```
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Group B: Machine Learning ¶

Assignment B2

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
https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv
(https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv)

In [1]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
df = pd.read_csv("emails.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	Email No.	the	to	ect	and	for	of	a	you	hou	...	connevey	jay	valued	lay	infrastructure
0	Email 1	0	0	1 0	0 0	0	0	2	0	0	...	0	0	0		
1	Email 2	8	13	24 0	6 0	6	2	102	1	27	...	0	0	0		
2	Email 3	0	0	1 0	0 0	0	0	8	0	0	...	0	0	0		
3	Email 4	0	5	22 0	0 0	5	1	51	2	10	...	0	0	0		
4	Email 5	7	6	17 0	1 0	5	2	57	0	9	...	0	0	0		

5 rows × 3002 columns

In [4]:
```
df.columns
```

Out[4]:
```
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 [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5172 entries, 0 to 5171
Columns: 3002 entries, Email No. to Prediction
dtypes: int64(3001), object(1) memory usage:
118.5+ MB
```

In [6]:
```
df.shape
```

Out[6]:
```
(5172, 3002)
```

In [7]:
```
df.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
df.describe()
```

Out[8]:

	the	to	ect	and	for	of	a
count	5172.000000	5172.000000	5172.000000	5172.000000	5172.000000	5172.000000	5172.000000
mean	6.640565	6.188128	5.143852	3.075599	3.124710	2.627030	55.517401
std	11.745009	9.534576	14.101142	6.045970	4.680522	6.229845	87.574172
min	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	1.000000	1.000000	0.000000	1.000000	0.000000	12.000000
50%	3.000000	3.000000	1.000000	1.000000	2.000000	1.000000	28.000000
75%	8.000000	7.000000	4.000000	3.000000	4.000000	2.000000	62.250000
max	210.000000	132.000000	344.000000	89.000000	47.000000	77.000000	1898.000000

8 rows × 3001 columns

In

In [9]:
```
# df.corr()
```

In [10]:
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

In [11]:
```
df[df.isnull().any(axis=1)]
```

Out[11]:

Email No.	the	to	ect	and	for	of	a	you	hou	...	connevey	jay	valued	lay	infrastructure	m

0 rows × 3002 columns

[12]:
```
df.Prediction.value_counts()
```

Out[12]:
```
0    3672 1
1500
Name: Prediction, dtype: int64
```

In [13]:
```
train,test= train_test_split(df,test_size=0.3,stratify=df.Prediction)
```

In [14]:
```
train.shape
```

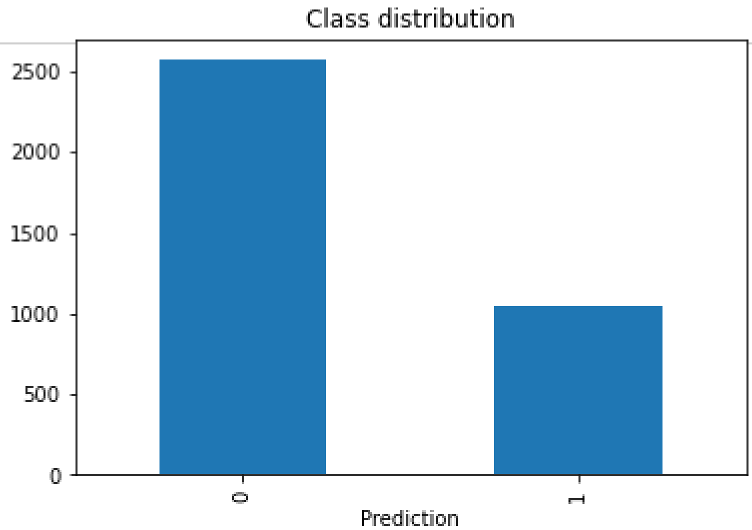
Out[14]:
```
(3620, 3002)
```

In [15]:
```
test.shape
```

Out[15]:
```
(1552, 3002)
```

In [16]:
```
train.pivot_table(index='Prediction',aggfunc='size').plot(kind='bar',title='Class
```

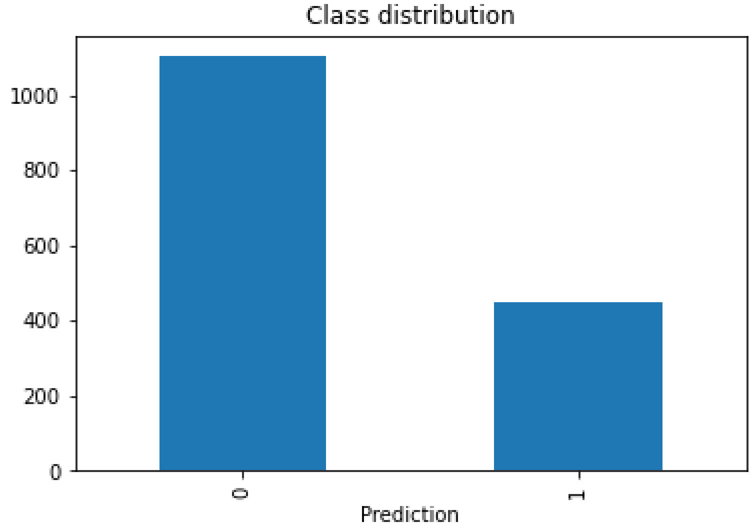
Out[16]:
```
<AxesSubplot:title={'center':'Class distribution'}, xlabel='Prediction'>
```


Class distribution
2500
2000
1500
1000
500
0
0
1
Prediction

In [17]:

```
test.pivot_table(index='Prediction',aggfunc='size').plot(kind='bar',title='Class
```

Out[17]: <AxesSubplot:title={'center':'Class distribution'}, xlabel='Prediction'>



In [18]:

```
X = df.iloc[:,1:3001]
```

In [19]:

```
Y = df.iloc[:,-1].values
Y
```

Out[19]: array([0, 0, 0, ..., 1, 1, 0], dtype=int64)

In [20]:

```
train_x,test_x,train_y,test_y = train_test_split(X,Y,test_size = 0.25,stratify =
```

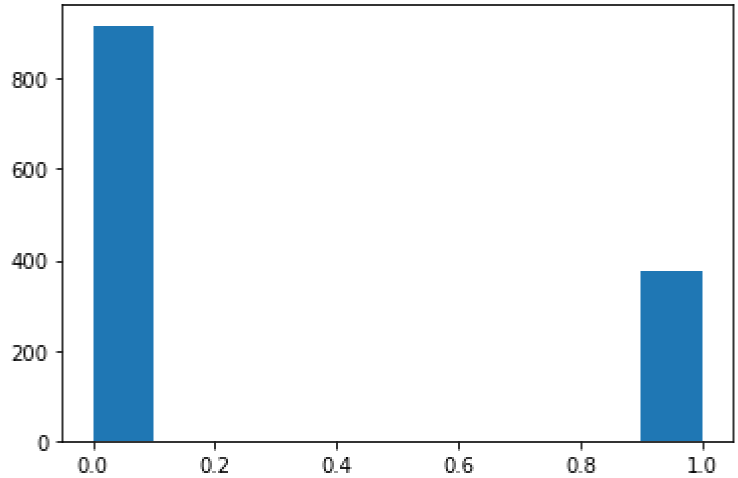
[21]:

```
plt.hist(test_y)
```

<IPython.core.display.Javascript object>

Out[21]: (array([918.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0., 375.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]), <BarContainer
 object of 10 artists>)

In



SVM

In [22]:
```
svc = SVC(C=1.0,kernel='rbf',gamma='auto')
# C here is the regularization parameter. Here, L2 penalty is used(default). It i
# As C increases, model overfits.
# Kernel here is the radial basis function kernel.
# gamma (only used for rbf kernel) : As gamma increases, model
overfits. svc.fit(train_x,train_y) y_pred = svc.predict(test_x)
print("Accuracy Score for SVC : ", accuracy_score(y_pred,test_y))
```

```
Accuracy Score for SVC :  0.8963650425367363
```

In [23]:
```
acc = accuracy_score(y_pred,test_y)
acc
```

Out[23]: 0.8963650425367363

[24]:
```
from sklearn.metrics import precision_score,recall_score,f1_score,fbeta_score,con
```

In [25]:
```
pre = precision_score(test_y,y_pred)
pre
```

Out[25]: 0.8801261829652997

In

In [26]:
```
recall = recall_score(test_y,y_pred)
recall
```

Out[26]: 0.744

In [27]:
```
f1 = f1_score(test_y,y_pred)
f1
```

Out[27]: 0.8063583815028901

In [28]:
```
fbeta0_5 = fbeta_score(test_y,y_pred,beta=0.5)
fbeta0_5
```

Out[28]: 0.8490566037735849

In [29]:
```
fbeta2 = fbeta_score(test_y,y_pred,beta=2)
fbeta2
```

Out[29]: 0.7677490368739681

In [30]:
```
result = pd.DataFrame(columns=['Accuracy score','Precision','Recall','F1 Score',
result.loc['SVM'] = [acc,pre,recall,f1,fbeta0_5,fbeta2] result
```

Out[30]:

	Accuracy score	Precision	Recall	F1 Score	Fbeta Score(0.5)	Fbeta Score(2)
SVM	0.896365	0.880126	0.744	0.806358	0.849057	0.767749

In [31]:
```
confusion_matrix(test_y,y_pred)
```

Out[31]:
```
array([[880,  38],
       [ 96, 279]], dtype=int64)
```

In [32]:
```
print(classification_report(test_y,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.96      0.93       918
 1       0.88      0.74      0.81       375

    accuracy                           0.90      1293
macro avg       0.89      0.85      0.87      1293
weighted avg       0.90      0.90      0.89      1293
```

SMOTE : a powerful solution for imbalanced data

In [33]:
```
from imblearn.over_sampling import SMOTE
```

In [34]:
```
oversample = SMOTE()
```

In [35]:
```
X_sampled, Y_sampled = oversample.fit_resample(X,Y)
```

In [36]:
```
X_sampled.shape
```

Out[36]:
```
(7344, 3000)
```

In [37]:
```
Y_sampled.shape
```

Out[37]:
```
(7344,)
```

In [38]:
```
X_sampled.head()
```

Out[38]:

	the	to	ect	and	for	of	a	you	hou	in	...	enhancements	connevey	jay	valued	lay
0	0	0	1	0	0	0	2	0	0	0	...	0	0	0	0	0
1	8	13	24 0	6 0	6	2	102	1	27	18	...	0	0	0		
2	0	0	1 0	0 0	0	0	8	0	0	4	...	0	0	0		
3	0	5	22 0	0 0	5	1	51	2	10	1	...	0	0	0		
4	7	6	17 0	1 0	5	2	57	0	9	3	...	0	0	0		

5 rows × 3000 columns

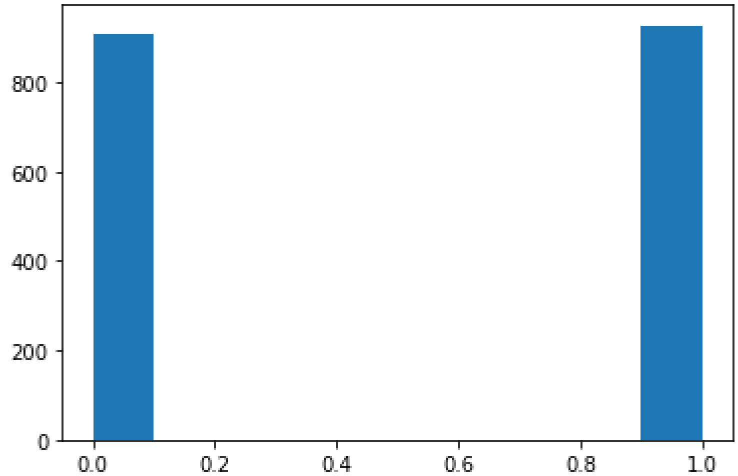
In [39]:
```
train_x1,test_x1,train_y1,test_y1 = train_test_split(X_sampled,Y_sampled,test_siz
```

[40]:
```
plt.hist(test_y1)
```

```
<IPython.core.display.Javascript object>
```

Out[40]:
```
(array([909.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0., 927.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]), <BarContainer
 object of 10 artists>)
```

In



In [41]:
```
svc = SVC(C=1.0,kernel='rbf',gamma='auto')
# C here is the regularization parameter. Here, L2 penalty is used(default). It i
# As C increases, model overfits.
# Kernel here is the radial basis function kernel.
# gamma (only used for rbf kernel) : As gamma increases, model overfits.
svc.fit(train_x1,train_y1) y_pred1 = svc.predict(test_x1)
print("Accuracy Score for SVC : ",
accuracy_score(y_pred1,test_y1))
```

```
Accuracy Score for SVC :  0.9449891067538126
```

In [42]:
```
confusion_matrix(test_y1,y_pred1)
```

Out[42]:
```
array([[842,  67],
       [ 34, 893]], dtype=int64)
```

[43]:
```
print(classification_report(test_y1,y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.96      0.93      0.94       909
   1       0.93      0.96      0.95       927
```

In

```
    accuracy                           0.94      1836
macro avg       0.95      0.94      0.94      1836
weighted avg       0.95      0.94      0.94      1836
```

In [44]:
```
acc = accuracy_score(y_pred1,test_y1)
acc
```

Out[44]: 0.9449891067538126

In [45]:
```
pre = precision_score(test_y1,y_pred1)
pre
```

Out[45]: 0.9302083333333333

In [46]:
```
recall = recall_score(test_y1,y_pred1)
recall
```

Out[46]: 0.9633225458468176

In [47]:
```
f1 = f1_score(test_y1,y_pred1)
f1
```

Out[47]: 0.9464758876523581

In [48]:
```
fbeta0_5 = fbeta_score(test_y1,y_pred1,beta=0.5)
fbeta0_5
```

Out[48]: 0.936647786868051

In [49]:
```
fbeta2 = fbeta_score(test_y1,y_pred1,beta=2)
fbeta2
```

Out[49]: 0.9565124250214223

In [50]:
```
result.loc['SVM_SMOTE'] = [acc,pre,recall,f1,fbeta0_5,fbeta2]
result
```

Out[50]:

	Accuracy score	Precision	Recall	F1 Score	Fbeta Score(0.5)	Fbeta Score(2)
SVM	0.896365	0.880126	0.744000	0.806358	0.849057	0.767749
SVM_SMOTE	0.944989	0.930208	0.963323	0.946476	0.936648	0.956512

[51]:
```
from sklearn.neighbors import KNeighborsClassifier
KNN= KNeighborsClassifier(n_neighbors=3)
# Train the model using the training sets
KNN.fit(train_x,train_y) y_pred = KNN.predict(test_x)
print("Accuracy Score for KNN : ",
accuracy_score(y_pred,test_y))
```

```
Accuracy Score for KNN :  0.8476411446249034
```

In

In [52]:
```
acc = accuracy_score(y_pred,test_y)
acc
```

Out[52]: 0.8476411446249034

In [53]:
```
pre = precision_score(test_y,y_pred)
pre
```

Out[53]: 0.7099056603773585

In [54]:
```
recall = recall_score(test_y,y_pred)
recall
```

Out[54]: 0.8026666666666666

In [55]:
```
f1 = f1_score(test_y,y_pred)
f1
```

Out[55]: 0.7534418022528159

In [56]:
```
fbeta0_5 = fbeta_score(test_y,y_pred,beta=0.5)
fbeta0_5
```

Out[56]: 0.7267020762916465

In [57]:
```
fbeta2 = fbeta_score(test_y,y_pred,beta=2)
fbeta2
```

Out[57]: 0.7822245322245321

In [58]:
```
result.loc['KNN'] = [acc,pre,recall,f1,fbeta0_5,fbeta2]
result
```

Out[58]:

	Accuracy score	Precision	Recall	F1 Score	Fbeta Score(0.5)	Fbeta Score(2)
SVM	0.896365	0.880126	0.744000	0.806358	0.849057	0.767749
SVM_SMOTE	0.944989	0.930208	0.963323	0.946476	0.936648	0.956512
KNN	0.847641	0.709906	0.802667	0.753442	0.726702	0.782225

[59]:
```
confusion_matrix(test_y,y_pred)
```

Out[59]:
```
array([[795, 123],
       [ 74, 301]], dtype=int64)
```

In [60]:
```
print(classification_report(test_y,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.87      0.89       918
   1       0.71      0.80      0.75       375
```

In

```
    accuracy                           0.85      1293
macro avg       0.81      0.83      0.82      1293
weighted avg       0.86      0.85      0.85      1293
```

In [61]:

```
from sklearn.neighbors import KNeighborsClassifier
KNN= KNeighborsClassifier(n_neighbors=3)
# Train the model using the training sets
KNN.fit(train_x1,train_y1) y_pred1 =
KNN.predict(test_x1)
print("Accuracy Score for KNN : ",
accuracy_score(y_pred1,test_y1)) acc =
accuracy_score(y_pred1,test_y1) pre =
precision_score(test_y1,y_pred1) recall =
recall_score(test_y1,y_pred1) f1 = f1_score(test_y1,y_pred1)
fbeta0_5 = fbeta_score(test_y1,y_pred1,beta=0.5)
fbeta2 = fbeta_score(test_y1,y_pred1,beta=2)
result.loc['KNN_SMOTE'] = [acc,pre,recall,f1,fbeta0_5,fbeta2]
result
```

```
Accuracy Score for KNN :  0.8371459694989106
```

Out[61]:

	Accuracy score	Precision	Recall	F1 Score	Fbeta Score(0.5)	Fbeta Score(2)
SVM	0.896365	0.880126	0.744000	0.806358	0.849057	0.767749
SVM_SMOTE	0.944989	0.930208	0.963323	0.946476	0.936648	0.956512
KNN	0.847641	0.709906	0.802667	0.753442	0.726702	0.782225
KNN_SMOTE	0.837146	0.756956	0.997843	0.860866	0.795357	0.938134

In [62]:

```
confusion_matrix(test_y1,y_pred1)
```

Out[62]:

```
array([[612, 297],
       [  2, 925]], dtype=int64)
```

[63]:

```
print(classification_report(test_y1,y_pred1))
```

```
              precision    recall  f1-score   support

           0       1.00      0.67      0.80       909
 1        0.76      1.00      0.86       927

    accuracy                           0.84      1836
macro avg       0.88      0.84      0.83      1836
weighted avg       0.88      0.84      0.83      1836
```

In

Using GridSearchCV

In [64]:
```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

In [65]:
```
knn_model=KNeighborsClassifier()
```

In [66]:
```
hyperparamters = {'n_neighbors':np.arange(2,10),
                  'p':[1,2]}
rscv_model= RandomizedSearchCV(knn_model,hyperparamters,cv=5)
rscv_model.fit(train_x1,train_y1)
```

Out[66]:
```
RandomizedSearchCV(cv=5, estimator=KNeighborsClassifier(),
 param_distributions={'n_neighbors': array([2, 3, 4, 5, 6, 7,
8, 9]),
                                        'p': [1, 2]})
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [67]:
```
rscv_model.best_params_
```

Out[67]:
```
{'p': 2, 'n_neighbors': 2}
```

[70]:
```
knn_model= KNeighborsClassifier(n_neighbors=2,p=2)
# Train the model using the training sets
knn_model.fit(train_x,train_y) y_pred =
knn_model.predict(test_x)
print("Accuracy Score for KNN : ",
accuracy_score(y_pred,test_y)) acc =
accuracy_score(y_pred,test_y) pre =
precision_score(test_y,y_pred) recall =
recall_score(test_y,y_pred) f1 = f1_score(test_y,y_pred)
fbeta0_5 = fbeta_score(test_y,y_pred,beta=0.5)
fbeta2 = fbeta_score(test_y,y_pred,beta=2)
result.loc['KNN_SMOTE_Hyperparameter_Tuning'] = [acc,pre,recall,f1,fbeta0_5,fbeta
result
```

```
Accuracy Score for KNN :  0.8592420726991493
```

Out[70]:

	Accuracy score	Precision	Recall	F1 Score	Fbeta Score(0.5)	Fbeta Score(2)
SVM	0.896365	0.880126	0.744000	0.806358	0.849057	0.767749
SVM_SMOTE	0.944989	0.930208	0.963323	0.946476	0.936648	0.956512
KNN	0.847641	0.709906	0.802667	0.753442	0.726702	0.782225

In

KNN_SMOTE	0.837146	0.756956	0.997843	0.860866	0.795357	0.938134
KNN_SMOTE_Hyperparameter_Tuning	0.859242	0.793313	0.696000	0.741477	0.771733	0.713505

In [71]:

```
knn_model= KNeighborsClassifier(n_neighbors=2,p=2)
# Train the model using the training sets
knn_model.fit(train_x1,train_y1) y_pred1
= knn_model.predict(test_x1)
print("Accuracy Score for KNN : ",
accuracy_score(y_pred1,test_y1)) acc =
accuracy_score(y_pred1,test_y1) pre =
precision_score(test_y1,y_pred1) recall =
recall_score(test_y1,y_pred1) f1 = f1_score(test_y1,y_pred1)
fbeta0_5 = fbeta_score(test_y1,y_pred1,beta=0.5)
fbeta2 = fbeta_score(test_y1,y_pred1,beta=2)
result.loc['KNN_SMOTE_Hyperparameter_Tuning1'] = [acc,pre,recall,f1,fbeta0_5,fbet
result
```

```
Accuracy Score for KNN :  0.8932461873638344
```

Out[71]:

	Accuracy score	Precision	Recall	F1 Score	Fbeta Score(0.5)	Fbet Score(2
SVM	0.896365	0.880126	0.744000	0.806358	0.849057	0.76774
SVM_SMOTE	0.944989	0.930208	0.963323	0.946476	0.936648	0.95651
KNN	0.847641	0.709906	0.802667	0.753442	0.726702	0.78222
KNN_SMOTE	0.837146	0.756956	0.997843	0.860866	0.795357	0.93813
KNN_SMOTE_Hyperparameter_Tuning	0.859242	0.793313	0.696000	0.741477	0.771733	0.71350
KNN_SMOTE_Hyperparameter_Tuning1	0.893246	0.829576	0.992449	0.903733	0.857729	0.95495

In [ ]: