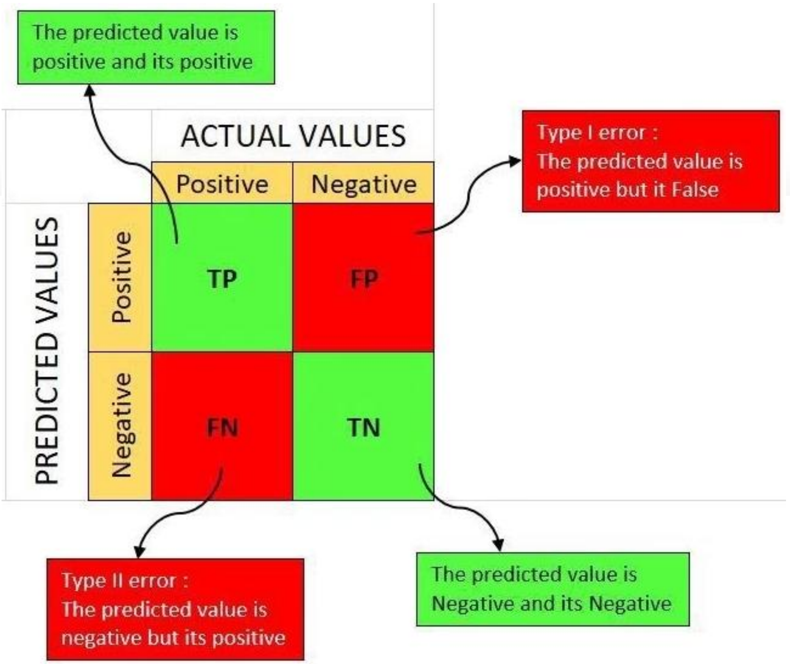
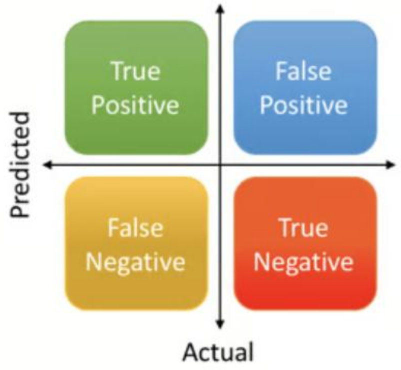
Metrics (Classification)



$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$



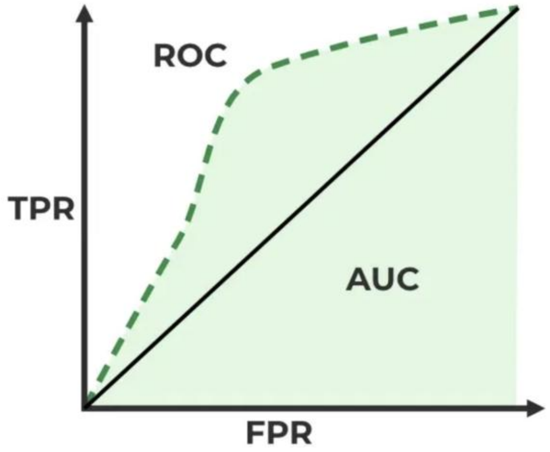
F1 Score

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Metrics (Classification)

- ROC Curve : It plots TPR vs. FPR at different thresholds. It represents the trade-off between the sensitivity and specificity of a classifier

- AUC (Area Under the Curve): measures the area under the ROC curve
  - The area under the ROC curve (AUC) represents the probability that the model, if given a randomly chosen positive and negative example, will rank the positive higher than the negative
  - A higher AUC value indicates better model performance as it suggests a greater ability to distinguish between classes
  - An AUC value of 1.0 indicates perfect performance while 0.5 suggests it is random guessing



Metrics (Prediction)

- Mean Squared Error (MSE) $MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
- Root Mean Squared Error (RMSE) $RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
- Mean Absolute Error (MAE) $MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$
- Mean Absolute Percentage Error (MAPE) $MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$
- Mean Absolute Scaled Error (MASE) $MASE = \frac{\frac{1}{h}\sum_{t=n+1}^{n+h}|y_t - \hat{y}_t|}{\frac{1}{n-1}\sum_{t=2}^{n}|y_t - y_{t-1}|}$

- From a geometric perspective, RMSE and MAE represent mean forms of the L2 and L1 norms, which correspond to the Euclidean distance and the Manhattan distance, respectively