DEEP LEARNING FOR NATURAL LANGUAGE PROCESSING

Lecture 2: Recurrent Neural Networks (RNNs)

Caio Corro

LECTURE 1 RECALL

Language modeling with a multi-layer perceptron

2nd order Markov chain: $p(y_1, \ldots, y_n) = \quad p(y_1) \quad p(y_2 \mid y_1) \quad \prod_{i=3}^{n} p(y_i \mid y_{i-1}, y_{i-2})$

$$\mathbf{x} = \begin{bmatrix} \textit{Embedding of } y_{i-1} \\ \textit{Embedding of } y_{i-2} \end{bmatrix} \quad \mathbf{z} = \sigma\left(\mathbf{U}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}\right) \quad \mathbf{w} = \mathbf{U}^{(2)}\mathbf{z} + \mathbf{b}^{(2)} \quad p(y_i \mid y_{i-1}, y_{i-2}) = \frac{\exp(\mathbf{w}_{y_i})}{\sum_{y'} \exp(\mathbf{w}_{y'})}$$

Concatenate the embeddings of the two previous words

Hidden representation

Output projection

Probability distribution

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Sentence classification with a Convolutional Neural Network

1. Convolution: sliding window of fixed size of the input sentence
2. Mean/max pooling over convolution outputs
3. Multi-linear perceptron

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1. Convolution: sliding window of fixed size of the input sentence
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Main issue

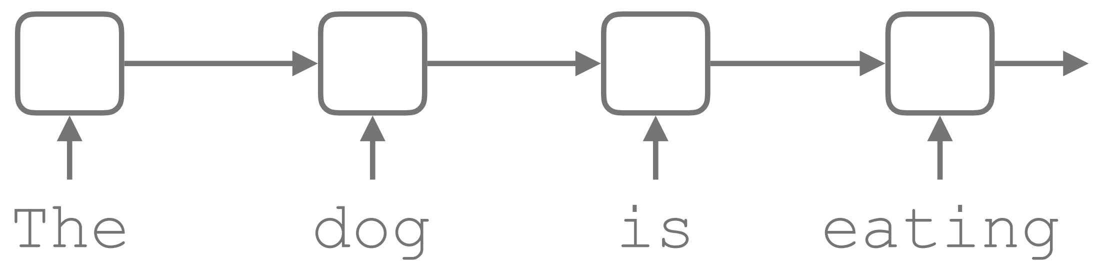
- These 2 networks only use local word-order information
- No long range dependencies

LONG RANGE DEPENDENCIES

Today

Recurrent neural networks

- Inputs are fed sequentially
- State representation updated at each input



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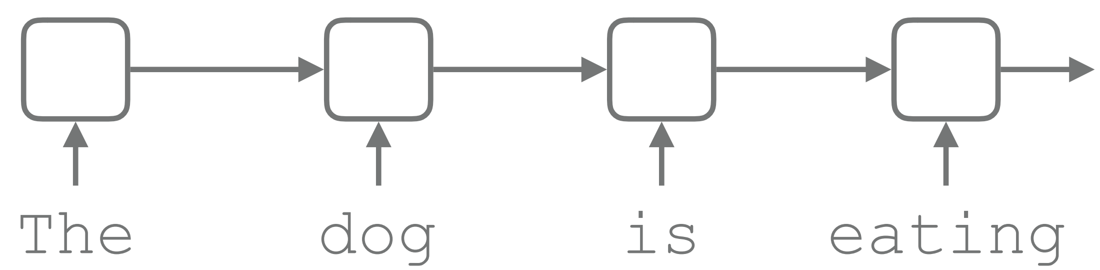
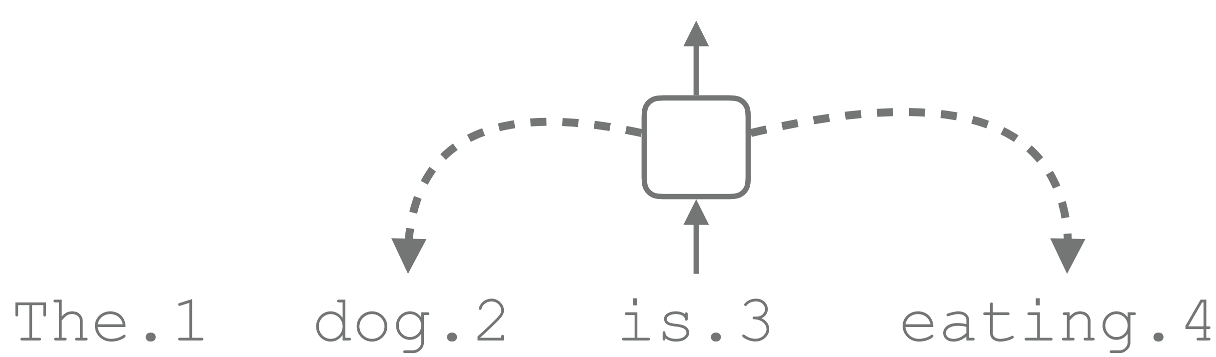


Next time!

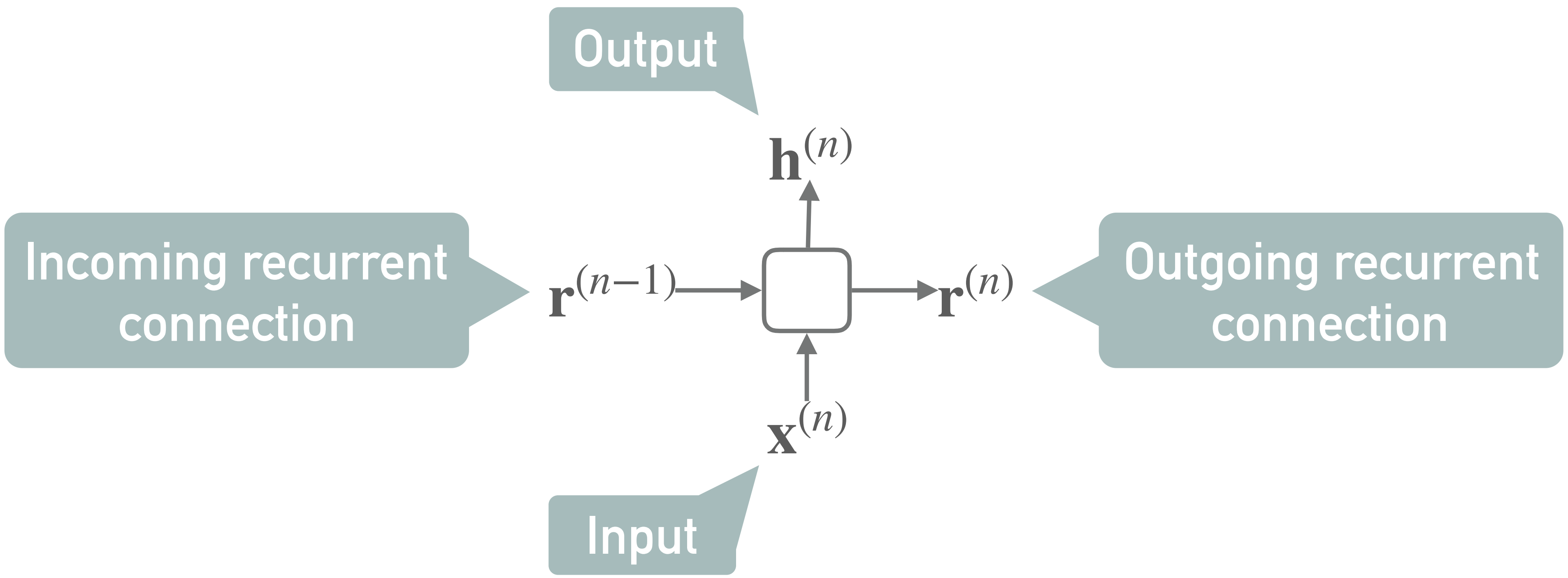
Attention network

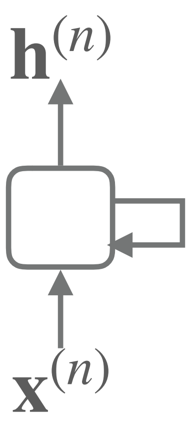
- Inputs contain position information
- At each position look at any input in the sentence



RECURRENT NEURAL NETWORK

Recurrent neural network cell





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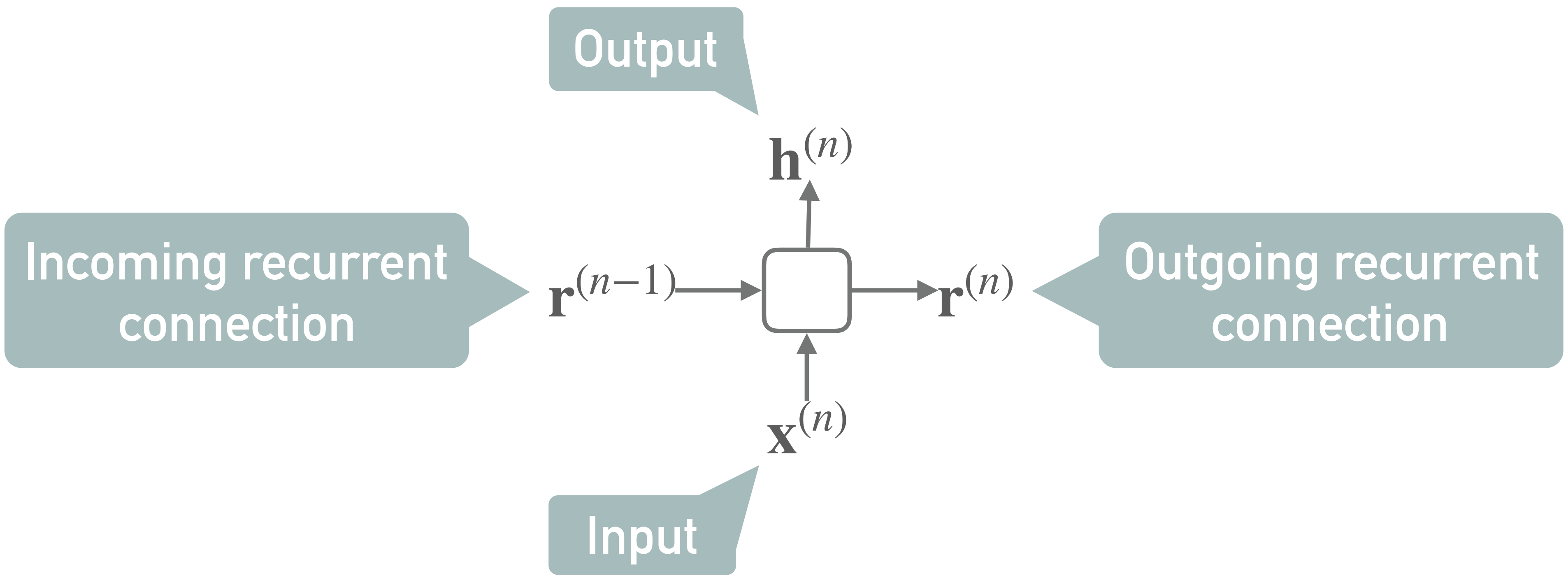
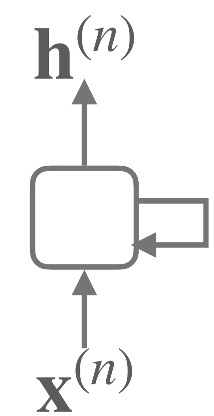
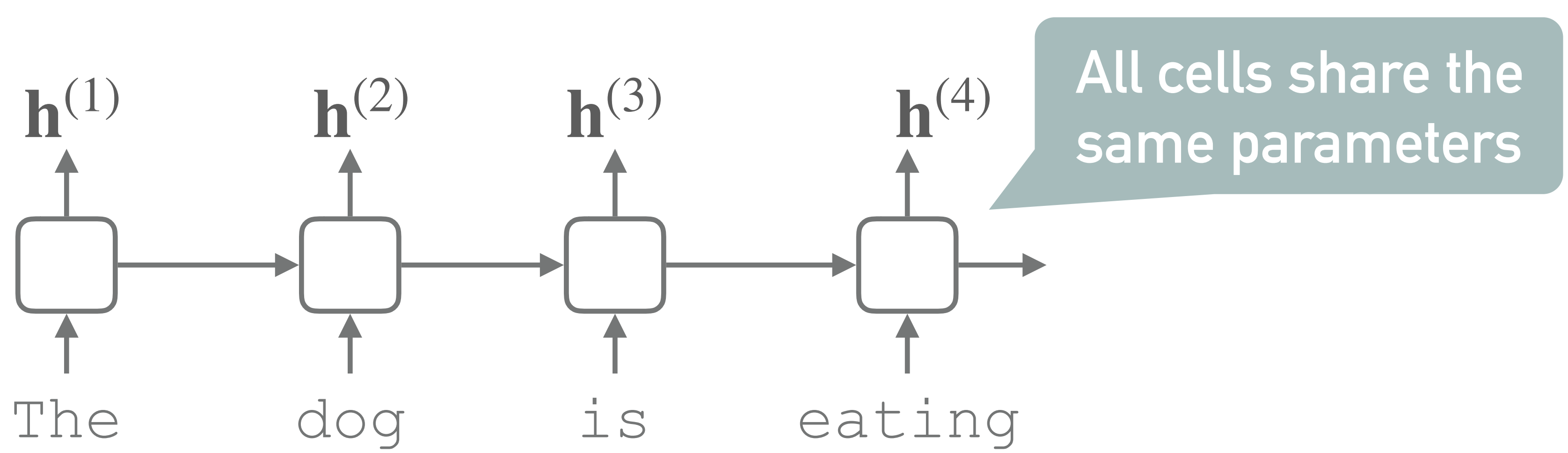




Dynamic neural network



LANGUAGE MODEL

Why do we usually make independence assumptions?

- Less parameters to learn
- Less sparsity

Non neural language model

$|V| \times |V|$ *parameters*

- 1st order Markov chain: $p(y_1, \ldots, y_n) = \quad p(y_1) \quad \prod_{i=2}^{n} p(y_i \,|\, y_{i-1})$
- 2nd order Markov chain: $p(y_1, \ldots, y_n) = \quad p(y_1) \quad p(y_2 \,|\, y_1) \quad \prod_{i=3}^{n} p(y_i \,|\, y_{i-1}, y_{i-2})$

$|V| \times |V| \times |V|$ *parameters*

Multi-layer perceptron language model

- No sparsity issue thanks to word embeddings
- Independence assumption, so no long range dependencies

LANGUAGE MODEL WITH RECURRENT NEURAL NETWORKS

$$p(y_1 \ldots y_n) = p(y_1, \ldots, y_{n-1}) p(y_n \,|\, y_1, \ldots, y_{n-1})$$

No independence assumption!

LANGUAGE MODEL WITH RECURRENT NEURAL NETWORKS

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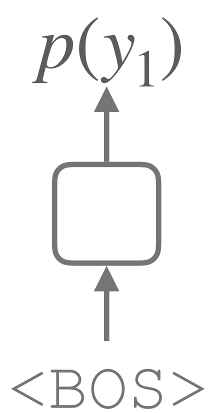

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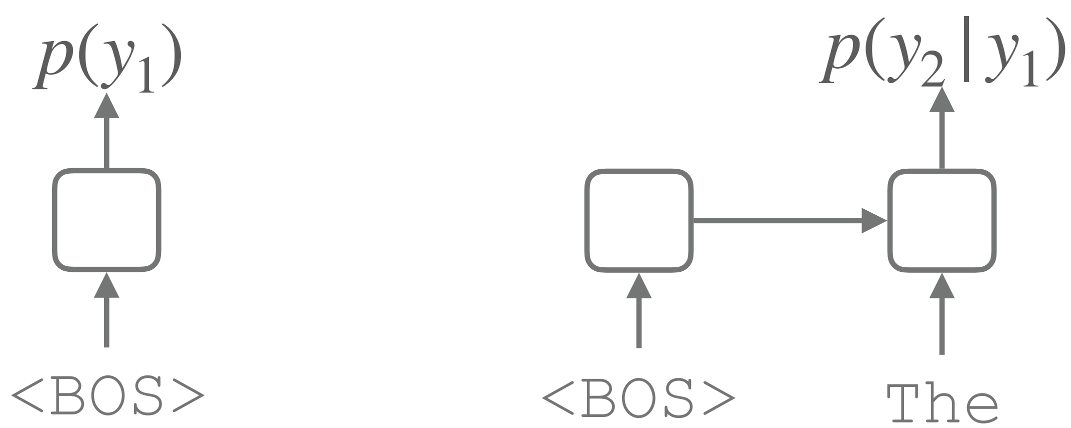

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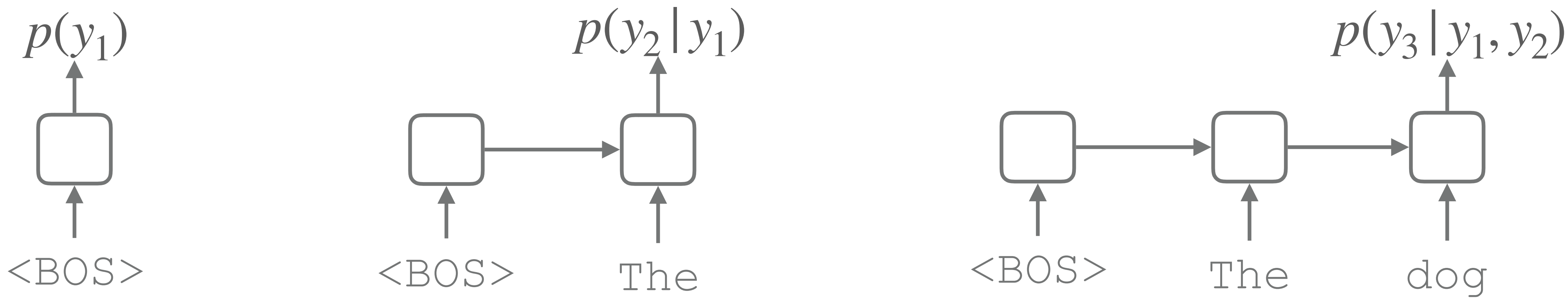

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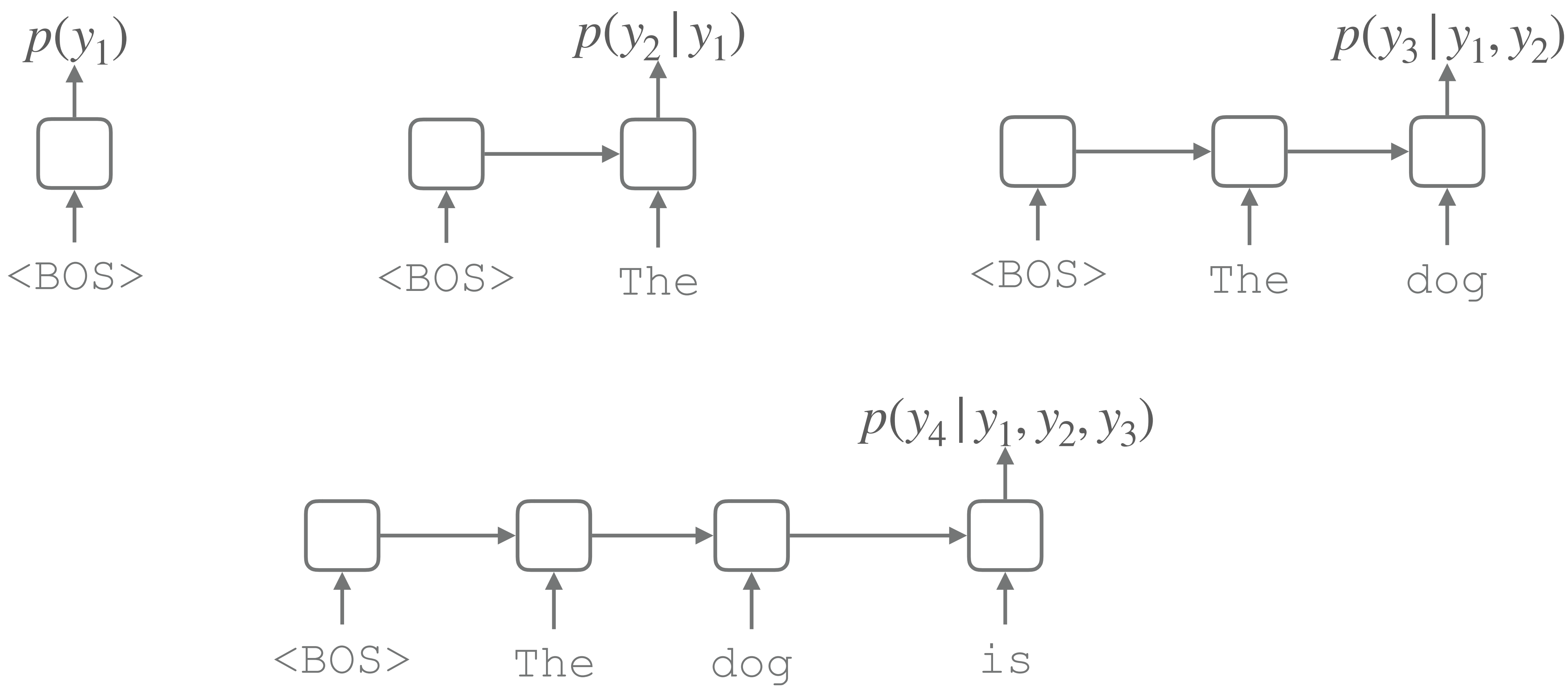

SENTENCE CLASSIFICATION

Neural architecture

1. A recurrent neural network (RNN) compute a context sensitive representation of the sentence

2. A multi-layer perceptron takes as input this representation and output class weights

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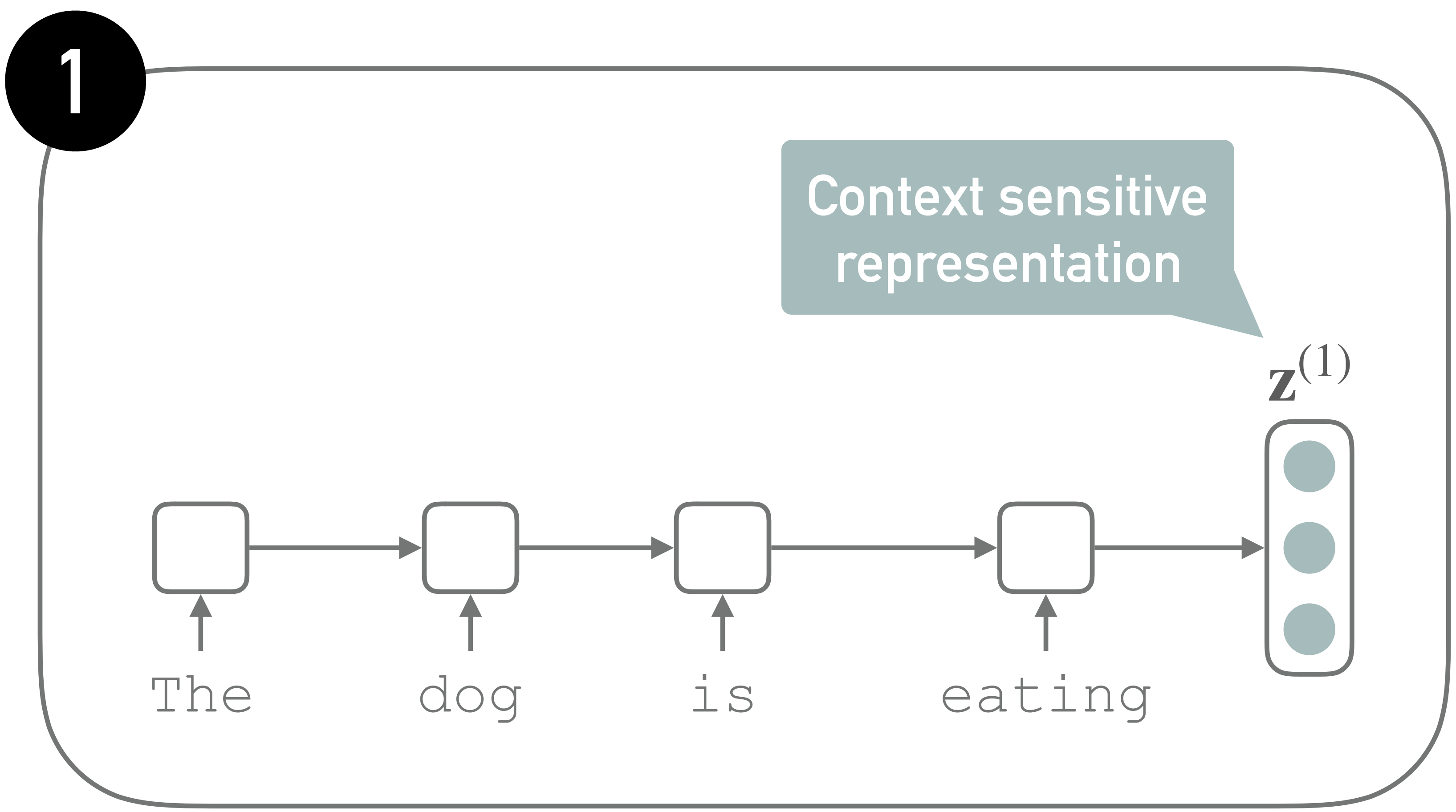

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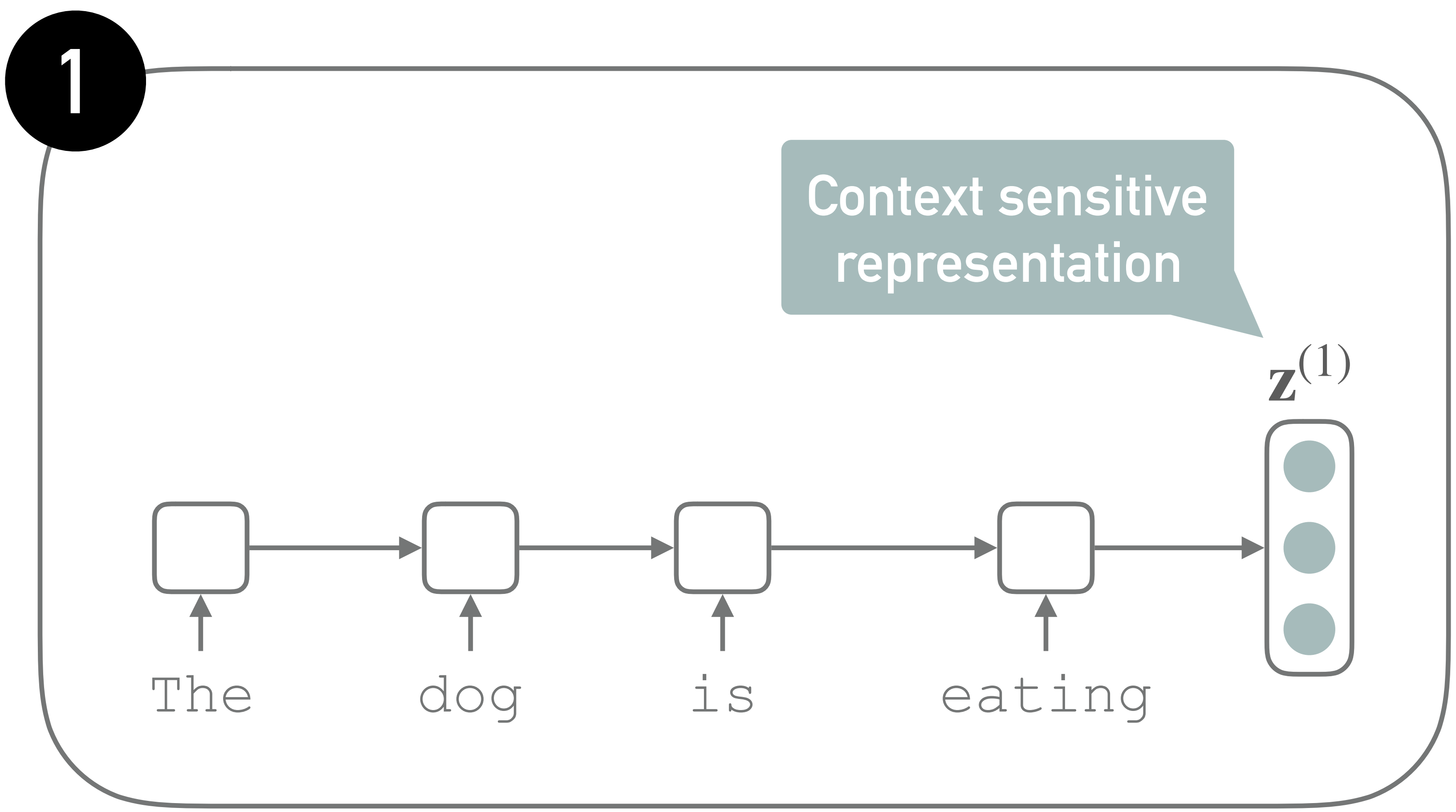

2

MLP hidden layer

$$\mathbf{z}^{(2)} = \sigma\left(\mathbf{U}^{(1)}\mathbf{z}^{(1)} + \mathbf{b}^{(1)}\right)$$

$$\mathbf{w} = \mathbf{U}^{(2)}\mathbf{z}^{(2)} + \mathbf{b}^{(2)}$$

Output weights

MACHINE TRANSLATION

Neural architecture: Encoder-Decoder

1. **Encoder:** a recurrent neural network (RNN) compute a context sensitive representation of the sentence

2. **Decoder:** a different recurrent neural network (RNN) compute the translation, word after word

Conditional language model

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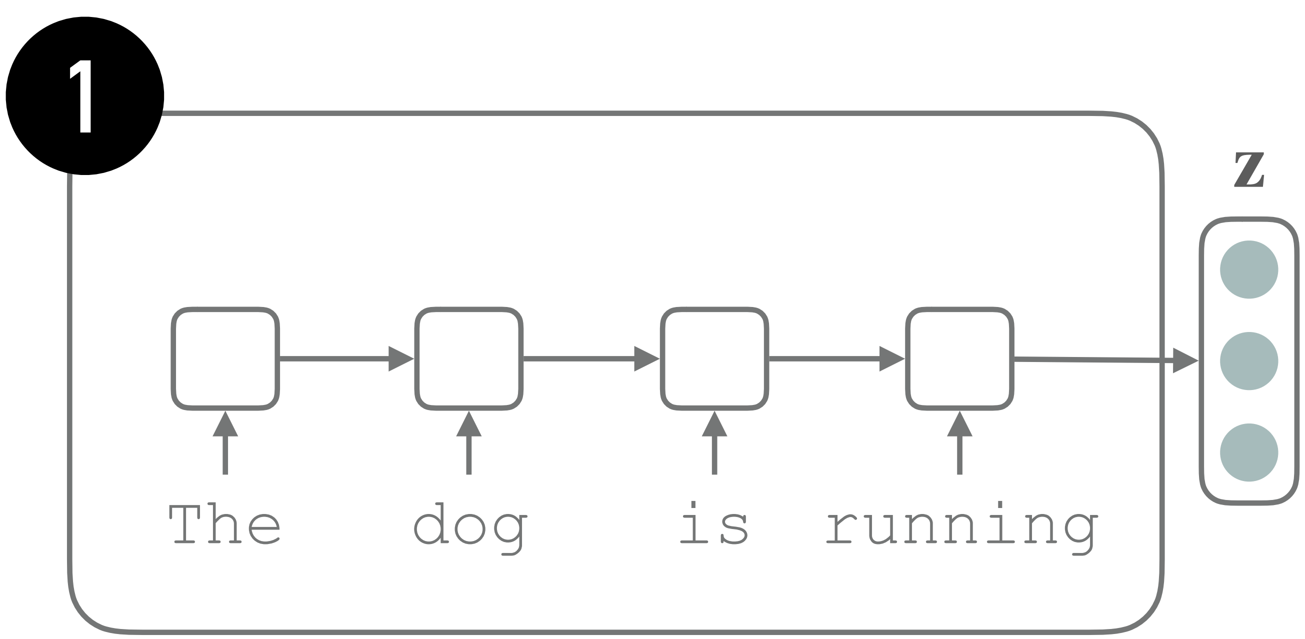

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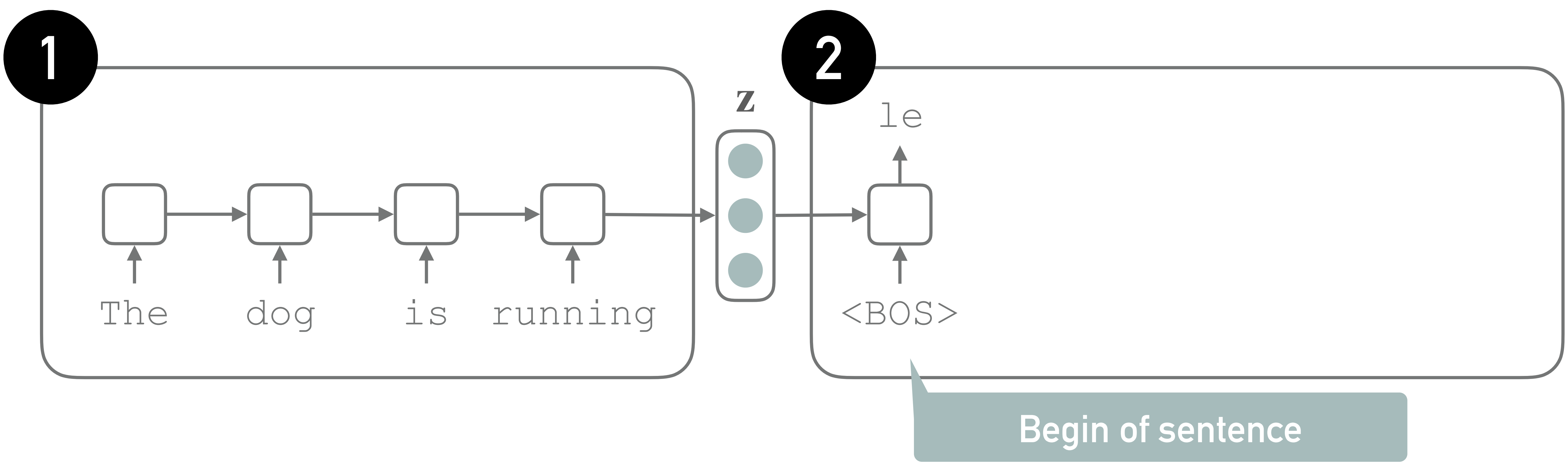

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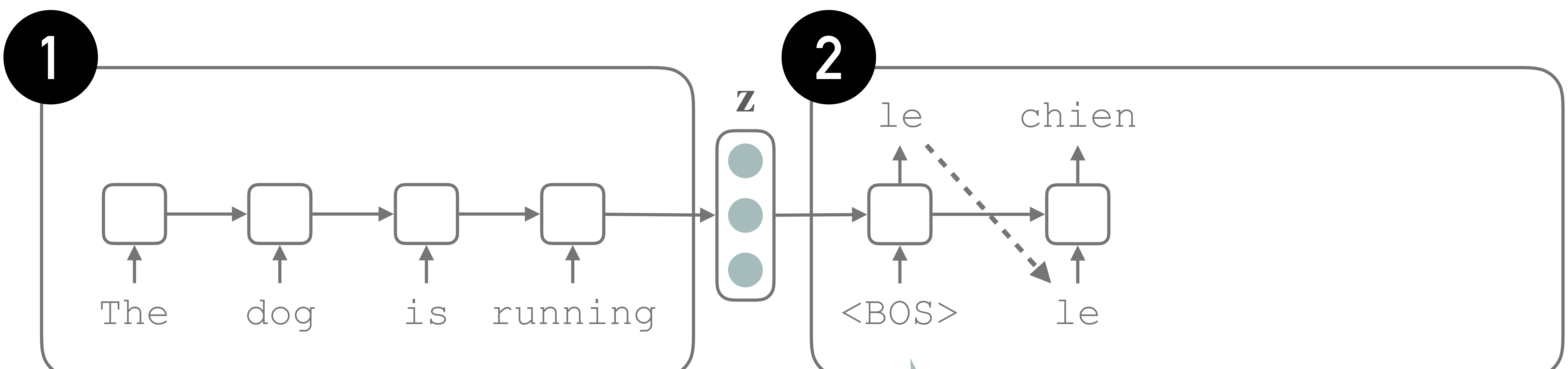

Begin of sentence

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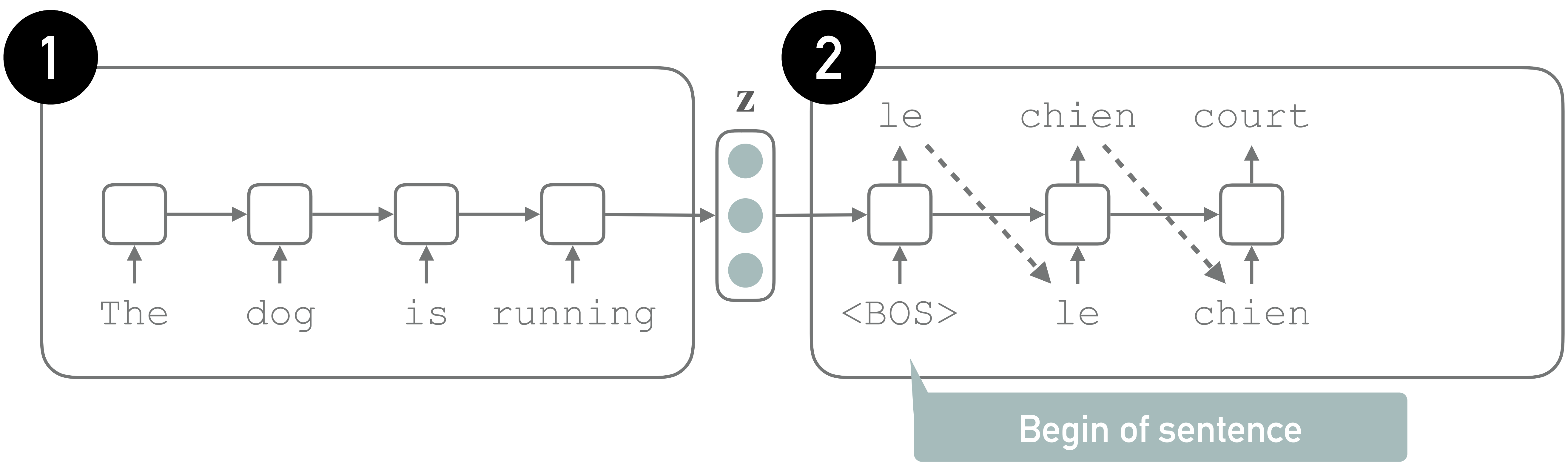

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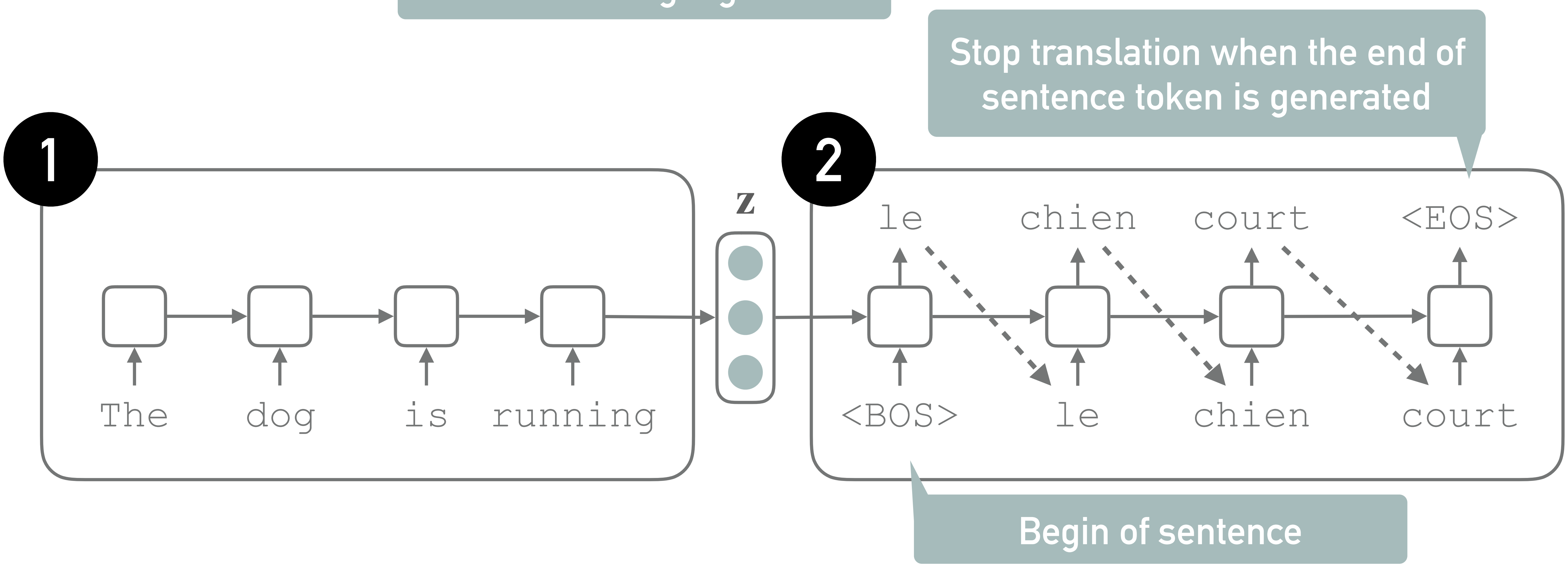


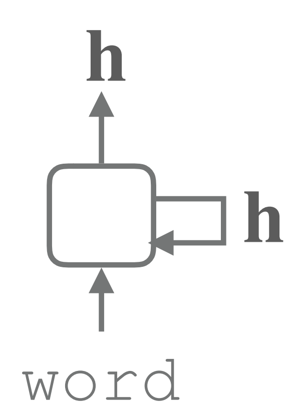
SIMPLE RECURRENT NEURAL NETWORK

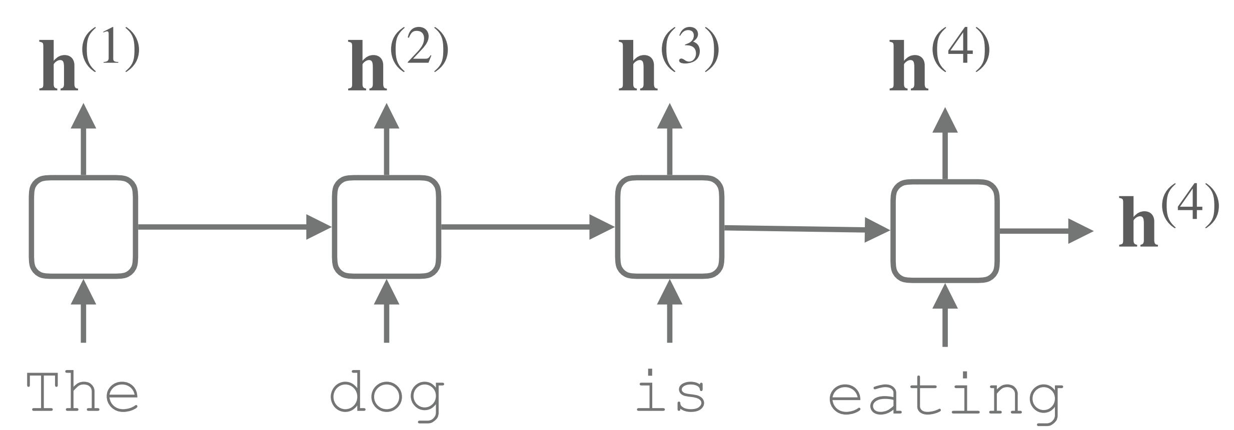
MULTI-LAYER PERCEPTRON RECURRENT NETWORK

Multi-linear perceptron cell

- Input: the current word and the previous output
- Output: the hidden representation

The recurrent connection is juste the output at each position



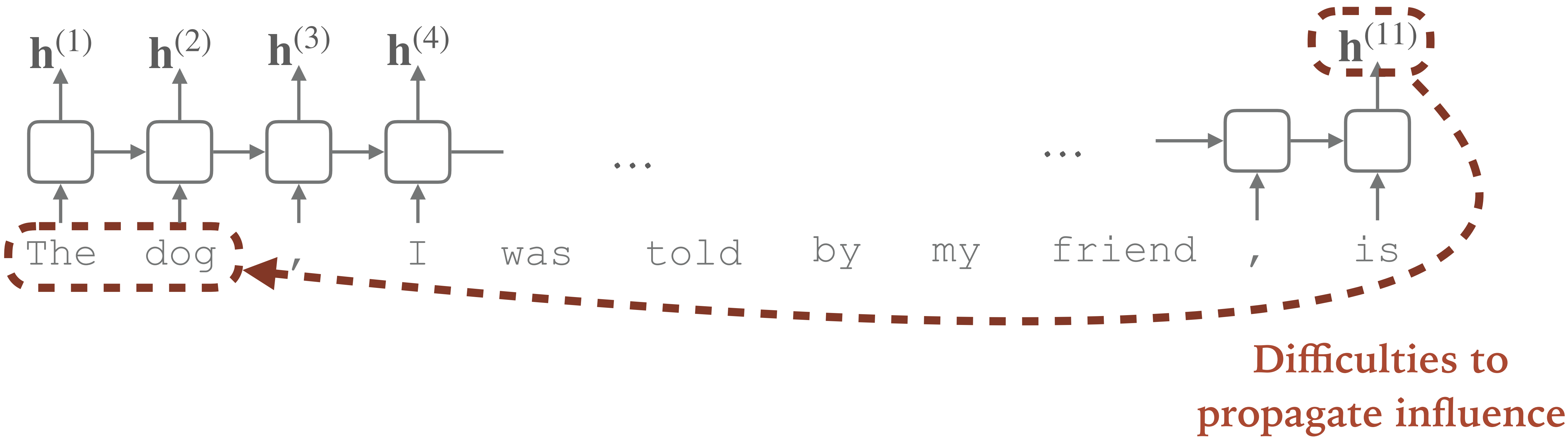


$$\mathbf{h}^{(n)} = \tanh\left(\mathbf{U}\begin{bmatrix}\mathbf{x}^{(n)}\\ \mathbf{h}^{(n-1)}\end{bmatrix} + \mathbf{b}\right)$$

GRADIENT BASED LEARNING PROBLEM

Does it work?

- In theory: yes
- In practice: no, gradient based learning of RNN fail to learn long range dependencies!



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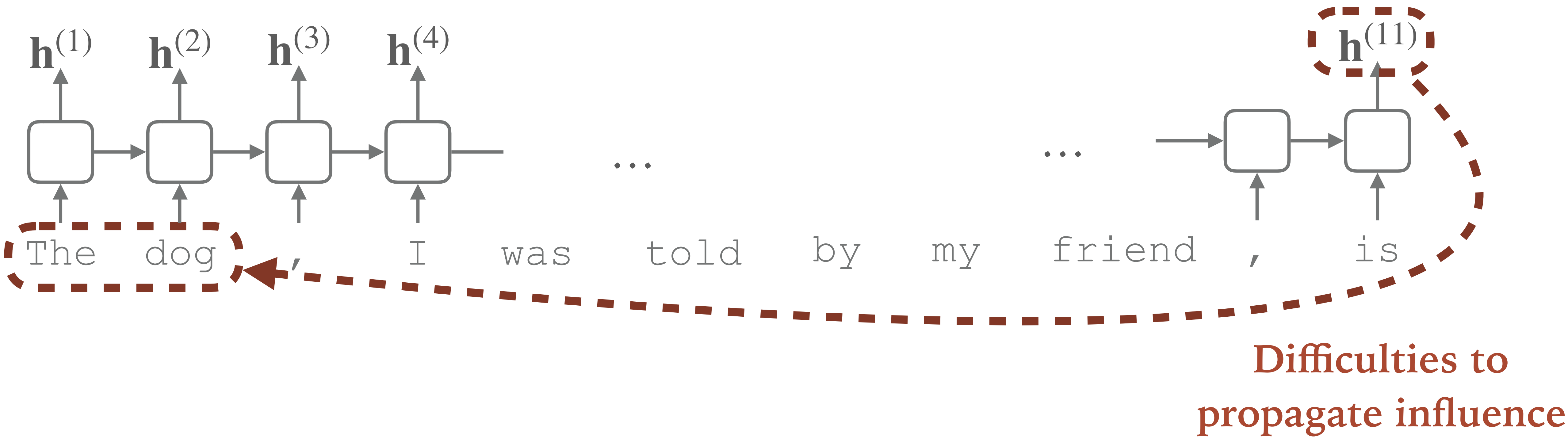


Deep learning is not a « single tool fits all problem » solution

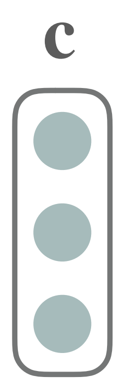
- You need to understand your data and prediction task
- You need to understand why a given neural architecture may fail for a given task
- You need to be able design tailored neural architectures for a given task

LONG SHORT-TERM MEMORY NETWORKS

LONG SHORT-TERM MEMORY NETWORKS (LSTM)

Intuition

Memory vector

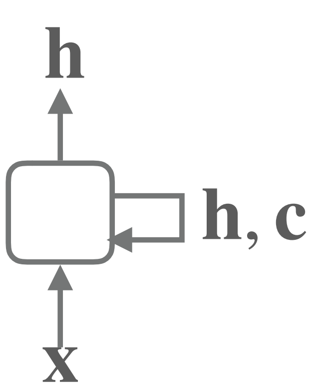


- Memory vector which is passed along the sequence
- At each time step, the network selects which cell of the memory to modify

The network can learn to keep track of long distance relationships

LSTM cell

- The recurrent connection pass the memory vector to the next cell



ERASING/WRITING VALUES IN A VECTOR

Erasing values in the memory

$$\begin{bmatrix} 3.02 \\ -4.11 \\ 21.00 \\ 4.44 \\ -6.9 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 \\ 0 \\ 21.00 \\ 4.44 \\ -6.9 \end{bmatrix}$$

« Forget » the first two cells

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Writing values in the memory

$$\begin{bmatrix} 0 \\ 0 \\ 21.00 \\ 4.44 \\ -6.9 \end{bmatrix} + \begin{bmatrix} 10.0 \\ 5.0 \\ 1.0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 10.0 \\ 5.0 \\ 22.00 \\ 4.44 \\ -6.9 \end{bmatrix}$$

Memory after update

Memory before update

Update

GATE MECHANISM

Erasing values in a vector

Not necessarily c, it can depends on anything

Let assume we want to remove some values from a vector $\mathbf{c}$:

1. A simple linear classifier compute the importance of each value in $\mathbf{c}$: $\mathbf{w} = \mathbf{U}\mathbf{c} + \mathbf{b}$
2. We erase non important value, i.e. values with a negative weight in $\mathbf{w}$

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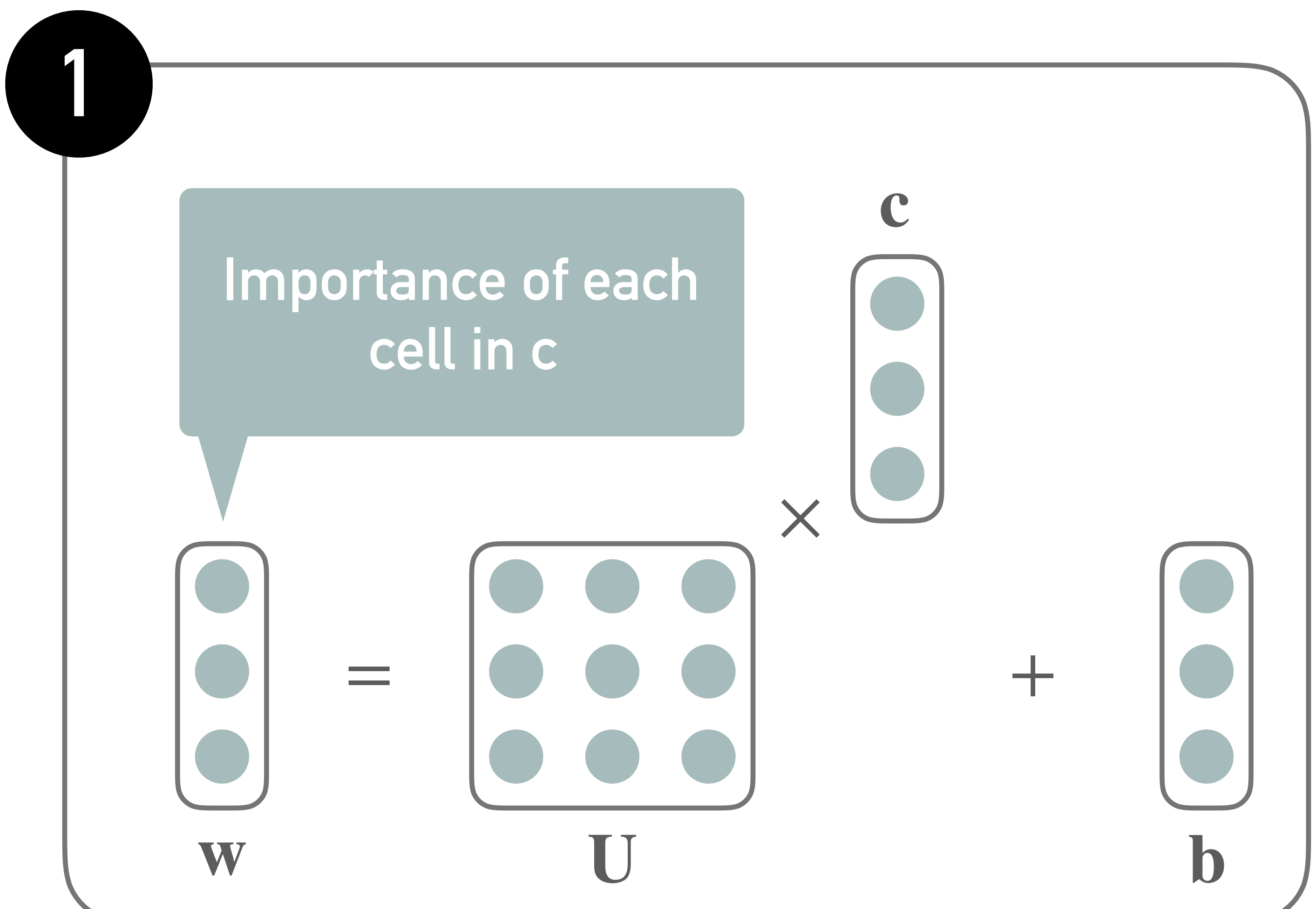

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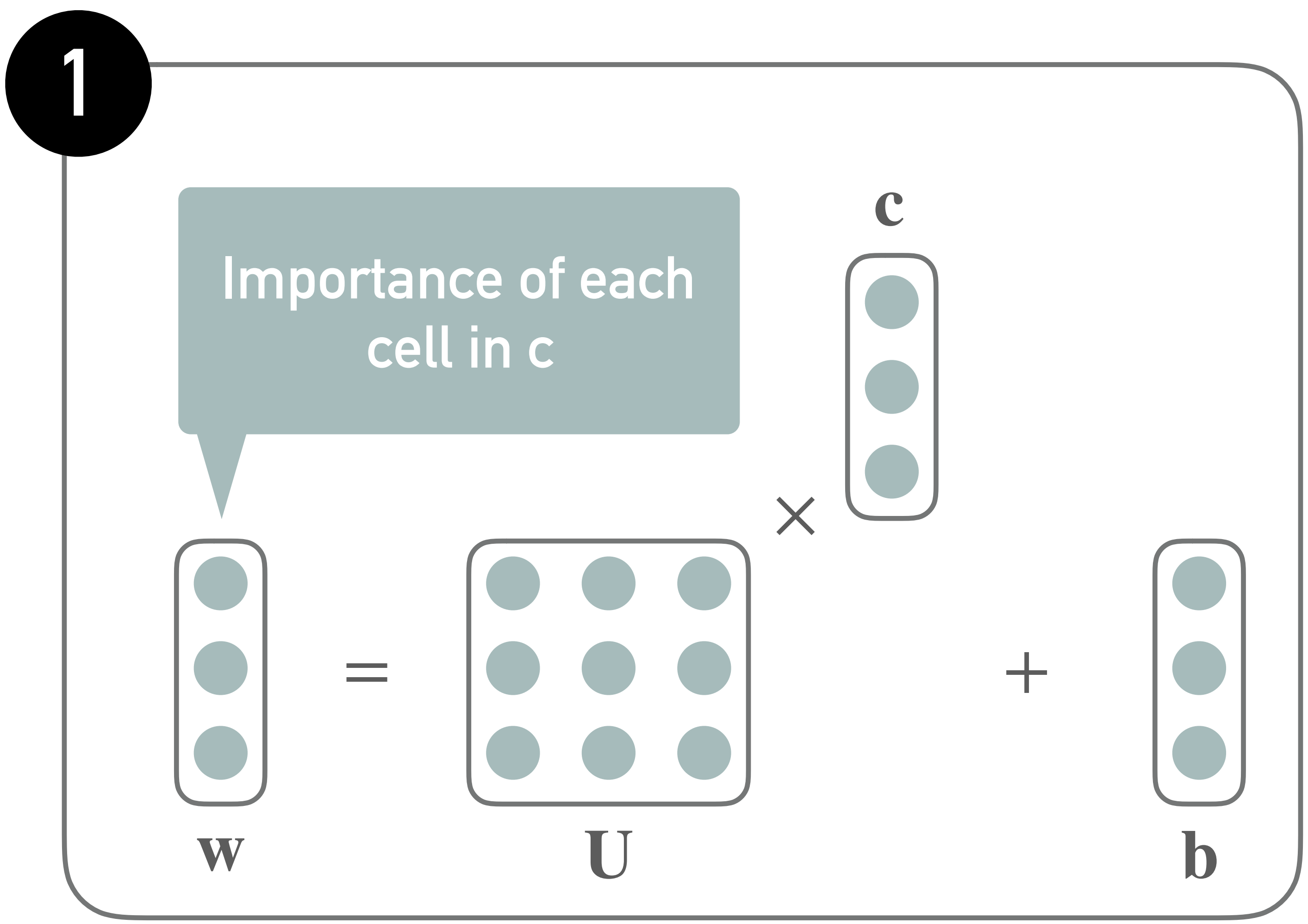

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$$\mathbf{c}'_i = \begin{cases} \mathbf{c}_i \; if \; \mathbf{w}_i > 0, \\ 0 \; otherwise \end{cases}$$

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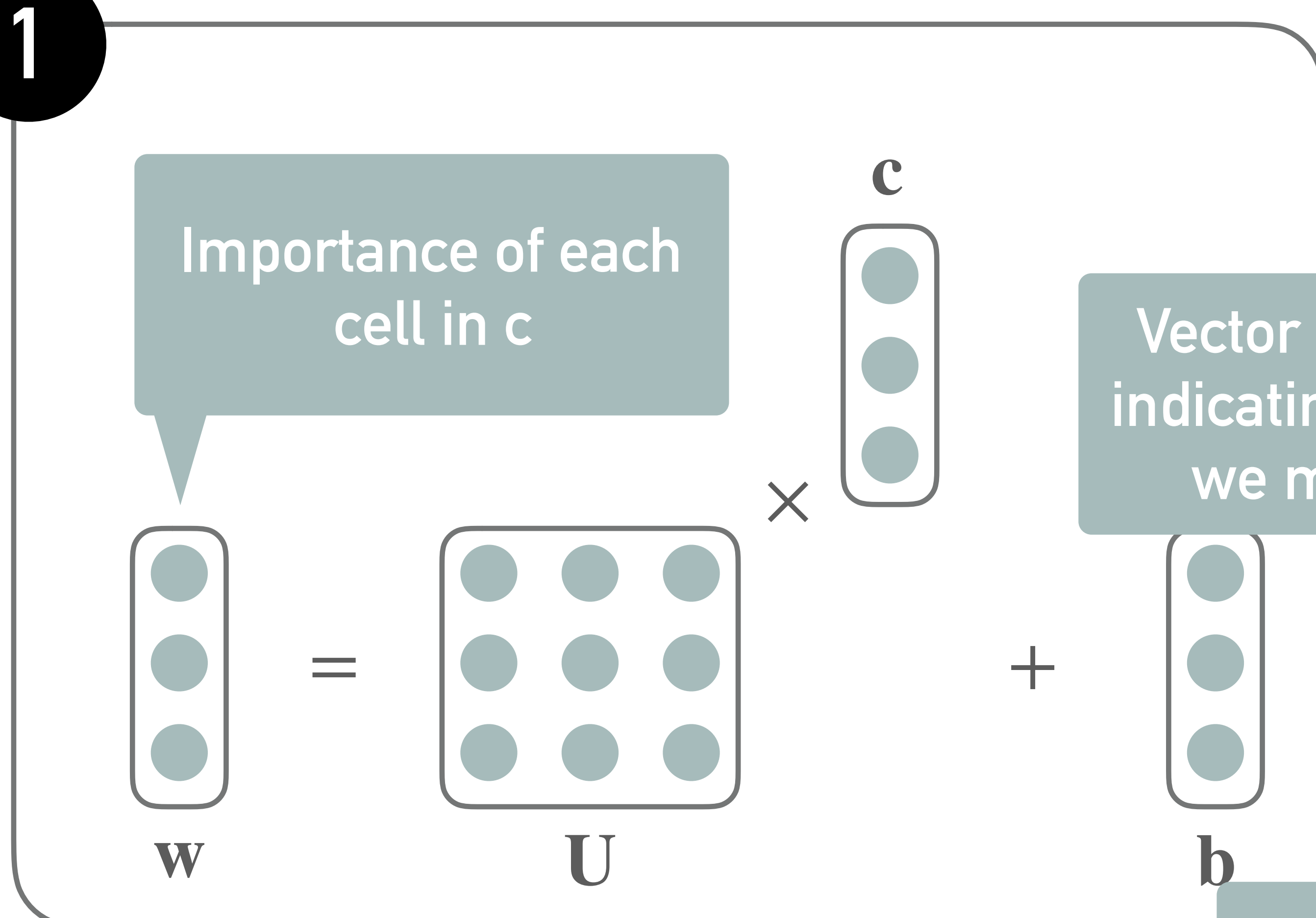

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$$\mathbf{c}'_i = \begin{cases} \mathbf{c}_i \; if \; \mathbf{w}_i > 0, \\ 0 \; otherwise \end{cases}$$

OR

$$\mathbf{b}_i = \begin{cases} 1 \; if \; \mathbf{w}_i > 0, \\ 0 \; otherwise \end{cases}$$

$$\mathbf{c}' = \mathbf{c} \odot \mathbf{b}$$

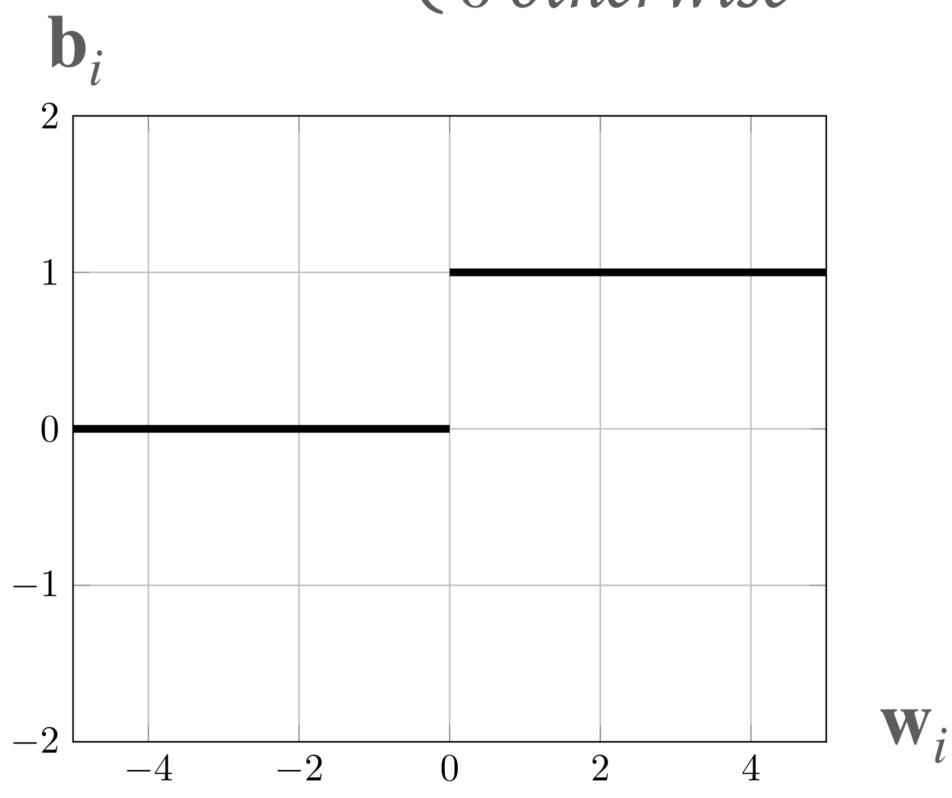
Element-wise multiplication

CELL SELECTION AND BACKPROPAGATION?

Forward pass

$$\mathbf{w} = \mathbf{U}\mathbf{c} + \mathbf{b}$$

$$\mathbf{b}_i = \begin{cases} 1 \ \textit{if} \ \mathbf{w}_i > 0, \\ 0 \ \textit{otherwise} \end{cases}$$



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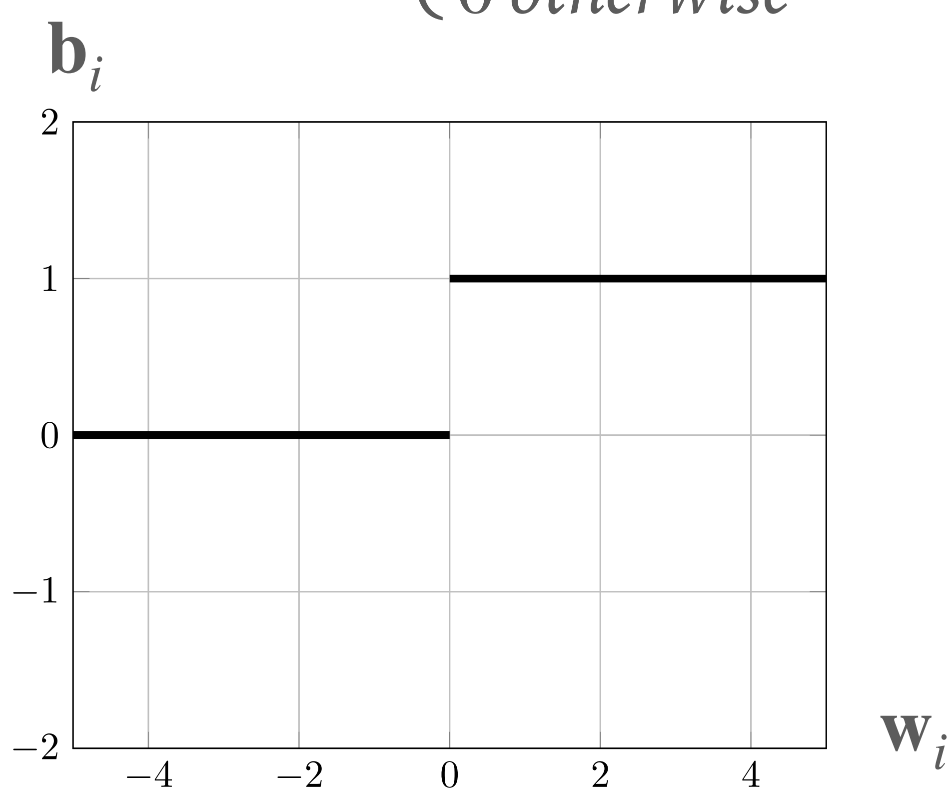

Backward pass

Gradient wrt the loss

By the chain rule: $$\frac{\partial \mathscr{L}}{\partial \mathbf{w}_i} = \frac{\partial \mathscr{L}}{\partial \mathbf{b}_i} \cdot \frac{\partial \mathbf{b}_i}{\partial \mathbf{w}_i} + \ldots$$

What does this term look like?

CELL SELECTION AND BACKPROPAGATION?

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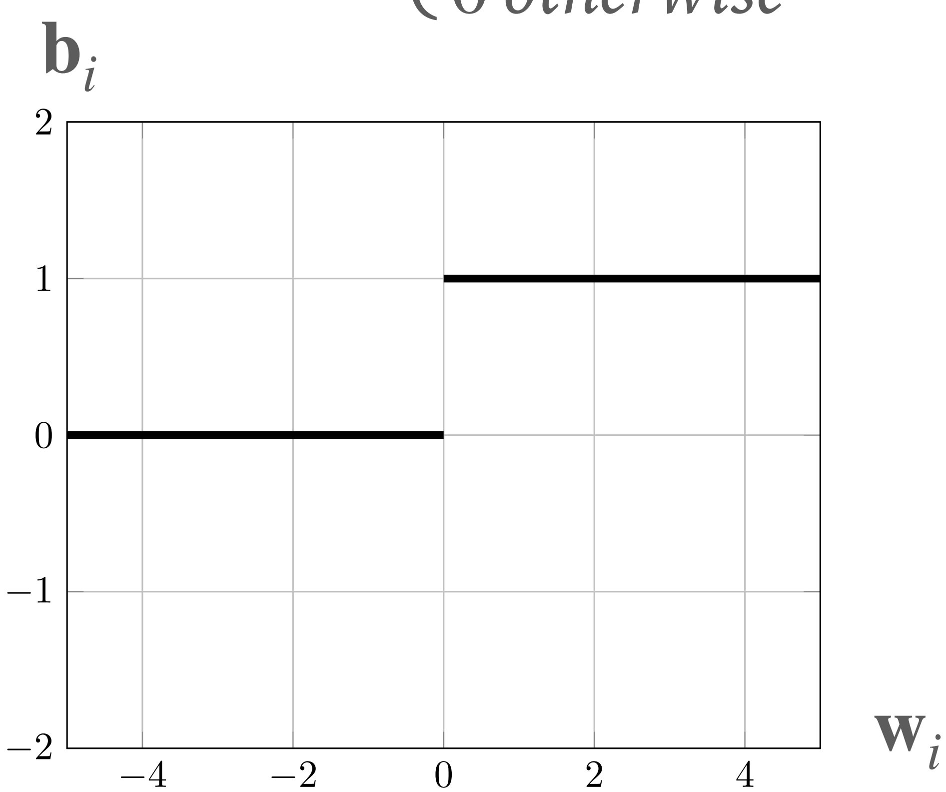

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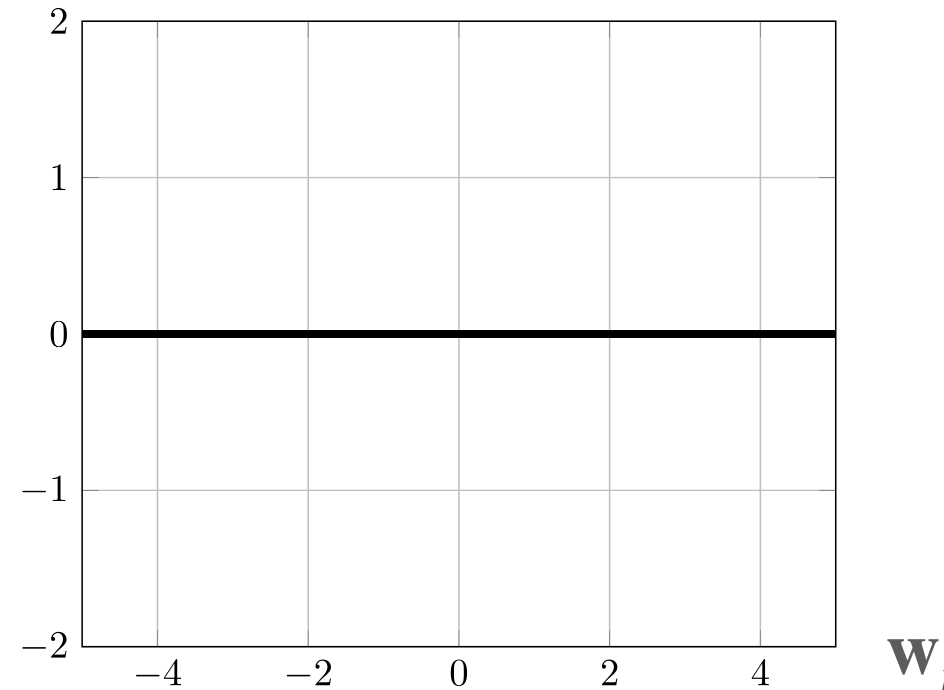

! Gradient is blocked!
No information is back propagated!

SMOOTH SELECTION 1/2

Equivalent formulation as a small optimization problem

$$\mathbf{b}_i = \begin{cases} 1 \; \mathit{if} \; \mathbf{w}_i > 0, \\ 0 \; \mathit{otherwise} \end{cases}$$

OR

$$\begin{aligned} \mathbf{b}_i = \operatorname{argmax}_{\mathbf{y}_i} \quad & \mathbf{y}_i \times \mathbf{w}_i \\ s.t. \quad & \mathbf{y}_i \leq 1 \\ & \mathbf{y}_i \geq 0 \end{aligned}$$

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Intuition

- At the optimal solution, one of the <u>**constraint is tight**</u>
  => small perturbation on $\mathbf{w}_i$ will not change the solution
- We can introduce a <u>**penalty in the objective**</u> so that <u>**constraints are never tight**</u> at the optimal solution

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$$\begin{aligned} \mathbf{b}_i = \operatorname{argmax}_{\mathbf{y}_i} \quad & \mathbf{y}_i \times \mathbf{w}_i - \Omega(\mathbf{y}_i) \\ s.t. \quad & \mathbf{y}_i \leq 1 \\ & \mathbf{y}_i \geq 0 \end{aligned}$$

Strong convex regularizer

SMOOTH SELECTION 1/2

$$\mathbf{b}_i = \text{argmax}_{\mathbf{y}_i} \quad \mathbf{y}_i \times \mathbf{w}_i - \Omega(\mathbf{y}_i)$$
$$s.t. \quad \mathbf{y}_i \leq 1$$
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How to choose the convex regularizer?

- We need to solve the program quickly
- We need to be able to back propagate easily
- Several solutions
  (i.e. similar to interior point method)

SMOOTH SELECTION 1/2

$$\mathbf{b}_i = \operatorname{argmax}_{\mathbf{y}_i} \quad \mathbf{y}_i \times \mathbf{w}_i - \Omega(\mathbf{y}_i)$$
$$s.t. \quad \mathbf{y}_i \leq 1$$
$$\mathbf{y}_i \geq 0$$

How to choose the convex regularizer?

- We need to solve the program quickly
- We need to be able to back propagate easily
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Negative Fermi-Dirac entropy

$$\mathbf{b}_i = \operatorname{argmax}_{\mathbf{y}_i} \quad \mathbf{y}_i \times \mathbf{w}_i - \mathbf{y}_i \log \mathbf{y}_i - (1 - \mathbf{y}_i)\log(1 - \mathbf{y}_i)$$
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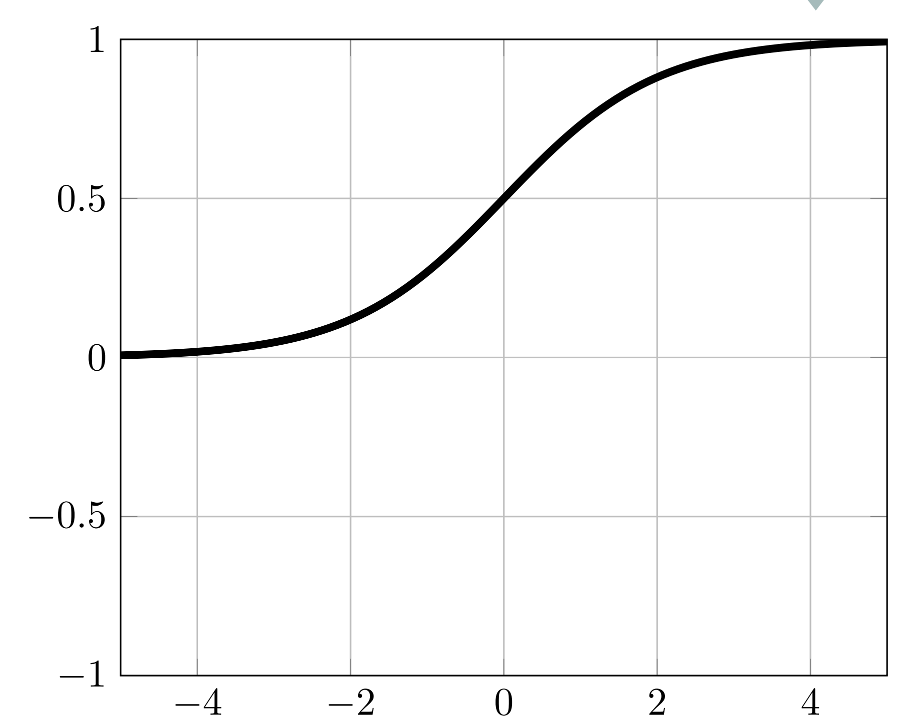
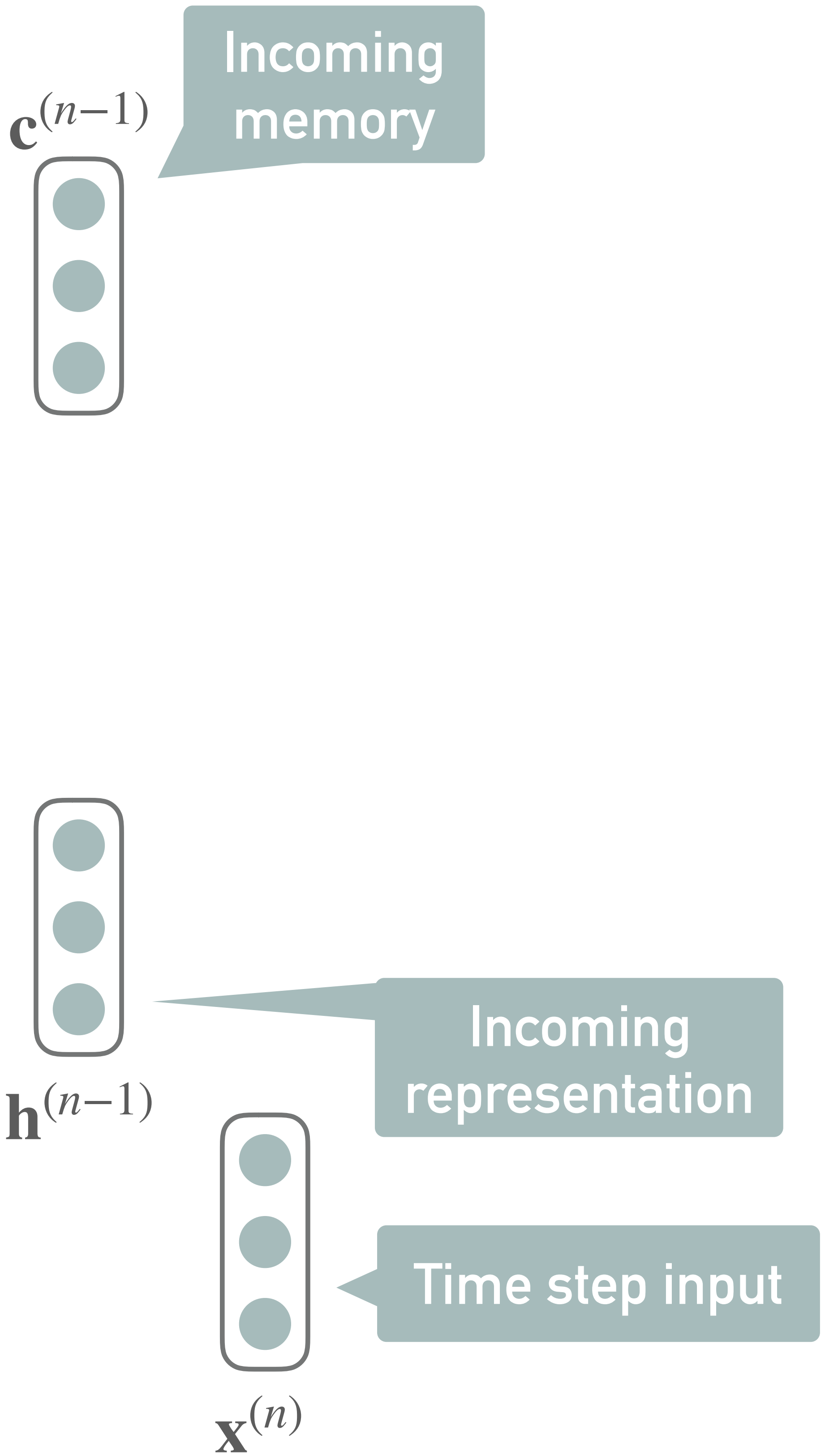
This is actually the sigmoid
(solve the KKT condition to see that)

$$\mathbf{b}_i = \frac{1}{(1 + exp(-\mathbf{w}_i))} = \sigma(\mathbf{w}_i)$$

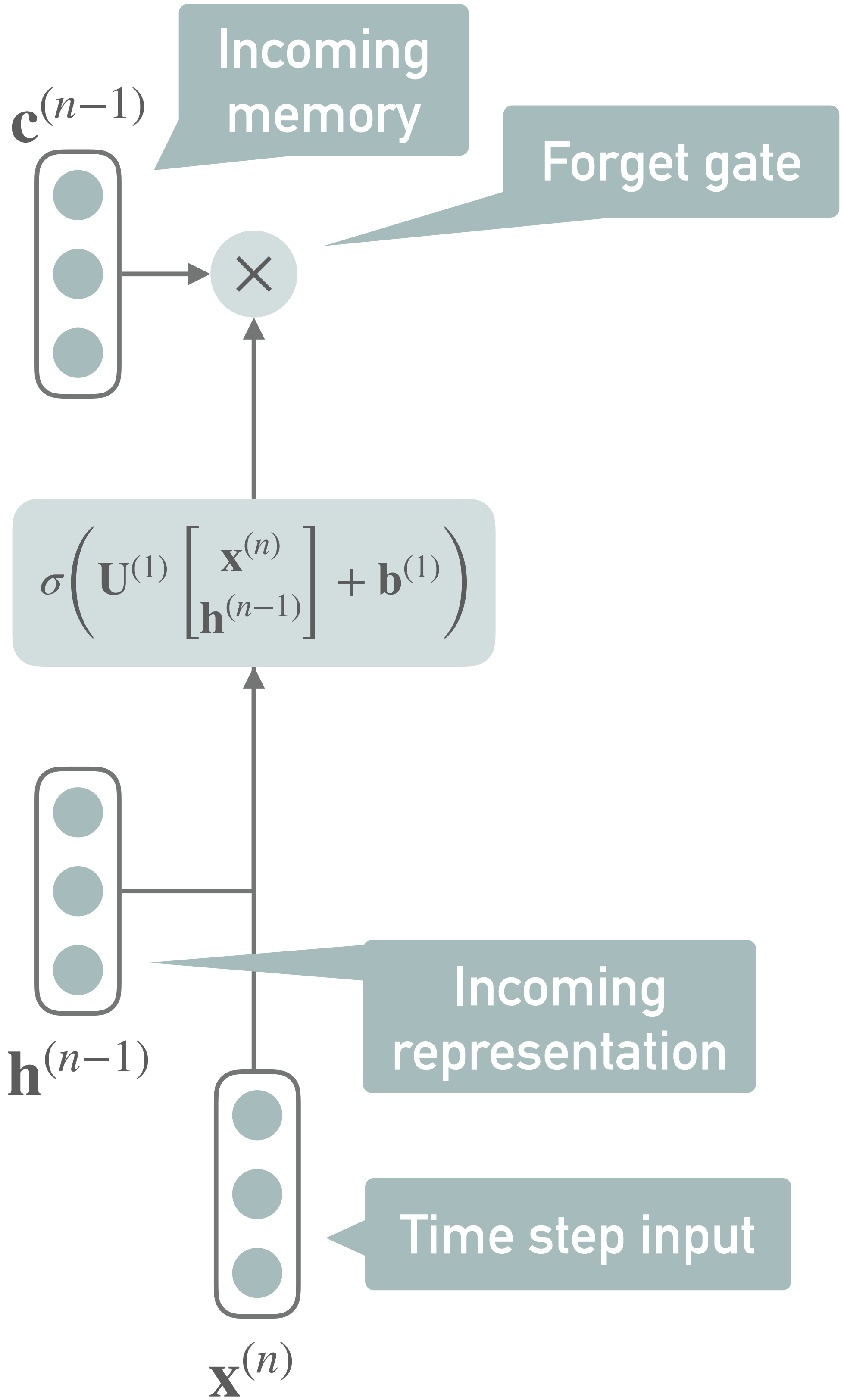
Smooth and differentiable approximation! :)



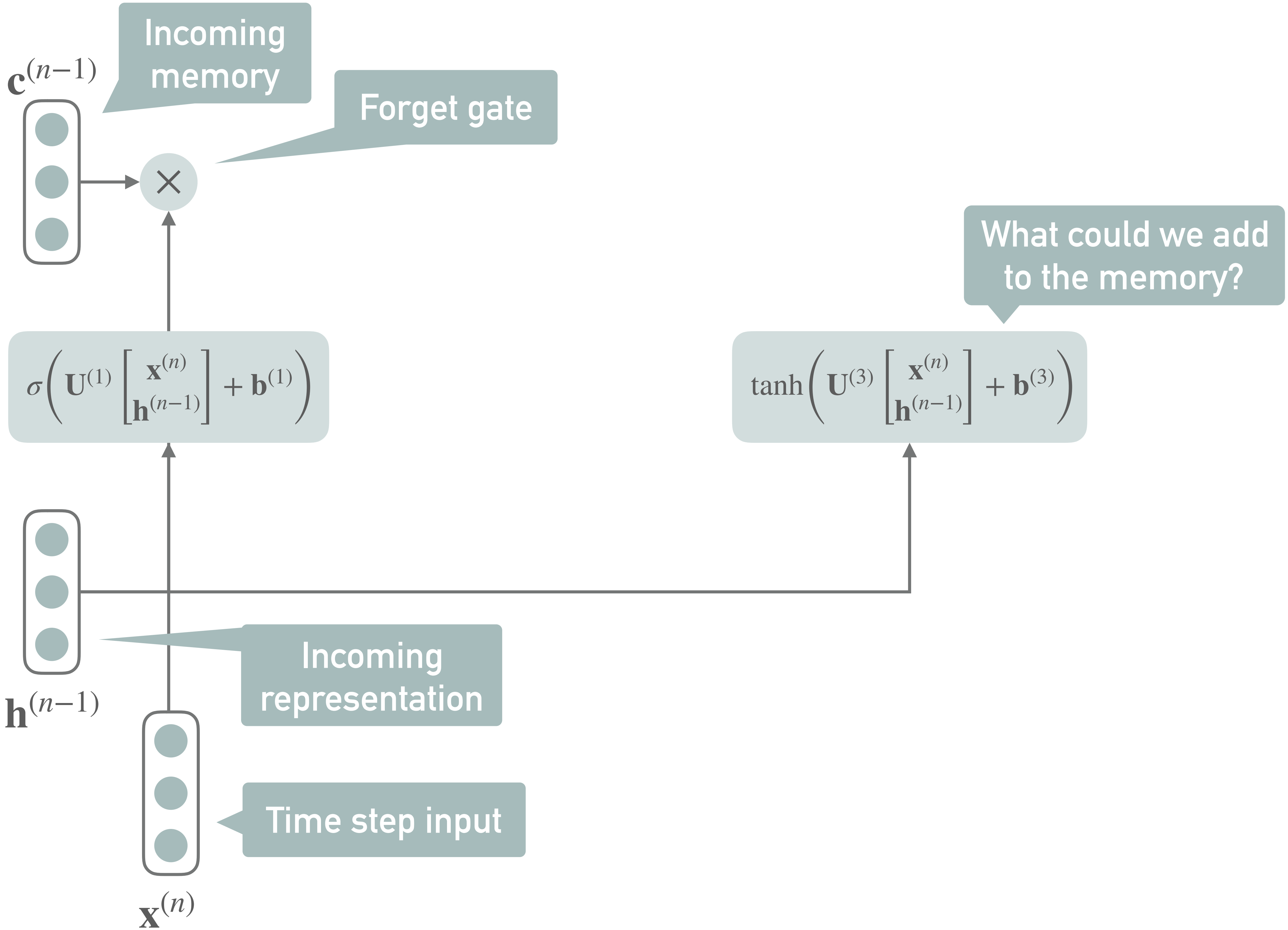
LSTM CELL 1/2


$\mathbf{c}^{(n-1)}$
Incoming memory
Incoming representation
$\mathbf{h}^{(n-1)}$
Time step input
$\mathbf{x}^{(n)}$

LSTM CELL 1/2


Incoming memory
$\mathbf{c}^{(n-1)}$
Forget gate
$\sigma\left(\mathbf{U}^{(1)}\begin{bmatrix}\mathbf{x}^{(n)}\\ \mathbf{h}^{(n-1)}\end{bmatrix}+\mathbf{b}^{(1)}\right)$
Incoming representation
$\mathbf{h}^{(n-1)}$
Time step input
$\mathbf{x}^{(n)}$

LSTM CELL 1/2



$\mathbf{c}^{(n-1)}$
Incoming memory
Forget gate
$\times$
What could we add to the memory?
$\sigma\left(\mathbf{U}^{(1)}\begin{bmatrix}\mathbf{x}^{(n)}\\\mathbf{h}^{(n-1)}\end{bmatrix}+\mathbf{b}^{(1)}\right)$
$\tanh\left(\mathbf{U}^{(3)}\begin{bmatrix}\mathbf{x}^{(n)}\\\mathbf{h}^{(n-1)}\end{bmatrix}+\mathbf{b}^{(3)}\right)$
Incoming representation
$\mathbf{h}^{(n-1)}$
Time step input
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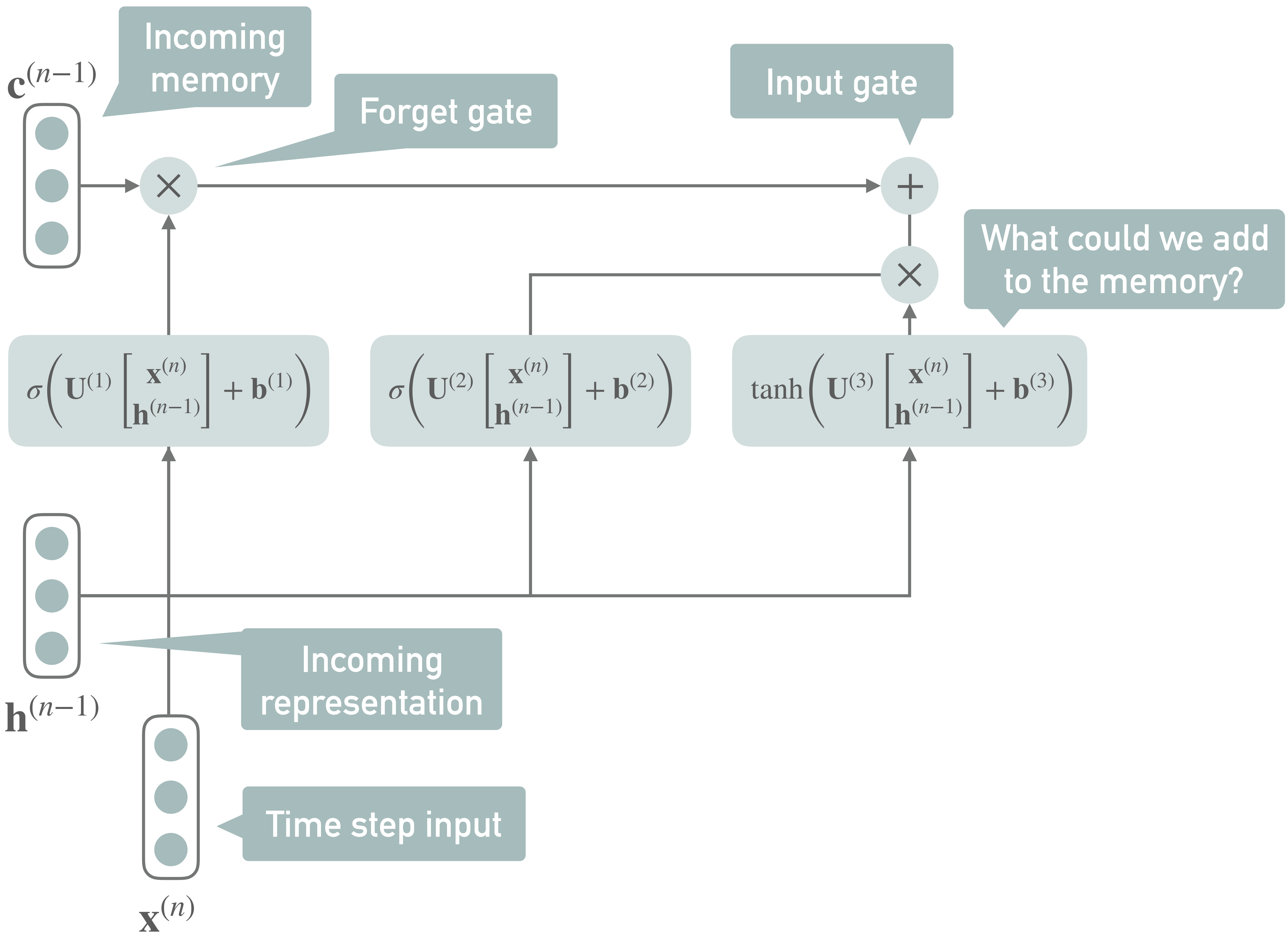
LSTM CELL 1/2



$\mathbf{c}^{(n-1)}$
Incoming memory
Forget gate
Input gate
What could we add to the memory?
$\sigma\left(\mathbf{U}^{(1)}\begin{bmatrix}\mathbf{x}^{(n)}\\ \mathbf{h}^{(n-1)}\end{bmatrix}+\mathbf{b}^{(1)}\right)$
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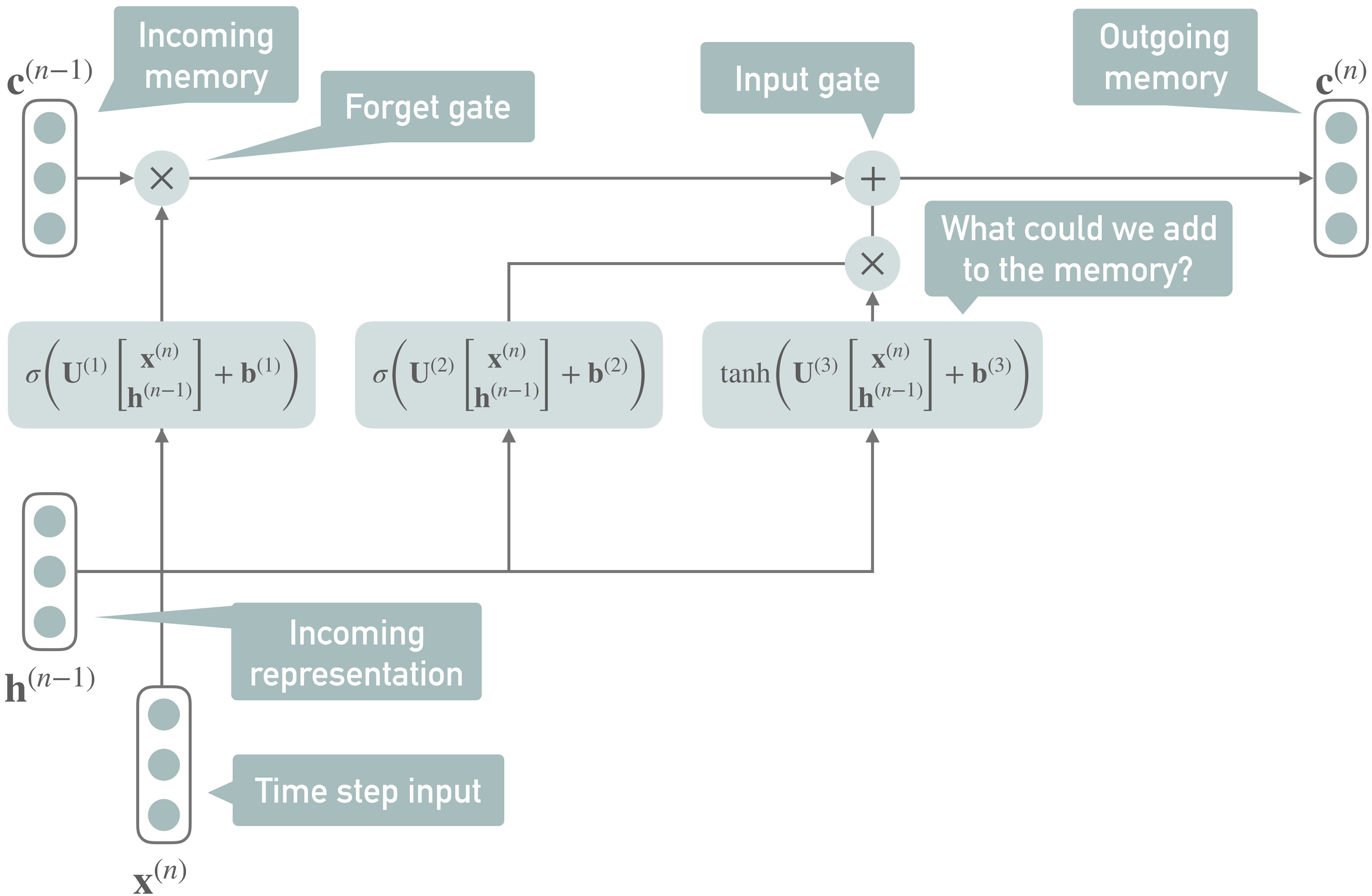
LSTM CELL 1/2



Incoming memory
Forget gate
Input gate
Outgoing memory
What could we add to the memory?
Incoming representation
Time step input
$\mathbf{c}^{(n-1)}$
$\mathbf{c}^{(n)}$
$\mathbf{h}^{(n-1)}$
$\mathbf{x}^{(n)}$
$\sigma\left(\mathbf{U}^{(1)}\begin{bmatrix}\mathbf{x}^{(n)}\\ \mathbf{h}^{(n-1)}\end{bmatrix}+\mathbf{b}^{(1)}\right)$
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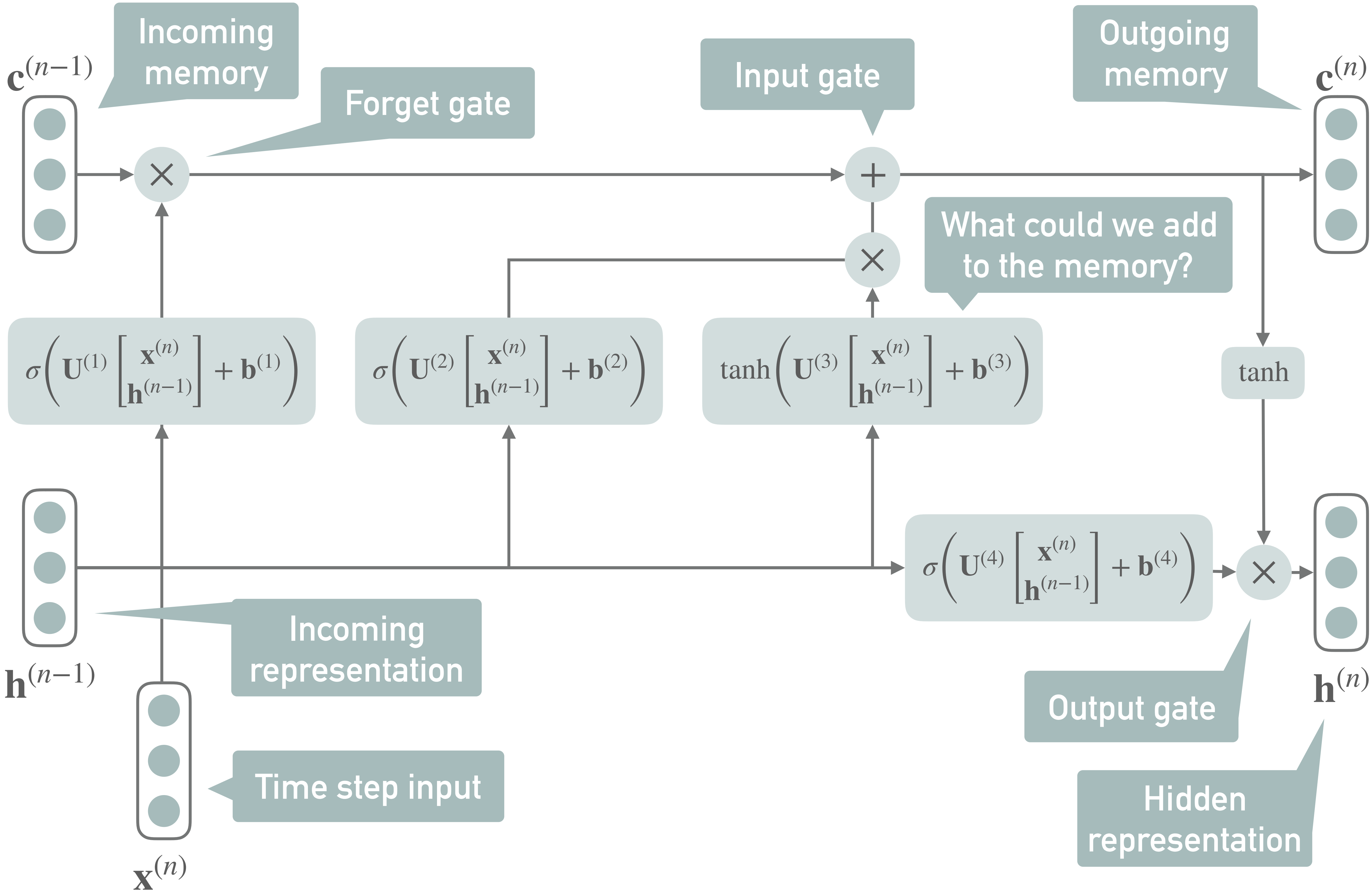
LSTM CELL 1/2



$\mathbf{c}^{(n-1)}$
Incoming memory
Forget gate
Input gate
Outgoing memory
$\mathbf{c}^{(n)}$
What could we add to the memory?
$\sigma\left(\mathbf{U}^{(1)}\begin{bmatrix}\mathbf{x}^{(n)}\\\mathbf{h}^{(n-1)}\end{bmatrix}+\mathbf{b}^{(1)}\right)$
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tanh
$\sigma\left(\mathbf{U}^{(4)}\begin{bmatrix}\mathbf{x}^{(n)}\\\mathbf{h}^{(n-1)}\end{bmatrix}+\mathbf{b}^{(4)}\right)$
Incoming representation
$\mathbf{h}^{(n-1)}$
Output gate
$\mathbf{h}^{(n)}$
Time step input
$\mathbf{x}^{(n)}$
Hidden representation

LSTM CELL 2/2

Gates

$$\mathbf{f}^{(n)} = \sigma\left(\mathrm{U}^{(1)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(1)}\right)$$

$$\mathbf{i}^{(n)} = \sigma\left(\mathrm{U}^{(2)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(2)}\right)$$

$$\mathbf{o}^{(n)} = \sigma\left(\mathrm{U}^{(4)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(4)}\right)$$

Outputs

$$\mathbf{c}^{(n)} = \underbrace{\mathbf{f}^{(n)} \times \mathbf{c}^{(n-1)}}_{\text{Erase memory}} + \underbrace{\mathbf{i}^{(n)} \times \tanh\left(\mathrm{U}^{(3)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(3)}\right)}_{\text{Update memory}}$$

$$\mathbf{h}^{(n)} = \mathbf{o}^{(n)} \times \tanh(\mathbf{c}^{(n)})$$

Compute output wrt memory

Number of parameters

4 times more parameters than a simple recurrent neural network!

LSTM VARIANT: COUPLED FORGET AND INPUT GATES

Intuition

- Tie forget and input gates
- Each memory cell is either kept as it or replaced by a new value

Gates

$$\mathbf{f}^{(n)} = \sigma\left(\mathbf{U}^{(1)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(1)}\right)$$

$$\boxed{\mathbf{i}^{(n)} = 1 - \mathbf{f}^{(n)}}$$

Input gate is tied to the forget gate

$$\mathbf{o}^{(n)} = \sigma\left(\mathbf{U}^{(4)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(4)}\right)$$

Outputs

$$\mathbf{c}^{(n)} = \boxed{\mathbf{f}^{(n)} \times \mathbf{c}^{(n-1)}} + \boxed{\mathbf{i}^{(n)} \times \tanh\left(\mathbf{U}^{(3)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(3)}\right)}$$

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LSTM VARIANT: PEEPHOLES

Intuition

- In standard LSTMs, gates **are not dependent** on the memory state
- In peephole LSTMs, gates **depend** on the memory

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Look memory content to choose which cell to change

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Look memory content to choose which cell to change

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Outputs

Unchanged

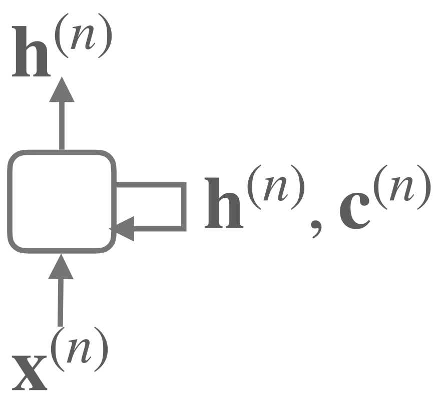
$$\mathbf{c}^{(n)} = \boxed{\mathbf{f}^{(n)} \times \mathbf{c}^{(n-1)}} + \boxed{\mathbf{i}^{(n)} \times \tanh\left(\mathbf{U}^{(3)} \begin{bmatrix} \mathbf{x}^{(n)} \\ \mathbf{h}^{(n-1)} \end{bmatrix} + \mathbf{b}^{(3)}\right)}$$

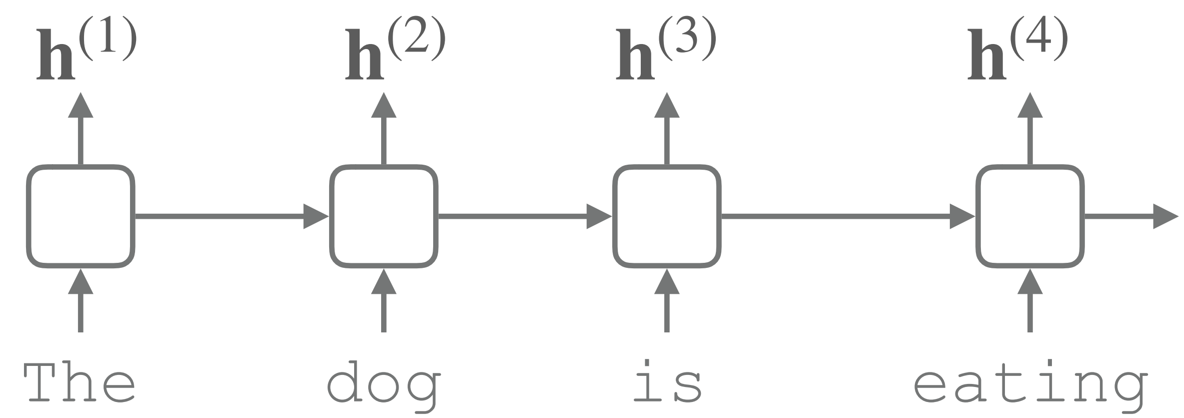
$$\mathbf{h}^{(n)} = \mathbf{o}^{(n)} \times \tanh(\mathbf{c}^{(n)})$$

RNN-BASED ARCHITECTURES

MULTI-LAYER RNN

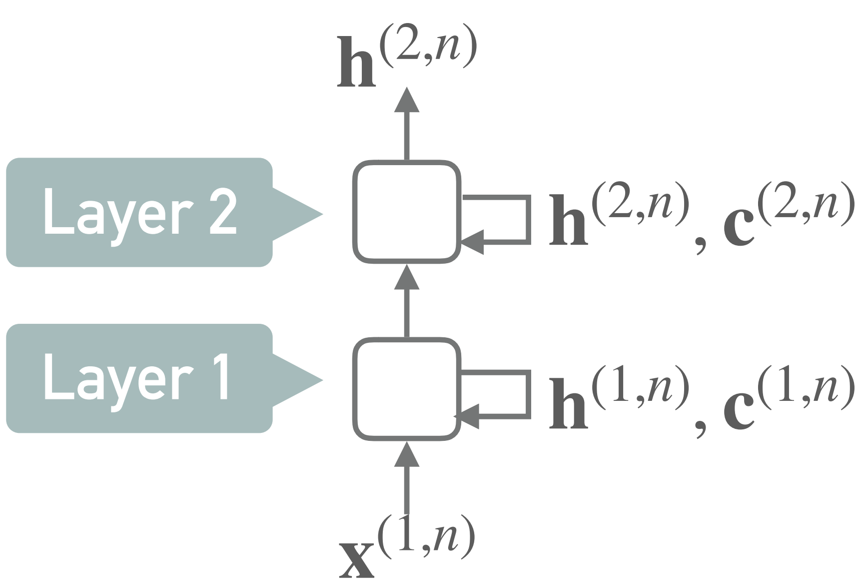
RNN with one layer

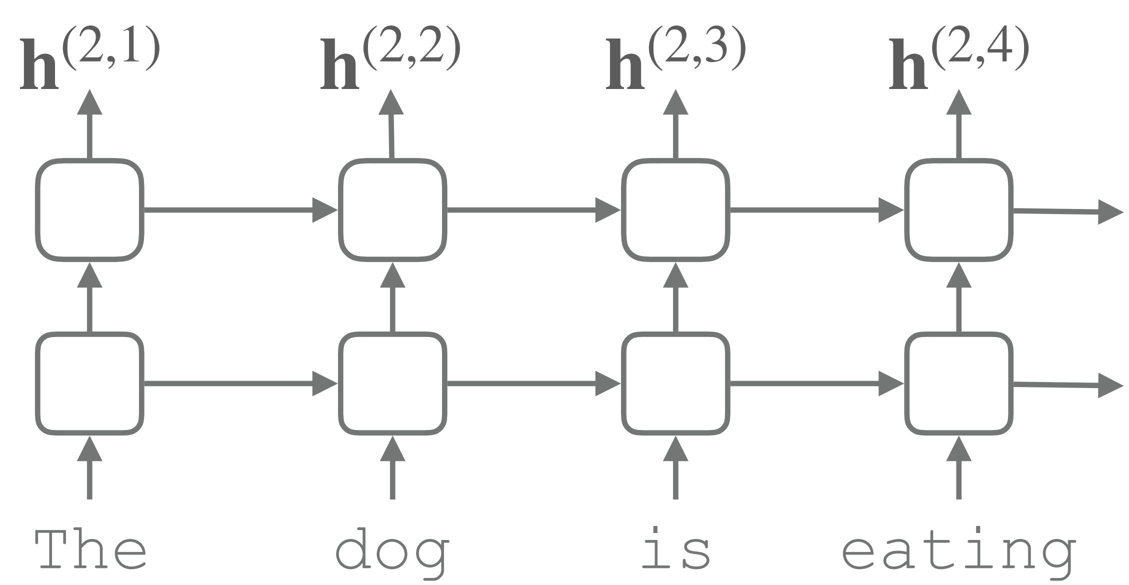




RNN with two layers

- Each layer as it own set of trainable parameters
- The recurrent connection is layer-dependent
- The input of layer n > 1 is the hidden representation at layer n





TAGGING WITH LSTMS

Part-of-speech tagging

PRP	**VB**	**DET**	**NN**
They	walk	the	dog

Named entity recognition

B-Per	**I-Per**	**O**	**O**	**B-Loc**
Neil	Armstrong	visited	the	moon

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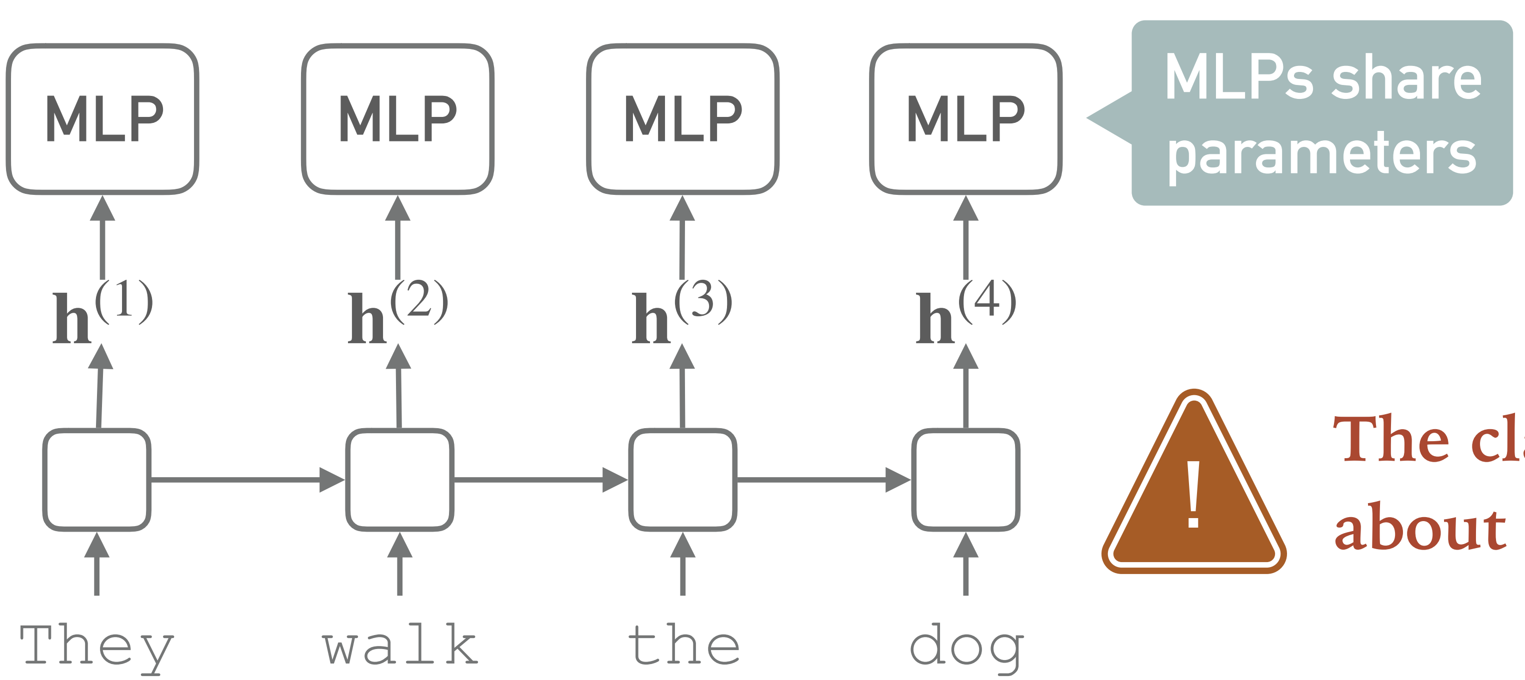
Neural architecture

1. A RNN computes a context sensitive representation of each word
2. At each time step, the output of the RNN if fed to a MLP for classification



! The classifiers receive no information about context on the right of each word!

BIRNN

Intuition

Use two RNNs with **different trainable parameters**:

- Forward RNN: visit the sentence from left to right
- Backward RNN: visit the sentence from right to left

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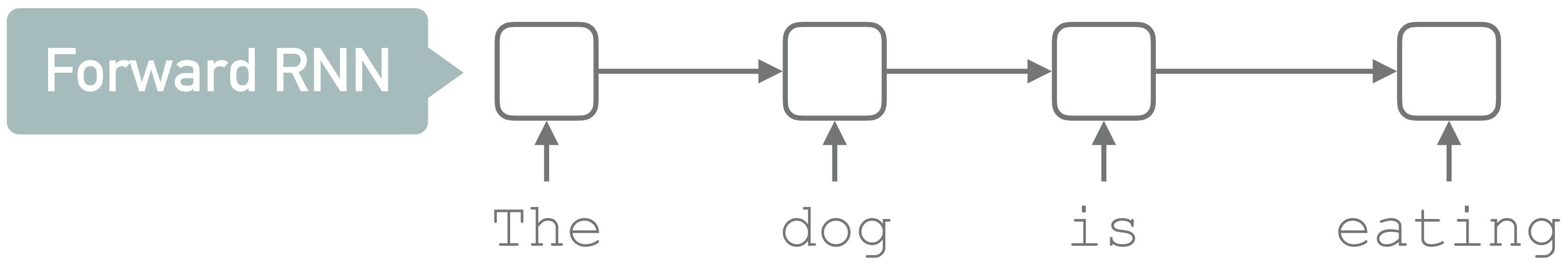

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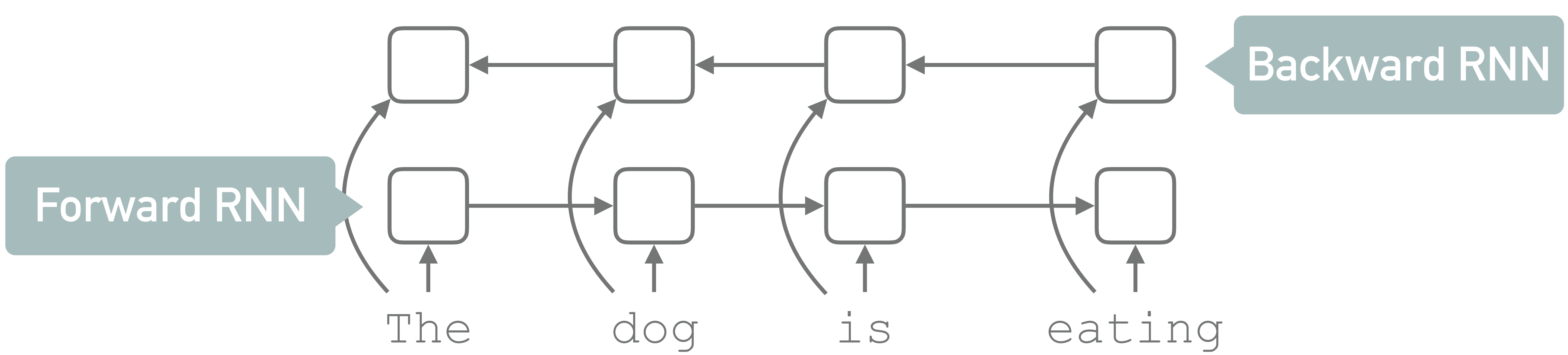

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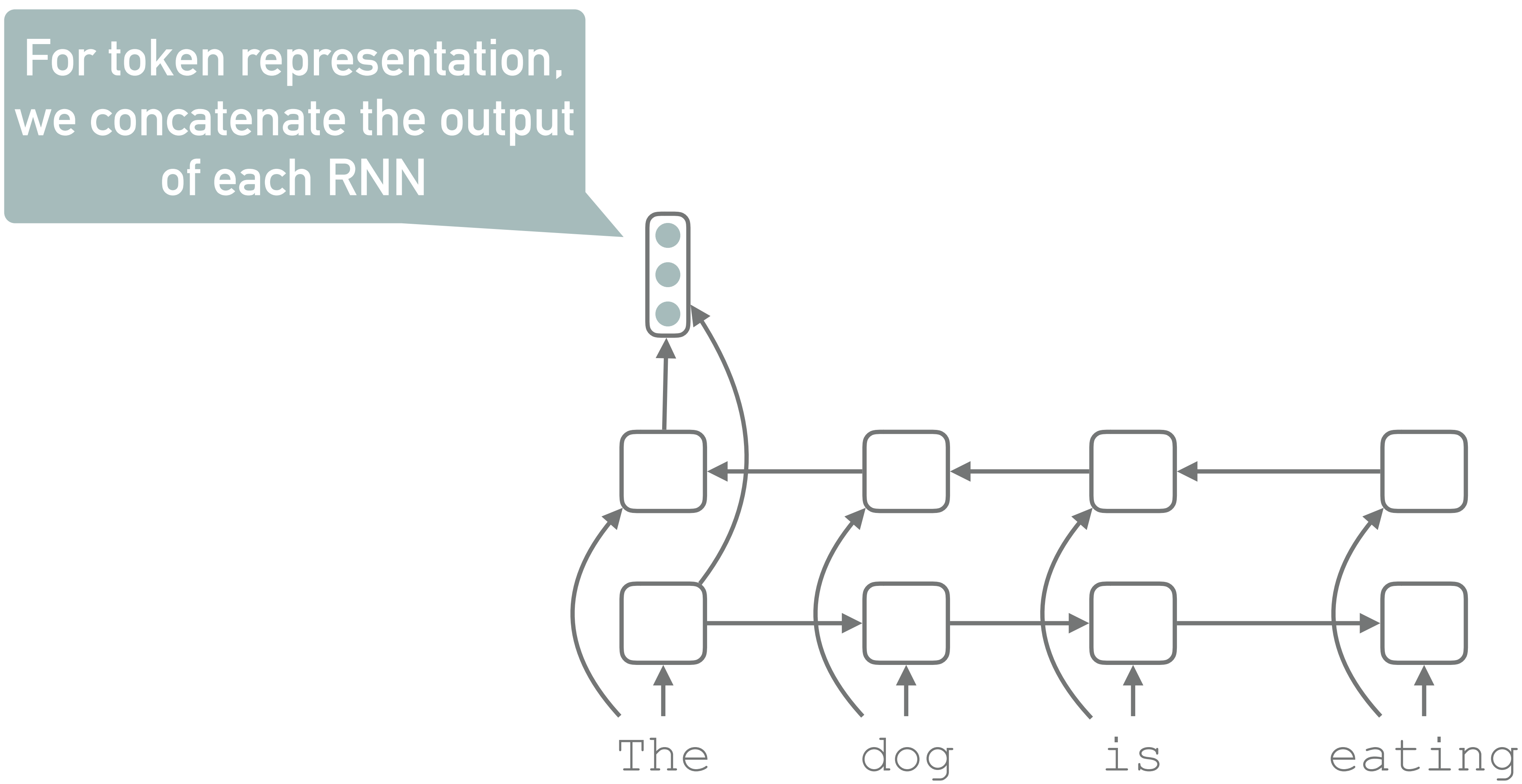

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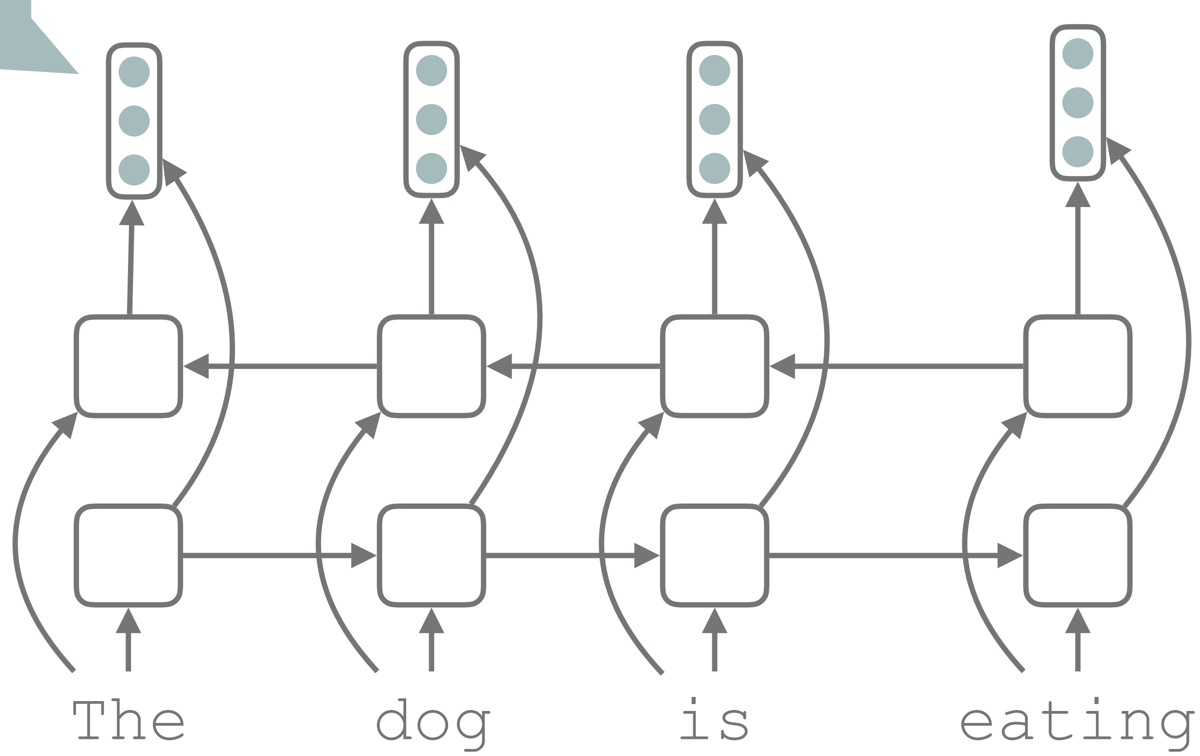
For token representation, we concatenate the output of each RNN



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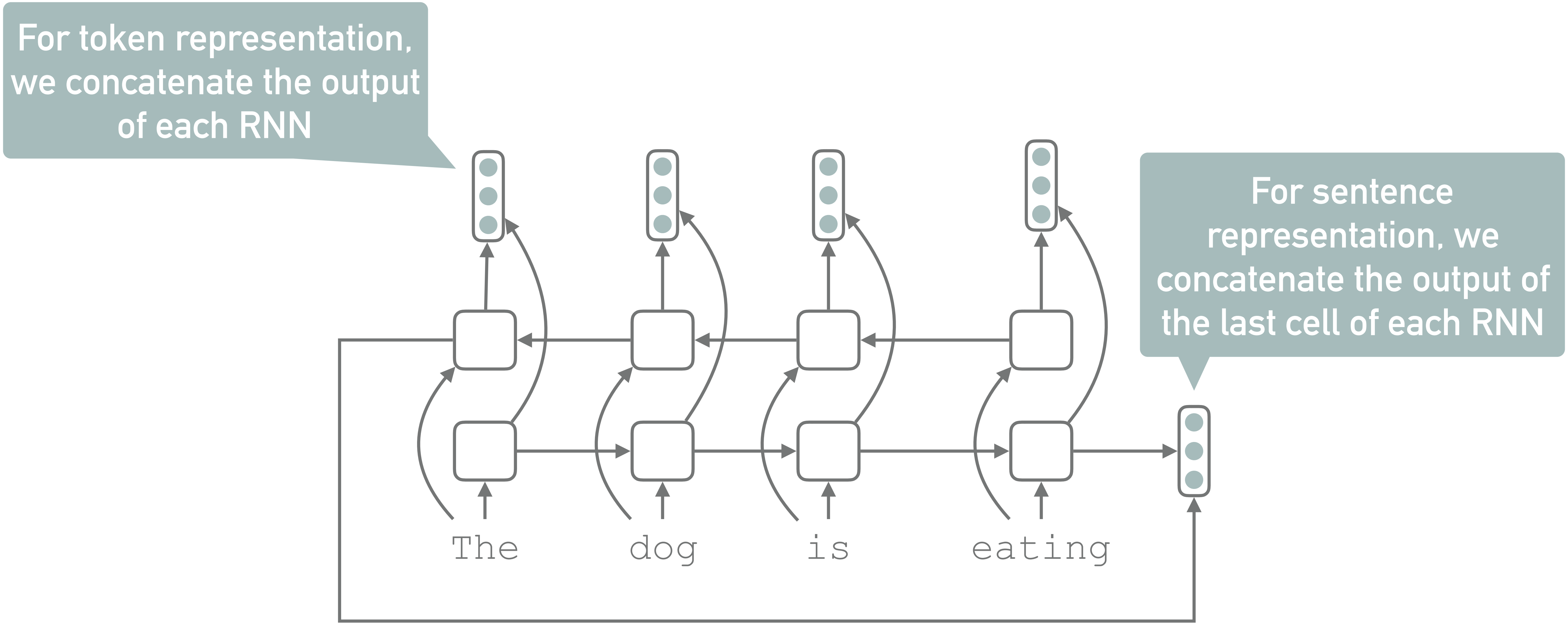

MULTI-STACK BIRNN

Intuition

Multi-layer RNNs have information only about previous words 👎

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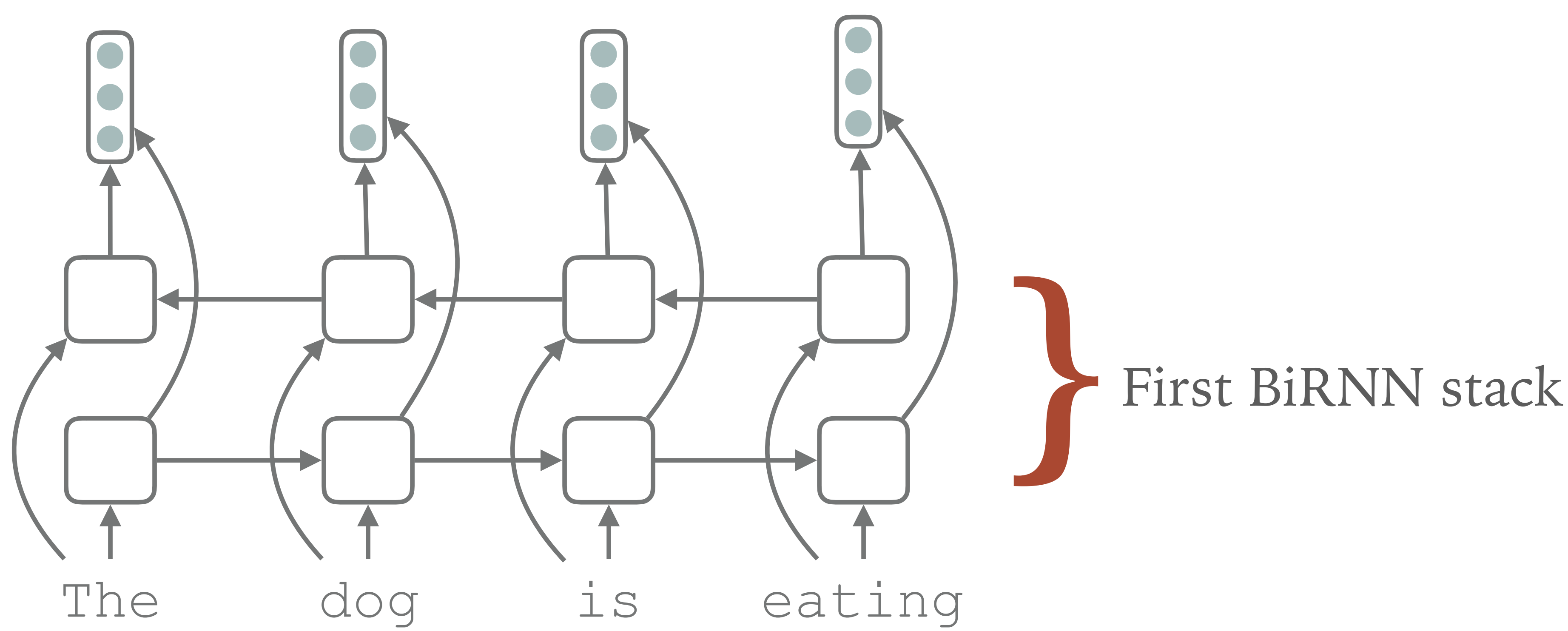

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