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.

Import Libraries

In [8]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import model_selection
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
```

Get the Data

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

In [9]:
```
df = pd.read_csv("Classified Data",index_col=0)
```

In [10]:
```
df.head()
```

Out[10]:

	WTT	PTI	EQW	SBI	LQE	QWG	FDJ	PJF	HQE	
0	0.913917	1.162073	0.567946	0.755464	0.780862	0.352608	0.759697	0.643798	0.879422	1.231
1	0.635632	1.003722	0.535342	0.825645	0.924109	0.648450	0.675334	1.013546	0.621552	1.492
2	0.721360	1.201493	0.921990	0.855595	1.526629	0.720781	1.626351	1.154483	0.957877	1.285
3	1.234204	1.386726	0.653046	0.825624	1.142504	0.875128	1.409708	1.380003	1.522692	1.153
4	1.279491	0.949750	0.627280	0.668976	1.232537	0.703727	1.115596	0.646691	1.463812	1.419

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 [11]:
```
from sklearn.preprocessing import StandardScaler
```

In [12]:
```
scaler = StandardScaler()
```

In [13]:
```
scaler.fit(df.drop('TARGET CLASS',axis=1))
```

Out[13]:
```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

In [14]:
```
scaled_features = scaler.transform(df.drop('TARGET CLASS',axis=1))
```

In [15]:
```
df_feat = pd.DataFrame(scaled_features,columns=df.columns[:-1])
df_feat.head()
```

Out[15]:

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

Train Test Split

In [16]:
```
from sklearn.model_selection import train_test_split
```

In [17]:
```
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 [18]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [19]:
```
knn = KNeighborsClassifier(n_neighbors=1)
```

In [20]:
```
knn.fit(X_train,y_train)
```

Out[20]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=1, p=2,
                     weights='uniform')
```

In [21]:
```
pred = knn.predict(X_test)
```

In [22]:
```
acc = accuracy_score(y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 1 is %d%%' % (acc))
```

```

****Test accuracy for k = 1 is 89%
```

Predictions and Evaluations

Let's evaluate our KNN model!

In [23]:
```
from sklearn.metrics import classification_report,confusion_matrix
```

In [24]:
```
print(confusion_matrix(y_test,pred))
```

```
[[136  20]
 [ 12 132]]
```

In [25]:
```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.87      0.89       156
           1       0.87      0.92      0.89       144

    accuracy                           0.89       300
   macro avg       0.89      0.89      0.89       300
weighted avg       0.89      0.89      0.89       300
```

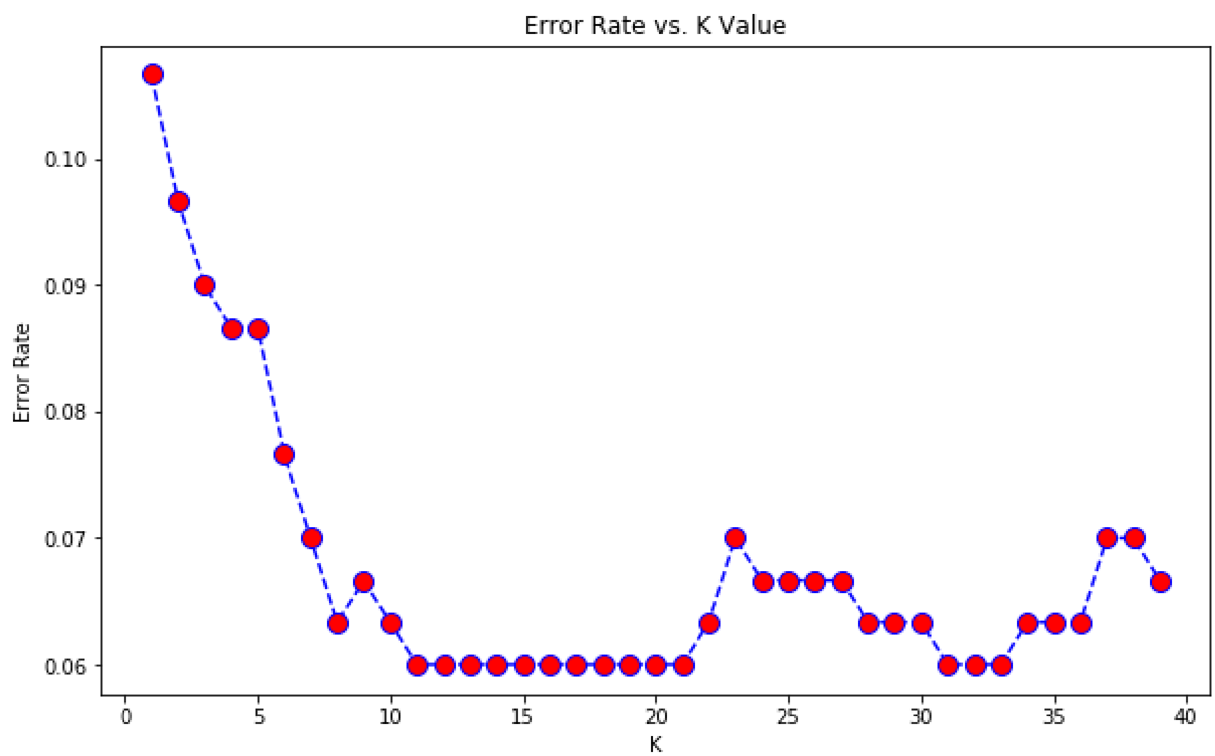
Choosing a K Value

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

In [26]:
```
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))
    #error_rate.append(np.mean(y_test != pred_i))
```

In [27]:
```
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')
```

Out[27]:
```
Text(0,0.5,'Error Rate')
```



Here we can see that that after arouns K>19 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 [28]:

```
# 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  20]
 [ 12 132]]


              precision    recall  f1-score   support

           0       0.92      0.87      0.89       156
           1       0.87      0.92      0.89       144

    accuracy                           0.89       300
   macro avg       0.89      0.89      0.89       300
weighted avg       0.89      0.89      0.89       300
```

In [29]:
```python
# NOW WITH K=19
knn = KNeighborsClassifier(n_neighbors=19)

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

print('WITH K=19')
print('\n')
print(confusion_matrix(y_test,pred))
print('\n')
print(classification_report(y_test,pred))
```

```
WITH K=19


[[144  12]
 [  6 138]]


              precision    recall  f1-score   support

           0       0.96      0.92      0.94       156
           1       0.92      0.96      0.94       144

    accuracy                           0.94       300
   macro avg       0.94      0.94      0.94       300
weighted avg       0.94      0.94      0.94       300
```

Simple Cross Validation

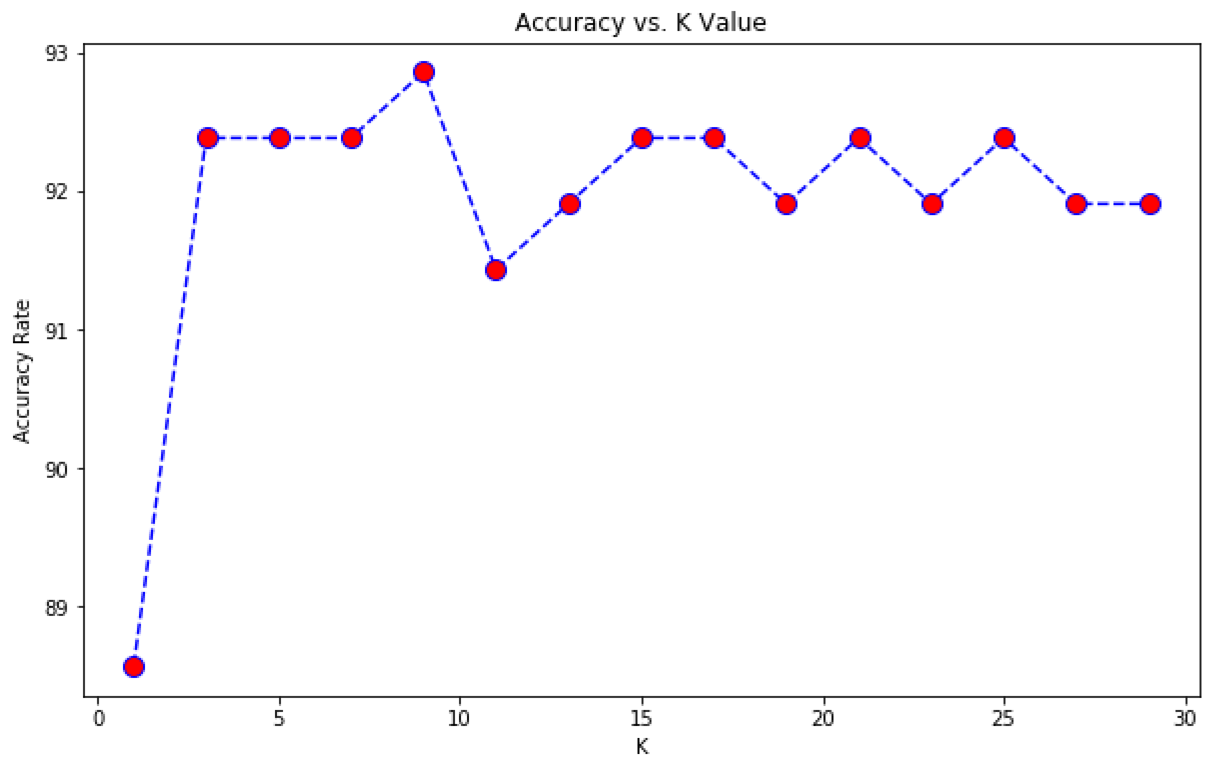
In [31]:

```python
# split the train data set into cross validation train and cross validation test
X_tr, X_cv, y_tr, y_cv = model_selection.train_test_split(X_train, y_train,
test_size=0.3)
neibhbors=[]
accuracy=[]
for i in range(1,30,2):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i)

    # fitting the model on crossvalidation train
    knn.fit(X_tr, y_tr)

    # predict the response on the crossvalidation train
    pred = knn.predict(X_cv)

    # evaluate CV accuracy
    acc = accuracy_score(y_cv, pred, normalize=True) * float(100)
    neibhbors.append(i)
    accuracy.append(acc)
    print('\nCV accuracy for k = %d is %d%%' % (i, acc))

plt.figure(figsize=(10,6))
plt.plot(range(1,30,2),accuracy,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Accuracy vs. K Value')
plt.xlabel('K')
plt.ylabel('Accuracy Rate')
```

```
CV accuracy for k = 1 is 88%

CV accuracy for k = 3 is 92%

CV accuracy for k = 5 is 92%

CV accuracy for k = 7 is 92%

CV accuracy for k = 9 is 92%

CV accuracy for k = 11 is 91%

CV accuracy for k = 13 is 91%

CV accuracy for k = 15 is 92%

CV accuracy for k = 17 is 92%

CV accuracy for k = 19 is 91%

CV accuracy for k = 21 is 92%

CV accuracy for k = 23 is 91%

CV accuracy for k = 25 is 92%
```

```
CV accuracy for k = 27 is 91%

CV accuracy for k = 29 is 91%
```

Out[31]:
```
Text(0,0.5,'Accuracy Rate')
```



In [60]:
```
knn1 = KNeighborsClassifier(13)
knn1.fit(X_tr,y_tr)
pred1 = knn1.predict(X_test)
acc = accuracy_score(y_test, pred1, normalize=True) * float(100)
print('\n****Test accuracy for k = 15 is %d%%' % (acc))
```

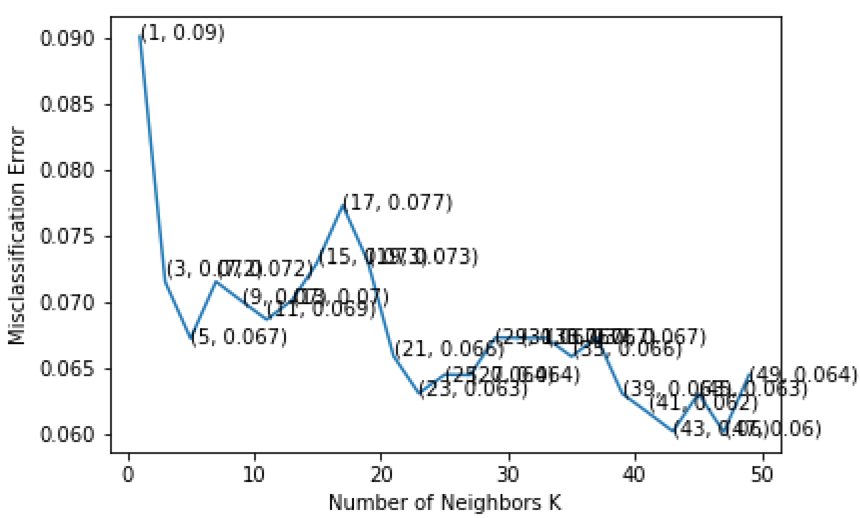
```
****Test accuracy for k = 15 is 94%
```

10 fold cross validation

In [32]:

```
# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

# empty list that will hold cv scores
cv_scores = []

# perform 10-fold cross validation
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy')
    cv_scores.append(scores.mean())

# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)

# plot misclassification error vs k
plt.plot(neighbors, MSE)

for xy in zip(neighbors, np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Number of Neighbors K')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each k value is : ", np.round(MSE,3))
```

```
The optimal number of neighbors is 47.
```



```
the misclassification error for each k value is :  [0.09  0.072 0.067 0.072 0.0
7  0.069 0.07  0.073 0.077 0.073 0.066 0.063
 0.064 0.064 0.067 0.067 0.067 0.066 0.067 0.063 0.062 0.06  0.063 0.06
 0.064]
```

In [33]:

```python
# NOW WITH K=27
knn2 = KNeighborsClassifier(n_neighbors=27)

knn2.fit(X_train,y_train)
pred2 = knn2.predict(X_test)

print('WITH K=27')
print('\n')
print(confusion_matrix(y_test,pred2))
print('\n')
print(classification_report(y_test,pred2))

acc = accuracy_score(y_test, pred2, normalize=True) * float(100)
print('\n****Test accuracy for k = 27 is %d%%' % (acc))
```

```
WITH K=27


[[143  13]
 [  7 137]]


              precision    recall  f1-score   support

           0       0.95      0.92      0.93       156
           1       0.91      0.95      0.93       144

    accuracy                           0.93       300
   macro avg       0.93      0.93      0.93       300
weighted avg       0.93      0.93      0.93       300


****Test accuracy for k = 27 is 93%
```

Great job!

We were able to squeeze some more performance out of our model by tuning to a better K value!

In [34]:
```python
# Predict output for some future data
dict_new = {'WTT': [0.635422],'PTI':[1.008422],'EQW':[0.538742],'SBI':
[0.725645],'LQE':[0.524109],'QWG':[0.148450],'FDJ':[0.975334],'PJF':
[1.913546],'HQE':[0.621552],'NXJ':[1.492702]}
df_new=pd.DataFrame(dict_new)
FuturePredict = knn2.predict(df_new)
print(FuturePredict[0])
```

```
0
```

In [ ]:
```python

```