

1. Confusion Metrics

In classification problem statement we generally use to identify the wheather our class are correctly classified based on our daatsets and model.In order to get the inference about the class classification accuracy we have metrics throgh which we easily identify how much good our model in order to get the get unbiased prediction.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

- Positive class may be exactly opposite to the Negative class.
- Here,We can see the **Actual values** are on **y-axis** and **predicted values** are on **x-axis**.

Here,We can see the exact elaboration of confusion metrics.

- A **true positive** is an outcome where the model **correctly predicts the positive class**.
- Similarly, a **true negative** is an outcome where the **model correctly predicts the negative class**.

- A **false positive** is an outcome where the model **incorrectly predicts the positive class**.
- Similarly, **false negative** is an outcome where the model **incorrectly predicts the negative class**..

- **FP** :- False Positive is called **F-1 error** .It means that model is predicting the opposite class that is 0 in this case or misclassifying the classed based on our requirement.

- **FN** :- False Negative is called as **F-2 error** .It means that the model is predicted a opposite class that is 1 in this case instead of same class.

2 False Postive and True Positive Rate.

- https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Binary_Diagnostic_Tests-Single_Sample.pdf
- https://en.wikipedia.org/wiki/Sensitivity_and_specificity

- **False positive** show in terms of ratio that is **False Positive Rate**.

- **False Negative** show in terms of ration that is **False Negative Rate**.

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Kindely Note.

- Whenever we have the balance datasets that time we will definly interpret the model with the help accuracy score instead of other parameter wheather our model is good or bad.

- Whenever we have the imbalance datasets that time we will not interpret the model with accuracy score for that purpose we will consider the other parameter that is Recall and Precision.

3. Recall and Precision

- In pattern recognition, information retrieval and classification (machine learning), precision and recall are performance metrics that apply to data retrieved from a collection, corpus or sample space.
- Precision (also called positive predictive value) is the fraction of relevant instances among the retrieved instances.
- Recall (also known as sensitivity) is the fraction of relevant instances that were retrieved.
- Both precision and recall are therefore based on relevance.

- Consider a computer program for recognizing dogs (the relevant element) in a digitized collection of photographs. Upon running a query, the program identifies eight dogs in a picture containing ten cats and twelve dogs, and of the eight it identifies as dogs, five actually are dogs (true positives)
- while the other three are cats (false positives). Seven dogs were missed (false negatives), and seven cats were correctly excluded (true negatives).

- The **program's precision** is then 5/8 (true positives / selected elements) while its **recall** is 5/12 (true positives / relevant elements).

- When a search engine returns 30 pages, only 20 of which are relevant, while failing to return 40 additional relevant pages, its precision is 20/30 = 2/3, which tells us how valid the results are, while its recall is 20/60 = 1/3, which tells us how complete the results are.

Recall.

Recall is the ratio where how much we are getting extact instances from sample to the number of instances available inside the sample.

Precision.

Precision is how much close data to each other.It is nothing but closeness of instances to the target from samples that we have taken from population.

Example :-Precision refers to the closeness of two or more measurements to each other. Using the example above, if you weight a given substance five times, and get 3.2 kg for each time, then your measurement is very precise at every time.

Mathematically Expression about the Recall and Precision.

Recall.

Recall = Correctly Classified FFrom the actual data / Total actual Data

This is called as **sensitivity**

Precision.

Precision = How much our data is close to actual data in each measurement or iteration.Precision count on predicted values.How much our model predicted correctly out of all of data.

Precision = Actual Correct data/Total data that we had selected.

This is also known as **+VE prediction values**.

Accuracy

It is nothing but obtaining the desired output out all the data point,the degree to which the result of a measurement, calculation, or specification conforms to the correct value or a standard.

Key Metrics:

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

- Whenever,we have consider the all the effect of Precision and recalll both together that time we have to consider one more score that is..

F-1 Score

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

$$F_{\text{Beta}} = (1 + \beta^2) \frac{\text{Precision} \times \text{Recall}}{\beta^2 \times \text{Precision} + \text{Recall}}$$

 $\beta = 1$

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 $\beta = 1$
$$2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$= \text{Harmonic mean}$$

$$\left\{ \frac{2xy}{x+y} \right\}$$

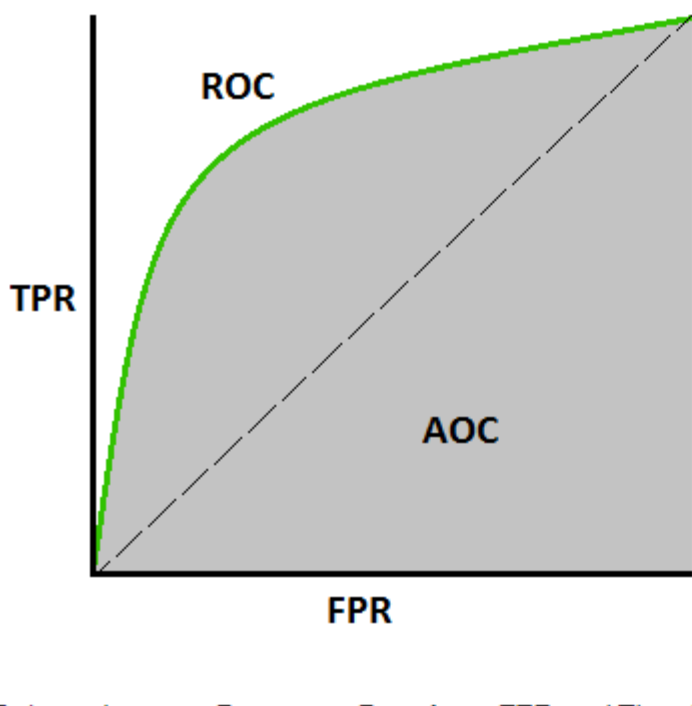
- When we will have to give the **equal importance** to the all the **FP** and **FN** classes that time we consider the
- When we will have to give the **more importance** to the the **FP** than **FN** classes that time we consider the and it ranges inbetween range.
- When we will have to give the **more importance** to the the **FN** than **FP** classes that time we consider the

Key points

- The recall is consider on the only the Actual classes.
- y-axis for the actual classes.
- Precision consider on the Predited classes outof the total.
- Predictive classes are on the x-axis.

4. ROC and AUC Curve

- **ROC is Receiver operating characteristic and AUC is Area under Curve**.
- AUC - ROC curve is a performance measurement for classification problem at various thresholds settings.
- ROC is a probability curve and AUC represents degree or measure of separability. It tells how much model is capable of distinguishing between classes.
- Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1s. By analogy,**Higher the AUC, better the model is at distinguishing between patients with disease and no disease**.
- The ROC curve is plotted with TPR against the FPR where TPR is on y-axis and FPR is on the x-axis.



Relation between Sensitivity, Specificity, FPR and Threshold.

Relation between Sensitivity, Specificity, FPR and Threshold.

Sensitivity and Specificity are inversely proportional to each other. So when we increase Sensitivity, Specificity decreases and vice versa.

Sensitivity↑, Specificity↓ and Sensitivity↓, Specificity↑

TPR↑, FPR↑ and TPR↓, FPR↓

In the AUC-ROC Curve the predicted probabilities are counted as values at the diffrent different threshold values.At each threshold values we will get the outcome.It all depends upon the bussiness intellegence which threshold they will prefer because at each threshold there is significant difference inbetween the True Positive rate and False Positive Rate.

How we can get the inference for the Multi-class classification Problem ?

actual = [0, 1, 2, 0, 1, 2, 0, 2, 2]
pred = [0, 2, 1, 0, 2, 1, 0, 0, 2]

recall $TPR = \frac{3}{3} = 1$
precis $\frac{TP}{TP+FP} = \frac{3}{4} = 0.75$

	0	1	2
0	3	0	1
1	0	0	2
2	0	2	1

actual

	0	1	2
0	3	0	1
1	0	0	2
2	0	2	1

recall = $\frac{0}{2} = 0$
preu = $\frac{0}{2} = 0$