# Predicting IBM Employee Attrition Python Jupyter Notebook

## Part 3 - Build a k-Nearest Neighbors Model

Import numpy and pandas.

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

Import data visualization libraries and set %matplotlib inline.

```
In [2]: import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Import churn modeling pickle file into a Pandas dataframe called churn\_model2.

```
In [3]: churn_model2 = pd.read_pickle('../data/churn_modeling_data.pickle')
```

Filter out numeric features of Age, DistanceFromHome, and MonthlyIncome, and scale them.

churn\_model2\_non\_scale\_feat = churn\_model2[non\_scale\_feat]
X scaled = preprocessing.scale(churn model2 scale feat)

Generate dataframe out of scaled numeric features.

```
In [6]: X_scaled_df = pd.DataFrame(X_scaled)
    X_scaled_df.columns = ['Age', 'DistanceFromHome', 'MonthlyIncome']
    X_scaled_df.head()
```

#### Out[6]:

Age		DistanceFromHome	MonthlyIncome		
0	0.446350	-1.010909	-0.108350		
1	1.322365	-0.147150	-0.291719		
2	0.008343	-0.887515	-0.937654		
3	-0.429664	-0.764121	-0.763634		
4	-1.086676	-0.887515	-0.644858		

Append remainder of churn\_model2 dataframe with scaled numeric feature columns.

#### Out[7]:

	Churn	EnvironmentSatisfaction	Joblnvolvement	StockOptionLevel	Sales_Rep	Single	BusTravL
0	1	1	2	0	0	1	
1	0	2	1	1	0	0	
2	1	3	1	0	0	1	
3	0	3	2	0	0	0	
4	0	0	2	1	0	0	
4							•

Define X and y to split data into training and test sets, and construct k-nearest neighbors model.

```
In [8]: X = churn_model2_scaled.drop(['Churn'], axis=1)
y = churn_model2_scaled['Churn']
```

Split scaled churn / attrition modeling data into training and test sets.

```
In [9]: from sklearn.model_selection import train_test_split
    from sklearn.neighbors import KNeighborsClassifier
    from sklearn import metrics
```

```
In [10]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_s
```

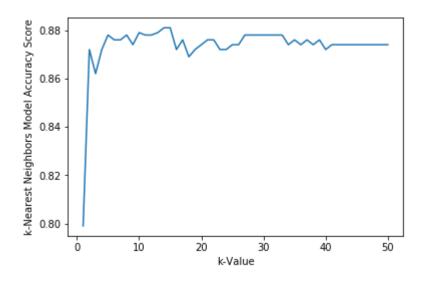
Fit a k-nearest neighbors model on training data set, make predictions on test data set, and calculate accuracy scores for k ranging from 1 to 50.

```
In [11]: k range = range(1, 51)
         acc_scores1 = []
         for k in k range:
             knn = KNeighborsClassifier(n_neighbors=k)
             knn.fit(X_train, y_train)
             y pred = knn.predict(X test)
             acc_scores1.append(metrics.accuracy_score(y_test, y_pred).round(3))
```

#### Plot model accuracy scores against k-values.

```
In [12]:
         plt.plot(k_range, acc_scores1)
         plt.xlabel('k-Value')
         plt.ylabel('k-Nearest Neighbors Model Accuracy Score')
```

### Out[12]: Text(0,0.5,'k-Nearest Neighbors Model Accuracy Score')



Generate dataframe of k-values and their respective accuracy scores, and determine which k-value has the highest accuracy score.

```
In [13]:
         knn_acc_scores1 = pd.DataFrame({'k-Value':k_range, 'AccuracyScore':acc_scores1}).
         knn_acc_scores1.iloc[7, :]
Out[13]: AccuracyScore
                           0.878
         Name: 8, dtype: float64
```

• The optimal k-value of 8 has the highest accuracy score of 0.878.

Check for consistency in 8 k-nearest neighbor model accuracy score for random state seed numbers from 115 to 130.

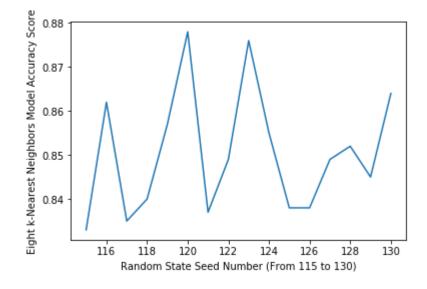
```
In [14]: seed_range = range(115, 131)
    acc_scores2 = []

for seed in seed_range:
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, rande knn = KNeighborsClassifier(n_neighbors=8)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    acc_scores2.append(metrics.accuracy_score(y_test, y_pred).round(3))
```

#### Plot 8 k-nearest neighbor model accuracy scores against random state seed numbers.

```
In [15]: plt.plot(seed_range, acc_scores2)
   plt.xlabel('Random State Seed Number (From 115 to 130)')
   plt.ylabel('Eight k-Nearest Neighbors Model Accuracy Score')
```

#### Out[15]: Text(0,0.5,'Eight k-Nearest Neighbors Model Accuracy Score')



 120 is the random state seed number that will produce the highest accuracy score and best knearest neighbors model.