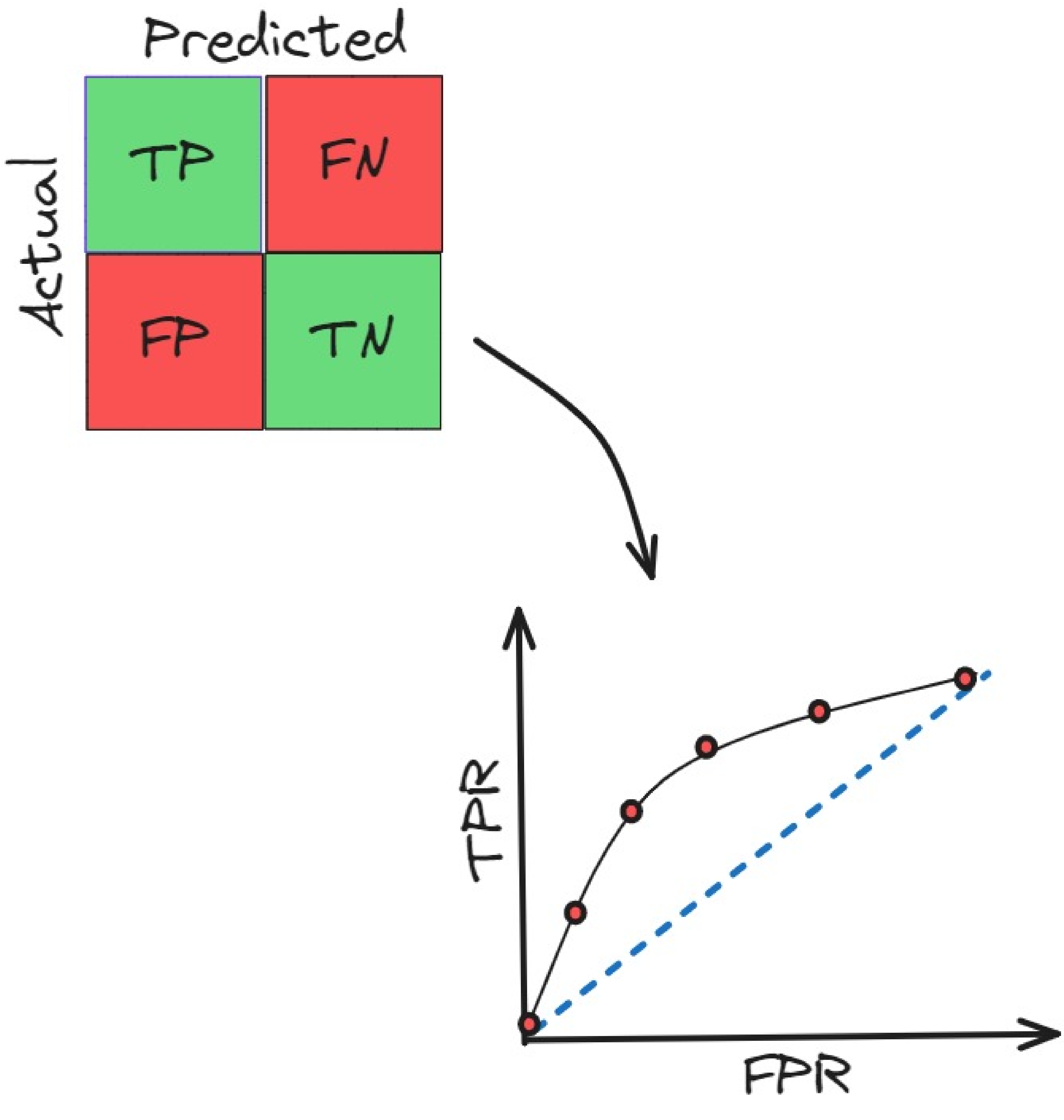
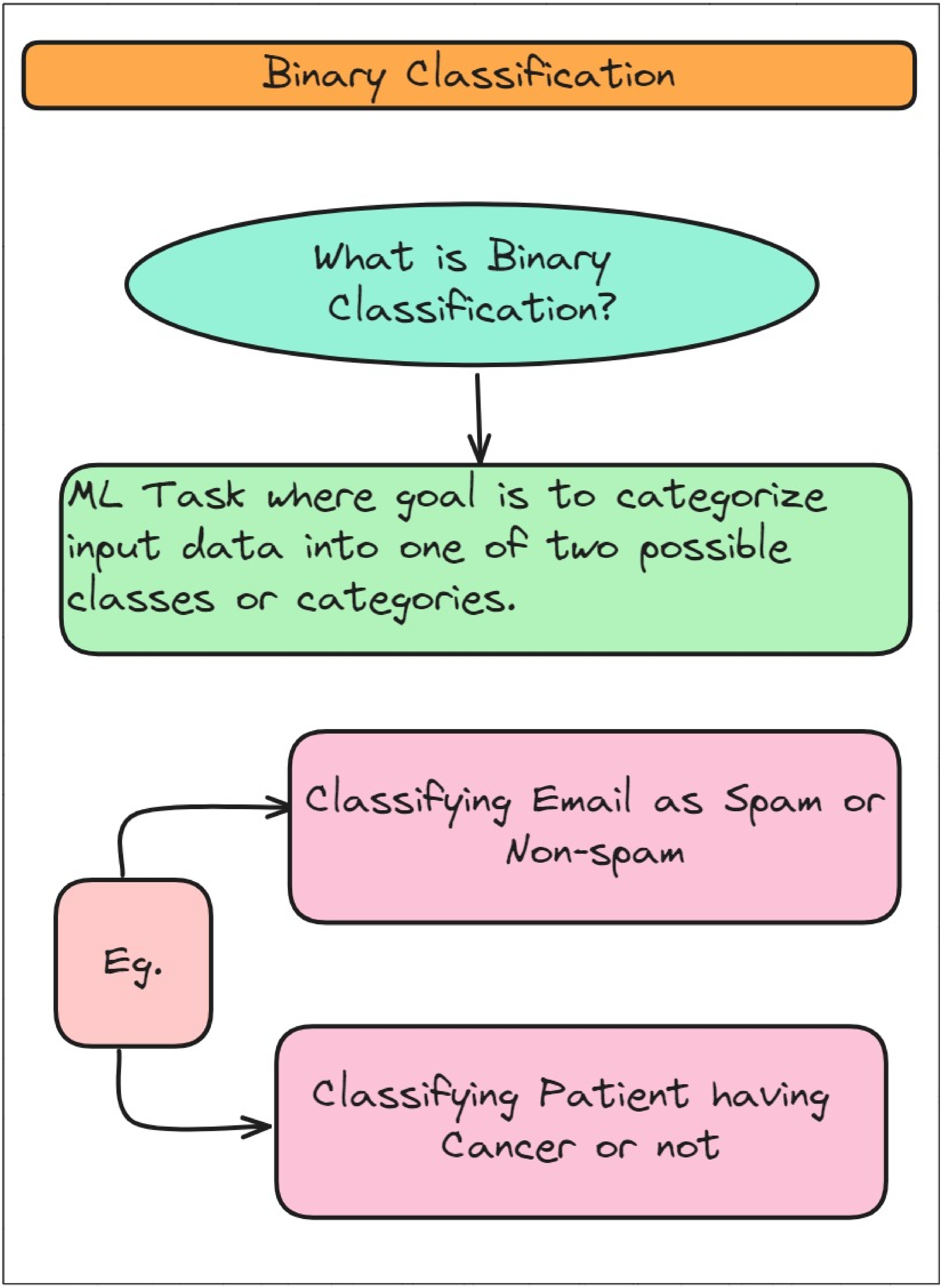
Simplifying AI

ROC Curve / AOC in Machine Learning

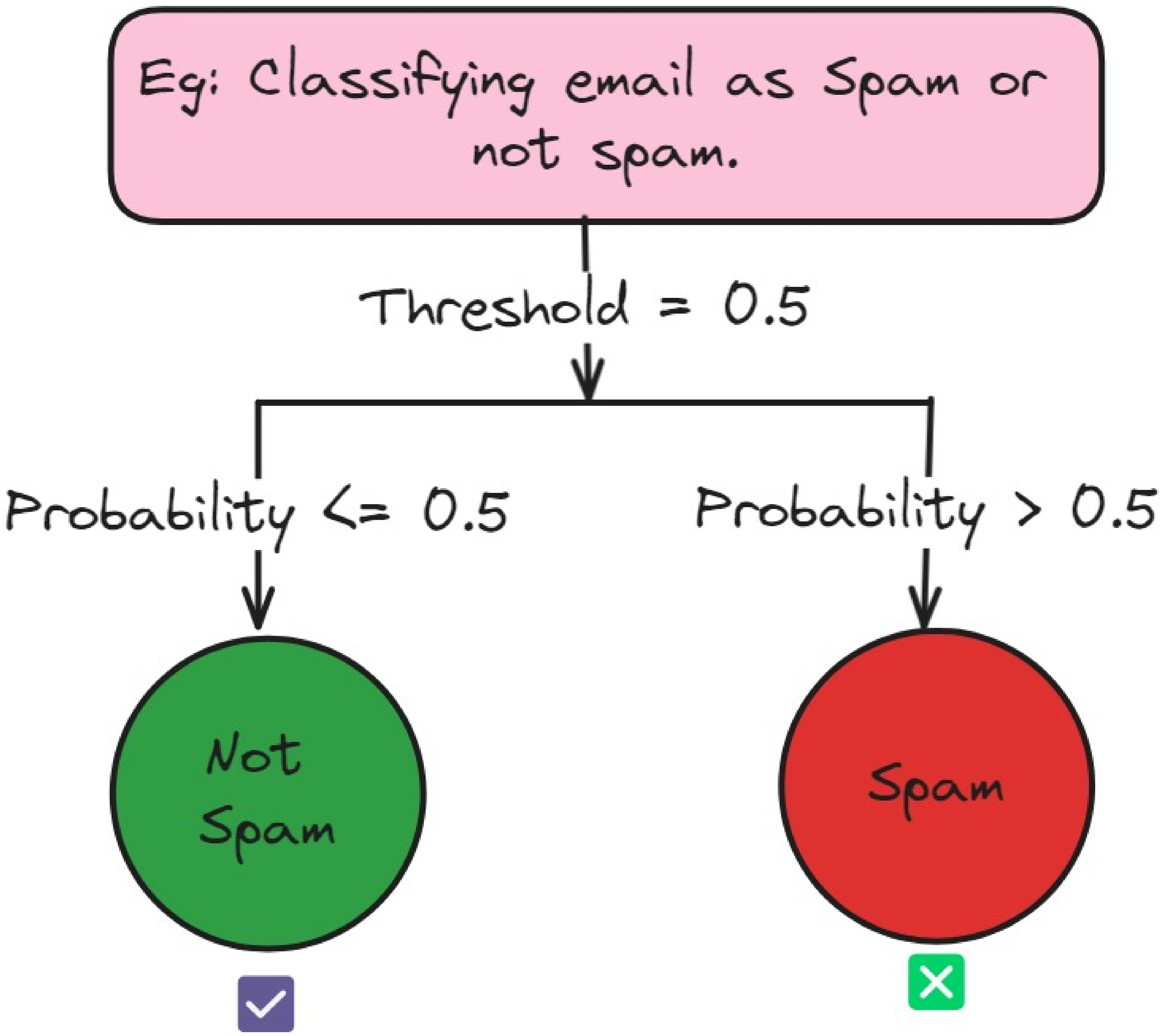


Contents


Binary Classification
What is Binary Classification?
ML Task where goal is to categorize input data into one of two possible classes or categories.
Eg.
Classifying Email as Spam or Non-spam
Classifying Patient having Cancer or not

Working of Binary Classification

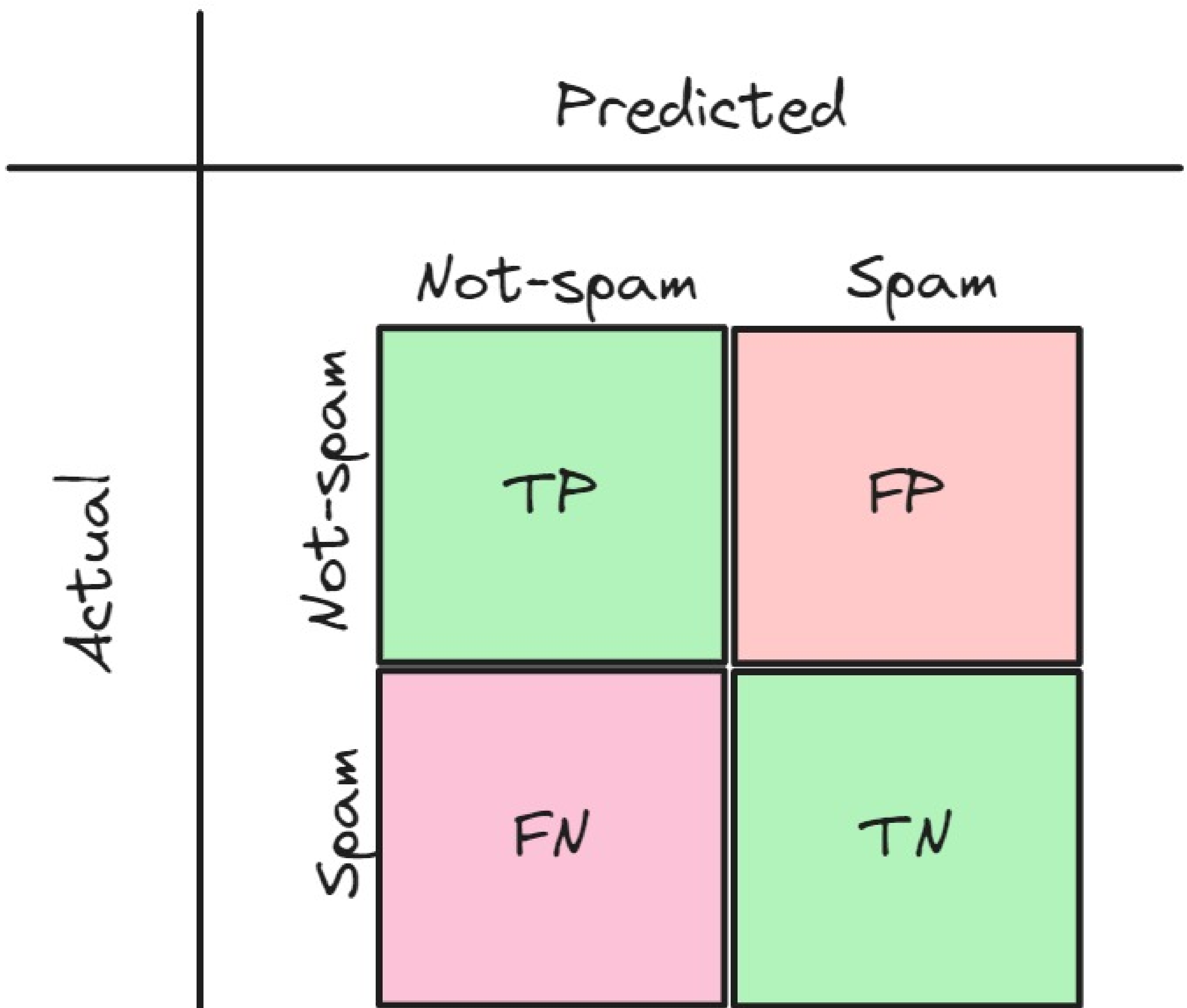
Binary Classification works by examining the features of input data & calculating the probability that it belongs to one of the two classes.



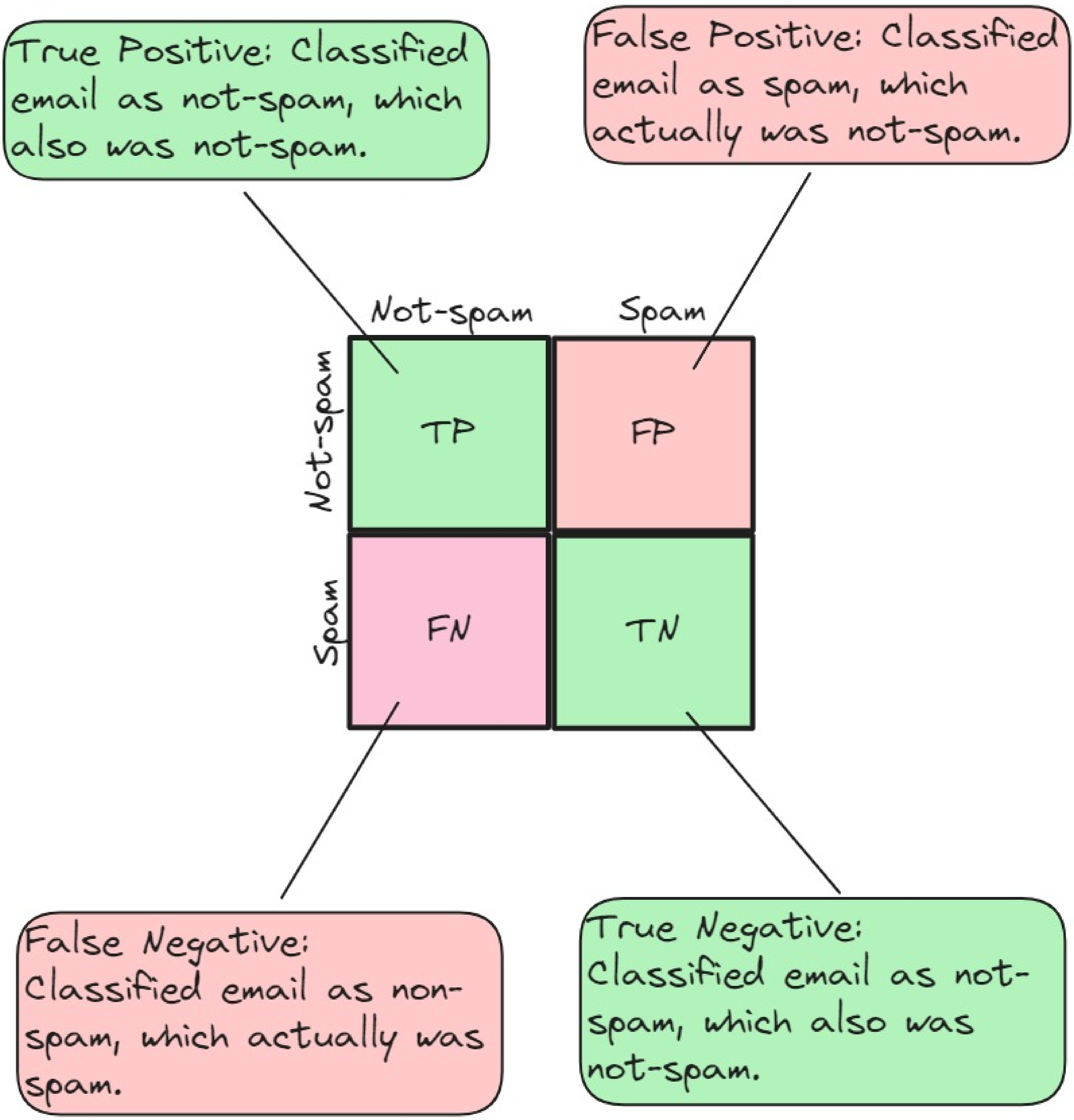
Confusion Matrix

Confusion Matrix is a table that helps to visualize the performance of classification model.

Consider the Email Spam Classifier



Explaination of Confusion Matrix



Importance of Confusion Matrix

Let's consider 2 cases

Important of False Positive

Email Spam Classifier

In this context, mistakenly labeling an email as spam when it's actually not can be highly undesirable because it might cause the recipient to miss important information. This emphasizes the importance of addressing false positives (FP), where non-spam emails are incorrectly classified as spam.

Importance of False Negative

Cancer Disease Classifier

In this context, erroneously diagnosing a person as not having cancer when they actually do can be highly problematic, potentially leading the patient to ignore symptoms and avoid seeking medical attention. This underscores the significance of addressing false negatives (FN), where individuals with the disease are incorrectly classified as not having it.

Why ROC curve?

Threshold Selection

In binary classification, the threshold value is typically set at 0.5 by default.

However, to effectively address specific issues, it's crucial to select the optimal threshold value that aligns with the problem's significance.

Examples

In an email spam classifier, if the algorithm categorizes spam based on a threshold of 0.5, it might be less significant. Yet, setting a higher threshold, say 0.7, indicates a need for stronger evidence to classify an email as non-spam. i.e. decreasing FP (False Positives)

In a cancer disease classifier, using a 0.5 probability threshold might be less significant. But lowering the threshold to, say, 0.1, signifies the need for substantial evidence to diagnose a patient with the disease. i.e. decreasing FN (False Negatives)

Selection of Threshold Value

The threshold value holds significant importance as it reflects the robustness of the algorithm's performance.

In an Email Spam Classifier, raising the threshold value reduces the false positive rate but simultaneously lowers the true negative rate.

Likewise, in a Cancer Disease Classifier, lowering the threshold value decreases the false negative rate but also diminishes the true positive rate.

Thus, selecting the optimal threshold value is determined by balancing the considerations of both true positive and true negative rates.

Selection of Threshold Value

The best threshold value is determined by maximizing the true positive rate while minimizing the false positive rate.

1. True Positive Rate (TPR)

The Ratio of True positive to the Sum of true positive & False Negative.

$$TPR = TP/(TP + FN)$$

Best TPR = 1, i.e. FN = 0
Worst TPR = 0, i.e. TP = 0

To achieve the Best Classifier TPR Should be ⬆️

2. False Positive Rate (FPR)

The Ratio of False positive to the Sum of False positive & True Negative.

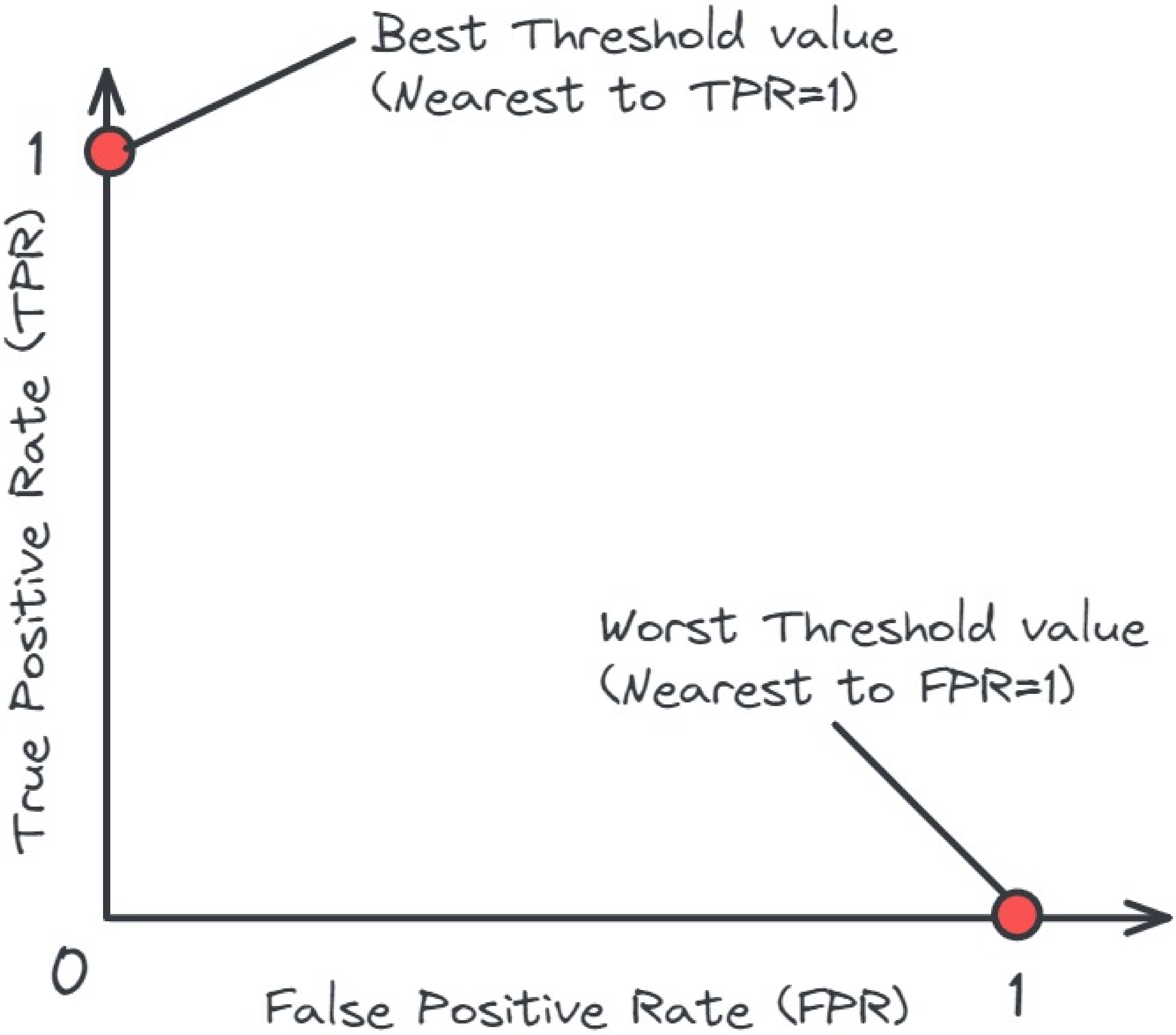
$$FPR = FP/(FP + TN)$$

Best FPR = 0, i.e. FP = 0
Worst FPR = 1, i.e. TN = 0

To achieve the Best Classifier FPR Should be ⬇️

How is ROC Curve plot?

ROC Curve is the relation between FPR vs TPR at different threshold value.

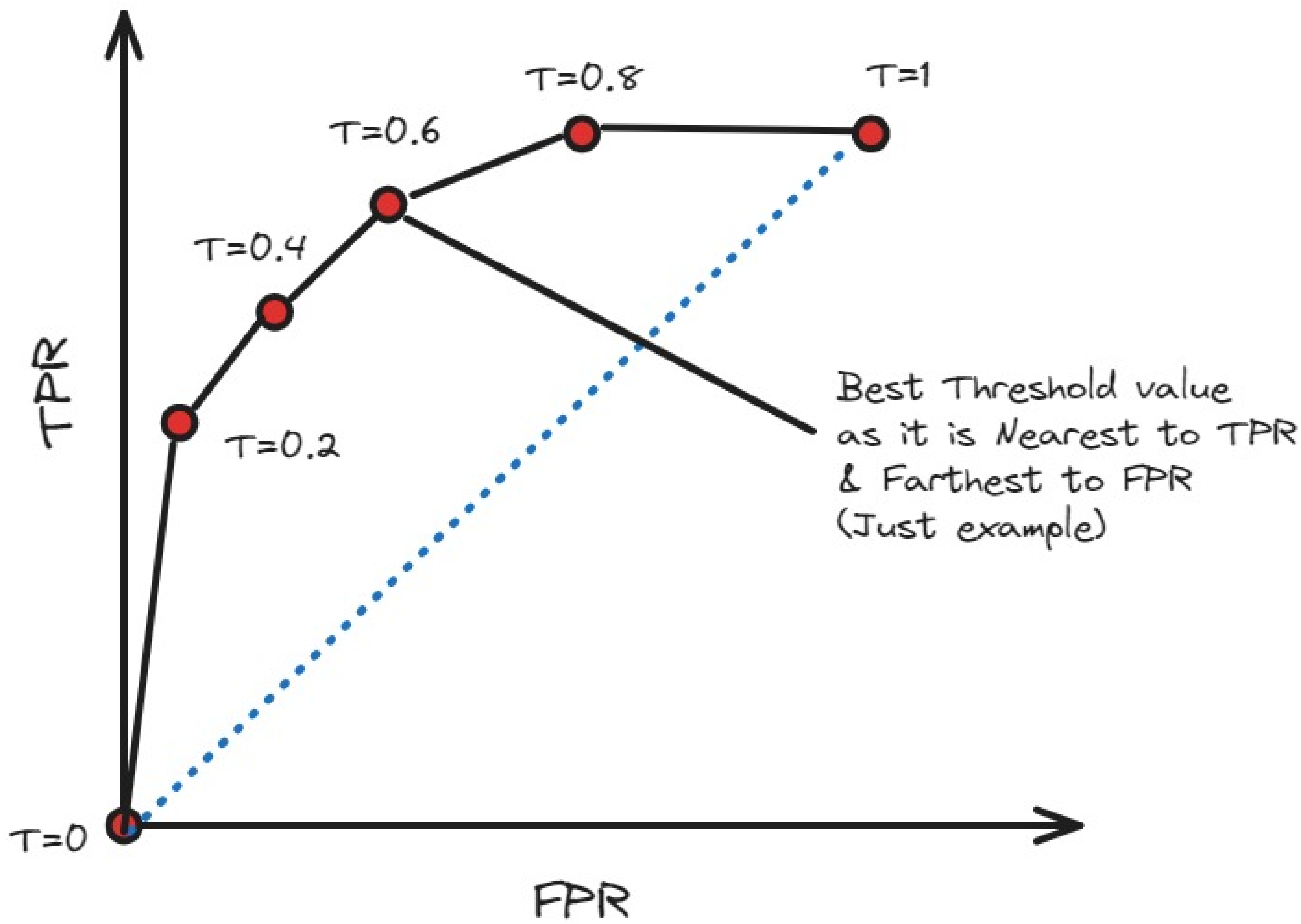


To summarize, the best threshold value for any classifier is the one closest to the True Positive Rate (TPR) and farthest from the False Positive Rate (FPR).

Plotting ROC Curve

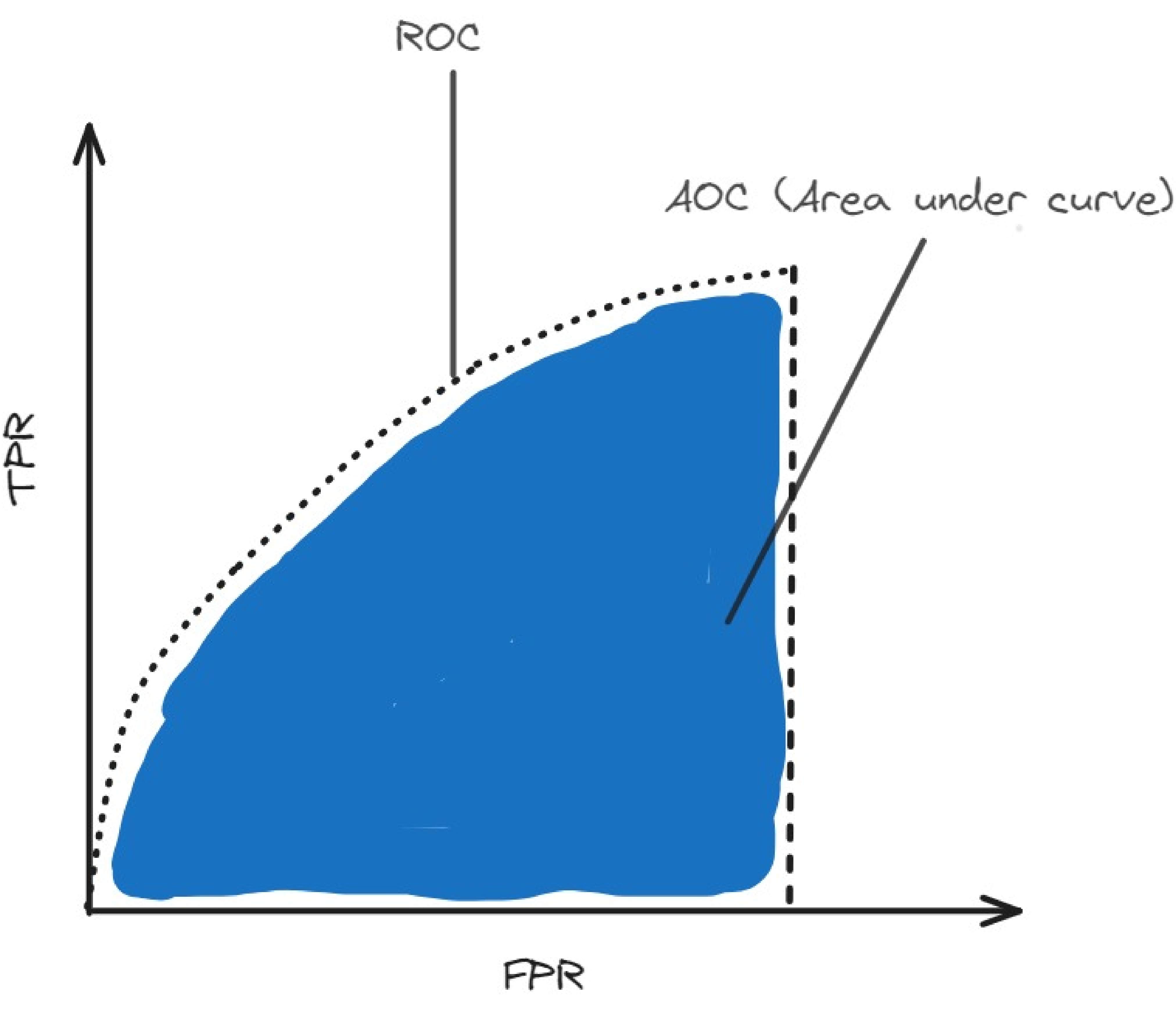
Consider following eg. for email spam classification

Threshold	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)
0	100	0	0	0
0.2	80	10	5	5
0.4	65	20	3	12
0.6	50	30	2	18
0.8	35	40	1	24
1	0	0	0	100



AUC (Area Under Curve)

AUC is the area under the ROC curve



Significance of AUC

AUC (Area under Curve) is computed by calculating area under the ROC curve. It lies between 0 to 1.

Significance

- If AUC = 1, it indicates a perfect classifier, where the model has perfect discrimination between positive & negative instances.
- If AUC = 0.5, it indicates a classifier has perform no better than random guessing.
- If AUC = 0, it indicates a classifier performs completely at random.

Follow Ayush Gandhi for more such content !!