Recurrent Neural Networks

Bruno Gonçalves
www.bgoncalves.com
github.com/bmtgoncalves/RNN

NYU DATA SCIENCE

Recurr Networks

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github.com NN

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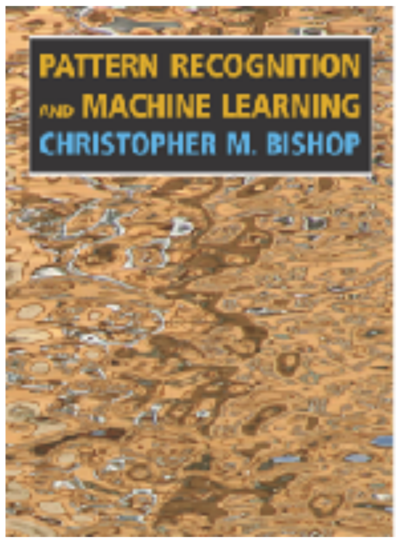
References


PATTERN RECOGNITION
AND MACHINE LEARNING
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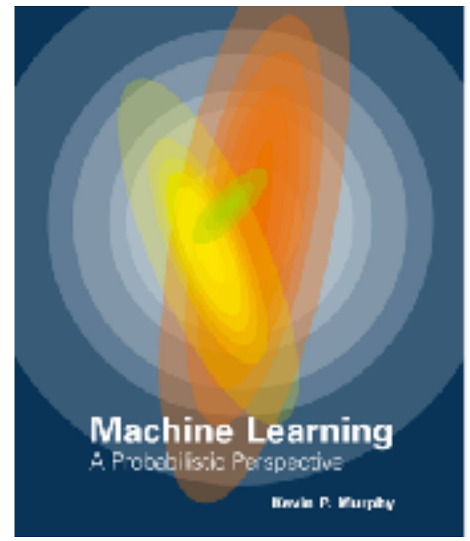
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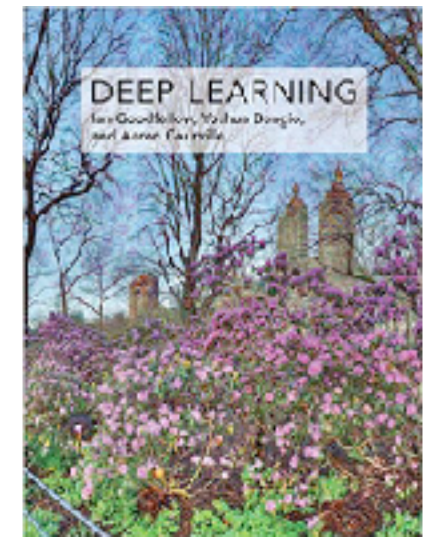
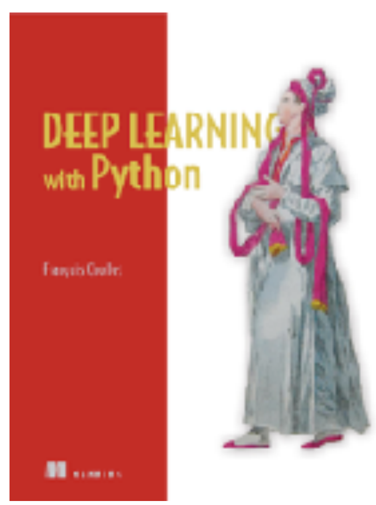
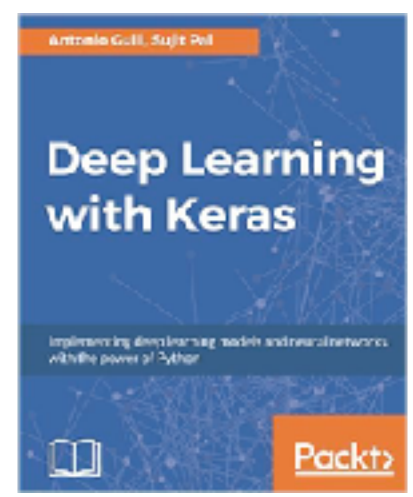

DEEP LEARNING


DEEP LEARNING
with Python


Antonio Gulli, Sujit Pal
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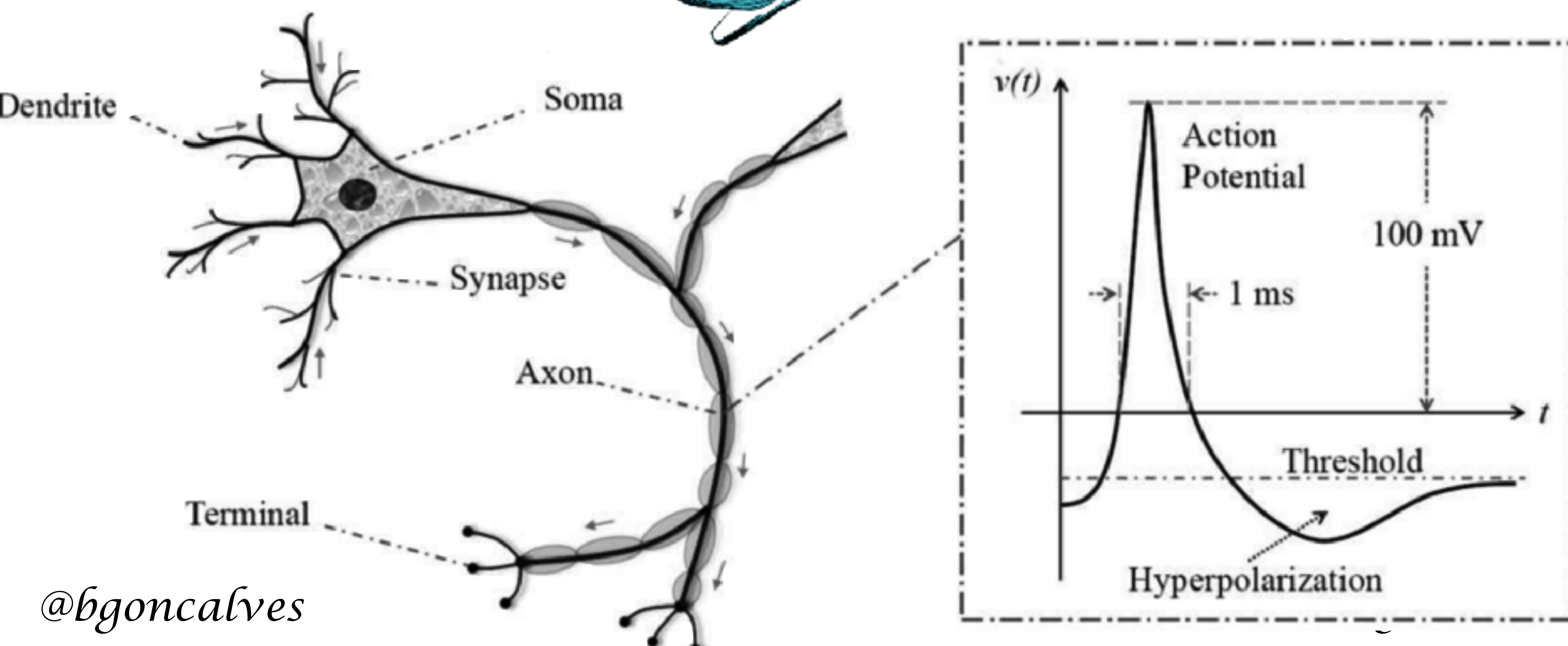
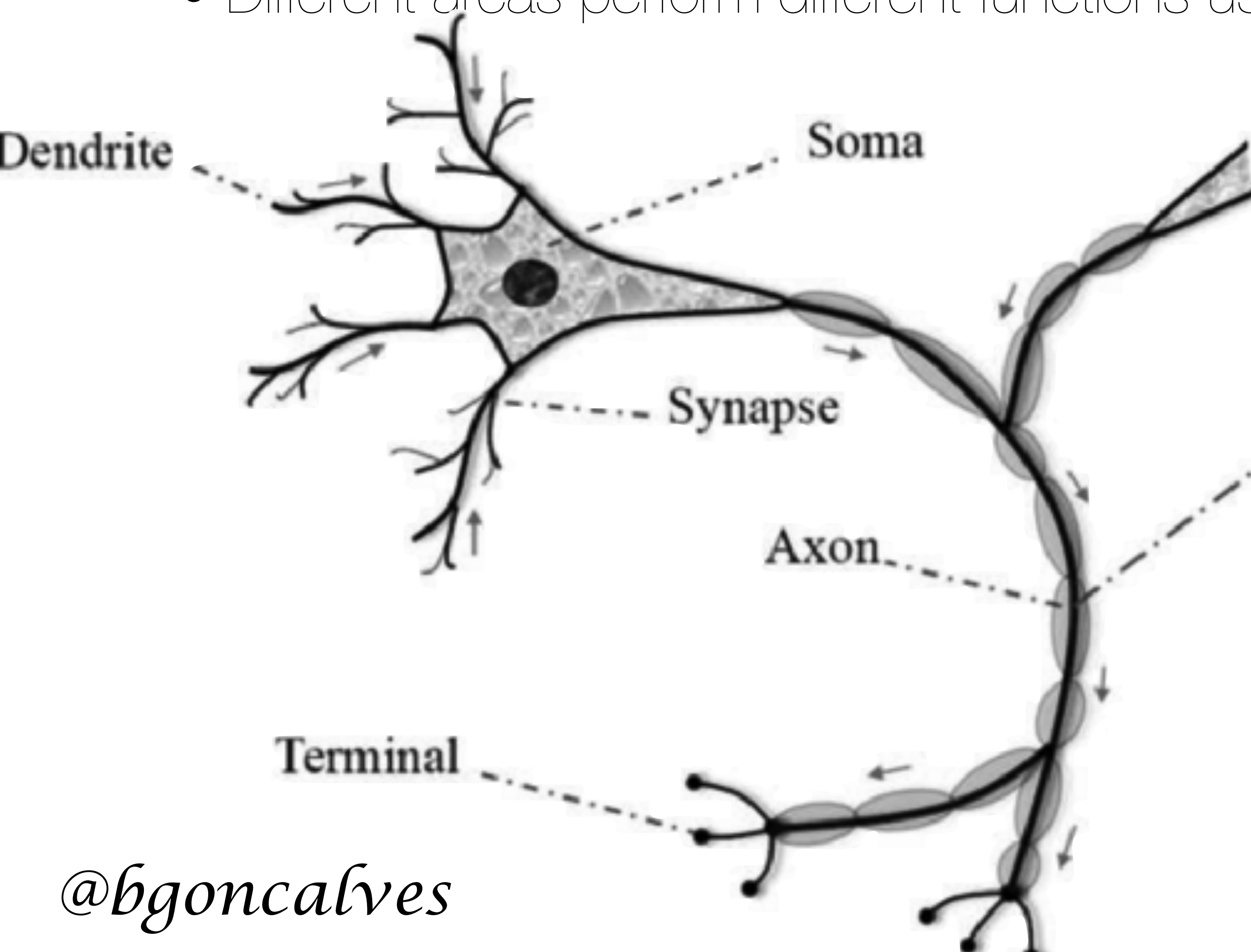
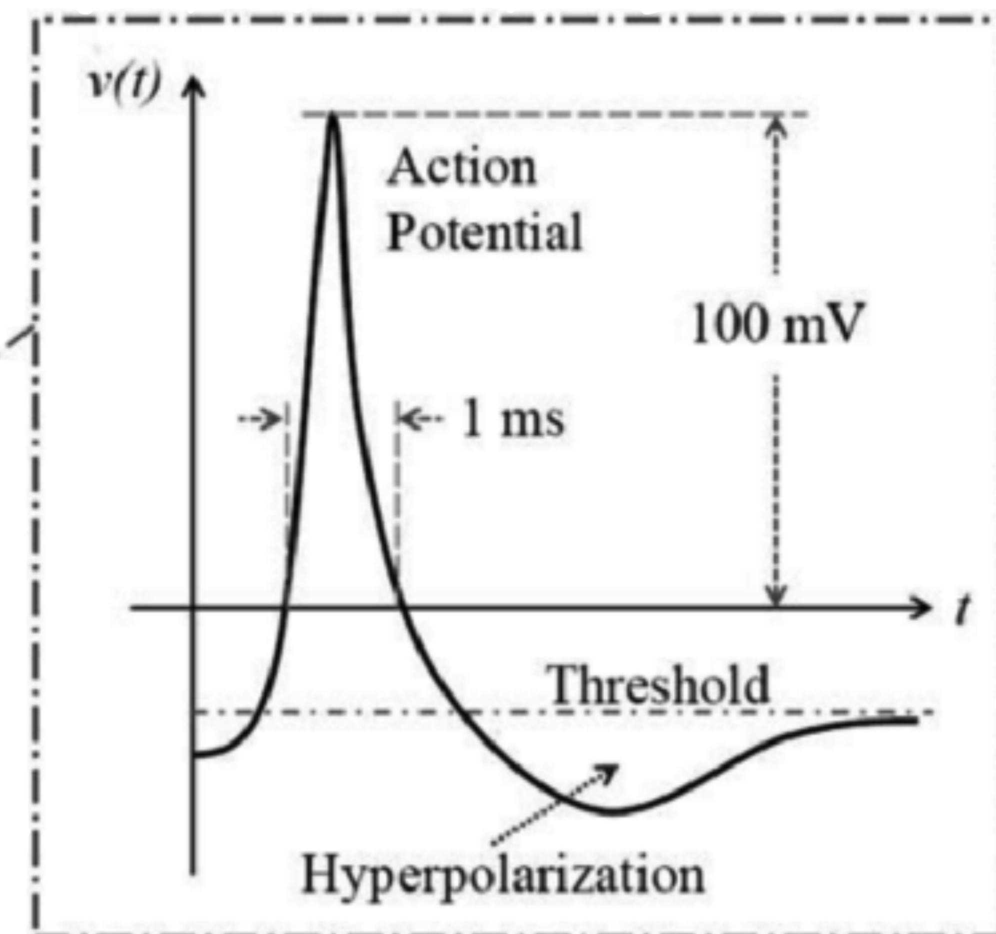
How the Brain "Works" (Cartoon version)



How the Brain “Works” (Cartoon version)

- Each neuron receives input from other neurons
- 10^{11} neurons, each with with 10^4 weights
- Weights can be positive or negative
- Weights adapt during the learning process
- “neurons that fire together wire together” (Hebb)
- Different areas perform different functions using same structure (Modularity)





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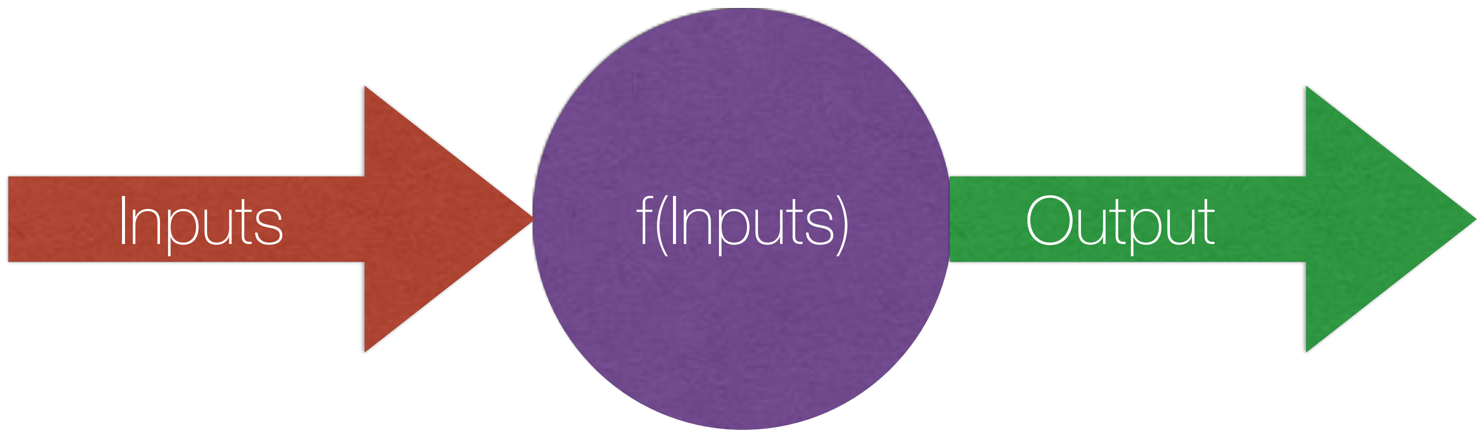
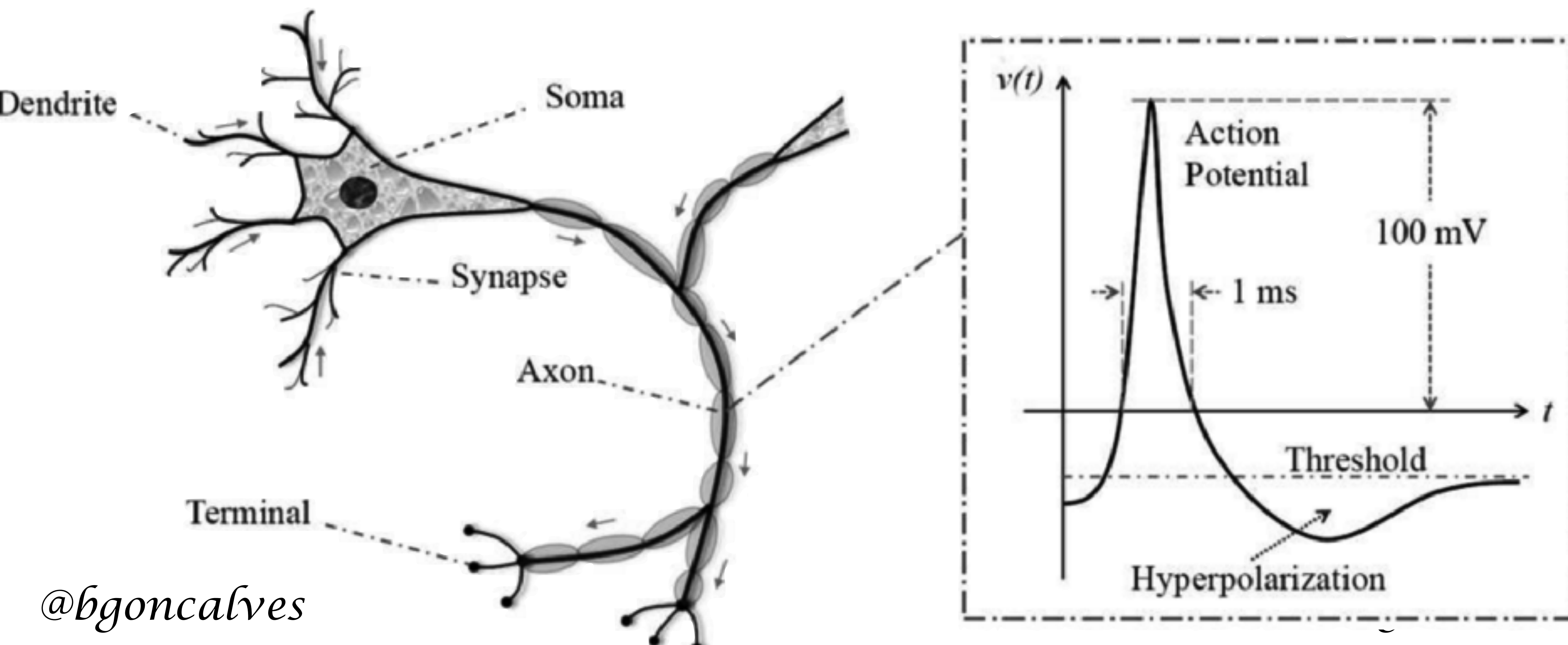
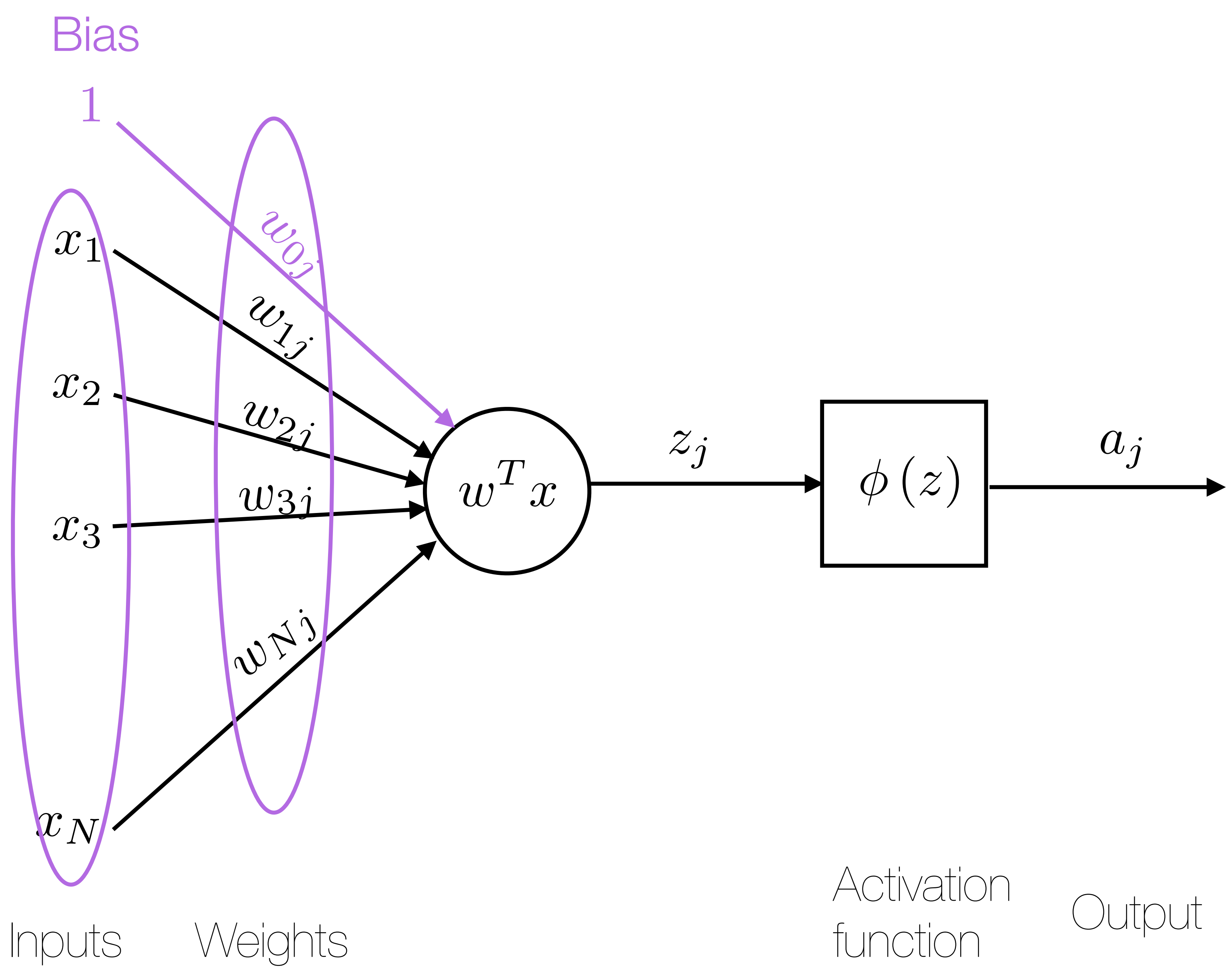




Optimization Problem

- (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

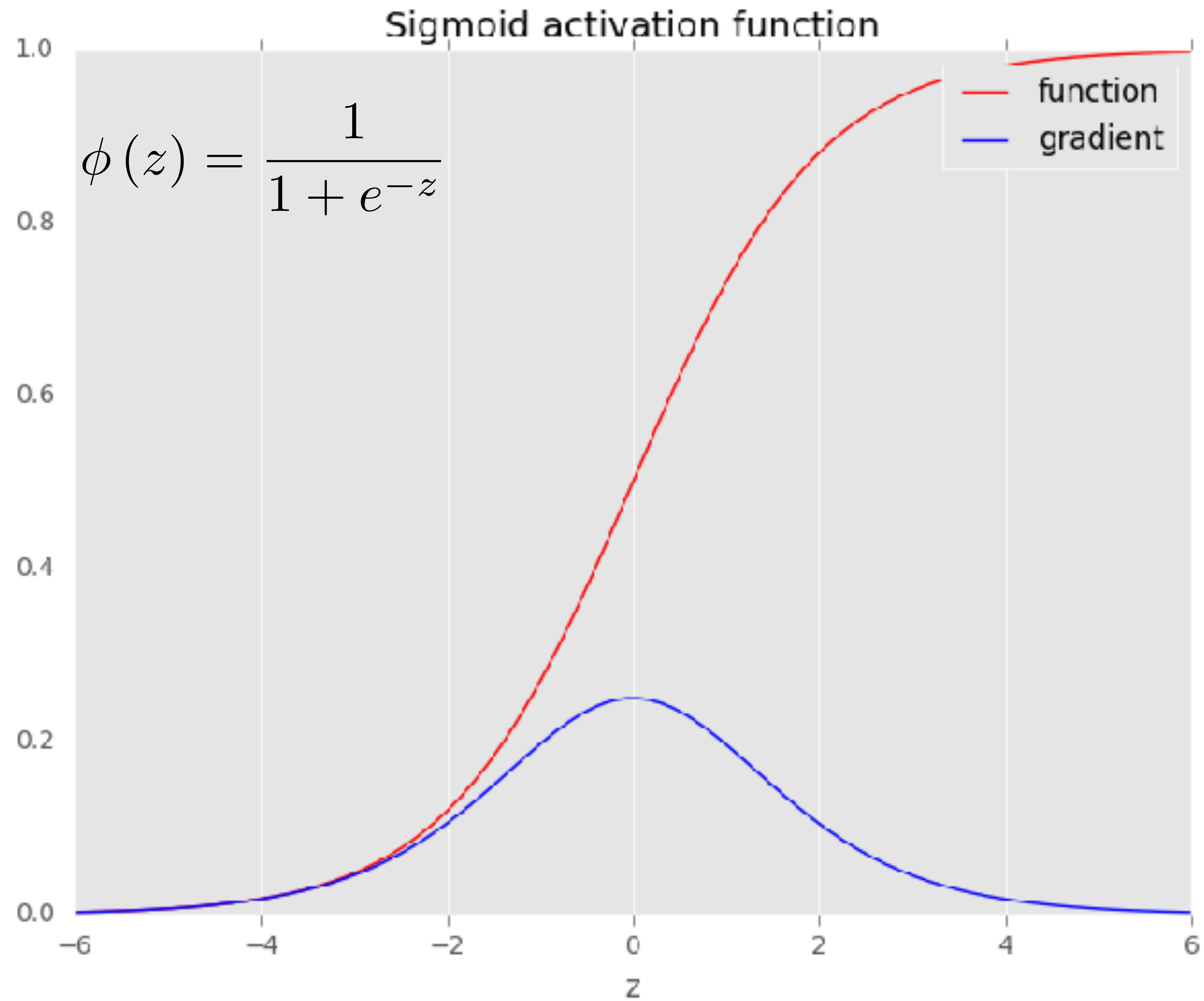
Artificial Neuron



Activation Function - Sigmoid

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

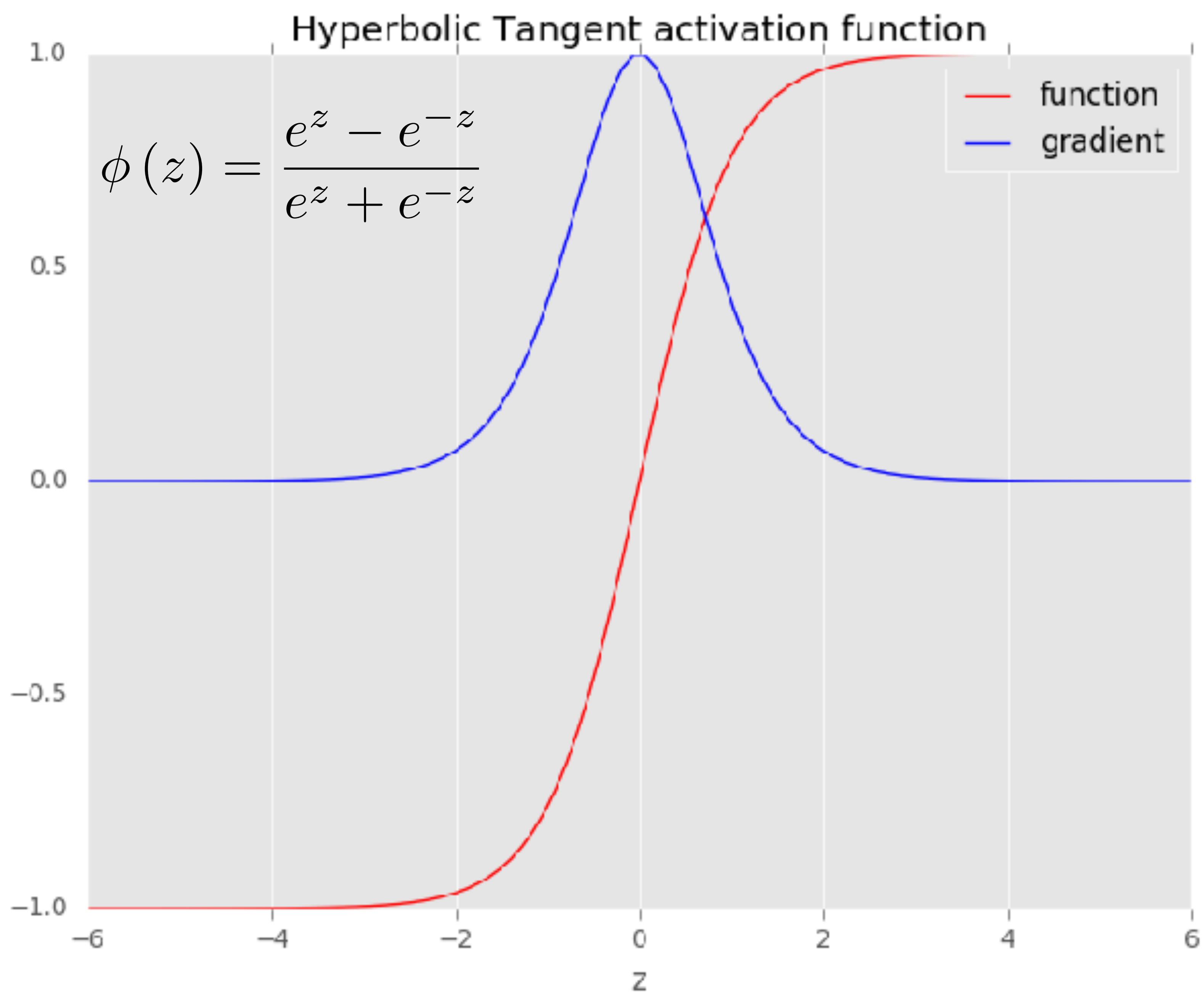
- Non-Linear function
- Differentiable
- non-decreasing
- Compute new sets of features
- Each layer builds up a more abstract representation of the data
- Perhaps the most common



Activation Function - tanh

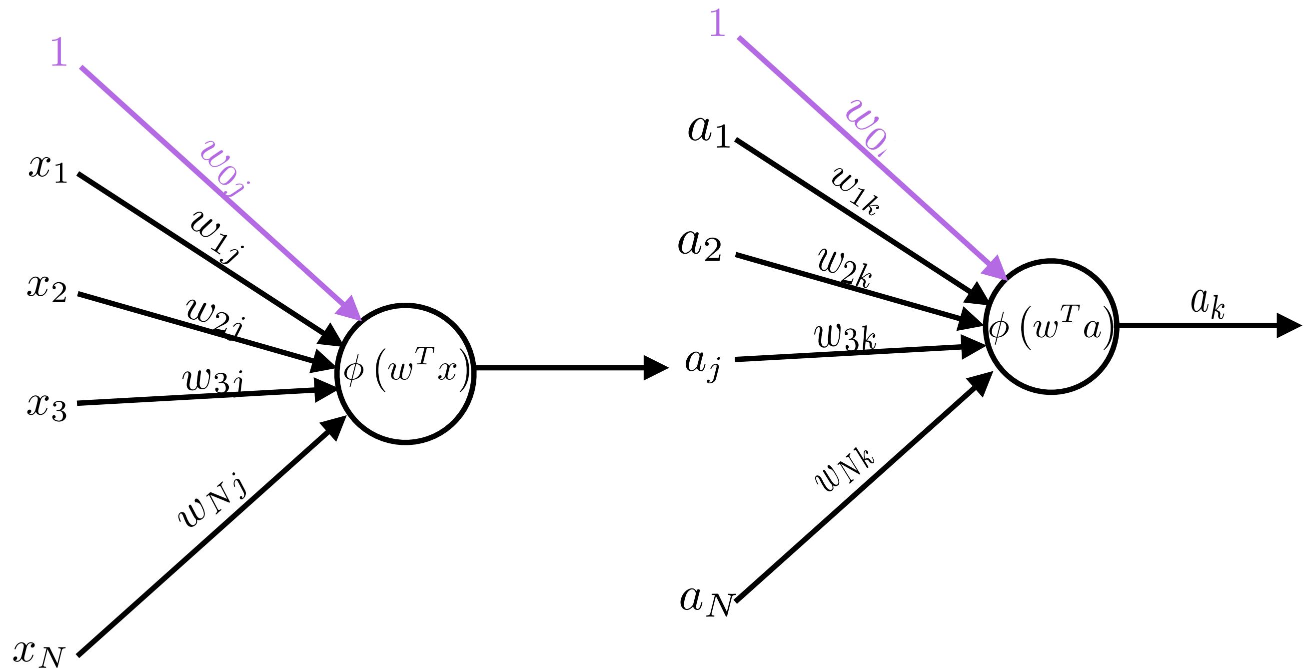
http://github.com/bmtgoncalves/Neural-Networks

- Non-Linear function
- Differentiable
- non-decreasing
- Compute new sets of features
- Each layer builds up a more abstract representation of the data



Forward Propagation

- The output of a perceptron is determined by a sequence of steps:
    - obtain the inputs
    - multiply the inputs by the respective weights
    - calculate output using the activation function
- To create a multi-layer perceptron, you can simply use the output of one layer as the input to the next one.



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

Backward Propagation of Errors (BackProp)

- BackProp operates in two phases:
  - Forward propagate the inputs and calculate the deltas
  - Update the weights
- The error at the output is a weighted average difference between predicted output and the observed one.
- For inner layers there is no “real output”!

Loss Functions

- For learning to occur, we must quantify how far off we are from the desired output. There are two common ways of doing this:

  - Quadratic error function:

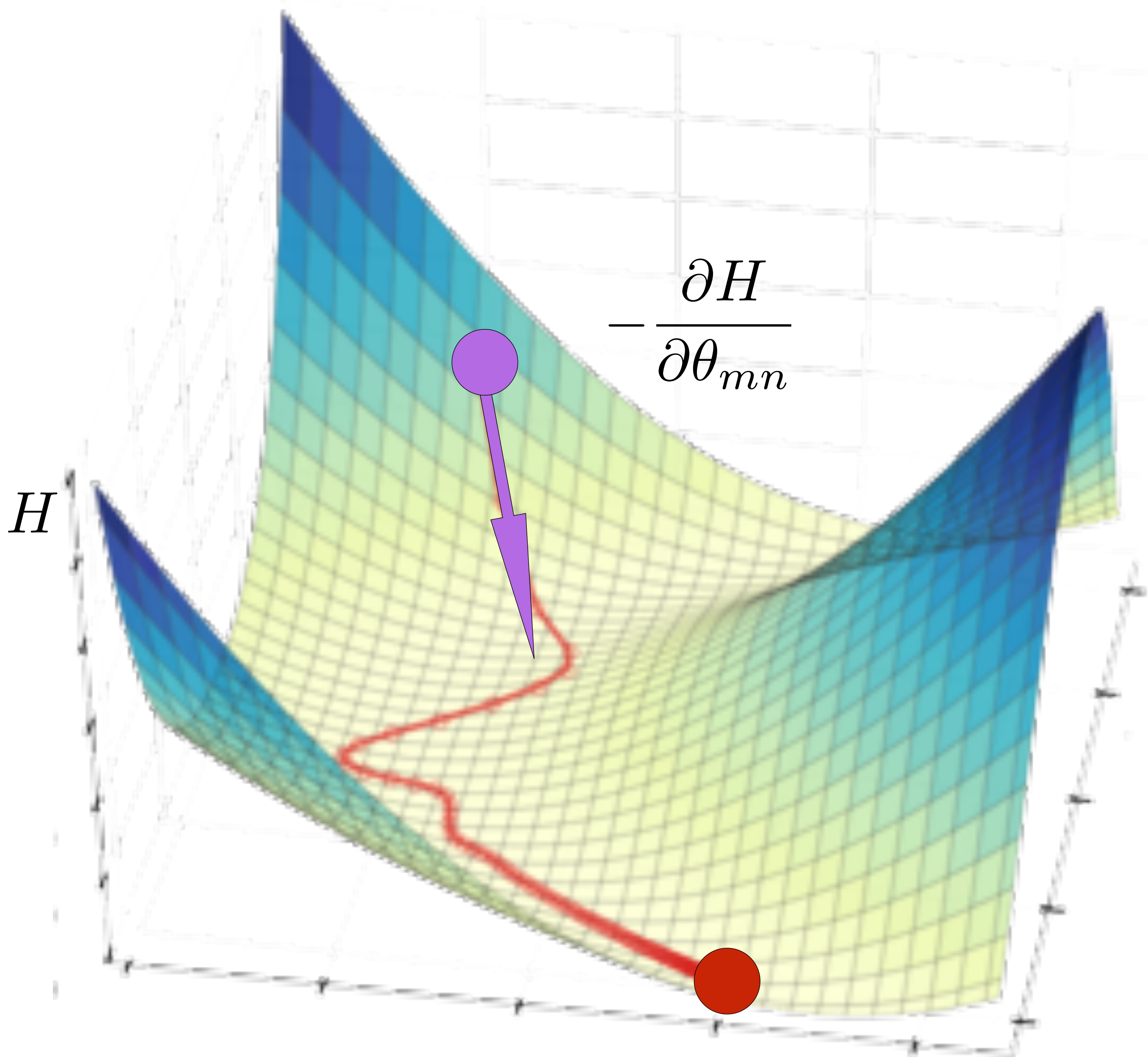
$$E = \frac{1}{N} \sum_n |y_n - a_n|^2$$

  - Cross Entropy

$$J = -\frac{1}{N} \sum_n \left[y_n^T \log a_n + (1 - y_n)^T \log (1 - a_n) \right]$$

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

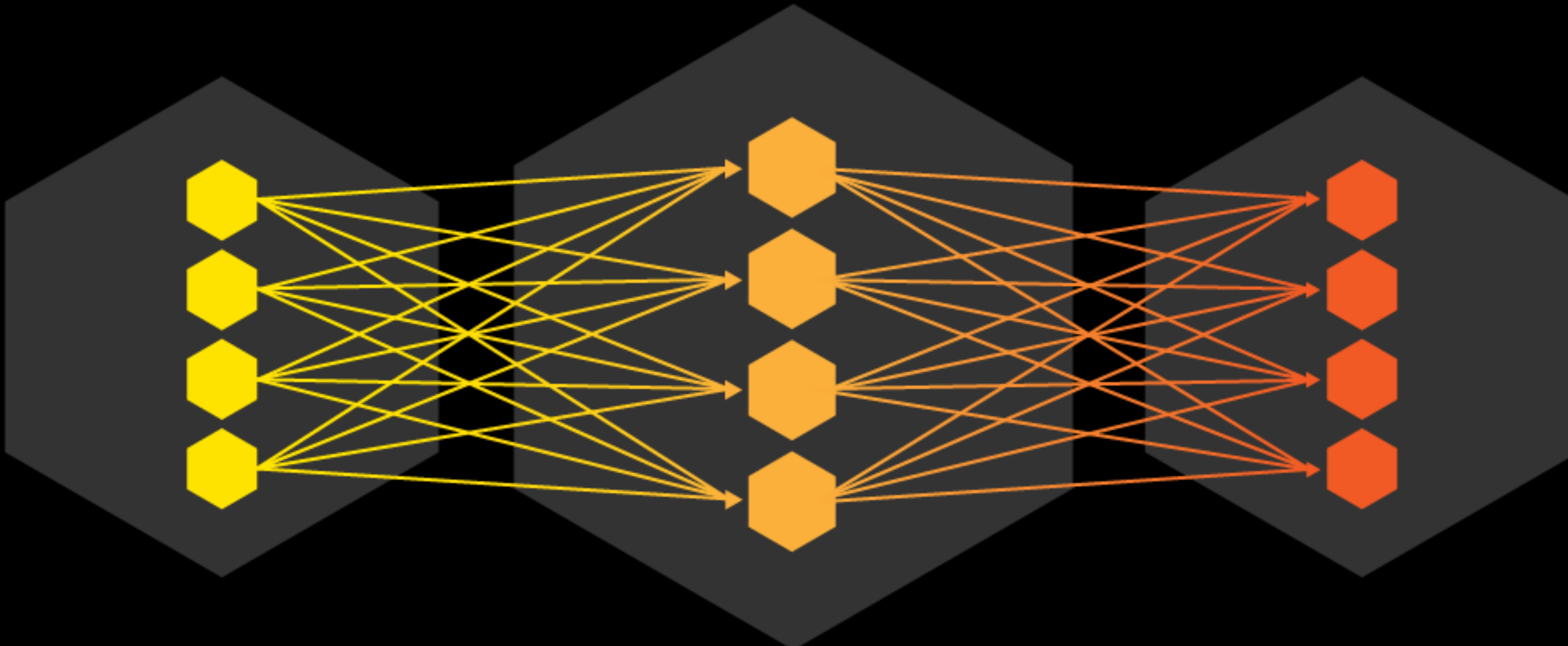
Gradient Descent



- 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.
- Repeat until "convergence".



INPUT TERMS

FEATURES
PREDICTIONS
ATTRIBUTES
PREDICTABLE VARIABLES

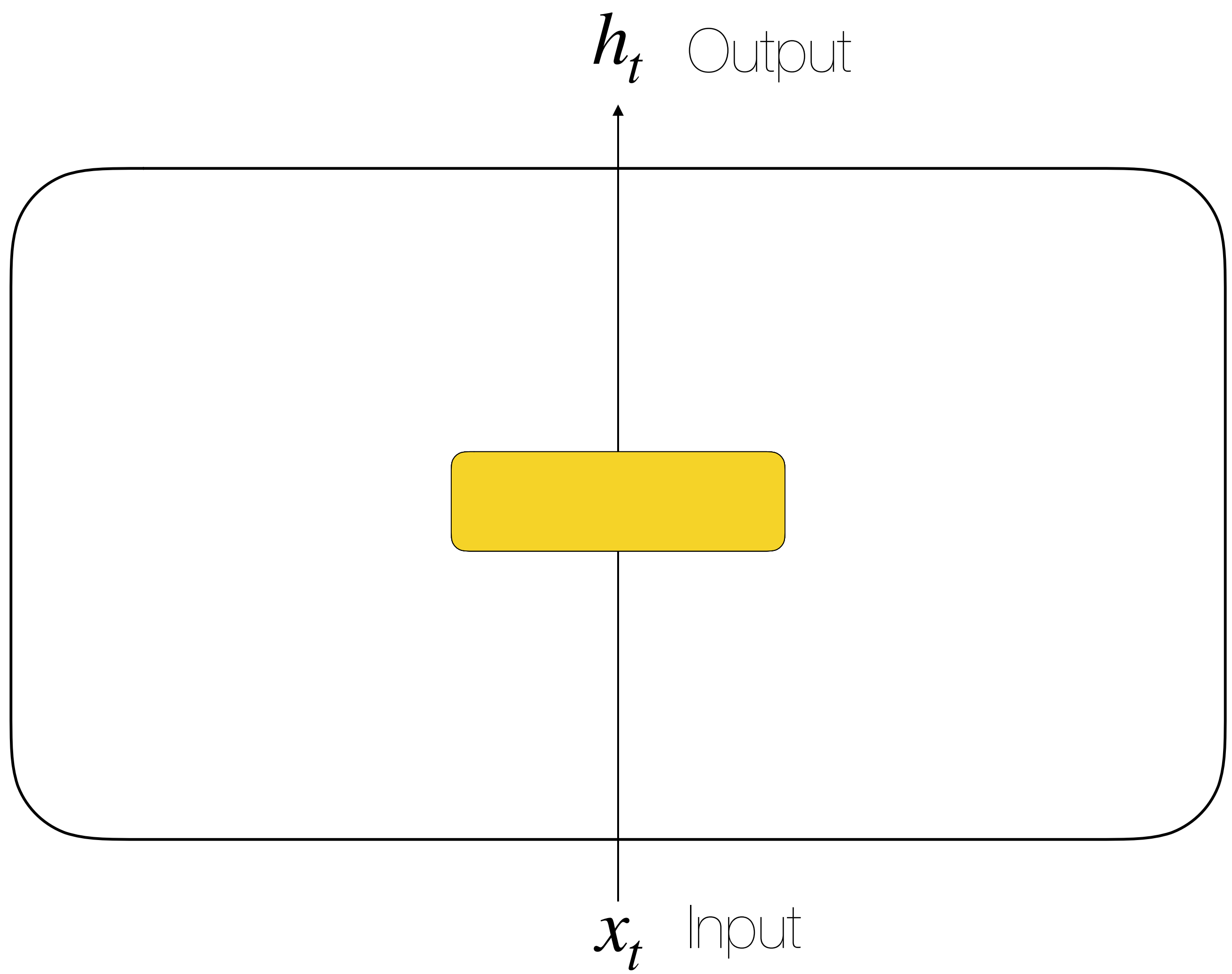
MACHINE

ALGORITHMS
TECHNIQUES
MODELS

OUTPUT TERMS

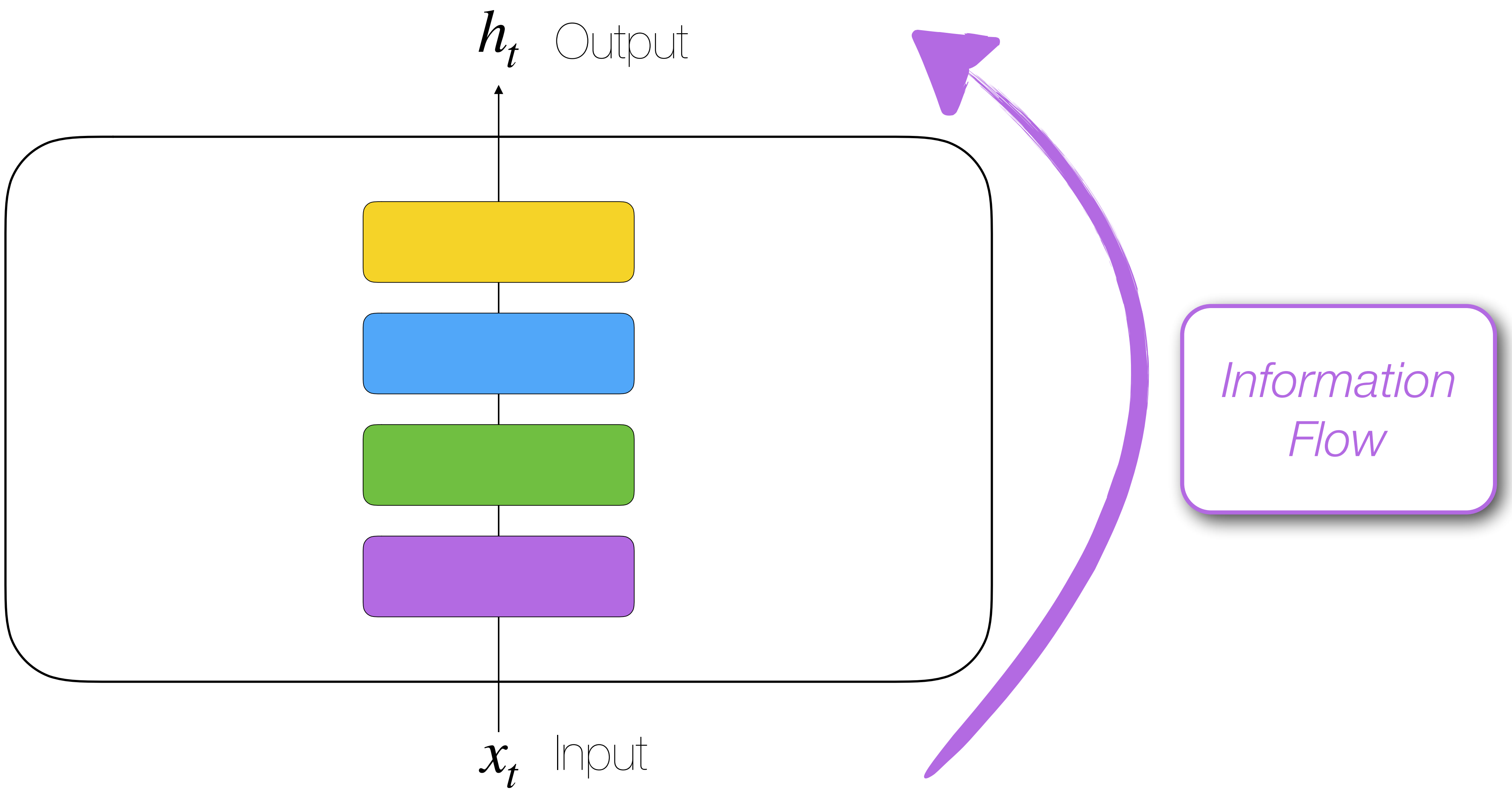
CLASSES
RESPONSES
TARGETS
DEPENDANT VARIABLES

Feed Forward Networks



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

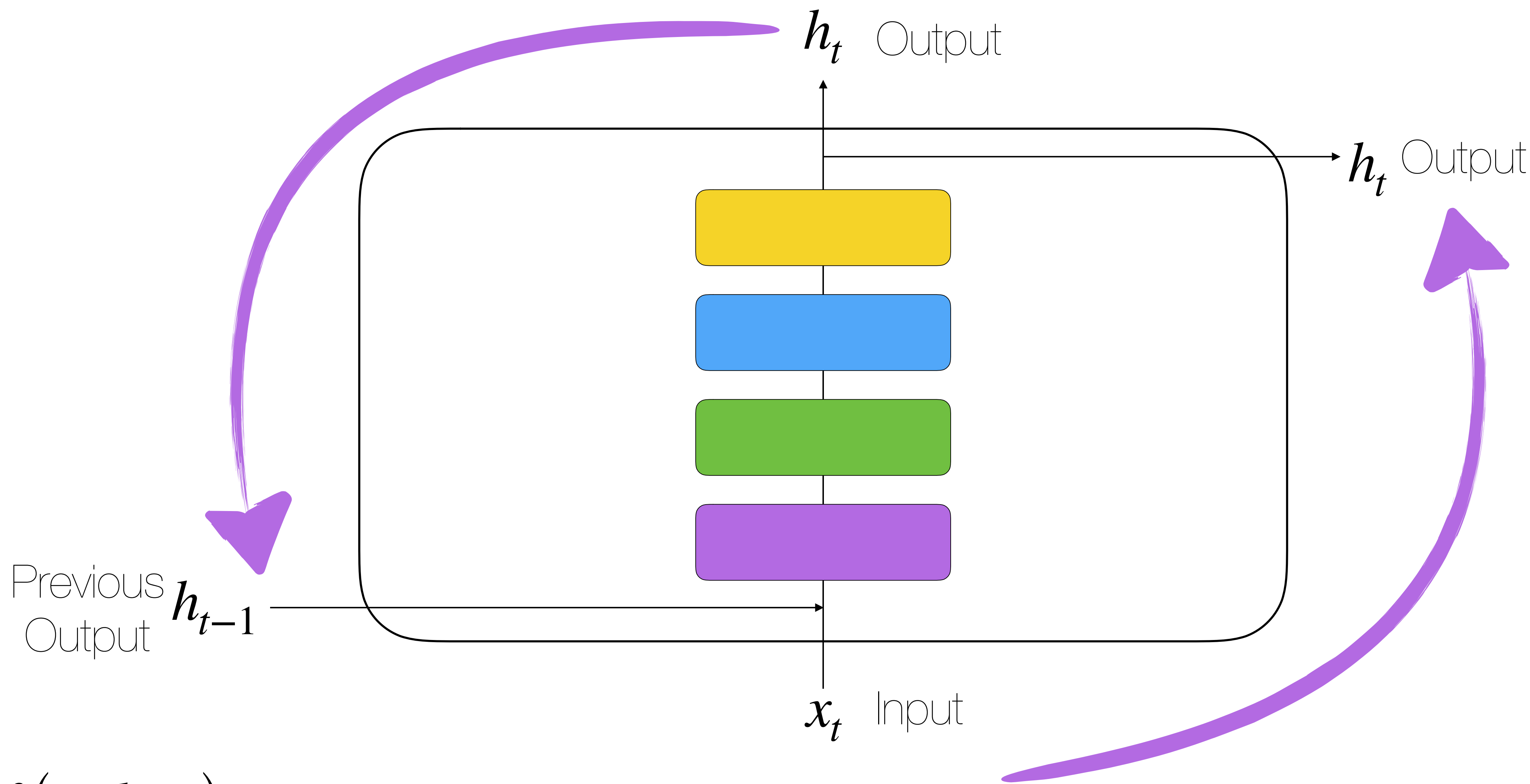
Feed Forward Networks



$$h_t = f(x_t)$$

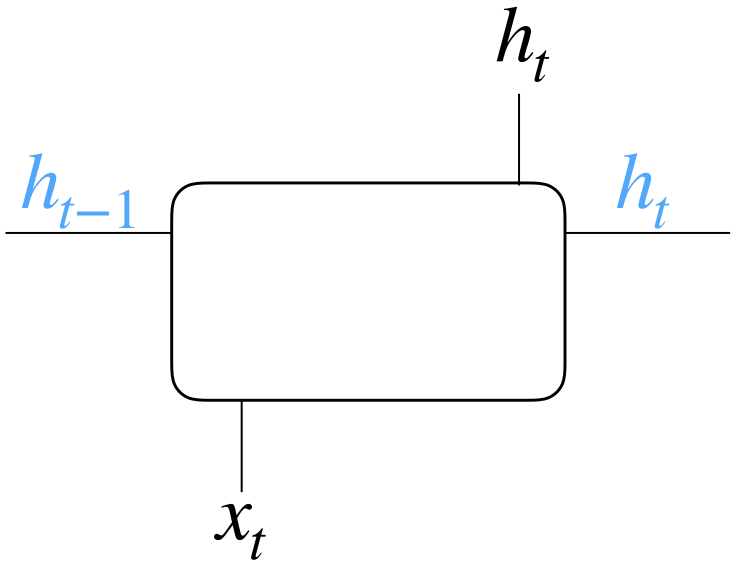
Recurrent Neural Network (RNN)

Information Flow



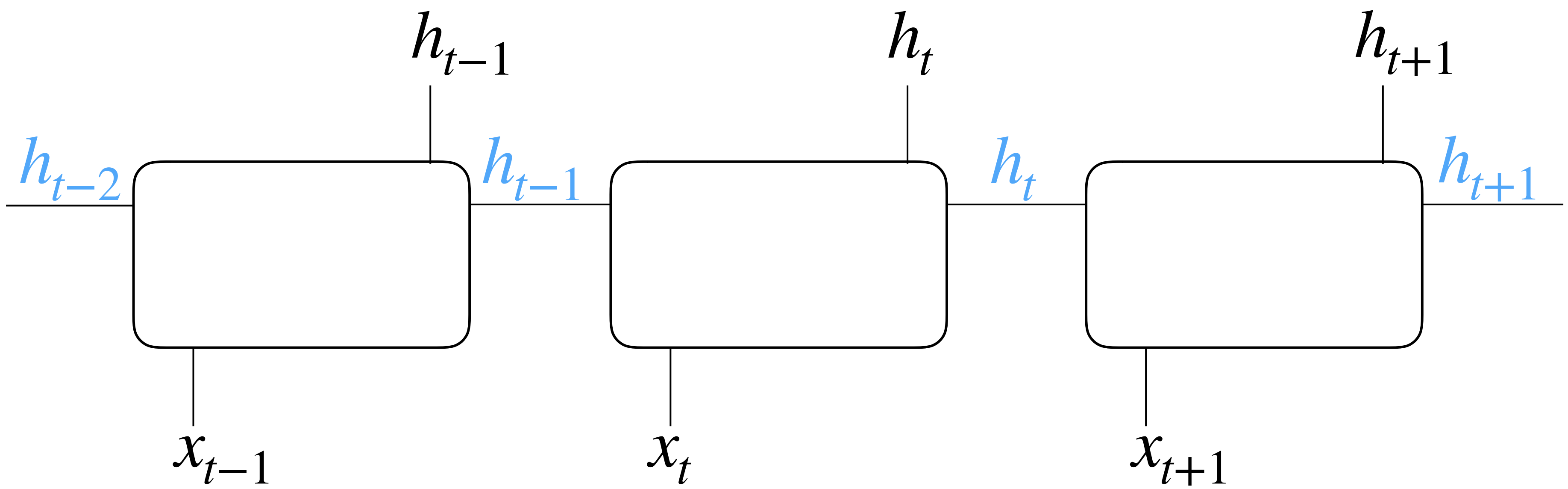
$$h_t = f\left(x_t, h_{t-1}\right)$$

Recurrent Neural Network (RNN)



Recurrent Neural Network (RNN)

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



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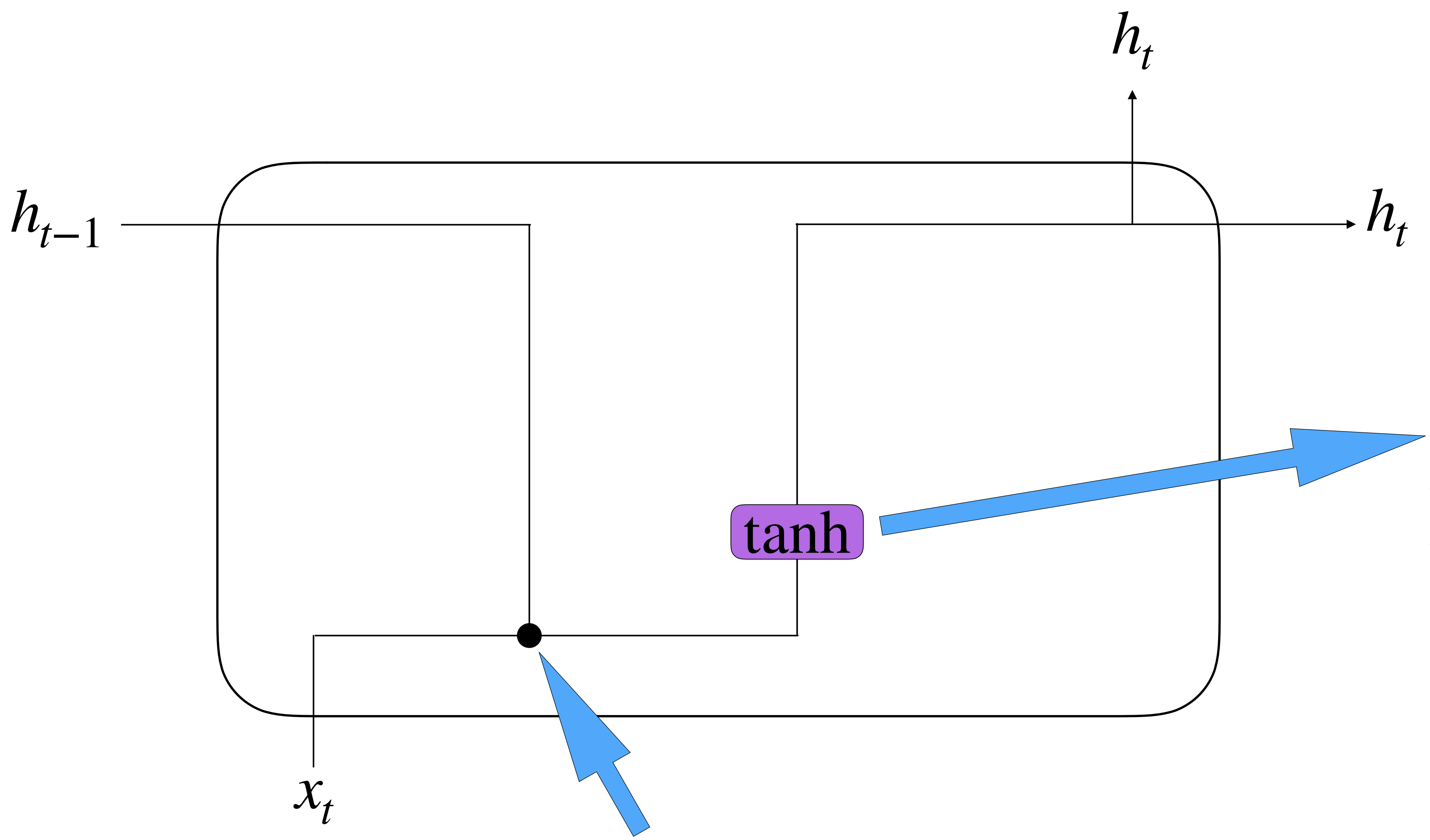
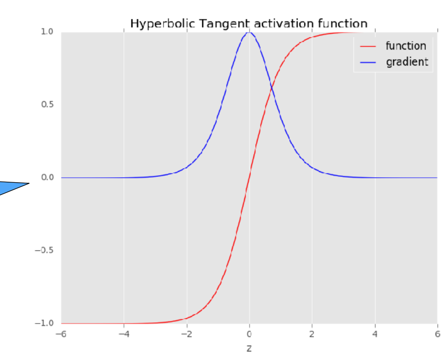
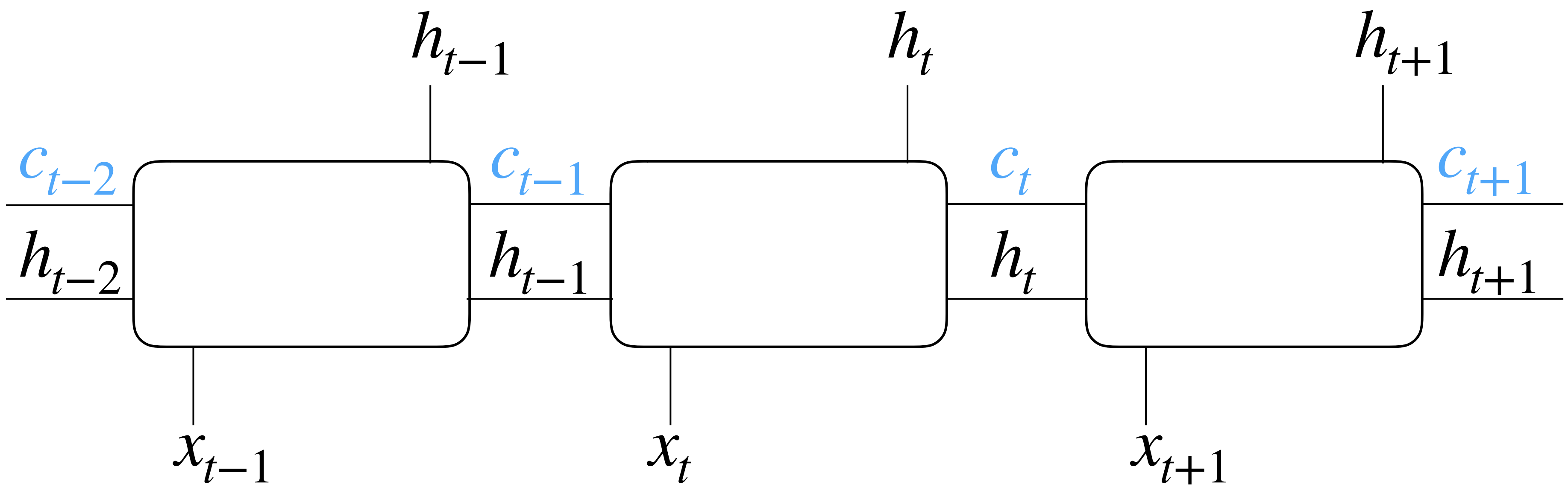




Concatenate both inputs.

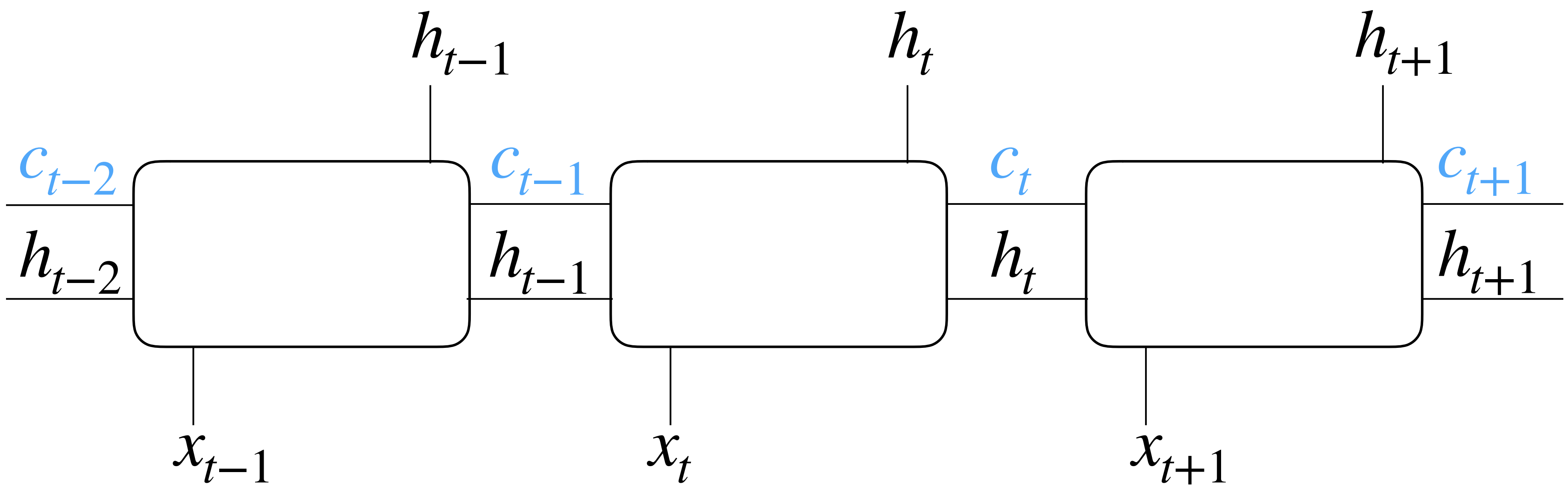
$$h_t = \tanh\left(Wh_{t-1} + Ux_t\right)$$

Long-Short Term Memory (LSTM)



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

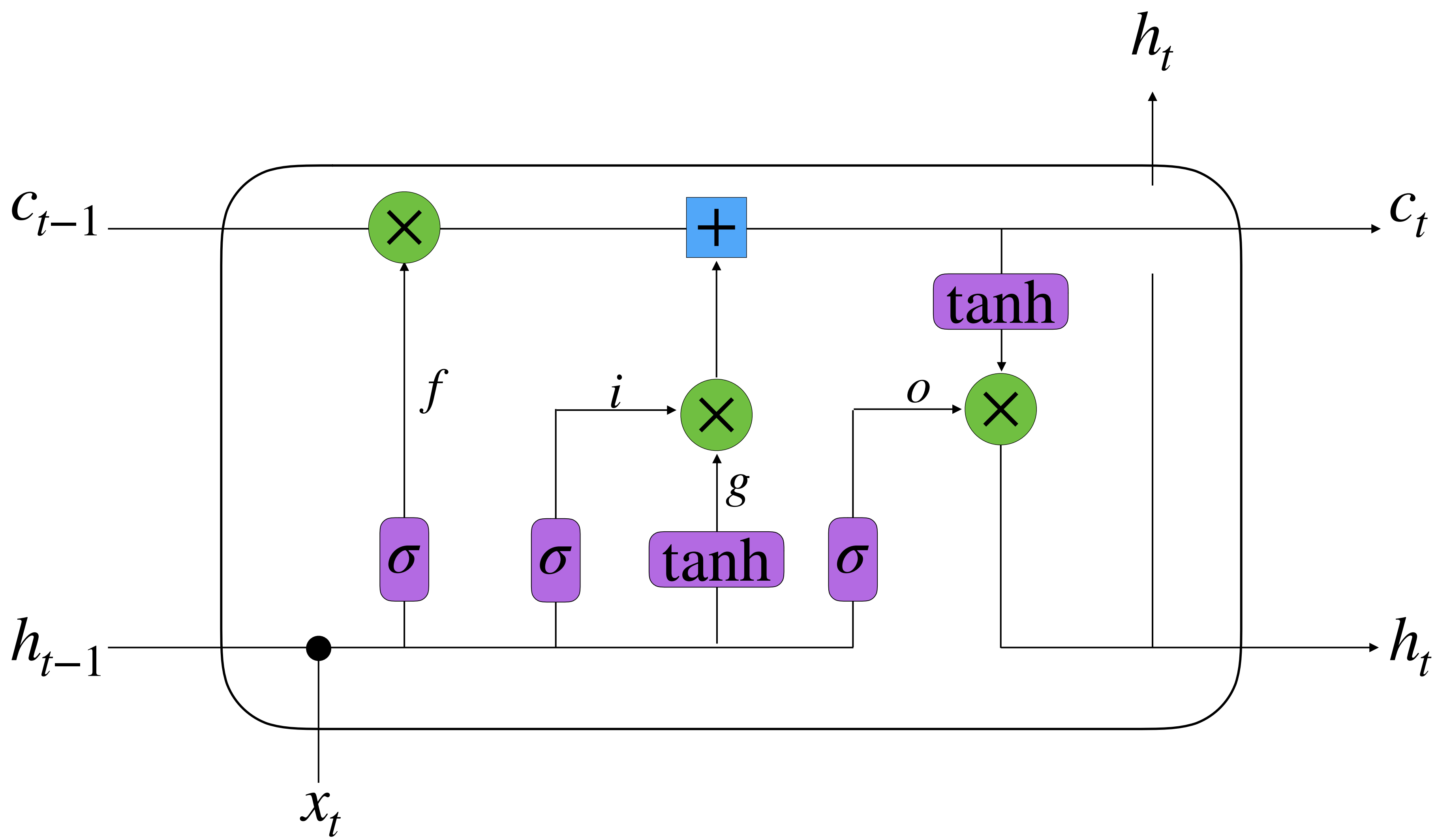


Long-Short Term Memory (LSTM)

Element wise addition

Element wise multiplication

1− 1 minus the input



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

$$i = \sigma\left(W_i h_{t-1} + U_i x_t\right) \qquad c_t = \left(c_{t-1} \otimes f\right) + \left(g \otimes i\right)$$

$$o = \sigma\left(W_o h_{t-1} + U_o x_t\right) \qquad h_t = \tanh\left(c_t\right) \otimes o$$

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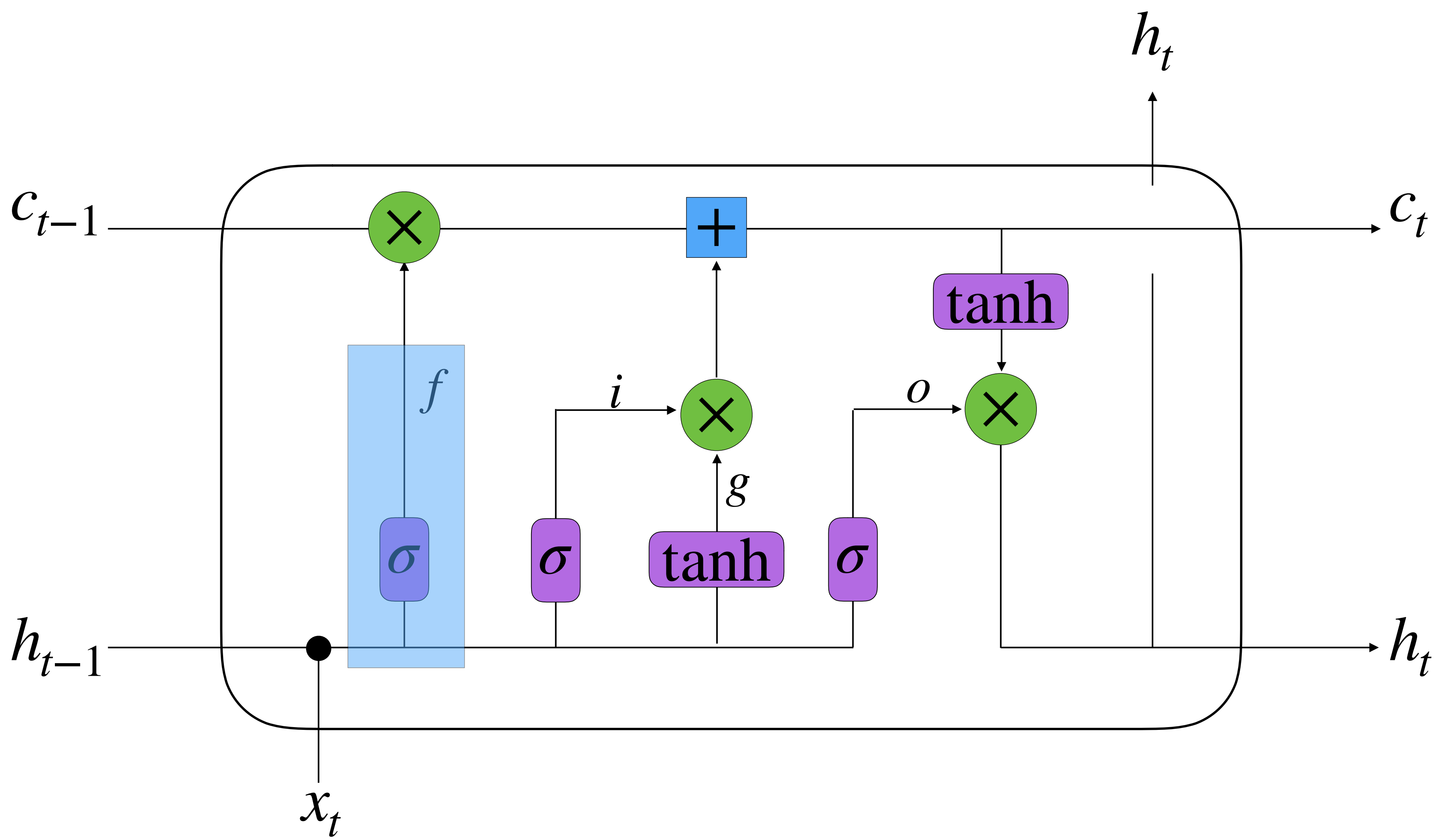
Long-Short Term Memory (LSTM)

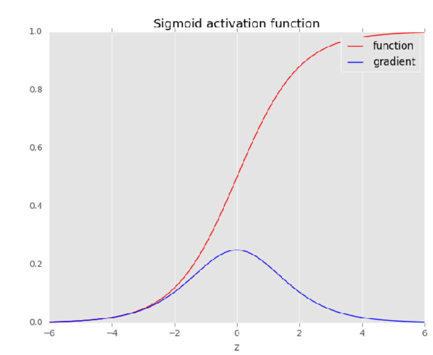
+ Element wise addition

× Element wise multiplication

1− 1 minus the input

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





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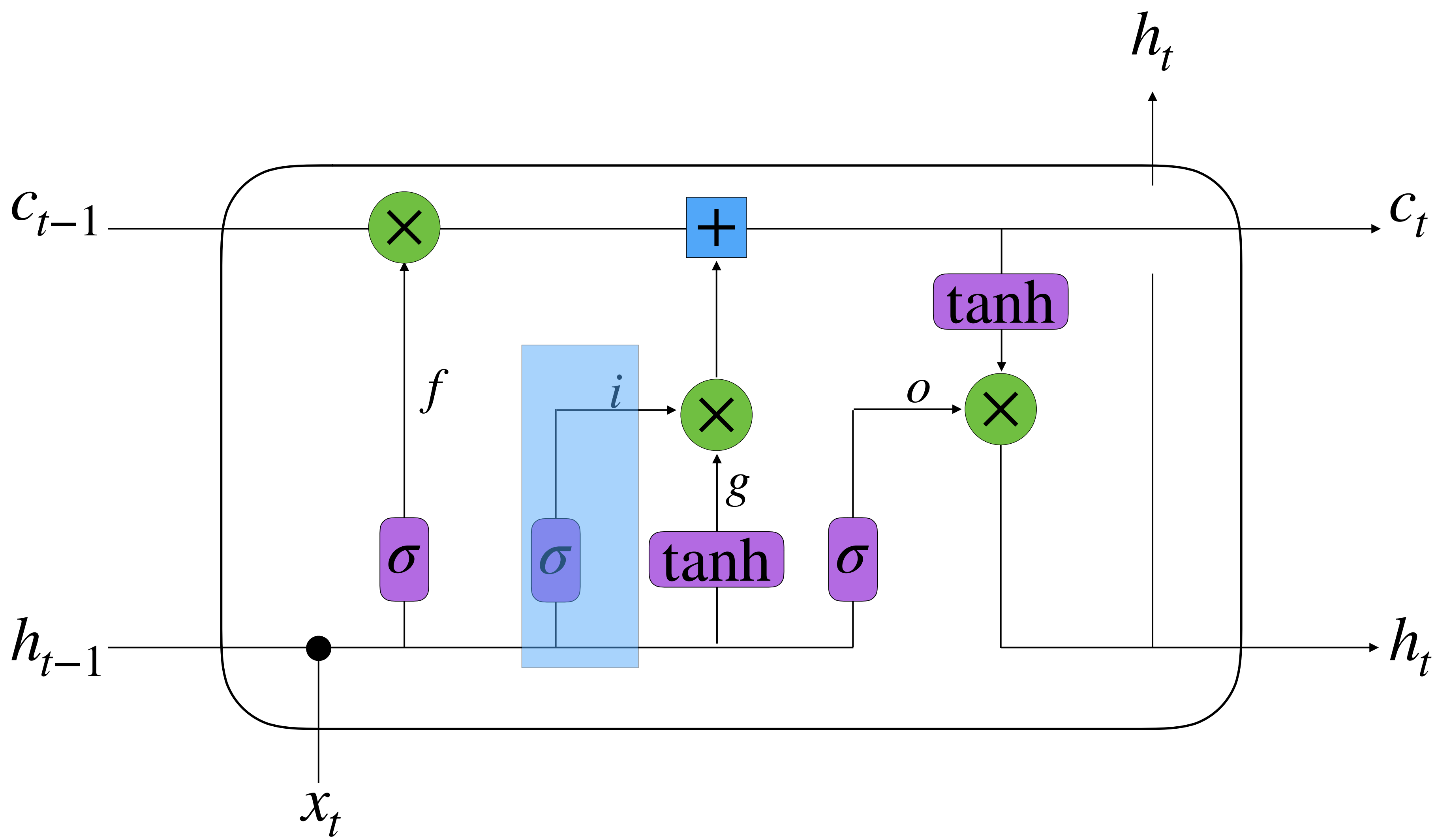
Long-Short Term Memory (LSTM)

Element wise addition

Element wise multiplication

1− 1 minus the input

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



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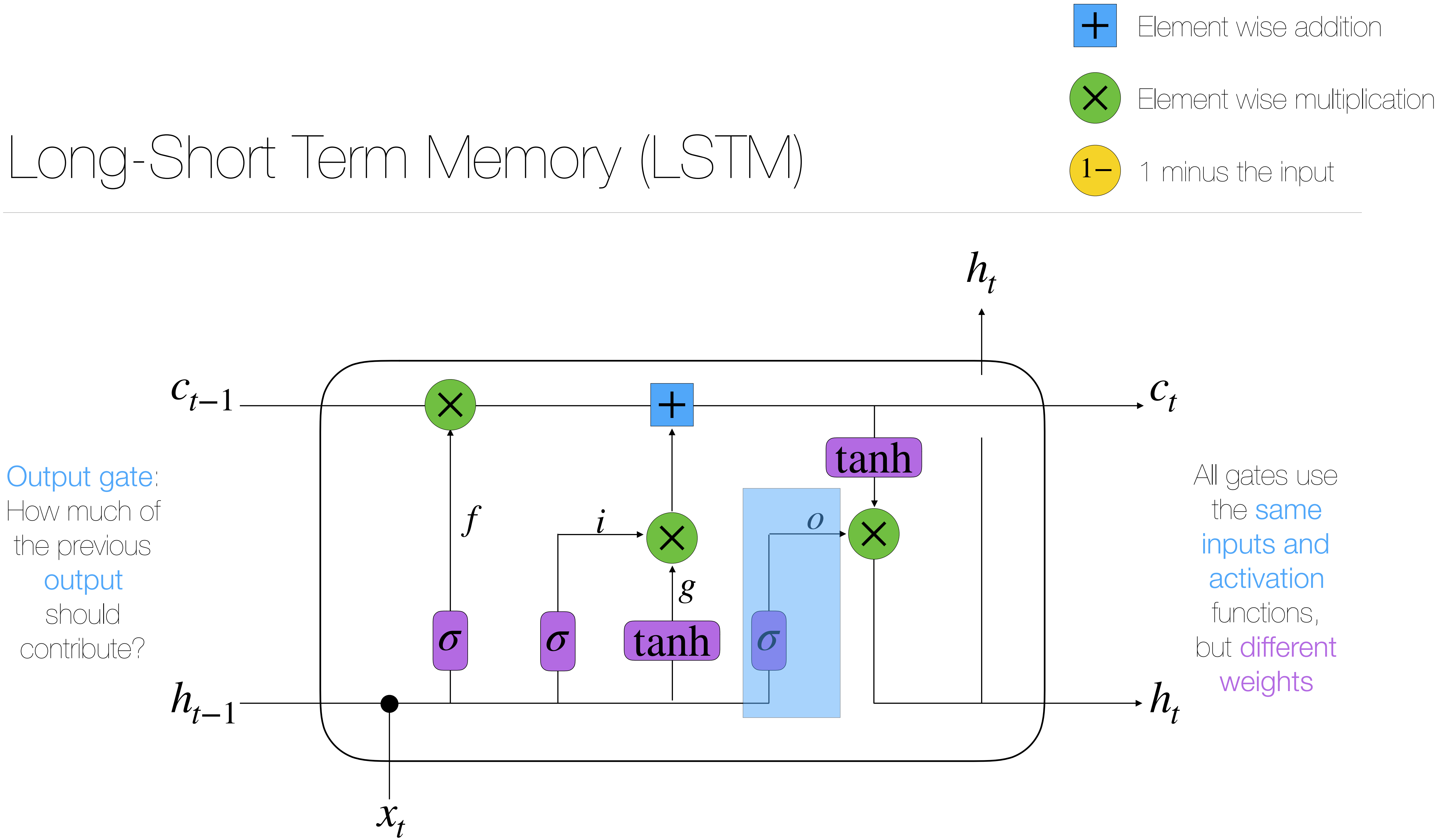
Long-Short Term Memory (LSTM)



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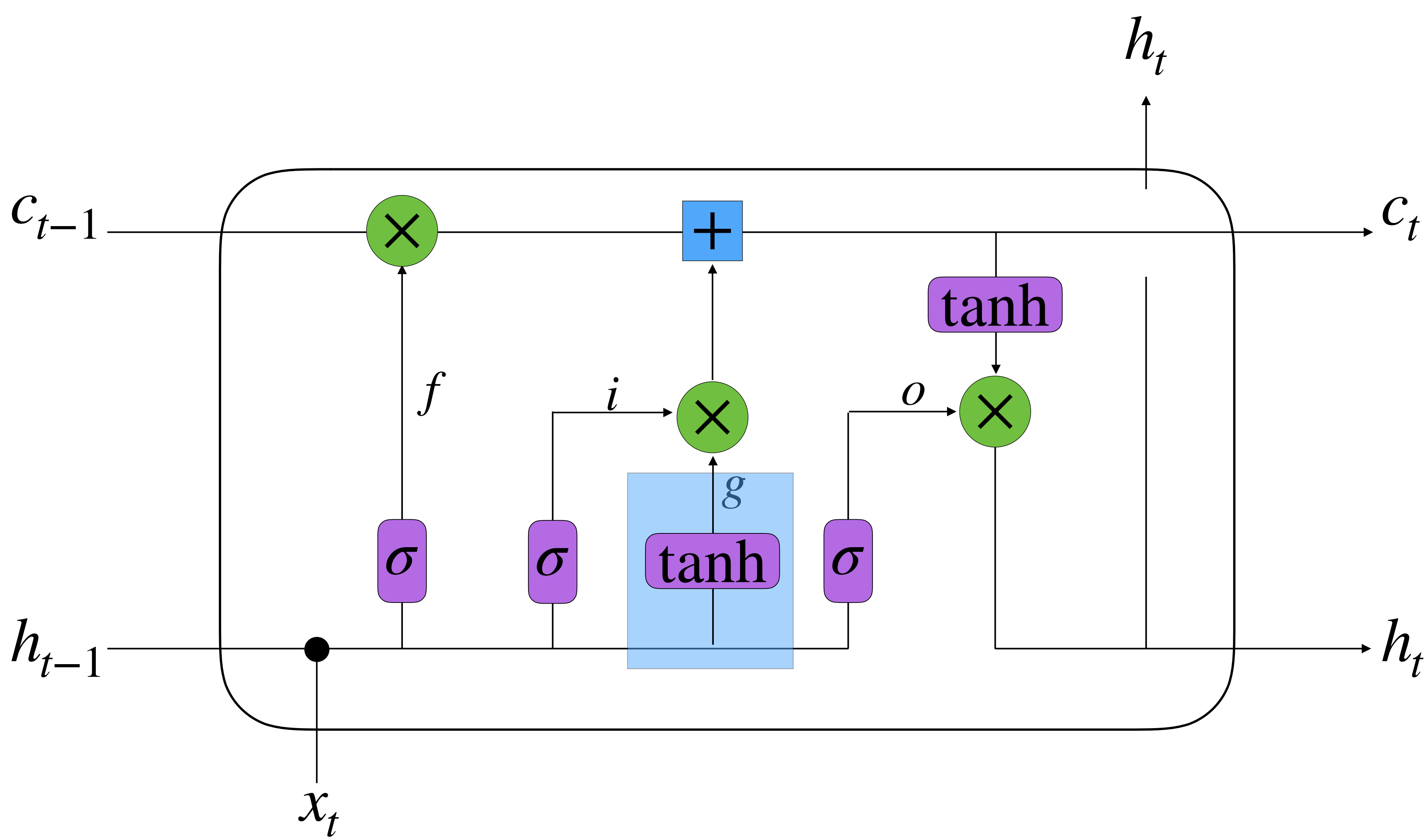
Long-Short Term Memory (LSTM)

Element wise addition

Element wise multiplication

1 minus the input



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

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

$$i = \sigma\left(W_i h_{t-1} + U_i x_t\right) \qquad c_t = \left(c_{t-1} \otimes f\right) + \left(g \otimes i\right)$$

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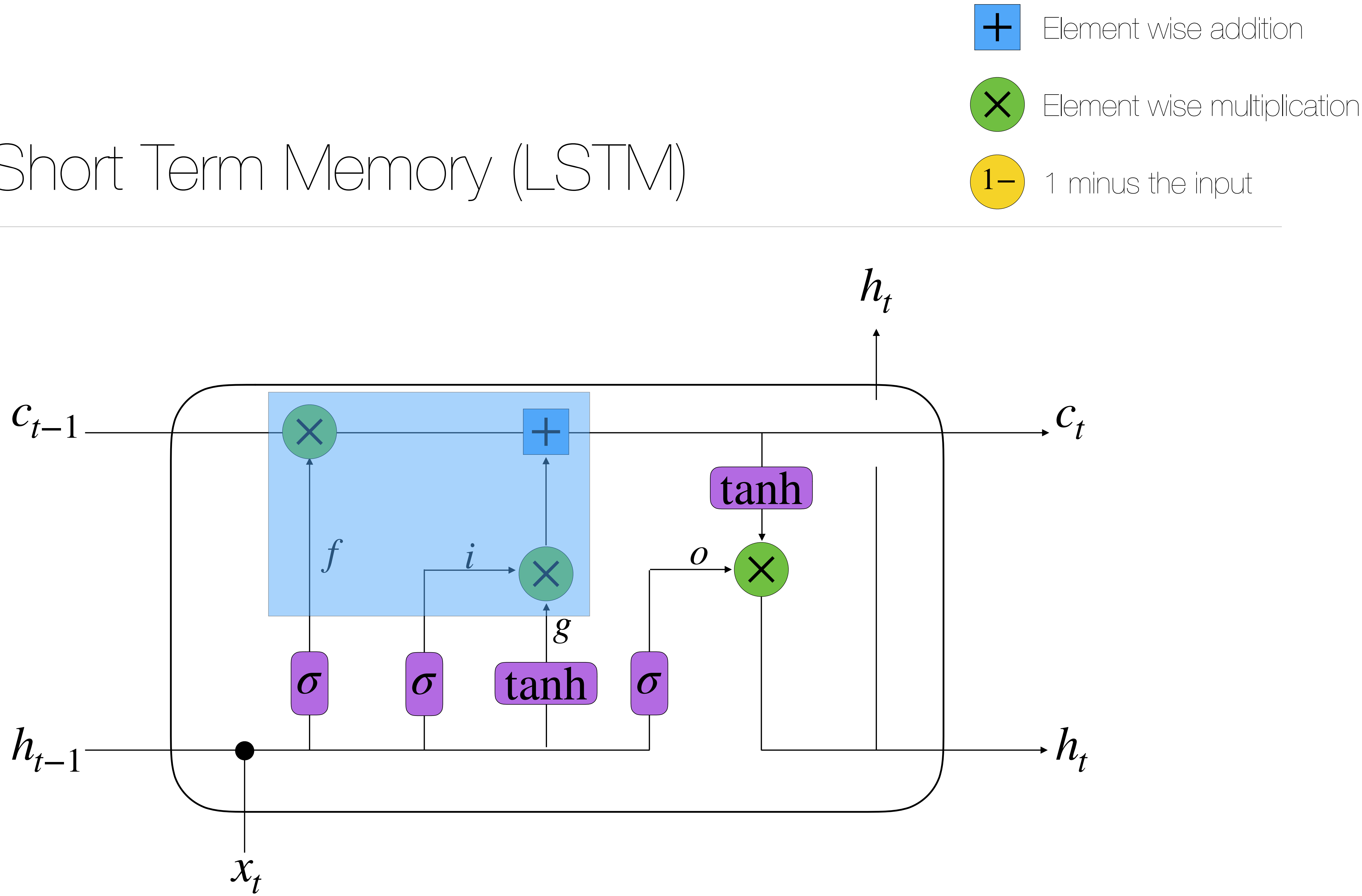
Long-Short Term Memory (LSTM)



State:
Update the
current state

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

$$i = \sigma\left(W_i h_{t-1} + U_i x_t\right) \qquad c_t = \left(c_{t-1} \otimes f\right) + \left(g \otimes i\right)$$

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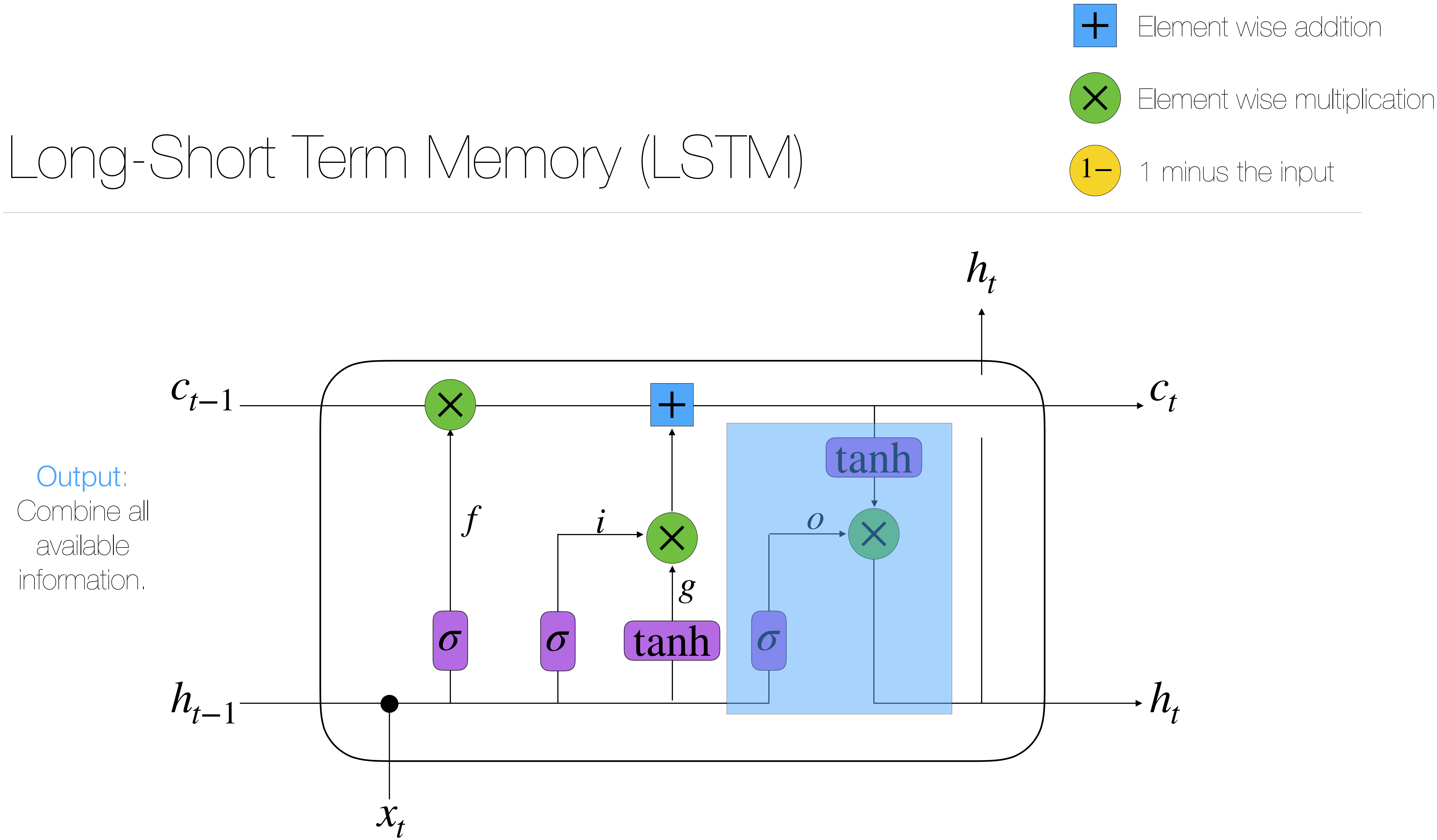

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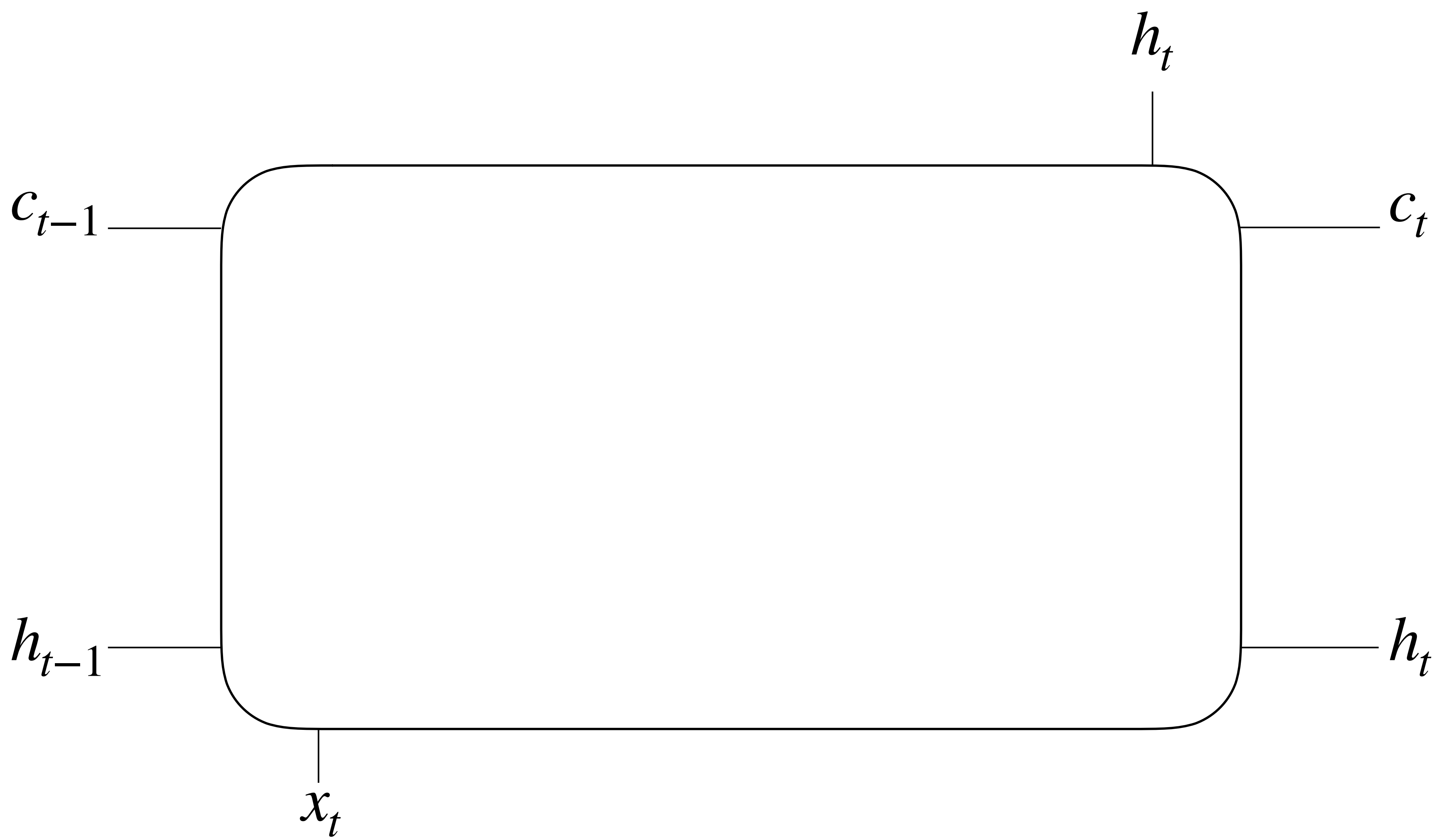
Neural Networks?



Or legos?

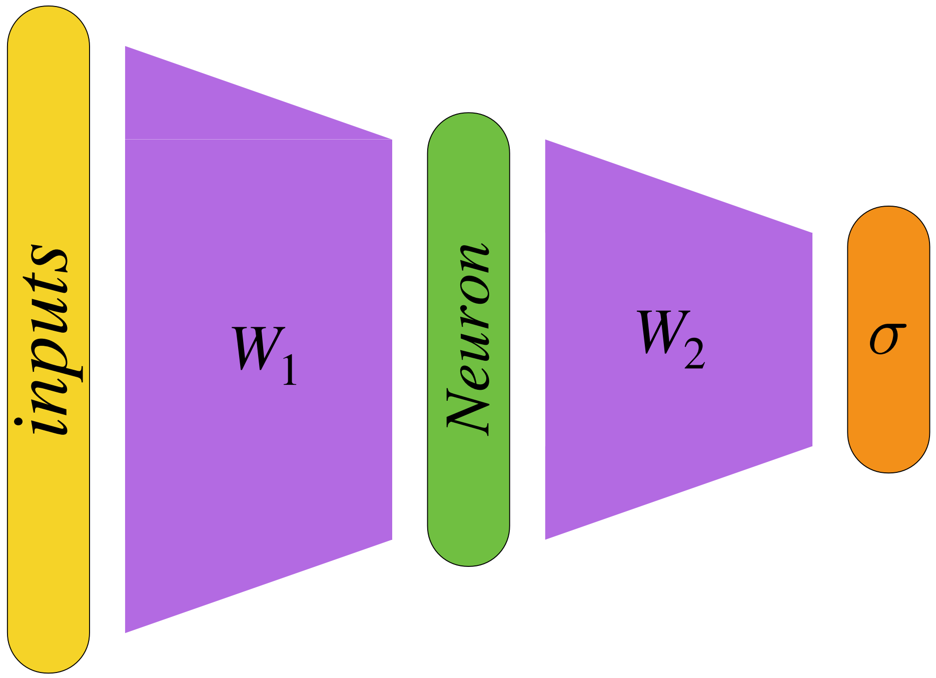
https://keras.io

Keras

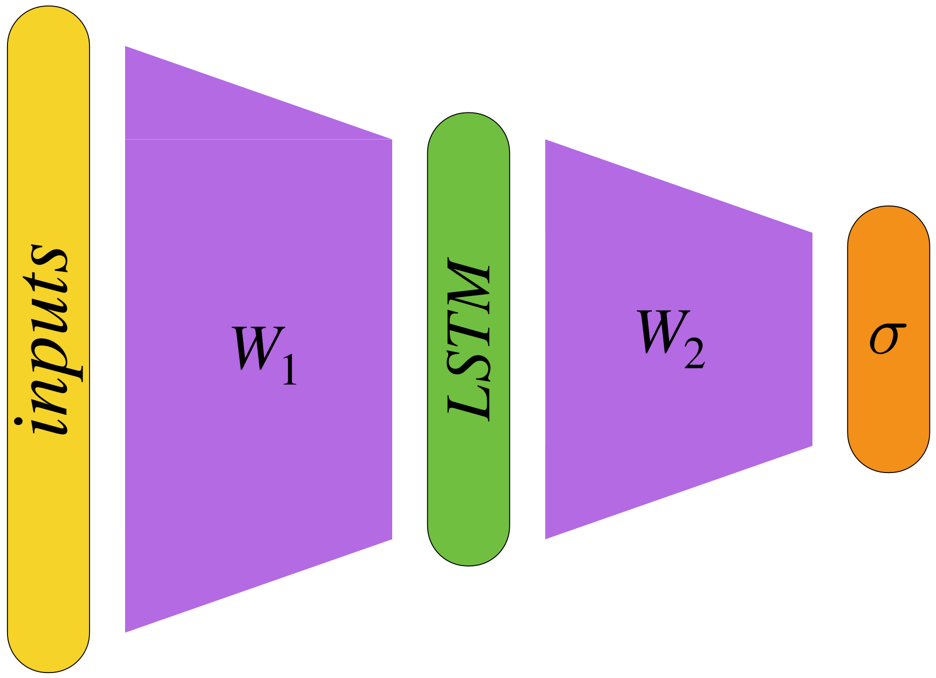
https://keras.io

- Open Source neural network library written in Python
- TensorFlow, Microsoft Cognitive Toolkit or Theano backends
- Enable fast experimentation
- Created and maintained by François Chollet, a Google engineer.
- Implements Layers, Objective/Loss functions, Activation functions, Optimizers, etc…

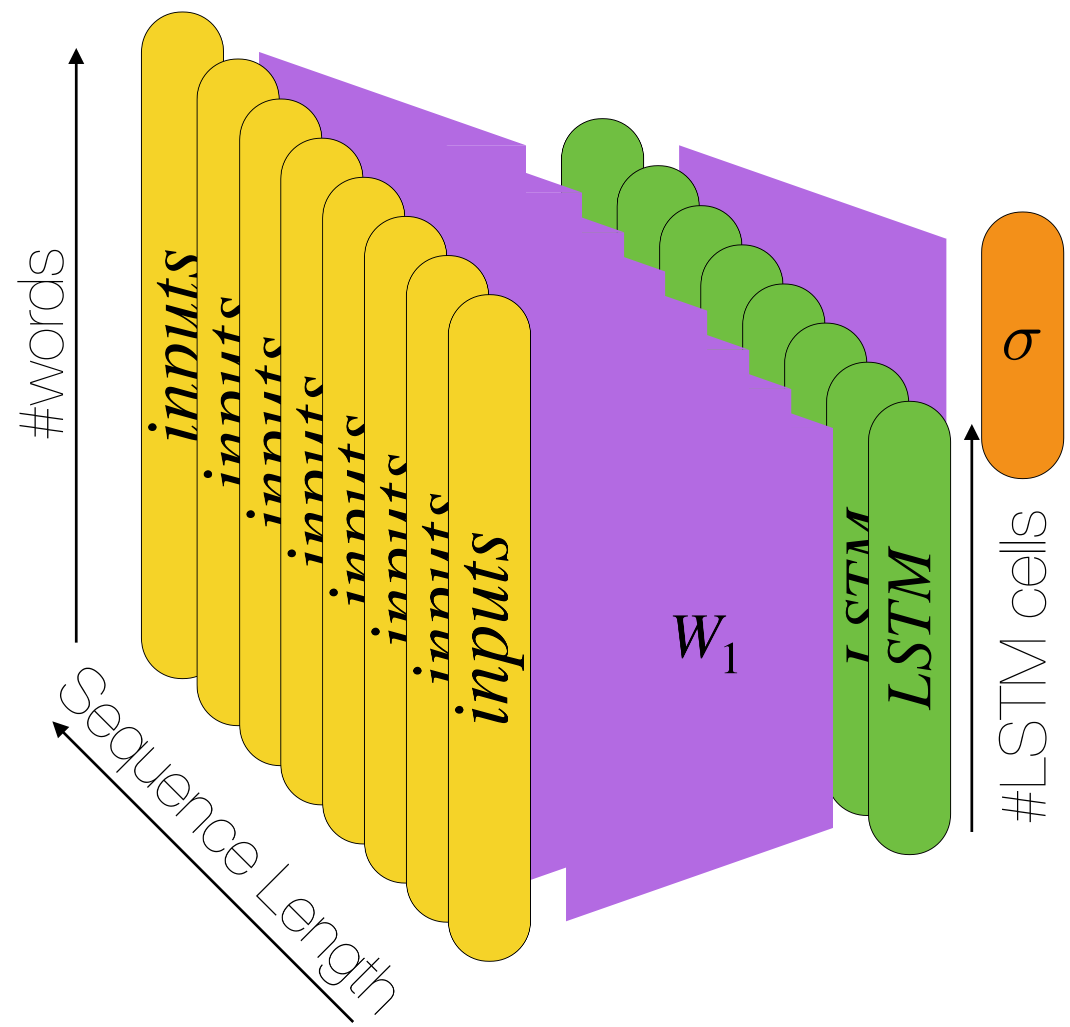
Using LSTMs



Using LSTMs



Using LSTMs



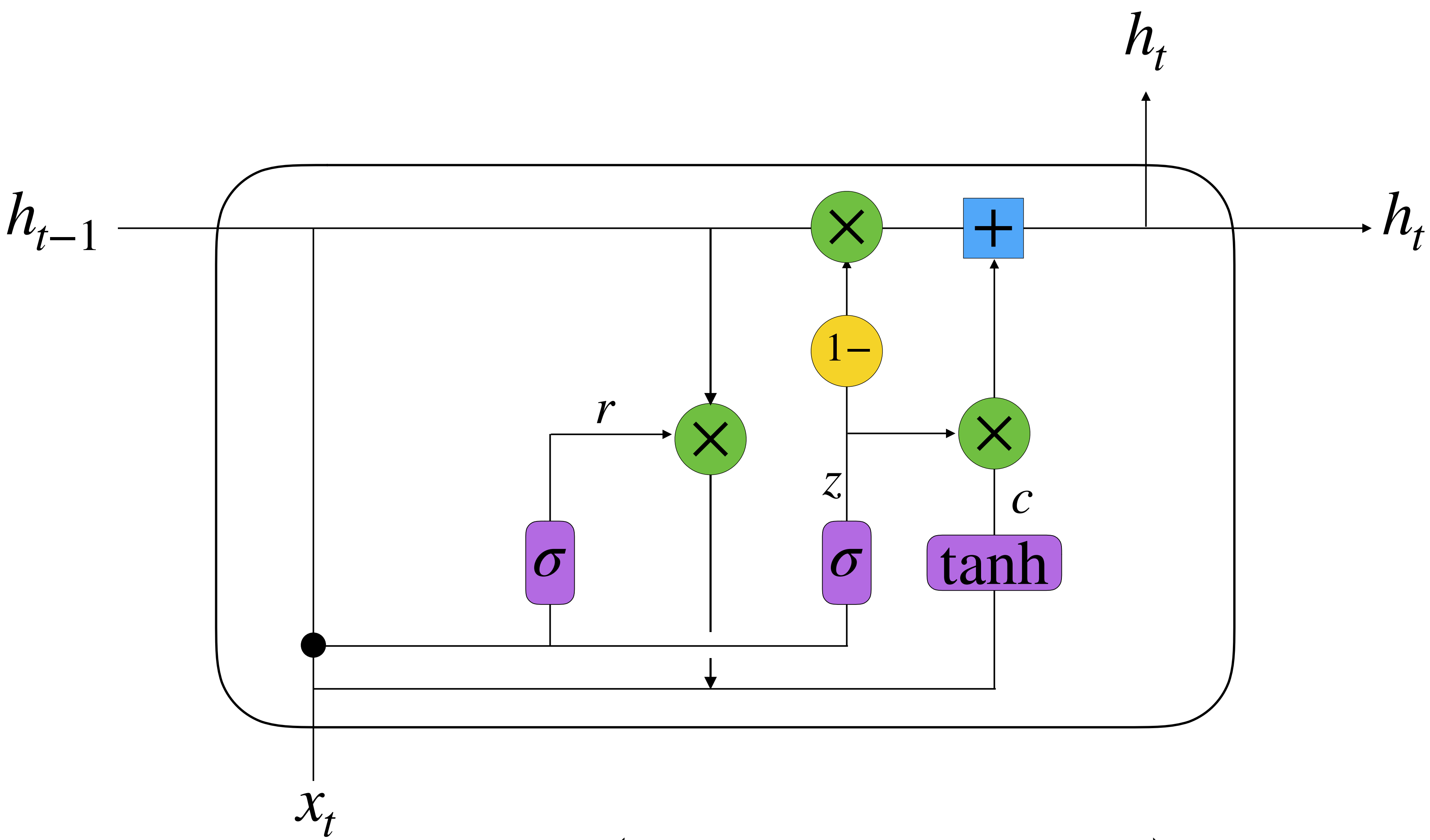
Applications

- Language Modeling and Prediction
- Speech Recognition
- Machine Translation
- Part-of-Speech Tagging
- Sentiment Analysis
- Summarization
- Time series forecasting

Gated Recurrent Unit (GRU)

- 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)



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

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

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

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

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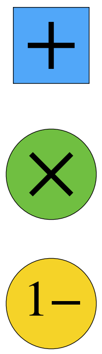
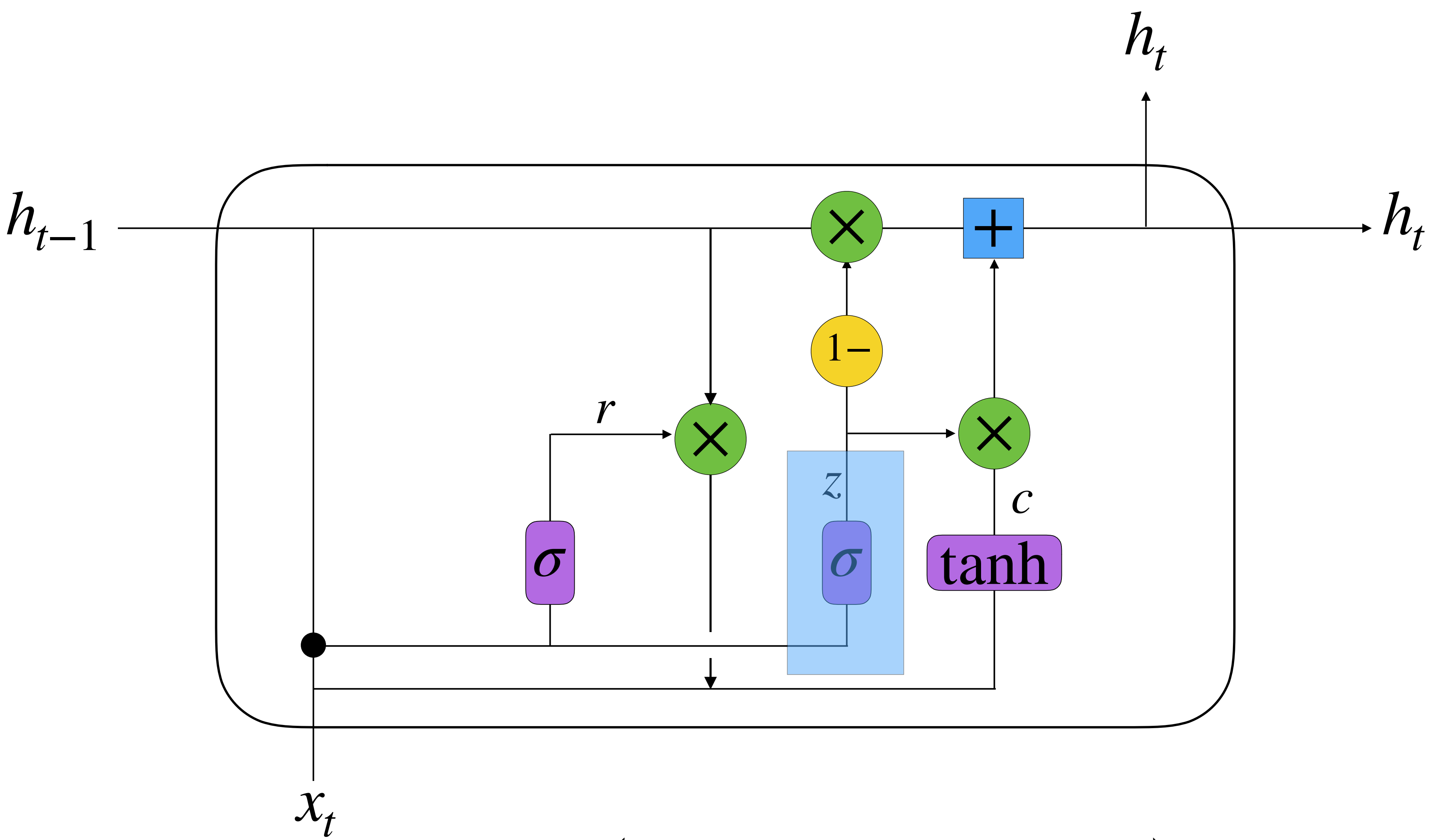
Gated Recurrent Unit (GRU)



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



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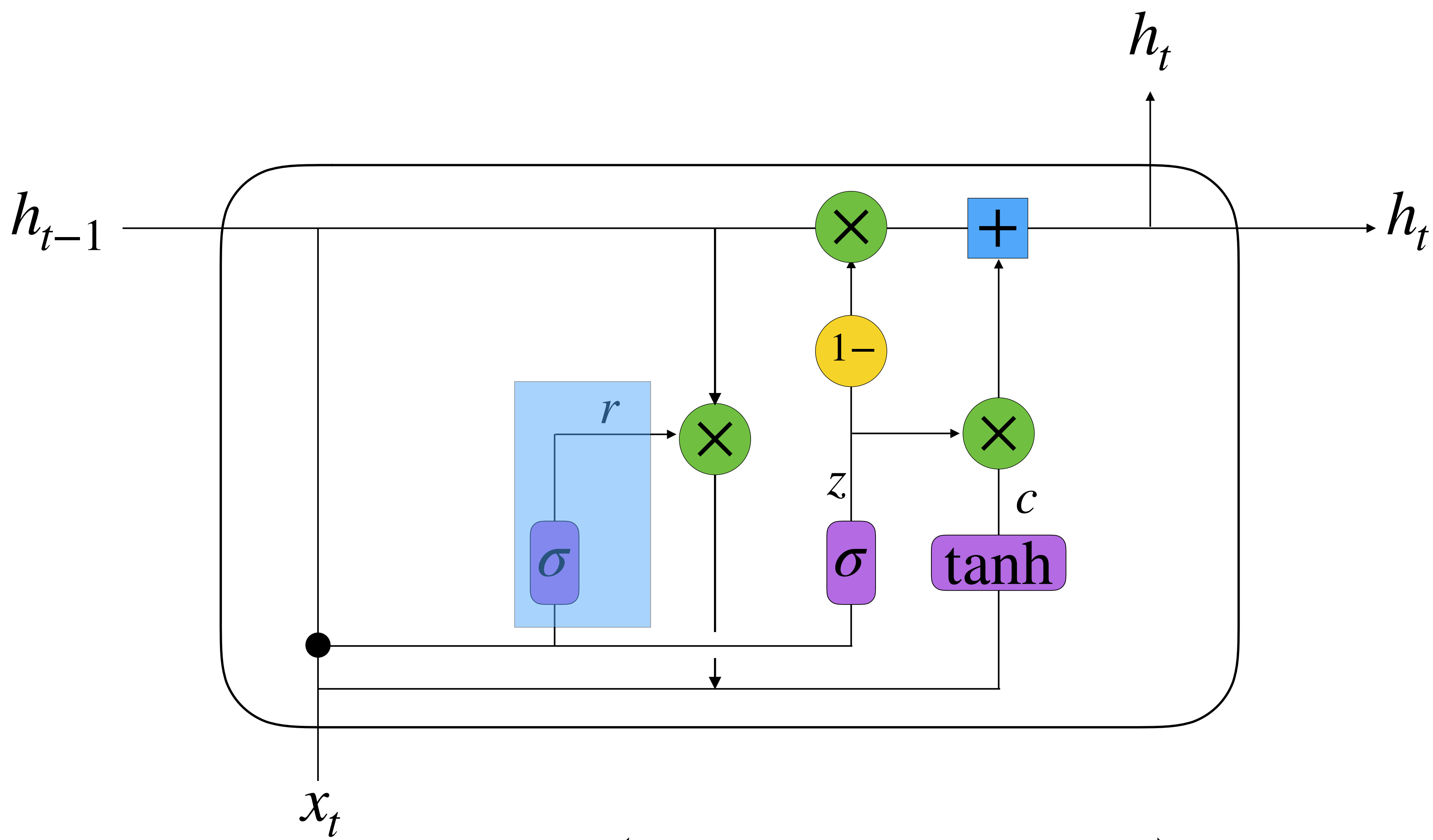
1− 1 minus the input

Element wise addition

Element wise multiplication

Gated Recurrent Unit (GRU)

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



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

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

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

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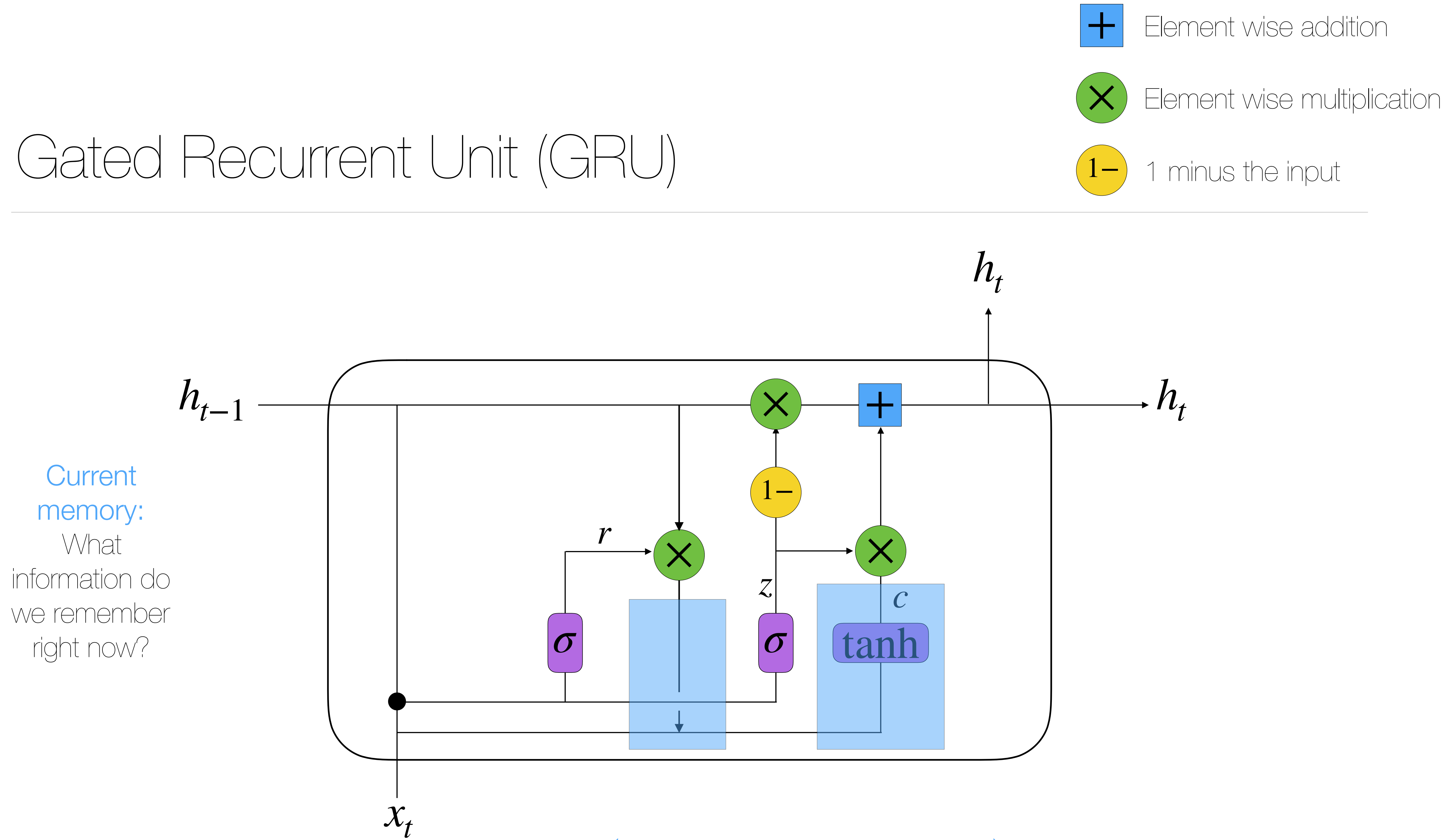
Gated Recurrent Unit (GRU)



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

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

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

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

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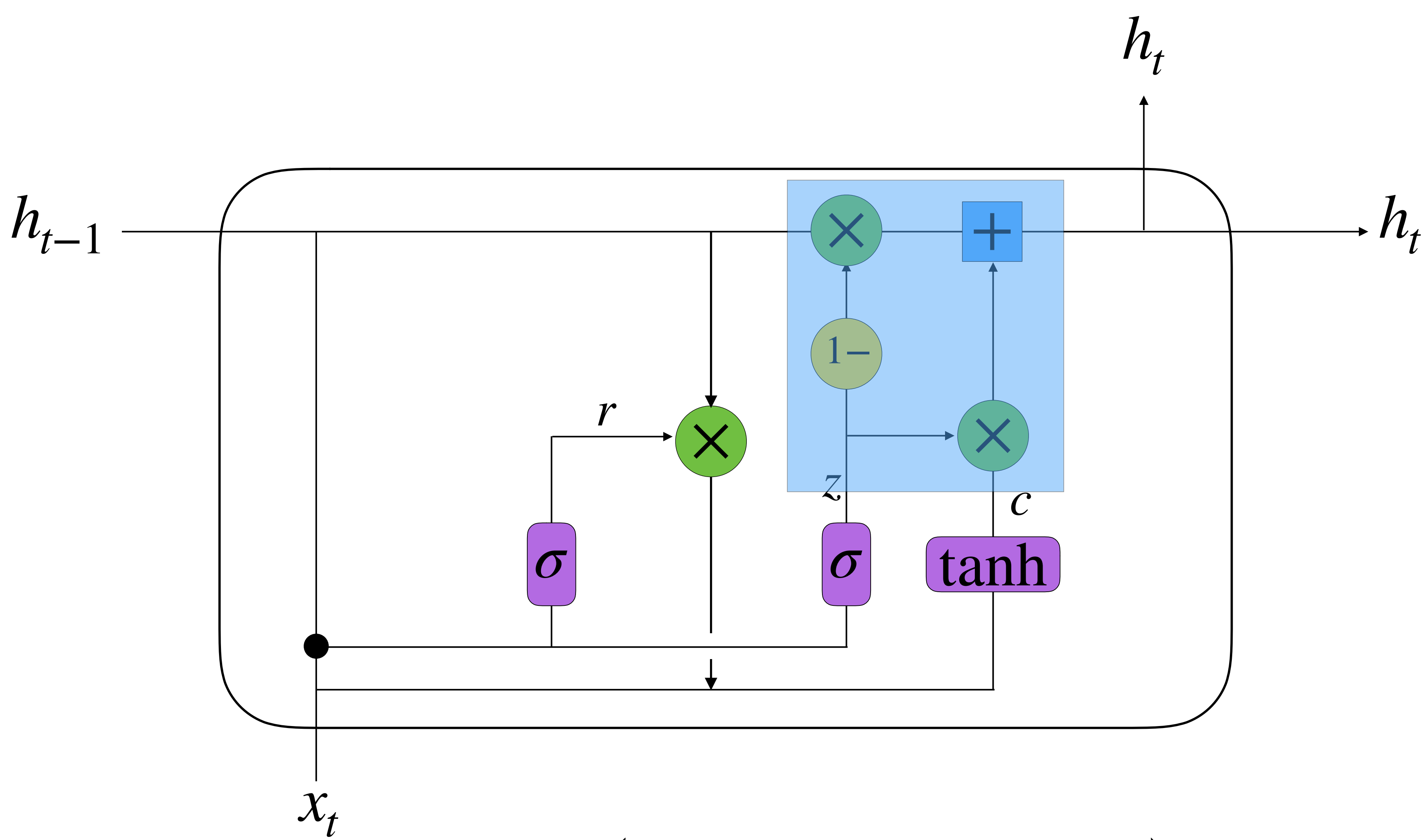
Element wise addition

Element wise multiplication

1 minus the input

Gated Recurrent Unit (GRU)

Output:
Combine all
available
information.



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

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

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

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