K-Nearest Neighbors

Import Packages

In [28]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Prepare Dataset

This is a classified Dataset and the meaning of the data and columns are ambiguous.

In [29]:
```
raw_data = pd.read_csv('classified_data.csv', index_col = 0)
display(raw_data)
```

	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	1.23
1	0.635632	1.003722	0.535342	0.825645	0.924109	0.648450	0.675334	1.013546	0.621552	1.49
2	0.721360	1.201493	0.921990	0.855595	1.526629	0.720781	1.626351	1.154483	0.957877	1.28
3	1.234204	1.386726	0.653046	0.825624	1.142504	0.875128	1.409708	1.380003	1.522692	1.15
4	1.279491	0.949750	0.627280	0.668976	1.232537	0.703727	1.115596	0.646691	1.463812	1.41
...	...	...	...	...	...	...	...	...	...	
995	1.010953	1.034006	0.853116	0.622460	1.036610	0.586240	0.746811	0.319752	1.117340	1.34
996	0.575529	0.955786	0.941835	0.792882	1.414277	1.269540	1.055928	0.713193	0.958684	1.66
997	1.135470	0.982462	0.781905	0.916738	0.901031	0.884738	0.386802	0.389584	0.919191	1.38
998	1.084894	0.861769	0.407158	0.665696	1.608612	0.943859	0.855806	1.061338	1.277456	1.18
999	0.837460	0.961184	0.417006	0.799784	0.934399	0.424762	0.778234	0.907962	1.257190	1.36

1000 rows × 11 columns

In [30]:
```
print(raw_data.columns)
```

```
Index(['WTT', 'PTI', 'EQW', 'SBI', 'LQE', 'QWG', 'FDJ', 'PJF', 'HQE', 'NXJ',
       'TARGET CLASS'],
      dtype='object')
```

Scale Data

The scale of the features within a Dataset matters since you need to use the observations closest to the data point in order to make predictions.

For this reason, Machine Learning Practitioners standardize the Dataset a lot of the time by adjusting every x-value so they're approximately on the same scale.

In [31]:
```
from sklearn.preprocessing import StandardScaler
```

In [32]:
```
scaler = StandardScaler().fit(raw_data.drop('TARGET CLASS', axis = 1))
```

In [33]:
```
scaled_features = scaler.transform(raw_data.drop('TARGET CLASS', axis = 1))
```

Standardize all of the features in the Dataset to be approximately the same scale.

In [34]:
```
scaled_data = pd.DataFrame(scaled_features, columns = raw_data.drop('TARGET CLASS',
```

Split Training and Test Data

Lets do the *70/30* split for training and testing.

In [35]:
```
from sklearn.model_selection import train_test_split
```

In [36]:
```
# Specify x-values as the scaled_data DataFrame we created.
x = scaled_data
# Specify y-values as the TARGET CLASS column of raw_data DataFrame.
y = raw_data['TARGET CLASS']
```

In [37]:
```
x_training_data, x_test_data, y_training_data, y_test_data = train_test_split(x, y,
```

K-Nearest Neighbors Model

In [38]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [39]:
```
model_k_1 = KNeighborsClassifier(n_neighbors = 1).fit(x_training_data, y_training_d
```

Make Predictions and Measure Performance

In [40]:
```
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

In [41]:
```
predictions_k_1 = model_k_1.predict(x_test_data)
```

In [42]:
```
performance_report = classification_report(y_test_data, predictions_k_1)
print(performance_report)
```

```
'              precision    recall  f1-score   support\n\n           0       0.92      0.91      0.92       158\n           1       0.90      0.92      0.91       142\n\n    accuracy                           0.91       300\n   macro avg       0.91      0.91      0.91       300\nweighted avg       0.91      0.91      0.91       300\n'
```

In [43]:
```
performance_matrix = confusion_matrix(y_test_data, predictions_k_1)
print(performance_matrix)
```

```
array([[144,  14],
       [ 12, 130]], dtype=int64)
```

Optimal K-Value

Let's use the elbow method to find the optimal *K*-value.

Loop through *K* values from *1* to *100* and select the value with the lowest error rate when applied to our Test Data. This is done by appending the error rates for the *K* values to a list `error_rates`.

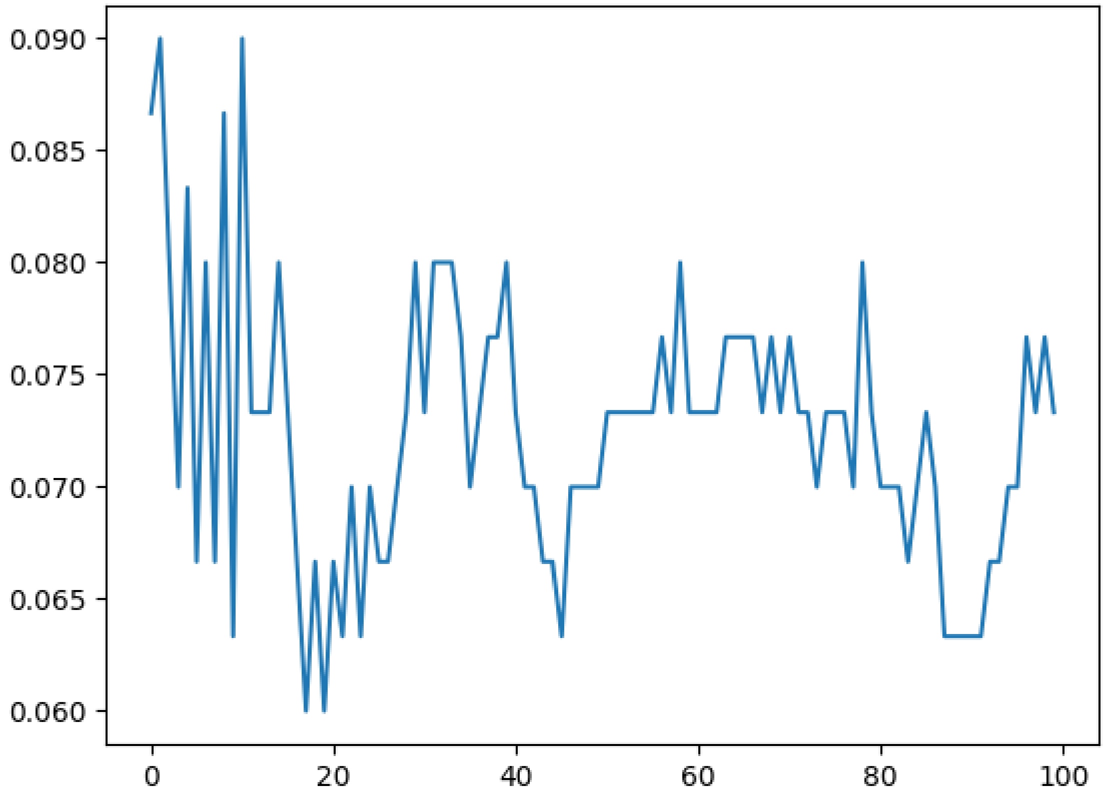
In [44]:
```
error_rates = []
for i in np.arange (1, 101) :
    # We must create a new instance of class KNeighborsClassifier from scikit-learn
    new_model = KNeighborsClassifier(n_neighbors = i)
    # Train the model by fitting it to our Training Data.
    new_model.fit(x_training_data, y_training_data)
    # Make predictions on the Test Data.
    new_predictions = new_model.predict(x_test_data)
    # Calculate the mean difference for every incorrect prediction.
    error_rates.append(np.mean(new_predictions != y_test_data))
```

K-Value Error Rate Plot

Visualize how our error rate changes with different *K* values using a `matplotlib` visualization.

In [45]:
```
plt.plot(error_rates)
```

Out[45]:
```
[<matplotlib.lines.Line2D at 0x2759a290820>]
```



Model With K = 50

We notice that the error rates tend to be minimized with *K* value of approximately *50*. This would balance both simplicity and predictive power to refrain from delving into overfitting and underfitting our model.

In [46]:
```
model_k_50 = KNeighborsClassifier(n_neighbors = 50).fit(x_training_data, y_training
```

Make Predictions and Measure Performance

In [47]:
```
predictions_k_50 = model_k_50.predict(x_test_data)
```

In [48]:
```
report_k_50 = classification_report(y_test_data, predictions_k_50)
print(report_k_50)
```

```
'              precision    recall  f1-score   support\n\n           0       0.95
     0.91      0.93       158\n           1       0.91      0.95      0.93       1
42\n\n    accuracy                           0.93       300\n   macro avg       0.
93       0.93      0.93       300\nweighted avg       0.93      0.93      0.93
  300\n'
```

In [49]:
```
matrix_k_50 = confusion_matrix(y_test_data, predictions_k_50)
print(matrix_k_50)
```

```
array([[144,  14],
       [  7, 135]], dtype=int64)
```