

# **AI in Built Environment**

## **DCP4300**

### **Lec07-08: Deep Learning**

#### **Part B**

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## **Outline:**

### **0. Recap**

### **1. Python**

### **2. ML algorithms and demos**

### **3. Build a neural network in TensorFlow / PyTorch (Part C)**

**You can install Python and Jupyter notebook on your computer,  
or use Google Colab in the browser instead, which needs your Google account.**

**For deep learning demonstrations, we'll always use Google Colab.**

0

## Recap



The diagram consists of three concentric circles. The outermost circle is light blue and labeled 'Artificial Intelligence'. Inside it is a medium blue circle labeled 'Machine Learning'. The innermost circle is dark blue and labeled 'Deep Learning'. This visualizes that Deep Learning is a subset of Machine Learning, which is a subset of Artificial Intelligence.

Artificial Intelligence

Machine Learning

Deep Learning

AI: Techniques that enable machines to mimic human.

ML: Techniques that enable machines to **learn from data**, **without being explicitly programmed**.

DL: Techniques that enable machines to learn from data, **hierarchically**, using **neural networks**.

# Types of Machine Learning:

**Supervised Learning:** Learn a function from **labeled** data.

- Classification
- Regression

**Semi-supervised Learning**

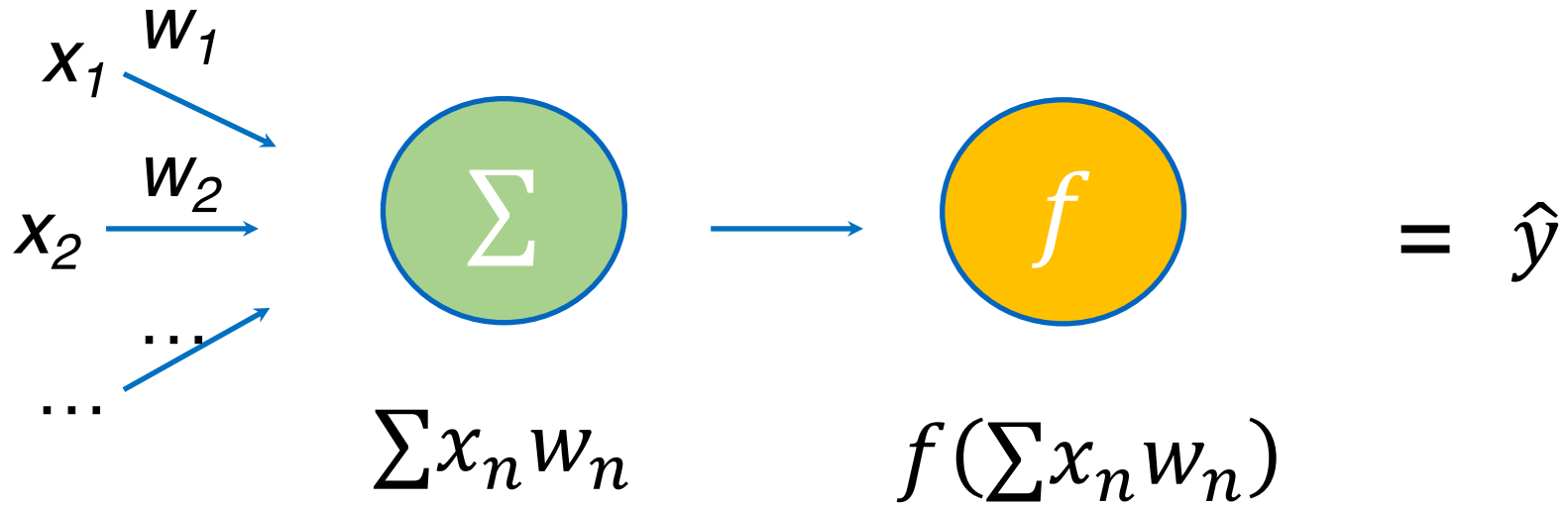
**Unsupervised Learning:** Learn the pattern from **unlabeled** data.

- Clustering
- Dimension reduction

**Reinforcement Learning:** Learn to react to an environment by **trial and error**.

- Decision making
- Robotics
- ...

## What does a perceptron do?

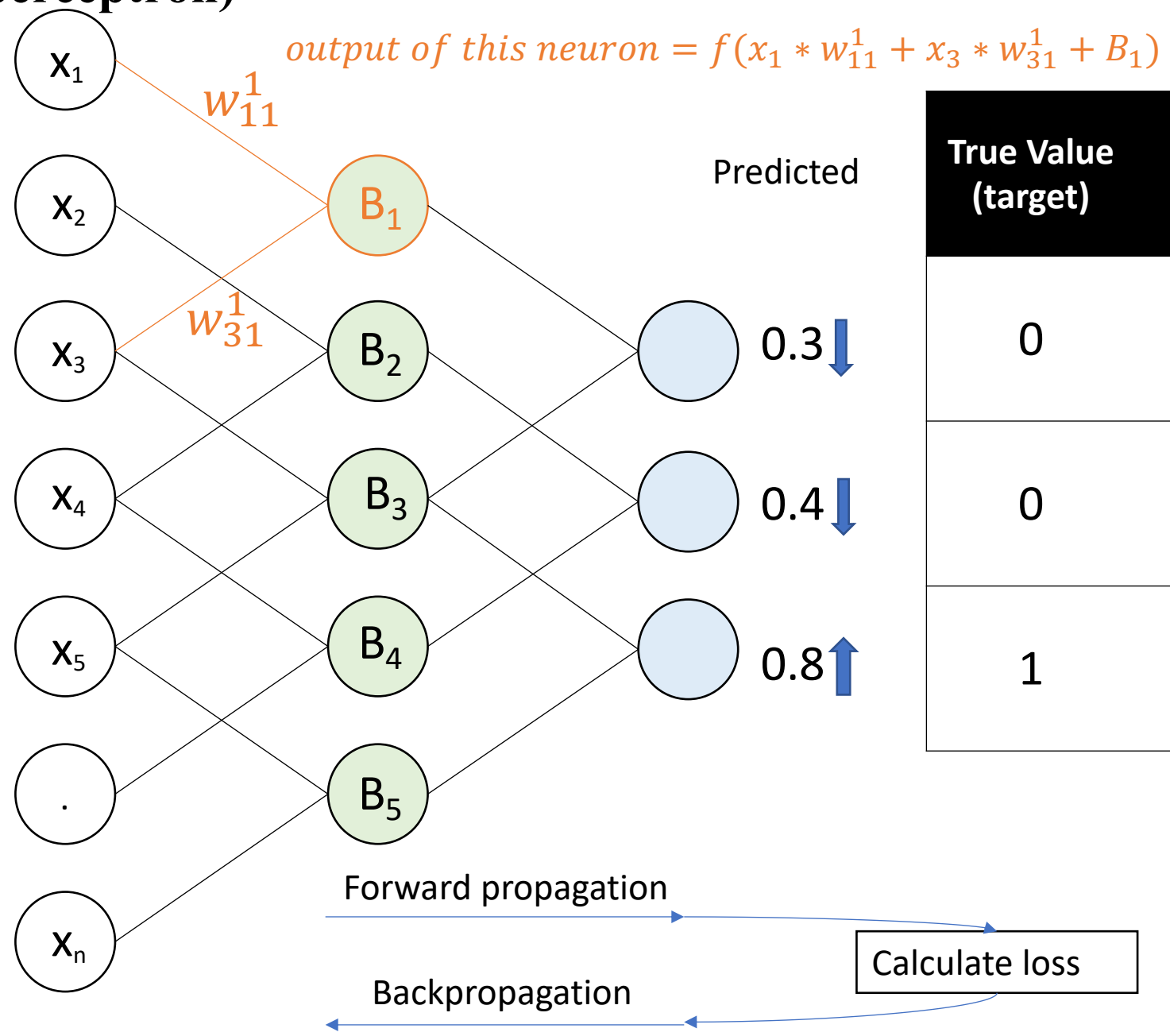
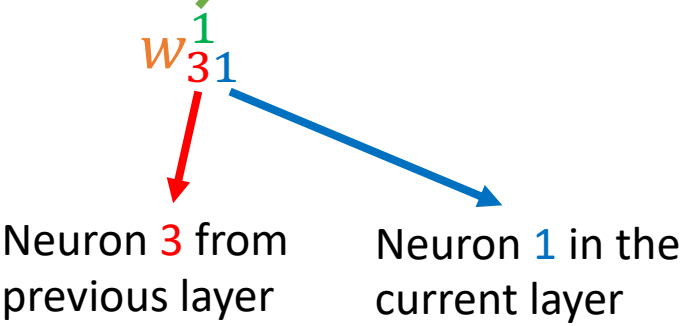


Sum and Activate

# Neural network (Multilayer perceptron)

## Weights

The weight linking the 1<sup>st</sup> hidden layer and its prior layer



True Value (target)		Error
0	-0.3	
0	-0.4	
1	0.2	

# Learning rate

## Gradient descent:

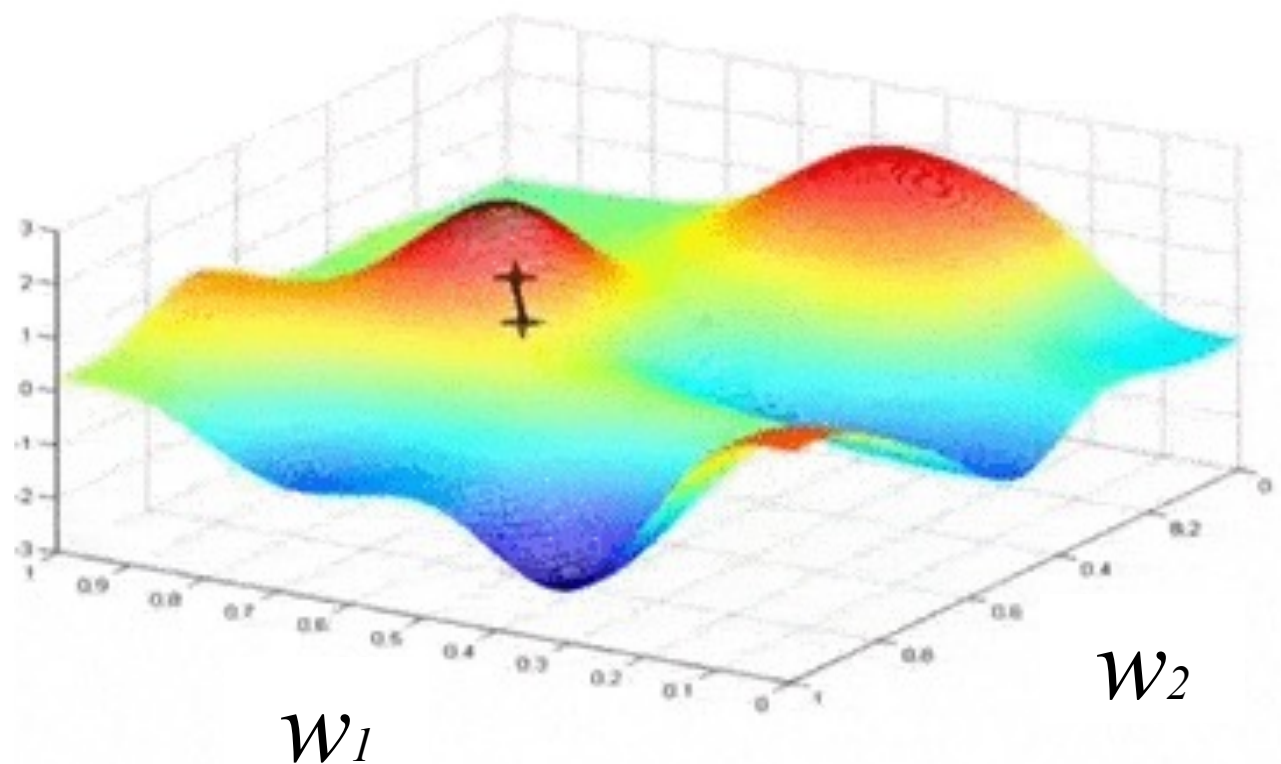
- 1. Compute the slope (gradient) at the current step  $\frac{\partial J}{\partial w}$
- 2. Make a move in the direction opposite to the slope

The move =  $-\eta \frac{\partial J}{\partial w}$

↑

Learning rate

$J(w)$





**At the end, what is learned?**

*The weights:  $\mathcal{W}$*

# Python

Based on

[https://www.w3schools.com/python/python\\_getstarted.asp](https://www.w3schools.com/python/python_getstarted.asp)

## Run codes on your computer

1.Install Python: <https://www.python.org/downloads/>

2.Install Jupyter: Run this in the command line

```
pip3 install --upgrade pip  
pip3 install jupyter
```

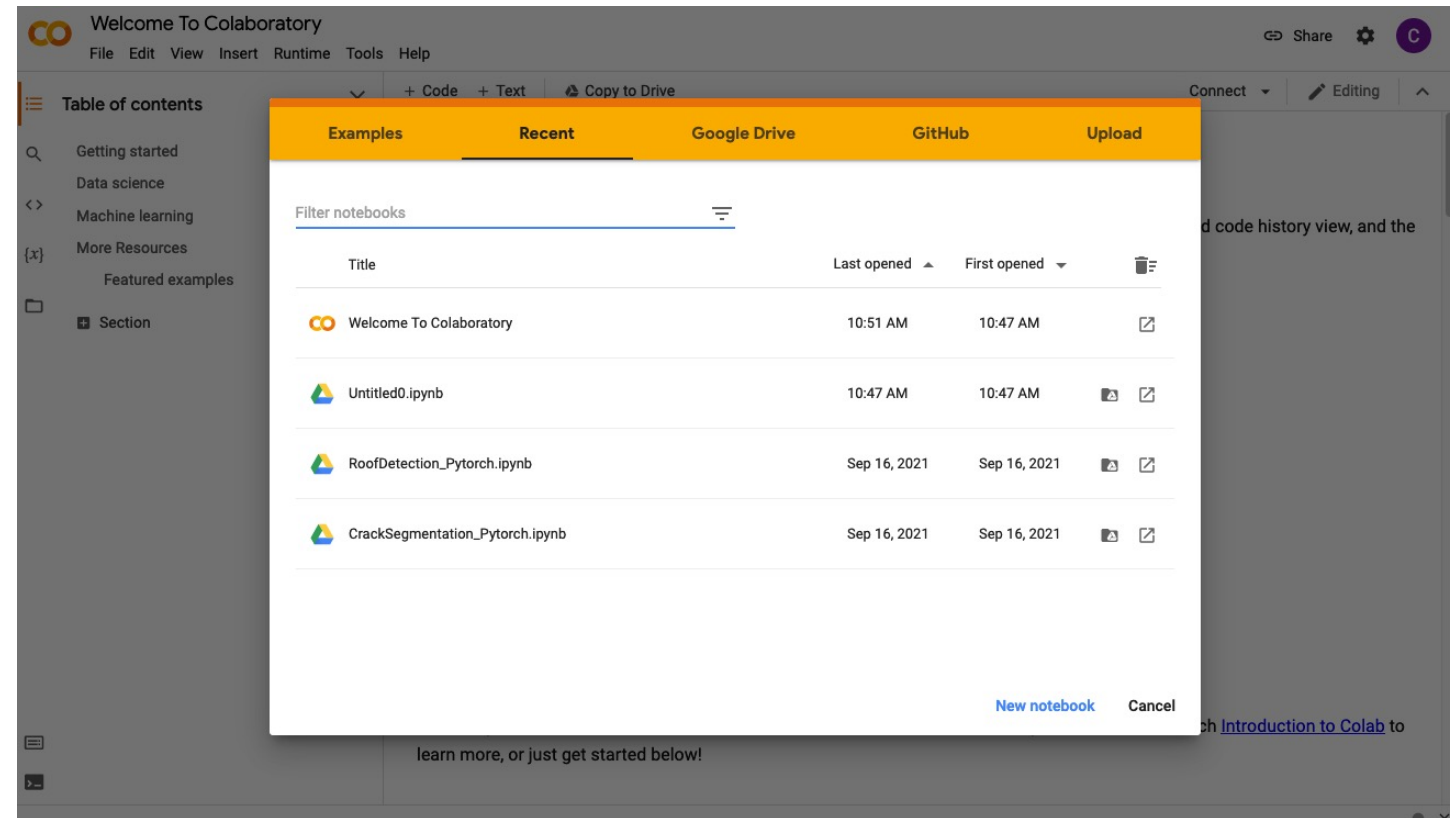
3.How to use Jupyter:

<https://jupyter-notebook-beginner-guide.readthedocs.io/en/latest/execute.html>

# Run codes in the cloud: Google Colab

Google Colab:

1. First you need a Google Account
2. Go to <https://colab.research.google.com>
3. Create a New notebook

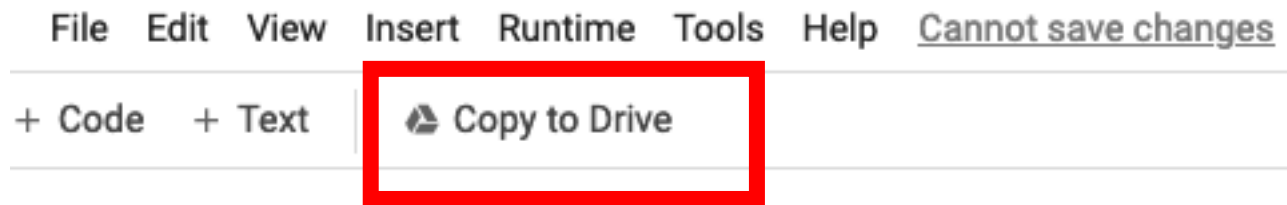


## Run codes in the cloud: Google Colab

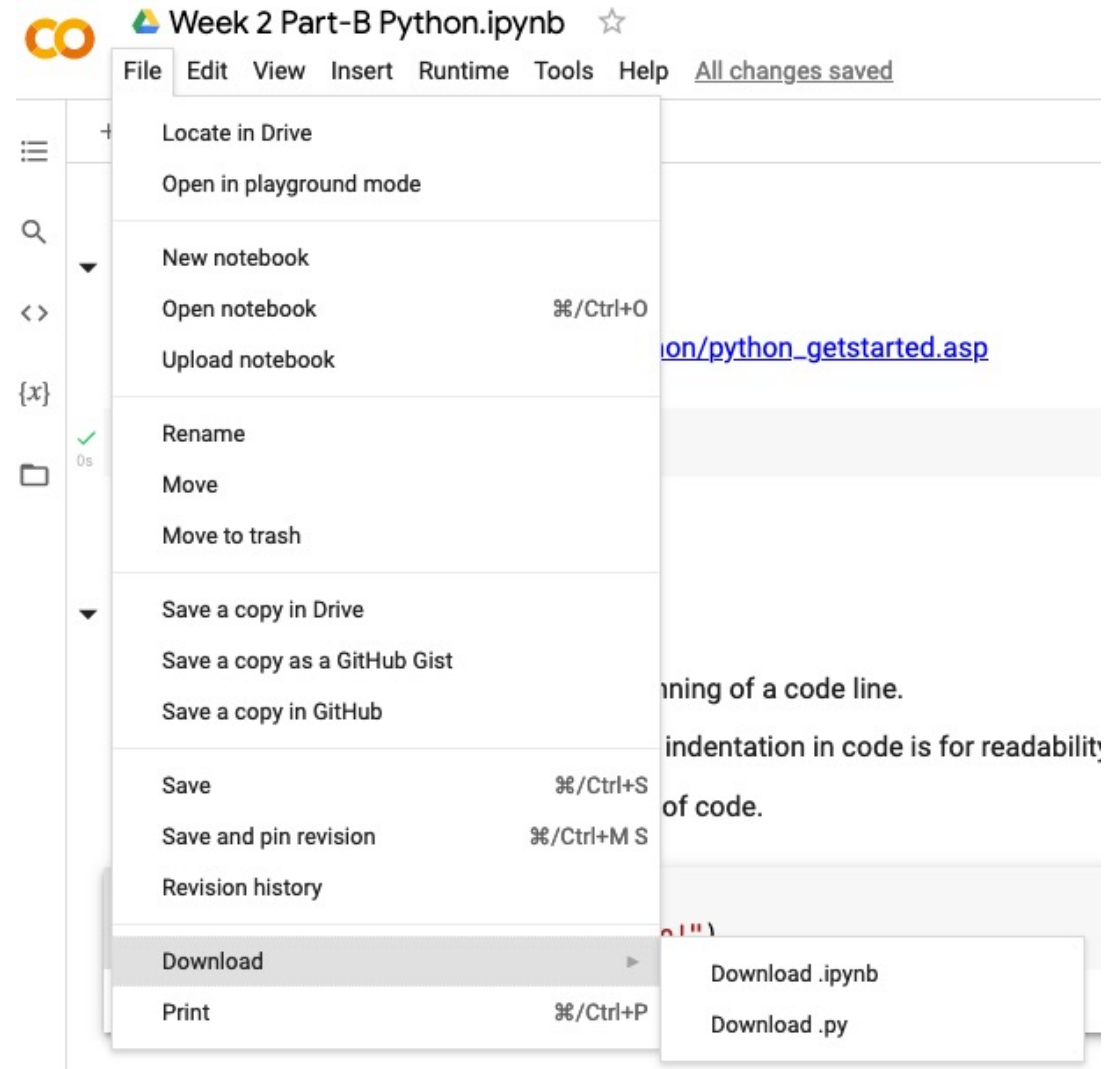
Now we run the Python tutorial in a Jupyter notebook that is hosted on Google Colab:

[https://colab.research.google.com/drive/1FsaIHg4G91zNJWarShbd\\_HrzBnKYL7c5?usp=sharing](https://colab.research.google.com/drive/1FsaIHg4G91zNJWarShbd_HrzBnKYL7c5?usp=sharing)

## Run codes in the cloud: Google Colab



**You can also download the notebook from Colab**



## Run codes on your computer (more than two ways...)

1

\*.py file:

contains Python code, mainly for the machine to execute

To execute a py file on your computer, go to the command line, and run the command in a folder that contains your file:

```
python filename.py
```

2.

\*.ipynb file:

a notebook, for you to write and run Python code, and visualize results interactively

If you run 'jupyter notebook' in the command line,  
Jupyter will open in your browser



## **2. ML algorithms and demos**

## Common algorithms in **Supervised Machine Learning**

Regression

Decision tree / Random forest

K-nearest neighbor

Support vector machines

Multilayer perceptron (Neural network)

...

**Keywords:**

**Data    Model    Training**

**Basic frame:**

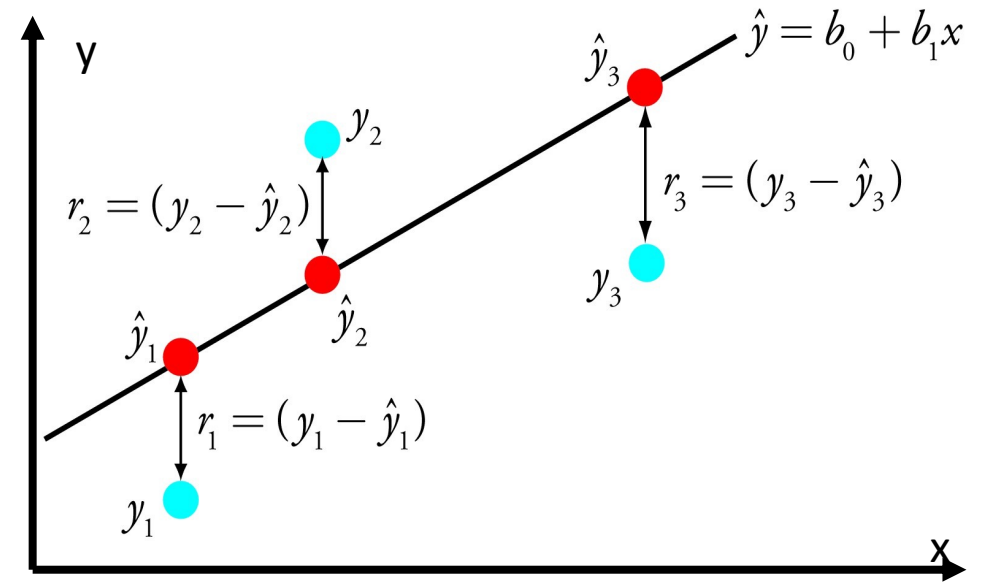
**Use data to set the parameters of a model to fit the labels.**

# Linear Regression

x	y
0.1	0.05
0.2	0.3
0.4	0.2
$x_i$	?

Fit the relation by  
a **linear function**:

$$y = X\boldsymbol{\beta} + \epsilon$$



Math:

Find **coefficient  $\boldsymbol{\beta}$  and error  $\epsilon$**  for

$$y = X\boldsymbol{\beta} + \epsilon$$

that minimize the **residual**:

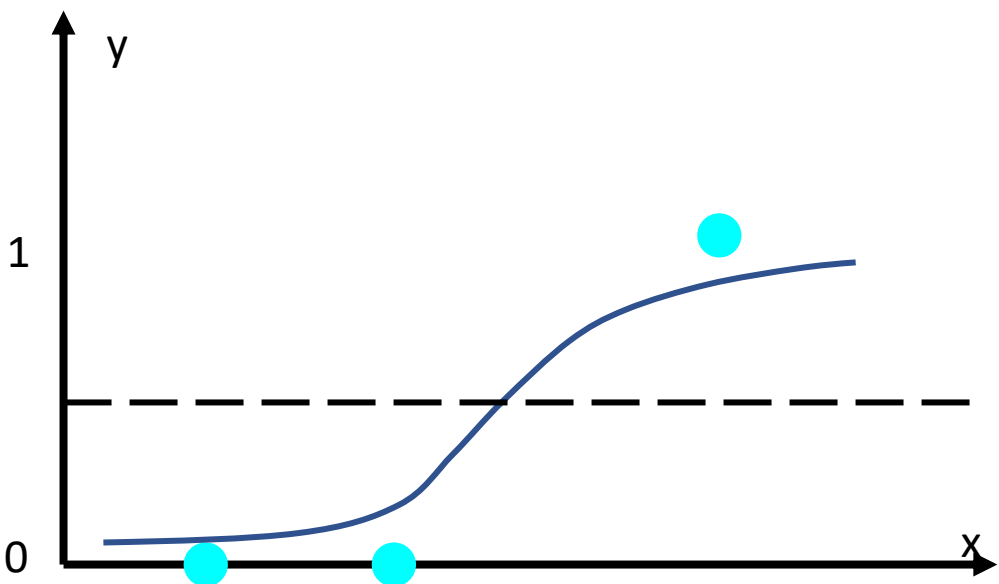
$$\mathcal{R} = \sum_1^n r_i^2$$

# Logistic Regression

x	y
0.1	0
0.2	0
0.4	1
$x_i$	?

Fit the relation by  
a **logistic function**:

$$P(y = 1|x) = \frac{1}{1+e^{-(\beta_0+\beta_1x)}}$$



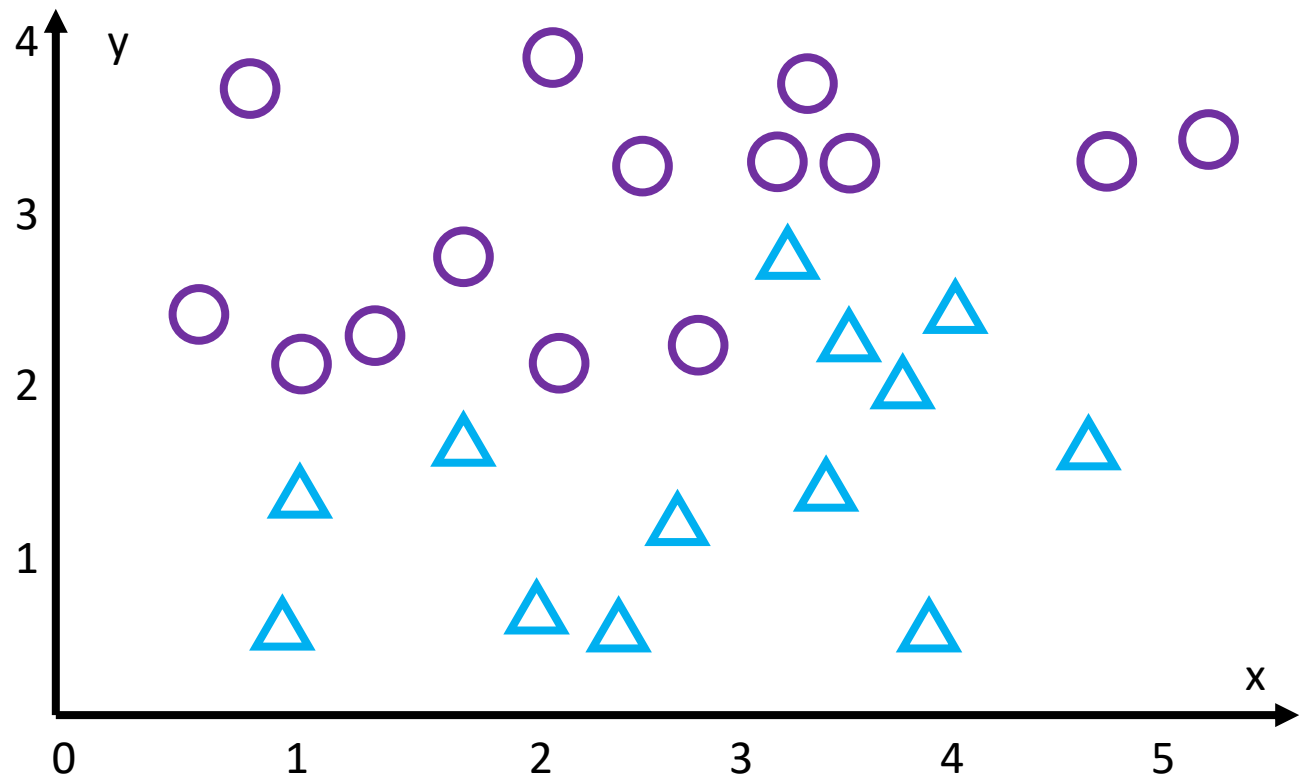
Math:

Find **coefficient  $\beta$**  for

$$P(y = 1|x) = \frac{1}{1 + e^{-(\beta_0+\beta_1x)}}$$

that minimize the residual between the  
prediction and the ground truth

# Decision Tree

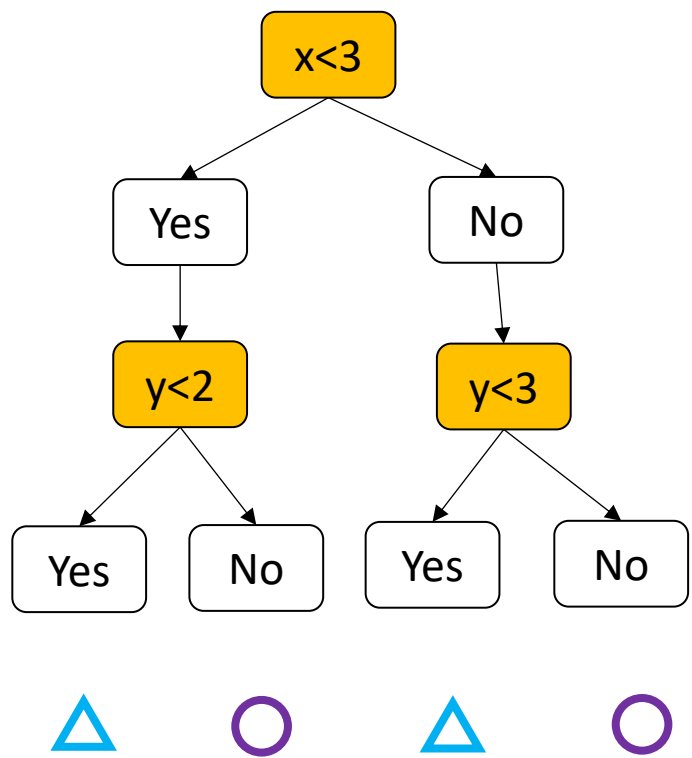
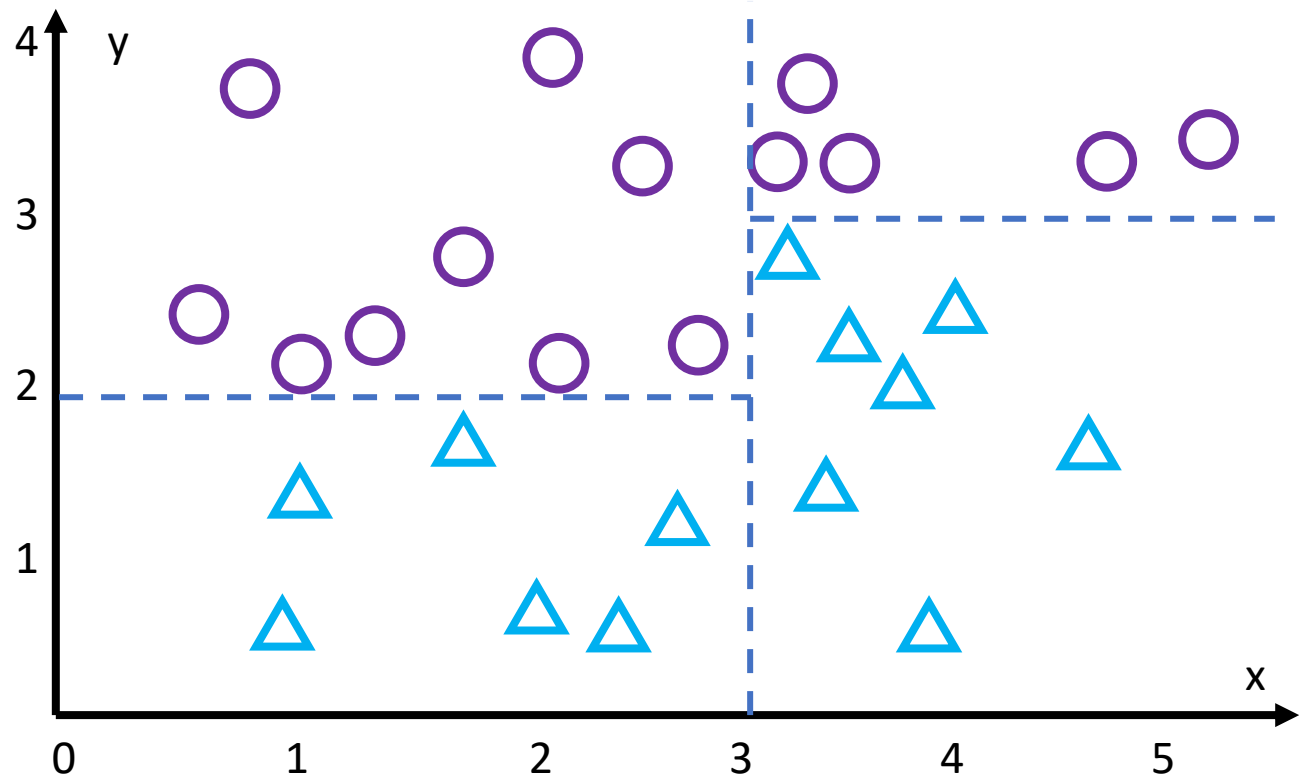


x and y are called features, each data point can be represented by features:

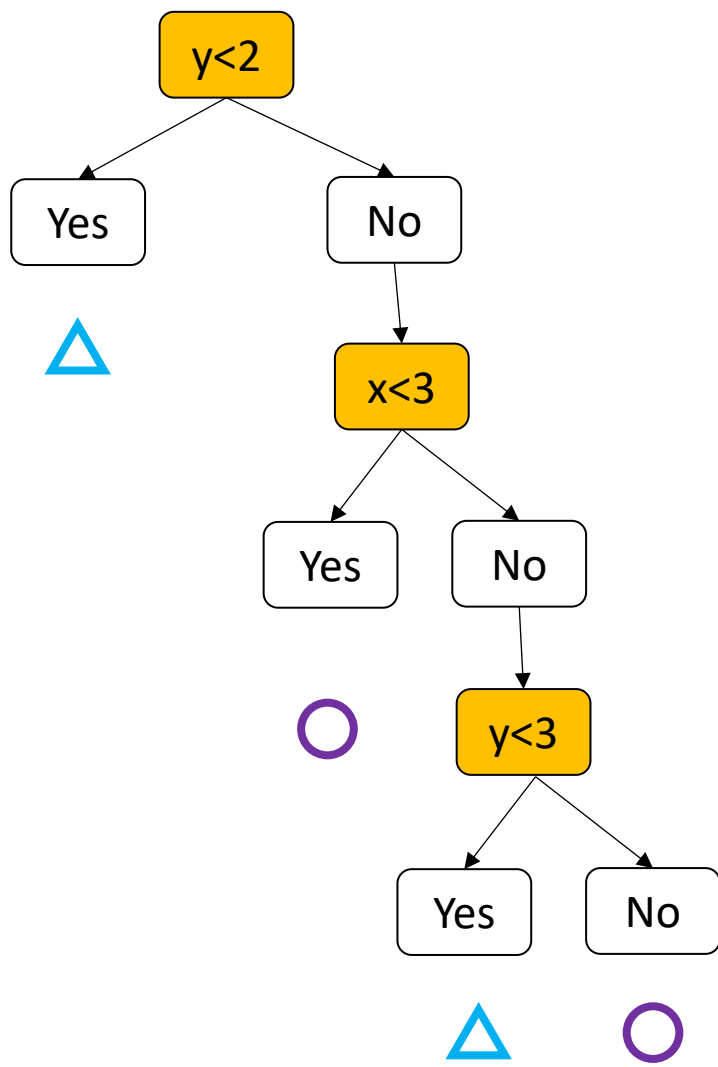
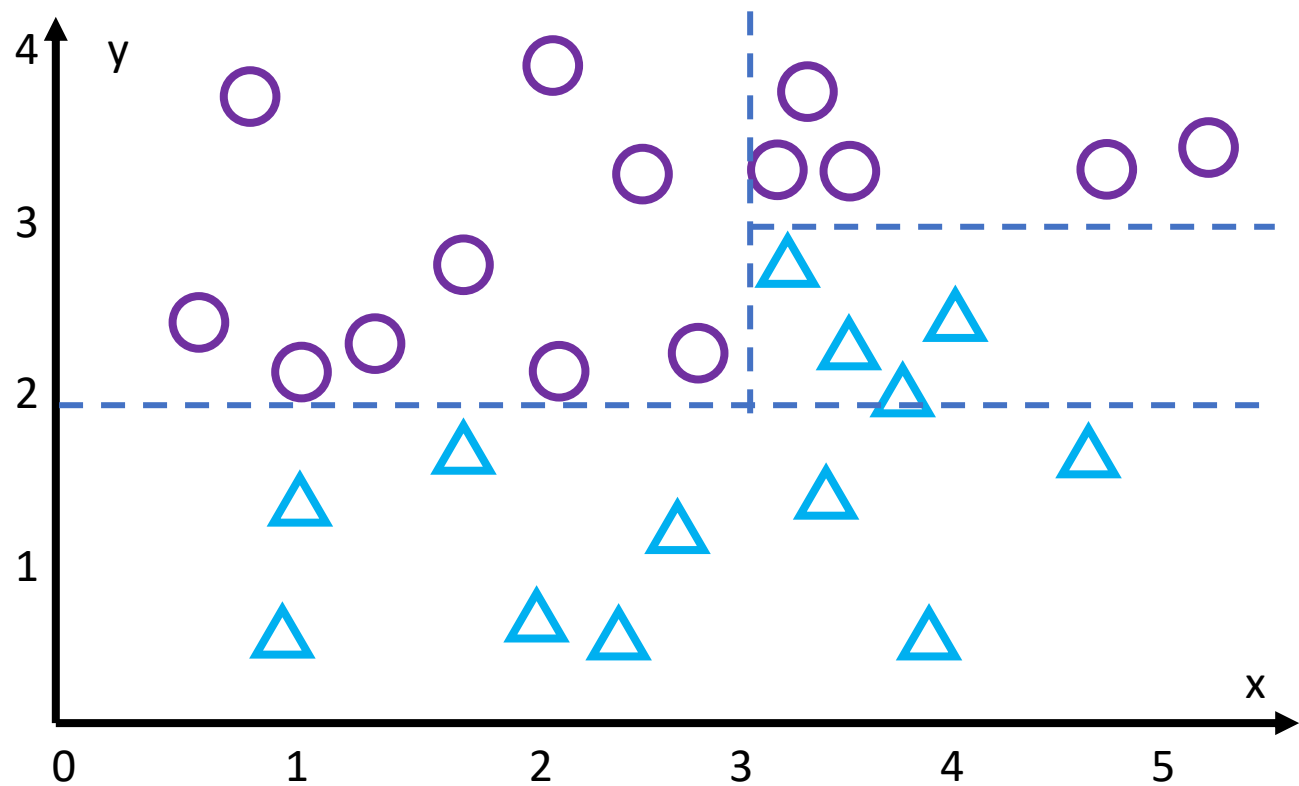
○ (x, y)

△ (x, y)

# Decision Tree

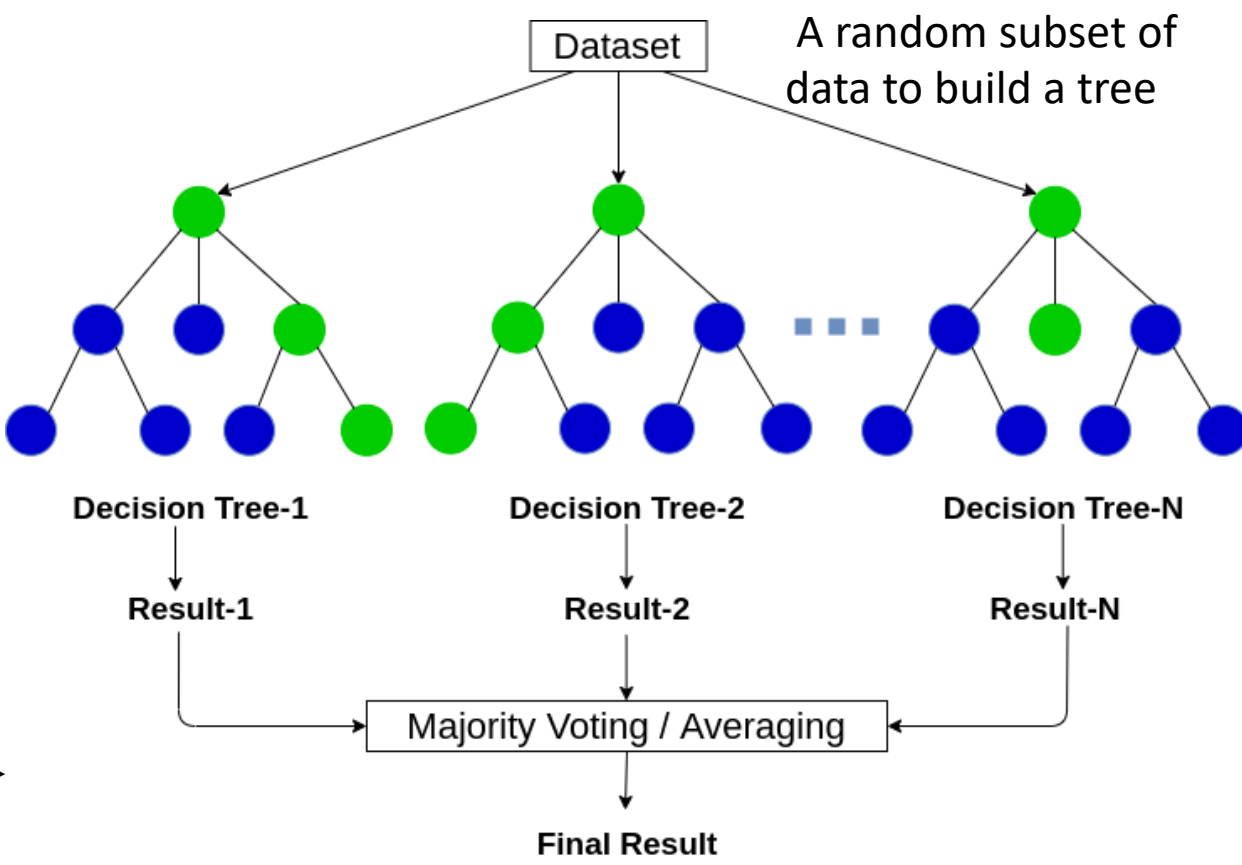
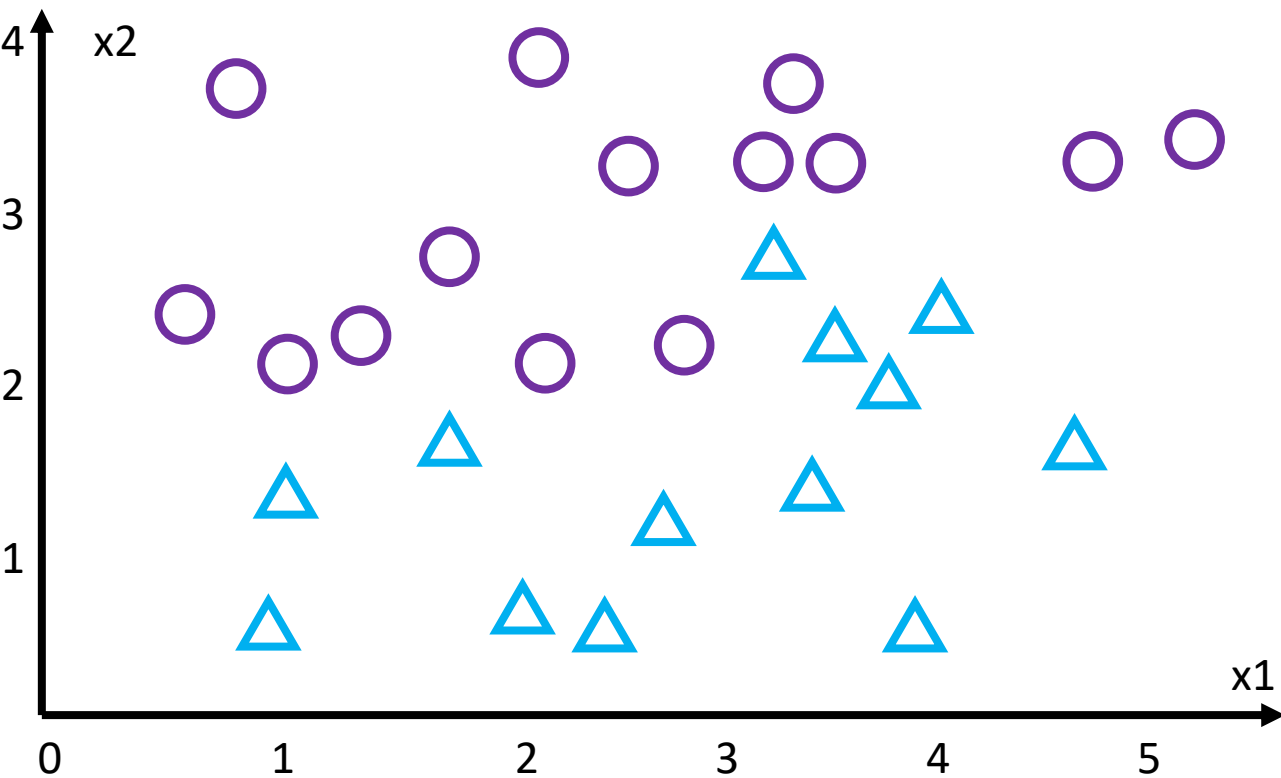


# Decision Tree



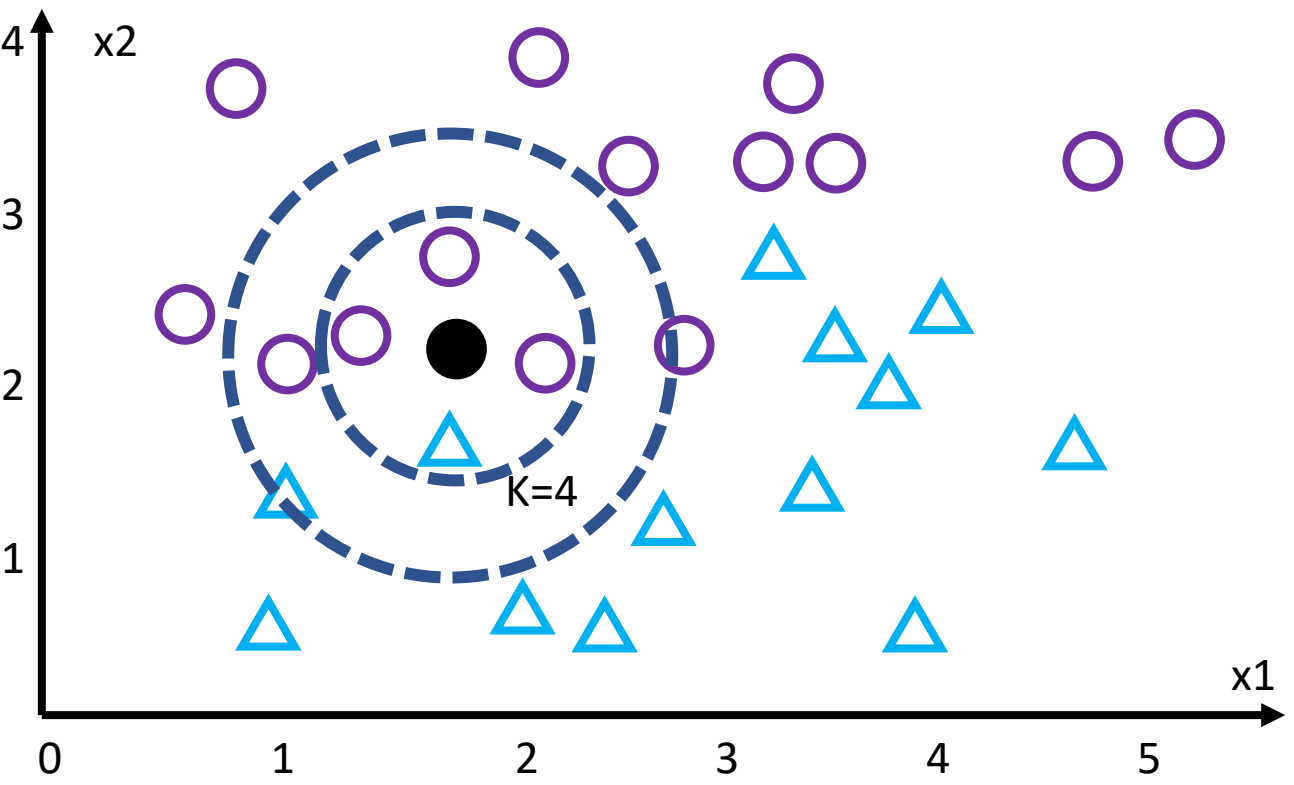
Another tree

# Random Forest

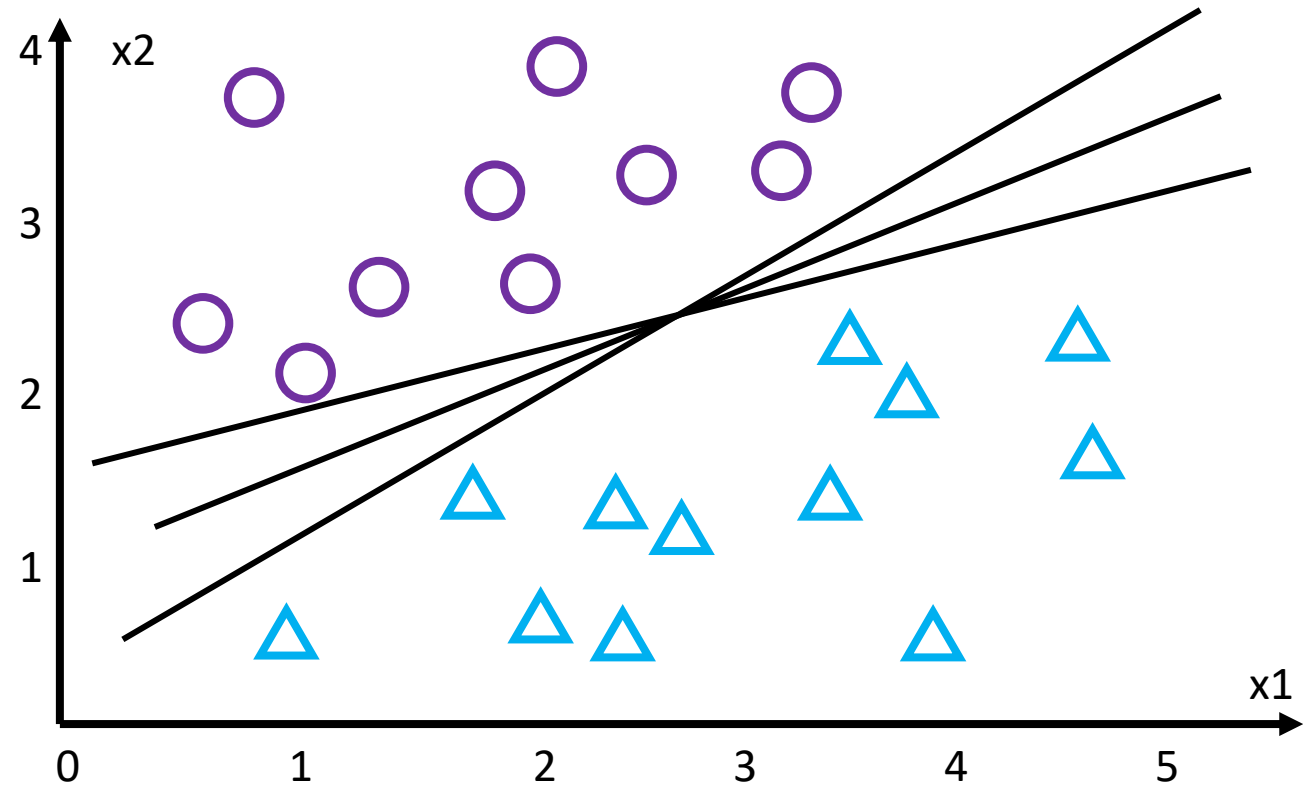




# K-nearest neighbor

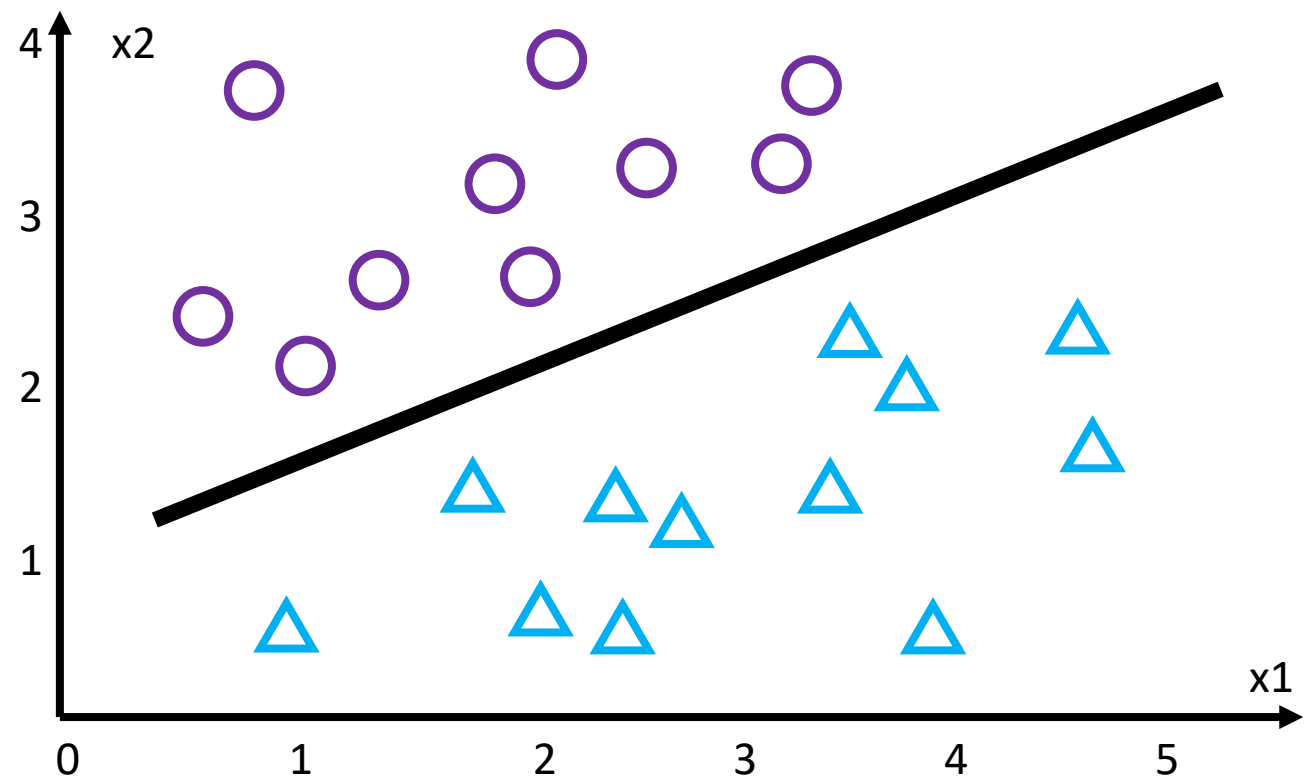


# Support vector machines

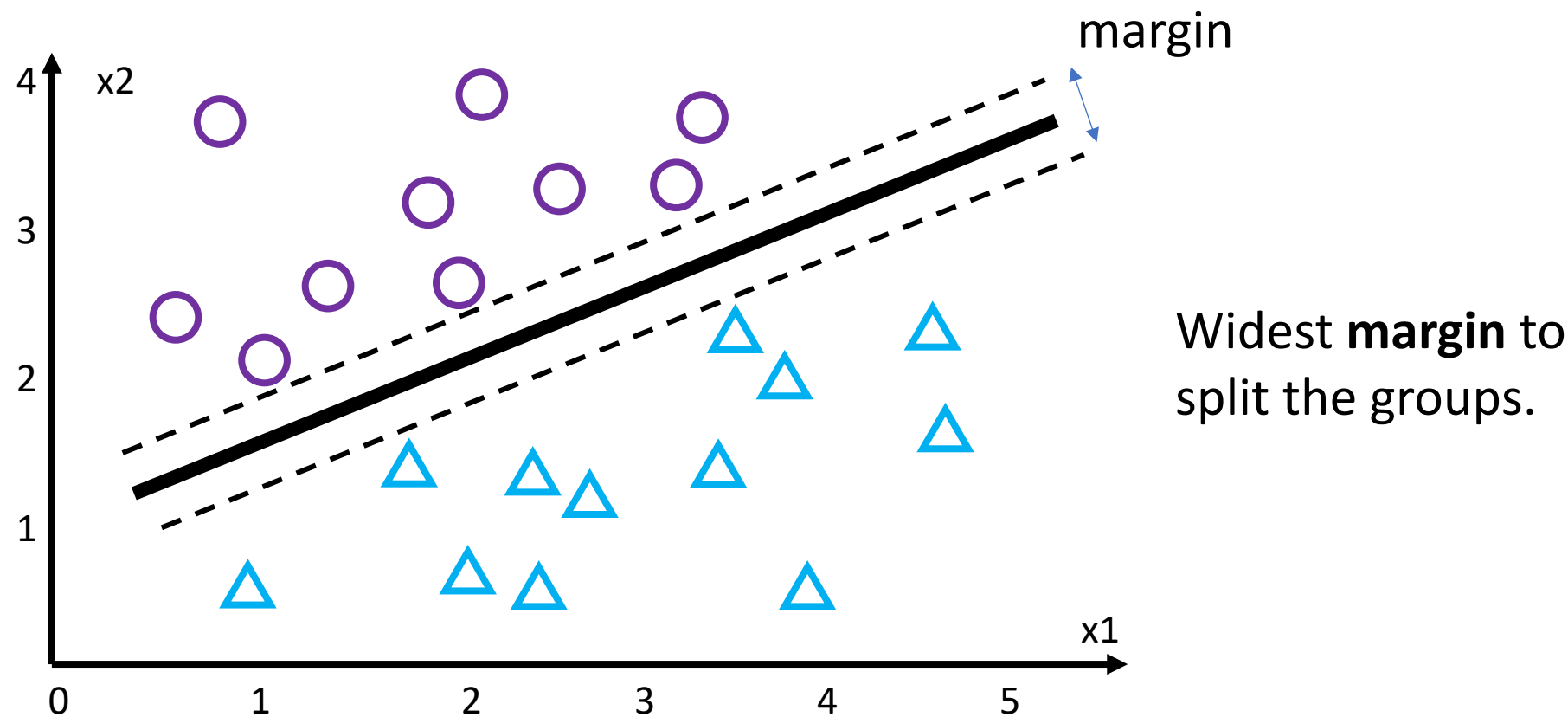


Which is the best?

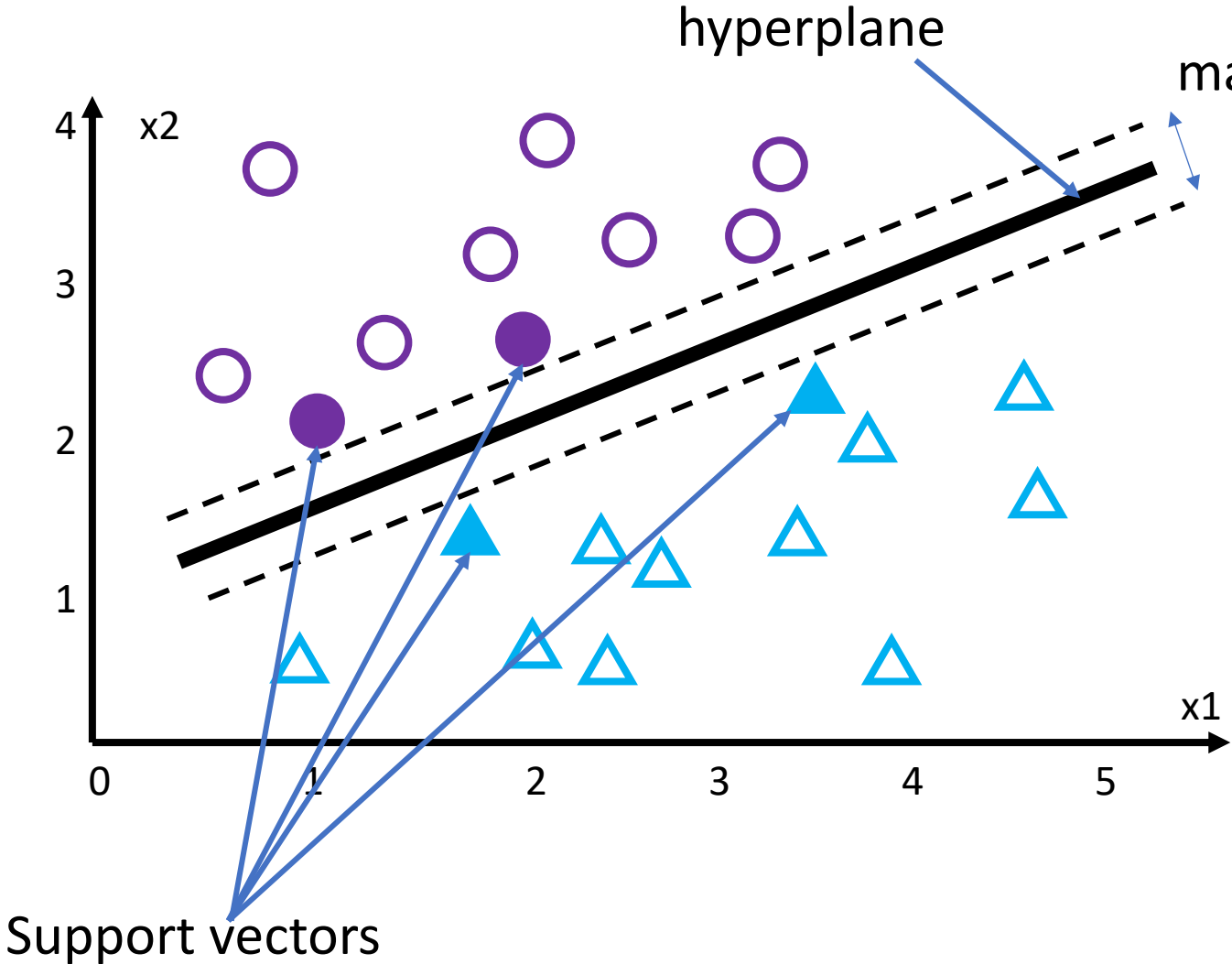
# Support vector machines



# Support vector machines



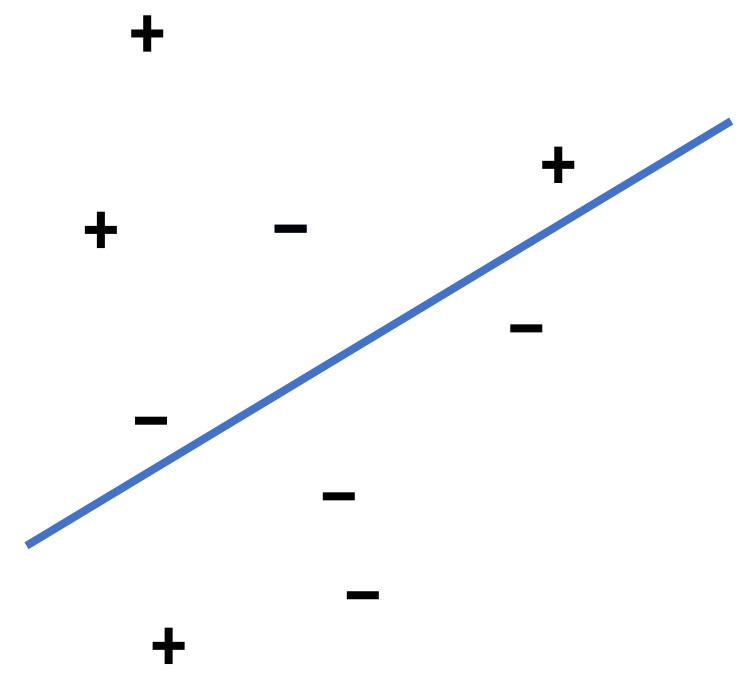
# Support vector machines



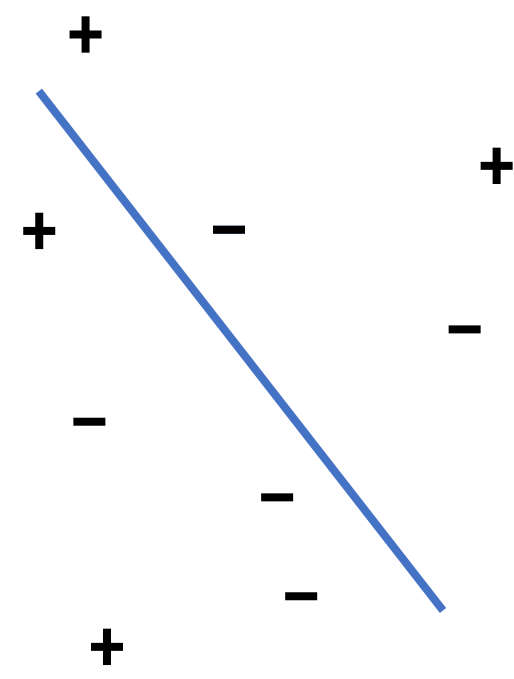
Widest **margin** to split the groups.

**margin** = distance between the **support vectors** and the **hyperplane**.

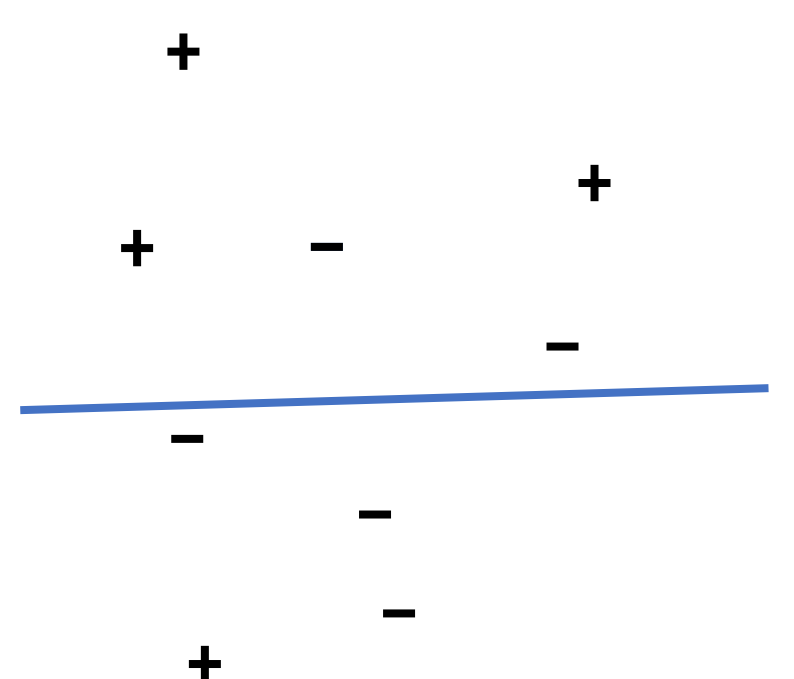
# Support vector machines: Kernel Trick



Not a good separator

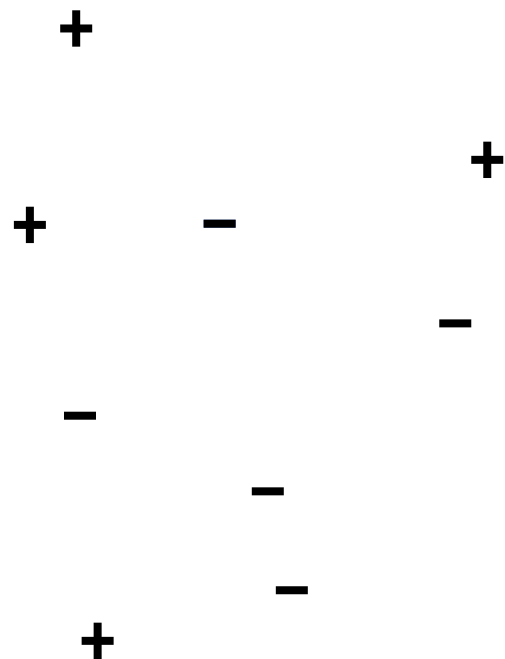


Not a good separator



Not a good separator

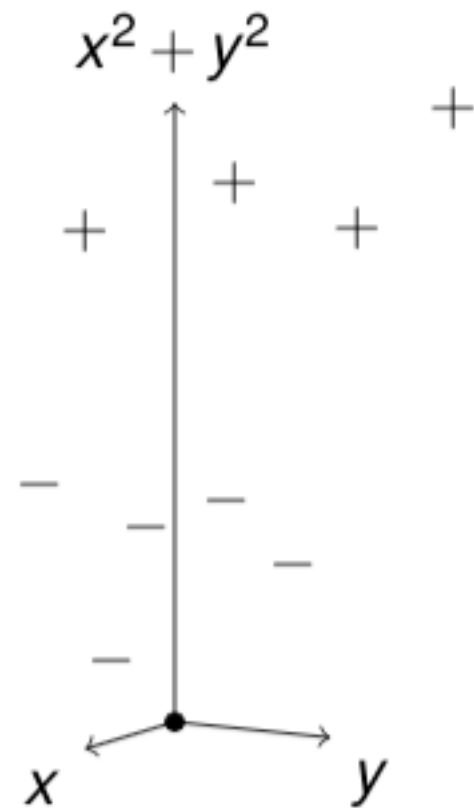
# Support vector machines: Kernel Trick



To map point  $(x,y)$  to point  $(x,y,x^2 + y^2)$

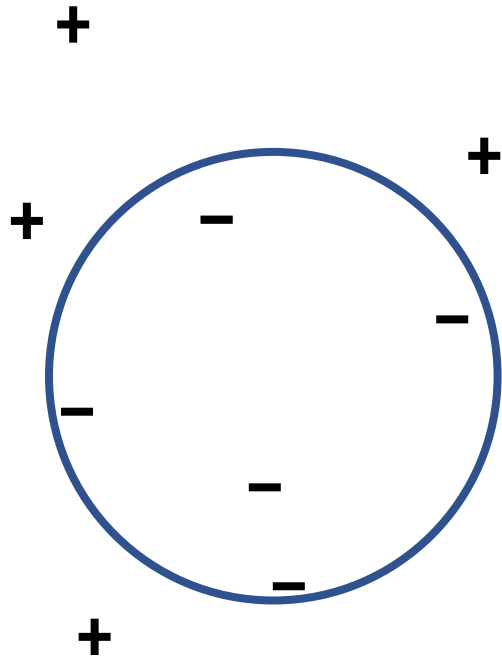
Kernel functions:

- Linear
- Radial Basis Function (RBF)
- Polynomial
- Sigmoid



# Support vector machines: Kernel Trick

A visualization: <https://www.youtube.com/watch?v=3liCbRZPrZA>



To map point  $(x, y)$  to point  $(x, y, x^2 + y^2)$

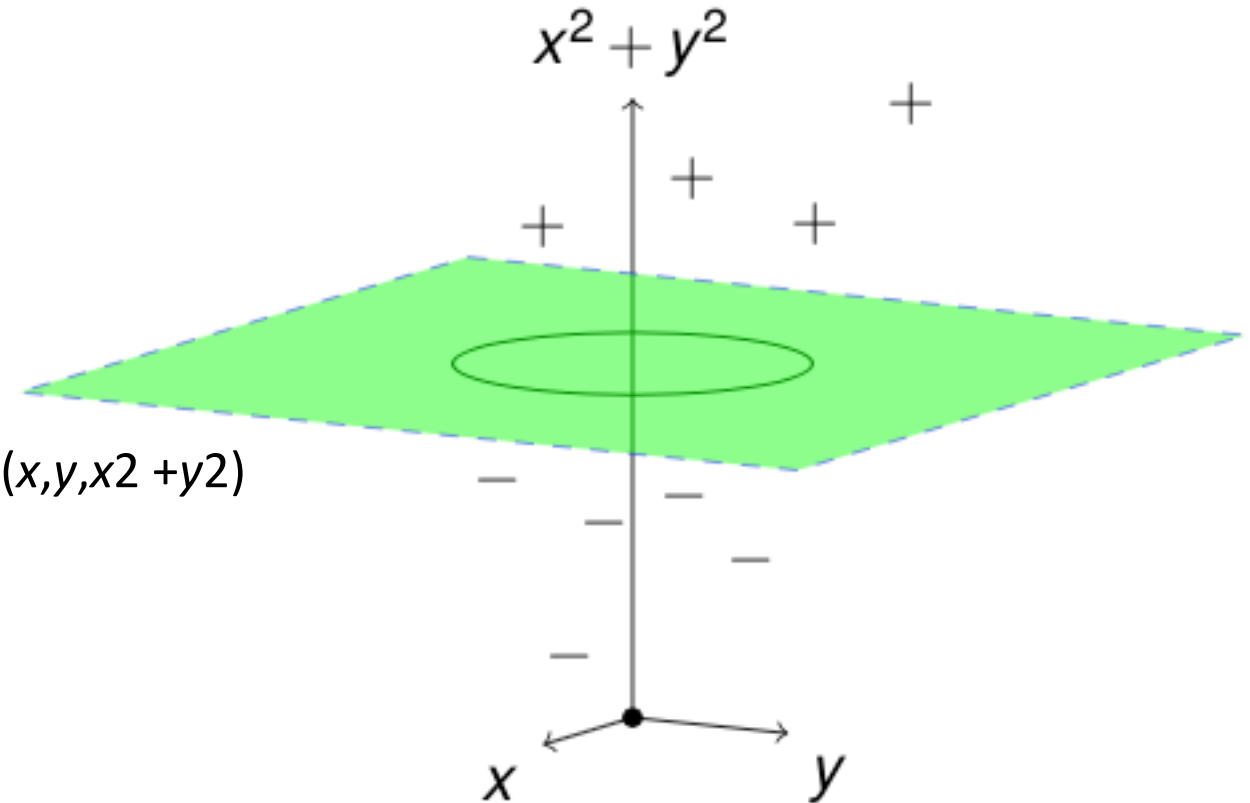
Kernel functions:

Linear

Radial Basis Function (RBF)

Polynomial

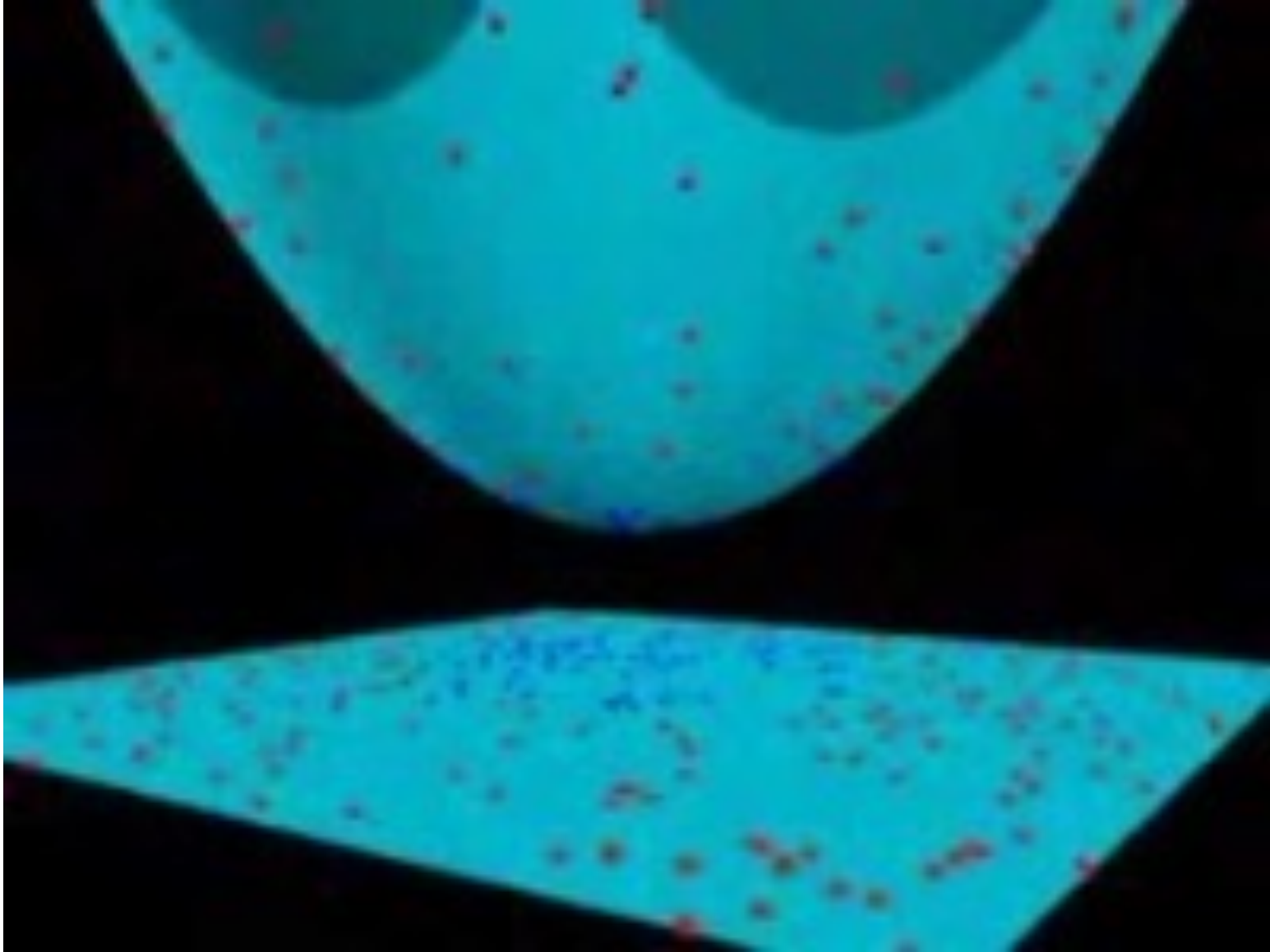
Sigmoid



Adapted from Satish Rao, CS270



A visualization: <https://www.youtube.com/watch?v=3liCbRZPrZA>



**Train:**

**Search for the optimal parameters of the model.**

**Infer:**

**Use the trained model to do the calculation.**

## How to evaluate the performance of a model?

Label	Prediction		
		1	0
	1	TP	FN
	0	FP	TN

TP: True Positive

TN: True Negative

FP: False Positive

FN: False Negative

Accuracy =  $(TP+TN)/all$

Precision =  $TP/(TP+FP)$

Recall =  $TP/(TP+FN)$

F1 Score =  $2*(Recall * Precision) / (Recall + Precision)$

Let's practice using this notebook:

[https://colab.research.google.com/drive/1\\_979SLMyXRD\\_zTr9mdy32EBKUDKrn7VF?usp=sharing](https://colab.research.google.com/drive/1_979SLMyXRD_zTr9mdy32EBKUDKrn7VF?usp=sharing)