K Nearest Neighbors with Python

You've been given a classified data set from a company! They've hidden the feature column names but have given you the data and the target classes.

We'll try to use KNN to create a model that directly predicts a class for a new data point based off of the features.

Let's grab it and use it!

Import Libraries

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

Get the Data

Set index_col=0 to use the first column as the index.

In [2]:
```
df = pd.read_csv("Classified Data",index_col=0)
```

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

Out[3]:

	WTT	PTI	EQW	SBI	LQE	QWG	FDJ	PJF	HQE	NXJ	TARGET CLASS
0	0.913917	1.162073	0.567946	0.755464	0.780862	0.352608	0.759697	0.643798	0.879422	1.231409	1
1	0.635632	1.003722	0.535342	0.825645	0.924109	0.648450	0.675334	1.013546	0.621552	1.492702	0
2	0.721360	1.201493	0.921990	0.855595	1.526629	0.720781	1.626351	1.154483	0.957877	1.285597	0
3	1.234204	1.386726	0.653046	0.825624	1.142504	0.875128	1.409708	1.380003	1.522692	1.153093	1
4	1.279491	0.949750	0.627280	0.668976	1.232537	0.703727	1.115596	0.646691	1.463812	1.419167	1

Standardize the Variables

Because the KNN classifier predicts the class of a given test observation by identifying the observations that are nearest to it, the scale of the variables matters. Any variables that are on a large scale will have a much larger effect on the distance between the observations, and hence on the KNN classifier, than variables that are on a small scale.

In [4]:
```
from sklearn.preprocessing import StandardScaler
```

In [5]:
```
scaler = StandardScaler()
```

In [6]:
```
scaler.fit(df.drop('TARGET CLASS',axis=1))
```

Out[6]:
```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

In [7]:
```
scaled_features = scaler.transform(df.drop('TARGET CLASS',axis=1))
```

In [8]:
```
df_feat = pd.DataFrame(scaled_features,columns=df.columns[:-1])
df_feat.head()
```

Out[8]:

	WTT	PTI	EQW	SBI	LQE	QWG	FDJ	PJF	HQE	NXJ
0	-0.123542	0.185907	-0.913431	0.319629	-1.033637	-2.308375	-0.798951	-1.482368	-0.949719	-0.643314
1	-1.084836	-0.430348	-1.025313	0.625388	-0.444847	-1.152706	-1.129797	-0.202240	-1.828051	0.636759
2	-0.788702	0.339318	0.301511	0.755873	2.031693	-0.870156	2.599818	0.285707	-0.682494	-0.377850
3	0.982841	1.060193	-0.621399	0.625299	0.452820	-0.267220	1.750208	1.066491	1.241325	-1.026987
4	1.139275	-0.640392	-0.709819	-0.057175	0.822886	-0.936773	0.596782	-1.472352	1.040772	0.276510

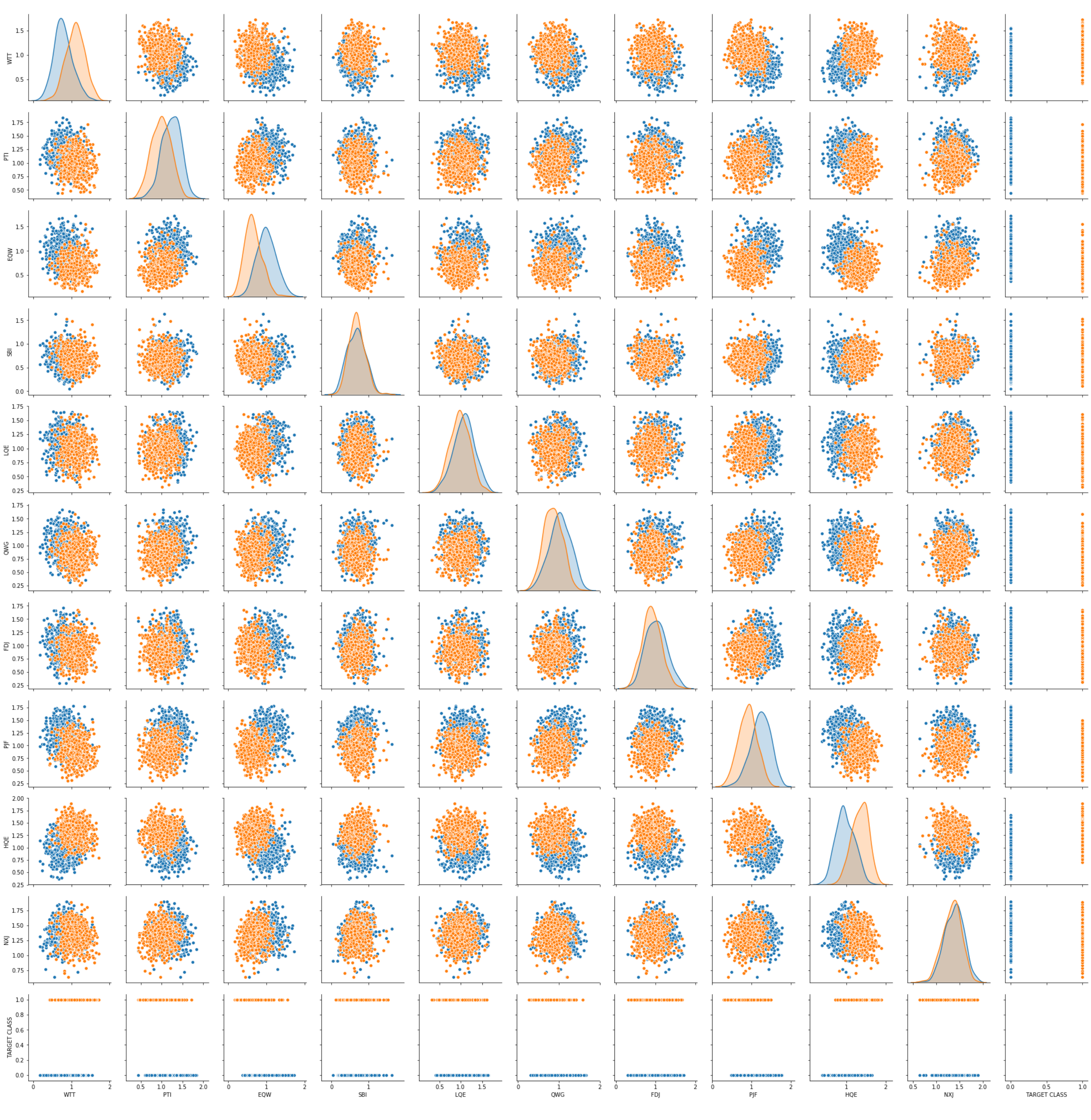
Pair Plot

In [9]:
```
import seaborn as sns

sns.pairplot(df,hue='TARGET CLASS')
```

```
C:\Users\krish.naik\AppData\Local\Continuum\anaconda3\envs\myenv\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
C:\Users\krish.naik\AppData\Local\Continuum\anaconda3\envs\myenv\lib\site-packages\statsmodels\nonparametric\kde.py:488: RuntimeWarning: invalid value encountered in true_divide
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
C:\Users\krish.naik\AppData\Local\Continuum\anaconda3\envs\myenv\lib\site-packages\statsmodels\nonparametric\kdetools.py:34: RuntimeWarning: invalid value encountered in double_scalars
  FAC1 = 2*(np.pi*bw/RANGE)**2
C:\Users\krish.naik\AppData\Local\Continuum\anaconda3\envs\myenv\lib\site-packages\numpy\core\fromnumeric.py:83: RuntimeWarning: invalid value encountered in reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
```

Out[9]:
```
<seaborn.axisgrid.PairGrid at 0x1edf103b710>
```



Train Test Split

In [10]:
```
from sklearn.model_selection import train_test_split
```

In [11]:
```
X_train, X_test, y_train, y_test = train_test_split(scaled_features,df['TARGET CLASS'],
                                                    test_size=0.30)
```

Using KNN

Remember that we are trying to come up with a model to predict whether someone will TARGET CLASS or not. We'll start with k=1.

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

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

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')
```

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

Predictions and Evaluations

Let's evaluate our KNN model!

In [21]:
```
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.model_selection import cross_val_score
```

In [18]:
```
print(confusion_matrix(y_test,pred))
```

```
[[135  14]
 [ 13 138]]
```

In [19]:
```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.91      0.91       149
           1       0.91      0.91      0.91       151

   micro avg       0.91      0.91      0.91       300
   macro avg       0.91      0.91      0.91       300
weighted avg       0.91      0.91      0.91       300
```

Choosing a K Value

Let's go ahead and use the elbow method to pick a good K Value:

In [22]:
```
accuracy_rate = []

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

    knn = KNeighborsClassifier(n_neighbors=i)
    score=cross_val_score(knn,df_feat,df['TARGET CLASS'],cv=10)
    accuracy_rate.append(score.mean())
```

In [23]:
```
error_rate = []

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

    knn = KNeighborsClassifier(n_neighbors=i)
    score=cross_val_score(knn,df_feat,df['TARGET CLASS'],cv=10)
    error_rate.append(1-score.mean())
```

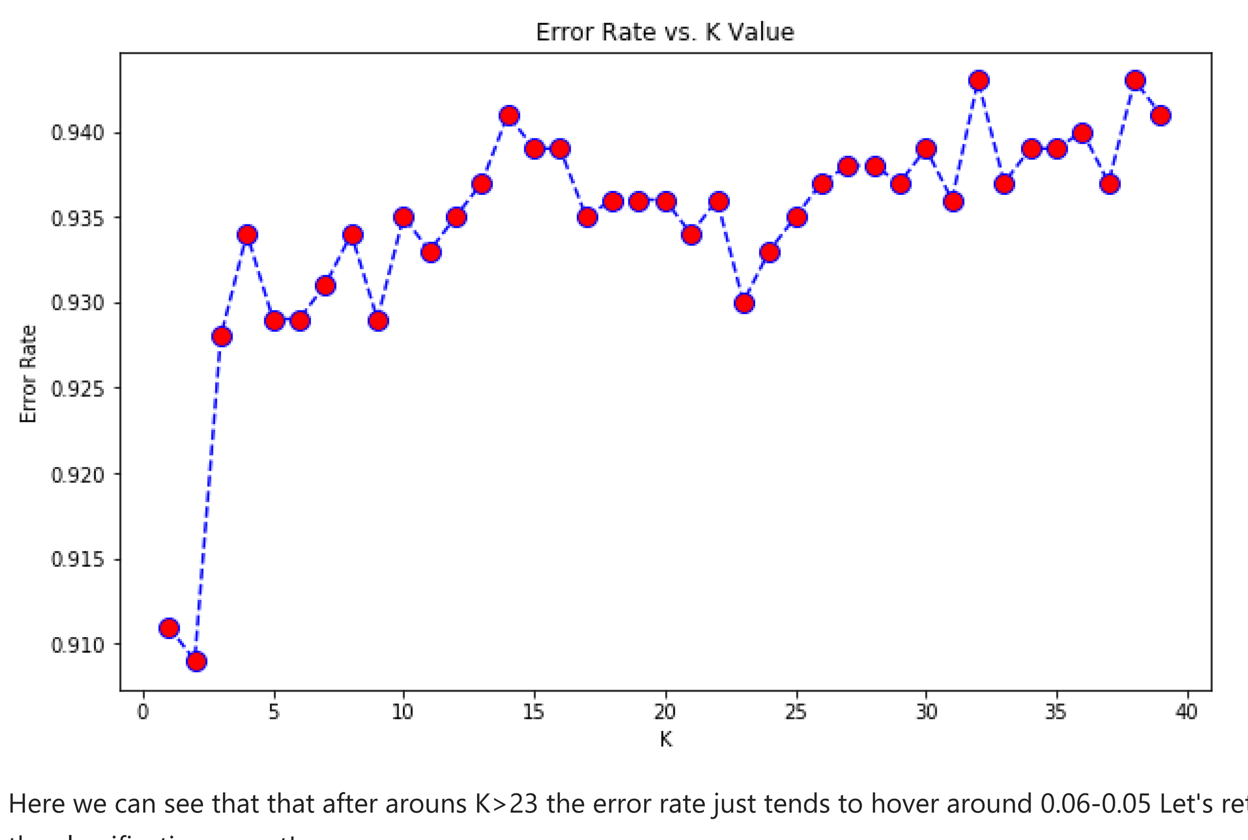
In [25]:
```
error_rate = []

# 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))
```

In [25]:
```
plt.figure(figsize=(10,6))
#plt.plot(range(1,40),error_rate,color='blue', linestyle='dashed', marker='o',
  #       markerfacecolor='red', markersize=10)
plt.plot(range(1,40),accuracy_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')
```

Out[25]:
```
Text(0, 0.5, 'Error Rate')
```



Here we can see that that after arouns K>23 the error rate just tends to hover around 0.06-0.05 Let's retrain the model with that and check the classification report!

In [100…
```
# 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


[[125  18]
 [ 13 144]]


             precision    recall  f1-score   support

          0       0.91      0.87      0.89       143
          1       0.89      0.92      0.90       157

avg / total       0.90      0.90      0.90       300
```

In [101…
```
# NOW WITH K=23
knn = KNeighborsClassifier(n_neighbors=23)

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

print('WITH K=23')
print('\n')
print(confusion_matrix(y_test,pred))
print('\n')
print(classification_report(y_test,pred))
```

```
WITH K=23


[[132  11]
 [  5 152]]


             precision    recall  f1-score   support

          0       0.96      0.92      0.94       143
          1       0.93      0.97      0.95       157

avg / total       0.95      0.95      0.95       300
```