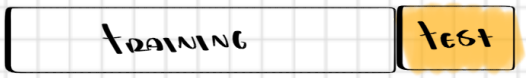
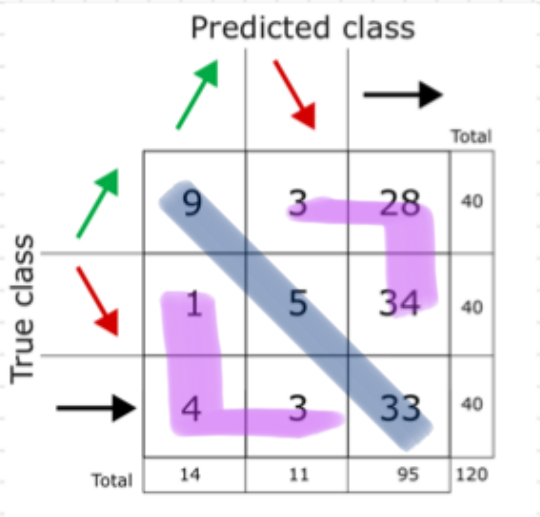
Lecture 9 - 24/09/24

- Is my classifier good?
  - Introduced common goal → minimize misclassification rate!
  - When introducing loss → not all errors are equal!
  - ∀ classification we have in 🌍 a specific ideal performance & errors to avoid!
  - Given that ≠ tasks require ≠ metrics → we have lots of performance metrics

- No matter which performance metric you choose:
  - metric is evaluated on test set



- At the ♡ of performance metrics:



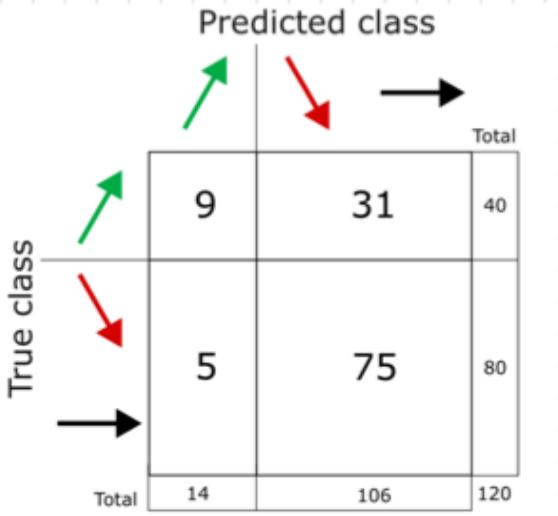
→ Confusion Matrix!

→ Accuracy: (9 + 5 + 33) / 120

→ misclassification rate: (1 + 4 + 3 + 3 + 28 + 34) / 120

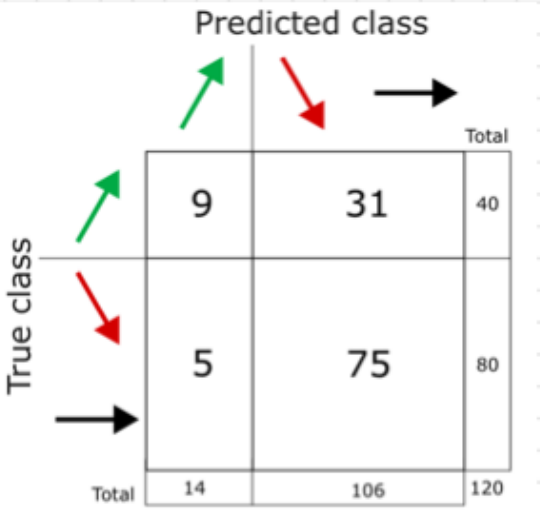
- Precision & Recall
  - How precise are its predictions?
  - Precision → # of true positives out of predicted positives
    - For a stock classified as increasing, what is the prob that it is actually increasing?
  - How good is it at detecting cases?
  - Recall → # of true positives out of positive cases
    - Given an increasing stock, what's the prob of detecting it?

Precision



$$\text{Precision} = \frac{9}{9+5} \approx 0.64$$

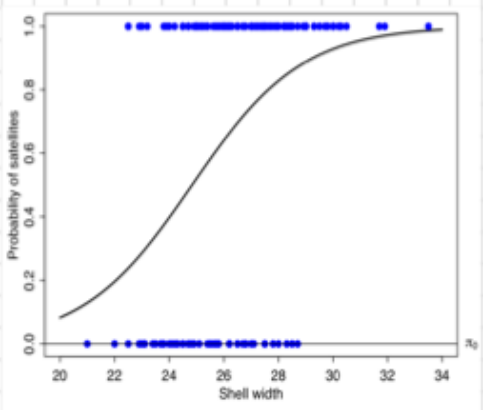
Recall



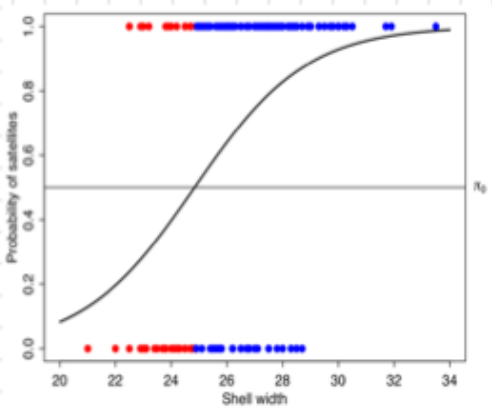
$$\text{Precision} = \frac{9}{40} \approx 0.225$$

- Ideally we want our model to have:
  - High Precision
  - High Recall
- Important is to know that:
  - Our choices impact the confusion matrix!
  - The above means that we impact precision & recall

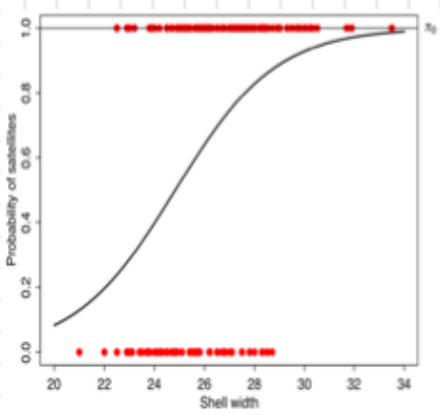
* We choose decision threshold which impacts confusion matrix!



	$\hat{Y}=0$	$\hat{Y}=1$	Total
$Y=1$	0	111	111
$Y=0$	0	62	62
Total	0	173	173



	$\hat{Y}=0$	$\hat{Y}=1$	Total
$Y=1$	16	95	111
$Y=0$	27	35	62
Total	43	130	173

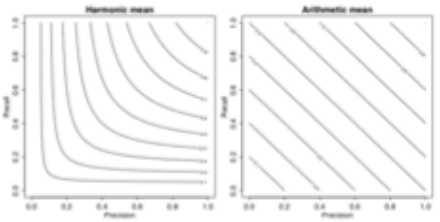


	$\hat{Y}=0$	$\hat{Y}=1$	Total
$Y=1$	111	0	111
$Y=0$	62	0	62
Total	173	0	173

F1-Score : Harmonic mean of Precision & Recall

$$F_1 = \frac{2}{\frac{1}{P} + \frac{1}{R}} = 2\frac{P \times R}{P + R}$$

The harmonic mean of $x_1, \ldots, x_n$ is $\left(\frac{1}{n}\sum_{i=1}^{n} x_i^{-1}\right)^{-1}$



Punishes single low numbers more than the arithmetic mean does.

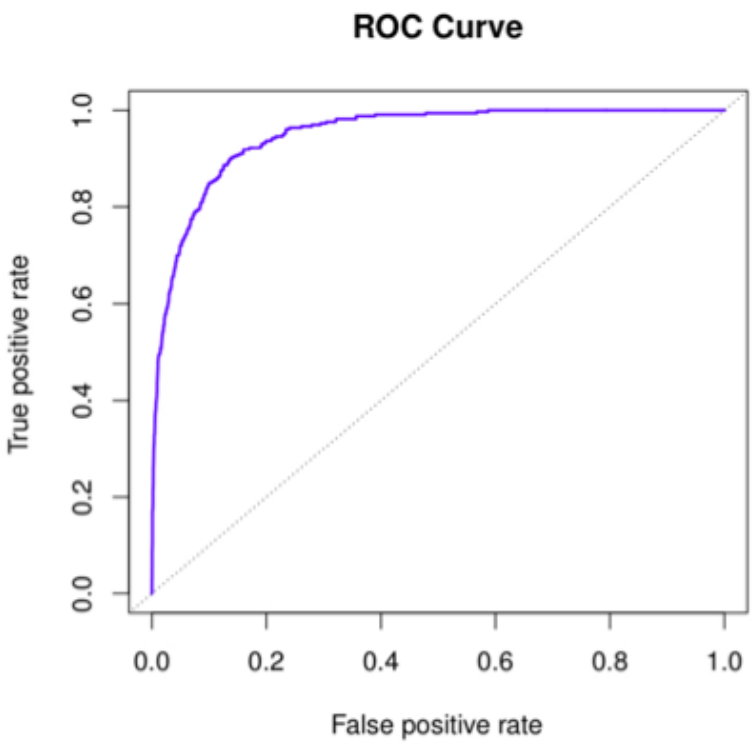
To get a high F1-score, high recall & precision is needed!!

For K classes ∃ K sets of precision & recall & K F1-scores

ROC curve (binary classification)

- The ROC curve plots:

  True positive rate (TP out of positives) VS False positive rate (FP out of negatives)



This is the param curve.

One point = one classifier

One curve = set of classifiers

Follow line from bottom left = change thr.

Ideal classifier: top left corner

Ideal families: have a huge AUC