# glovo

April 3, 2019

## 1 Glovo Interview Ricardo Huarte

In [6275]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
from fancyimpute import KNN
from sklearn.model_selection import train_test_split,cross_val_score, KFold, Strati
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from scipy.stats import uniform
from sklearn.preprocessing import StandardScaler,OneHotEncoder, LabelEncoder, Impute
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score,confusion_matrix, classification_report, a
average_precision_score,make_scorer,recall_score, accuracy_score, precision_score
from sklearn import svm
from xgboost.sklearn import XGBClassifier
from xgboost.sklearn import XGBRegressor
import warnings; warnings.simplefilter('ignore')
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.pipeline import Pipeline
```

### 1.1 About Data Set:

You will find 2 .csv files attached to this task. 1 of the files consist of courier's lifetime dependent features and other consist courier's weekly variant features. Features are renamed for confidentiality purposes and data dictionary will NOT be provided. However, in 2 different .csv files, same courier ID represents same courier.

### 1.2 Task 1: Exploratory Analysis and Data Munging

In this task, you are being expected to clean data, treat missing values, find out related features and finally label the data. Every courier did not work every week. Thus, some of courier-week combinations' data are not provided. First, come up with a way to treat these missing values. Removing missing values are not suggested since provided data set is small and it will affect your predictive model's evaluation metric. Create a report / dashboard and correlation matrix, in addition to results of your univariate and bivariate analysis and explain your findings. Finally, label your data. If a specific courier's week 9, 10 and 11 data is not provided, we label this courier as "1" otherwise "0". After labeling, remove week 8(Yes including 8!), 9, 10 and 11 data to avoid bias in your next task. In addition, distribution of feature_3 is a hint how the data is generated.

```
In [6276]: %matplotlib inline

In [6277]: weekly = pd.read_csv(filepath_or_buffer='Courier_weekly_data.csv')
```

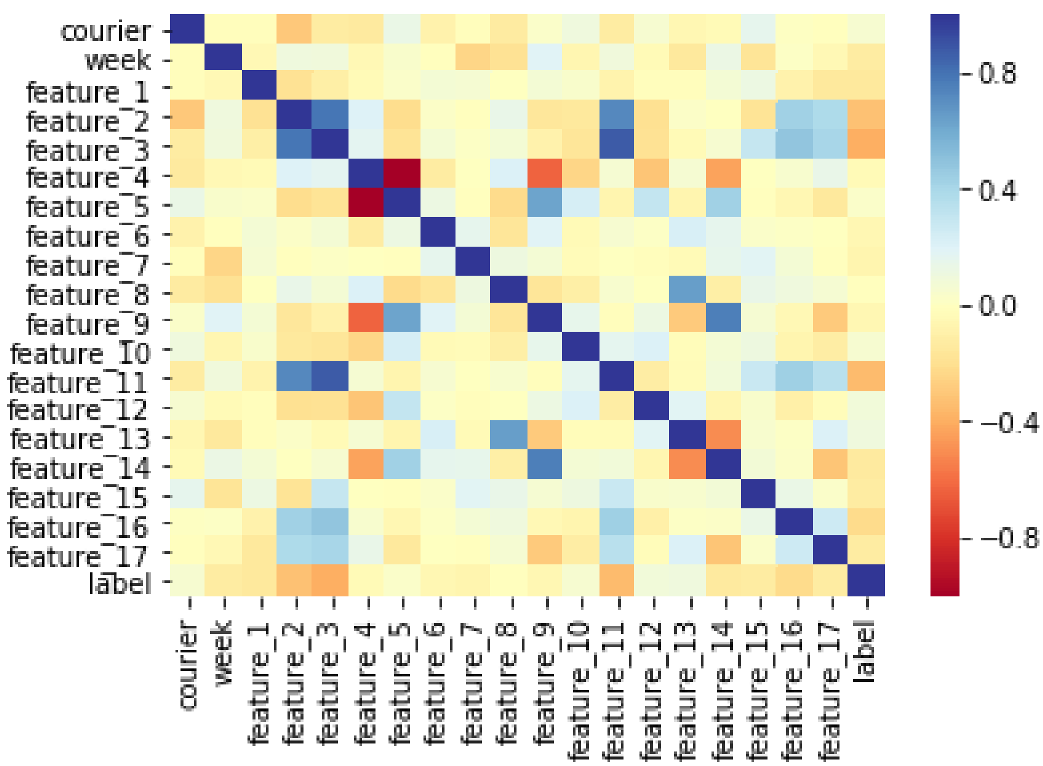
#### 1.2.1 Checking how many couriers worked on the given weeks

```
In [6278]: weekly[(weekly.week==11) | (weekly.week==10) | (weekly.week==9)]['courier'].drop_du

Out[6278]: 387

In [6279]: weeks=weekly.copy()

In [6280]: # function to create the label for the pertinent weeks
           def week_label(row):
               courier_set=weekly[(weekly.courier==row['courier']) & ((weekly.week==9) | (week
               if courier_set['courier'].count() == 0:
                   label=1
               else:
                   label=0
               return label

In [6281]: weeks['label']=weeks.apply(week_label, axis=1)
           # keeping only given weeks for prediction
           weeks=weeks[(weeks.week<8)]
           weeks.head(5)

Out[6281]:    courier  week  feature_1  feature_2  feature_3  feature_4  feature_5  \
           0     3767     2          6         34         38     0.0789     0.9211
           1     3767     4         -1         42         37     0.0000     1.0000
           2     3767     5         24         41         43     0.0233     0.9767
           3     3767     6        -22         65         66     0.0606     0.9394
           4     6282     2          9         33         27     0.0741     0.9259

              feature_6  feature_7  feature_8  feature_9  feature_10  feature_11  \
           0   140.4737     0.1316  2162.4737     0.7632    7.340776           8
           1   135.5946     0.0811  2097.4054     0.9459   11.883784          19
           2   131.0930     0.0233  2043.8837     0.9302    7.072100          16
           3   120.1515     0.0000  2124.2727     0.7727    7.356567          33
           4   100.0000     0.0370  4075.7407     0.8889    8.501233           5

              feature_12  feature_13  feature_14  feature_15  feature_16  feature_17  \
           0   20.208158    5.236316      0.8158   43.384804           1          19
           1   18.855405    5.689459      0.8919   35.078042           3          11
```

```
2   18.925116    5.138605      0.9302   31.455285             1           10
3   18.259697    4.704394      0.7879   34.252991             1           30
4   26.863704    4.828519      0.8889   46.478114             1            4

   label
0      1
1      1
2      1
3      1
4      0
```

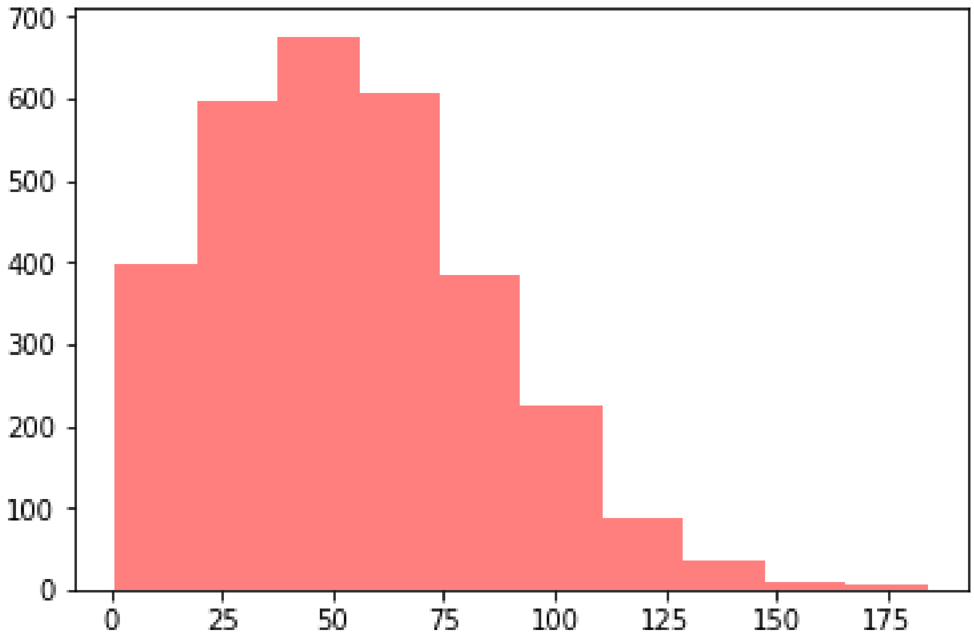
In [6282]:
```python
week_corr=weeks.corr()
sns.heatmap(week_corr, vmax=1., square=False,cmap="RdYlBu")
```

Out[6282]: <matplotlib.axes._subplots.AxesSubplot at 0x146e7e6ce80>

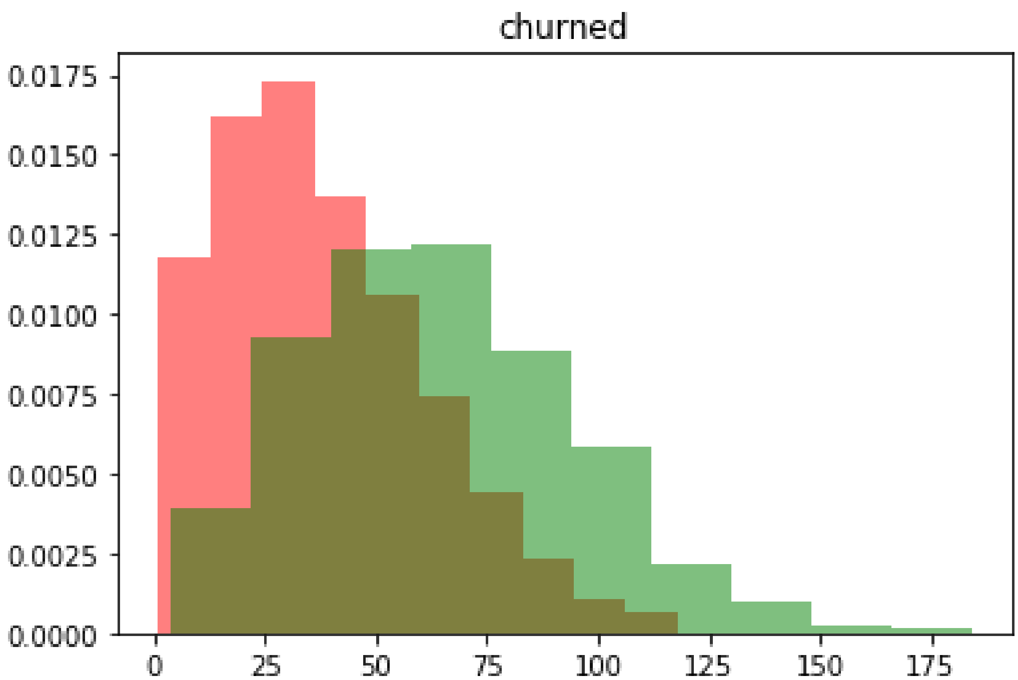



In [6283]:
```python
plt.hist(weeks.feature_3,alpha=0.5,color='red')
```

Out[6283]:
```
(array([398., 596., 676., 608., 383., 226.,  89.,  34.,   9.,   6.]),
 array([  1. ,  19.3,  37.6,  55.9,  74.2,  92.5, 110.8, 129.1, 147.4,
        165.7, 184. ]),
 <a list of 10 Patch objects>)
```




```
In [6284]: #normalize histogram
           plt.hist(weeks[(weeks.label==1)].feature_3,alpha=0.5,color='red',density=1)
           plt.hist(weeks[(weeks.label==0)].feature_3,alpha=0.5,color='green',density=1)
           plt.title('churned')

Out[6284]: Text(0.5,1,'churned')
```



In [6285]:
```
# creating some functions for new features
def max_consecutive(vector):
    longest = 0
    current = 0
    for num in vector:
        if num == 1:
            current += 1
        else:
            longest = max(longest, current)
            current = 0

    return max(longest, current)
def latest_streak(series):
    week_vector=[0,0,0,0,0,0,0,0]
    count=0

    for i in series:
        week_vector[i]=1
    reversed_week=list(reversed(week_vector))
    for i in reversed_week:
        if i==1:
            count+=1
        else:
            break
    return count
def max_streak(series):
    week_vector=[0,0,0,0,0,0,0,0]

    for i in series:
        week_vector[i]=1
    streak=max_consecutive(week_vector)
    return streak
def get_range(series):
    return max(series)-min(series)
def lifetime_mean(series):
    return np.sum(series)/8
```

In [6286]:
```
max_consecutive([0,1,1,1,0,0,1,0,1,1,1,1,1,1,0])
```

Out[6286]: 6

# 2 About dealing with the sparse week information

#### 2.0.1 In order to have a dataset in the form of a vector per courier, I try with different aggregation methods along with defined new features that will give us information about the time sparsity

#### 2.0.2 Week Count is just the amount of weeks that the courier worked

#### 2.0.3 Week Max Streak is the number of maximum weeks in a row a courier worked

#### 2.0.4 Week latest streak is the maximum number of weeks worked towards the end of the period, meaning from the 7th week backwards

#### 2.0.5 Although for some features we apparently have integers instead of doubles, we will take the mean or the lifetime average (in this one we take the sum and divide by all 8 weeks), if data dictionary was provided then would be easier to choose how to deal with such features, otherwise, we will treat them the same

## 2.1 trying different aggregation methods on the data

In [6287]:
```
aggreg=get_range
aggreg='mean'
#aggreg=lifetime_mean
aggregname='mean'
```

In [6288]:
```
gold=weeks.groupby(['courier','label'], as_index=False )\
.agg({'week':['count',  max_streak,latest_streak],\
               'feature_1':aggreg,\
                'feature_2':aggreg,'feature_3':aggreg\
      ,'feature_4':aggreg,'feature_5':aggreg\
      ,'feature_6':aggreg,'feature_7':aggreg\
      ,'feature_8':aggreg,'feature_9':aggreg\
      ,'feature_10':aggreg,'feature_11':aggreg\
     ,'feature_12':aggreg,'feature_13':aggreg\
     ,'feature_14':aggreg,'feature_15':aggreg\
     ,'feature_16':aggreg,'feature_17':aggreg})
```

In [6289]:
```
gold[(gold.courier==6282)]
```

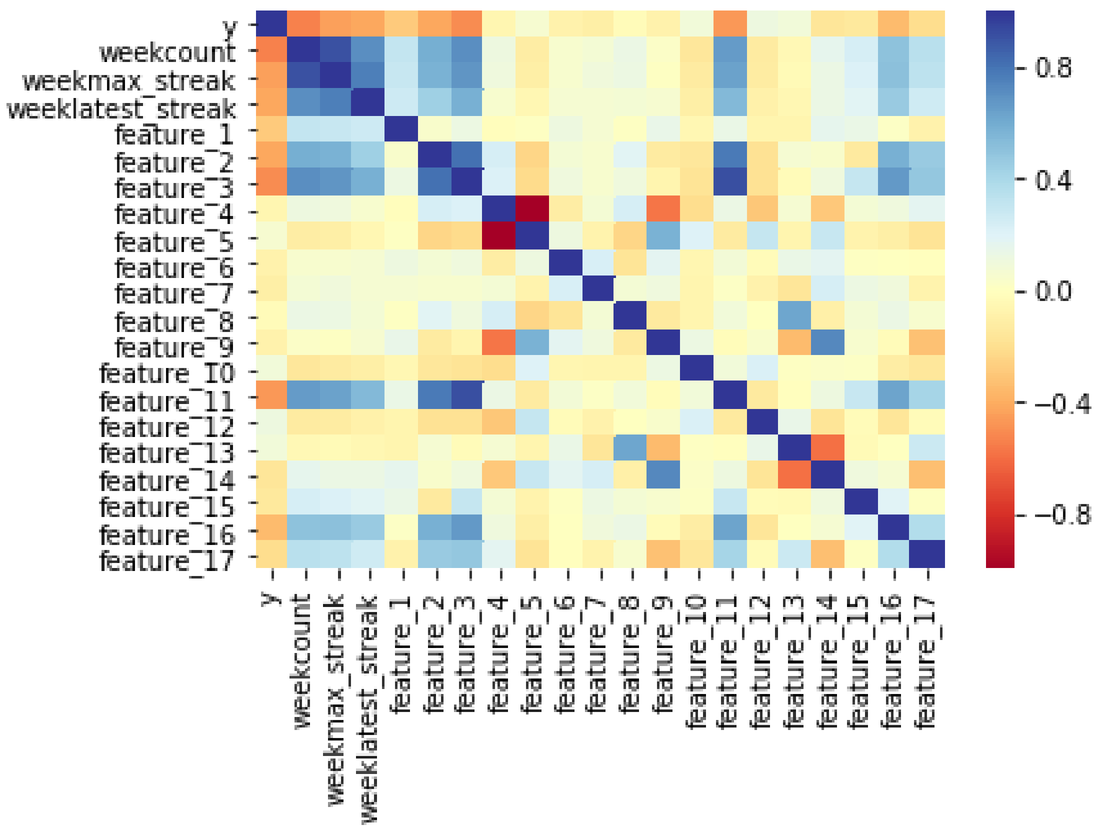
Out[6289]:
```
  courier label  week                          feature_1  feature_2 feature_3  \
                count max_streak latest_streak      mean       mean      mean
1    6282     0     6          6             6  1.333333  36.666667      48.5

  feature_4 feature_5    ...      feature_8 feature_9 feature_10 feature_11  \
       mean      mean    ...           mean      mean       mean       mean
1  0.075517  0.924483    ...     4300.18395  0.881117   8.317717       13.0

  feature_12 feature_13 feature_14 feature_15 feature_16 feature_17
        mean       mean       mean       mean       mean       mean
1  21.595879   5.379692    0.88055  72.957087        1.5   6.166667

[1 rows x 22 columns]
```

```
In [6290]: gold.columns = [gold + i for gold, i in zip(gold.columns.get_level_values(0), gold.c
           golden_names=[w.replace(aggregname,'') for w in gold.columns.get_level_values(0)]
           gold.columns = golden_names
           gold=gold.rename(columns={'label':'y'})
           gold.set_index('courier', inplace=True)
```

```
In [6291]: #gold.columns = [gold  for gold in gold.columns.get_level_values(0)]
```

```
In [6292]: gold_corr=gold.corr()
           sns.heatmap(gold_corr, vmax=1., square=False,cmap="RdYlBu")
```

```
Out[6292]: <matplotlib.axes._subplots.AxesSubplot at 0x146e806d780>
```




```
In [6293]: gold.head(3)
```

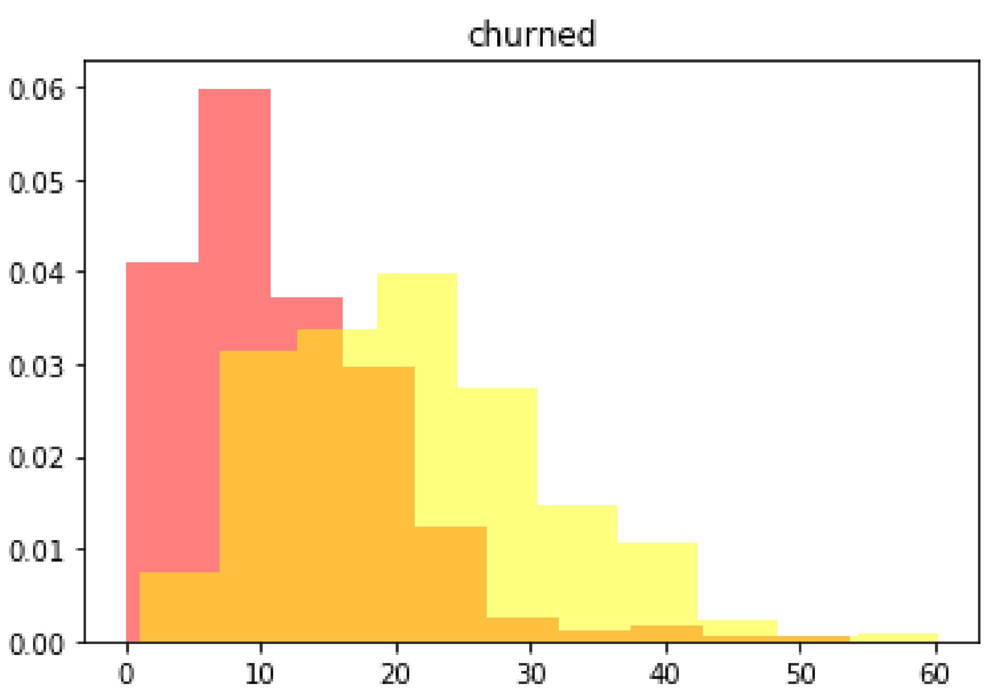
Out[6293]:

| | y | weekcount | weekmax_streak | weeklatest_streak | feature_1 \ |
|---|---|---|---|---|---|
| courier | | | | | |
| 3767 | 1 | 4 | 3 | 0 | 1.750000 |
| 6282 | 0 | 6 | 6 | 6 | 1.333333 |
| 10622 | 1 | 2 | 2 | 0 | -3.500000 |

```
         feature_2  feature_3  feature_4  feature_5  feature_6     ...       \
courier                                                            ...
3767     45.500000       46.0   0.040700   0.959300  131.82820     ...
6282     36.666667       48.5   0.075517   0.924483  111.29100     ...
10622    84.500000       54.0   0.119050   0.880950  100.15875     ...

           feature_8  feature_9  feature_10  feature_11  feature_12  \
courier
3767     2107.008875   0.853000    8.413307        19.0   19.062094
6282     4300.183950   0.881117    8.317717        13.0   21.595879
10622    2576.890500   0.623800   10.199895        20.5   21.568016

         feature_13  feature_14  feature_15  feature_16  feature_17
courier
3767       5.192193     0.85645   36.042781         1.5   17.500000
6282       5.379692     0.88055   72.957087         1.5    6.166667
10622      4.179873     0.66030   35.646190         2.5   15.500000

[3 rows x 21 columns]
```

In [6294]:
```python
plt.hist(gold[(gold.y==1)].feature_11,alpha=0.5,color='red',density=1)
plt.hist(gold[(gold.y==0)].feature_11,alpha=0.5,color='yellow',density=1)
plt.title('churned')
```

Out[6294]:
```
Text(0.5,1,'churned')
```



plt.hist(gold[(gold.y==1)].weekmax_streak,alpha=0.5,color='red',density=1)
plt.hist(gold[(gold.y==0)].weekmax_streak,alpha=0.5,color='yellow',density=1)
plt.title('churned')

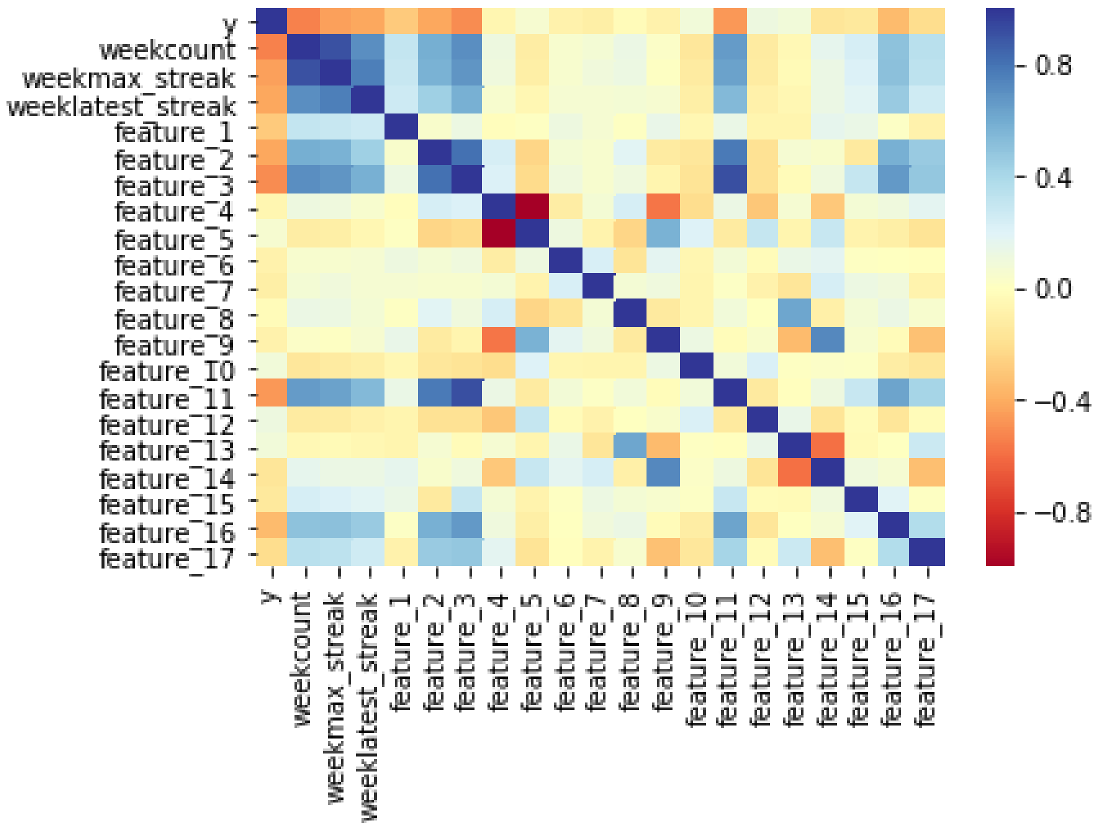
**There seems to be a difference between the distribution of feature 2. 3. and 11 per class**

```
In [6295]: gold.head()
```

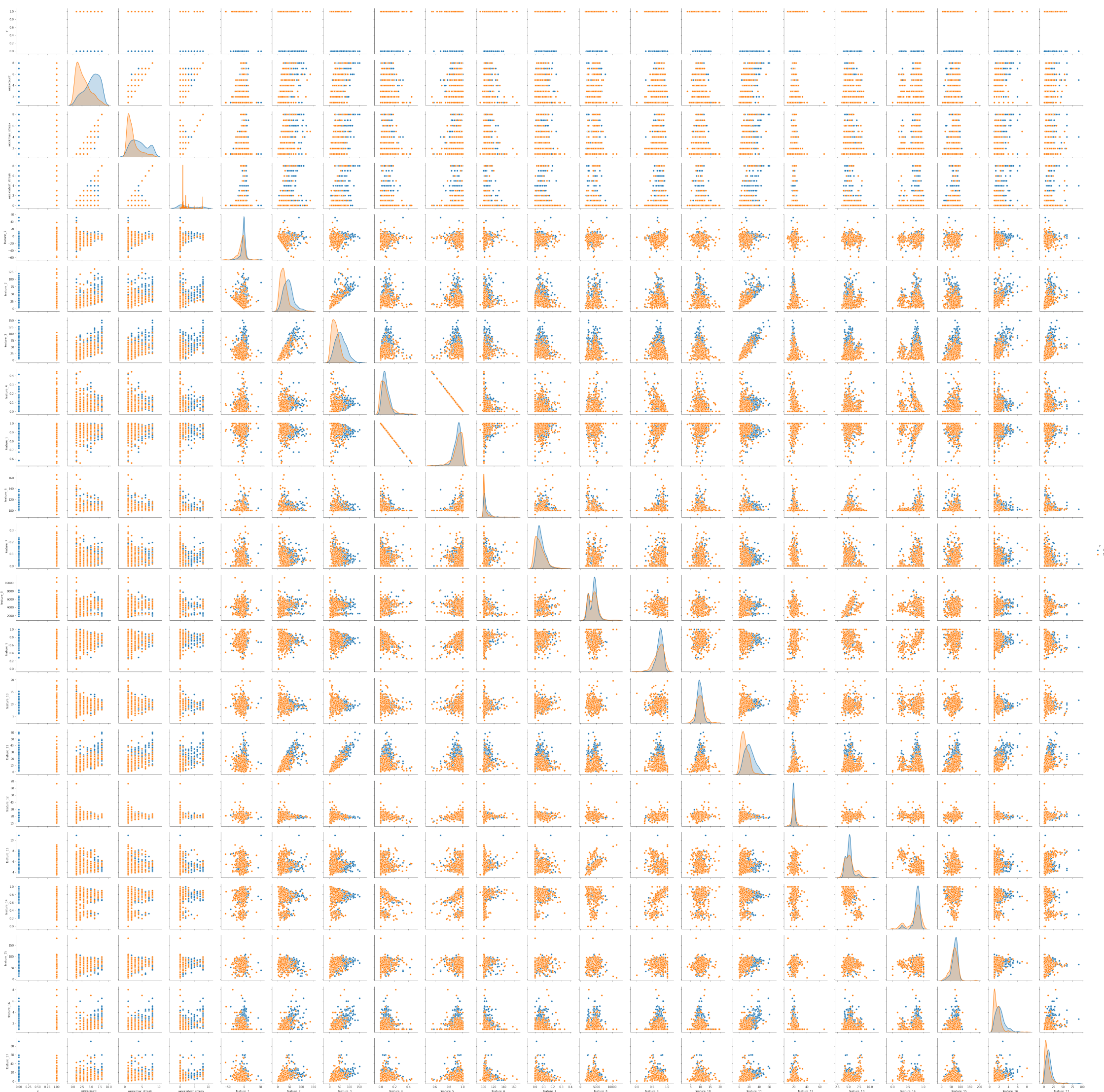
```
Out[6295]:         y  weekcount  weekmax_streak  weeklatest_streak  feature_1  \
           courier
           3767     1          4               3                  0   1.750000
           6282     0          6               6                  6   1.333333
           10622    1          2               2                  0  -3.500000
           13096    0          2               2                  0   0.000000
           14261    1          8               8                  8  -3.625000

                    feature_2  feature_3  feature_4  feature_5  feature_6    ...      \
           courier                                                           ...
           3767     45.500000     46.000   0.040700   0.959300  131.82820    ...
           6282     36.666667     48.500   0.075517   0.924483  111.29100    ...
           10622    84.500000     54.000   0.119050   0.880950  100.15875    ...
           13096    59.000000     89.500   0.161600   0.838400  104.29600    ...
           14261    75.500000     70.875   0.018425   0.981575  115.62990    ...

                      feature_8  feature_9  feature_10  feature_11  feature_12  \
           courier
           3767     2107.008875   0.853000    8.413307      19.000   19.062094
           6282     4300.183950   0.881117    8.317717      13.000   21.595879
           10622    2576.890500   0.623800   10.199895      20.500   21.568016
           13096    4590.275250   0.686000    9.630672      34.500   17.902412
           14261    3870.750225   0.892537   10.001638      34.875   21.166889

                    feature_13  feature_14  feature_15  feature_16  feature_17
           courier
           3767       5.192193    0.856450   36.042781         1.5   17.500000
           6282       5.379692    0.880550   72.957087         1.5    6.166667
           10622      4.179873    0.660300   35.646190         2.5   15.500000
           13096      5.166684    0.720300   84.347978         3.0   19.000000
           14261      5.433909    0.900662   49.311612         2.5    6.750000

           [5 rows x 21 columns]
```

```
In [6296]: sns.heatmap(gold_corr, vmax=1., square=False,cmap="RdYlBu")
```

```
Out[6296]: <matplotlib.axes._subplots.AxesSubplot at 0x146e81acbe0>
```




```
In [6297]: sns.pairplot(gold, hue='y')

Out[6297]: <seaborn.axisgrid.PairGrid at 0x146e82556d8>
```



```
In [6298]: #gold=gold[['y','weekcount','weekmax_streak','weeklatest_streak','feature_5','featu

In [6299]: gold=gold[['y','weekcount','weekmax_streak','weeklatest_streak','feature_1','feature

In [6300]: # After running several test with multiple features and after having almost the sam

In [6301]: #gold=gold[['y','weekcount','weekmax_streak','weeklatest_streak','feature_3','featu
```

## 2.2 Bringing lifetime info into the mix

```
In [6302]: #adding lifetime info
           lifetime = pd.read_csv(filepath_or_buffer='Courier_lifetime_data.csv')

In [6303]: lifetime.head()
```

Out[6303]:
```
   courier feature_1  feature_2
0      208         a       25.0
1      218         c        0.0
2      225         c        NaN
3      231         c        0.0
4      242         c        NaN
```

In [6304]:
```
lifetime.rename(columns={'feature_1':'lifetime_feature_1','feature_2':'lifetime_fea
```

In [6305]:
```
gen_le = LabelEncoder()
gen_labels = gen_le.fit_transform(lifetime['lifetime_feature_1'])
lifetime['lifetime_feature_1'] = gen_labels
```

In [6306]:
```
lifetime_encoded= pd.get_dummies(lifetime, columns=['lifetime_feature_1'])
```

In [6307]:
```
#lifetime_encoded=lifetime.copy()
```

In [6308]:
```
lifetime_encoded.set_index('courier', inplace=True)
```

In [6309]:
```
lifetime_encoded.head()
```

Out[6309]:
```
         lifetime_feature_2  lifetime_feature_1_0  lifetime_feature_1_1  \
courier
208                    25.0                     1                     0
218                     0.0                     0                     0
225                     NaN                     0                     0
231                     0.0                     0                     0
242                     NaN                     0                     0

         lifetime_feature_1_2  lifetime_feature_1_3
courier
208                         0                     0
218                         1                     0
225                         1                     0
231                         1                     0
242                         1                     0
```

In [6310]:
```
#lifetime_encoded=lifetime_encoded.drop('feature_2', axis=1)
```

In [6311]:
```
gold=gold.merge(lifetime_encoded, how='left', left_index=True, right_index=True)
```

In [6312]:
```
gold.head()
```

Out[6312]:
```
         y  weekcount  weekmax_streak  weeklatest_streak  feature_1  \
courier
3767     1          4               3                  0   1.750000
6282     0          6               6                  6   1.333333
10622    1          2               2                  0  -3.500000
13096    0          2               2                  0   0.000000
14261    1          8               8                  8  -3.625000
```

```
         feature_2  feature_3  feature_11  feature_16  lifetime_feature_2  \
courier
3767     45.500000     46.000      19.000         1.5                33.0
6282     36.666667     48.500      13.000         1.5                35.0
10622    84.500000     54.000      20.500         2.5                35.0
13096    59.000000     89.500      34.500         3.0                35.0
14261    75.500000     70.875      34.875         2.5                44.0

         lifetime_feature_1_0  lifetime_feature_1_1  lifetime_feature_1_2  \
courier
3767                        0                     1                     0
6282                        1                     0                     0
10622                       0                     1                     0
13096                       1                     0                     0
14261                       1                     0                     0

         lifetime_feature_1_3
courier
3767                        0
6282                        0
10622                       0
13096                       0
14261                       0
```

### 2.2.1 Using the selected features to impute the missing values from lifetime with KNN imputation

```
In [6313]: #gold =  pd.DataFrame(KNN(k=2).fit_transform(gold), columns=gold.columns, index=gol
```

```
In [6314]: gold.head()
```

```
Out[6314]:          y  weekcount  weekmax_streak  weeklatest_streak  feature_1  \
           courier
           3767     1          4               3                  0   1.750000
           6282     0          6               6                  6   1.333333
           10622    1          2               2                  0  -3.500000
           13096    0          2               2                  0   0.000000
           14261    1          8               8                  8  -3.625000

                    feature_2  feature_3  feature_11  feature_16  lifetime_feature_2  \
           courier
           3767     45.500000     46.000      19.000         1.5                33.0
           6282     36.666667     48.500      13.000         1.5                35.0
           10622    84.500000     54.000      20.500         2.5                35.0
           13096    59.000000     89.500      34.500         3.0                35.0
           14261    75.500000     70.875      34.875         2.5                44.0
```

| courier | lifetime_feature_1_0 | lifetime_feature_1_1 | lifetime_feature_1_2 |
|---|---|---|---|
| 3767 | 0 | 1 | 0 |
| 6282 | 1 | 0 | 0 |
| 10622 | 0 | 1 | 0 |
| 13096 | 1 | 0 | 0 |
| 14261 | 1 | 0 | 0 |

| courier | lifetime_feature_1_3 |
|---|---|
| 3767 | 0 |
| 6282 | 0 |
| 10622 | 0 |
| 13096 | 0 |
| 14261 | 0 |

In [6315]:
```
gold_mt=gold.corr()
gold_mt
```

Out[6315]:

| | y | weekcount | weekmax_streak | weeklatest_streak |
|---|---|---|---|---|
| y | 1.000000 | -0.534864 | -0.442932 | -0.415129 |
| weekcount | -0.534864 | 1.000000 | 0.912668 | 0.706565 |
| weekmax_streak | -0.442932 | 0.912668 | 1.000000 | 0.758359 |
| weeklatest_streak | -0.415129 | 0.706565 | 0.758359 | 1.000000 |
| feature_1 | -0.287069 | 0.308786 | 0.291029 | 0.267561 |
| feature_2 | -0.420368 | 0.590266 | 0.570816 | 0.440527 |
| feature_3 | -0.502446 | 0.707429 | 0.686554 | 0.582624 |
| feature_11 | -0.464239 | 0.660209 | 0.640439 | 0.539818 |
| feature_16 | -0.346133 | 0.504314 | 0.514343 | 0.462136 |
| lifetime_feature_2 | -0.200355 | 0.242526 | 0.227177 | 0.188627 |
| lifetime_feature_1_0 | -0.153103 | 0.206490 | 0.191525 | 0.195845 |
| lifetime_feature_1_1 | 0.175943 | -0.252722 | -0.228066 | -0.215066 |
| lifetime_feature_1_2 | 0.052522 | -0.025867 | -0.041832 | -0.032577 |
| lifetime_feature_1_3 | -0.053252 | 0.094180 | 0.078020 | 0.039158 |

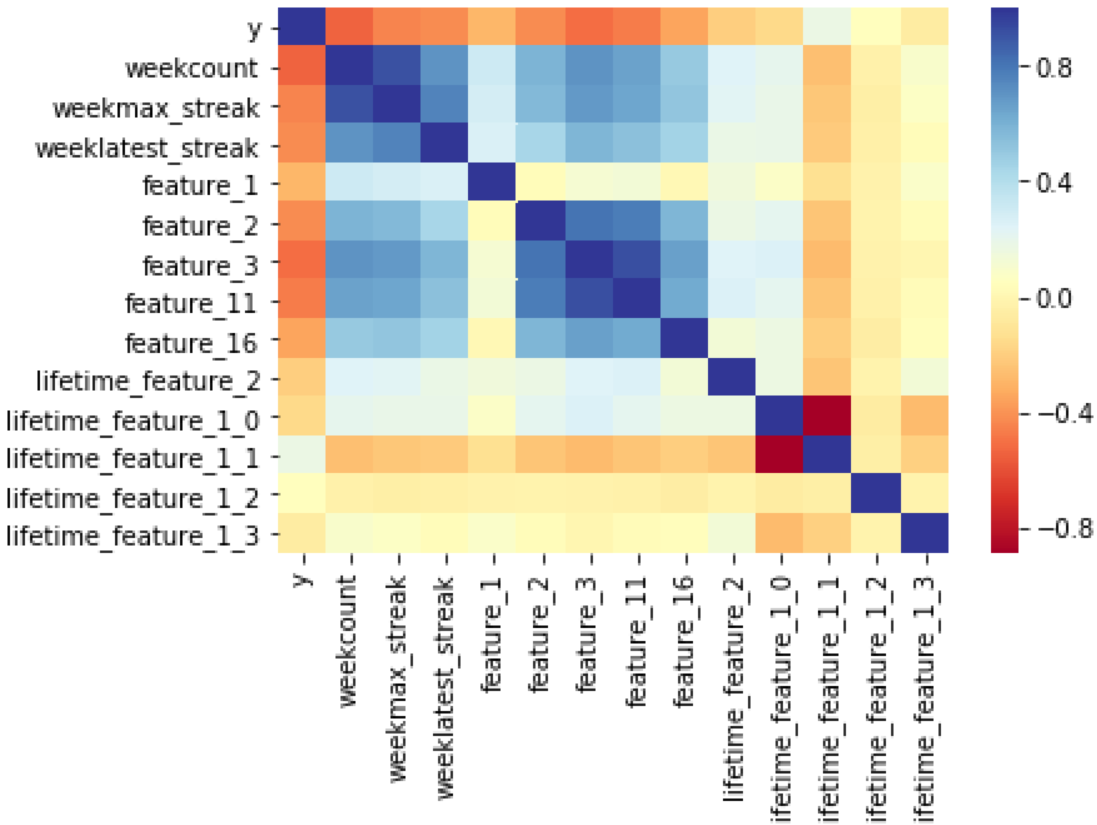
| | feature_1 | feature_2 | feature_3 | feature_11 | feature_16 |
|---|---|---|---|---|---|
| y | -0.287069 | -0.420368 | -0.502446 | -0.464239 | -0.346133 |
| weekcount | 0.308786 | 0.590266 | 0.707429 | 0.660209 | 0.504314 |
| weekmax_streak | 0.291029 | 0.570816 | 0.686554 | 0.640439 | 0.514343 |
| weeklatest_streak | 0.267561 | 0.440527 | 0.582624 | 0.539818 | 0.462136 |
| feature_1 | 1.000000 | 0.042441 | 0.121433 | 0.136845 | 0.015898 |
| feature_2 | 0.042441 | 1.000000 | 0.809809 | 0.779639 | 0.580537 |
| feature_3 | 0.121433 | 0.809809 | 1.000000 | 0.920134 | 0.666711 |
| feature_11 | 0.136845 | 0.779639 | 0.920134 | 1.000000 | 0.625702 |
| feature_16 | 0.015898 | 0.580537 | 0.666711 | 0.625702 | 1.000000 |
| lifetime_feature_2 | 0.150614 | 0.180502 | 0.241822 | 0.257226 | 0.135372 |
| lifetime_feature_1_0 | 0.082449 | 0.216367 | 0.261974 | 0.216313 | 0.174378 |
| lifetime_feature_1_1 | -0.124961 | -0.236613 | -0.267140 | -0.234803 | -0.194260 |

```
lifetime_feature_1_2  -0.018950  -0.012582  -0.023151   -0.026124   -0.046458
lifetime_feature_1_3   0.090340   0.035859   0.004369    0.035228    0.044673

                      lifetime_feature_2  lifetime_feature_1_0  \
y                              -0.200355             -0.153103
weekcount                       0.242526              0.206490
weekmax_streak                  0.227177              0.191525
weeklatest_streak               0.188627              0.195845
feature_1                       0.150614              0.082449
feature_2                       0.180502              0.216367
feature_3                       0.241822              0.261974
feature_11                      0.257226              0.216313
feature_16                      0.135372              0.174378
lifetime_feature_2              1.000000              0.172418
lifetime_feature_1_0            0.172418              1.000000
lifetime_feature_1_1           -0.234322             -0.885355
lifetime_feature_1_2           -0.013384             -0.058804
lifetime_feature_1_3            0.134673             -0.273690

                      lifetime_feature_1_1  lifetime_feature_1_2  \
y                                 0.175943              0.052522
weekcount                        -0.252722             -0.025867
weekmax_streak                   -0.228066             -0.041832
weeklatest_streak                -0.215066             -0.032577
feature_1                        -0.124961             -0.018950
feature_2                        -0.236613             -0.012582
feature_3                        -0.267140             -0.023151
feature_11                       -0.234803             -0.026124
feature_16                       -0.194260             -0.046458
lifetime_feature_2               -0.234322             -0.013384
lifetime_feature_1_0             -0.885355             -0.058804
lifetime_feature_1_1              1.000000             -0.041419
lifetime_feature_1_2             -0.041419              1.000000
lifetime_feature_1_3             -0.192776             -0.012804

                      lifetime_feature_1_3
y                                -0.053252
weekcount                         0.094180
weekmax_streak                    0.078020
weeklatest_streak                 0.039158
feature_1                         0.090340
feature_2                         0.035859
feature_3                         0.004369
feature_11                        0.035228
feature_16                        0.044673
lifetime_feature_2                0.134673
lifetime_feature_1_0             -0.273690
lifetime_feature_1_1             -0.192776
```

```
lifetime_feature_1_2             -0.012804
lifetime_feature_1_3              1.000000
```

In [6316]:
```
sns.heatmap(gold_mt, vmax=1., square=False,cmap="RdYlBu")
```

Out[6316]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x146fdd714e0>
```




In [6317]:
```
#gold=gold.drop('feature_1',axis=1)
```

## 3 We prepare the golden set

In [6318]:
```
golden_x= gold.drop(['y'], axis=1)
golden_y= gold['y']
```

In [6319]:
```
#golden_x =  pd.DataFrame(KNN(k=2).fit_transform(golden_x), columns=golden_x.column
```

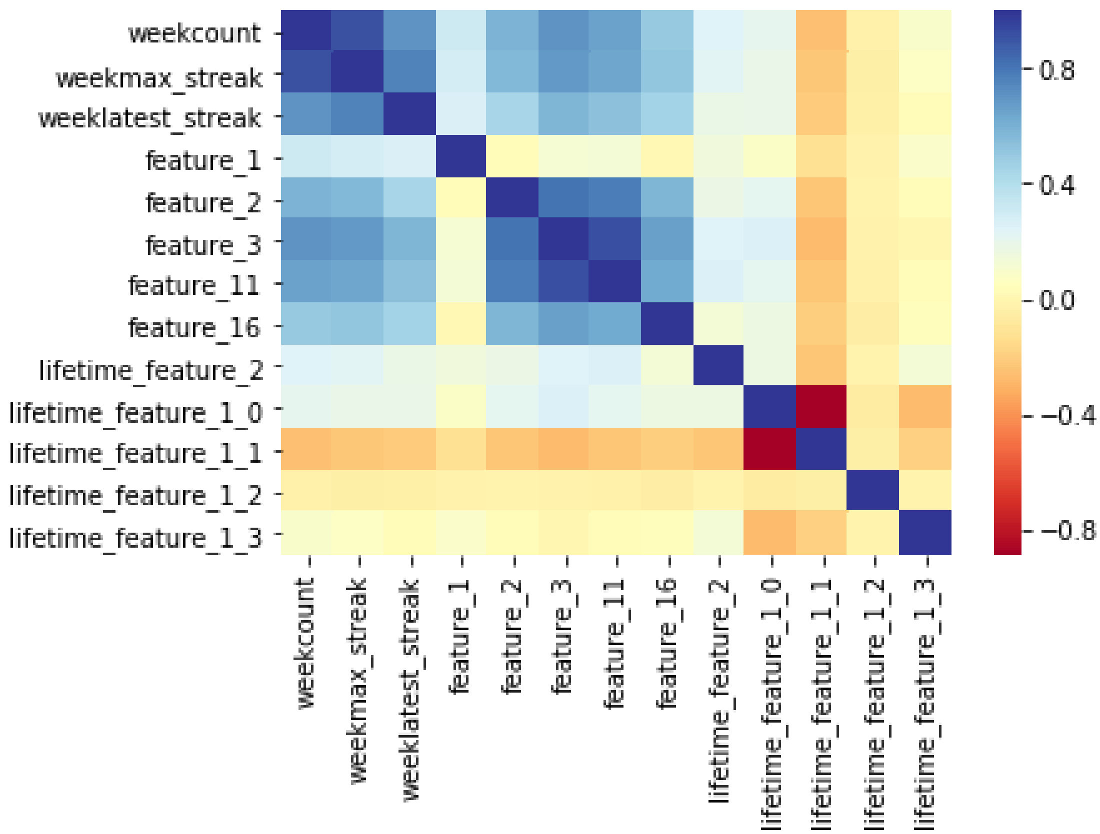
In [6320]:
```
golden_x_mt=golden_x.corr()
golden_x_mt
```

```
Out[6320]:                      weekcount  weekmax_streak  weeklatest_streak  feature_1  \
           weekcount             1.000000        0.912668           0.706565   0.308786
           weekmax_streak        0.912668        1.000000           0.758359   0.291029
           weeklatest_streak     0.706565        0.758359           1.000000   0.267561
           feature_1             0.308786        0.291029           0.267561   1.000000
           feature_2             0.590266        0.570816           0.440527   0.042441
           feature_3             0.707429        0.686554           0.582624   0.121433
           feature_11            0.660209        0.640439           0.539818   0.136845
           feature_16            0.504314        0.514343           0.462136   0.015898
           lifetime_feature_2    0.242526        0.227177           0.188627   0.150614
           lifetime_feature_1_0  0.206490        0.191525           0.195845   0.082449
           lifetime_feature_1_1 -0.252722       -0.228066          -0.215066  -0.124961
           lifetime_feature_1_2 -0.025867       -0.041832          -0.032577  -0.018950
           lifetime_feature_1_3  0.094180        0.078020           0.039158   0.090340

                                feature_2  feature_3  feature_11  feature_16  \
           weekcount             0.590266   0.707429    0.660209    0.504314
           weekmax_streak        0.570816   0.686554    0.640439    0.514343
           weeklatest_streak     0.440527   0.582624    0.539818    0.462136
           feature_1             0.042441   0.121433    0.136845    0.015898
           feature_2             1.000000   0.809809    0.779639    0.580537
           feature_3             0.809809   1.000000    0.920134    0.666711
           feature_11            0.779639   0.920134    1.000000    0.625702
           feature_16            0.580537   0.666711    0.625702    1.000000
           lifetime_feature_2    0.180502   0.241822    0.257226    0.135372
           lifetime_feature_1_0  0.216367   0.261974    0.216313    0.174378
           lifetime_feature_1_1 -0.236613  -0.267140   -0.234803   -0.194260
           lifetime_feature_1_2 -0.012582  -0.023151   -0.026124   -0.046458
           lifetime_feature_1_3  0.035859   0.004369    0.035228    0.044673

                                lifetime_feature_2  lifetime_feature_1_0  \
           weekcount                      0.242526              0.206490
           weekmax_streak                 0.227177              0.191525
           weeklatest_streak              0.188627              0.195845
           feature_1                      0.150614              0.082449
           feature_2                      0.180502              0.216367
           feature_3                      0.241822              0.261974
           feature_11                     0.257226              0.216313
           feature_16                     0.135372              0.174378
           lifetime_feature_2             1.000000              0.172418
           lifetime_feature_1_0           0.172418              1.000000
           lifetime_feature_1_1          -0.234322             -0.885355
           lifetime_feature_1_2          -0.013384             -0.058804
           lifetime_feature_1_3           0.134673             -0.273690

                                lifetime_feature_1_1  lifetime_feature_1_2  \
           weekcount                       -0.252722             -0.025867
           weekmax_streak                  -0.228066             -0.041832
```

```
weeklatest_streak            -0.215066         -0.032577
feature_1                    -0.124961         -0.018950
feature_2                    -0.236613         -0.012582
feature_3                    -0.267140         -0.023151
feature_11                   -0.234803         -0.026124
feature_16                   -0.194260         -0.046458
lifetime_feature_2           -0.234322         -0.013384
lifetime_feature_1_0         -0.885355         -0.058804
lifetime_feature_1_1          1.000000         -0.041419
lifetime_feature_1_2         -0.041419          1.000000
lifetime_feature_1_3         -0.192776         -0.012804

                      lifetime_feature_1_3
weekcount                         0.094180
weekmax_streak                    0.078020
weeklatest_streak                 0.039158
feature_1                         0.090340
feature_2                         0.035859
feature_3                         0.004369
feature_11                        0.035228
feature_16                        0.044673
lifetime_feature_2                0.134673
lifetime_feature_1_0             -0.273690
lifetime_feature_1_1             -0.192776
lifetime_feature_1_2             -0.012804
lifetime_feature_1_3              1.000000
```

In [6321]:
```
sns.heatmap(golden_x_mt, vmax=1., square=False,cmap="RdYlBu")
```

Out[6321]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x146f98cf9b0>
```




```
In [6322]: x_train, x_test, y_train, y_test = train_test_split(golden_x,golden_y , test_size=0
           #stratified train test split to have balanced classes in training and testing sets
```

# 4 About imputing missing values

#### 4.0.1 I use KNN to impute missing values for lifetime dataset feature_2, I do it separately in the testing and training set, I do so to prevent data leakage altough may come with a cost on the accuracy of the imputation

```
In [6323]: x_train =  pd.DataFrame(KNN(k=2).fit_transform(x_train), columns=x_train.columns, in
           x_test =  pd.DataFrame(KNN(k=2).fit_transform(x_test), columns=x_test.columns, inde
```

```
Imputing row 1/546 with 0 missing, elapsed time: 0.062
Imputing row 101/546 with 0 missing, elapsed time: 0.063
Imputing row 201/546 with 0 missing, elapsed time: 0.064
Imputing row 301/546 with 0 missing, elapsed time: 0.064
Imputing row 401/546 with 0 missing, elapsed time: 0.065
Imputing row 501/546 with 0 missing, elapsed time: 0.065
Imputing row 1/183 with 0 missing, elapsed time: 0.009
Imputing row 101/183 with 0 missing, elapsed time: 0.009
```

In [6324]:
```
scaler=StandardScaler()
scaler.fit(x_train)
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)
```

# 5 Building model for prediction

In [6325]:
```
y_train.value_counts()
```

Out[6325]:
```
1    273
0    273
Name: y, dtype: int64
```

In [6326]:
```
y_test.value_counts()
```

Out[6326]:
```
0    92
1    91
Name: y, dtype: int64
```

### 5.0.1 Although the classes are balanced, still the amount of data is small we'll use Logistic regression and random forest to try to compensate for the size of the sample set

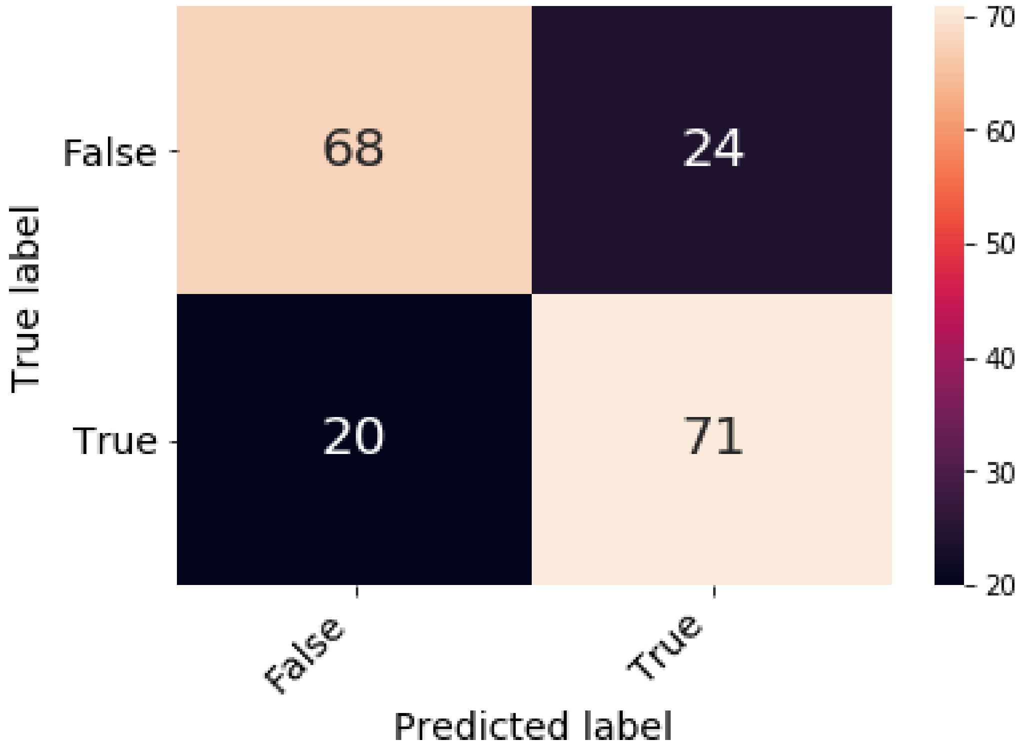
### 5.0.2 I display metrics like ROC and PR Curve but we will try to optimize accuracy since we have balanced classes

## 5.1 LogisticRegression

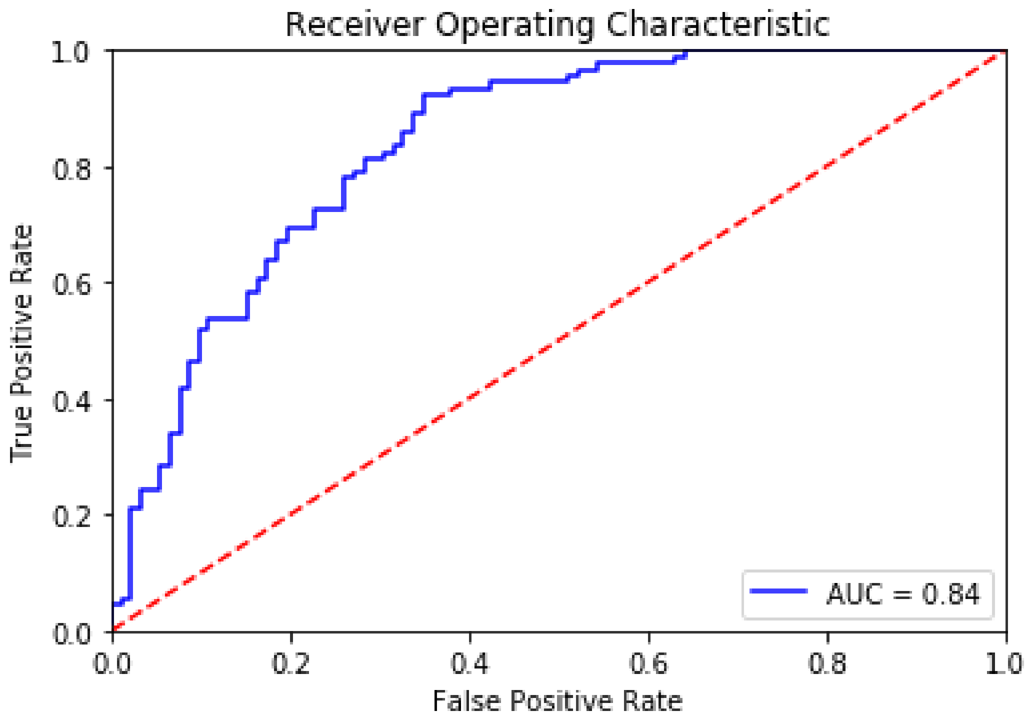
In [6327]:
```
clf = LogisticRegression(C=0.1, penalty='l1', class_weight='balanced')
clf.fit(x_train, y_train)
test_y_pred = clf.predict(x_test)
cf_mt = confusion_matrix(y_test, test_y_pred)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(clf.s
print(classification_report(y_test, test_y_pred))
confusion_matrix_df = pd.DataFrame(cf_mt, ('False', 'True'), ('False', 'True'))
heatmap = sns.heatmap(confusion_matrix_df, annot=True, annot_kws={"size": 20}, fmt='
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right'
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45, ha='right
plt.ylabel('True label', fontsize = 14)
plt.xlabel('Predicted label', fontsize = 14)
```

```
Accuracy of logistic regression classifier on test set: 0.76
             precision    recall  f1-score   support

          0       0.77      0.74      0.76        92
          1       0.75      0.78      0.76        91

avg / total       0.76      0.76      0.76       183
```

Out[6327]: Text(0.5,15,'Predicted label')

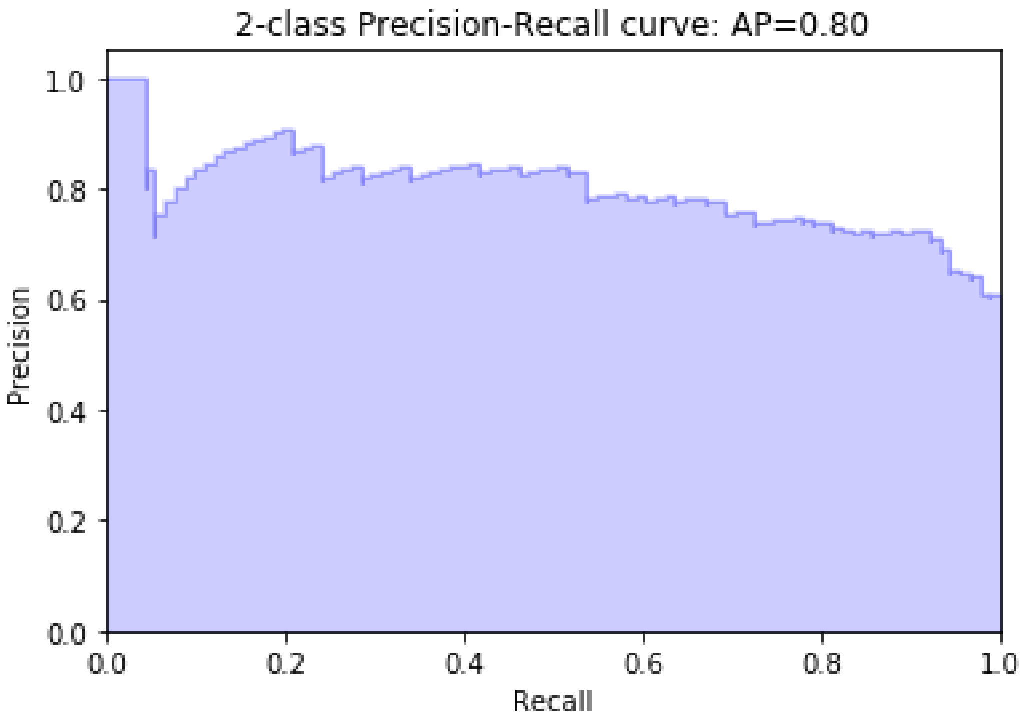



In [6328]:
```
probs = clf.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




In [6329]:
```
average_precision = average_precision_score(y_test, preds)
precision, recall, _ = precision_recall_curve(y_test, preds)
plt.step(recall, precision, color='b', alpha=0.2, where='post')
plt.fill_between(recall, precision, step='post', alpha=0.2,  color='b')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format( average_precision))
```

Out[6329]:
```
Text(0.5,1,'2-class Precision-Recall curve: AP=0.80')
```




# 6 Logistic regression grid search

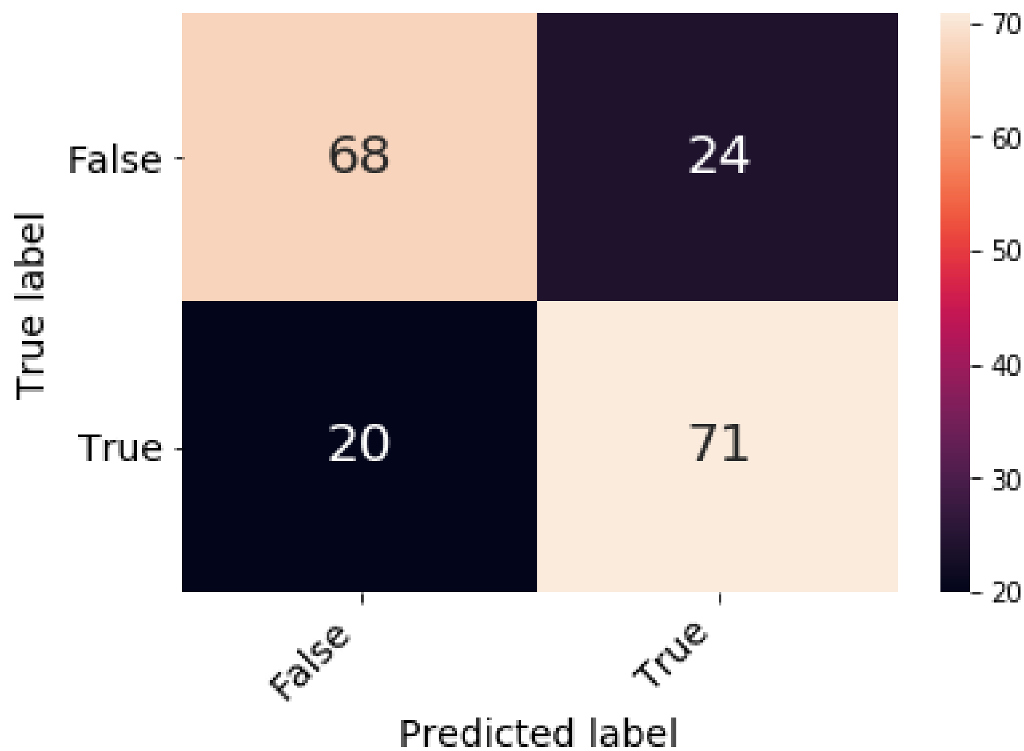
```
In [6330]: grid={"C":[0.001, 0.01, 0.1, 1, 10, 100, 1000] , "penalty":["l1","l2"]}# l1 lasso l2
           logreg=LogisticRegression(class_weight='balanced')
           logreg_cv=GridSearchCV(logreg,grid,cv=2)
           logreg_cv.fit(x_train,y_train)
           print("tuned hpyerparameters :(best parameters) ",logreg_cv.best_params_)
           print("accuracy :",logreg_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 0.1, 'penalty': 'l1'}
accuracy : 0.7655677655677655
```

```
In [6331]: test_y_pred = logreg_cv.predict(x_test)
           cf_mt = confusion_matrix(y_test, test_y_pred)
           print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg
           print(classification_report(y_test, test_y_pred))
           confusion_matrix_df = pd.DataFrame(cf_mt, ('False', 'True'), ('False', 'True'))
           heatmap = sns.heatmap(confusion_matrix_df, annot=True, annot_kws={"size": 20}, fmt="
           heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right'
           heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45, ha='right
           plt.ylabel('True label', fontsize = 14)
           plt.xlabel('Predicted label', fontsize = 14)
```

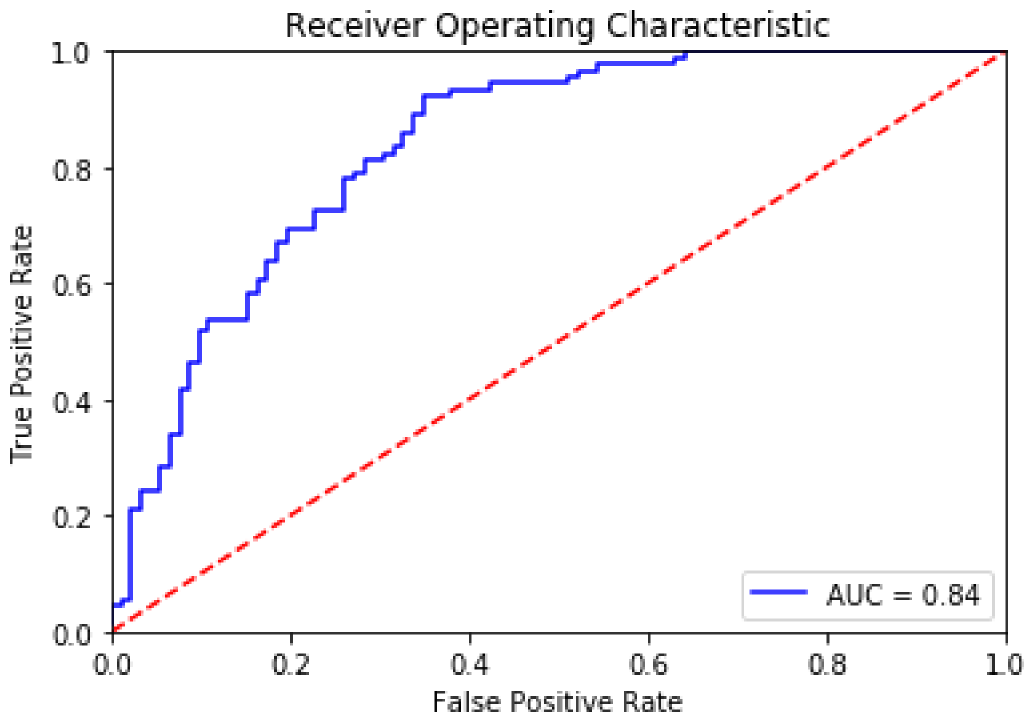
```
Accuracy of logistic regression classifier on test set: 0.76
             precision    recall  f1-score   support

          0       0.77      0.74      0.76        92
          1       0.75      0.78      0.76        91

avg / total       0.76      0.76      0.76       183
```

Out[6331]: Text(0.5,15,'Predicted label')



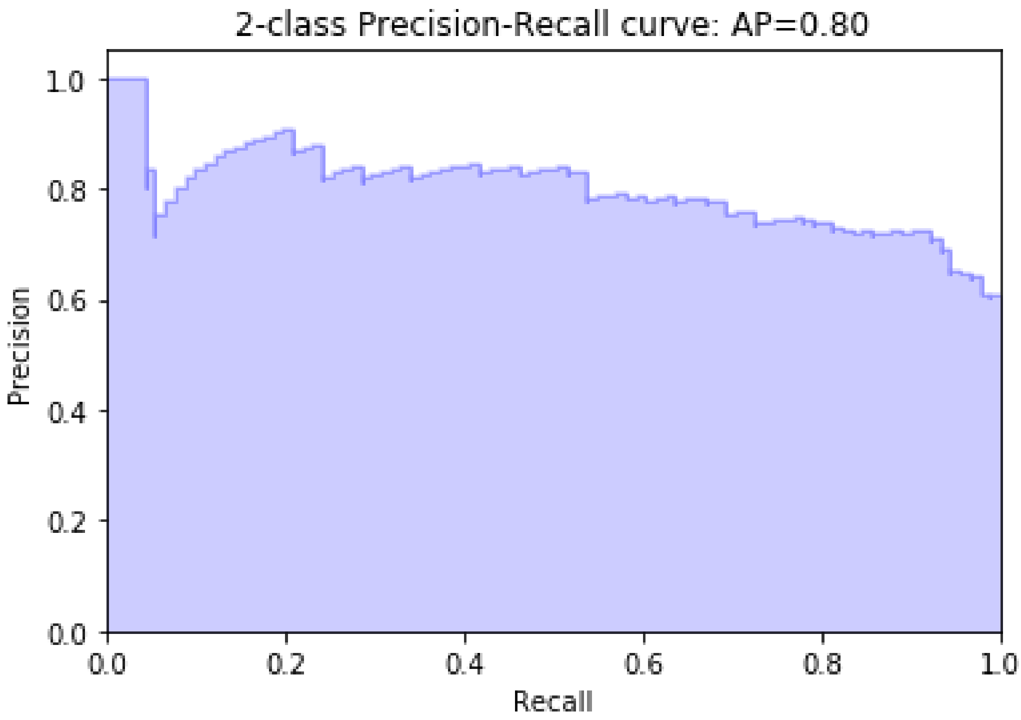

In [6332]:
```
probs = logreg_cv.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
```

```
plt.xlabel('False Positive Rate')
plt.show()
```




In [6333]:
```
average_precision = average_precision_score(y_test, preds)
precision, recall, _ = precision_recall_curve(y_test, preds)
plt.step(recall, precision, color='b', alpha=0.2, where='post')
plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision))
```

Out[6333]:
```
Text(0.5,1,'2-class Precision-Recall curve: AP=0.80')
```

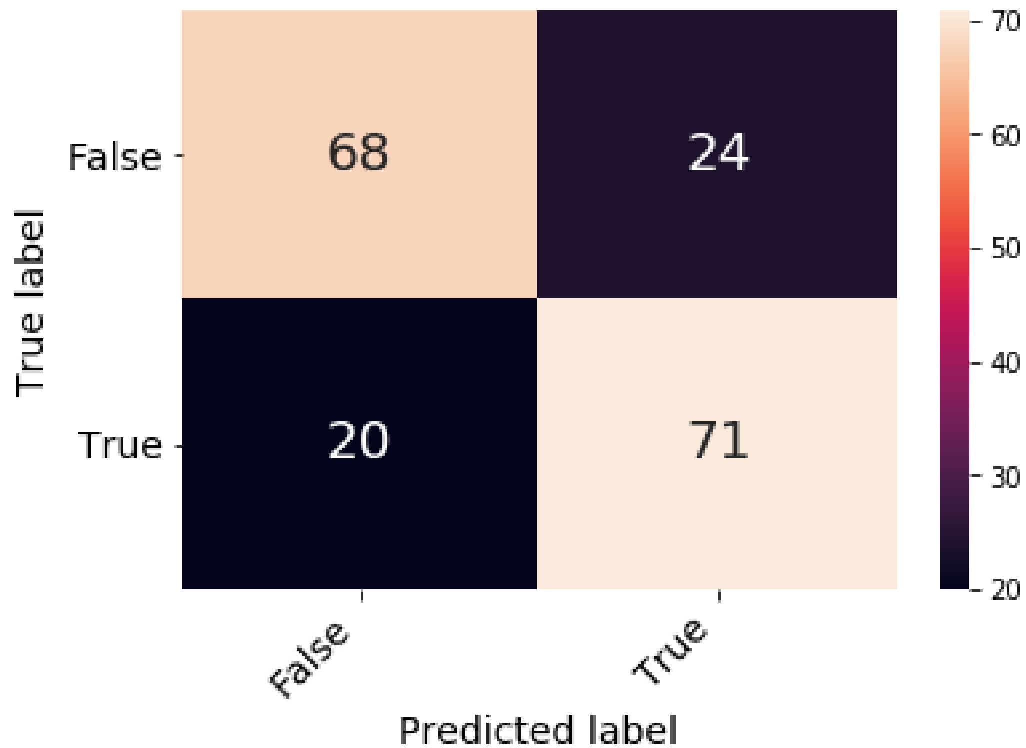



## 7 Logistic cross validation score

In [6334]:
```
logreg_cv.fit(x_train,y_train)
seed = 7
k_fold = KFold(n_splits=5, random_state=seed)
scoring = 'accuracy'
results=cross_val_score(logreg_cv, x_train, y_train, cv=k_fold, n_jobs=1, scoring=sc
print("Accuracy: %.3f (%.3f)" % (results.mean(), results.std()))
predicted=logreg_cv.predict(x_test)
matrix = confusion_matrix(y_test, predicted)
confusion_matrix_df = pd.DataFrame(matrix, ('False', 'True'), ('False', 'True'))
heatmap = sns.heatmap(confusion_matrix_df, annot=True, annot_kws={"size": 20}, fmt='
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right'
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45, ha='right
plt.ylabel('True label', fontsize = 14)
plt.xlabel('Predicted label', fontsize = 14)
```

```
Accuracy: 0.747 (0.028)
```

Out[6334]:
```
Text(0.5,15,'Predicted label')
```



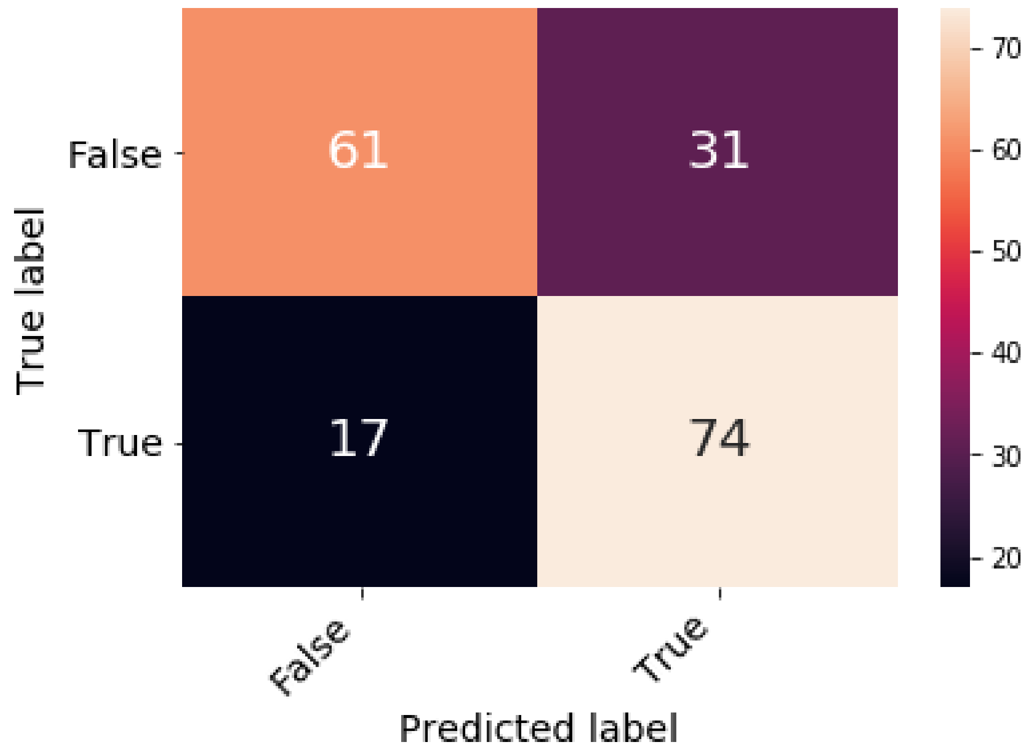

## 8 Adaboost

```
In [6335]: clf = AdaBoostClassifier(n_estimators=50,learning_rate=0.01,algorithm='SAMME')
           clf.fit(x_train,y_train)

           seed = 7
           k_fold = KFold(n_splits=2)
           scoring = 'accuracy'
           results=cross_val_score(clf, x_train, y_train, cv=k_fold, n_jobs=1, scoring=scoring)
           print("Accuracy: %.3f (%.3f)" % (results.mean(), results.std()))
           print(clf.score(x_test, y_test))
           clf.fit(x_train,y_train)
           predicted=clf.predict(x_test)
           matrix = confusion_matrix(y_test, predicted)
           confusion_matrix_df = pd.DataFrame(matrix, ('False', 'True'), ('False', 'True'))
           heatmap = sns.heatmap(confusion_matrix_df, annot=True, annot_kws={"size": 20}, fmt="
           heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right'
           heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45, ha='right
           plt.ylabel('True label', fontsize = 14)
           plt.xlabel('Predicted label', fontsize = 14)
```

```
Accuracy: 0.755 (0.007)
```

```
0.7377049180327869
```

```
Out[6335]: Text(0.5,15,'Predicted label')
```



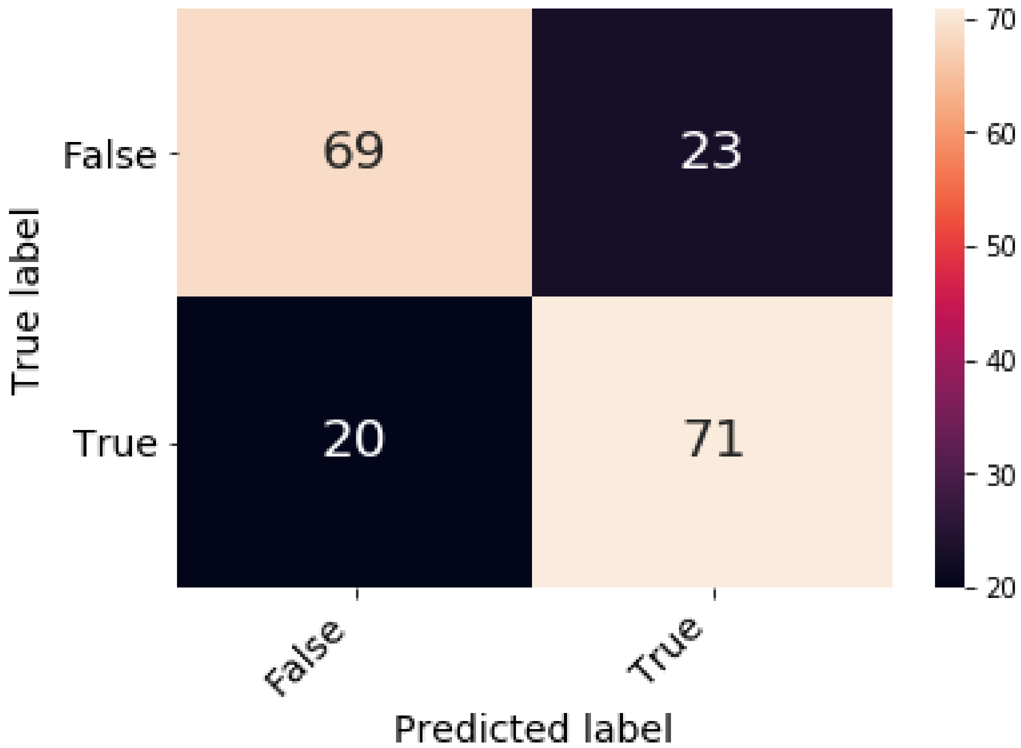

```
In [6336]: param_dist = {
            'n_estimators': [50, 100],
            'learning_rate' : [0.01,0.05,0.1,0.3,1,10],
            'algorithm' : ['SAMME', 'SAMME.R']
            }
           ada_tuned = GridSearchCV(AdaBoostClassifier(),
           param_dist,
            cv=2,

            n_jobs=-1)

           ada_tuned.fit(x_train, y_train)
           print("tuned hpyerparameters :(best parameters) ",ada_tuned.best_params_)
           print("accuracy :",ada_tuned.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'algorithm': 'SAMME', 'learning_rate': 0.3, 'n_esti
accuracy : 0.7673992673992674
```

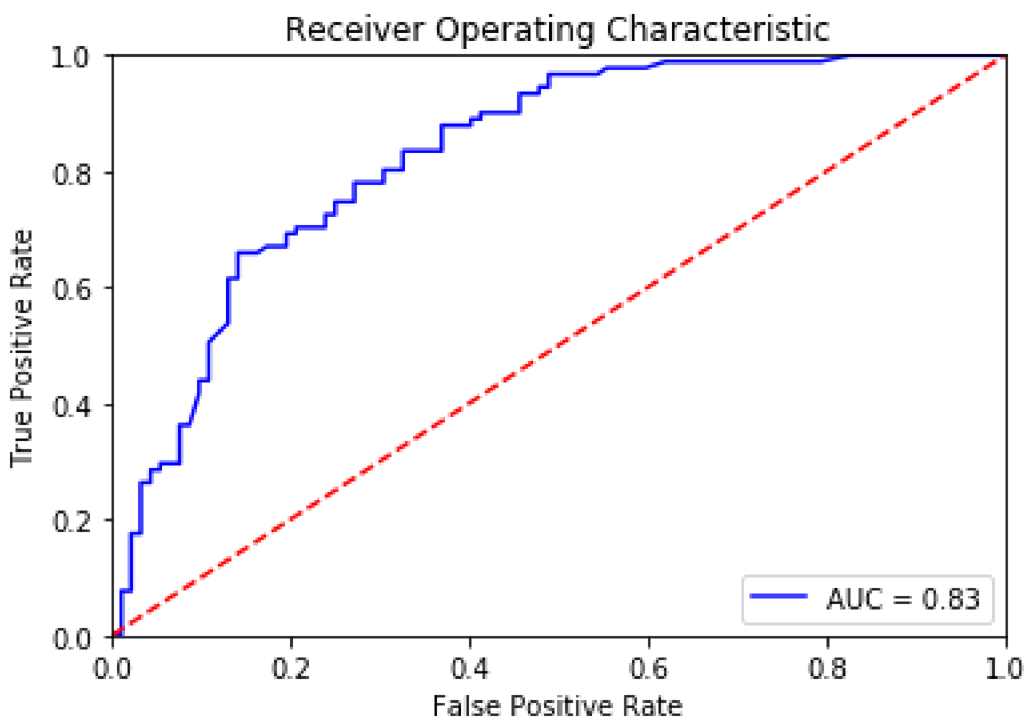
```
In [6337]: test_y_pred = ada_tuned.predict(x_test)
           cf_mt = confusion_matrix(y_test, test_y_pred)
           print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(ada_tu
           print(classification_report(y_test, test_y_pred))
           confusion_matrix_df = pd.DataFrame(cf_mt, ('False', 'True'), ('False', 'True'))
           heatmap = sns.heatmap(confusion_matrix_df, annot=True, annot_kws={"size": 20}, fmt="
           heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right'
           heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45, ha='right
           plt.ylabel('True label', fontsize = 14)
           plt.xlabel('Predicted label', fontsize = 14)
```

```
Accuracy of logistic regression classifier on test set: 0.77
             precision    recall  f1-score   support

          0       0.78      0.75      0.76        92
          1       0.76      0.78      0.77        91

avg / total       0.77      0.77      0.76       183
```

```
Out[6337]: Text(0.5,15,'Predicted label')
```



In [6338]:
```
probs = ada_tuned.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




# 9 SVC

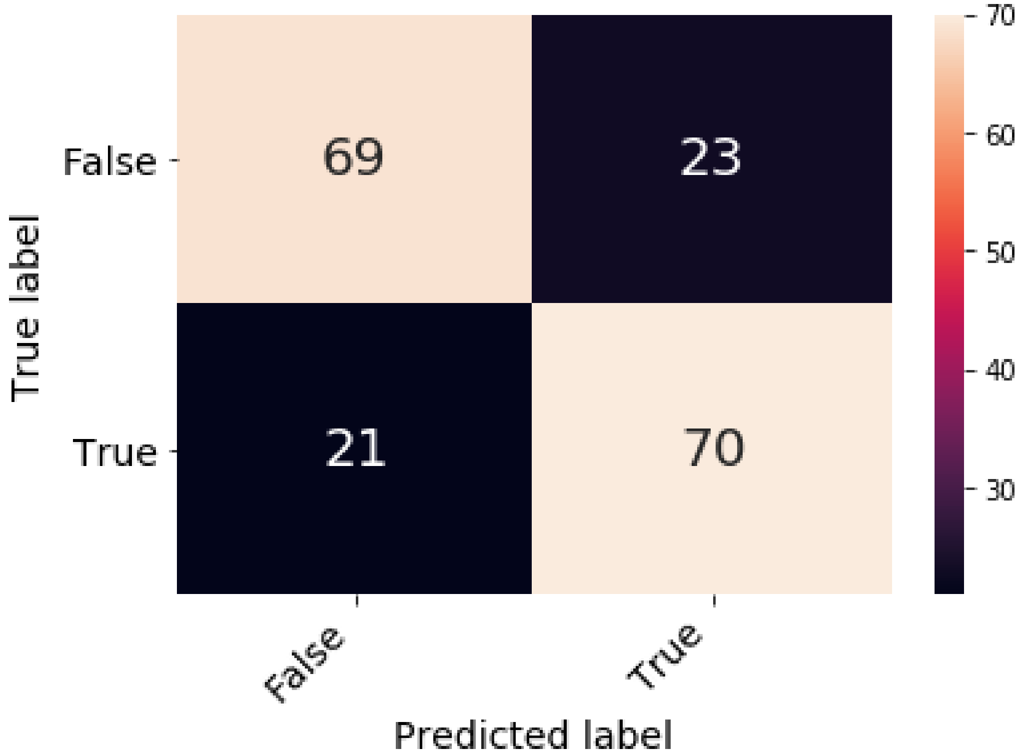
In [6339]:
```
param_dist =  [{'kernel': ['rbf'], 'gamma': [1e-3, 1e-4],
                     'C': [1, 10, 100, 1000]},
                    {'kernel': ['linear'], 'C': [1, 10, 100, 1000]}]
svc_grid = GridSearchCV(svm.SVC(),  param_dist,cv=2)
svc_grid.fit(x_train, y_train)
print("tuned hpyerparameters :(best parameters) ",svc_grid.best_params_)
print("accuracy :",svc_grid.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 10, 'kernel': 'linear'}
accuracy : 0.7673992673992674
```

```
In [6340]: clf = svm.SVC(C=10,kernel='rbf',probability=True,gamma=0.001)
           clf.fit(x_train,y_train)
           print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(clf.sc
           print(classification_report(y_test, test_y_pred))
           seed = 7
           k_fold = KFold(n_splits=2, random_state=seed)
           scoring = 'accuracy'
           results=cross_val_score(clf, x_train, y_train, cv=k_fold, scoring=scoring)
           print("Accuracy: %.3f (%.3f)" % (results.mean(), results.std()))
           clf.fit(x_train,y_train)
           predicted=clf.predict(x_test)
           matrix = confusion_matrix(y_test, predicted)
           print(matrix)
           confusion_matrix_df = pd.DataFrame(matrix, ('False', 'True'), ('False', 'True'))
           heatmap = sns.heatmap(confusion_matrix_df, annot=True, annot_kws={"size": 20}, fmt="
           heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right'
           heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45, ha='right
           plt.ylabel('True label', fontsize = 14)
           plt.xlabel('Predicted label', fontsize = 14)
```

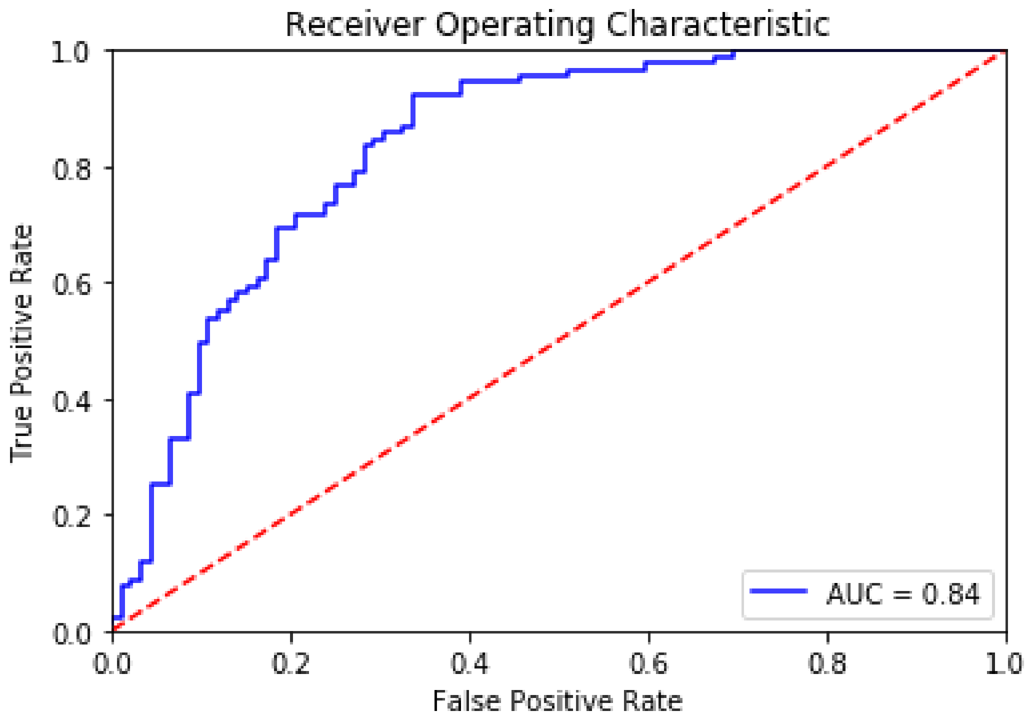
```
Accuracy of logistic regression classifier on test set: 0.76
             precision    recall  f1-score   support

          0       0.78      0.75      0.76        92
          1       0.76      0.78      0.77        91

avg / total       0.77      0.77      0.76       183

Accuracy: 0.740 (0.018)
[[69 23]
 [21 70]]
```

```
Out[6340]: Text(0.5,15,'Predicted label')
```

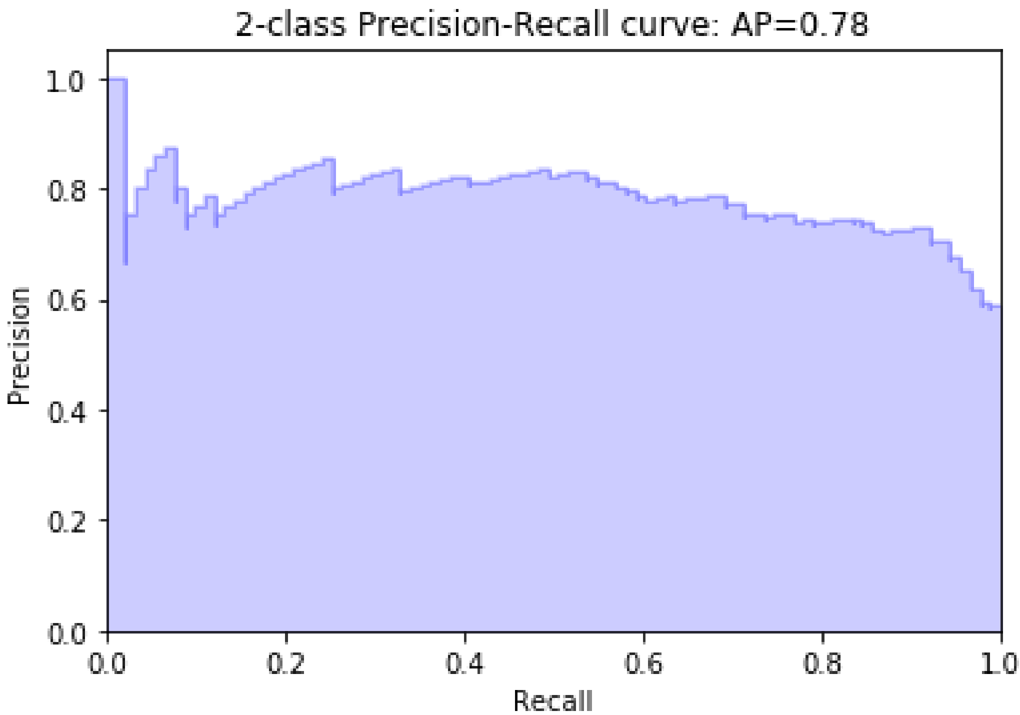



In [6341]:
```
probs = clf.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
print(classification_report(y_test, test_y_pred))
plt.show()
```

```
             precision    recall  f1-score   support

          0       0.78      0.75      0.76        92
          1       0.76      0.78      0.77        91

avg / total       0.77      0.77      0.76       183
```




```
In [6342]: average_precision = average_precision_score(y_test, preds)
           precision, recall, _ = precision_recall_curve(y_test, preds)

           plt.step(recall, precision, color='b', alpha=0.2,
                    where='post')
           plt.fill_between(recall, precision, step='post', alpha=0.2,
                            color='b')

           plt.xlabel('Recall')
           plt.ylabel('Precision')
           plt.ylim([0.0, 1.05])
           plt.xlim([0.0, 1.0])
           plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(
                     average_precision))

Out[6342]: Text(0.5,1,'2-class Precision-Recall curve: AP=0.78')
```




## 10 Random Forest

```
In [6343]: randomForest = RandomForestClassifier( max_depth=5, max_features=5, min_samples_spli
           randomForest.fit(x_train, y_train)
           print('Accuracy of random forest classifier on test set: {:.2f}'.format(randomForest
```

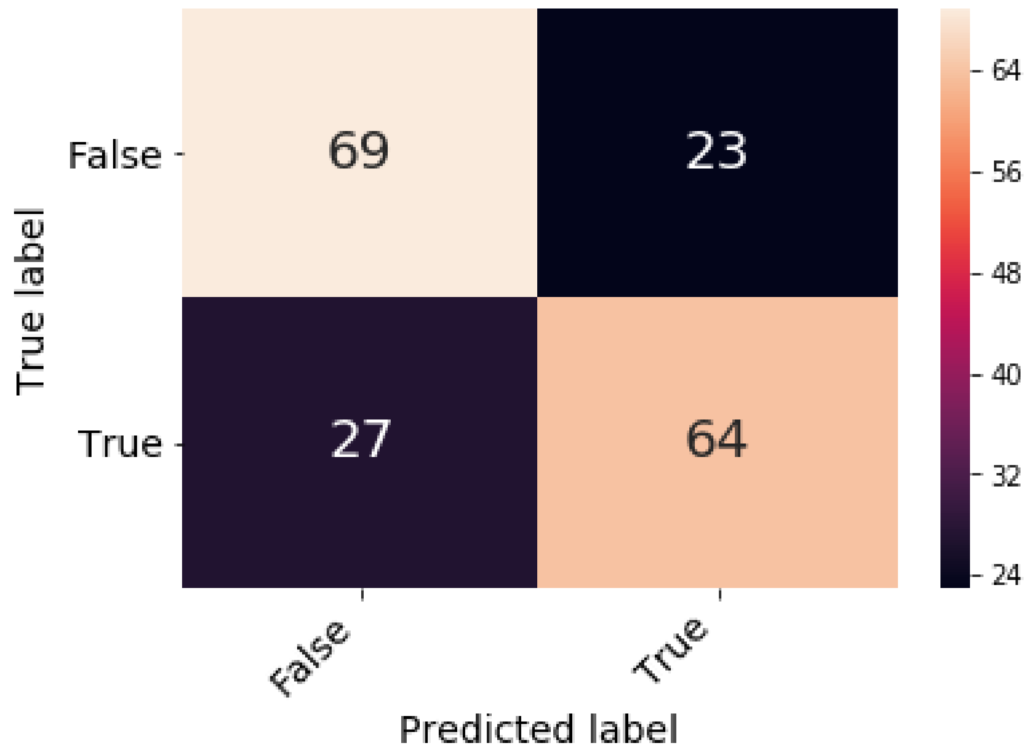
```
Accuracy of random forest classifier on test set: 0.75
```

```
In [6344]: seed = 7
           k_fold = KFold(n_splits=2, random_state=seed)
           scoring = 'accuracy'
           results = results=cross_val_score(randomForest, x_train, y_train, cv=k_fold, n_jobs=
           print("Accuracy: %.3f (%.3f)" % (results.mean(), results.std()))


           randomForest.fit(x_train,y_train)
           predicted=randomForest.predict(x_test)
           matrix = confusion_matrix(y_test, predicted)

           confusion_matrix_df = pd.DataFrame(matrix, ('False', 'True'), ('False', 'True'))
           heatmap = sns.heatmap(confusion_matrix_df, annot=True, annot_kws={"size": 20}, fmt='
           heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right'
```

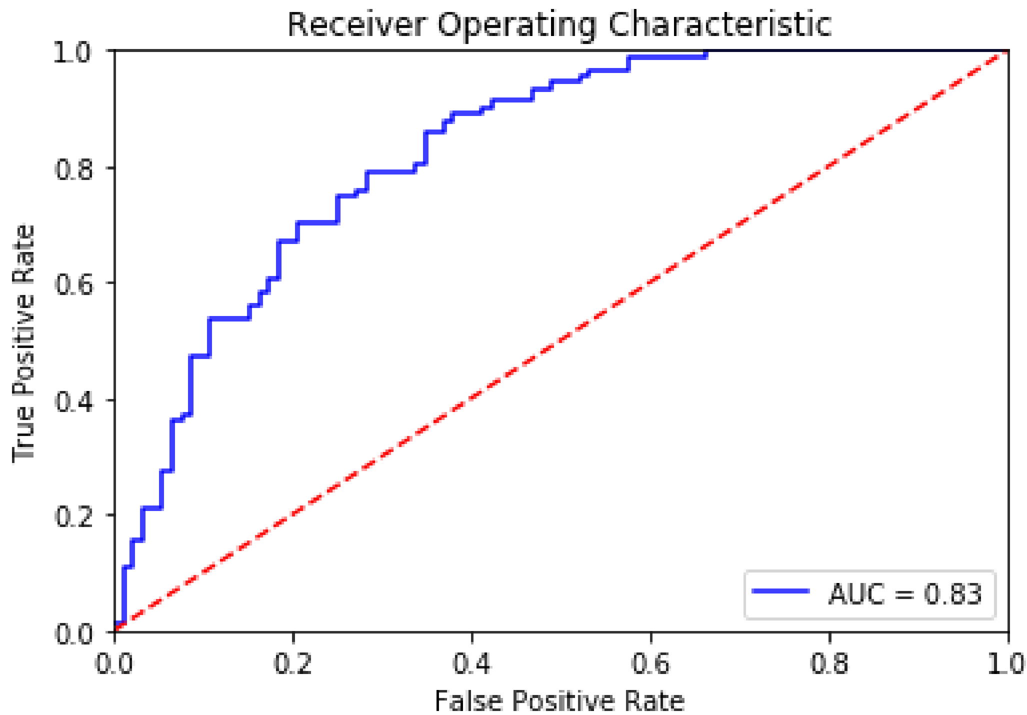
```
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45, ha='right
plt.ylabel('True label', fontsize = 14)
plt.xlabel('Predicted label', fontsize = 14)
```

```
Accuracy: 0.734 (0.024)
```

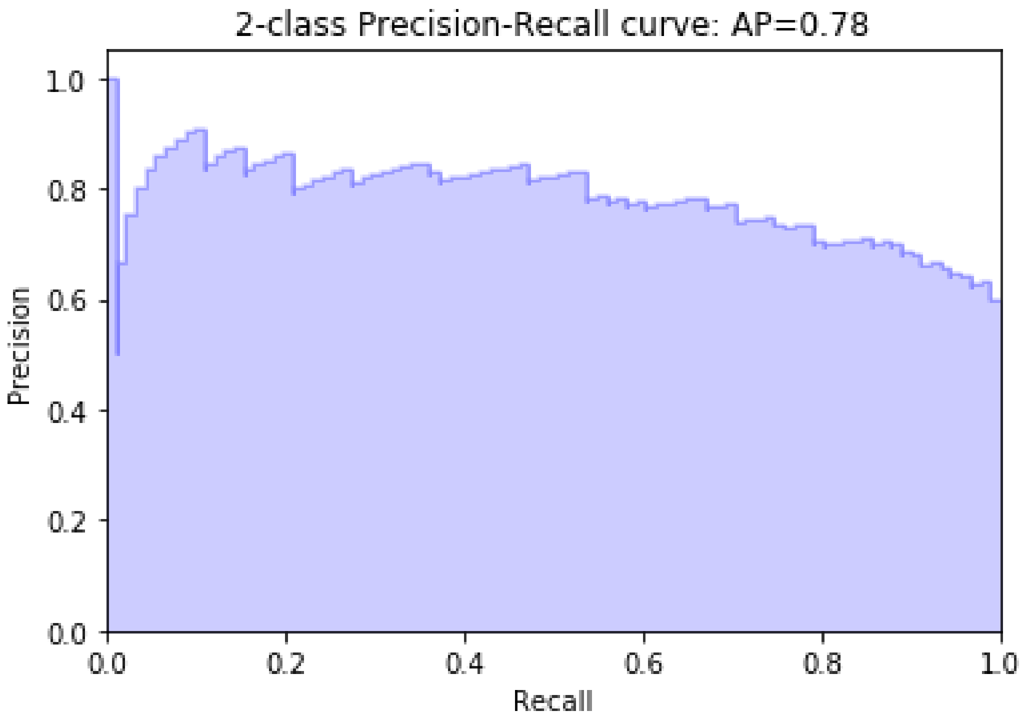
Out[6344]: Text(0.5,15,'Predicted label')




In [6345]:
```
probs = randomForest.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)


plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



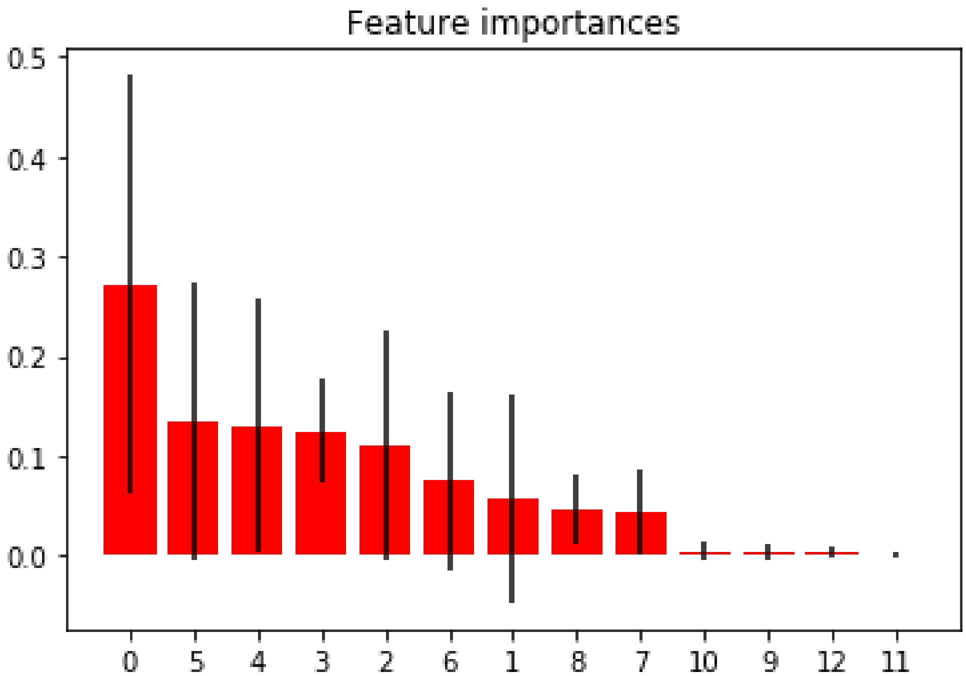

```
In [6346]: average_precision = average_precision_score(y_test, preds)
           precision, recall, _ = precision_recall_curve(y_test, preds)
           plt.step(recall, precision, color='b', alpha=0.2, where='post')
           plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')
           plt.xlabel('Recall')
           plt.ylabel('Precision')
           plt.ylim([0.0, 1.05])
           plt.xlim([0.0, 1.0])
           plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision))

Out[6346]: Text(0.5,1,'2-class Precision-Recall curve: AP=0.78')
```




```
In [6347]: importances = randomForest.feature_importances_
           std = np.std([tree.feature_importances_ for tree in randomForest.estimators_],
                        axis=0)
           indices = np.argsort(importances)[::-1]

           # Print the feature ranking
           print("Feature ranking:")

           for f in range(golden_x.shape[1]):
               print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

           # Plot the feature importances of the forest
           plt.figure()
           plt.title("Feature importances")
           plt.bar(range(golden_x.shape[1]), importances[indices],
                  color="r", yerr=std[indices], align="center")
           plt.xticks(range(golden_x.shape[1]), indices)
           plt.xlim([-1, golden_x.shape[1]])
           plt.show()
```

```
Feature ranking:
1. feature 0 (0.272229)
2. feature 5 (0.133662)
3. feature 4 (0.129853)
```

```
4. feature 3 (0.124288)
5. feature 2 (0.110018)
6. feature 6 (0.074240)
7. feature 1 (0.056309)
8. feature 8 (0.045283)
9. feature 7 (0.043814)
10. feature 10 (0.004307)
11. feature 9 (0.003463)
12. feature 12 (0.002283)
13. feature 11 (0.000250)
```




In [6348]:
```
clf = RandomForestClassifier(n_jobs=-1)

param_grid = {
    'min_samples_split': [3, 4, 5,8],
    'n_estimators' : [100, 300],
    'max_depth': [3, 5, 15, 25],
    'max_features': [3, 5,8]
}

scorers = {
    'precision_score': make_scorer(precision_score),
    'recall_score': make_scorer(recall_score),
    'accuracy_score': make_scorer(accuracy_score)
}
```

```
In [6349]: def grid_search_wrapper(refit_score='precision_score'):
               """
               fits a GridSearchCV classifier using refit_score for optimization
               prints classifier performance metrics
               """
               skf = StratifiedKFold(n_splits=3)
               grid_search = GridSearchCV(clf, param_grid, scoring=scorers, refit=refit_score,
                                       cv=skf, return_train_score=True, n_jobs=-1)
               grid_search.fit(x_train, y_train)


               y_pred = grid_search.predict(x_test)

               print('Best params for {}'.format(refit_score))
               print(grid_search.best_params_)

               # confusion matrix on the test data.
               print('\nConfusion matrix of Random Forest optimized for {} on the test data:'.f
               print(pd.DataFrame(confusion_matrix(y_test, y_pred),
                            columns=['pred_neg', 'pred_pos'], index=['neg', 'pos']))
               return grid_search
```

```
In [6350]: grid_search_clf = grid_search_wrapper(refit_score='accuracy_score')
```

```
Best params for accuracy_score
{'max_depth': 3, 'max_features': 3, 'min_samples_split': 8, 'n_estimators': 300}

Confusion matrix of Random Forest optimized for accuracy_score on the test data:
     pred_neg  pred_pos
neg        69        23
pos        24        67
```

```
In [6351]: models = [{    'label': 'Logistic Regression',
               'model': LogisticRegression(),
                      'grid': {"C":[0.001, 0.01, 0.1, 1, 10, 100, 1000] , "penalty":["l1","l2"

           },
           {    'label': 'RandomForest',
               'model': RandomForestClassifier( ),
            'grid' : {    'min_samples_split': [3, 4, 5,8],
               'n_estimators' : [100, 300],
               'max_depth': [3, 5, 15, 25],
               'max_features': [3, 5,8]},
           },
           {    'label': 'SVC',
               'model': svm.SVC(probability=True),
            'grid':  {'kernel': ['rbf'], 'gamma': [1e-3, 1e-4],   'C': [1, 10, 100, 1000]},
```

```
},
{    'label': 'Adaboost',
    'model': AdaBoostClassifier(),
 'grid': { 'n_estimators': [50, 100], 'learning_rate' : [0.01,0.05,0.1,0.3,1,10], 'a
} ]
```

In [6352]:
```
models = [{    'label': 'Logistic Regression',
    'model': LogisticRegression(C=0.1, penalty='l1', class_weight='balanced'),
},
{    'label': 'RandomForest',
    'model': RandomForestClassifier( max_depth=5, max_features=3, min_samples_split=
},
{    'label': 'SVC',
    'model': svm.SVC(C=1000,kernel='rbf',probability=True,gamma=0.001),
},
{    'label': 'Adaboost',
    'model': AdaBoostClassifier(n_estimators=100,learning_rate=0.1,algorithm='SAMME
} ]
```

In [6353]:
```
print('Cross-Validation Score')
for m in models:
    model = m['model'] # select the model
    model.fit(x_train, y_train) # train the model

    seed = 7
    k_fold = KFold(n_splits=3, random_state=seed)
    scoring = 'accuracy'
    results=cross_val_score(model, x_train, y_train, cv=k_fold, n_jobs=1, scoring=sc
    print("Accuracy of %s: %.3f (%.3f)" % (m['label'],results.mean(), results.std()
```

```
Cross-Validation Score
Accuracy of Logistic Regression: 0.767 (0.019)
Accuracy of RandomForest: 0.749 (0.018)
Accuracy of SVC: 0.749 (0.011)
Accuracy of Adaboost: 0.764 (0.018)
```

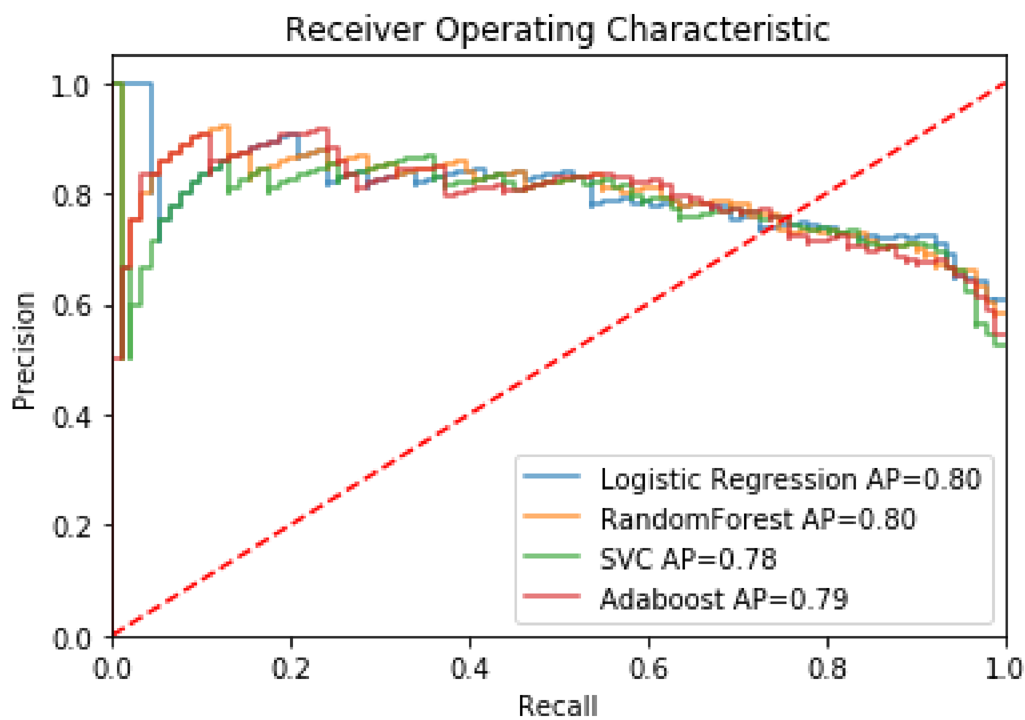
## 10.1 The one that performs the best in both the cross-validation and the the score on the tesing set is the Logistic regression

In [6354]:
```
print('Validation on testing set')
for m in models:
    model = m['model']# select the model
    model.fit(x_train, y_train) # train the model
    test_y_pred = model.predict(x_test)
    cf_mt = confusion_matrix(y_test, test_y_pred)
    print('Accuracy of %s: classifier on test set: %.3f'%(m['label'],model.score(x_
    print(classification_report(y_test, test_y_pred))
```

```
Validation on testing set
Accuracy of Logistic Regression: classifier on test set: 0.760
             precision    recall  f1-score   support

          0       0.77      0.74      0.76        92
          1       0.75      0.78      0.76        91

avg / total       0.76      0.76      0.76       183

Accuracy of RandomForest: classifier on test set: 0.738
             precision    recall  f1-score   support

          0       0.73      0.76      0.74        92
          1       0.75      0.71      0.73        91

avg / total       0.74      0.74      0.74       183

Accuracy of SVC: classifier on test set: 0.749
             precision    recall  f1-score   support

          0       0.73      0.79      0.76        92
          1       0.77      0.70      0.74        91

avg / total       0.75      0.75      0.75       183

Accuracy of Adaboost: classifier on test set: 0.765
             precision    recall  f1-score   support

          0       0.77      0.76      0.77        92
          1       0.76      0.77      0.77        91

avg / total       0.77      0.77      0.77       183
```

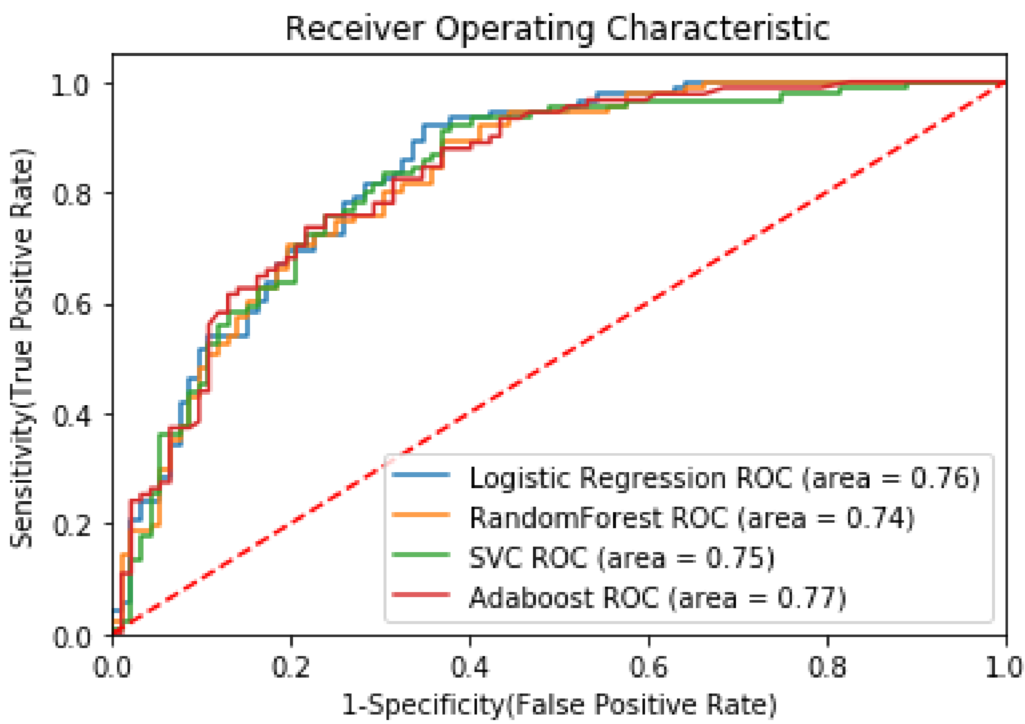
In [6355]:
```
plt.figure()

# Below for loop iterates through your models list
for m in models:
    model = m['model']# select the model
    model.fit(x_train, y_train) # train the model
    y_pred=model.predict(x_test) # predict the test data
    probs = model.predict_proba(x_test)
    preds = probs[:,1]
    average_precision = average_precision_score(y_test, preds)
    precision, recall, _ = precision_recall_curve(y_test, preds)
    plt.step(recall, precision,  alpha=0.8, where='post',label='%s AP=%0.2f' % (m['
    #plt.fill_between(recall, precision, step='post', alpha=0.2)
```

```
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()   # Display
```




```
In [6356]: plt.figure()

# Below for loop iterates through your models list
for m in models:
    model = m['model'] # select the model
    model.fit(x_train, y_train) # train the model
    y_pred=model.predict(x_test) # predict the test data
# Compute False postive rate, and True positive rate
    fpr, tpr, thresholds = roc_curve(y_test, model.predict_proba(x_test)[:,1])
# Calculate Area under the curve to display on the plot
    auc_ = roc_auc_score(y_test,model.predict(x_test))
# Now, plot the computed values
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (m['label'], auc_))
```

```
# Custom settings for the plot
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()    # Display
```




## 10.2 Provided we had a data dictionary we could look into other imputation methods for the weeks that were not available for all couriers and try to do the prediction with the sequential information.