AUC and ROC

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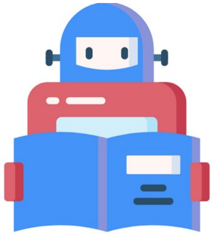


Probability of Predictions

- A machine learning classification model can be used to predict the actual class of the data point directly or predict its probability of belonging to different classes.
- The latter gives us more control over the result. We can determine our own threshold to interpret the result of the classifier.
- This is sometimes more prudent than just building a completely new model!

Probability of Predictions

- Setting different thresholds for classifying positive class for data points will inadvertently change the Sensitivity and Specificity of the model.
- And one of these thresholds will probably give a better result than the others, depending on whether we are aiming to lower the number of False Negatives or False Positives.

Probability of Predictions

ID	Actual	Prediction Probability	>0.6	>0.7	> 0.8	Metric
1	0	0.98	1	1	1	
2	1	0.67	1	0	0	
3	1	0.58	0	0	0	
4	0	0.78	1	1	0	
5	1	0.85	1	1	1	
6	0	0.86	1	1	1	
7	0	0.79	1	1	0	
8	0	0.89	1	1	1	
9	1	0.82	1	1	1	
10	0	0.86	1	1	1	
			0.75	0.5	0.5	TPR
			1	1	0.66	FPR
			0	0	0.33	TNR
			0.25	0.5	0.5	FNR

Probability of Predictions

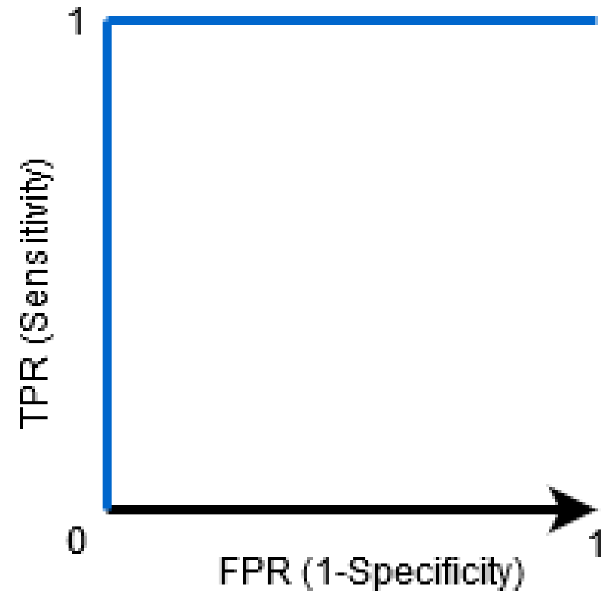
- The metrics change with the changing threshold values. We can generate different confusion matrices and compare the various metrics that we discussed in the previous section.
- But that would not be a prudent thing to do. Instead, what we can do is generate a plot between some of these metrics so that we can easily visualize which threshold is giving us a better result.
- The AUC-ROC curve solves just that problem!

AUC-ROC

- The Receiver Operator Characteristic (ROC) curve is an evaluation metric for binary classification problems.
- It is a probability curve that plots the TPR against FPR at various threshold values and essentially separates the ‘signal’ from the ‘noise’.
- The Area Under the Curve (AUC) is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve.

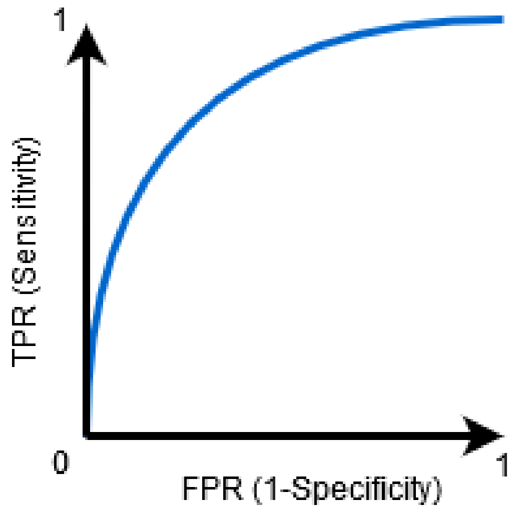
AUC-ROC

- The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes.



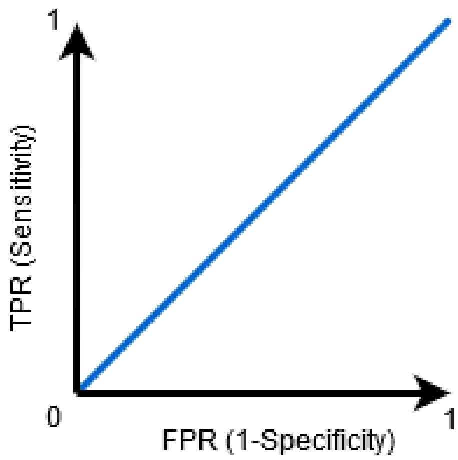
AUC-ROC

- When AUC = 1, then the classifier is able to perfectly distinguish between all the Positive and the Negative class points correctly.
- If, however, the AUC had been 0, then the classifier would be predicting all Negatives as Positives, and all Positives as Negatives.



AUC-ROC

- When 0.5<AUC<1, there is a high chance that the classifier will be able to distinguish the positive class values from the negative class values.
- This is so because the classifier is able to detect more numbers of True positives and True negatives than False negatives and False positives.



AUC-ROC

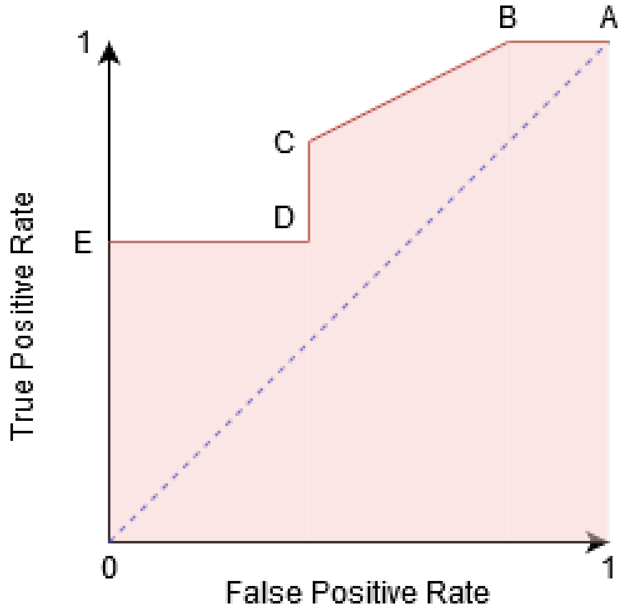
- When AUC=0.5, then the classifier is not able to distinguish between Positive and Negative class points.
- Meaning either the classifier is predicting random class or constant class for all the data points.
- So, the higher the AUC value for a classifier, the better its ability to distinguish between positive and negative classes.

AUC-ROC - how it works?

- In a ROC curve, a higher X-axis value indicates a higher number of False positives than True negatives.
- While a higher Y-axis value indicates a higher number of True positives than False negatives.
- So, the choice of the threshold depends on the ability to balance between False positives and False negatives.

AUC-ROC - how it works?

- Let's dig a bit deeper and understand how our ROC curve would look like for different threshold values and how the specificity and sensitivity would vary.



AUC-ROC - how it works?

- We can try and understand this graph by generating a confusion matrix for each point corresponding to a threshold and talk about the performance of our classifier:

		Actual	
		+ve	-ve
Predicted	+ve	5	5
	-ve	0	0

- Point A is where the Sensitivity is the highest and Specificity the lowest. This means all the Positive class points are classified correctly and all the Negative class points are classified incorrectly.

AUC-ROC - how it works?

- Point A is where the Sensitivity is the highest and Specificity the lowest.
- This means all the Positive class points are classified correctly and all the Negative class points are classified incorrectly.
- In fact, any point on the blue line corresponds to a situation where True Positive Rate is equal to False Positive Rate.

AUC-ROC - how it works?

- All points above this line correspond to the situation where the proportion of correctly classified points belonging to the Positive class is greater than the proportion of incorrectly classified points belonging to the Negative class.

		Actual	
		+ve	-ve
Predicted	+ve	5	4
	-ve	0	1

AUC-ROC - how it works?

- Although Point B has the same Sensitivity as Point A, it has a higher Specificity.
- Meaning the number of incorrectly Negative class points is lower compared to the previous threshold.
- This indicates that this threshold is better than the previous one.

AUC-ROC - how it works?

Point C

	Actual +ve	Actual -ve
Predicted +ve	4	2
Predicted -ve	1	3

TPR/Sensitivity = 0.8
FPR = 0.4
Specificity = 1-FPR = 0.6

Point D

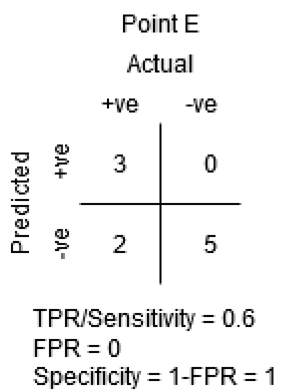
	Actual +ve	Actual -ve
Predicted +ve	3	2
Predicted -ve	2	3

TPR/Sensitivity = 0.6
FPR = 0.4
Specificity = 1-FPR = 0.6

AUC-ROC - how it works?

- Between points C and D, the Sensitivity at point C is higher than point D for the same Specificity.
- This means, for the same number of incorrectly classified Negative class points, the classifier predicted a higher number of Positive class points.
- Therefore, the threshold at point C is better than point D.
- Now, depending on how many incorrectly classified points we want to tolerate for our classifier, we would choose between point B or C for predicting whether you can defeat me in PUBG or not.

AUC-ROC - how it works?

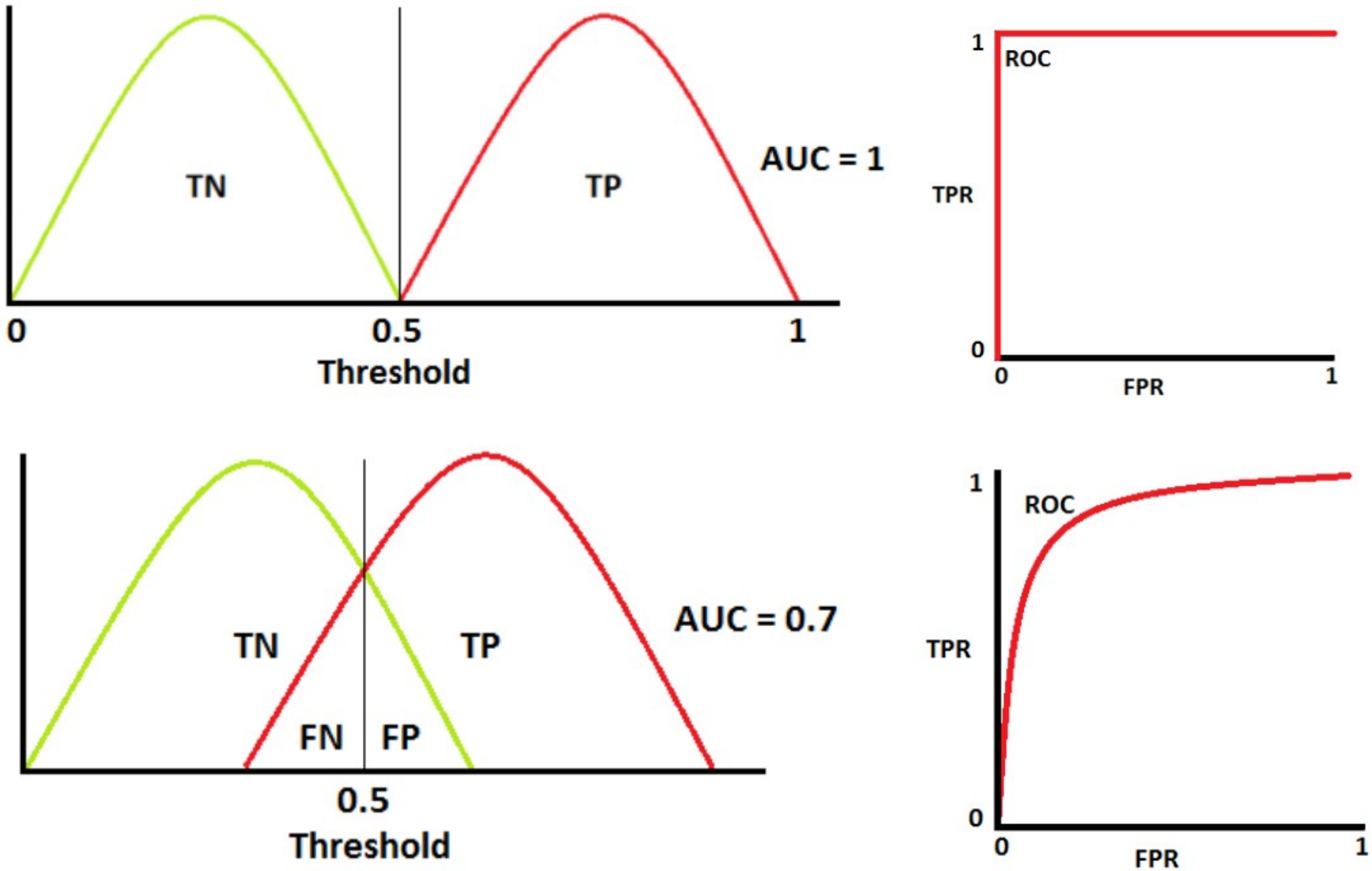


- Point E is where the Specificity becomes highest. Meaning there are no False Positives classified by the model.
- The model can correctly classify all the Negative class points! We would choose this point if our problem was to give perfect song recommendations to our users.

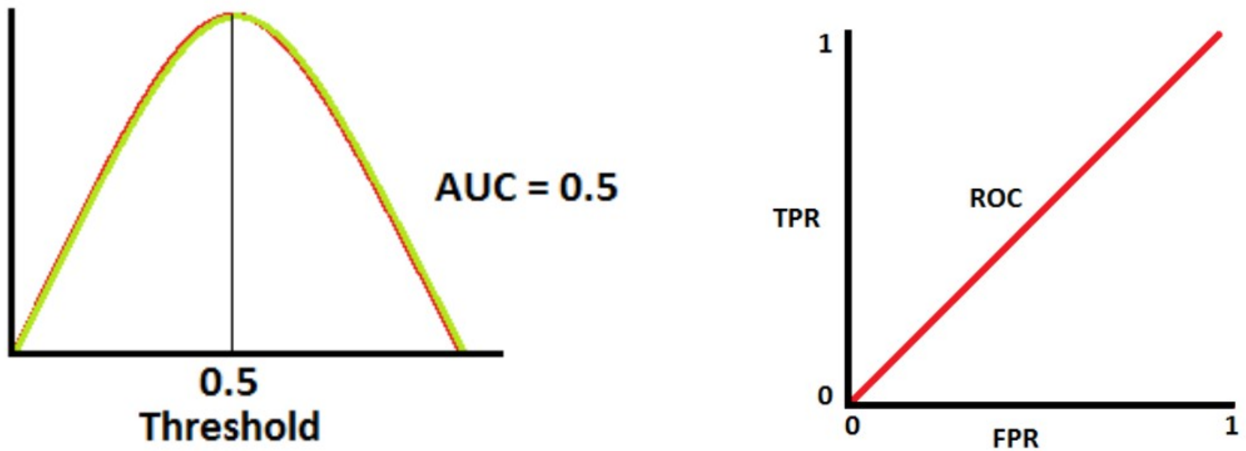
AUC-ROC - how it works?

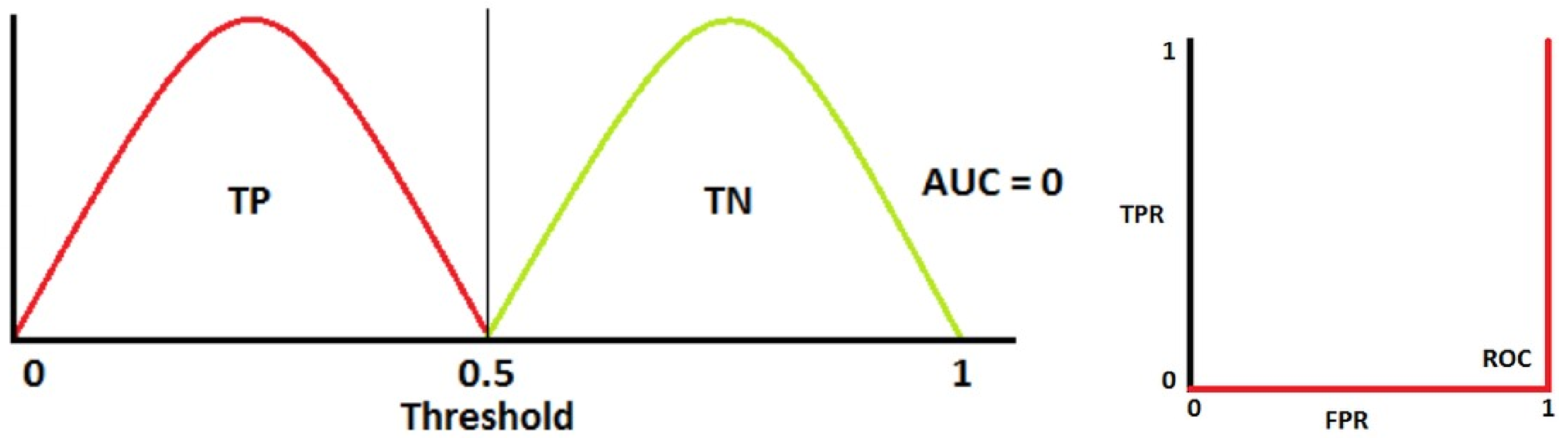
- Going by this logic, can you guess where the point corresponding to a perfect classifier would lie on the graph?
- Yes! It would be on the top-left corner of the ROC graph corresponding to the coordinate (0, 1) in the cartesian plane.
- It is here that both, the Sensitivity and Specificity, would be the highest and the classifier would correctly classify all the Positive and Negative class points.

Summary: Relations



Summary: Relations





Thank you

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