Attention mechanisms

CS 685, Fall 2022

Advanced Natural Language Processing

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some slides from Richard Socher & Emma Strubell

stuff from last time…

- HW0 grading hopefully done by next week
- All project assignments finalized!
- HW1 will be out within the next 2 weeks
- Compute resources for projects?

A RNN Language Model

$\hat{\boldsymbol{y}}^{(4)} = P(\boldsymbol{x}^{(5)}|\text{the students opened their})$

output distribution

$$\hat{y} = \text{softmax}(W_2 h^{(t)} + b_2)$$

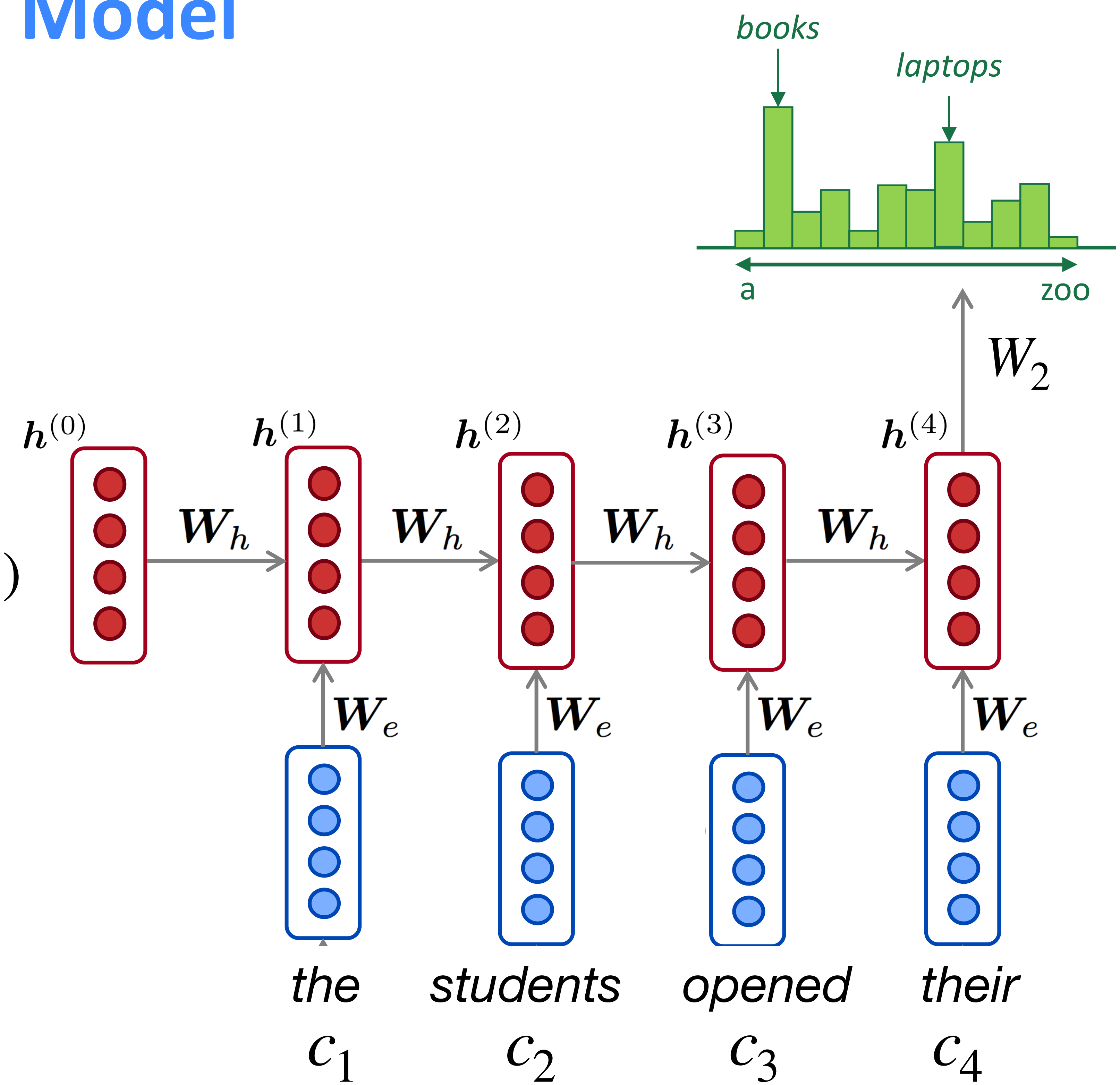
hidden states

$$h^{(t)} = f(W_h h^{(t-1)} + W_e c_t + b_1)$$

$h^{(0)}$ is initial hidden state!

word embeddings

$$c_1, c_2, c_3, c_4$$



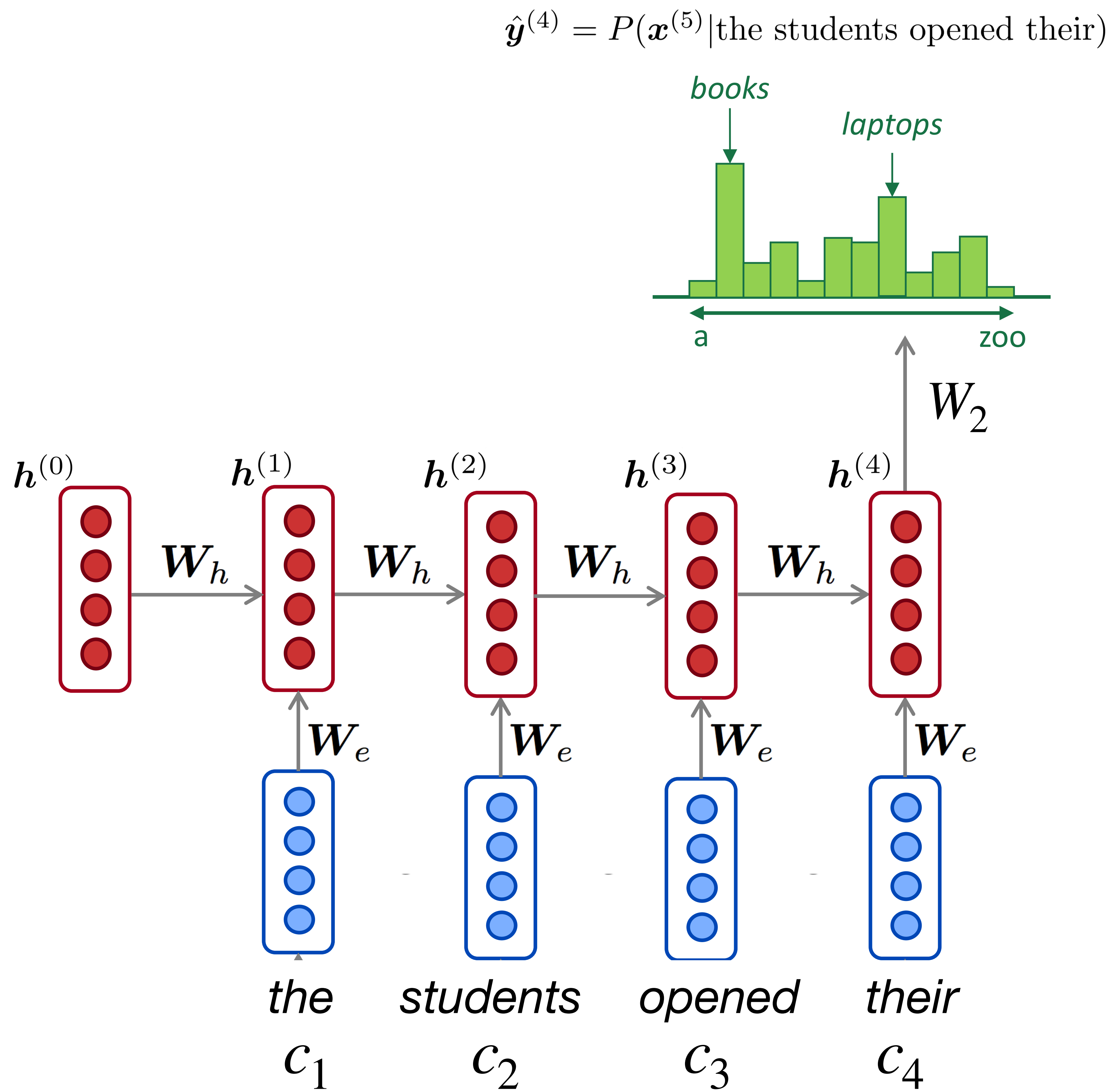
why is this good?

RNN **Advantages**:

- Can process any length input
- Model size doesn't increase for longer input
- Computation for step *t* can (in theory) use information from many steps back
- Weights are shared across timesteps → representations are shared

RNN **Disadvantages**:

- Recurrent computation is slow
- In practice, difficult to access information from many steps back



Training a RNN Language Model

- Get a big corpus of text which is a sequence of words $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}$
- Feed into RNN-LM; compute output distribution $\hat{\boldsymbol{y}}^{(t)}$ for *every step t*.
    - i.e. predict probability dist of *every word*, given words so far

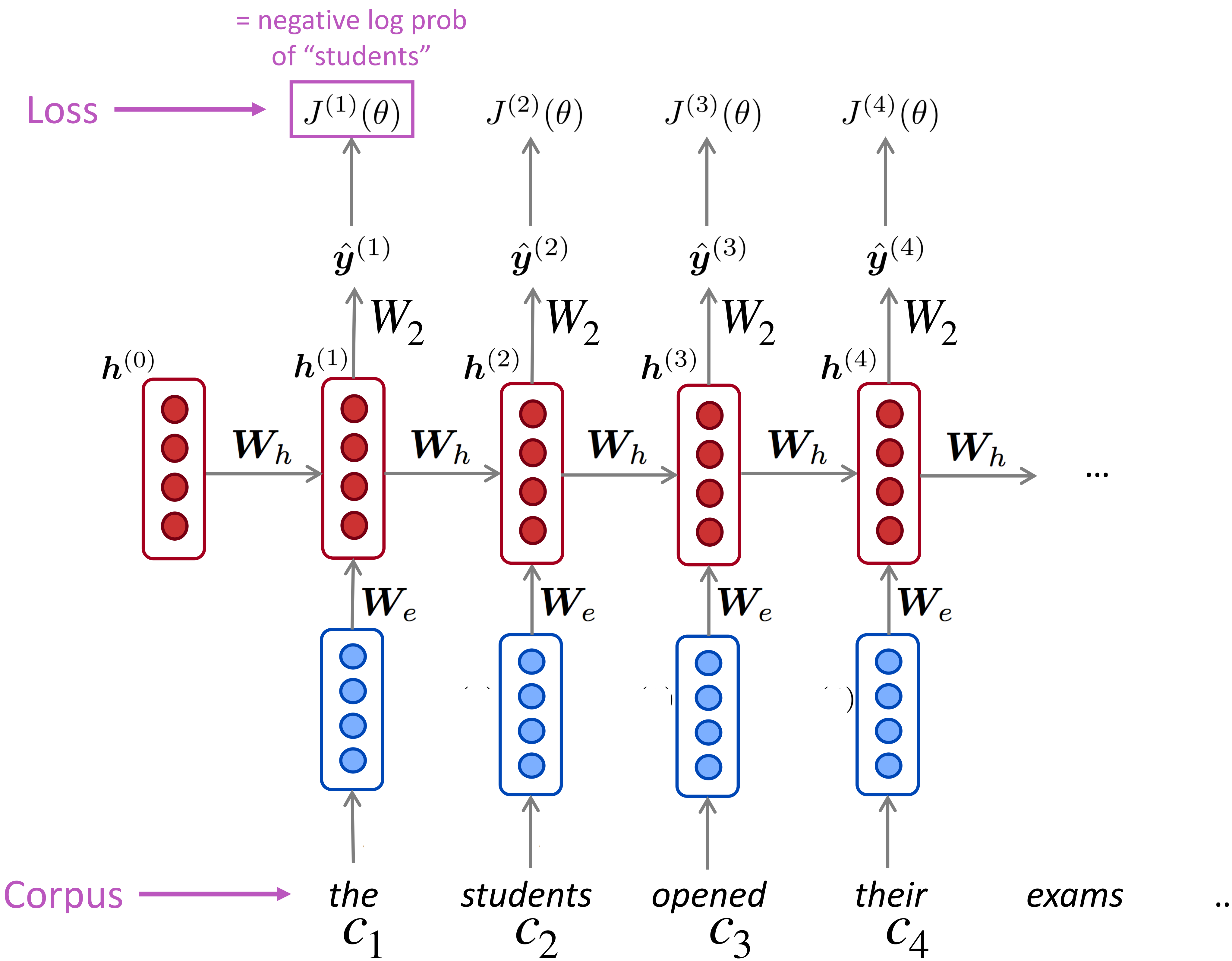
- Loss function on step *t* is usual cross-entropy between our predicted probability distribution $\hat{\boldsymbol{y}}^{(t)}$, and the true next word $\boldsymbol{y}^{(t)} = \boldsymbol{x}^{(t+1)}$:

$$J^{(t)}(\theta) = CE(\boldsymbol{y}^{(t)}, \hat{\boldsymbol{y}}^{(t)}) = -\sum_{j=1}^{|V|} y_j^{(t)} \log \hat{y}_j^{(t)}$$

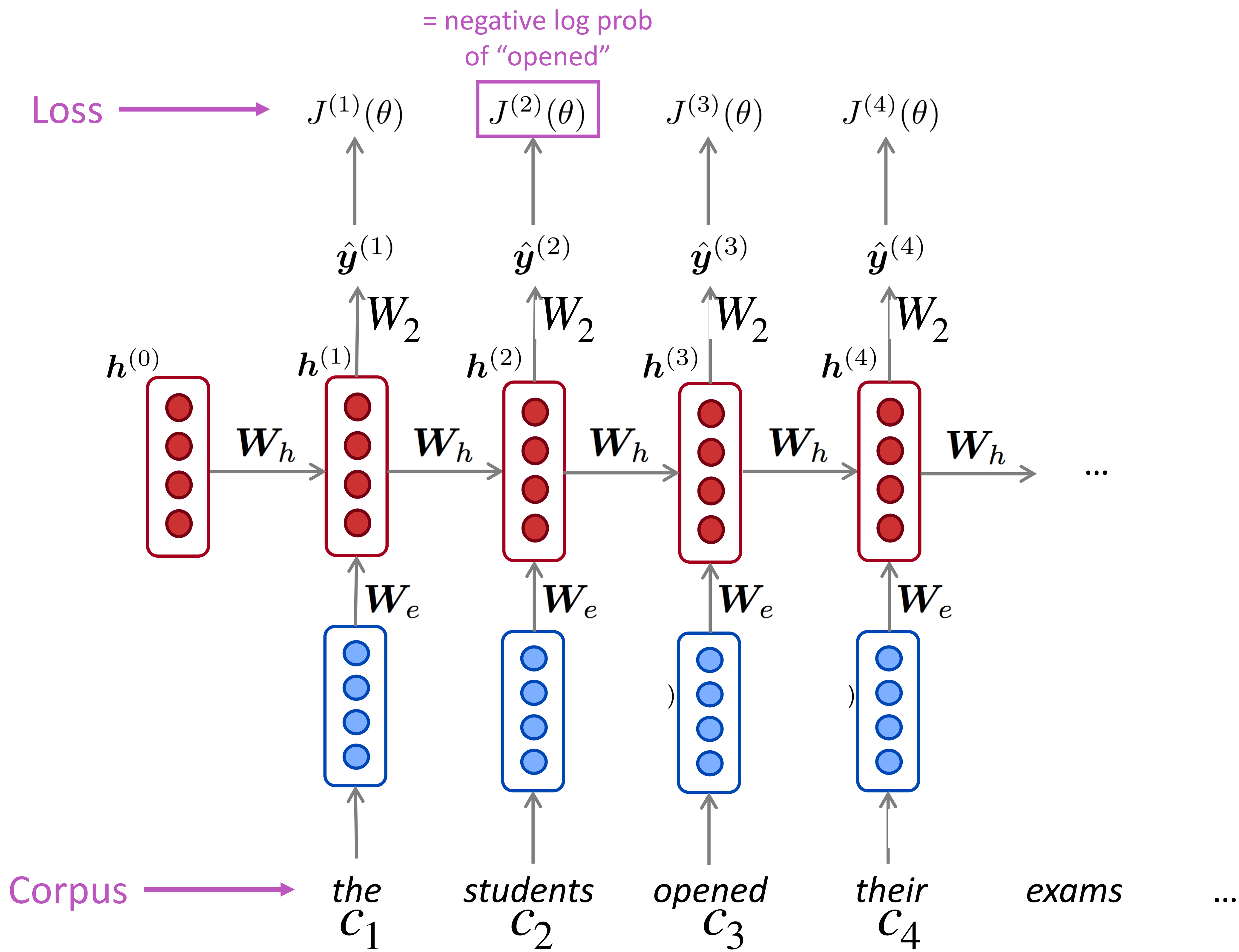
- Average this to get overall loss for entire training set:

$$J(\theta) = \frac{1}{T} \sum_{t=1}^{T} J^{(t)}(\theta)$$

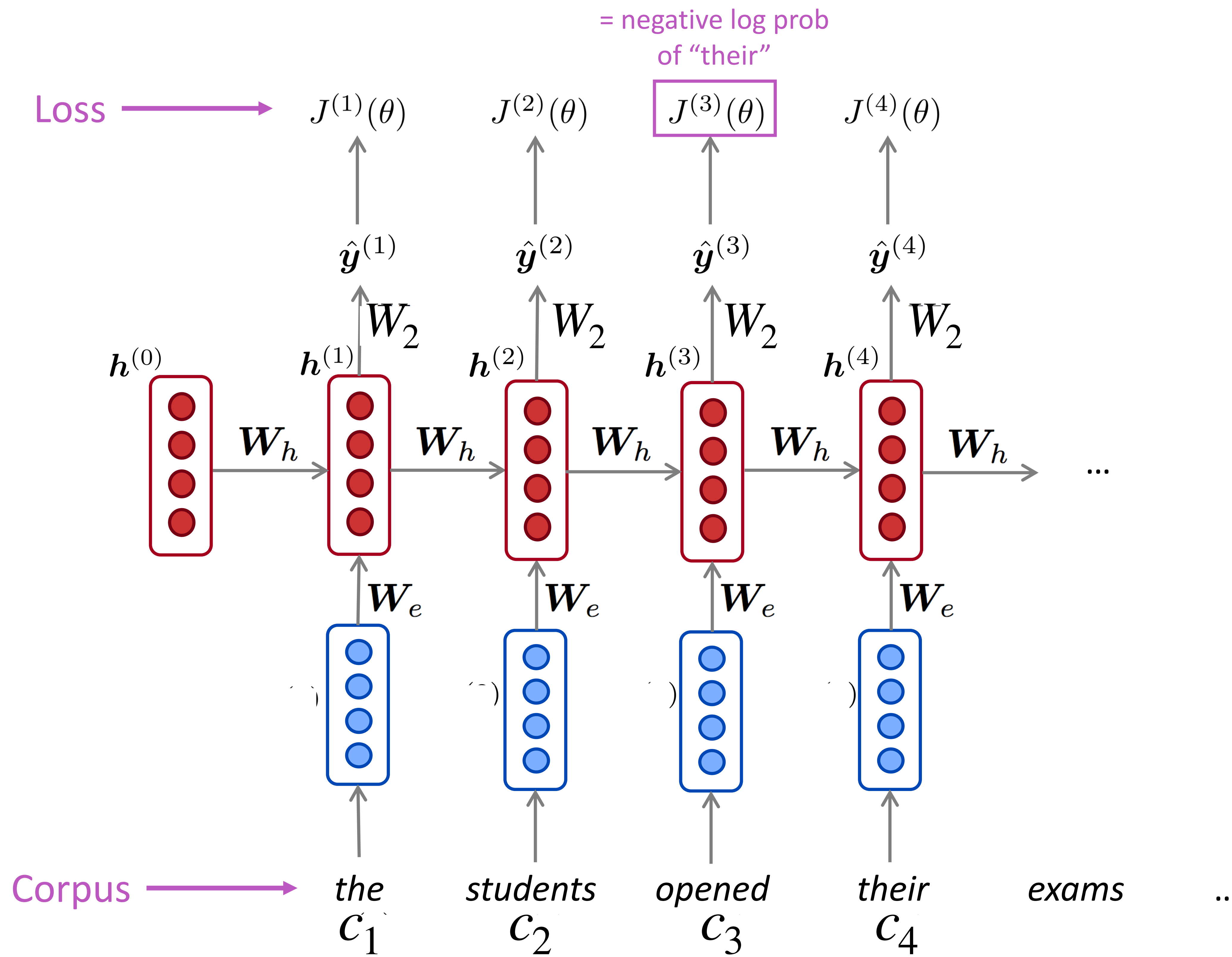
Training a RNN Language Model



Training a RNN Language Model



Training a RNN Language Model



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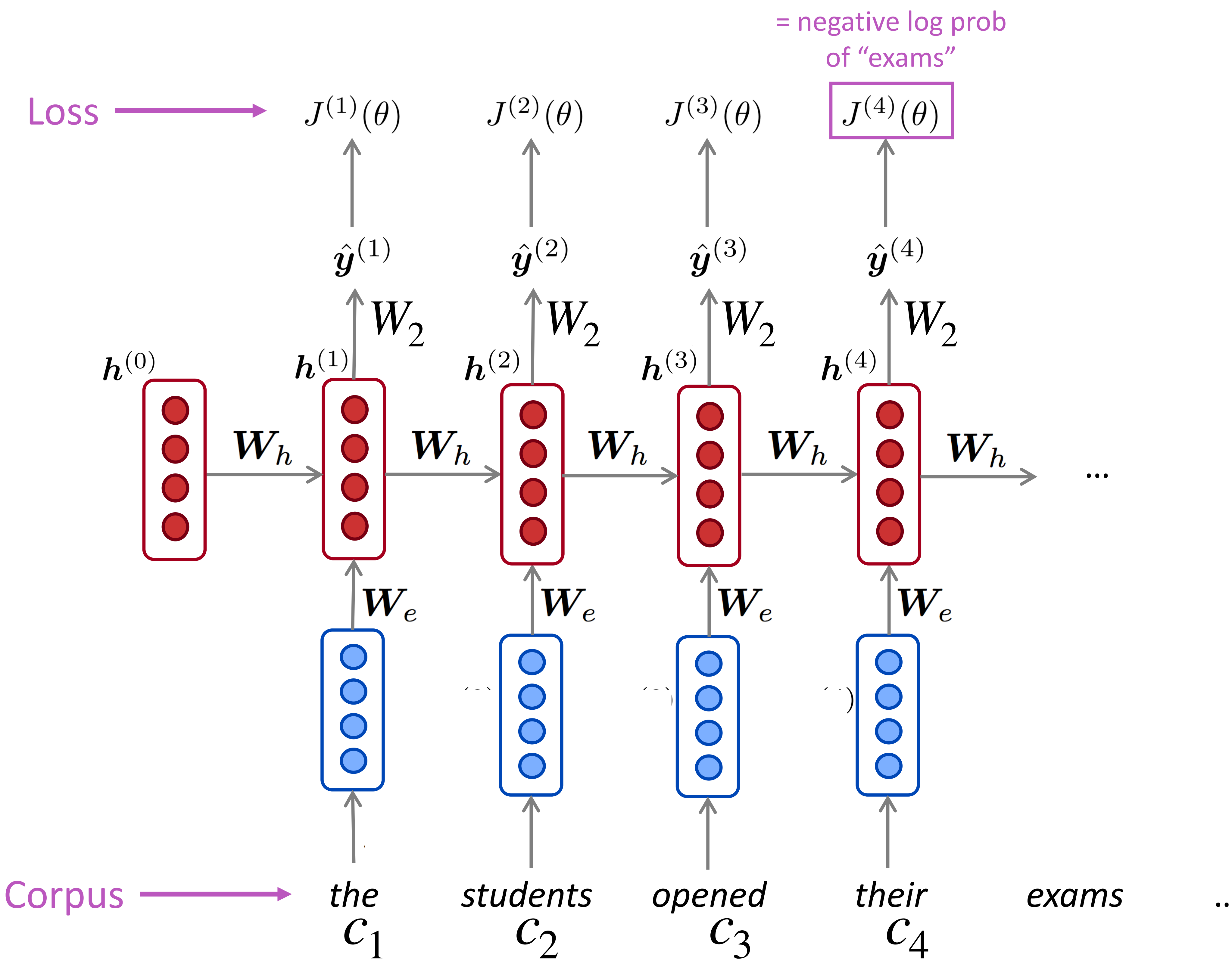
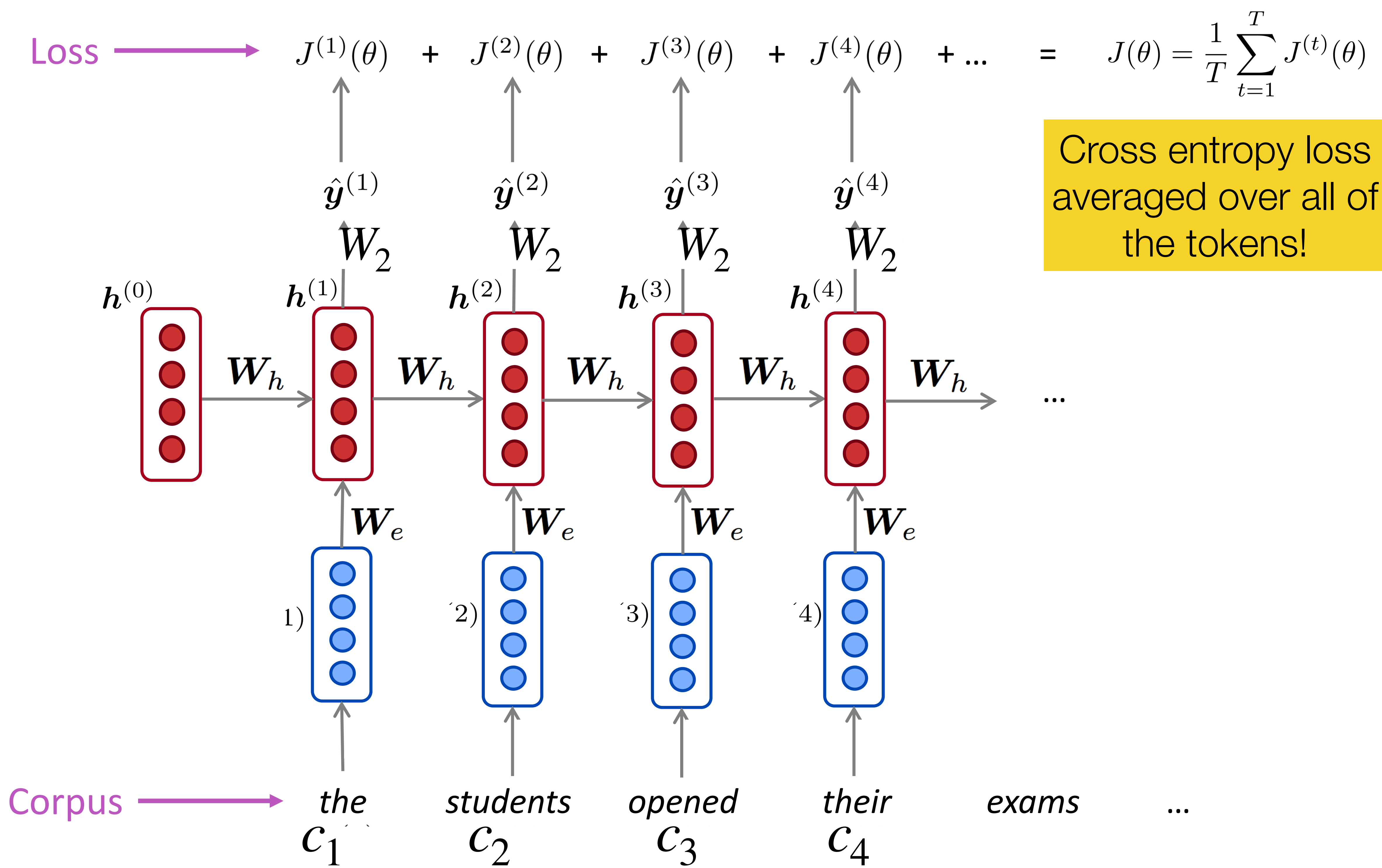
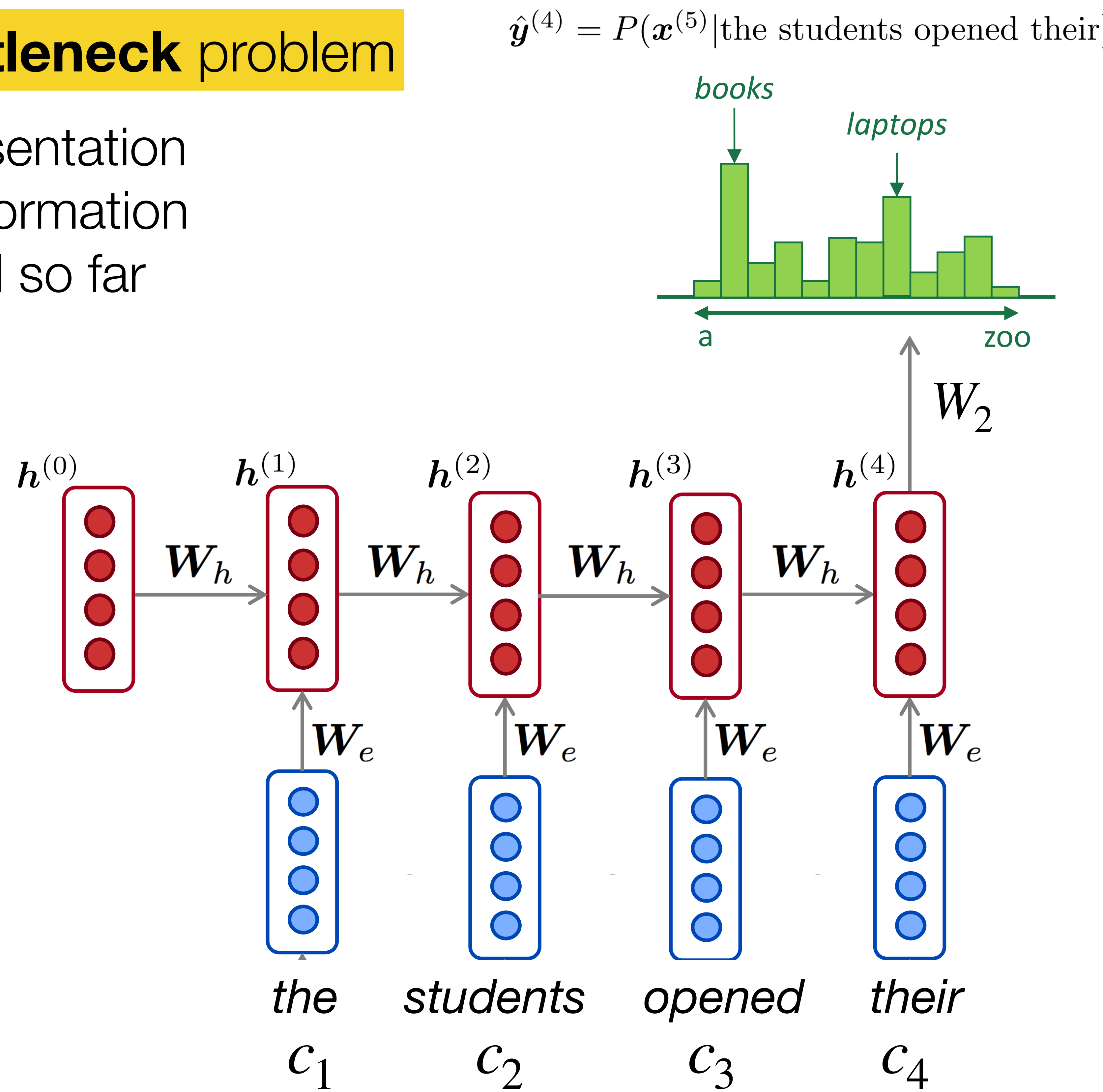


Training a RNN Language Model



RNNs suffer from a **bottleneck** problem

The current hidden representation must encode all of the information about the text observed so far



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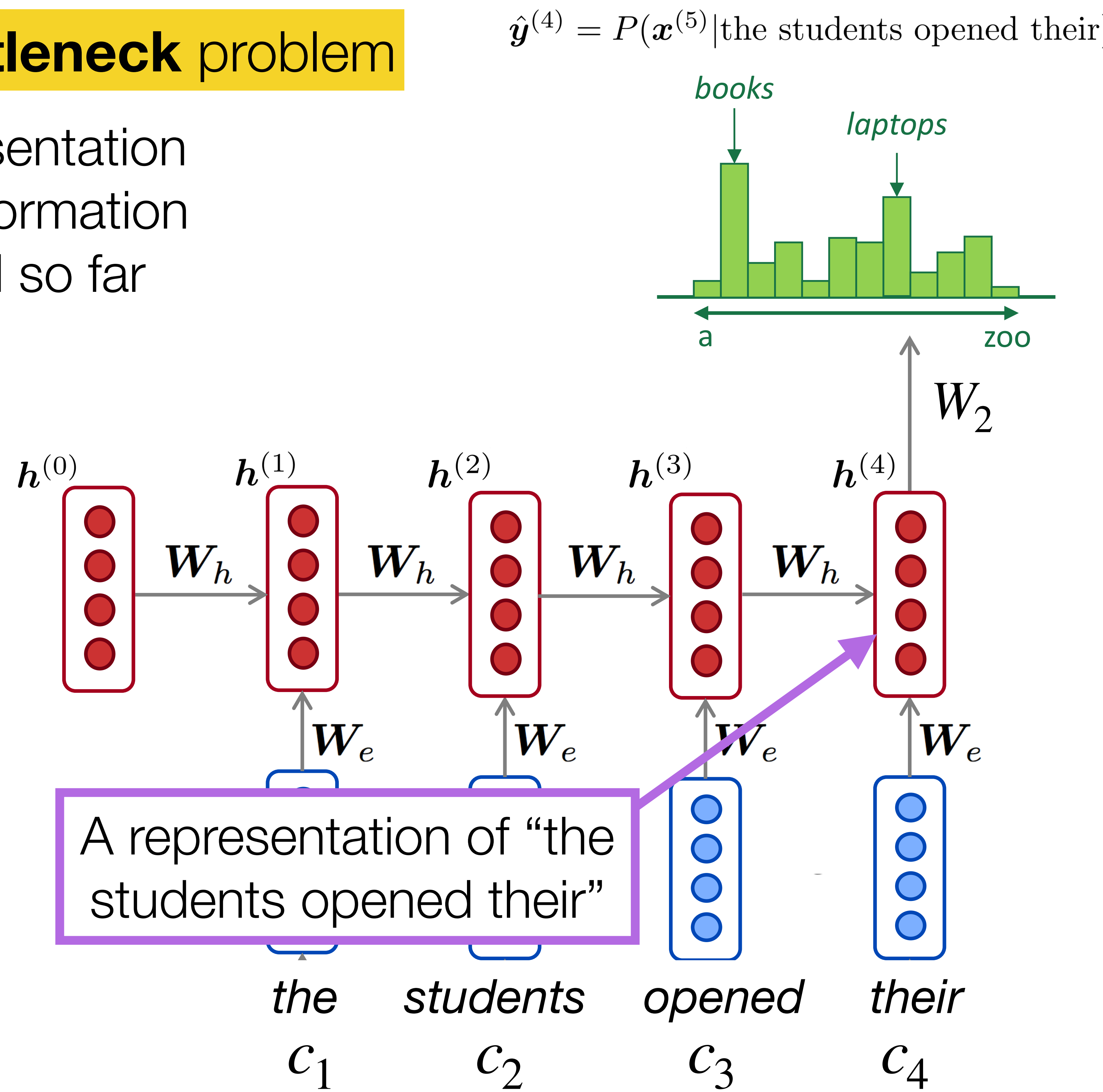
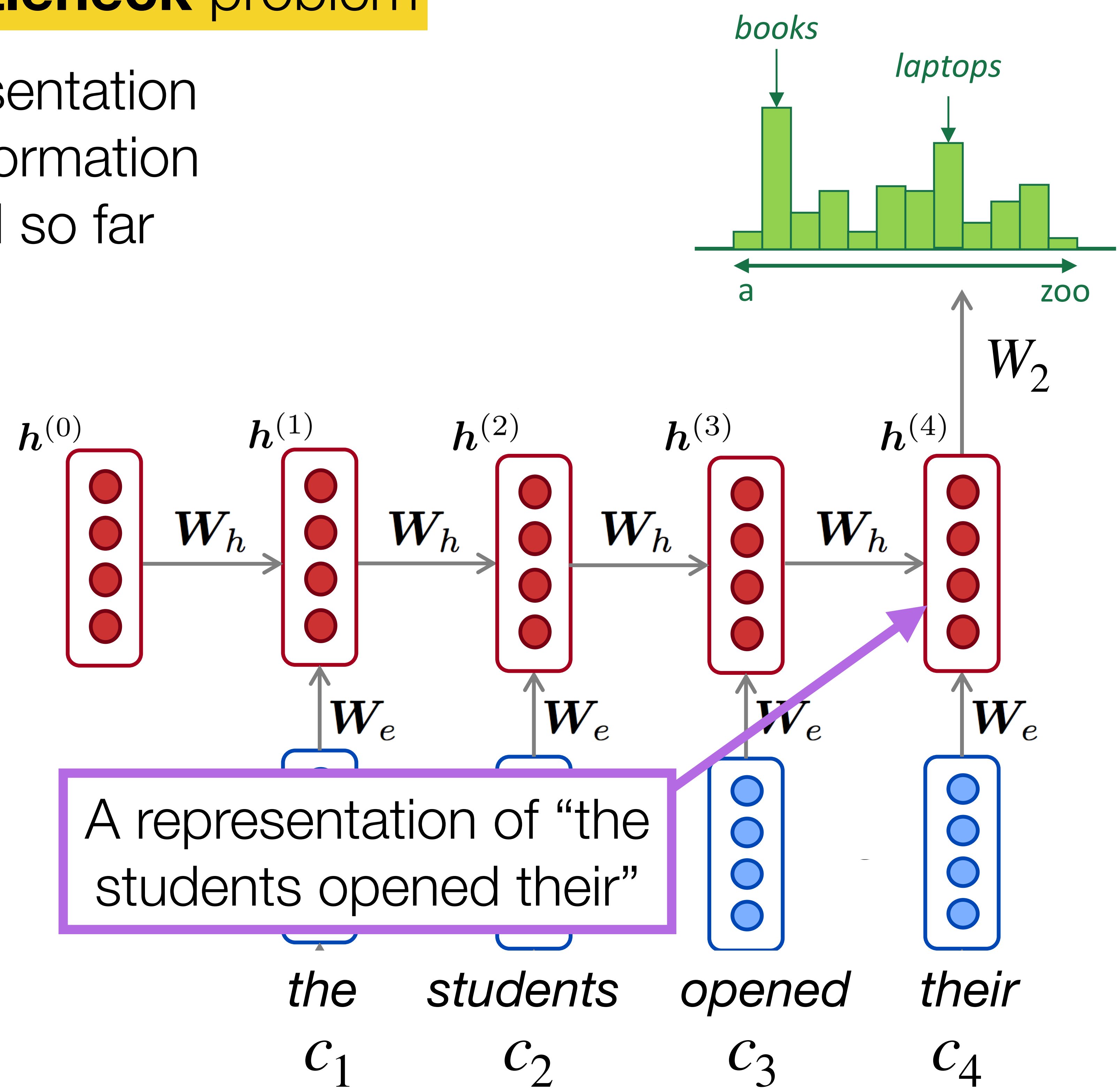


RNNs suffer from a **bottleneck** problem

The current hidden representation must encode all of the information about the text observed so far

This becomes difficult especially with longer sequences

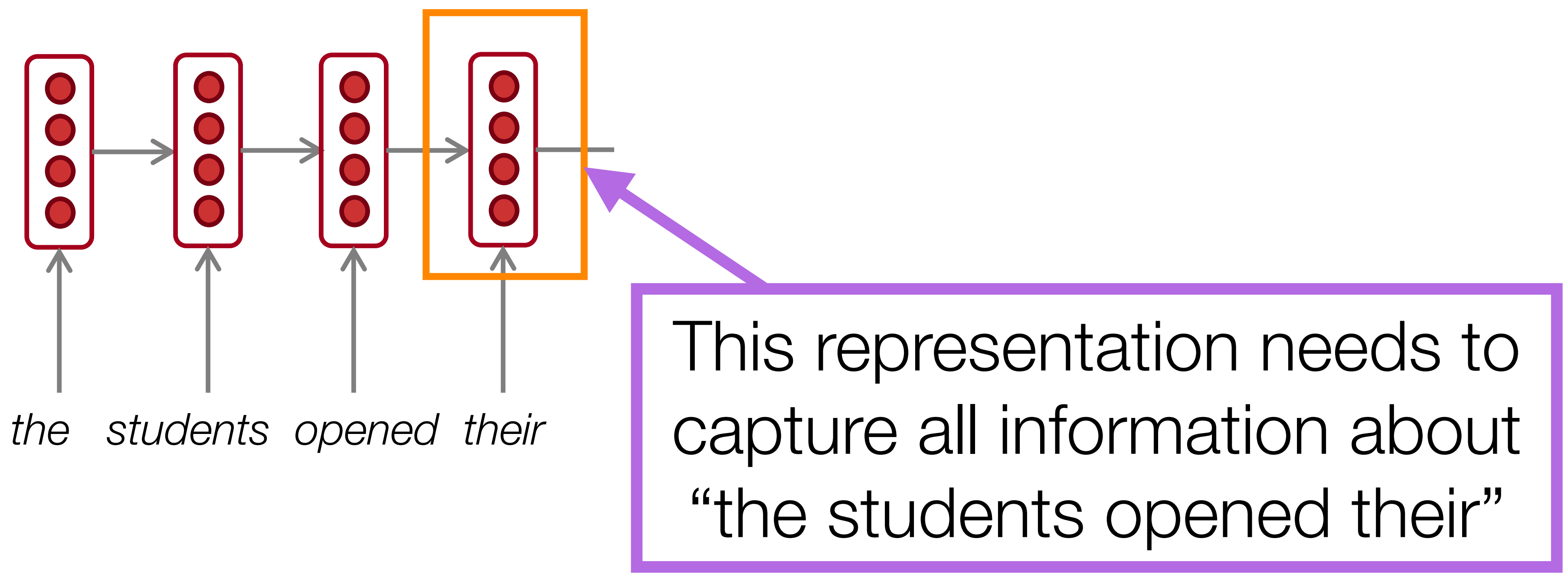
$$\hat{\boldsymbol{y}}^{(4)} = P(\boldsymbol{x}^{(5)} | \text{the students opened their})$$



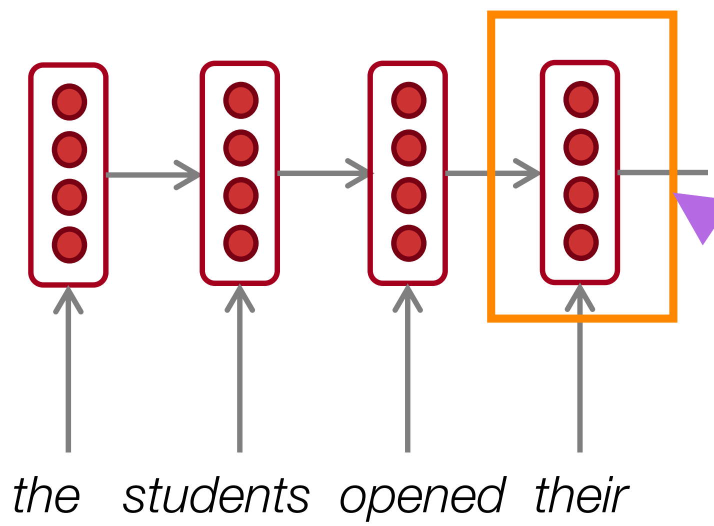
“you can’t cram the meaning of a whole %&@#&ing sentence into a single $*(&@ing vector!”

— Ray Mooney (NLP professor at UT Austin)

idea: what if we use multiple vectors?

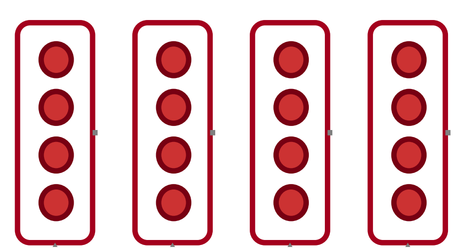


idea: what if we use multiple vectors?



This representation needs to capture all information about "the students opened their"

Instead of this, let's try:

the students opened their =  **(all 4 hidden states!)**

The solution: **attention**

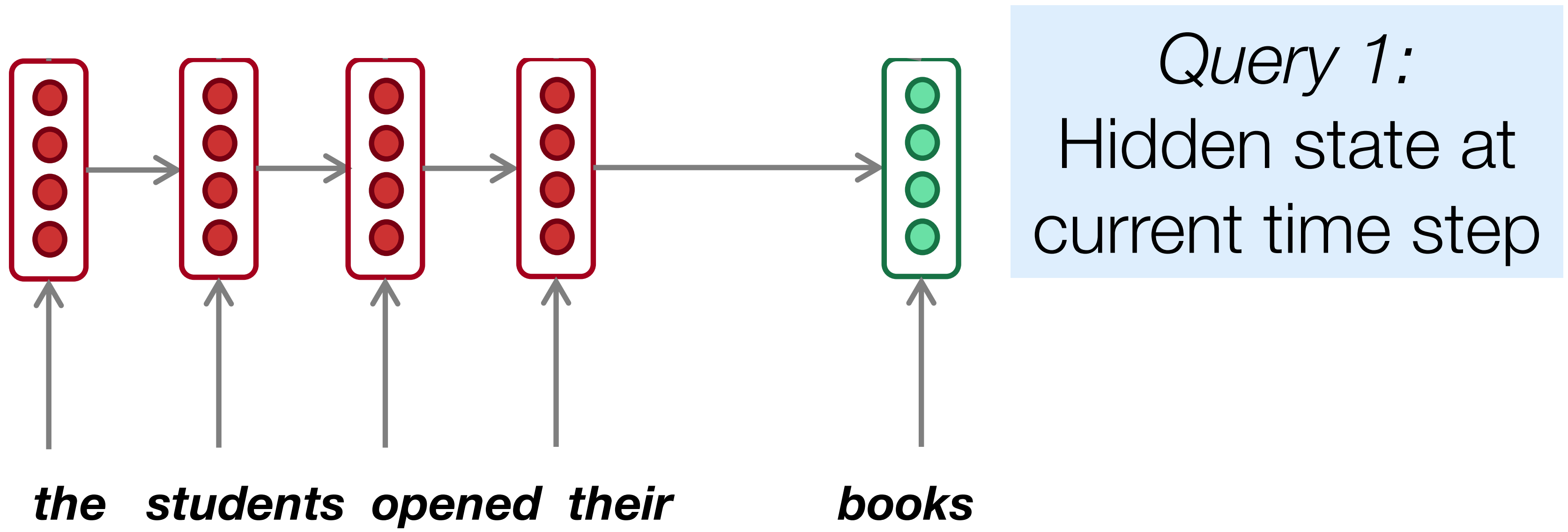
- **Attention mechanisms** (Bahdanau et al., 2015) allow language models to focus on a particular part of the observed context at each time step
    - Originally developed for machine translation, and intuitively similar to *word alignments* between different languages

How does it work?

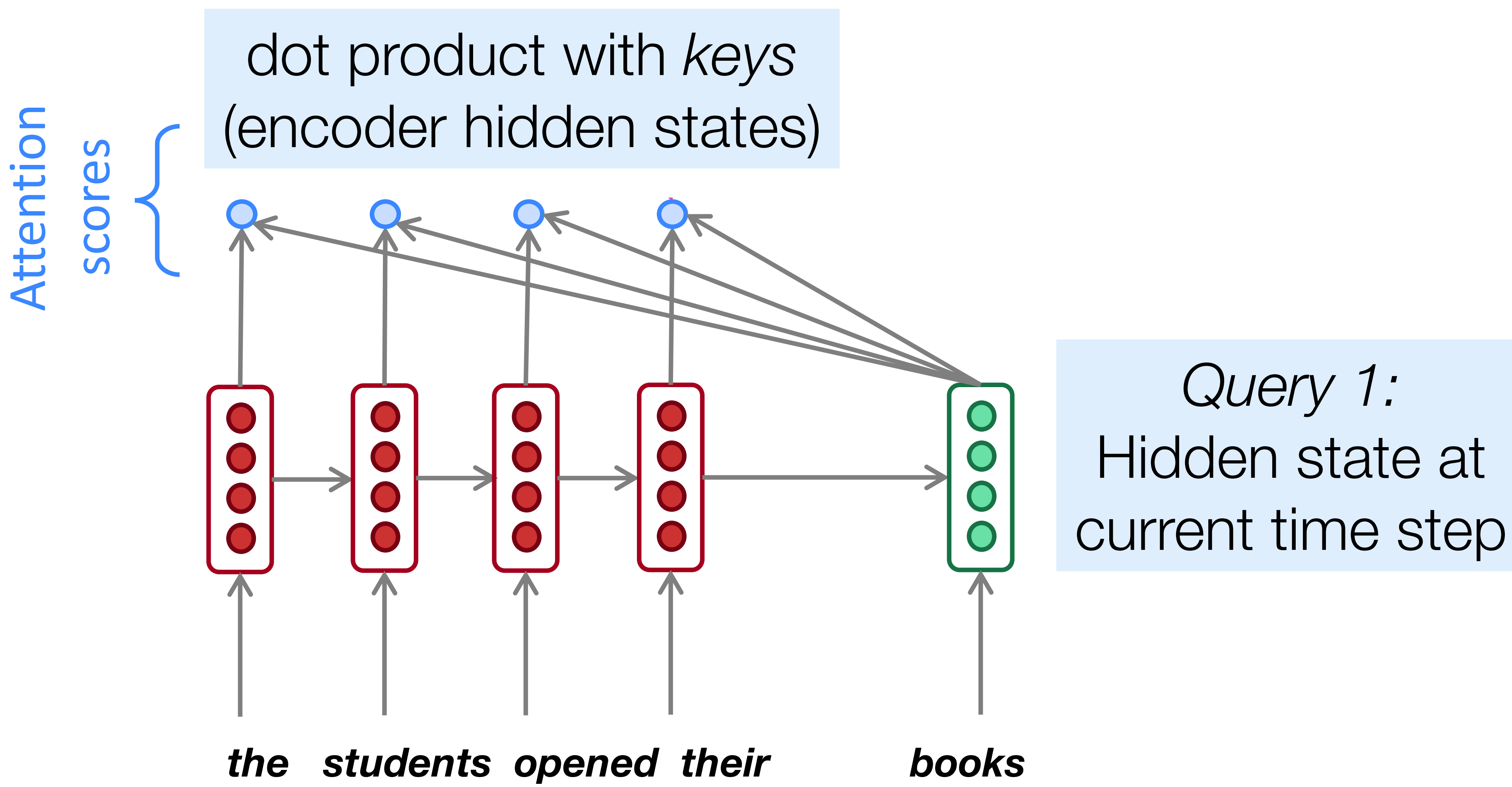
- in general, we have a single *query* vector and multiple *key* vectors. We want to score each query-key pair

in a neural language model, what are the queries and keys?

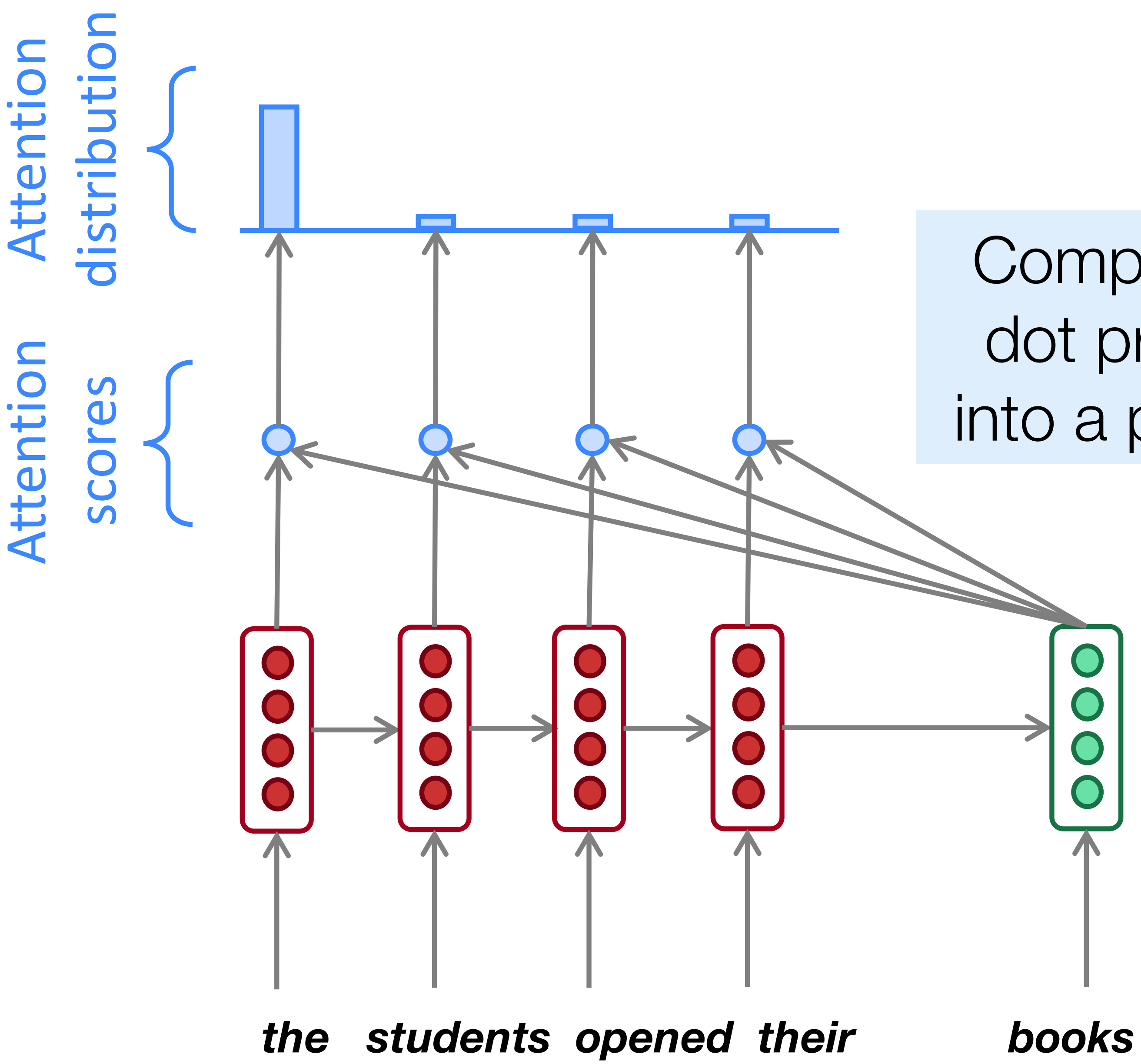
Attention mechanisms in neural language models



Attention mechanisms in neural language models

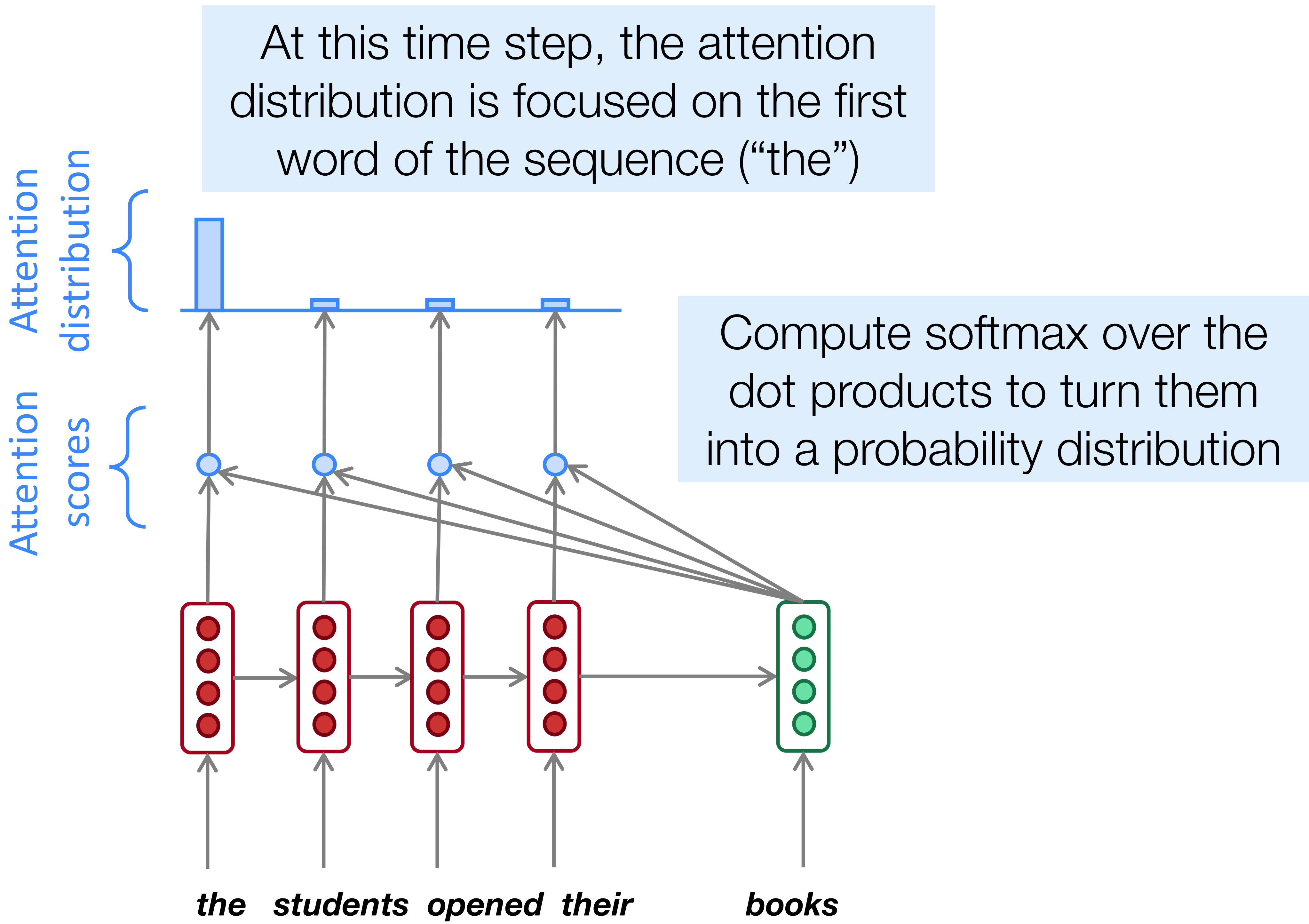


Attention mechanisms in neural language models

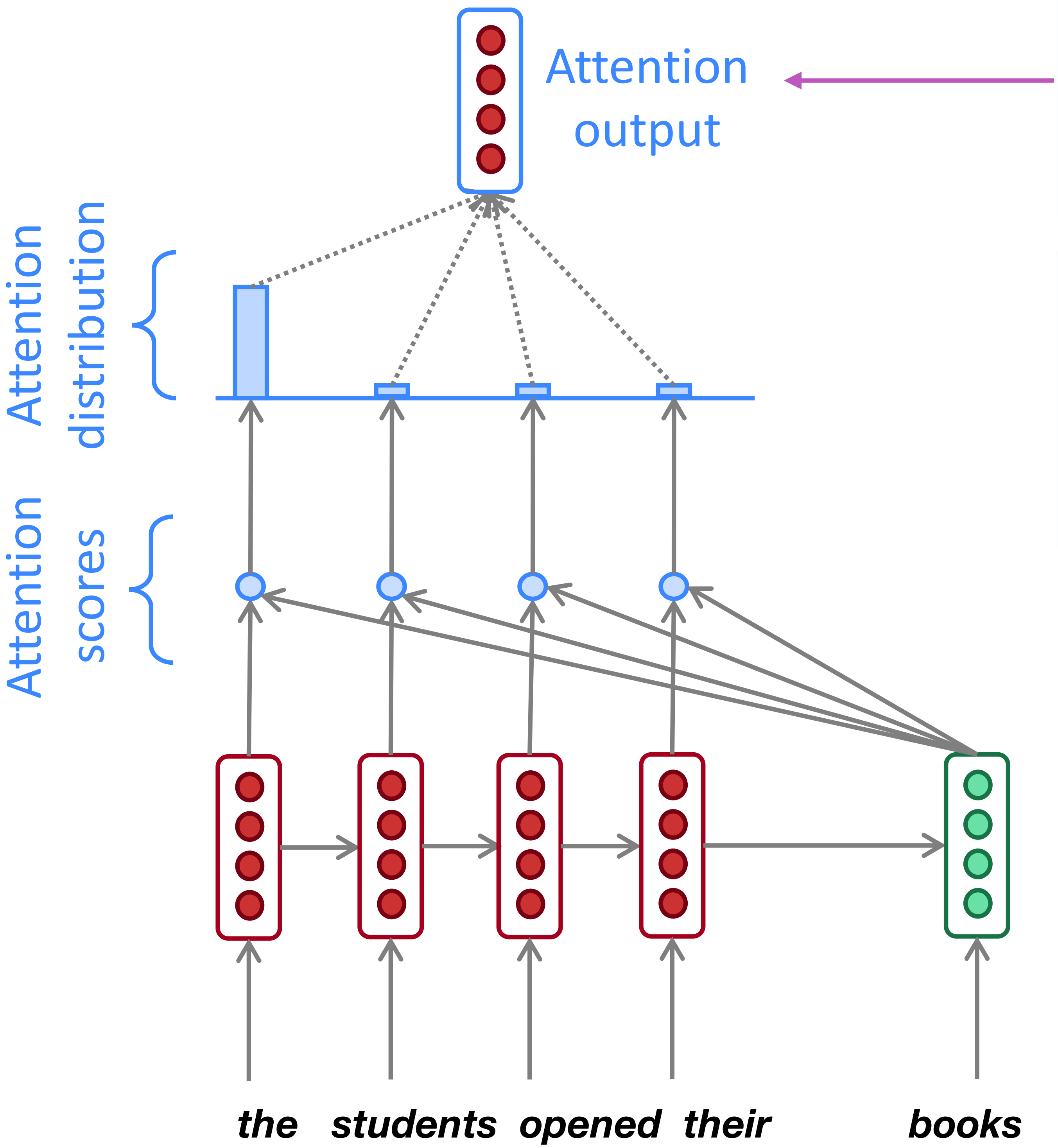


Compute softmax over the dot products to turn them into a probability distribution

Attention mechanisms in neural language models



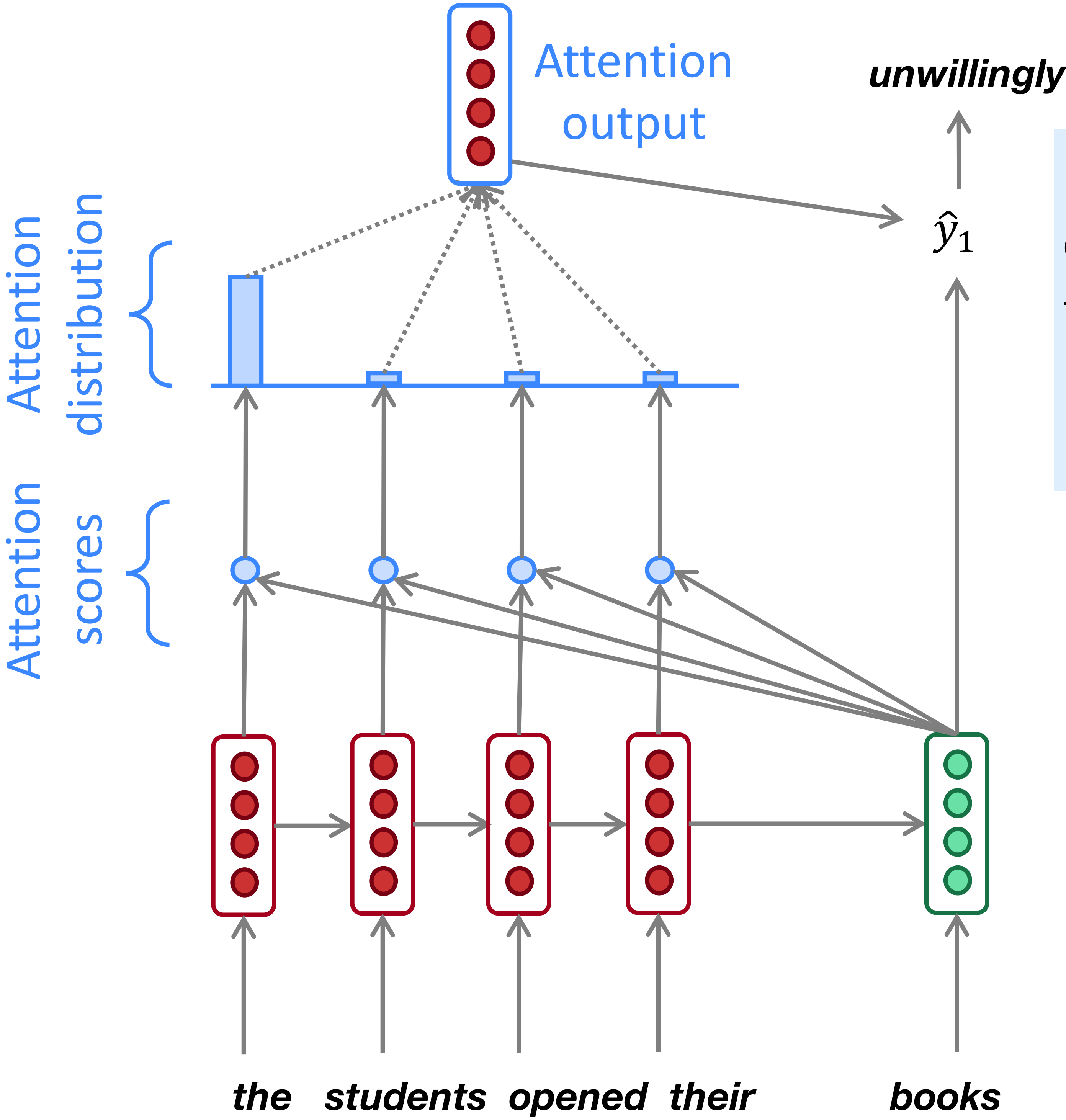
Attention mechanisms in neural language models



We use the attention distribution to compute a weighted average of the hidden states.

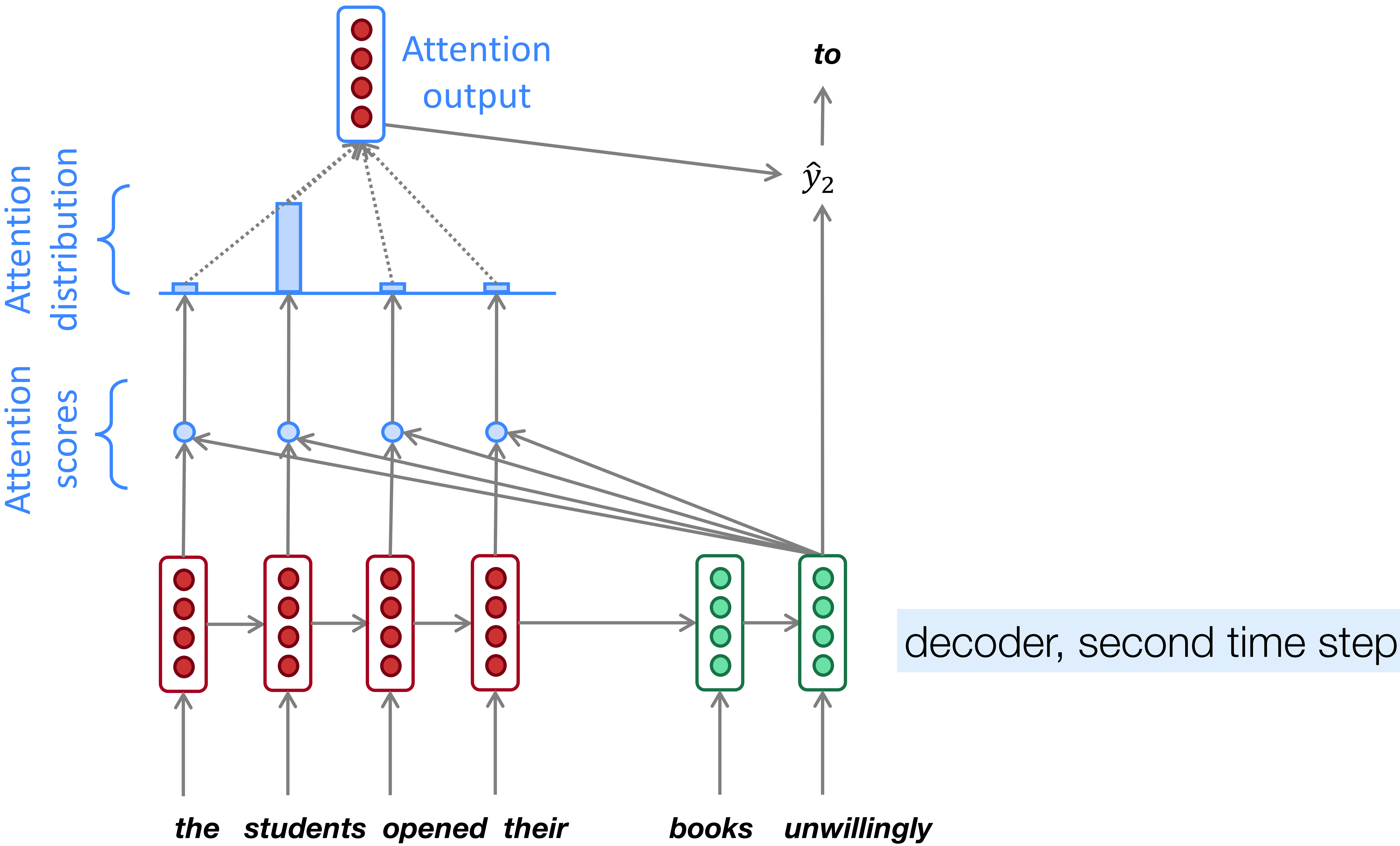
Intuitively, the resulting attention output contains information from hidden states that received high attention scores

Sequence-to-sequence with attention

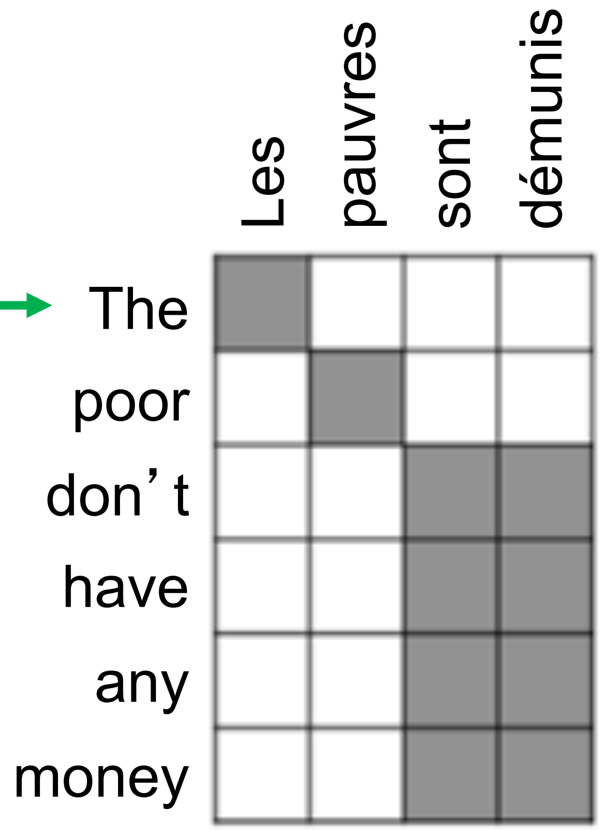


Concatenate (or otherwise compose) the attention output with the current hidden state, then pass through a softmax layer to predict the next word

Sequence-to-sequence with attention



- Attention solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides some interpretability
  - By inspecting attention distribution, we can see what the decoder was focusing on
  - We get alignment for free!
  - This is cool because we never explicitly trained an alignment system
  - The network just learned alignment by itself



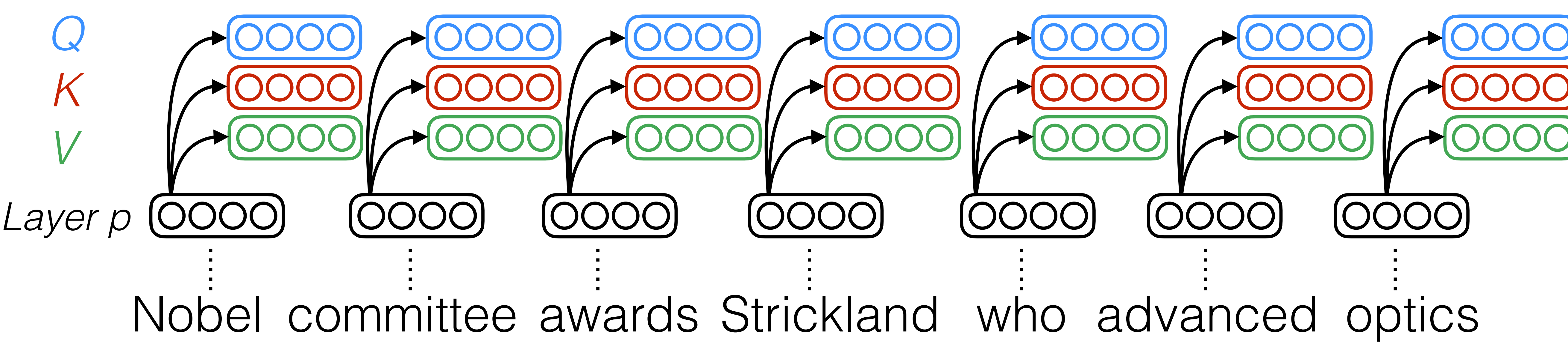
Many variants of attention

- Original formulation: $a(\mathbf{q}, \mathbf{k}) = w_2^T \tanh(W_1[\mathbf{q}; \mathbf{k}])$
- Bilinear product: $a(\mathbf{q}, \mathbf{k}) = \mathbf{q}^T W \mathbf{k}$ Luong et al., 2015
- Dot product: $a(\mathbf{q}, \mathbf{k}) = \mathbf{q}^T \mathbf{k}$ Luong et al., 2015
- Scaled dot product: $a(\mathbf{q}, \mathbf{k}) = \dfrac{\mathbf{q}^T \mathbf{k}}{\sqrt{|\mathbf{k}|}}$ Vaswani et al., 2017

iPad

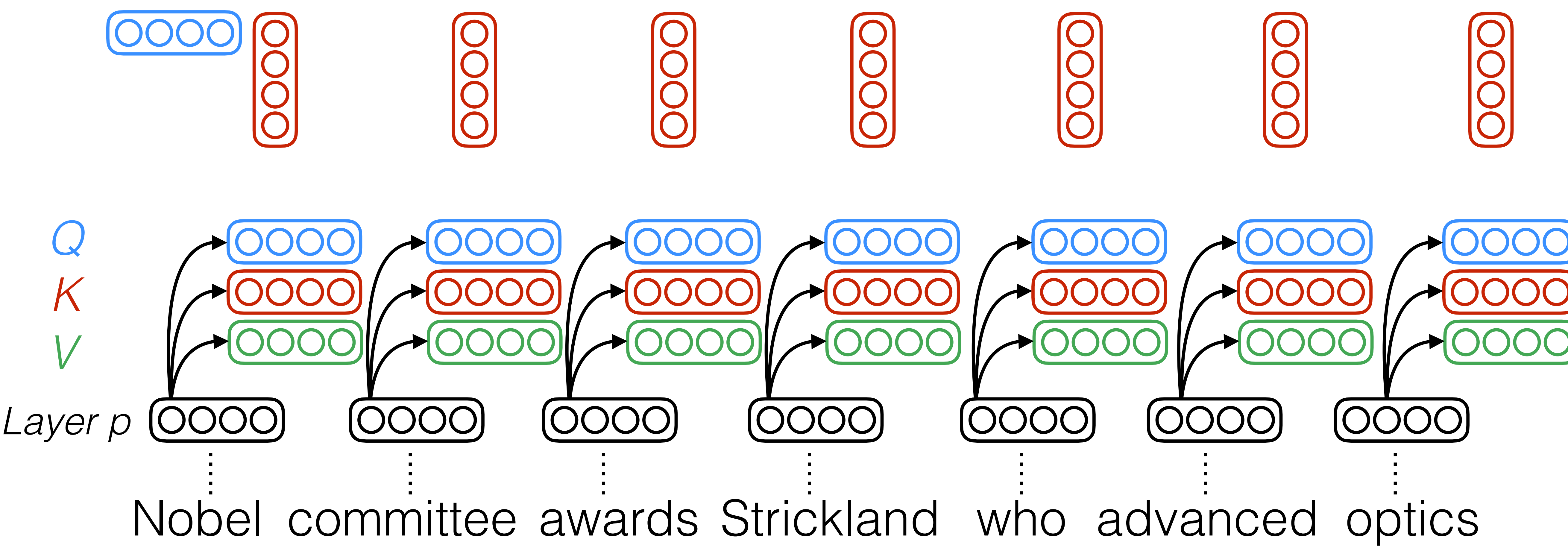
Self-attention

[Vaswani et al. 2017]



Self-attention

[Vaswani et al. 2017]



Slides by Emma Strubell!

[Vaswani et al. 2017]

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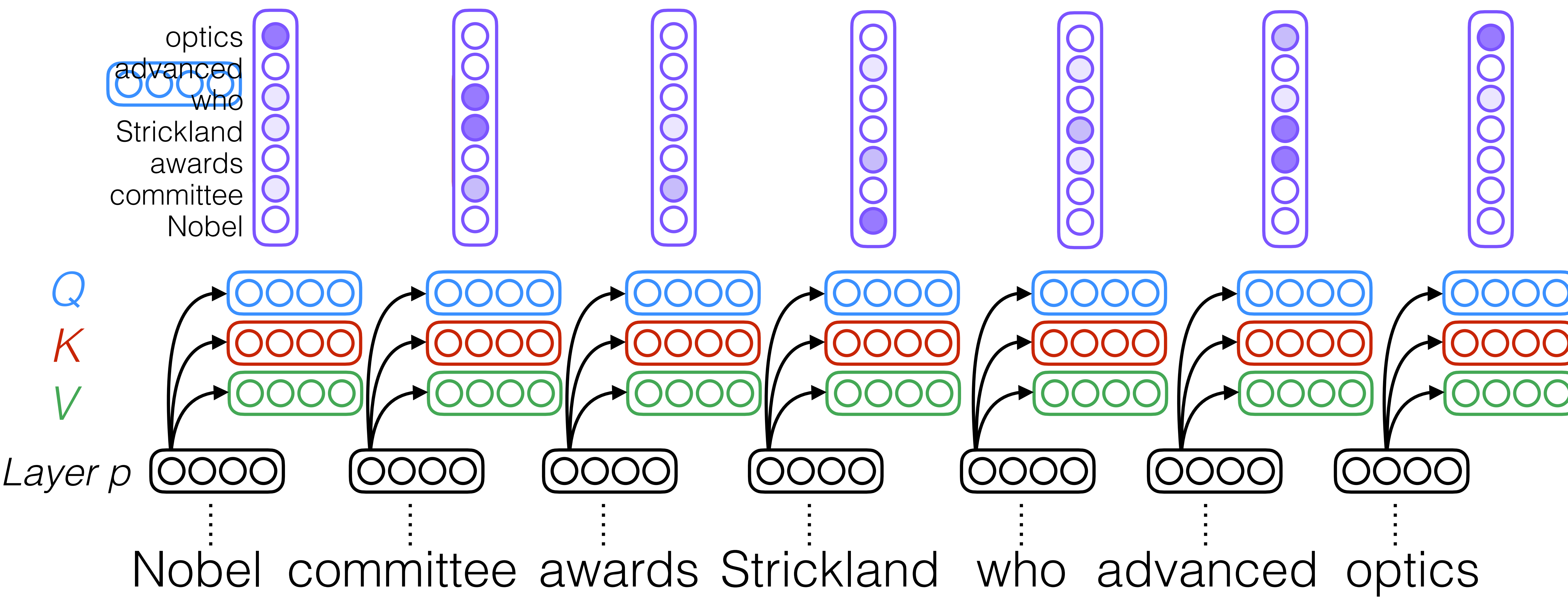

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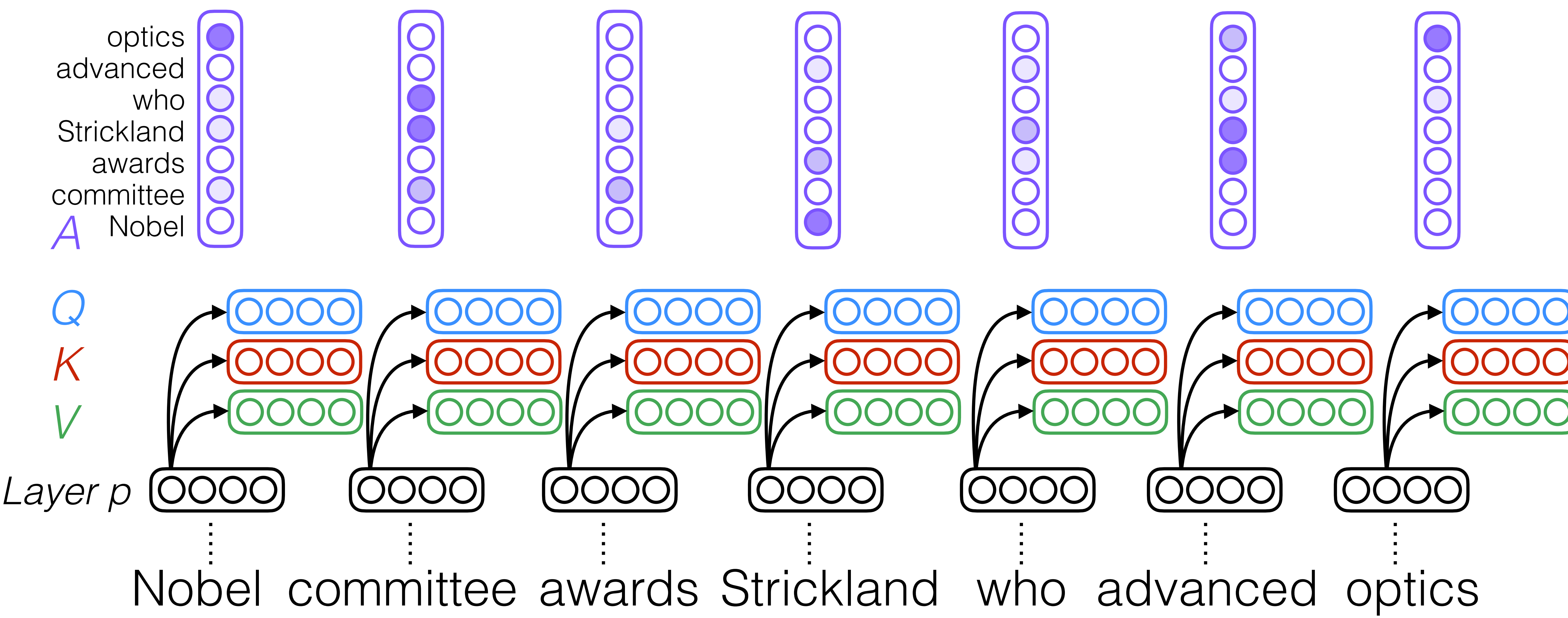

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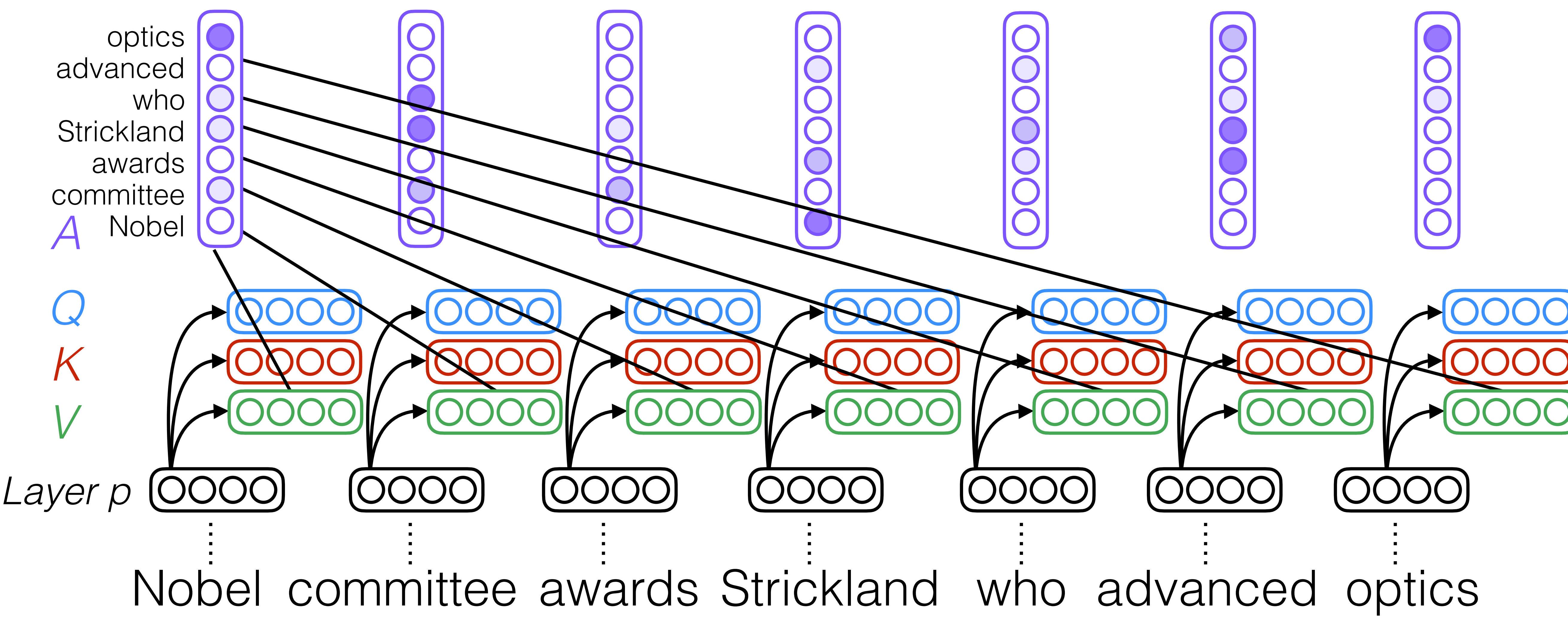

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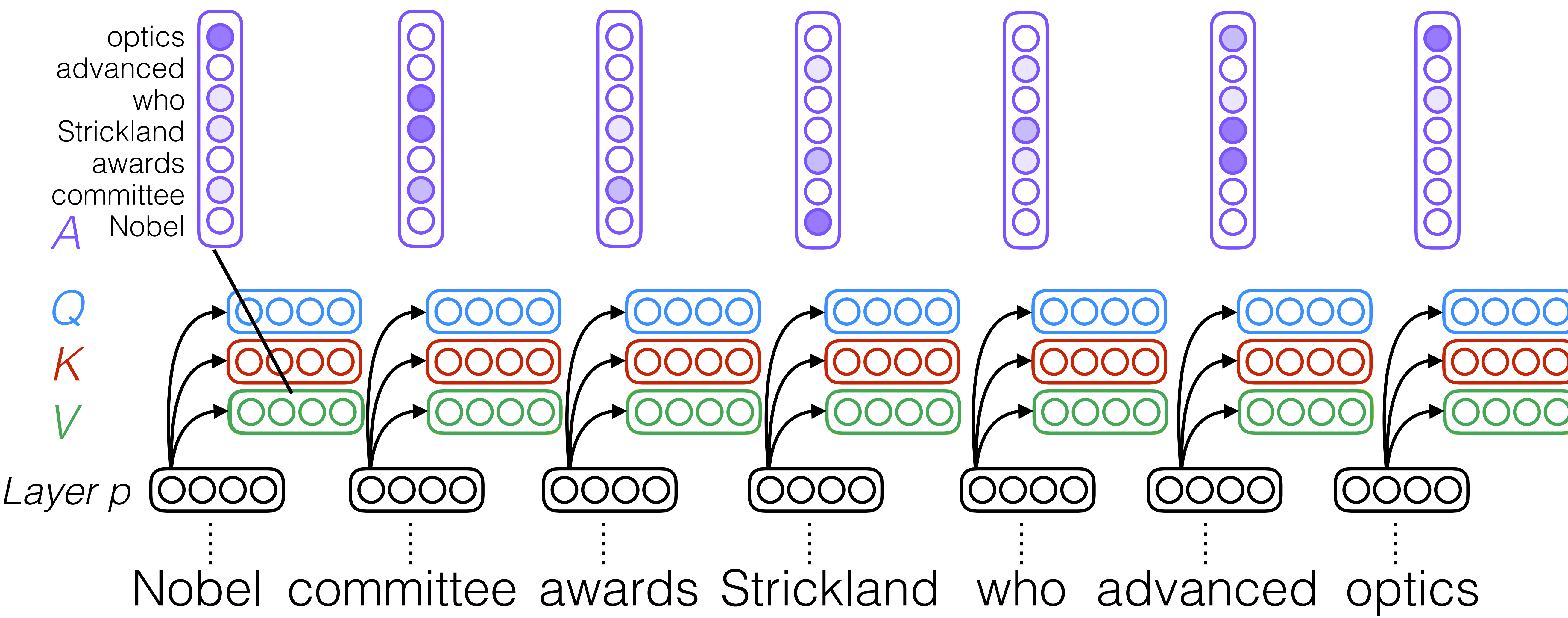

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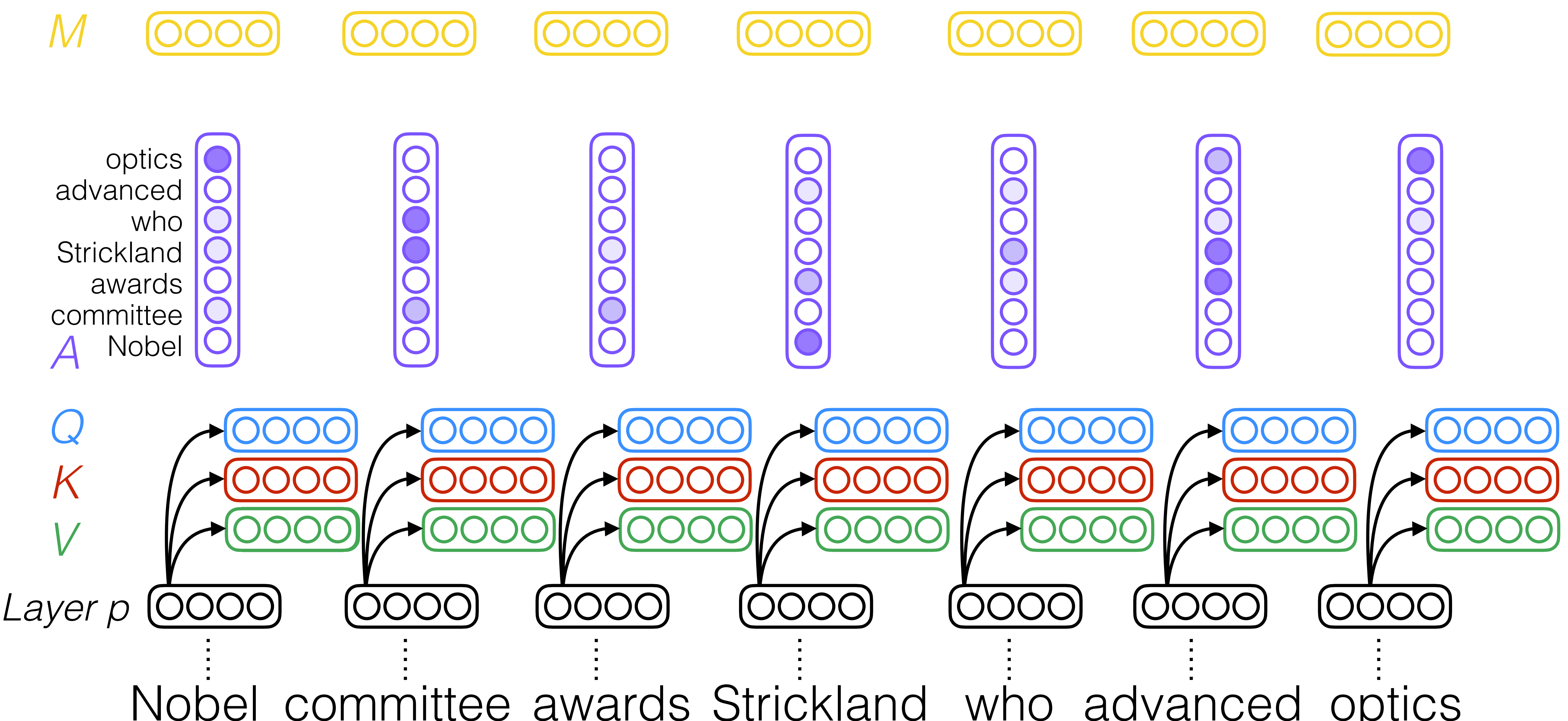

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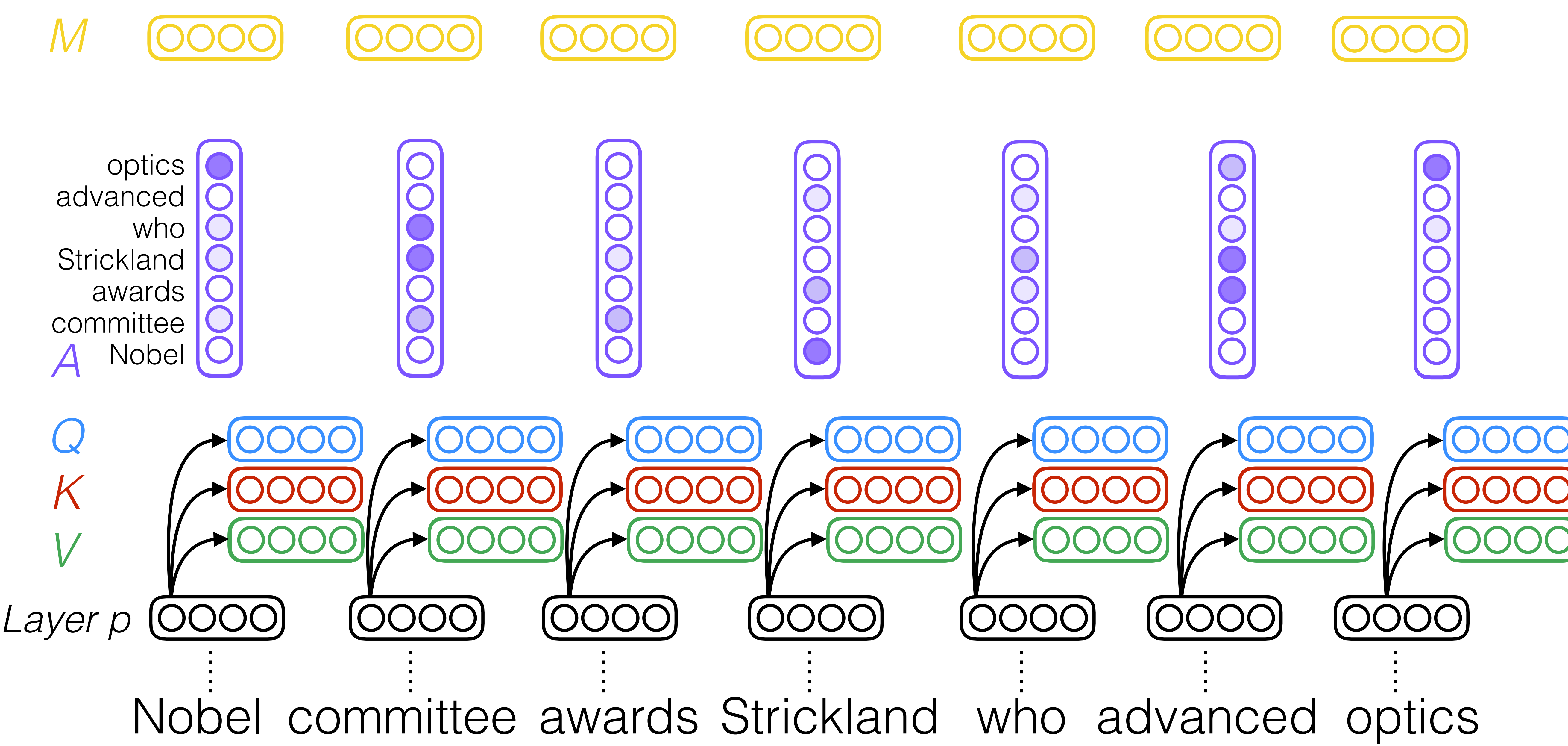

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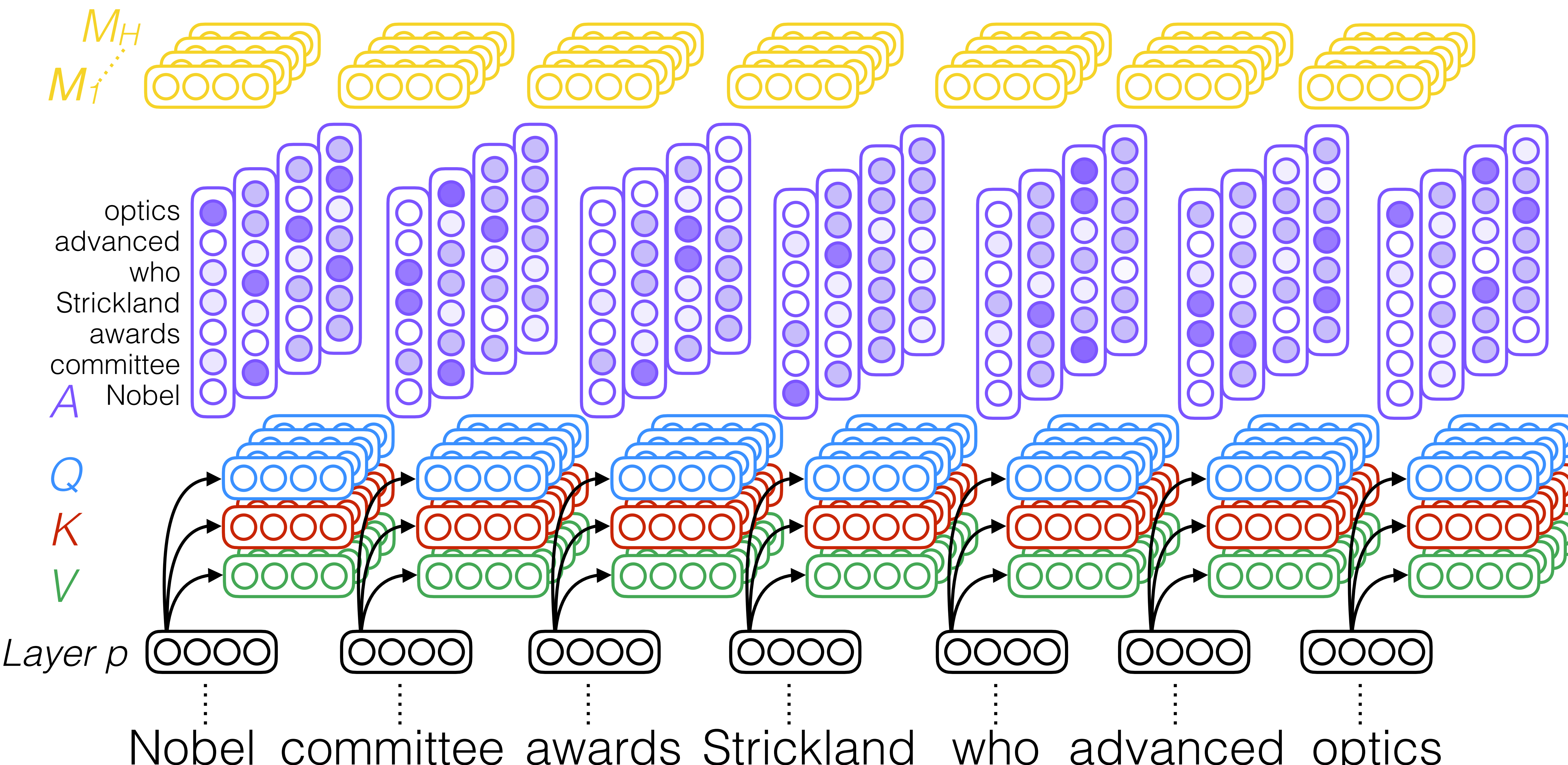
Multi-head self-attention



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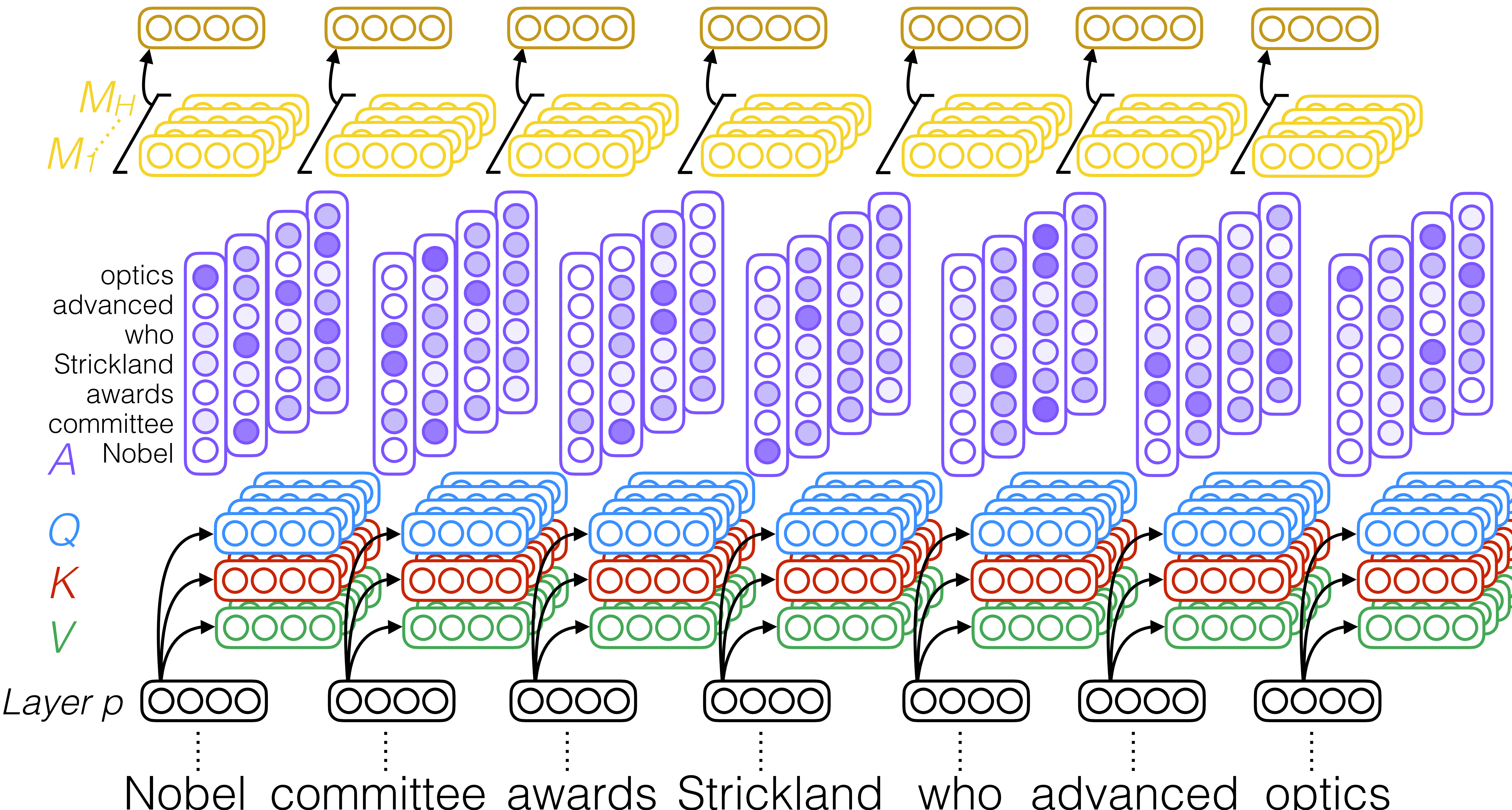

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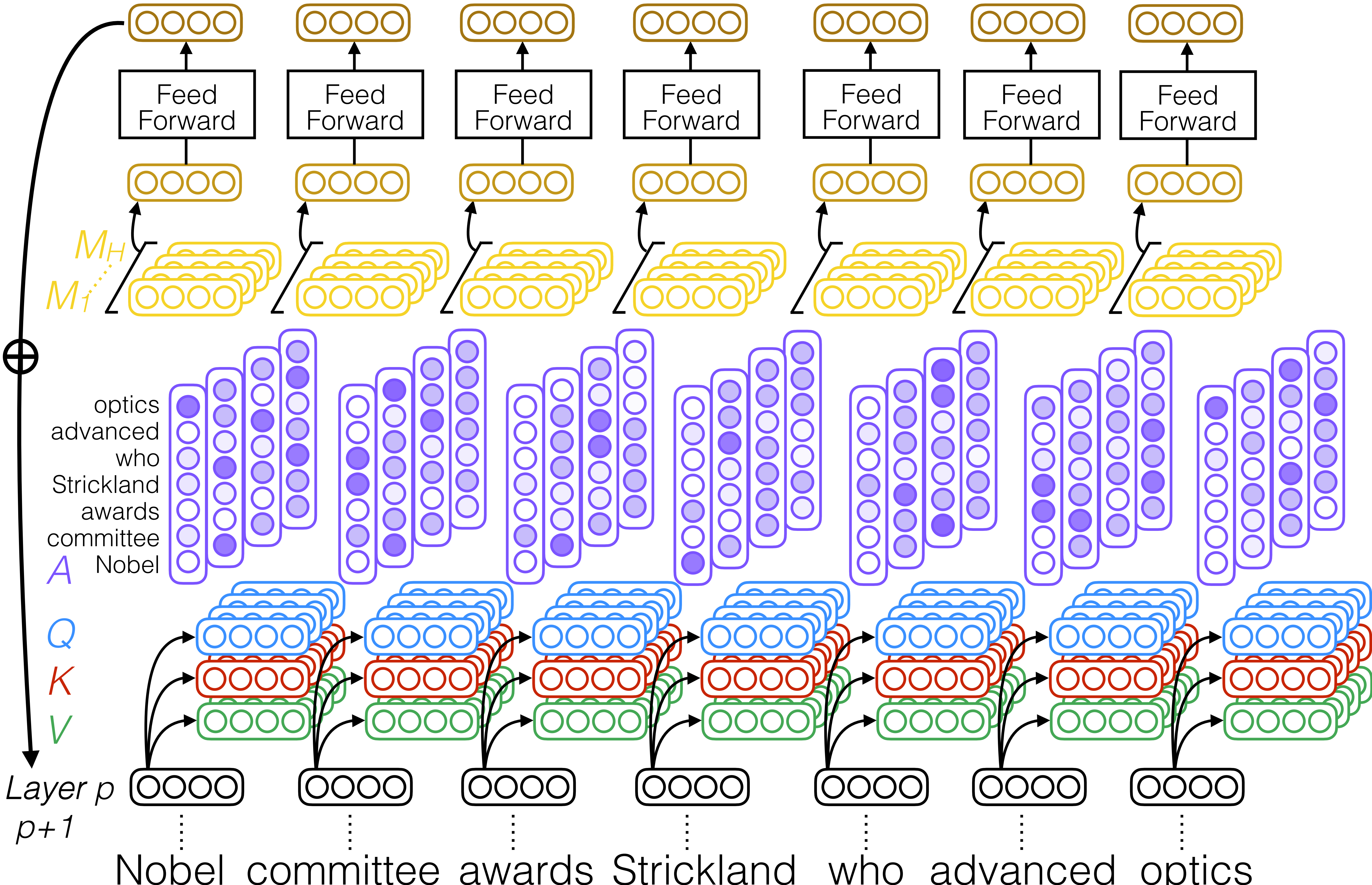

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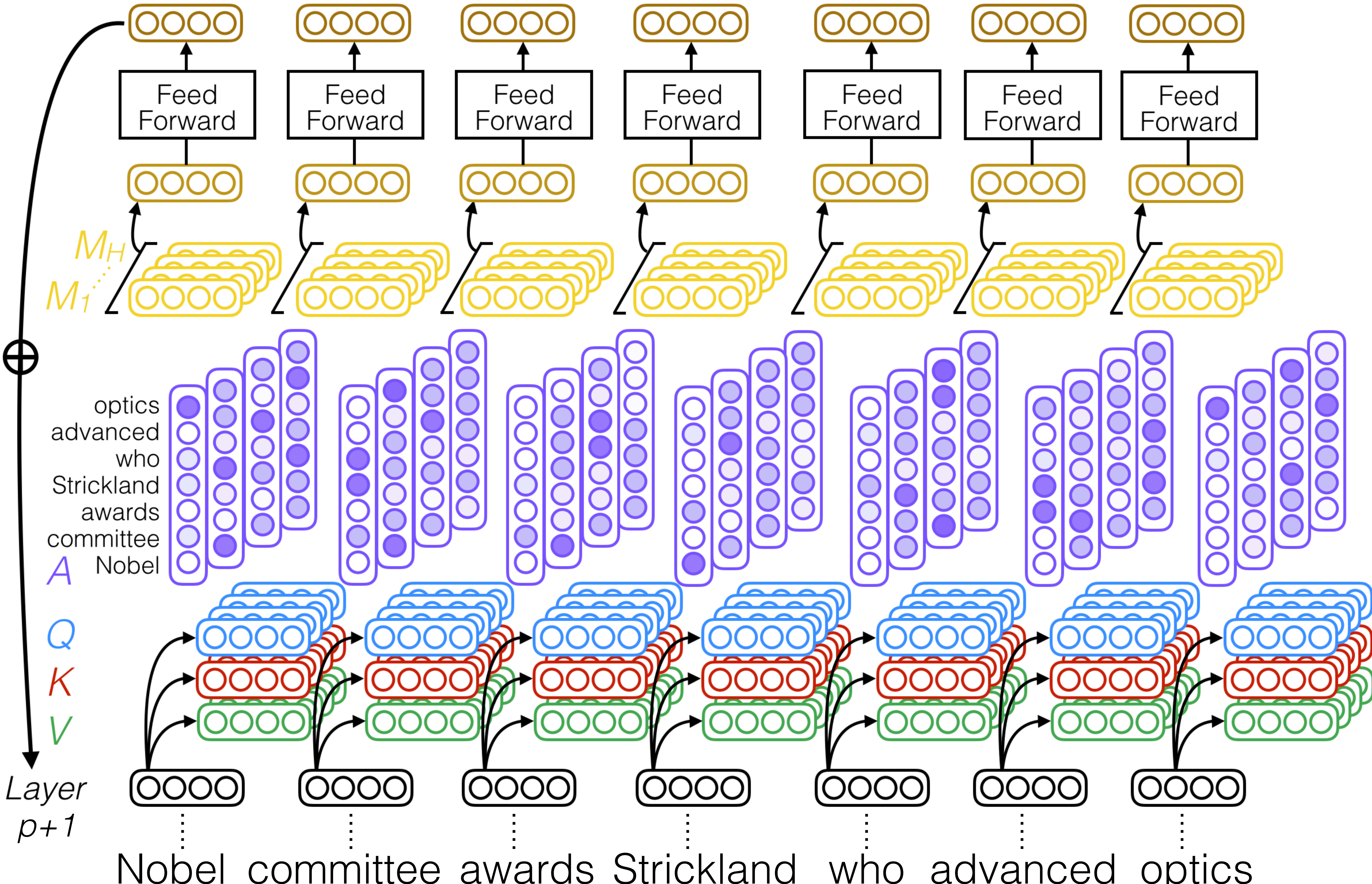

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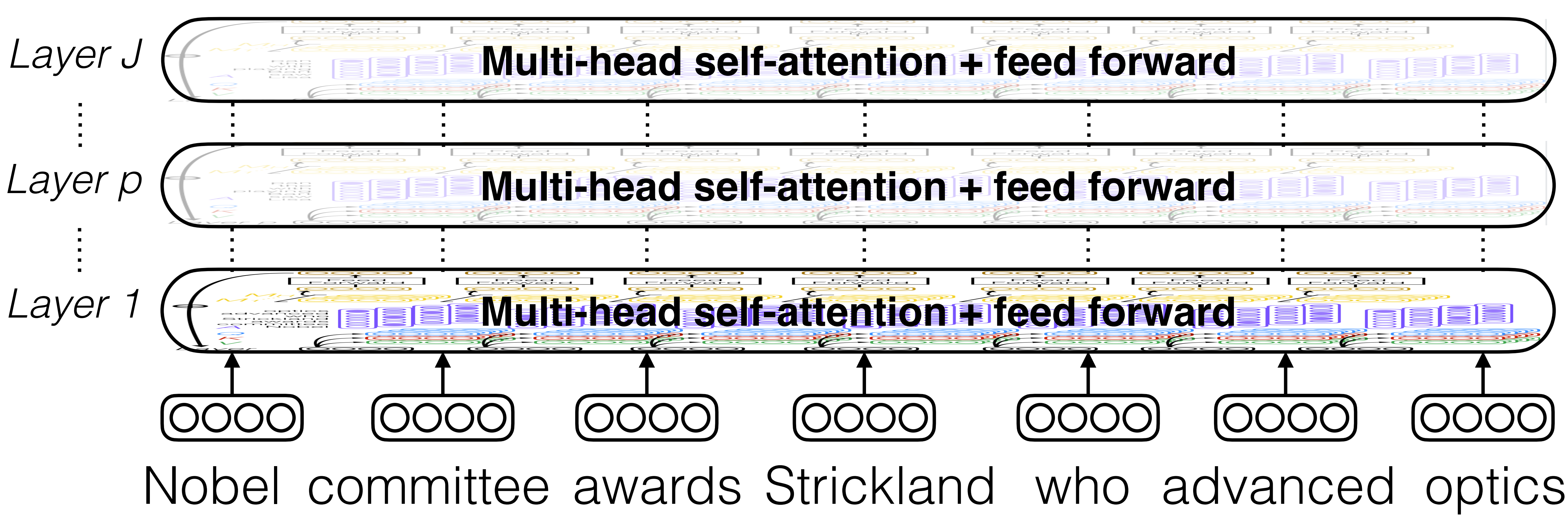

Note: the previous example does *not* describe a language model (the attention looks at both past and future words!)