In [1]:

```
import pandas as pd
import numpy as np
import datetime
```

Downloading data

In [2]:

```
data = pd.ExcelFile("risk_tz.xlsx")
```

In [3]:

```
data.sheet_names
```

Out[3]:

```
['Задание', '1_data jan-may', '2_Data jun-jul Fcst']
```

In [4]:

```
train_data = data.parse('1_data jan-may')
```

In [5]:

```
test_data = data.parse('2_Data jun-jul Fcst')
```

Preprocessing of data

Removing skips and incorrect dates

In [6]:

```
train_data['Дата начала работы на текущей должности'] = train_data['Дата начала работы на т
    train_data['Дата начала'])
test_data['Дата начала работы на текущей должности'] = test_data['Дата начала работы на тек
    test_data['Дата начала'])

def func_year(date):
    return int(date.split('.')[2])
train_data = train_data[train_data['Дата начала работы на текущей должности'].apply(func_ye
test_data = test_data[test_data['Дата начала работы на текущей должности'].apply(func_year)
```

Converting columns that contain a date into a date type from object

In [7]:

```
date_column = ['Дата начала', 'Дата окончания', 'Дата окончания сПролонгацией', 'Дата рожде
               'Дата окончания начислений', 'Дата окончательной оплаты', 'Дата начала работ

for column in date_column:
    train_data[column] = pd.to_datetime(train_data[column], dayfirst=True)
    test_data[column] = pd.to_datetime(test_data[column], dayfirst=True)
```

Removing gaps in numeric columns

In [8]:

```
number_columns = ['Количество детей', 'Количество иждивенцев', 'Номер клиента','Сумма займа
                  'Количество иждивенцев', 'Сумма дохода заемщика', 'Оплаты по процентам', 'С
                  'Долг по телу (на дату отчета)', 'Долг по процентам (на дату отчета)', 'Про
                  'Просрочка по процентам (на дату отчета)', 'К-во дней просрочки по телу (на
                  'макс размер тела, которое было в просрочке 30+ дней просрочки', 'Начисленн
                  'макс к-во дней просрочки по телу (исторически за все время жизни кредита)'
train_data[number_columns] = train_data[number_columns].fillna(0)
test_data[number_columns] = test_data[number_columns].fillna(0)
```

Removing gaps in columns with categorical data

In [9]:

```
cat_columns = ['Договор номер', 'Пол', 'Подразделение', 'Город выдачи', 'Область выдачи', '
            'Занятость не трудоустроен','Занятость трудоустроен не официально', 'Занятость
            'Занятость пенсионер', 'Занятость студент', 'Должность', 'Сфера деятельности',
train_data[cat_columns] = train_data[cat_columns].fillna('Нет').applymap(str)
test_data[cat_columns] = test_data[cat_columns].fillna('Нет').applymap(str)
```

Finding the age, length of service and duration of prolongation

In [10]:

```
train_data['Возраст'] = train_data['Дата начала'] - train_data['Дата рождения']
train_data['Стаж работы'] = train_data['Дата начала'] - train_data['Дата начала работы на т

test_data['Возраст'] = test_data['Дата начала'] - test_data['Дата рождения']
test_data['Стаж работы'] = test_data['Дата начала'] - test_data['Дата начала работы на теку

date_int_columns = ['Стаж работы', 'Возраст']

for column in date_int_columns:
    train_data[column] = train_data[column].dt.days
    test_data[column] = test_data[column].dt.days
```

In [11]:

```
train_data['Пролонгация'] = train_data['Дата окончания сПролонгацией'] - train_data['Дата н
train_data['Пролонгация'] = train_data['Пролонгация'].dt.days + 1
```

Removing columns with a date (except for the initial one), since they are not in the test dataset

In [12]:

```
train_data['Стаж работы'][train_data['Стаж работы'] < 0]= 0
test_data['Стаж работы'][test_data['Стаж работы'] < 0]= 0

train_data.drop(date_column[1:], inplace = True, axis = 1)
test_data.drop(date_column[1:], inplace = True, axis = 1)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingW
ithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
  """Entry point for launching an IPython kernel.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingW
ithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
```

In [13]:

```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13346 entries, 0 to 13386
Data columns (total 37 columns):
Договор номер
   13346 non-null object
Номер клиента
   13346 non-null int64
Дата начала
   13346 non-null datetime64[ns]
Длительность кредита
   13346 non-null float64
Сумма займа
   13346 non-null int64
Пол
   13346 non-null object
Подразделение
   13346 non-null object
Город выдачи
   13346 non-null object
Область выдачи
   13346 non-null object
Семейное положение
   13346 non-null object
Количество детей
   13346 non-null float64
Количество иждивенцев
   13346 non-null float64
Занятость не трудоустроен
   13346 non-null object
Занятость трудоустроен не официально
   13346 non-null object
Занятость трудоустроен официально
   13346 non-null object
Занятость пенсионер
   13346 non-null object
Занятость студент
   13346 non-null object
Должность
   13346 non-null object
Сфера деятельности
   13346 non-null object
Периодичность дохода
   13346 non-null object
Сумма дохода заемщика
   13346 non-null float64
Погашен
   13346 non-null object
Оплаты по процентам
   13346 non-null float64
Оплаты по телу
   13346 non-null float64
Начисленно по процентам
   13346 non-null float64
Долг по телу (на дату отчета)
   13346 non-null float64
Долг по процентам (на дату отчета)
   13346 non-null float64
```

```
Просрочка по телу (на дату отчета)
   13346 non-null float64
Просрочка по процентам (на дату отчета)
   13346 non-null float64
К-во дней просрочки по телу (на дату отчета)
   13346 non-null float64
макс размер тела, которое было в просрочке 30+ дней просрочки
   13346 non-null float64
макс к-во дней просрочки по телу (исторически за все время жизни кредита)
   13346 non-null float64
Этап контроля
   13346 non-null object
Долг всего
   13346 non-null float64
Долг всего просроченно
   13346 non-null float64
Возраст
   13346 non-null int64
Стаж работы
   13346 non-null int64
dtypes: datetime64[ns](1), float64(16), int64(4), object(16)
memory usage: 4.5+ MB
```

Counting the number of unique values among categorical attributes

In [14]:

```
position_unique = train_data['Должность'].unique()
activity_unique = train_data['Сфера деятельности'].unique()
subdivision_unique = train_data['Подразделение'].unique()
city_unique = train_data['Город выдачи'].unique()
region_unique = train_data['Область выдачи'].unique()
sex_unique = train_data['Пол'].unique()
marital_unique = train_data['Семейное положение'].unique()
periodicity_unique = train_data['Периодичность дохода'].unique()
extinguished_unique = train_data['Погашен'].unique()
control_unique = train_data['Этап контроля'].unique()
```

In [15]:

```
cat_unique = {'Должность': len(position_unique), 'Сфера деятельности': len(activity_unique)
    'Город выдачи': len(city_unique), 'Область выдачи': len(region_unique), 'Пол': len(sex_
    'Семейное положение': len(marital_unique), 'Периодичность дохода': len(periodicity_unic
```

In [16]:

```
cat_unique
```

Out[16]:

```
{'Город выдачи': 38,
 'Должность': 1867,
 'Область выдачи': 10,
 'Периодичность дохода': 4,
 'Погашен': 2,
 'Подразделение': 78,
 'Пол': 2,
 'Семейное положение': 4,
 'Сфера деятельности': 772,
 'Этап контроля': 11}
```

In the variables: 'Должность' and 'Сфера деятельности' too many unique values, therefore it is possible to retrain. As a result of further testing, the variables - 'Этап контроля' and 'Подразделение' did not affect the quality of the algorithms, and in some cases, worsened the quality

Creation of new clients based on the variables of the training dataset

In [17]:

```
income_person_dict = {'общая сумма тела': 0, 'общий доход от процентов': 0, 'количество кре
                      'максимальный размер тела в просрочке': 0}
income_dict = {person_id: {'общая сумма тела': 0, 'общий доход от процентов': 0, 'количеств
                      'максимальный размер тела в просрочке': 0} for person_id in train_dat
```

In [18]:

```
history_person_dict = {'1-29DayLate': 0, '30-59DayLate': 0, '60-89DayLate': 0, 'over89DayLa
history_dict = {person_id: {'1-29DayLate': 0, '30-59DayLate': 0, '60-89DayLate': 0, 'over89
```

In [19]:

```
for income in income_person_dict.keys():
    train_data[income] = 0
    test_data[income] = 0
for history in history_person_dict.keys():
    train_data[history] = 0
    test_data[history] = 0
```

In [20]:

```
train_data.sort_values(by=['Дата начала', 'Номер клиента'], inplace = True)
train_data.reset_index(drop=True, inplace = True)
test_data.reset_index(drop=True, inplace = True)
```

In [21]:

```
%%time
#INCOME
for index in range(train_data.shape[0]):
    client_id = train_data.loc[index, 'Номер клиента']
    if client_id in income_dict.keys():
        for income in income_person_dict.keys():
            train_data.loc[index, income] = income_dict[client_id][income]
        income_dict[client_id]['максимальный размер тела в просрочке'] = train_data.loc[inc
                                                        'макс размер тела, которое было в п
        income_dict[client_id]['общая сумма тела'] += train_data.loc[index, 'Сумма займа']
        income_dict[client_id]['общий доход от процентов'] += train_data.loc[index, 'Оплать
        income_dict[client_id]['количество кредитов'] += 1
```

```
Wall time: 2min 2s
```

In [22]:

```
#INCOME test
for index in range(test_data.shape[0]):
    client_id = test_data.loc[index, 'Номер клиента']
    if client_id in income_dict.keys():
        for income in income_person_dict.keys():
            test_data.loc[index, income] = income_dict[client_id][income]
```

In [23]:

```
%%time
#HISTORY
for index in range(train_data.shape[0]):
    client_id = train_data.loc[index, 'Номер клиента']
    if client_id in history_dict.keys():
        for history in history_person_dict.keys():
            train_data.loc[index, history] = history_dict[client_id][history]
        history_dict[client_id]['maxLate'] = train_data.loc[index, 'макс к-во дней просрочк

        if train_data.loc[index, 'К-во дней просрочки по телу (на дату отчета)'] < 1:
            pass
        elif train_data.loc[index, 'К-во дней просрочки по телу (на дату отчета)'] < 30:
            history_dict[client_id]['1-29DayLate'] += 1
        elif train_data.loc[index, 'К-во дней просрочки по телу (на дату отчета)'] < 60:
            history_dict[client_id]['30-59DayLate'] += 1
        elif train_data.loc[index, 'К-во дней просрочки по телу (на дату отчета)'] < 90:
            history_dict[client_id]['60-89DayLate'] += 1
        else:
            history_dict[client_id]['over89DayLate'] += 1
```

```
Wall time: 2min 26s
```

In [24]:

```
#HISTORY tets
for index in range(test_data.shape[0]):
    client_id = test_data.loc[index, 'Номер клиента']
    if client_id in history_dict.keys():
        for history in history_person_dict.keys():
            test_data.loc[index, history] = history_dict[client_id][history]
```

Allocation of people from the initial data base that repaid the loan, and creating a target variable y_delay_train for them, where 0 - the loan was repaid in time, 1- was overdue, 2 - the rollover date is longer than the original loan end date. Also for these three categories was found the average amount of interest (mean_pay, mean_pay_pr, mean_percents) paid by them during the loan

In [25]:

```
train_good = train_data[train_data['Погашен'] == 'Да']
y_delay_train = [1 if i > 0 else 0 for i in train_good['макс к-во дней просрочки по телу (и
train_good_fine = train_good[train_good['макс к-во дней просрочки по телу (исторически за в
mean_pay_df = train_good_fine['Оплаты по процентам'] / train_good_fine['Сумма займа']
mean_pay = mean_pay_df.mean()

dif_date = train_good['Пролонгация'] - train_good['Длительность кредита']
dif_date = np.asarray(dif_date)
y_delay_pr = [1 if (dif_date[i] > 0 and y_delay_train[i] == 0) else 0 for i in range(len(y_
train_good_fine_pr = train_good[np.logical_and(train_good['макс к-во дней просрочки по телу
                            (train_good['Пролонгация'] - train_good['Длительность кредита']
mean_pay_pr_df = train_good_fine_pr['Оплаты по процентам'] / train_good_fine_pr['Сумма займ
mean_pay_pr = mean_pay_pr_df.mean()

train_good_not_fine = train_good[np.logical_and(train_good['макс к-во дней просрочки по тел
                            (train_good['Пролонгация'] - train_good['Длительность кредита']
mean_percents_df = train_good_not_fine['Оплаты по процентам'] / train_good_not_fine['Сумма
mean_percents = mean_percents_df.mean()
```

In [26]:

```
for i in range(len(y_delay_pr)):
    if y_delay_pr[i] > 0:
        y_delay_train[i] = 2
```

Removing unnecessary features

In [27]:

```
train_data.drop('Пролонгация', axis = 1, inplace = True)
train_good.drop('Пролонгация', axis = 1, inplace = True)
drop_columns = ['Договор номер', 'Дата начала', 'Длительность кредита', 'Должность', 'Сфера
       'Оплаты по телу', 'Начисленно по процентам','Долг по телу (на дату отчета)',
       'Долг по процентам (на дату отчета)', 'Просрочка по телу (на дату отчета)', 'Просроч
       'К-во дней просрочки по телу (на дату отчета)','Долг всего', 'Долг всего просроченно
       'Этап контроля', 'макс размер тела, которое было в просрочке 30+ дней просрочки',
       'макс к-во дней просрочки по телу (исторически за все время жизни кредита)']

train = train_data.drop(drop_columns, axis = 1)
train_good = train_good.drop(drop_columns, axis = 1)
test = test_data.drop(drop_columns, axis = 1)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingW
ithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
```

In [28]:

```
y = train['Погашен']
loan_amount = train['Сумма займа']
X = train.drop(['Погашен', 'Оплаты по процентам', 'Подразделение',  'Номер клиента'], axis
X_good = train_good.drop(['Погашен', 'Оплаты по процентам', 'Подразделение',  'Номер клиент
test = test.drop(['Погашен', 'Оплаты по процентам', 'Подразделение', 'Номер клиента'], axis
```

Allocation of categorical features cat_train

In [29]:

```
cat_train = ['Пол', 'Семейное положение','Город выдачи', 'Область выдачи',
       'Занятость не трудоустроен', 'Занятость трудоустроен не официально','Занятость трудо
       'Занятость пенсионер','Занятость студент', 'Периодичность дохода']

X_cat = X[cat_train]
X_cat_good = X_good[cat_train]
test_cat = test[cat_train]
X_numeric = X.drop(cat_train, axis = 1)
X_numeric_good = X_good.drop(cat_train, axis = 1)
test_numeric = test.drop(cat_train, axis = 1)
```

Identification of numerical features that need to be normalized norm_columns

In [30]:

```
norm_columns = ['Сумма займа', 'Сумма дохода заемщика', 'maxLate','максимальный размер тела
                'Стаж работы']
X_numeric_norm = X_numeric[norm_columns]
X_numeric_norm_good = X_numeric_good[norm_columns]
test_numeric_norm = test_numeric[norm_columns]
X_numeric.drop(norm_columns, axis = 1, inplace = True)
X_numeric_good.drop(norm_columns, axis = 1, inplace = True)
test_numeric.drop(norm_columns, axis = 1, inplace = True)
```

In [31]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.feature_extraction import DictVectorizer as DV
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score, StratifiedShuffleSpl
%matplotlib inline
```

Normalization of numerical features

In [32]:

```
scaler = StandardScaler()
scaler.fit(X_numeric_norm)
X_numeric_norm = scaler.transform(X_numeric_norm)
X_numeric_norm_good = scaler.transform(X_numeric_norm_good)
test_numeric_norm = scaler.transform(test_numeric_norm)
```

Coding of categorical features

In [33]:

```
encoder = DV(sparse = False)
X_cat = encoder.fit_transform(X_cat.T.to_dict().values())
X_cat_good = encoder.fit_transform(X_cat_good.T.to_dict().values())
test_cat = encoder.transform(test_cat.T.to_dict().values())
```

Coding the target attribute and displaying the percentage of the classes

In [34]:

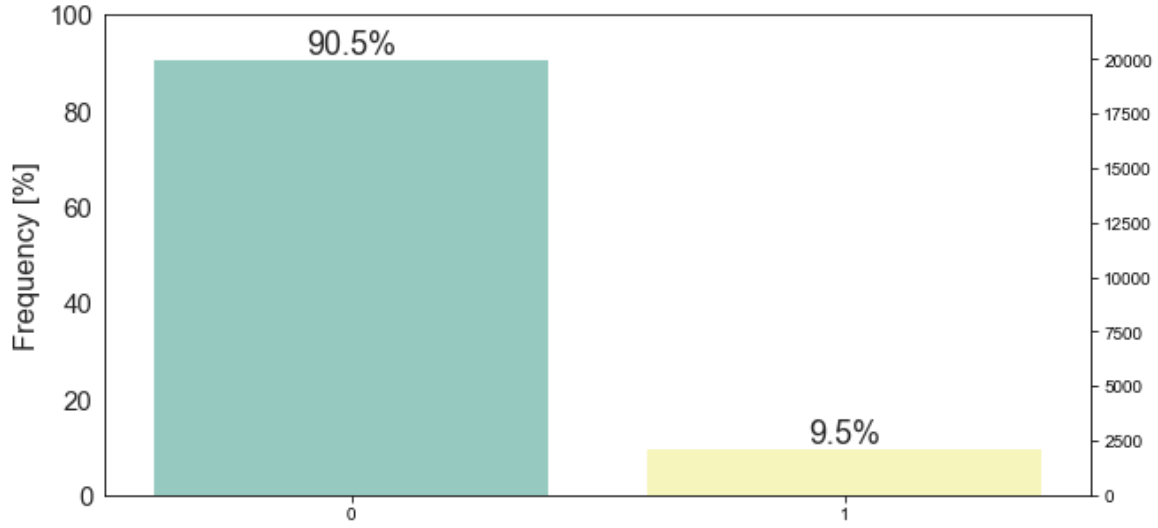
```
y = y.map({'Нет': 1, 'Да': 0})
```

In [35]:

```
def add_freq(y):
    ncount = y.shape[0]
    ax2=ax.twinx()
    ax2.yaxis.tick_left()
    ax.yaxis.tick_right()
    ax.yaxis.set_label_position('right')
    ax2.yaxis.set_label_position('left')
    ax2.set_ylabel('Frequency [%]')

    for p in ax.patches:
        x=p.get_bbox().get_points()[:,0]
        y=p.get_bbox().get_points()[1,1]
        ax.annotate('{:.1f}%'.format(100.*y/ncount), (x.mean(), y),
                ha='center', va='bottom')

    ax2.set_ylim(0,100)
    ax2.grid(None)
```

In [36]:

```
ax = sns.countplot(x = y ,palette="Set3")
sns.set(font_scale=1.5)
ax.set_ylim(top = 150000)
ax.set_xlabel(' ')
ax.set_ylabel(' ')
fig = plt.gcf()
fig.set_size_inches(10,5)
ax.set_ylim(top=y.shape[0])
add_freq(y)
plt.show()
```



Creating arrays for learning based on our features

In [37]:

```
X_full = np.hstack((X_numeric, X_numeric_norm, X_cat))
X_full_good = np.hstack((X_numeric_good, X_numeric_norm_good, X_cat_good))
test_full = np.hstack((test_numeric, test_numeric_norm, test_cat))
```

Training

Separation of the training dataset and target variable into test and training using stratification of samples

In [38]:

```
X_train, X_test, y_train, y_test = train_test_split(X_full, y, test_size=0.2, random_state=
```

In [39]:

```
def cvDictionary(functions, scoring_metric, X_train=X_train, y_train=y_train, verbose=1):
    cvDict = {}
    cv = StratifiedShuffleSplit(n_splits = 5, test_size = 0.2, random_state = 241)
    for func in functions:
        cvScore = cross_val_score(func, X_train, y_train, cv=cv, verbose=verbose, scoring=s
        cvDict[str(func).split('(')[0]] = [cvScore.mean(), cvScore.std()]

    return cvDict
```

In [40]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier, RandomForestCl
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
```

Create classifiers and find the optimal for a given sample, using both the roc_auc metric

In [41]:

```
knMod = KNeighborsClassifier(n_neighbors = 5, n_jobs = 3)
glmMod = LogisticRegression(penalty = 'l1', C = 1.0)
adaMod = AdaBoostClassifier(n_estimators = 200, learning_rate = 1.0)
gbMod = GradientBoostingClassifier(n_estimators = 50)
rfMod = RandomForestClassifier(n_estimators = 50)
```

In [42]:

```
cvD = cvDictionary([knMod, glmMod, adaMod, gbMod, rfMod], 'roc_auc', X_train, y_train)
```

```
[Parallel(n_jobs=3)]: Done   5 out of   5 | elapsed:   15.7s finished
[Parallel(n_jobs=3)]: Done   5 out of   5 | elapsed:   12.6s finished
[Parallel(n_jobs=3)]: Done   5 out of   5 | elapsed:   28.5s finished
[Parallel(n_jobs=3)]: Done   5 out of   5 | elapsed:   18.5s finished
[Parallel(n_jobs=3)]: Done   5 out of   5 | elapsed:   13.5s finished
```

In [43]:

```
cvD
```

Out[43]:

```
{'AdaBoostClassifier': [0.8030278895595796, 0.006936492656776652],
 'GradientBoostingClassifier': [0.80006287726358138, 0.0065951657514010283],
 'KNeighborsClassifier': [0.6556025970638647, 0.011569499221281775],
 'LogisticRegression': [0.79814181384603911, 0.0039023497920167528],
 'RandomForestClassifier': [0.76870929279379985, 0.012346003231386045]}
```

As you can see, the best values were shown by AdaBoostClassifier, GradientBoostingClassifier, LogisticRegression. We will try to walk through their parameters and improve the quality using GridSearchCV

In [44]:

```
from sklearn.model_selection import GridSearchCV
cv = StratifiedShuffleSplit(n_splits = 3, test_size = 0.2, random_state = 241)
```

In [45]:

```
%%time
glmHyperParams = {'C' : [0.1, 1, 10, 100],
                  'penalty': ['l2', 'l1']}
grid_cv_lr = GridSearchCV(glmMod, glmHyperParams, scoring = 'roc_auc', cv=cv, n_jobs = 3)
grid_cv_lr.fit(X_train, y_train)
```

```
Wall time: 15.3 s
```

In [46]:

```
grid_cv_lr.best_params_, grid_cv_lr.best_score_
```

Out[46]:

```
({'C': 1, 'penalty': 'l1'}, 0.79530982189432908)
```

Classifier LogisticRegression didn't improve result

In [47]:

```
%%time
adaHyperParams = {'n_estimators': [50, 100, 150, 200]}
grid_cv_ada = GridSearchCV(adaMod, adaHyperParams, scoring = 'roc_auc', cv=cv, n_jobs = 3)
grid_cv_ada.fit(X_train, y_train)
```

```
Wall time: 43.1 s
```

In [48]:

```
grid_cv_ada.best_params_, grid_cv_ada.best_score_
```

Out[48]:

```
({'n_estimators': 100}, 0.80085637280472954)
```

In [49]:

```
bestAdaModFitted = grid_cv_ada.best_estimator_.fit(X_train, y_train)
```

In [50]:

```
from sklearn.metrics import auc, roc_curve
```

Finding the auc and gini metrics for AdaBoostClassifier

In [51]:

```
preds = bestAdaModFitted.predict_proba(X_test)[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
auc_ada = auc(fpr, tpr)
gini_ada = 2 * auc_ada - 1
(auc_ada, gini_ada)
```

Out[51]:

```
(0.81914362038328981, 0.63828724076657961)
```

Function for constructing the roc curve

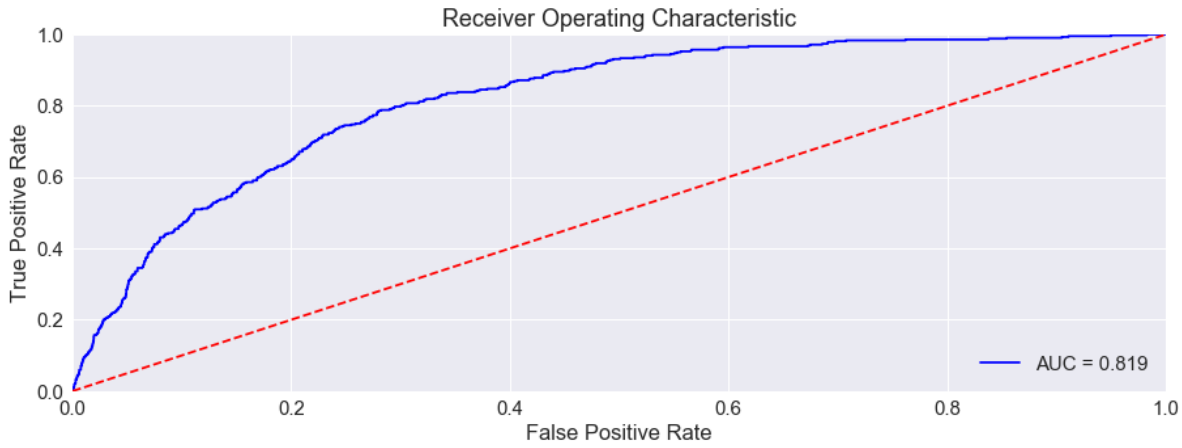
In [52]:

```
def build_roc_auc(auc):
    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.3f' % 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')
    fig = plt.gcf()
    fig.set_size_inches(15,5)
    plt.show()
```

Building a roc curve for AdaBoostClassifier

In [53]:

```
build_roc_auc(auc_ada)
```



In [54]:

```
%%time
gbHyperParams = {'n_estimators': [150, 200, 250],
                 'max_depth': [2, 3, 4]}
grid_cv_gb = GridSearchCV(gbMod, gbHyperParams, scoring = 'roc_auc', cv=cv, n_jobs = 3)
grid_cv_gb.fit(X_train, y_train)
```

```
Wall time: 3min 15s
```

In [55]:

```
grid_cv_gb.best_params_, grid_cv_gb.best_score_
```

Out[55]:

```
({'max_depth': 2, 'n_estimators': 250}, 0.80606773356186512)
```

In [56]:

```
bestGbModFitted = grid_cv_gb.best_estimator_.fit(X_train, y_train)
```

Finding the auc and gini metrics for the GradientBoostingClassifier

In [57]:

```
preds = bestGbModFitted.predict_proba(X_test)[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
auc_gb = auc(fpr, tpr)
gini_gb = 2 * auc_gb - 1
(auc_gb, gini_gb)
```

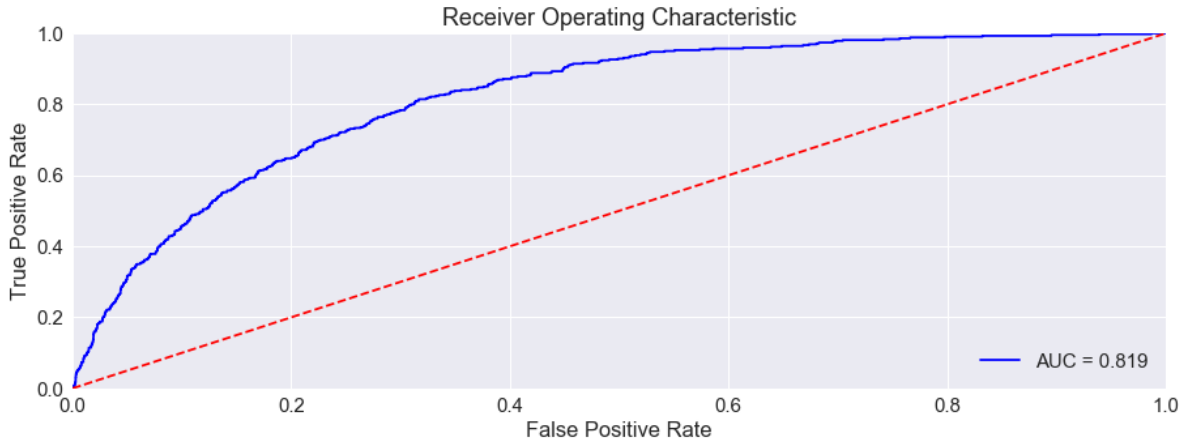
Out[57]:

```
(0.8187226455821498, 0.6374452911642996)
```

Building a roc curve for the GradientBoostingClassifier

In [58]:

```
build_roc_auc(auc_gb)
```



Variant of the function for counting gini without using the auc metric from sklearn.metrics

In [59]:

```
def gini(actual, pred, cmpcol = 0, sortcol = 1):
    assert( len(actual) == len(pred) )
    all = np.asarray(np.c_[ actual, pred, np.arange(len(actual)) ], dtype=np.float)
    all = all[ np.lexsort((all[:,2], -1*all[:,1])) ]
    totalLosses = all[:,0].sum()
    giniSum = all[:,0].cumsum().sum() / totalLosses
    giniSum -= (len(actual) + 1) / 2.
    return giniSum / len(actual)

def gini_normalized(a, p):
    return gini(a, p) / gini(a, a)
```

In [60]:

```
gini_normalized(y_test, preds)
```

Out[60]:

```
0.63744767629065147
```

Function for finding the optimal point on roc_curve

In [61]:

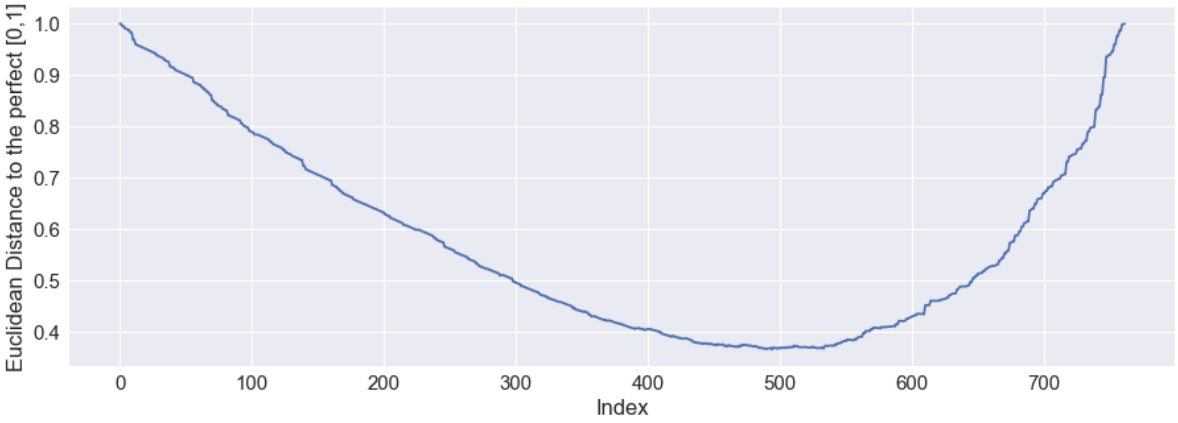
```
def rocZeroOne(y_true, y_predicted_porba):

    from sklearn.metrics import roc_curve
    from scipy.spatial.distance import euclidean

    fpr, tpr, thresholds = roc_curve(y_true, y_predicted_porba[:, 1])

    best = [0, 1]
    dist = []
    for (x, y) in zip(fpr, tpr):
        dist.append([euclidean([x,y], best)])

    bestPoint = [fpr[dist.index(min(dist))], tpr[dist.index(min(dist))]]

    bestCutOff1 = thresholds[list(fpr).index(bestPoint[0])]
    bestCutOff2 = thresholds[list(tpr).index(bestPoint[1])]

    print ('\n' + 'Best point on the ROC: TPR = {:0.3f}%, FPR = {:0.3f}%'.format(bestPoint[
    print ('\n' + 'Best Cut-Off point: {:0.4f}'.format(bestCutOff1))

    plt.plot(dist)
    plt.xlabel('Index')
    plt.ylabel('Euclidean Distance to the perfect [0,1]')
    fig = plt.gcf()
    fig.set_size_inches(15,5)
```

Finding the optimal point on roc_curve for GradientBoostingClassifier

In [62]:

```
rocZeroOne(y_test, bestGbModFitted.predict_proba(X_test))
```

```
Best point on the ROC: TPR = 76.429%, FPR = 27.899%

Best Cut-Off point: 0.0912
```

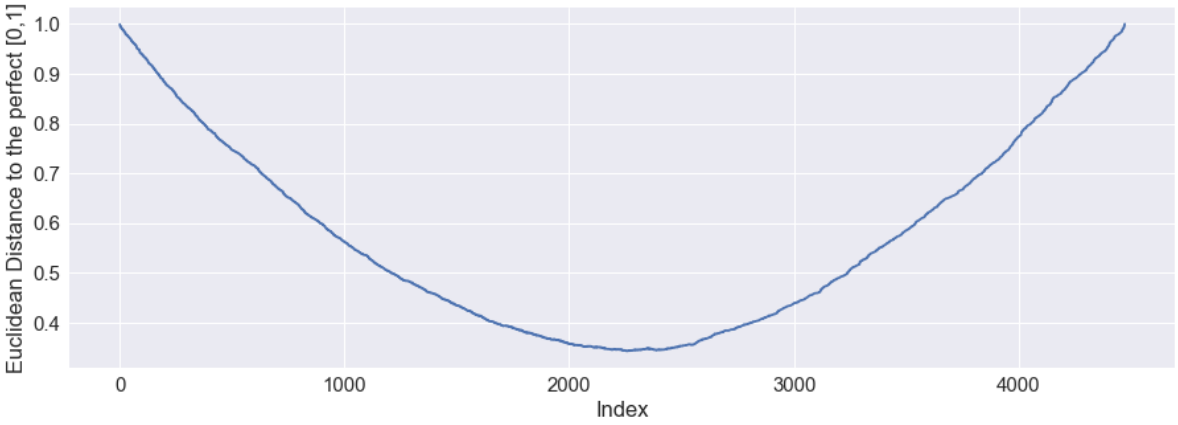


Finding the optimal point on roc_curve for AdaBoostClassifier

In [63]:

```
rocZeroOne(y_train, bestAdaModFitted.predict_proba(X_train))
```

```
Best point on the ROC: TPR = 78.129%, FPR = 26.374%

Best Cut-Off point: 0.4944
```



Function of constructing an error matrix

In [64]:

```
def plot_confusion_matrix(y_true, y_pred, title = 'Confusion matrix', cmap=plt.cm.Blues):
    from sklearn.metrics import classification_report
    from sklearn.metrics import confusion_matrix
    print('Classification Report:\n')
    print(classification_report(y_true, y_pred))
    cm = confusion_matrix(y_true, y_pred)
    def plot_confusion_matrix_plot(cm, title = 'Confusion matrix', cmap=plt.cm.Blues):
        plt.imshow(cm, interpolation='nearest', cmap=cmap)
        plt.title(title)
        plt.colorbar()
        tick_marks = np.arange(len(y_test.unique()))
        plt.xticks(tick_marks, rotation=45)
        plt.yticks(tick_marks)
        plt.tight_layout()
        plt.ylabel('True label')
        plt.xlabel('Predicted label')

    print('\n Confusion matrix, without normalization: \n')
    print(cm)
    plot_confusion_matrix_plot(cm=cm)

    cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    print('\n Normalized confusion matrix \n')
    print(cm_normalized)
    plt.figure()
    plot_confusion_matrix_plot(cm_normalized, title='Normalized confusion matrix')

def makePredThresh(fittedCls, thr, X_test):
    prob = fittedCls.predict_proba(X_test)[: ,1]
    final = []
    for p in prob:
        if p >= thr:
            final.append(1)
        else:
            final.append(0)

    return final
```

In [65]:

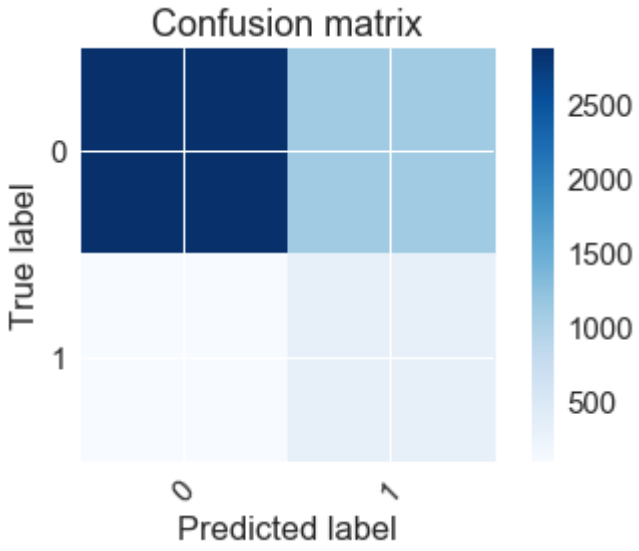
```
pred = makePredThresh(bestGbModFitted, 0.0912, X_test)
```

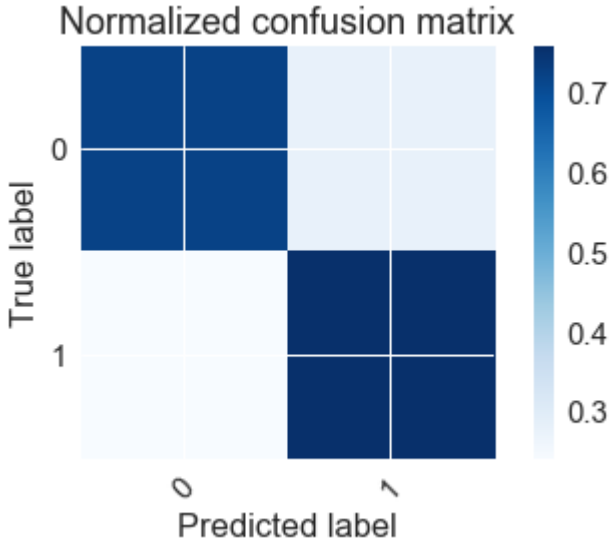
error matrix for GradientBoostingClassifier

In [66]:

```
plot_confusion_matrix(y_test, pred)
```

```
Classification Report:

             precision    recall  f1-score   support

          0       0.97      0.72      0.83      3993
          1       0.22      0.76      0.34       420

avg / total       0.90      0.72      0.78      4413


 Confusion matrix, without normalization:

[[2880 1113]
 [ 101  319]]

 Normalized confusion matrix

[[ 0.72126221  0.27873779]
 [ 0.24047619  0.75952381]]
```





In [67]:

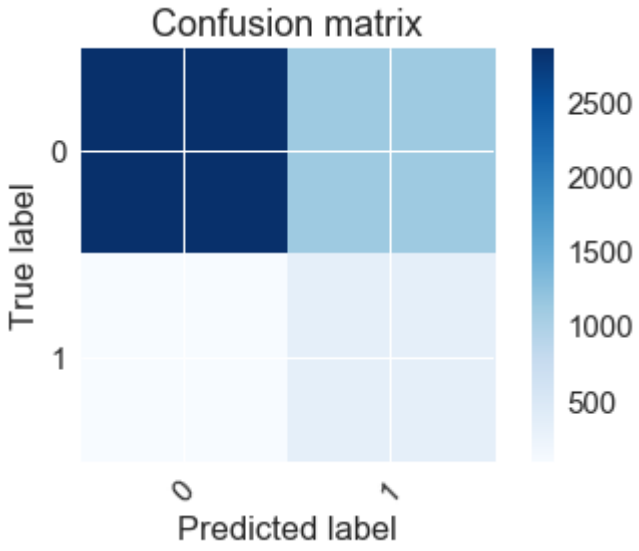
```
predAda = makePredThresh(bestAdaModFitted, 0.4943, X_test)
```

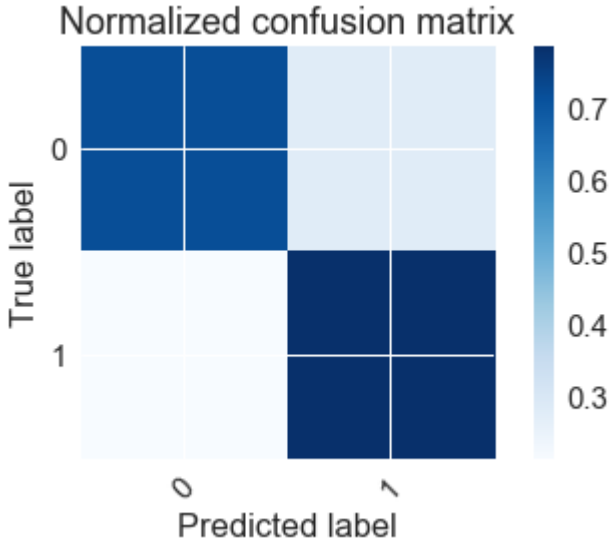
error matrix for AdaBoostClassifier

In [68]:

```
plot_confusion_matrix(y_test, predAda)
```

```
Classification Report:

             precision    recall  f1-score   support

          0       0.97      0.72      0.83      3993
          1       0.23      0.79      0.35       420

avg / total       0.90      0.73      0.78      4413


 Confusion matrix, without normalization:

[[2870 1123]
 [  90  330]]

 Normalized confusion matrix

[[ 0.71875783  0.28124217]
 [ 0.21428571  0.78571429]]
```





Both algorithms showed approximately the same quality, we will stop at GradientBoostingClassifier, as it interprets probabilities in a more familiar mode. Find the probability matrix for the test and training dataset.