Deep learning

Transformers

2024/12/16

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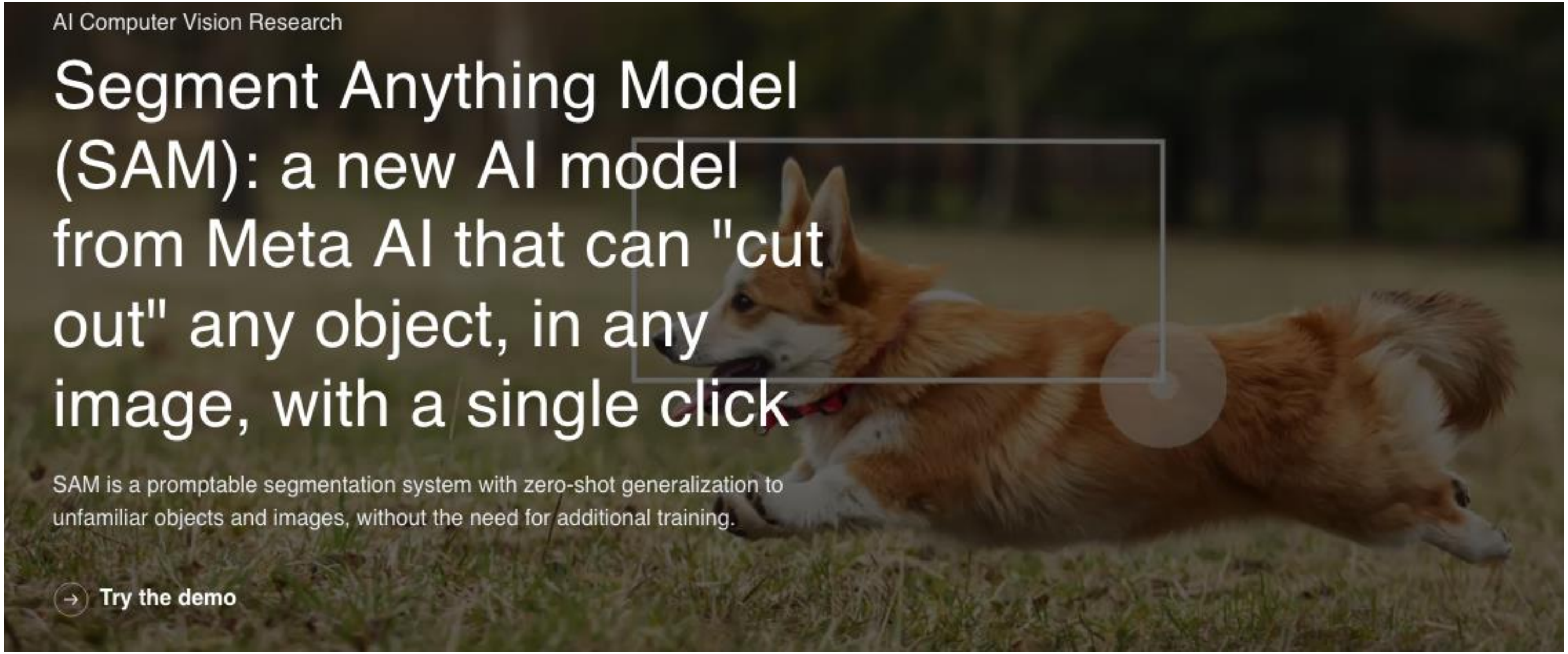
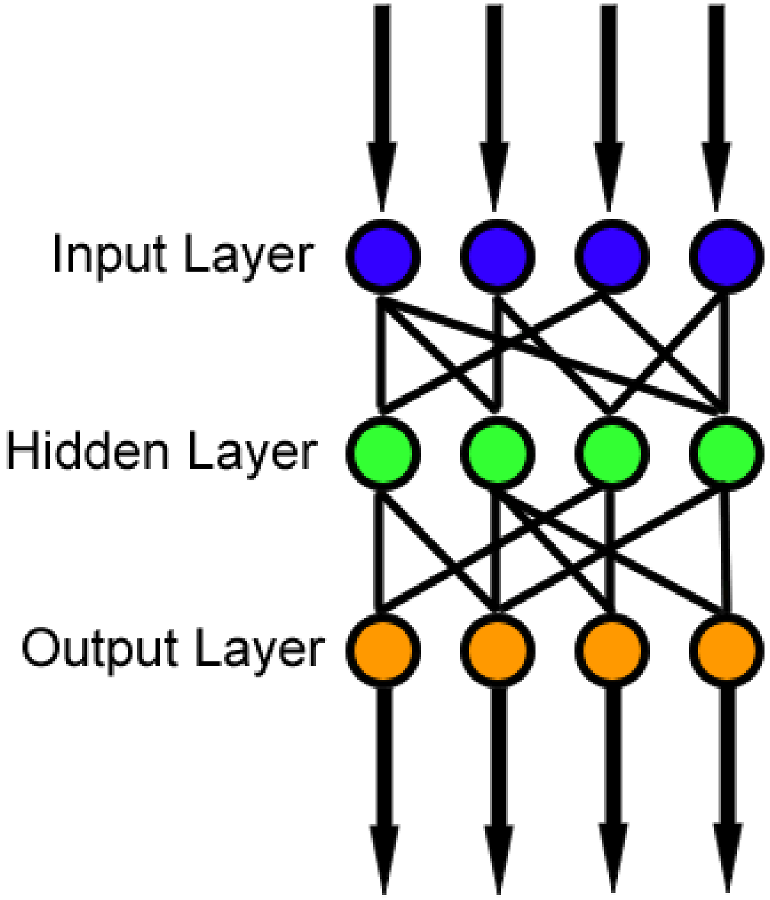
Segment Anyting
https://segment-anything.com/



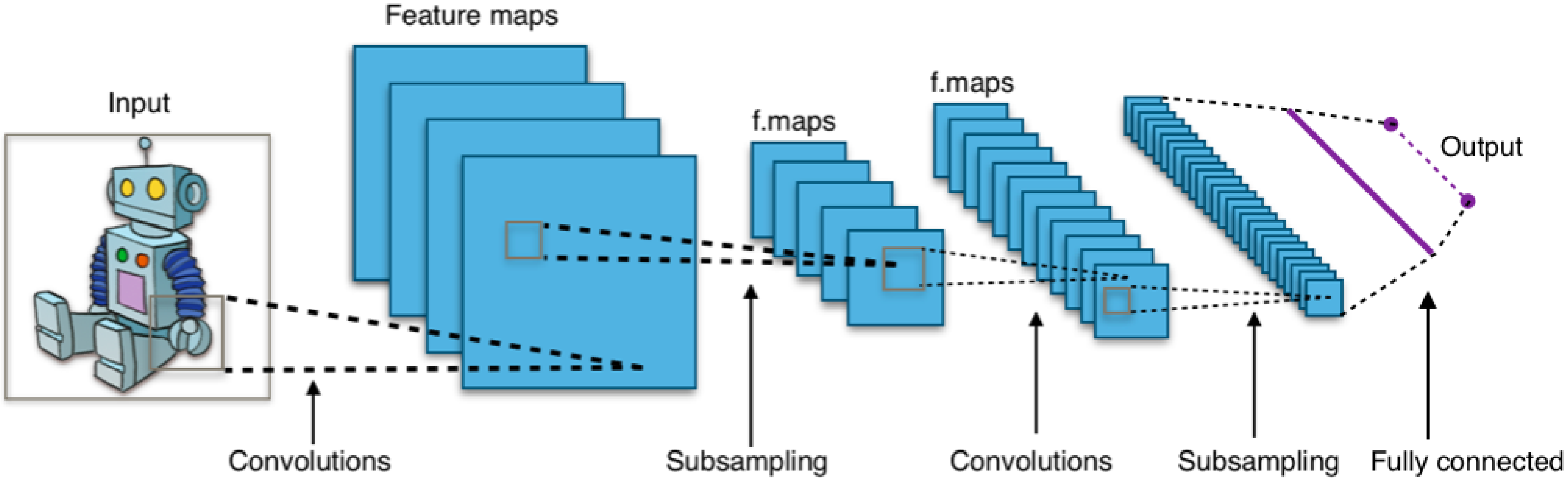
Feed forward neural networks

- Gauss, Legendre (around 1800): Single layer, least squares
- McCulloch & Pitts (1940's): Artificial neuron
- RosenBlatt, Jospeh (around 1960): Multilayer perceptron
- Linnainmaa (1970's): Backpropagation
- Bengio ea (early 2000's): Deep learning



- By Paskari at the English-language Wikipedia, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=146663611

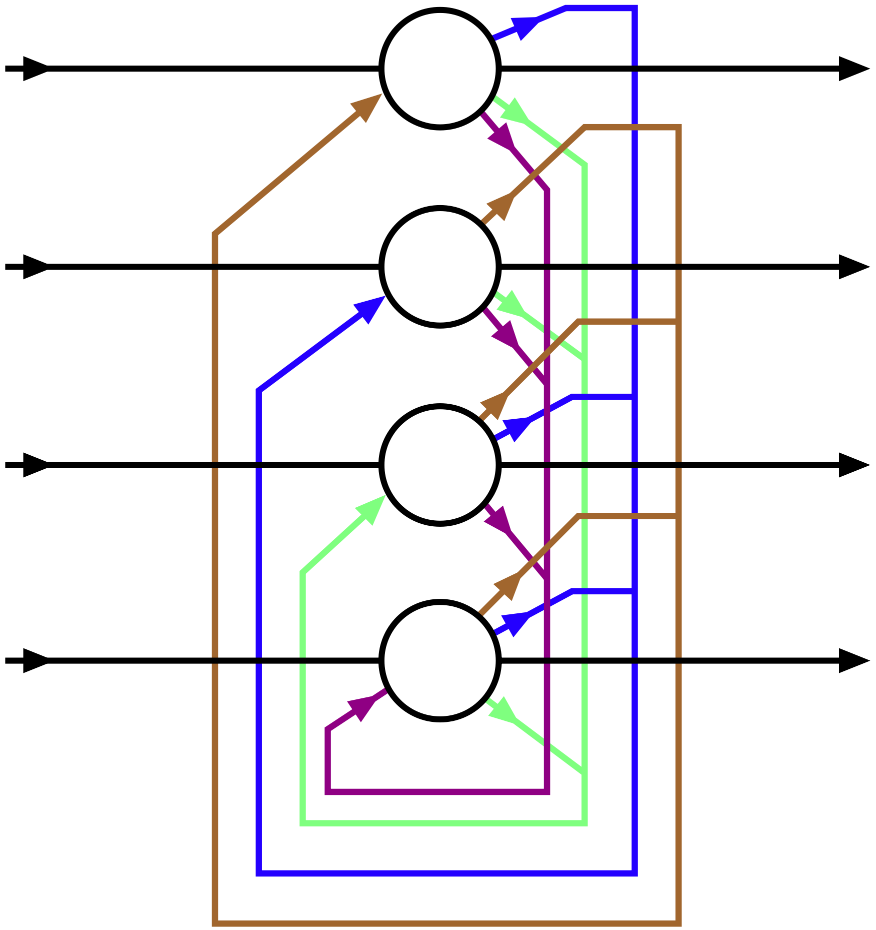
Convolutional neural networks



- Hubel & Wiesel (1950’s): visual cortex studies
- Fukushima (1969): CNN + ReLU, hand-designed kernels
- Fukushima (1979), LeCun (1987): training kernels
- Oh & Jung (2004): GPU implementation

Recurrent neural networks

- Cajal (early 1900's): Recurrence in cerebellar cortex
- McCulloch & Pitss: Recurrent neuron
- Rosenblatt (1960's), Hopfield (1982): Hebbian learning
- Hochreiter & Schmidhuber (1995): Long short-term memory (LSTM)
- Schuster ea (1997): Bidrectional recurrent neural networks (BRNN)



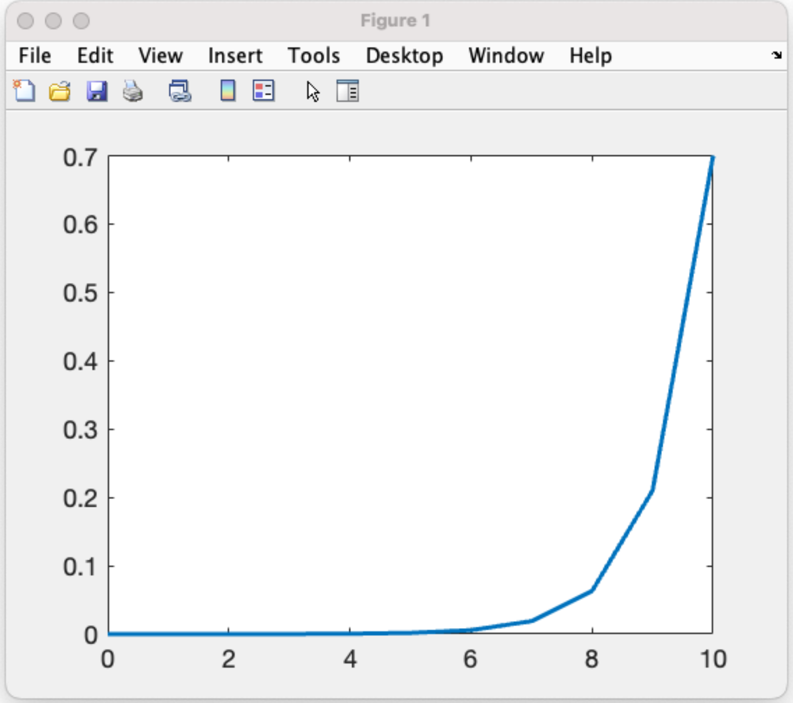
Recurrence

Consider: $x_t, \alpha \in \mathbb{R}$

Running average: $y_0 = x_0,\ y_t = \alpha y_{t-1} + (1-\alpha)x_t$

Exampel:

$$x = [7 \quad 0 \quad 3 \quad 0 \quad 1 \quad 8 \quad 7 \quad 3 \quad 10 \quad 0]$$
$$y_{\alpha=0.3} = [7 \quad 2 \quad 3 \quad 1 \quad 1 \quad 6 \quad 7 \quad 4 \quad 8 \quad 2]$$
$$y_{\alpha=0.7} = [7 \quad 5 \quad 5 \quad 4 \quad 3 \quad 4 \quad 5 \quad 5 \quad 7 \quad 5]$$

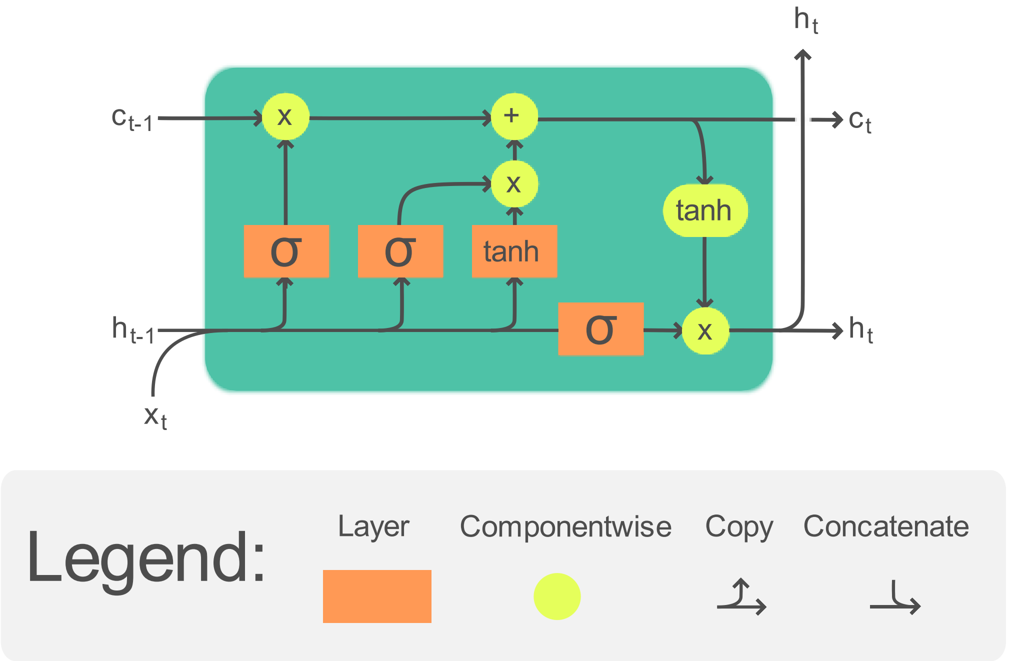


$$y_0 = x_0$$
$$y_1 = \alpha y_0 + (1-\alpha)x_1 = \alpha x_0 + (1-\alpha)x_1$$
$$y_2 = \alpha y_1 + (1-\alpha)x_2 = \alpha^2 x_0 + \alpha(1-\alpha)x_1 + (1-\alpha)x_2$$
$$y_3 = \alpha y_2 + (1-\alpha)x_3 = \alpha^3 x_0 + \alpha^2(1-\alpha)x_1 + \alpha(1-\alpha)x_2 + (1-\alpha)x_3$$
$$\dots$$
$$y_t = (1-\alpha)\sum_{i=0}^{t} \alpha^{t-i} x_i$$

Long short-term memory (LSTM) https://en.wikipedia.org/wiki/Long_short-term_memory

$x = [7 \quad 0 \quad 3 \quad 0 \quad 1 \quad 8 \quad 7 \quad 3 \quad 10 \quad 0]$

$$
\begin{aligned}
f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
\tilde{c}_t &= \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
h_t &= o_t \odot \sigma_h(c_t)
\end{aligned}
$$

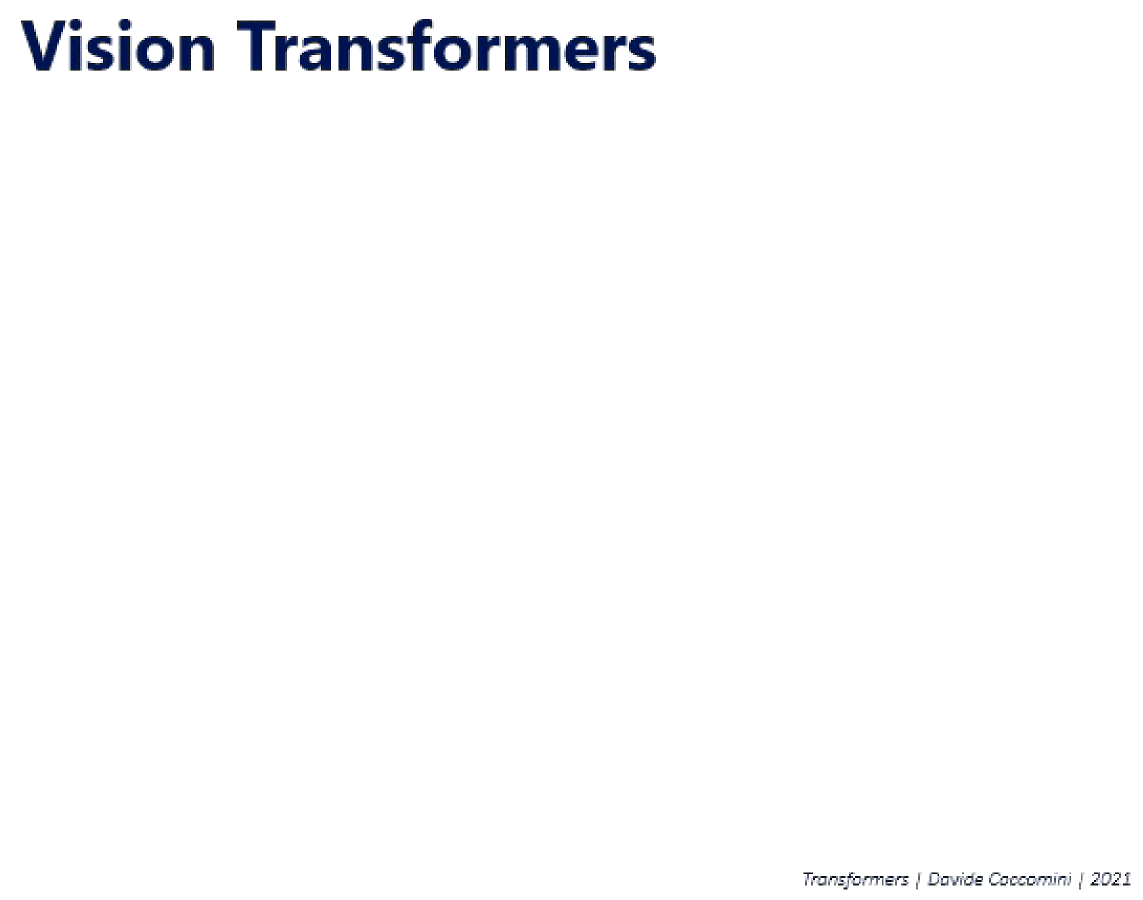


- $x_t \in \mathbb{R}^d$: input vector to the LSTM unit
- $f_t \in (0,1)^h$: forget gate's activation vector
- $i_t \in (0,1)^h$: input/update gate's activation vector
- $o_t \in (0,1)^h$: output gate's activation vector
- $h_t \in (-1,1)^h$: hidden state vector also known as output vector of the LSTM unit
- $\tilde{c}_t \in (-1,1)^h$: cell input activation vector
- $c_t \in \mathbb{R}^h$: cell state vector
- $W \in \mathbb{R}^{h \times d}$, $U \in \mathbb{R}^{h \times h}$ and $b \in \mathbb{R}^h$: weight matrices and bias vector parameters which need to be learned during training

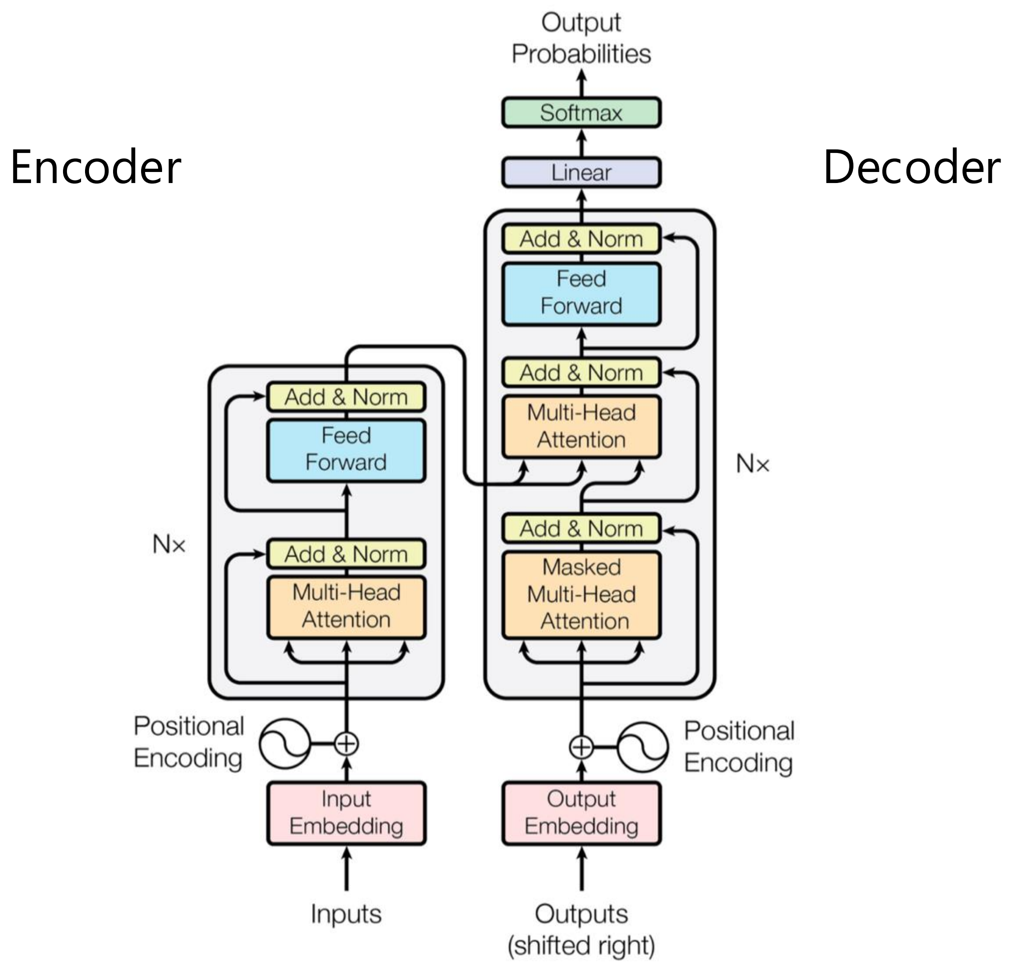
- By Guillaume Chevalier - File:The_LSTM_Cell.svg, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=109362147

Transformer networks

- Cho ea, Sutskever ea (2014): seq2seq
- Vaswani ea (2017): Attention is all you need
- Dosovitskiy ea (2020): An Image is Worth 16x16 Words ···

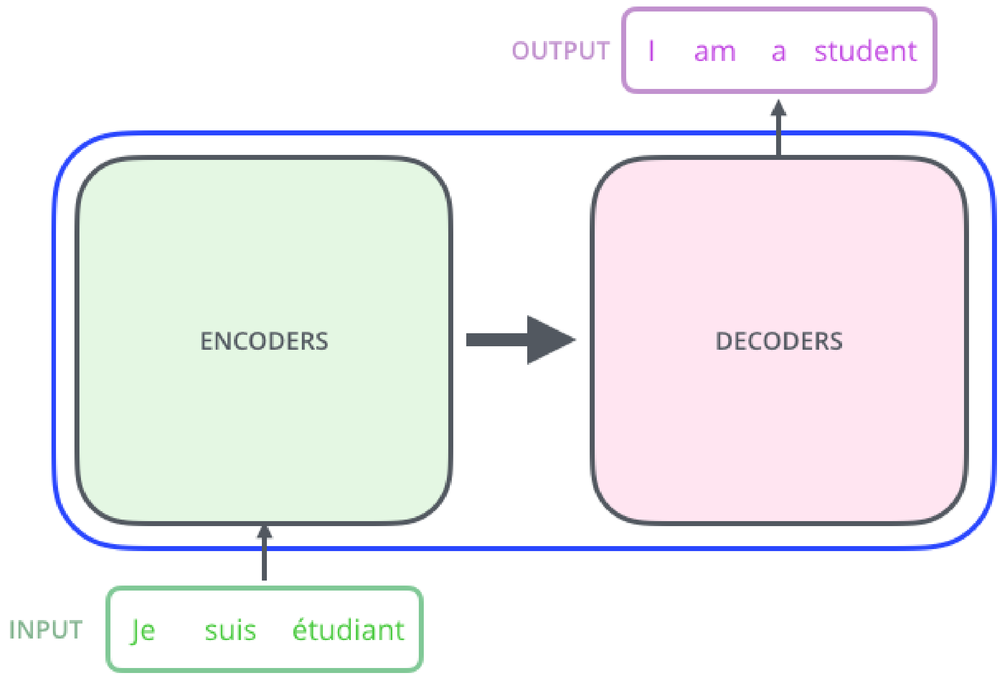


Vaswani: Attention Is All You Need
Dosovitskiy ea (2020): An Image is Worth 16x16 Words···

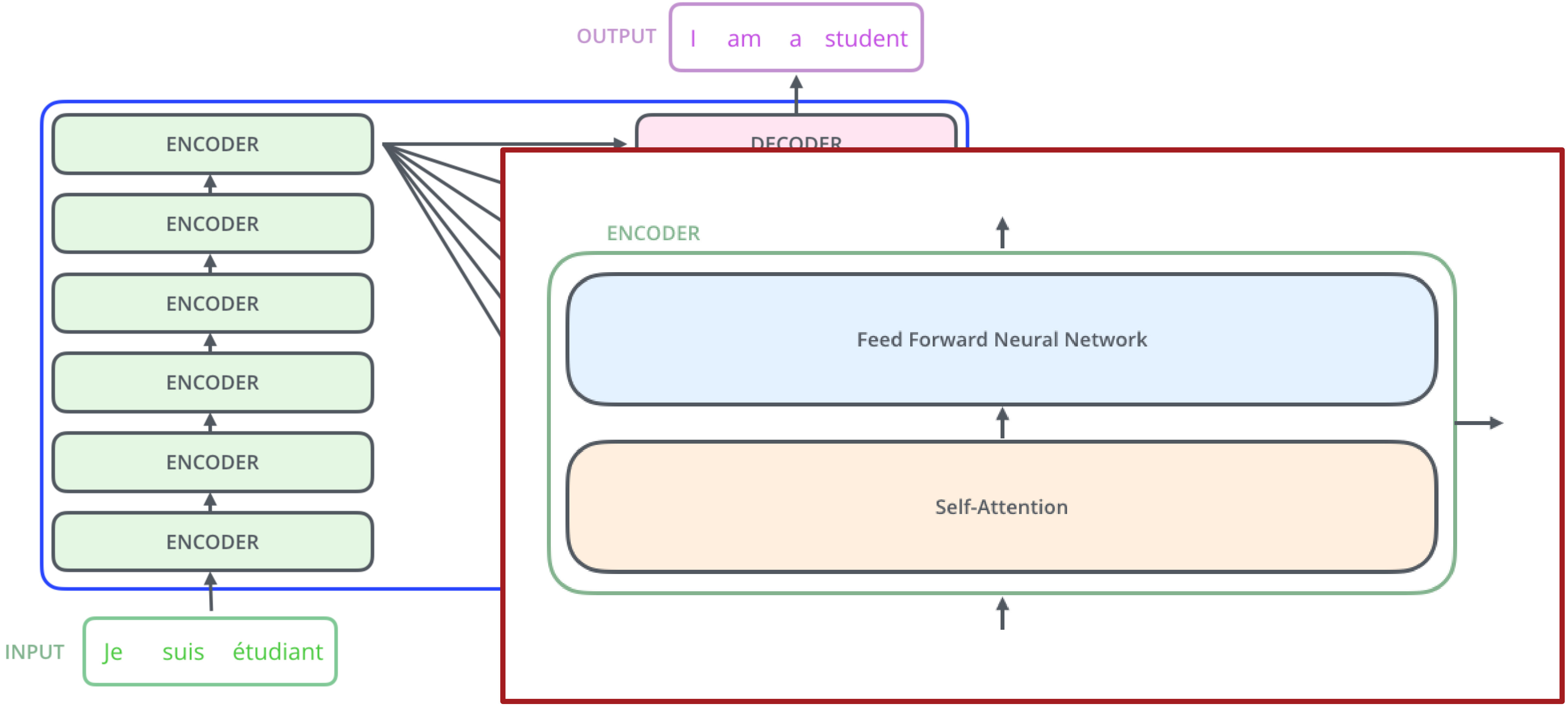


The Illustrated Transformer http://jalammar.github.io/illustrated-transformer/

Transformers in the context of languages:



Encoder (and decoder) are stacks of identical units



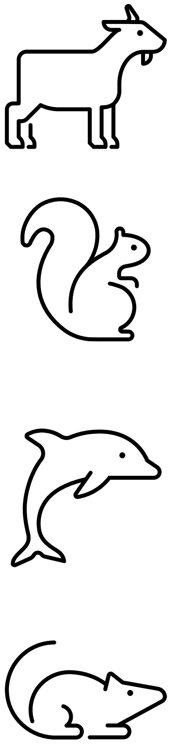
Classification by Query, Key, Value and Tokens

query

?

key

value



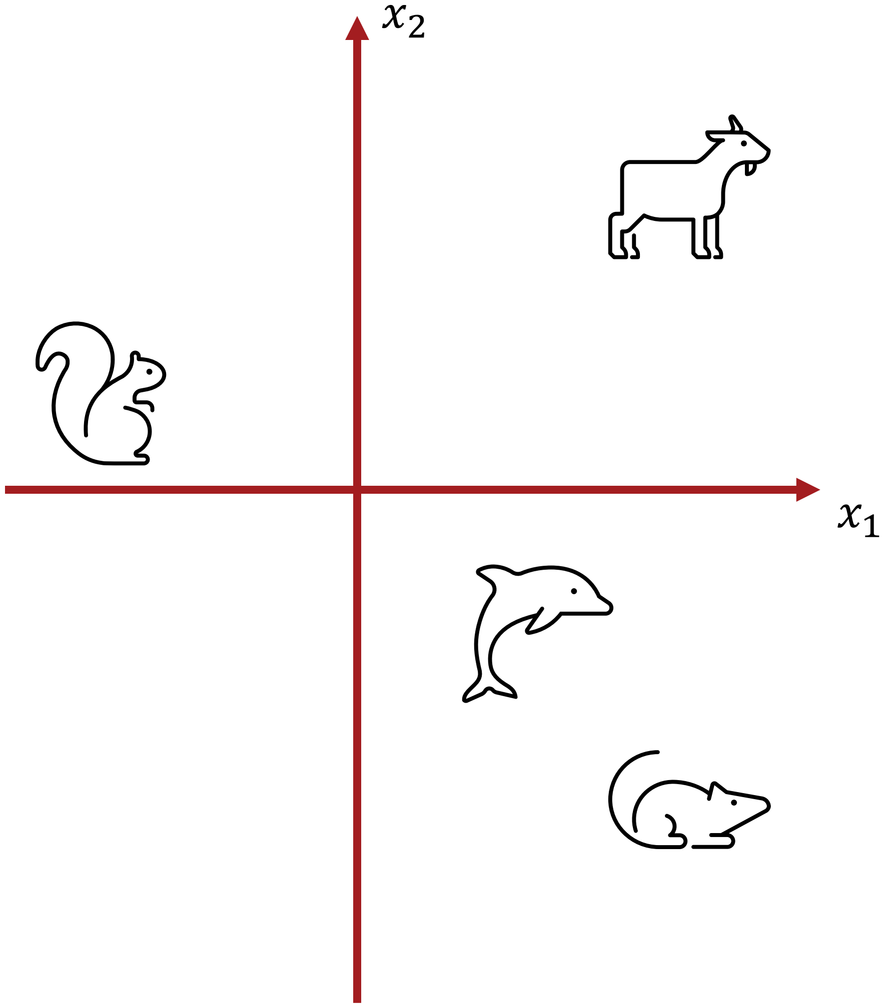
Goat

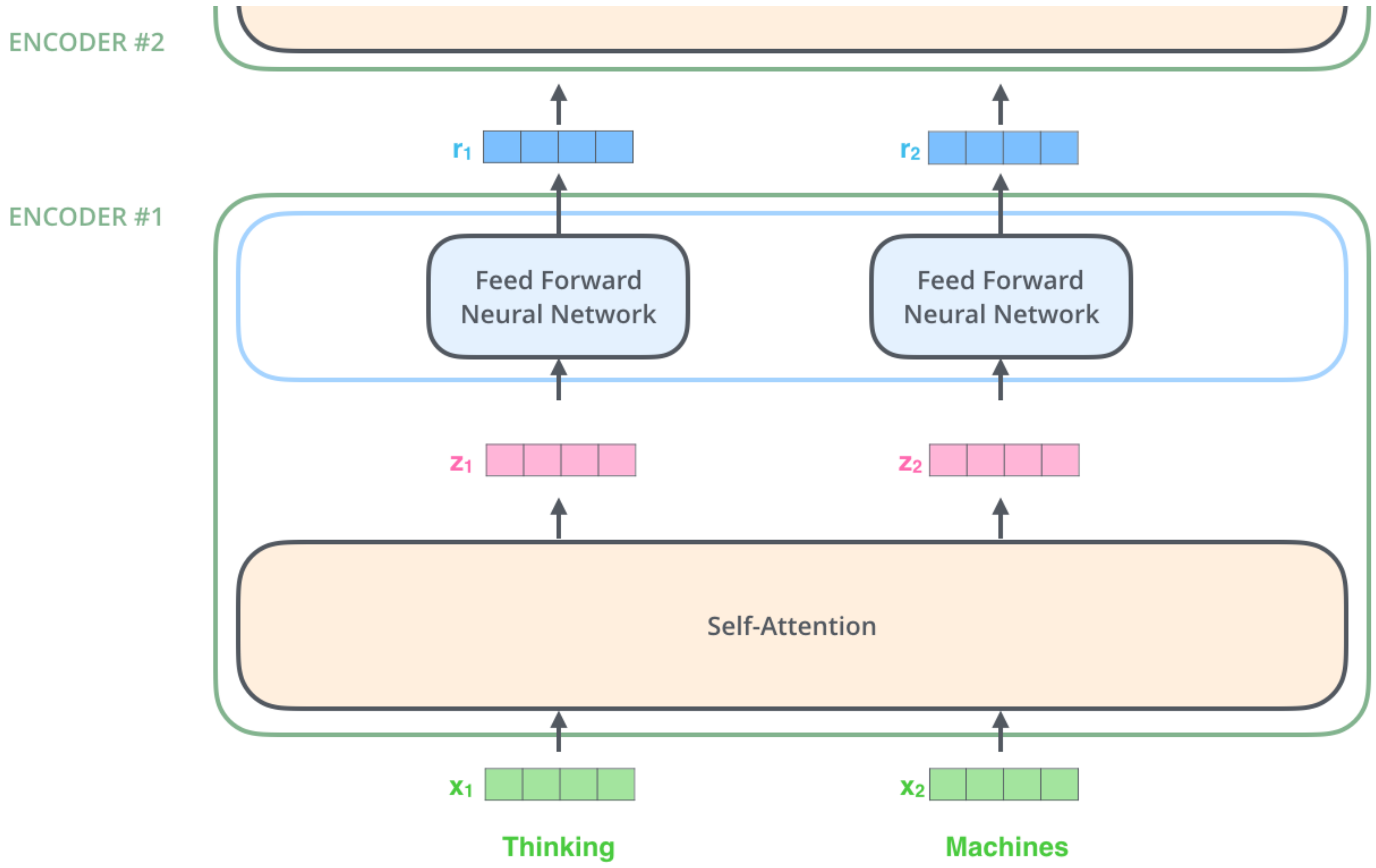
Squirrel

Dolphin

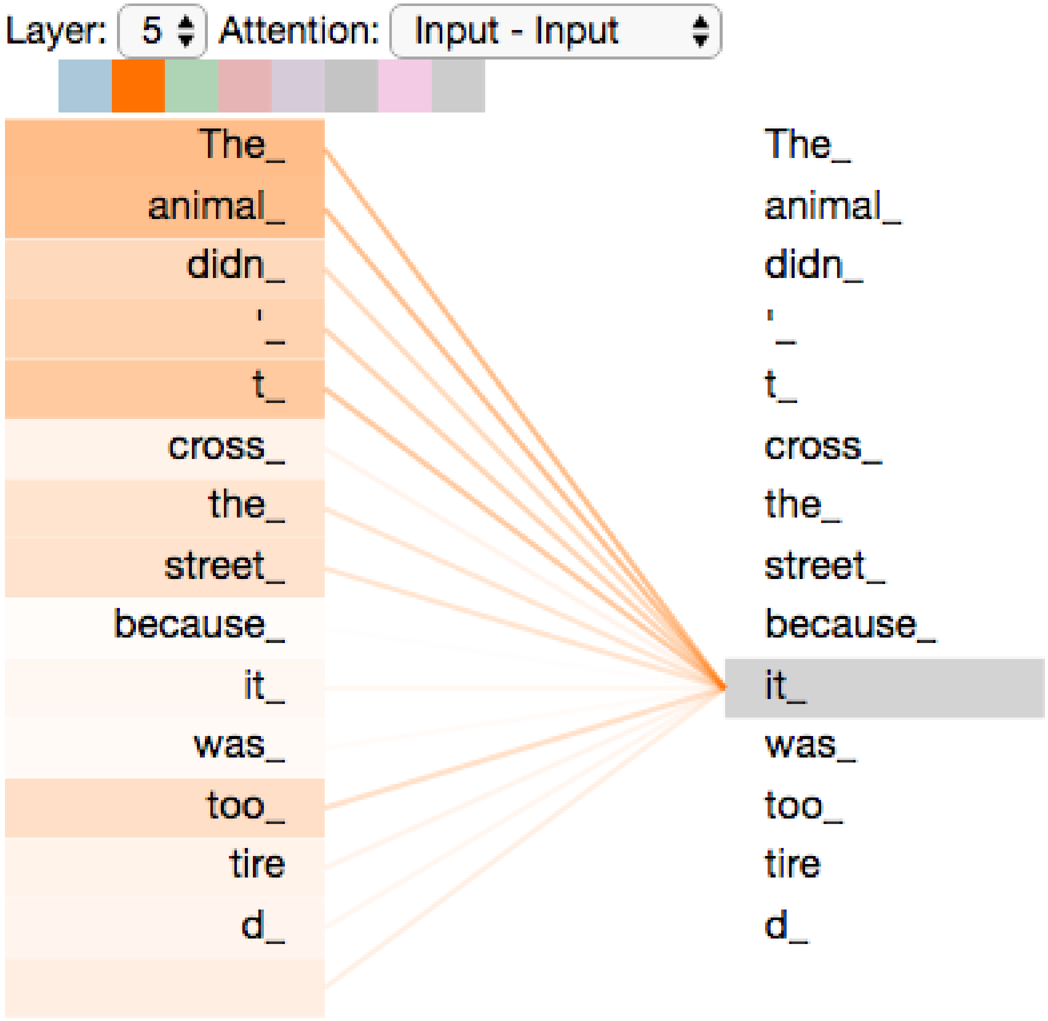
Mouse

Tokens as embedding



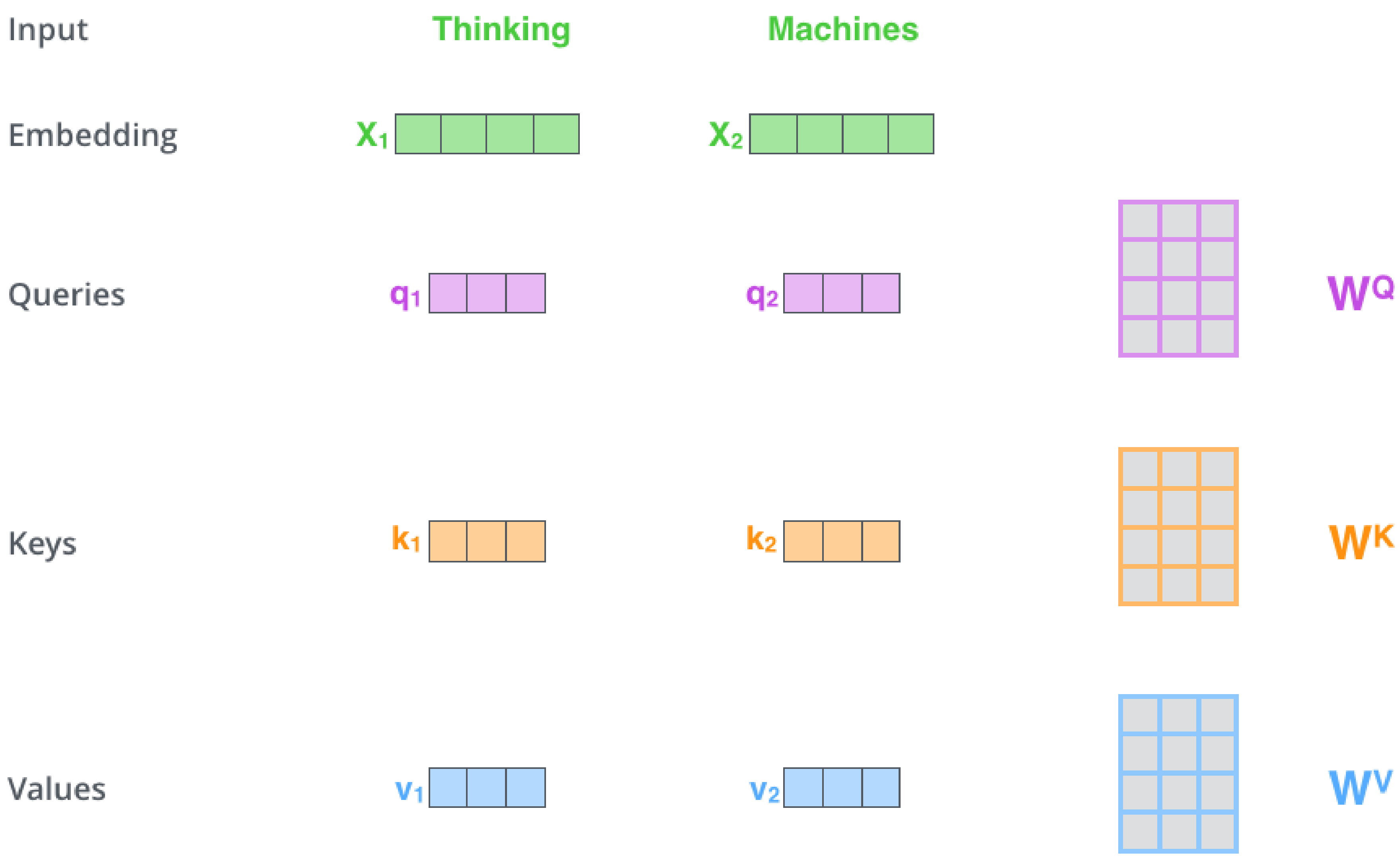

ENCODER #2
r1
r2
ENCODER #1
Feed Forward Neural Network
Feed Forward Neural Network
z1
z2
Self-Attention
x1
x2
Thinking
Machines

Self attention: The animal didn't cross the street because it was too tired

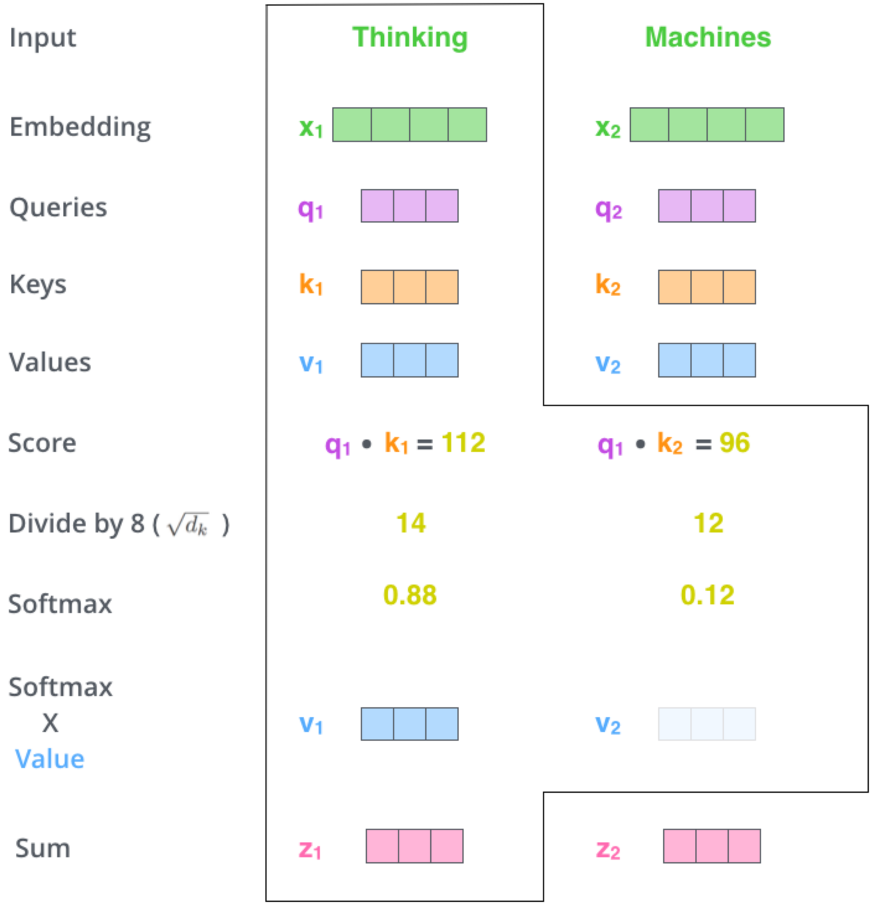


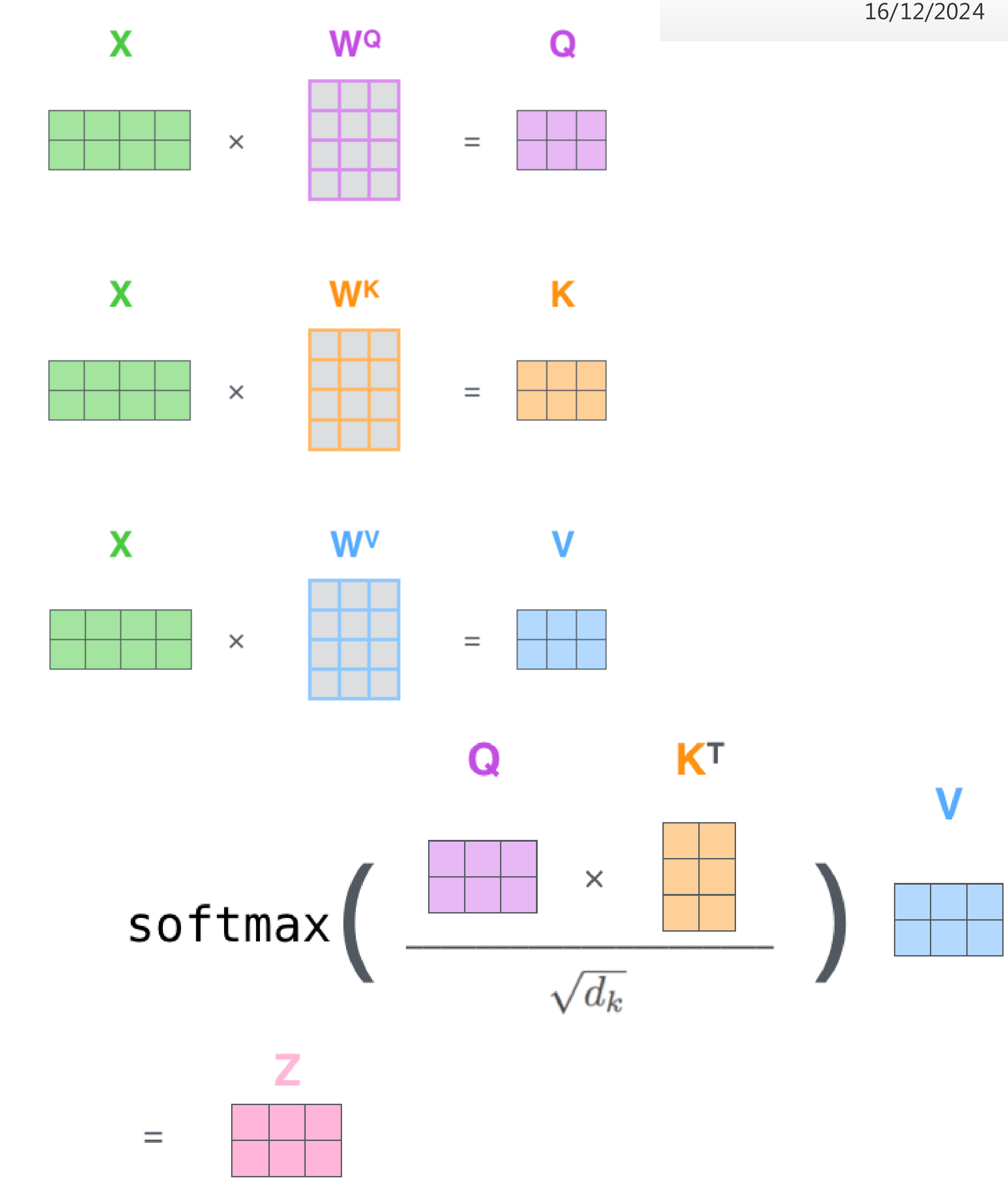
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Matrix form


Input
Thinking
Machines
Embedding
X_1
X_2
Queries
q_1
q_2
W^Q
Keys
k_1
k_2
W^K
Values
v_1
v_2
W^V

Self attention, single head





Papers with code
https://paperswithcode.com/method/transformer