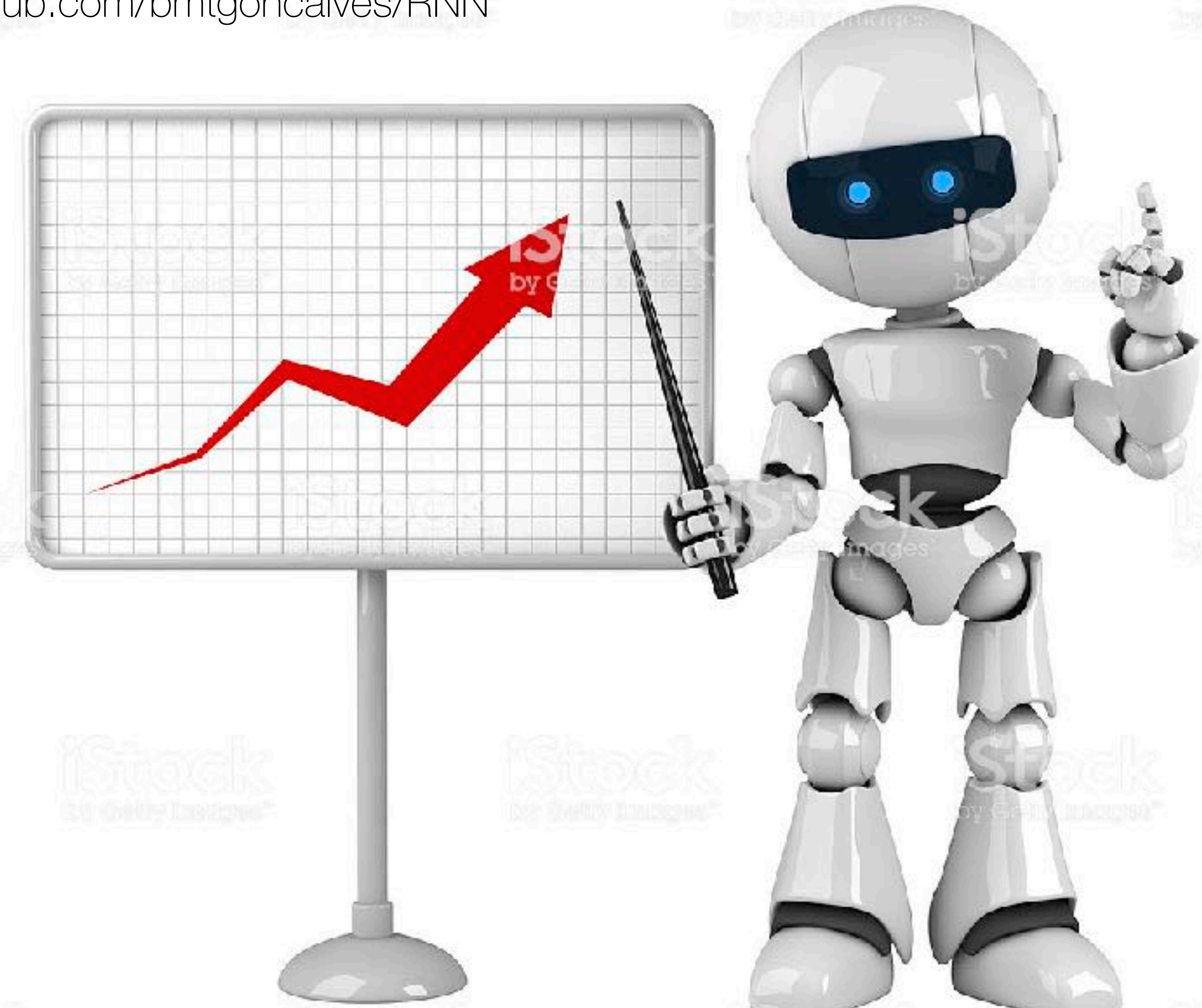
NYU DATA SCIENCE

RNNs for Timeseries Analysis

Bruno Gonçalves

www.bgoncalves.com

github.com/bmtgoncalves/RNN



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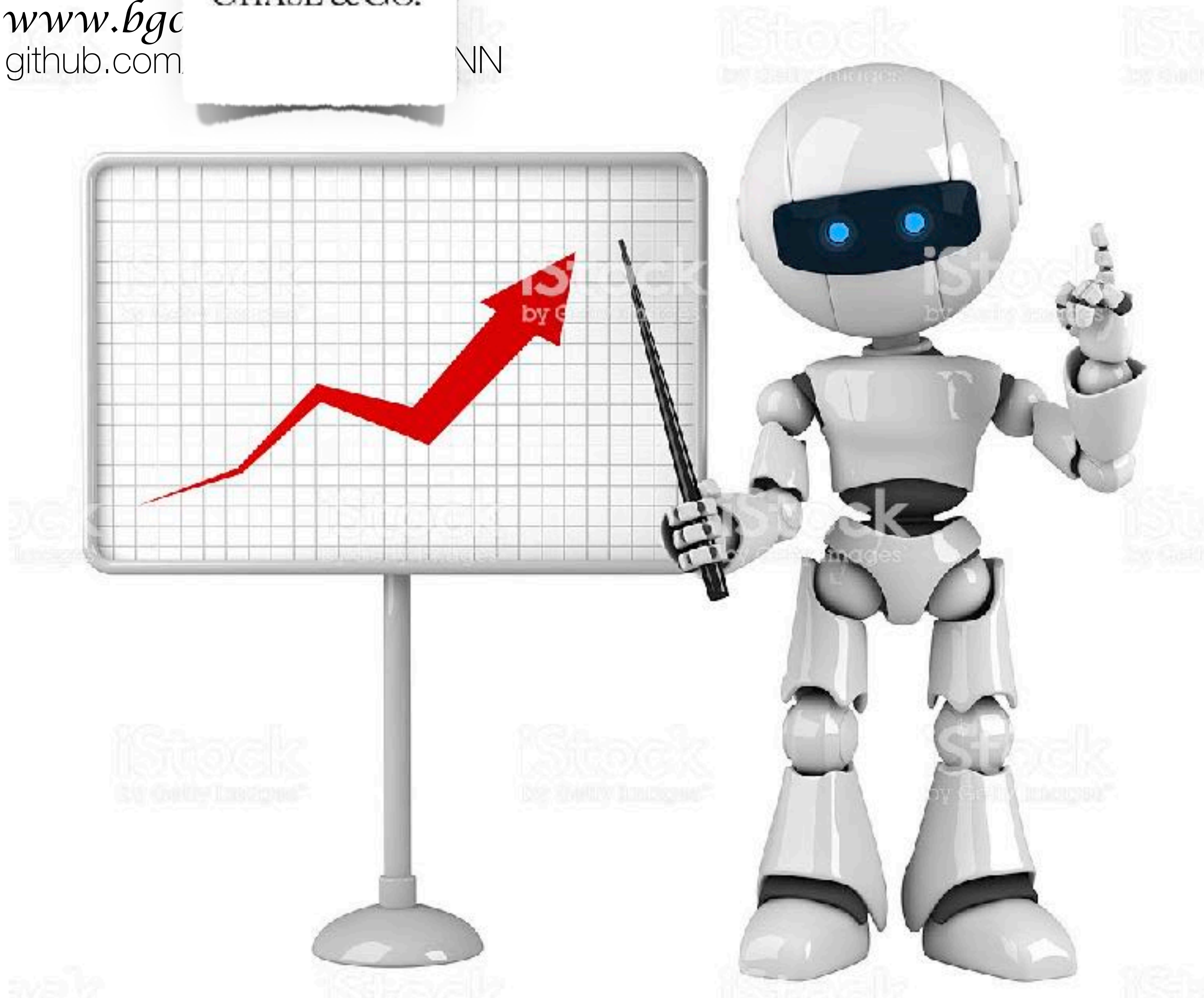

JPMorgan Chase & Co.

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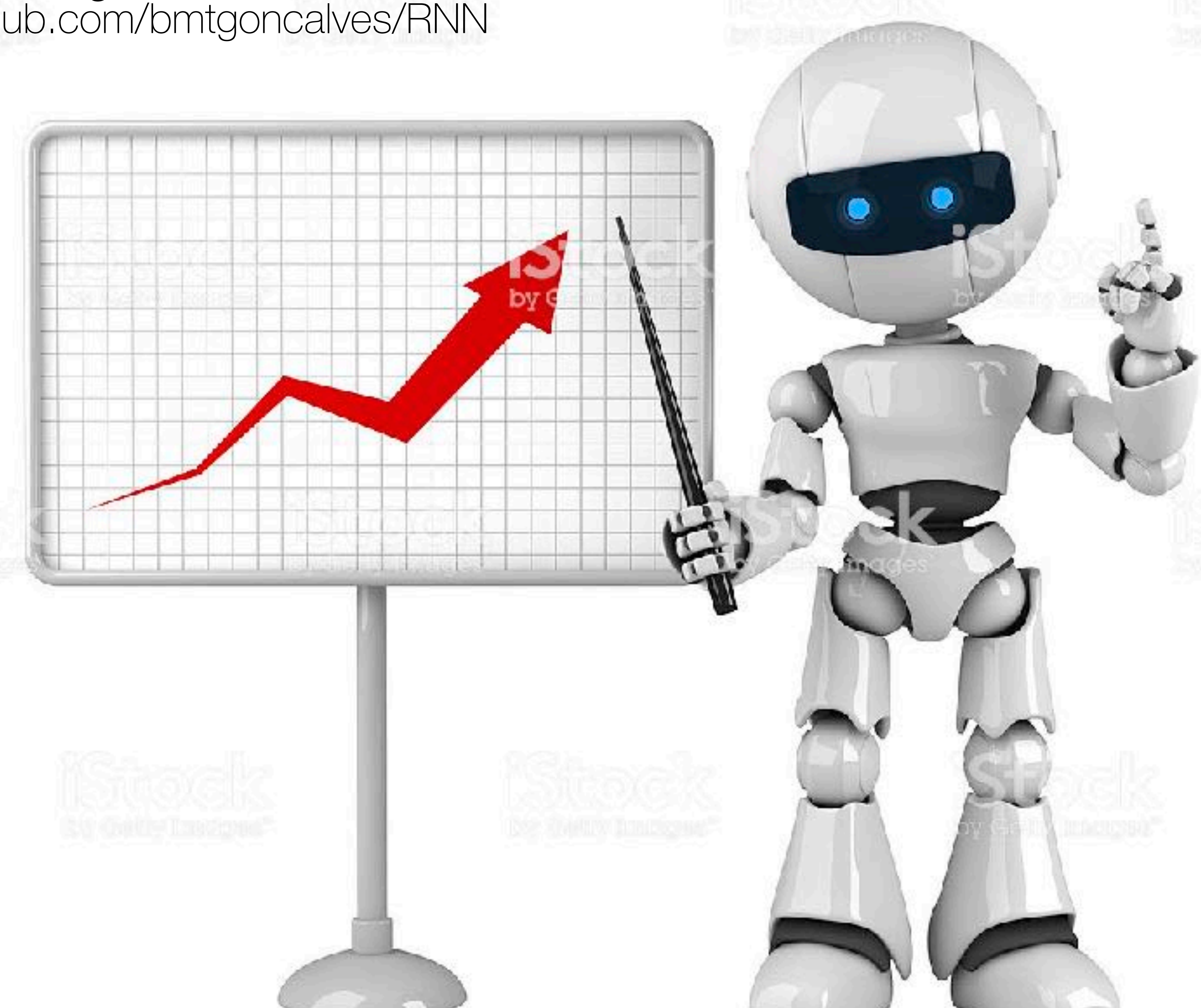

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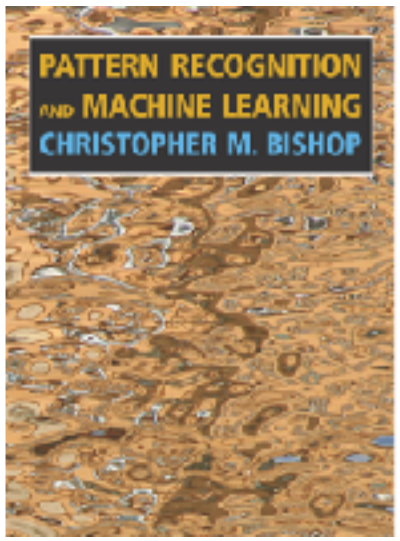
References


PATTERN RECOGNITION
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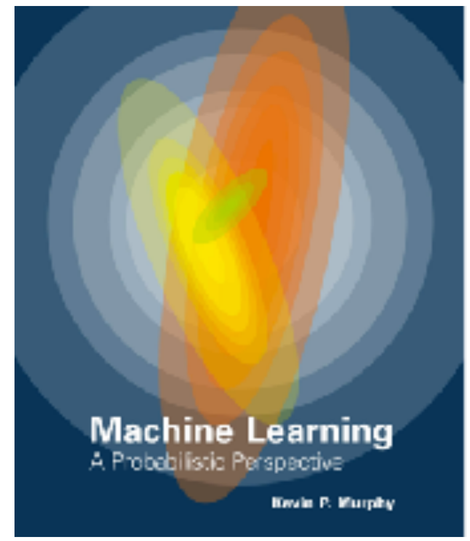
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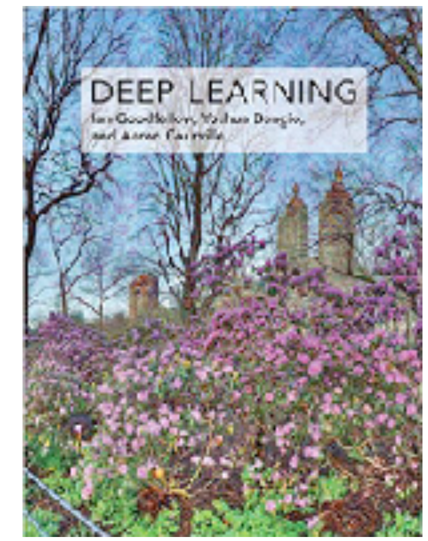
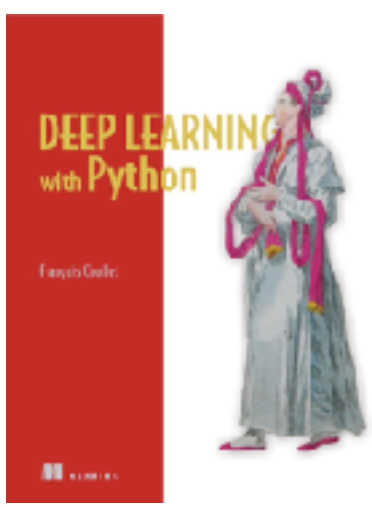

DEEP LEARNING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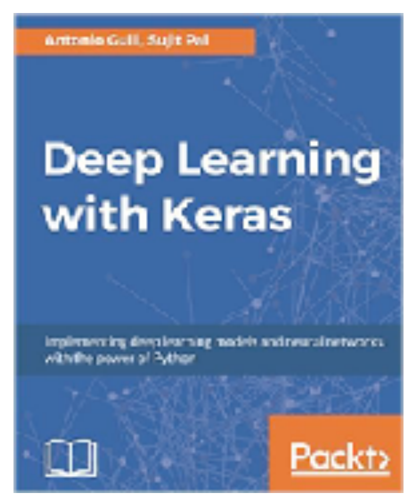
with Python


Antonio Gulli, Sujit Pal
Deep Learning with Keras
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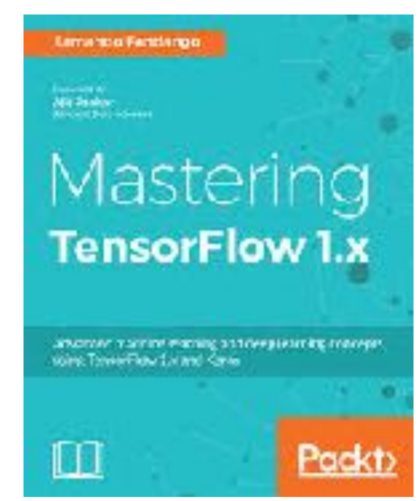
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How the Brain "Works" (Cartoon version)

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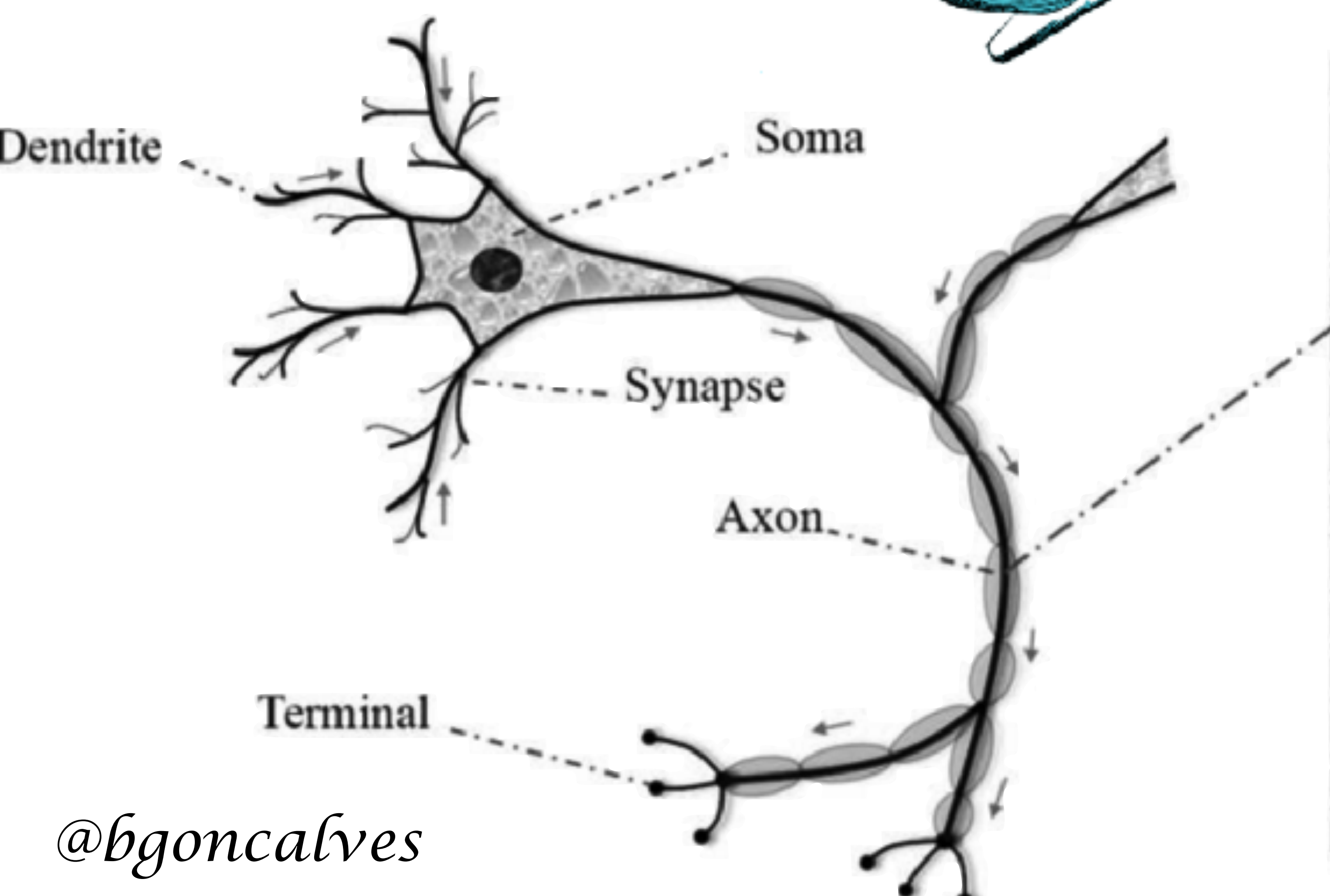
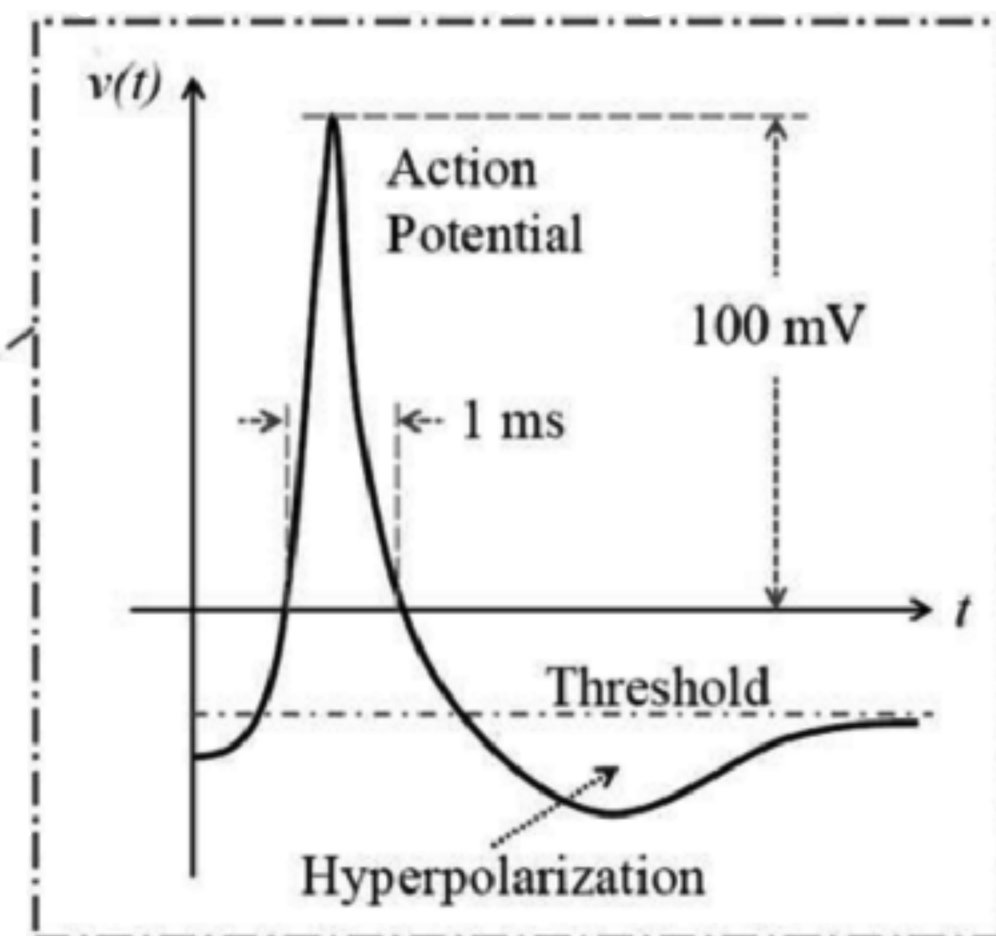
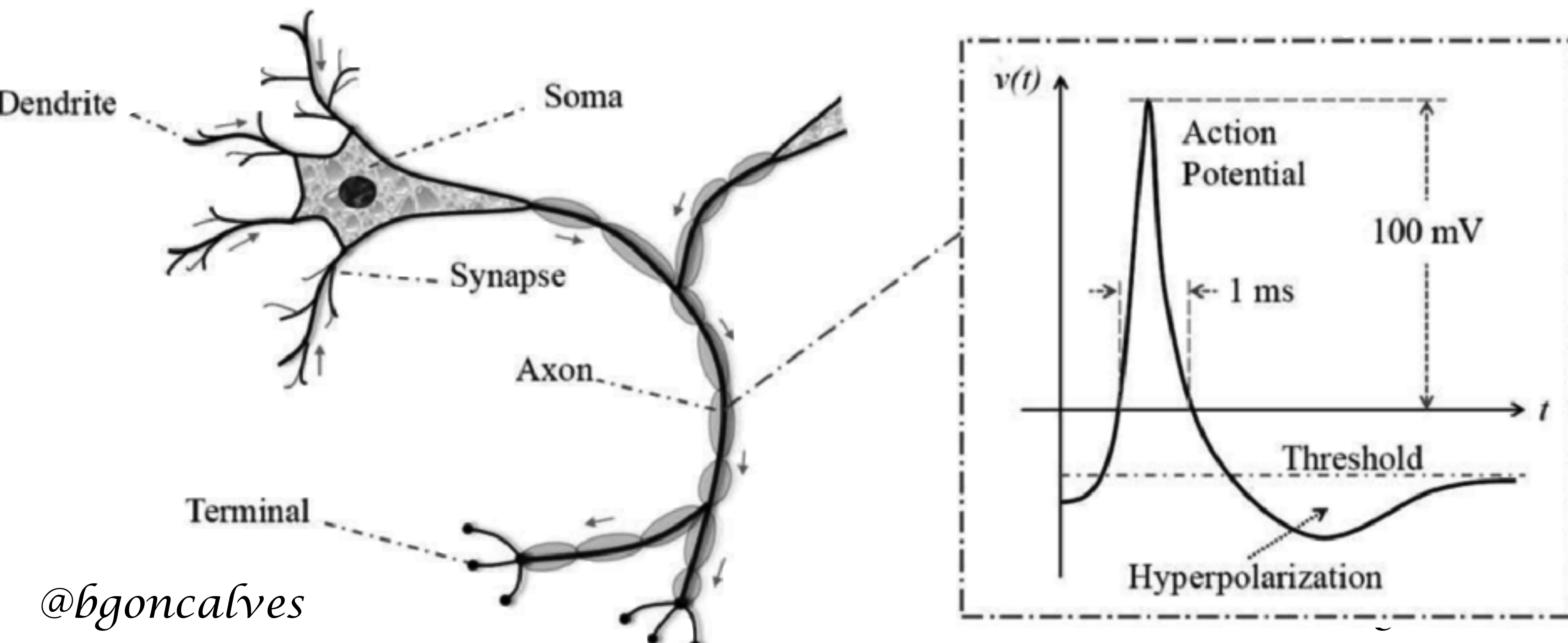




How the Brain “Works” (Cartoon version)

- Each neuron receives input from other neurons



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- Each neuron receives input from other neurons
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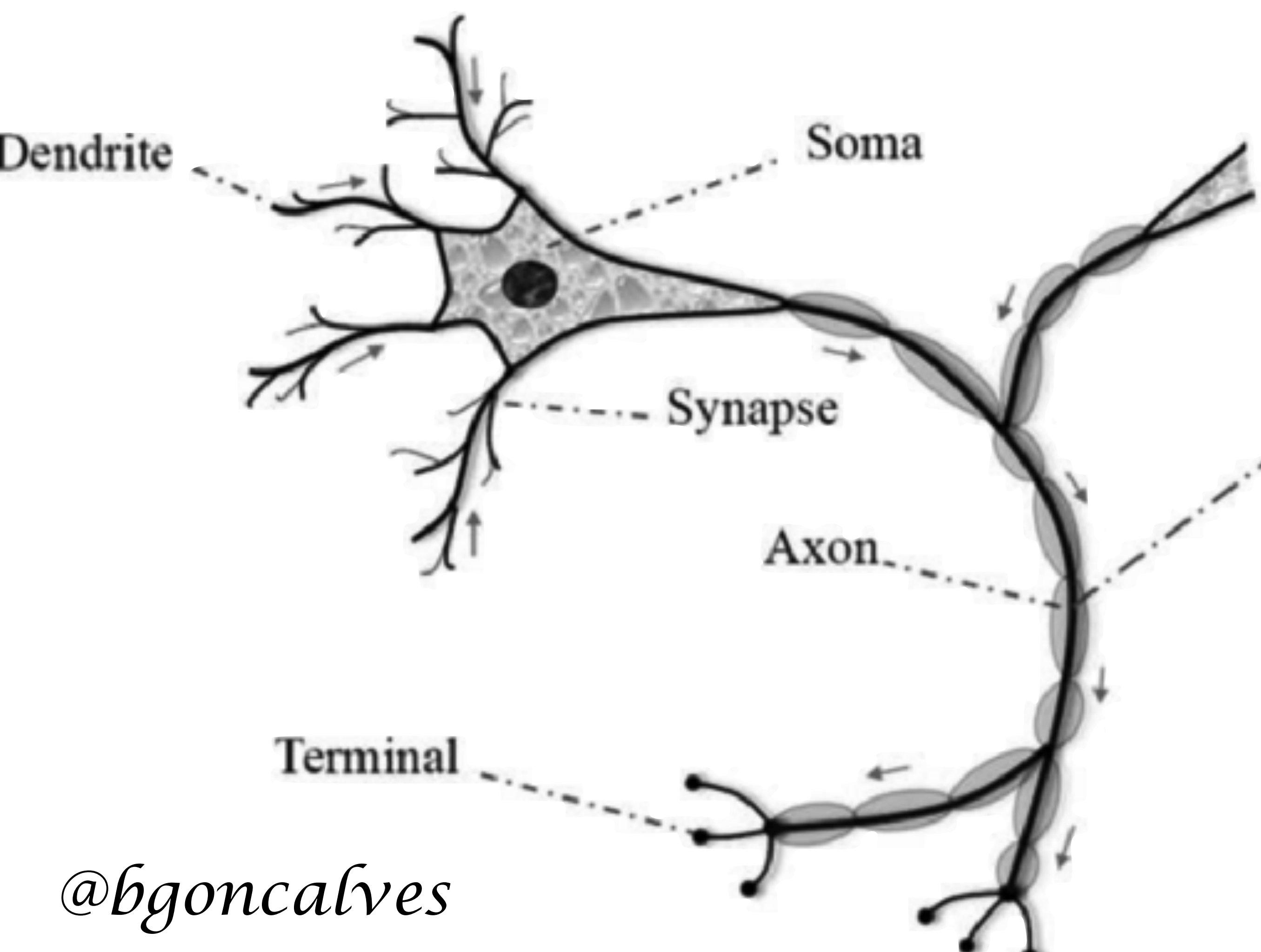

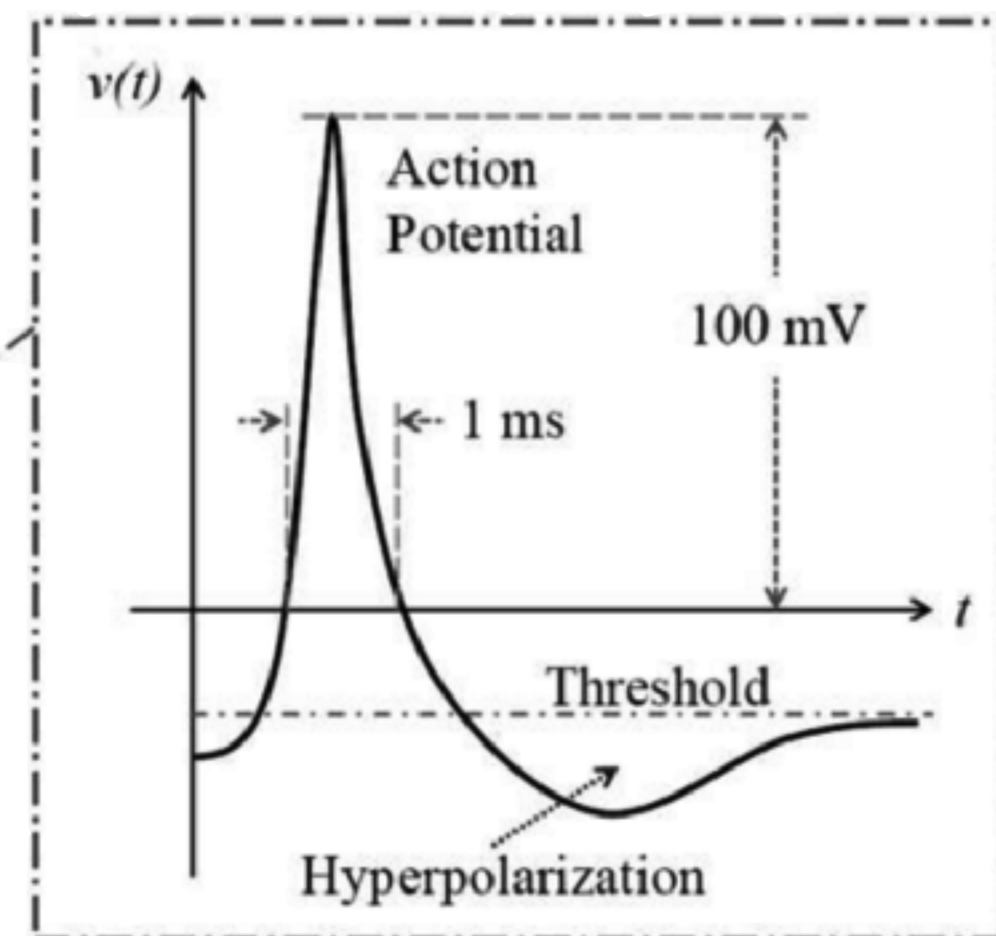

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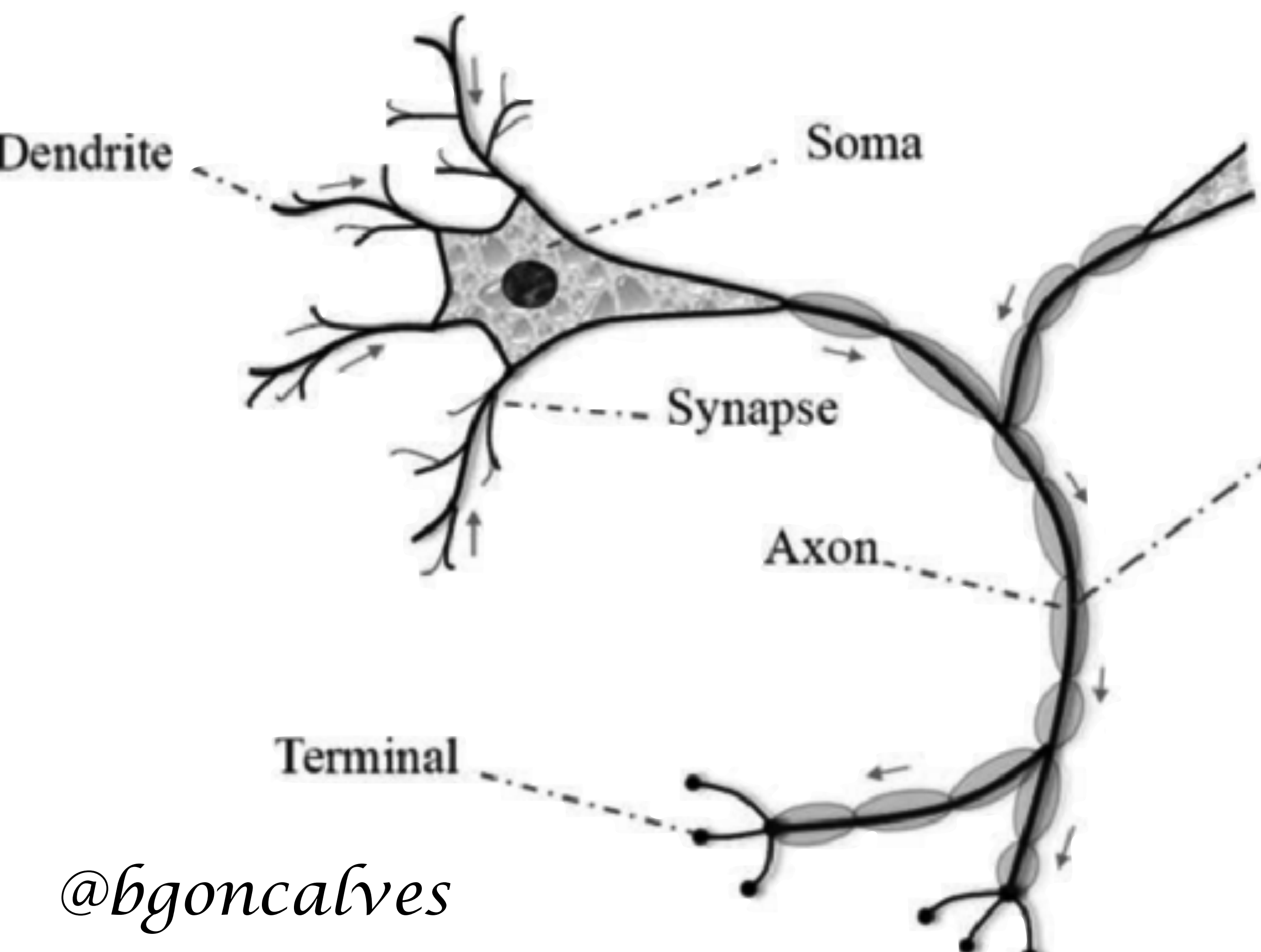

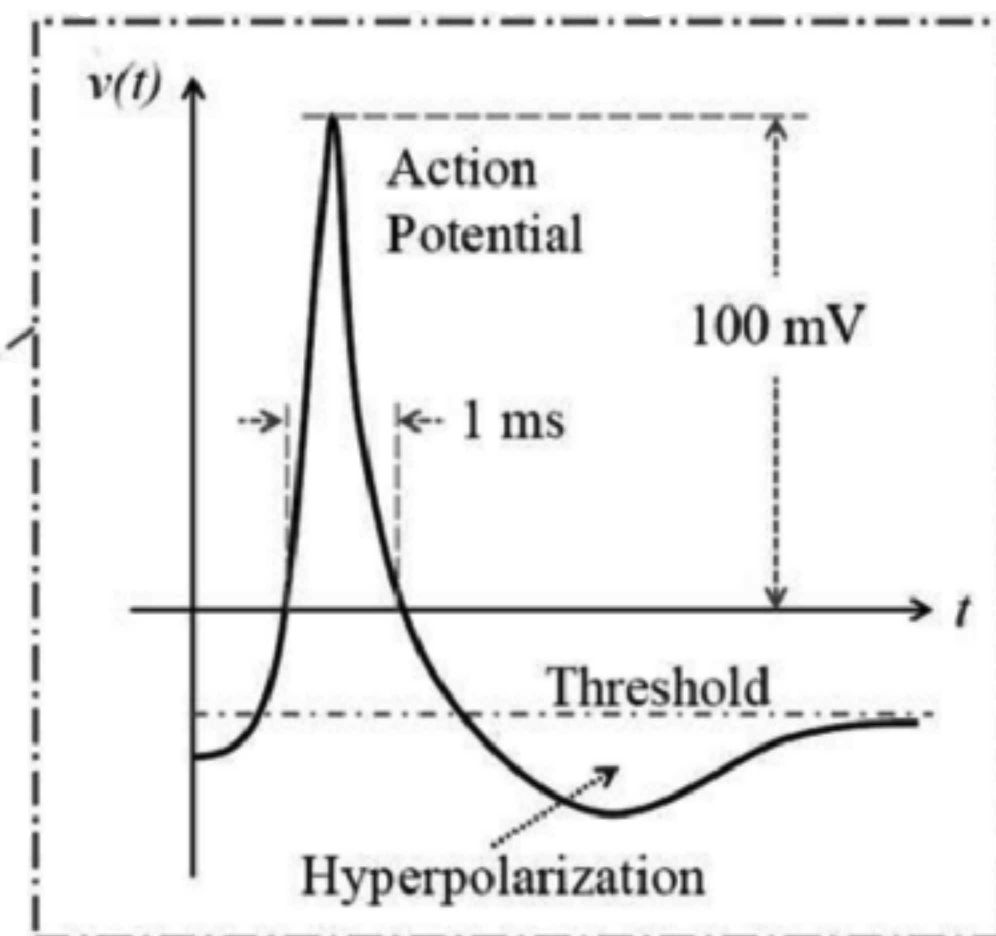

@bgoncalves

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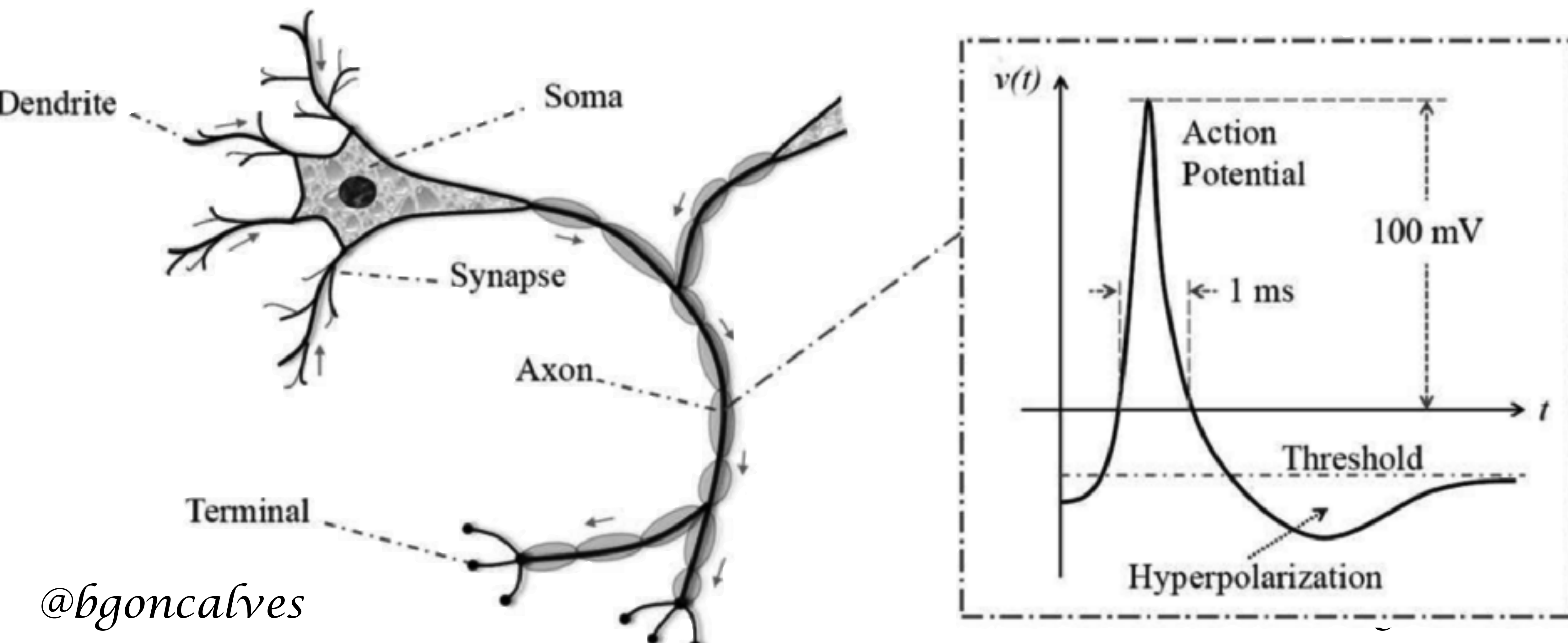

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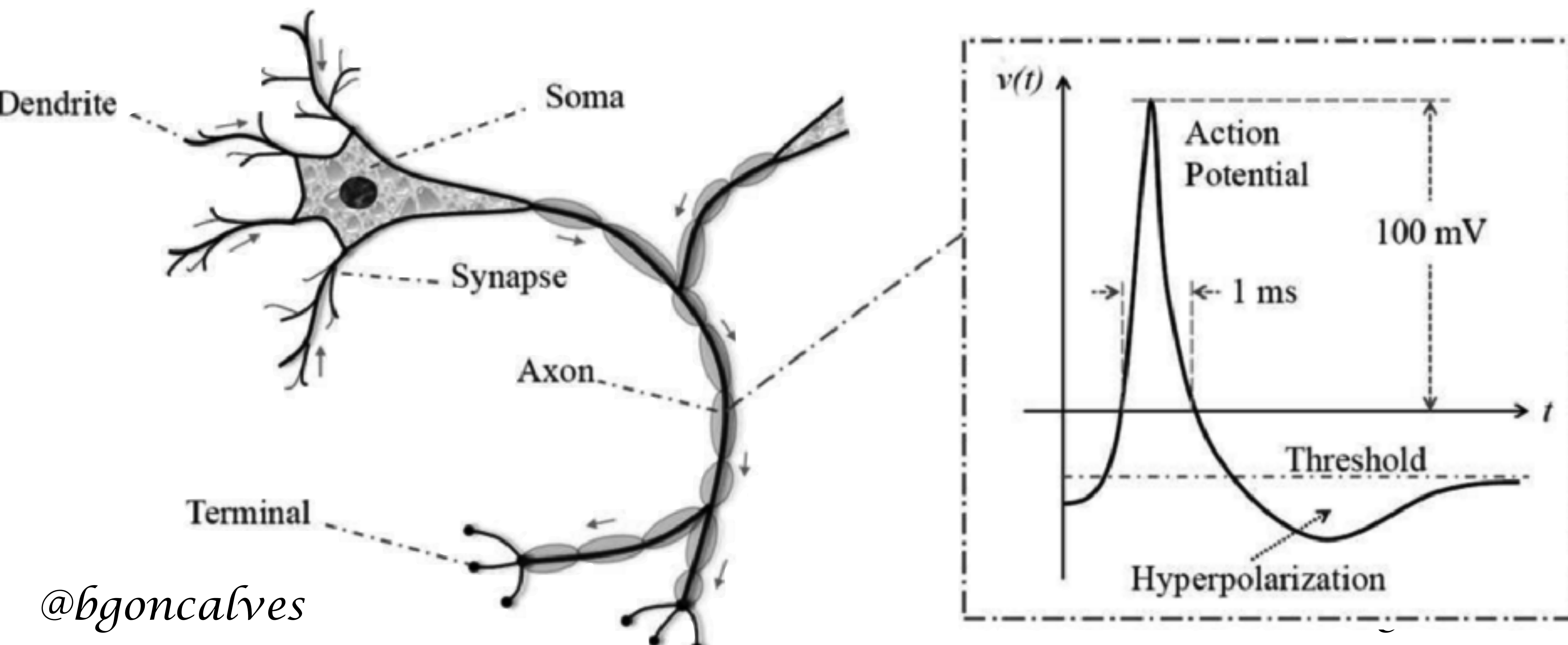

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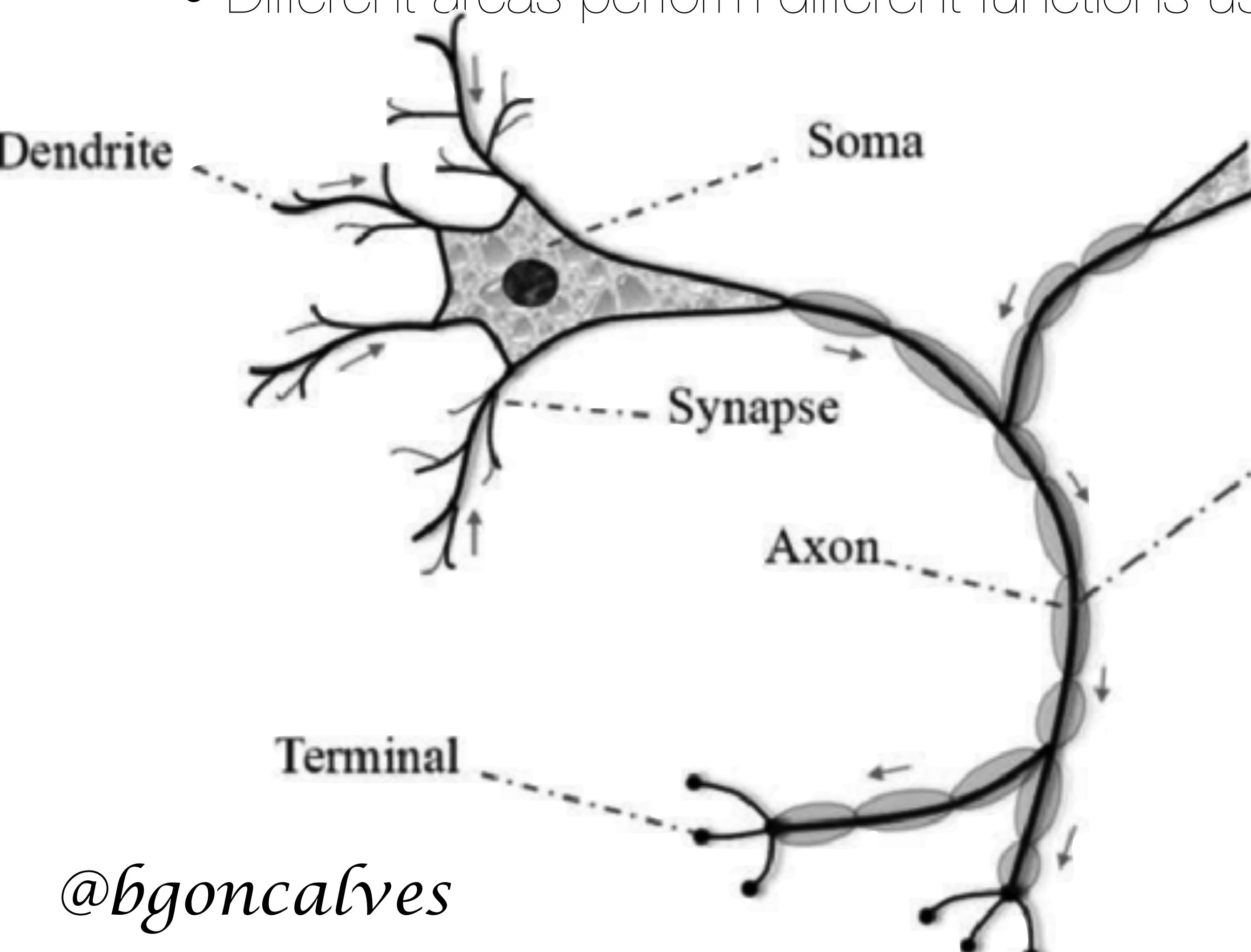
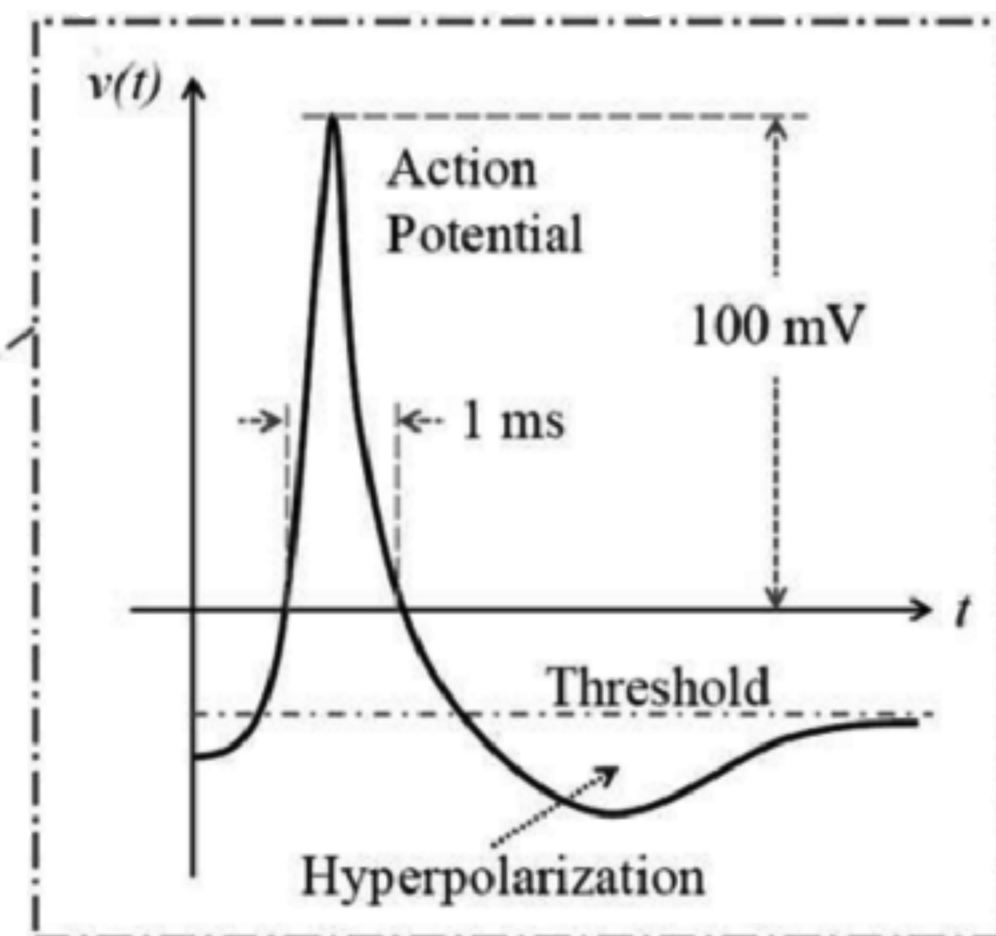
- Different areas perform different functions using same structure (Modularity)





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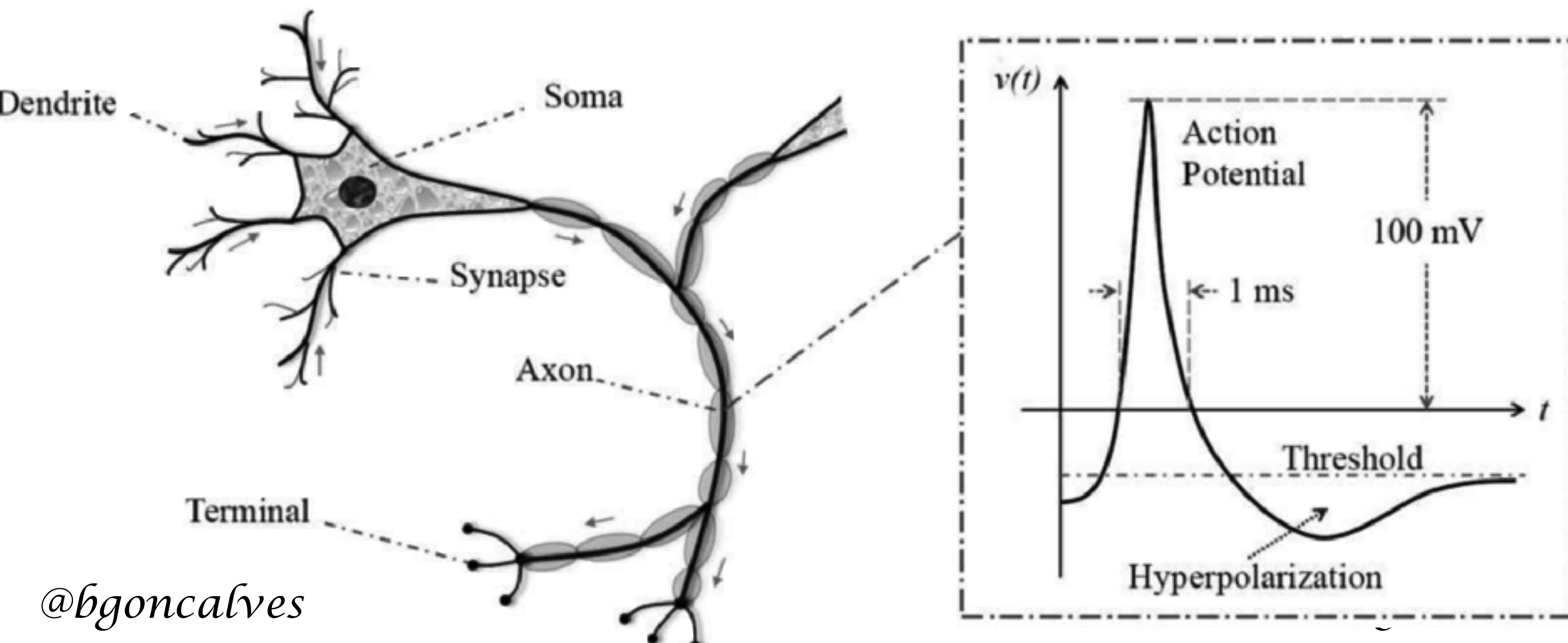

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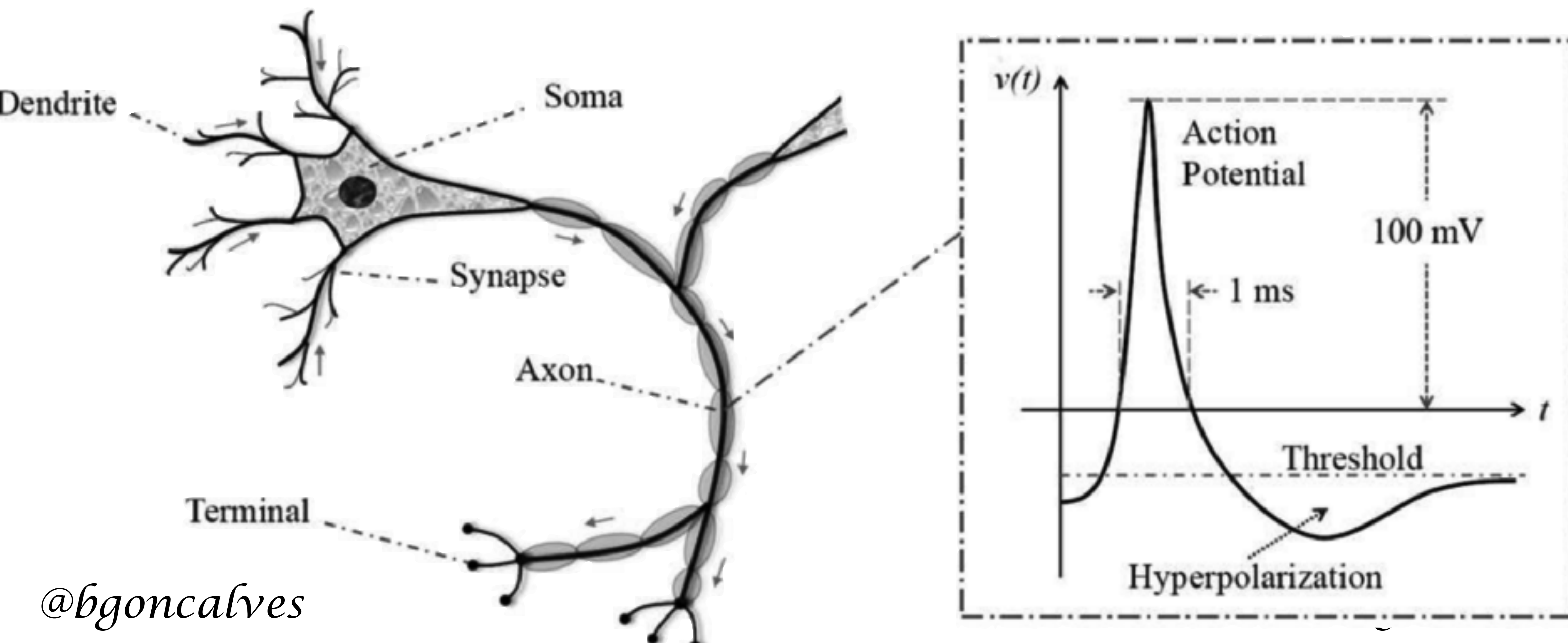
Inputs



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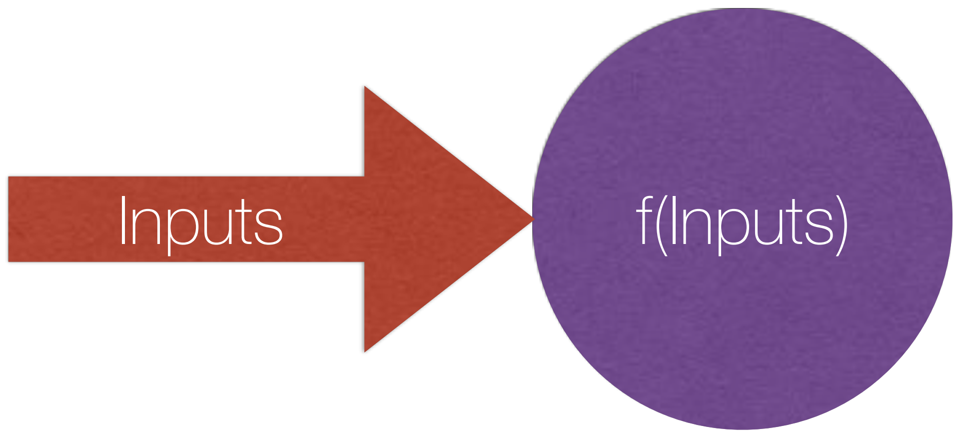

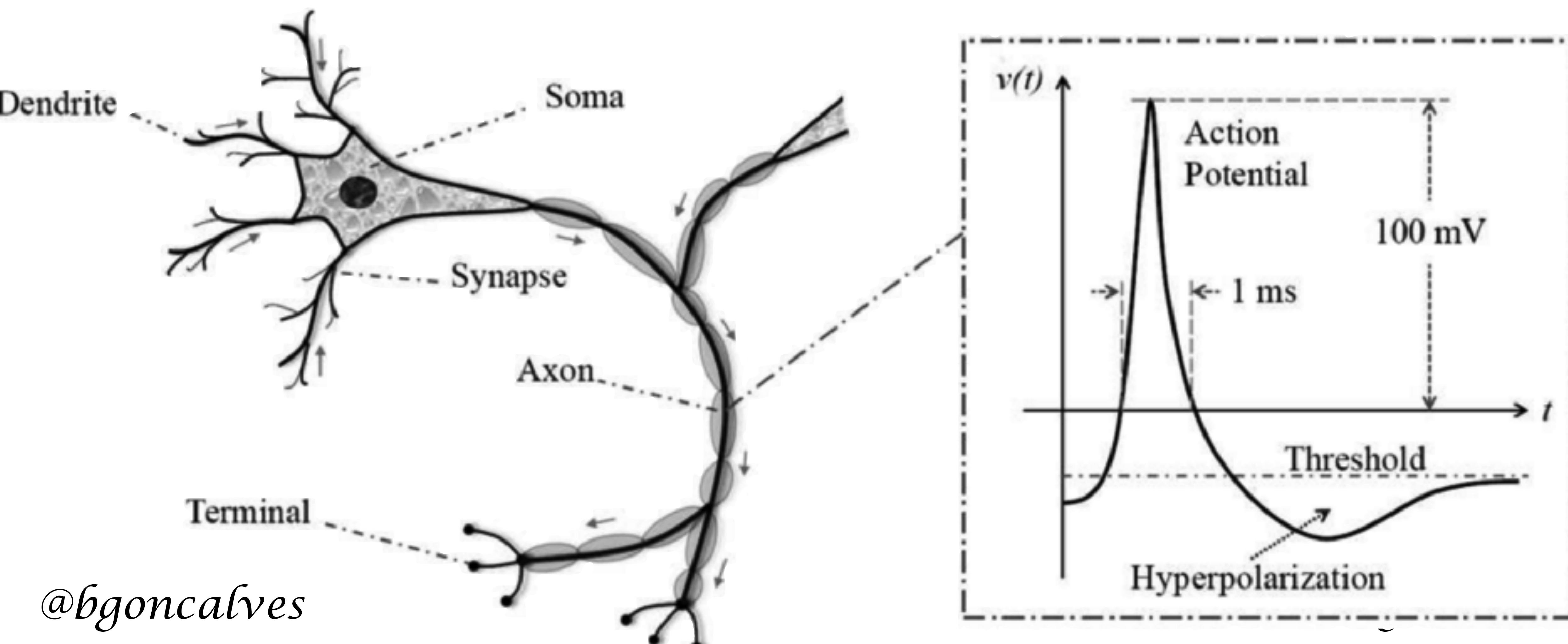

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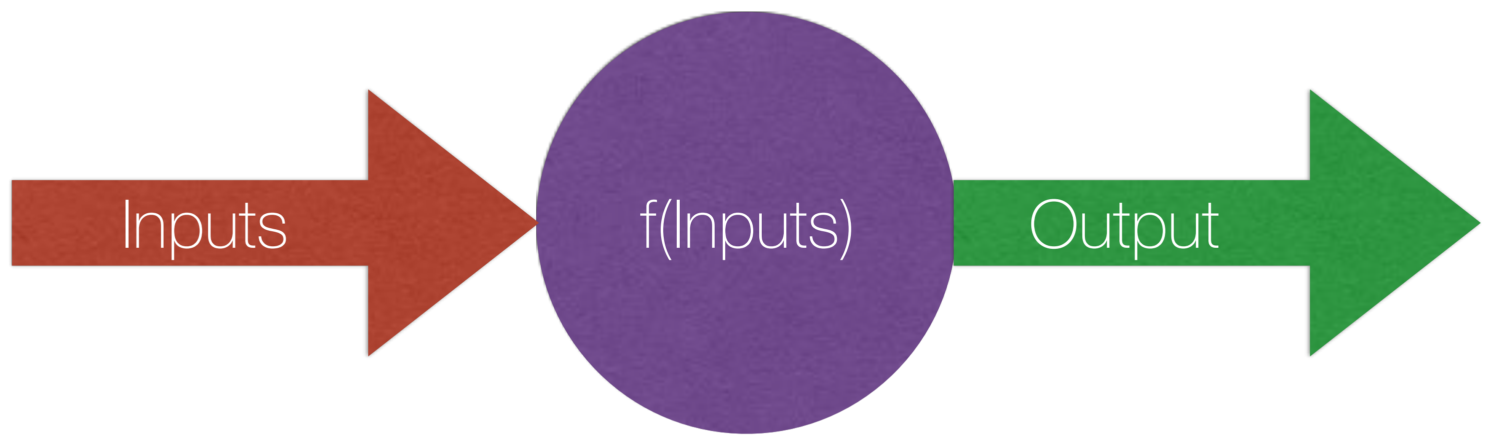

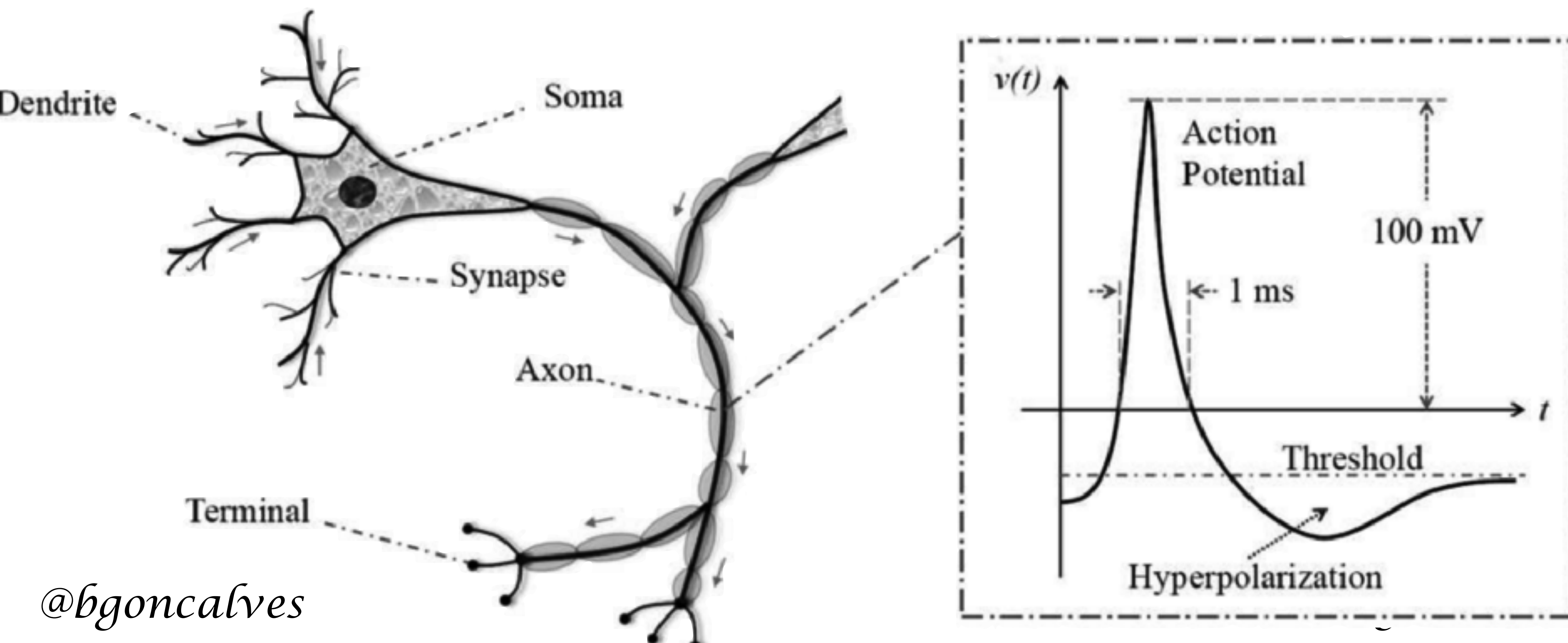

Optimization Problem

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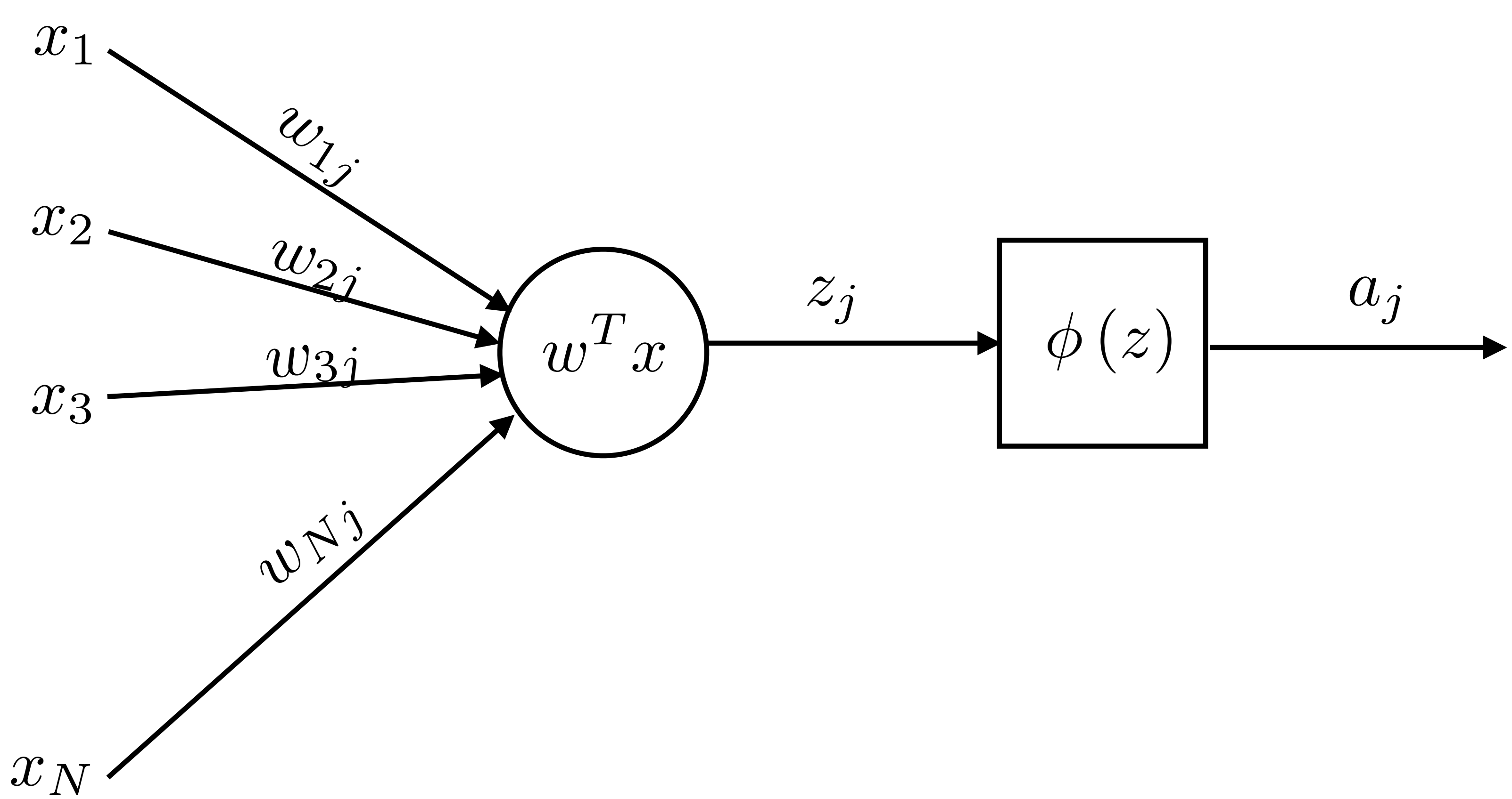
Optimization Problem

- (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

Artificial Neuron



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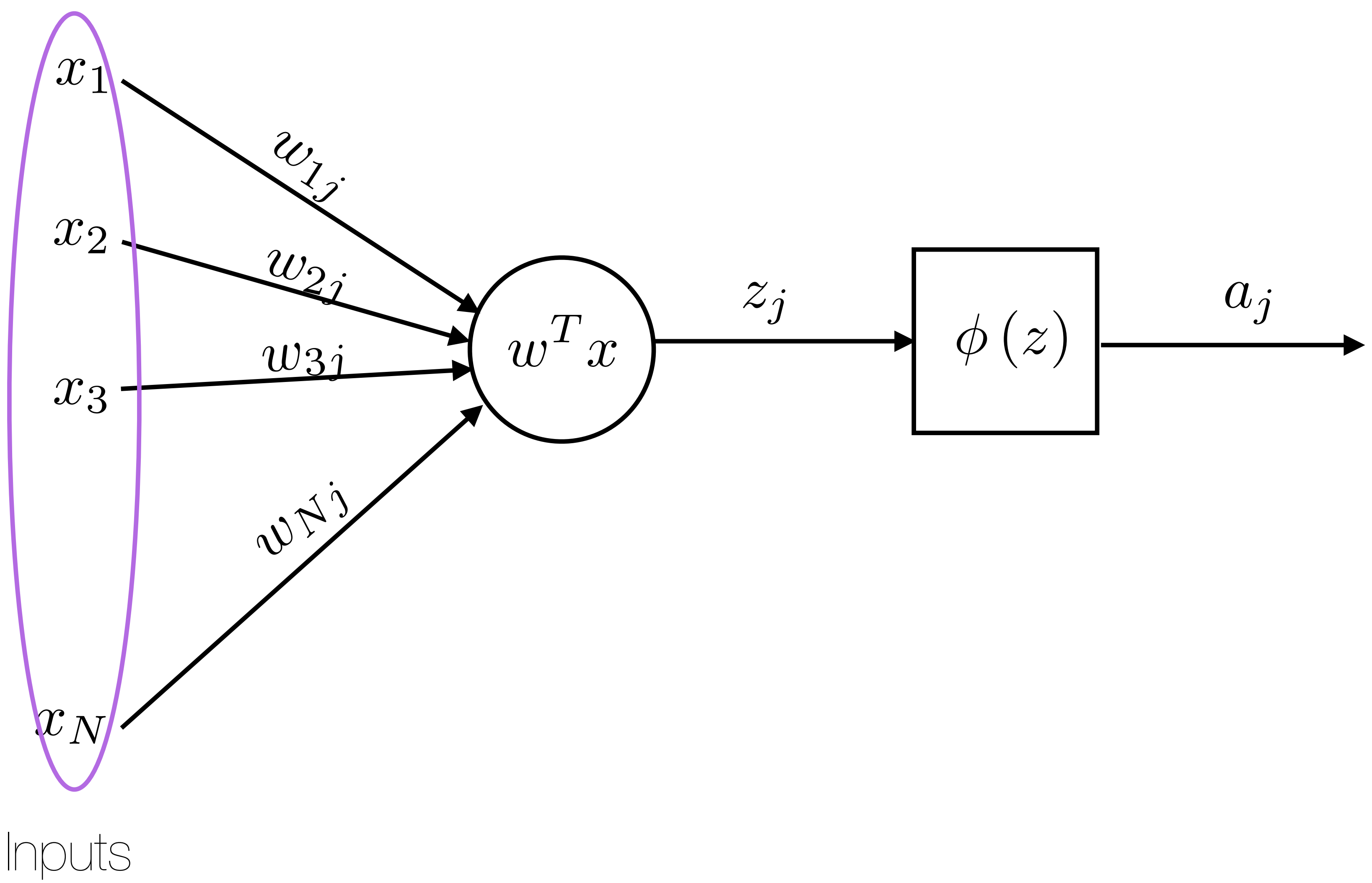

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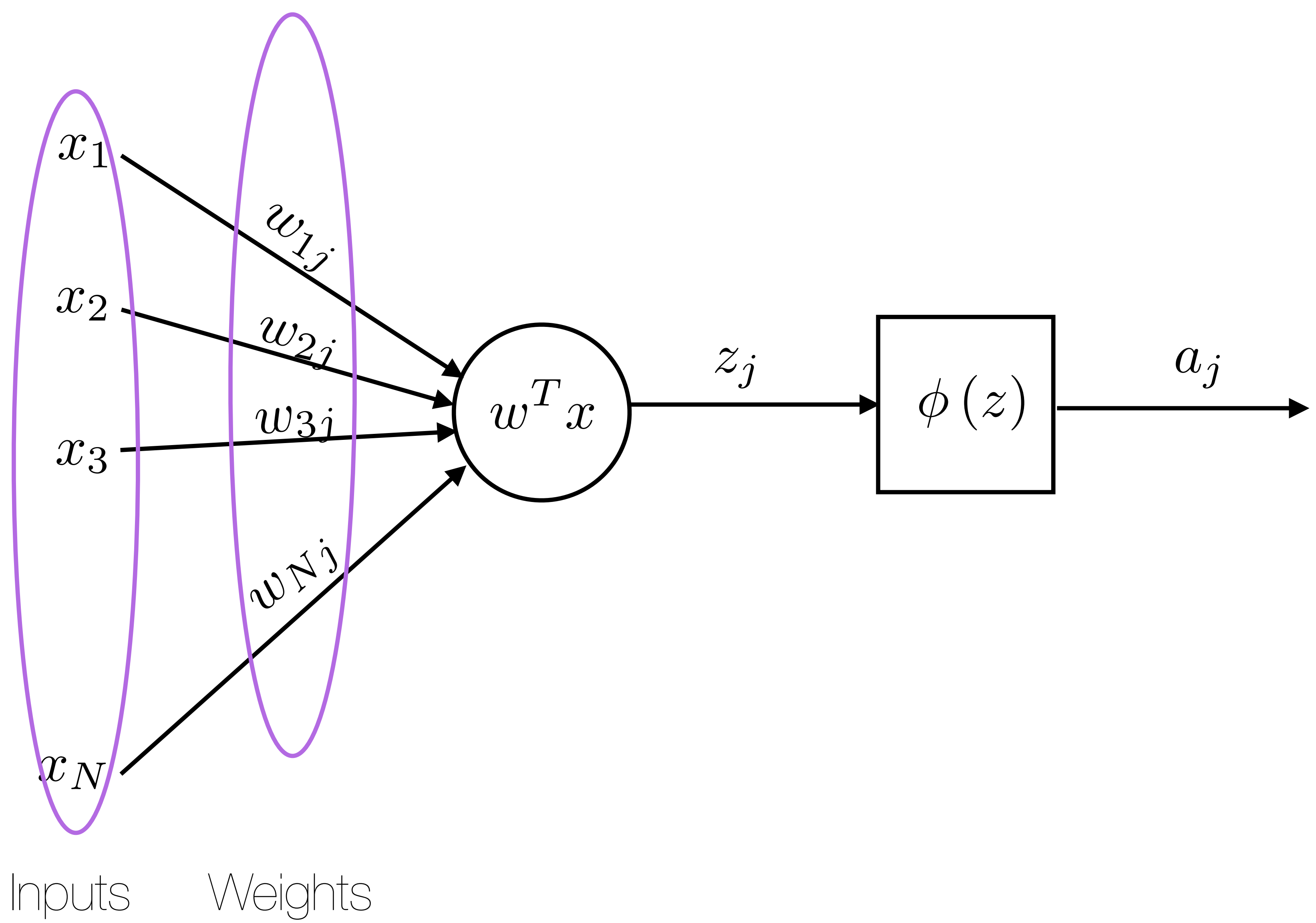

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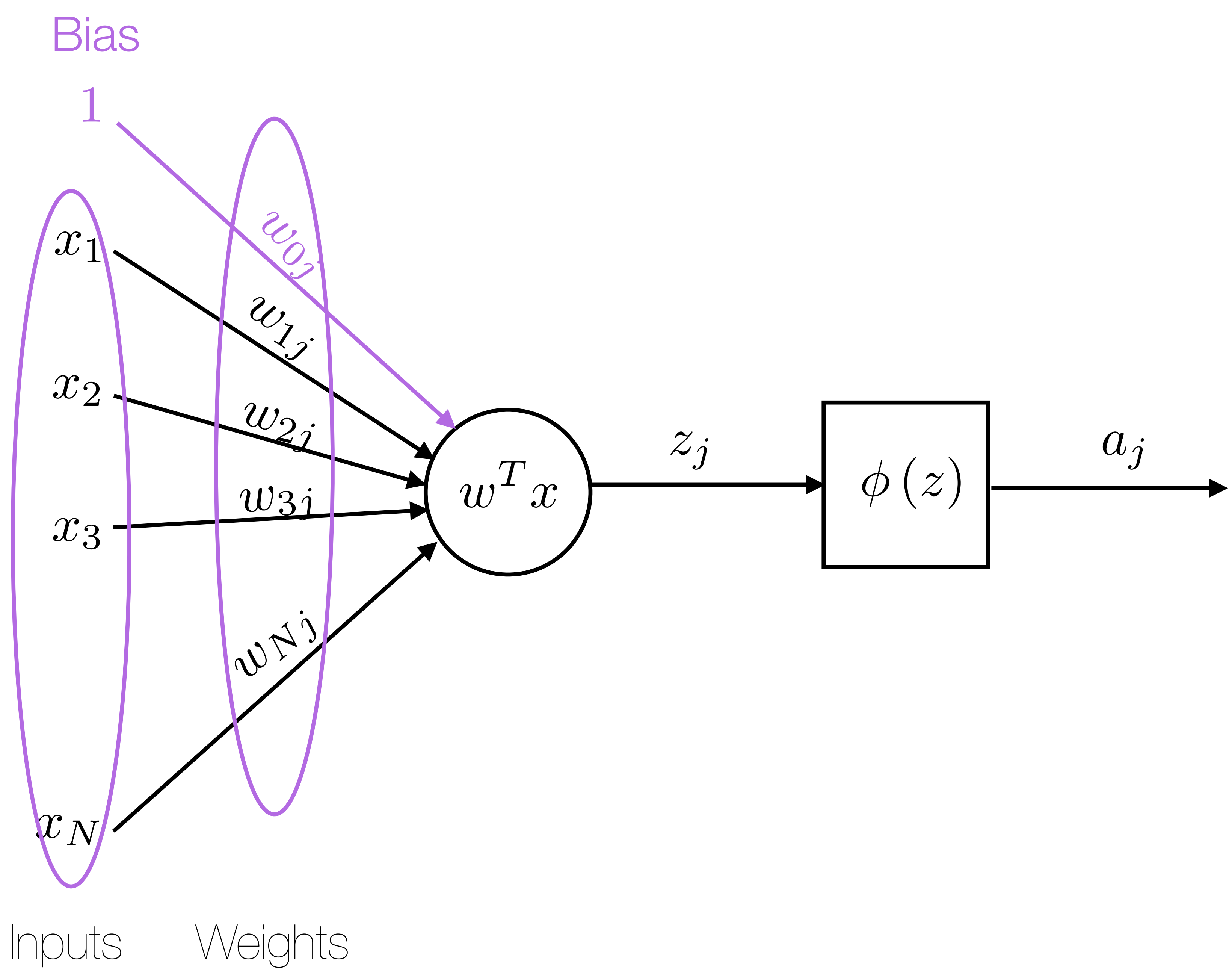

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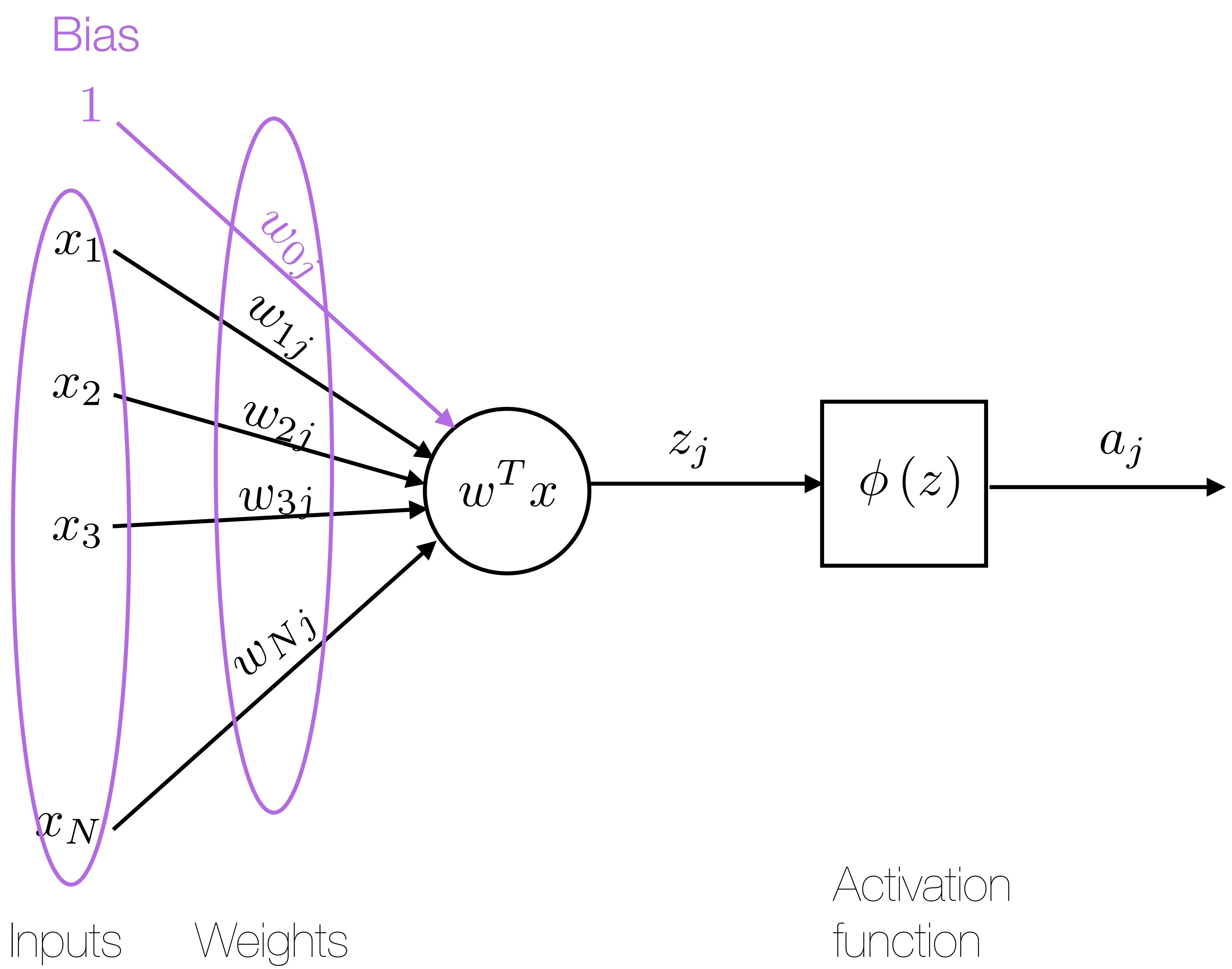

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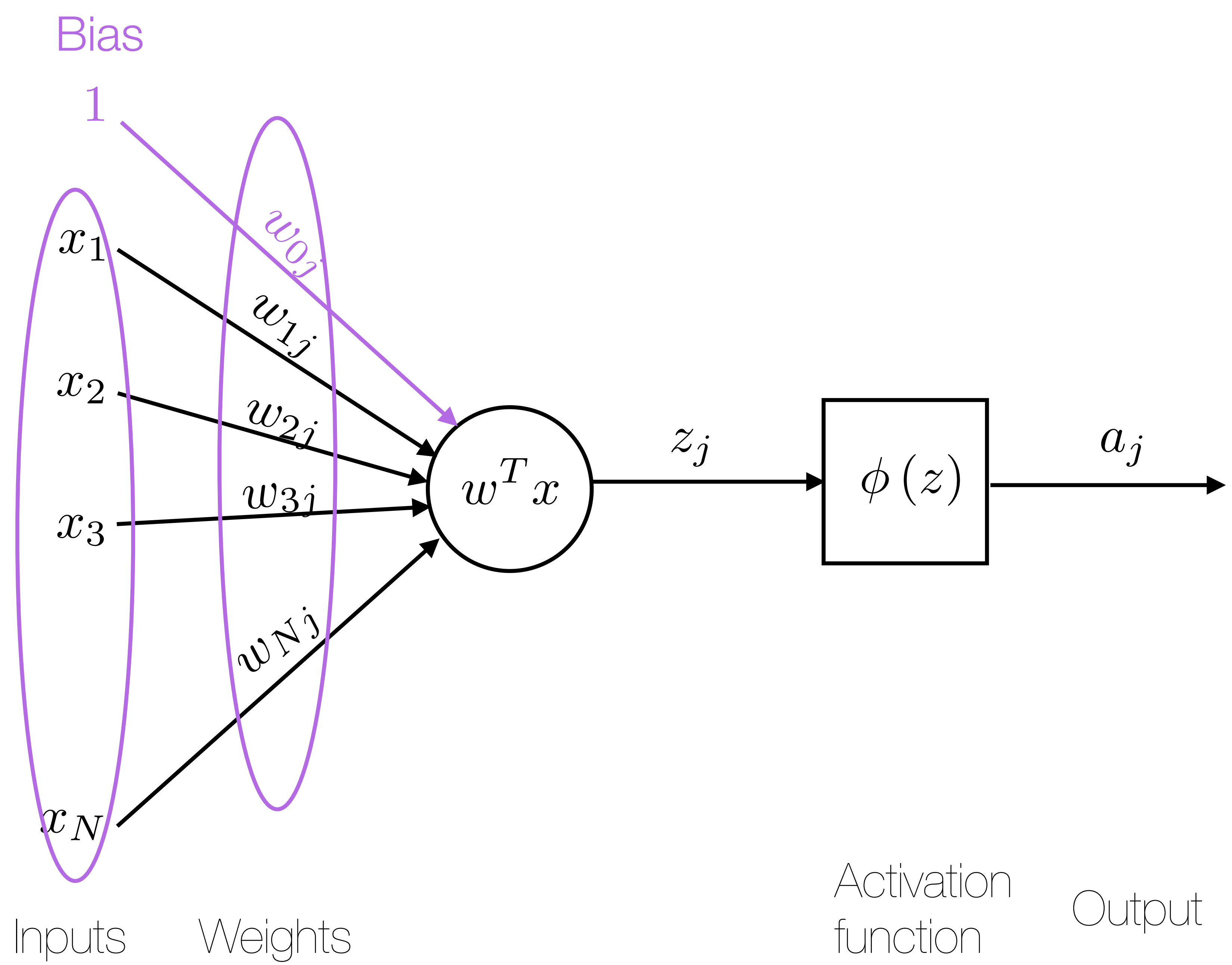
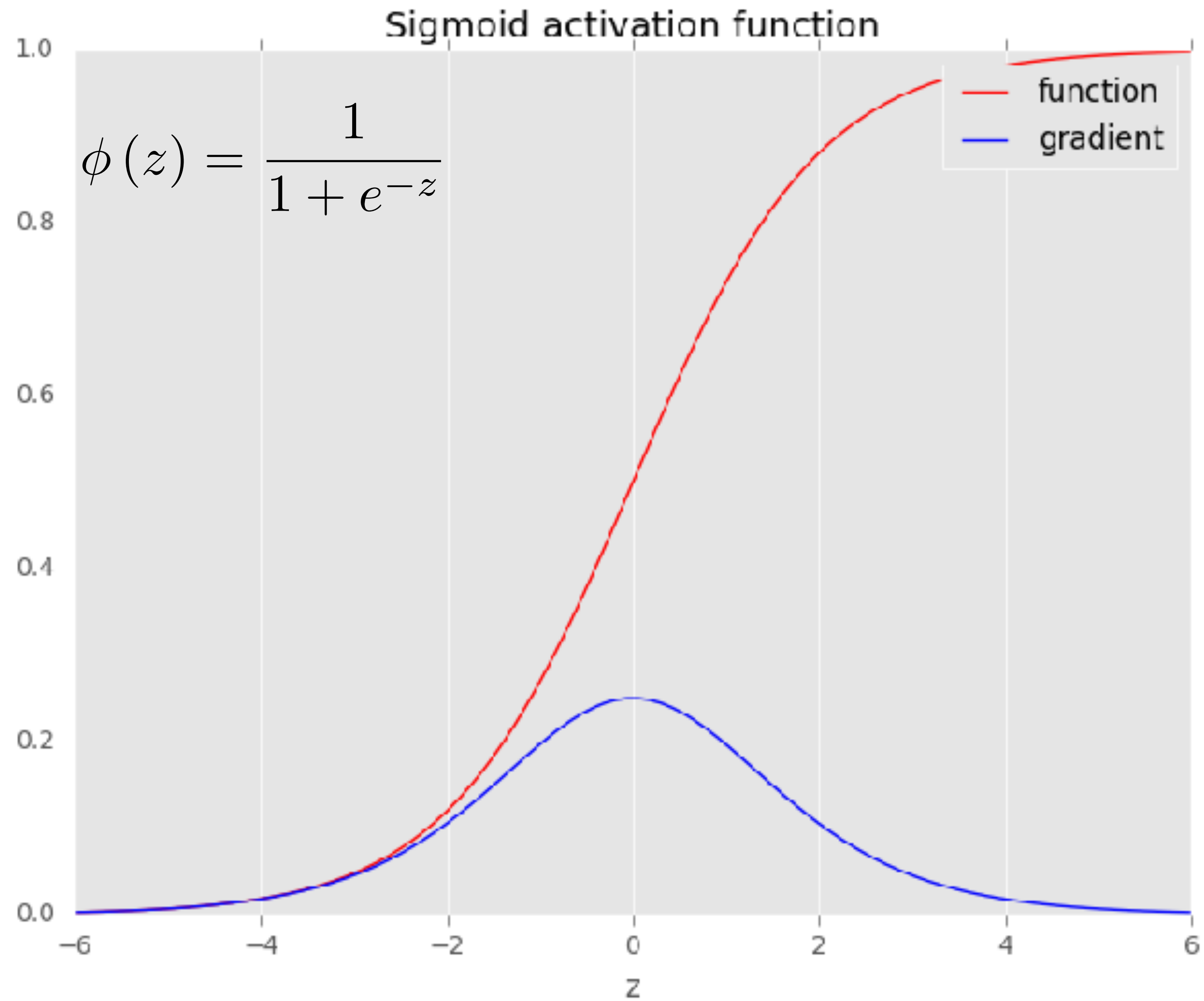


Activation Function - Sigmoid

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



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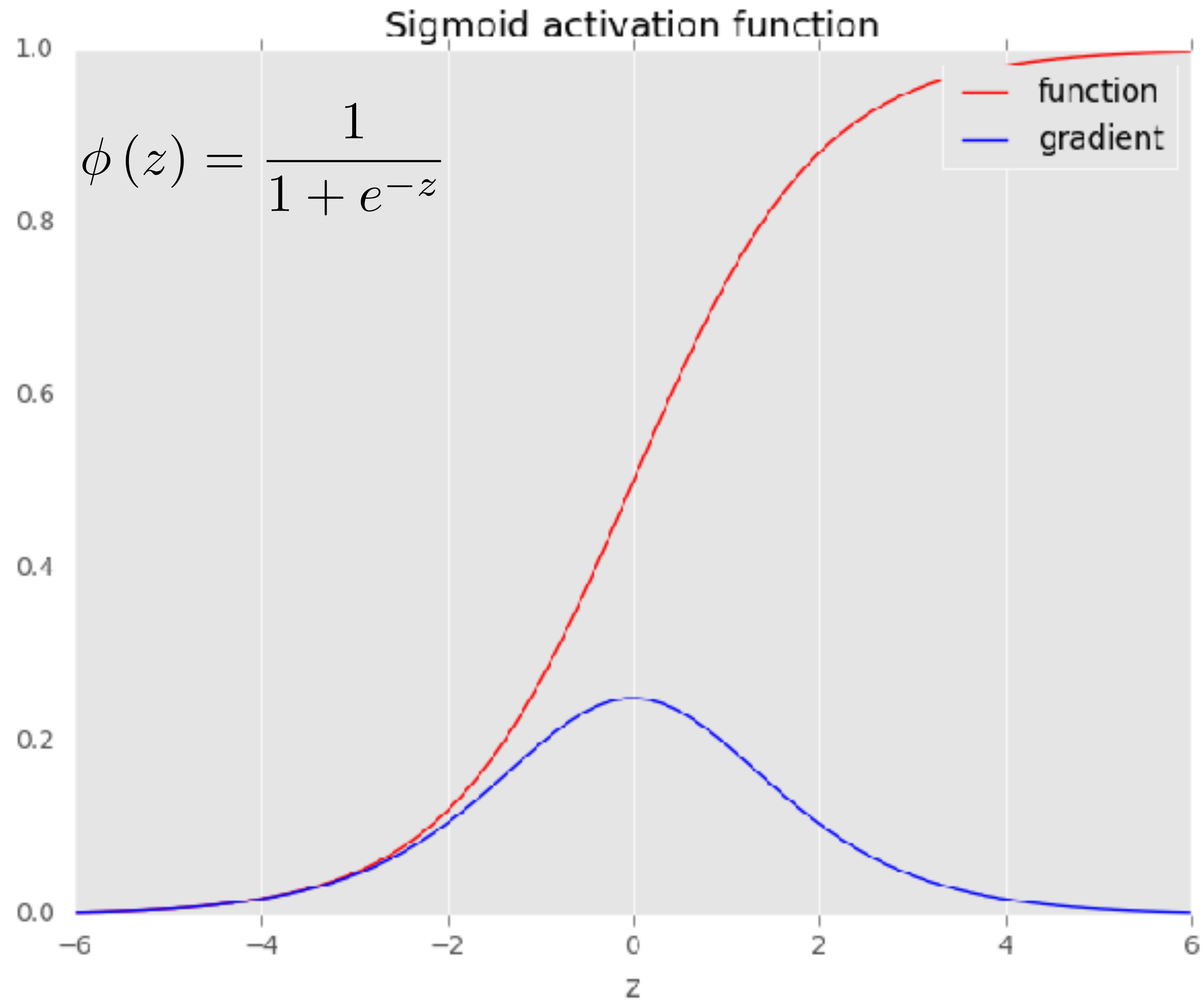

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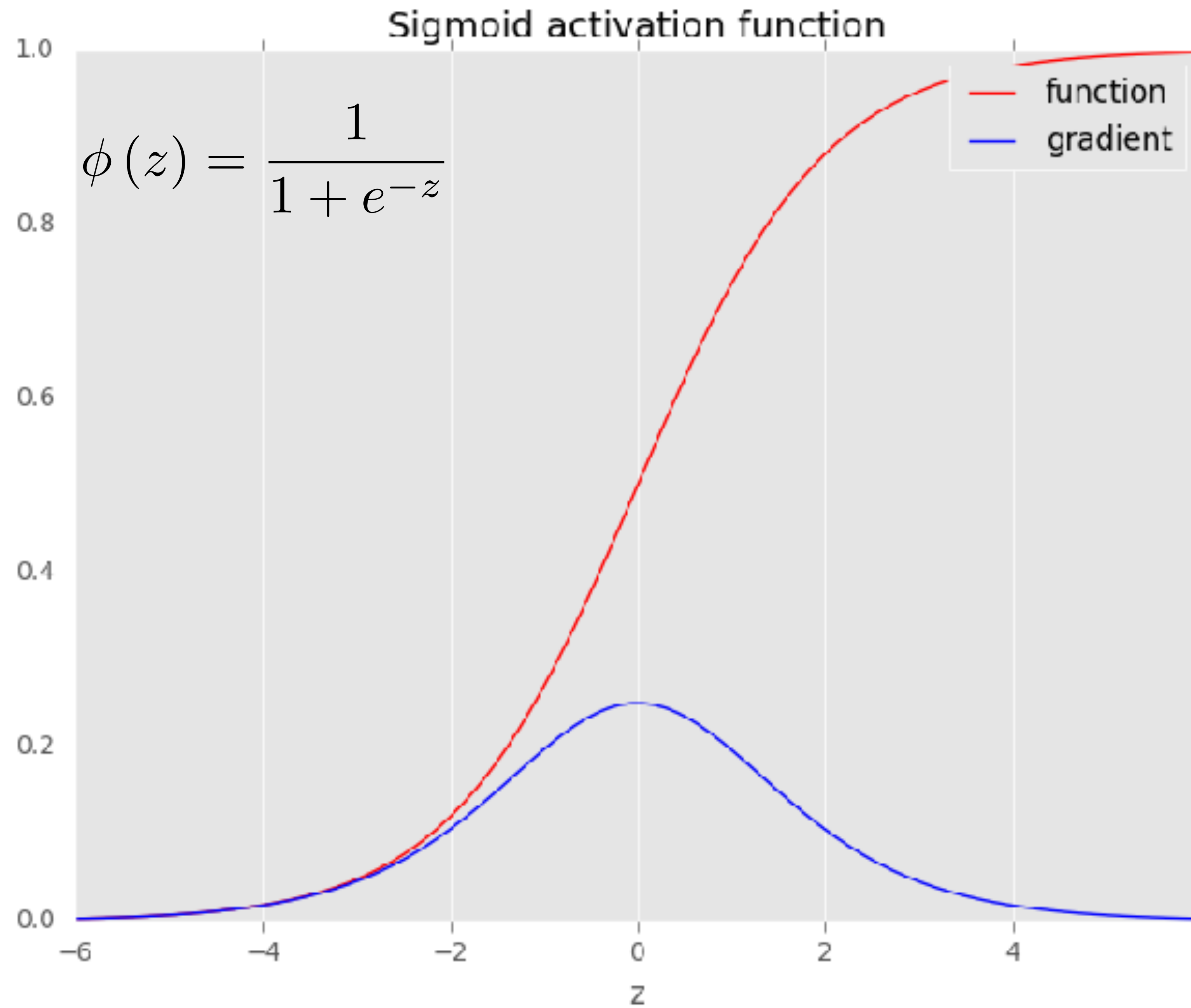

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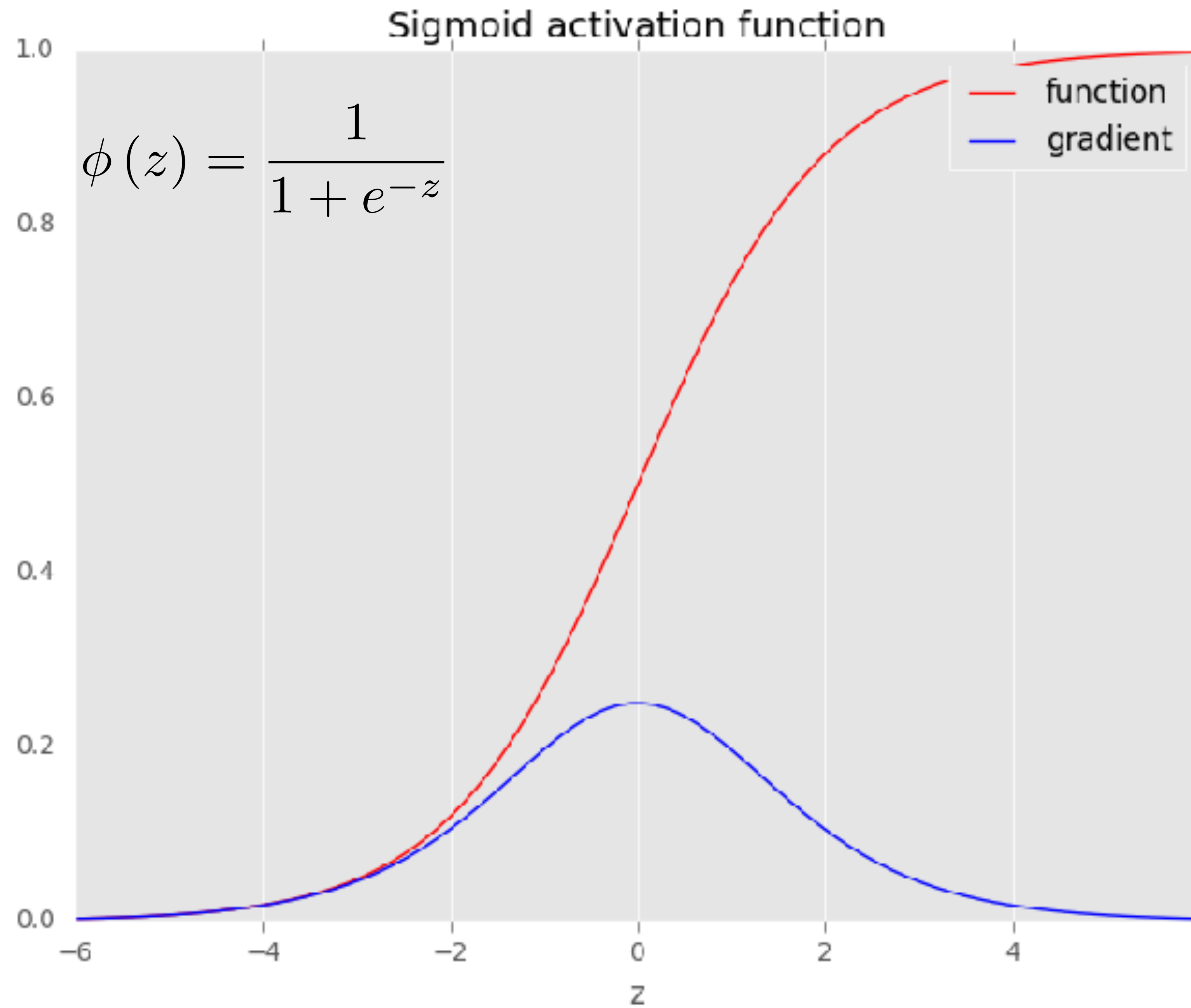

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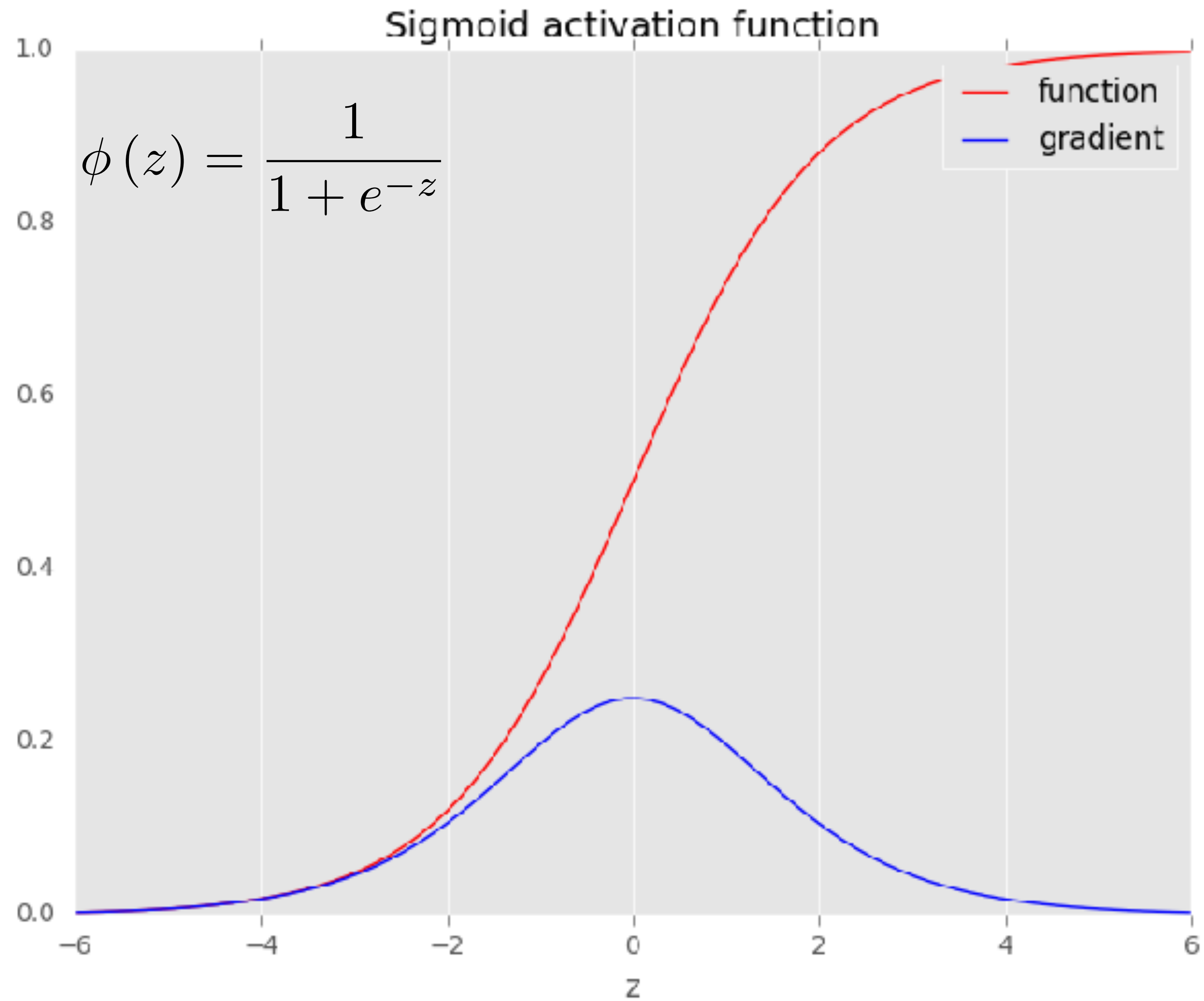

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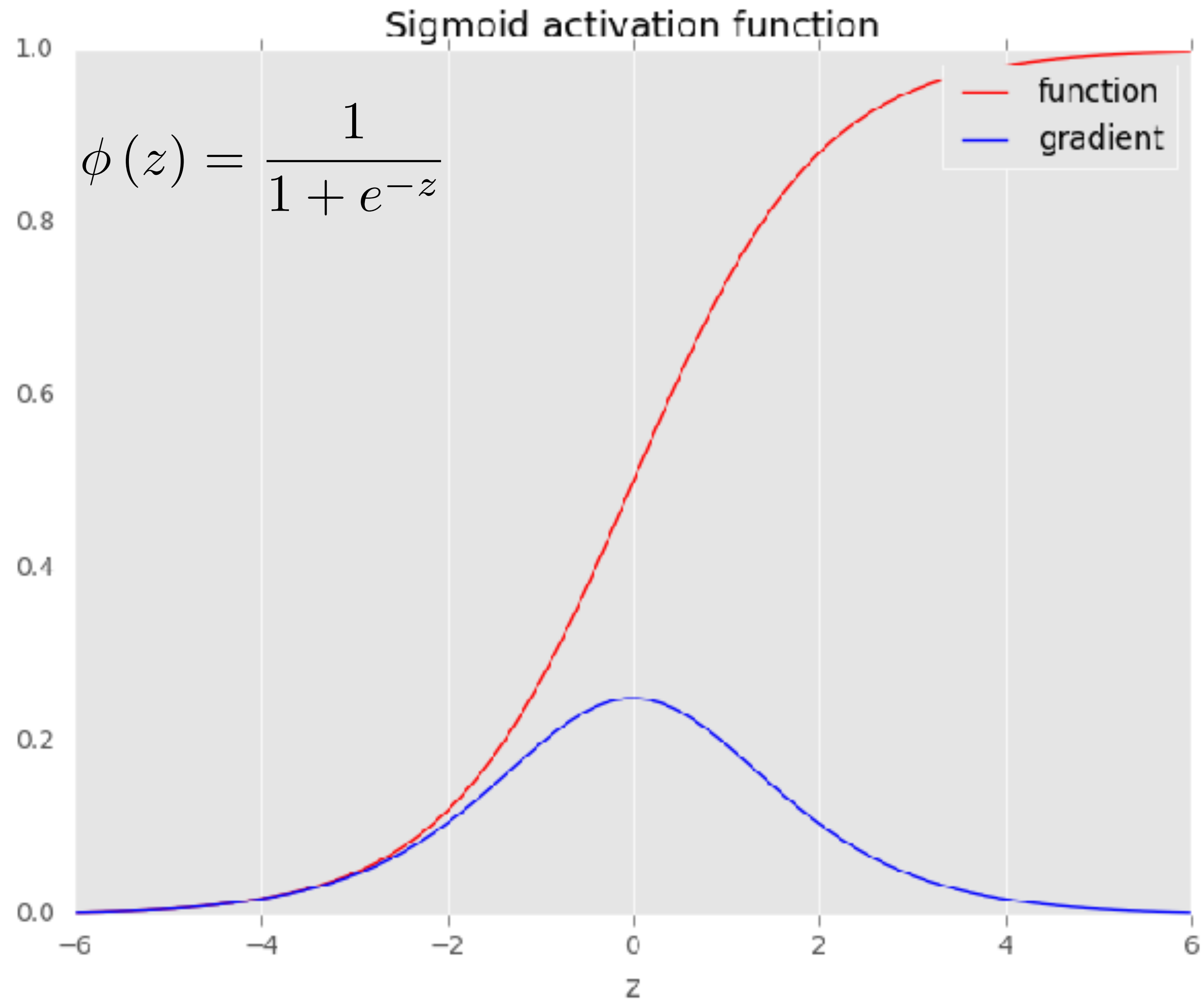

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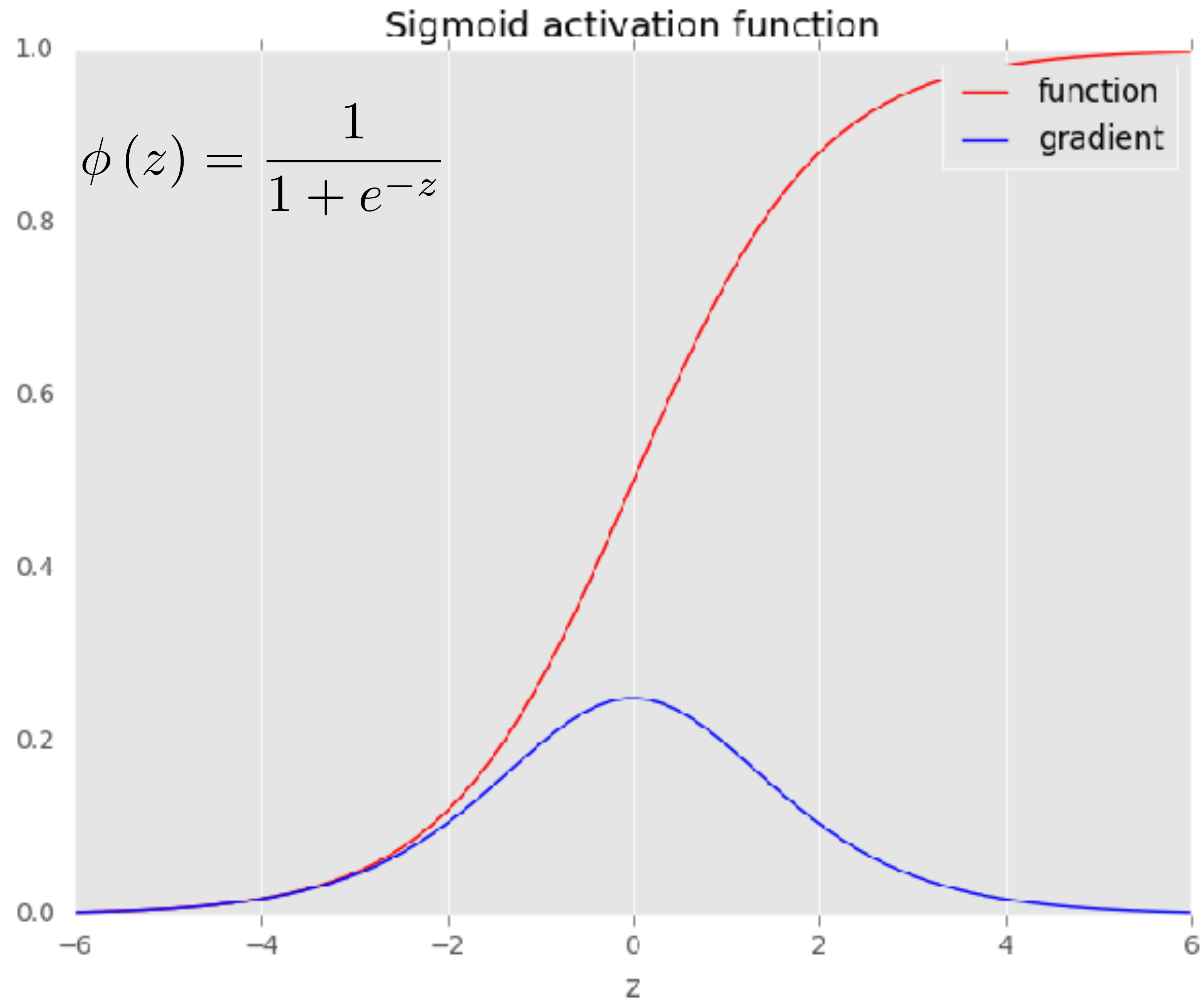
- Perhaps the most common



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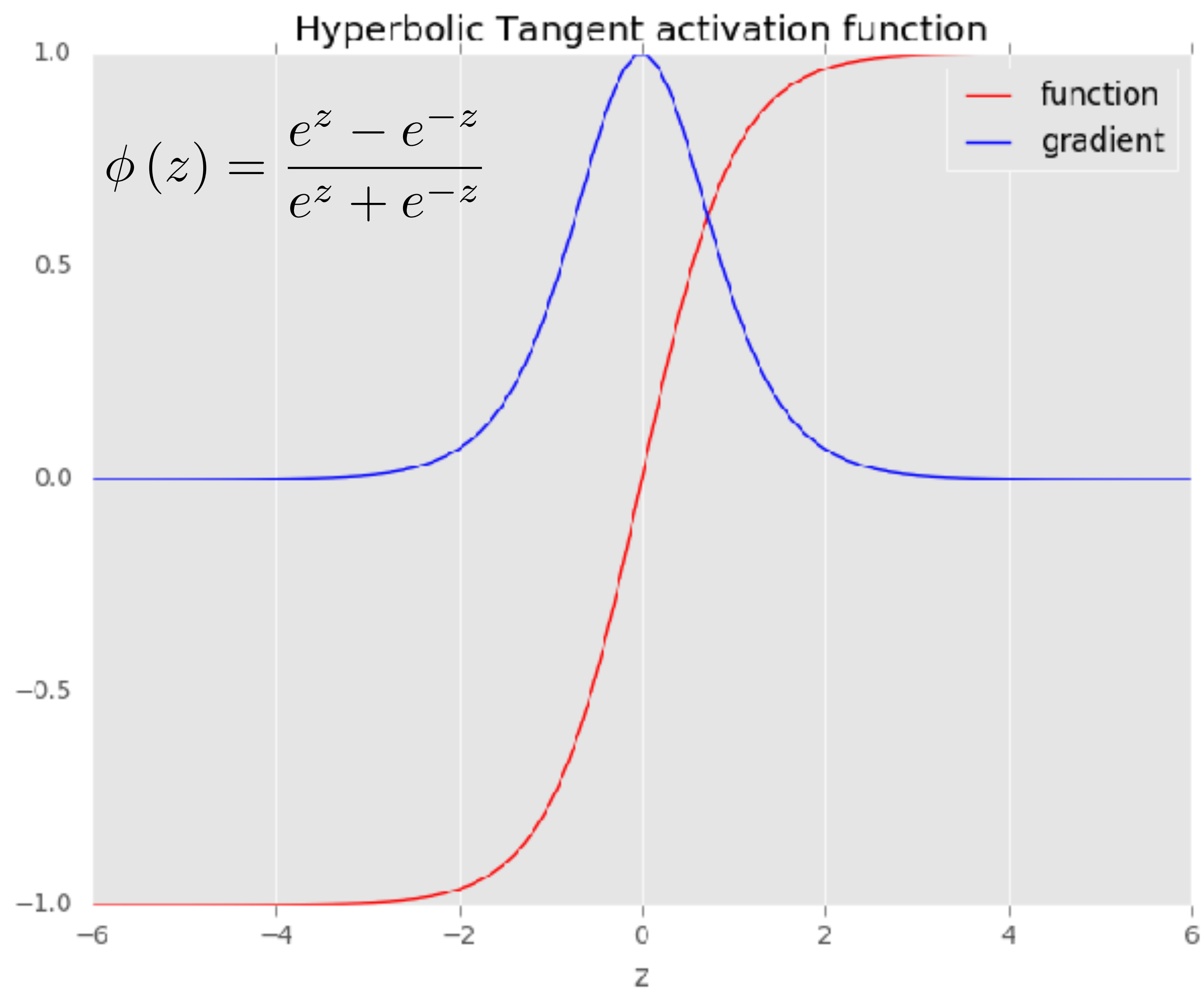

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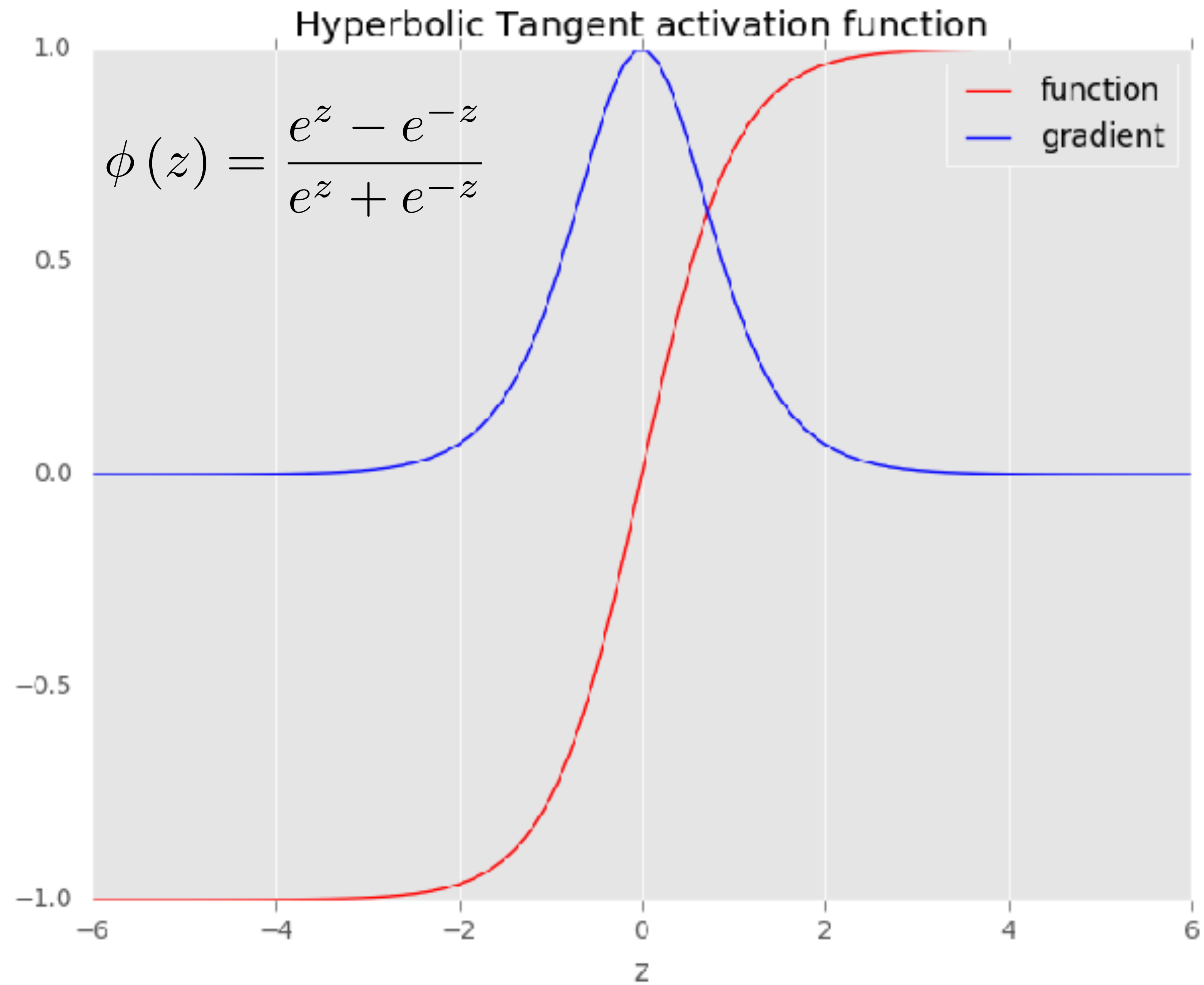

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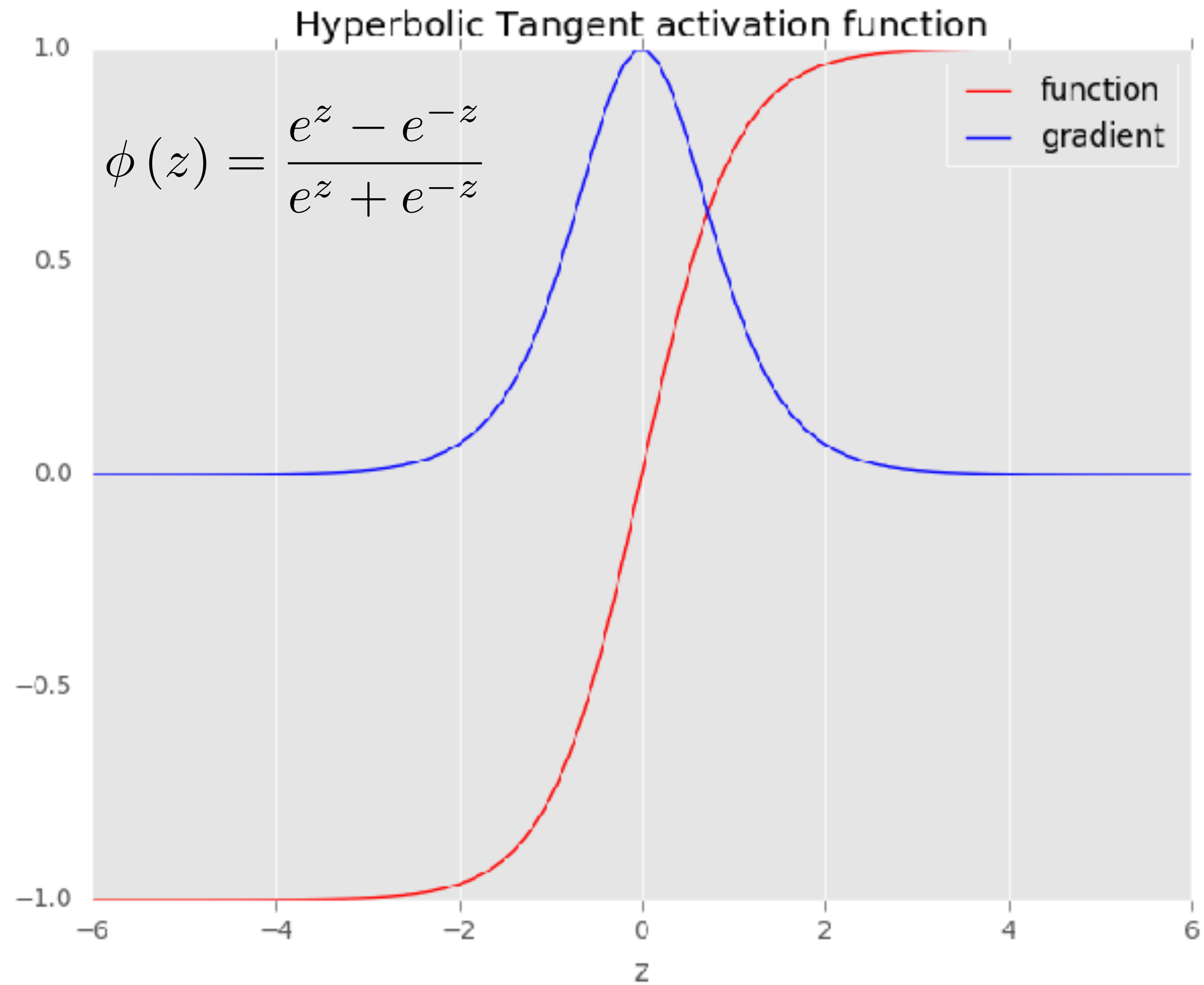

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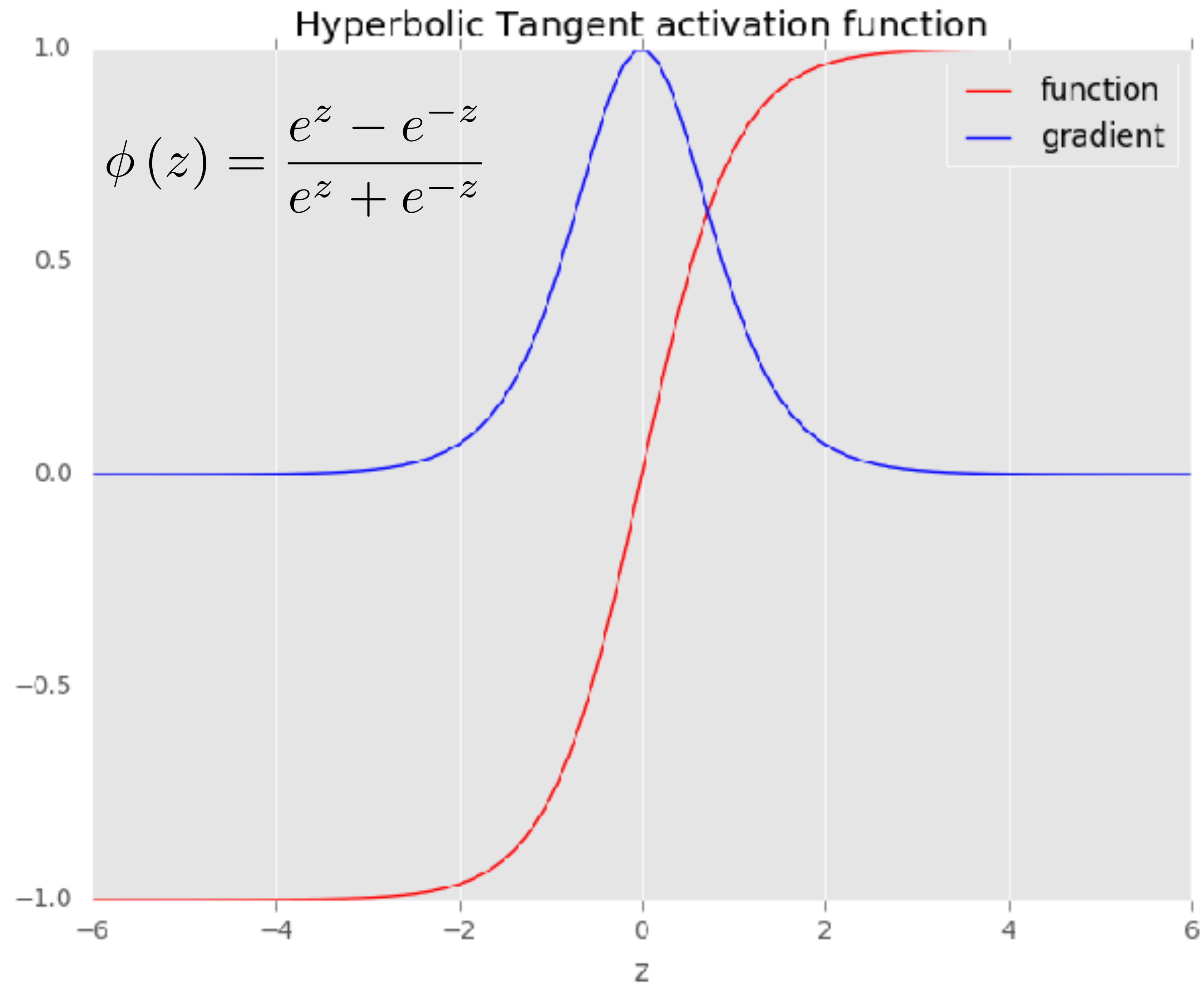

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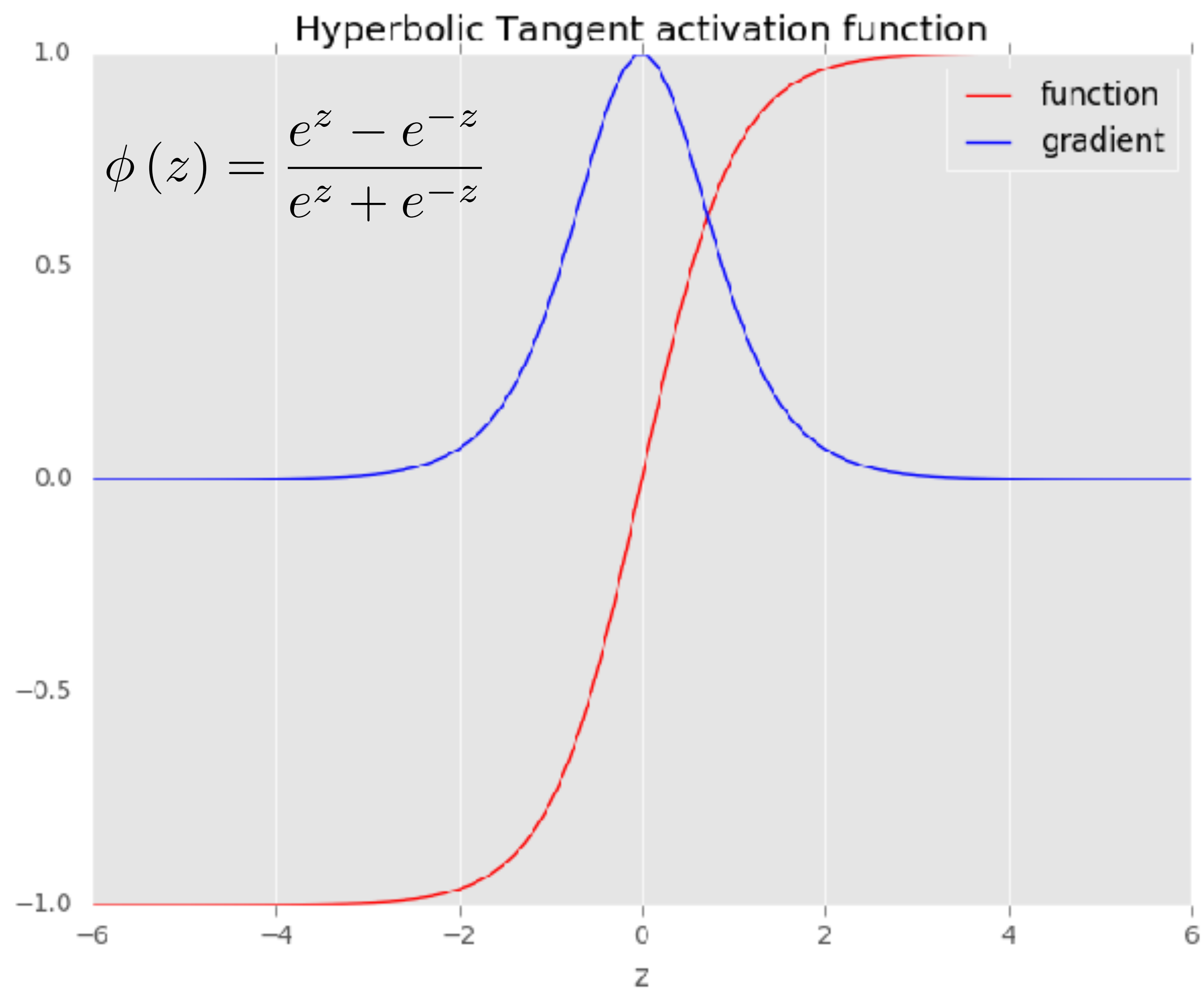

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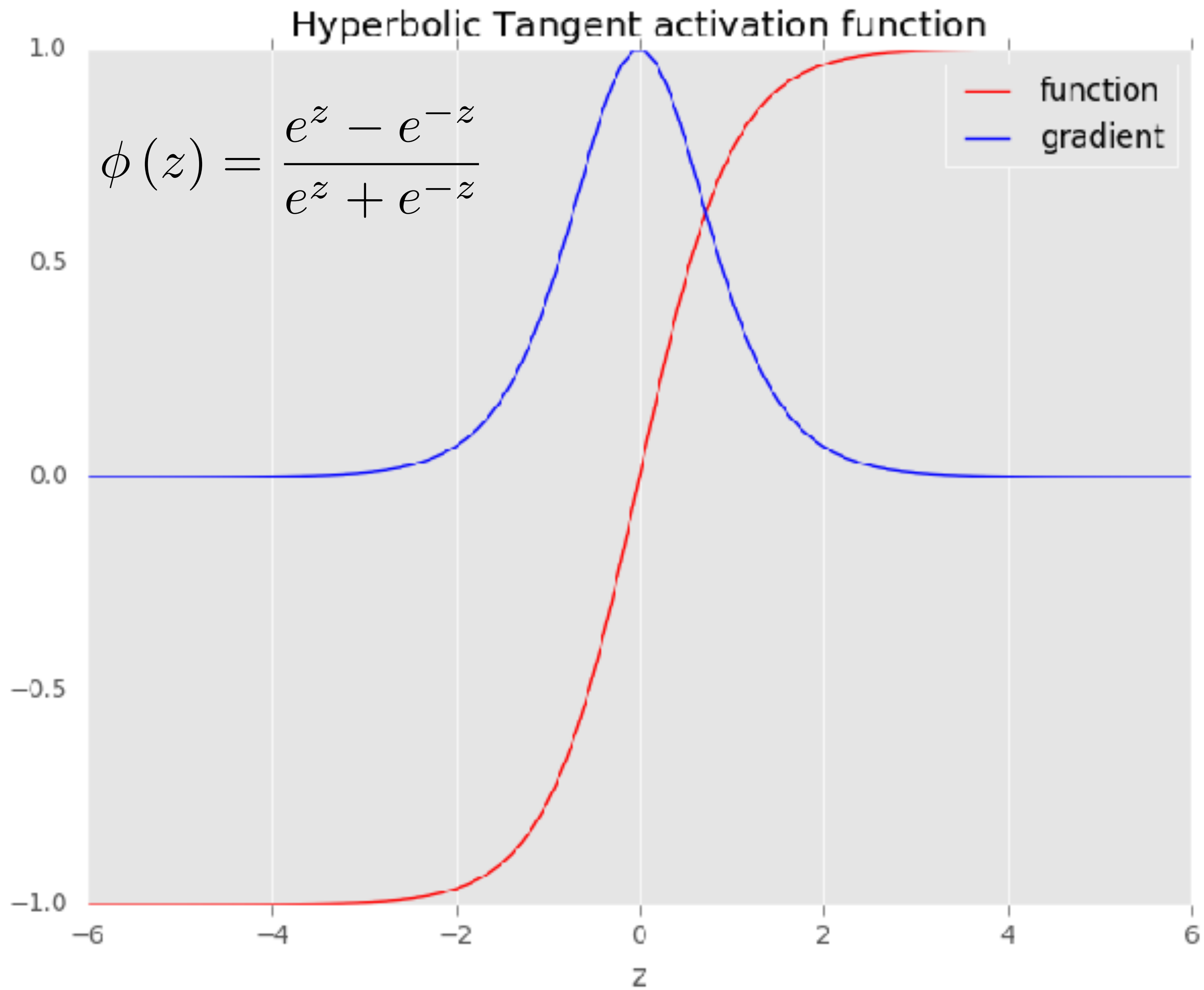

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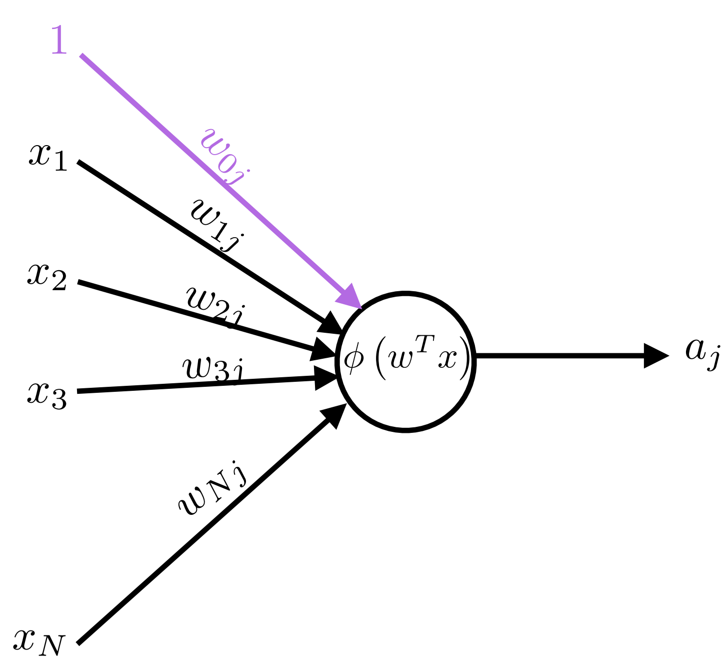

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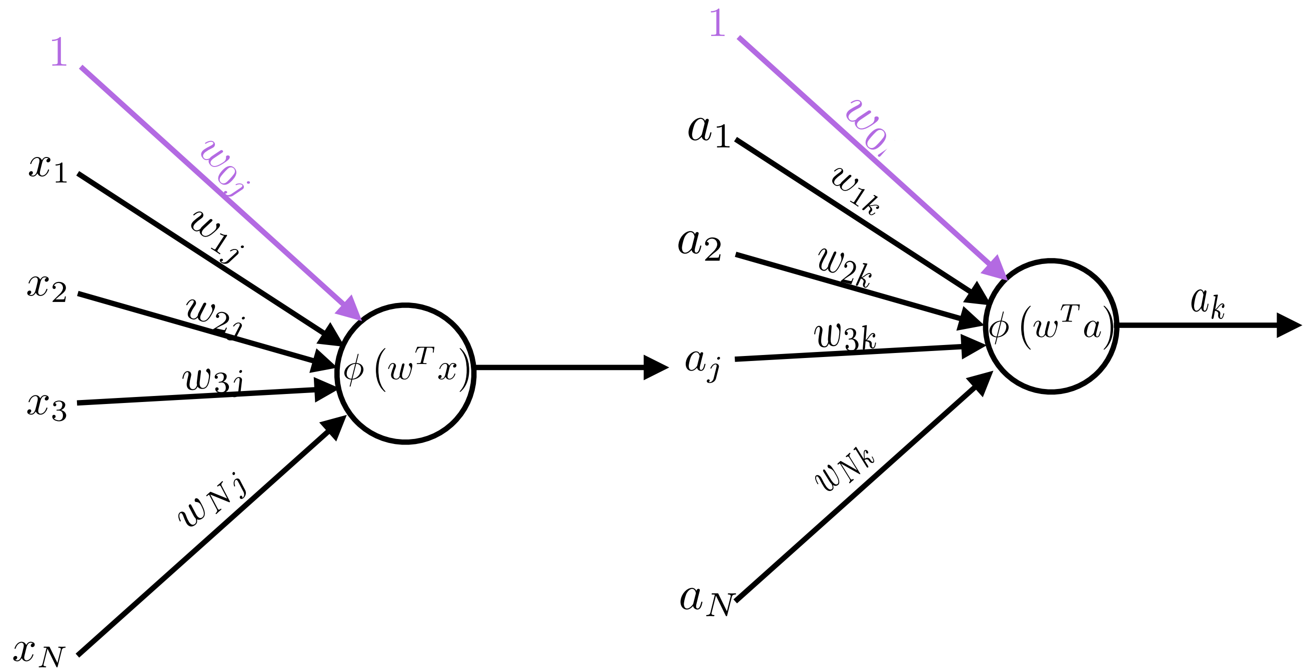

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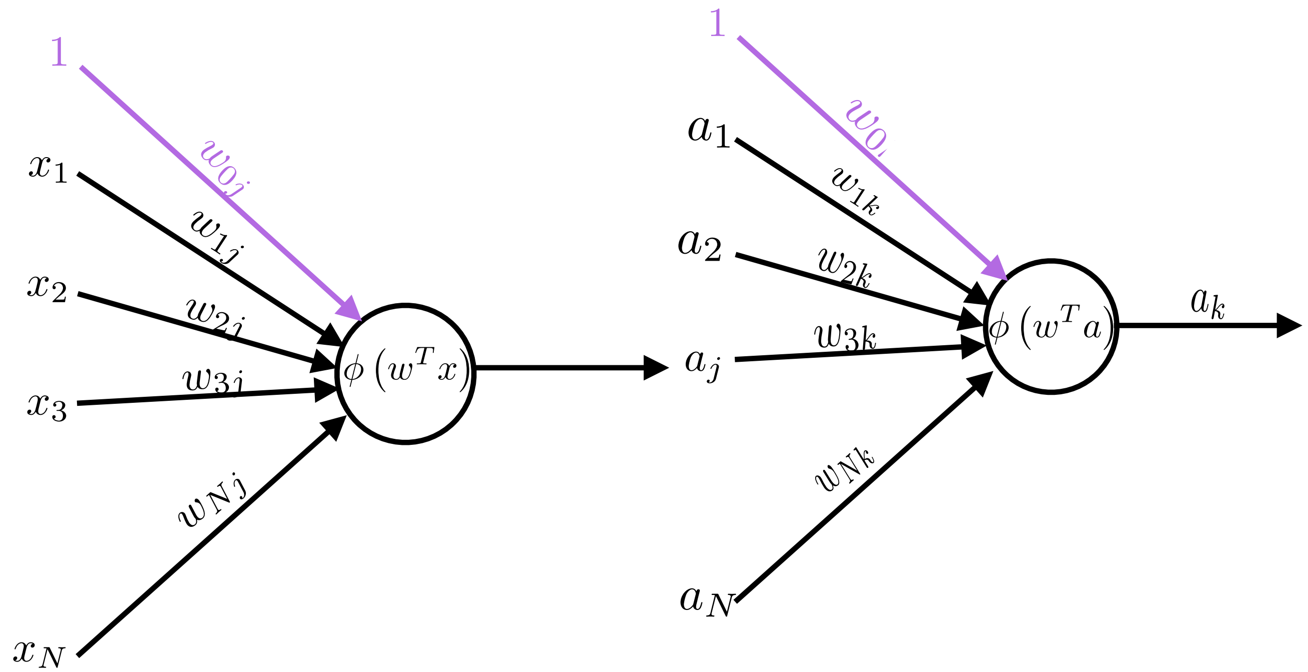

- But how can we propagate back the errors and update the weights?

Backward Propagation of Errors (BackProp)

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

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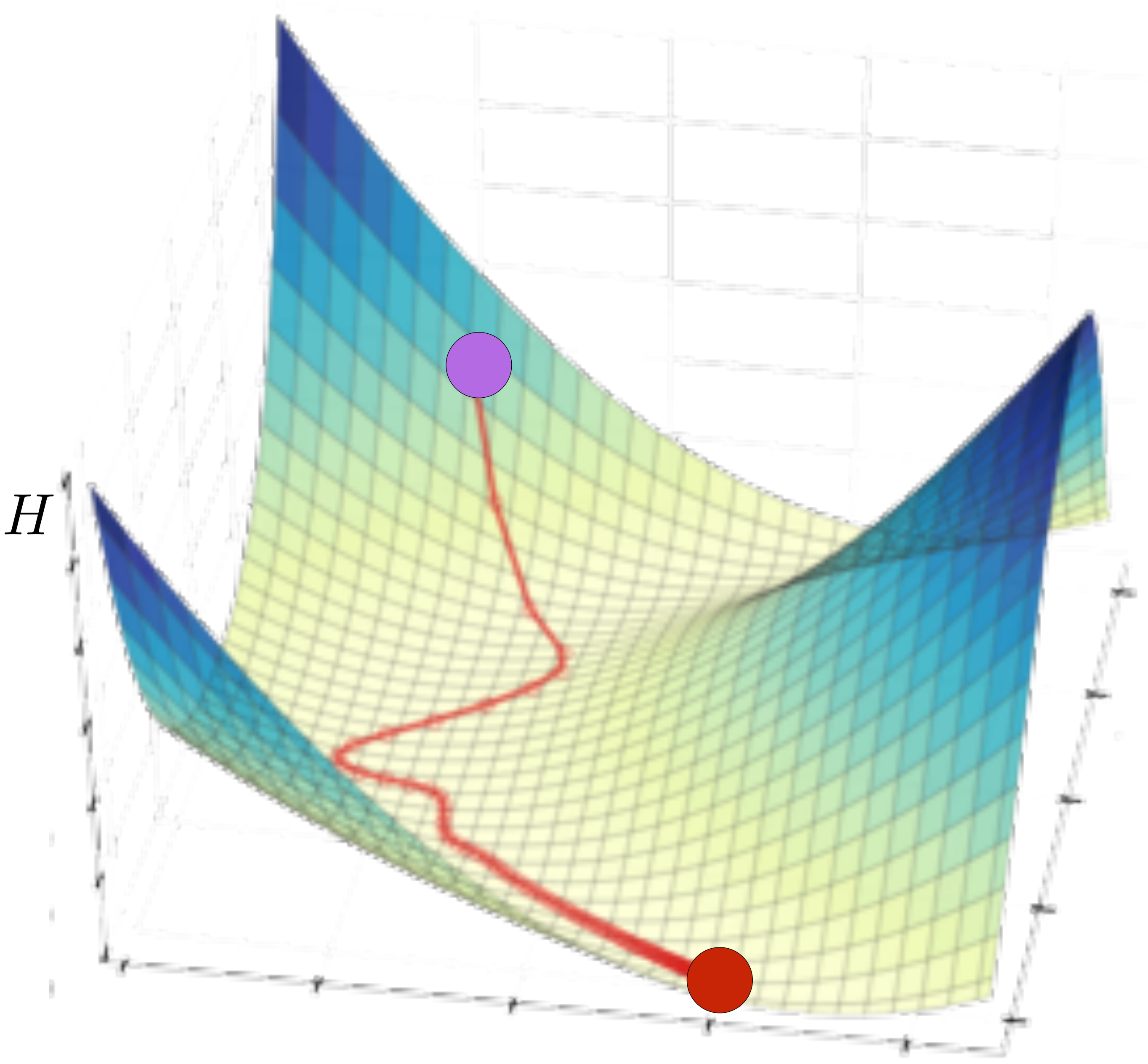
The Cross Entropy is complementary to sigmoid activation in the output layer and improves its stability.

Gradient Descent



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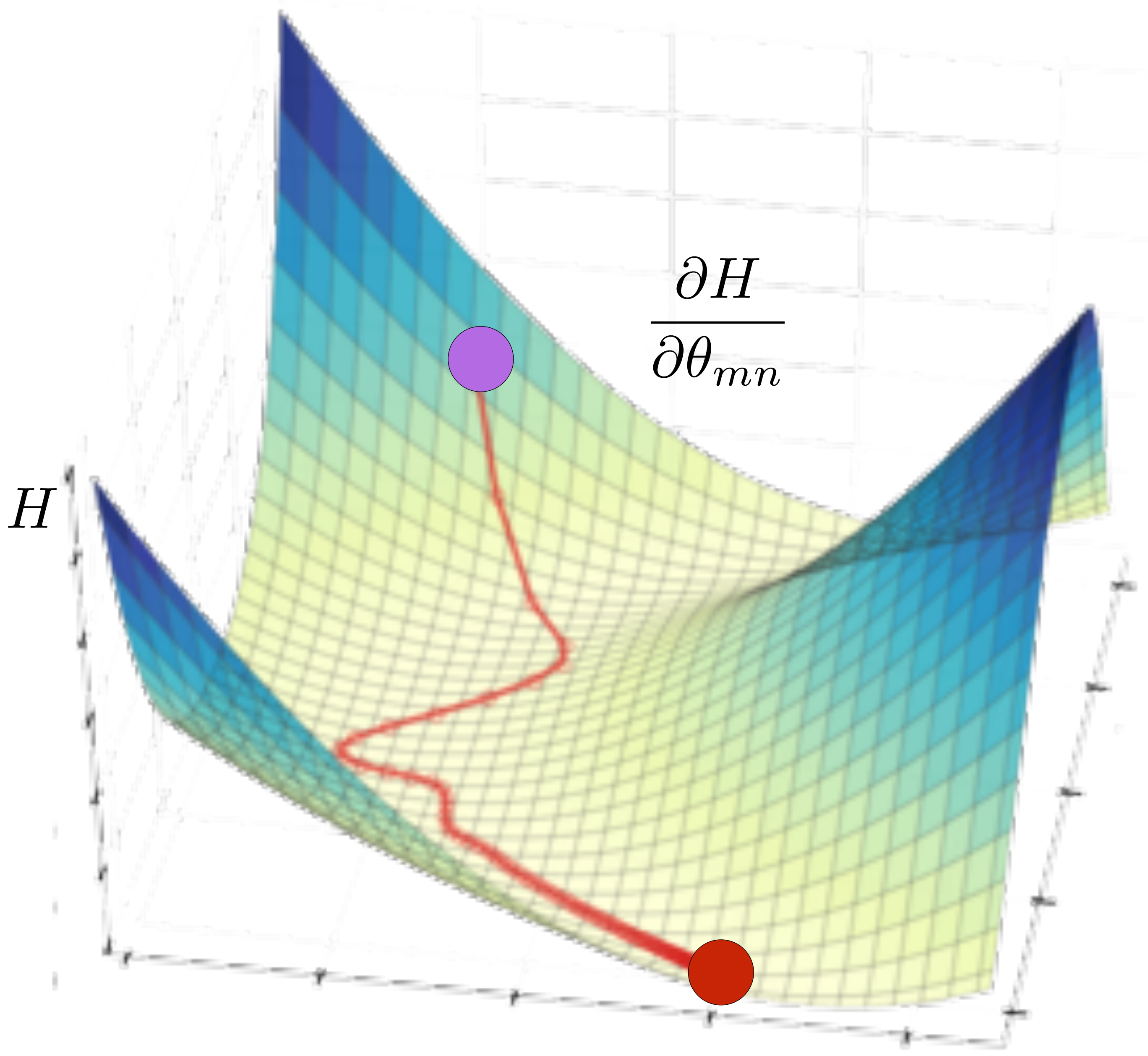

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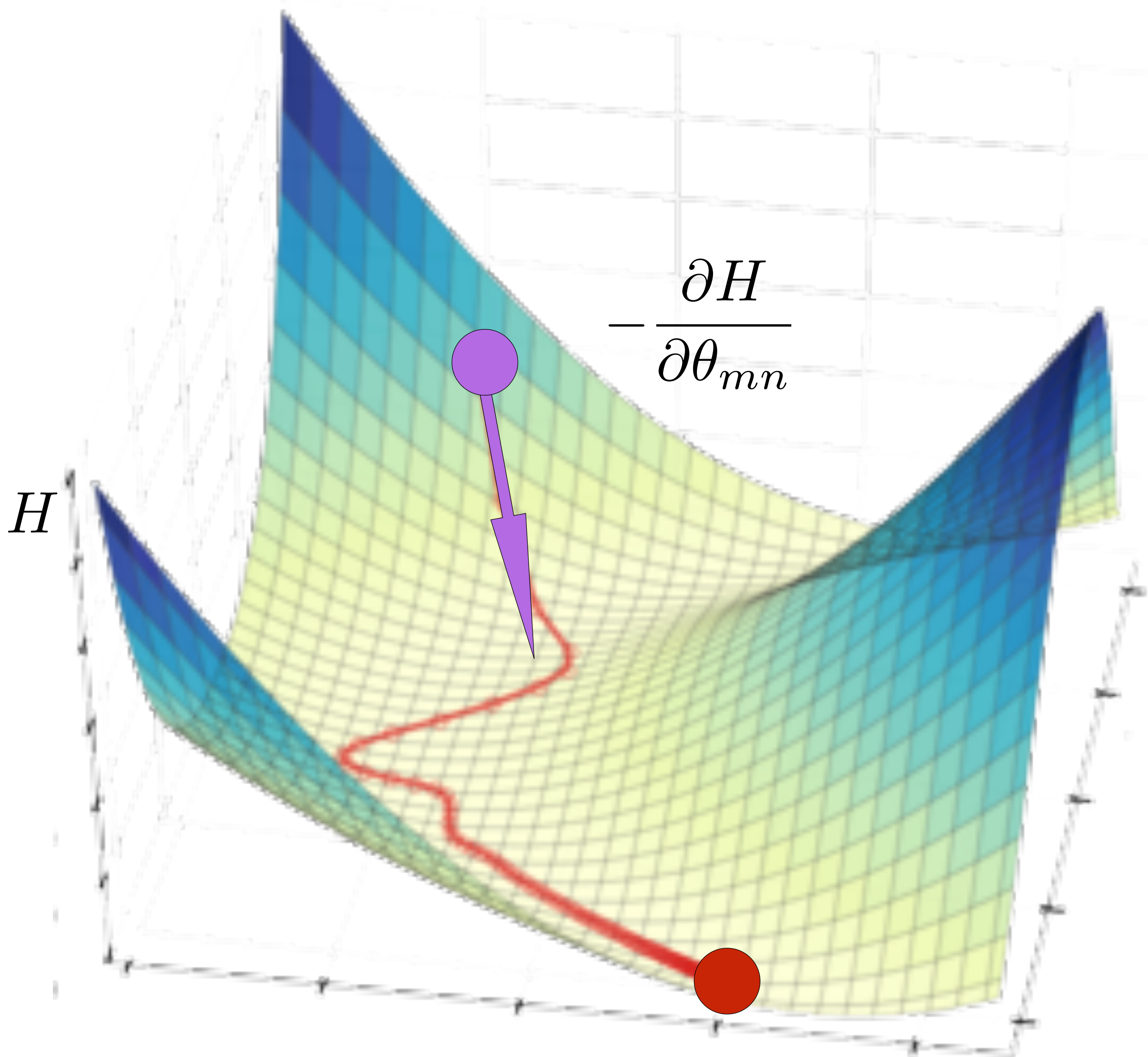
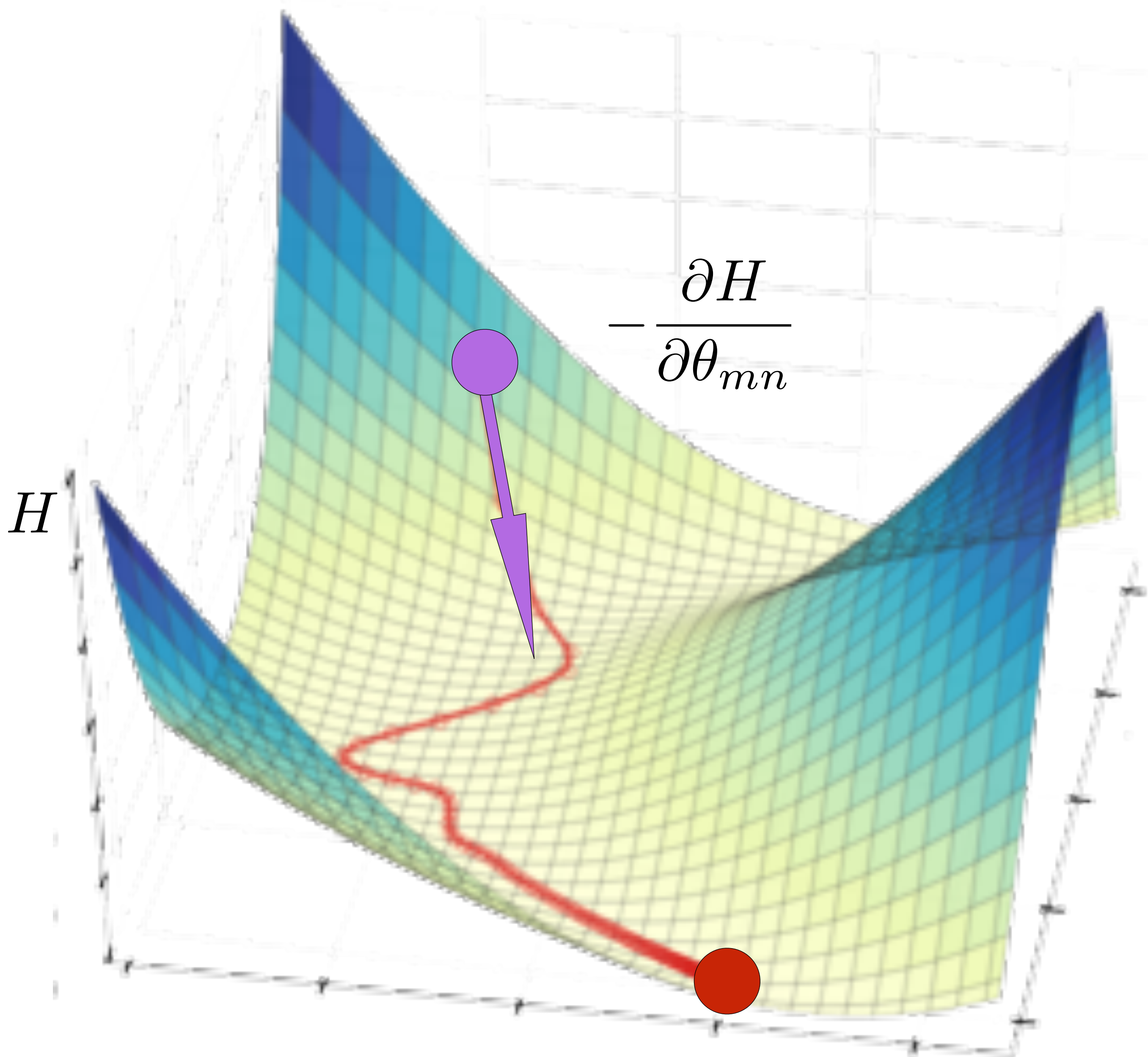


- Find the gradient for each training batch
- Take a step **downhill** along the direction of the gradient

$$\theta_{mn} \leftarrow \theta_{mn} - \alpha \frac{\partial H}{\partial \theta_{mn}}$$

Gradient Descent

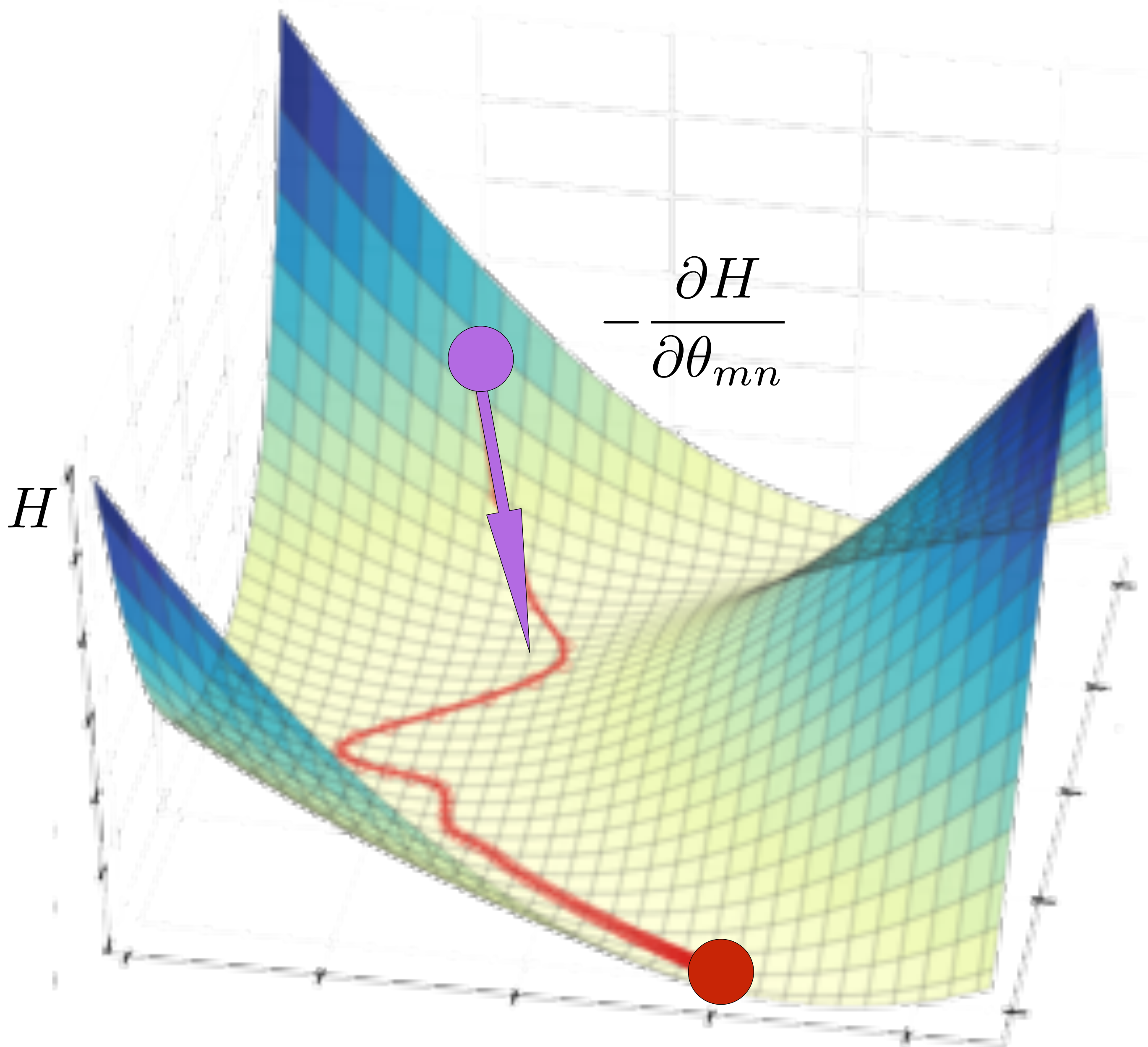


- Find the gradient for each training batch
- Take a step **downhill** along the direction of the gradient

$$\theta_{mn} \leftarrow \theta_{mn} - \alpha \frac{\partial H}{\partial \theta_{mn}}$$

- where α is the step size.

Gradient Descent



- Find the gradient for each training batch
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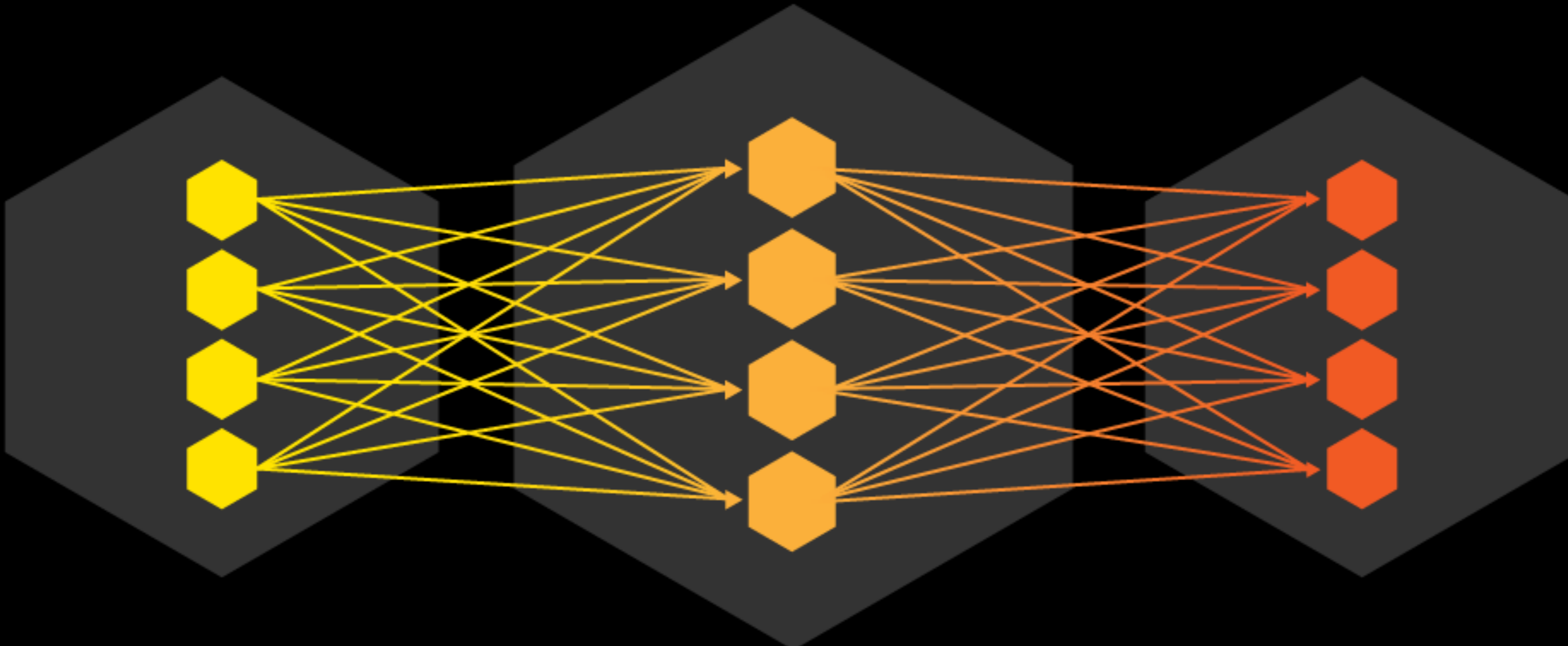
$$\theta_{mn} \leftarrow \theta_{mn} - \alpha \frac{\partial H}{\partial \theta_{mn}}$$

- where α is the step size.
- Repeat until "convergence".



INPUT TERMS

FEATURES
PREDICTIONS
ATTRIBUTES
PREDICTABLE VARIABLES

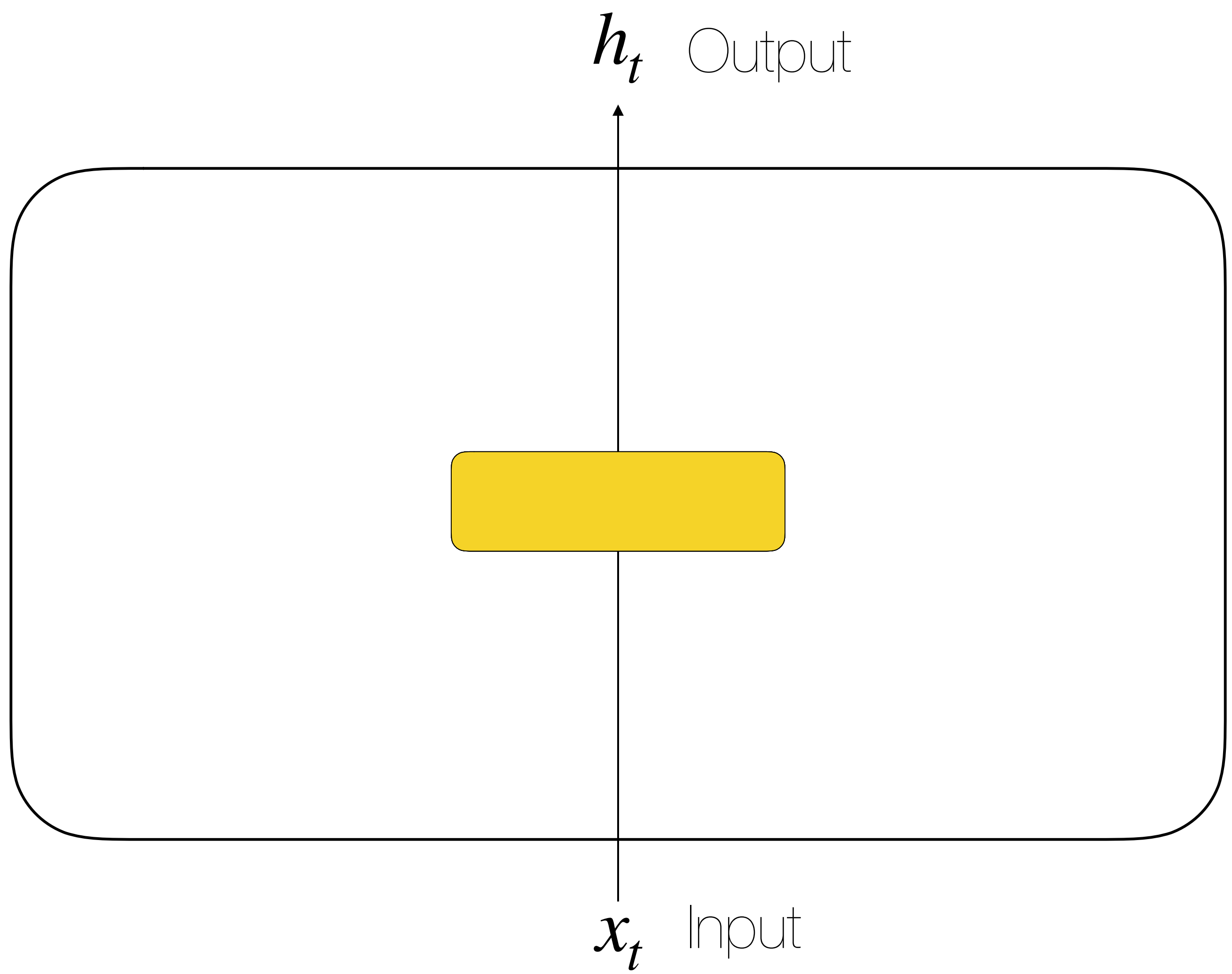
MACHINE

ALGORITHMS
TECHNIQUES
MODELS

OUTPUT TERMS

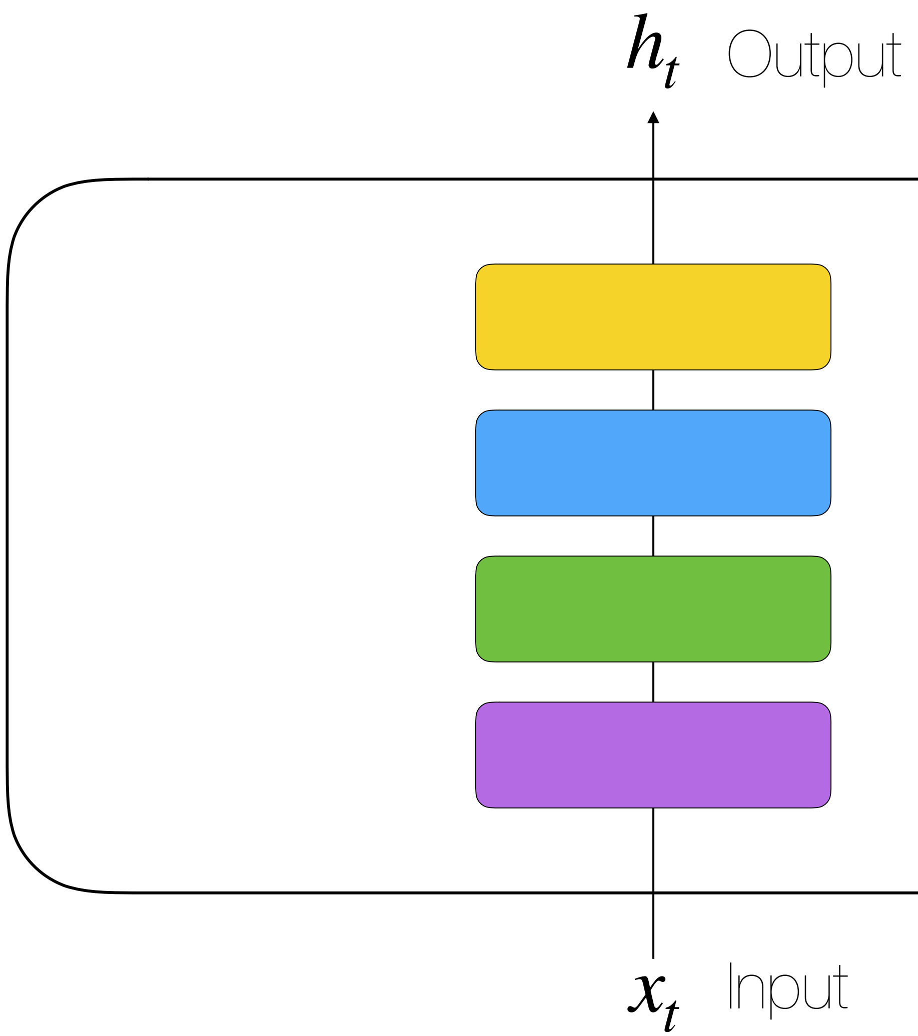
CLASSES
RESPONSES
TARGETS
DEPENDANT VARIABLES

Feed Forward Networks



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

Feed Forward Networks



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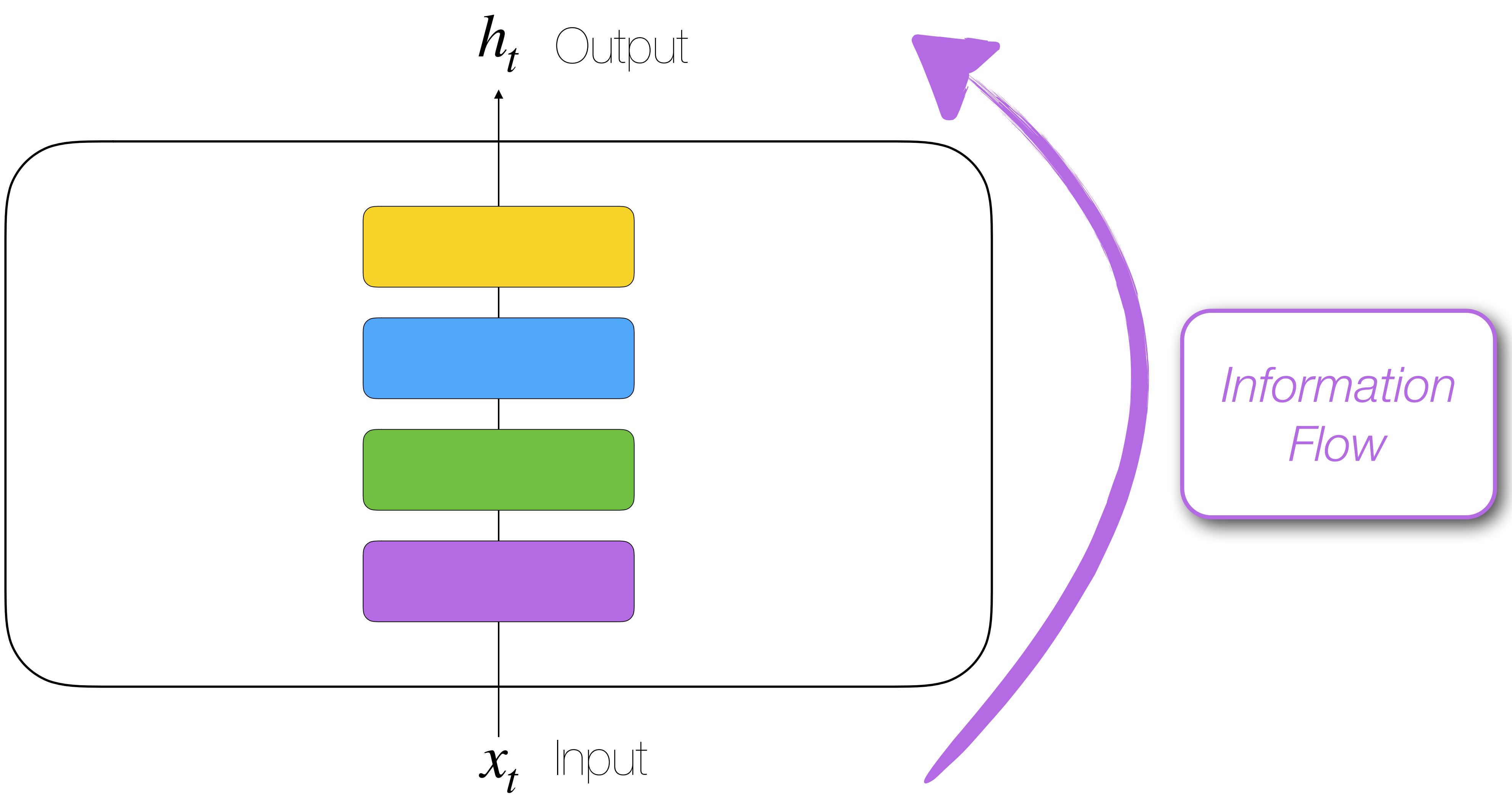

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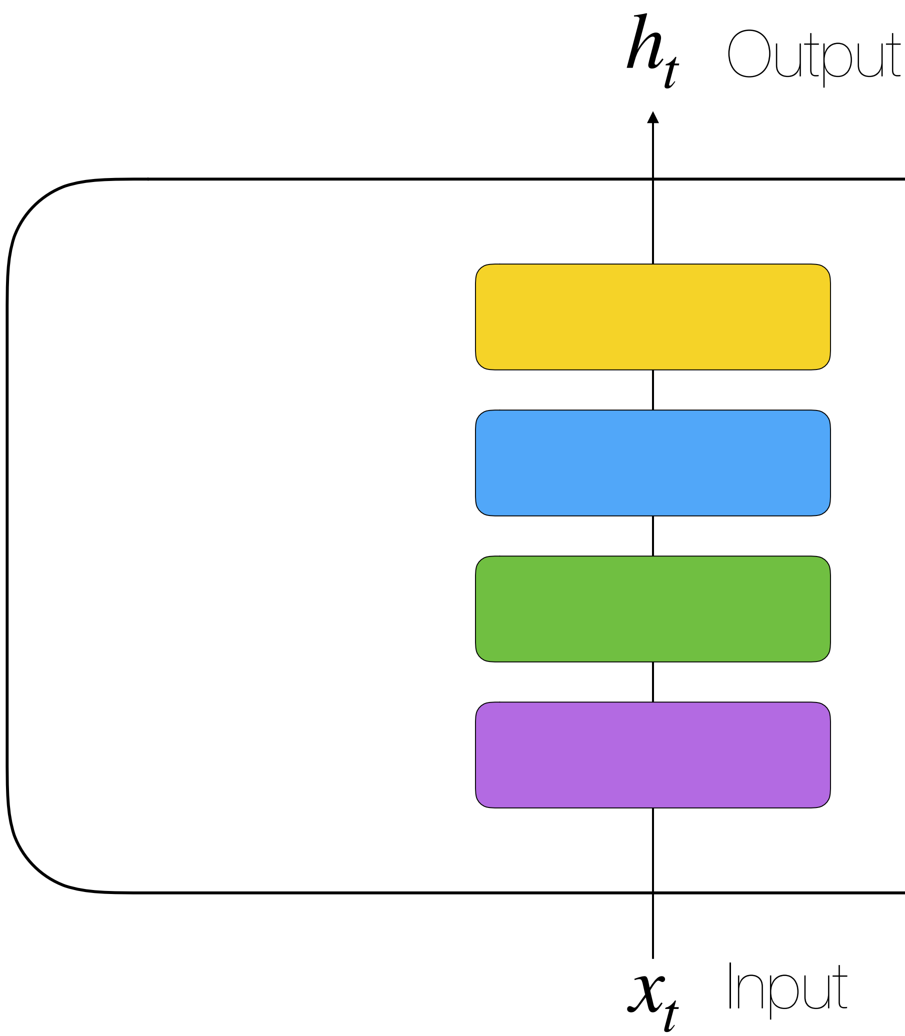
Recurrent Neural Network (RNN)

Information Flow



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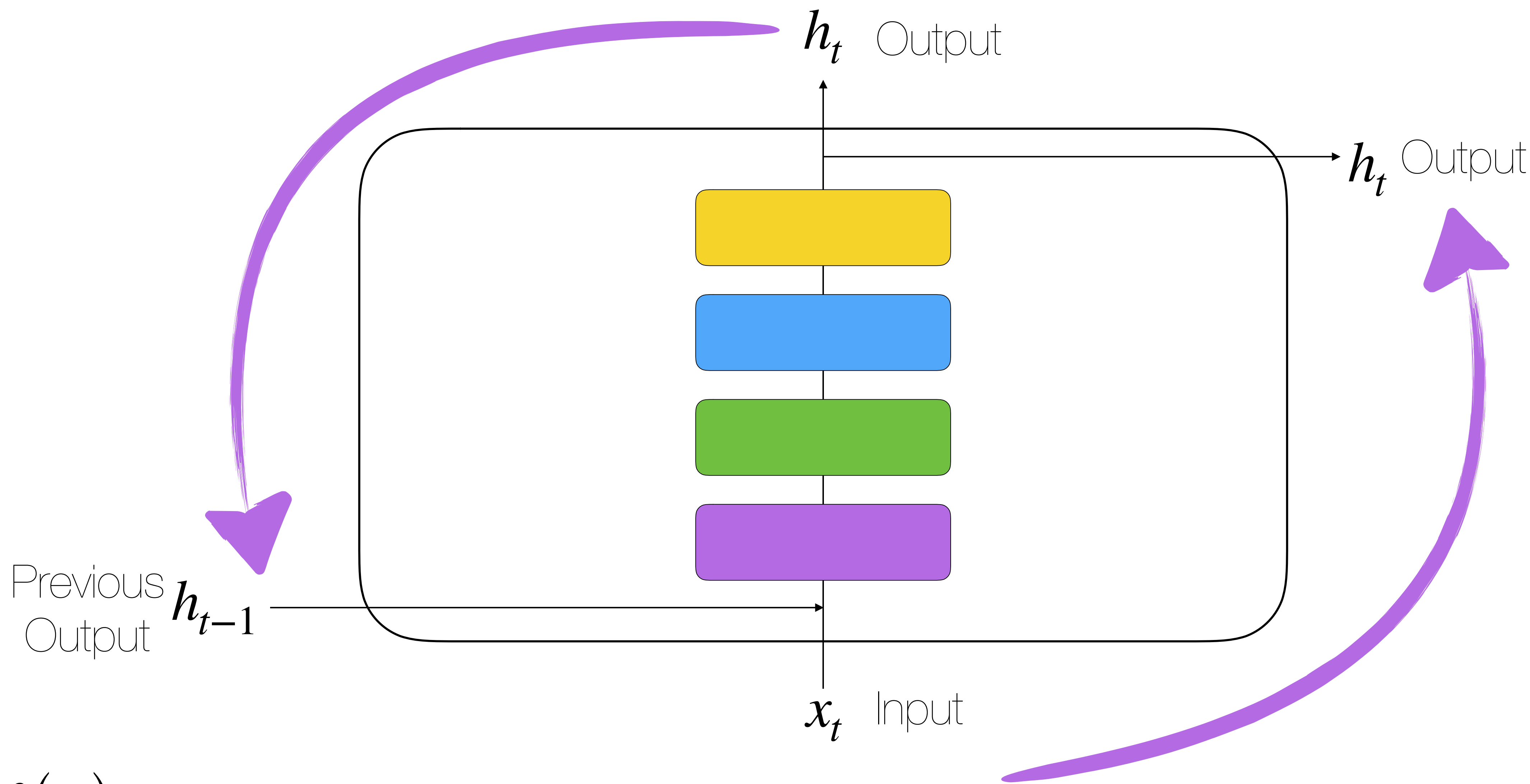

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Recurrent Neural Network (RNN)

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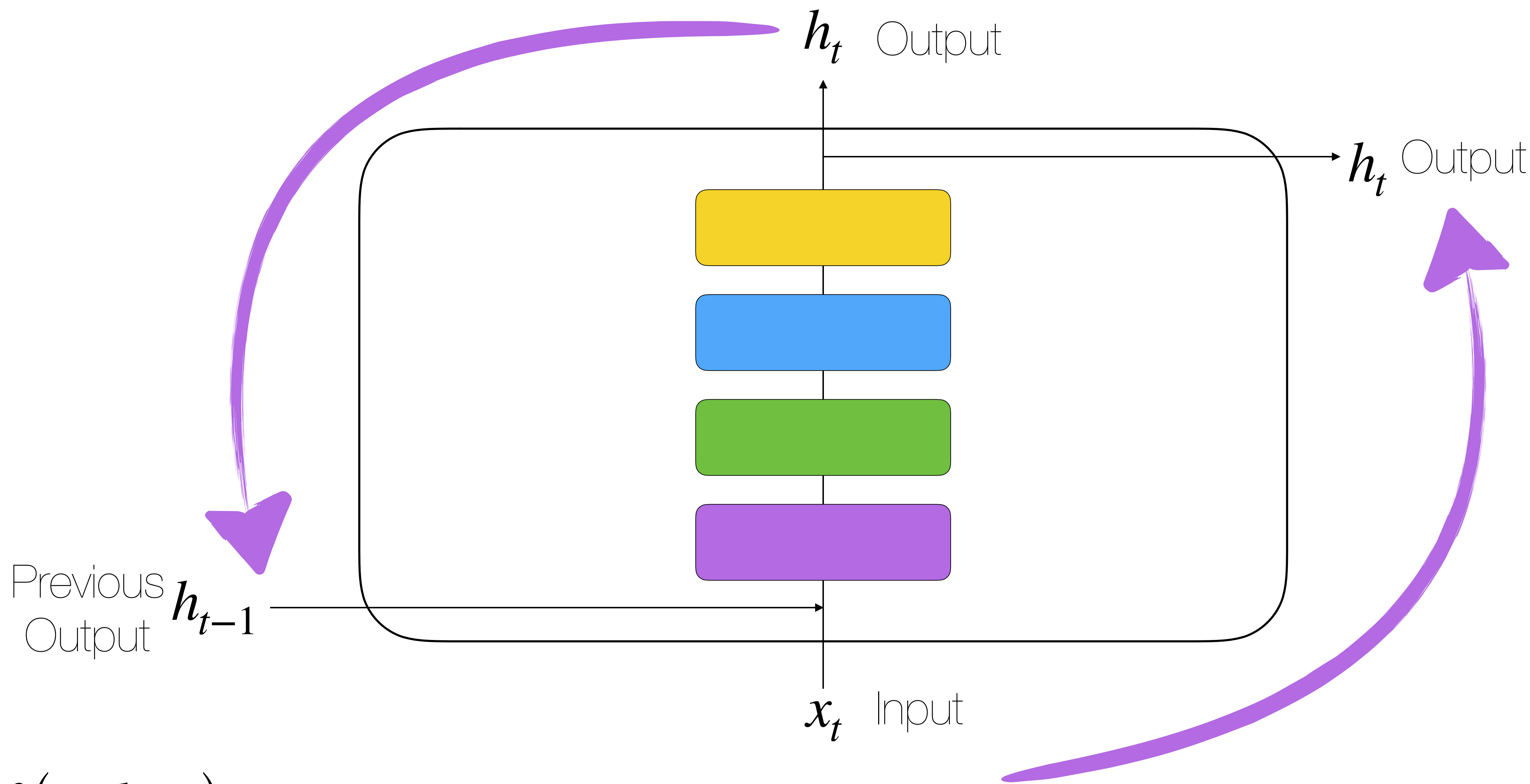
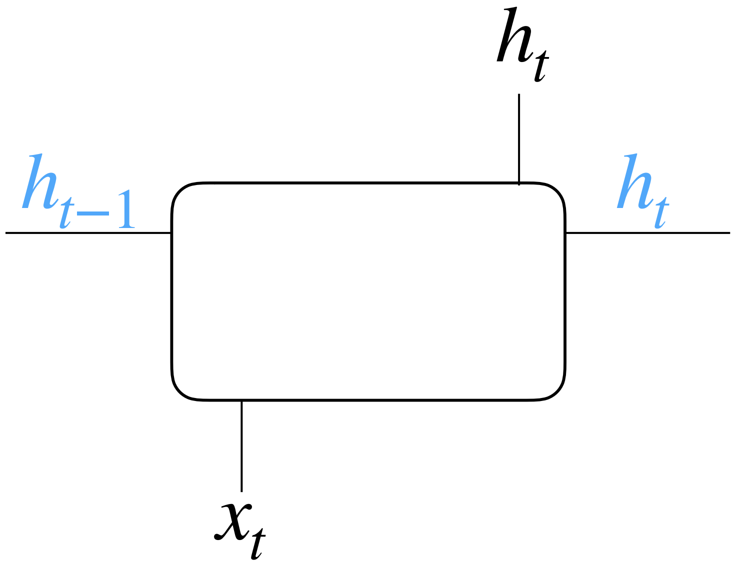


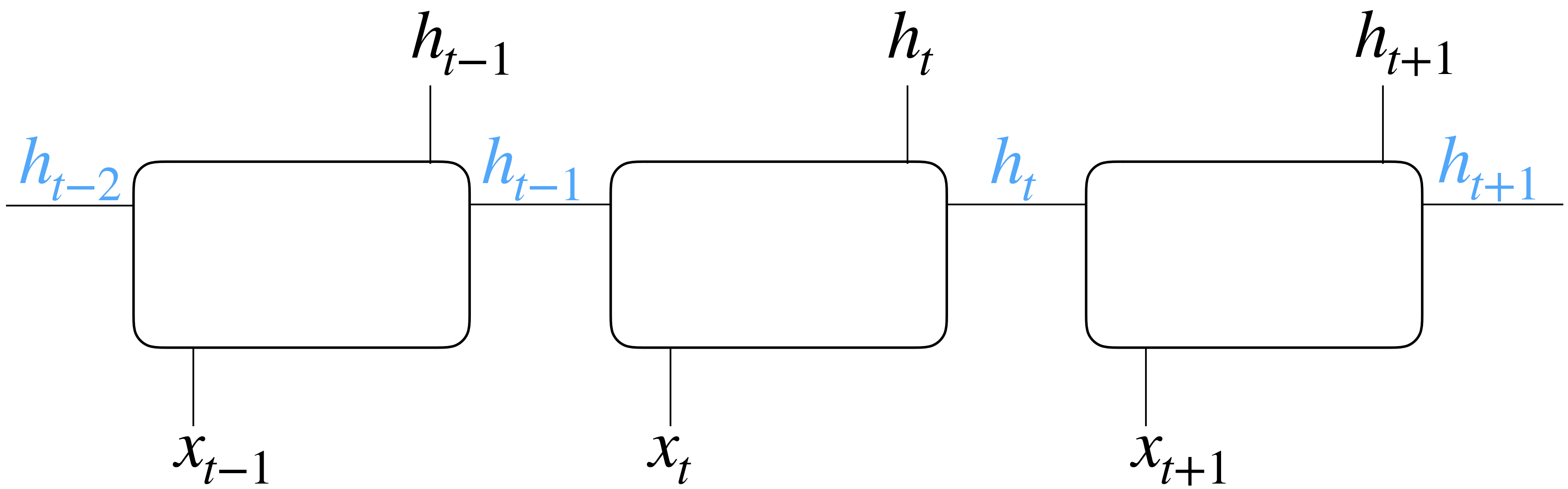
$$h_t = f\left(x_t, h_{t-1}\right)$$

Recurrent Neural Network (RNN)



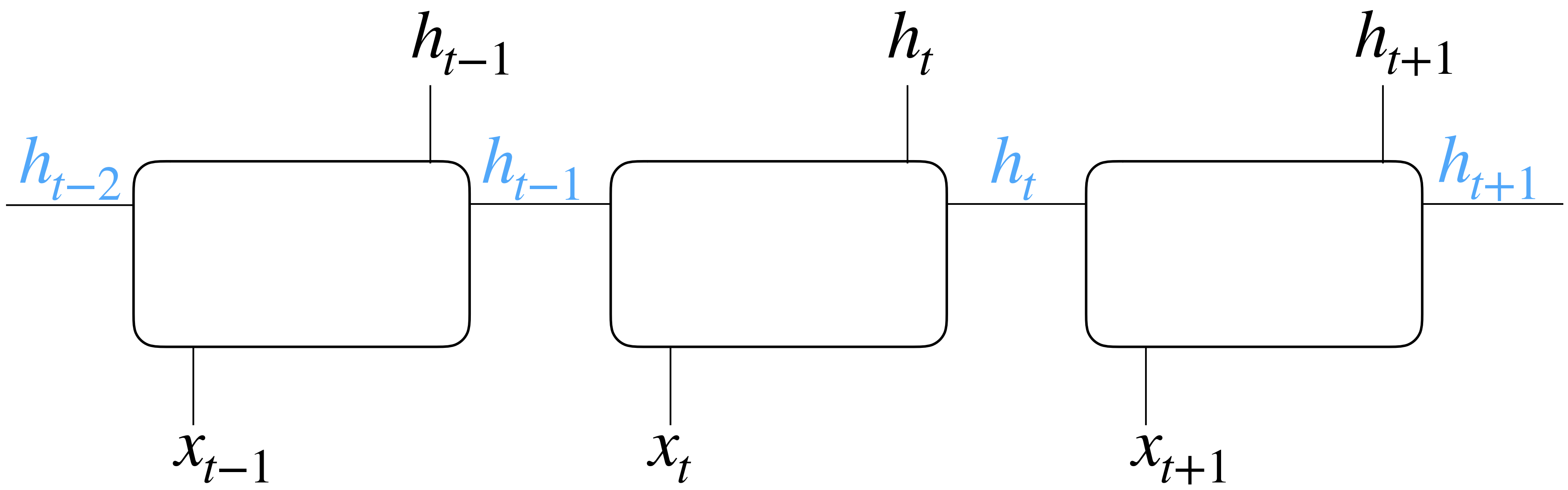
Recurrent Neural Network (RNN)

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

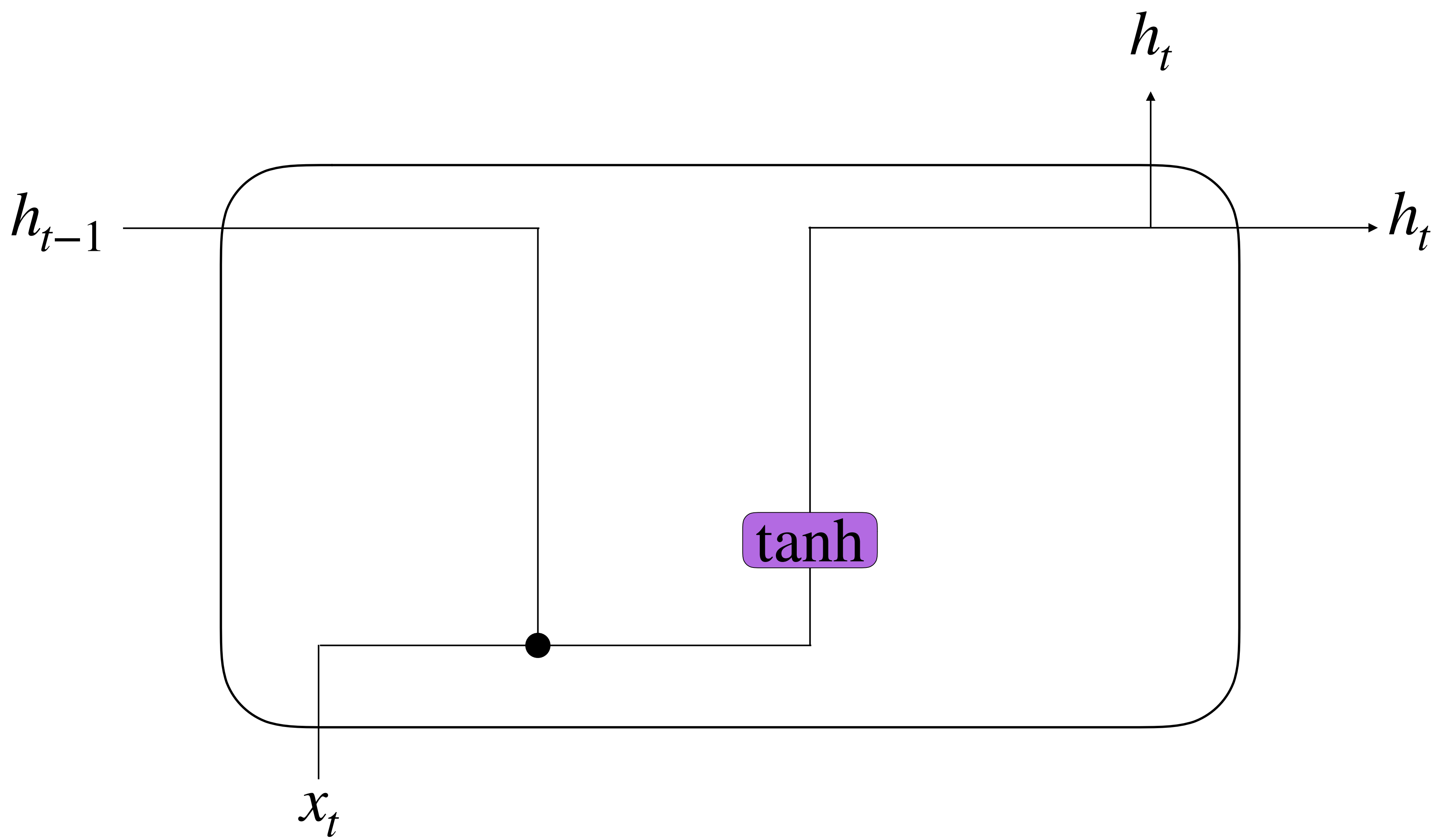


Recurrent Neural Network (RNN)

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

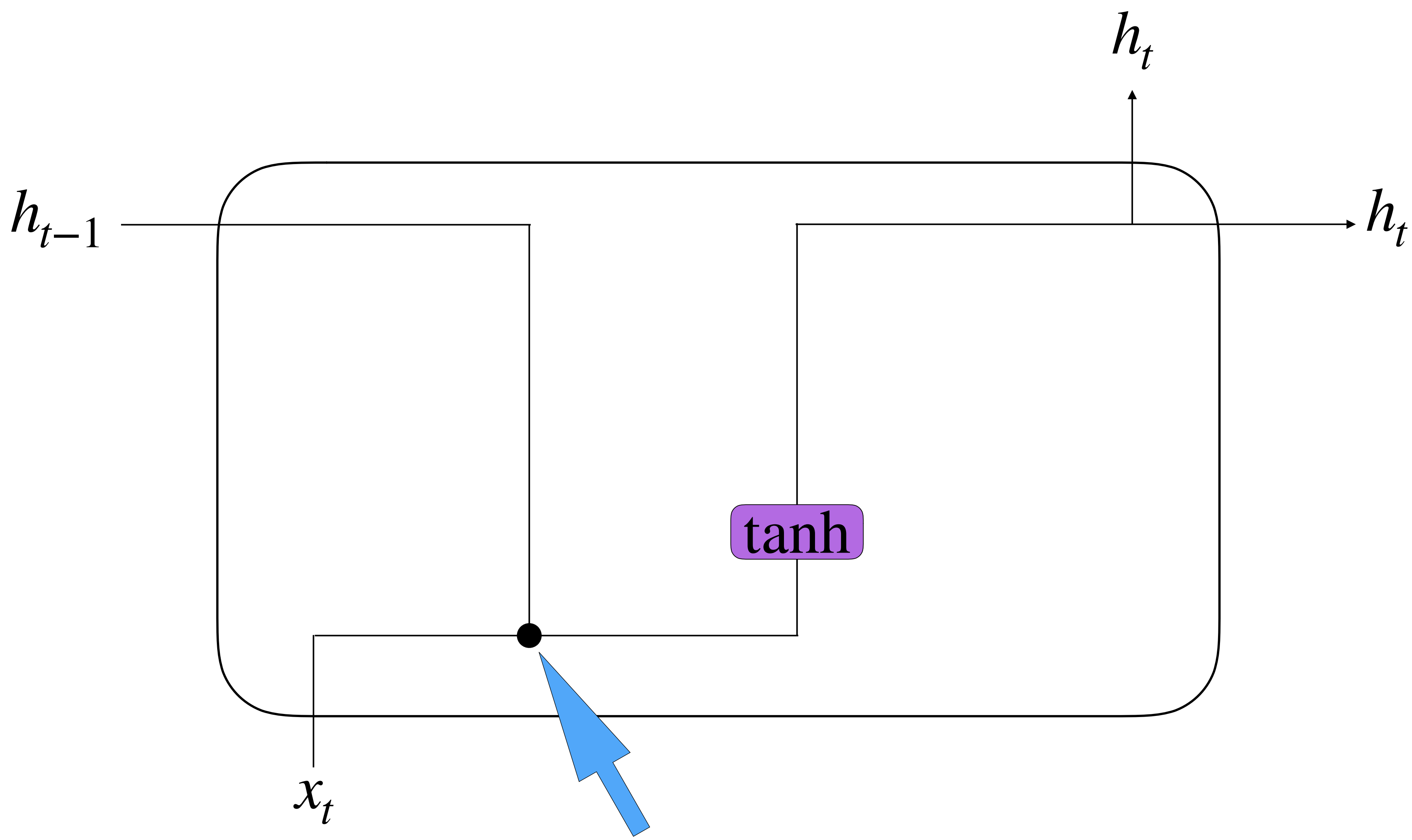


Recurrent Neural Network (RNN)



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

Recurrent Neural Network (RNN)



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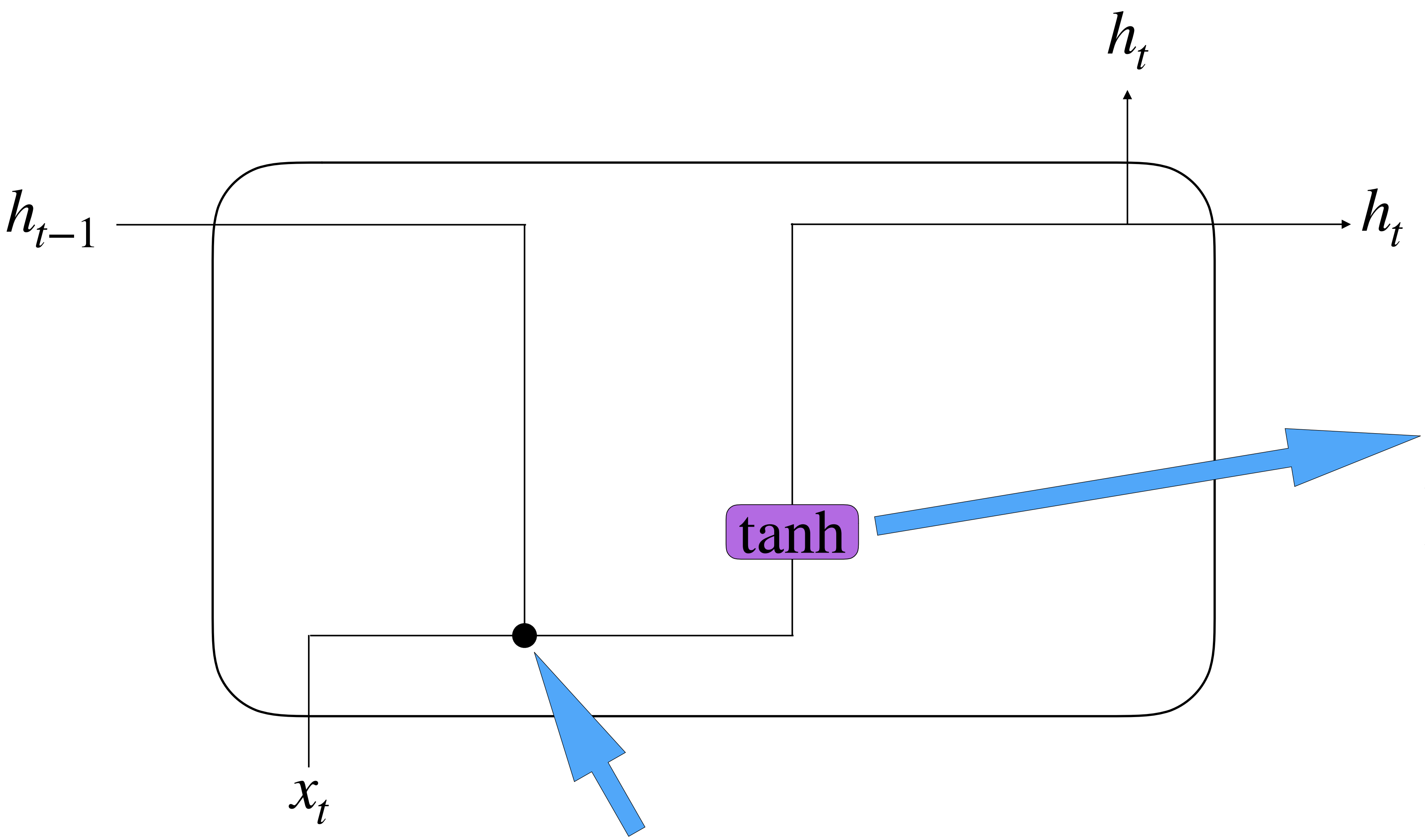
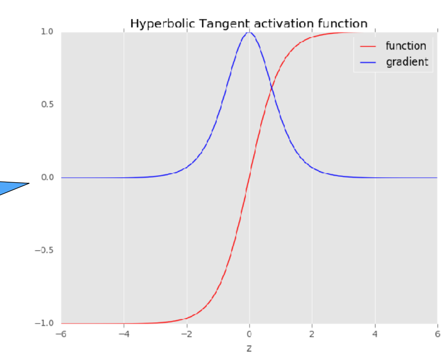
Concatenate
both inputs.

Recurrent Neural Network (RNN)





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Timeseries

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- Temporal sequence of data points

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- Consecutive points are strongly correlated

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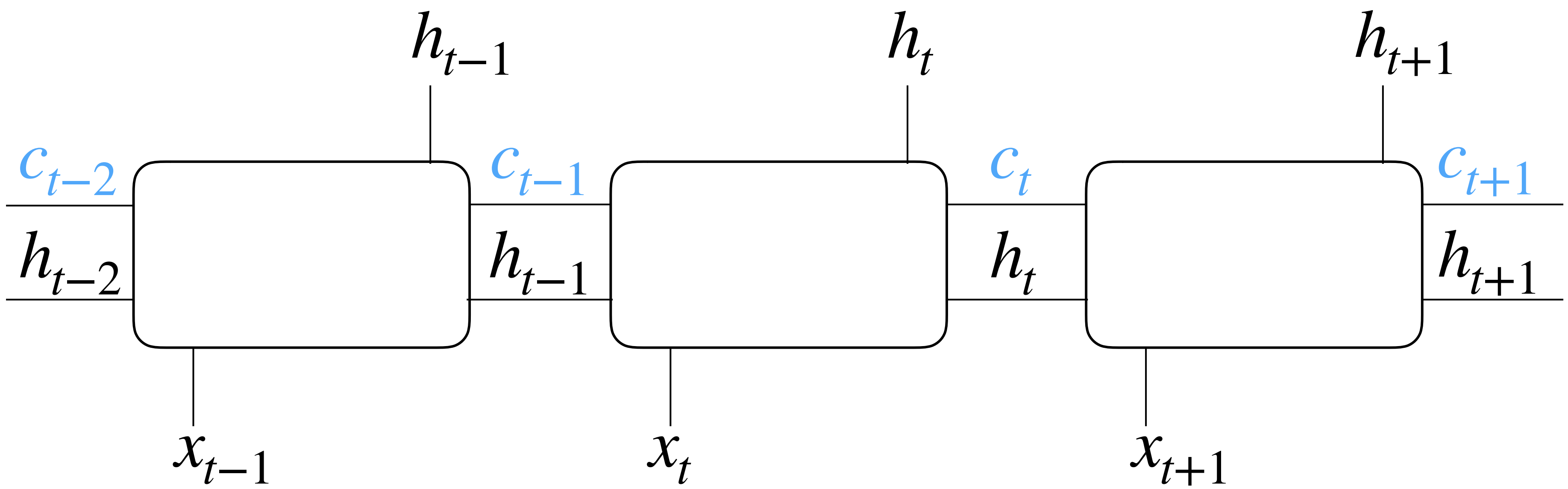
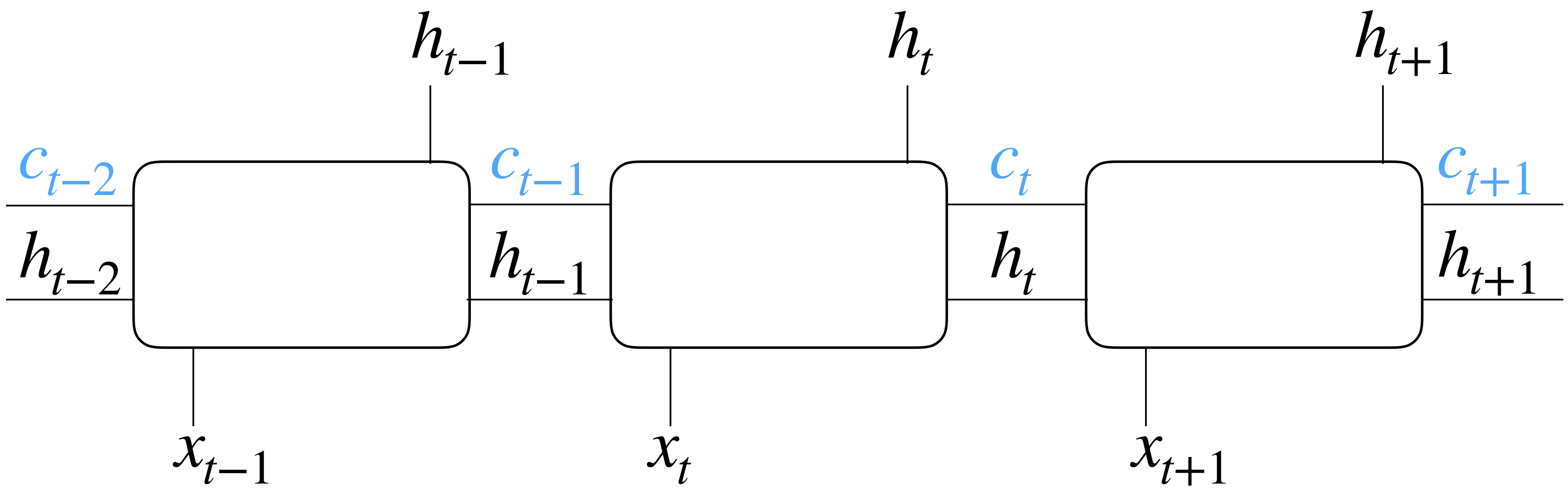
Long-Short Term Memory (LSTM)



Long-Short Term Memory (LSTM)

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



Long-Short Term Memory (LSTM)

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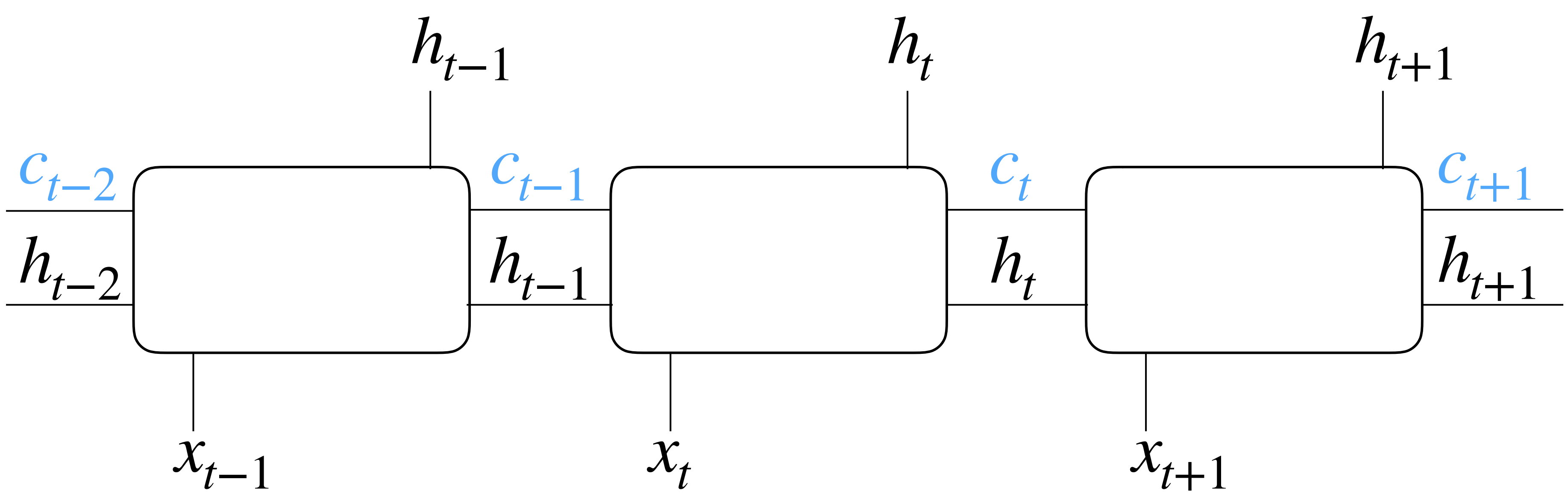
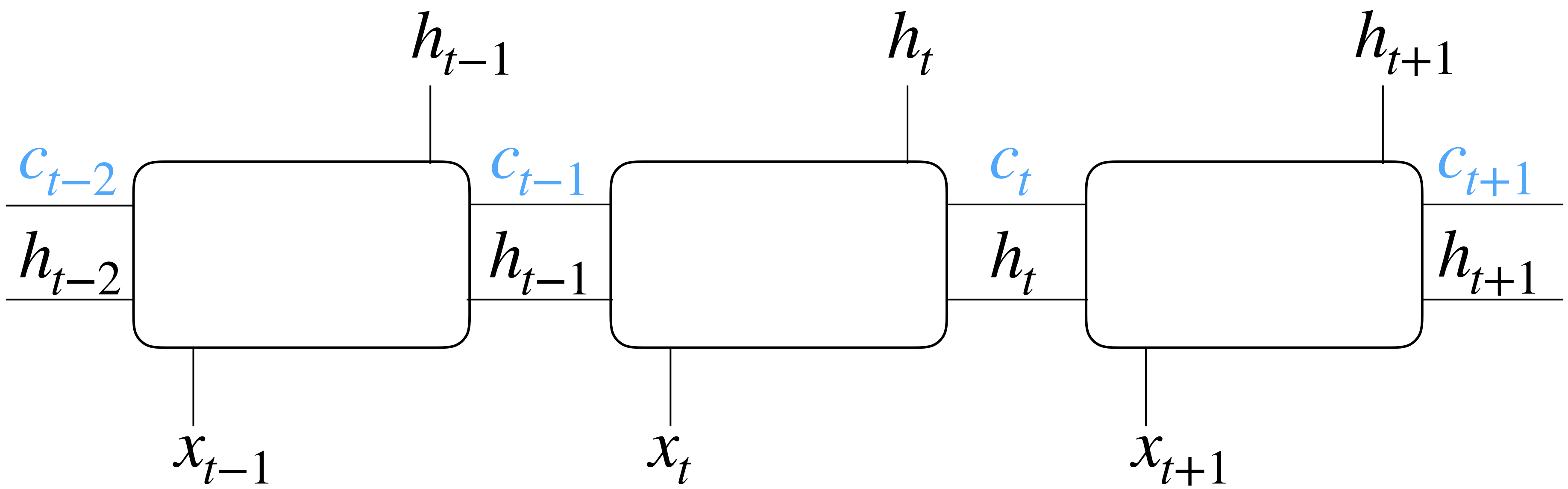
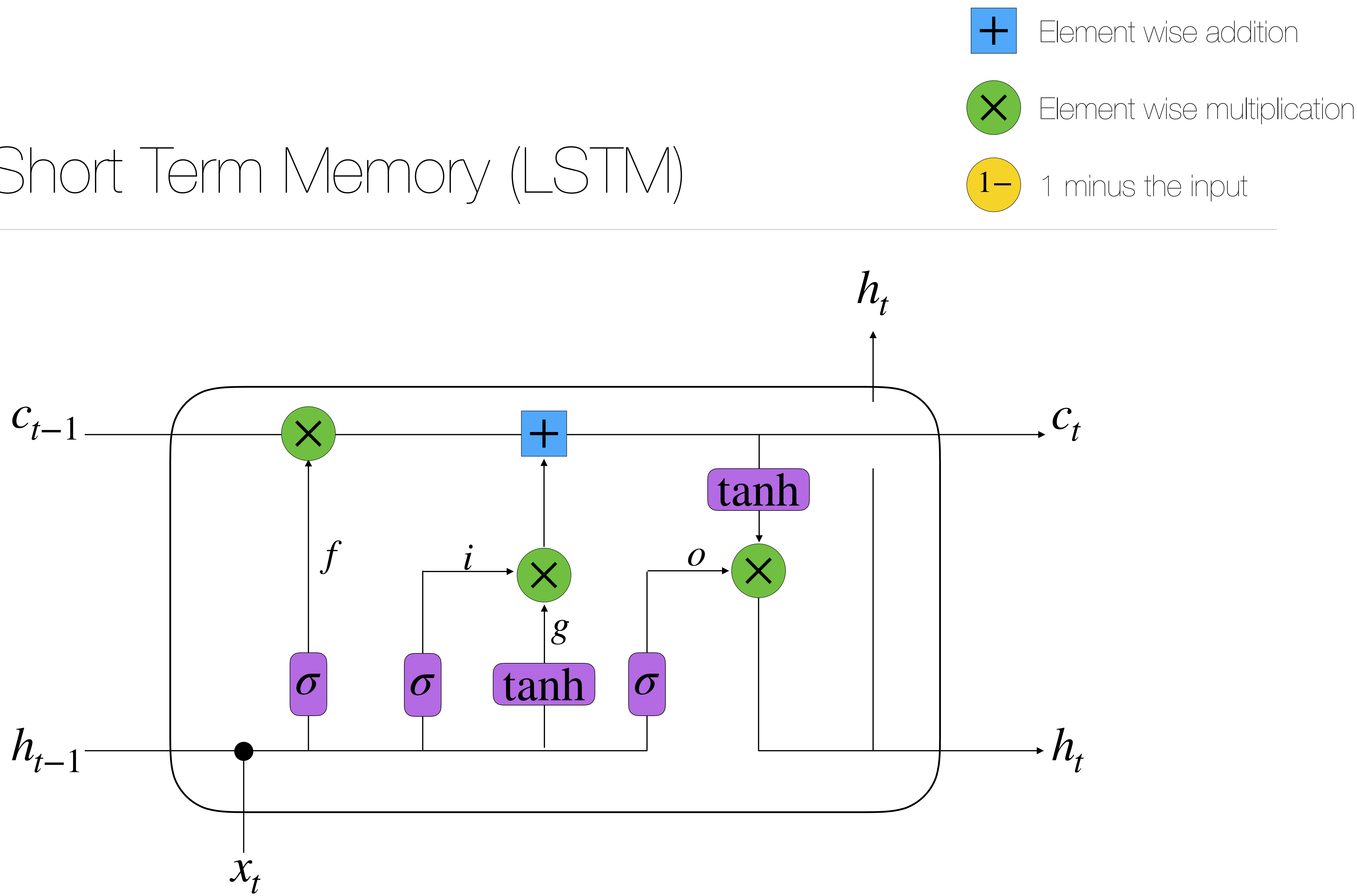


Long-Short Term Memory (LSTM)

- What if we want to keep explicit information about previous states (memory)?
- How much information is kept, can be controlled through gates.
- LSTMs were first introduced in 1997 by Hochreiter and Schmidhuber



Long-Short Term Memory (LSTM)



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

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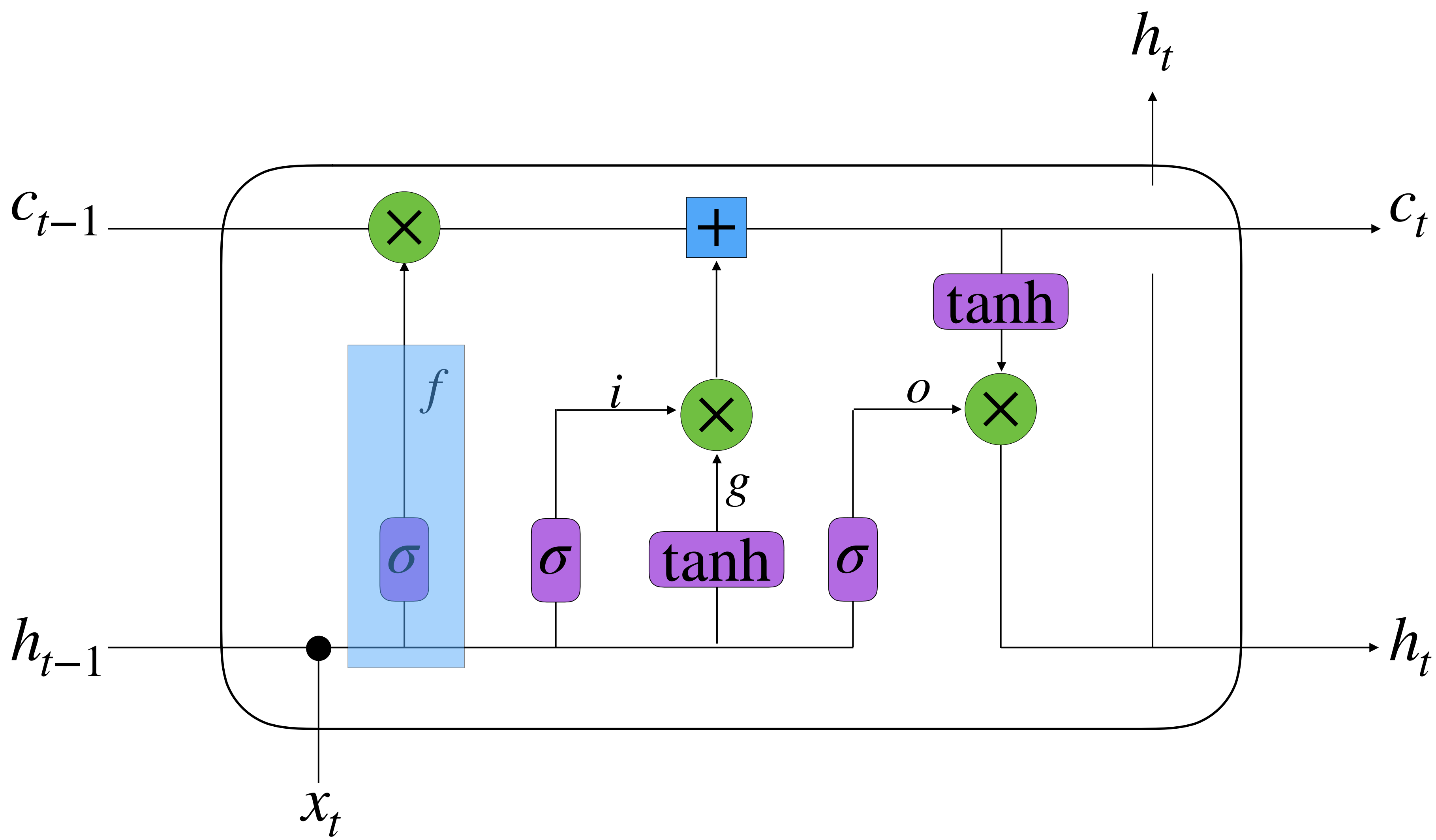
Element wise addition

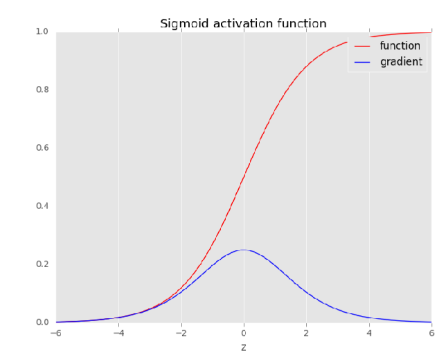
Element wise multiplication

1 minus the input

Long-Short Term Memory (LSTM)

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





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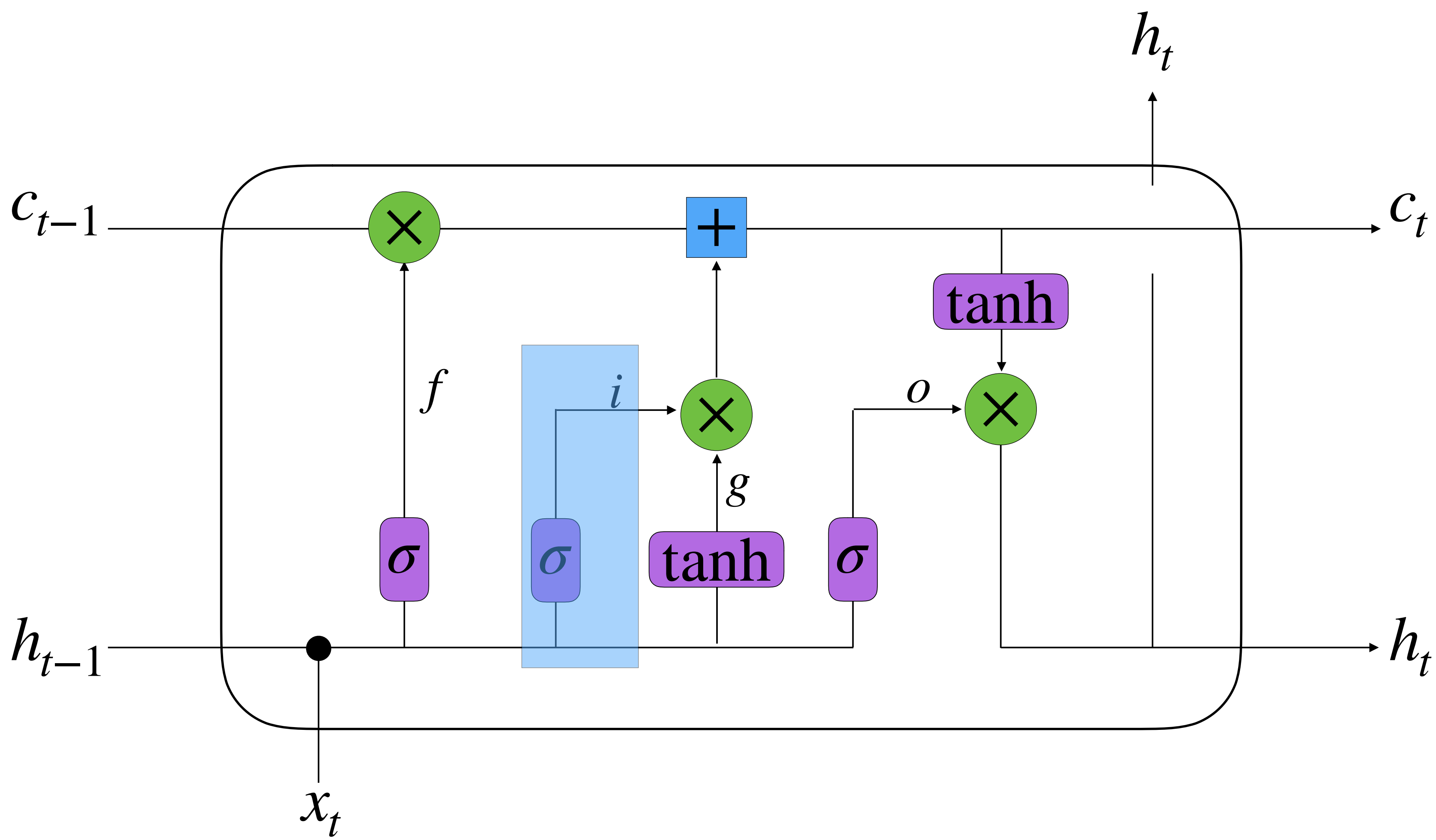
Element wise addition

Element wise multiplication

1 minus the input

Long-Short Term Memory (LSTM)

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



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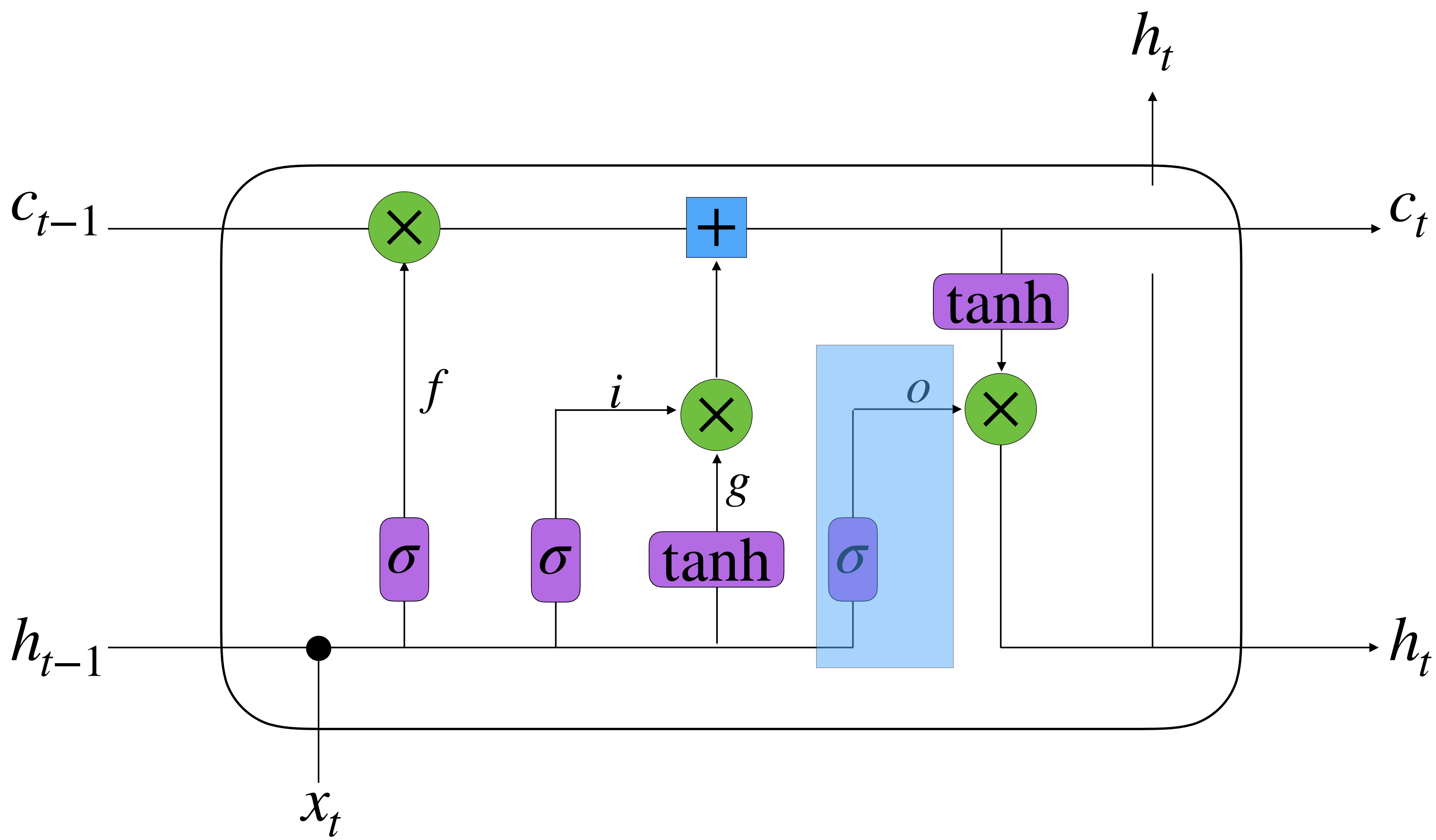
Long-Short Term Memory (LSTM)

Element wise addition

Element wise multiplication

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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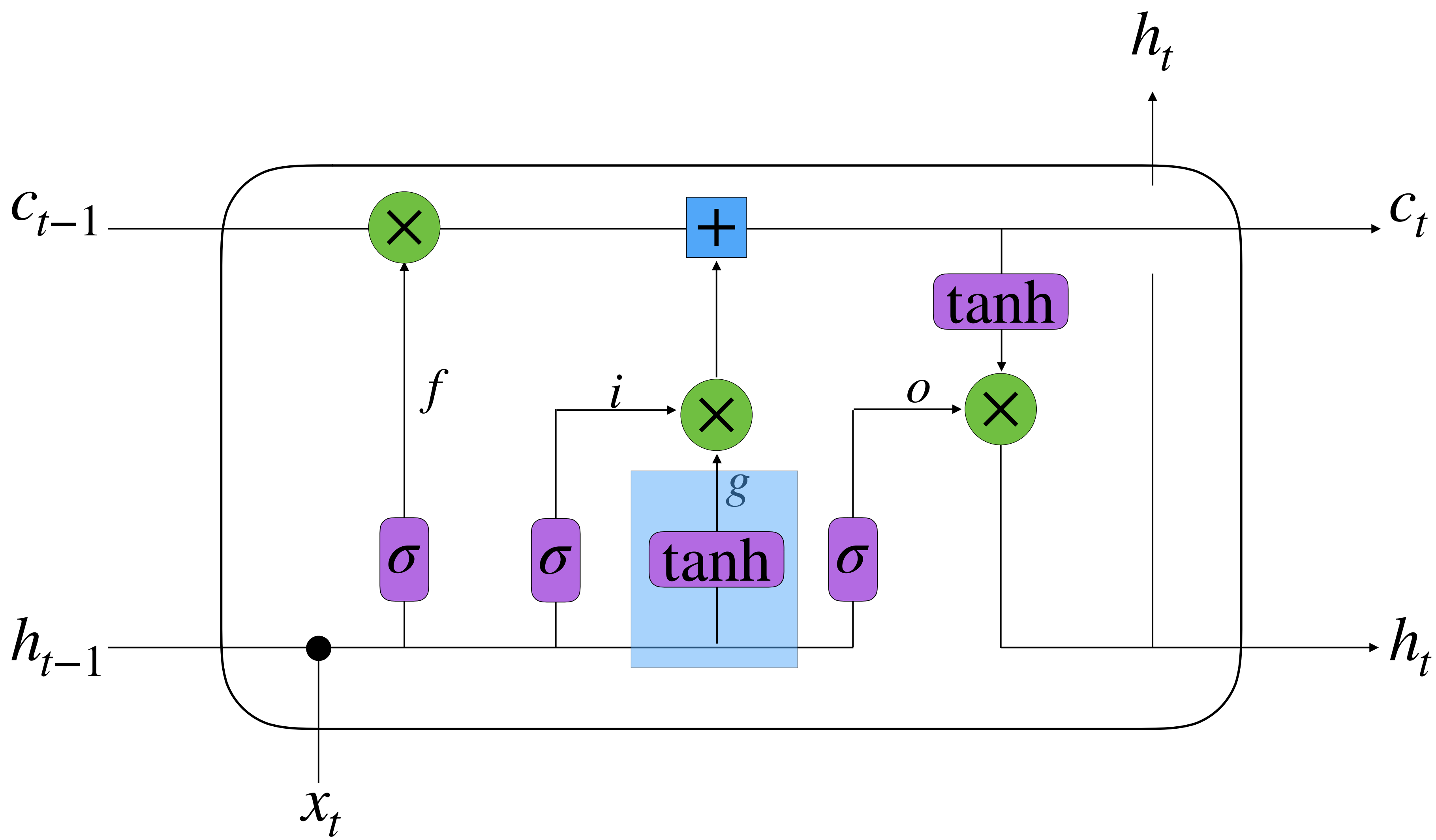
Long-Short Term Memory (LSTM)

+ Element wise addition

× Element wise multiplication

1− 1 minus the input

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



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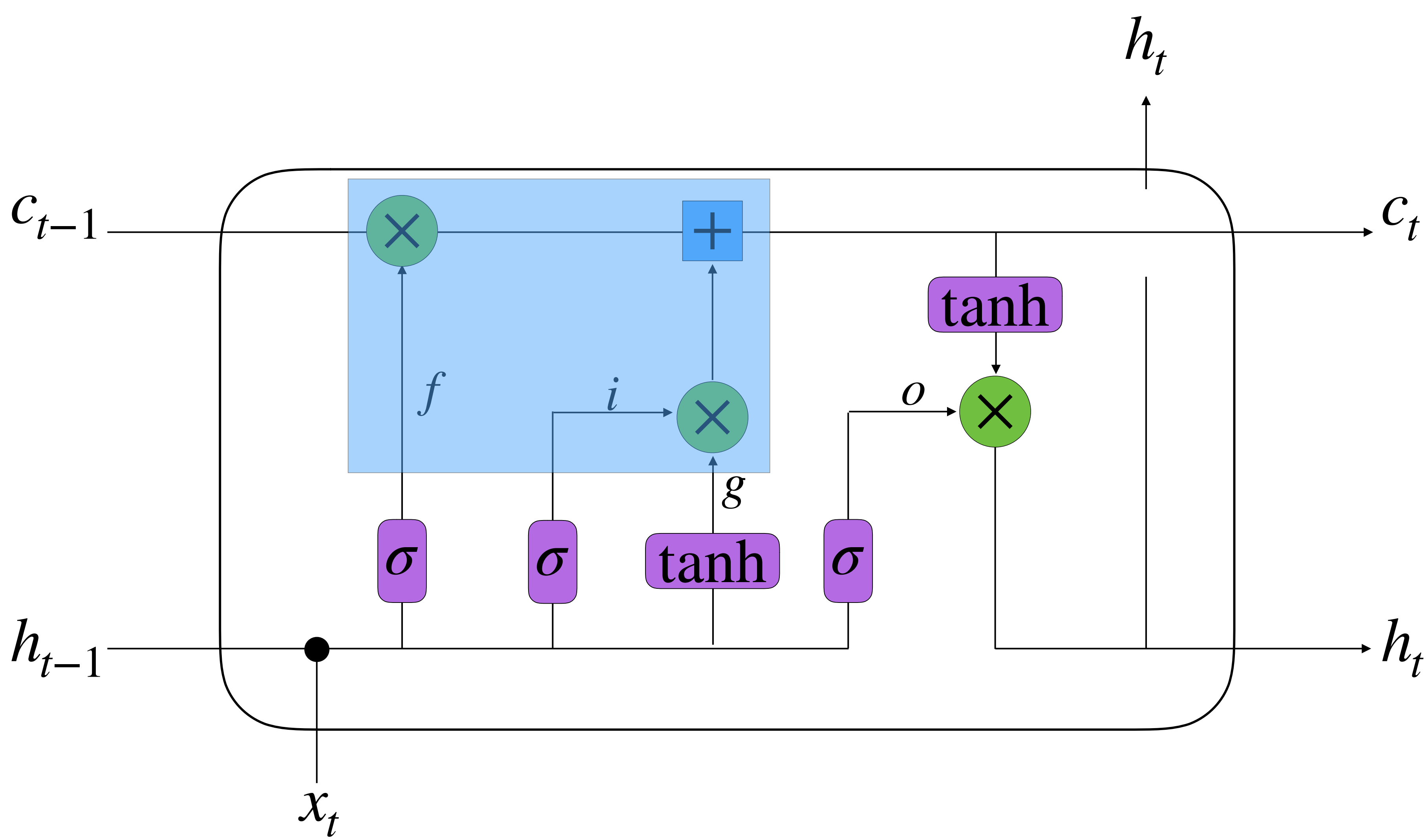
Long-Short Term Memory (LSTM)

Element wise addition

Element wise multiplication

1 minus the input

State:
Update the
current state



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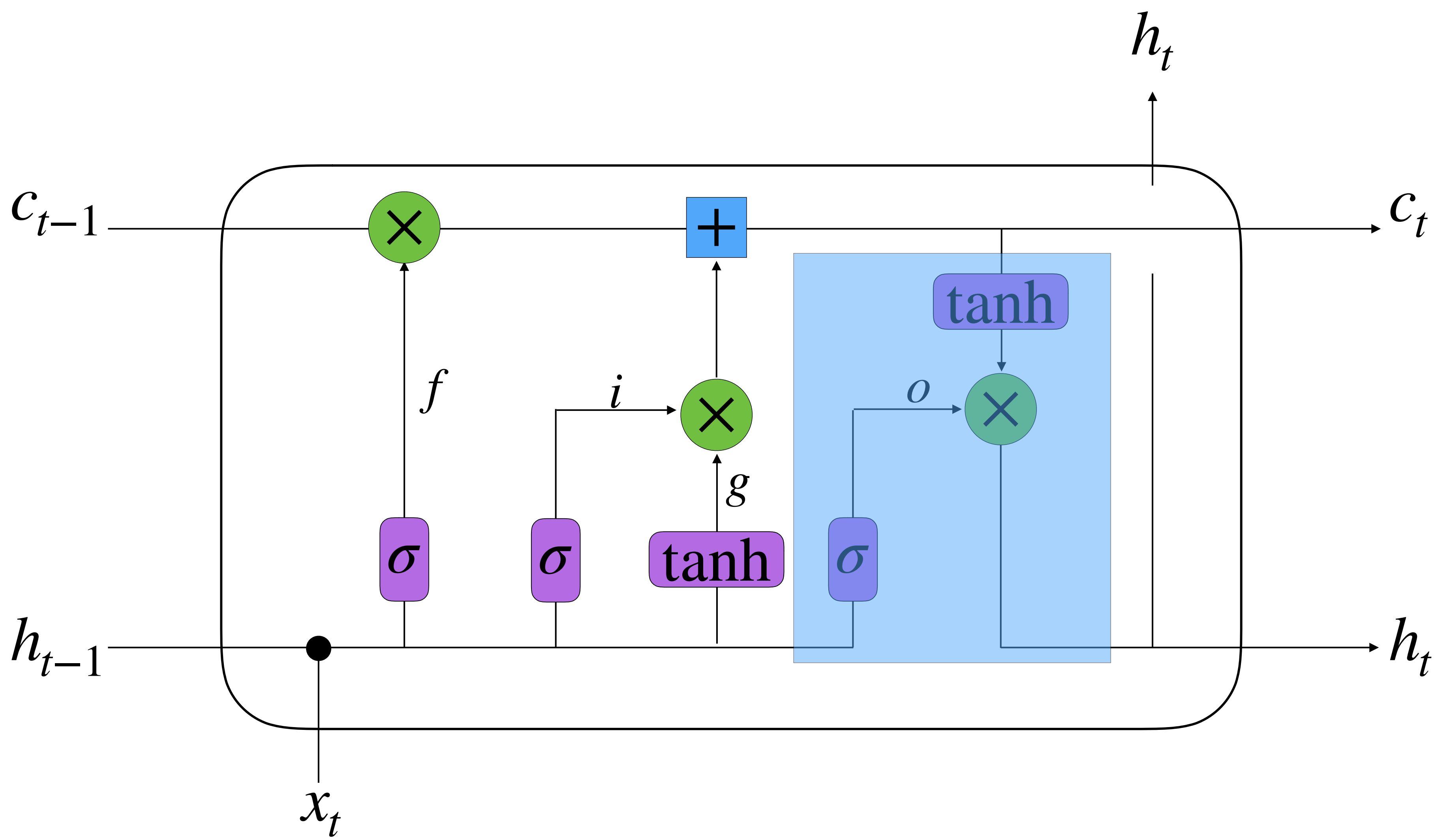
Element wise addition

Element wise multiplication

1 minus the input

Long-Short Term Memory (LSTM)

Output:
Combine all available information.



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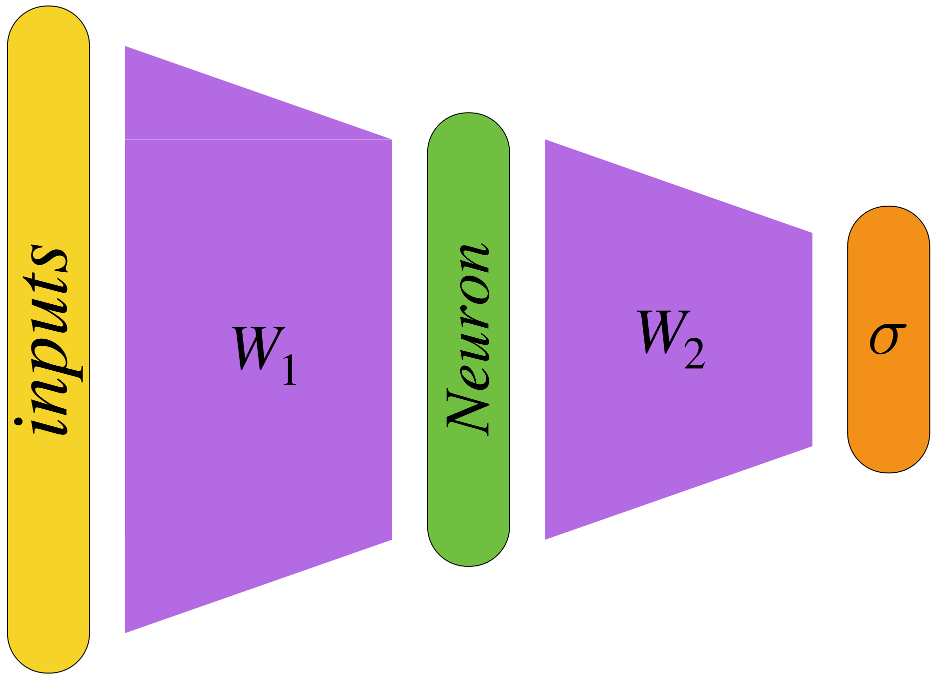
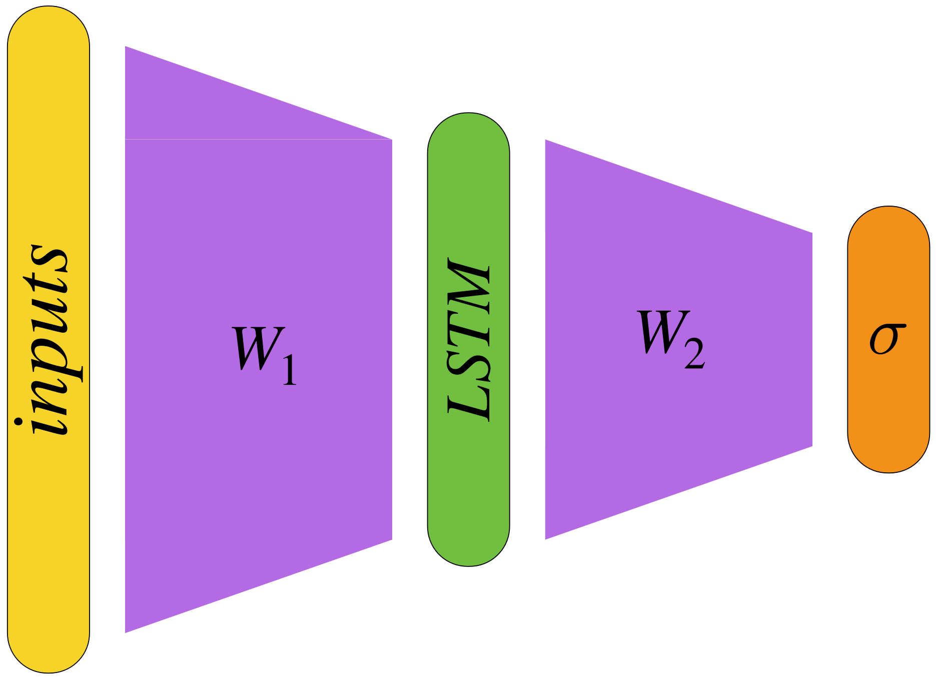
Using LSTMs



Using LSTMs



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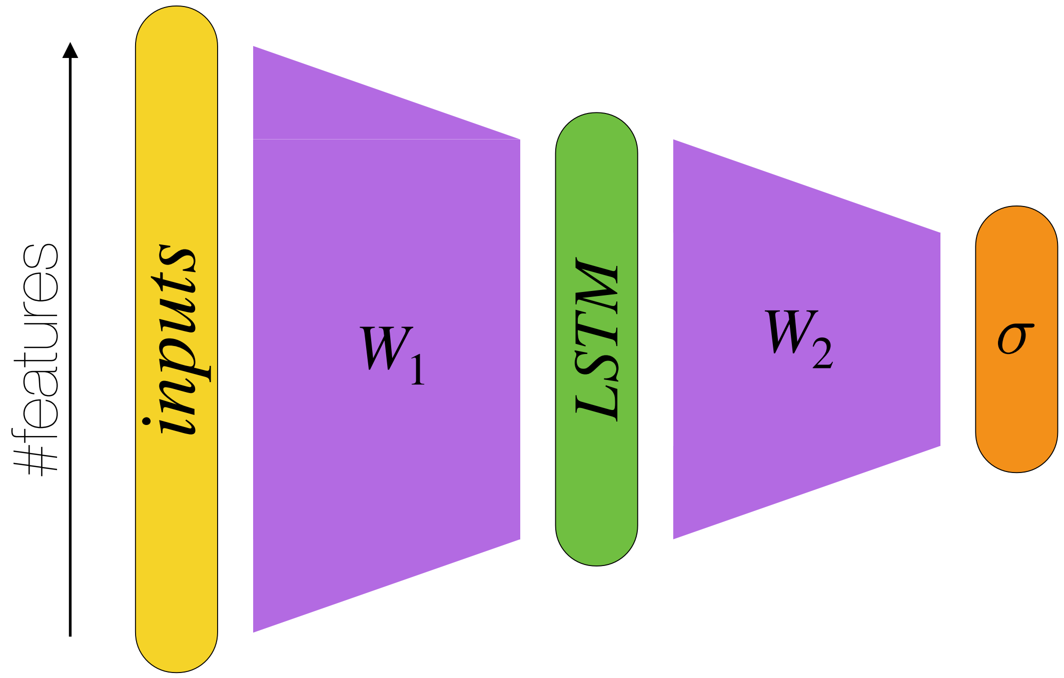

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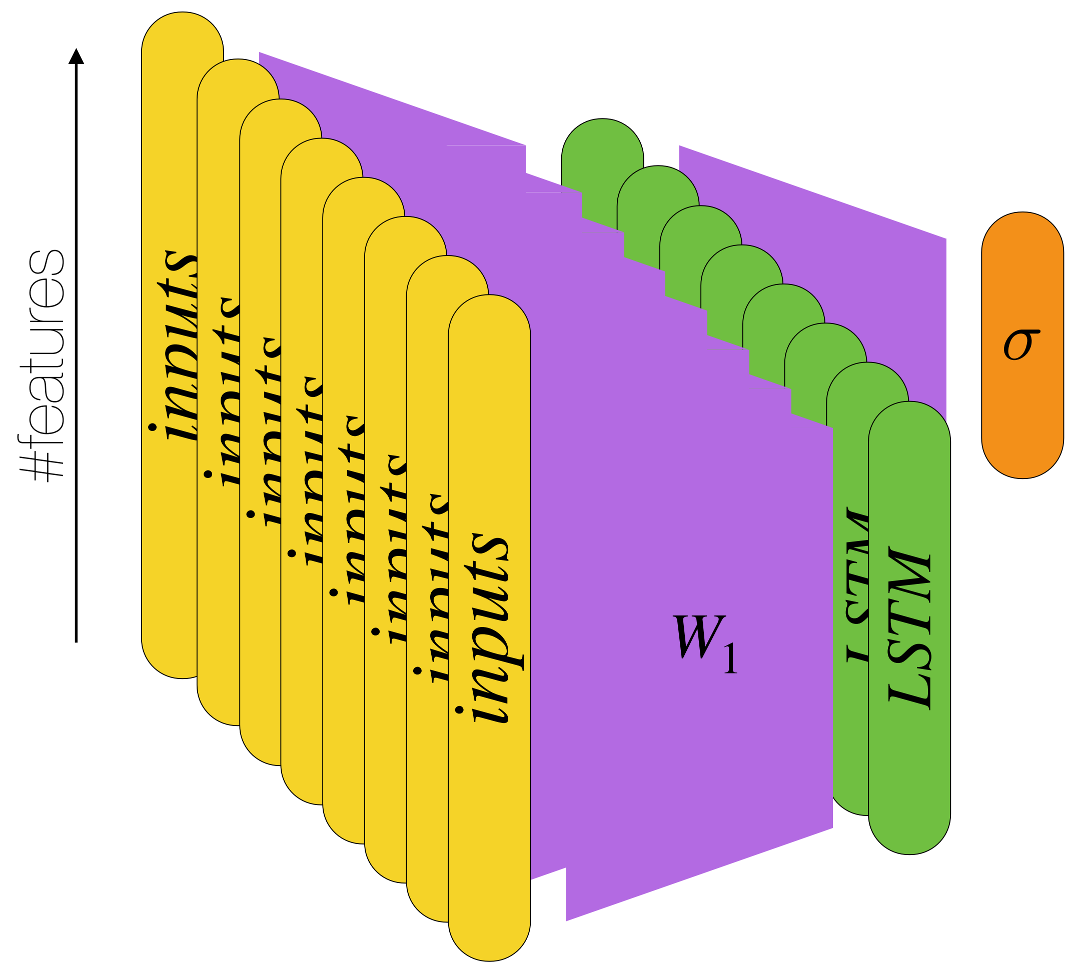
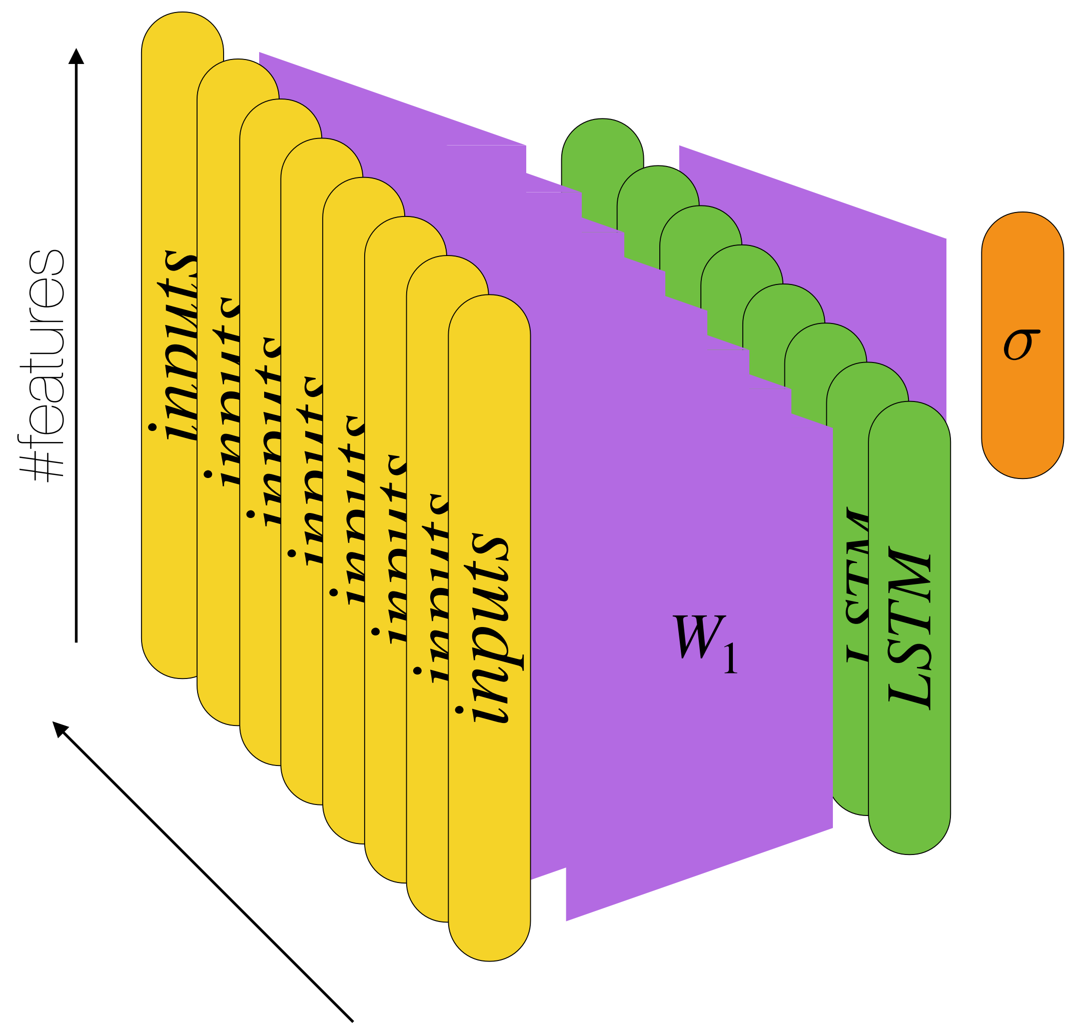
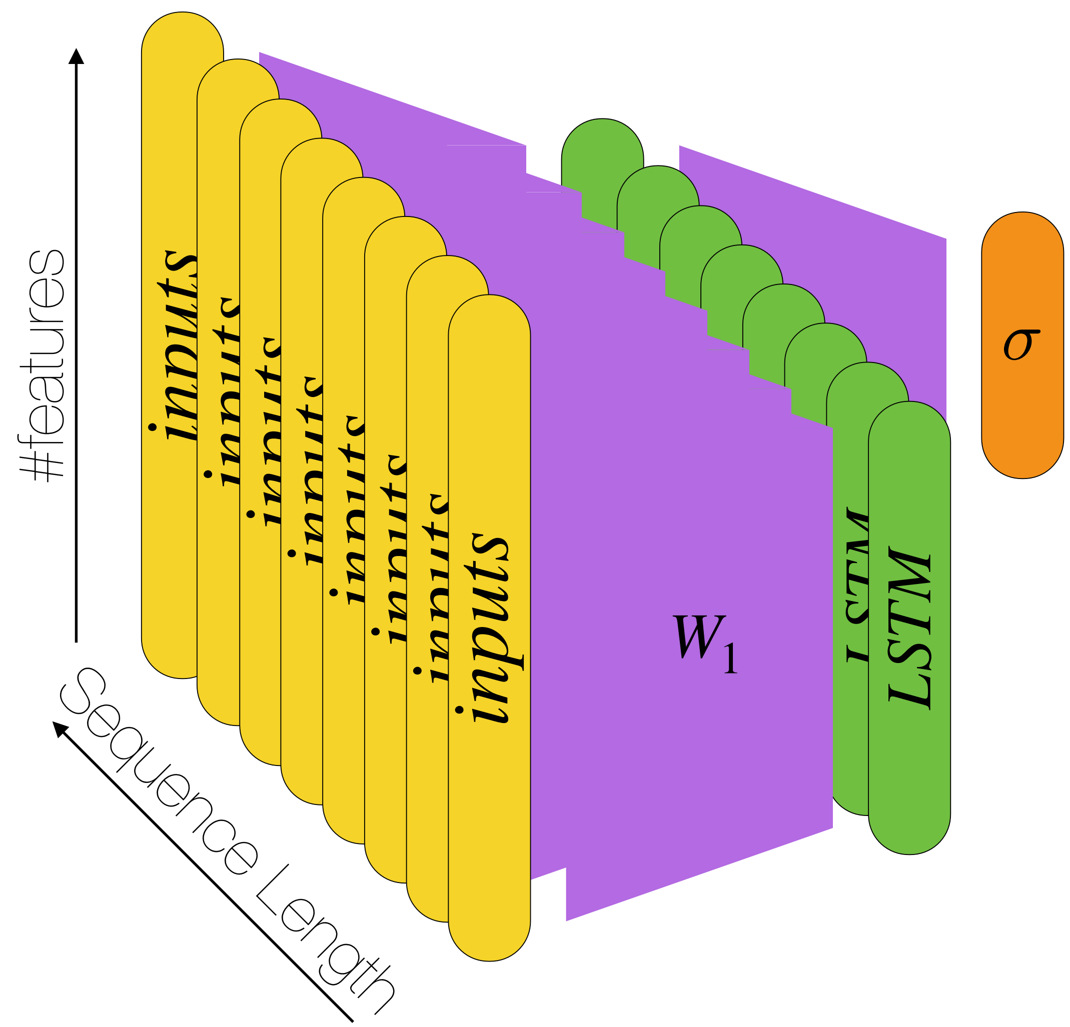

#features
inputs
inputs
inputs
inputs
inputs
inputs
inputs
inputs
W_1
LSTM
LSTM
σ

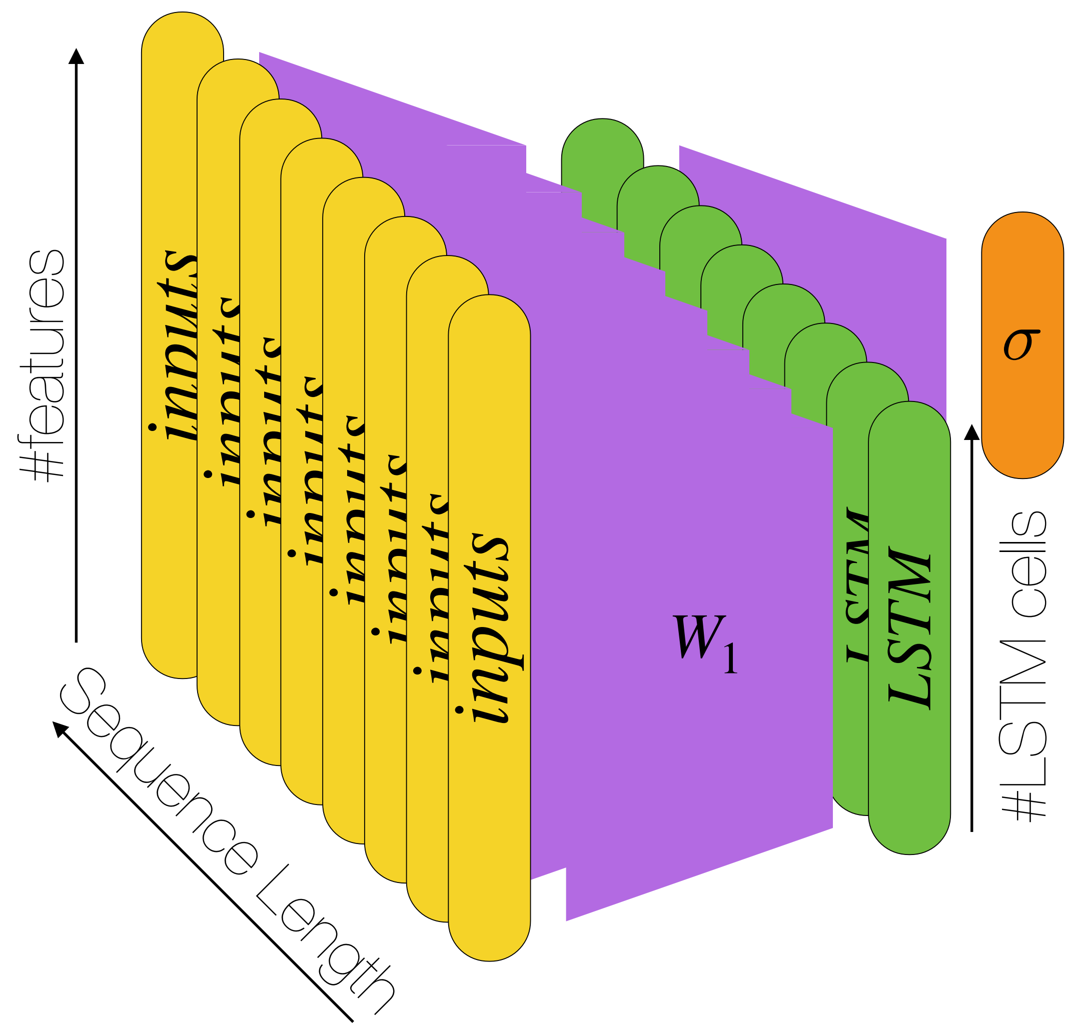
Using LSTMs



Using LSTMs


#features
Sequence Length
inputs
inputs
inputs
inputs
inputs
inputs
inputs
inputs
W_1
LSTM
LSTM
σ

Using LSTMs



#features
inputs
inputs
inputs
inputs
inputs
inputs
inputs
inputs
Sequence Length
W_1
LSTM
LSTM
#LSTM cells
σ

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
- Speech Recognition
- Machine Translation
- Part-of-Speech Tagging

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Applications

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- Time series forecasting

Gated Recurrent Unit (GRU)

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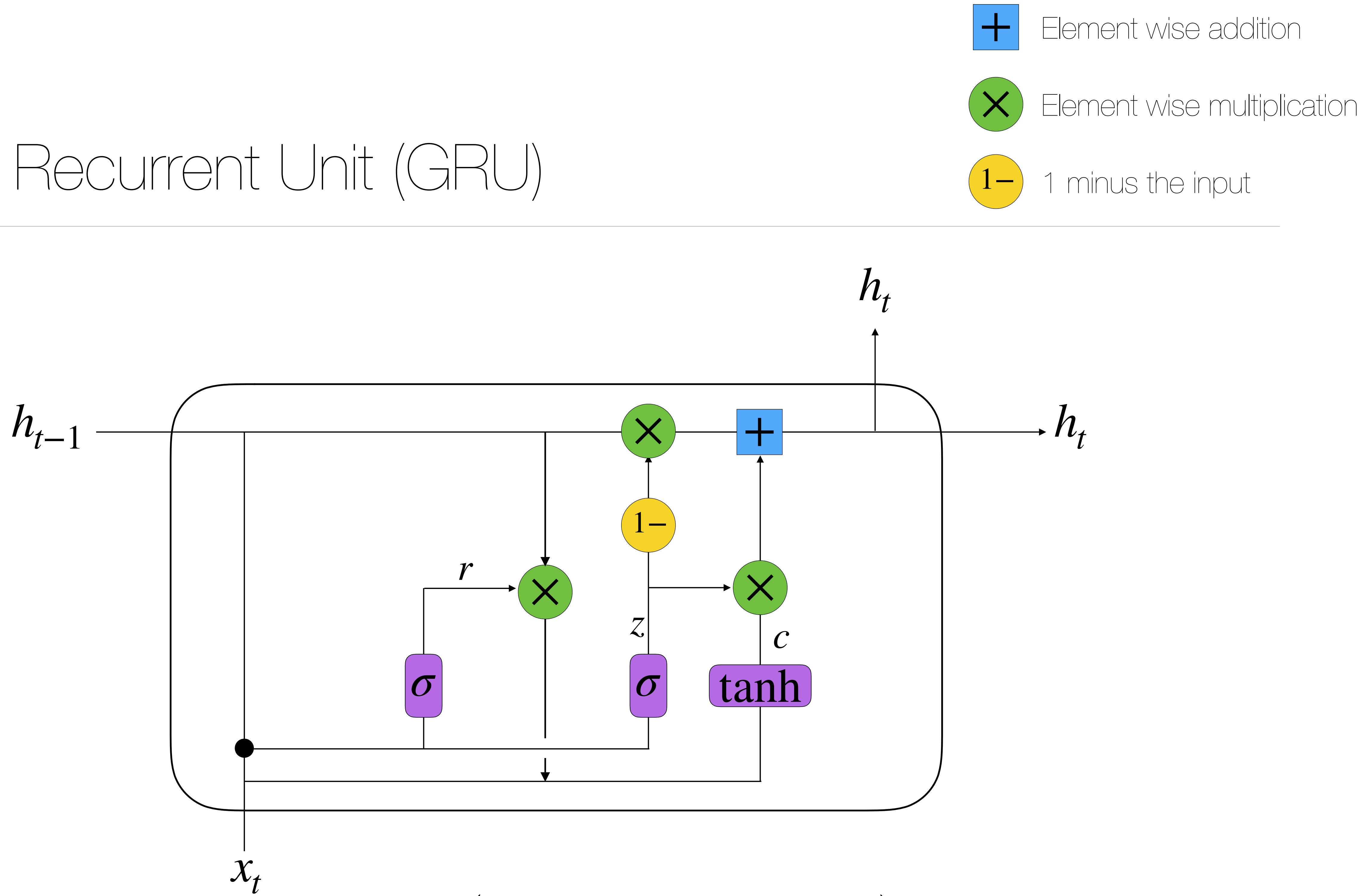
- Introduced in 2014 by Cho
- Meant to solve the Vanishing Gradient Problem
- Can be considered as a simplification of LSTMs
- Similar performance to LSTM in some applications, better performance for smaller datasets.

Gated Recurrent Unit (GRU)



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

$$r = \sigma\left(W_r h_{t-1} + U_r x_t\right)$$

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

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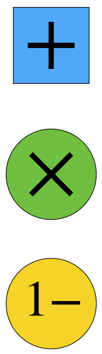
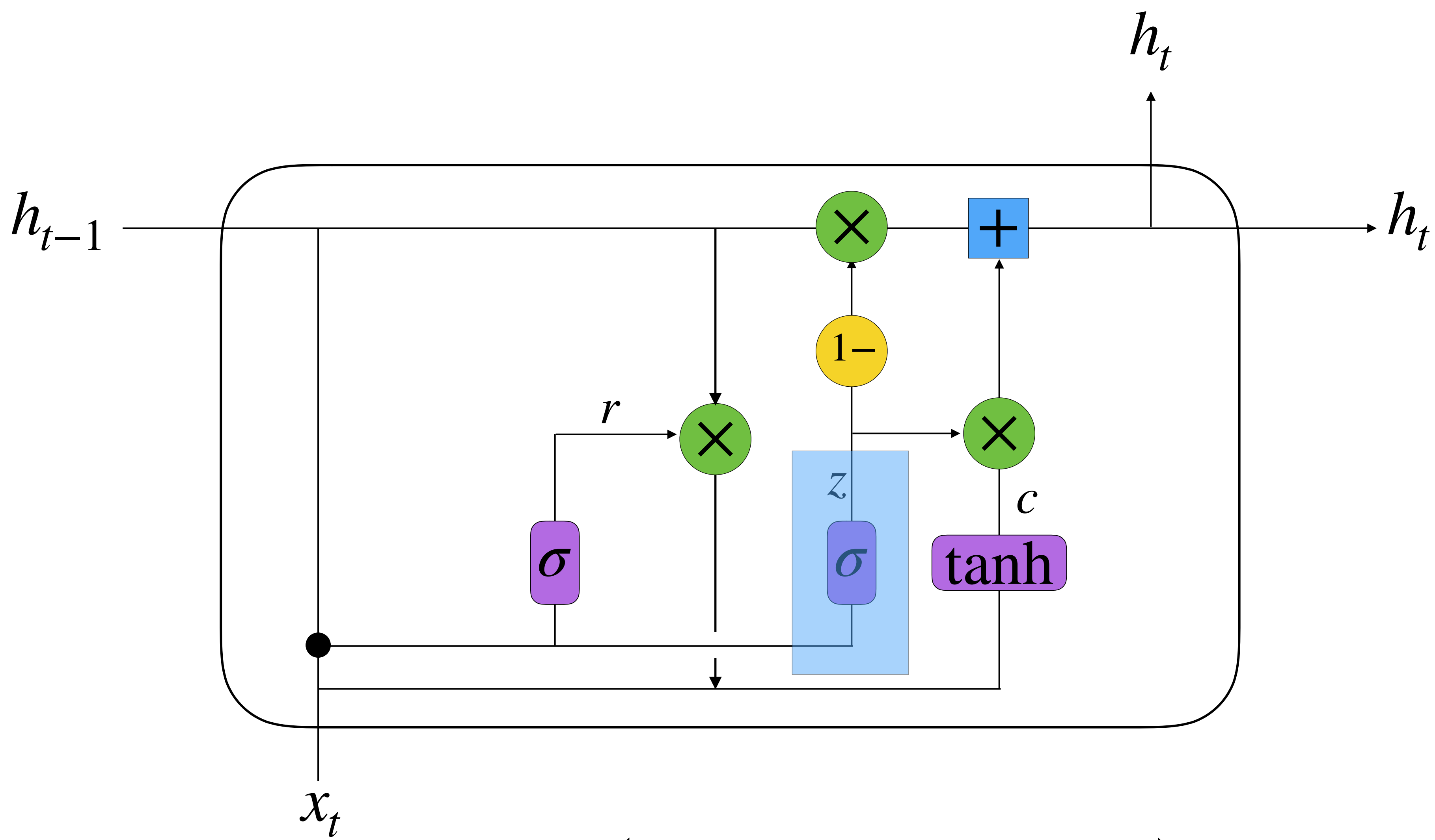
Gated Recurrent Unit (GRU)





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

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

$$r = \sigma\left(W_r h_{t-1} + U_r x_t\right)$$

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

$$h_t = (z \otimes c) + \left((1 - z) \otimes h_{t-1}\right)$$

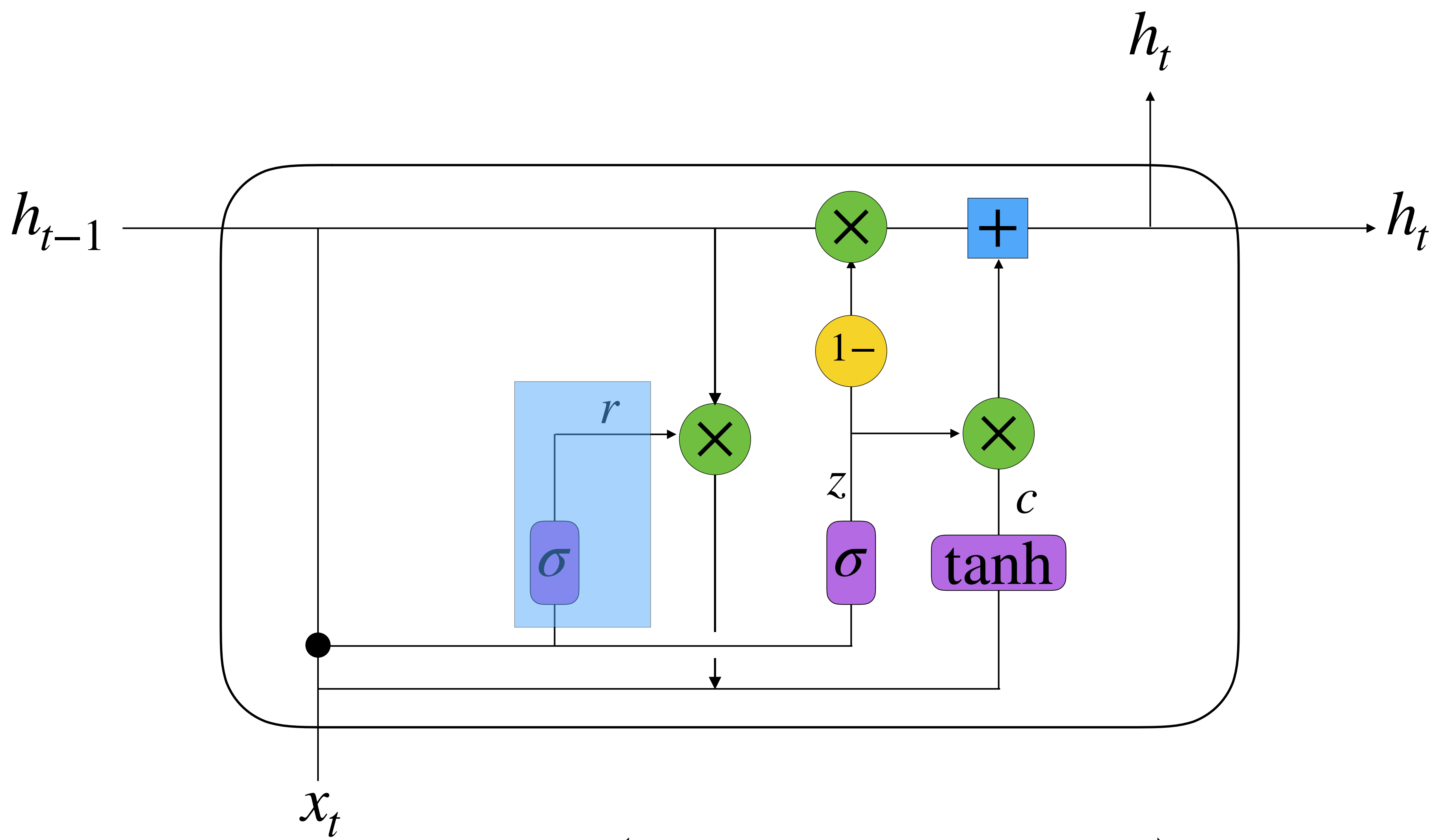
Gated Recurrent Unit (GRU)

+ Element wise addition

× Element wise multiplication

1− 1 minus the input

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



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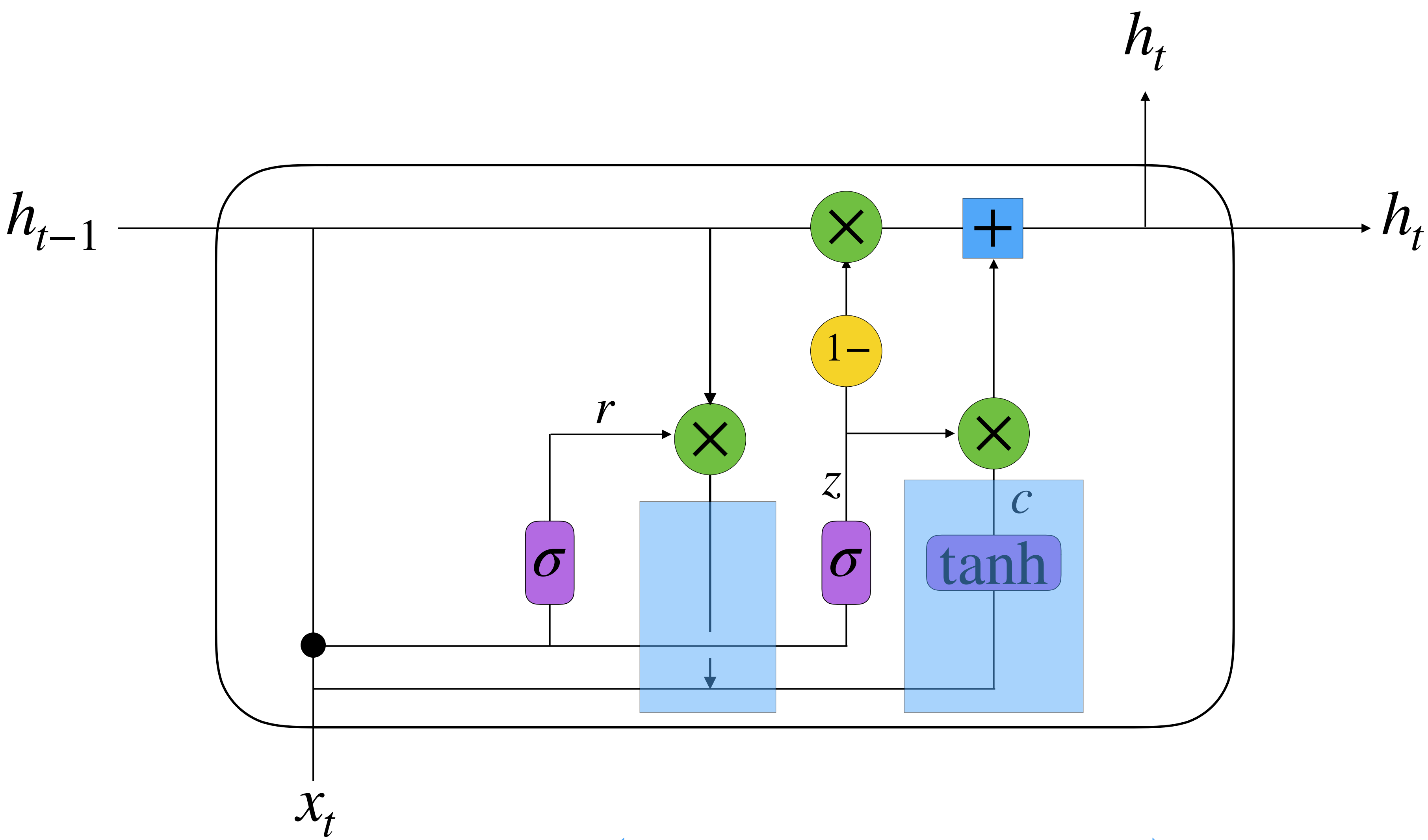
Gated Recurrent Unit (GRU)

Element wise addition

Element wise multiplication

1 minus the input



Current memory: What information do we remember right now?

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

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

$$r = \sigma\left(W_r h_{t-1} + U_r x_t\right)$$

$$h_t = (z \otimes c) + \left((1 - z) \otimes h_{t-1}\right)$$

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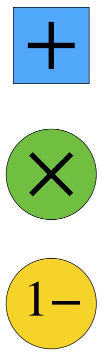
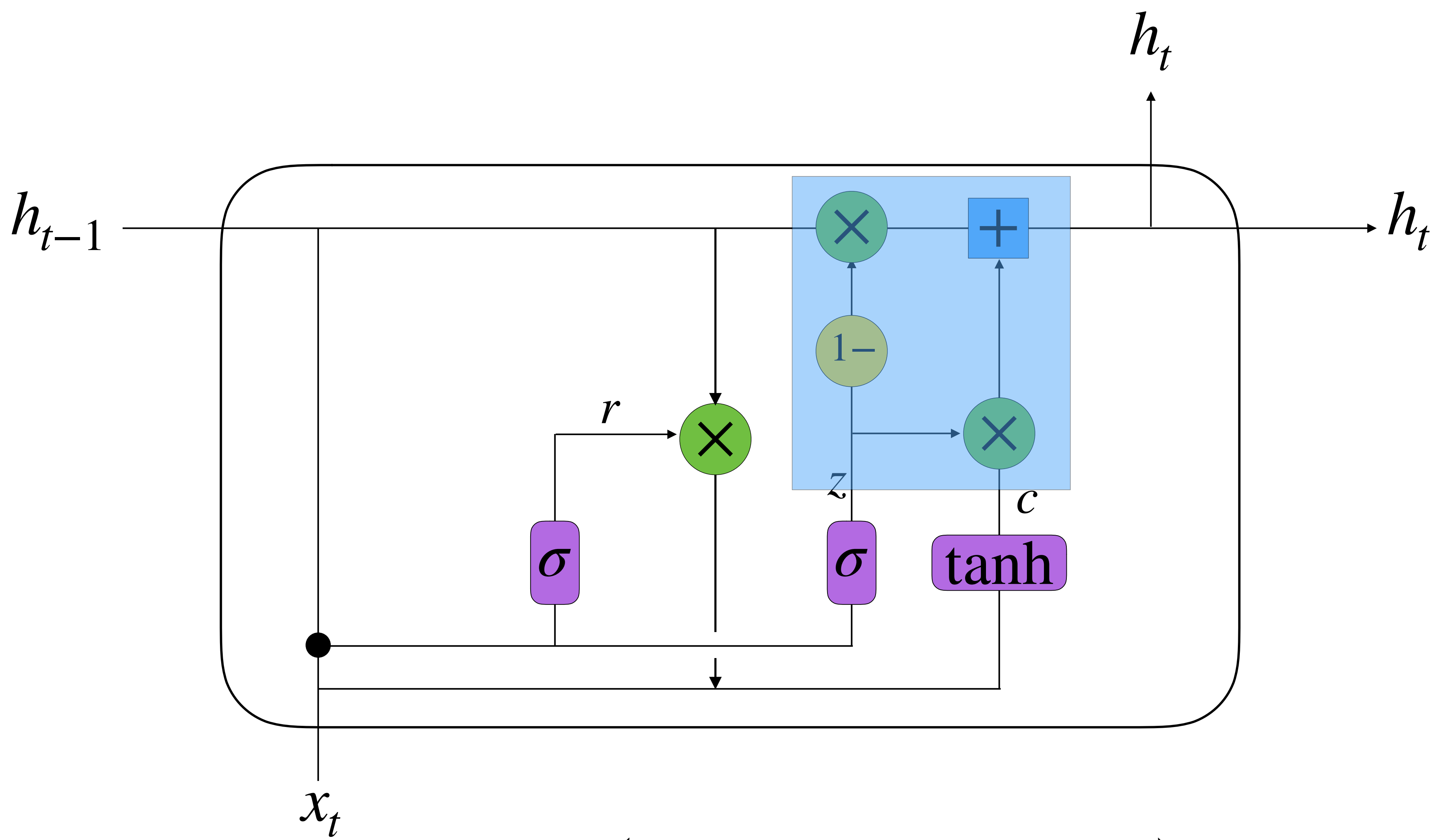
Gated Recurrent Unit (GRU)



Output:
Combine all
available
information.



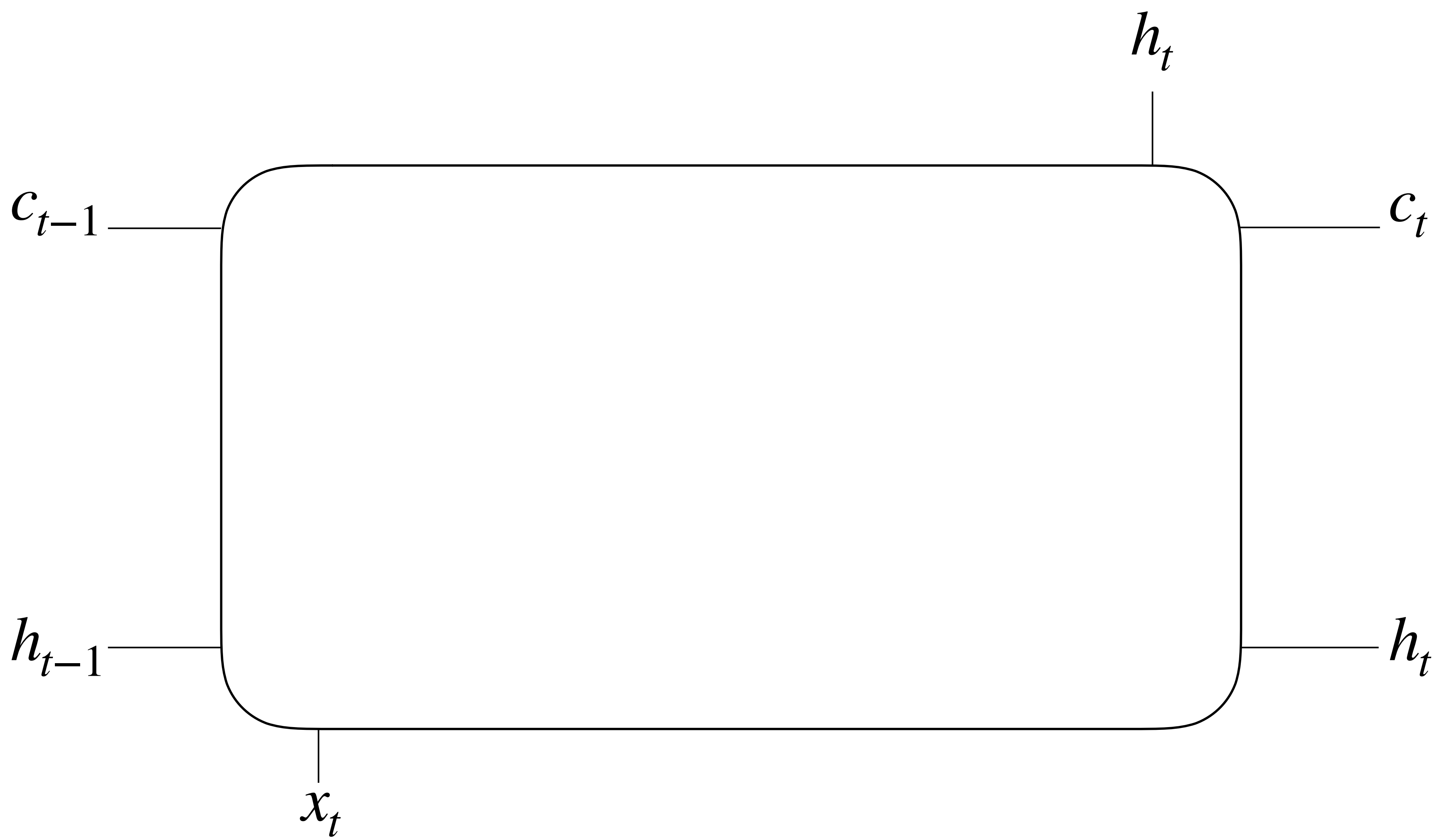
$$z = \sigma\left(W_z h_{t-1} + U_z x_t\right)$$

$$r = \sigma\left(W_r h_{t-1} + U_r x_t\right)$$

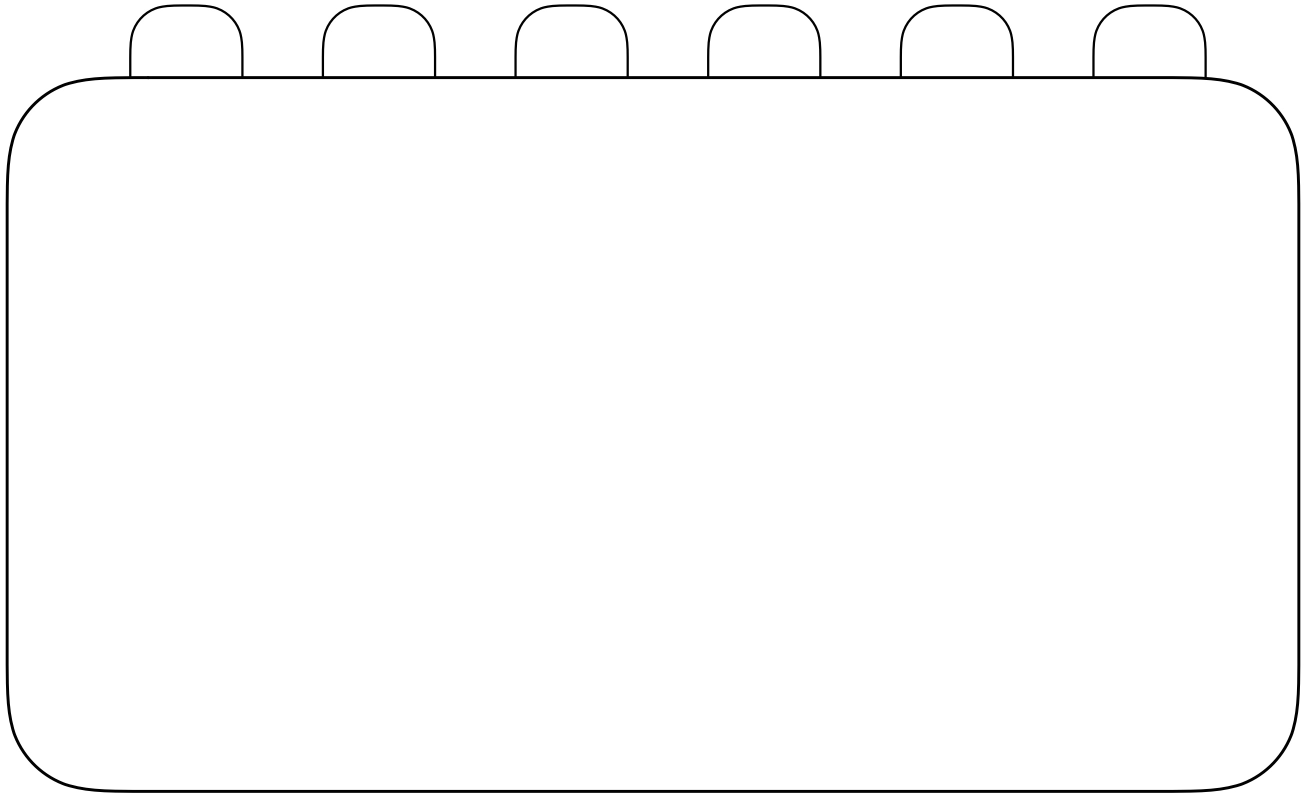
$$c = \tanh\left(W_c\left(h_{t-1} \otimes r\right) + U_c x_t\right)$$

$$h_t = (z \otimes c) + \left((1 - z) \otimes h_{t-1}\right)$$

Neural Networks?



Or legos?



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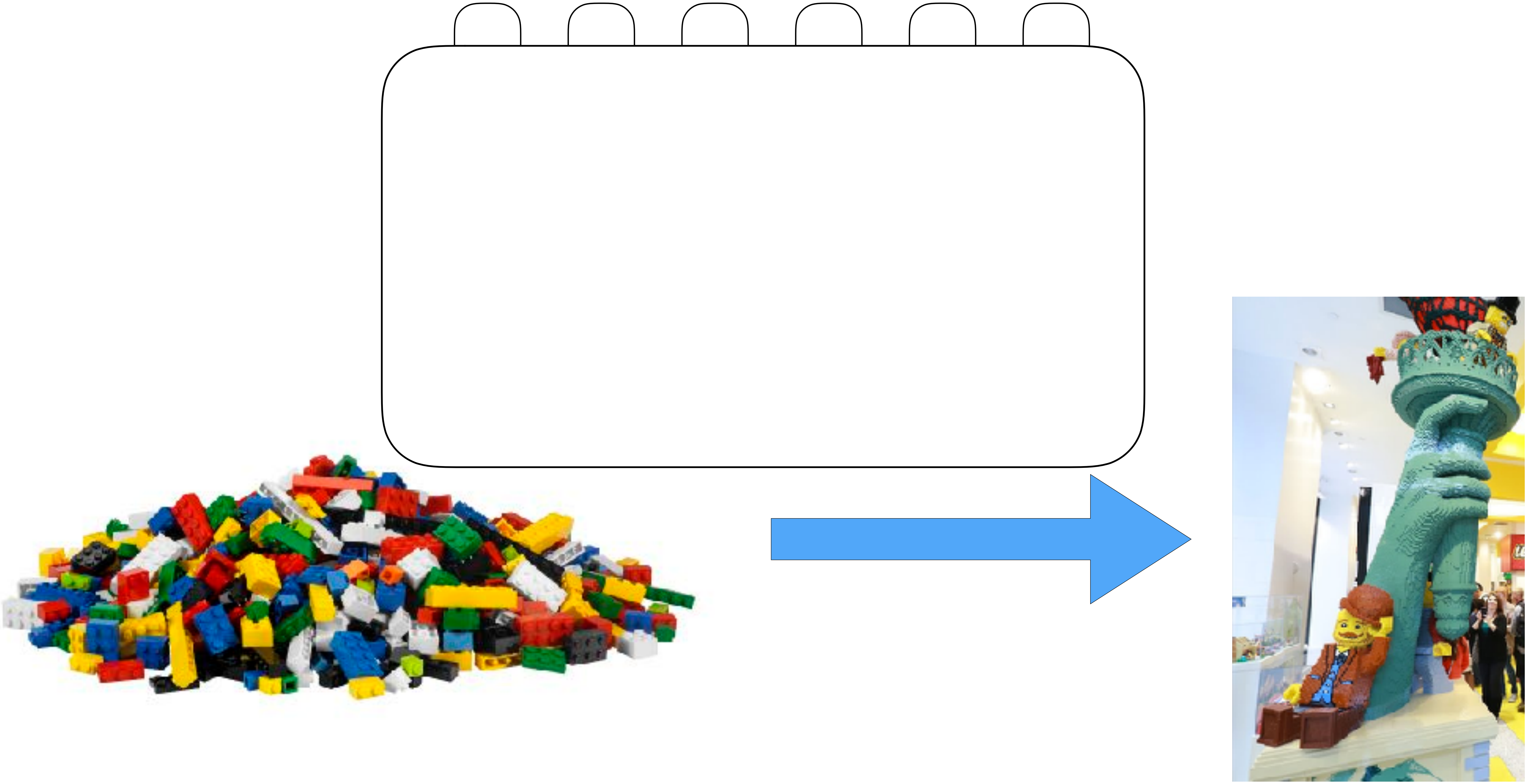

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https://keras.io

Keras

@bgoncalves

www.bgoncalves.com

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- 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