Model evaluation techniques

1. Accuracy: The ratio of correctly predicted instances to the total instances in the dataset.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

2. Precision: The ratio of true positive predictions to the total positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

3. Recall (Sensitivity): The ratio of true positive predictions to the total actual positive instances.

$$Recall = \frac{TP}{TP + FN}$$

4. F1 Score: The harmonic mean of precision and recall, providing a balanced measure of a model's performance.

$$F1-score = \frac{2 * Precision * Recall}{Precision + Recall}$$

5. Specificity: The ratio of true negative predictions to the total actual negative instances.

$$\textbf{Specificity} = \frac{\textbf{True Negatives}}{\textbf{True Negatives} + \textbf{False Positives}}$$

6. ROC Curve (Receiver Operating Characteristic): A graphical representation of a classifier's performance at various thresholds.

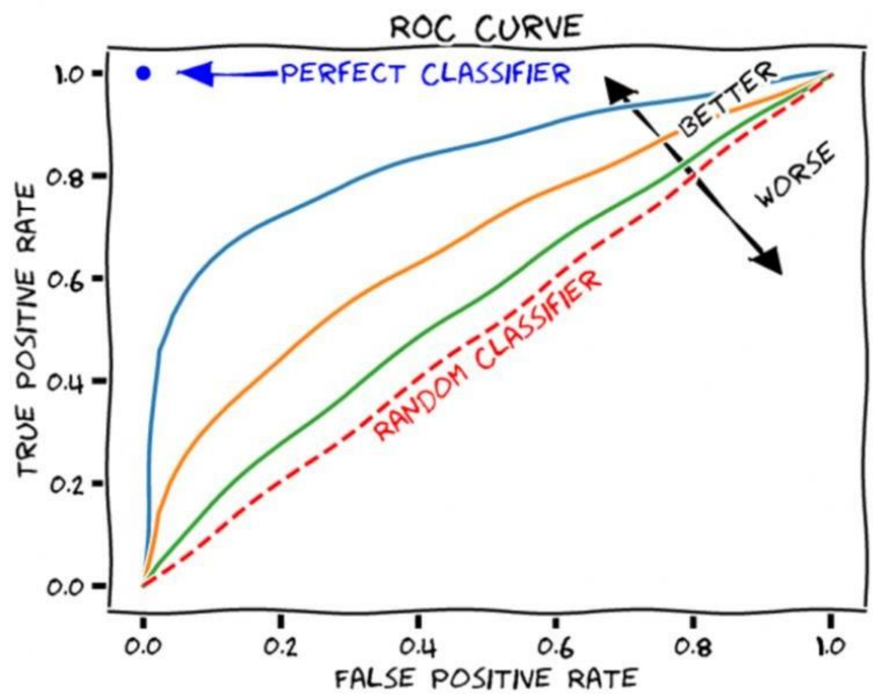
7. AUC-ROC (Area Under the ROC Curve): A metric that quantifies the overall performance of a binary classifier.

The True Positive Rate or Recall is defined as

$$TPR = \frac{TP}{TP + FN}$$

The False Positive Rate is defined as

$$FPR = \frac{FP}{FP + TN}$$



8. Confusion Matrix: A table that describes the performance of a classification model by comparing predicted and actual class labels.

	Class 1 Predicted	Class 2 Predicted
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

9. Mean Absolute Error (MAE): The average of absolute errors between predicted and actual values in regression tasks.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

10. Mean Squared Error (MSE): The average of squared errors between predicted and actual values in regression tasks.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

11. Root Mean Squared Error (RMSE): The square root of the MSE, providing a more interpretable error measure.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}}$$

12. R-squared (R^2): A measure of how well a regression model fits the data, indicating the proportion of variance explained.

13. Log-Loss: A measure of the accuracy of a probabilistic classifier's predictions.

14. Cohen's Kappa: A statistic that measures inter-rater agreement for categorical items.

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)}$$

15. Matthew's Correlation Coefficient (MCC): A measure of the quality of binary classifications.

A

		Predicted: Control	Predicted: Disease
Actual	Control	TN	FP
	Disease	FN	TP

B

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

16. Gini Coefficient: A metric for evaluating the inequality in a distribution.

17. Brier Score: A metric for assessing the accuracy of probabilistic forecasts.

18. Silhouette Score: A measure of cluster quality, indicating how similar an object is to its own cluster compared to others.

$$silhouettescore = (p - q)/max(p, q)$$

p = mean distance to the points in the nearest cluster

q = mean intra-cluster distance to all the points.

19. Adjusted Rand Index (ARI): A measure of the similarity between two data clusterings.

20. Cross-Validation: A technique for assessing a model's performance by splitting data into multiple subsets, training and testing on different subsets.

Performance Metrics For Classification and Regression

In [1]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Classification Metrics
actual_labels = [0, 1, 1, 0, 1, 0, 1, 0, 1, 1]
predicted_labels = [0, 1, 0, 1, 1, 0, 1, 0, 0, 1]


accuracy = accuracy_score(actual_labels, predicted_labels)
precision = precision_score(actual_labels, predicted_labels)
recall = recall_score(actual_labels, predicted_labels)
f1 = f1_score(actual_labels, predicted_labels)
conf_matrix = confusion_matrix(actual_labels, predicted_labels)


print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1)
print("Confusion Matrix:\n", conf_matrix)
```

```
Accuracy: 0.7
Precision: 0.8
Recall: 0.6666666666666666
F1-Score: 0.7272727272727272
Confusion Matrix:
 [[3 1]
 [2 4]]
```

In [2]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,

# Regression Metrics
actual_values = [10, 15, 20, 25, 30]
predicted_values = [12, 14, 18, 28, 33]

mae = mean_absolute_error(actual_values, predicted_values)
mse = mean_squared_error(actual_values, predicted_values)
r2 = r2_score(actual_values, predicted_values)
medae = median_absolute_error(actual_values, predicted_values)

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("R-squared:", r2)
print("Median Absolute Error:", medae)
```

```
Mean Absolute Error: 2.2
Mean Squared Error: 5.4
R-squared: 0.892
Median Absolute Error: 2.0
```

In [ ]: