

$$\rightarrow \text{Accuracy} = \frac{TP + TN}{\text{all}} = \frac{60 + 79}{60 + 79 + 7 + 4} = 0.93$$

\rightarrow Misclassification (incorrect ~~etc~~ predictions)

$$= \frac{4 + 7}{60 + 79 + 7 + 4} = 0.09$$

\rightarrow True Positive Rate (TPR) / Sensitivity

$$= \frac{TP}{TP + FN} = \frac{79}{79 + 7} = 0.92$$

how sensitive my class to true pos.

actual positive samples (86)

from 86 samples; how many were guessed correctly.

\rightarrow False Positive Rate (FPR) / False Alarm

$$= \frac{FP}{TN + FP} = \frac{4}{60 + 4} = 0.06$$

Actual negative samples (64)

out of actual negative classes, how many times we predicted wrong

when we divide our data, our test set / data set may get biased.

Biasness \rightarrow what if our selection of validation / test set is biased. what happens to our model during training? what happens to our estimate of accuracy?

\rightarrow True negative rate (TNR) / specificity

$$= \frac{TN}{TN + FP} = \frac{60}{60 + 4} = 0.94$$

\rightarrow False Neg rate (FNR)

$$= \frac{FN}{TP + FN} = \frac{7}{79 + 7} = 0.08$$

check: $FPR = 1 - TNR = 1 - \text{specificity}$.

* Precision, Recall

how many classes are actually +ve.

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{79}{79+4} = 0.95$$

→ Ratio of correctly predicted +ve obs to the total predicted +ve observations.

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{79}{79+7} = 0.92$$

at given +ve classes
of correctly +ve class

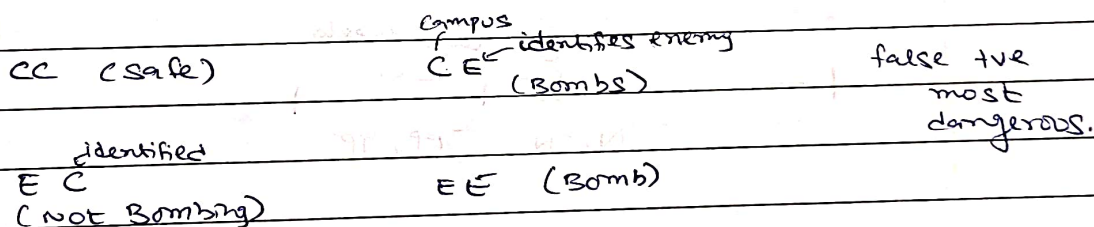
→ Ratio of correctly predicted +ve obs to the total +ve obs in the actual class.

* which rates are imp?

→ screening for a terminal disease.

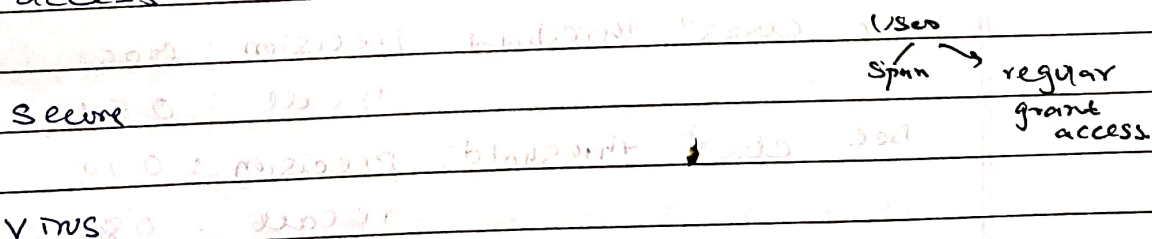
- DO NOT want to miss anyone, low false negative, high recall

→ Automatic bombing on detecting a target from a drone.



- should not hurt civilians: zero false alarms/
zero false positive.

→ Giving access to secure installation



Precision vs Recall Tradeoff

- * Extension to multi-class classifier - Conf matrix
 scikit → confusion matrix
 diagonal values → correctly classified

* Classification Threshold

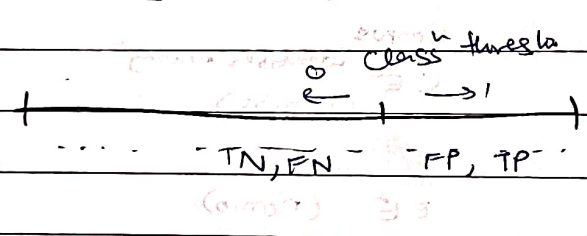
$\leq 0.5 = 0$
 $> 0.5 = 1$

→ A classification threshold (also called the decision threshold) is a value that determines how the model assigns data points to one of the 2 classes.

→ A value above the threshold indicates "class 1"
 below "class 0"

→ It is tempting to assume that the classification threshold should always be 0.5, but thresholds are problem-dependent & ∴ values that you must tune.

Classifying Diseases



$$\text{Precision} = \frac{TP}{TP + FP} = \frac{7}{7 + 2} = 0.77$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{7}{7 + 4} = 0.63$$

Inc classⁿ threshold; precision : 0.85

recall : 0.54

Del classⁿ threshold; precision : 0.70

recall : 0.81

* Confusion matrix

3x3 matrix

(0,0) \rightarrow 13 elements that belong to 0 and are actually predicted as 0

(0,2) \rightarrow 0 elements that were actually labelled as 0 were predicted as 2.

diagonal elements \rightarrow correctly classified

True +ve : Samples that belong to +ve
(correctly classified)

True -ve : Belong to -ve class
act

False +ve : Belongs to +ve class

False -ve : wrongly predicted as -ve
but were actually +ve

Accuracy : correctly classified
positive class

Precision : all elements correctly predicted as +ve
only 5 samples corrected as -ve

* Area Under the Curve

- Area under curve measures the entire 2-D area underneath the entire ROC curve (calculus) from (0,0) to (1,1).
- An excellent model has AUC near to ~~the~~ 1; which means it has a good measure of separability.
- A poor model has an AUC near 0 which means it has the worst measure of separability.

Some illustrations.

