Evaluation

Accuracy is the simplest metric and can be defined as the number of test cases correctly classified divided by the total number of test cases. * Not very useful when it comes to unbalanced datasets

Precision: Precision is the metric used to identify the correctness of classification True positives/(true positives + false positives). It is valuable when the focus is on minimizing false positives

Recall (sensitivity): Recall tells us the number of positive cases correctly identified out of the total number of positive cases. true positives / (true positives + false negatives) It is crucial when the goal is to minimize false negatives

F1 Score: F1 score is the harmonic mean of Recall and Precision and therefore, balances out the strengths of each. * useful when the classes are imbalanced

AUC-ROC: ROC curve is a plot of true positive rate (recall) against false positive rate *Good for heavily imbalanced data* care equally about positive and negative classes

ROC curve: is The ROC curve is the plot of the true positive rate (TPR) against the false positive rate (FPR), at various threshold settings..

Precision-Recall (PR) curve : binary classification tasks where the focus is on positive instances PR curves provide insights into the trade-off between precision and recall at various thresholds or confidence levels.

Feature Scaling

Normalization (min-max scaling) $x' = \frac{x - min(x)}{max(x)-min(x)}$	Gradient Descent Based Algorithms
Standardization $x'=\frac{x-\overline{x}}{\sigma}$	Distance-Based Algorithms
Scaling to unit length	For feature engineering using PCA