CS 383: Machine Learning

Prof Adam Poliak

Fall 2024

11/19/2024

Lecture 25

Announcements – Remaining Assignments

HW07: due Wednesday 11/27

HW08: due Friday 12/06 (might extend this too)

Project Presentations – 12/17 10:00am

Outline

Issues when training NNs

Pytorch

FFN’s for variable length input

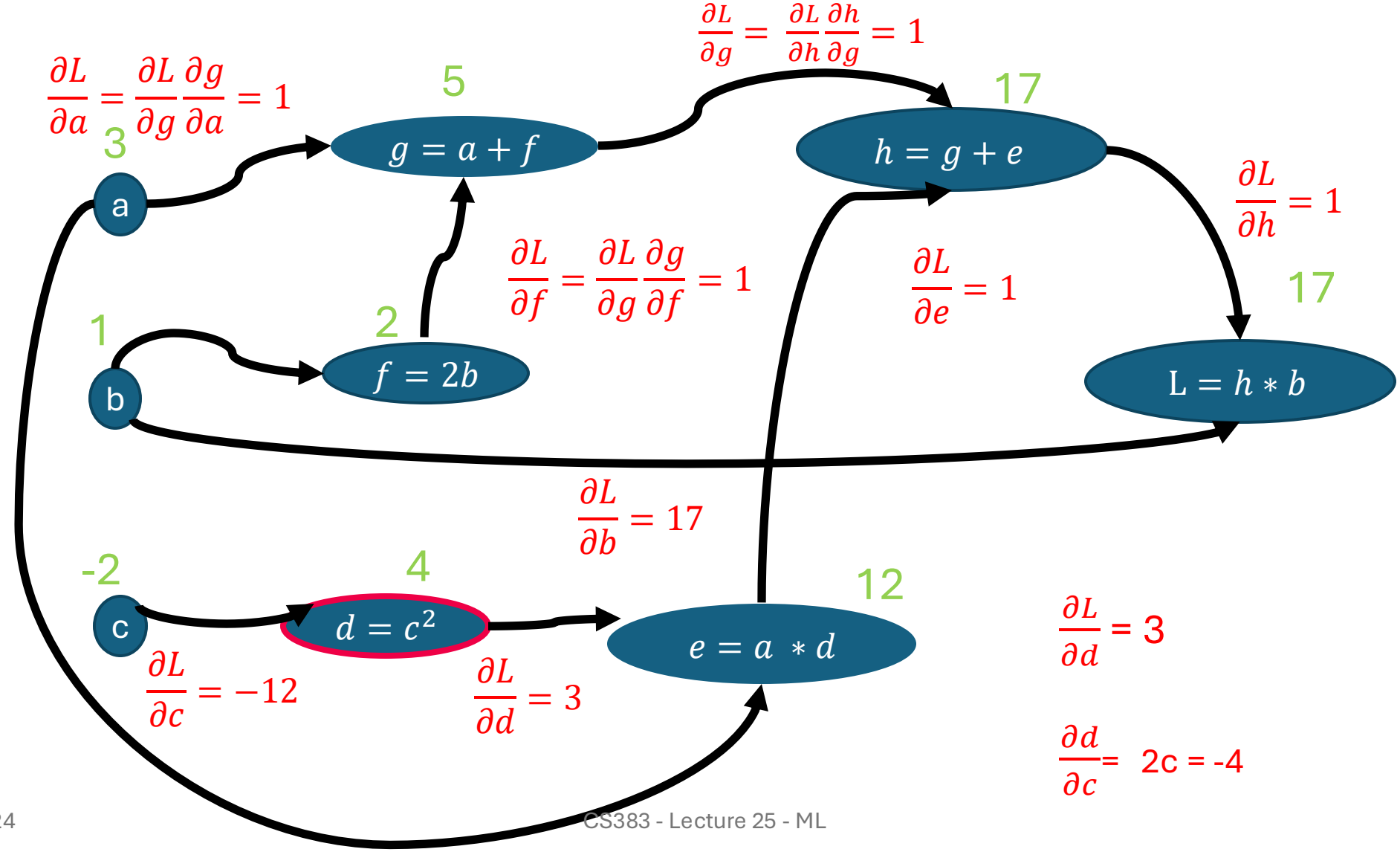
RNN

LSTM

Attention

Self Attention

backward pass



Exploding gradient

The gradient can accumulate, becoming very big

Issues:

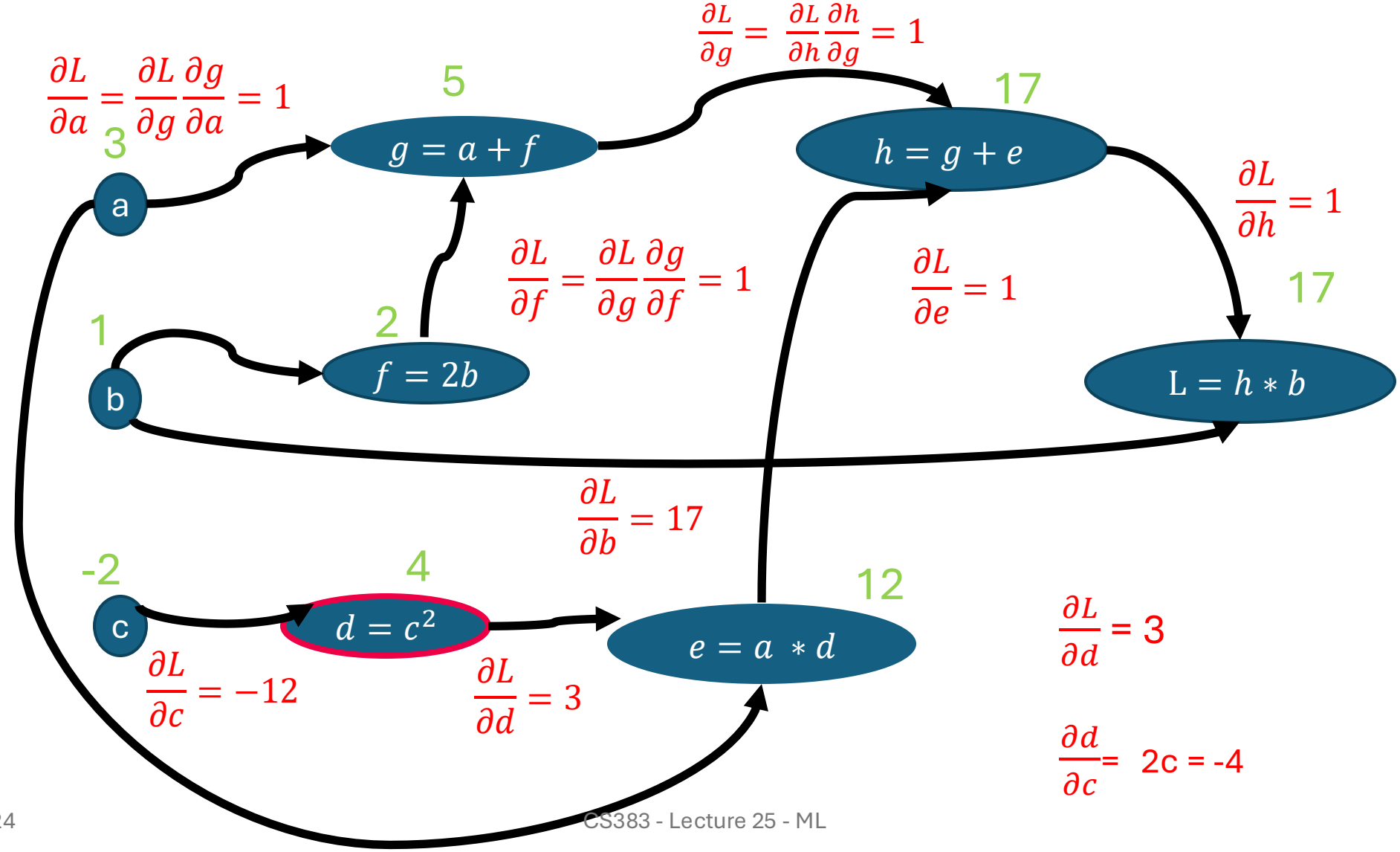
- might move our weights too much
- result in Nan

Solution:

Clipping

- Maximum value for gradients
- Can be dynamic

backward pass



Vanishing gradient

The gradient become 0

Issues:

wont be able to update weights (because 0 gets passed all the way back)

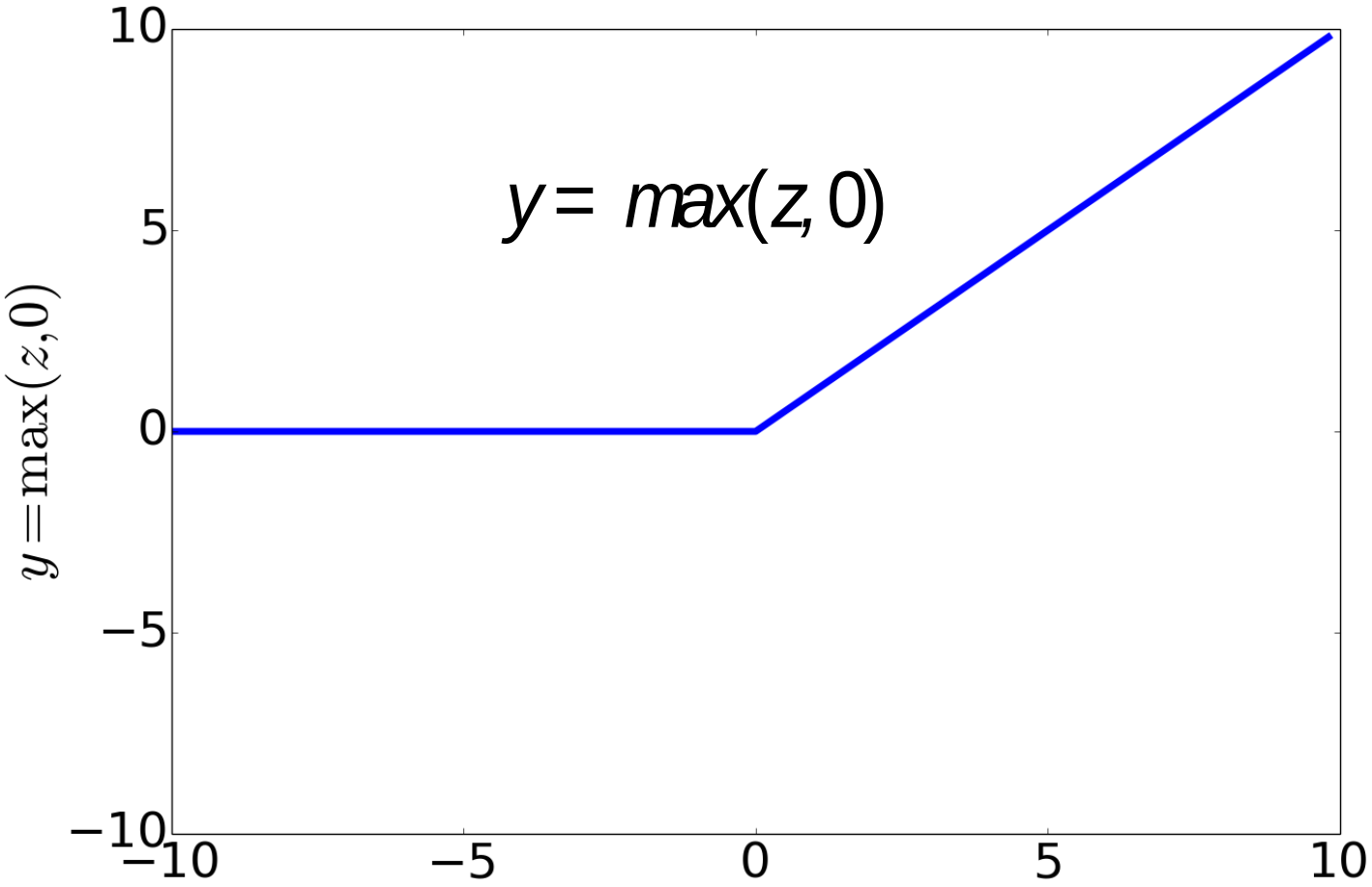
stuck in a local optima

Solution:

ReLU activation function

z = max(0, z)

ReLU



One node view

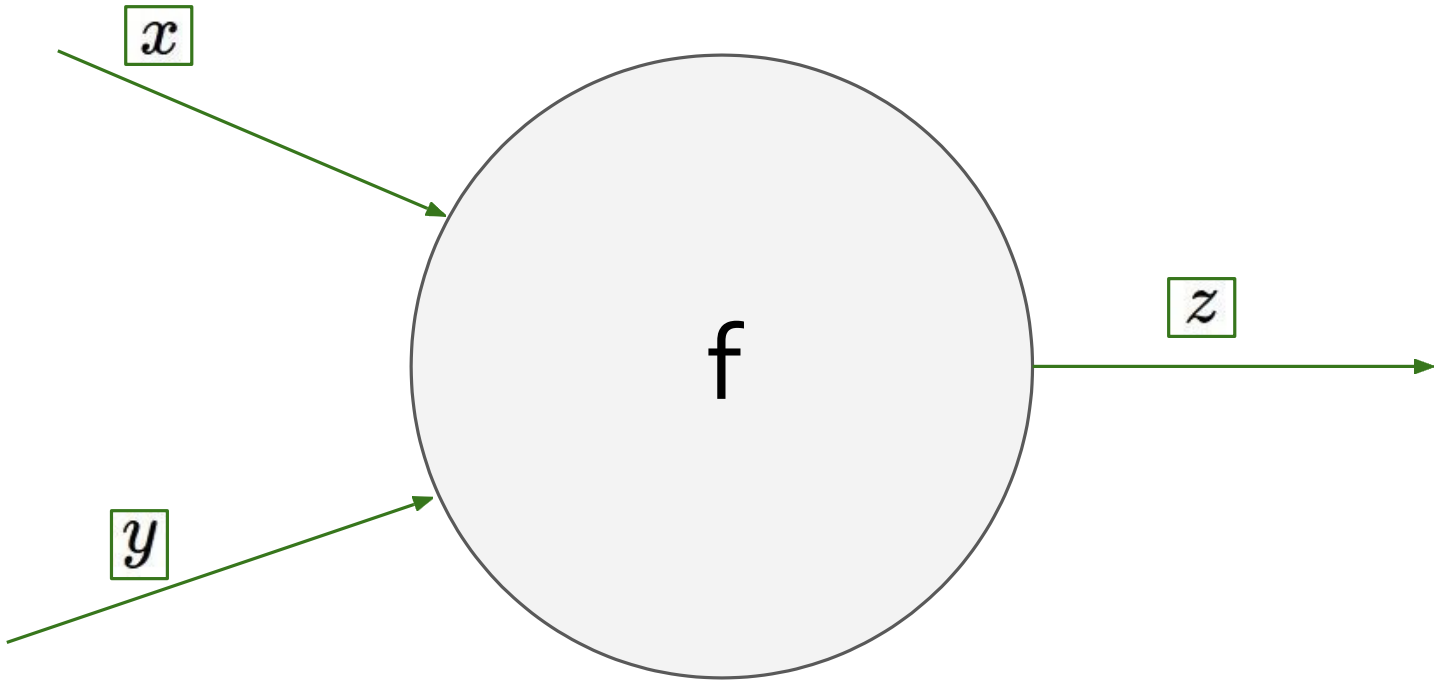


Figure from Andrej Karpathy

Dead neuron

In forward pass, output of a node w/ ReLU activation often will be 0

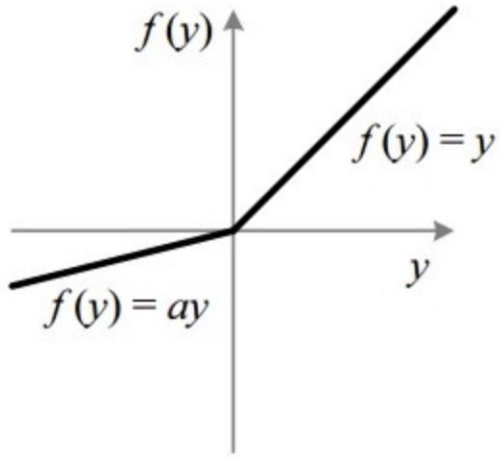
Issues:

wont pass information from one node to the next

lots of useless nodes

Solution:

Leaky ReLU activation function



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Pytorch

Torch: Facebook’s deep learning framework

Originally written in Lua (C backend)

Optimized to run computations on GPU

Mature, industry-supported framework

Defining a model

```
import torch
from torch import nn


class LogisticRegression(nn.Module):
    def __init__(self, input_size, num_classes):
        super(LogisticRegression, self).__init__()
        self.linear = nn.Linear(input_size, num_classes)

    def forward(self, x):
        out = self.linear(x)
        return out
```

nn.Module

Base class for all neural network modules.

Creates a computation graph

Define the model in __init__

Specify how to make predictions in forward

If only use built-in modules, no need to implement backprop

Defining a model

```
import torch
from torch import nn

class FNN(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super(FNN, self).__init__()
        self.input_size = input_size
        self.l1 = nn.Linear(input_size, hidden_size)
        self.relu = nn.ReLU()
        self.l2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        out = self.l1(x)
        out = self.relu(out)
        out = self.l2(out)
        # no activation and no softmax at the end
        return out
```

Train a model

Define:

- Loss function
- Learning algorithm (e.g. SGD)
- Learning rate
- Number of epochs

```
num_epochs = 100
learning_rate = 0.003
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
loss_fn = nn.CrossEntropyLoss()
```

Train a model

In each iteration:

- Make a prediction
- Compute the loss
- Autograd (Automatic differentiation), backprop
- Update the weights

```
optimizer.zero_grad()
prediction = model(X[i])
loss_val = loss_fn(prediction, labels[0][i])
loss_val.backward()
optimizer.step()
```

Train a model

```
# Training the Model
for epoch in range(num_epochs):
  num_correct = 0
  for i in range(100):
    optimizer.zero_grad()
    prediction = model(X[i])
    loss_val = loss_fn(prediction, labels[0][i])
    loss_val.backward()
    optimizer.step()

  print(f"loss at epoch {epoch}: {loss_val}")
  print(f"accuracy at epoch {epoch}: {num_correct / 100}")
```

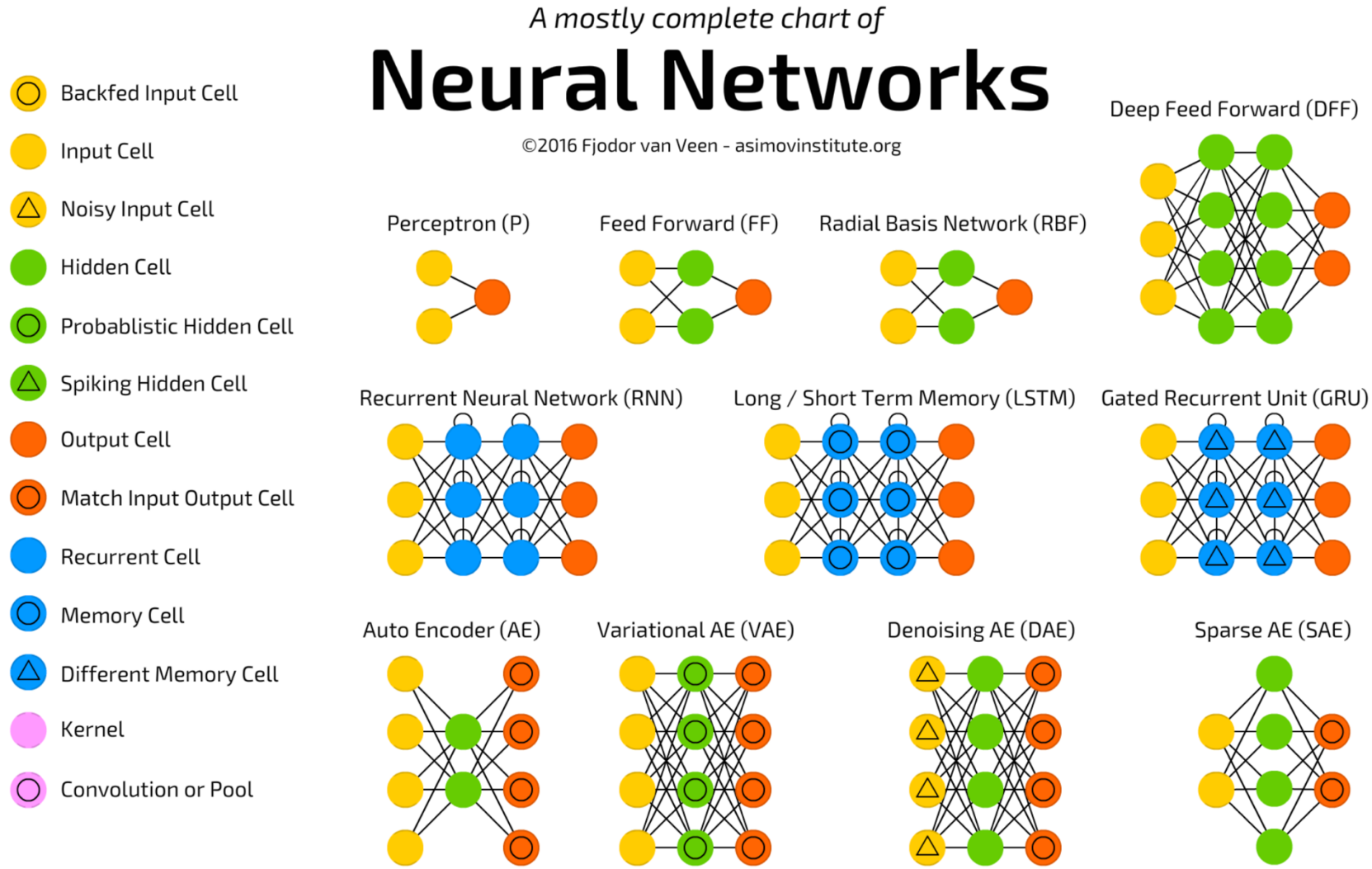
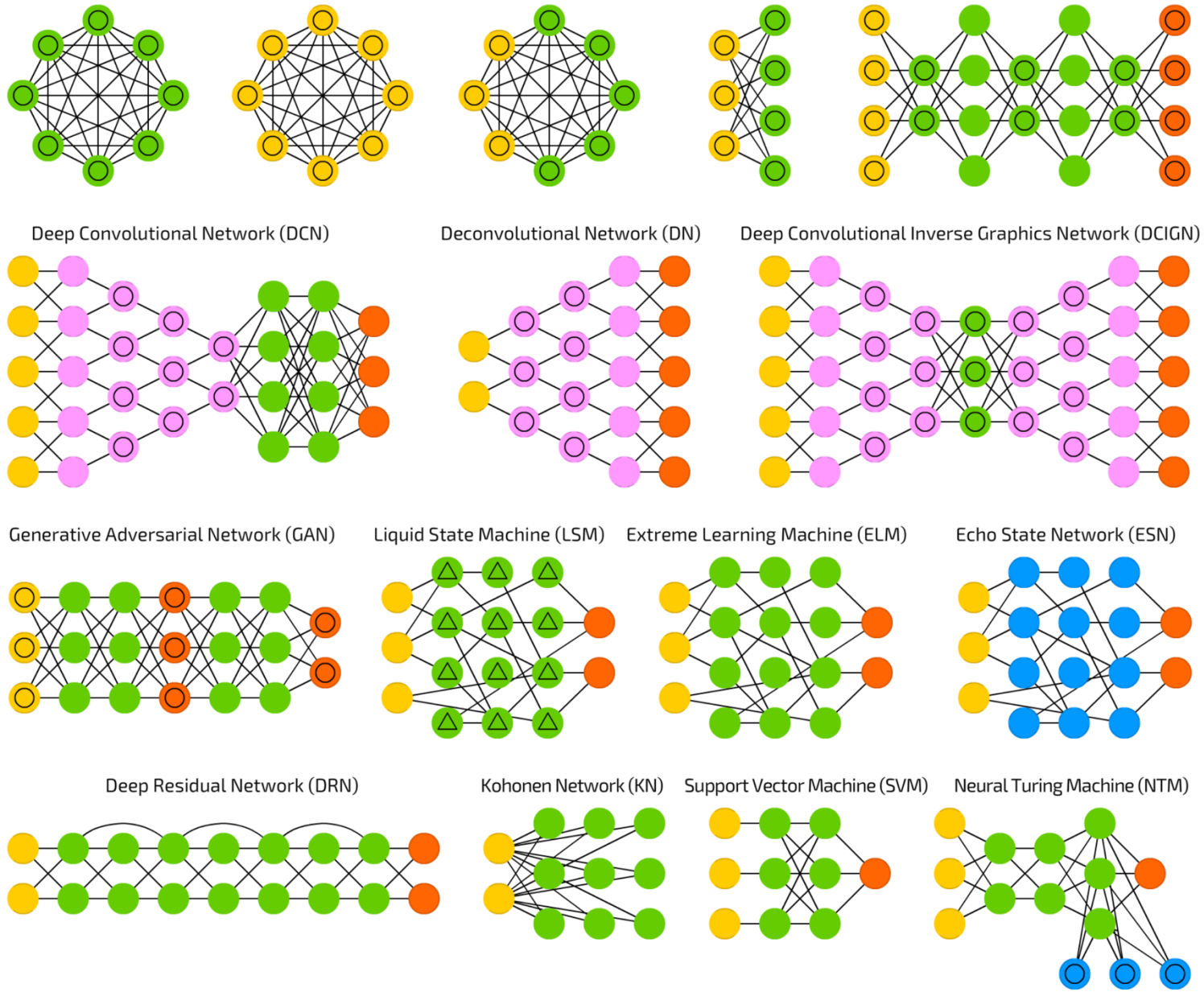


Image from Neural Network Zoo: http://www.asimovinstitute.org/neural-network-zoo/



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Classify a tweet as viral or not

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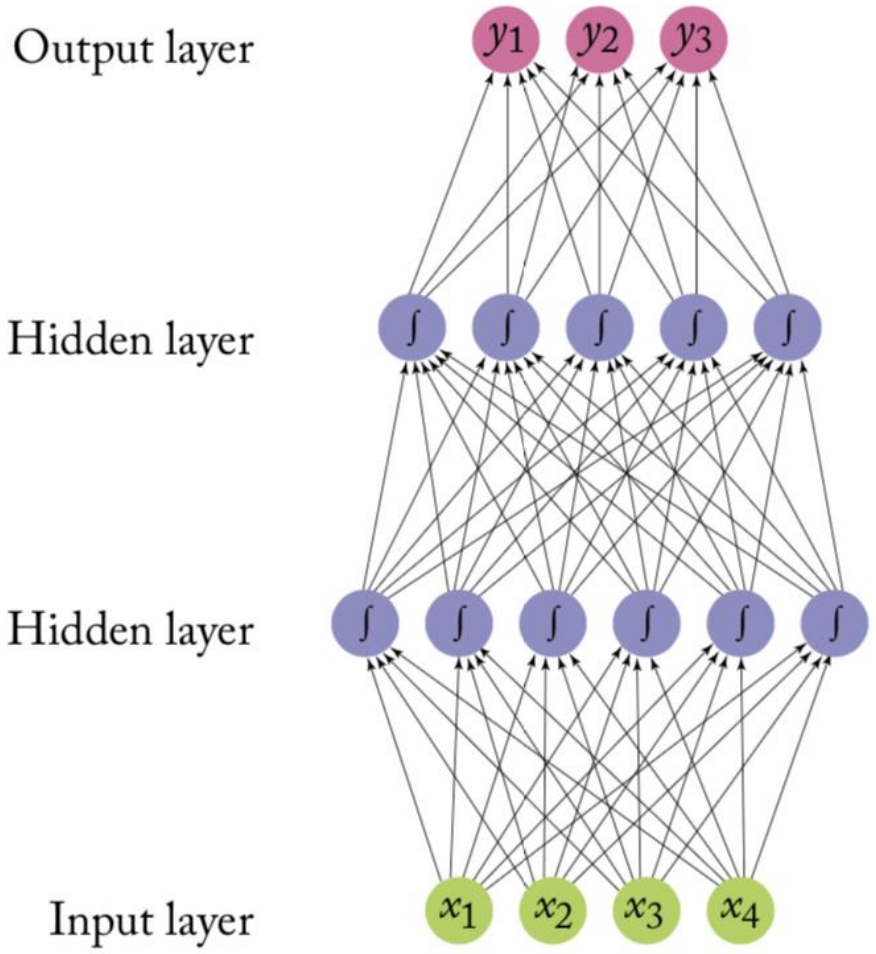
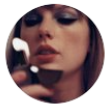
Classify a tweet as viral or not

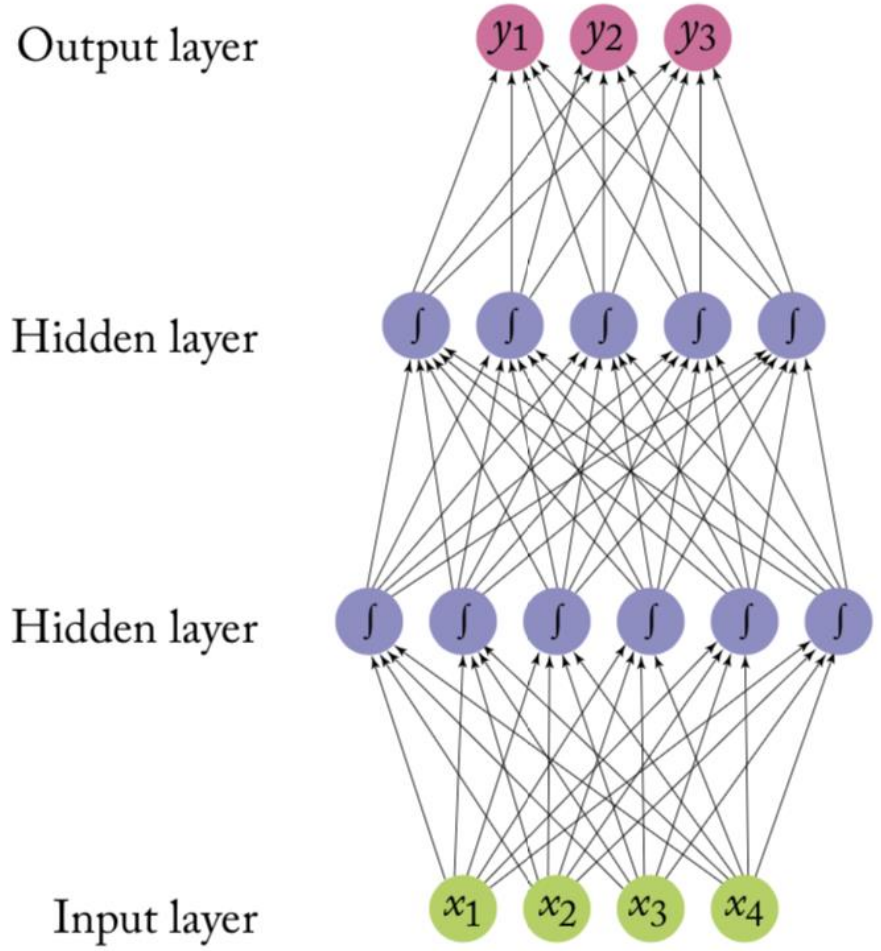


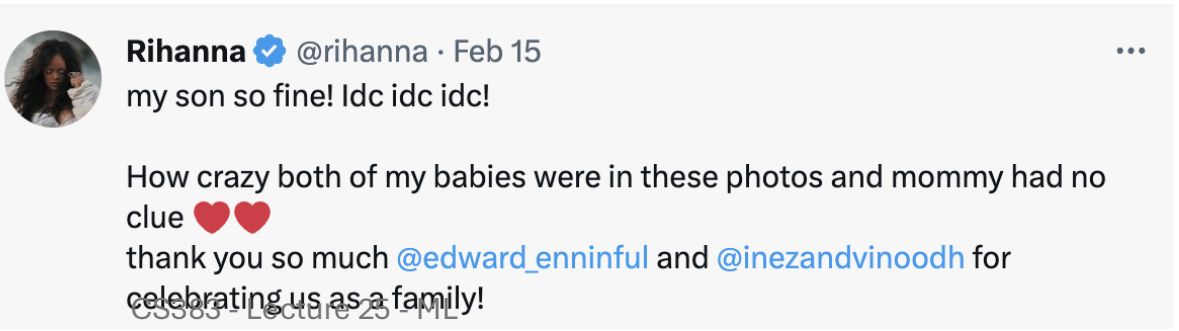


Taylor Swift @taylorswift13 · Jan 27

The Lavender Haze video is out now. There is lots of lavender. There is lots of haze. There is my incredible costar @laith_ashley who I absolutely adored working with.

Classify a tweet as viral or not





Rihanna @rihanna · Feb 15

my son so fine! Idc idc idc!

How crazy both of my babies were in these photos and mommy had no clue ❤️❤️
thank you so much @edward_enninful and @inezandvinoodh for celebrating us as a family!

Approach 1: Feature Engineering

Create a fixed-length vector to represent the input

Examples:

- Length of vector is V: size of vocabulary
- Value at index i represents static of word i
  - How many times word i appears in input
  - Term-frequency inverse document frequency of word i
    - Penalize words that appear in lots of inputs

Approach 1: Feature Engineering

Create a fixed-length vector to represent the input

$x = w_1, w_2, \ldots w_n$

$z_0 = [count(w_1), count(w_2), count(w_3), \ldots, count(w_v)]$

$\hat{y} = MLP(z_o)$

Approach 2: Deep Averaging Network

Represent each document as a continuous bag of words, averaging the word embeddings

$$x = w_1, w_2, \ldots w_n$$

$$z_0 = CBOW(w_1, w_2, \ldots w_n). CBOW = \sum_i E[w_i]$$

$$\hat{y} = MLP(z_o)$$

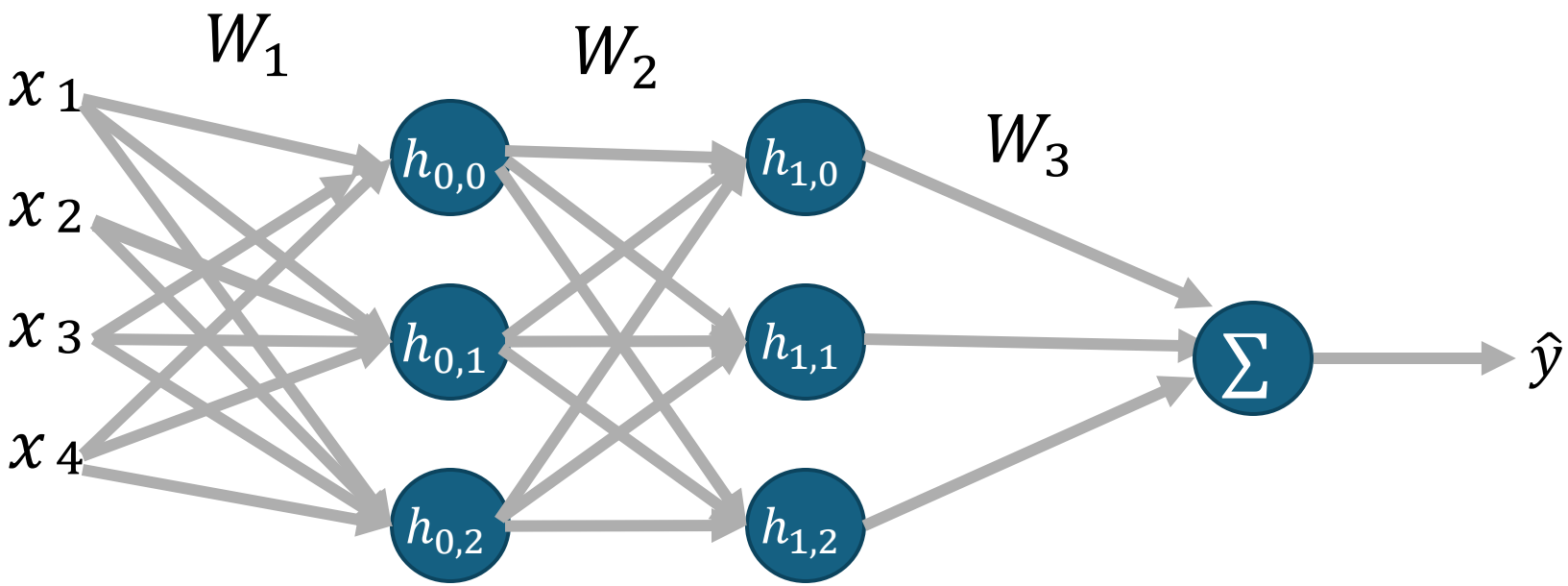
Multilayer Perceptron

Feed-forward NN

$$MLP_1 = g(xW_1 + b_1)W_2 + b_2$$

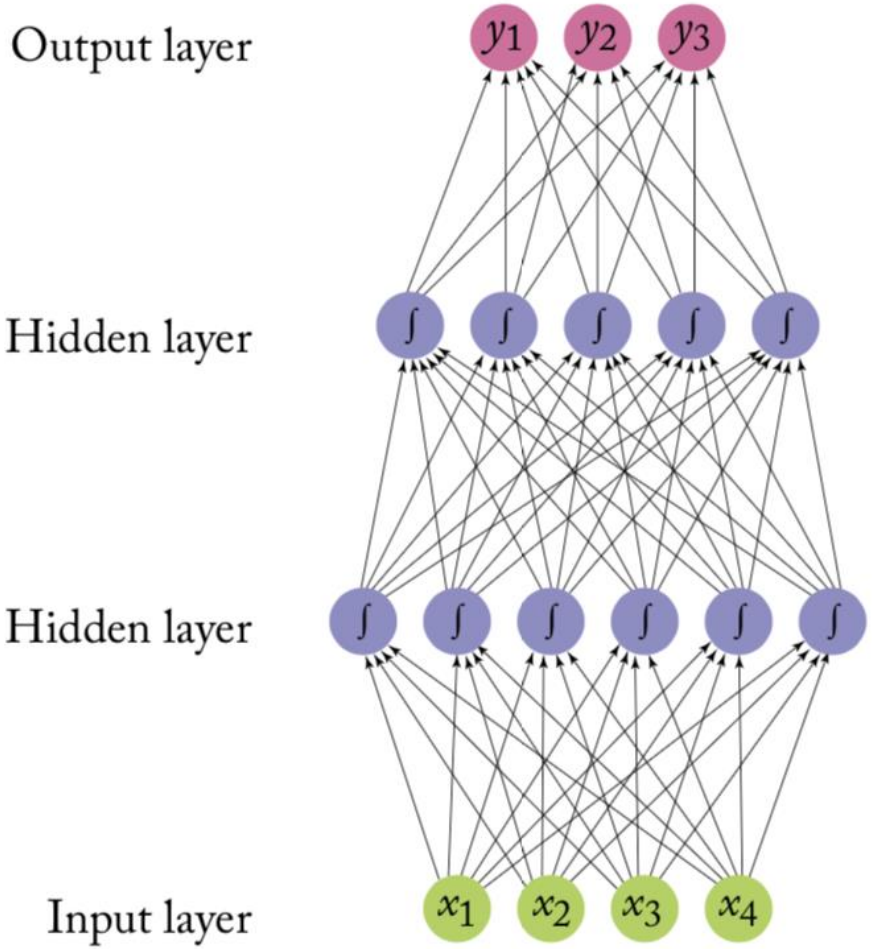
$$MLP_2 = g(g(xW_1 + b_1)W_2 + b_2)\,W_3 + b_3$$

MLP_2



$$\boldsymbol{h}_0 = \sigma(xW_1) \qquad \boldsymbol{h}_1 = \sigma(\sigma(xW_1)W_2$$

MLP_2


Output layer
Hidden layer
Hidden layer
Input layer
y_1
y_2
y_3
x_1
x_2
x_3
x_4

FFN’s issues

Fixed input size

Solutions:

1. Create a fixed length representation
2. Recurrent Neural Networks

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RNN - motivation

How can we model a **long** (possibly infinite) context using a finite **model?**

Recursion

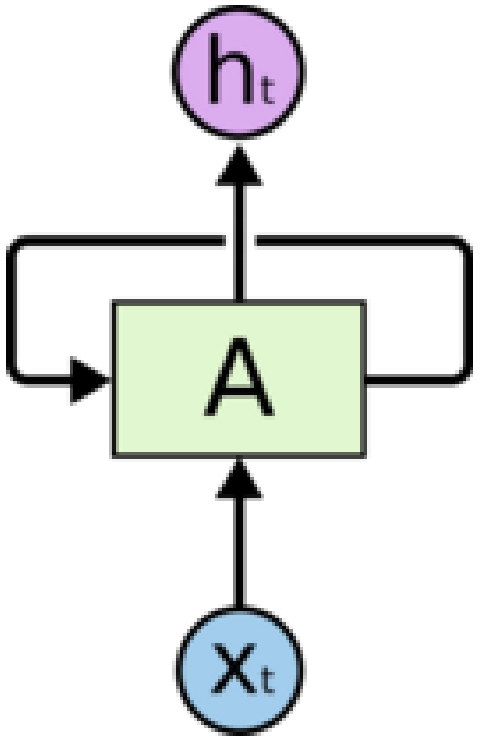
Recurrent Neural Networks are a family of NNs that learn sequential data via **recursive dynamics**

Recurrent Neural Network (RNN)

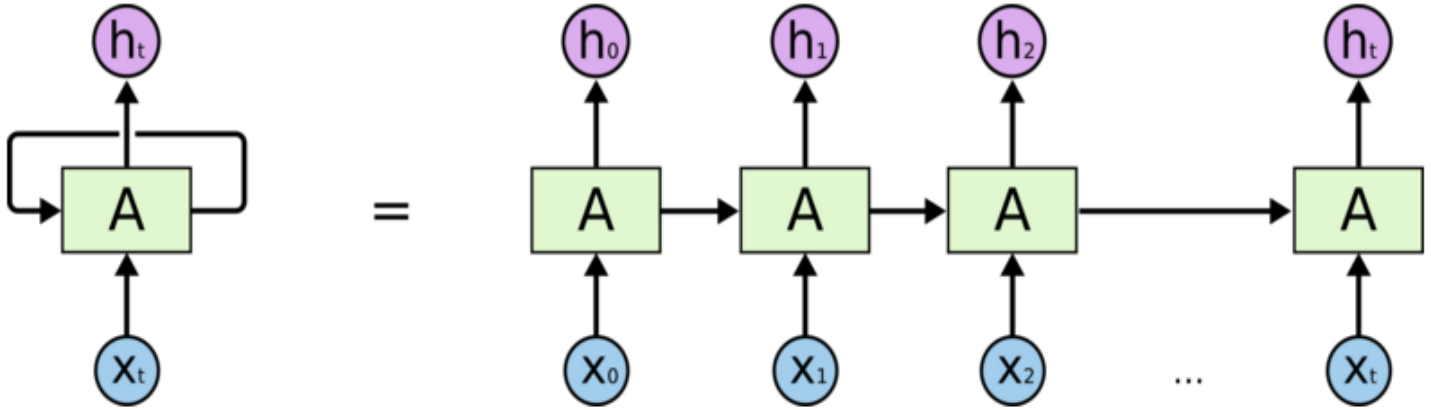
$h_t = f(h_{t-1}, x_t)$

In the diagram, $f(\dots)$ looks at some input x_t and its previous hidden state h_{t-1} and outputs a revised state h_t.

A loop allows information to be passed from one step of the network to the next.



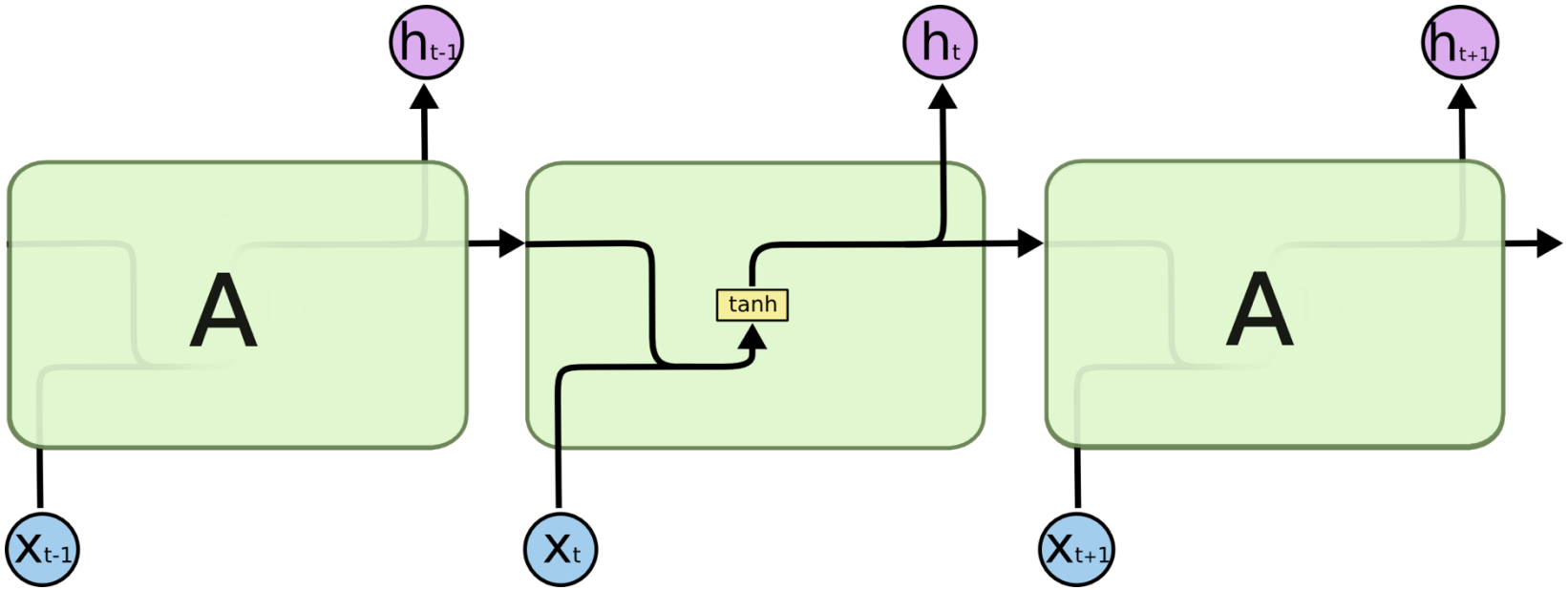
Unrolling an RNN



A recurrent neural network can be thought of as multiple copies of the same network, each passing a message to a successor.

RNN internal

$$h_t = \tanh(x_t W_{ih}^T + b_{ih} + h_{t-1} W_{hh}^T + b_{hh})$$



Updating weights in a RNN

$$h_t = \tanh(x_t W_{ih}^T + b_{ih} + h_{t-1} W_{hh}^T + b_{hh})$$

$$\frac{\partial \tan(x)}{\partial x} = 1 - \tan(x)^2$$

So what variables do we need to update?

Our weights and biases

Updating weights in a RNN

$$h_t = \tanh(x_t W_{ih}^T + b_{ih} + h_{t-1} W_{hh}^T + b_{hh})$$

$$\frac{\partial \tan(x)}{\partial x} = 1 - \tan(x)^2$$

$$\frac{\partial L}{\partial \theta} = \begin{bmatrix} \frac{\partial L}{\partial W_{ih}} \\ \frac{\partial L}{\partial b_{ih}} \\ \frac{\partial L}{\partial W_{ih}} \\ \frac{\partial L}{\partial b_{ih}} \end{bmatrix}$$

$$\frac{\partial \tan(x)}{\partial x} = 1 - \tan(x)^2$$

Updating weights in a RNN

$$h_t = \tanh(x_t W_{ih}^T + b_{ih} + h_{t-1} W_{hh}^T + b_{hh})$$

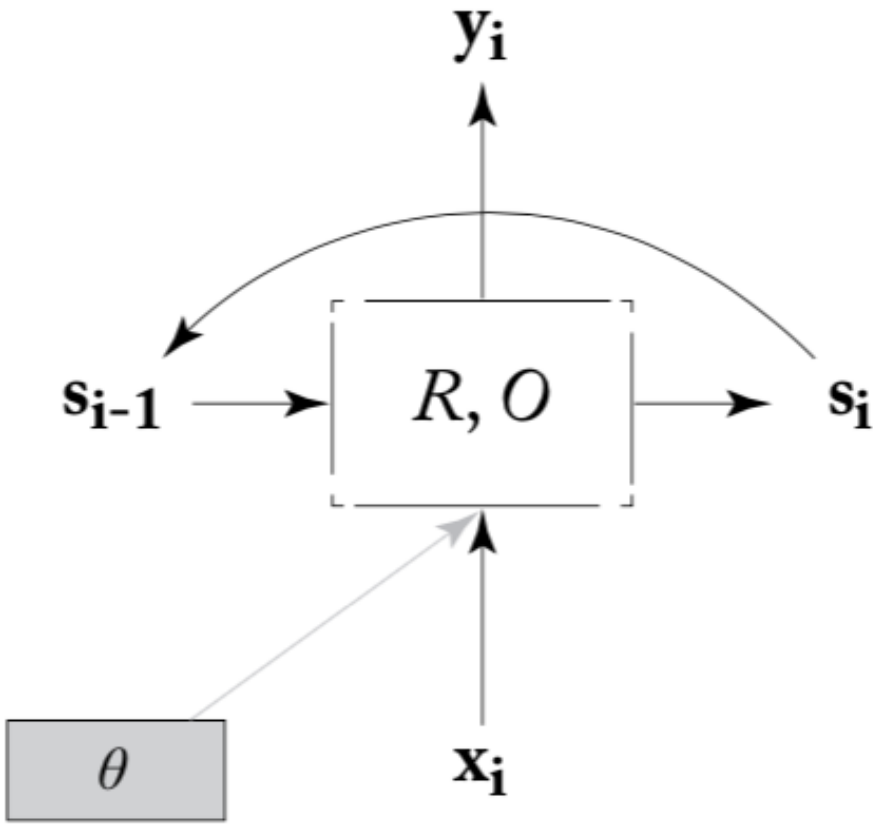
Lets let this be **g**

$$\frac{\partial L}{\partial \theta} = \begin{bmatrix} \frac{\partial L}{\partial W_{ih}} \\ \frac{\partial L}{\partial b_{ih}} \\ \frac{\partial L}{\partial W_{ih}} \\ \frac{\partial L}{\partial b_{ih}} \end{bmatrix} = \begin{bmatrix} 1 - \tan(g)\, x_t \\ 1 - \tan(g) \\ 1 - \tan(g)\, h_{t-1} \\ 1 - \tan(g)\, x_t \end{bmatrix}$$

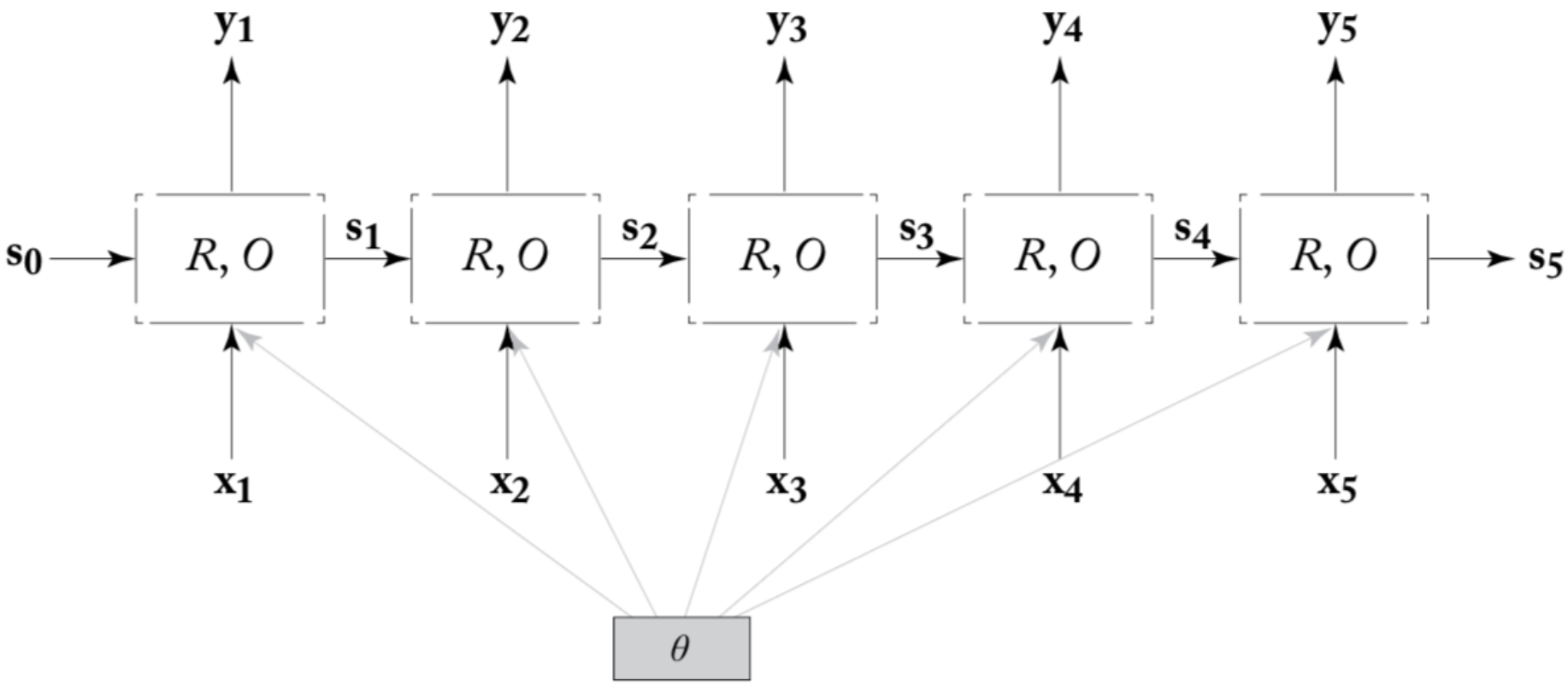
RNN cell

$$s_i = R(x_i, s_{i-1}, \theta)$$

$$\widehat{y_i} = O(s_i)$$

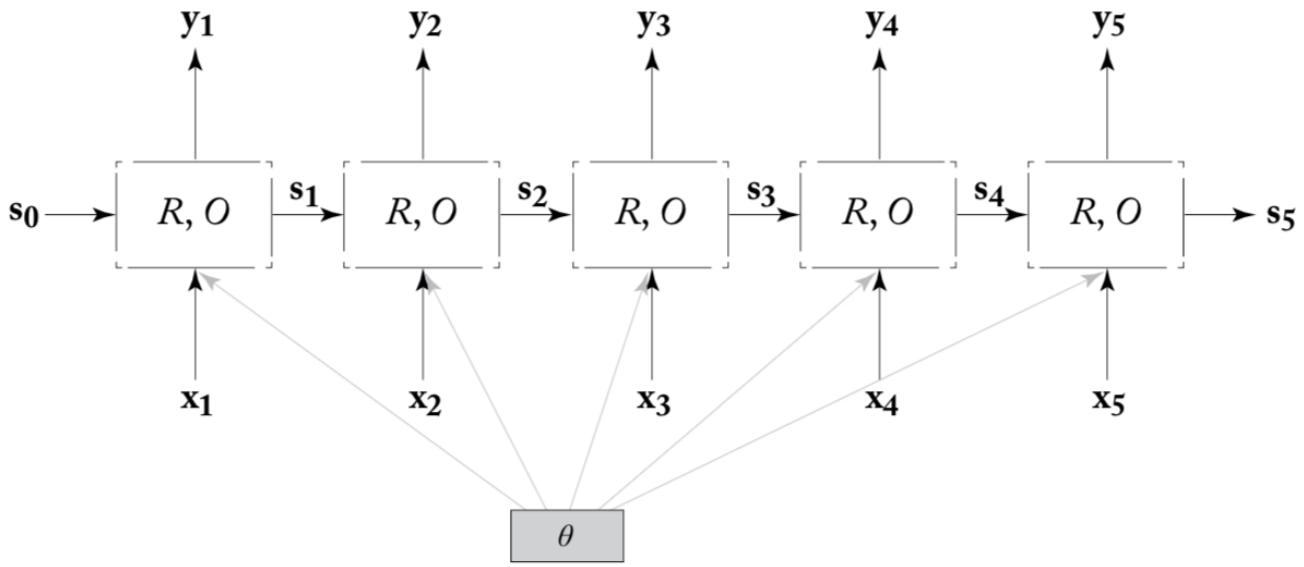


Unrolling RNN



Revisiting LM

$$P(x_t|x_{t-1}, x_{t-2}, \ldots x_1)$$

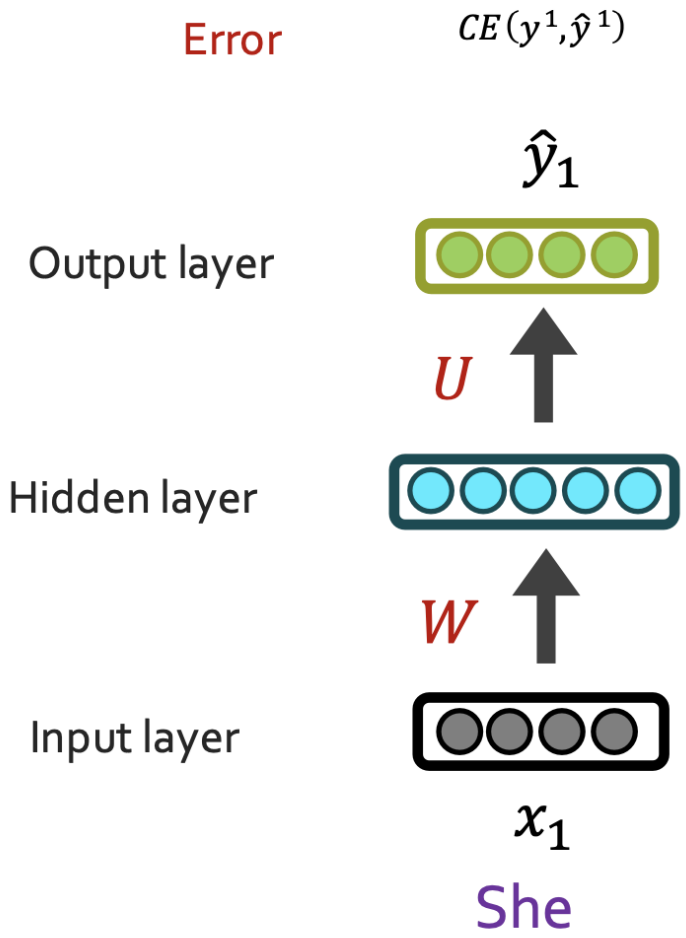


Pass in one word at a time

Compute probability over entire vocab by applying predictive head to last output

RNN: Forward

$$CE(y, \hat{y}) = -\sum_{w \in V} y_w \log \widehat{y_w}$$



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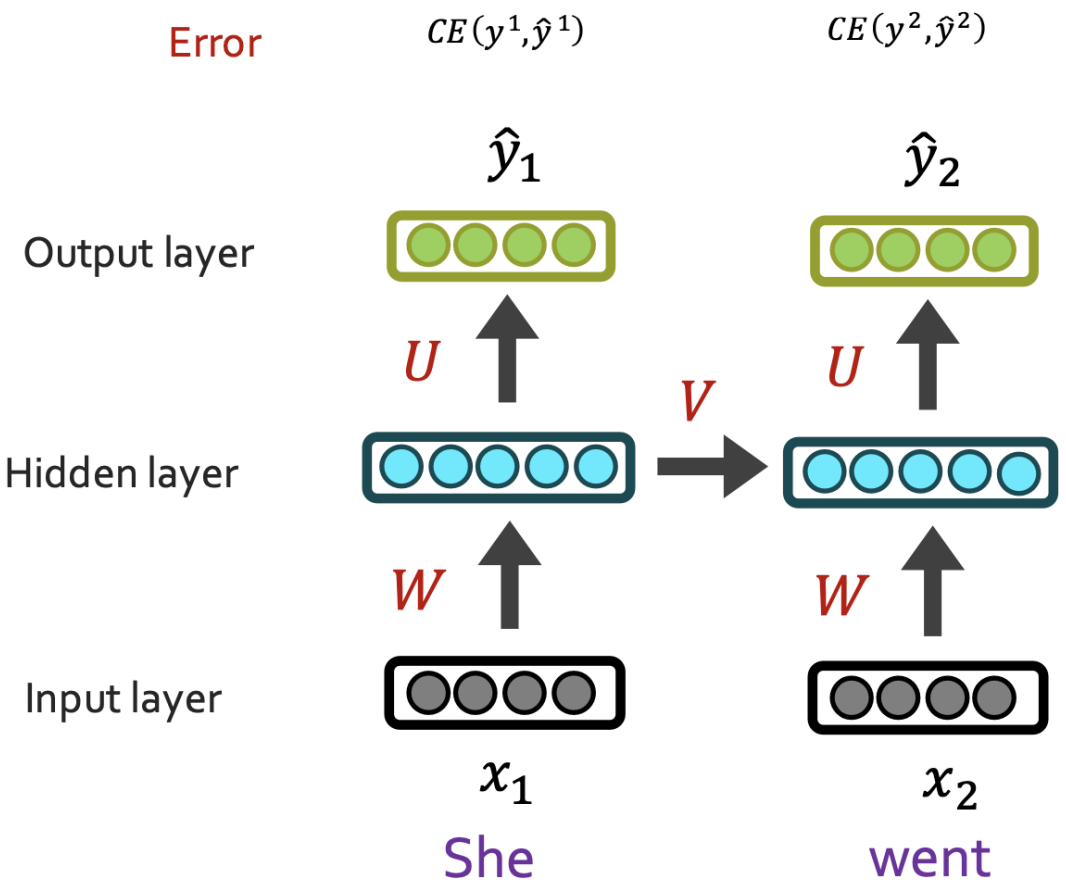

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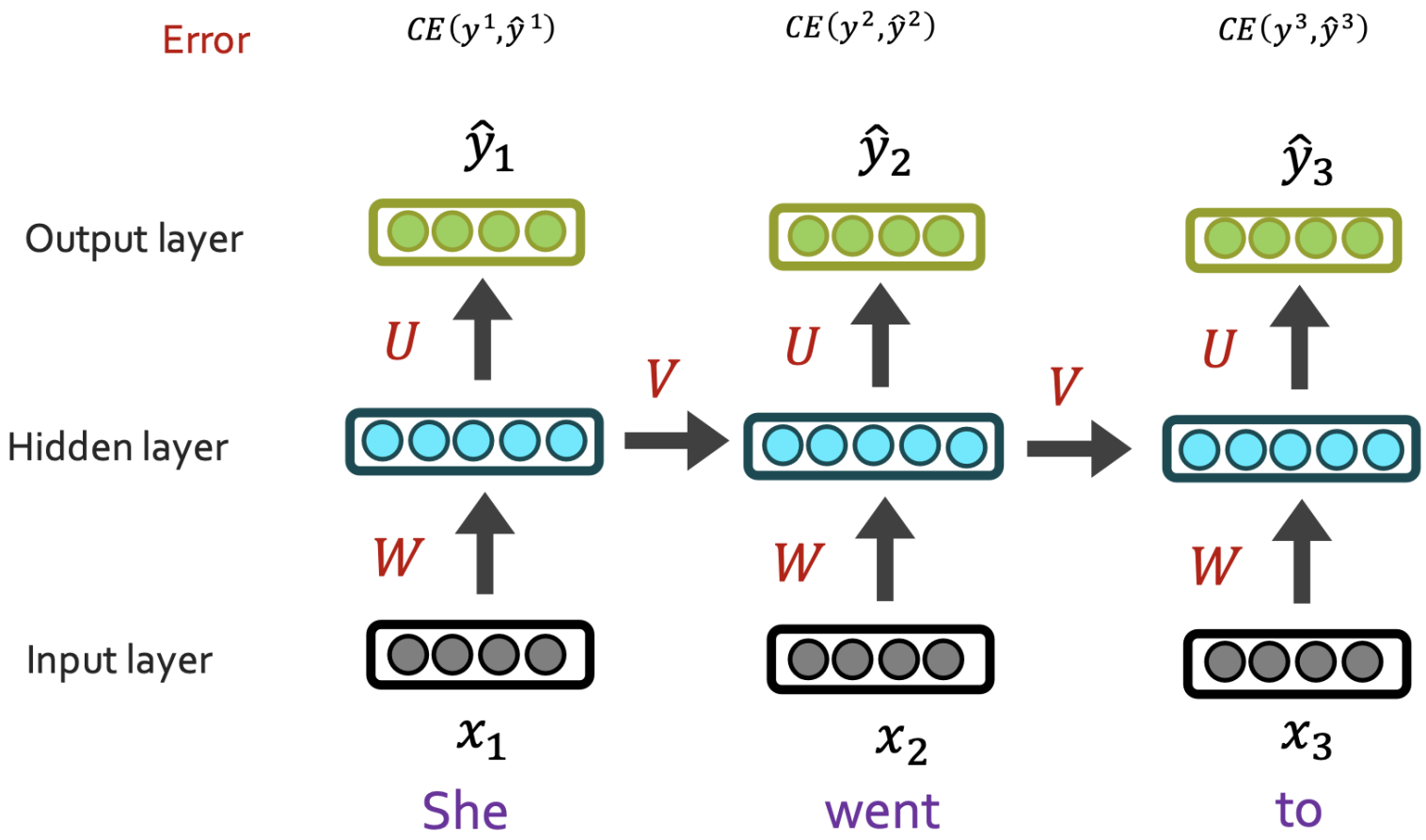

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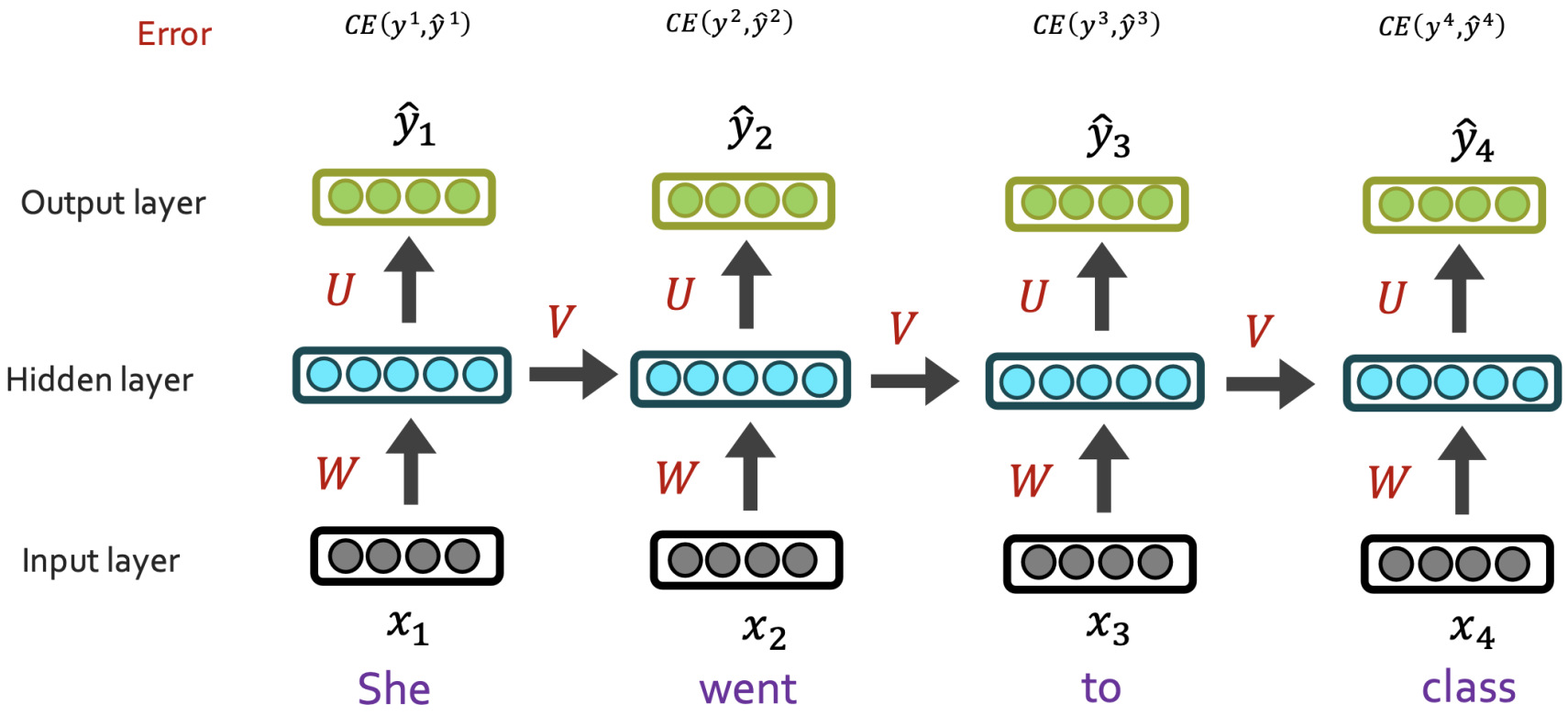
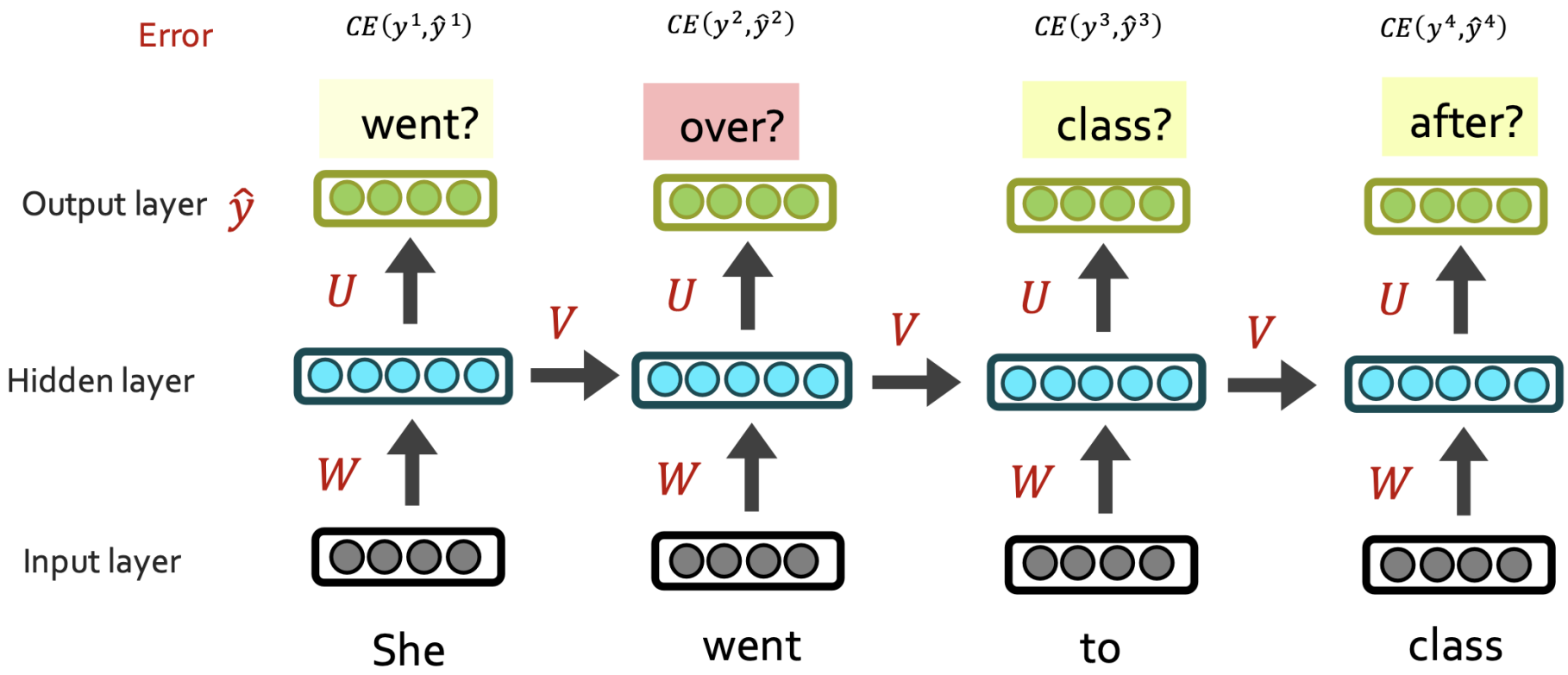


RNN: Forward

$$CE(y, \hat{y}) = -\sum_{w \in V} y_w \log \widehat{y_w}$$

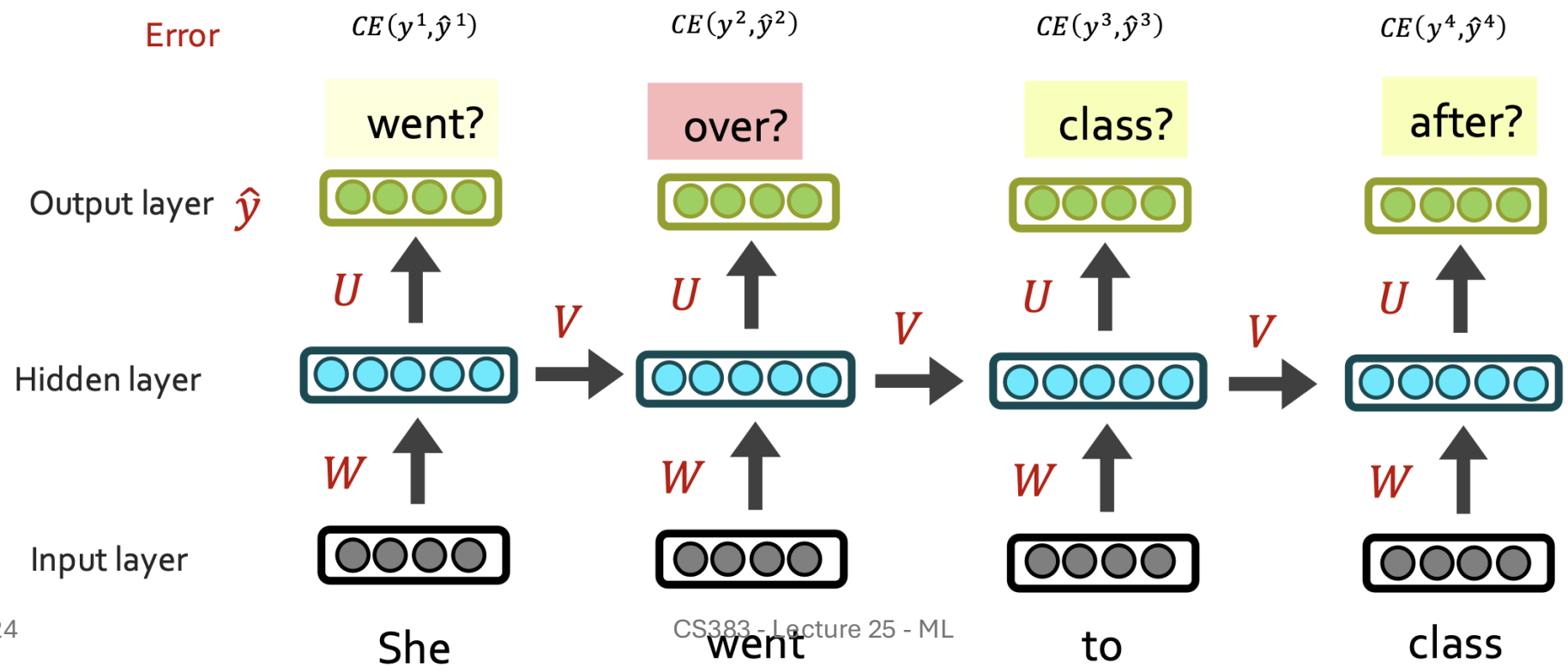
Loss is just averaging Cross-Entropy all predictions



RNN: Backwards

$$CE(y, \hat{y}) = -\sum_{w \in V} y_w \log \hat{y_w}$$

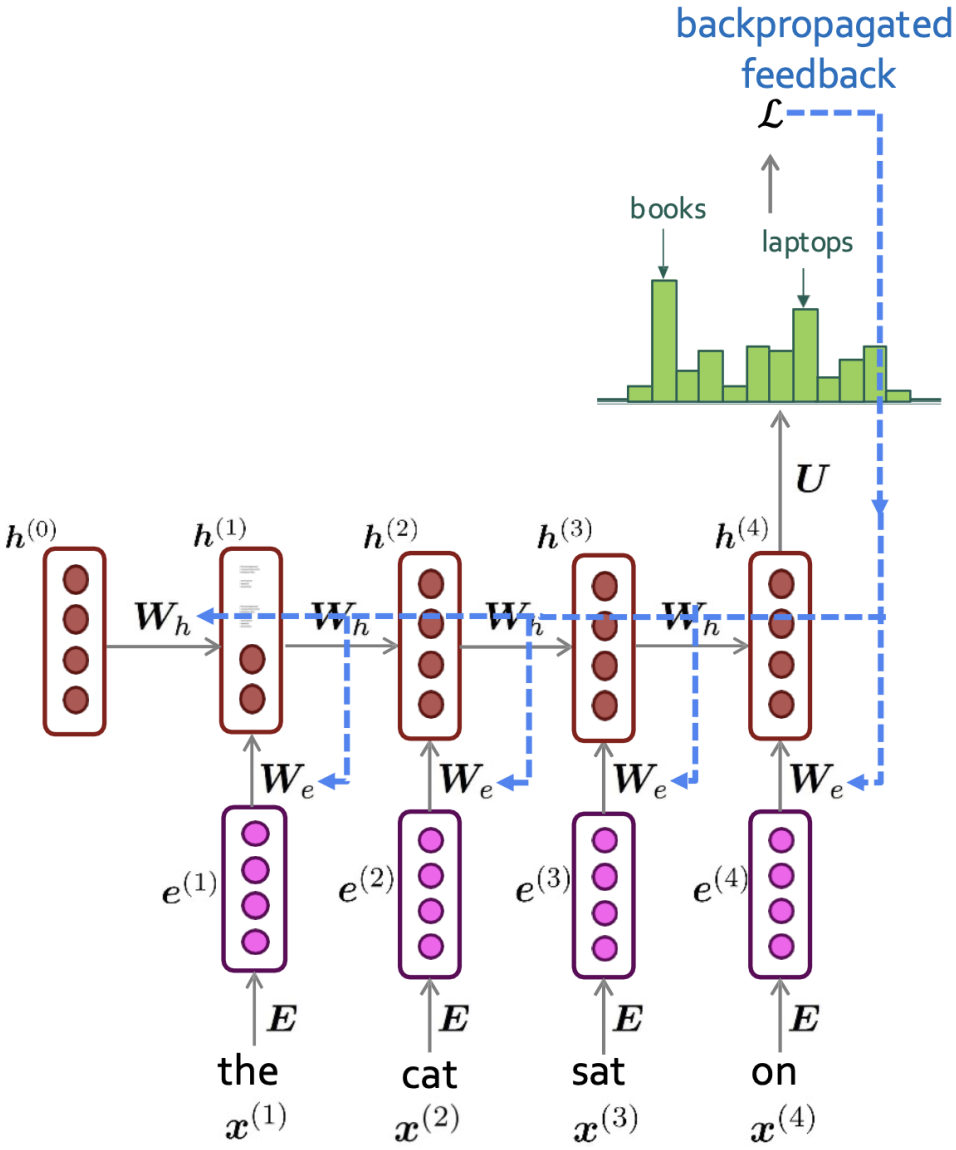
Compute the loss at the end, then propagate derivative of loss back to update the parameters



Training RNNs

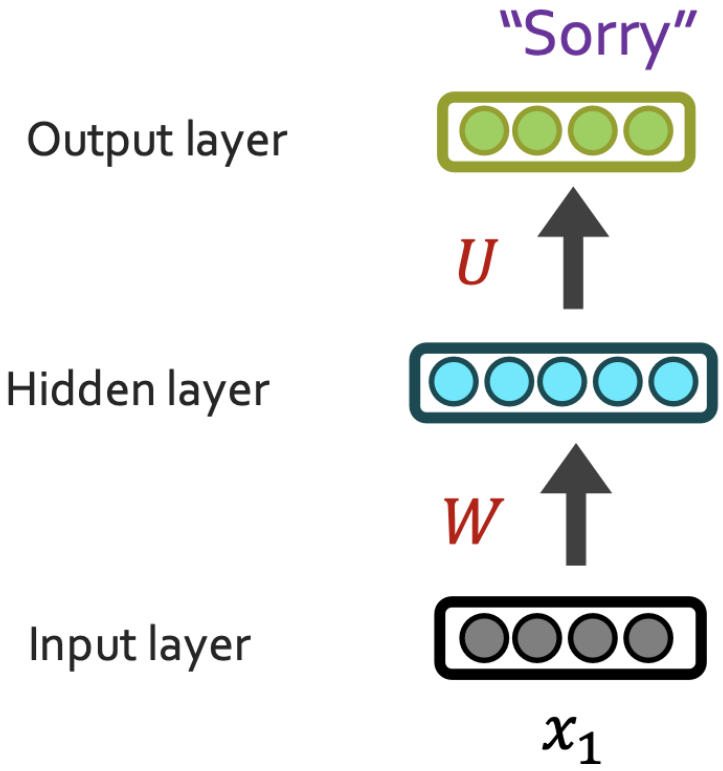
"Backprop over time"

1. Compute $\mathcal{L}$ for a batch of sentences
2. Compute gradients of $\mathcal{L}$ in respect to parameters
3. Repeat



Generating with RNNs

Until we see a </s>, generate the most likely next word by sampling from previously predicted word



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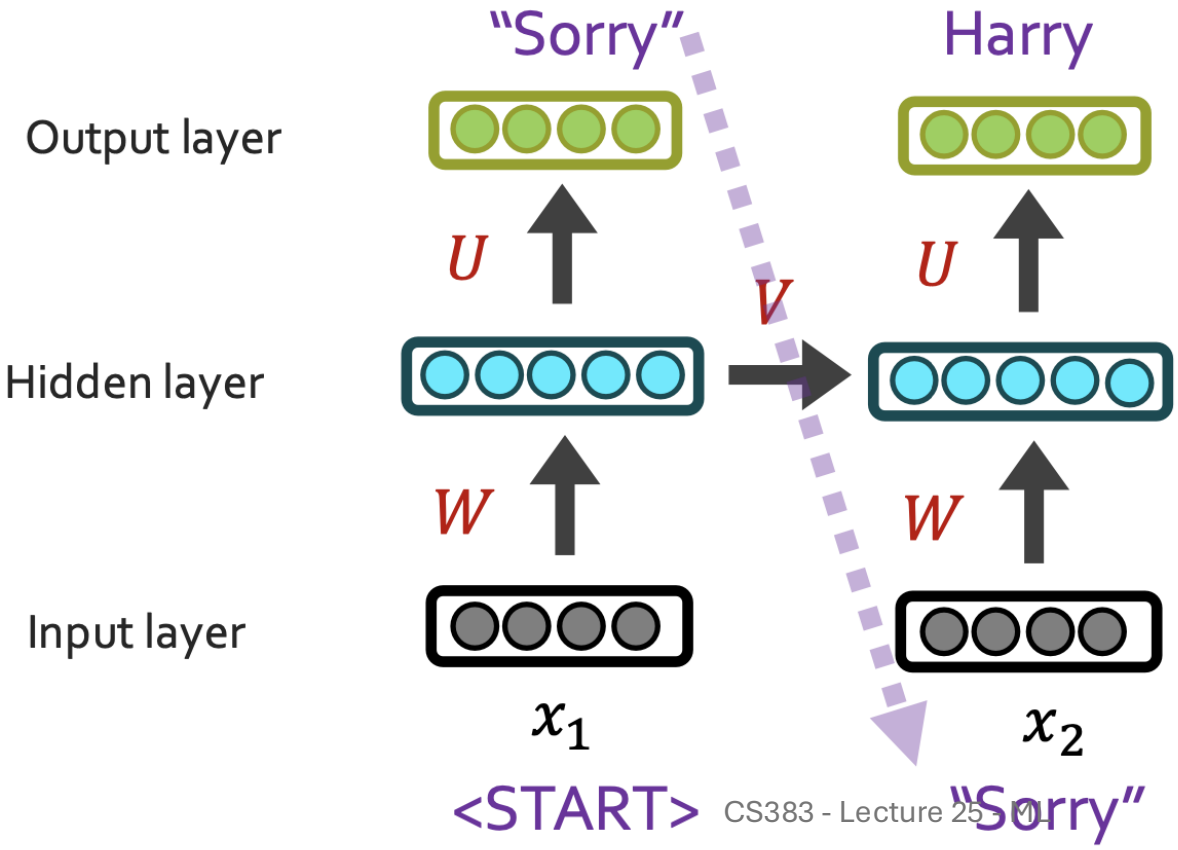

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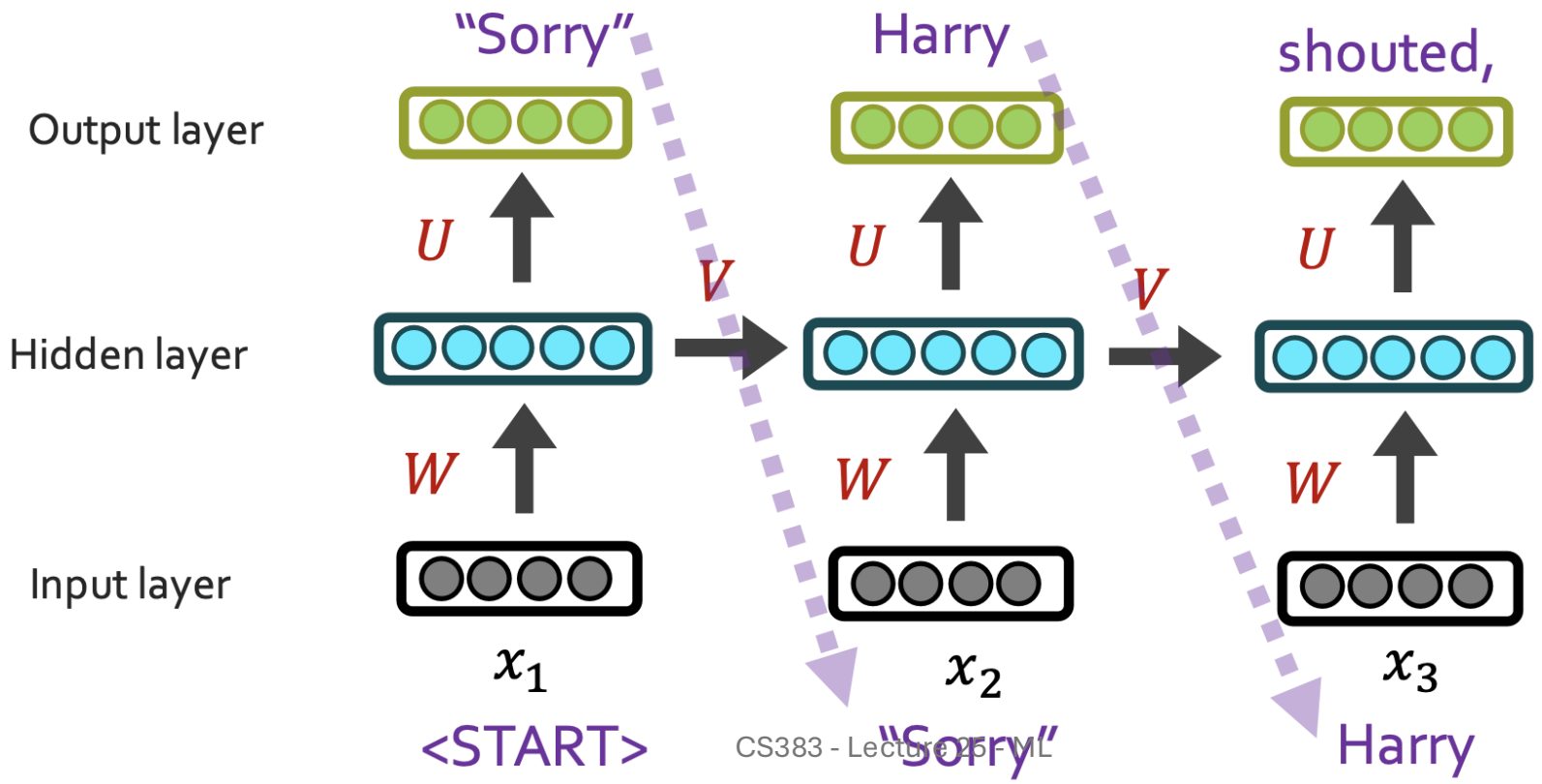

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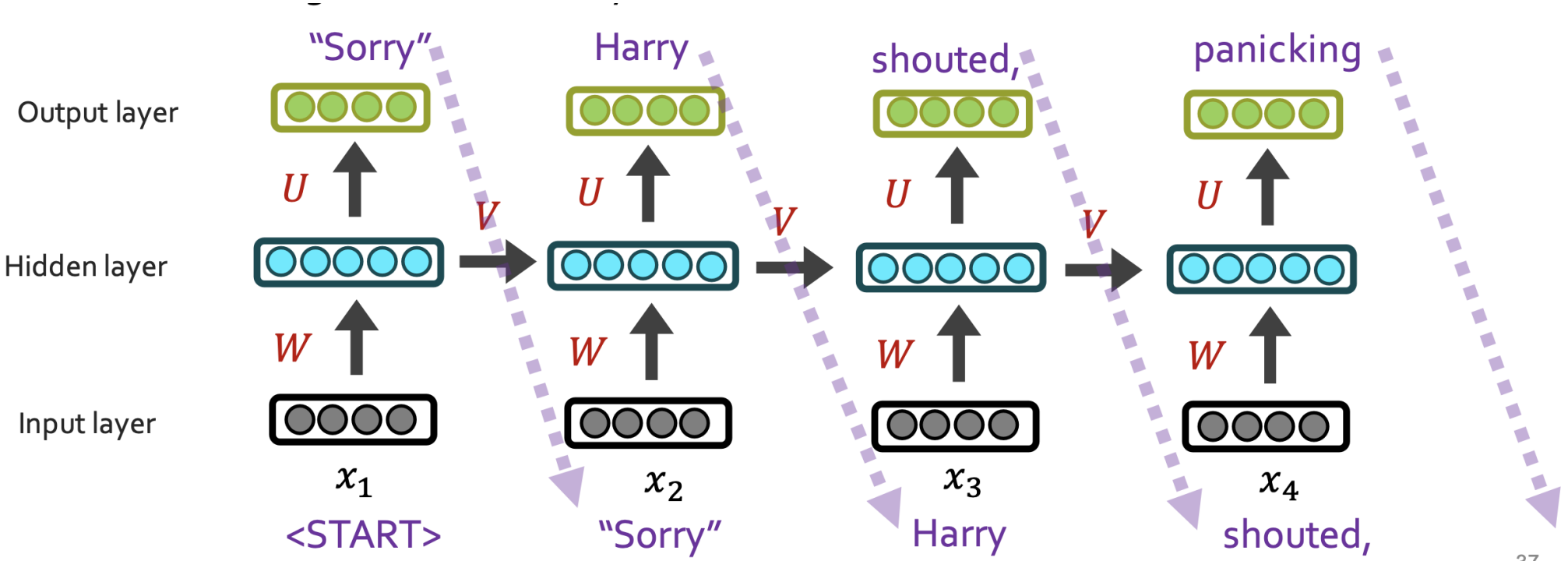


RNN's: Pros and Cons

Pros:

- Model size doesn't increase for longer inputs.
  - Reusing same parameters
- Computation can use information from many previous steps

Cons:

- Slow computation
- Can forget longer history/context
- Vanishing/exploding gradients

Exploding/Vanishing gradient

Backpropagated loss multiplied at each layer

If |loss|> 1,

exponential growth -> ∞

If loss > 0 and <1

exponential decay -> 0

Solution – Gradient Clipping

If the gradient is greater than some threshold, scale it before updating weights

Pascanu et al. 2013
http://proceedings.mlr.press/v28/pascanu13.pdf

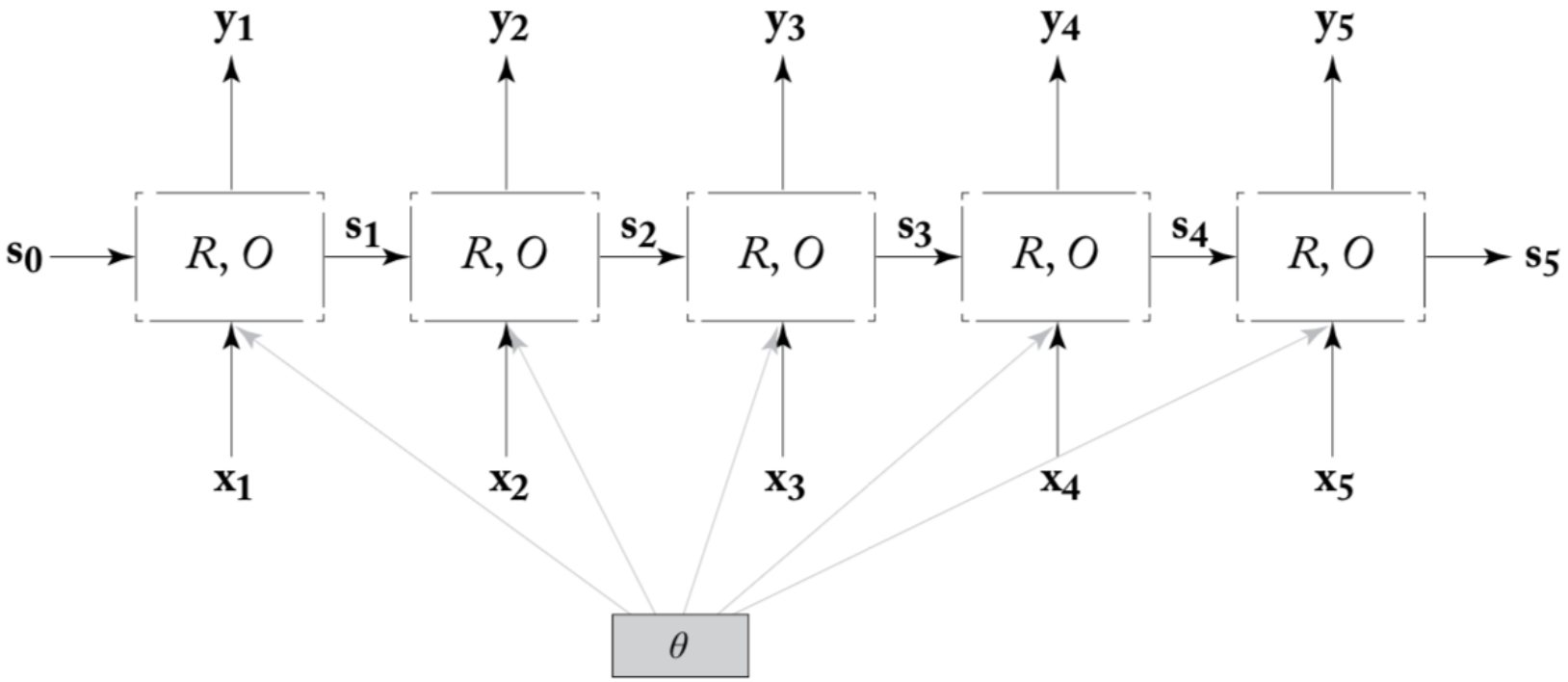
Intuition:

Take a step in the same direction, but smaller

Algorithm 1 Pseudo-code for norm clipping

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|}\hat{\mathbf{g}}$
end if

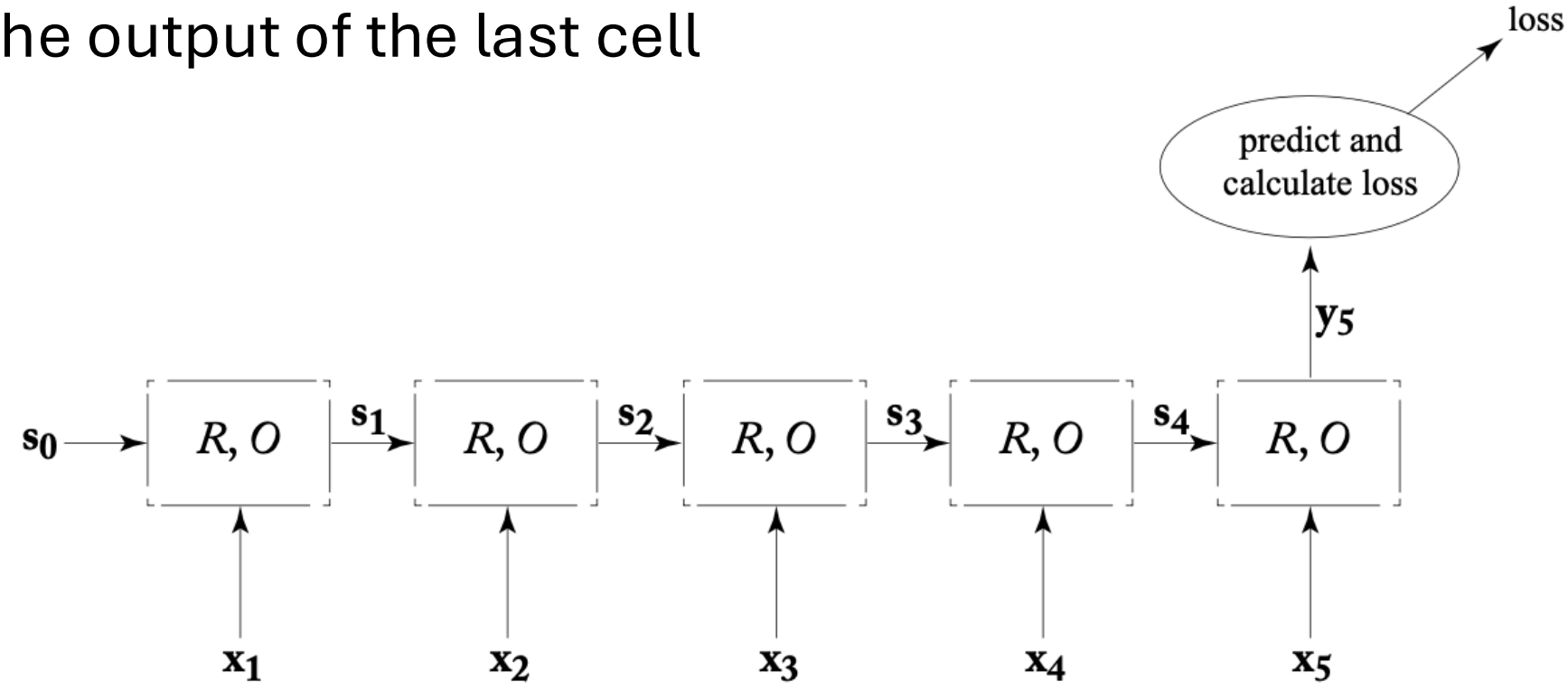
Extracting representation from RNN layer



Extracting representation from RNN layer

Acceptor

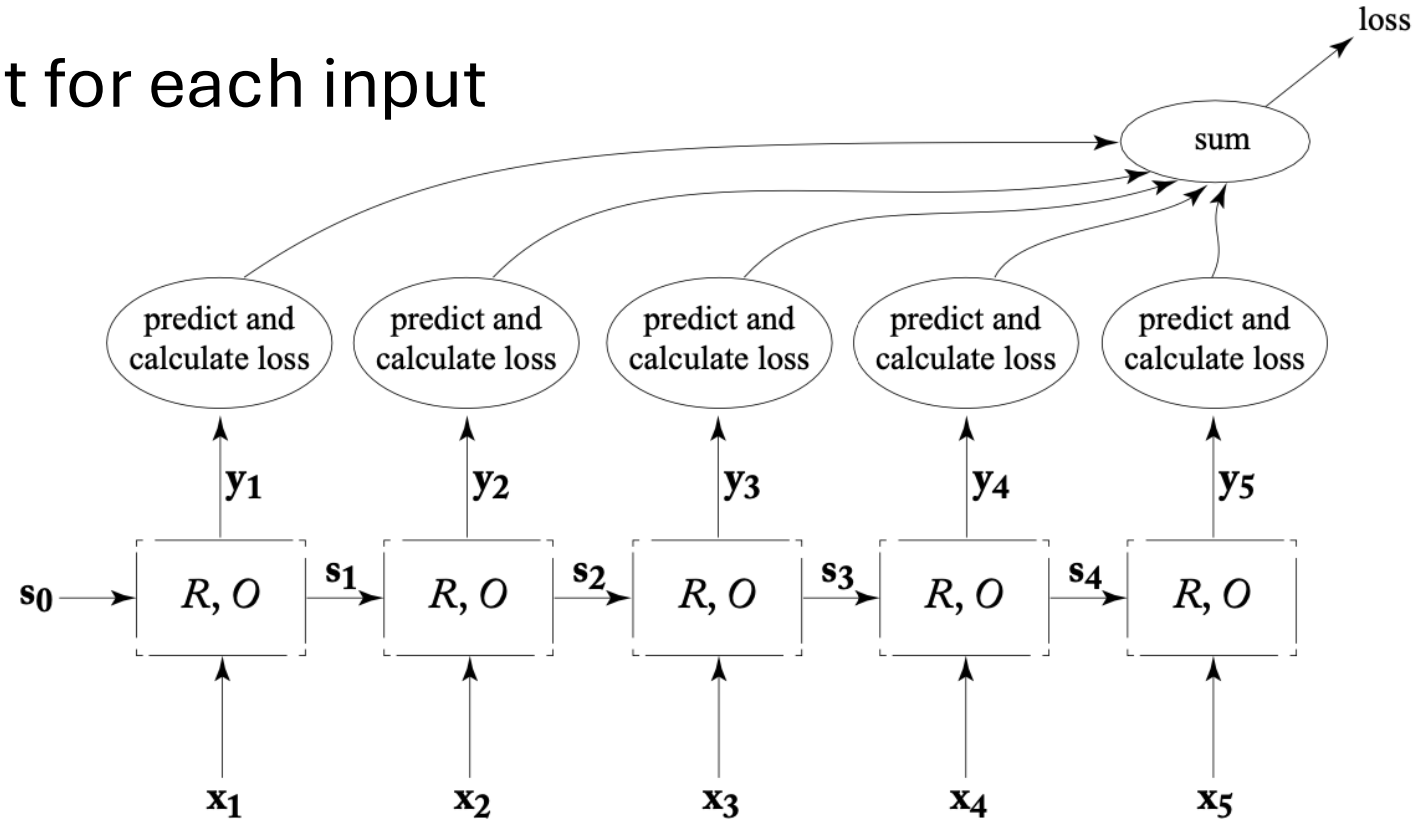
- Take the output of the last cell



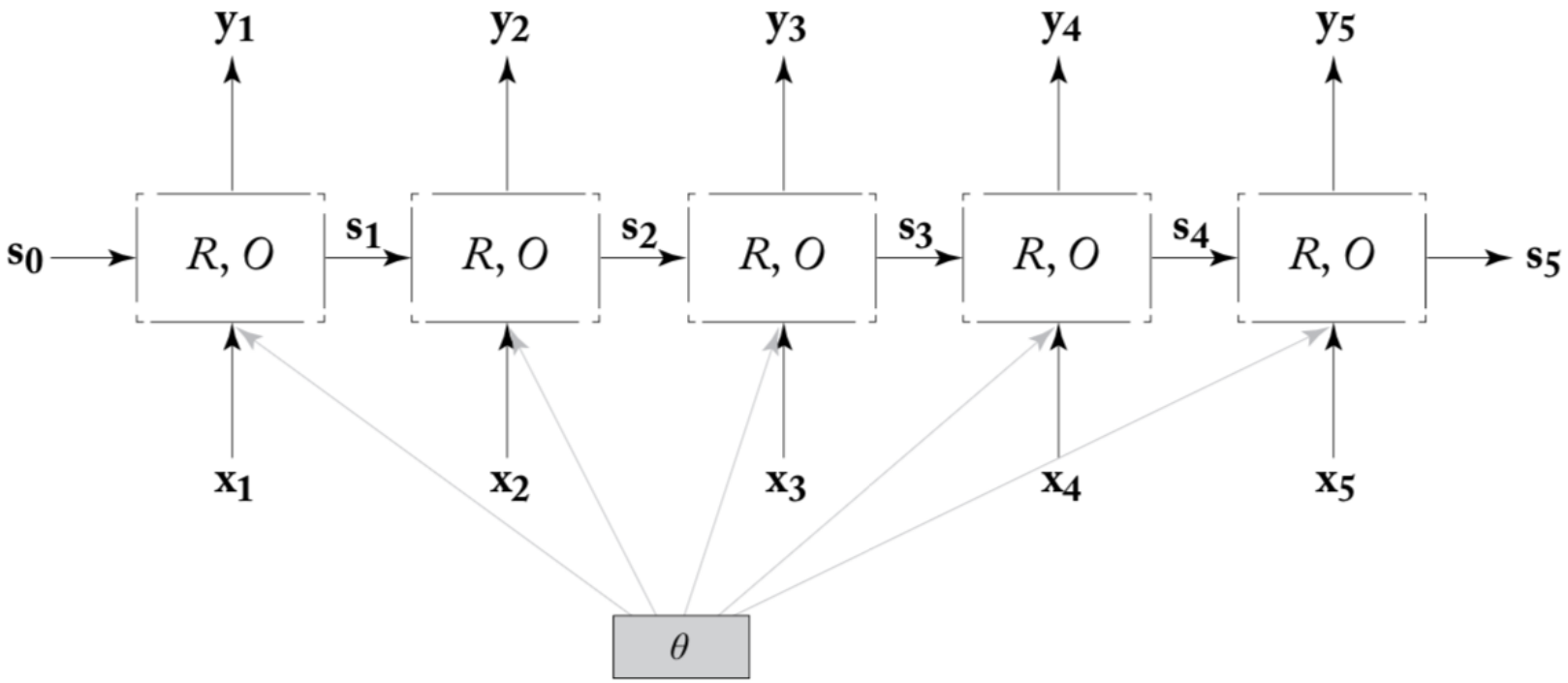
Extracting representation from RNN layer

Transducer

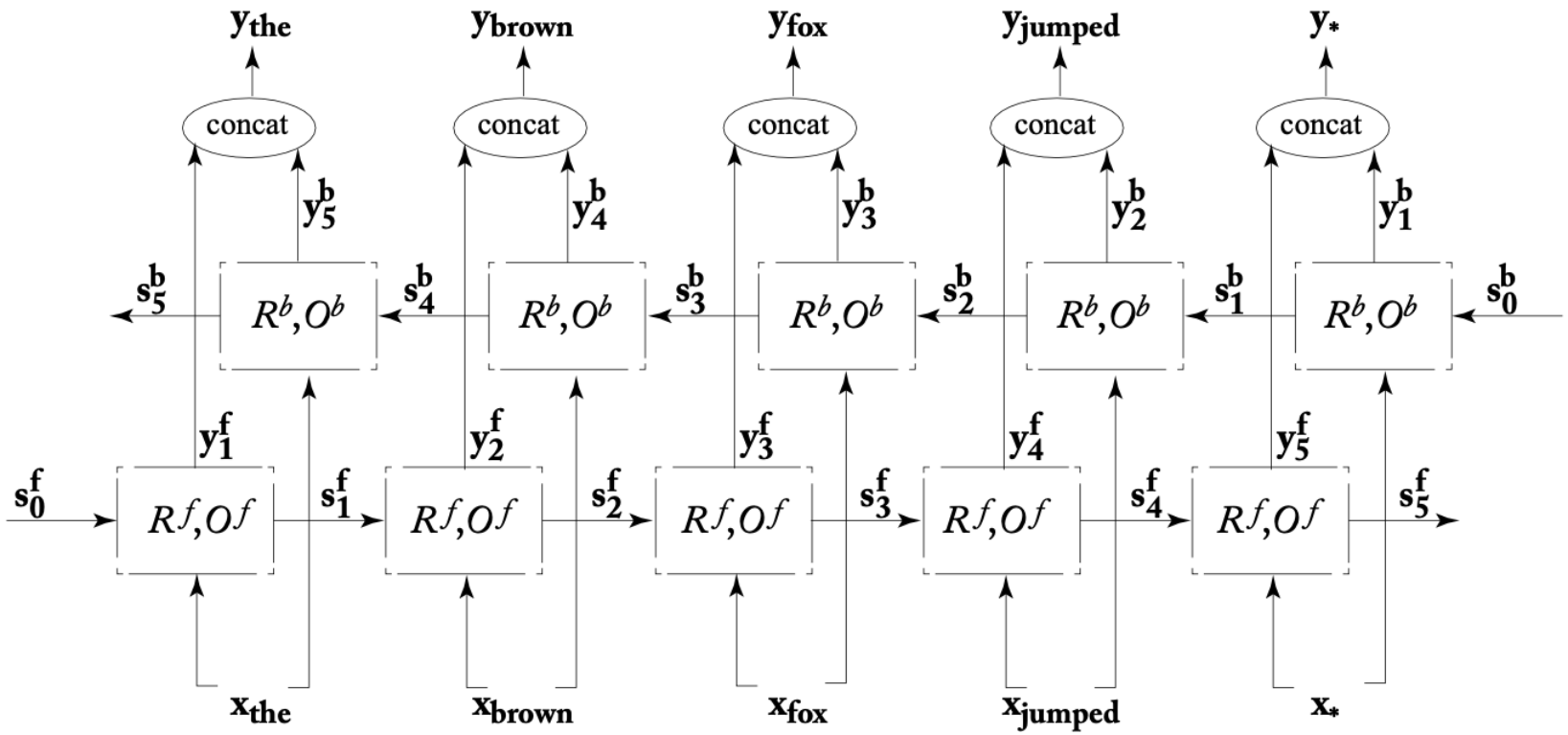
- Create an output for each input



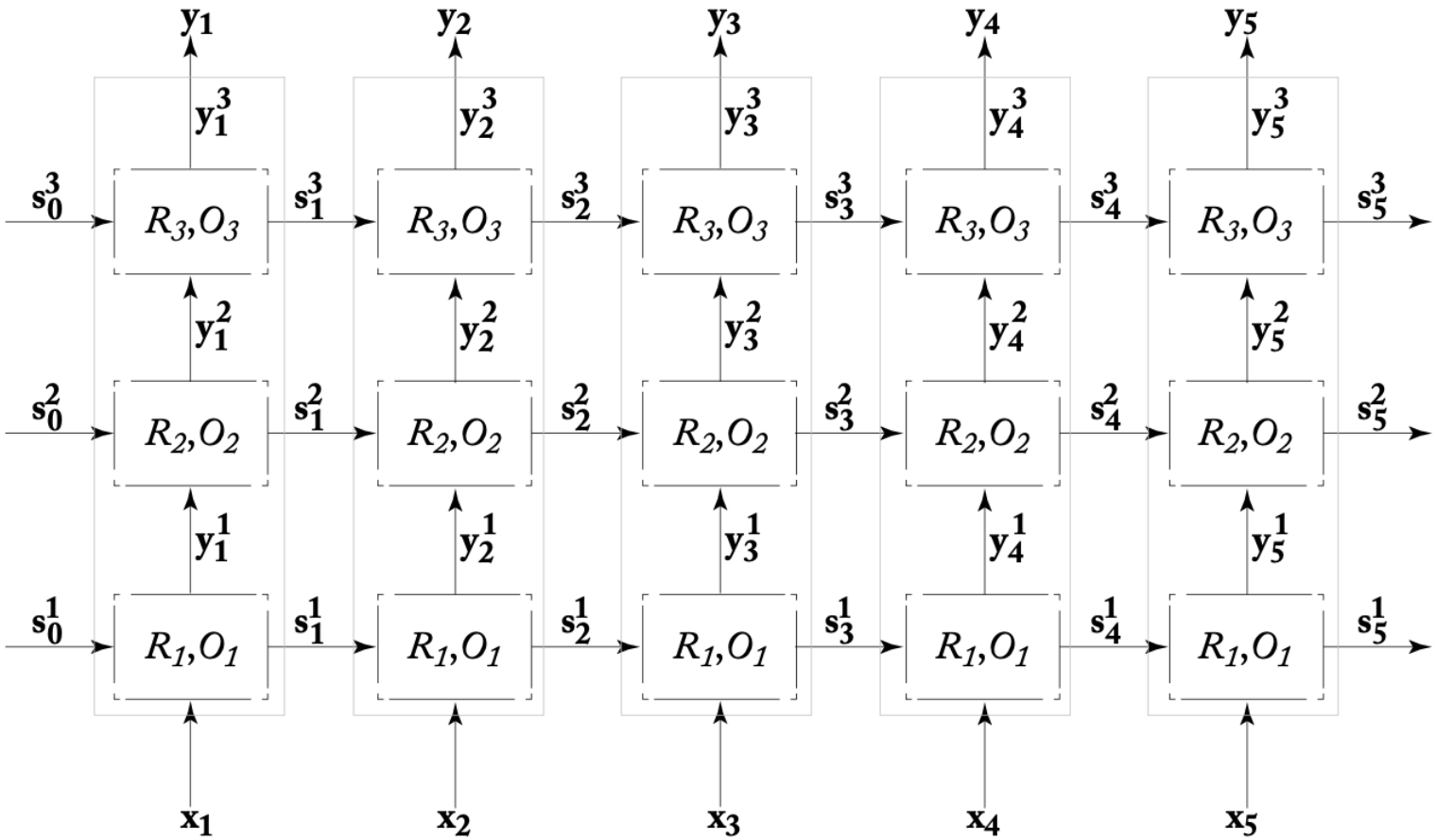
How else can we expand this?



Bi-directional



Stack more layers



Pytorch - nn.RNN

Parameters:

- **input_size** – The number of expected features in the input *x*
- **hidden_size** – The number of features in the hidden state *h*
- **num_layers** – Number of recurrent layers. E.g., setting `num_layers=2` would mean stacking two RNNs together to form a *stacked RNN*, with the second RNN taking in outputs of the first RNN and computing the final results. Default: 1
- **nonlinearity** – The non-linearity to use. Can be either `'tanh'` or `'relu'`. Default: `'tanh'`
- **bias** – If `False`, then the layer does not use bias weights *b_ih* and *b_hh*. Default: `True`
- **batch_first** – If `True`, then the input and output tensors are provided as (*batch, seq, feature*) instead of (*seq, batch, feature*). Note that this does not apply to hidden or cell states. See the Inputs/Outputs sections below for details. Default: `False`
- **dropout** – If non-zero, introduces a *Dropout* layer on the outputs of each RNN layer except the last layer, with dropout probability equal to `dropout`. Default: 0
- **bidirectional** – If `True`, becomes a bidirectional RNN. Default: `False`

RNNs – long input

RNNs can remember anything (in theory)

Sometimes its important to forget

Solution: Long-Short Term Memory (LSTM)

Outline

Issues when training NNs

Pytorch

FFN’s for variable length input

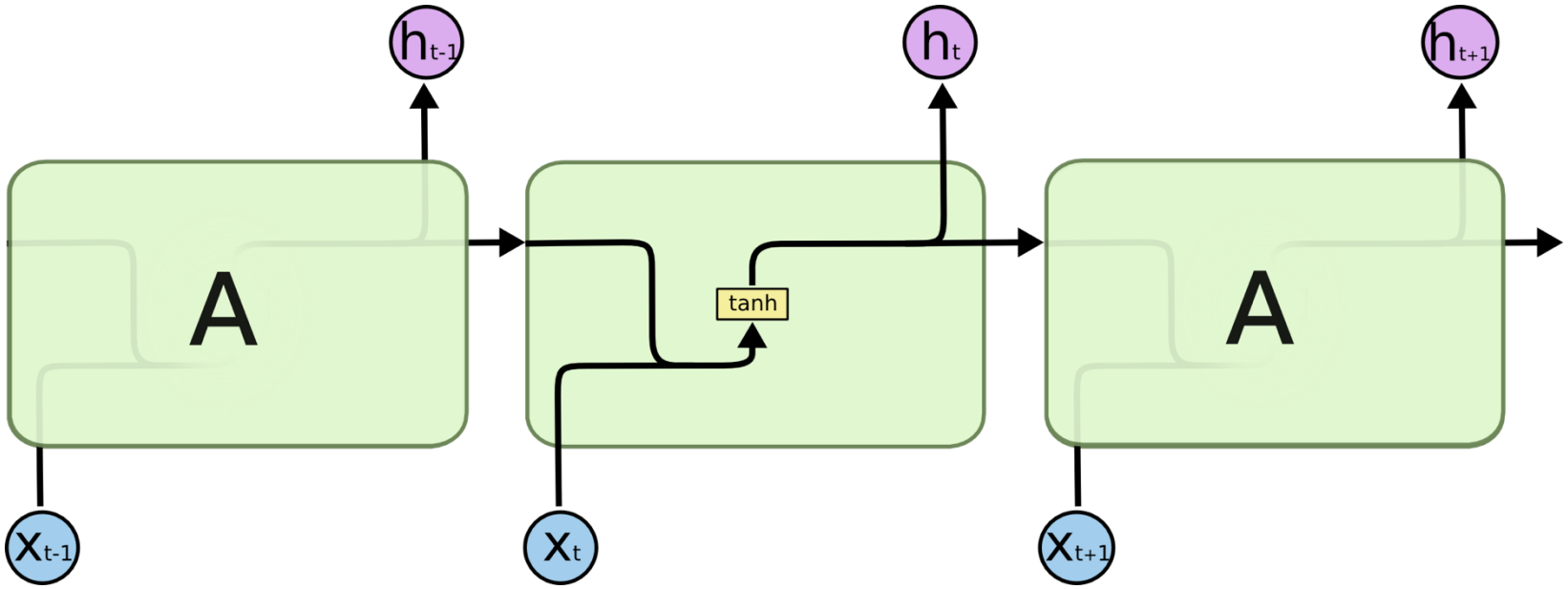
RNN

LSTM

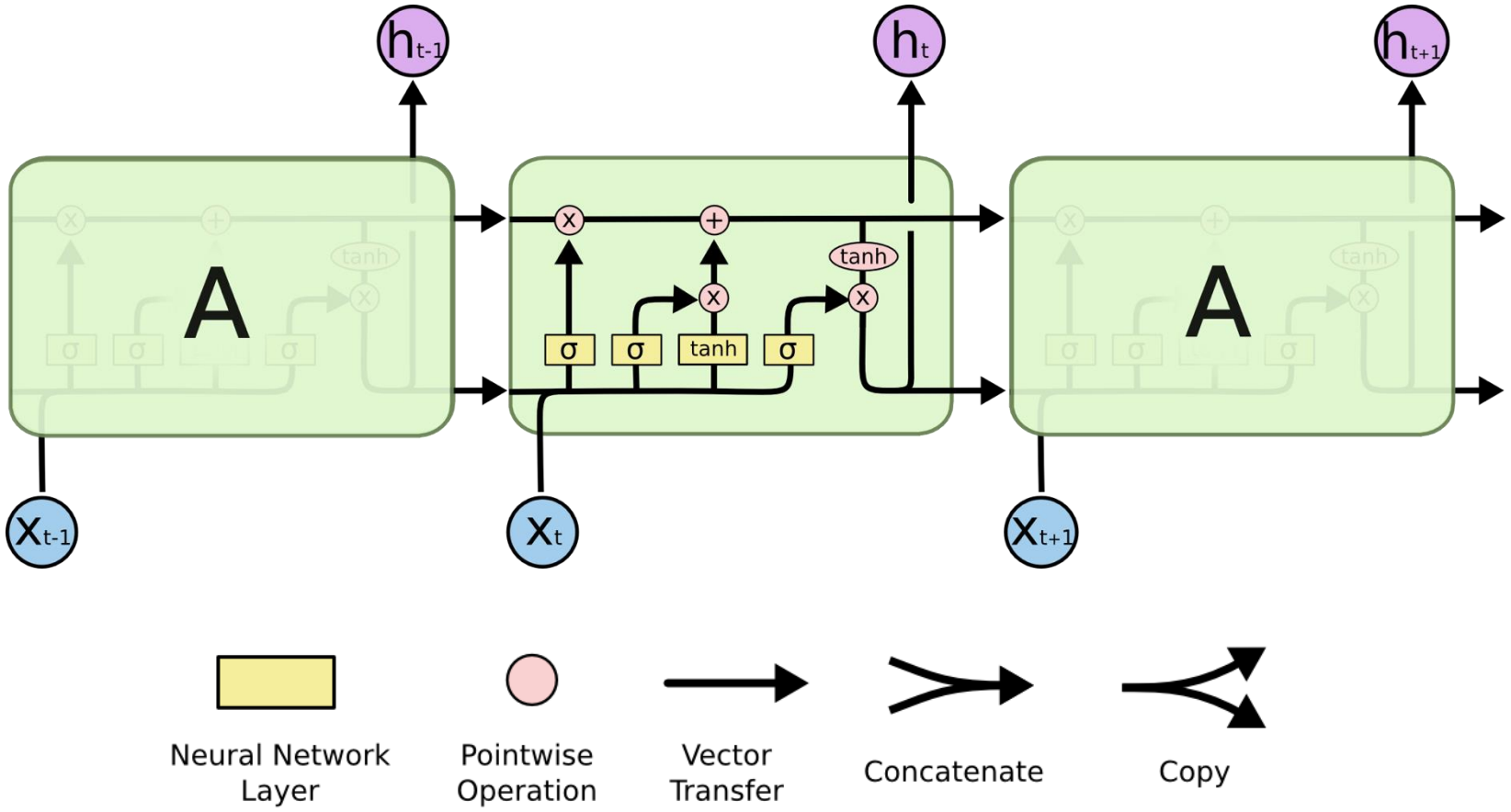
Attention

Self Attention

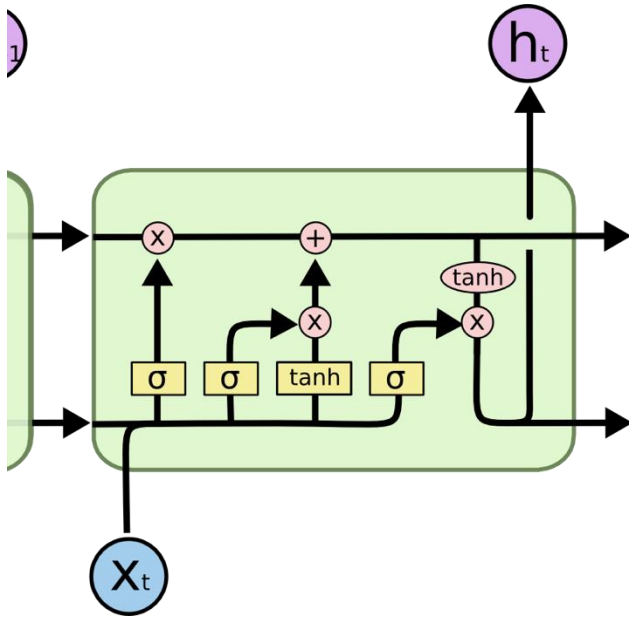
RNN internal



LSTM internal



LSTM internal



$$s_j = R_{\text{LSTM}}(s_{j-1}, x_j) = [c_j; h_j]$$

$$c_j = f \odot c_{j-1} + i \odot z$$

$$h_j = o \odot \tanh(c_j)$$

$$i = \sigma(x_j W^{xi} + h_{j-1} W^{hi})$$

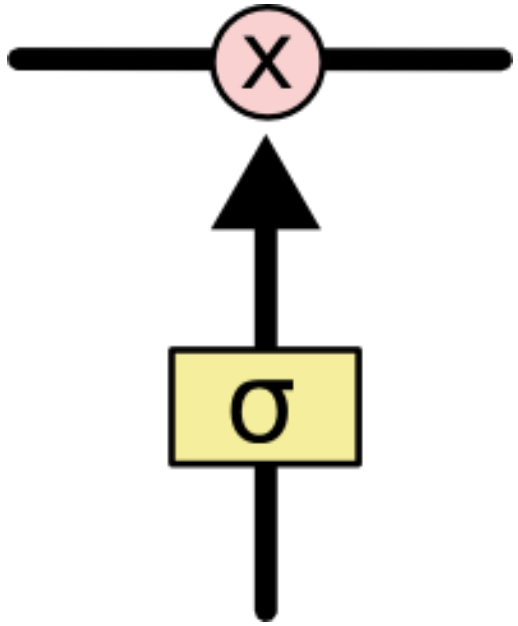
$$f = \sigma(x_j W^{xf} + h_{j-1} W^{hf})$$

$$o = \sigma(x_j W^{xo} + h_{j-1} W^{ho})$$

$$z = \tanh(x_j W^{xz} + h_{j-1} W^{hz})$$

$$y_j = O_{\text{LSTM}}(s_j) = h_j$$

LSTM's rely on gates

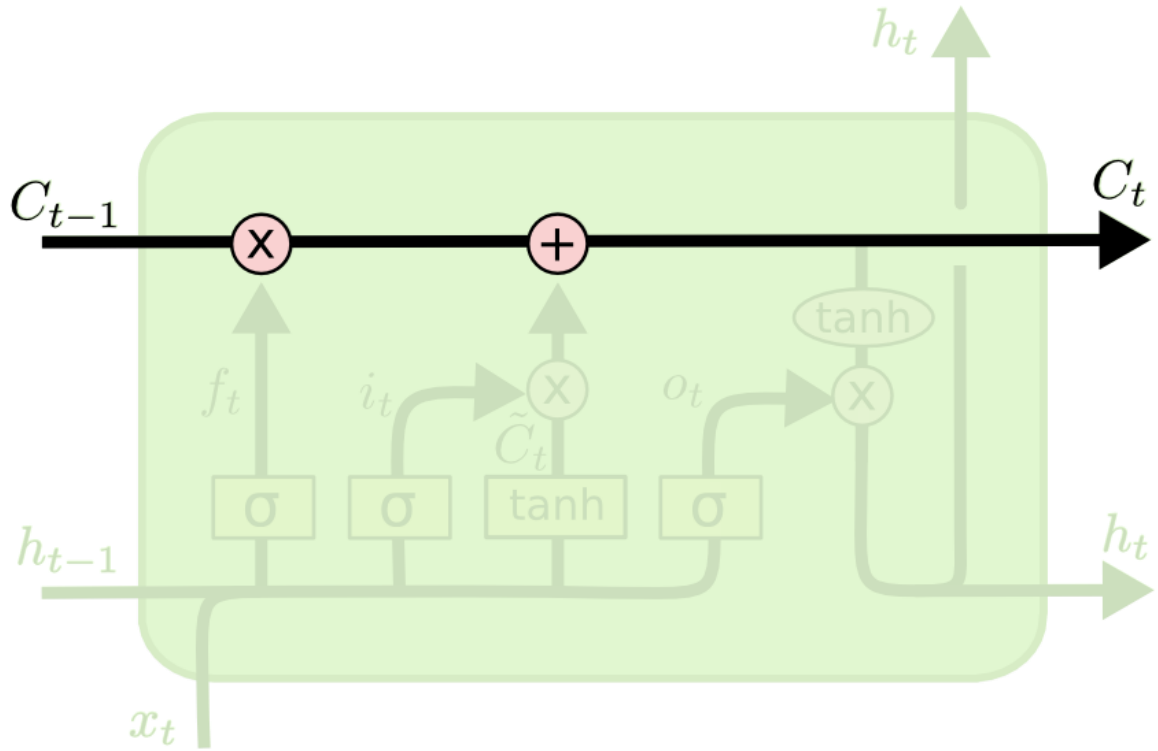


- Multiply input by value in 0,1]
- Zero means forget everything
- 1 means carry everything through (unchanged)

- 4 gates used in LSTM

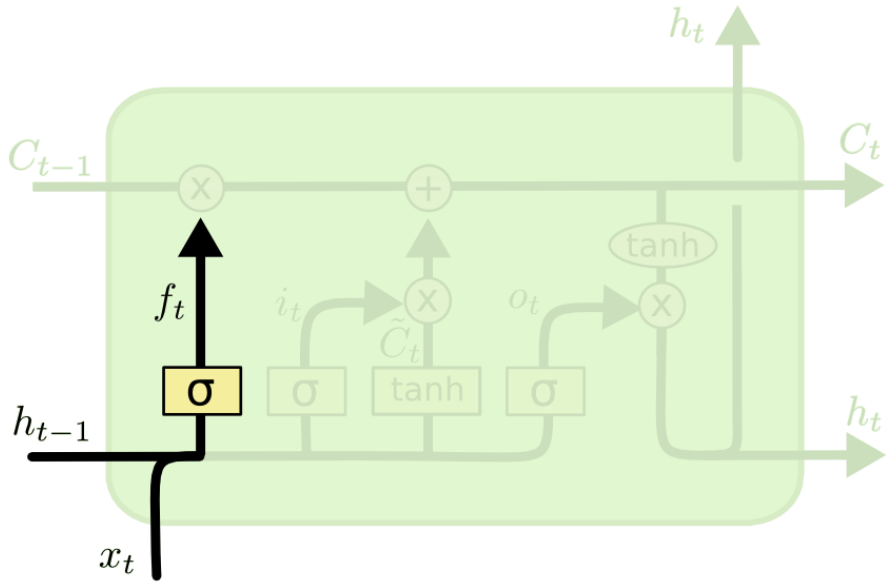
LSTM gates: cell state

- Passes the memory through the cell



LSTM gates: forget

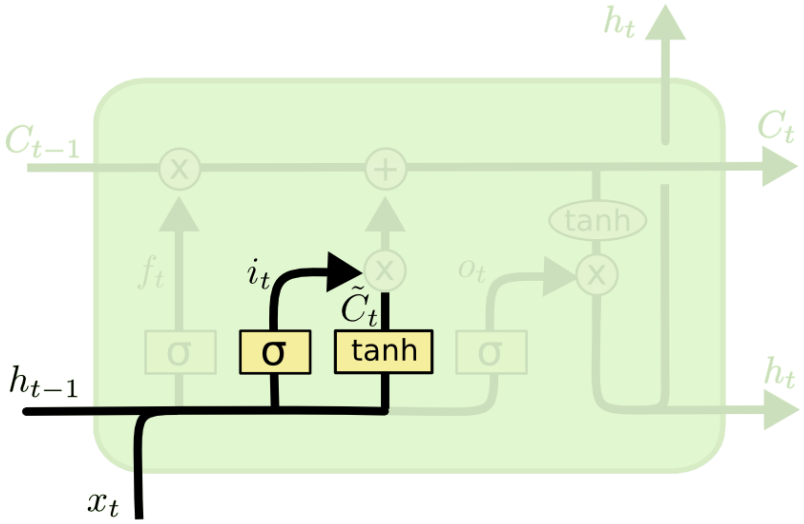
- Can decide to forget the previous state h_{t-1}



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

LSTM gates: update

- Compute new contribution to cell state based on hidden state and input.

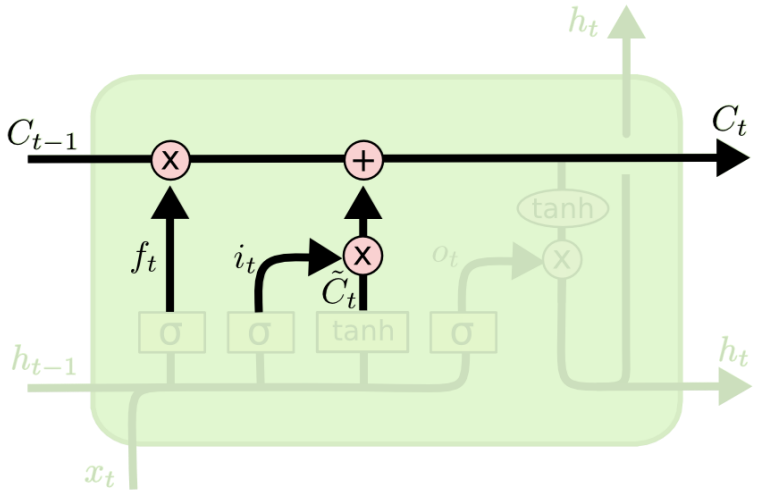


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

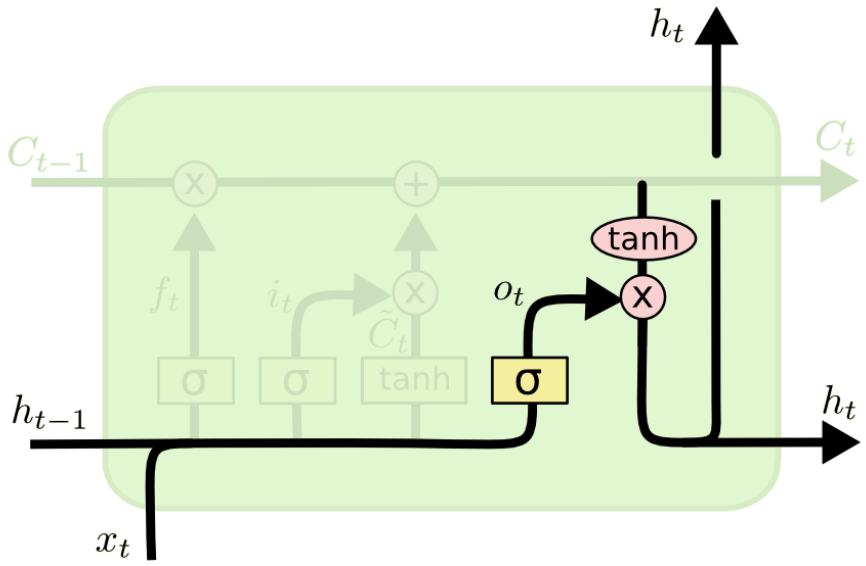
LSTM gates: update (interpolate)

- Can decide to forget the previous state h_{t-1}



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

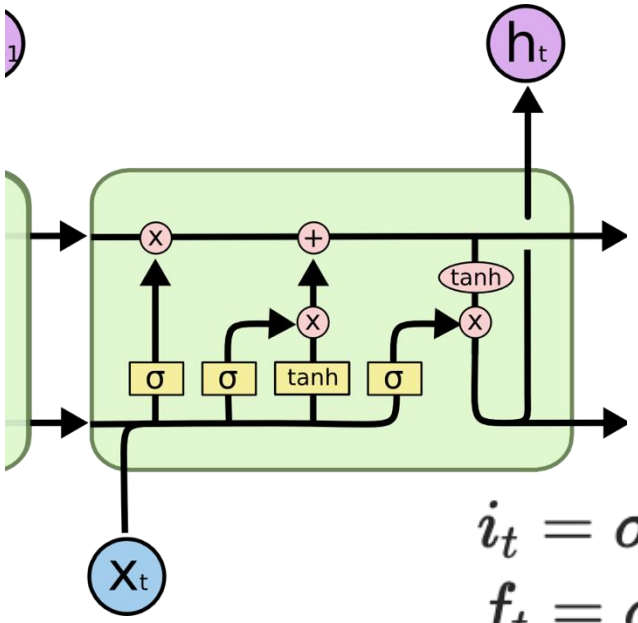
LSTM output (hidden)



$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

LSTM internal



$$
\begin{aligned}
i_t &= \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \\
f_t &= \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \\
g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \\
o_t &= \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \\
c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\
h_t &= o_t \odot \tanh(c_t)
\end{aligned}
$$

Pytorch - nn.LSTM

Parameters:

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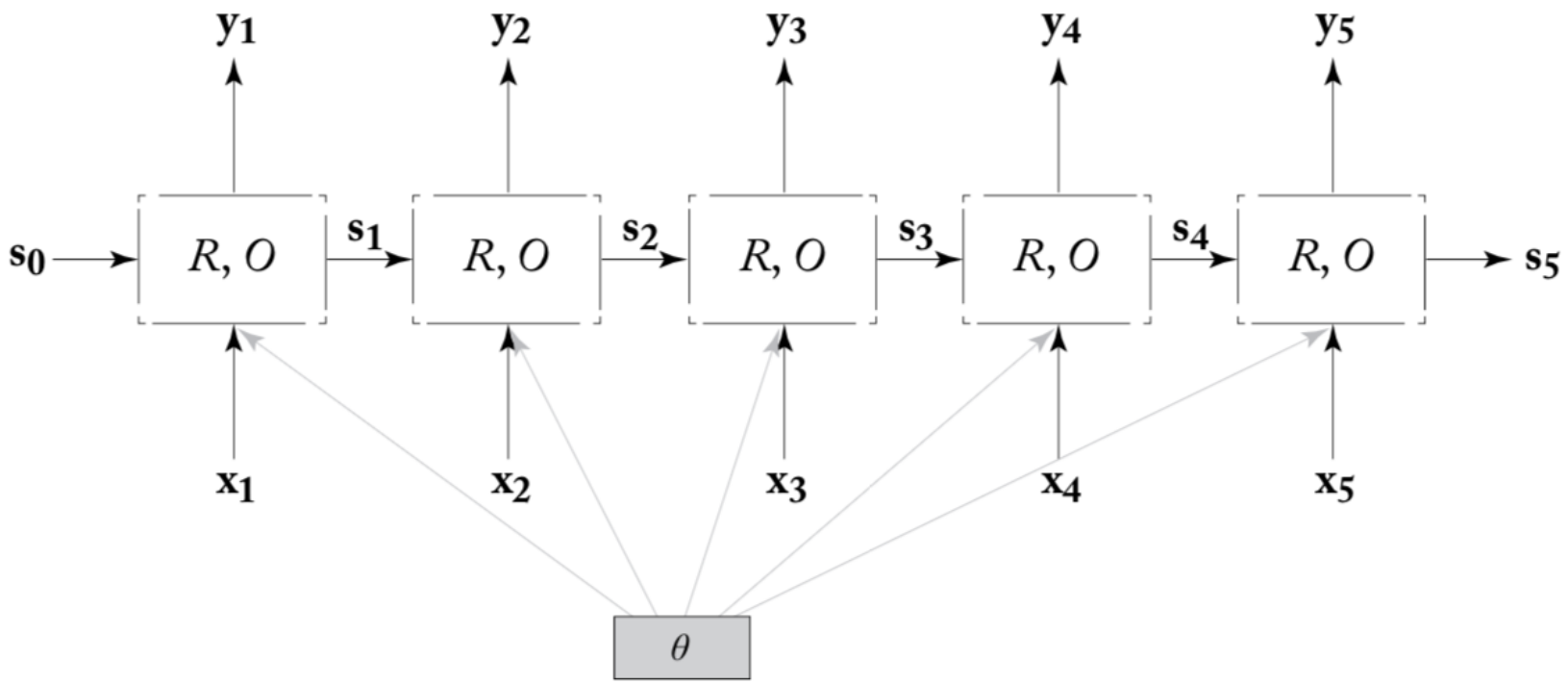
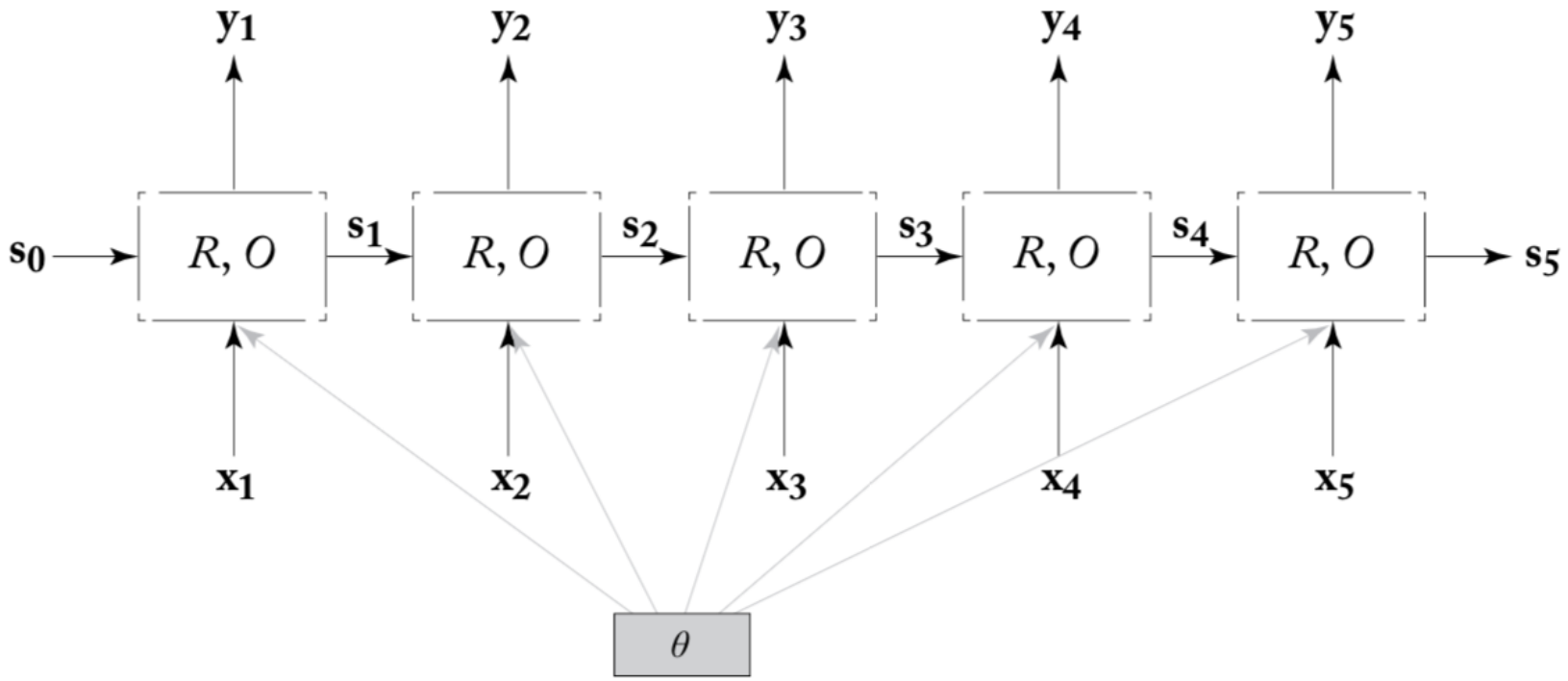
- **bidirectional** – If `True`, becomes a bidirectional LSTM. Default: `False`
- **proj_size** – If `> 0`, will use LSTM with projections of corresponding size. Default: 0

Extracting representation from RNN layer



Extracting representation from RNN layer

How might we combine the output layers



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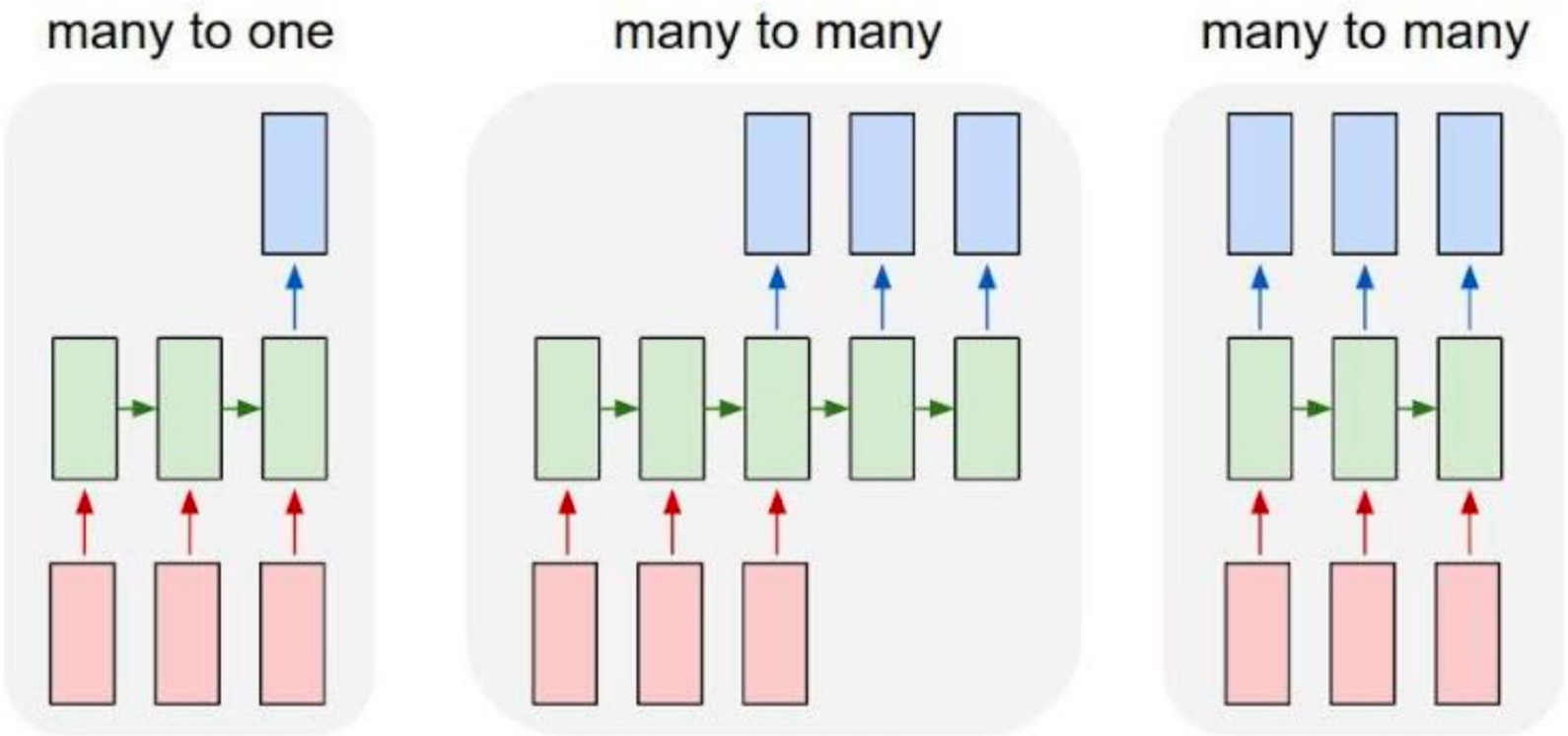
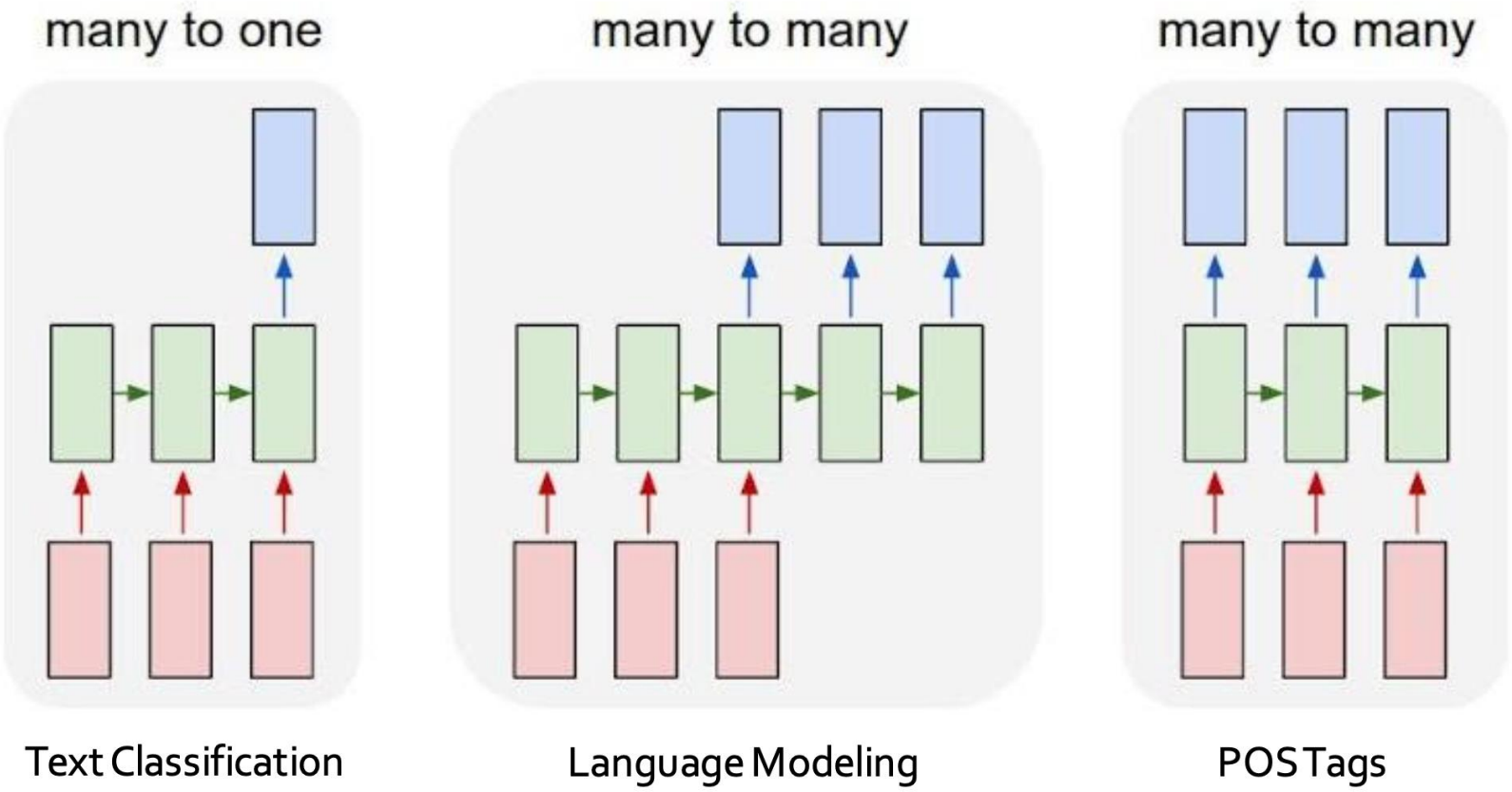
RNNs applied to NLP tasks

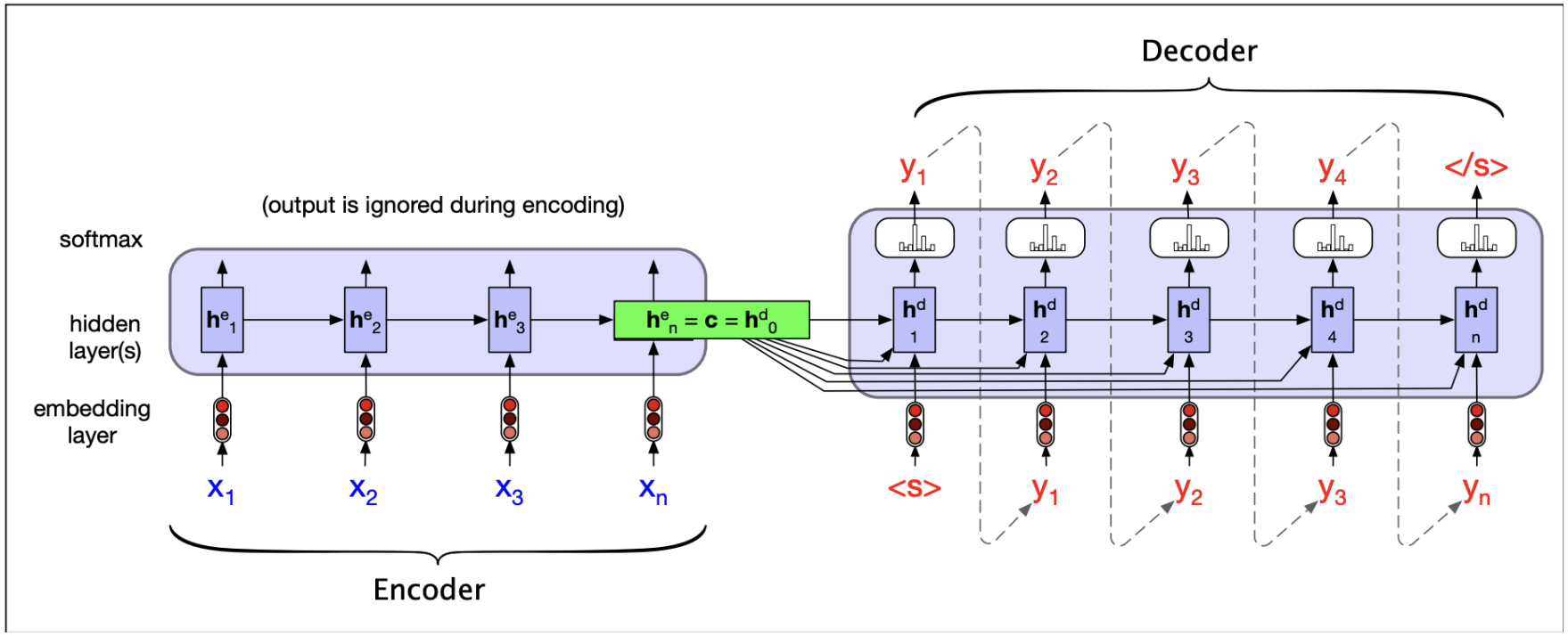


RNNs applied to NLP tasks



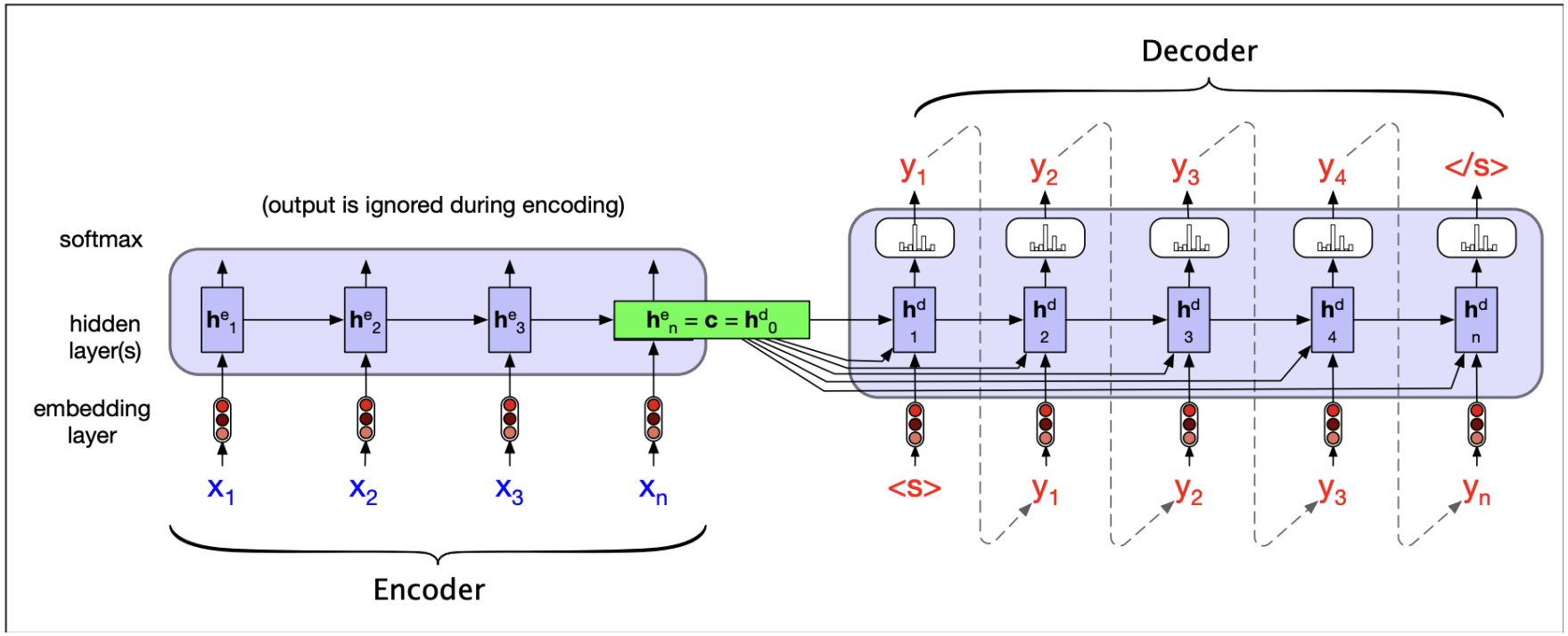
Encoder-decoder

Decoder only uses information from last hidden cell!



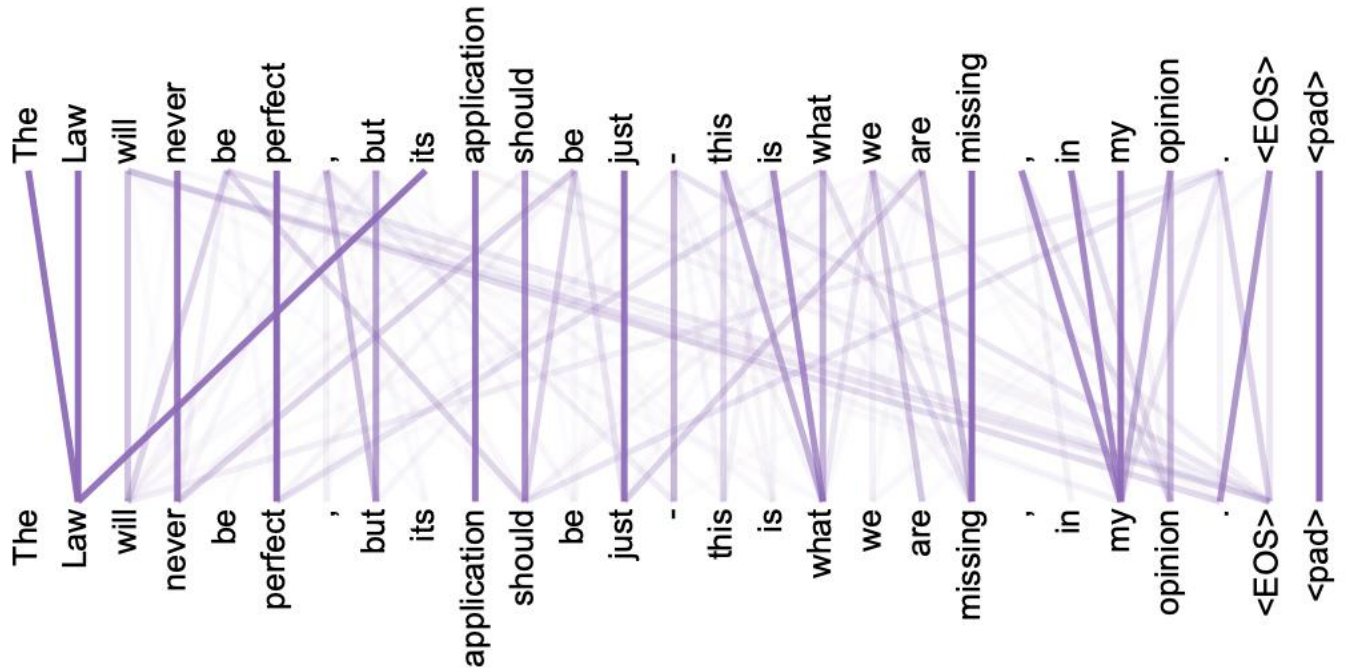
Bottleneck

Last hidden cell is a bottleneck



Solution: Attention!

Core idea: on each step of the decoder, use direct connection to the encoder to focus on a particular part of the source sequence

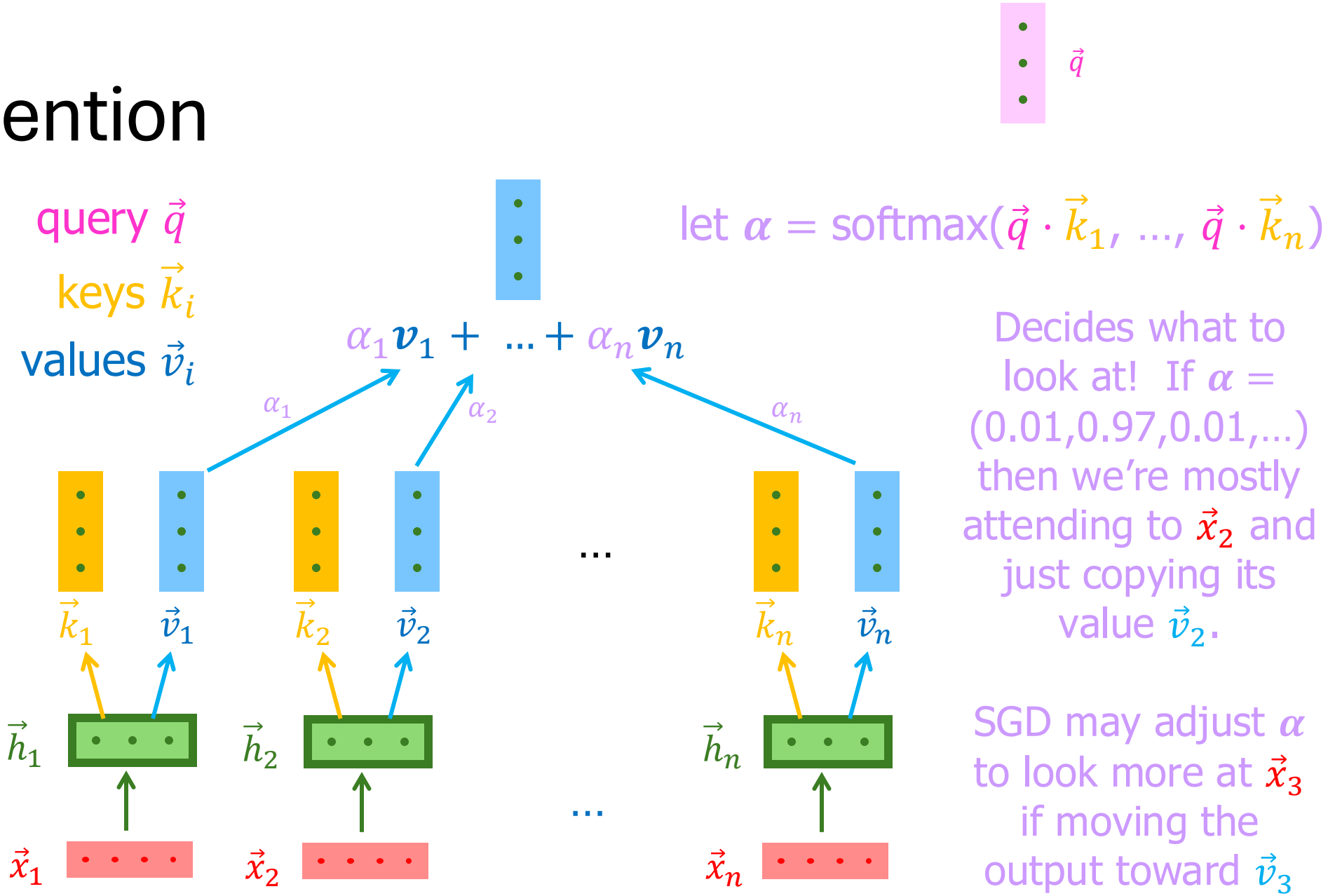


Attention is all you need Vaswani et al 2017

Have we been cramming?

- RNNs etc. – decide early what to keep
  - Encode context into $\mathbb{R}^d$
  - Hope it supports later decoding needs
    - E.g., any reading comprehension question
- Attention – keep it <u>all</u>, decide later what to look at
  - At each decoding step, get to look back at all of the n encoded context objects, each in $\mathbb{R}^d$
  - Take a weighted average of them, where the weights depend on a query created at decoding time
  - This average "completes the encoding" into $\mathbb{R}^d$

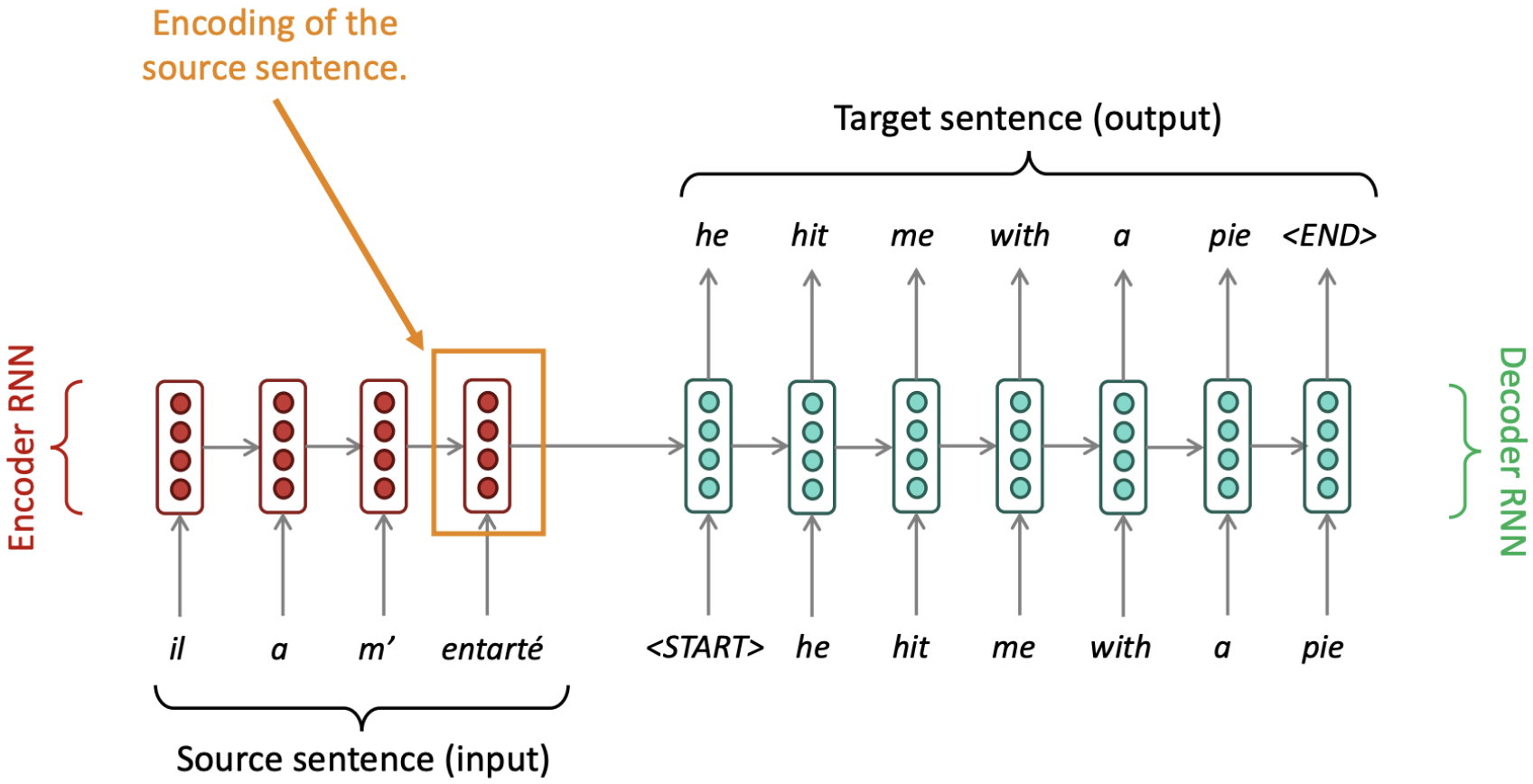
Attention



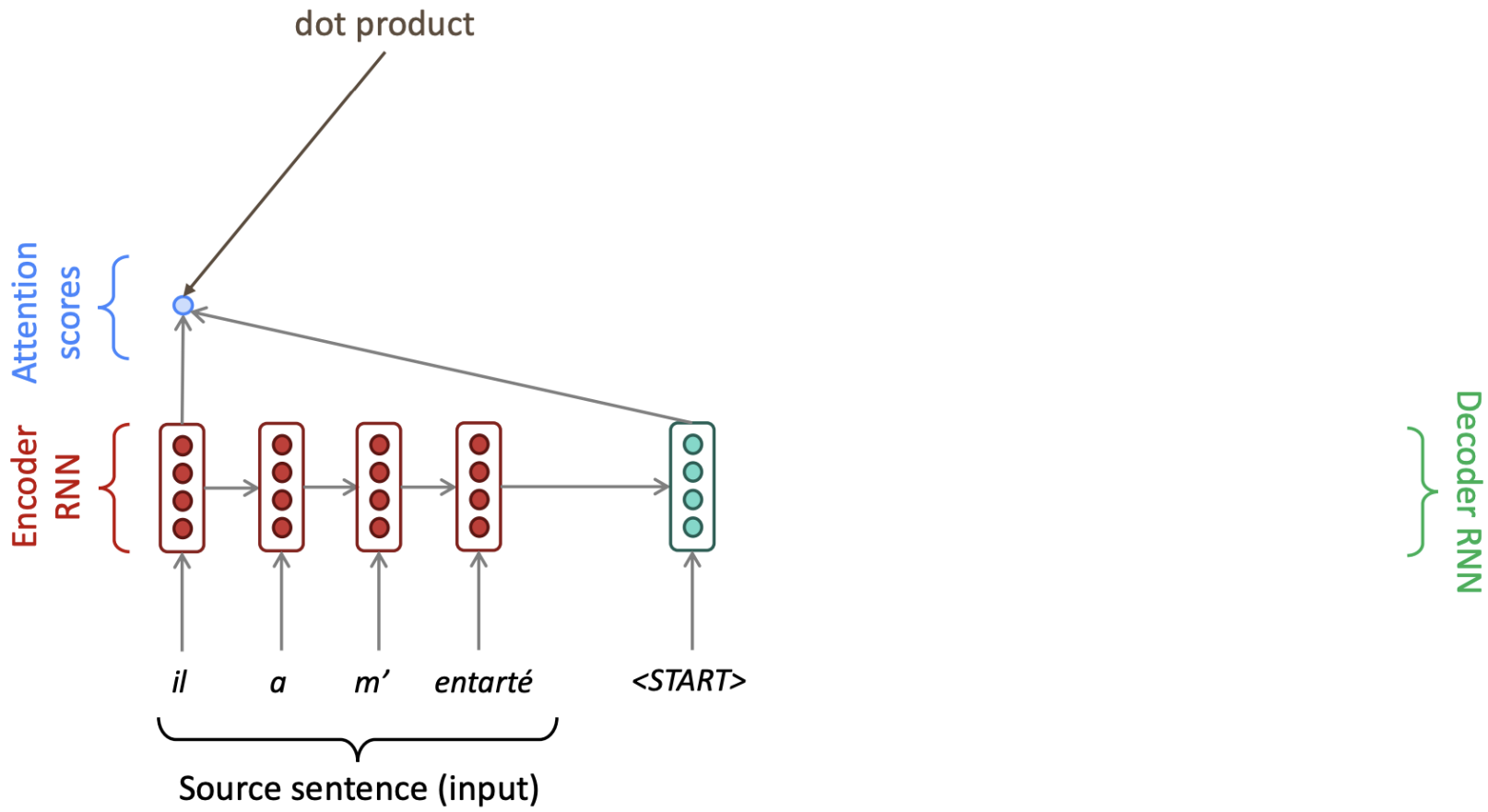
Decides what to look at! If α = (0.01,0.97,0.01,…) then we're mostly attending to $\vec{x}_2$ and just copying its value $\vec{v}_2$.

SGD may adjust α to look more at $\vec{x}_3$ if moving the output toward $\vec{v}_3$ would help loss.

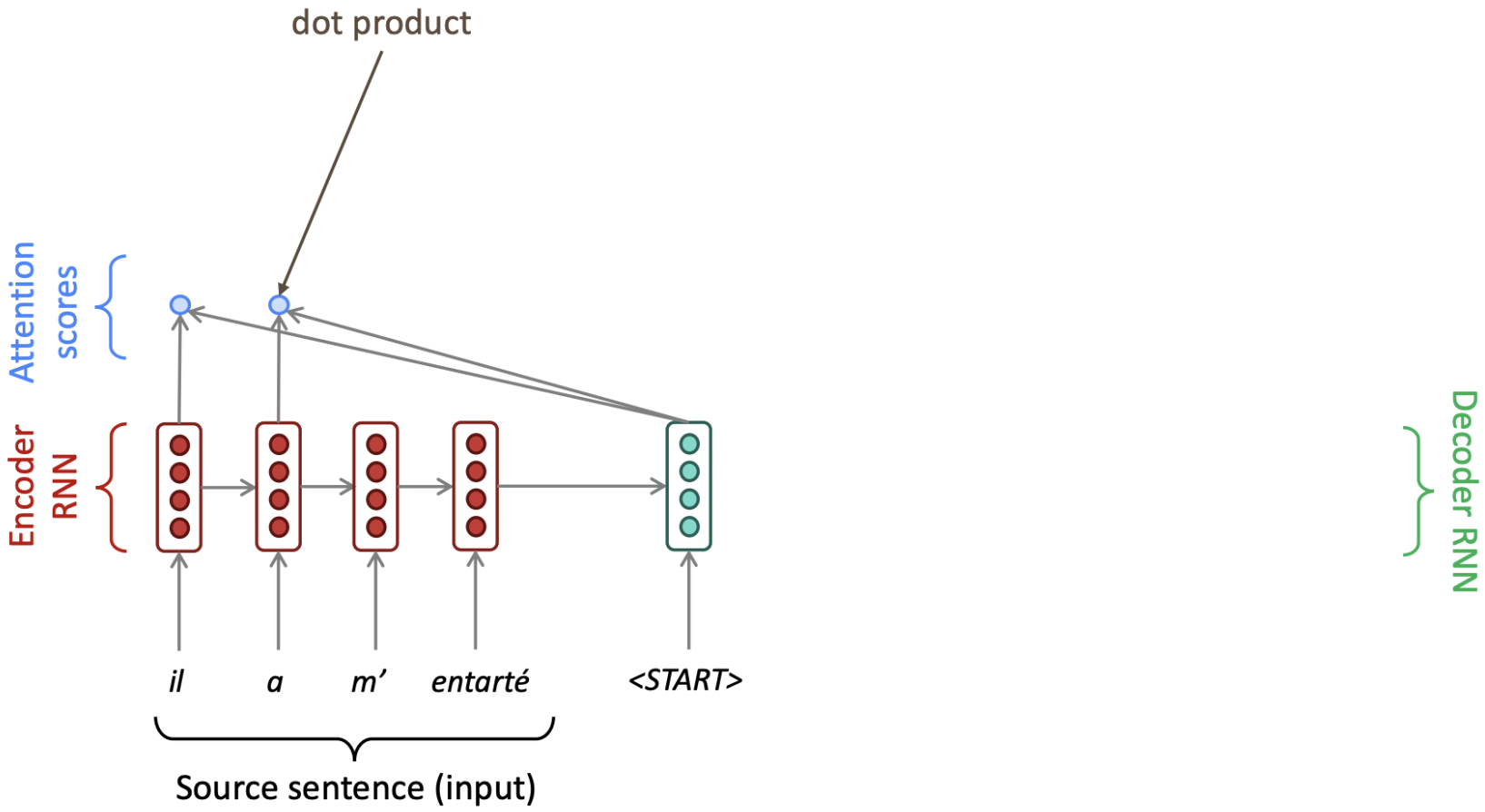
Seq2Seq Model



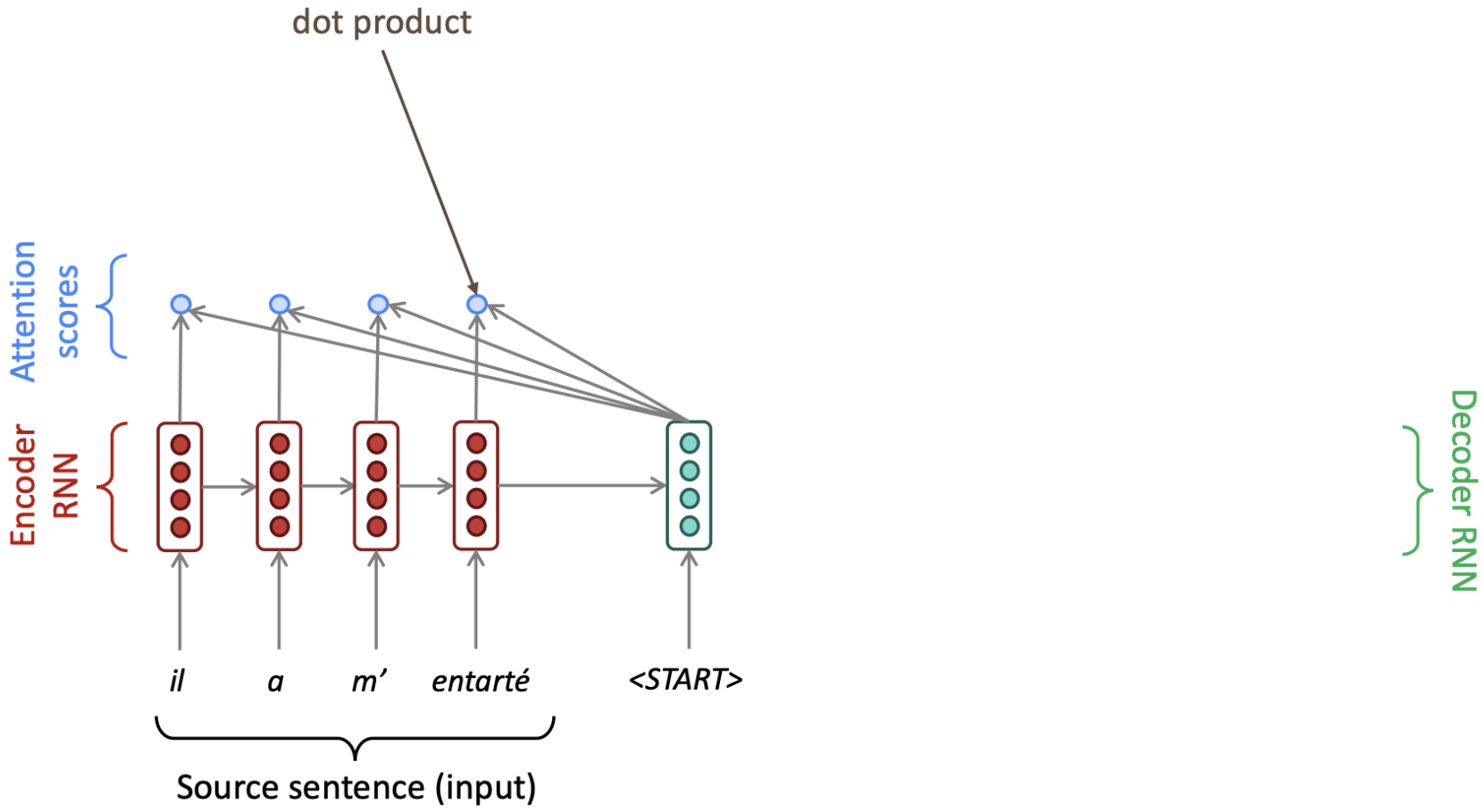
Seq2Seq w/ Attention



Seq2Seq w/ Attention



Seq2Seq w/ Attention



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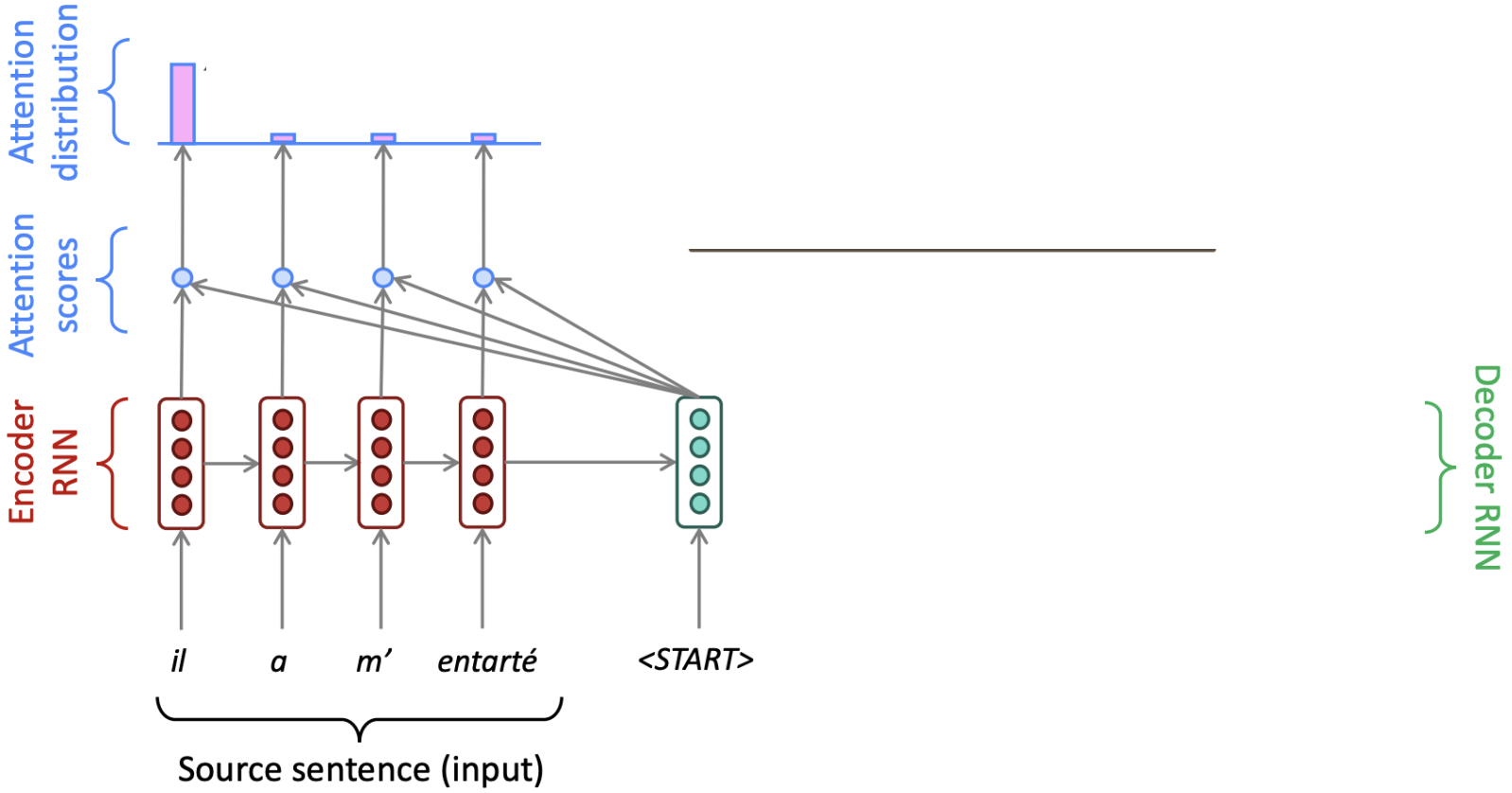
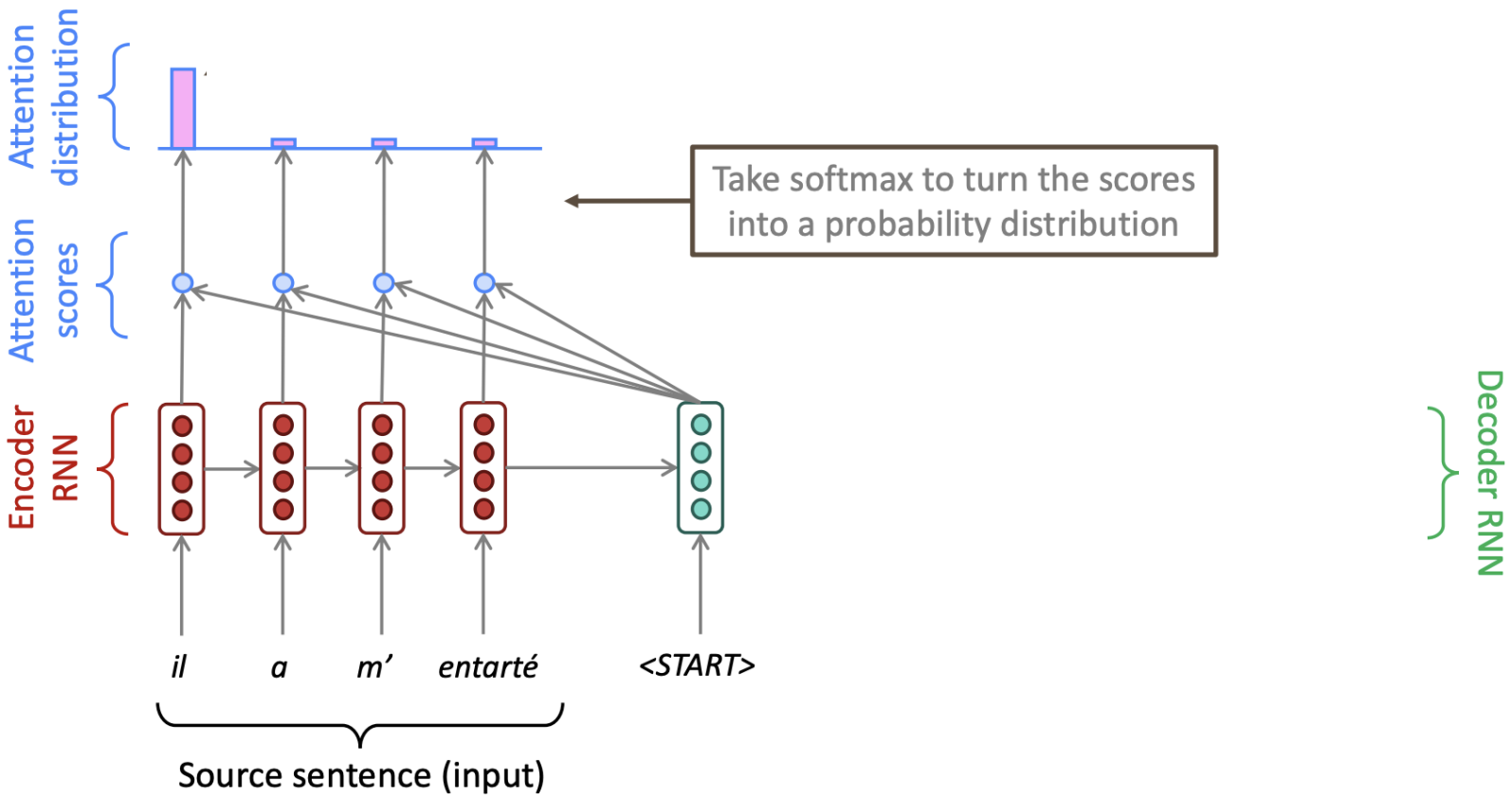


Seq2Seq w/ Attention



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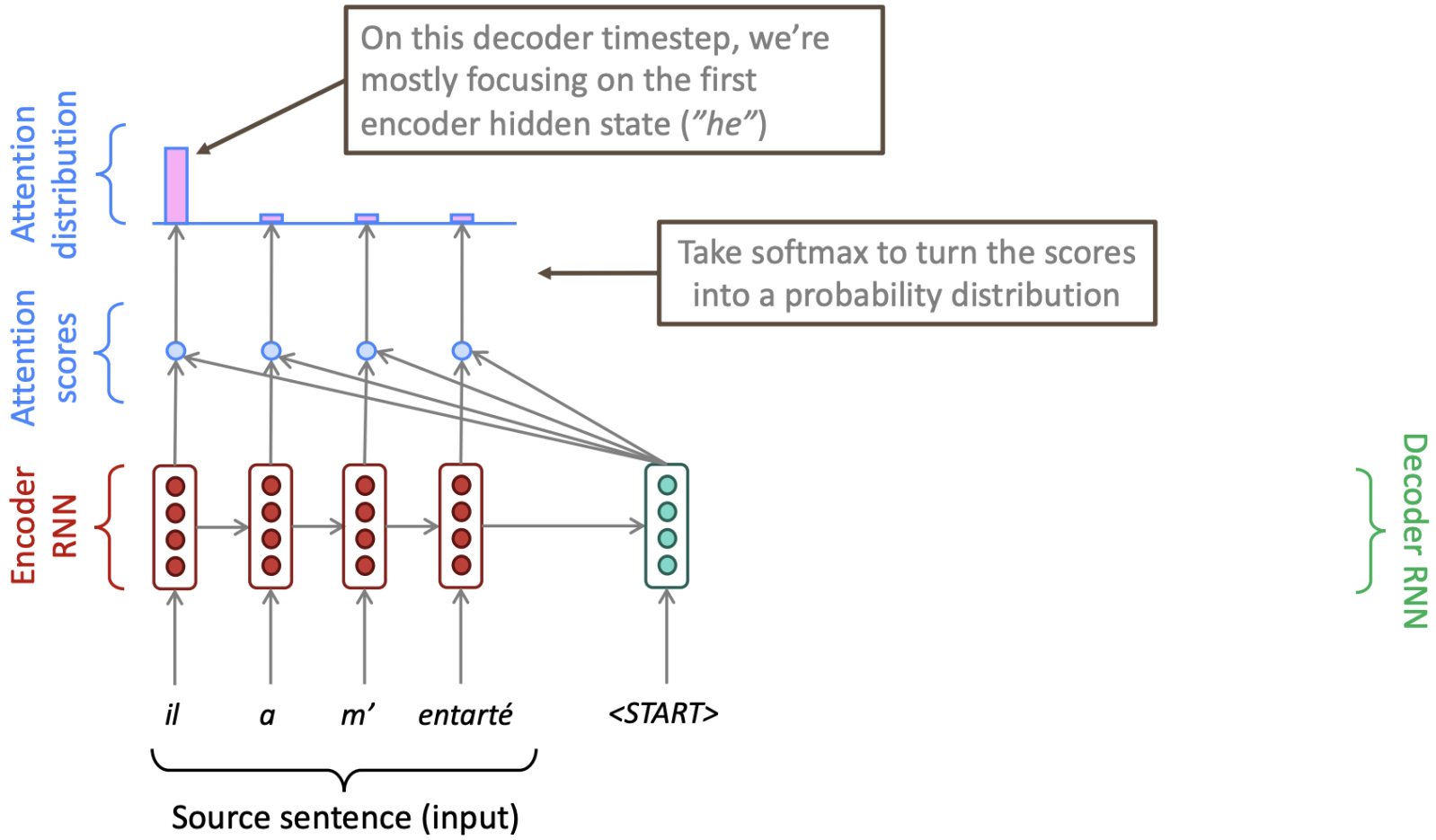

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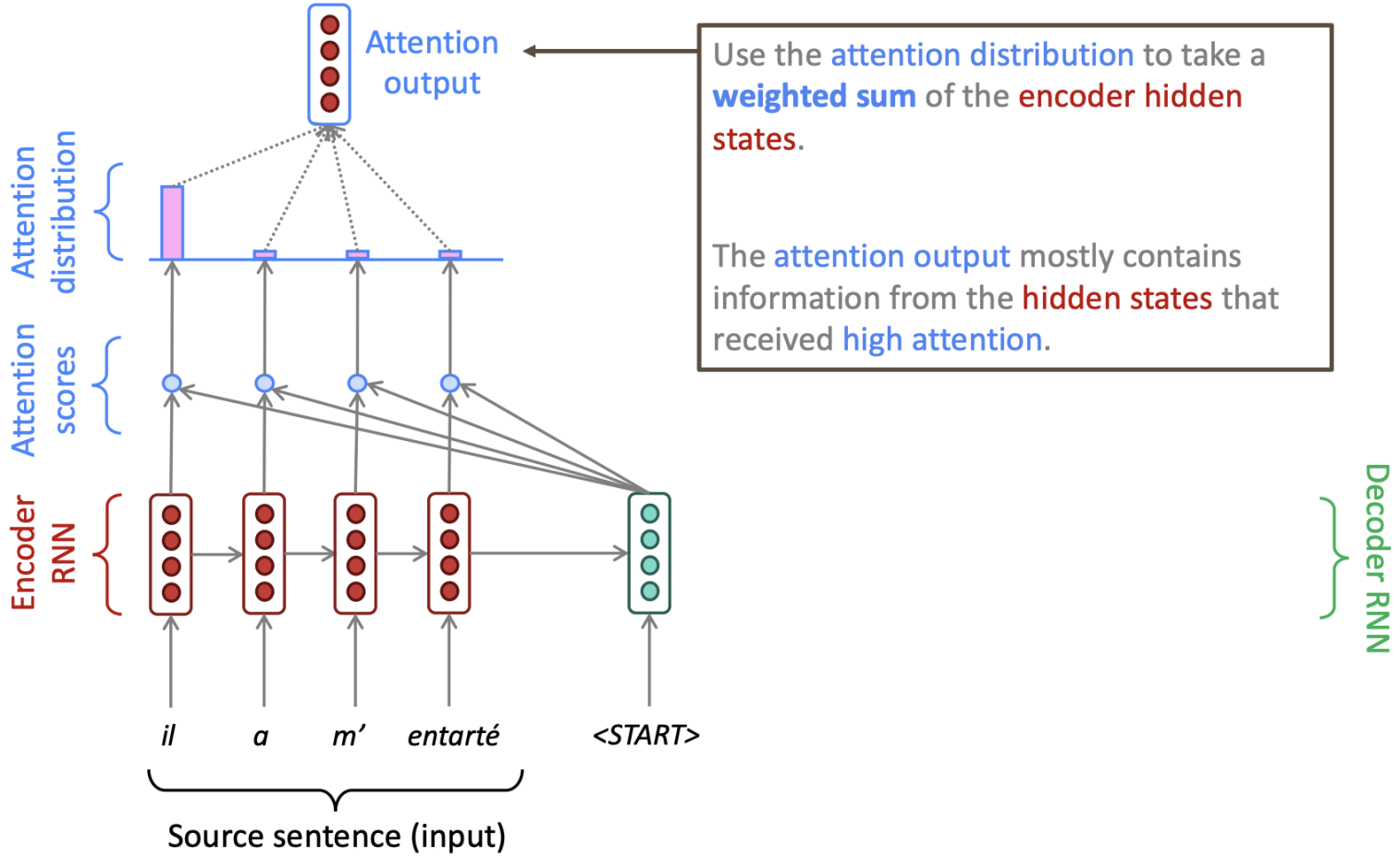

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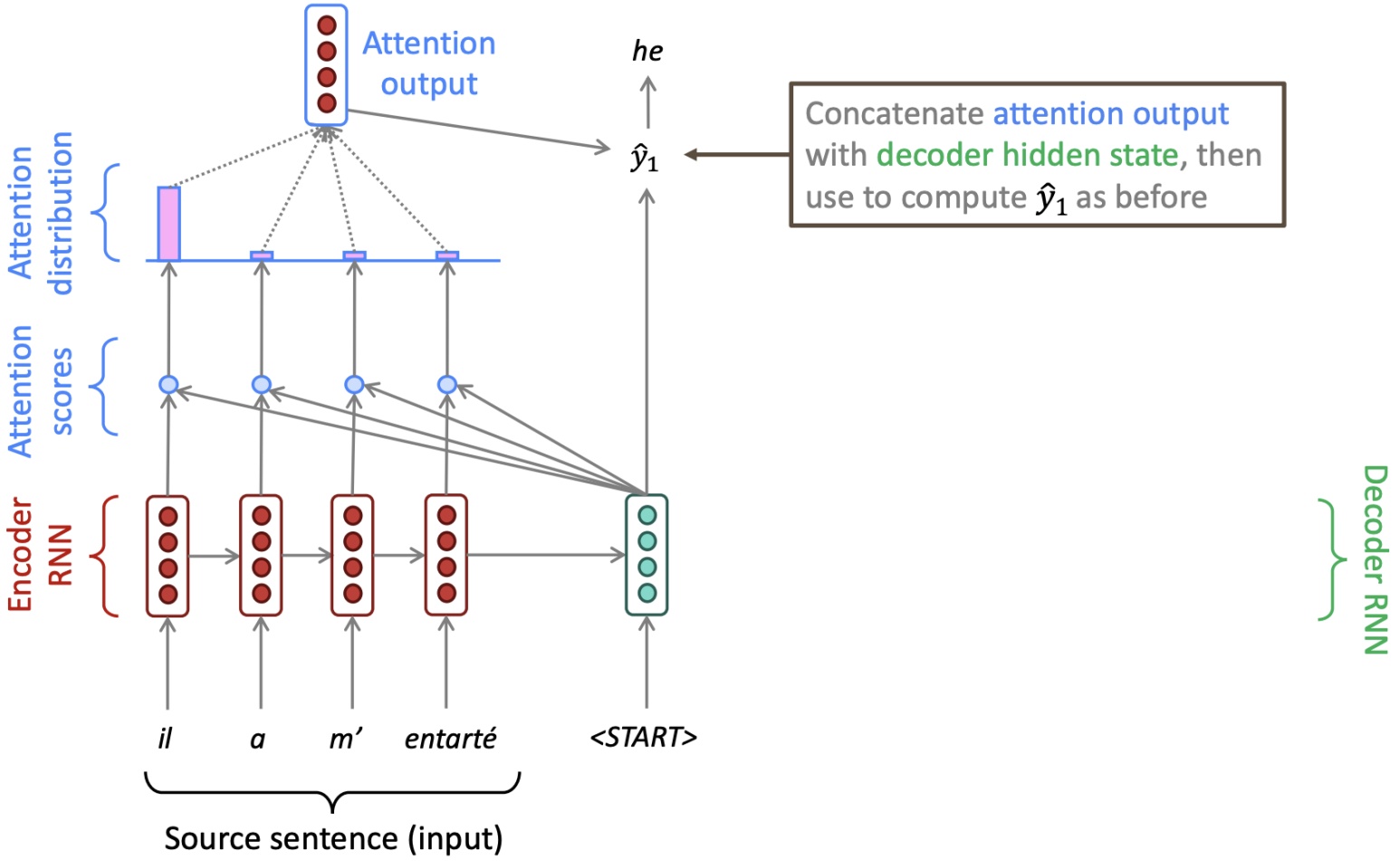
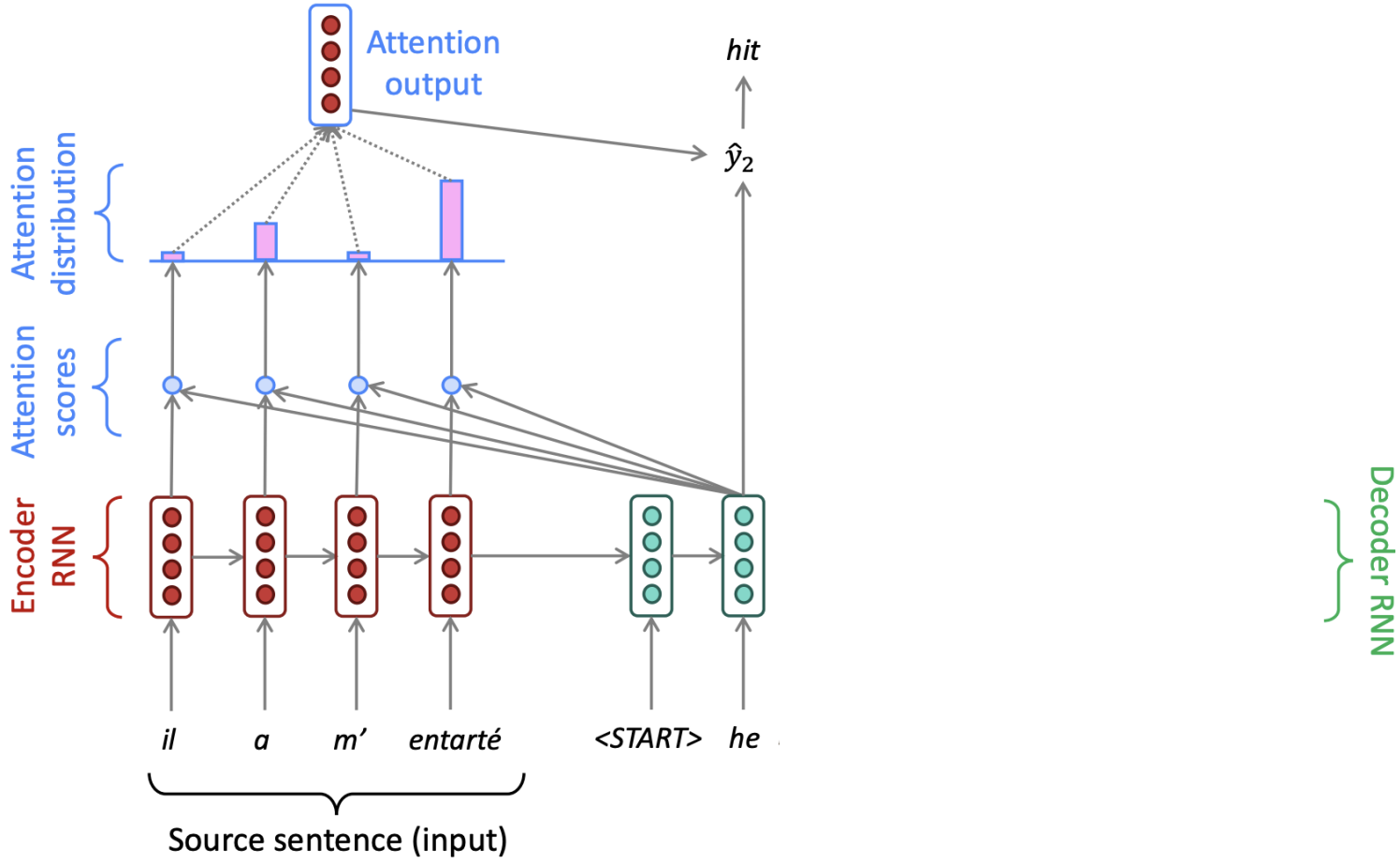


Seq2Seq w/ Attention



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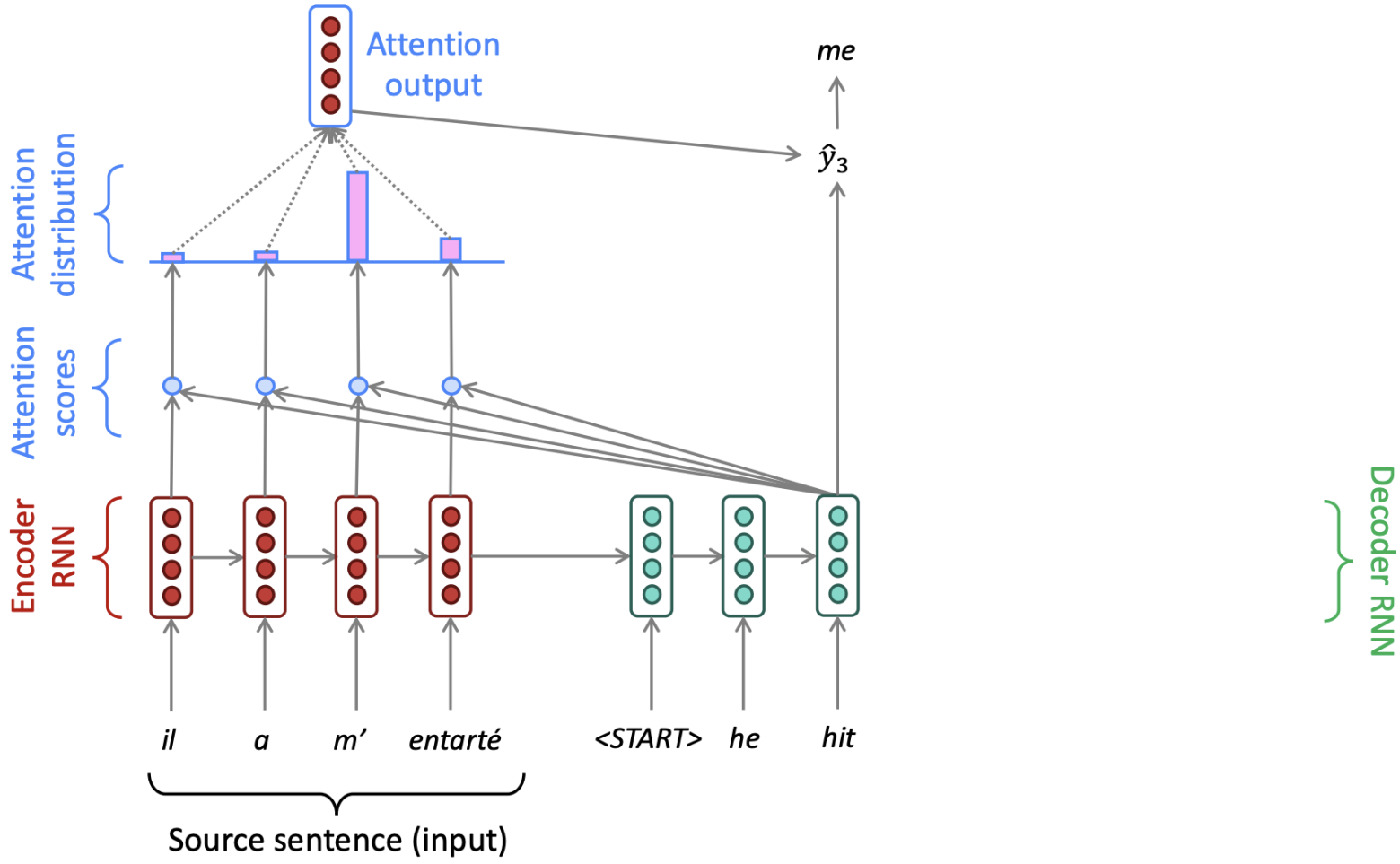
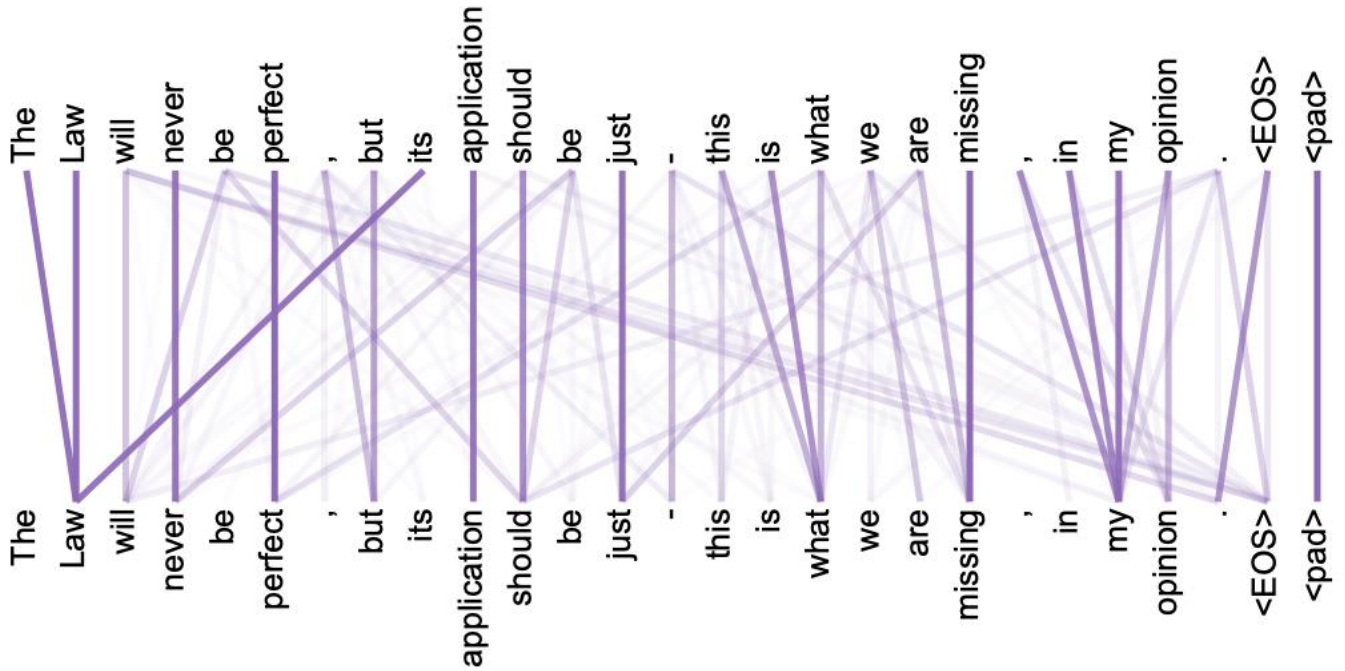


Attention pros!

- Significantly improves performance
  - It's very useful to allow decoder to focus on certain parts of the source
- Solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Provides some interpretability
  - By inspecting attention distribution, we can see what the decoder was focusing on

Interpretability



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- Solves the bottleneck problem
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- Hwith vanishing gradient problem
  - Provides shortcut to faraway states
- Provides some interpretability
  - By inspecting attention distribution, we can see what the decoder was focusing on
- Can be applied to any neural model, not just decoder

Attention in a nutshell

For a new item, figure out how relevant each items is in a collection of different items

W/o attention: we are just relying on a naïve summary of the collection

Encoder-decoder setting:

- How relevant are all the words from the input to a single word in the output

Encoder-MLP setting:

- How relevant are all the words from the input to our prediction

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Self-attention in a nutshell

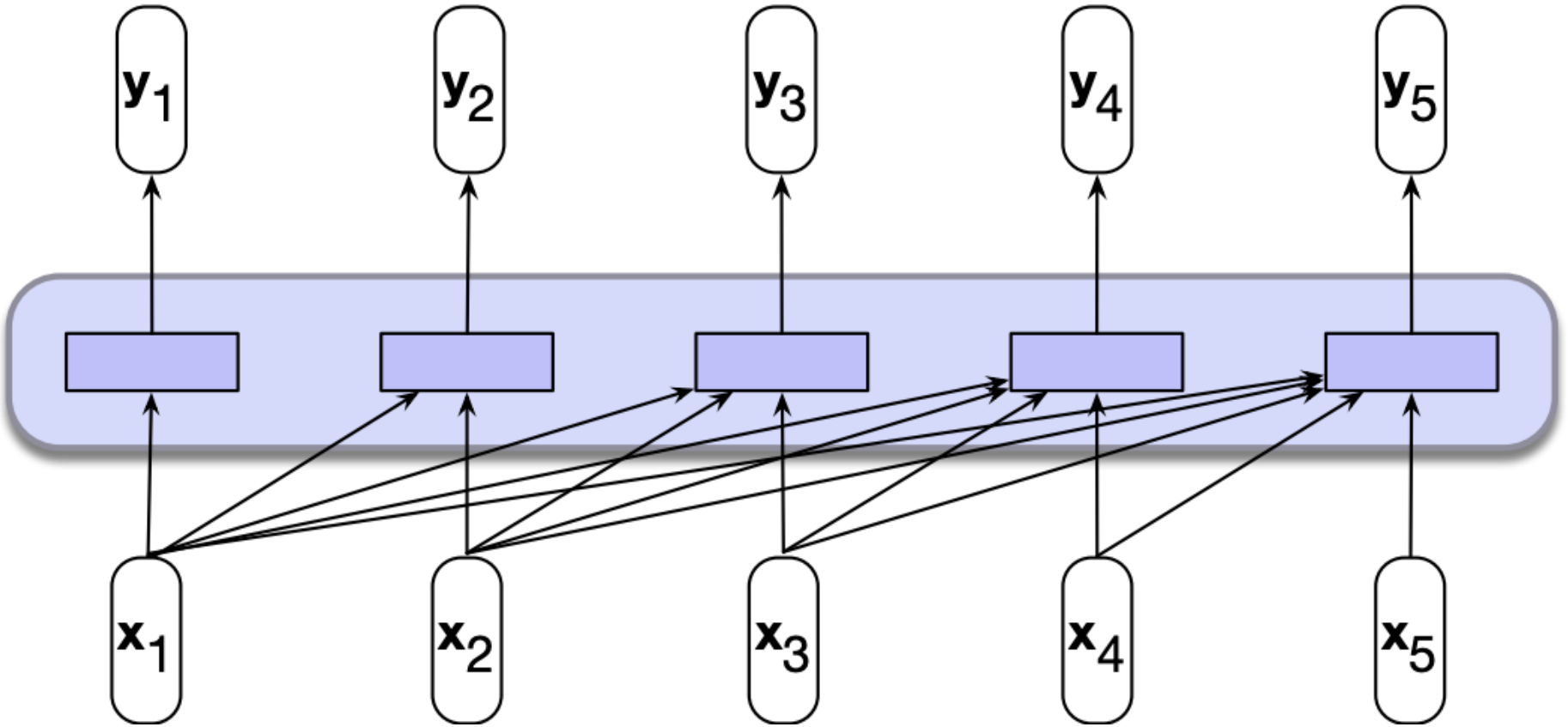
Attention:

- For a new item, figure out how relevant items are in a collection of different items

Self-attention

- How relevant are all the words from the input to a single word in the input

Self-attention



Terminology

Query:

Key:

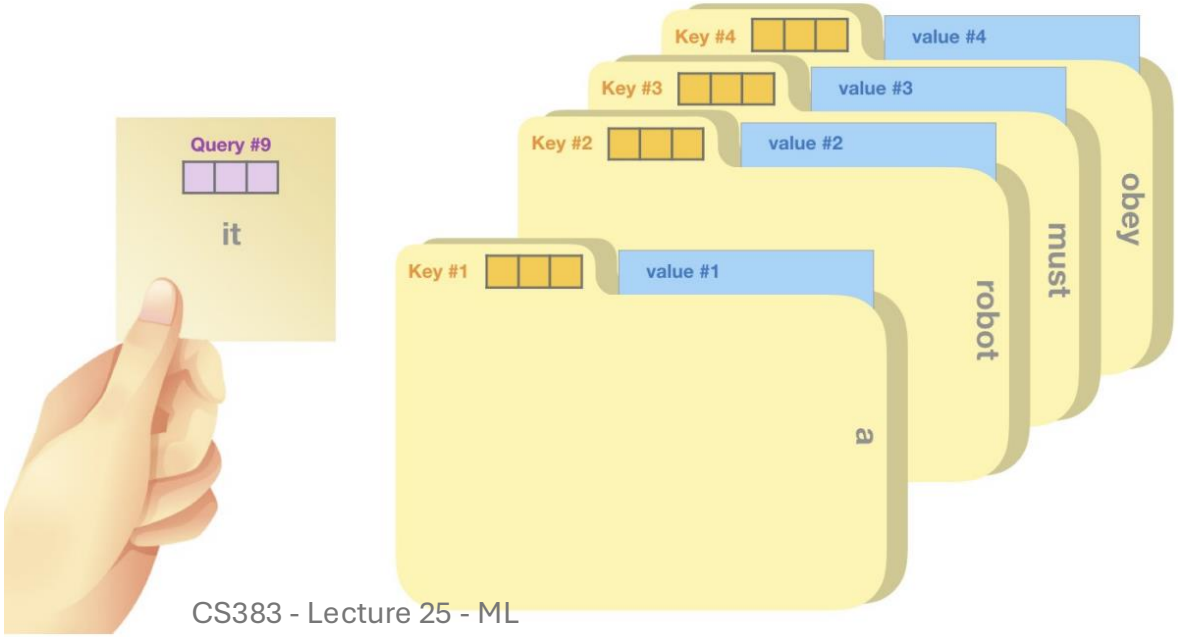
Value:

Terminology

Query: what to match

Key: the thing to match

Value: what to be extracted from the match



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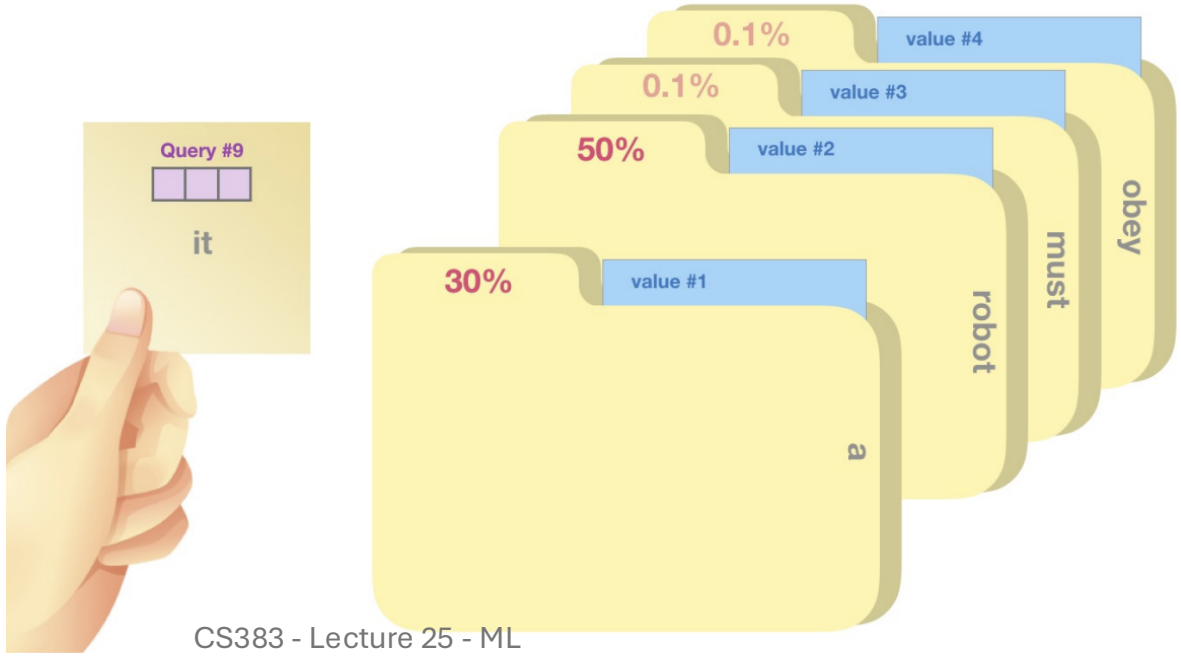
Key: the thing to match

Value: what to be extracted from the match



Terminology

Query: what to match:

$$q_i = W^q x_i$$

Key: the thing to match:

Value: what to be extracted from the match

Terminology

Query: what to match:

$$q_i = W^q x_i$$

Key: the thing to match:

$$k_i = W^k x_i$$

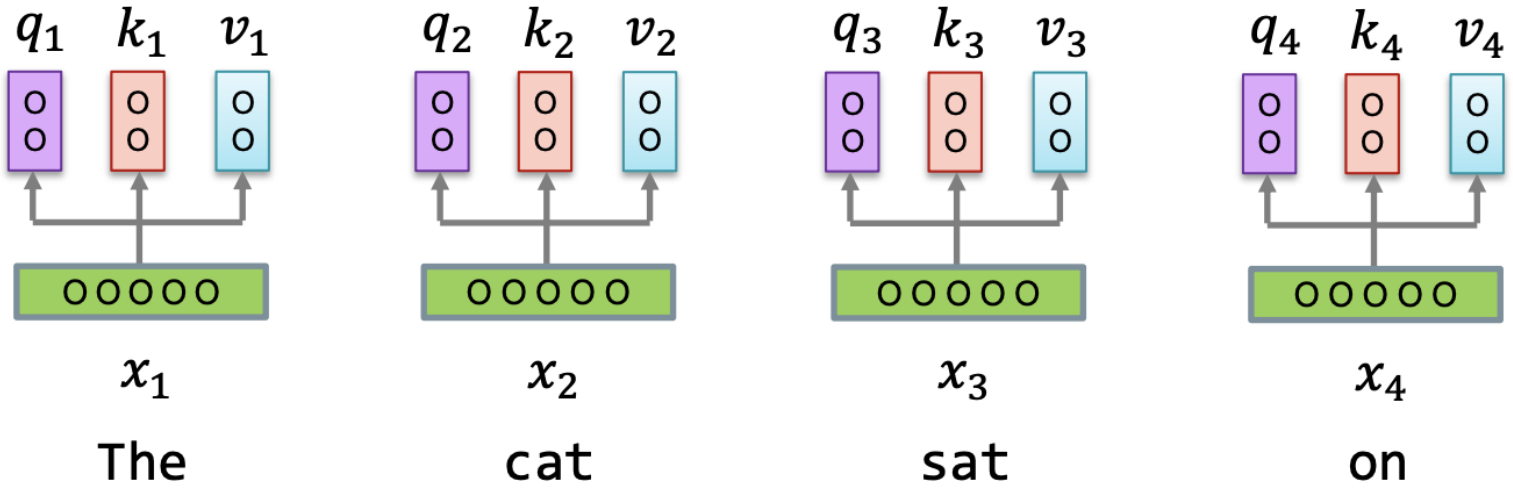
Value: what to be extracted from the match

$$v_i = W^v x_i$$

Output of each input cell

These are three representations of each input

Each representation is created by multiplying the input by a weight matrix



Self-Attention Scores

When creating a representation for x_i, how much weight/focus/attention should we give to x_j

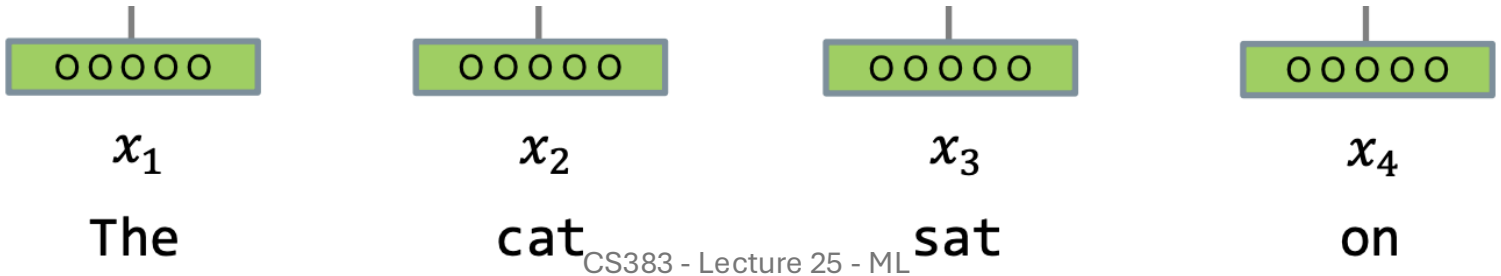
$\forall i, j \in |x|$ we must compute $score(x_i, x_j)$

Self-Attention Scores

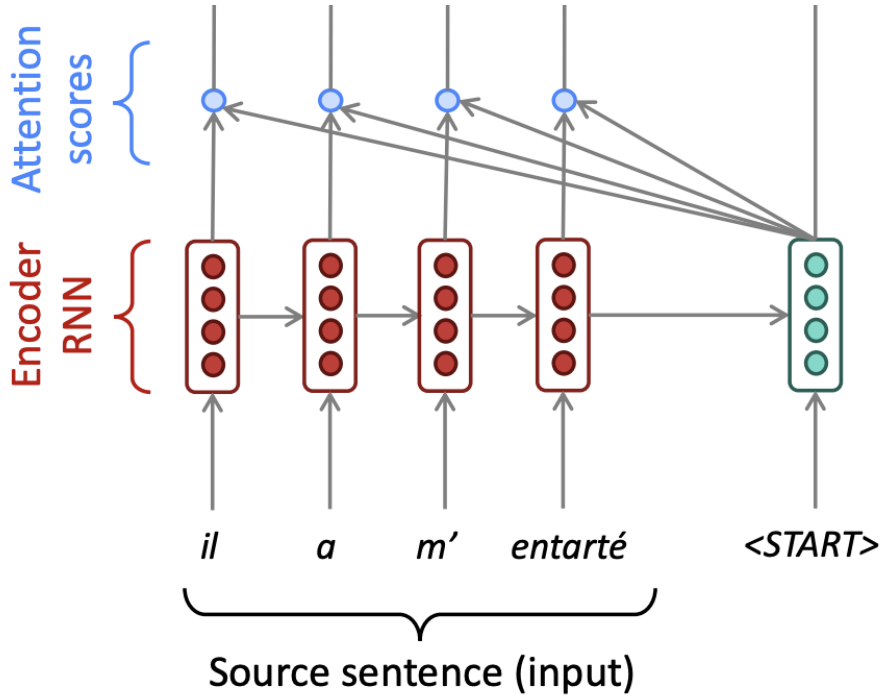
$\forall i, j \in |x|$ we must compute $score(x_i, x_j)$

Question: are these scores distance functions?

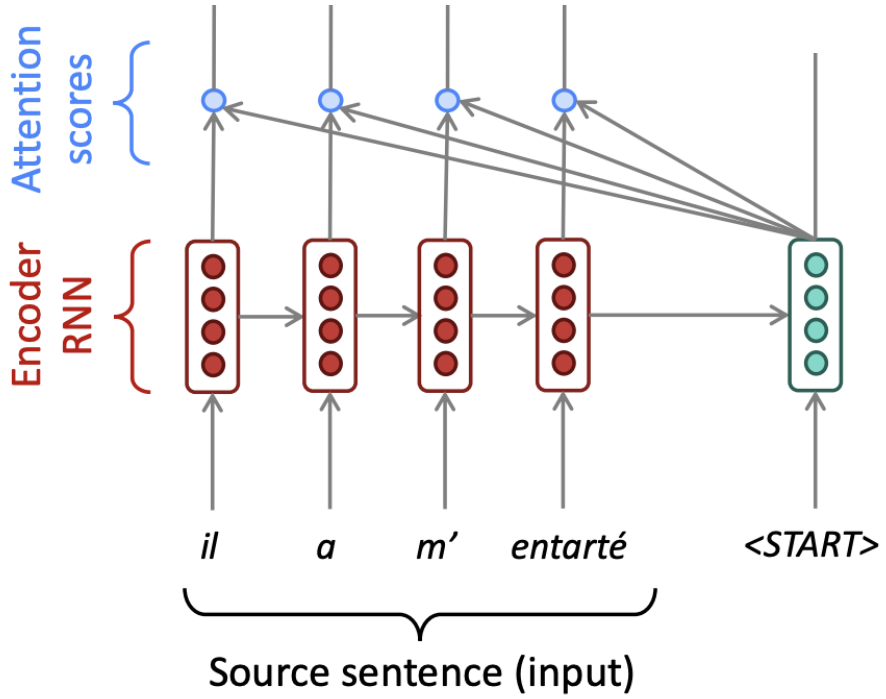
No! $score(x_i, x_j)$ shouldn't be equal to $score(x_i, x_j)$

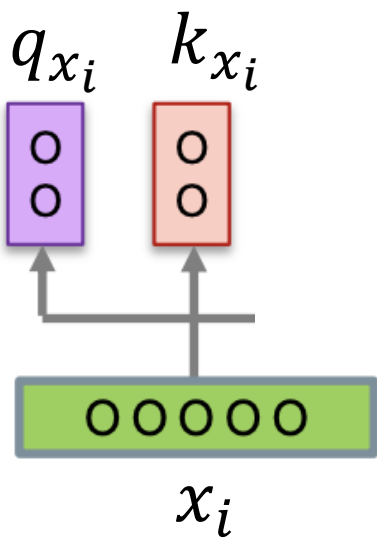


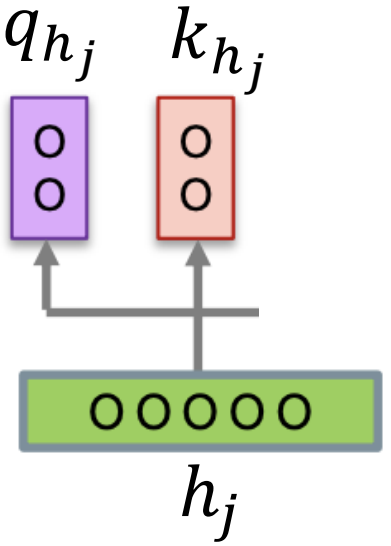
Attention score



Attention score

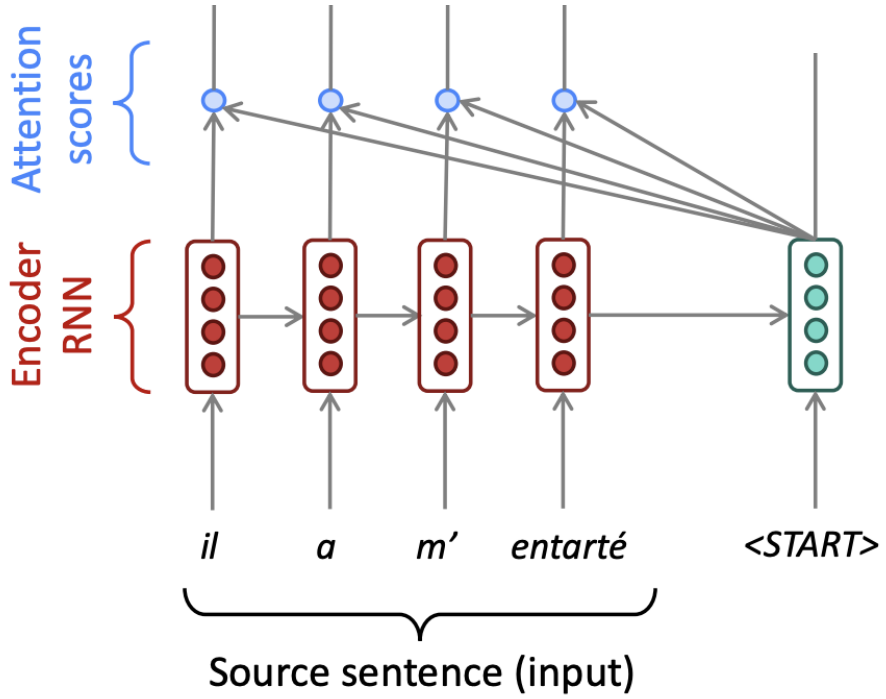


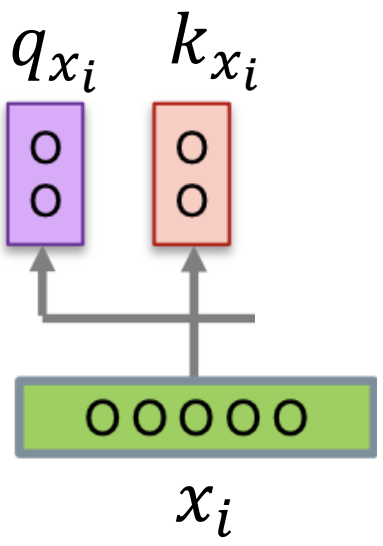


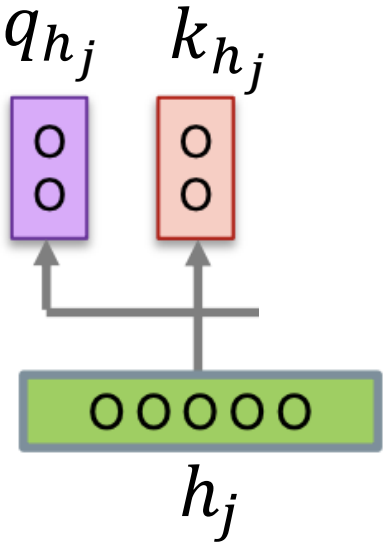


$$score(h_j, x_i) = ?$$

Attention score

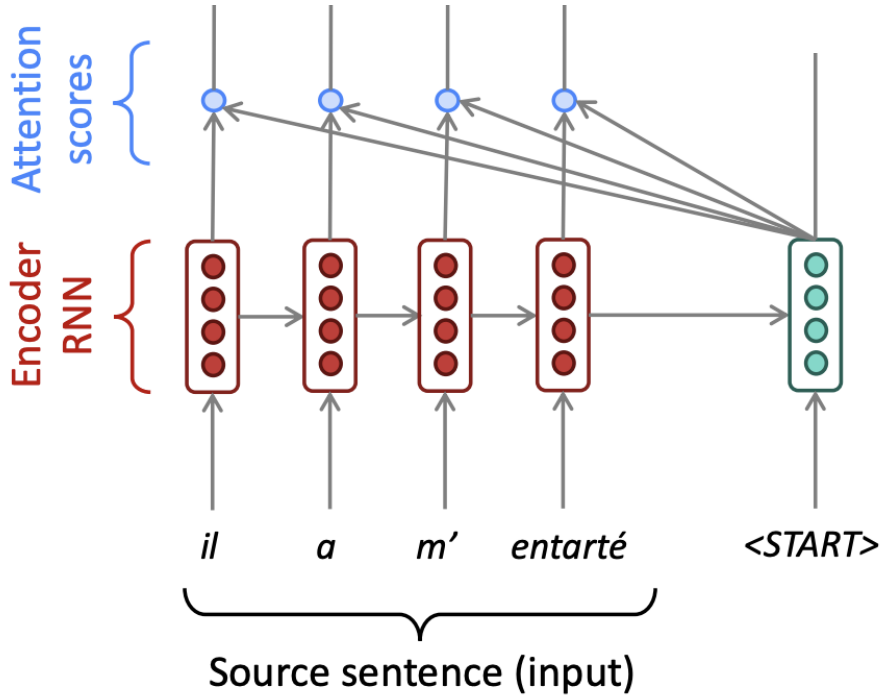


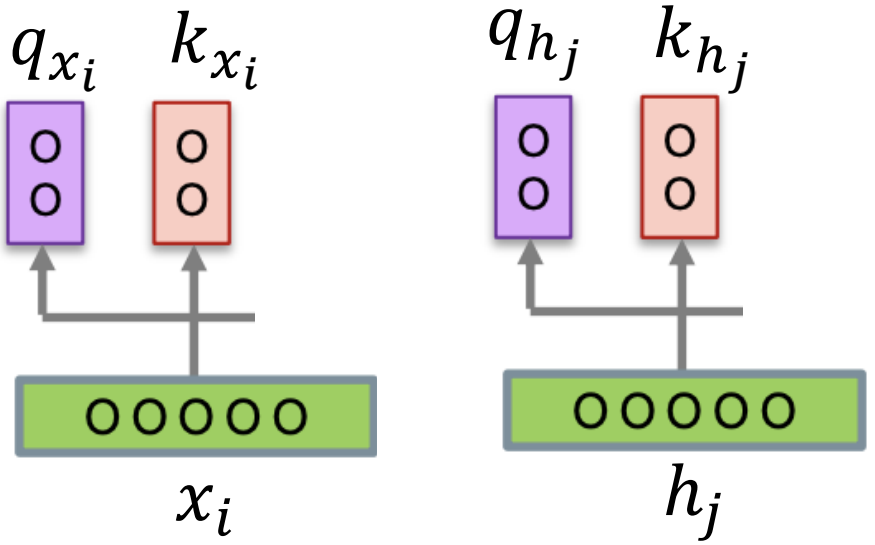




$$score(h_j, x_i) = q_{h_j} \cdot k_{x_i}$$

Attention score





$$score(h_j, x_i) = \frac{q_{h_j} \cdot k_{x_i}}{\sqrt{d_k}}$$

Attention Scores

$$A_{score} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,n} \\ \vdots & \ddots & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,n} \end{bmatrix}$$

$$= \begin{bmatrix} score(h_1, x_1) & \cdots & score(h_1, x_n) \\ \vdots & \ddots & \vdots \\ score(h_m, x_1) & \cdots & score(h_m, x_n) \end{bmatrix}$$

$$= \begin{bmatrix} \frac{q_{h_1} \cdot k_{x_1}}{\sqrt{d_k}} & \cdots & \frac{q_{h_1} \cdot k_{x_n}}{\sqrt{d_k}} \\ \vdots & \ddots & \vdots \\ \frac{q_{h_m} \cdot k_{x_1}}{\sqrt{d_k}} & \cdots & \frac{q_{h_m} \cdot k_{x_n}}{\sqrt{d_k}} \end{bmatrix}$$

We can store all the q's and k's in a matrix as well

Attention Scores

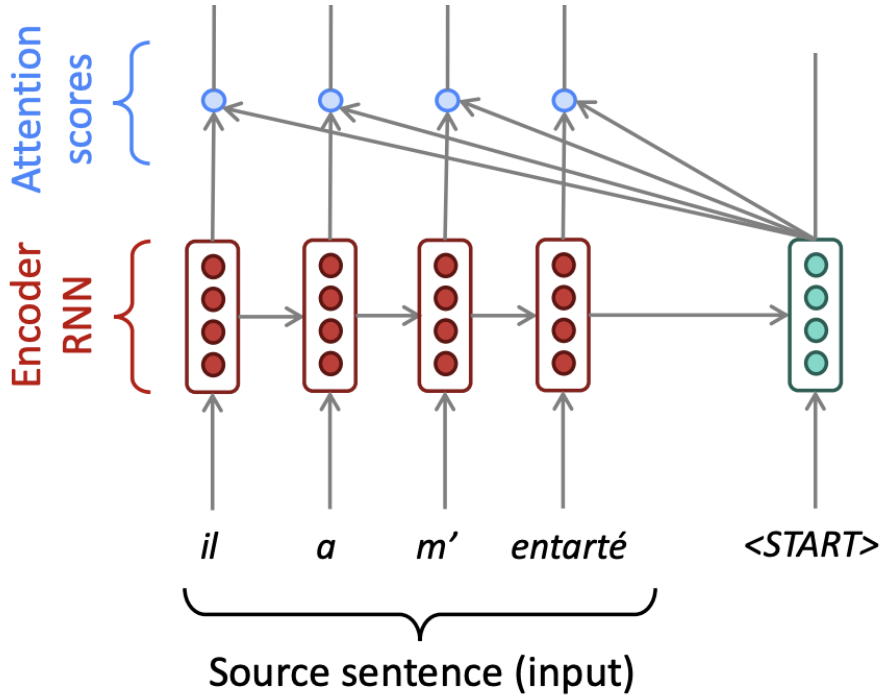
$$A_{score} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,n} \\ \vdots & \ddots & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,n} \end{bmatrix}$$

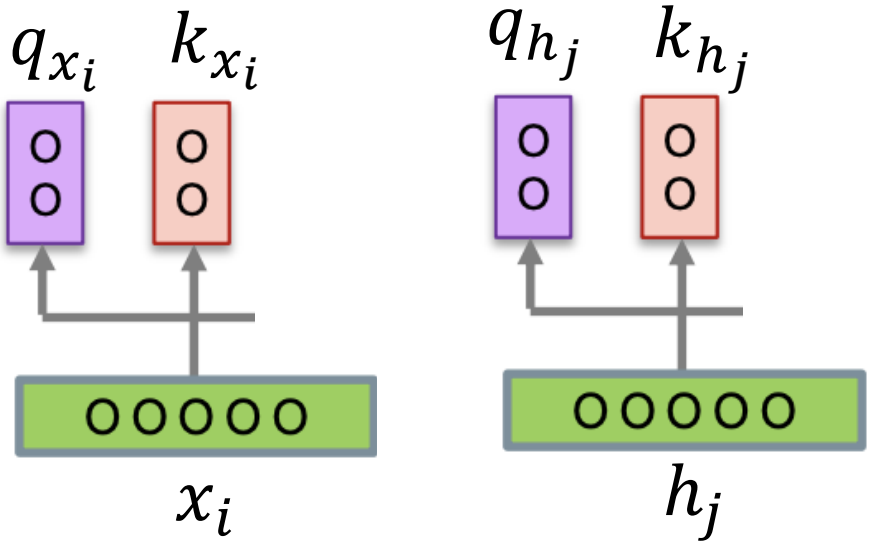
$$= \begin{bmatrix} \frac{q_{h_1} \cdot k_{x_1}}{\sqrt{d_k}} & \cdots & \frac{q_{h_1} \cdot k_{x_n}}{\sqrt{d_k}} \\ \vdots & \ddots & \vdots \\ \frac{q_{h_m} \cdot k_{x_1}}{\sqrt{d_k}} & \cdots & \frac{q_{h_m} \cdot k_{x_n}}{\sqrt{d_k}} \end{bmatrix}$$

$$A_{score} = \frac{QK^T}{\sqrt{d_k}}$$

We can store all the q's and k's in a matrix as well

Attention score

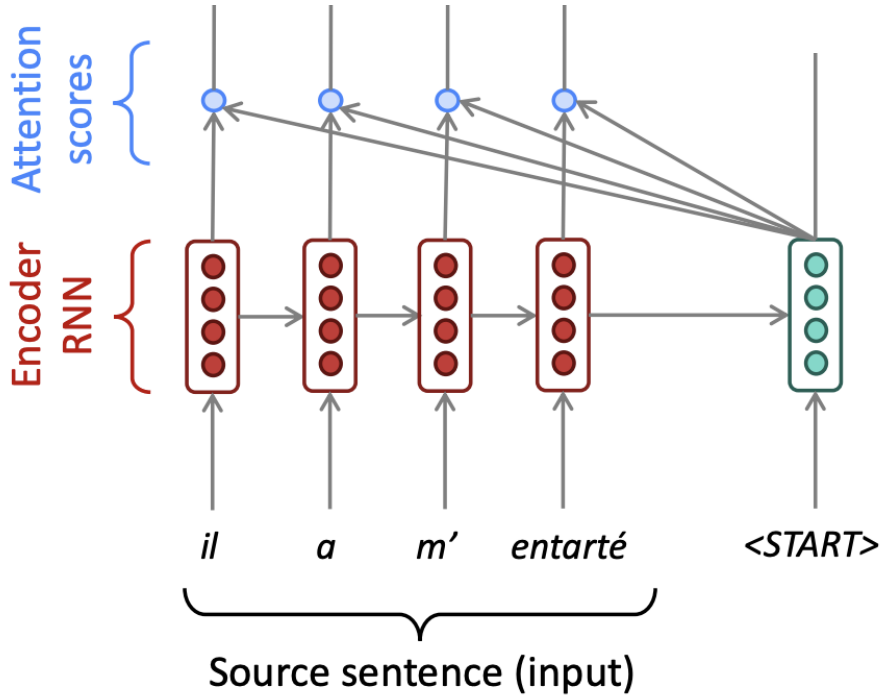


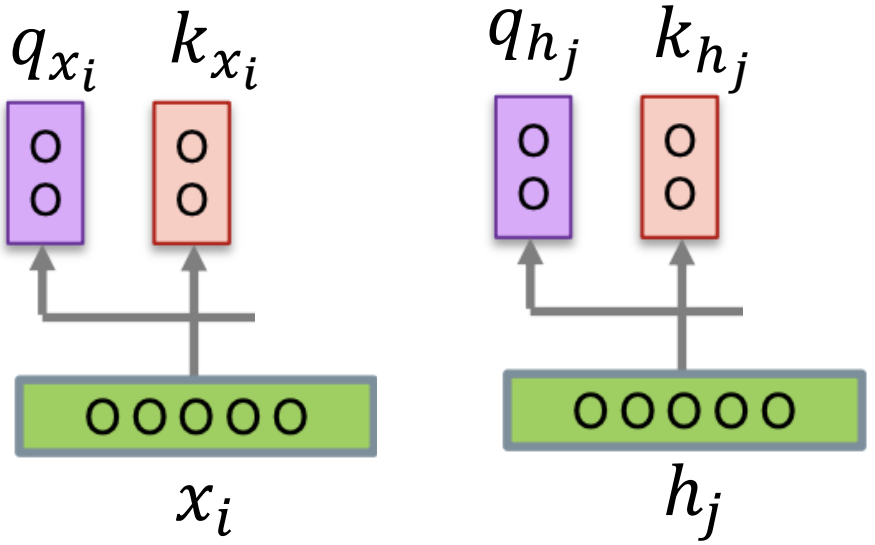


$$score(h_j, x_i) = \frac{q_{h_j} \cdot k_{x_i}}{\sqrt{d_k}}$$

$$A_{score} = \frac{QK^T}{\sqrt{d_k}}$$

Attention

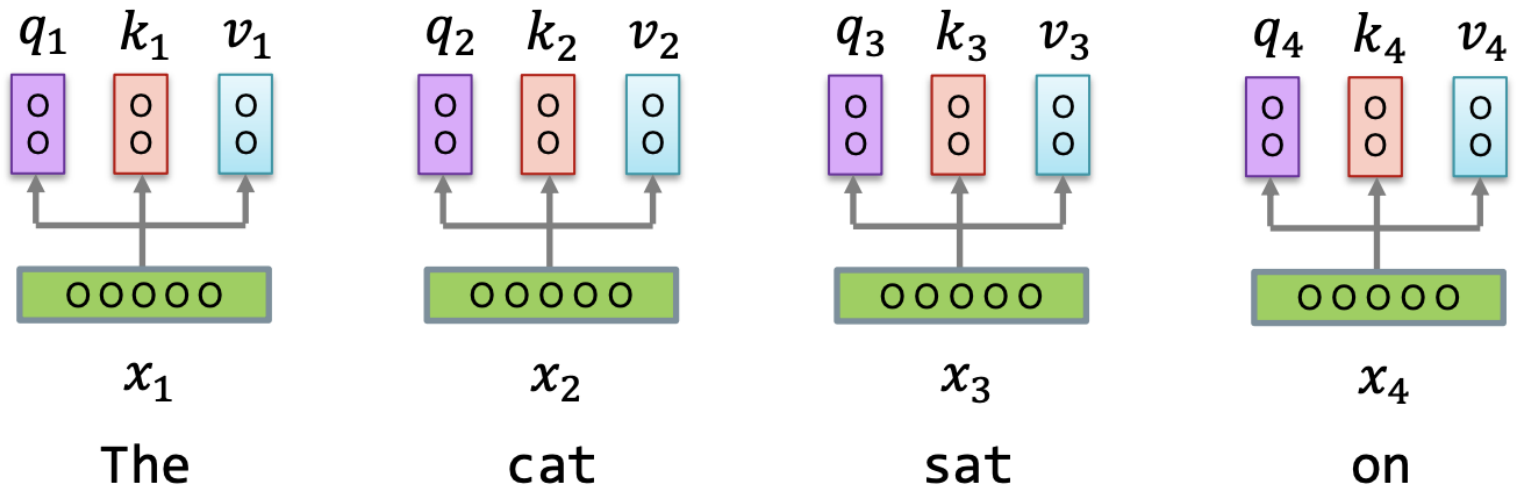




$$A = softmax(\frac{QK^T}{\sqrt{d_k}})$$

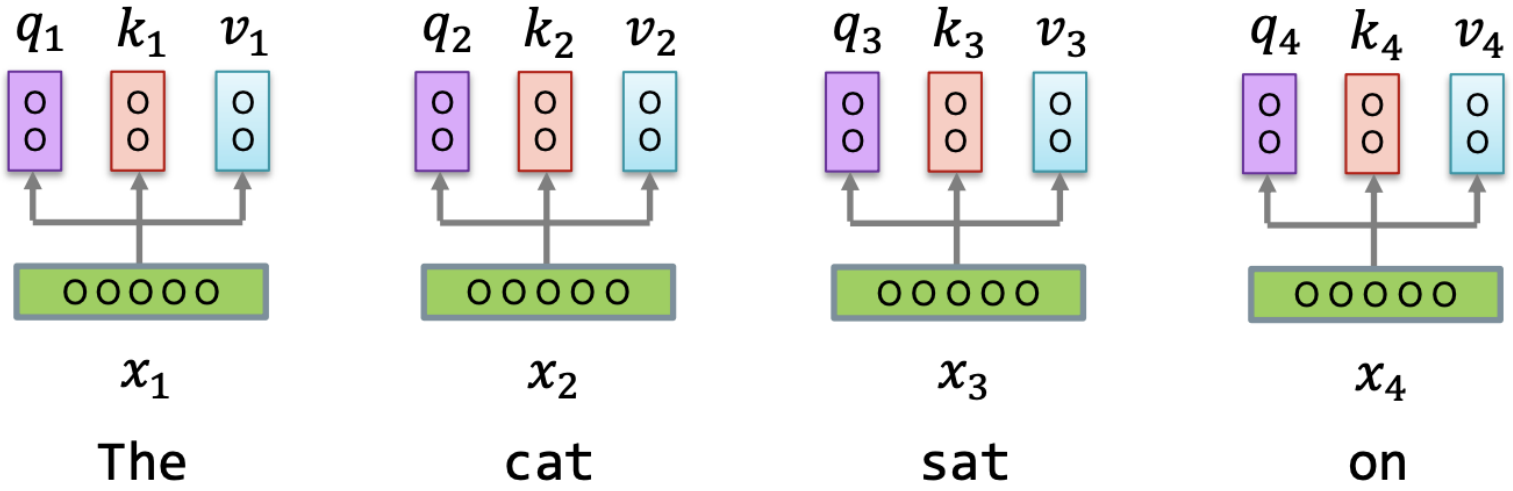
Self-attention

When creating a representation for x_i, how much weight/focus/attention should we give to x_j

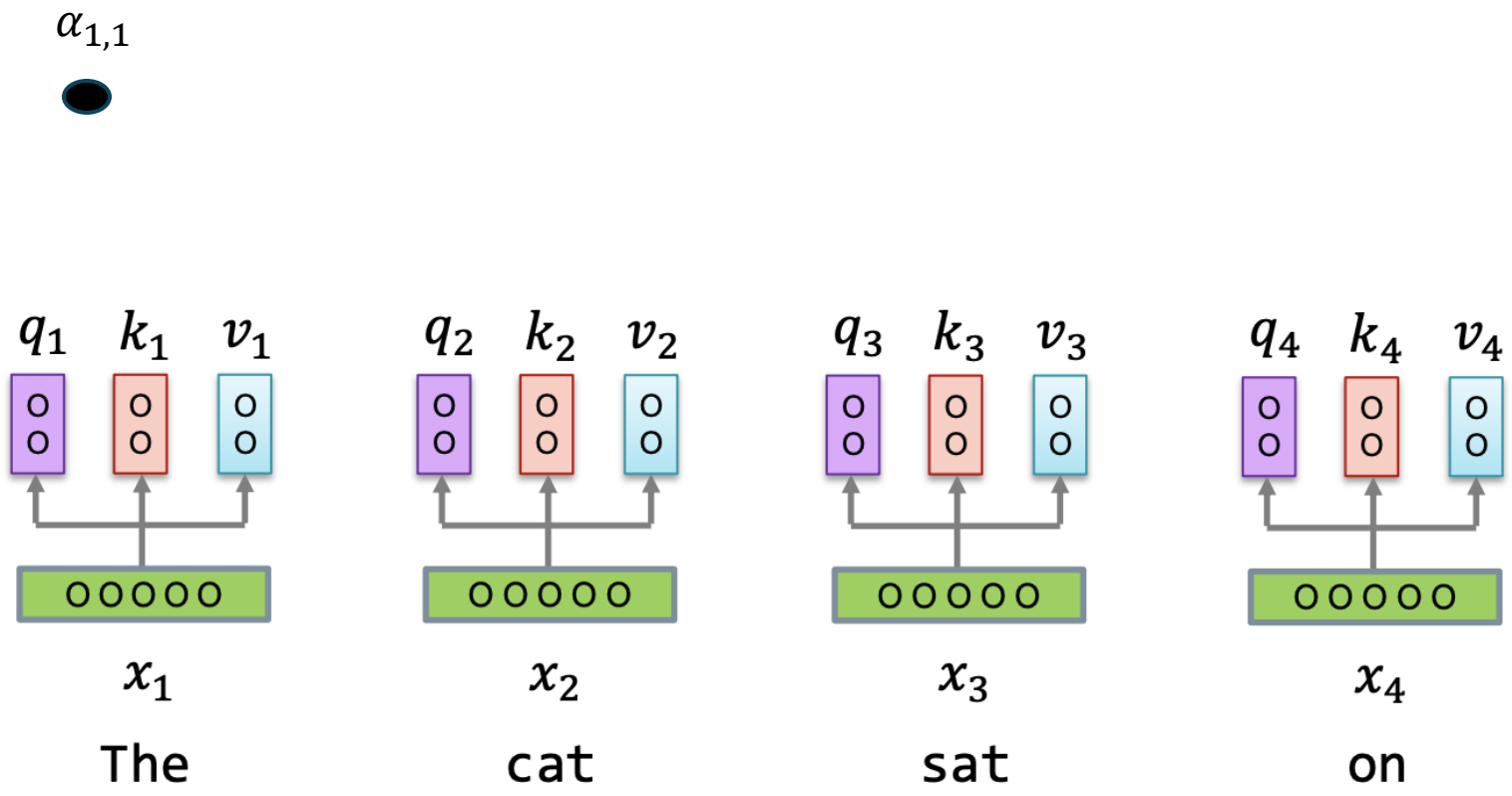


Self-attention

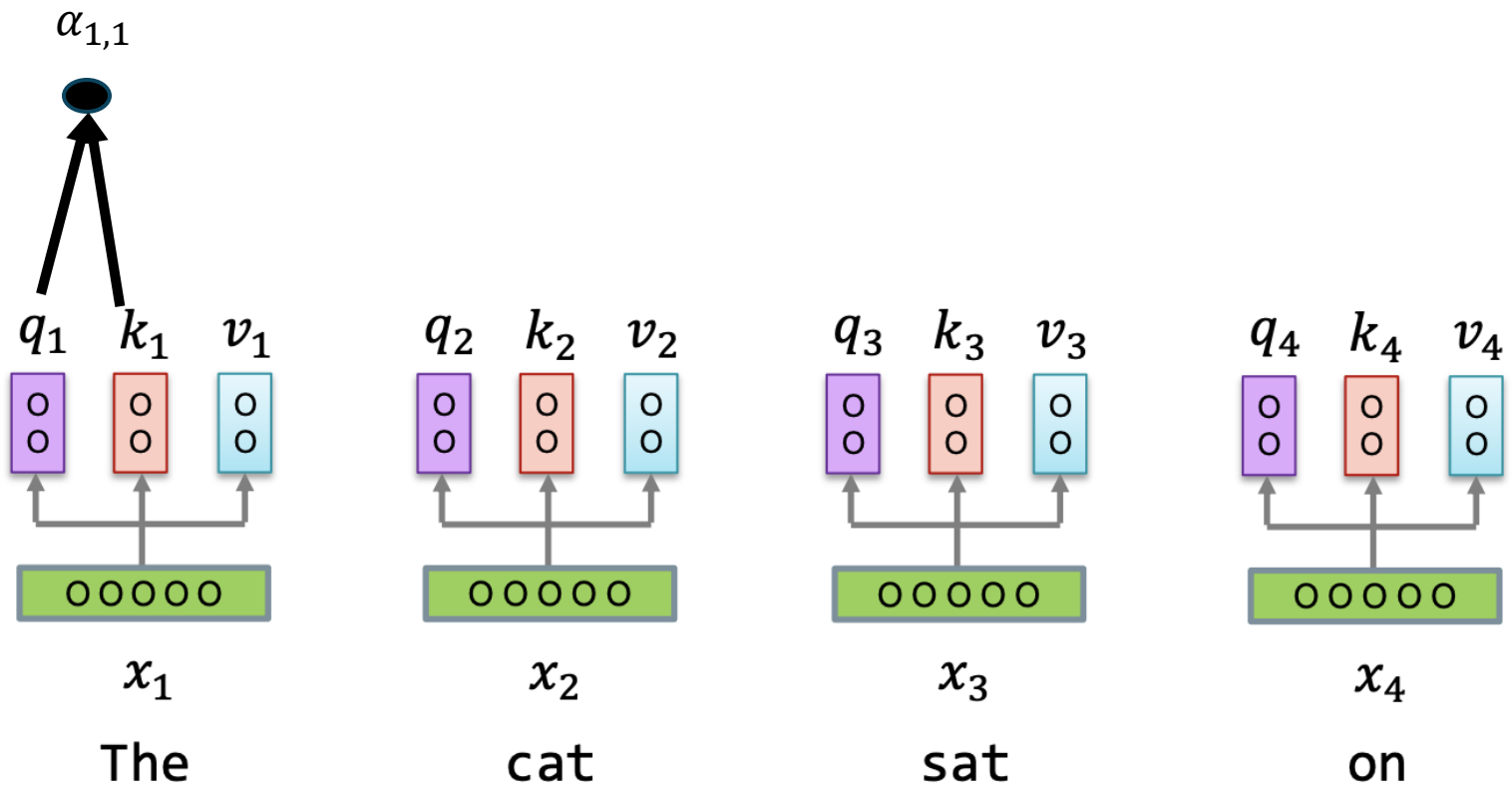
When creating a representation for x_1, how much weight/focus/attention should we give to x_j



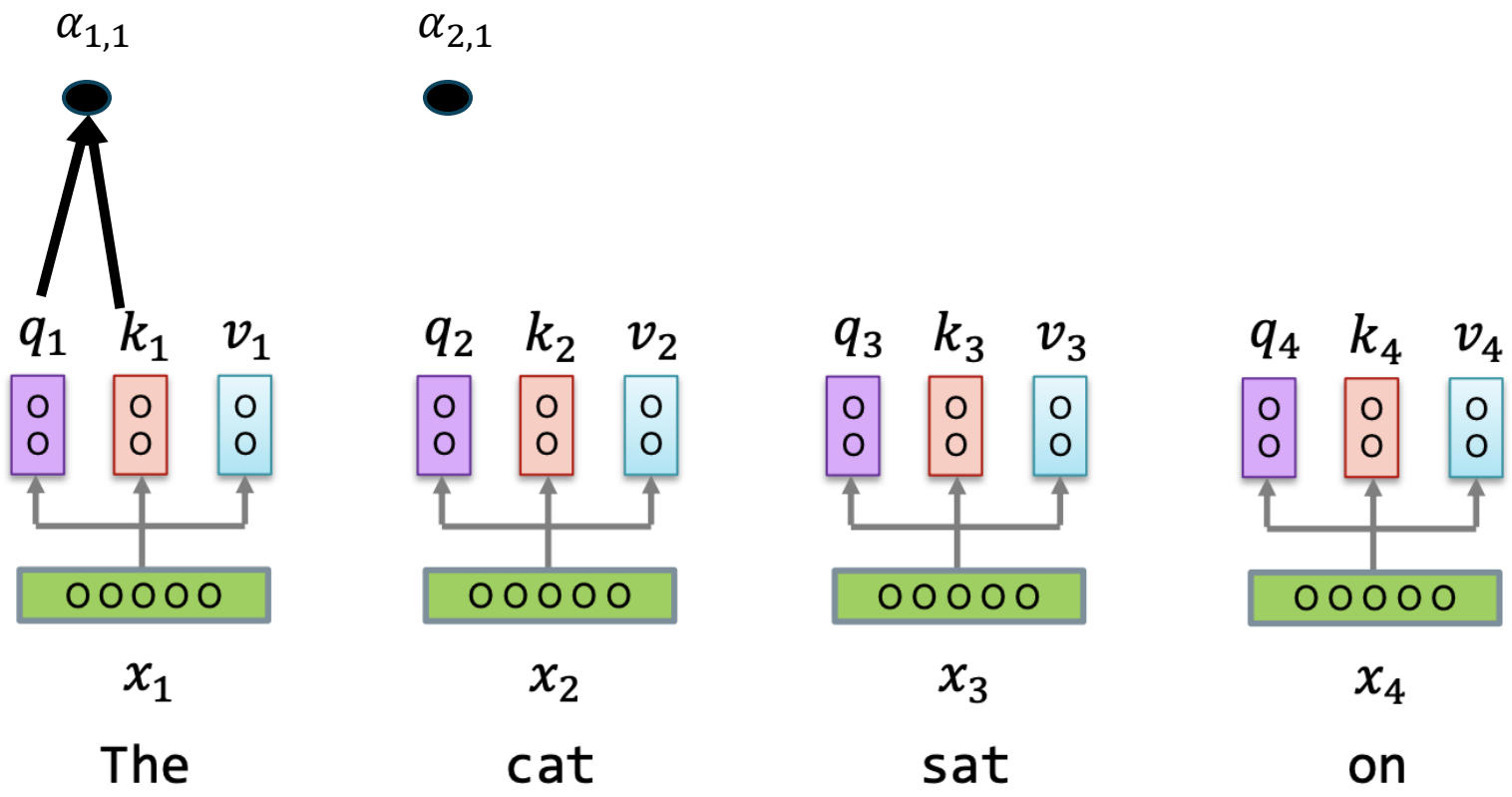
Self-attention



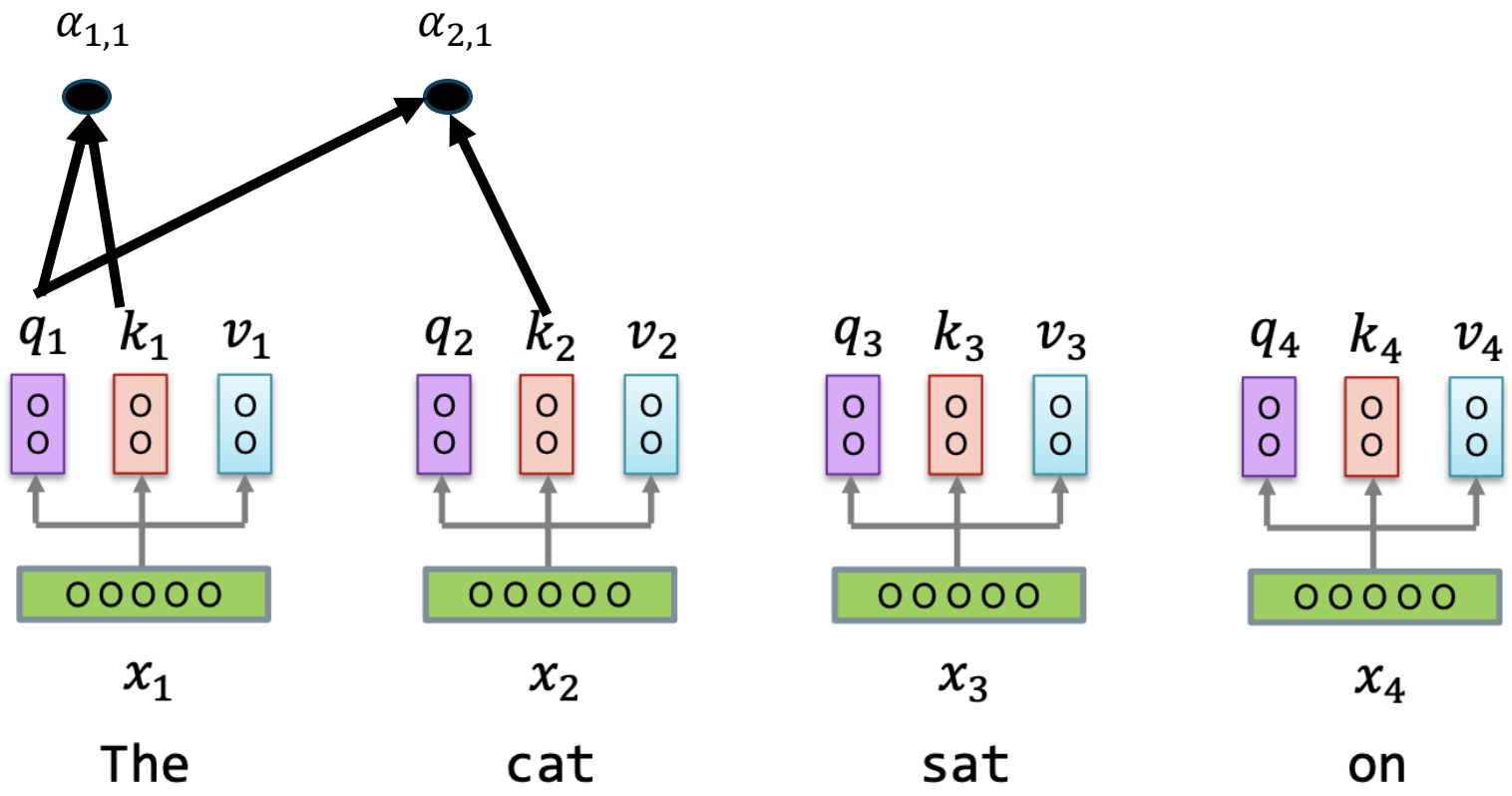
Self-attention



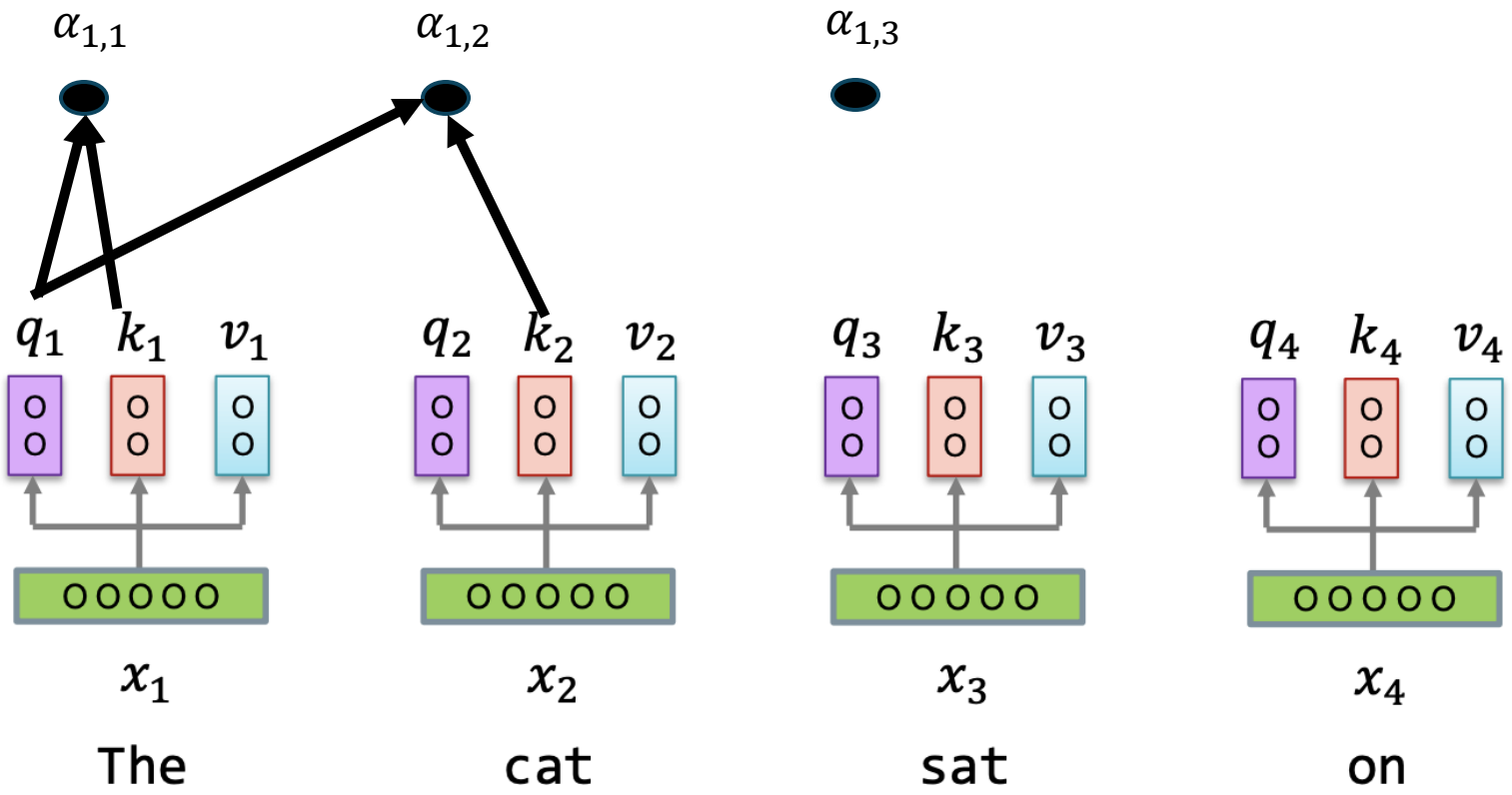
Self-attention



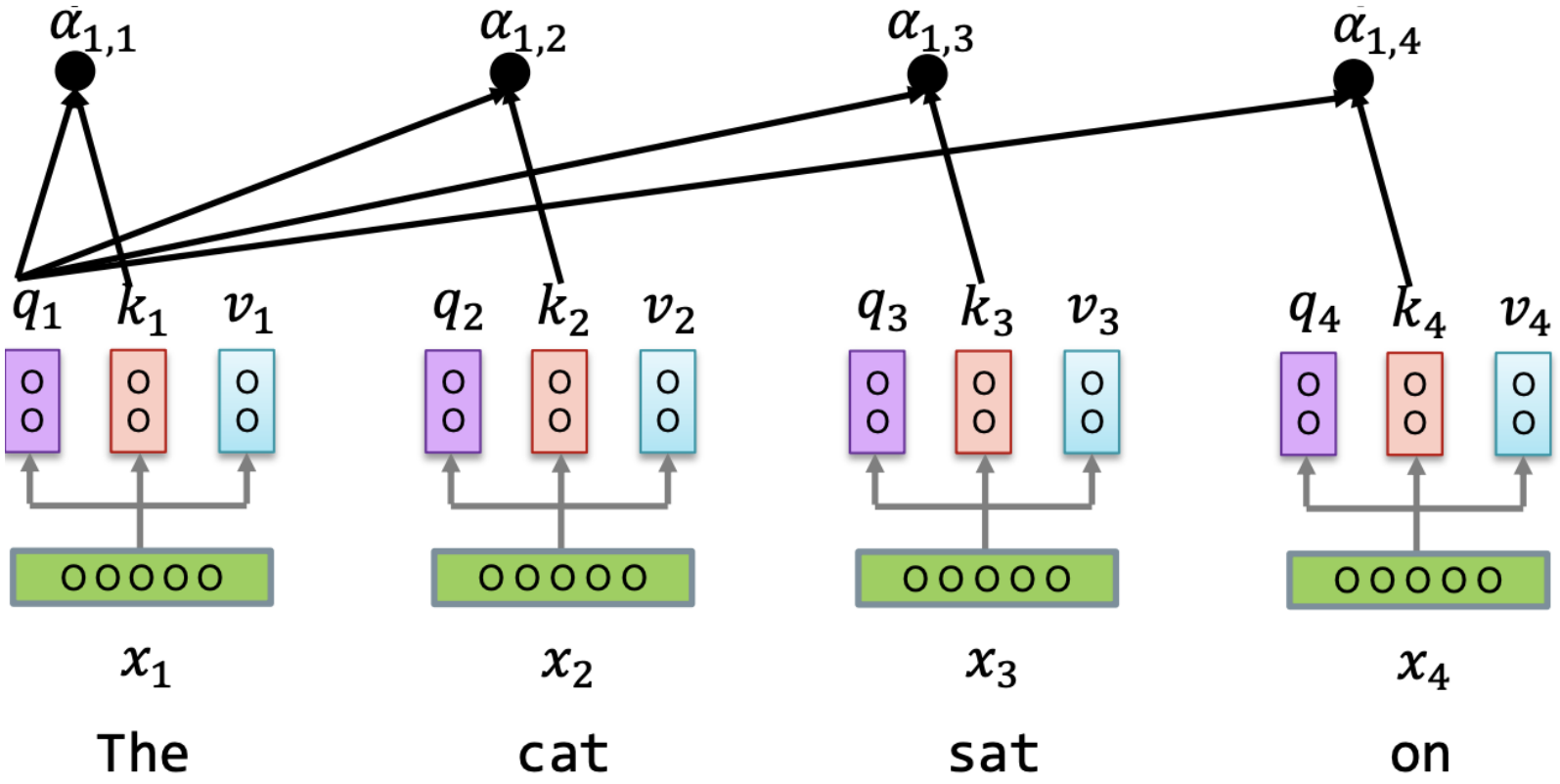
Self-attention



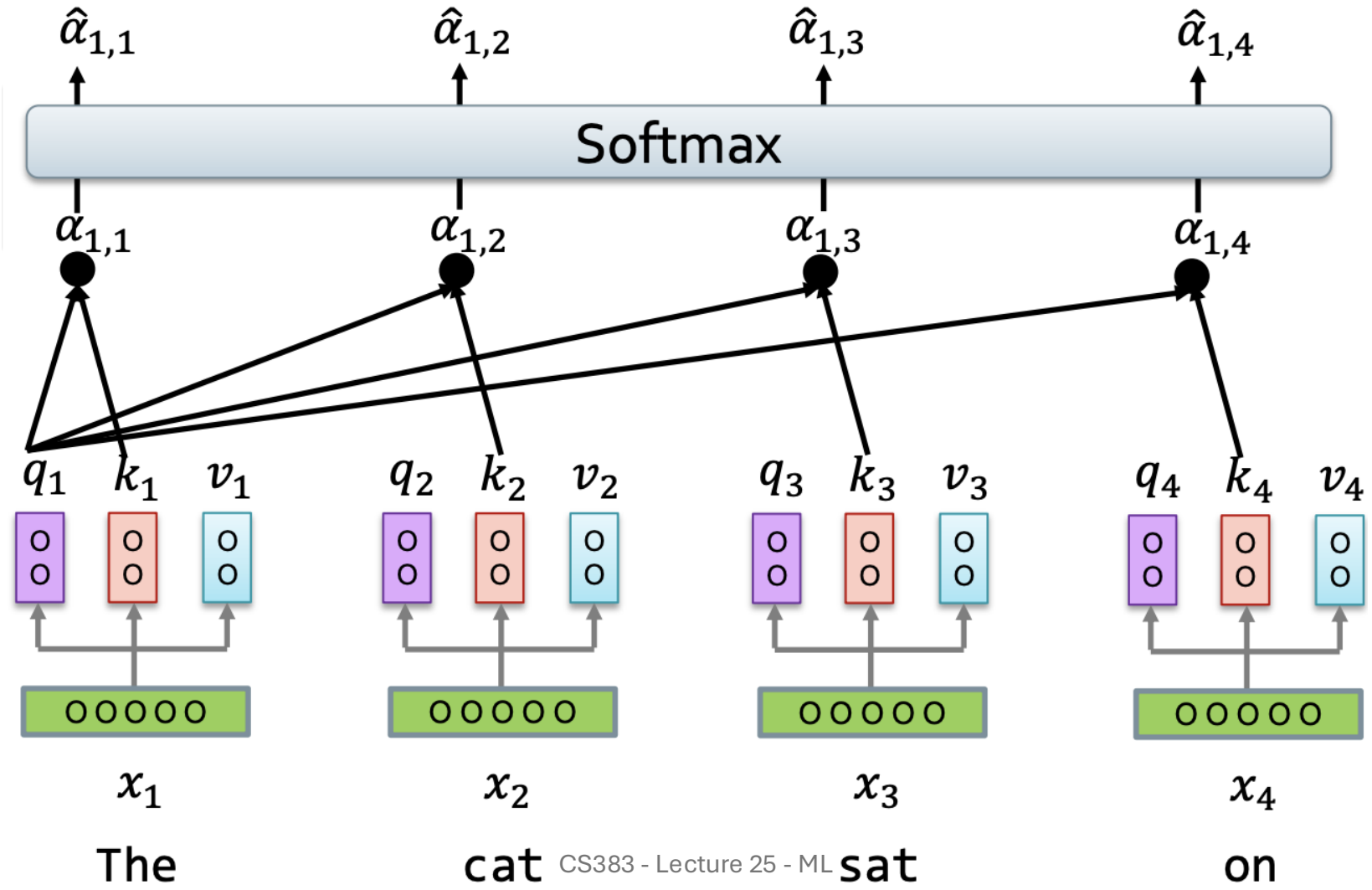
Self-attention



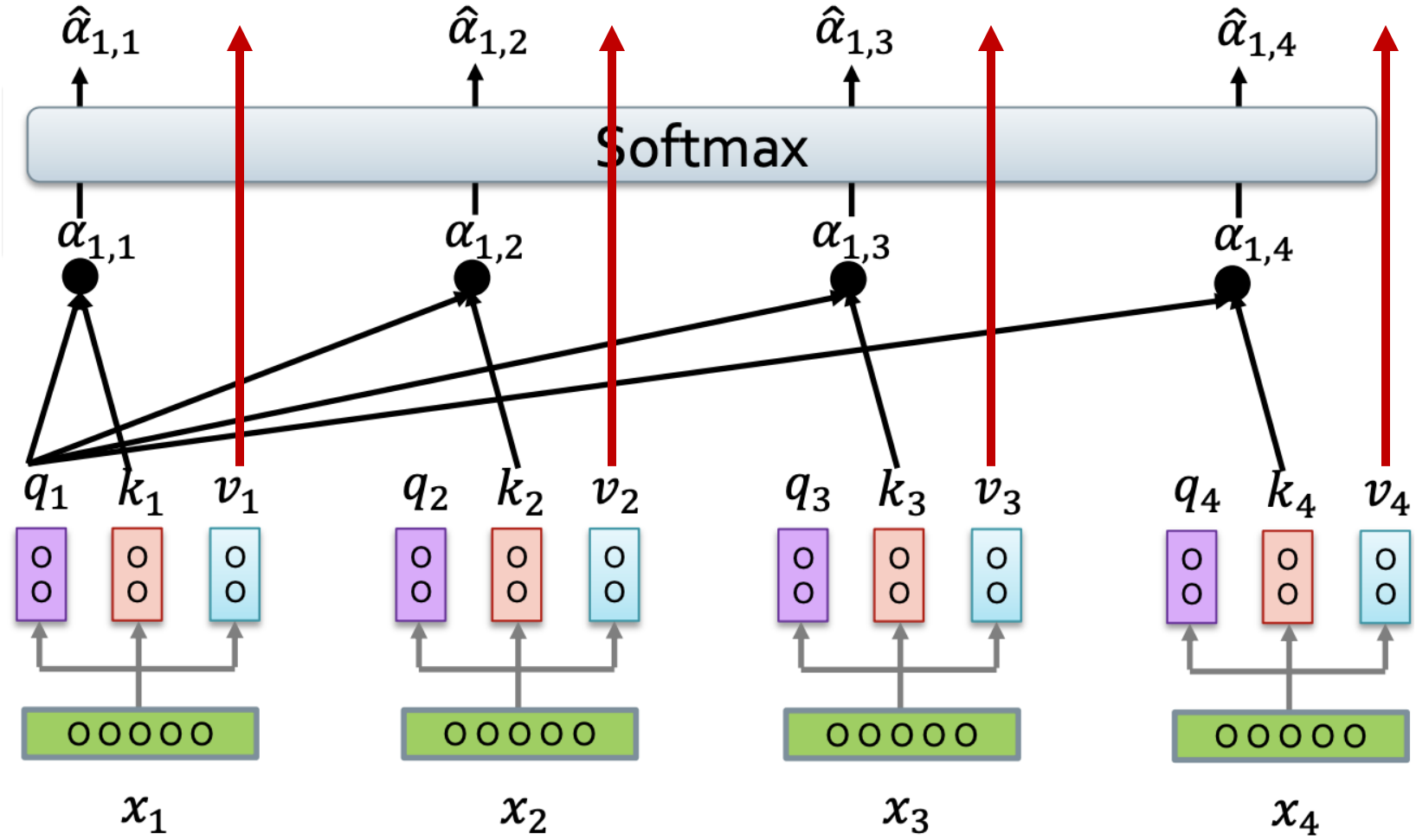
Self-attention



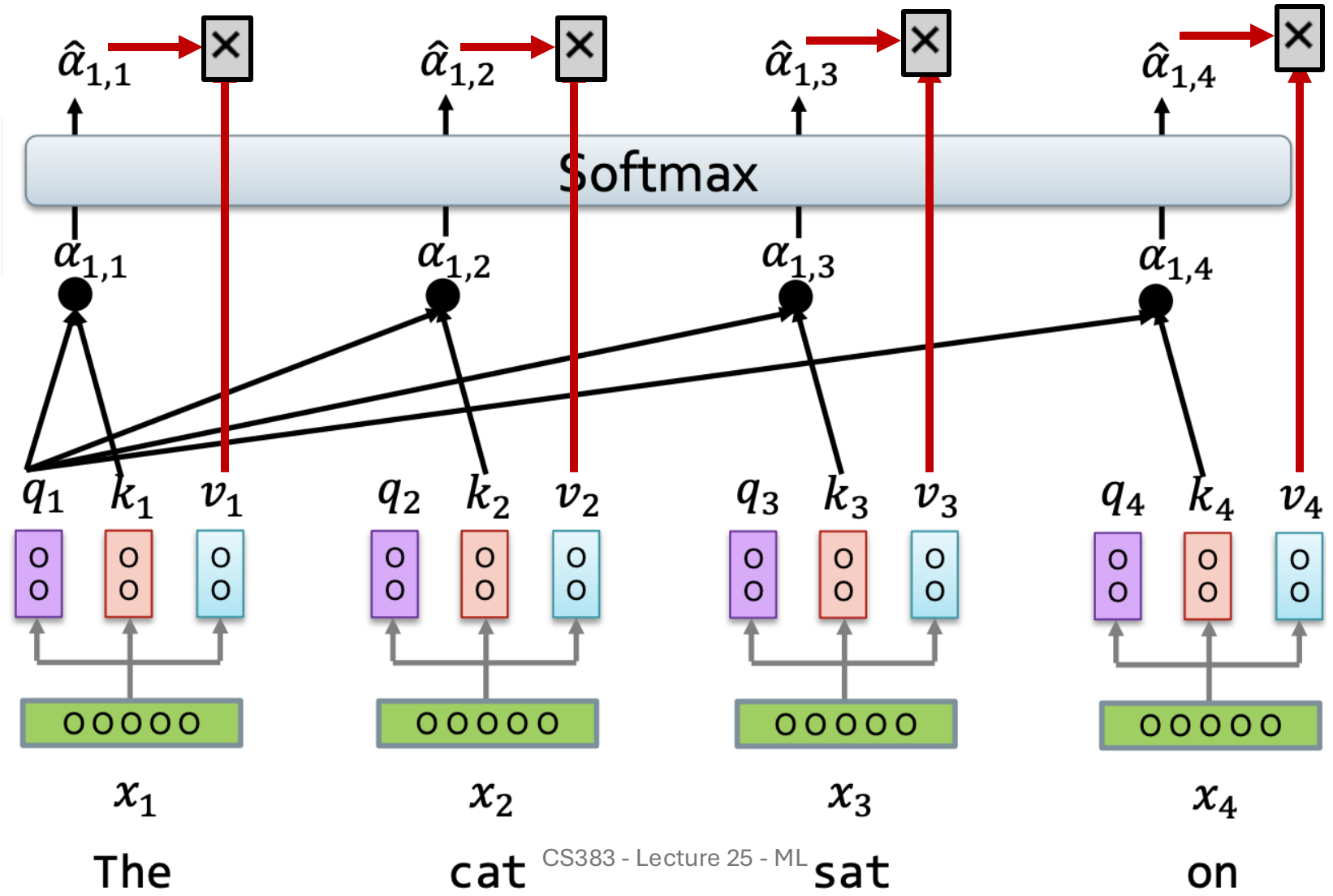
Self-attention



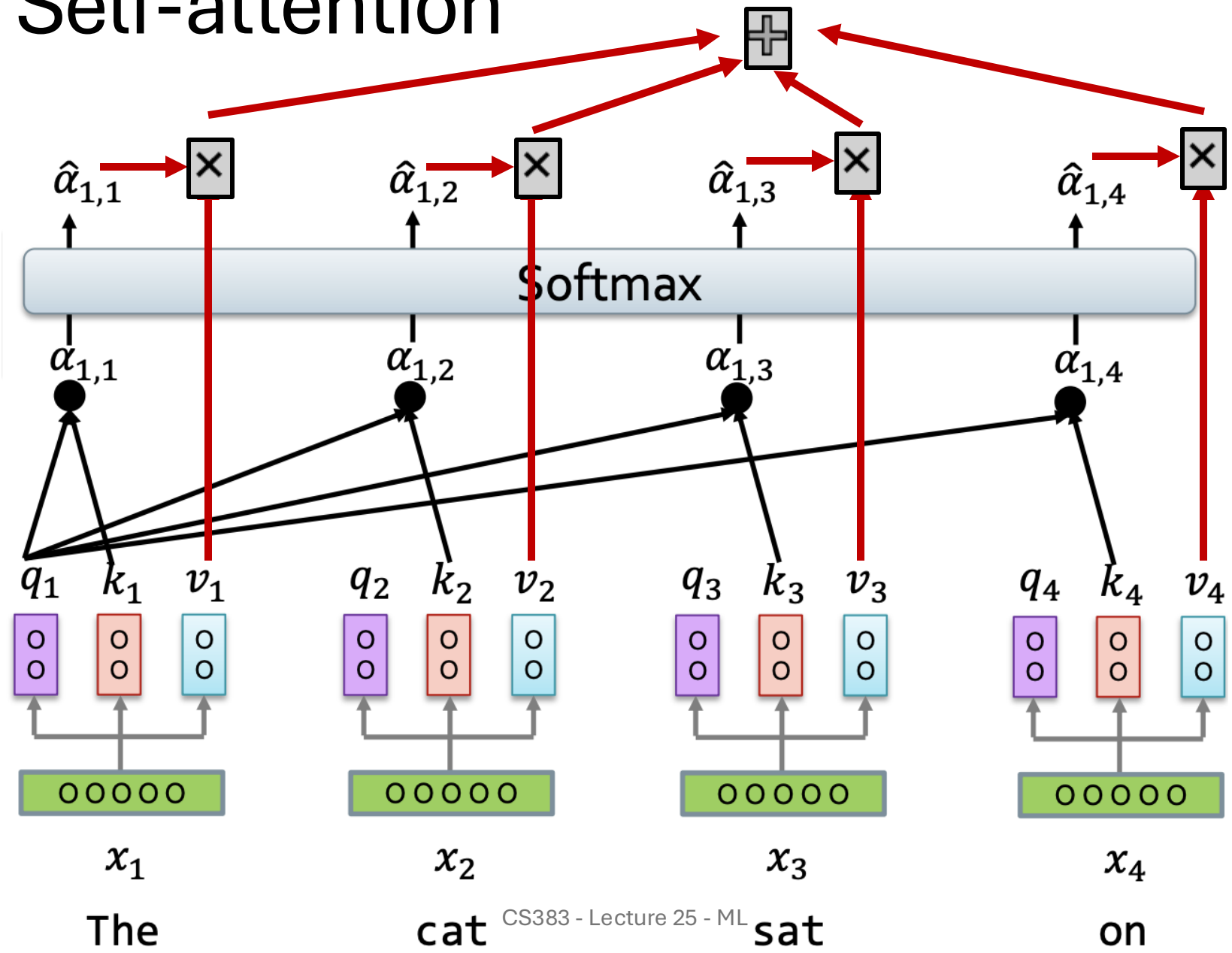
Self-attention



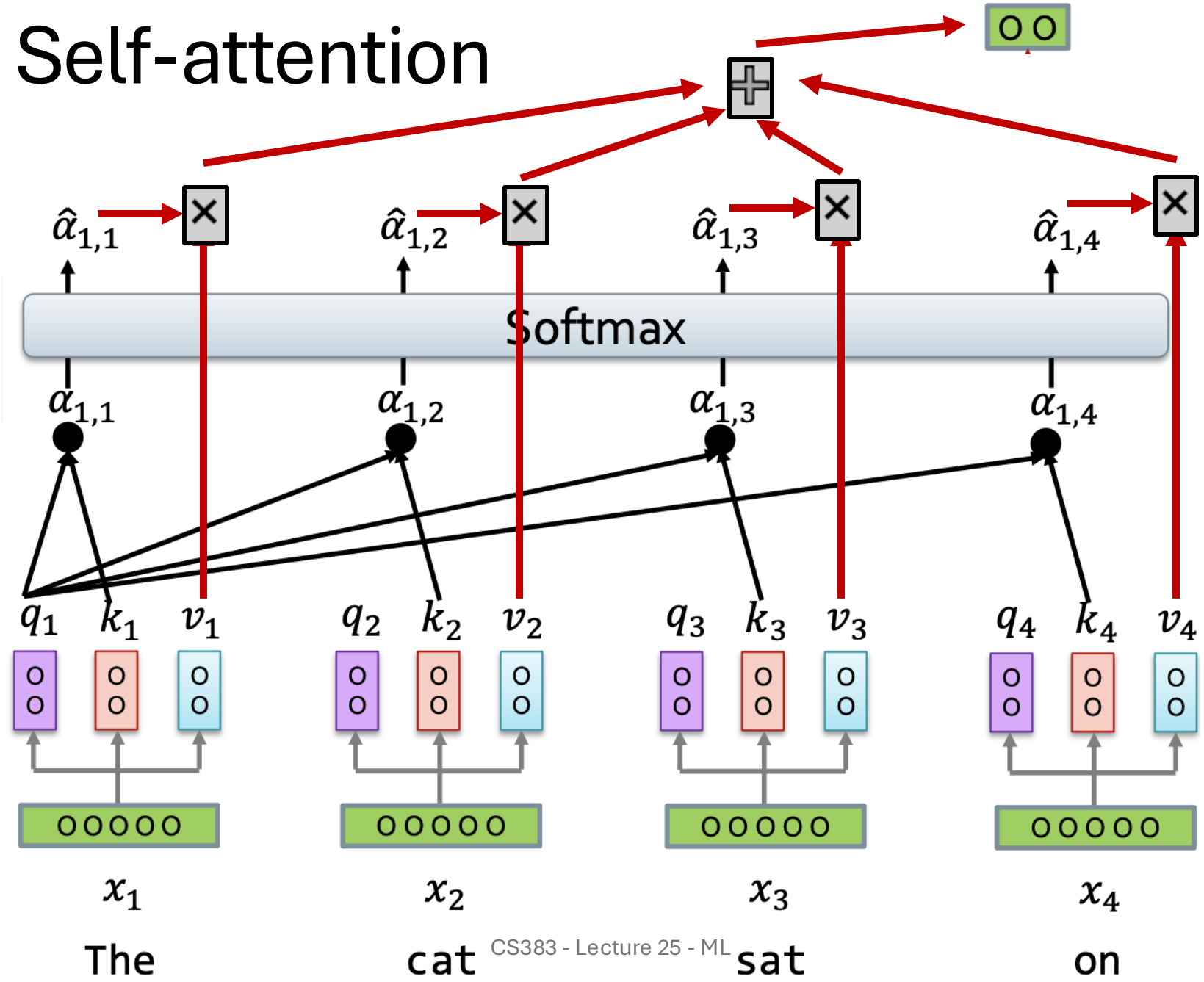
Self-attention



Self-attention

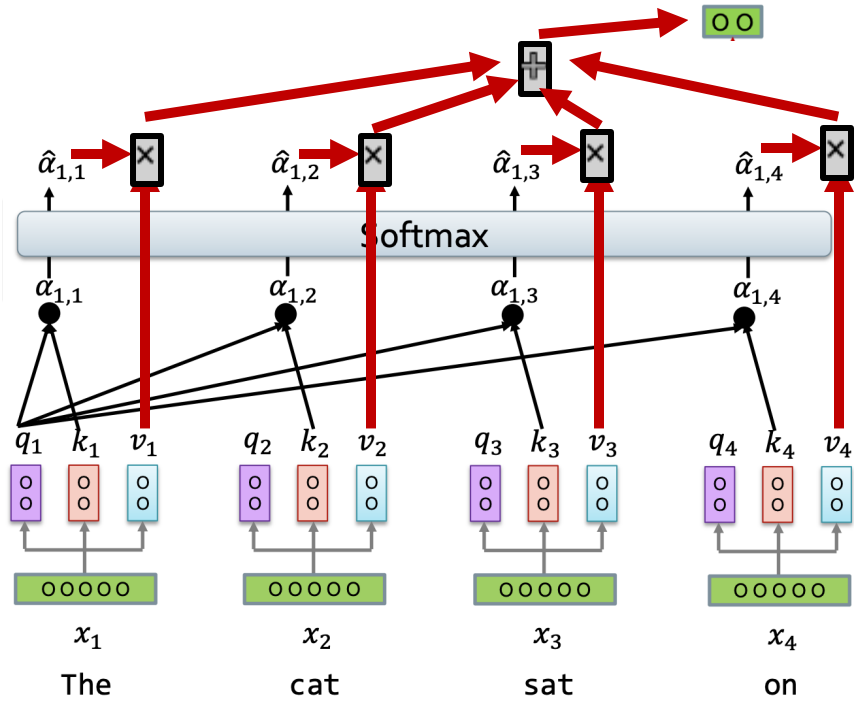


Self-attention



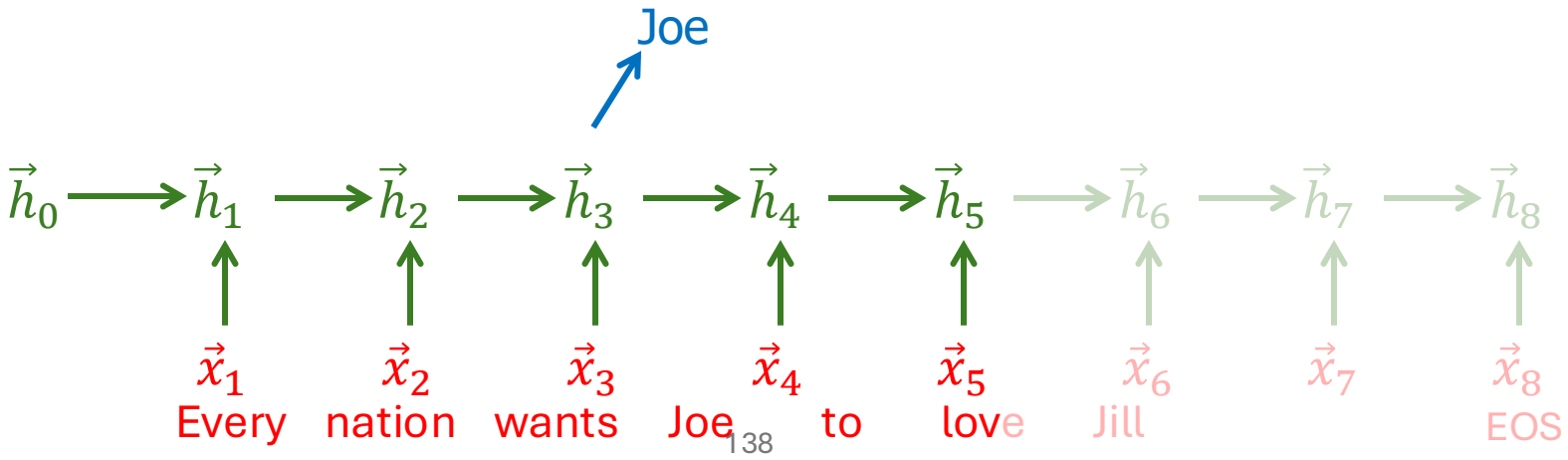
Self-attention

$$A = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

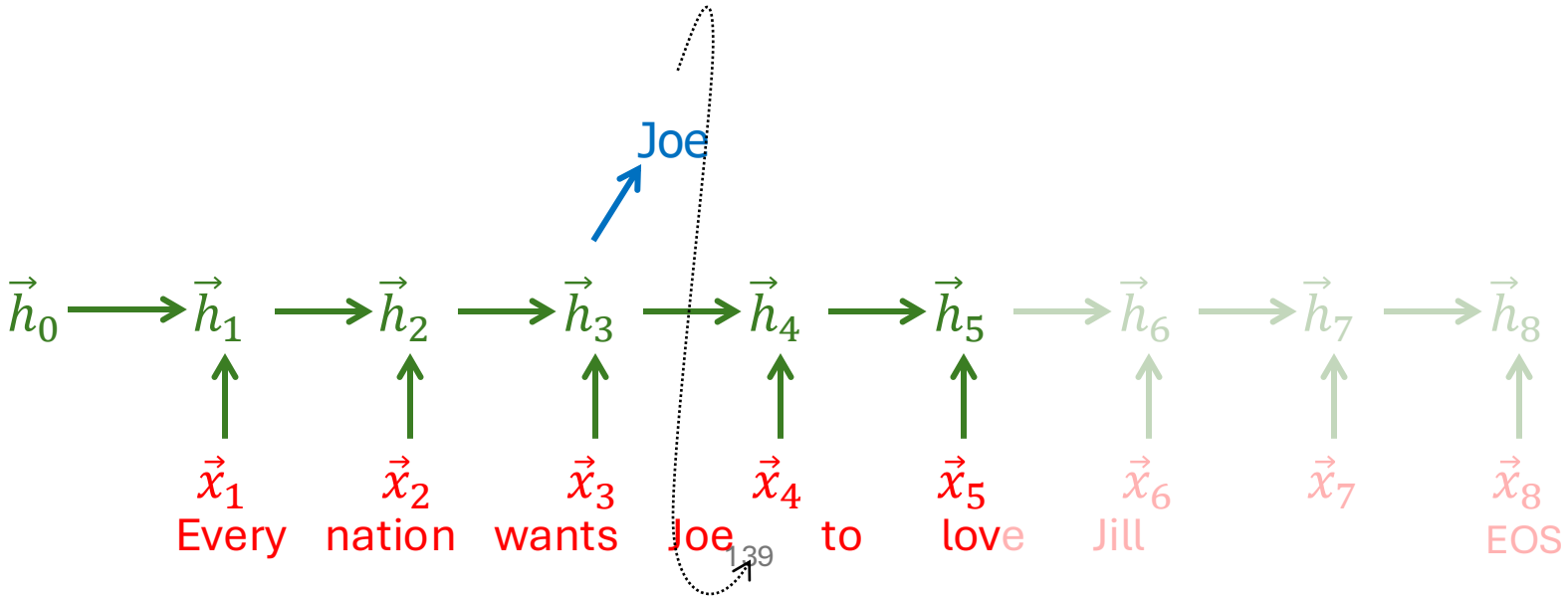


This is the main idea behind a **transformer**

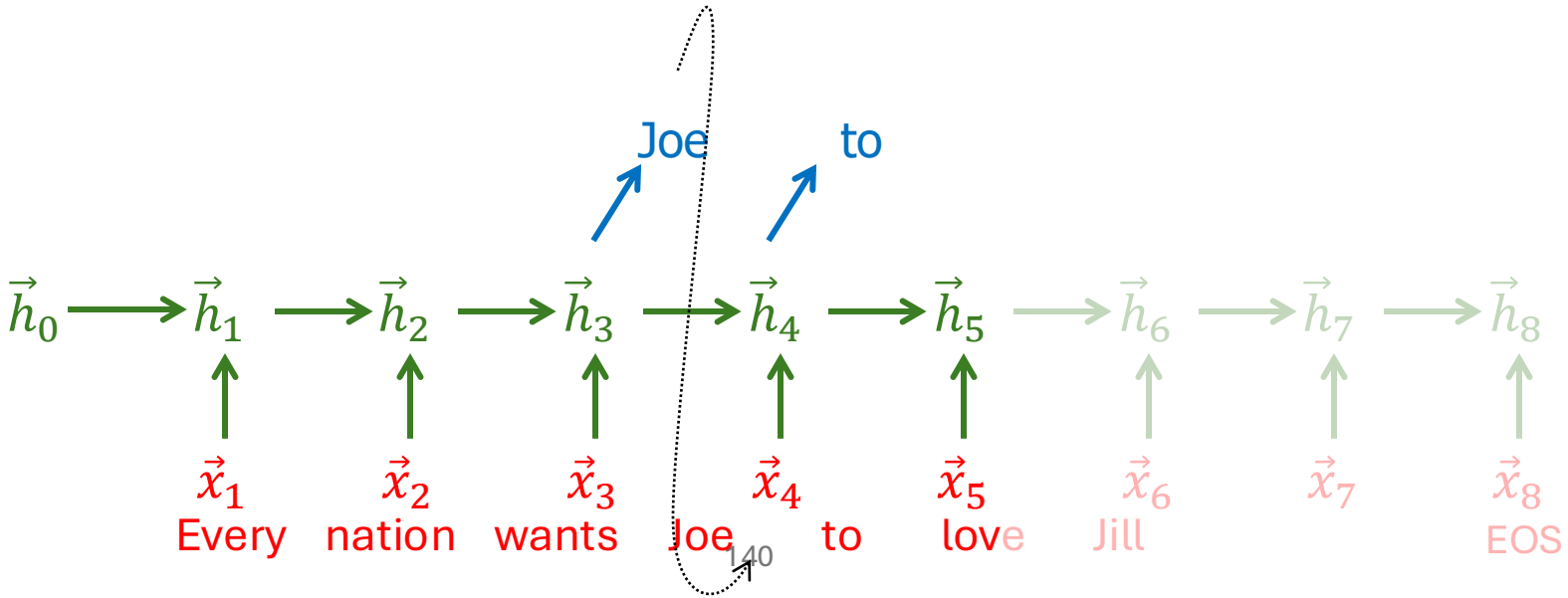
RNN LM


Joe
$\vec{h}_0$
$\vec{h}_1$
$\vec{h}_2$
$\vec{h}_3$
$\vec{h}_4$
$\vec{h}_5$
$\vec{h}_6$
$\vec{h}_7$
$\vec{h}_8$
$\vec{x}_1$
$\vec{x}_2$
$\vec{x}_3$
$\vec{x}_4$
$\vec{x}_5$
$\vec{x}_6$
$\vec{x}_7$
$\vec{x}_8$
Every
nation
wants
Joe
to
love
Jill
EOS

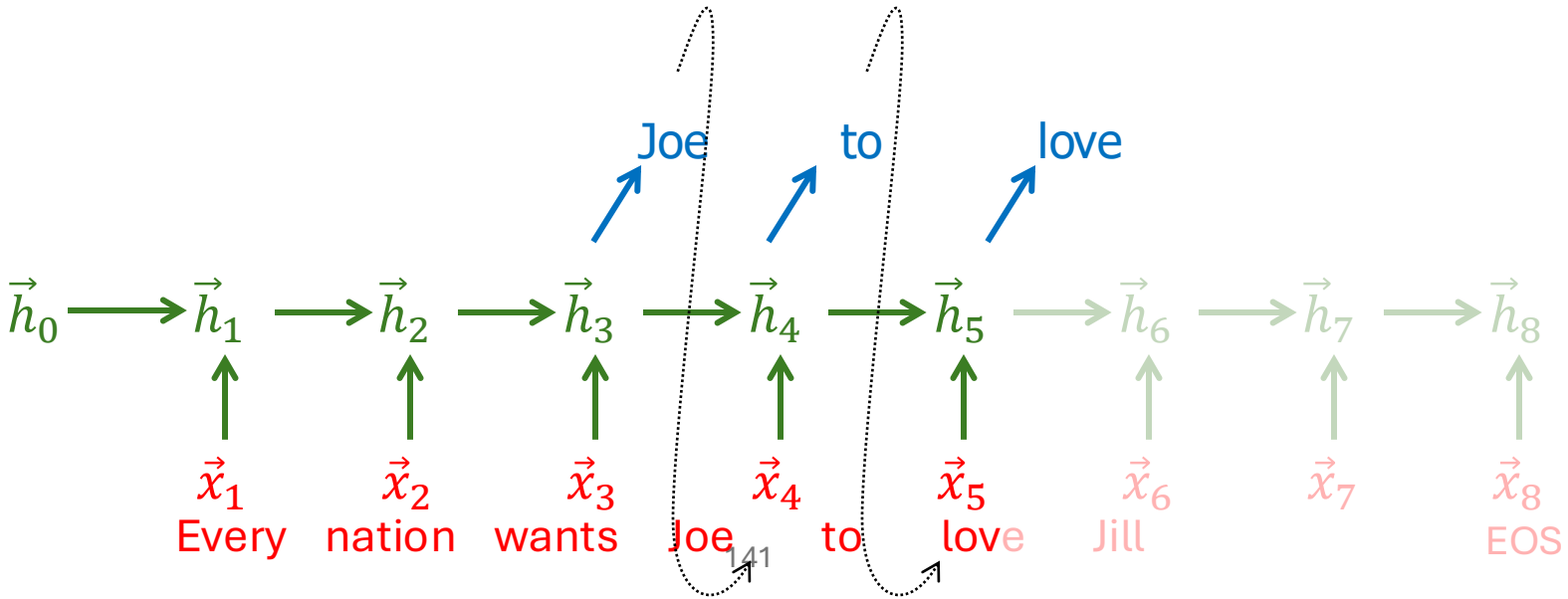
RNN LM


Joe
$\vec{h}_0$ $\vec{h}_1$ $\vec{h}_2$ $\vec{h}_3$ $\vec{h}_4$ $\vec{h}_5$ $\vec{h}_6$ $\vec{h}_7$ $\vec{h}_8$
$\vec{x}_1$ $\vec{x}_2$ $\vec{x}_3$ $\vec{x}_4$ $\vec{x}_5$ $\vec{x}_6$ $\vec{x}_7$ $\vec{x}_8$
Every nation wants Joe to love Jill EOS
139

RNN LM


Joe
to
$\vec{h}_0$
$\vec{h}_1$
$\vec{h}_2$
$\vec{h}_3$
$\vec{h}_4$
$\vec{h}_5$
$\vec{h}_6$
$\vec{h}_7$
$\vec{h}_8$
$\vec{x}_1$
$\vec{x}_2$
$\vec{x}_3$
$\vec{x}_4$
$\vec{x}_5$
$\vec{x}_6$
$\vec{x}_7$
$\vec{x}_8$
Every
nation
wants
Joe
to
love
Jill
EOS
140

RNN LM


Joe
to
love
$\vec{h}_0$
$\vec{h}_1$
$\vec{h}_2$
$\vec{h}_3$
$\vec{h}_4$
$\vec{h}_5$
$\vec{h}_6$
$\vec{h}_7$
$\vec{h}_8$
$\vec{x}_1$
$\vec{x}_2$
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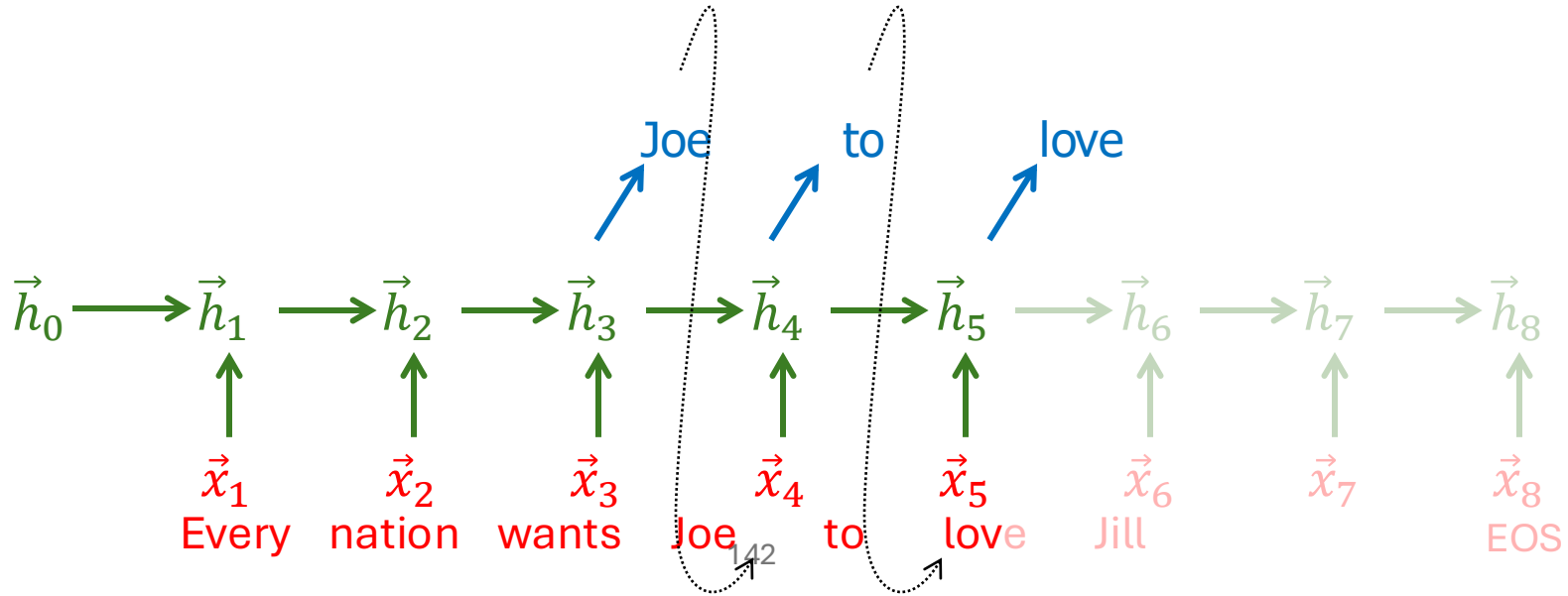
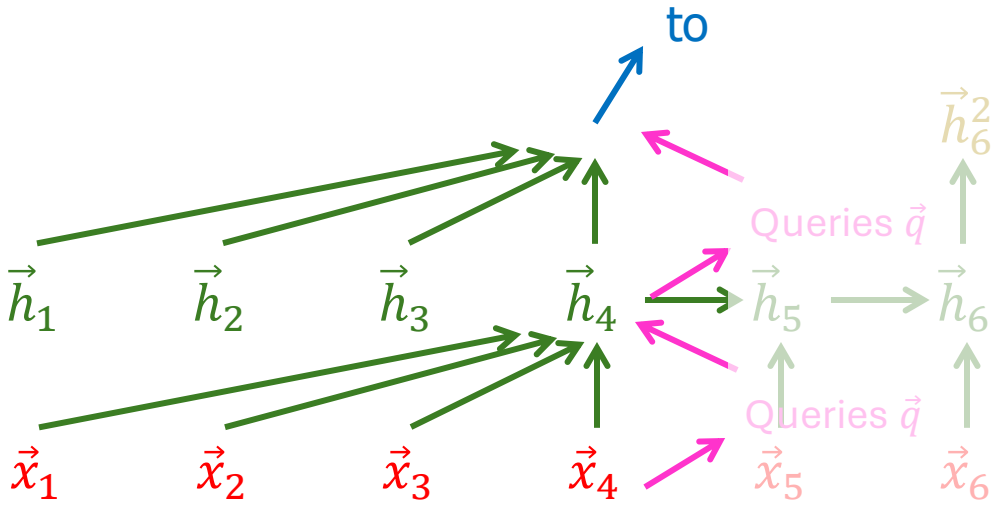
EOS

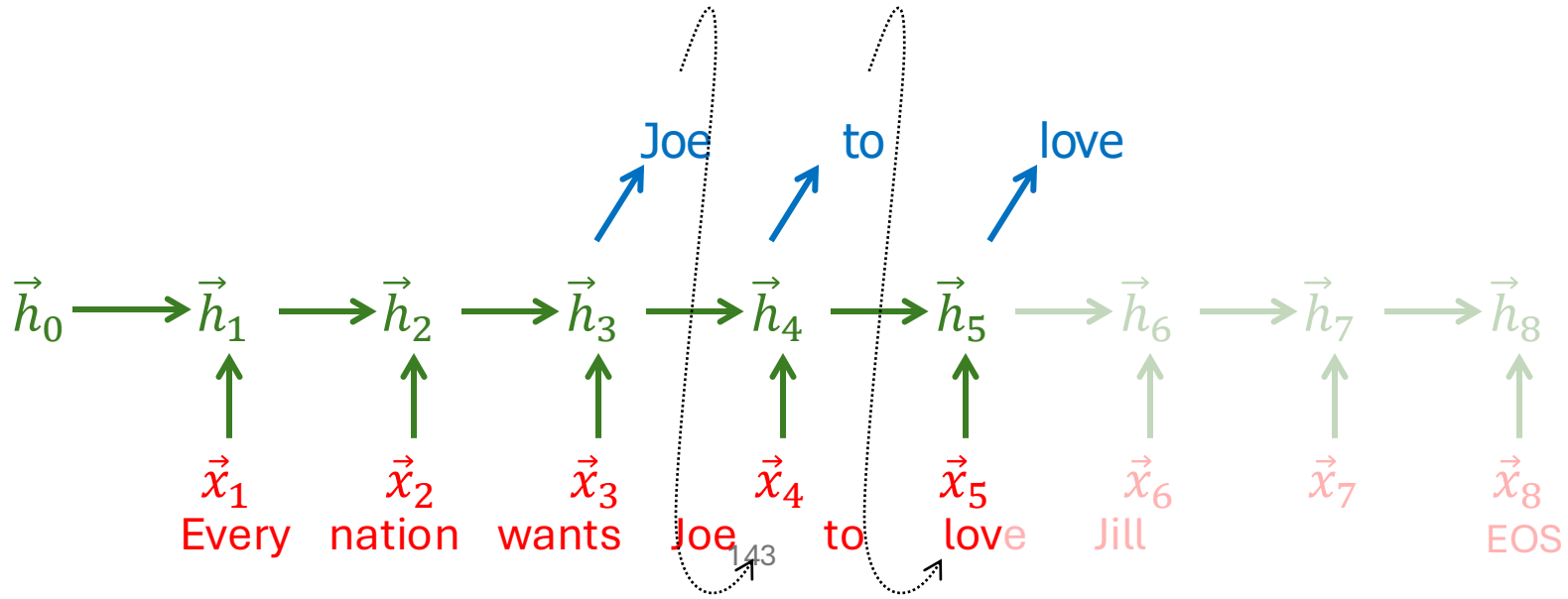
RNN LM



Transformer (self-attention) LM

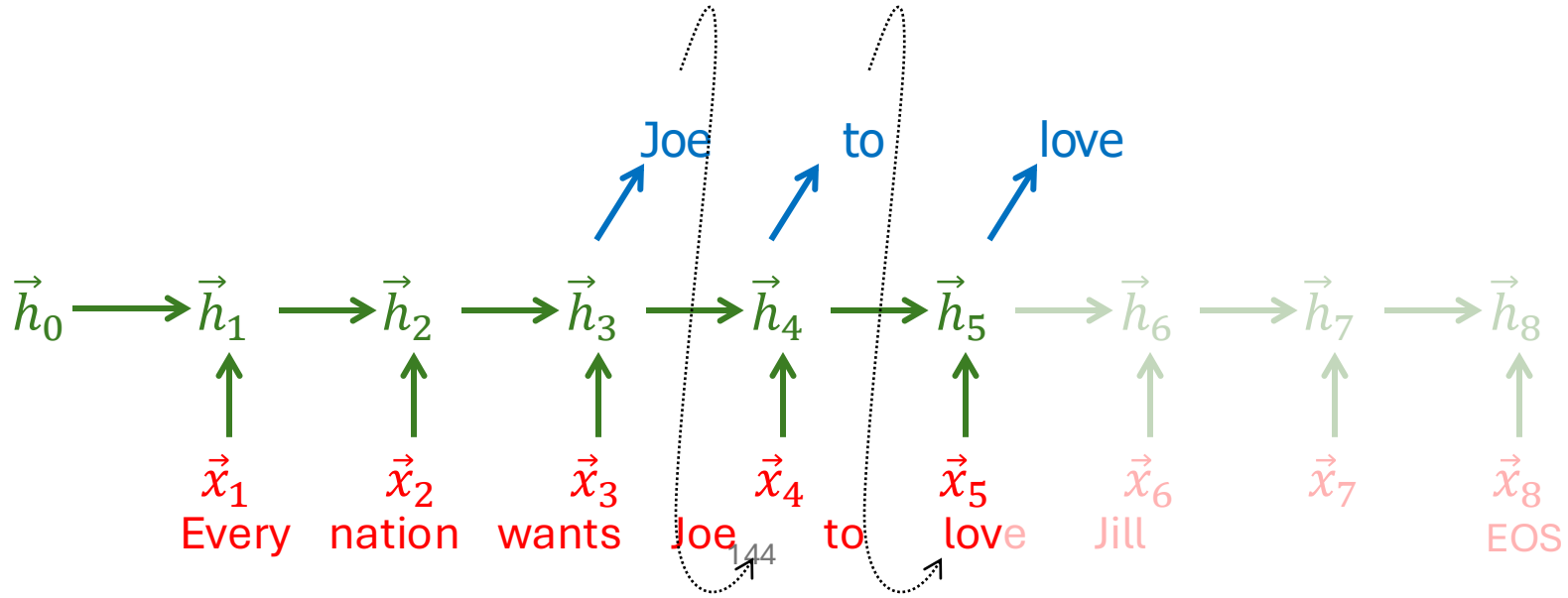


RNN LM

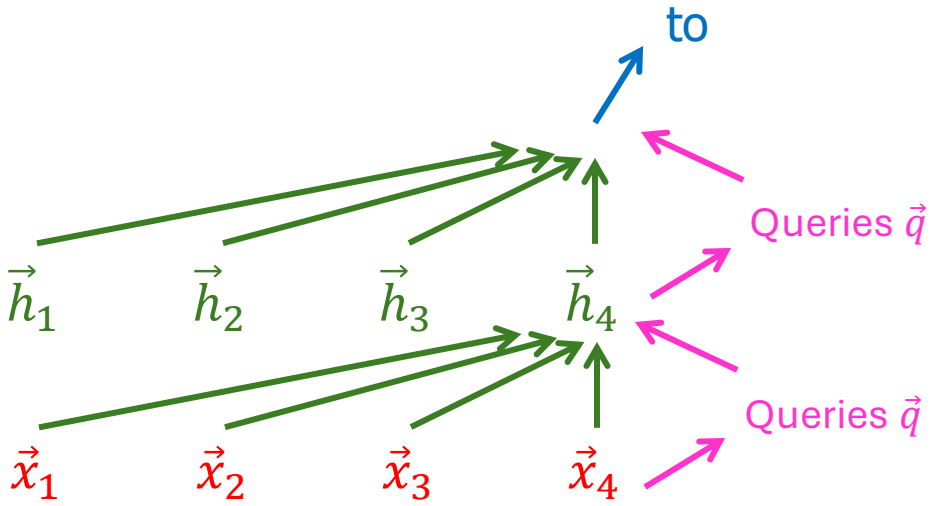


Transformer (self-attention) LM

RNN LM

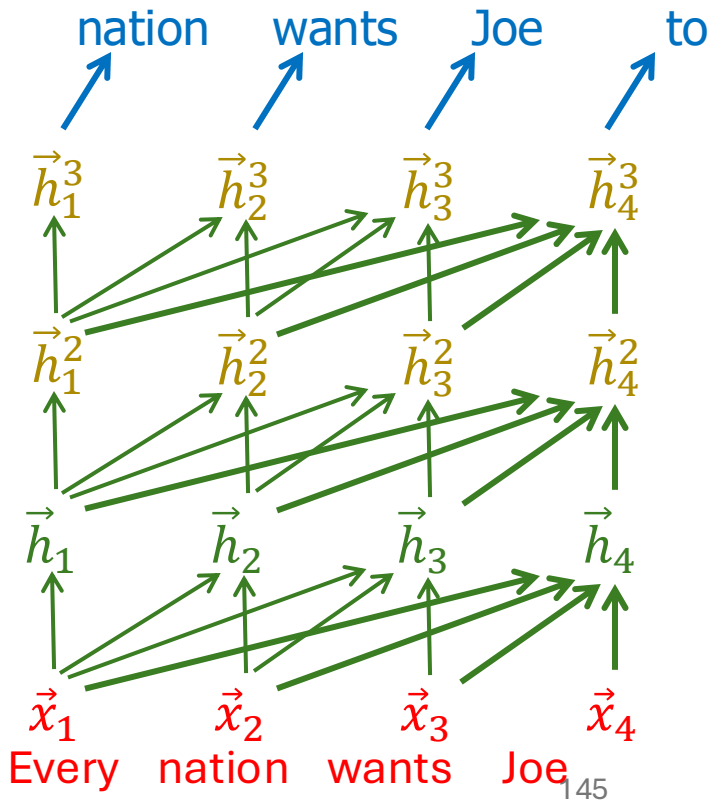


Transformer (self-attention) LM



Training can be parallelized

At training time, the whole sentence is known.
Layer-L representations can be computed in parallel, with each word attending to the layer-(L-1) representations of itself and previous words



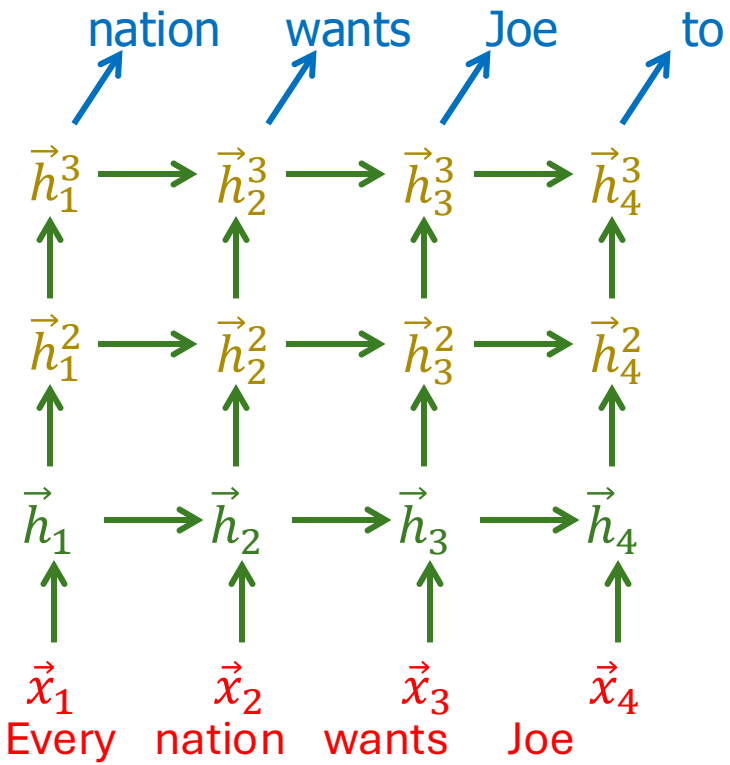
(oops, to predict the very first word, we needed $\vec{x}_0 =< s >$!
It's missing from our diagrams.)

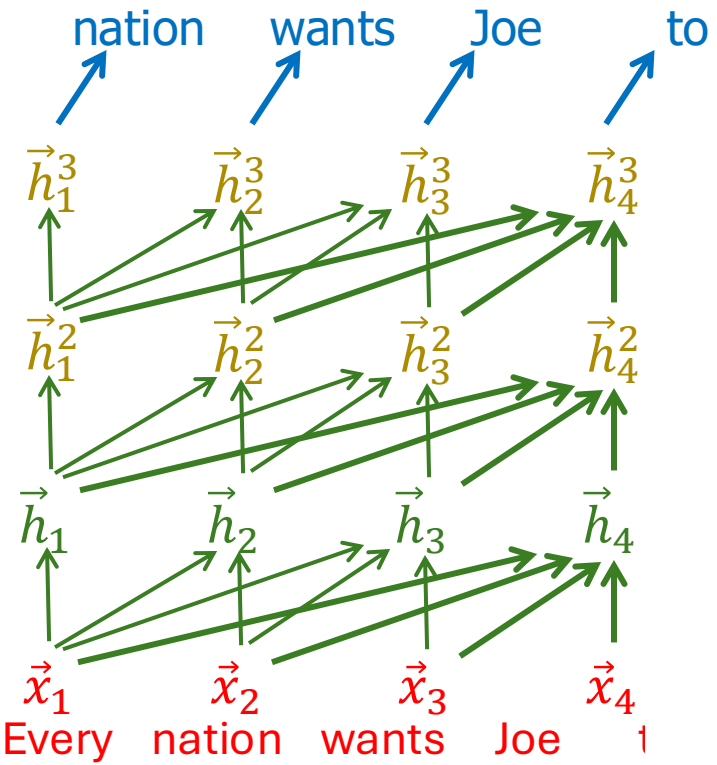
RNN vs. Transformer

Training, on GPU, per layer ↓

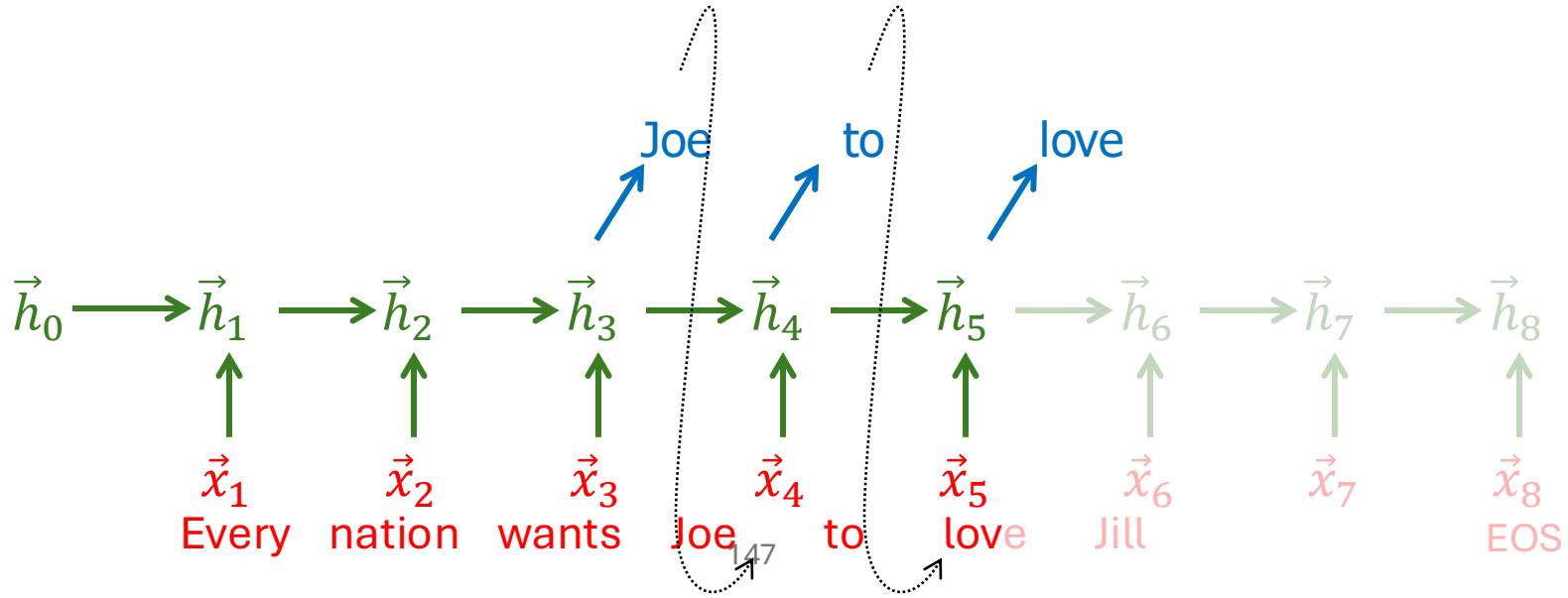
Computations: ☺ O(n)
serial steps: ☹ O(n) due to →

☹ $O(n^2)$
☺ O(1): all ↗↑ in parallel
+ O(log n) to sum n inputs

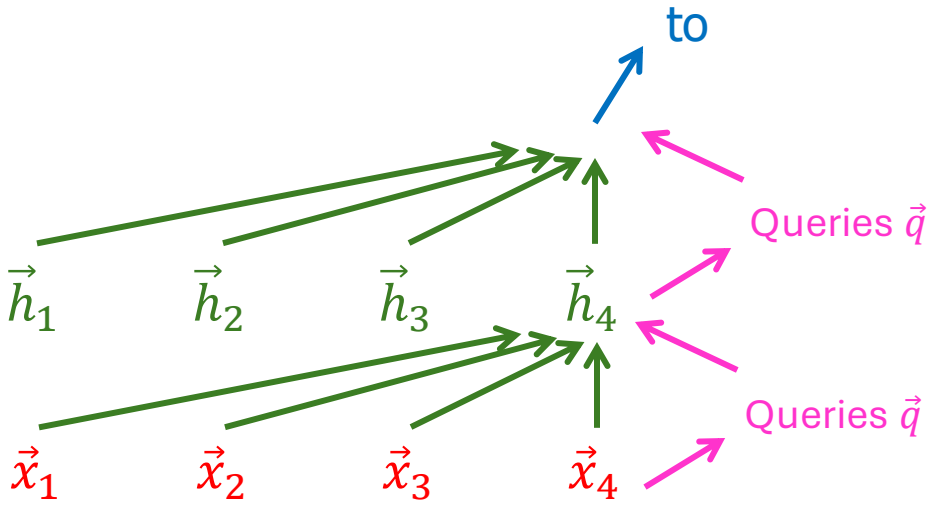




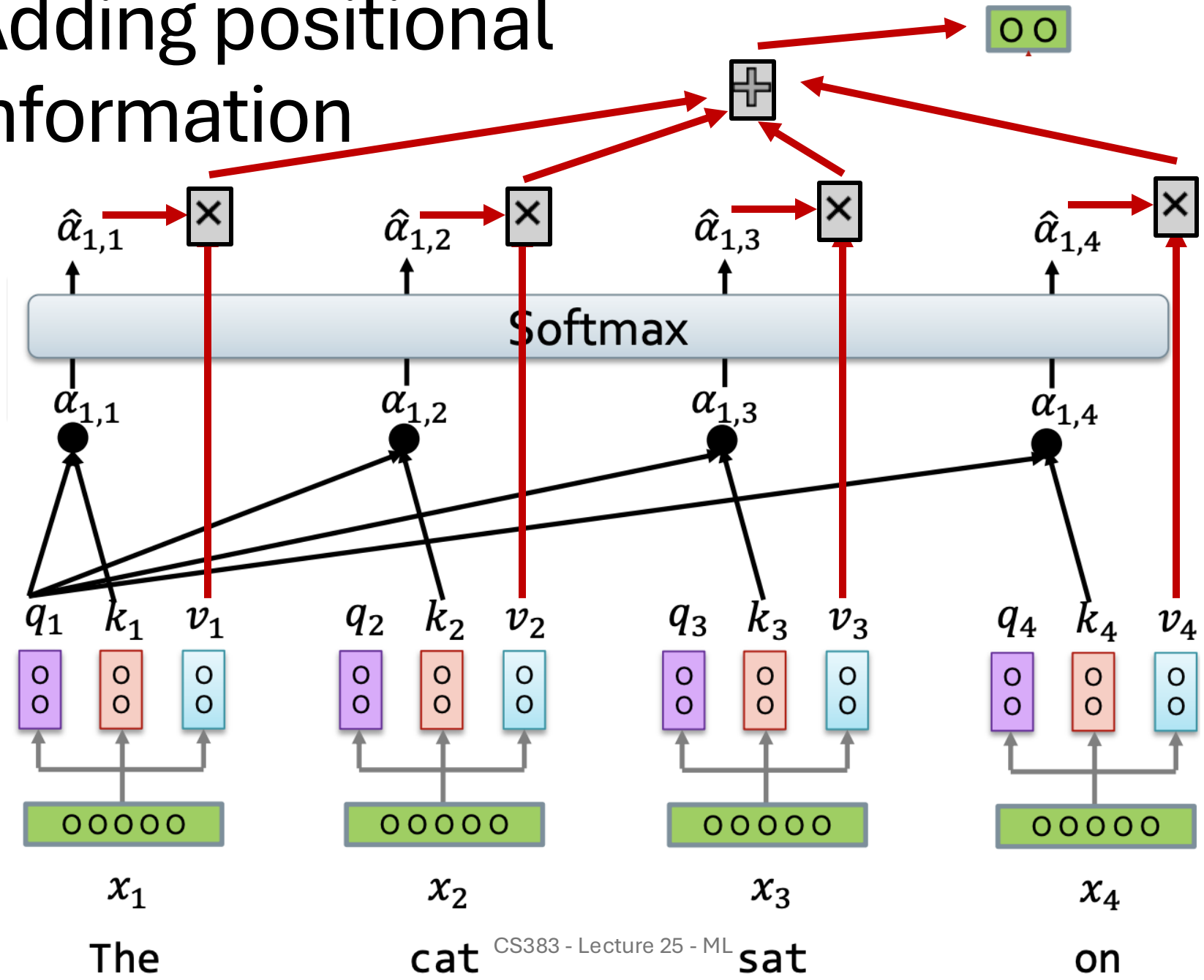
RNN LM



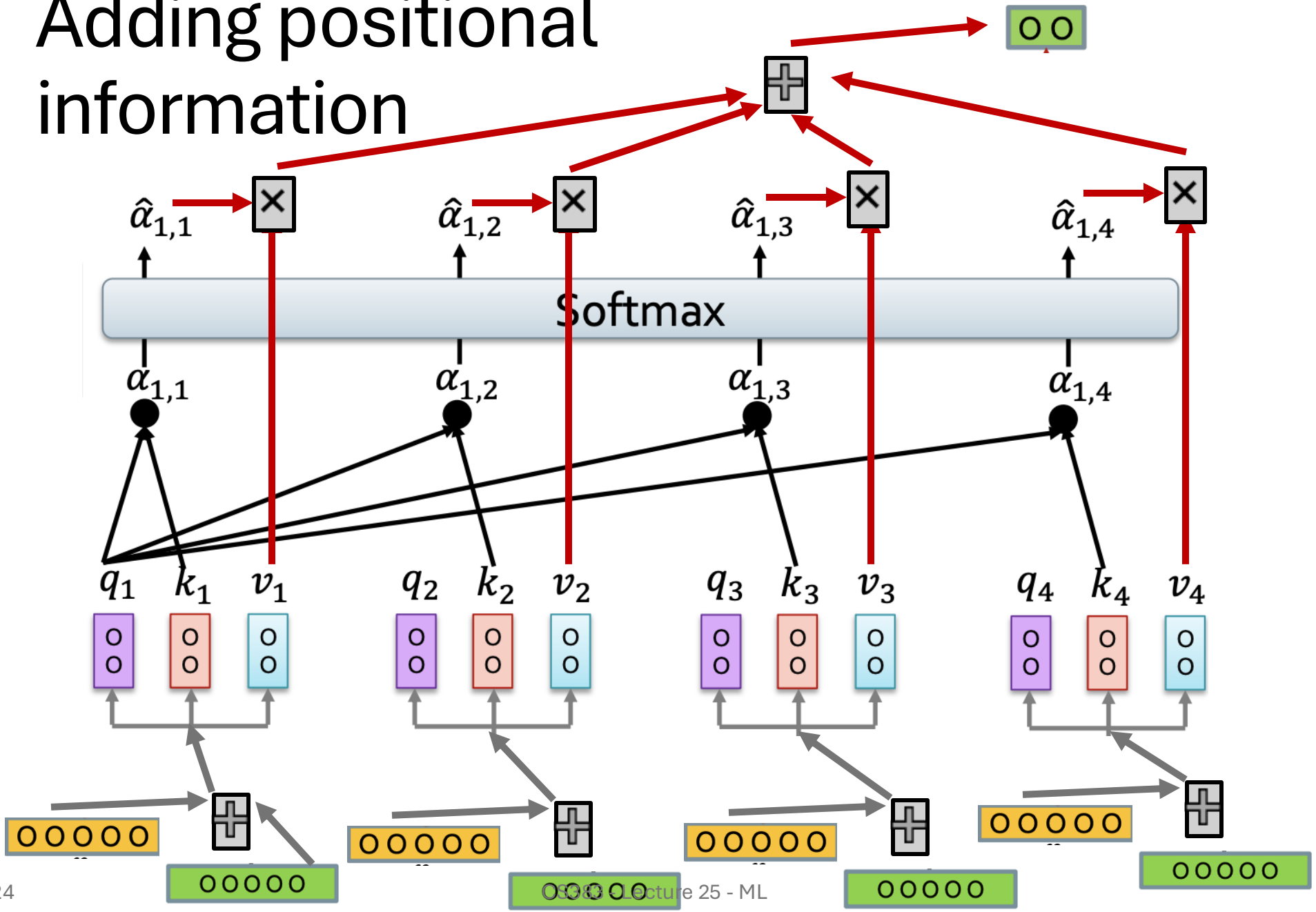
Transformer (self-attention) LM



Adding positional information

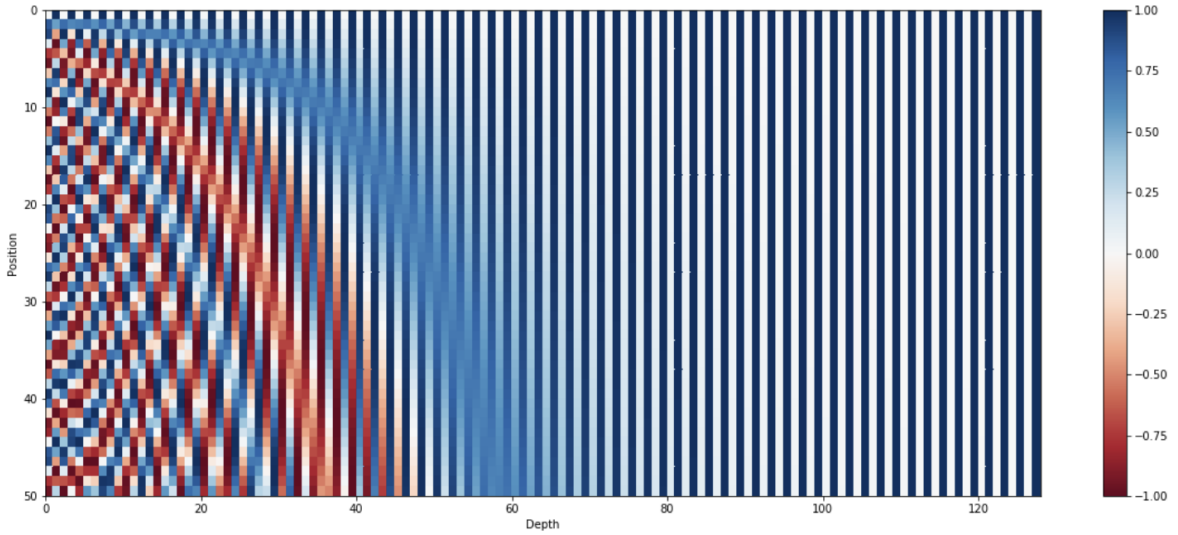


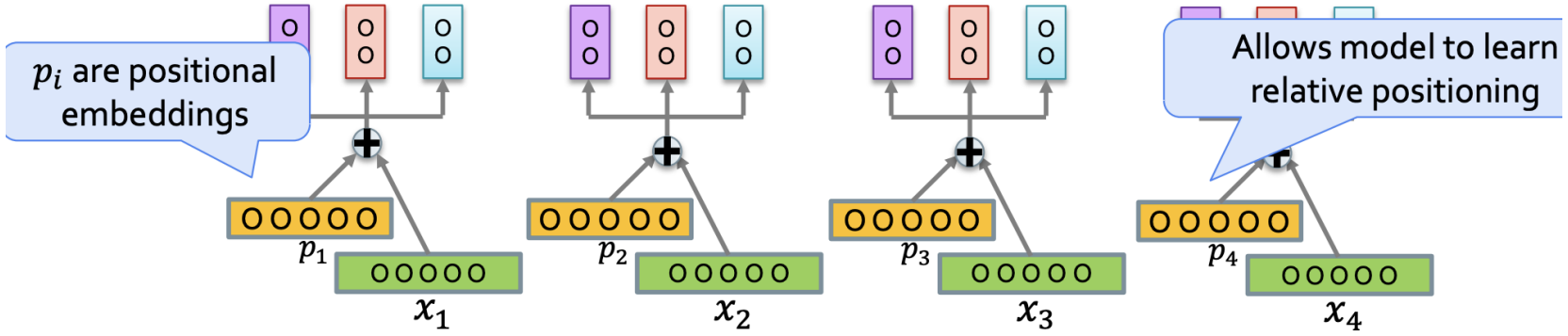
Adding positional information



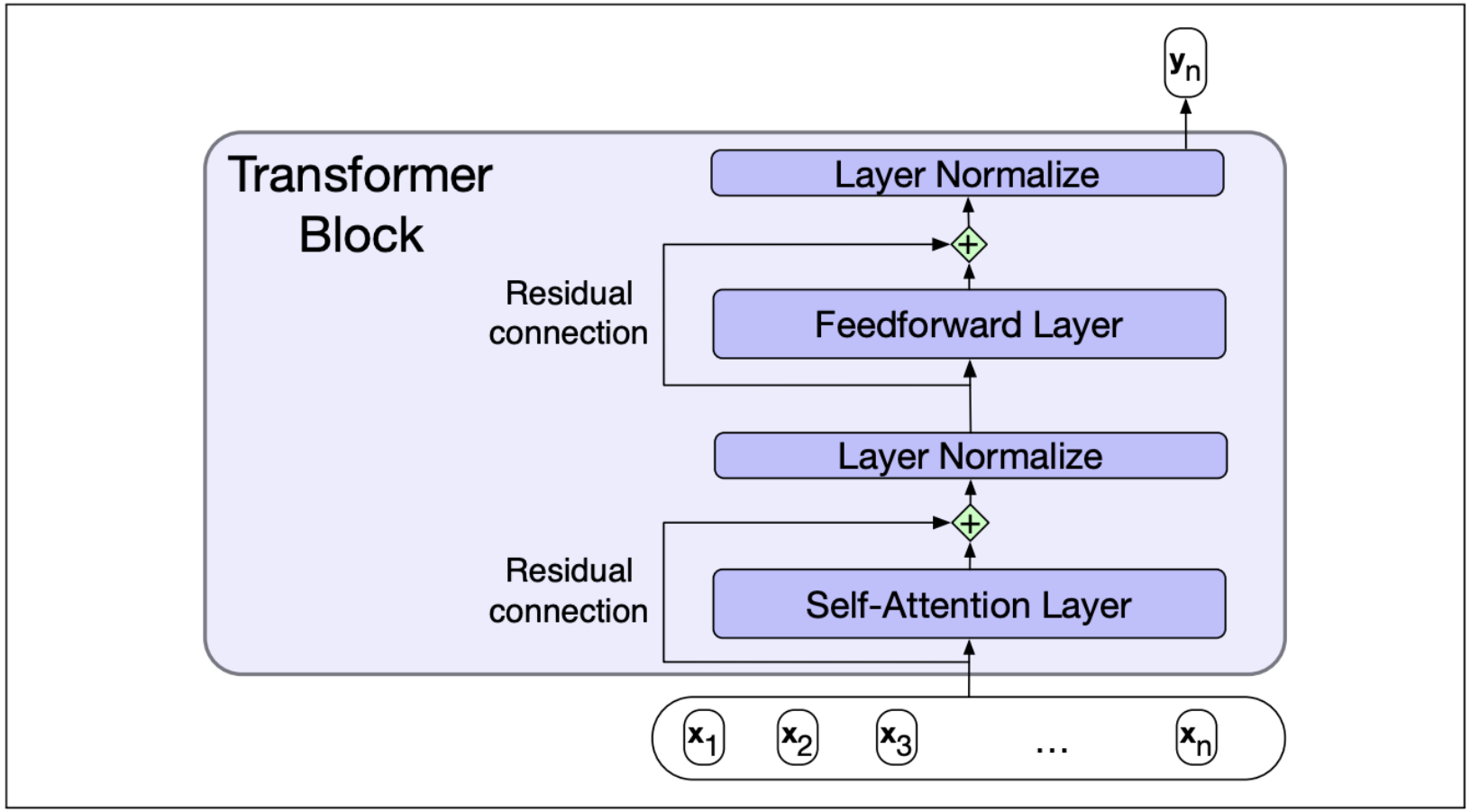
Adding positional information

An approach:
Sine/Cosine encoding





Transformer block



Transformer block

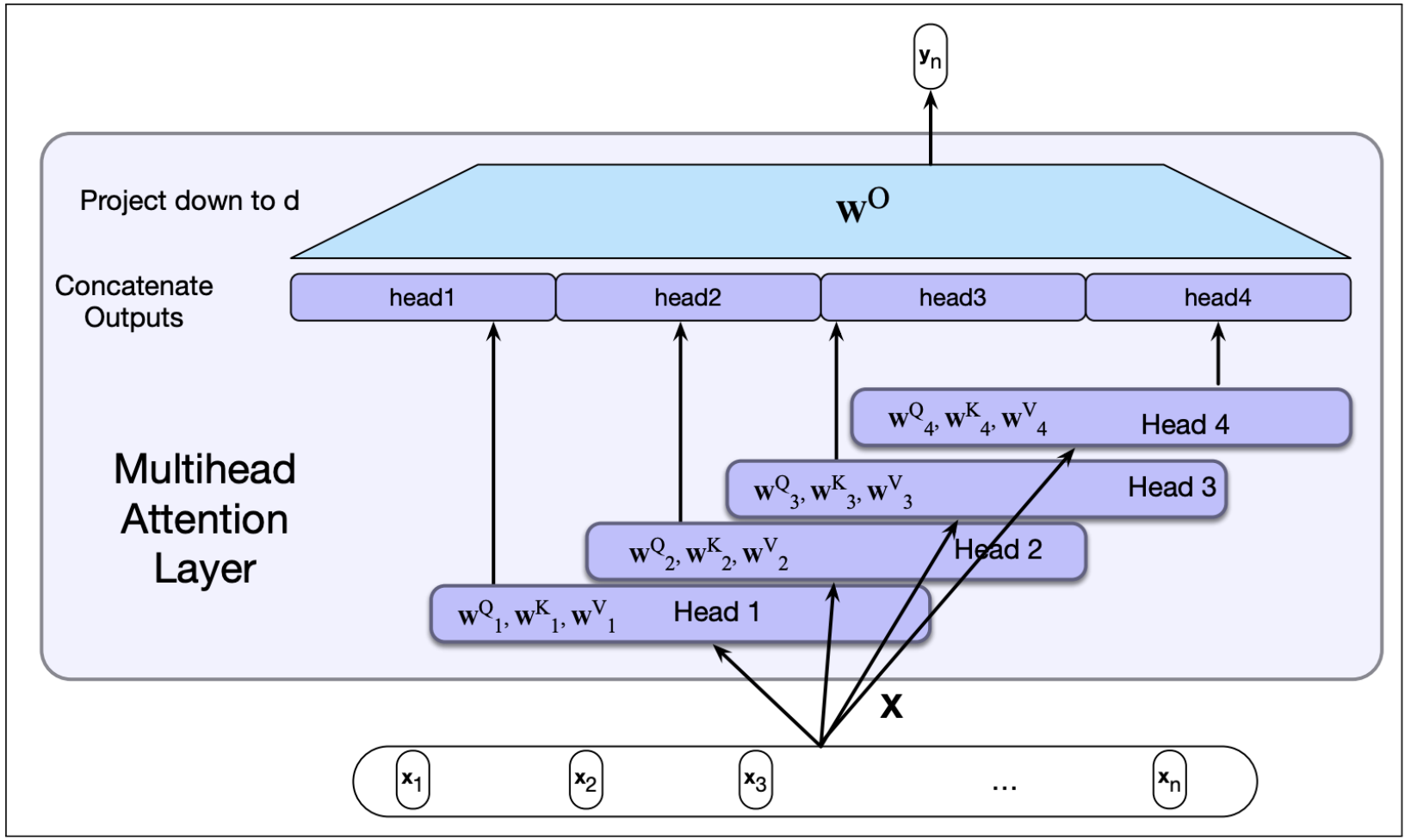
Residual connection:

- Passes information from a lower layer to a higher layer directly (w/out going through intermediate layers)

Layer normalization

- Ensures the values in a layer are in an appropriate range
- Based on normalization/z-scores in statistics (we'll cover normalization later this semester)

Multi-head attention



Transformers as LM

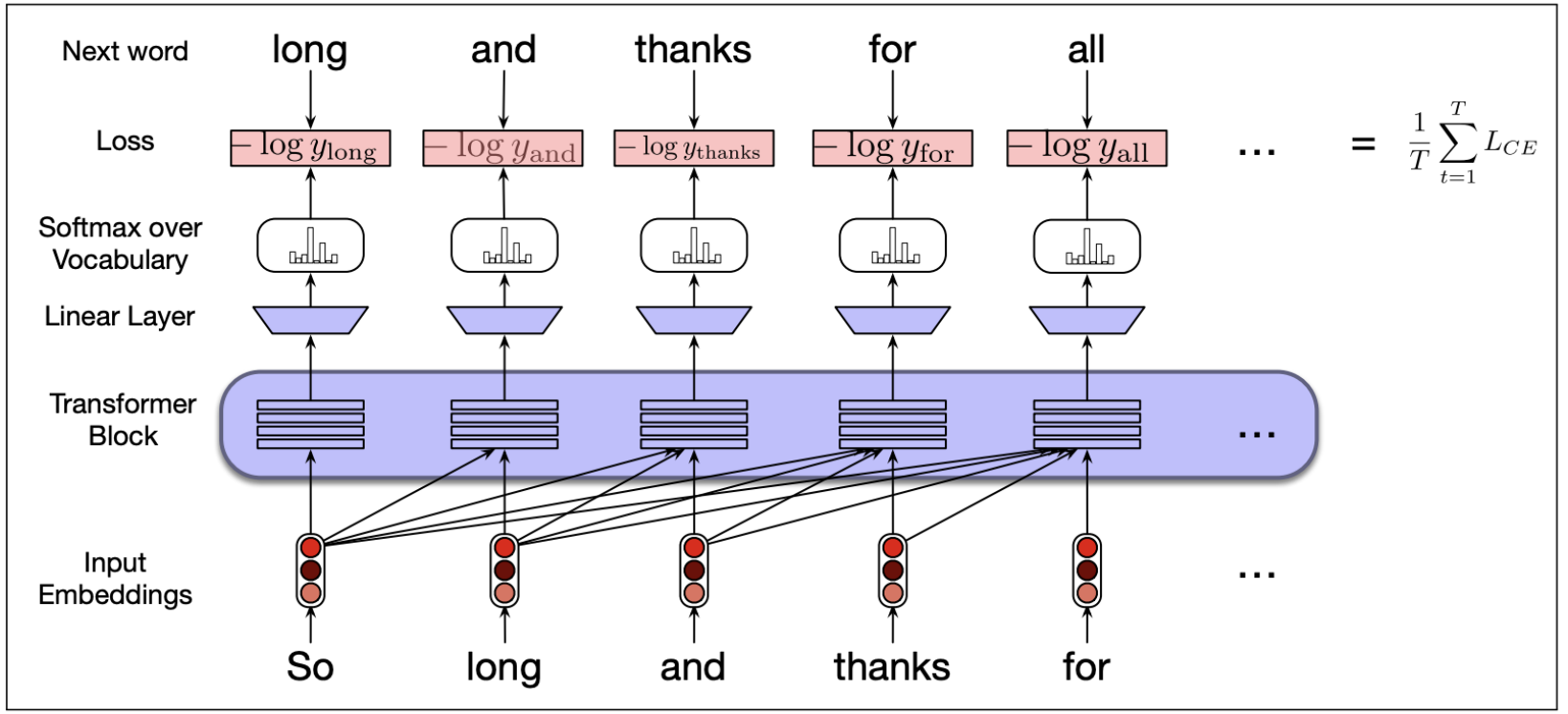


Figure 10.7 Training a transformer as a language model.

Training tansformers

parameters in transformer >> # parameters in LSTM

So, training requires a lot of data

We can pre-train a transformer, and then use it as a sentence-representation/feature extracter

Led to State-of-the-art models