Predicting IBM Employee Attrition Python Jupyter Notebook

Part 2 - Build a Logistic Regression 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')
```

Check number of rows and columns in churn_model2 dataframe.

In [4]:
```
churn_model2.shape
```

Out[4]:
```
(1470, 11)
```

View structure of churn_model2 dataframe.

In [5]:
```
churn_model2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 11 columns):
Churn                       1470 non-null int64
Age                         1470 non-null int64
BusTravLevel                1470 non-null int64
DistanceFromHome            1470 non-null int64
EnvironmentSatisfaction     1470 non-null int64
JobInvolvement              1470 non-null int64
MonthlyIncome               1470 non-null int64
Overtime_Dum                1470 non-null int64
Sales_Rep                   1470 non-null uint8
Single                      1470 non-null uint8
StockOptionLevel            1470 non-null int64
dtypes: int64(9), uint8(2)
memory usage: 106.3 KB
```

View first five rows of churn_model2 dataframe.

In [6]:
```
churn_model2.head()
```

Out[6]:

	Churn	Age	BusTravLevel	DistanceFromHome	EnvironmentSatisfaction	JobInvolvement	Month
0	1	41	1	1	1	2	
1	0	49	2	8	2	1	
2	1	37	1	2	3	1	
3	0	33	2	3	3	2	
4	0	27	1	2	0	2	

Define X and y to split data into training and test sets, and construct logistic regression model.

In [7]:
```
feature_cols = ['Age', 'BusTravLevel', 'DistanceFromHome', 'EnvironmentSatisfacti
                'Overtime_Dum', 'Sales_Rep', 'Single', 'StockOptionLevel']
X = churn_model2[feature_cols]
y = churn_model2['Churn']
```

Decide which random state seed number will provide the highest area under the ROC curve (AUC).

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
```

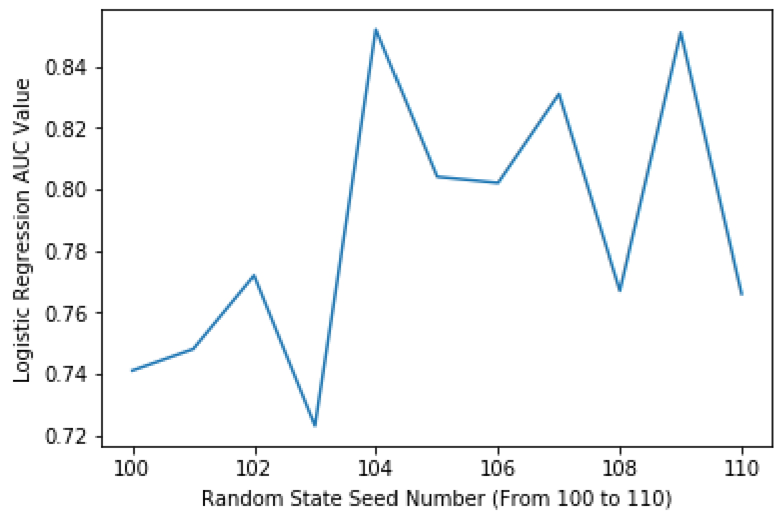
In [9]:
```
seed_range = range(100, 111)

auc_scores = []

for seed in seed_range:
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=seed)
    logreg = LogisticRegression(C=1e9)
    logreg.fit(X_train, y_train)
    y_pred_prob = logreg.predict_proba(X_test)[:, 1]
    auc_scores.append(metrics.roc_auc_score(y_test, y_pred_prob).round(3))
```

In [10]:
```
plt.plot(seed_range, auc_scores)
plt.xlabel('Random State Seed Number (From 100 to 110)')
plt.ylabel('Logistic Regression AUC Value')
```

Out[10]:
```
Text(0,0.5,'Logistic Regression AUC Value')
```



In [11]:
```
print(auc_scores)
```

```
[0.741, 0.748, 0.772, 0.723, 0.852, 0.804, 0.802, 0.831, 0.767, 0.851, 0.766]
```

- 104 is the random state seed number that will produce the highest AUC value.

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

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=104)
```

In [13]:
```
print(churn_model2.shape)
print(X_train.shape)
print(X_test.shape)
```

```
(1470, 11)
(1102, 10)
(368, 10)
```

Fit a logistic regression model on training data set.

In [14]:
```
logreg = LogisticRegression(C=1e9)
logreg.fit(X_train, y_train)
```

Out[14]:
```
LogisticRegression(C=1000000000.0, class_weight=None, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

Print logistic regression model intercept and coefficients.

In [15]:
```
print(logreg.intercept_)
dict(zip(feature_cols, logreg.coef_[0]))
```

```
[-0.18865456]
```

Out[15]:
```
{'Age': -0.0274829751500014,
 'BusTravLevel': 0.46911981350227566,
 'DistanceFromHome': 0.028108320637503983,
 'EnvironmentSatisfaction': -0.4071496160619036,
 'JobInvolvement': -0.46555972067784707,
 'MonthlyIncome': -8.220225041555184e-05,
 'Overtime_Dum': 1.6580896530527565,
 'Sales_Rep': 0.7618572071539449,
 'Single': 0.6125197826230039,
 'StockOptionLevel': -0.35917080532394896}
```

Express logistic regression model coefficients as odds.

In [16]:
```
dict(zip(feature_cols, np.exp(logreg.coef_[0])))
```

Out[16]:
```
{'Age': 0.9728912457399844,
 'BusTravLevel': 1.5985865195306195,
 'DistanceFromHome': 1.0285070869310544,
 'EnvironmentSatisfaction': 0.6655446066889791,
 'JobInvolvement': 0.6277836233577854,
 'MonthlyIncome': 0.9999178011280968,
 'Overtime_Dum': 5.249273326653939,
 'Sales_Rep': 2.142251132365487,
 'Single': 1.8450747334793316,
 'StockOptionLevel': 0.6982550754810202}
```

Make predictions on test data set and calculate test set accuracy.

In [17]:
```
y_pred_class = logreg.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred_class).round(3))
```

```
0.861
```

Compute null accuracy manually.

In [18]:
```
print(1 - y_test.mean())
```

```
0.8396739130434783
```

Calculate test set AUC value for logistic regression model.

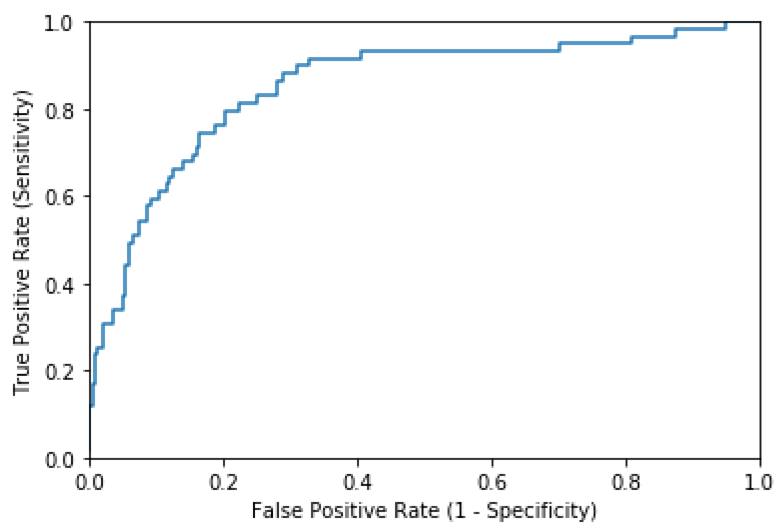
In [19]:
```
y_pred_prob = logreg.predict_proba(X_test)[:, 1]
print(metrics.roc_auc_score(y_test, y_pred_prob).round(3))
```

```
0.852
```

Plot logistic regression model ROC curve for test set.

In [20]:
```
thresholds = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_prob)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
```

Out[20]:
```
Text(0,0.5,'True Positive Rate (Sensitivity)')
```



Print confusion matrix to calculate test set accuracy and error rates plus precision and recall.

In [21]:
```
print(metrics.confusion_matrix(y_test, y_pred_class))
```

```
[[297  12]
 [ 39  20]]
```

Calculate test set accuracy rate.

In [22]:
```
float(297 + 20) / float(297 + 12 + 39 + 20)
```

Out[22]: 0.8614130434782609

Calculate test set misclassification / error rate.

In [23]:
```
float(39 + 12) / float(297 + 12 + 39 + 20)
```

Out[23]: 0.13858695652173914

Calculate precision to measure how confident the logistic regression model is for capturing the positives in test set.

In [24]:
```
float(20) / float(20 + 12)
```

Out[24]: 0.625

Calculate recall / sensitivity to measure how well the logistic regression model is capturing the positives in test set.

In [25]:
```
float(20) / float(39 + 20)
```

Out[25]: 0.3389830508474576

Calculate specificity to measure how well the logistic regression model is capturing the negatives in test set.

In [26]:
```
float(297) / float(297 + 12)
```

Out[26]: 0.9611650485436893

Print out test set classification report for logistic regression model.

In [27]:
```
from sklearn.metrics import classification_report
```

In [28]:
```
print(classification_report(y_test, y_pred_class))
```

```
             precision    recall  f1-score   support

          0       0.88      0.96      0.92       309
          1       0.62      0.34      0.44        59

avg / total       0.84      0.86      0.84       368
```

List out false positives in test data set.

In [29]:
```
X_test[y_test < y_pred_class]
```

Out[29]:

	Age	BusTravLevel	DistanceFromHome	EnvironmentSatisfaction	JobInvolvement	MonthlyInc
665	47	1	2	3	1	3
632	42	2	2	1	2	2
1308	38	1	2	1	0	5
1188	29	1	5	0	1	4
55	33	2	1	0	2	13
318	27	1	5	2	2	2
1102	36	1	2	2	2	2
284	26	2	11	0	2	4
652	37	0	19	0	2	7
909	19	1	25	1	3	2
1168	24	2	2	0	2	3
1436	21	1	5	2	2	2

List out false negatives in test data set.

In [30]:
```python
X_test[y_test > y_pred_class]
```

Out[30]:

	Age	BusTravLevel	DistanceFromHome	EnvironmentSatisfaction	JobInvolvement	MonthlyInc
1442	29	1	1	0	2	4
645	29	1	1	1	1	2
1246	30	2	8	2	1	2
439	31	2	20	0	2	9
293	26	1	4	3	1	5
1333	46	1	10	2	2	7
573	26	1	8	3	1	5
2	37	1	2	3	1	2
480	30	2	12	1	1	2
997	27	1	17	3	2	2
100	37	1	6	2	2	2
779	51	1	4	0	2	2
296	18	1	3	2	2	1
1379	27	2	22	0	1	2
981	35	2	18	3	2	4
136	51	2	8	0	0	10
415	34	2	6	3	0	2
239	32	1	1	3	1	3
1297	26	1	20	3	2	2
370	21	1	12	2	3	2
663	21	1	18	3	2	2
777	21	1	10	2	1	1
204	38	1	29	1	2	6
1162	35	1	10	3	1	10
435	33	1	15	1	2	13
947	52	1	5	1	2	8
636	35	2	25	3	2	2
1186	35	2	12	3	2	4
21	36	1	9	2	1	3
1036	31	2	2	1	2	3
264	28	1	2	0	2	3
1112	38	1	2	2	2	4
585	23	1	6	2	3	1
1136	28	1	24	2	2	2

	Age	BusTravLevel	DistanceFromHome	EnvironmentSatisfaction	JobInvolvement	MonthlyInc
667	41	1	2	1	0	2
791	35	1	4	3	2	9
422	19	1	2	0	1	2
831	31	2	15	2	2	2
813	39	2	2	0	2	12

List out whole sample logistic regression model accuracy scores and their average using 10-fold cross-validation.

In [31]:
```
from sklearn.cross_validation import cross_val_score
```

```
C:\Users\kyrma\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\cros
s_validation.py:41: DeprecationWarning: This module was deprecated in version
0.18 in favor of the model_selection module into which all the refactored class
es and functions are moved. Also note that the interface of the new CV iterator
s are different from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [32]:
```
acc_scores = cross_val_score(logreg, X, y, cv=10, scoring='accuracy').round(3)
print(acc_scores)
print(acc_scores.mean().round(3))
```

```
[0.885 0.865 0.872 0.864 0.864 0.837 0.85  0.842 0.863 0.856]
0.86
```

List out whole sample logistic regression model AUC values and their average using 10-fold cross-validation.

In [33]:
```
auc_scores = cross_val_score(logreg, X, y, cv=10, scoring='roc_auc').round(3)
print(auc_scores)
print(auc_scores.mean().round(3))
```

```
[0.799 0.875 0.864 0.698 0.86  0.743 0.808 0.745 0.826 0.724]
0.794
```