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

→ Misclassification (incorrect ~~et~~ predictions)

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

→ True Positive Rate (TPR) / Sensitivity

$= \frac{TP}{TP+FN} = \frac{79}{79+7} = 0.92$ how sensitive my class to true +ve.

actual positive samples (86)

From 86 samples; how many were guessed correctly.

→ 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 wr...

test set for final pred

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

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

→ True negative rate (TNR) / specificity

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

→ False Neg rate (FNR)

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

check: FPR = 1 − TNR = 1 − 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.

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

~~out~~ 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.

CC (safe)	CE (Campus, identifies enemy) (Bombs) — false +ve most dangerous.
EC (identified) (Not Bombing)	EE (Bomb)

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

→ Giving access to secure installation

Users: Spam → regular grant access

Secure

Virus

Precision vs Recall Tradeoff:

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

* Classification Threshold
  <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.

classⁿ thresh
0 ← | → 1
... TN, FN   FP, TP

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

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

Inc classⁿ threshold; precision : 0.85
recall : 0.54

Dec classⁿ threshold; precision : 0.70
recall : 0.81

* ## Confusion matrix

3 x 3 matrix

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

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

diagonal elements → correctly classified

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

True -ve : Belong to -ve class act

False +ve : Belongs to +ve cla

False -ve : wrongly printed 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 seperability.
→ A poor model has an AUC near 0 which means it has the worst measure of seperability.

Some illustrations.