Attention mechanisms

CS 685, Fall 2020
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
- HW1 will be out within the next 1-2 weeks
- Project proposals due 9/21, all group assignments have been finalized

A RNN Language Model

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

output distribution

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

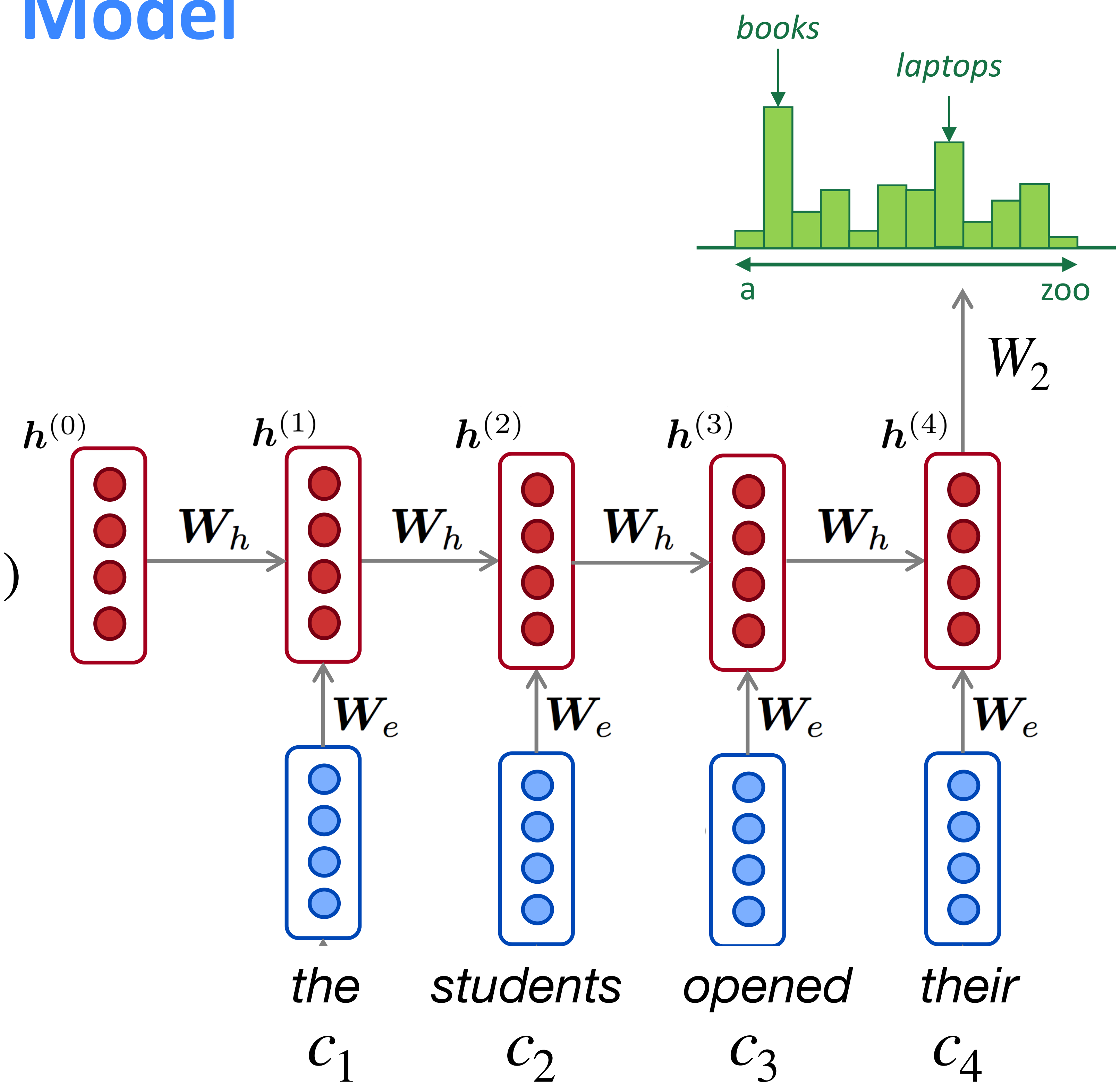
hidden states

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

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

word embeddings

$$c_1, c_2, c_3, c_4$$



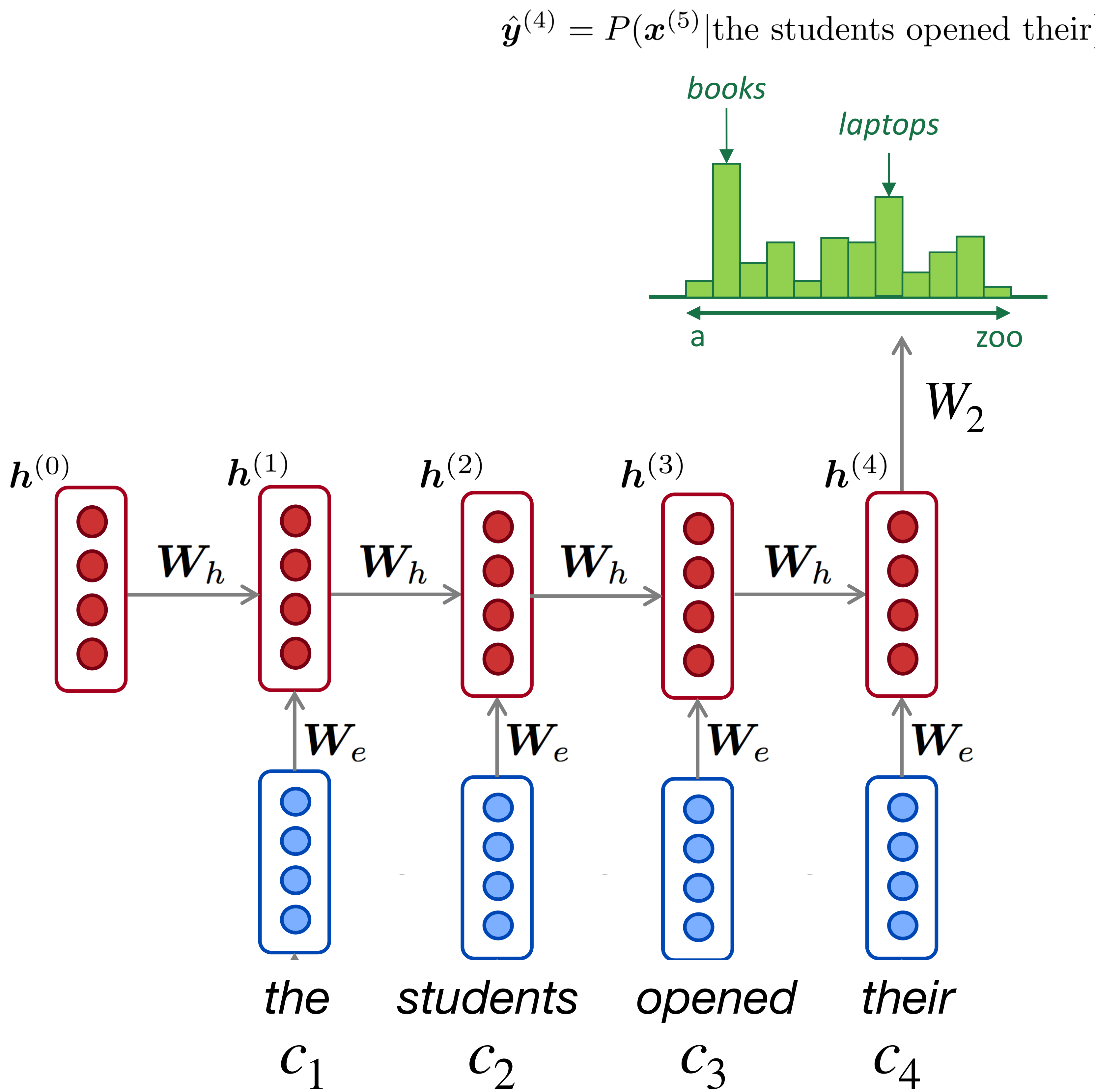
why is this good?

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

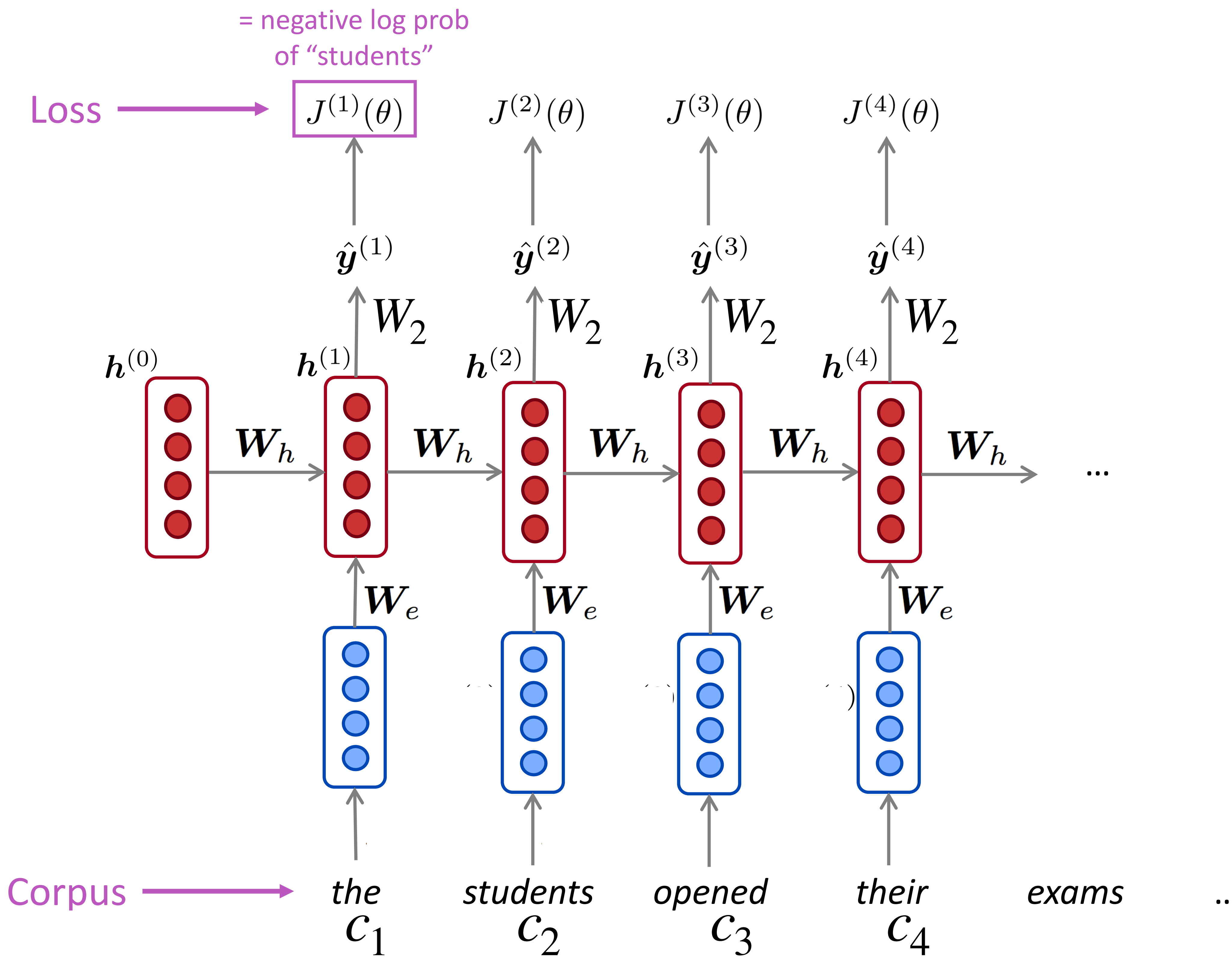
- Loss function on step *t* is usual cross-entropy between our predicted probability distribution $\hat{\boldsymbol{y}}^{(t)}$, and the true next word $\boldsymbol{y}^{(t)} = \boldsymbol{x}^{(t+1)}$:

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

- 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



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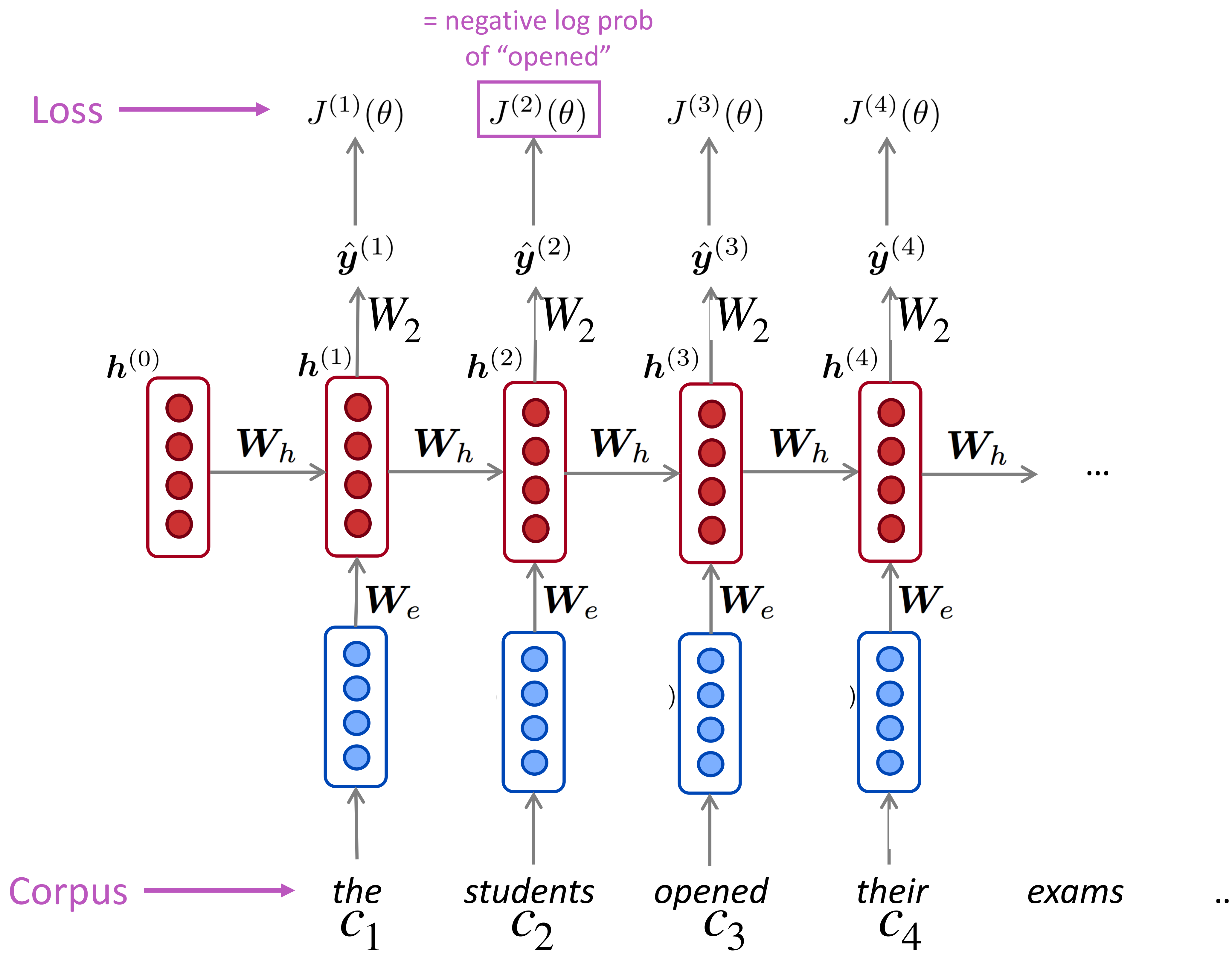

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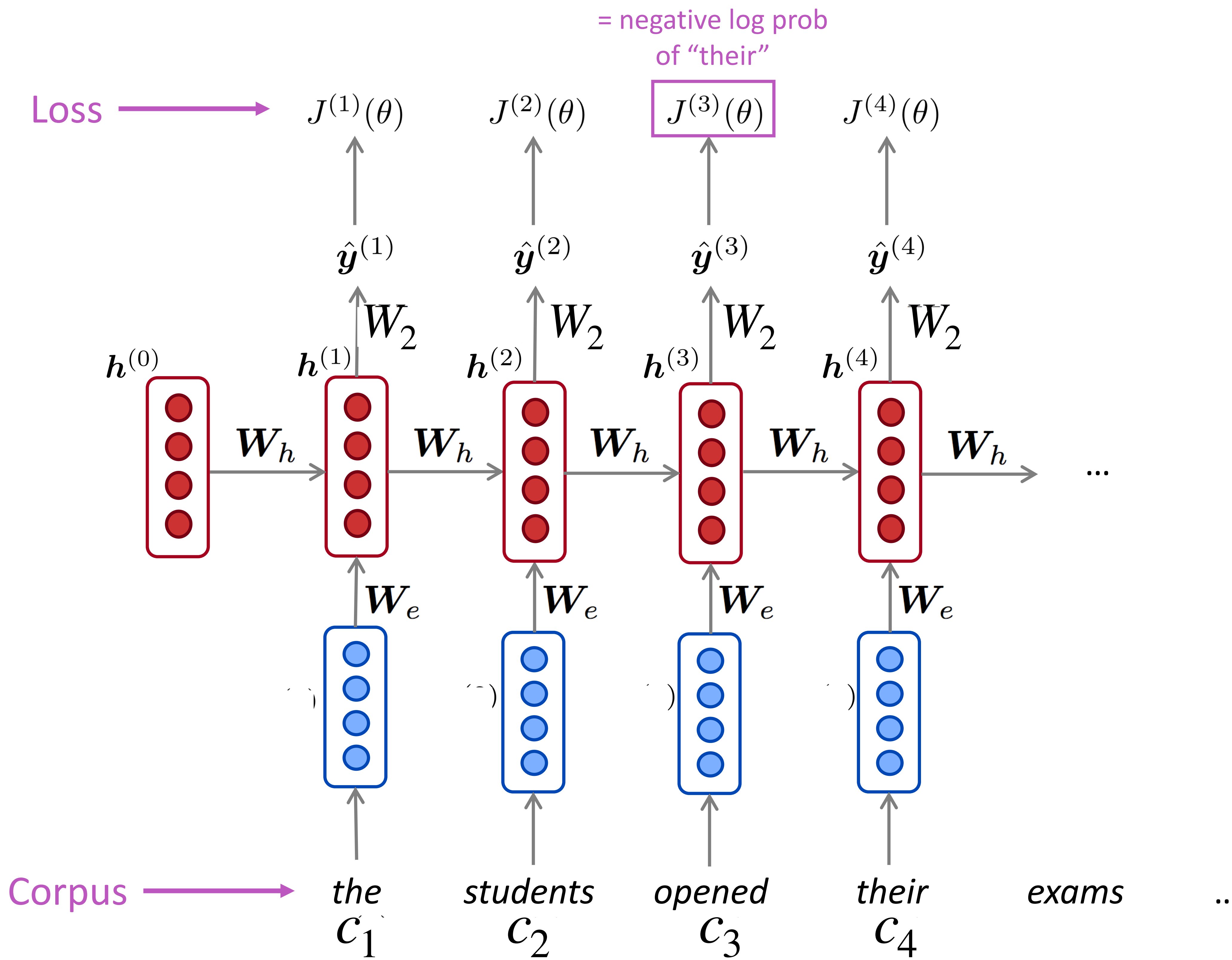

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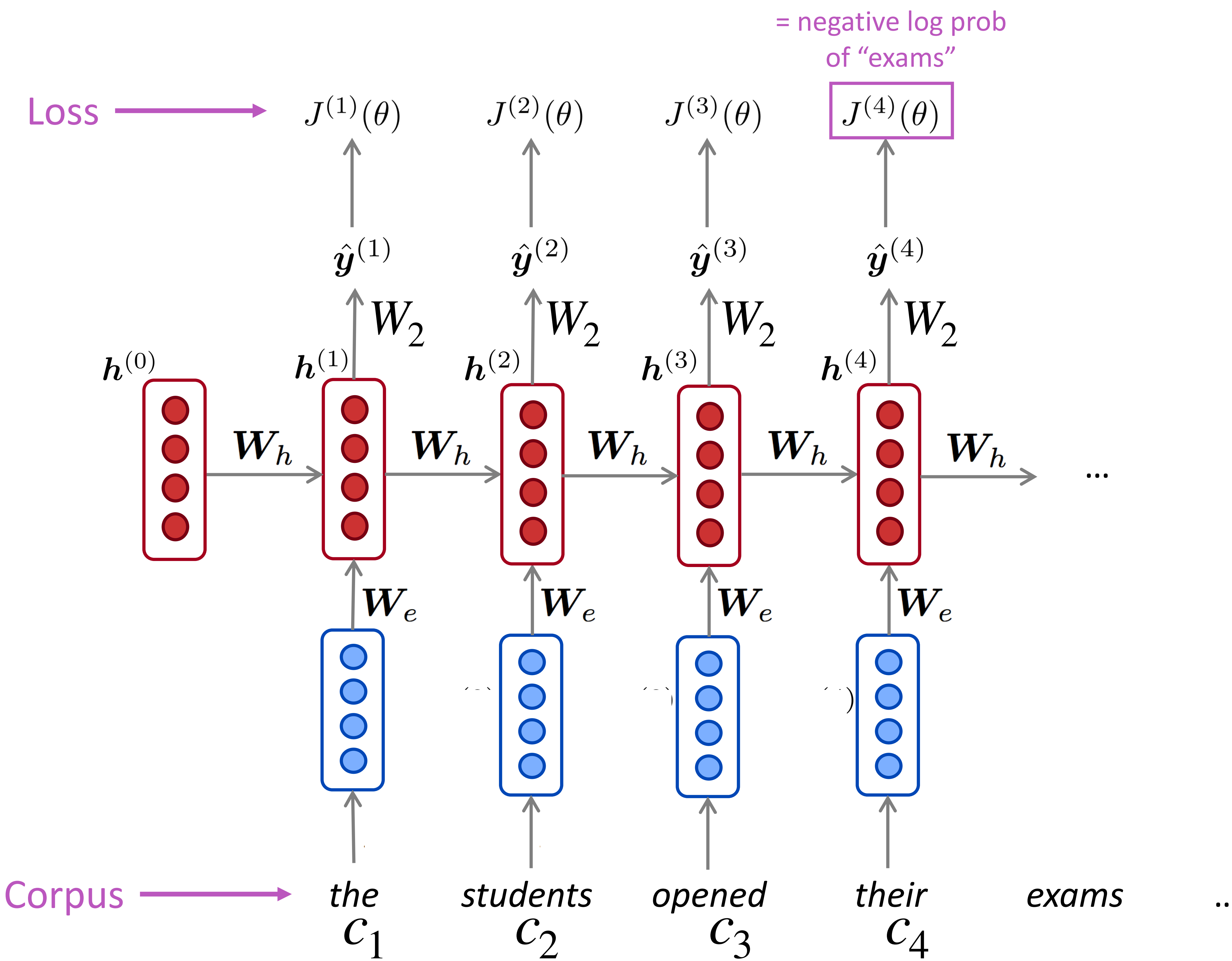
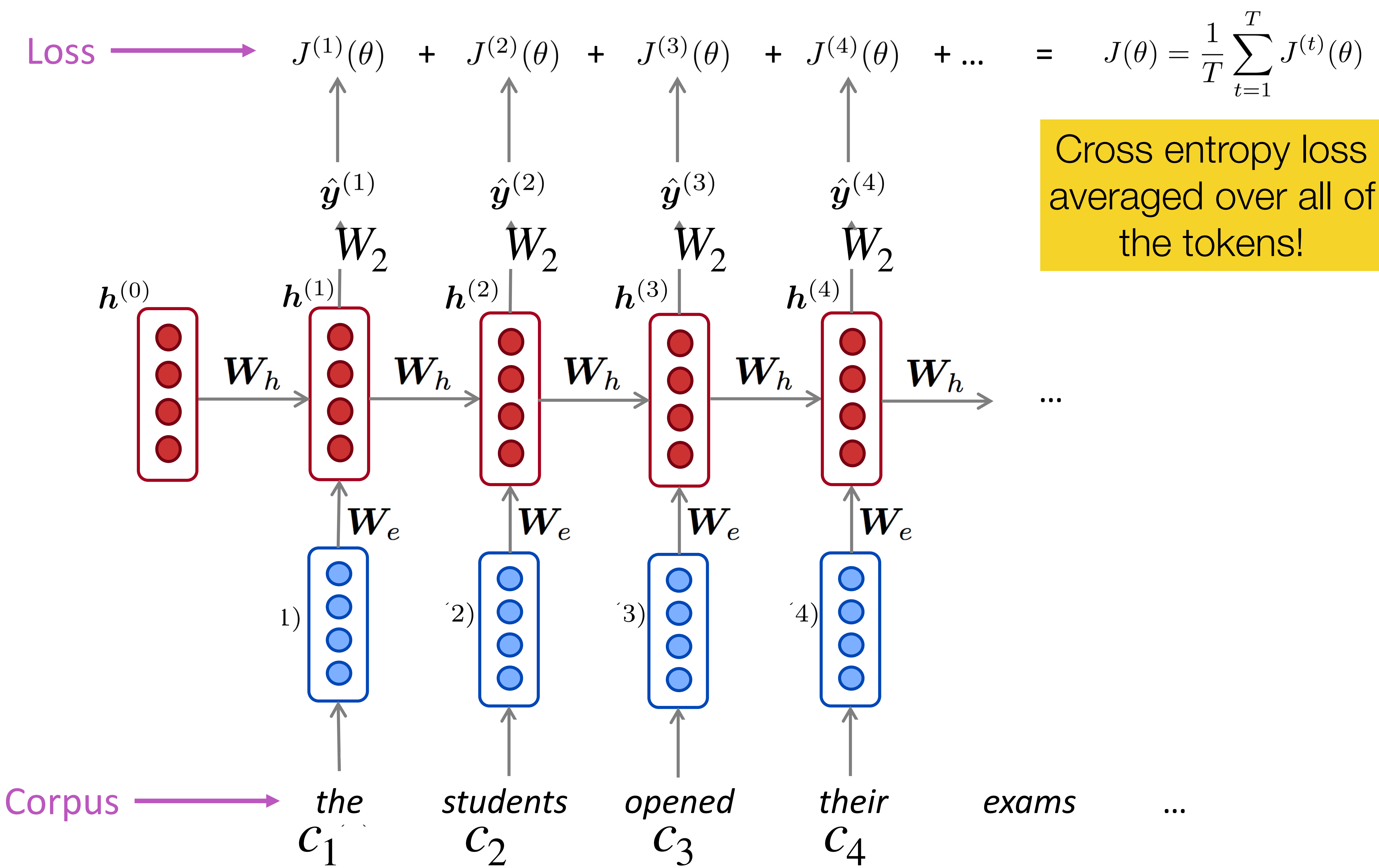
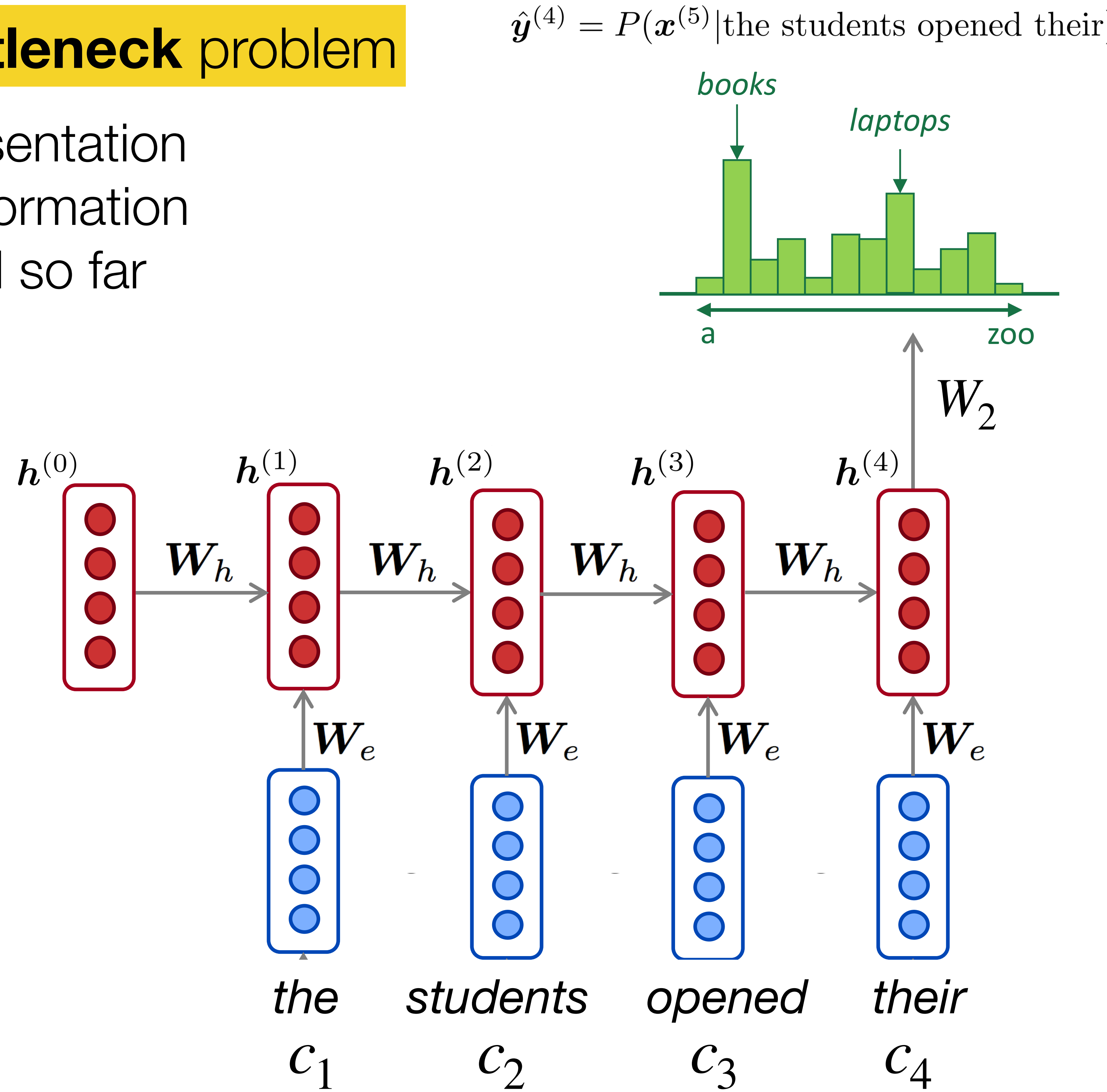


Training a RNN Language Model



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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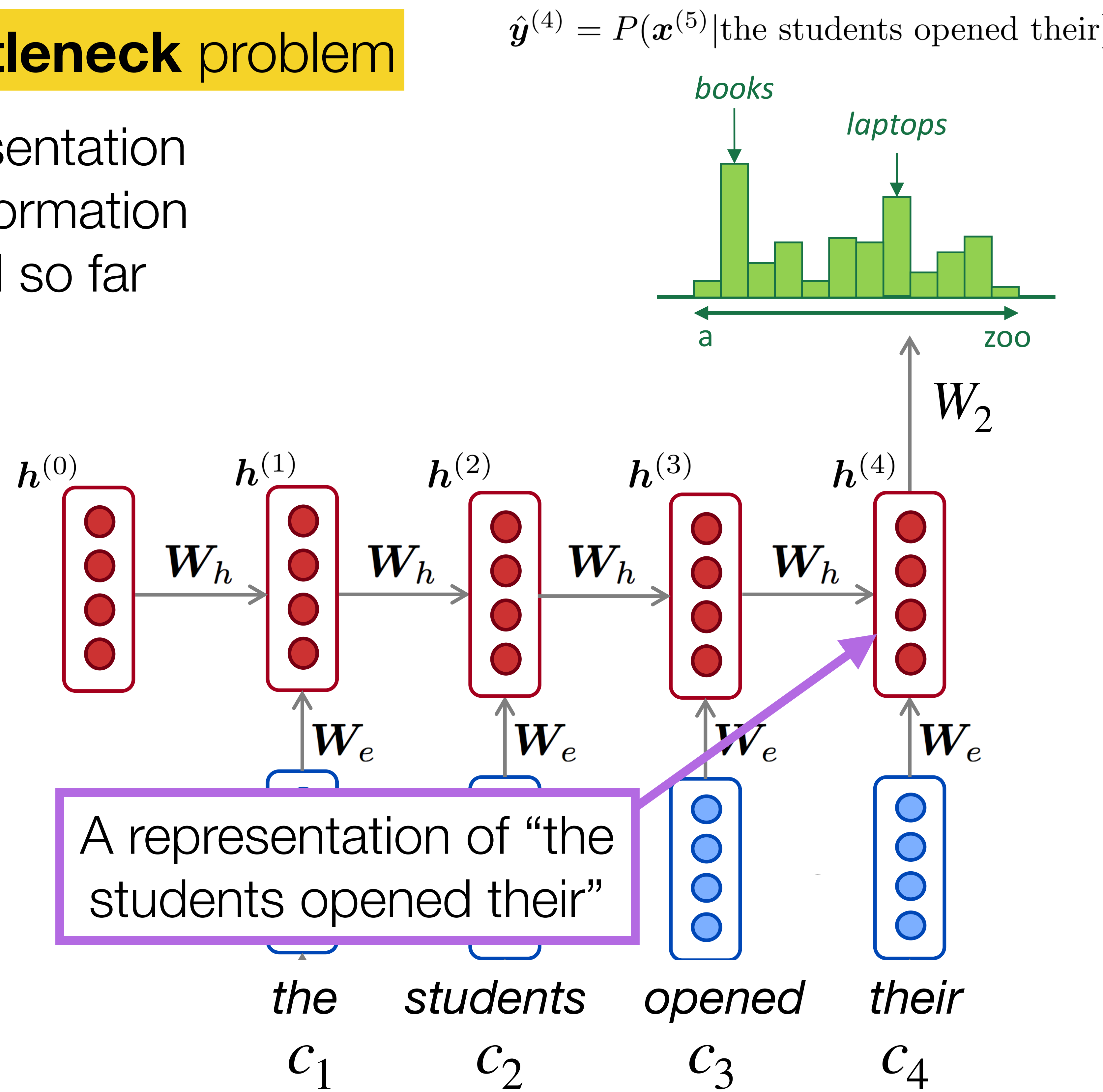

RNNs suffer from a **bottleneck** problem

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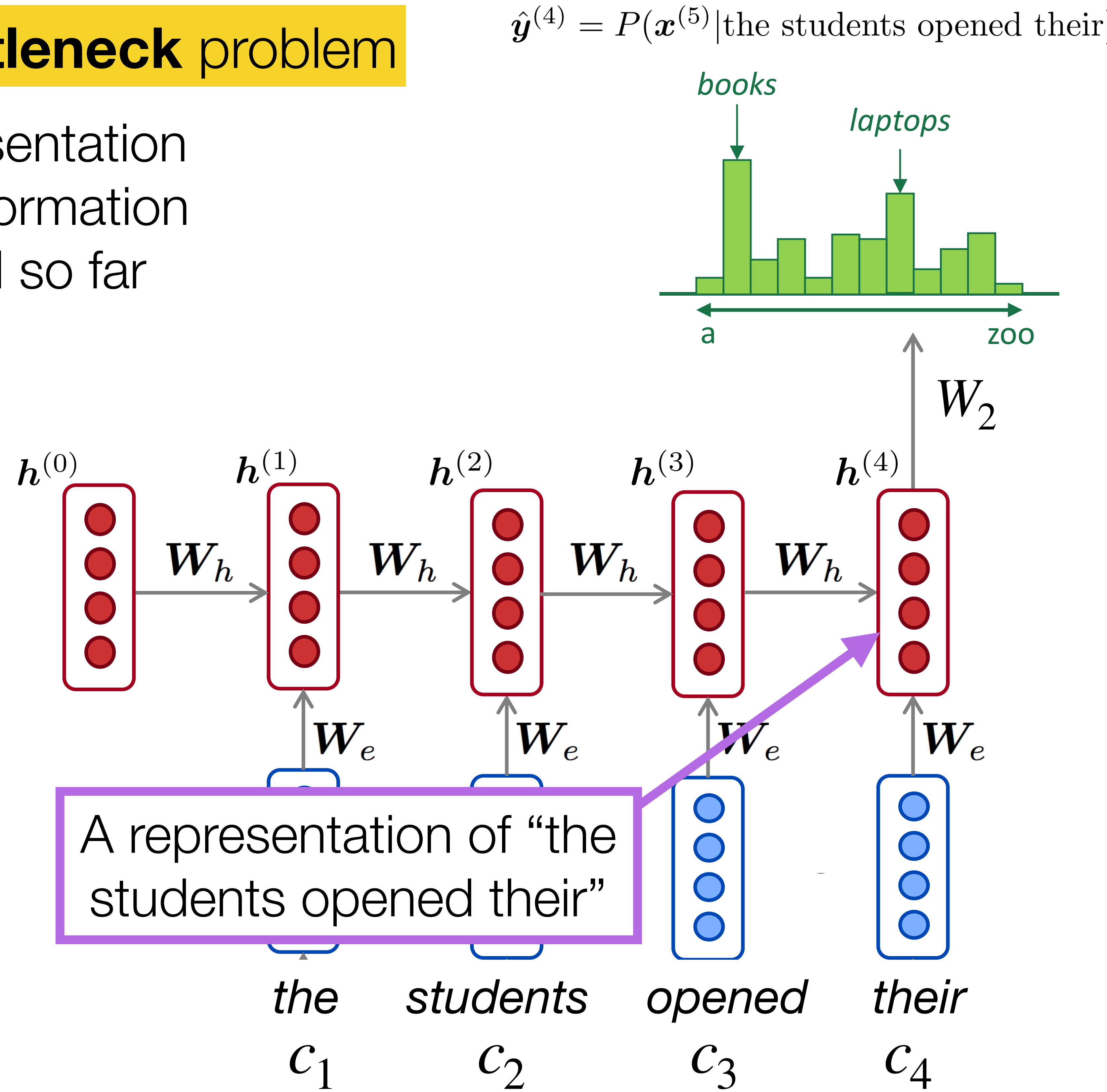
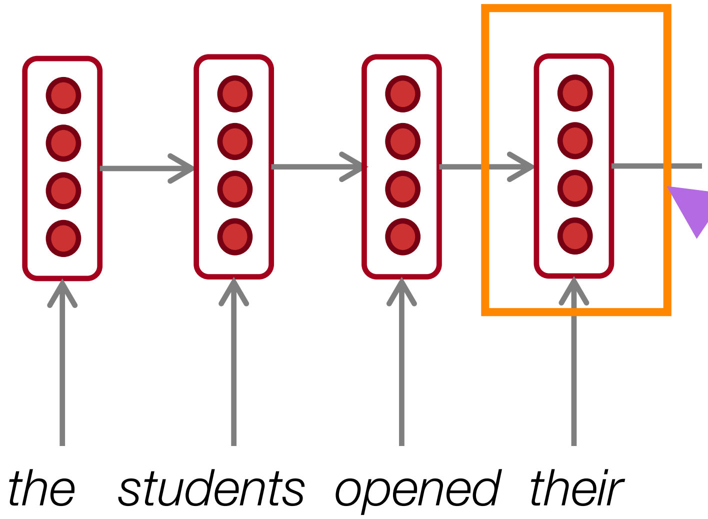
This becomes difficult especially with longer sequences



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

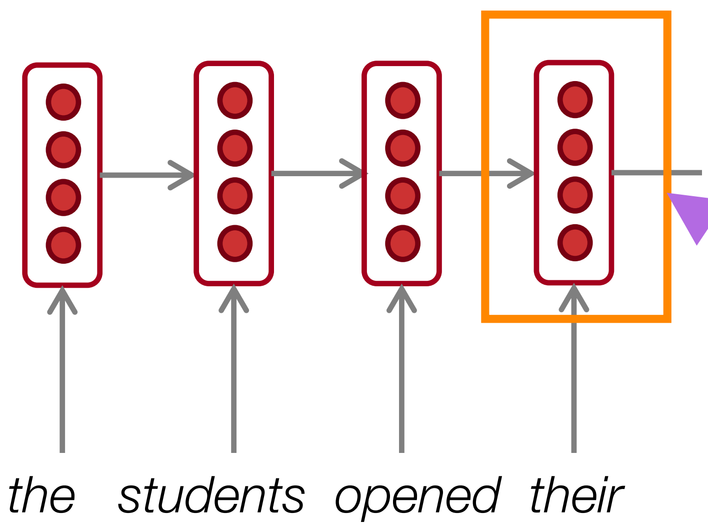
— Ray Mooney (NLP professor at UT Austin)

idea: what if we use multiple vectors?



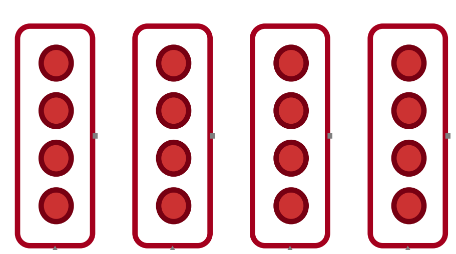
This representation needs to capture all information about "the students opened their"

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**

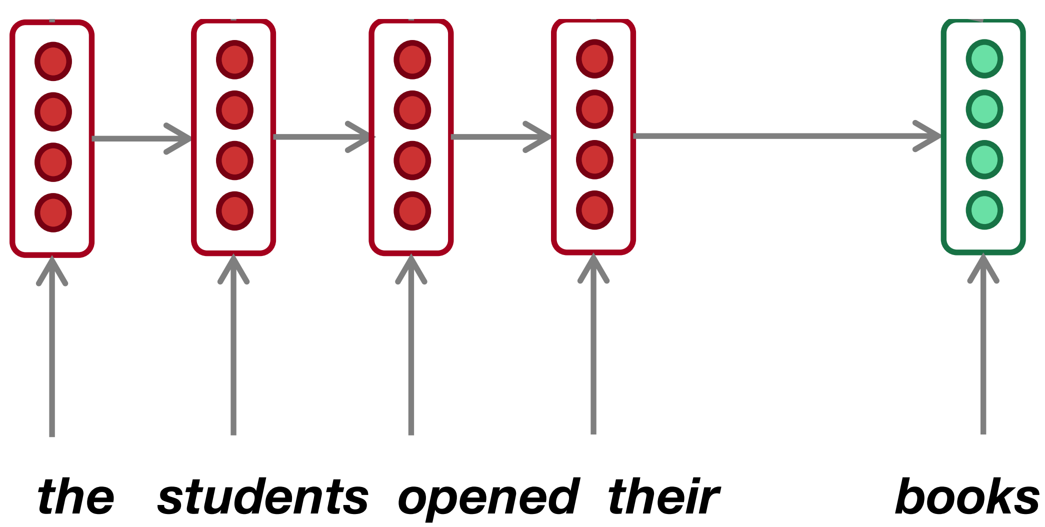
- **Attention mechanisms** (Bahdanau et al., 2015) allow language models to focus on a particular part of the observed context at each time step
    - Originally developed for machine translation, and intuitively similar to *word alignments* between different languages

How does it work?

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

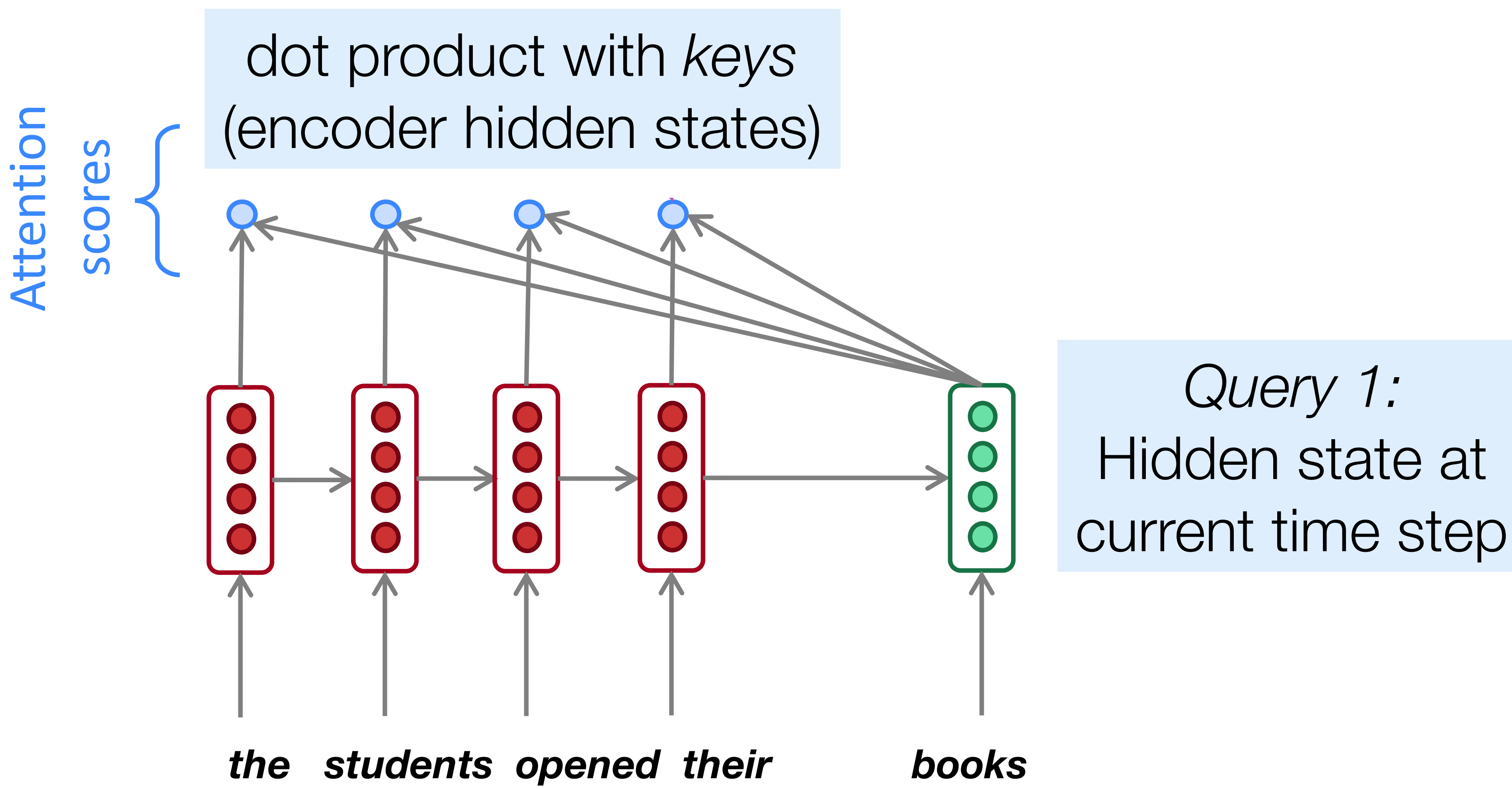
in a neural language model, what are the queries and keys?

Attention mechanisms in neural language models



Query 1:
Hidden state at
current time step

Attention mechanisms in neural language models



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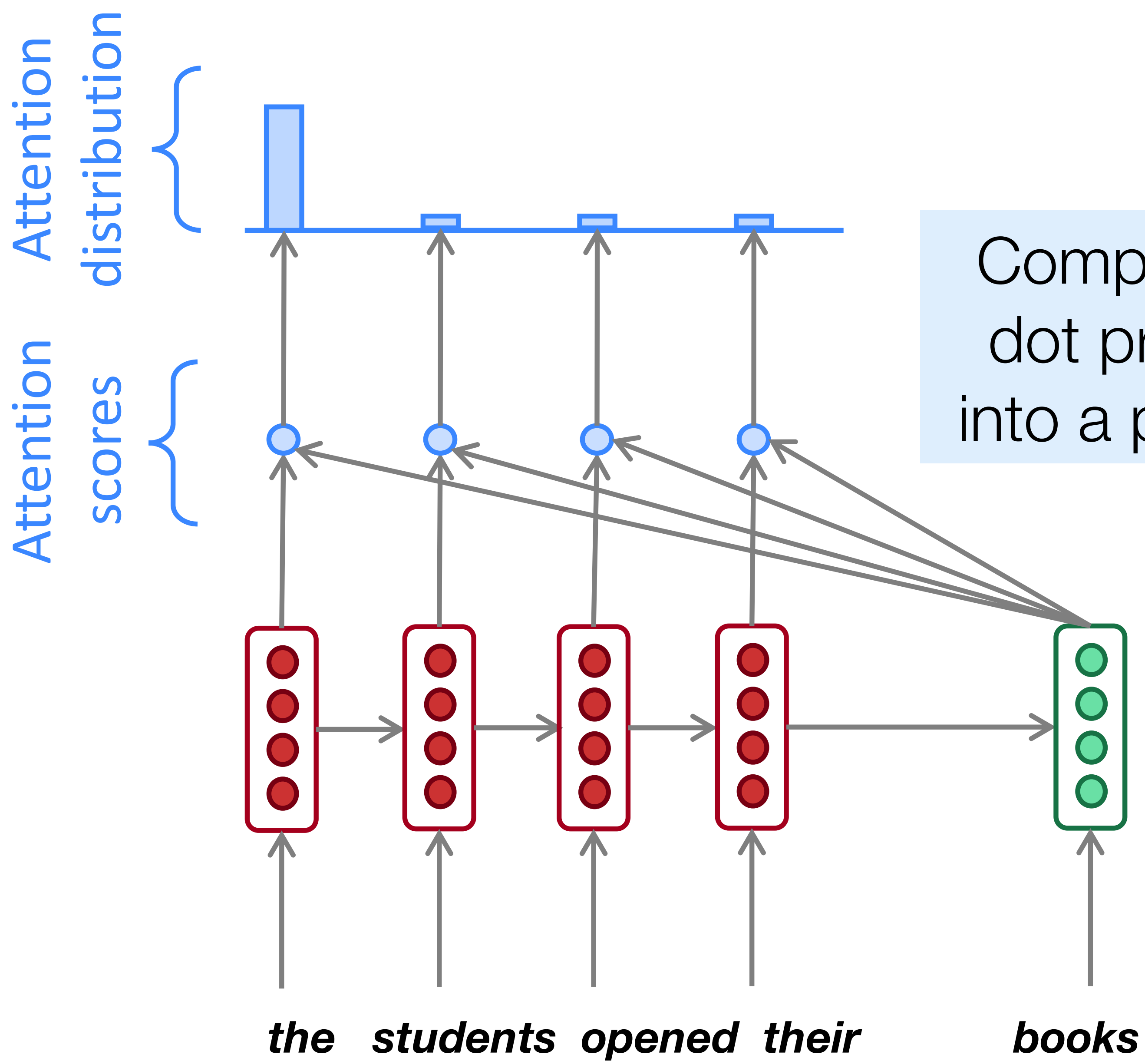
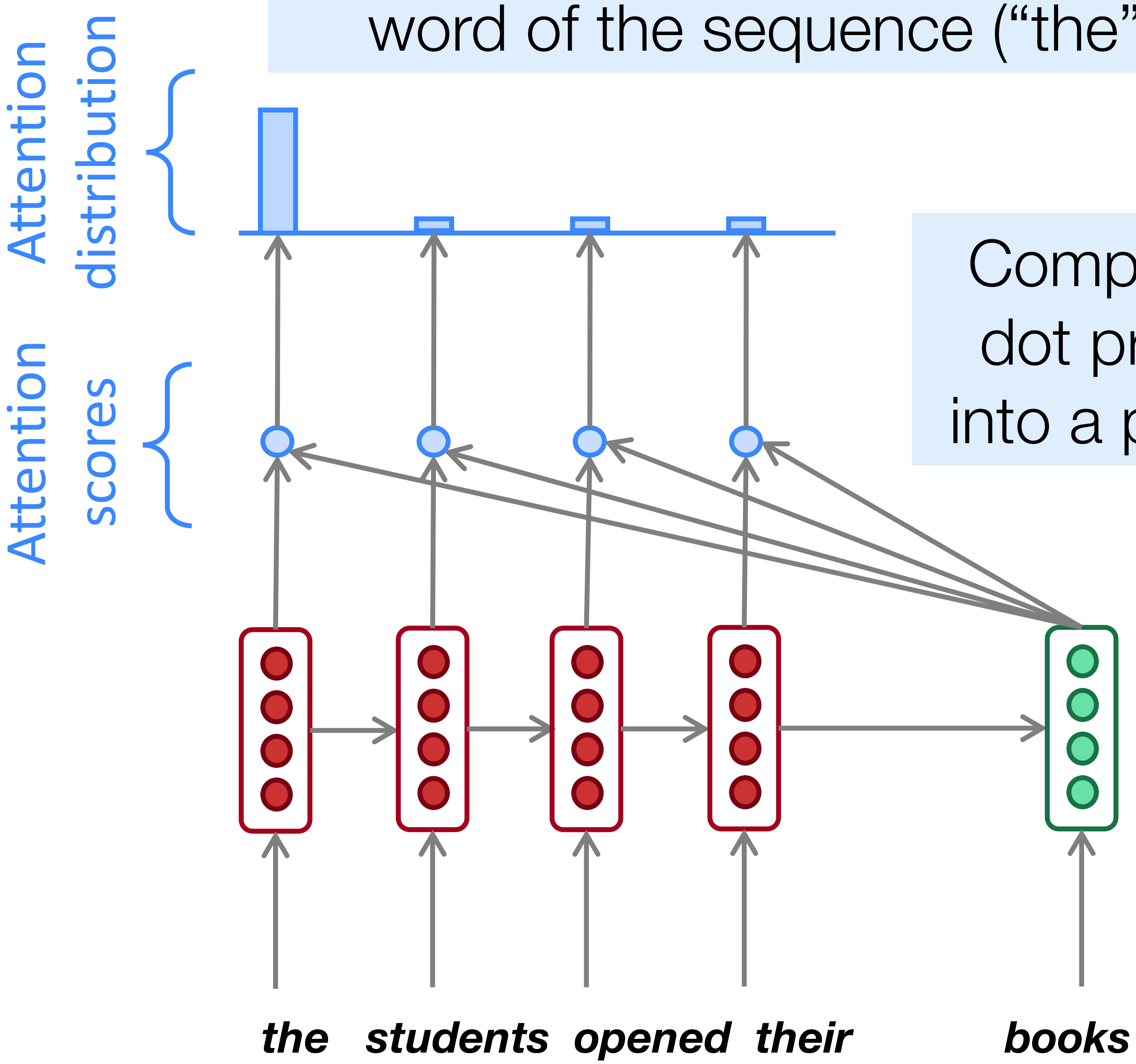


Compute softmax over the dot products to turn them into a probability distribution

Attention mechanisms in neural language models

At this time step, the attention distribution is focused on the first word of the sequence (“the”)



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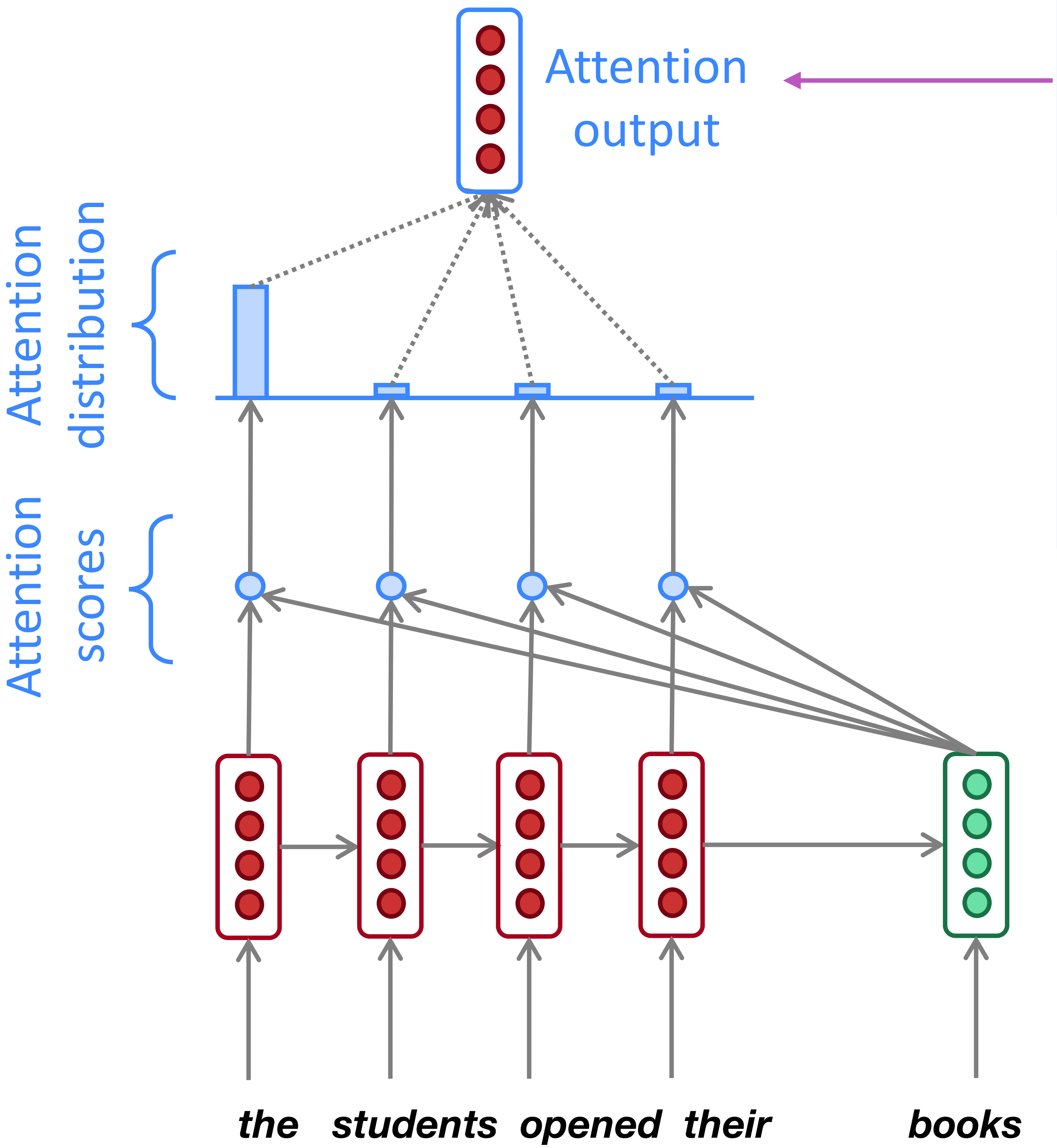
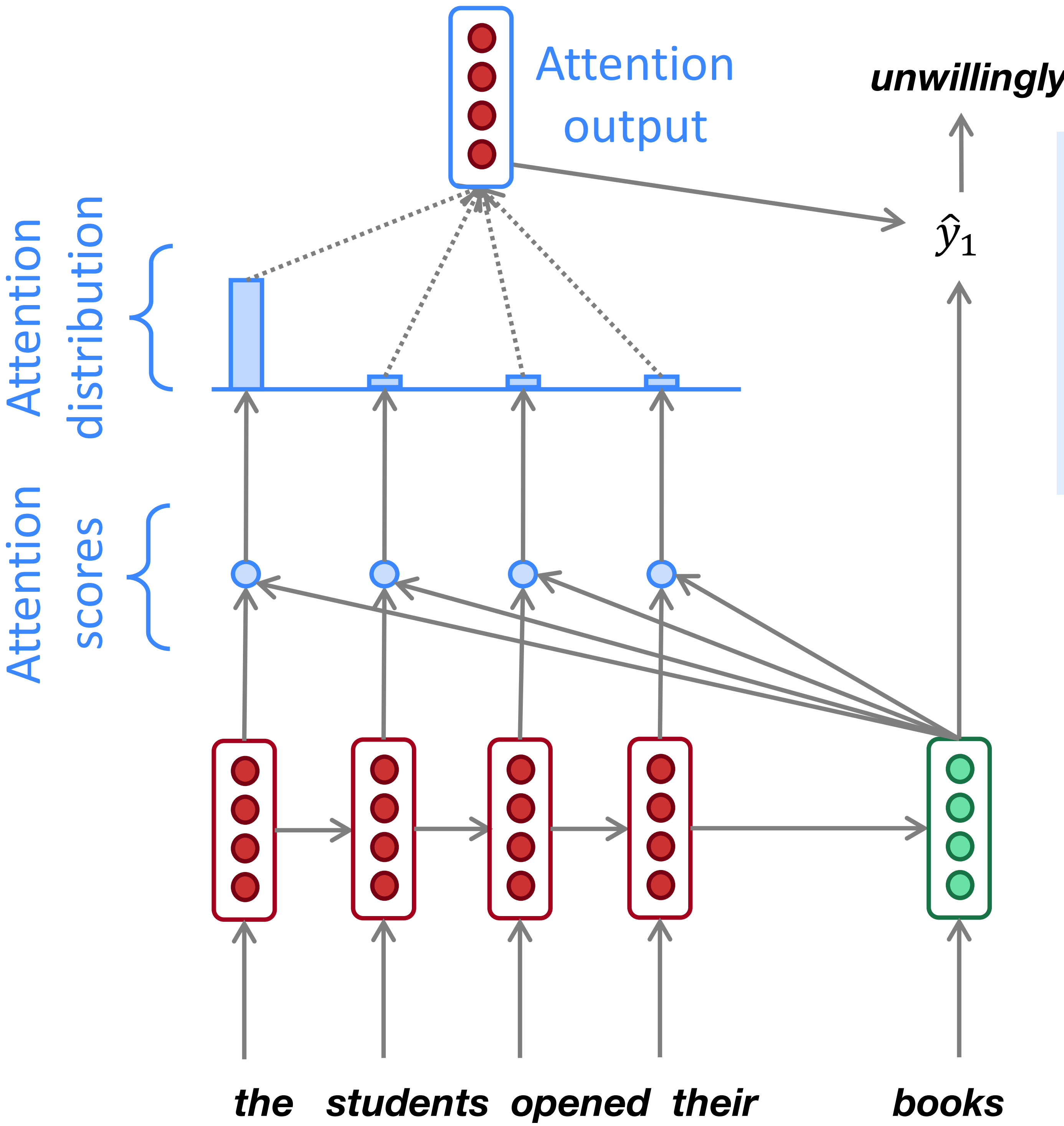


We use the attention distribution to compute a weighted average of the hidden states.

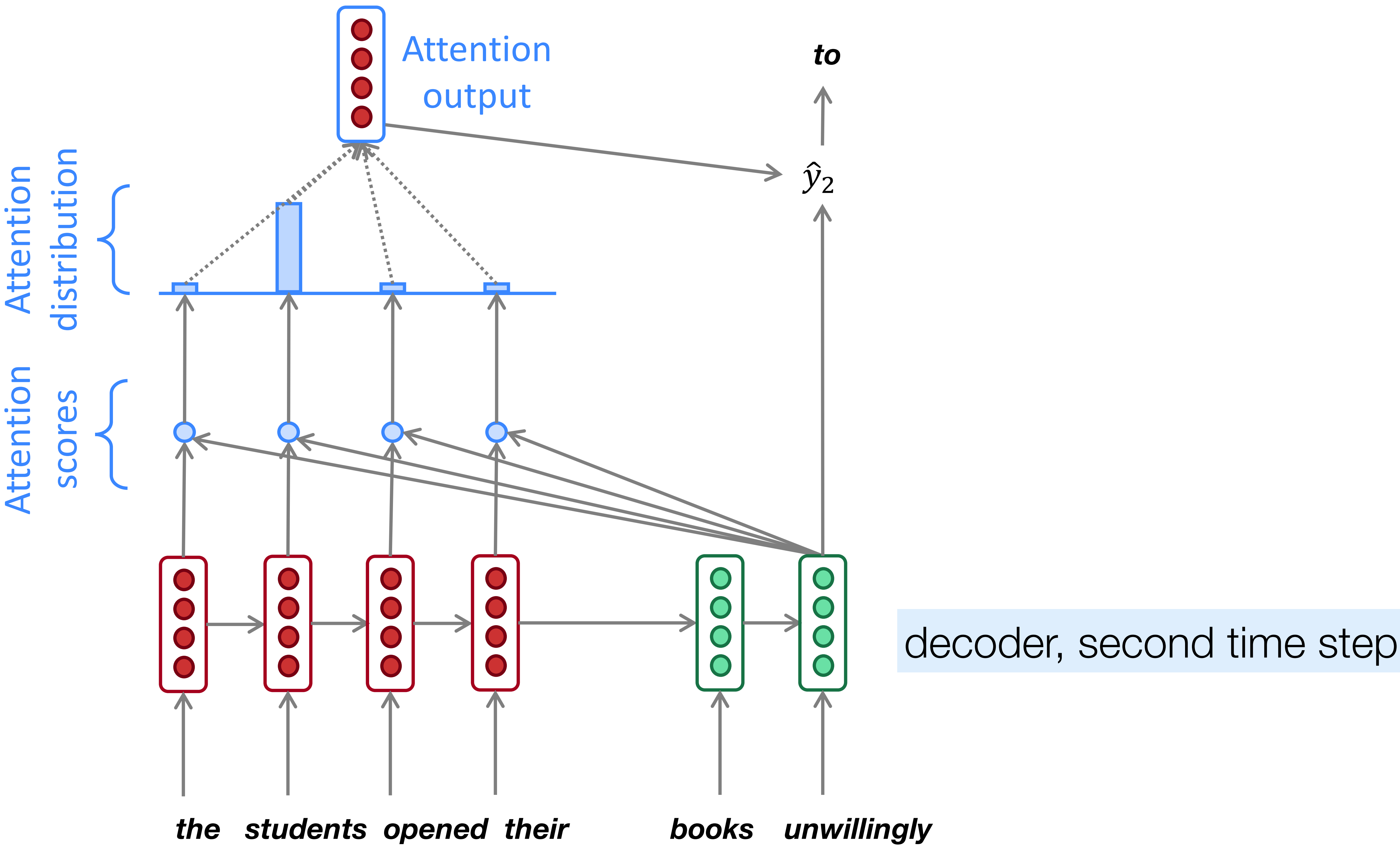
Intuitively, the resulting attention output contains information from hidden states that received high attention scores

Sequence-to-sequence with attention

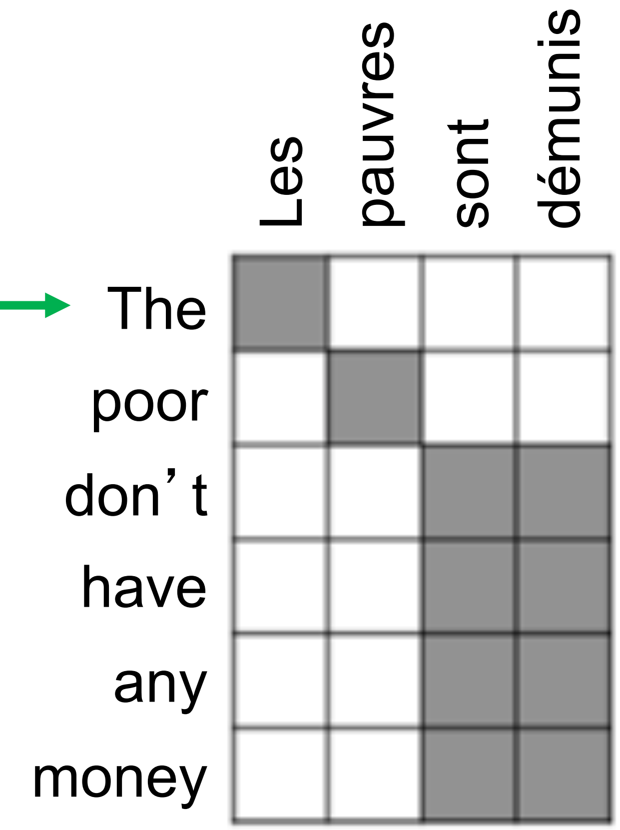


Concatenate (or otherwise compose) the attention output with the current hidden state, then pass through a softmax layer to predict the next word

Sequence-to-sequence with attention



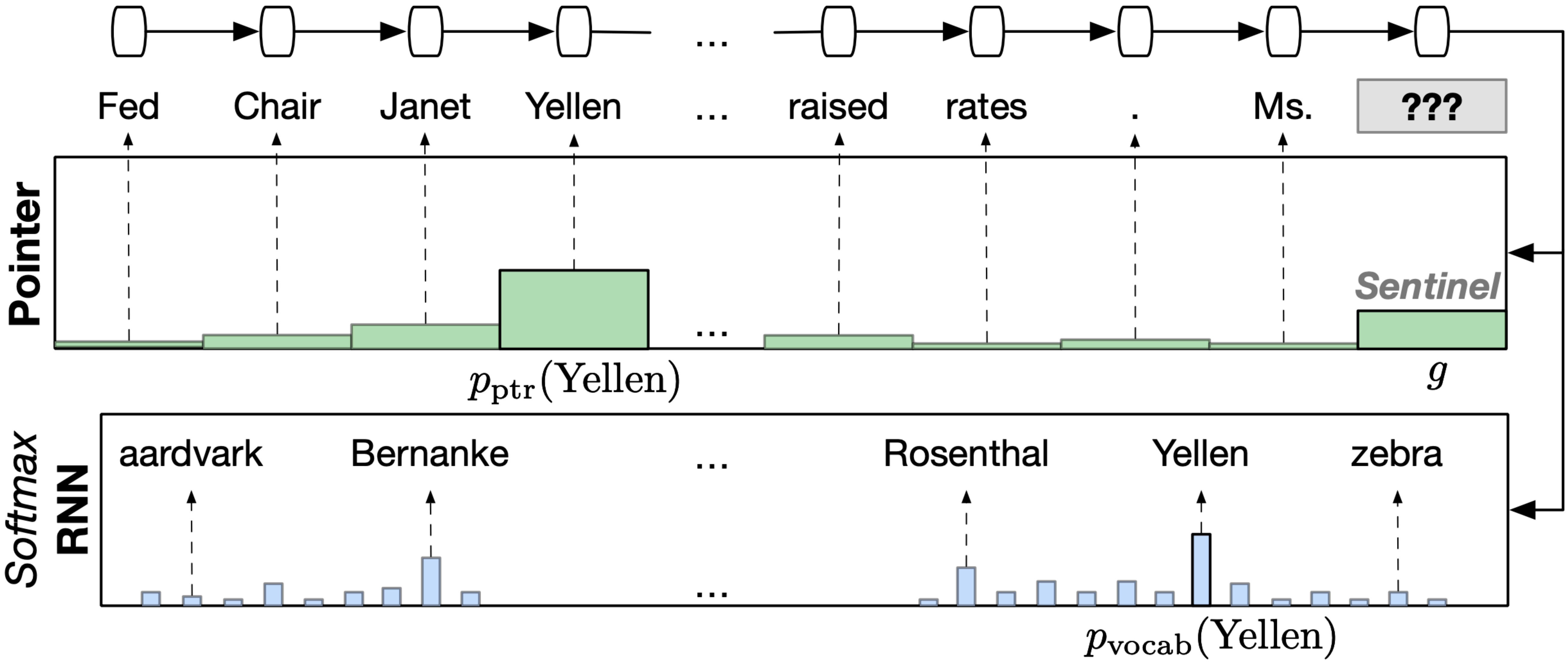
- Attention solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides some interpretability
  - By inspecting attention distribution, we can see 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

Attention can also be used to copy tokens from the context!

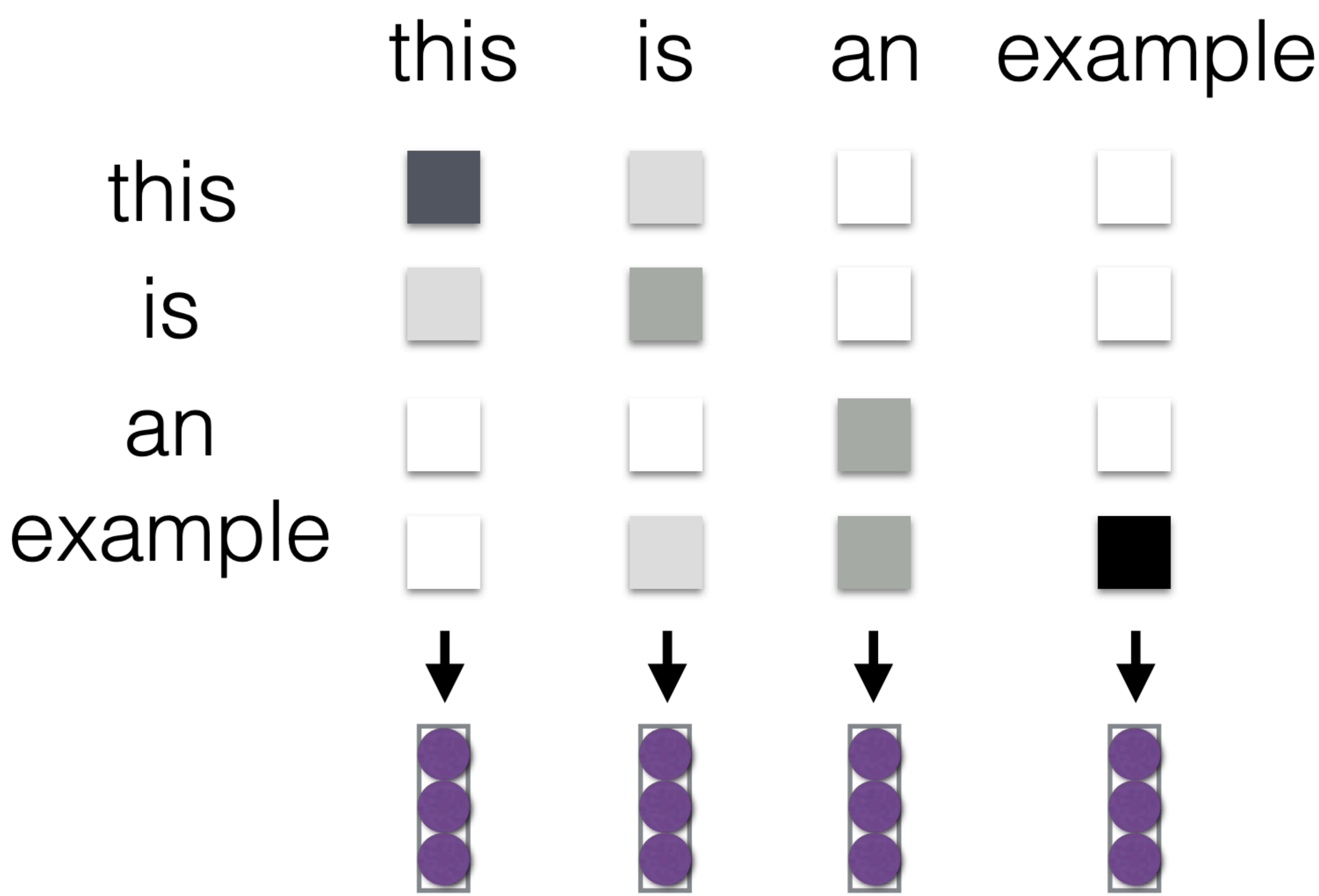


$$p(\mathrm{Yellen}) = g\, p_{\mathrm{vocab}}(\mathrm{Yellen}) + (1-g)\, p_{\mathrm{ptr}}(\mathrm{Yellen})$$

Merity et al., 2016

Self-attention can completely replace recurrence!

Each element in the sentence attends to the other elements



Cheng et al., 2016

Figure: Graham Neubig

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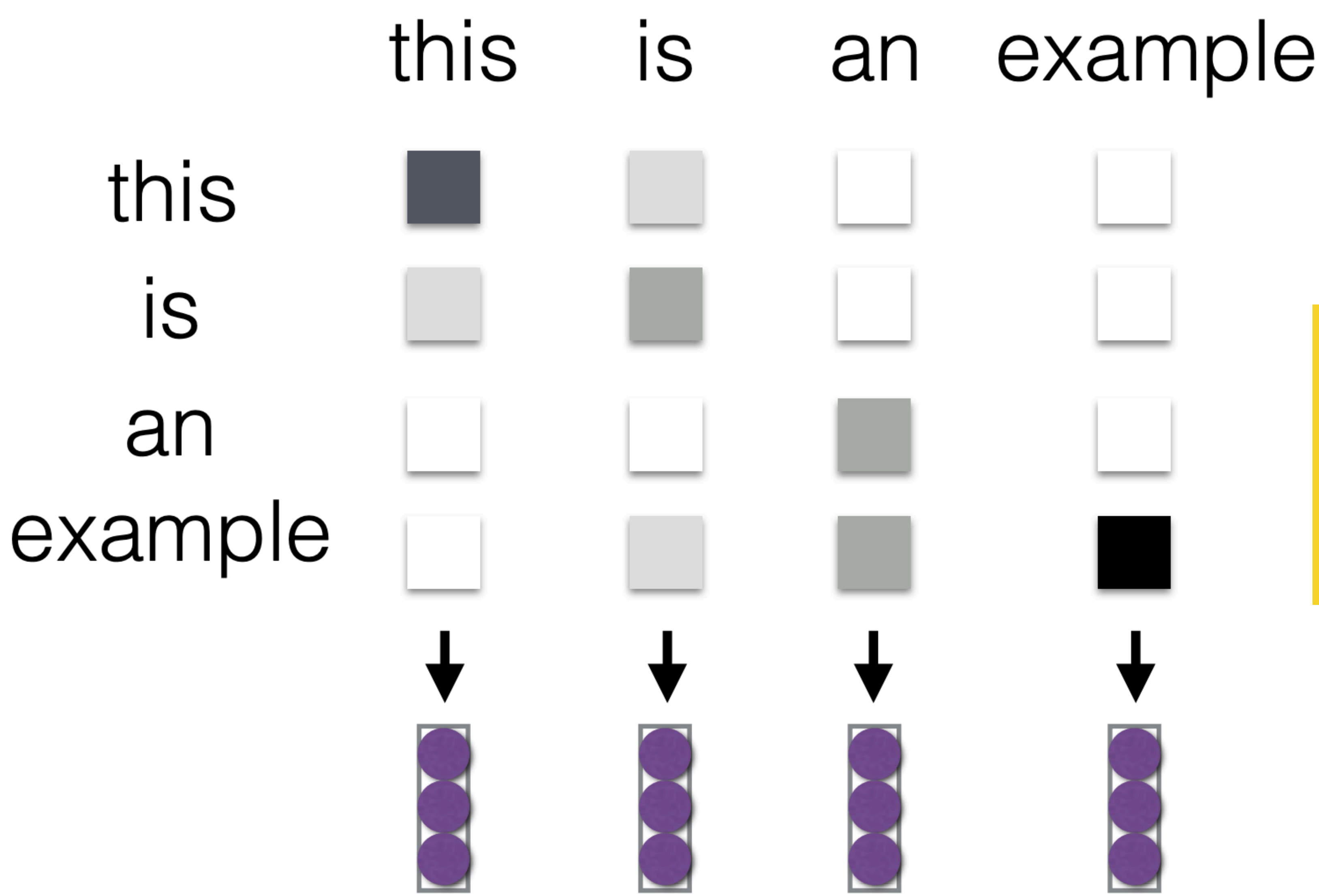
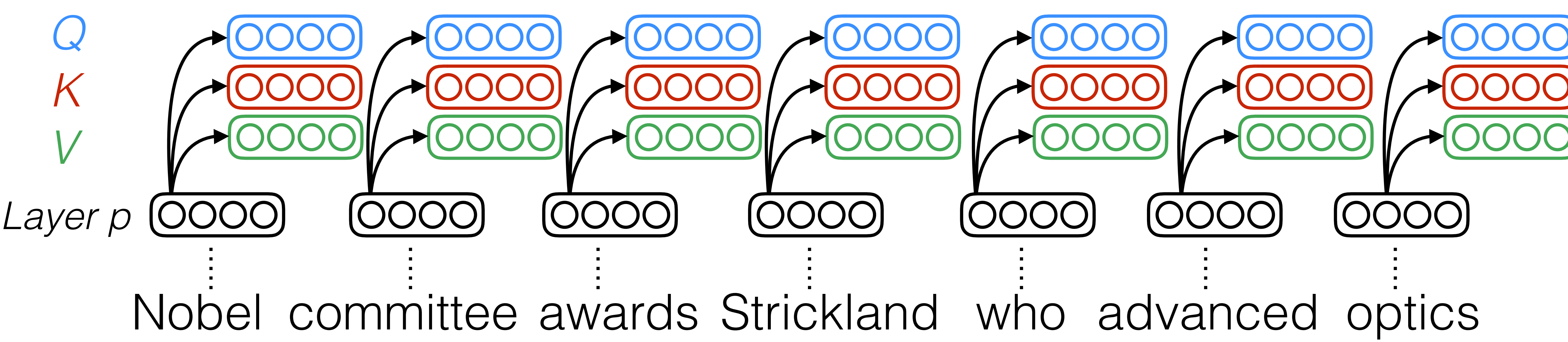


What are the queries and keys here?

Self-attention

[Vaswani et al. 2017]



Slides by Emma Strubell!

[Vaswani et al. 2017]

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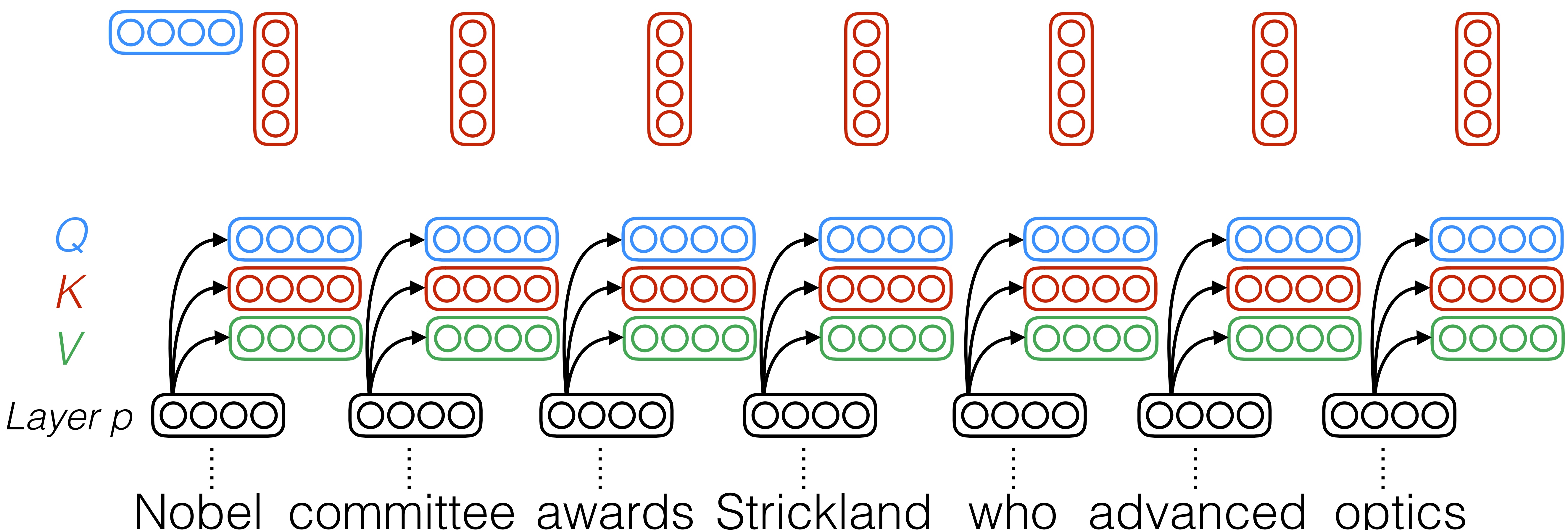

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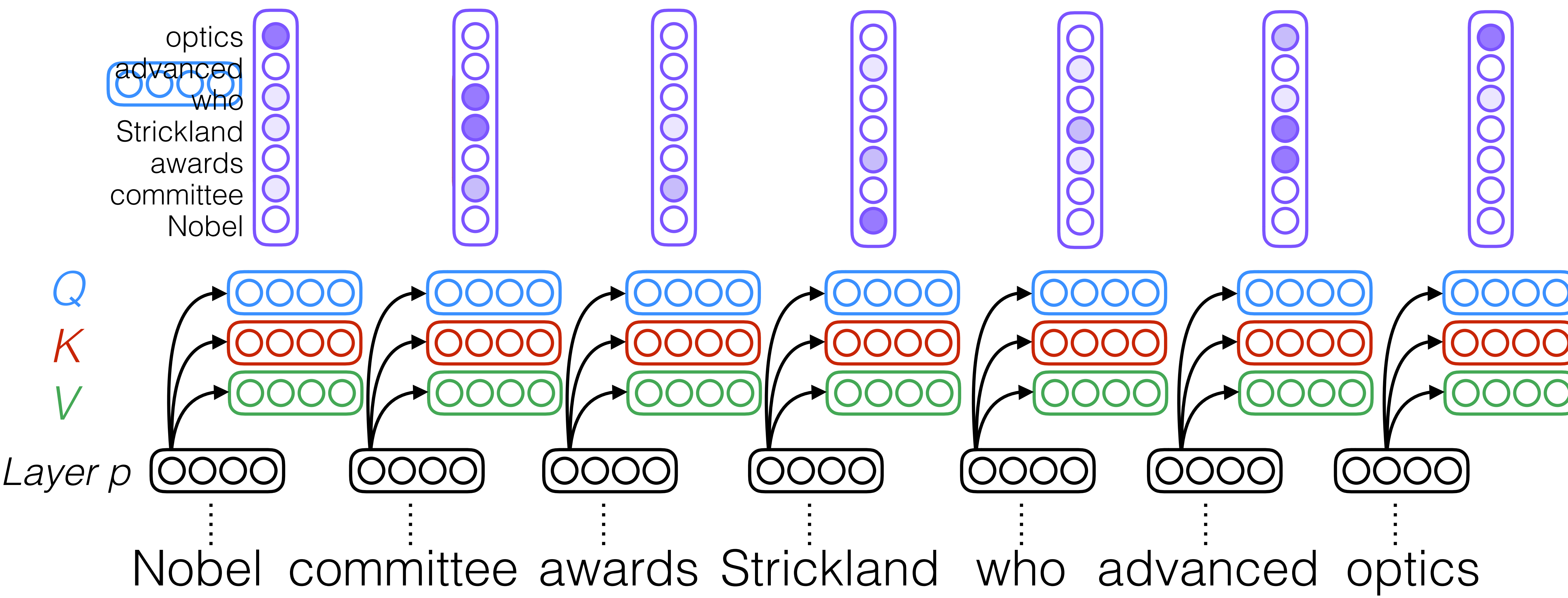

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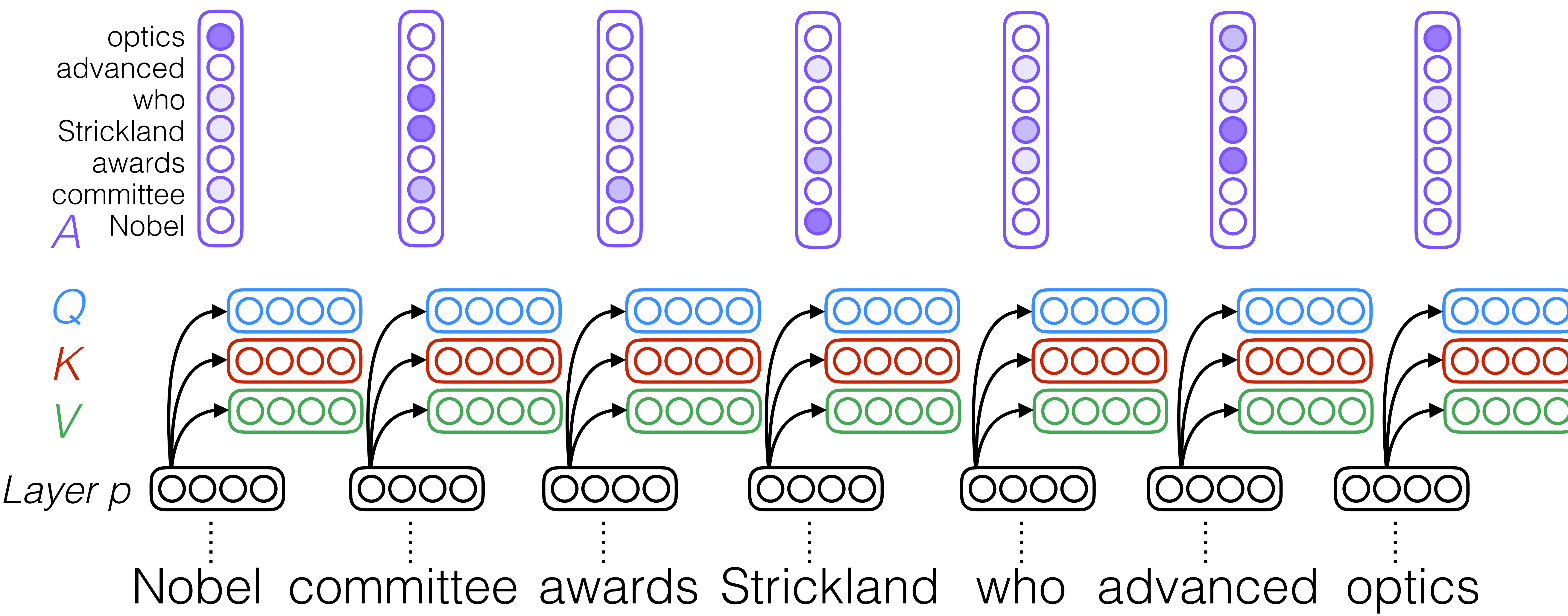

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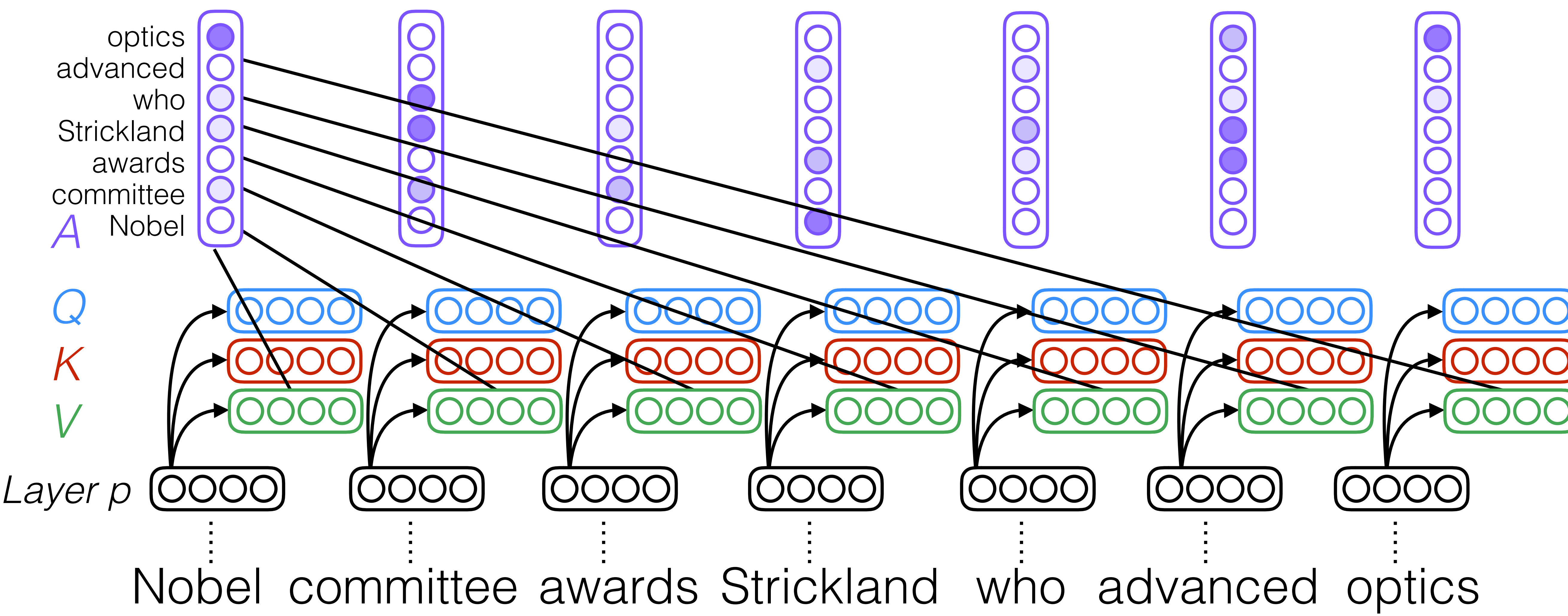

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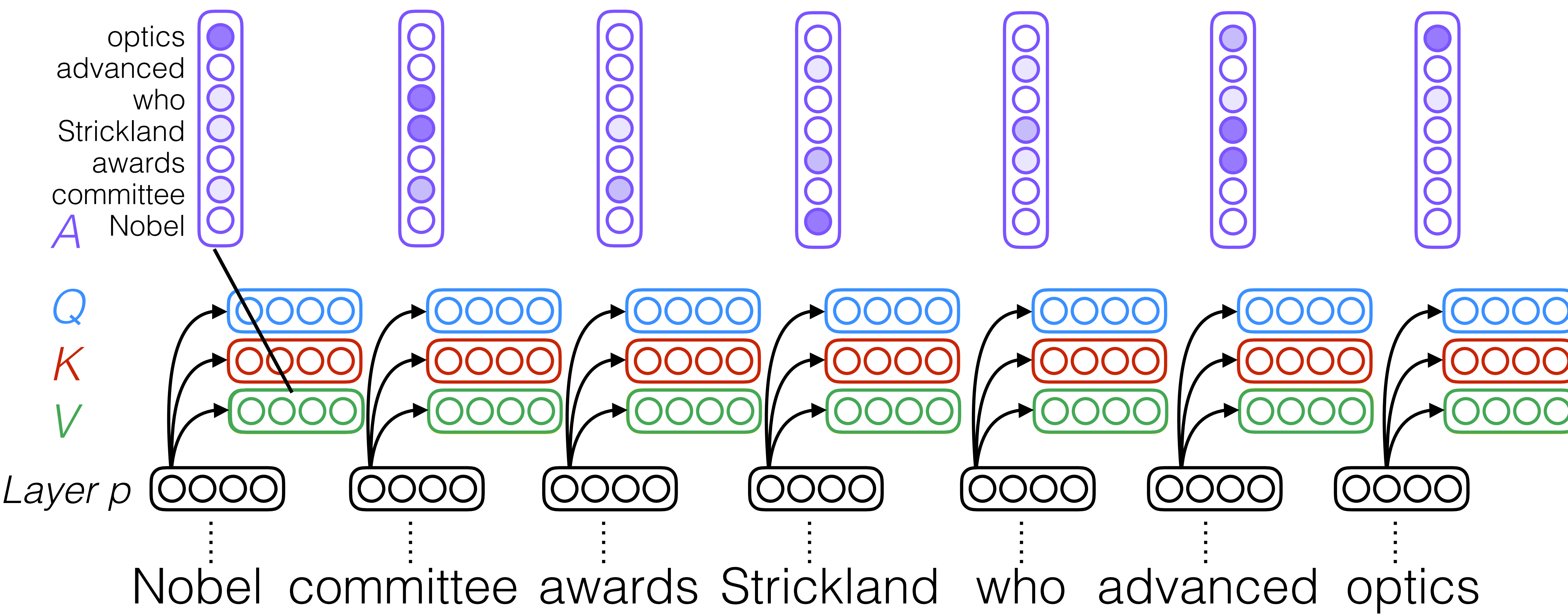

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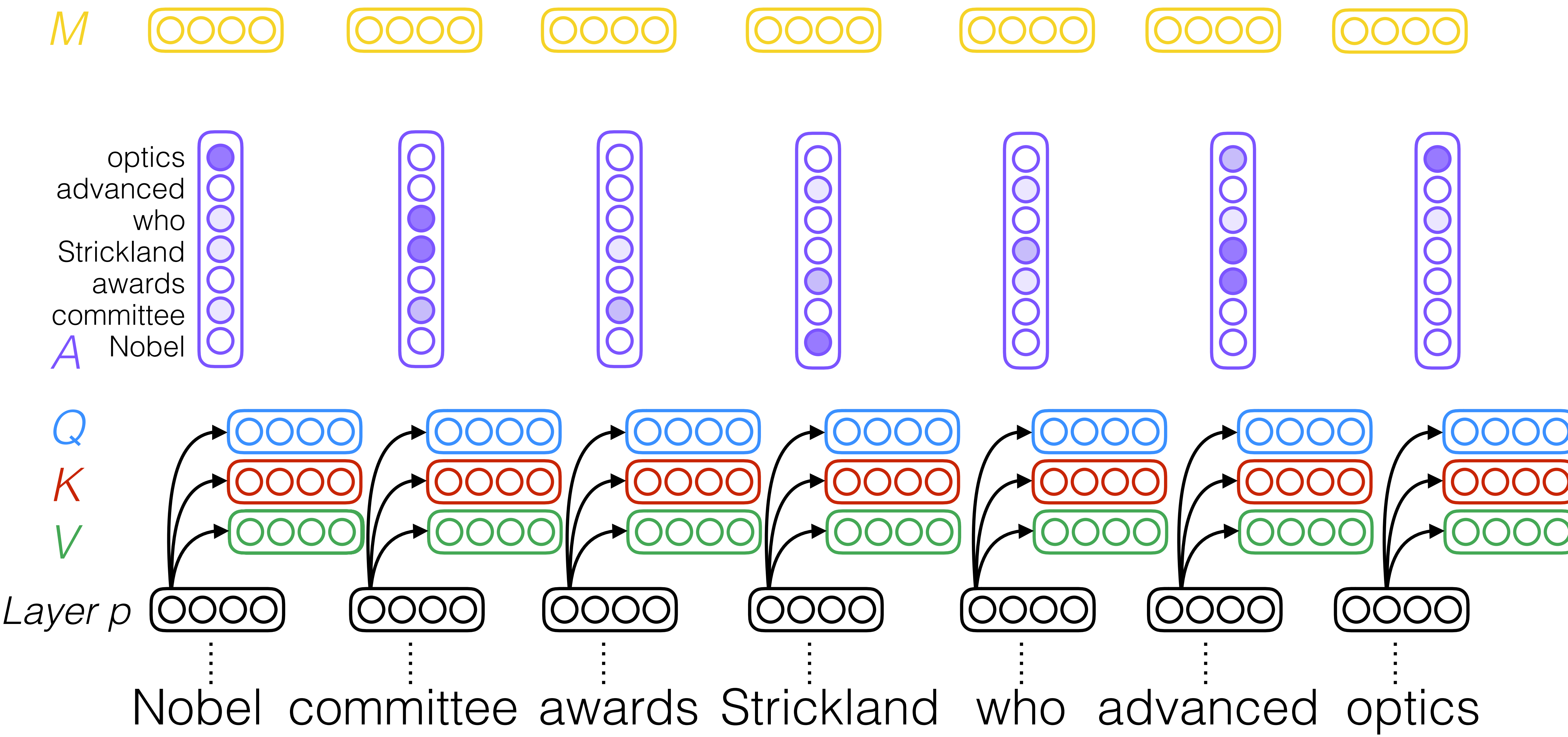

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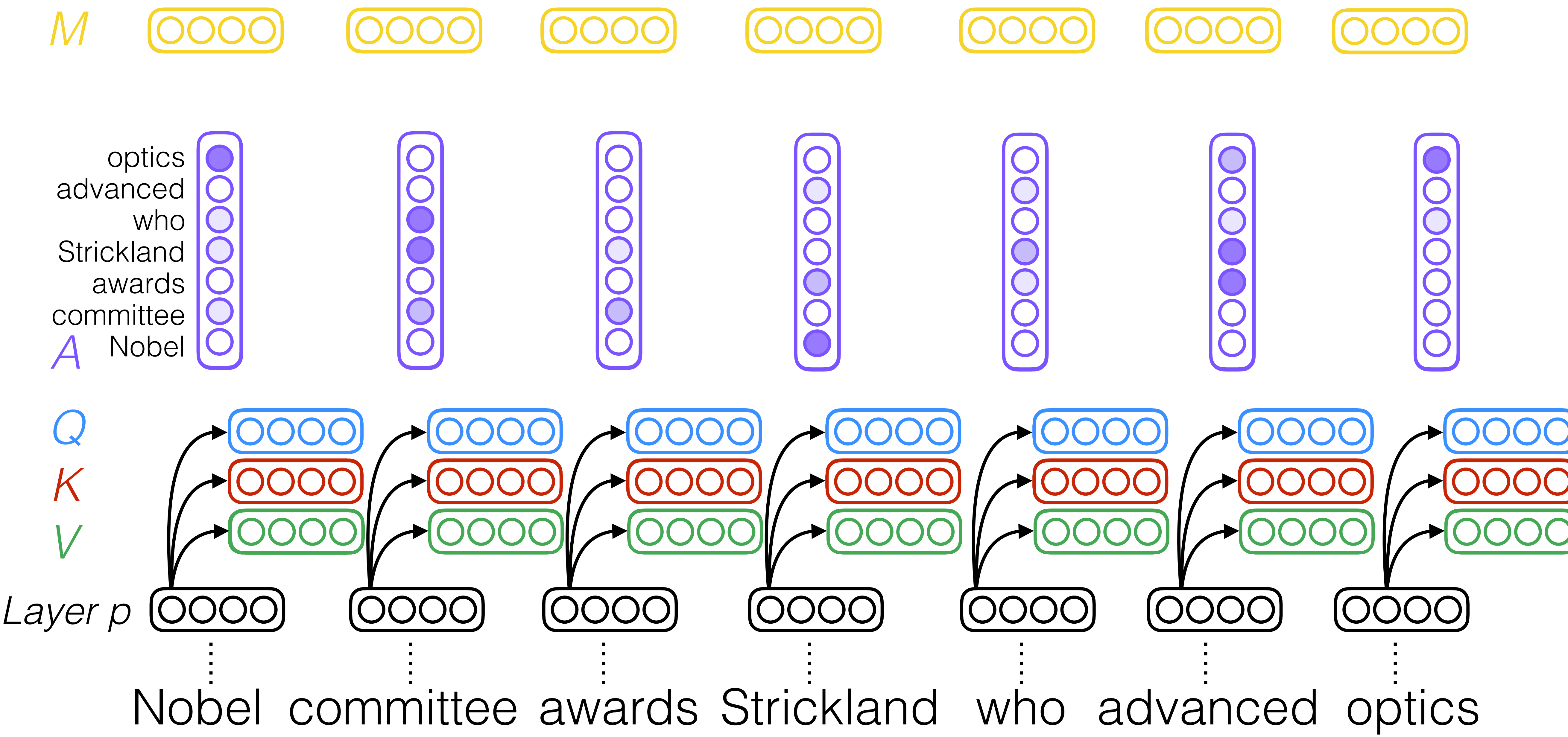
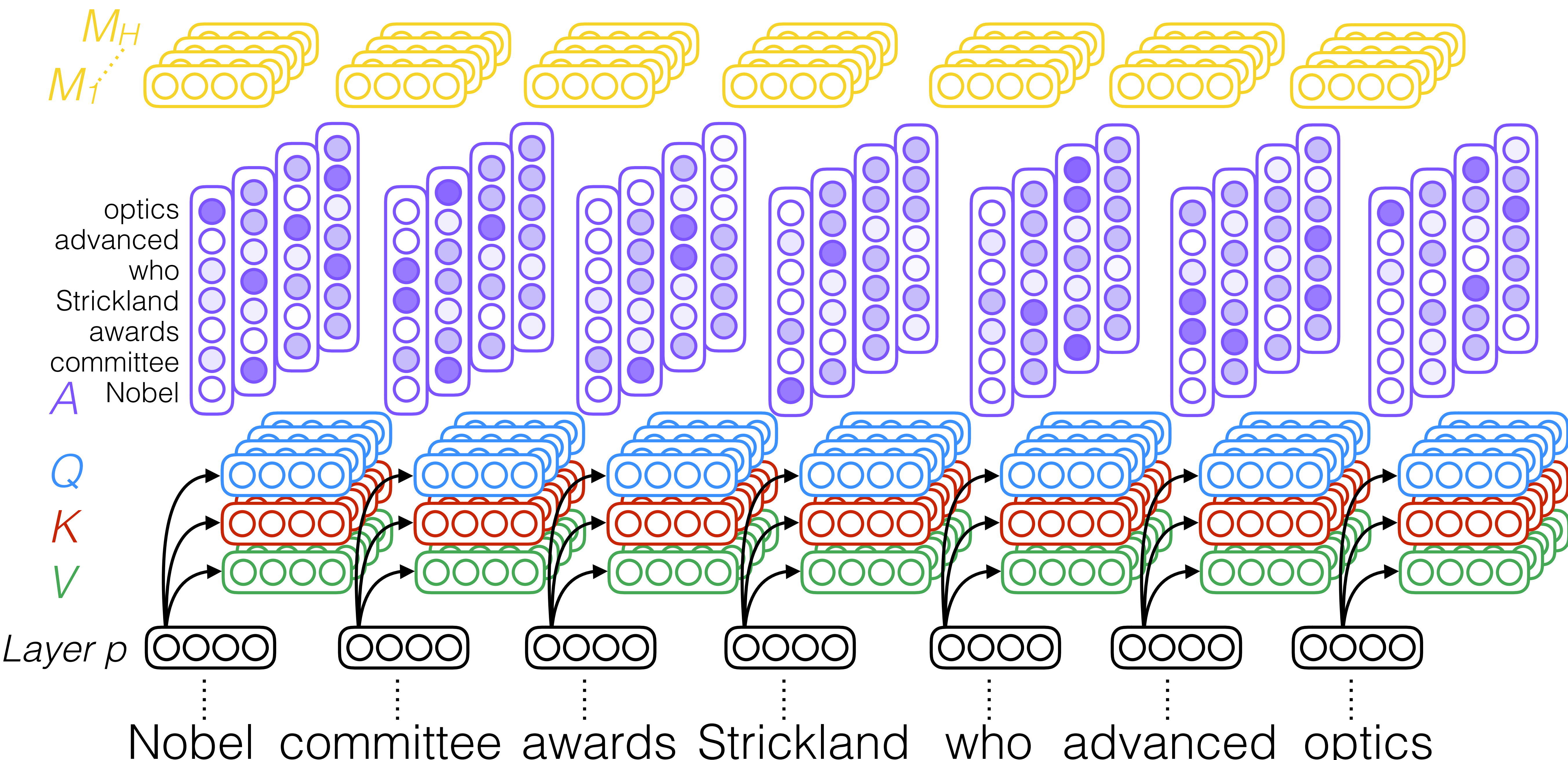


[Vaswani et al. 2017]

Multi-head self-attention



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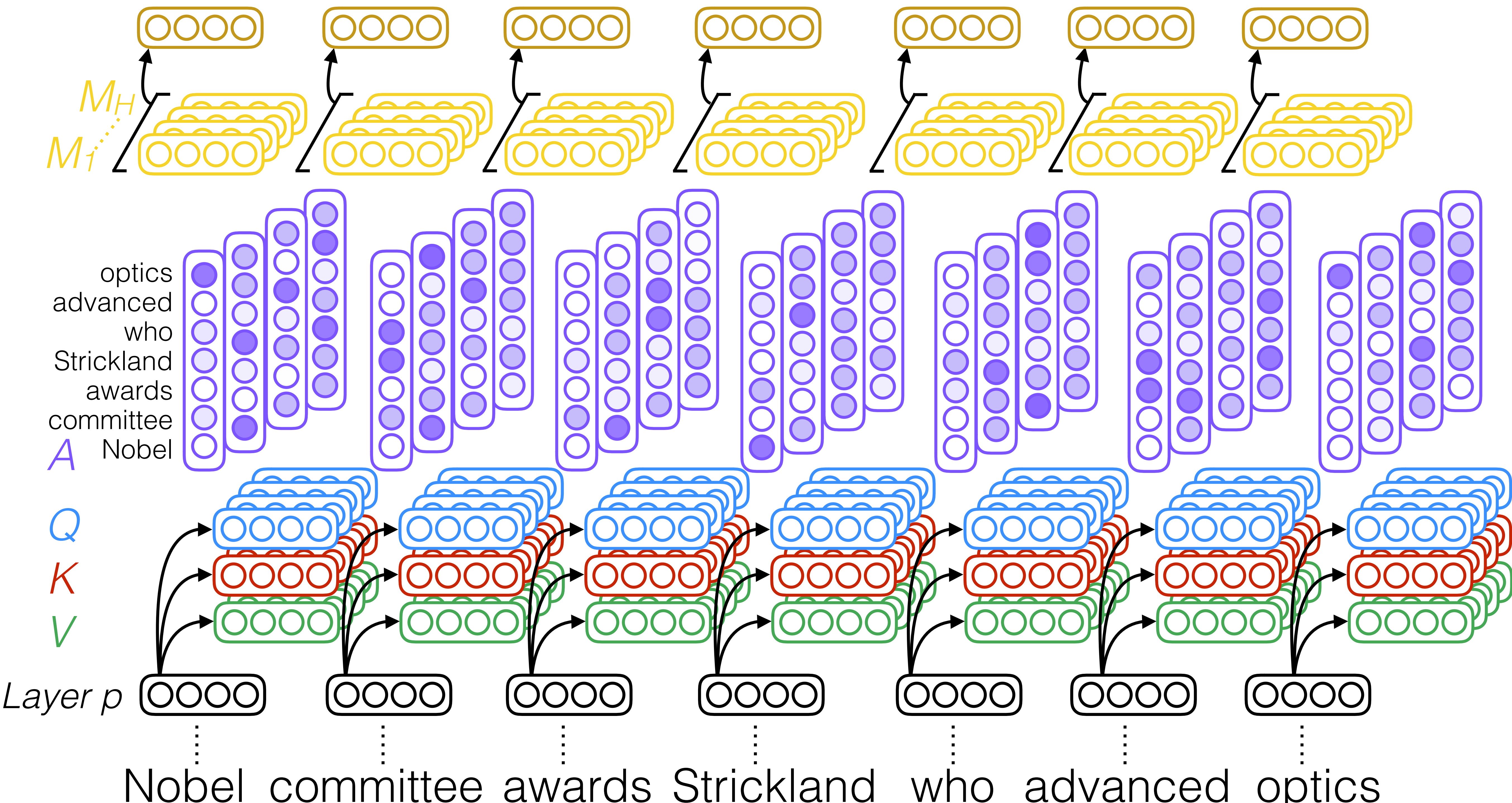

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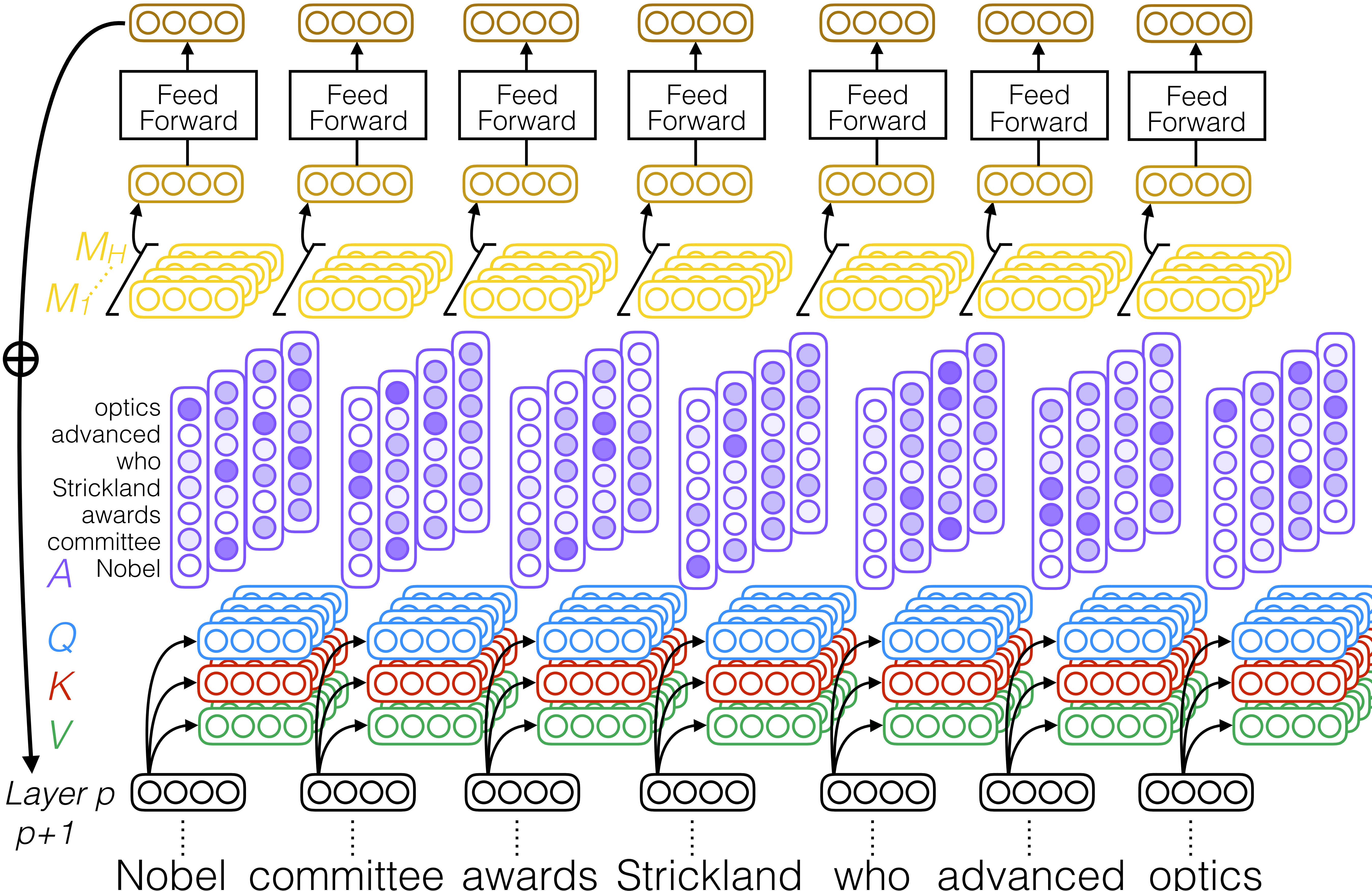

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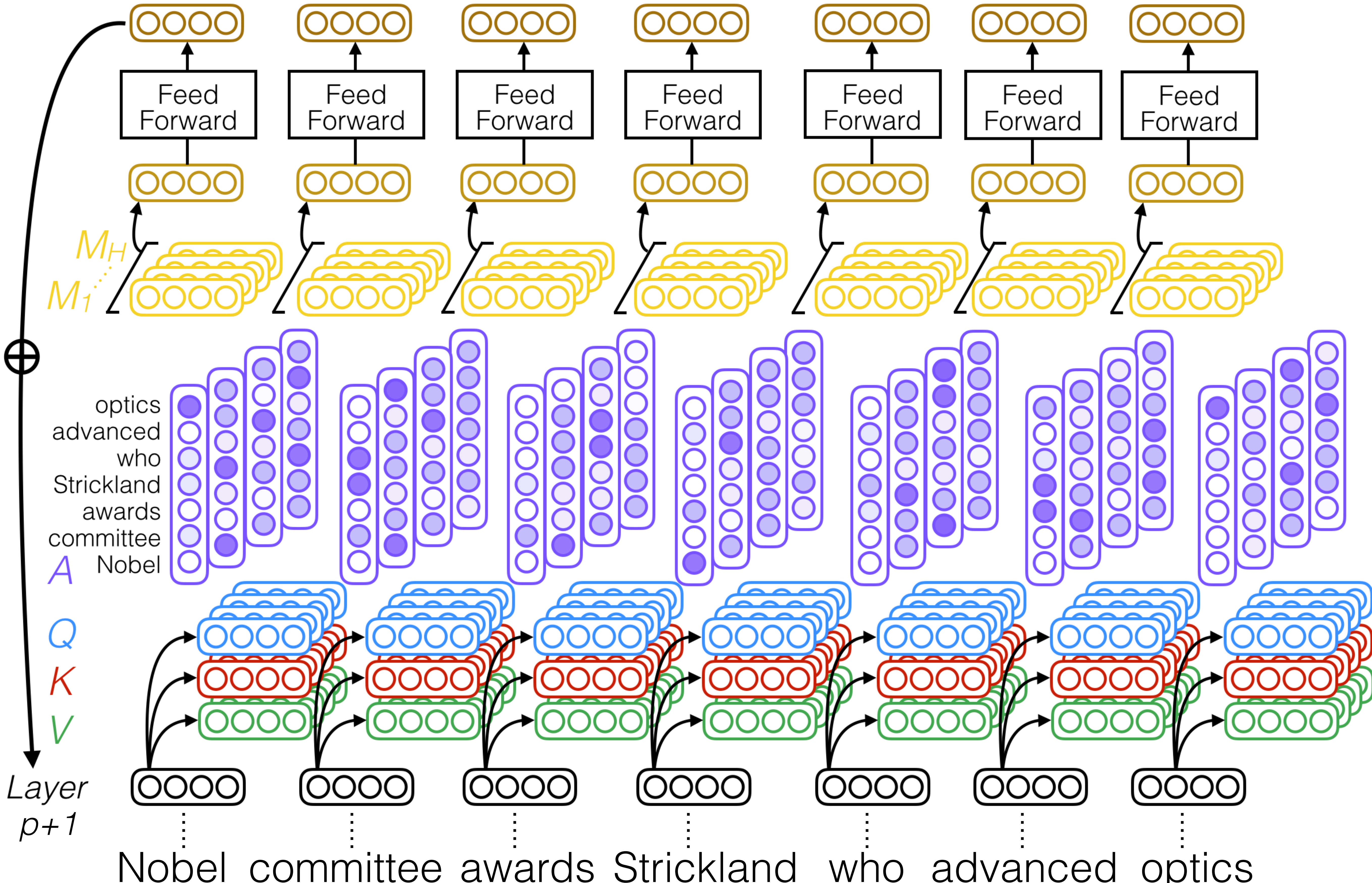

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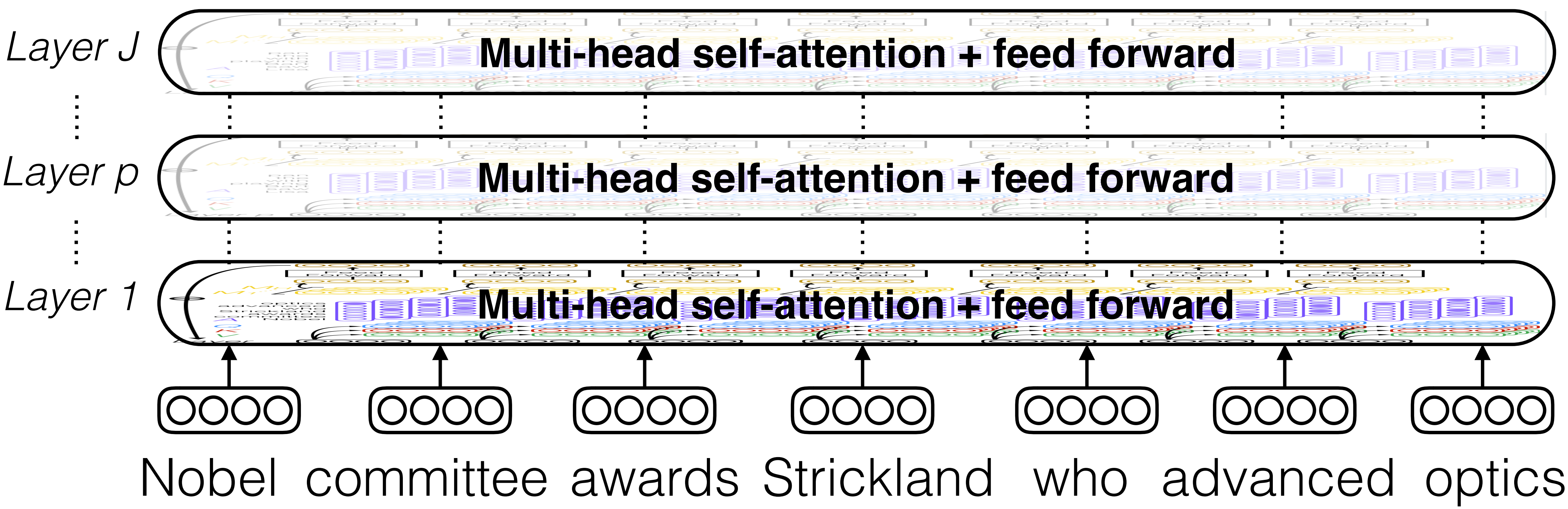

For next week:

- The full Transformer architecture
- The encoder/decoder paradigm
- Using neural language models for transfer learning: ELMo and BERT