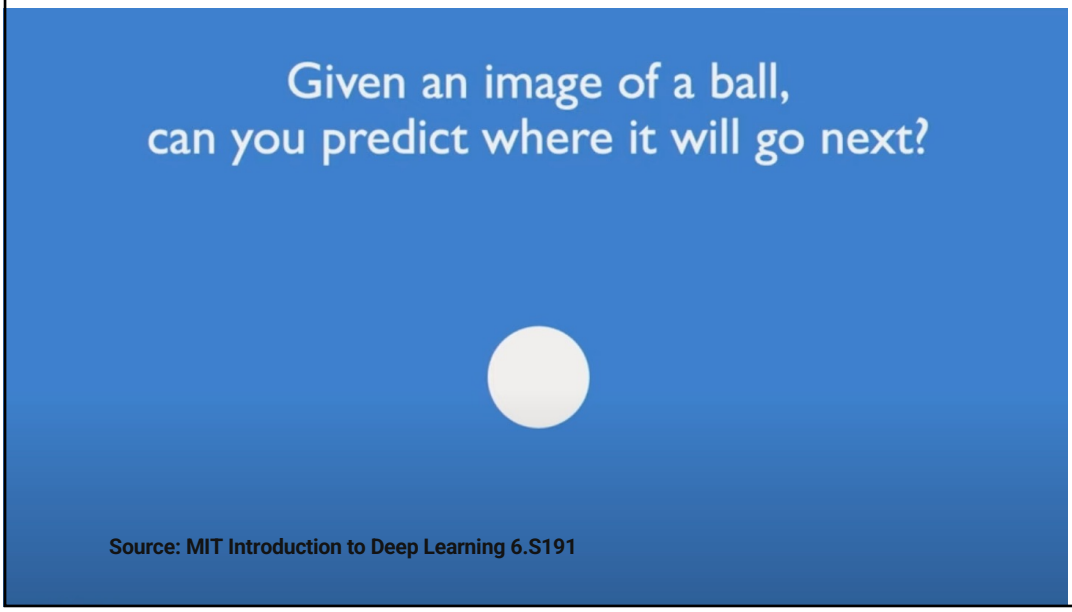
1

Outline

- Recurrent Neural Networks (RNNs)
  - Motivation, basic concepts, examples
- LSTM & GRU
- Transformer
  - Example applications

2

Sequences & Sequence modelling



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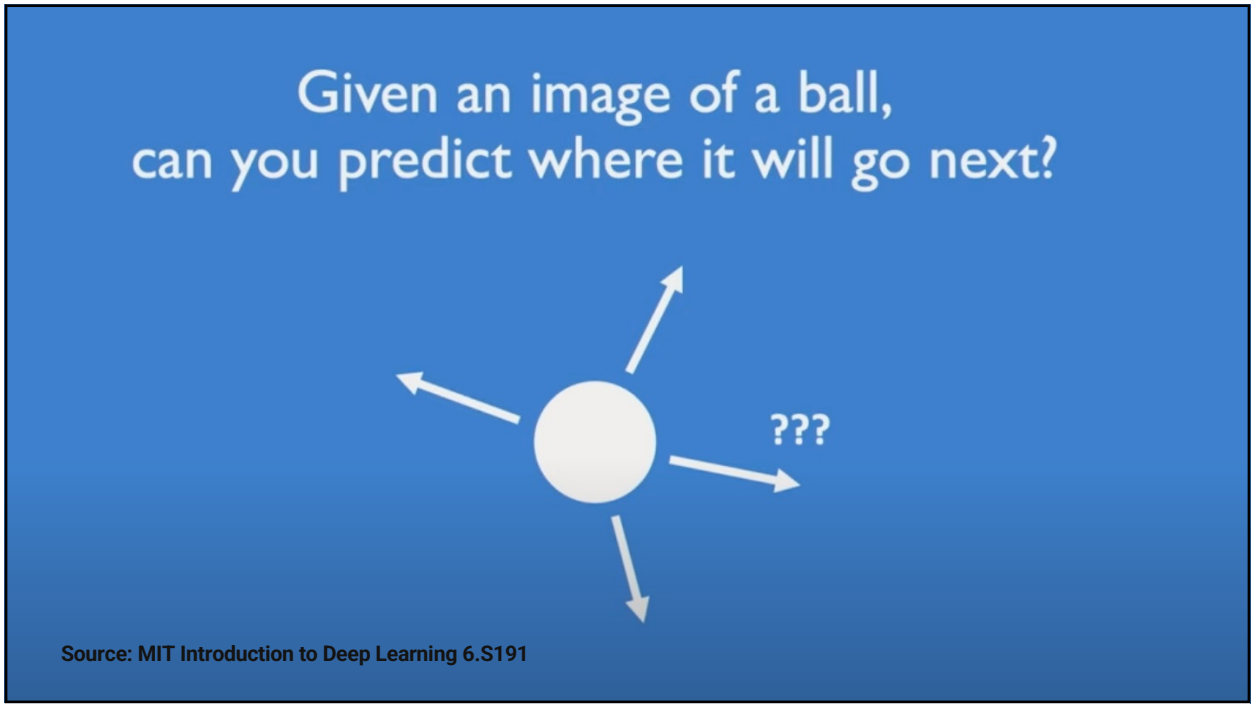
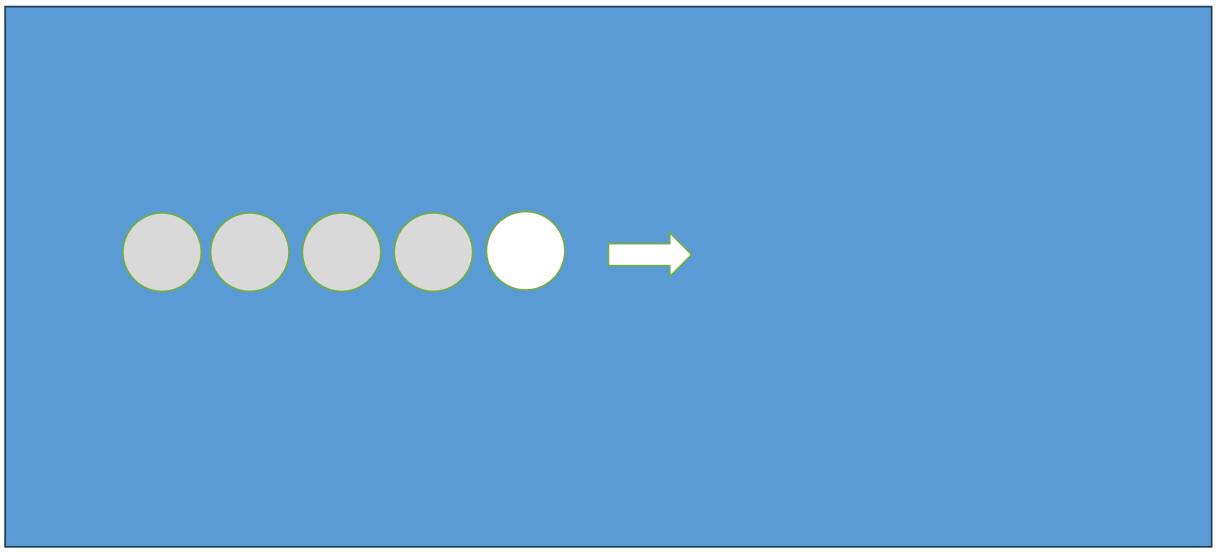


4

Now, given a history of the ball's positions



Source: MIT Introduction to Deep Learning 6.S191

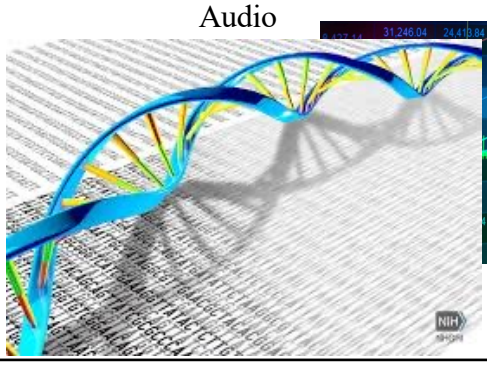
5

Sequences & Sequence modelling

Audio

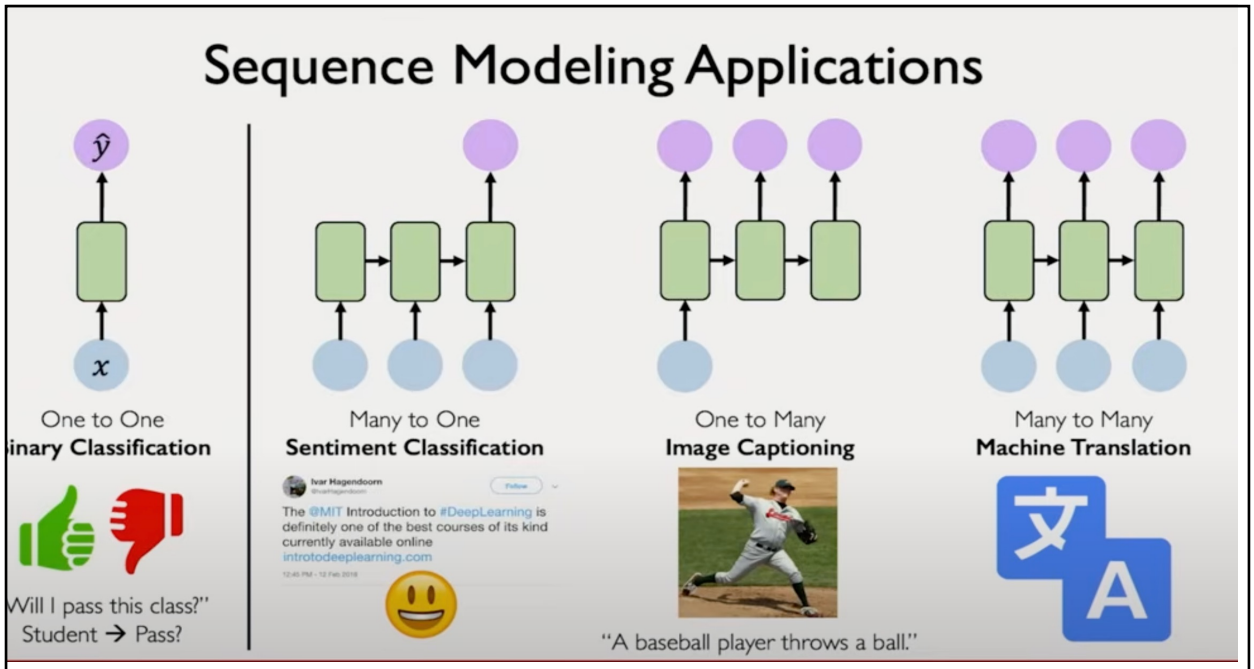
> Theo had been staring at the same sentence so long the letters bled together.
>
> (*A Doorway on Lenox* by Ovett Chapman)

Text



Video

6



Source: MIT Introduction to Deep Learning 6.S191

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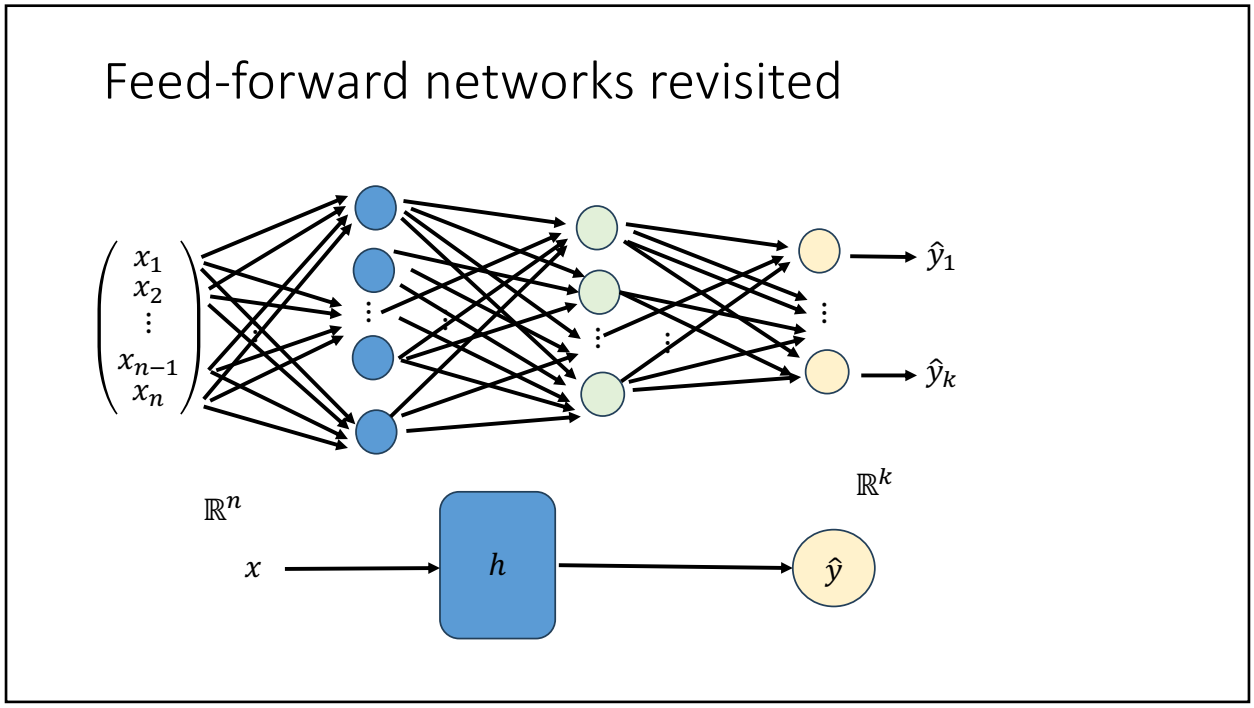
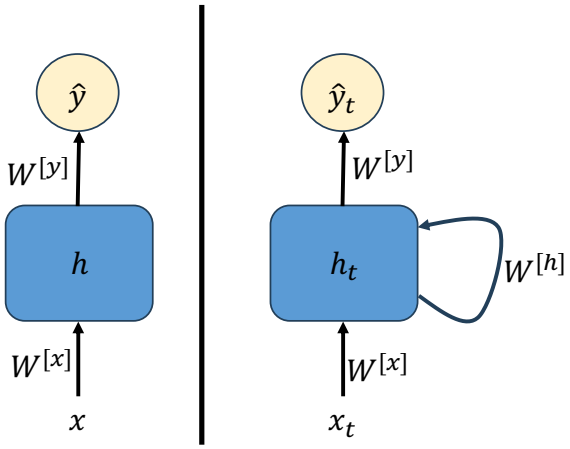


8

Extending traditional FF networks to deal with sequences



$$h_t = G^{[h]}(W^{[x]}.\, x_t + W^{[h]}.\, h_{t-1})$$

h_0 (the initial hidden state) is typically determined by initializing it to a zero vector.

x_t is the t^{th} element of the sequence (aka. the input at time step t)

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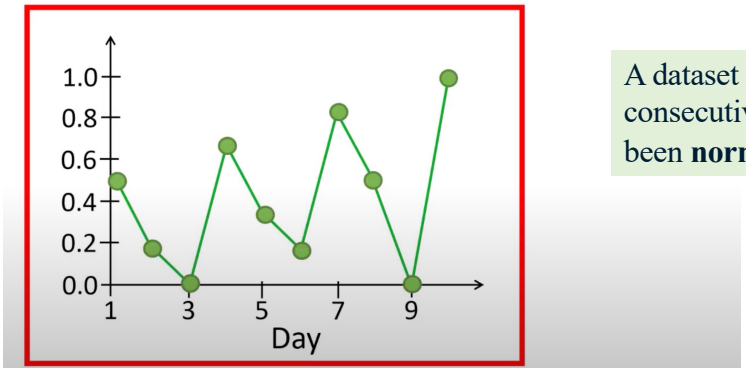
Intuition of RNNs

	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
X	0.5	0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0



A dataset for stock prices (for 10 consecutive business days) that have been **normalized** into the [0,1] range.

Source: YouTube TileStats

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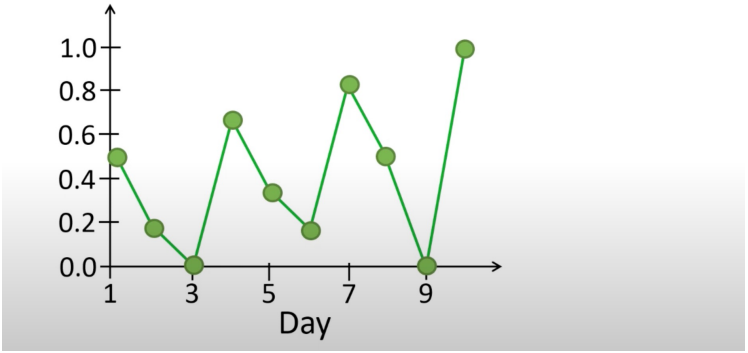
Intuition of RNNs

	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
X	0.5	0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0



Source: YouTube TileStats

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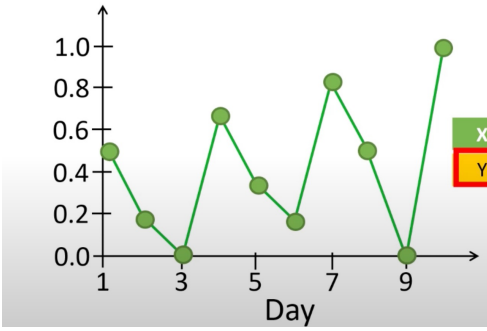
Intuition of RNNs

	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
X	0.5	0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0
Y		0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0



X	0.5	0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0
Y	0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0	

Source: YouTube TileStats

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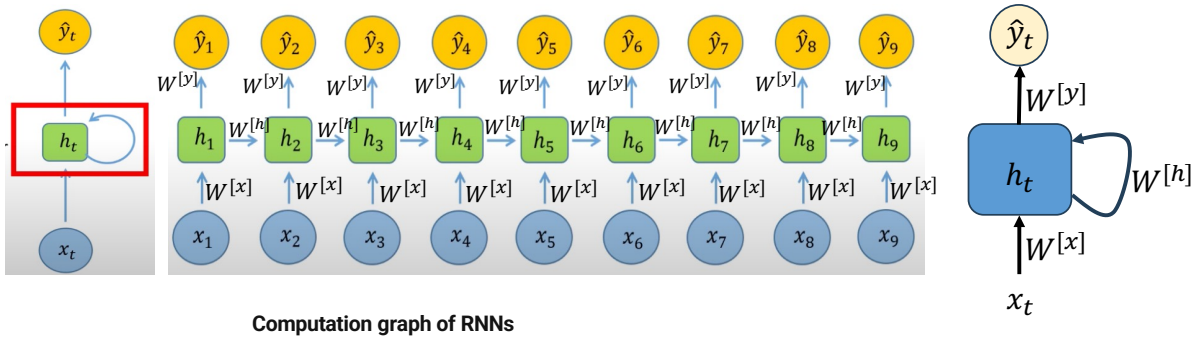
Intuition of RNNs

X	0.5	0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0
Y	0.17	0.0	0.67	0.33	0.17	0.83	0.5	0.0	1.0	



Computation graph of RNNs

Source: YouTube TileStats

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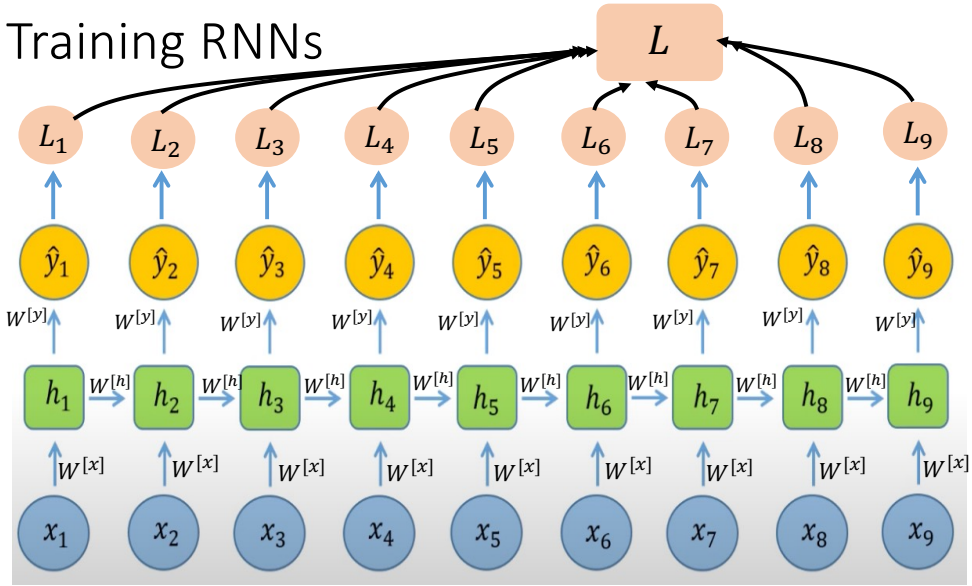
Training RNNs



Computation graph of RNNs

forward pass

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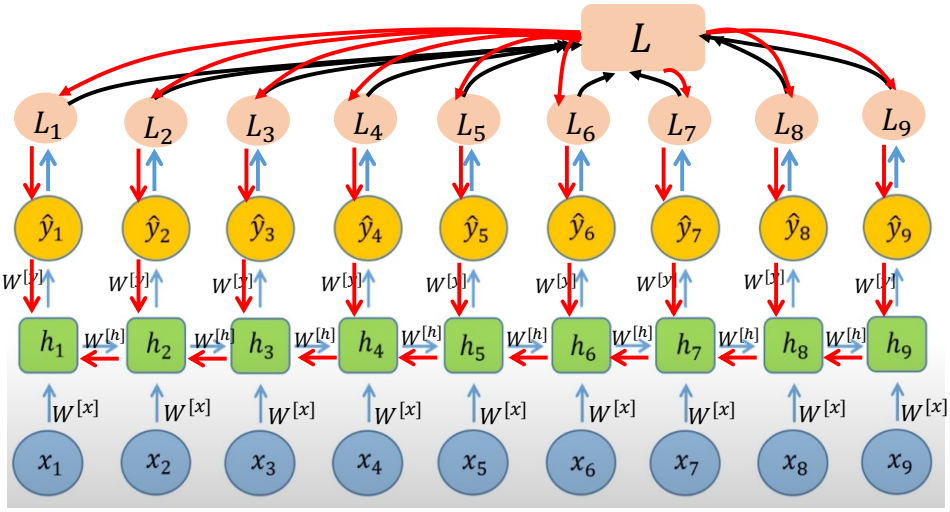
RNNs: Backpropagation through Time (BPTT)



Computation graph of RNNs

forward pass
backward pass

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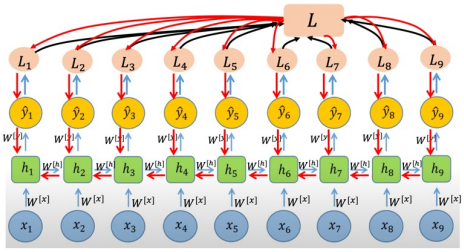
RNNs: Backpropagation through Time (BPTT)

The loss function:

$$L = \frac{1}{T}\sum_{t=1}^{T} L_t = \frac{1}{T}\sum_{t=1}^{T} loss(y_t, \hat{y}_t)$$



We'll show the hardest derivative:

$$\frac{\partial L}{\partial W^{[h]}} = \frac{1}{T}\sum_{t=1}^{T} \frac{\partial loss(y_t,\hat{y}_t)}{\partial W^{[h]}} = \frac{1}{T}\sum_{t=1}^{T} \frac{\partial loss(y_t,\hat{y}_t)}{\partial \hat{y}_t} \cdot \frac{\partial \hat{y}_t}{\partial h_t} \cdot \frac{\partial h_t}{\partial W^{[h]}}$$

The thi… ute the effect o… $_{t-1}))$

Very long recursive calculations of $\frac{\partial h_t}{\partial W^{[h]}}$ for all $t = 1, .., T$

$$\frac{\partial h_t}{\partial W^{[h]}} = \frac{\partial f(W^{[h]}, W^{[x]}, x_t, h_{t-1})}{\partial W^{[h]}} + \frac{\partial f(W^{[h]}, W^{[x]}, x_t, h_{t-1})}{\partial h_{t-1}} \cdot \frac{\partial h_{t-1}}{\partial W^{[h]}}$$

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RNNs: Issues and Challenges

- Intensive computation (esp. for long sequences)
  - Truncation: Approximating the computation of $\frac{\partial h_t}{\partial W^{[h]}}$ by going back only τ steps.
- Numerical instability:
  - High powers of matrices can lead to divergent or vanishing eigenvalues.

  → exploding or vanishing gradients

Many values > 1:
Exploding gradients
→ Gradient clipping

Many values < 1:
Vanishing gradients
- Activation function
- Parameter initialization
- Network architecture

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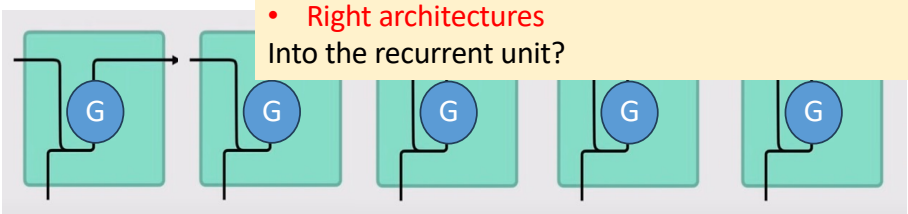
RNNs: Limitations

- Encoding bottleneck (not all data are numerical, e.g., text, audio, video, etc.)
- Slow computation (due to no parallelization)
- No long memory

Question: Can we overcome (some of) these limitations by introducing the:
- Right activation functions
- Right architectures

Into the recurrent unit?



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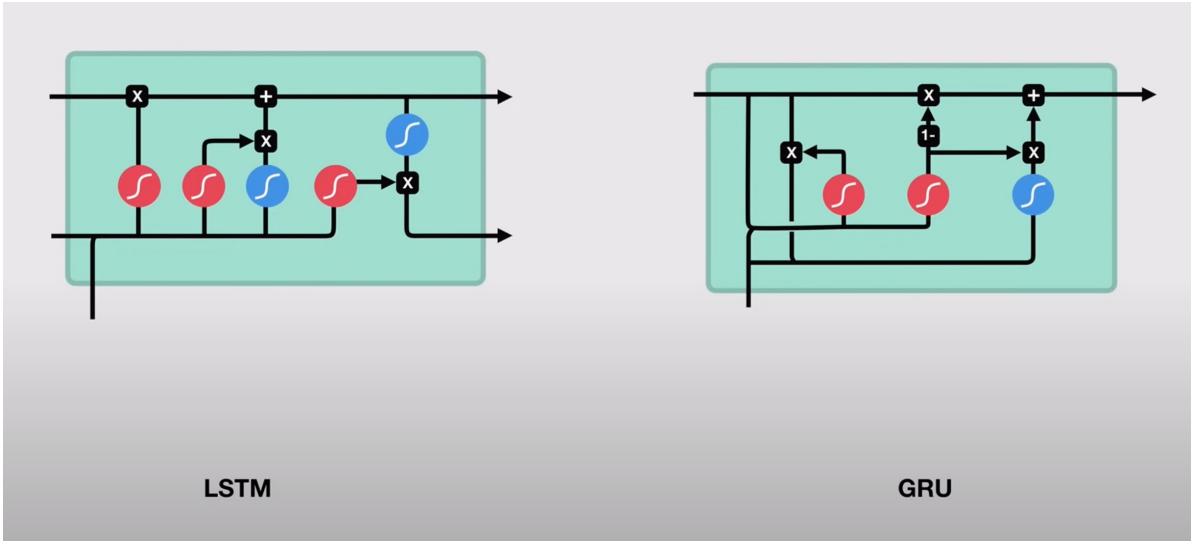
LSTM & GRU



Source: YouTube The AI Hacker

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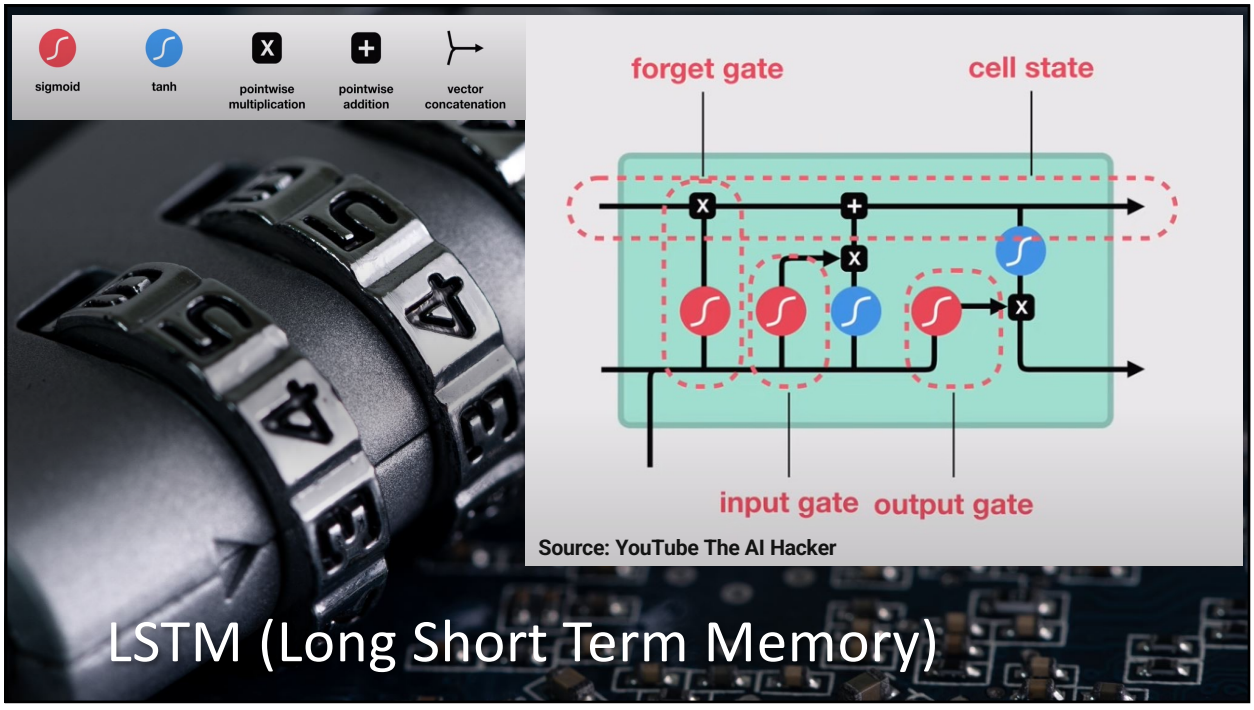

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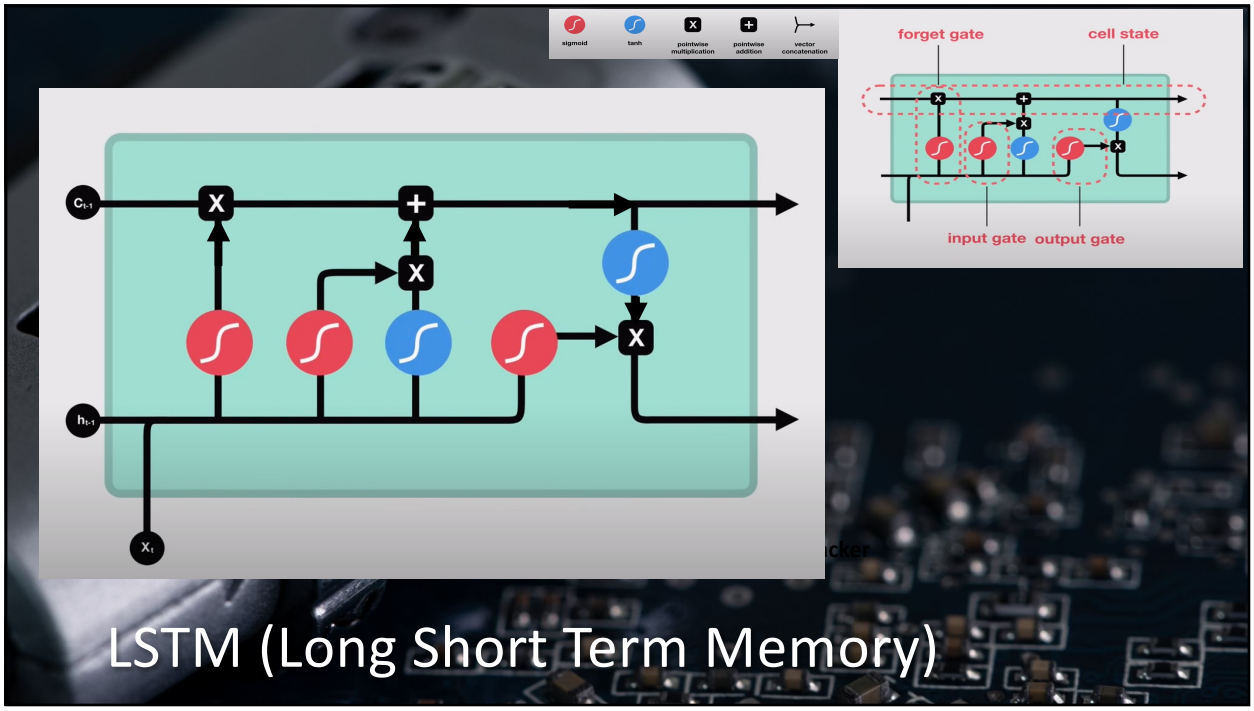
sigmoid
tanh
pointwise multiplication
pointwise addition
vector concatenation
forget gate
cell state
input gate
output gate
LSTM (Long Short Term Memory)

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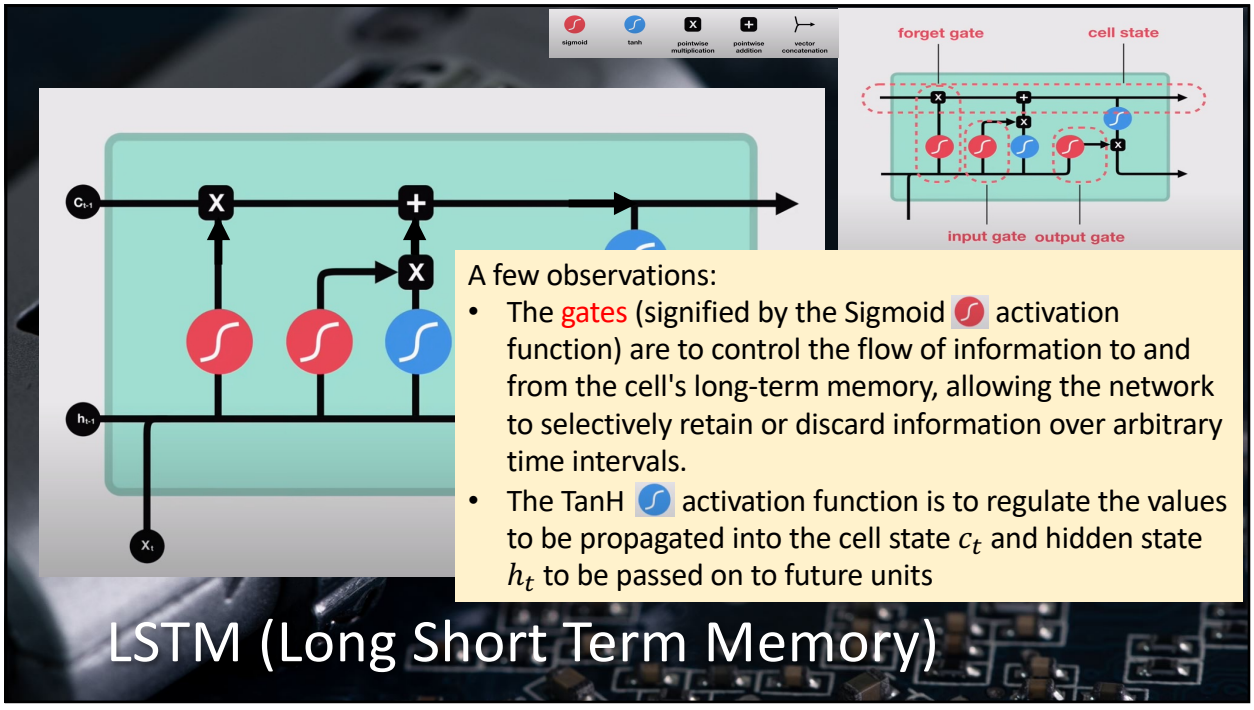
sigmoid
tanh
pointwise multiplication
pointwise addition
vector concatenation
forget gate
cell state
input gate
output gate
A few observations:
• The gates (signified by the Sigmoid activation function) are to control the flow of information to and from the cell's long-term memory, allowing the network to selectively retain or discard information over arbitrary time intervals.
• The TanH activation function is to regulate the values to be propagated into the cell state c_t and hidden state h_t to be passed on to future units
LSTM (Long Short Term Memory)

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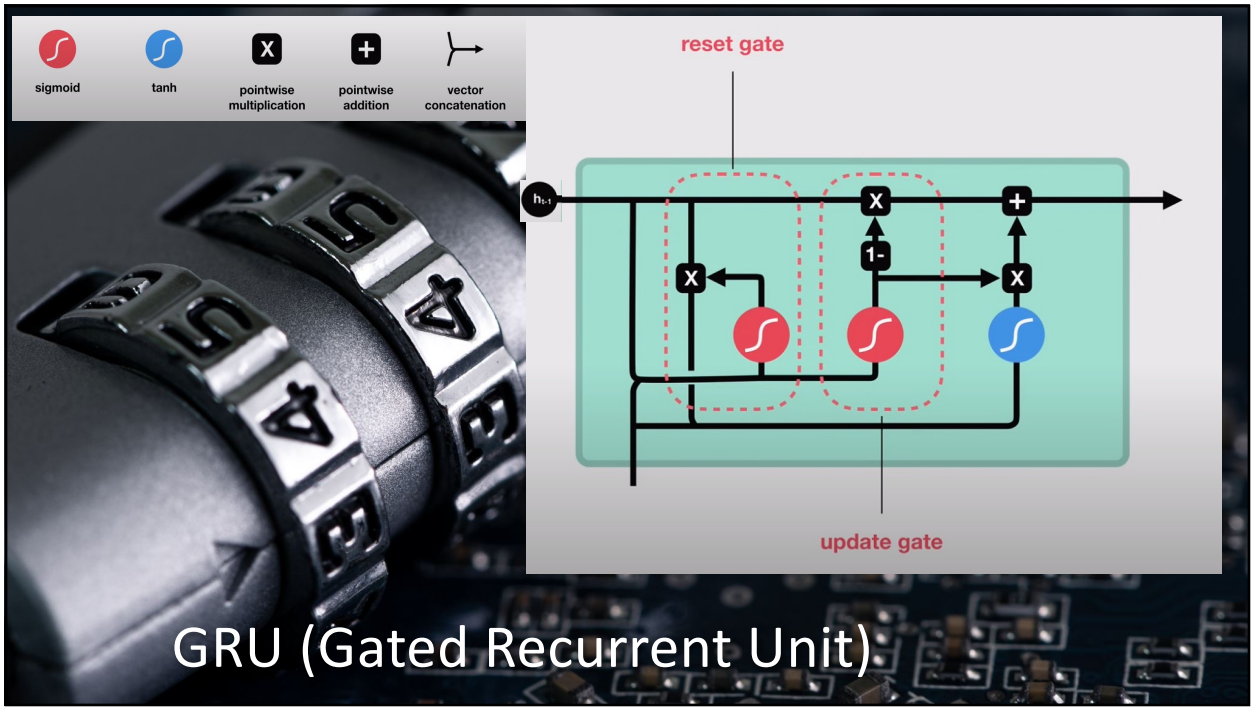
sigmoid
tanh
pointwise multiplication
pointwise addition
vector concatenation
reset gate
update gate
GRU (Gated Recurrent Unit)

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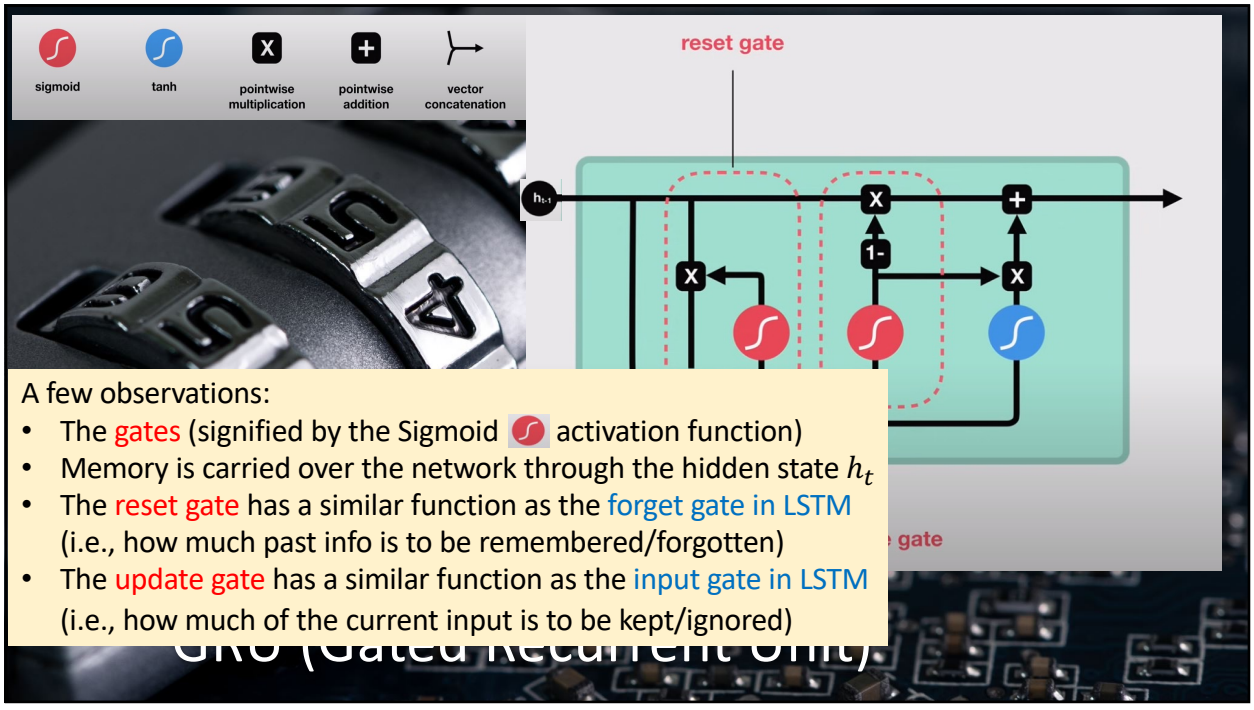
sigmoid
tanh
pointwise multiplication
pointwise addition
vector concatenation
reset gate
A few observations:
• The gates (signified by the Sigmoid activation function)
• Memory is carried over the network through the hidden state h_t
• The reset gate has a similar function as the forget gate in LSTM (i.e., how much past info is to be remembered/forgotten)
• The update gate has a similar function as the input gate in LSTM (i.e., how much of the current input is to be kept/ignored)

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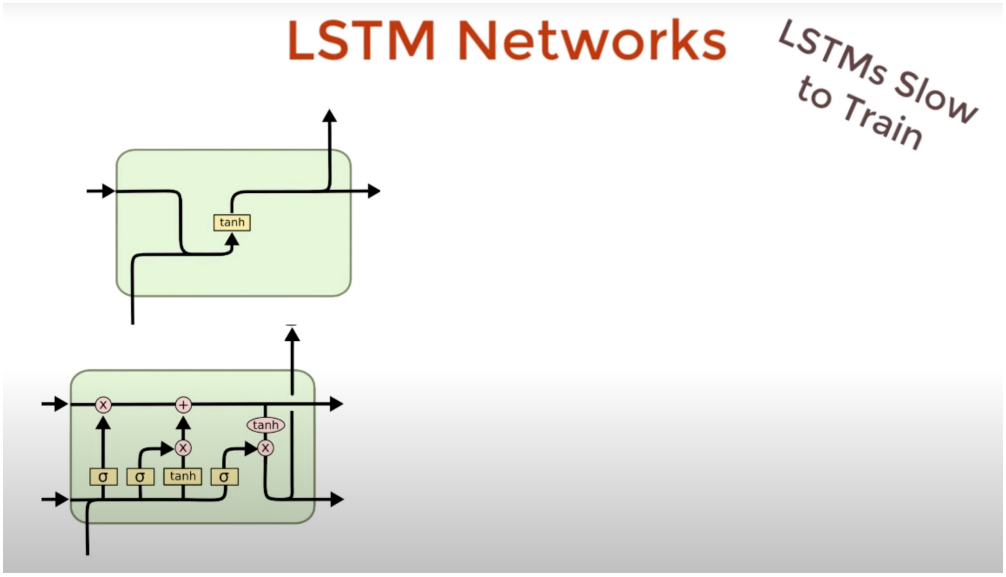
LSTM drawbacks

Source: YouTube CodeEmporium



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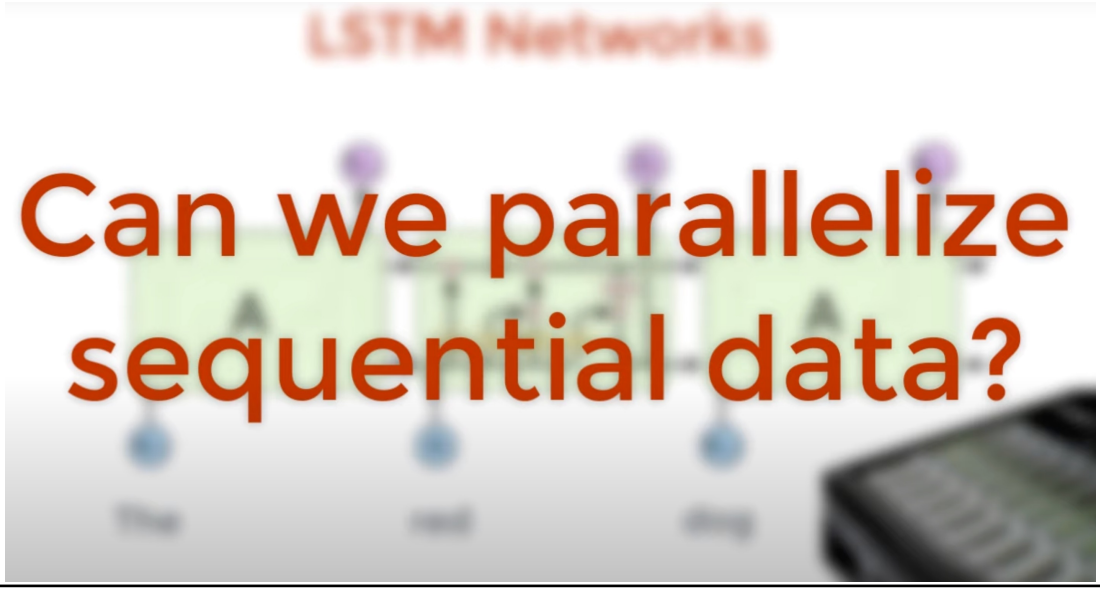
LSTM drawbacks

Source: YouTube CodeEmporium



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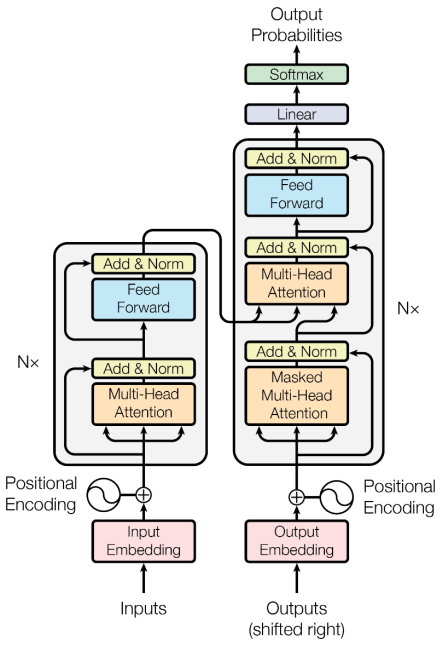

Enter the Transformer (Vaswani et al., 2017)

"Attention Is All You Need"

Figure 1: The Transformer - model architectu ء

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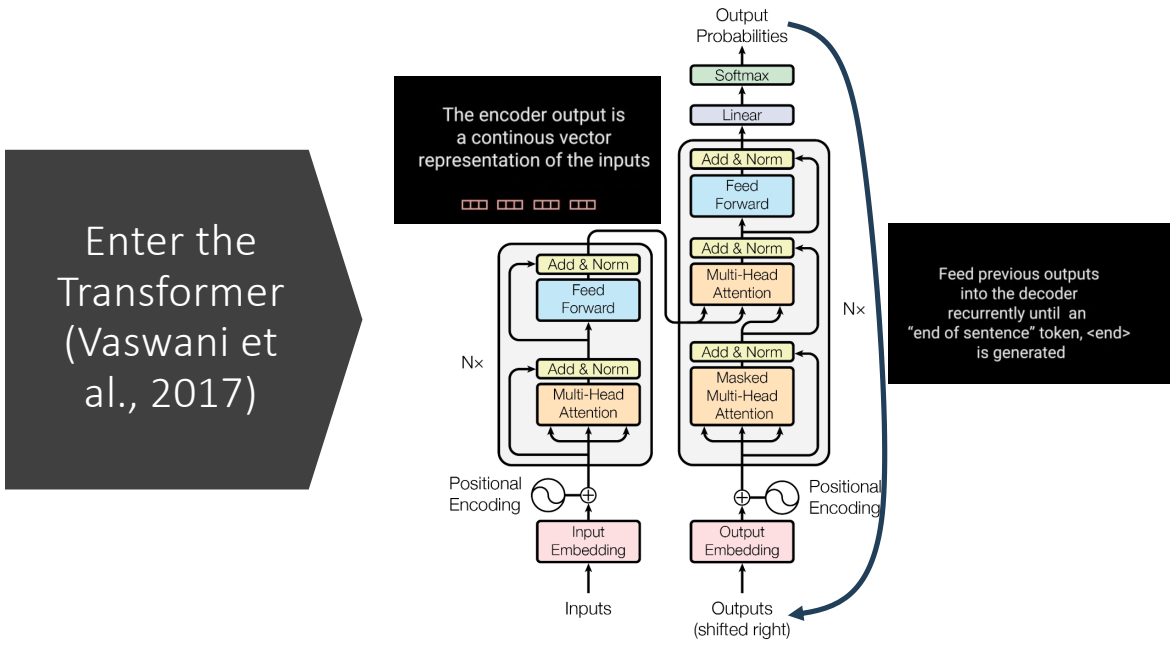

Figure 1: The Transformer - model architecture.

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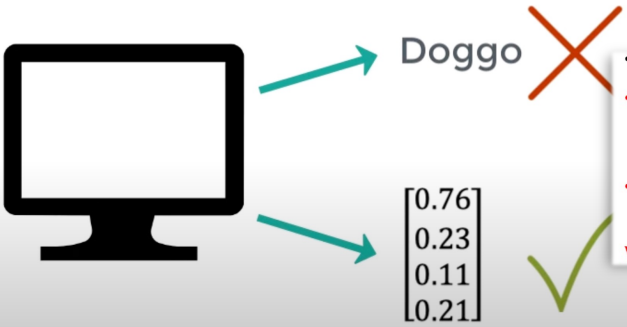
Transformer Components

Input Embedding

Remember our one-hot encoding in Week 5?



- Given a 10,000-word English dictionary (e.g., the top-10,000 English words seen in emails)
- The feature vector:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_{10,000} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = 1\{ \begin{bmatrix} a \\ aardvark \\ aardwolf \\ \vdots \\ zymurgy \end{bmatrix} \}$$

where 1{} is again the indicator function.

- (Very) high dimension
- Sparse matrix

Source: YouTube CodeEmporium

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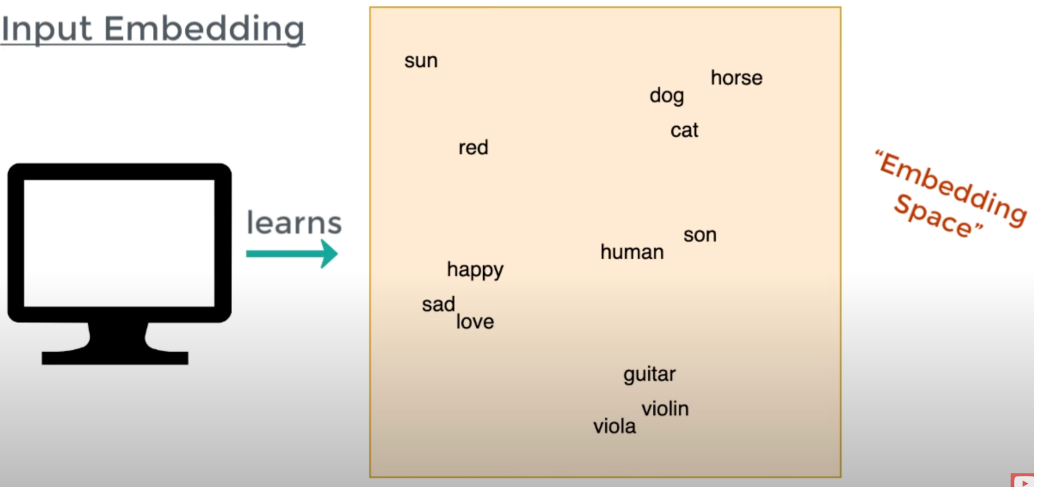
Transformer Components

Input Embedding



Source: YouTube CodeEmporium

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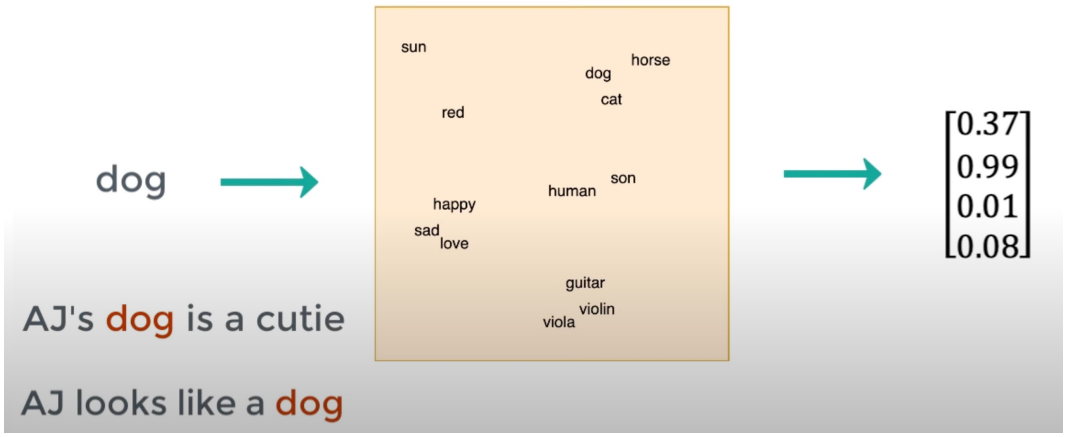
Transformer Components

Input Embedding



Source: YouTube CodeEmporium

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Transformer 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

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

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

Source: YouTube CodeEmporium

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Transformer Components

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

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

Source: YouTube CodeEmporium

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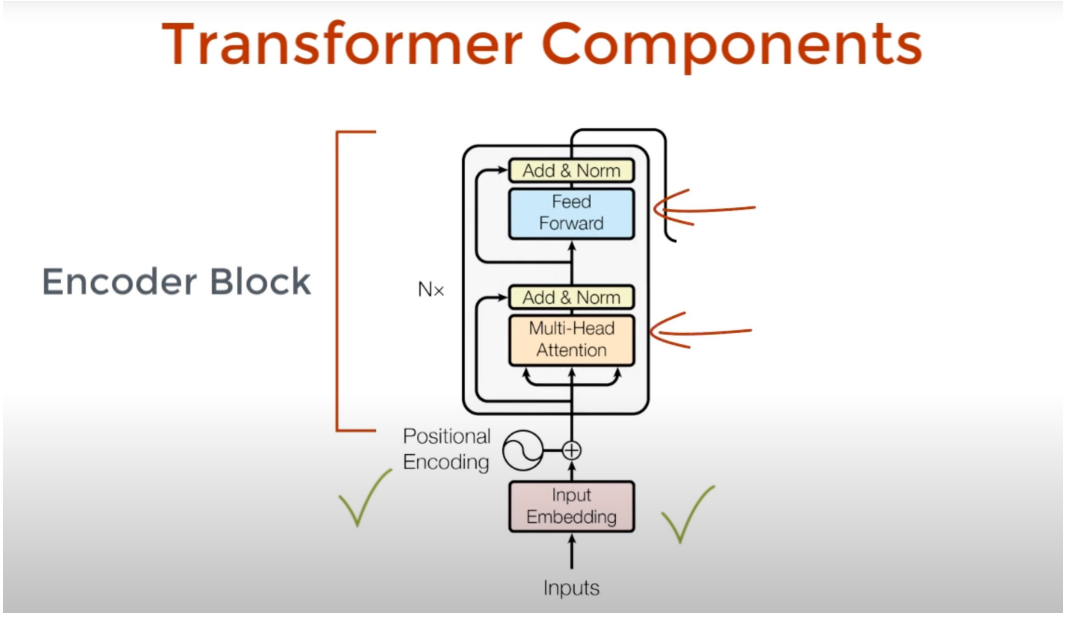
Transformer Components



Source: YouTube CodeEmporium

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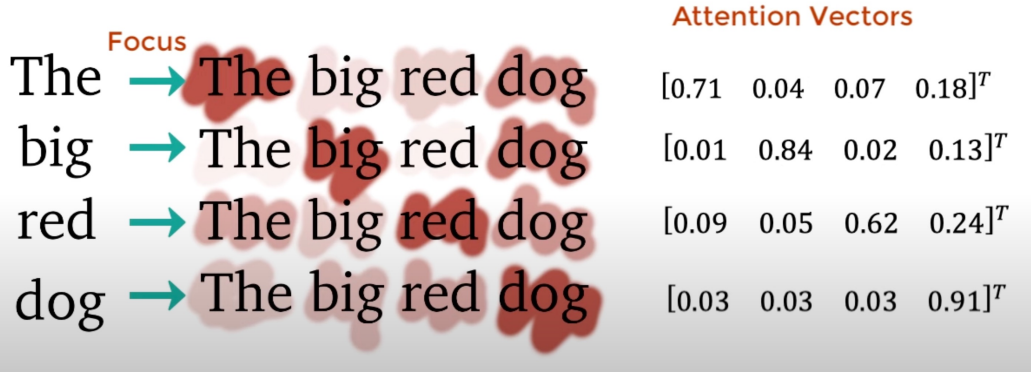
Transformer Components

Attention : What part of the input should we focus?



Source: YouTube CodeEmporium

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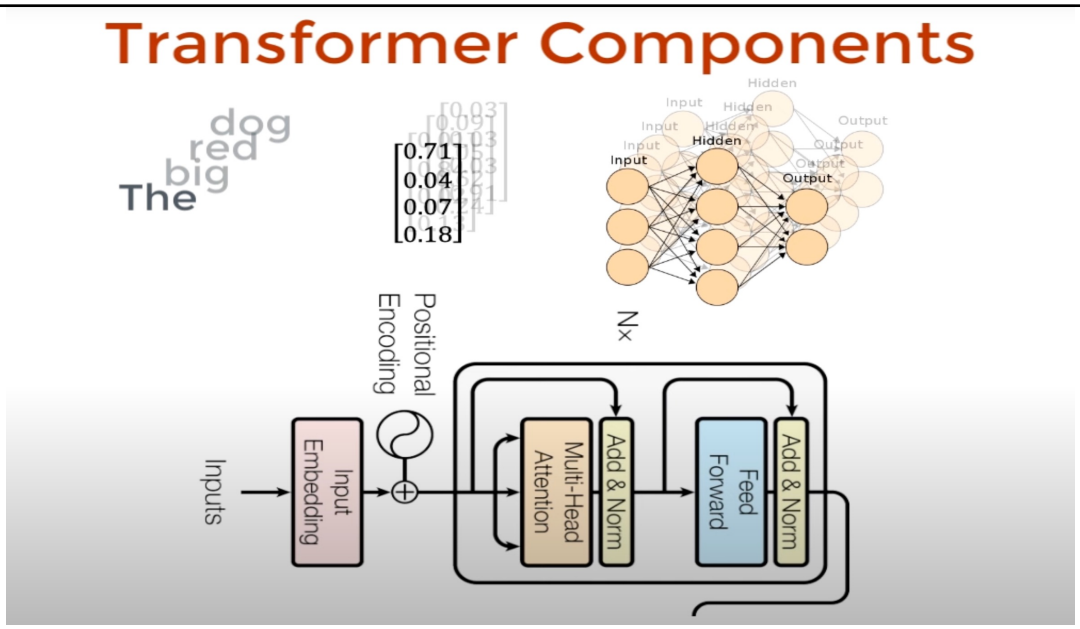
Transformer Components



Source: YouTube CodeEmporium

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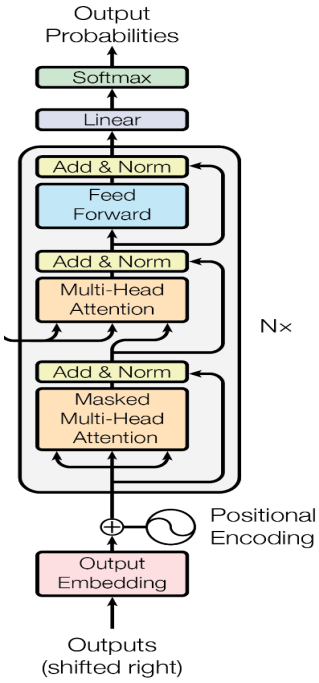
Transformer Components

Decoder



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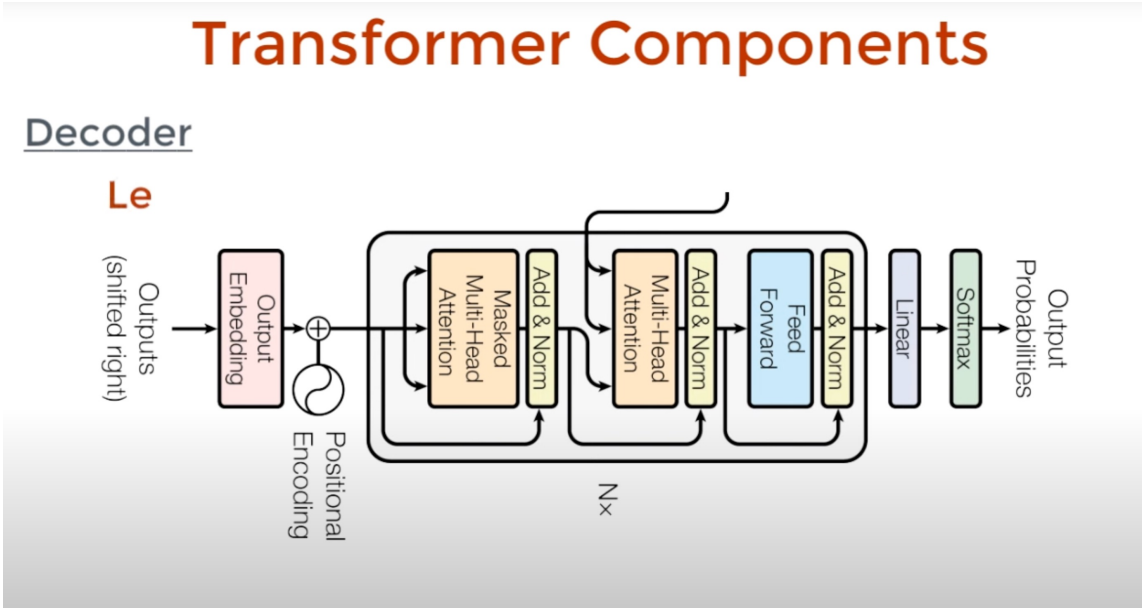
Transformer Components



Source: YouTube CodeEmporium

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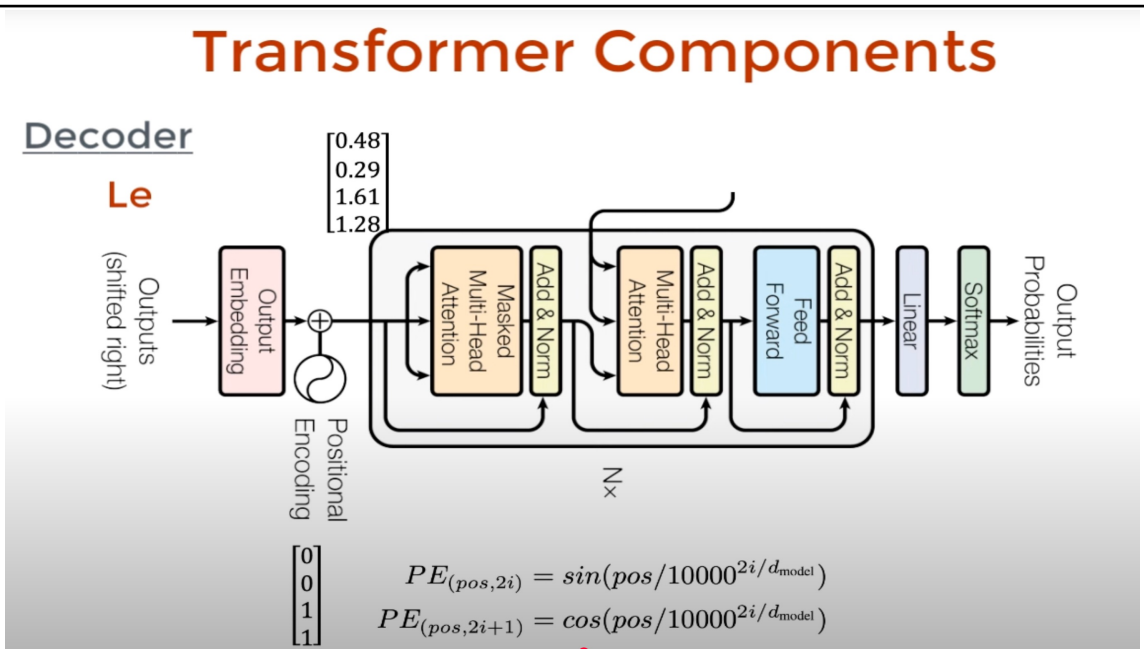
Transformer Components



Source: YouTube CodeEmporium

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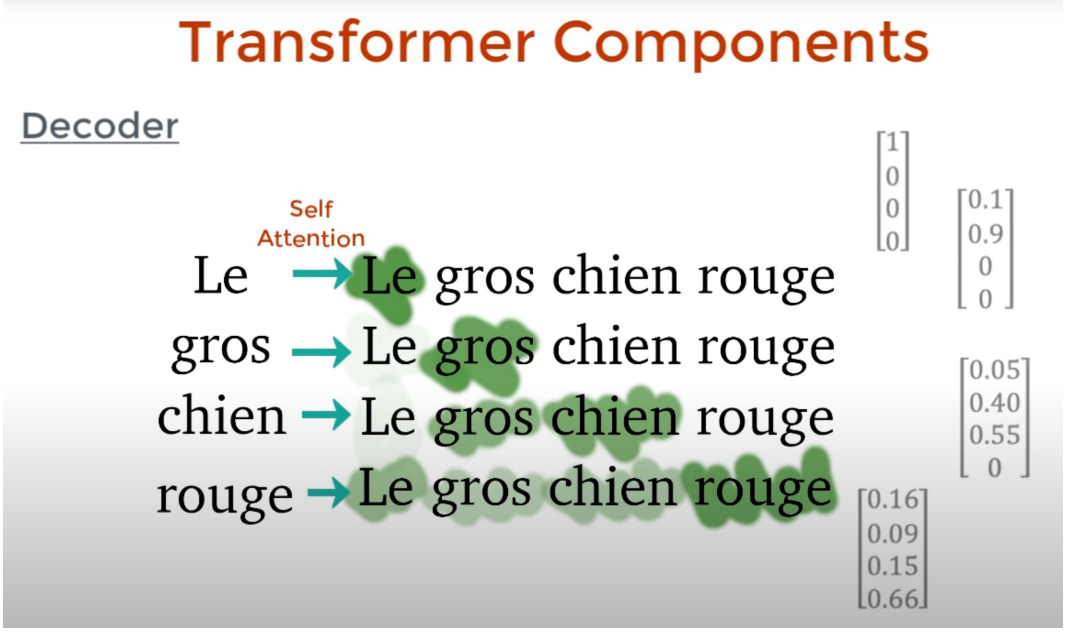
Transformer Components



Source: YouTube CodeEmporium

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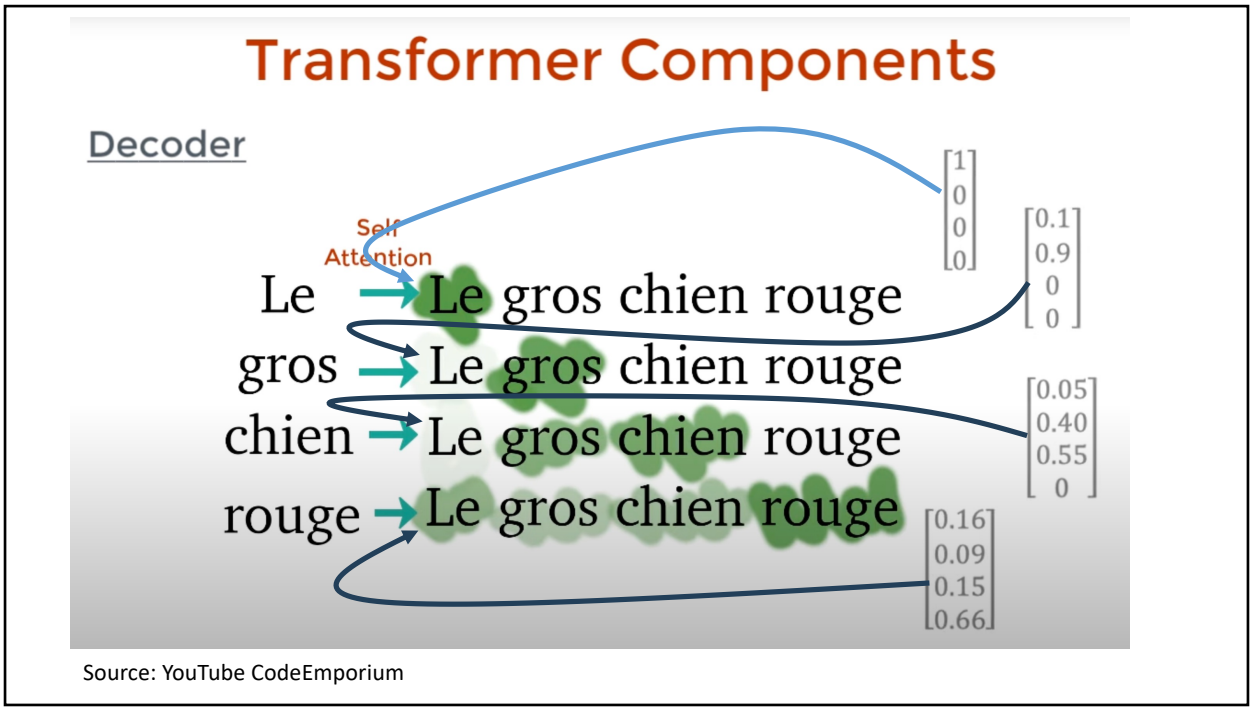

Source: YouTube CodeEmporium

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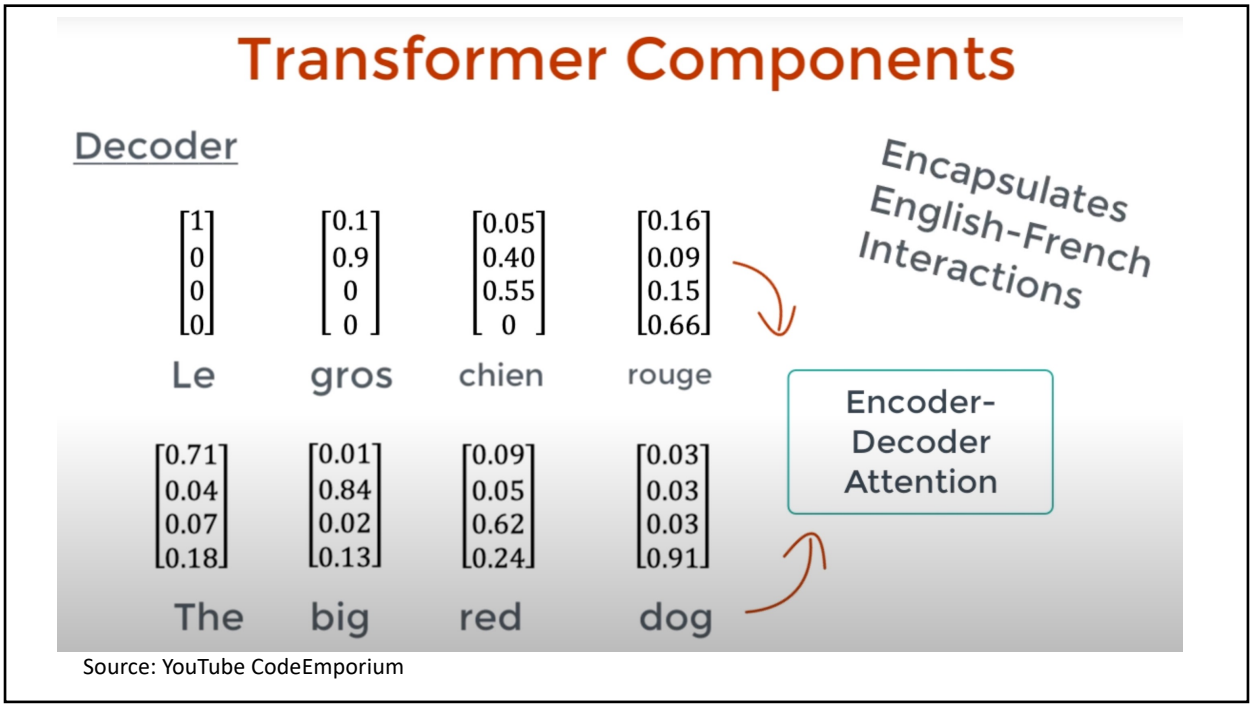

Source: YouTube CodeEmporium

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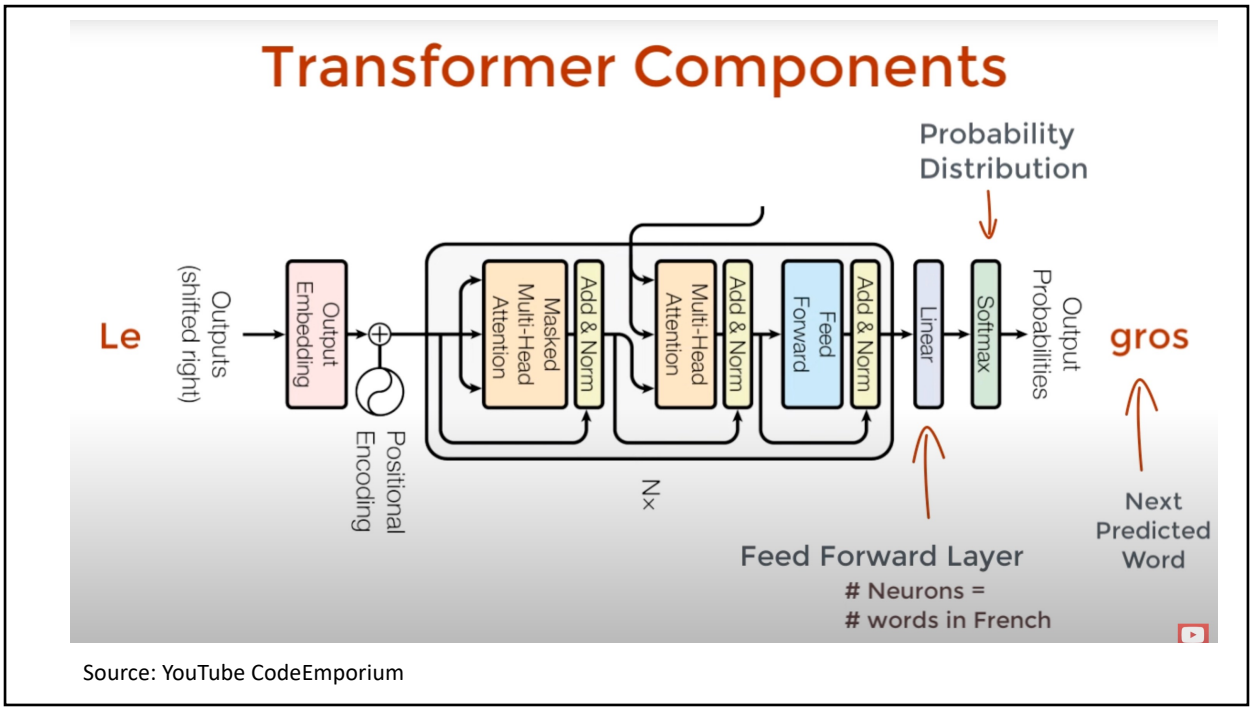

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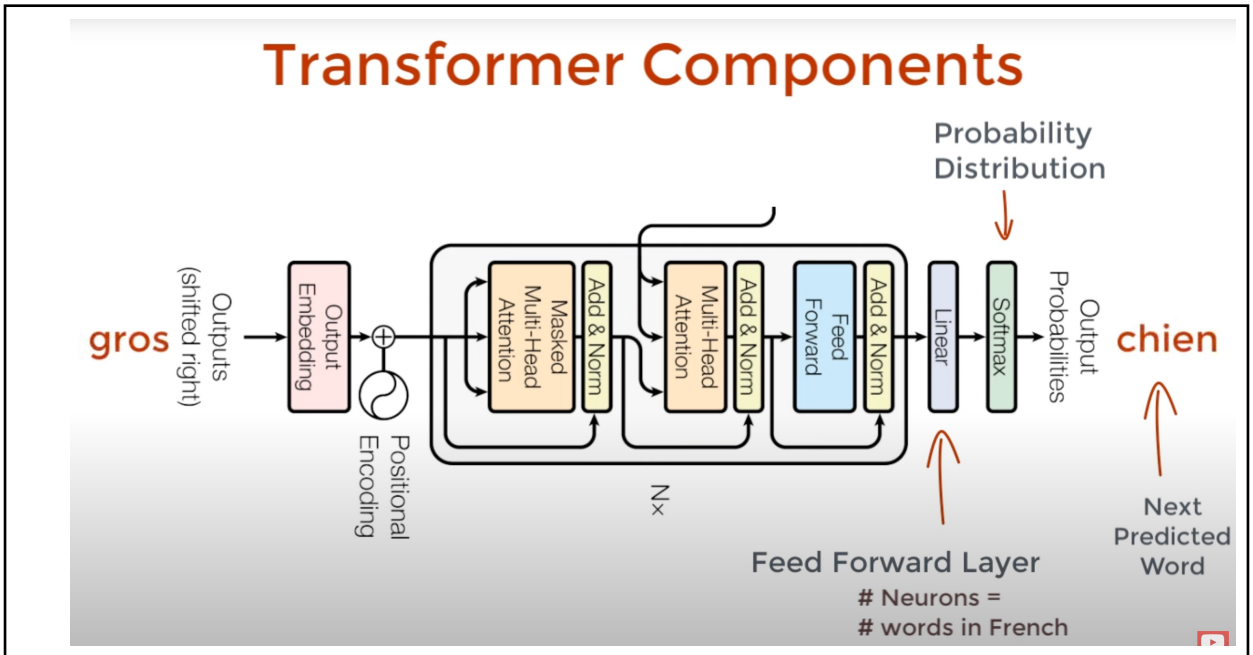

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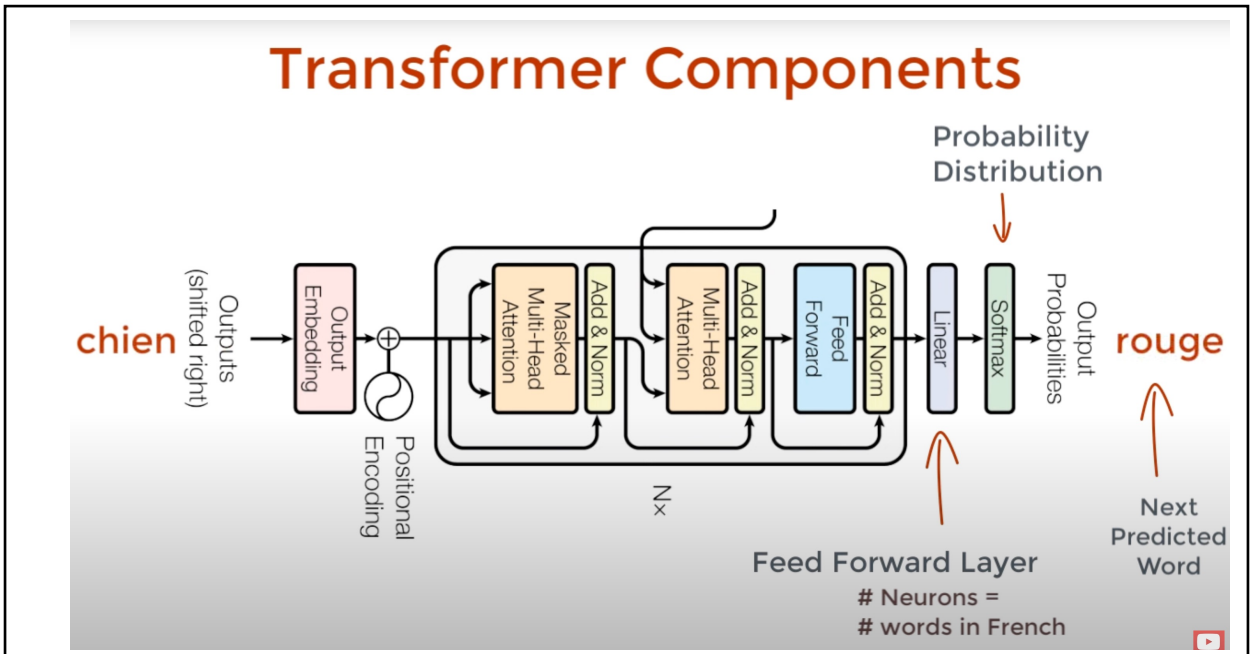

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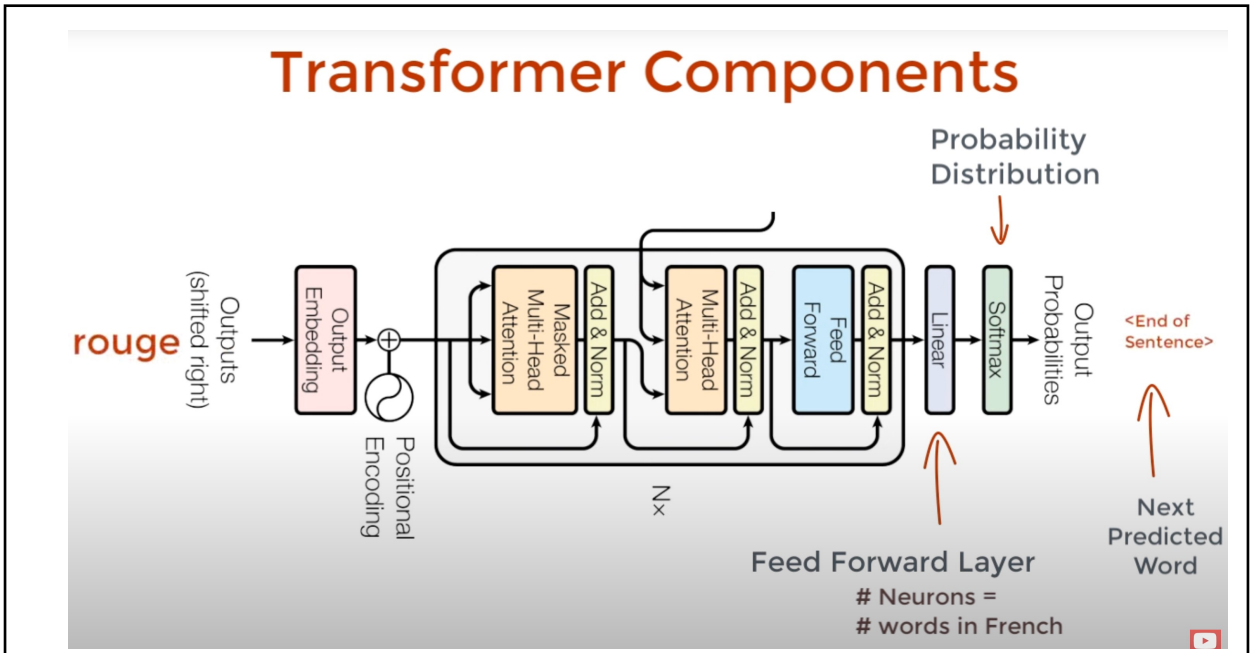

Source: YouTube CodeEmporium

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Summary

- DL architectures for sequence data
- RNN
  - Encoding bottleneck
  - Slow computation (due to no parallelization)
  - No long memory
- LSTM & GRU
  - Advanced architectures for RNN
  - Address the issues of exploding/vanishing gradients
- Transformer
  - Foundation of most advanced DL systems
  - Architectural foundation for LLMs/LFMs
  - The combination of self-supervised learning (SSL) and transformers allows models to learn from large amounts of unlabeled data.

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