Sequence modeling

Prototyping with Deep Learning

Learning outcomes

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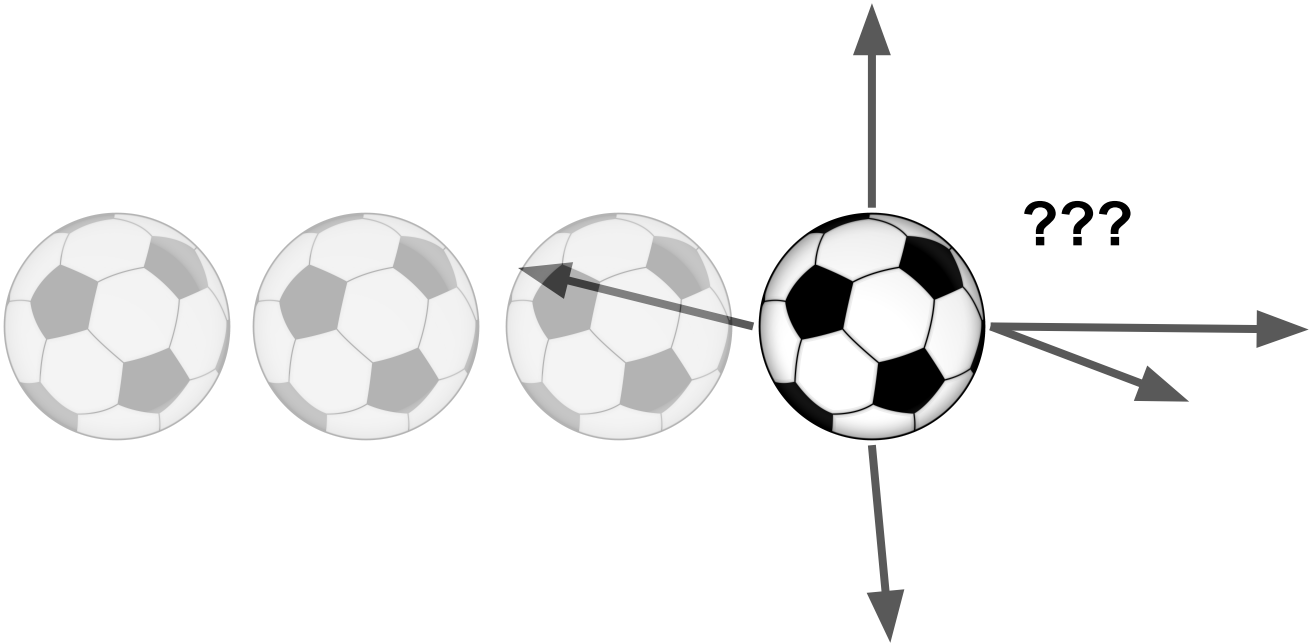
After this lesson you will be able to:

- Understand fundamentals of Sequence modelling
- Understand the limitations of RNNs for Sequence modeling tasks.
- Understand the concept of Self-Attention for Sequence modeling.
- Know a powerful DL architecture based on self-Attention called Transformers.
- Know popular transformer models and their applications.

Sequence Modeling

Given the current position of the ball can you predict where it will go next?



Sequence Modeling

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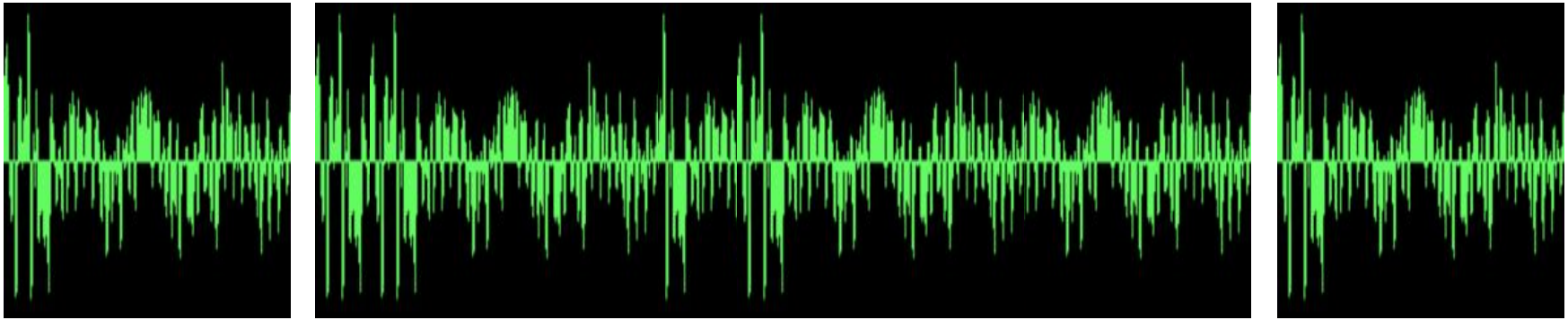
Sequential data



Audio

Sequence Modeling

Sequential data

Character: P r o t o t y p i n g

Prototyping with Deep Learning

Word: with Deep Learning

Text

Sequence Modeling

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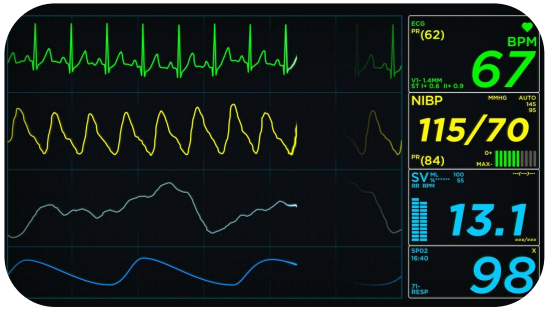
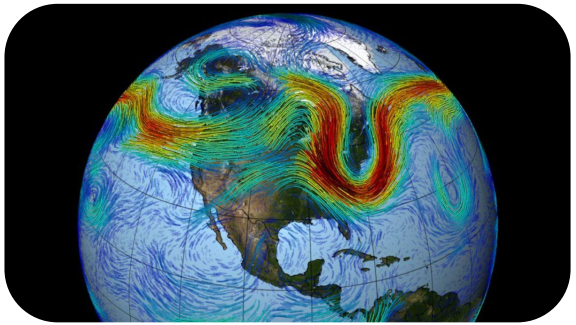
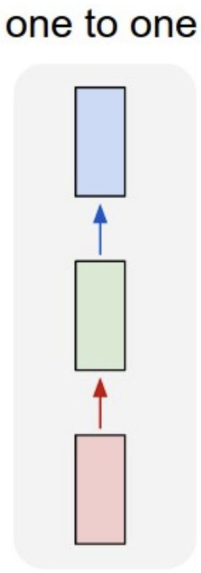
Sequential data





Sequence Modeling Application



Binary classification

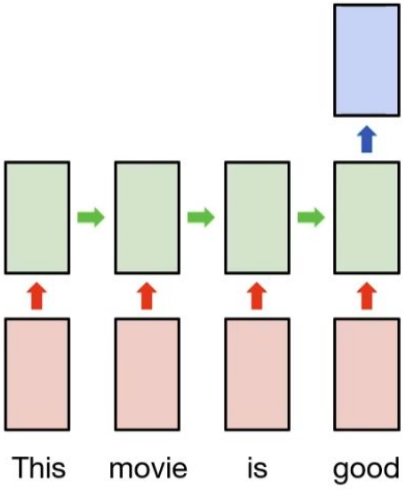
Cat or Dog

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Sequence Modeling

Example: Sentiment Classification Task

Classification : Positive or negative?



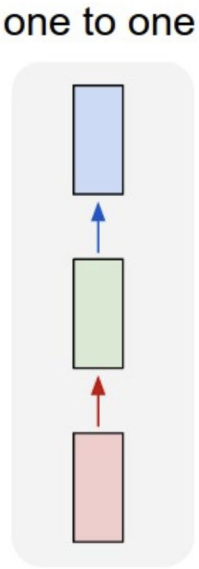
RNN many to one

Input: Sequence of words
Output: Probability of having positive sentiment

```
loss = tf.nn.softmax_cross_entropy_wiht_logits(y, predited)
```

Predicting sentiment associated with a tweet

Sequence Modeling Application



Binary classification
Cat or Dog

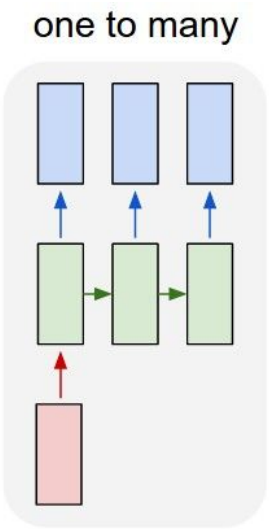
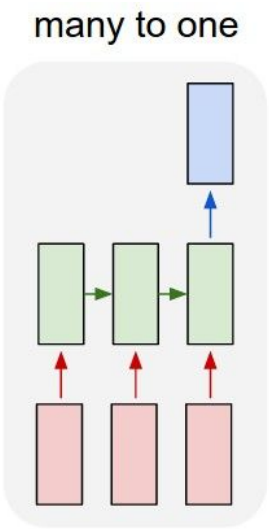
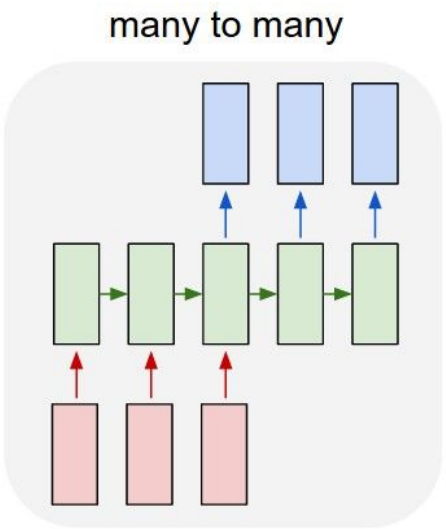


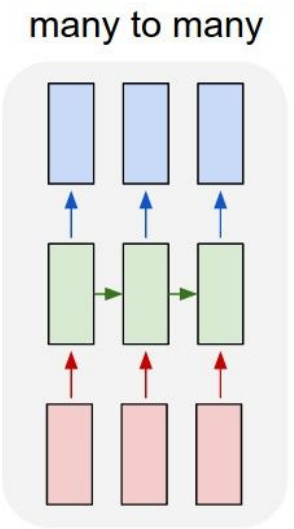
Image captioning



Sentiment classification



Machine translation

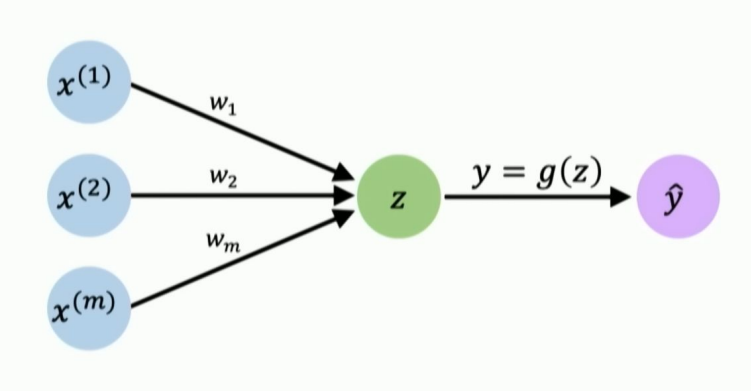


Video classification (label each frame)

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

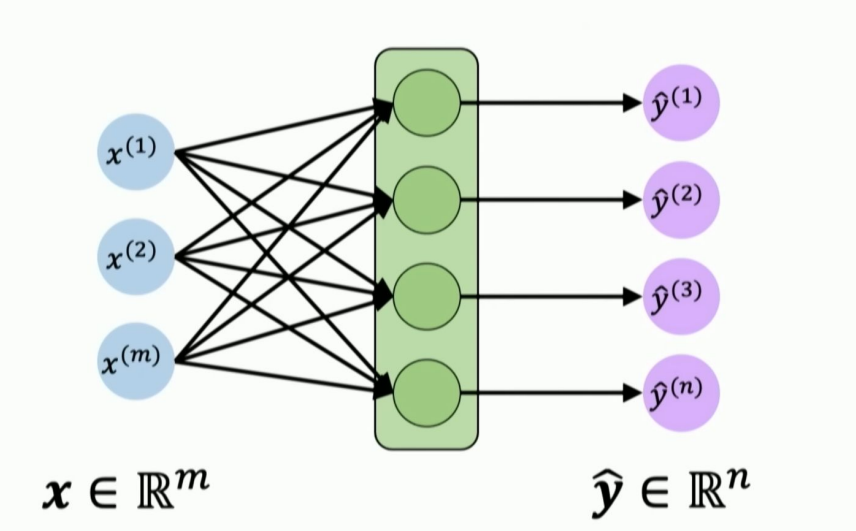
Sequence Modeling

Feed-Forward: No notion of time or temporal dependency



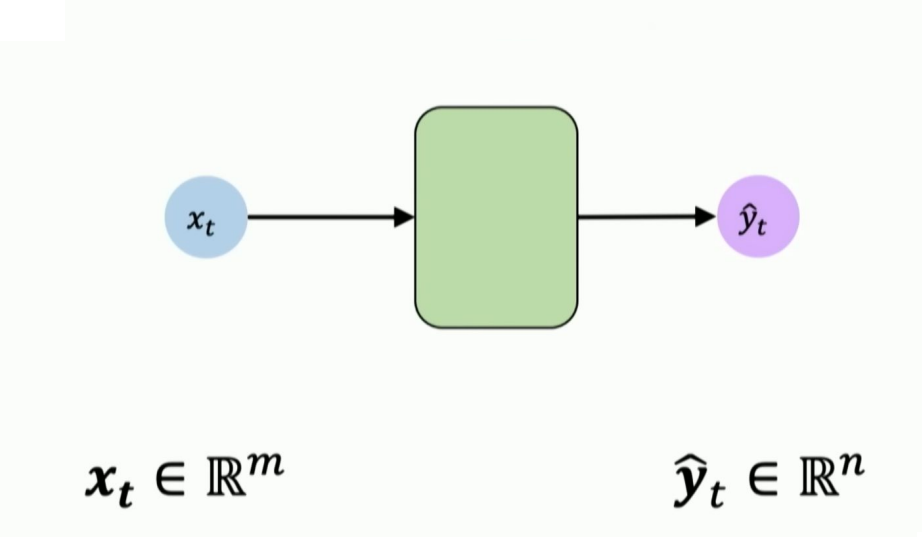
Sequence Modeling

Feed-Forward: No notion of time or temporal dependency



Sequence Modeling

Feed-Forward: No notion of time or temporal dependency



How can we extend this to model multiple time steps of a sequential data?

Sequence Modeling

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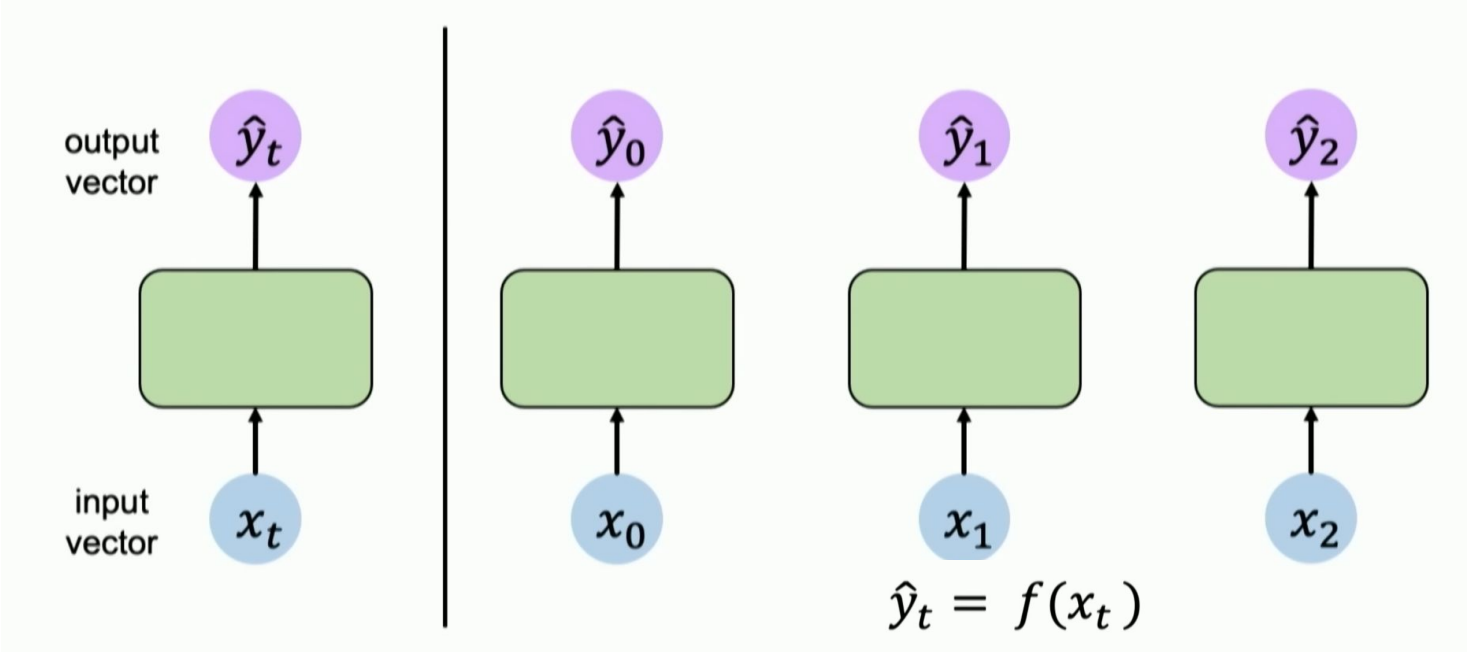
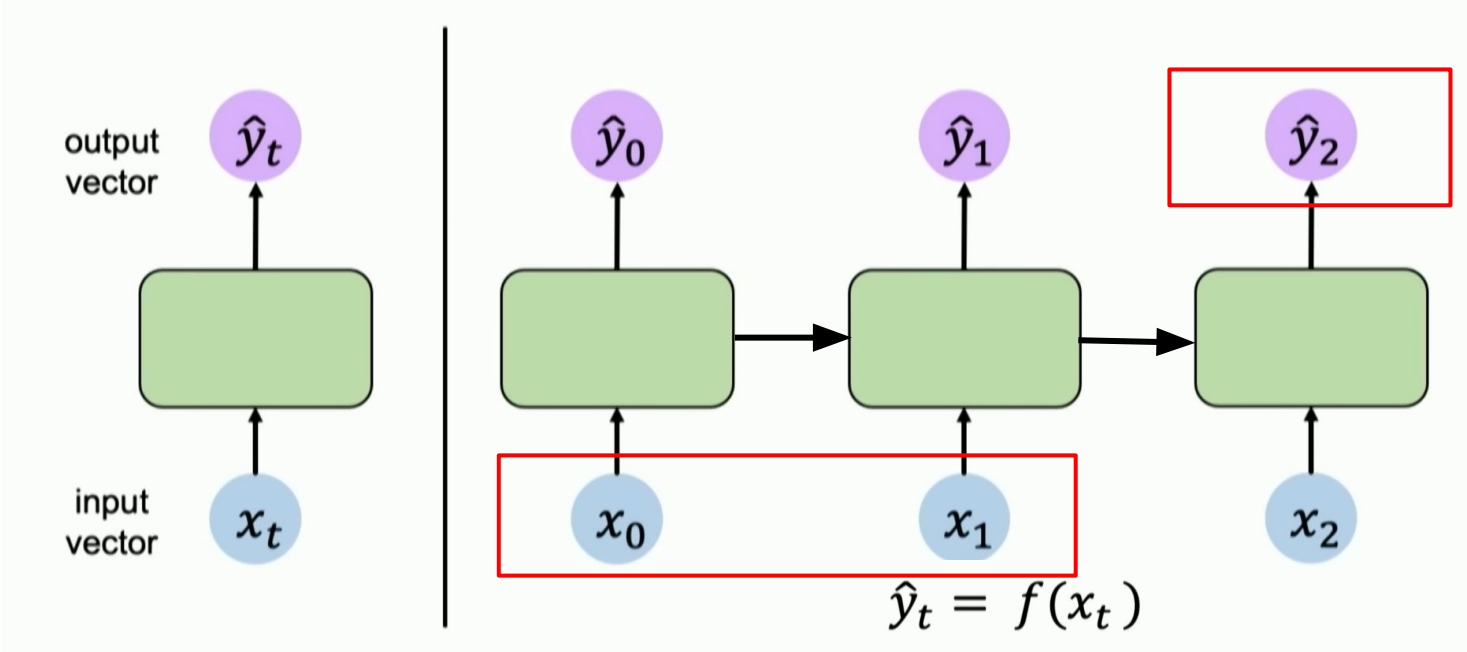
Handling individual time steps



Sequence Modeling

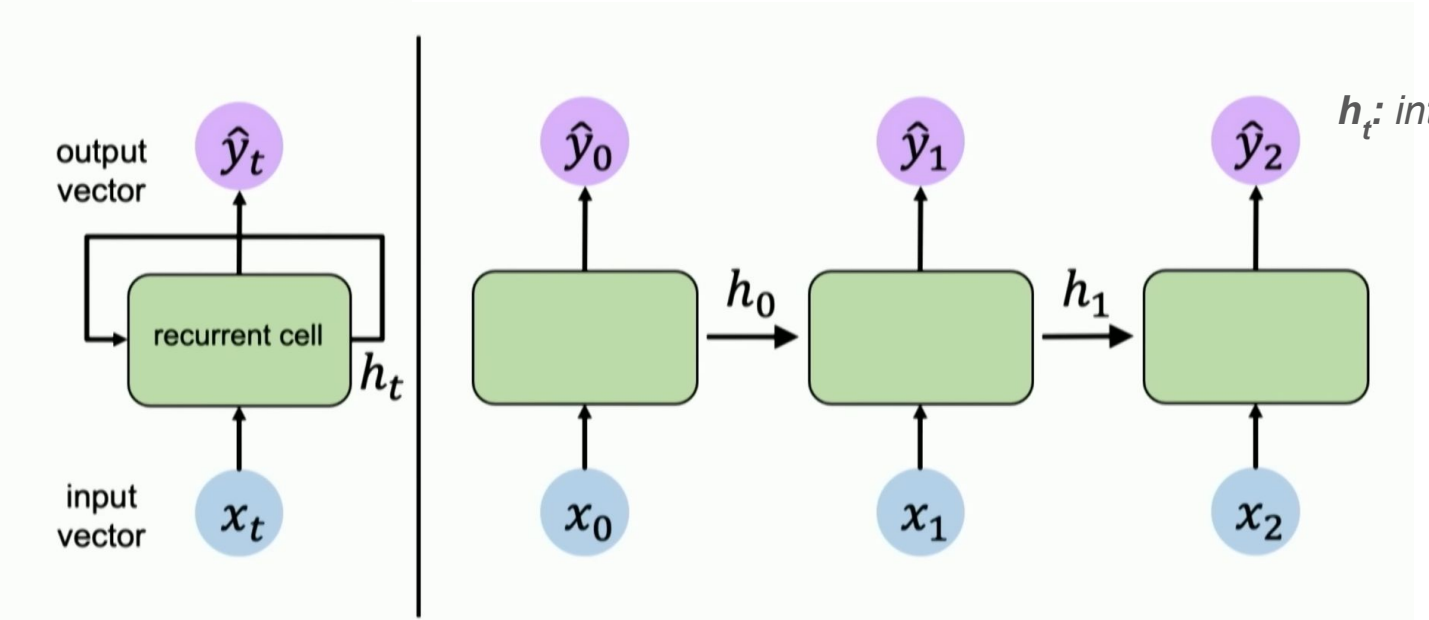
Handling individual time steps



Recurrence relation

Sequence Modeling

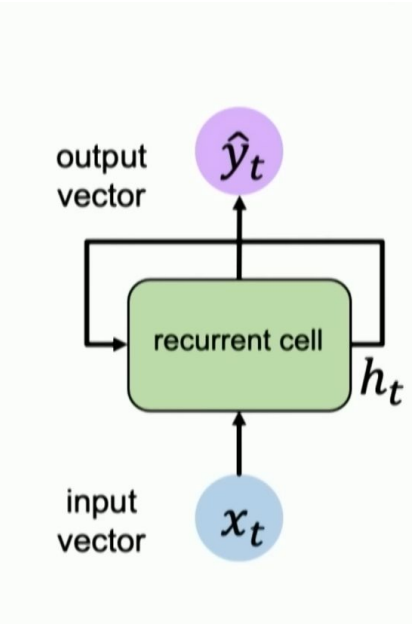
Handling individual time steps



h_t: internal state/ memory term

$$\underbrace{\hat{y}_t}_{\text{output}} = f(\underbrace{x_t}_{\text{input}}, \underbrace{h_{t-1}}_{\text{past memory}})$$

Sequence Modeling: RNNs



Apply recurrence relation at every time step to process the sequence:

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

Cell State

function with weights W

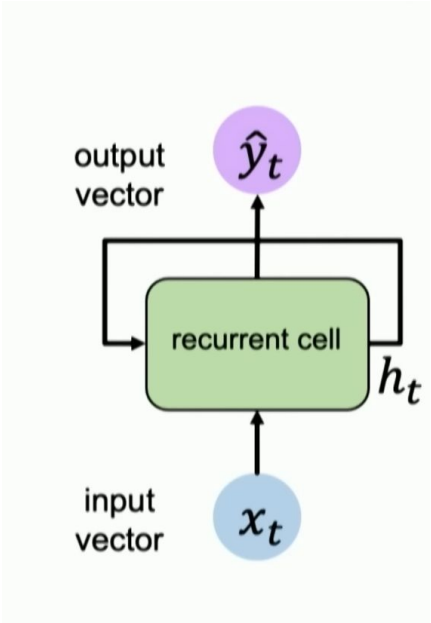
input

Old State

- The same function and set of parameters are used at every time step

RNNs have internal state h_t that is updated at each time step as a sequence is processed

Sequence Modeling: RNNs



Output Vector

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

Update Hidden State

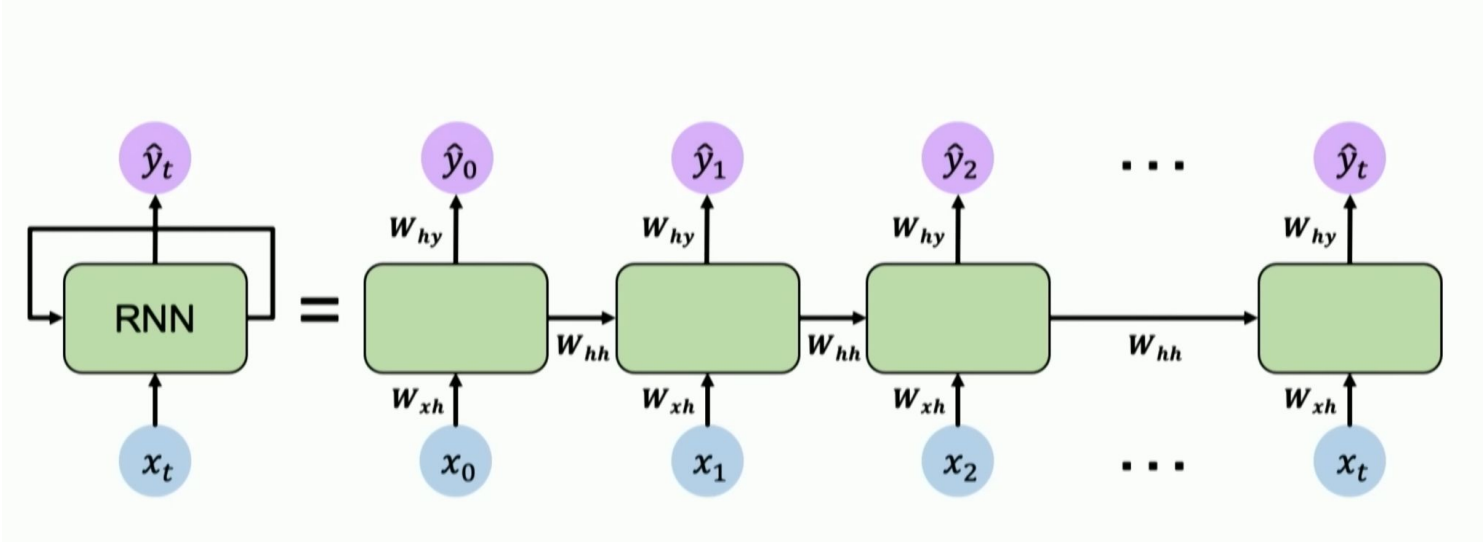
$$h_t = \tanh(\boldsymbol{W}_{\boldsymbol{hh}}^{\boldsymbol{T}} h_{t-1} + \boldsymbol{W}_{\boldsymbol{xh}}^{\boldsymbol{T}} x_t)$$

Input Vector

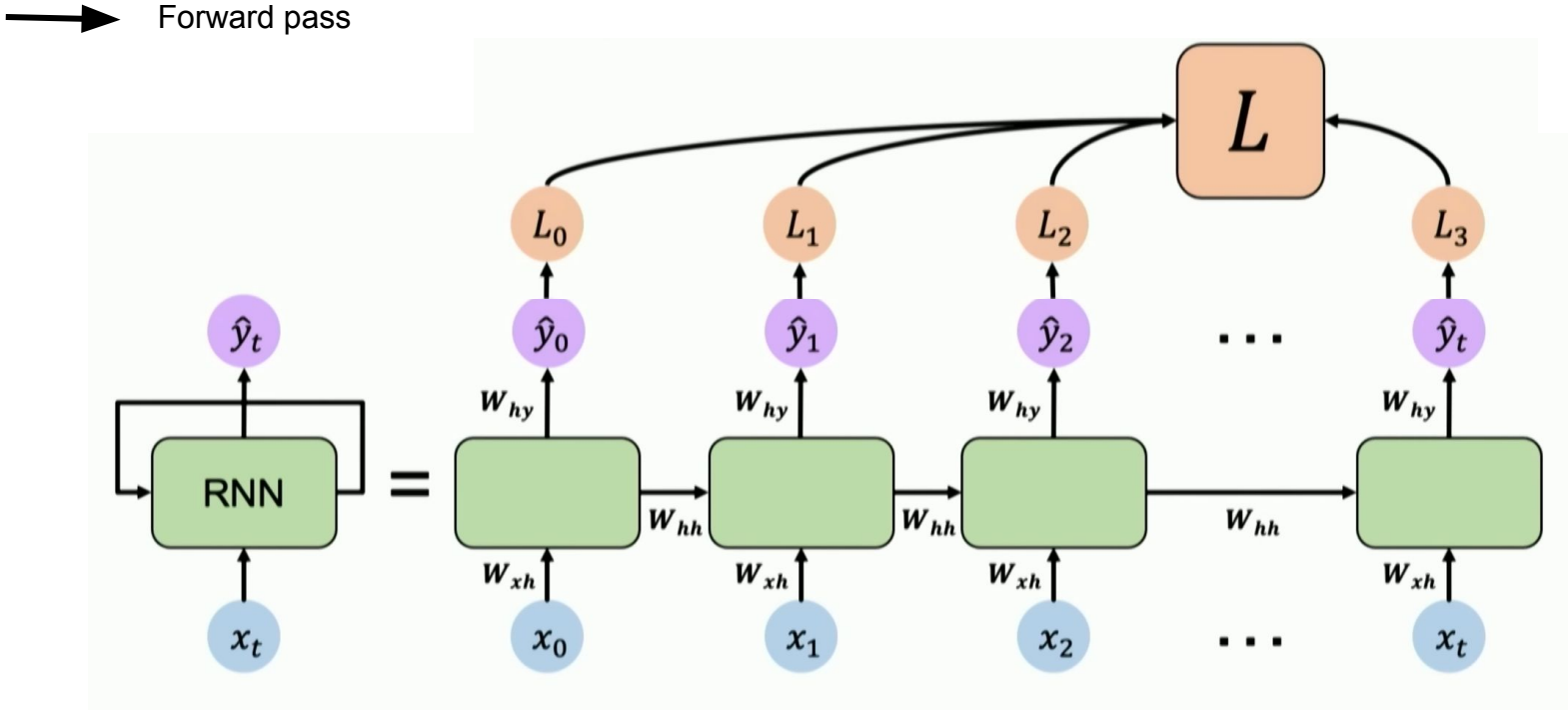
$$x_t$$

Sequence Modeling: RNNs

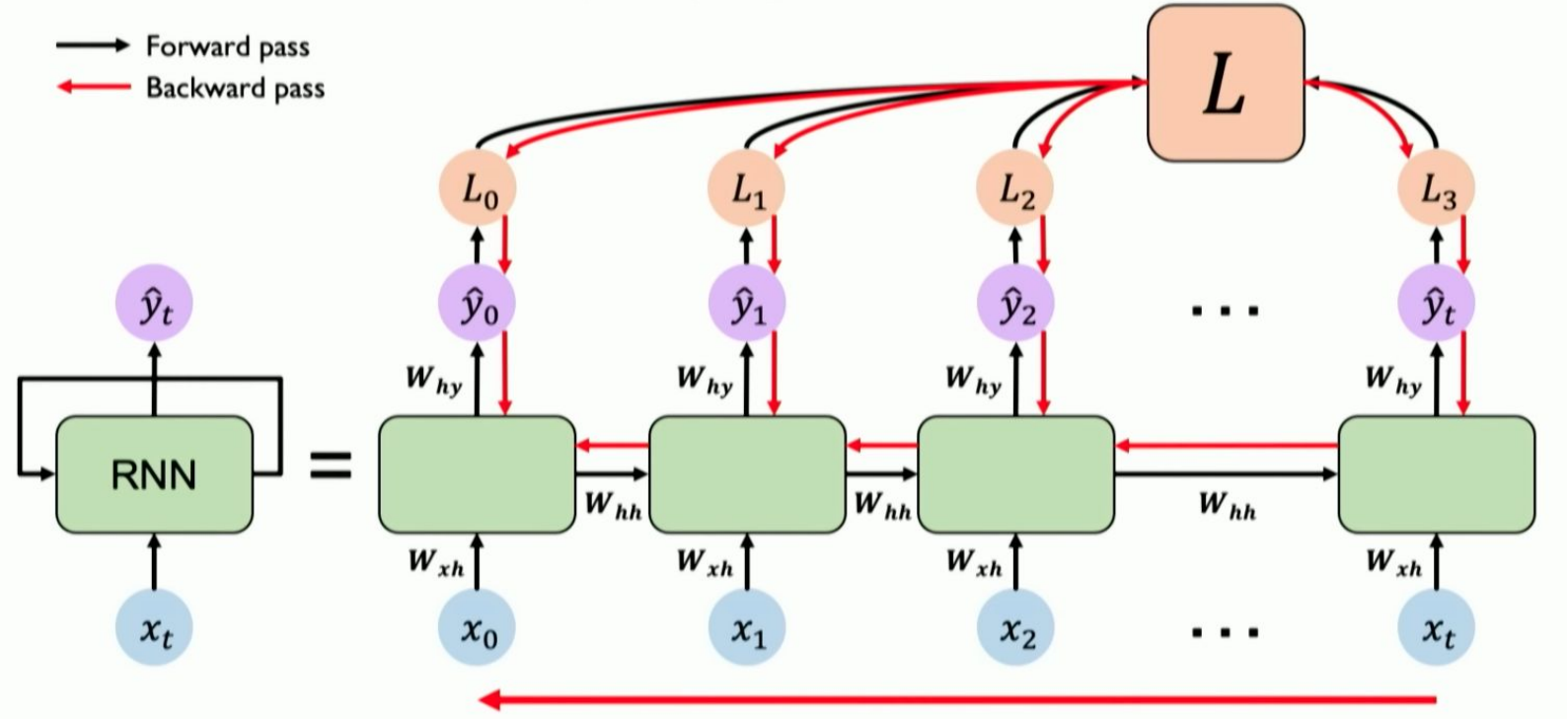
Re-using the same weight matrices at every time step



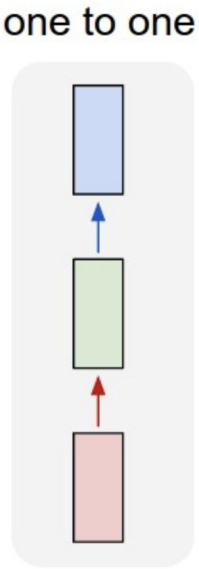
Sequence Modeling: RNNs



Sequence Modeling: RNNs



Sequence Modeling Application



Binary classification
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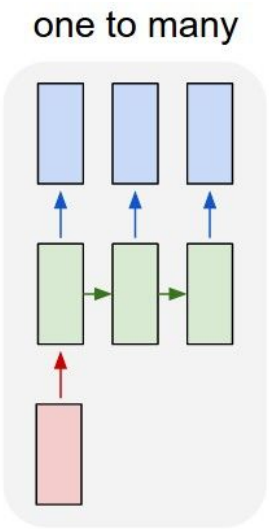
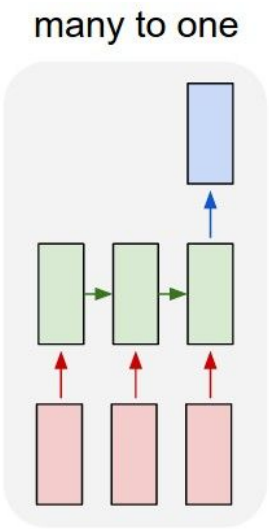
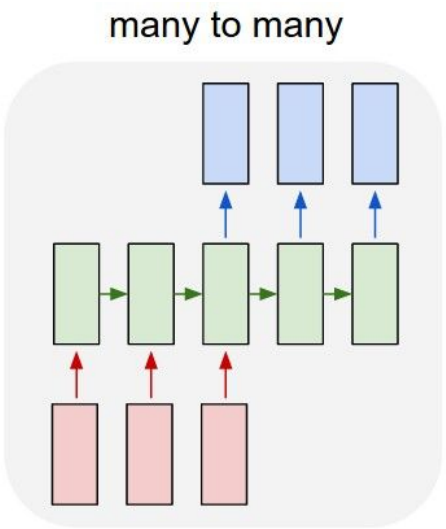


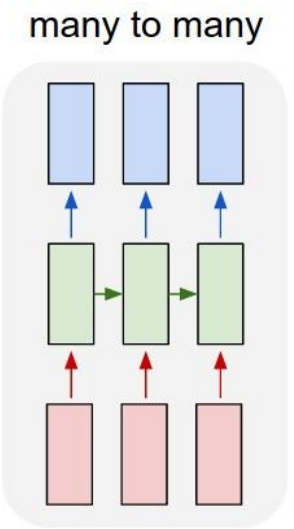
Image captioning



Sentiment classification



Machine translation



Video classification (label each frame)

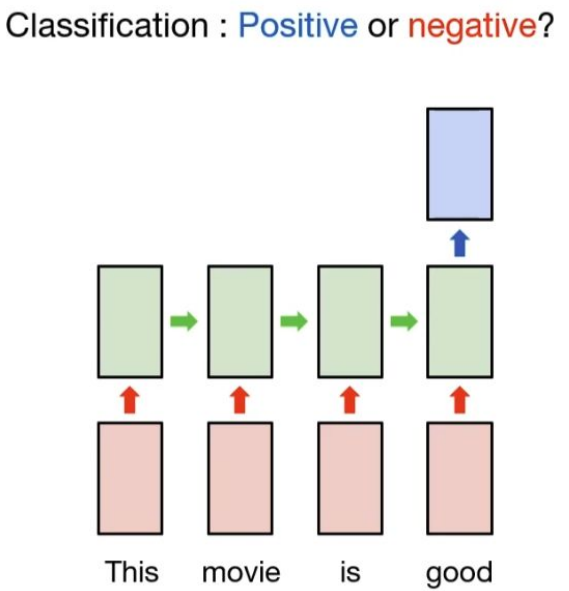
http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Sequence Modeling: Design Criteria

To model sequence we need to:

- Handle **Variable-length** sequences
- Handle **long-term** dependencies
- Maintain information about **Order**

RNN Limitations

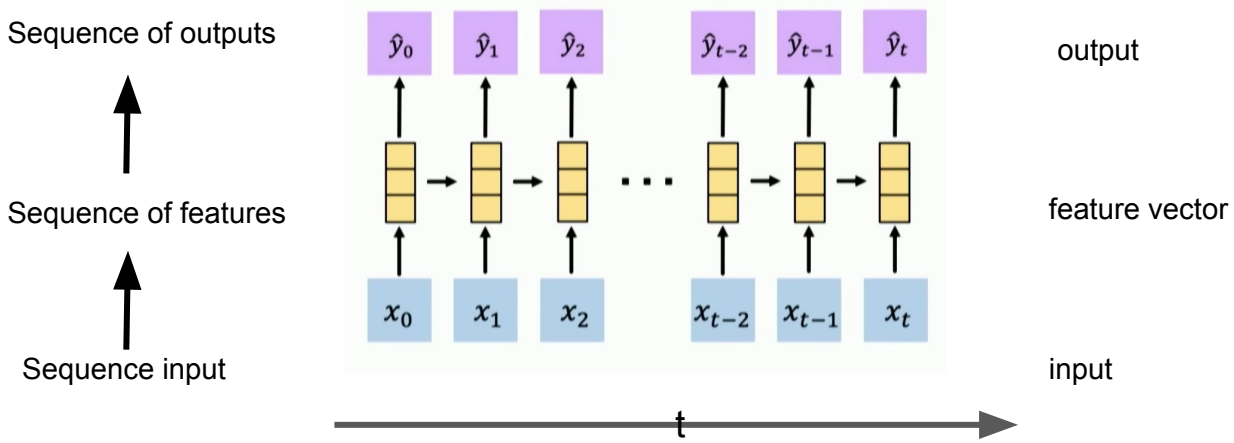


Limitations of Recurrent Models

- **Encoding bottleneck:** Information can be lost
- **Slow, No parallelization:** Not efficient training
- **No long memory:** Don't scale well for *very* long sequences

RNN Limitations

RNNs: recurrence to model sequence dependencies



RNN Limitations

- Encoding bottleneck:
- Slow, No parallelization
- No long memory

Desired Capabilities

- Continuous stream
- Parallelization
- Long memory

Transformers

Google

Bidirectional Encoder Representation from Transformers

OpenAI

Generative Pre-Training

CHAT GPT

GPT-4

Attention Is All You Need

Self-Attention

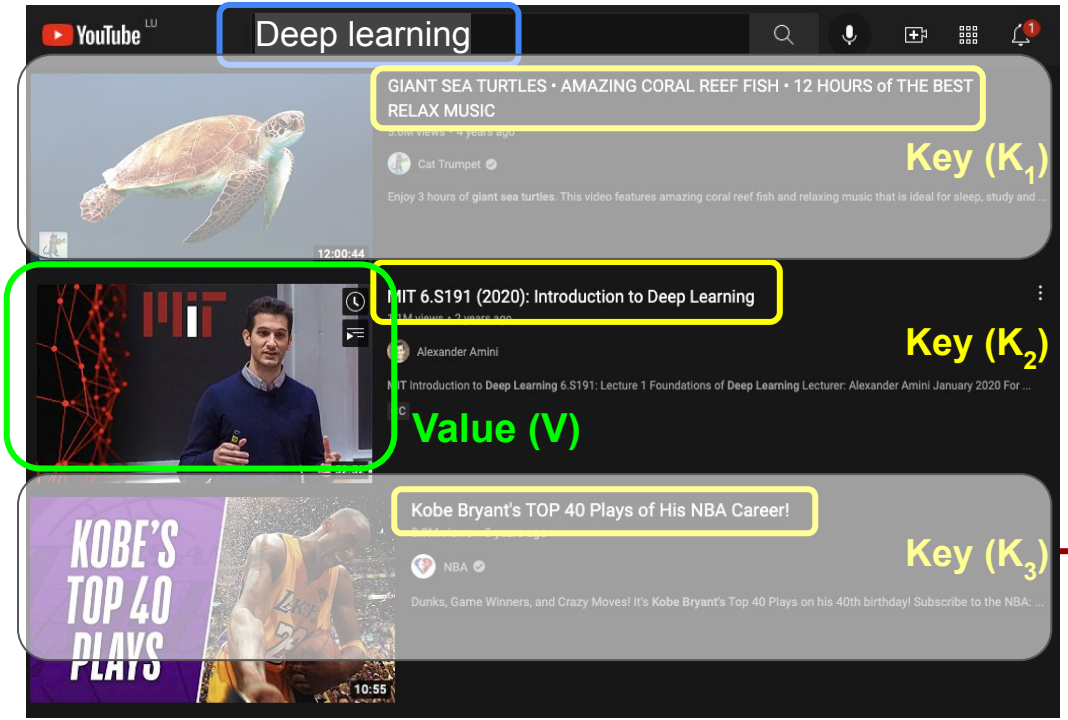
Self-Attention: Attending to the most important part of an input

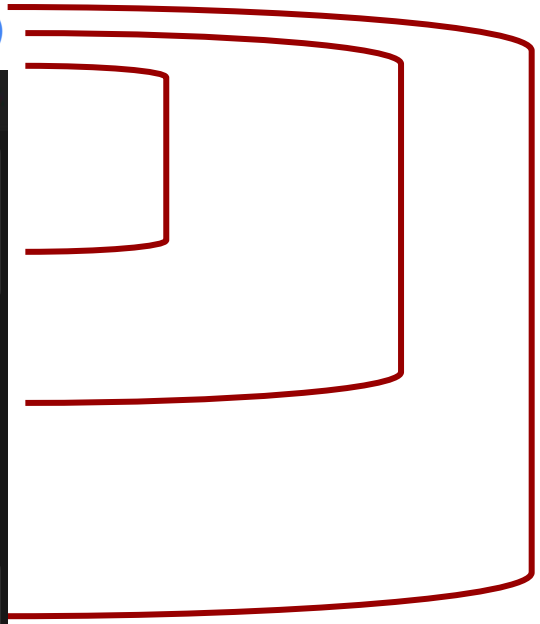
Similar to a search problem

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

Self-Attention

Example: Search





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

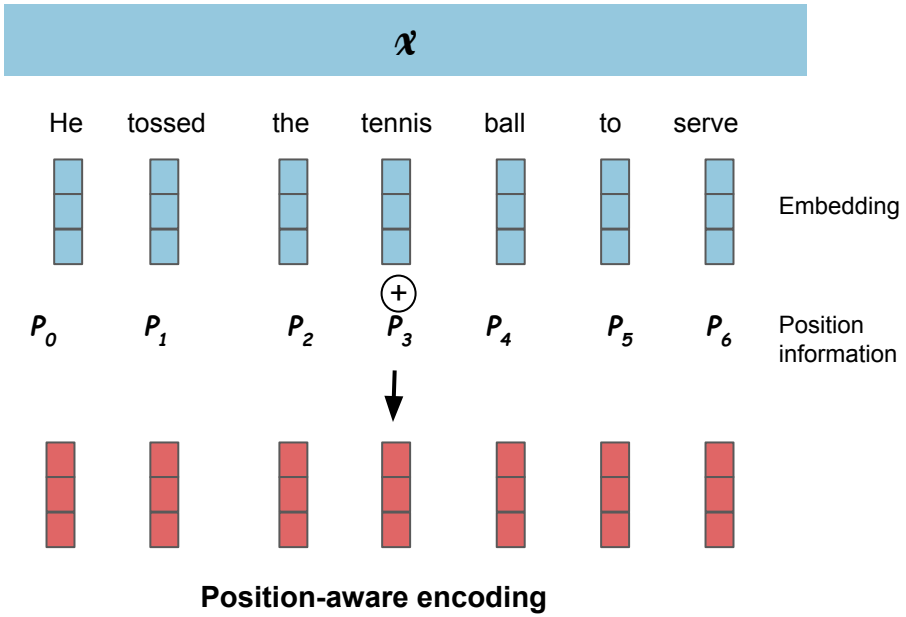
2. Extract values based on attention: Return the values with highest attention

Self-Attention

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input

1. Encode **position** information



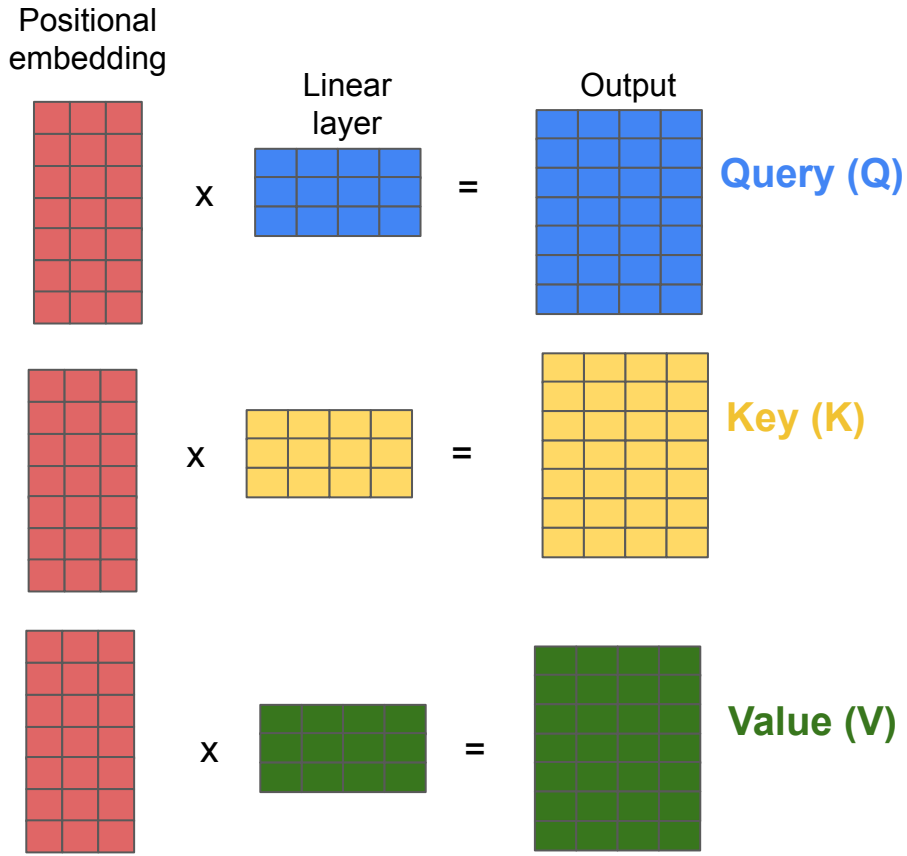
Data is fed in *all at once*! Need to encode position information to understand **order**

Self-Attention

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input

1. Enode **position** information
2. Extract **query, key, value** for search



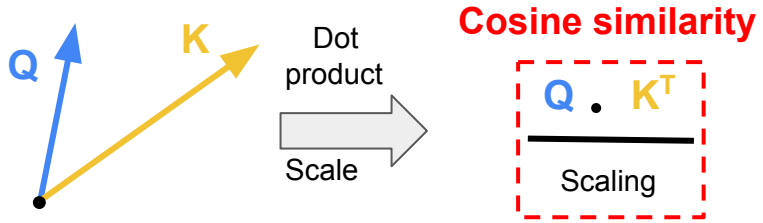
Self-Attention

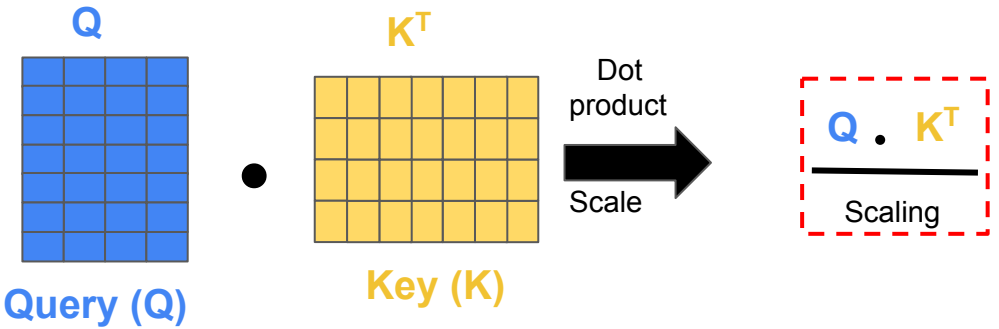
Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input

1. Enode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**

Attention score: compute pairwise similarity between each **Query (Q)** and **Key (K)**





Self-Attention

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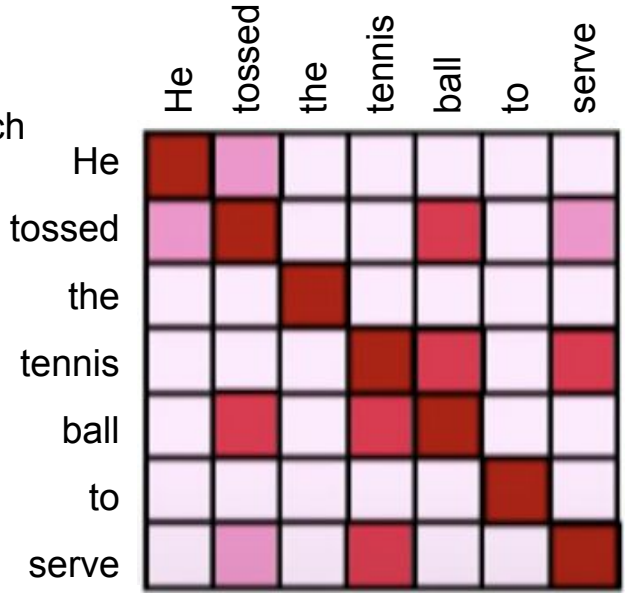
Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input

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

1. Enode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**



Attention weighting

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

Where in the input to self-attend

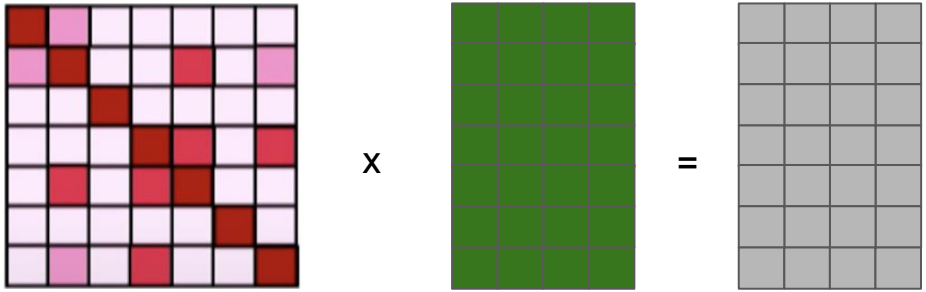
Self-Attention

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input

1. Enode **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



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

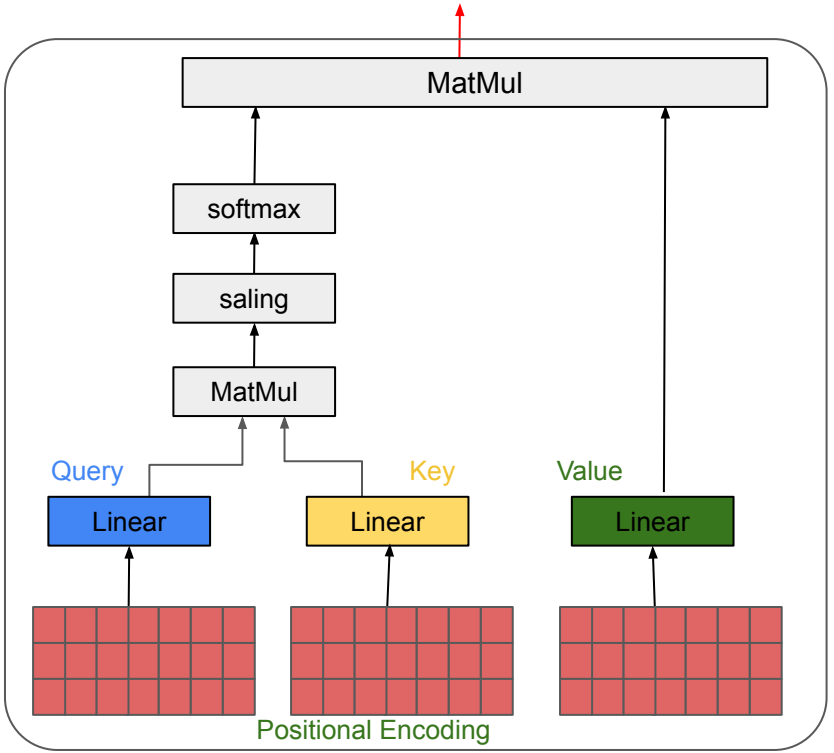
Self-Attention

Goal: identify and attend to most important features in input

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

$$softmax\left(\frac{Q \cdot K^T}{\text{Scaling}}\right) \cdot V$$

Self-Attention head that can plug into larger network
Each head attends to different parts of the input



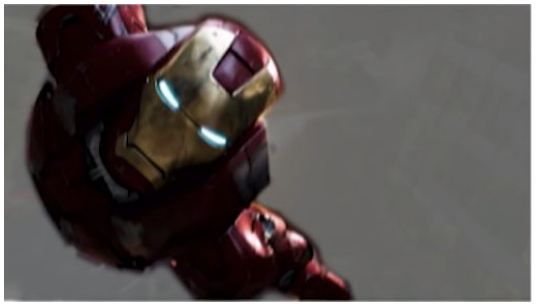
Applying Multiple Self-Attention Heads

Attention weighting

x

Value

=



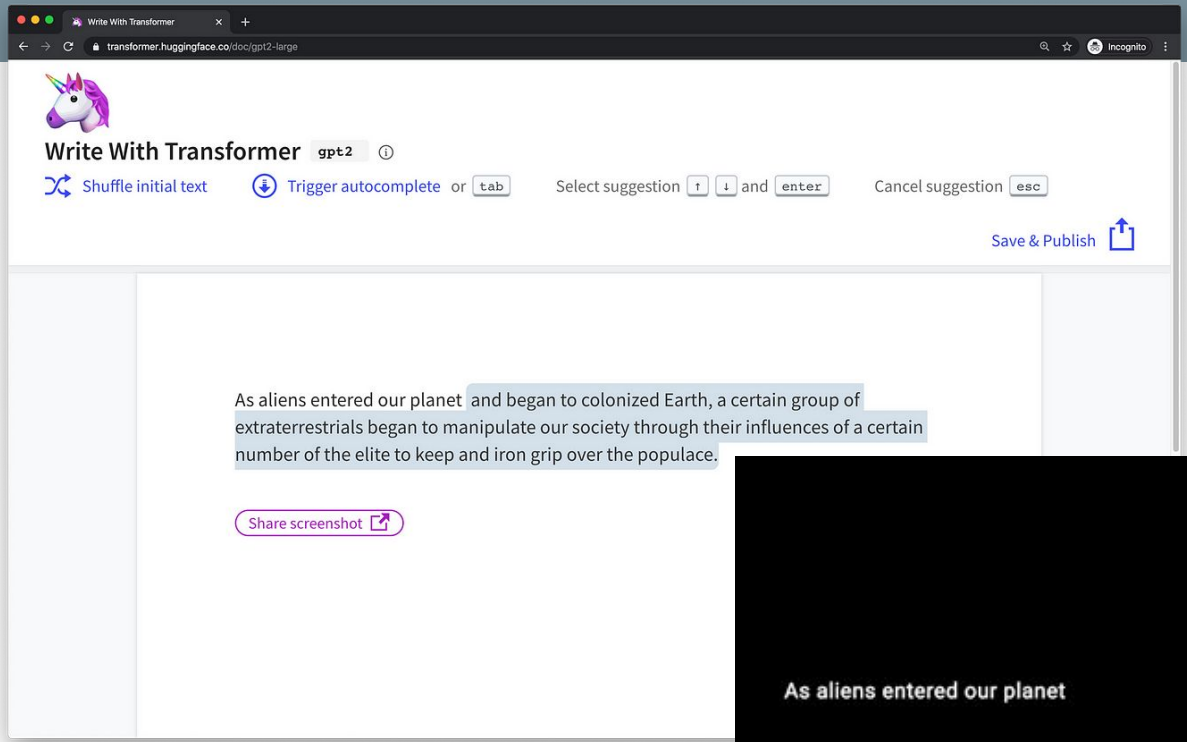
Output

Output of attention head 1

Output of attention head 2

Output of attention head 3

Self-Attention

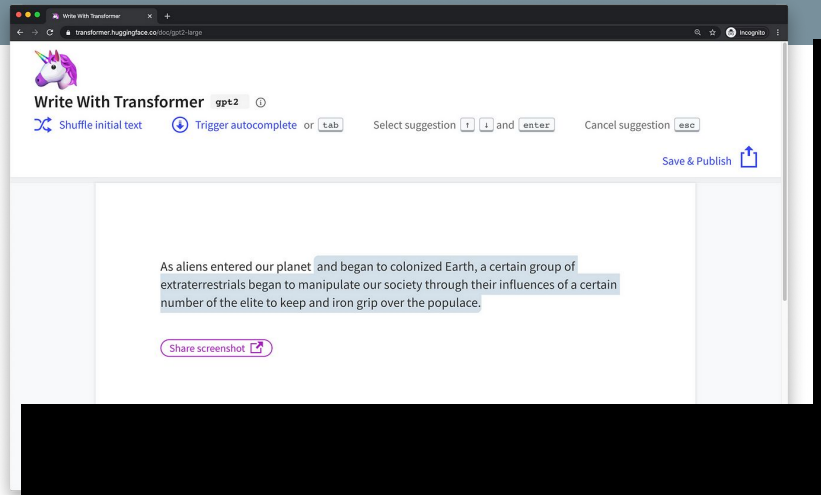


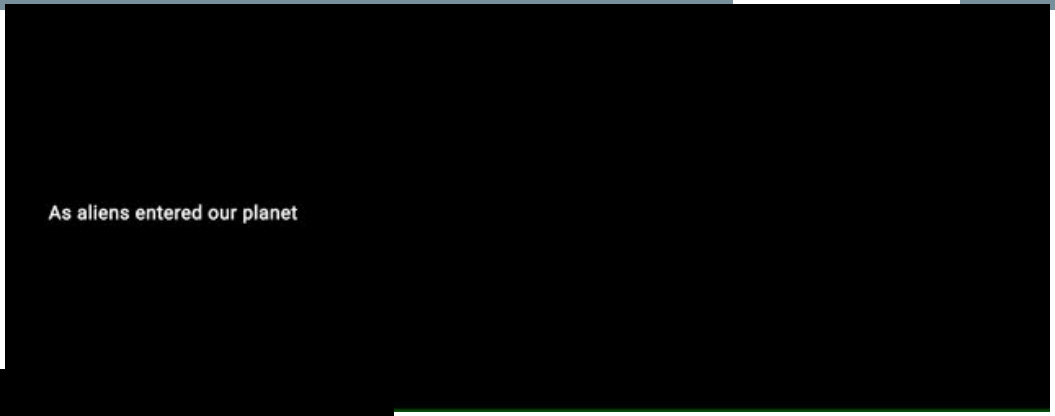
Our input: *"As Aliens entered our planet".*

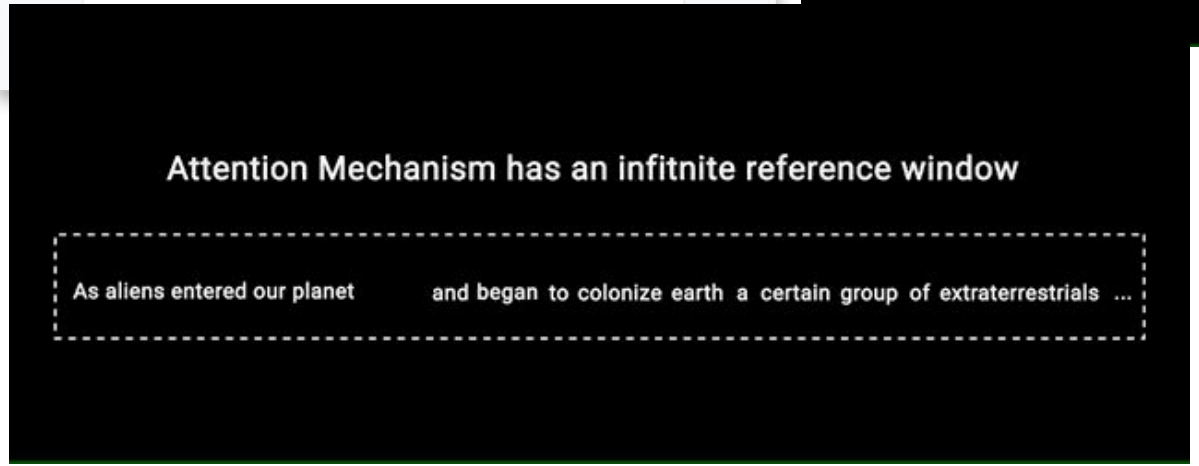
The ability to reference/ attend to parts of the input relevant to the generated word.

https://transformer.huggingface.co/

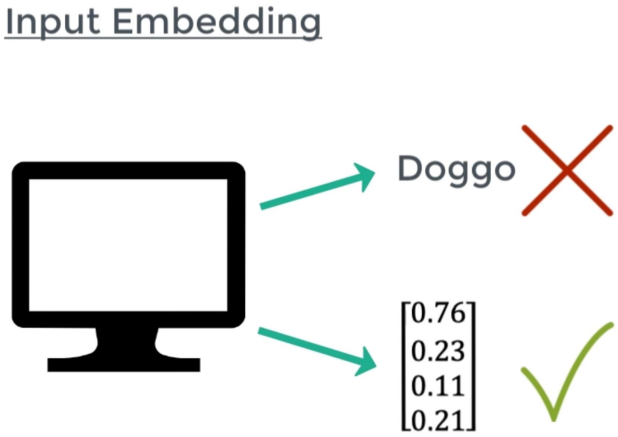
Self-Attention

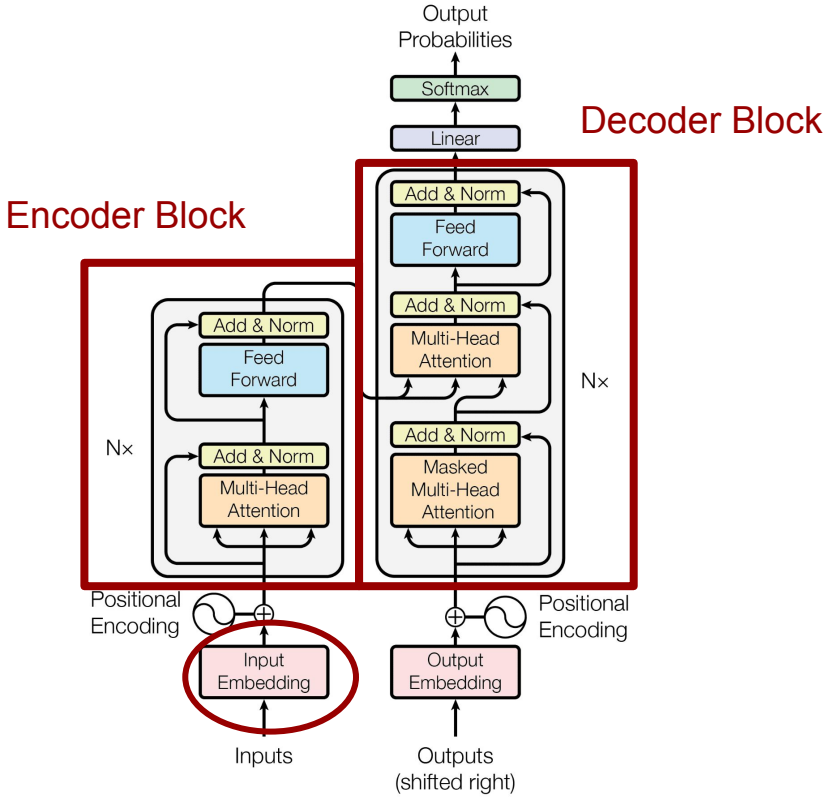




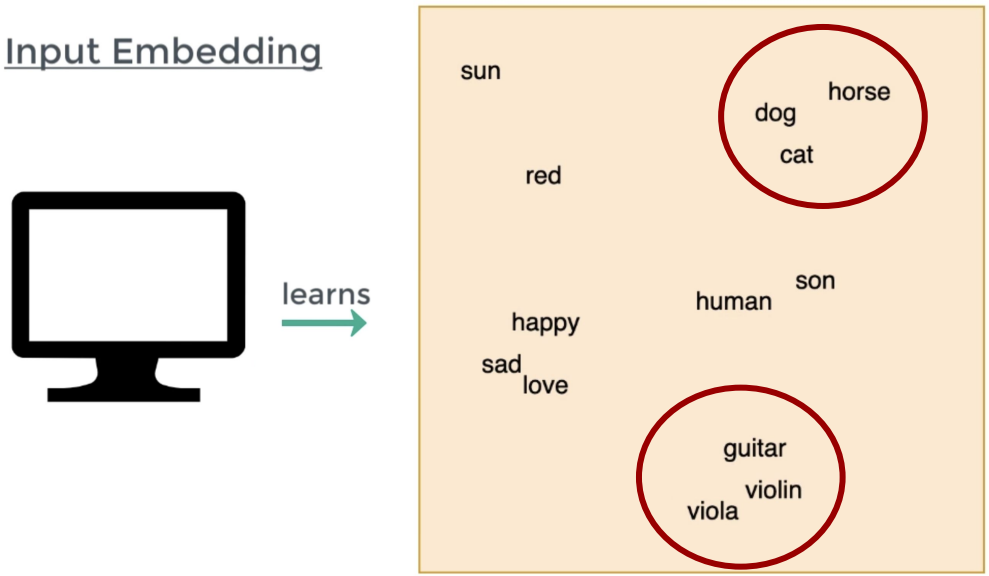


Transformers components





Transformers components



Embedding Space

Transformers components

dog → learns →

Embedding Space

→ $\begin{bmatrix} 0.37 \\ 0.99 \\ 0.01 \\ 0.08 \end{bmatrix}$

AJ's dog is a cutie

AJ looks like a dog

The same word may have different meaning in different sentences

Transformers components

Positional Encoder :vector that gives context based on position of word in sentence

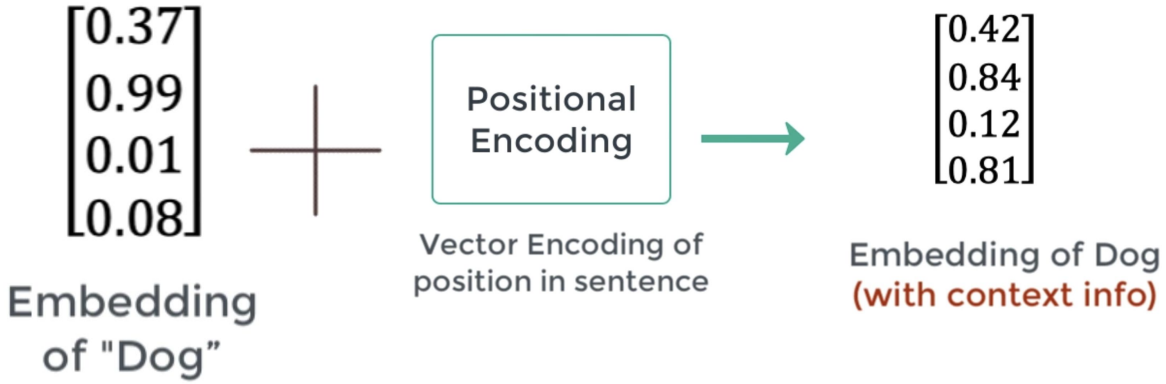
AJ's dog is a cutie → Position 2

AJ looks like a dog → Position 5

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{model}})$$

Transformers components



$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{model}})$$

Transformers components

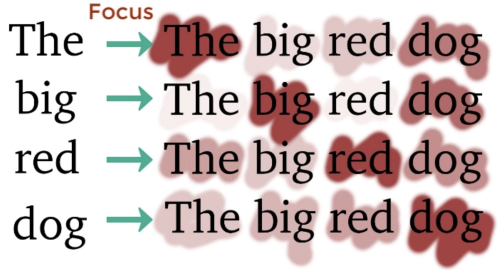
Attention Vectors

$[0.71 \quad 0.04 \quad 0.07 \quad 0.18]^T$

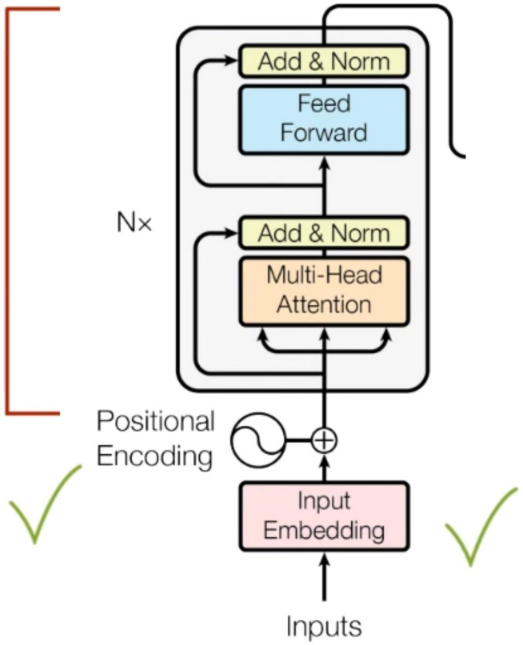
$[0.01 \quad 0.84 \quad 0.02 \quad 0.13]^T$

$[0.09 \quad 0.05 \quad 0.62 \quad 0.24]^T$

$[0.03 \quad 0.03 \quad 0.03 \quad 0.91]^T$



Encoder Block



Transformers components

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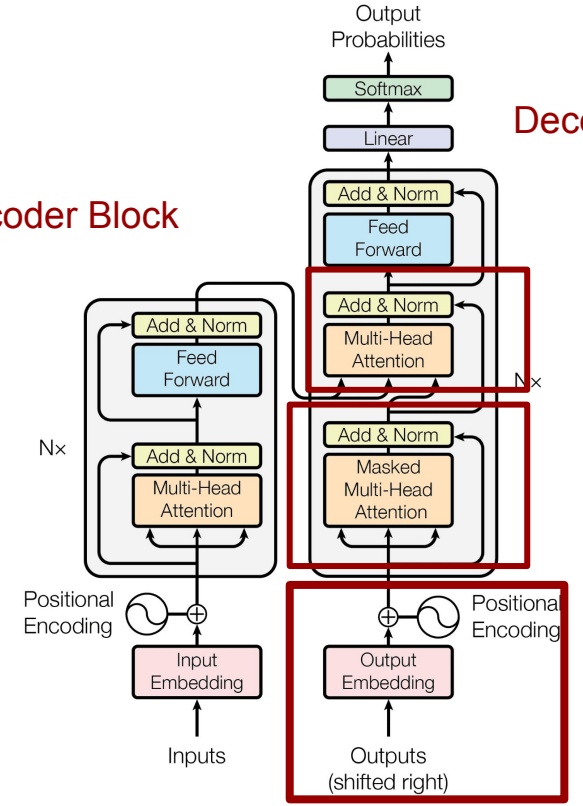
Attention Vectors

$$[0.71 \quad 0.04 \quad 0.07 \quad 0.18]^T$$
$$[0.01 \quad 0.84 \quad 0.02 \quad 0.13]^T$$
$$[0.09 \quad 0.05 \quad 0.62 \quad 0.24]^T$$
$$[0.03 \quad 0.03 \quad 0.03 \quad 0.91]^T$$

Focus

The → The big red dog
big → The big red dog
red → The big red dog
dog → The big red dog

Encoder Block



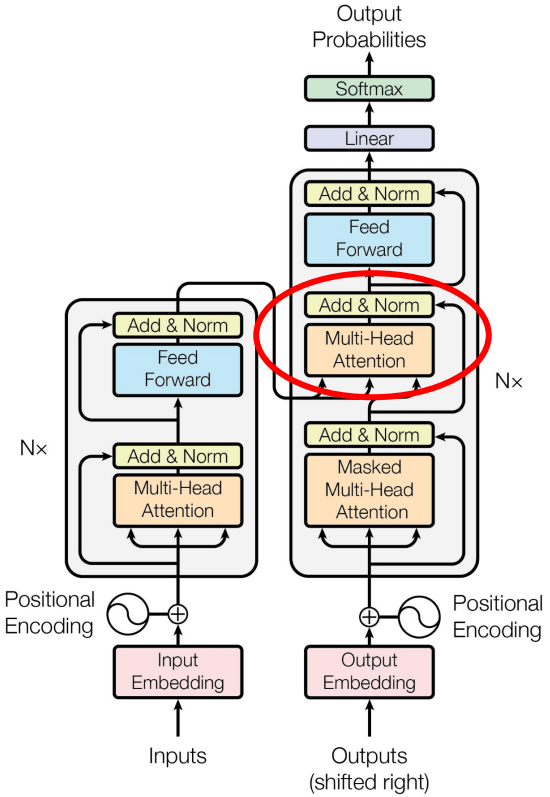
Decoder Block

$$\begin{bmatrix} 1 & 0.1 & 0.05 & 0.16 \\ 0 & 0.9 & 0.40 & 0.09 \\ 0 & 0 & 0.55 & 0.15 \\ 0 & 0 & 0 & 0.66 \end{bmatrix}$$

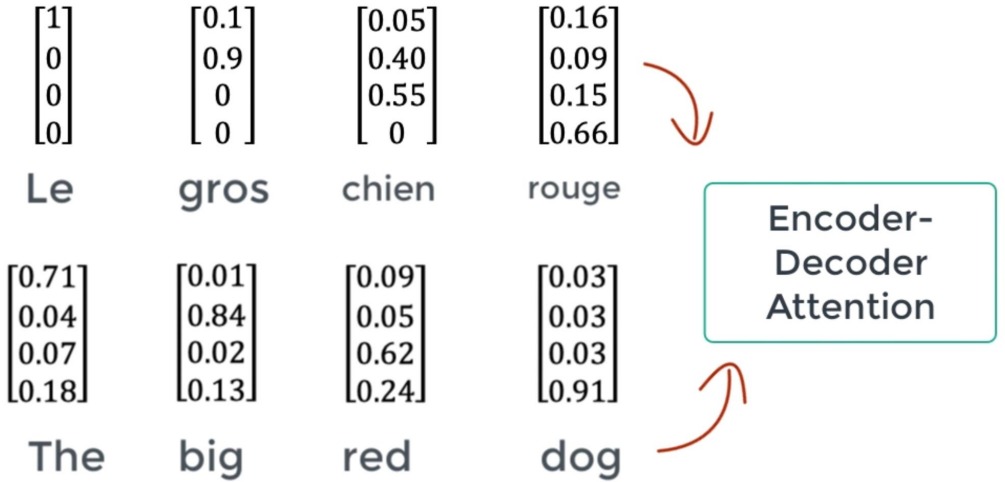
Self Attention

Le → Le gros chien rouge
gros → Le gros chien rouge
chien → Le gros chien rouge
rouge → Le gros chien rouge

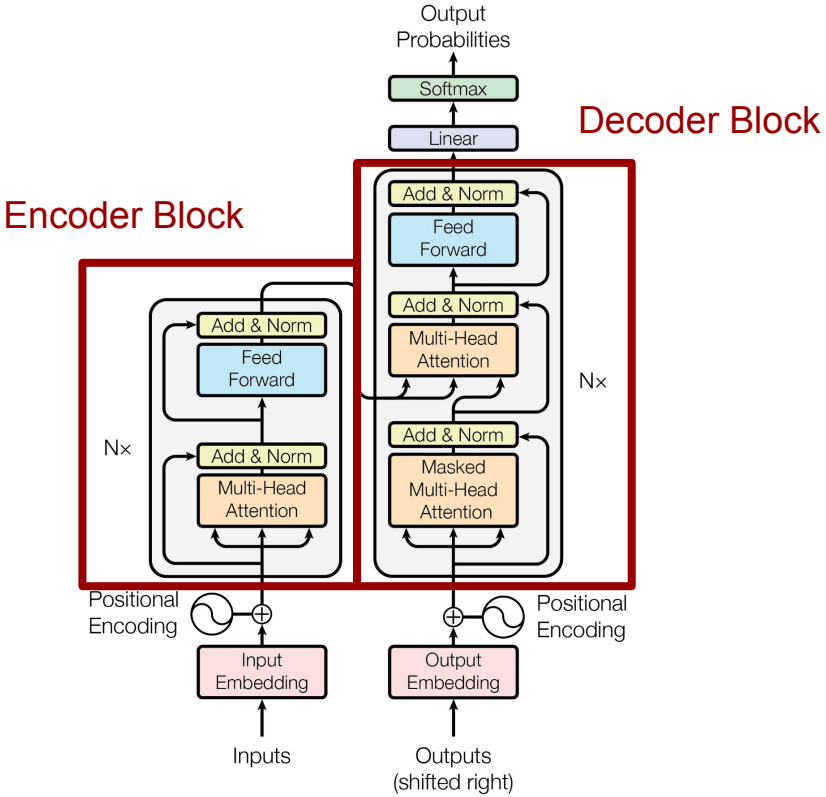
Transformers components



Encapsulates **English-French** interaction



Transformers components



Transformers applications

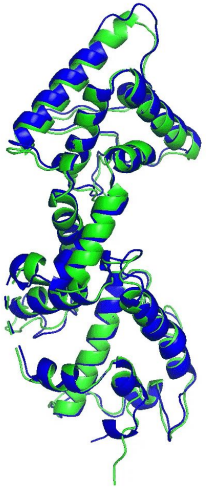
Beyond
Language processing:
Text-to-image

"An armchair in the shape of avocado"

BERT, GPT-3 DALL.E

Biological Sequence

AlphaFold2

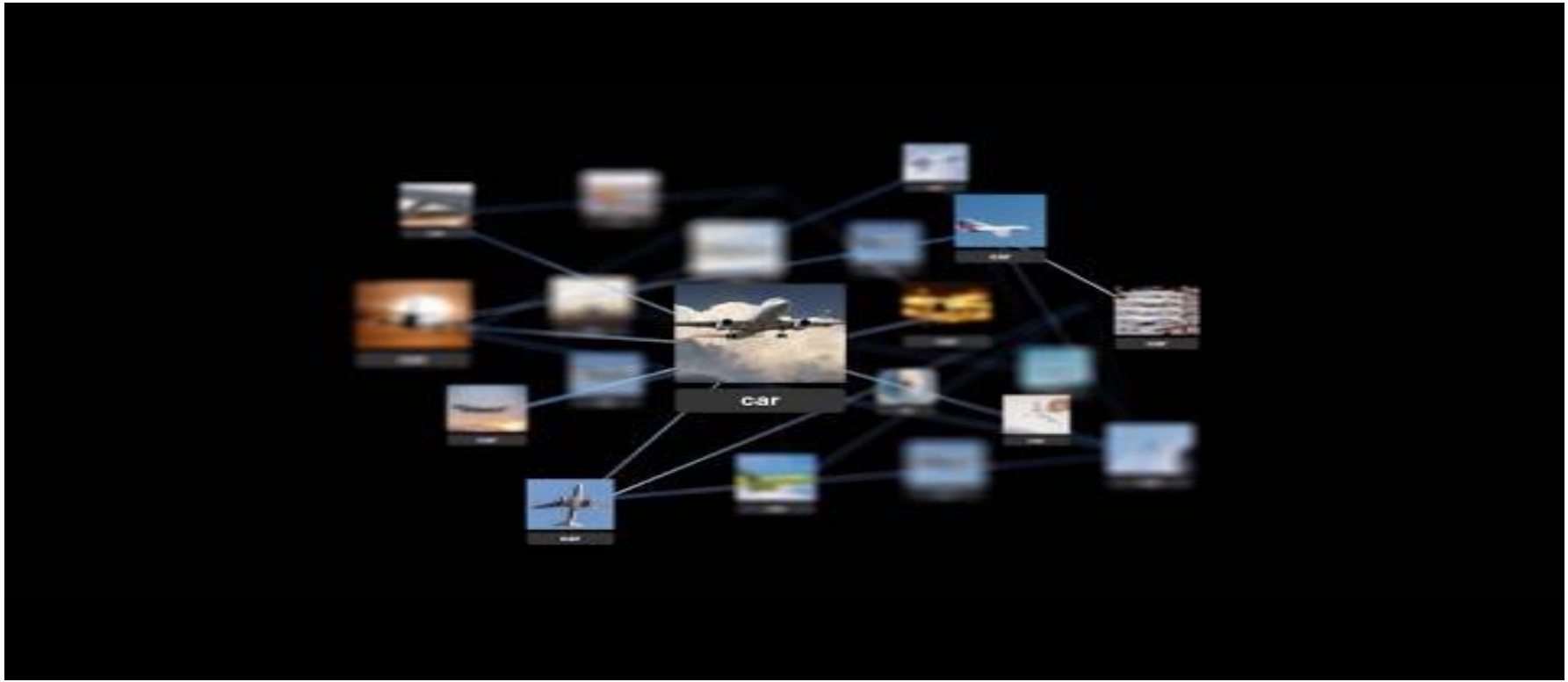


Protein structure
predictions

Image segmentation

Vision Transformers

Sequence Modeling



Sequence Modeling

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LSTM is dead. Long Live Transformers!

- **Multi-Headed Attention:** fully parallelizable
- **Positional encoding:** preserve sequential information

🤗 Hugging Face's Transformers

- Both PyTorch and Tensorflow implementations
- Pre-trained models
- Easy to fine-tune

Further resources:

- The Illustrated Transformer
- The Illustrated Retrieval Transformer