## **Assignment 2**

Classify the email using the binary classification method. Email Spam detection has two states: a)
 Normal State – Not Spam, b) Abnormal State – Spam. Use K-Nearest Neighbors and Support Vector
 Machine for classification. Analyze their performance. Dataset link: The emails.csv dataset on the
 Kaggle <a href="https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv">https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv</a>

```
In [19]: import pandas as pd
          import numpy as np
          import seaborn as sns
          import matplotlib.pyplot as plt
          %matplotlib inline
          import warnings
          warnings.filterwarnings('ignore')
          from sklearn.model_selection import train_test_split
          from sklearn.svm import SVC
          from sklearn import metrics
In [20]: df=pd.read_csv('emails.csv')
In [21]:
          df.head()
Out[21]:
              Email
                     the
                         to ect and for of
                                                a you hou ... connevey jay valued lay infrastructure militar
                No.
              Email
                      0
                                           0
                                                2
                                                     0
                                                                                   0
                                                                                        0
                                                                                                     0
              Email
                                                                                                     0
                        13
                             24
                                   6
                                       6
                                           2
                                              102
                                                     1
                                                         27
                                                                       0
                                                                            0
                                                                                   0
              Email
                          0
                               1
                                   0
                                       0
                                           0
                                                8
                                                     0
                                                          0
                                                                       0
                                                                            0
                                                                                   0
                                                                                                     0
              Email
                              22
                                   0
                                       5
                                           1
                                               51
                                                     2
                                                         10
                                                                       0
                                                                                   0
                                                                                                     0
              Email
                                                          9 ...
                                           2
                                               57
                                                     0
                                                                       0
                                                                            0
                                                                                   0
                                                                                                     0
          5 rows × 3002 columns
In [22]: df.columns
Out[22]: Index(['Email No.', 'the', 'to', 'ect', 'and', 'for', 'of', 'a', 'you', 'hou',
                  'connevey', 'jay', 'valued', 'lay', 'infrastructure', 'military', 'allowing', 'ff', 'dry', 'Prediction'],
                 dtype='object', length=3002)
```

```
In [23]: df.isnull().sum()
Out[23]: Email No.
                       0
                       0
         the
                       0
         to
                       0
         ect
         and
                       0
         military
                       0
         allowing
                       0
         ff
                       0
         dry
                       0
         Prediction
                       0
         Length: 3002, dtype: int64
In [24]: df.dropna(inplace = True)
In [25]: | df.drop(['Email No.'],axis=1,inplace=True)
         X = df.drop(['Prediction'],axis = 1)
         y = df['Prediction']
In [26]: from sklearn.preprocessing import scale
         X = scale(X)
         # split into train and test
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state
         ##KNN classifier
In [35]: from sklearn.neighbors import KNeighborsClassifier
         knn = KNeighborsClassifier(n_neighbors=7)
         knn.fit(X_train, y_train)
         y_pred = knn.predict(X_test)
In [36]: print("Prediction",y_pred)
         Prediction [0 0 1 ... 1 1 1]
In [37]: print("KNN accuracy = ",metrics.accuracy_score(y_test,y_pred))
         KNN accuracy = 0.8009020618556701
In [39]: |print("Confusion matrix",metrics.confusion_matrix(y_test,y_pred))
         Confusion matrix [[804 293]
          [ 16 439]]
```

## **SVM** classifier