

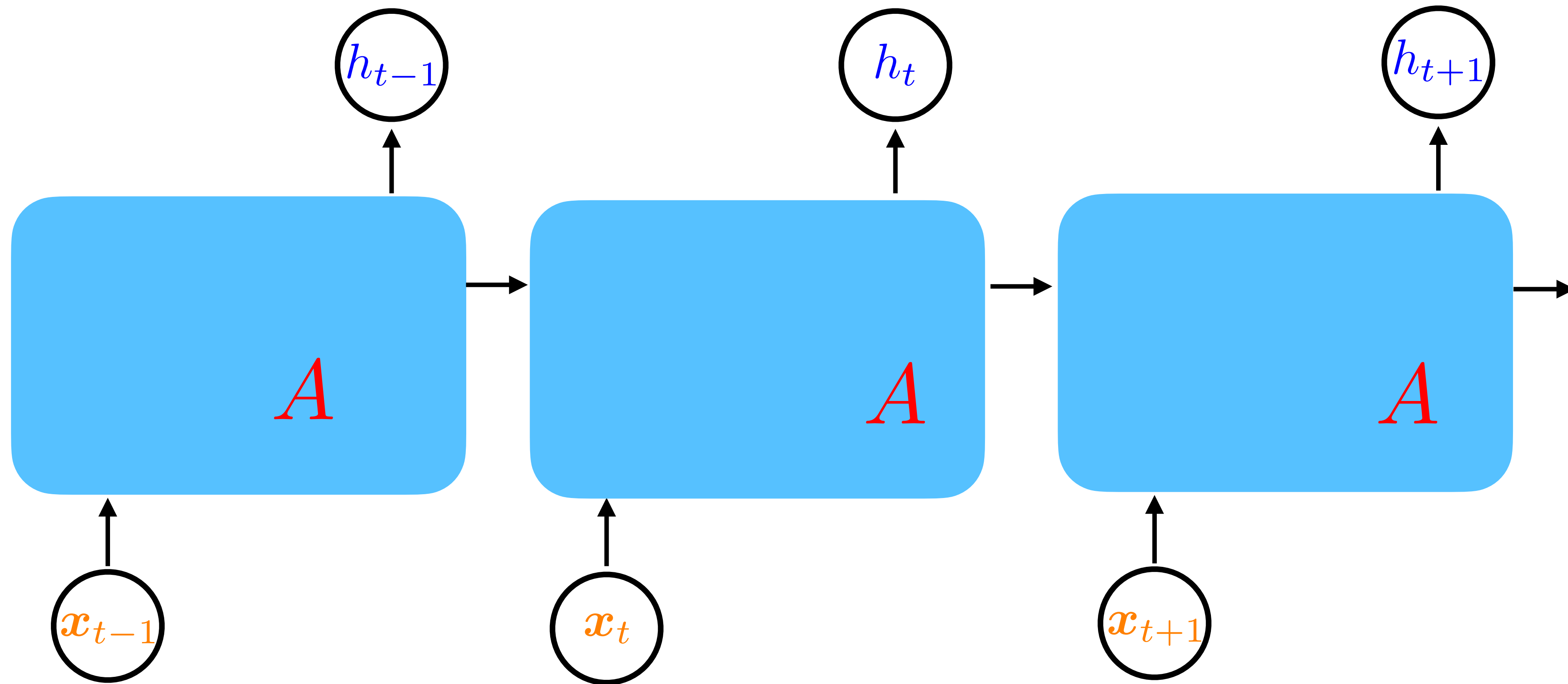
# Sequence to Sequence Model and Attention

COMP7607 — Lecture 3

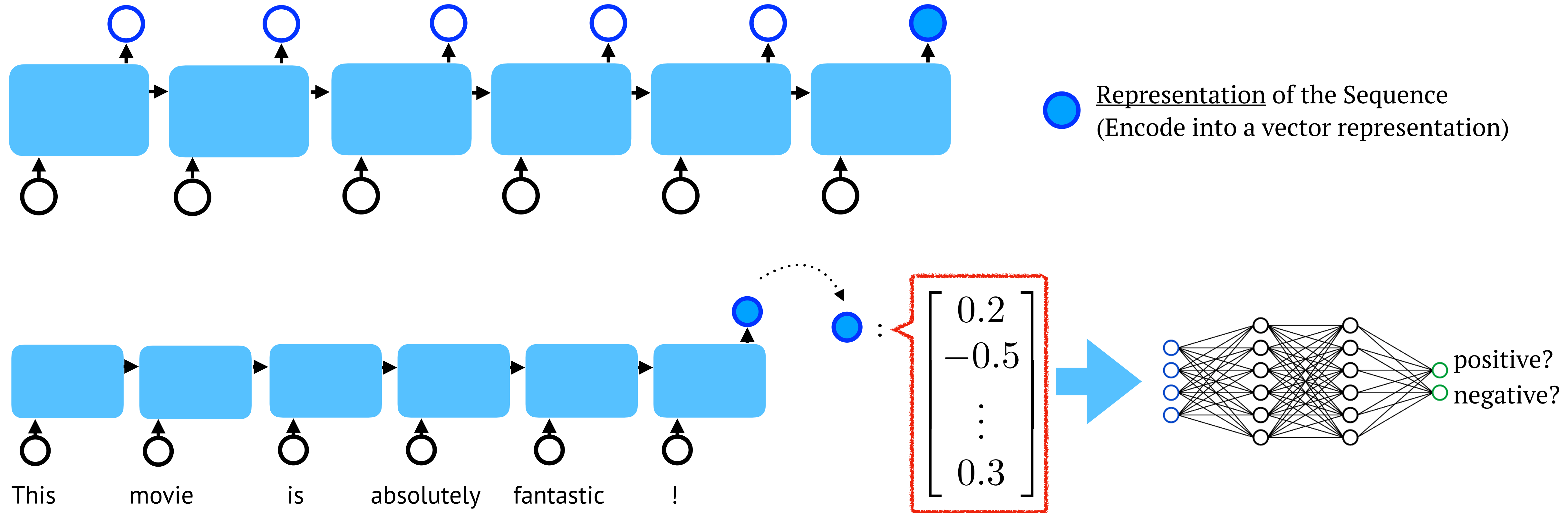
Lingpeng Kong

Department of Computer Science, The University of Hong Kong

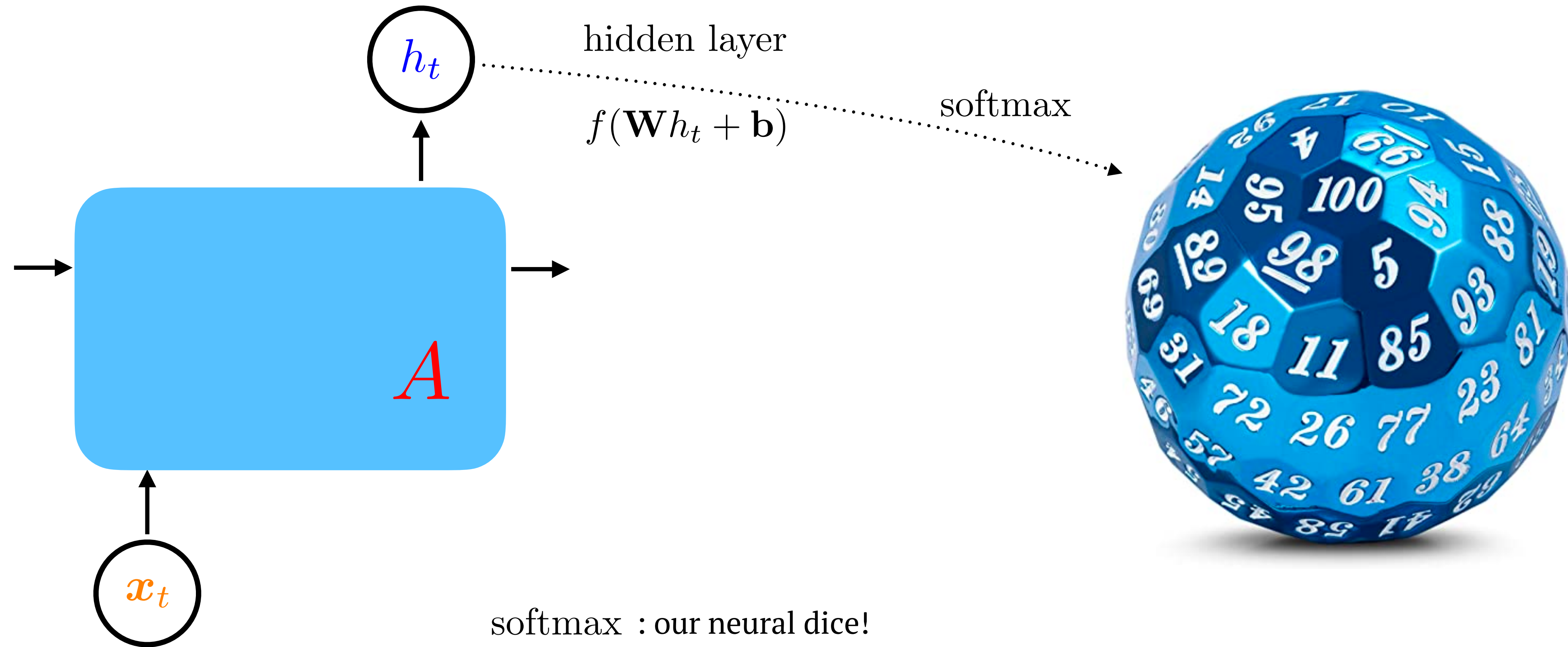
# Recurrent Neural Network



# RNN as Encoder

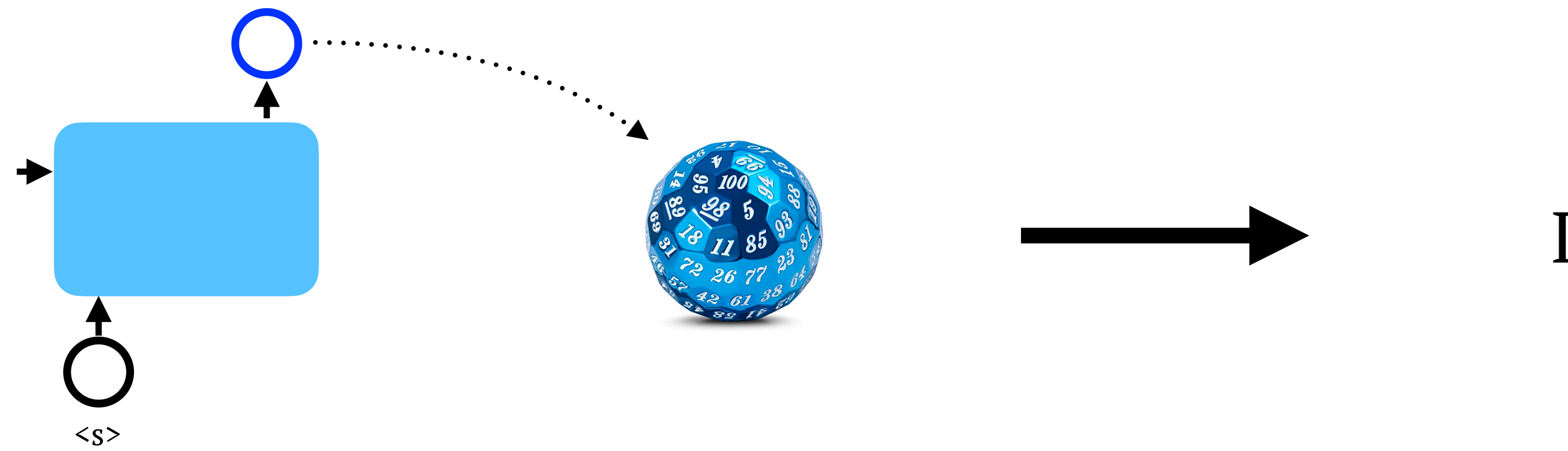


# Sample a sentence from RNNLMs



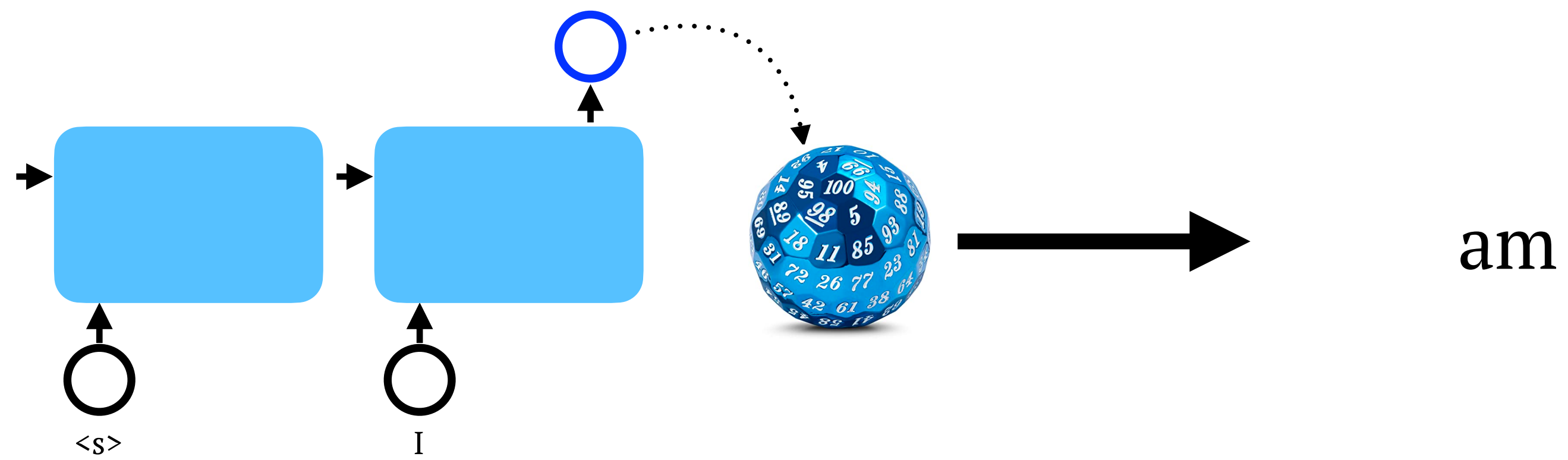
# Sample a sentence from RNNLMs

I



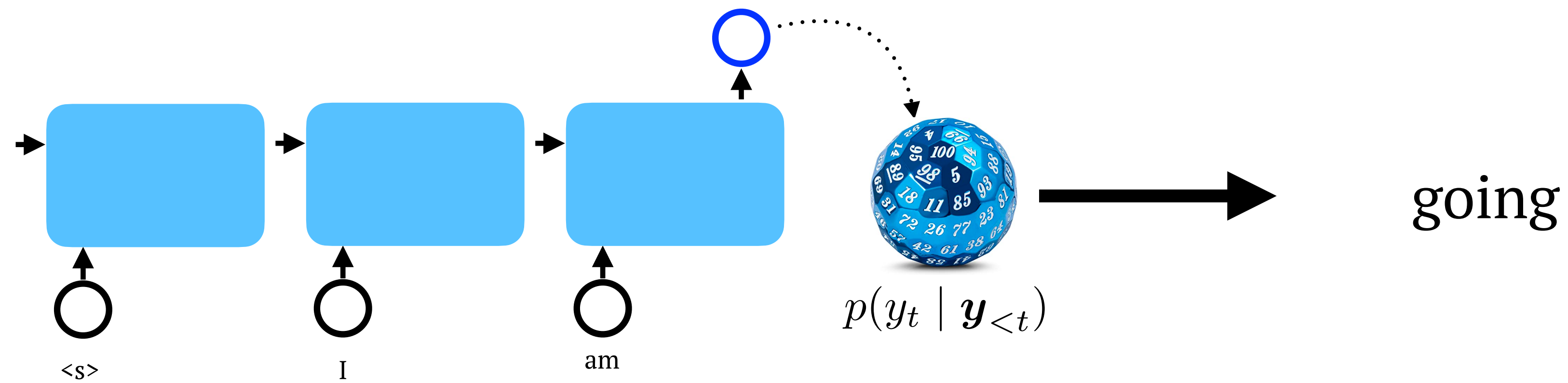
# Sample a sentence from RNNLMs

I am



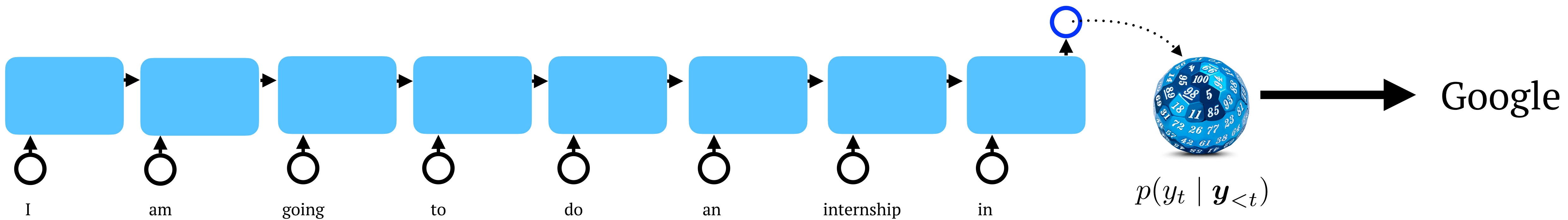
# Sample a sentence from RNNLMs

I am going



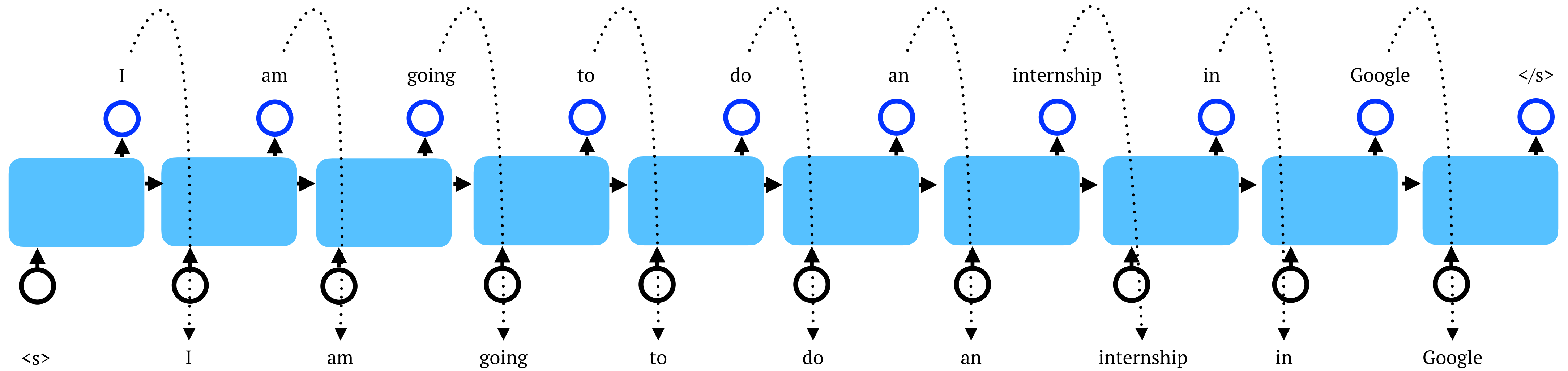
# Sample a sentence from RNNLMs

I am going to do an internship in Google





# RNN as Decoder (RNNDLM)



$$p(y_t | \mathbf{y}_{<t})$$

# Machine Translation

中秋快樂！

$x$

Happy mid autumn festival !

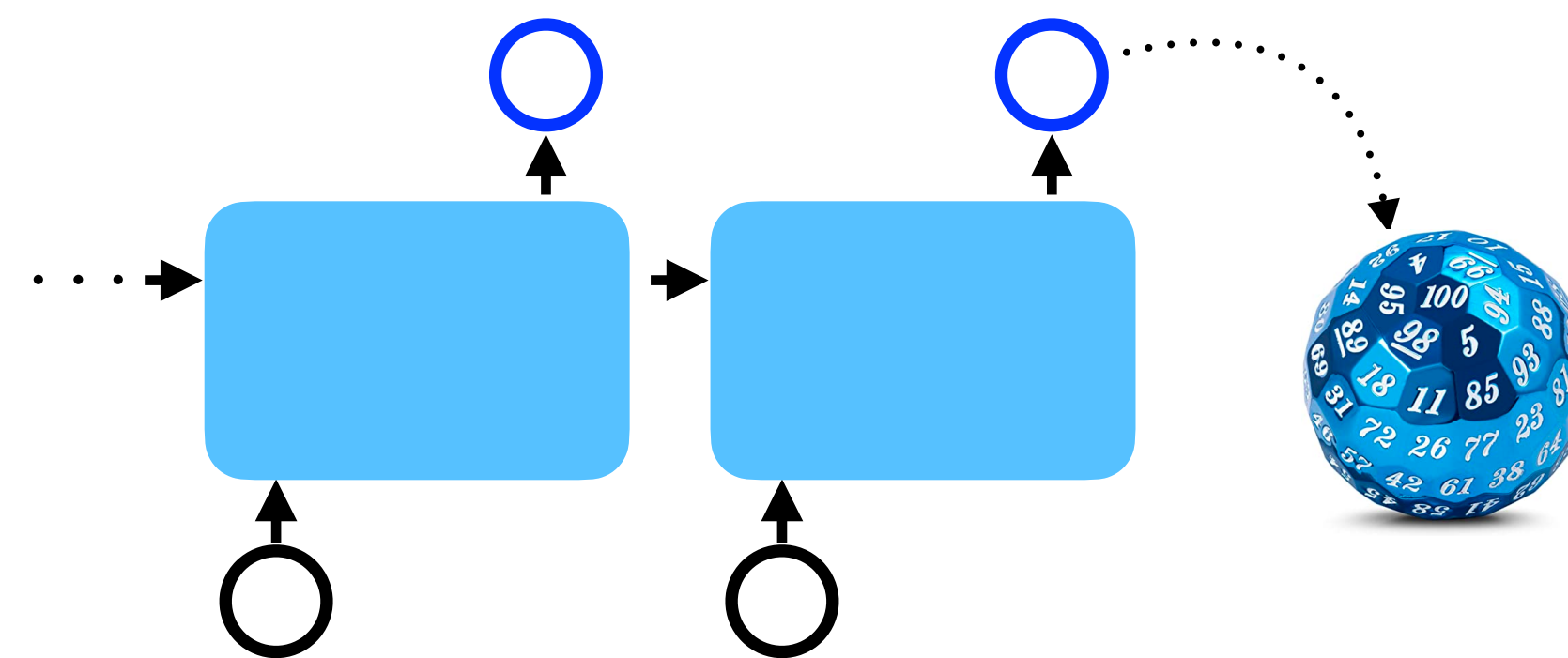
$y$

Happy mid autumn festival !

$$p(\mathbf{y}) = p(y_1 \dots y_n) = \prod_{t=1}^n p(y_t | \mathbf{y}_{<t})$$



$p(y_t | \mathbf{y}_{<t})$



# Machine Translation

中秋快樂！

$x$

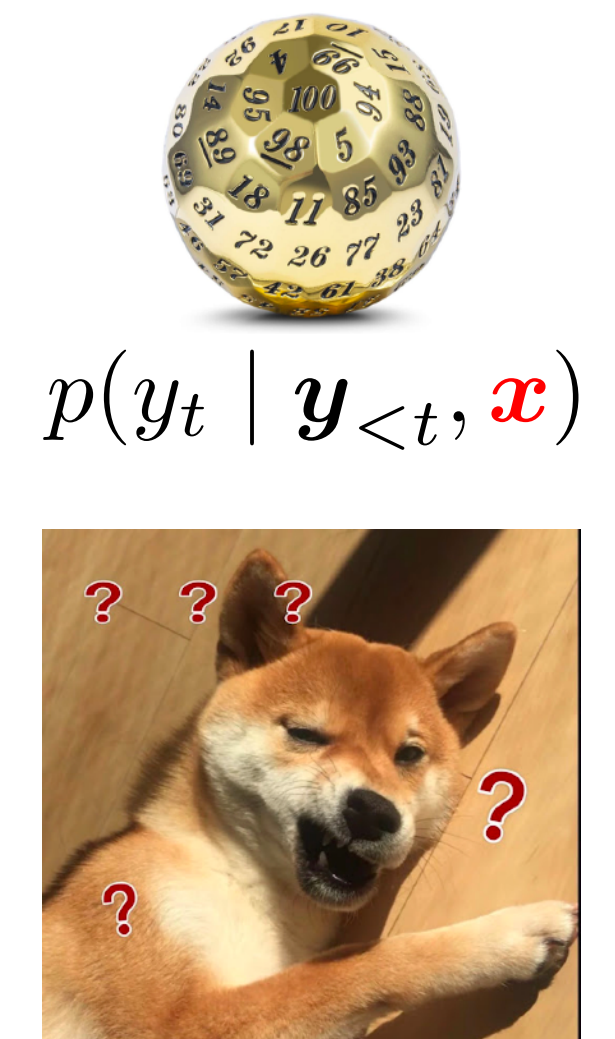
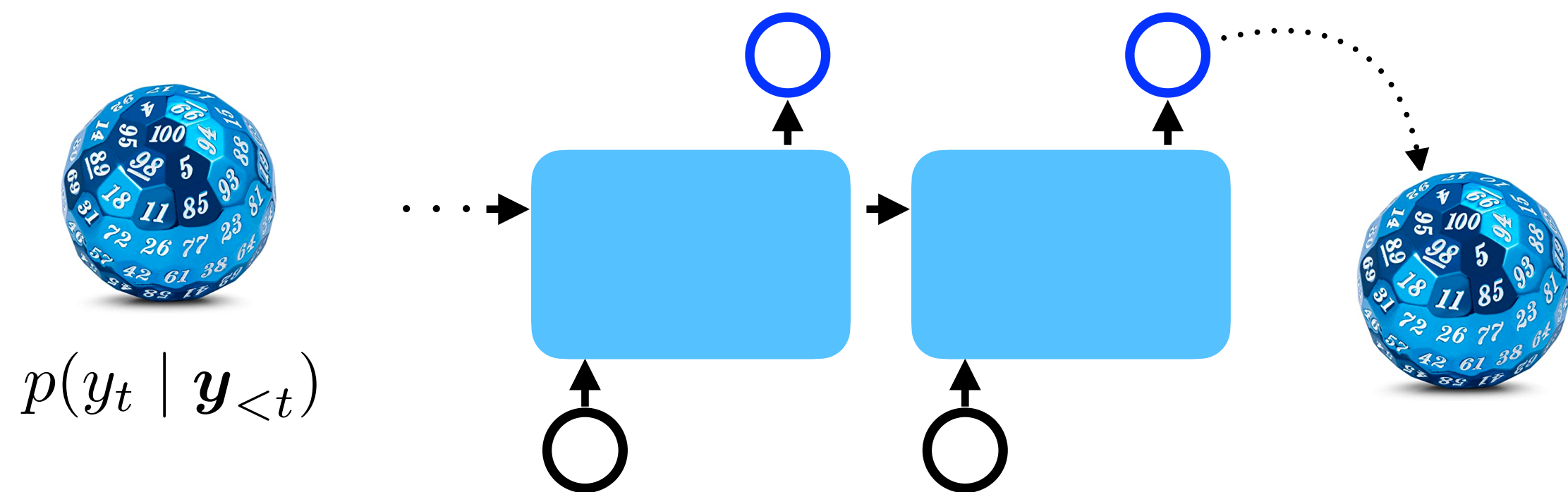
Happy mid autumn festival !

$y$

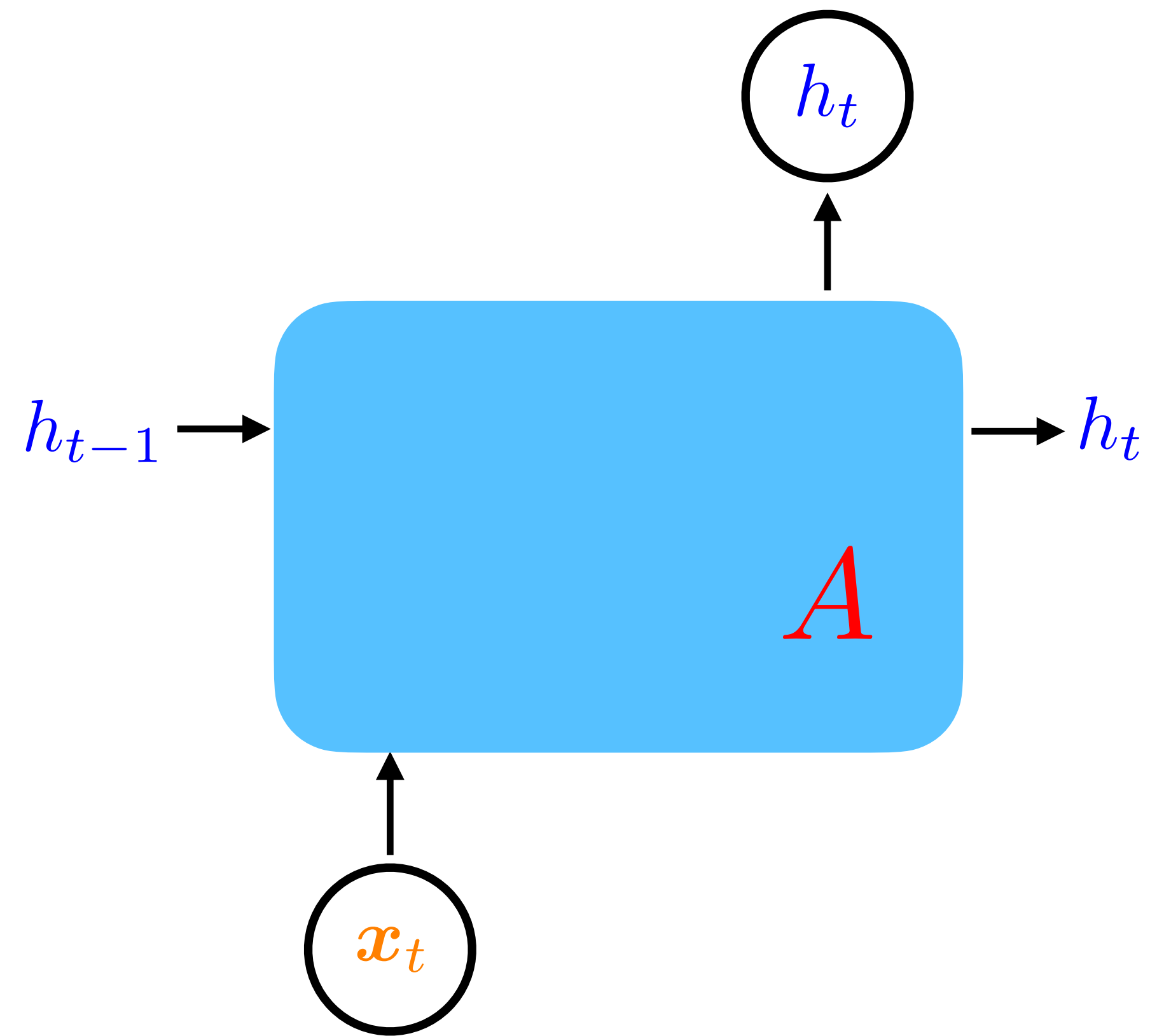
$$p(\mathbf{y} | \mathbf{x}) = p(y_1 \dots y_n | x_1 \dots x_m) = \prod_{t=1}^n p(y_t | \mathbf{y}_{<t}, \mathbf{x})$$

↑ target  
↑ source

Conditional Language Model



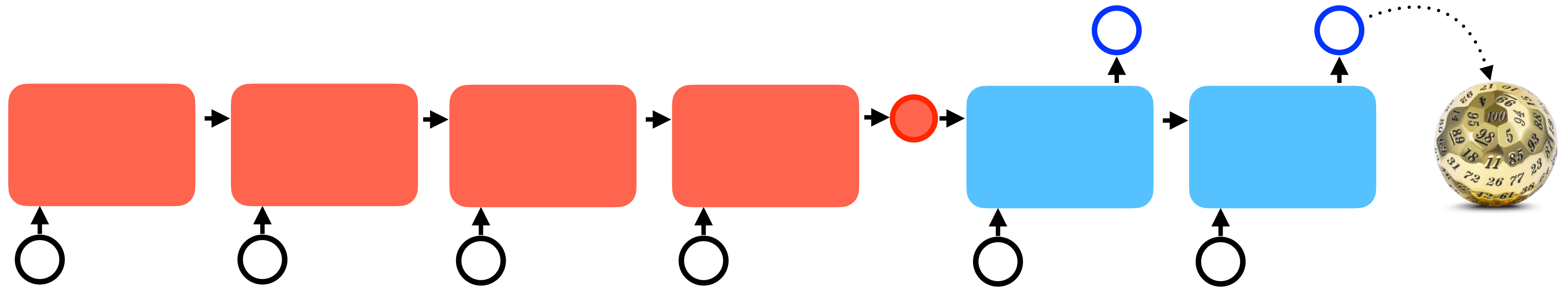
# Recurrent Neural Network




# Encoder + Decoder



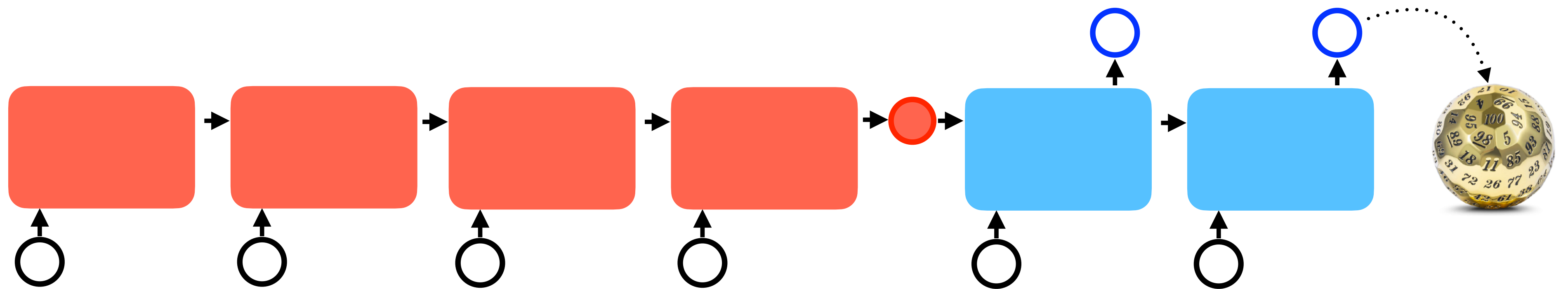
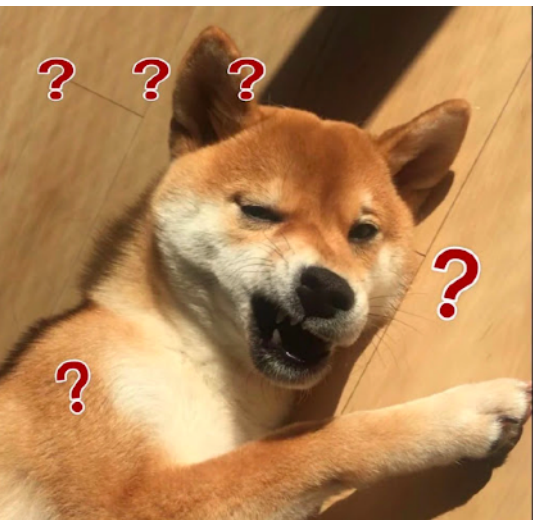
$$p(y_t | \mathbf{y}_{<t}, \mathbf{x})$$



# Sequence to Sequence Model



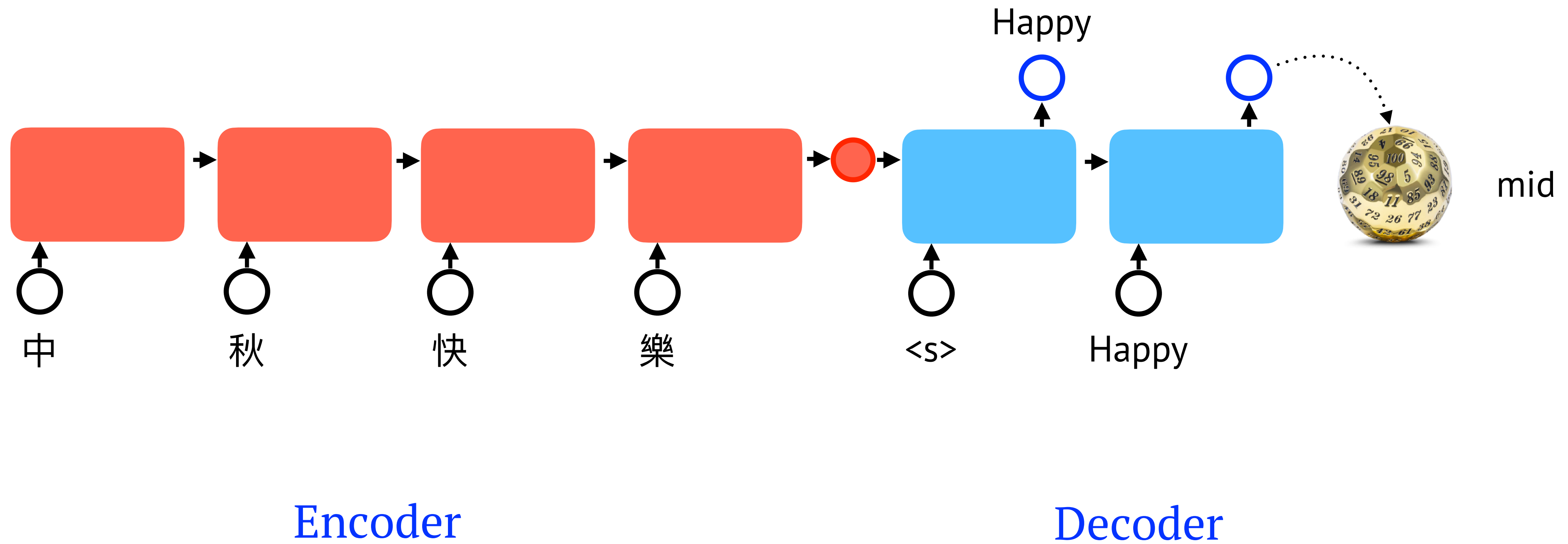
$p(y_t | \mathbf{y}_{<t}, \mathbf{x})$



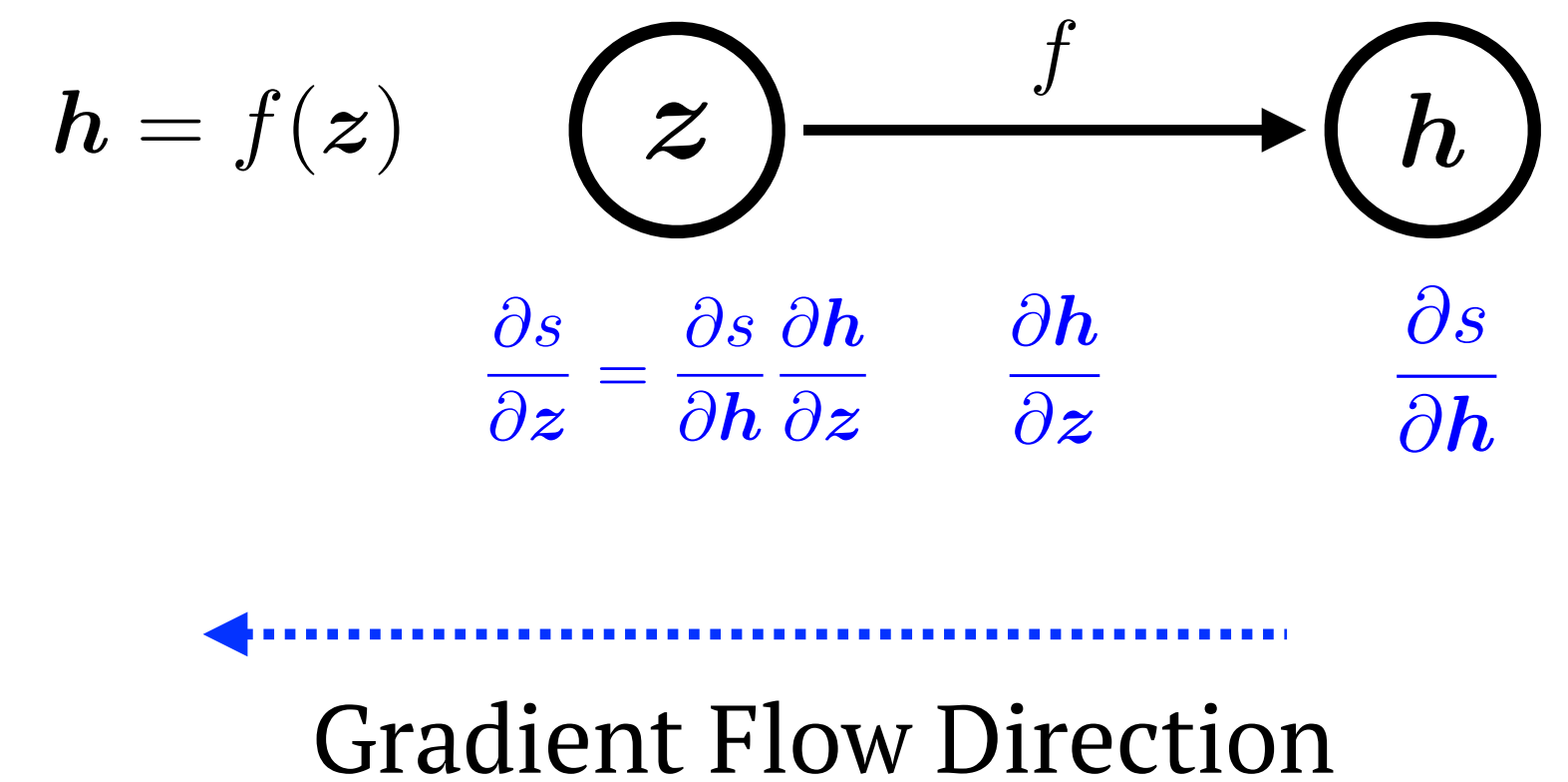
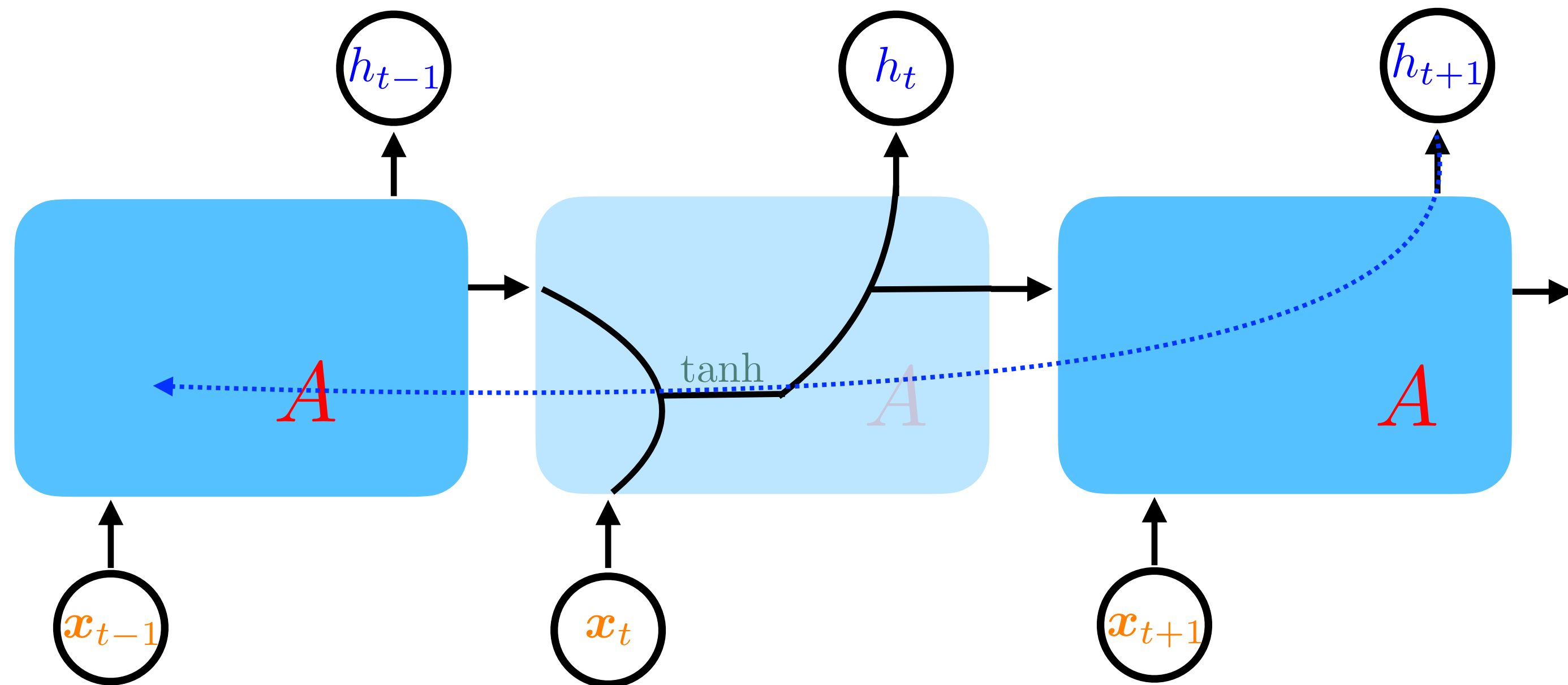
Encoder

Decoder

# Sequence to Sequence Model



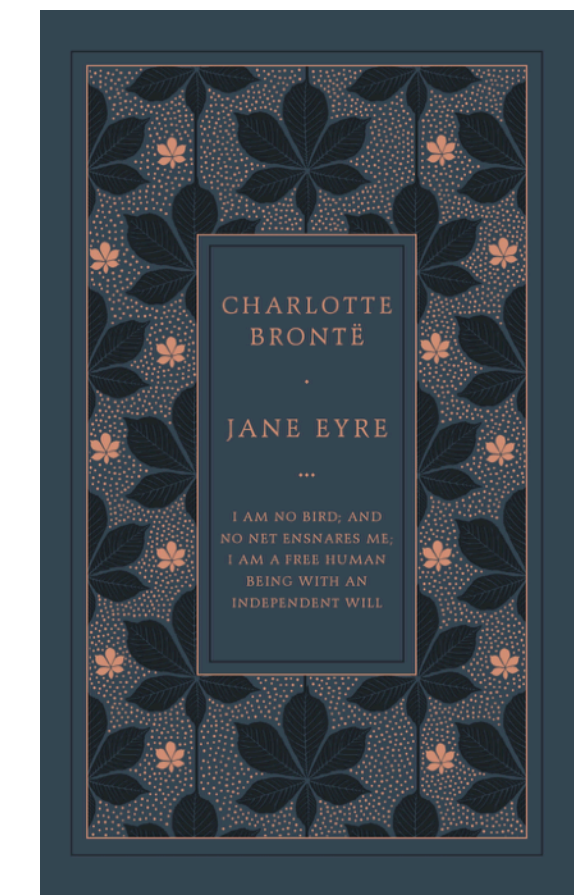
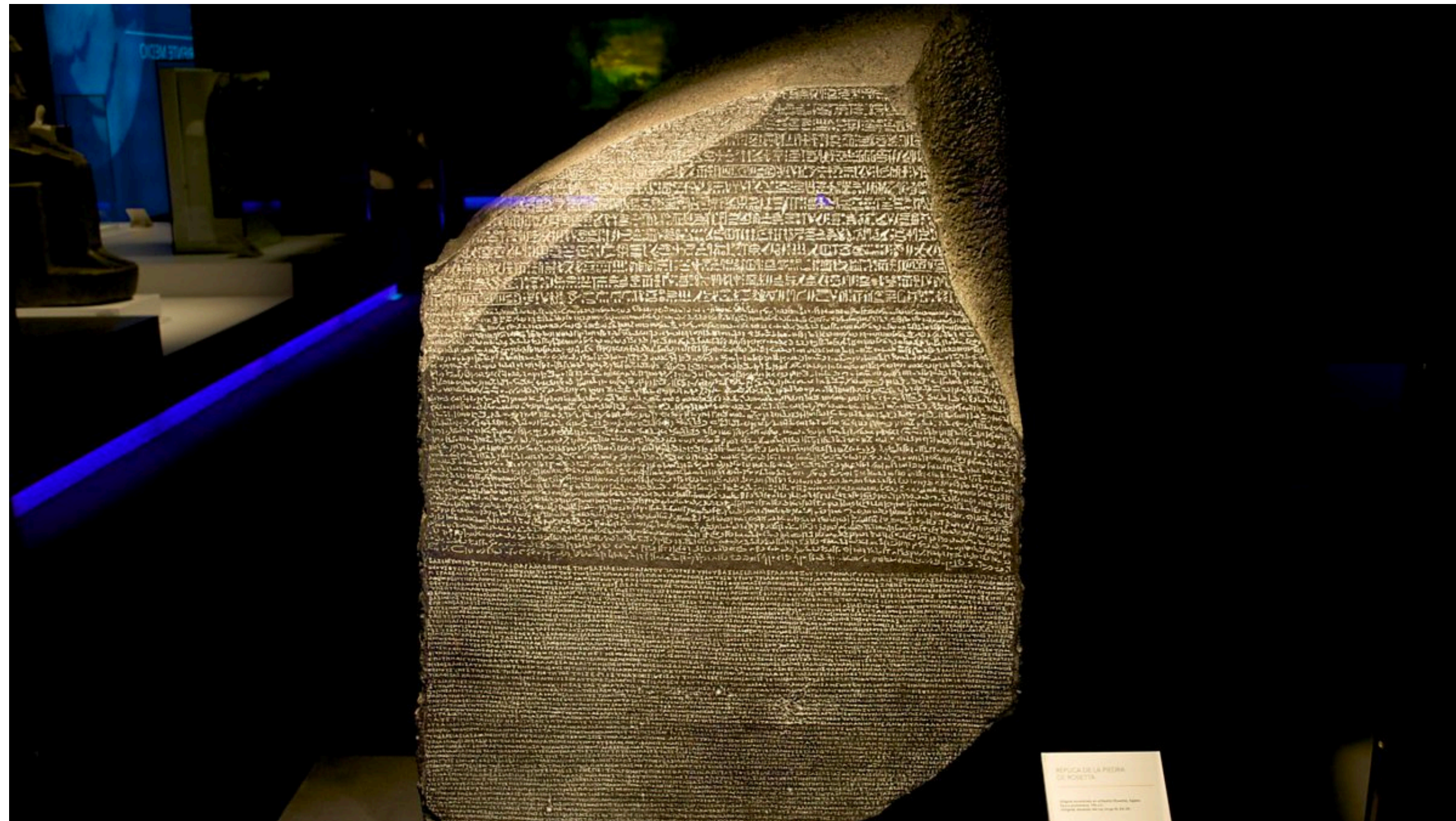
# Vanishing Gradient in RNNs



In general, the longer the path, the smaller the gradient signal.

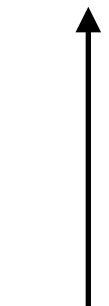


# Alignment in Machine Translation



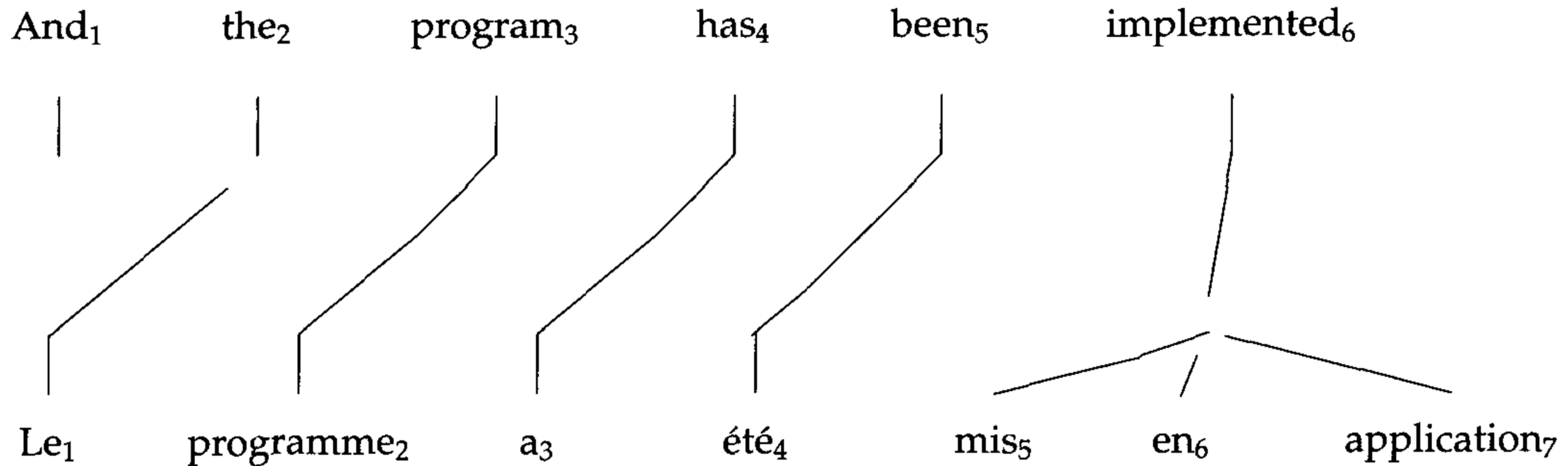
Parallel Corpus

$$p(\mathbf{y} | \mathbf{x})$$



target source

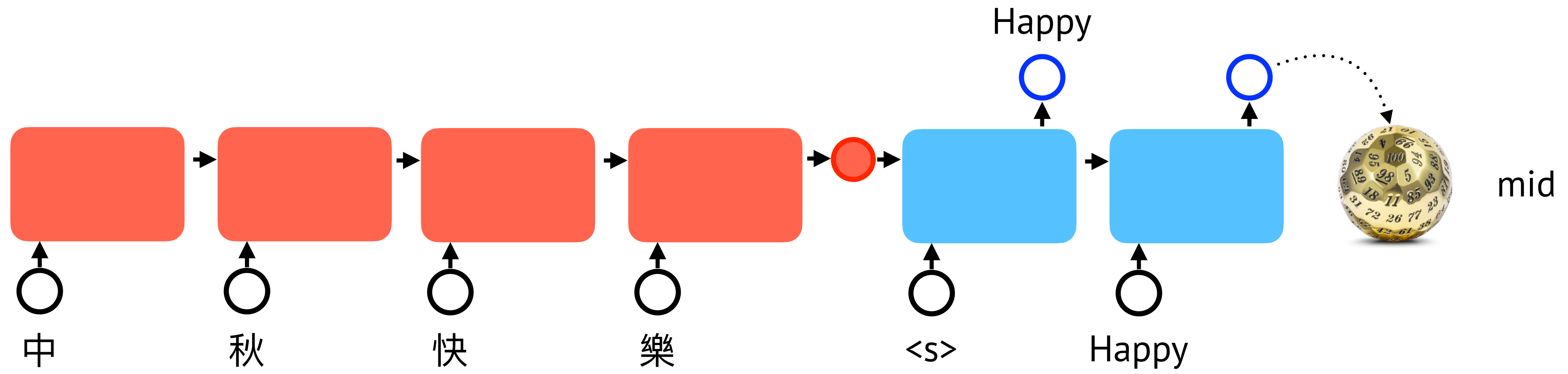
# Alignment in Machine Translation



Some words might have no “counter-part”.

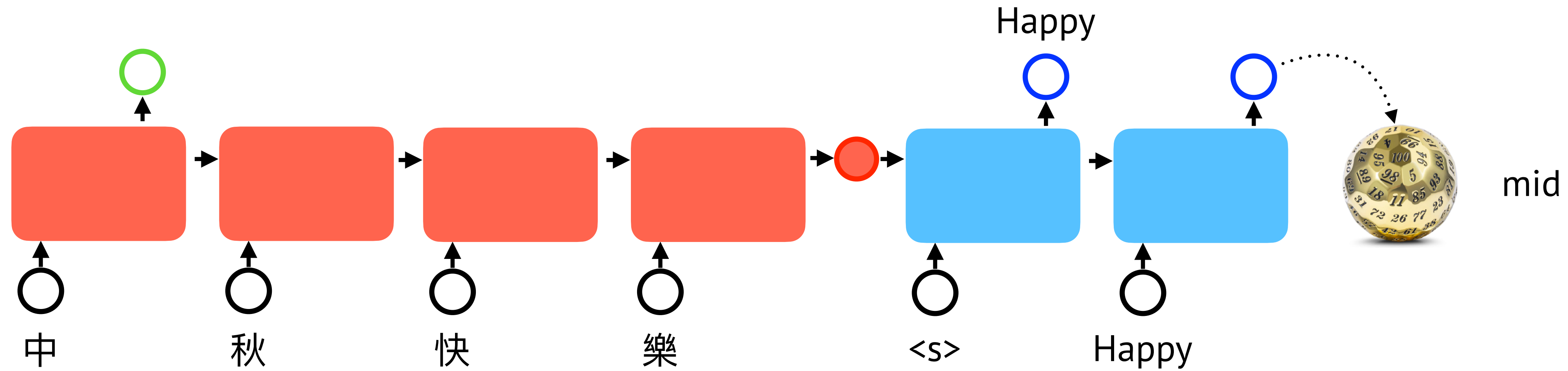
Alignment can be many-to-one (or one-to-many).


# Sequence to Sequence Model

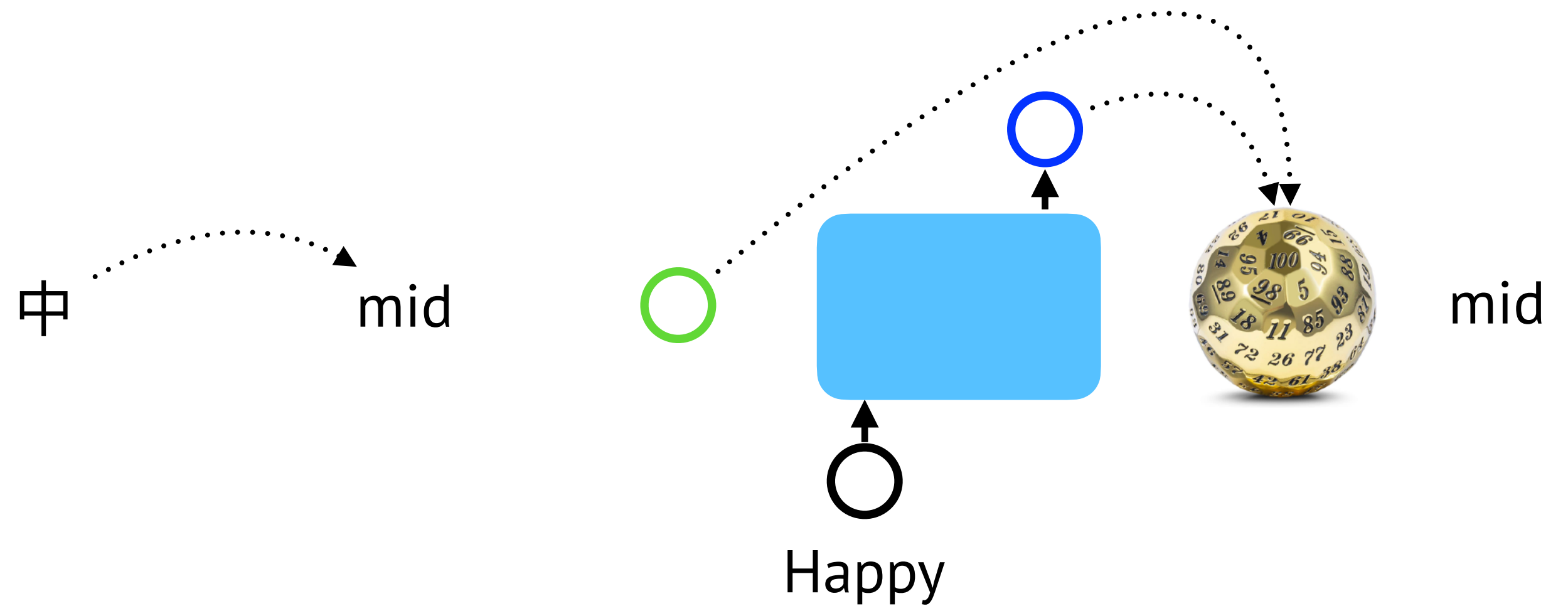
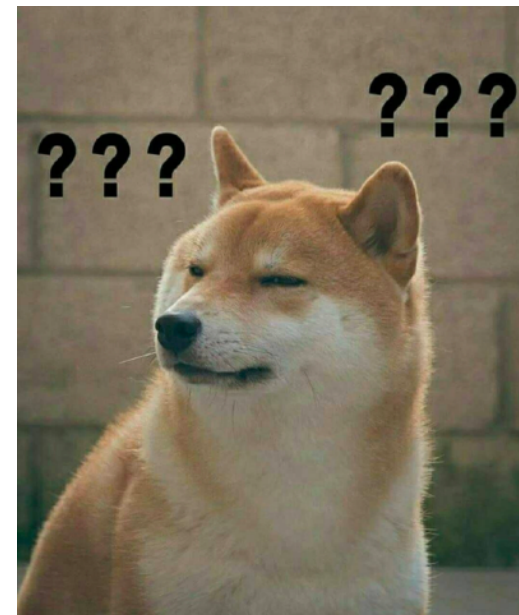


$$p(y_t | \mathbf{y}_{<t}, \mathbf{x})$$

# Sequence to Sequence Model

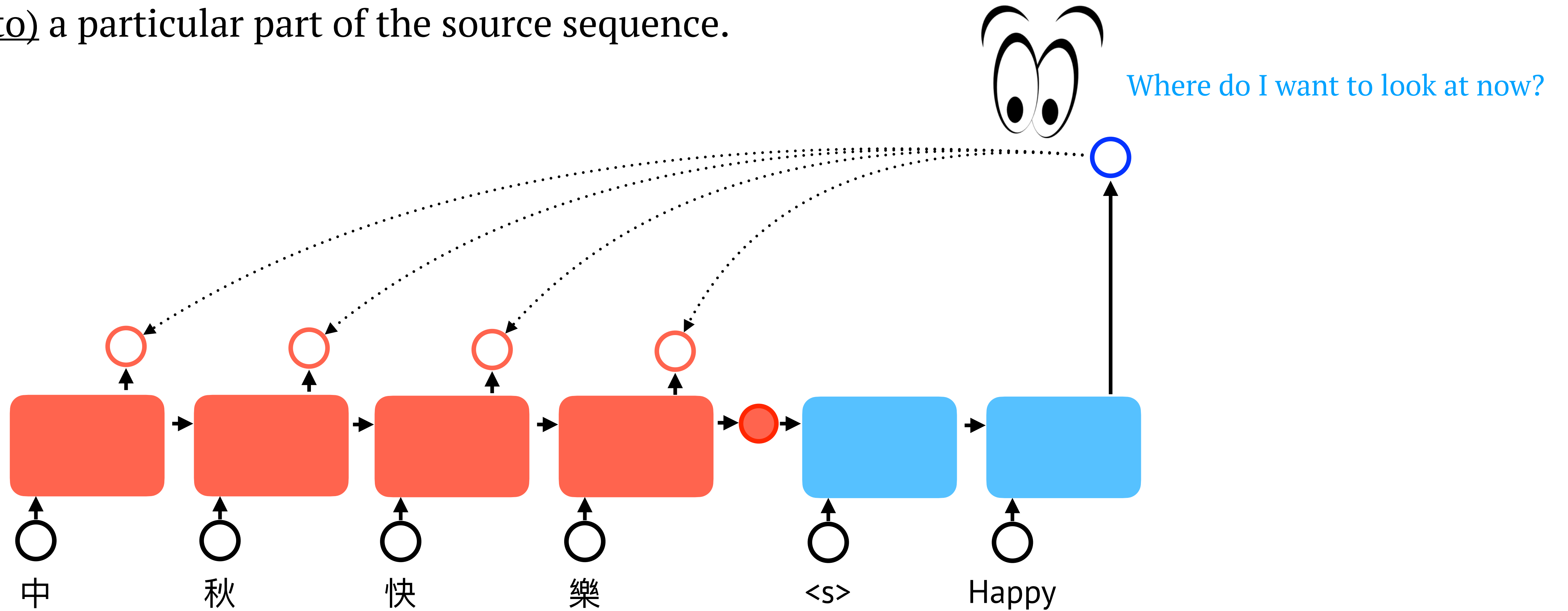



$$p(y_t | \mathbf{y}_{<t}, \mathbf{x})$$



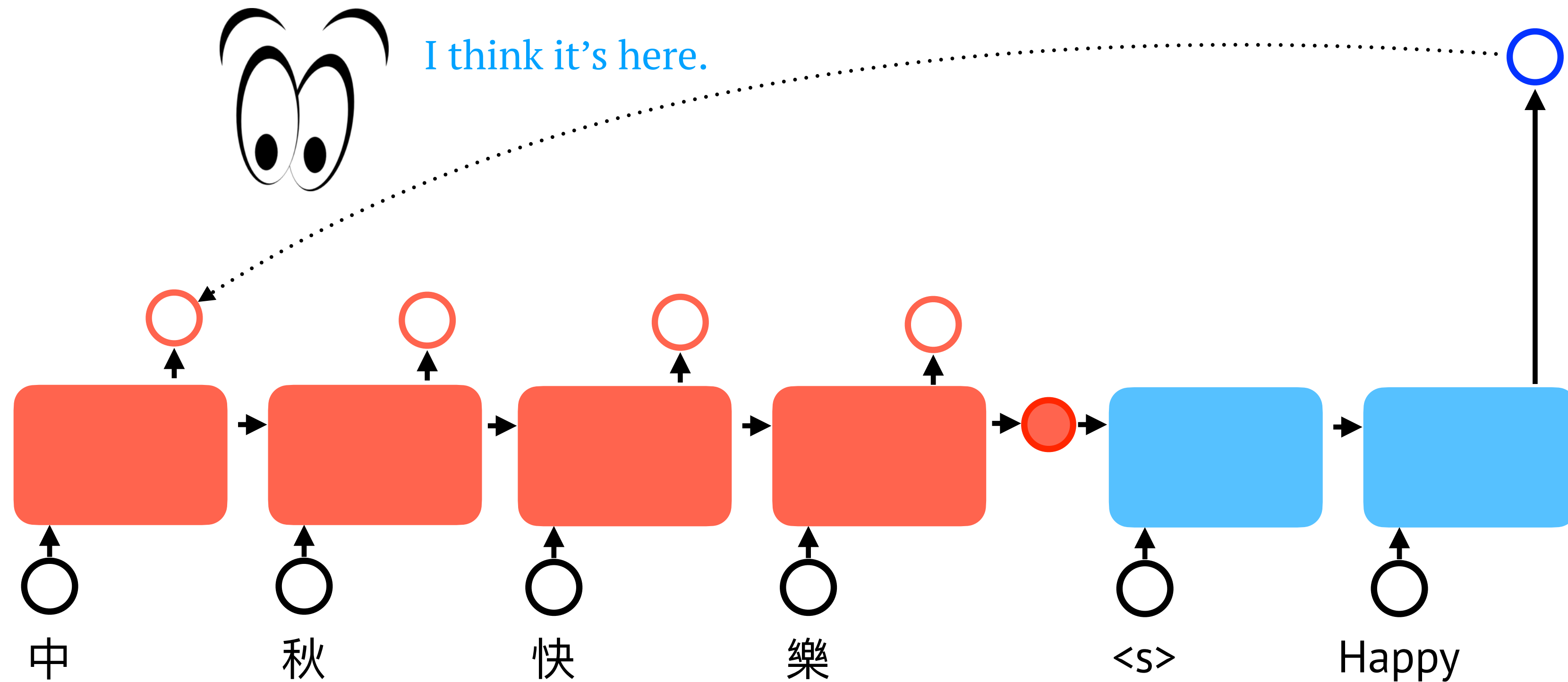
# Attention Mechanism

Use direct connection to the encoder to focus on (attend to) a particular part of the source sequence.



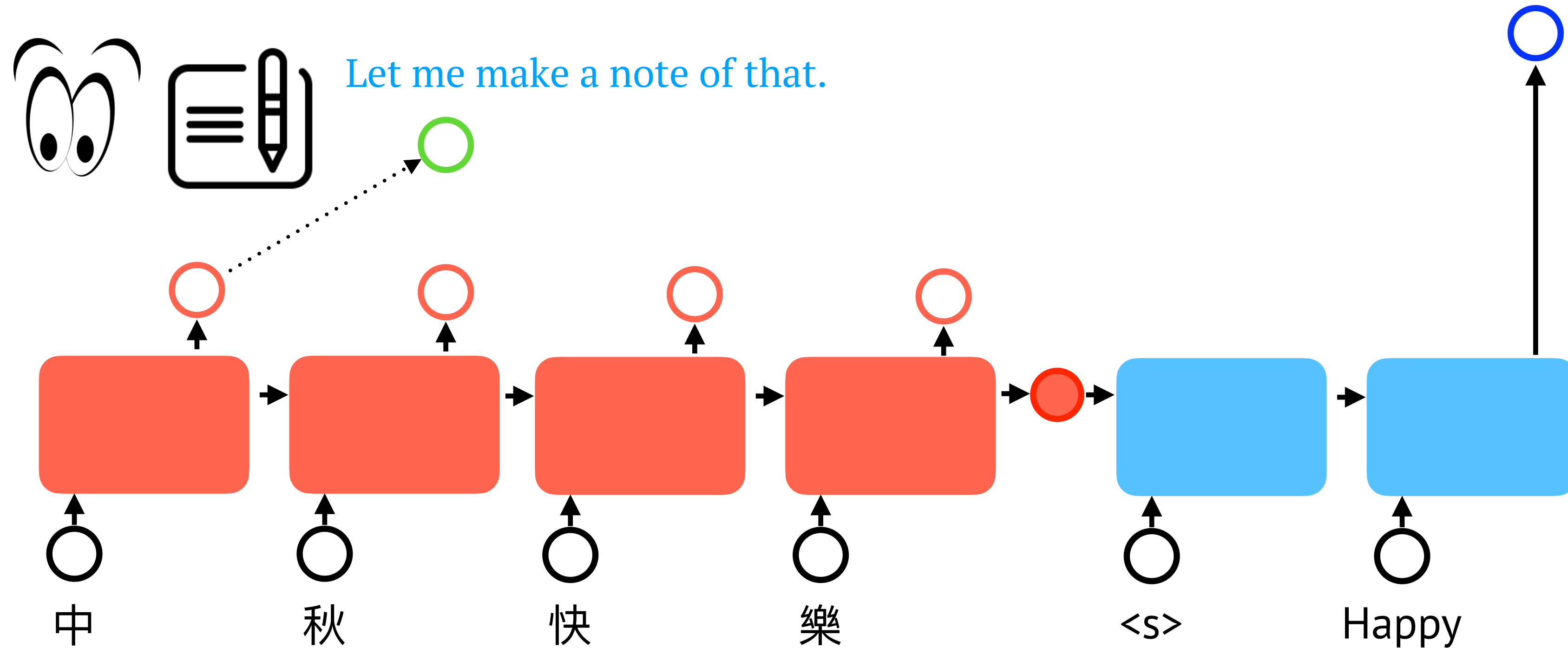
# Attention Mechanism

Use direct connection to the encoder to focus on (attend to) a particular part of the source sequence.



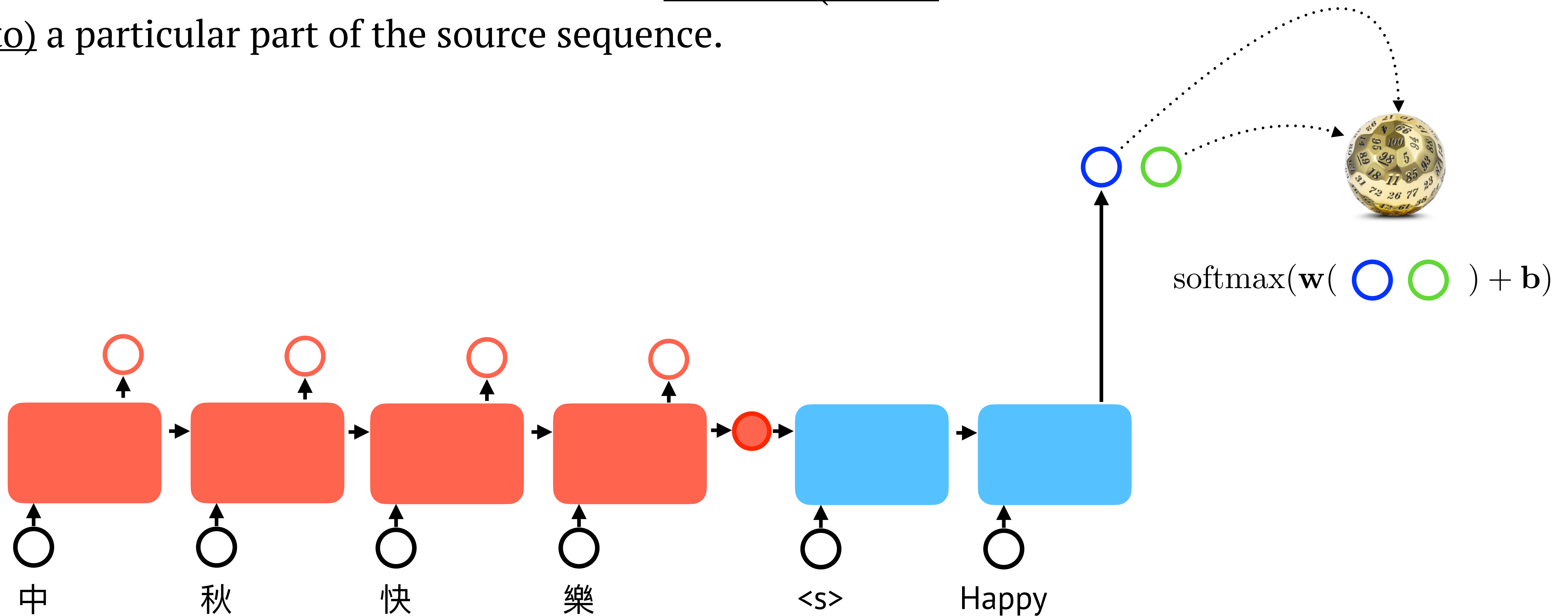
# Attention Mechanism

Use direct connection to the encoder to focus on (attend to) a particular part of the source sequence.



# Attention Mechanism

Use direct connection to the encoder to focus on (attend to) a particular part of the source sequence.

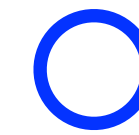




# Memory Abstraction

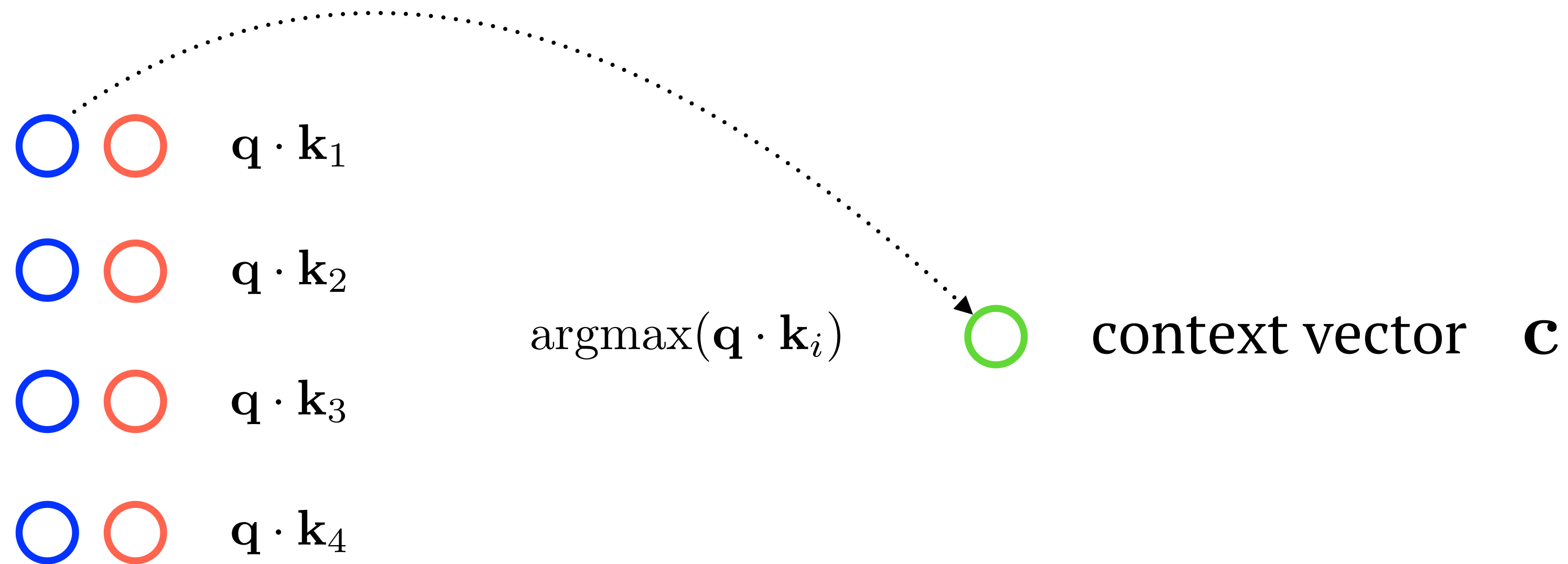


Memory (keys)



Query

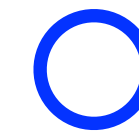
Task: Finding the most “relevant” item in the memory.



# Dot-Product-Softmax Attention

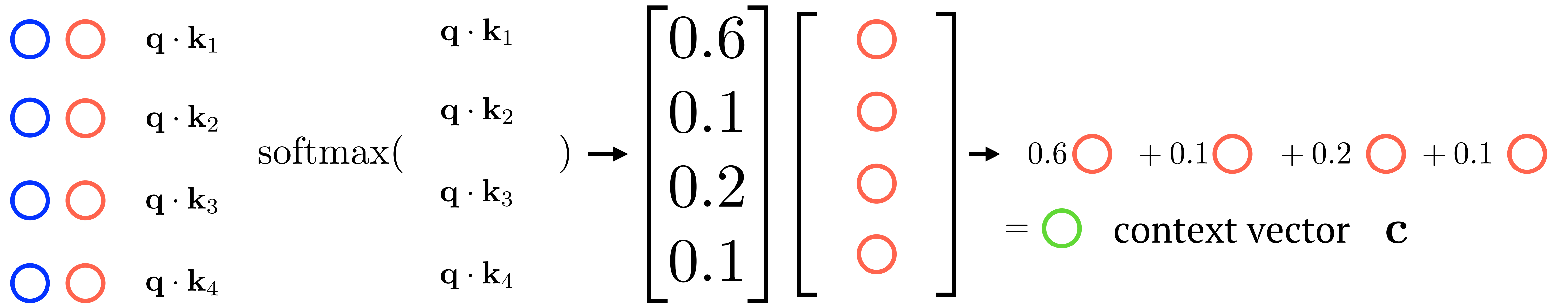


Memory (keys)

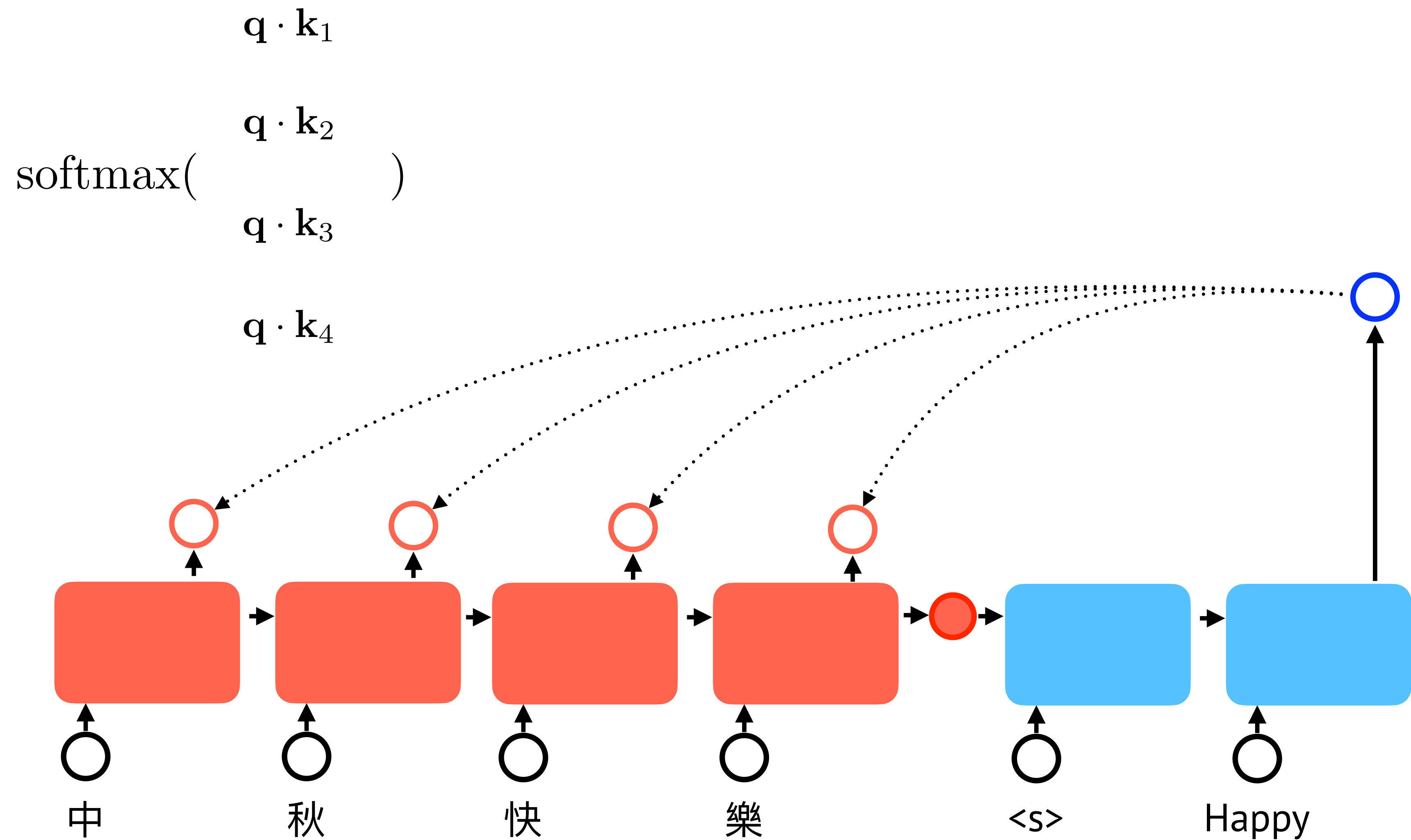


Query

Task: Finding the most “relevant” item in the memory.

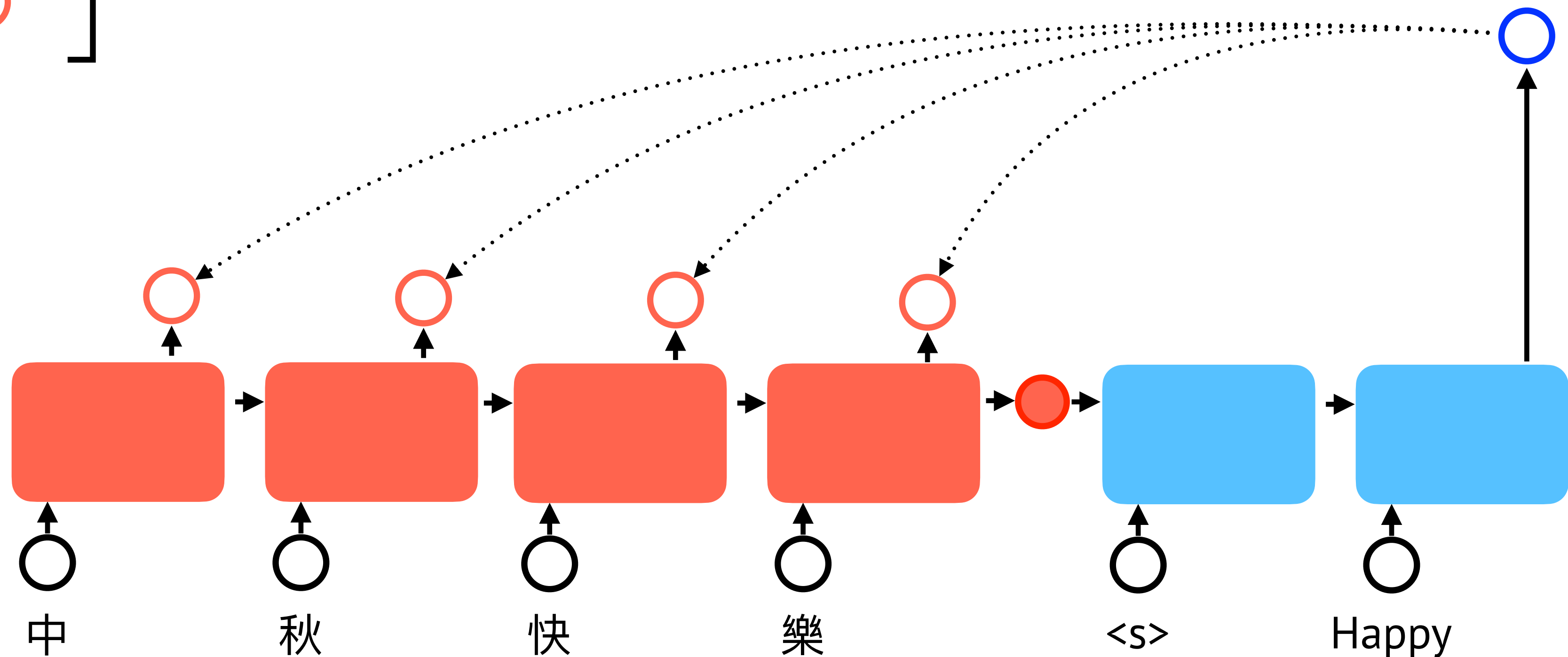


# Attention Mechanism

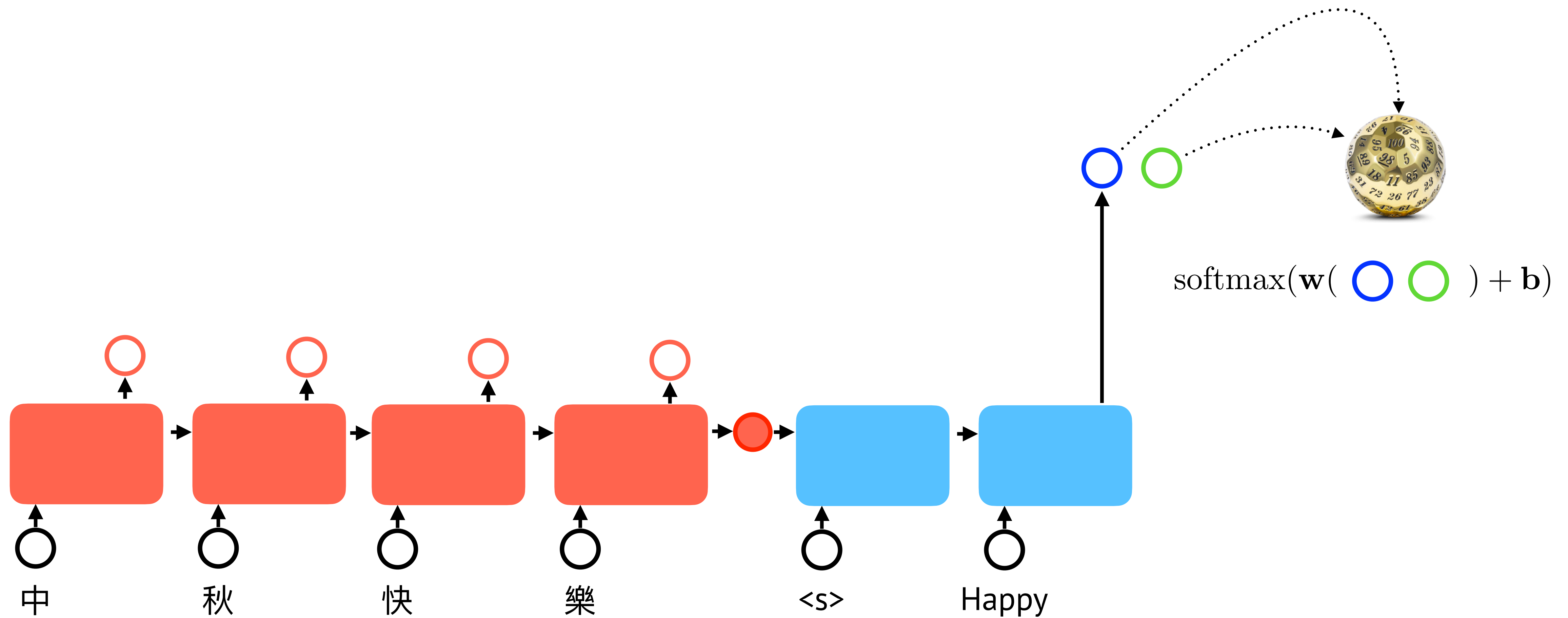


# Attention Mechanism

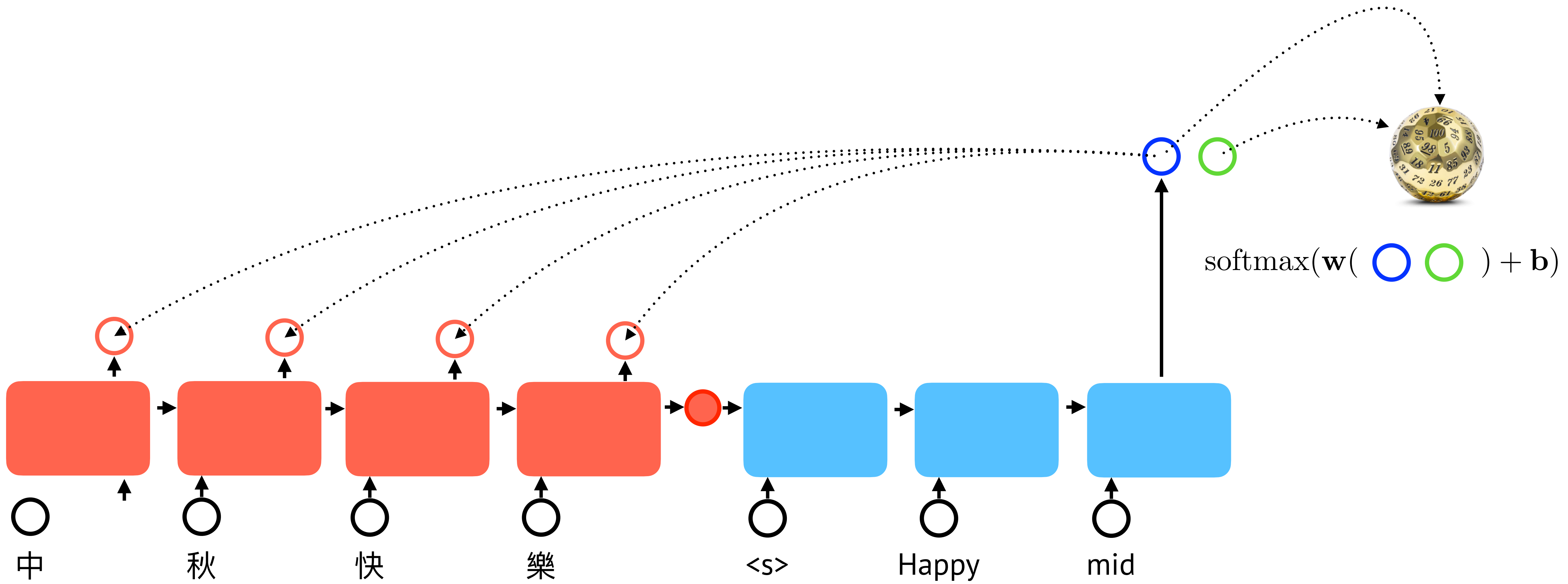
$$\begin{bmatrix} 0.6 \\ 0.1 \\ 0.2 \\ 0.1 \end{bmatrix} \begin{bmatrix} \bigcirc \\ \bigcirc \\ \bigcirc \\ \bigcirc \end{bmatrix} \rightarrow 0.6 \bigcirc + 0.1 \bigcirc + 0.2 \bigcirc + 0.1 \bigcirc \\ = \bigcirc \text{ context vector } \mathbf{c}$$



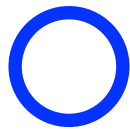
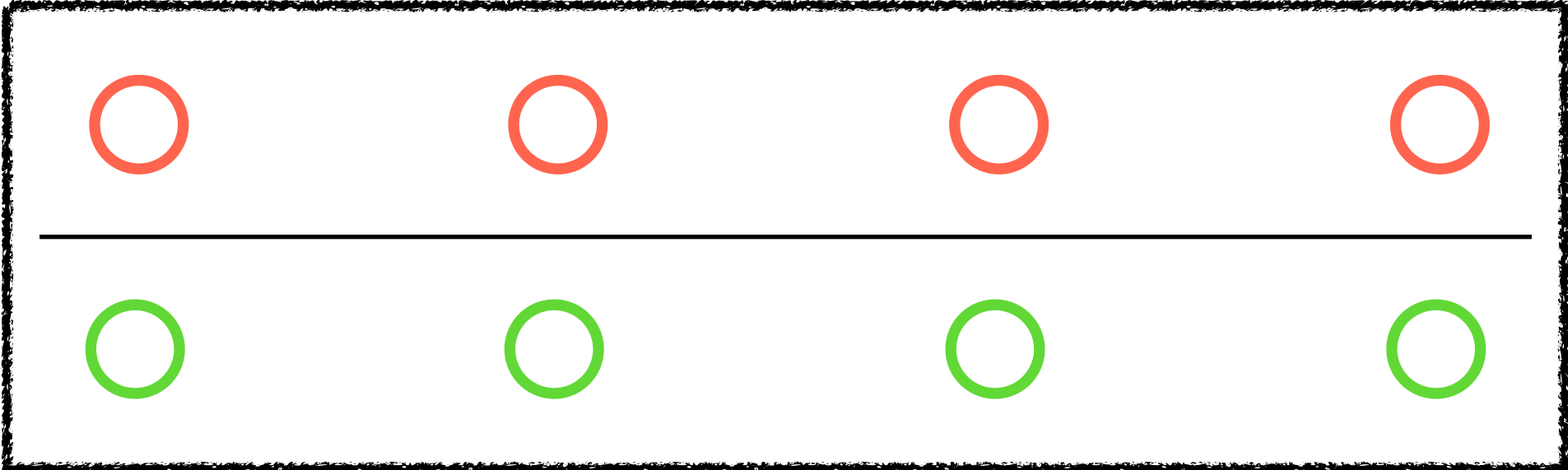
# Attention Mechanism



# Attention Mechanism



# Dot-Product-Softmax Attention



Query

Memory (key-value pairs)

$$\begin{array}{l}
 \text{○} \text{○} \quad \mathbf{q} \cdot \mathbf{k}_1 \quad \mathbf{q} \cdot \mathbf{k}_1 \\
 \text{○} \text{○} \quad \mathbf{q} \cdot \mathbf{k}_2 \quad \mathbf{q} \cdot \mathbf{k}_2 \\
 \text{○} \text{○} \quad \mathbf{q} \cdot \mathbf{k}_3 \quad \mathbf{q} \cdot \mathbf{k}_3 \\
 \text{○} \text{○} \quad \mathbf{q} \cdot \mathbf{k}_4 \quad \mathbf{q} \cdot \mathbf{k}_4
 \end{array}
 \text{softmax}(\quad) \rightarrow
 \begin{bmatrix} 0.6 \\ 0.1 \\ 0.2 \\ 0.1 \end{bmatrix}
 \begin{bmatrix} \text{○} \\ \text{○} \\ \text{○} \\ \text{○} \end{bmatrix}
 \rightarrow
 0.6 \text{○} + 0.1 \text{○} + 0.2 \text{○} + 0.1 \text{○}$$

= ○ context vector **c**

# Dot-Product-Softmax Attention

$$\sum_{m=1}^M \frac{\exp(\mathbf{q}_n \mathbf{k}_m)}{\sum_{m'=1}^M \exp(\mathbf{q}_n \mathbf{k}_{m'})} \mathbf{v}_m^\top = \mathbf{V}^\top \text{softmax}(\mathbf{K} \mathbf{q}_n)$$

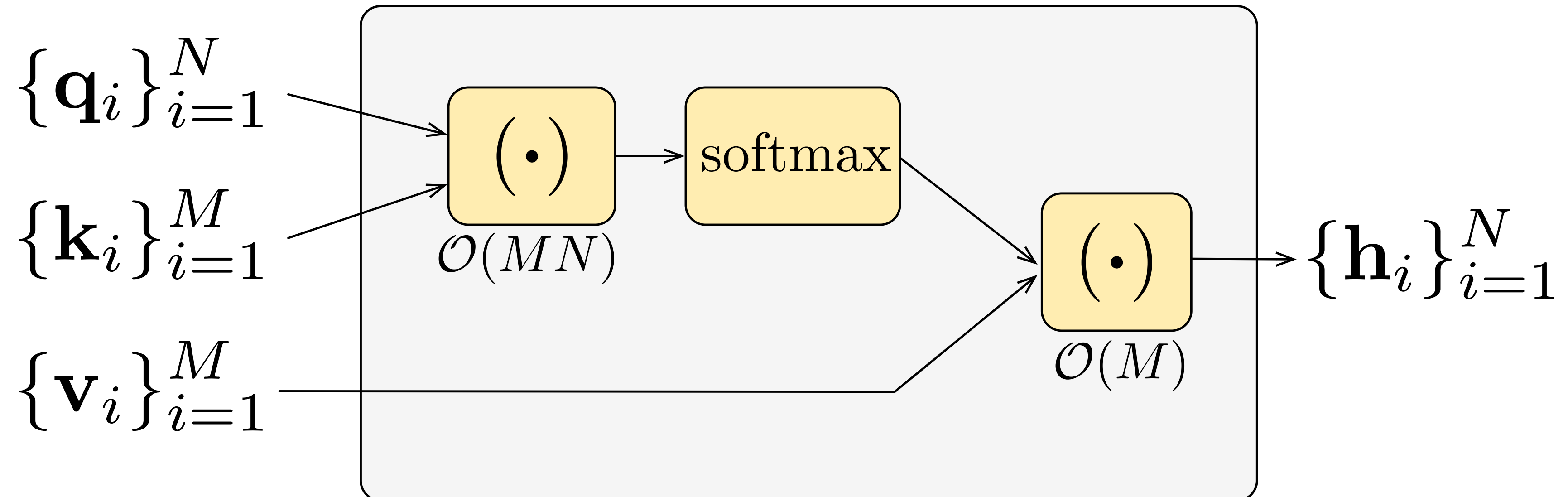
The diagram highlights the components of the attention mechanism:

- The term  $\exp(\mathbf{q}_n \mathbf{k}_m)$  is labeled as **similarity** (indicated by a red box).
- The denominator  $\sum_{m'=1}^M \exp(\mathbf{q}_n \mathbf{k}_{m'})$  is labeled as **normalized similarity** (indicated by a blue box).
- The entire fraction is labeled as **weighted sum** (indicated by a black box).

weighted sum

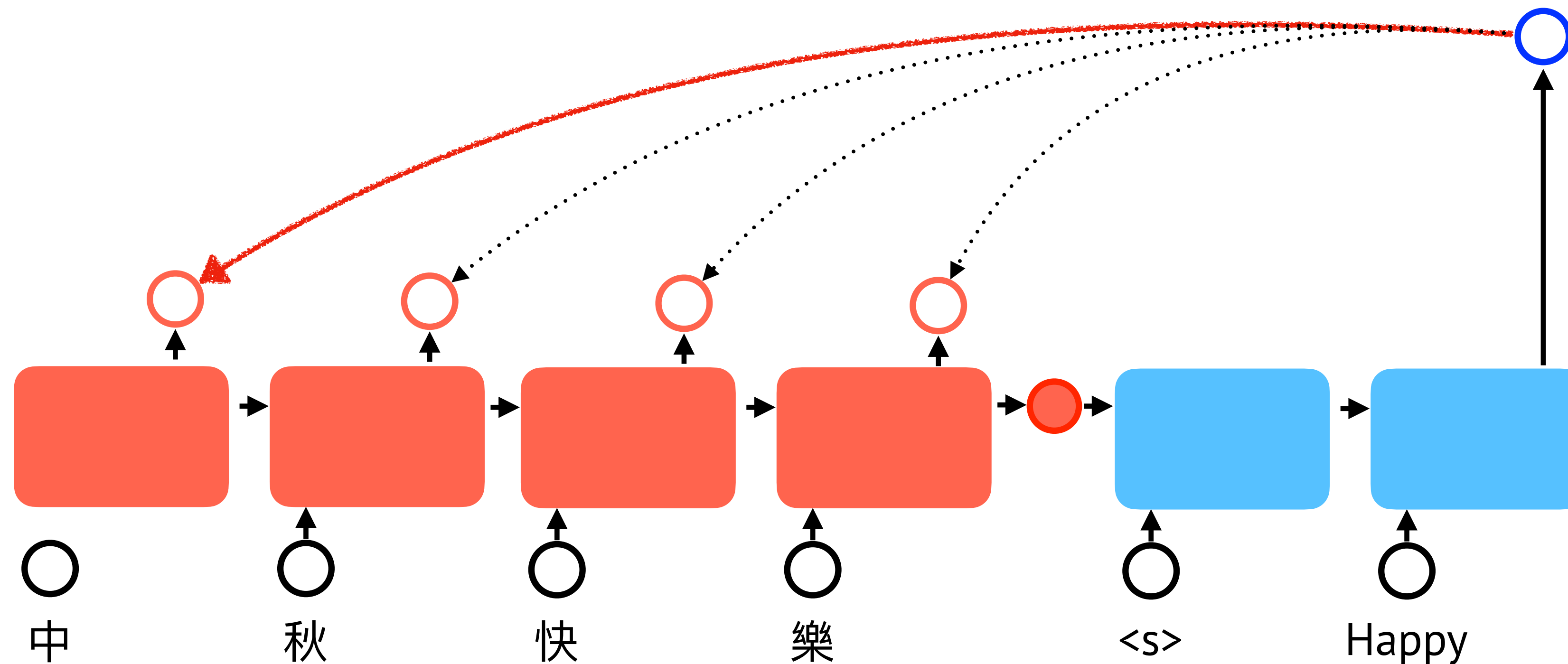


# Computational Complexity



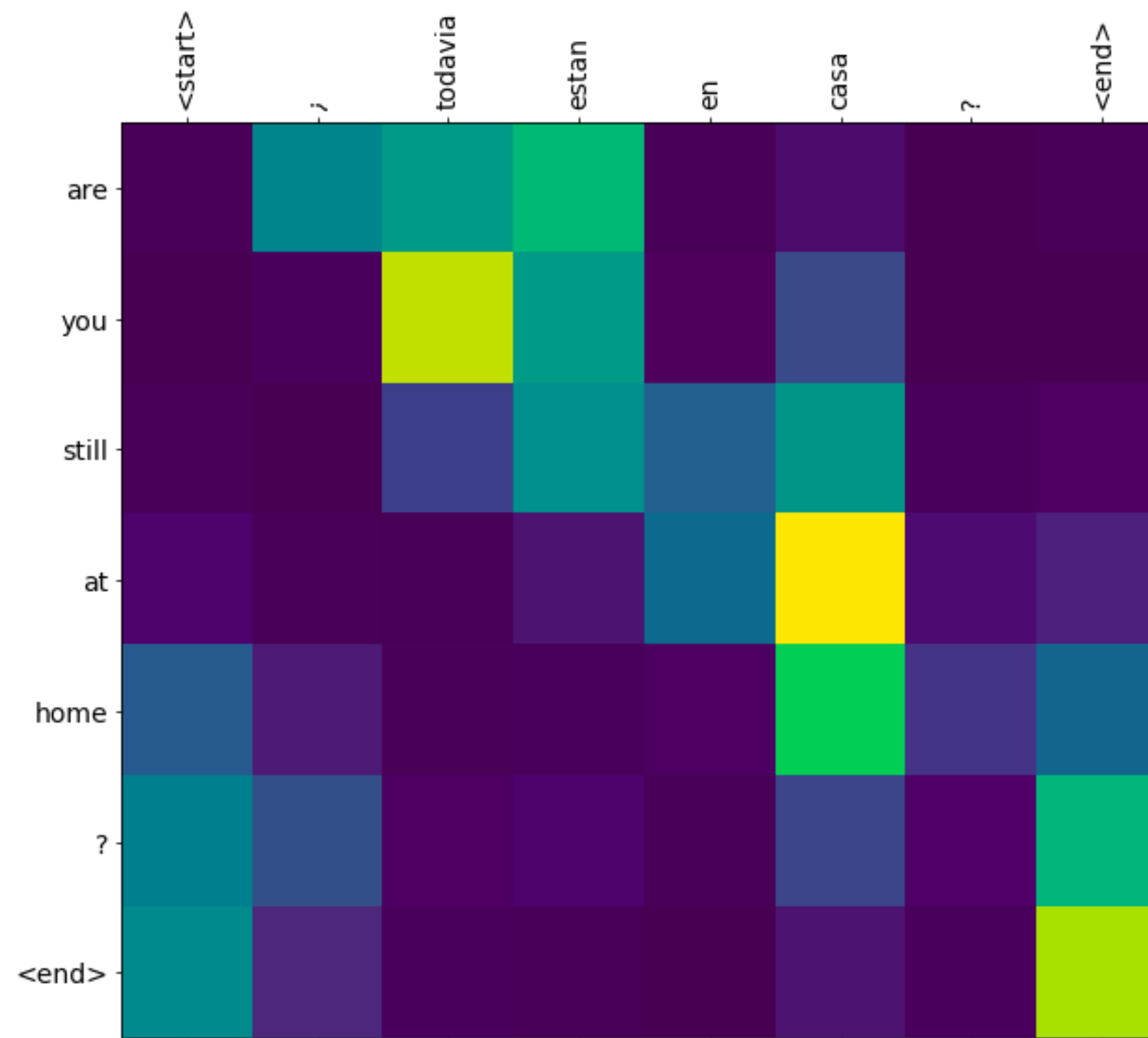
# Attention Mechanism

It helps with vanishing gradient problem.



# Attention Mechanism

It offers some interpretability.

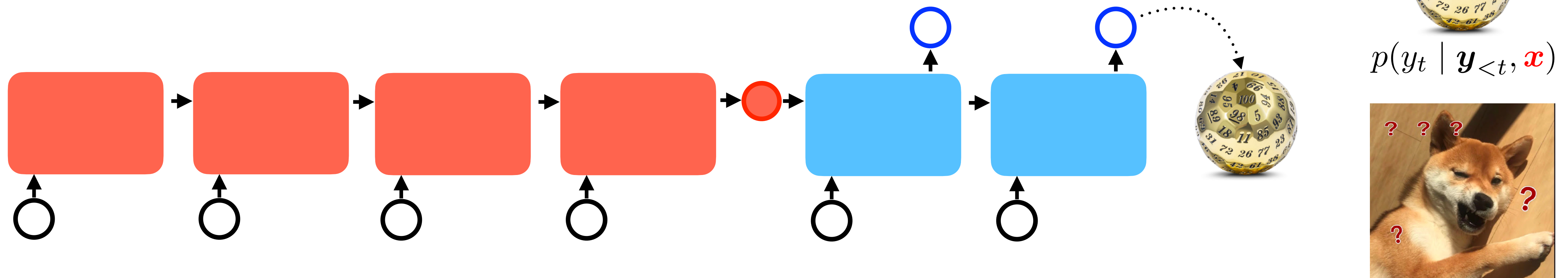


# Generation as (Conditional) Language Modeling

$$p(\mathbf{y} \mid \mathbf{x}) = p(y_1 \dots y_n \mid x_1 \dots x_m) = \prod_{t=1}^n p(y_t \mid \mathbf{y}_{<t}, \mathbf{x})$$

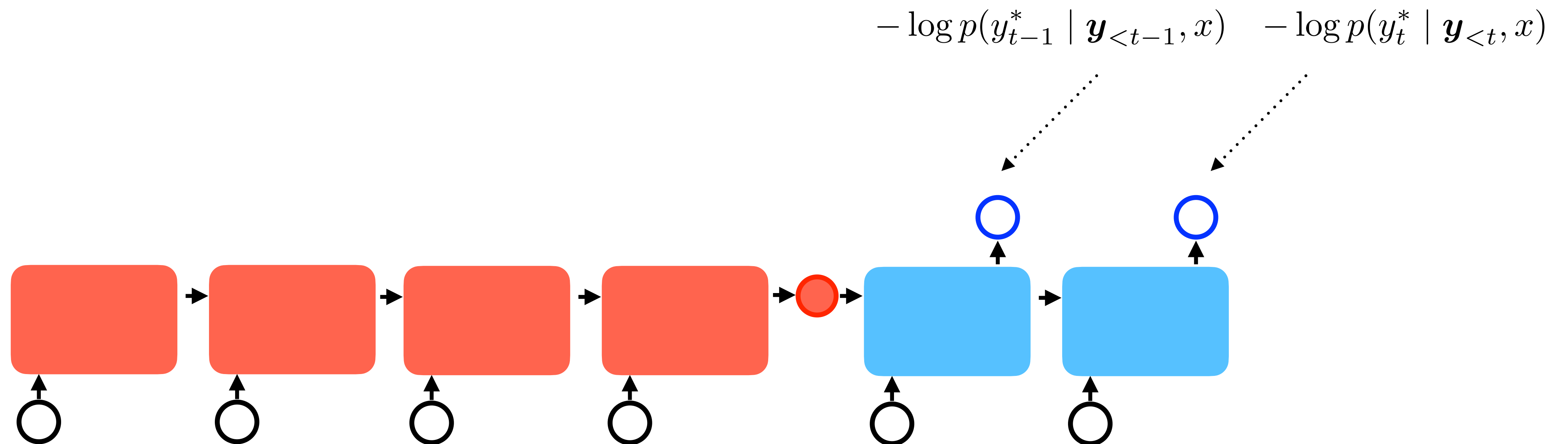
↑      ↑  
target source

Conditional Language Model

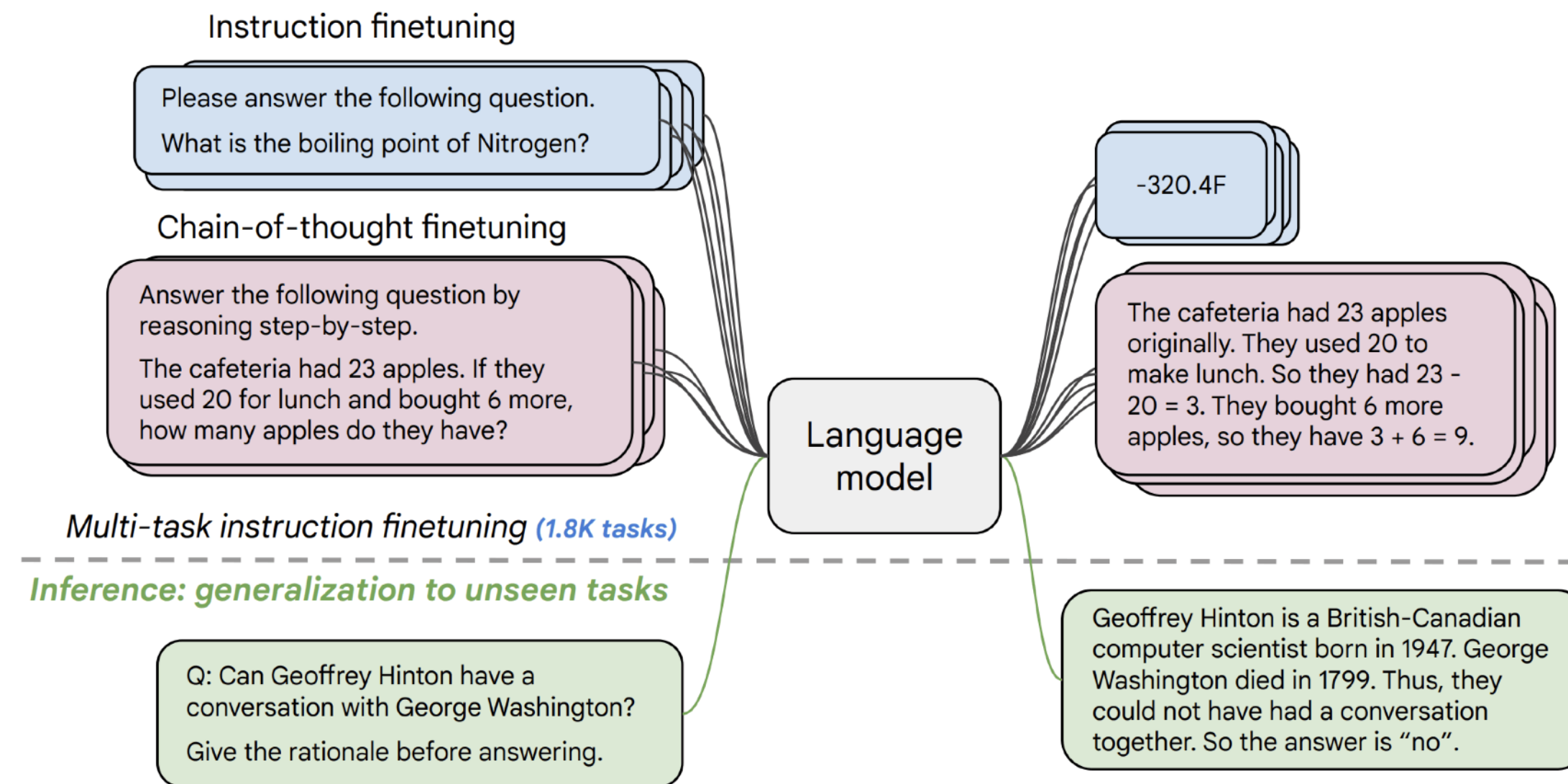
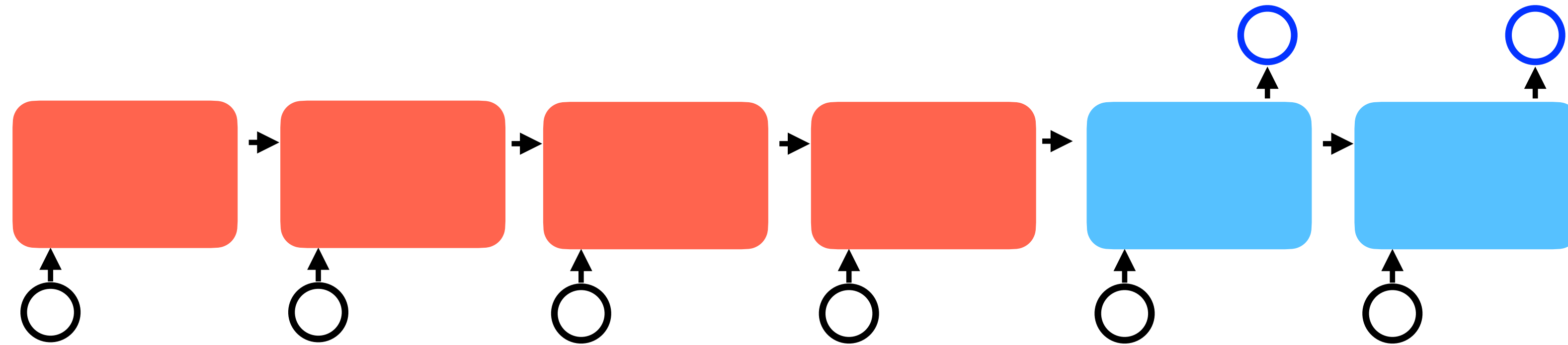


# Generation as (Conditional) Language Modeling

$$p(\mathbf{y} \mid \mathbf{x}) = p(y_1 \dots y_n \mid x_1 \dots x_m) = \prod_{t=1}^n p(y_t \mid \mathbf{y}_{<t}, \mathbf{x})$$

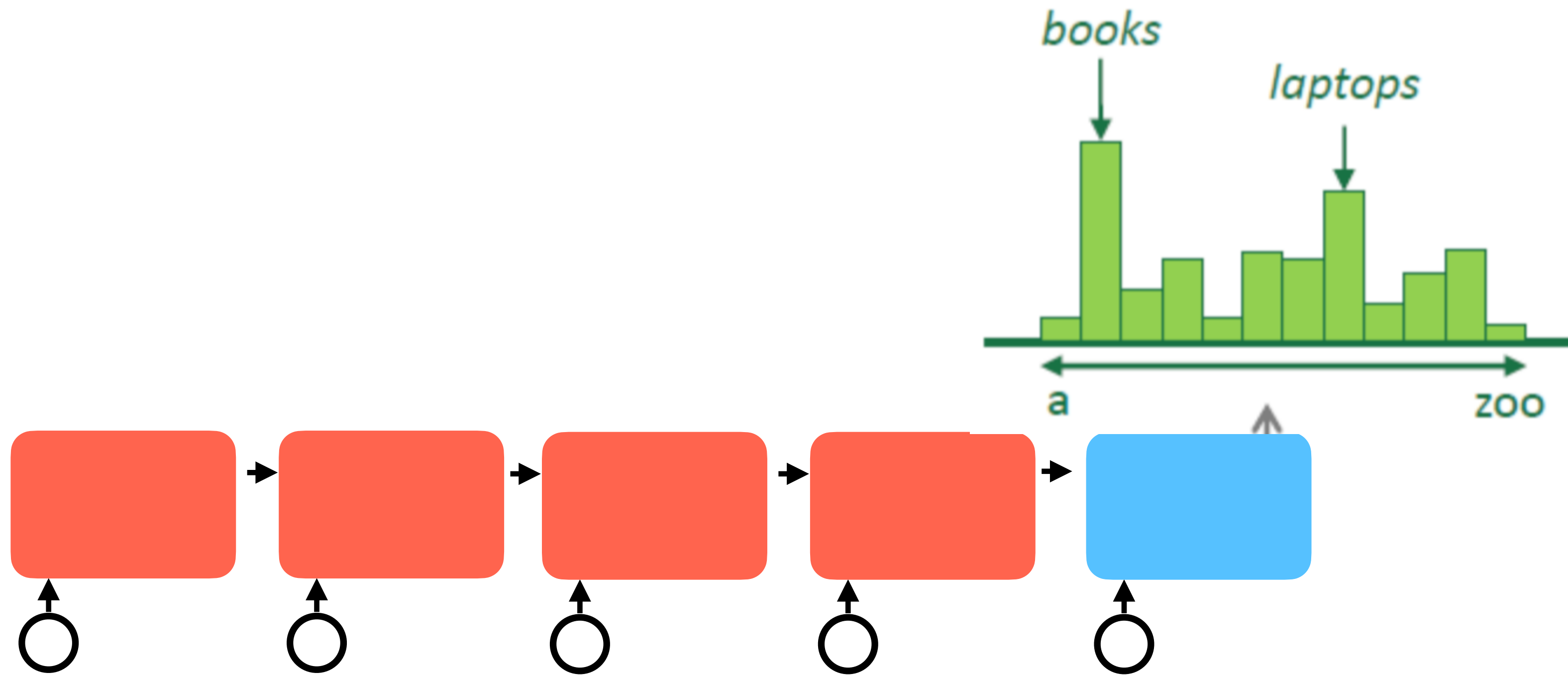


# Continue Training / Post-Training / Instruction Tuning



# How to perform decoding?

$$p(y_t \mid \mathbf{y}_{<t}, \mathbf{x})$$



arg max  
beam search



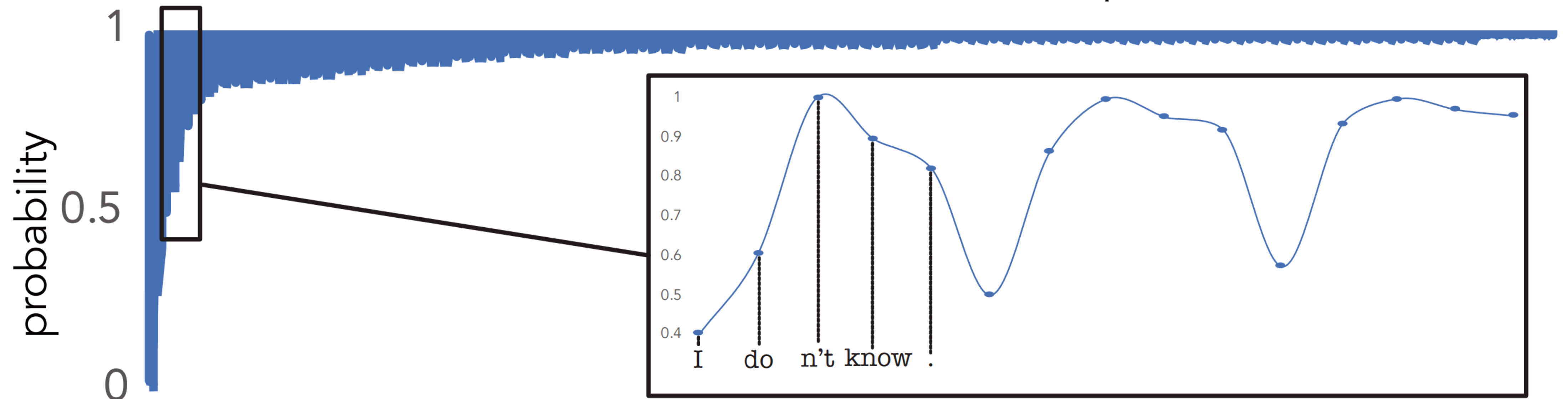






# What happened?

Token Probabilities for "I don't know." Repeated 200 times

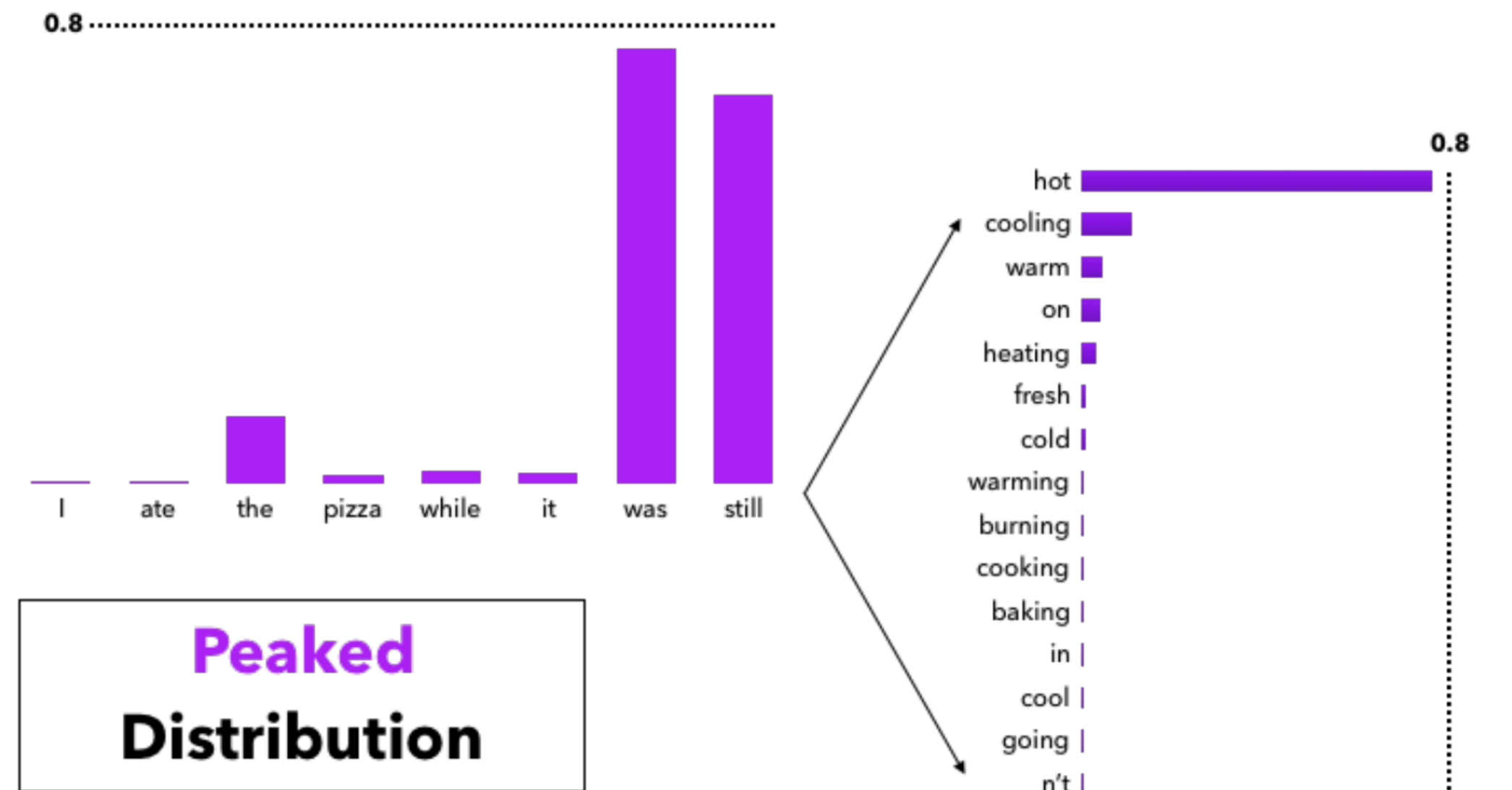
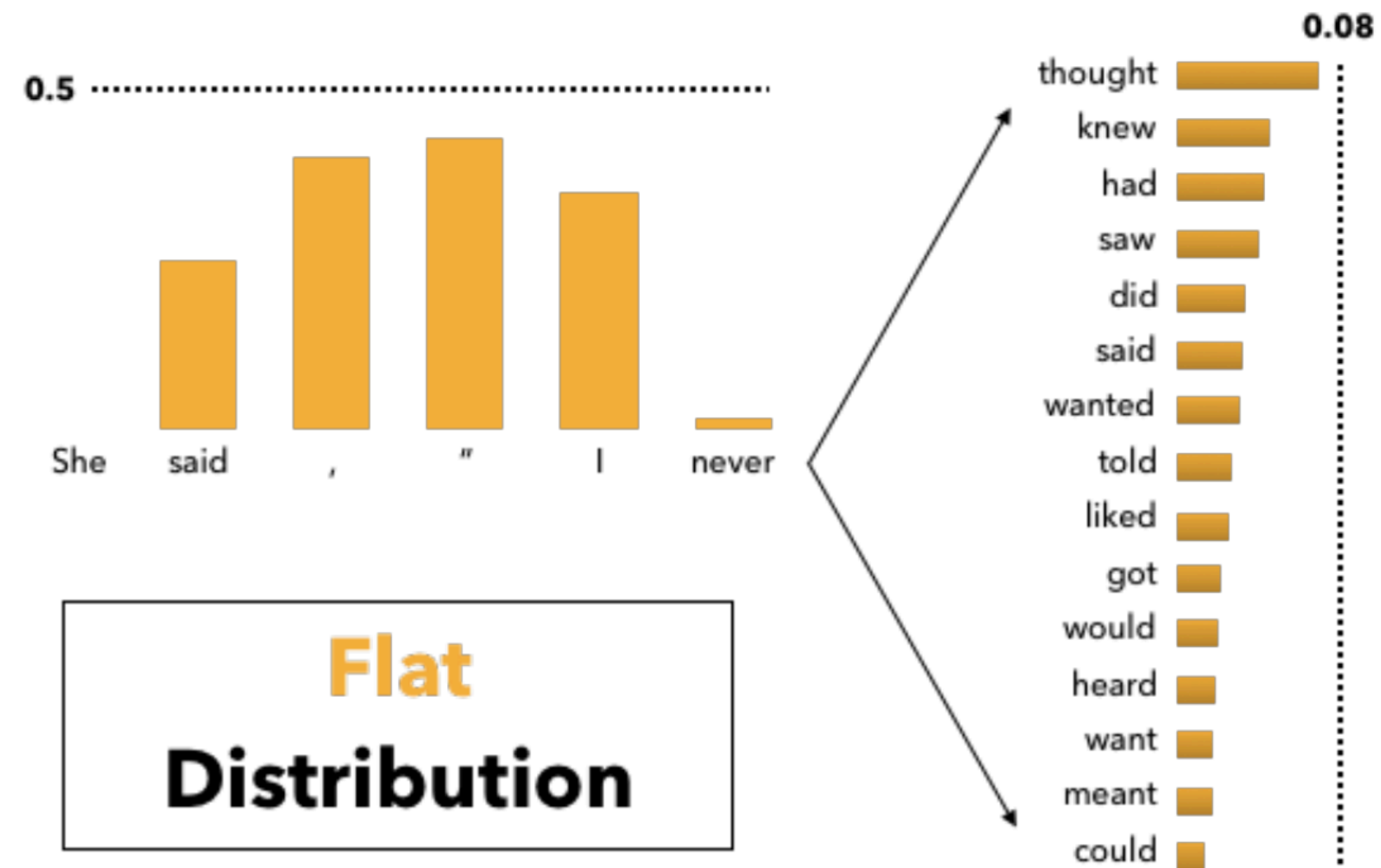


The probability of a repeated phrase increases with each repetition, creating a feedback loop.

# Top-K Sampling



# Top-K Sampling



# Top-p (nucleus) Sampling

To cut off by the cumulative probability mass, rather than the first K terms.

