

# **Week09: Supervised Learning Part 3**

## **Multiclass classification, k-NN and SVM**

21/03/2024

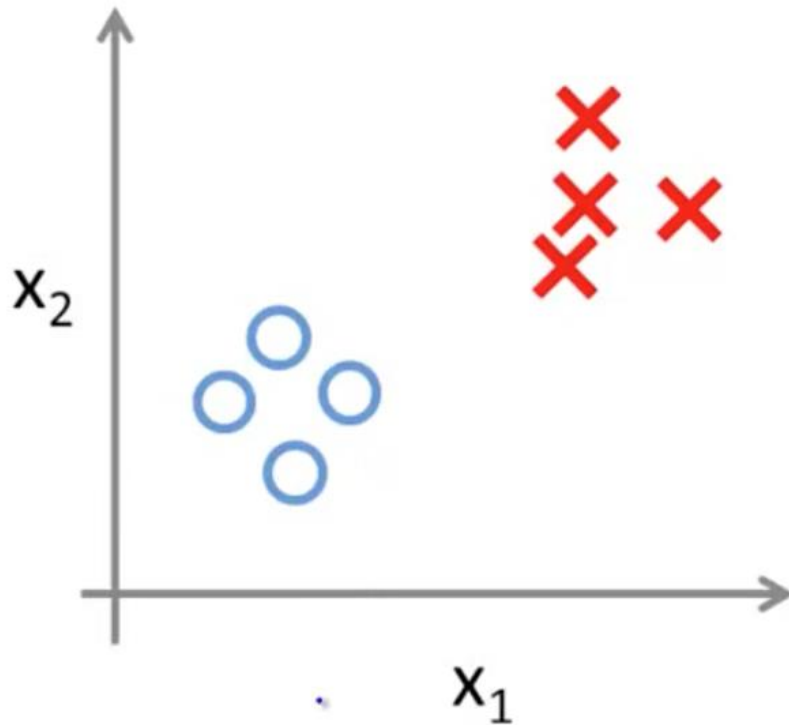
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# **Multi-Class Classification**

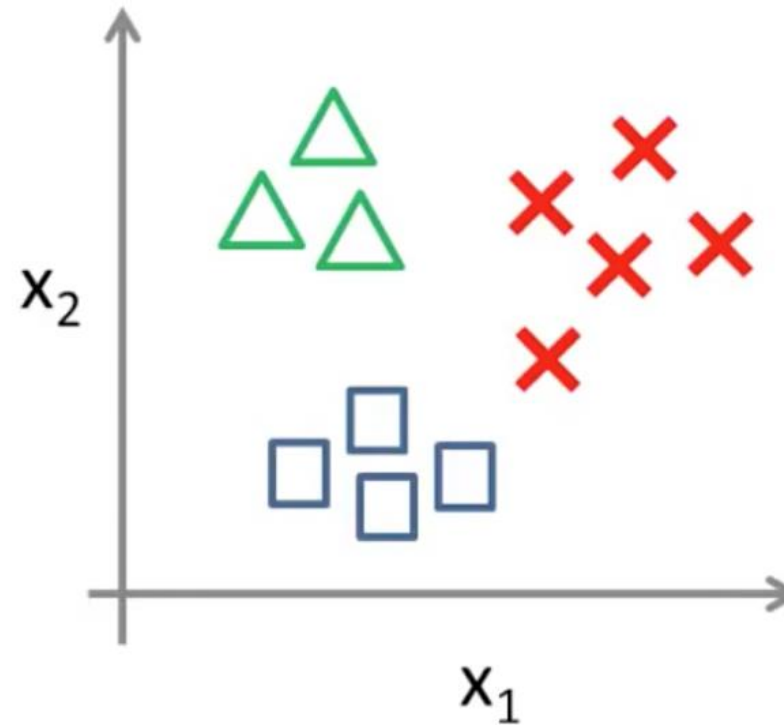
# Multi-Class Classification

Binary classification:



$$y = \{0, 1\}$$

Multi-class classification:



$$y = \{0, 1, \dots, n\}$$

# Softmax Regression (Normalized Exponential Function)

## Sigmoid

2 classes

$$\text{out} = P(Y=\text{class1}|X)$$

$$X = \begin{bmatrix} 3 \\ 1.75 \\ -2 \\ 0.5 \end{bmatrix}$$

Input vector

$$\xrightarrow[\frac{1}{1 + e^{-X}}]{\text{Sigmoid}}$$

$$\text{Out} = \begin{bmatrix} 0.95 \\ 0.85 \\ 0.12 \\ 0.62 \end{bmatrix}$$

Output vector

Not a probability distribution

## SoftMax

k>2 classes

$$\text{out} = \begin{bmatrix} P(Y=\text{class1}|X) \\ P(Y=\text{class2}|X) \\ P(Y=\text{class3}|X) \\ \vdots \\ P(Y=\text{classk}|X) \end{bmatrix}$$

$$X = \begin{bmatrix} 3 \\ 1.75 \\ -2 \\ 0.5 \end{bmatrix}$$

Input vector

$$\xrightarrow[\frac{e^{x_i}}{\sum_{j=1}^K e^{x_j}}]{\text{SoftMax}}$$

$$\text{Out} = \begin{bmatrix} 0.725 \\ 0.21 \\ 0.005 \\ 0.06 \end{bmatrix}$$

Output vector

Probability distribution

The output vector must be a probability distribution over all the predicted classes, i.e. all the entries of the vector must add up to 1.

# Softmax function

- Softmax function outputs a vector that represents the probability distributions of a list of potential outcomes.
- *For example,*
  - `array([0.09003057, 0.24472847, 0.66524096])`
  - Class 1 = 9.00%
  - Class 2 = 24.47%
  - Class 3 = 66.52%
  - Softmax function selects Class 3 (The highest probability).

# Example of Multinomial Logistic Regression

<https://www.kaggle.com/code/vitorgamalemos/multinomial-logistic-regression-from-scratch>

# **K-Nearest Neighbors (KNN)**

# K-Nearest Neighbors (KNN)

- **Simple**, but a very powerful classification algorithm
- Classifies based on a **similarity measure**
  - Make predictions based on the **k** most similar training patterns for a new data instance.
- Lazy learning (Instance-based Learning)
  - Learning = storing all training instances
  - Does not **"learn"** until the test example is given
  - Whenever we have a new data to classify, we find its K-nearest neighbors from the training data.



# Lazy learning



# Lazy learning

Training set

Attributes x							y
							1
							0
							1
							0

Test set

Attributes x							y
							1
							0

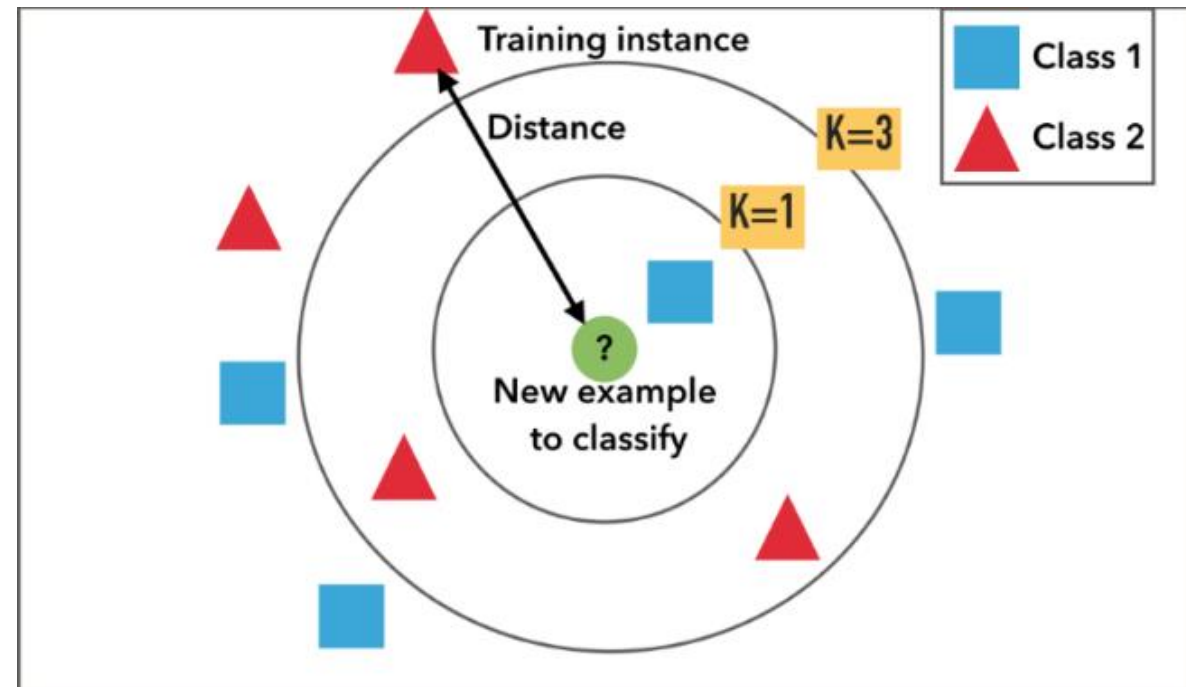
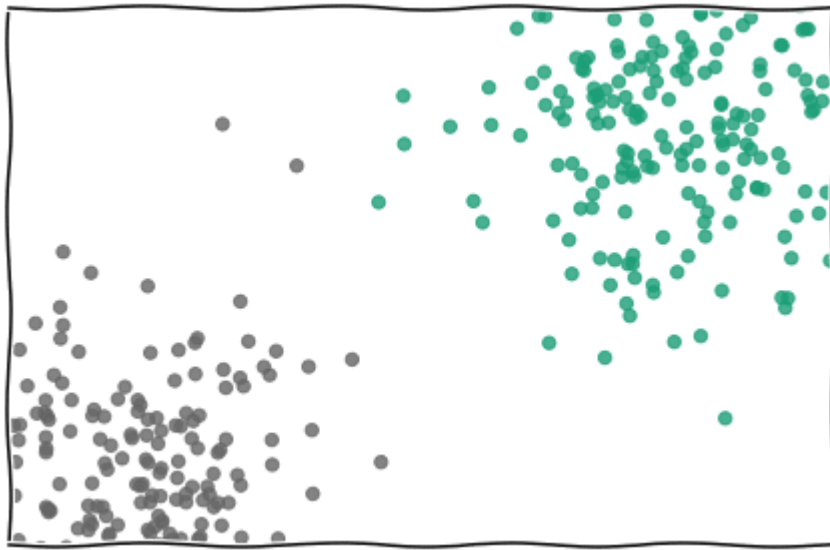
Compare to the most similar training patterns and make a decision

Test set (Unseen data)

Attributes x							y
							?
							?

# K-Nearest Neighbors (KNN)

- Its purpose is to use a database in which the *data points* are separated into **several classes** to predict the classification of a new sample point.
- How **closely** out-of-sample features resemble our training set determines how we classify a given data point.



[https://milliams.com/courses/applied\\_data\\_analysis/Nearest%20Neighbours.html](https://milliams.com/courses/applied_data_analysis/Nearest%20Neighbours.html)

## What is it used for?

K nearest neighbors is used for

- Classifying samples according to their numerical features
- Performing a regression of numerical values based on the features of the sample.

# Examples

Example 1: Forecast the sales of a mathematics textbook based on features such as price, length, number of university courses in the area, etc.

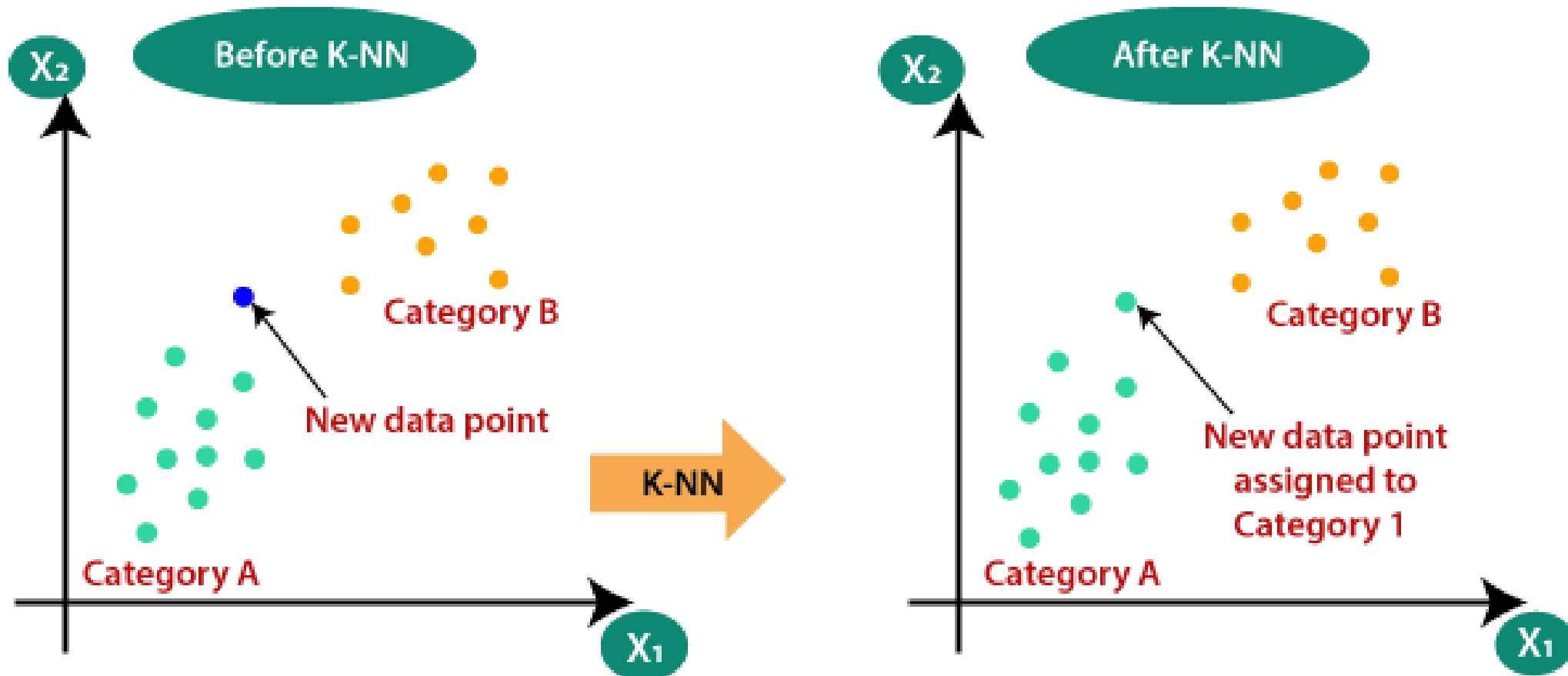
Example 2: Credit scoring, classify as good or bad risk, or on a scale, based on features such as income, value of assets, etc.

Example 3: Predict movie rating (number of 'stars') based on features such as amount of action sequences, quantity of romance, budget, etc.

## How it works

- K nearest neighbors (KNN) is perhaps the easiest machine learning technique to grasp conceptually.
- Although really there is **no learning** at all.
- It can be used for classification, determining into which group an individual belongs.
- Or it can be used for regression, predicting for a new individual of a variable based on the values for similar individuals.

# How does K-NN work?



# How does K-NN work?

The K-NN working can be explained based on the below algorithm:

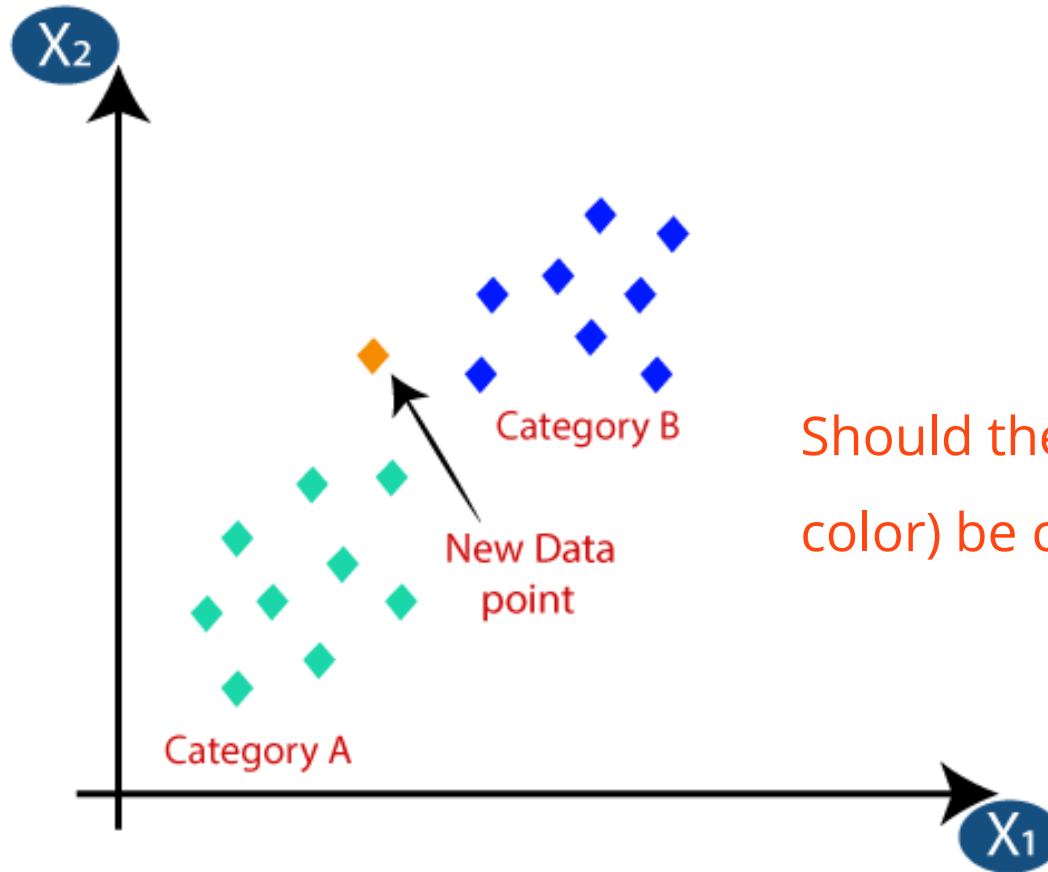
- Step-1:** Select the number K of the neighbors
- Step-2:** Calculate the **Euclidean distance\*** of **K number of neighbors**
- Step-3:** Take the K nearest neighbors as per the calculated Euclidean distance.
- Step-4:** Among these k neighbors, count the number of the data points in each category.
- Step-5:** Assign the new data points to that category for which the number of the neighbor is maximum.
- Step-6:** Our model is ready.

\*There are several distance metrics used in k-NN.



# How does K-NN work?

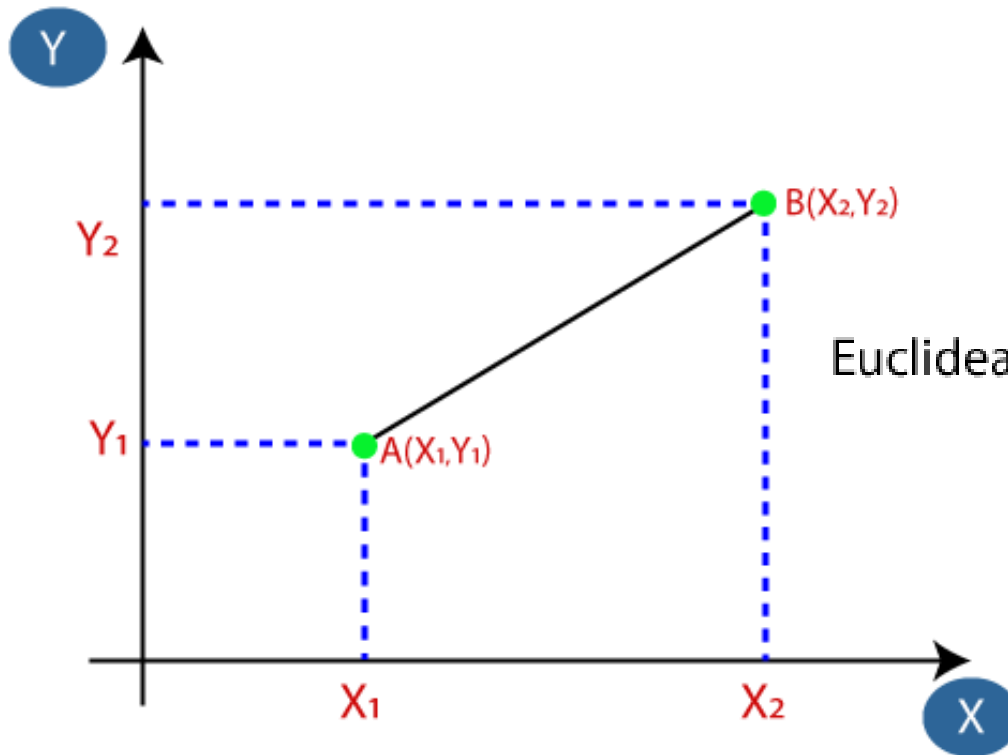
Suppose we have a new data point and we need to put it in the required category.



Should the new point (temporarily marked an orange color) be classified as category A or category B?

# How does K-NN work?

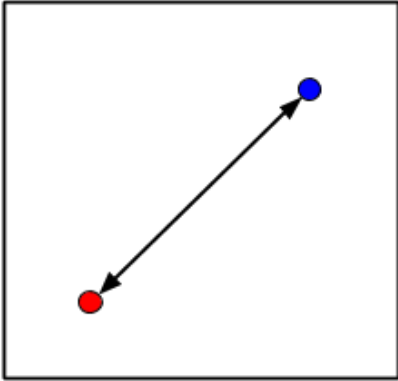
- **Step 1:** Firstly, we will choose the number of neighbors, so we will choose the  $k=5$ .
- **Step 2:** Next, we will calculate the **Euclidean distance** between the data points.
- It calculates the ordinary straight-line distance between two points in a Euclidean space.



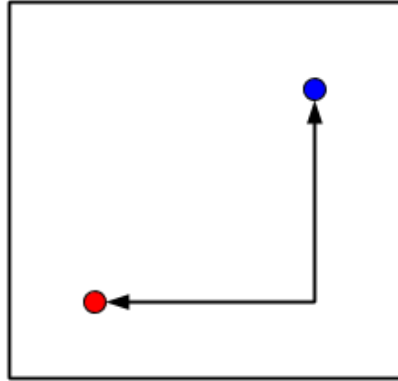
$$\text{Euclidean Distance between } A_1 \text{ and } B_2 = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2}$$

## 6 Distance measures

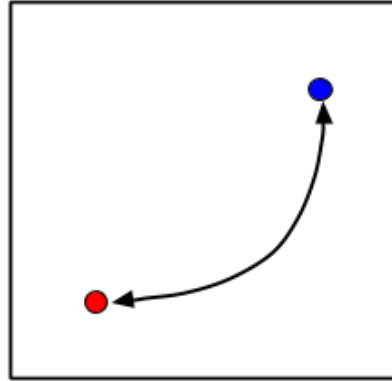
Euclidean



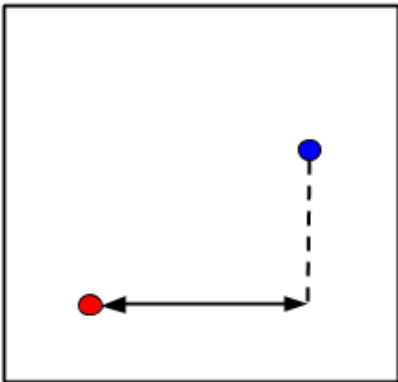
Manhattan



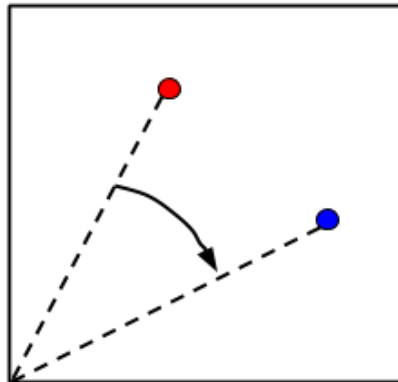
Minkowski



Chebychev



Cosine Similarity

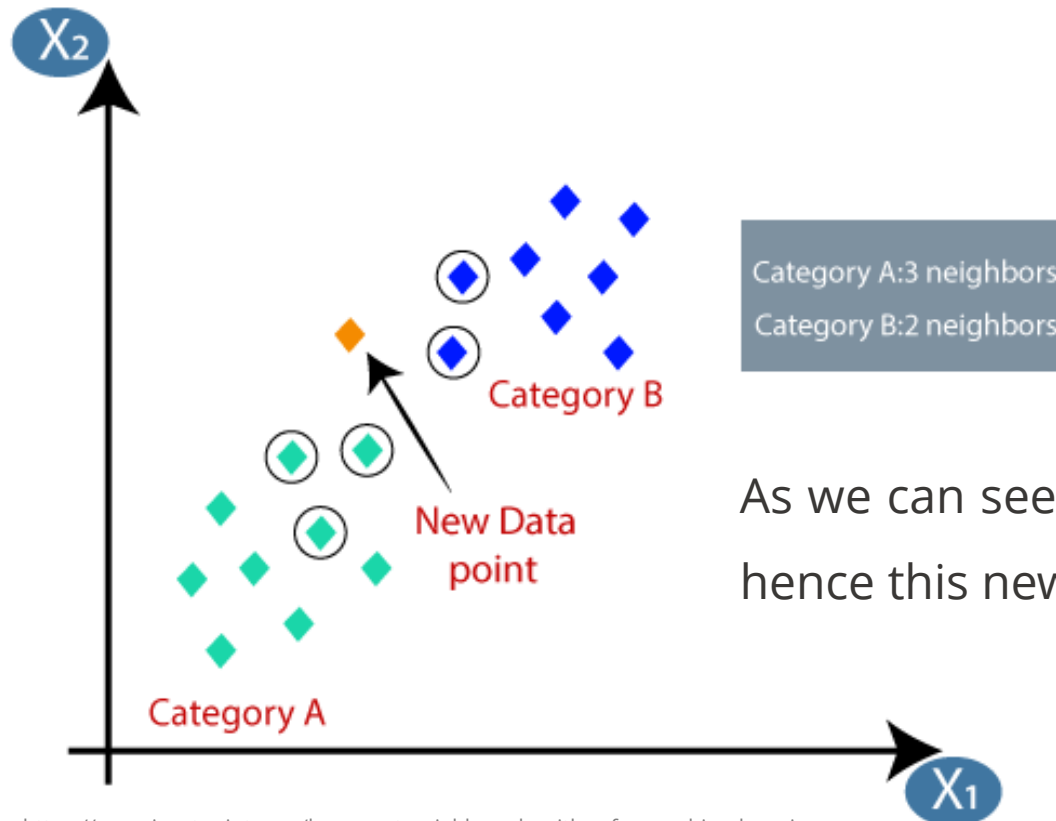


Hamming



# How does K-NN work?

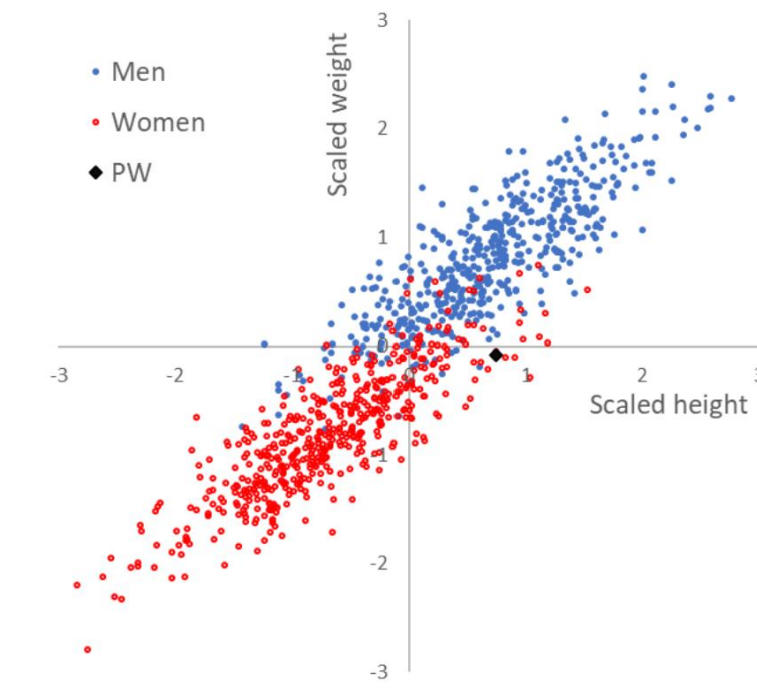
- **Step 3 & 4:** By calculating the Euclidean distance we got the **nearest neighbors**,
  - as 3 nearest neighbors in category A and
  - 2 nearest neighbors in category B.



As we can see the 3 nearest neighbors are from category A, hence this new data point must belong to category A.

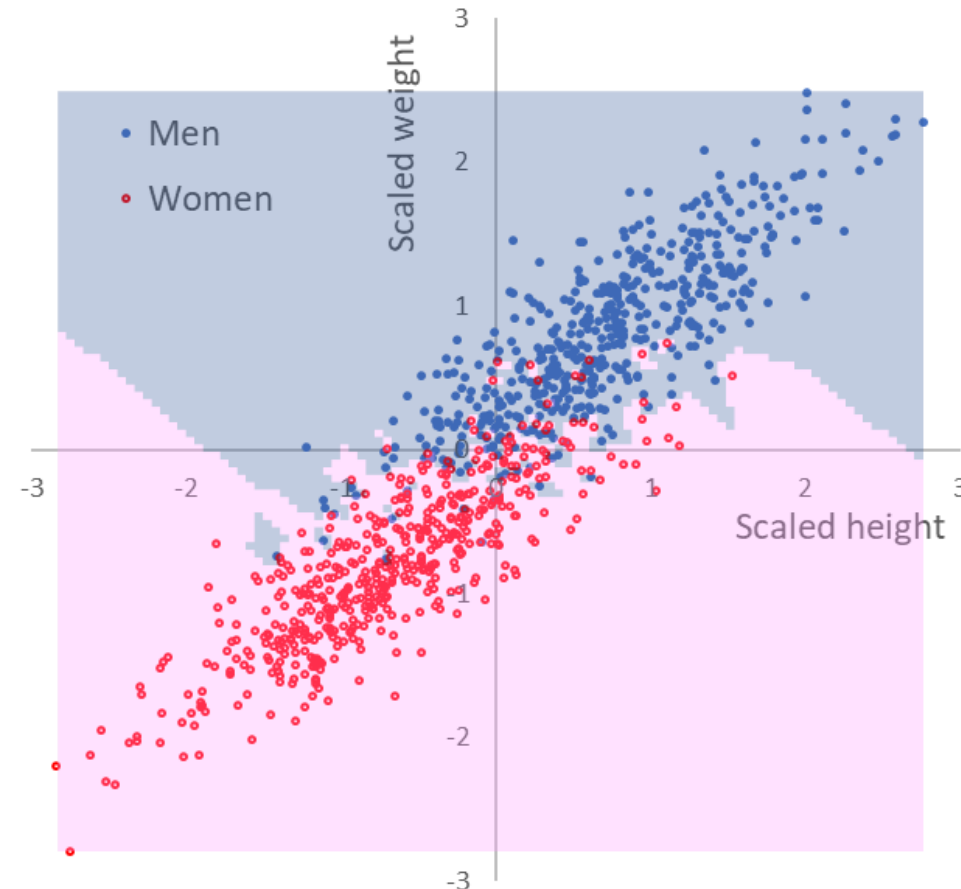
## Example: Heights and weights

- Easily find online data for men's and women's heights and weights.
- In the figure, just 500 points for each gender.
- The data has been shifted and scaled for both genders.
- So, have a mean of zero and a standard deviation of one.



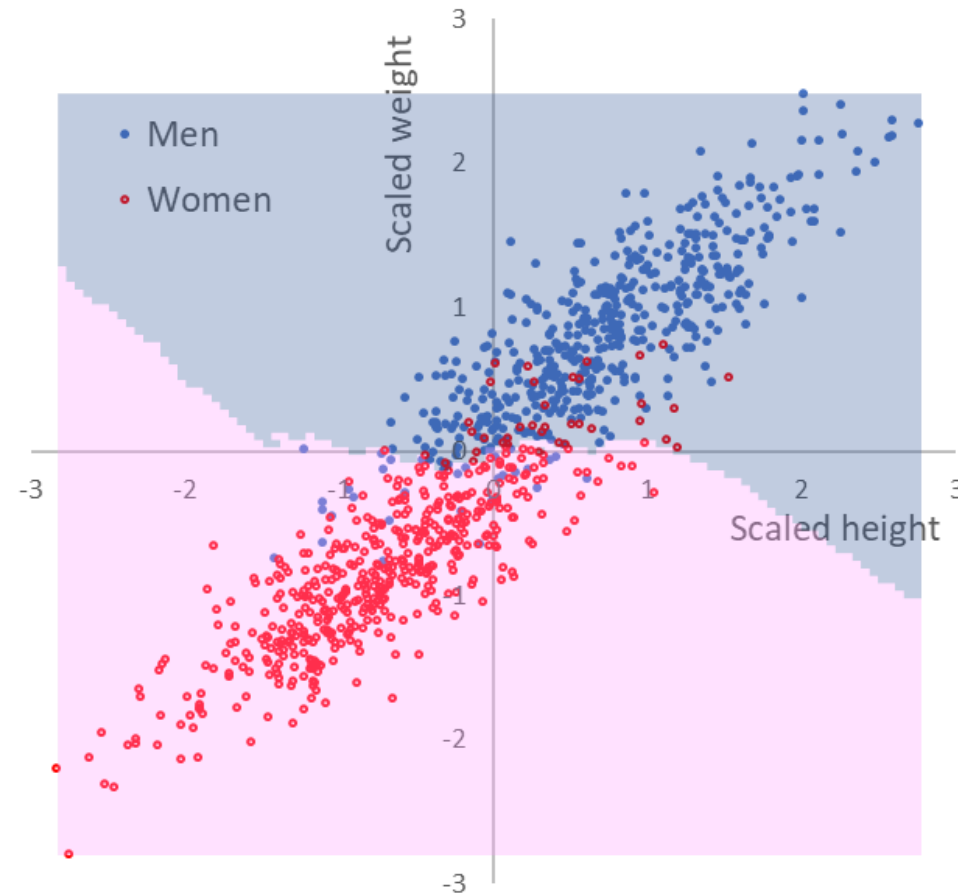
## Example: Heights and weights (contd.)

- When  $K = 1$  the male/female regions are as shown below.
- We can see several islands, pockets of males within what looks like, otherwise female zones and vice versa.



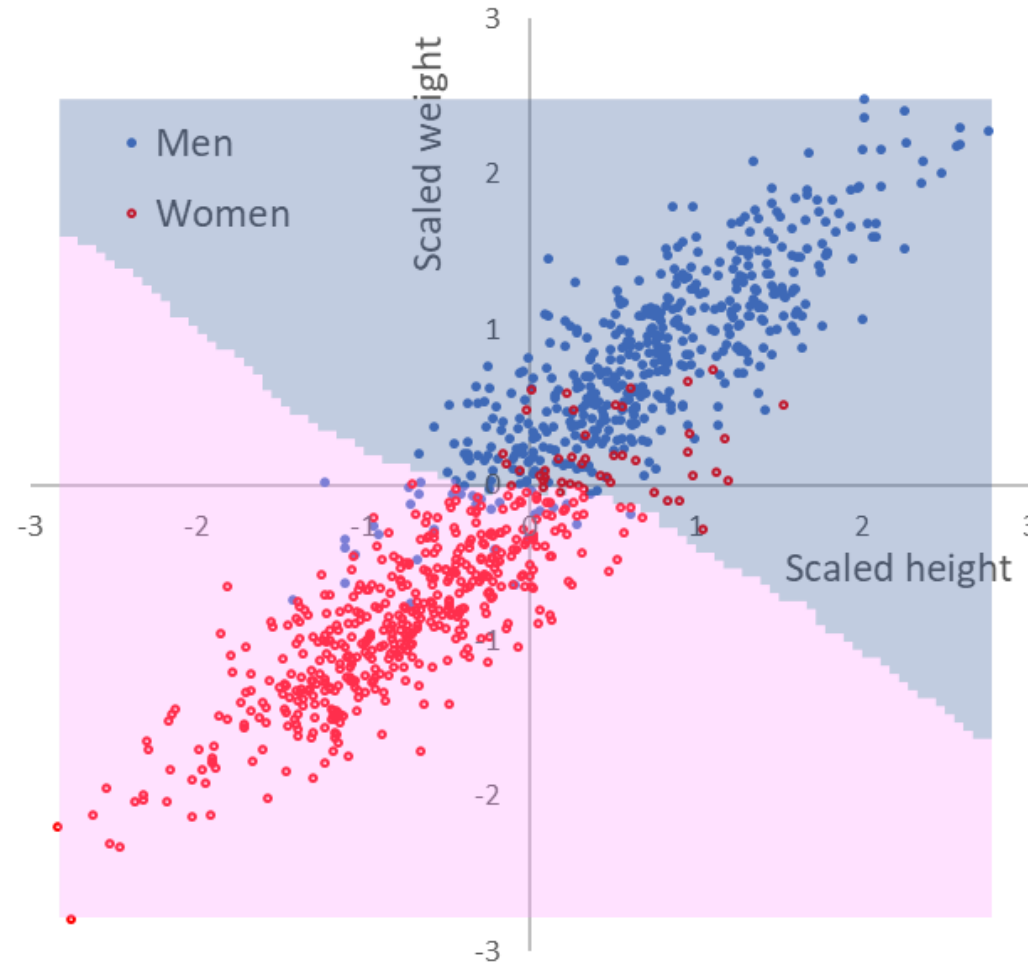
## Example: Heights and weights (contd.)

- When  $K = 21$  the boundary has been smoothed out.
- There is just a single solitary island left.



## Example: Heights and weights (contd.)

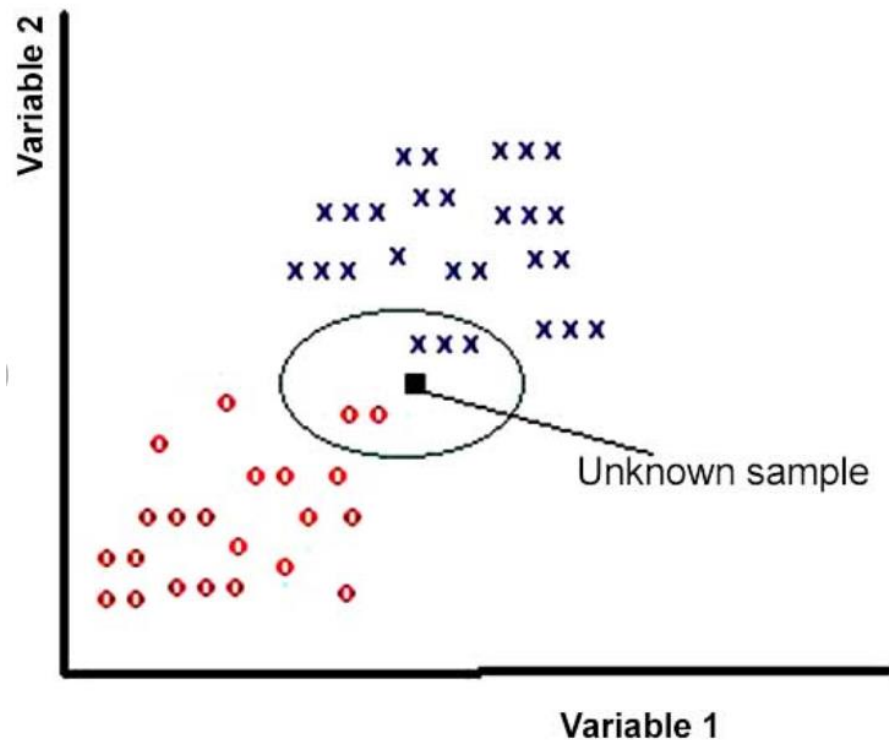
- As an extreme case take  $K = 101$ .





# How to select the value of K in the K-NN Algorithm?

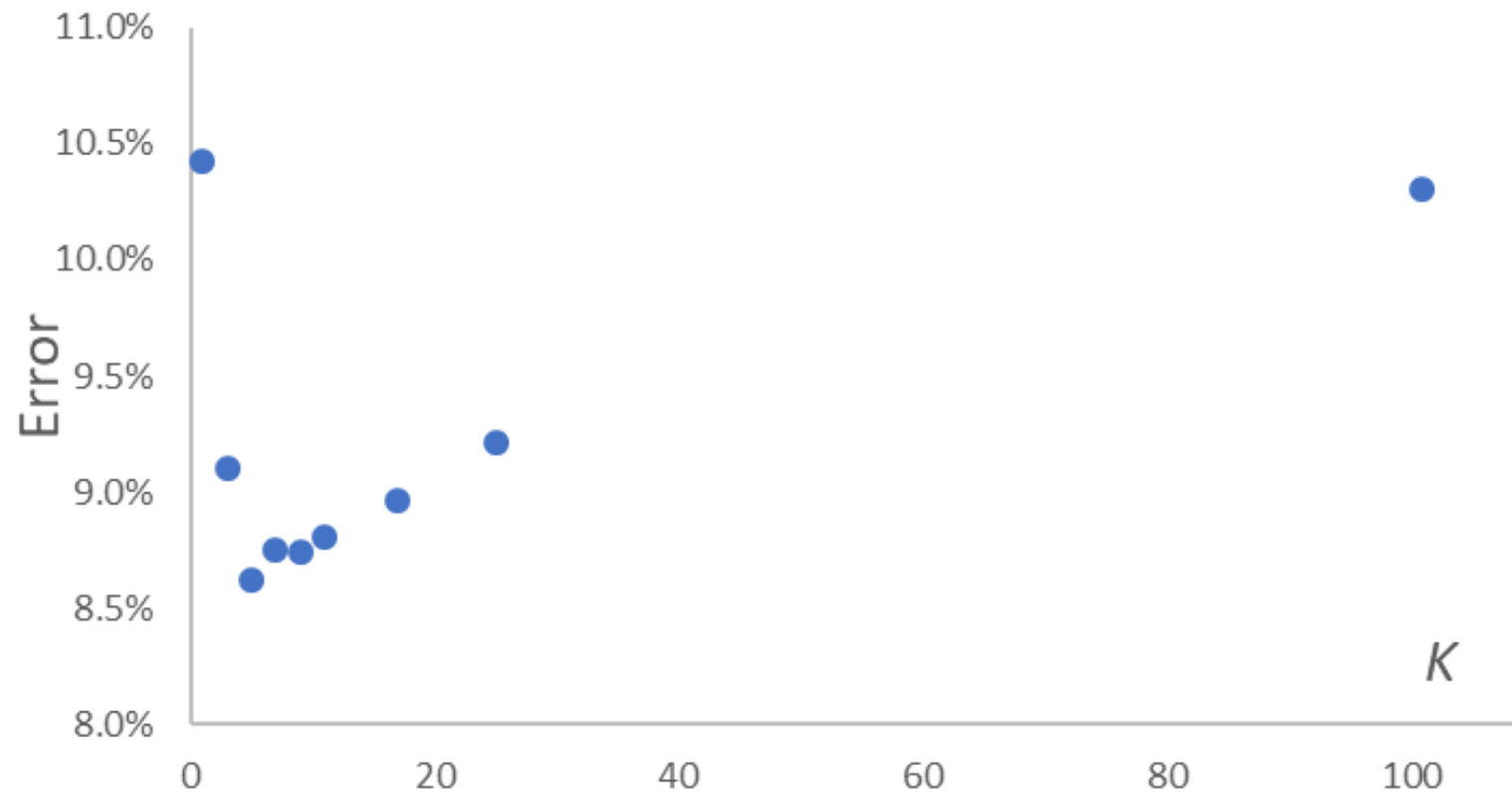
- There is **no particular way** to determine the best value for "K", so we need to try some values to find the best out of them (lowest error).
- The most preferred value for K is 5 (default value).



[https://www.researchgate.net/figure/fig-4-k-NN-classification-with-k5-since-among-the-5-nearest-neighbors-of-the\\_fig2\\_232696878](https://www.researchgate.net/figure/fig-4-k-NN-classification-with-k5-since-among-the-5-nearest-neighbors-of-the_fig2_232696878)

# How to select the value of K in the K-NN Algorithm?

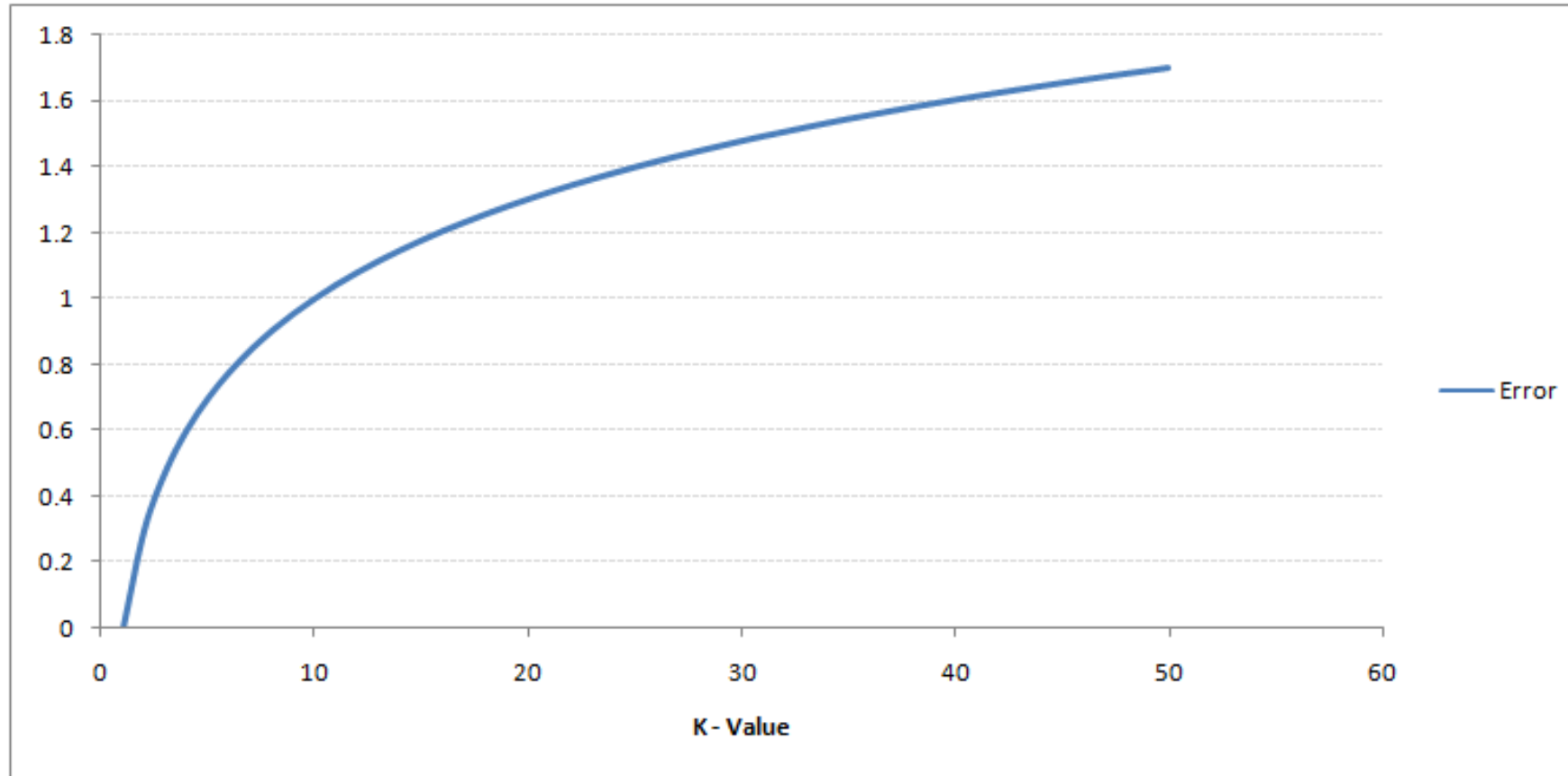
- We can plot misspecification error as a function of the number of neighbors, K.
- It looks like  $K = 5$  is optimal.



# How to select the value of K in the K-NN Algorithm?

- The most preferred value for K is 5 (default value).
- A very low value for K such as  $K=1$  or  $K=2$ , can be noisy and lead to the effects of outliers in the model.
- Large values for K are good, but it may find some difficulties.

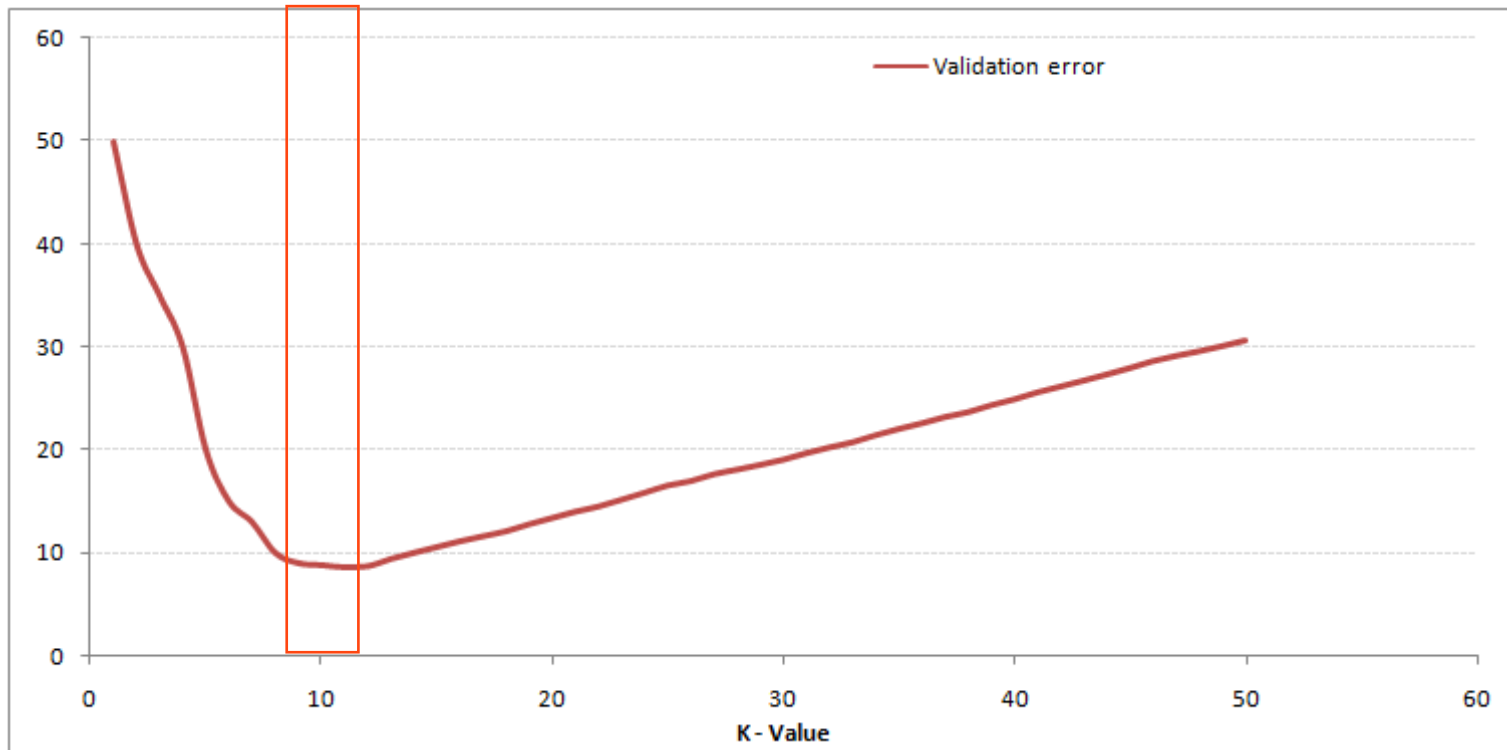
# How to select the value of K in the K-NN Algorithm?



- The error rate at  $K=1$  is always zero for the training sample.
- This is because the closest point to any training data point is itself.

<https://www.analyticsvidhya.com/blog/2018/03/introduction-k-neighbours-algorithm-clustering/>

# How to select the value of K in the K-NN Algorithm?



- At  $K=1$ , we were overfitting the boundaries.
- Thus, error rate initially decreases and reaches a minima.
- After the minima point, it then increase with increasing  $K$ .

<https://www.javatpoint.com/k-nearest-neighbor-algorithm-for-machine-learning>

## Limitations of k-NN classifier

- KNN is very sensitive to outliers.
- As dataset grows, the classification becomes slower.
- KNN is not capable of dealing with missing values.
- It is computationally expensive due to high storage requirements.

# Summary

Please take away the following important ideas

- $K$  nearest neighbors is possibly the easiest machine-learning technique.
- But there isn't any learning.
- It is very easy to understand and can be used for classification or regression.

# Support Vector Machine (SVM)



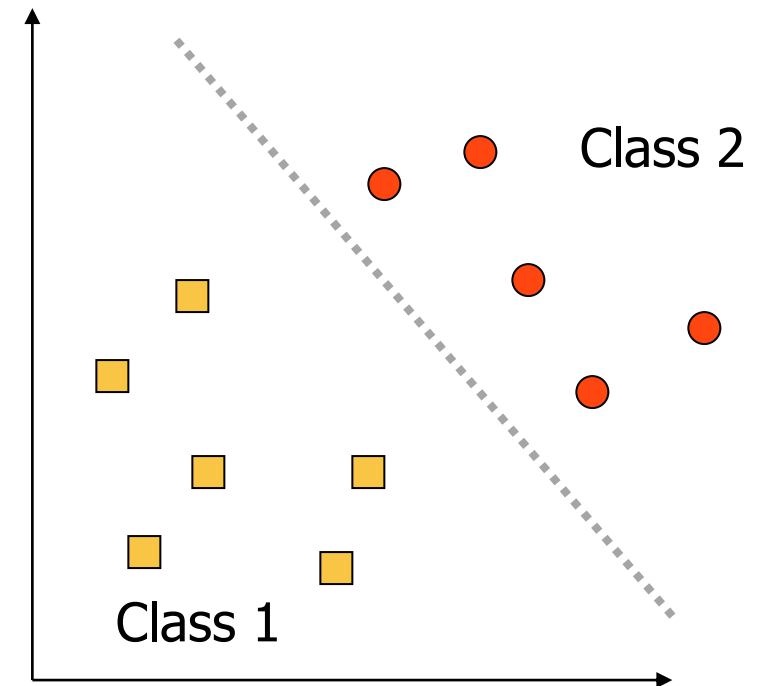
# History of SVM

- SVM was first introduced in 1992. [1]
- SVM becomes popular because of its success in handwritten digit recognition
  - 1.1% test error rate for SVM.
- SVM is now regarded as an important example of “kernel methods”, one of the key area in machine learning
  - Note: the meaning of “kernel” is different from the “kernel” function for Parzen windows
  - In SVM, a kernel is a way of computing the dot product of two vectors in a high dimensional feature space.

[1] B.E. Boser *et al.* A Training Algorithm for Optimal Margin Classifiers. Proceedings of the Fifth Annual Workshop on Computational Learning Theory 5 144-152, Pittsburgh, 1992.

# What is a good Decision Boundary?

- Consider a two-class, linearly separable classification problem
- Many decision boundaries!
  - Different algorithms have been proposed
- Are all decision boundaries equally good?

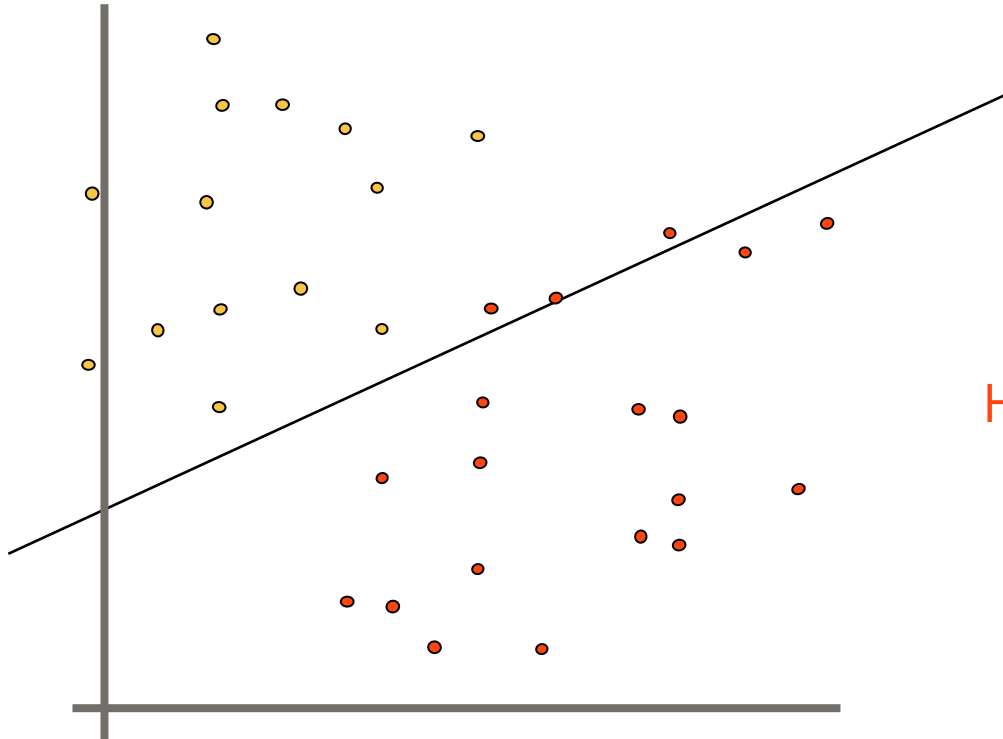


# What is a good Decision Boundary?

## Linear Classifiers

● denotes +1

● denotes -1



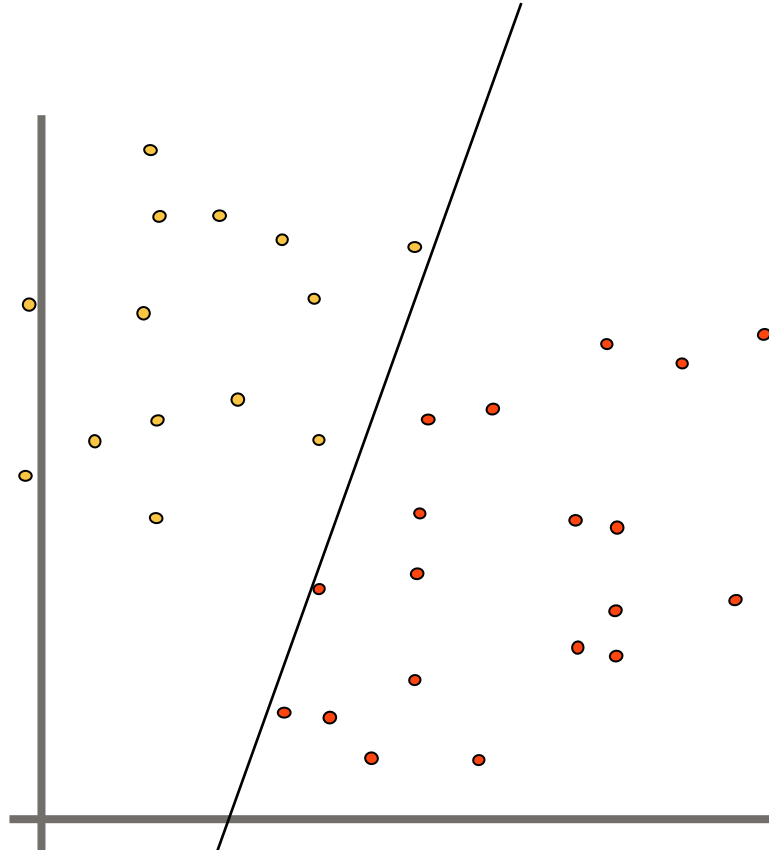
How would you classify this data?

# What is a good Decision Boundary?

## Linear Classifiers

● denotes +1

● denotes -1



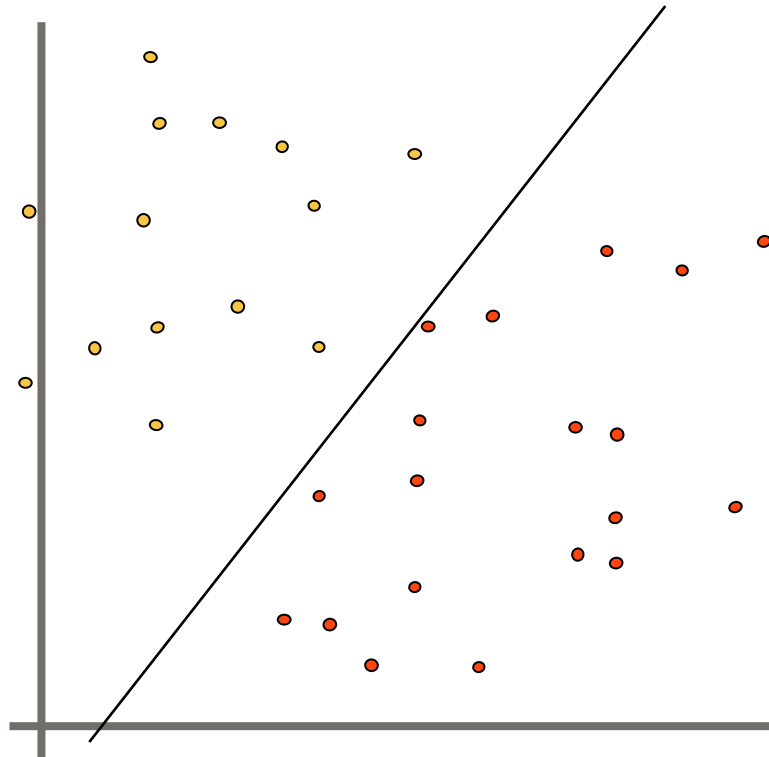
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# What is a good Decision Boundary?

## Linear Classifiers

● denotes +1

● denotes -1



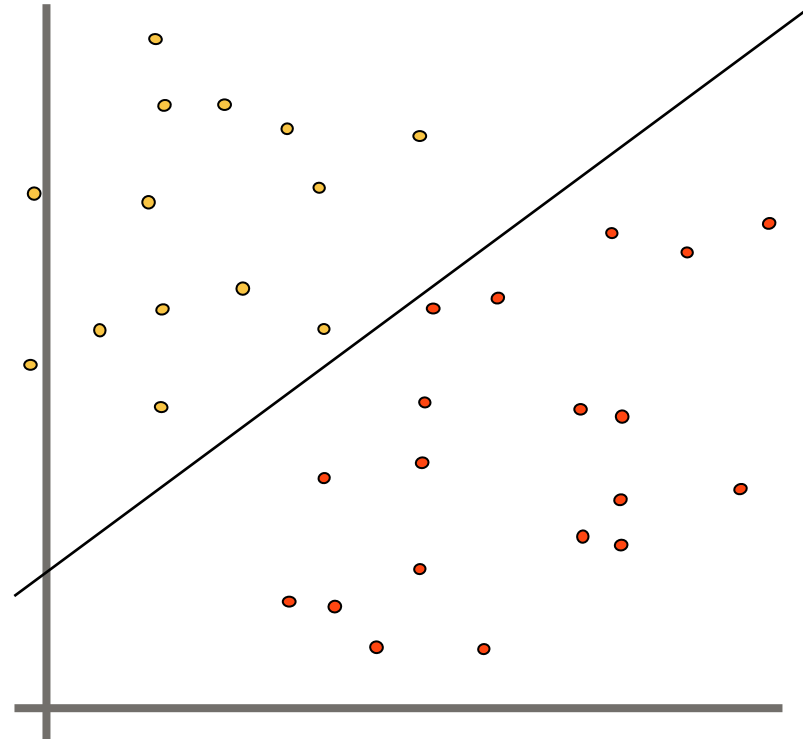
How would you classify this data?

# What is a good Decision Boundary?

## Linear Classifiers

● denotes +1

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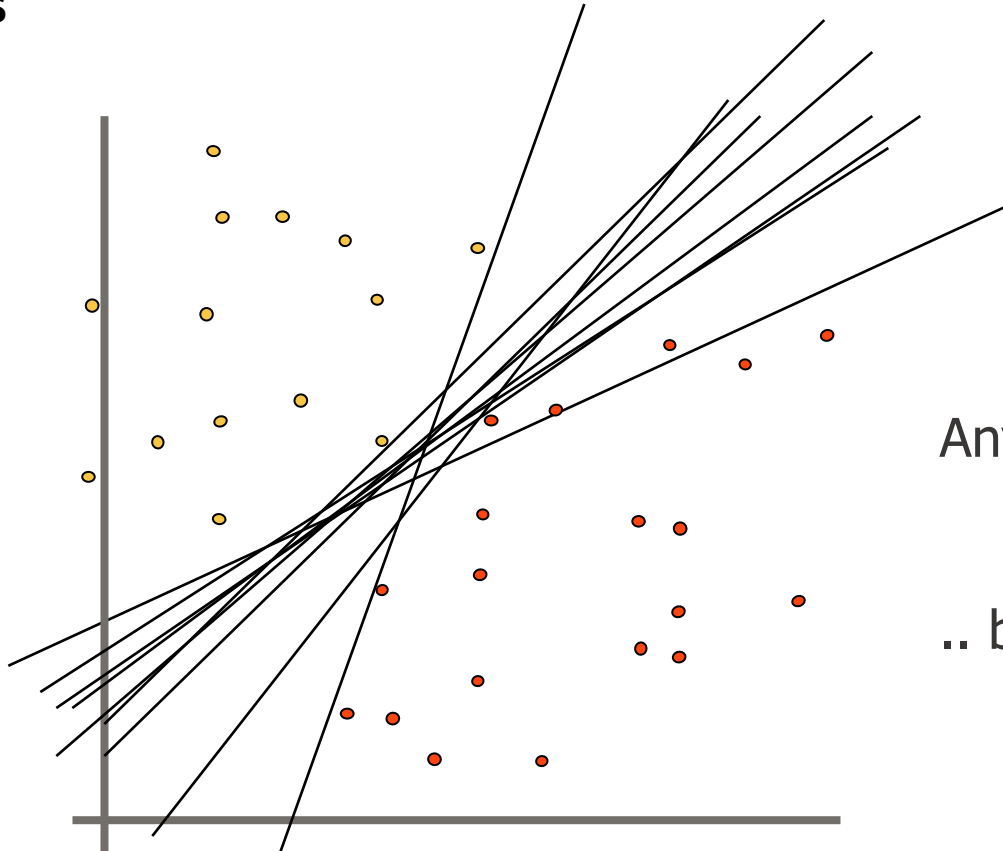
How would you classify this data?

# What is a good Decision Boundary?

## Linear Classifiers

● denotes +1

● denotes -1



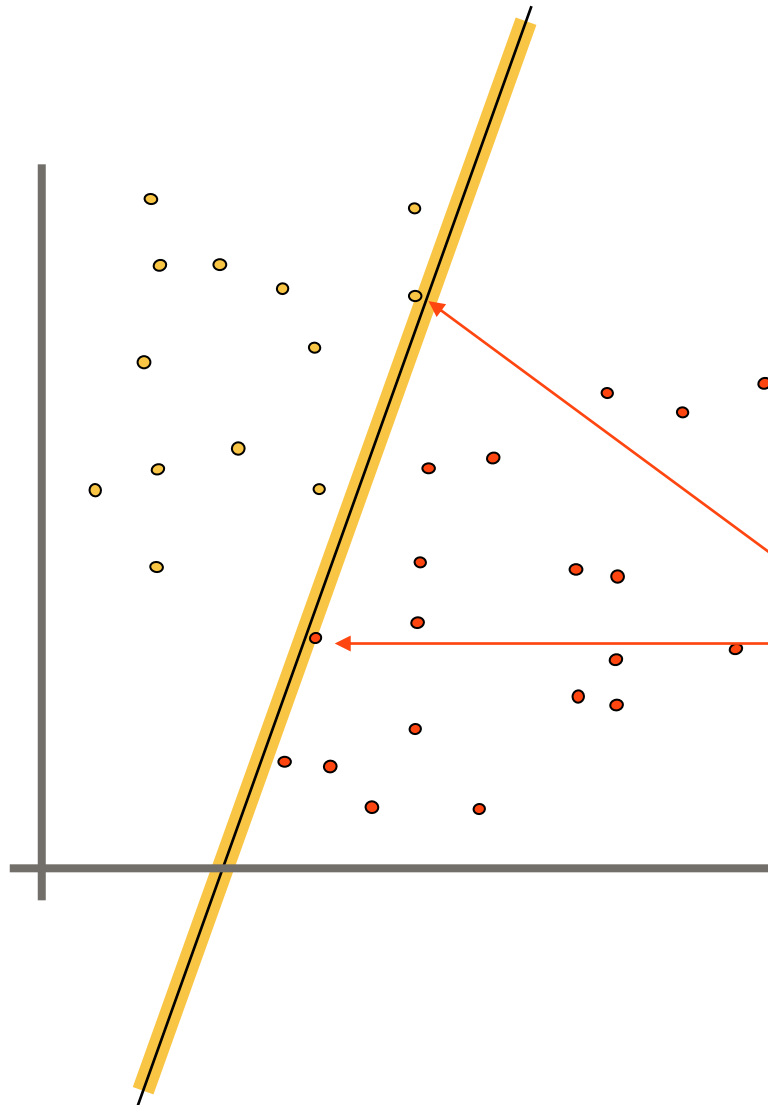
Any of these would be fine..

.. but **which is best?**

# Classifier Margin

● denotes +1

● denotes -1



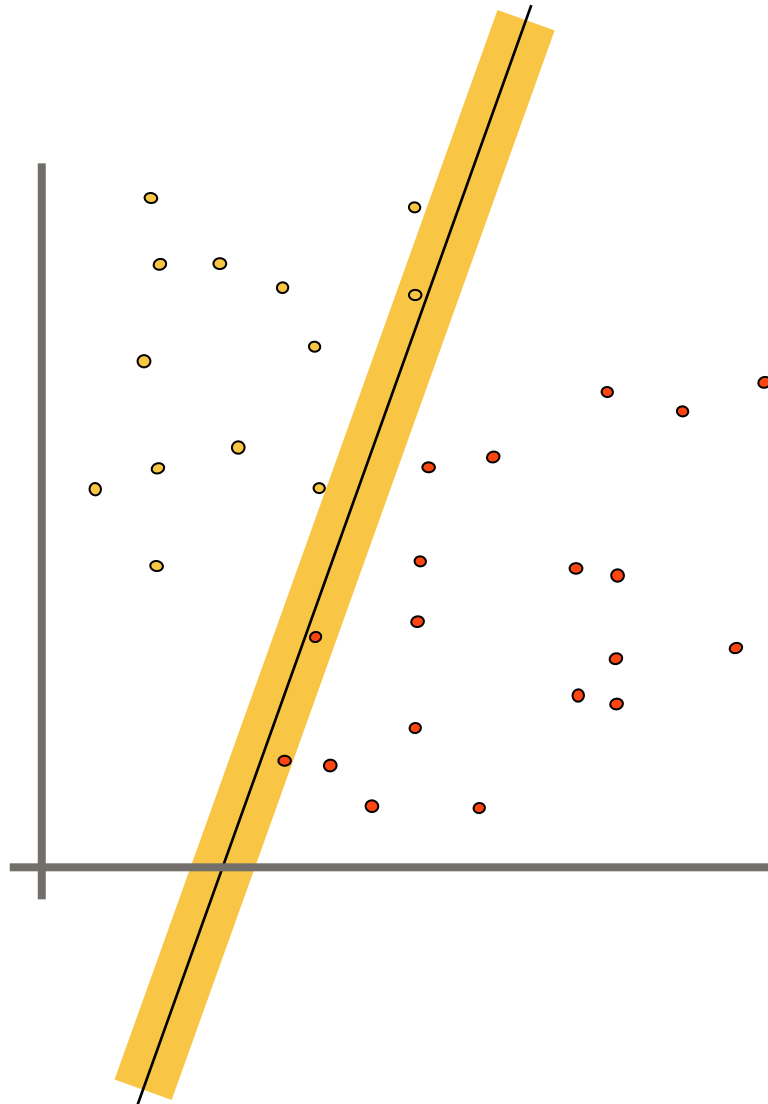
Define the **margin** of a linear classifier as the width that the boundary could be increased by before hitting a datapoint.



# Maximum Margin

● denotes +1

● denotes -1

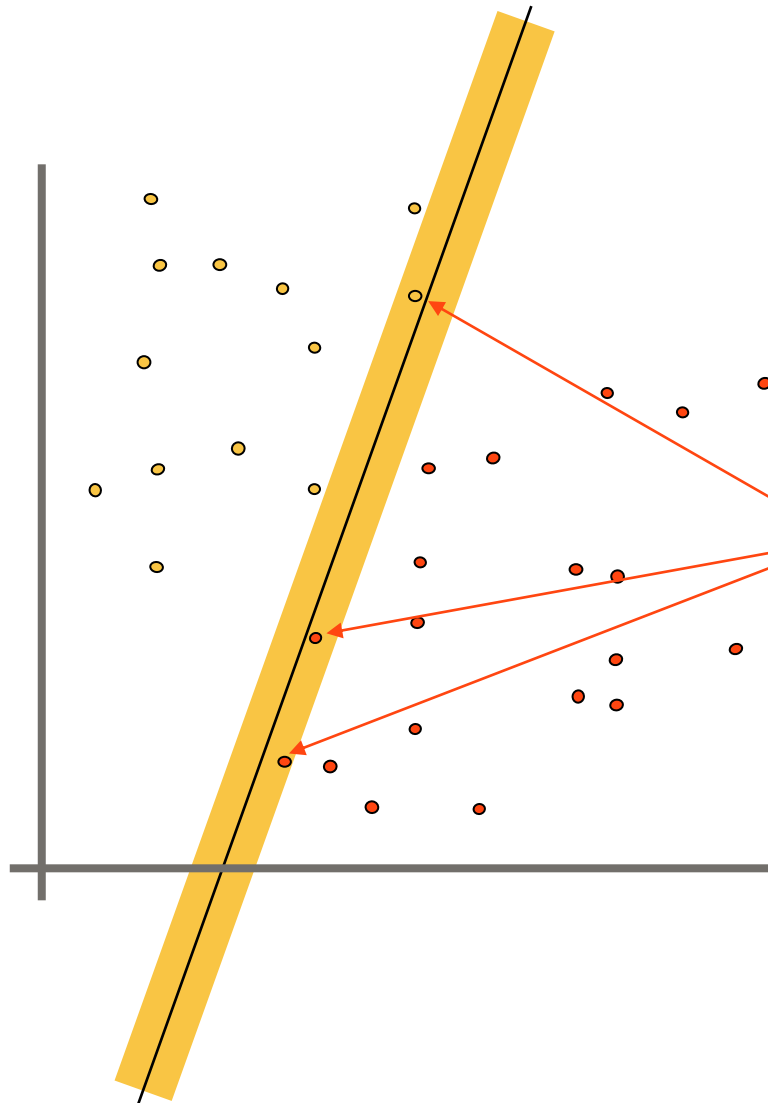


The maximum margin linear classifier is the linear classifier with the, **maximum margin**.

This is the simplest kind of SVM (Called a **Linear SVM or LSVM**)

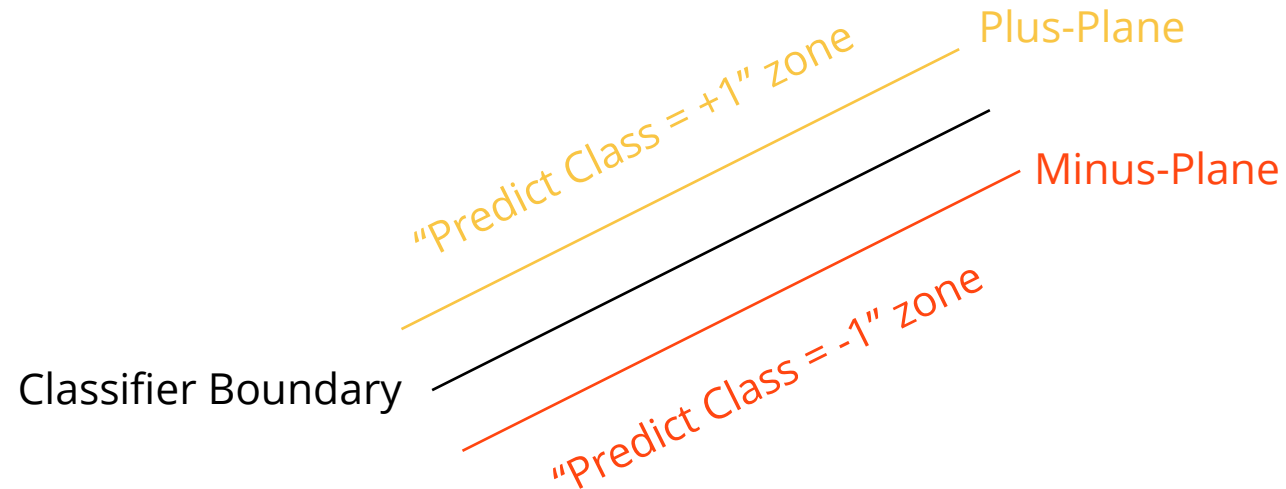
# Why Maximum Margin?

- denotes +1
- denotes -1



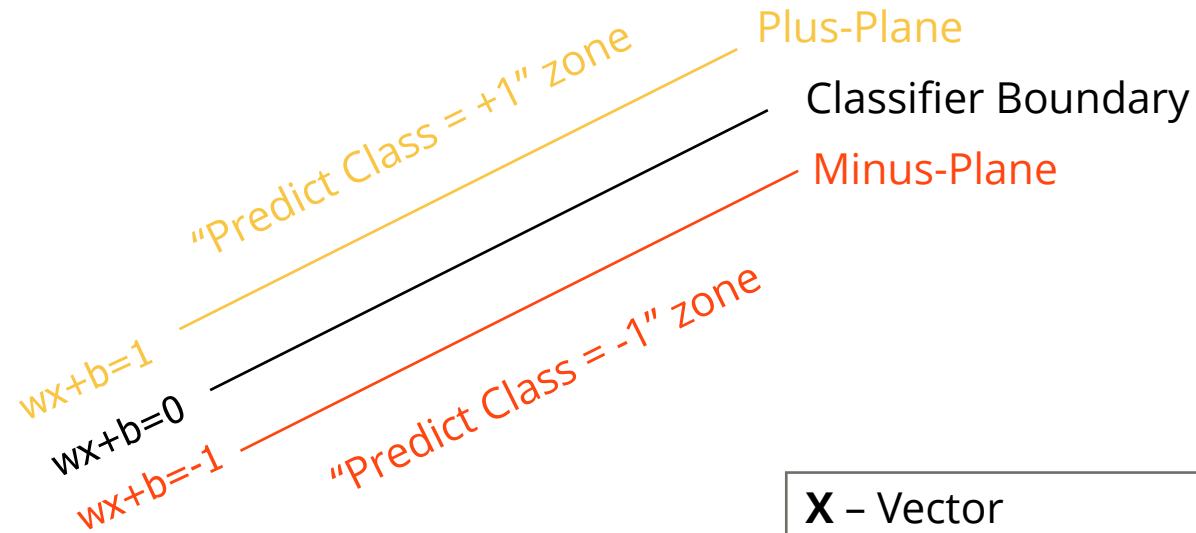
**Support Vectors** are those datapoints that the margin pushes up against.

# Specifying a line and margin



- How do we represent this mathematically?
- ...in  $m$  input dimensions?

# Specifying a line and margin



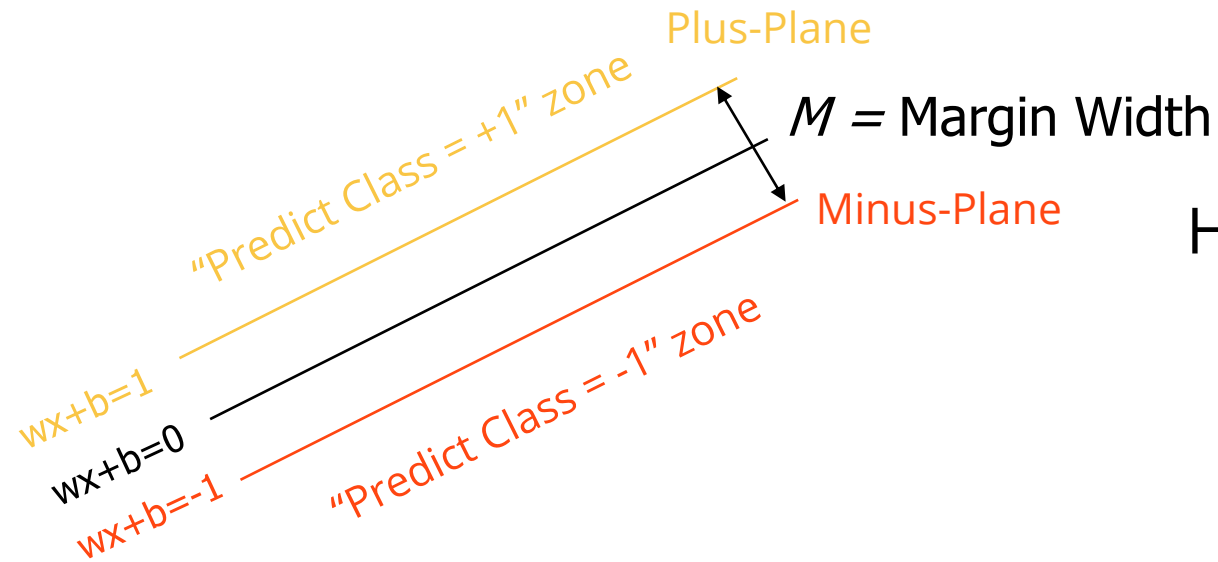
- Plus-plane =  $\{ \mathbf{x} : \mathbf{w} \cdot \mathbf{x} + b = +1 \}$
- Minus-plane =  $\{ \mathbf{x} : \mathbf{w} \cdot \mathbf{x} + b = -1 \}$

$\mathbf{x}$  – Vector  
 $\mathbf{w}$  – Normal Vector  
 $b$  – Scale Value

Classify as..

+1	if	$\mathbf{w} \cdot \mathbf{x} + b \geq 1$
-1	if	$\mathbf{w} \cdot \mathbf{x} + b \leq -1$
Universe explodes	if	$-1 < \mathbf{w} \cdot \mathbf{x} + b < 1$

# Specifying a line and margin

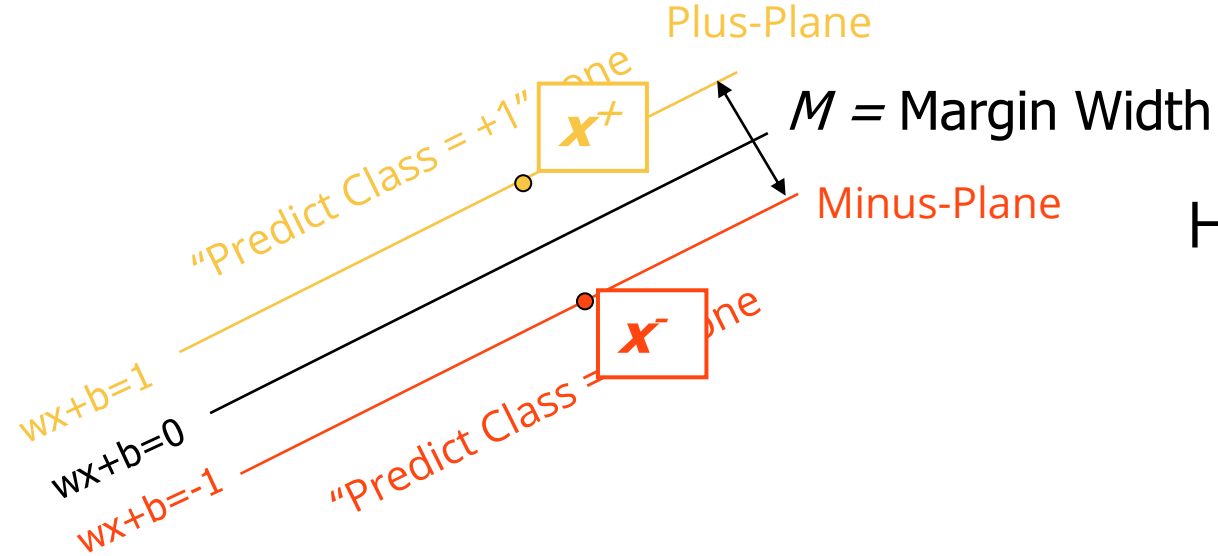


How do we compute  $M$  in terms of  $\mathbf{w}$  and  $b$ ?

- Plus-plane =  $\{\mathbf{x} : \mathbf{w} \cdot \mathbf{x} + b = +1\}$
- Minus-plane =  $\{\mathbf{x} : \mathbf{w} \cdot \mathbf{x} + b = -1\}$

**Claim:** The vector  $\mathbf{w}$  is perpendicular (ตั้งฉาก) to the Plus Plane.

# Specifying a line and margin

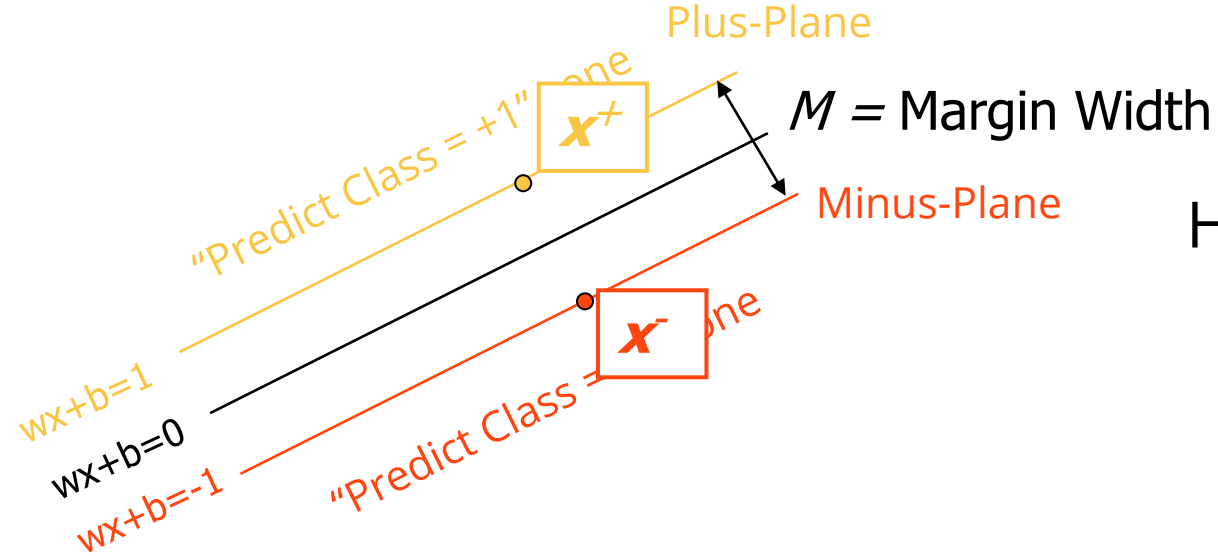


How do we compute  $M$  in terms of  $\mathbf{w}$  and  $b$ ?

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**Claim:** The vector  $\mathbf{w}$  is perpendicular (ตั้งฉาก) to the Plus Plane.

# Specifying a line and margin



How do we compute  $M$  in terms of  $\mathbf{w}$  and  $b$ ?

- What is the distance expression for a point  $\mathbf{x}$  to a line  $\mathbf{w}\mathbf{x}+b=0$ ?

$$d(\mathbf{x}) = \frac{|\mathbf{x} \cdot \mathbf{w} + b|}{\sqrt{\|\mathbf{w}\|_2^2}} = \frac{|\mathbf{x} \cdot \mathbf{w} + b|}{\sqrt{\sum_{i=1}^d w_i^2}}$$

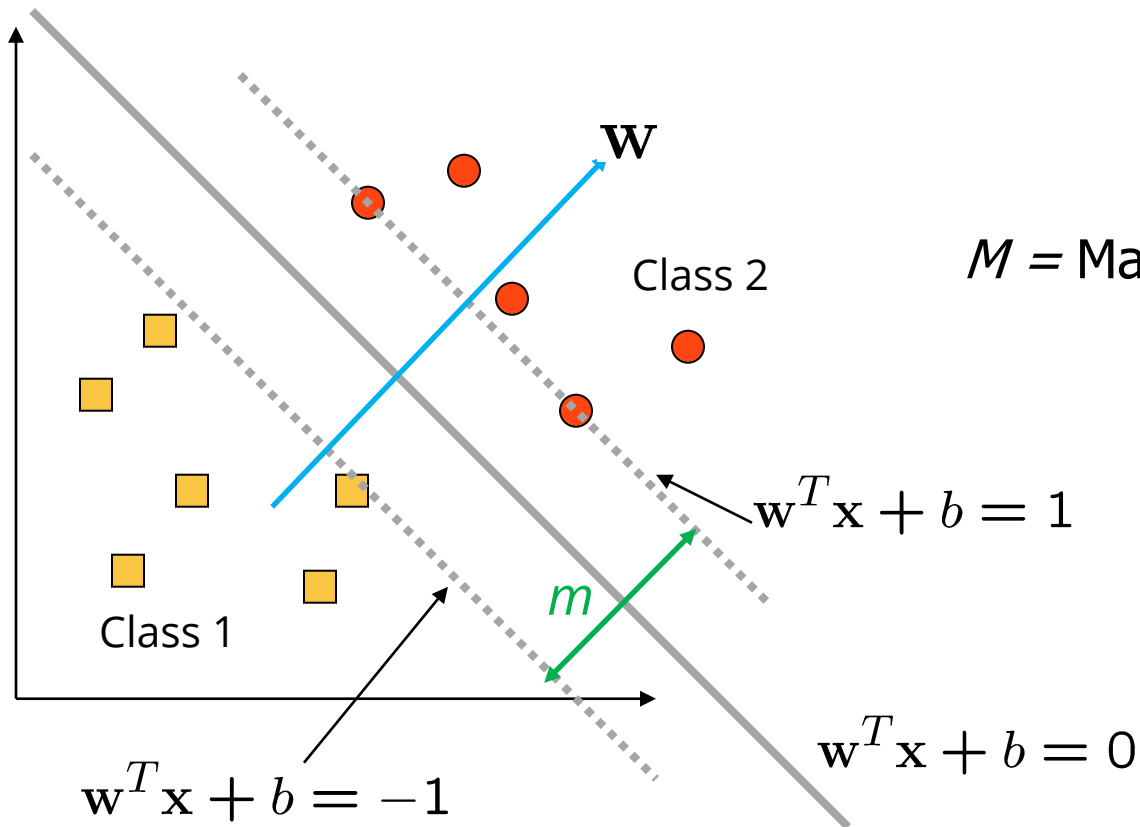
$\mathbf{x}$  – Vector

$\mathbf{w}$  – Normal Vector

$b$  – Scale Value

# Large-margin Decision Boundary

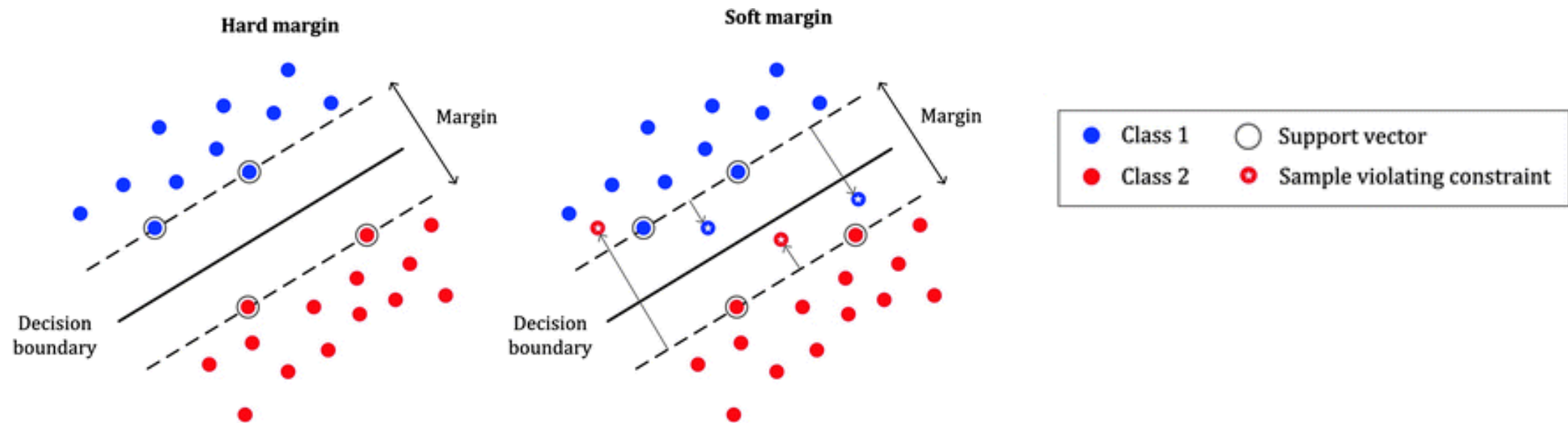
- The decision boundary should be as far away from the data of both classes as possible
  - We should maximize the margin,  $m$
  - Distance between the origin and the line  $\mathbf{w}^T \mathbf{x}$



$$M = \text{Margin Width} = \frac{2}{\sqrt{\mathbf{w} \cdot \mathbf{w}}}$$



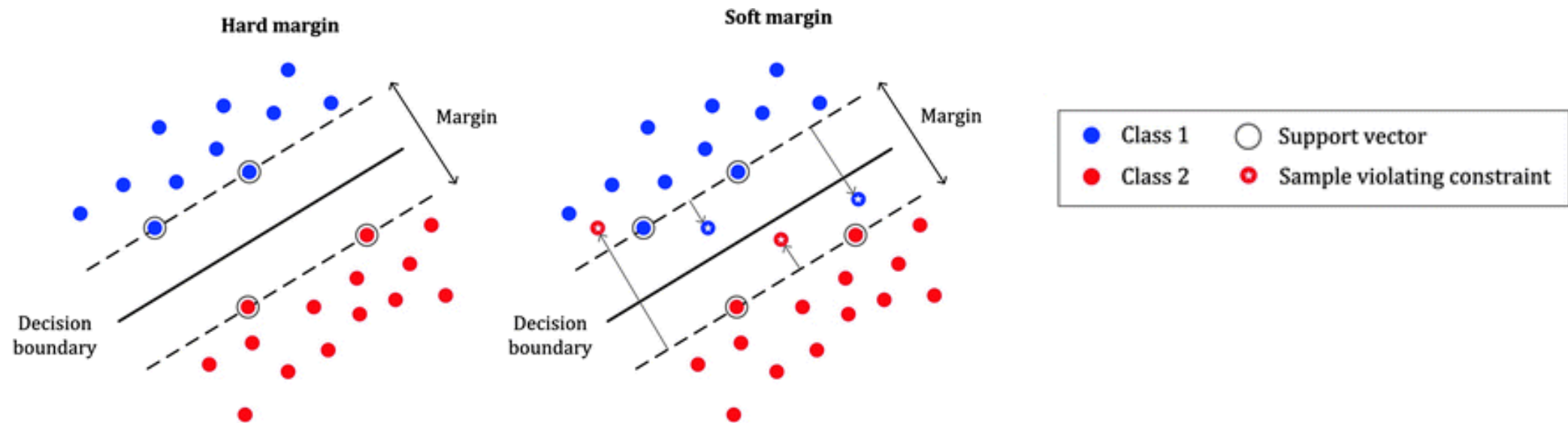
# Robustness of soft margin and hard margin



- **Hard margin** does not allow any misclassification to happen.
- In case our data is **non-separable/ nonlinear** then the Hard margin SVM will not return any hyperplane.
- **Soft margin** allows some misclassification to happen by relaxing the hard constraints of SVM.
- Soft margin SVM is implemented with the help of the **Regularization parameter (C)**.
- **Trade-off: width of the margin vs. number of training errors committed by the decision boundary.**

<https://ankitnitjsr13.medium.com/math-behind-svm-support-vector-machine-864e58977fdb>

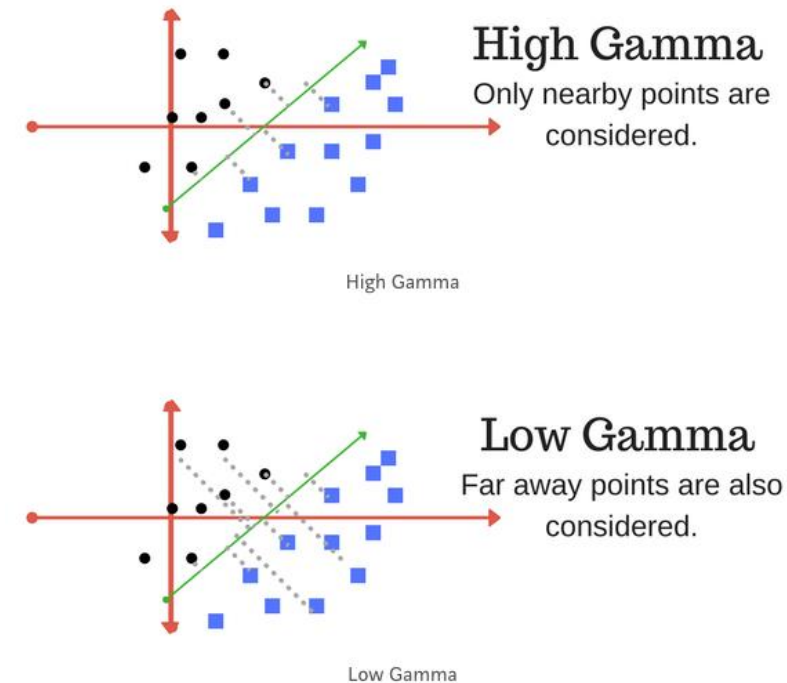
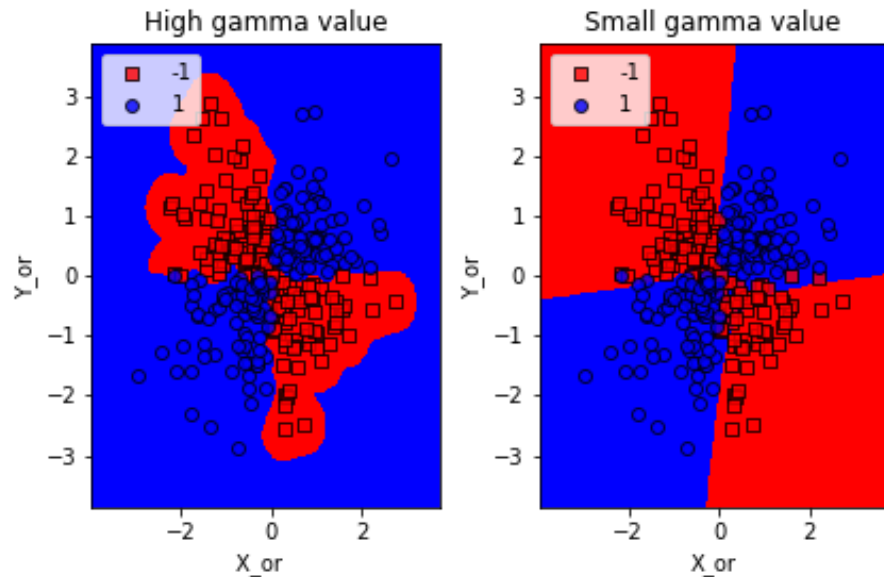
# Robustness of soft margin and hard margin (contd.)



- As the value of  $C$  increases the margin decreases thus Hard SVM.
- If the values of  $C$  are very small the margin increases thus Soft SVM.
- Large value of  $C$  can cause overfitting therefore we need to select the correct value using Hyperparameter Tuning.

# Other Parameters of SVM (Gamma values)

- It tells us **how much will be the influence of the individual data points** on the decision boundary.
  - Large Gamma:** Fewer data points will influence the decision boundary.
  - Therefore, decision boundary becomes non-linear leading to overfitting
  - Small Gamma:** More data points will influence the decision boundary.
  - Therefore, the decision boundary is more generic.



# Types of SVMs

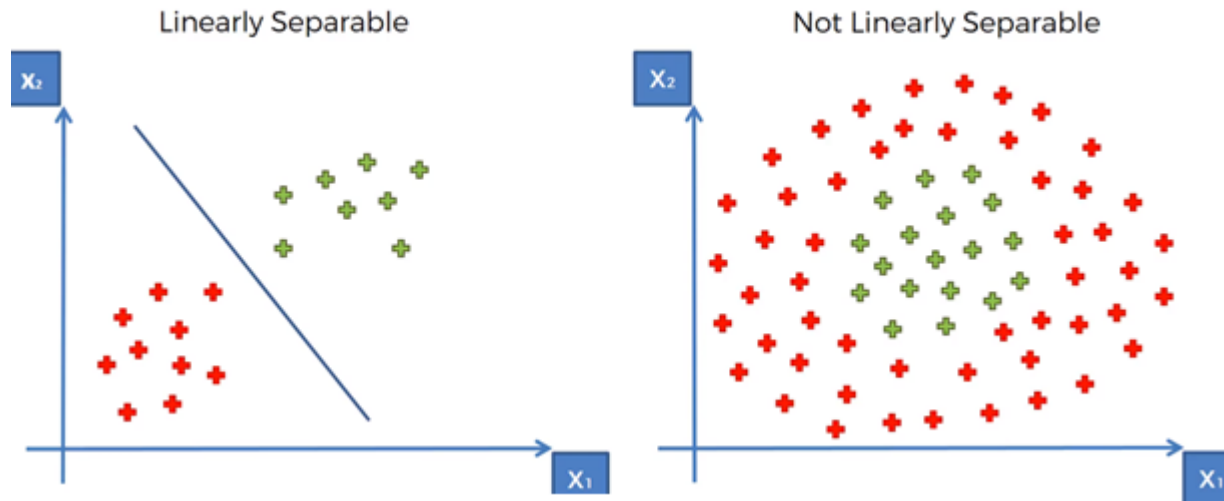
There are 2 different types of SVMs, each used for different things:

- **Simple SVM:** Typically used for linear regression and classification problems.
- **Kernel SVM:** Has more flexibility for non-linear data because you can add more features to fit a hyperplane instead of a two-dimensional space.

# Types of SVMs

There are 2 different types of SVMs, each used for different things:

- **Simple SVM:** Typically used for linear regression and classification problems.
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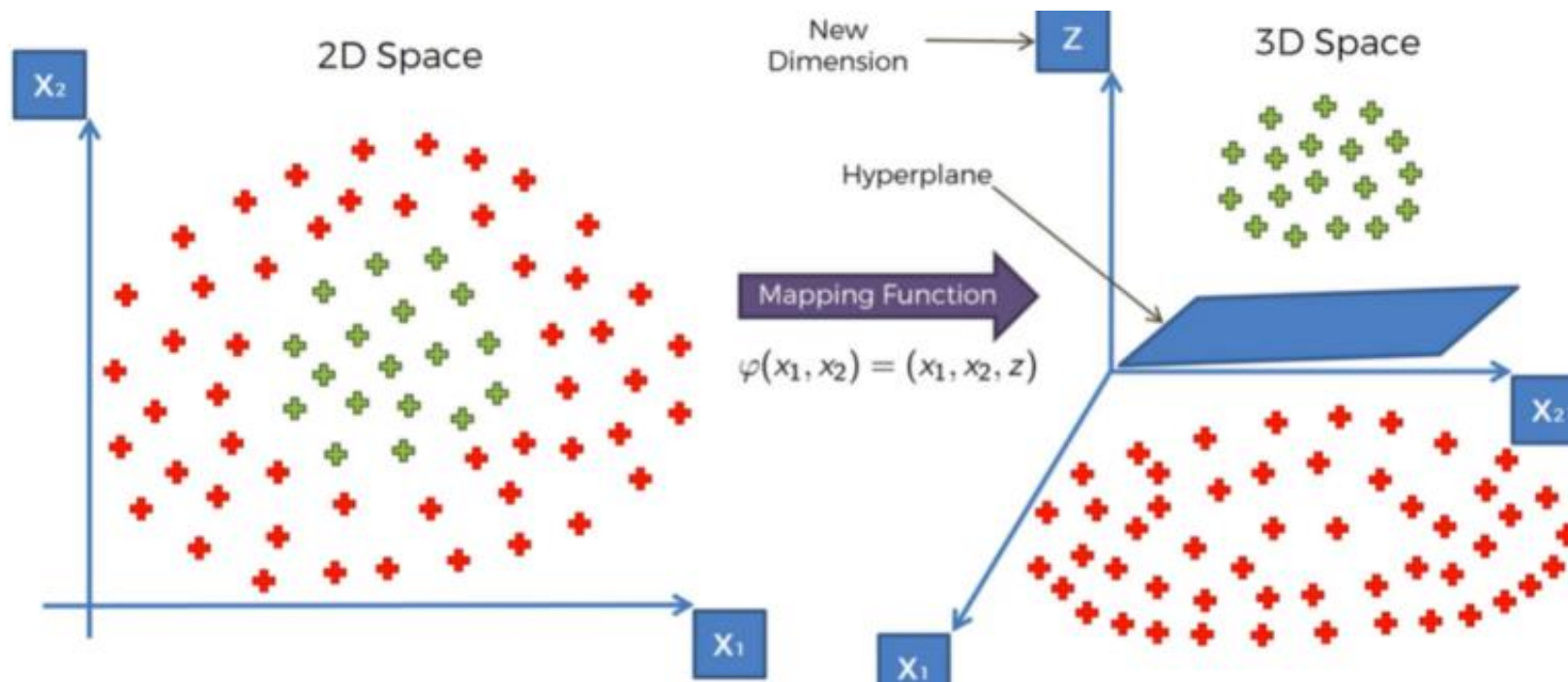


We have to separate green points from the red points by drawing a circle around them and to do so we use the

**Gaussian RBF Kernel Function.**

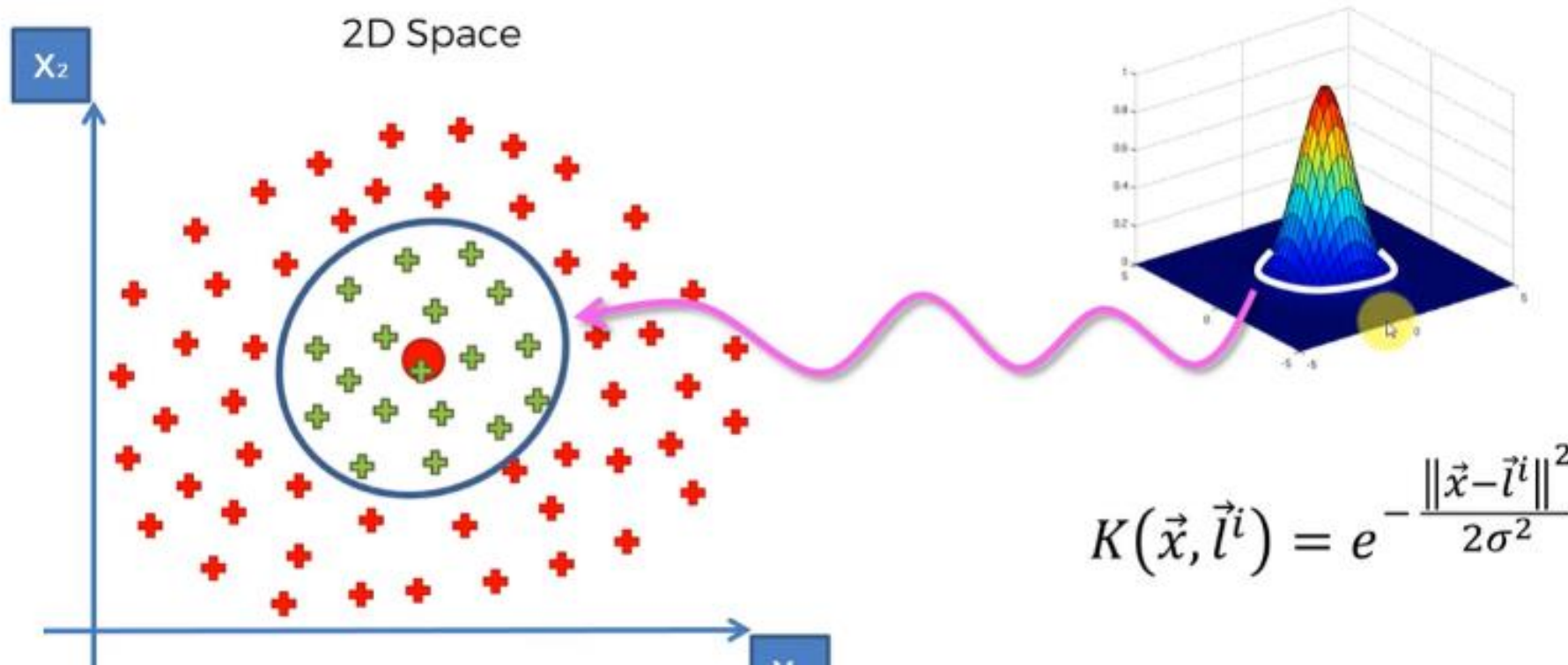
# Gaussian RBF Kernel Function

We can *shift* the points from a 2D plane to a 3D plane by just shifting all the green points above the red ones by using a mapping function like gaussian RBF.



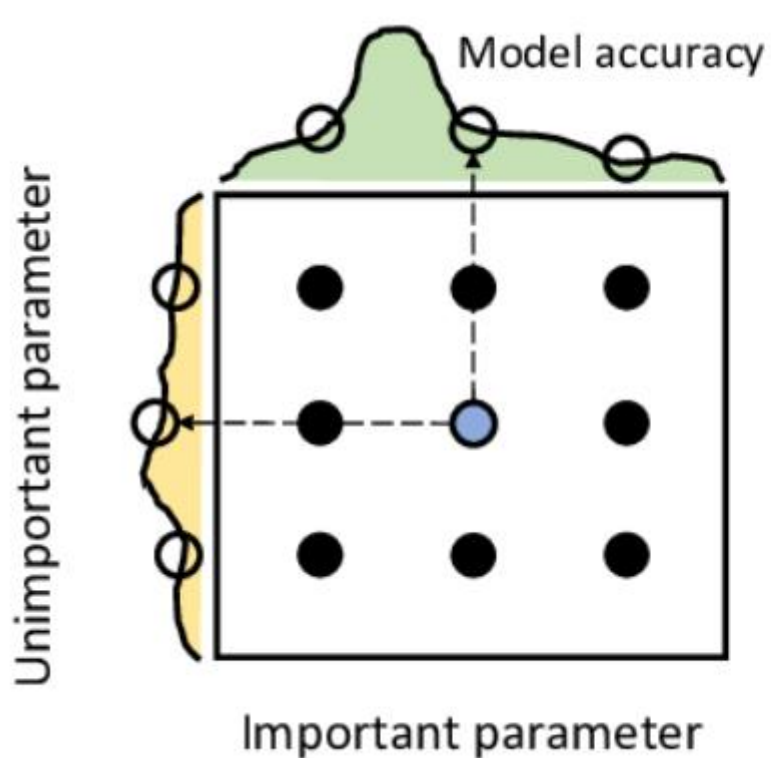
## Gaussian RBF Kernel Function (contd.)

We can *shift* the points from a 2D plane to a 3D plane by just shifting all the green points above the red ones by using a mapping function like gaussian RBF.

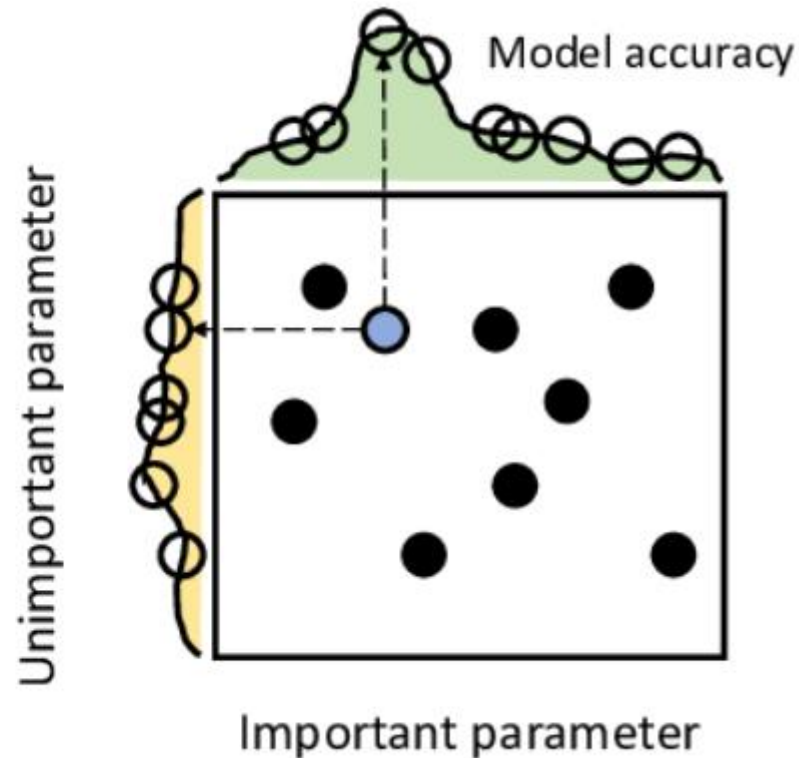


# Grid search

**Grid-search** is used to find the optimal hyperparameters of a model which results in the most 'accurate' predictions.



**Grid search**



**Random search**