Part-C

December 16, 2019

In [1]:
```
import numpy as np
import pandas as pd
import sklearn
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score, accuracy_score, precision_score, recall_sco
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_validate
from sklearn.model_selection import cross_val_predict
from sklearn.ensemble import RandomForestClassifier

%matplotlib inline
```

In [2]:
```
# Reading data from input file
df = pd.read_csv("Appointment-No-Show-Data.csv")
print(df.dtypes)
print("------------------------------------------")
df.shape
```

```
PatientId          float64
AppointmentID        int64
Gender              object
ScheduledDay        object
AppointmentDay      object
Age                  int64
Neighbourhood       object
Scholarship          int64
Hipertension         int64
Diabetes             int64
Alcoholism           int64
Handcap              int64
SMS_received         int64
No-show             object
dtype: object
------------------------------------------
```

Out[2]: (110527, 14)

In [3]:
```
# Renaming No-Show column entity

df = df.rename(columns={"No-show": "no_show"})
df.no_show = df.no_show.map({ 'No': 0, 'Yes': 1 })
df['ScheduledDay'] = pd.to_datetime(df['ScheduledDay']).dt.date.astype('datetime64[ns]
df["AppointmentDay"] = pd.to_datetime(df["AppointmentDay"])
df["WeekdayScheduled"] = df["ScheduledDay"].dt.weekday
df['awaiting_time_days'] = (df.AppointmentDay - df.ScheduledDay).dt.days
df = df[(df.awaiting_time_days >= 0)]
```

In [4]:
```
df = df[df["Age"] <100]
df = df[df["Age"] > -1]

# Question 1
no_show = len(df.query('no_show == "1"'))
no_show_ratio = int(round(no_show/len(df)*100))

print("Total proportion of patients with no show:",no_show_ratio)
```

```
Total proportion of patients with no show: 20
```

In [5]:
```
# Performing dummies operation
df[['Handcap']] = df[['Handcap']].astype('str')
df_cat = pd.get_dummies(df[['Gender'] + ['Handcap']],drop_first = True)
cols_all_cat = list(df_cat.columns)
print(df_cat.head())
df = pd.concat([df,df_cat], axis = 1)

cols_input = ['Scholarship','Hipertension', 'Diabetes', 'Alcoholism',
       'SMS_received', 'Age', 'awaiting_time_days', 'WeekdayScheduled','no_show']
```

```
   Gender_M  Handcap_1  Handcap_2  Handcap_3  Handcap_4
0         0          0          0          0          0
1         1          0          0          0          0
2         0          0          0          0          0
3         0          0          0          0          0
4         0          0          0          0          0
```

In [6]:
```
df_final = df[cols_input+cols_all_cat]
```

In [7]:
```
# Train and test data

df_final = df_final.sample(n = len(df_final), random_state = 20)
df_final = df_final.reset_index(drop = True)

df_test=df_final.sample(frac=0.20,random_state=20)
df_train = df_final.drop(df_test.index)
```

In [8]:
```
def calc_prevalence(y_actual):
    return (sum(y_actual)/len(y_actual))

print('Train prevalence(n = %d):%.3f'%(len(df_train), calc_prevalence(df_train.no_show
print('Test prevalence(n = %d):%.3f'%(len(df_test),calc_prevalence(df_test.no_show.valu
```

```
Train prevalence(n = 88408):0.201
Test prevalence(n = 22102):0.205
```

In [9]:
```
# Balancing the data

rows_pos = df_train.no_show == 1
df_train_pos = df_train.loc[rows_pos]
df_train_neg = df_train.loc[~rows_pos]

n = np.min([len(df_train_pos), len(df_train_neg)])

# merge the balanced data
df_train = pd.concat([df_train_pos.sample(n = n, random_state = 20),
                      df_train_neg.sample(n = n, random_state = 20)],axis = 0,
                     ignore_index = True)

# shuffle the order of training samples
df_train = df_train.sample(n = len(df_train), random_state = 20).reset_index(drop = Tru

print('Train balanced prevalence(n = %d):%.3f'%(len(df_train), calc_prevalence(df_trai
```

```
Train balanced prevalence(n = 35566):0.500
```

In [10]:
```
#
cols_input = ['Scholarship','Hipertension', 'Diabetes', 'Alcoholism',
       'SMS_received', 'Age', 'awaiting_time_days', 'WeekdayScheduled'] + cols_all_ca


X_train = df_train[cols_input].values
y_train = df_train['no_show'].values

X_test = df_test[cols_input].values
y_test = df_test['no_show'].values

print('Training shapes:',X_train.shape, y_train.shape)
print('Testing shapes:',X_test.shape, y_test.shape)
```

```
Training shapes: (35566, 13) (35566,)
Testing shapes: (22102, 13) (22102,)
```

```
In [11]: # Metrics selection
         def calc_specificity(y_actual, y_pred, thresh):
             return sum((y_pred < thresh) & (y_actual == 0)) /sum(y_actual ==0)

         def print_report(y_actual, y_pred, thresh):
             auc = roc_auc_score(y_actual, y_pred)
             accuracy = accuracy_score(y_actual, (y_pred > thresh))
             recall = recall_score(y_actual, (y_pred > thresh))
             precision = precision_score(y_actual, (y_pred > thresh))
             specificity = calc_specificity(y_actual, y_pred, thresh)
             f1score = f1_score(y_actual,y_pred,thresh)
             print('AUC:%.3f'%auc)
             print('accuracy:%.3f'%accuracy)
             print('recall:%.3f'%recall)
             print('precision:%.3f'%precision)
             print('specificity:%.3f'%specificity)
             print('prevalence:%.3f'%calc_prevalence(y_actual))
             print('F1_score:%.3f'%f1score)
             print(' ')
             return auc, accuracy, recall, precision, specificity
```

```
In [12]: # Logistic Regression
         lr = LogisticRegression(random_state = 20)
         y_train_preds = cross_val_predict(lr, X_train, y_train, cv=5)

         print(y_train_preds)

         print('Logistic Regression - 5 folds')
         print('Training:')
         lr_train_auc, lr_train_accuracy, lr_train_recall, \
             lr_train_precision, lr_train_specificity = print_report(y_train,y_train_preds, .5
```

```
[1 0 0 ... 1 0 0]
Logistic Regression - 5 folds
Training:
AUC:0.628
accuracy:0.628
recall:0.558
precision:0.649
specificity:0.698
prevalence:0.500
F1_score:0.600
```

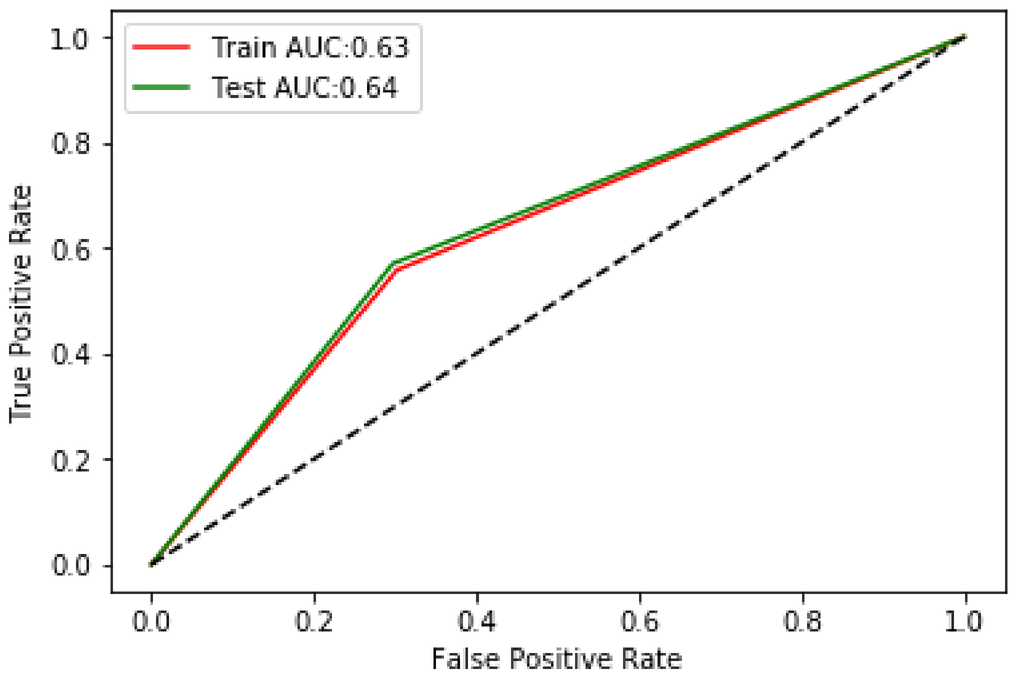
```
In [13]: # Comments - The Logistic regression model with 5-folds CV is better than the naive m
         # as show up because we have a model accuracy of 62% which is greater than 50%(Tossin
```

```
In [13]: fpr_train, tpr_train, thresholds_train = roc_curve(y_train, y_train_preds)
         auc_train = roc_auc_score(y_train, y_train_preds)
```

```
# lr=LogisticRegression(random_state = 20)
a = lr.fit(X_train, y_train)
y_test_preds = lr.predict(X_test)

fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_test_preds)
auc_test = roc_auc_score(y_test, y_test_preds)

plt.plot(fpr_train, tpr_train, 'r-',label ='Train AUC:%.2f'%auc_train)
plt.plot(fpr_test, tpr_test, 'g-',label ='Test AUC:%.2f'%auc_test)
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```




```
In [ ]: # The results obtained show a marginal AUC curve with 63% accuracy. Hence the model is
        # Still the model can be improved is we have additional data.
```

```
In [ ]: # Details needed for better prediction
        # Schedule of patients on date of arrival. We need to have patients schedule in advanc
        # Receiving the message - Patients should acknowledge the message received by them.
        # Demographical and Climatic conditions on a given day
        # We could do the same analysis with over sampling to see the performance improvement
```

```
In [ ]:
```