Results : confusion matrix

confusion matrix.

```
> confusionMatrix(crashTest_1_TEST$LogisPred,crashTest_1_TEST$CarType)
Confusion Matrix and Statistics

           Reference
Prediction  Hatchback SUV
  Hatchback        10   1
  SUV               0   9

               Accuracy : 0.95
                 95% CI : (0.7513, 0.9987)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : 2.003e-05

                  Kappa : 0.9
 Mcnemar's Test P-Value : 1

            Sensitivity : 1.0000
            Specificity : 0.9000
         Pos Pred Value : 0.9091
         Neg Pred Value : 1.0000
             Prevalence : 0.5000
         Detection Rate : 0.5000
   Detection Prevalence : 0.5500
      Balanced Accuracy : 0.9500

       'Positive' Class : Hatchback
```

Confusion matrix

		True condition	
	Total population	Condition positive	Condition negative
Predicted condition	Predicted condition positive	**True positive**, Power	**False positive**, Type I error
	Predicted condition negative	**False negative**, Type II error	**True negative**

Source: https://en.wikipedia.org/wiki/Receiver_operating_characteristic

Measures of performance

- Terminology
  - $TP \rightarrow$ true positives, $TN \rightarrow$ true negatives,
  - $FP \rightarrow$ false positives, $FN \rightarrow$ false negatives

$$N = TP + TN + FP + FN$$

  - TP – Correct identification of positive labels
  - TN – Correct identification of negative labels
  - FP – Incorrect identification of positive labels
  - FN – Incorrect identification of negative labels

Measures of performance

- Accuracy: Overall effectiveness of a classifier
  - $\mathrm{A} = \frac{TP+TN}{N}$
  - Maximum value that accuracy can take is 1
  - This happens when the classifier exactly classifies two groups (i.e, $FP = 0$ and $FN = 0$)
- Remember
  - Total number of true positive labels = TP+FN
- Similarly
  - Total number of true negative labels = TN+FP

Measures of performance

- Sensitivity: Effectiveness of a classifier to identify positive labels
  - $S_e = \frac{TP}{TP + FN}$
- Specificity: Effectiveness of a classifier to identify negative labels
  - $S_p = \frac{TN}{FP + TN}$
- Both S_e and S_p lie between $0 \; and \; 1$, 1 is an ideal value for each of them
- Balanced accuracy
  - $BA = (sensitivity + specificity)/2$

Measures of performance

- Prevalence: How often does the yes condition actually occur in our sample

$$P = \frac{TP + FN}{N}$$

- Positive predictive value: Proportion of correct results in labels identified as positive
    - $PPV = \frac{(sensitivity * prevalence)}{((sensitivity*prevalence) + ((1-specificity)*(1-prevalence)))}$
- Negative prediction value: Proportion of correct results in labels identified as negative
    - $NPV = \frac{specificity * (1-prevalence)}{(((1-sensitivity)*prevalence) + ((specificity)*(1-prevalence)))}$

Measures of performance

- Detection rate:
  - $DR = \frac{TP}{N}$
- Detection prevalence: prevalence of predicted events
  - $DP = \frac{TP+FP}{N}$
- The Kappa statistic (or value) is a metric that compares an **observed accuracy** with an **expected accuracy** (random chance)
- Kappa = $\frac{observed\ accuracy - expected\ accuracy}{1 - expected\ accuracy}$

Measures of performance

- Observed accuracy
  - $OA = \frac{a+d}{N}$
- Expected accuracy
  - $EA = \frac{(a+c)(a+b) + (b+d)(c+d)}{N}$
- Kappa $= \dfrac{\frac{(a+d)}{N} - \left(\frac{(a+c)(a+b) + (b+d)(c+d)}{N}\right)}{\left(1 - \left(\frac{(a+c)(a+b) + (b+d)(c+d)}{N}\right)\right)}$
  - Where a, b, c and d are TP, FP, FN and TN respectively

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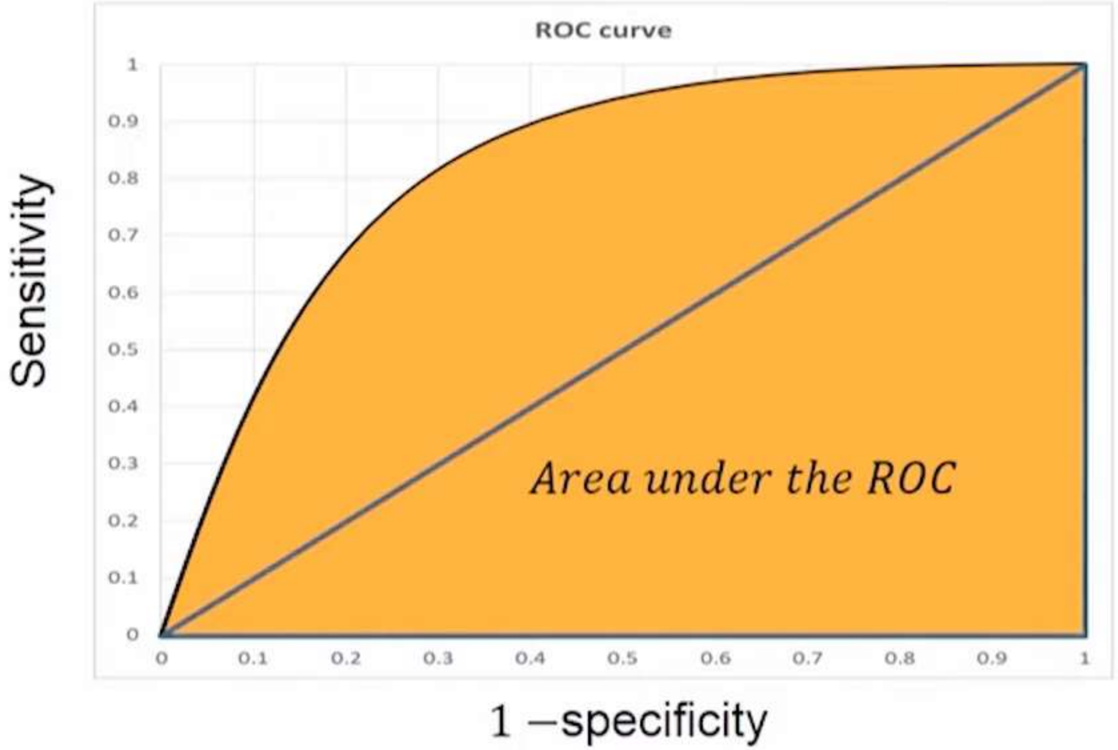
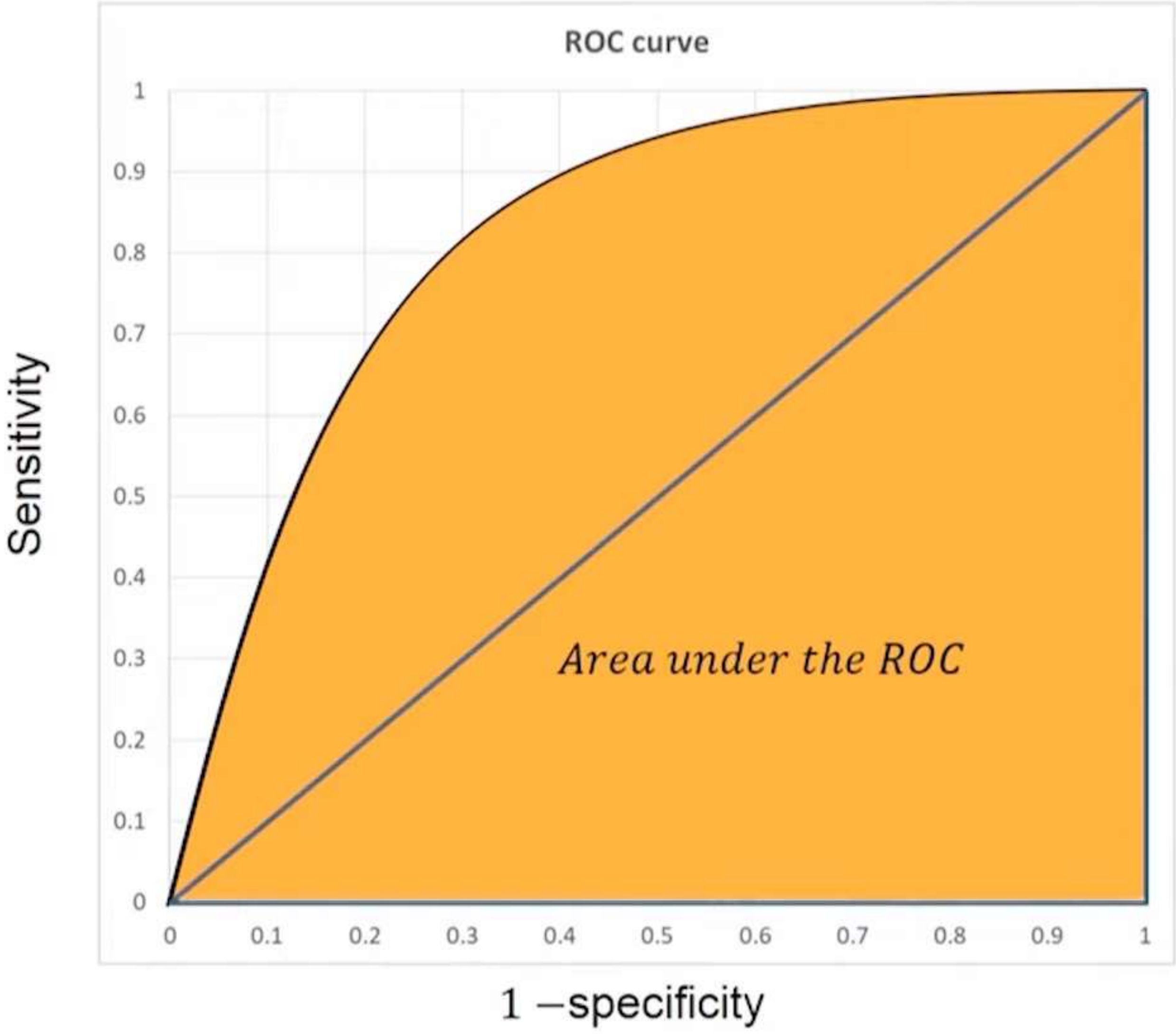
ROC

- ROC –An acronym for Receiver Operating Characteristics
- Originally developed and used in signal detection theory
- ROC graph:
  - Sensitivity as a function of specificity
  - sensitivity (Y-axis) and 1 −specificity (X-axis)



ROC

- ROC can be used to
  - See the classifier performance at different threshold levels (from 0 to 1)
  - AUC- Area under the ROC
    - An area of 1 represents a perfect test; an area of 0.5 represents a worthless model.
    - $.90 - 1$ = excellent
    - $.80 - .90$ = good
    - $.70 - .80$ = fair
    - $.60 - .70$ = poor
  - AUC < 0.5, check whether your labels are marked in opposite



ROC

- ROC can be used to
  - Compare different classifiers at one threshold or overall threshold levels
  - Performance
  - Model 3 > Model 2 > Model 1