

The background is a solid black field. A large, thin white circle is centered on the slide. A thick, light green arc is positioned at the bottom of this white circle. To the left of the circle, there are two white zigzag lines. Below the circle, there is a small light orange circle. To the right of the circle, there is a light orange ring. Further to the right, there are five parallel white diagonal lines. In the bottom right corner, there is a large, solid light orange semi-circle.

# Evaluation metrics for classification

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# Outline



Why Model Evaluation?



Confusion Matrix



Accuracy



Precision



Recall



F1-Score

# Some Terminologies

- Features/Independent Variables/Input (X)
- Binary Classification/Multiclass Classification
- Dependent Variable/Target Variable/Output(Y)
- Training Data vs Testing Data

# Why Model Evaluation?

It allows us to determine strength and weakness of a model

Evaluation on separate training and validation data, helps us to identify overfitting and underfitting

We can train different models on same data and compare which one performs best

# Performance Metrics

We can evaluate our Model based on different performance metrics like:

- Accuracy
- Precision
- Recall
- F1-Score

These performance metrics are calculated from confusion Matrix

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- \_\_\_\_\_

[illegible]

# Titanic Dataset (Survived/Not Survived)

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

# Confusion Matrix

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- Hence the output class has only two possible outcomes: 1 or 0, so we will have a 2\*2 confusion matrix

		Prediction outcome	
		positive	negative
Actual value	positive		
	negative		



# Confusion Matrix

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

# Confusion Matrix

- True Positive: Actual values were positive in dataset, and model also predicted those values as positive
  - Exp: In a medical test for a disease, a true positive would be a patient who has the disease and tests positive.
- True Negative: Actual values were negative in the dataset, and model also predicted those values as negative
  - Exp: A true negative would be a healthy patient who tests negative for the disease.

# Confusion Matrix

- False Positive: Actual values were negative in dataset, and model predicted those values as positive
  - Exp: In a medical test for a disease, a false positive would be a healthy patient who tests positive for the disease.
- False Negative: Actual values were positive in the dataset, and model predicted those values as negative
  - Exp: A false negative would be a patient who has the disease but tests negative.

# Titanic Dataset

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	

# Titanic Dataset

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

**Build a Confusion Matrix Now**

# Confusion Matrix

- TP=3
- FN=2
- FP=1
- TN=2

# Accuracy

- Ratio of correct predicted values over the total predicted values

		POSITIVE	NEGATIVE
ACTUAL VALUES	POSITIVE	<b>TP</b>	<b>FN</b>
	NEGATIVE	<b>FP</b>	<b>TN</b>

$$Precision = \frac{TP}{TP + FP} \quad Recall = \frac{TP}{TP + FN}$$

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

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



# Accuracy

- We Train a Model to detect cancer
- This model will take inputs like: age,gender, previous medical history etc
- Confusion Matrix was like this suppose:

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

500 Patients with Cancer symptoms



# Practice Problem

- Calculate accuracy from the confusion matrix on previous slide
- Do you get 98% accuracy?

# Accuracy

- Now let's build a dumb model to detect cancer:
  - **Negative Report for every patient or No Patient has cancer**

You can observe all values  
in negative column in the  
confusion matrix!

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

# Accuracy

- In Practical Scenario Accuracy doesn't work when we have **class imbalance problems**.

$$TPR = \frac{TP}{TP + FN} = 0$$

$$FNR = \frac{FN}{TP + FN} = 1$$

$$TNR = \frac{TN}{FP + TN} = 1$$

$$FPR = \frac{FP}{FP + TN} = 0$$

Look at FNR Rate, Means all those patients who had cancer were classified as not having the cancer

98.8% Accuracy for dumb model!

# What to do for class imbalance problem

- Precision
- Recall

# Precision

- Out of all positive predictions, how many are positive

		POSITIVE	NEGATIVE
ACTUAL VALUES	POSITIVE	<b>TP</b>	<b>FN</b>
	NEGATIVE	<b>FP</b>	<b>TN</b>

$$Precision = \frac{TP}{TP + FP} \quad Recall = \frac{TP}{TP + FN}$$

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

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

# Precision

- Out of all positive predictions, how many are actually positive

We train a model to detect cancer

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

500 Patients with Cancer symptoms



# Precision

- Calculate Precision
- Is it 33.33%



# Recall

- Out of all actual positives, how many are predicted positives
- Minimize False Negatives

We train a model to detect cancer

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

500 Patients with Cancer symptoms



# Problem

- Calculate Recall for the confusion matrix

We train a model to detect cancer

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

500 Patients with Cancer symptoms

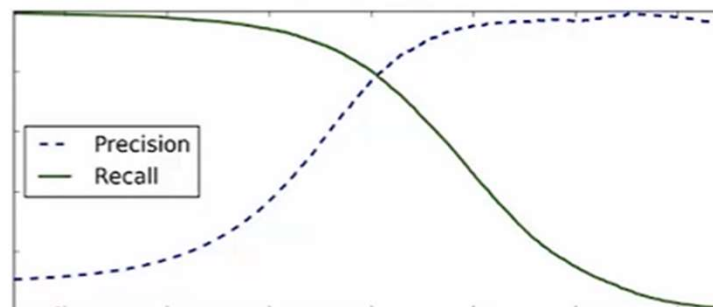


# Solution

- 66.66%
- We can again infer that accuracy was misleading

# Tradeoff between Precision and Recall

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



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