

# Data Science and Artificial Intelligence

## Machine Learning



**Classification**

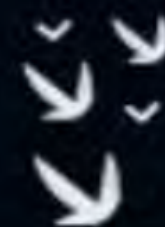
**Lecture No. 6**



**By- SIDDHARTH SABHARWAL SIR**



# Recap of Previous Lecture



Topic

Confusion matrix

Topic

ROC, AUC

Topic

TPR, FPR

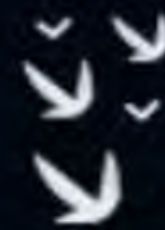
Topic

Sensitivity | Specificity.

Topic



# Topics to be Covered



Topic

Precision / Recall

Topic

Time & space Complexity

Topic

Questions

Topic

Topic

**SUCCESS IS  
HIDDEN IN  
YOUR DAILY  
ROUTINE**

Correct—  
daily plan  
of the daily  
routine





## Confusion matrix...

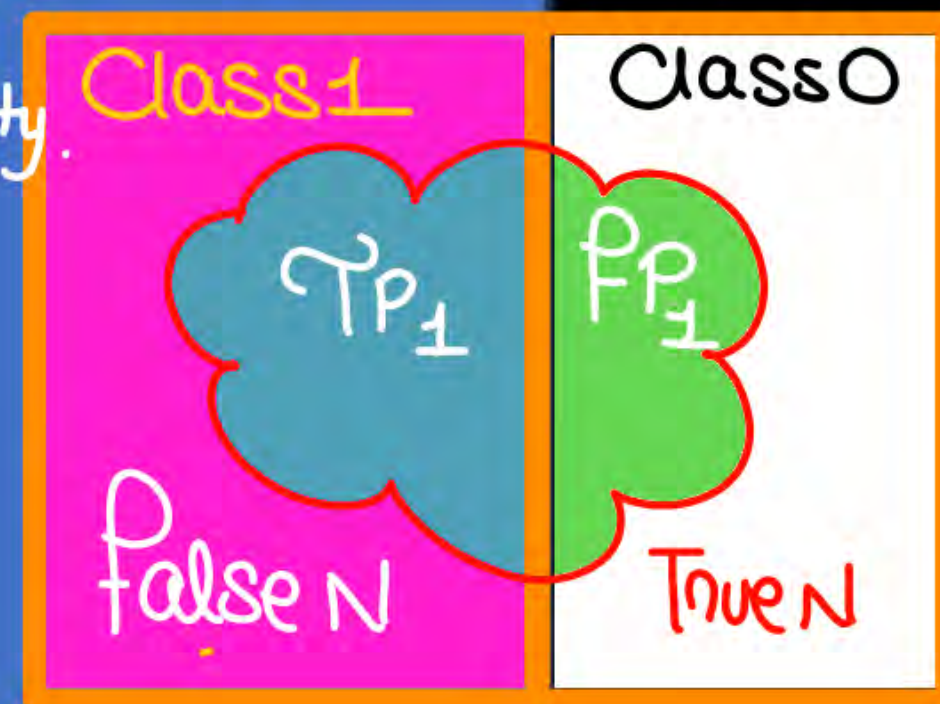
		Actual	
		1	0
Predicted	1	TP	FP
	0	FN	TN

TPR FPR

Sensitivity

$$TPR = TP / \text{actual } P$$
$$FPR = FP / \text{actual } N$$

1-Specificity



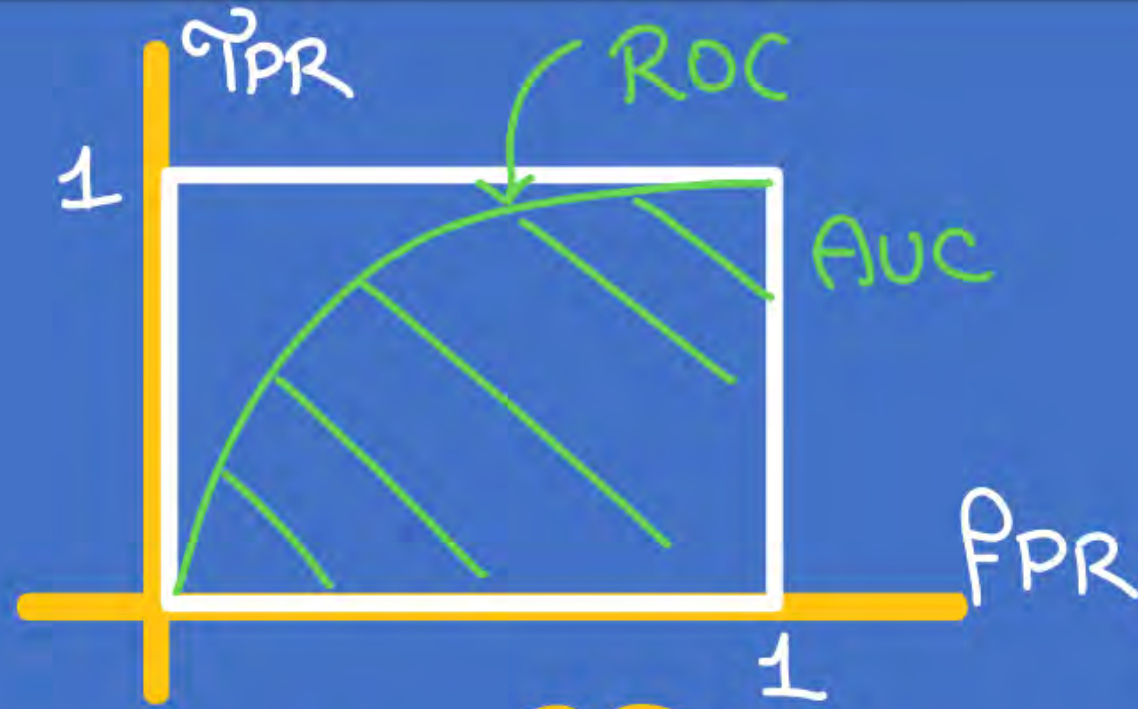




# Basics of Machine Learning



TPR and FPR done



Why only TPR and FPR?  $\Rightarrow$  we want

$$\begin{aligned} \text{TPR} &\Rightarrow 1 \\ \text{FPR} &\Rightarrow 0 \end{aligned}$$



• AUC = always b/w

$0 \rightarrow 1$

← Bekar Classifier → ideal Class.

If  $\checkmark$  TPR = 1  $\Rightarrow$   $\checkmark$  TP = Actual P  $\rightarrow$  FN = 0

$\checkmark$  FPR = 0  $\Rightarrow$  FP = 0  $\rightarrow$  TN = Actual N

So if we improve  
TPR and dec FPR  
then automatically  
the performance  
on Neg class  
improve





What is Specificity and ~~sensitivity~~...

done

accuracy on N class

$$\rightarrow \frac{TN}{Actual N}$$

Sensitivity

accuracy on P class

$$\frac{TP}{Actual P}$$





## What is ROC and AUC?

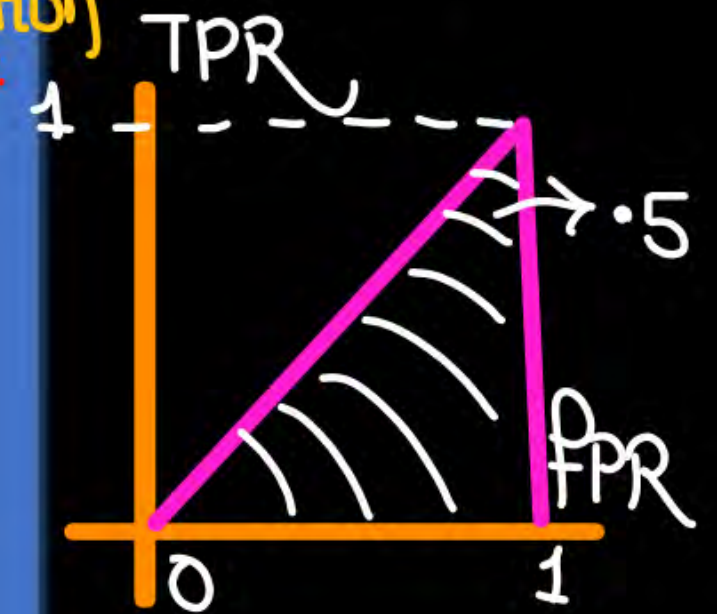
Q If AUC for any classifier is 0.5

→ a) good

~~b) equivalent to Random classification~~

c) No Comment.

So classifier  $(TPR = FPR)$





generally in any data 2 class  $\Rightarrow$

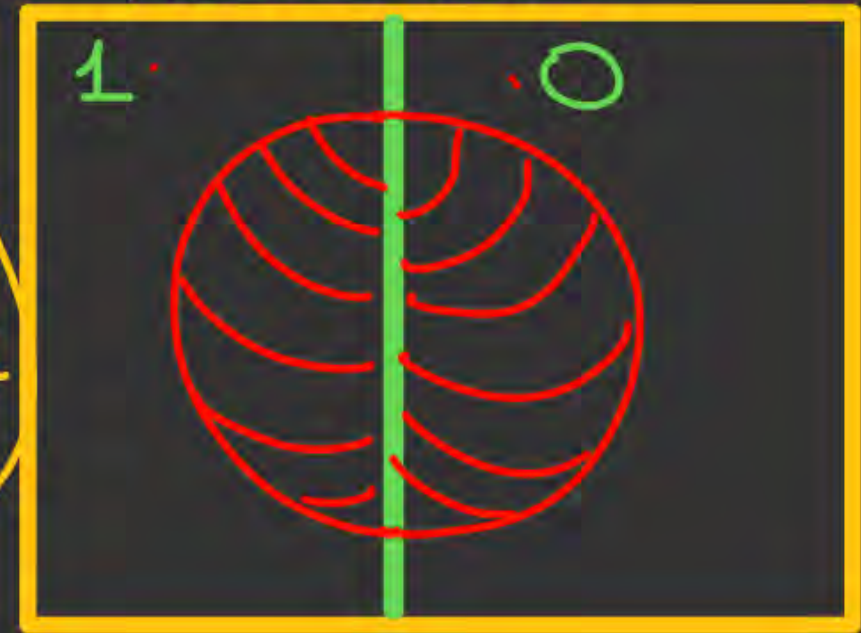
class 0  $\sim$  50%

class 1  $\sim$  50%

So  $TPR = FPR$

$\Rightarrow$  No of Correct 1 Predicted = No of wrong 1 Predicted

Actual class



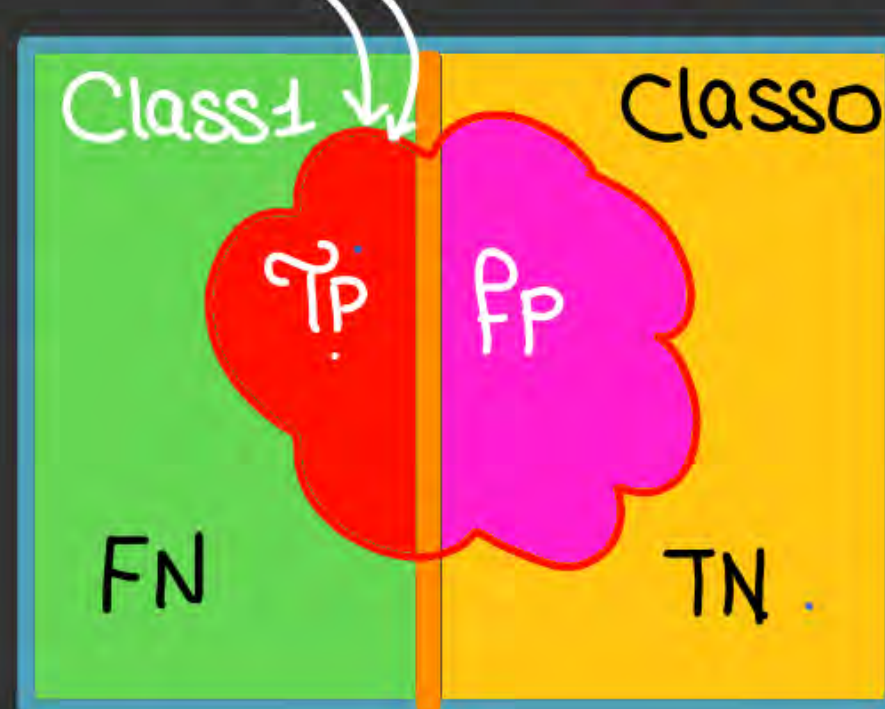


## Recall and Precision



- So we want Recall and precision shd be equal to '1' ideally.

Precision  $\Rightarrow \frac{TP}{TP + FP} = \left( \frac{TP}{\text{Total No of Predicted P}} \right)$



$\Rightarrow \text{Accuracy} \Rightarrow \frac{TP + TN}{\text{Total No of Points}}$





## What is Recall and Precision

Precision =

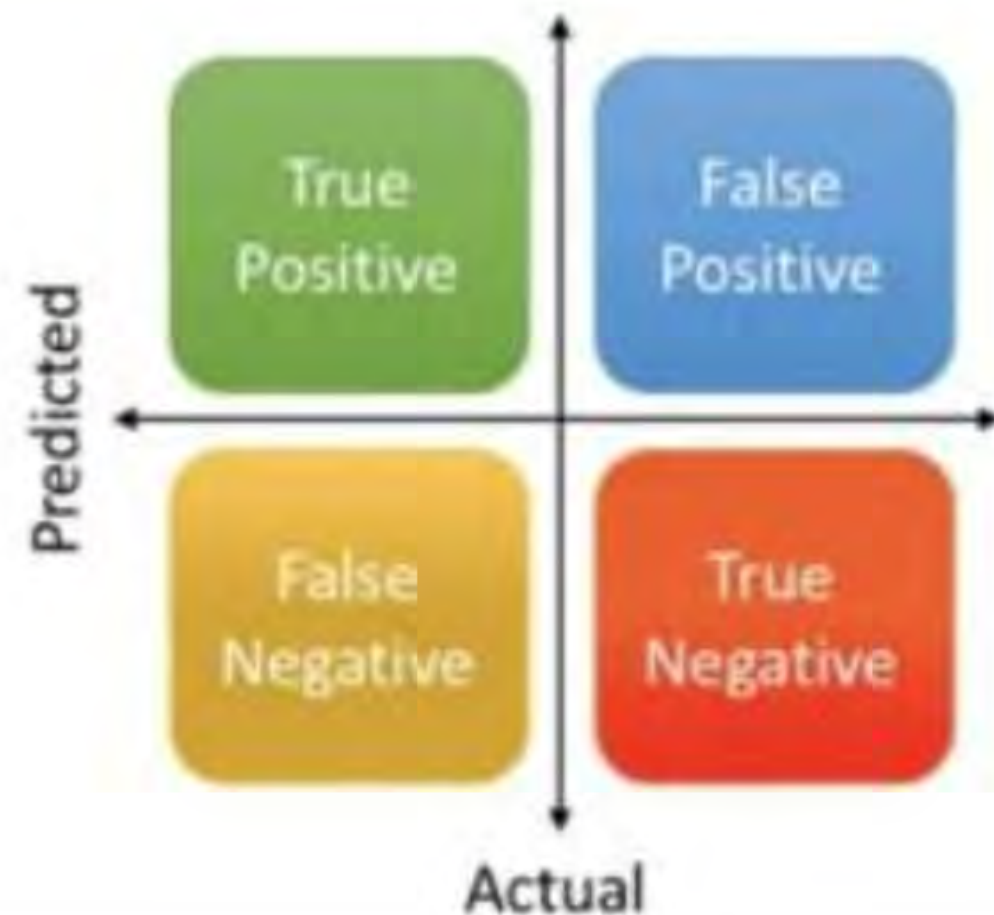
$$\frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall =

$$\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Accuracy =

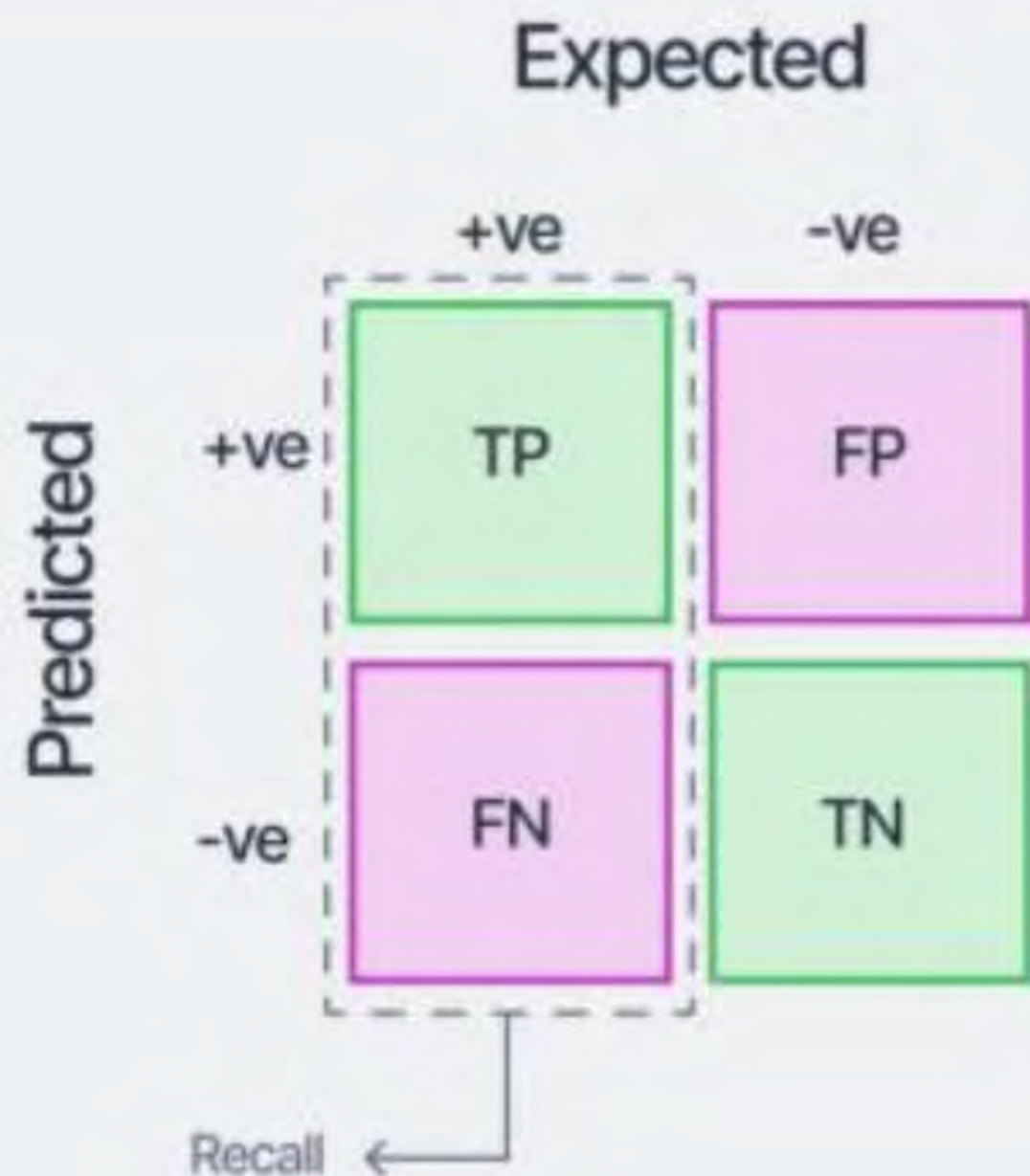
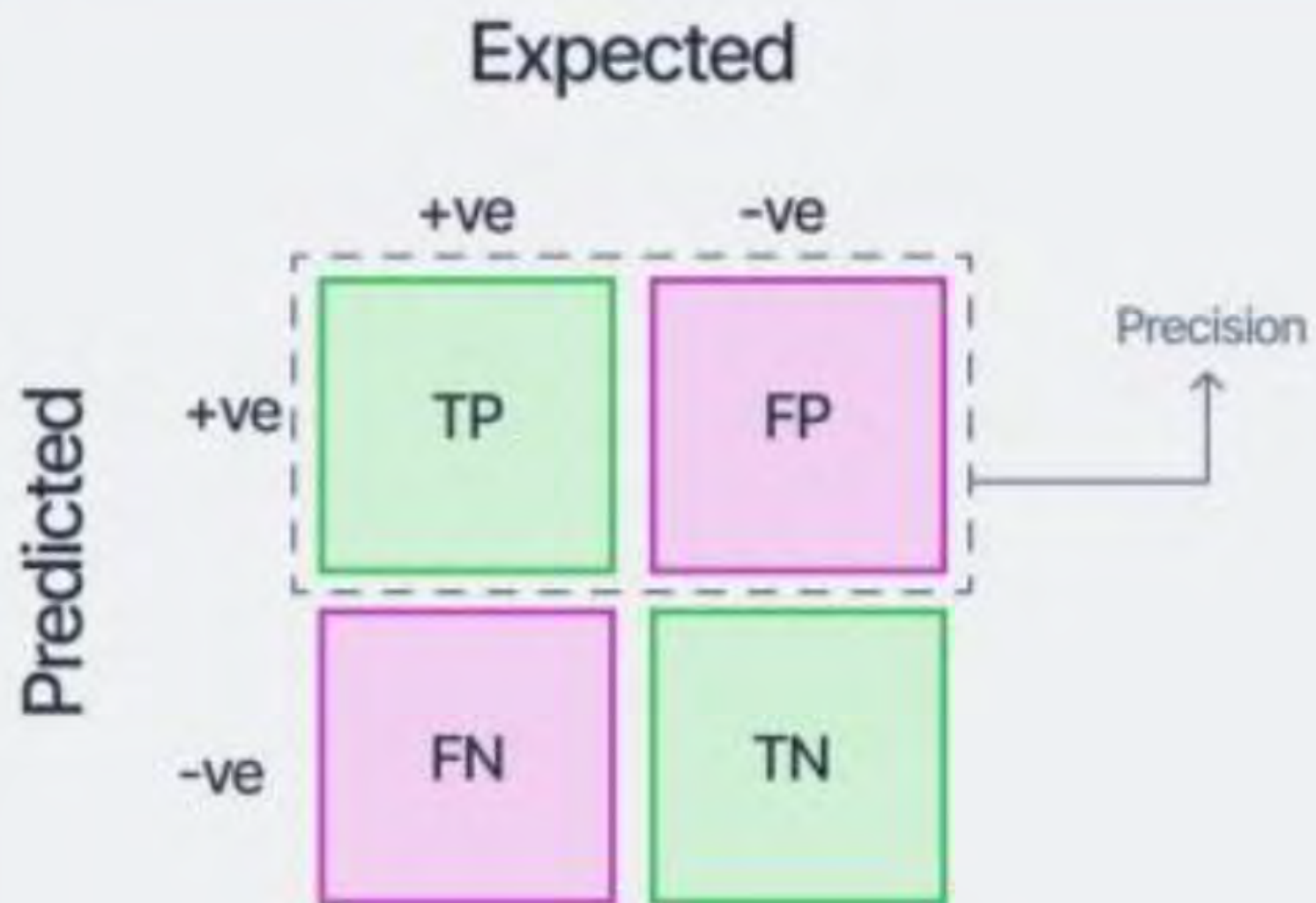
$$\frac{\text{True Positive} + \text{True Negative}}{\text{Total}}$$







## What is Recall and Precision





# Recall Vs Precision

$$\frac{TP}{TP + FN}$$

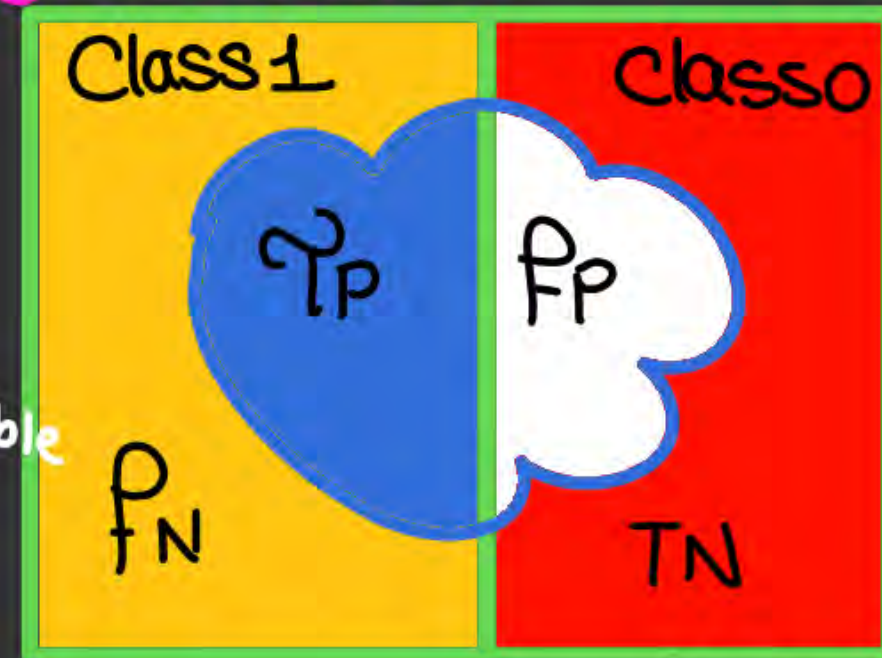
• Video was good but also decline

↑ more imp.

$$\frac{TP}{TP + FP}$$

Video has objectionable but also allowed it

QYT algorithm to check videos and allow (Positive) or not allow (Neg) the video to <18 year children



• In this case FP is very dangerous, it has to be zero.  
FN can be non zero

Precision shd be high.



# Recall Vs Precision

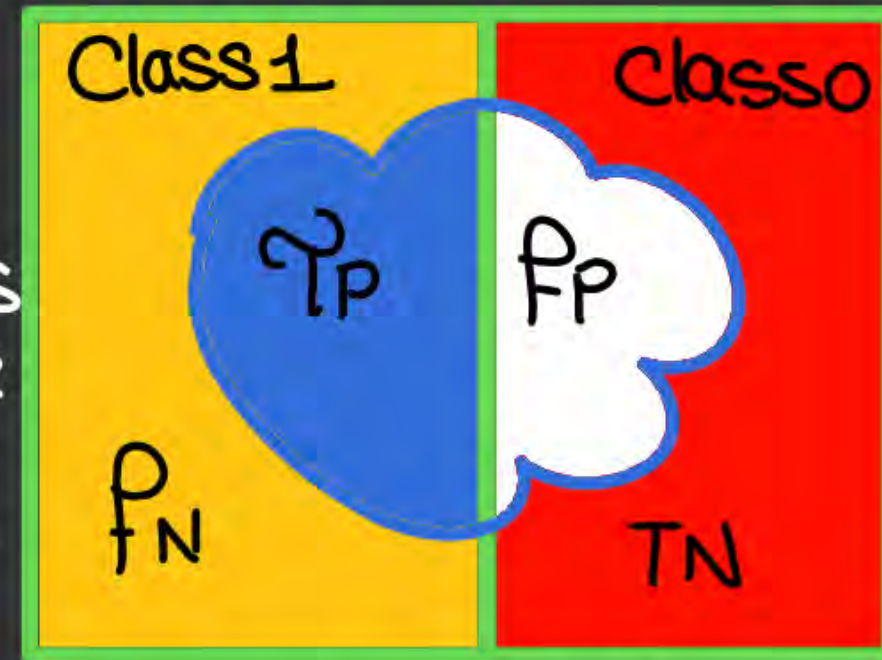
$$\frac{TP}{TP + FN}$$

• Patient was Covid+ve but algo say false No

$$\frac{TP}{TP + FP}$$

patient was not Covid+ve but doctor say false P

Q. if the patient is Covid+ve (P) and if patient is Covid-ve (N)



- ➔ FN and FP both shd be zero
- ➔ FN has to be zero

- + • ➔ Predicted P
- + • ➔ Predicted N
- + • ➔ Actual P
- + • ➔ Actual N





## Linear Classification



What is macro recall and precision

⇒ Since we have 2 classes

$$\text{Recall}_P = \frac{TP}{\text{Actual } P}$$

$$\text{Recall}_N = \frac{TN}{\text{Actual } N}$$

$$\text{Precision}_P = \frac{TP}{\text{Predicted } P}$$

$$\text{Precision}_N = \frac{TN}{\text{Predicted } N}$$

$$\text{macro Recall} = \frac{1}{2} (\text{Recall}_P + \text{Recall}_N)$$

$$\text{macro Precision} = \frac{1}{2} (\text{Precision}_P + \text{Precision}_N)$$



done

### What is Recall and Precision

Both precision and recall may be useful in cases where there is imbalanced data.

It may be valuable to prioritize one over the other in cases where the outcome of a false positive or false negative is costly.

For example, in medical diagnosis, a false positive test can lead to unnecessary treatment and expenses.

In this situation, it is useful to value precision over recall. In other cases, the cost of a false negative is high.

For instance, the cost of a false negative in fraud detection is high, as failing to detect a fraudulent transaction can result in significant financial loss.





### What is F-1 Score

In most problems, you could either give a higher priority to maximizing precision, or recall, depending upon the problem you are trying to solve. But in general, there is a simpler metric which takes into account both precision and recall, and therefore, you can aim to maximize this number to make your model better. This metric is known as F1-score, which is simply the harmonic mean of precision and recall.

*F1 Score  $\Rightarrow$  Harmonic mean of Recall & Precision.*

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$F_1 \text{ score} \Rightarrow 2 \times \frac{P \times R}{P + R}$$

→ Since max value of

$$P = 1$$

$$R = 1$$

$$\Rightarrow F_1 \text{ score}_{\max} = 2 \times \frac{1 \times 1}{1 + 1} \\ \Rightarrow 1$$

- the harmonic mean is more effected by the smaller value
- if P is low, R is large then also F1 score will be low
- So a good classifier shd have a large F1 score which is possible only when both R and P are large





# Linear Classification



## Practise

The confusion matrix visualizes the \_\_\_\_ of a classifier by comparing the actual and predicted classes.

- ☒ Accuracy
- ☐ Stability
- ☐ Connectivity
- ☐ Comparativity

Why gradient descent is not used in logistic Reg??

$$\max \prod (P_i)^{y_i} (1-P_i)^{1-y_i}$$

$$\sum (y - \hat{y})^2$$

→ min of a f(x)

→ Convex nature  
Cost f(x)  
linear reg w.

$$\beta^{\text{new}} = \beta^{\text{old}} - \eta \frac{\partial L}{\partial \beta}$$





## Practise

From the above Table

$N=200$

$n=200$	Prediction=NO	Prediction = YES
Actual = NO	60	10
Actual = YES	5	125

$$\begin{aligned} \text{TPR} &\Rightarrow \frac{TP}{\text{Actual } P} \Rightarrow \frac{125}{130} & \text{Recall} &\Rightarrow \text{TPR} = \frac{125}{130} & \text{Accuracy} &\Rightarrow \frac{TP+TN}{\text{Total}} \Rightarrow \frac{125+60}{200} \\ \text{FPR} &\Rightarrow \frac{FP}{\text{Actual } N} \Rightarrow \frac{10}{70} & \text{Precision} &\Rightarrow \frac{TP}{\text{Total } P \text{ Predicted}} \Rightarrow \frac{125}{135} \end{aligned}$$



## Linear Classification



### Practise

For the below confusion matrix, what is the recall?

*Predicted*

<i>Actual</i>	Not 5	5
Not 5	53272	1307
5	1077	4344

☐ 0.7

☒ 0.8

☐ 0.9

☐ 0.95

$$\begin{aligned}\text{Recall} &\Rightarrow \text{TPR} \\ &\Rightarrow \frac{\text{TP}}{\text{Actual P}}\end{aligned}$$

$$\begin{aligned}&\Rightarrow \frac{4344}{1077 + 4344} \\ &\Rightarrow 0.8\end{aligned}$$





## Linear Classification



### Practise

For the below confusion matrix, what is the precision?

Actual P	Predicted P	
	Not 5	5
Not 5	53272	1307
5	1077	4344

☐ 0.73

☒ 0.76

☐ 0.78

☐ 0.82

$$\begin{aligned} P &= \frac{TP}{\text{Total Predicted P}} \\ &= \frac{4344}{4344 + 1307} \\ &= 0.76 \end{aligned}$$



### What is F-1 Score

F1 score is:

- ☐ absolute mean of precision and recall
- ☒ harmonic mean of precision and recall ✓.
- ☐ squared mean of precision and recall





## What is F-1 Score

For the below confusion matrix, what is the F1 score?

	Not 5	5
Not 5	53272	1307
5	1077	4344

☐ 0.72

☒ 0.784

☐ 0.82

☐ 0.84

$$R = 0.8$$

$$P = 0.76$$

$$F_1 \text{ score} = \frac{2 \times 0.8 \times 0.76}{0.8 + 0.76} = (0.77948) \approx 0.78$$



### What is F-1 Score

For a model to detect videos that are unsafe for kids, we need (safe video = positive class)

done

- ☐ High precision, low recall
- ☐ High recall, low precision



Question 1: Accuracy is simply a ratio of correctly predicted observations to the total observations. From the above confusion matrix, how would you define Accuracy?

(A)  $\text{Accuracy} = (\text{FP} + \text{FN}) / (\text{TP} + \text{FN} + \text{FP} + \text{TN})$

☒ (B)  $\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{FN} + \text{FP} + \text{TN})$

(C)  $\text{Accuracy} = (\text{TP} + \text{FN}) / (\text{TP} + \text{FN} + \text{FP} + \text{TN})$

(D)  $\text{Accuracy} = (\text{FP} + \text{TN}) / (\text{TP} + \text{FN} + \text{FP} + \text{TN})$

Question 2: From the above confusion matrix, how would you define Error?

- ☒ (A)  $\text{Error} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}$
- (B)  $\text{Error} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}$
- (C)  $\text{Error} = \frac{\text{TP} + \text{FN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}$
- (D)  $\text{Error} = \frac{\text{FP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}$



Question 7: Which statements about the Type-I and Type-II errors are correct? (Select two)

- ☒ (A) Type-I error = FPR
- ☒ (B) Type-II error = FNR
- (C) Type-I error = FNR
- (D) Type-II error = FPR

$$\begin{aligned} \rightarrow \left\{ \begin{array}{l} \text{Type 1 error} \Rightarrow \text{FPR} \Rightarrow \frac{FP}{\text{Total Actual N}} \\ \text{Type 2 error} \Rightarrow \text{FNR} \Rightarrow \frac{FN}{\text{Total Actual P}} \end{array} \right. \end{aligned}$$

Question 8: The F1 score is the harmonic mean of Precision and Recall.  
What's the correct formula for the F1 score?

(A)  $F1 \text{ score} = (2 * \text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$

(B)  $F1 \text{ score} = (2 * \text{Precision} * \text{TPR}) / (\text{Precision} + \text{TPR})$

(C)  $F1 \text{ score} = (2 * \text{Precision} * \text{Sensitivity}) / (\text{Precision} + \text{Sensitivity})$

☒ (D) All of the above



Question 9: Which statement about the Receiver Operating Characteristic (ROC)-(Area Under the Curve) AUC Curve is correct?

- (A) ROC is a probability curve that plots the true positive rate (sensitivity or recall) against the false positive rate ( $1 - \text{specificity}$ ) at various thresholds.
- (B) AUC is the area under the ROC curve. If the AUC is high (close to 1), the model is better at distinguishing between positive and negative classes.
- (C) If  $\text{AUC} = 0.5$ , it represents a model that is no better than random.
- ☒ (D) All of the above.

What is the purpose of the ROC curve in logistic regression?

- A) To assess the goodness of fit of the model.
- B) To evaluate the impact of outliers on the model.
- C) To visualize the relationships between independent variables.
- ☒ D) To assess the trade-off between sensitivity and specificity.



What statistic is commonly used to evaluate the overall performance of a logistic regression model?

A) R-squared ( $R^2$ )

B) Mean squared error (MSE)

☒ C) AUC-ROC (Area Under the Receiver Operating Characteristic Curve)

D) Pearson correlation coefficient ( $r$ )



## Time and Space Complexity of Linear Classification

- $\begin{matrix} D+1 \\ \Downarrow \\ K \end{matrix}$
- Linear regression  
Ridge Regression
  - Time Complexity  $O(K^3 + NK^2)$
  - Testing  $O(K)$
  - Space  $\Rightarrow O(K)$

Linear classification  $\Rightarrow$

$$\text{Cost } f_{X\eta} \Rightarrow \max \sum_{i=1}^N y_i x_i \beta$$

N data points  
 $K = (D+1)$ ,  $\beta$  values

$$\begin{aligned} \Rightarrow \text{Overall Mult} &\Rightarrow N(D+2) \\ &\Rightarrow N(K+1) \\ &\approx NK \end{aligned}$$

$\Rightarrow$  The time Complexity  $\Rightarrow O(NK)$

$$y_i \left[ \beta_0 + \beta_1 x_i^1 + \dots + \beta_D x_i^D \right]$$

$(D+1)$  Multiplication  
 $+1$   
 $\Rightarrow (D+2)$





# Linear Classification



## Time and Space Complexity of Linear Classification

Testing  $\Rightarrow$  Time Complexity

we have  $\beta$

$$\text{Only Find } (x_i \beta) = \left( \beta_0 + \beta_1 x_i^1 + \dots + \beta_D x_i^D \right)$$

$\Rightarrow (D+1)$  multiplication

$\Rightarrow O(k)$  Complexity

Space Complexity  $\Rightarrow$  we have to store  $D+1$   $\beta$ 's  
 $\Rightarrow O(k)$ .



## Nearest Neighbour Method

**K-NN method of Supervised Learning**

**The general flow of the Supervised Learning Algorithms**





## Nearest Neighbour Method



### K-NN method of Supervised Learning

Lets understand NN with a simplest example...

K-nearest neighbour classification

query  $\Rightarrow x = (\text{Maths} = 6, \text{CS} = 8), (K=3)$

	maths	CS	Result
1)	4	3	Fail
2)	6	7	Pass
3)	7	8	Pass
4)	5	5	Fail
5)	8	8	Pass

Euclidean distance

①  $\sqrt{(6-4)^2 + (8-3)^2} = \sqrt{29} = 5.38$

②  $\sqrt{(6-6)^2 + (8-7)^2} = 1$

③  $\sqrt{(6-7)^2 + (8-8)^2} = 1$

④  $\sqrt{(6-5)^2 + (8-5)^2} = \sqrt{10} = 3.16$

⑤  $\sqrt{(6-8)^2 + (8-8)^2} = 2$

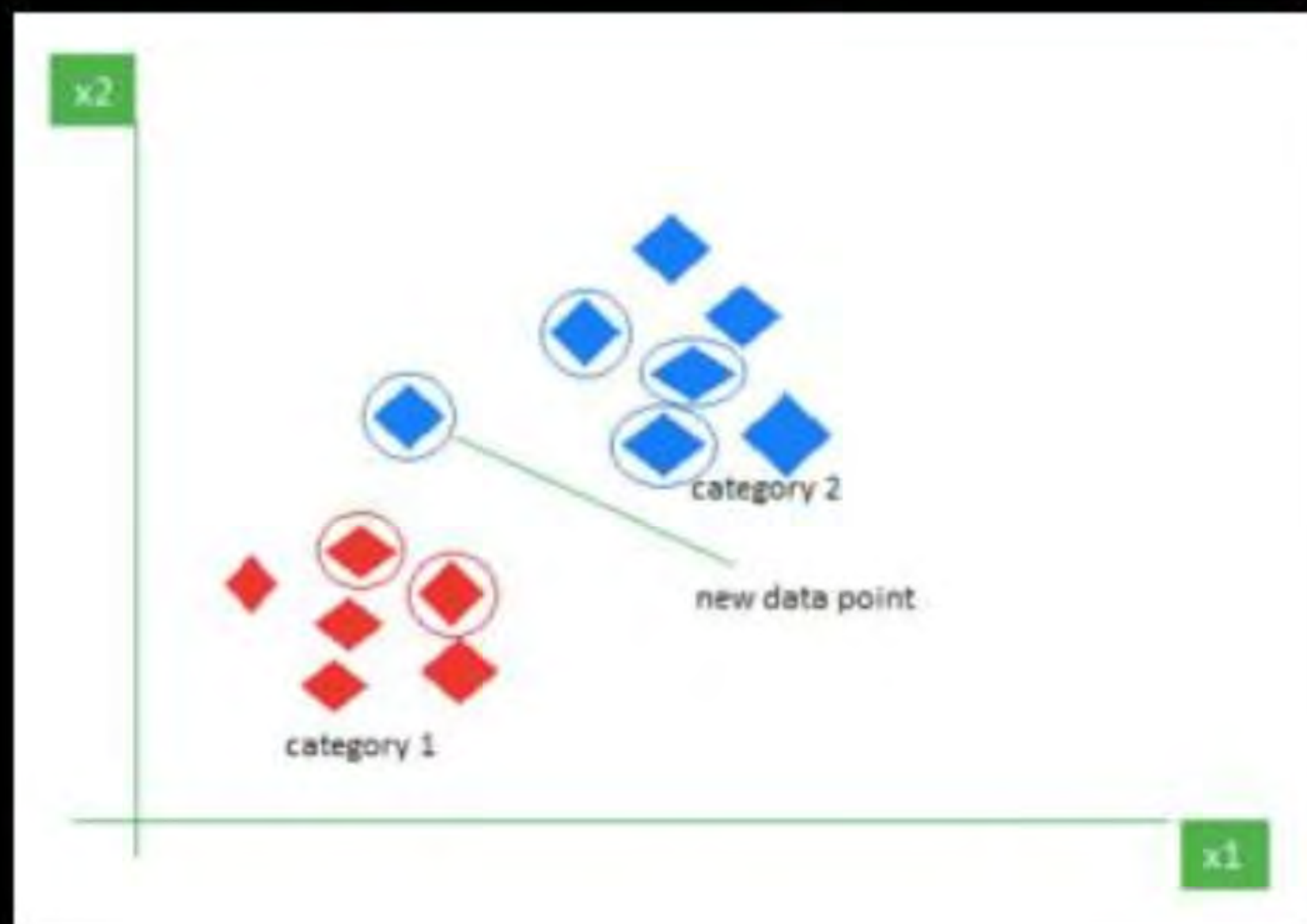


# Nearest Neighbour Method



## K-NN method of Supervised Learning

Lets understand NN with a simplest example...



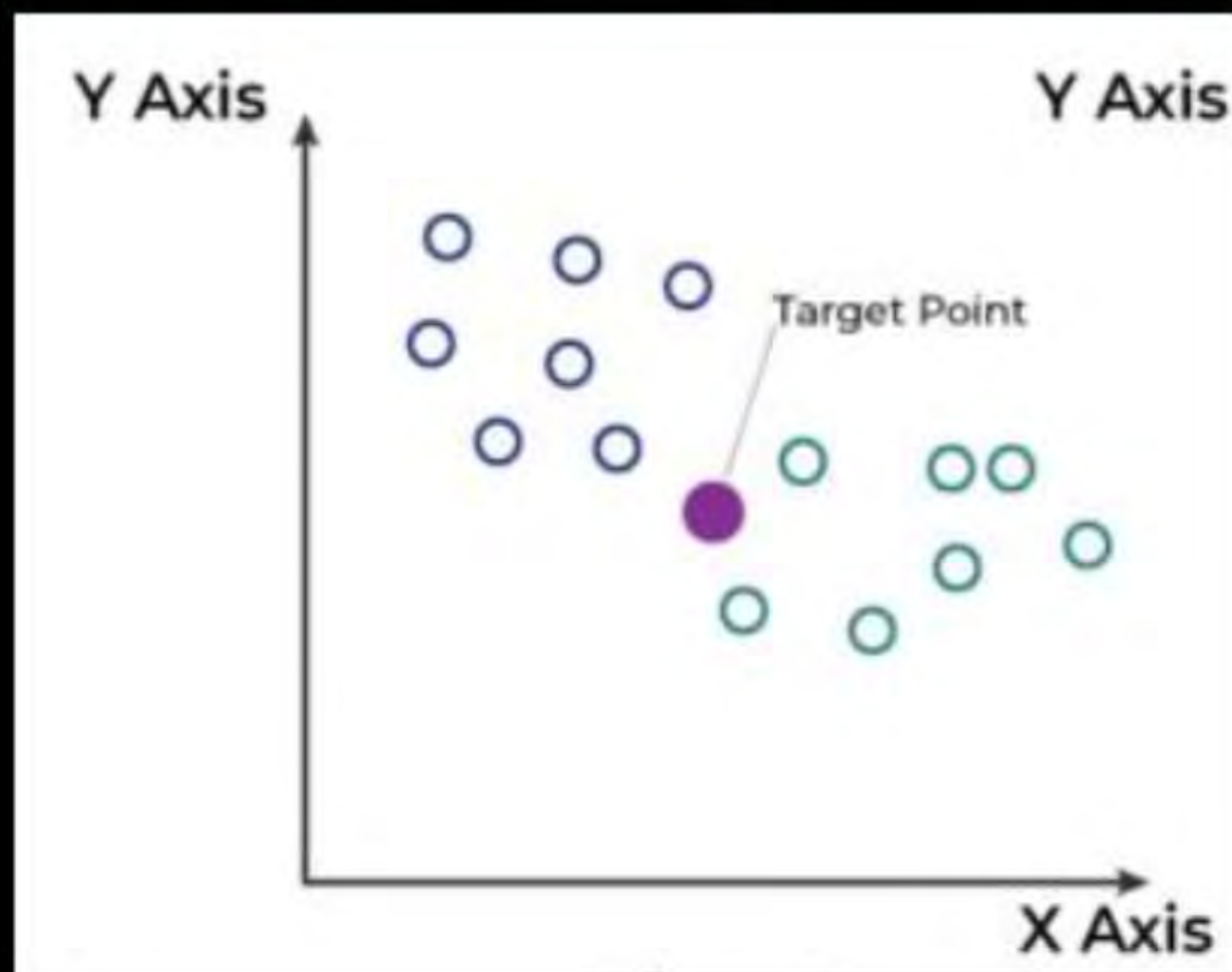




## Nearest Neighbour Method

### K-NN method of Supervised Learning

Lets understand NN with a simplest example...





## Nearest Neighbour Method



### K-NN method of Supervised Learning

#### The general flow of the Supervised Learning Algorithms

##### Step 1

Process the data, train the model, find the parameters



##### Step 2

Use the parameters for regression and classification

This is one of the simplest supervised Learning model

This method can be used for  
1. Regression  
2. Classification

We have instance based learning.

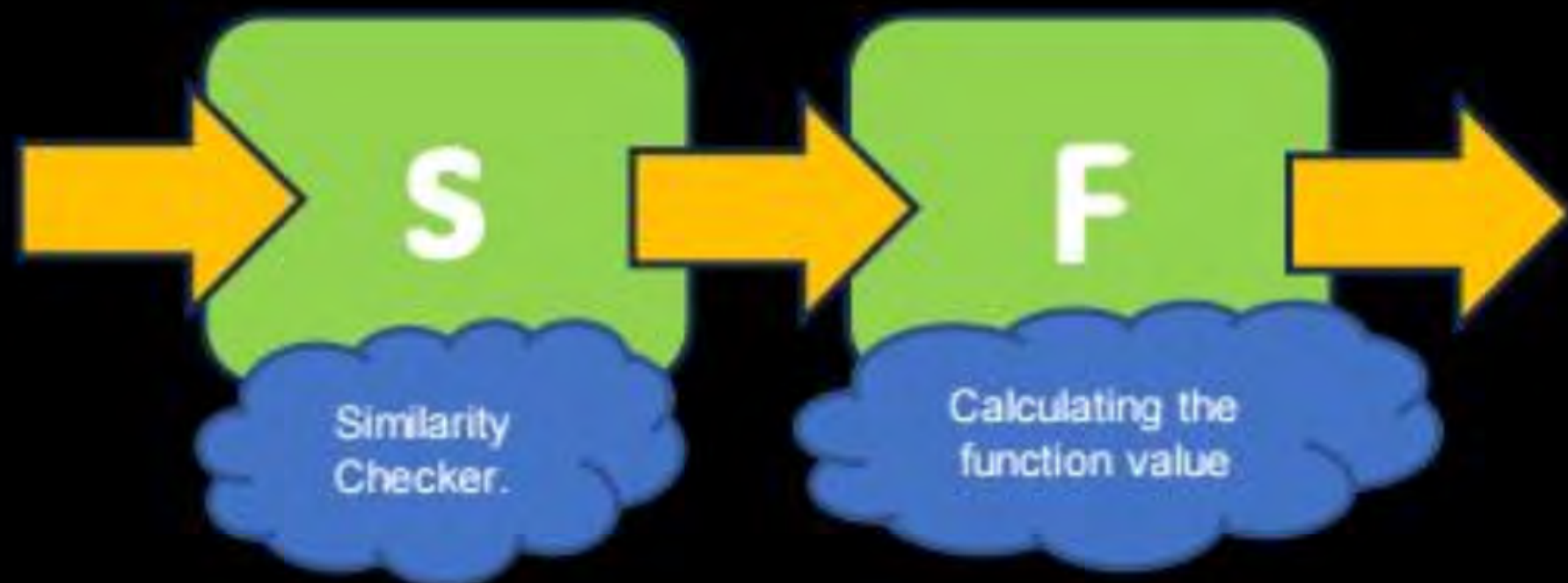




## Nearest Neighbour Method

Nearest Neighbour method of Supervised Learning

But in Nearest Neighbour the process is as follows...



This is the lazy learner

This is the instance-based learning



## Nearest Neighbour Method

### Nearest Neighbour method of Supervised Learning

**But in Nearest Neighbour the process is as follows...**

It is widely disposable in real-life scenarios since it is non-parametric, meaning it does not make any underlying assumptions about the distribution of data

**This is non  
parametric in  
nature**





## Nearest Neighbour Method



Nearest Neighbour method of Supervised Learning

But in Nearest Neighbour the process is as follows...

This can work as  
classifier and  
regressor...



## Nearest Neighbour Method

Nearest Neighbour method of Supervised Learning

Similarity between the two points...

Similarity measure the  
distance between the  
two data points

Euclidian distance





## Nearest Neighbour Method



Step 1 : find  
the distance of  
new point from  
all the other  
points in the  
data

Step 2 : Find  
the distance  
closest to the  
point under  
query

Step 3 : Now  
Simply assign  
the value of Y  
of the closest  
point to the  
new point

Finish



## Nearest Neighbour Method



**Nearest Neighbour method of Supervised Learning**

**Similarity between the two points...**

**So we first of all we find  
the training instance  
which is closest to the  
new point**





## Nearest Neighbour Method

Nearest Neighbour method of Supervised Learning

Now how to find the label or value of new point ?

Now finding the closest or similar instance we then give the same label or value to the new data point



## Nearest Neighbour Method



Nearest Neighbour method of Supervised Learning

Decision Boundary in Classification Problem (NN)

The motive is to  
find out the region  
influenced by each  
point



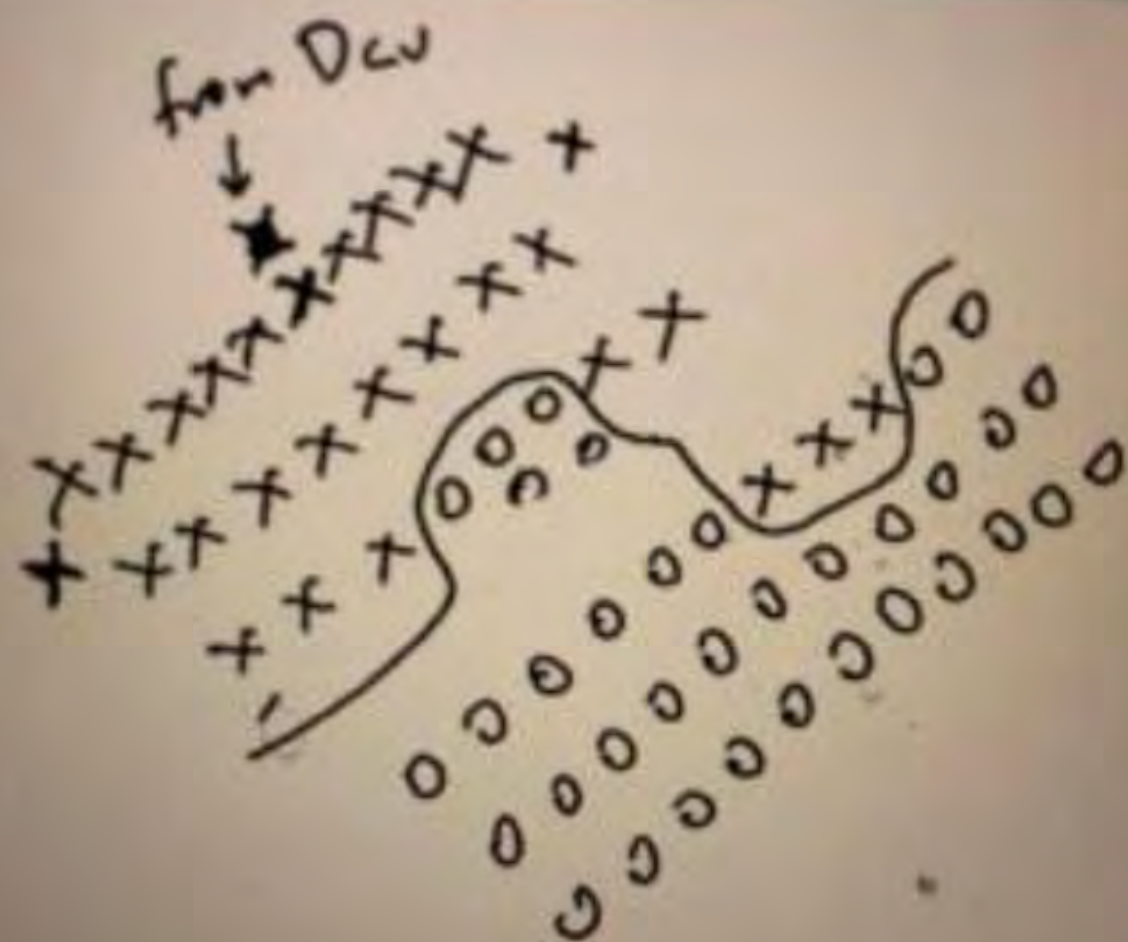


## Nearest Neighbour Method



### Nearest Neighbour method of Supervised Learning

Thus we get this decision boundary (Voronoi Diagram)



So the final  
decision boundary  
will be ...



DataSet D

$x_1$	$x_2$	$y$
1	7	0
1.5	8	0
2	9	0
2.2	7	0
1.8	10	0
2.3	8.5	0
2.9	11	0
6	7	1
6.6	8	1
6.5	6	1
7.5	6	1
7	7	1
8	8	1

$x \rightarrow y_i = 1$   
 $o \rightarrow y_i = 0$

What is impact of k on knn algo.



More perfect





**THANK - YOU**