```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

df = pd.read_csv("Classified Data",index_col=0)
df
```

```
          WTT       PTI       EQW       SBI       LQE       QWG  
FDJ  \
0    0.913917  1.162073  0.567946  0.755464  0.780862  0.352608  
0.759697   
1    0.635632  1.003722  0.535342  0.825645  0.924109  0.648450  
0.675334   
2    0.721360  1.201493  0.921990  0.855595  1.526629  0.720781  
1.626351   
3    1.234204  1.386726  0.653046  0.825624  1.142504  0.875128  
1.409708   
4    1.279491  0.949750  0.627280  0.668976  1.232537  0.703727  
1.115596   
..        ...       ...       ...       ...       ...       ...  
...   
995  1.010953  1.034006  0.853116  0.622460  1.036610  0.586240  
0.746811   
996  0.575529  0.955786  0.941835  0.792882  1.414277  1.269540  
1.055928   
997  1.135470  0.982462  0.781905  0.916738  0.901031  0.884738  
0.386802   
998  1.084894  0.861769  0.407158  0.665696  1.608612  0.943859  
0.855806   
999  0.837460  0.961184  0.417006  0.799784  0.934399  0.424762  
0.778234   

          PJF       HQE       NXJ  TARGET CLASS  
0    0.643798  0.879422  1.231409             1  
1    1.013546  0.621552  1.492702             0  
2    1.154483  0.957877  1.285597             0  
3    1.380003  1.522692  1.153093             1  
4    0.646691  1.463812  1.419167             1  
..        ...       ...       ...           ...  
995  0.319752  1.117340  1.348517             1  
996  0.713193  0.958684  1.663489             0  
997  0.389584  0.919191  1.385504             1  
998  1.061338  1.277456  1.188063             1  
999  0.907962  1.257190  1.364837             1  

[1000 rows x 11 columns]
```

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(df.drop('TARGET CLASS',axis=1))
```

```
StandardScaler()
```

```
scaled_features = scaler.transform(df.drop('TARGET CLASS',axis=1))
df_feat = pd.DataFrame(scaled_features,columns=df.columns[:-1])
df_feat.head()
```

```
        WTT       PTI       EQW       SBI       LQE       QWG       
FDJ  \
0 -0.123542  0.185907 -0.913431  0.319629 -1.033637 -2.308375 -
0.798951
1 -1.084836 -0.430348 -1.025313  0.625388 -0.444847 -1.152706 -
1.129797
2 -0.788702  0.339318  0.301511  0.755873  2.031693 -0.870156  
2.599818
3  0.982841  1.060193 -0.621399  0.625299  0.452820 -0.267220  
1.750208
4  1.139275 -0.640392 -0.709819 -0.057175  0.822886 -0.936773  
0.596782

        PJF       HQE       NXJ
0 -1.482368 -0.949719 -0.643314
1 -0.202240 -1.828051  0.636759
2  0.285707 -0.682494 -0.377850
3  1.066491  1.241325 -1.026987
4 -1.472352  1.040772  0.276510
```

```
df_feat.tail()
```

```
          WTT       PTI       EQW       SBI       LQE       QWG       
FDJ  \
995  0.211653 -0.312490  0.065163 -0.259834  0.017567 -1.395721 -
0.849486
996 -1.292453 -0.616901  0.369613  0.482648  1.569891  1.273495  
0.362784
997  0.641777 -0.513083 -0.179205  1.022255 -0.539703 -0.229680 -
2.261339
998  0.467072 -0.982786 -1.465194 -0.071465  2.368666  0.001269 -
0.422041
999 -0.387654 -0.595894 -1.431398  0.512722 -0.402552 -2.026512 -
0.726253

          PJF       HQE       NXJ
995 -2.604264 -0.139347 -0.069602
996 -1.242110 -0.679746  1.473448
997 -2.362494 -0.814261  0.111597
998 -0.036777  0.406025 -0.855670
999 -0.567789  0.336997  0.010350
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test =
train_test_split(scaled_features,df['TARGET CLASS'],
                                                    test_size=0.30)
```

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train,y_train)
```

```
KNeighborsClassifier(n_neighbors=1)
```

```
pred = knn.predict(X_test)
```

```
from sklearn.metrics import classification_report,confusion_matrix
print(confusion_matrix(y_test,pred))
```

```
[[136  11]
 [ 12 141]]
```

```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.93      0.92       147
           1       0.93      0.92      0.92       153

    accuracy                           0.92       300
   macro avg       0.92      0.92      0.92       300
weighted avg       0.92      0.92      0.92       300
```

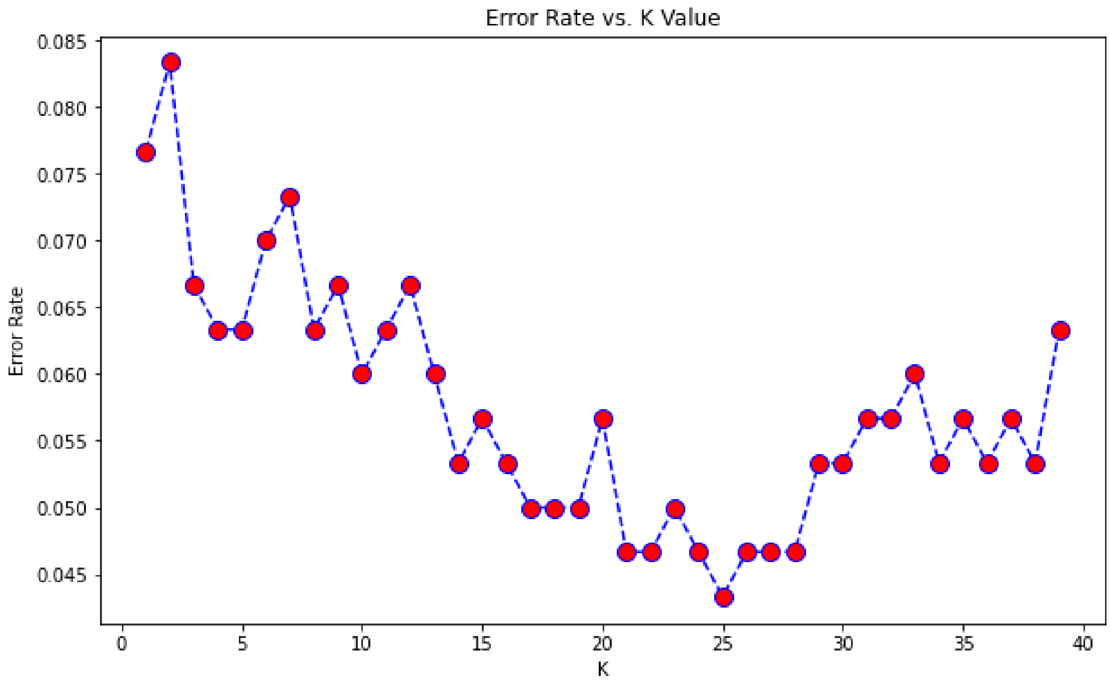
```
error_rate = []

# Will take some time
for i in range(1,40):

    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train,y_train)
    pred_i = knn.predict(X_test)
    error_rate.append(np.mean(pred_i != y_test))
```

```
plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate,color='blue', linestyle='dashed',
marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

```
Text(0, 0.5, 'Error Rate')
```




```
# FIRST A QUICK COMPARISON TO OUR ORIGINAL K=1
knn = KNeighborsClassifier(n_neighbors=1)

knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print('WITH K=1')
print('\n')
print(confusion_matrix(y_test,pred))
print('\n')
print(classification_report(y_test,pred))
```

```
WITH K=1


[[136  11]
 [ 12 141]]


              precision    recall  f1-score   support

           0       0.92      0.93      0.92       147
           1       0.93      0.92      0.92       153

    accuracy                           0.92       300
   macro avg       0.92      0.92      0.92       300
weighted avg       0.92      0.92      0.92       300
```