Cagri Ozcinar, PhD

LTTI.00.032 – Machine Learning in Synthetic Biology

Machine Learning

≈Looking for function

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Machine Learning

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- Speech Recognition $f($  $)=$ "How are you"

Machine Learning

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- Speech Recognition $f($  $)=$ "How are you"
- Image Recognition $f($  $)=$ "Cat"

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Machine Learning

≈Looking for function

- Speech Recognition $f($  $)=$ "How are you"
- Image Recognition $f($  $)=$ "Cat"
- Playing Go $f($  $)=$ "5-5"

Different types of Functions

- Regression: The function outputs a scalar.

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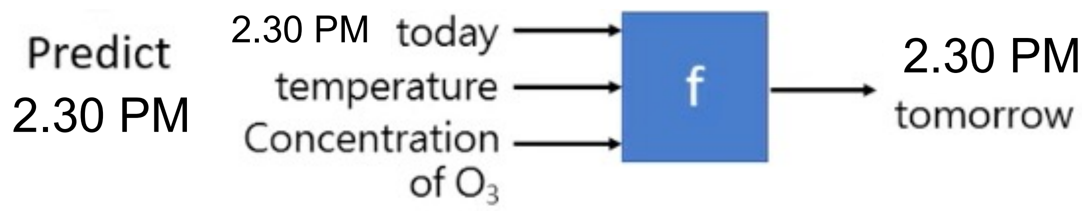

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Different types of Functions

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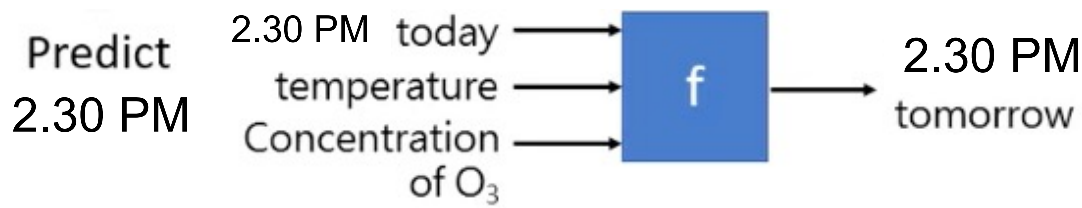

- Classification: Given options (classes), the function outputs the correct one.

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Different types of Functions

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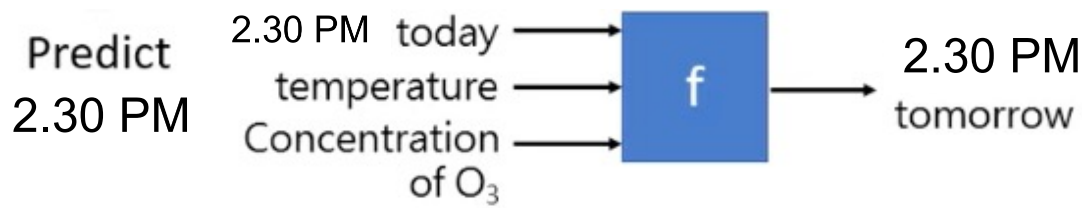

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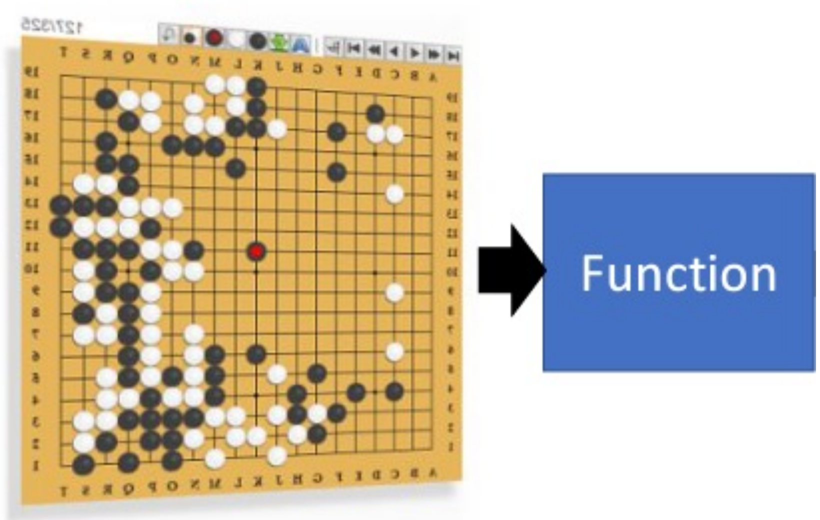

Playing GO

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Different types of Functions

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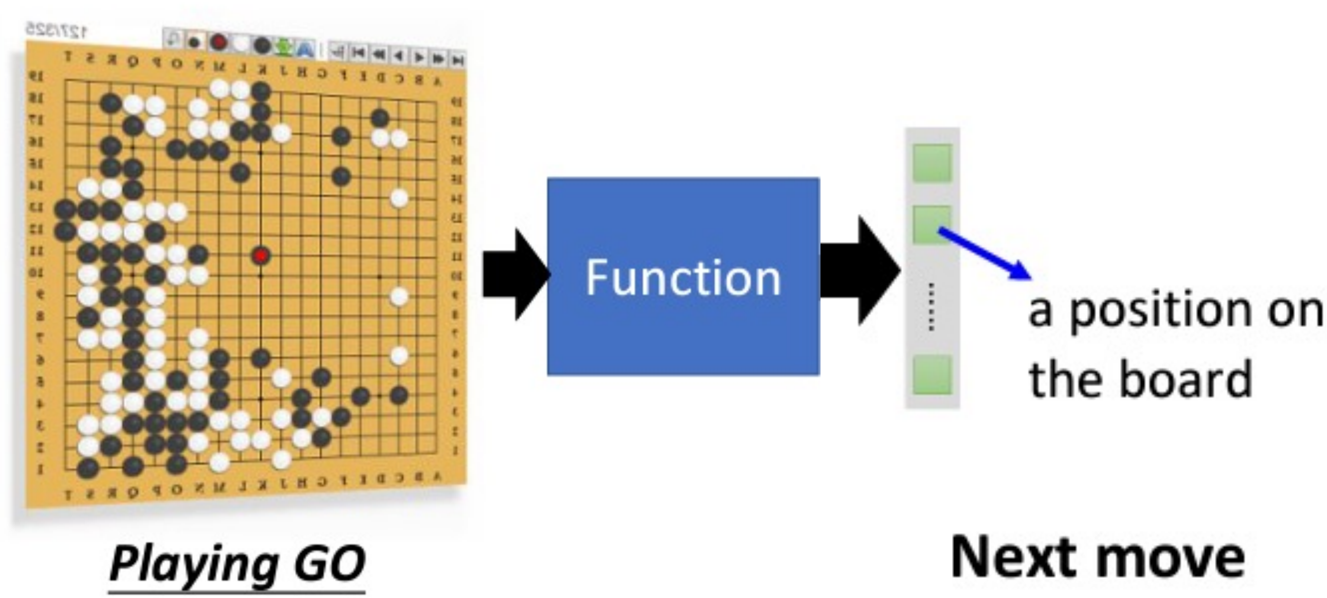
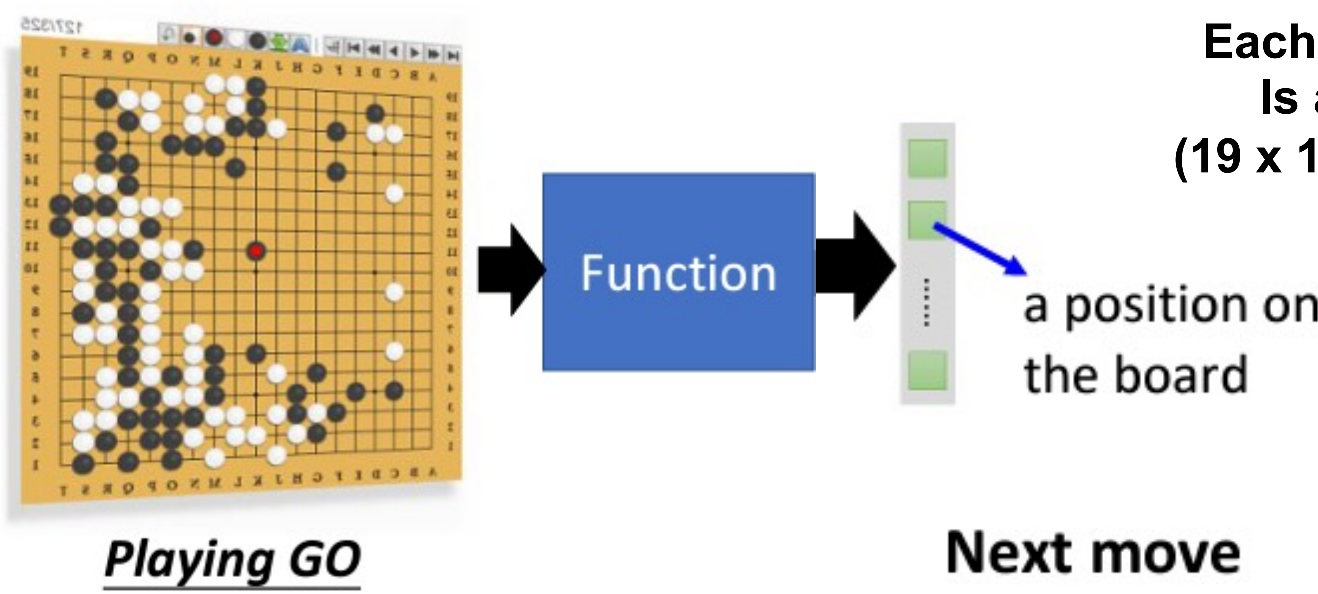


Different types of Functions

- Classification: Given options (classes), the function outputs the correct one.

Each position Is a class (19 x 19 Classes)



Structured learning

- Create something with structure (image, document, sound)

Framework of ML

Training data: $\{(\boldsymbol{x}^{\mathbf{1}}, \hat{y}^1), (\boldsymbol{x}^{\mathbf{2}}, \hat{y}^2), \dots, (\boldsymbol{x}^{\boldsymbol{N}}, \hat{y}^N)\}$

Testing data: $\{\boldsymbol{x}^{\boldsymbol{N+1}}, \boldsymbol{x}^{\boldsymbol{N+2}}, \dots, \boldsymbol{x}^{\boldsymbol{N+M}}\}$

Framework of ML

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Speech Recognition

$\boldsymbol{x}$:  $\hat{y}$: phoneme

Image Recognition

$\boldsymbol{x}$:  $\hat{y}$: soup

Speaker Recognition

$\boldsymbol{x}$:  $\hat{y}$: John (speaker)

Machine Translation

$\boldsymbol{x}$: 痛みを知れ

$\hat{y}$: 了解痛苦吧

Framework of ML

Training data: $\{(\boldsymbol{x}^1, \hat{y}^1), (\boldsymbol{x}^2, \hat{y}^2), \dots, (\boldsymbol{x}^N, \hat{y}^N)\}$

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Use $y = f_{\boldsymbol{\theta}^*}(\boldsymbol{x})$ to label the testing data

Framework of ML

Training data: $\{(\boldsymbol{x}^1, \hat{y}^1), (\boldsymbol{x}^2, \hat{y}^2), \ldots, (\boldsymbol{x}^N, \hat{y}^N)\}$

Training:

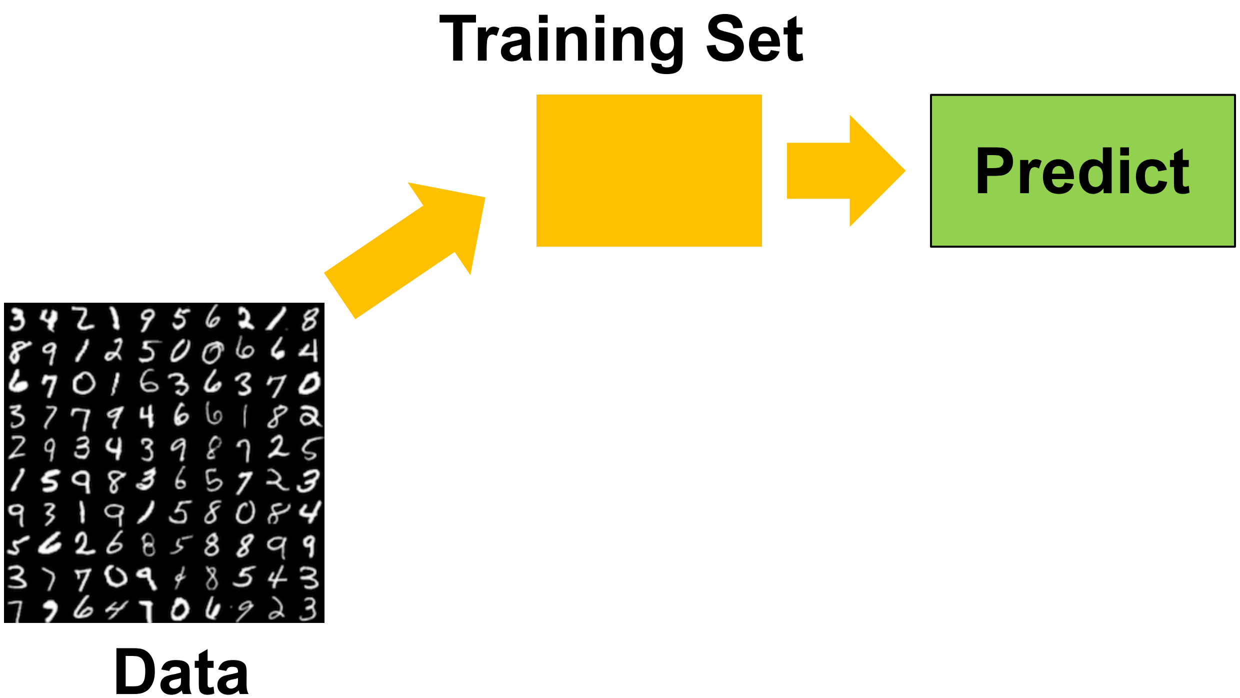
Step 1: function with unknown → **Step 2: define loss from training data** → **Step 3: optimization**

$y = f_{\boldsymbol{\theta}}(\boldsymbol{x})$ $\qquad$ $L(\boldsymbol{\theta})$ $\qquad$ $\boldsymbol{\theta}^* = arg \min_{\boldsymbol{\theta}} L$

Testing data: $\{\boldsymbol{x}^{N+1}, \boldsymbol{x}^{N+2}, \ldots, \boldsymbol{x}^{N+M}\}$

Use $y = f_{\boldsymbol{\theta}^*}(\boldsymbol{x})$ to label the testing data

Basics of deep learning



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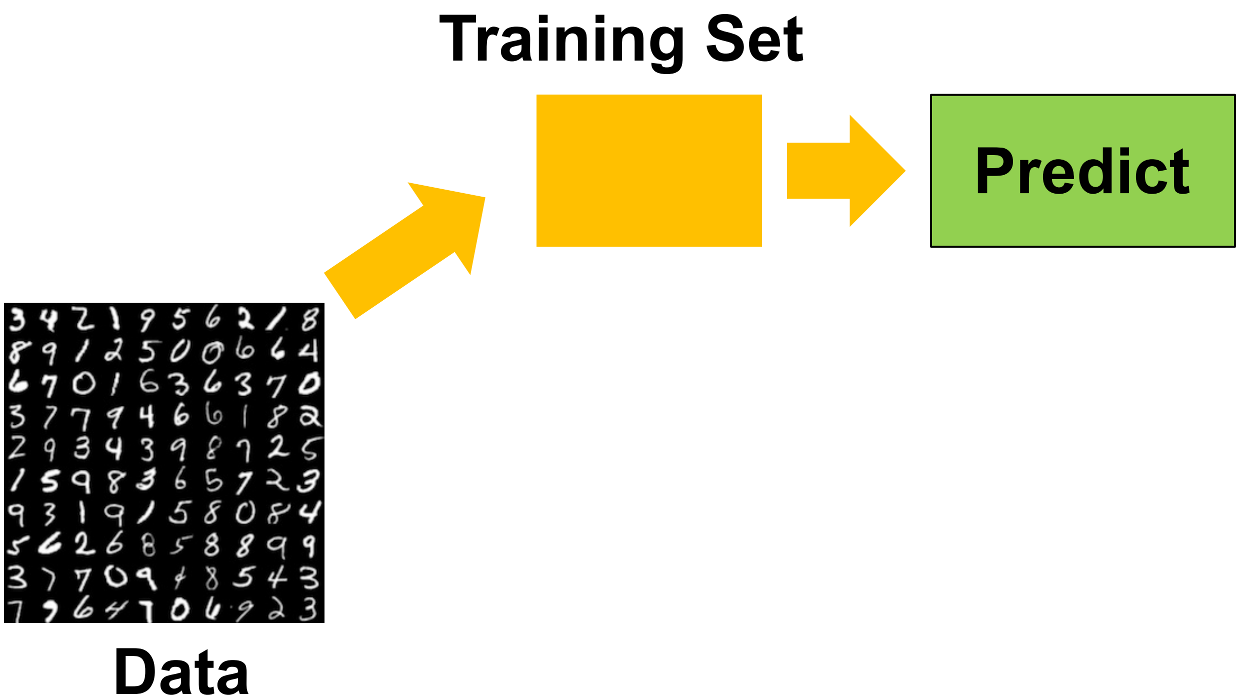
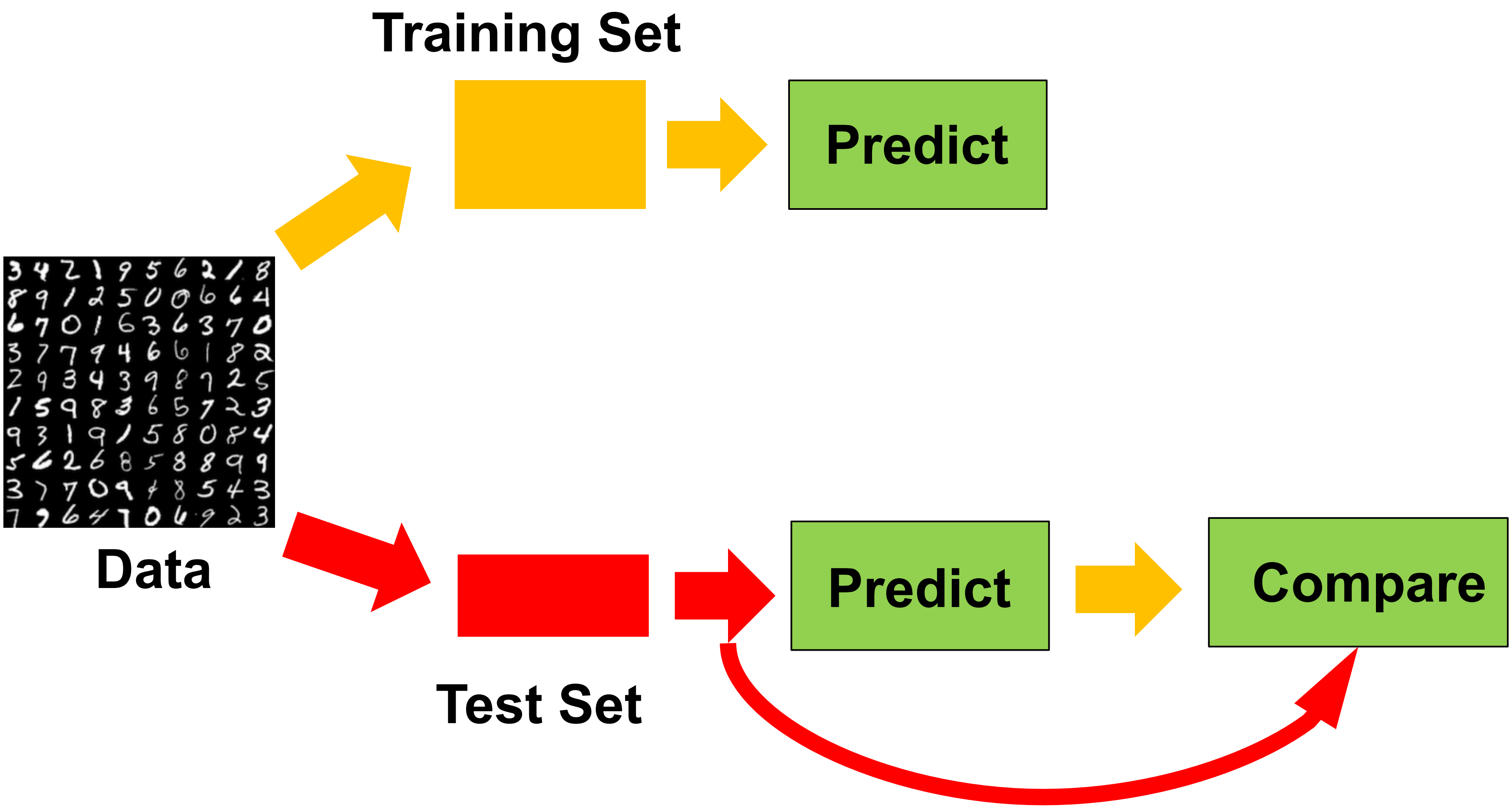
Basics of deep learning



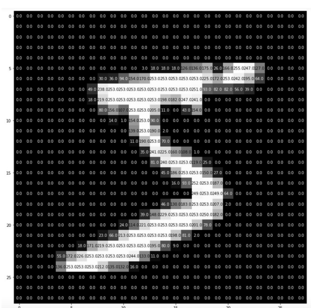
The number of epochs defines the number of times that the learning algorithm will work through the entire training dataset.

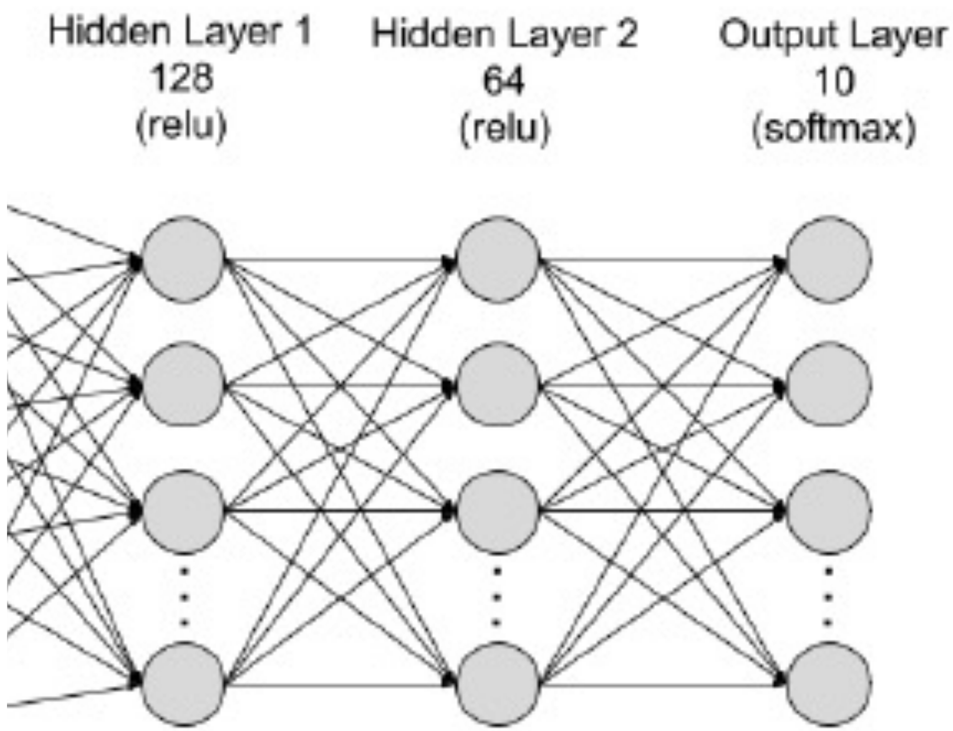
Basics of deep learning



An example neural network

f





[0,…**5**, ..9]

X: Input: 784 values (28x28)

Y= Output: 10 values

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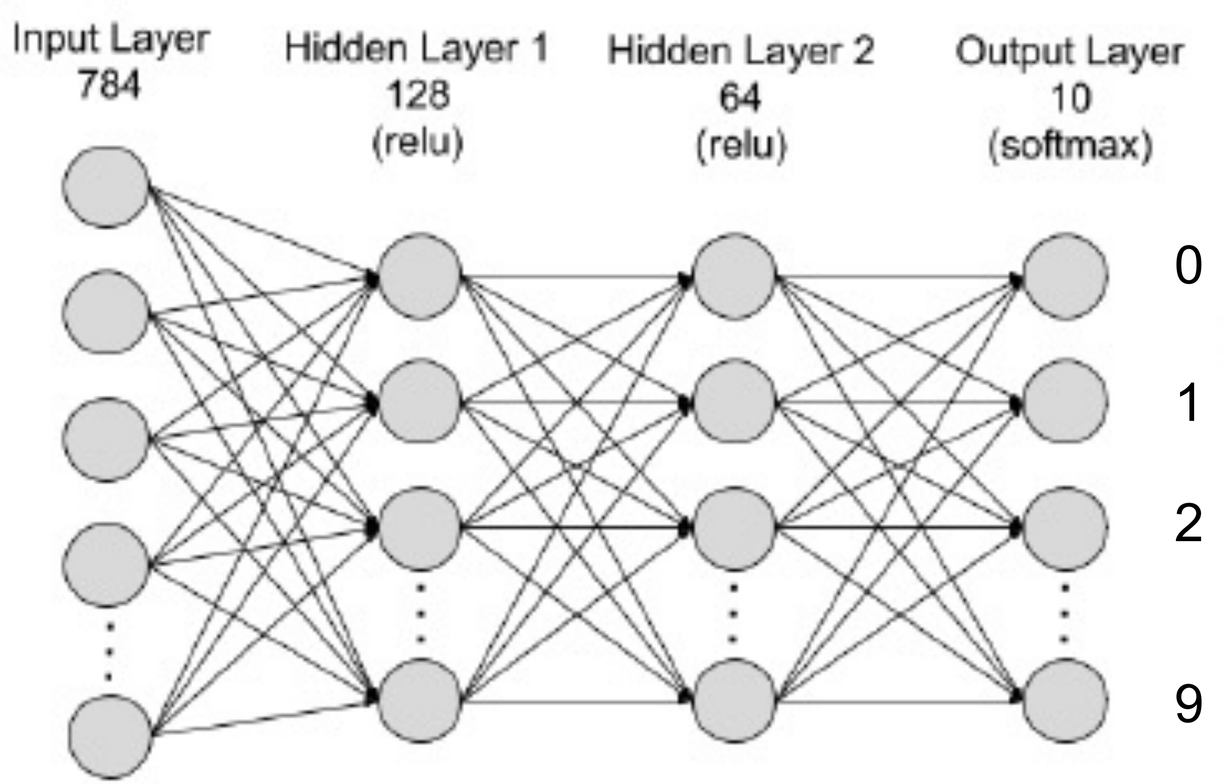
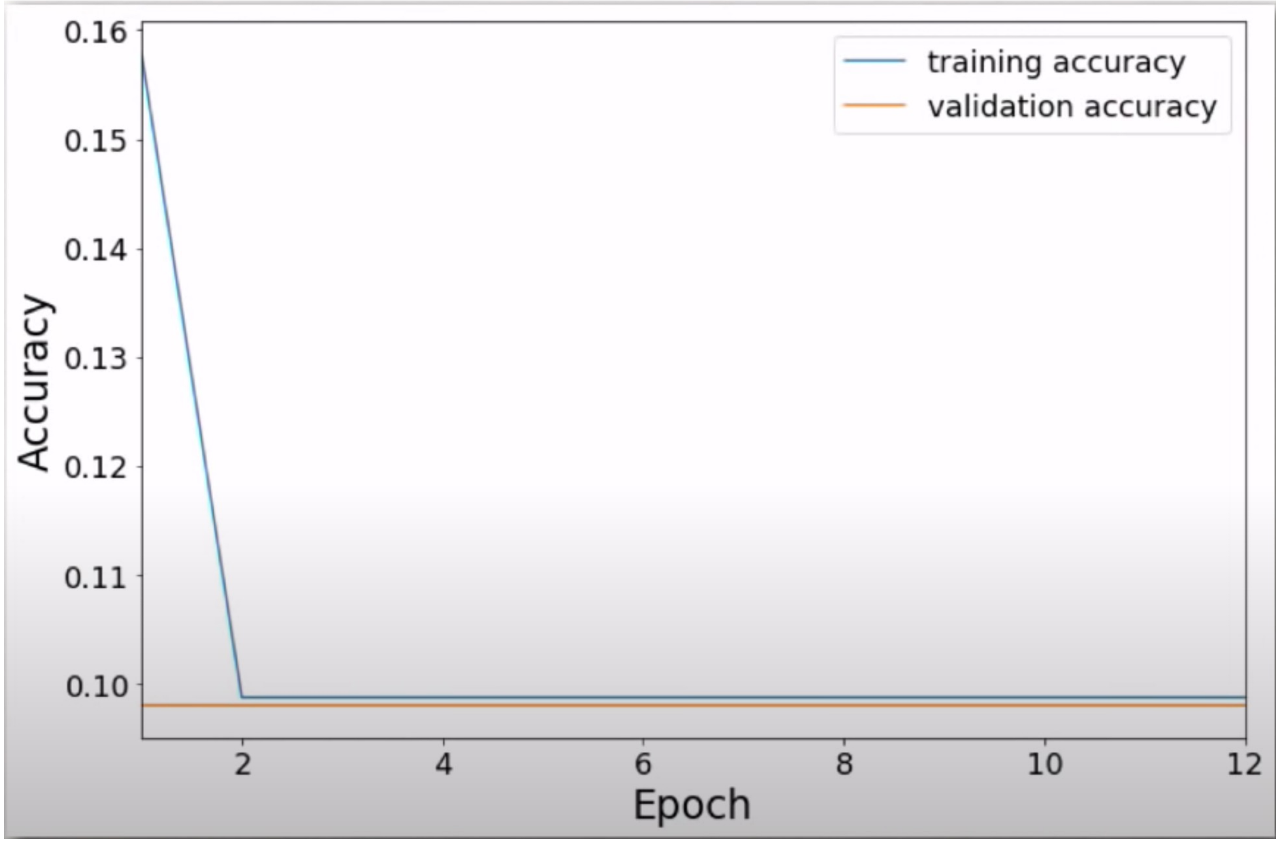
An example neural network



Input: 784 values (28x28)

Output: 10 values

Training Results: Terrible!



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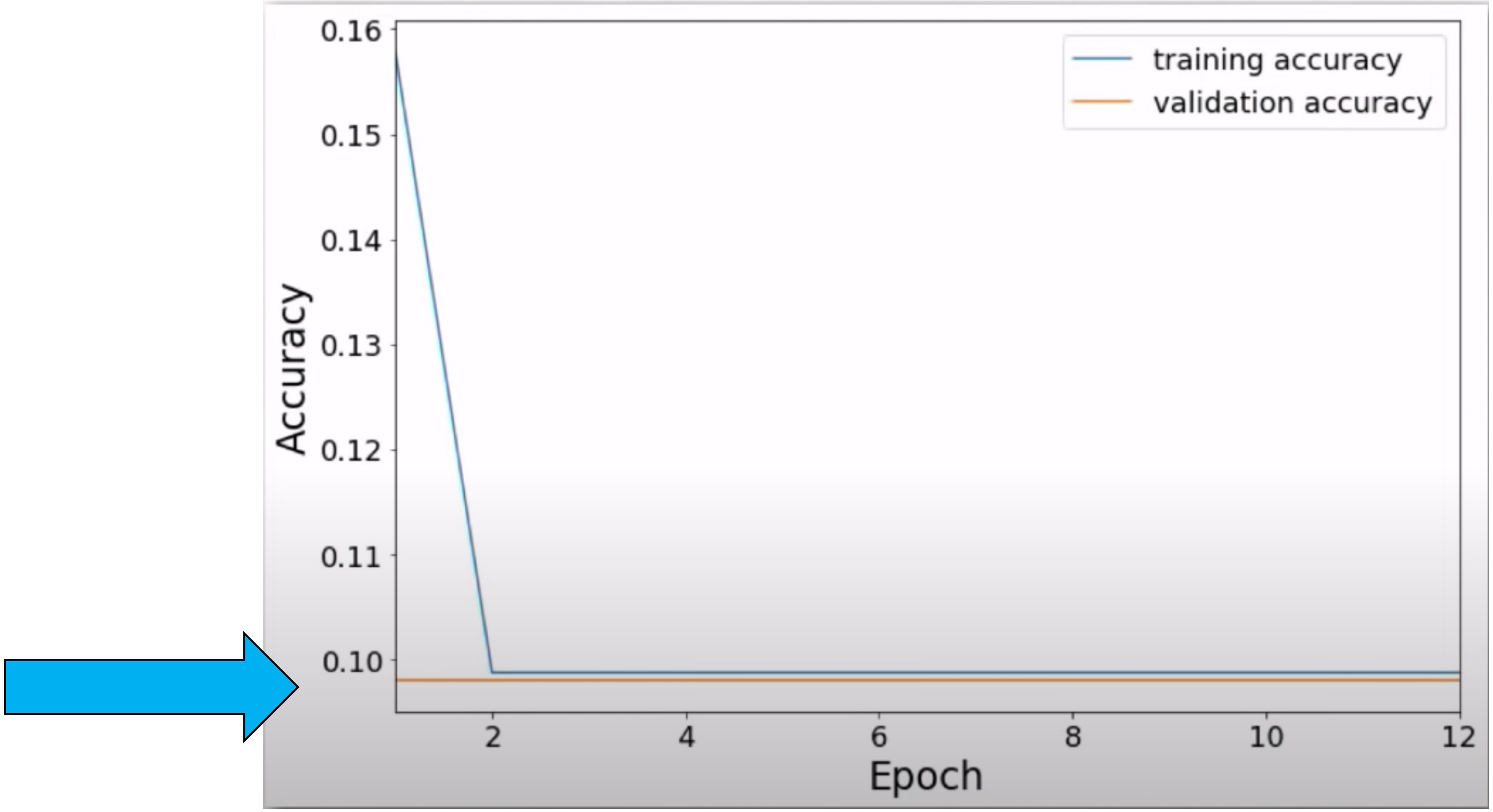

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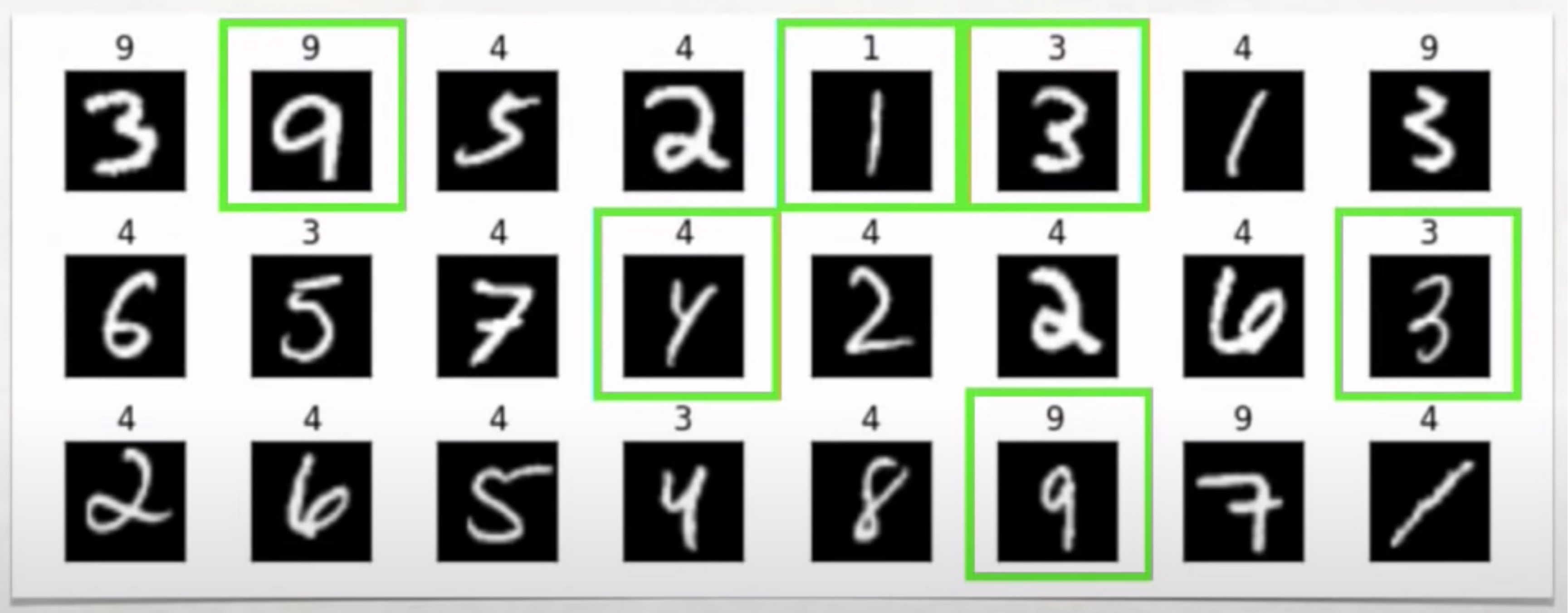
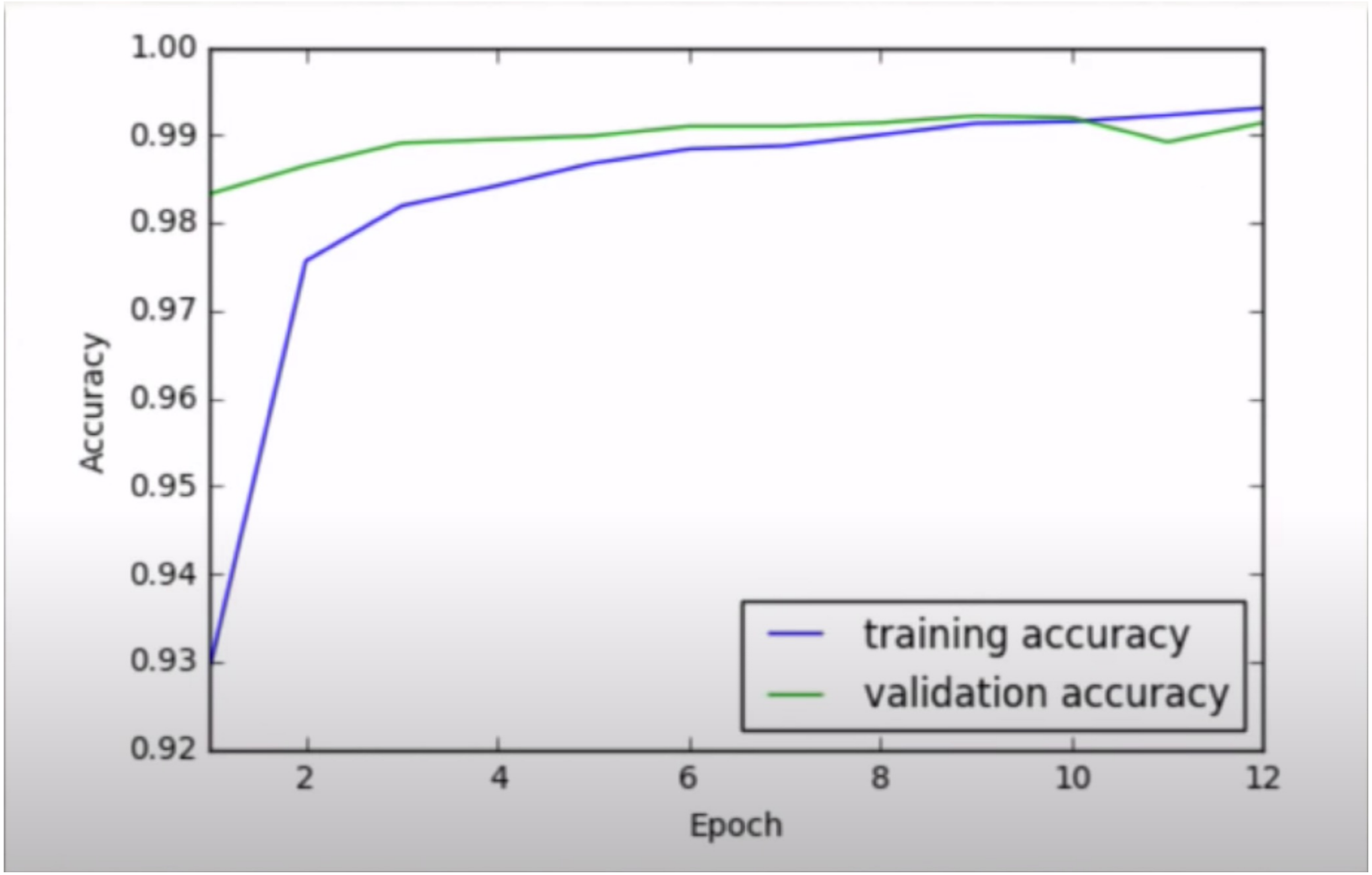
Network Prediction: Terrible!



Training Results We Want



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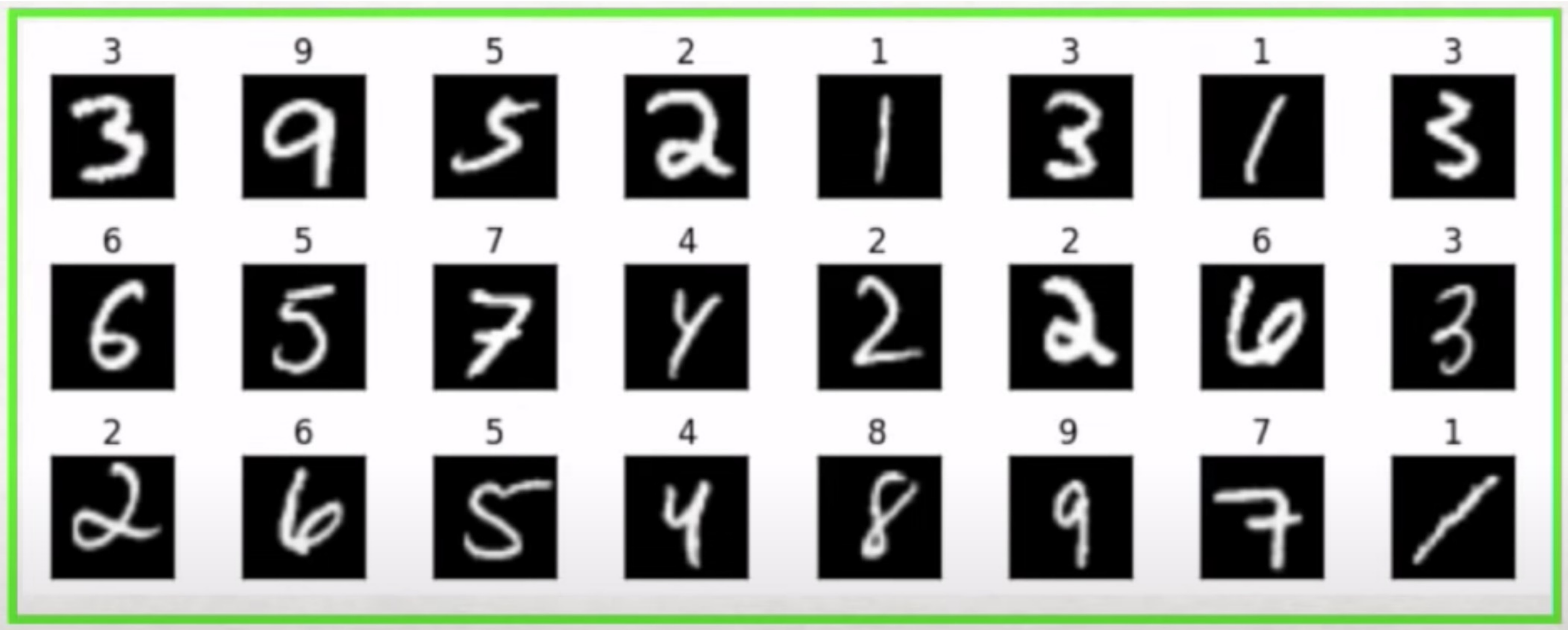
Network Predictions We Want



How to
get there

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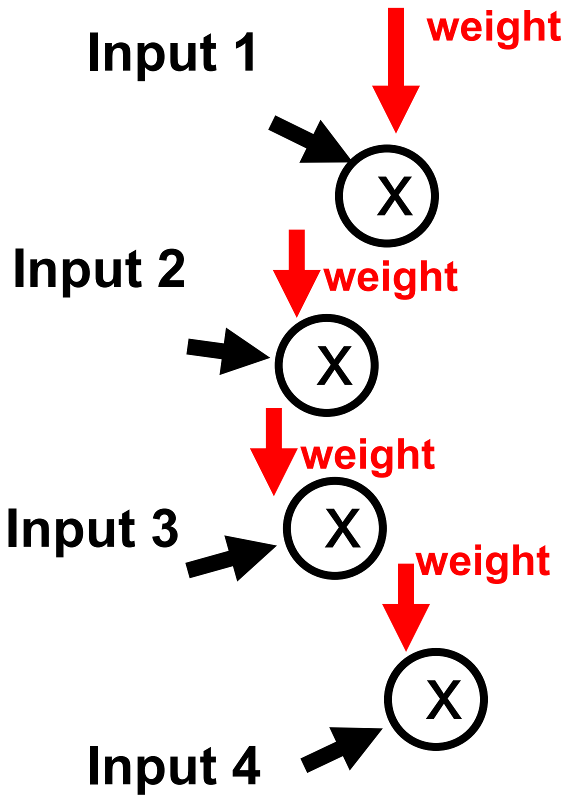

Each neuron has its own weight

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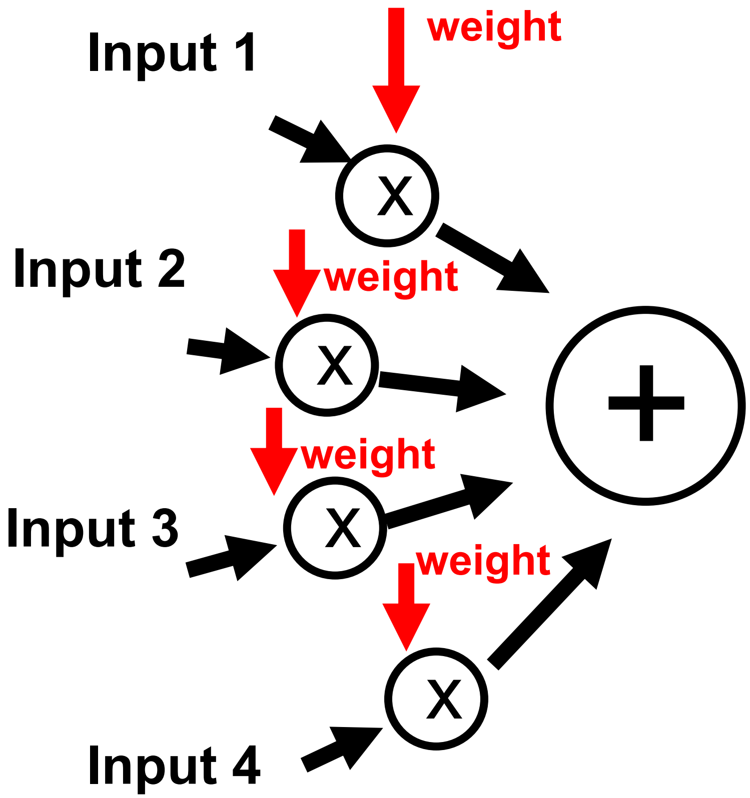

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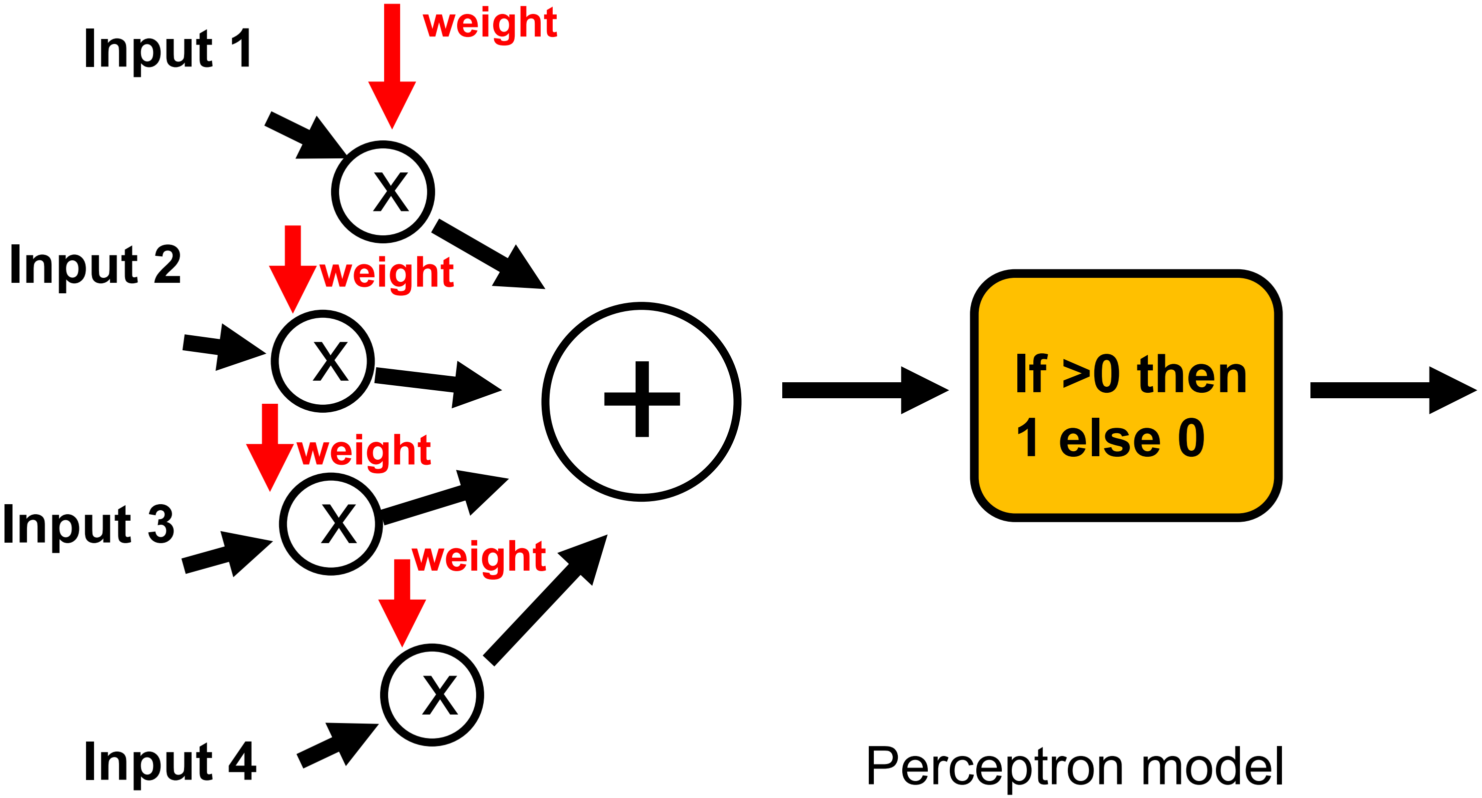
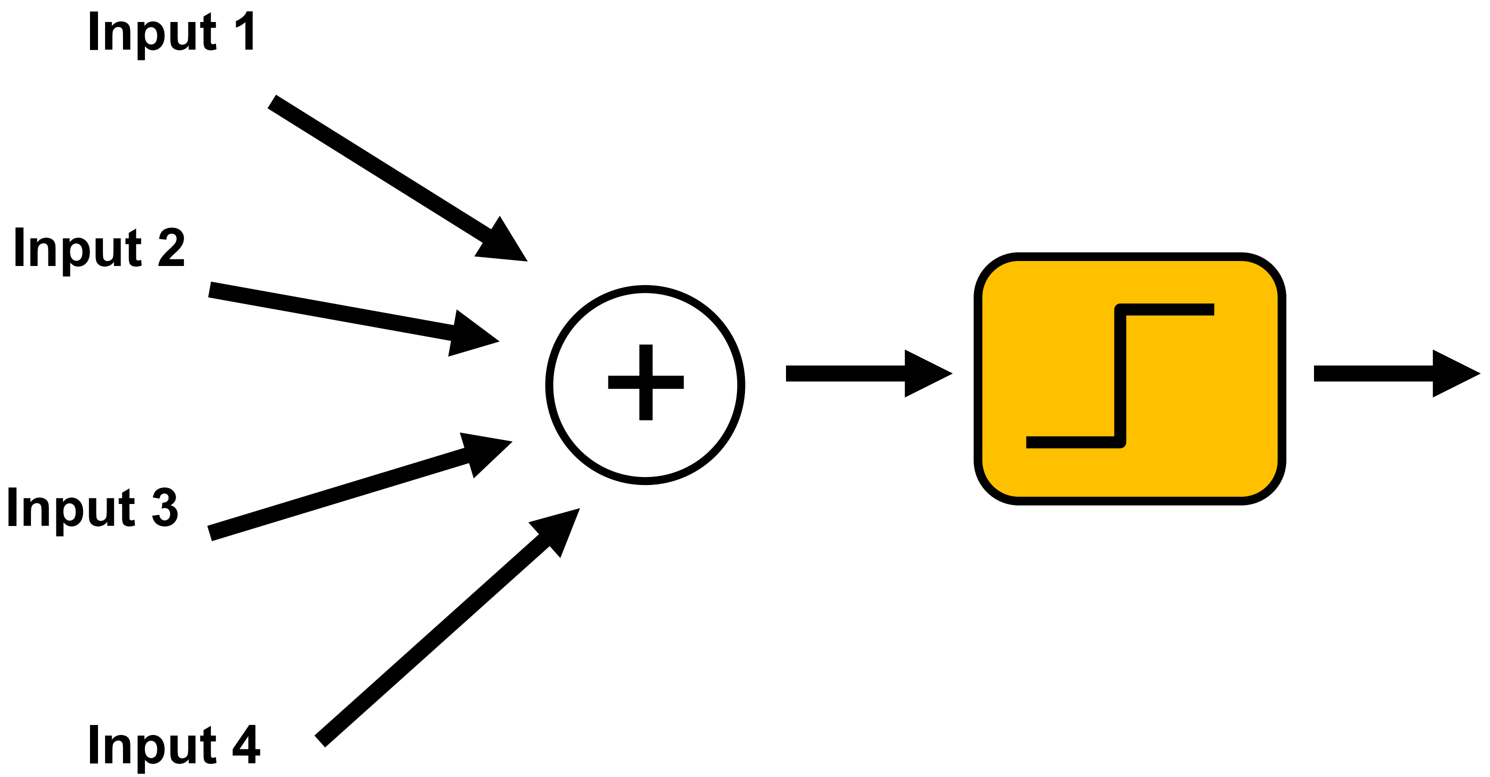
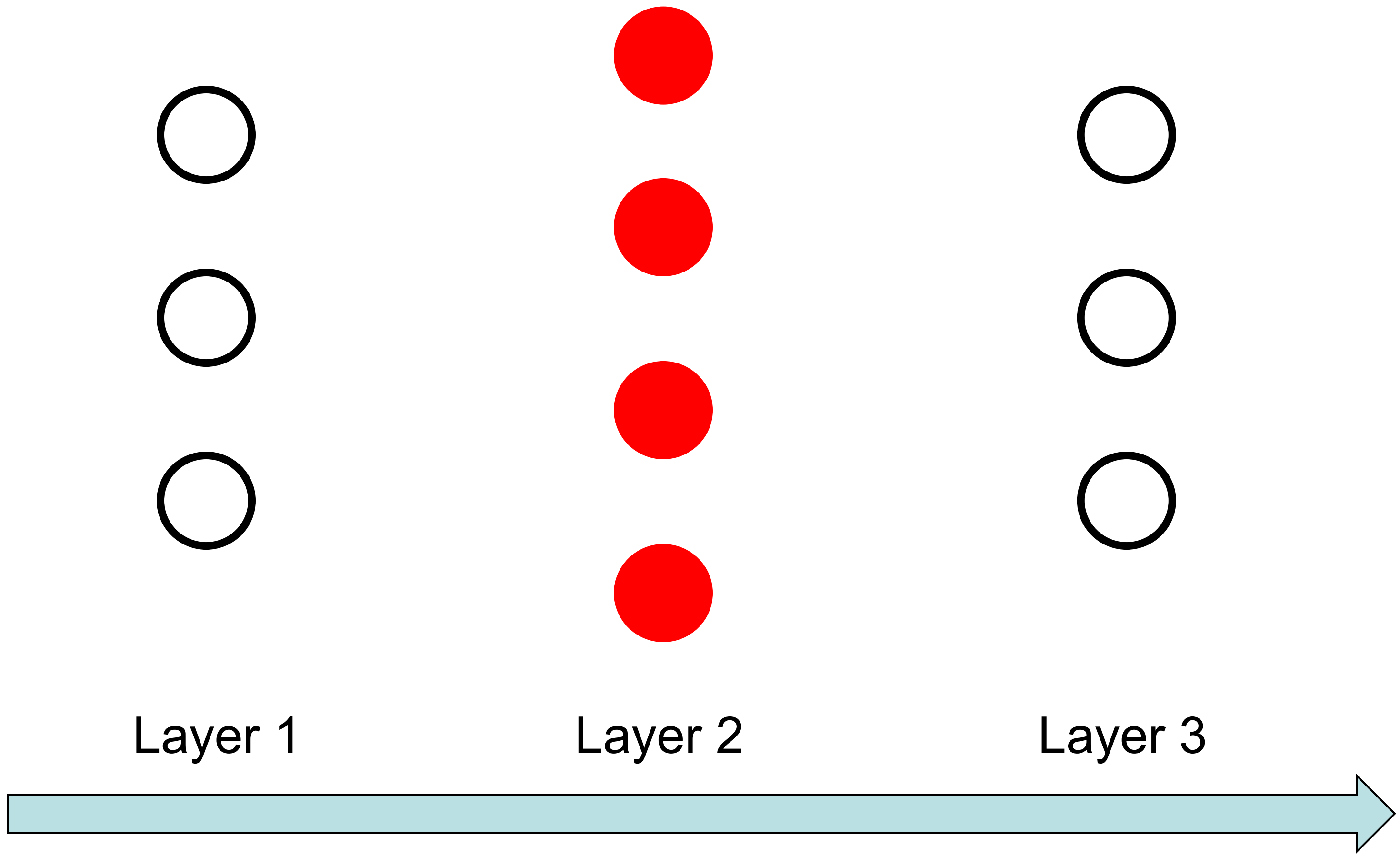


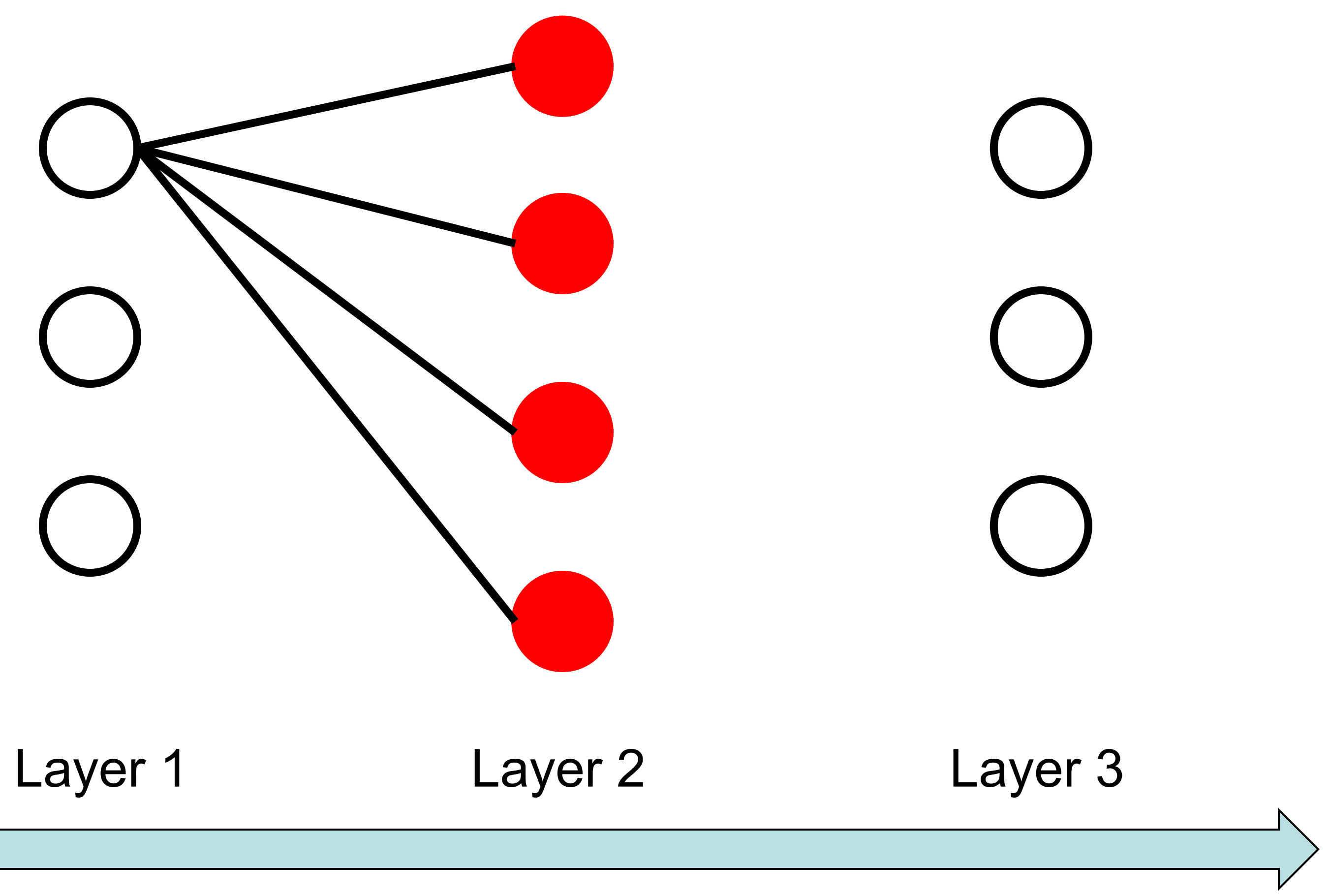
Perceptron model


Input 1
Input 2
Input 3
Input 4
+

Fully-connected Layers

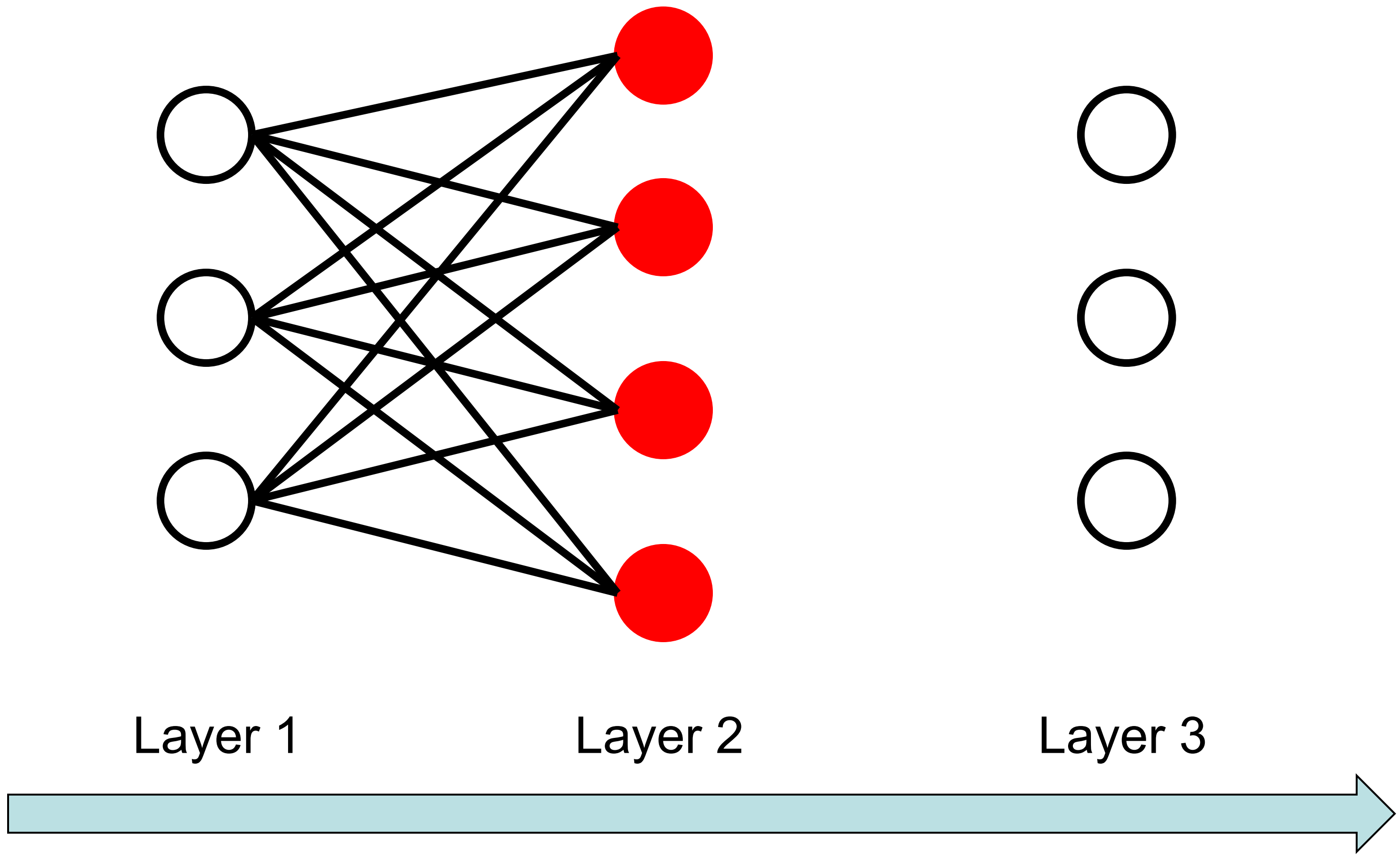


Fully-connected Layers



Fully-connected Layers

Now we have a fully-connected layer



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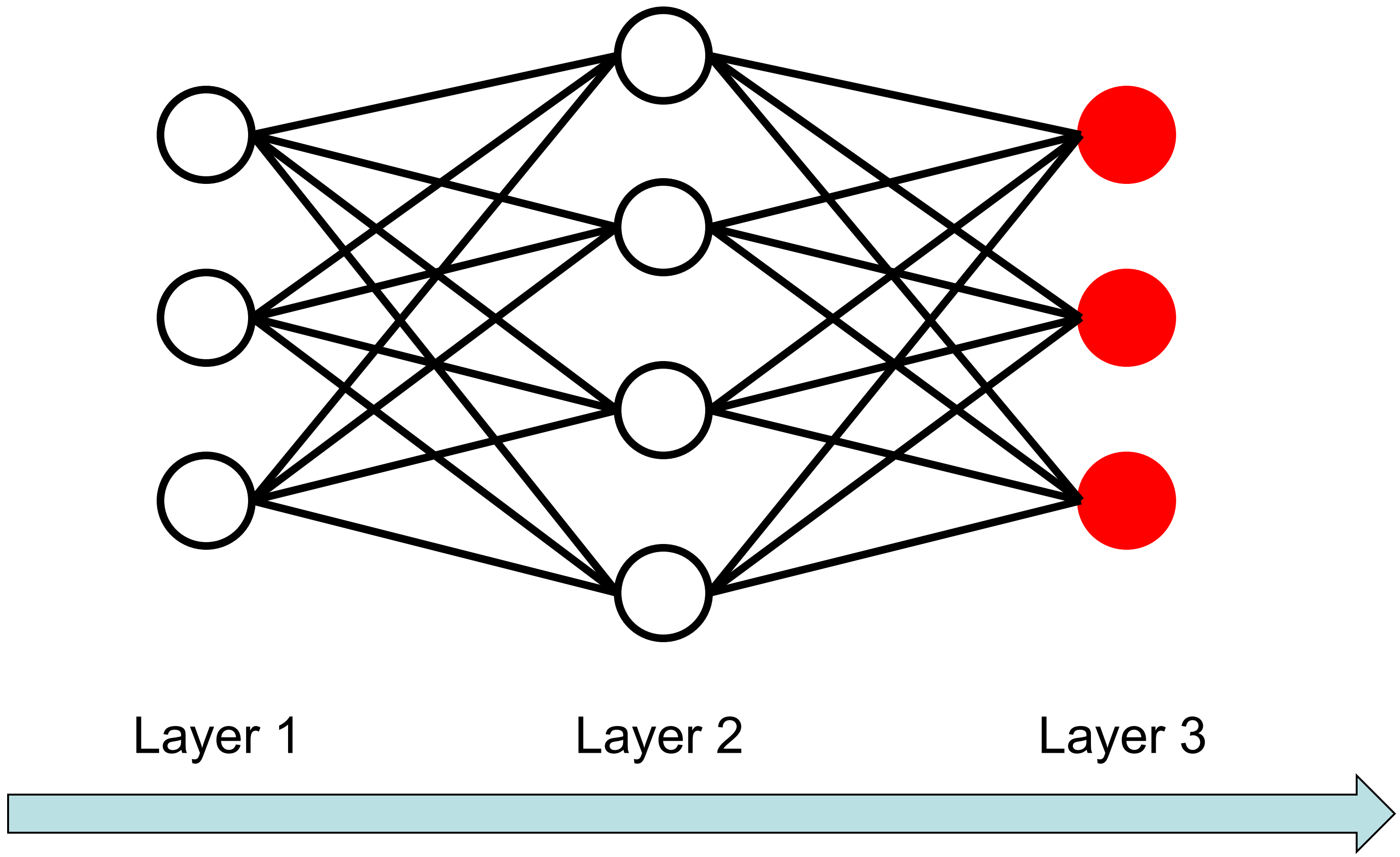

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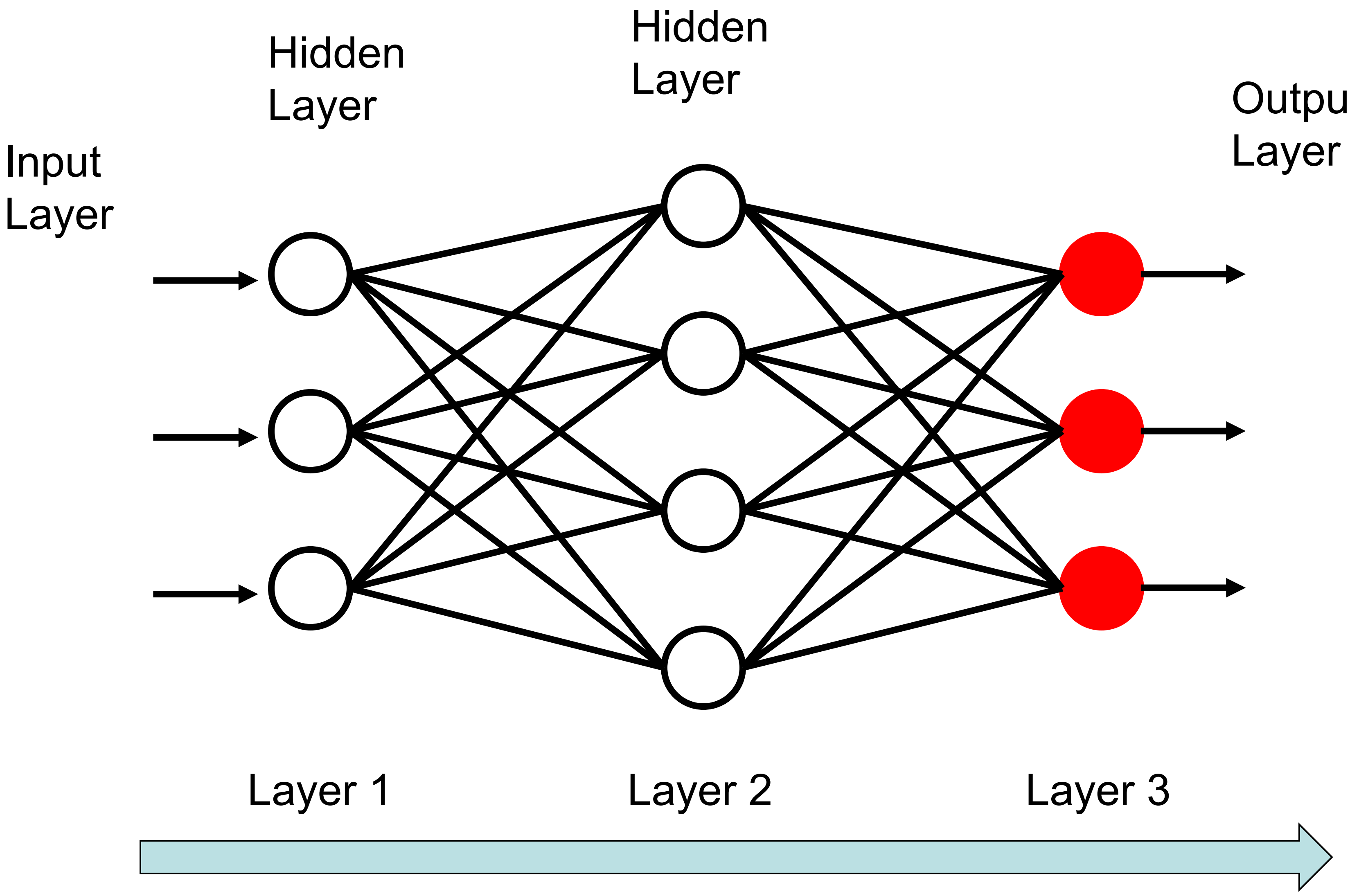

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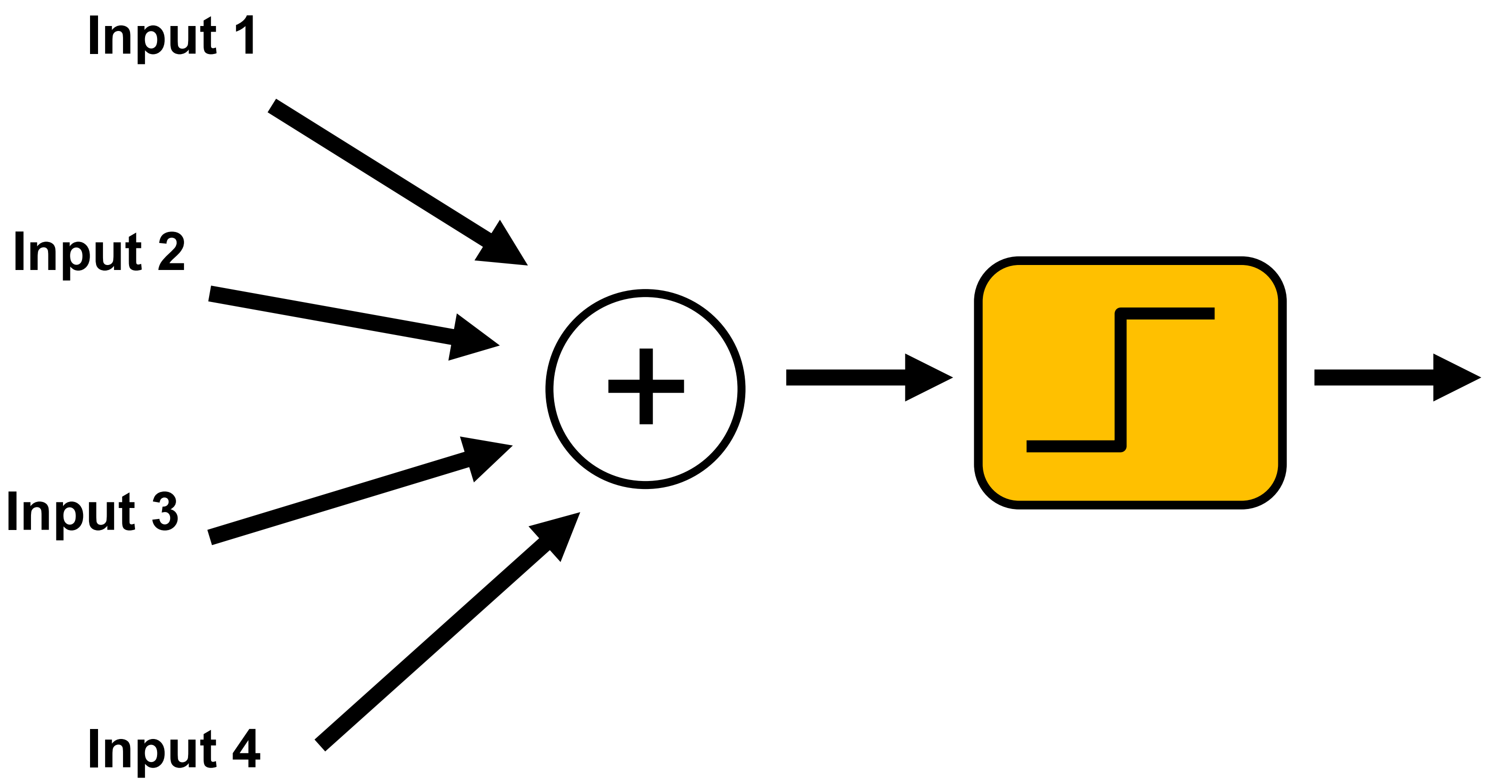

Activation functions

- Rectified Linear Unit (ReLU). The most used activation function.
- Sigmoid. It is especially used for models where we have to predict the probability.
- Hyperbolic tangent activation function (Tanh).

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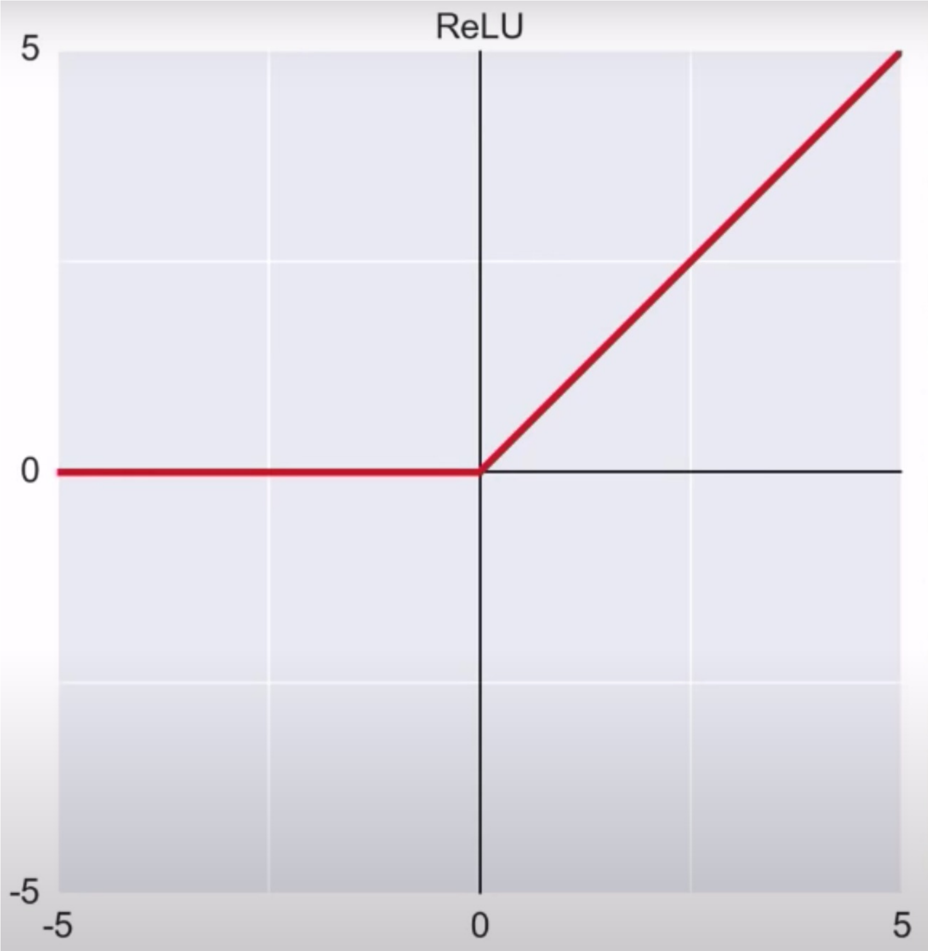
Activation functions

Rectified Linear Unit (ReLU)



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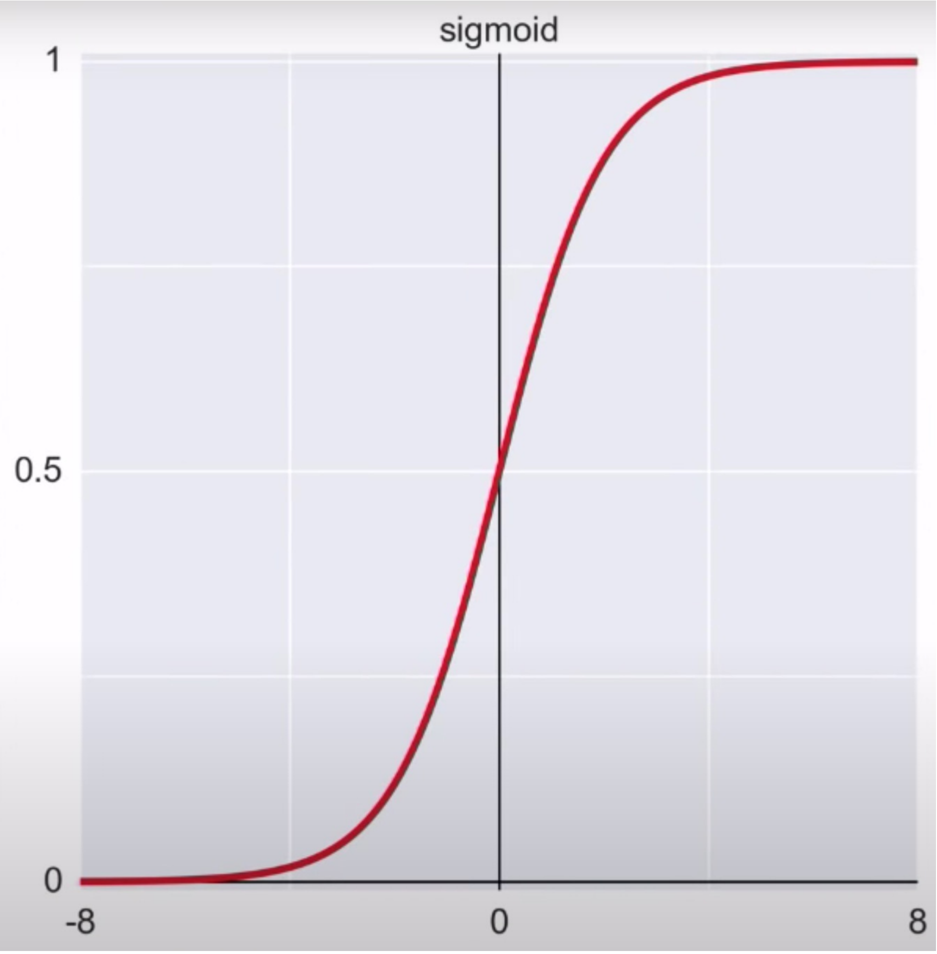
Activation functions

Sigmoid



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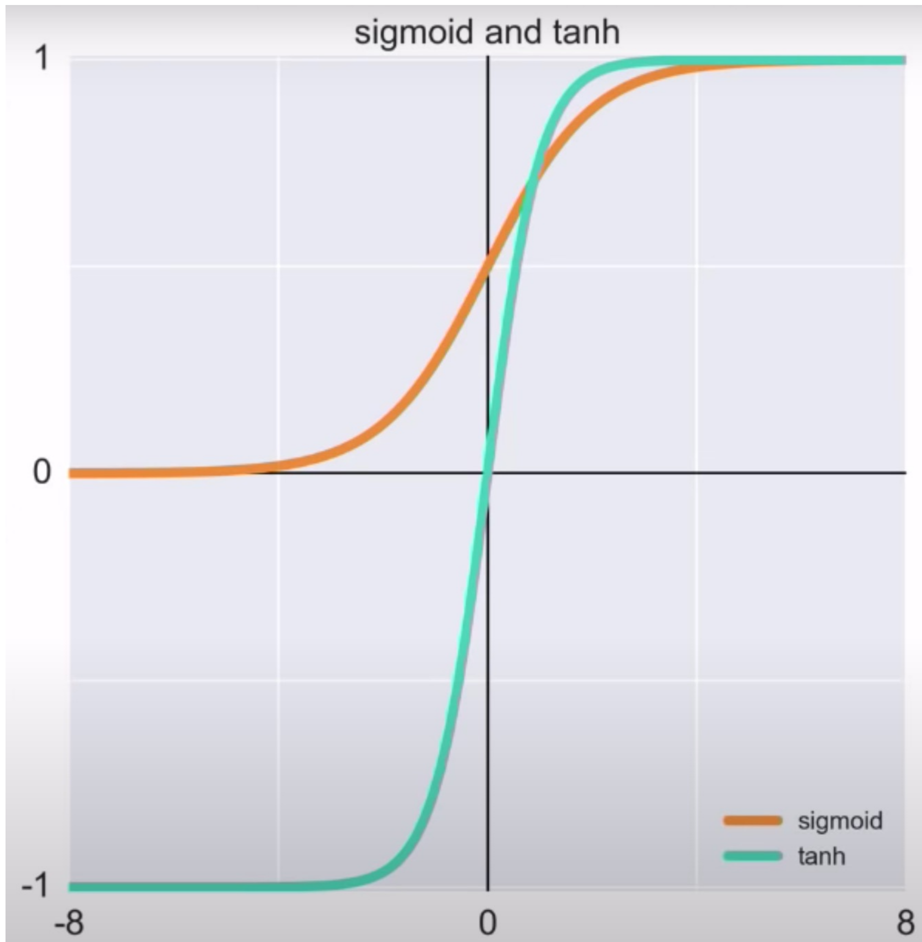
Activation functions

Hyperbolic tangent activation function (Tanh)



Activation functions

- Any given layer, we assign one activation function to all of the neurons in that layer.

Activation functions

- Softmax

More generalized logistic activation function which is used for multiclass activation

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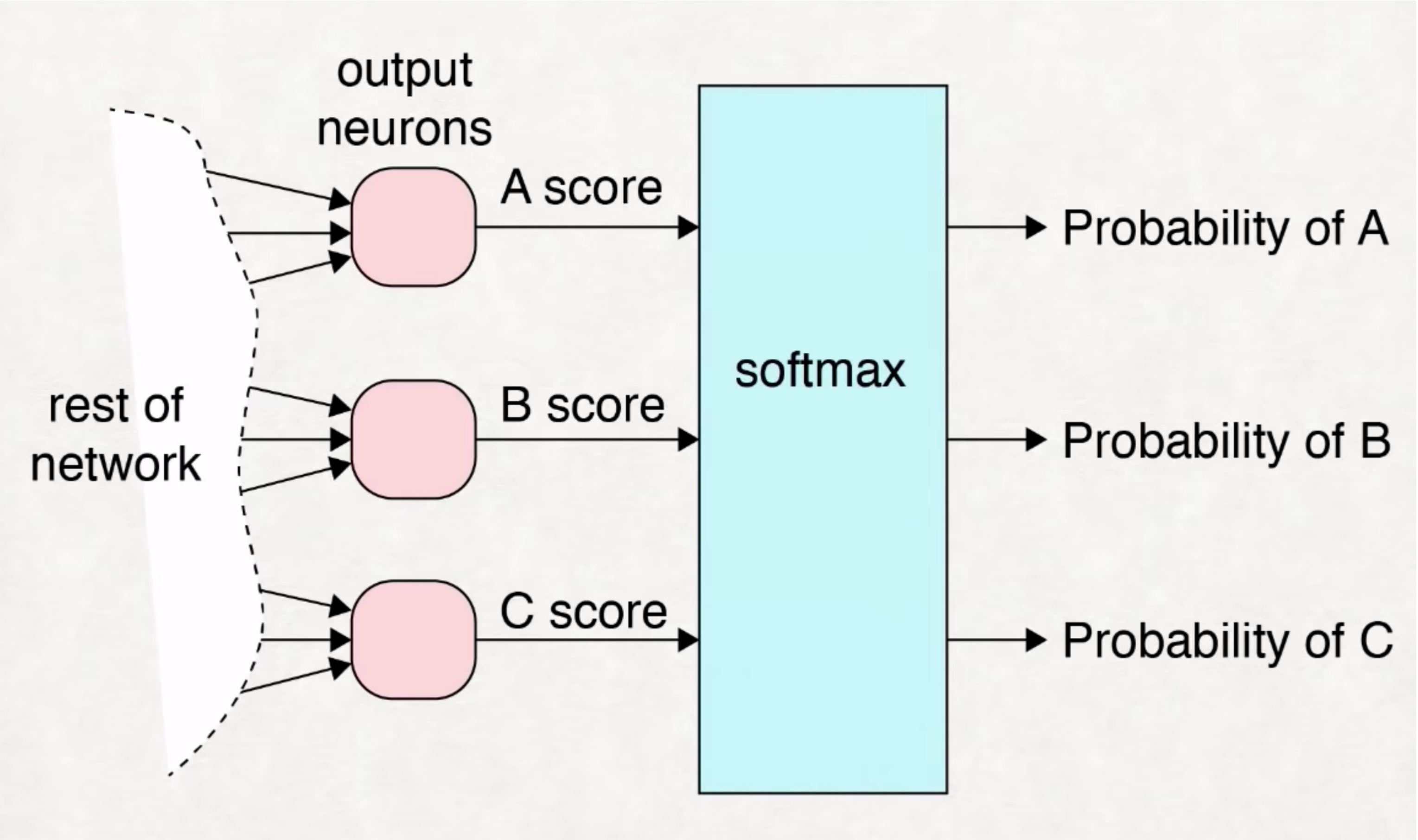
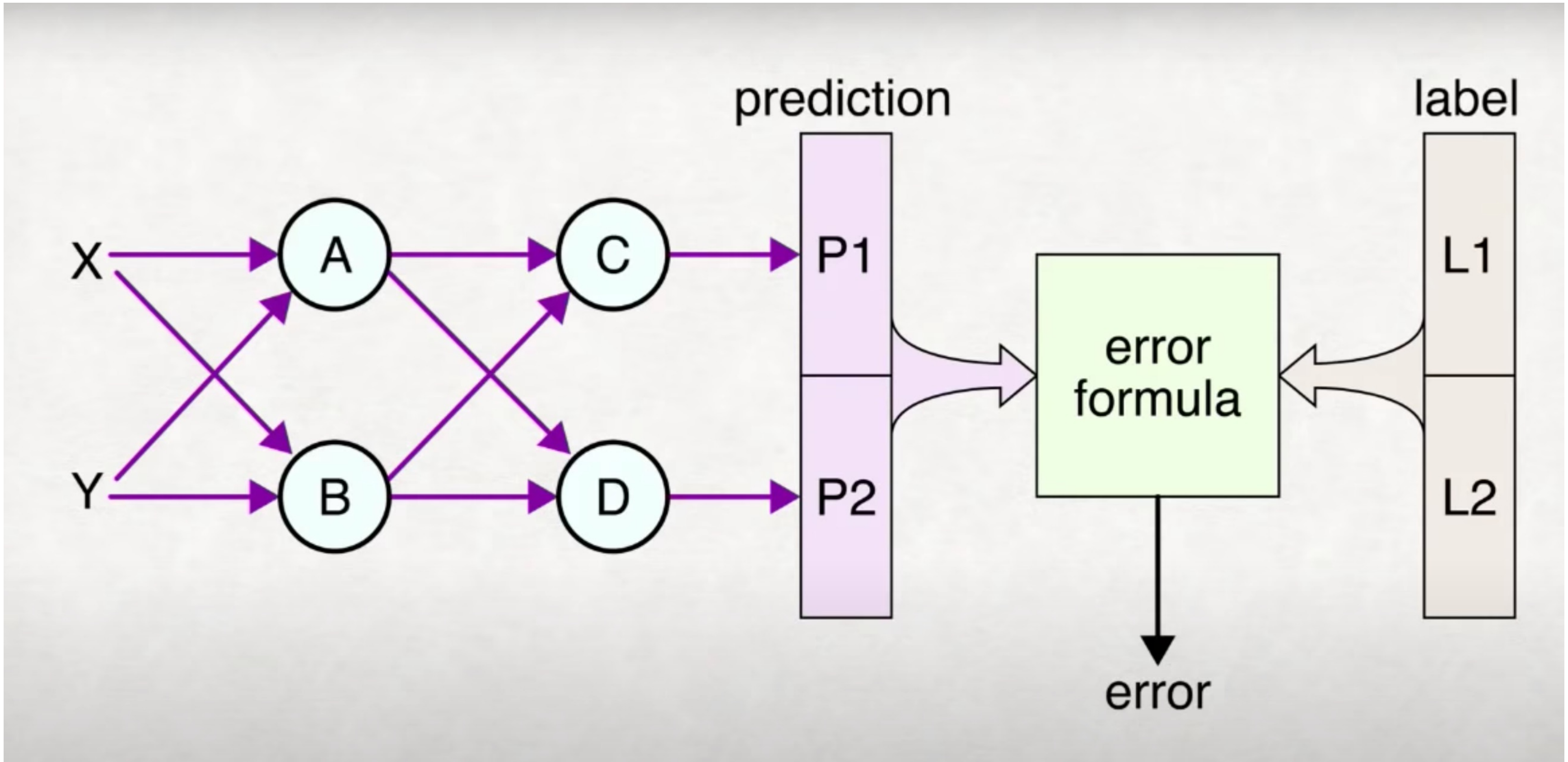
Softmax



Loss functions



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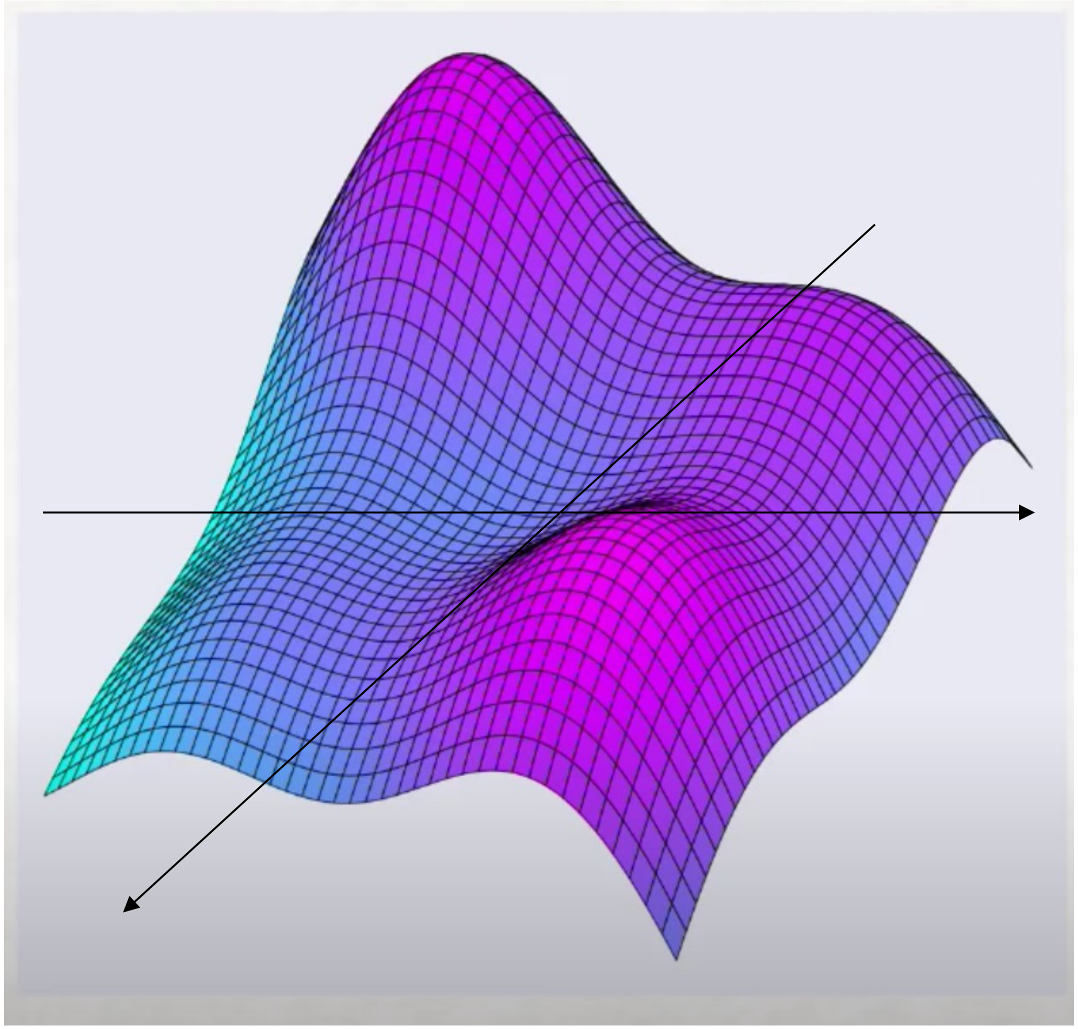
Gradient Decent

- Learning from mistakes

Gradient Decent



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Gradient Decent