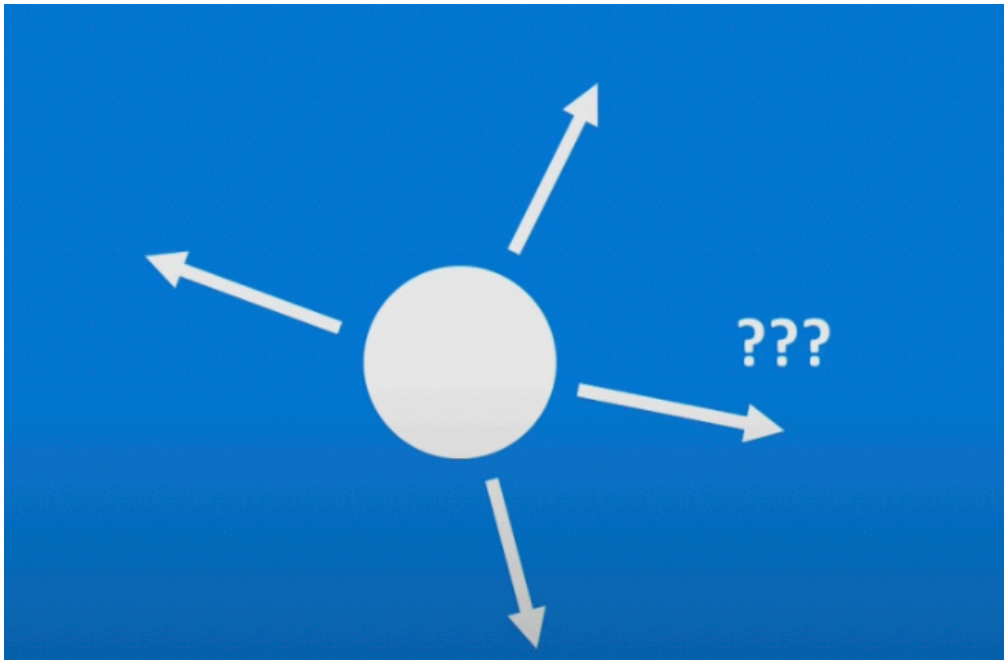
SEQUENCE MODELLING

*based on MIT Lecture by Ava Soleimany

GIVEN AN IMAGE OF A BALL, CAN YOU PREDICT WHERE IT WILL GO NEXT?



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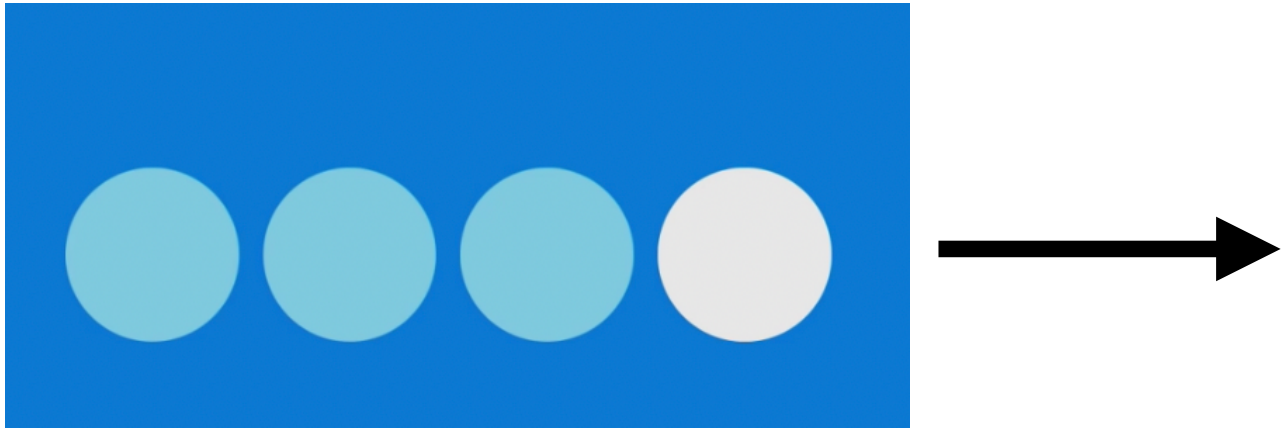
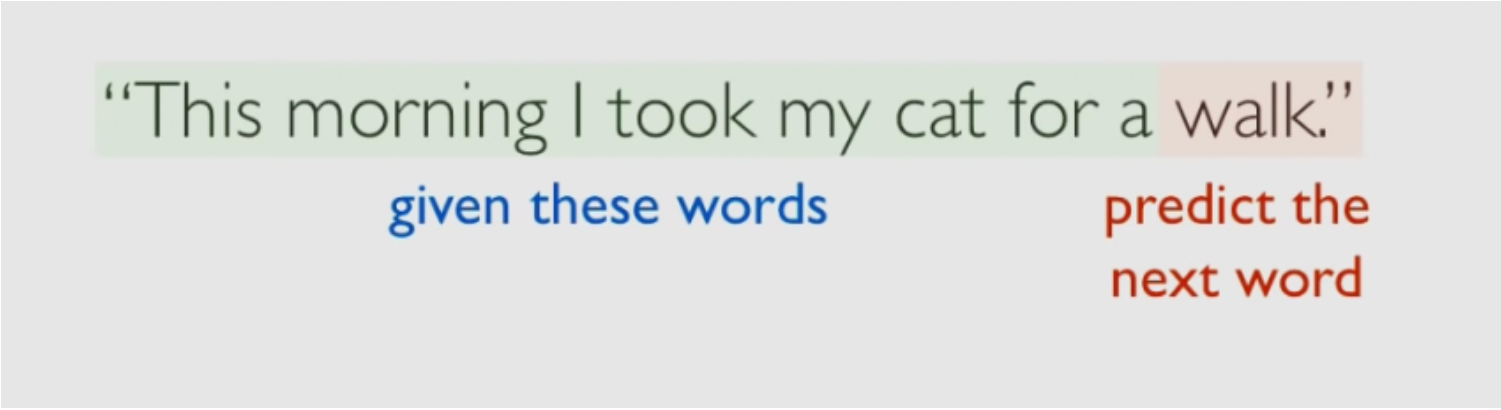


Previous positions help guessing the future

LET'S TAKE A SIMPLE EXAMPLE OF LANGUAGE MODELLING



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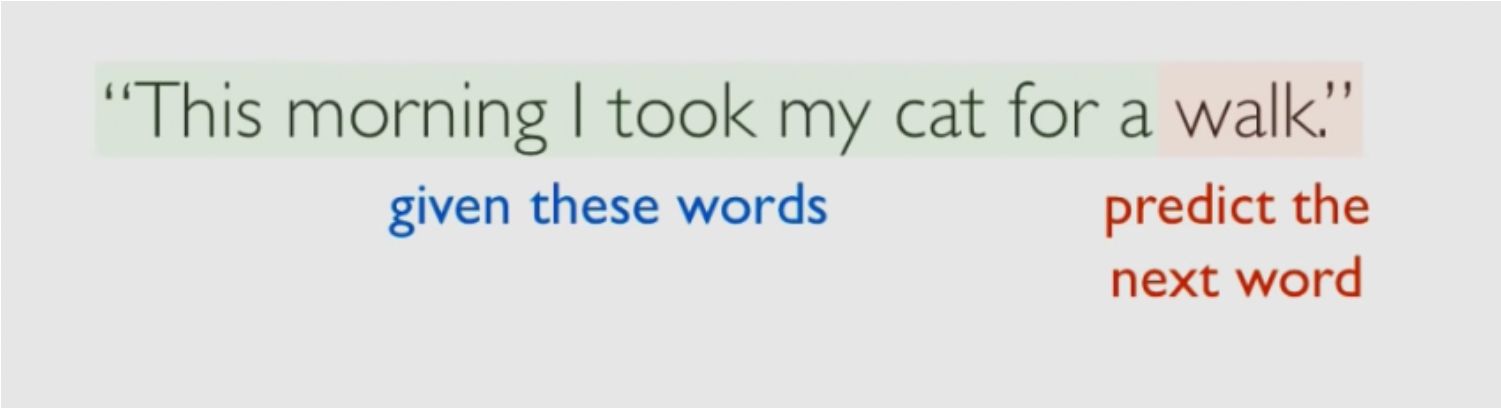
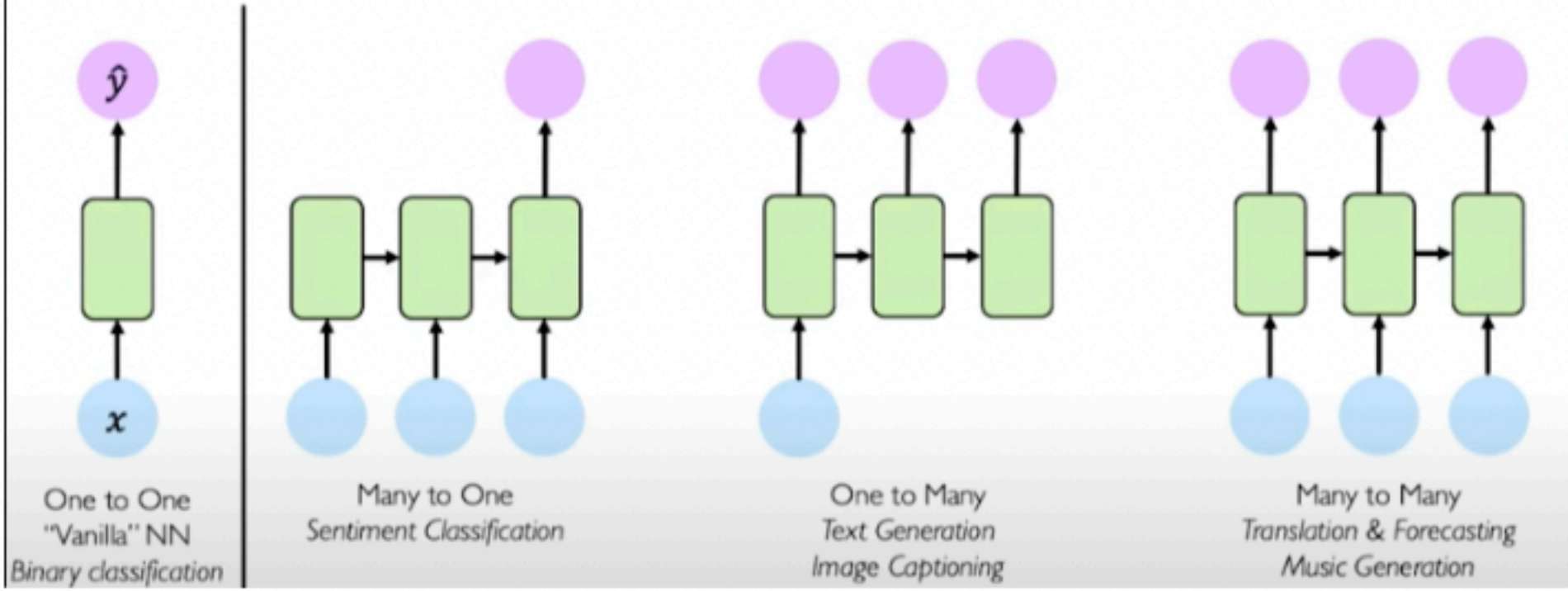
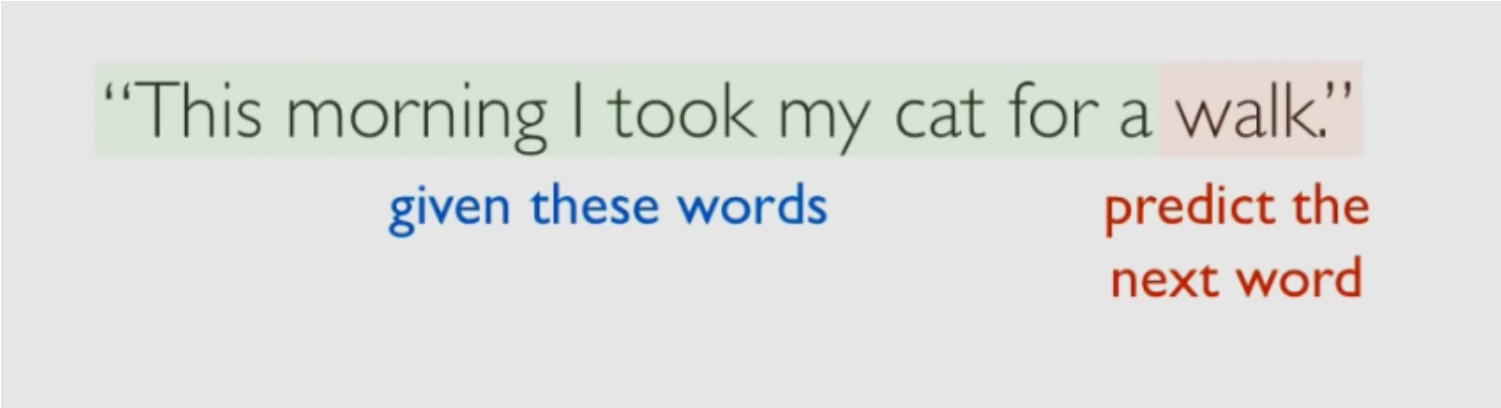


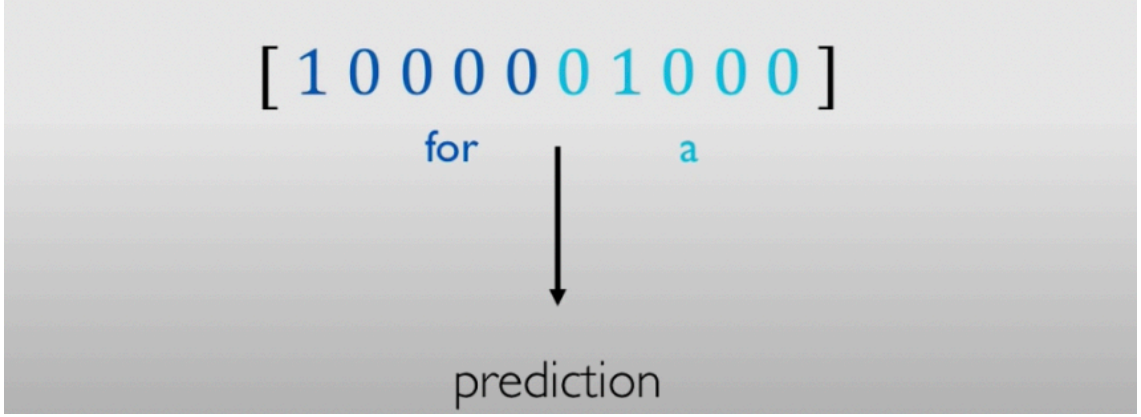
Normal ANNs and CNNs cannot handle variable length inputs …

RNNs for Sequence Modeling



WE COULD SIMPLY USE A FIXED WINDOW…

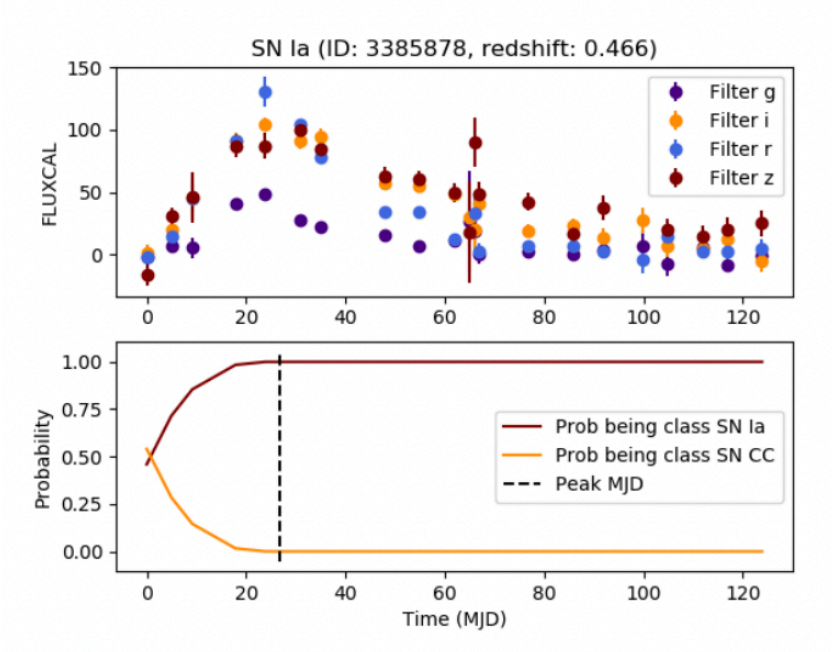




HOWEVER THIS CANNOT HANDLE LONG TERM MEMORY

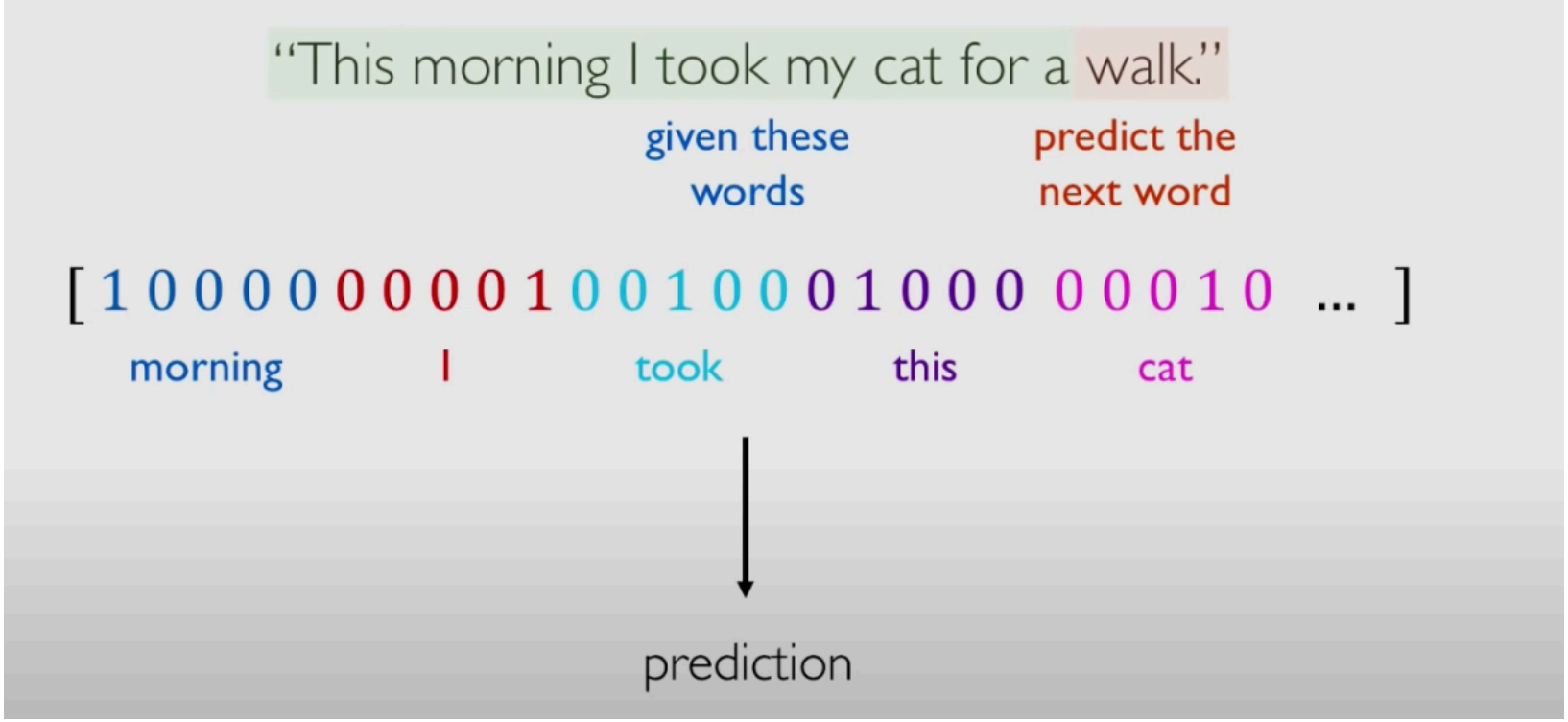
"**France** is where I grew up, but I now live in Boston. I speak fluent ____."

IN SOME CASES, INFORMATION FROM THE DISTANT PAST IS NEEDED FOR A CORRECT PREDICTION



Moller+19

ANOTHER ALTERNATIVE COULD BE TO FEED A REALLY LARGE WINDOW



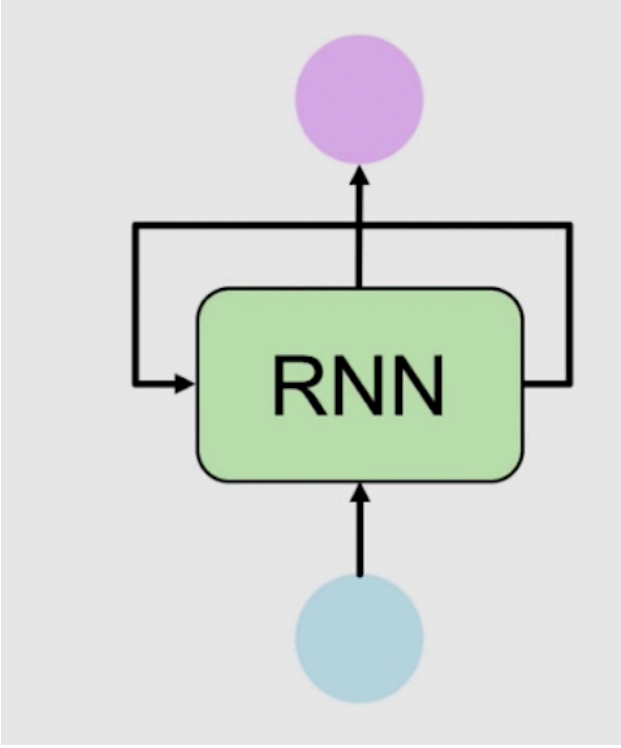
BUT WE STILL HAVE THE PROBLEM THAT THERE IS NO PARAMETER SHARING (SAME AS PIXELS)

RECURRENT NEURAL NETWORKS (RNNs)

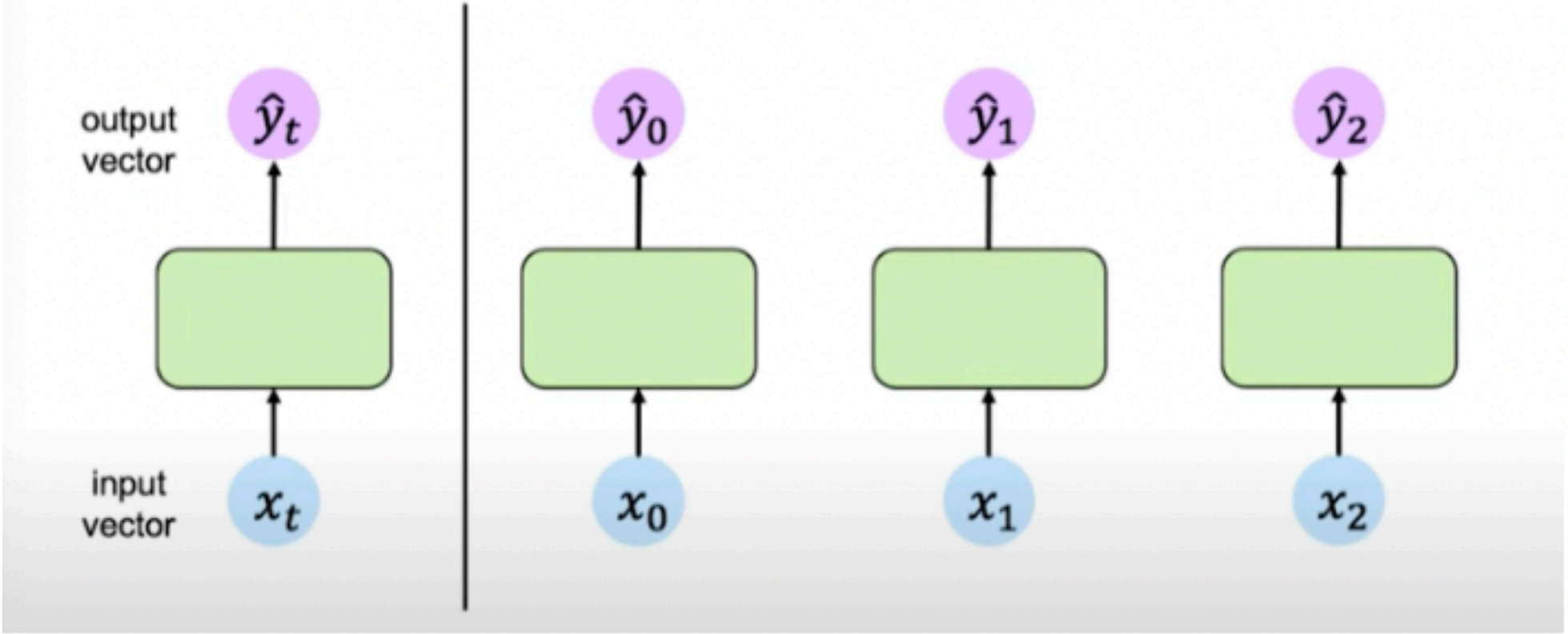
OUR WISH LIST:

1. Handle variable-length sequences
2. Track long term dependencies
3. Maintain information about order
4. Share parameters across the sequence

Recurrent Neural Networks
offer a first solution to this problem



Handling Individual Time Steps



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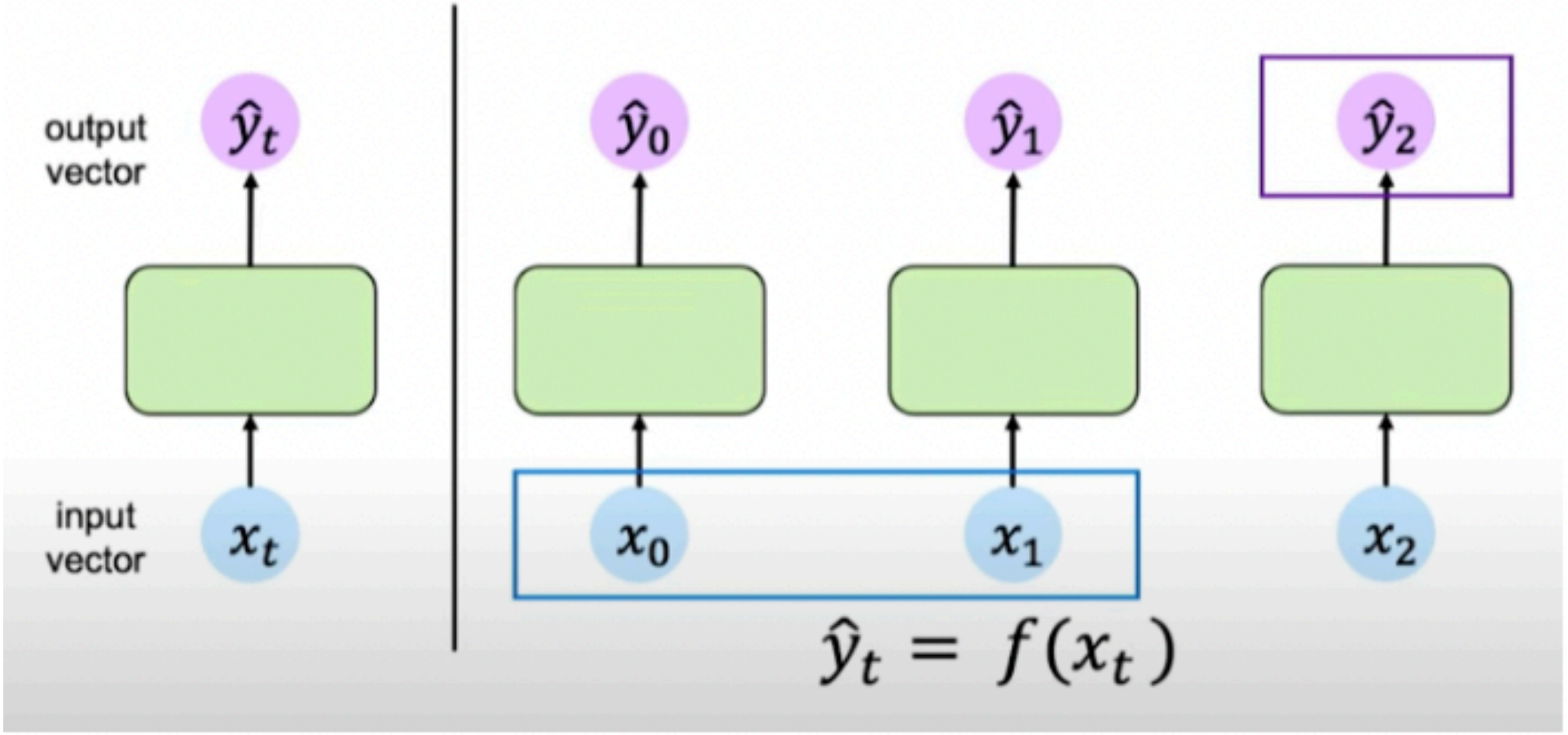
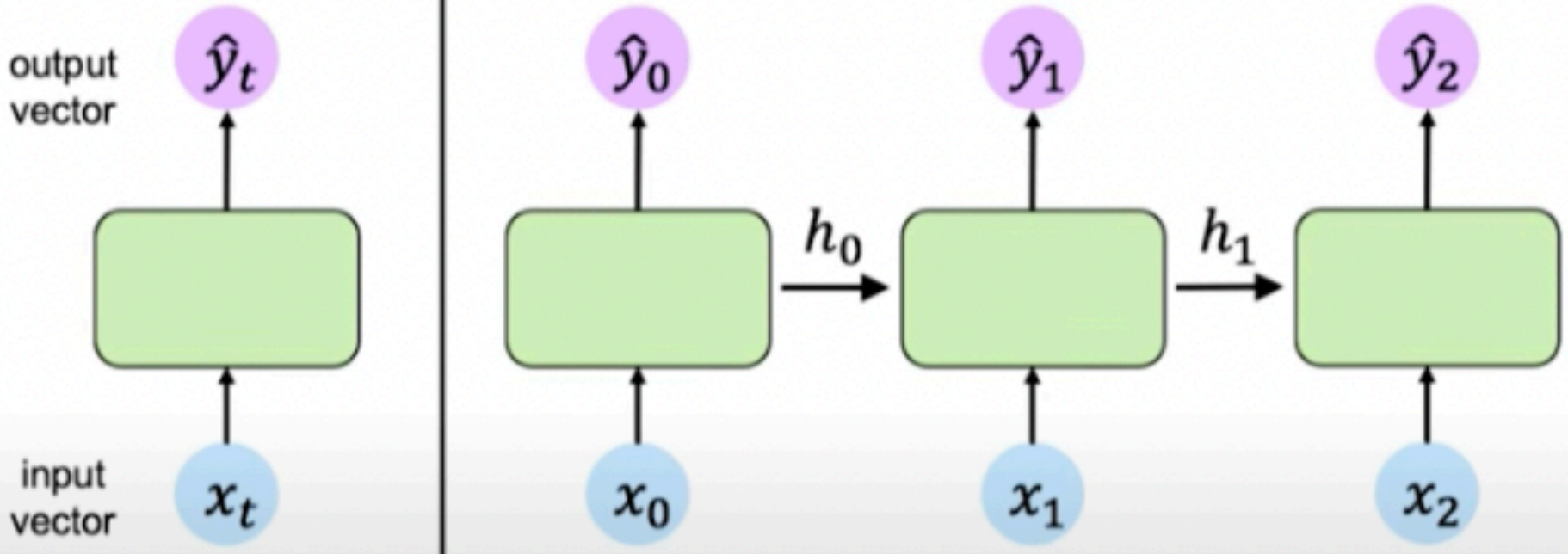
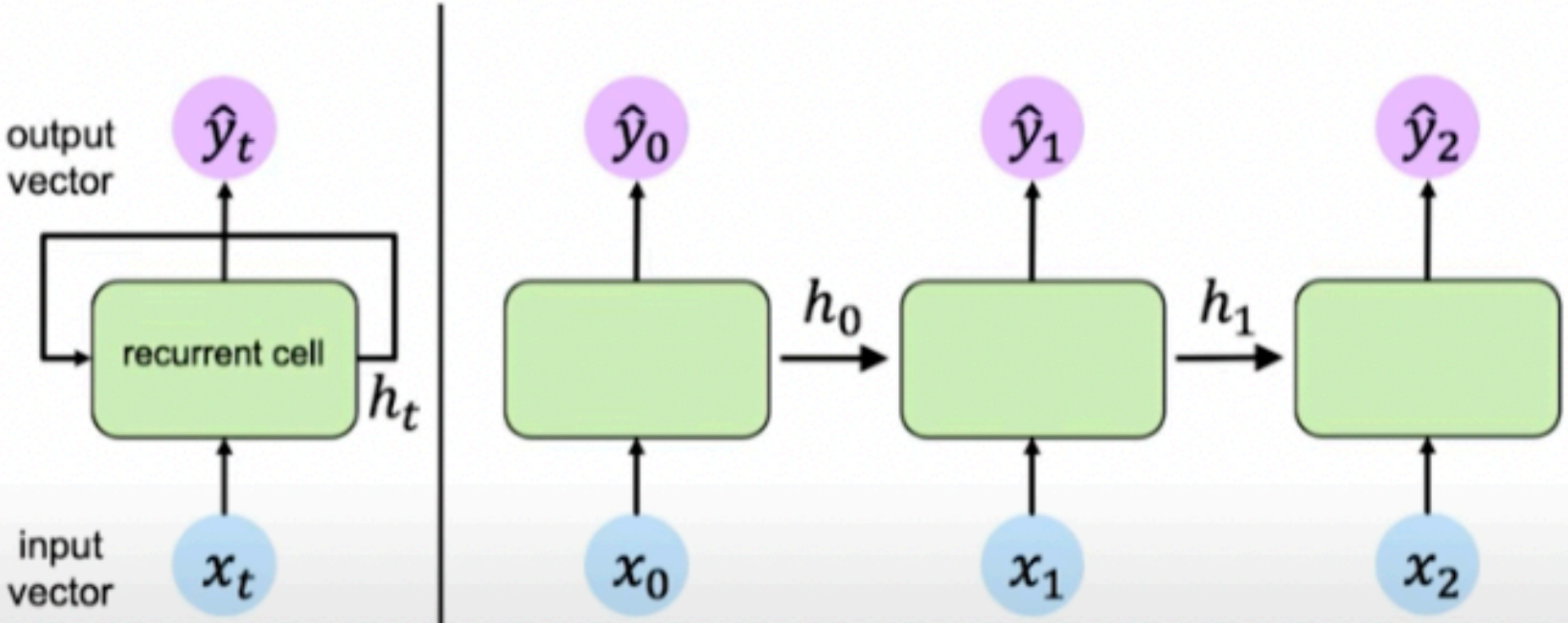


Neurons with Recurrence



$$\hat{y}_t = f(x_t, h_{t-1})$$

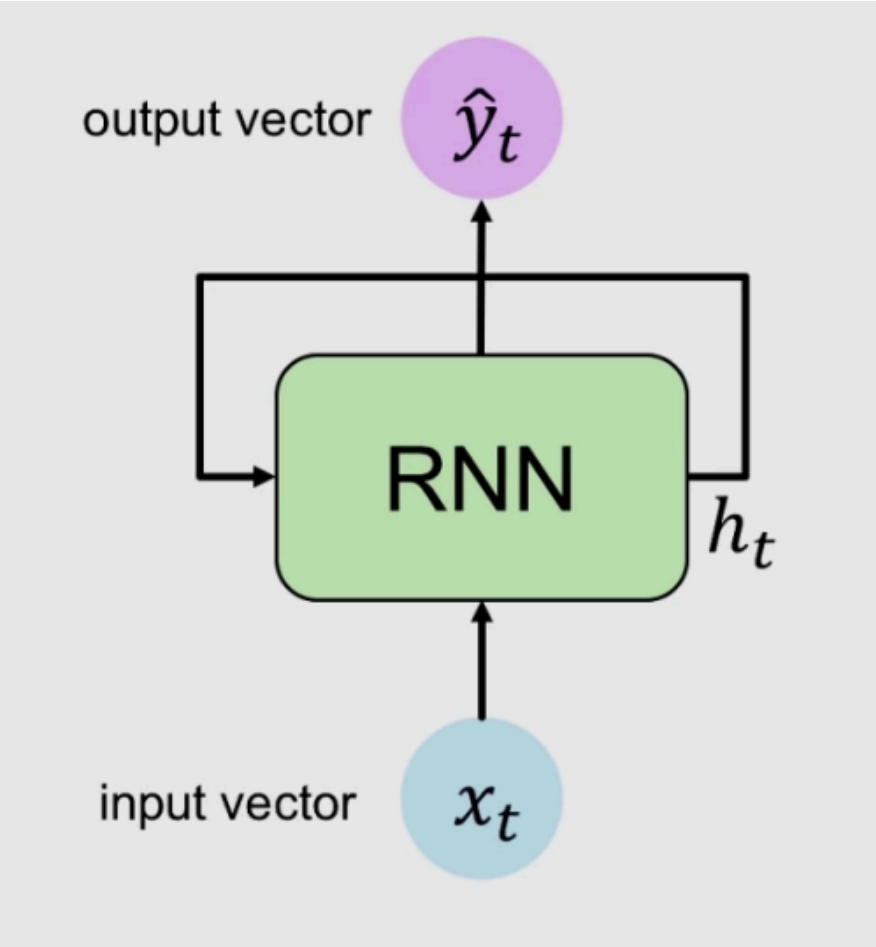
Neurons with Recurrence



$$\underline{\hat{y}_t} = f(\underline{x_t}, \underline{h_{t-1}})$$

output input past memory

The RNN Block



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

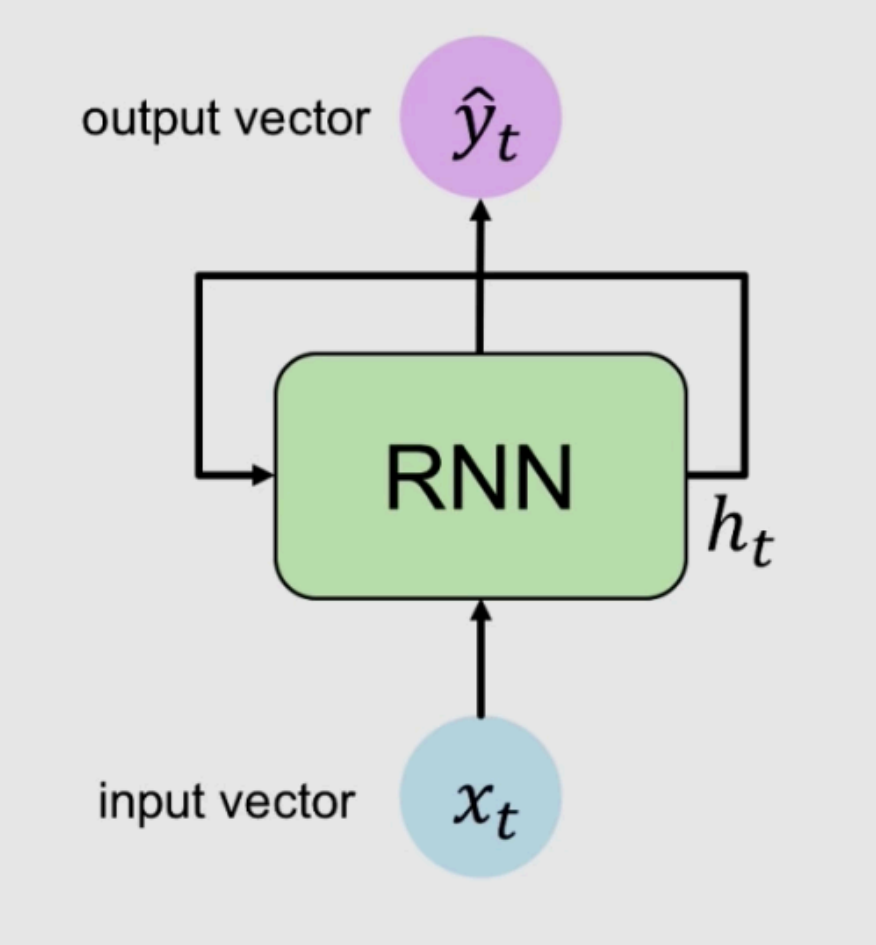
cell state

function parameterized by W

old state

input vector at time step *t*

The RNN Block



Output Vector

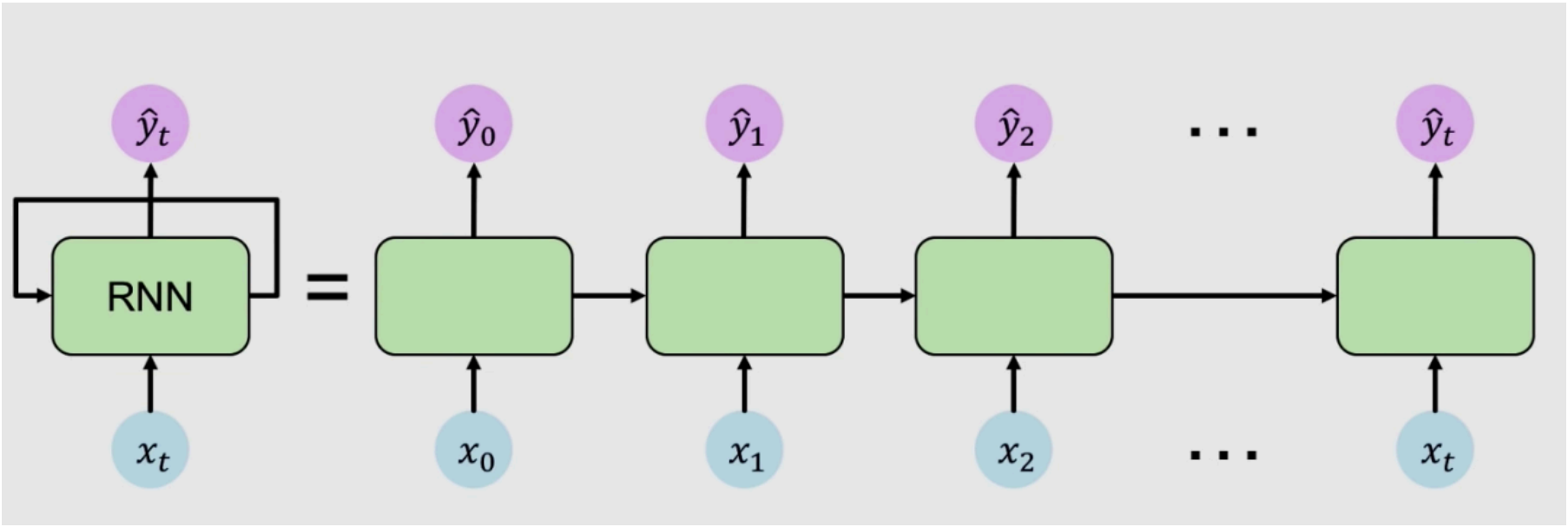
$$\hat{y}_t = \boldsymbol{W}_{\boldsymbol{hy}}^{\boldsymbol{T}} h_t$$

Update Hidden State

$$h_t = \tanh(\boldsymbol{W}_{\boldsymbol{hh}}^{\boldsymbol{T}} h_{t-1} + \boldsymbol{W}_{\boldsymbol{xh}}^{\boldsymbol{T}} x_t)$$

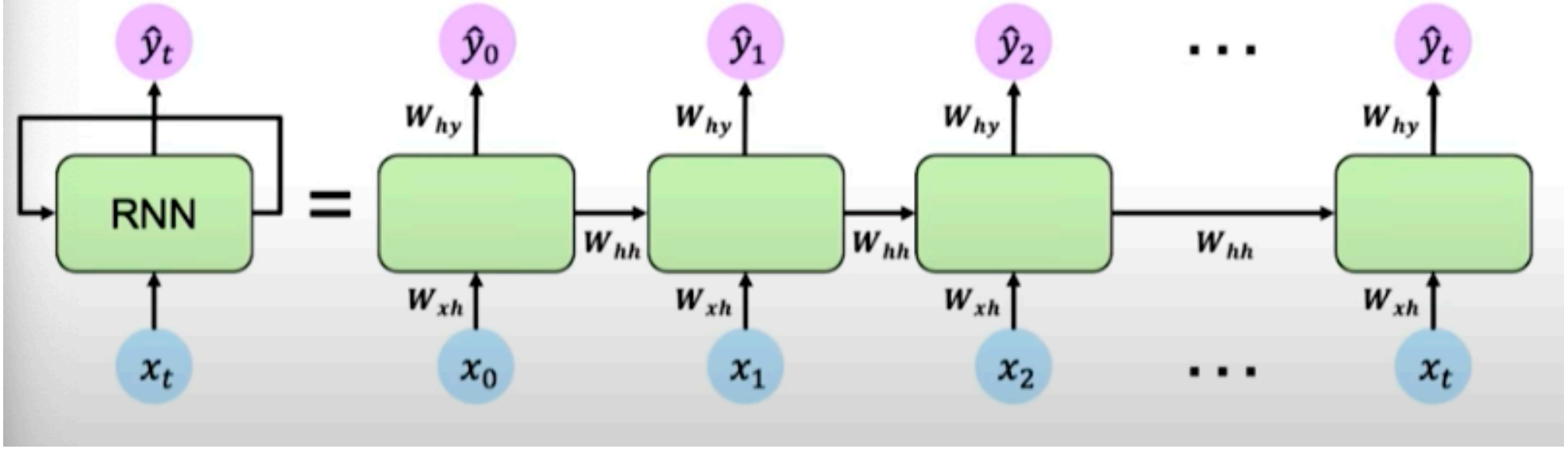
Input Vector

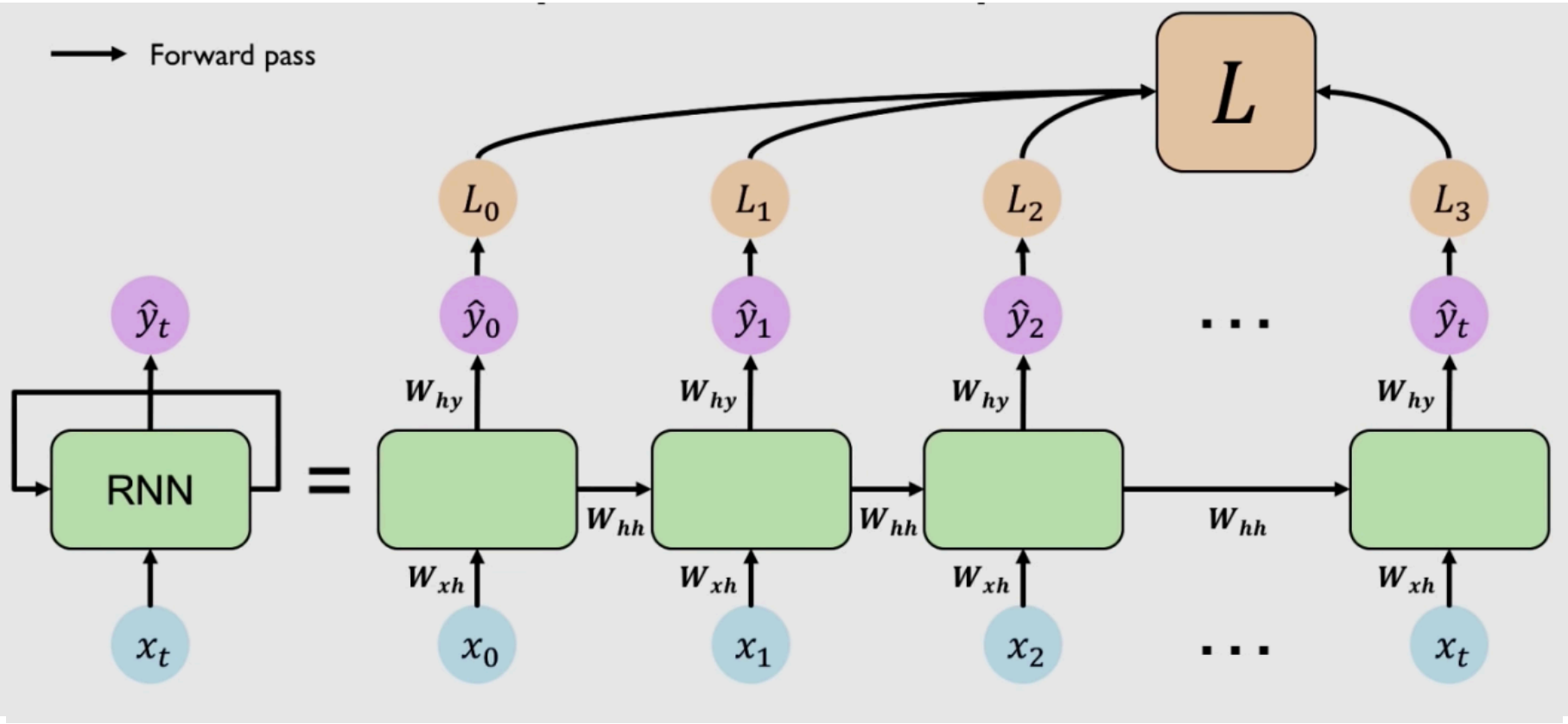
$$x_t$$


$\hat{y}_t$
RNN
x_t
=
$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
...
$\hat{y}_t$
x_0
x_1
x_2
...
x_t

RNNs: Computational Graph Across Time

Re-use the **same weight matrices** at every time step




Forward pass
L
L_0
L_1
L_2
L_3
$\hat{y}_t$
$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_t$
RNN
=
W_{hy}
W_{hh}
W_{xh}
x_t
x_0
x_1
x_2
x_t

A Sequence Modeling Problem: Predict the Next Word

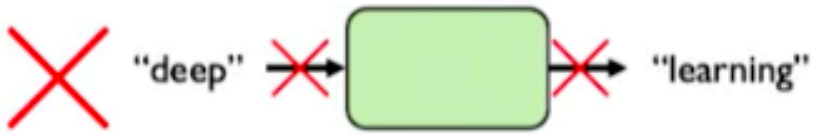
"This morning I took my cat for a walk."

given these words

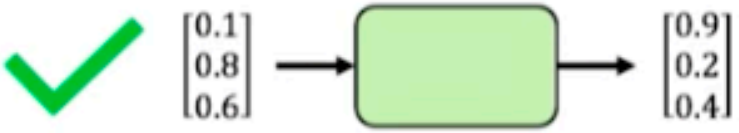
predict the next word

Representing Language to a Neural Network

Encoding Language for a Neural Network

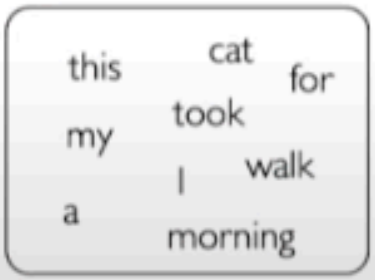


Neural networks cannot interpret words

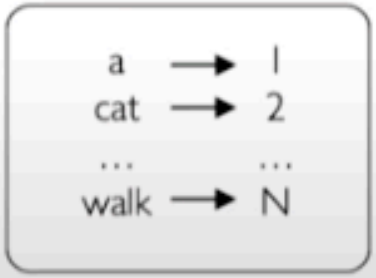


Neural networks require numerical inputs

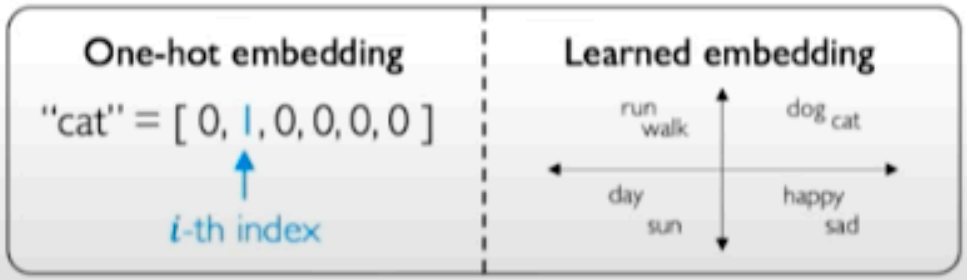
Embedding: transform indexes into a vector of fixed size.



1. Vocabulary:
Corpus of words

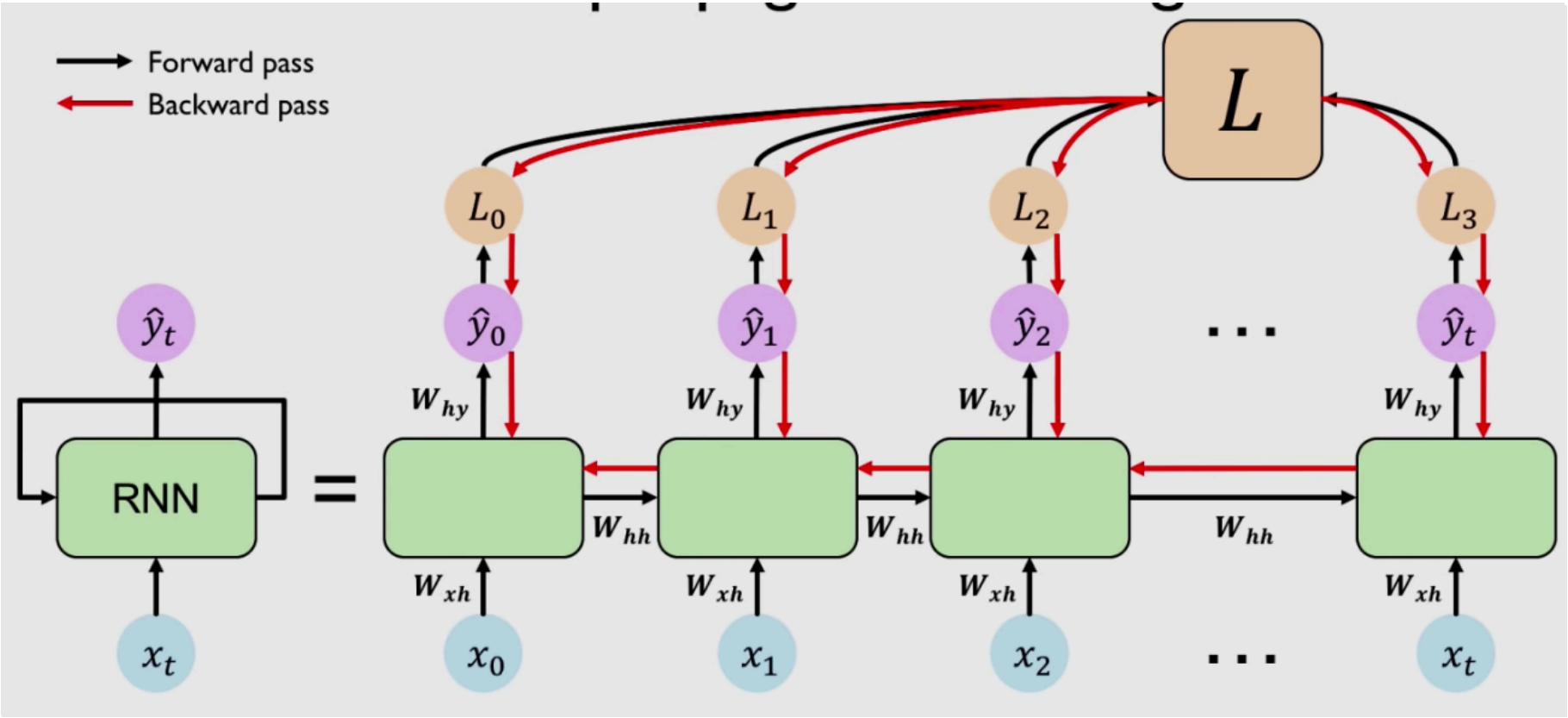


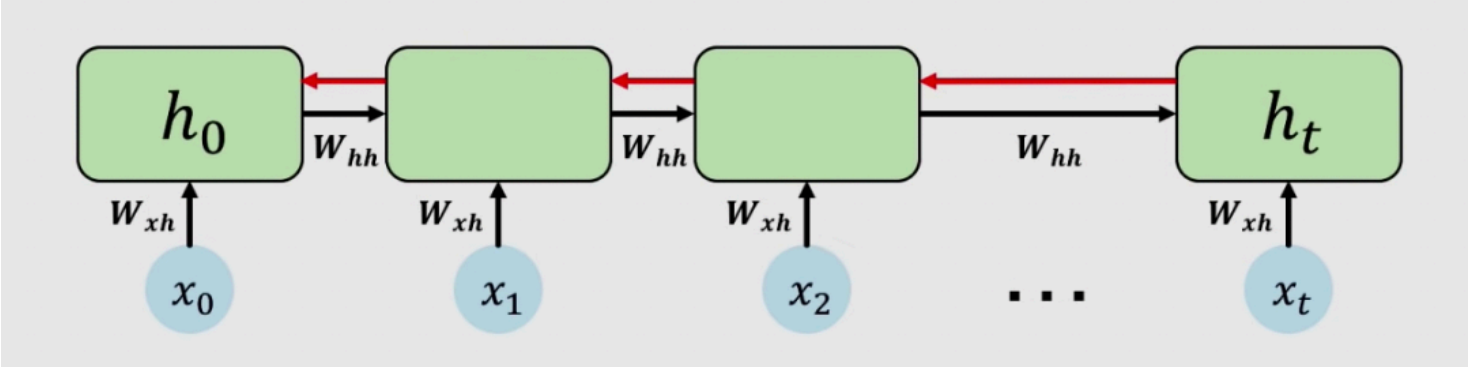
2. Indexing:
Word to index



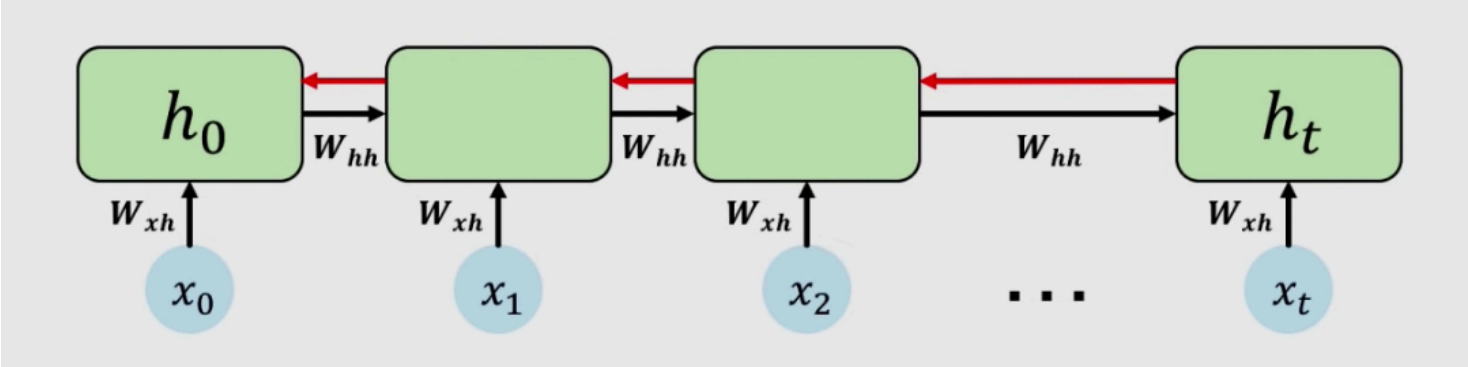
3. Embedding:
Index to fixed-sized vector

BACKPROPAGATION THROUGH TIME (BPTT)





BPTT implies a large amount of weight multiplications: if we want to take into account long term memory, networks become quickly very deep and so are subjected to vanishing and exploding gradients problems (see previous lecture)

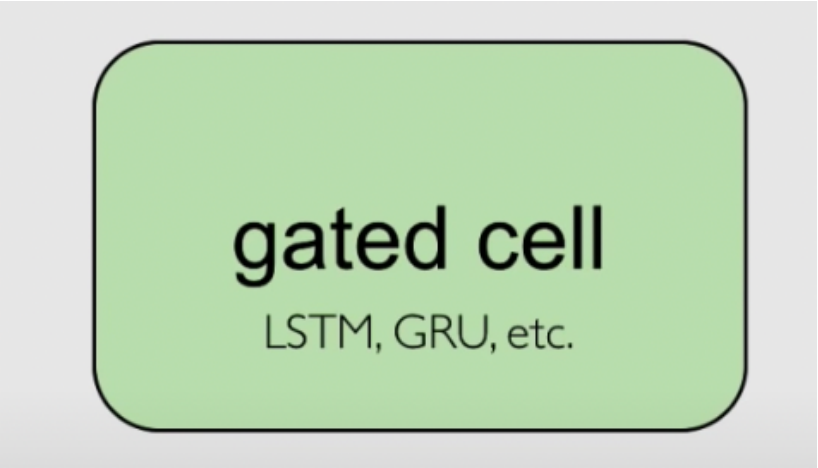


BPTT implies a large amount of weight multiplications: if we want to take into account long term memory, networks become quickly very deep and so are subjected to vanishing and exploding gradients problems (see previous lecture)

ONE CAN USE THE SAME TRICKS THAT WE DISCUSSED FOR DEEP CNNs (WEIGTH INITIALISATION, RELU ACTIVATION FUNCTION …)

ANOTHER SPECIFIC SOLUTION: GATED CELLS

Use a more complex recurrent unit with gates to control what information is passed through…



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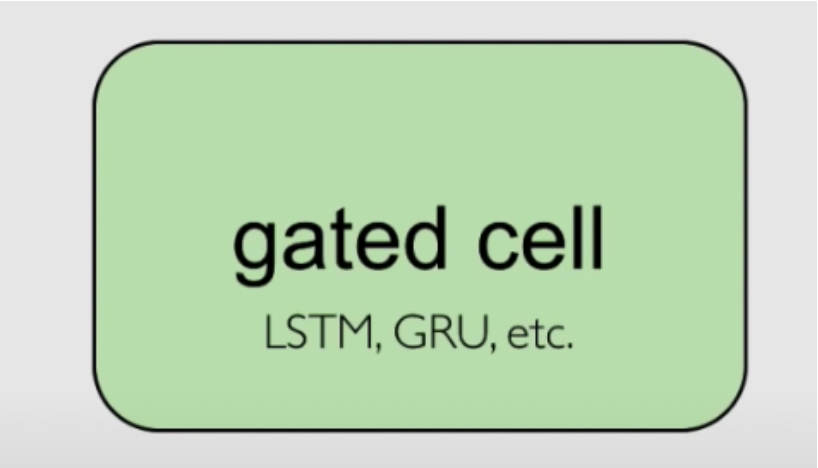
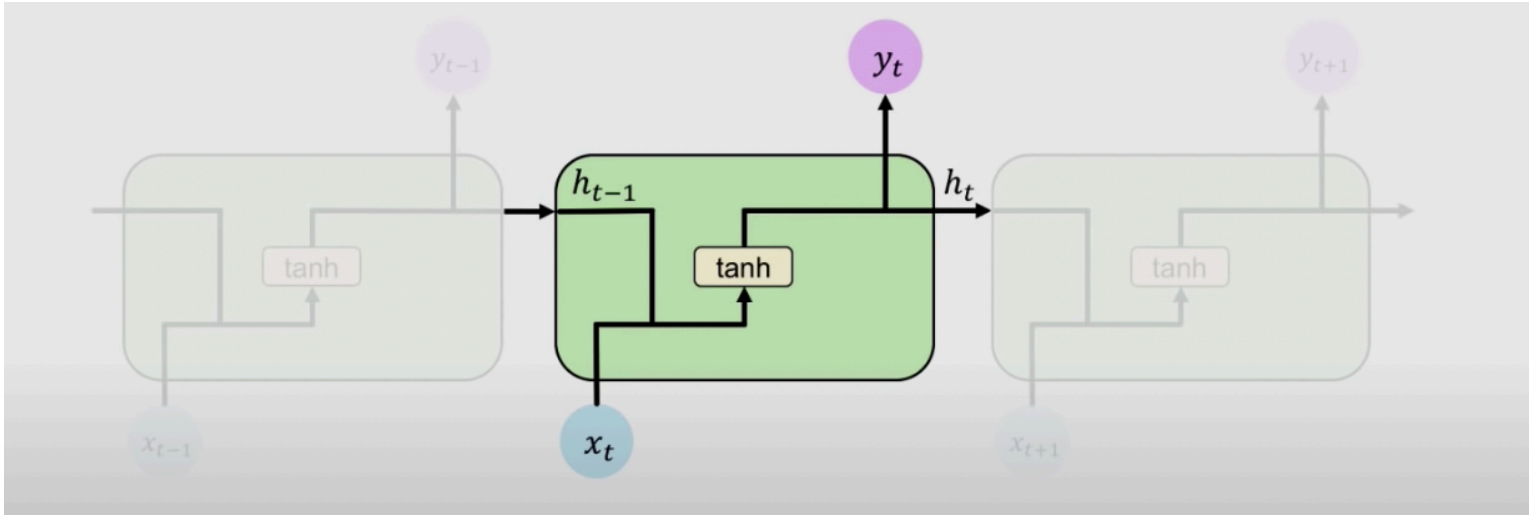
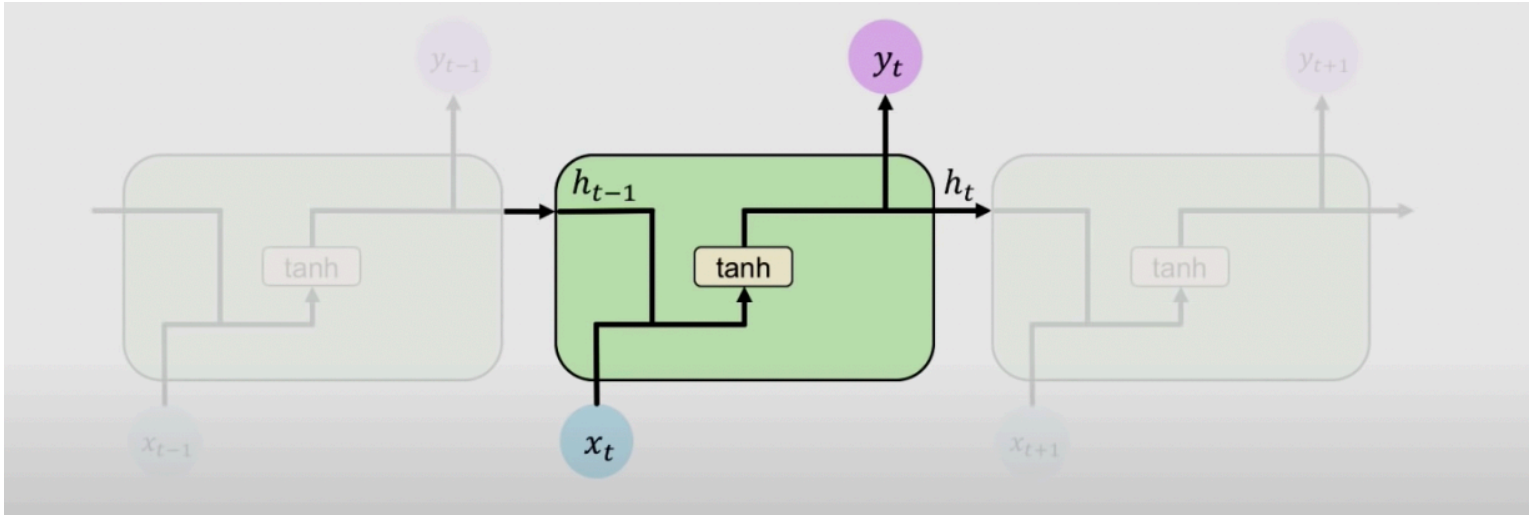


Long Short Term Memory (LSTMs) networks are an example of this

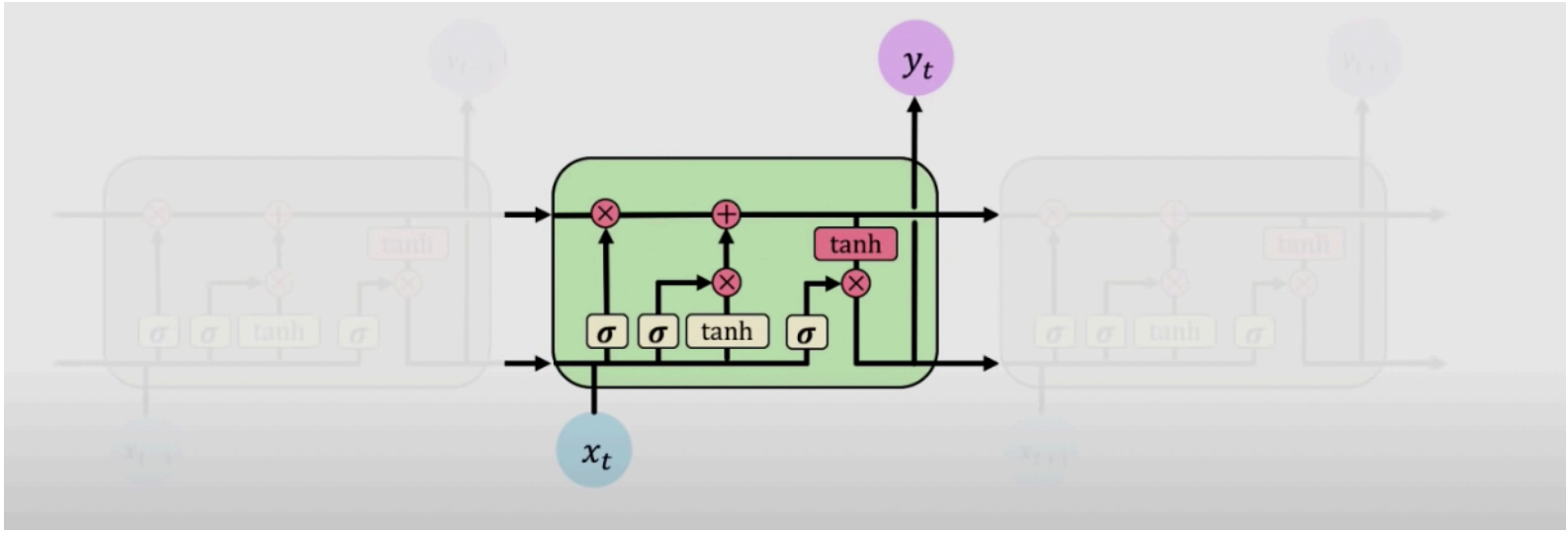
Standard RNN



Standard RNN



LSTM unit



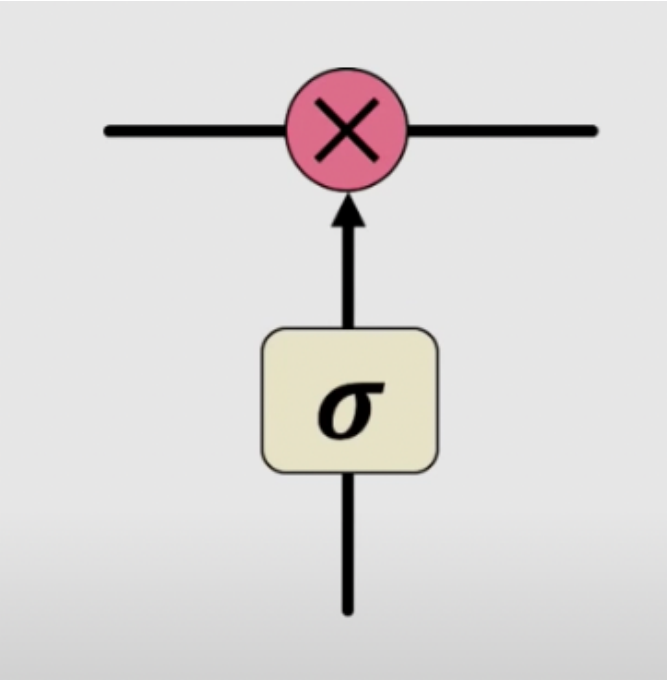
Each memory cell is equipped with an *internal state* and a number of multiplicative gates that determine whether

(i) a given input should impact the internal state (the *input gate*),

(ii) the internal state should be flushed to (the *forget gate*), and

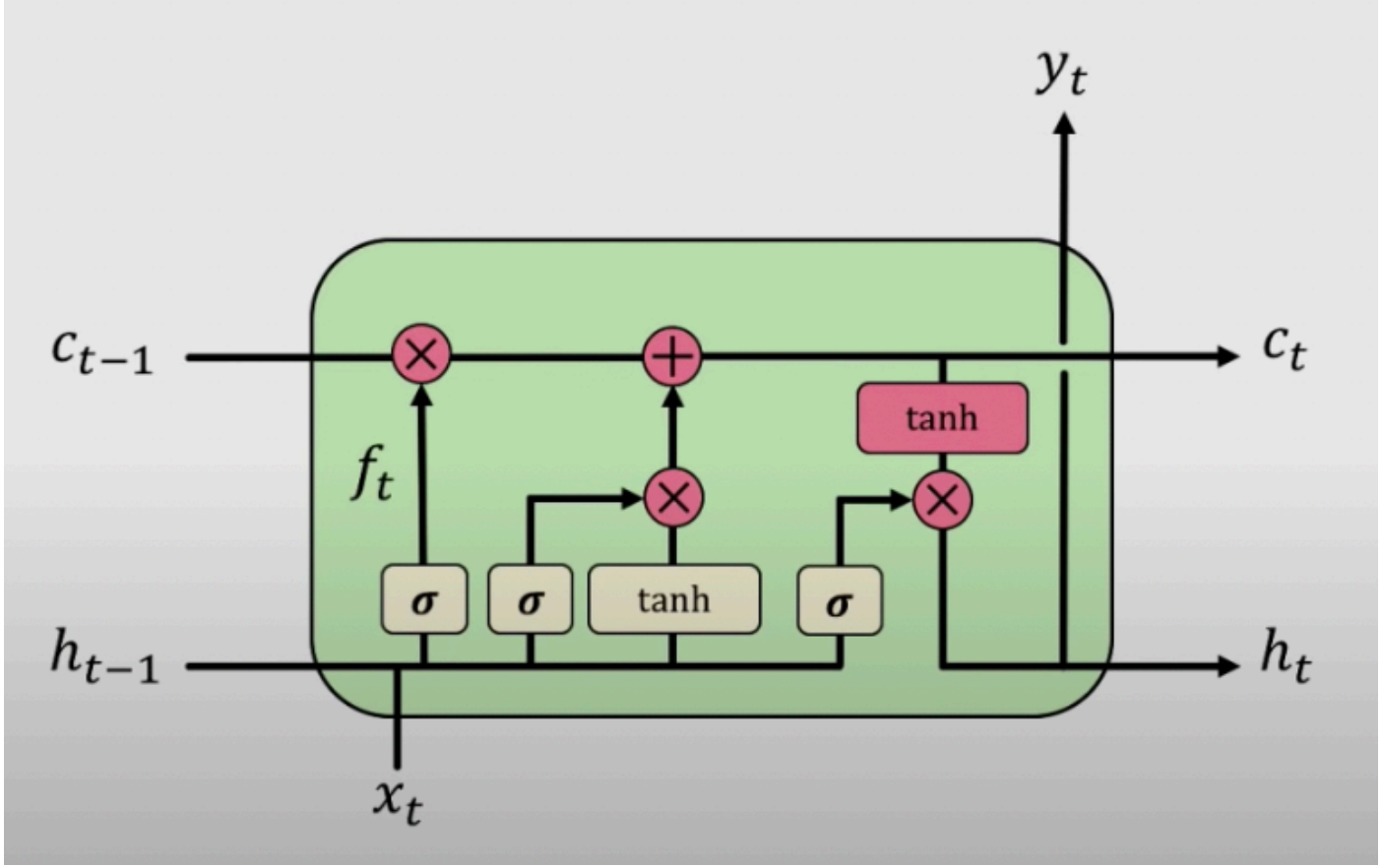
(iii) the internal state of a given neuron should be allowed to impact the cell's output (the *output* gate).

The key building block are the so-called gates



INFORMATION IS PASSED OR NOT WITH A COMBINATION OF A SIGMOID NN AND A POINTWISE MULTIPLICATION

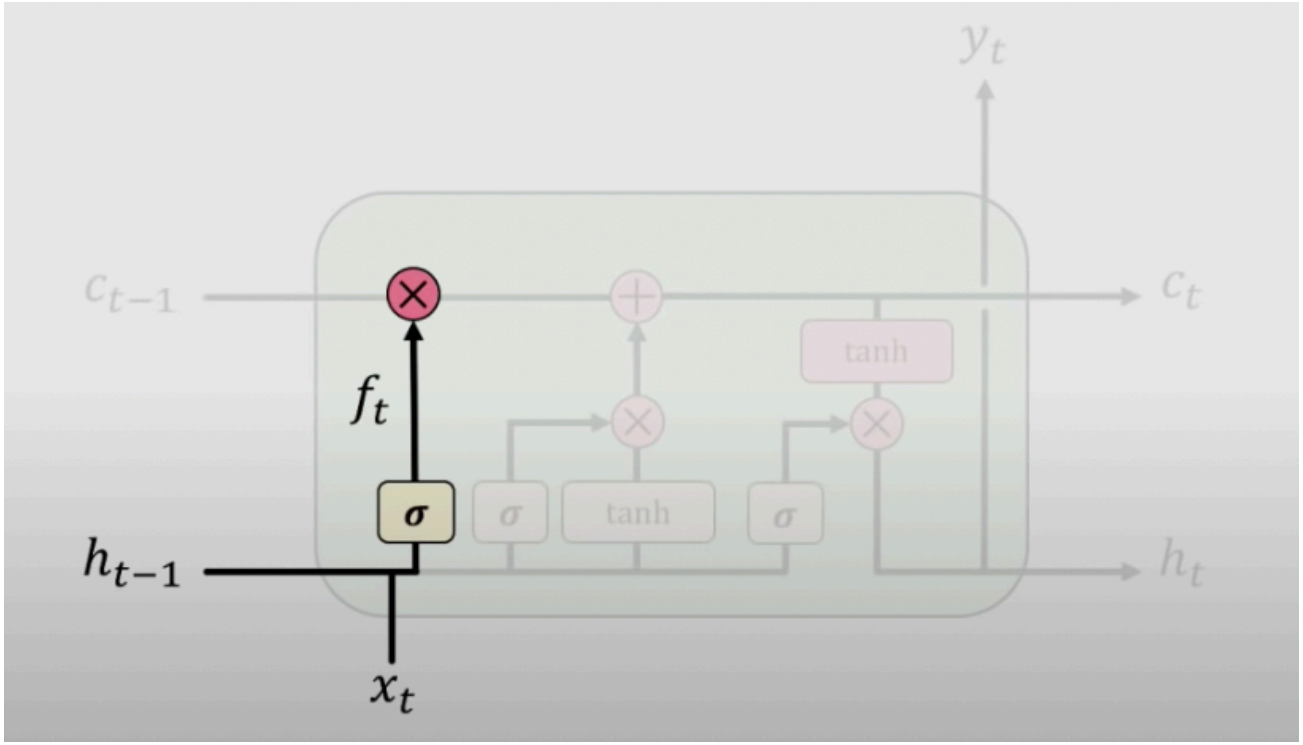
Long Short Term Memory (LSTMs)



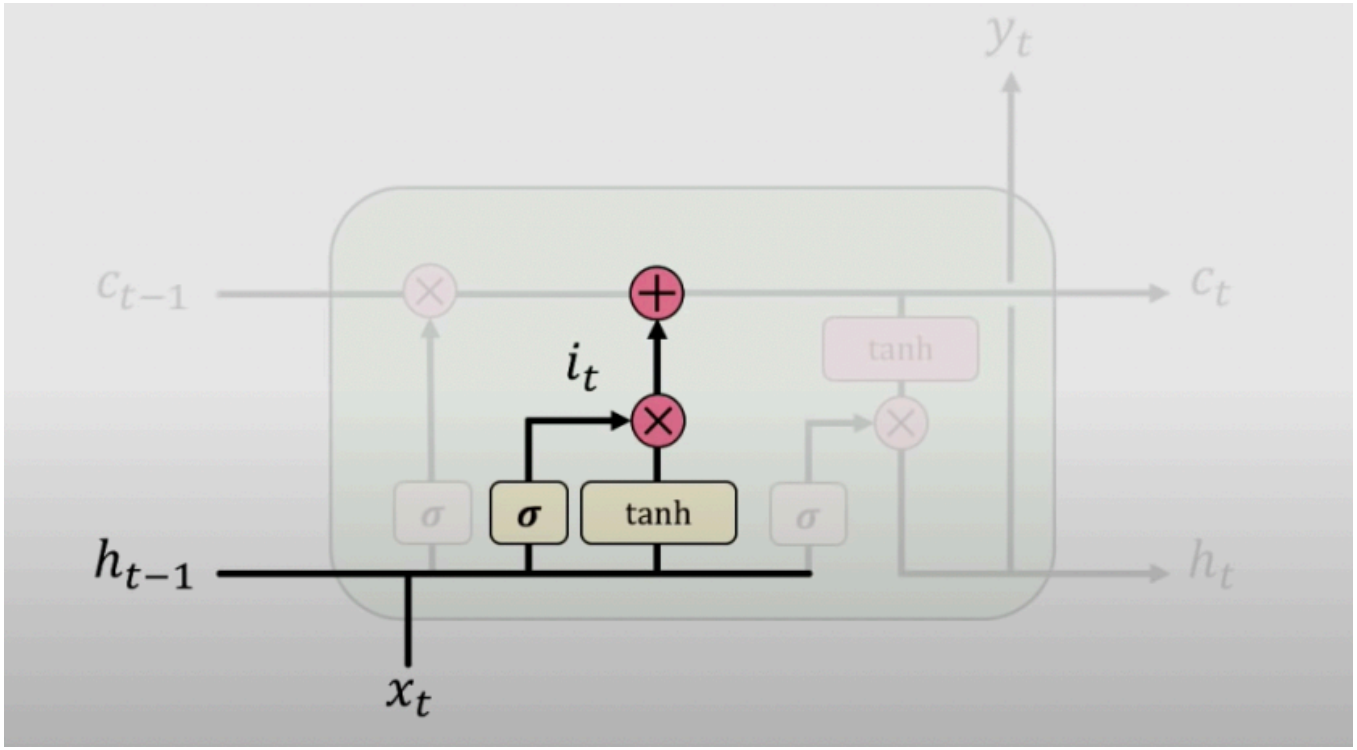
4 main steps:

1-Forget 2-Store 3-Update 4-Output

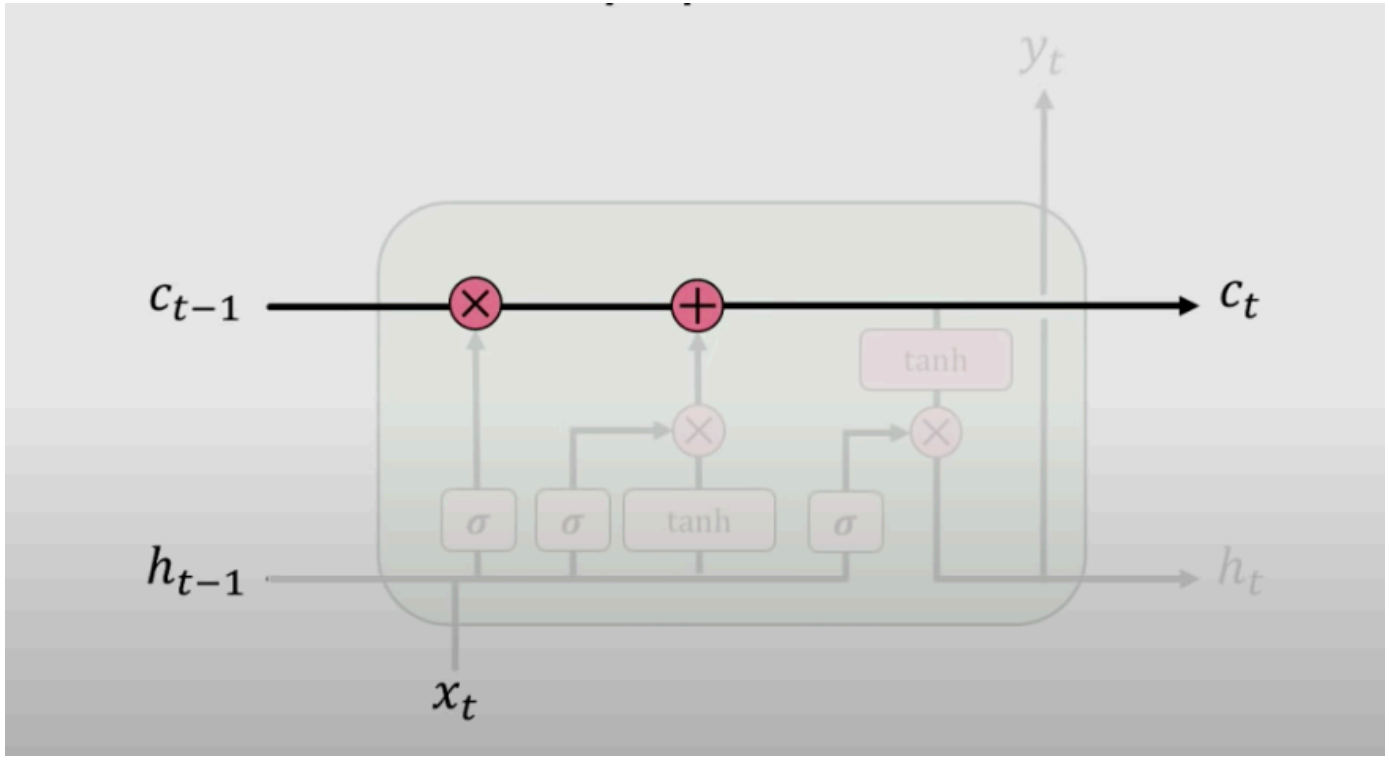
STEP 1: FORGET



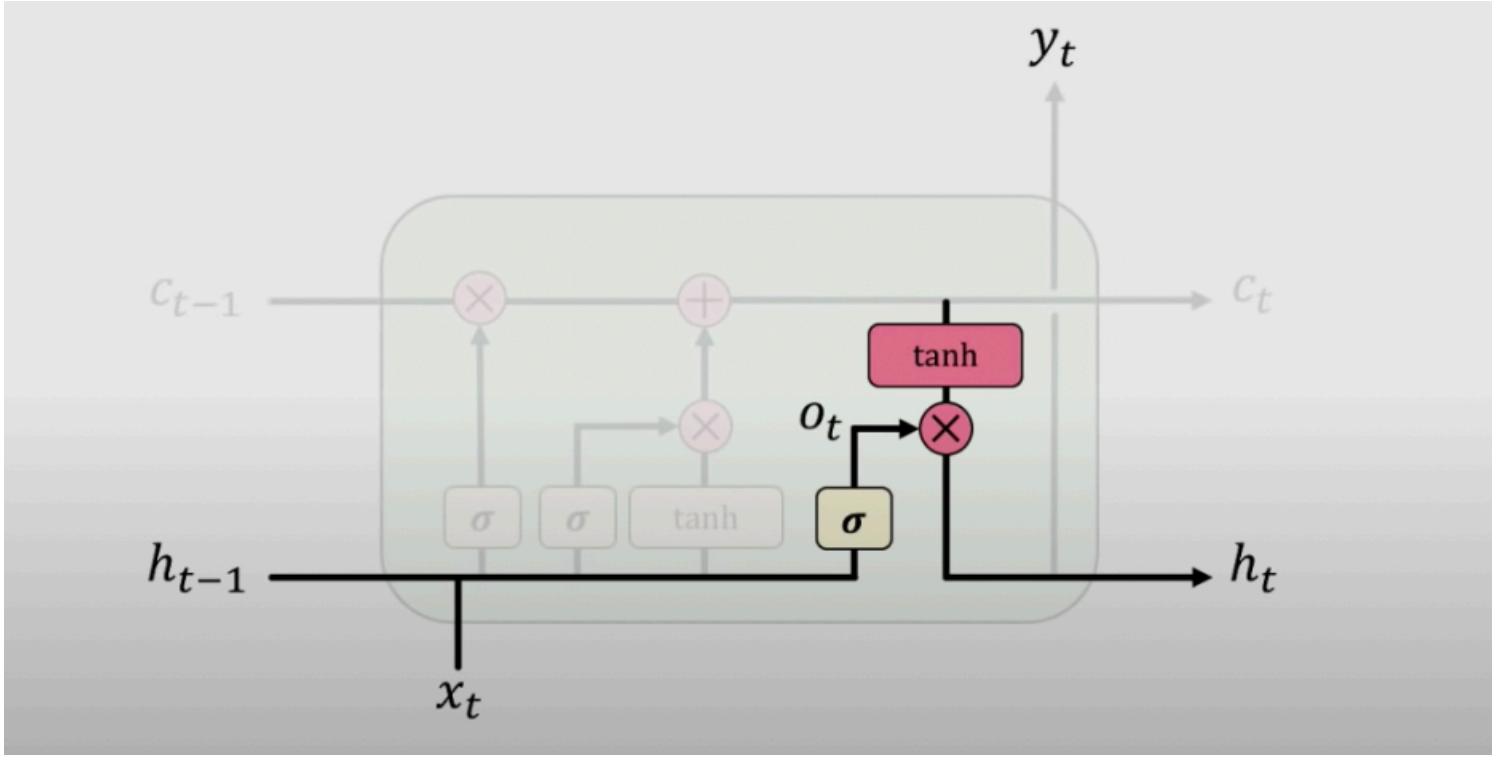
STEP 2: STORE



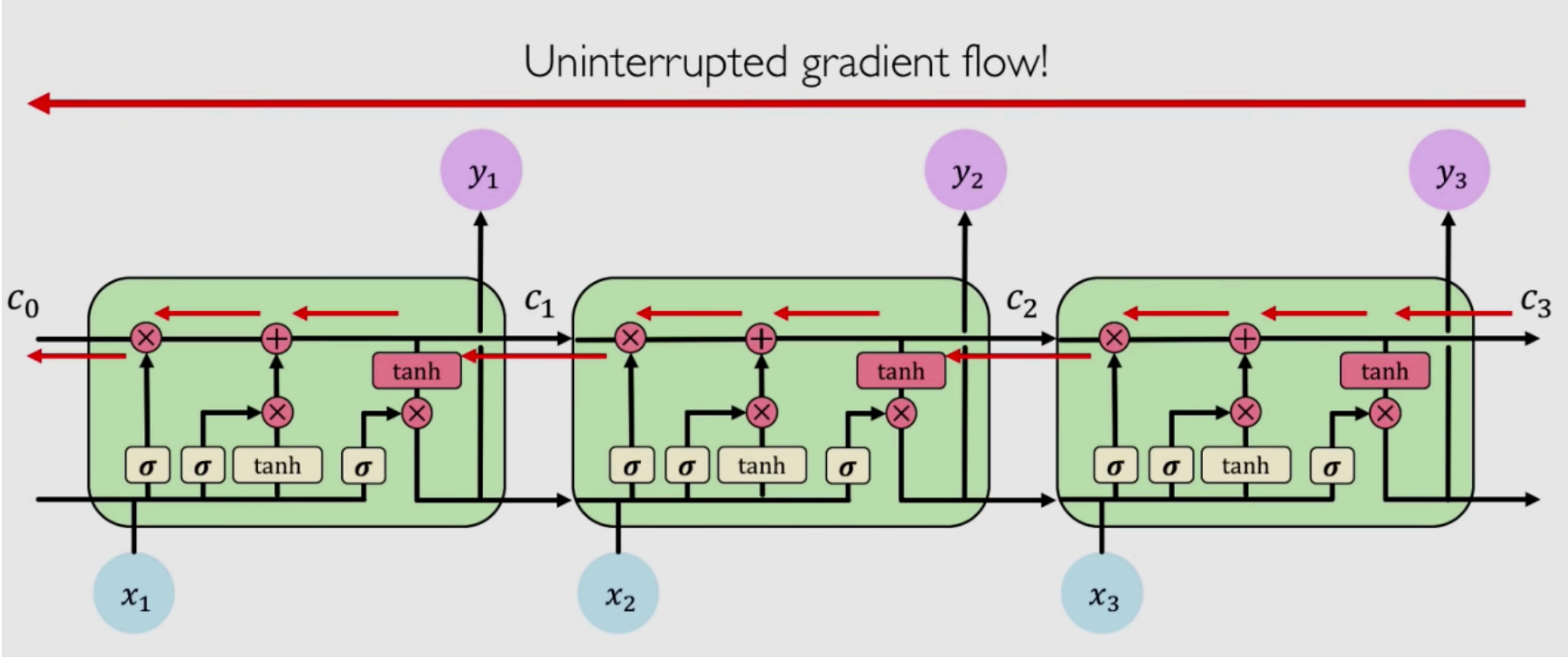
STEP 3: UPDATE



STEP 4: OUTPUT



LSTMs help mitigating the vanishing gradient problem



LSTMs KEY CONCEPTS

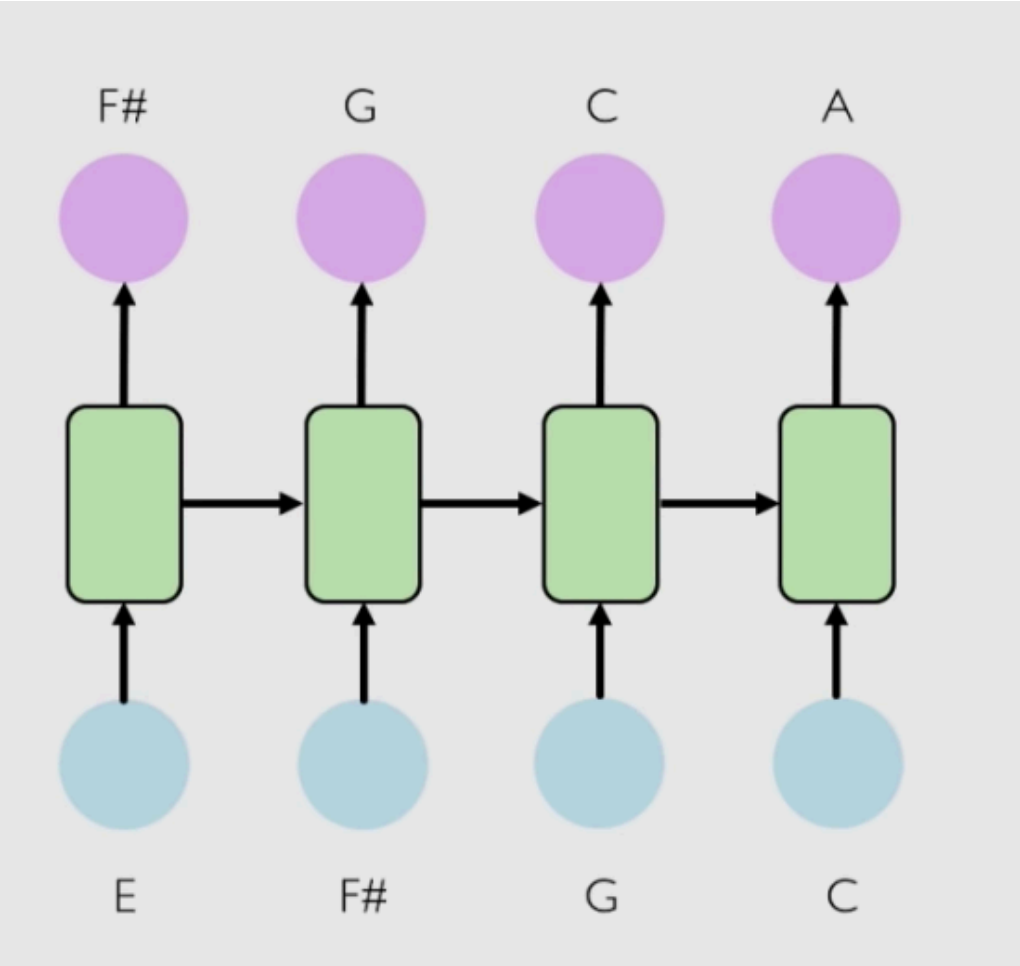
1. Maintain a separate cell state from what is outputted

2. Use gates to control the flow of information

- Forget gates get rid of irrelevant information
- Store relevant information from current input
- Selectively update cell state
- Output gate returns a filtered version of the cell state

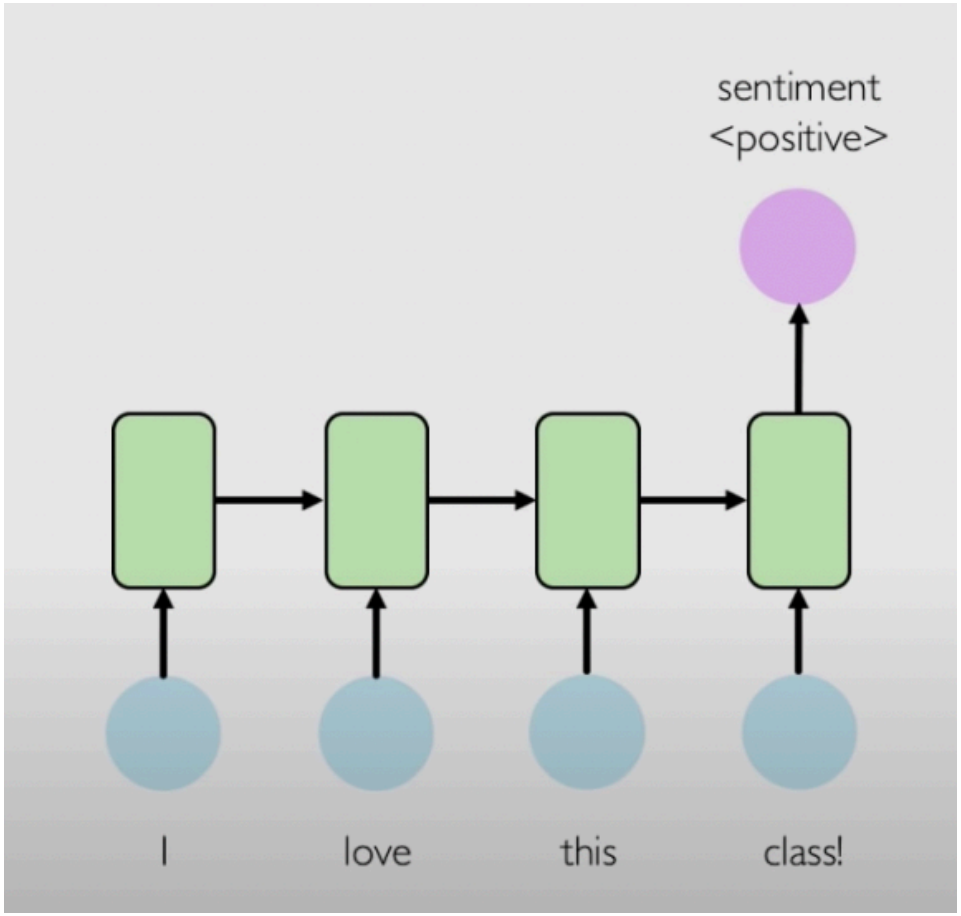
3. Backpropagation through time with uninterrupted gradient flow

SOME APPLICATIONS (OUTSIDE ASTRONOMY)



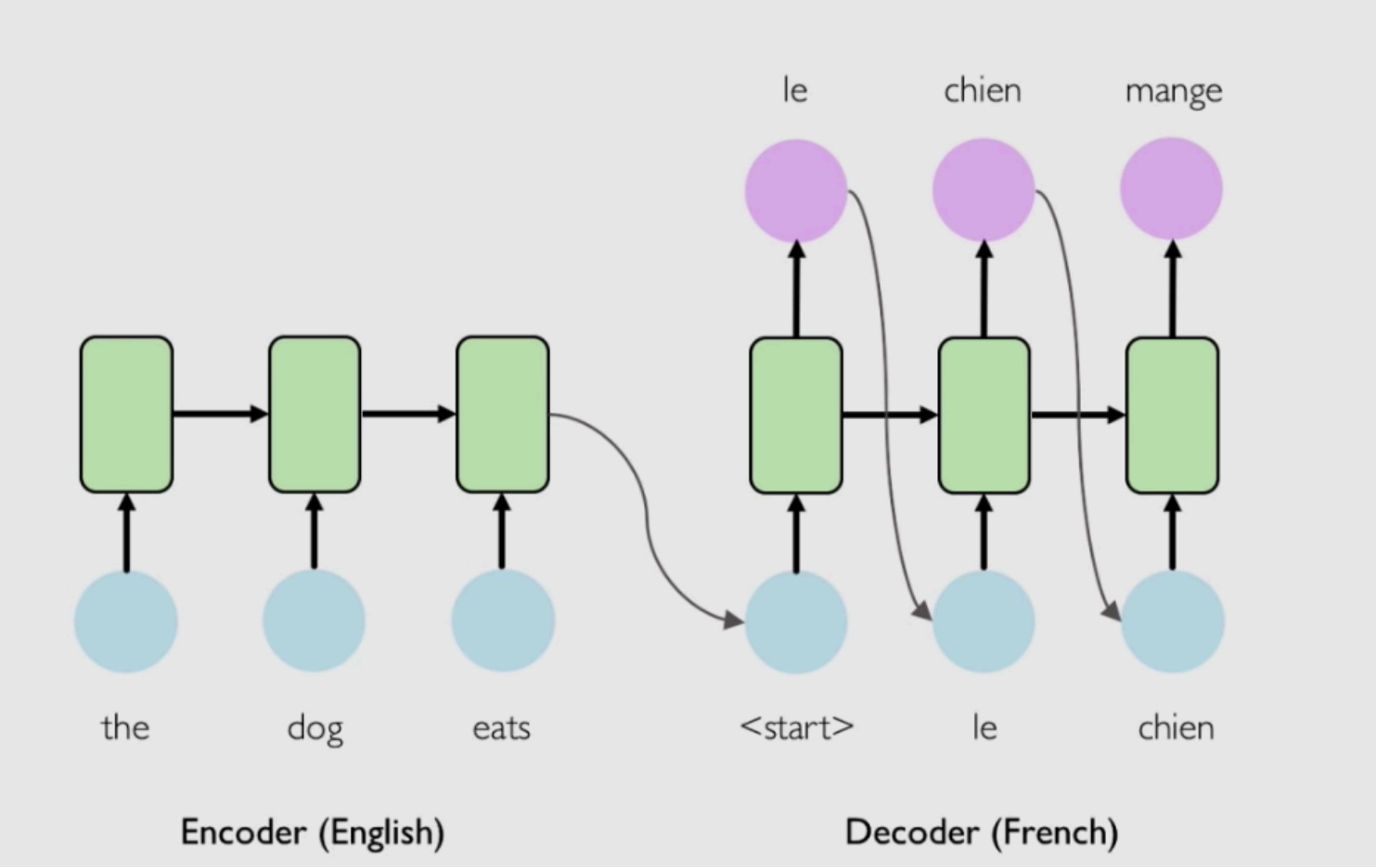
Automatic music generation

SOME APPLICATIONS (OUTSIDE ASTRONOMY)



SENTIMENT CLASSIFICATION

MACHINE TRANSLATION



Intuition Behind Self-Attention

Attending to the most important parts of an input.

Intuition Behind Self-Attention

Attending to the most important parts of an input.

1. Identify which parts to attend to
2. Extract the features with high attention

Intuition Behind Self-Attention

Attending to the most important parts of an input.

1. Identify which parts to attend to
2. Extract the features with high attention

Similar to a search problem!

Understanding Attention with Search

Query (Q)

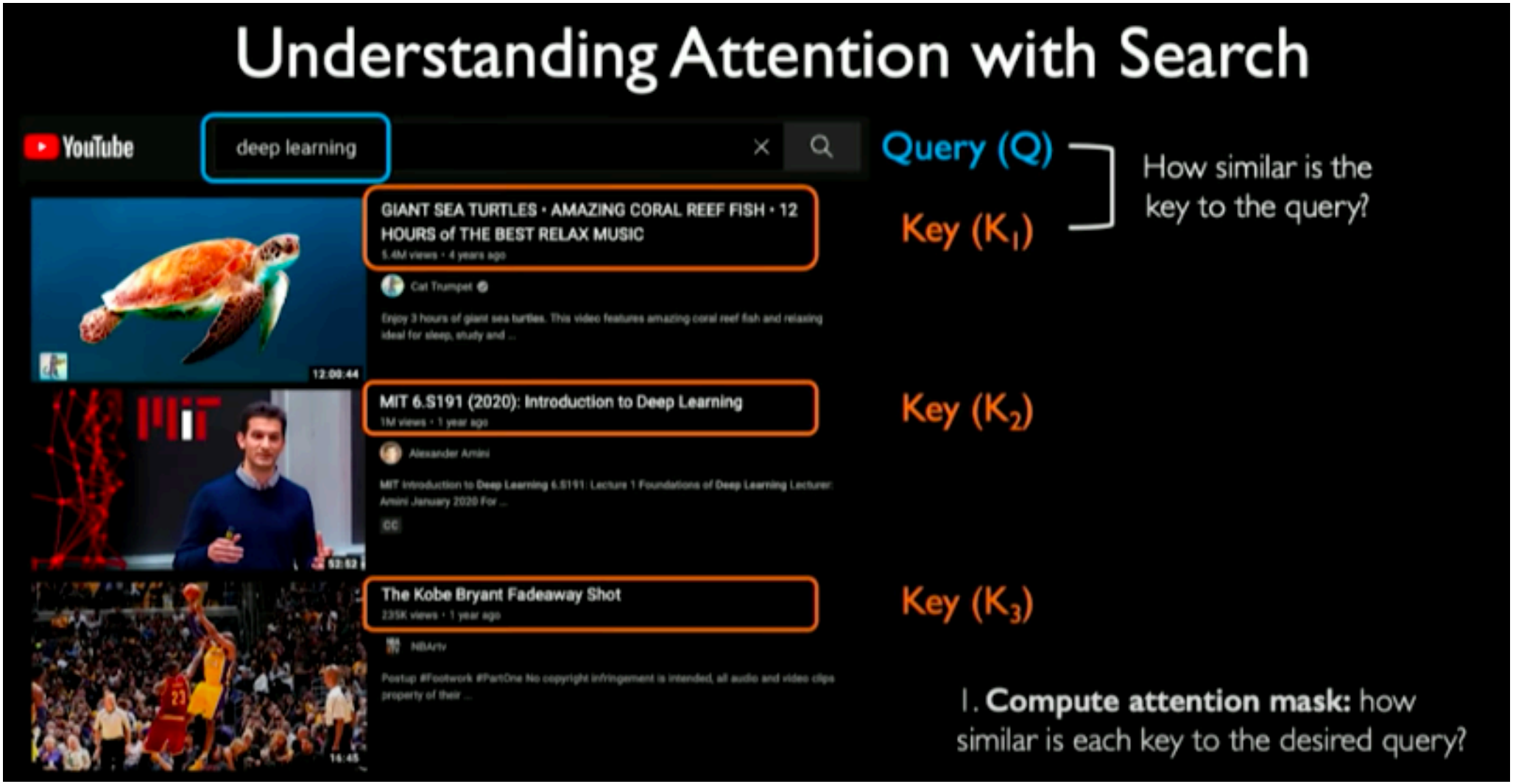
Key (K_1)

Key (K_2)

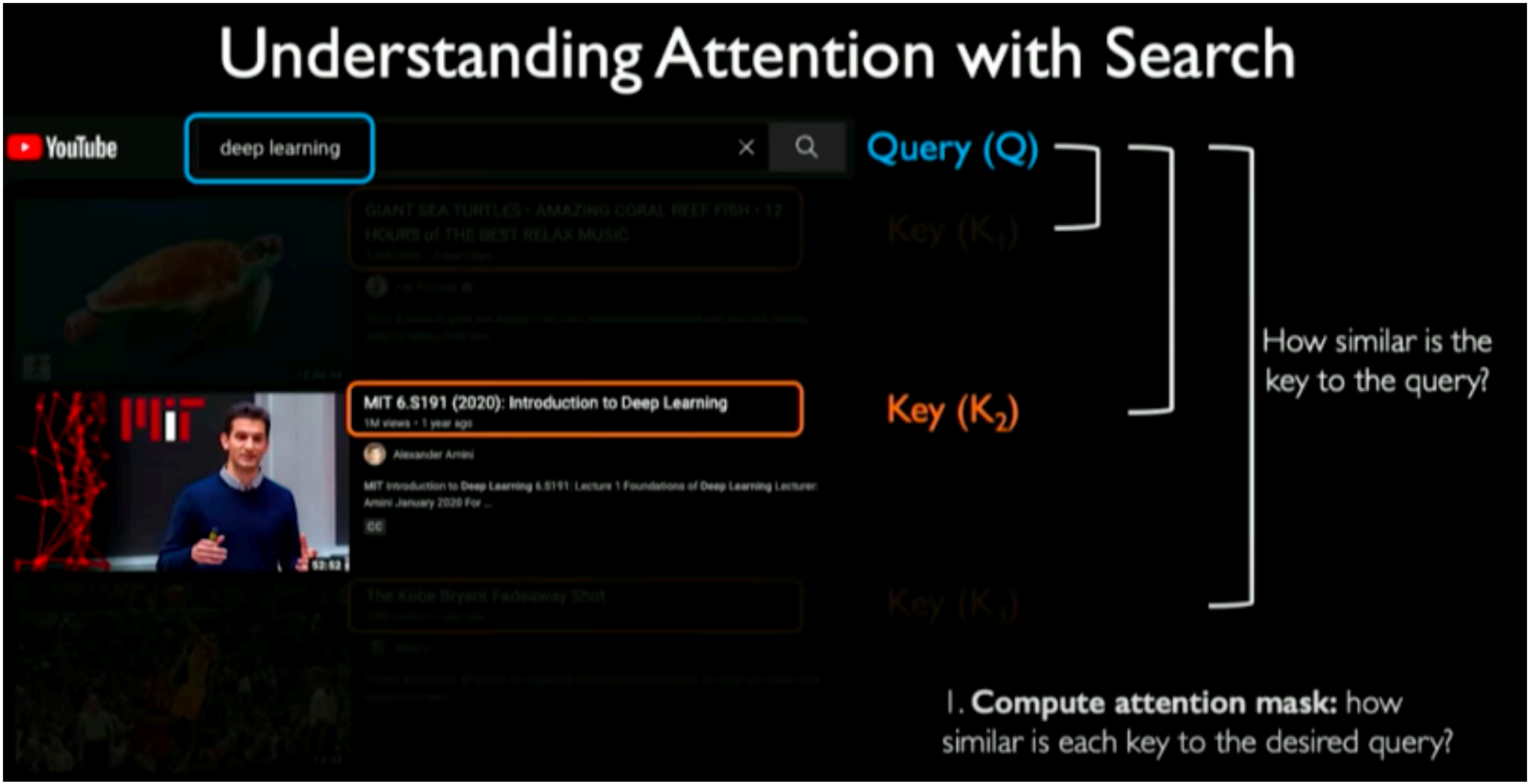
Key (K_3)

1. **Compute attention mask:** how similar is each key to the desired query?

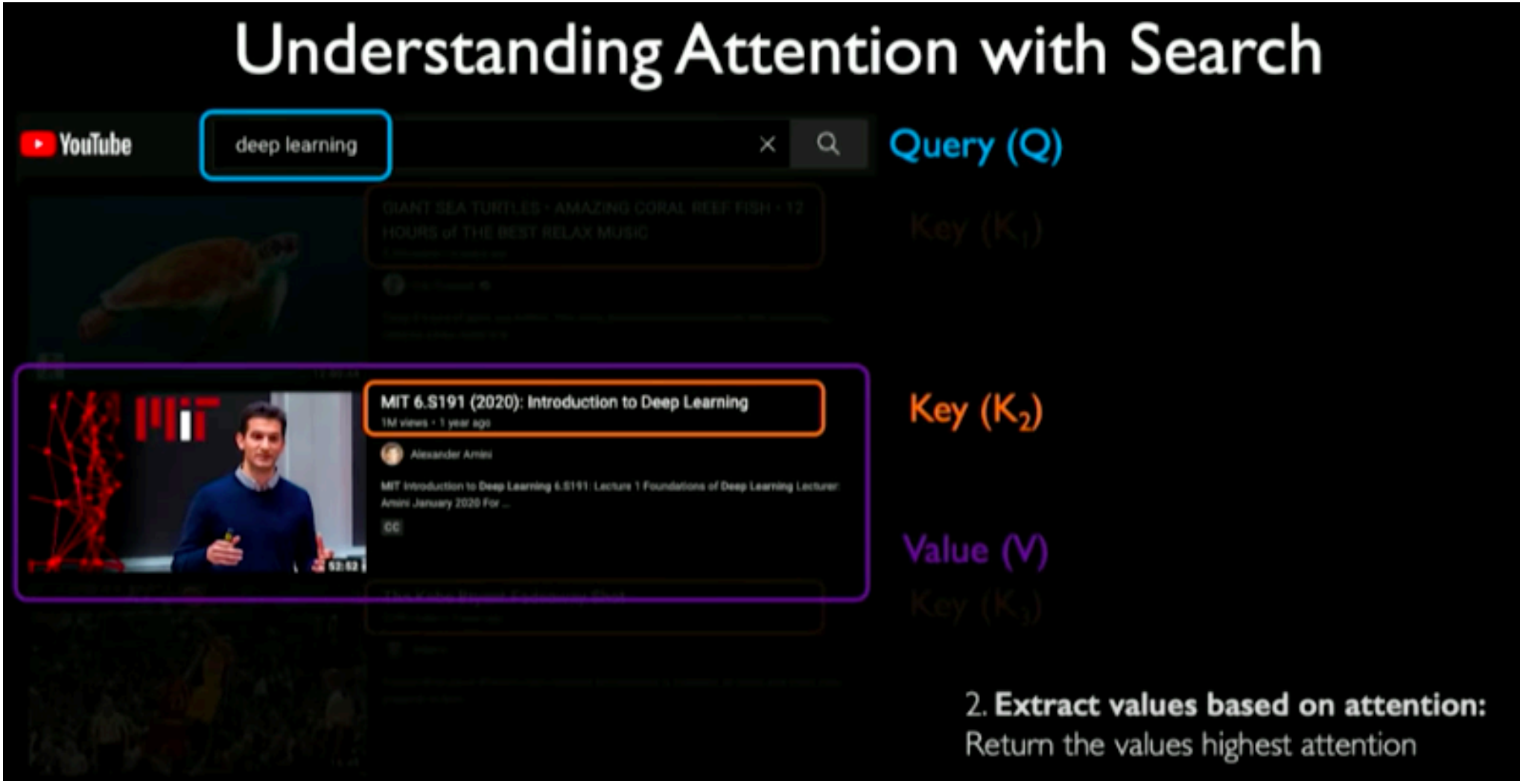
Understanding Attention with Search



Understanding Attention with Search



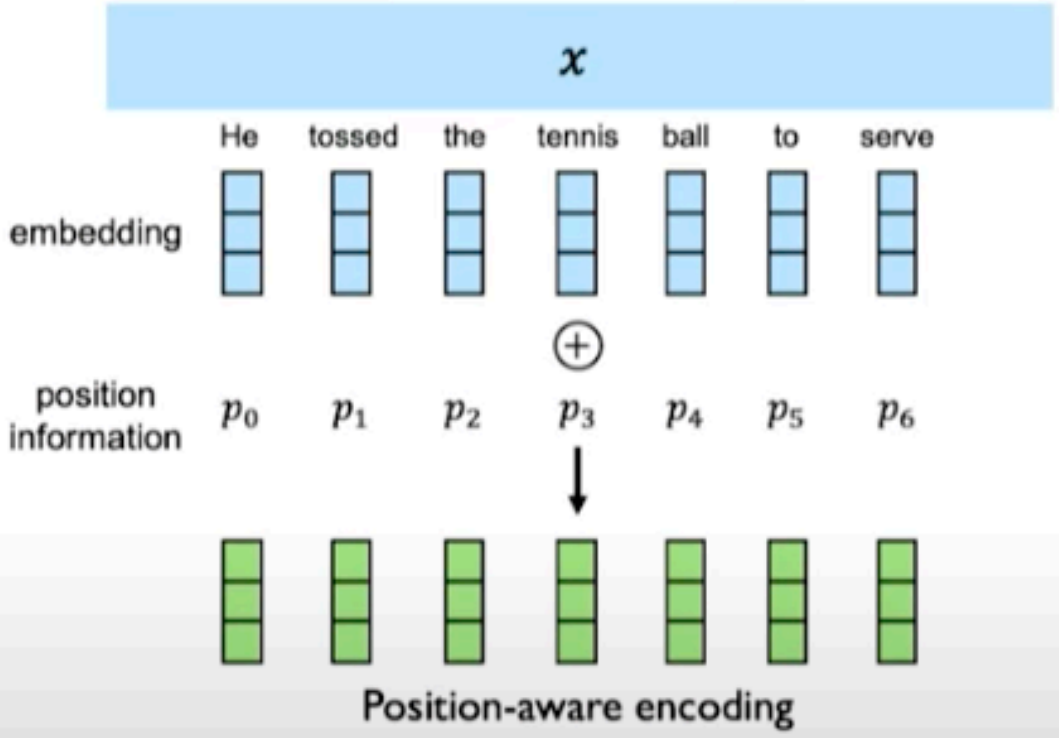
Understanding Attention with Search



Learning Self-Attention with Neural Networks

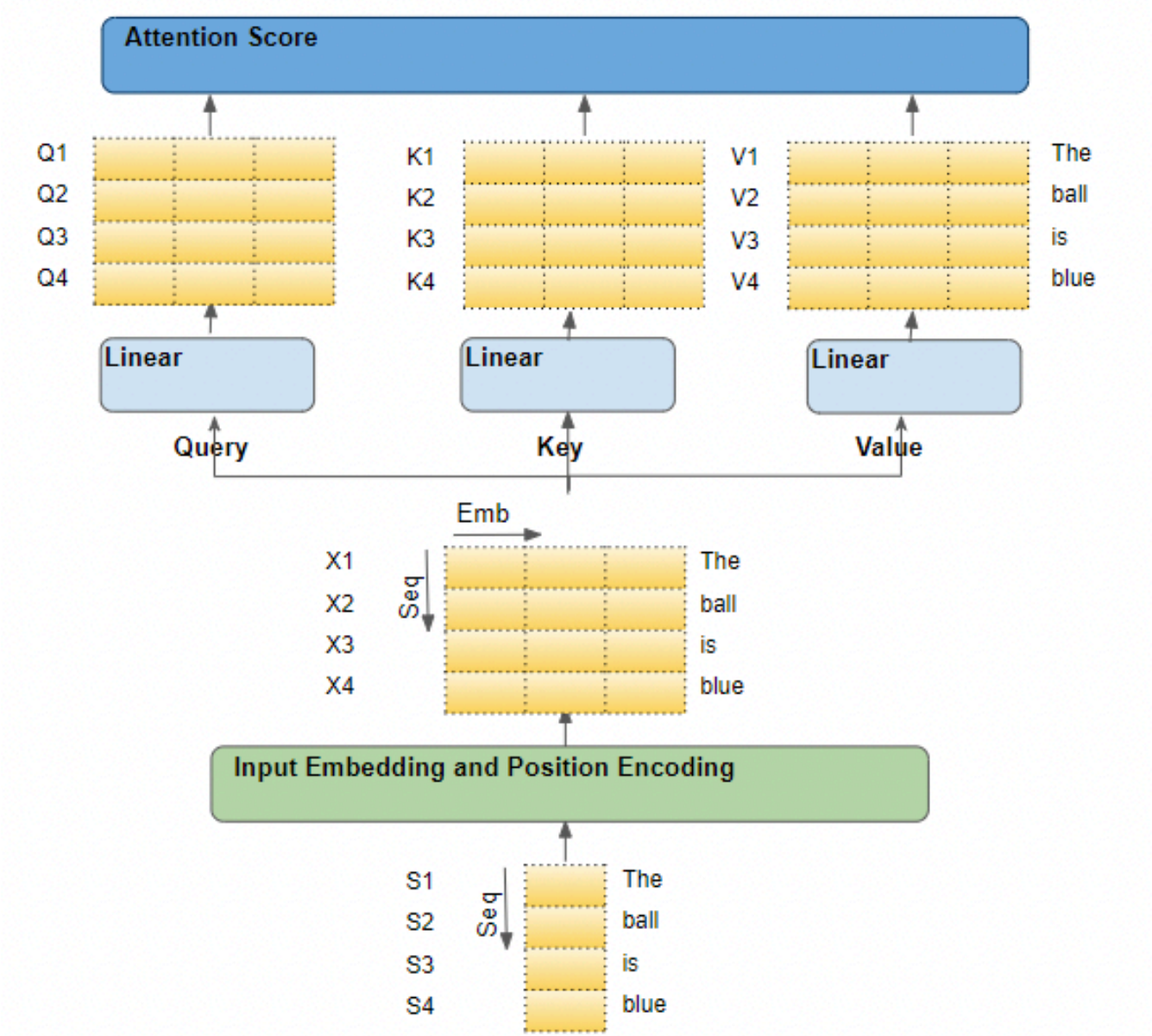
Goal: identify and attend to most important features in input.

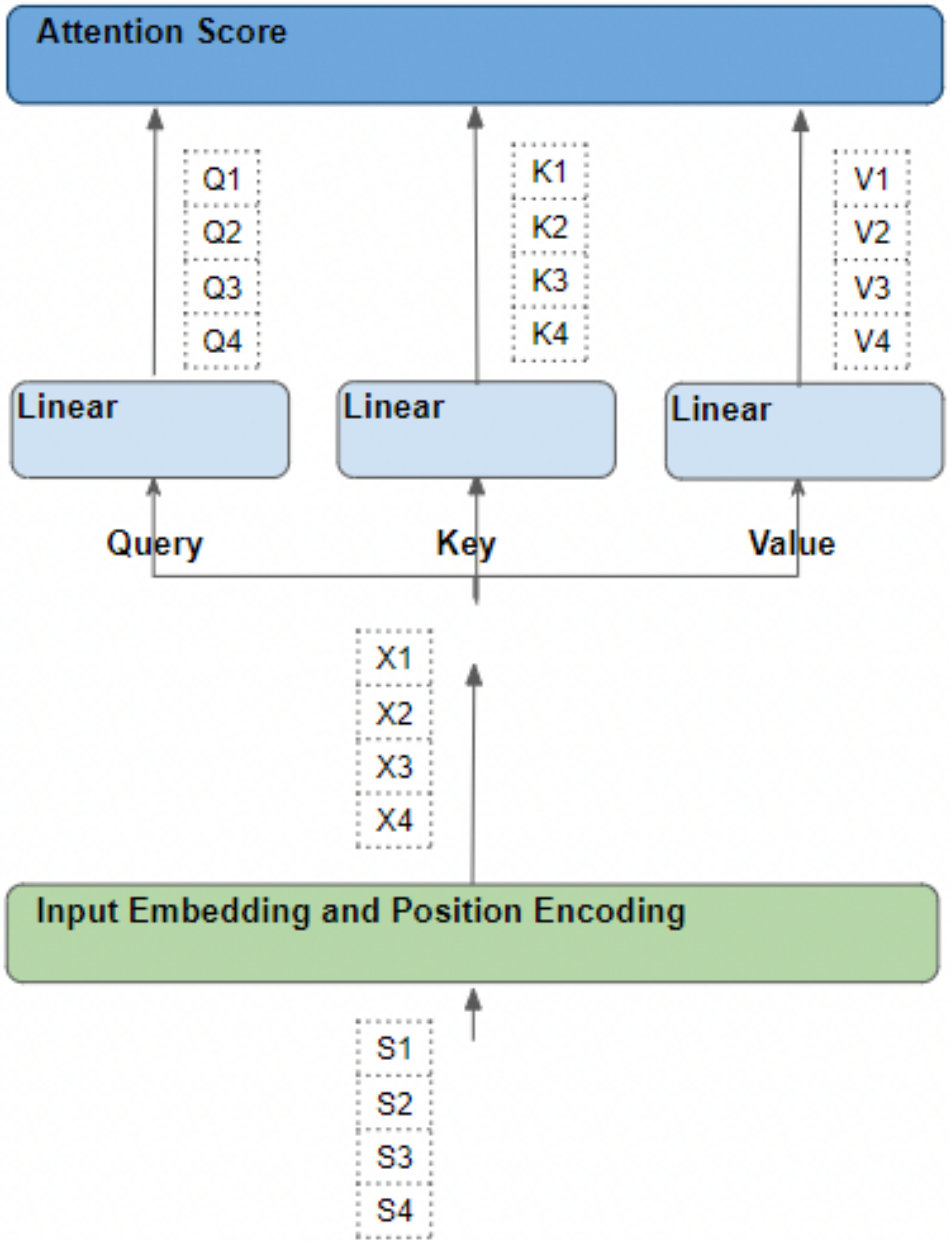
1. Encode **position** information

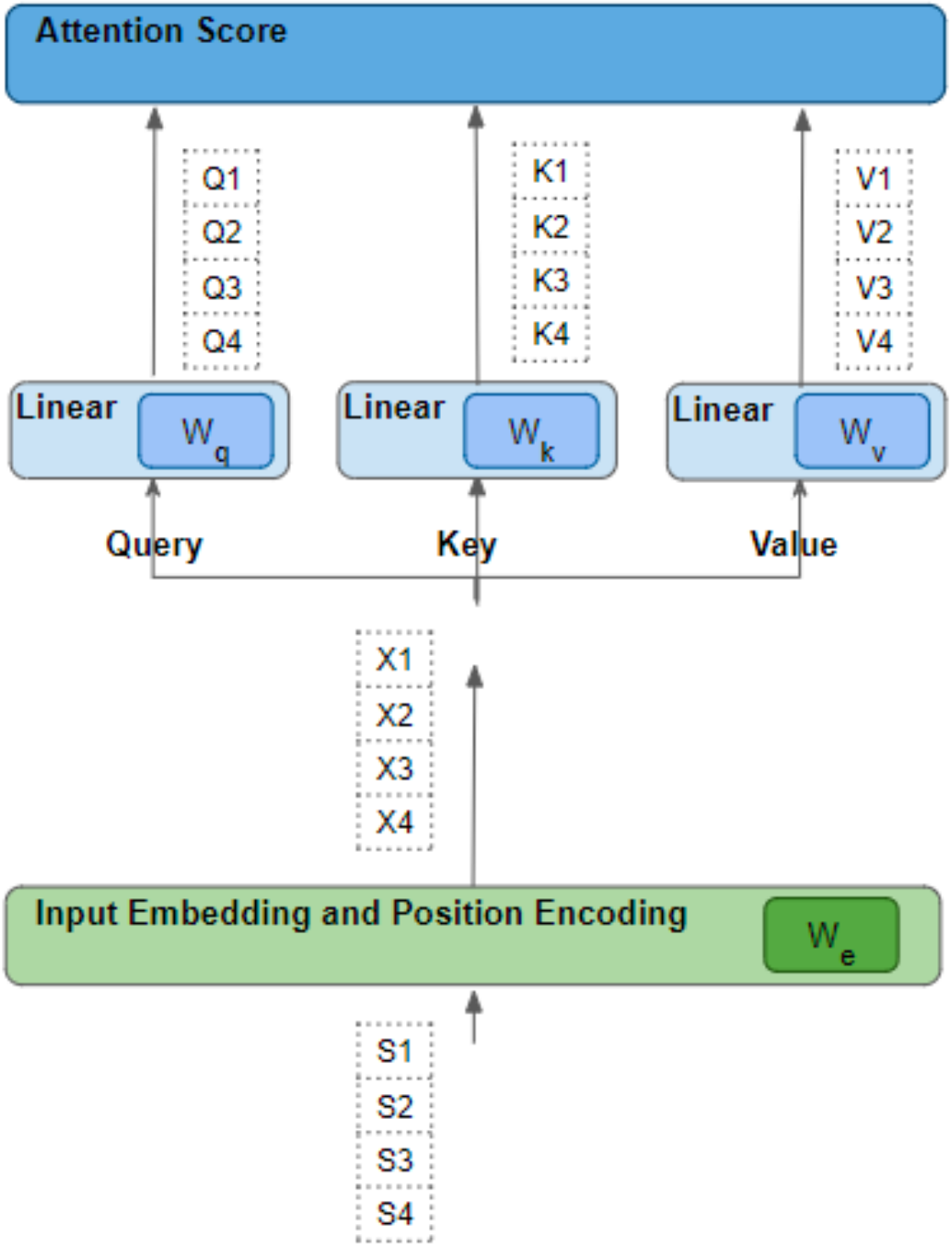


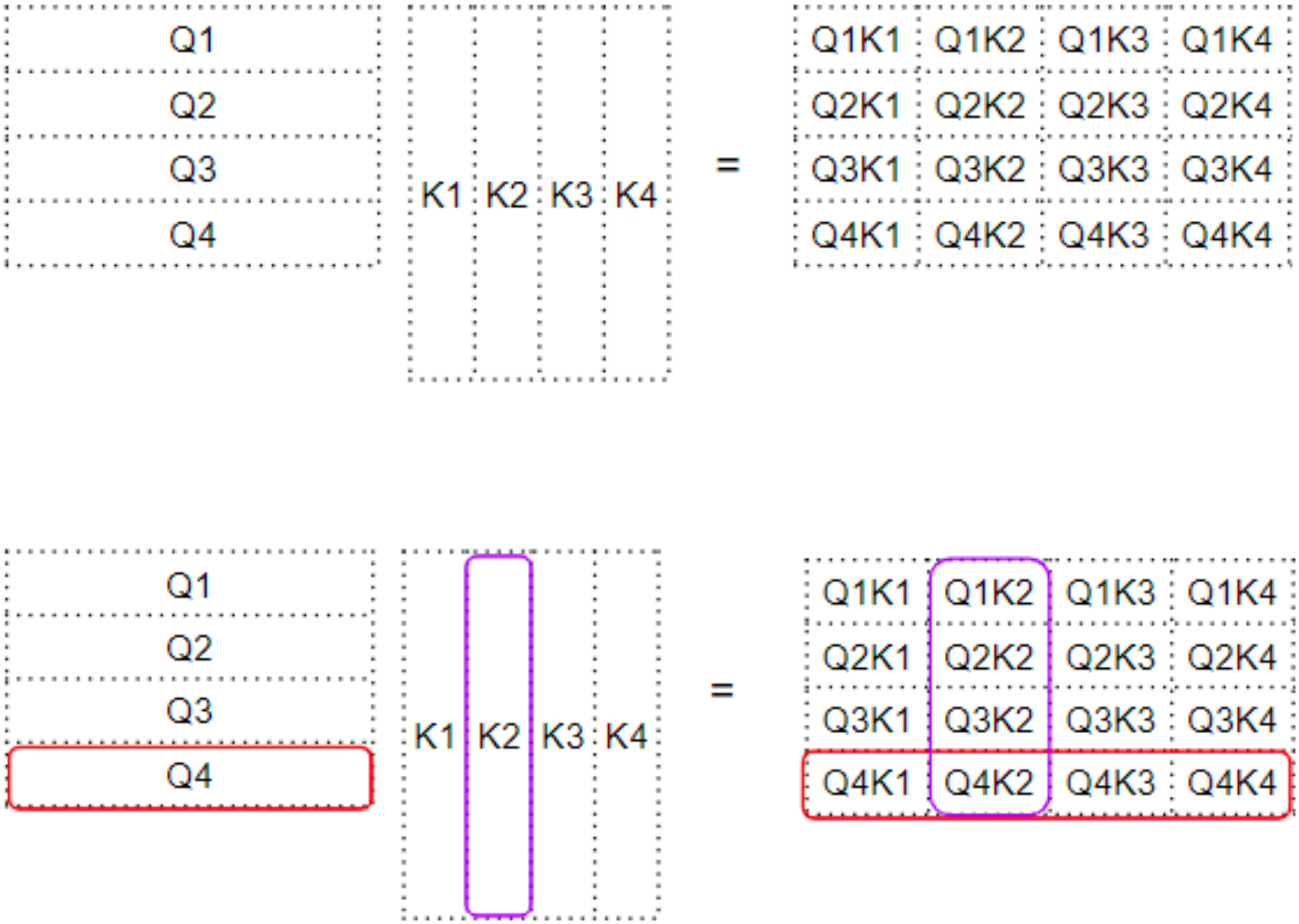
Data is fed in all at once! Need to encode position information to understand order.

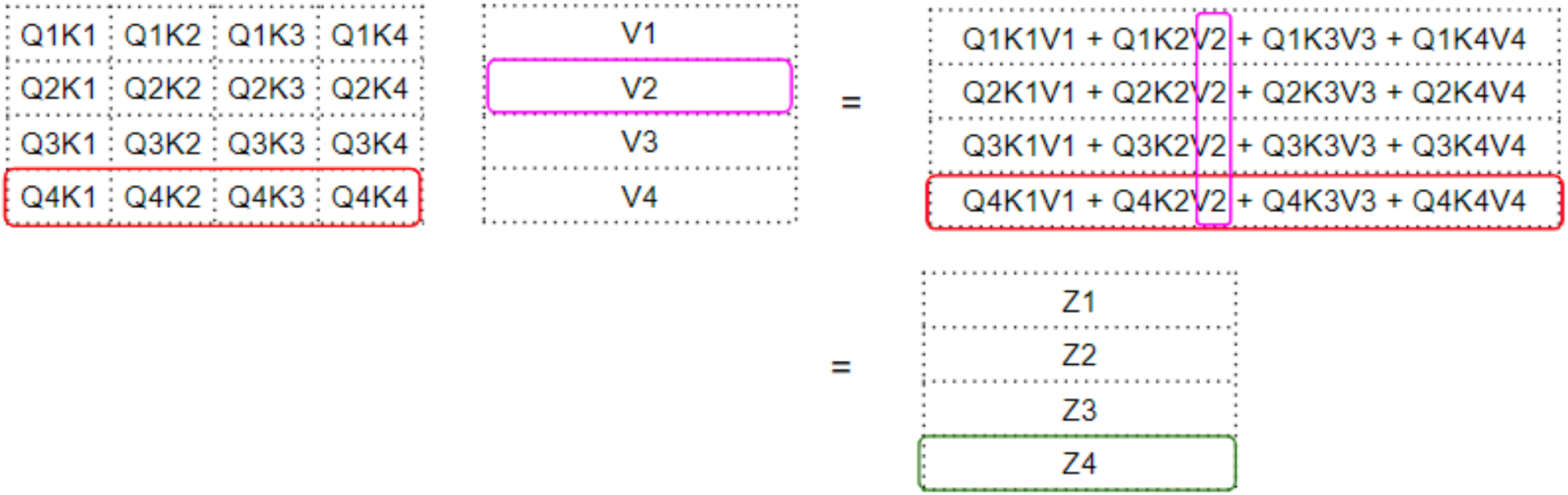
The Attention Module

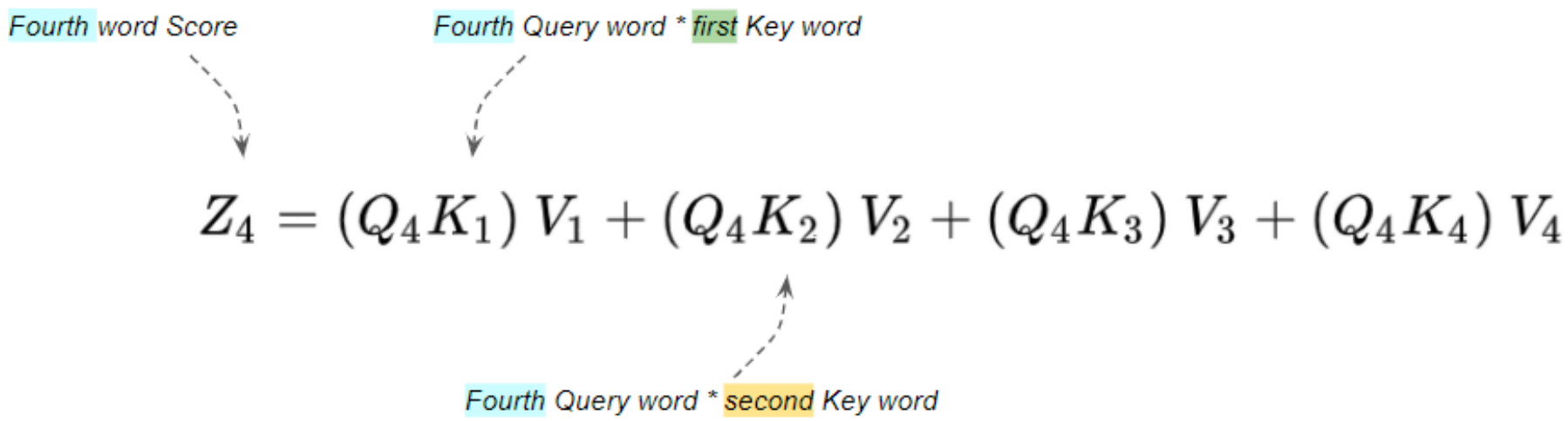



Attention Score
Q1
Q2
Q3
Q4
K1
K2
K3
K4
V1
V2
V3
V4
Linear
Linear
Linear
Query
Key
Value
X1
X2
X3
X4
Input Embedding and Position Encoding
S1
S2
S3
S4

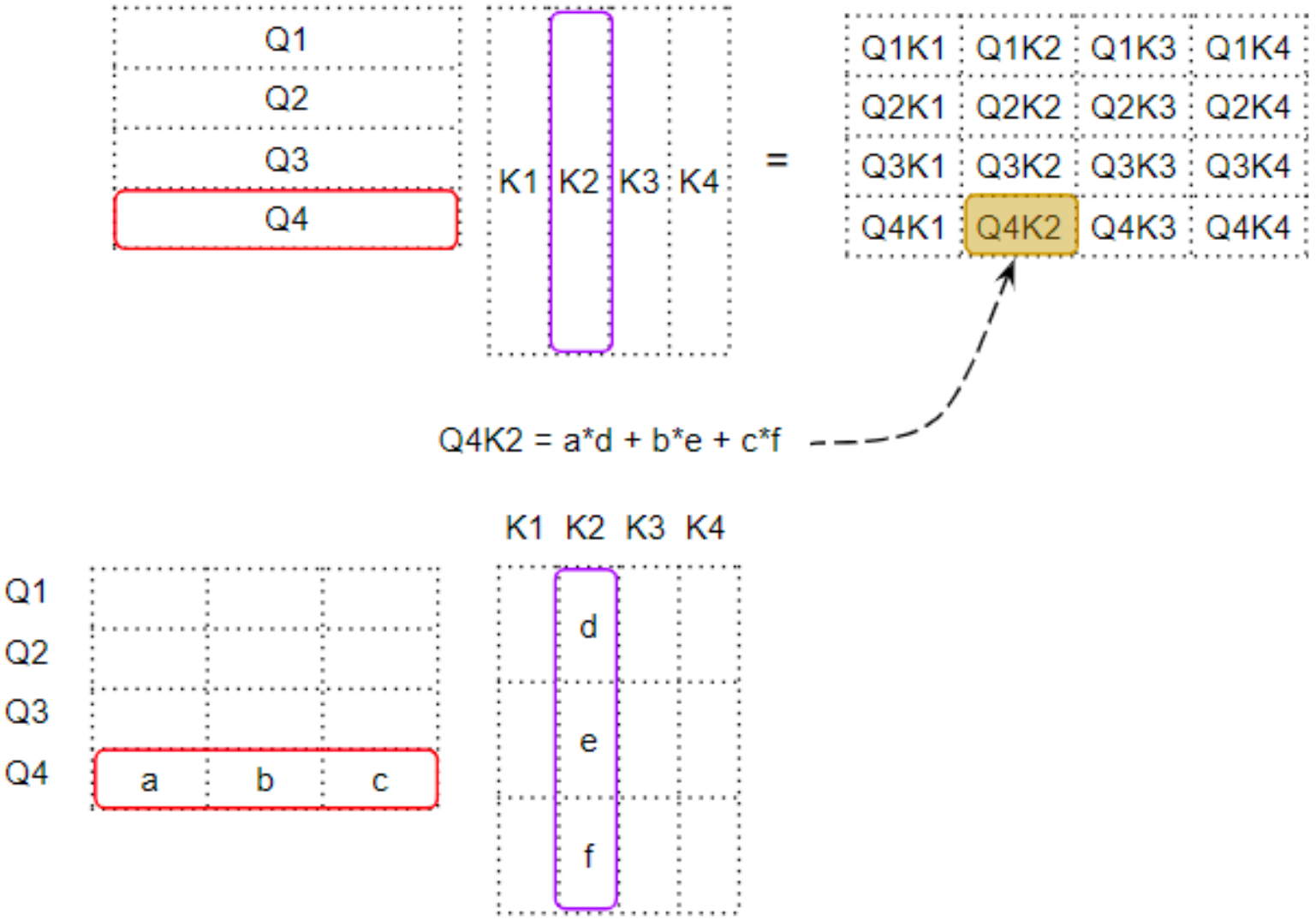

Attention Score
Q1
Q2
Q3
Q4
K1
K2
K3
K4
V1
V2
V3
V4
Linear
W_q
Linear
W_k
Linear
W_v
Query
Key
Value
X1
X2
X3
X4
Input Embedding and Position Encoding
W_e
S1
S2
S3
S4


Q1
Q2
Q3
Q4
K1
K2
K3
K4
=
Q1K1
Q1K2
Q1K3
Q1K4
Q2K1
Q2K2
Q2K3
Q2K4
Q3K1
Q3K2
Q3K3
Q3K4
Q4K1
Q4K2
Q4K3
Q4K4
Q1
Q2
Q3
Q4
K1
K2
K3
K4
=
Q1K1
Q1K2
Q1K3
Q1K4
Q2K1
Q2K2
Q2K3
Q2K4
Q3K1
Q3K2
Q3K3
Q3K4
Q4K1
Q4K2
Q4K3
Q4K4


Q1K1 Q1K2 Q1K3 Q1K4
Q2K1 Q2K2 Q2K3 Q2K4
Q3K1 Q3K2 Q3K3 Q3K4
Q4K1 Q4K2 Q4K3 Q4K4
V1
V2
V3
V4
=
Q1K1V1 + Q1K2V2 + Q1K3V3 + Q1K4V4
Q2K1V1 + Q2K2V2 + Q2K3V3 + Q2K4V4
Q3K1V1 + Q3K2V2 + Q3K3V3 + Q3K4V4
Q4K1V1 + Q4K2V2 + Q4K3V3 + Q4K4V4
=
Z1
Z2
Z3
Z4



$$Z = Softmax(\frac{QK^T}{\sqrt{d_k}})V$$


Q1
Q2
Q3
Q4
K1 K2 K3 K4
=
Q1K1 Q1K2 Q1K3 Q1K4
Q2K1 Q2K2 Q2K3 Q2K4
Q3K1 Q3K2 Q3K3 Q3K4
Q4K1 Q4K2 Q4K3 Q4K4
Q4K2 = a*d + b*e + c*f
K1 K2 K3 K4
Q1
Q2
Q3
Q4
a b c
d
e
f

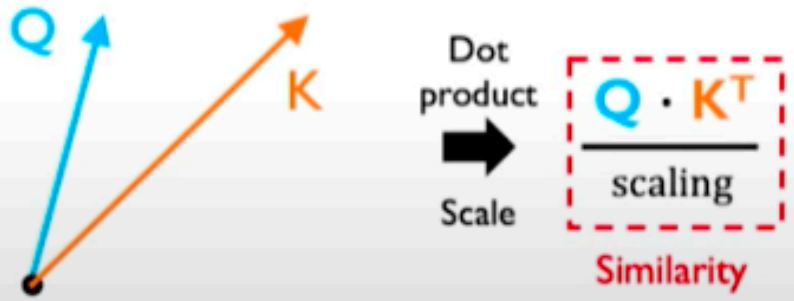
Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract features with high attention

Attention score: compute pairwise similarity between each query and key

How to compute similarity between two sets of features?



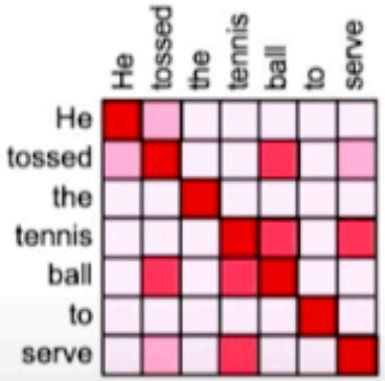
Also known as the "cosine similarity"

Learning Self-Attention with Neural Networks

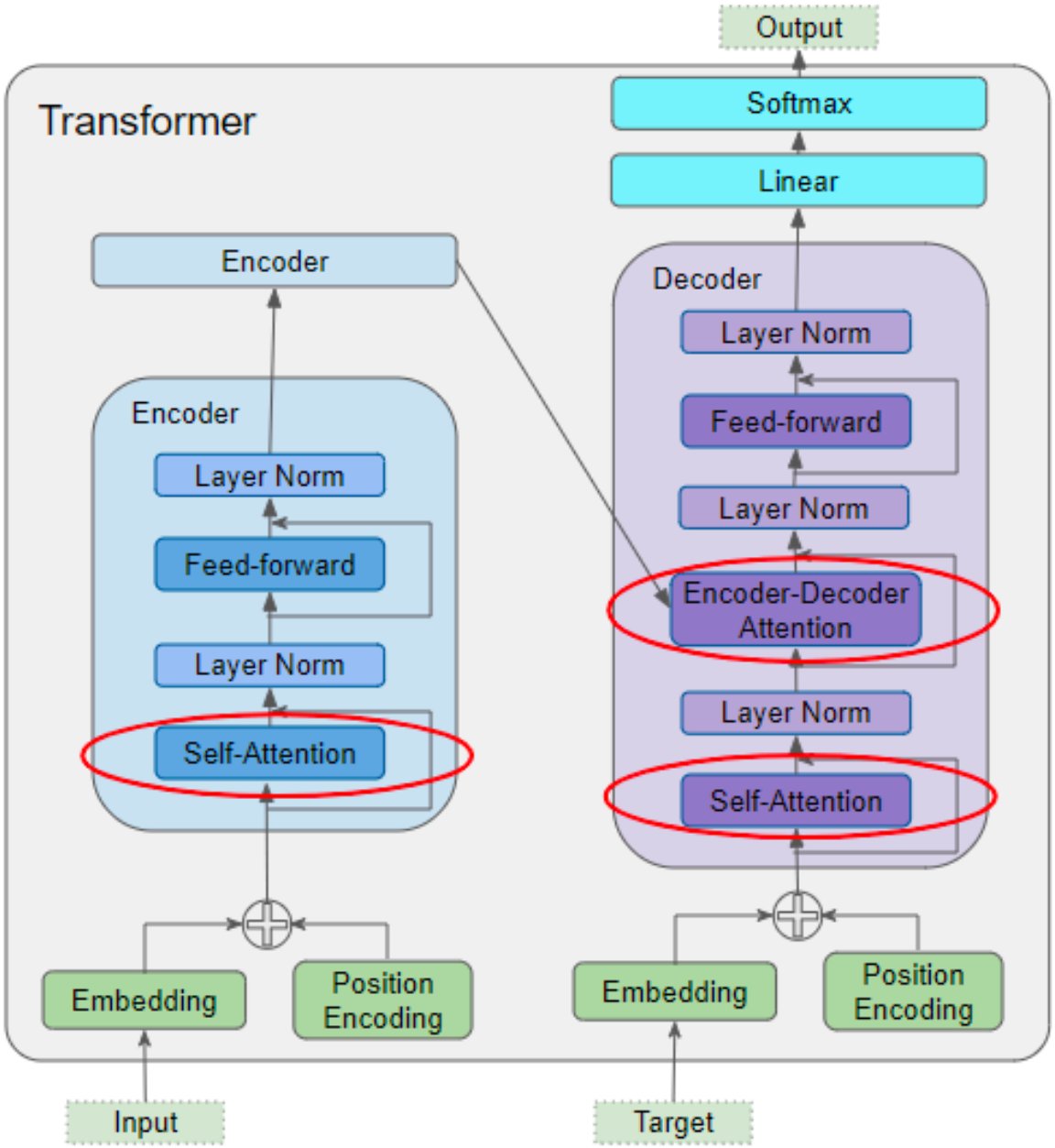
Goal: identify and attend to most important features in input.

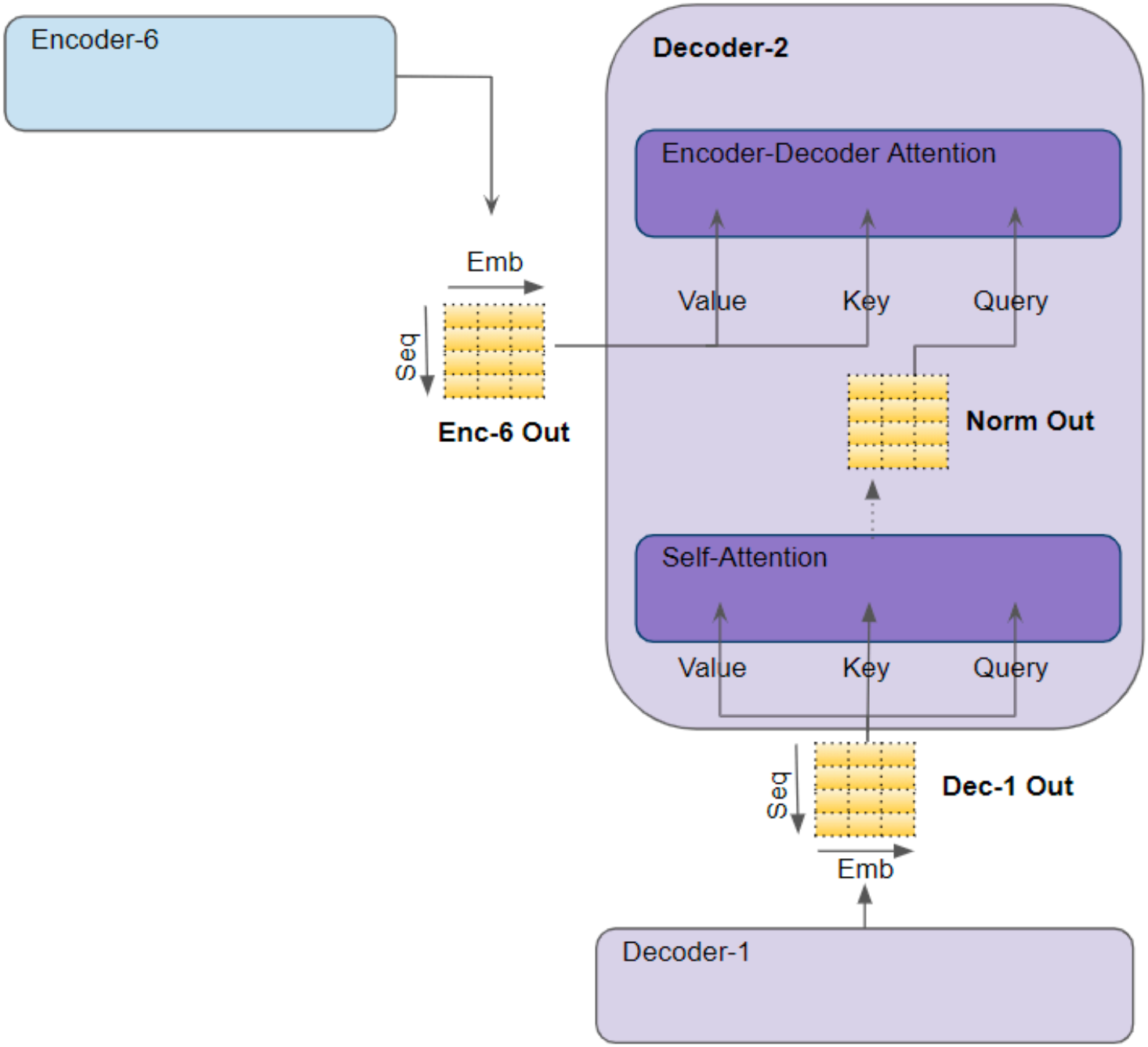
1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract features with high attention

Attention weighting: where to attend to! How similar is the key to the query?



$$softmax\left(\frac{Q \cdot K^T}{scaling}\right)$$


Output
Transformer
Softmax
Linear
Encoder
Decoder
Layer Norm
Feed-forward
Layer Norm
Encoder-Decoder Attention
Layer Norm
Self-Attention
Encoder
Layer Norm
Feed-forward
Layer Norm
Self-Attention
Embedding
Position Encoding
Embedding
Position Encoding
Input
Target

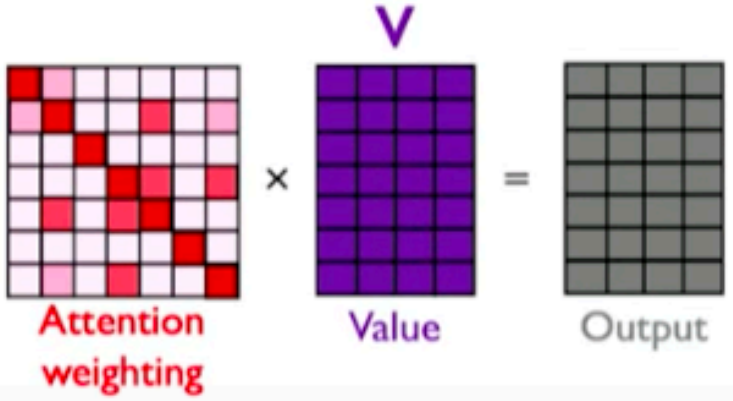

Encoder-6
Decoder-2
Encoder-Decoder Attention
Emb
Value
Key
Query
Seq
Enc-6 Out
Norm Out
Self-Attention
Value
Key
Query
Seq
Dec-1 Out
Emb
Decoder-1

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract **features with high attention**

Last step: self-attend to extract features



$$softmax\left(\frac{Q \cdot K^T}{scaling}\right) \cdot V = A(Q,K,V)$$