State Farm Classification Coding Exercise

Part 4 - Build a Logistic Regression Model

A. Construct Logistic Regression Model Upon Training Data

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 training model data into a Pandas dataframe called train_model1.

In [3]:
```
train_model1 = pd.read_pickle('../State_Farm/Data/train_model.pickle')
```

Check number of rows and columns in train_model1 dataframe.

In [4]:
```
train_model1.shape
```

Out[4]:
```
(40000, 15)
```

View structure of train_model1 dataframe.

In [5]:
```
train_model1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40000 entries, 0 to 39999
Data columns (total 15 columns):
y          40000 non-null int64
x75        40000 non-null float64
x37        40000 non-null float64
x58        40000 non-null float64
x97        40000 non-null float64
x41_flt    40000 non-null float64
x99        40000 non-null float64
x1         40000 non-null float64
x40        40000 non-null float64
x70        40000 non-null float64
x44        40000 non-null float64
x63        40000 non-null float64
x56        40000 non-null float64
x83        40000 non-null float64
x96        40000 non-null float64
dtypes: float64(14), int64(1)
memory usage: 4.6 MB
```

View first five rows of train_model1 dataframe.

In [6]:
```
train_model1.head()
```

Out[6]:

	y	x75	x37	x58	x97	x41_flt	x99	x1	x40	
0	0	40.617107	-10.839200	2.078396	-2.125570	449.48	1.237667	74.425320	4.550518	41
1	1	-49.303165	57.917006	-2.696257	-36.030599	-525.06	1.952183	24.320711	-9.476135	36
2	1	-19.706659	-12.991058	-2.417447	26.212736	-599.50	0.558988	-66.160459	6.876065	49
3	0	-7.301283	37.658926	4.443710	19.221130	-220.71	0.214462	33.210943	-16.933984	82
4	0	-2.751656	-59.497091	-2.421952	-5.703269	-1405.59	-1.191319	-26.717872	-9.551514	-19

Gather summary statistics of train_model1 dataframe.

In [7]:
```
train_model1.describe()
```

Out[7]:

	y	x75	x37	x58	x97	x41_flt	
count	40000.00000	40000.000000	40000.000000	40000.000000	40000.000000	40000.000000	40000.0
mean	0.20360	5.417519	4.814694	-0.892583	-2.514305	0.315315	0.0
std	0.40268	35.653631	31.561154	6.319470	18.551630	1001.659950	1.1
min	0.00000	-146.967384	-127.651997	-31.395877	-73.908741	-4496.460000	-4.3
25%	0.00000	-17.971049	-16.589036	-5.175537	-15.023076	-669.295000	-0.7
50%	0.00000	5.592658	4.493183	-0.891371	-2.514305	6.040000	0.0
75%	0.00000	28.988799	25.968530	3.413382	9.882079	678.325000	0.7
max	1.00000	144.548014	126.924294	22.420511	76.120119	4062.630000	4.4

Define X and y.

In [8]:
```
feature_cols = ['x75', 'x37', 'x58', 'x97', 'x41_flt', 'x99', 'x1', 'x40', 'x70',
```

In [9]:
```
X = train_model1[feature_cols]
y = train_model1['y']
print(X.shape)
print(y.shape)
```

```
(40000, 14)
(40000,)
```

Fit a logistic regression model on training model data.

In [10]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
```

In [11]:
```
logreg = LogisticRegression(C=1e9)
logreg.fit(X, y)
```

Out[11]:
```
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 [12]:
```
print(logreg.intercept_)
dict(zip(feature_cols, logreg.coef_[0]))
```

```
[-1.3847385]
```

Out[12]:
```
{'x1': 0.007047416085280777,
 'x37': -0.016105211331098775,
 'x40': 0.00578891080883736,
 'x41_flt': -0.0003401854661650888,
 'x44': 0.006037683479860255,
 'x56': -0.009542535312387216,
 'x58': 0.1112156582386664l,
 'x63': 0.02966891202668157 2,
 'x70': -0.005447882703786845,
 'x75': -0.023153039385620668,
 'x83': 0.08761590096736244,
 'x96': -0.010344079456438539,
 'x97': 0.03871572430063214,
 'x99': 0.4788438298145828}
```

Express logistic regression model coefficients as odds.

In [13]:
```
dict(zip(feature_cols, np.exp(logreg.coef_[0])))
```

Out[13]:
```
{'x1': 1.007072307561193,
 'x37': 0.9840237841566418,
 'x40': 1.0058056989323634,
 'x41_flt': 0.9996598723903498,
 'x44': 1.0060559470287698,
 'x56': 0.9905028501986991,
 'x58': 1.1176359082580003,
 'x63': 1.0301134193228654,
 'x70': 0.9945669300975146,
 'x75': 0.977112935566845,
 'x83': 1.0915687709881947,
 'x96': 0.9897092365401361,
 'x97': 1.0394749441780715,
 'x99': 1.6142070248626739}
```

Make predictions on training model data and calculate accuracy for training model data.

In [14]:
```
y_pred_class = logreg.predict(X)
print(metrics.accuracy_score(y, y_pred_class).round(3))
```

```
0.843
```

Compute training model data null accuracy manually.

In [15]:
```
print(1 - y.mean())
```

```
0.7964
```

Calculate area under the ROC curve (AUC) value for training data logistic regression model.

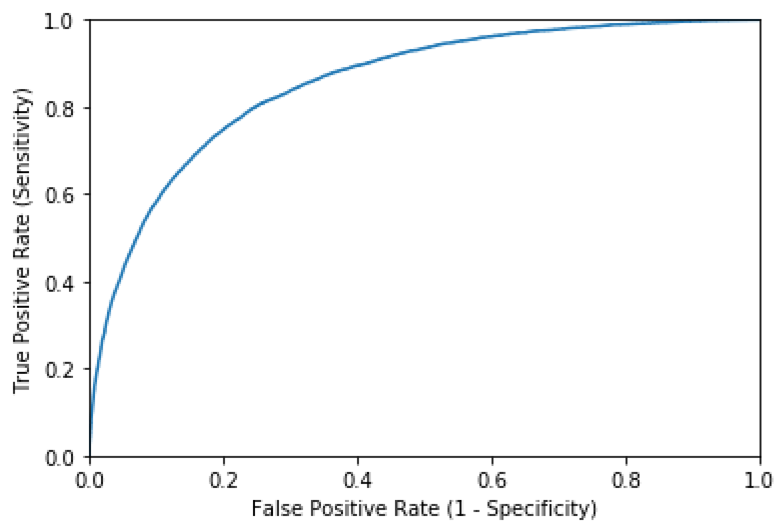
In [16]:
```
y_pred_prob = logreg.predict_proba(X)[:, 1]
print(metrics.roc_auc_score(y, y_pred_prob).round(3))
```

```
0.854
```

Plot logistic regression model ROC curve for training data.

In [17]:
```
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, 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[17]:
```
Text(0,0.5,'True Positive Rate (Sensitivity)')
```



Print confusion matrix to calculate training model data accuracy and error rates plus precision and recall.

In [18]:
```
print(metrics.confusion_matrix(y, y_pred_class))
```

```
[[30265  1591]
 [ 4706  3438]]
```

Calculate training model data accuracy rate.

In [19]:
```
float(30265 + 3438) / float(30265 + 1591 + 4706 + 3438)
```

Out[19]:
```
0.842575
```

Calculate training model data misclassification / error rate.

In [20]:
```
float(4706 + 1591) / float(30265 + 1591 + 4706 + 3438)
```

Out[20]:
```
0.157425
```

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

In [21]:
```
float(3438) / float(3438 + 1591)
```

Out[21]:
```
0.6836349174786239
```

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

In [22]:
```
float(3438) / float(4706 + 3438)
```

Out[22]:
```
0.42215127701375244
```

Calculate specificity to measure how well the logistic regression model is capturing the negatives in training model data.

In [23]:
```
float(30265) / float(30265 + 1591)
```

Out[23]:
```
0.9500565042692114
```

Print out training model data classification report for logistic regression model.

In [24]:
```
from sklearn.metrics import classification_report
```

In [25]:
```
print(classification_report(y, y_pred_class))
```

```
             precision    recall  f1-score   support

          0       0.87      0.95      0.91     31856
          1       0.68      0.42      0.52      8144

avg / total       0.83      0.84      0.83     40000
```

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

In [26]:
```
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 [27]:
```
acc_scores = cross_val_score(logreg, X, y, cv=10, scoring='accuracy').round(3)
print(acc_scores)
print(acc_scores.mean().round(3))
```

```
[0.837 0.839 0.843 0.84  0.842 0.847 0.84  0.846 0.849 0.844]
0.843
```

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

In [28]:
```
auc_scores = cross_val_score(logreg, X, y, cv=10, scoring='roc_auc').round(3)
print(auc_scores)
print(auc_scores.mean().round(3))
```

```
[0.849 0.845 0.849 0.854 0.85  0.86  0.853 0.854 0.87  0.858]
0.854
```

B. Generate Predictions in Cleaned Test Data

Import cleaned test data pickle file into a Pandas dataframe called test_model1.

In [29]:
```
test_model1 = pd.read_pickle('../State_Farm/Data/test_model.pickle')
```

Check number of rows and columns in test_model1 dataframe.

In [30]:
```
test_model1.shape
```

Out[30]:
```
(10000, 14)
```

View structure of test_model1 dataframe.

In [31]:
```
test_model1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
x75        10000 non-null float64
x37        10000 non-null float64
x58        10000 non-null float64
x97        10000 non-null float64
x41_flt    10000 non-null float64
x99        10000 non-null float64
x1         10000 non-null float64
x40        10000 non-null float64
x70        10000 non-null float64
x44        10000 non-null float64
x63        10000 non-null float64
x56        10000 non-null float64
x83        10000 non-null float64
x96        10000 non-null float64
dtypes: float64(14)
memory usage: 1.1 MB
```

View first five rows of test_model1 dataframe.

In [32]:
```
test_model1.head()
```

Out[32]:

	x75	x37	x58	x97	x41_flt	x99	x1	x40	
0	80.851384	-32.086998	5.093232	13.739194	2475.46	1.141799	54.479467	-8.776231	44.26
1	-21.295879	29.391786	-5.989844	-13.018951	-1109.10	0.568757	-20.244923	23.337240	5.663
2	27.719905	-30.329997	6.115105	0.791425	-187.70	-0.816682	-61.467354	-8.845933	-47.647
3	-4.053955	11.088216	-2.750484	-16.716012	525.65	0.603007	-18.454831	-57.516611	-14.01
4	21.743536	-21.955105	-4.286183	23.003355	-1113.53	1.929231	15.810515	-13.207037	13.267

Define X_test.

In [33]:
```
X_test = test_model1[feature_cols]
print(X_test.shape)
```

```
(10000, 14)
```

Make predictions on cleaned test data by calculating probabilities for belonging to positive class (labeled '1').

In [34]:
```
y_test_pred_prob = logreg.predict_proba(X_test)[:, 1]
```

Construct results1_logreg Pandas dataframe out of test data y predicted class probabilities.

In [35]:
```
results1_logreg = pd.DataFrame({'y_test_pred_prob': y_test_pred_prob[:]})
results1_logreg.head()
```

Out[35]:

	y_test_pred_prob
0	0.146379
1	0.178329
2	0.211236
3	0.034441
4	0.413519

Check number of rows and columns in results1 dataframe.

In [36]:
```
results1_logreg.shape
```

Out[36]:
```
(10000, 1)
```

Export results1 Pandas dataframe containing test data y predicted class probabilities to CSV file.

In [37]:
```
results1_logreg.to_csv('../State_Farm/Data/results1_logreg.csv', sep=',', index=F
```