K Nearest Neighbour Project

Given a classified data set from a company haven't hidden the feature column names but have given you a data set which include a target class column.

- This tutorial and execerise was gotten from the internet from Pierian Data which is an artificial data set.

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

```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
pf= pd.read_csv('KNN_Project_Data')
```

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

Out[3]:

	XVPM	GWYH	TRAT	TLLZ	IGGA	HYKR	EDFS	GUUB	MGJM	JHZC	TARGET CLASS
0	1636.670614	817.988525	2565.995189	358.347163	550.417491	1618.870897	2147.641254	330.727893	1494.878631	845.136088	0
1	1013.402760	577.587332	2644.141273	280.428203	1161.873391	2084.107872	853.404981	447.157619	1193.032521	861.081809	1
2	1300.035501	820.518697	2025.854469	525.562292	922.206261	2552.355407	818.676686	845.491492	1968.367513	1647.186291	1
3	1059.347542	1066.866418	612.000041	480.827789	419.467495	685.666983	852.867810	341.664784	1154.391368	1450.935357	0
4	1018.340526	1313.679056	950.622661	724.742174	843.065903	1370.554164	905.469453	658.118202	539.459350	1899.850792	0

In [4]:
```
pf.describe()
```

Out[4]:

	XVPM	GWYH	TRAT	TLLZ	IGGA	HYKR	EDFS	GUUB	MGJM	JHZC	TARGET CLASS
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000
mean	1055.071157	991.851567	1529.373525	495.107156	940.590072	1550.637455	1561.003252	561.346117	1089.067338	1452.521629	0.50000
std	370.980193	392.278890	640.286092	142.789188	345.923136	493.491988	598.608517	247.357552	402.666953	568.132005	0.50025
min	21.170000	21.720000	31.800000	8.450000	17.930000	27.930000	31.960000	13.520000	23.210000	30.890000	0.00000
25%	767.413366	694.859326	1062.600806	401.788135	700.763295	1219.267077	1132.097865	381.704293	801.849802	1059.499689	0.00000
50%	1045.904805	978.355081	1522.507269	500.197421	939.348662	1564.996551	1565.882879	540.420379	1099.087954	1441.554053	0.50000
75%	1326.065178	1275.528770	1991.128626	600.525709	1182.578166	1891.937040	1981.739411	725.762027	1369.923665	1864.405512	1.00000
max	2117.000000	2172.000000	3180.000000	845.000000	1793.000000	2793.000000	3196.000000	1352.000000	2321.000000	3089.000000	1.00000

In [5]:

```
pf.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   XVPM          1000 non-null   float64
 1   GWYH          1000 non-null   float64
 2   TRAT          1000 non-null   float64
 3   TLLZ          1000 non-null   float64
 4   IGGA          1000 non-null   float64
 5   HYKR          1000 non-null   float64
 6   EDFS          1000 non-null   float64
 7   GUUB          1000 non-null   float64
 8   MGJM          1000 non-null   float64
 9   JHZC          1000 non-null   float64
 10  TARGET CLASS  1000 non-null   int64  
dtypes: float64(10), int64(1)
memory usage: 86.1 KB
```

Exploratory data analysis (EDA)

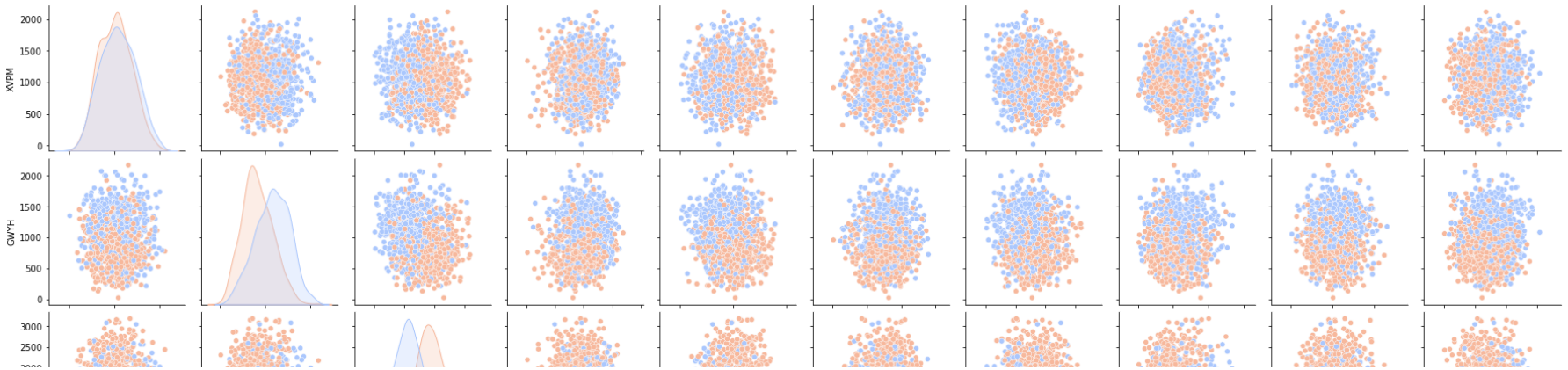
In [6]:

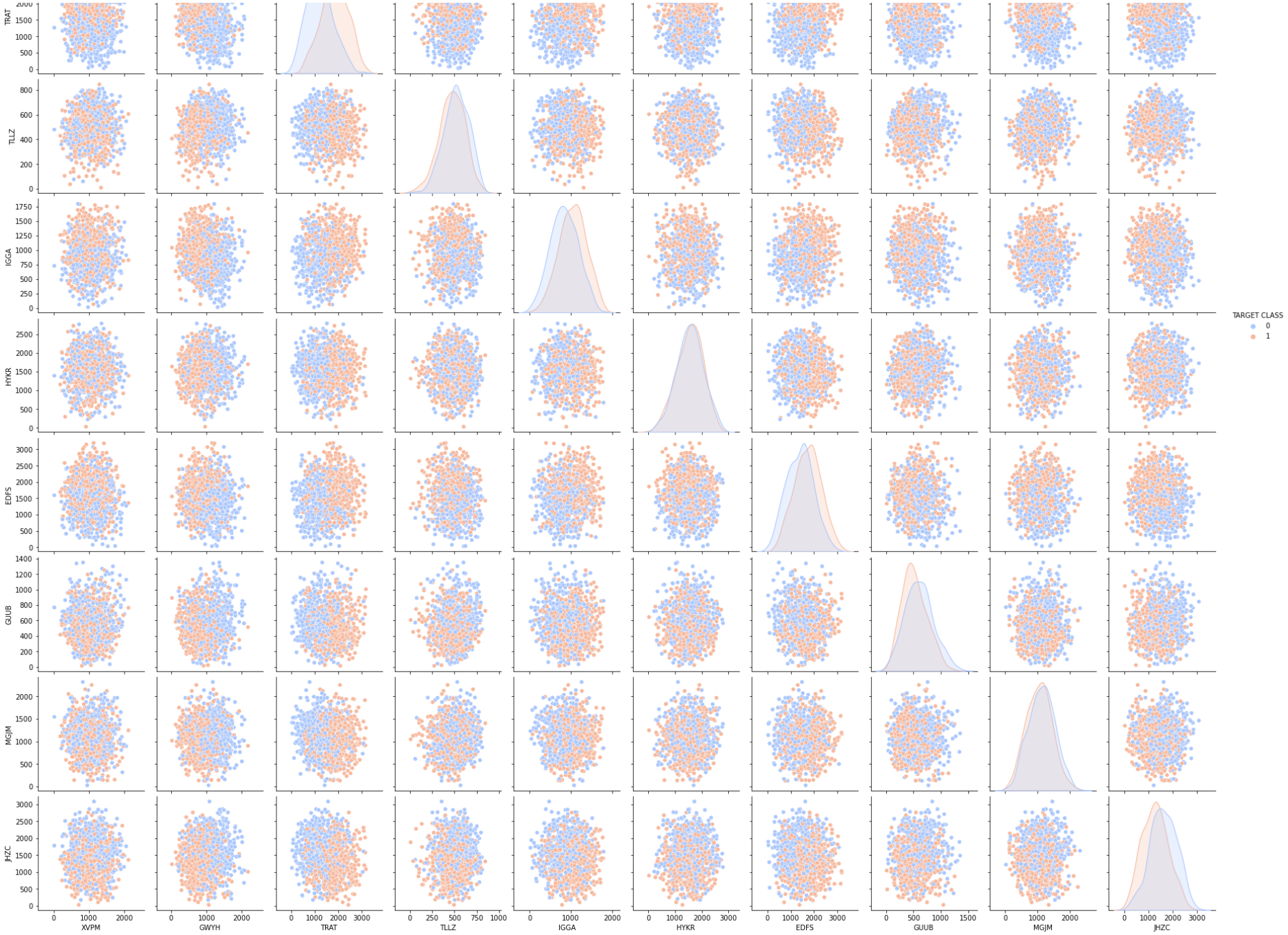
```
#sns.pairplot(pf,hue='TARGET CLASS',palette='coolwarm')


# THIS IS GOING TO BE A VERY LARGE PLOT
sns.pairplot(pf,hue='TARGET CLASS',palette='coolwarm')
```

Out[6]:

```
<seaborn.axisgrid.PairGrid at 0x181bbdd02b0>
```




TRAT
TLLZ
IGGA
HYKR
EDFS
GUUB
MGJM
JHZC
XVPM
GWYH
TRAT
TLLZ
IGGA
HYKR
EDFS
GUUB
MGJM
JHZC
TARGET CLASS
0
1

Standardize the Variables

Importing StandardScaler from sklearn

In [7]:
```
from sklearn.preprocessing import StandardScaler
```

crarting a standard scealer object called scaler

In [8]:
```
scaler = StandardScaler()
```

Fit scaler to the features

In [9]:
```
scaler.fit(pf.drop('TARGET CLASS', axis =1 ))
```

Out[9]:
```
StandardScaler()
```

In [10]:
```
scaled_features = scaler.transform(pf.drop('TARGET CLASS',axis=1))
```

Converting the scaled features to dataframe and check the head of the dataframe to make suure the scaling worked

In [11]:
```
pf
```

Out[11]:

	XVPM	GWYH	TRAT	TLLZ	IGGA	HYKR	EDFS	GUUB	MGJM	JHZC	TARGET CLASS
0	1636.670614	817.988525	2565.995189	358.347163	550.417491	1618.870897	2147.641254	330.727893	1494.878631	845.136088	0
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4	1018.340526	1313.679056	950.622661	724.742174	843.065903	1370.554164	905.469453	658.118202	539.459350	1899.850792	0
...	...	...	...	...	...	...	...	...	...	...	...

	XVPM	GWYH	TRAT	TLLZ	IGGA	HYKR	EDFS	GUUB	MGJM	JHZC	TARGET CLASS
995	1343.060600	1289.142057	407.307449	567.564764	1000.953905	919.602401	485.269059	668.007397	1124.772996	2127.628290	0
996	938.847057	1142.884331	2096.064295	483.242220	522.755771	1703.169782	2007.548635	533.514816	379.264597	567.200545	1
997	921.994822	607.996901	2065.482529	497.107790	457.430427	1577.506205	1659.197738	186.854577	978.340107	1943.304912	1
998	1157.069348	602.749160	1548.809995	646.809528	1335.737820	1455.504390	2788.366441	552.388107	1264.818079	1331.879020	1
999	1287.150025	1303.600085	2247.287535	664.362479	1132.682562	991.774941	2007.676371	251.916948	846.167511	952.895751	1

1000 rows × 11 columns

In [12]:
```
pf_feat=pd.DataFrame(scaled_features,columns=pf.columns[:-1])
pf_feat.head()
```

Out[12]:

	XVPM	GWYH	TRAT	TLLZ	IGGA	HYKR	EDFS	GUUB	MGJM	JHZC
0	1.568522	-0.443435	1.619808	-0.958255	-1.128481	0.138336	0.980493	-0.932794	1.008313	-1.069627
1	-0.112376	-1.056574	1.741918	-1.504220	0.640009	1.081552	-1.182663	-0.461864	0.258321	-1.041546
2	0.660647	-0.436981	0.775793	0.213394	-0.053171	2.030872	-1.240707	1.149298	2.184784	0.342811
3	0.011533	0.191324	-1.433473	-0.100053	-1.507223	-1.753632	-1.183561	-0.888557	0.162310	-0.002793
4	-0.099059	0.820815	-0.904346	1.609015	-0.282065	-0.365099	-1.095644	0.391419	-1.365603	0.787762

Train Test Split

In [20]:
```
from sklearn.model_selection import train_test_split
```

In [21]:
```
X=pf_feat
y=pf['TARGET CLASS']
```

In [22]:
```
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.3, random_state=101)
```

Using KNN

In [24]:
```
from sklearn.neighbors import KNeighborsClassifier
```

creating a KNN model instance with n_neighbors=1

In [25]:
```
knn = KNeighborsClassifier(n_neighbors=1)
```

Fit tis KNN model to the training data

In [29]:
```
knn.fit(X_train,y_train)
```

Out[29]:
```
KNeighborsClassifier(n_neighbors=1)
```

Prediction and Evaluations

In [30]:
```
pred = knn.predict(X_test)
```

creating a confusion matrix and classification report

In [31]:
```
from sklearn.metrics import classification_report, confusion_matrix
```

In [32]:
```
print(confusion_matrix(y_test,pred))
```

```
[[109  43]
 [ 41 107]]
```

In [33]:
```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.73      0.72      0.72       152
           1       0.71      0.72      0.72       148

    accuracy                           0.72       300
```

```
   macro avg       0.72      0.72      0.72       300
weighted avg       0.72      0.72      0.72       300
```

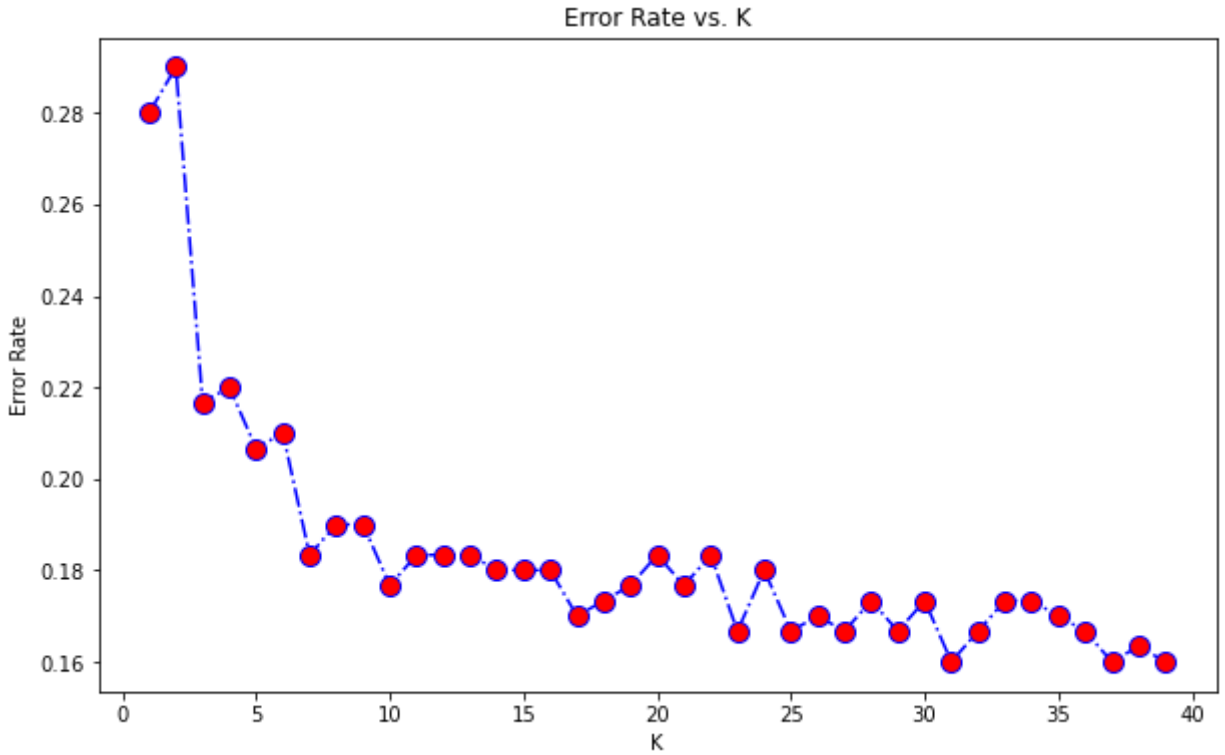
Choosing a K vale

creating a for loop trains varoius KNN model differnt K values, then keep track of the error_rate for each of these models with a list

In [37]:
```
error_rate = []

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))
```

In [58]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate, color='blue',linestyle='dashdot',marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[58]:
```
Text(0, 0.5, 'Error Rate')
```



In [ ]:

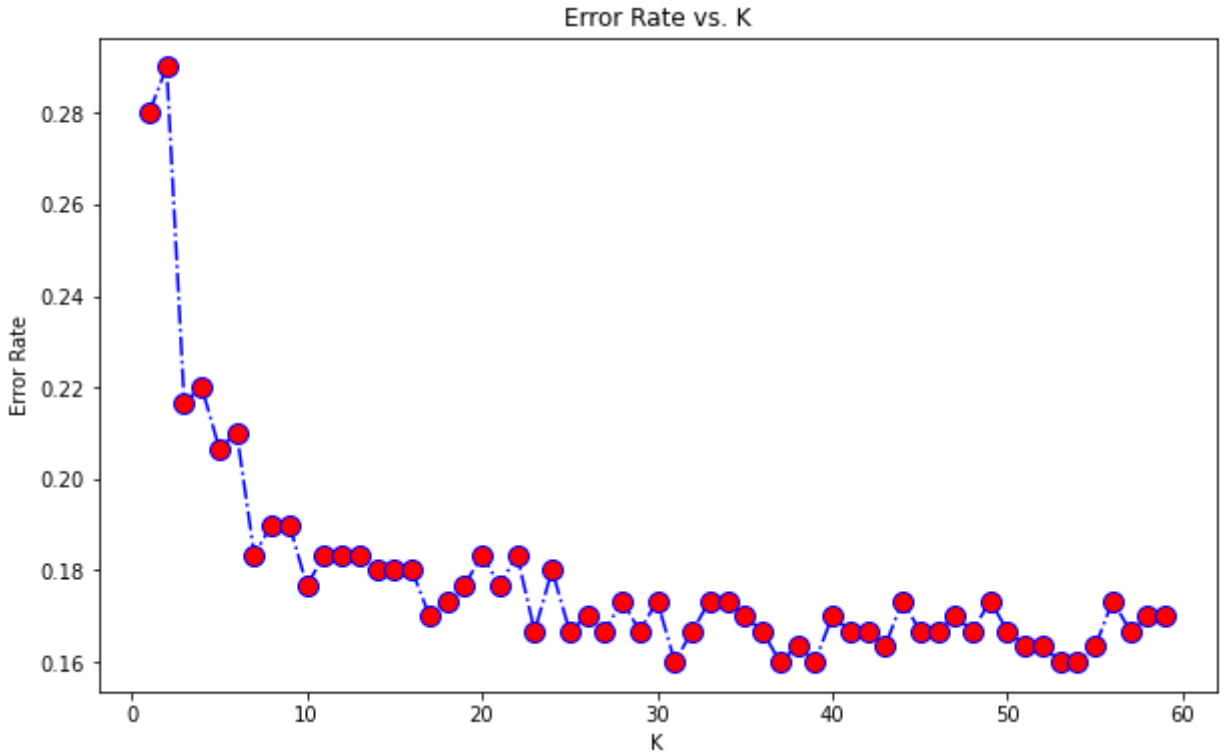
Note:- Repeating the process using a large K value to see the different between the error rate

In [62]:
```
error_rate = []

for i in range (1,60):

    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))
```

In [65]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,60),error_rate, color='blue',linestyle='dashdot',marker='o',
```

```
          markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[65]: Text(0, 0.5, 'Error Rate')



Retraining with new K vale of 30

In [73]:

```
knn=KNeighborsClassifier(n_neighbors=30)
knn.fit(X_train,y_train)
pred = knn.predict(X_test)
print(confusion_matrix(y_test,pred))
print('\n')
print(classification_report(y_test,pred))
```

```
[[124  28]
 [ 24 124]]
```

	precision	recall	f1-score	support
0	0.84	0.82	0.83	152
1	0.82	0.84	0.83	148
accuracy			0.83	300
macro avg	0.83	0.83	0.83	300
weighted avg	0.83	0.83	0.83	300

conclusion

chosing a new K value there is an increase of 10% after retarin and choosing the new K of 30.
You can see from the 2nd classification report.

Due to the data is classified can't really know what the data was used for that why KNN was used.

In [ ]: