Excercise_7_solutions_part_1

May 30, 2019

1 K Nearest Neighbors Project

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv('KNN_Project_Data.csv')
```

In [2]:
```
df.head()
```

Out[2]:

	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 [3]:
```
df.info()
```

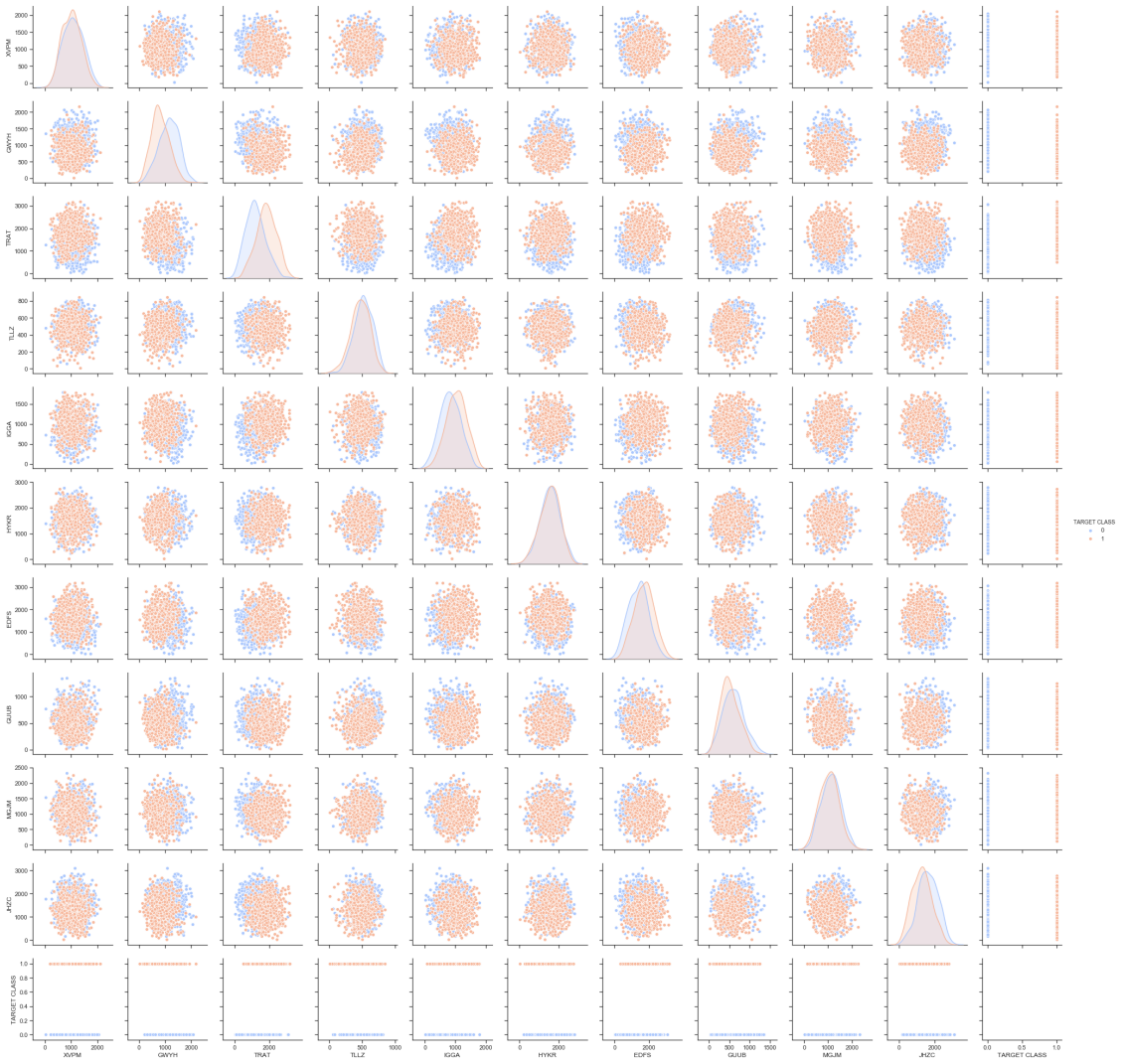
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
```

```
XVPM            1000 non-null float64
GWYH            1000 non-null float64
TRAT            1000 non-null float64
TLLZ            1000 non-null float64
IGGA            1000 non-null float64
HYKR            1000 non-null float64
EDFS            1000 non-null float64
GUUB            1000 non-null float64
MGJM            1000 non-null float64
JHZC            1000 non-null float64
TARGET CLASS    1000 non-null int64
dtypes: float64(10), int64(1)
memory usage: 86.0 KB
```

```
In [4]: sns.set(style="ticks")
        sns.pairplot(df, hue='TARGET CLASS', palette='coolwarm')
```

```
C:\Users\Kamil\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
C:\Users\Kamil\Anaconda3\lib\site-packages\statsmodels\nonparametric\kde.py:488: RuntimeWarning
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
C:\Users\Kamil\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py:34: RuntimeWar
  FAC1 = 2*(np.pi*bw/RANGE)**2
C:\Users\Kamil\Anaconda3\lib\site-packages\numpy\core\fromnumeric.py:83: RuntimeWarning: invali
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
```

```
Out[4]: <seaborn.axisgrid.PairGrid at 0x2a1ea7c2ef0>
```



2 Standardize the Variables

Import StandardScaler from Scikit learn.

```
In [5]: from sklearn.preprocessing import StandardScaler
```

Create a StandardScaler() object called scaler.

```
In [6]: scaler = StandardScaler()
```

Fit scaler to the features.

```
In [7]: df.head()
```

```
Out[7]:           XVPM         GWYH         TRAT        TLLZ         IGGA  \
        0  1636.670614   817.988525  2565.995189  358.347163   550.417491
        1  1013.402760   577.587332  2644.141273  280.428203  1161.873391
        2  1300.035501   820.518697  2025.854469  525.562292   922.206261
        3  1059.347542  1066.866418   612.000041  480.827789   419.467495
        4  1018.340526  1313.679056   950.622661  724.742174   843.065903

                HYKR         EDFS        GUUB         MGJM         JHZC  \
        0  1618.870897  2147.641254  330.727893  1494.878631   845.136088
        1  2084.107872   853.404981  447.157619  1193.032521   861.081809
        2  2552.355407   818.676686  845.491492  1968.367513  1647.186291
        3   685.666983   852.867810  341.664784  1154.391368  1450.935357
        4  1370.554164   905.469453  658.118202   539.459350  1899.850792

           TARGET CLASS
        0             0
        1             1
        2             1
        3             0
        4             0
```

```
In [8]: scaler.fit(df.drop('TARGET CLASS', axis=1))
```

```
Out[8]: StandardScaler(copy=True, with_mean=True, with_std=True)
```

Use the .transform() method to transform the features to a scaled version.

```
In [9]: scaled_feature = scaler.transform(df.drop('TARGET CLASS', axis=1))
```

Convert the scaled features to a dataframe and check the head of this dataframe to make sure the scaling worked.

```
In [10]: X_features = pd.DataFrame(scaled_feature, columns=df.columns[:-1])
         X_features.head()
```

```
Out[10]:        XVPM      GWYH      TRAT      TLLZ      IGGA      HYKR      EDFS  \
         0  1.568522 -0.443435  1.619808 -0.958255 -1.128481  0.138336  0.980493
         1 -0.112376 -1.056574  1.741918 -1.504220  0.640009  1.081552 -1.182663
         2  0.660647 -0.436981  0.775793  0.213394 -0.053171  2.030872 -1.240707
         3  0.011533  0.191324 -1.433473 -0.100053 -1.507223 -1.753632 -1.183561
         4 -0.099059  0.820815 -0.904346  1.609015 -0.282065 -0.365099 -1.095644

                GUUB      MGJM      JHZC
         0 -0.932794  1.008313 -1.069627
         1 -0.461864  0.258321 -1.041546
         2  1.149298  2.184784  0.342811
         3 -0.888557  0.162310 -0.002793
         4  0.391419 -1.365603  0.787762
```

3 Train Test Split

Use train_test_split to split your data into a training set and a testing set.

```
In [11]: from sklearn.model_selection import train_test_split
```

```
In [12]: X = X_features
         y = df['TARGET CLASS']
         X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3, random_state=
```

4 Using KNN

- Import KNeighborsClassifier from scikit learn.

```
In [13]: from sklearn.neighbors import KNeighborsClassifier
```

- Create a KNN model instance with n_neighbors=1

```
In [14]: knn = KNeighborsClassifier(n_neighbors=1)
```

- Fit this KNN model to the training data.

```
In [15]: knn.fit(X_train,y_train)
```

```
Out[15]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=1, p=2,
                     weights='uniform')
```

5 Predictions and Evaluations

- Use the predict method to predict values using your KNN model and X_test.

```
In [16]: y_pred = knn.predict(X_test)
```

- Create a confusion matrix and classification report

```
In [17]: from sklearn.metrics import classification_report, confusion_matrix
```

```
In [18]: print('Classification report:',classification_report(y_test,y_pred))
         print('Confusion matrix:', confusion_matrix(y_test,y_pred))
```

```
Classification report:               precision    recall  f1-score   support

           0       0.70      0.75      0.73       146
           1       0.75      0.69      0.72       154

   micro avg       0.72      0.72      0.72       300
   macro avg       0.72      0.72      0.72       300
weighted avg       0.73      0.72      0.72       300

Confusion matrix: [[110  36]
 [ 47 107]]
```

6 Choosing a K Value

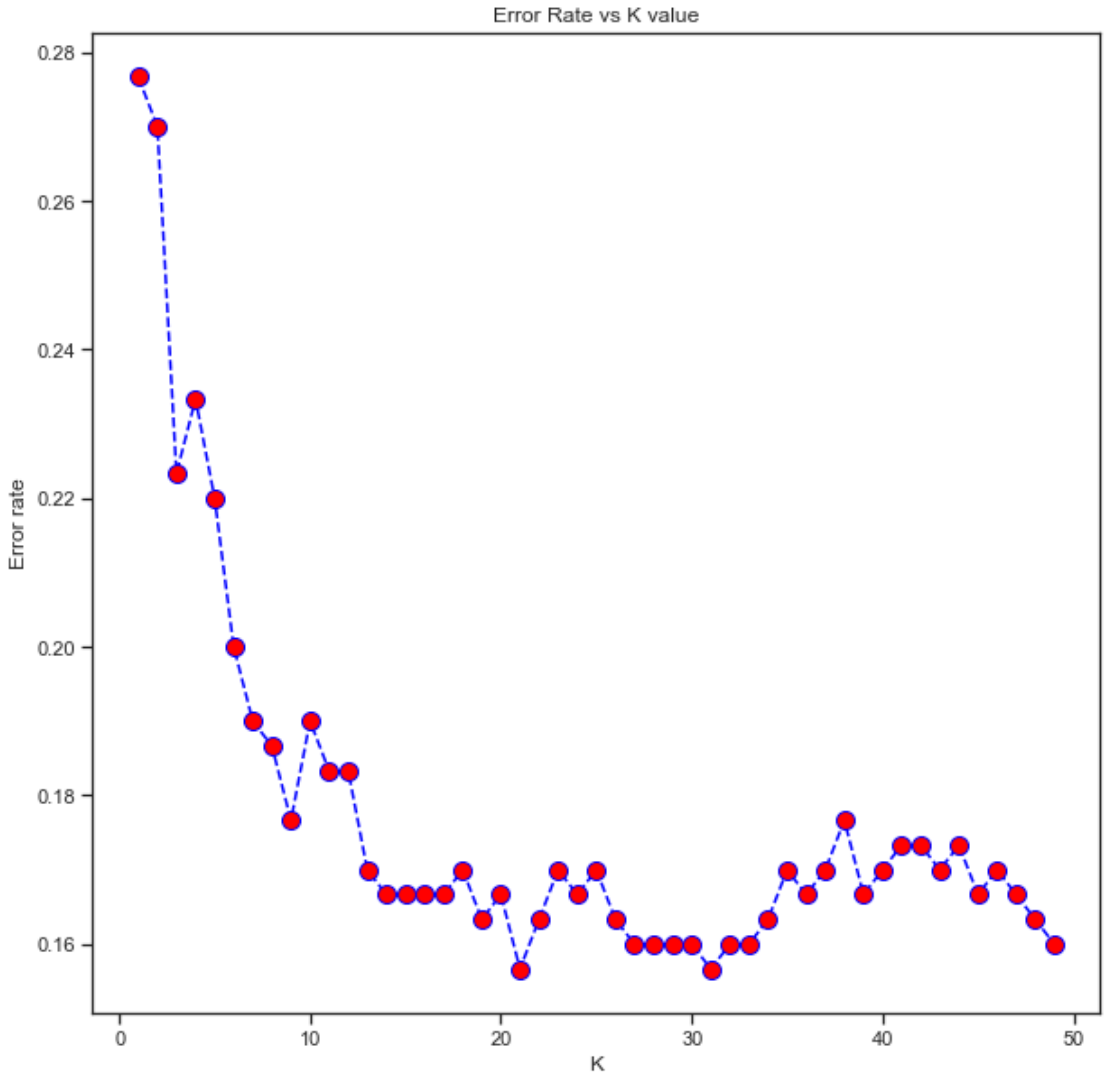
Create a for loop that trains various KNN models with different k values, then keep track of the error_rate for each of these models with a list. Refer to the lecture if you are confused on this step.

```
In [19]: error_rate =[]
         for i in range(1,50):
             knn = KNeighborsClassifier(n_neighbors=i)
             knn.fit(X_train,y_train)
             y_pred_i = knn.predict(X_test)
             error_rate.append(np.mean(y_pred_i != y_test))
```

Now create the following plot using the information from your for loop.

```
In [20]: plt.figure(figsize=(10,10))
         plt.plot(range(1,50), error_rate, color='blue',linestyle='--',marker='o',markerfaceco
         plt.title('Error Rate vs K value')
         plt.xlabel('K')
         plt.ylabel('Error rate')

Out[20]: Text(0, 0.5, 'Error rate')
```



7 Retrain with new K Value

Retrain your model with the best K value (up to you to decide what you want) and re-do the classification report and the confusion matrix.

```
In [21]: knn = KNeighborsClassifier(n_neighbors=30)
         knn.fit(X_train,y_train)
         y_pred = knn.predict(X_test)
         print (confusion_matrix(y_test,y_pred))
         print ('\n')
         print (classification_report(y_test,y_pred))
```

```
[[127  19]
 [ 29 125]]
```

	precision	recall	f1-score	support
0	0.81	0.87	0.84	146
1	0.87	0.81	0.84	154
micro avg	0.84	0.84	0.84	300
macro avg	0.84	0.84	0.84	300
weighted avg	0.84	0.84	0.84	300