Conditional Language Modeling with Attention

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Review: Conditional LMs

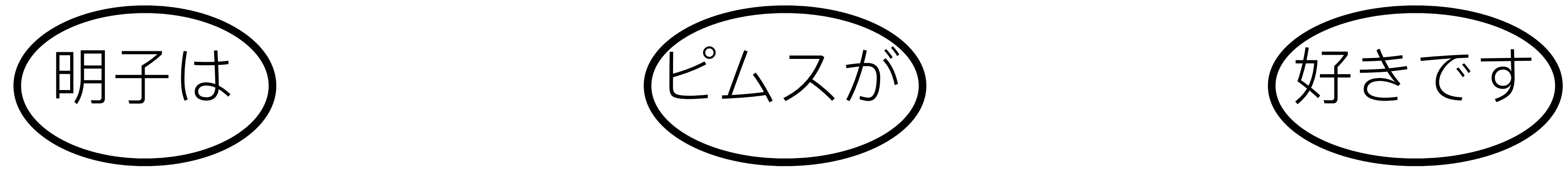
A **conditional language model** assigns probabilities to sequences of words, $\boldsymbol{w} = (w_1, w_2, \ldots, w_\ell)$, given some conditioning context, $\boldsymbol{x}$.

As with unconditional models, it is again helpful to use the chain rule to decompose this probability:

$$p(\boldsymbol{w} \mid \boldsymbol{x}) = \prod_{t=1}^{\ell} p(w_t \mid \boldsymbol{x}, w_1, w_2, \ldots, w_{t-1})$$

*What is the probability of the next word, given the history of previously generated words **and** conditioning context* $\boldsymbol{x}$*?*

Sutskever et al. (2014)



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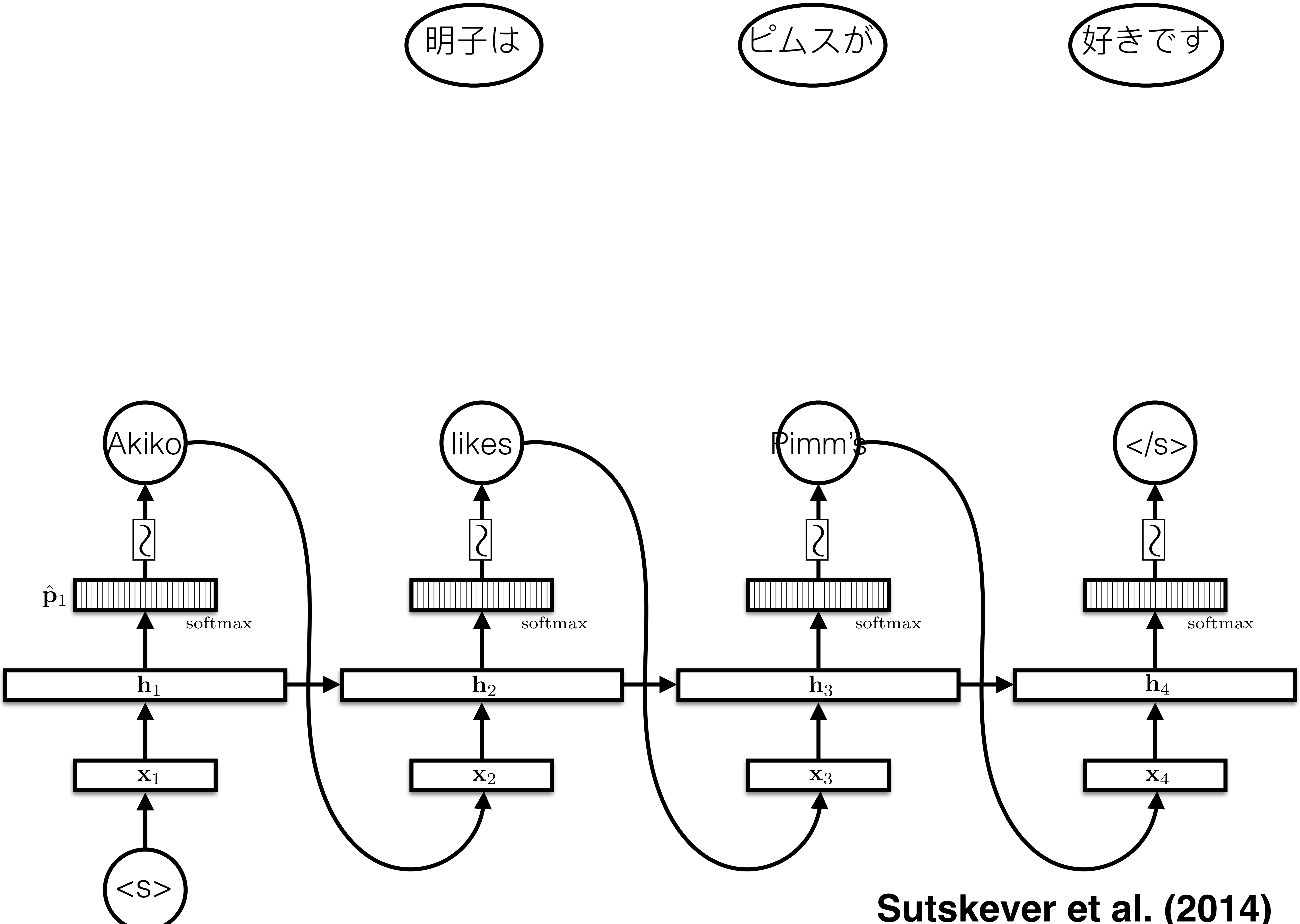

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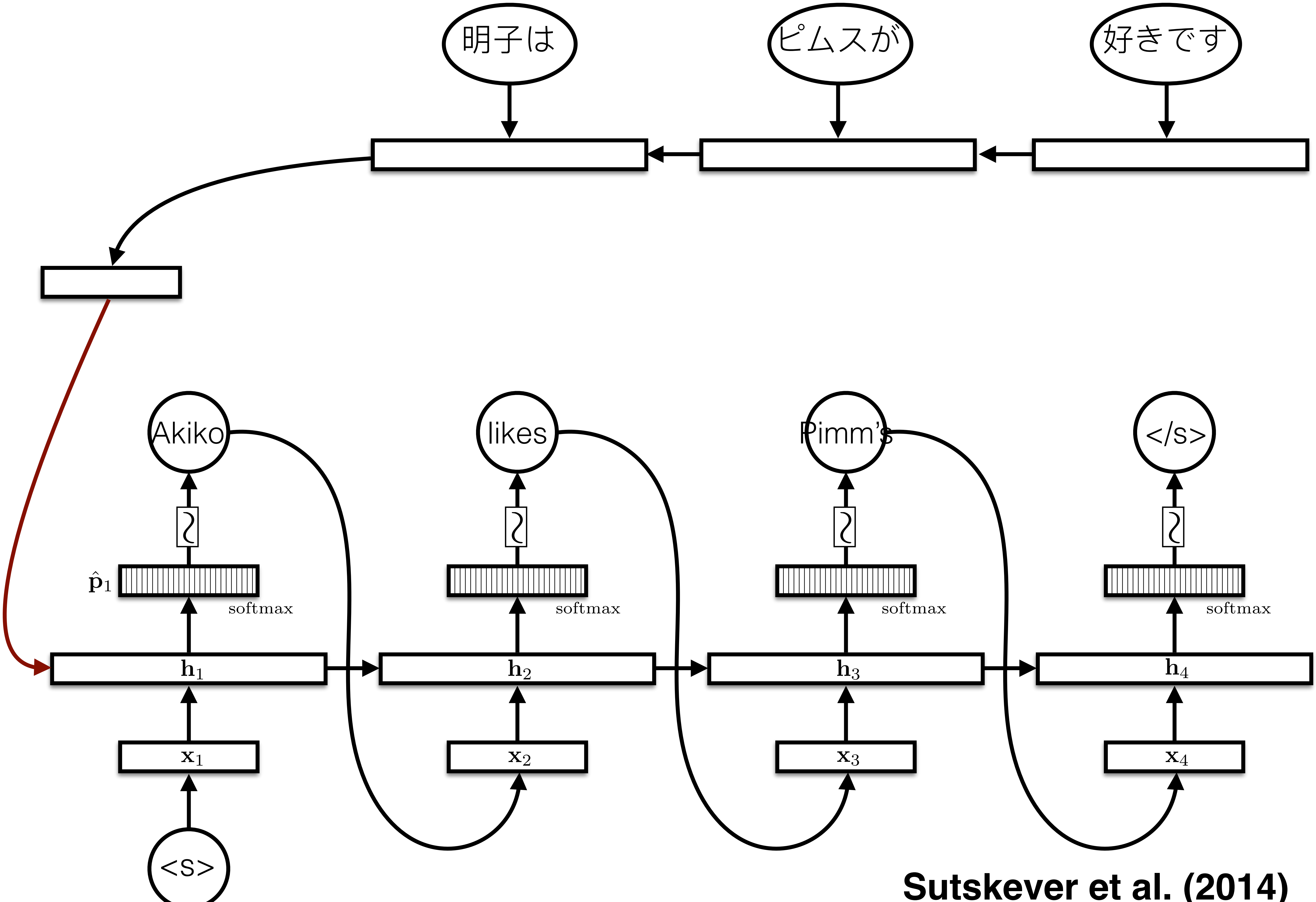


Sutskever et al. (2014)

Conditiong with vectors

We are compressing a lot of information in a finite-sized vector.

Conditiong with vectors

We are compressing a lot of information in a finite-sized vector.

Prof. Ray Mooney

"You can't cram the meaning of a whole %&!$# sentence into a single $&!#* vector!"

Conditiong with vectors

We are compressing a lot of information in a finite-sized vector.

Gradients have a long way to travel. Even LSTMs forget!

Conditiong with vectors

We are compressing a lot of information in a finite-sized vector.

Gradients have a long way to travel. Even LSTMs forget!

What is to be done?

Outline of Lecture

- Machine translation with attention
- Image caption generation with attention

Solving the Vector Problem in Translation

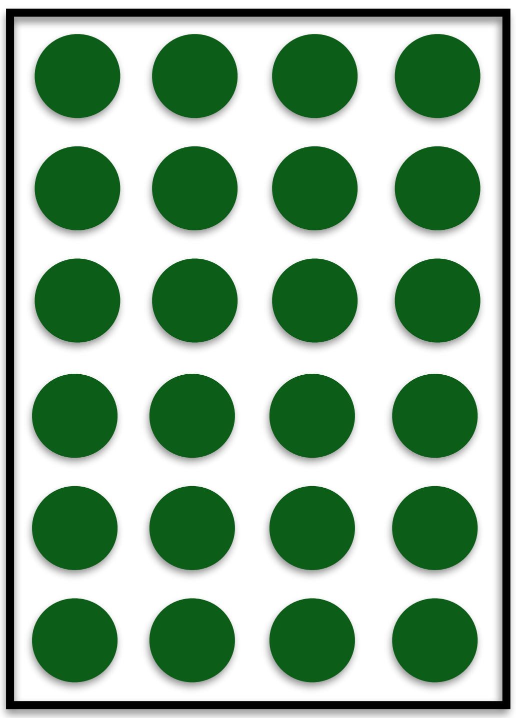
- Represent a source sentence as a matrix
- Generate a target sentence from a matrix

- This will
  - Solve the capacity problem
  - Solve the gradient flow problem

Sentences as Matrices

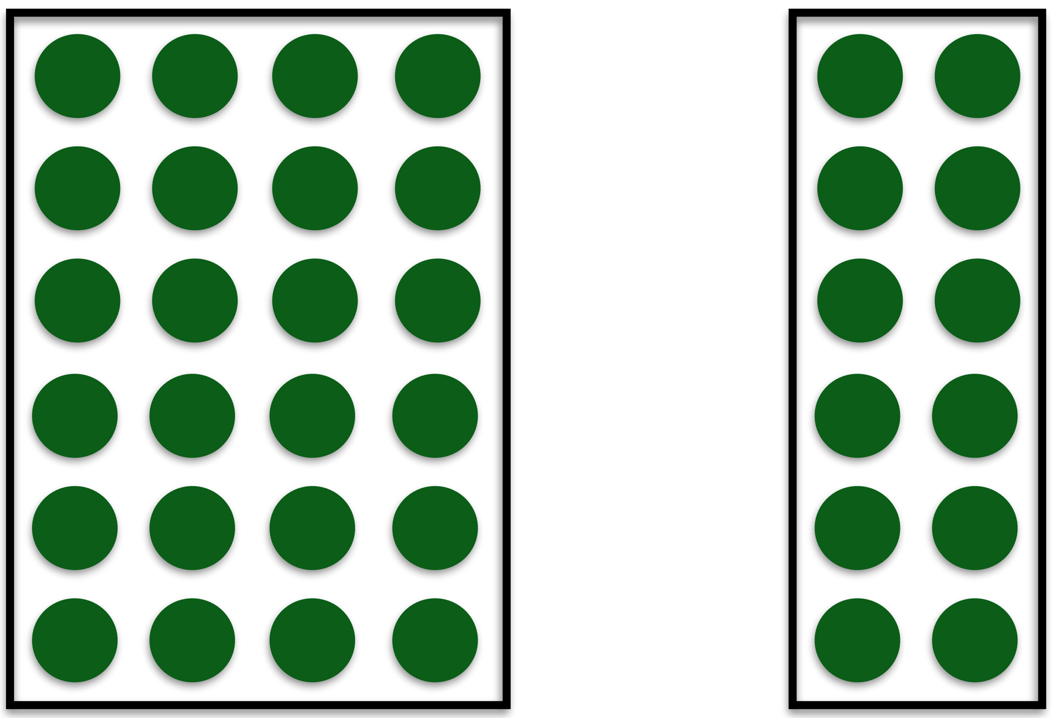
- Problem with the fixed-size vector model
  - Sentences are of different sizes but vectors are of the same size
- Solution: use matrices instead
  - Fixed number of rows, but number of columns depends on the number of words
  - Usually $|\boldsymbol{f}|$ = #cols

Sentences as Matrices



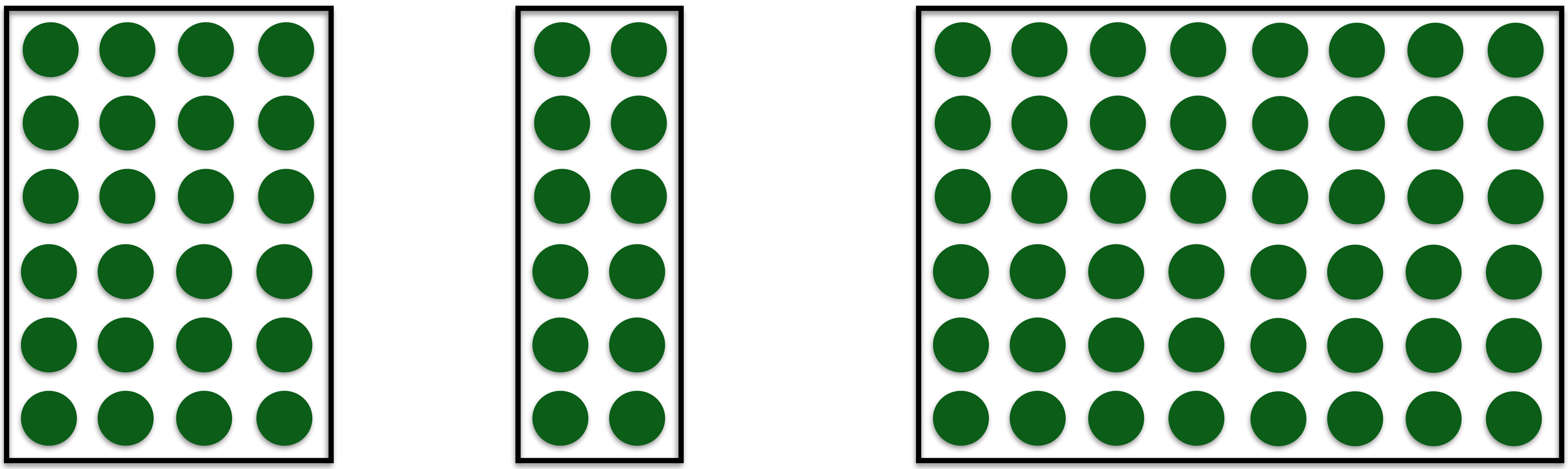
Ich möchte ein Bier

Sentences as Matrices



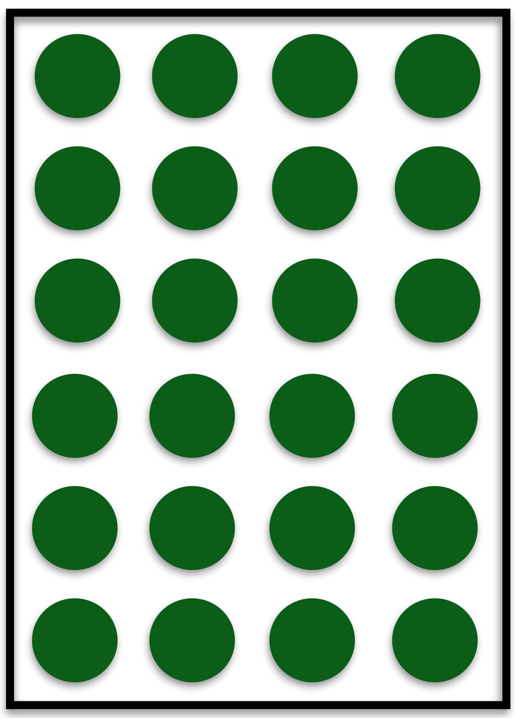
Ich möchte ein Bier *Mach's gut*

Sentences as Matrices



Ich möchte ein Bier   *Mach's gut*   *Die Wahrheiten der Menschen sind die unwiderlegbaren Irrtümer*

Sentences as Matrices



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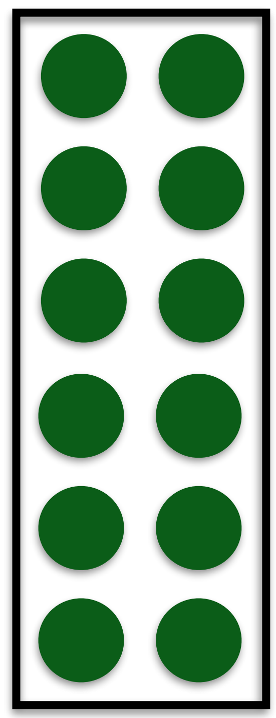

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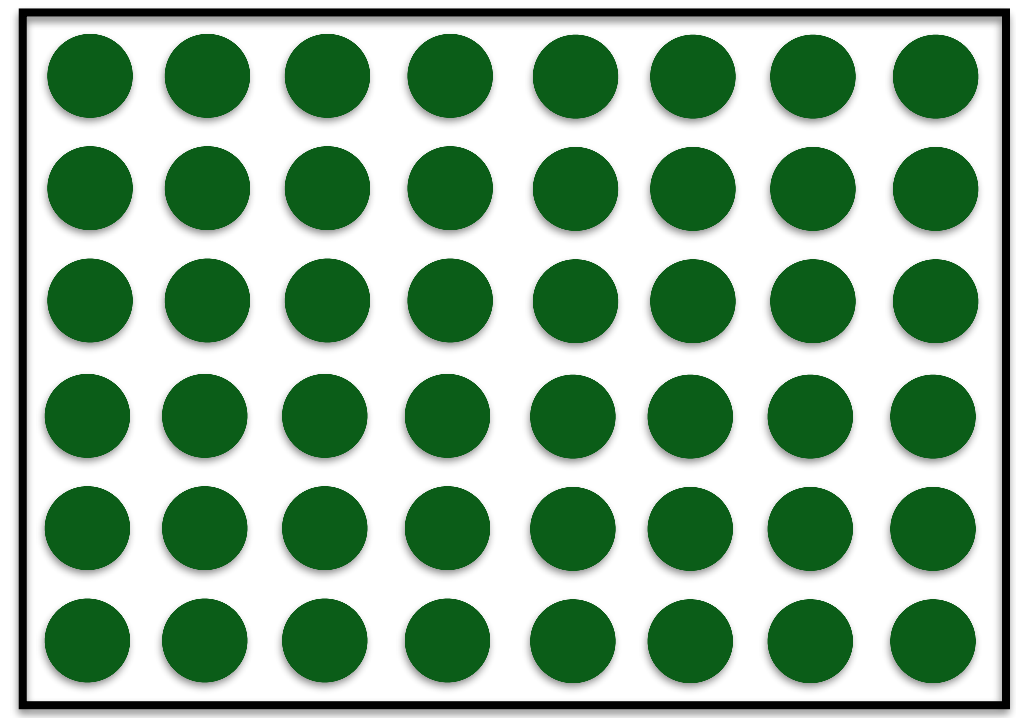
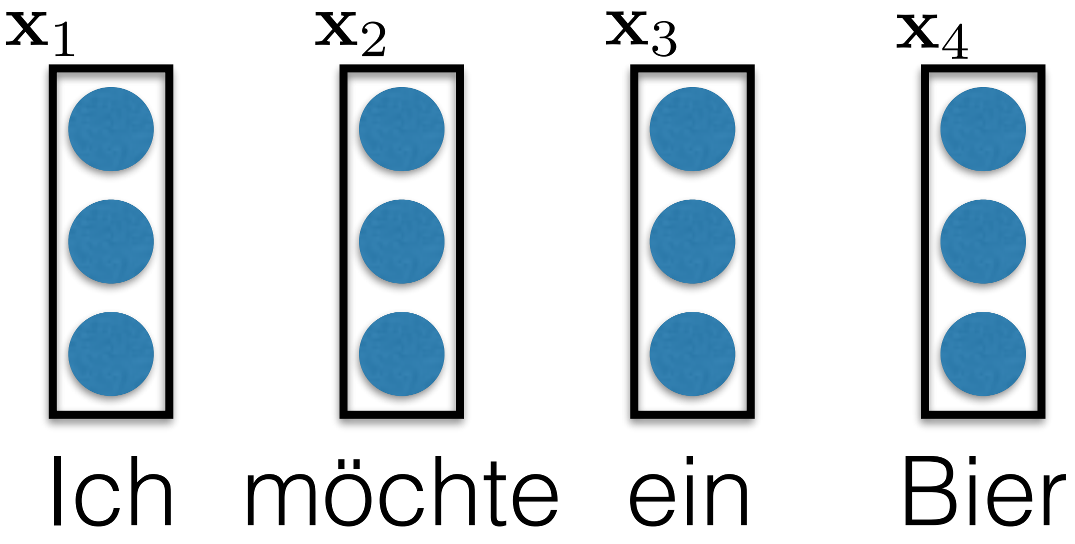


Die Wahrheiten der Menschen sind die unwiderlegbaren Irrtümer

Question: How do we build these matrices?

With Concatenation

- Each word type is represented by an n-dimensional vector
- Take all of the vectors for the sentence and concatenate them into a matrix
- Simplest possible model
  - So simple, no one has bothered to publish how well/badly it works!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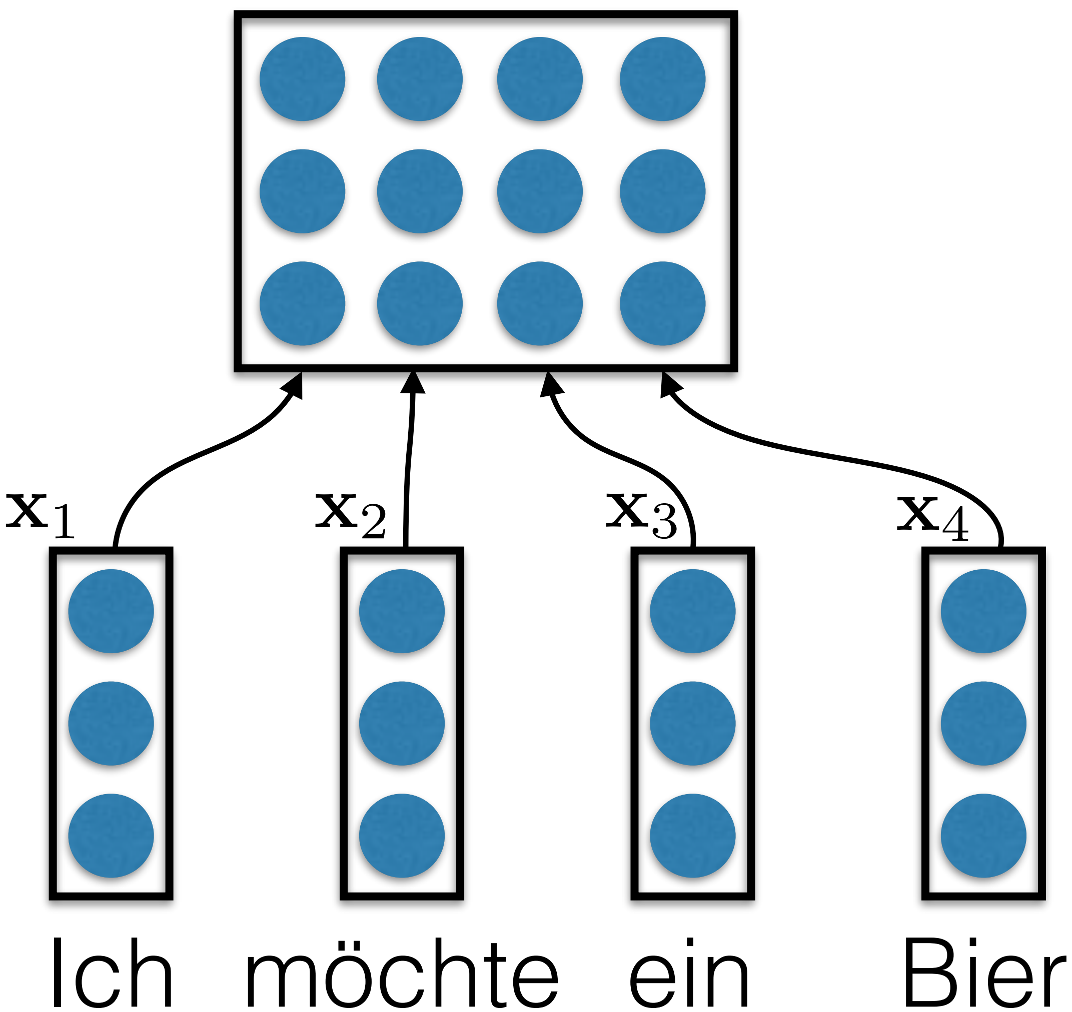
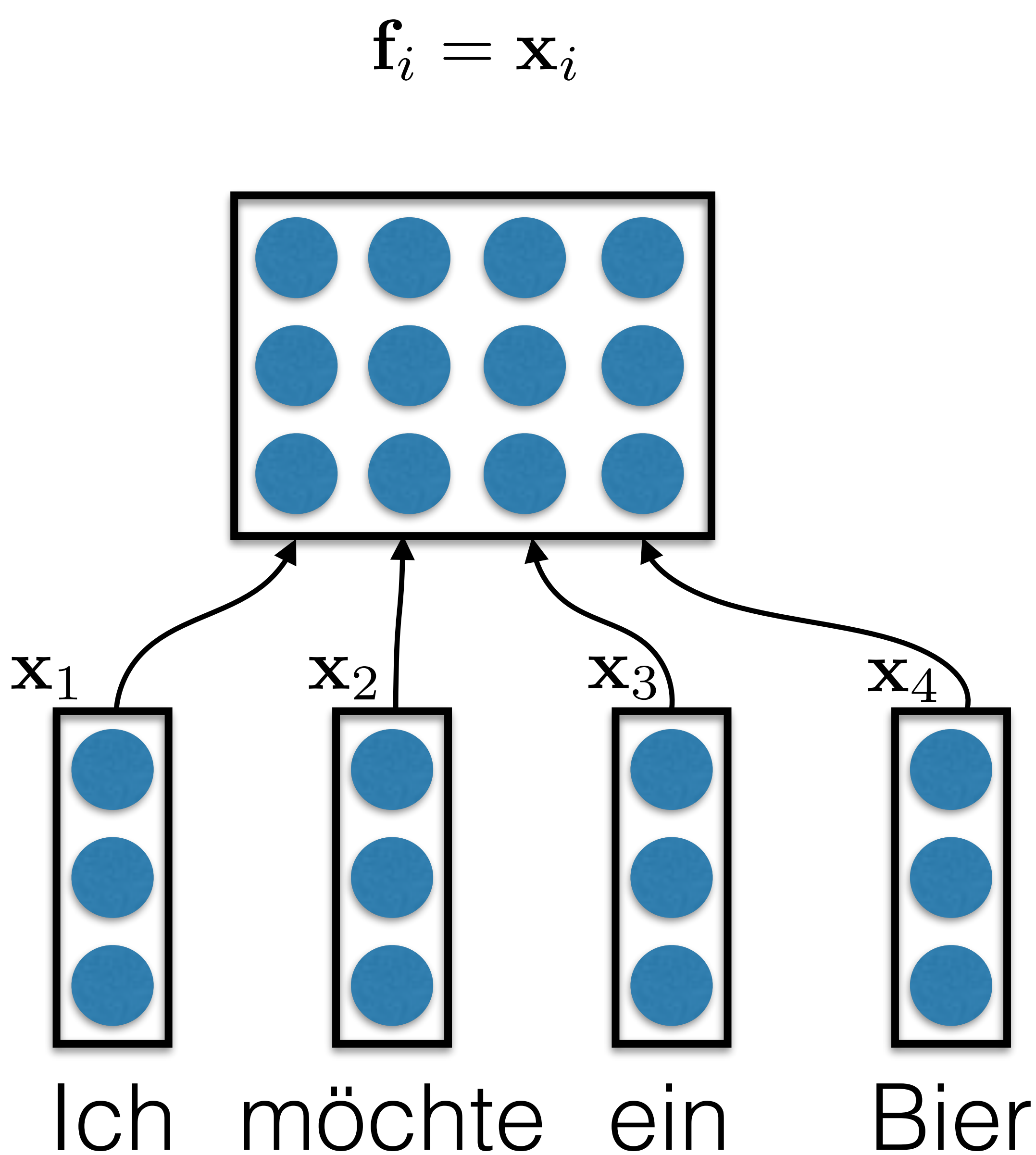
$$\mathbf{f}_i = \mathbf{x}_i$$

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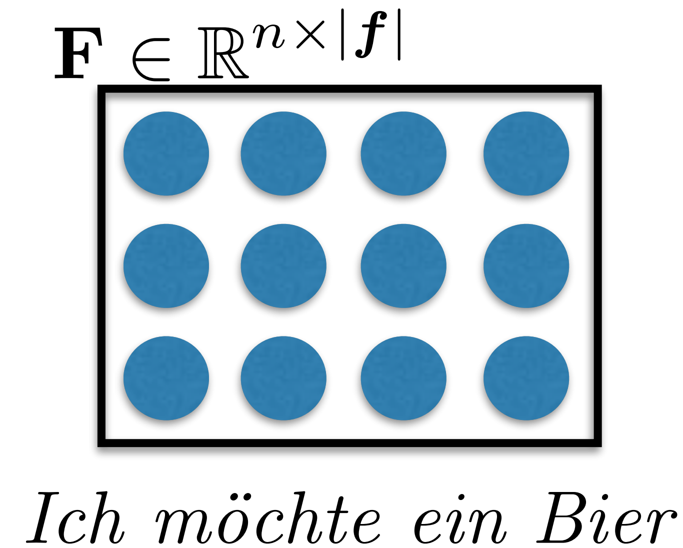
$\mathbf{F} \in \mathbb{R}^{n \times |\boldsymbol{f}|}$
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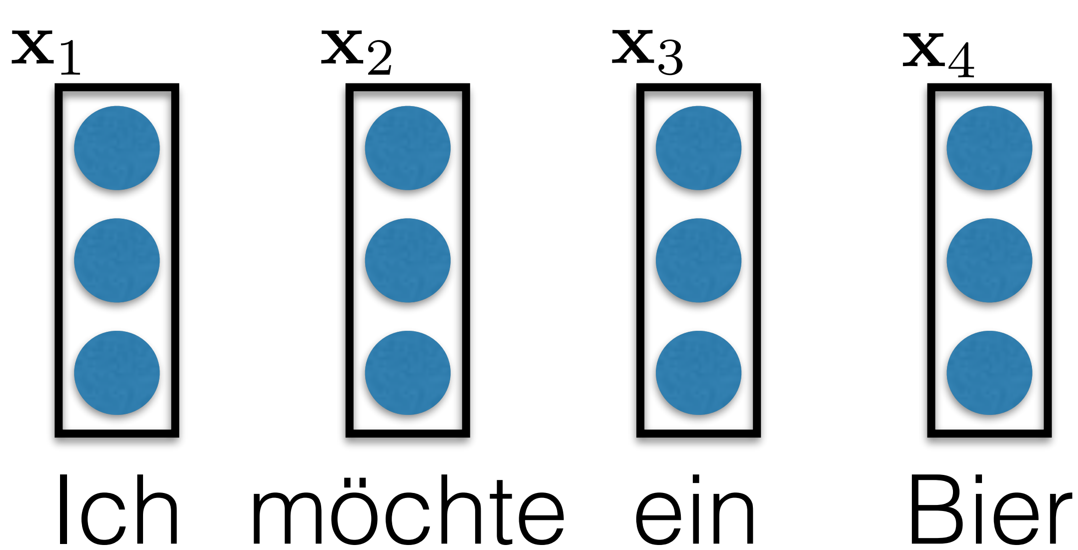
With Convolutional Nets

- Apply convolutional networks to transform the naive concatenated matrix to obtain a context-dependent matrix
- Explored in a recent ICLR submission by Gehring et al., 2016 (from FAIR)
    - Closely related to the neural translation model proposed by Kalchbrenner and Blunsom, 2013
- Note: convnets usually have a “pooling” operation at the top level that results in a fixed-sized representation. For sentences, leave this out.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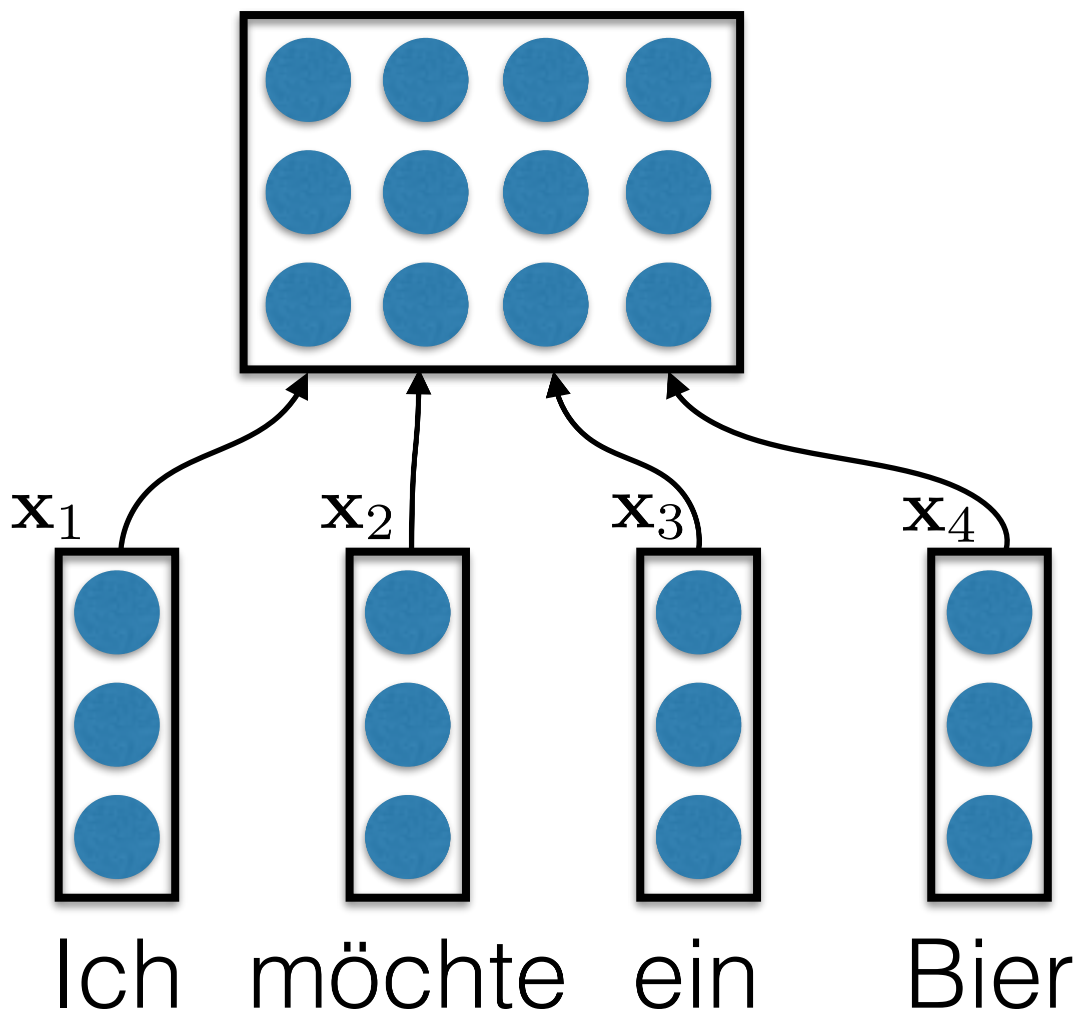
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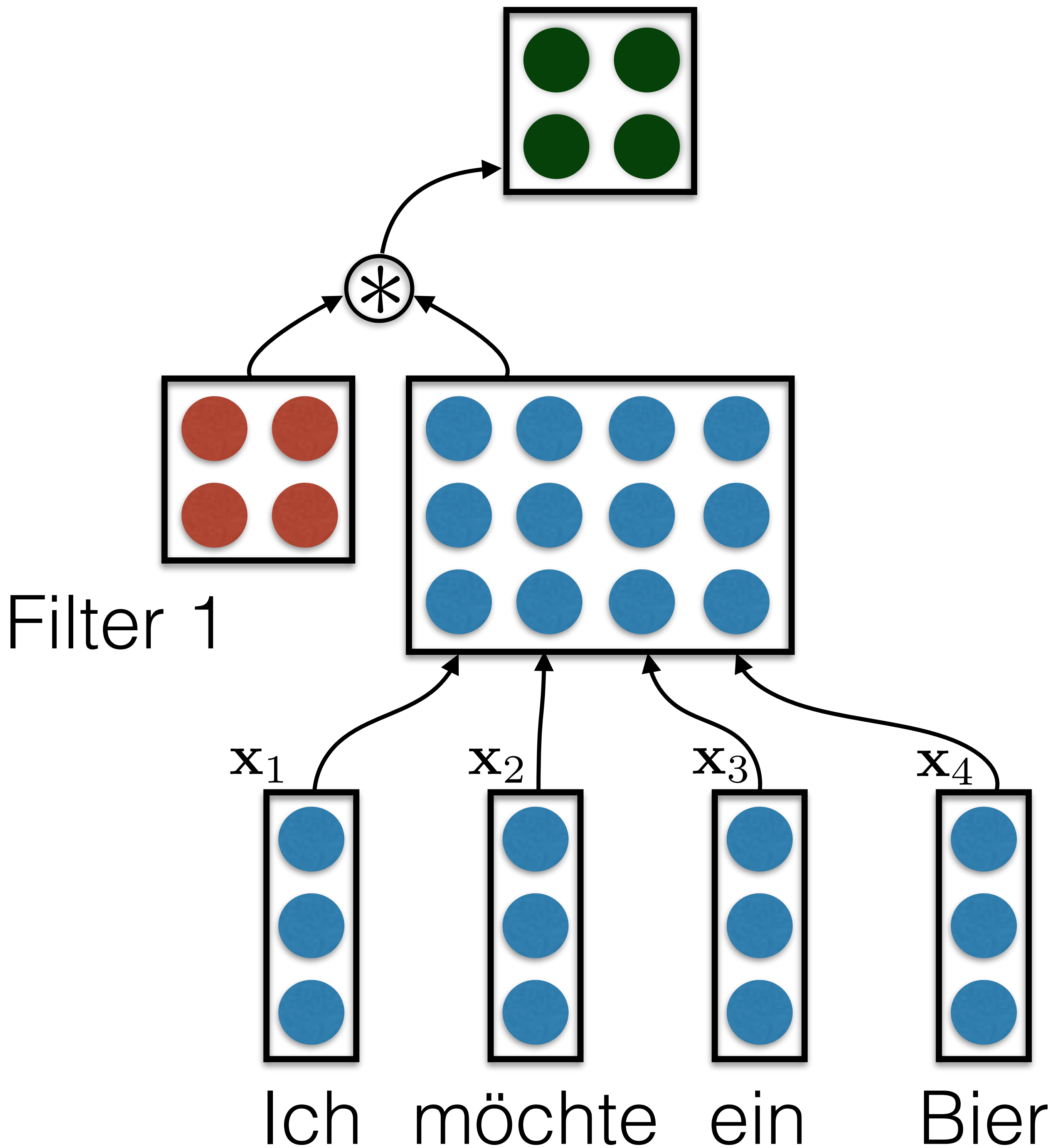
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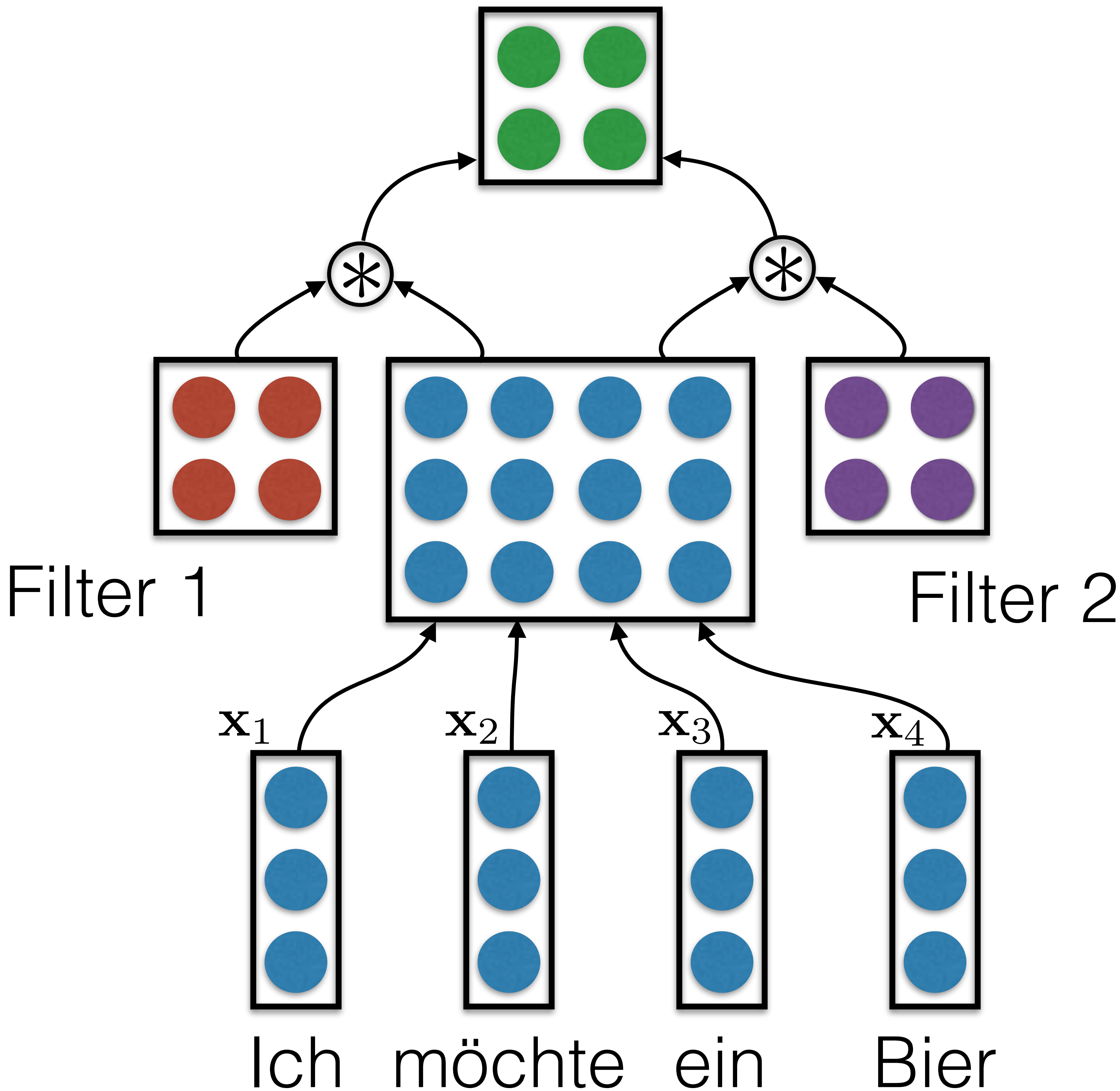

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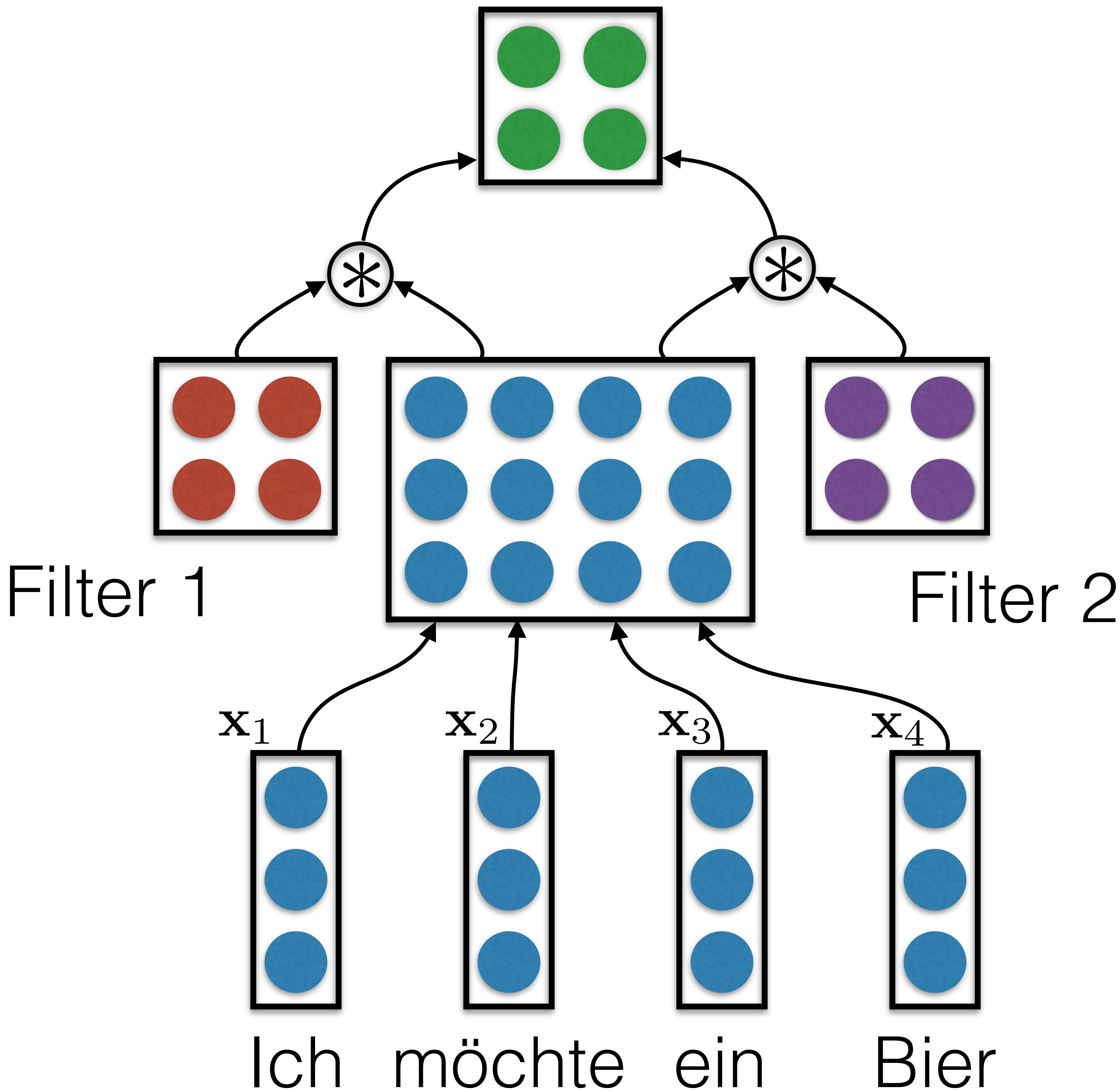
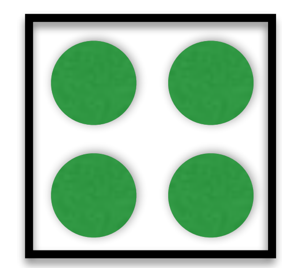


$\mathbf{F} \in \mathbb{R}^{f(n)\times g(|\boldsymbol{f}|)}$



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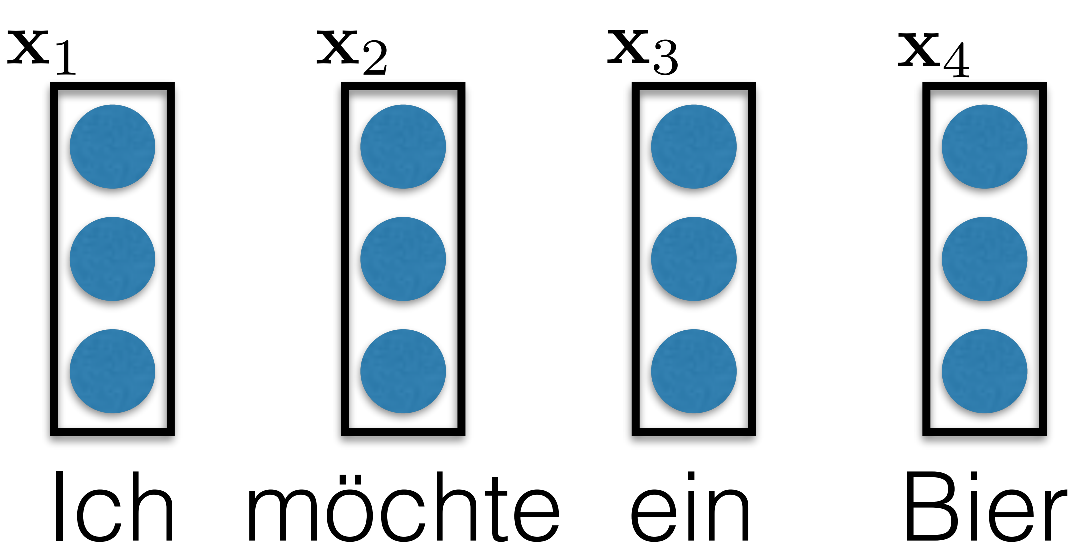
With Bidirectional RNNs

- By far the most widely used matrix representation, due to Bahdanau et al (2015)
- One column per word
- Each column (word) has two halves concatenated together:
    - a “forward representation”, i.e., a word and its left context
    - a “reverse representation”, i.e., a word and its right context
- Implementation: bidirectional RNNs (GRUs or LSTMs) to read ***f*** from left to right and right to left, concatenate representations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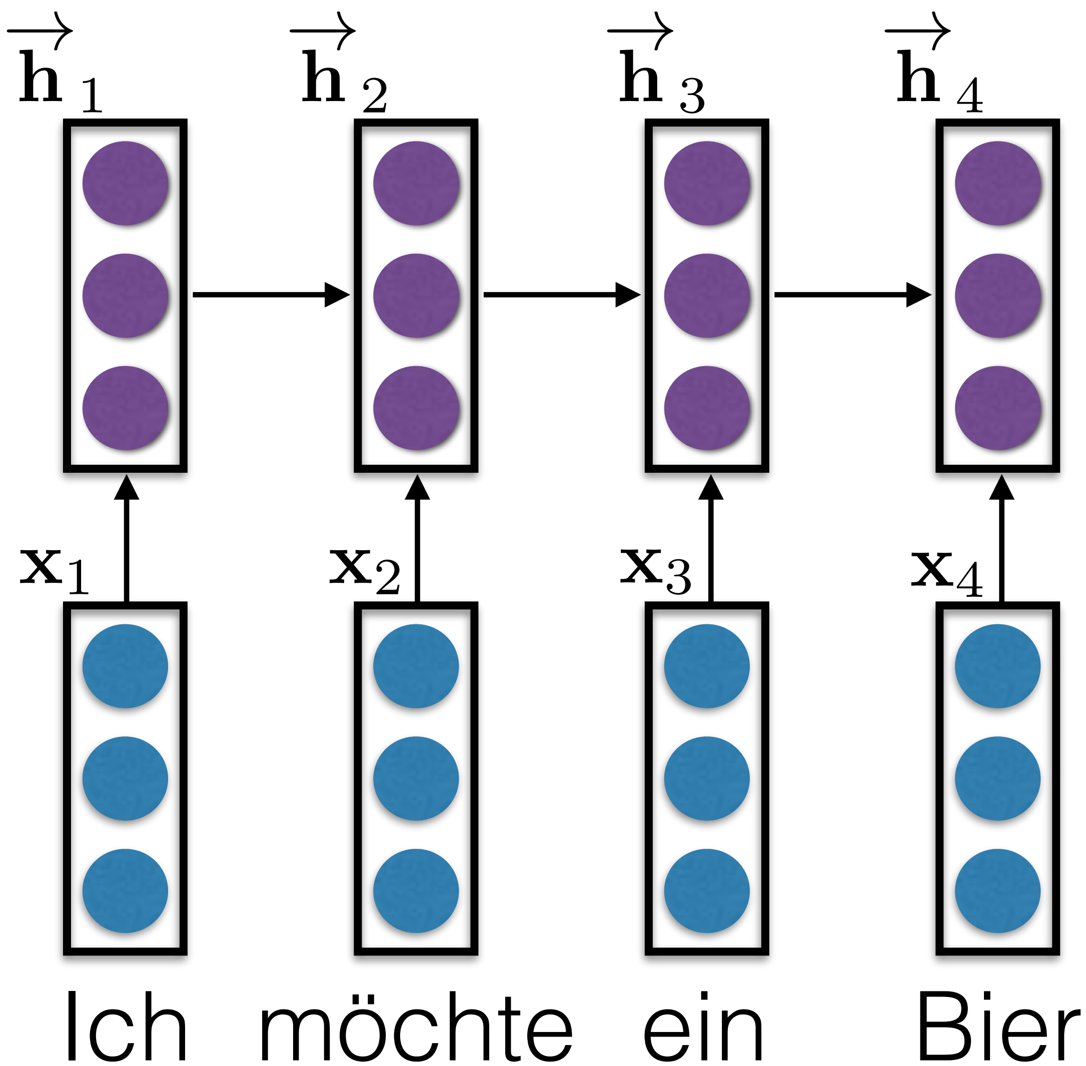
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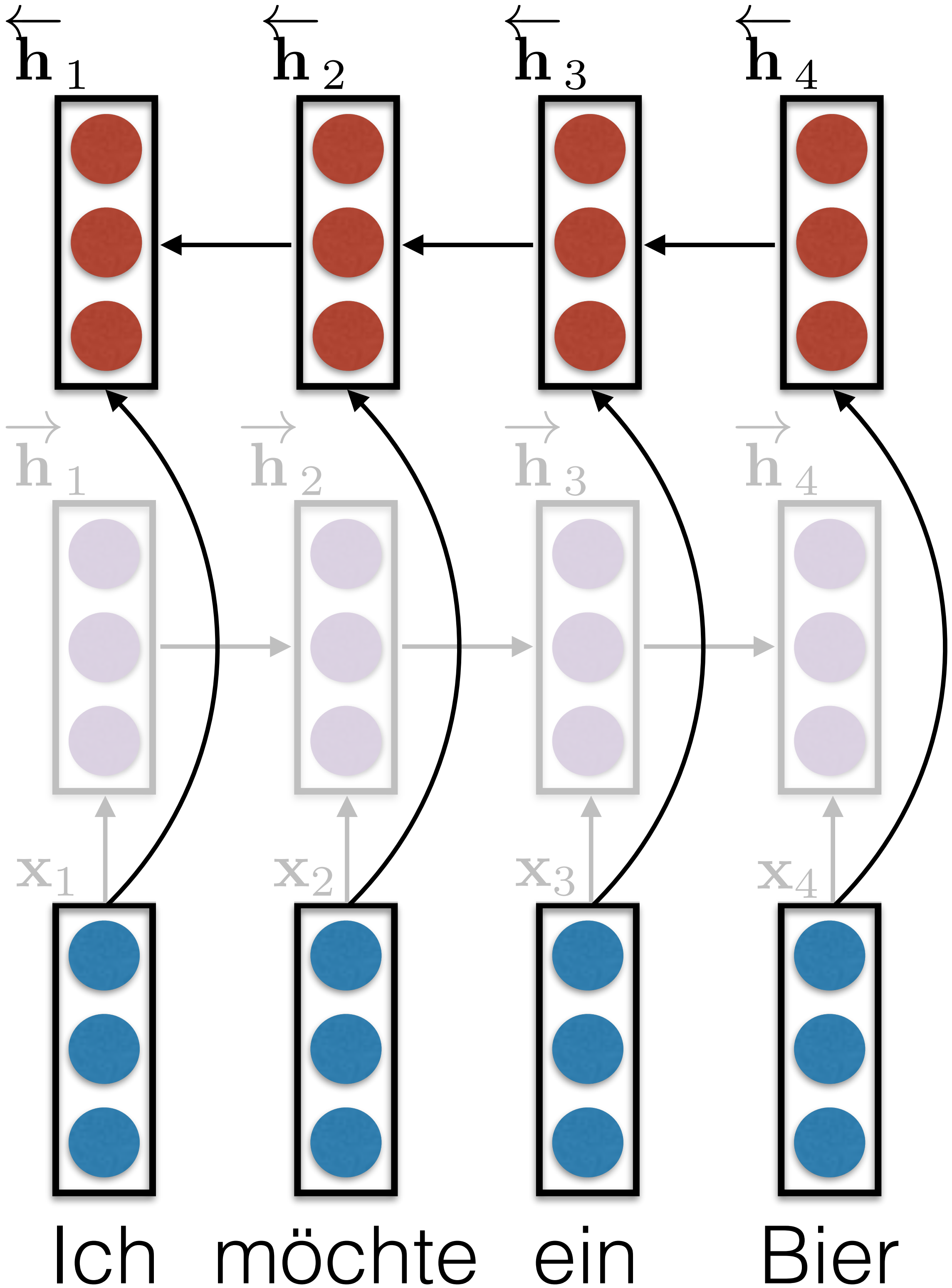

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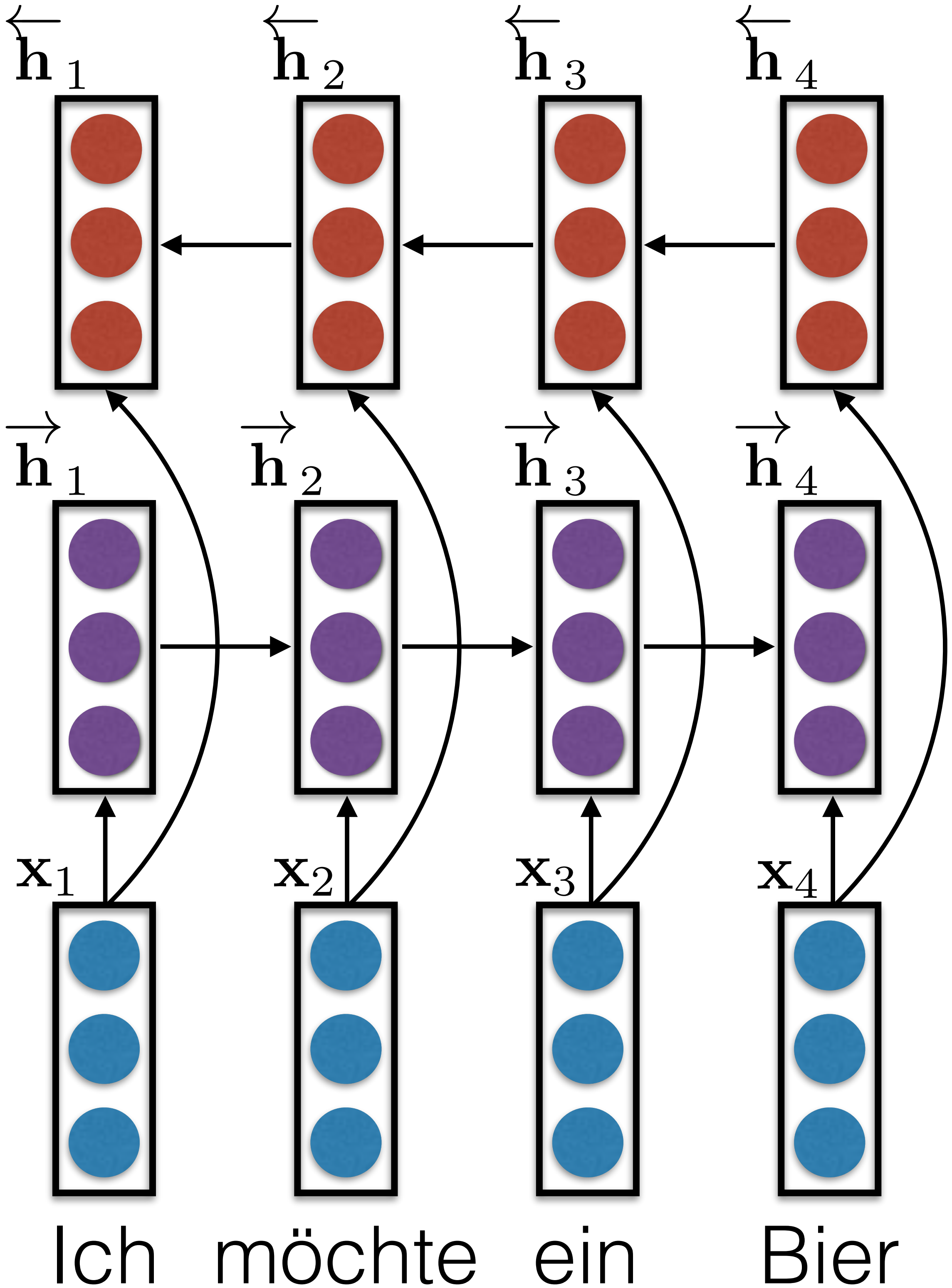
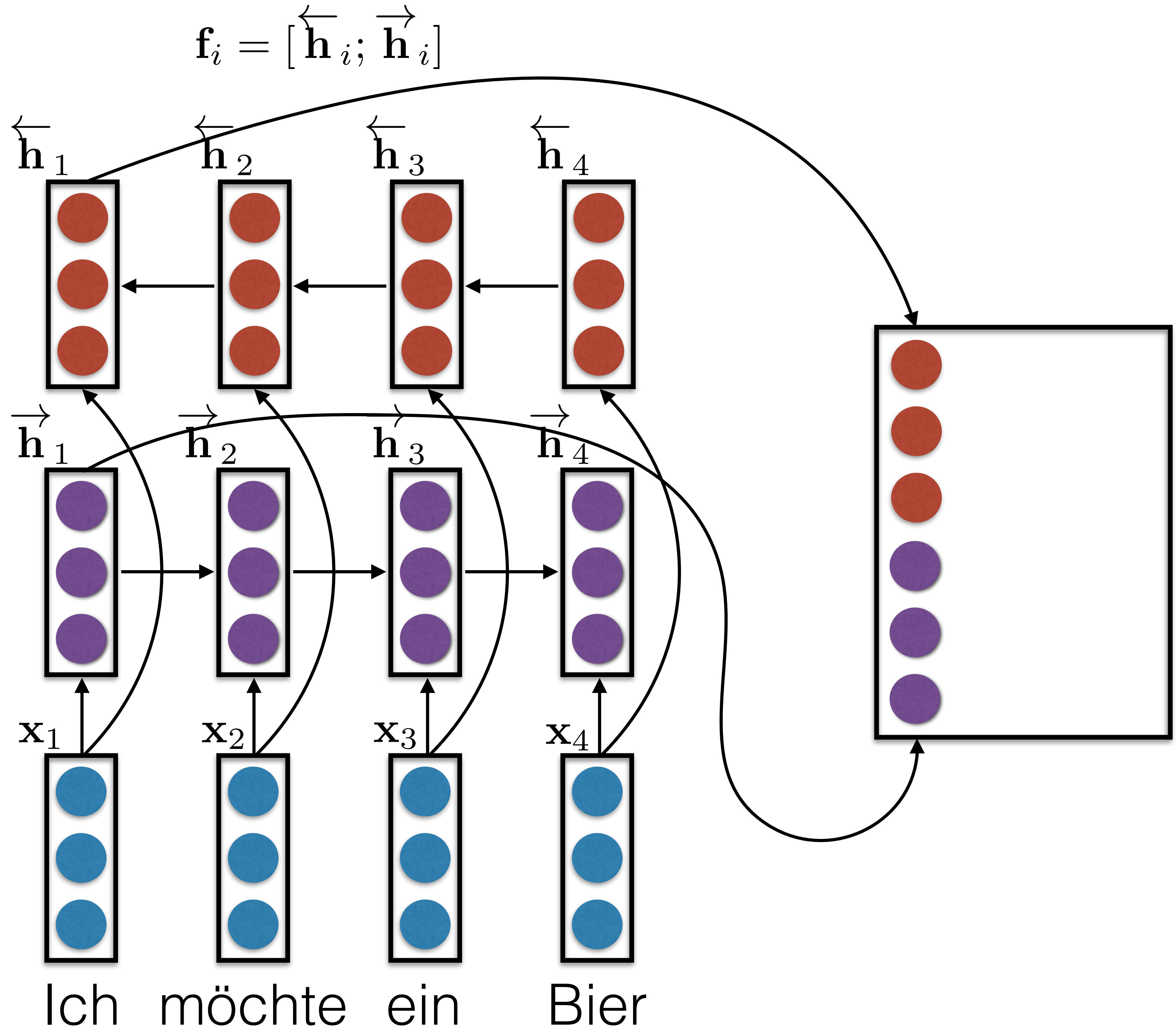
$$\mathbf{f}_i = [\overleftarrow{\mathbf{h}}_i ; \overrightarrow{\mathbf{h}}_i]$$

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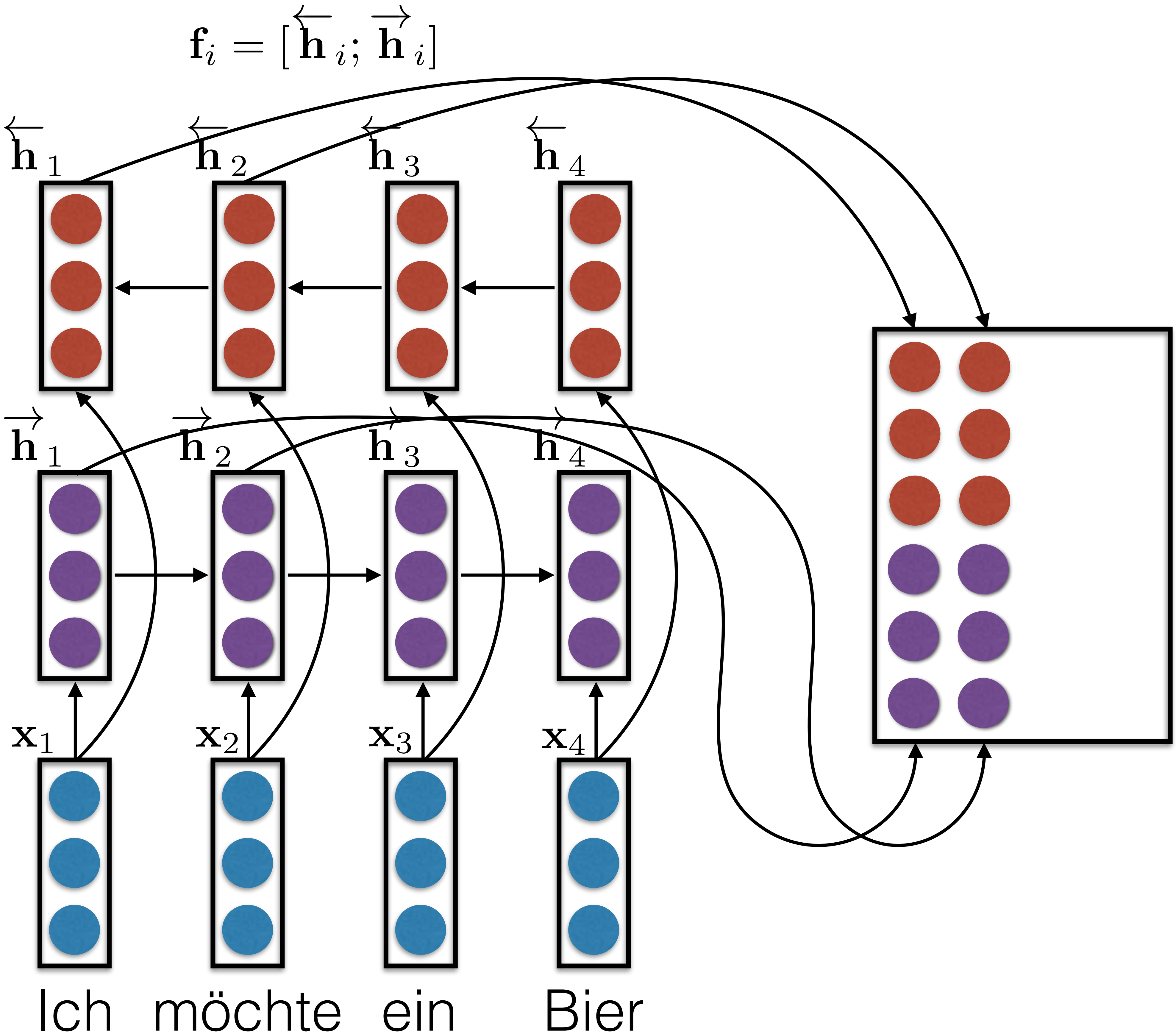
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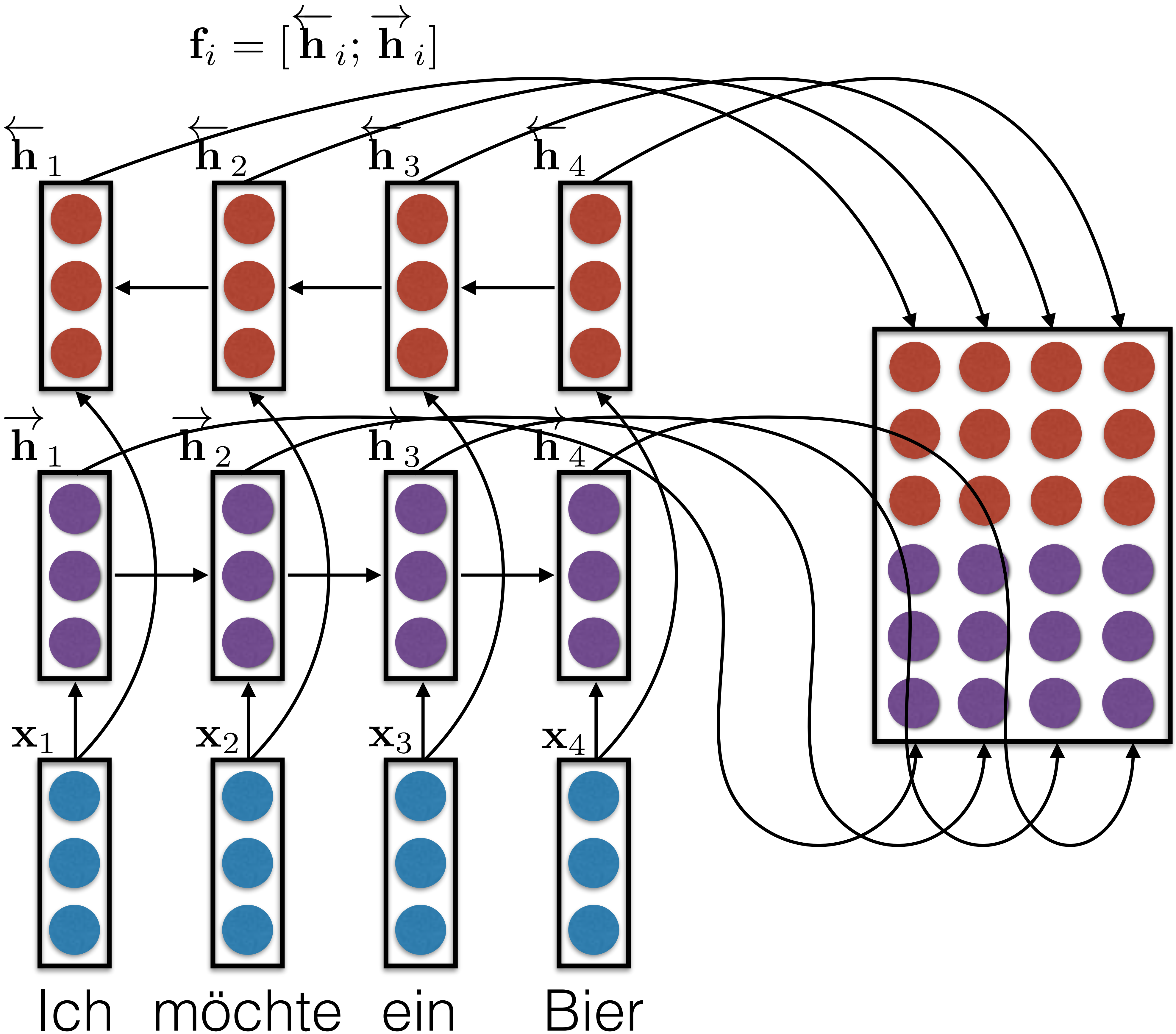
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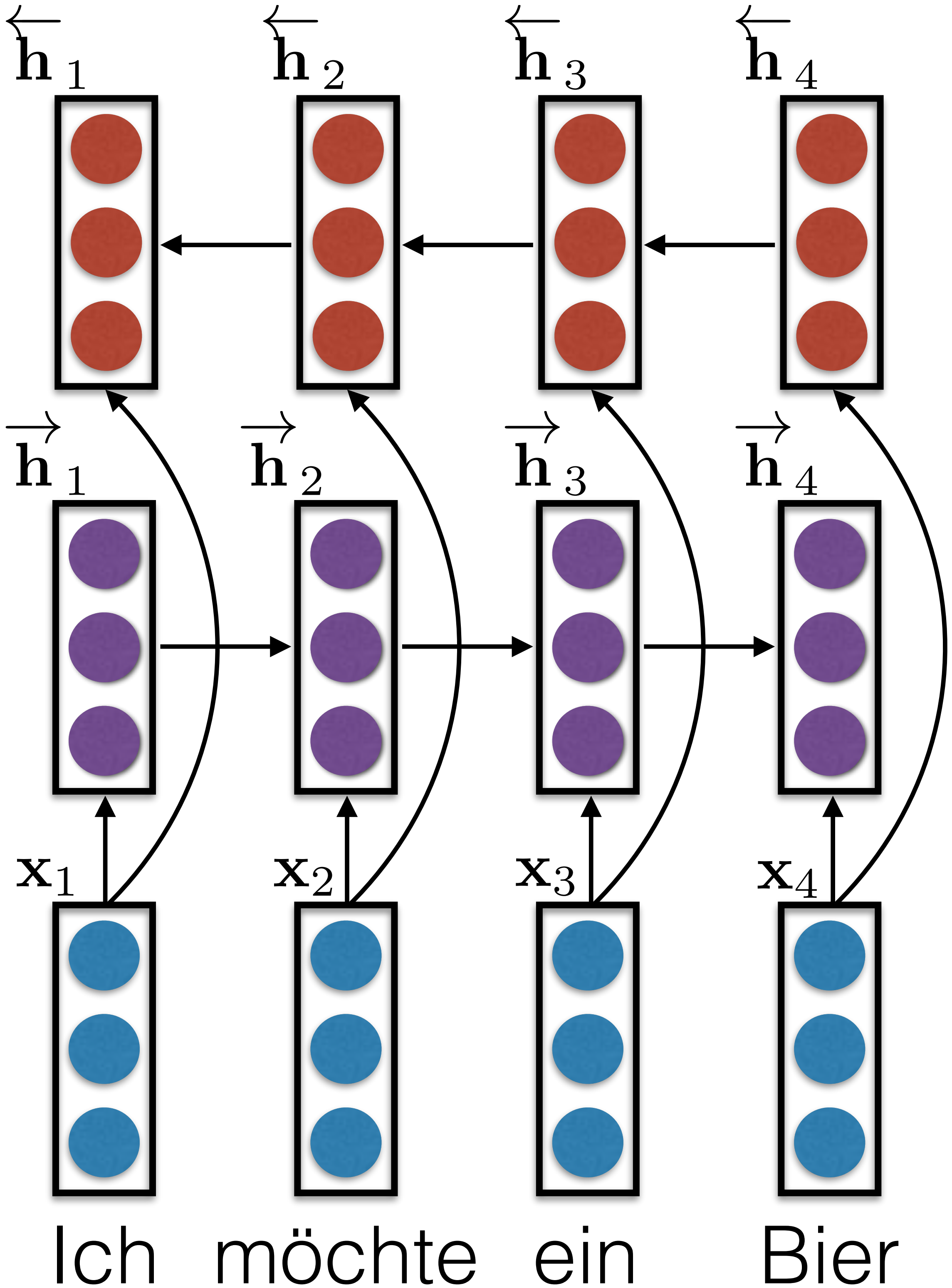
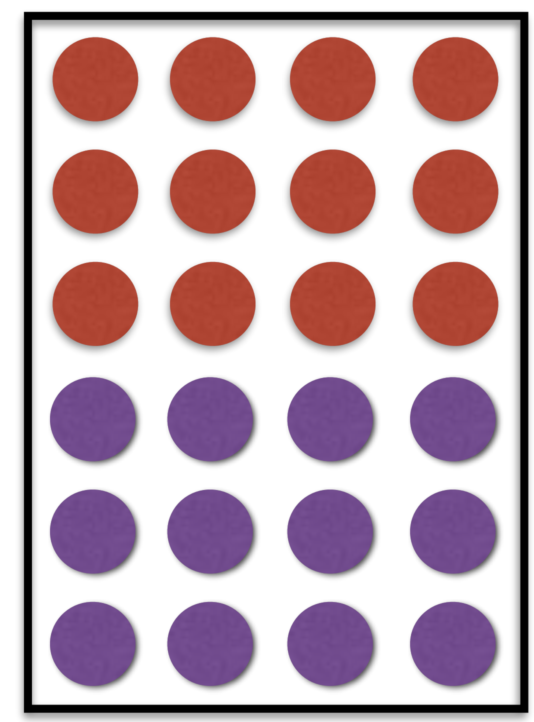


$$\mathbf{F} \in \mathbb{R}^{2n \times |\boldsymbol{f}|}$$



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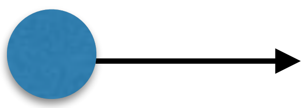
Where are we in 2017?

- There are lots of ways to construct **F**
  - Very little systematic work comparing them
  - There are many more undiscovered things out there
    - convolutions are particularly interesting and under-explored
    - syntactic information can help (Sennrich & Haddow, 2016; Nadejde et al., 2017), but many more integration strategies are possible
    - try something with phrase types instead of word types?

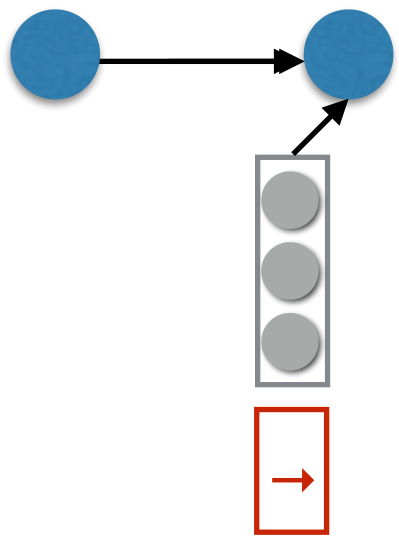
Multi-word expressions are a pain in the neck .

Generation from Matrices

- We have a matrix **F** representing the input, now we need to generate from it
- Bahdanau et al. (2015) were the first to propose using ***attention*** for translating from matrix-encoded sentences
- High-level idea
  - Generate the output sentence word by word using an RNN
  - At each output position t, the RNN receives **two** inputs (in addition to any recurrent inputs)
    - a fixed-size vector embedding of the previously generated output symbol e_{t-1}
    - a fixed-size vector encoding a “view” of the input matrix
  - How do we get a fixed-size vector from a matrix that changes over time?
    - Bahdanau et al: do a weighted sum of the columns of **F** (i.e., words) based on how important they are *at the current time step*. (i.e., just a matrix-vector product $\mathbf{F}\mathbf{a}_t$)
    - The weighting of the input columns at each time-step ($\mathbf{a}_t$) is called ***attention***



Recall RNNs…



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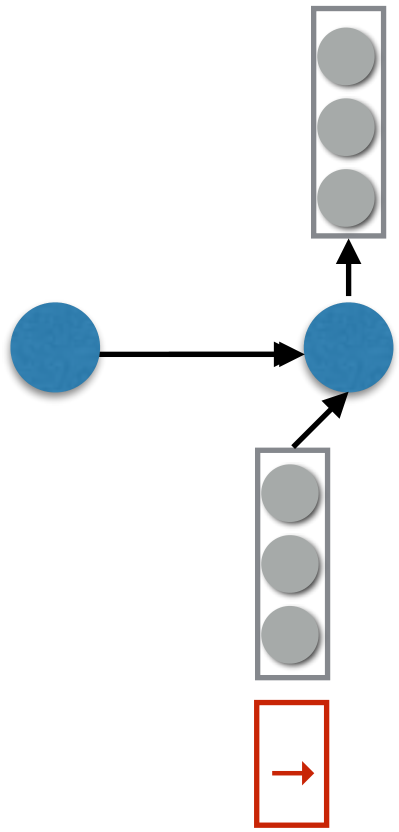

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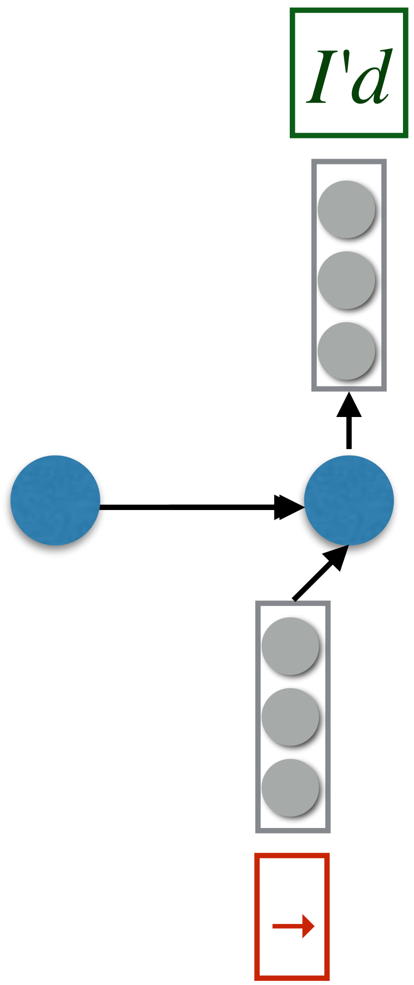

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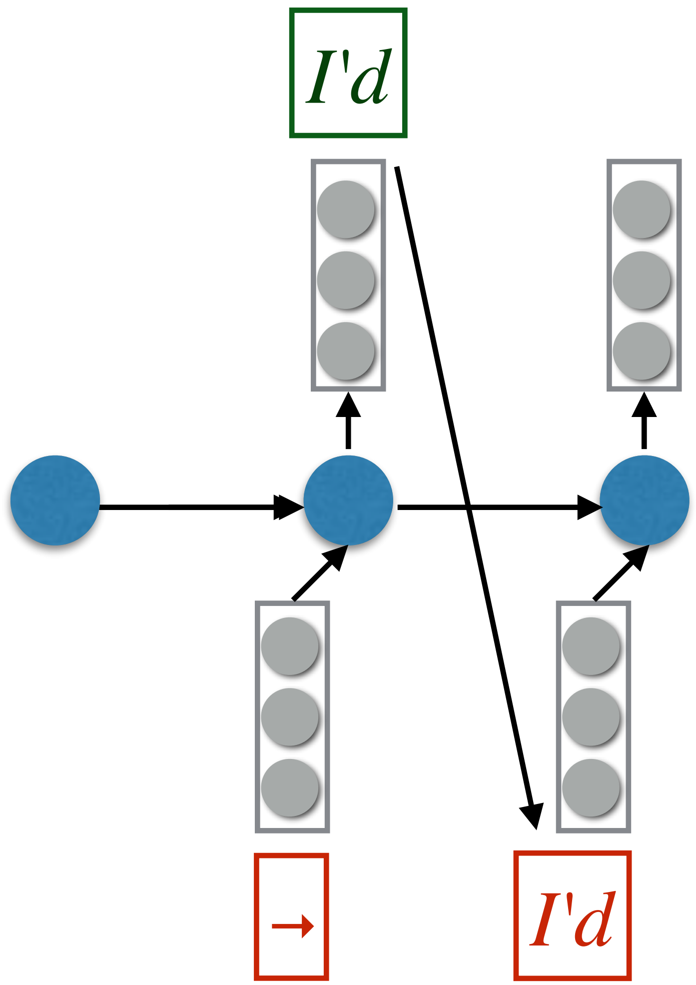

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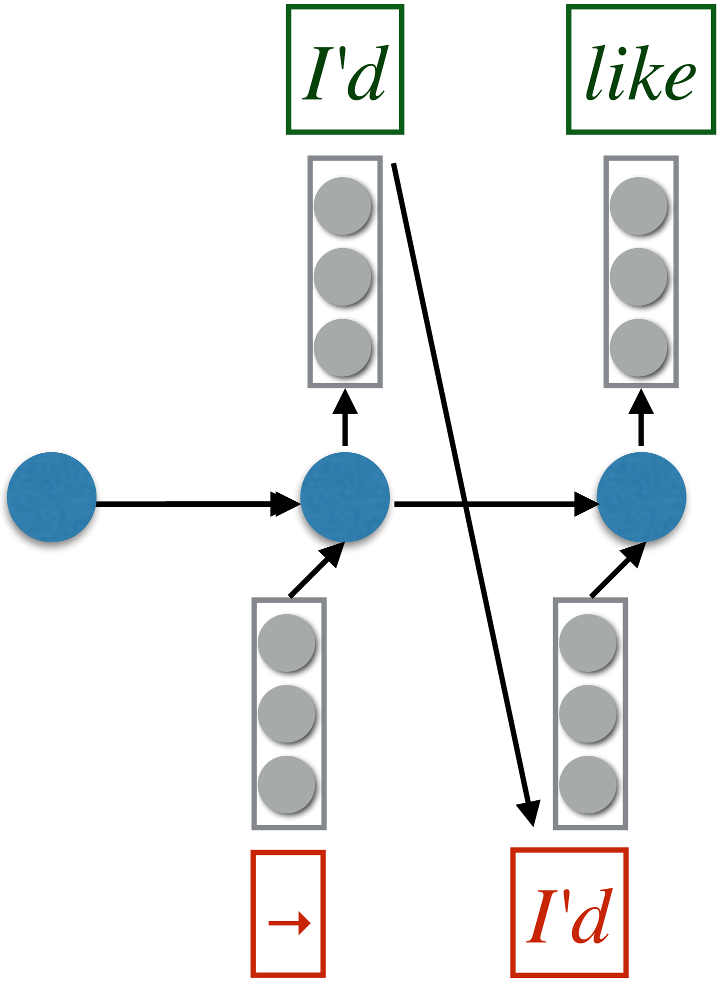

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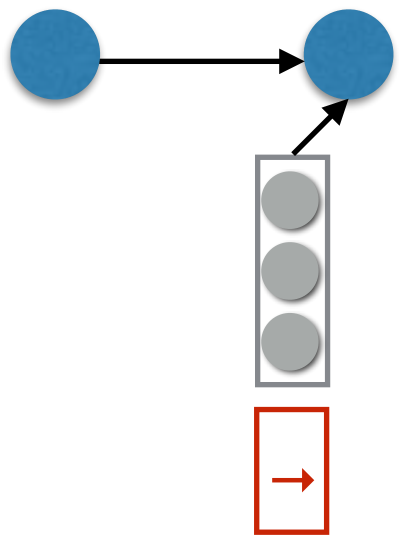

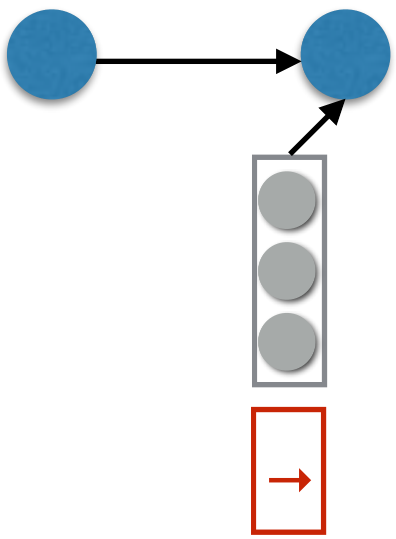

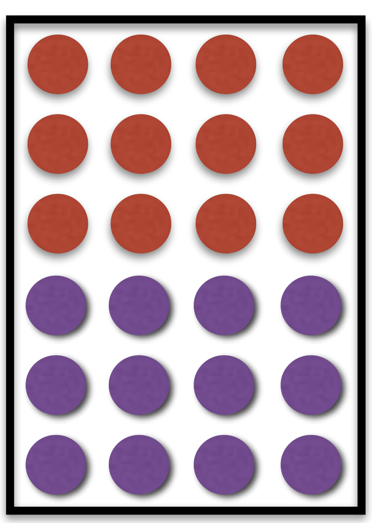

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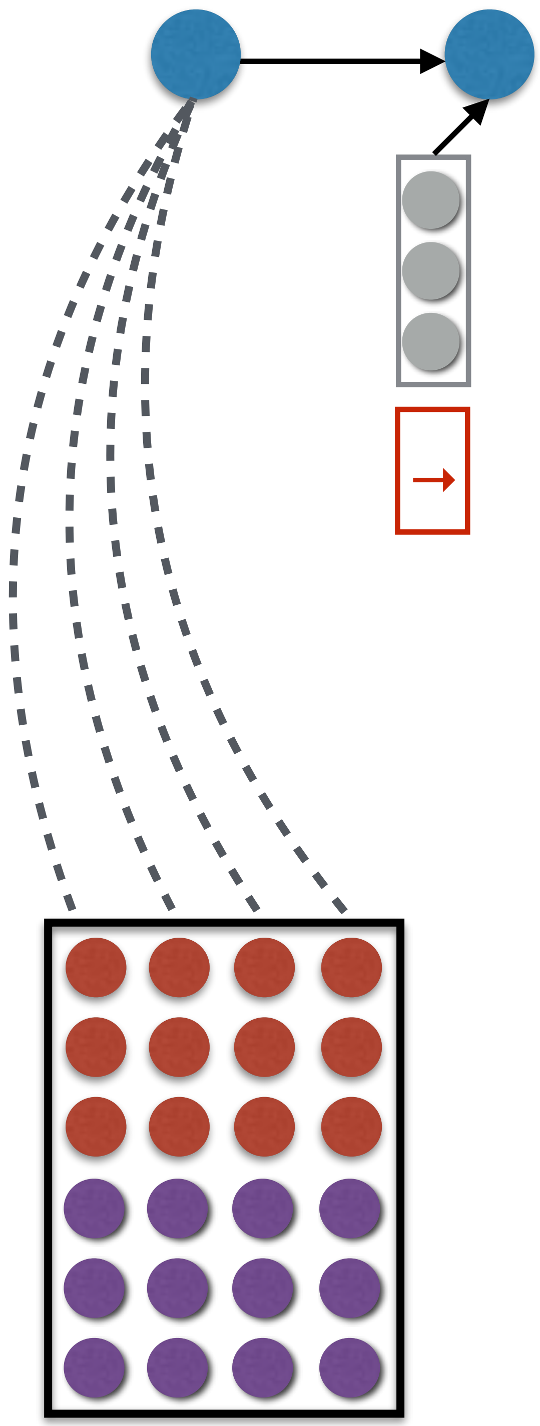

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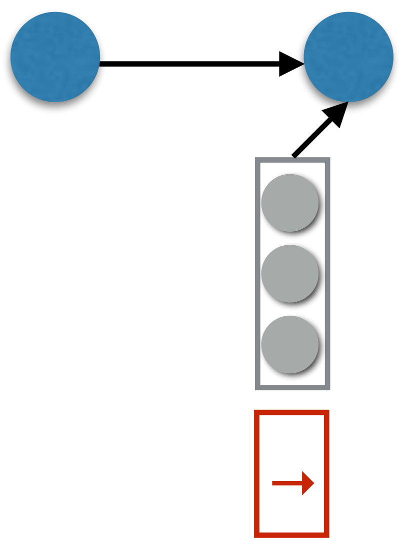

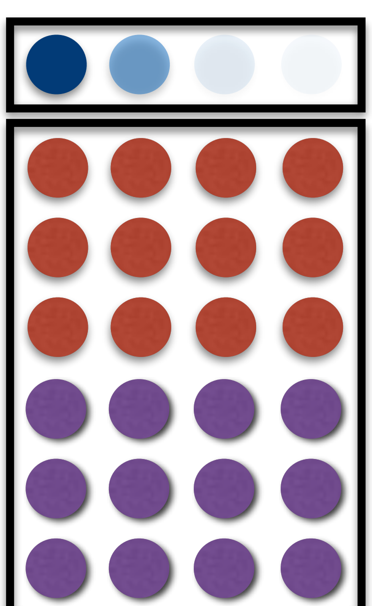

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Attention history:

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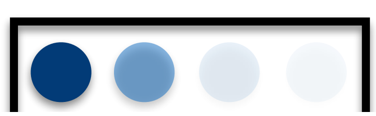

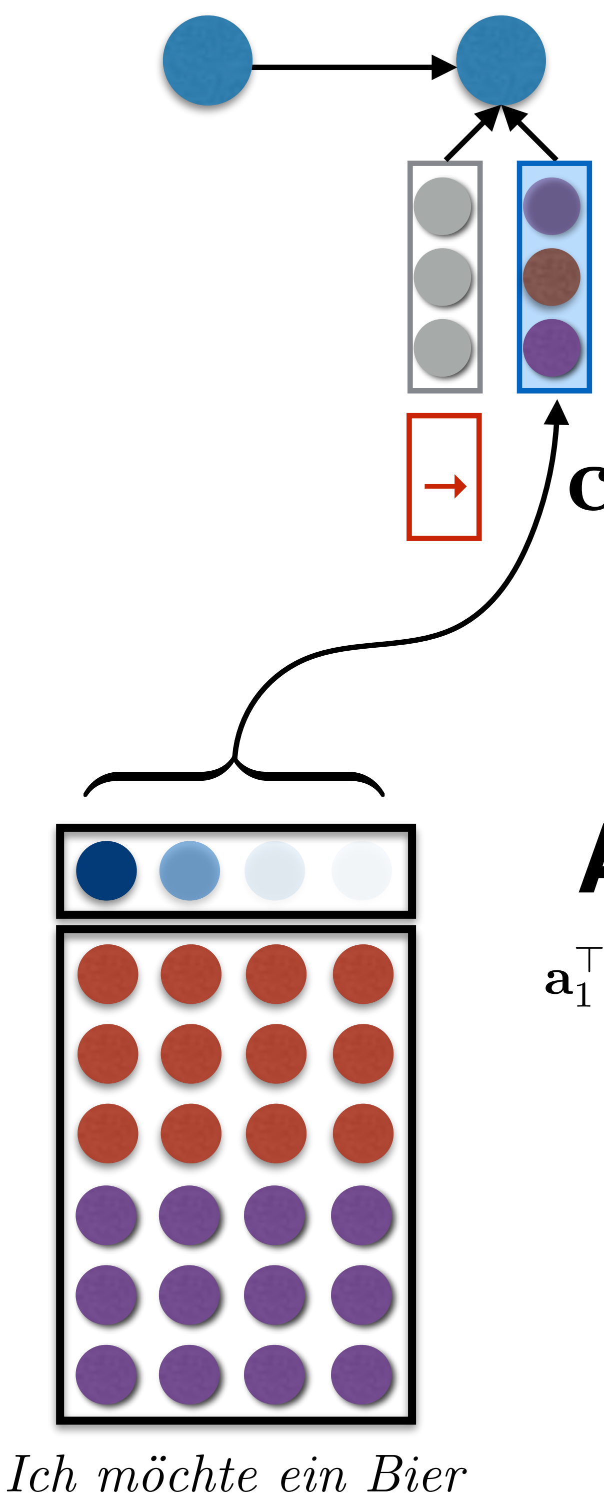

$$\mathbf{c}_1 = \mathbf{F}\mathbf{a}_1$$

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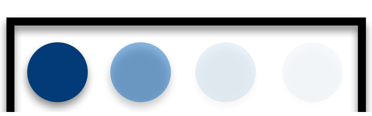
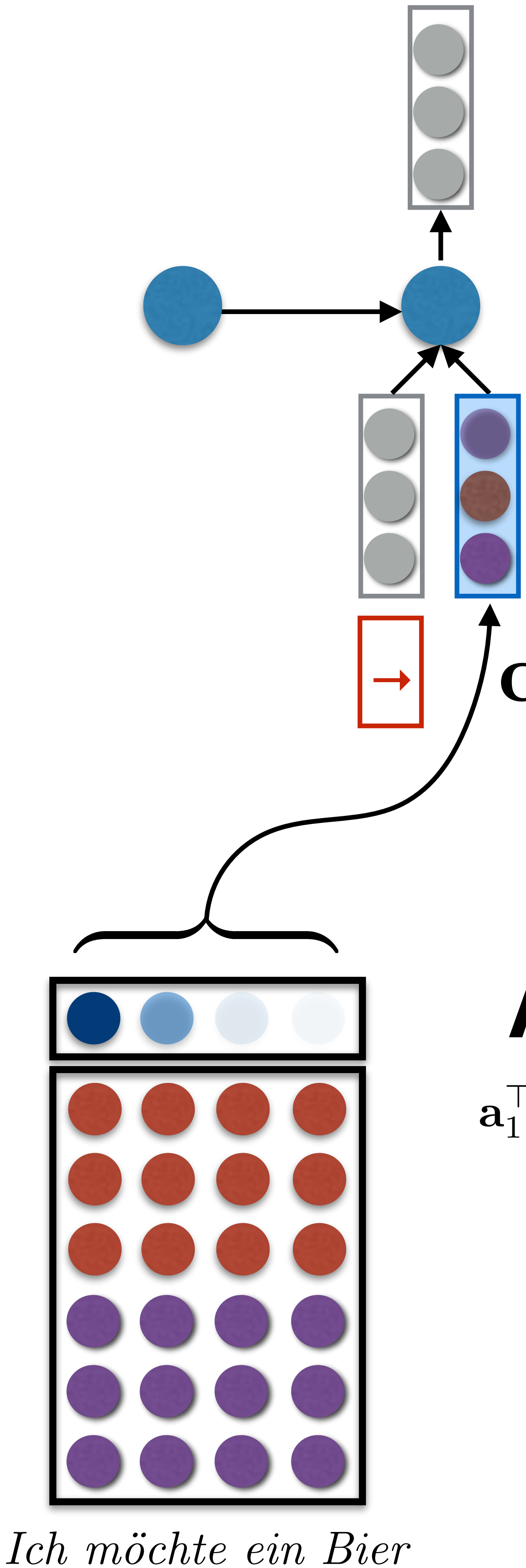
$\mathbf{a}_1^\top$ 



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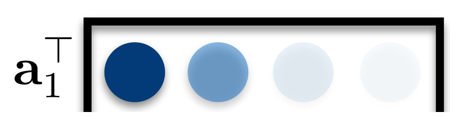

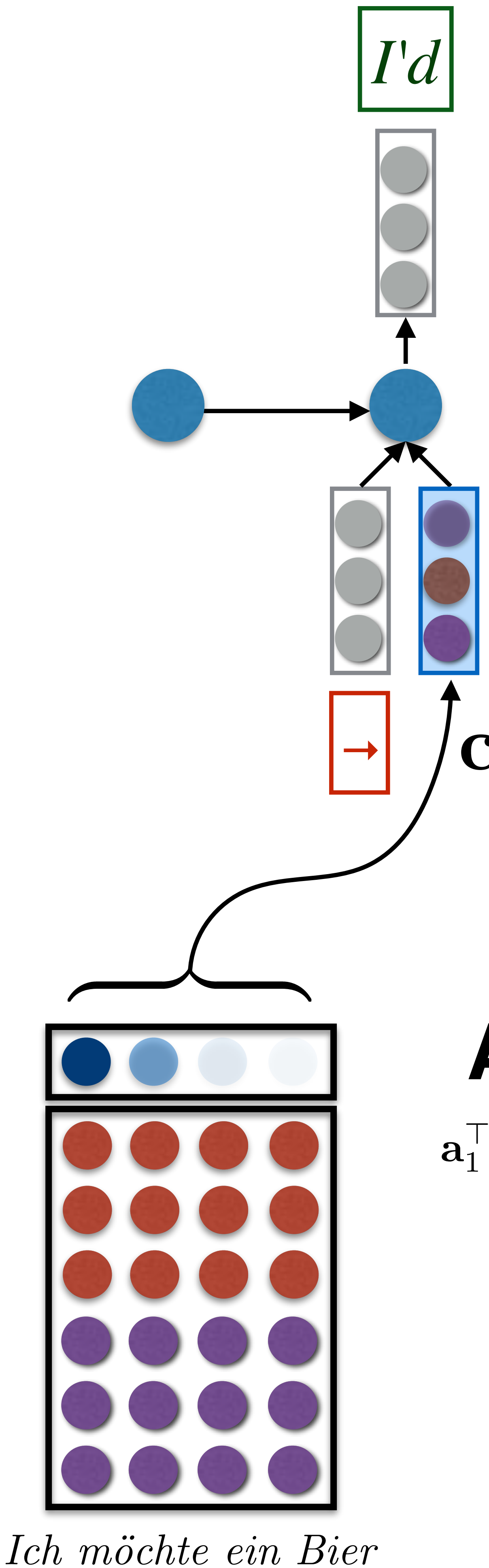

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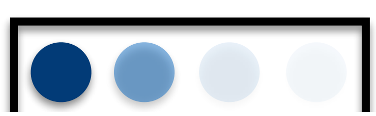
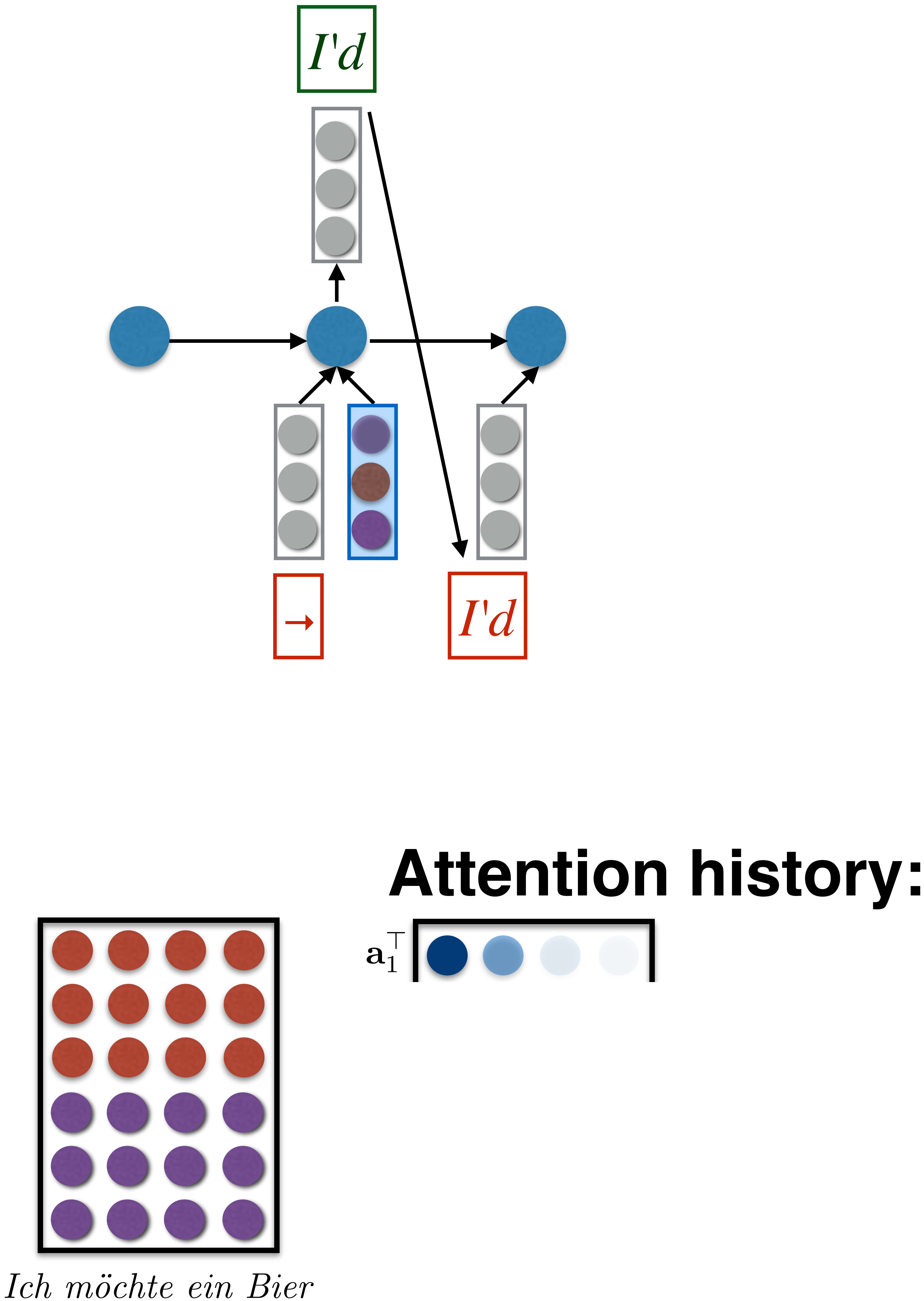
$\mathbf{a}_1^\top$ 



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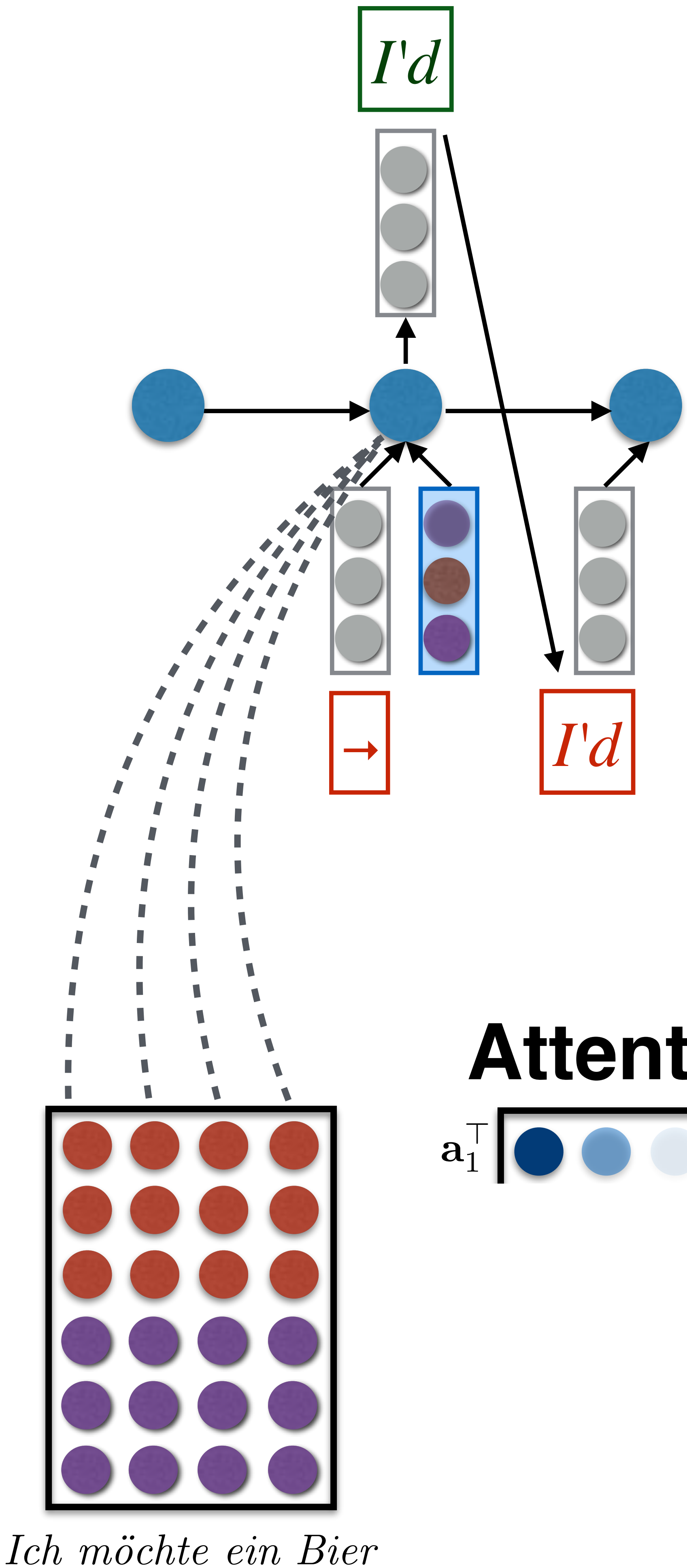

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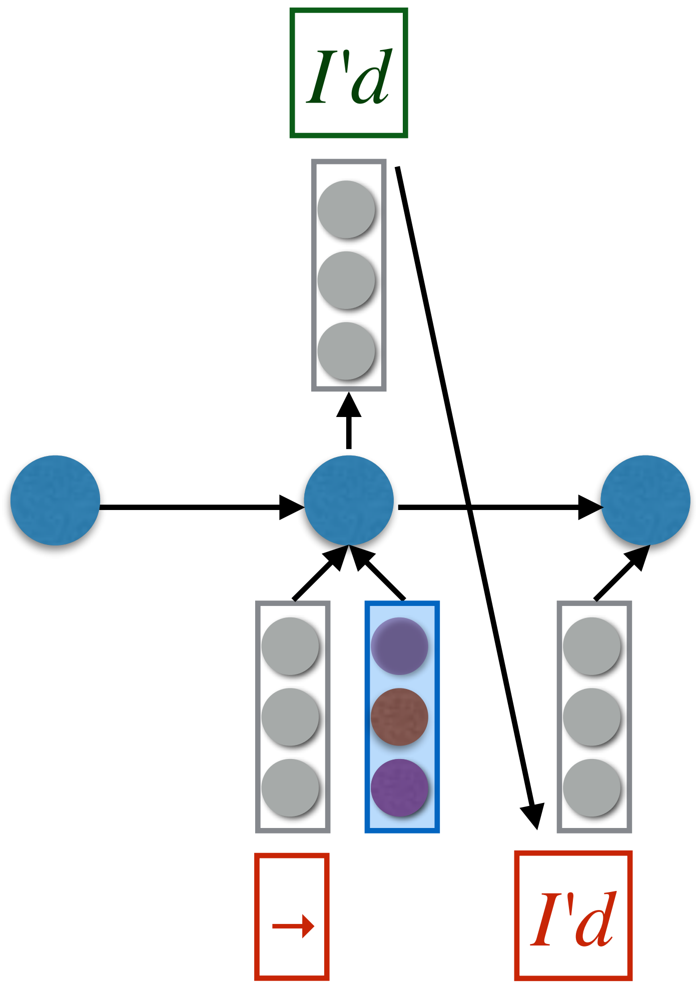
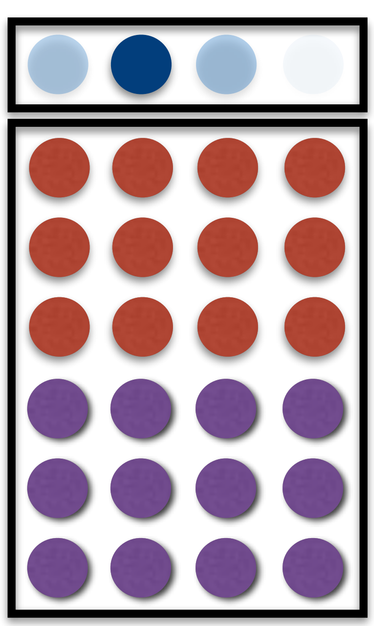
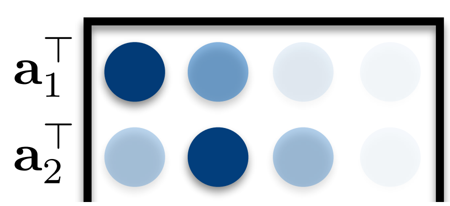
$\mathbf{a}_1^\top$

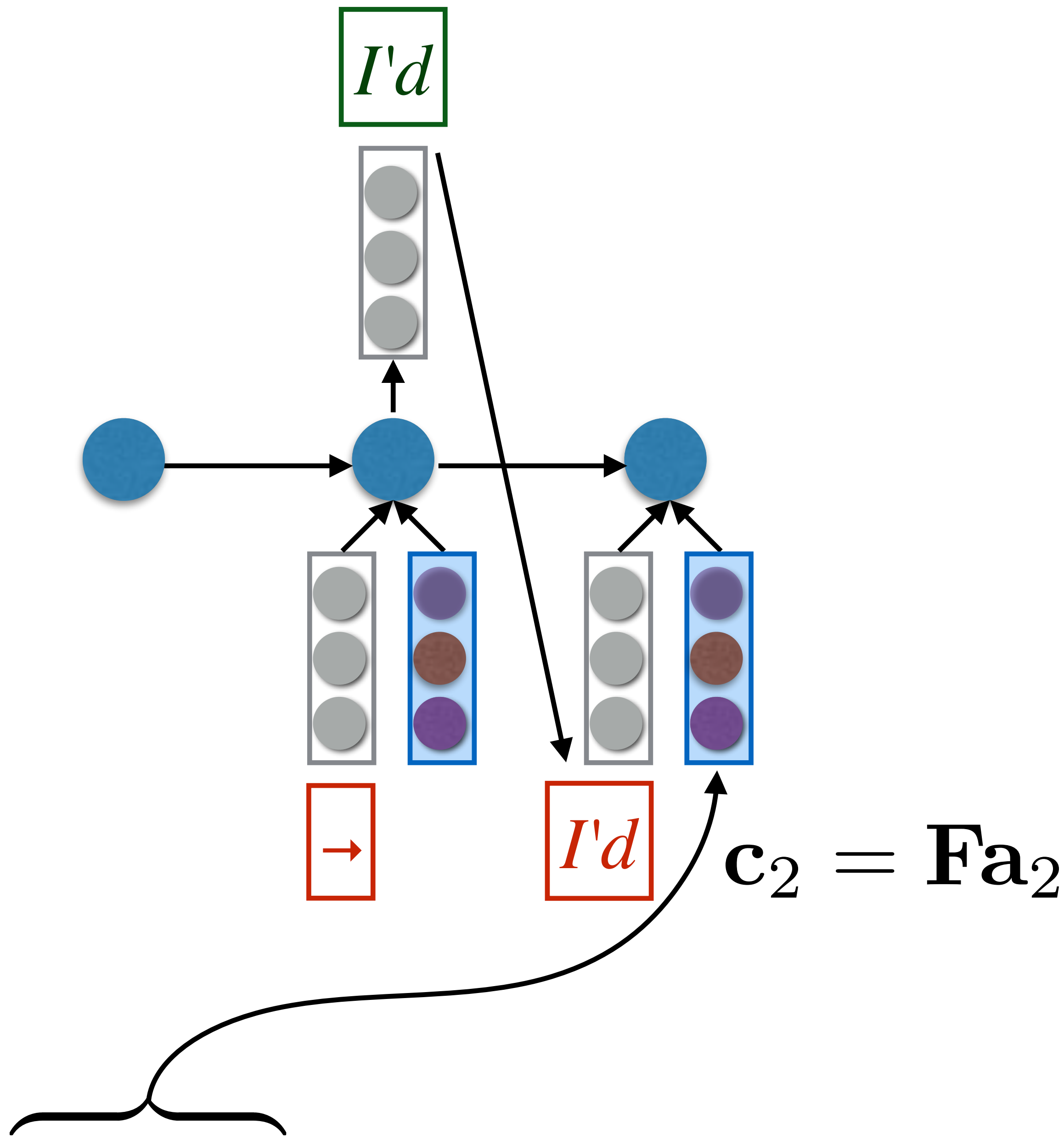


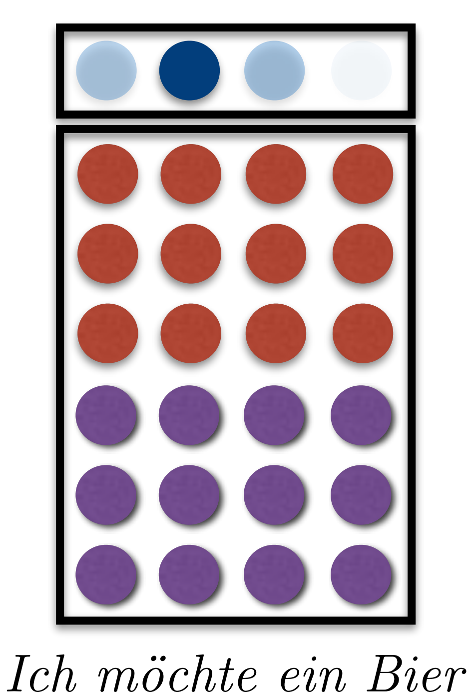


Ich möchte ein Bier

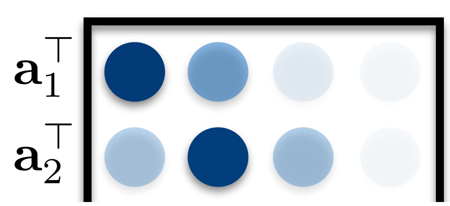
Attention history:

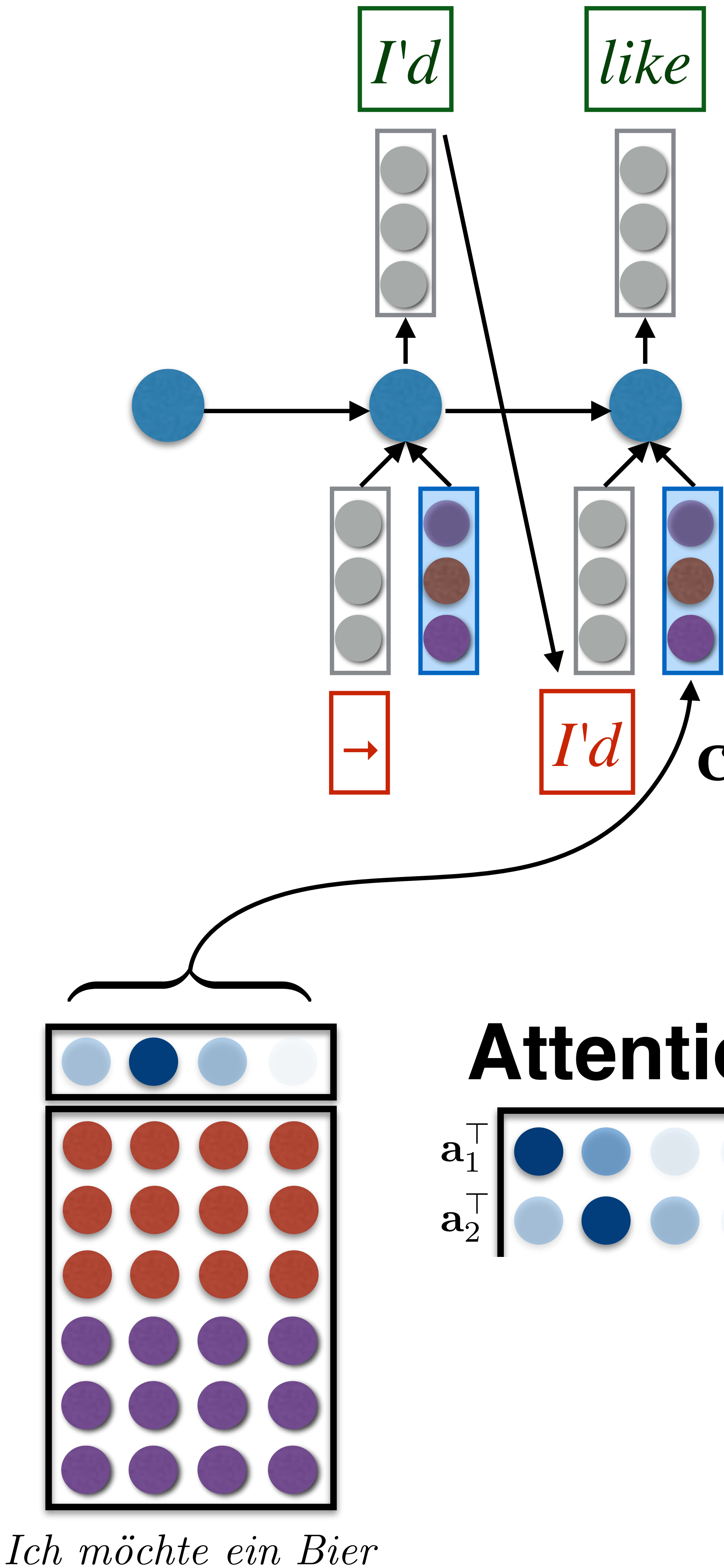






Attention history:

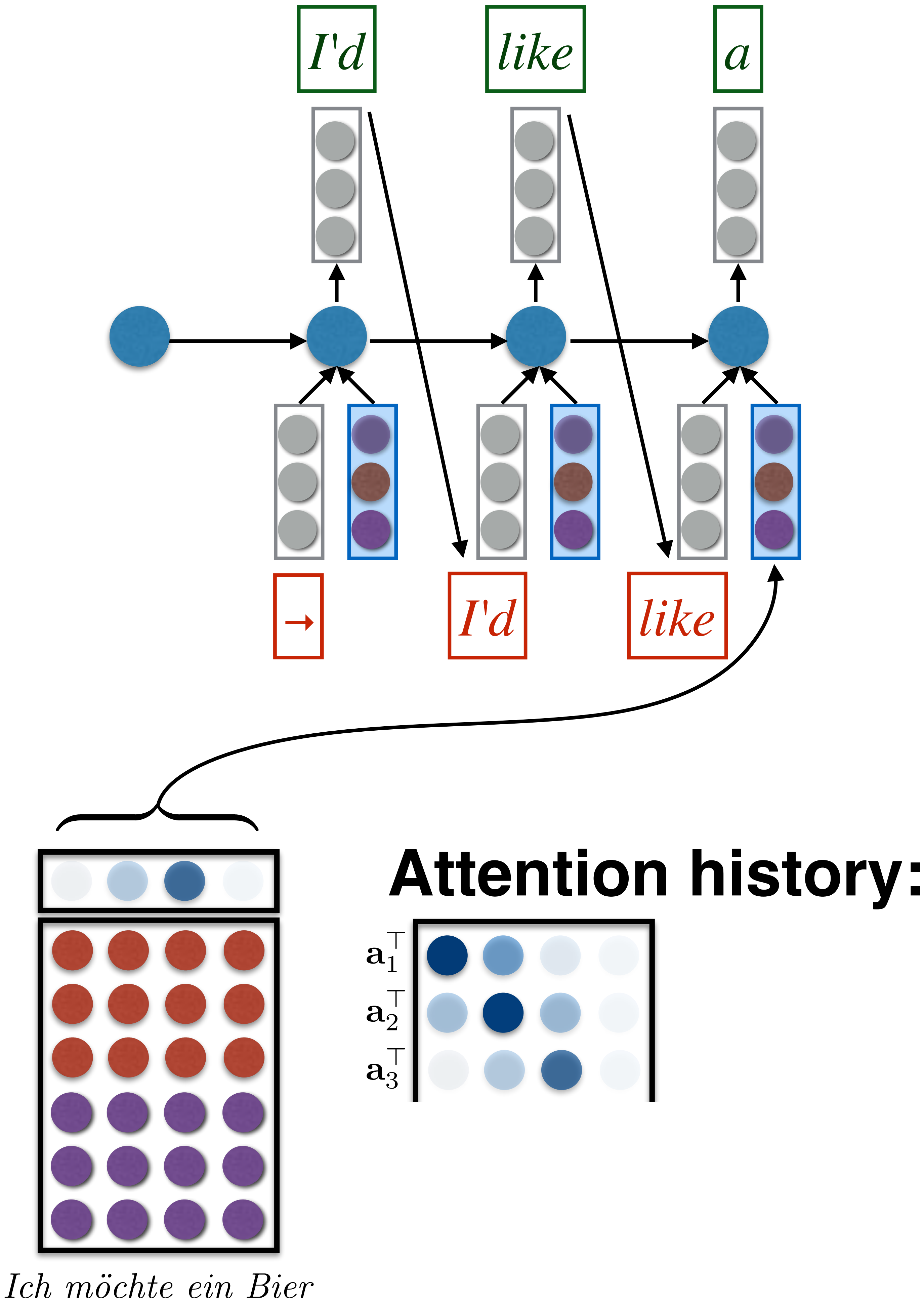


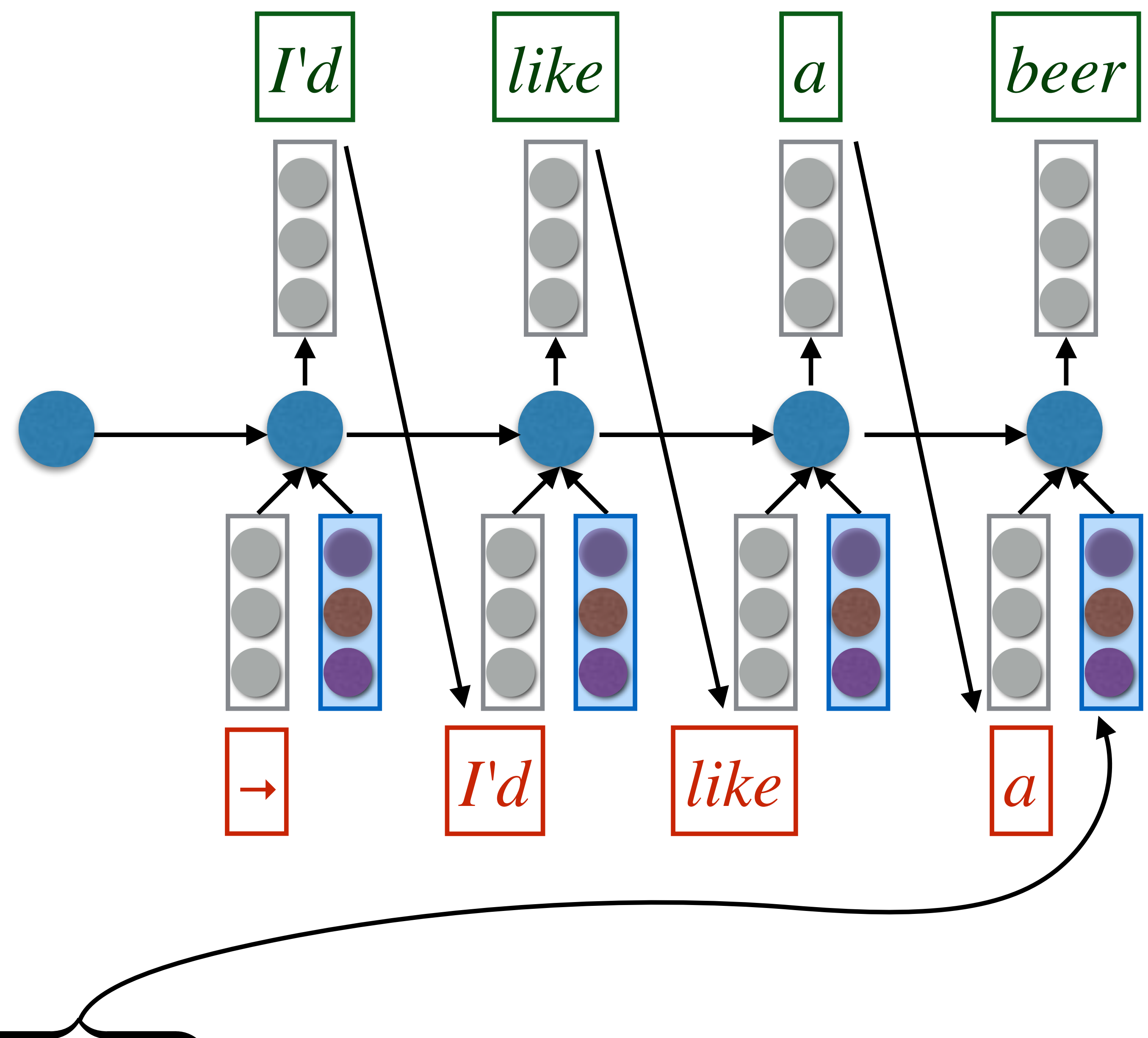


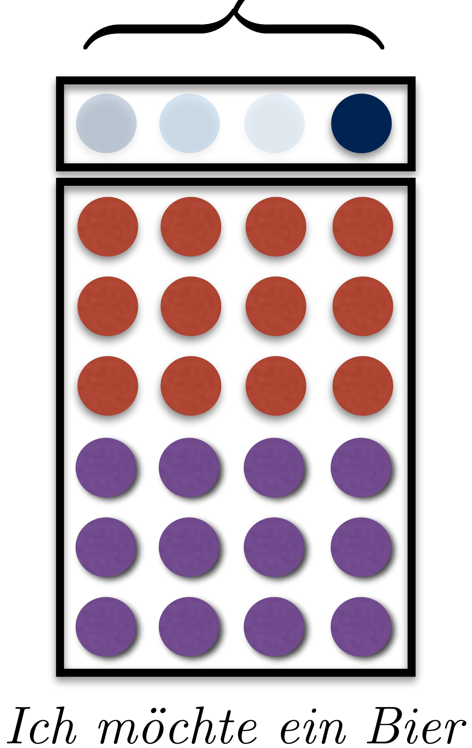
$$\mathbf{c}_2 = \mathbf{F}\mathbf{a}_2$$

Attention history:

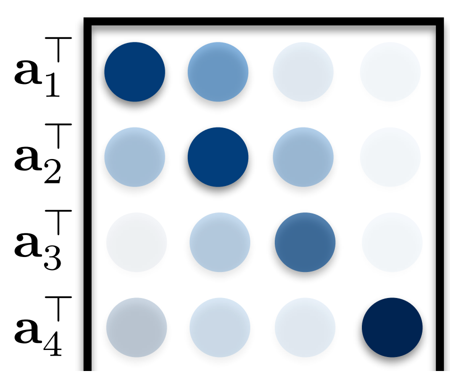
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$

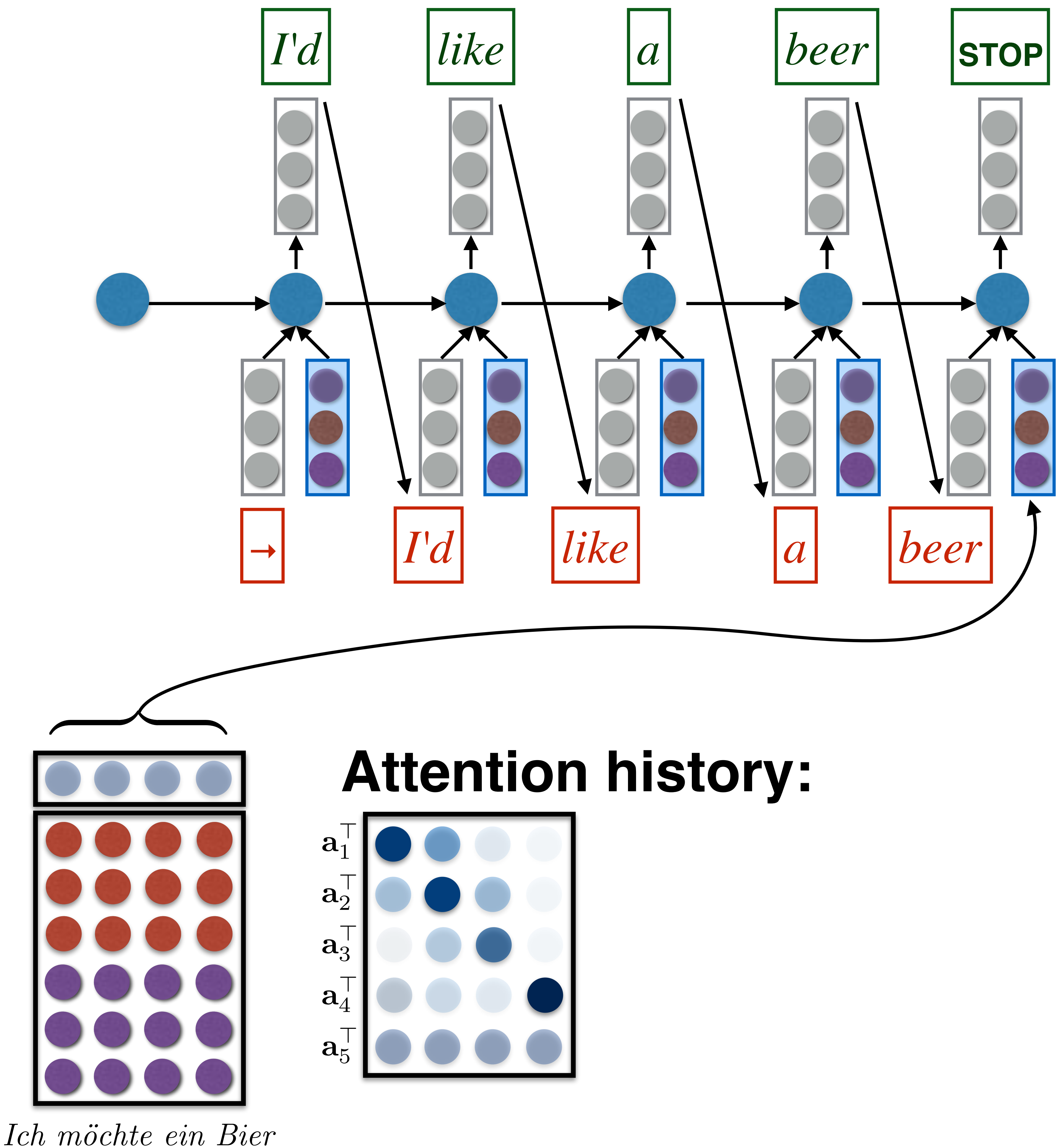

I'd
like
a
→
I'd
like
Attention history:
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$
$\mathbf{a}_3^\top$
Ich möchte ein Bier





Attention history:





I'd
like
a
beer
STOP
→
I'd
like
a
beer
Attention history:
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$
$\mathbf{a}_3^\top$
$\mathbf{a}_4^\top$
$\mathbf{a}_5^\top$
Ich möchte ein Bier

Attention

- How do we know what to attend to at each time-step?
- That is, how do we compute $\mathbf{a}_t$?

Computing Attention

- At each time step (one time step = one output word), we want to be able to "attend" to different words in the source sentence
    - We need a weight for every column: this is an $|\boldsymbol{f}|$-length vector $\mathbf{a}_t$
    - Here is a simplified version of Bahdanau et al.'s solution
        - Use an RNN to predict model output, call the hidden states $\mathbf{s}_t$
          ($\mathbf{s}_t$ has a fixed dimensionality, call it m)

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    - Exponentiate and normalize to 1: $\mathbf{a}_t = \mathrm{softmax}(\mathbf{u}_t)$
      (called $\boldsymbol{\alpha}_t$ in the paper)
    - Finally, the ***input source vector*** for time *t* is $\mathbf{c}_t = \mathbf{F}\mathbf{a}_t$

Nonlinear Attention-Energy Model

- In the actual model, Bahdanau et al. replace the dot product between the columns of **F** and $\mathbf{r}_t$ with an MLP:

$$\mathbf{u}_t = \mathbf{F}^\top \mathbf{r}_t \qquad \text{(simple model)}$$

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- Here, **W** and **v** are learned parameters of appropriate dimension and + "broadcasts" over the $|\boldsymbol{f}|$ columns in **WF**

- This can learn more complex interactions

  - It is unclear if the added complexity is necessary for good performance

Putting it all together

$\mathbf{F} = \mathrm{EncodeAsMatrix}(\boldsymbol{f})$ (Part 1 of lecture)

$e_0 = \langle \mathbf{s} \rangle$

$\mathbf{s}_0 = \mathbf{w}$ (Learned initial state; Bahdanau uses $\mathbf{U}\overleftarrow{\mathbf{h}}_1$)

$t = 0$

$\textbf{while } e_t \neq \langle \mathbf{/s} \rangle :$

$$t = t + 1$$

$$\left.\begin{aligned} \mathbf{r}_t &= \mathbf{V}\mathbf{s}_{t-1} \\ \mathbf{u}_t &= \mathbf{v}^\top \tanh(\mathbf{W}\mathbf{F} + \mathbf{r}_t) \\ \mathbf{a}_t &= \mathrm{softmax}(\mathbf{u}_t) \end{aligned}\right\} \text{(Compute attention; part 2 of lecture)}$$

$$\mathbf{c}_t = \mathbf{F}\mathbf{a}_t$$

$\mathbf{s}_t = \mathrm{RNN}(\mathbf{s}_{t-1}, [\mathbf{e}_{t-1}; \mathbf{c}_t])$ ($\mathbf{e}_{t-1}$ is a learned embedding of e_t)

$\mathbf{y}_t = \mathrm{softmax}(\mathbf{P}\mathbf{s}_t + \mathbf{b})$ ($\mathbf{P}$ and $\mathbf{b}$ are learned parameters)

$$e_t \mid \boldsymbol{e}_{<t} \sim \mathrm{Categorical}(\mathbf{y}_t)$$

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$\mathbf{a}_t = \text{softmax}(\mathbf{u}_t)$

(Compute attention; part 2 of lecture)

doesn't depend on output decisions

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$$
\begin{aligned}
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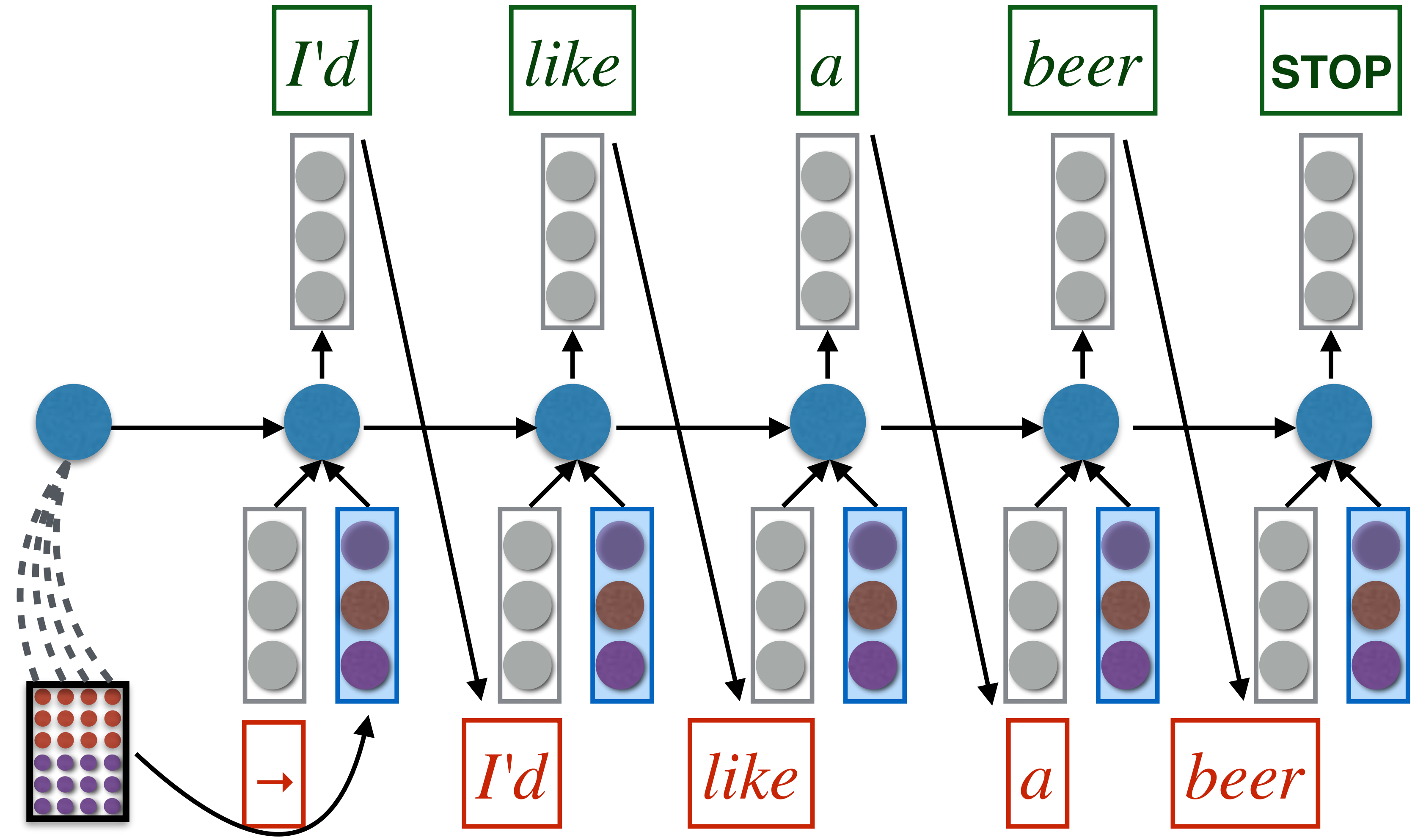
&\mathbf{y}_t = \mathrm{softmax}(\mathbf{P}\mathbf{s}_t + \mathbf{b}) \quad (\mathbf{P} \text{ and } \mathbf{b} \text{ are learned parameters}) \\
&e_t \mid \boldsymbol{e}_{<t} \sim \mathrm{Categorical}(\mathbf{y}_t)
\end{aligned}
$$

Attention in MT

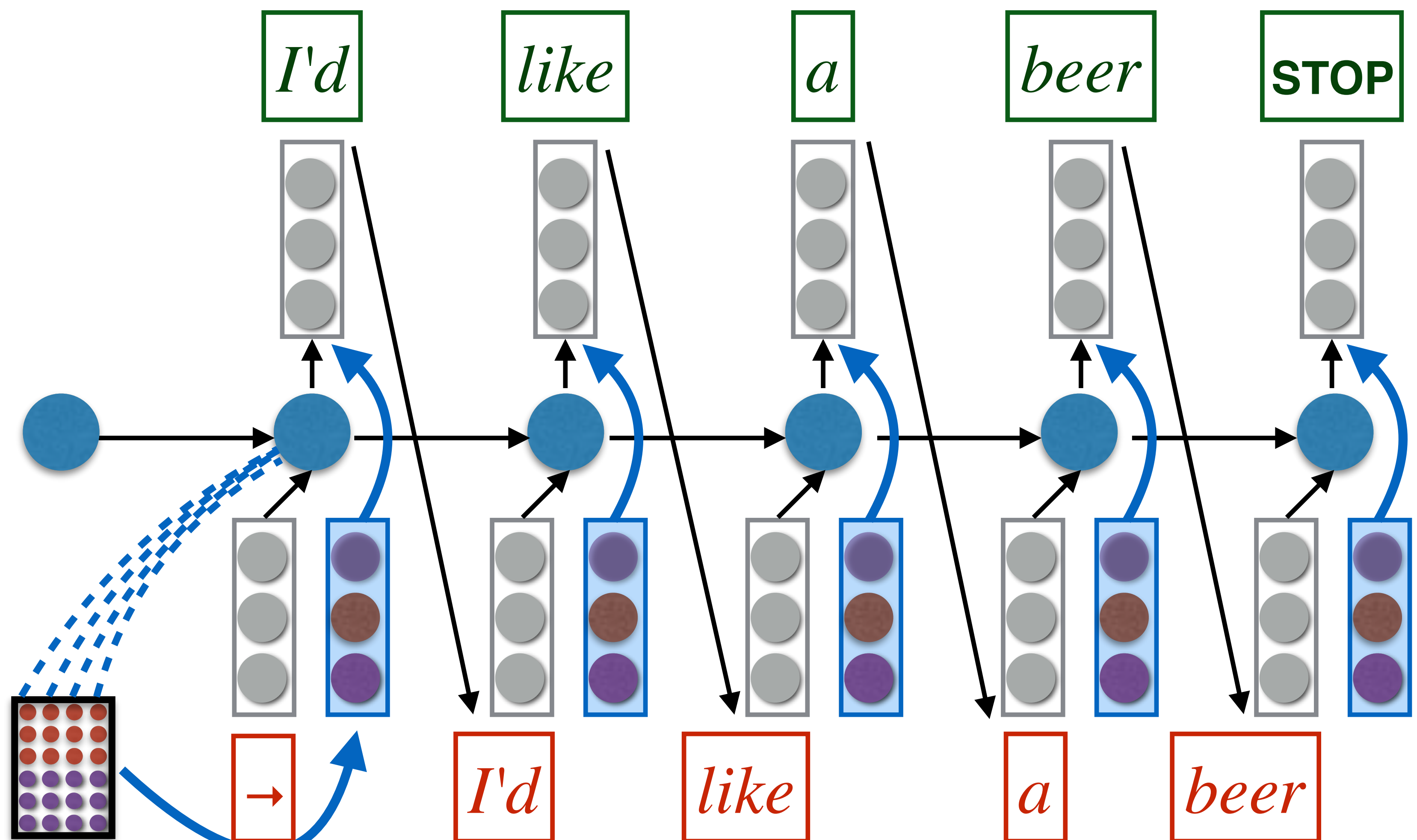
Add attention to seq2seq translation: **+11 BLEU**

Model Variant

“Early binding”



“Late binding”

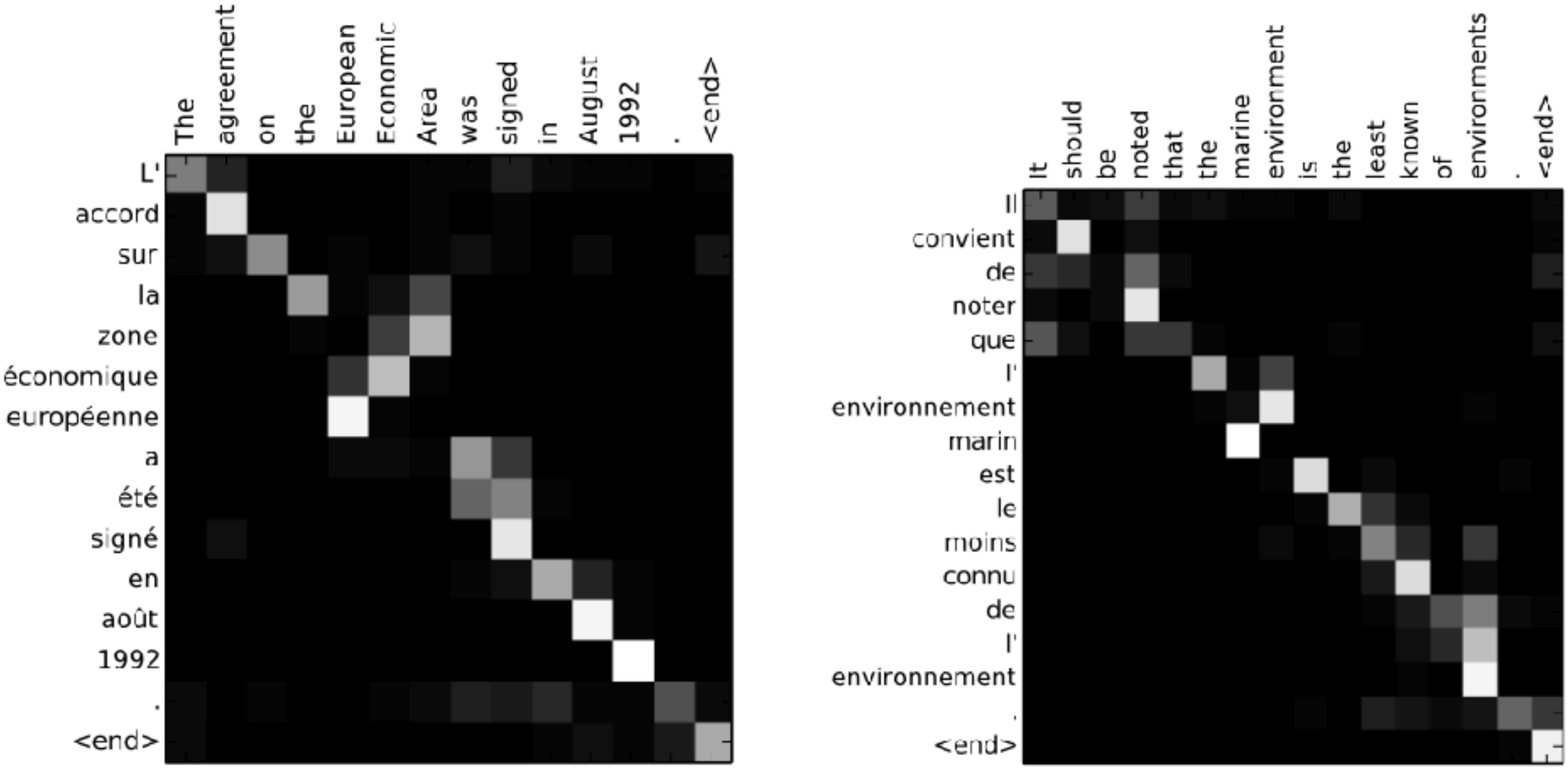


Model Variant

- What are the relative advantages of early binding versus late binding?

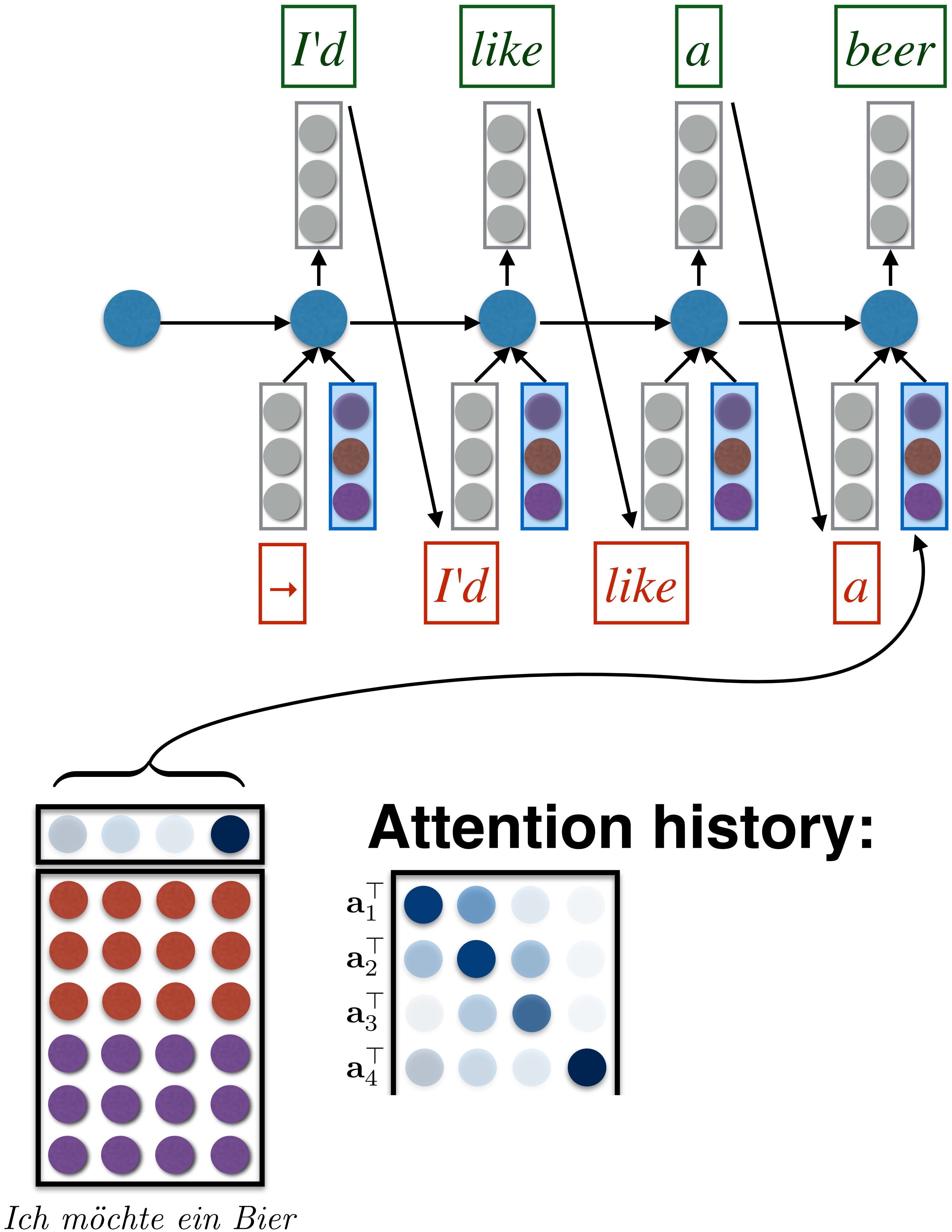
Summary

- Attention is closely related to “pooling” operations in convnets (and other architectures)
- Bahdanau’s attention model seems to only cares about “content”
  - No obvious bias in favor of diagonals, short jumps, fertility, etc.
  - Some work has begun to add other “structural” biases (Luong et al., 2015; Cohn et al., 2016), but there are lots more opportunities
- Attention weights provide interpretation you can look at

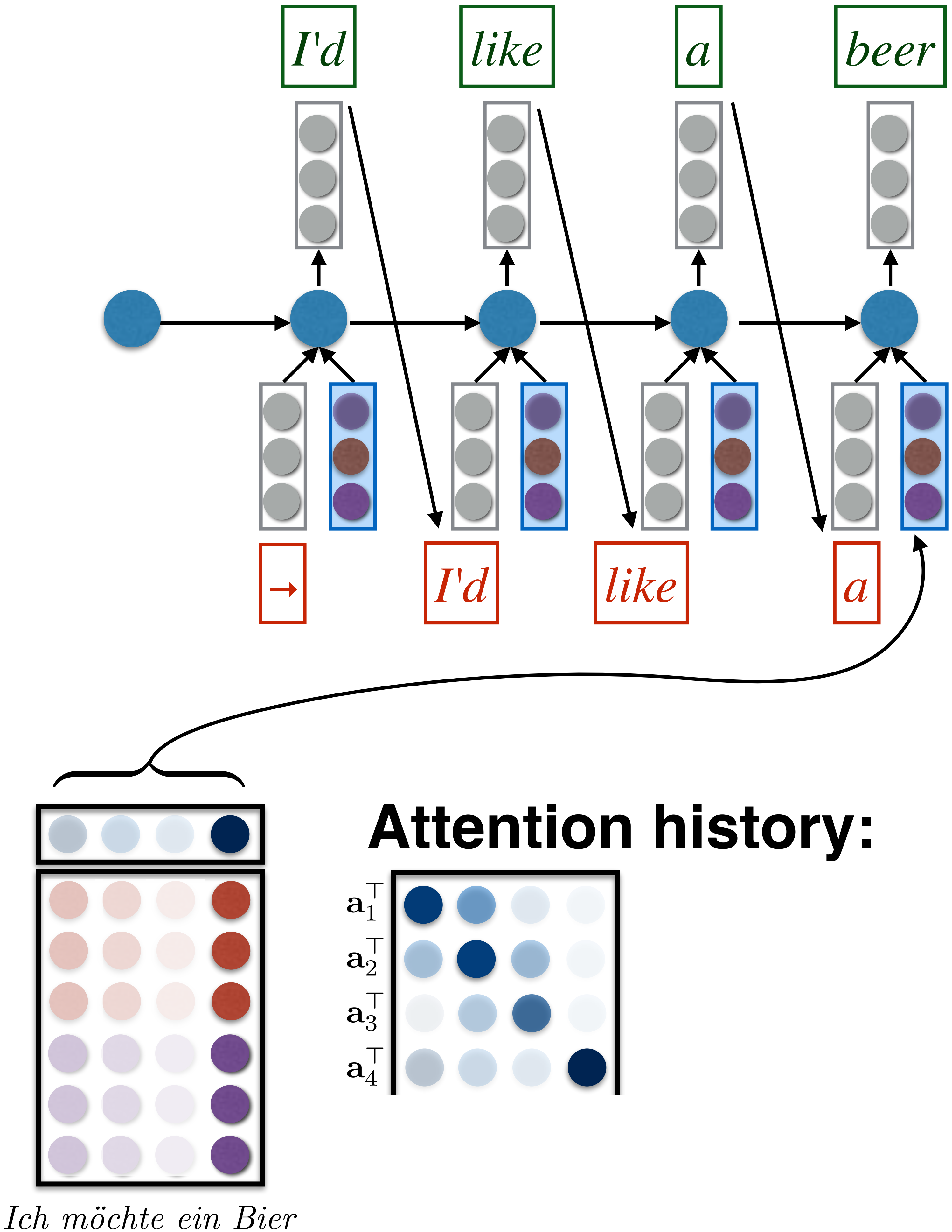

The agreement on the European Economic Area was signed in August 1992 . <end>
L' accord sur la zone économique européenne a été signé en août 1992 . <end>
It should be noted that the marine environment is the least known of environments . <end>
Il convient de noter que l' environnement marin est le moins connu de l' environnement . <end>

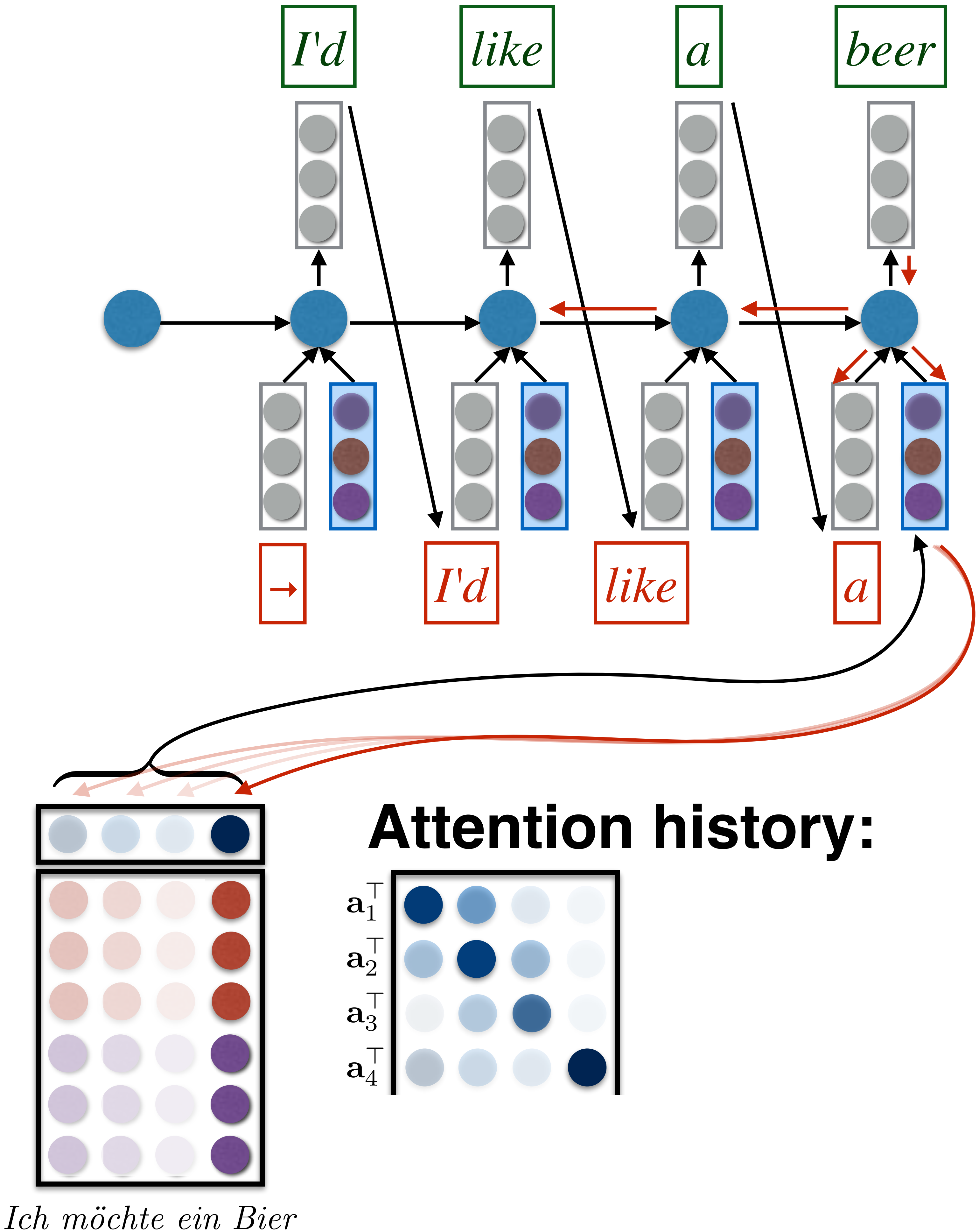
(a) (b)

A word about gradients


I'd
like
a
beer
→
I'd
like
a
Attention history:
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$
$\mathbf{a}_3^\top$
$\mathbf{a}_4^\top$
Ich möchte ein Bier

Attention history:



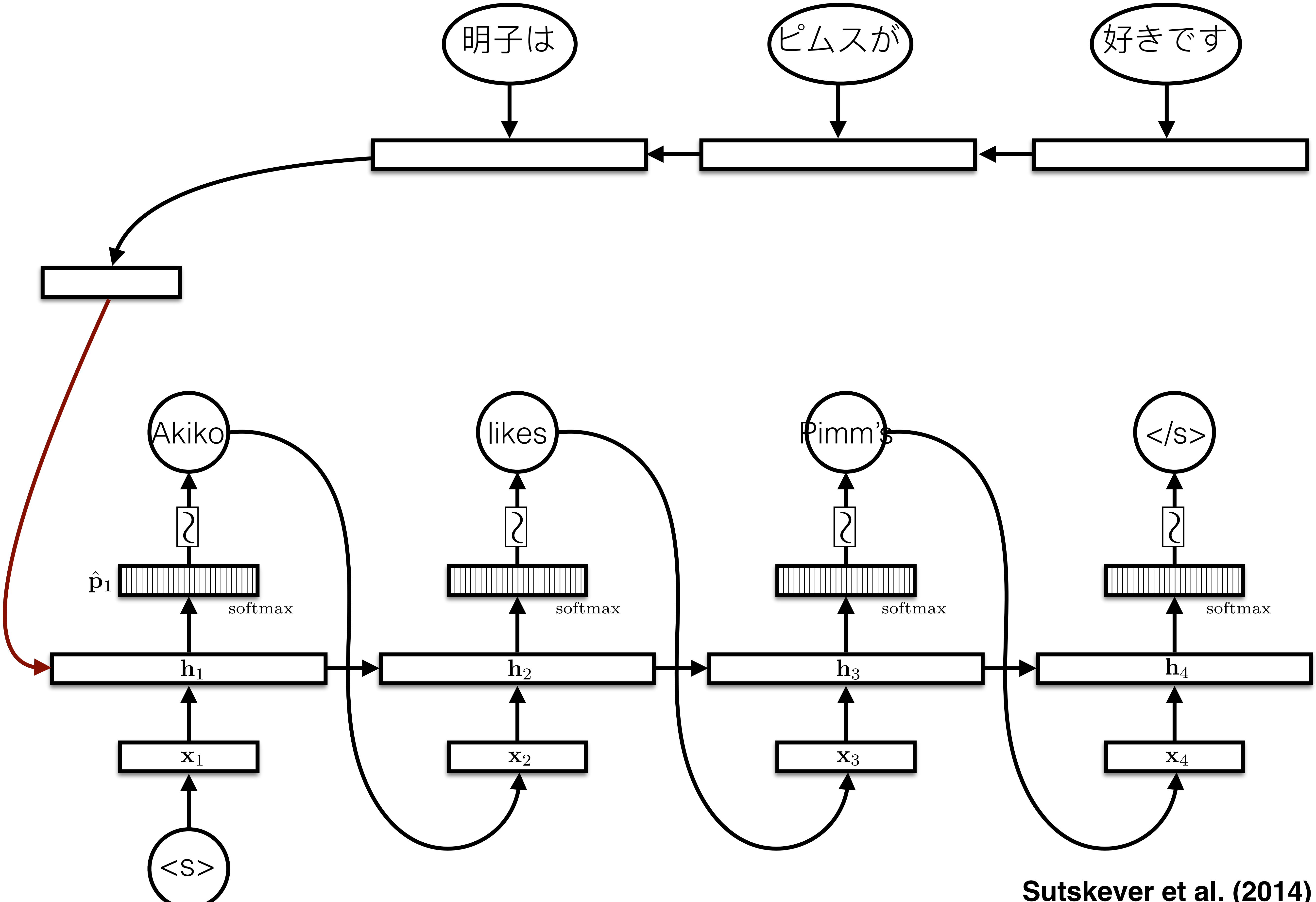

I'd
like
a
beer
→
I'd
like
a
Attention history:
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$
$\mathbf{a}_3^\top$
$\mathbf{a}_4^\top$
Ich möchte ein Bier

Attention and Translation

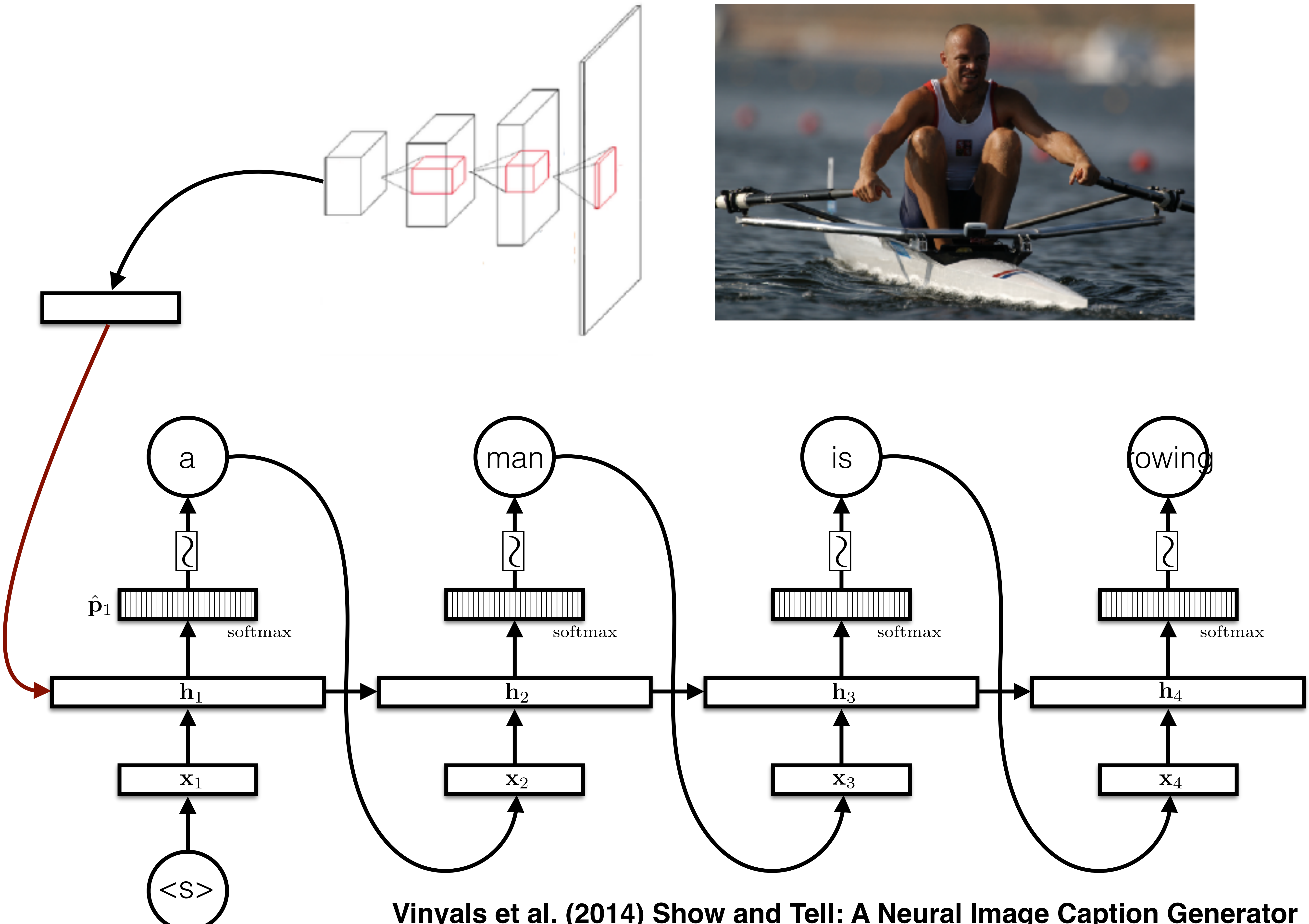
- Cho’s question: does a translator read and memorize the input sentence/document and then generate the output?
  - Compressing the entire input sentence into a vector basically says “memorize the sentence”
  - Common sense experience says translators refer back and forth to the input. (also backed up by eye-tracking studies)
- Should humans be a model for machines?

Outline of Lecture

- Machine translation with attention
- Image caption generation with attention



Sutskever et al. (2014)



Vinyals et al. (2014) Show and Tell: A Neural Image Caption Generator

Image Caption Generation

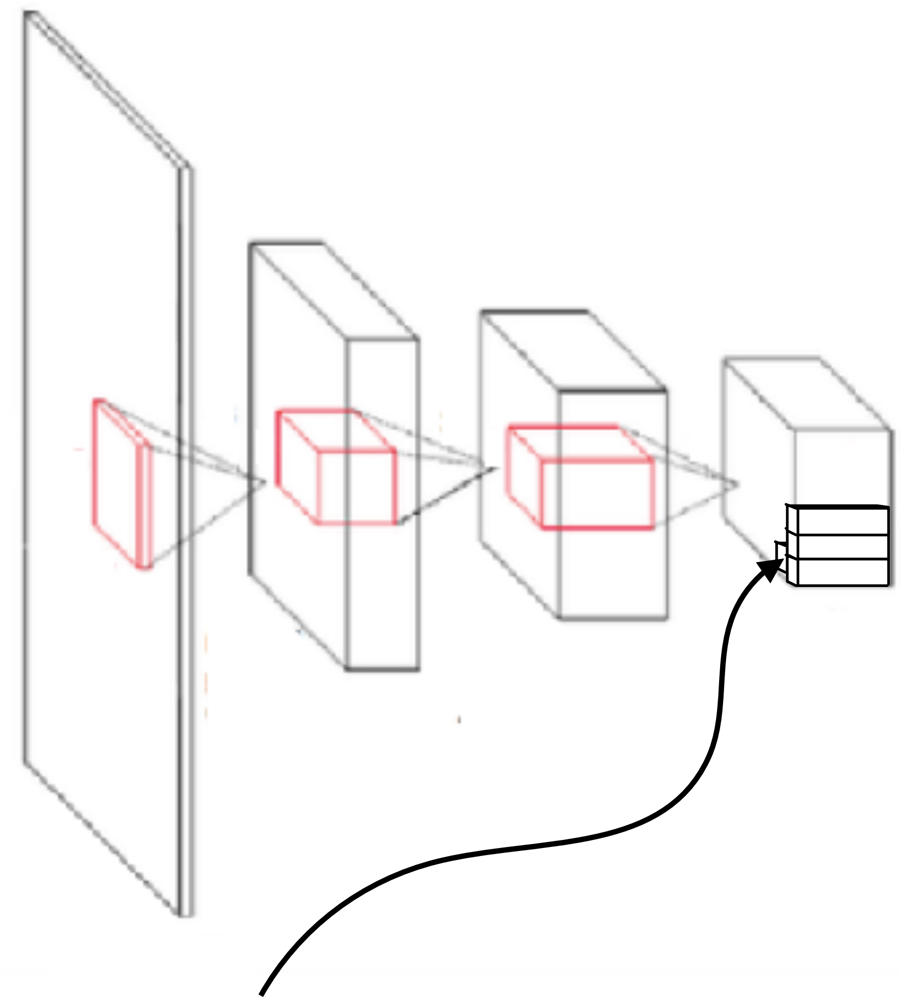
- Can attention help caption modeling?

Show, Attend and Tell: Neural Image Caption Generation with Visual Attention

Kelvin Xu KELVIN.XU@UMONTREAL.CA
Jimmy Lei Ba JIMMY@PSI.UTORONTO.CA
Ryan Kiros RKIROS@CS.TORONTO.EDU
Kyunghyun Cho KYUNGHYUN.CHO@UMONTREAL.CA
Aaron Courville AARON.COURVILLE@UMONTREAL.CA
Ruslan Salakhutdinov RSALAKHU@CS.TORONTO.EDU
Richard S. Zemel ZEMEL@CS.TORONTO.EDU
Yoshua Bengio FIND-ME@THE.WEB

Xu et al. (2015, ICML)

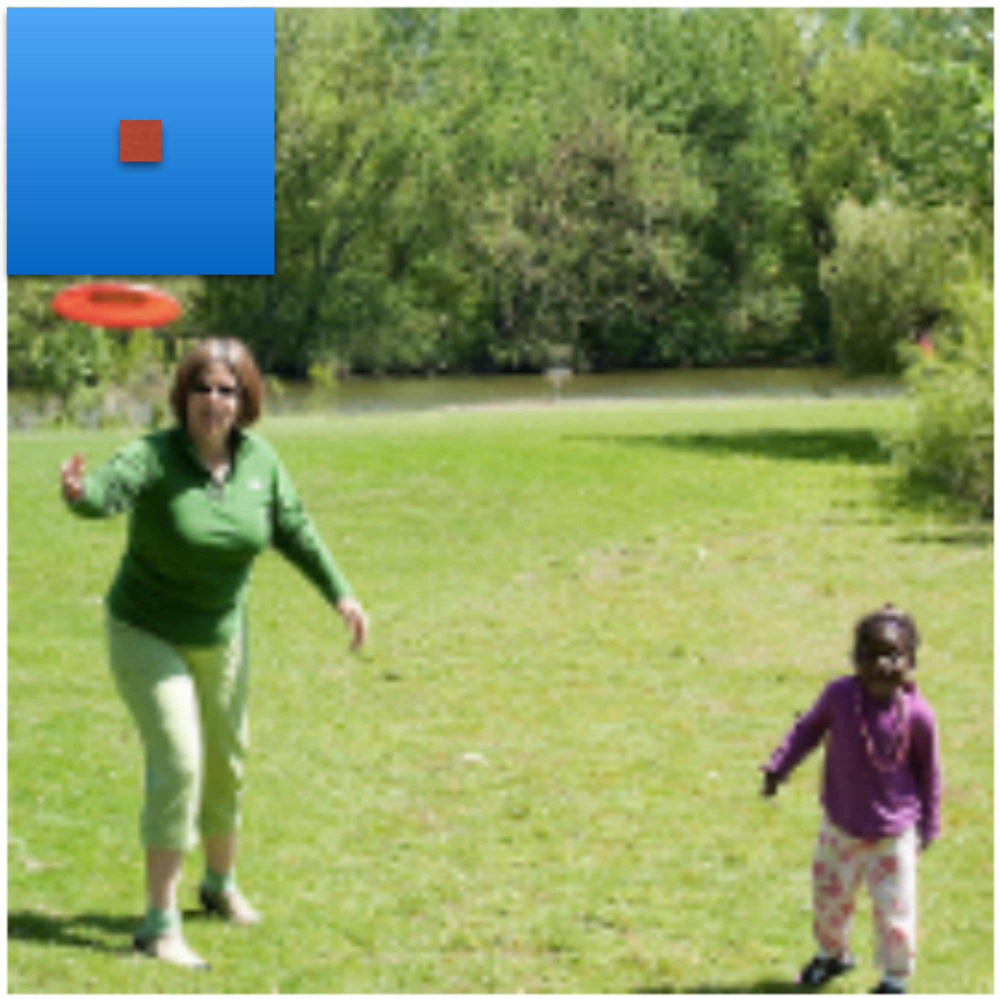
Regions in ConvNets



Each point in a "higher" level of a convnet defines spatially localised feature vectors(/matrices).

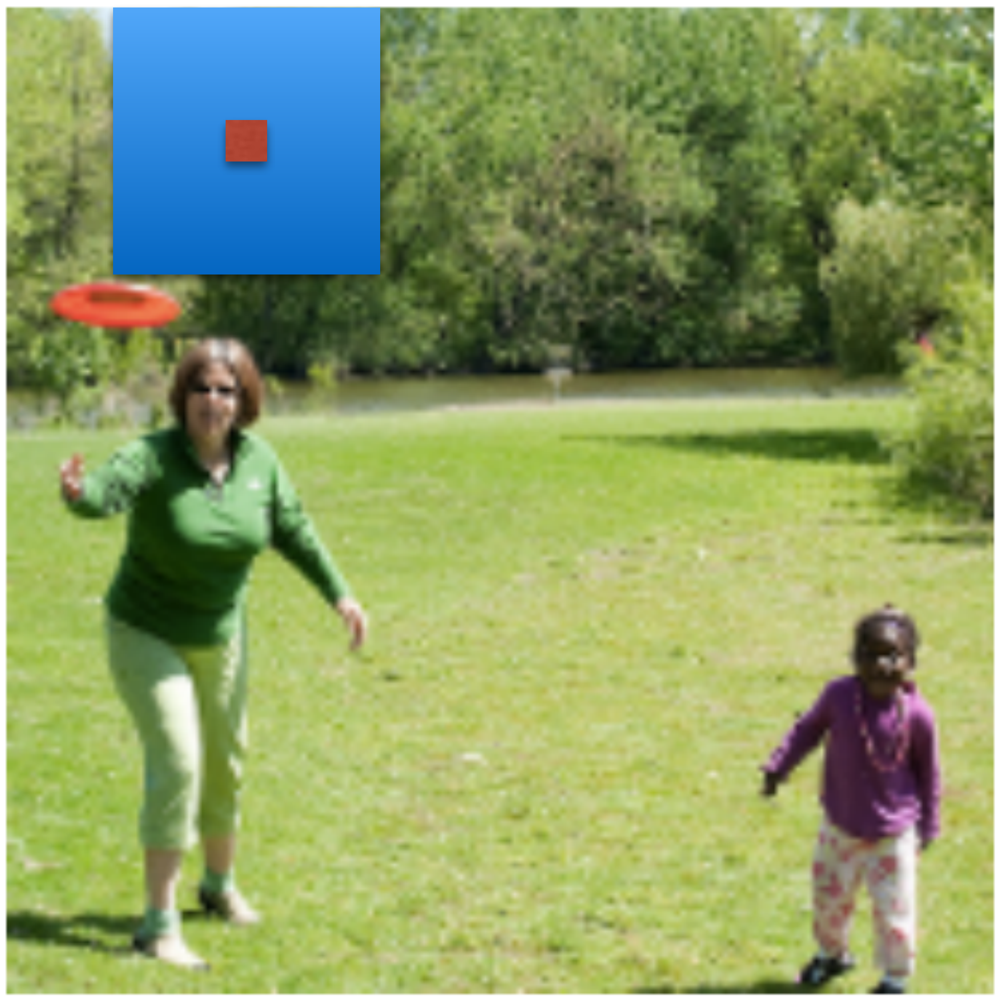
Xu et al. calls these "annotation vectors", $\mathbf{a}_i, \ i \in \{1, \ldots, L\}$

$\mathbf{a}_1$



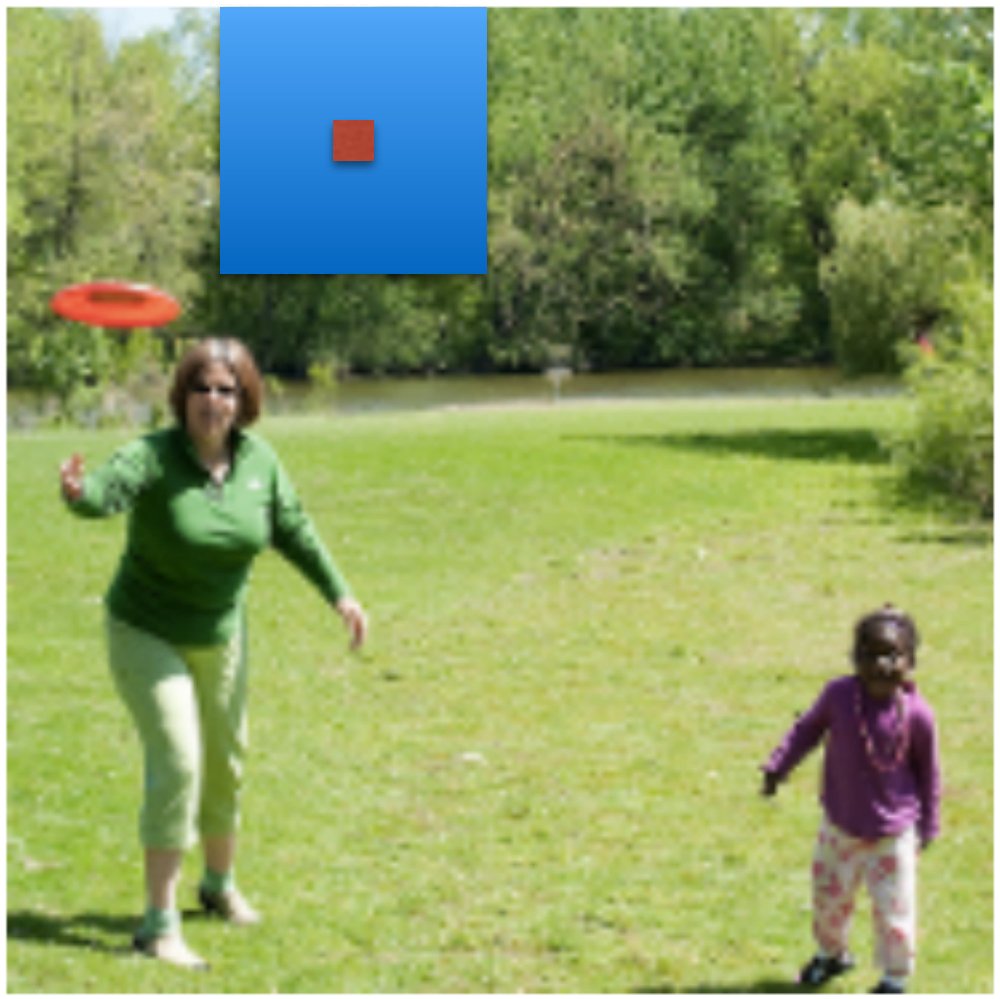
$$\mathbf{F} = \begin{bmatrix} | & & \\ \mathbf{a}_1 & & \\ | & & \end{bmatrix}$$

$\mathbf{a}_2$



$$\mathbf{F} = \begin{bmatrix} | & | & \\ \mathbf{a}_1 & \mathbf{a}_2 & \\ | & | & \end{bmatrix}$$

$\mathbf{a}_3$



$$\mathbf{F} = \begin{bmatrix} | & | & | & \\ \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 & \cdots \\ | & | & | & \end{bmatrix}$$

Attention

- Attention “weights” ($\mathbf{a}_t$) are computed using exactly the same technique as discussed above

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$$\mathbf{c}_t = \mathbf{F}\mathbf{a}_t \qquad \text{(weighted average)}$$

Attention

- Attention "weights" ($\mathbf{a}_t$) are computed using exactly the same technique as discussed above

- Deterministic soft attention (Bahdanau et al., 2014)

$$\mathbf{c}_t = \mathbf{F}\mathbf{a}_t$$

(weighted average)

- Stochastic hard attention (Xu et al., 2015)

$$s_t \sim \mathrm{Categorical}(\mathbf{a}_t)$$

$$\mathbf{c}_t = \mathbf{F}_{:,s_t}$$

(sample a column)

  - What are the benefits of this model?

  - What are the challenges of learning the parameters of this model?

Learning Hard Attention

$$
\begin{aligned}
\mathcal{L} &= -\log p(\boldsymbol{w} \mid \boldsymbol{x}) \\
&= -\log \sum_{\boldsymbol{s}} p(\boldsymbol{w}, \boldsymbol{s} \mid \boldsymbol{x}) \\
&= -\log \sum_{\boldsymbol{s}} p(\boldsymbol{s} \mid \boldsymbol{x}) p(\boldsymbol{w} \mid \boldsymbol{x}, \boldsymbol{s})
\end{aligned}
$$

Learning Hard Attention

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&= -\log \sum_{\boldsymbol{s}} p(\boldsymbol{s} \mid \boldsymbol{x}) p(\boldsymbol{w} \mid \boldsymbol{x}, \boldsymbol{s}) \\
&\leq -\sum p(\boldsymbol{s} \mid \boldsymbol{x}) \log p(\boldsymbol{w} \mid \boldsymbol{x}, \boldsymbol{s}) \quad \text{(Jensen's inequality)}
\end{aligned}$$

Learning Hard Attention

$$
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&\leq -\sum_{\boldsymbol{s}} p(\boldsymbol{s} \mid \boldsymbol{x}) \log p(\boldsymbol{w} \mid \boldsymbol{x}, \boldsymbol{s}) \qquad \text{(Jensen's inequality)} \\
&\overset{\text{MC}}{\approx} -\frac{1}{N} \sum_{i=1}^{N} p(\boldsymbol{s}^{(i)} \mid \boldsymbol{x}) \log p(\boldsymbol{w} \mid \boldsymbol{x}, \boldsymbol{s})
\end{aligned}
$$

Learning Hard Attention

- Sample *N* sequences of attention decisions from the model

- The gradient is the probability of the gradient of the probability of this sequence scaled by the log probability of generating the target words using that sequence of attention decisions

- This is equivalent to using the REINFORCE algorithm (Williams, 1992) using the log probability of the observed words as a “reward function”. REINFORCE a policy gradient algorithm used for reinforcement learning.


A(0.98)
woman(0.54)
is(0.37)
throwing(0.33)
a(0.28)
frisbee(0.37)
in(0.21)
a(0.18)
park(0.35)
.(0.33)

A woman holding a clock in her hand.

A large white bird standing in a forest.

Attention in Captioning

Add soft attention to image captioning: **+2 BLEU**

Add hard attention to image captioning: **+4 BLEU**

Summary

- Significant performance improvements
  - Better performance over vector-based encodings
  - Better performance with smaller training data sets
- Model interpretability
- Better gradient flow
- Better capacity (especially obvious for translation)

Questions?