Spam Detection using Bag of Words (BoW)

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1 Importing Libraries

```
In [1]: # Importing required libraries
        import numpy as np
        import pandas as pd
        from collections import Counter
        import matplotlib.pyplot as plt; plt.style.use('ggplot')
        import seaborn as sns;
        import warnings; warnings.filterwarnings('ignore')
        import scipy.io as io
        from scipy.sparse import csr_matrix
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import accuracy_score, classification_report
        from sklearn.metrics import precision_recall_curve,roc_curve, confusion_matrix
        from sklearn.metrics import precision_score, recall_score,f1_score
        from sklearn.metrics import auc, average_precision_score
        from sklearn.linear_model import LogisticRegression
        from sklearn.ensemble import RandomForestClassifier
        import pickle
```

2 Loading Data

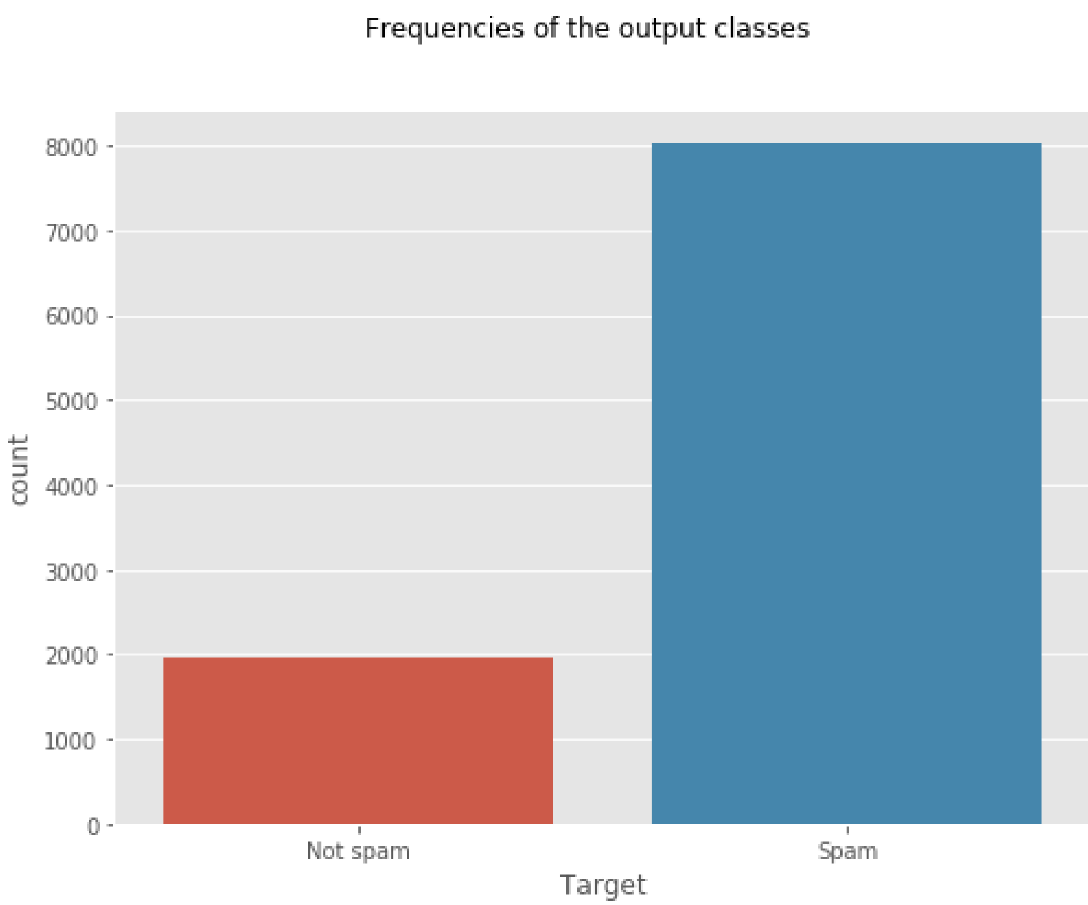
```
In [2]: # Loading the datatset
        data =  io.loadmat("../data/raw/emails.mat")
        print('# obervations:',data['X'].shape)
        print('# class observations:',data['Y'].shape)
```

```
# obervations: (57173, 10000)
# class observations: (1, 10000)
```

3 Data Exploration

3.1 exploring labels

In [3]:
```
# plot the frequencies of the classes
YData = pd.DataFrame(data['Y'].T)
fig, ax = plt.subplots(figsize=(8,6))
sns.countplot(x = YData[0], ax=ax)
ax.set_xticklabels(['Not spam','Spam'])
ax.set_xlabel('Target')
fig.suptitle('Frequencies of the output classes')
plt.show()
plt.savefig('../reports/frequencies_class_distribution.png', bbox_inches='tight')
```




```
<Figure size 432x288 with 0 Axes>
```

3.2 exploring features

```
In [20]: sparse_matrix = csr_matrix(data['X'])
         #Converting the sparse matrix to a dense matrix
         dense_matrix = sparse_matrix.todense()
         # N.B.:This operation is computationally expensive,
         #so we'll perform it just once to explore the data
         print('*'*50)
         print('Sparcity of the matrix')
         print('*'*50)
         #calculating sparcity of the matrix
         sparcity = 1-(np.count_nonzero(dense_matrix) / float(dense_matrix.size))
         print(sparcity)
         df = pd.DataFrame(dense_matrix.T)
```

```
**************************************************
Sparcity of the matrix
**************************************************
0.9958870463330594
```

```
In [5]: # Converting to dataframe for easier operation
        # displaying first few rows
        df = pd.DataFrame(dense_matrix.T)
        df.head()
```

```
Out[5]:    0      1      2      3      4      5      6      7      8      9      \
        0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        1    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        2    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        3    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        4    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0

           ...    57163  57164  57165  57166  57167  57168  57169  57170  57171  57172
        0  ...      0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        1  ...      0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        2  ...      0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        3  ...      0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0
        4  ...      0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0    0.0

        [5 rows x 57173 columns]
```

```
In [6]: # checking the ranges in the word count for each word
        print(df[322].value_counts())
        print(df[2848].value_counts())
```

```
0.0    9867
1.0     133
Name: 322, dtype: int64
```

```
0.0    9991
1.0       8
2.0       1
Name: 2848, dtype: int64
```

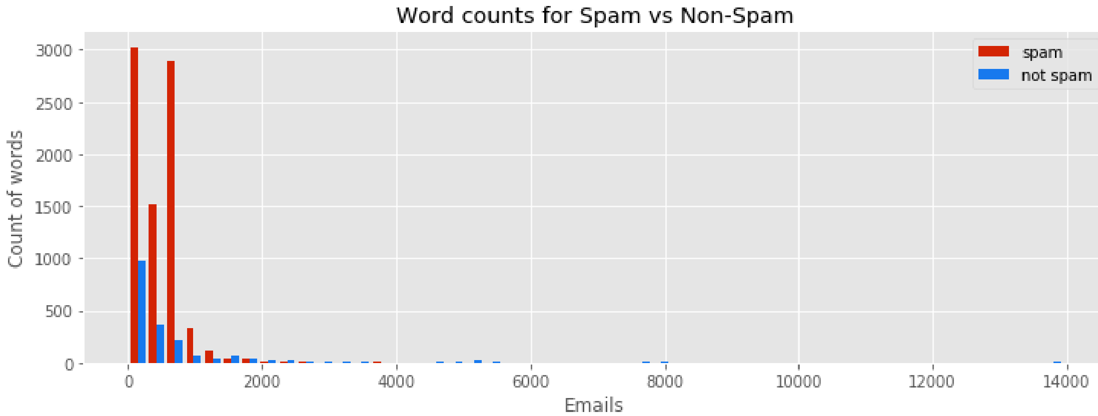
```
In [7]: # Calculating the word frequencies of different words in feature set
        words_frequency = np.sum(df, axis=0)
        word_freq_df= pd.DataFrame(data=words_frequency, columns=['Word Count'])
        word_freq_df['Word Id']=word_freq_df.index
        word_freq_df=word_freq_df.reset_index(drop=True)
        word_freq_df=word_freq_df.set_index('Word Id')
        # some words have occured more often
        word_freq_df.sort_values(by='Word Count',ascending=False).head()
```

```
Out[7]:          Word Count
        Word Id
        46208       75793.0
        46434       63806.0
        54075       55856.0
        4148        52935.0
        12835       52705.0
```

```
In [8]: # some occured less
        word_freq_df.sort_values(by='Word Count',ascending=False).tail()
```

```
Out[8]:          Word Count
        Word Id
        6463            2.0
        25459           2.0
        33595           2.0
        50438           2.0
        38637           2.0
```

```
In [9]: # Plotting for understanding the word count distribution of spam/Ham emails
        len_emails = np.sum(df, axis=1)
        y_values = np.array(data['Y'][0])
        len_spam = len_emails[y_values==1]
        len_not_spam = len_emails[y_values==-1]

        plt.figure(figsize=(12,4))
        plt.hist([len_spam, len_not_spam], bins=50, color=['#D32404', '#1779EE'],
                 label=['spam', 'not spam'],density=False)
        plt.title('Word counts for Spam vs Non-Spam')
        plt.xlabel('Emails')
        plt.ylabel('Count of words')
        plt.legend()
        plt.savefig('../reports/Length_distribution_based_on_category.png',
                    bbox_inches='tight')
```



4 Data preparation

```
In [10]: # Preparing data for further operations
         X = data['X'].T
         y = data['Y']
```

```
In [11]: def upsampling(X,y):
             """ Balance the class instances using upsampling the minority class

                 Parameters
                 ------------
                 X: array
                     Features
                 y: array
                     Labels

                 Returns
                 --------------
                 tuple
                     Returns new features and labels
             """
             from sklearn.utils import resample
             from scipy.sparse import vstack
             #Separating the samples with class '-1' from X
             minorityClassX= X[y[0] == -1,:]
             #Separating the samples with class '1' from X
             majorityClassX= X[y[0] == 1,:]

             print(minorityClassX.shape)
             print(majorityClassX.shape)

             resampledMinorityClassX= resample(minorityClassX,replace=True,n_samples=8030)
```

```
        newSparseMatrix = vstack([majorityClassX,resampledMinorityClassX])
        #Separating the samples with class '-1' from Y
        minorityClassY= y.T[y[0] == -1]
        #Separating the samples with class '1' from Y
        majorityClassY= y.T[y[0] == 1]

        newMinorityClassValueY = np.full((len(majorityClassY), 1), -1)
        #Creating new Y value with balanced '1' and '-1'
        newYValue = np.vstack((majorityClassY,newMinorityClassValueY))

        return newSparseMatrix, newYValue
```

```
In [12]: # Upsampling the minority class

         X_upsample,y_upsample=upsampling(X,y)
         print('# observations:',X_upsample.shape)
         print("# labels:",y_upsample.shape)
         print("# Not spam:",len(np.where(y_upsample==-1)[0]))
         print('# Spam:',len(np.where(y_upsample==1)[0]))
```

```
(1970, 57173)
(8030, 57173)
# observations: (16060, 57173)
# labels: (16060, 1)
# Not spam: 8030
# Spam: 8030
```

```
In [13]: # Normalizing the data

         from sklearn.feature_extraction.text import TfidfTransformer
         transformer = TfidfTransformer()
         X_upsample_tfidf= transformer.fit_transform(X_upsample)
         print('# observations:',X_upsample_tfidf.shape)
```

```
# observations: (16060, 57173)
```

5 Training

```
In [14]: def adjusted_classes(y_scores, t):
             """
             Predicts the classes based on the specifed threshold

             Parameters
             -----------
             y_scores: list
                 Probabilites of the positive classes
```

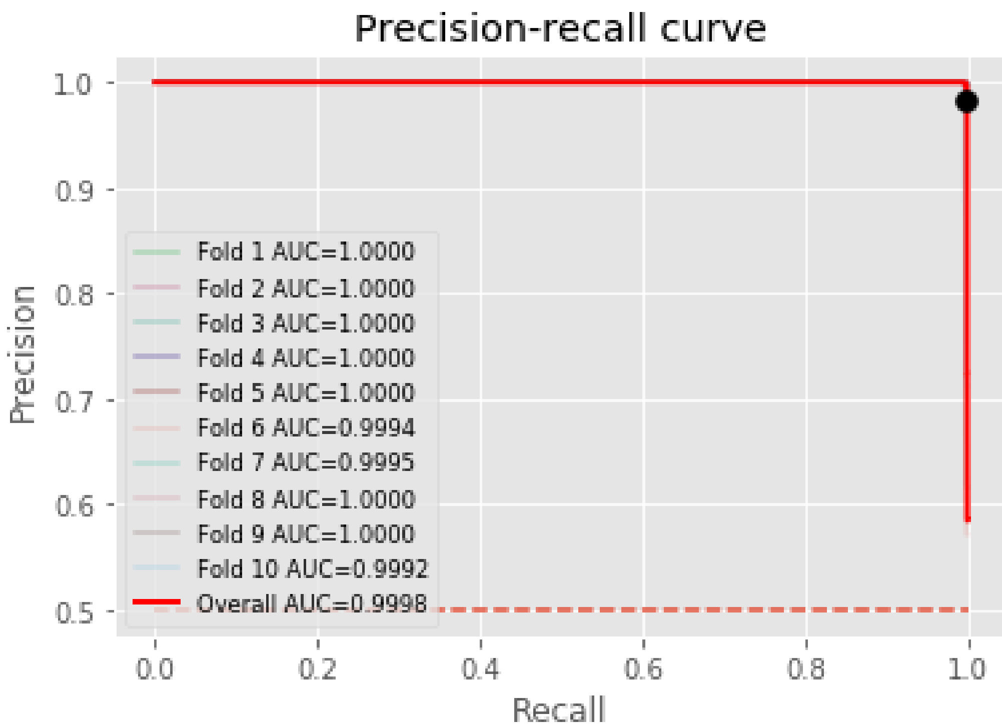
```
        t: float
            Threshold

        Returns
        -----------
        list
            Returns list of the predicted outcome
        """
        return [1 if y >= t else -1 for y in y_scores]
```

```
In [15]: def cross_validation(splits, X, Y, model, average_method='binary',t=0.5):
        ''' Performs k -fold cross validation and print the
            classification report for each fold
            Parameter
            ---------
            splits: int
                Number of splits to be done
            X: array
                Feature set
            Y: array
                Labels
            model: Estimator
                Model to be trained on
            average_method: str
                method for the classification metrics (optional)
            t: float
                Defines the threshold
        '''
        from sklearn.model_selection import KFold
        kfold = KFold(n_splits=splits, shuffle=True, random_state=10)
        accuracy = []
        precision = []
        recall = []
        f1 = []
        y_real = []
        y_proba = []

        fold=0
        #KFold Cross Validation so that the model performs good in future samples
        for train, test in kfold.split(X, Y):
            fold=fold+1
            predictor = model.fit(X[train], Y[train])
            scores = predictor.score(X[test],Y[test])
            pred_proba =  predictor.predict_proba(X[test])
            # prediction of the classes based on threshold
            prediction = adjusted_classes(pred_proba[:,1], t)

            print('          Ham       Spam')
```

```
    accuracy.append(scores * 100)
    precision.append(precision_score(Y[test], prediction,
                                     average=average_method)*100)
    print('precision:',precision_score(Y[test], prediction, average=None))
    recall.append(recall_score(Y[test], prediction, average=average_method)*100)
    print('recall:    ',recall_score(Y[test], prediction, average=None))
    f1.append(f1_score(Y[test], prediction, average=average_method)*100)
    print('-'*50)

    # precision- recall curve for each folds
    precision_fold, recall_fold, thresh = precision_recall_curve(
        Y[test], pred_proba[:,1])

    pr_auc= auc(recall_fold,precision_fold)
    label_fold = 'Fold %d AUC=%.4f' % (fold, pr_auc)
    plt.plot(recall_fold, precision_fold, alpha=0.3,
             label=label_fold, color=np.random.rand(3,))

    y_real.append(Y[test])
    y_proba.append(pred_proba[:,1])

# Report #
# Prints the overall accuracy, precision and recall
print("accuracy: %.2f%% (+/- %.2f%%)" % (np.mean(accuracy), np.std(accuracy)))
print("precision: %.2f%% (+/- %.2f%%)" % (np.mean(precision), np.std(precision)))
print("recall: %.2f%% (+/- %.2f%%)" % (np.mean(recall), np.std(recall)))
print("f1 score: %.2f%% (+/- %.2f%%)" % (np.mean(f1), np.std(f1)))

# plots the overall Precision-recall curve
y_real = np.concatenate(y_real)
y_proba = np.concatenate(y_proba)
precision, recall, threshold = precision_recall_curve(y_real, y_proba)
final_label = 'Overall AUC=%.4f' % (auc(recall, precision))
plt.plot(recall, precision, lw=2,color='red', label=final_label)
plt.plot([0, 1], [0.5, 0.5], linestyle='--')
plt.legend(loc='lower left', fontsize='small')

# plot the current threshold on the line
close_default_clf = np.argmin(np.abs(threshold - t))
plt.plot(recall[close_default_clf], precision[close_default_clf], '.', c='k',
        markersize=15)

plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-recall curve')
plt.show()
```

```
In [16]: # logistic regression
         lr = LogisticRegression(random_state=42)
         cross_validation(10,X_upsample_tfidf,y_upsample,lr,t=0.2)
```

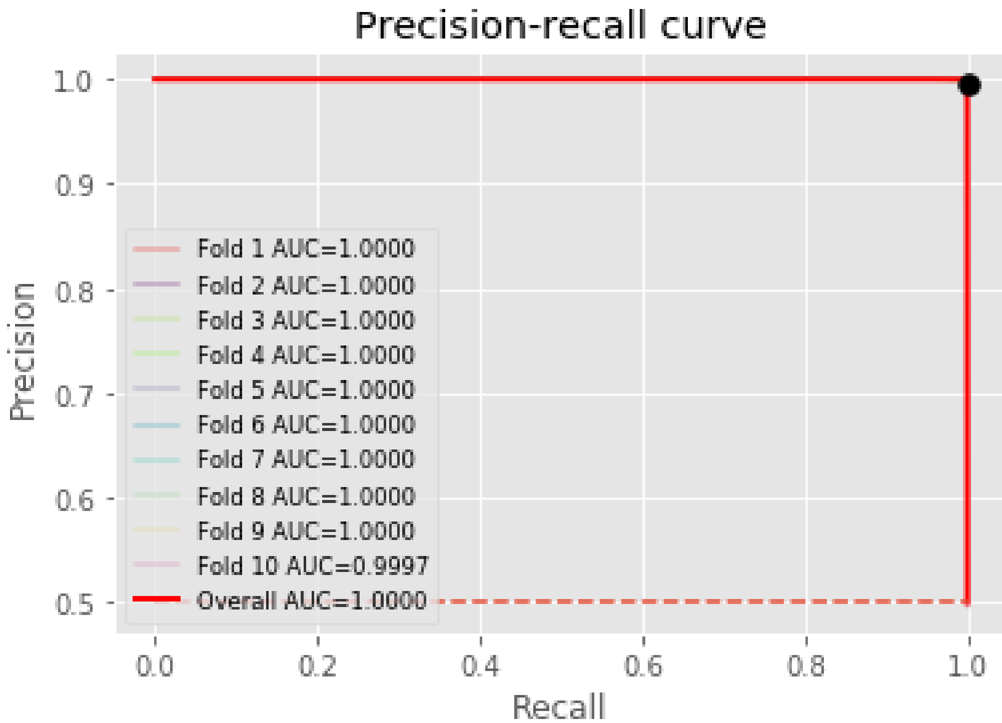
```
          Ham       Spam
precision: [1.         0.98385093]
recall:    [0.98402948 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.98205742]
recall:    [0.98089172 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.98569726]
recall:    [0.98459564 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.98684211]
recall:    [0.98591549 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.        0.9800995]
recall:    [0.9804401 1.       ]
--------------------------------------------------
          Ham       Spam
precision: [0.99877451 0.98734177]
recall:    [0.98787879 0.99871959]
--------------------------------------------------
          Ham       Spam
precision: [0.99874372 0.98765432]
recall:    [0.98757764 0.99875156]
--------------------------------------------------
          Ham       Spam
precision: [1.        0.9769697]
recall:    [0.97625 1.     ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.98019802]
recall:    [0.98034398 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [0.9962406  0.98267327]
recall:    [0.98269468 0.99623588]
--------------------------------------------------
accuracy: 99.84% (+/- 0.11%)
precision: 98.33% (+/- 0.34%)
recall: 99.94% (+/- 0.12%)
f1 score: 99.13% (+/- 0.17%)
```




```
In [17]: # random forest
         rf = RandomForestClassifier(random_state=42)
         cross_validation(10,X_upsample_tfidf,y_upsample,rf,t=0.2)
```

```
          Ham       Spam
precision: [1.         0.99497487]
recall:    [0.995086 1.      ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.99635922]
recall:    [0.99617834 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.99399038]
recall:    [0.99358151 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.99158654]
recall:    [0.99103713 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.99494949]
```

```
recall:    [0.99511002 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.99617347]
recall:    [0.99636364 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [0.99875467 0.99626401]
recall:    [0.99627329 0.99875156]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.99017199]
recall:    [0.99 1.  ]
--------------------------------------------------
          Ham       Spam
precision: [1.         0.99372647]
recall:    [0.99385749 1.        ]
--------------------------------------------------
          Ham       Spam
precision: [0.99876238 0.99749373]
recall:    [0.99752781 0.99874529]
--------------------------------------------------
accuracy: 99.73% (+/- 0.16%)
precision: 99.46% (+/- 0.22%)
recall: 99.97% (+/- 0.05%)
f1 score: 99.72% (+/- 0.10%)
```



6 Save the models

```
In [18]: # save the best model for prediction to disk
         filename = '../models/finalized_model_rf.sav'
         pickle.dump(rf, open(filename, 'wb'))

         # save the best model for prediction to disk
         filename = '../models/finalized_model_lr.sav'
         pickle.dump(lr, open(filename, 'wb'))
```

7 Comment:

Both the models achieved high recall i.e. more than 99.8%. However, Random forest works better for the same threshold and also gave high AUC.