

SMS Spam Classification

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Motivation & Objective

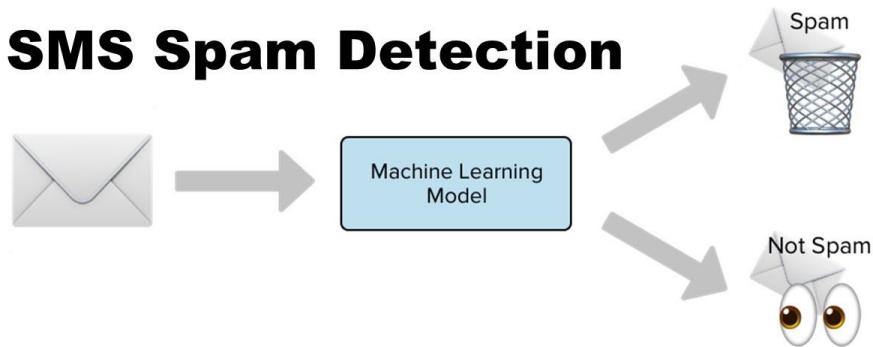
- SMS messaging is a widely used method for communication
- Spam messages are a significant problem that can cause inconvenience and harm
- Our project aims to classify SMS messages as either spam or legitimate
- The objective is to build an effective spam detection script
- We will explore and evaluate classification methods such as Naive Bayes, Random Forest, SVM, and KNN algorithms
- Our goal is to achieve high reliability in identifying spam messages



Overview

- Explored 4 types of classification algorithms: Naive Bayes, Random Forest, SVM, and KNN.
- Evaluated their performance using metrics such as accuracy, precision, and recall.
- Selected Random Forest as the algorithm to build an executable script on.
- Used Python programming language and various libraries including pandas, NumPy, scikit-learn, Matplotlib, and Seaborn for data processing, feature extraction, model training, and performance evaluation.

SMS Spam Detection

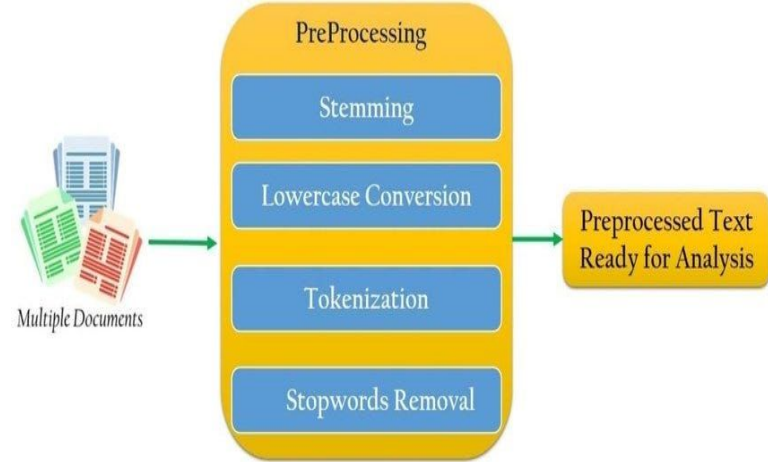


Dataset

- SMS Spam Collection
- UCI Machine Learning Repository
- The dataset consists of text messages which are either spam or ham (not spam).
- The dataset consists of 5574 records.

Pre-Processing

- Convert the labels to binary values
- Lowercase Conversion
- Tokenization
- Stopwords Removal
- Stemming/Lemmatization
- Removal of Punctuation and Numbers
- Vectorization



SVM

Support Vector Machines (SVM) is a popular machine learning algorithm used for both classification and regression analysis. It is a supervised learning algorithm that uses a hyperplane to separate data into classes.

Here's how SVM works:

- The algorithm takes labeled training data and finds the optimal hyperplane that best separates the data into classes.
- The hyperplane is chosen such that it maximizes the margin between the two classes, i.e., the distance between the hyperplane and the nearest points of each class.
- Once the optimal hyperplane is found, new data points are classified based on which side of the hyperplane they fall.

Advantages of SVM:

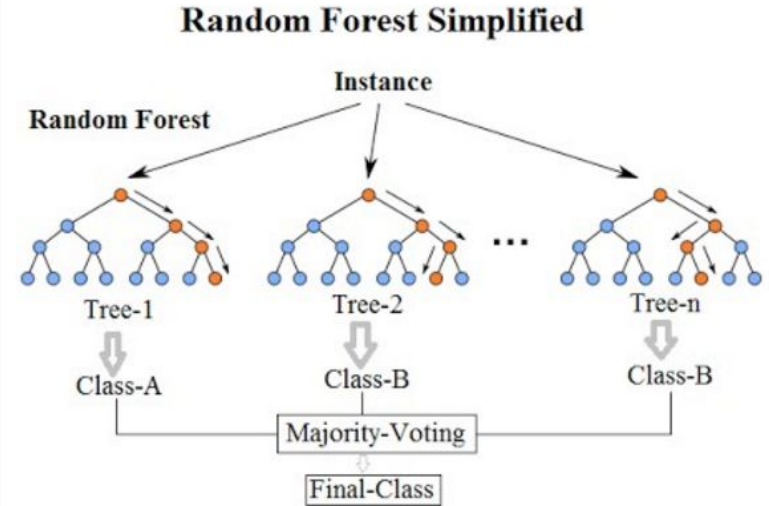
- High accuracy
- Robust to outliers
- Effective in non-linearly separable data

Disadvantages of SVM:

- Computationally intensive
- Difficult to interpret
- Sensitive to the choice of kernel

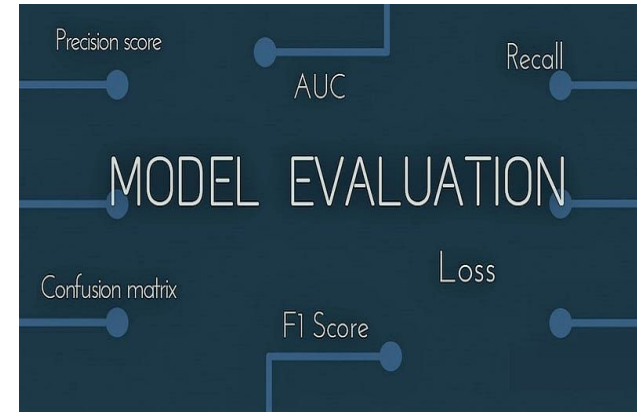
Random Forest

- Random Forest Method leverages the idea of ensemble learning to build and develop an ensemble of decision trees.
- It works by constructing multiple decision trees during training time and outputs the class that is the mode of the classes output by individual trees. In a Random Forest classifier, each decision tree is built by selecting a random subset of the training data and a random subset of the features.
- Advantages of using Random Forest for SMS spam classification:
 - Feature importance: Random Forest can provide information about the importance of each feature, which can help in identifying the most relevant features for SMS spam classification.
 - Random Forest is robust to overfitting and can handle missing data, which makes it a reliable choice for SMS spam classification.



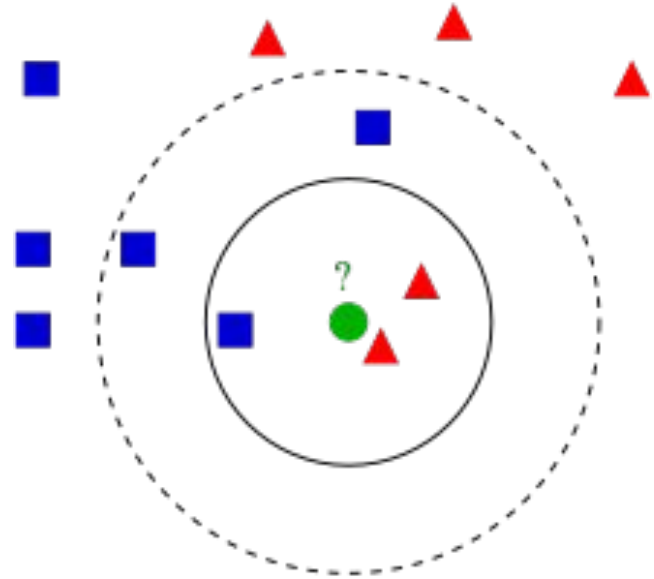
Random Forest Classifier Evaluation

- The Random Forest Classifier performance is evaluated using K-fold cross-validation. The dataset is split into four folds, with each fold training and testing the classifier. The text data is first vectorized using the TF-IDF vectorizer for each fold. This generates a feature matrix representing the frequency of each word in each message, weighted by its relevance in the corpus. The feature matrix dimensionality is then reduced to 50 primary components using primary Component Analysis (PCA). This is done to expedite training and minimize overfitting.
- The Random Forest Classifier is trained and evaluated on the reduced feature matrix. For each fold, the performance metrics (accuracy, precision, F1-score) and the ROC curve are produced. The end result is the average AUC of the ROC curve across all folds, as well as a plot of the ROC curve.
- After K-Fold cross-validation the model performance obtained an precision of 0.975. Accuracy using the algorithm is 0.96671 and F1 Score:0.8491.



K-Nearest Neighbors

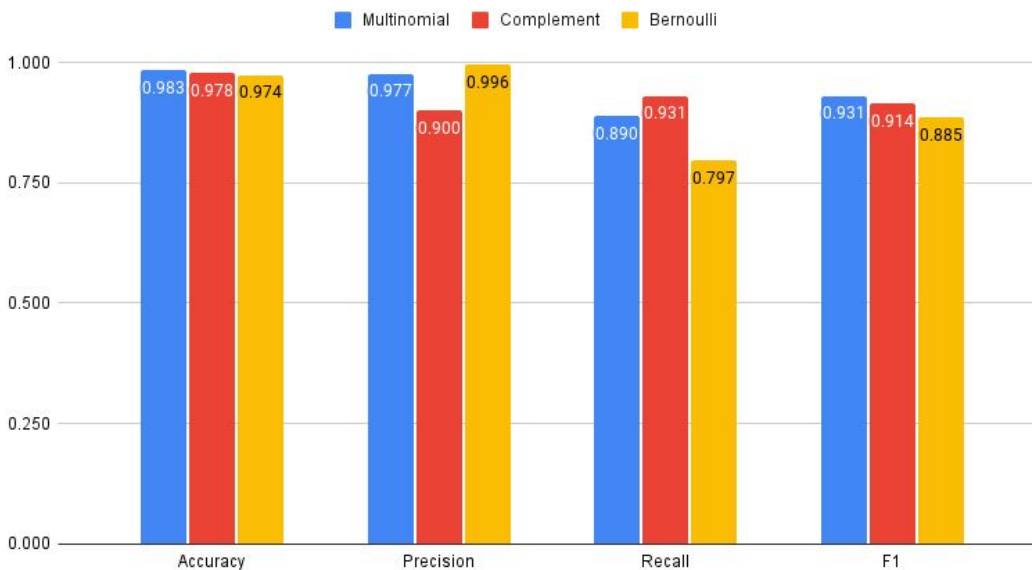
- KNN can handle both binary and multiclass classification problems, which makes it a versatile algorithm for various datasets.
- KNN doesn't require any training time, as the model simply stores the training dataset and uses it to make predictions at runtime, making it efficient for small to medium-sized datasets.
- It assigns labels to new data points based on their k-nearest neighbors in the training dataset.
- An accuracy of 0.92 was achieved in our implementation of KNN on the SMS spam dataset.
- This algorithm was chosen based on its simplicity and effectiveness in similar tasks.



Naive Bayes

- Multinomial: commonly used in text classification
- Complement: re-weights features in favor of minority classes
- Bernoulli: features represented as binary 0 or 1
- Evaluated using k-fold cross validation of k=5

Performance of Multinomial, Complement, and Bernoulli Naive Bayes Algorithms



Conclusion

- Precision was the most determinant metric for our case
- High precision = good at preventing false positives
- KNN had the best precision score, but recall is way too low
- Bernoulli NB had second highest precision, and tolerable recall
- Built executable script based on Bernoulli NB - see demo

