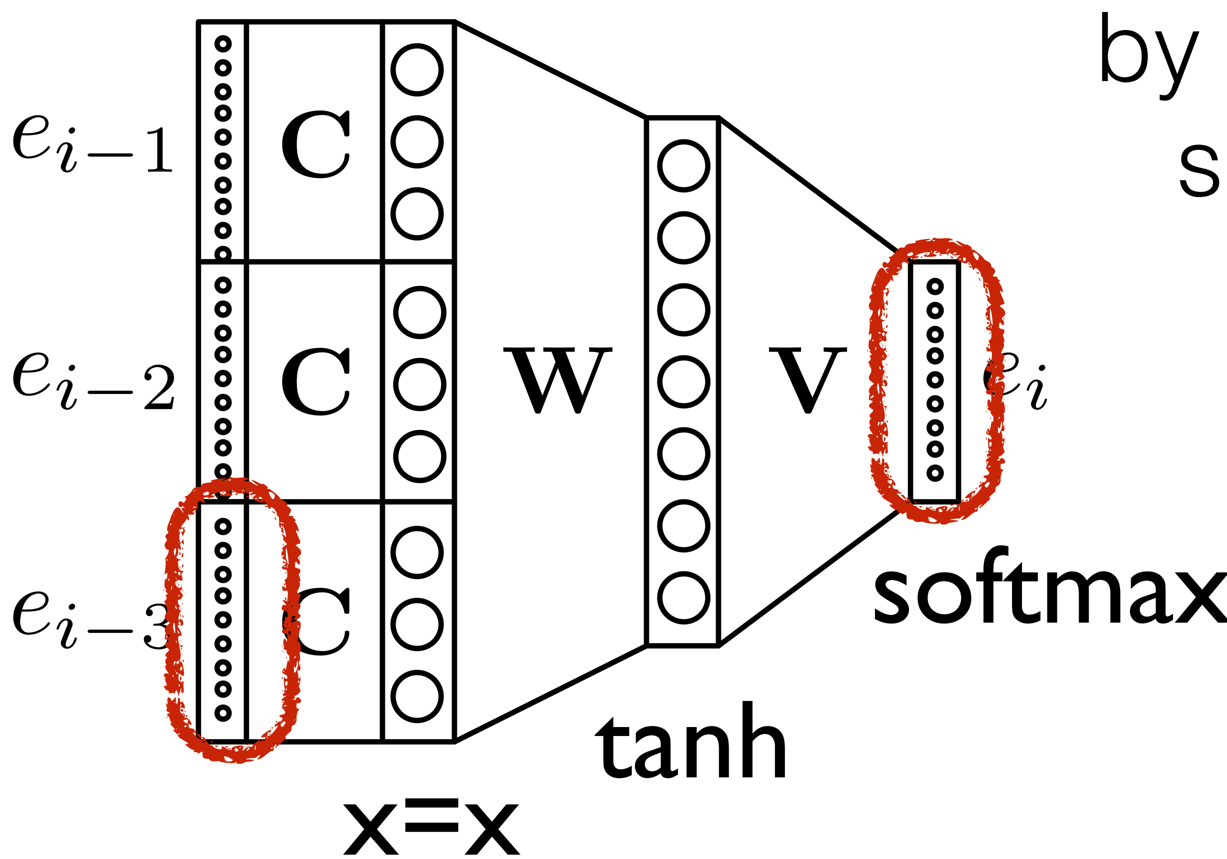

Every model inspired by this one has the same problem!

Actually, this problem is even older…

Language modeling

For language modeling, we seek

$$p(\mathbf{e}) > 0 \quad \forall \mathbf{e} \in \Sigma^*$$

We will assume that Σ is known and finite.

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$$p(\mathbf{e}) > 0 \quad \forall \mathbf{e} \in \Sigma^*$$

We will assume that Σ is known and finite.

When does this assumption make sense for language modeling?

Known and finite

- Practical problem: softmax computation is linear in vocabulary size.

Problems with this?

- Bengio et al.: “Rare words with frequency ≤ 3 were merged into a single symbol, reducing the vocabulary size to $|V| = 16{,}383$.”

- Bahdanau et al.: “we use a shortlist of 30,000 most frequent words in each language to train our models. Any word not included in the shortlist is mapped to a special token ([UNK]).”

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```
-----------------------------------------------
Src | 日本 の 主要 作物 は 米 で あ る 。
Ref | the main crop of japan is rice .
Hyp | the _UNK is popular of _UNK . _EOS
-----------------------------------------------
```

Approaches

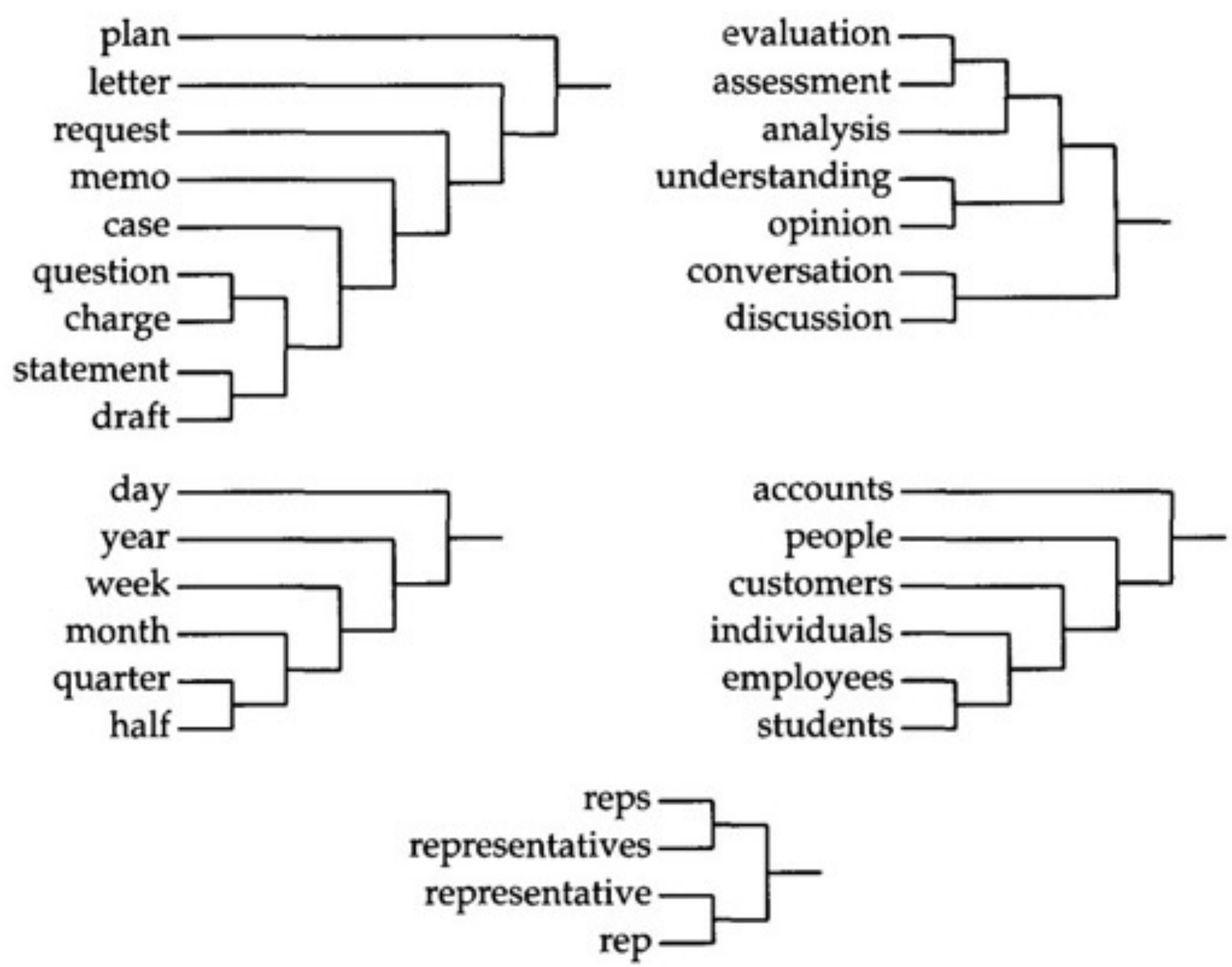
- Partition the vocabulary into smaller pieces.

$$p(w_i|h_i) = p(c_i|h_i)p(w_i|c_i, h_i)$$

Class-based LM

Approaches

- Partition the vocabulary into smaller pieces hierarchically (*hierarchical* softmax).



Brown clustering: hard clustering based on mutual information

Approaches

- Differentiated softmax: assign more parameters to more frequent words, fewer to less frequent words.

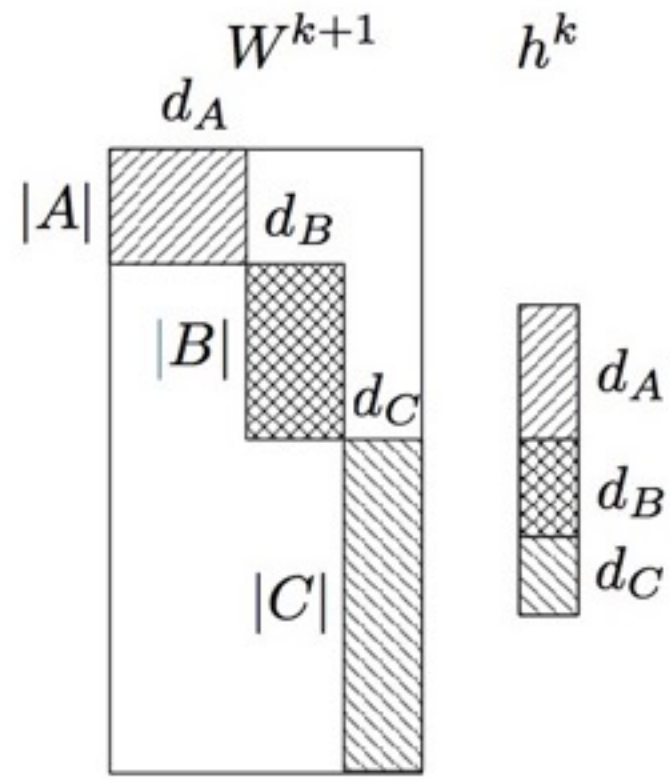
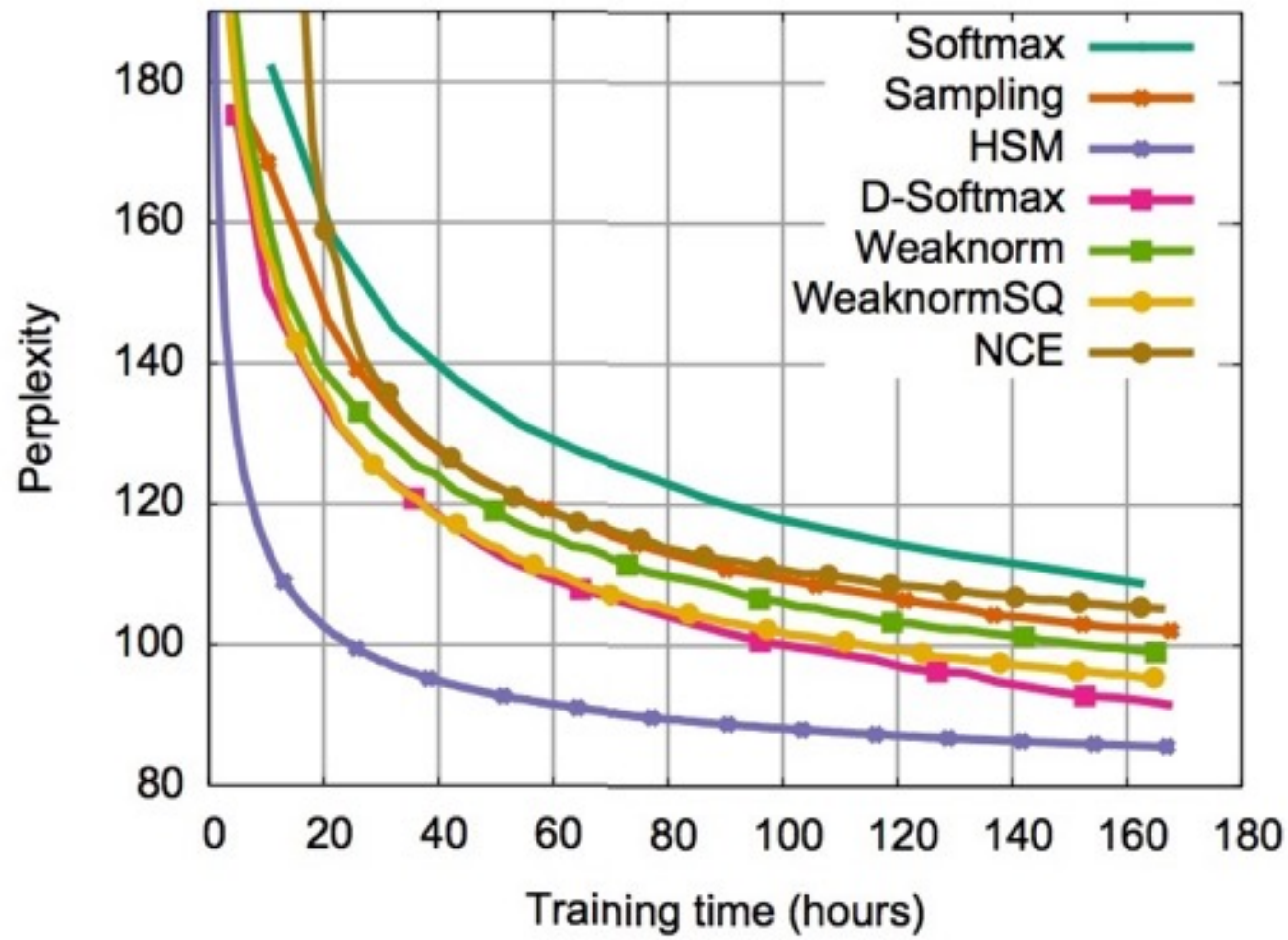


Figure 1: Final weight matrix W^{k+1} and hidden layer h^k for differentiated softmax for partitions A, B, C of the output vocabulary with embedding dimensions d_A, d_B, d_C; non-shaded areas are zero.

Comparisons



Dataset	Train	Test	Vocab	OOV
PTB	1M	0.08M	10k	5.8%
gigaword	4,631M	279M	100k	5.6%
billionW	799M	8.1M	793k	0.3%

Table 1: Dataset statistics. Number of tokens for train and test set, vocabulary size and ratio of out-of-vocabulary words in the test set.

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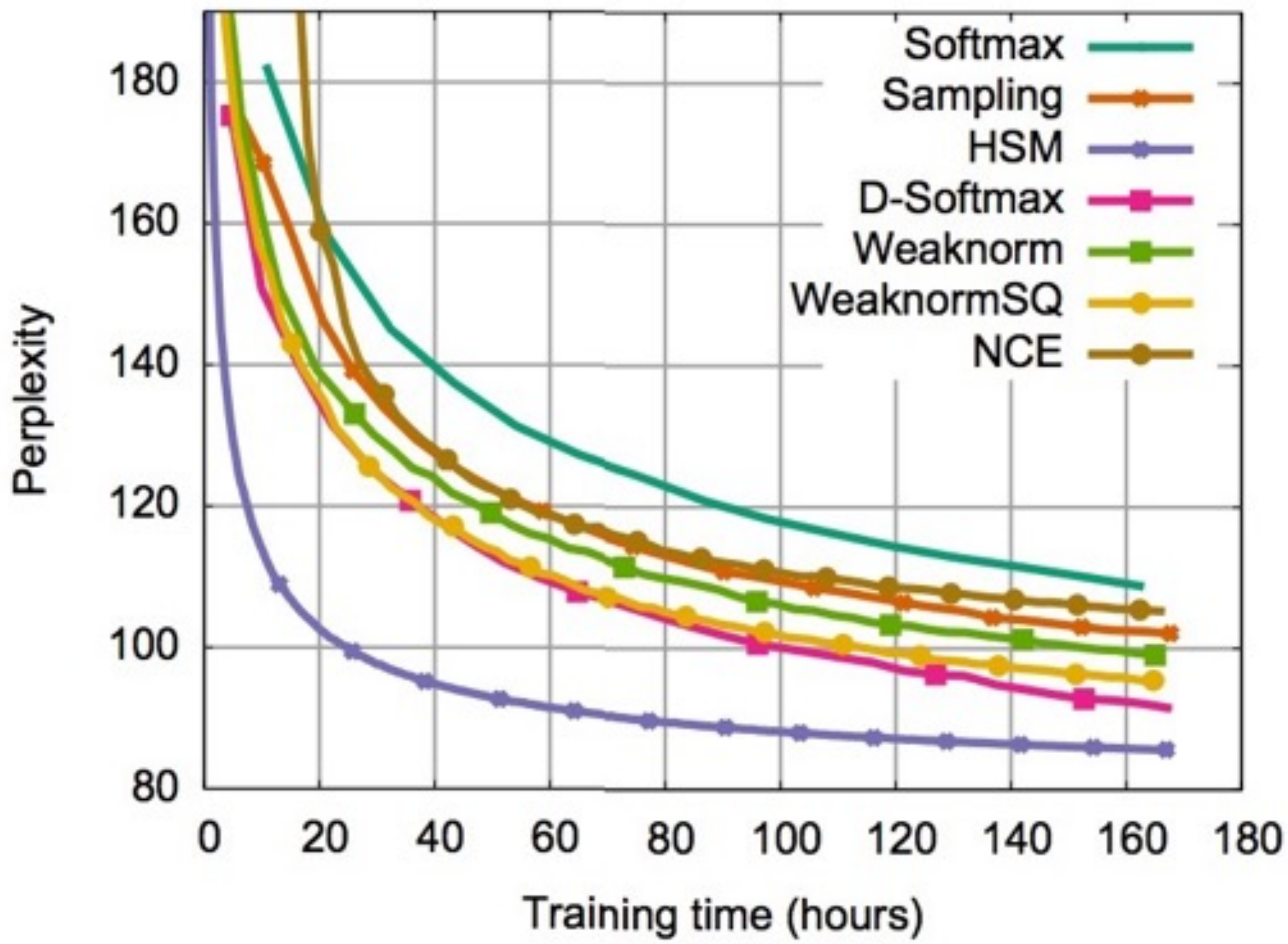

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Comparisons

	PTB	gigaword	billionW
KN	141.2	57.1	70.2
Softmax	123.8	56.5	108.3
D-Softmax	121.1	52.0	91.2
Sampling	124.2	57.6	101.0
HSM	138.2	57.1	85.2
NCE	143.1	78.4	104.7
Weaknorm	124.4	56.9	98.7
WeaknormSQ	122.1	56.1	94.9
KN+Softmax	108.5	43.6	59.4
KN+D-Softmax	107.0	42.0	56.3
KN+Sampling	109.4	43.8	58.1
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Table 2: Test perplexity of individual models and interpolation with Kneser-Ney.

Comparisons

Noise contrastive estimation

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Comparisons

Skip normalization step altogether

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Room for improvement

Table 2: Test perplexity of individual models and interpolation with Kneser-Ney.

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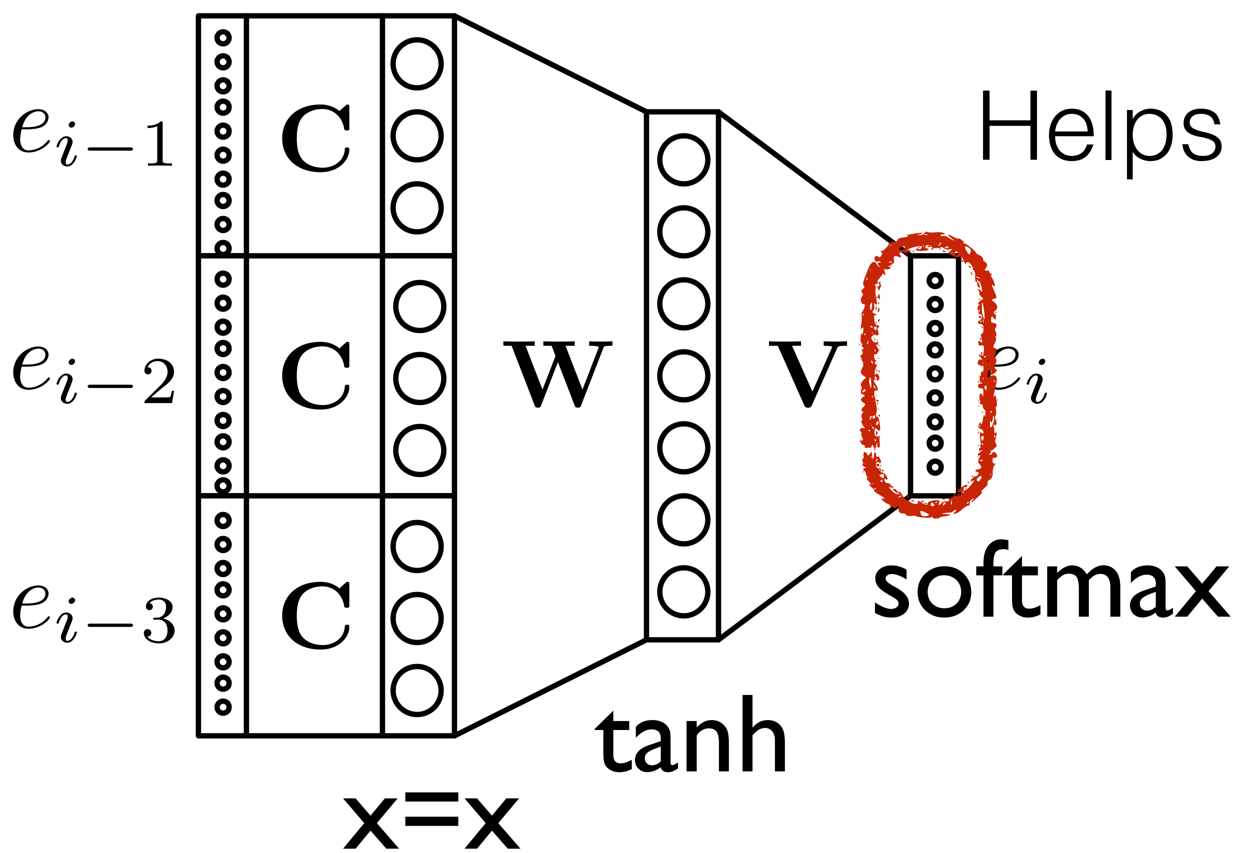

Helps with this problem

Known and finite

- Practical problem: softmax computation is linear in vocabulary size.
- **Theorem.** The vocabulary of word types is infinite.
  Proof 1. productive morphology and loanwords.
  Proof 2. 1, 2, 3, 4, …

What set is finite?

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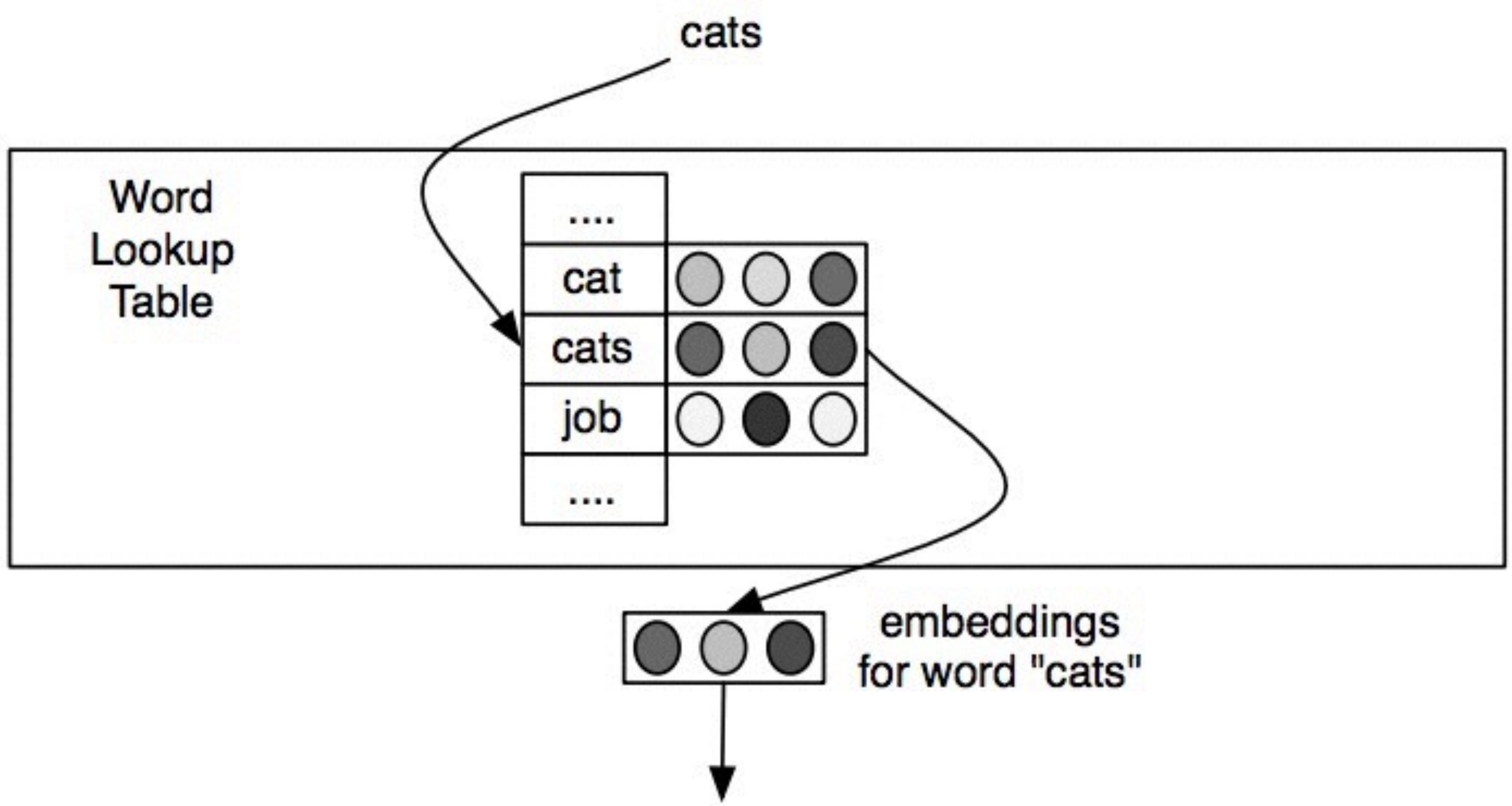

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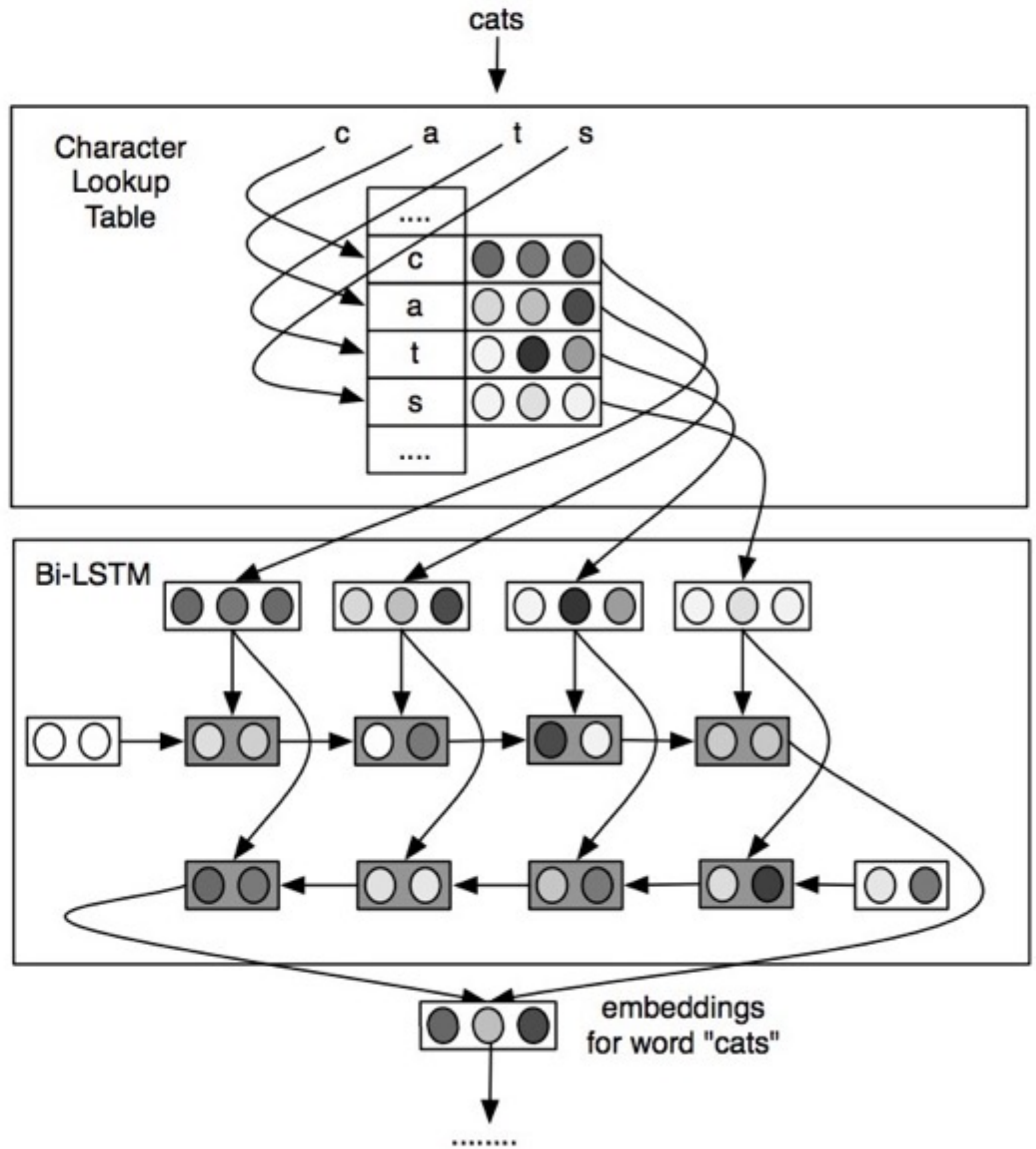

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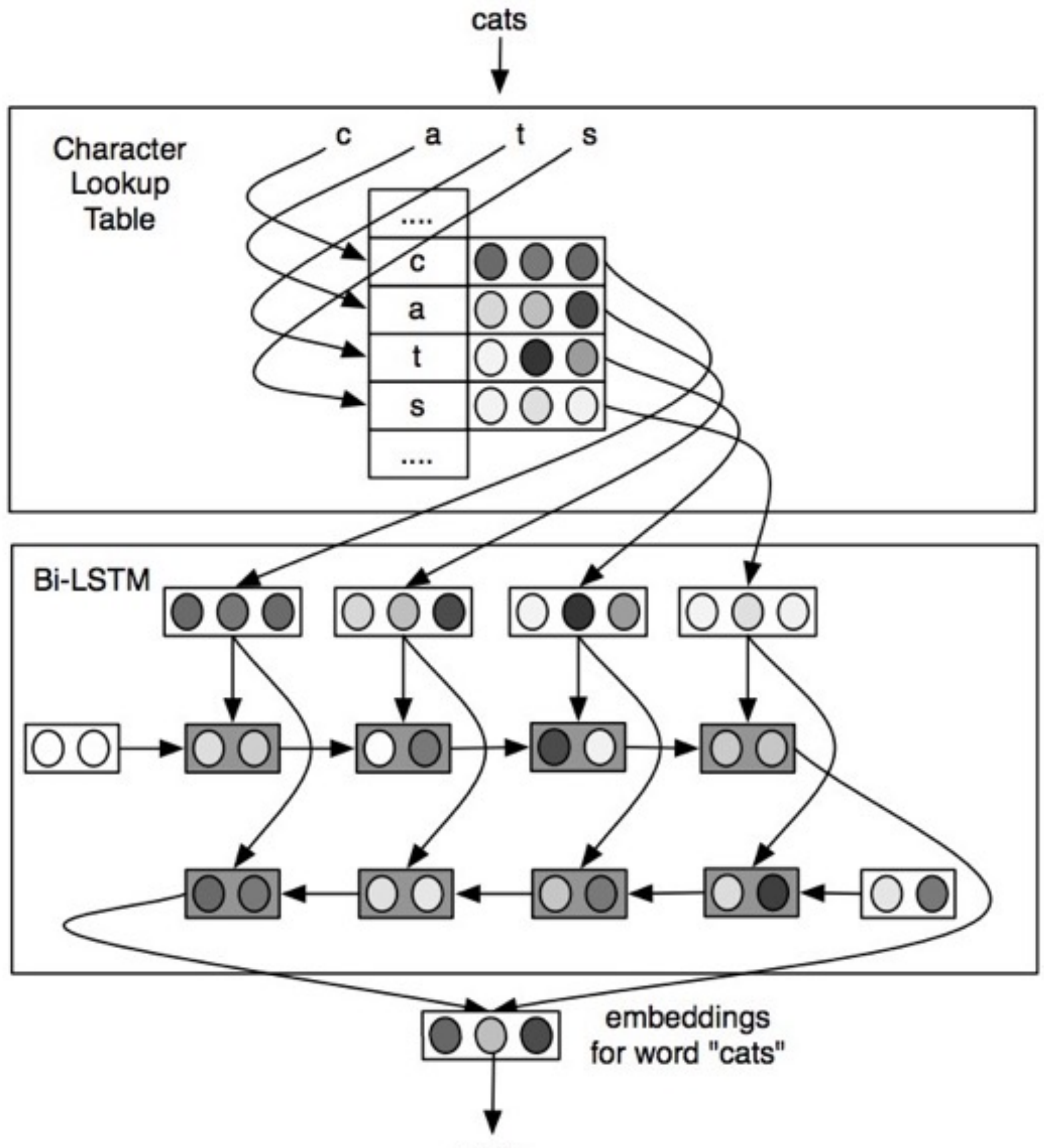

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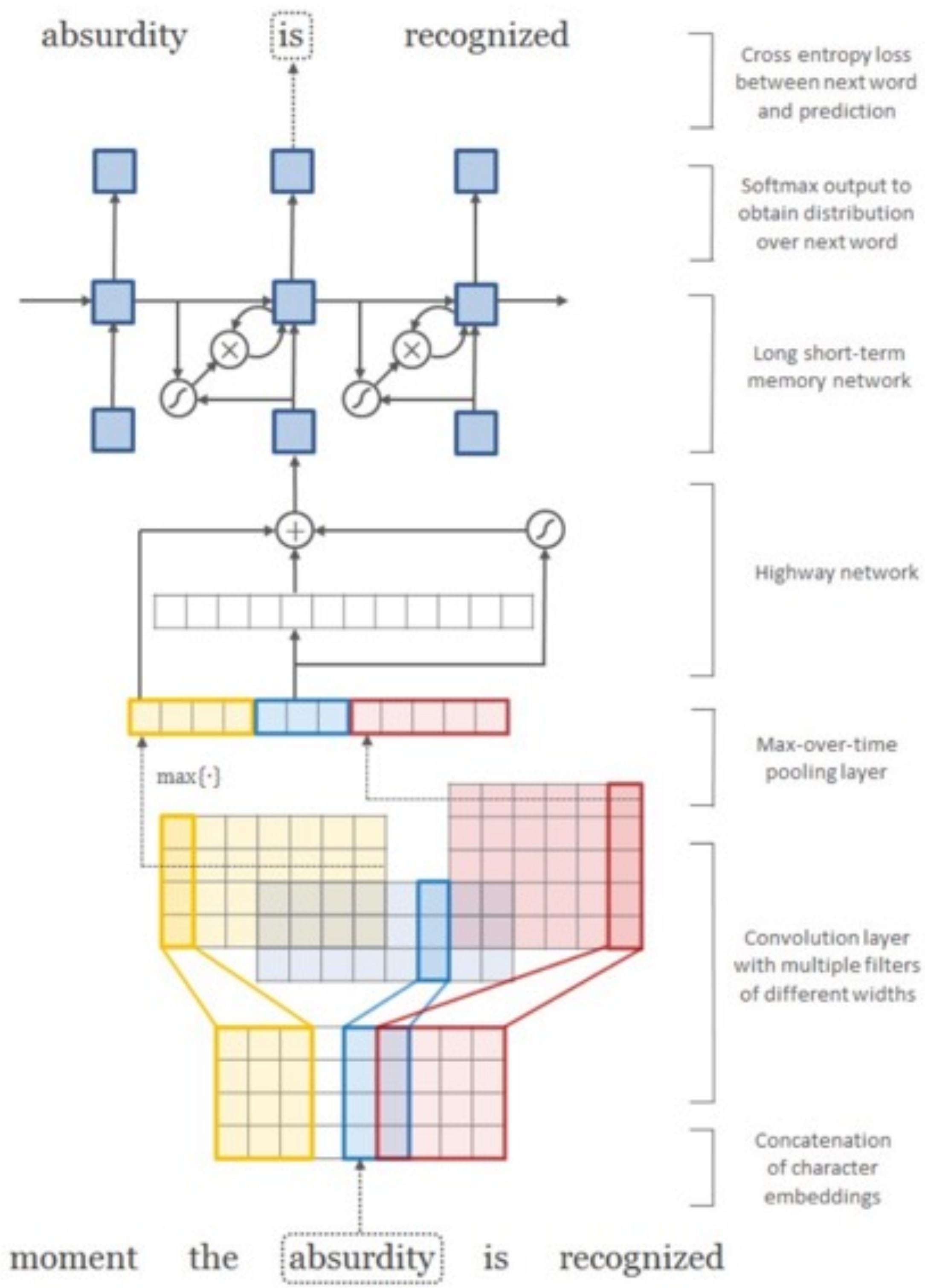

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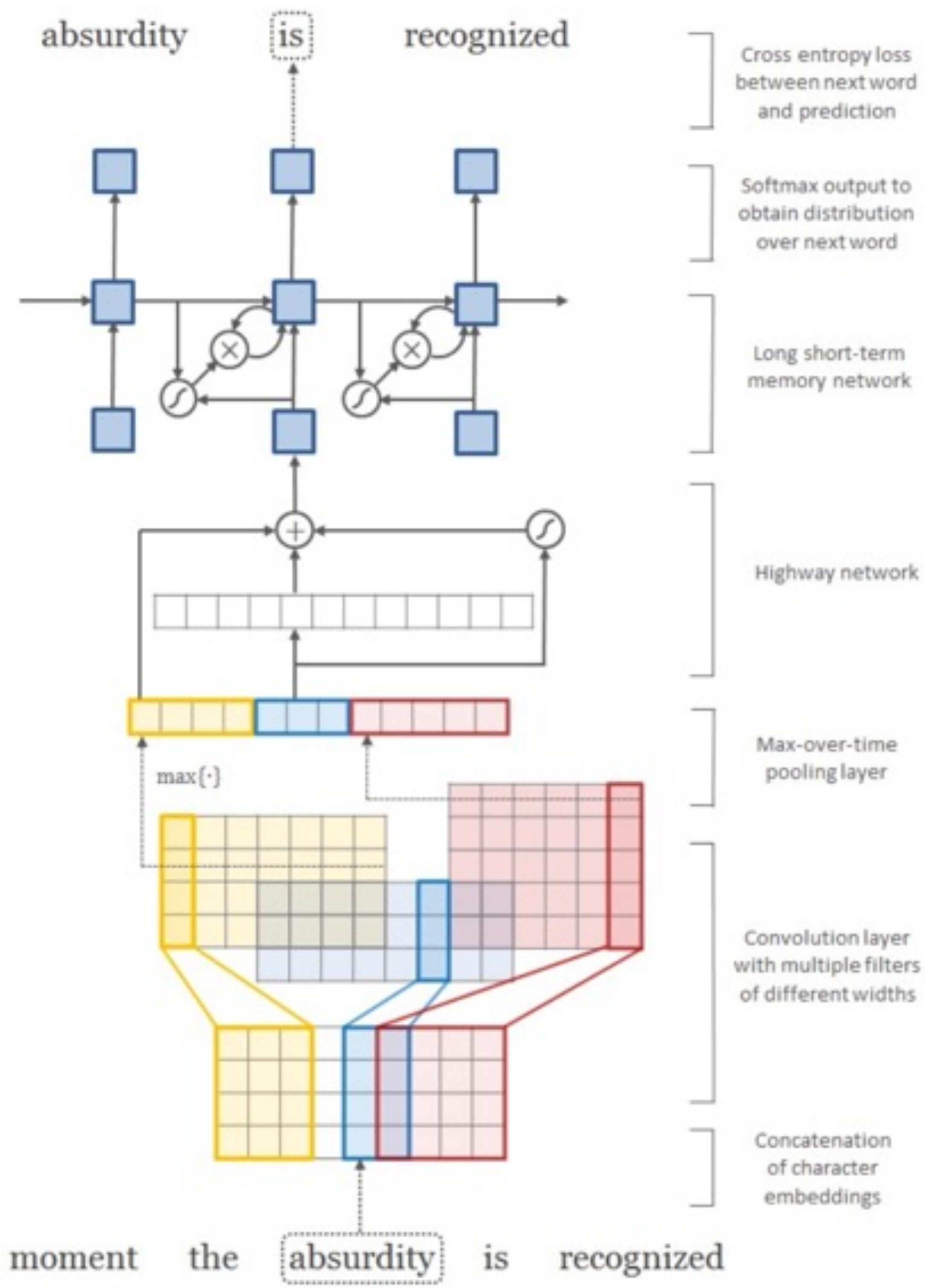

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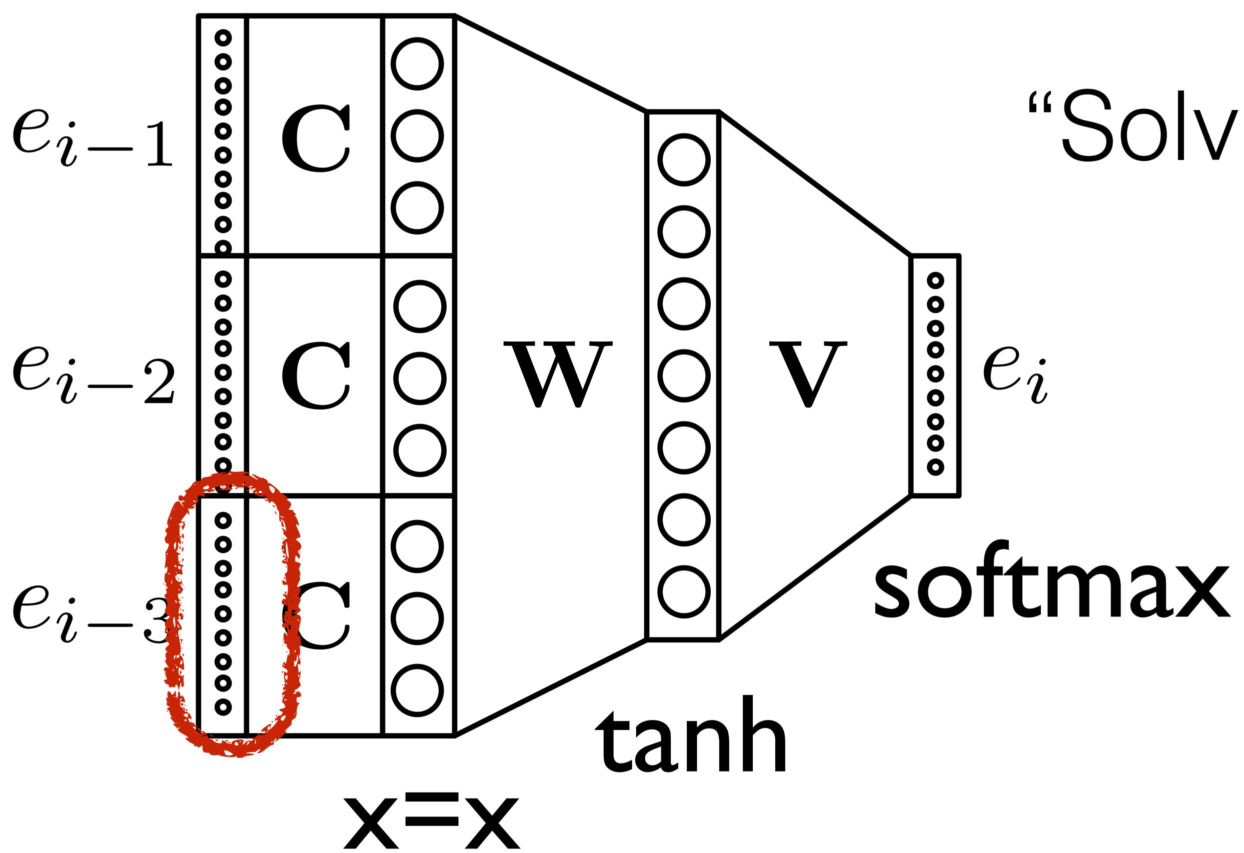

"Solves" this problem

Bengio et al. (2003)

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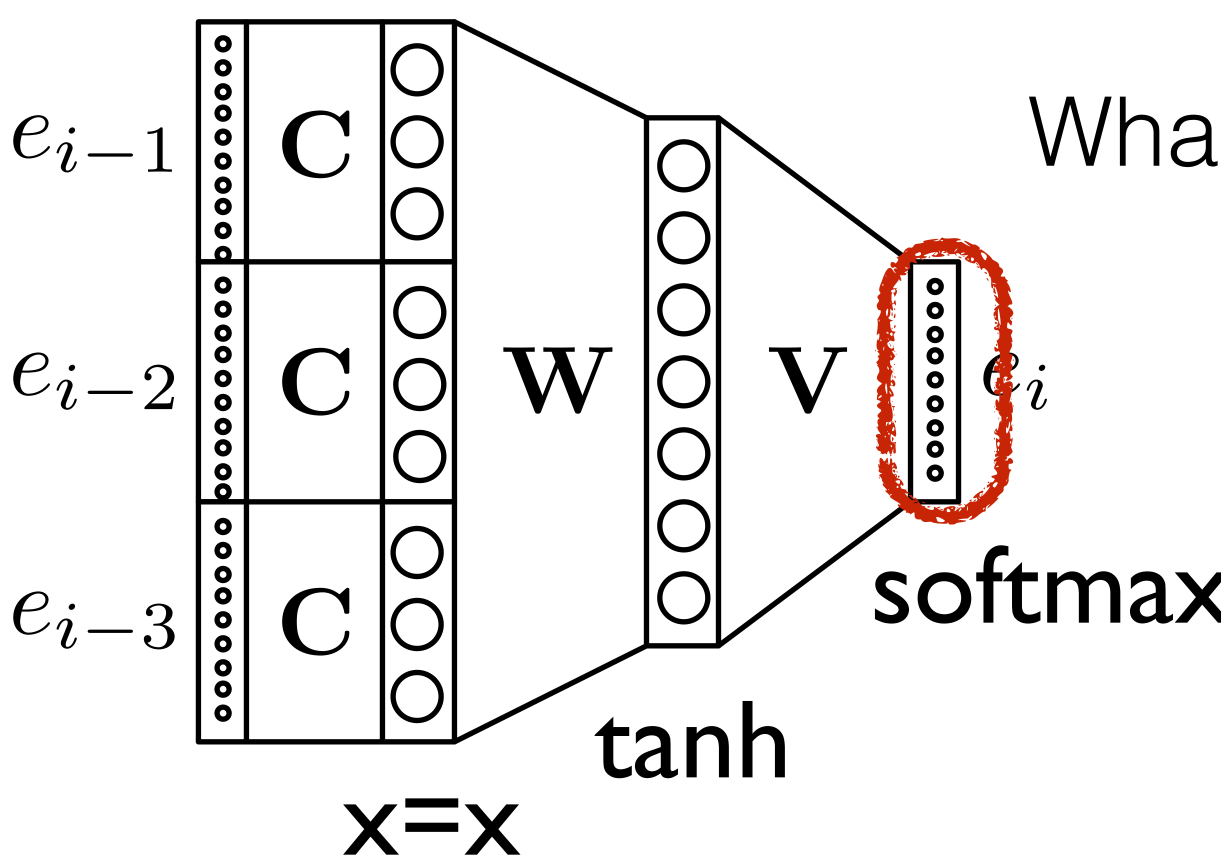

What about this one?