

## AI for Good Workshop

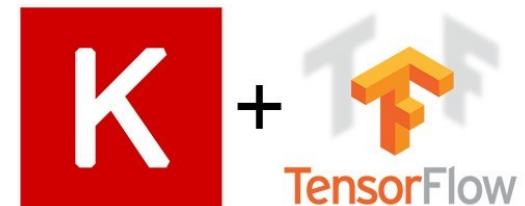
March 2019

Session 3

# Artificial Intelligence for everyone

Understands concepts of  
Deep Learning

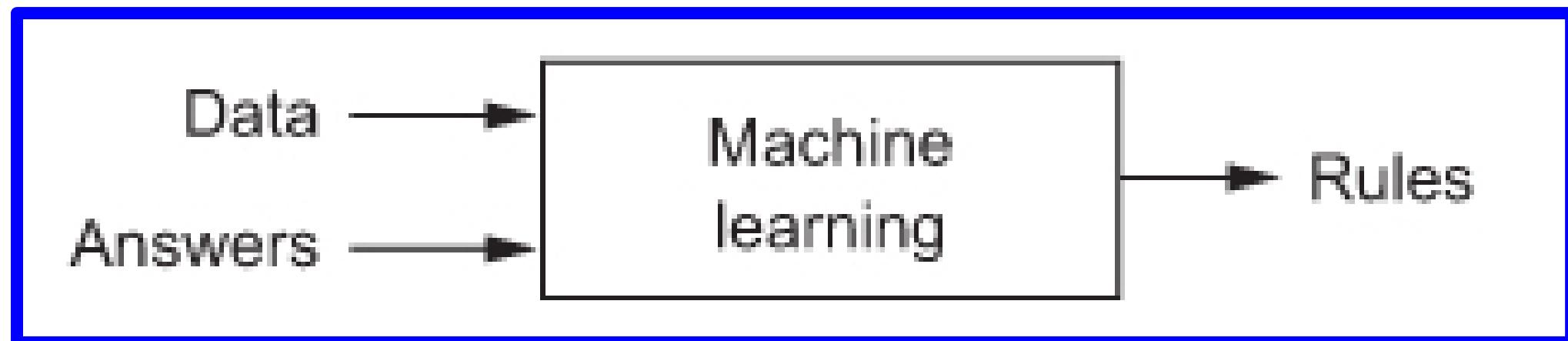
<https://sites.google.com/view/AlforEveryone>



# Topics in this presentation

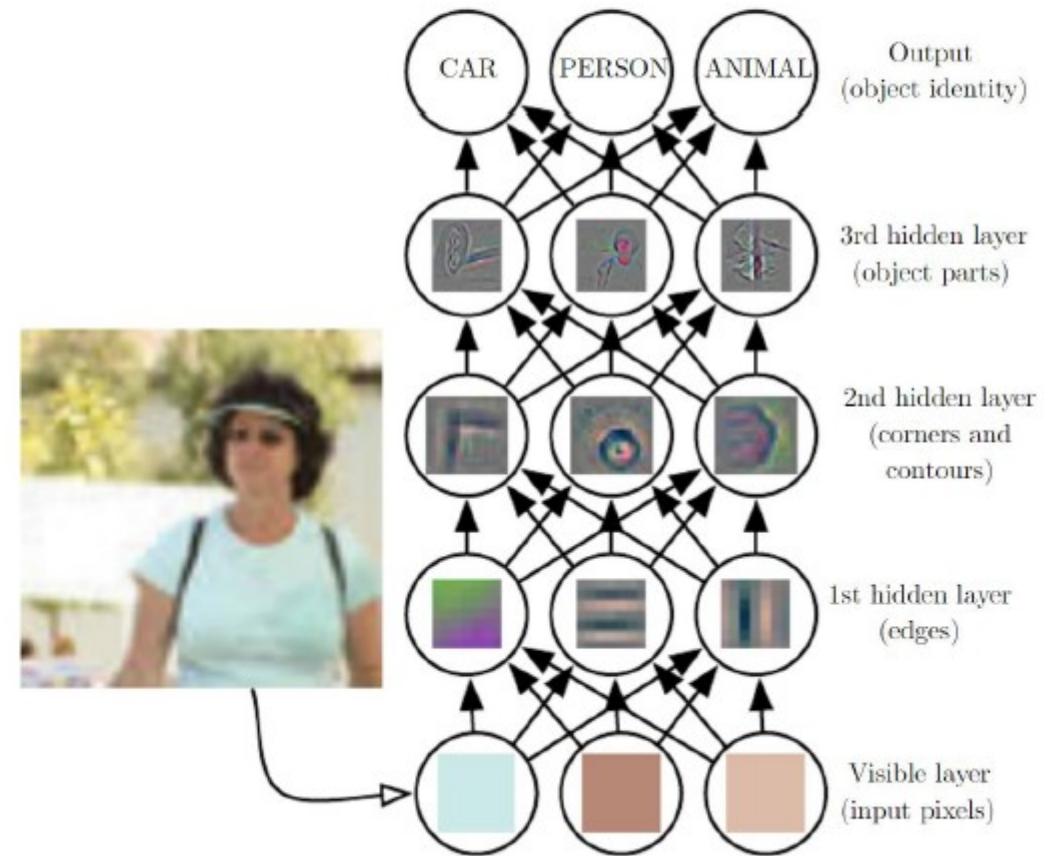
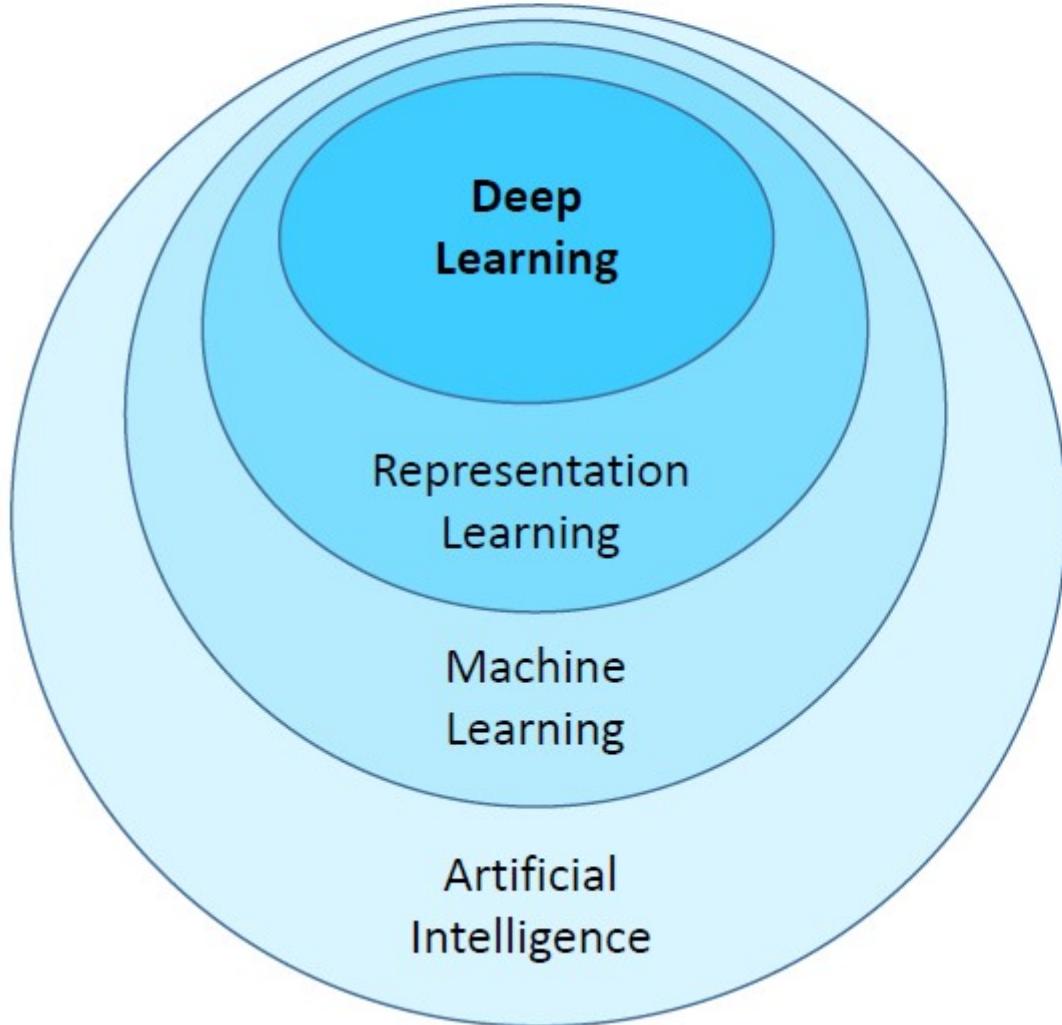
**Basic conceptual understanding of  
Neural Networks, Gradient Descent**

# New way to think from today !

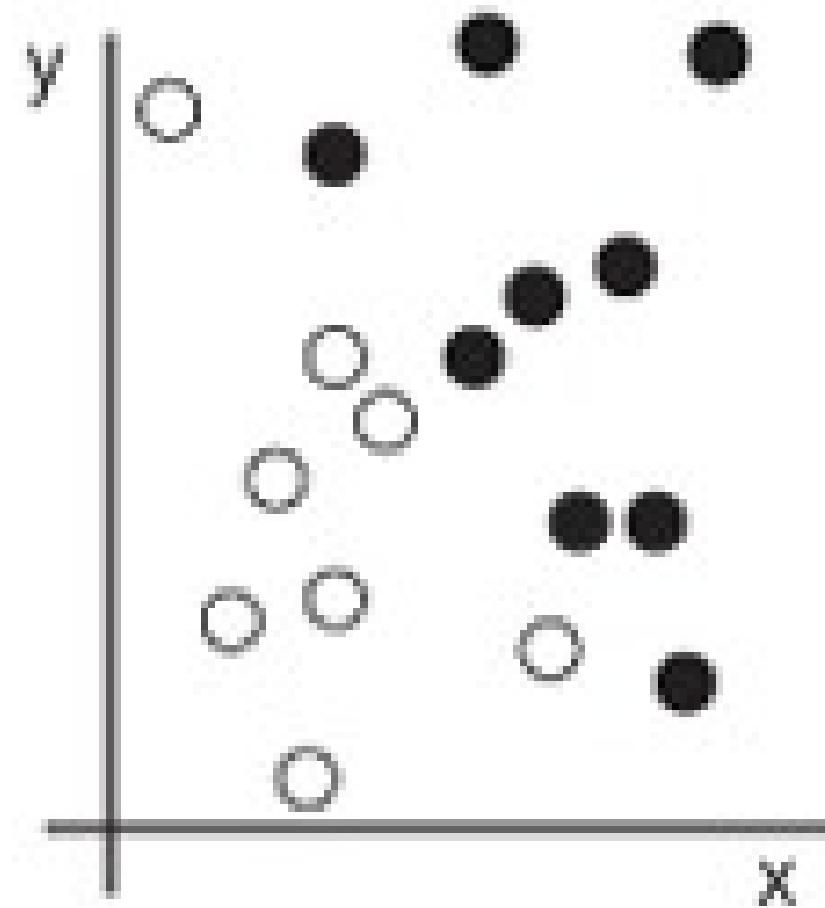


# Deep Learning is Representation Learning

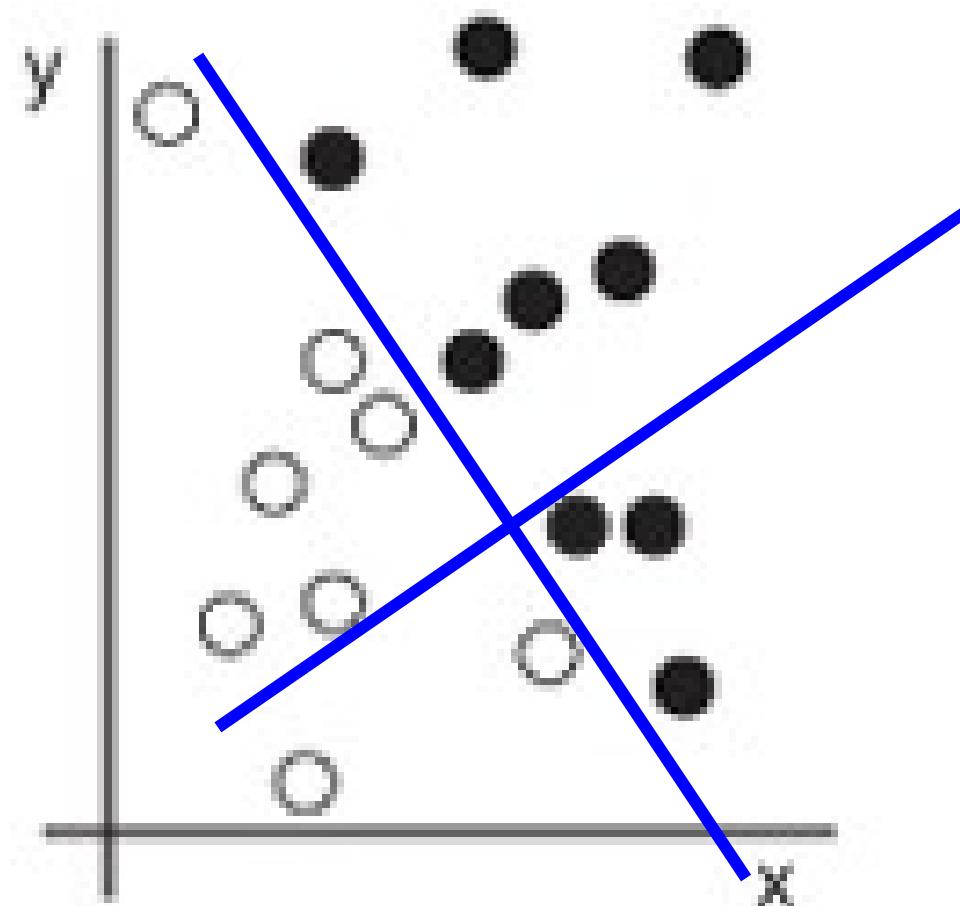
(aka Feature Learning)



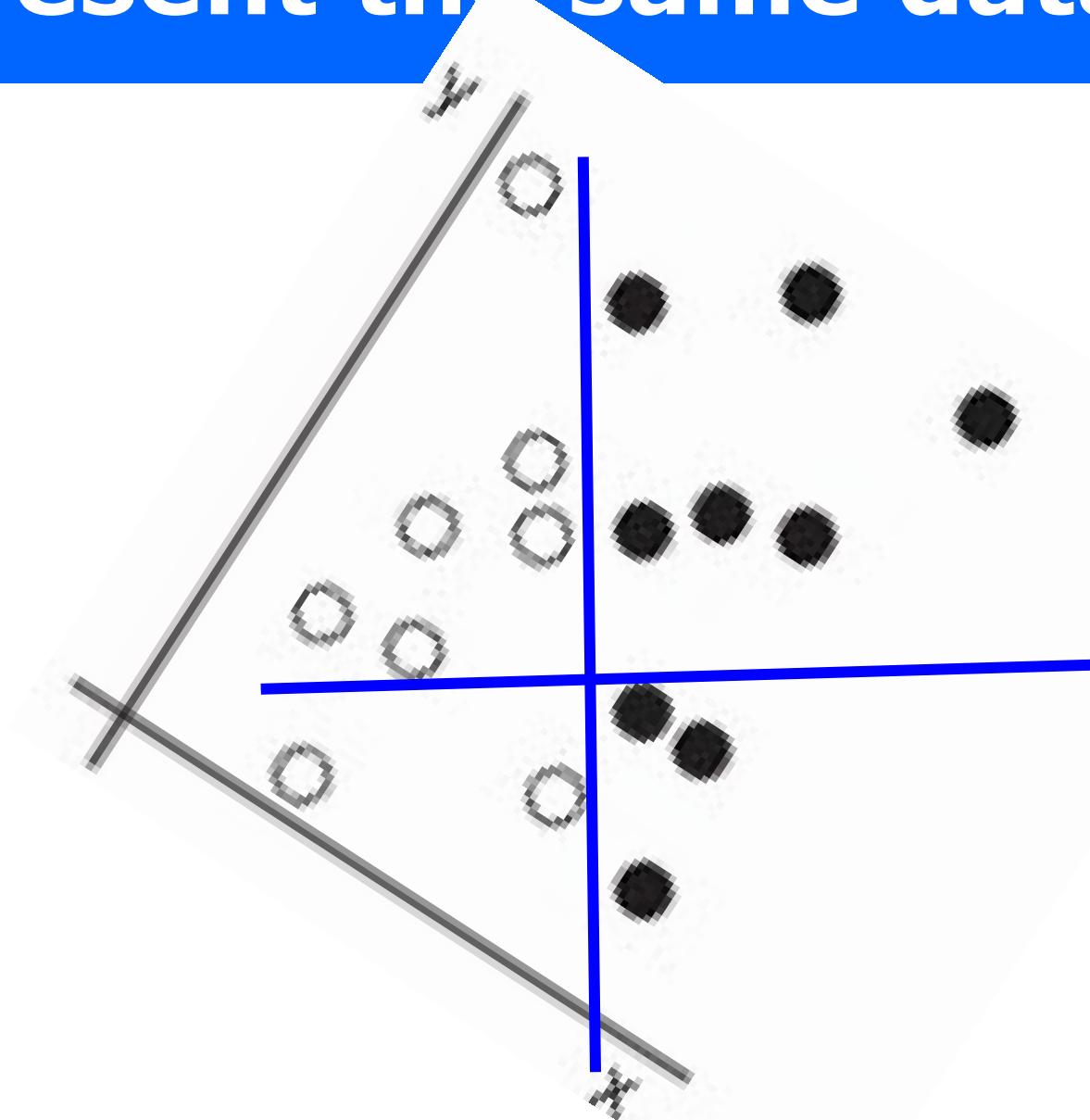
# Represent the same data in a new way



# Represent the same data in a new way



# Represent the same data in a new way

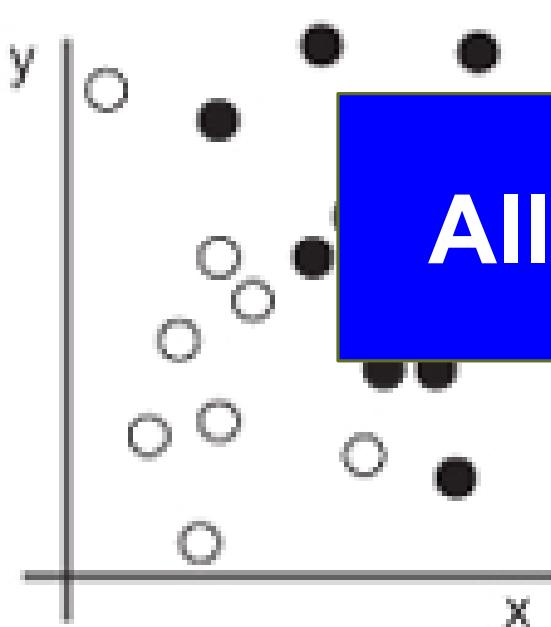


# Find a way to represent the data in a better way?

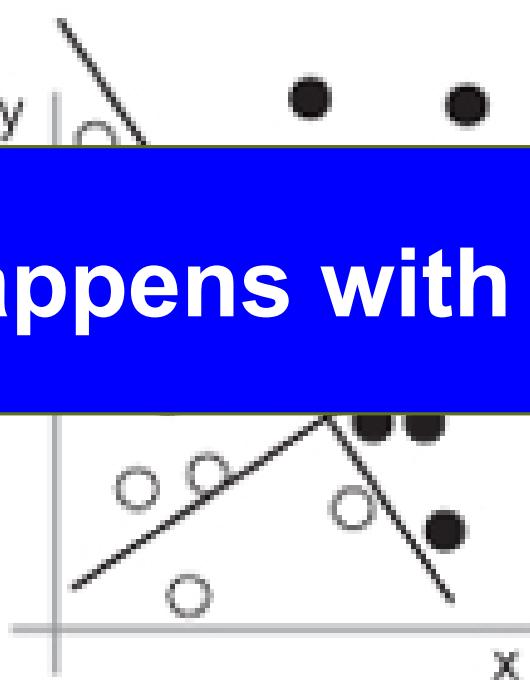
Deep learning is === a multistage way to learn data representations.

It's a simple idea—but, as it turns out, very simple mechanisms, sufficiently scaled, can end up looking like magic.

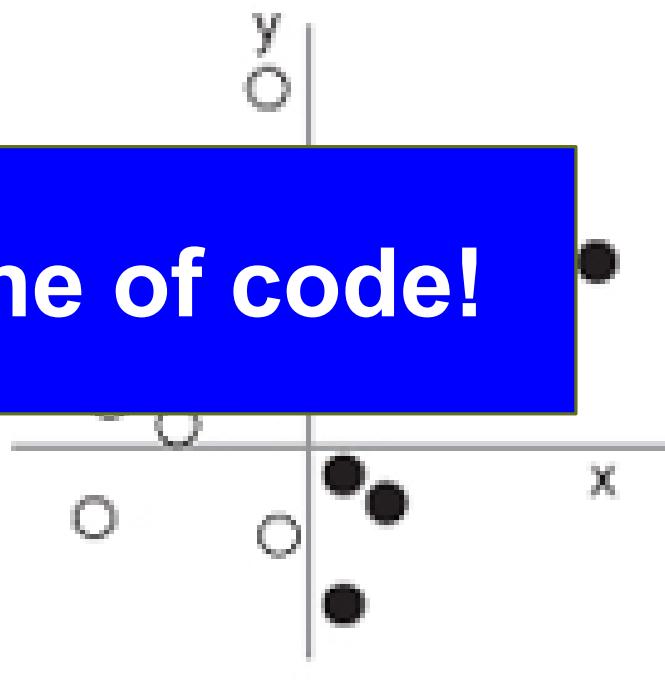
1: Raw data



2: Coordinate change



3: Better representation



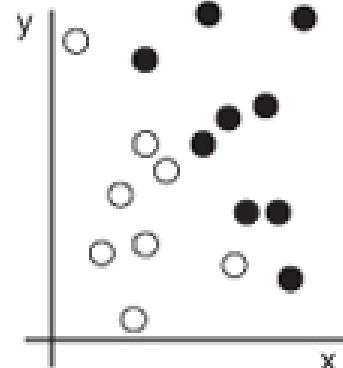
# Just 1 line of code == magic!

**Deep learning is === a multistage way to learn data representations.**

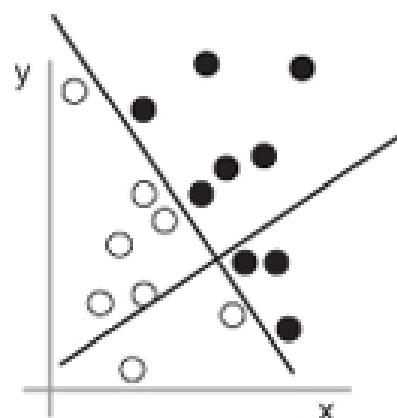
It's a simple idea—but, as it turns out, very simple mechanisms, sufficiently scaled, can end up looking like magic.

**myModel. fit ( X , Y )**

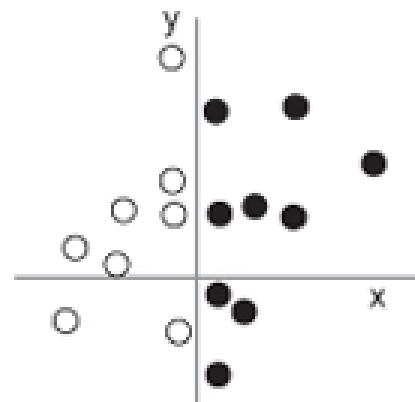
1: Raw data



2: Coordinate change



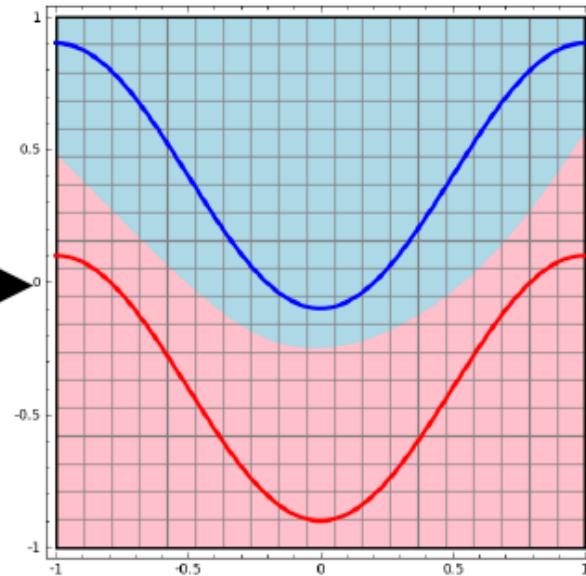
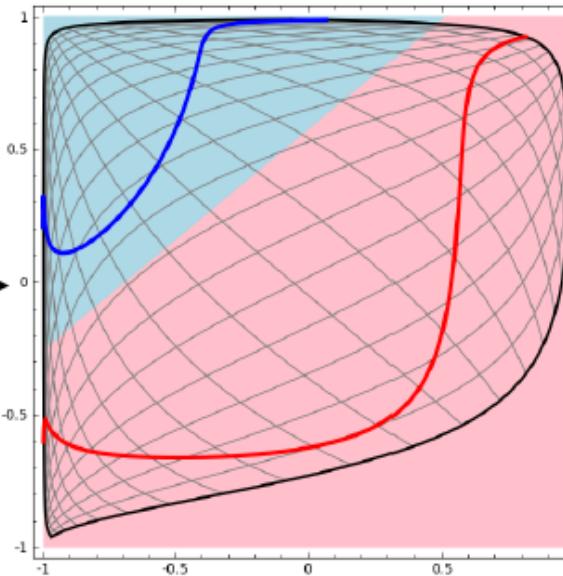
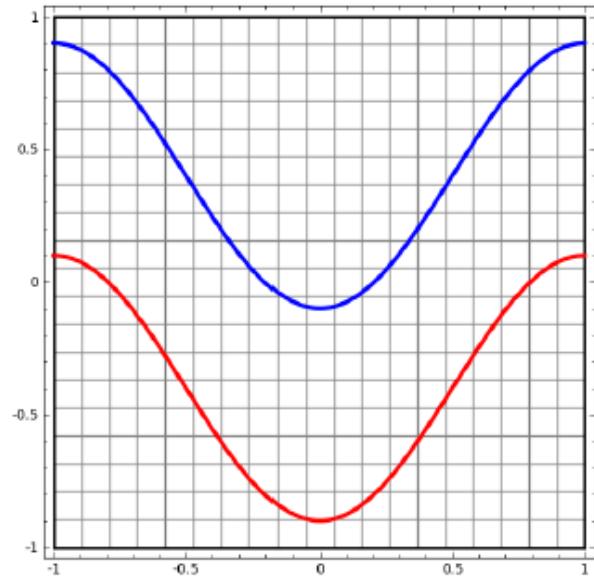
3: Better representation



# Deep Learning is Representation Learning

(aka Feature Learning)

All this happens with just 1 line of code!

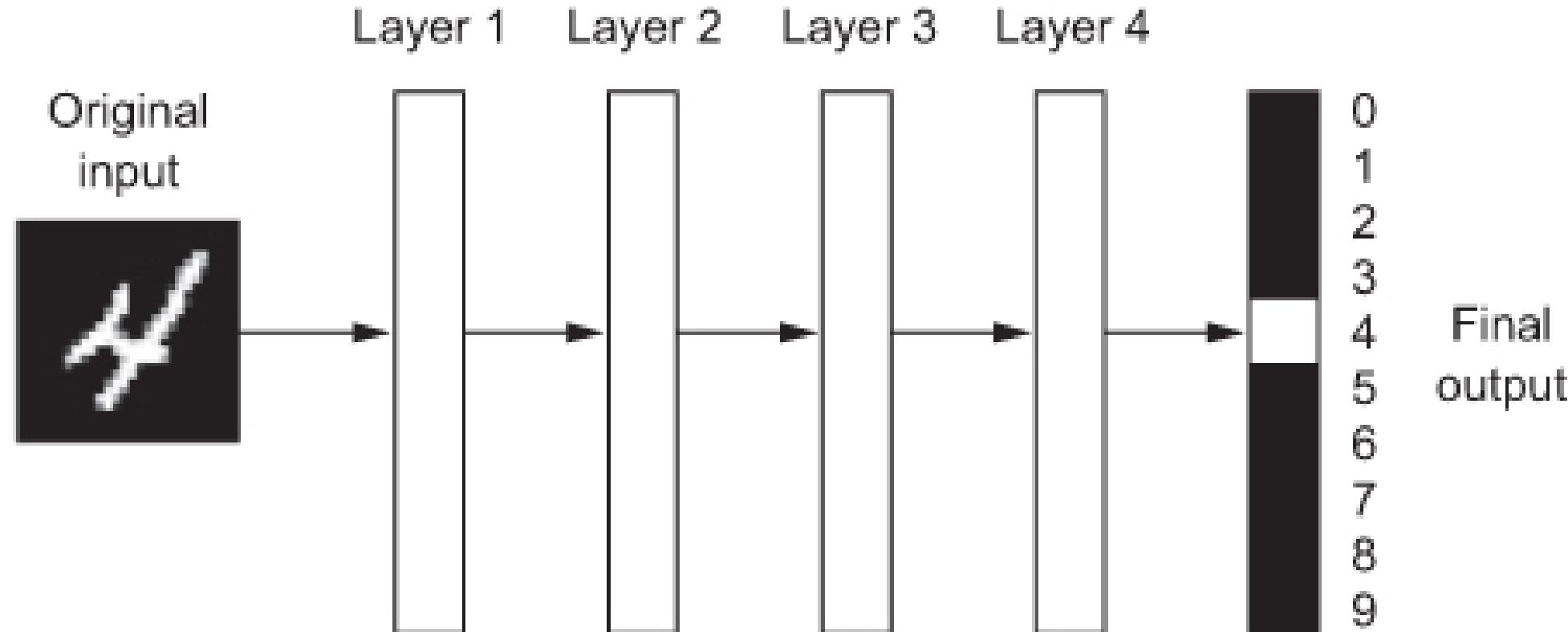


**Task:** Draw a line to separate the **blue curve** and **red curve**

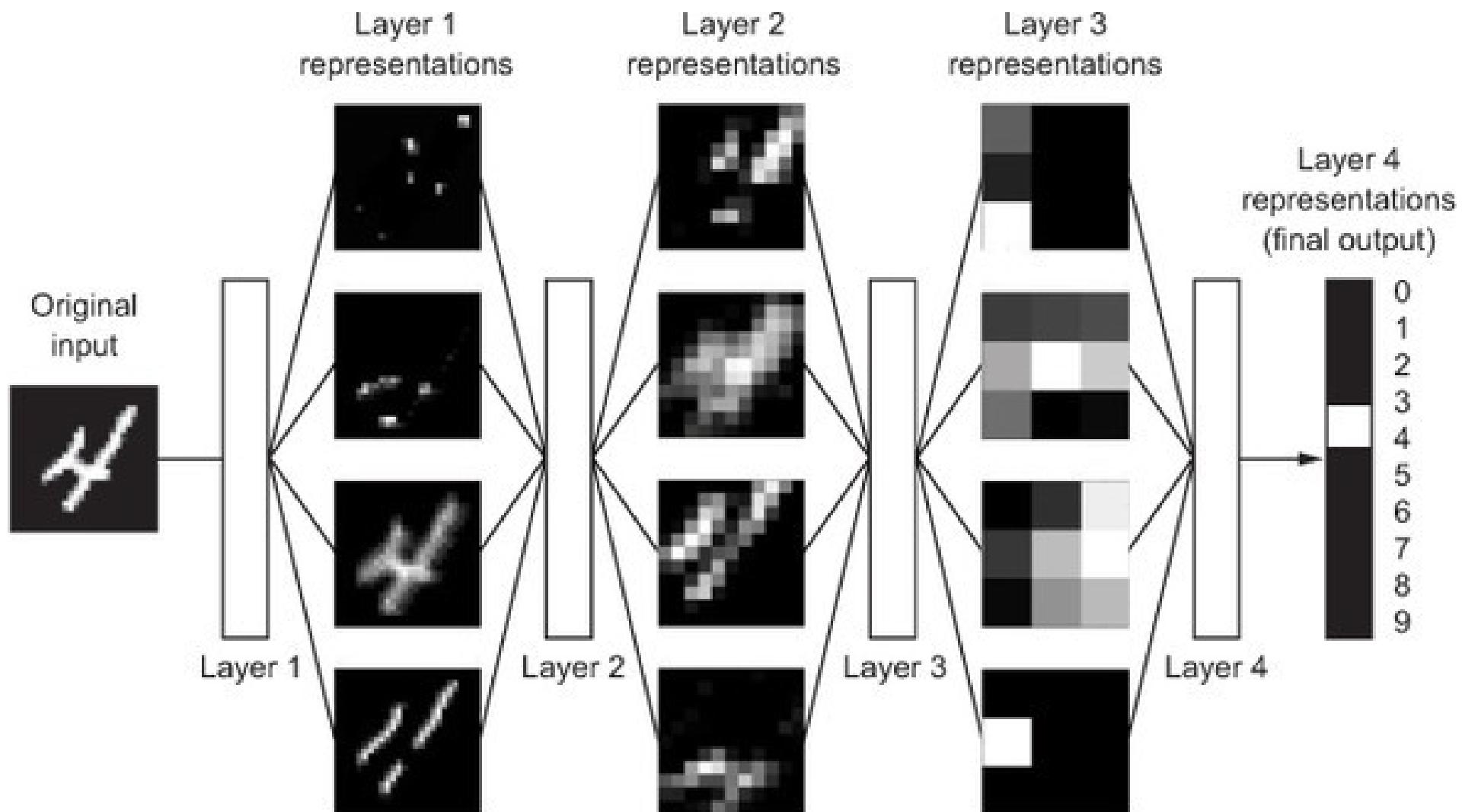
# How did the magic happen?

```
import keras  
  
(x, y) = load_data()  
  
model = keras.Sequential()  
  
model.add(layers.Dense)  
model.add(layers.Dense)  
  
model.fit(x, y )
```

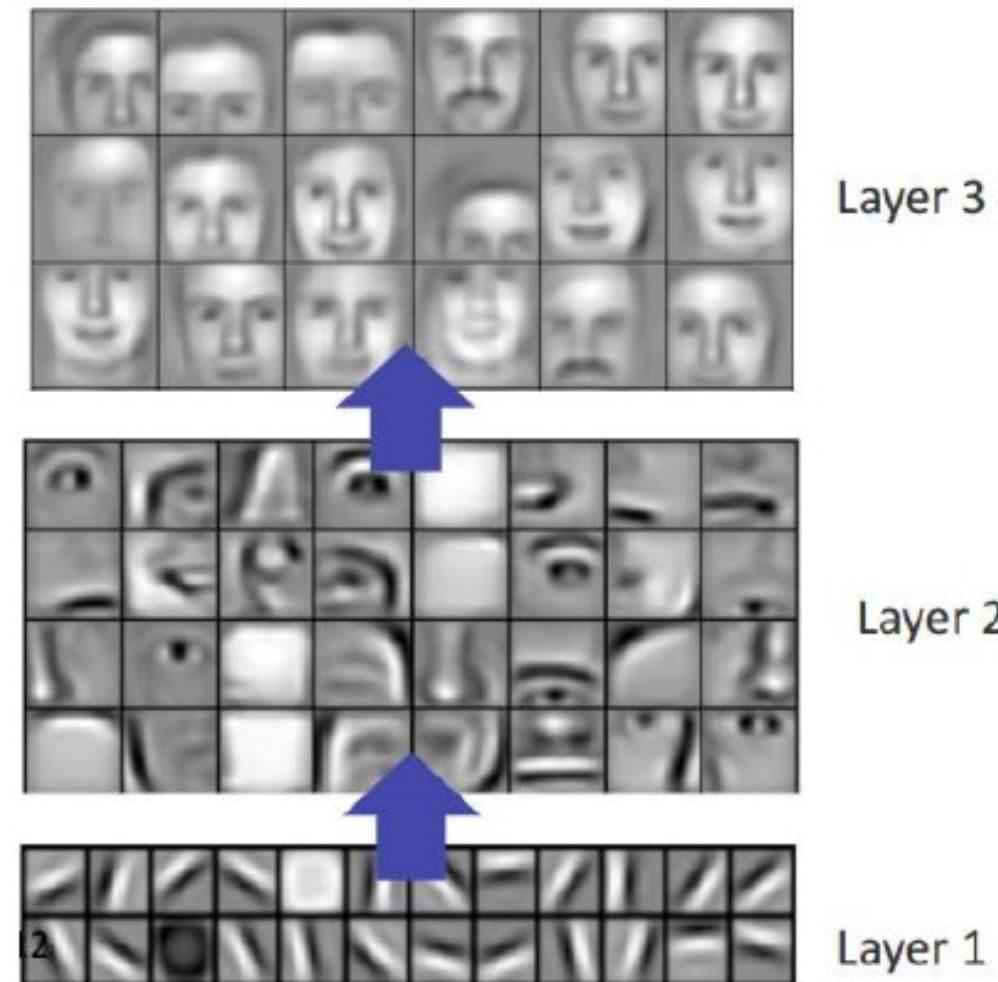
# Can a neural network automatically represent the raw data into another way?



# Deep representations learned by a neural network model

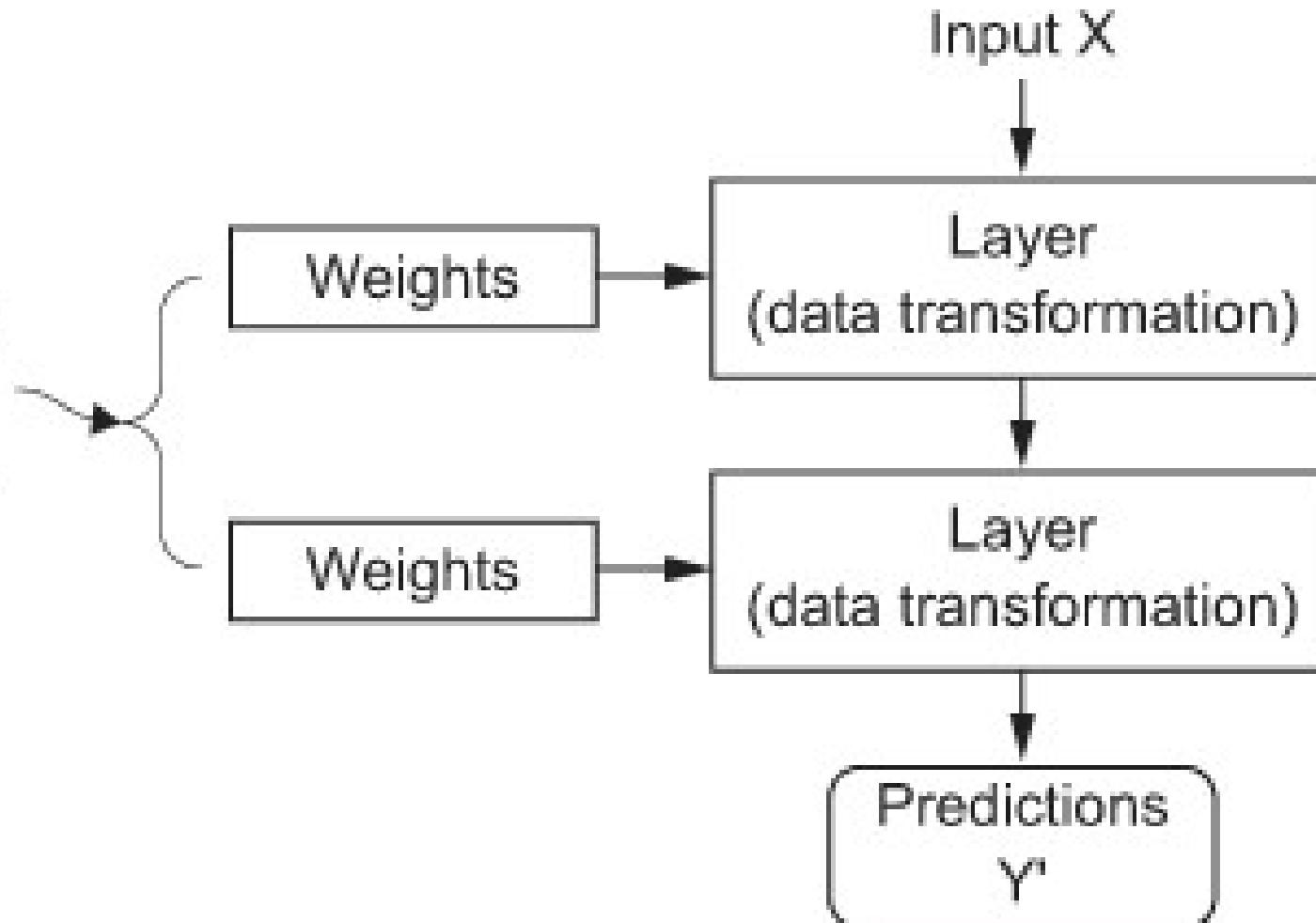


# representations “learned” automatically

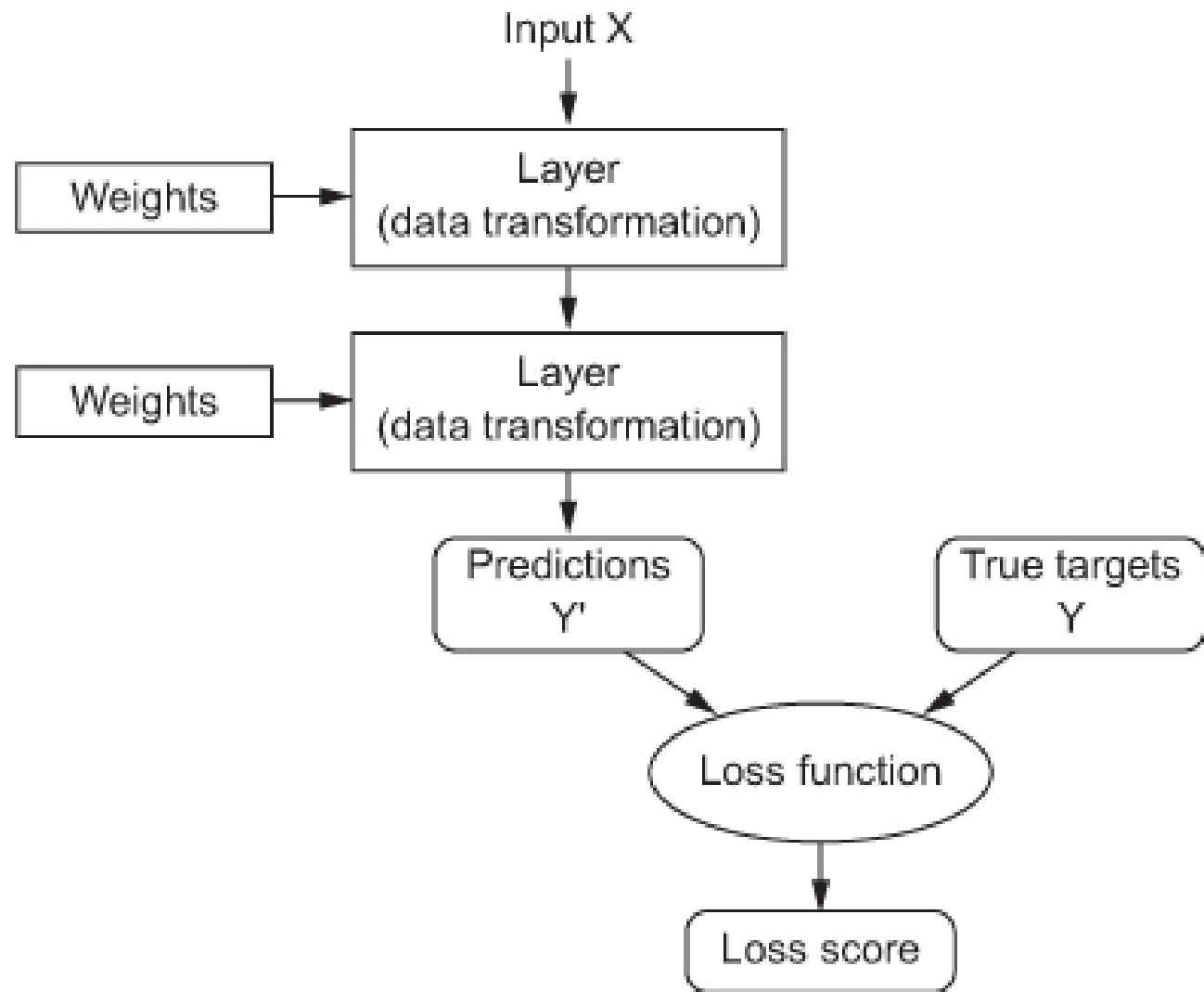


# A neural network is parameterized by its weights

**Goal: finding the right values for these weights**

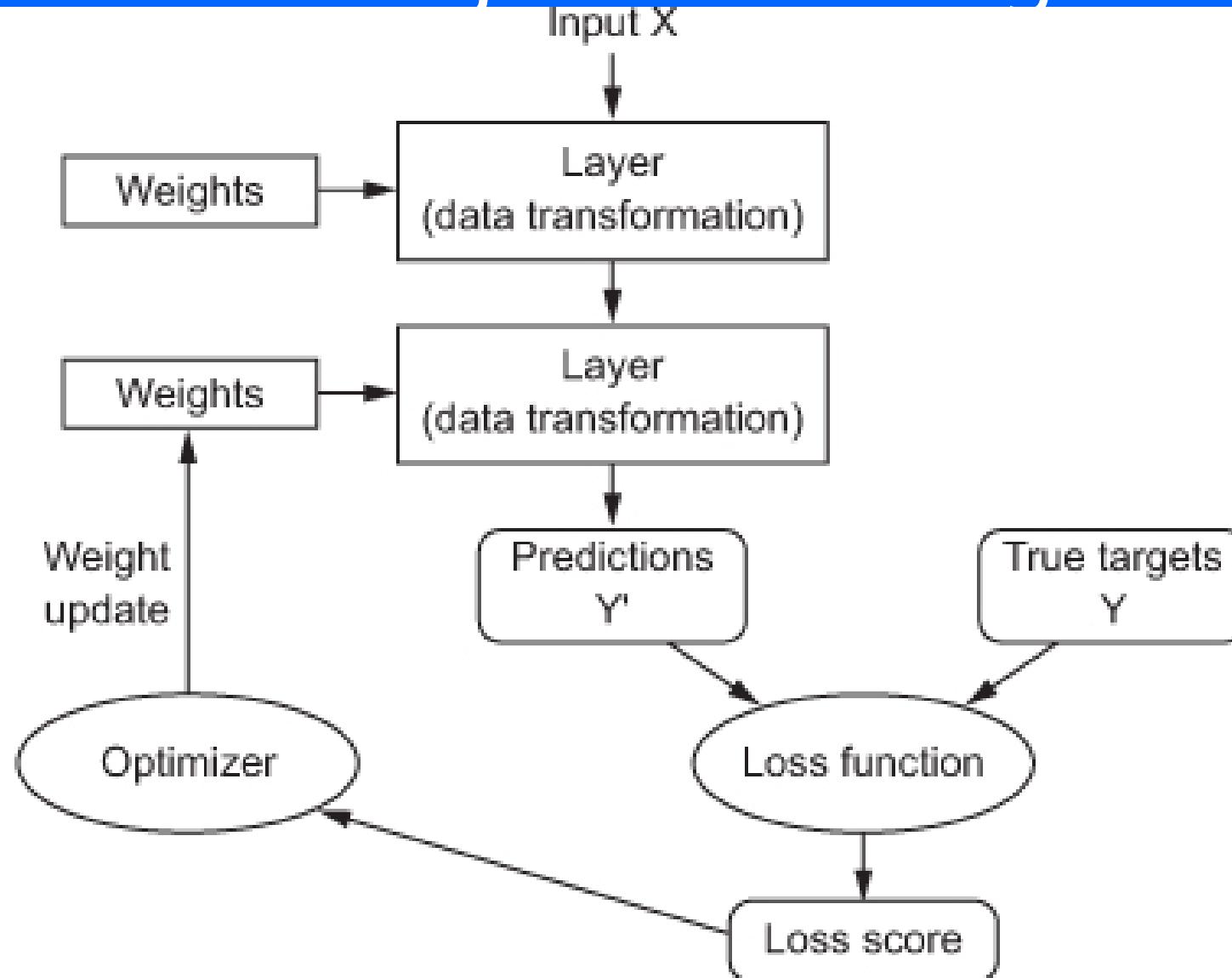


# A loss function measures the quality of the network's output



The loss function takes the predictions of the network and the true target, and computes a distance score, capturing how well the network has done on this specific example

# The loss score is used as a feedback signal to adjust the weights



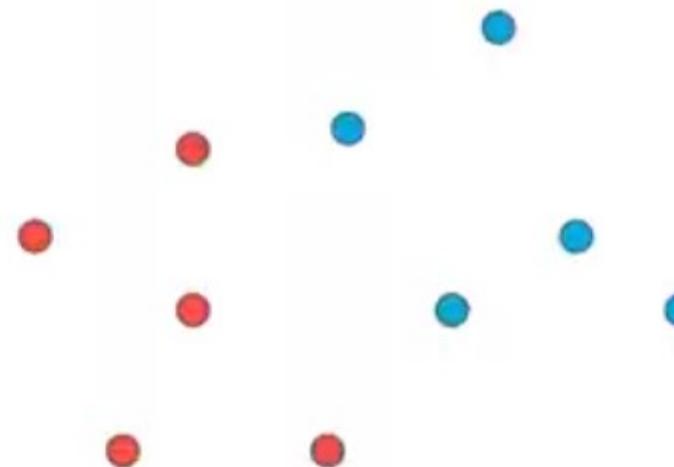
# Neural Networks



Credits: Luis Serrano

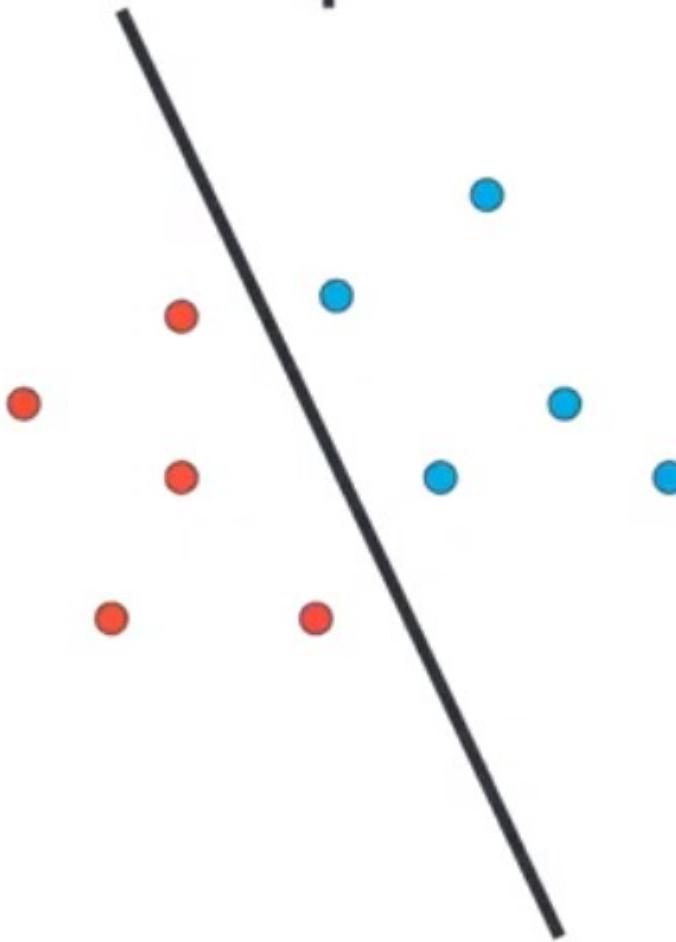
<https://www.youtube.com/watch?v=BR9h47Jtqyw>

# Goal: Split Data

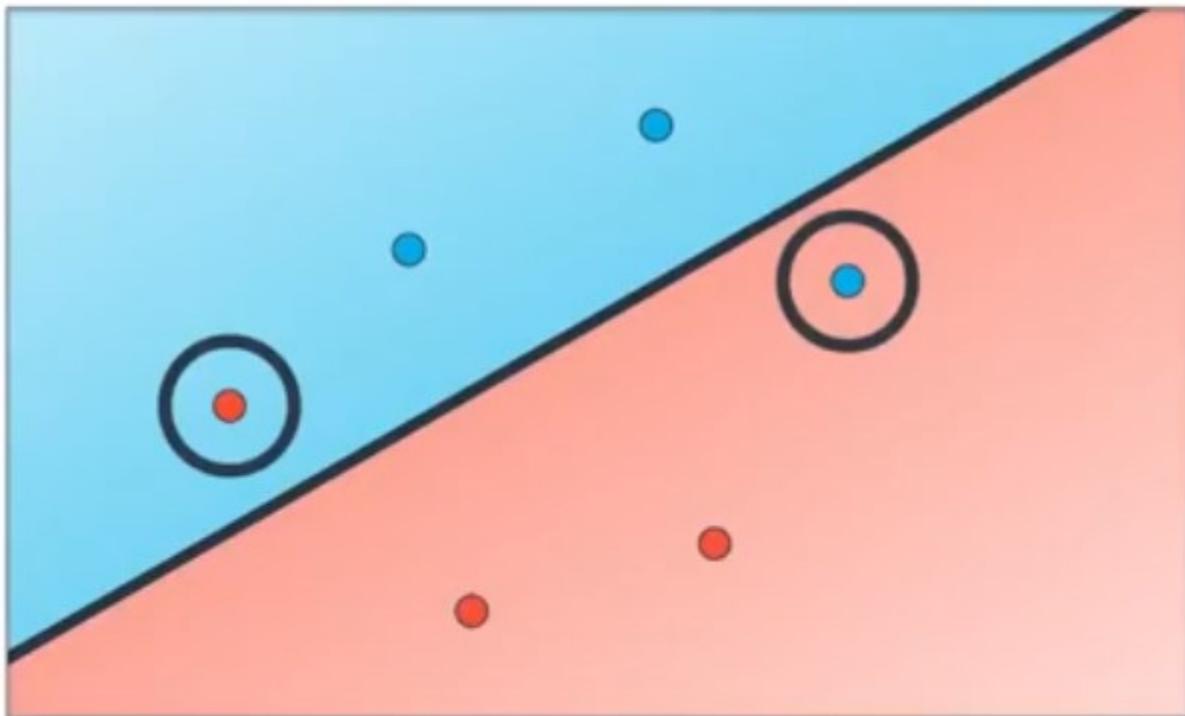


# Teach a computer how to split the data

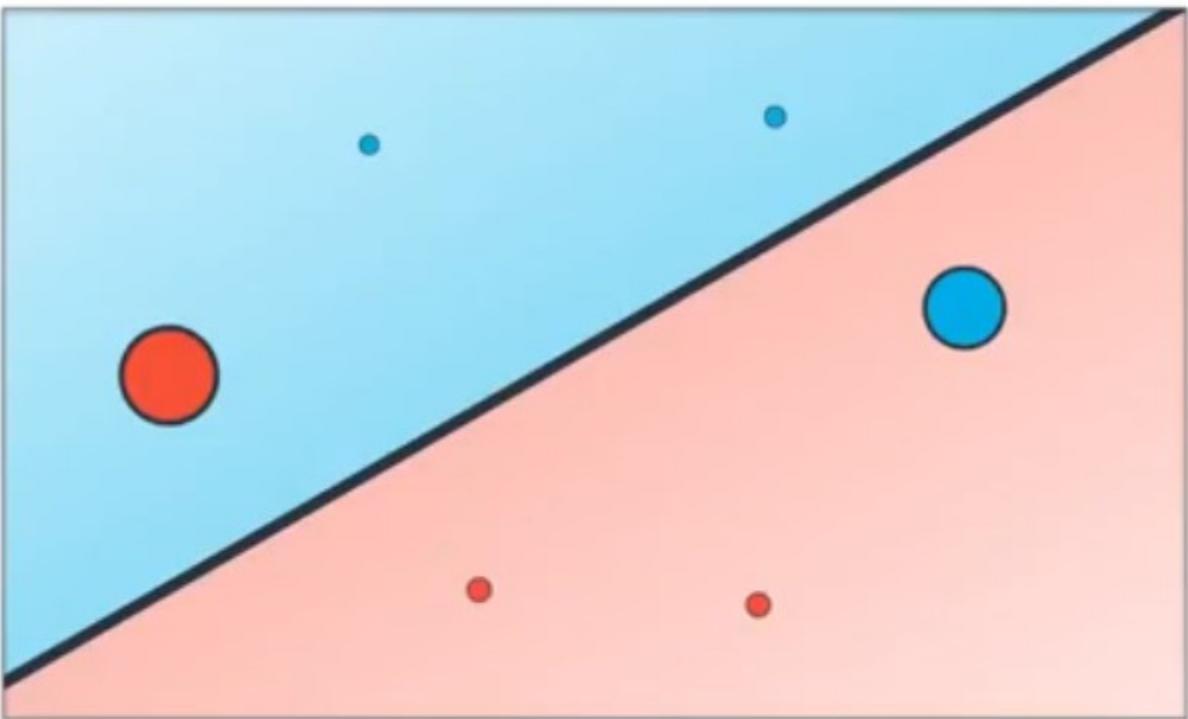
## Goal: Split Data



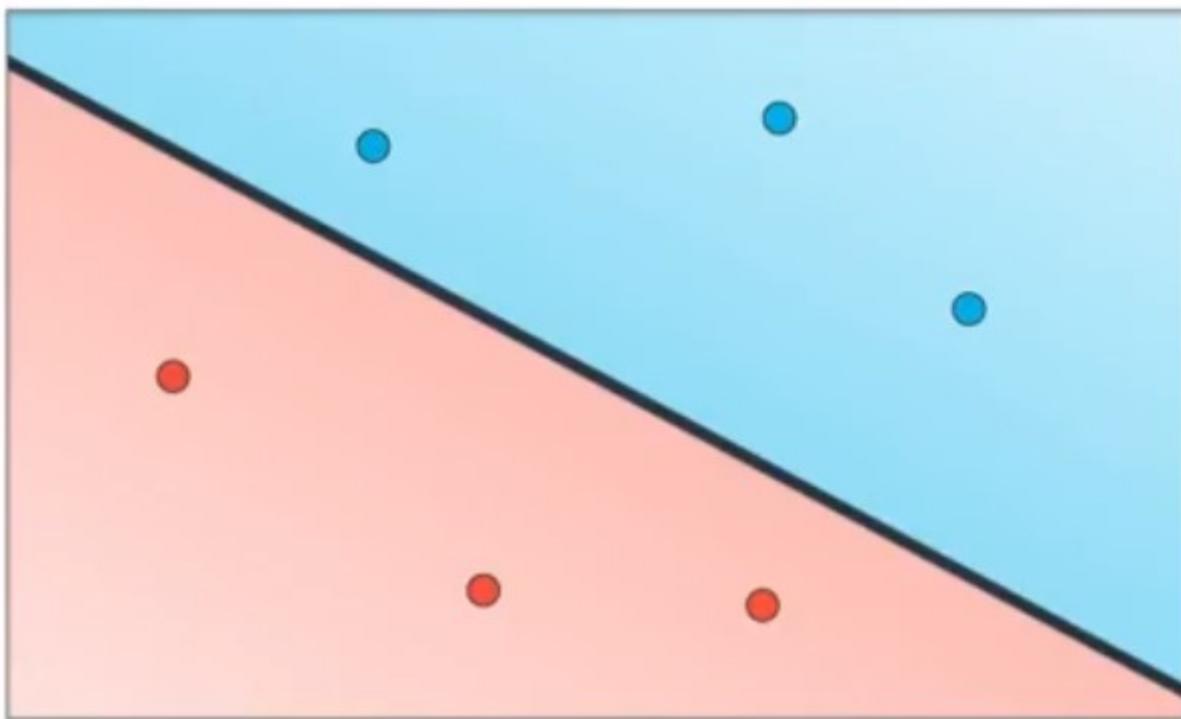
# Goal: Split Data



2 errors



Error = • + • + ● + ○ + • + •



Error = • + • + ● + ○ + ● + • + •

Error = ● + • + ● + ● + • + ● + • + •

Minimize error

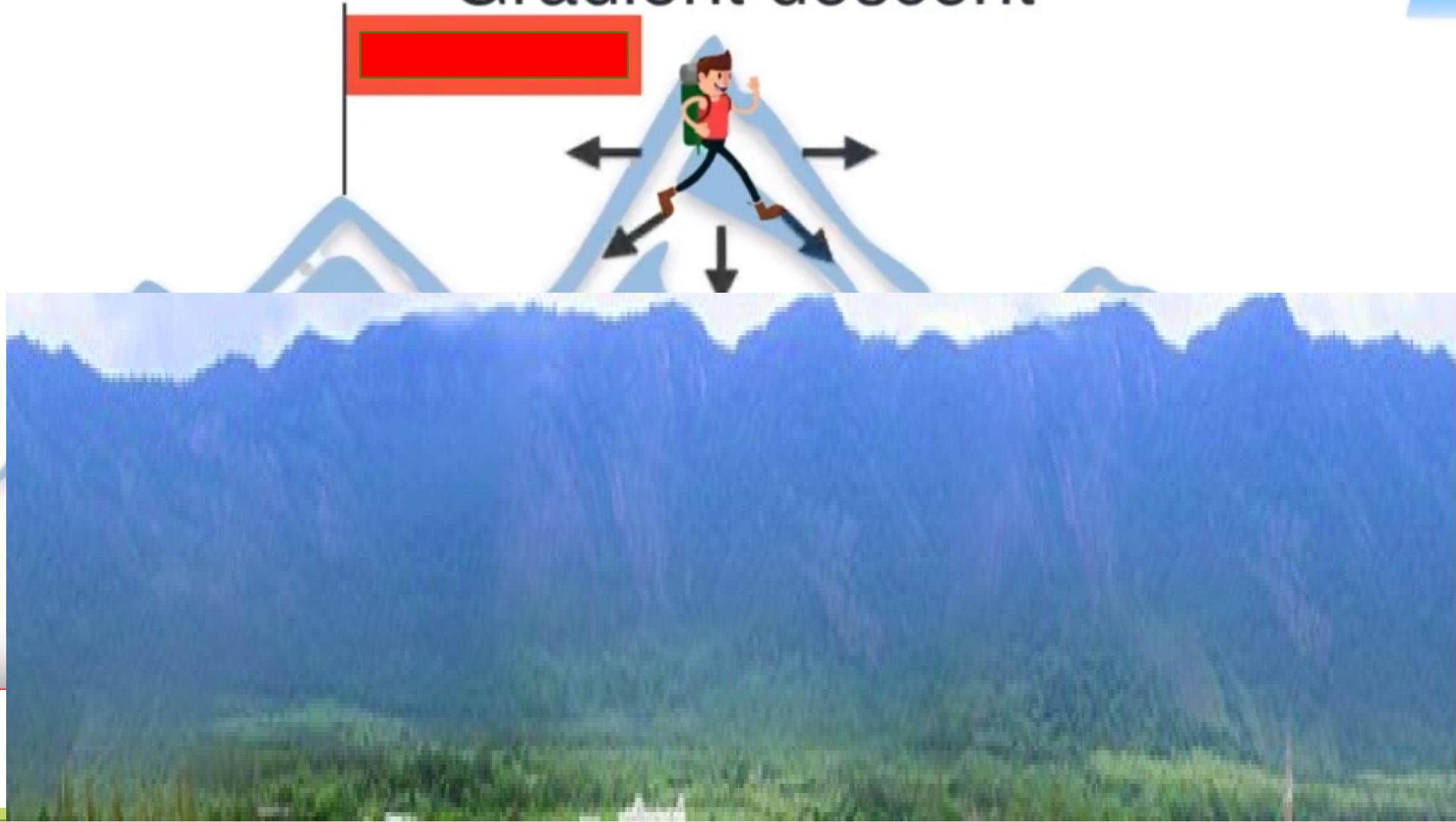


Gradient descent

# Group Activity game to learn Gradient Descent



# Gradient descent



# Gradient descent



Credits: Luis Serrano

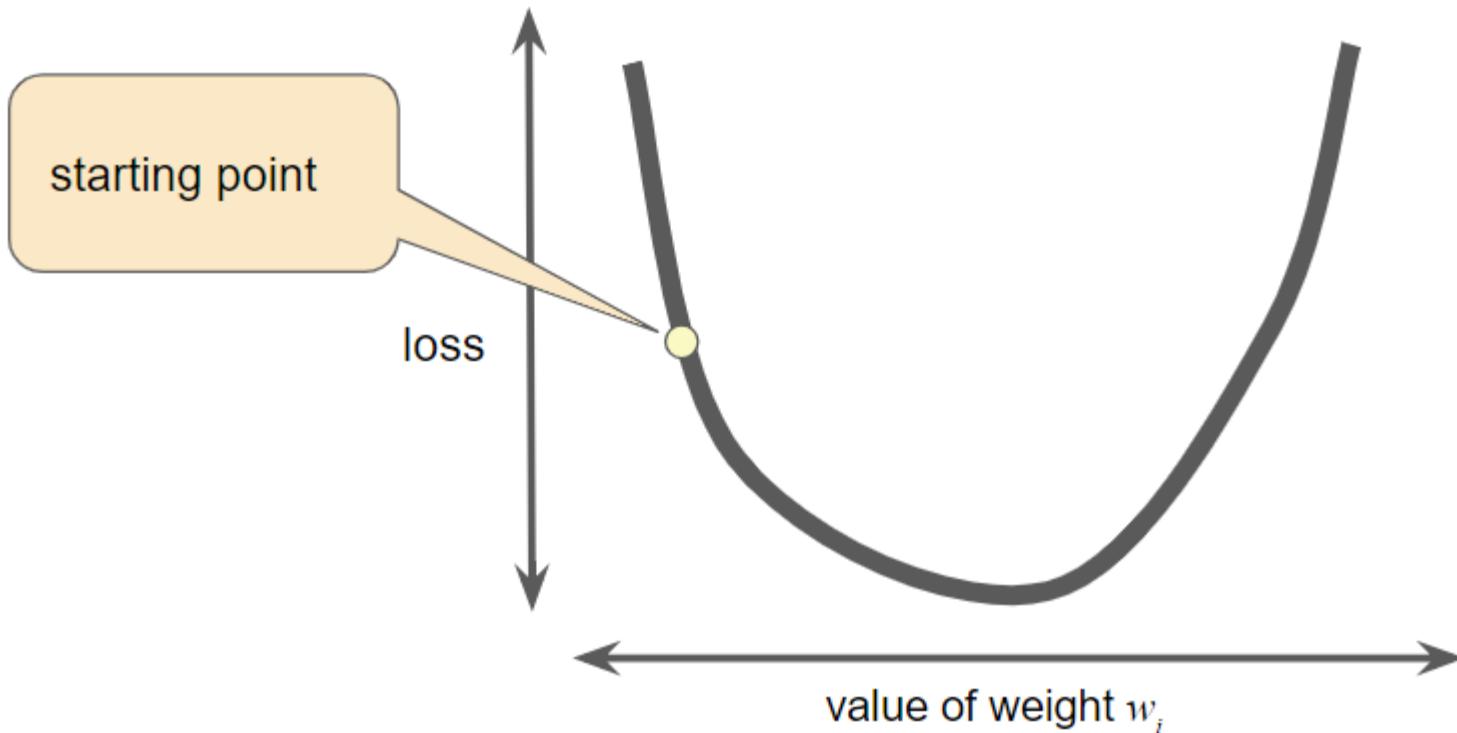
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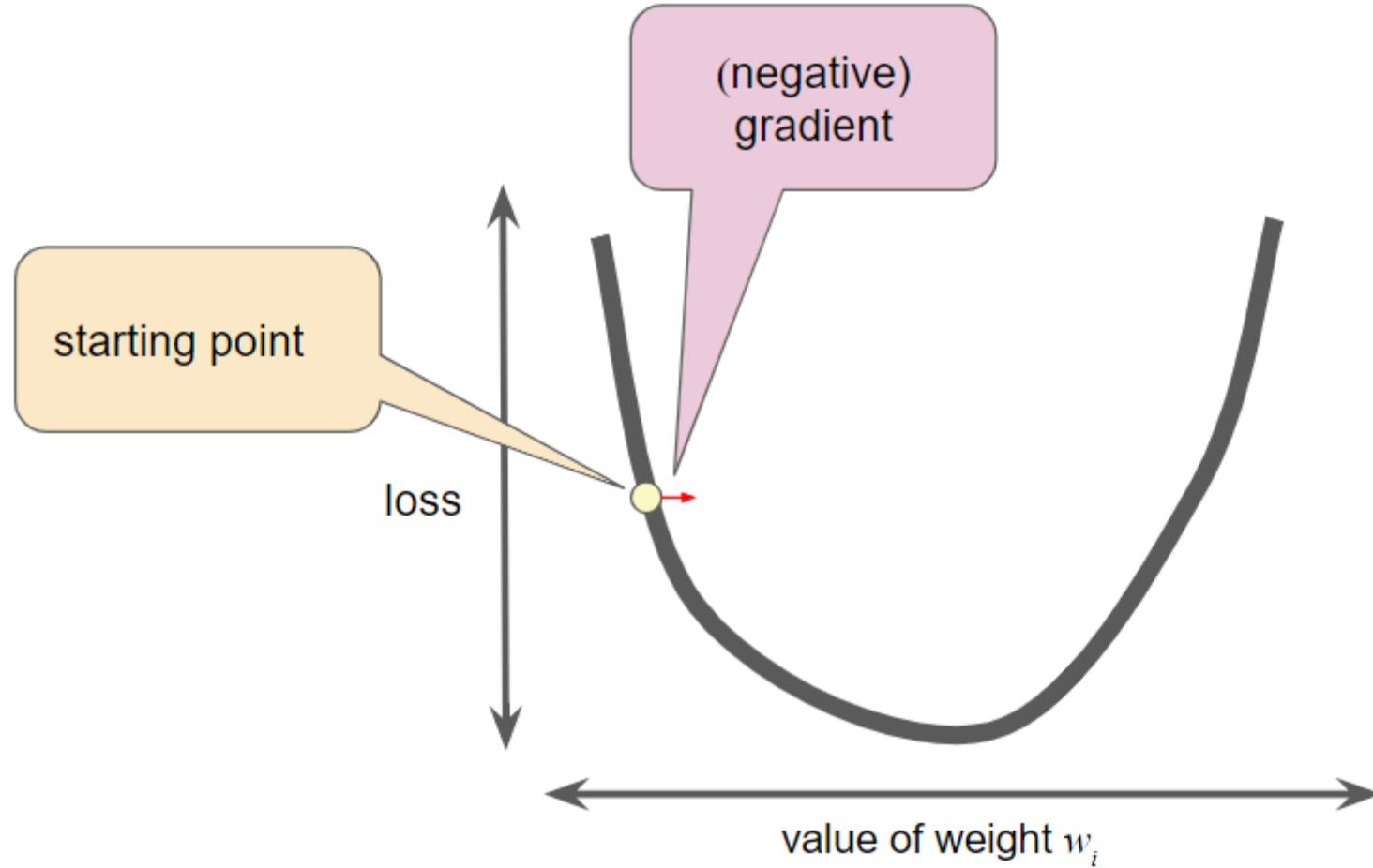
4 Gradient descent 1145 game

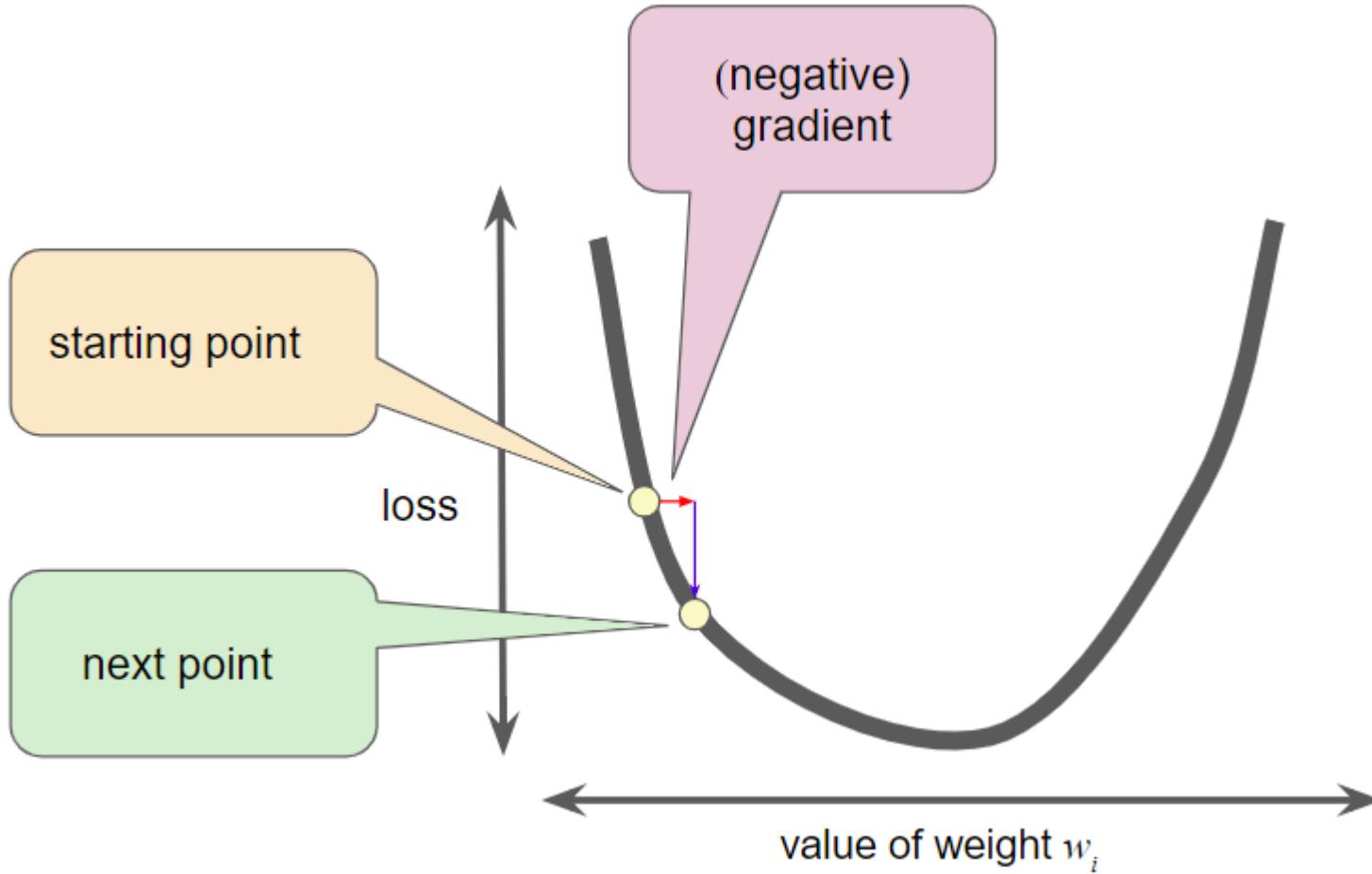
# Gradient descent



# Gradient descent



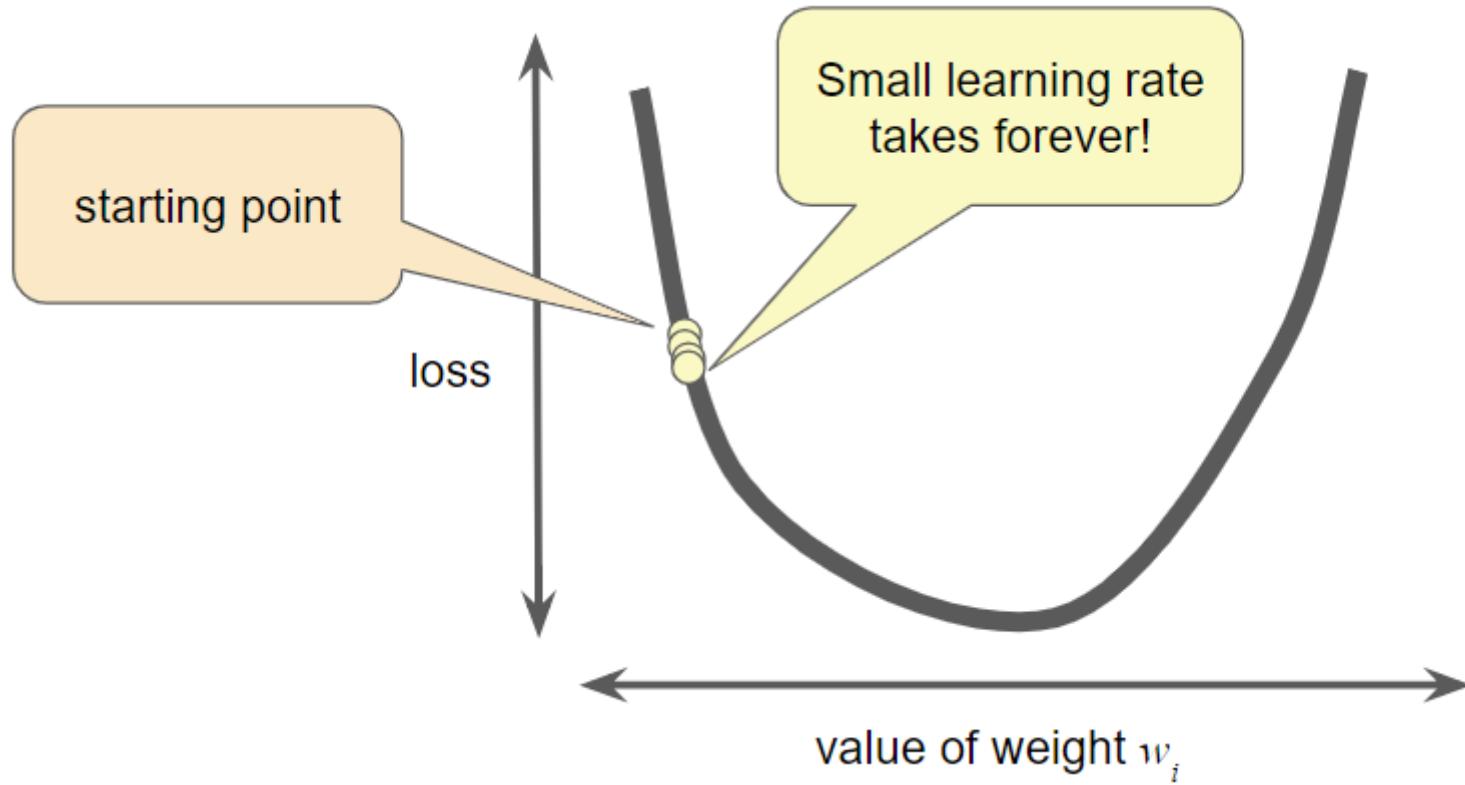


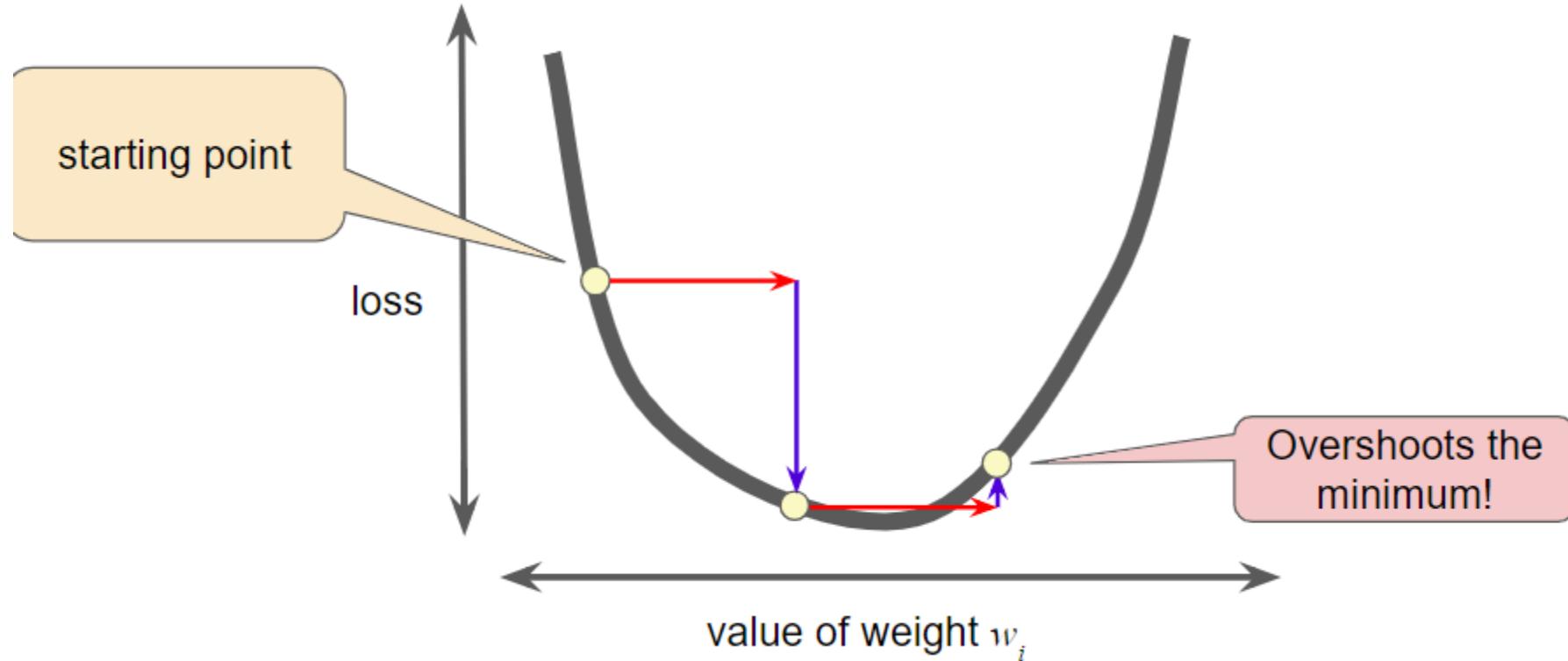


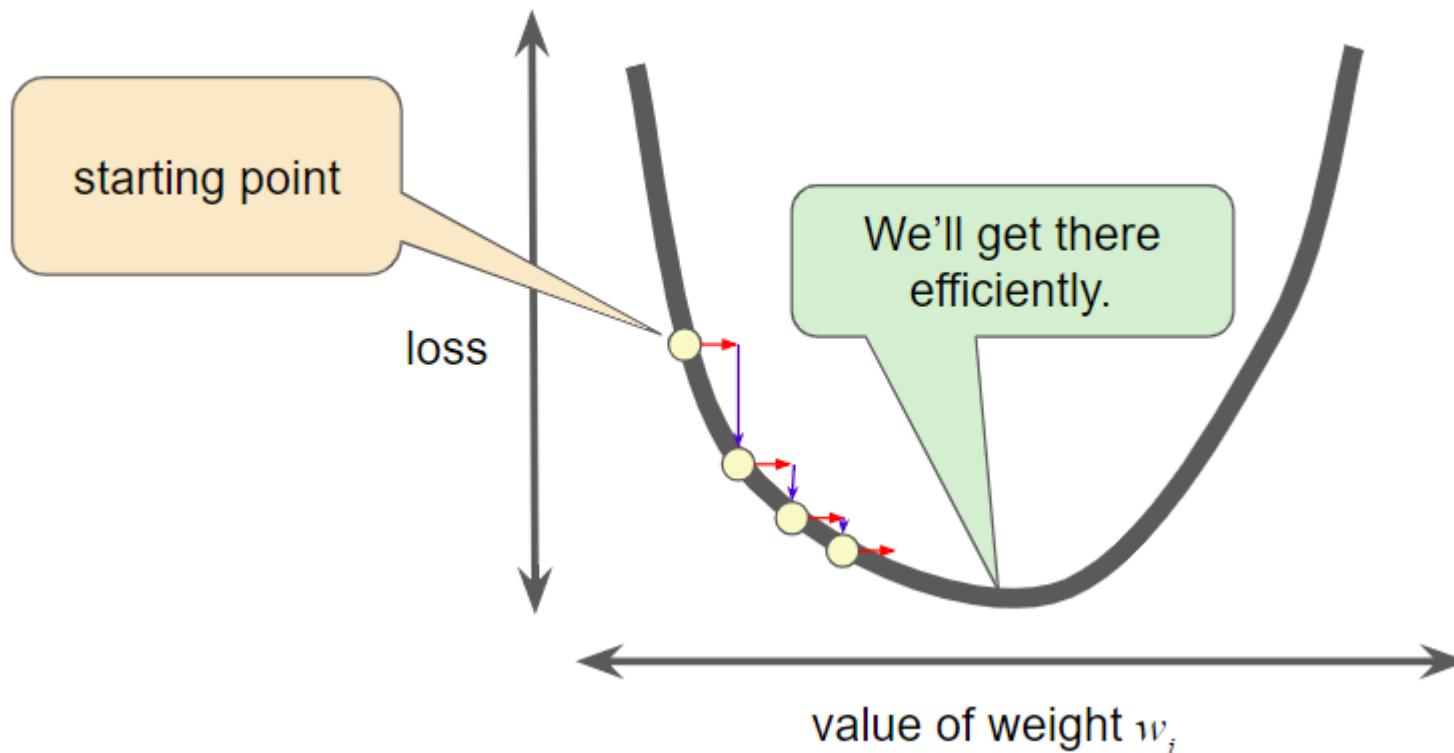
Credits: Google Machine Learning Crash Course

<https://developers.google.com/machine-learning/crash-course/>

Acknowledgments & Credits are mentioned to inspirational resources presented in the end of presentation. For more like this, <https://sites.google.com/view/aiforall/>

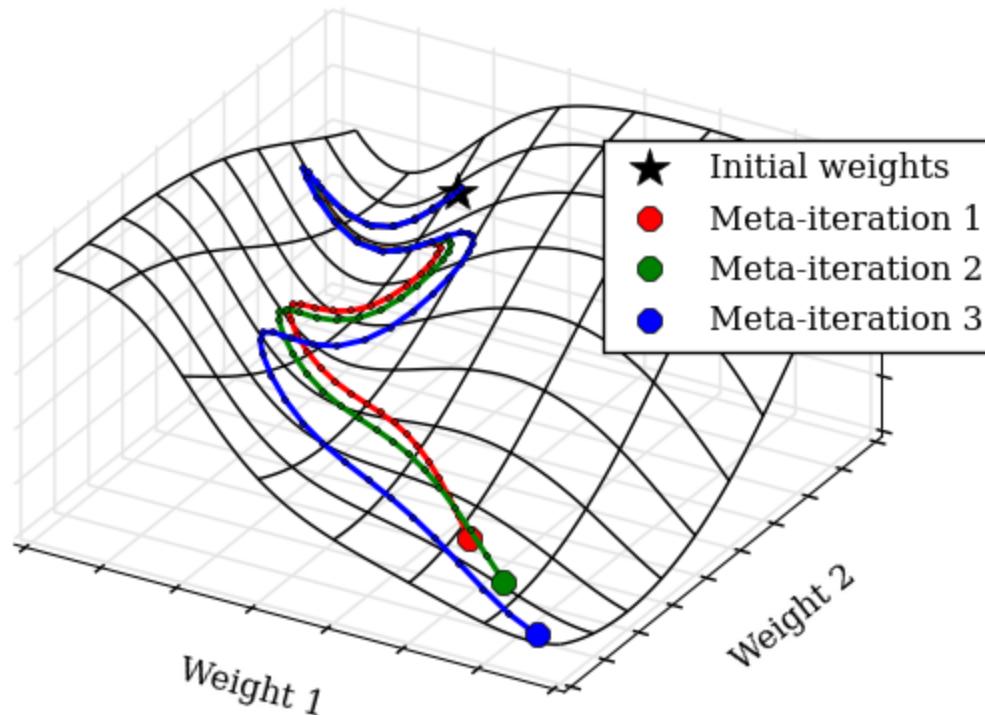


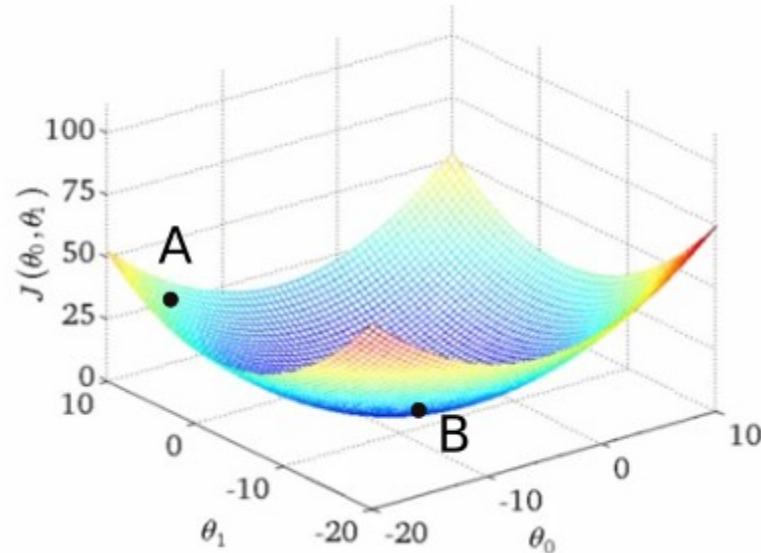


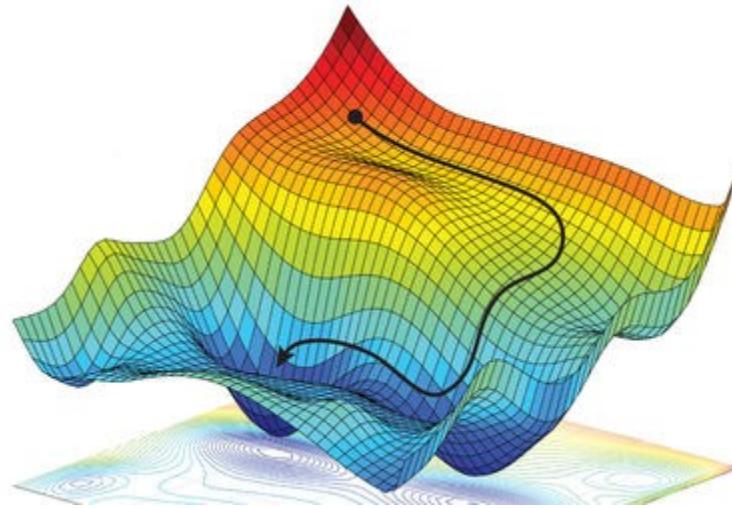


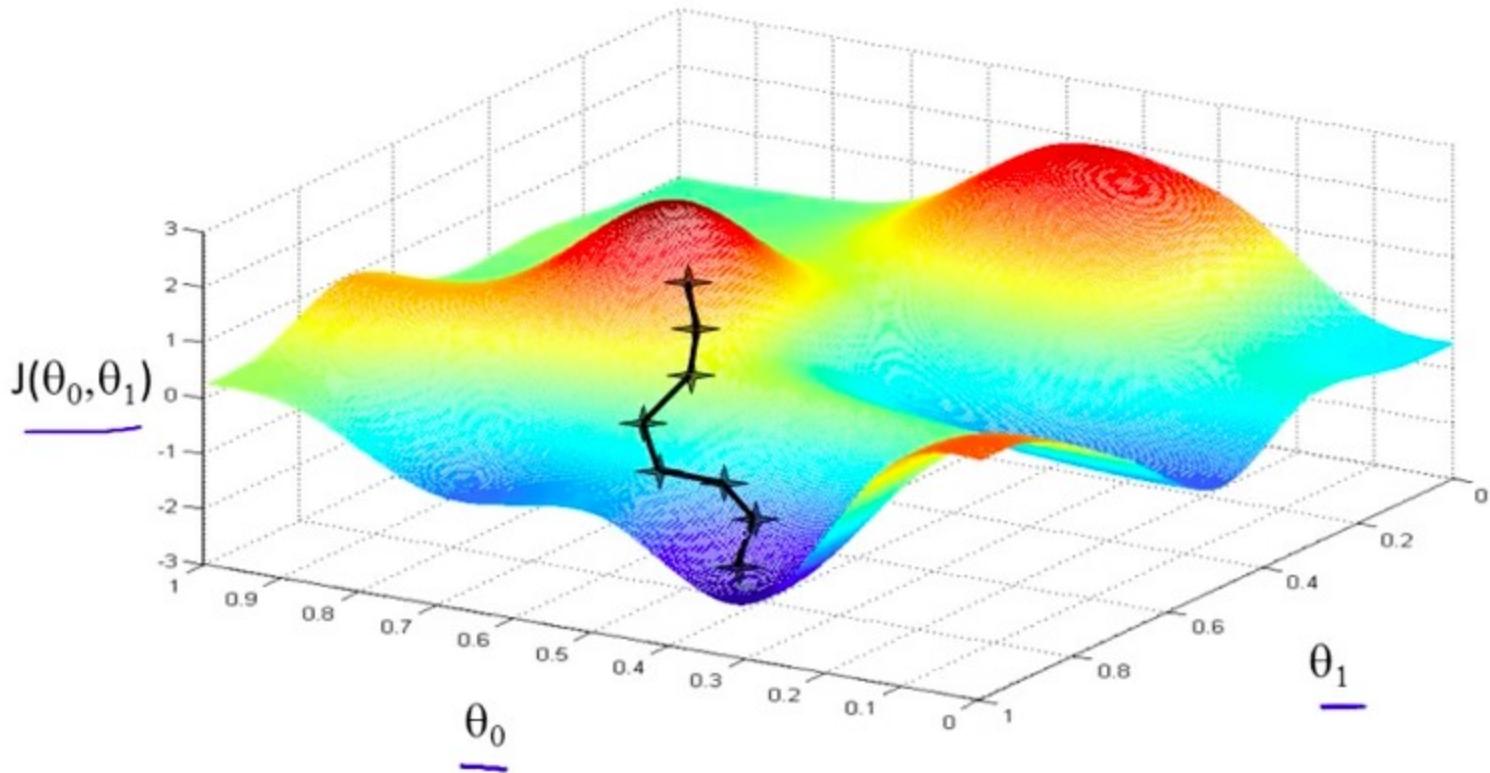
Credits: Google Machine Learning Crash Course

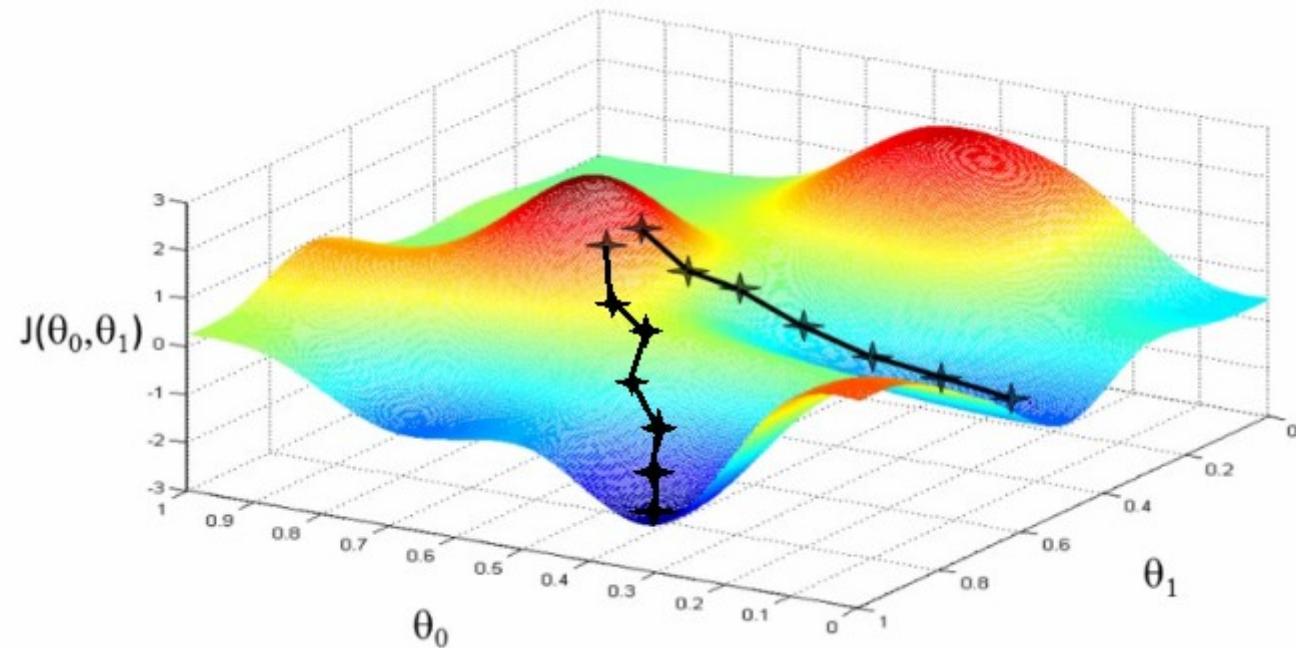
<https://developers.google.com/machine-learning/crash-course/>











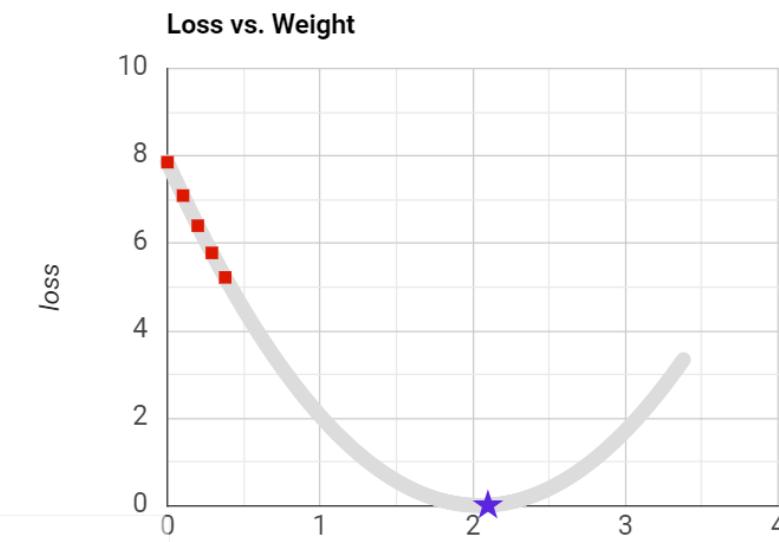
# What should be Learning rate ?

- <https://developers.google.com/machine-learning/crash-course/fitter/graph>

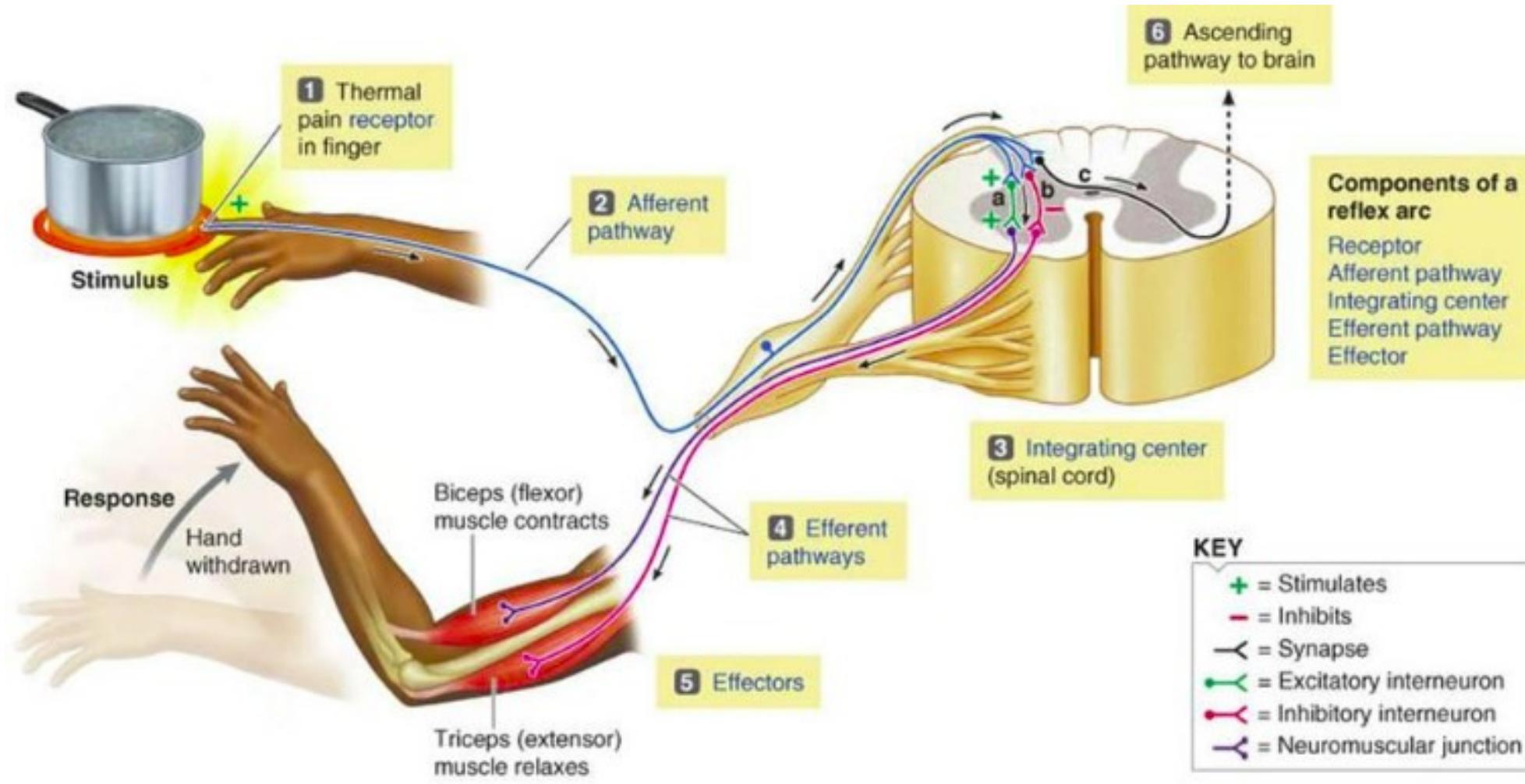
Set learning rate:  0.08

Execute single step: **STEP** 4

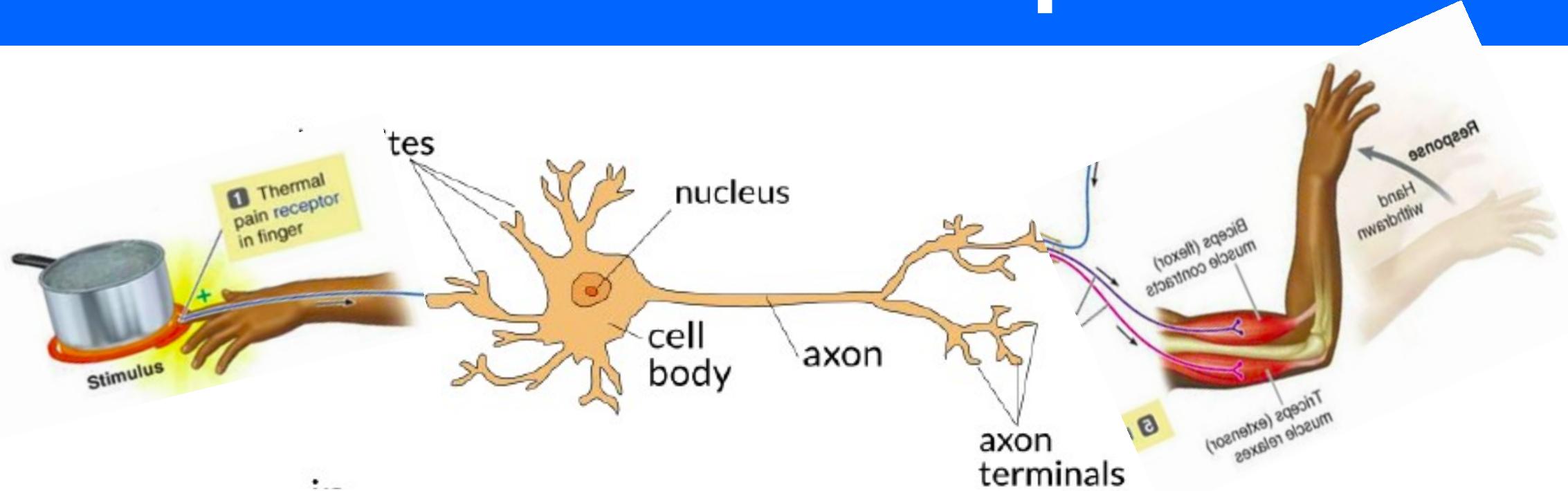
Reset the graph: **RESET**



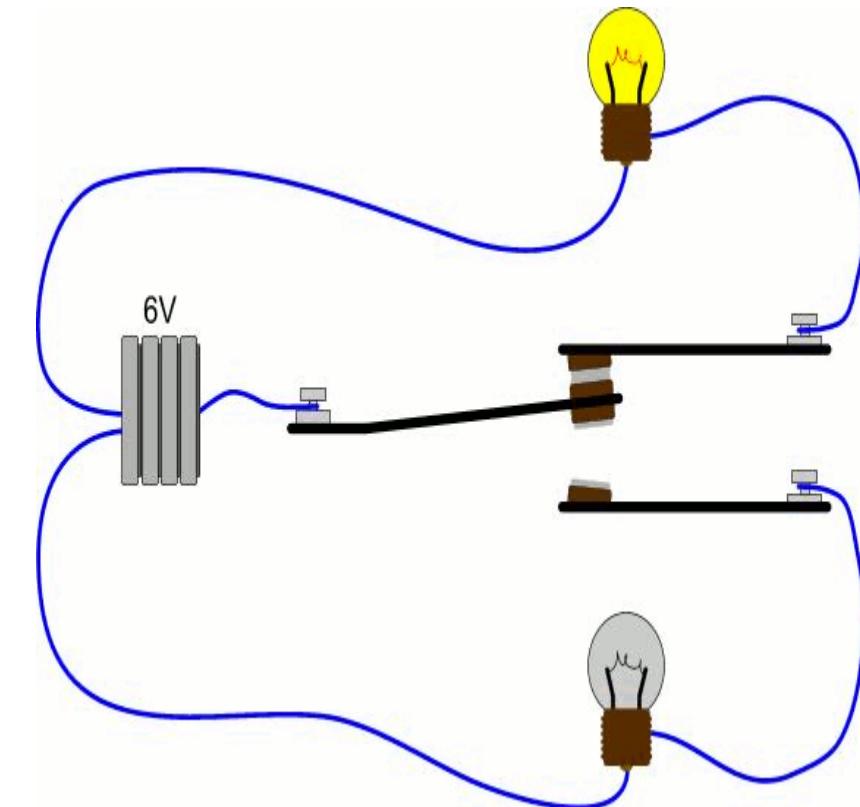
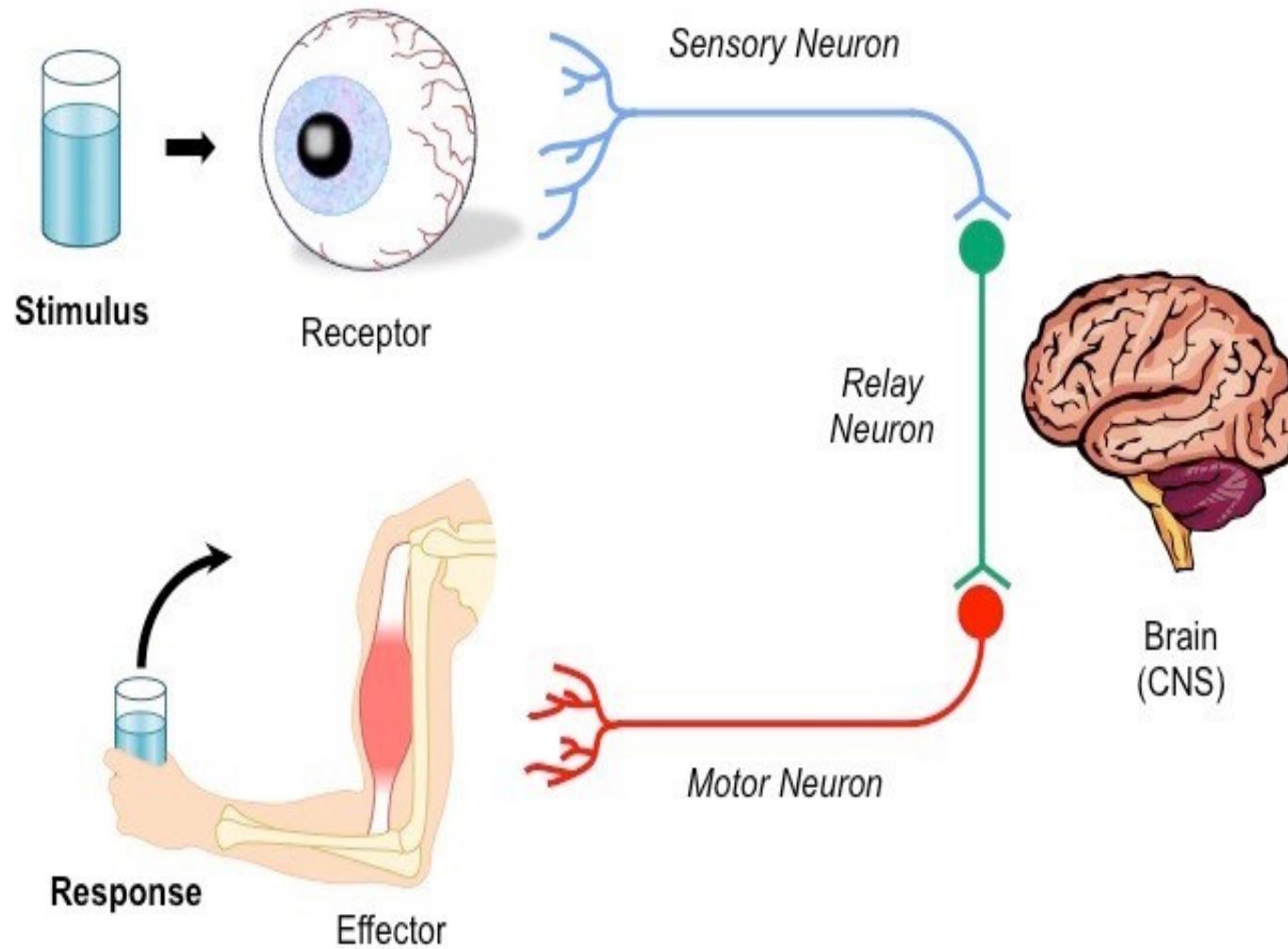
# Neural network is inspired by biology, In reality, it just a mathematical function



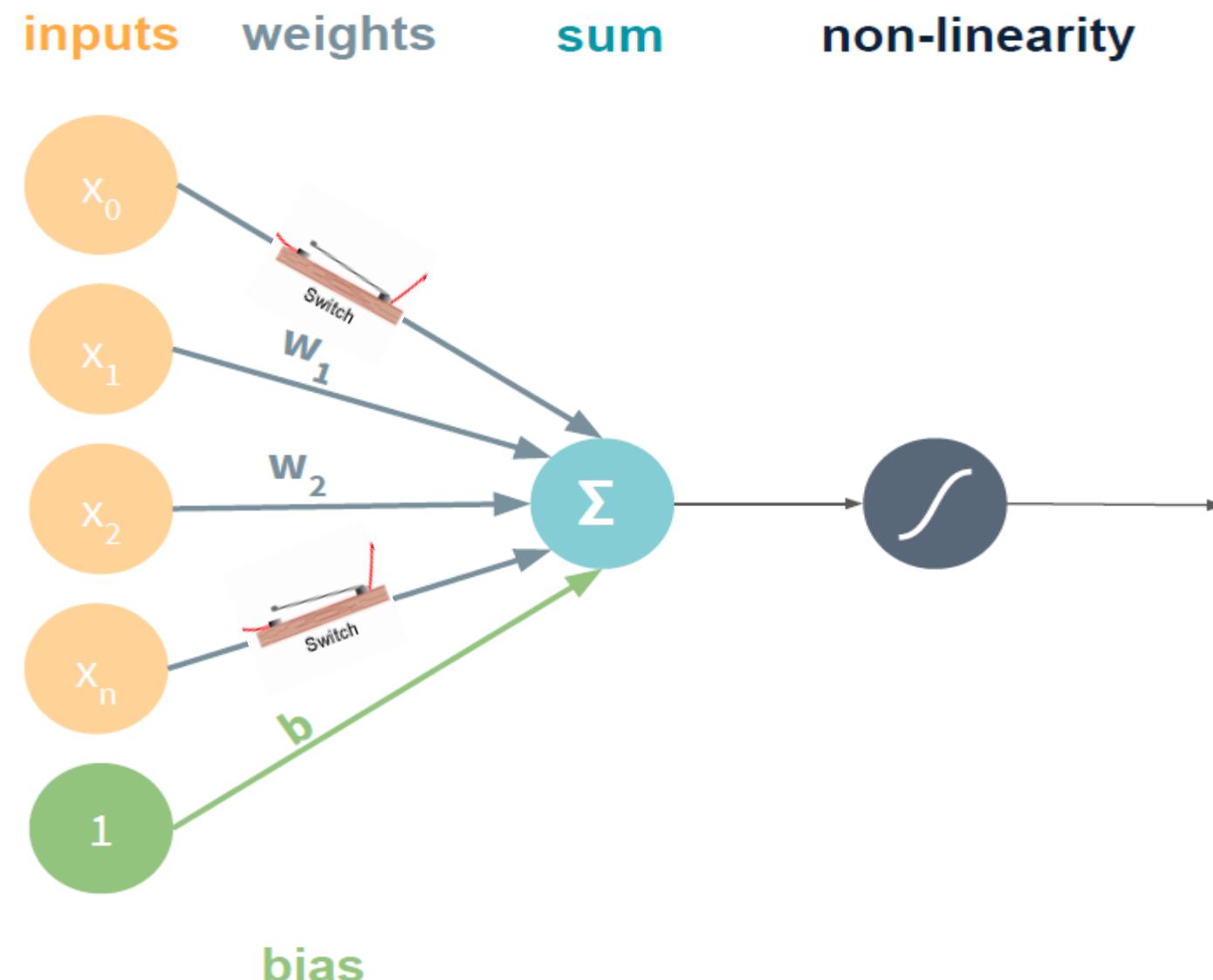
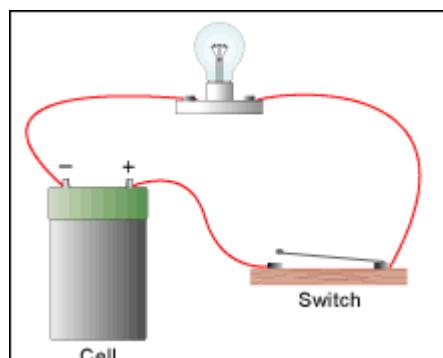
# Neuron === Perceptron



# Switches On/Off a nerve connection

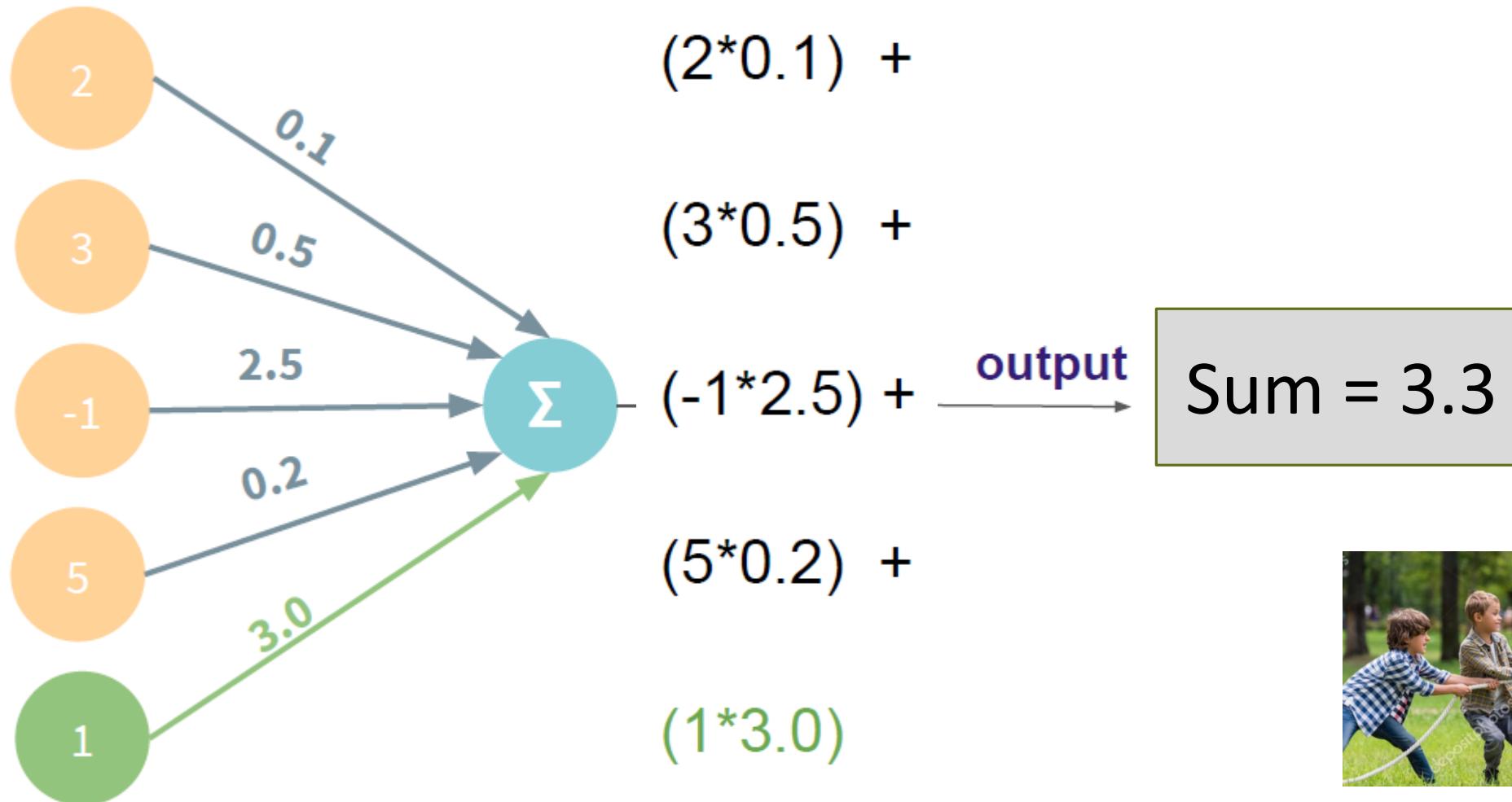


# Switches On/Off a nerve connection



# Simply an weighted average

- inputs    weights    sum

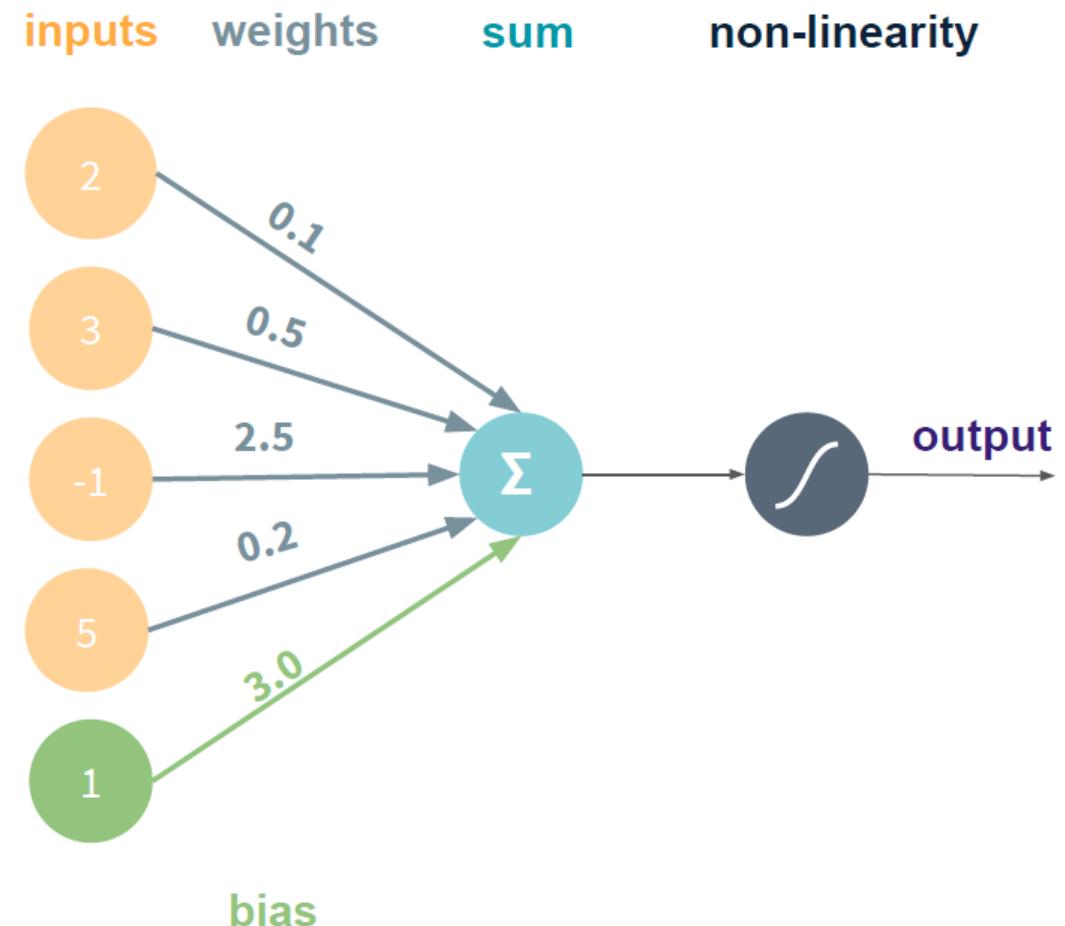


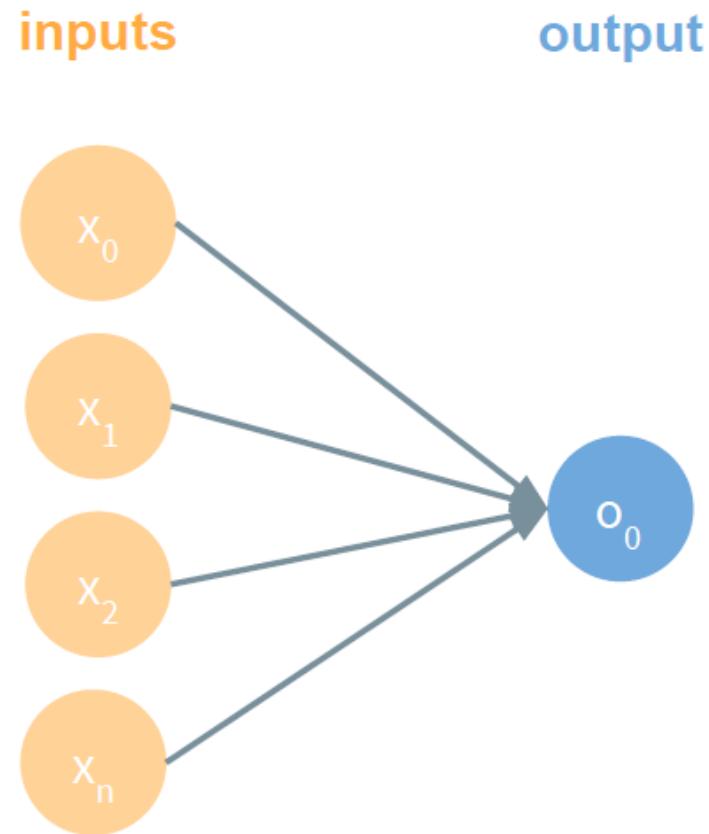
# Then a “activation function”

## Perceptron Forward Pass

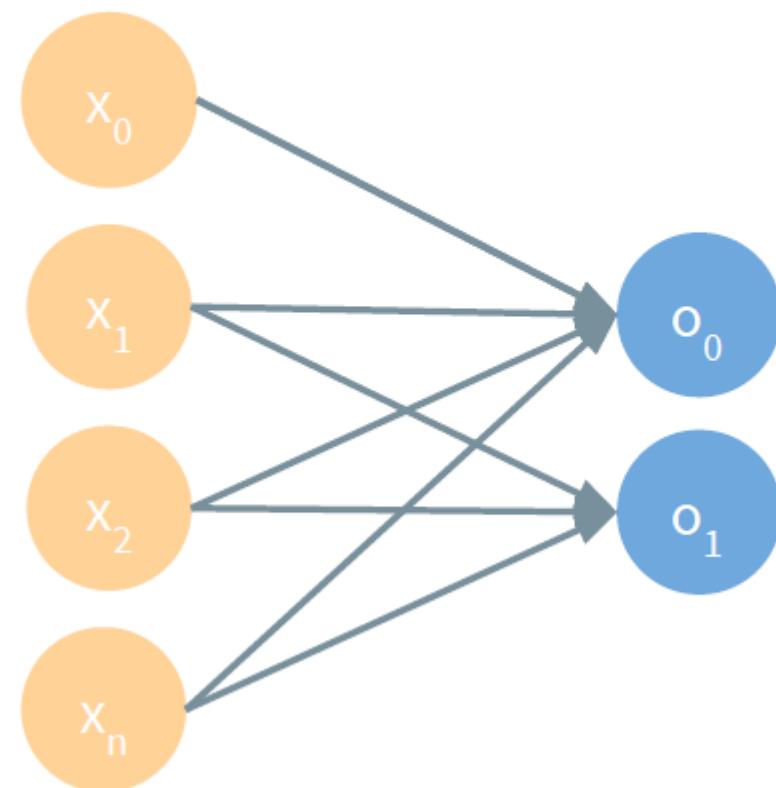
$$output = g(3.2) = \sigma(3.2)$$

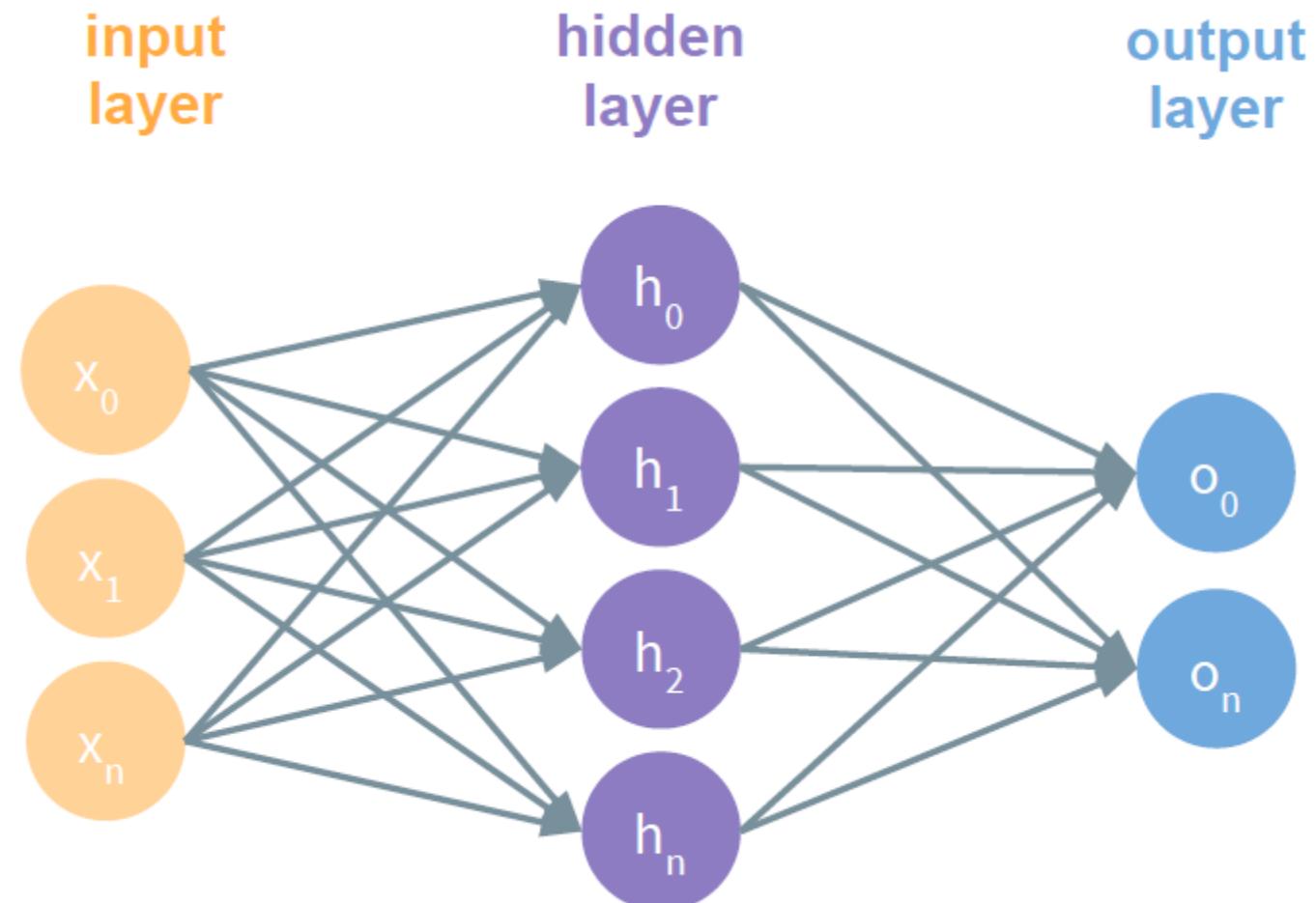
$$= \frac{1}{(1 + e^{-3.2})} = 0.96$$



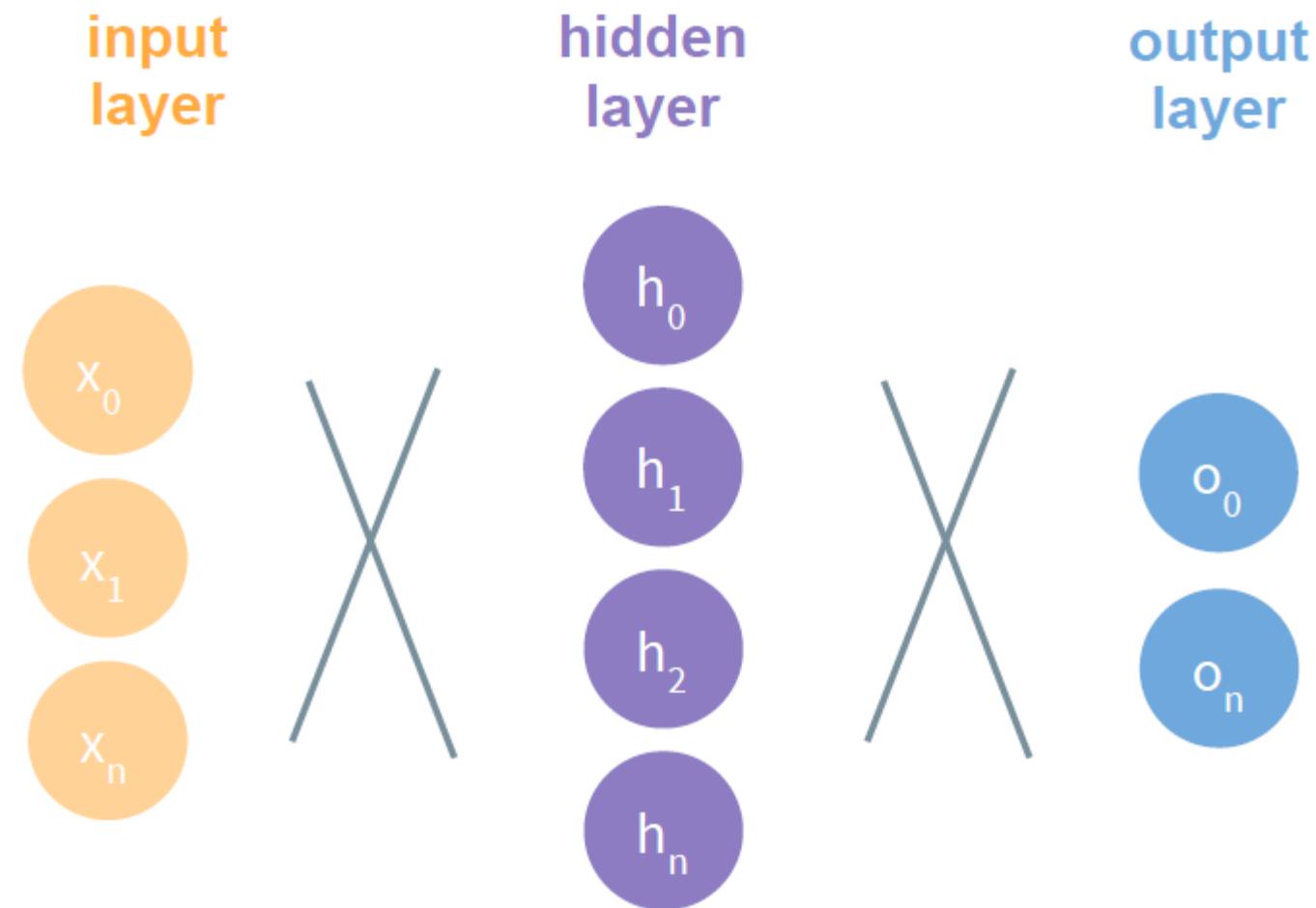


## Input layer      output layer

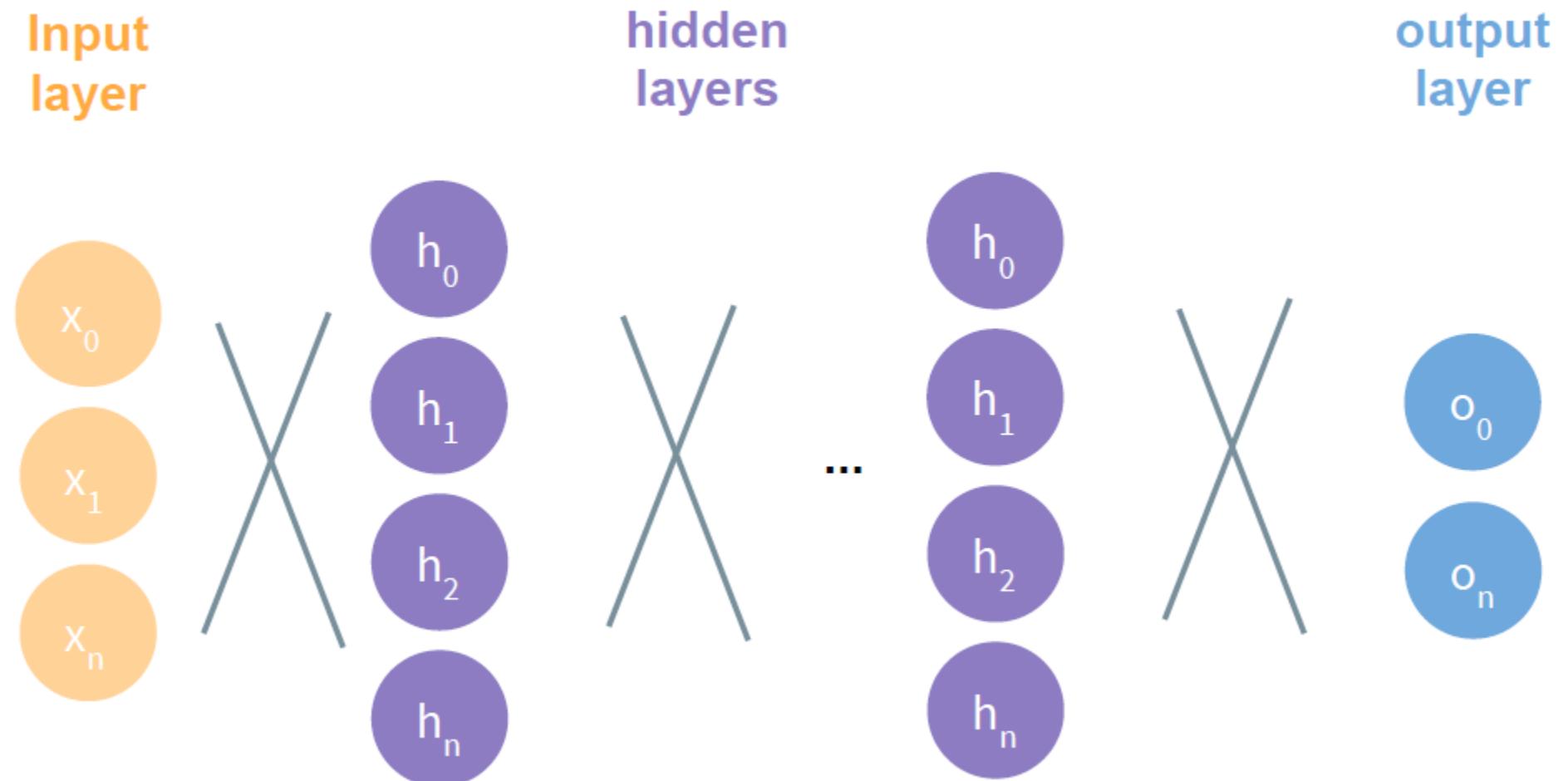




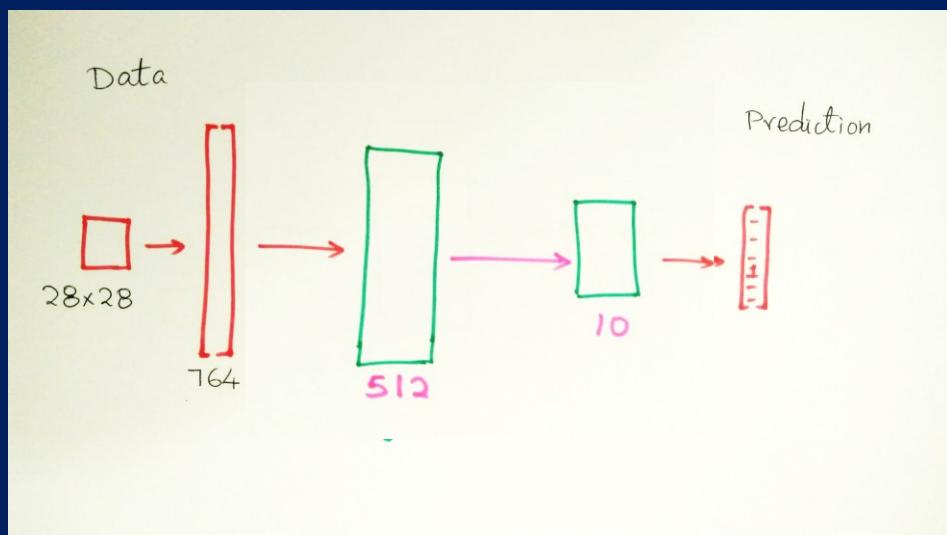
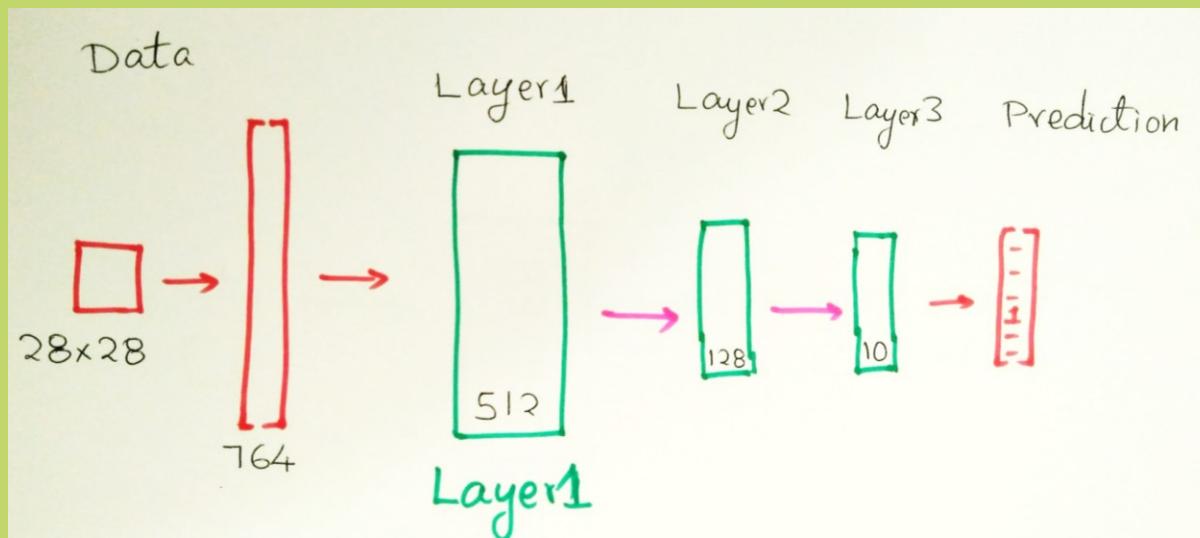
# Multi-Layer Perceptron (MLP)



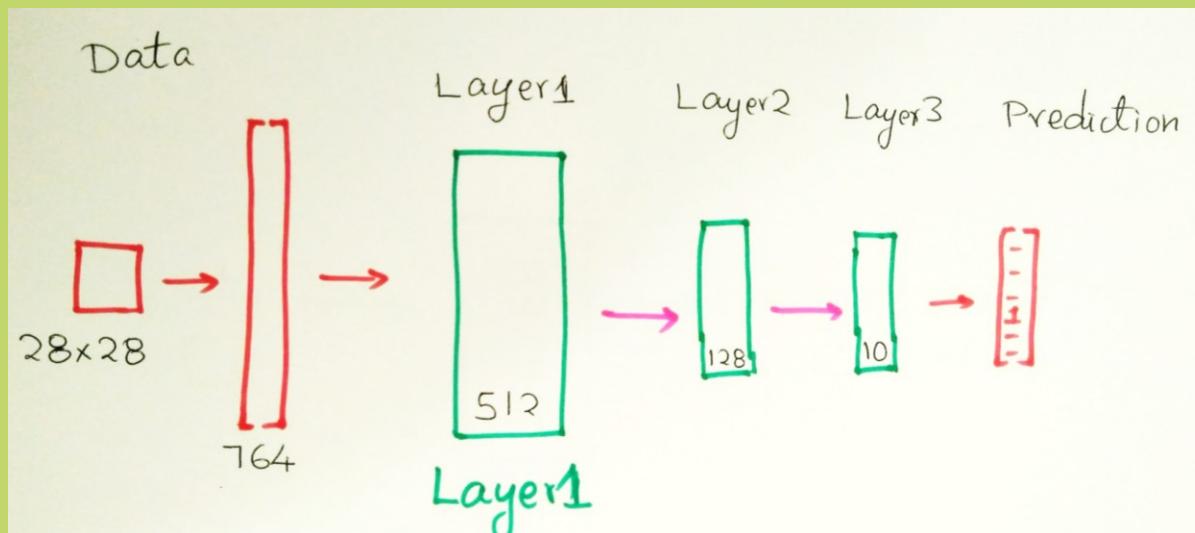
# Deep Neural Network



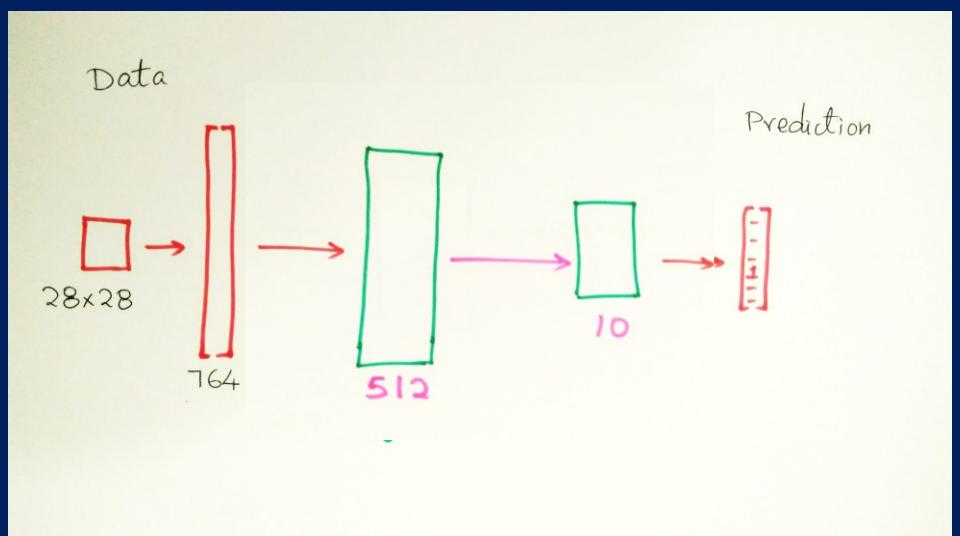
# Design the network architecture



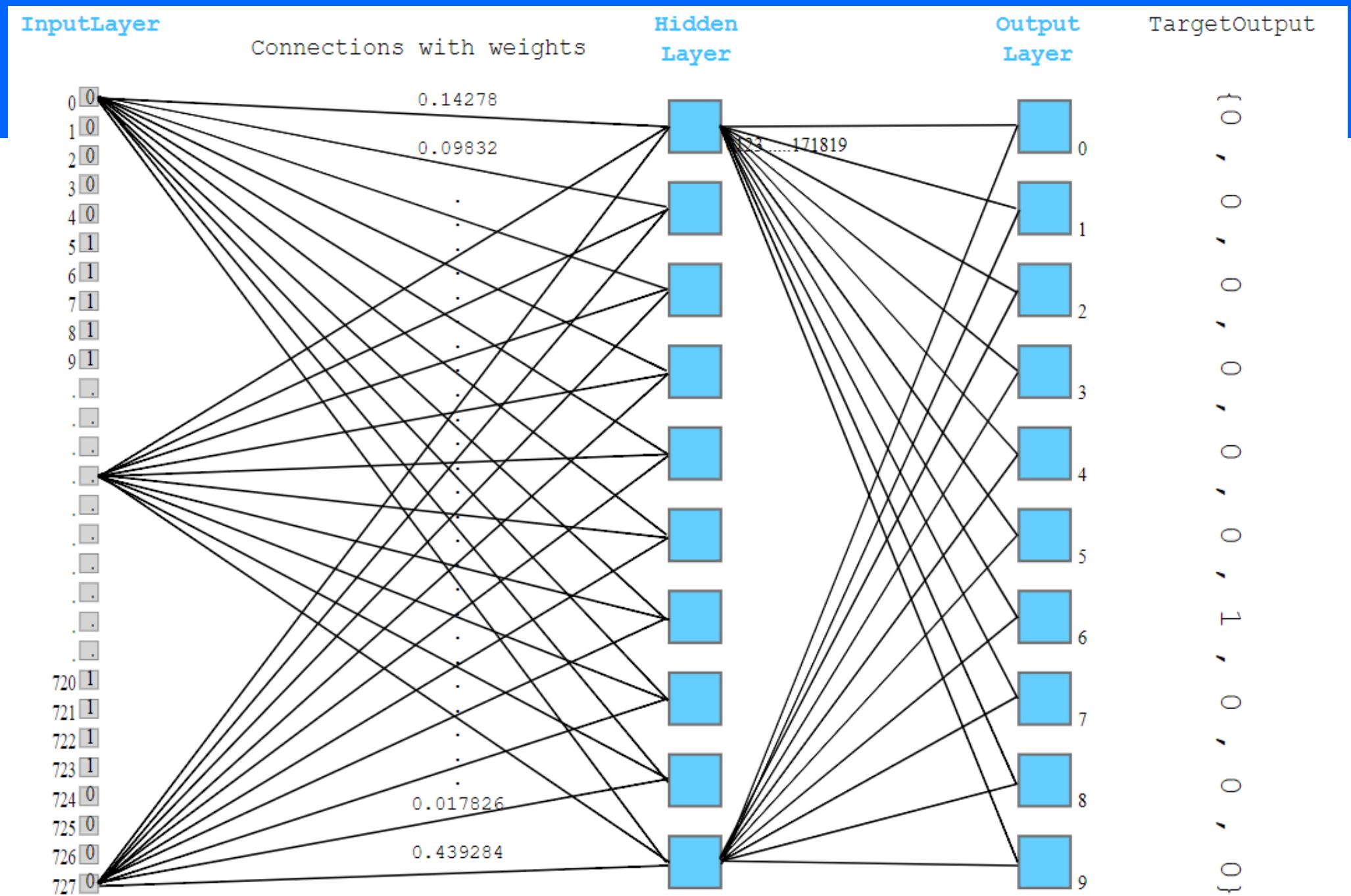
# Design the network architecture



```
network.add( keras.layers.Dense(512) )
network.add( keras.layers.Dense(128) )
network.add( keras.layers.Dense(10) )
```



```
network.add( keras.layers.Dense(512) )
network.add( keras.layers.Dense(10) )
```





# Regression vs Classification



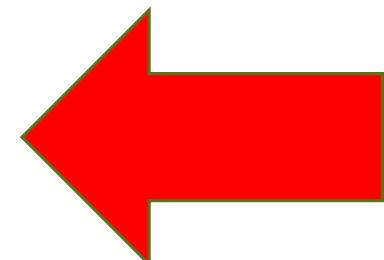
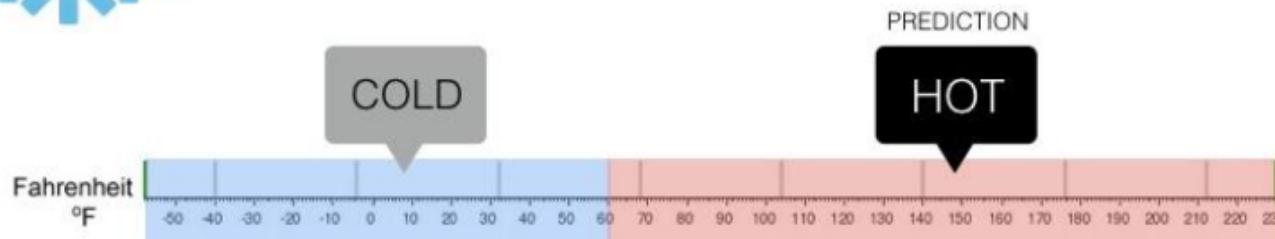
## Regression

What is the temperature going to be tomorrow?



## Classification

Will it be Cold or Hot tomorrow?



# Loss Functions



## Regression

What is the temperature going to be tomorrow?



## Classification

Will it be Cold or Hot tomorrow?



- Loss function quantifies gap between prediction and ground truth

- For regression:

- Mean Squared Error (MSE)

- For classification:

- Cross Entropy Loss

## Mean Squared Error

$$MSE = \frac{1}{N} \sum (t_i - s_i)^2$$

Prediction  
Ground Truth

## Cross Entropy Loss

$$CE = - \sum_i t_i \log(s_i)$$

Classes  
 $i$   
Prediction  
Ground Truth {0,1}

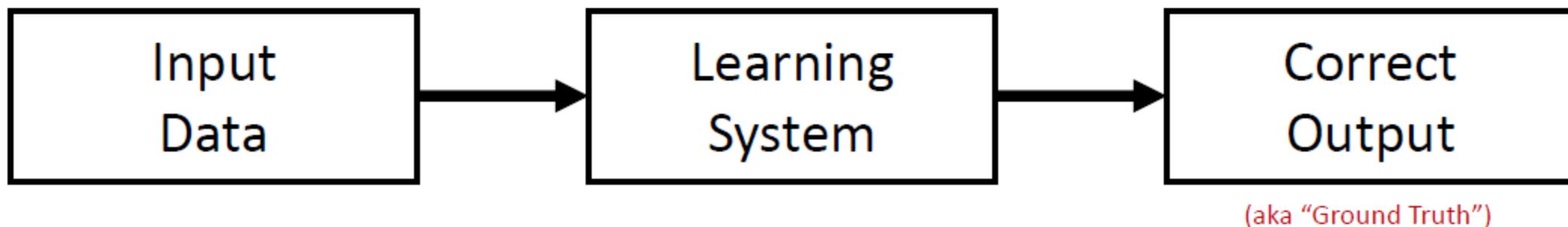
# Keras: Loss Functions

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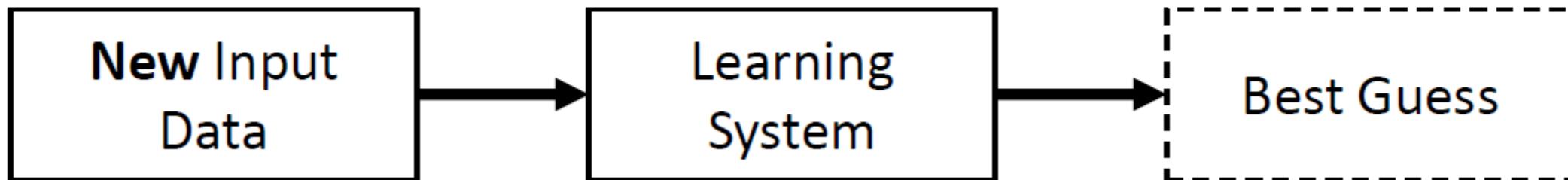
- Loss functions are used to compare the network's predicted output with the real output, in each pass of the backpropagation algorithm
  - Loss functions are used to tell the model how the weights should be updated
- Common loss functions are:
  - Mean squared error
  - Cross-entropy
  - etc.

# Deep Learning: Training and Testing

## Training Stage:

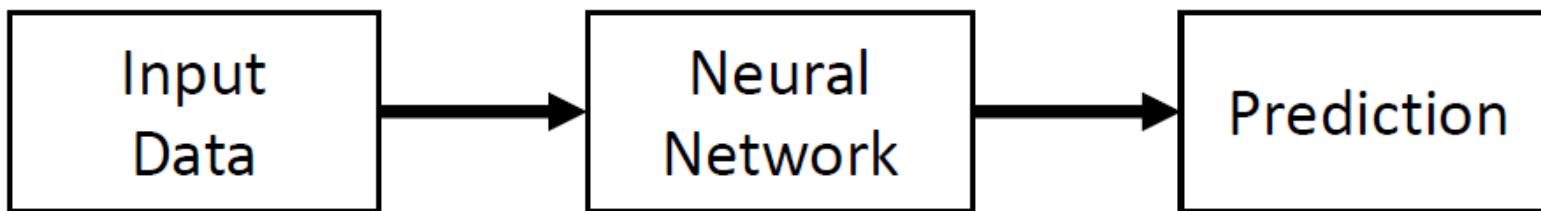


## Testing Stage:

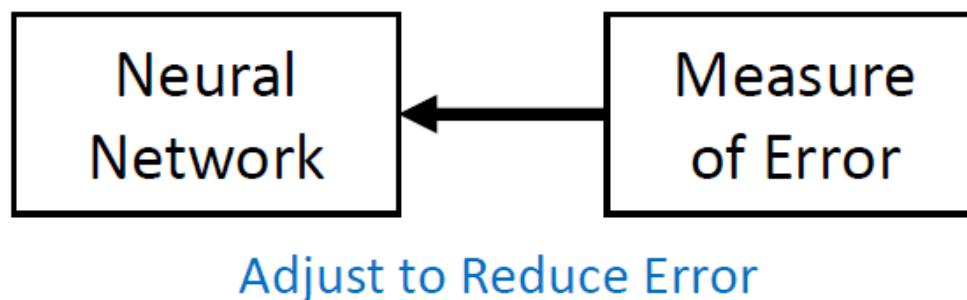


# How Neural Networks Learn: Backpropagation

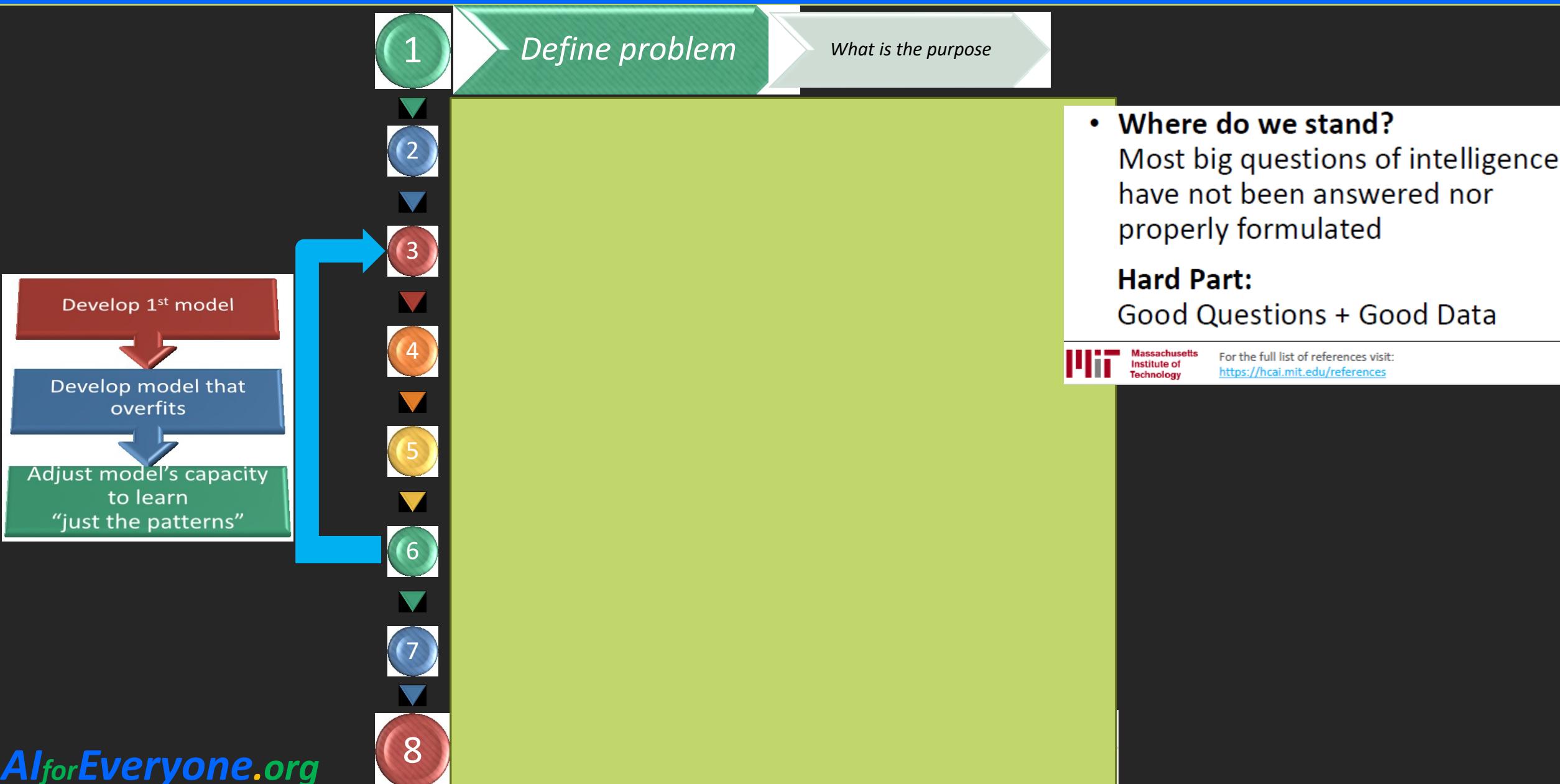
Forward Pass:



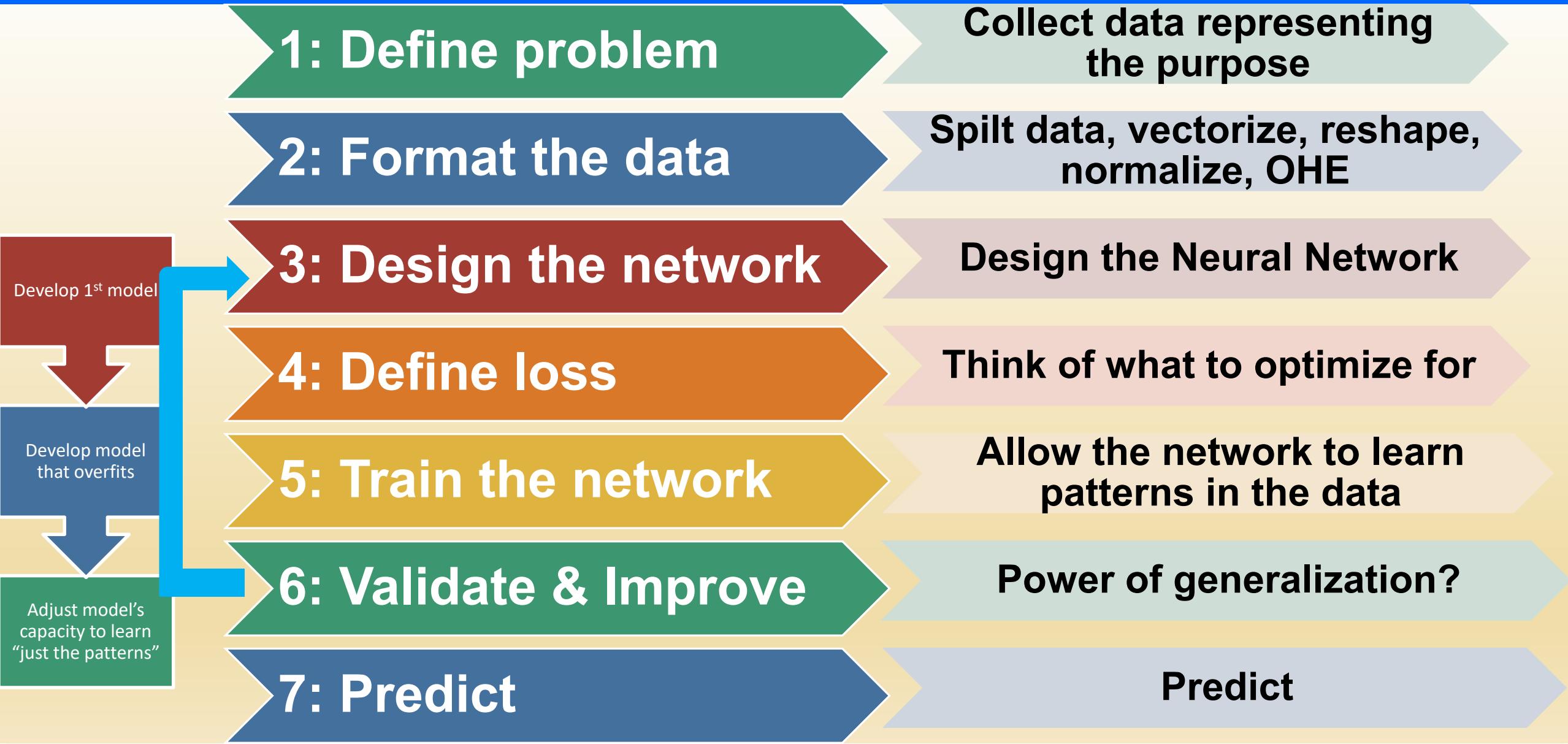
Backward Pass (aka Backpropagation):



# Design of Deep Learning experiment



# Method: 7 steps to develop your Deep Learning model



## 2. Prepare the data

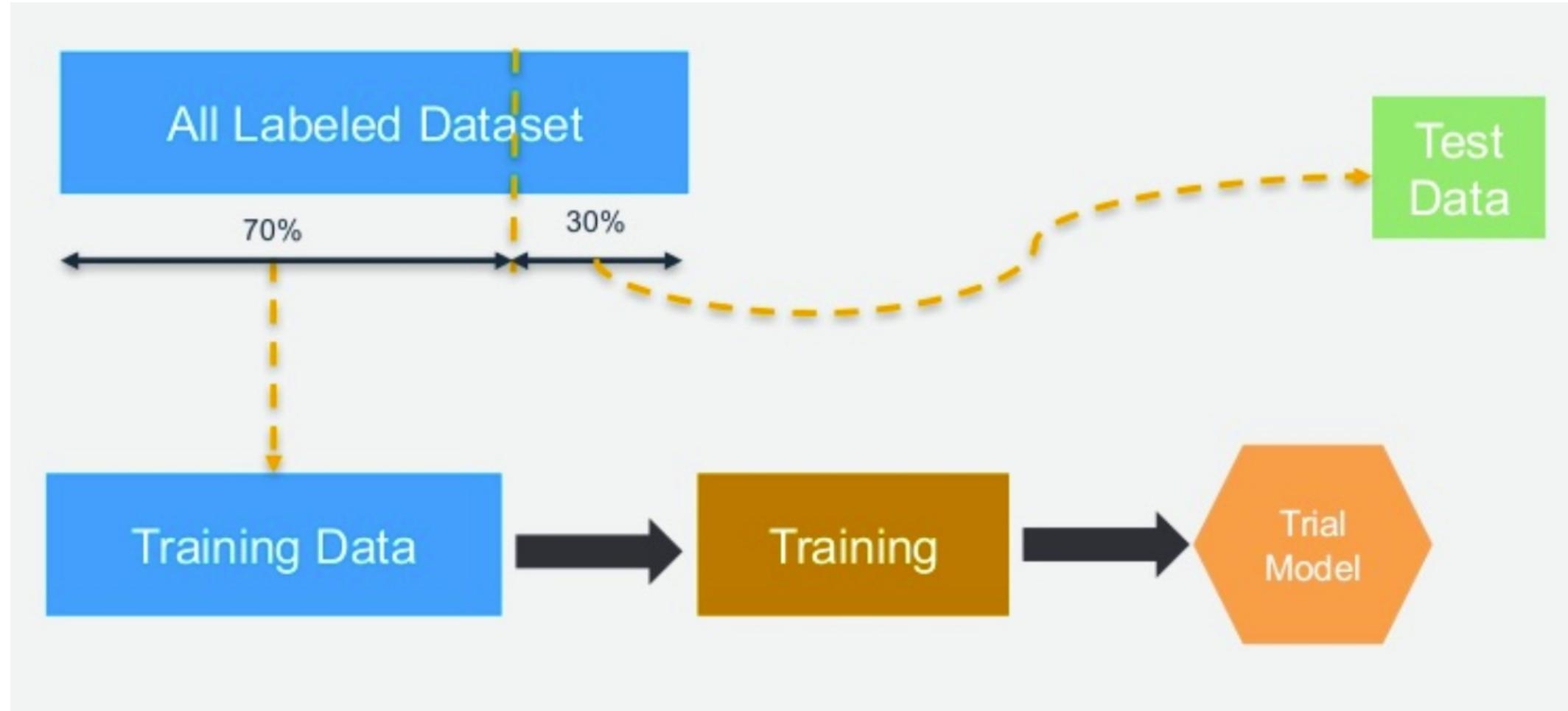
Spilt data in training & testing

Vectortize as tensors

Reshape

Normalize

One Hot encode



`(trainX, trainY), (testX, testY) = mnist.load_data()`

No of training records = 60000  
No of test records = 10000

# Multi dimensional Array == Tensor

What\_is\_size\_of\_array = myArray.shape

1D array

7	2	9	10
---	---	---	----

axis 0 →

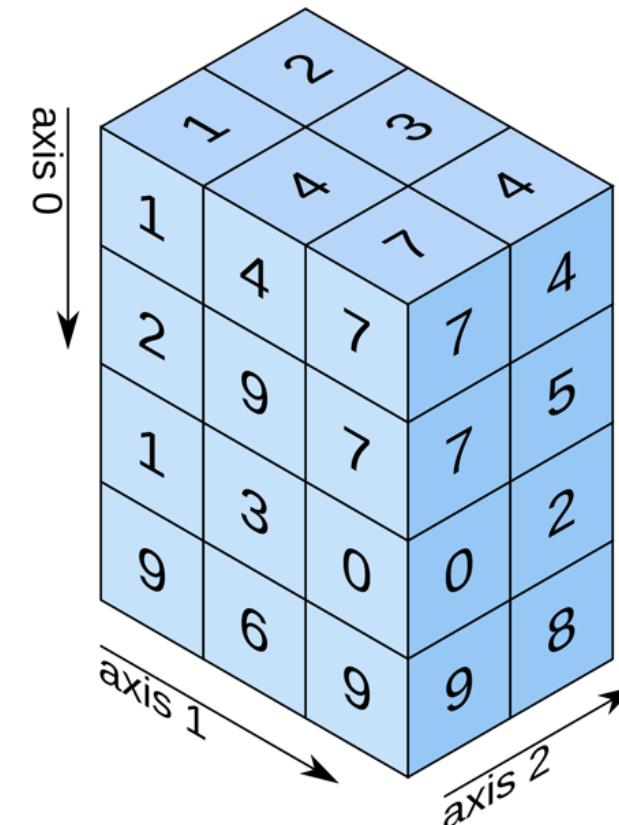
shape: (4,)

2D array

5.2	3.0	4.5
9.1	0.1	0.3

shape: (2, 3)

3D array



shape: (4, 3, 2)

- 1D Tensor
  - Array
- 2D Tensor
  - 2D array
  - Matrix
- 3D Tensor
  - 3D array
- 4D Tensor
  -
- 5D Tensor

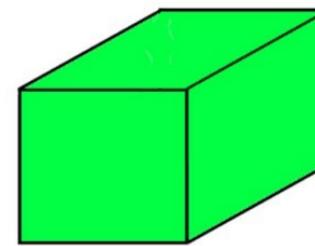
**1 D TENSOR /  
VECTOR**

5
7
4 5
1 2
- 6
3
2 2
1
6
3
- 9

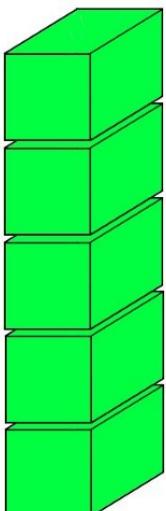
**2 D TENSOR /  
MATRIX**

- 9	4	2	5	7
3	0	1 2	8	6 1
1	2 3	- 6	4 5	2
2 2	3	- 1	7 2	6

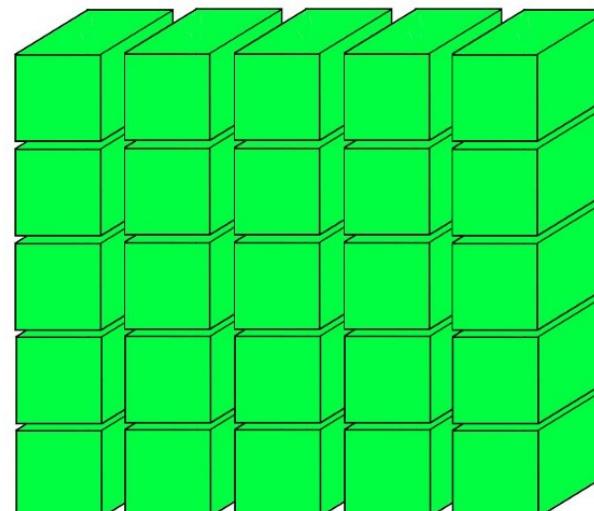
**3 D TENSOR /  
CUBE**



- 9	4	2	5	7
3	0	1 2	8	6 1
1	2 3	- 6	4 5	2
2 2	3	- 1	7 2	6



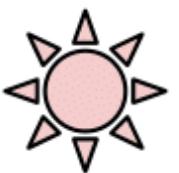
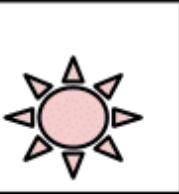
**4 D TENSOR  
VECTOR OF CUBES**



**5 D TENSOR  
MATRIX OF CUBES**

# One Hot Encoding

Multi-Class

$C = 3$	Samples
	
	
	

Labels ( $t$ )

[0 0 1] [1 0 0] [0 1 0]

`yNew = to_categorical (y)`

Data:  
[2]

Data after **One Hot Encoding**:  
[[ 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. ]]

2. Prepare  
the data

Spilt data in  
training &  
testing

Vectortize  
as tensors

Reshape

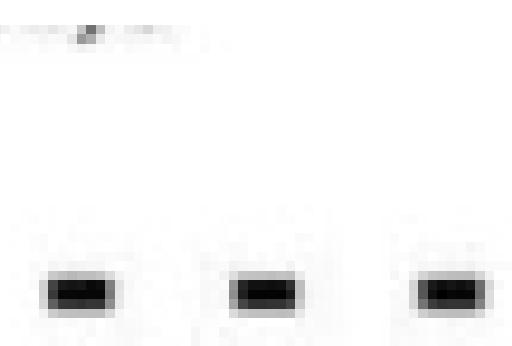
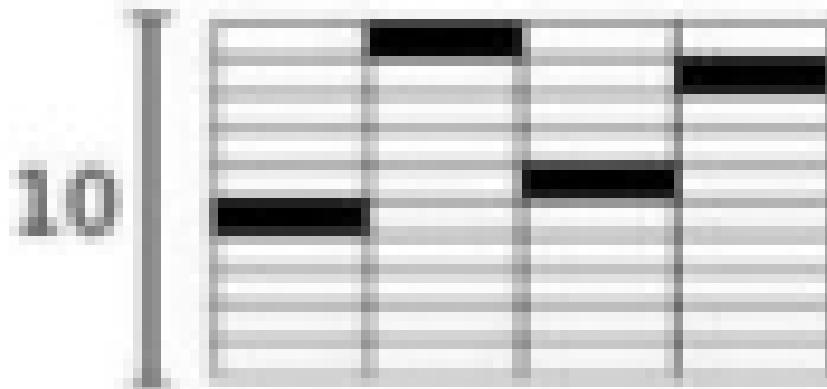
Normalize

One Hot  
encode

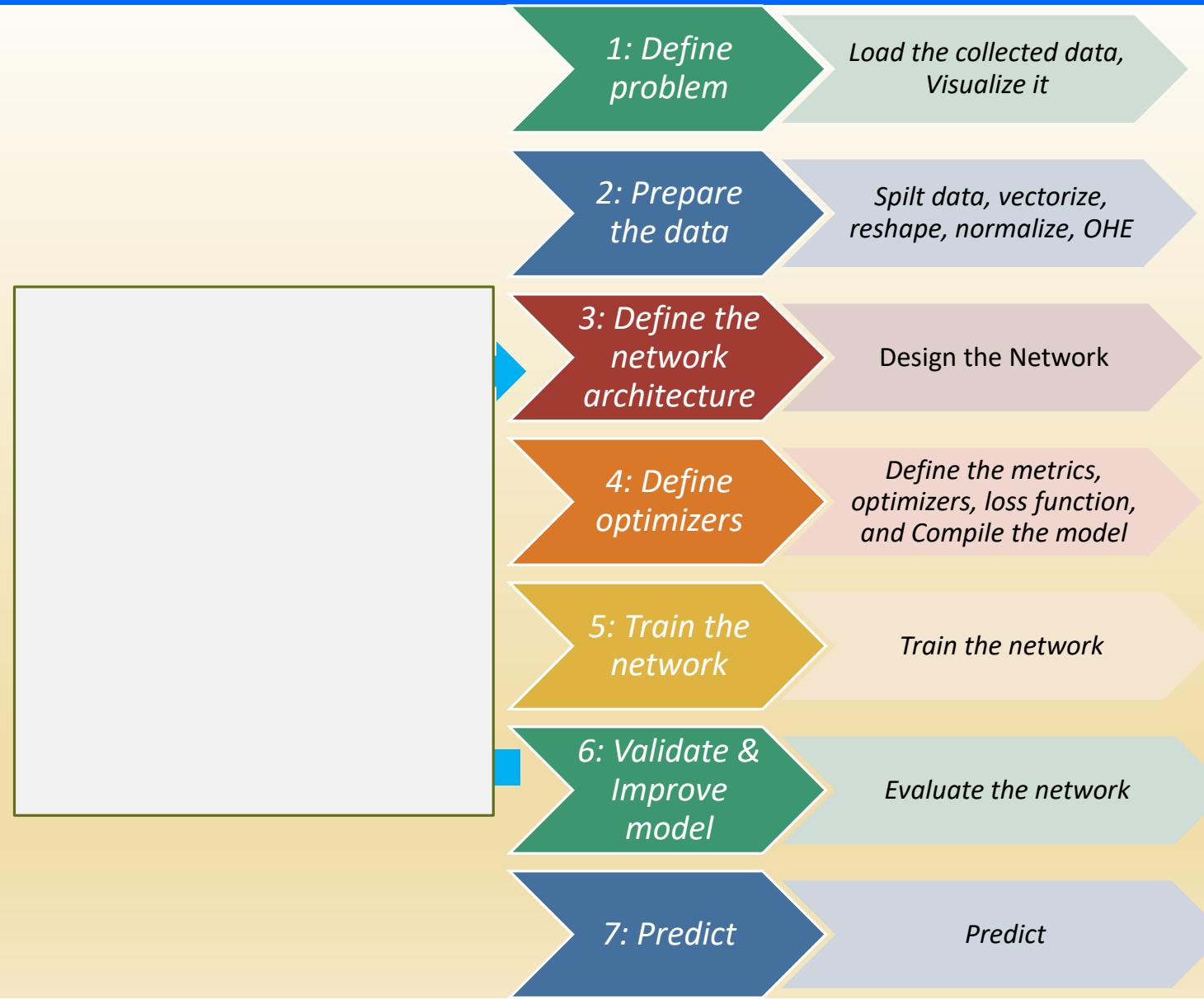
**myArray = keras.utils. to\_categorical ( alnteger)**

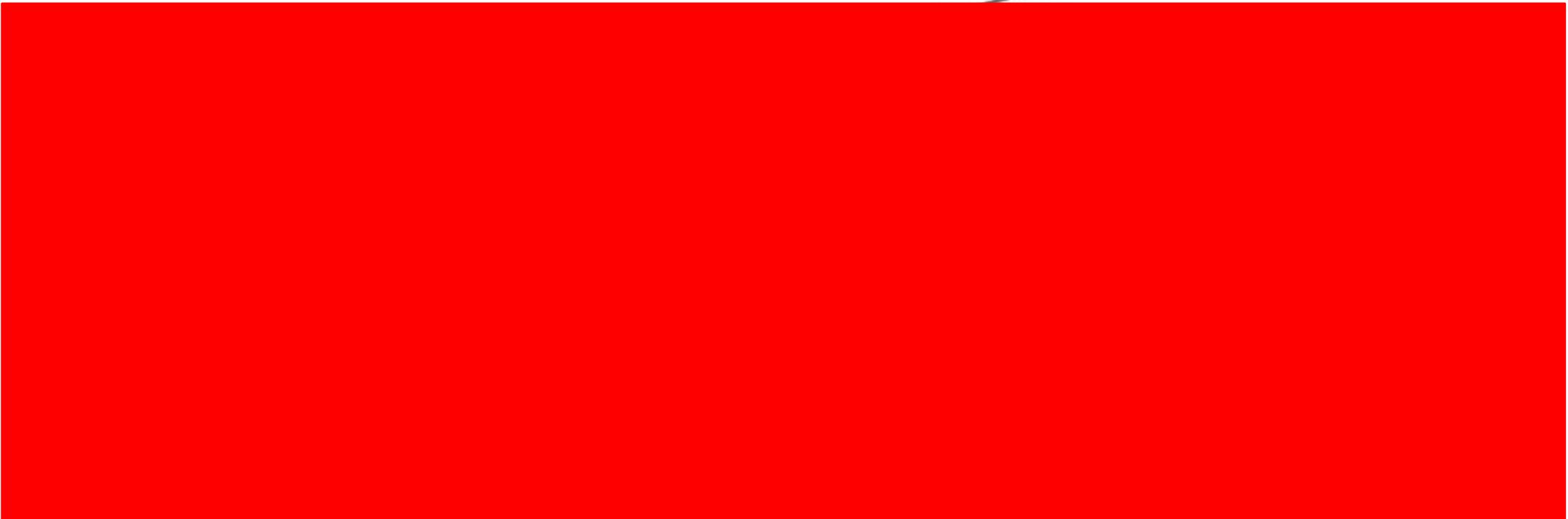
Data: [2]

Data after OHE : [[ 0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]]



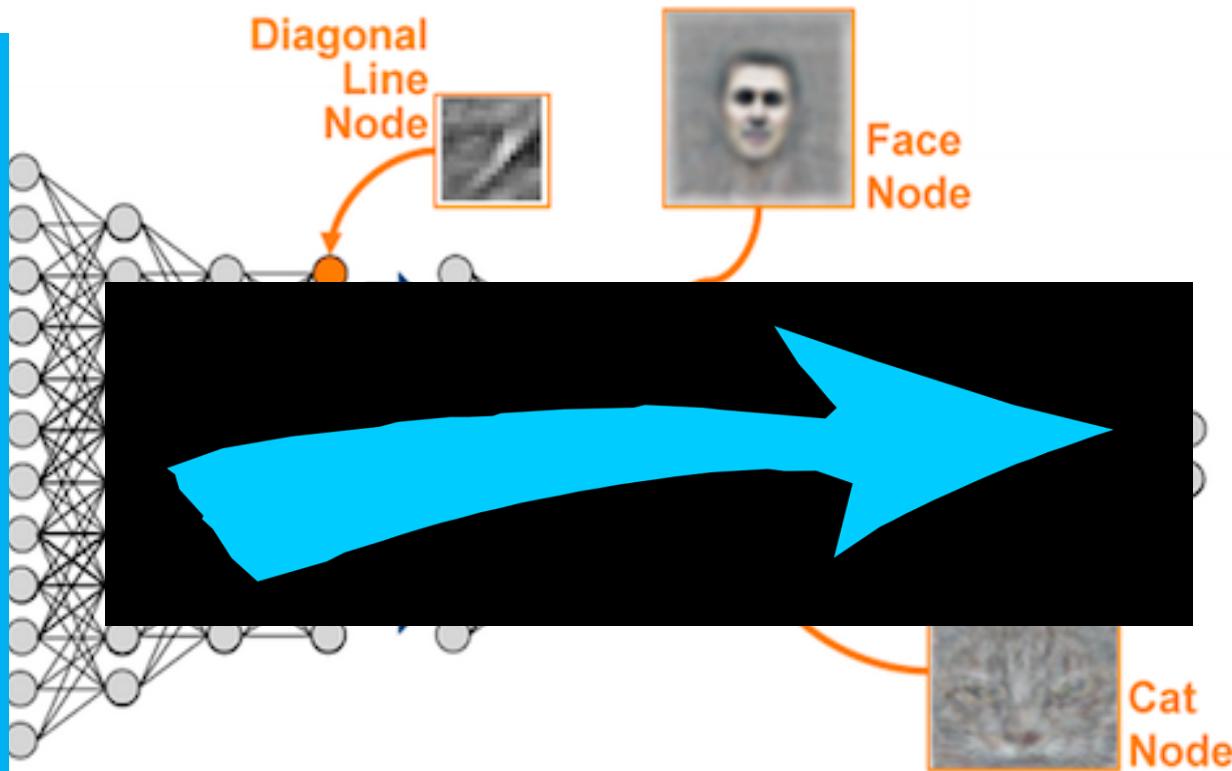
# 7 easy steps to develop your 1<sup>st</sup> Deep Learning model





# 3. Design the network

Data



Representation of Data

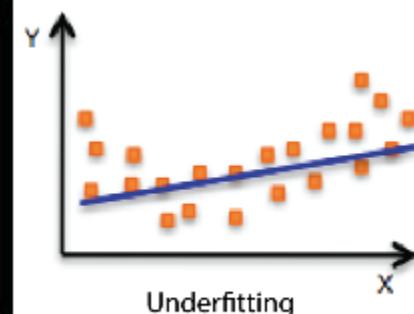
Develop 1<sup>st</sup> model

Develop model that overfits

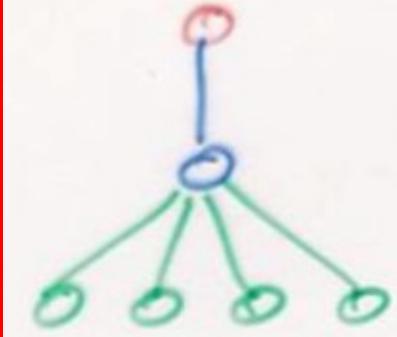
Adjust model's capacity to learn  
“just the patterns”

# 3. Design the network

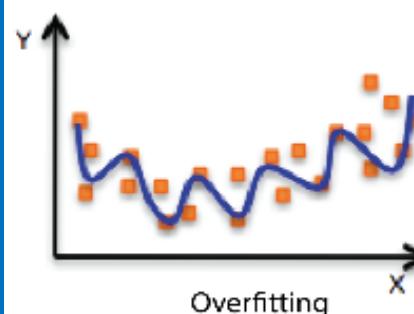
Develop 1<sup>st</sup> model



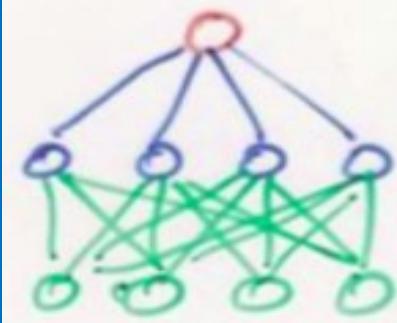
small capacity may prevent it from representing all structure in data



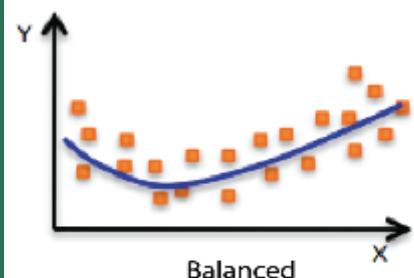
Develop model that overfits



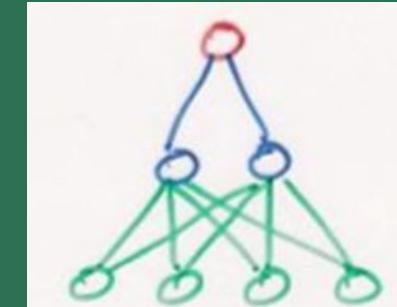
large capacity may allow it to memorize data and fail to capture regularities



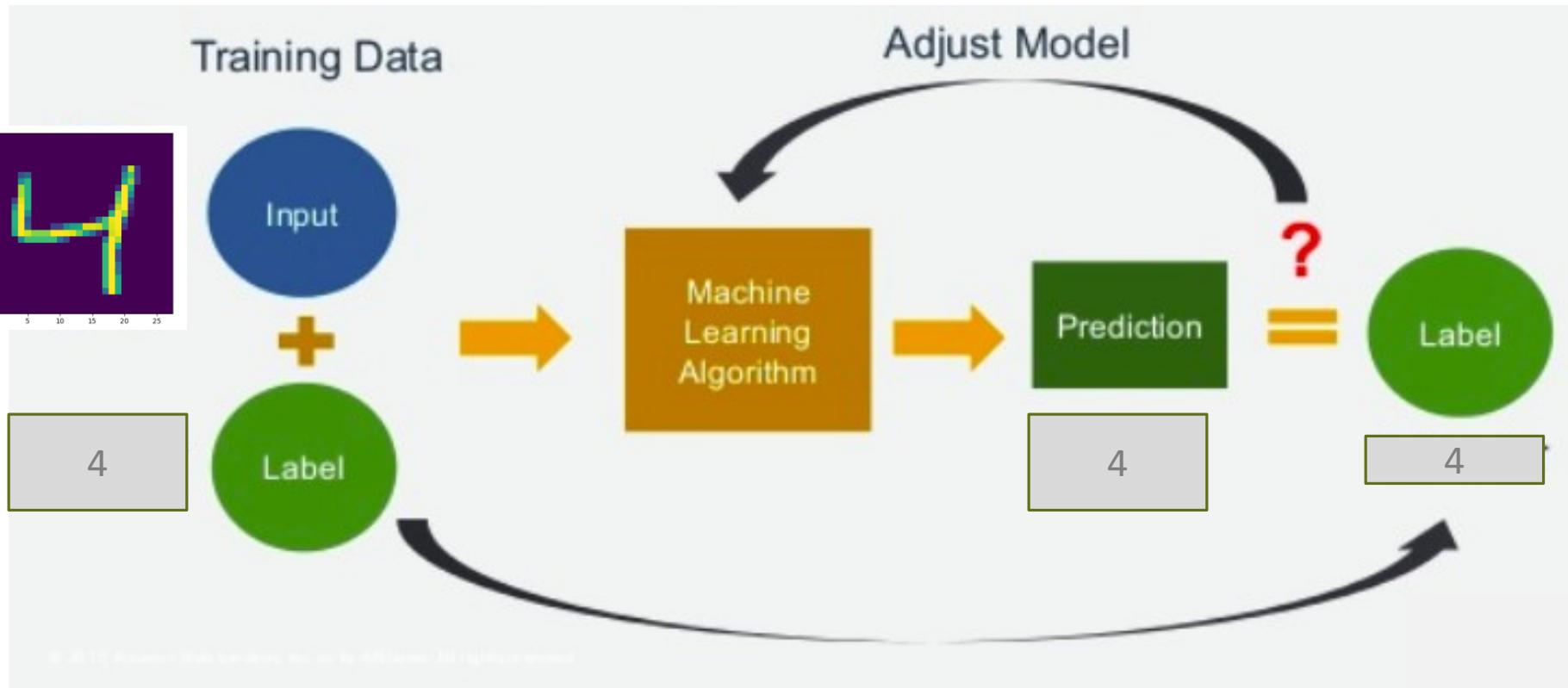
Adjust model's capacity to learn “just the patterns”



Limit the capacity so that only the representations can be learnt

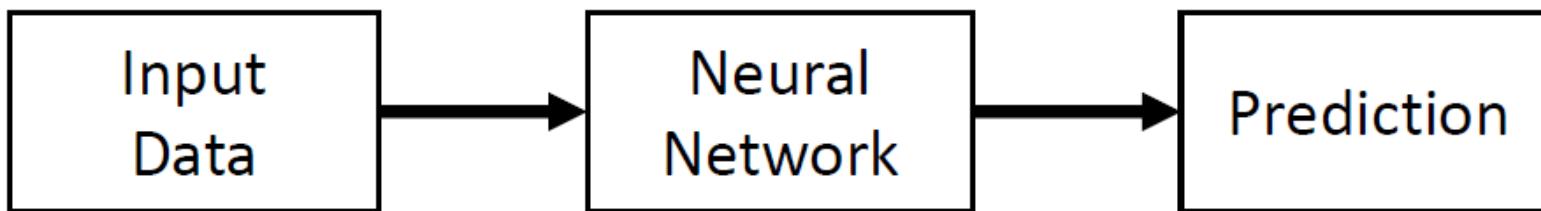


# 5. Train

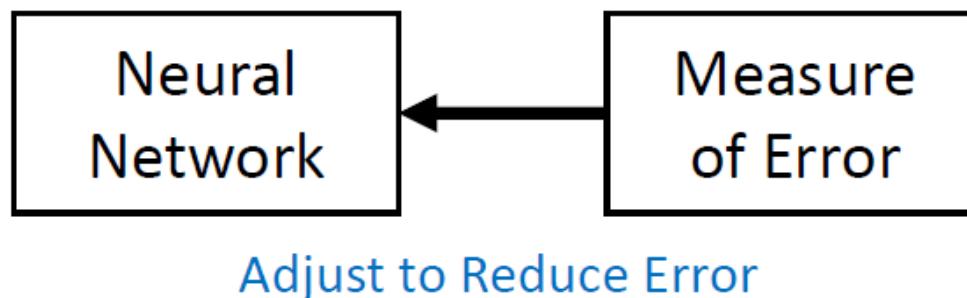


# How Neural Networks Learn: Backpropagation

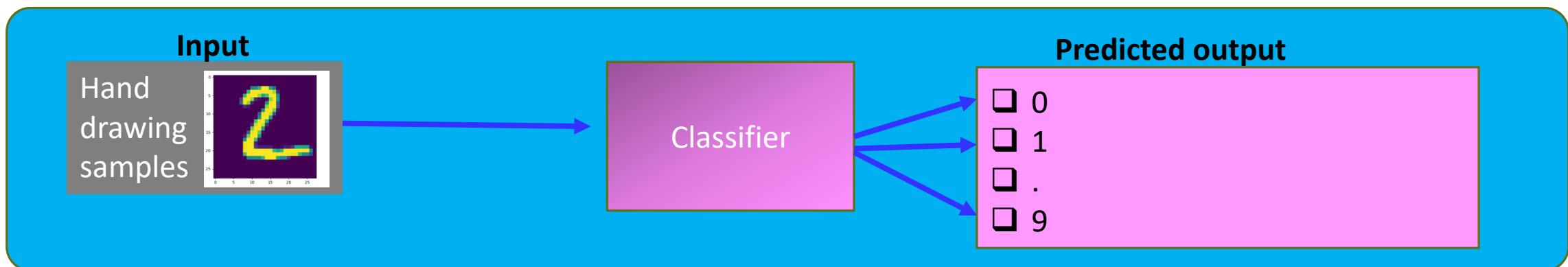
Forward Pass:



Backward Pass (aka Backpropagation):



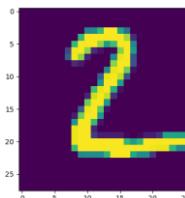
# 7. Predict



# 7. Predict

Problem: Users draws a hand drawn gestures , your app predicts it.

```
predictedResults = network.predict(testXready[1:3])
```



**Predicted Results:**

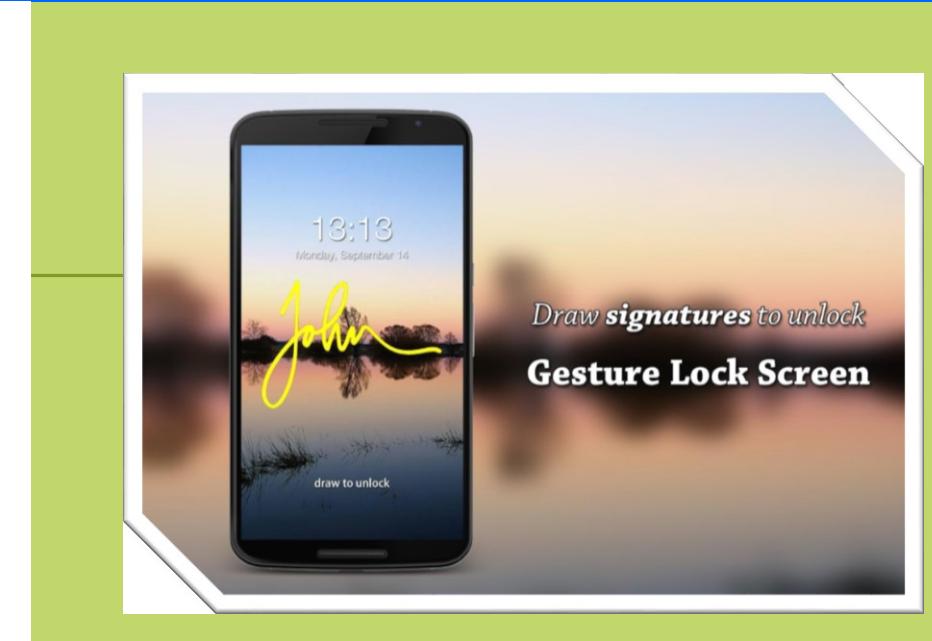
```
[ 1.35398892e-08  3.91871922e-08  9.99876499e-01  1.22501457e-04  
  1.77109036e-10  1.30937892e-07  2.99046292e-07  2.58880729e-11  
  4.58700157e-07  2.09212196e-11]
```

**Ground Truth :** [2]

**Ground Truth OHE :** [[ 0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]]

# Let's it together

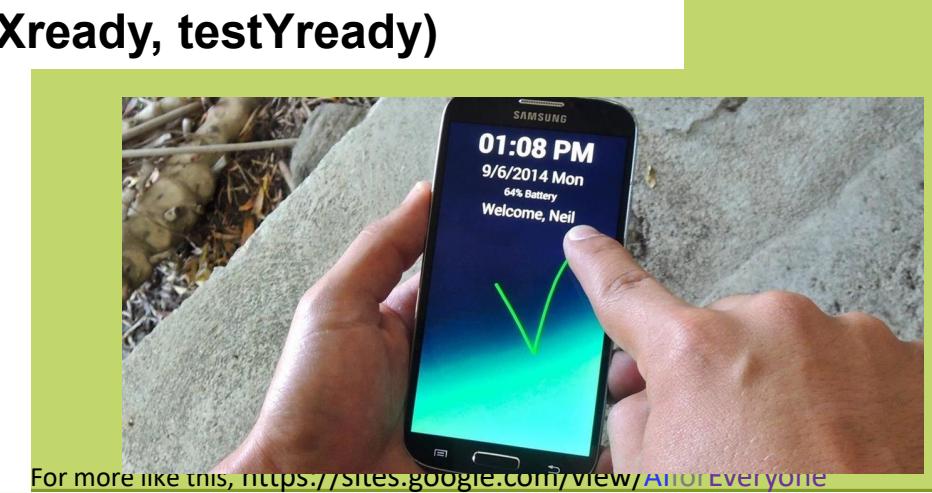
- App idea: Recognize your hand gesture to unlock your smartphone (Secure unlock)
- Biz outcome: Recognize hand draw gestures to unlock your phone



#Step 6: Evaluate the network

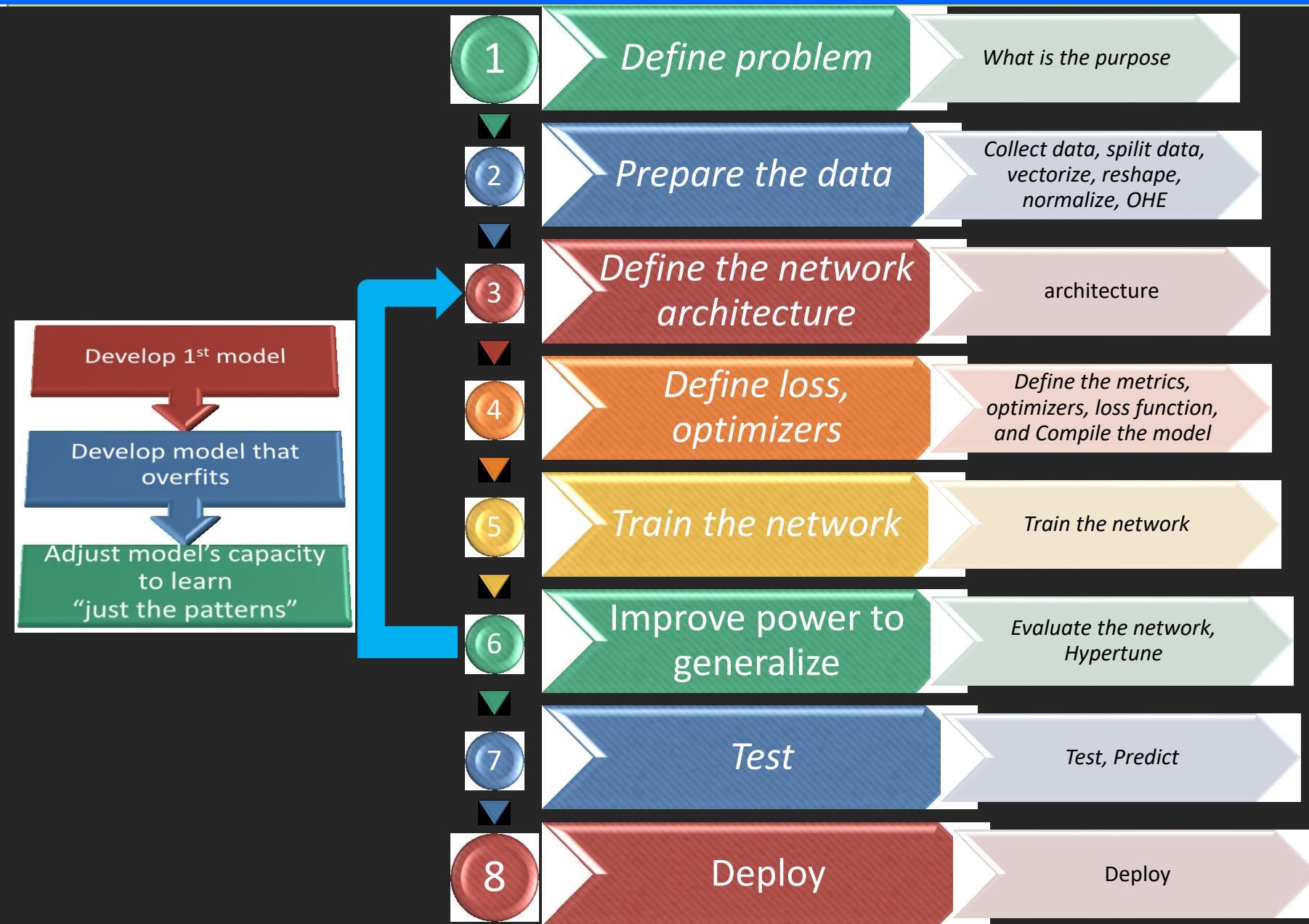
```
metrics_test_loss, metrics_test_accuracy = network.evaluate(testXready, testYready)
```

Test accuracy is: 0.9157



For more like this, <https://sites.google.com/view/Artforeveryone>

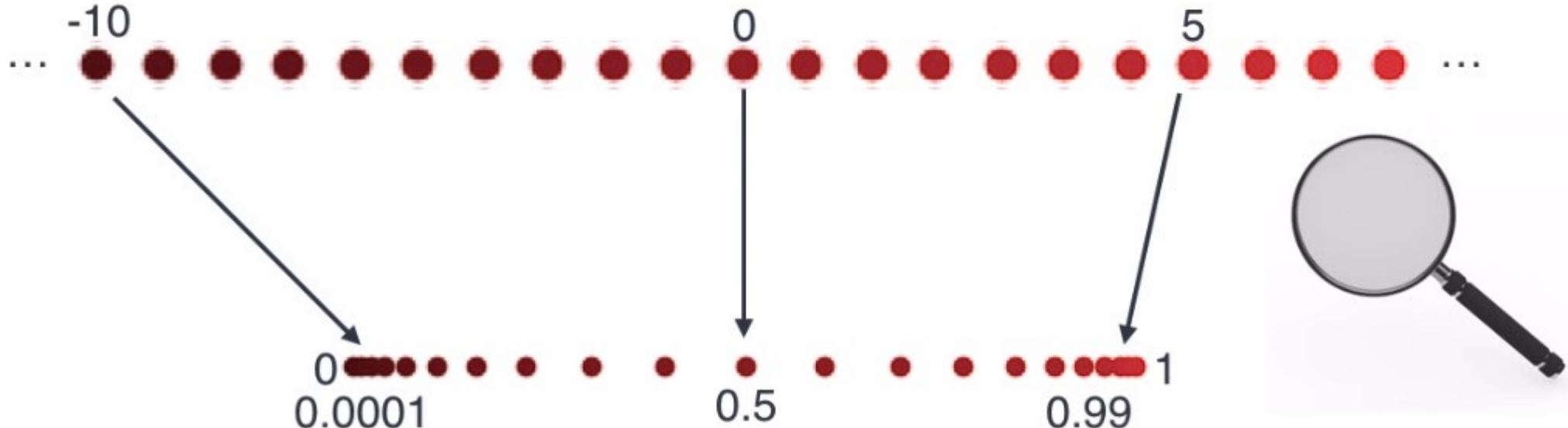
# Design of Deep Learning experiment



# Experiment 2

- MNIST\_Predict\_with\_Dense\_and\_Tune\_Capacity

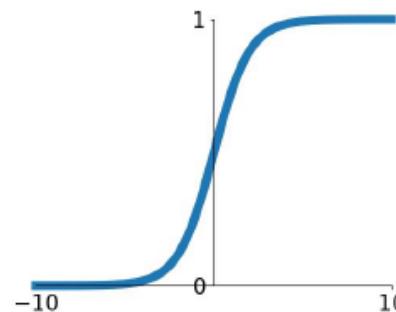
# Activation function



# Activation functions

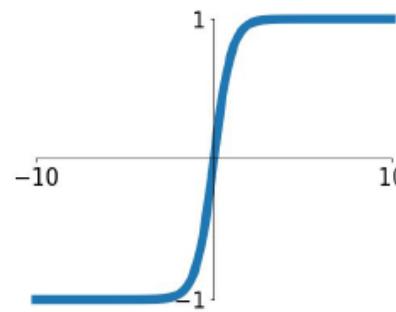
## Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



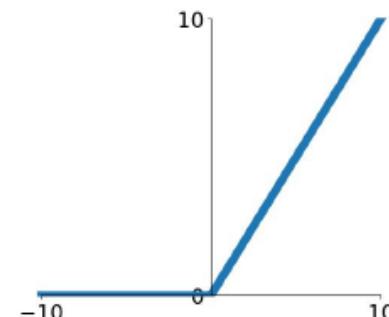
## tanh

$$\tanh(x)$$



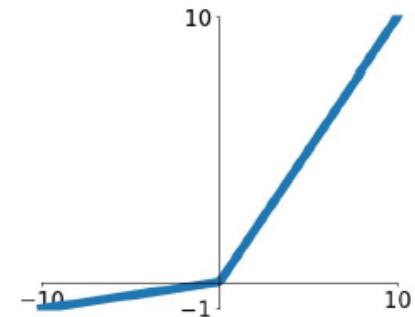
## ReLU

$$\max(0, x)$$



## Leaky ReLU

$$\max(0.1x, x)$$

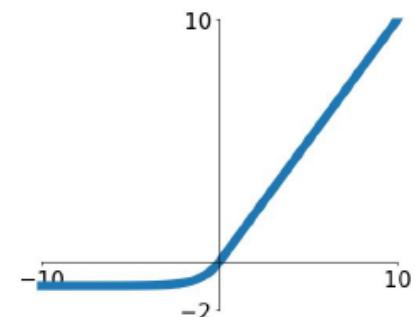


## Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

## ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

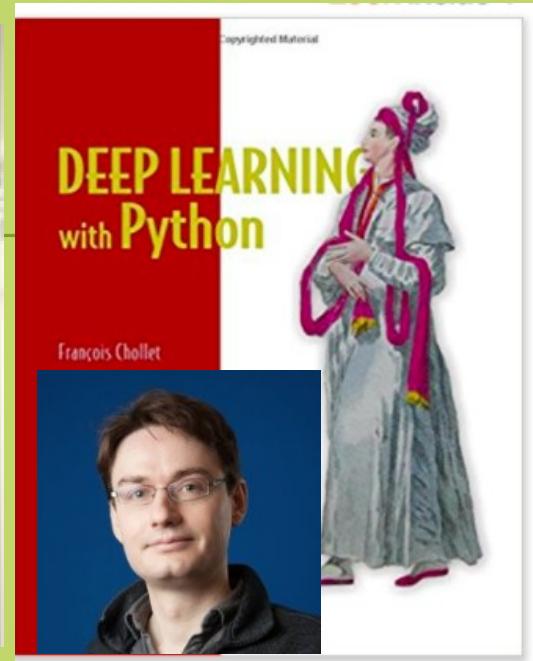


# Our inspiration

## Friendly approaches :

### 1) KERAS.io

François Chollet's  
Book on "Deep Learning with Python"



### 2) Deeplearning.ai (Coursera.org)

Andrew Ng

Deep Learning with Fast.Ai



### 3) Google Machine Learning Course

<https://developers.google.com/machine-learning/crash-course/>



# More inspiration

## Excellent Resources

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- **Stanford cs231 n**

<http://cs231n.stanford.edu>

- **MIT Deep Learning**

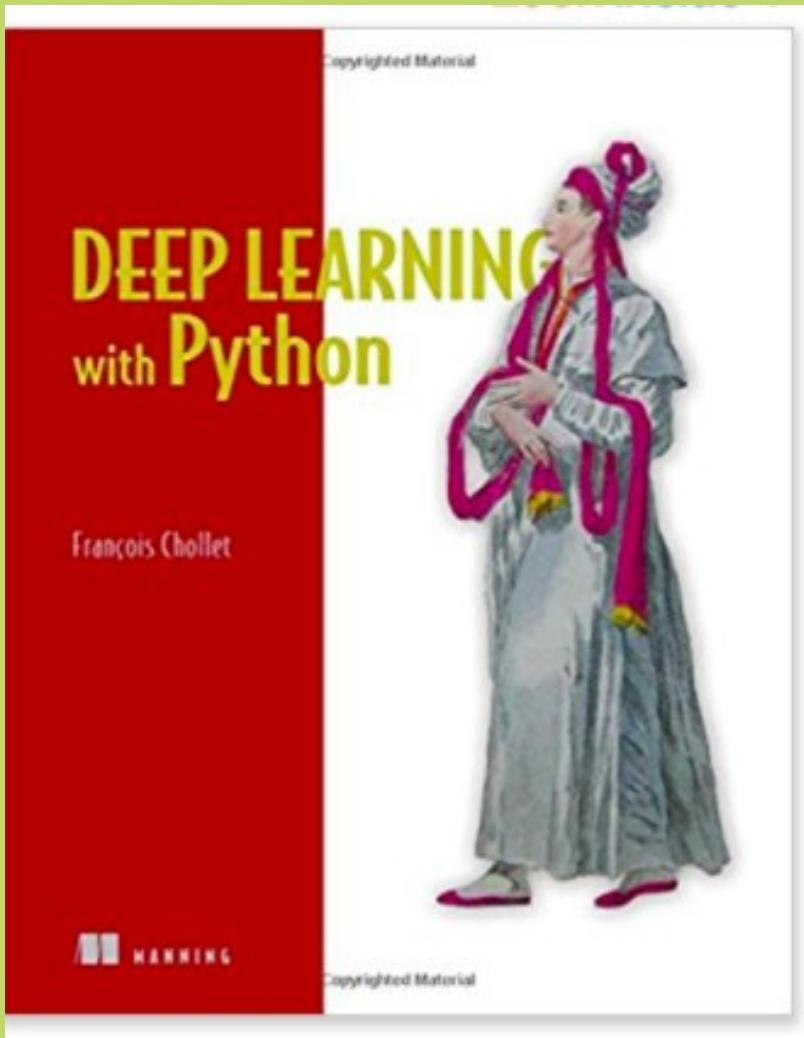
<http://introtodeeplearning.com/>

<https://deeplearning.mit.edu>

- **IIT Madras**

my classes notes with Prof. Anurag (**Deep Learning**)

# Want a Book?



Francois Chollet

Artificial Intelligence Researcher,  
**Google**

Check free chapters at Manning Website!

## Deep Learning with Python

<https://www.manning.com/books/deep-learning-with-python>

**ISBN-13:** 978-1617294433

Book Published: December 22, 2017