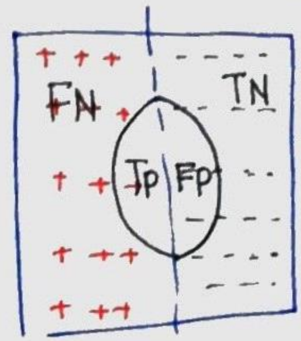
# Lecture: 44 - 2 Class Evaluation Measures.

Misclassification: $\frac{FN+FP}{N}$ Accuracy: $\frac{TN+TP}{N}$

Precision: $\frac{TP}{TP+FP}$ → How many them are really +ves




Recall : $\frac{TP}{TP+FN}$

When is this a good measure:

— (INFormation Retrival)

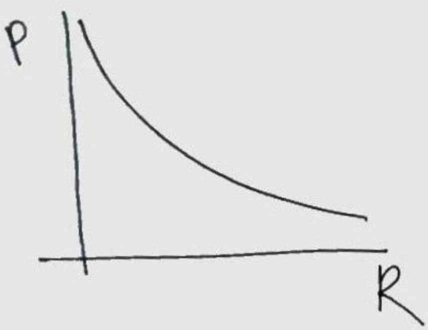
— Class Imbalance 99% accurate for class 1

1% accurate For class 0

Precision ↑ ⇒ FP ↓ ⇒ FN ↑ ⇒ Recall ↓

Trade off between precision and Recall

PR-curves




Specificity: $\frac{TN}{TN+FN}$

(Medical literature)

~~Person having negative~~

High specificity ⇒ FN → 0

⇒

$\boxed{\text{Sensitivity : } \cancel{\text{Precision}}}$

Recall

# Lecture: 45 : ROC CURVE

$$FPR = \frac{FP}{FP+TN}, \quad TPR = \frac{TP}{TP+FP}$$

Threshold decreases ⇒ More samples are classified as ⊕ ⇒ TPR↑ FPR↑

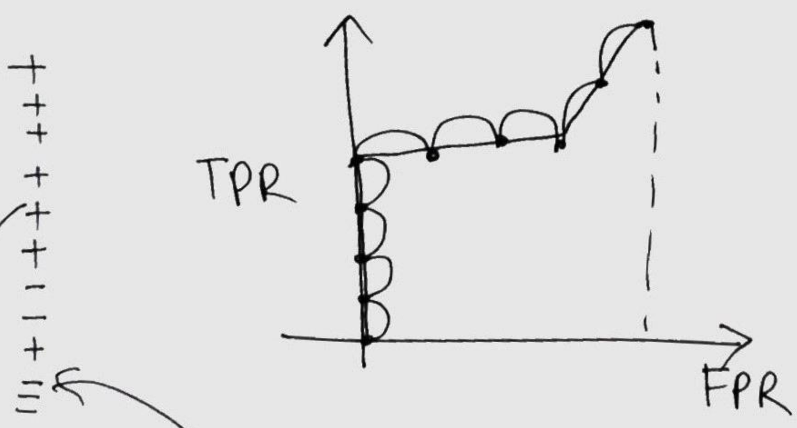
AUC Ranges from (0-1) : (For measuring model's quality)

Classifier having 100% error ⇒ AUC=0
0% error ⇒ AUC=1

→ Classification-threshold-invariant → Measures the Model's quality irrespective of threshold.

limitation of AUC.

- When it is critical to minimize one type of of classification error: For example in Email spam detection, we want minimizing false ⊕; AUC is not a good metric.




go right when you see negative data point.

go up when you see ⊕ data point.