JPMorgan Chase & Co.

Recurrent Neural Networks

Bruno Gonçalves

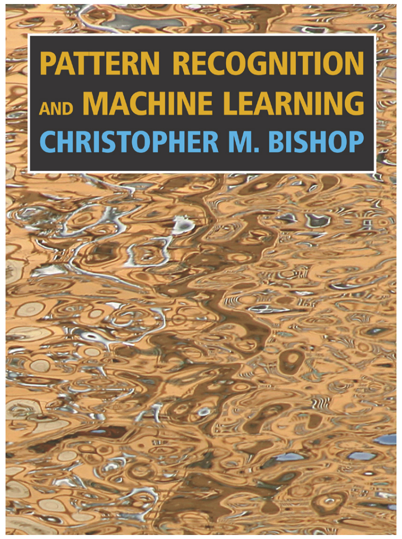
www.bgoncalves.com

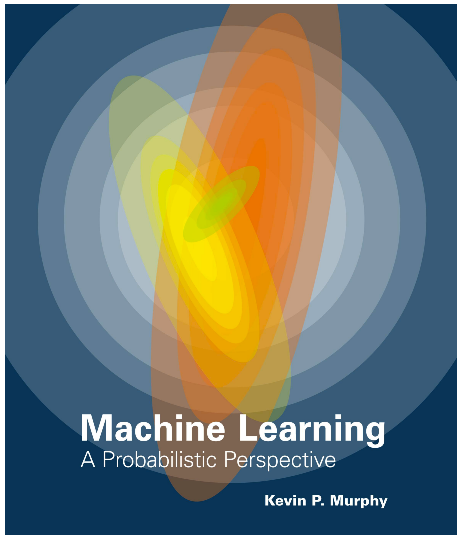
github.com/bmtgoncalves/RNN

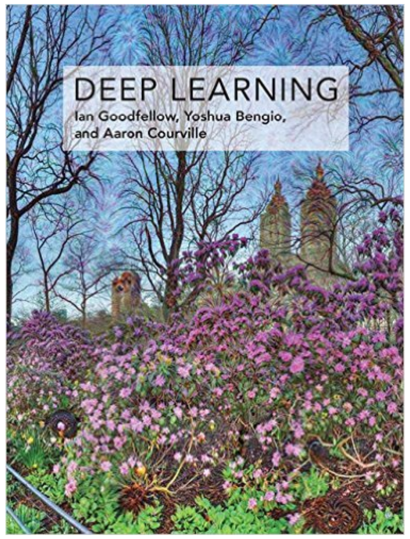
Disclaimer

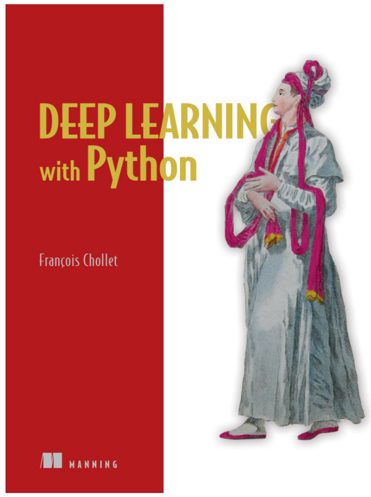
The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of my employer. The examples provided with this tutorial were chosen for their didactic value and are not mean to be representative of my day to day work.

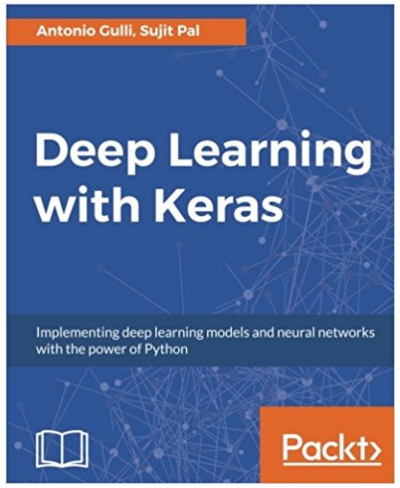
References











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How the Brain “Works” (Cartoon version)

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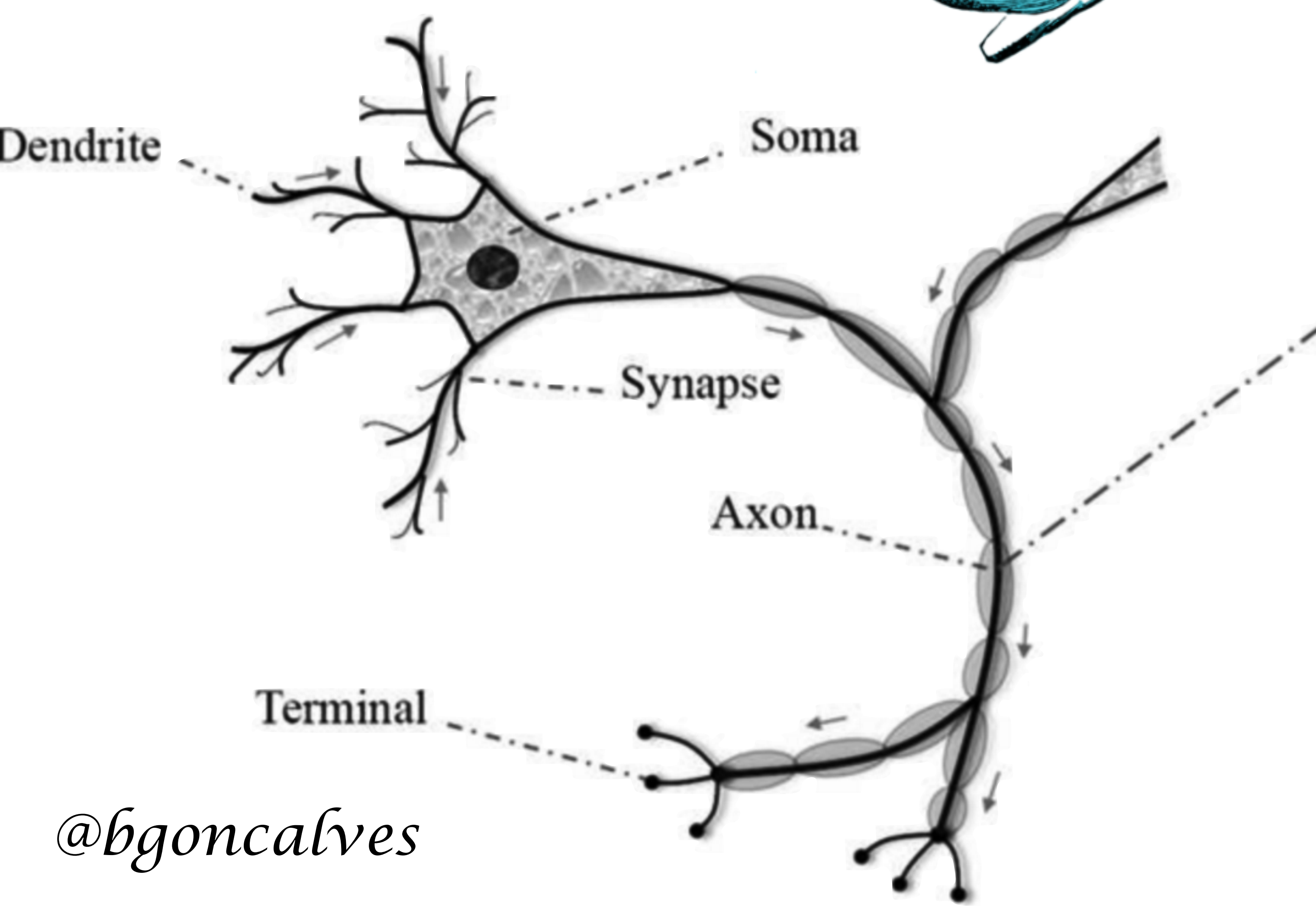

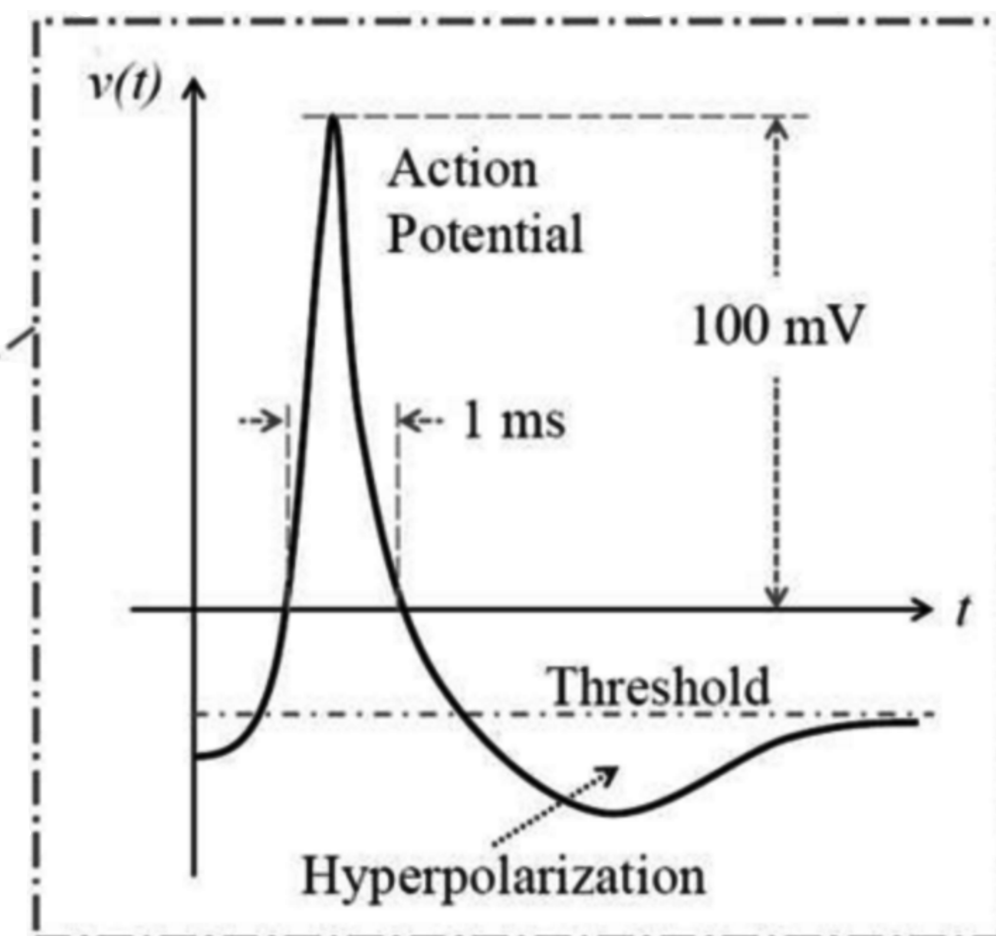

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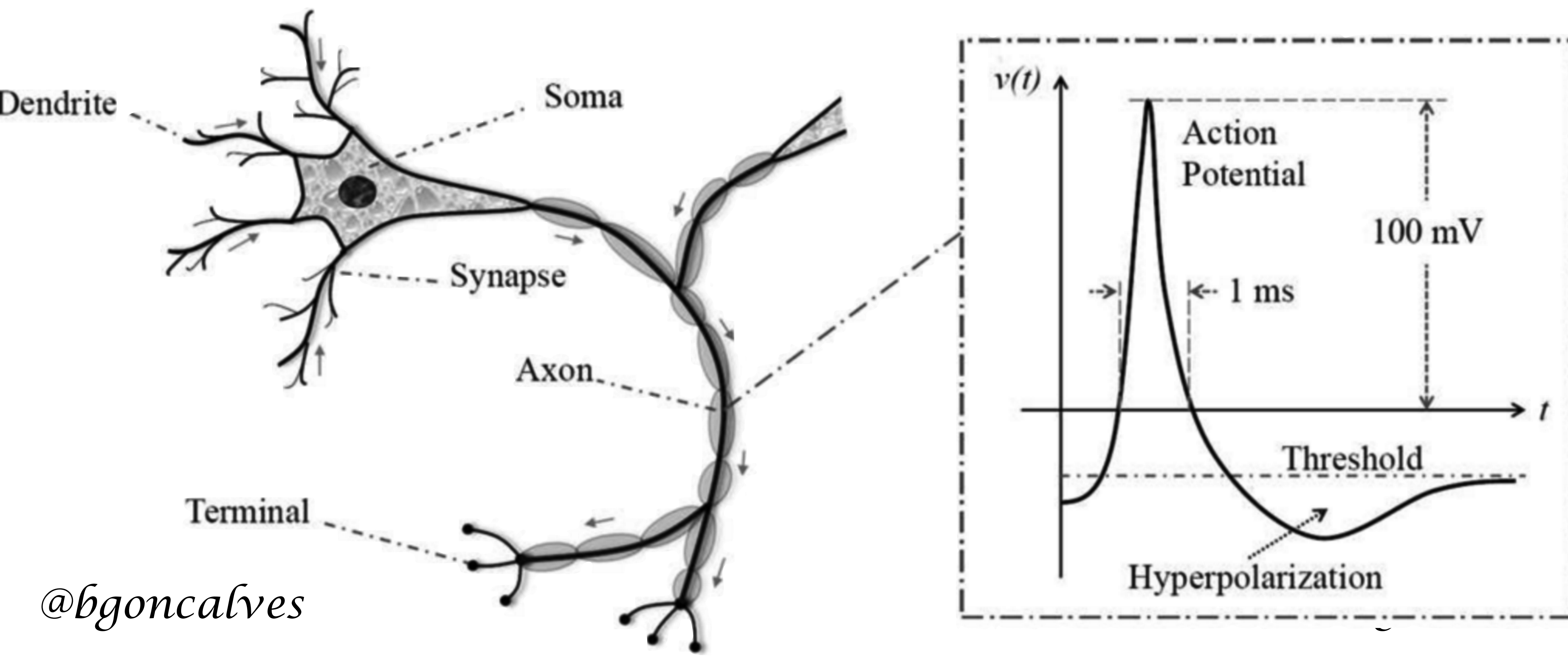
- Each neuron receives input from other neurons



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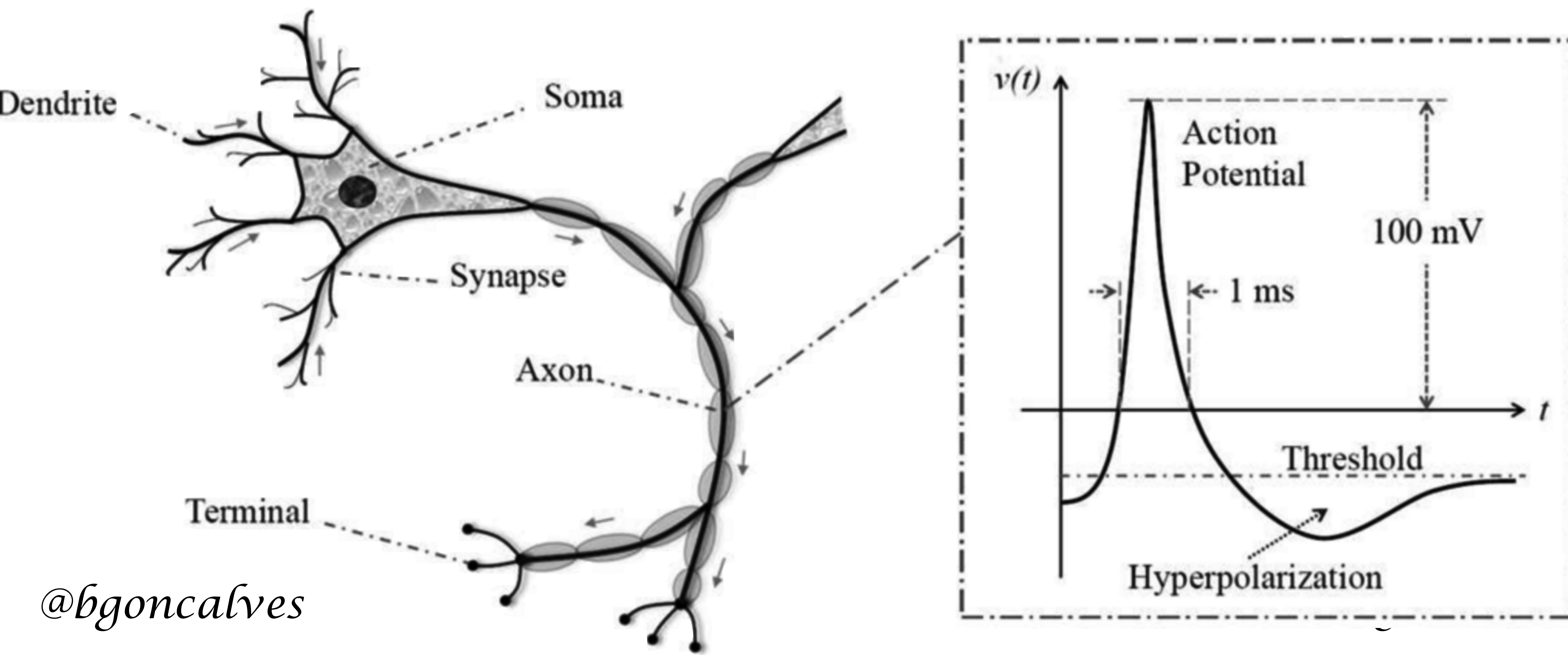

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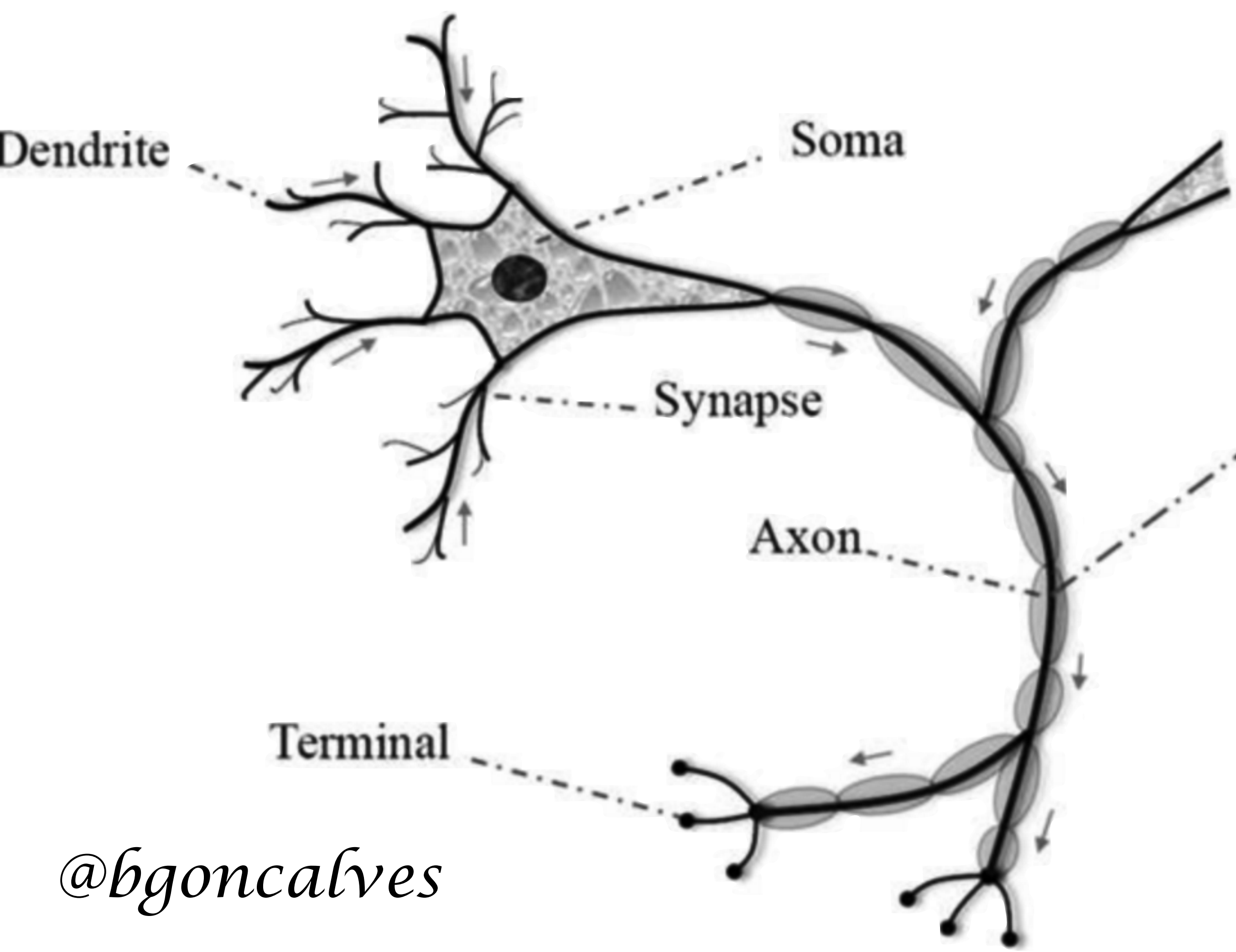

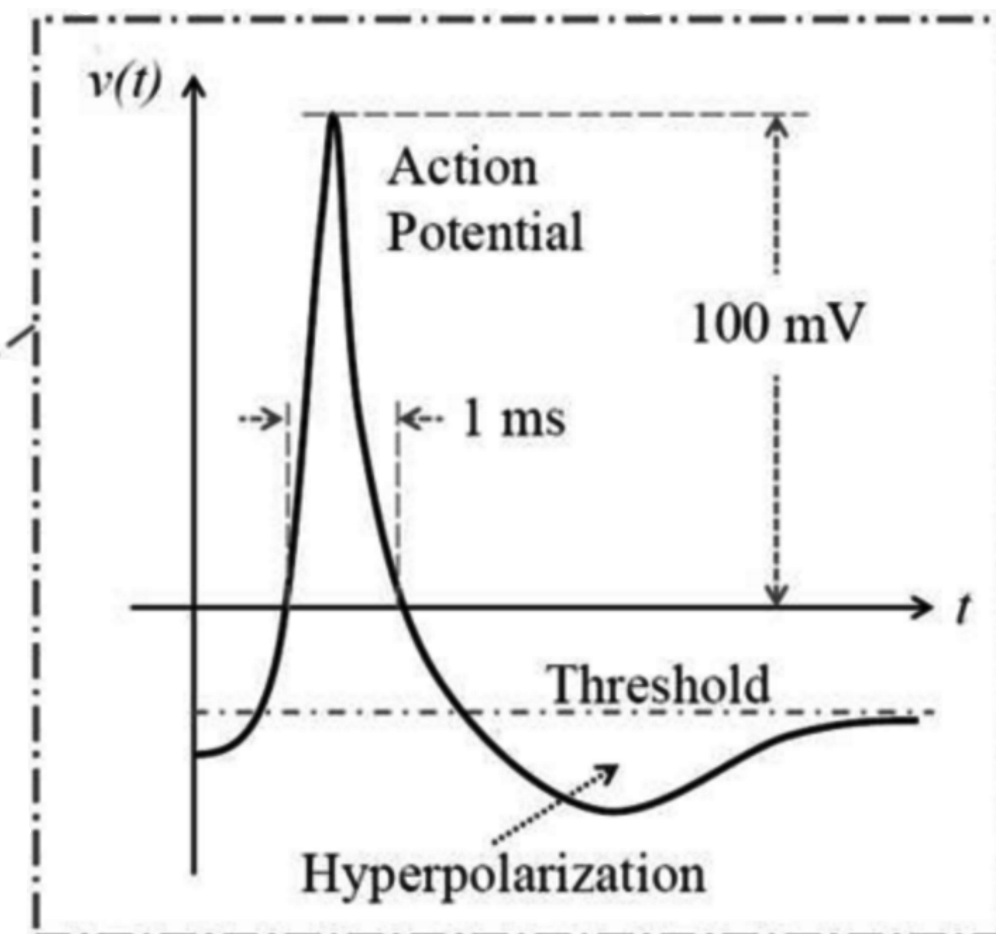

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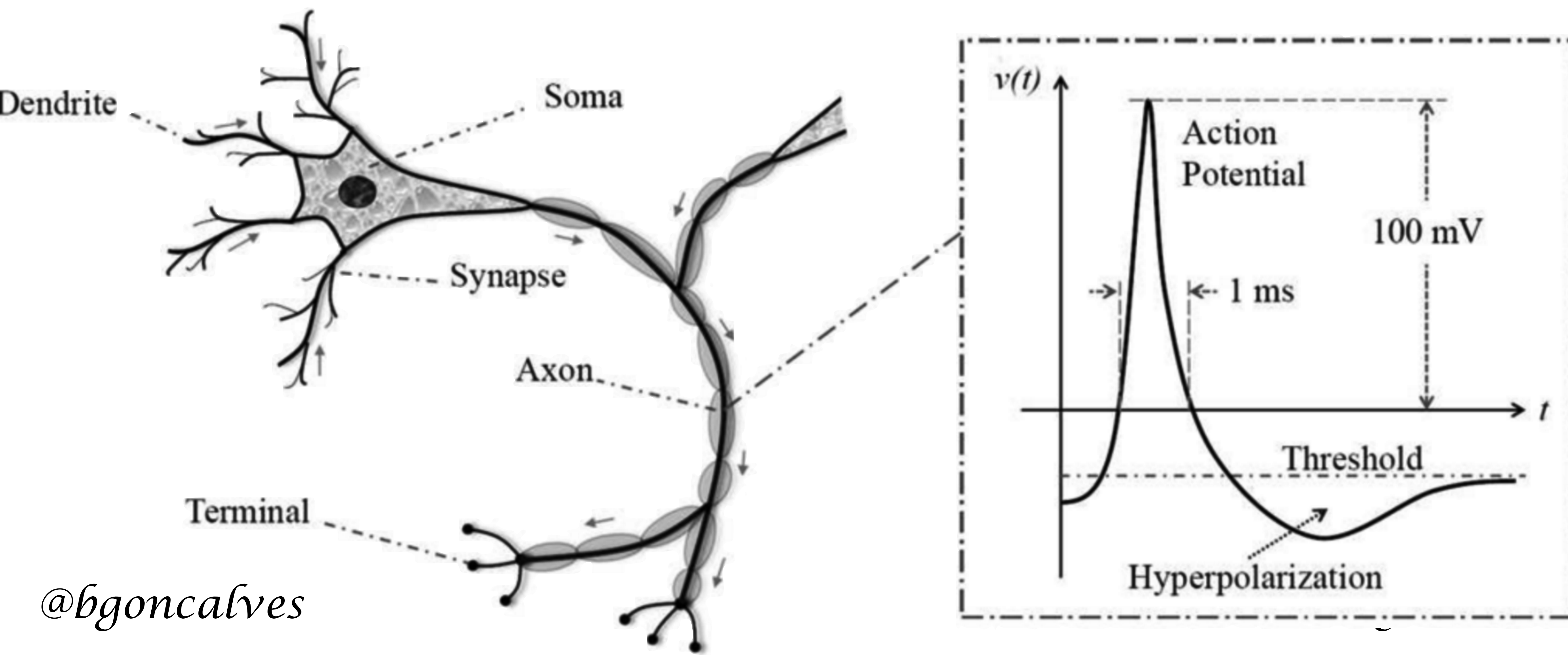

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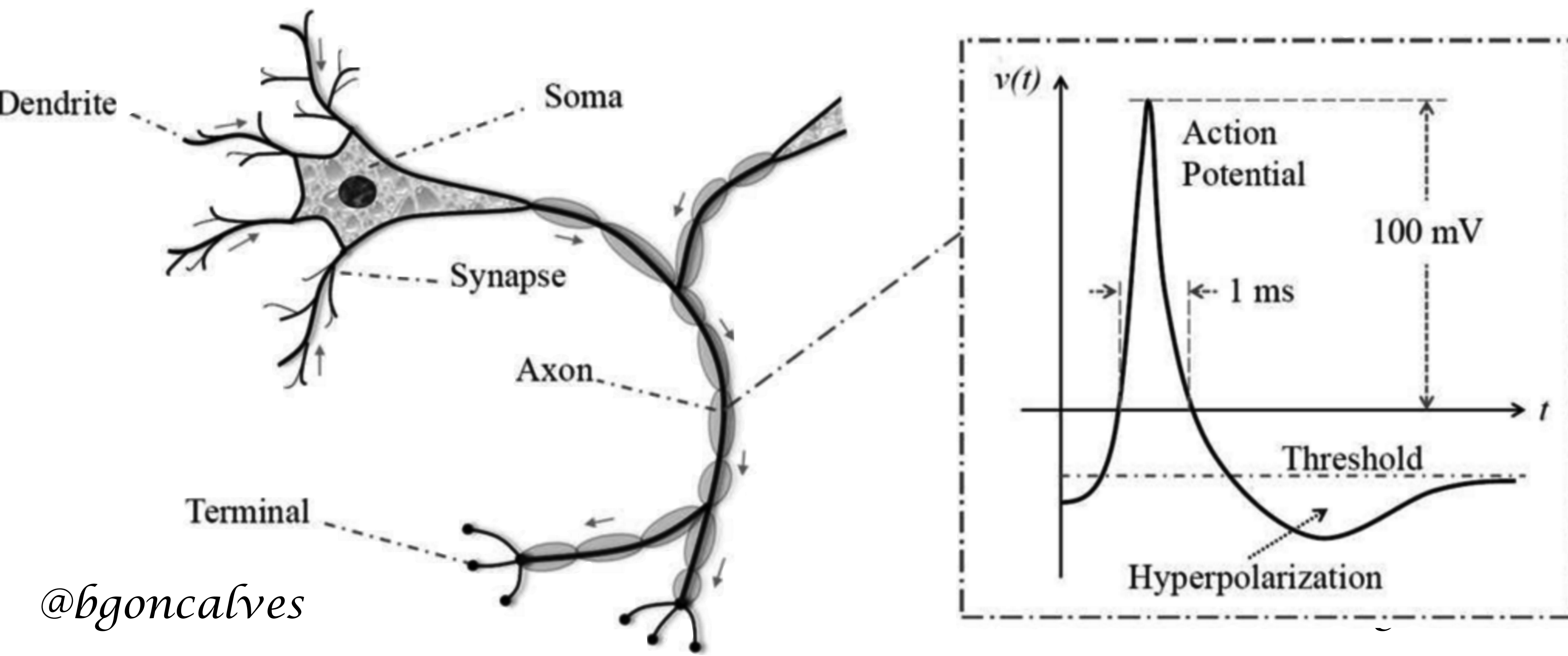

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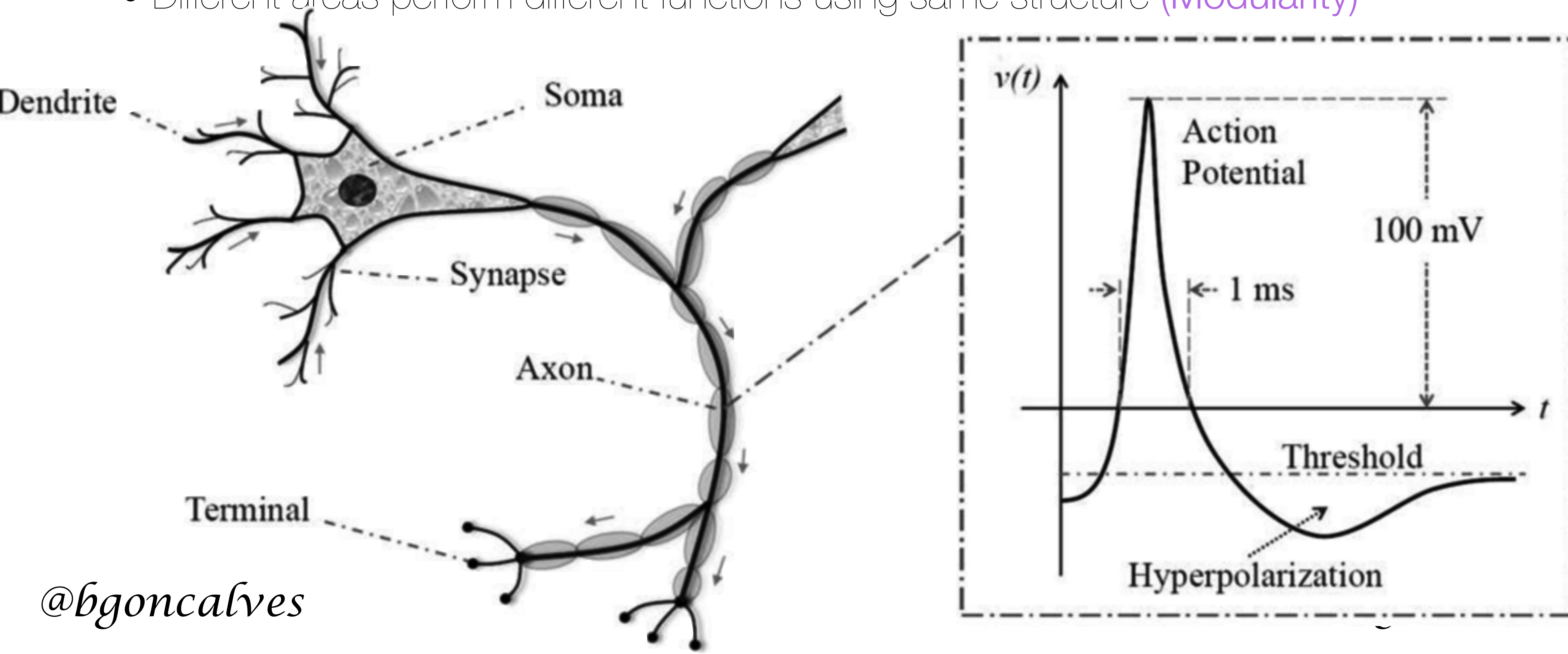
- Different areas perform different functions using same structure (Modularity)



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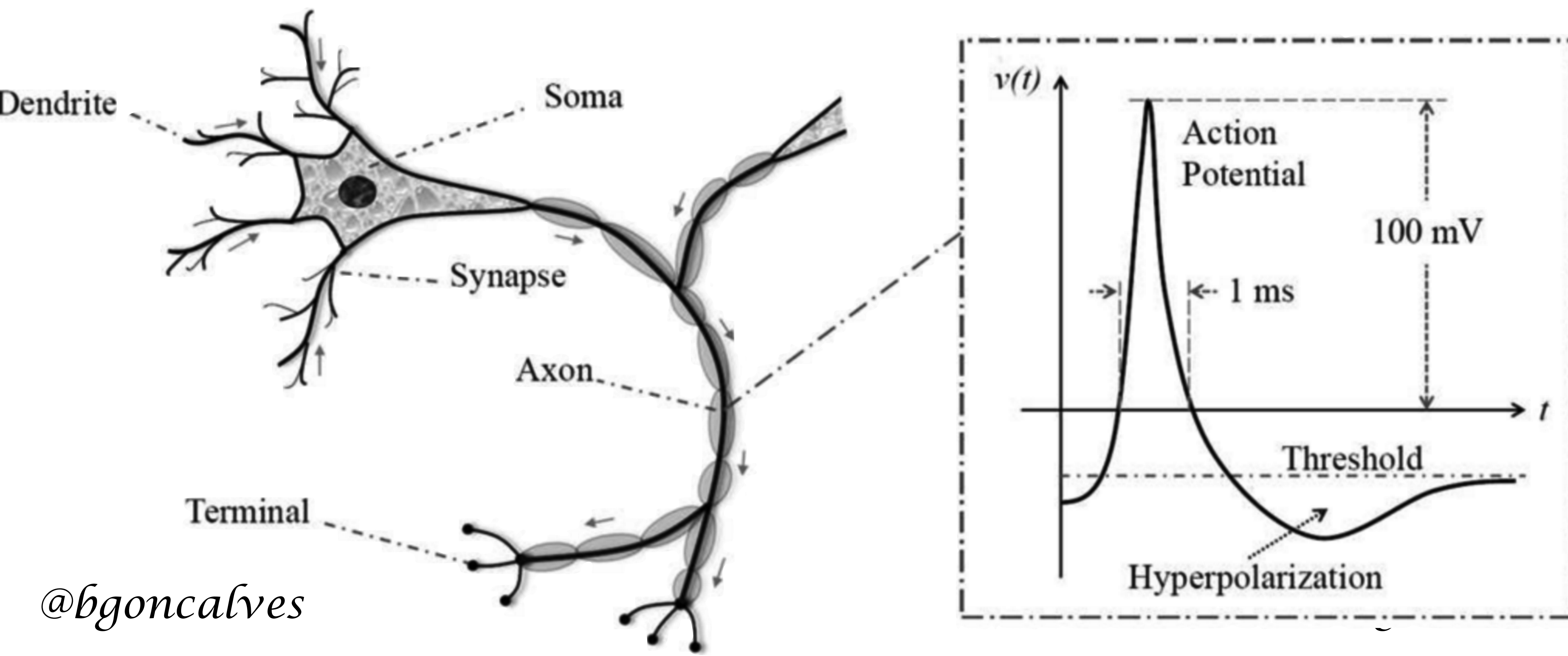

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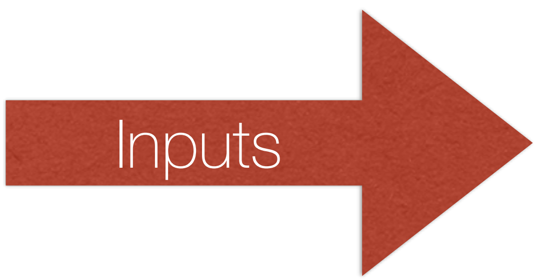

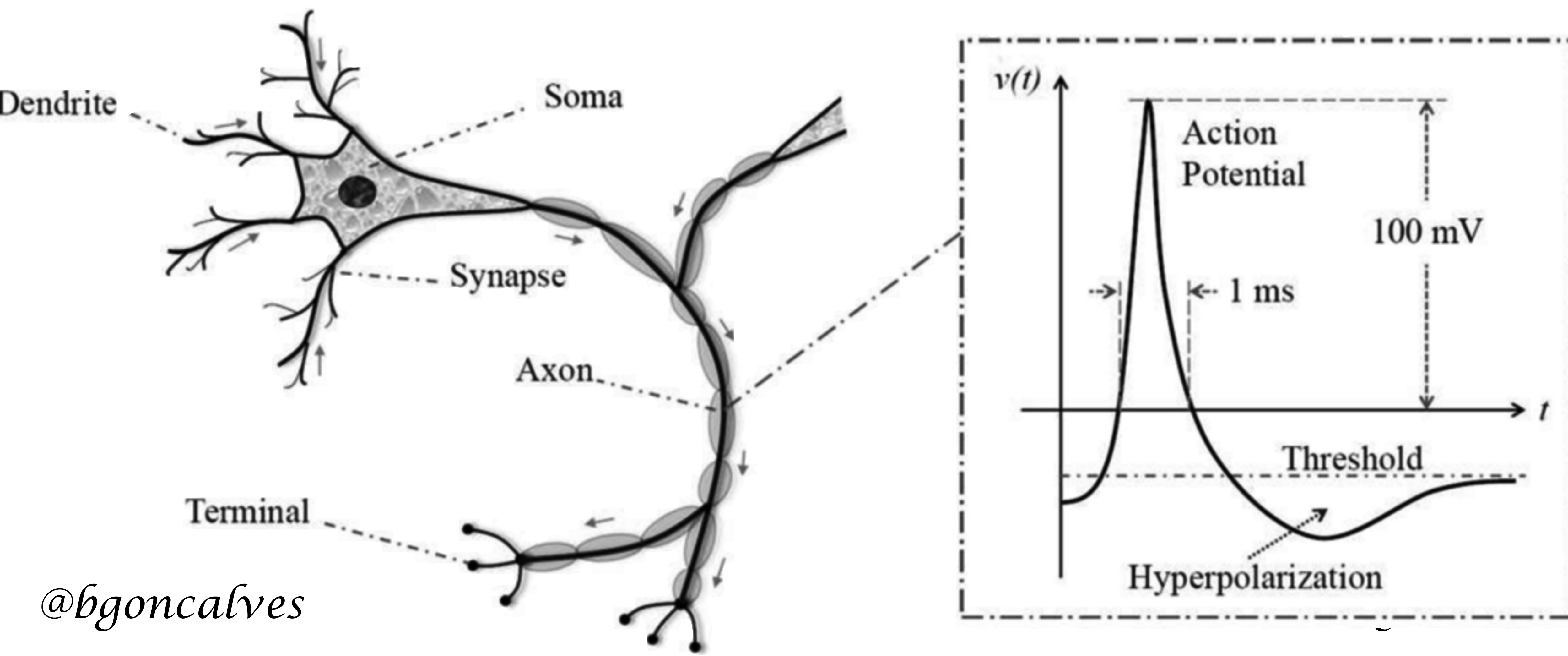

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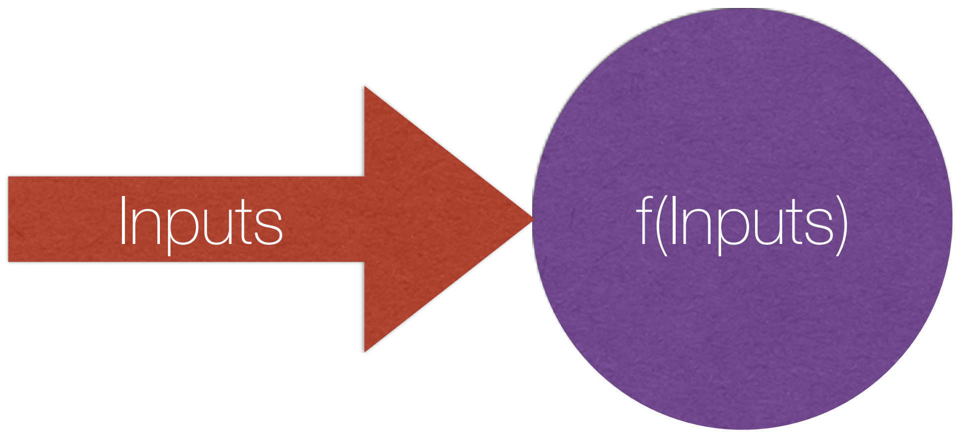

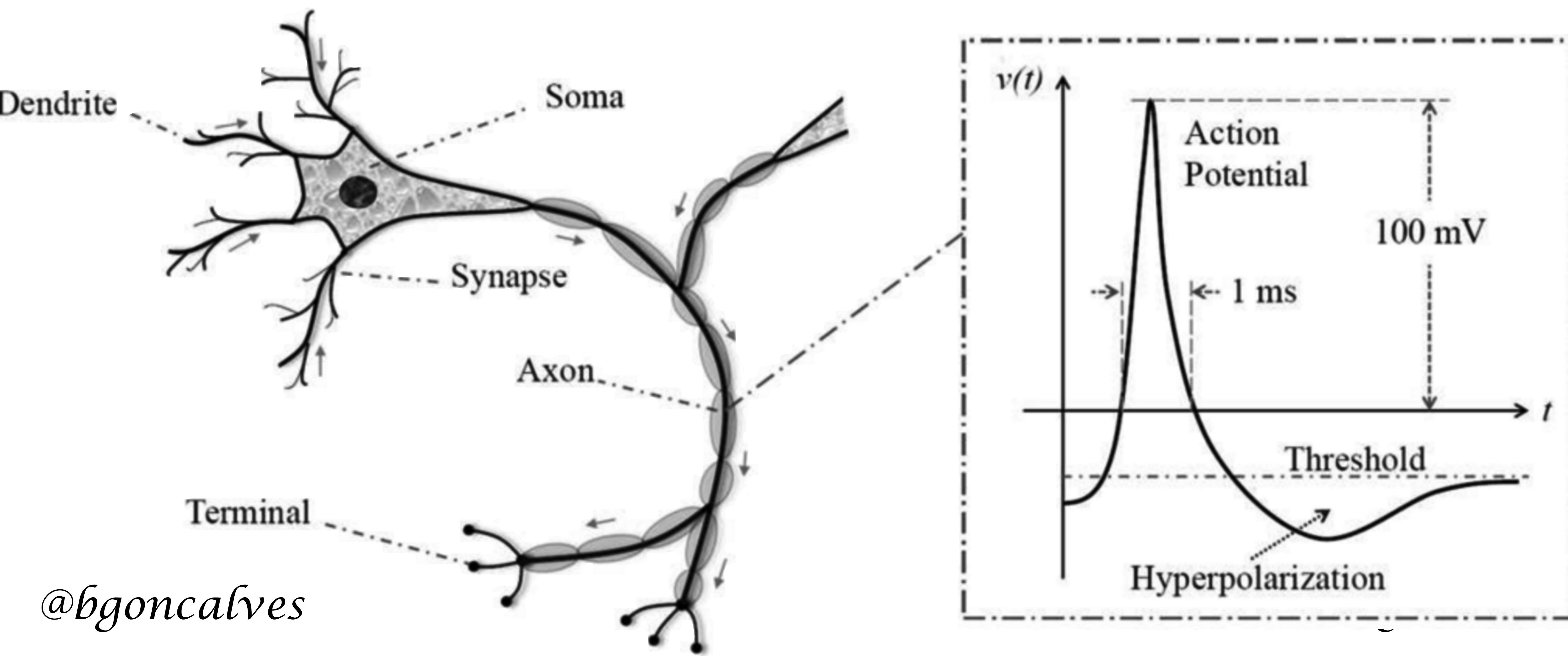

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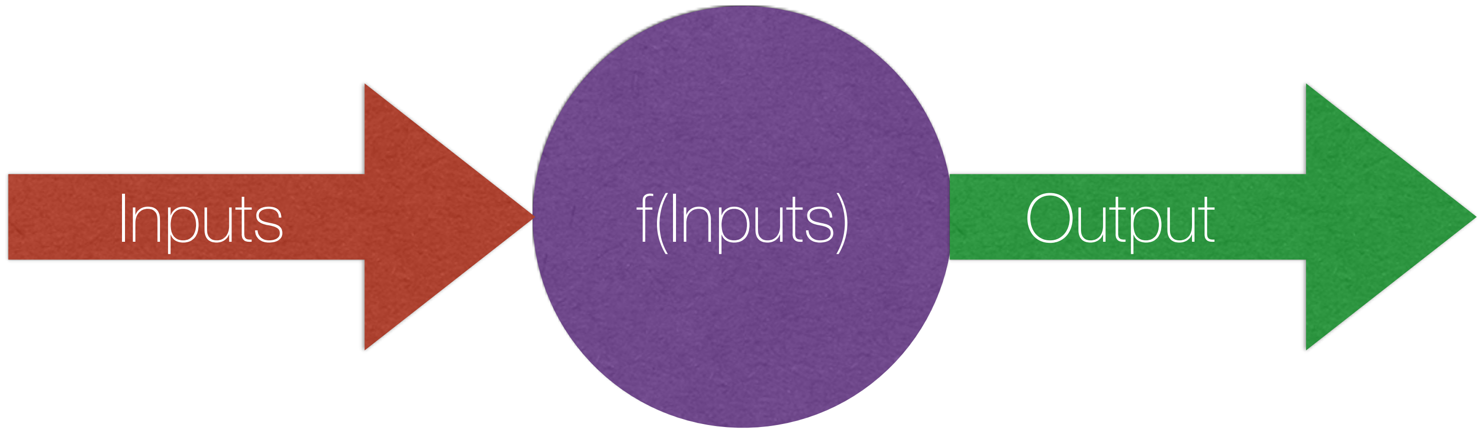

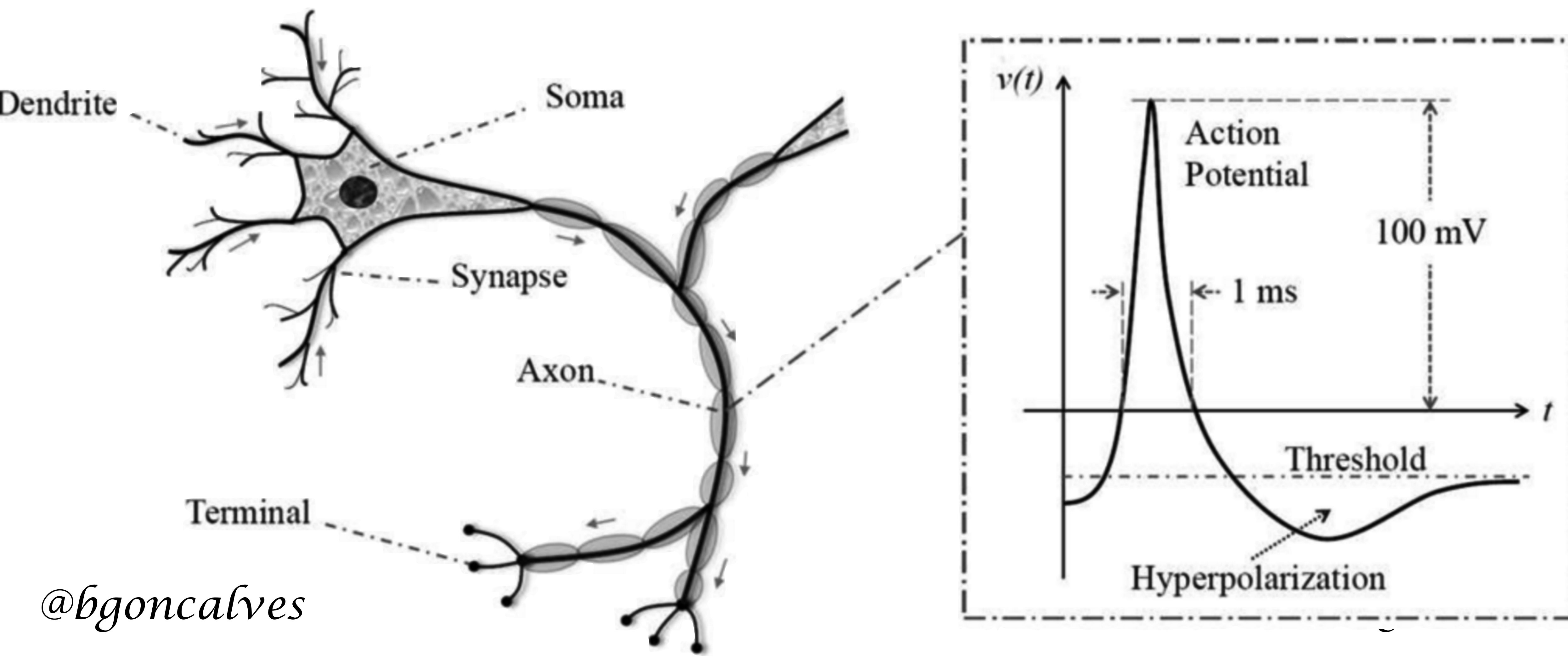

Optimization Problem

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Optimization Problem

- (Machine) Learning can be thought of as an optimization problem.
- Optimization Problems have 3 distinct pieces:
  - The constraints — Neural Network
  - The function to optimize — Prediction Error
  - The optimization algorithm. — Gradient Descent

Artificial Neuron

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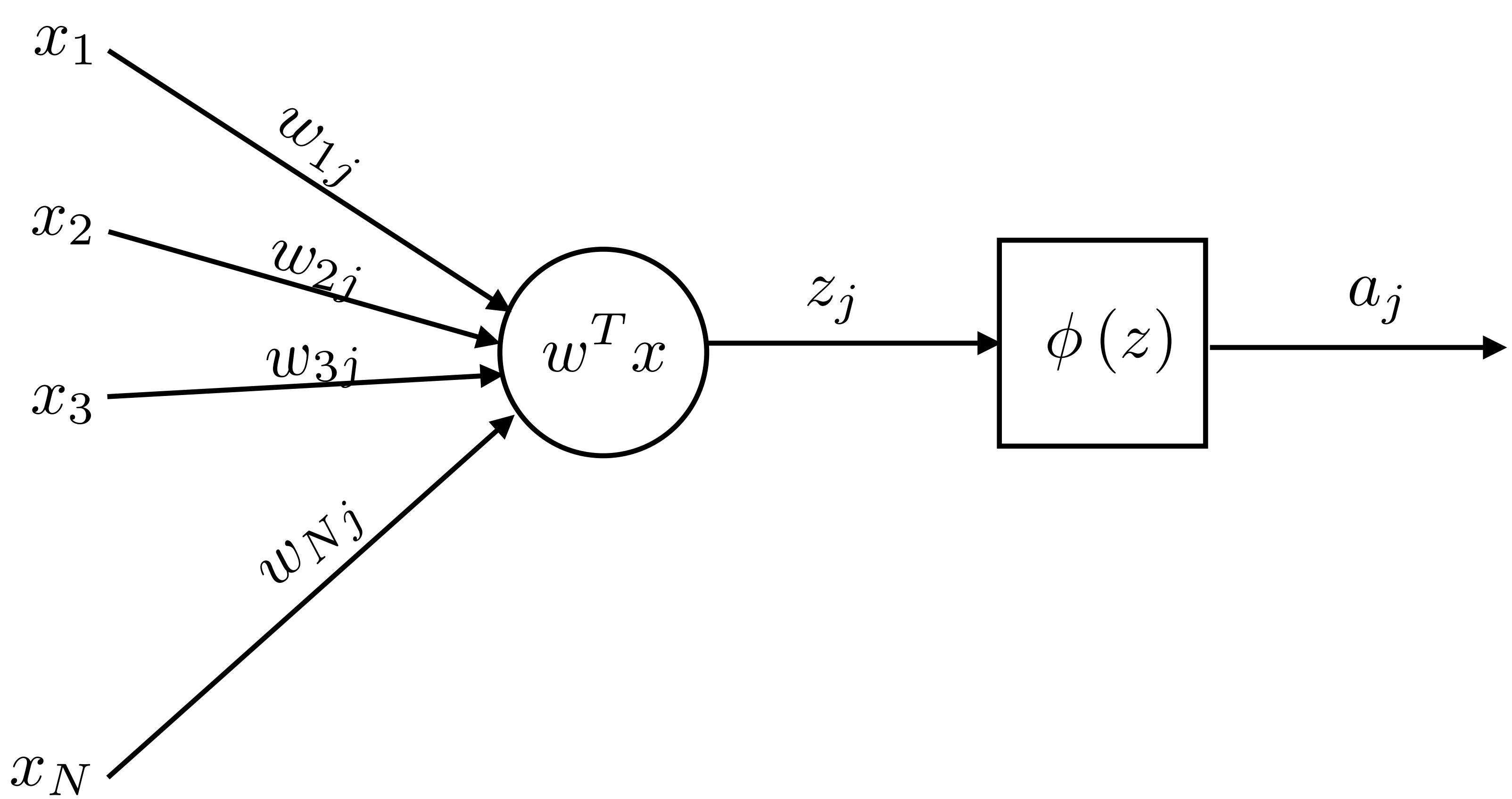

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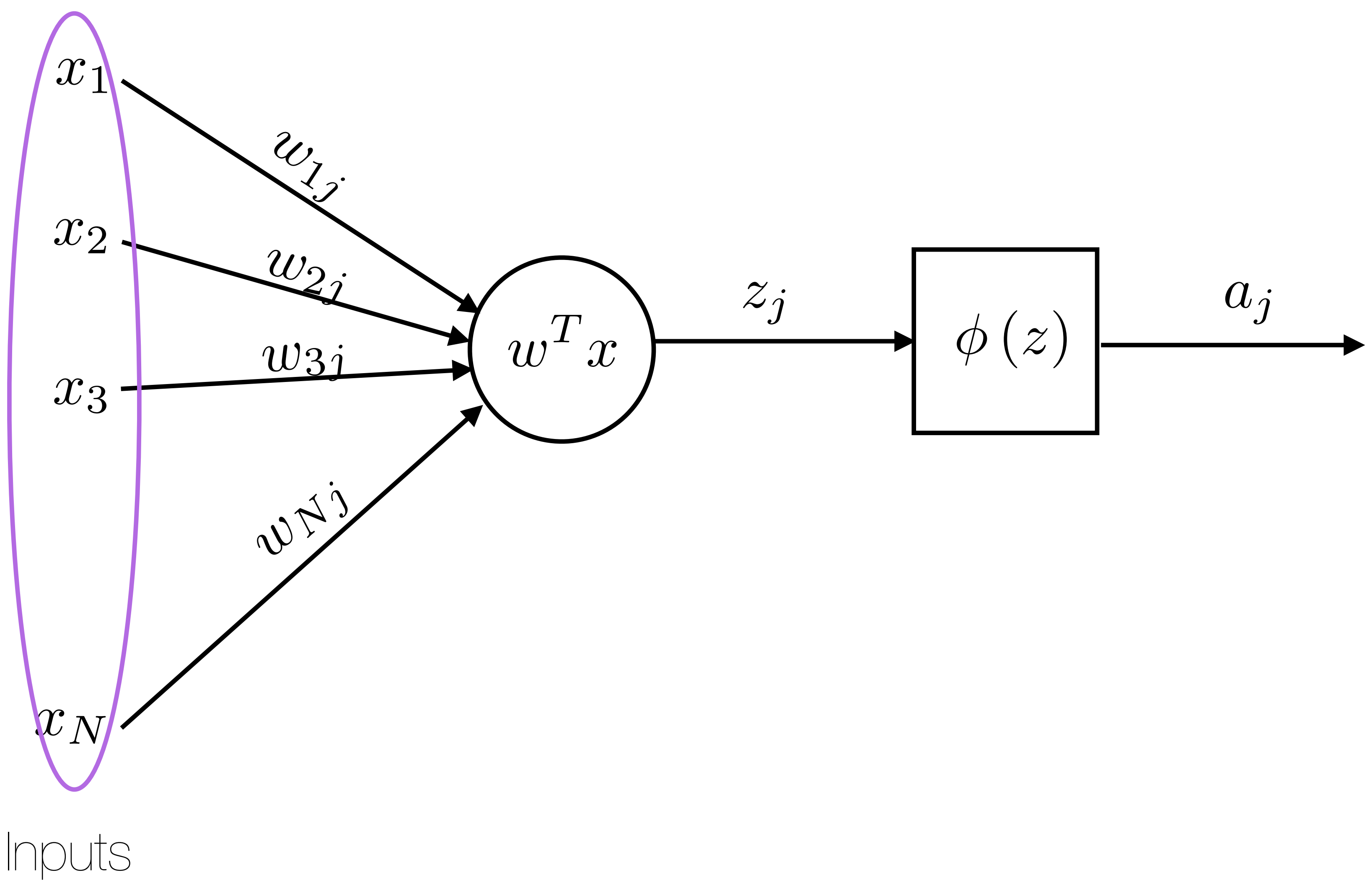

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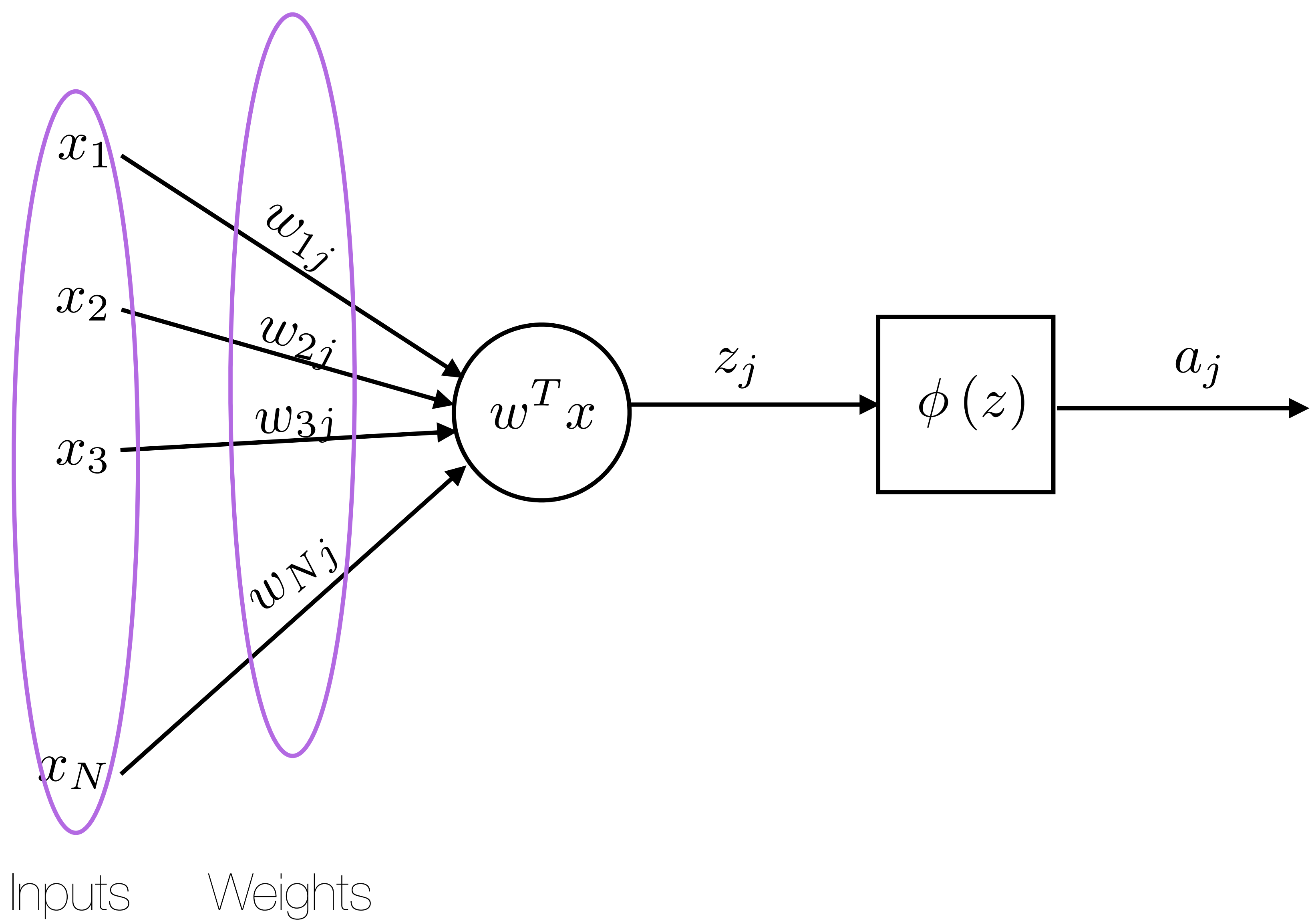

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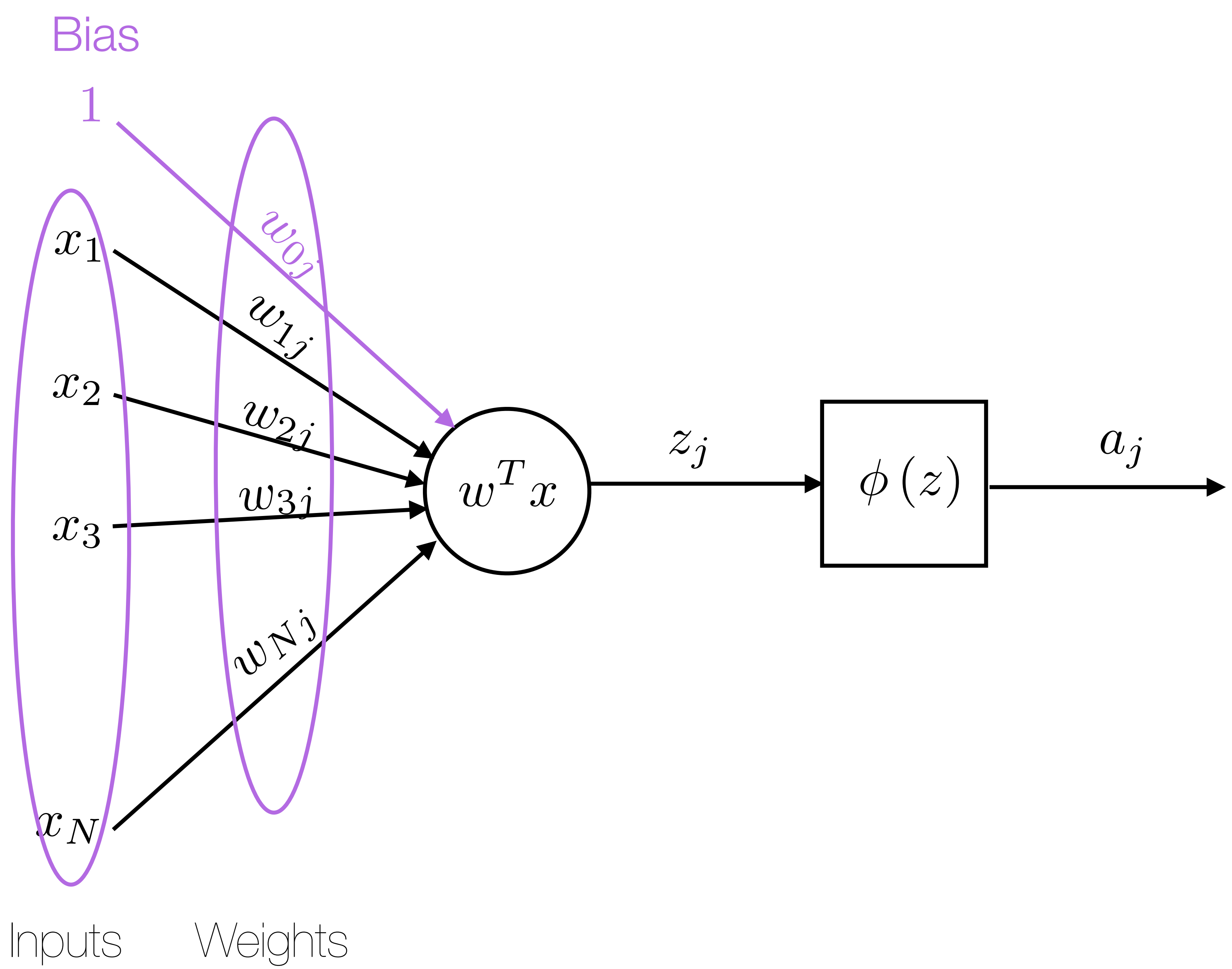

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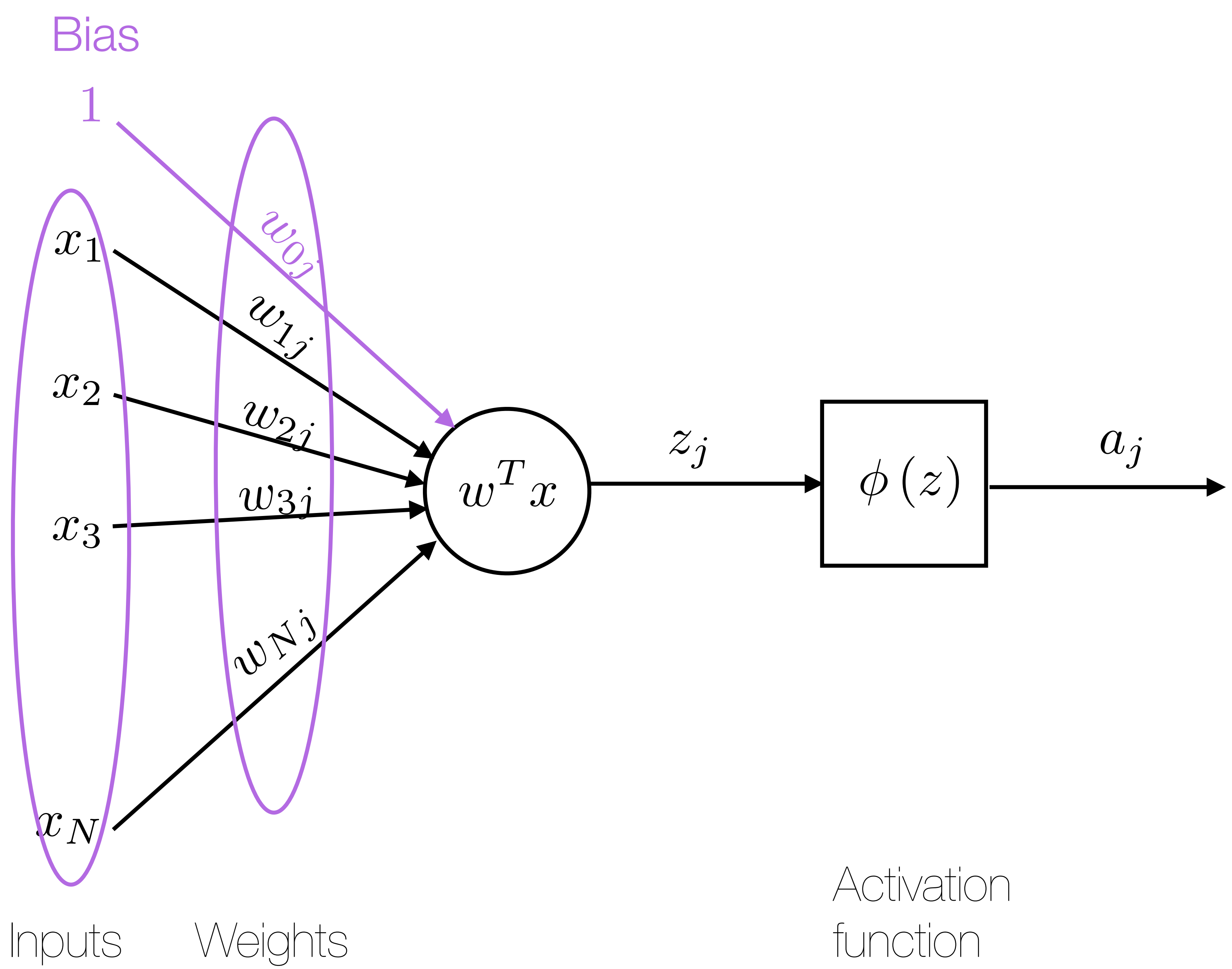

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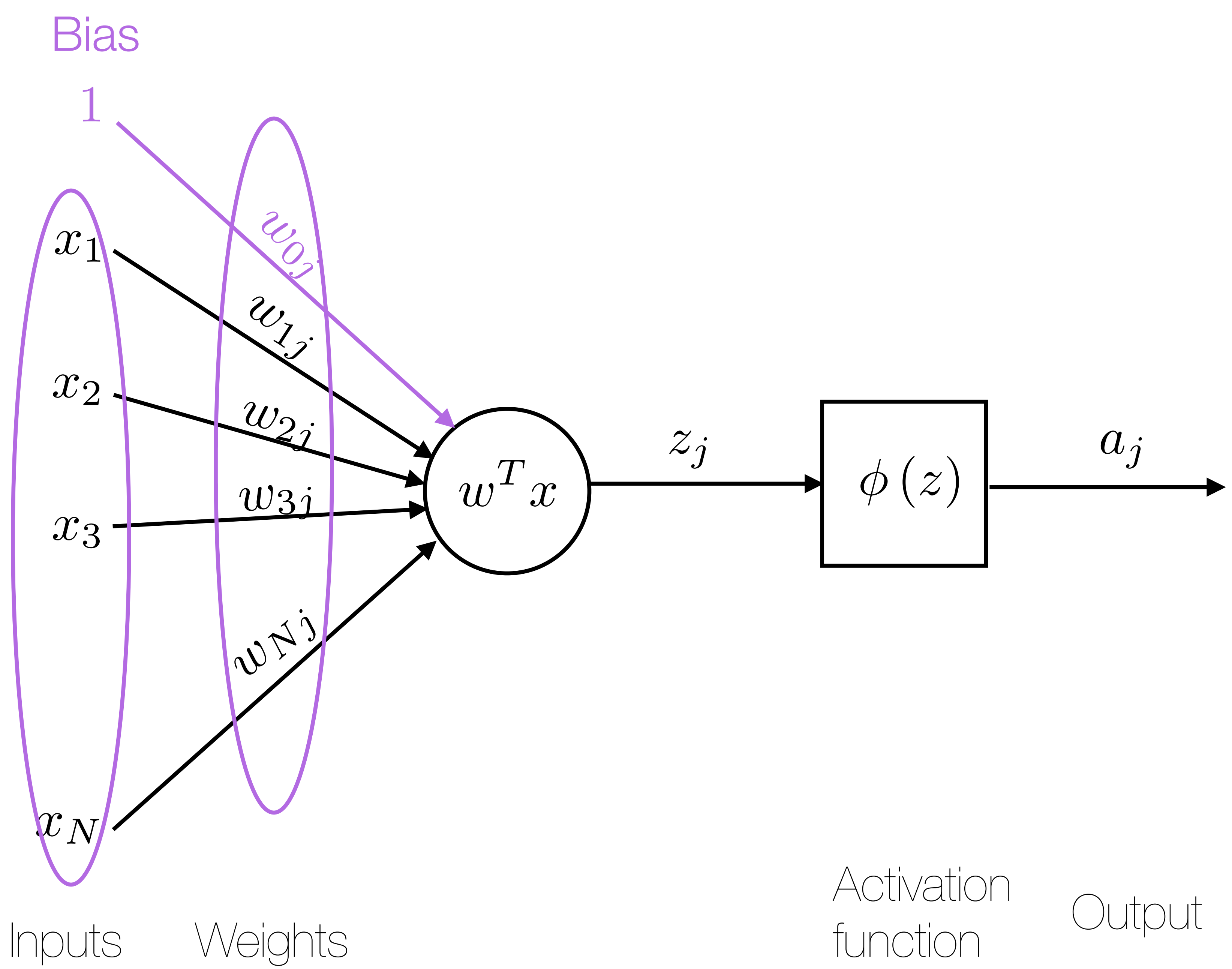

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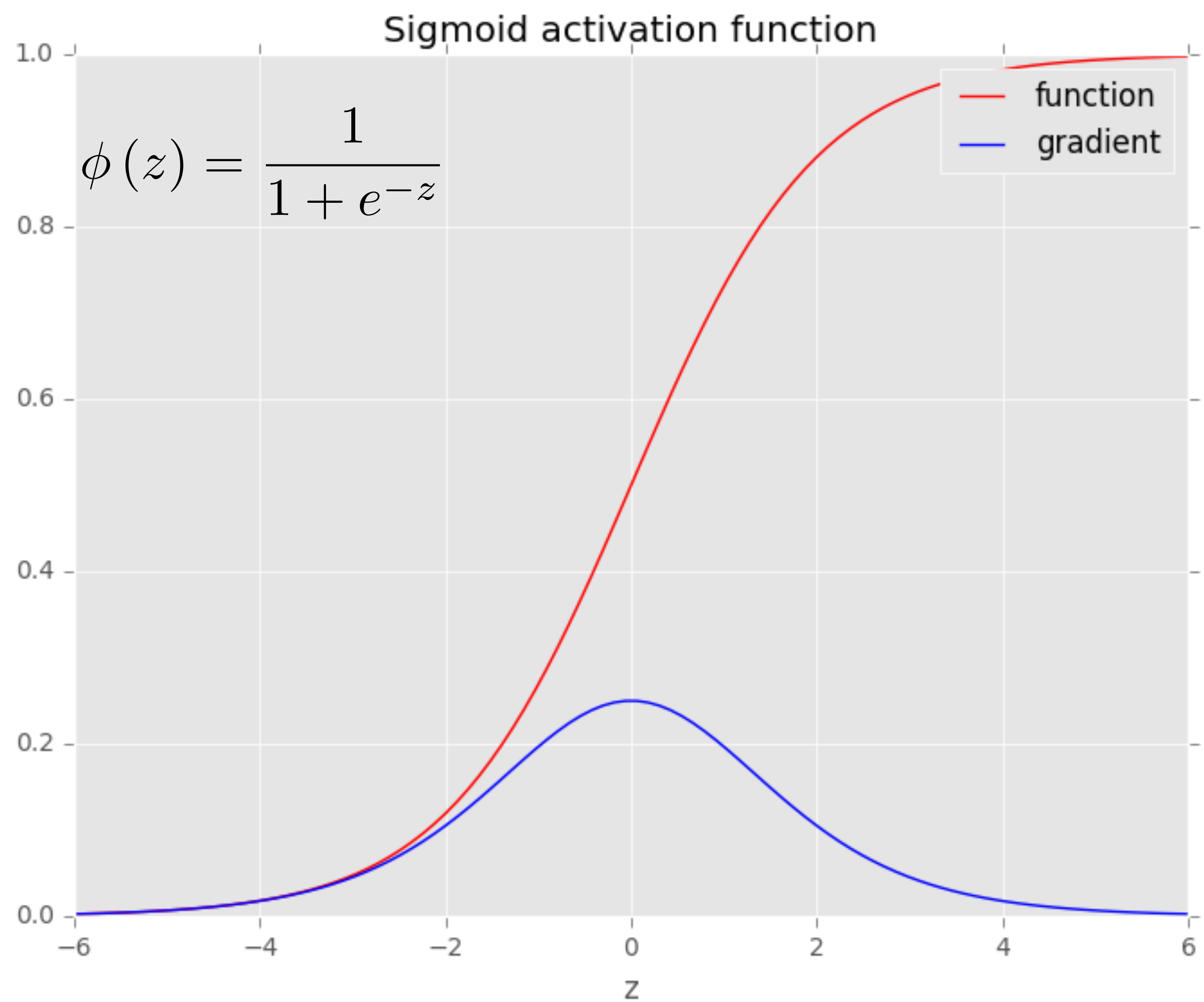
Activation Function - Sigmoid

http://github.com/bmtgoncalves/Neural-Networks



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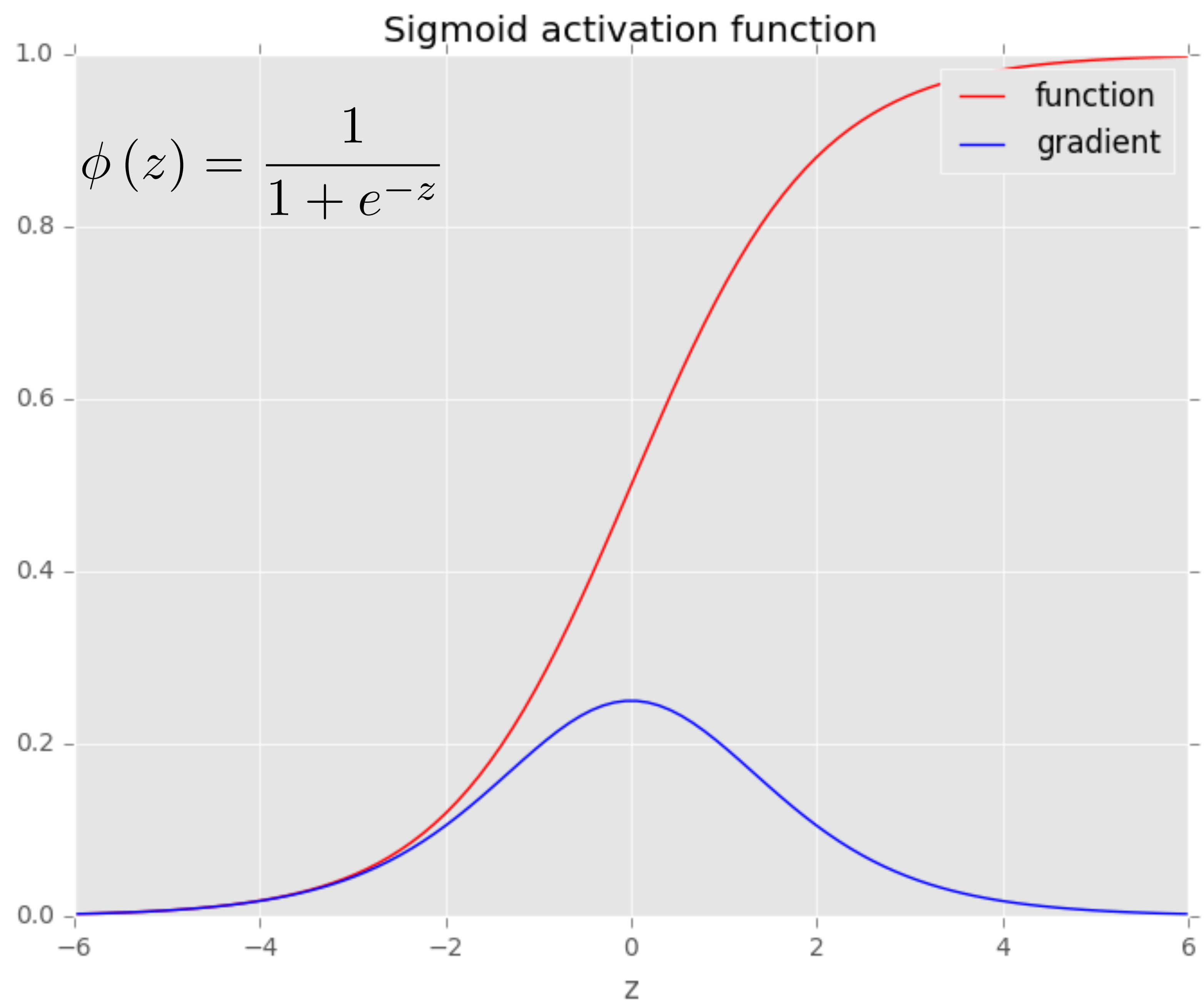

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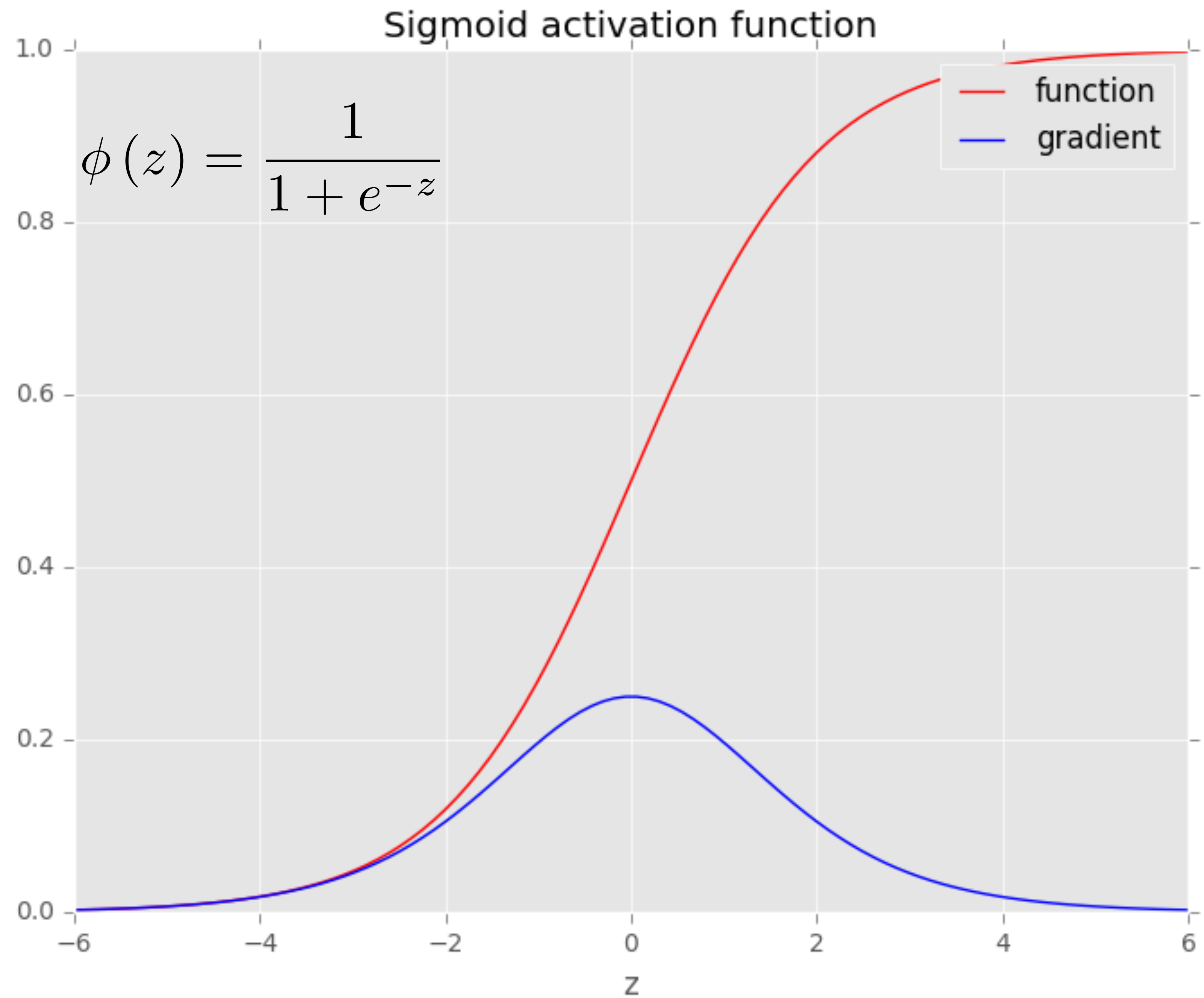

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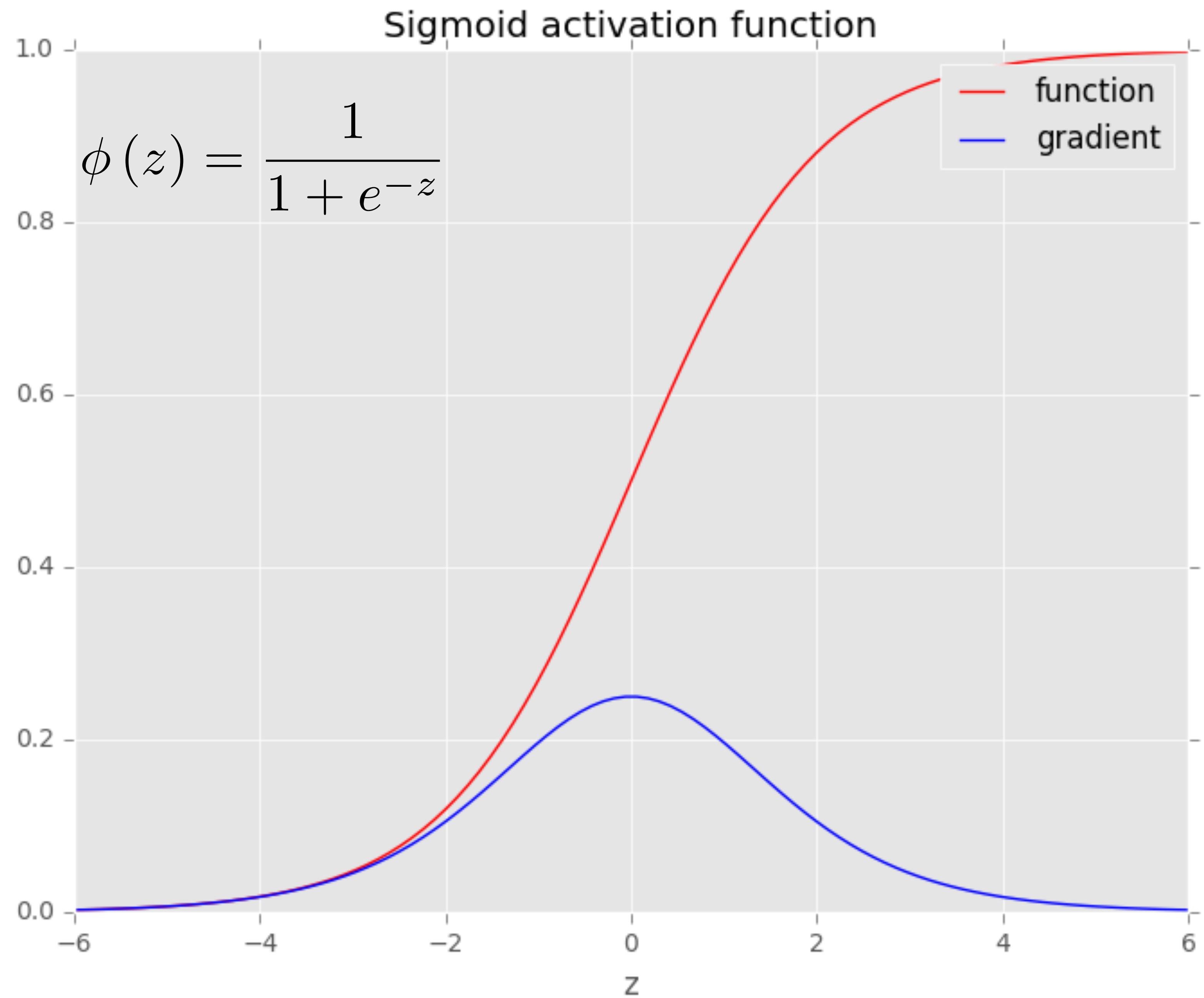

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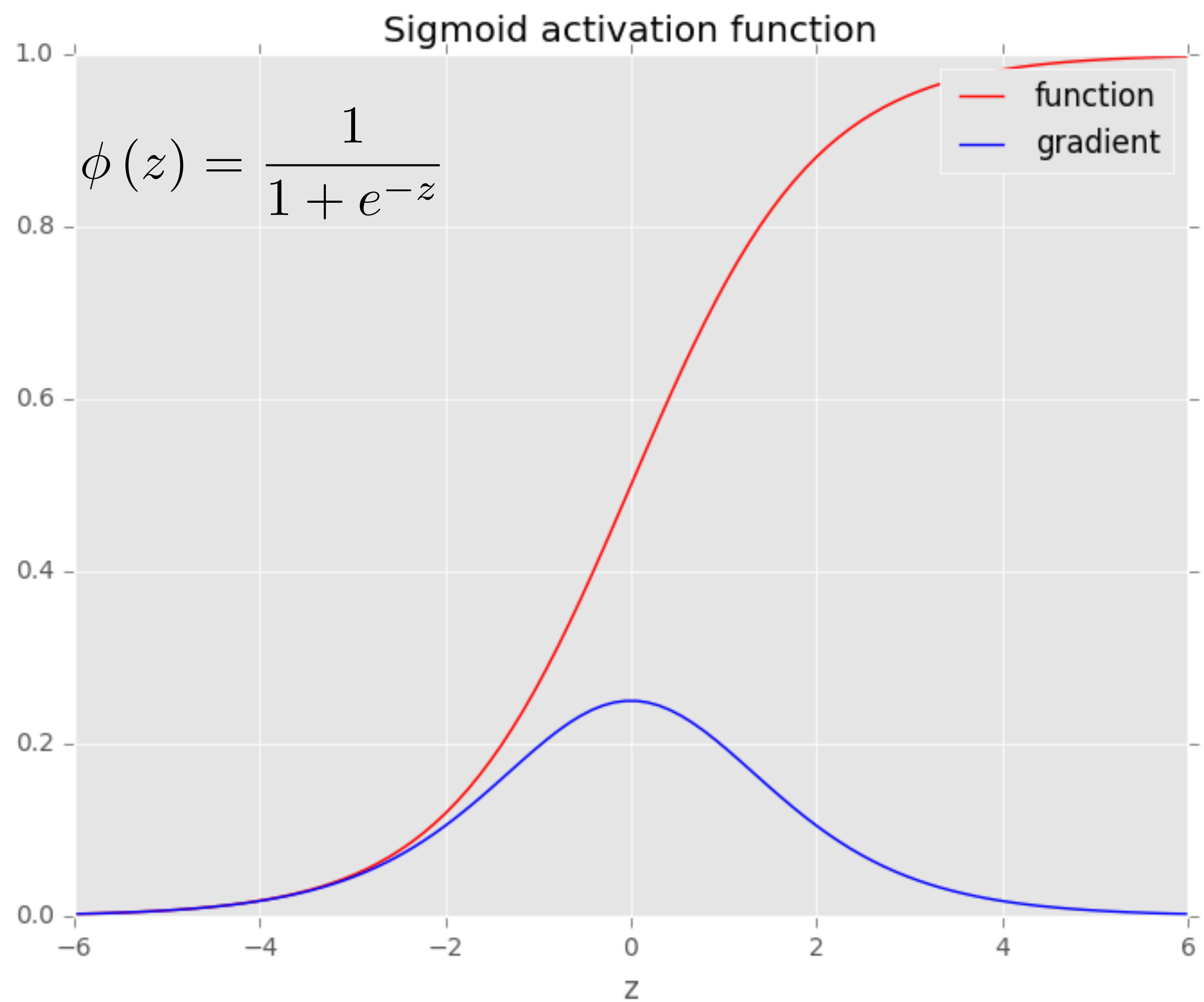

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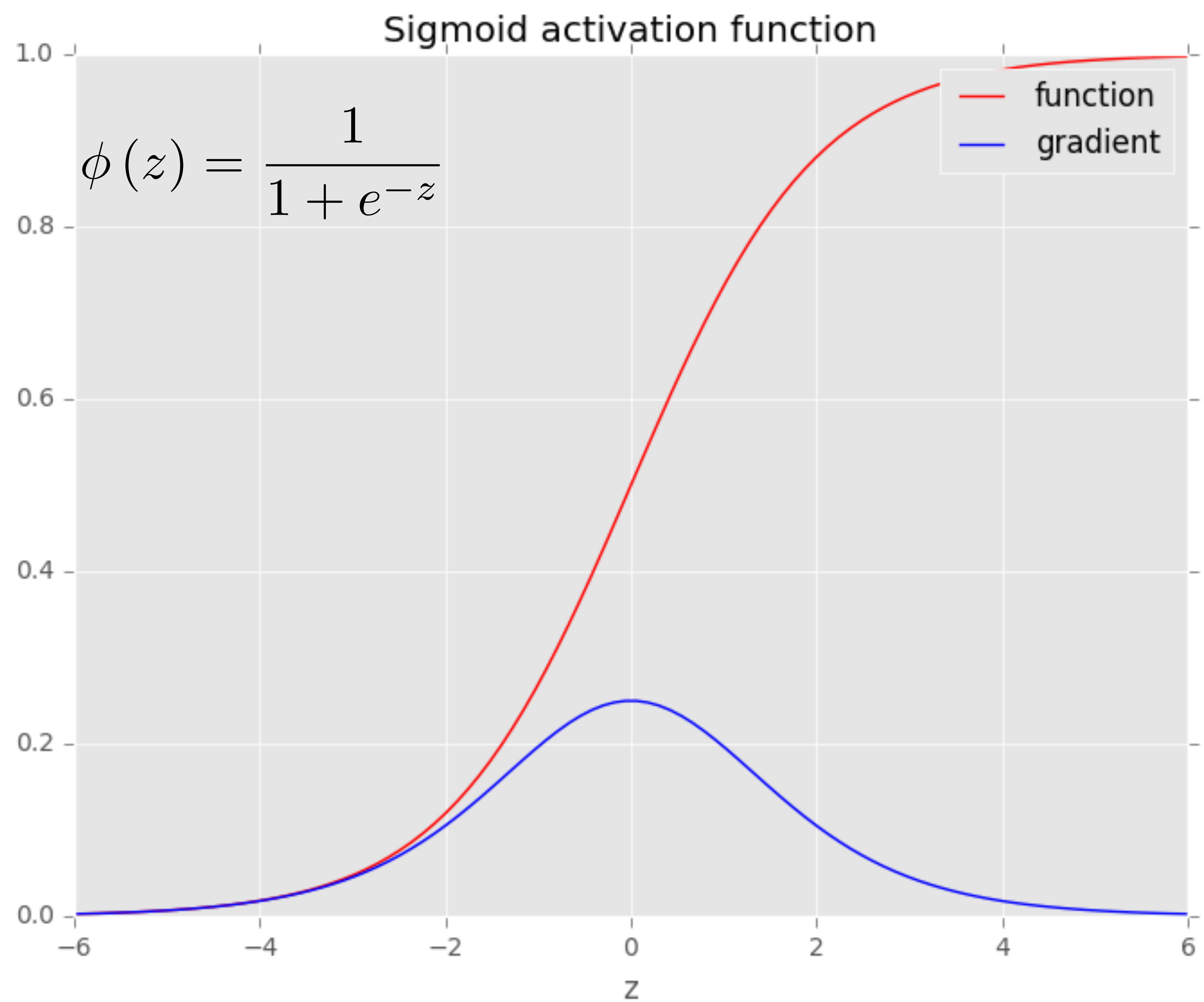

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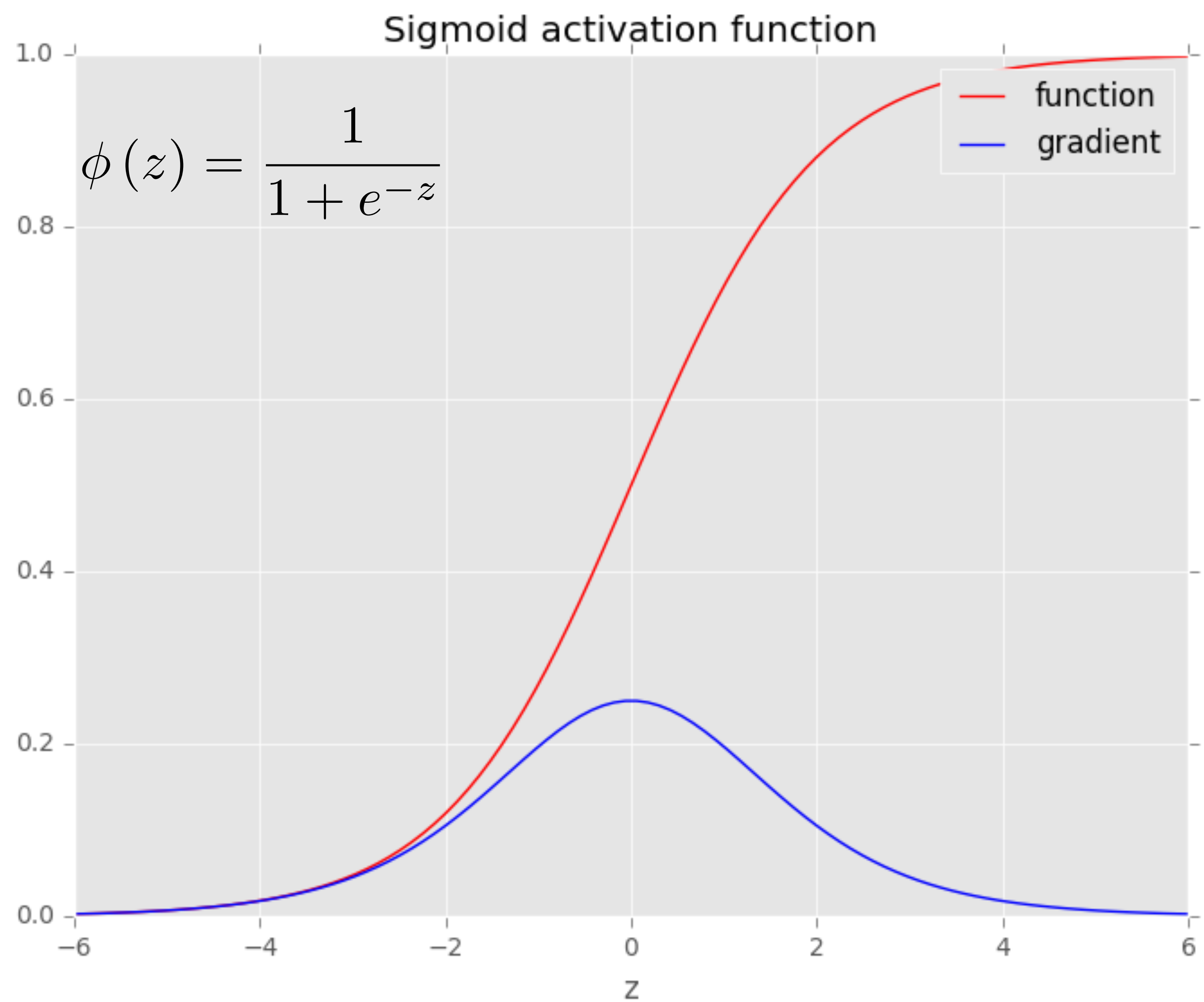

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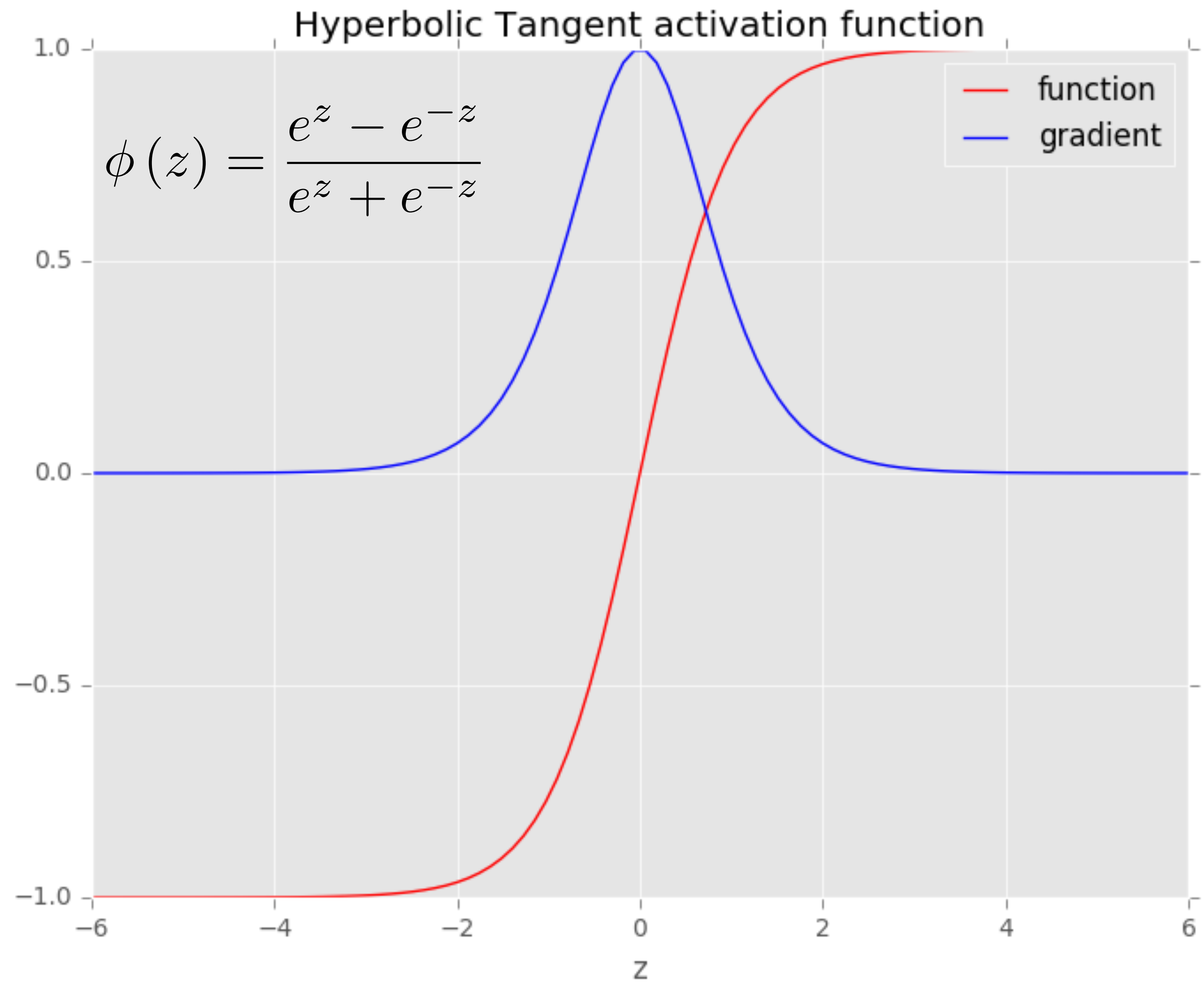

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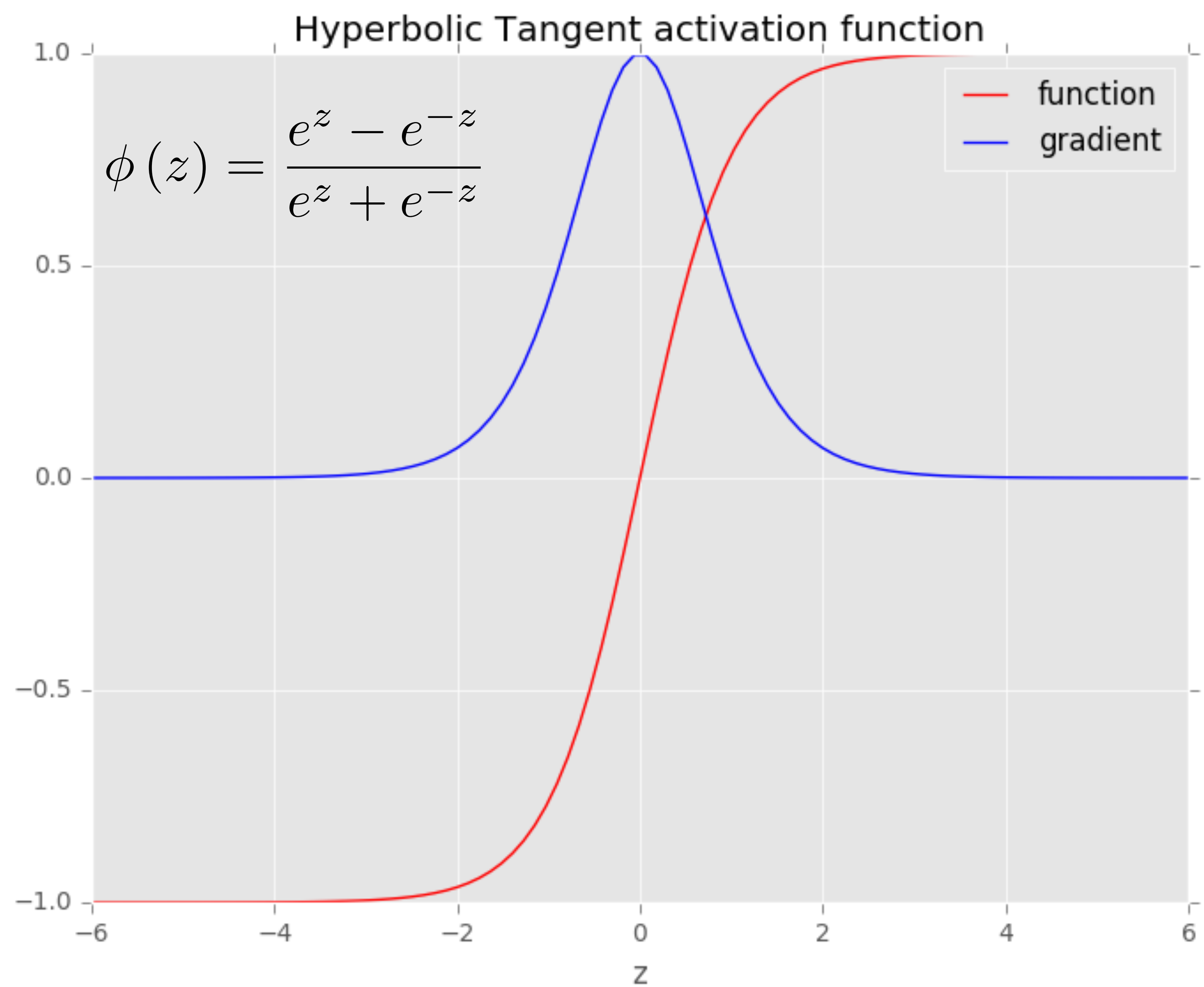

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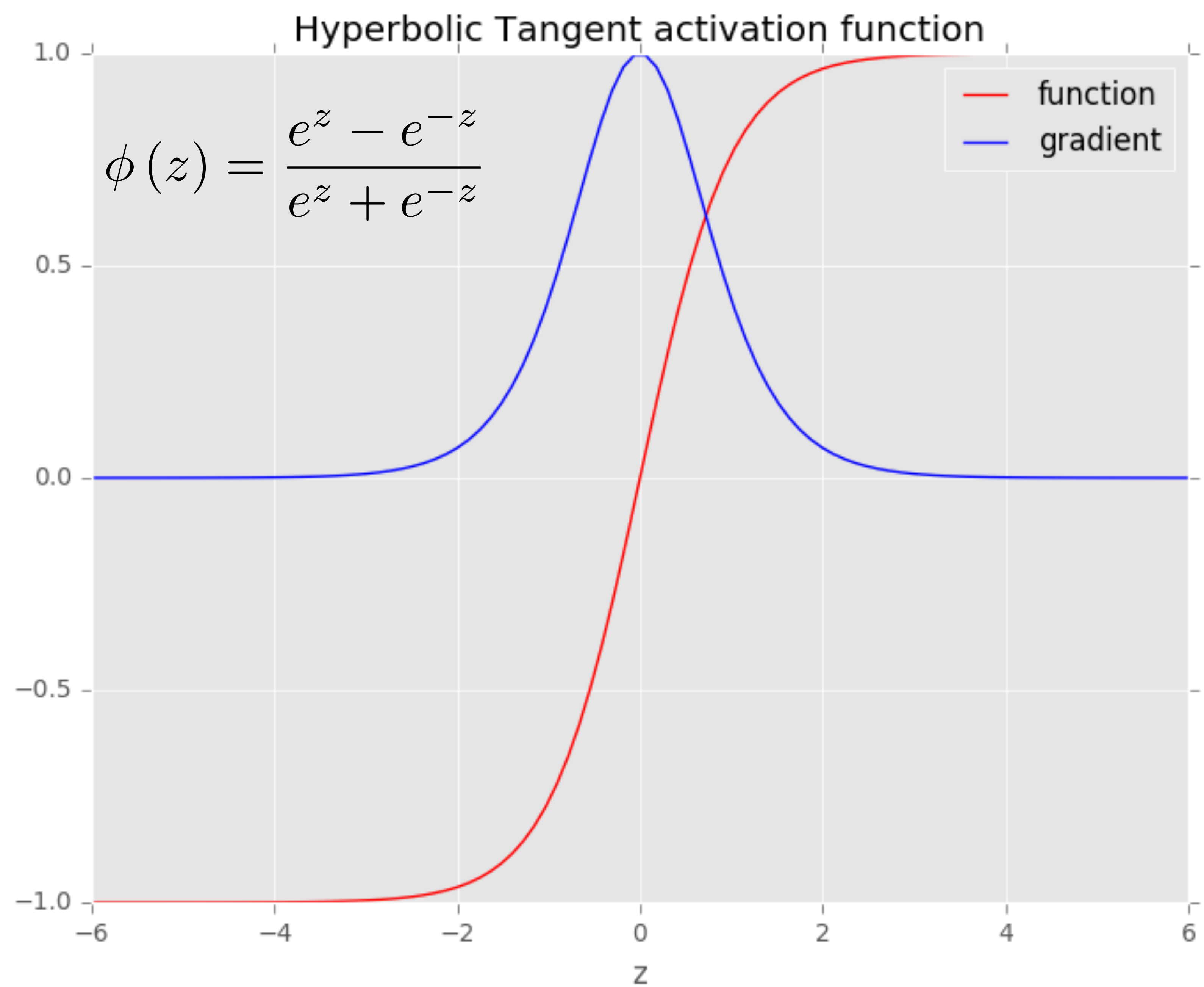

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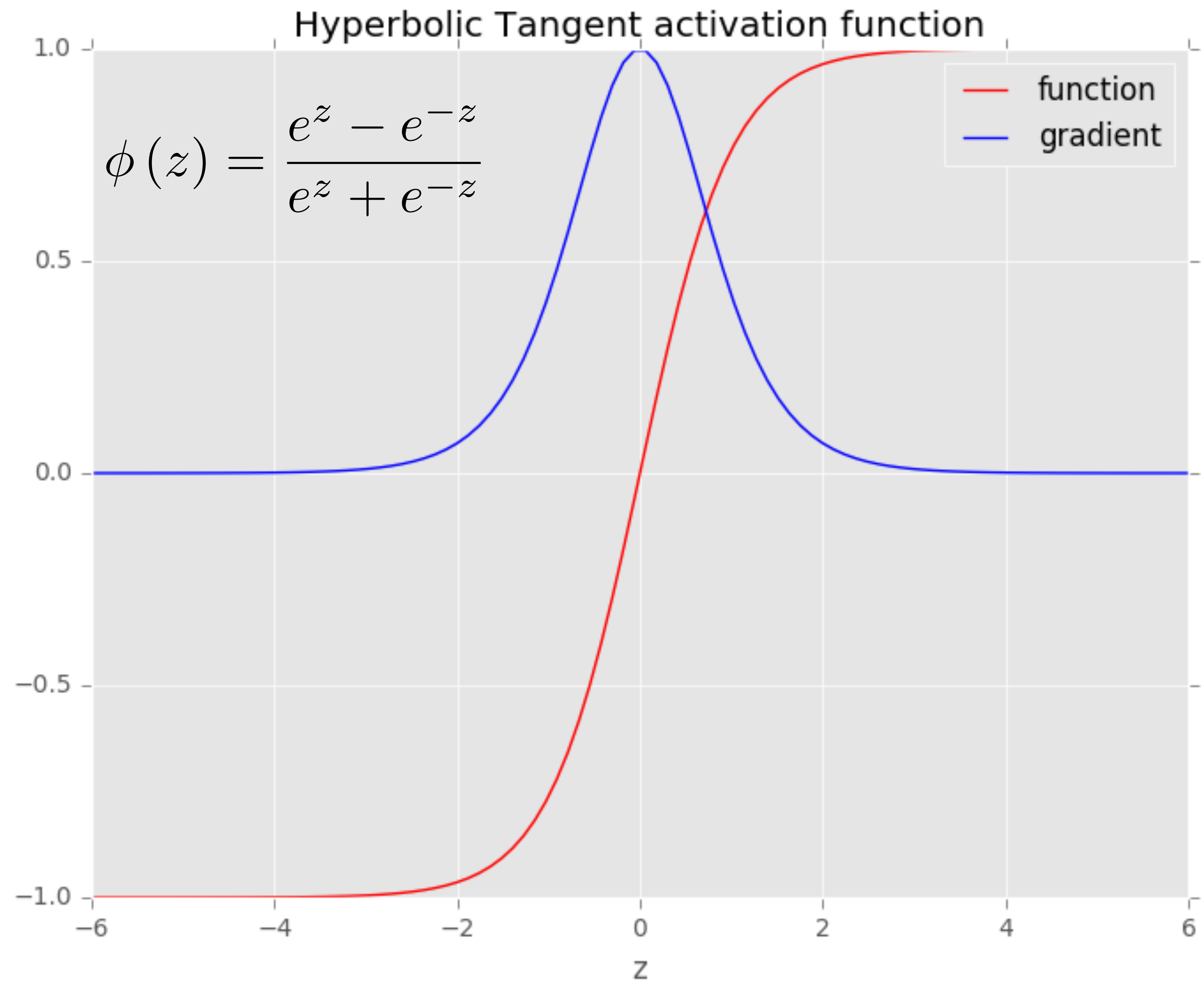

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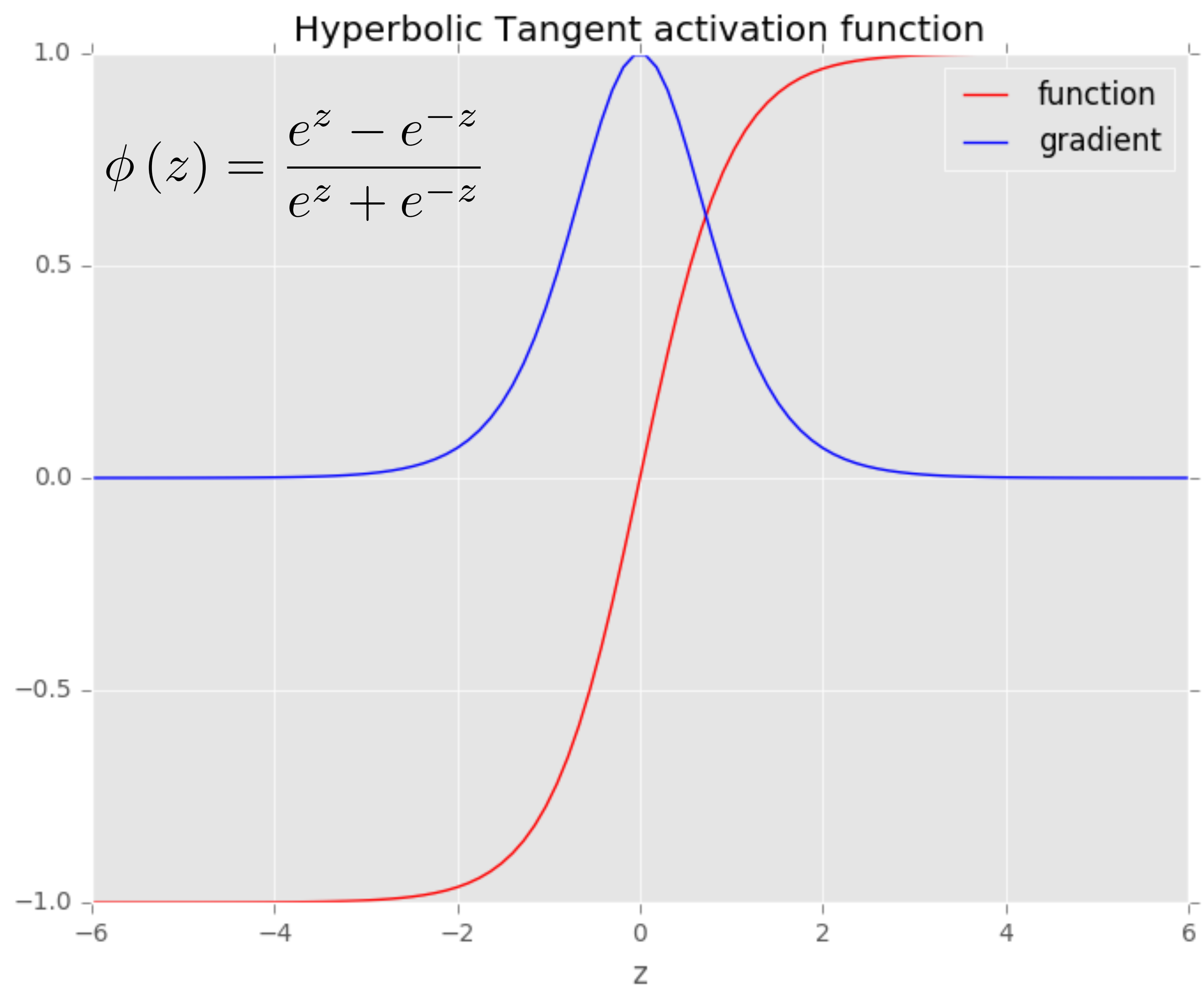

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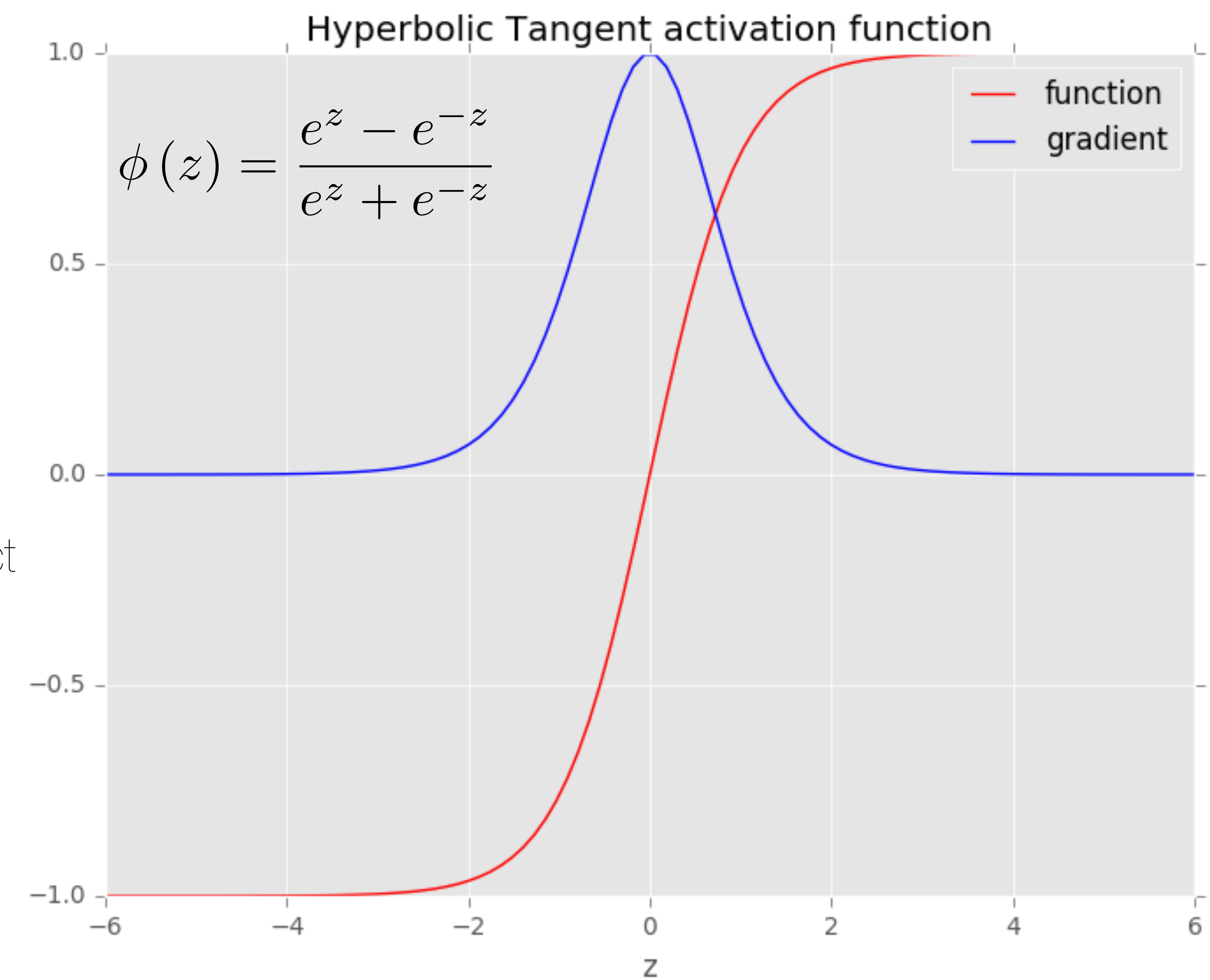

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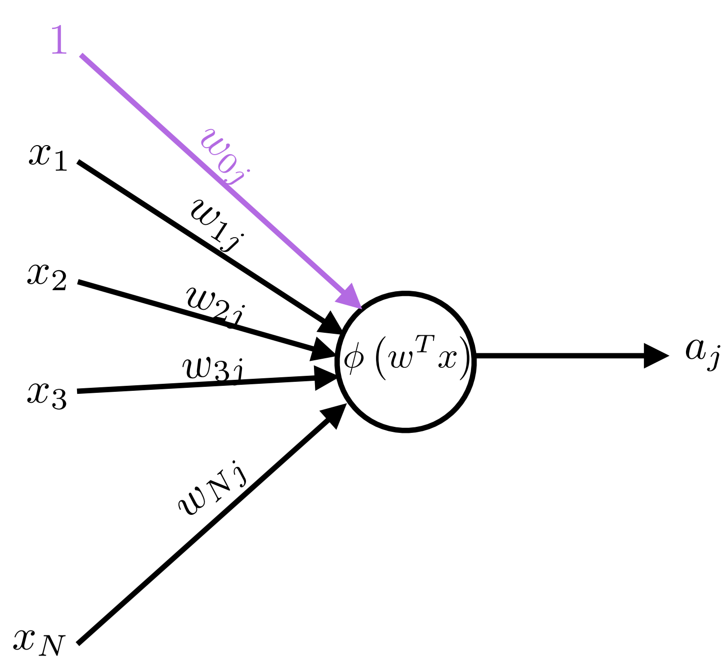

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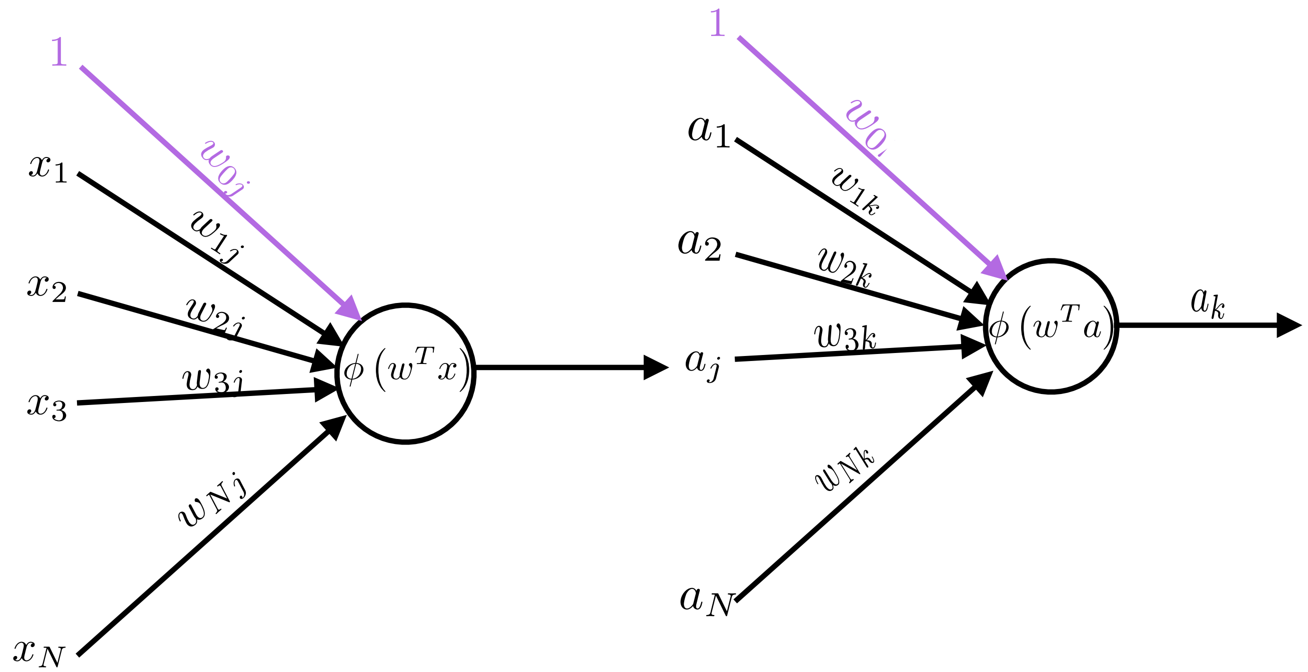

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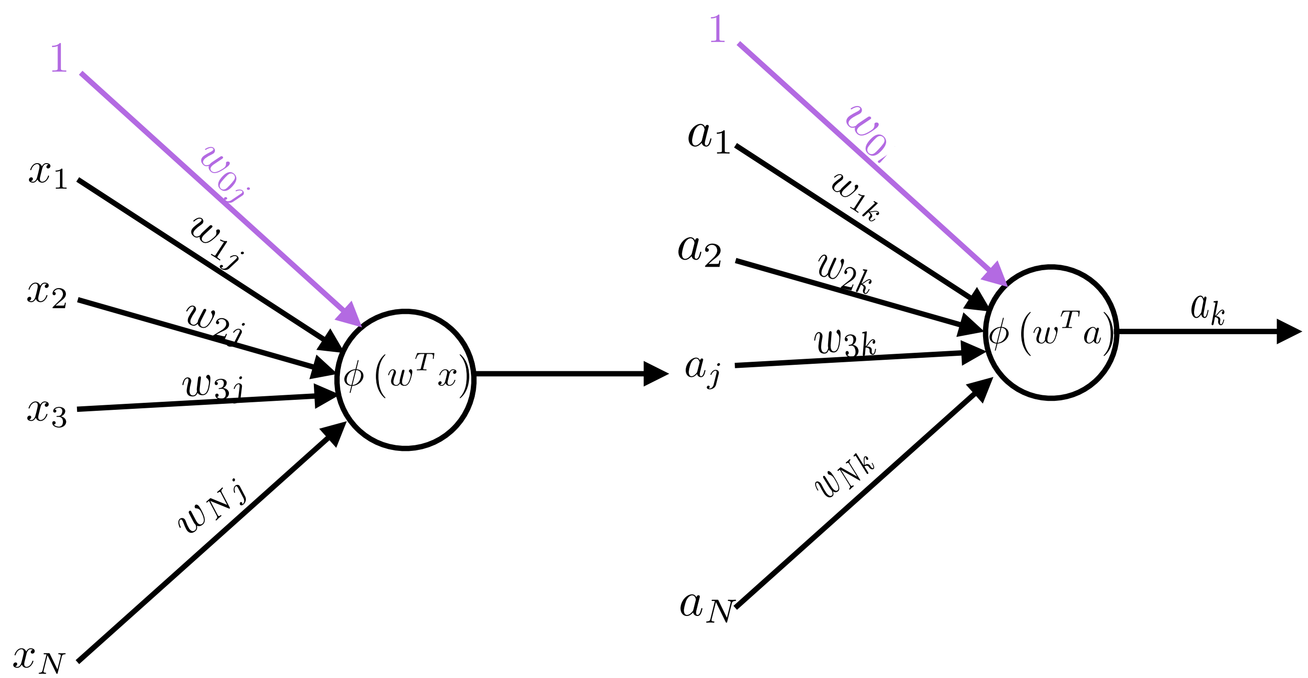

- But how can we propagate back the errors and update the weights?

Backward Propagation of Errors (BackProp)

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- For inner layers there is no “real output”!

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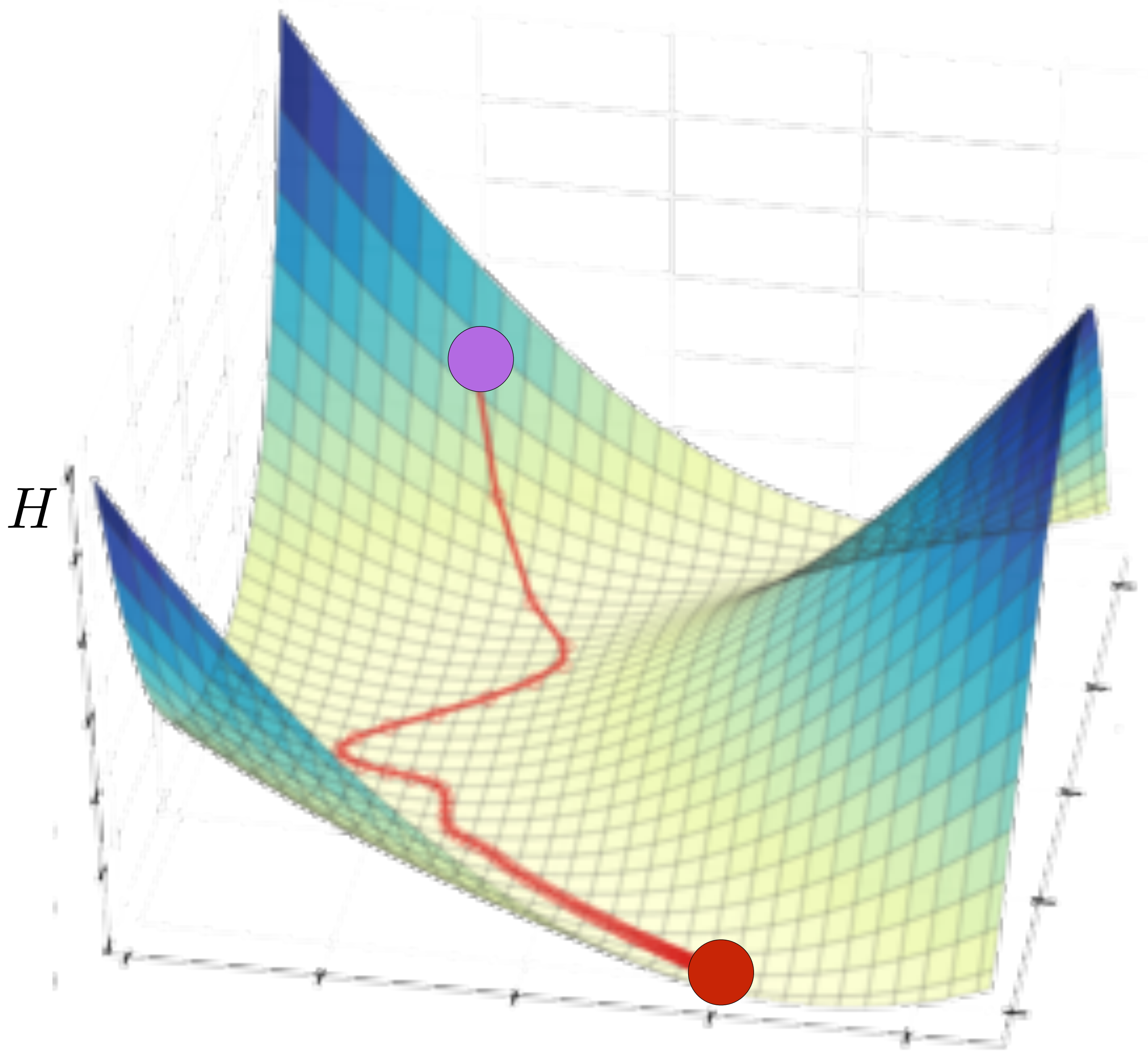
The Cross Entropy is complementary to sigmoid activation in the output layer and improves its stability.

Gradient Descent



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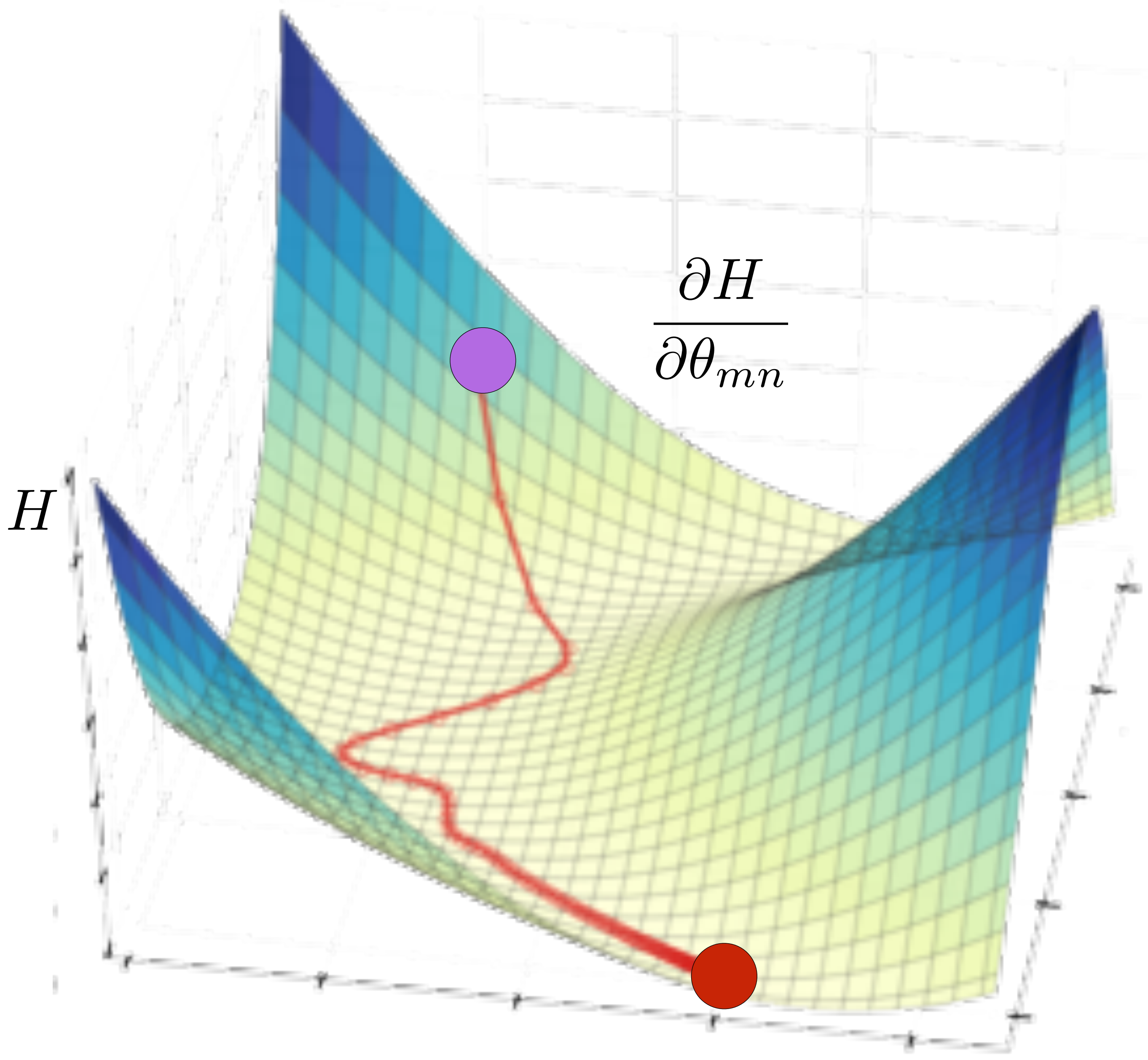

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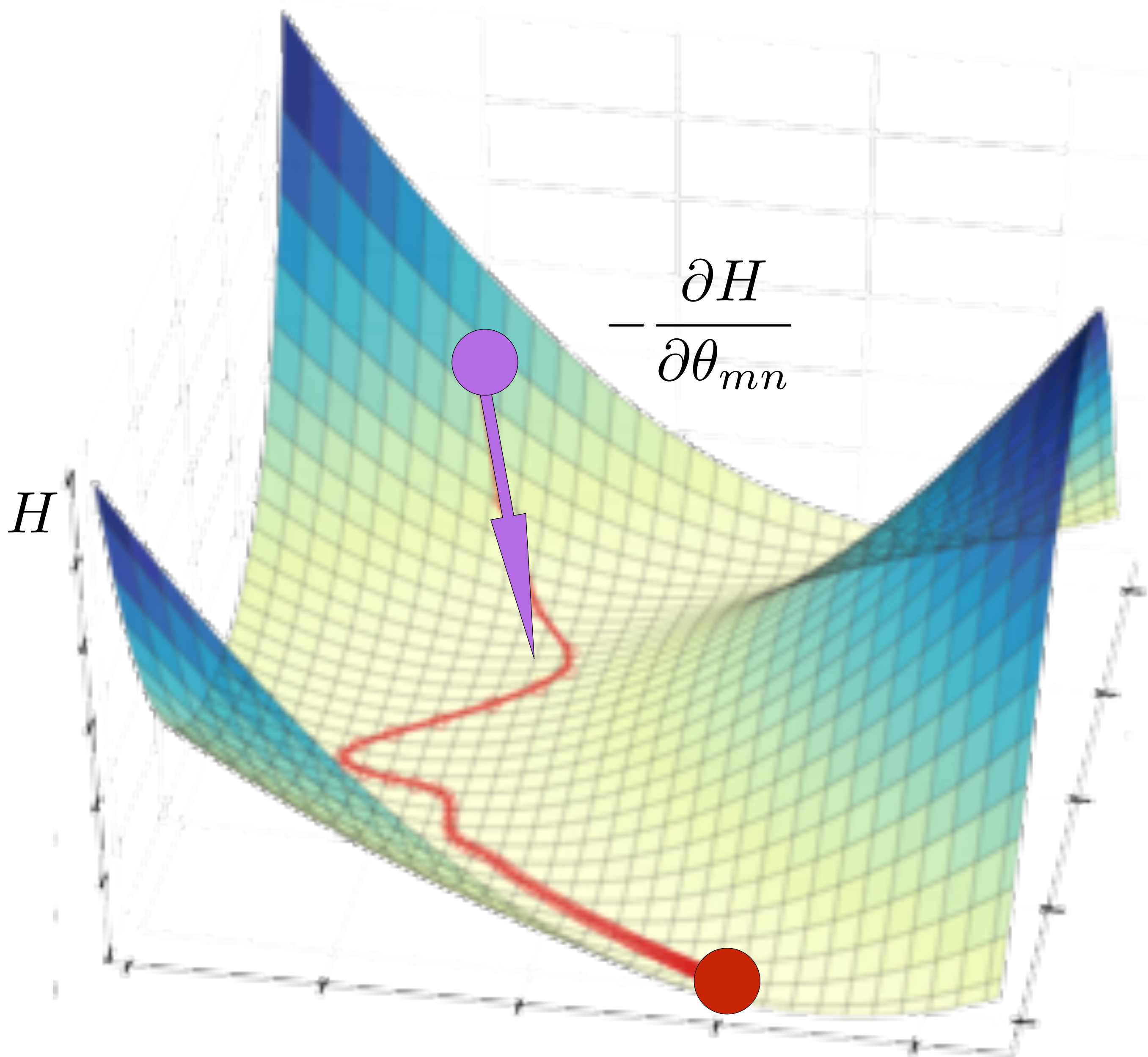

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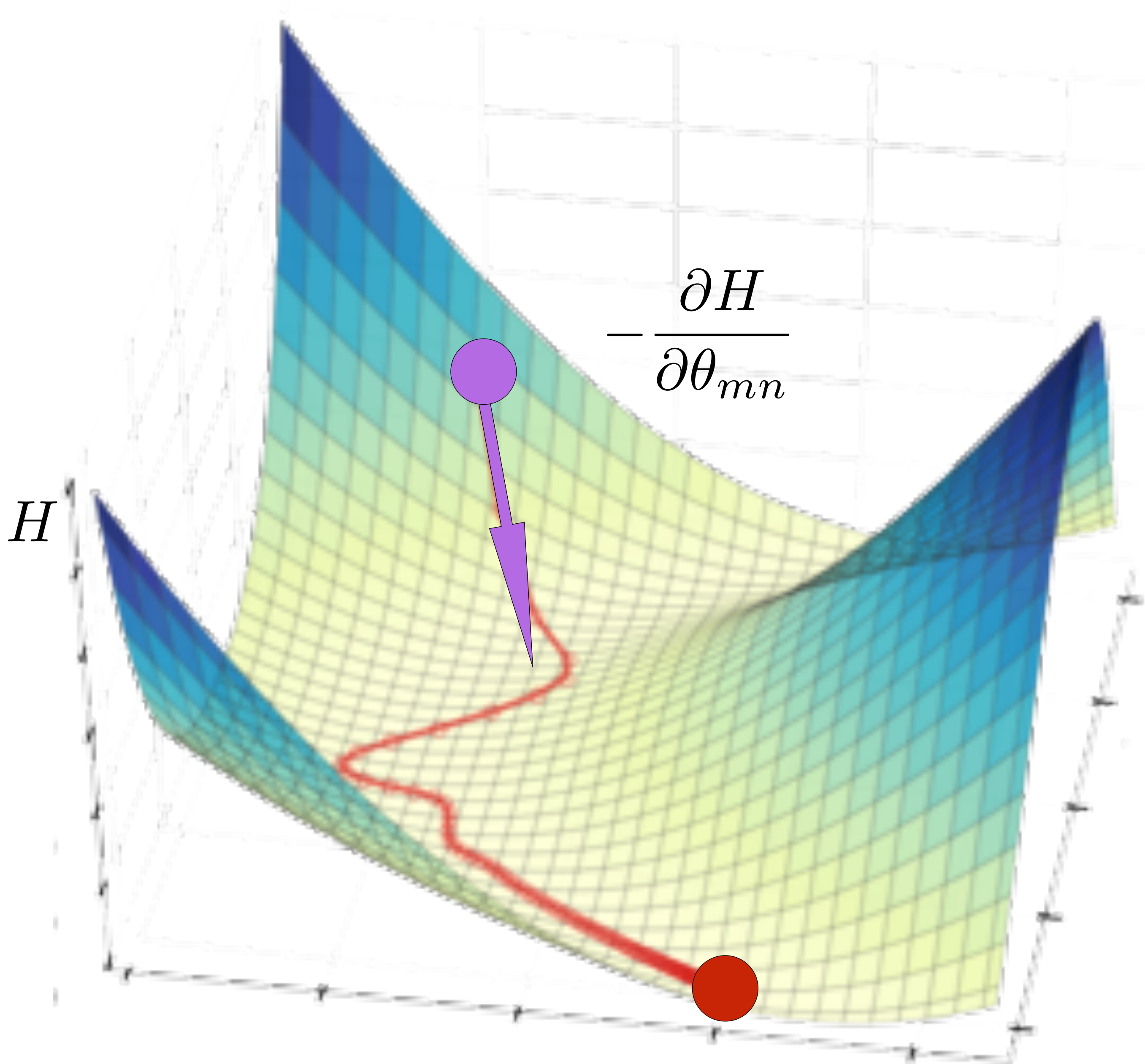

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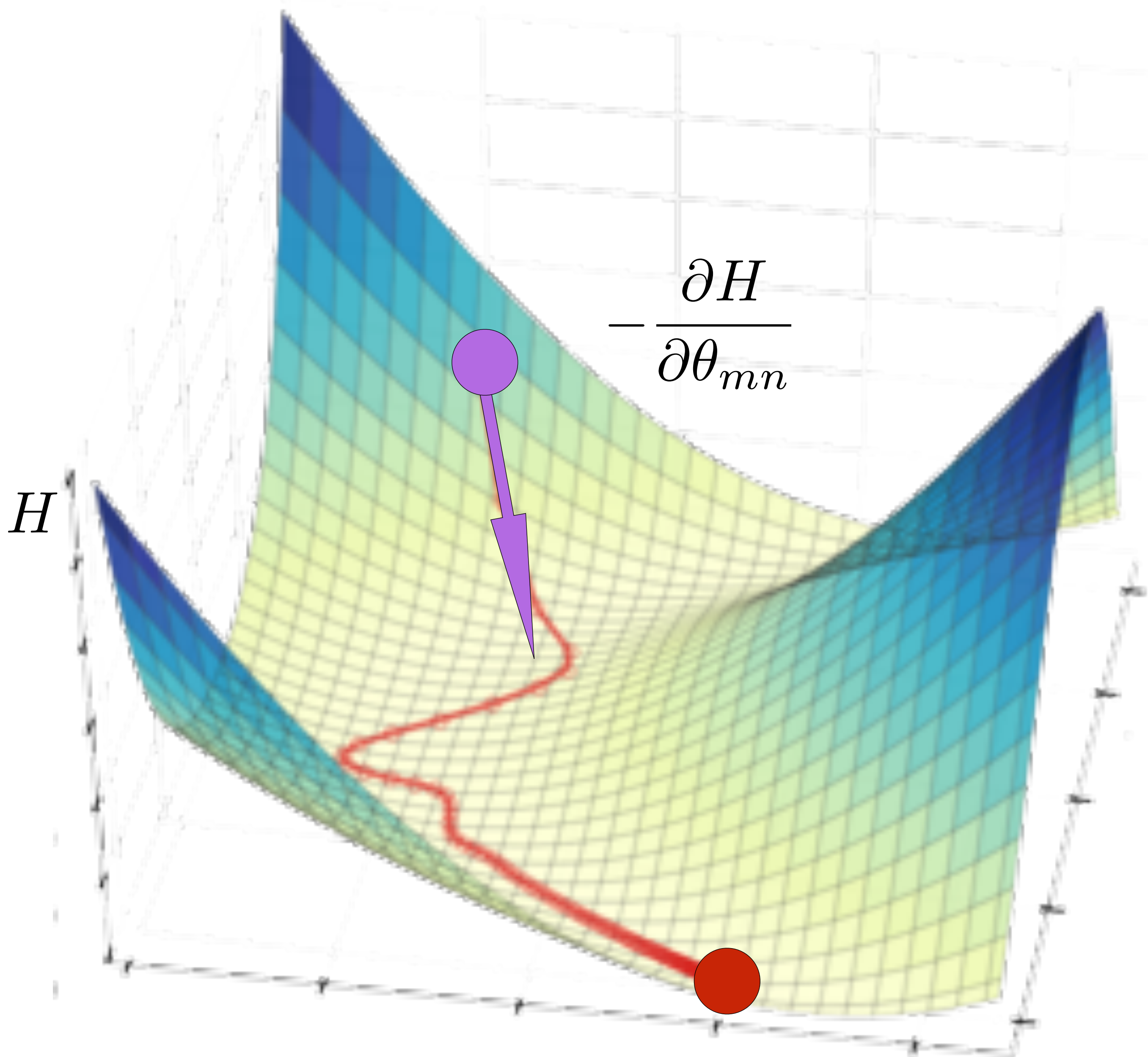

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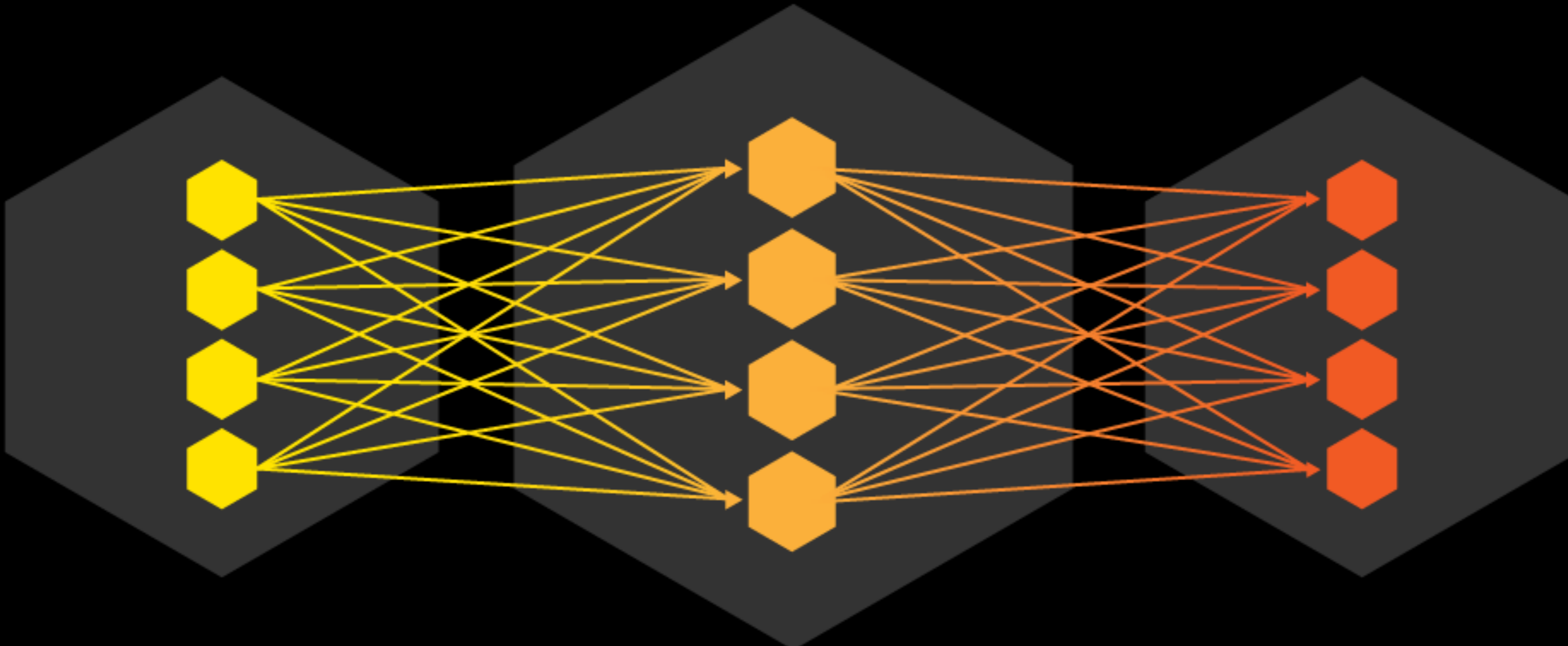
- Repeat until "convergence".



INPUT TERMS

FEATURES
PREDICTIONS
ATTRIBUTES
PREDICTABLE VARIABLES

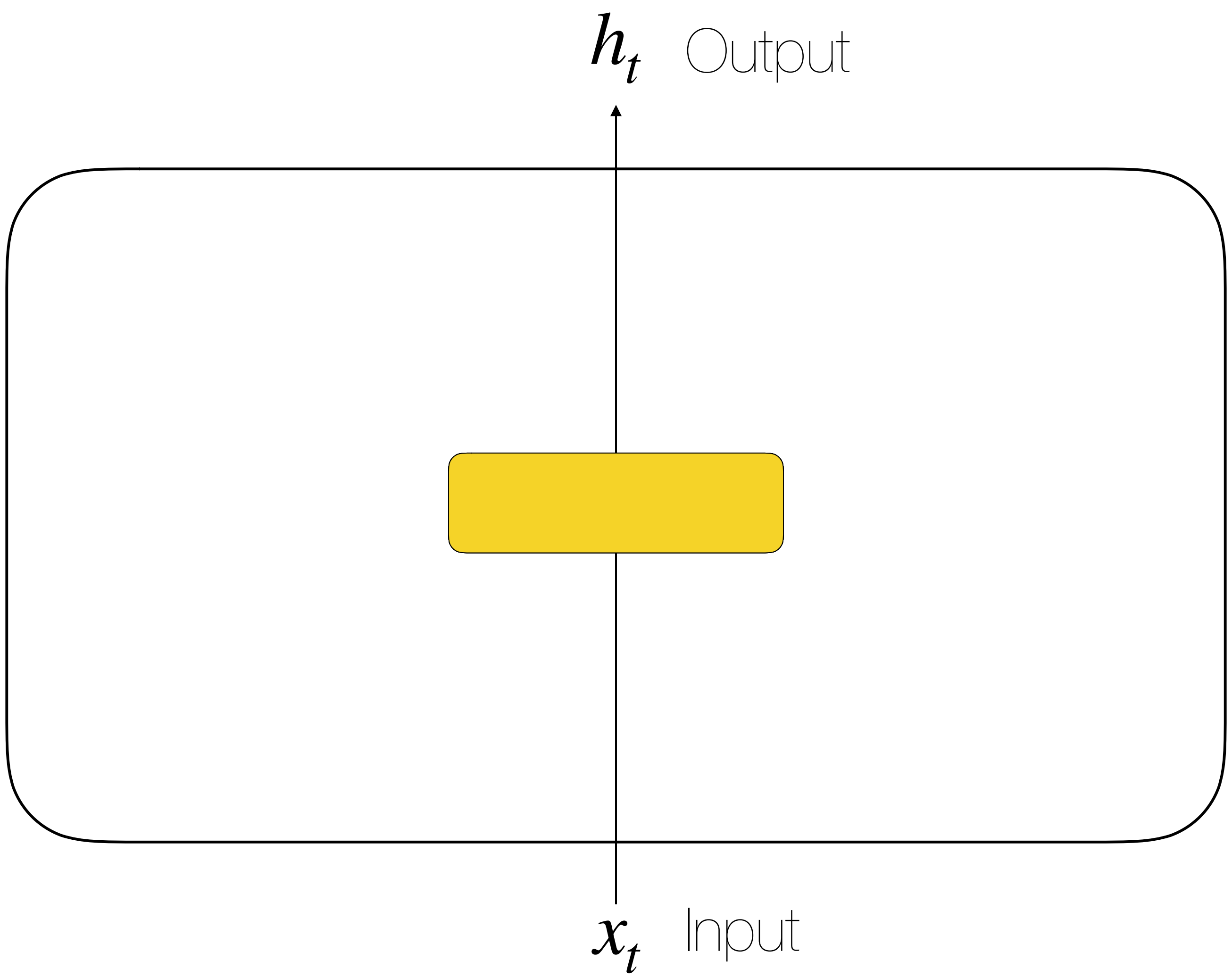
MACHINE

ALGORITHMS
TECHNIQUES
MODELS

OUTPUT TERMS

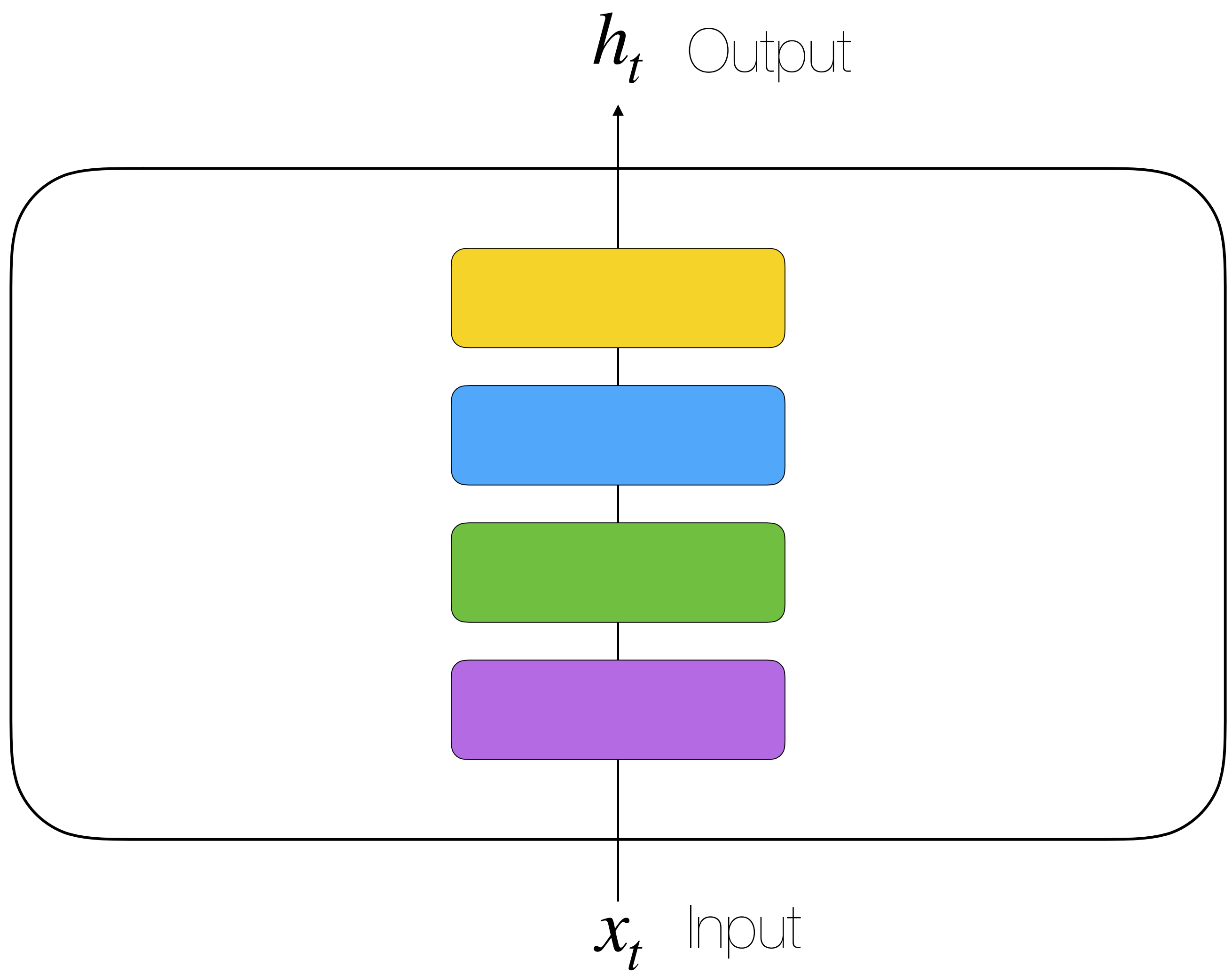
CLASSES
RESPONSES
TARGETS
DEPENDANT VARIABLES

Feed Forward Networks



$$h_t = f\left(x_t\right)$$

Feed Forward Networks



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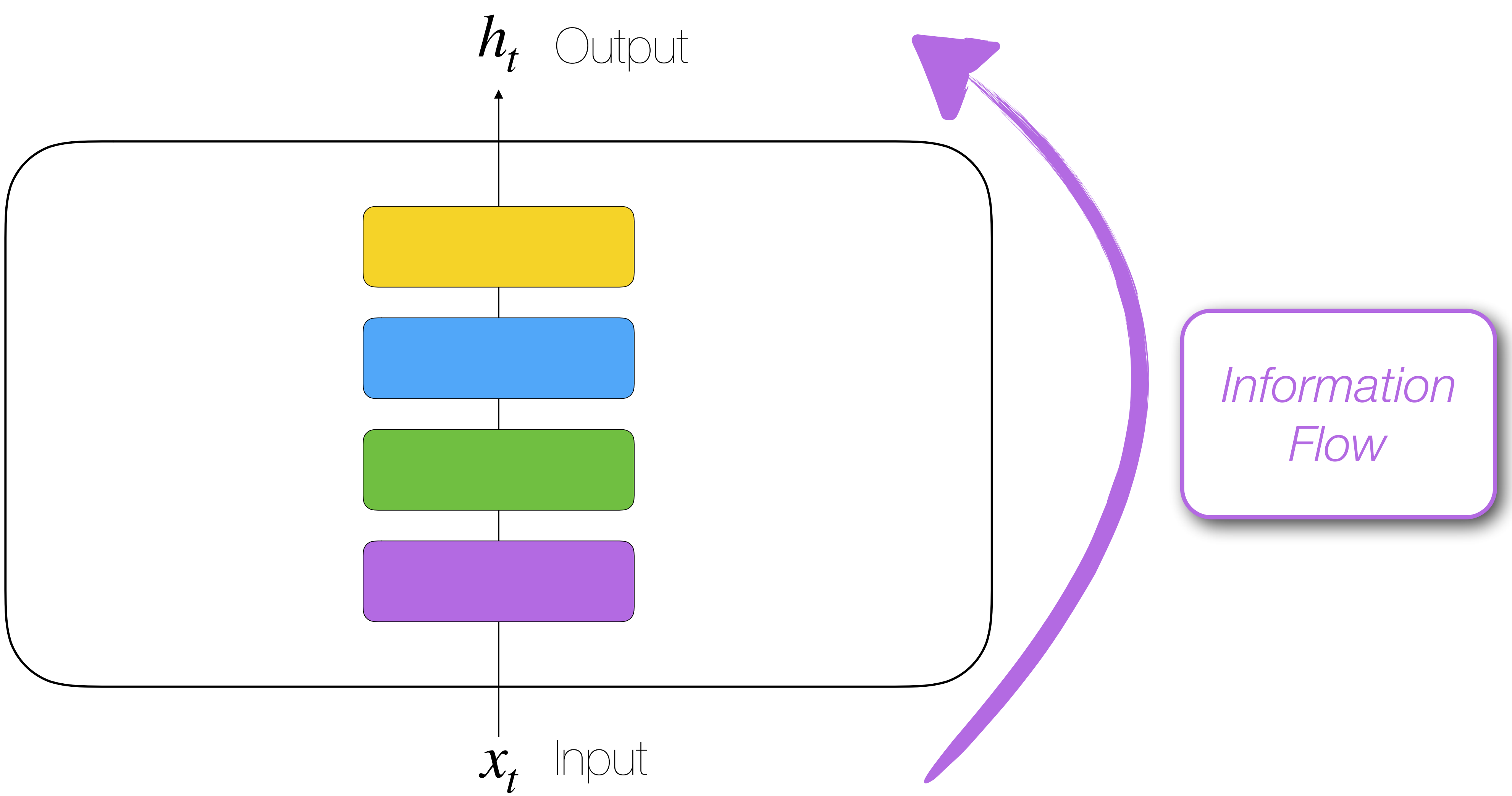

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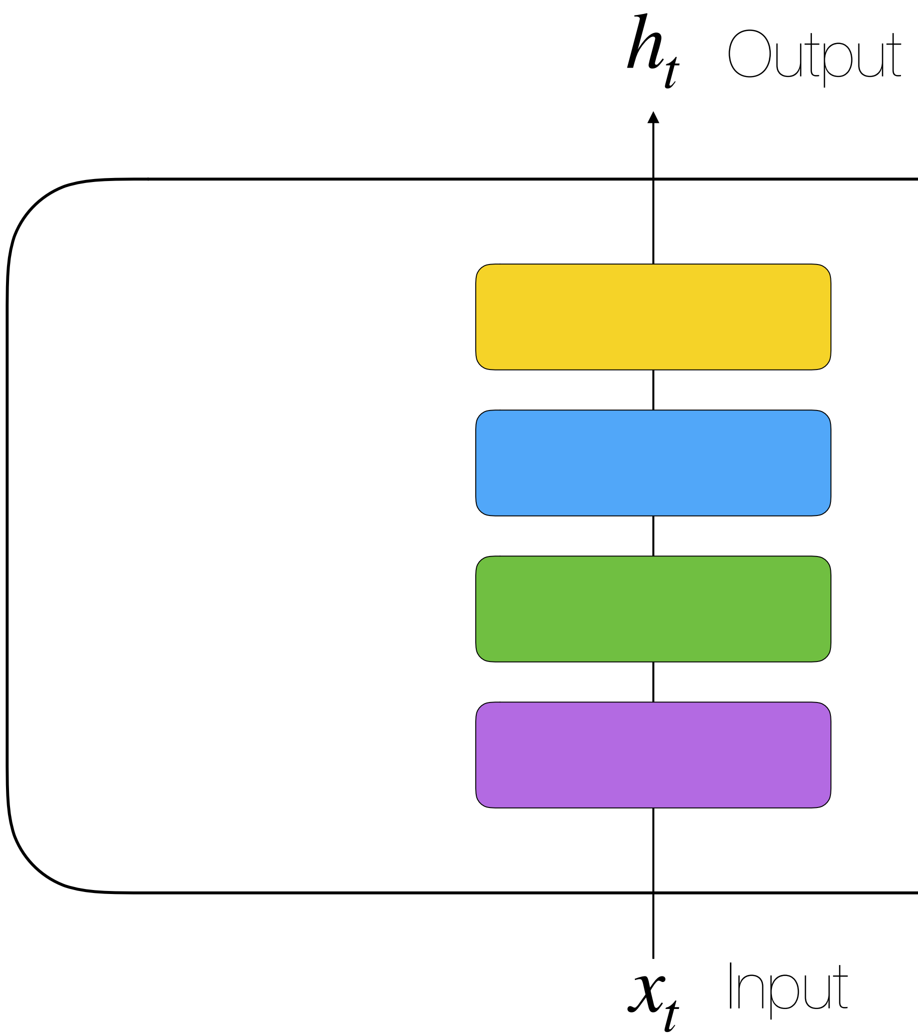
Recurrent Neural Network (RNN)

Information Flow



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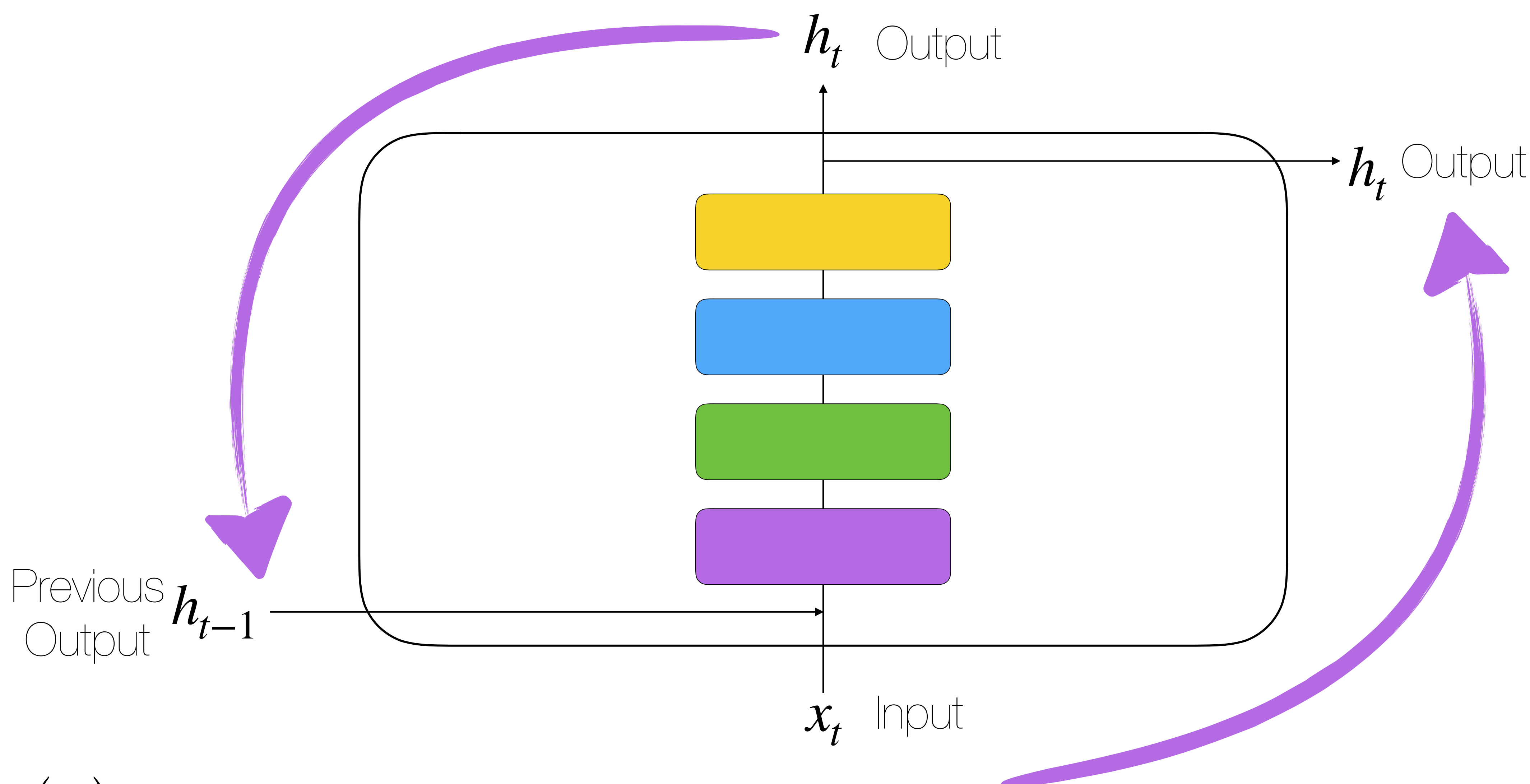

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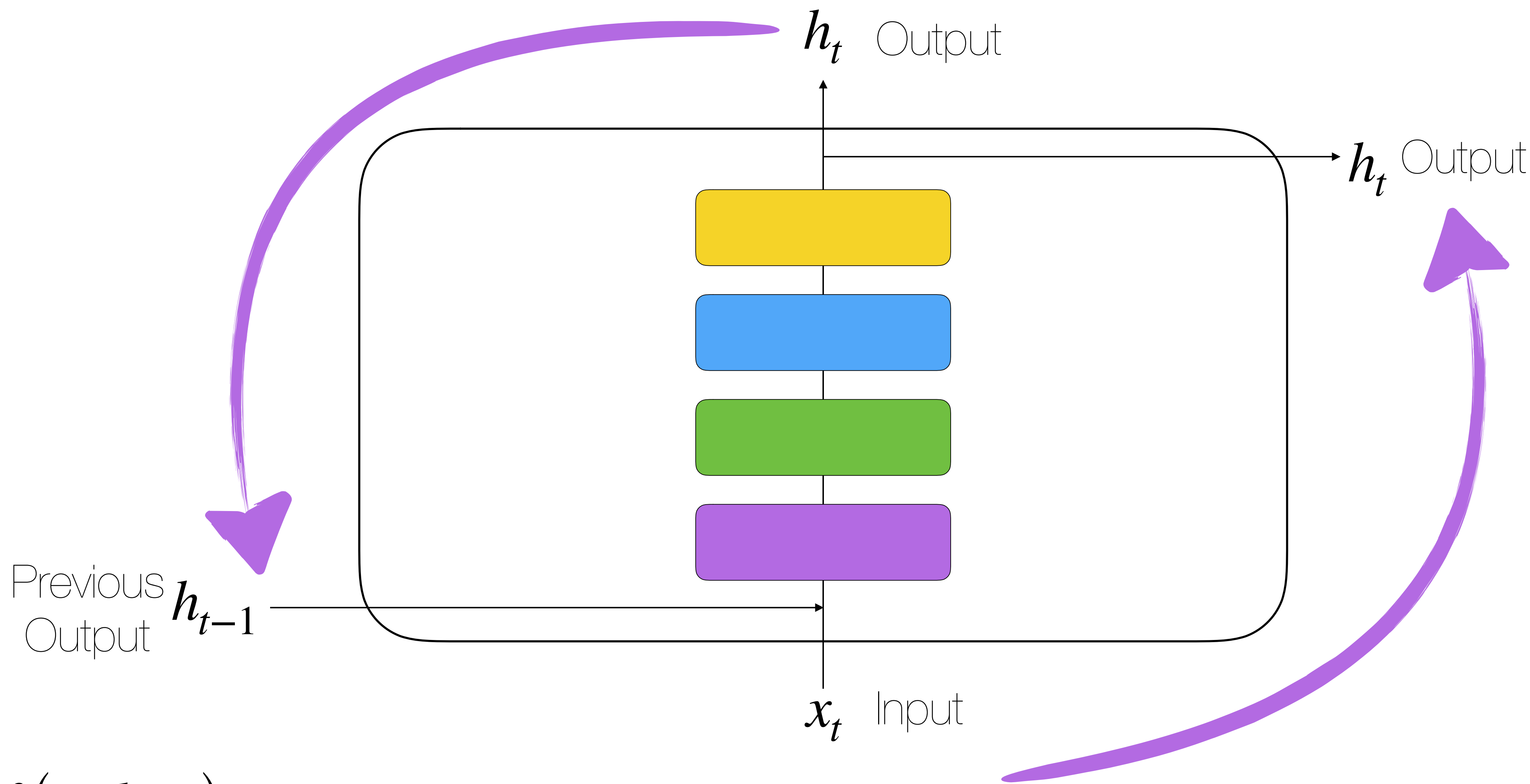
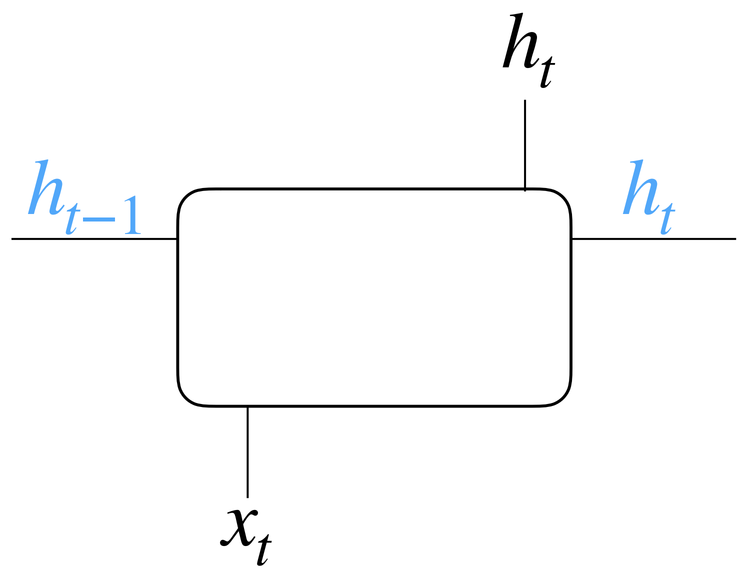


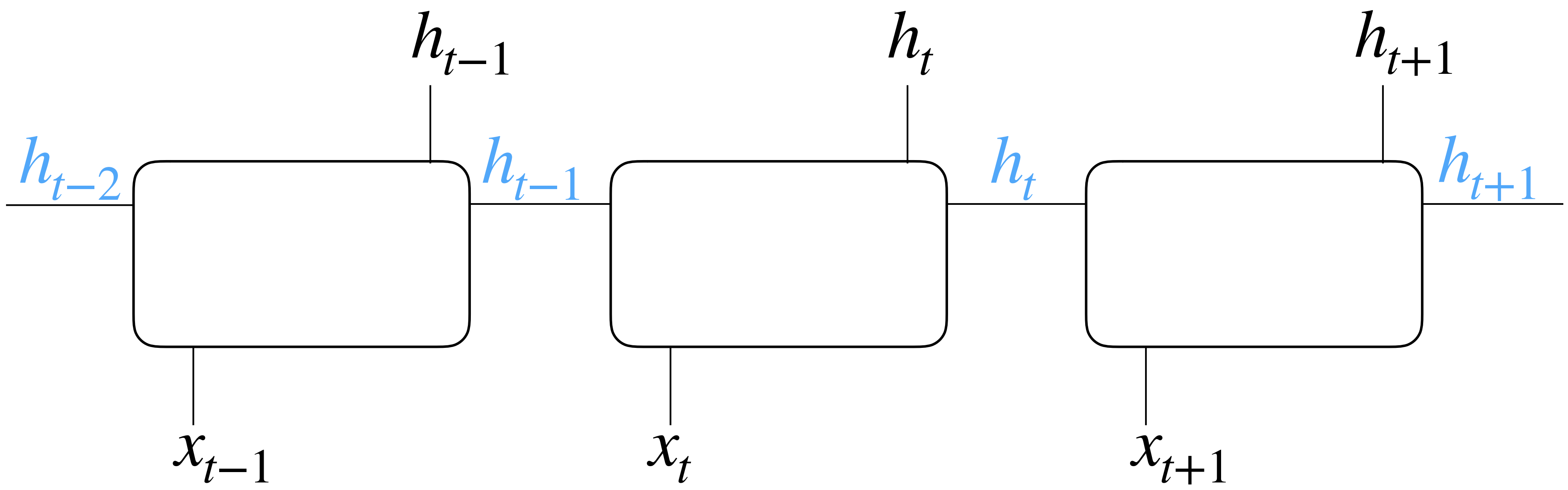
$$h_t = f\left(x_t, h_{t-1}\right)$$

Recurrent Neural Network (RNN)



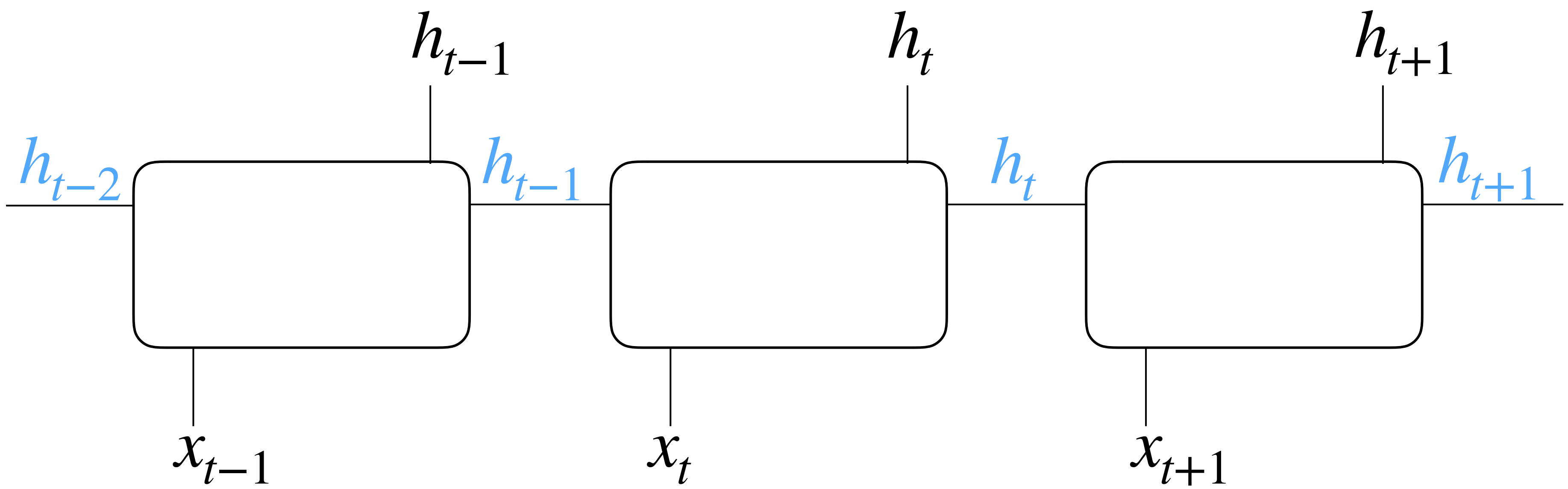
Recurrent Neural Network (RNN)

- Each output depends (implicitly) on all previous outputs.



Recurrent Neural Network (RNN)

- Each output depends (implicitly) on all previous outputs.
- Input sequences generate output sequences (seq2seq)



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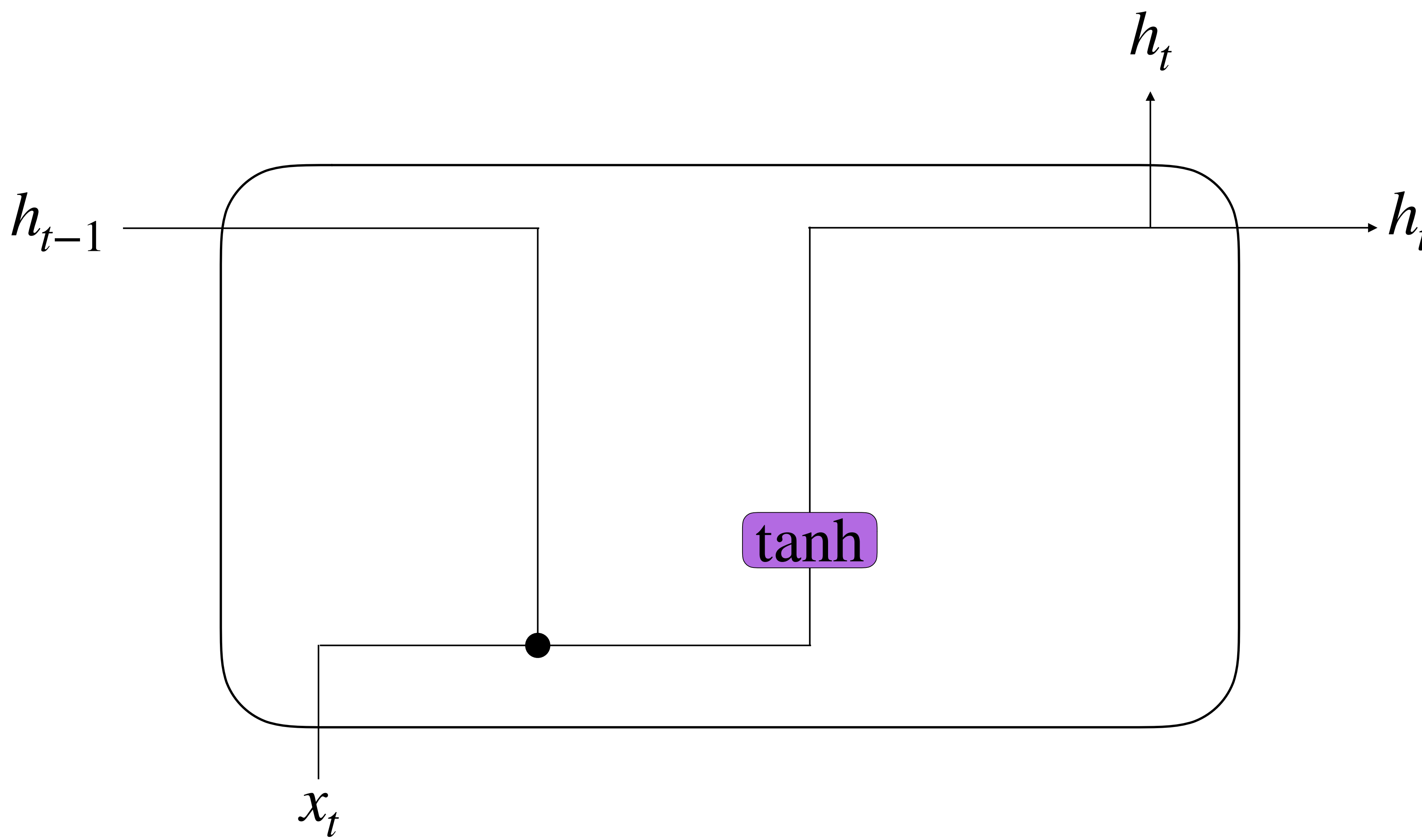

$$h_t = \tanh\left(Wh_{t-1} + Ux_t\right)$$

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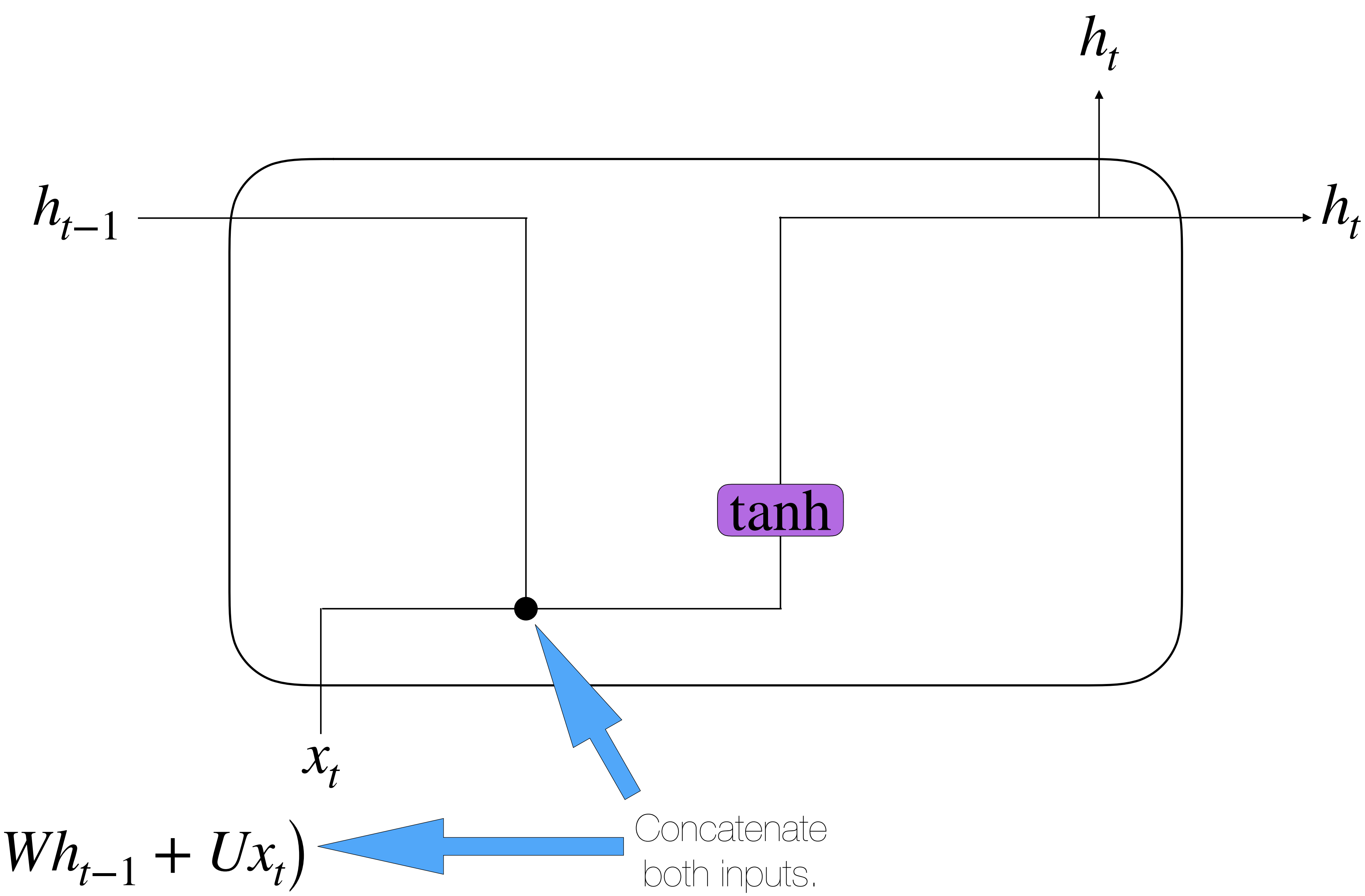

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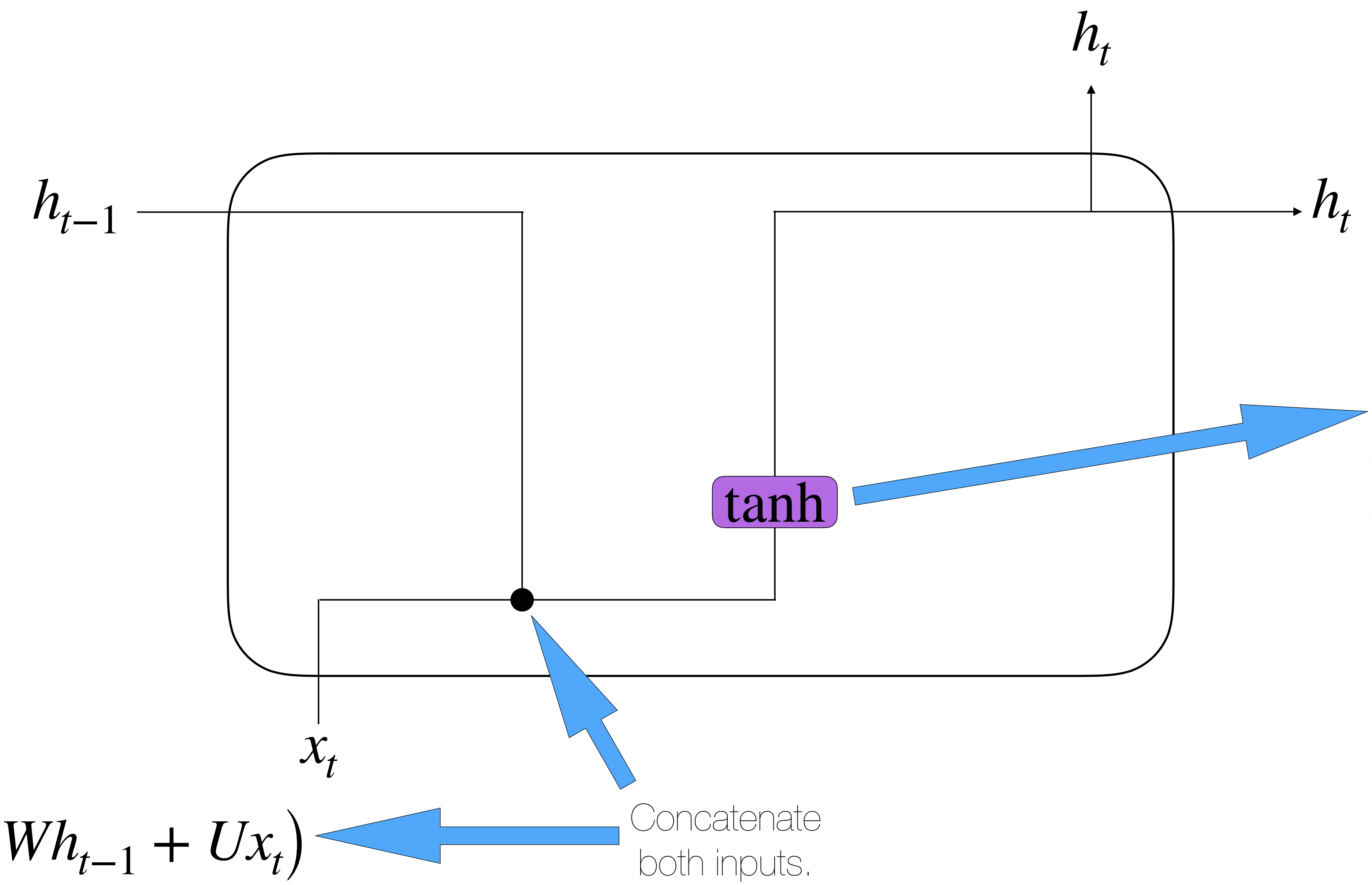

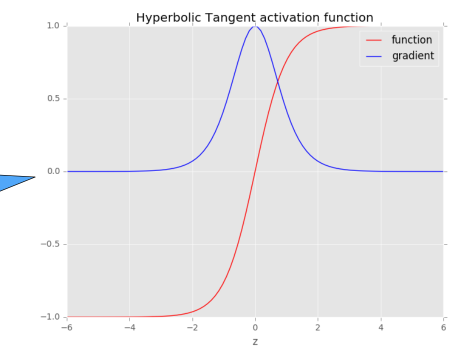

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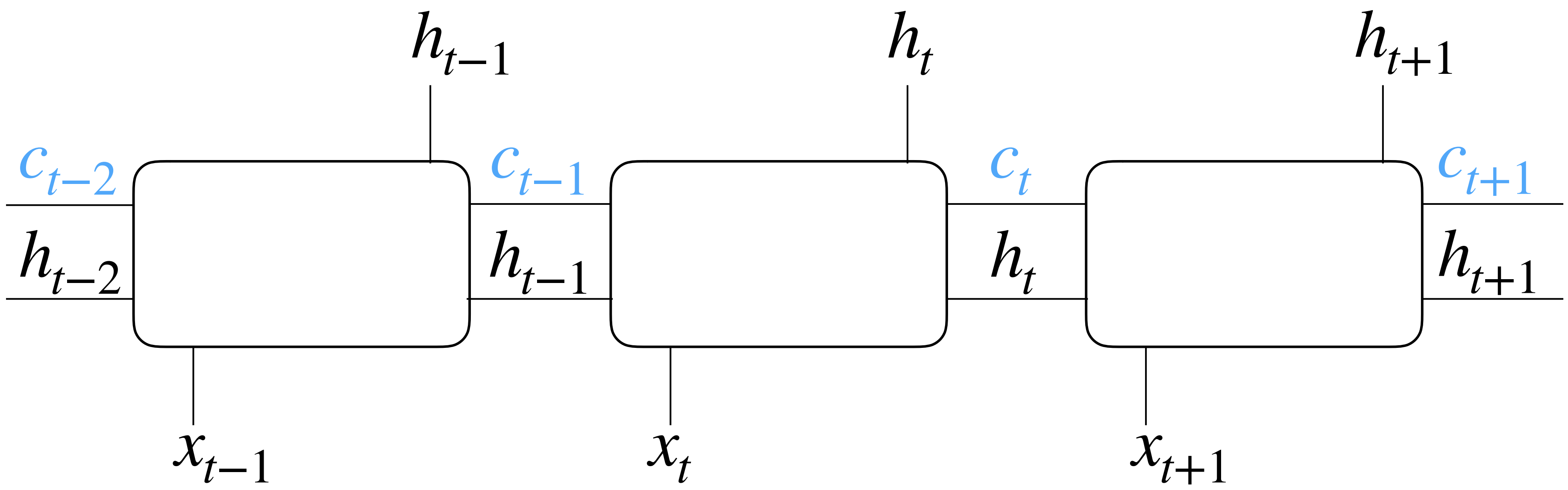
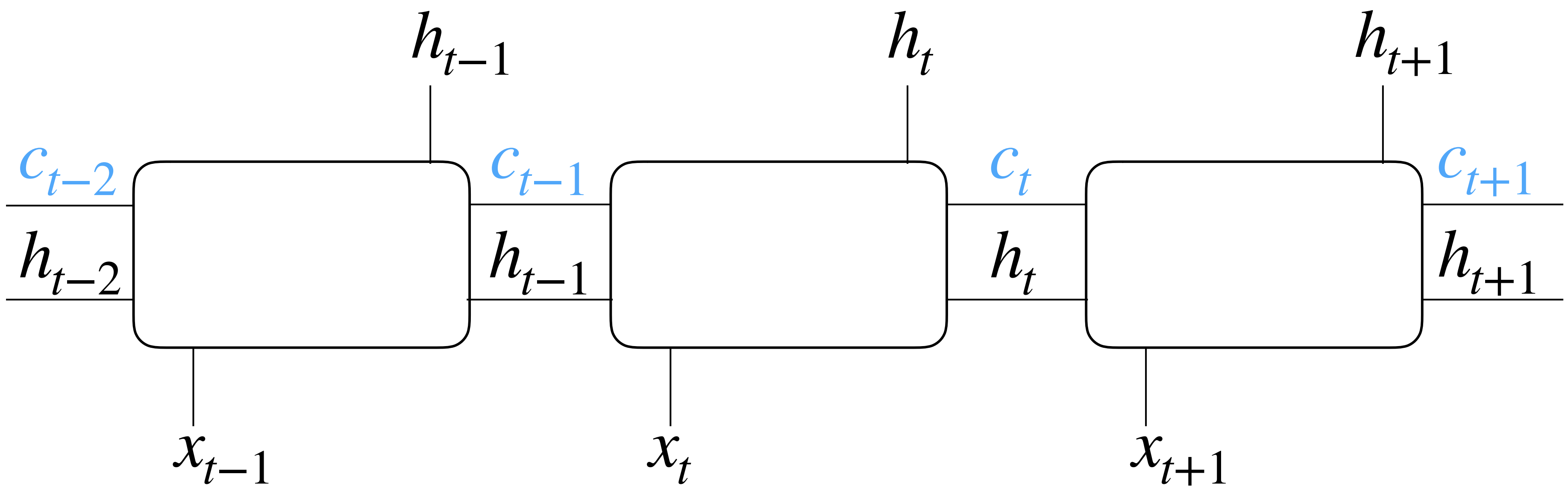
Long-Short Term Memory (LSTM)



Long-Short Term Memory (LSTM)

- What if we want to keep explicit information about previous states (memory)?



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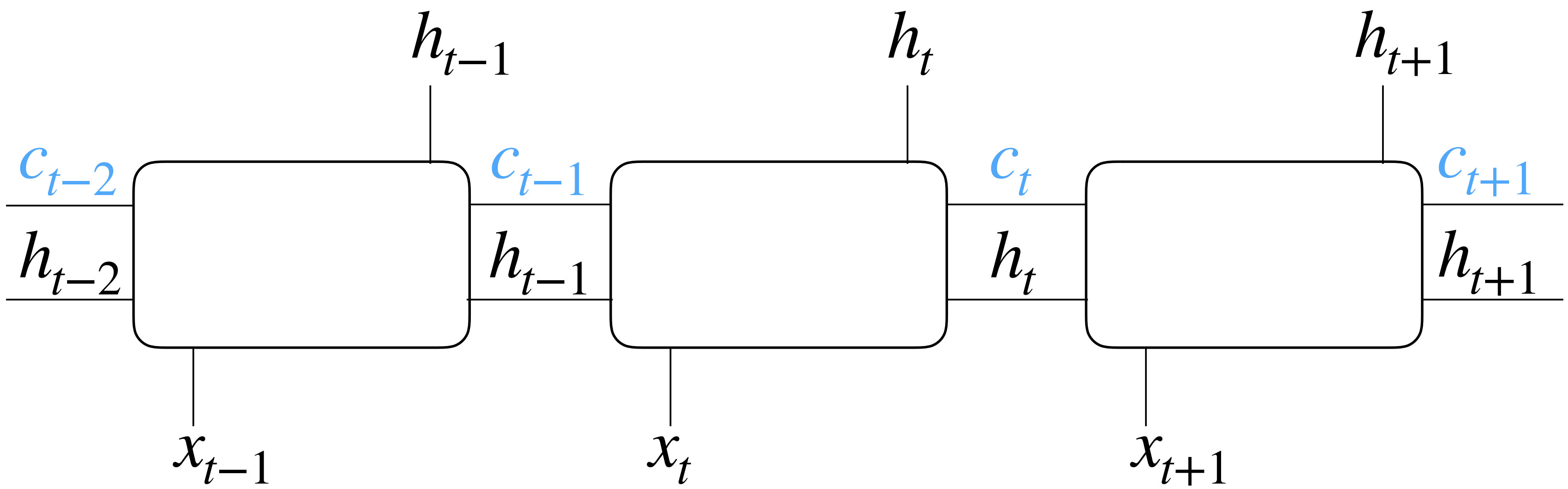

Long-Short Term Memory (LSTM)

- What if we want to keep explicit information about previous states (memory)?
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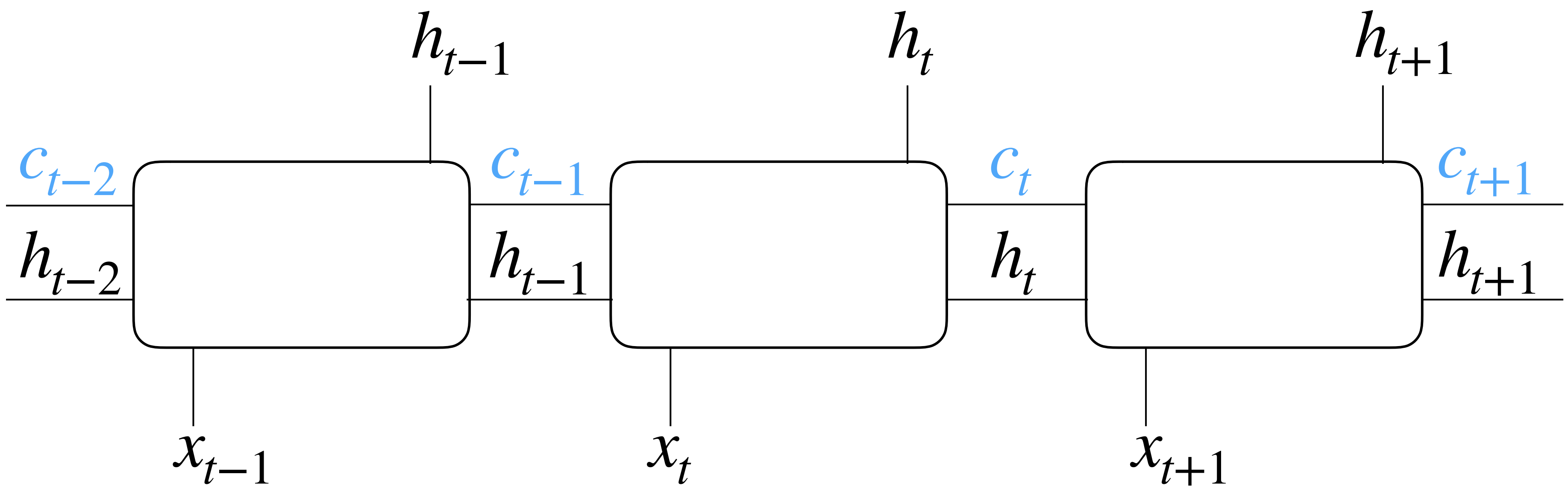
- LSTMs were first introduced in 1997 by Hochreiter and Schmidhuber

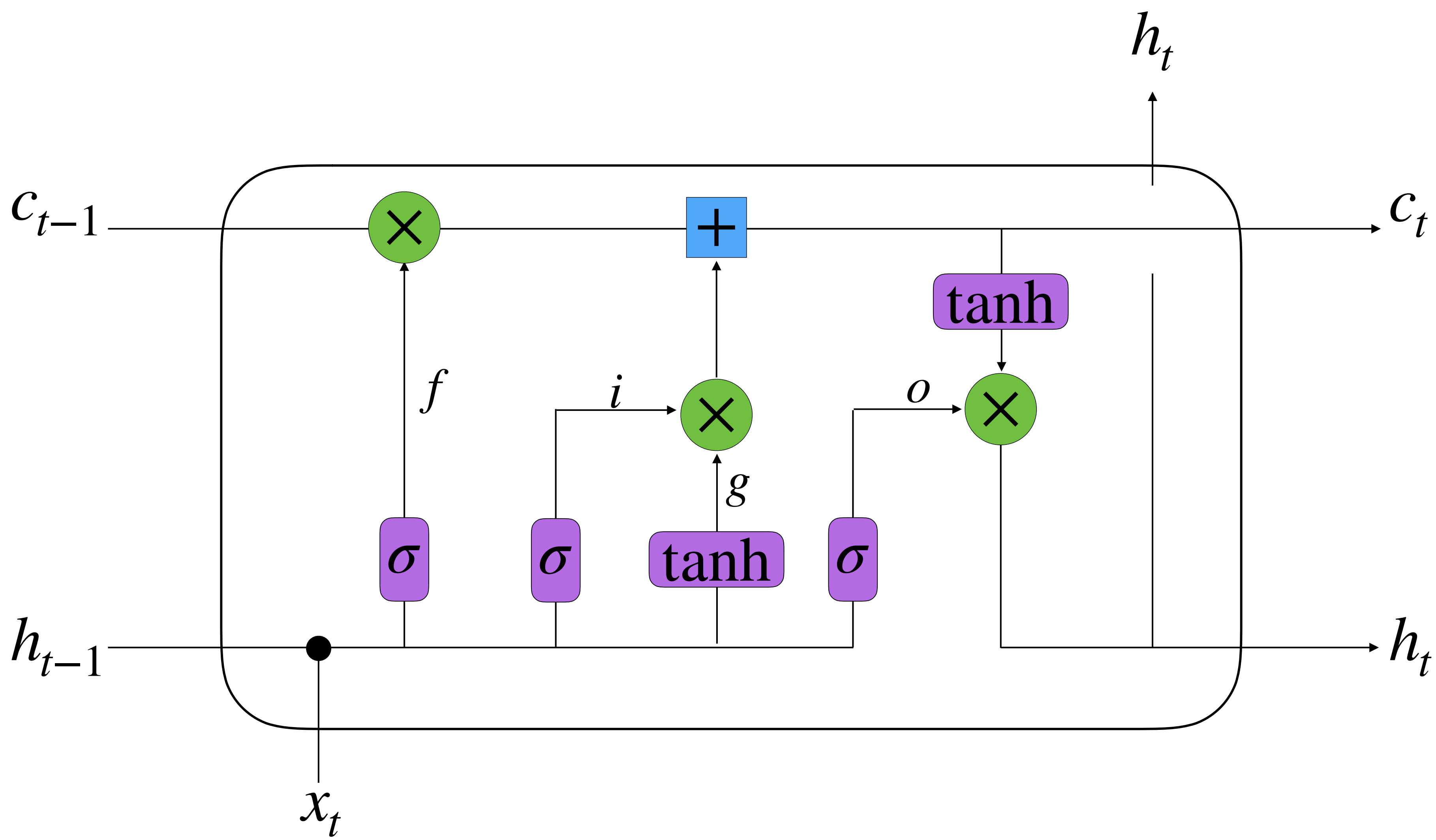


Long-Short Term Memory (LSTM)

Element wise addition

Element wise multiplication

1 minus the input



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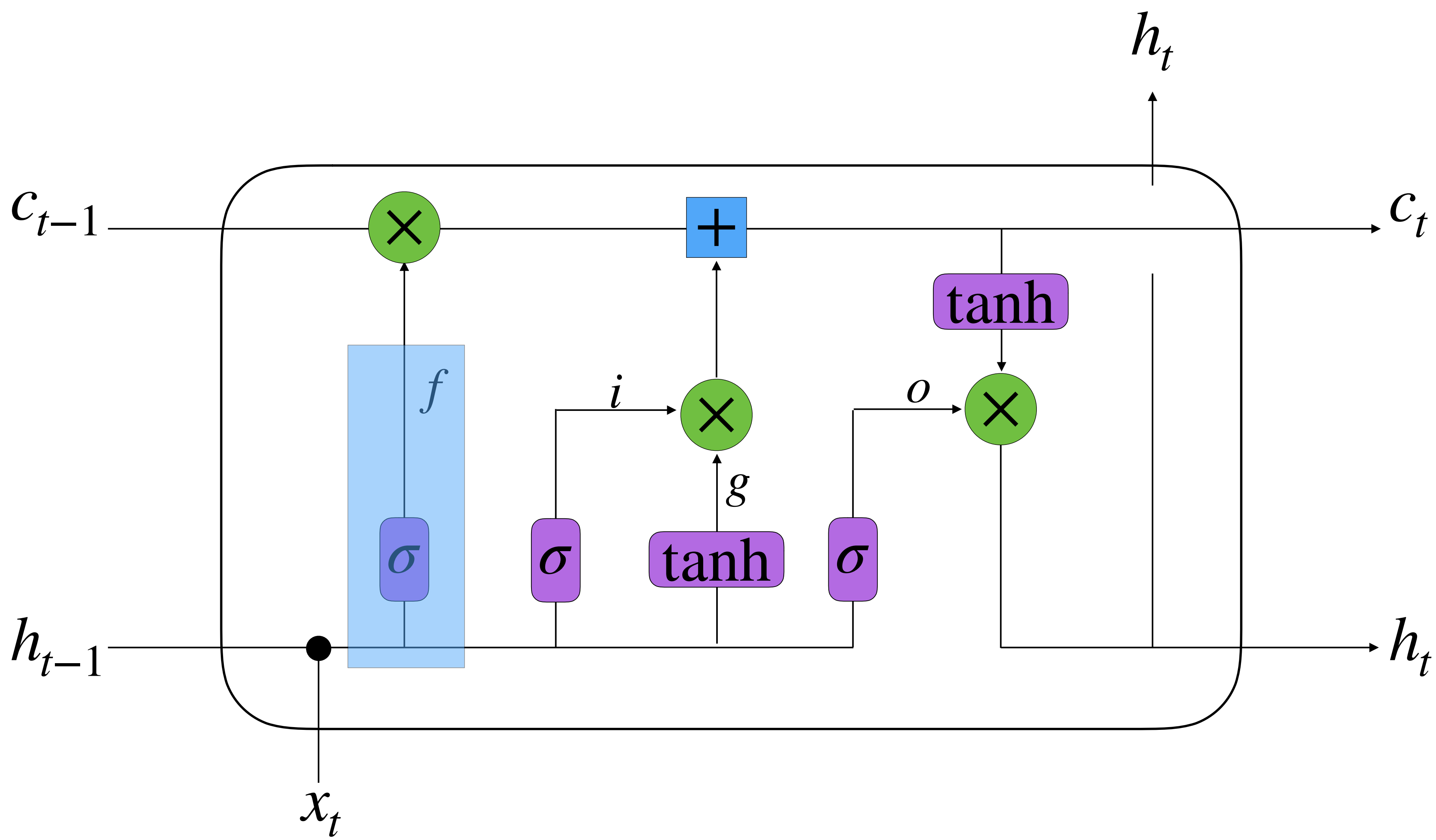
Element wise addition

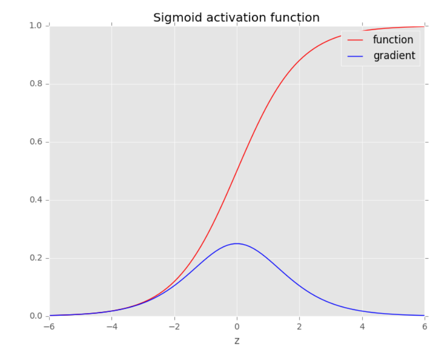
Element wise multiplication

1 minus the input

Long-Short Term Memory (LSTM)

Forget gate: How much of the previous state should be kept?





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Long-Short Term Memory (LSTM)

Element wise addition

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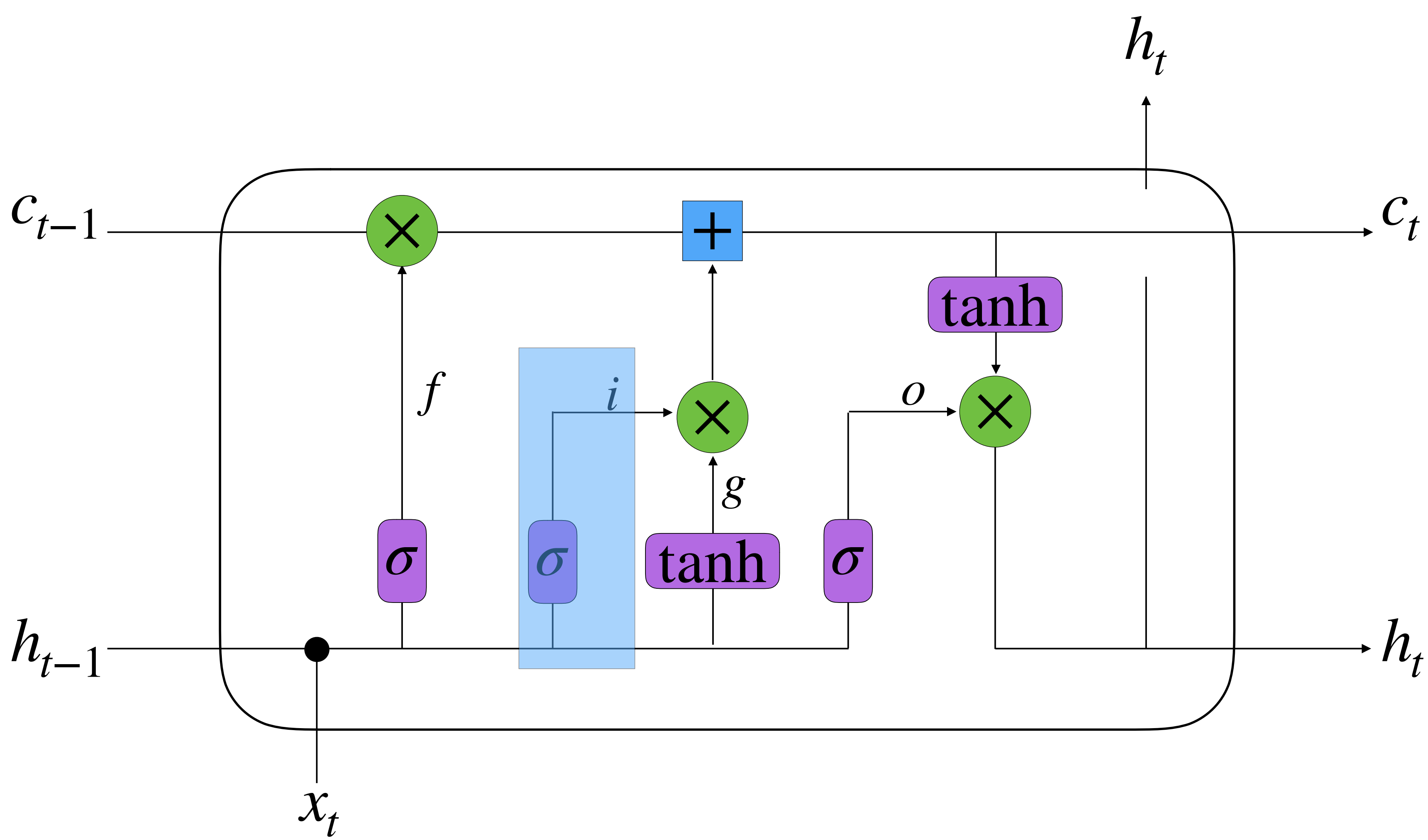
Input gate: How much of the previous output should be remembered?



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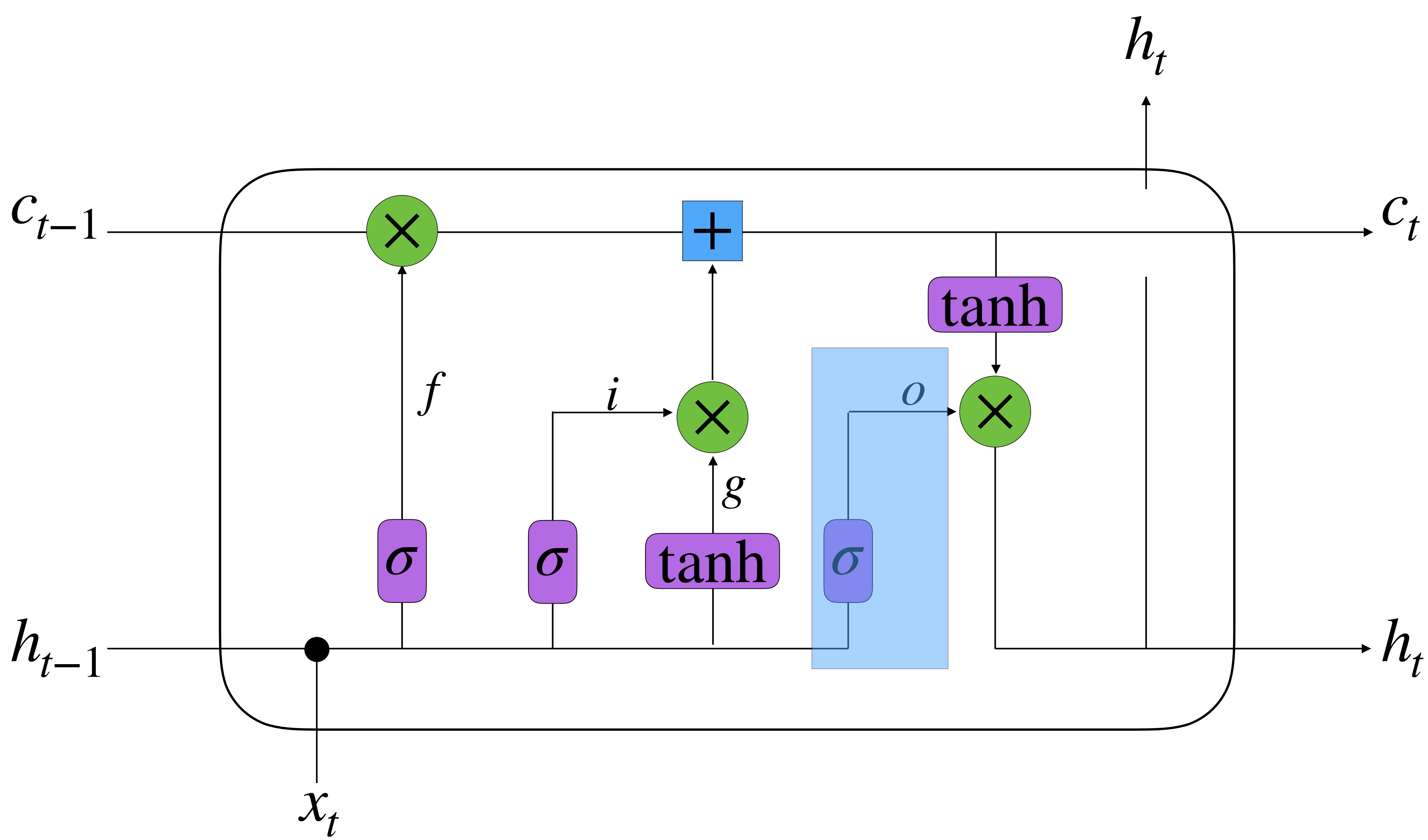
Long-Short Term Memory (LSTM)

$+$ Element wise addition

$\times$ Element wise multiplication

$1-$ 1 minus the input

Output gate: How much of the previous output should contribute?



All gates use the same inputs and activation functions, but different weights

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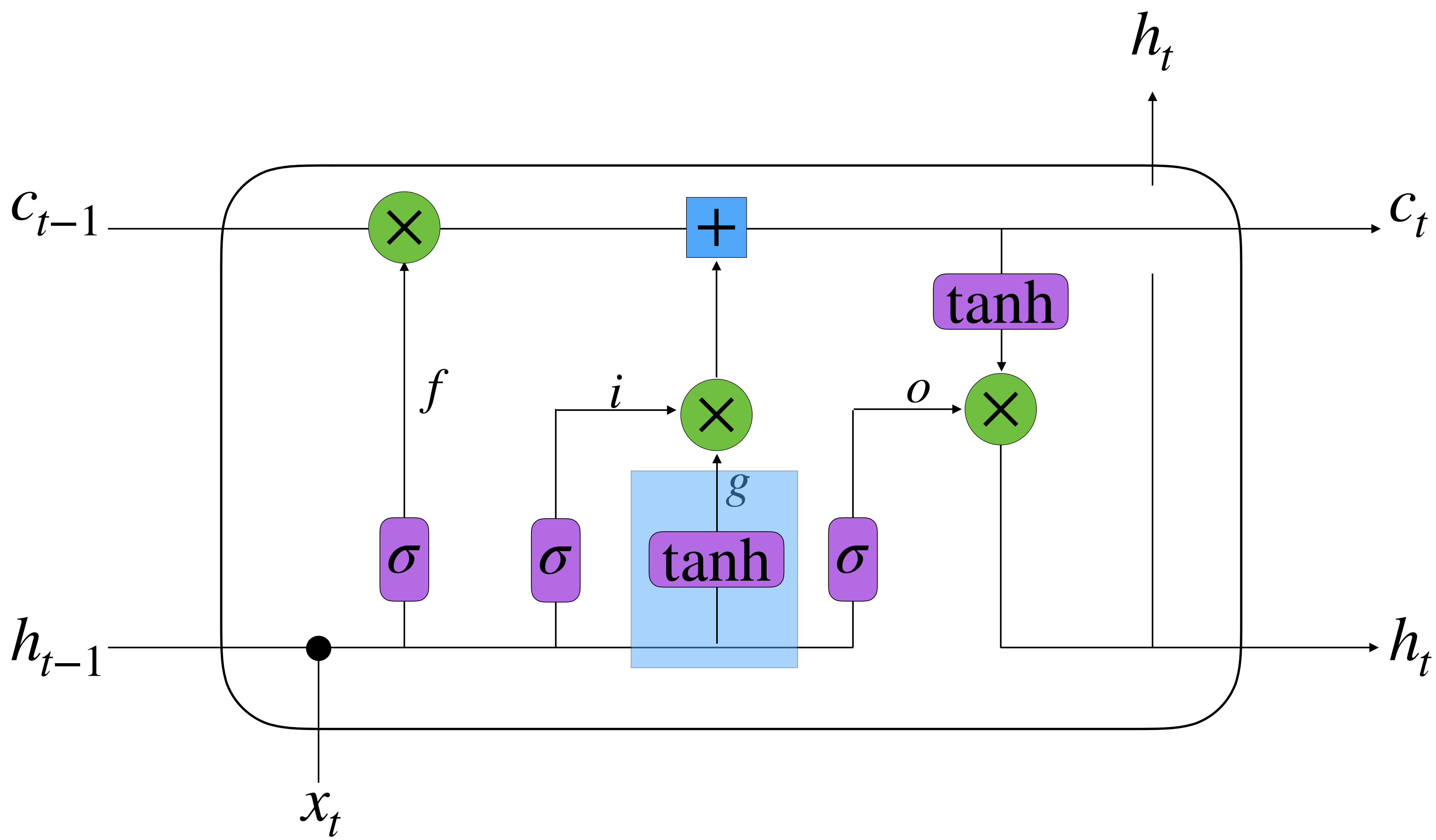

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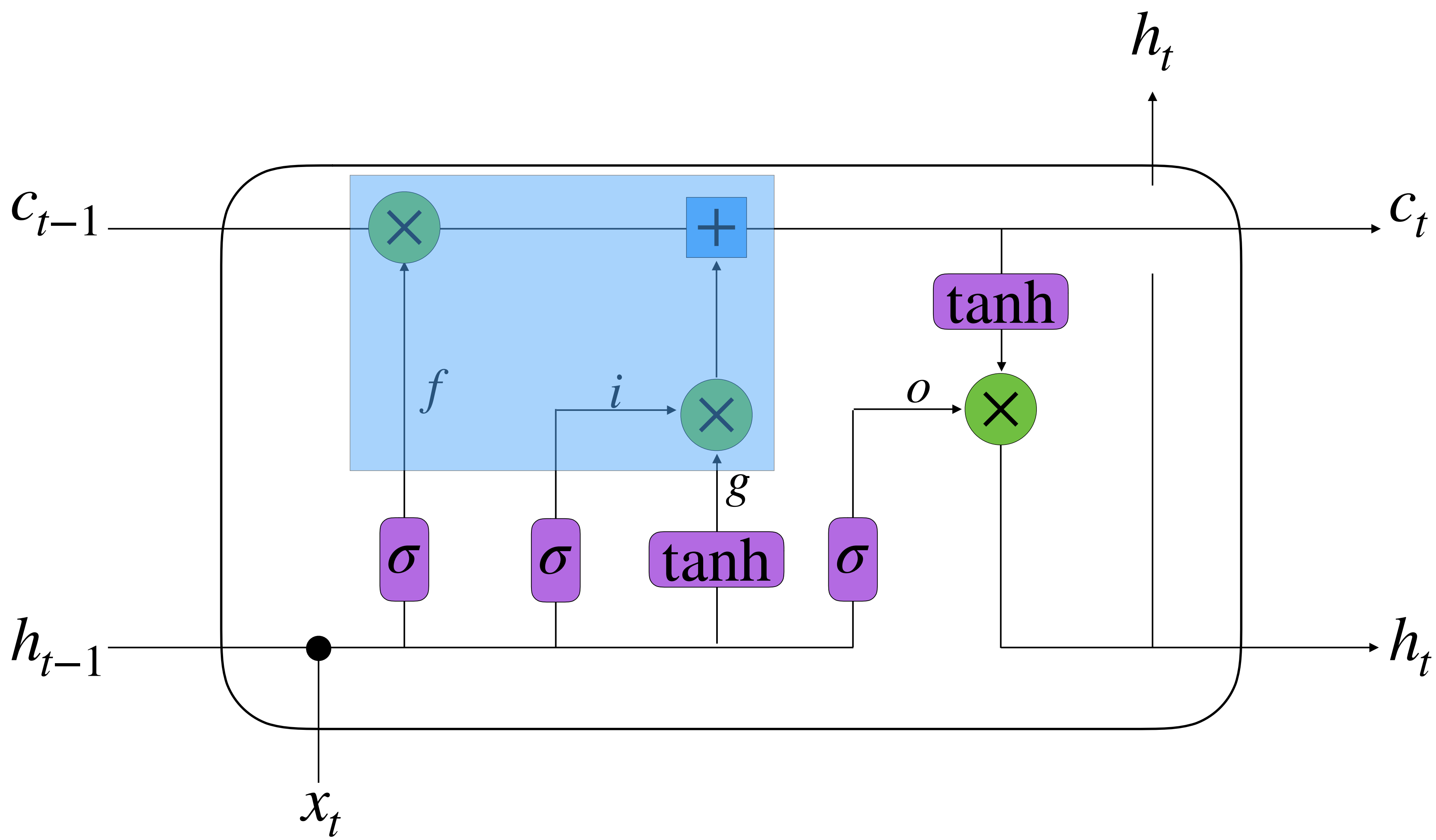
Long-Short Term Memory (LSTM)



State:
Update the
current state

$$f = \sigma\left(W_f h_{t-1} + U_f x_t\right) \qquad g = \tanh\left(W_g h_{t-1} + U_g x_t\right)$$

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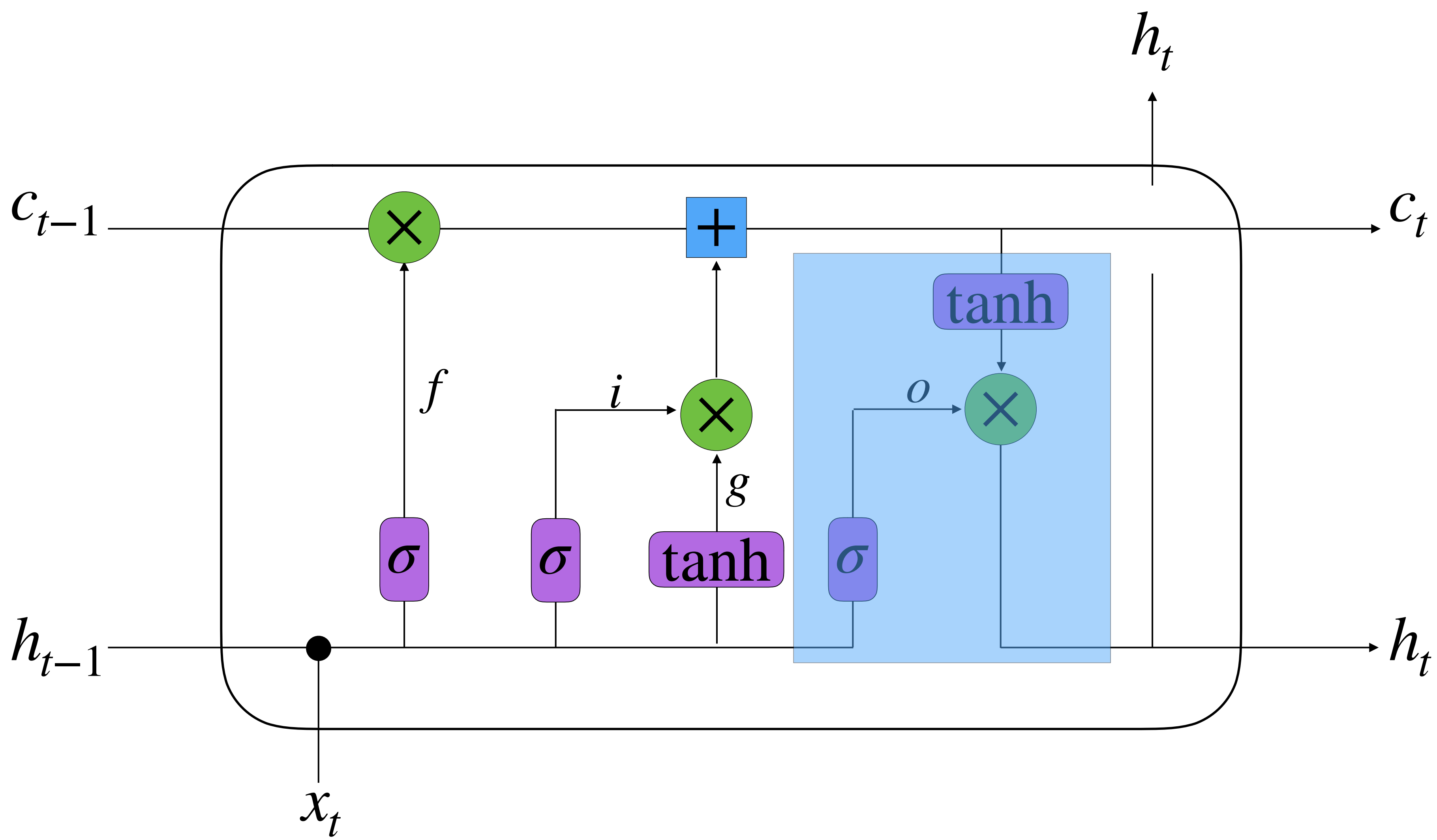
Long-Short Term Memory (LSTM)

$+$ Element wise addition

$\times$ Element wise multiplication

1− 1 minus the input

Output:
Combine all available information.



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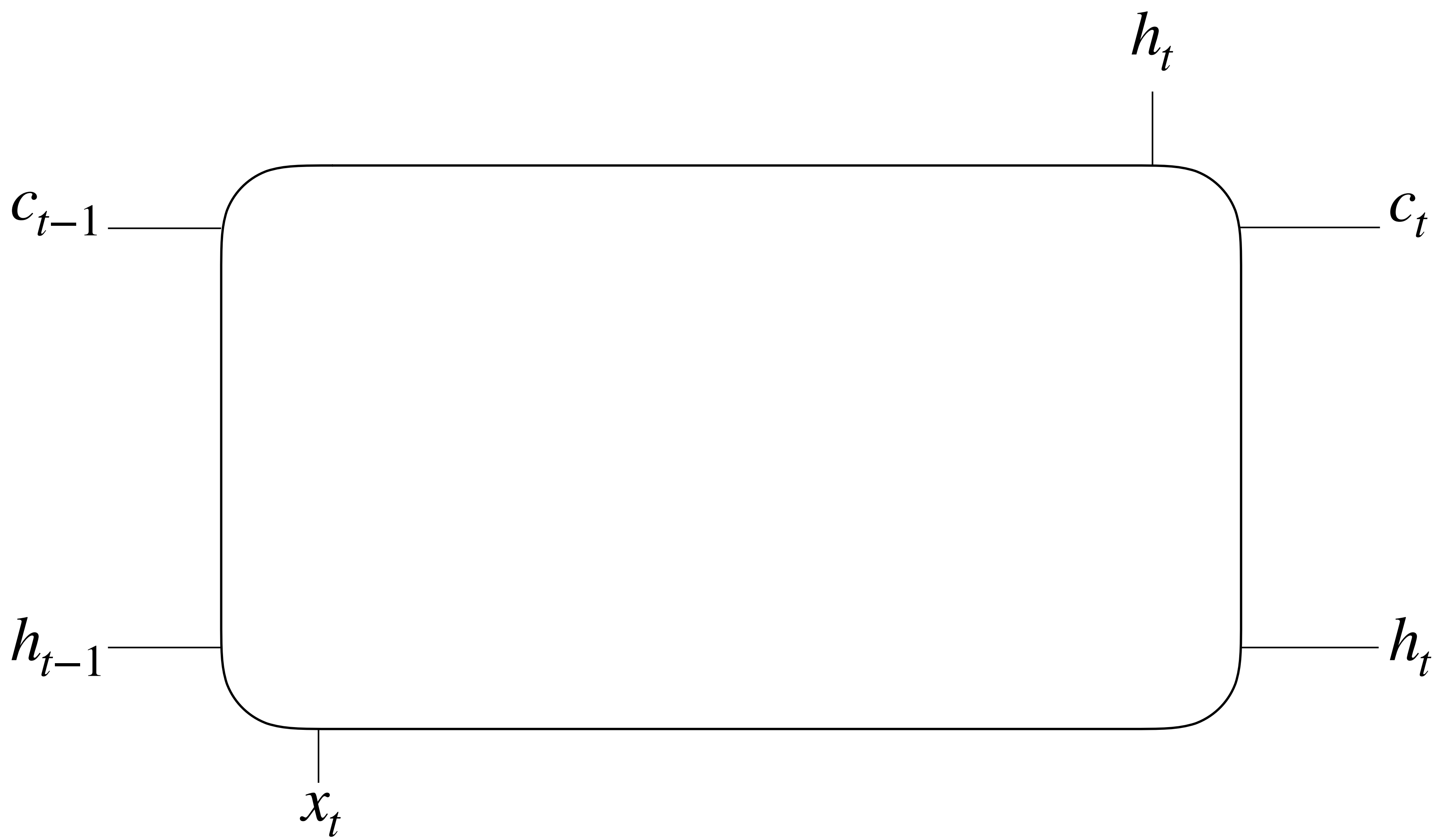
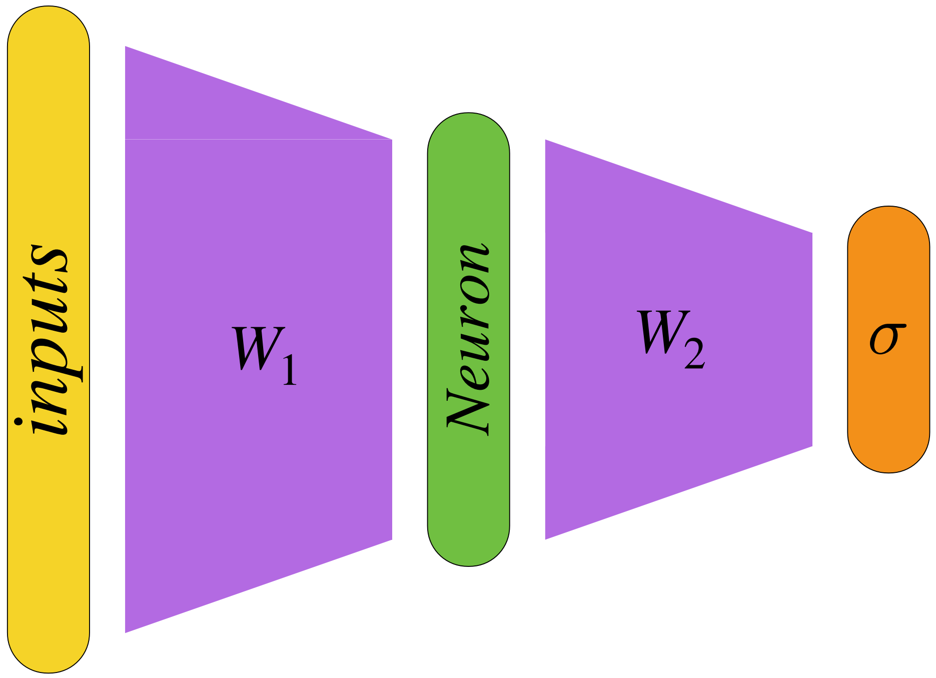
Neural Networks?



Using LSTMs



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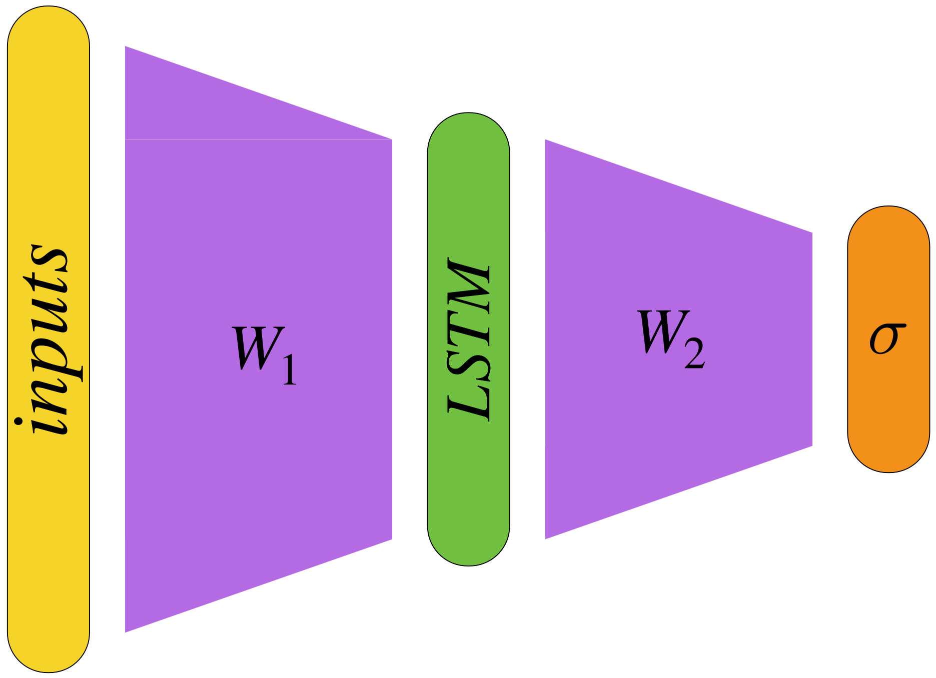

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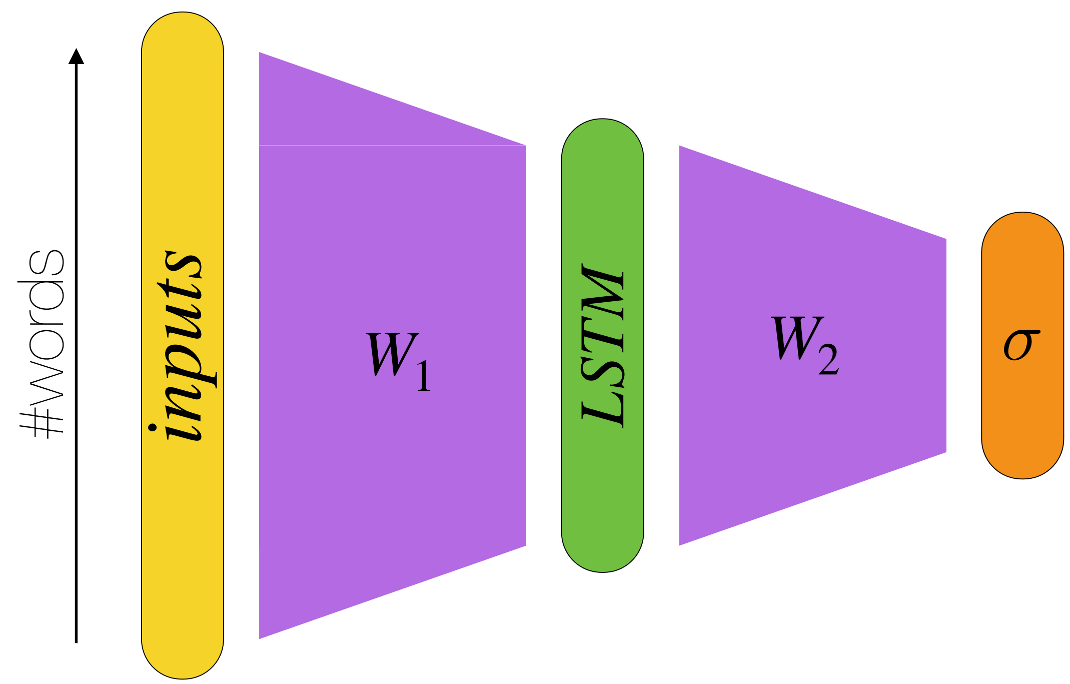

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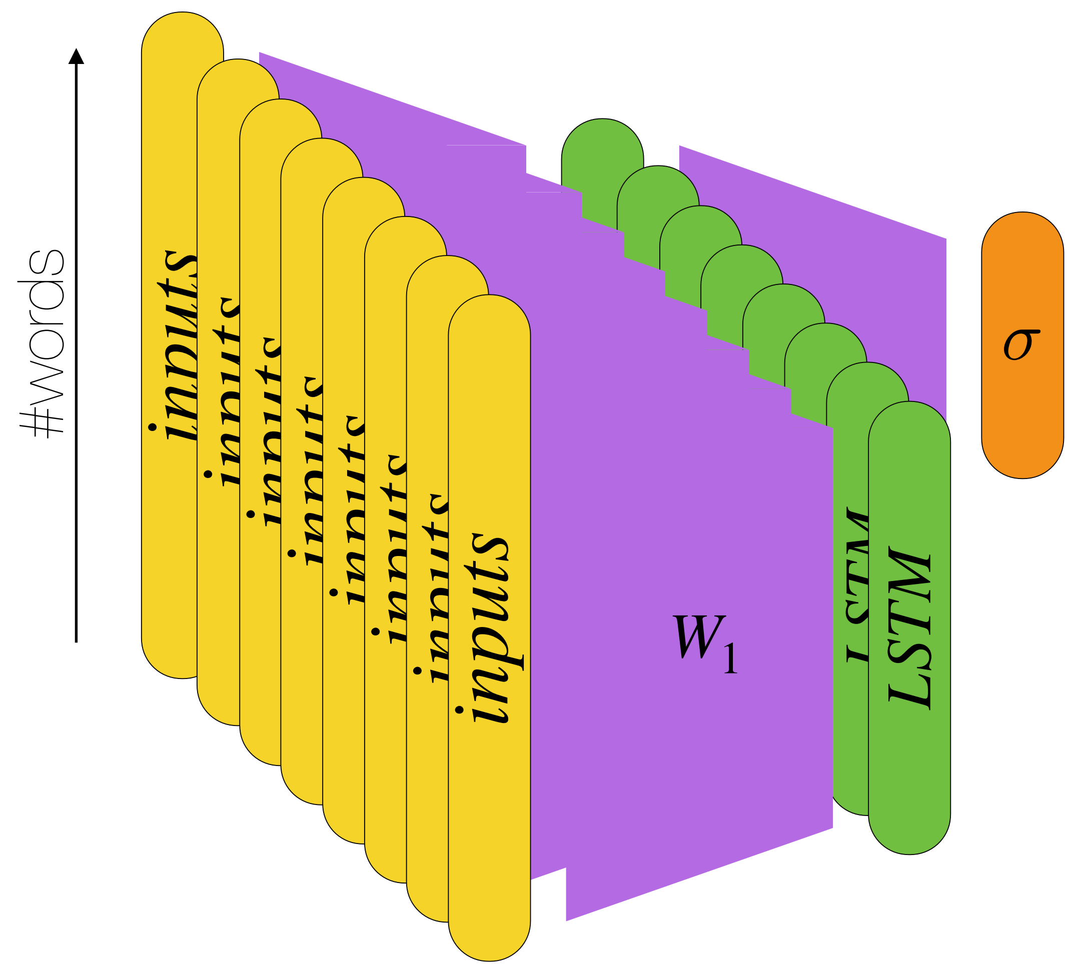
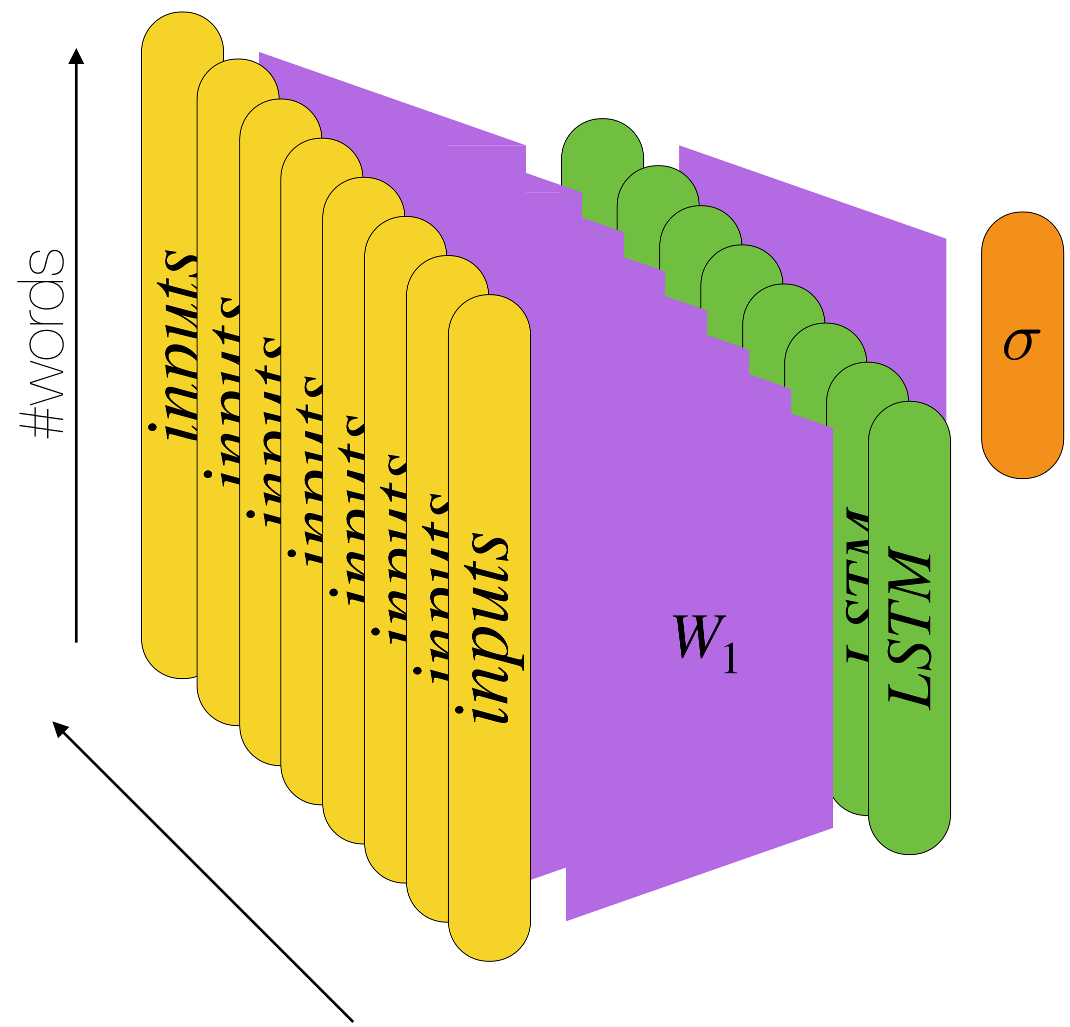


#words
inputs
inputs
inputs
inputs
inputs
inputs
inputs
inputs
W_1
LSTM
LSTM
σ

Using LSTMs



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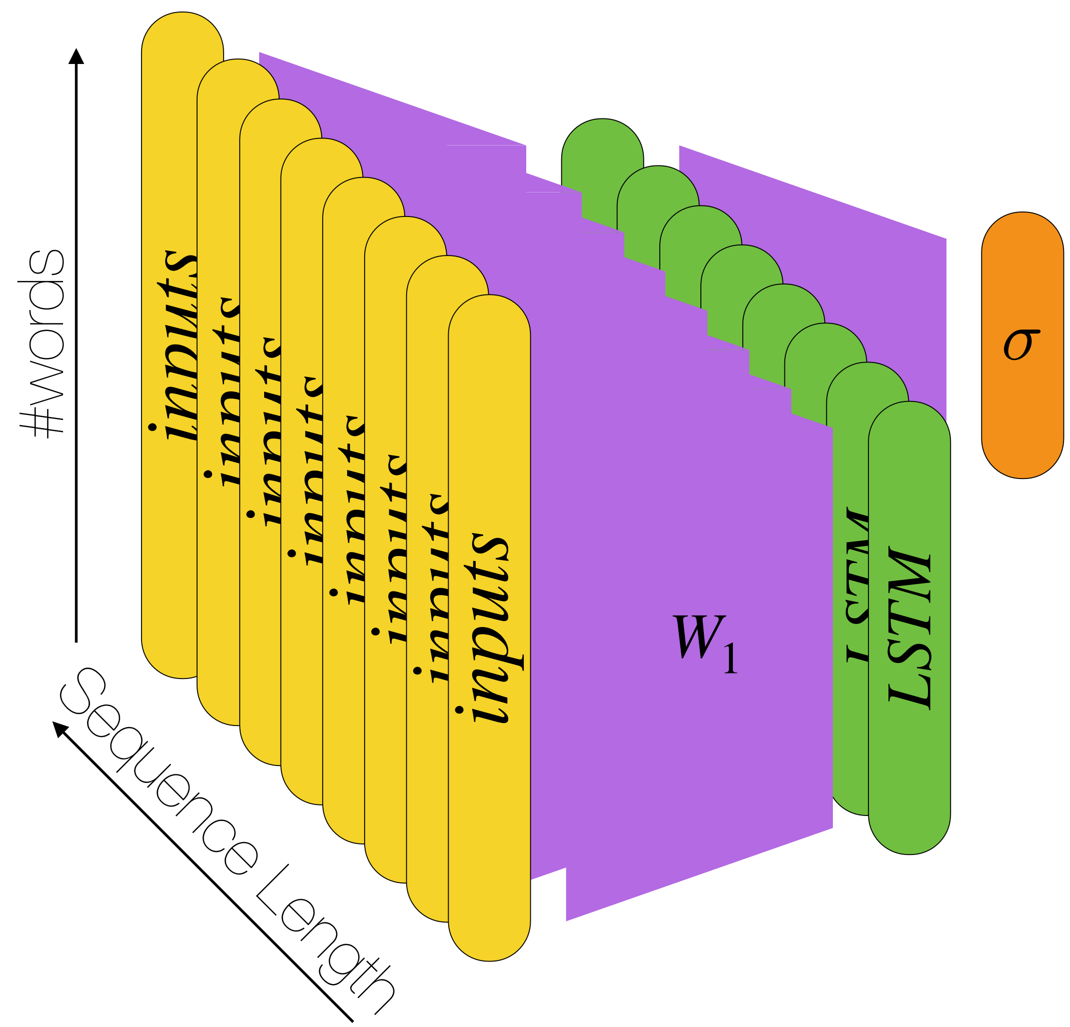
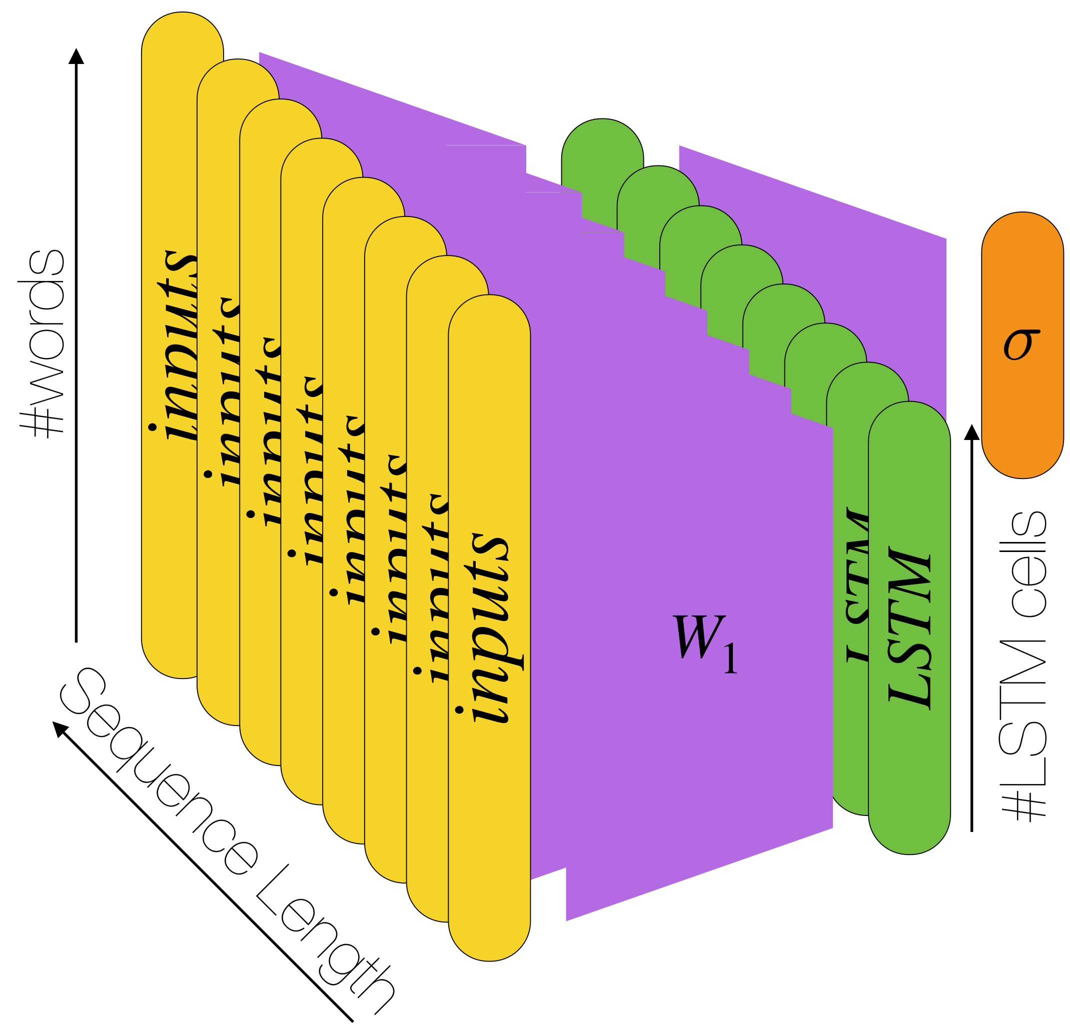
Using LSTMs



Using LSTMs



Applications

Applications

- Language Modeling and Prediction

Applications

- Language Modeling and Prediction
- Speech Recognition

Applications

- Language Modeling and Prediction
- Speech Recognition
- Machine Translation

Applications

- Language Modeling and Prediction
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- Part-of-Speech Tagging

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- Summarization

Applications

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- Time series forecasting

Gated Recurrent Unit (GRU)

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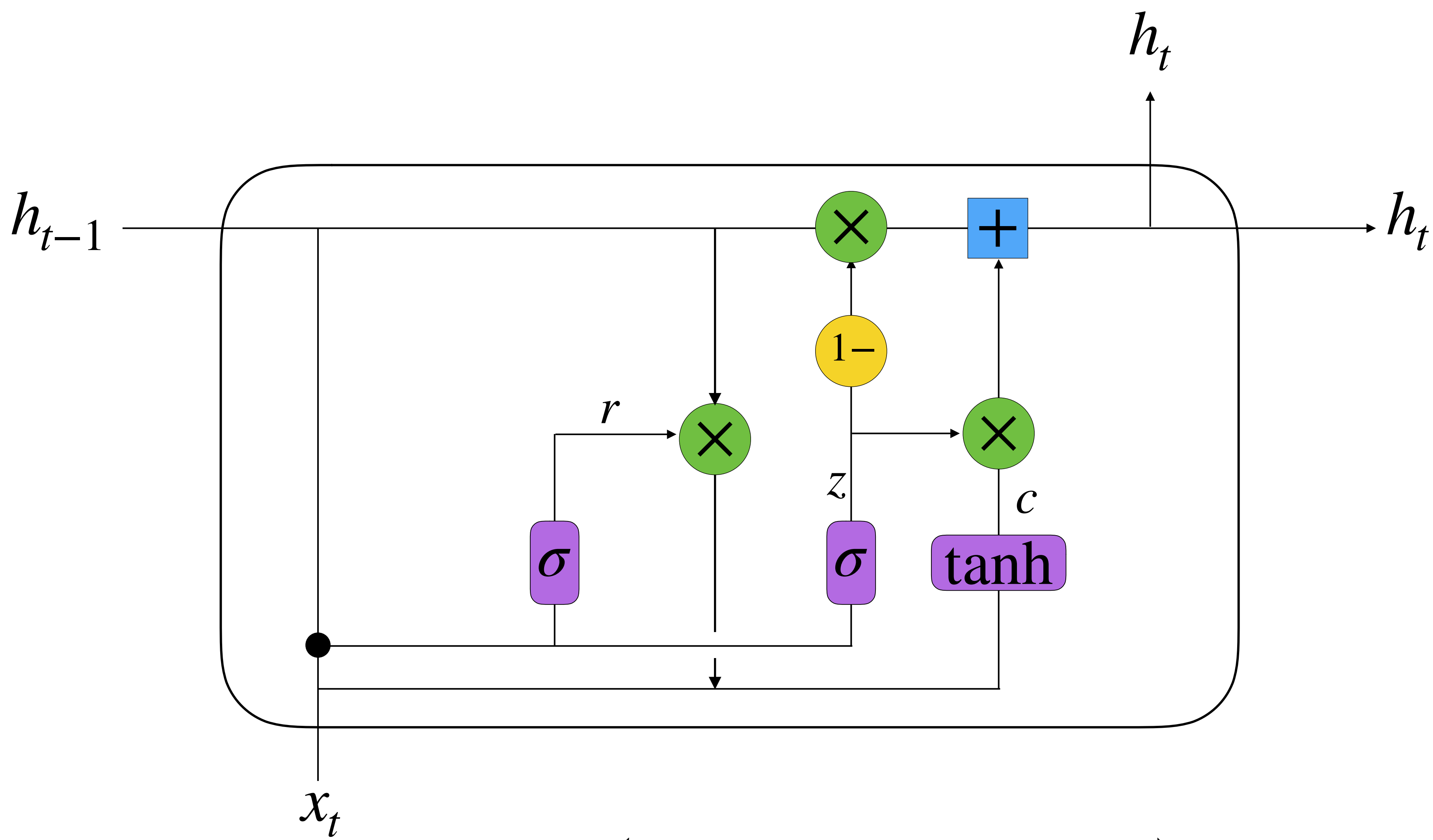
- Introduced in 2014 by Cho
- Meant to solve the Vanishing Gradient Problem
- Can be considered as a simplification of LSTMs
- Similar performance to LSTM in some applications, better performance for smaller datasets.

Element wise addition

Element wise multiplication

1 minus the input

Gated Recurrent Unit (GRU)



$$z = \sigma\left(W_z h_{t-1} + U_z x_t\right)$$

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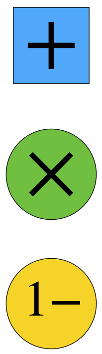
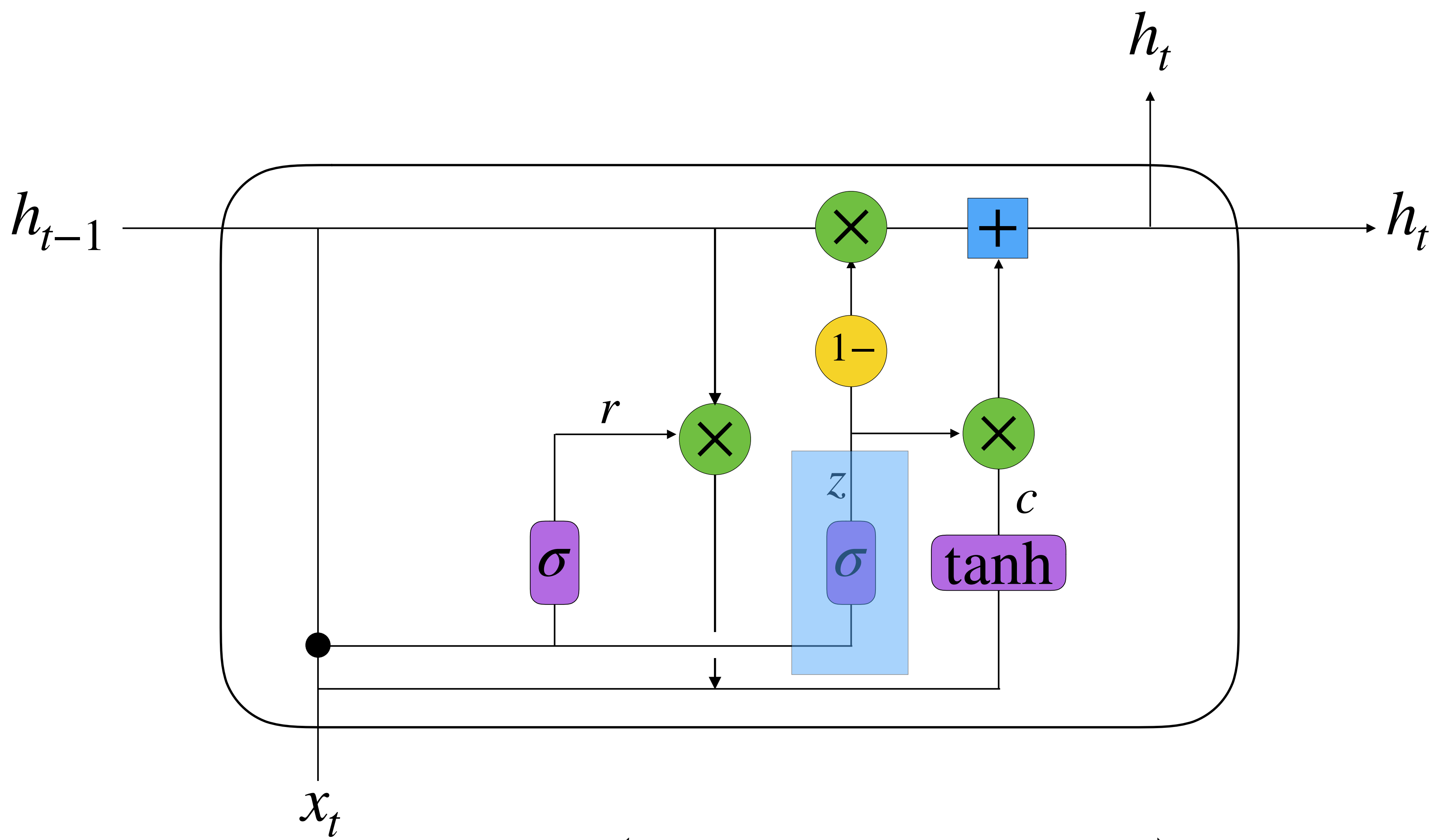
Gated Recurrent Unit (GRU)





Update gate:
How much of
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Gated Recurrent Unit (GRU)

Element wise addition

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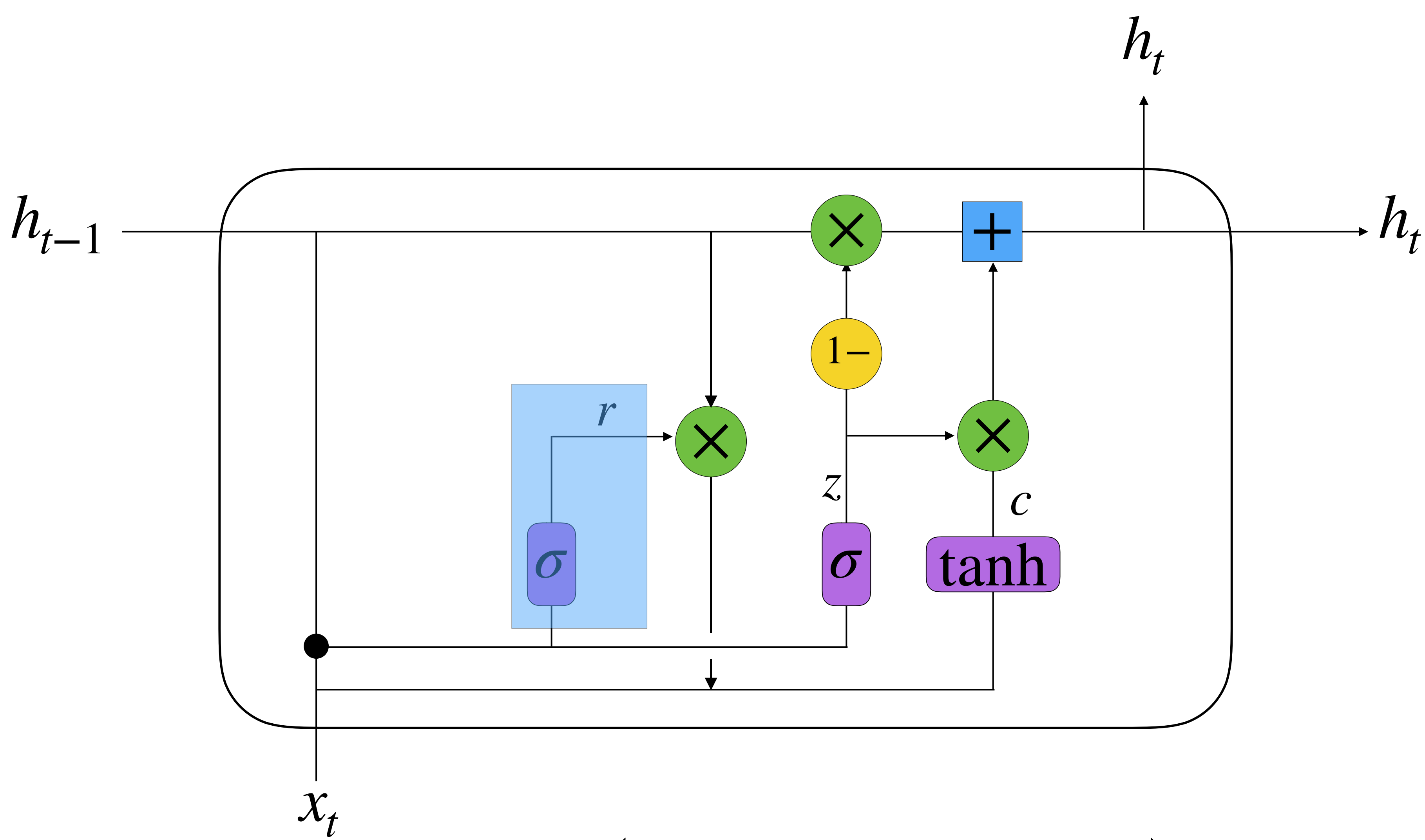
Reset gate: How much of the previous output should be removed?



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Gated Recurrent Unit (GRU)

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Element wise multiplication

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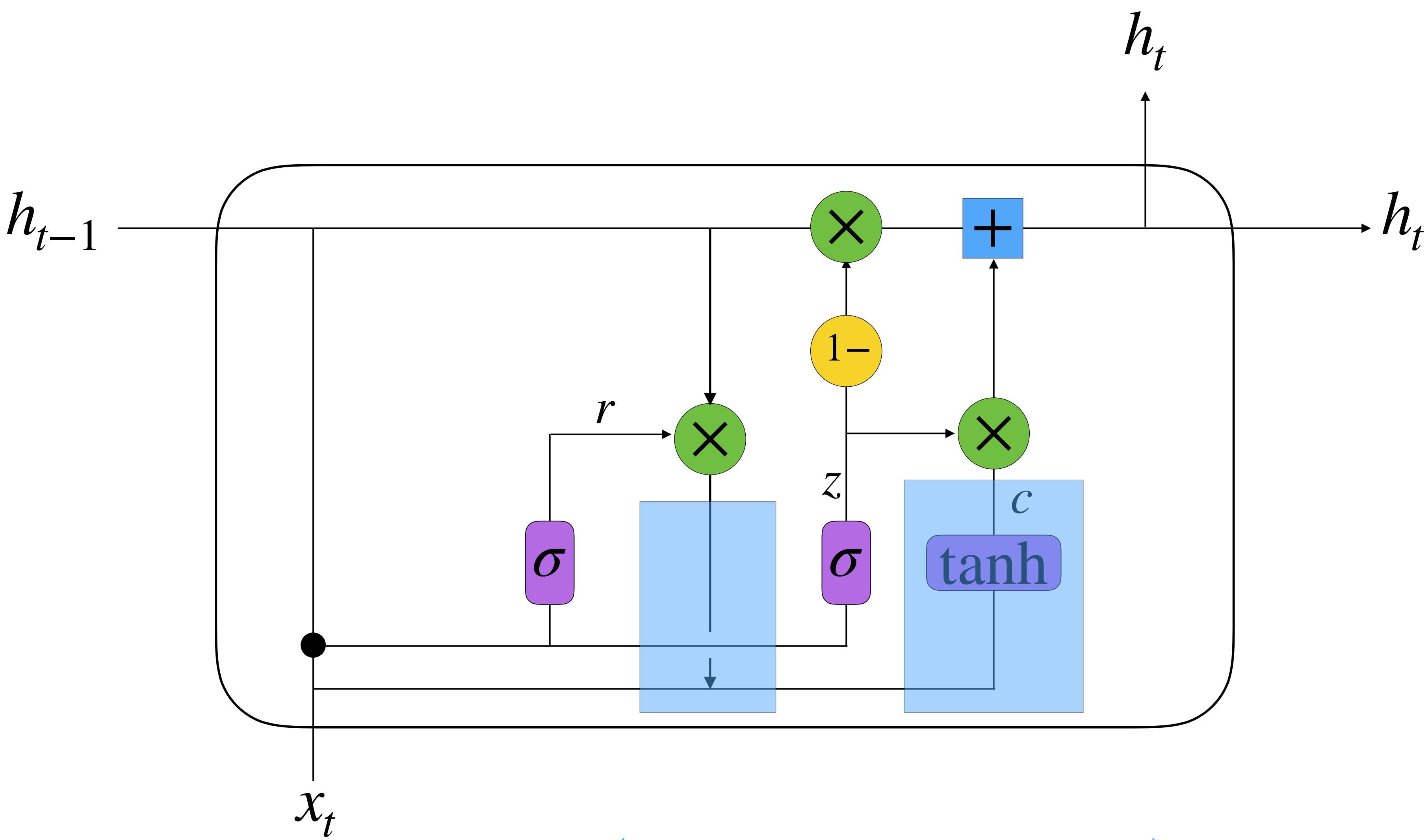
Current memory: What information do we remember right now?



$$c = \tanh\left(W_c\left(h_{t-1} \otimes r\right) + U_c x_t\right)$$

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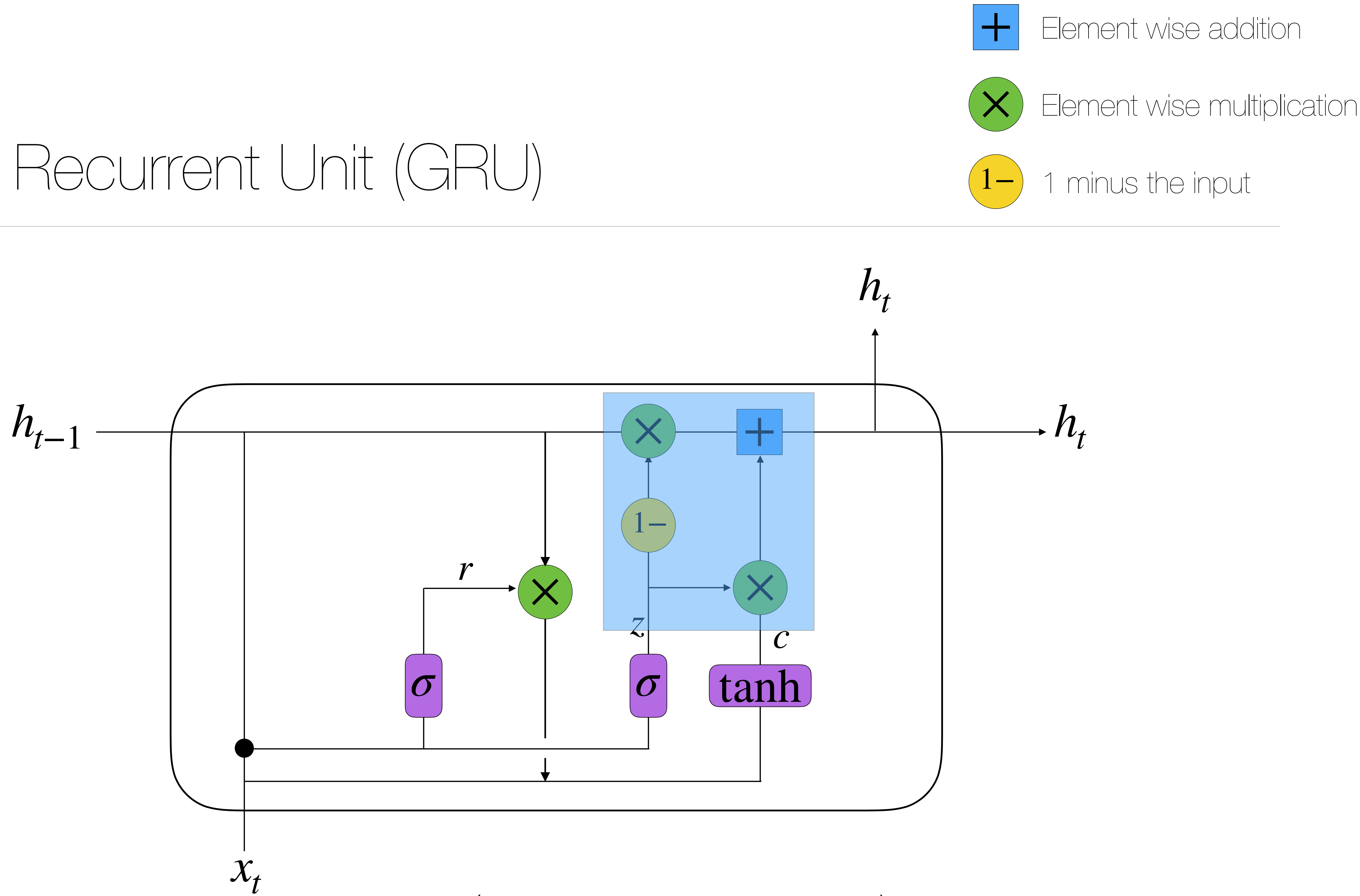

Output: Combine all available information.

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Language Models

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- Assigns a probability to a sequence of words.

$$P\left(w_1, w_2, \cdots, w_n\right)$$

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- Can be formulated as find the next word:

My name is ______.
The sky is ______.

$$P\left(Bruno \,|\, my, name, is\right) \gg P\left(red \,|\, my, name, is\right)$$
$$P\left(Red \,|\, the, sky, is\right) \gg P\left(Bruno \,|\, the, sky, is\right)$$

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- So given a piece of **text**, we build a training dataset:

Mary had a little lamb whose fleece was white as snow.

Using a running window of a certain length

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- So given a piece of **text**, we build a training dataset:

Mary had a little lamb whose fleece was white as snow.

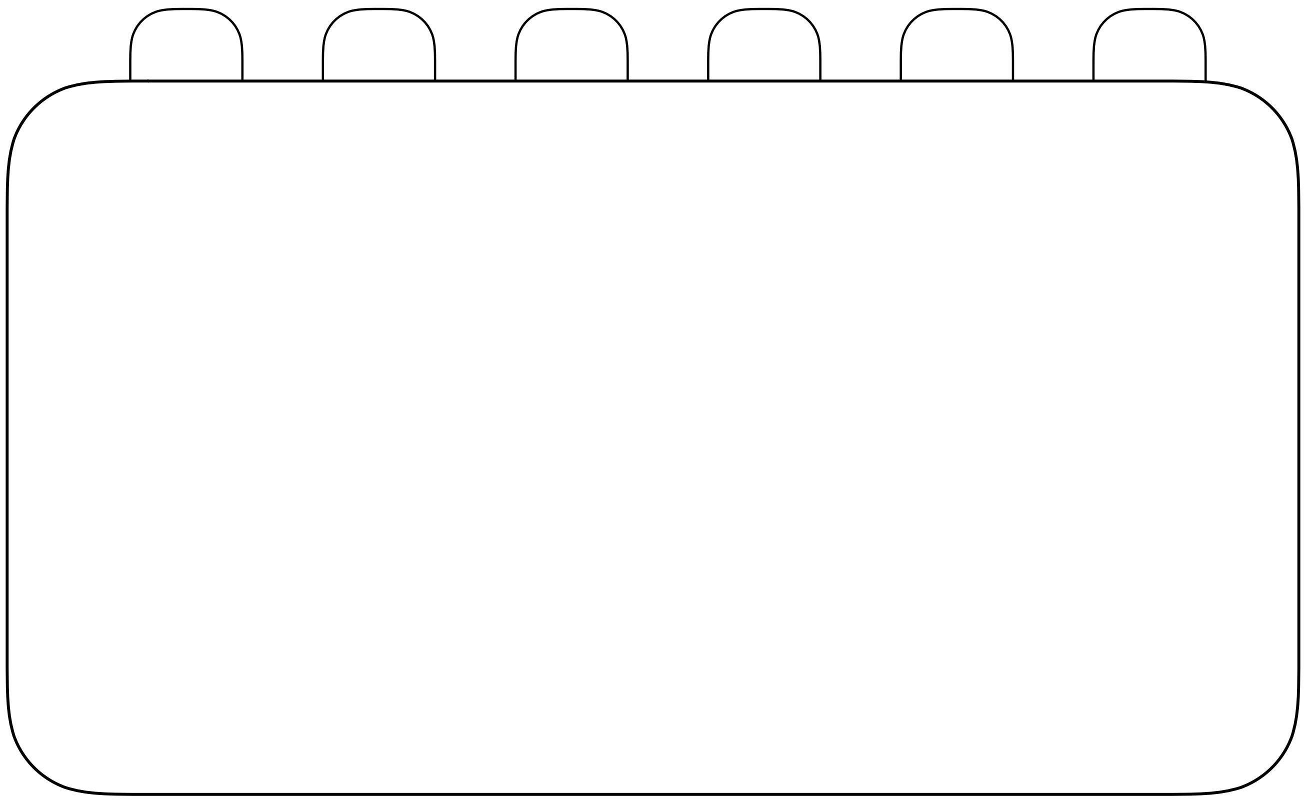
Using a running window of a certain length

Input Sequence	output
Mary had a little	lamb
had a little lamb	whose
a little lamb whose	fleece
little lamb whose fleece	was
lamb whose fleece was	white
whose fleece was white	as
fleece was white as	snow

- Supervised learning model

@bgoncalves

Or legos?



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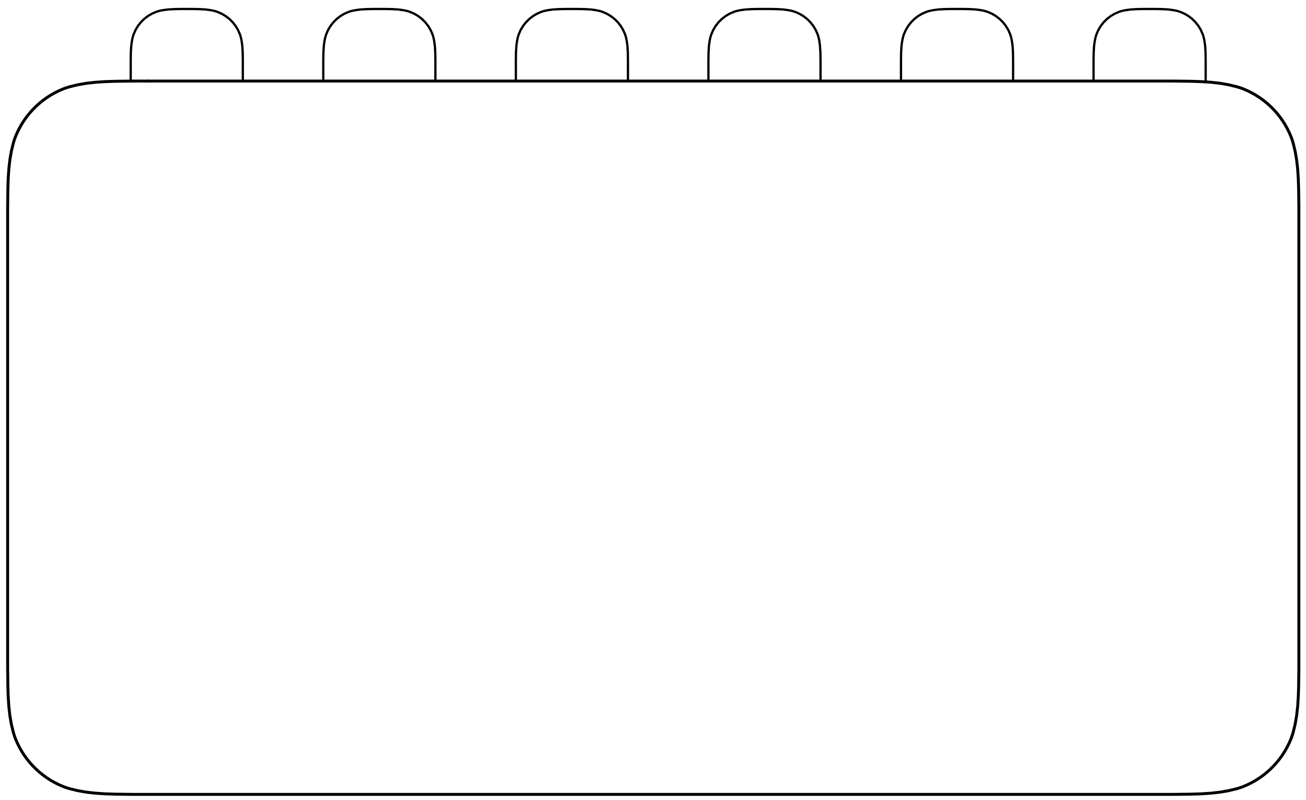

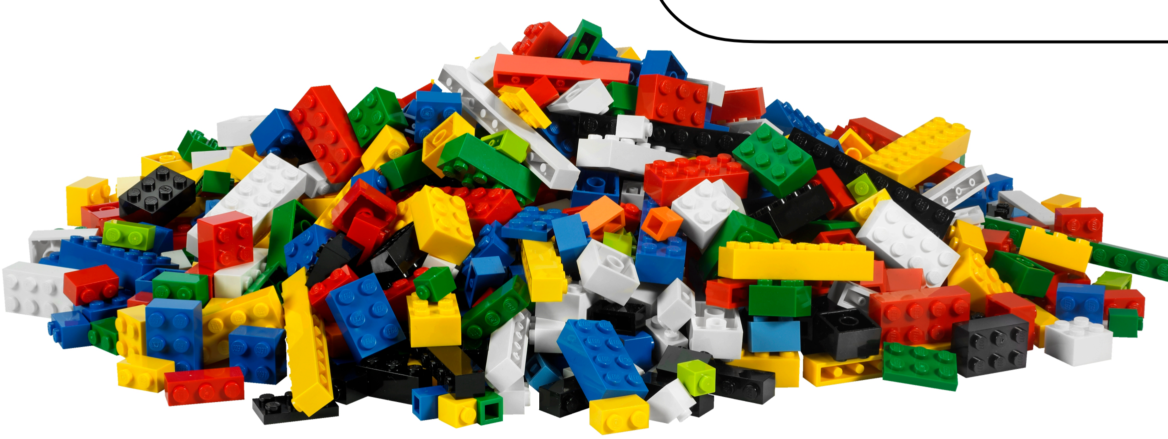

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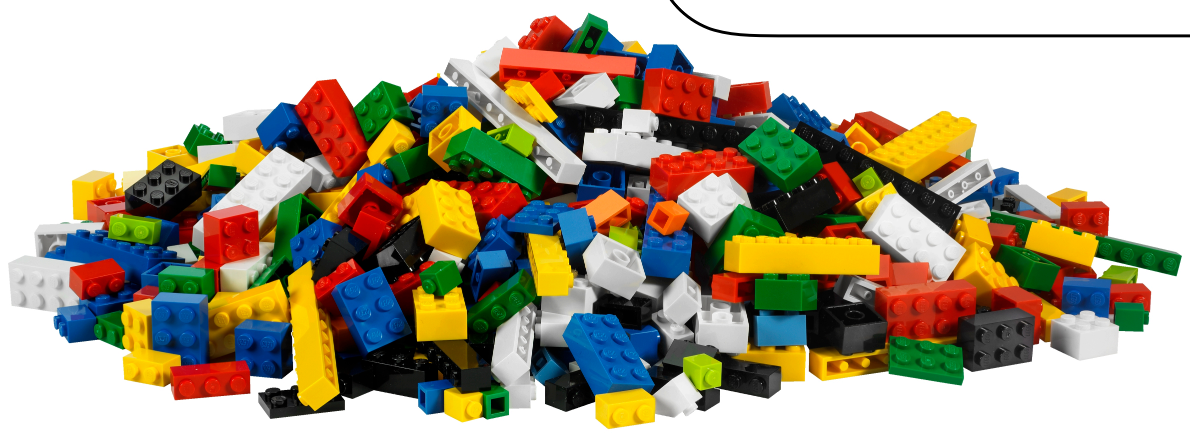
https://keras.io



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https://keras.io

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- Created and maintained by François Chollet, a Google engineer.
- Implements Layers, Objective/Loss functions, Activation functions, Optimizers, etc…

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- model.summary() - Output a textual representation of the model

github.com/bmtgoncalves/RNN