Lecture 21 – Evaluation Metrics

- continuation of classification metrics
  - binary class classification

⇒ which model is good?
⇒ is there any algo
⇒ which model have less issue.

① accuracy ⇒ Not suitable for in-balanced dataset
(only suitable when data is balanced)

confusion matrix

TP ⇒ Model predicted +ve that were actually +ve
FP ⇒ model predicted +ve that were actually −ve
- T, F ∈ ماڈل کا صحیح ہونا / غلط ہونا
- P, N ∈ آپ کا رزلٹ ہے۔

TN : Things correctly predicted as −ve
FN :- model predicted −ve that were actually +ve

② Recall (Sensitivity) / True +ve Rate

$$\frac{\text{predicted positive}}{\text{Total actual positive}} \qquad \frac{\text{True +ve}}{\text{True +ve + False −ve}}$$

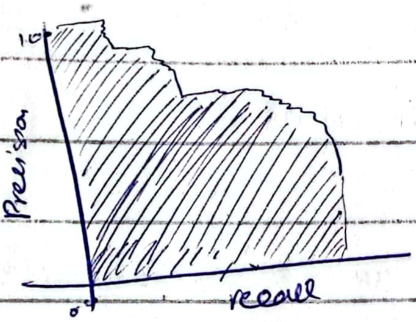
③ Precision

(measure total +ve reach among how many false +ve)

$$\text{Precision} = \frac{\text{True +ve}}{\text{True +ve} + \text{False +ve}}$$

→ <u>Precision Recall Curve</u>

(studying precision & recall collectively)



④ <u>F1- Score</u>

(weighted average of precision & recall)

harmonic mean of precision & recall

The closer it is to 1, the better model

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

TPR (True positive rate) Benefit

also called "sensitivity" or "recall"

proportion of actual +ve that the model correctly identified.

→ cost

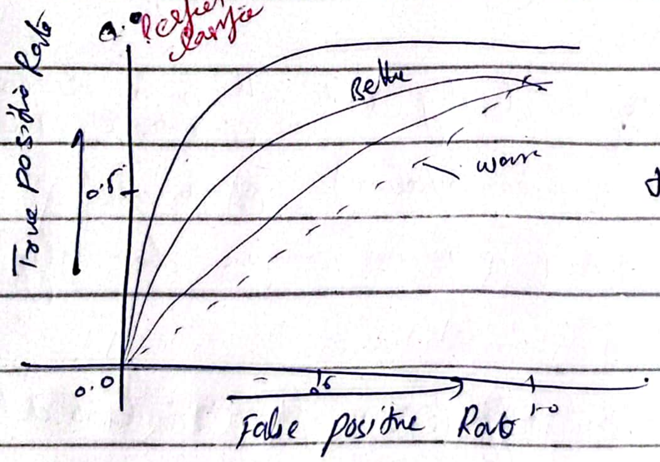
FPR (False +ve rate)

↳ measure the actual negative that the model correctly identifies.

Formula ⇒ $\dfrac{\text{False positive}}{(\text{True Negative} + \text{False positive})}$

⇒ cost-Benefit analysis

(5) AUC-ROC curve (plotting pair of TPR & FPR)



The more value close to 1 the more better it is.

Perfect classifier → FPR (cost) 0
TPR (Benefit) ⇒ 1

ROC ⇒ Receiver operator characteristic curve

AUC ⇒ Area under the curve

represents model's overall ability to distinguish classes.