Card Data- Predictive Model Building

June 16, 2018

In [1]:
```
# importing required libraries
import numpy as np
import pandas as pd
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

In [2]:
```
# loading data into dataframe

train = pd.read_csv('.\cc\Test 1.csv',sep=',')
```

In [3]:
```
# viewing first few rows
train.head(10)
```

Out[3]:
```
   customer_id demographic_slice country_reg ad_exp    est_income   hold_bal  \
0       713782           AX03efs           W      N  33407.901749   3.000000
1       515901           AX03efs           E      N  19927.533533  20.257927
2        95166           AX03efs           W      Y  51222.470997   4.000000
3       425557           AX03efs           E      Y  67211.587467  18.653631
4       624581           AX03efs           W      N  20093.342158   4.000000
5       721691           AX03efs           E      N  73896.096129  12.906641
6       269858           AX03efs           W      N  73609.404135   3.000000
7       219196           AX03efs           W      N  57619.668582   9.000000
8       413020           AX03efs           W      Y  49282.620299   0.000000
9       174424           AX03efs           W      N  57173.061392   6.000000

   pref_cust_prob  imp_cscore   RiskScore  imp_crediteval  axio_score  \
0        0.531112         619  503.249027       23.977827    0.137289
1        0.297439         527  820.108146       22.986398    0.052264
```

```
2        0.018463          606  586.605795        24.939219     0.452035
3        0.089344          585  634.701982        24.841147     0.564619
4        0.094948          567  631.949979        24.679363     0.917304
5        0.656848          560  809.333963        22.702967     0.198511
6        0.137818          620  697.308163        24.271112     0.179141
7        0.367879          658  668.075472        25.886646     0.035338
8        0.182079          519  656.111591        21.838909     0.054130
9        0.288242          645  547.767117        24.467187     0.648325

   card_offer
0       False
1       False
2       False
3       False
4       False
5        True
6       False
7       False
8       False
9       False
```

In [4]:
```python
# Replcaing
train.card_offer.replace([True, False], ['true', 'false'], inplace=True)
```

In [5]:
```python
# Dimension of dataset
train.shape
```

Out[5]: (10000, 12)

In [6]:
```python
# Statistical summary

train.describe()
```

Out[6]:
```
         customer_id     est_income      hold_bal  pref_cust_prob  \
count   10000.000000   10000.000000  10000.000000    10000.000000
mean   496819.831400   65853.355259     20.962621        0.329419
std    287391.314157   31093.369592     18.841121        0.223299
min       244.000000       2.054543     -2.140206        0.001781
25%    245172.500000   39165.786086      6.150577        0.156965
50%    495734.000000   76903.628763     11.913366        0.272263
75%    745475.250000   91032.514900     32.238914        0.459890
max    999870.000000  150538.809704     81.759632        1.144357

         imp_cscore     RiskScore  imp_crediteval    axio_score
count  10000.000000  10000.000000    10000.000000  10000.000000
mean     662.548800    670.042869       25.692162      0.393211
std       90.549985     89.965854        1.889274      0.288243
min      500.000000    324.436647       21.363123     -0.000052
25%      600.000000    609.231181       24.295435      0.139424
```

```
50%      655.000000   669.493442     25.611903     0.337841
75%      727.000000   730.484985     27.062519     0.624886
max      849.000000  1004.497869     30.131214     1.000000
```

In [7]:
```python
# correlation between the parameters

train.corr()
```

Out[7]:

	customer_id	est_income	hold_bal	pref_cust_prob	imp_cscore
customer_id	1.000000	0.004925	0.006856	-0.005716	0.009107
est_income	0.004925	1.000000	0.010331	0.008689	0.003514
hold_bal	0.006856	0.010331	1.000000	0.001825	0.269361
pref_cust_prob	-0.005716	0.008689	0.001825	1.000000	-0.011499
imp_cscore	0.009107	0.003514	0.269361	-0.011499	1.000000
RiskScore	-0.004207	0.004530	0.013931	-0.012570	-0.004809
imp_crediteval	0.005665	-0.000174	0.256165	-0.013733	0.926908
axio_score	0.000762	-0.004673	0.000158	-0.020388	0.005362

	RiskScore	imp_crediteval	axio_score
customer_id	-0.004207	0.005665	0.000762
est_income	0.004530	-0.000174	-0.004673
hold_bal	0.013931	0.256165	0.000158
pref_cust_prob	-0.012570	-0.013733	-0.020388
imp_cscore	-0.004809	0.926908	0.005362
RiskScore	1.000000	-0.004359	0.000654
imp_crediteval	-0.004359	1.000000	0.006725
axio_score	0.000654	0.006725	1.000000

In [8]:
```python
# distribution of target values

print(train.groupby('card_offer').size())
```

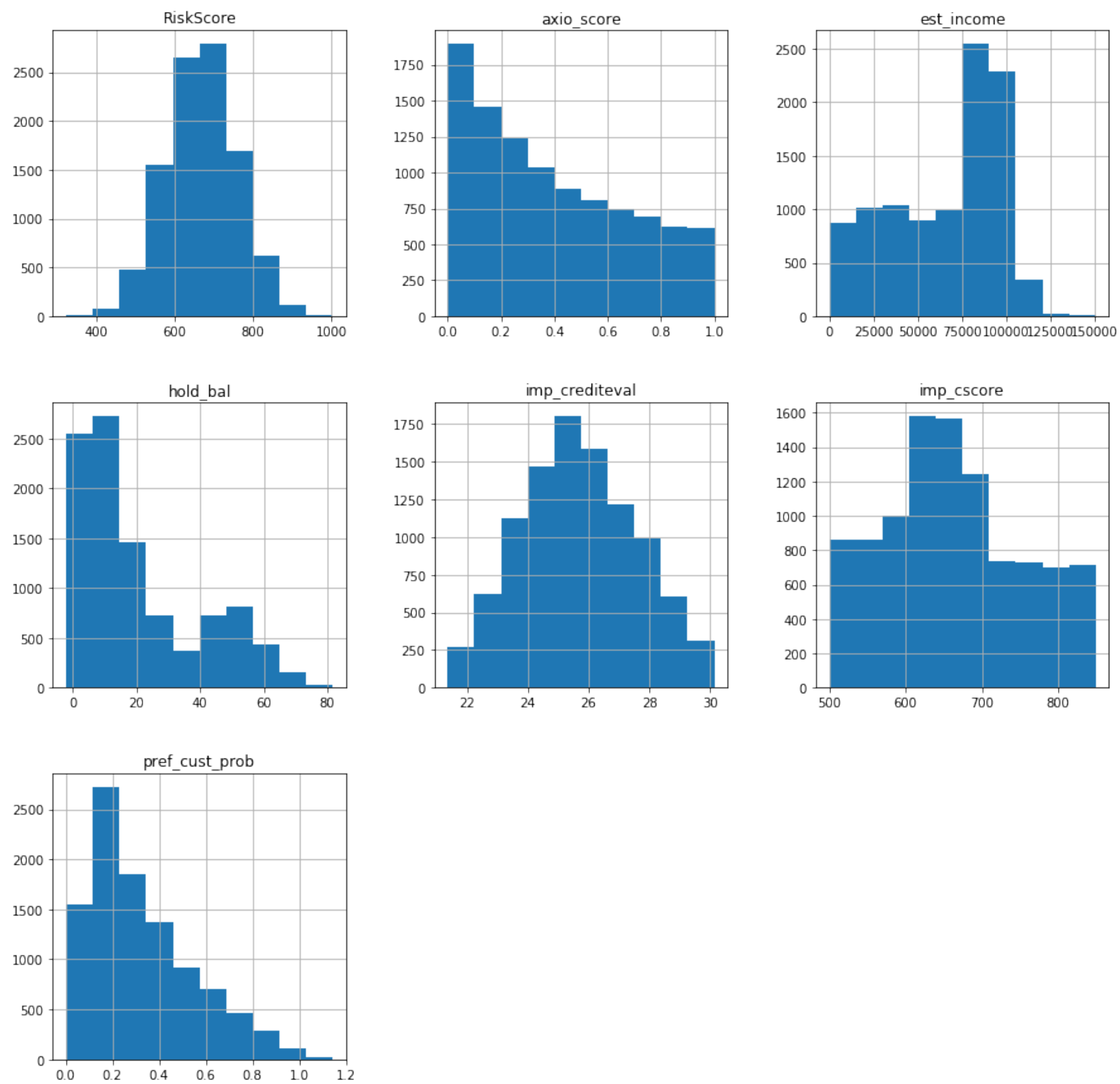
```
card_offer
false    8469
true     1531
dtype: int64
```

In [9]:
```python
# check for missing values

print(train.isnull().any())
```

```
customer_id          False
demographic_slice    False
country_reg          False
ad_exp               False
est_income           False
hold_bal             False
pref_cust_prob       False
```

```
imp_cscore          False
RiskScore           False
imp_crediteval      False
axio_score          False
card_offer          False
dtype: bool
```

In [10]:
```python
# distribution of various numerical parameters

train[['est_income', 'hold_bal', 'pref_cust_prob', 'imp_cscore', 'RiskScore', 'imp_cre
plt.show()
```



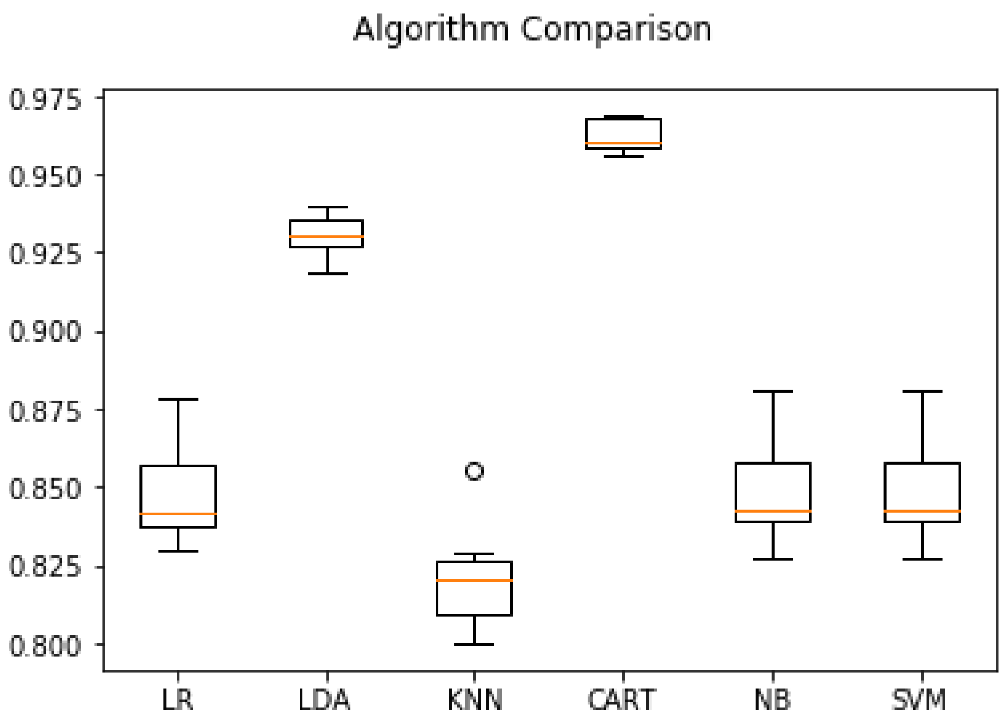
In [11]:
```python
array = train.values
X = array[:,4:11]
```

```
Y = array[:,11]
validation_size = 0.20
seed = 7
X_train, X_validation, Y_train, Y_validation = model_selection.train_test_split(X, Y,
scoring = 'accuracy'
```

```
In [12]: models = []
         models.append(('LR', LogisticRegression()))
         models.append(('LDA', LinearDiscriminantAnalysis()))
         models.append(('KNN', KNeighborsClassifier()))
         models.append(('CART', DecisionTreeClassifier()))
         models.append(('NB', GaussianNB()))
         models.append(('SVM', SVC()))
         # evaluate each model in turn
         results = []
         names = []
         for name, model in models:
             kfold = model_selection.KFold(n_splits=10, random_state=seed)
             cv_results = model_selection.cross_val_score(model, X_train, Y_train, cv=kfold, s
             results.append(cv_results)
             names.append(name)
             msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
             print(msg)
```

```
LR: 0.847375 (0.014475)
LDA: 0.930500 (0.006619)
KNN: 0.820500 (0.014835)
CART: 0.962250 (0.004867)
NB: 0.848125 (0.015044)
SVM: 0.848125 (0.015044)
```

```
In [13]: fig = plt.figure()
         fig.suptitle('Algorithm Comparison')
         ax = fig.add_subplot(111)
         plt.boxplot(results)
         ax.set_xticklabels(names)
         plt.show()
```



0.0.1 Since Decision Tree Classifier seems to be giving most accurate results, I have used it for making predictions on the new data set.

```
In [14]: # Classification Metrics

         dtc = DecisionTreeClassifier()
         dtc.fit(X_train, Y_train)
         predictions = dtc.predict(X_validation)
         print('Accuracy Score: ', accuracy_score(Y_validation, predictions))
         print(confusion_matrix(Y_validation, predictions))
         print(classification_report(Y_validation, predictions))
```

```
Accuracy Score:  0.9655
[[1659   25]
 [  44  272]]
             precision    recall  f1-score   support

      false       0.97      0.99      0.98      1684
       true       0.92      0.86      0.89       316

avg / total       0.96      0.97      0.97      2000
```

In [15]:
```
# Loading the test data set.
test = pd.read_csv('.\cc\Test 2.csv',sep=',')
test.head()
```

Out[15]:

```
   customer_id demographic_slice country_reg ad_exp    est_income   hold_bal  \
0       596723           AX03efs           W      N  26323.092375   3.000000
1       841834           AX03efs           E      Y  67374.621654  17.861095
2       402401           AX03efs           E      N   1728.369713  21.604489
3       734431           AX03efs           E      Y  15814.210261  22.058403
4       739547           AX03efs           W      Y  45233.588193   1.000000

   pref_cust_prob  imp_cscore   RiskScore  imp_crediteval  axio_score  \
0        0.461364         603  505.509062       23.806688    0.351222
1        0.473517         650  466.158076       26.068803    0.080106
2        0.486220         606  603.346280       23.628955    0.208180
3        0.462249         530  747.158221       22.533957    0.080122
4        0.541660         640  704.781194       24.298782    0.667270

   card_offer
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN
```

In [16]:
```
# Assigning the parameters and predicting the customer response
Xtest = test.values[:,4:11]
Ytest = dtc.predict(Xtest)
```

In [17]:
```
# Updating the predicted values in the test dataframe
test['card_offer']=Ytest
```

In [18]:
```
# Brief overview of the updated test dataframe
test.head()
```

Out[18]:

```
   customer_id demographic_slice country_reg ad_exp    est_income   hold_bal  \
0       596723           AX03efs           W      N  26323.092375   3.000000
1       841834           AX03efs           E      Y  67374.621654  17.861095
2       402401           AX03efs           E      N   1728.369713  21.604489
3       734431           AX03efs           E      Y  15814.210261  22.058403
4       739547           AX03efs           W      Y  45233.588193   1.000000

   pref_cust_prob  imp_cscore   RiskScore  imp_crediteval  axio_score  \
0        0.461364         603  505.509062       23.806688    0.351222
1        0.473517         650  466.158076       26.068803    0.080106
2        0.486220         606  603.346280       23.628955    0.208180
3        0.462249         530  747.158221       22.533957    0.080122
4        0.541660         640  704.781194       24.298782    0.667270
```

```
  card_offer
0      false
1      false
2      false
3      false
4      false
```

In [19]:
```
# Replacing the card_offer string values with boolean values as in the original data
test.card_offer.replace(['true', 'false'], [True, False], inplace=True)
```

In [20]:
```
# Writing the dataset to the disk as ds4.csv
test.to_csv('ds4.csv', index=False)
```