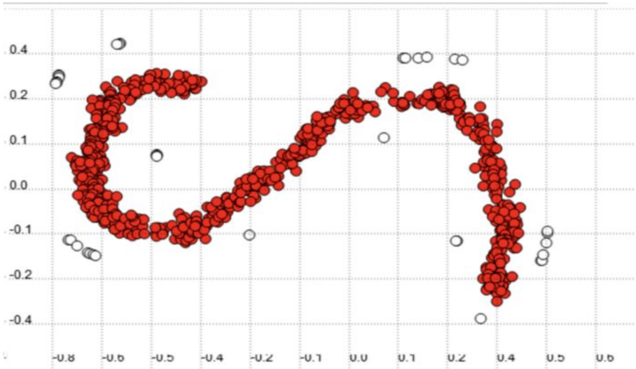
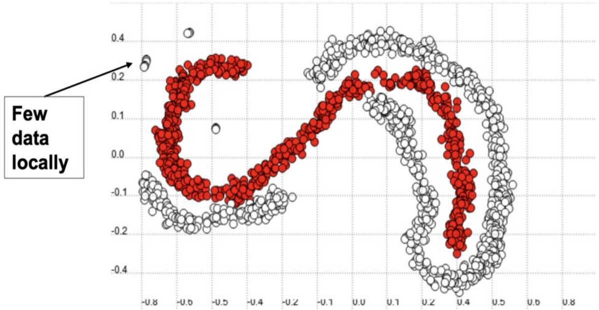
Imbalanced Dataset & Model Evaluation

Imbalanced Dataset

- An unequal distribution of classes
  - Example: In a credit card fraud detection dataset, most of the credit card transactions are not fraud and a very few classes are fraud transactions.
- Types of Imbalance Dataset



Between Class


Few data locally

Within Class

Imbalanced Dataset

- An unequal distribution of classes
  - Example: In a credit card fraud detection dataset, most of the credit card transactions are not fraud and a very few classes are fraud transactions.
- Types of Imbalance Dataset
- Cause of Imbalance Dataset
  - Biased Sampling
  - Measurement Error
- The imbalance might be a property of the problem domain
- Approaches to handling Imbalanced Dataset
  - Act on Data (Sampling)
  - Act on Cost Function (Evaluation Methods)

Sampling

- Undersampling (If enough data is available)
  - Remove some data from **Majority Class**

- Oversampling
  - Add new data for **Minority Class**
  - SMOTE (Synthetic Minority Oversampling Technique)
  - Random oversampling

- Resampling

Evaluation Methods

- Upweighting
- Downweighting
- Evaluation Metrics
- Ensemble Method

Evaluation Metrics

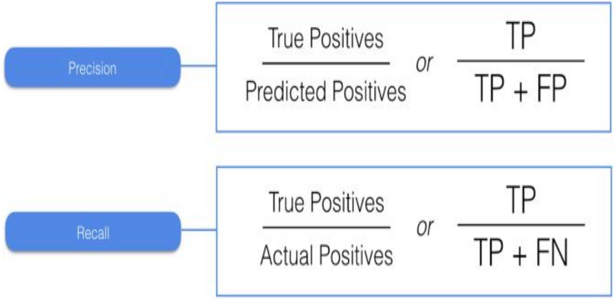
Precision/Specificity: how many selected instances are relevant

Recall/Sensitivity: how many relevant instances are selected

F1 score: harmonic mean of precision and recall

Confusion Matrix: a table showing the relation of predicted and expected result

ROC Curve: true positive vs false positive curve



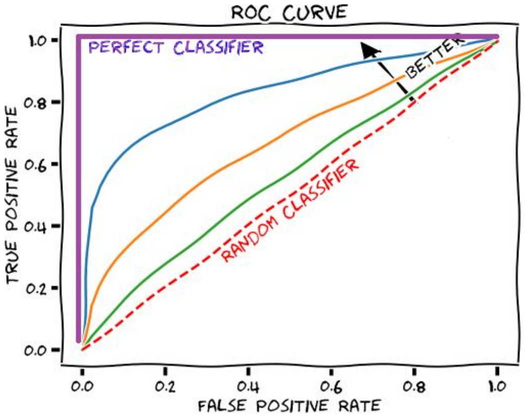
Precision

$$\frac{\text{True Positives}}{\text{Predicted Positives}} \text{ or } \frac{TP}{TP + FP}$$

Recall

$$\frac{\text{True Positives}}{\text{Actual Positives}} \text{ or } \frac{TP}{TP + FN}$$

$$F1 = \frac{(1+\beta^2) \times \text{precision} \times \text{recall}}{(\beta^2 \times \text{precision}) \times \text{recall}}$$



Model Evaluation (Holdout)

- Randomly partitioned in two independent sets
  - Training set
  - Test set
- Training set is used to train the model
- Test set is used to validate the accuracy of the model
- Estimation is Pessimistic

Model Evaluation (Random Sampling)

- Variation of Holdout method
- Holdout method is used for some n times
- Average result is considered

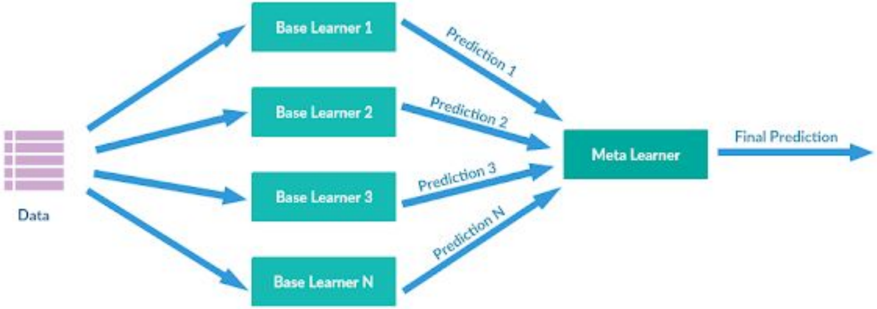
Model Evaluation (Cross Validation)

- k-fold
  - Randomly partitioned into k subsets
  - Training performs k times
  - Each time one subset of data is kept test data
  - Other (k-1) subsets are used as training dataset
- Leave-one-out
  - Special case of k-fold
  - Each fold contains only one data tuple
- Stratified cross validation
  - Preserves the data distribution in subsets

Model Evaluation (Bootstrap)

- Uniformly sample tuple with replacement
- On average, 63.2% data as Training data
- On average, 36.8% data as Test data
- Model accuracy is weighted

Model Evaluation (Ensemble Method)



- Use a set of classifiers
- Data is sampled for each classifier
- Final prediction based on majority voting
- Techniques:
    - Bagging
    - Boosting

Model Evaluation (Bagging)

- Bagging stands for Bootstrap Aggregation
- Each Training is a bootstrap sample

Model Evaluation (Boosting)

- Weights are assigned to each tuple
- A series of n classifiers are learned
- Weights are updated after each iteration
    - Increased if predicted incorrectly
    - Decreased if predicted correctly
- Adaboost
    - Weights are updated based on error rate
    - Models are weighted based on error

Thank You

References

- https://towardsdatascience.com/guide-to-classification-on-imbalanced-datasets-d6653aa5fa23
- https://www.kdnuggets.com/2017/06/7-techniques-handle-imbalanced-data.html
- https://machinelearningmastery.com/what-is-imbalanced-classification/#:~:text=Imbalanced%20classification%20refers%20to%20a,is%20instead%20biased%20or%20skewed.
- https://towardsdatascience.com/handling-imbalanced-datasets-in-machine-learning-7a0e84220f28
- Chapter 6, Data Mining Concepts and Techniques, Jiawei Han and Micheline Kamber, Second Edition