

## Confusion Matrix



## Confusion Matrix : Intuition

PassengerId	Survived	Pclass
1	0	3
2	1	1
3	1	3
4	1	1
5	0	3

survived and not survived respectively  
therefore

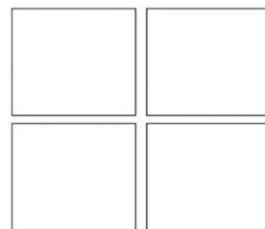


Survived only 2 classes yes or no so  $2 \times 2$  matrix

## Confusion Matrix : Intuition

Survived
0
1
1
1
0

2+2

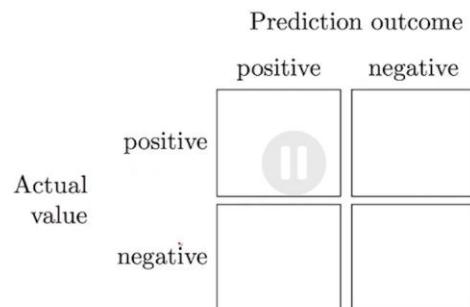


in the dependent variable but for this video we are



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## Confusion Matrix : Intuition



represents a class under the actual value and each



Rows-> actual value

Col→ predicted values

## Confusion Matrix : Intuition

Prediction outcome	
positive	negative
	N
P	N̂

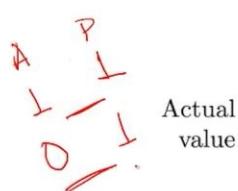
as negative wire model  
once



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## Confusion Matrix : Intuition



Prediction outcome	
positive	negative
TP	N
P	N

Are the values we predicted as positive actually positive in the dataset?  
value is negative in this case the prediction is incorrect or



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## Confusion Matrix : Intuition

		Prediction outcome	
		positive	negative
Actual value	positive	$TP$	$FN$
	negative	$FP$	$TN$

+ 5 &gt;

positive I can say the prediction is incorrect or false so the total number



## Confusion Matrix : Intuition

		Prediction outcome		
		positive	negative	
Actual value	positive	$TP$	$FN$	$TP + FN$ Total Actual positive
	negative	$FP$	$TN$	$FP + TN$ Total Actual negative



negative now that we have understood the notation what they mean and

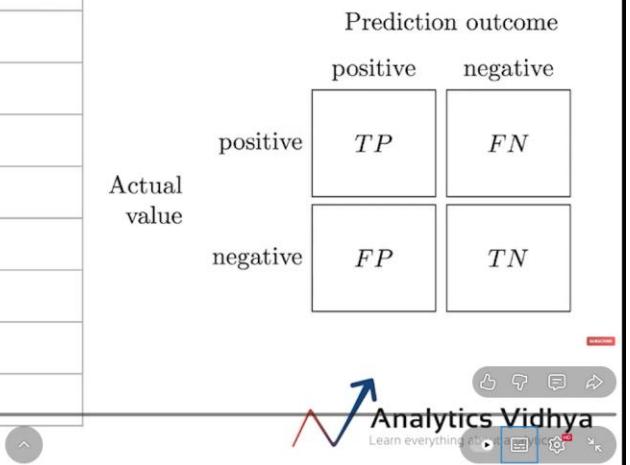


## Confusion Matrix : Intuition

ID	Actual Survived?	Predicted Survived?	Notation
ID1	1	0	
ID2	1	1	
ID3	1	0	
ID4	0	0	
ID5	1	1	
ID6	1	1	
ID7	0	1	
ID8	0	0	

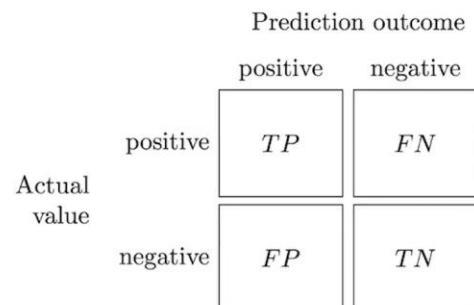


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## Confusion Matrix : Intuition

ID	Actual Survived?	Predicted Survived?	Notation
ID1	1	0	N
ID2	1	1	
ID3	1	0	
ID4	0	0	
ID5	1	1	
ID6	1	1	
ID7	0	1	
ID8	0	0	



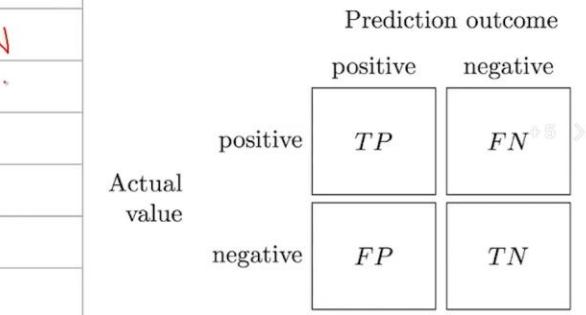
from predicted survived N

## Confusion Matrix : Intuition

ID	Actual Survived?	Predicted Survived?	Notation
ID1	1	0	FN
ID2	1	1	
ID3	1	0	
ID4	0	0	
ID5	1	1	
ID6	1	1	
ID7	0	1	
ID8	0	0	

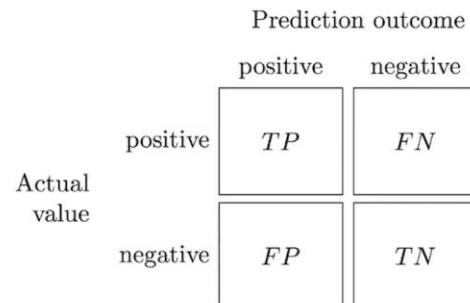


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## Confusion Matrix : Intuition

ID	Actual Survived?	Predicted Survived?	Notation
ID1	1	0	FN
ID2	1	1	TP
ID3	1	0	FN
ID4	0	0	TN
ID5	1	1	TP
ID6	1	1	TP
ID7	0	1	FP
ID8	0	0	TN



## Confusion Matrix : Intuition

ID	Actual Survived?	Predicted Survived?	Notation
ID1	1	0	FN
ID2	1	1	TP
ID3	1	0	FN
ID4	0	0	TN
ID5	1	1	TP
ID6	1	1	TP
ID7	0	1	FP
ID8	0	0	TN

		Prediction outcome	
		positive	negative
Actual value	positive	TP 3	FN 2
	negative	FP 1	TN 2*

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## Accuracy

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# Accuracy

It is the ratio of correct predicted values over the total predicted values.



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# Accuracy

Accuracy: It is the ratio of correct predicted values over the total predicted values.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

		Prediction outcome	
		positive	negative
Actual value	positive	TP	FN
	negative	FP	TN



## Accuracy

We train a model to detect cancer

		Prediction outcome	
		positive	negative
Actual value	positive	4	2
	negative	8	486

500 Patients with Cancer symptoms



494 Negative Results      6 Positive Results



## Accuracy

We train a model to detect cancer

		Prediction outcome	
		positive	negative
Actual value	positive	4	2
	negative	8	486

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

$$\begin{aligned} & \cancel{4} + 486 \\ & \cancel{4} + 8 + 2 + \cancel{486} \\ & = 0.98 \end{aligned}$$



## Accuracy : dumb model

We train a “dumb” model to detect cancer

Negative report for every patient

Or

No patient has cancer

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

$$\frac{0 + 494}{0 + 6 + 0 + 494} = \underline{\underline{98.8\%}}$$

		Prediction outcome	
		positive	negative
Actual value	positive	0	6
	negative	0	494

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Accuracy not great on unbalanced data..



# Alternatives of Accuracy

## True Positive Rate

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

		Prediction outcome			
		positive	negative		
Actual value	positive	TP	FN	TP + FN	Total Actual positive
	negative	FP	TN	FP + TN	Total Actual negative

Ratio of actual positive predictions over total actual positives

## False Negative Rate

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

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

Prediction outcome

		positive	negative	
		positive	FN	TP + FN
Actual value	positive	TP		Total Actual positive
	negative	FP	TN	FP + TN Total Actual negative

Ratio of actual positive, predicted as negative; over total actual positive



## False Positive Rate

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

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

$$TNR = \frac{TN}{FP + TN}$$

$$FPR = \frac{FP}{FP + TN}$$

Prediction outcome

		positive	negative	
		positive	FN	TP + FN Total Actual positive
Actual value	positive	TP		
	negative	FP	TN	FP + TN Total Actual negative

Ratio of actual negative, predicted as positive; over total actual negative



# Precision and Recall

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## Evaluation Metrics : Precision

Out of all the positive predictions, how many are actually positive.

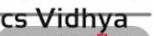
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$$\text{precision} = \frac{\text{Predictions Actually Positive}}{\text{Total Predicted positive}}$$

$$\text{precision} = \frac{TP}{TP + FP}$$

		Prediction outcome	
		positive	negative
Actual value	positive	TP	FN
	negative	FP	TN

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## Evaluation Metrics : Precision

- Aim: Arrest “only” the criminals
- Avoid VIP > Catch Criminal
- Minimise false positives  
(arresting innocents)
- False negative rate is high  
(all criminals may not be arrested)

$$\text{precision} = \frac{TP}{TP + FP}$$

*FP*

*FN*↑

to catch criminals in party full of innocent businessman

## Evaluation Metrics : Recall

Out of all actual positive, how many are predicted positive.

$$\text{recall} = \frac{\text{Predictions Actually Positive}}{\text{Total Actual Positive}}$$

$$\text{recall} = \frac{TP}{TP + FN}$$

		Prediction outcome	
		positive	negative
Actual value	positive	TP	FN
	negative	FP	TN

## Evaluation Metrics : Recall

- Aim: "ALL" weapon carriers "MUST" be caught
- Catching weapon > checking innocent
- Minimize False Negative  
( undetected weapon carrier)
- False positive rate is high  
(detects innocent as weapon carrier)

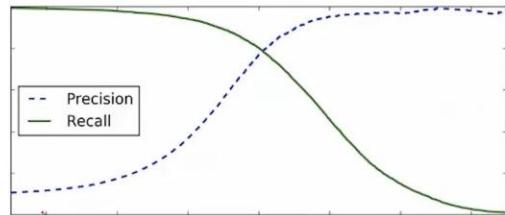
$$\text{recall} = \frac{TP}{TP + FN}$$



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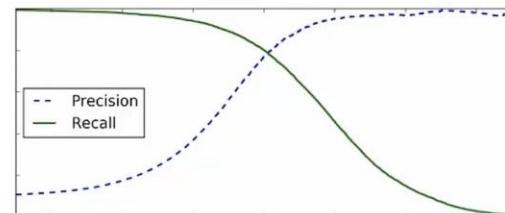
## Evaluation Metrics : Precision/Recall tradeoff

- High Precision, Low Recall
- High Recall, Low Precision
- Choice depends upon the use case



## Evaluation Metrics : Precision/Recall tradeoff

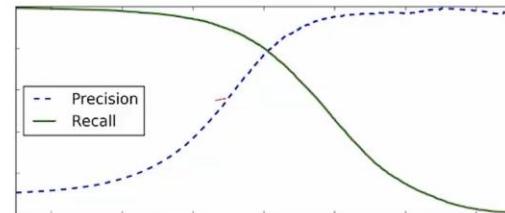
- High Precision, Low Recall
- High Recall, Low Precision
- Choice depends upon the use case
- Combined using F1 Score



$$F_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}}$$

## Evaluation Metrics : Precision/Recall tradeoff

- High Precision, Low Recall
- High Recall, Low Precision
- Choice depends upon the use case
- Combined using F1 Score
- F1 is maximum when precision = recall



$$F_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}}$$

**Machine Learning**

Host

**Question:**

For a given classifier, suppose the first 10 predictions of our classifier and 10 true observations are as follows:

True Label	0	1	1	1	0	0	0	1	1	1
Prediction	1	1	1	1	1	0	1	1	1	1

i. [1 Pt] What is the accuracy of our classifier on these 10 predictions?  $\frac{7}{10} = 0.7$

ii. [1 1/2 Pts] What is the precision on these 10 predictions?  $\frac{6}{9} = \frac{2}{3}$

iii. [1 1/2 Pts] What is the recall on these 10 predictions?  $\frac{6}{6} = 1$

<https://ds100.org/fa21/resources/assets/exams/fa19/fa19midterm2sol.pdf>

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**Machine Learning**

Host

i. [1 Pt] What is the accuracy of our classifier on these 10 predictions?

Solution: 7 of our predictions were correct, out of 10 total. Thus, our accuracy is  $\frac{7}{10}$ .

ii. [1 1/2 Pts] What is the precision on these 10 predictions?

Solution: The number of true positives,  $TP$ , is 6. The number of false positives,  $FP$ , is 3. Then, the precision is  $\frac{TP}{TP+FP} = \frac{6}{9} = \frac{2}{3}$ .

iii. [1 1/2 Pts] What is the recall on these 10 predictions?

Solution: From the solution to the previous part, we know that  $TP = 6$ . The number of false negatives,  $FN$ , here is 0 (we only predicted 0 once, and in that case the true value was actually 0). Thus, the recall is  $\frac{TP}{TP+FN} = \frac{6}{6+0} = 1$ .

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**GO CLASSES**

[T, T, F, T, F, T, F, T] *→ correct*  
[T, F, T, T, F, F, F, T] *→ predicted*

Acc. =  $\frac{5}{8}$

Precision =  $\frac{3}{4}$

Recall =  $\frac{3}{5}$

Host

**GO CLASSES**

[T, F, F, F, F, F, F, F, T] *→ correct*  
[F, T, F, F, F, F, F, F] *→ predicted*

Acc. =  $\frac{5}{8}$

Precision =  $\frac{0}{1} = 0$

Recall =  $\frac{0}{2} = 0$

Host

**Machine Learning**

**Question:**

9. Suppose we train a binary classifier on some dataset. Suppose  $y$  is the set of true labels, and  $\hat{y}$  is the set of predicted labels.

$y$	0	0	0	0	0	1	1	1	1	1
$\hat{y}$	0	1	1	1	1	1	1	0	0	0

Determine each of the following quantities.

(a) [1 Pt] The number of true positives

**Solution:** \_\_\_\_\_

(b) [1 Pt] The number of false negatives

**Solution:** \_\_\_\_\_

(c) [1 Pt] The precision of our classifier. Write your answer as a simplified fraction.

**Solution:** \_\_\_\_\_

<https://ds100.org/fa20/resources/assets/exams/fa18/fa18finalsol.pdf>

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**Machine Learning**

**Question:**

9. Suppose we train a binary classifier on some dataset. Suppose  $y$  is the set of true labels, and  $\hat{y}$  is the set of predicted labels.

$y$	0	0	0	0	0	1	1	1	1	1
$\hat{y}$	0	1	1	1	1	1	1	0	0	0

Determine each of the following quantities.

(a) [1 Pt] The number of true positives

**Solution:** 2

(b) [1 Pt] The number of false negatives

**Solution:** 3

(c) [1 Pt] The precision of our classifier. Write your answer as a simplified fraction.

**Solution:**  $\frac{2}{2+4} = \frac{1}{3}$

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**Machine Learning**

**Confusion Matrix**

what does the model think?

		dog	cat	mouse
what is it actually?	dog	4	0	0
	cat	2	2	0
	mouse	0	0	2

**Cat Recall:** when we **actually** have a cat (row!), what percentage of the time is the model right?  $\frac{2}{4}$

**Dog Recall:** when we **actually** have a dog (row!), what percentage of the time is the model right?  $\frac{4}{4}$

**Dog Precision:** when the model **predicts** a dog (column!), what percentage is it right?  $\frac{4}{6}$

**Cat Precision:** when the model **predicts** a cat (column!), what percentage is it right?  $\frac{2}{2}$

Host

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**Machine Learning**

**Question:**

Given the following confusion matrix for a classification task with three classes (A, B, and C), which of the following statements is correct?

		Ground Truth		
Predicted				A
	A	B	C	
	A	0	0	2
B	1	3	1	
C	0	0	3	

A. Precision(B) = 1.0  
B. Precision(C) = 0.5  
C. Recall(B) = 1.0  
D. Recall(C) = 0.5

[https://archive.ntel.ac.in/content/storage2/courses/downloads\\_new/106106213/noc20\\_rs44\\_assignment\\_2.pdf](https://archive.ntel.ac.in/content/storage2/courses/downloads_new/106106213/noc20_rs44_assignment_2.pdf)

**Machine Learning**

Host

3. (1 point) Again, consider a binary classification data set with 9000 positively labelled examples and 1000 negatively labelled examples. What is the precision and the recall of a classifier that always classifies any example as positive?

A. The precision is 0.1, and the recall is 0.9.  
 B. The precision is 0.9, and the recall is 0.1.  
 C. The precision is 1.0, and the recall is 0.9.  
~~D.~~ The precision is 0.9, and the recall is 1.0.  
 E. The precision is 0.1, and the recall is 1.0.

**Solution:** D. The precision is  $9000/10000 = 0.9$  since all examples are classified as positive. The recall is  $9000/9000 = 1.0$  (perfect recall) since all positive examples are classified as positive.

**Machine Learning**

Host

**Combining precision and recall**

- ▶ **Key insight:** Two moderate values are better than two extremes. Use the product, which shrinks when either term in the product is small.
- ▶ New way of combining precision and recall: F-score

$$\frac{2PR}{P+R}$$

(harmonic mean of P, R)

$$F = \frac{1}{\frac{1}{P} + \frac{1}{R}}$$

Compare:

- ▶ Classifier A ( $P = 0, R = 1$ )  $\rightarrow \frac{2 \cdot 0 \cdot 1}{0+1} = 0$  bad
- ▶ Classifier B ( $P = 0.5, R = 0.6$ )  $\rightarrow \frac{2 \cdot 0.5 \cdot 0.6}{0.5+0.6} = \frac{6}{11}$

# Thresholding

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# AUC-ROC

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Area Under Curve

AUC - ROC

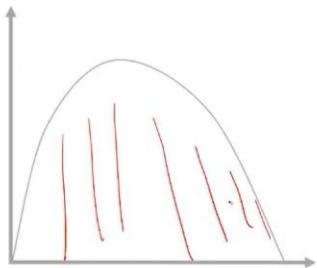
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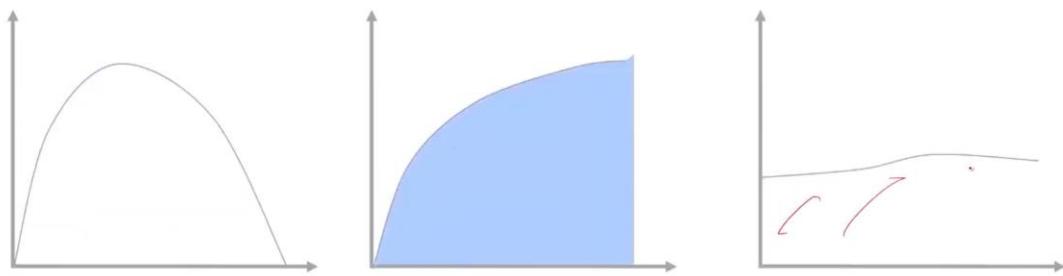
## Area Under Curve



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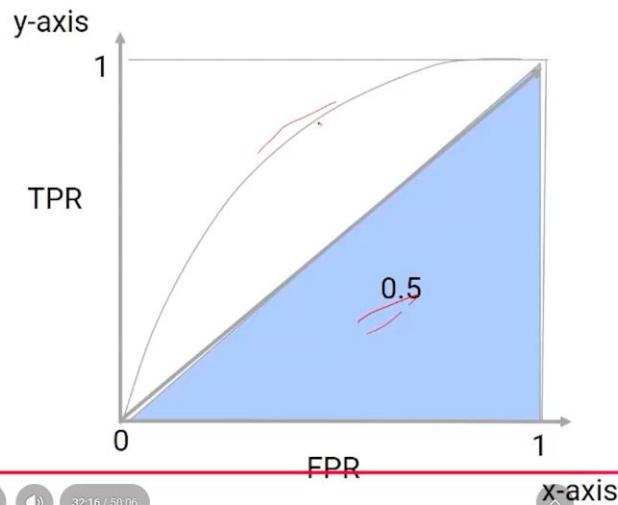
## Area Under Curve



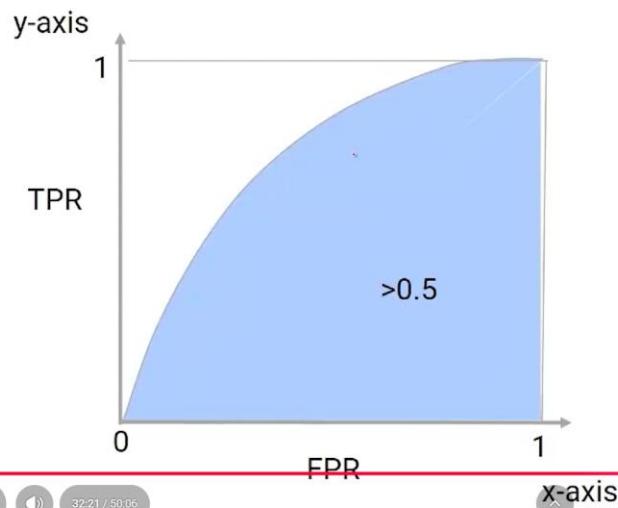
## The ROC Curve

- ROC: Receiver Operating Characteristic
- Originally used for distinguishing 'noise' from 'not noise'
- Evaluation Metric for Binary Classification
- Gives trade-off between True Positives and False Positives

## The ROC Curve



## The ROC Curve



The more the area under curve better the prediction

## Problem with AUC-ROC

- Considers only the order of probability
- Cannot be used for comparing two models

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