Model Evaluation
Regression

Regression Model Evaluation Metrics

- For evaluation of regression model, following metrics are used
  - MAE
  - MSE
  - RMSE
  - R2
  - Adjusted R2

Mean Absolute Error (MAE)

- The MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction
- It measures accuracy for continuous variables
- The MAE is the average over the verification sample of the absolute values of the differences between forecast and the corresponding observation
- The MAE is a linear score which means that all the individual differences are weighted equally in the average

$$MAE = \frac{\Sigma |(y-\hat{y})|}{n}$$

Mean Squared Error (MSE)

- In statistics, the mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the error
- That is, the average squared difference between the estimated values and the actual value
- MSE is a risk function, corresponding to the expected value of the squared error loss
- The fact that MSE is almost always strictly positive (and not zero) is because of randomness or because the estimator does not account for information that could produce a more accurate estimate
- The MSE is a measure of the quality of an estimator
- As it is derived from the square of Euclidean distance, it is always a positive value with the error decreasing as the error approaches zero

$$MSE = \frac{\Sigma (y - \hat{y})^2}{n}$$

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\Sigma(y-\hat{y})^2}{n}}$$

- RMSE is the most popular evaluation metric used in regression problems
- It follows an assumption that error are unbiased and follow a normal distribution
- Here are the key points to consider on RMSE:
  - The power of 'square root' empowers this metric to show large number deviations
  - The 'squared' nature of this metric helps to deliver more robust results which prevents cancelling the positive and negative error values
- It avoids the use of absolute error values which is highly undesirable in mathematical calculations
- When we have more samples, reconstructing the error distribution using RMSE is considered to be more reliable
- RMSE is highly affected by outlier values. Hence, make sure you've removed outliers from your data set prior to using this metric.
- As compared to mean absolute error, RMSE gives higher weightage and punishes large errors

R-Squared (R2)

- We learned that when the RMSE decreases, the model's performance will improve
- But these values alone are not intuitive
- When we talk about the RMSE metrics, we do not have a benchmark to compare
- This is where we can use R-Squared metric
- In other words how good our regression model as compared to a very simple model that just predicts the mean value of target from the train set as predictions

Adjusted R-Squared

- A model performing equal to baseline would give R-Squared as 0
- Better the model, higher the r2 value
- The best model with all correct predictions would give R-Squared as 1
- However, on adding new features to the model, the R-Squared value either increases or remains the same
- R-Squared does not penalize for adding features that add no value to the model
- So an improved version over the R-Squared is the adjusted R-Squared

$$\bar{R}^2 = 1 - \left(1 - R^2\right)\left[\frac{n-1}{n-(k+1)}\right]$$

- k: number of features
- n: number of samples

Model Evaluation
Classification

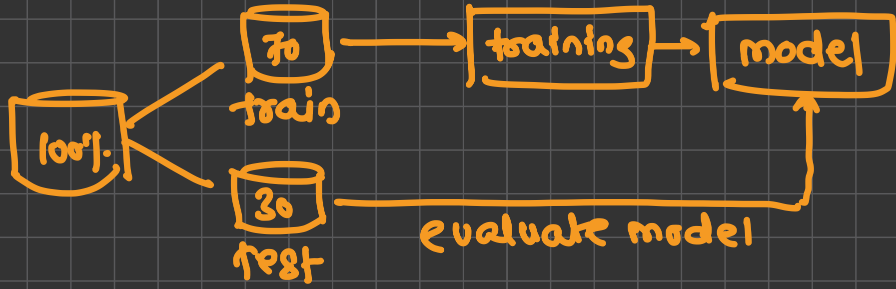
Classification Model Evaluation Metrics

- For evaluation of classification model, following metrics are used
  - Confusion Matrix
  - F1 Score
  - AuC-Roc

Confusion Matrix

- A confusion matrix is an N X N matrix, where N is the number of classes being predicted
- The confusion matrix provides more insight into not only the performance of a predictive model, but also which classes are being predicted correctly, which incorrectly, and what type of errors are being made

		Predicted Class		
		Positive	**Negative**	
Actual Class	**Positive**	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$



observed		predicted	
x	y	$\hat{y}$	
38	1	1	✓
39	0	1	✗
68	0	0	✓
92	1	0	✗
55	1	1	✓
80	0	1	✗

→

No of classes / categories / labels = 2 (0 and 1)

		predicted 1	predicted 0
observed	1	1 + 1 = 2 True positive	1 False Negative
	0	1 + 1 = 2 False positive	1 True Negative

	0	1
0	TN	FP
1	FN	TP

TP vs FP vs TN vs FN

0 No Cat	1 Cat	0 No cat	1 cat	0 no cat	1 cat	0 no cat	1 cat	1 cat
								
Cat	Cat	Cat	Cat	No Cat	No Cat	No Cat	Cat	Cat
✓ 1	✓ 1	✓ 1	✓ 1	✓ 0	✓ 0	✓ 0	1	1

	1	0	
1	TP 4	1 FN	total +ve
0	FP 2	2 TN	total -ve
	total +ve	total -ve	

actual

prediction

TP = 4
FP = 2
FN = 1
TN = 2

Accuracy

Cat	Cat	Cat	Cat	No Cat	No Cat	No Cat	Cat	Cat
✗	✓	✗	✓	✓	✗	✓	✓	✓

$$\text{accuracy} = \frac{TN + TP}{TN + TP + FN + FP} = \frac{6}{9} = 2/3 = 0.66 \approx 66\%$$

How many we got right ?

Precision

- Precision talks about how precise/accurate your model is out of those predicted positive, how many of them are actual positive
- Precision is a good measure to determine, when the costs of False Positive is high
- For instance, in email spam detection, a false positive means that an email that is non-spam (actual negative) has been identified as spam (predicted spam). The email user might lose important emails if the precision is not high for the spam detection model.

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

$$= \frac{\textit{True Positive}}{\textit{Total Predicted Positive}}$$

Precision

×		×						
Cat	Cat	Cat	Cat	No Cat	No Cat	No Cat	Cat	Cat
1	1	1	1				1	1

$TP = 4$

$FP = 2$

$$\text{precision} = \frac{TP}{TP + FP} = \frac{4}{6} = 2/3 = 66\%$$

Out of all Cat predictions how many we got right ?

Recall

- Recall actually calculates how many of the Actual Positives our model capture through labelling it as Positive (True Positive)
- Applying the same understanding, we know that Recall shall be the model metric we use to select our best model when there is a high cost associated with False Negative
- For instance, in fraud detection or sick patient detection, if a fraudulent transaction (Actual Positive) is predicted as non-fraudulent (Predicted Negative), the consequence can be very bad for the bank
- Similarly, in sick patient detection, if a sick patient (Actual Positive) goes through the test and predicted as not sick (Predicted Negative), the cost associated with False Negative will be extremely high if the sickness is contagious

$$\text{Recall} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Negative}}$$

$$= \frac{\textit{True Positive}}{\textit{Total Actual Positive}}$$

Recall

	1		1		1		1	1
								
Cat	Cat	Cat	Cat	No Cat	No Cat	No Cat	Cat	Cat
	✓		✓		✗		✓	✓

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{4}{5} = 0.8 = 80\%$$

Out of all Cat truth how many we got right ?

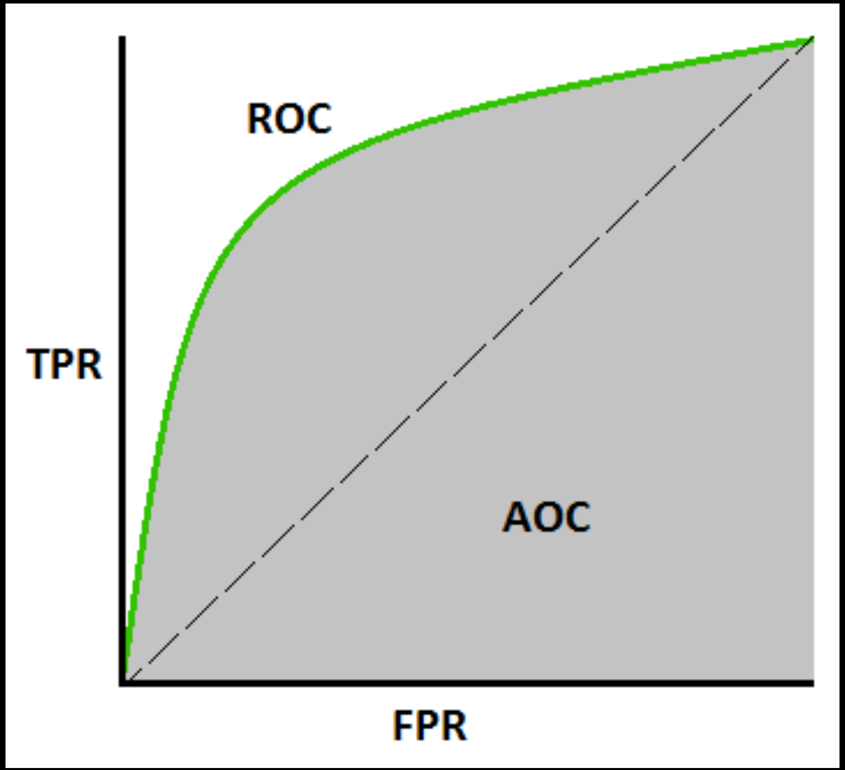
F1 Score

- The F1 score is the harmonic mean of the precision and recall
- The highest possible value of an F-score is 1.0, indicating perfect precision and recall, and the lowest possible value is 0, if either the precision or the recall is zero
- The F1 score is also known as the Sørensen–Dice coefficient or Dice similarity coefficient (DSC)

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

Receiver Operating Characteristic (ROC)

- ROC curve is a metric that assesses the model ability to distinguish between binary classes
- It is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings
- The TPR is also known as sensitivity, recall or probability of detection in machine learning
- The FPR is also known as the probability of false alarm and can be calculated as 1– specificity
- Points above the diagonal line represent good classification (better than random)
- The model performance improves if it becomes skewed towards the upper left corner



Receiver Operating Characteristic (ROC)

TPR (True Positive Rate) / Recall /Sensitivity

$$\text{TPR /Recall / Sensitivity} = \frac{TP}{TP + FN}$$

Image 3

Specificity

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Image 4

FPR

$$\text{FPR} = 1 - \text{Specificity}$$

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