Santander_Customer_Transaction_Prediction

December 12, 2019

Santander Customer Transaction Prediction

1. Business Problem

1.1. Description
Source: https://www.kaggle.com/c/santander-customer-transaction-prediction
Problem statement :
Based on an anonymized dataset containing numeric feature variables, the binary target column, and a string ID_code column, the task is to predict the value of target column in the test set.
1.2. Real-world/Business objectives and constraints.

- No low-latency requirement.
- Interpretability is important.
- Errors can be very costly.

2. Machine Learning Problem Formulation

2.1. Data
2.1.1. Data Overview

- Source: https://www.kaggle.com/c/santander-customer-transaction-prediction/data

- The link above contains two csv files that are important for this analysis and prediction task, one of these files, train.csv is the training data, it contains a binary target column, a string ID_code and 200 numerical features that must be taken into consideration during the prediction task. The next csv file, test.csv is the test set which is not provided with target column and we must only use the bare numreical feature to complete this task

2.2. Mapping the real-world problem to an ML problem
2.2.1. Type of Machine Learning Problem

```
There are two different classes thus this task can said to of the type => binary class
```

2.2.2. Performance Metric
Source: https://www.kaggle.com/c/santander-customer-transaction-prediction/overview/evaluation
Metric: * Area under the ROC curve
2.2.3. Machine Learing Objectives and Constraints
Objective: Predict if a transaction will happen based on the given 200 numerical features.
Constraints:

- Interpretability
- Class probabilities are needed.
- Penalize the errors in class probabilites => Metric is Area under the ROC curve.
- No Latency constraints.

3. Exploratory Data Analysis

3.1 Importing the required libraries

```
In [0]: import gc
        import os
        import time
        import logging
        import datetime
        import warnings
        import numpy as np
        import pandas as pd
        import seaborn as sns
        import lightgbm as lgb
        import pickle
        from collections import defaultdict
        import matplotlib.pyplot as plt
        from collections import OrderedDict
        from sklearn.model_selection import cross_val_predict
        from tqdm import tqdm
        from scipy.stats import norm, rankdata
        from scipy.special import erfc
        from sklearn.preprocessing import StandardScaler
        from sklearn.decomposition import PCA
        from sklearn.pipeline import Pipeline
        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import cross_val_score
        from sklearn.linear_model import LogisticRegression
        from sklearn import preprocessing
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.naive_bayes import GaussianNB
        from sklearn.datasets import make_classification
        from sklearn.metrics import mean_squared_error
        from sklearn.metrics import roc_auc_score, roc_curve, accuracy_score, fbeta_score, con
        from sklearn.model_selection import GridSearchCV
        from sklearn.model_selection import StratifiedKFold, KFold
        import gplearn
        from gplearn.genetic import SymbolicTransformer, SymbolicRegressor
        from gplearn.functions import make_function
        from gplearn.fitness import make_fitness
        from prettytable import PrettyTable
        warnings.filterwarnings('ignore')
```

3.2 Converting the downloaded csv files to Pandas Dataframe

```
In [26]: start=time.time()
         train_df=pd.read_csv('train.csv')
         test_df=pd.read_csv('test.csv')
         print ('Time taken for loading the dataset is {} minutes\n'.format((int(time.time()-s
```

```
Time taken for loading the dataset is 0.18333333333333332 minutes
```

3.3 Getting acquainted with the structure of the dataset

```
In [0]: print(train_df.shape)
        print(test_df.shape)
```

```
(200000, 202)
(200000, 201)
```

Both train and test data have 200,000 entries and 202, respectivelly 201 columns.

Let's glimpse train and test dataset.

```
In [0]: train_df.head()
```

```
Out[0]:    ID_code  target    var_0   var_1  ...  var_196  var_197  var_198  var_199
        0  train_0       0   8.9255 -6.7863  ...   7.8784   8.5635  12.7803  -1.0914
        1  train_1       0  11.5006 -4.1473  ...   8.1267   8.7889  18.3560   1.9518
        2  train_2       0   8.6093 -2.7457  ...  -6.5213   8.2675  14.7222   0.3965
        3  train_3       0  11.0604 -2.1518  ...  -2.9275  10.2922  17.9697  -8.9996
        4  train_4       0   9.8369 -1.4834  ...   3.9267   9.5031  17.9974  -8.8104

        [5 rows x 202 columns]
```

```
In [0]: test_df.head()
```

```
Out[0]:   ID_code    var_0    var_1    var_2  ...  var_196  var_197  var_198  var_199
        0  test_0  11.0656   7.7798  12.9536  ...   4.3654  10.7200  15.4722  -8.7197
        1  test_1   8.5304   1.2543  11.3047  ...  -1.4852   9.8714  19.1293 -20.9760
        2  test_2   5.4827 -10.3581  10.1407  ...  -7.1086   7.0618  19.8956 -23.1794
        3  test_3   8.5374  -1.3222  12.0220  ...   3.9567   9.2295  13.0168  -4.2108
        4  test_4  11.7058  -0.1327  14.1295  ...  -5.1612   7.2882  13.9260  -9.1846

        [5 rows x 201 columns]
```

Train contains:

- ID_code (string)
- target (int 0 & 1)
- 200 numerical float variables, named from var_0 to var_199

Test contains:

- ID_code (string)
- 200 numerical float variables, named from var_0 to var_199

3.4 Finding if there is any sort of missing data in the dataset

```
In [0]: def missing_data(data):
            total = data.isnull().sum()
            percent = (data.isnull().sum()/data.isnull().count()*100)
            tt = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
            types = []
            for col in data.columns:
                dtype = str(data[col].dtype)
                types.append(dtype)
            tt['Types'] = types
            return(np.transpose(tt))
```

3.4.1 First checking for the train dataset

```
In [0]: missing_data(train_df)
```

```
Out[0]:         ID_code target    var_0    var_1  ...  var_196  var_197  var_198  var_199
        Total         0      0        0        0  ...        0        0        0        0
        Percent       0      0        0        0  ...        0        0        0        0
        Types    object  int64  float64  float64  ...  float64  float64  float64  float64

        [3 rows x 202 columns]
```

From above result we can see that there isn't any missing data in the train dataset. 3.4.2 Now checking for the test dataset

```
In [0]: missing_data(test_df)
```

```
Out[0]:         ID_code    var_0    var_1    var_2  ...  var_196  var_197  var_198  var_199
        Total         0        0        0        0  ...        0        0        0        0
        Percent       0        0        0        0  ...        0        0        0        0
        Types    object  float64  float64  float64  ...  float64  float64  float64  float64

        [3 rows x 201 columns]
```

From above result we can see that there isn't any missing data in the test dataset either. 3.5. Outlier Detection

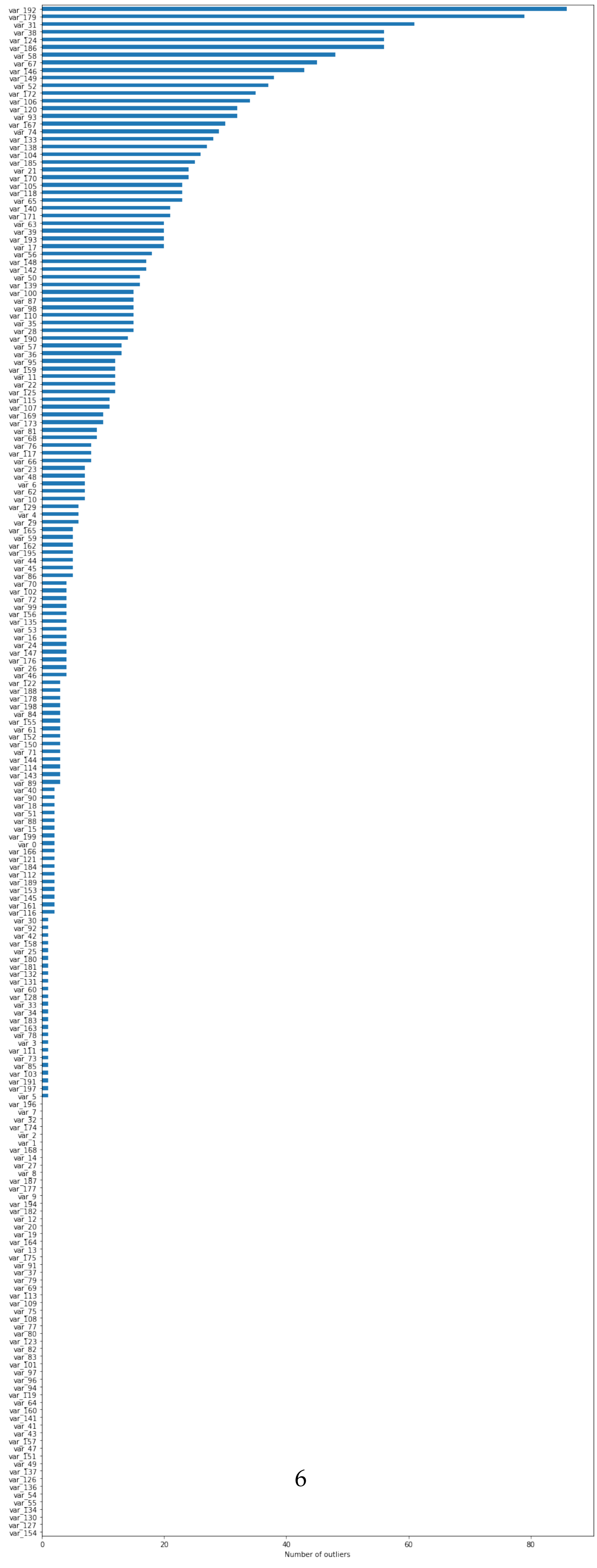
- The technique used in this case study for outlier detection is 'chavenet criterion' more information regarding it can be found at 'https://en.wikipedia.org/wiki/Chauvenet%27s_criterion'

```
In [0]: def chauvenet(array):
            mean = array.mean()           # Mean of incoming array
            stdv = array.std()            # Standard deviation
            N = len(array)                # Lenght of incoming array
            criterion = 1.0/(2*N)         # Chauvenet's criterion
            d = abs(array-mean)/stdv      # Distance of a value to mean in stdv's
            prob = erfc(d)                # Area normal dist.
            return prob < criterion       # Use boolean array outside this function
```

```
In [0]: numerical_features=train_df.columns[2:]
```

```
In [29]: train_outliers = dict()
         for col in tqdm([col for col in numerical_features]):
             train_outliers[col] = train_df[chauvenet(train_df[col].values)].shape[0]
         train_outliers = pd.Series(train_outliers)

         train_outliers.sort_values().plot(figsize=(14, 40), kind='barh').set_xlabel('Number o
```

```
100%|| 200/200 [00:01<00:00, 152.69it/s]
```

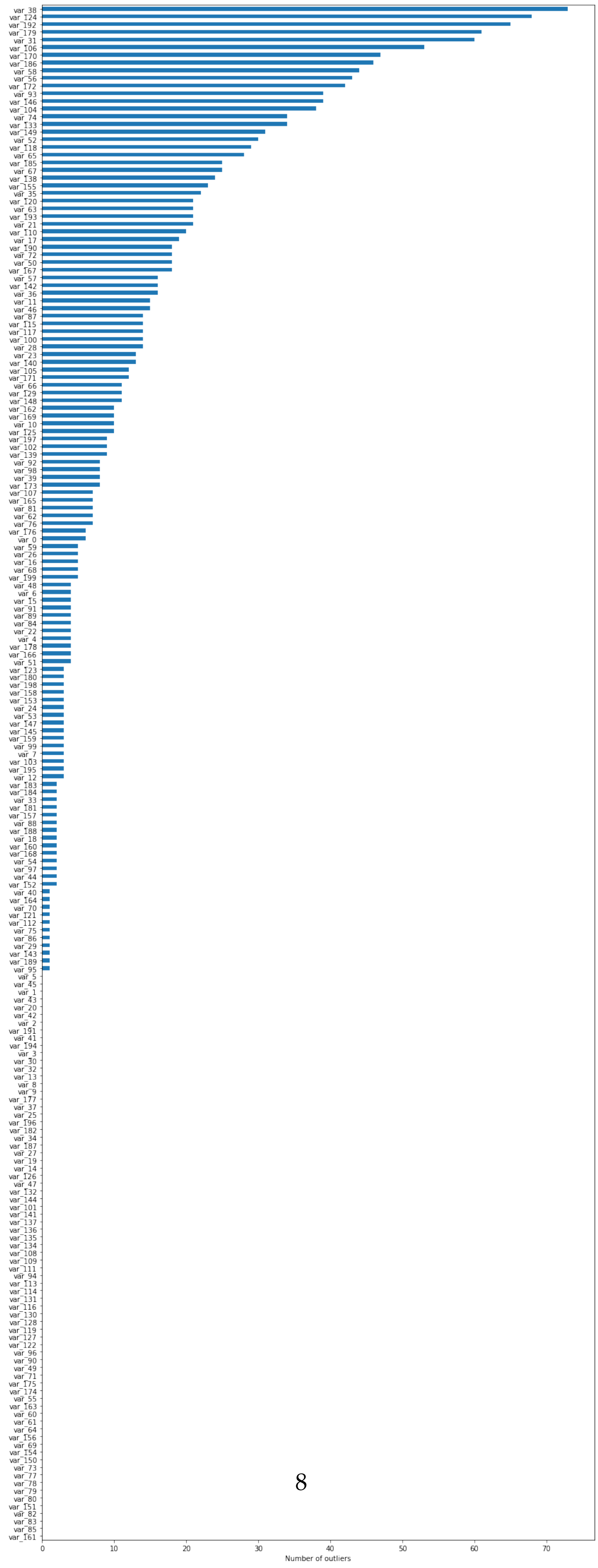

var_192
var_179
var_31
var_38
var_124
var_186
var_58
var_67
var_146
var_149
var_52
var_172
var_106
var_120
var_93
var_167
var_74
var_133
var_138
var_104
var_185
var_21
var_170
var_105
var_118
var_65
var_140
var_171
var_63
var_39
var_193
var_17
var_56
var_148
var_142
var_50
var_139
var_100
var_87
var_98
var_110
var_35
var_28
var_190
var_57
var_36
var_95
var_159
var_11
var_22
var_125
var_115
var_107
var_169
var_173
var_81
var_68
var_76
var_117
var_66
var_23
var_48
var_6
var_62
var_10
var_129
var_4
var_29
var_165
var_59
var_162
var_195
var_44
var_45
var_86
var_70
var_102
var_72
var_99
var_156
var_135
var_53
var_16
var_24
var_147
var_176
var_26
var_46
var_122
var_188
var_178
var_198
var_84
var_155
var_61
var_152
var_150
var_71
var_144
var_114
var_143
var_89
var_40
var_90
var_18
var_51
var_88
var_15
var_199
var_0
var_166
var_121
var_184
var_112
var_189
var_153
var_145
var_161
var_116
var_30
var_92
var_42
var_158
var_25
var_180
var_181
var_132
var_131
var_60
var_128
var_33
var_34
var_183
var_163
var_78
var_3
var_111
var_73
var_85
var_103
var_191
var_197
var_5
var_196
var_7
var_32
var_174
var_2
var_1
var_168
var_14
var_27
var_8
var_187
var_177
var_9
var_194
var_182
var_12
var_20
var_19
var_164
var_13
var_175
var_91
var_37
var_79
var_69
var_113
var_109
var_75
var_108
var_77
var_80
var_123
var_82
var_83
var_101
var_97
var_96
var_94
var_119
var_64
var_160
var_141
var_41
var_43
var_157
var_47
var_151
var_49
var_137
var_126
var_136
var_54
var_55
var_134
var_130
var_127
var_154
0
20
40
60
80
Number of outliers

```
In [30]: print('Total number of outliers in training set: {} ({:.2f}%)'.format(sum(train_outli
```

```
Total number of outliers in training set: 1740 (0.87%)
```

```
In [31]: #outliers in each variable in test data
         test_outliers = dict()
         for col in tqdm([col for col in numerical_features]):
             test_outliers[col] = test_df[chauvenet(test_df[col].values)].shape[0]
         test_outliers = pd.Series(test_outliers)

         test_outliers.sort_values().plot(figsize=(14, 40), kind='barh').set_xlabel('Number of
```

```
100%|| 200/200 [00:01<00:00, 159.49it/s]
```


Number of outliers
0
10
20
30
40
50
60
70

```
In [32]: print('Total number of outliers in testing set: {} ({:.2f}%)'.format(sum(test_outlier
```

```
Total number of outliers in testing set: 1748 (0.87%)
```

```
In [33]: #remove these outliers in train and test data
         for col in tqdm(numerical_features):
             train_df=train_df.loc[(~chauvenet(train_df[col].values))]
         for col in tqdm(numerical_features):
             test_df=test_df.loc[(~chauvenet(test_df[col].values))]
```

```
100%|| 200/200 [00:20<00:00,  9.95it/s]
100%|| 200/200 [00:19<00:00, 10.40it/s]
```

```
In [34]: #shape of train and test data after removal of outliers
         train_df.shape, test_df.shape
```

```
Out[34]: ((198264, 202), (198250, 201))
```

3.6 Checking the numerical values in train and test dataset

```
In [0]: train_df.describe()
```

```
Out[0]:               target          var_0  ...        var_198        var_199
        count  198264.000000  198264.000000  ...  198264.000000  198264.000000
        mean        0.100412      10.679648  ...      15.871506      -3.326076
        std         0.300549       3.039746  ...       3.010625      10.437785
        min         0.000000       0.597900  ...       6.299300     -37.696200
        25%         0.000000       8.454175  ...      13.829875     -11.207900
        50%         0.000000      10.524200  ...      15.935700      -2.822200
        75%         0.000000      12.758200  ...      18.065800       4.836800
        max         1.000000      20.315000  ...      25.857100      28.500700

        [8 rows x 201 columns]
```

```
In [0]: test_df.describe()
```

```
Out[0]:                var_0          var_1  ...        var_198        var_199
        count  198250.000000  198250.000000  ...  198250.000000  198250.000000
        mean       10.658132      -1.623584  ...      15.868352      -3.244830
        std         3.036247       4.040598  ...       3.008109      10.395702
        min         0.922000     -15.043400  ...       6.584000     -36.325100
        25%         8.441800      -4.699350  ...      13.845900     -11.121975
        50%        10.514200      -1.589400  ...      15.942700      -2.725950
        75%        12.739600       1.343900  ...      18.044800       4.935700
        max        20.064900       9.385100  ...      25.463400      27.907400

        [8 rows x 200 columns]
```

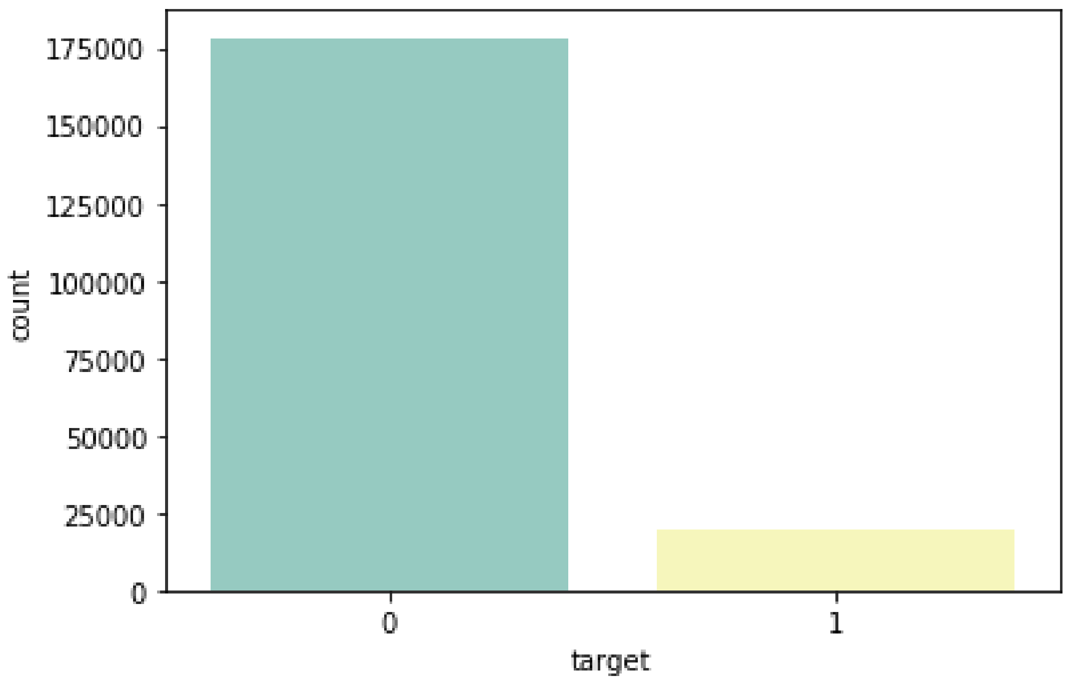
3.6.1We can make few observations here:

- standard deviation is relatively large for both train and test variable data
- min, max, mean values for train and test data looks quite close
- mean values are distributed over a large range.

3.7 Checking the distribution of target value in train dataset.

```
In [0]: sns.countplot(train_df['target'], palette='Set3')
```

```
Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1a54e51c50>
```



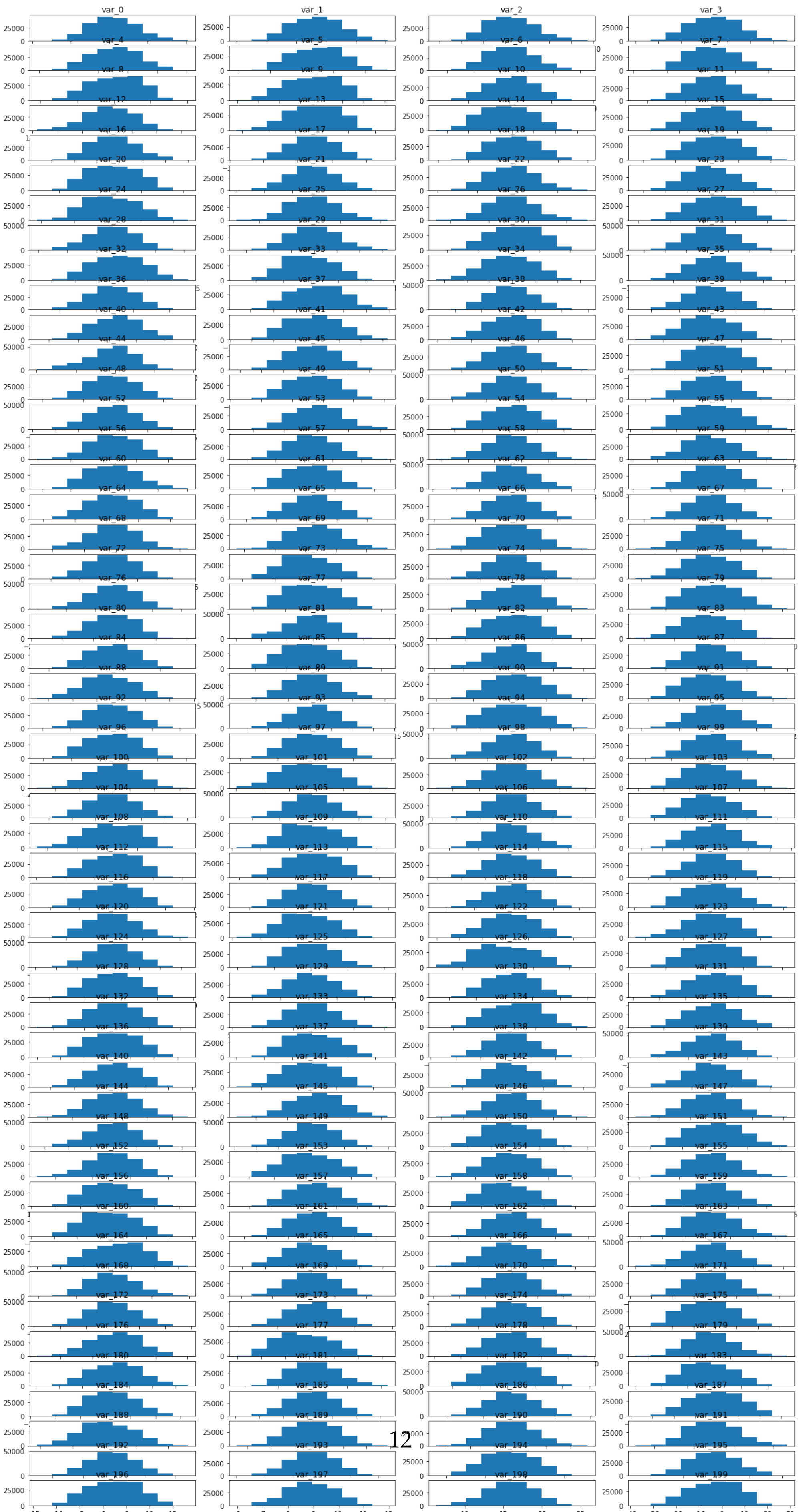

```
In [0]: print("There are {}% target values with 0".format(100 * train_df["target"].value_counts
        print("There are {}% target values with 1".format(100 * train_df["target"].value_counts
```

```
There are 89.95884275511439% target values with 0
There are 10.041157244885607% target values with 1
```

- From the above plot and the result we can see that the dataset is heavily imbalanced with approximately only one out of every ten datapoints having a target value '1'.

3.8 Histogram of every column in train dataset

In [0]:
```
numerical_features=train_df.columns[2:]
plt.figure(figsize=(20, 40))
plt.title('Distribution of column')
for i,col in enumerate(numerical_features):
    plt.subplot(50,4,i+1)
    plt.hist(train_df[col])
    plt.title(col)
```

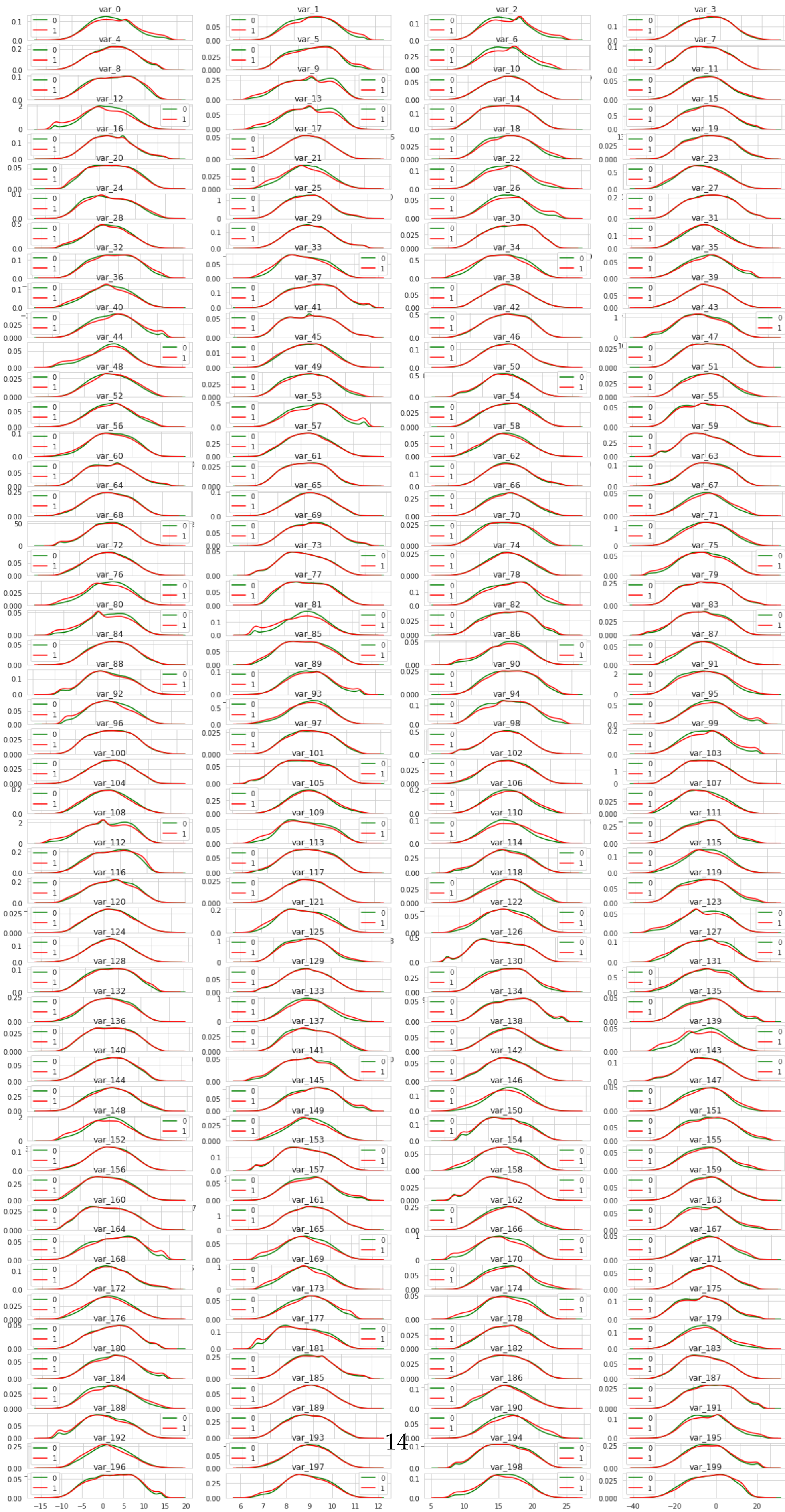


var_0
var_1
var_2
var_3
var_4
var_5
var_6
var_7
var_8
var_9
var_10
var_11
var_12
var_13
var_14
var_15
var_16
var_17
var_18
var_19
var_20
var_21
var_22
var_23
var_24
var_25
var_26
var_27
var_28
var_29
var_30
var_31
var_32
var_33
var_34
var_35
var_36
var_37
var_38
var_39
var_40
var_41
var_42
var_43
var_44
var_45
var_46
var_47
var_48
var_49
var_50
var_51
var_52
var_53
var_54
var_55
var_56
var_57
var_58
var_59
var_60
var_61
var_62
var_63
var_64
var_65
var_66
var_67
var_68
var_69
var_70
var_71
var_72
var_73
var_74
var_75
var_76
var_77
var_78
var_79
var_80
var_81
var_82
var_83
var_84
var_85
var_86
var_87
var_88
var_89
var_90
var_91
var_92
var_93
var_94
var_95
var_96
var_97
var_98
var_99
var_100
var_101
var_102
var_103
var_104
var_105
var_106
var_107
var_108
var_109
var_110
var_111
var_112
var_113
var_114
var_115
var_116
var_117
var_118
var_119
var_120
var_121
var_122
var_123
var_124
var_125
var_126
var_127
var_128
var_129
var_130
var_131
var_132
var_133
var_134
var_135
var_136
var_137
var_138
var_139
var_140
var_141
var_142
var_143
var_144
var_145
var_146
var_147
var_148
var_149
var_150
var_151
var_152
var_153
var_154
var_155
var_156
var_157
var_158
var_159
var_160
var_161
var_162
var_163
var_164
var_165
var_166
var_167
var_168
var_169
var_170
var_171
var_172
var_173
var_174
var_175
var_176
var_177
var_178
var_179
var_180
var_181
var_182
var_183
var_184
var_185
var_186
var_187
var_188
var_189
var_190
var_191
var_192
var_193
var_194
var_195
var_196
var_197
var_198
var_199
−15 −10 −5 0 5 10 15
6 7 8 9 10 11 12
10 15 20 25
−40 −30 −20 −10 0 10 20 30

- We can observe from the above plots that every feature follows normal distribution.

3.8.1 Distribution of columns per target class in train dataset

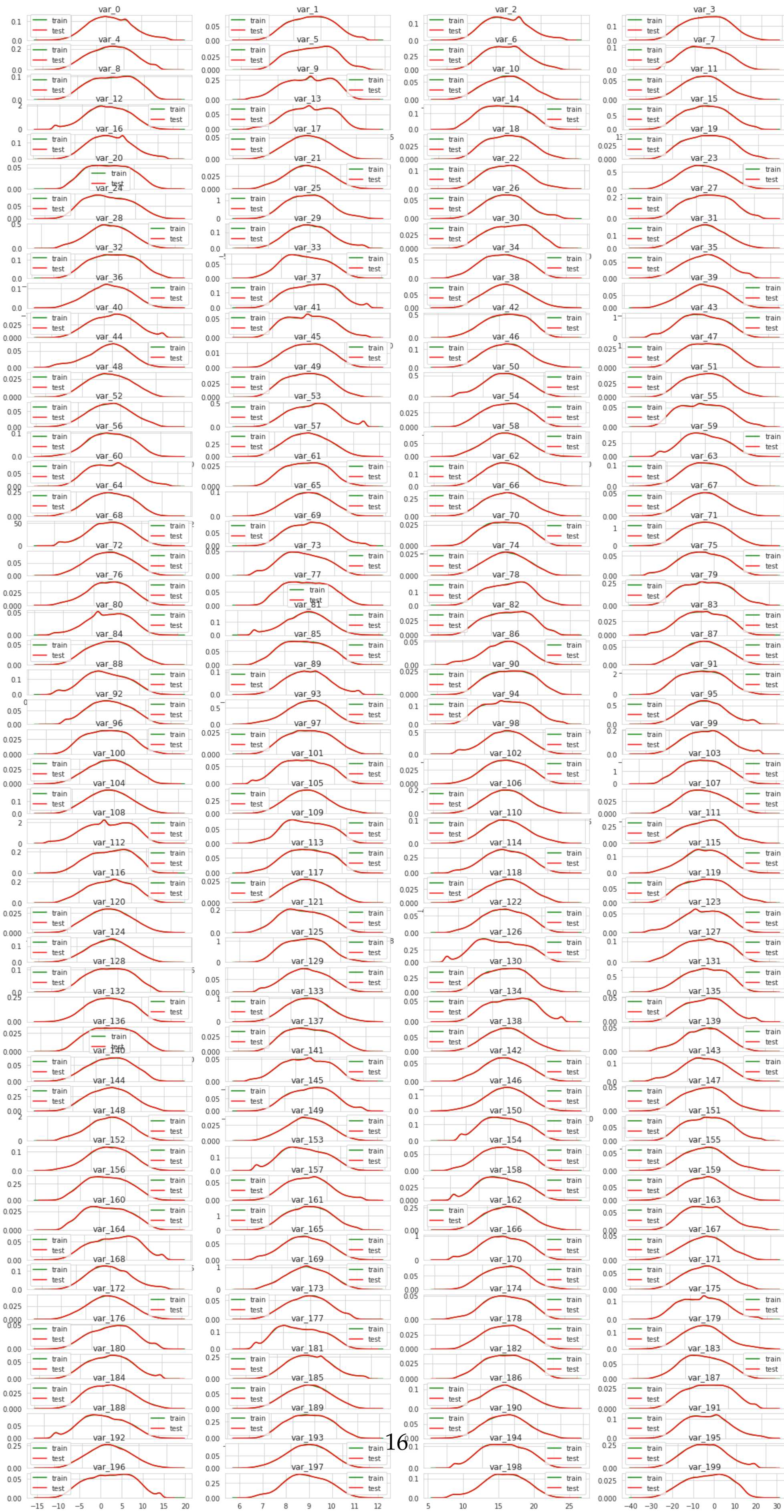
```
In [0]: sns.set_style('whitegrid')
        plt.figure(figsize=(20, 40))
        for i,col in enumerate(numerical_features):
            plt.subplot(50,4,i+1)
            sns.distplot(train_df[train_df['target']==0][col],hist=False,label='0',color='gree
            sns.distplot(train_df[train_df['target']==1][col],hist=False,label='1',color='red')
            plt.title(col)
```



- From the above plots it can be observed that the plots for target '0' and target '1' overlap for each column except for a few features like var_40, var148, var_190, var_191, etc

3.9 Distribution of columns for test and train datset

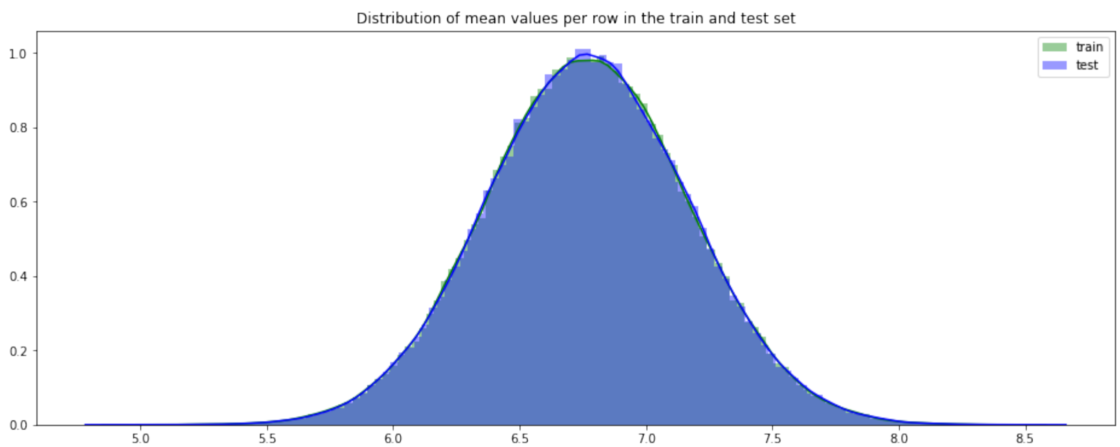
In [0]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(20, 40))
for i,col in enumerate(numerical_features):
    plt.subplot(50,4,i+1)
    sns.distplot(train_df[col],hist=False,label='train',color='green')
    sns.distplot(test_df[col],hist=False,label='test',color='red')
    plt.title(col)
```


var_0
var_1
var_2
var_3
var_4
var_5
var_6
var_7
var_8
var_9
var_10
var_11
var_12
var_13
var_14
var_15
var_16
var_17
var_18
var_19
var_20
var_21
var_22
var_23
var_24
var_25
var_26
var_27
var_28
var_29
var_30
var_31
var_32
var_33
var_34
var_35
var_36
var_37
var_38
var_39
var_40
var_41
var_42
var_43
var_44
var_45
var_46
var_47
var_48
var_49
var_50
var_51
var_52
var_53
var_54
var_55
var_56
var_57
var_58
var_59
var_60
var_61
var_62
var_63
var_64
var_65
var_66
var_67
var_68
var_69
var_70
var_71
var_72
var_73
var_74
var_75
var_76
var_77
var_78
var_79
var_80
var_81
var_82
var_83
var_84
var_85
var_86
var_87
var_88
var_89
var_90
var_91
var_92
var_93
var_94
var_95
var_96
var_97
var_98
var_99
var_100
var_101
var_102
var_103
var_104
var_105
var_106
var_107
var_108
var_109
var_110
var_111
var_112
var_113
var_114
var_115
var_116
var_117
var_118
var_119
var_120
var_121
var_122
var_123
var_124
var_125
var_126
var_127
var_128
var_129
var_130
var_131
var_132
var_133
var_134
var_135
var_136
var_137
var_138
var_139
var_140
var_141
var_142
var_143
var_144
var_145
var_146
var_147
var_148
var_149
var_150
var_151
var_152
var_153
var_154
var_155
var_156
var_157
var_158
var_159
var_160
var_161
var_162
var_163
var_164
var_165
var_166
var_167
var_168
var_169
var_170
var_171
var_172
var_173
var_174
var_175
var_176
var_177
var_178
var_179
var_180
var_181
var_182
var_183
var_184
var_185
var_186
var_187
var_188
var_189
var_190
var_191
var_192
var_193
var_194
var_195
var_196
var_197
var_198
var_199
train
test

- The train and test seems to be well balanced with respect with distribution of the numeric variables.

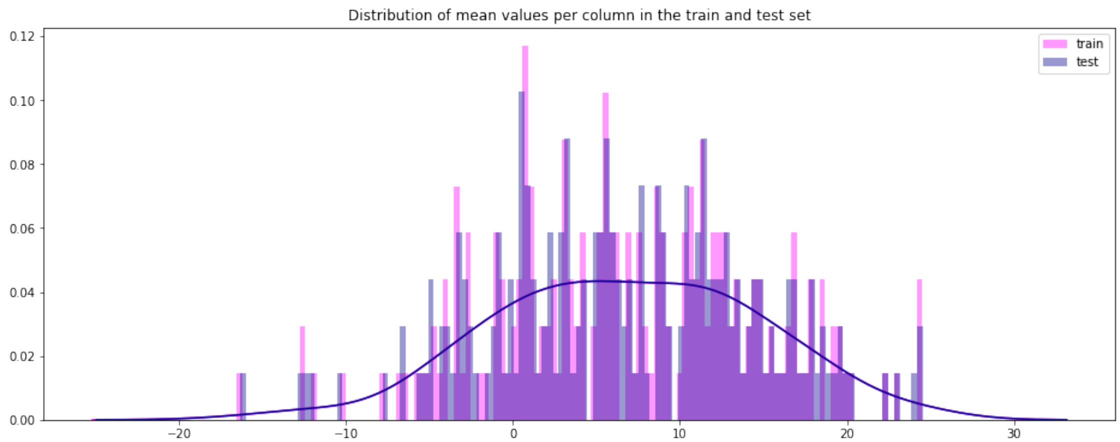
3.10 Univariate analysis of mean and standard deviation of train and test sets
3.10.1 Checking the mean values per row in the train and the test set.

```
In [0]: plt.figure(figsize=(16,6))
        features = train_df.columns.values[2:]
        plt.title("Distribution of mean values per row in the train and test set")
        sns.distplot(train_df[features].mean(axis=1),color="green", kde=True,bins=120, label='
        sns.distplot(test_df[features].mean(axis=1),color="blue", kde=True,bins=120, label='tes
        plt.legend()
        plt.show()
```



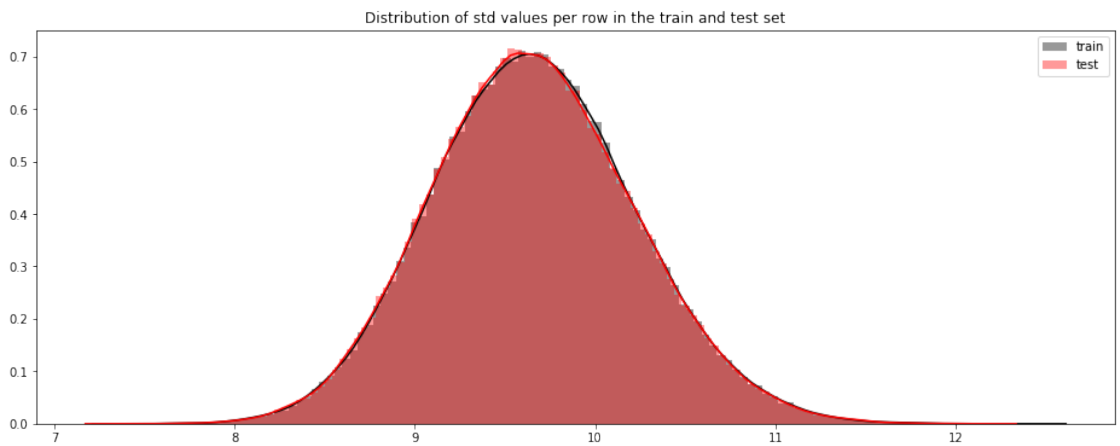
3.10.2 Checking the mean values per column in the train and the test set.

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of mean values per column in the train and test set")
        sns.distplot(train_df[features].mean(axis=0),color="magenta",kde=True,bins=120, label=
        sns.distplot(test_df[features].mean(axis=0),color="darkblue", kde=True,bins=120, label=
        plt.legend()
        plt.show()
```



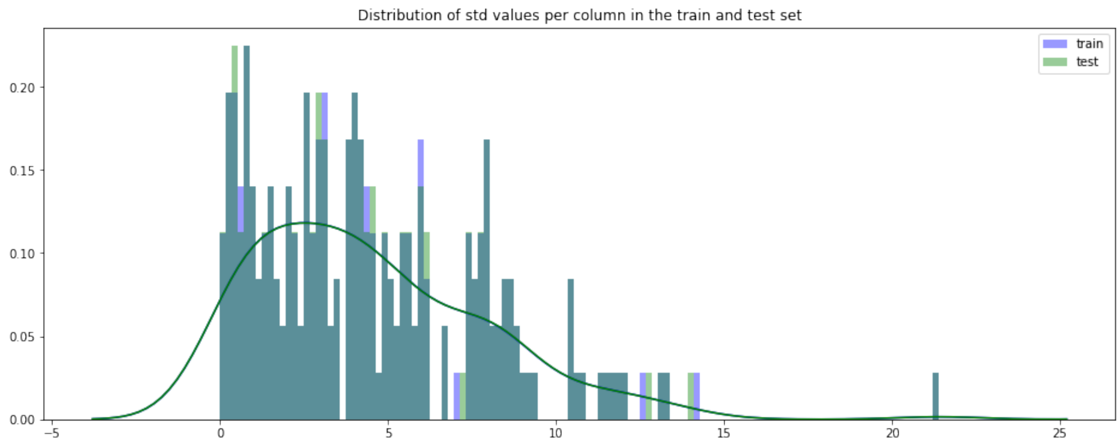
3.10.3 Checking the standard deviation per row in the train and test set.

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of std values per row in the train and test set")
        sns.distplot(train_df[features].std(axis=1),color="black", kde=True,bins=120, label='t
        sns.distplot(test_df[features].std(axis=1),color="red", kde=True,bins=120, label='test
        plt.legend();plt.show()
```



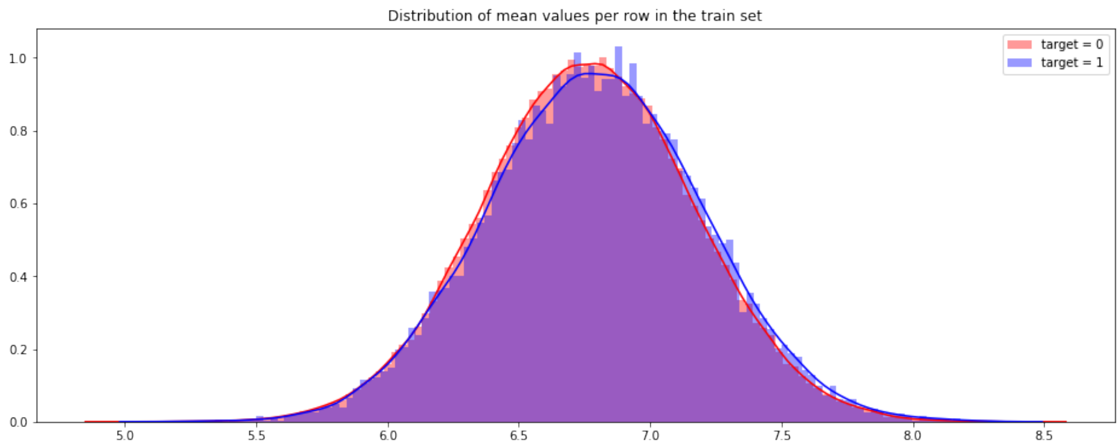
3.10.4 Checking the standard deviation per column in the train and test set.

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of std values per column in the train and test set")
        sns.distplot(train_df[features].std(axis=0),color="blue",kde=True,bins=120, label='tra
        sns.distplot(test_df[features].std(axis=0),color="green", kde=True,bins=120, label='te
        plt.legend(); plt.show()
```



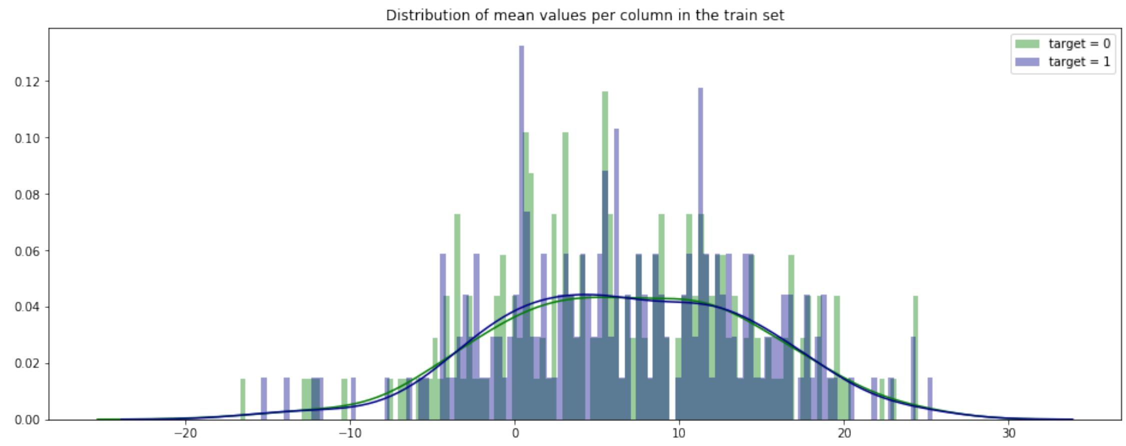
3.11 Univariate analysis on mean values based on targets of the train set.
3.11.1 Mean values per row in the train set

In [0]:
```
t0 = train_df.loc[train_df['target'] == 0]
t1 = train_df.loc[train_df['target'] == 1]
plt.figure(figsize=(16,6))
plt.title("Distribution of mean values per row in the train set")
sns.distplot(t0[features].mean(axis=1),color="red", kde=True,bins=120, label='target =
sns.distplot(t1[features].mean(axis=1),color="blue", kde=True,bins=120, label='target =
plt.legend(); plt.show()
```



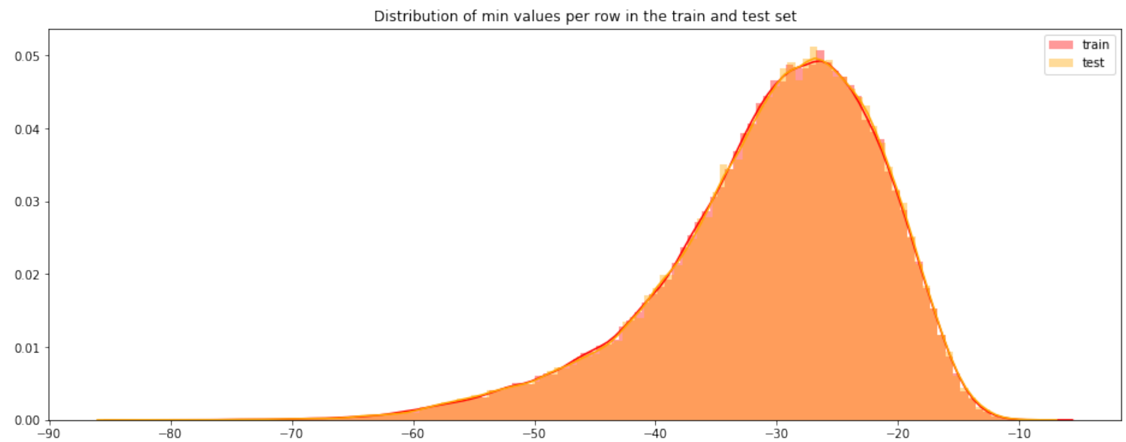
3.11.2 Mean values per column in the train set.

In [0]:
```
plt.figure(figsize=(16,6))
plt.title("Distribution of mean values per column in the train set")
sns.distplot(t0[features].mean(axis=0),color="green", kde=True,bins=120, label='target
sns.distplot(t1[features].mean(axis=0),color="darkblue", kde=True,bins=120, label='targ
plt.legend(); plt.show()
```



3.12 Univariate analysis on min values in the train set and the test set.
3.12.1 Distribution of min values per row in the train and test set

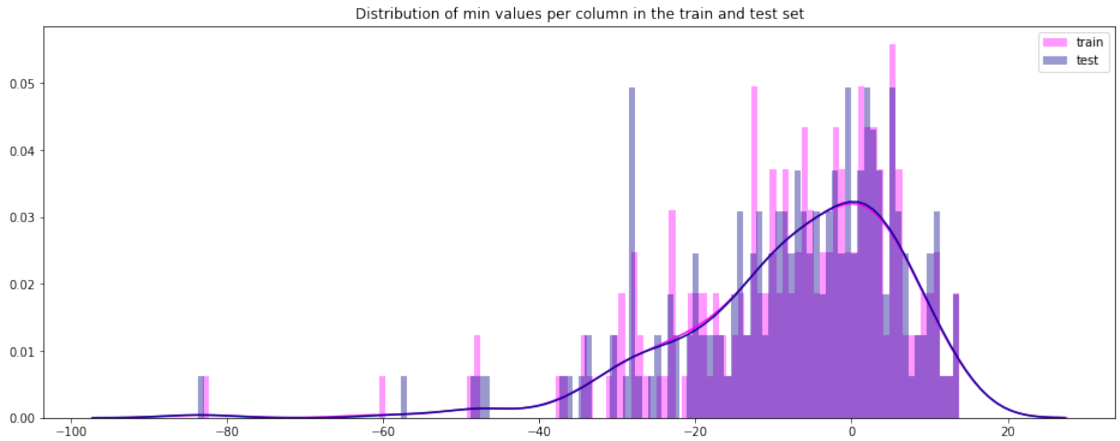
In [0]:
```
plt.figure(figsize=(16,6))
features = train_df.columns.values[2:202]
plt.title("Distribution of min values per row in the train and test set")
sns.distplot(train_df[features].min(axis=1),color="red", kde=True,bins=120, label='trai
sns.distplot(test_df[features].min(axis=1),color="orange", kde=True,bins=120, label='te
plt.legend()
plt.show()
```



3.12.2 Distribution of min values per column in the train and test set

In [0]:
```
plt.figure(figsize=(16,6))
features = train_df.columns.values[2:202]
plt.title("Distribution of min values per column in the train and test set")
sns.distplot(train_df[features].min(axis=0),color="magenta", kde=True,bins=120, label=
```

```
sns.distplot(test_df[features].min(axis=0),color="darkblue", kde=True,bins=120, label=
plt.legend()
plt.show()
```

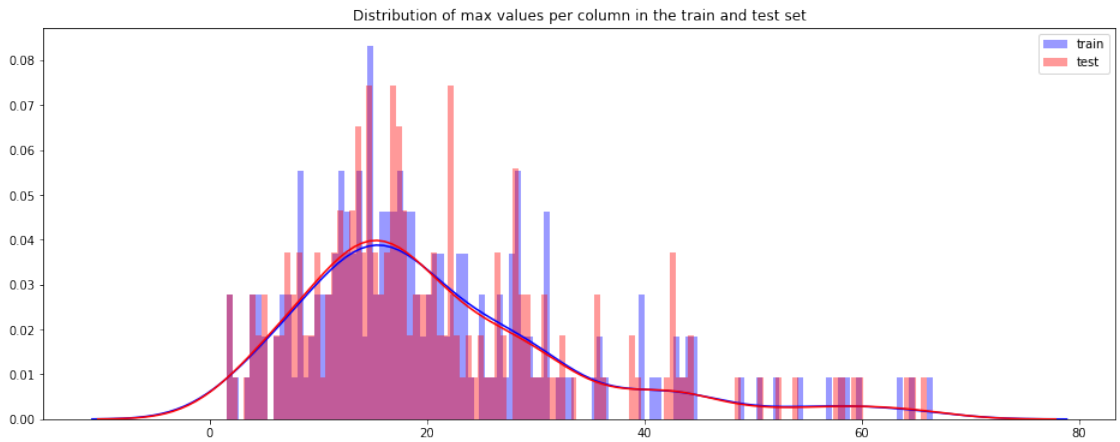


3.13 Univariate analysis on max values in the train set and the test set.
3.13.1 Distribution of max values per row in the train and test set

```
In [0]: plt.figure(figsize=(16,6))
        features = train_df.columns.values[2:202]
        plt.title("Distribution of max values per row in the train and test set")
        sns.distplot(train_df[features].max(axis=1),color="brown", kde=True,bins=120, label='tr
        sns.distplot(test_df[features].max(axis=1),color="yellow", kde=True,bins=120, label='te
        plt.legend()
        plt.show()
```

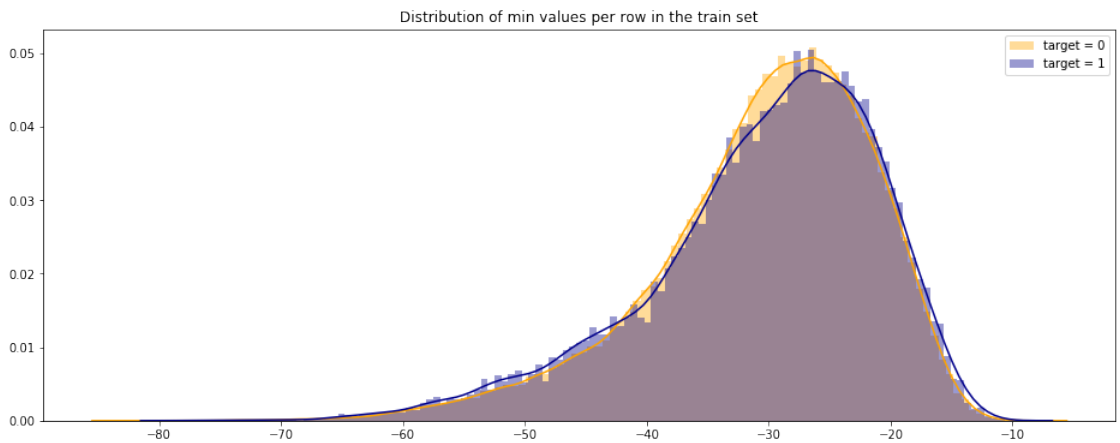
3.13.2 Distribution of max values per column in the train and test set

```
In [0]: plt.figure(figsize=(16,6))
        features = train_df.columns.values[2:202]
        plt.title("Distribution of max values per column in the train and test set")
        sns.distplot(train_df[features].max(axis=0),color="blue", kde=True,bins=120, label='tra
        sns.distplot(test_df[features].max(axis=0),color="red", kde=True,bins=120, label='test
        plt.legend()
        plt.show()
```



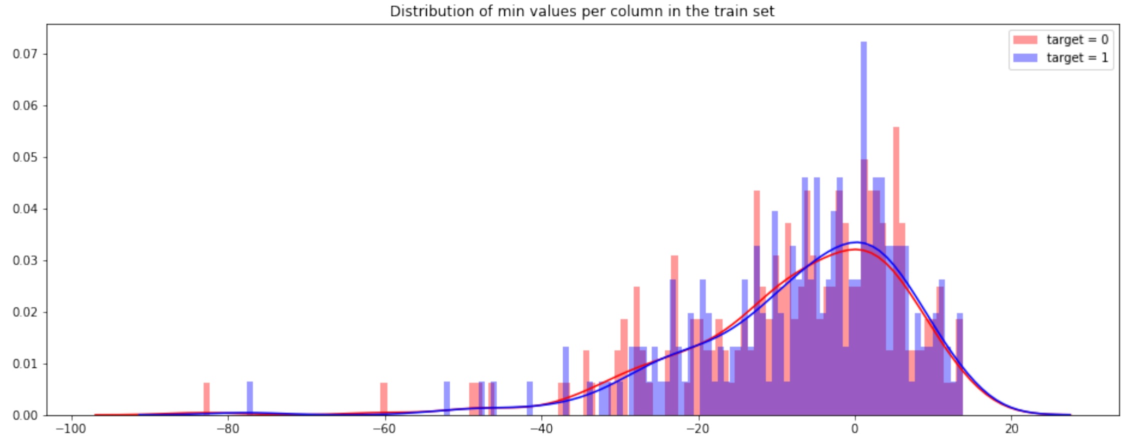
3.14 Univariate analysis on min values based on targets of the train set.
3.14.1 Distribution of min values per row in the train set

```
In [0]: t0 = train_df.loc[train_df['target'] == 0]
        t1 = train_df.loc[train_df['target'] == 1]
        plt.figure(figsize=(16,6))
        plt.title("Distribution of min values per row in the train set")
        sns.distplot(t0[features].min(axis=1),color="orange", kde=True,bins=120, label='target
        sns.distplot(t1[features].min(axis=1),color="darkblue", kde=True,bins=120, label='targe
        plt.legend(); plt.show()
```



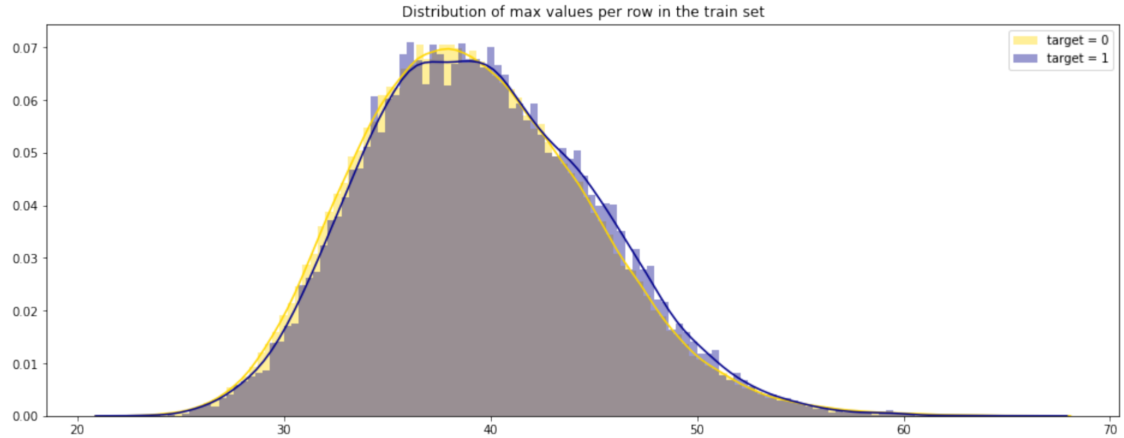
3.14.2 Distribution of min values per column in the train set

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of min values per column in the train set")
        sns.distplot(t0[features].min(axis=0),color="red", kde=True,bins=120, label='target = 0
        sns.distplot(t1[features].min(axis=0),color="blue", kde=True,bins=120, label='target =
        plt.legend(); plt.show()
```



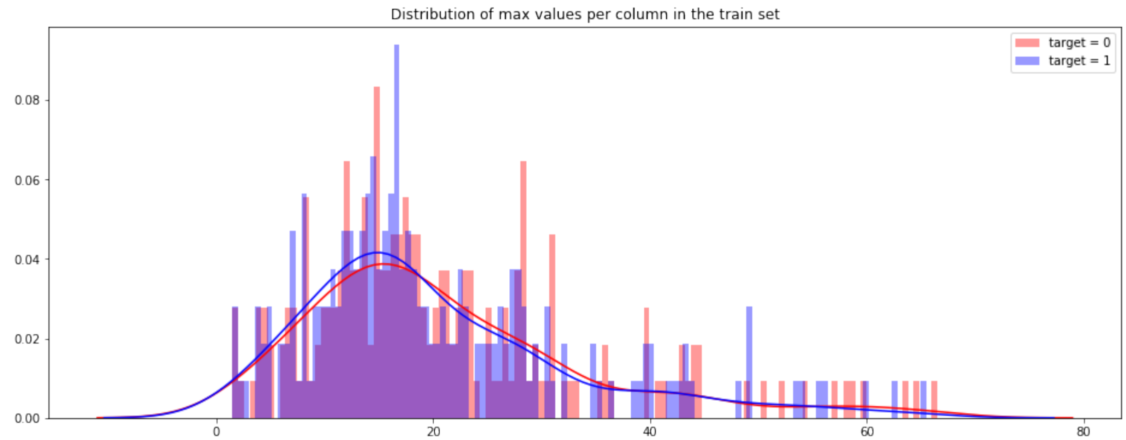
3.15 Univariate analysis on max values based on targets of the train set.
3.15.1 Distribution of max values per row in the train set

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of max values per row in the train set")
        sns.distplot(t0[features].max(axis=1),color="gold", kde=True,bins=120, label='target =
        sns.distplot(t1[features].max(axis=1),color="darkblue", kde=True,bins=120, label='targe
        plt.legend(); plt.show()
```



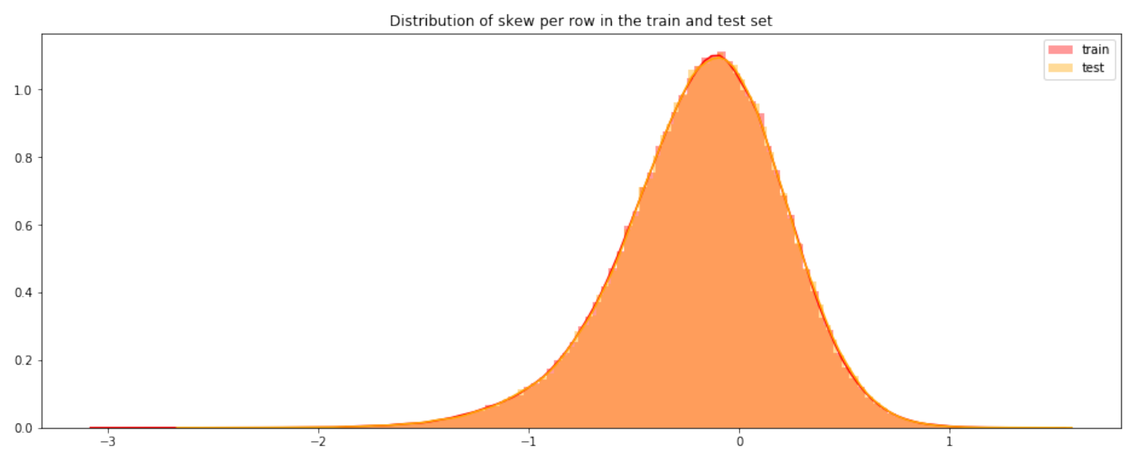
3.15.2 Distribution of max values per column in the train set

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of max values per column in the train set")
        sns.distplot(t0[features].max(axis=0),color="red", kde=True,bins=120, label='target = (
        sns.distplot(t1[features].max(axis=0),color="blue", kde=True,bins=120, label='target =
        plt.legend(); plt.show()
```



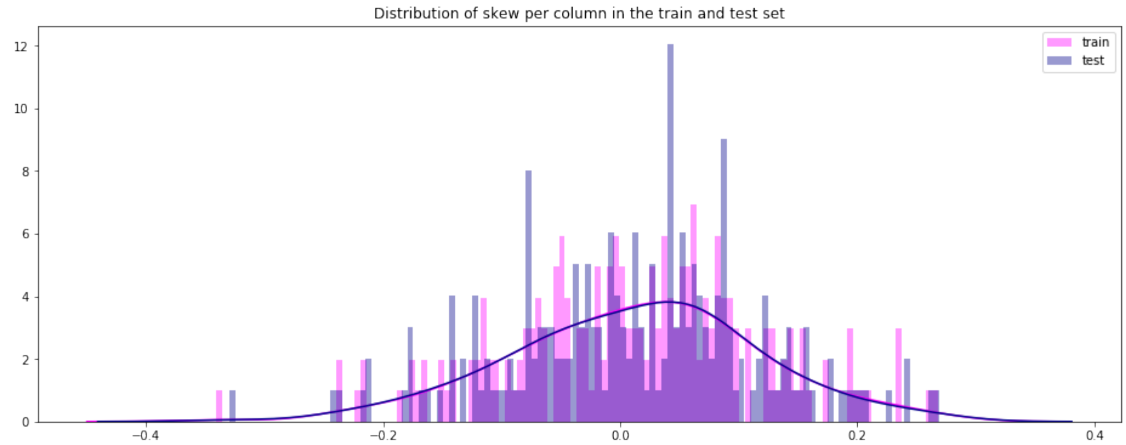
3.16 Univariate analysis on skew values in the train set and the test set.
3.16.1 Distribution of skew per row in the train and test set

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of skew per row in the train and test set")
        sns.distplot(train_df[features].skew(axis=1),color="red", kde=True,bins=120, label='tra
        sns.distplot(test_df[features].skew(axis=1),color="orange", kde=True,bins=120, label='
        plt.legend()
        plt.show()
```



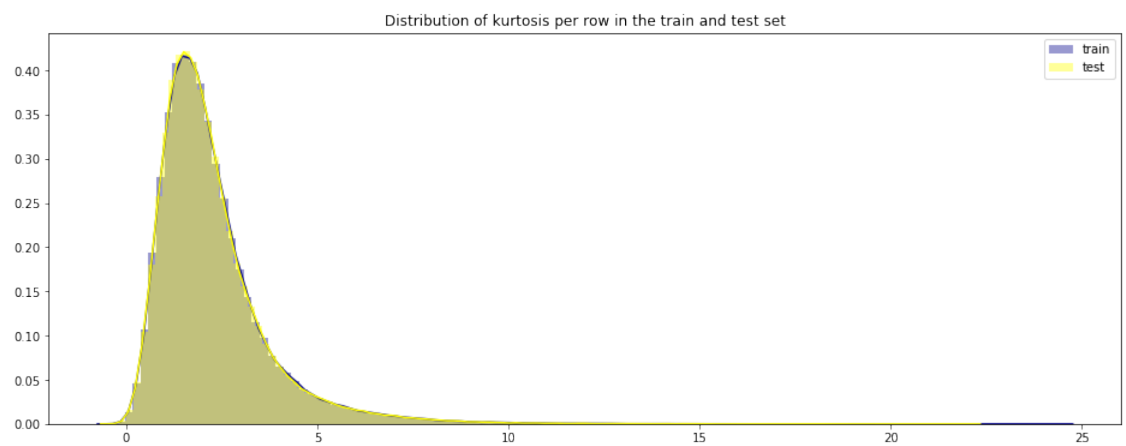
3.16.2 Distribution of skew per column in the train and test set

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of skew per column in the train and test set")
        sns.distplot(train_df[features].skew(axis=0),color="magenta", kde=True,bins=120, label=
        sns.distplot(test_df[features].skew(axis=0),color="darkblue", kde=True,bins=120, label=
        plt.legend()
        plt.show()
```



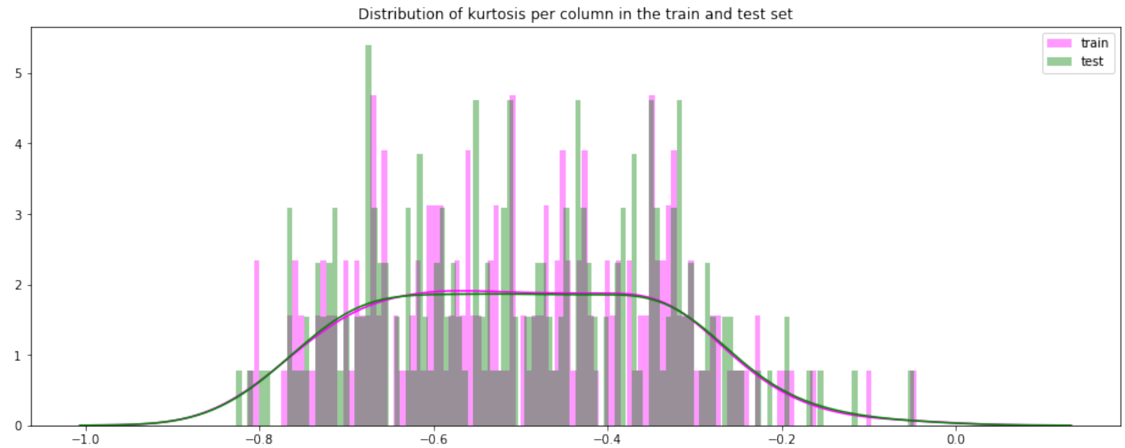
3.17 Univariate analysis on kurtosis values in the train set and the test set.
3.17.1 Distribution of kurtosis per row in the train and test set

```
In [0]: plt.figure(figsize=(16,6))
        plt.title("Distribution of kurtosis per row in the train and test set")
        sns.distplot(train_df[features].kurtosis(axis=1),color="darkblue", kde=True,bins=120, l
        sns.distplot(test_df[features].kurtosis(axis=1),color="yellow", kde=True,bins=120, labe
        plt.legend()
        plt.show()
```



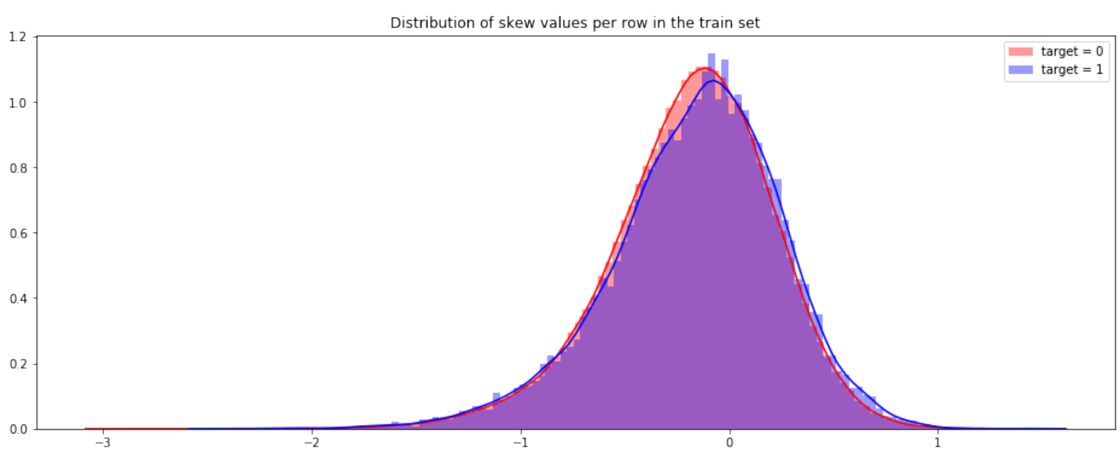
3.17.2 Distribution of kurtosis per column in the train and test set

In [0]:
```
plt.figure(figsize=(16,6))
plt.title("Distribution of kurtosis per column in the train and test set")
sns.distplot(train_df[features].kurtosis(axis=0),color="magenta", kde=True,bins=120, la
sns.distplot(test_df[features].kurtosis(axis=0),color="green", kde=True,bins=120, label
plt.legend()
plt.show()
```



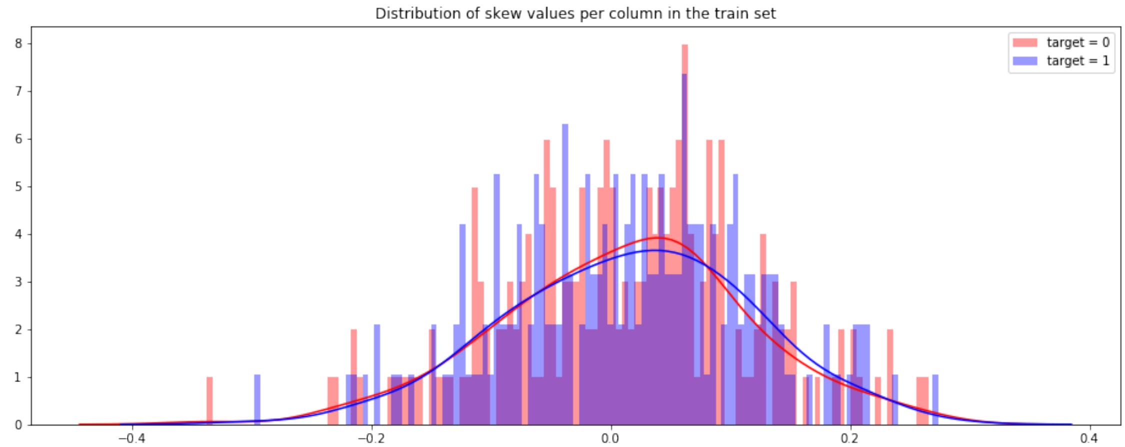
3.18 Univariate analysis on skew values based on targets of the train set.
3.18.1 Distribution of skew values per row in the train set

In [0]:
```
t0 = train_df.loc[train_df['target'] == 0]
t1 = train_df.loc[train_df['target'] == 1]
plt.figure(figsize=(16,6))
plt.title("Distribution of skew values per row in the train set")
sns.distplot(t0[features].skew(axis=1),color="red", kde=True,bins=120, label='target =
sns.distplot(t1[features].skew(axis=1),color="blue", kde=True,bins=120, label='target =
plt.legend(); plt.show()
```



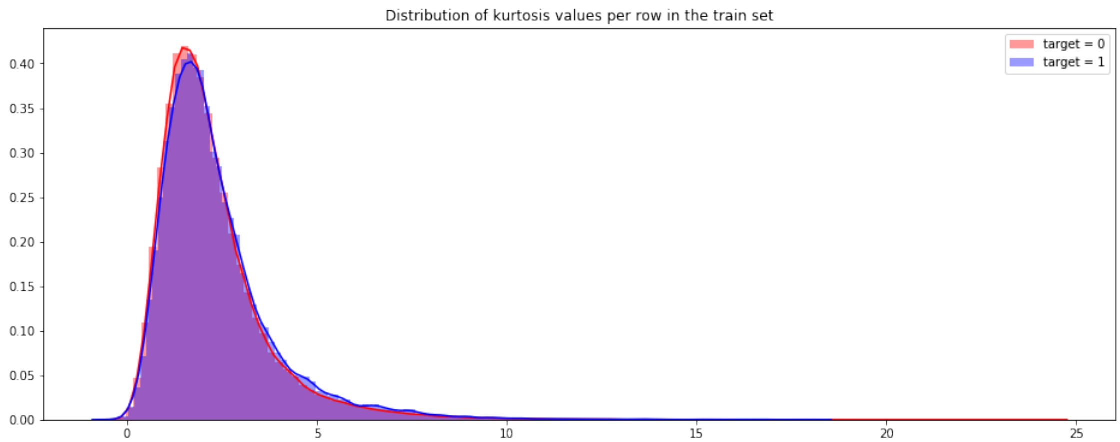
3.18.2 Distribution of skew values per column in the train set

```
In [0]: t0 = train_df.loc[train_df['target'] == 0]
        t1 = train_df.loc[train_df['target'] == 1]
        plt.figure(figsize=(16,6))
        plt.title("Distribution of skew values per column in the train set")
        sns.distplot(t0[features].skew(axis=0),color="red", kde=True,bins=120, label='target =
        sns.distplot(t1[features].skew(axis=0),color="blue", kde=True,bins=120, label='target =
        plt.legend(); plt.show()
```



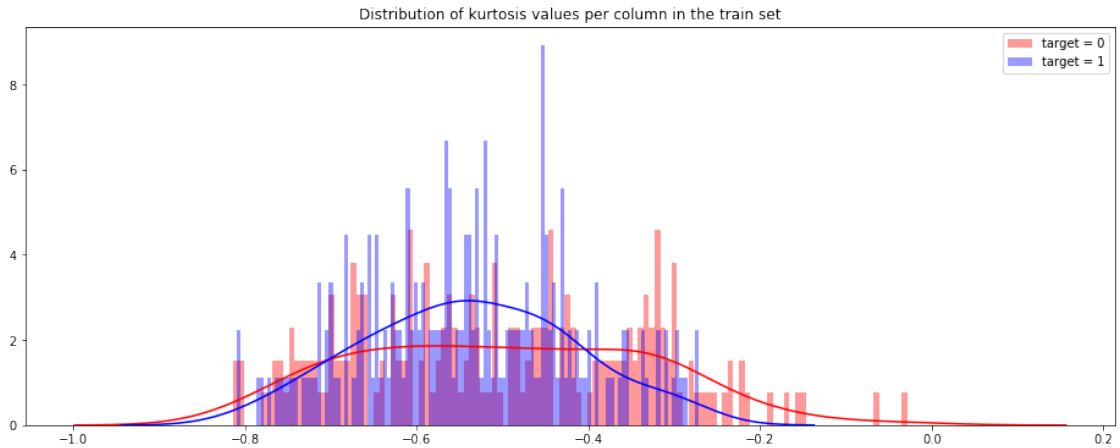
3.19 Univariate analysis on kurtosis values based on targets of the train set.
3.19.1 Distribution of kurtosis values per row in the train set

```
In [0]: t0 = train_df.loc[train_df['target'] == 0]
        t1 = train_df.loc[train_df['target'] == 1]
        plt.figure(figsize=(16,6))
        plt.title("Distribution of kurtosis values per row in the train set")
        sns.distplot(t0[features].kurtosis(axis=1),color="red", kde=True,bins=120, label='targe
        sns.distplot(t1[features].kurtosis(axis=1),color="blue", kde=True,bins=120, label='targ
        plt.legend(); plt.show()
```



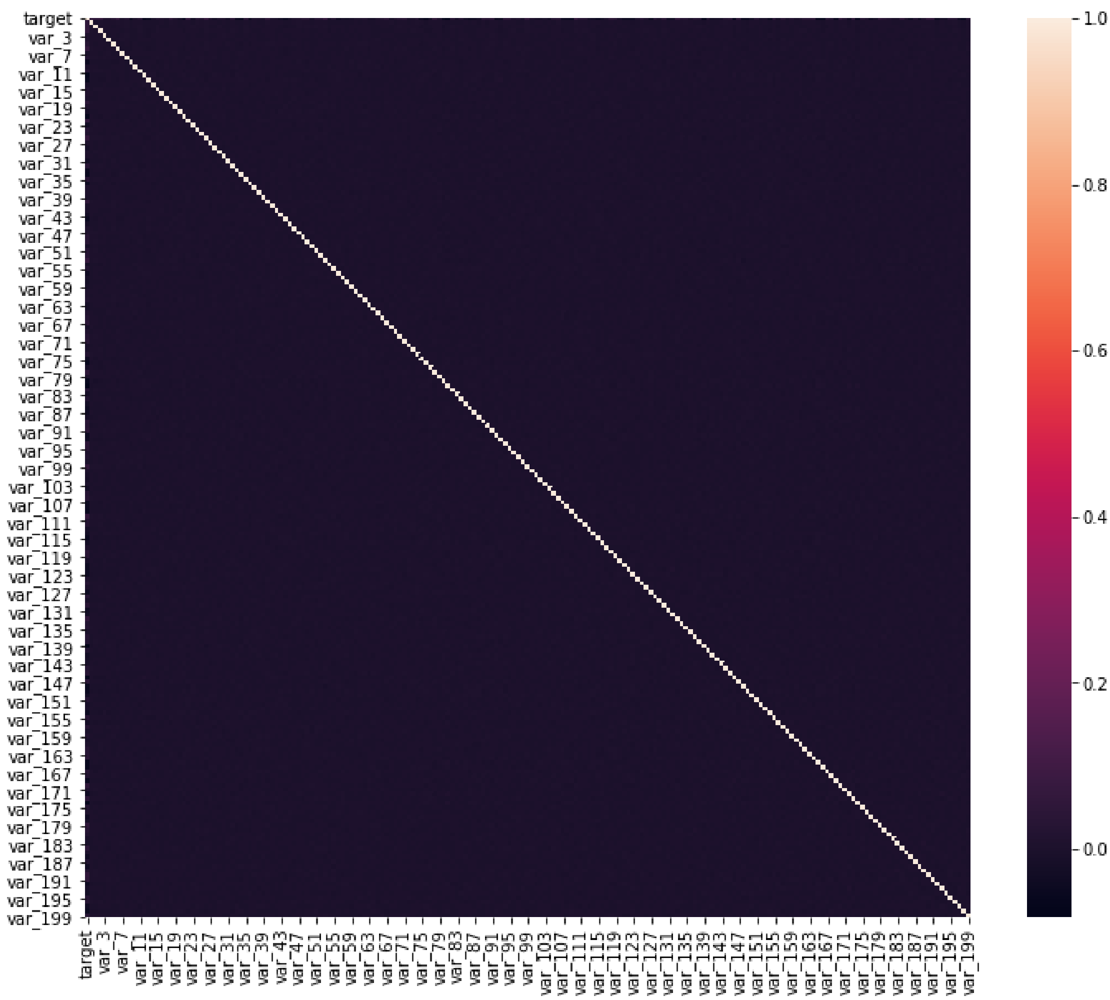
3.19.2 Distribution of kurtosis values per column in the train set

```
In [0]: t0 = train_df.loc[train_df['target'] == 0]
        t1 = train_df.loc[train_df['target'] == 1]
        plt.figure(figsize=(16,6))
        plt.title("Distribution of kurtosis values per column in the train set")
        sns.distplot(t0[features].kurtosis(axis=0),color="red", kde=True,bins=120, label='targe
        sns.distplot(t1[features].kurtosis(axis=0),color="blue", kde=True,bins=120, label='targ
        plt.legend(); plt.show()
```



4. Correlation Analysis

```
In [0]: train_corr=train_df.corr()
        plt.figure(figsize=(12, 10))
        sns.heatmap(train_corr)

Out[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9526146978>
```



- If value of correlation coefficient is +1 or -1, then variables are strongly connected to each other and when correlation is 0, then variables are not correlated to each other and are independent. Here, variables are independent to each other.

5. Analysing the unique value count of the features.

```
In [0]: df_no=train_df.loc[train_df.target==0,:].drop(['ID_code','target'],axis=1)
        df_yes=train_df.loc[train_df.target==1,:].drop(['ID_code','target'],axis=1)
```

```
In [37]: df_yes.head(1)
```

```
Out[37]:       var_0    var_1    var_2  var_3  ...  var_196  var_197  var_198  var_199
         13  16.3699  1.5934  16.7395  7.333  ...   9.6846   9.0419  15.6064 -10.8529

         [1 rows x 200 columns]
```

```
In [38]: df_no.head(1)
```

```
Out[38]:      var_0    var_1     var_2  var_3  ...  var_196  var_197  var_198  var_199
         0  8.9255 -6.7863  11.9081  5.093  ...   7.8784   8.5635  12.7803  -1.0914

         [1 rows x 200 columns]
```

```
In [40]: df_no_unique=df_no.nunique()
         df_yes_unique=df_yes.nunique()
         df_yes_unique.var_170
```

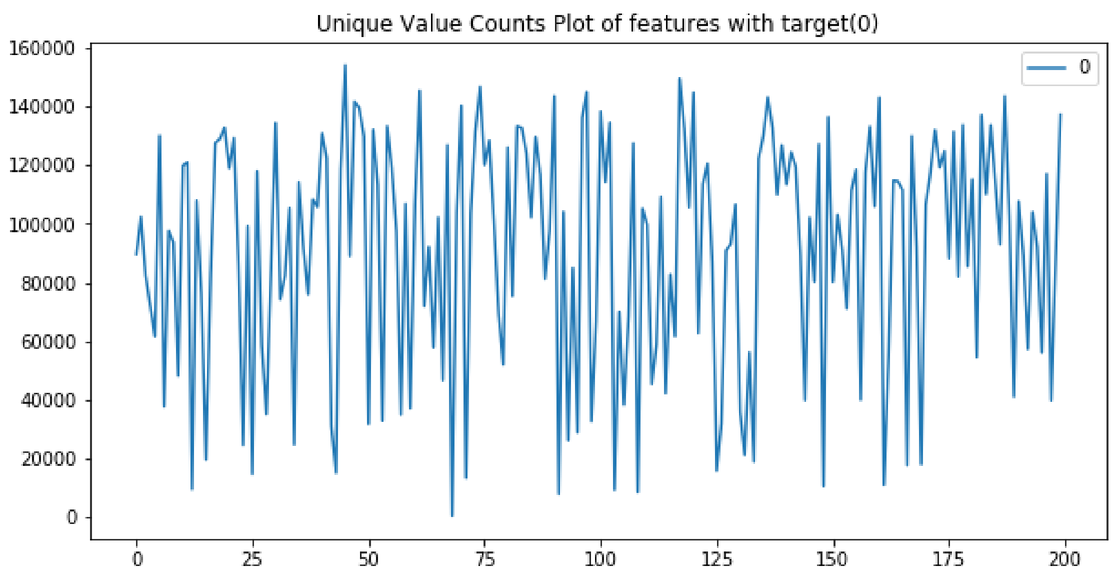
```
Out[40]: 18646
```

```
In [41]: df_no_unique.var_170
```

```
Out[41]: 106555
```

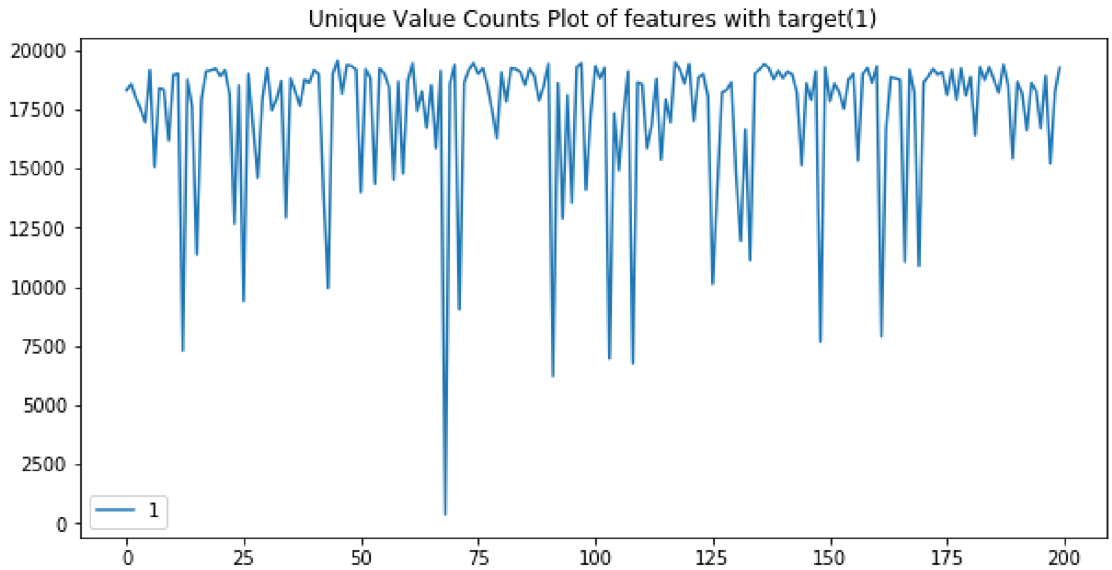
```
In [43]: plt.figure(figsize=(10,5))
         plt.plot(df_no_unique.values, label = '0')
         plt.title('Unique Value Counts Plot of features with target(0)')
         plt.legend()
```

```
Out[43]: <matplotlib.legend.Legend at 0x7f469a0b9ef0>
```

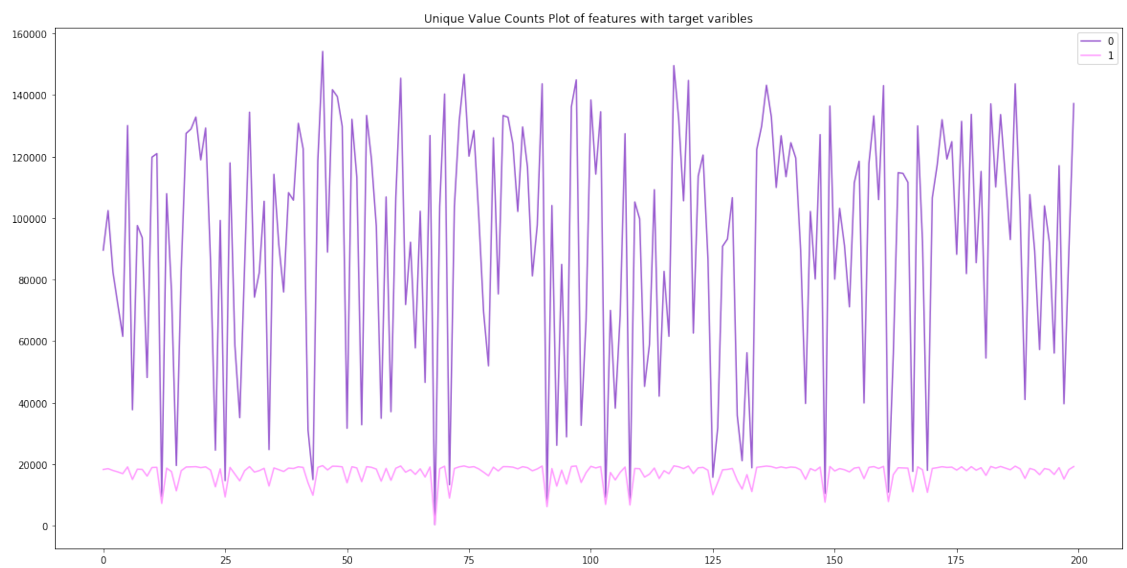



```
In [44]: plt.figure(figsize=(10,5))
         plt.plot(df_yes_unique.values, label = '1')
         plt.title('Unique Value Counts Plot of features with target(1)')
         plt.legend()
```

```
Out[44]: <matplotlib.legend.Legend at 0x7f469a95e1d0>
```



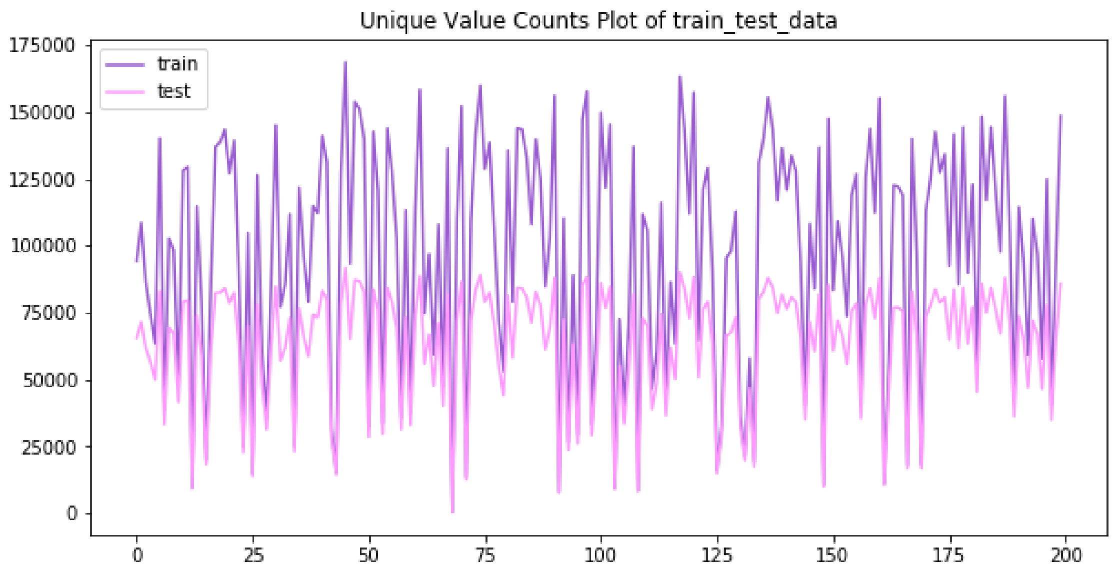

```
In [45]: plt.figure(figsize=(20,10))
         plt.plot(df_no_unique.values, label = '0',c='#995BD0')
         plt.plot(df_yes_unique.values, label = '1',c='#FF99FF')
         plt.title('Unique Value Counts Plot of features with target varibles')
         plt.legend()

Out[45]: <matplotlib.legend.Legend at 0x7f469a8430f0>
```



- As the data is imbalanced there will be some difference in there count values. So 200 new features representing the count of that particular value in that feature can be been created.

```
In [0]: data = train_df.drop(['ID_code','target'],axis=1)
        test = test_df.drop(['ID_code'],axis=1)
        d_uq=data.nunique()
        t_uq=test.nunique()
```

```
In [47]: plt.figure(figsize=(10,5))
         plt.plot(d_uq.values, label = 'train',c='#995BD0')
         plt.plot(t_uq.values, label = 'test',c='#FF99FF')
         plt.title('Unique Value Counts Plot of train_test_data')
         plt.legend()
         plt.show()
```



It can be seen that there are less unique values in test data as compared to train data.

6. PCA

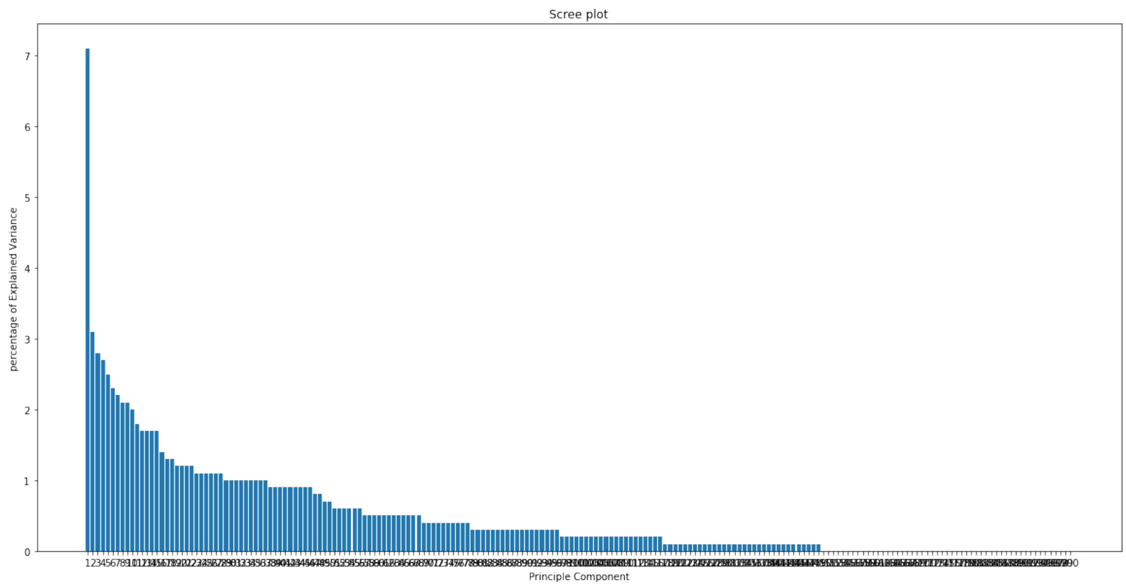
Performing Principal Component Analysis to find how many features of the total existing features explain the maximum variance in the dataset

```
In [0]: train_tran = train_df.iloc[:, 2:]
```

```
In [0]: pca = PCA()
        pca.fit(train_tran)
        pca.data = pca.transform(train_tran)
```

```
In [0]: #Percentage variance of each pca component stands for
        per_var = np.round(pca.explained_variance_ratio_*100, decimals = 1)
        #Create labels for the scree plot
        labels = [str(x) for x in range(1, len(per_var)+1)]
```

```
#Plot the data
plt.figure(figsize = (20, 10))
plt.bar(x=range(1, len(per_var)+1), height=per_var, tick_label = labels)
plt.ylabel('percentage of Explained Variance')
plt.xlabel('Principle Component')
plt.title('Scree plot')
plt.show()
```




```
In [0]: print('PC1 + PC150 add up to ' +  str(sum(per_var[:150])) + ' % of the variance')
```

```
PC1 + PC150 add up to 99.3999999999999 % of the variance
```

- It turns out that out of the existing 200 features top 150 features explain approximately 99.5% of the total variance of the dataset

7. Feature Engineering

Adding some basic features

```
In [20]: #creating new features and storing them by creating a new pandas dataframe
         train_df_basic_f=pd.read_csv('train.csv')
         test_df_basic_f=pd.read_csv('test.csv')
         #remove outliers in train and test data
         for col in tqdm(numerical_features):
             train_df_basic_f=train_df_basic_f.loc[(~chauvenet(train_df_basic_f[col].values))]
         for col in tqdm(numerical_features):
             test_df_basic_f=test_df_basic_f.loc[(~chauvenet(test_df_basic_f[col].values))]
```

```
100%|| 200/200 [00:16<00:00, 12.19it/s]
100%|| 200/200 [00:16<00:00, 11.97it/s]
```

7.1 New features by taking the unique value count of all 200 originally existing features and thus creating 200 more new features

```
In [0]: for feat in ['var_' + str(x) for x in range(200)]:
          train_count_values=train_df_basic_f.groupby(feat)[feat].count()
          test_count_values=test_df_basic_f.groupby(feat)[feat].count()
          train_df_basic_f['new_'+feat]=train_count_values.loc[train_df[feat]].values
          test_df_basic_f['new_'+feat]=test_count_values.loc[test_df_basic_f[feat]].values
```

```
In [22]: train_df_basic_f.head()
```

```
Out[22]:    ID_code  target    var_0  ...  new_var_197  new_var_198  new_var_199
         0  train_0       0   8.9255  ...           13            5            2
         1  train_1       0  11.5006  ...           12            2            1
         2  train_2       0   8.6093  ...            8            2            2
         3  train_3       0  11.0604  ...            4            2            2
         4  train_4       0   9.8369  ...            6            2            2

         [5 rows x 402 columns]
```

```
In [23]: test_df_basic_f.head()
```

```
Out[23]:   ID_code    var_0    var_1  ...  new_var_197  new_var_198  new_var_199
         0  test_0  11.0656   7.7798  ...            5            5            4
         1  test_1   8.5304   1.2543  ...            9            3            7
         2  test_2   5.4827 -10.3581  ...            5            6            2
         3  test_3   8.5374  -1.3222  ...            1            6            3
         4  test_4  11.7058  -0.1327  ...            6            5            5

         [5 rows x 401 columns]
```

- From the above result it can be seen that 200 new features have been derived.

7.2 New features by taking the sum, min_value, max_value, mean_value, std_dev_value, skew_value, kurtosis_value and the median value of the originally existing 200 features of the train set.

```
In [0]: idx = features = train_df_basic_f.columns.values[2:202]
        for df in [test_df_basic_f, train_df_basic_f]:
            df['sum'] = df[idx].sum(axis=1)
            df['min'] = df[idx].min(axis=1)
            df['max'] = df[idx].max(axis=1)
            df['mean'] = df[idx].mean(axis=1)
            df['std'] = df[idx].std(axis=1)
            df['skew'] = df[idx].skew(axis=1)
            df['kurt'] = df[idx].kurtosis(axis=1)
            df['med'] = df[idx].median(axis=1)
```

In [25]: train_df_basic_f.head()

```
Out[25]:    ID_code  target    var_0   var_1  ...        std      skew      kurt      med
         0  train_0       0   8.9255 -6.7863  ...   9.331540  0.101580  1.331023  6.77040
         1  train_1       0  11.5006 -4.1473  ...  10.336130 -0.351734  4.110215  7.22315
         2  train_2       0   8.6093 -2.7457  ...   8.753387 -0.056957  0.546438  5.89940
         3  train_3       0  11.0604 -2.1518  ...   9.594064 -0.480116  2.630499  6.70260
         4  train_4       0   9.8369 -1.4834  ...  11.287122 -1.463426  9.787399  6.94735

         [5 rows x 410 columns]
```

In [26]: test_df_basic_f.head()

```
Out[26]:   ID_code    var_0    var_1    var_2  ...        std      skew      kurt      med
         0  test_0  11.0656   7.7798  12.9536  ...   9.910632 -0.088518  1.871262  7.31440
         1  test_1   8.5304   1.2543  11.3047  ...   9.541267 -0.559785  3.391068  6.43960
         2  test_2   5.4827 -10.3581  10.1407  ...   9.967466 -0.135084  2.326901  7.26355
         3  test_3   8.5374  -1.3222  12.0220  ...   8.257204 -0.167741  2.253054  6.89675
         4  test_4  11.7058  -0.1327  14.1295  ...  10.043542  0.293484  2.044943  6.83375

         [5 rows x 409 columns]
```

- From the above result it can be seen that 8 new features have been derived.

In [0]:
```python
#saving to csv
train_df_basic_f.to_csv('basic_train.csv')
test_df_basic_f.to_csv('basic_test.csv')
```

In [27]:
```python
print(train_df.shape)
print(test_df.shape)
print(train_df_basic_f.shape)
print(test_df_basic_f.shape)
```

```
(198264, 202)
(198250, 201)
(198264, 410)
(198250, 409)
```

From the above result it can be seen that in total of 408 new features have been derived by using some basic feature engineering techniques.

Genetic Feature Engineering.

Using 199 of the 200 features to create an estimation of the missing feature. This estimation can be considered to be a "new feature" or a new classification of the current 199 features as being a member of the missing feature target. This can be repeated for every feature, giving 200 new features to add to the training (and testing) sets.

In [0]:
```python
#creating new features and storing them by creating a new pandas dataframe
train_df_genetic_f=pd.read_csv('train.csv')
```

```
test_df_genetic_f=pd.read_csv('test.csv')
#remove outliers in train and test data
for col in tqdm(numerical_features):
    train_df_genetic_f=train_df_genetic_f.loc[(~chauvenet(train_df_genetic_f[col].valu
for col in tqdm(numerical_features):
    test_df_genetic_f=test_df_genetic_f.loc[(~chauvenet(test_df_genetic_f[col].values)
```

```
100%|| 200/200 [00:23<00:00,  8.08it/s]
100%|| 200/200 [00:22<00:00,  8.42it/s]
```

```
In [0]: X1 = train_df_genetic_f.drop(['ID_code','target'],axis=1)
        X_test1 = test_df_genetic_f.drop('ID_code',axis=1)
```

Using the python library 'gplearn' for the process

From the website 'https://gplearn.readthedocs.io/en/stable/intro.html'

"Symbolic regression is a machine learning technique that aims to identify an underlying mathematical expression that best describes a relationship. It begins by building a population of naive random formulas to represent a relationship between known independent variables and their dependent variable targets in order to predict new data. Each successive generation of programs is then evolved from the one that came before it by selecting the fittest individuals from the population to undergo genetic operations."

```
In [0]: # Create a fitness function that is the mean absolute percentage error
        def _my_fit(y, y_pred, w):
            diffs = np.abs(y - y_pred)
            return 100. * np.average(diffs, weights=w)
        my_fit = make_fitness(_my_fit, greater_is_better=False)
```

```
In [0]: # Choose the mathematical functions we will combine together
        function_set = ['add', 'sub', 'mul', 'div', 'log',
                         'sqrt', 'log', 'abs', 'neg', 'inv',
                         'max', 'min',
                         'sin', 'cos', 'tan' ]

        # Create the genetic learning regressor
        gp = SymbolicRegressor(function_set=function_set, metric = my_fit,
                               verbose=1, generations = 3,
                               random_state=0, n_jobs=-1)
```

```
In [0]: # Using NUMPY structures, remove one feature (column of data) at a time from the train
        # Use that removed column as the target for the algorithm
        # Use the genetically engineered formula to create the new feature
        # Do this for both the training set and the test set

        X1a = np.array(X1)
        sam = X1a.shape[0]
        col = X1a.shape[1]
        X2a = np.zeros((sam, col))
```

```
X_test1a = np.array(X_test1)
sam_test = X_test1a.shape[0]
col_test = X_test1a.shape[1]
X_test2a = np.zeros((sam_test, col_test))

for i in range(col) :
    X = np.delete(X1a,i,1)
    y = X1a[:,i]
    gp.fit(X, y)
    X2a[:,i] = gp.predict(X)
    X = np.delete(X_test1a, i, 1)
    X_test2a[:,i] = gp.predict(X)

X2 = pd.DataFrame(X2a)
X_test2 = pd.DataFrame(X_test2a)
```

In [0]:
```
train_genetic = X1.to_numpy()
```

In [0]:
```
test_genetic = X_test1.to_numpy()
```

In [0]:
```
train_genetic_ = X2.to_numpy()
test_genetic_ = X_test2.to_numpy()
```

In [0]:
```
X_train_genetic_f=np.column_stack((train_genetic, train_genetic_))
```

In [0]:
```
X_test_genetic_f=np.column_stack((test_genetic, test_genetic_))
```

In [0]:
```
print(X_train_genetic_f.shape)
print(X_test_genetic_f.shape)
```

```
(198264, 400)
(198250, 400)
```

In [0]:
```
train_genetic_df=pd.DataFrame(data=X_train_genetic_f[0:, 0:],
                              index=[i for i in range(X_train_genetic_f.shape[0])],
                              columns=['var'+str(i) for i in range(X_train_genetic_f.sh
```

In [0]:
```
test_genetic_df=pd.DataFrame(data=X_test_genetic_f[0:, 0:],
                             index=[i for i in range(X_test_genetic_f.shape[0])],
                             columns=['var'+str(i) for i in range(X_test_genetic_f.sha
```

In [0]:
```
train_genetic_df['ID_code']=train_df['ID_code']
```

In [0]:
```
train_genetic_df['target']=train_df['target']
test_genetic_df['ID_code']=test_df['ID_code']
```

In [0]:
```
print(train_genetic_df.shape)
print(test_genetic_df.shape)
```

```
(198264, 402)
(198250, 401)
```

```
In [0]: #saving to csv
        train_genetic_df.to_csv('genetic_train.csv')
        test_genetic_df.to_csv('genetic_test.csv')
```

8. Models for Classification.

Note:- Since after the feature engineering now there are three sets of datasets,

- Original dataset with no additional features.
- Dataset with the original features as well as new basic features.
- Dataset with the original features as well as genetically engineered features.

All the machine learning models are tried on these three variants of the datasets.
8.1. Logistic Regression without class balancing.
8.1.1 On the original dataset with no added features.
Preparing the dataset.

```
In [0]: features = train_df.drop(['ID_code','target'],axis=1)
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 200) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 200) (158611,)
(39653, 200) (39653,)
```

Finding the suitable parameters for the model.

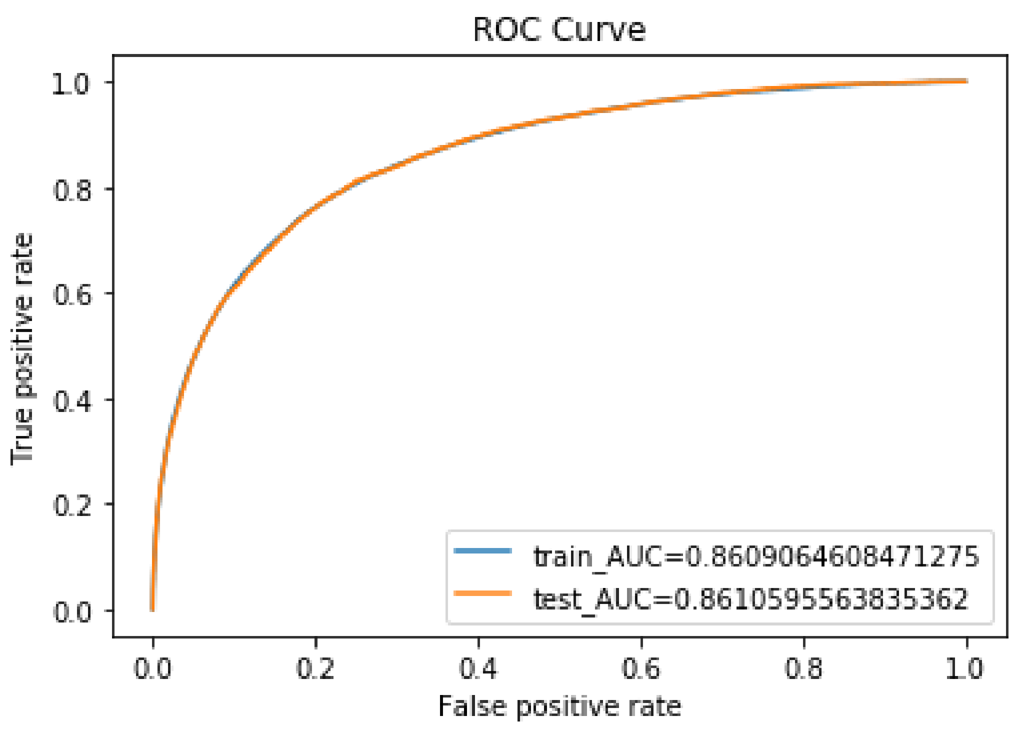
```
In [0]: parameters={'C':[10**-6, 10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10, 10**2, 10*
        lr=LogisticRegression()
        model=GridSearchCV(lr, parameters, scoring='roc_auc', cv=2, n_jobs=-1)
        model.fit(X_train, y_train)
        print(model.best_estimator_)
```

```
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

Running the optimal model and looking at the results.

```
In [0]: lr_optimal=LogisticRegression(C=0.001, penalty='l2')

        lr_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, lr_optimal.predict_proba(X_train)
        test_fpr, test_tpr, thresholds = roc_curve(y_test, lr_optimal.predict_proba(X_test)[:,
```

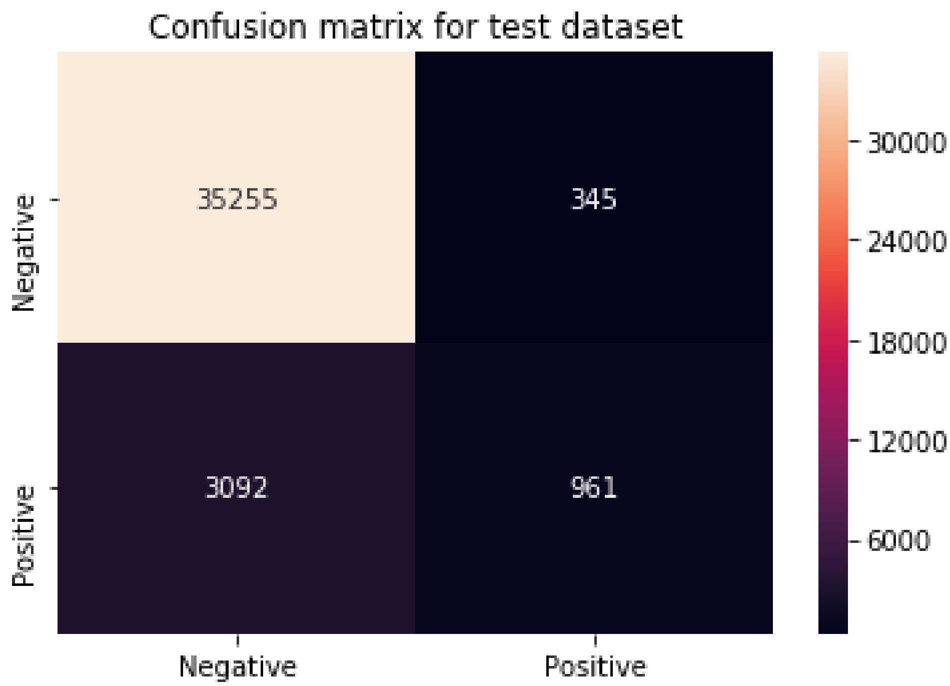
```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```




```
In [0]: pred=lr_optimal.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
```

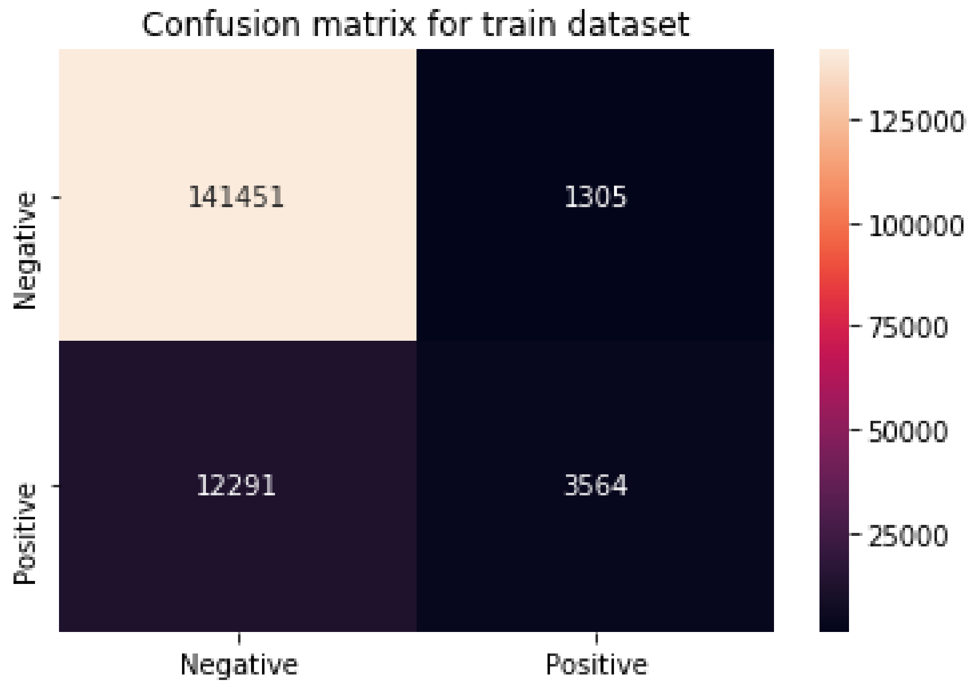
```
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "]
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')




```
In [0]: predictions=lr_optimal.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "]
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")
```

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.92      0.99      0.95     35600
positive_class       0.74      0.24      0.36      4053

      accuracy                           0.91     39653
     macro avg       0.83      0.61      0.66     39653
  weighted avg       0.90      0.91      0.89     39653
```

From the above results it can be observed that only logistic regression on the original dataset with no added features gave good results.

8.1.2 On the dataset with the original and the basic features.

Preparing the dataset.

```
In [0]: features = train_df_basic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 408) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 408) (158611,)
(39653, 408) (39653,)
```

Finding the suitable parameters for the model.

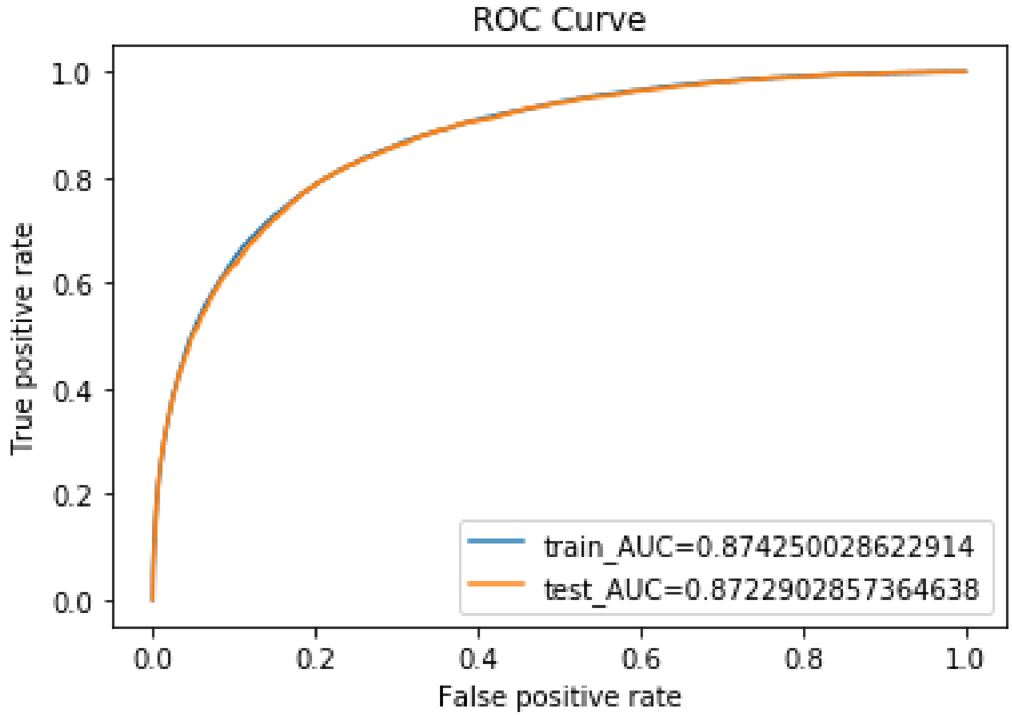
```
In [0]: parameters={'C':[10**-6, 10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10, 10**2, 10*
        lr=LogisticRegression(solver='saga')
        model=GridSearchCV(lr, parameters, scoring='roc_auc', cv=2, n_jobs=-1)
        model.fit(X_train, y_train)
        print(model.best_estimator_)
```

```
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l1',
                   random_state=None, solver='saga', tol=0.0001, verbose=0,
                   warm_start=False)
```

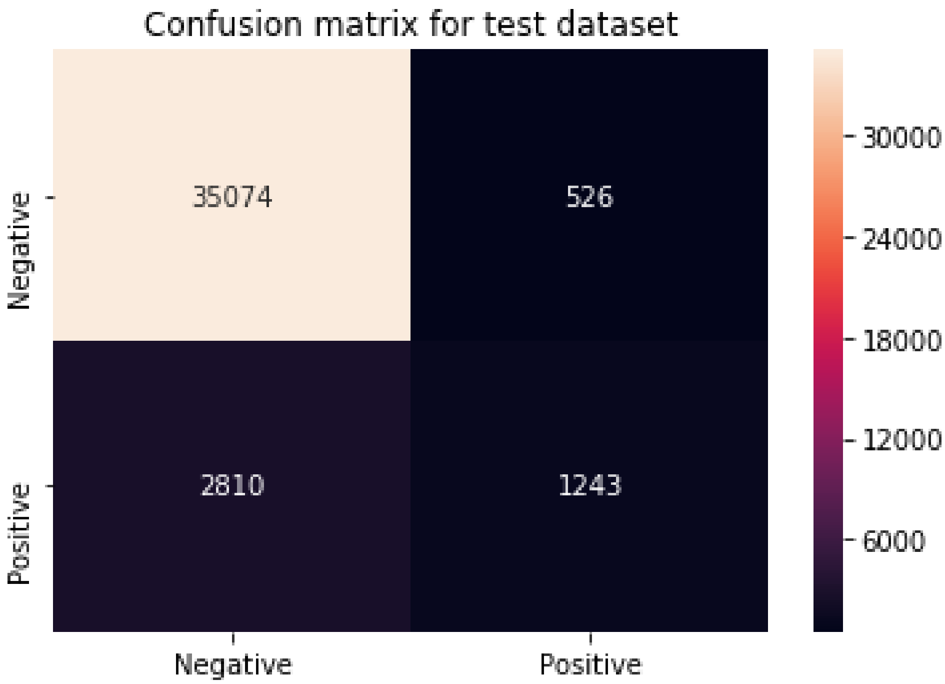
Running the optimal model and looking at the results.

```
In [0]: lr_optimal=LogisticRegression(C=0.1, penalty='l1', solver='saga')

        lr_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, lr_optimal.predict_proba(X_train
        test_fpr, test_tpr, thresholds = roc_curve(y_test, lr_optimal.predict_proba(X_test)[:,
```

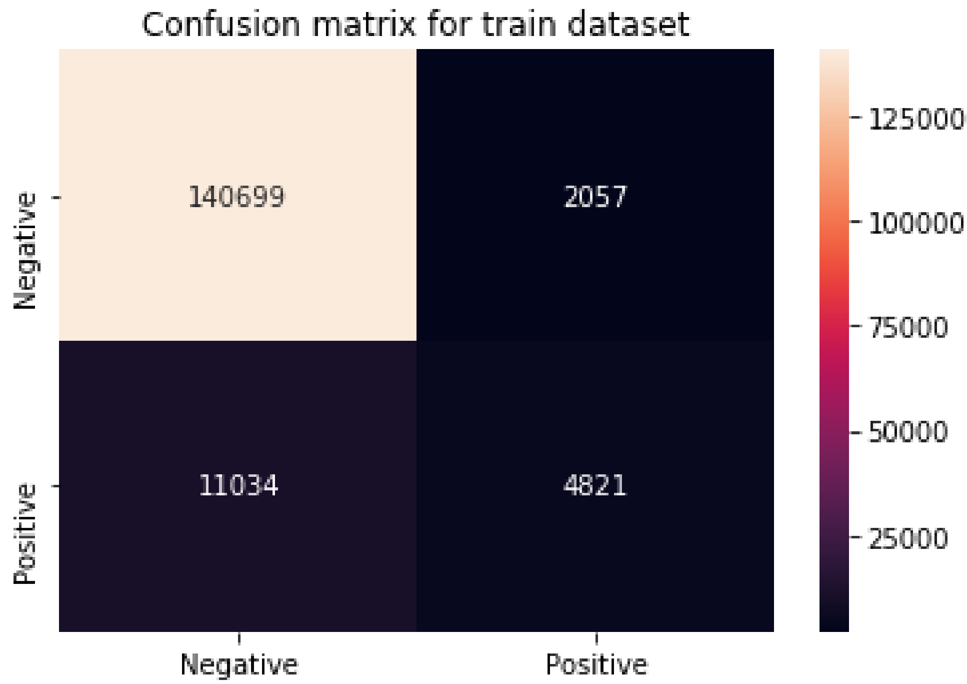
```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```




```
In [0]: pred=lr_optimal.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=lr_optimal.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.93      0.99      0.95     35600
positive_class       0.70      0.31      0.43      4053

      accuracy                           0.92     39653
     macro avg       0.81      0.65      0.69     39653
  weighted avg       0.90      0.92      0.90     39653
```

From the above results it can be seen that there is an improvement in the performance of the model due to the added parameters but the improvement is very minute.

8.1.3 On the dataset with original features and the genetic features

Preparing the dataset.

```
In [0]: features = train_df_genetic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 400) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 400) (158611,)
(39653, 400) (39653,)
```

Finding the optimal parameters for the model.

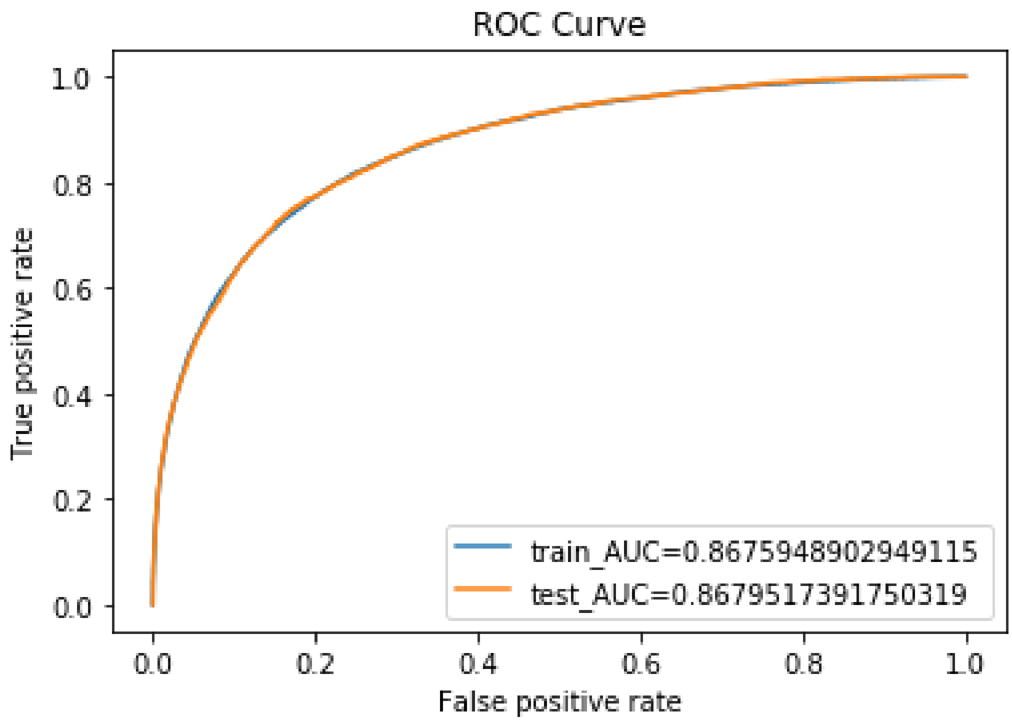
```
In [0]: parameters={'C':[10**-6, 10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10, 10**2, 10*
        lr=LogisticRegression(solver='saga')
        model=GridSearchCV(lr, parameters, scoring='roc_auc', cv=2, n_jobs=-1)
        model.fit(X_train, y_train)
        print(model.best_estimator_)
```

```
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l1',
                   random_state=None, solver='saga', tol=0.0001, verbose=0,
                   warm_start=False)
```

Running the model and looking at the results.

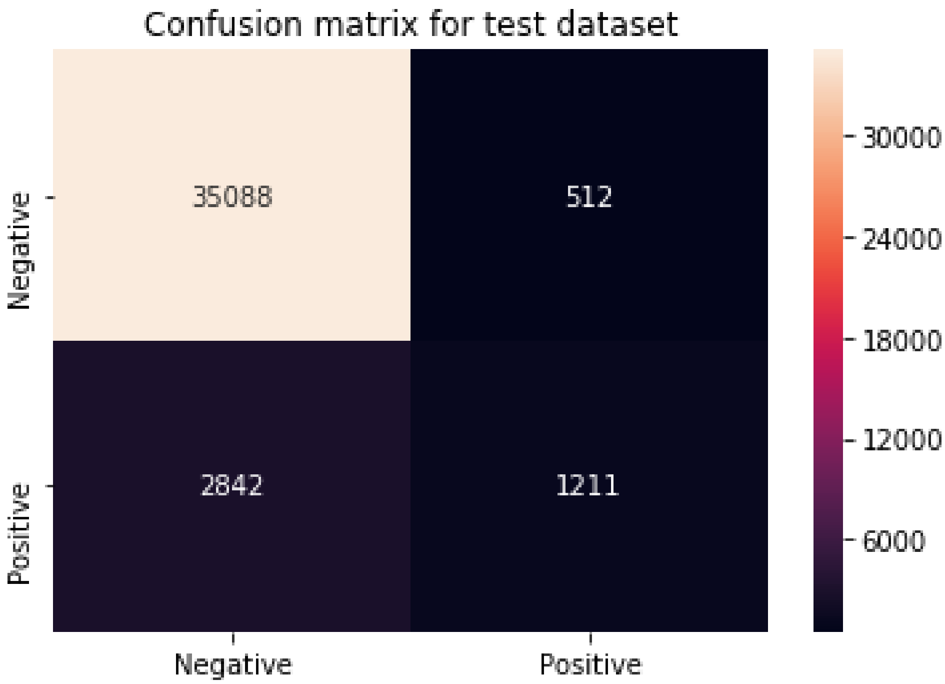
```
In [0]: lr_optimal=LogisticRegression(C=100, penalty='l1',solver='saga')

        lr_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, lr_optimal.predict_proba(X_train)
        test_fpr, test_tpr, thresholds = roc_curve(y_test, lr_optimal.predict_proba(X_test)[:,
```

```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```



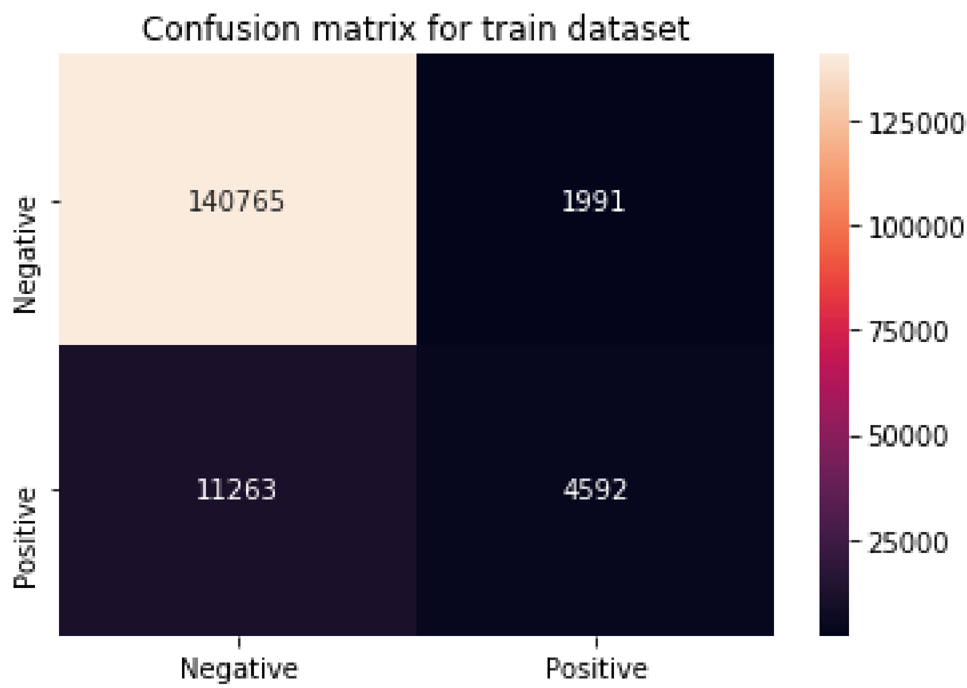
In [0]:
```
pred=lr_optimal.predict(X_test)
conf_matrix=confusion_matrix(y_test, pred)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')



In [0]:
```
predictions=lr_optimal.predict(X_train)
conf_matrix=confusion_matrix(y_train, predictions)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for train dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.93      0.99      0.95     35600
positive_class       0.70      0.30      0.42      4053

      accuracy                           0.92     39653
     macro avg       0.81      0.64      0.69     39653
  weighted avg       0.90      0.92      0.90     39653
```

From the above results it can be seen that their is no significant improvement in the results if compared to the results obtained from just the original dataset with no added features.

Comparing the results of all the three logistic regression (with no class balancing) models.

```
In [2]: x = PrettyTable()
        x.title = 'Results of all the three logistic regression (with no class balancing) mode
        x.field_names = ['Dataset form', 'Test AUC score', 'Train AUC score']
        x.add_row(['Only with original features', 0.86105, 0.86090])
        x.add_row(['With original and basic features', 0.87229, 0.87425 ])
        x.add_row(['With original and genetic features',0.86795, 0.86759])
        print(x)
```

```
+------------------------------------------------------------------------------------+
|   Results of all the three logistic regression (with no class balancing) models.  |
+-------------------------------------------+-------------------+--------------------+
|              Dataset form                 |   Test AUC score  |  Train AUC score   |
+-------------------------------------------+-------------------+--------------------+
|       Only with original features         |      0.86105      |       0.8609       |
|     With original and basic features      |      0.87229      |      0.87425       |
|    With original and genetic features     |      0.86795      |      0.86759       |
+-------------------------------------------+-------------------+--------------------+
```

8.2. Logistic Regression with class balancing.
8.2.1. On the original dataset with no added features.
Preparing the dataset.

```
In [0]: features = train_df.drop(['ID_code','target'],axis=1)
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 200) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 200) (158611,)
(39653, 200) (39653,)
```

Finding the suitable parameters for the models.

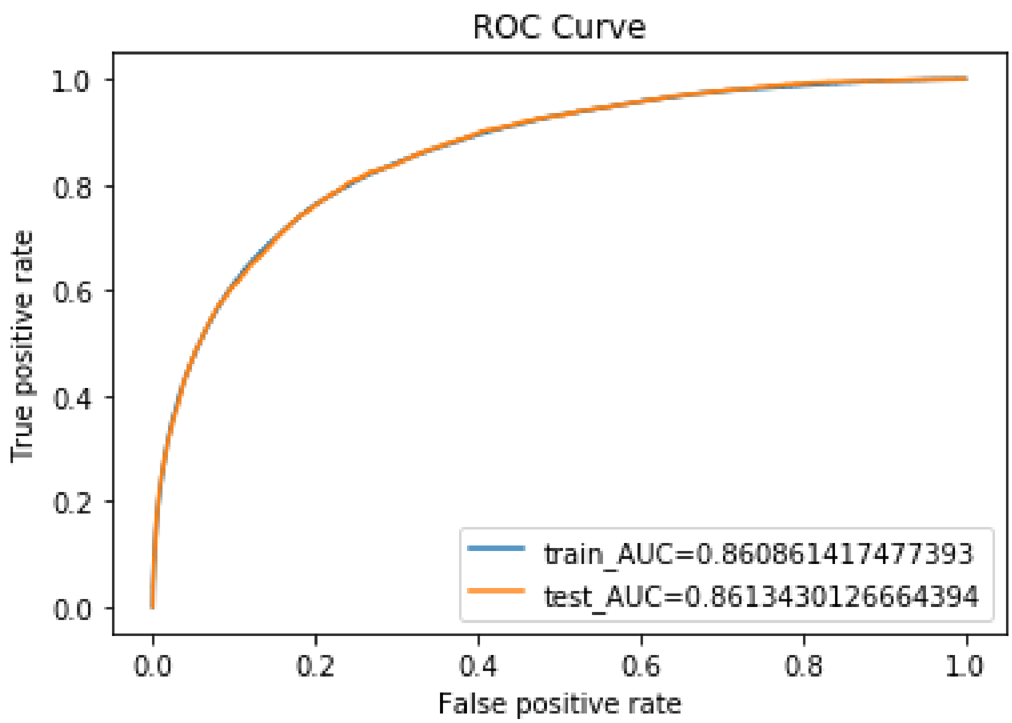
```
In [0]: parameters={'C':[10**-6, 10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10, 10**2, 10**
        lr=LogisticRegression(class_weight='balanced')
        model=GridSearchCV(lr, parameters, scoring='roc_auc', cv=2, n_jobs=-1)
        model.fit(X_train, y_train)
        print(model.best_estimator_)
```

```
LogisticRegression(C=1e-05, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

Running the model and looking at the results.

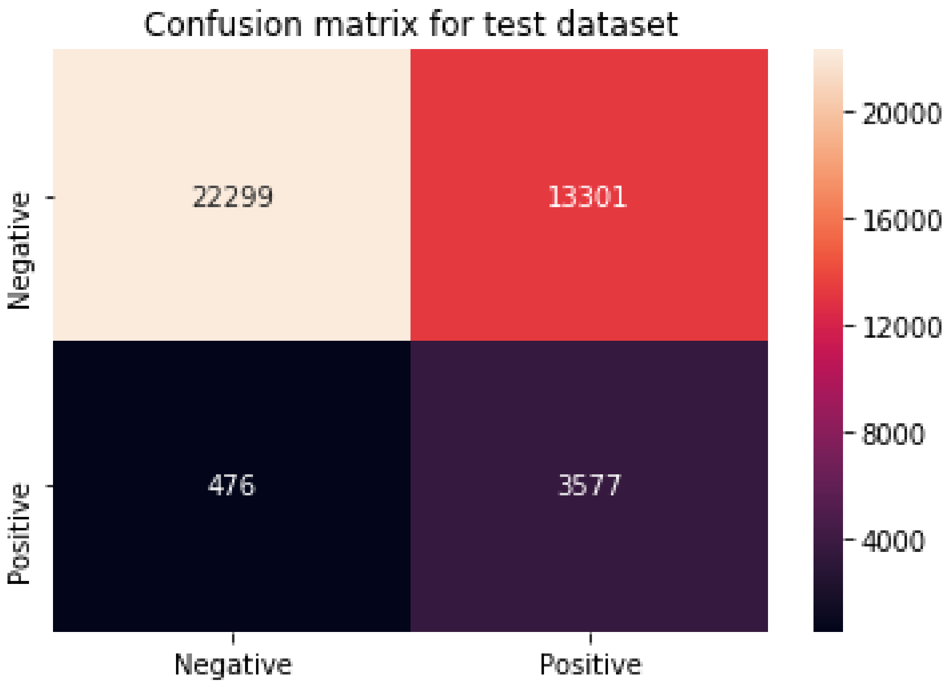
```
In [0]: lr_optimal=LogisticRegression(C=1e-05, penalty='l2', class_weight='balanced')

        lr_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, lr_optimal.predict_proba(X_train)
        test_fpr, test_tpr, thresholds = roc_curve(y_test, lr_optimal.predict_proba(X_test)[:,
```

```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```

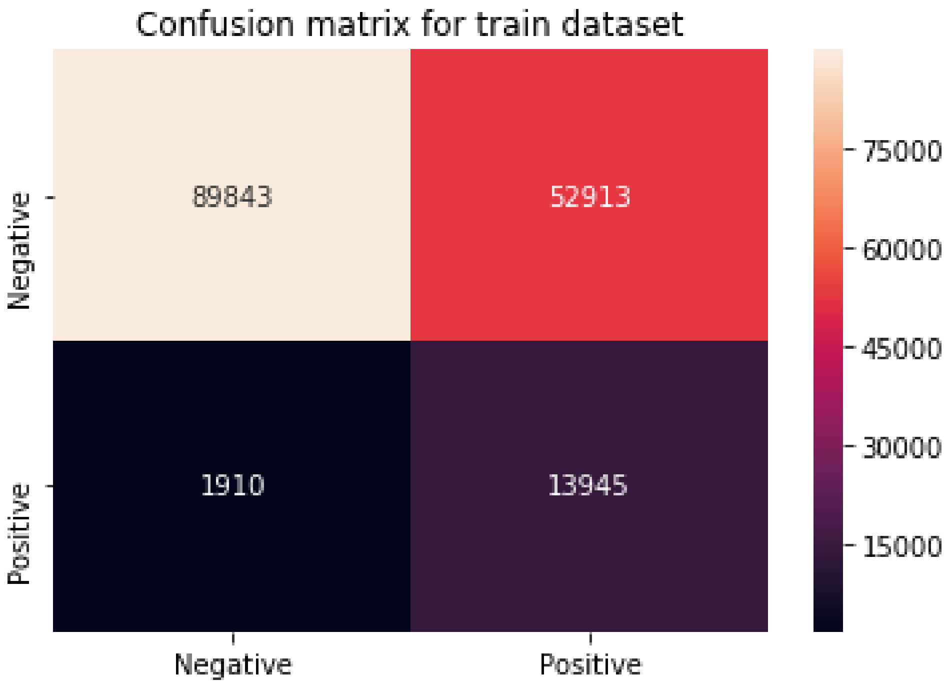



```
In [0]: pred=lr_optimal.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")
```

```
Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=lr_optimal.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.98      0.63      0.76     35600
positive_class       0.21      0.88      0.34      4053

      accuracy                           0.65     39653
     macro avg       0.60      0.75      0.55     39653
  weighted avg       0.90      0.65      0.72     39653
```

From the above cells it can be observed that there is no change in the AUC score but the model began to perform better on positive datapoints and worse on negative datapoints.

8.2.2. On the dataset with original and basic features

Preparing the dataset.

```
In [0]: features = train_df_basic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 408) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 408) (158611,)
(39653, 408) (39653,)
```

Finding the suitable parameters for the model.

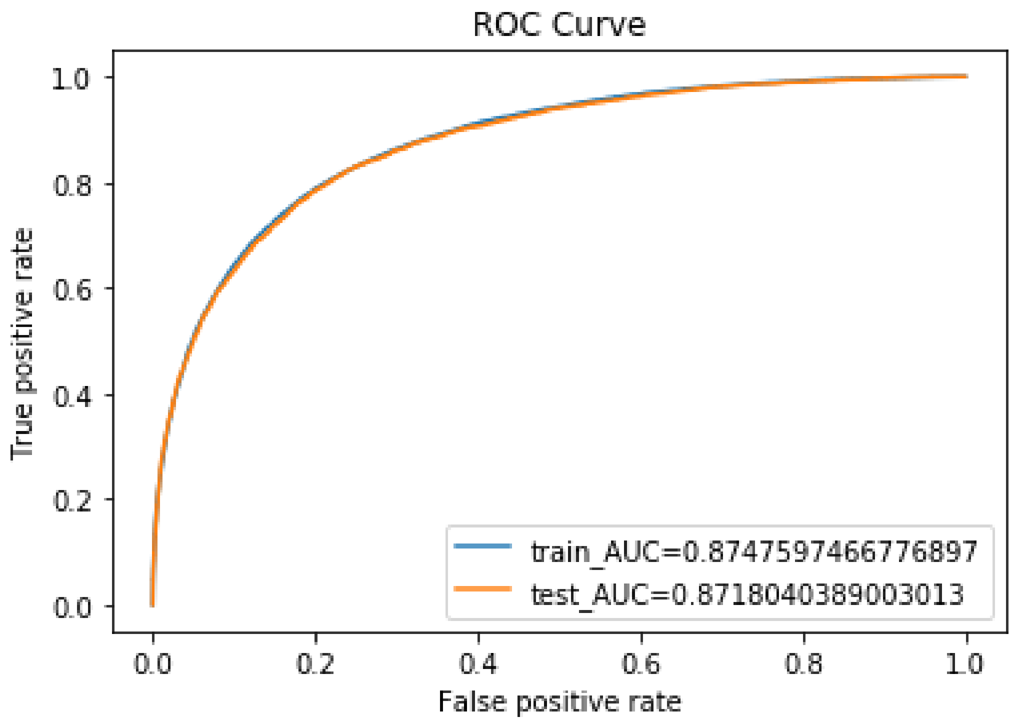
```
In [0]: parameters={'C':[10**-6, 10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10, 10**2, 10*
        lr=LogisticRegression(solver='saga', class_weight='balanced')
        model=GridSearchCV(lr, parameters, scoring='roc_auc', cv=2, n_jobs=-1)
        model.fit(X_train, y_train)
        print(model.best_estimator_)
```

```
LogisticRegression(C=0.1, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='warn', n_jobs=None, penalty='l1',
                   random_state=None, solver='saga', tol=0.0001, verbose=0,
                   warm_start=False)
```

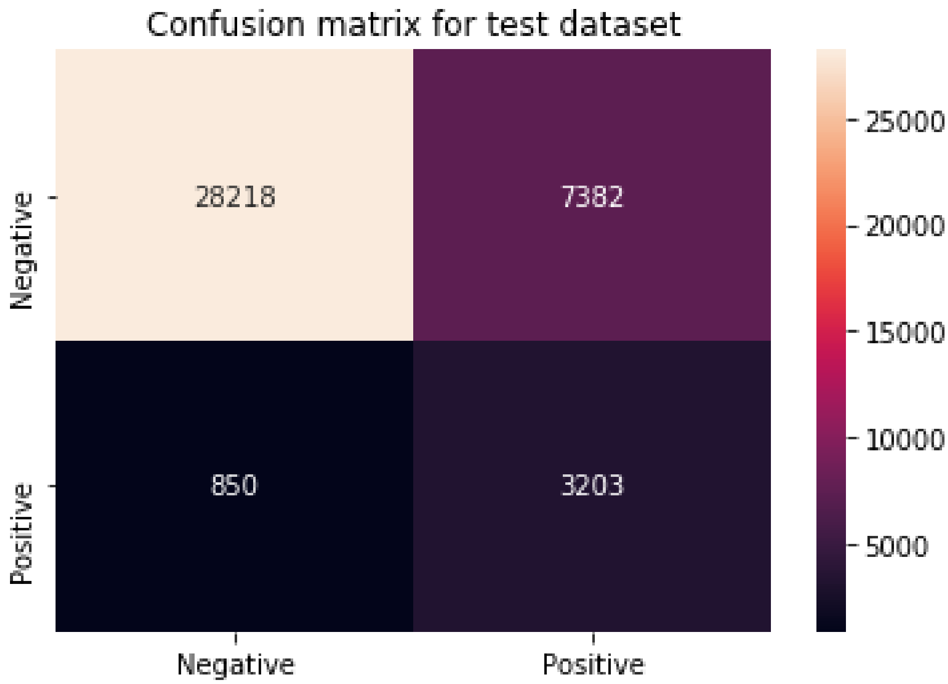
Running the model and looking at the results.

```
In [0]: lr_optimal=LogisticRegression(C=0.1, penalty='l1', solver='saga', class_weight='balanc

        lr_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, lr_optimal.predict_proba(X_train
        test_fpr, test_tpr, thresholds = roc_curve(y_test, lr_optimal.predict_proba(X_test)[:,
```

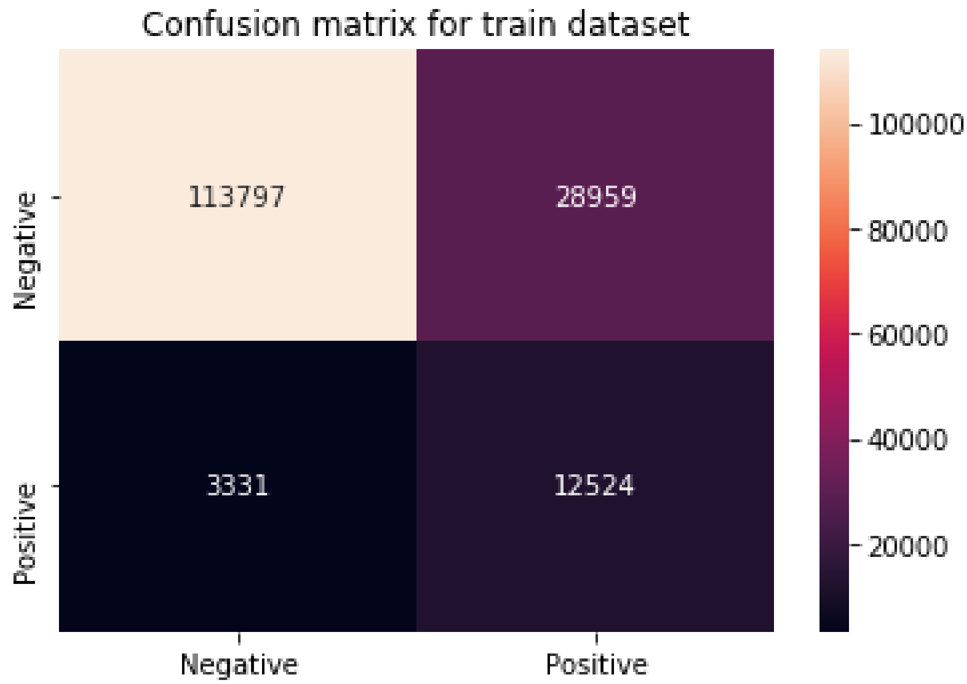
```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```




```
In [0]: pred=lr_optimal.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=lr_optimal.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.97      0.79      0.87     35600
positive_class       0.30      0.79      0.44      4053

      accuracy                           0.79     39653
     macro avg       0.64      0.79      0.66     39653
  weighted avg       0.90      0.79      0.83     39653
```

There is no improvement in the results but the model began to perform better on positive datapoints and worse on negative datapoints.

8.2.3. On the dataset with original features and genetic features.

Preparing the dataset.

```
In [0]: features = train_df_genetic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 400) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 400) (158611,)
(39653, 400) (39653,)
```

Finding the suitable parameters for the model.

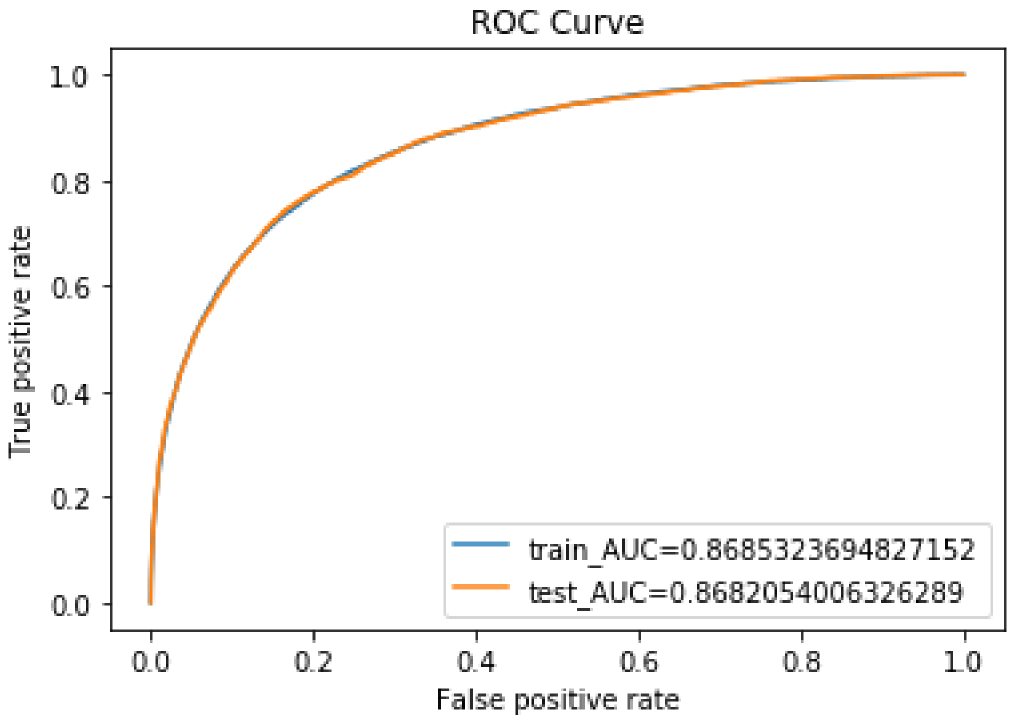
```
In [0]: parameters={'C':[10**-6, 10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10, 10**2, 10*
        lr=LogisticRegression(solver='saga', class_weight='balanced')
        model=GridSearchCV(lr, parameters, scoring='roc_auc', cv=2, n_jobs=-1)
        model.fit(X_train, y_train)
        print(model.best_estimator_)
```

```
LogisticRegression(C=100, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='saga', tol=0.0001, verbose=0,
                   warm_start=False)
```

Running the optimal model and looking at the results.

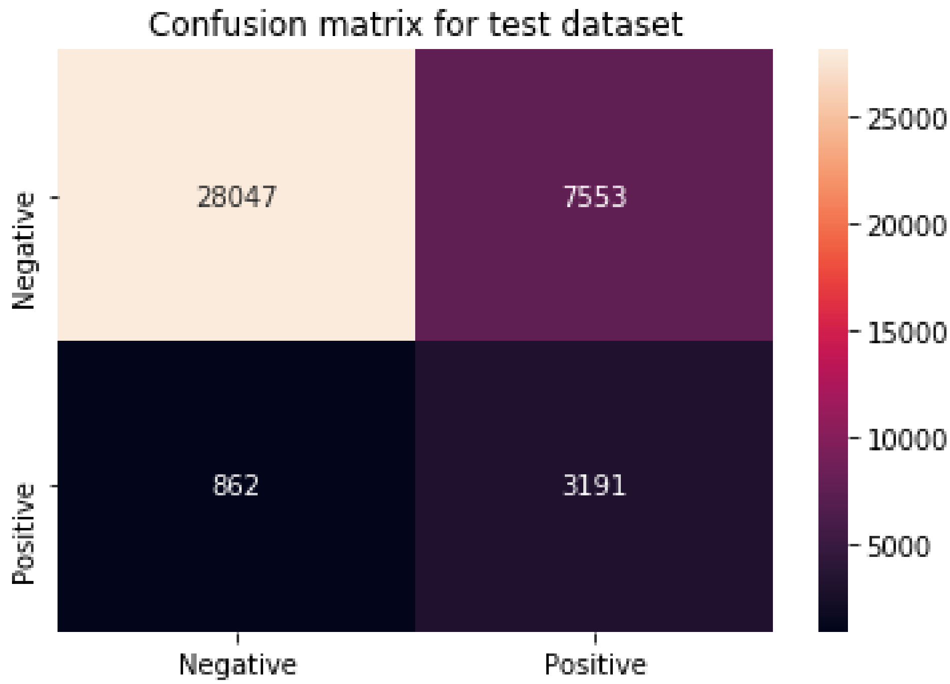
```
In [0]: lr_optimal=LogisticRegression(C=100, penalty='l2',solver='saga', class_weight='balance

        lr_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, lr_optimal.predict_proba(X_train
        test_fpr, test_tpr, thresholds = roc_curve(y_test, lr_optimal.predict_proba(X_test)[:,
```

```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```

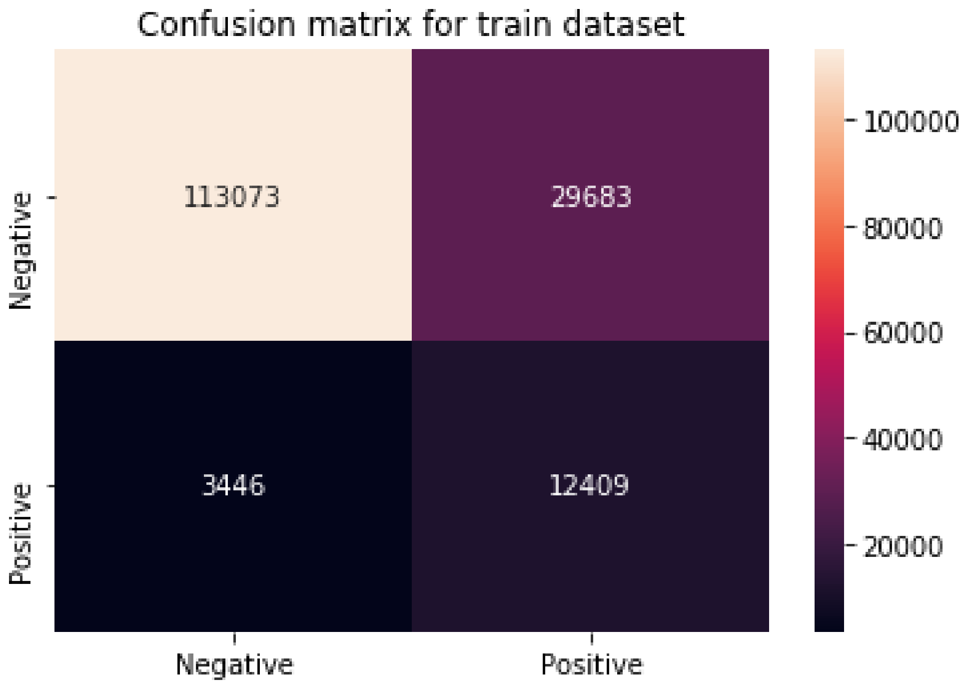


In [0]:
```
pred=lr_optimal.predict(X_test)
conf_matrix=confusion_matrix(y_test, pred)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=lr_optimal.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.97      0.79      0.87     35600
positive_class       0.30      0.79      0.43      4053

      accuracy                           0.79     39653
     macro avg       0.63      0.79      0.65     39653
  weighted avg       0.90      0.79      0.82     39653
```

Once again the AUC score didn't change but the model seem to perform better on positive datapoint than on negative datapoint

Comparing the results of all the three logistic regression (with class balancing) models

```
In [4]: x = PrettyTable()
        x.title = 'Results of all the three logistic regression (with class balancing) models.
        x.field_names = ['Dataset form', 'Test AUC score', 'Train AUC score']
        x.add_row(['Only with original features', 0.86134, 0.86086])
        x.add_row(['With original and basic features', 0.87180, 0.87475 ])
        x.add_row(['With original and genetic features',0.86820, 0.86853])
        print(x)
```

```
+----------------------------------------------------------------------------------+
|  Results of all the three logistic regression (with class balancing) models.  |
+----------------------------------------+-------------------+--------------------+
|              Dataset form              |  Test AUC score   |  Train AUC score   |
+----------------------------------------+-------------------+--------------------+
|       Only with original features      |      0.86134      |      0.86086       |
|     With original and basic features   |       0.8718      |      0.87475       |
|    With original and genetic features  |       0.8682      |      0.86853       |
+----------------------------------------+-------------------+--------------------+
```

8.3. Decision Tree
8.3.1 On the original dataset with no added features.
Preparing the dataset.

```
In [0]: features = train_df.drop(['ID_code','target'],axis=1)
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 200) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 200) (158611,)
(39653, 200) (39653,)
```

Finding the suitable parameters for model.

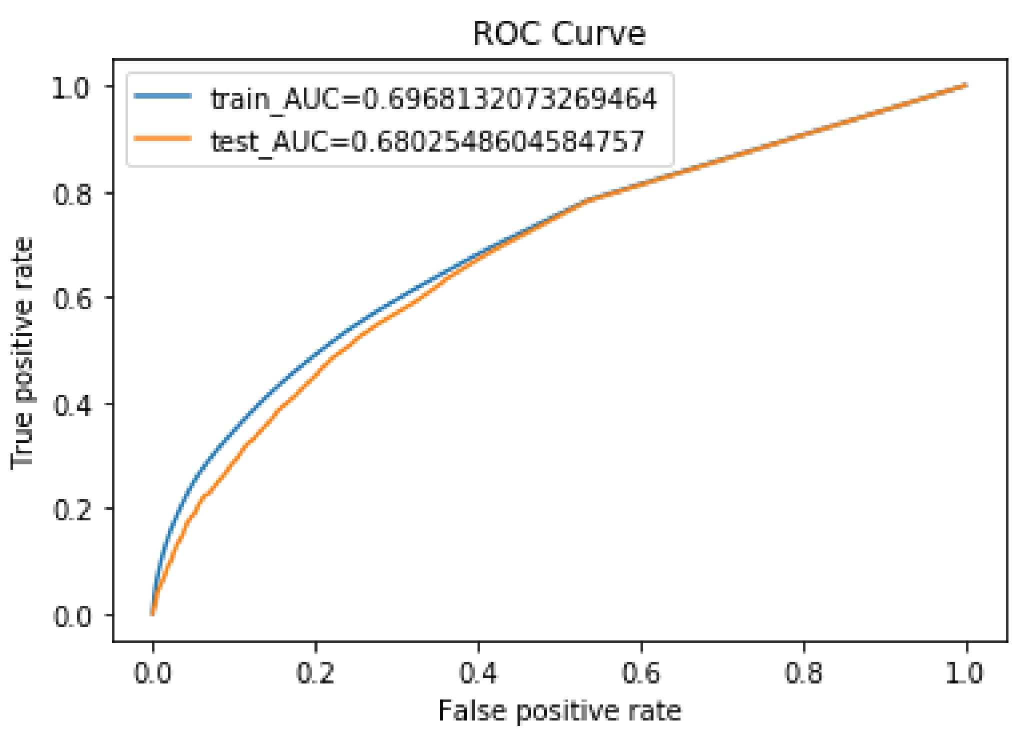
```
In [0]: tuned_parameters = {'max_depth':[1, 5, 10, 50, 100, 500, 1000], 'min_samples_split':[5


        DT_model = DecisionTreeClassifier()
        model = GridSearchCV(DT_model,tuned_parameters,
                             scoring='roc_auc',cv=2,n_jobs=-1)

        model.fit(X_train, y_train)

        print(model.best_estimator_)
```

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=10,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=500,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

Running the suitable model and looking at the results.

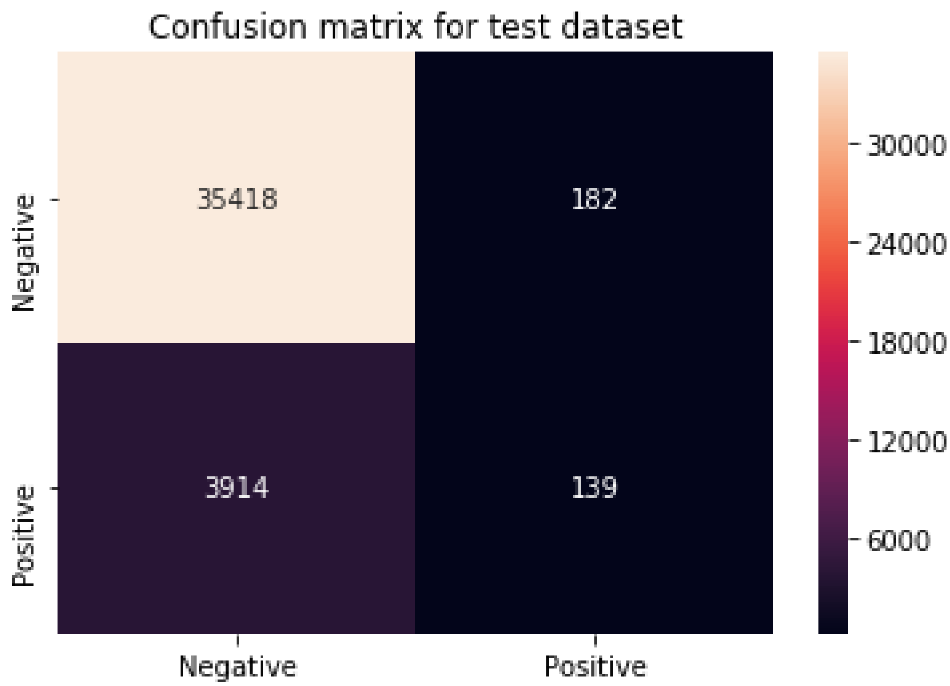
```
In [0]: model=DecisionTreeClassifier(max_depth=10, min_samples_split=500)

        model.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds=roc_curve(y_train, model.predict_proba(X_train)[:, 1]
        test_fpr, test_tpr, thresholds=roc_curve(y_test, model.predict_proba(X_test)[:, 1])
```

```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```



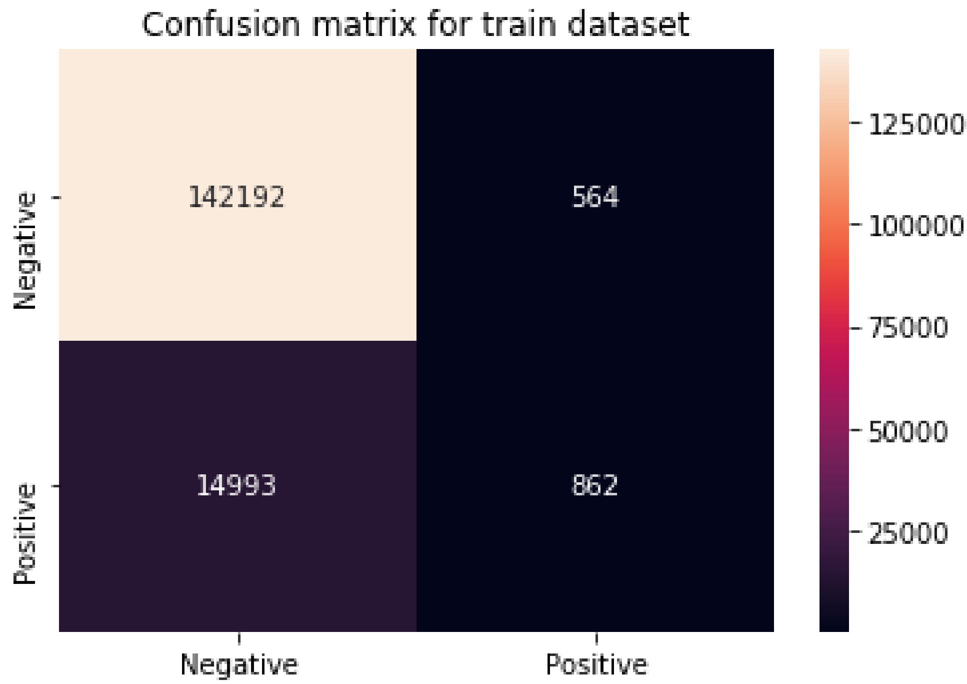
```
In [0]: pred=model.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")
```

```
Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=model.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")
```

```
Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.90      0.99      0.95     35600
positive_class       0.43      0.03      0.06      4053

      accuracy                           0.90     39653
     macro avg       0.67      0.51      0.50     39653
  weighted avg       0.85      0.90      0.86     39653
```

The AUC score is pretty bad if compared to both the logistic regression models but if the confusion matrix is compared to both the logistic regression models than it can be seen that this model performed better on negative datapoints and worse on positive datapoints.

8.3.2 On the dataset with original and basic features

```
In [0]: features = train_df_basic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 408) (198264,)
```

In [0]:
```
X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
X_train=np.asarray(X_train)
X_test=np.asarray(X_test)
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(158611, 408) (158611,)
(39653, 408) (39653,)
```

FInding the suitable parameters for the model.

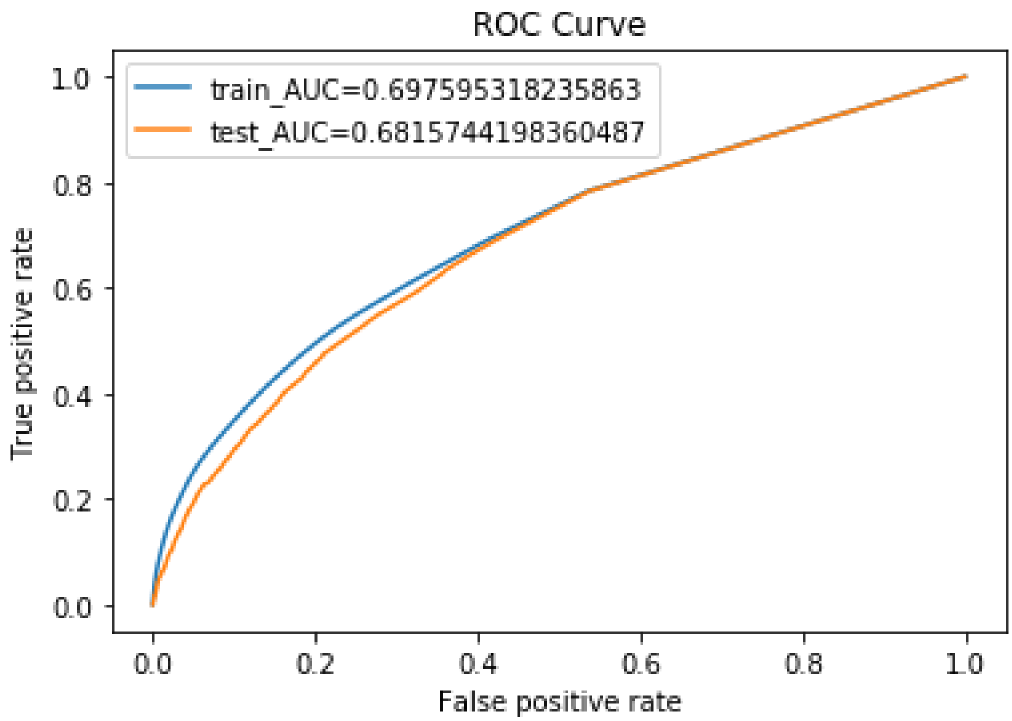
In [0]:
```
tuned_parameters = {'max_depth':[1, 5, 10, 50, 100, 500, 1000], 'min_samples_split':[5


DT_model = DecisionTreeClassifier()
model = GridSearchCV(DT_model,tuned_parameters,
                     scoring='roc_auc',cv=2,n_jobs=-1)

model.fit(X_train, y_train)

print(model.best_estimator_)
```

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=10,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=500,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

Running the model and looking at the results.

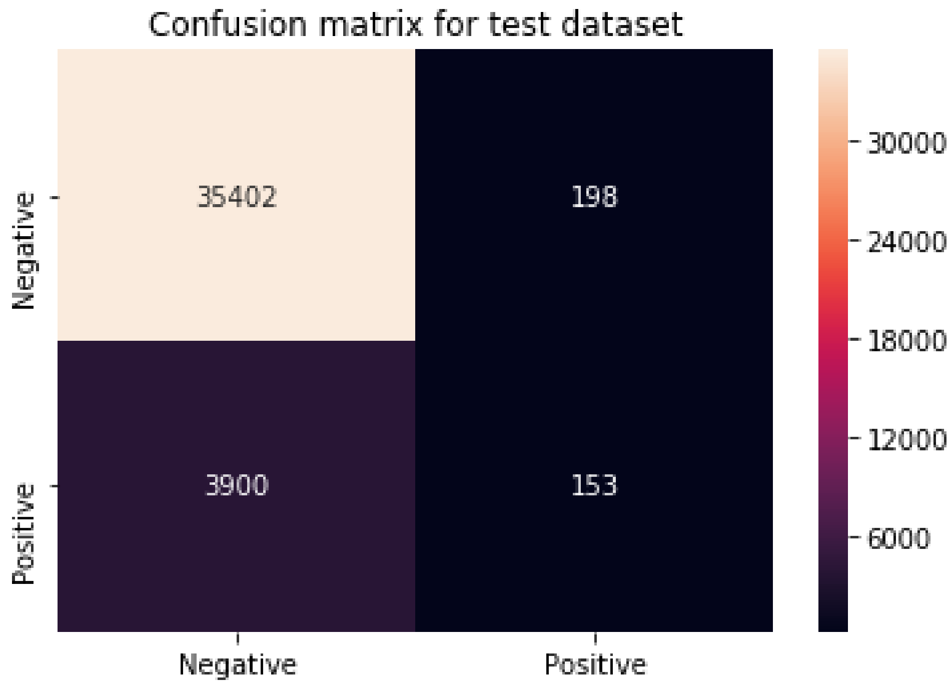
In [0]:
```
model=DecisionTreeClassifier(max_depth=10, min_samples_split=500)

model.fit(X_train, y_train)
train_fpr, train_tpr, thresholds=roc_curve(y_train, model.predict_proba(X_train)[:, 1]
test_fpr, test_tpr, thresholds=roc_curve(y_test, model.predict_proba(X_test)[:, 1])
```

In [0]:
```
plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.title("ROC Curve")
plt.show()
```



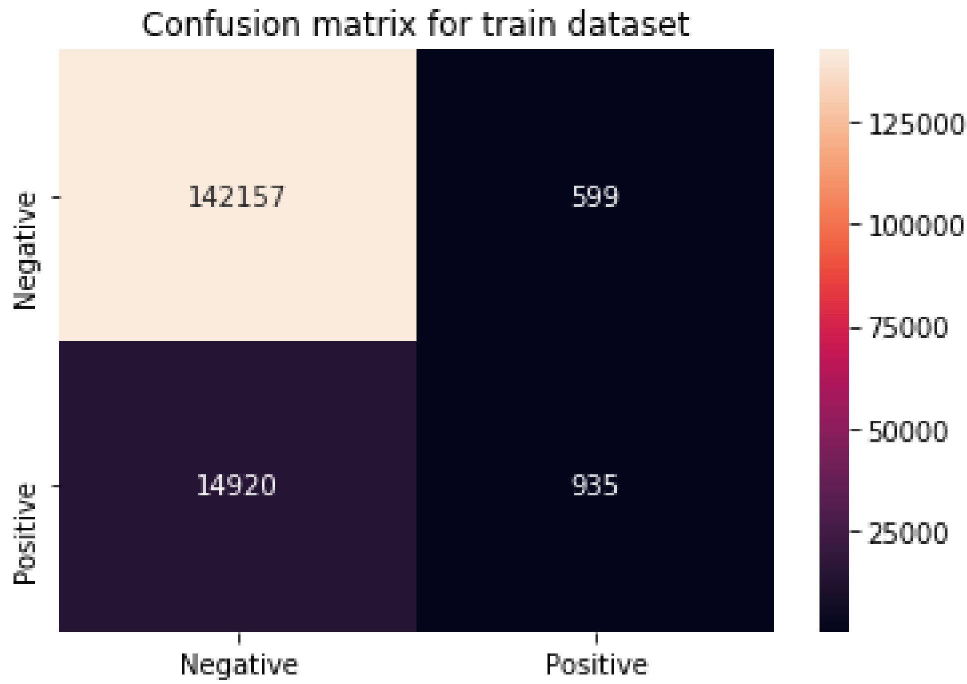
In [0]:
```
pred=model.predict(X_test)
conf_matrix=confusion_matrix(y_test, pred)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=model.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")
```

```
Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.90      0.99      0.95     35600
positive_class       0.44      0.04      0.07      4053

      accuracy                           0.90     39653
     macro avg       0.67      0.52      0.51     39653
  weighted avg       0.85      0.90      0.86     39653
```

Here also the AUC result is worse if compared to both the logistic regression models but this model again performed better on negative than on positive datapoints.

8.3.3. On the dataset with original and genetic features.

Preparing the dataset.

```
In [0]: features = train_df_genetic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 400) (198264,)
```

In [0]:
```
X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
X_train=np.asarray(X_train)
X_test=np.asarray(X_test)
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(158611, 400) (158611,)
(39653, 400) (39653,)
```

Finding the right hyperparameters for the model.

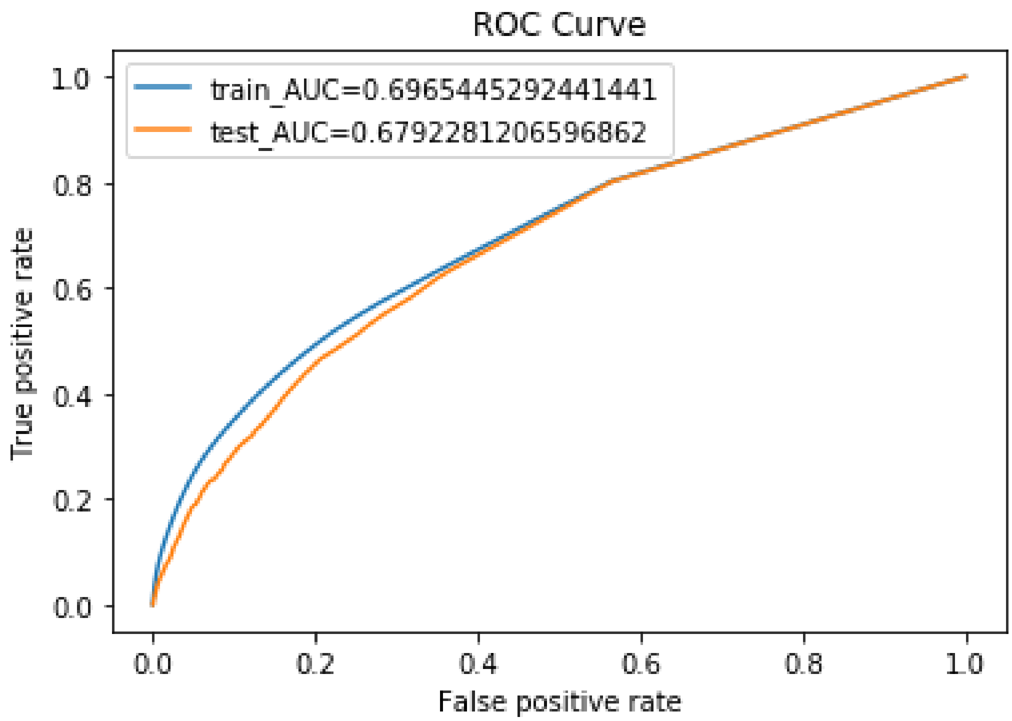
In [0]:
```
tuned_parameters = {'max_depth':[1, 5, 10, 50, 100, 500, 1000], 'min_samples_split':[5


DT_model = DecisionTreeClassifier()
model = GridSearchCV(DT_model,tuned_parameters,
                     scoring='roc_auc',cv=2,n_jobs=-1)

model.fit(X_train, y_train)

print(model.best_estimator_)
```

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=10,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=500,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

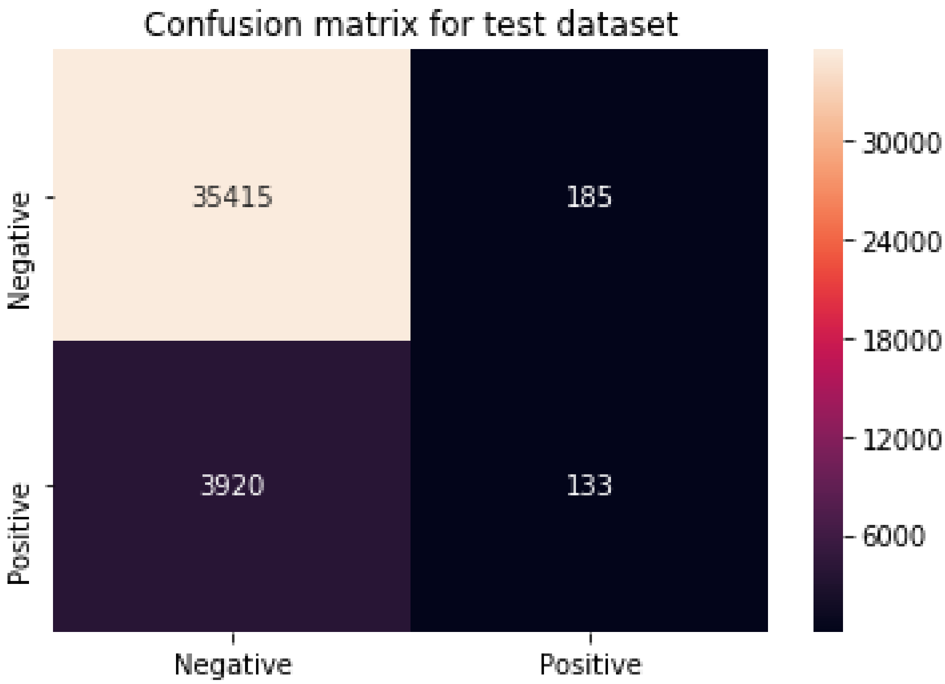
Running the optimal model and comparing the results

In [0]:
```
model=DecisionTreeClassifier(max_depth=10, min_samples_split=500)

model.fit(X_train, y_train)
train_fpr, train_tpr, thresholds=roc_curve(y_train, model.predict_proba(X_train)[:, 1]
test_fpr, test_tpr, thresholds=roc_curve(y_test, model.predict_proba(X_test)[:, 1])
```

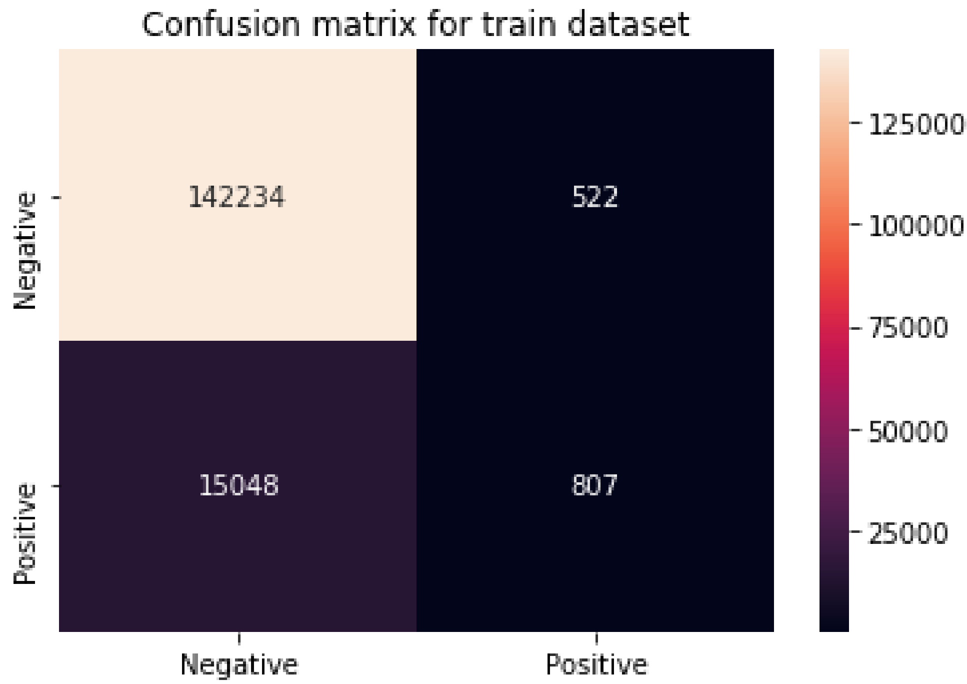
In [0]:
```
plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.title("ROC Curve")
plt.show()
```




```
In [0]: pred=model.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=model.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.90      0.99      0.95     35600
positive_class       0.42      0.03      0.06      4053

      accuracy                           0.90     39653
     macro avg       0.66      0.51      0.50     39653
  weighted avg       0.85      0.90      0.85     39653
```

Once again if the AUC score is compared than it can be seen that it is quite bad but the model once and proved to be fruitful on negative datapoints if compared to both the logistic regression models than the positive datapoints

Comparing the AUC results of all the three decision tree models.

```
In [5]: x = PrettyTable()
        x.title = 'AUC results of all the three decision tree models.'
        x.field_names = ['Dataset form', 'Test AUC score', 'Train AUC score']
        x.add_row(['Only with original features', 0.68025, 0.69681])
        x.add_row(['With original and basic features', 0.68157, 0.69759 ])
        x.add_row(['With original and genetic features',0.67922, 0.69654])
        print(x)
```

```
+-------------------------------------+----------------+-----------------+
|          AUC results of all the three decision tree models.           |
+-------------------------------------+----------------+-----------------+
|            Dataset form             | Test AUC score | Train AUC score |
+-------------------------------------+----------------+-----------------+
|    Only with original features      |    0.68025     |     0.69681     |
|  With original and basic features   |    0.68157     |     0.69759     |
| With original and genetic features  |    0.67922     |     0.69654     |
+-------------------------------------+----------------+-----------------+
```

8.4. Gaussian Naive Bayes
8.4.1. On the original dataset with no added features.
Preparing the dataset.

```
In [0]: features = train_df.drop(['ID_code','target'],axis=1)
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 200) (198264,)
```

```
In [0]: X_train, X_CV, y_train, y_CV=train_test_split(features, target, test_size=0.2, random_s
        X_CV, X_test, y_CV, y_test=train_test_split(X_CV, y_CV, test_size=0.5, random_state=42)
        X_train=np.asarray(X_train)
        X_CV=np.asarray(X_CV)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_CV=sc.transform(X_CV)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_CV.shape, y_CV.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 200) (158611,)
(19826, 200) (19826,)
(19827, 200) (19827,)
```

Finding the suitable parameters for the model.

```
In [0]: tr_scores=[]
        cv_scores=[]
        smoothing=[10**-9, 10**-7, 10**-5, 10**-3, 10**-1, 1]
        for s in tqdm(smoothing):
          gnb=GaussianNB(var_smoothing=s)
          gnb.fit(X_train, y_train)
          y_train_predict=gnb.predict_proba(X_train)[:,1]
```

```
    y_cv_predict=gnb.predict_proba(X_CV)[:,1]
    tr_scores.append(roc_auc_score(y_train, y_train_predict))
    cv_scores.append(roc_auc_score(y_CV, y_cv_predict))
```

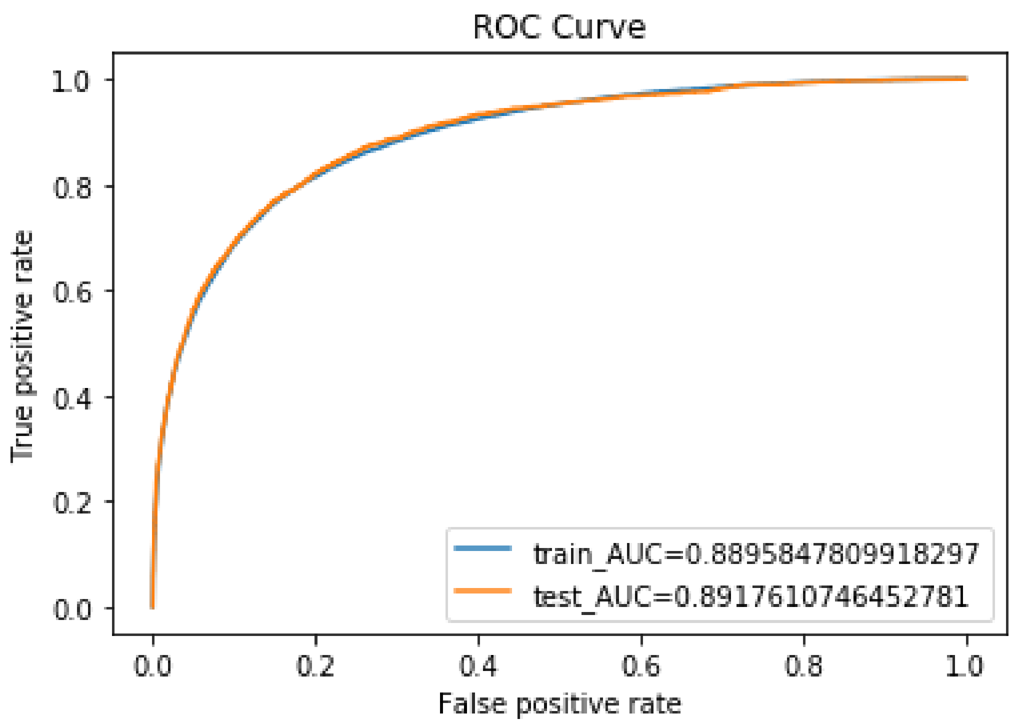
```
100%|| 6/6 [00:06<00:00,  1.10s/it]
```

Running the optimal model and looking at the results

```
In [0]: optimal=smoothing[cv_scores.index(max(cv_scores))]
```

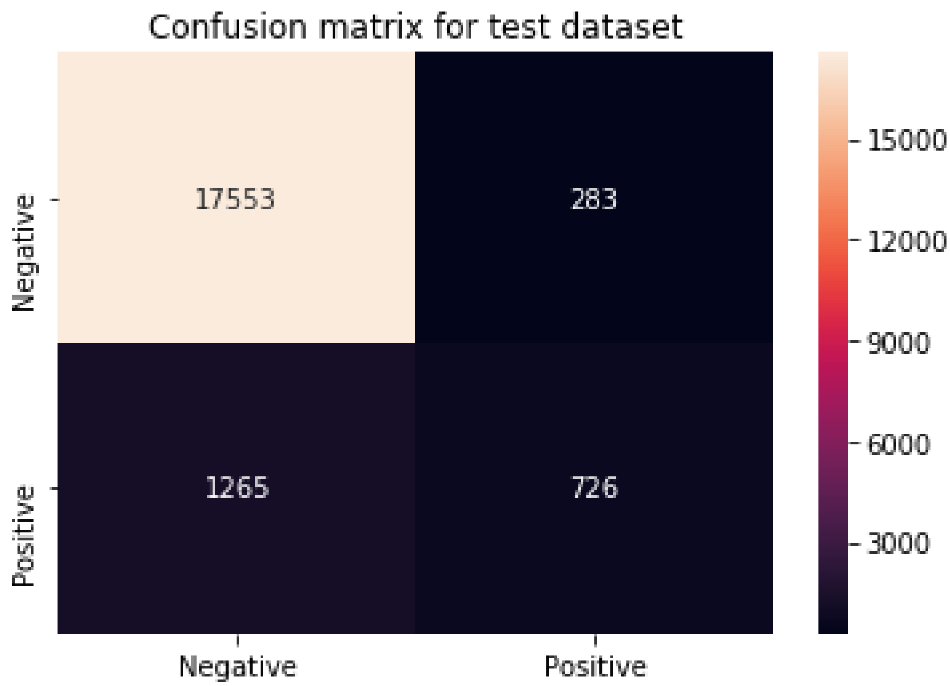
```
In [0]: gnb_optimal=GaussianNB(var_smoothing=optimal)

        gnb_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, gnb_optimal.predict_proba(X_trai
        test_fpr, test_tpr, thresholds = roc_curve(y_test, gnb_optimal.predict_proba(X_test)[:
```

```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```



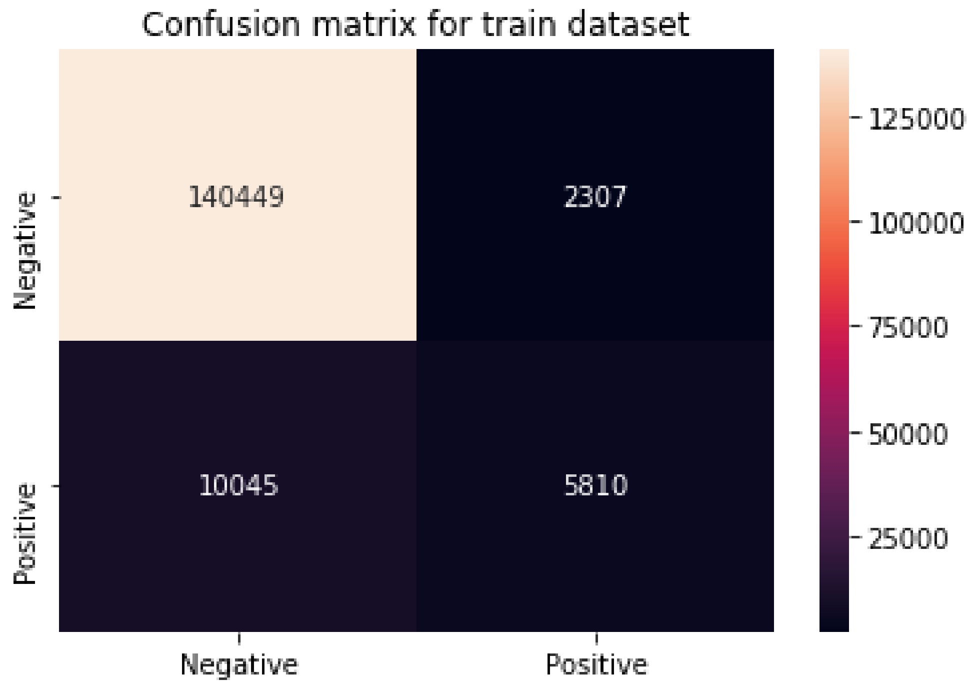
In [0]:
```
pred=gnb_optimal.predict(X_test)
conf_matrix=confusion_matrix(y_test, pred)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')



In [0]:
```
predictions=gnb_optimal.predict(X_train)
conf_matrix=confusion_matrix(y_train, predictions)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for train dataset")
```

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.93      0.98      0.96     17836
positive_class       0.72      0.36      0.48      1991

      accuracy                           0.92     19827
     macro avg       0.83      0.67      0.72     19827
  weighted avg       0.91      0.92      0.91     19827
```

The AUC result is higher if compared to both the logistic regression model.
8.4.2 On the dataset with original and basic features.
Preparing the dataset.

```
In [0]: features = train_df_basic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 408) (198264,)
```

```
In [0]: X_train, X_CV, y_train, y_CV=train_test_split(features, target, test_size=0.2, random_s
        X_CV, X_test, y_CV, y_test=train_test_split(X_CV, y_CV, test_size=0.5, random_state=42)
        X_train=np.asarray(X_train)
        X_CV=np.asarray(X_CV)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_CV=sc.transform(X_CV)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_CV.shape, y_CV.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 408) (158611,)
(19826, 408) (19826,)
(19827, 408) (19827,)
```

Finding the optimal parameters for the model.

```
In [0]: tr_scores=[]
        cv_scores=[]
        smoothing=[10**-9, 10**-7, 10**-5, 10**-3, 10**-1, 1]
        for s in tqdm(smoothing):
          gnb=GaussianNB(var_smoothing=s)
          gnb.fit(X_train, y_train)
          y_train_predict=gnb.predict_proba(X_train)[:,1]
          y_cv_predict=gnb.predict_proba(X_CV)[:,1]
          tr_scores.append(roc_auc_score(y_train, y_train_predict))
          cv_scores.append(roc_auc_score(y_CV, y_cv_predict))
```

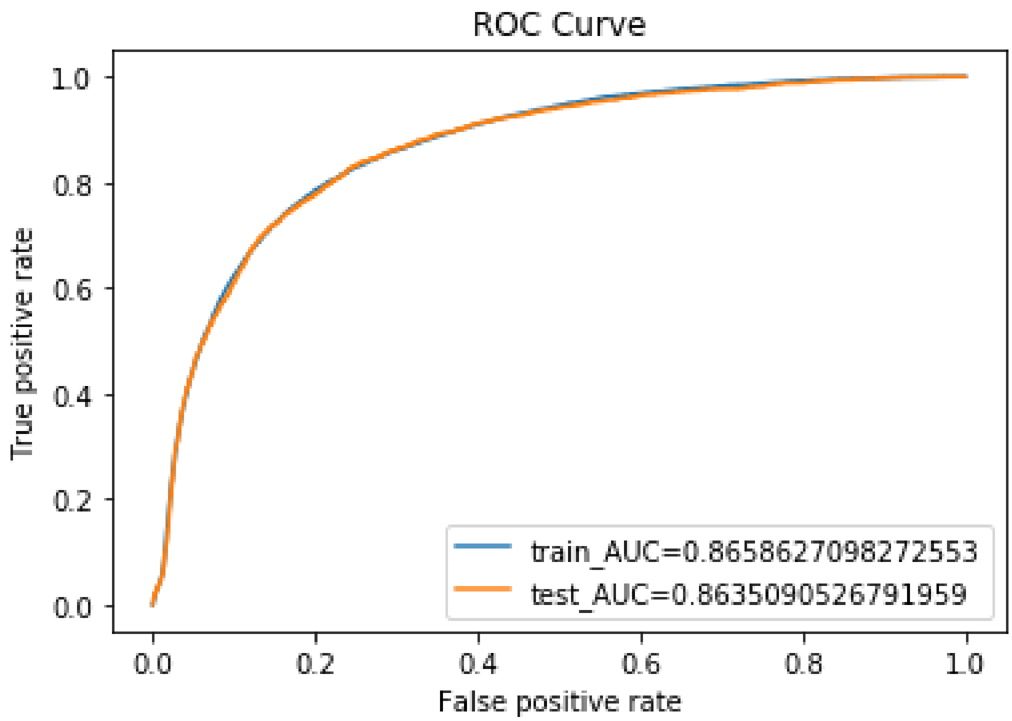
```
100%|| 6/6 [00:12<00:00,  2.02s/it]
```

Running the suitable model and looking the results.

```
In [0]: optimal=smoothing[cv_scores.index(max(cv_scores))]
```

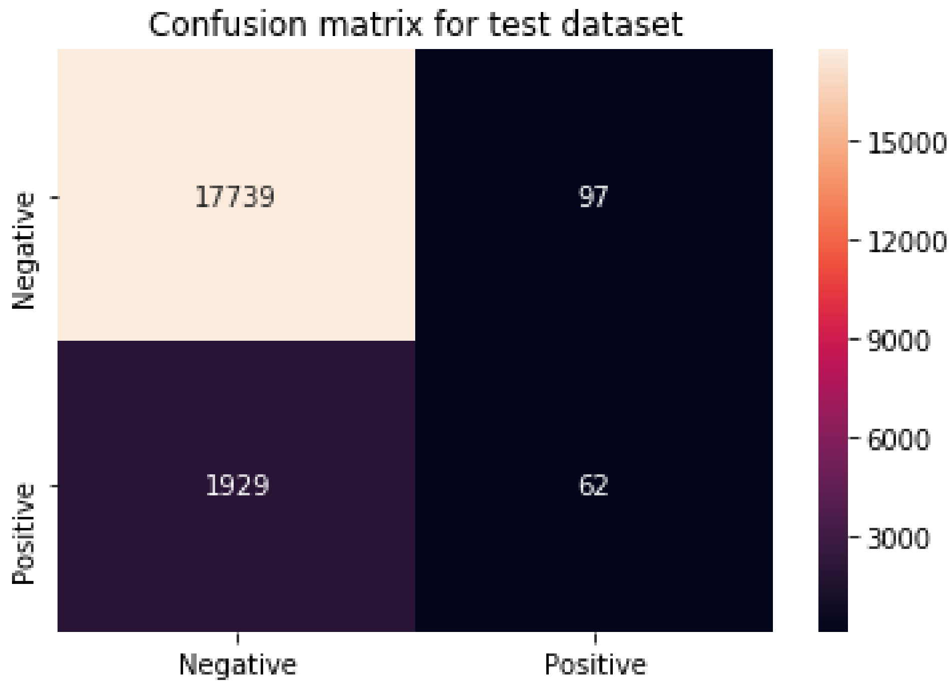
```
In [0]: gnb_optimal=GaussianNB(var_smoothing=optimal)

        gnb_optimal.fit(X_train, y_train)
        train_fpr, train_tpr, thresholds = roc_curve(y_train, gnb_optimal.predict_proba(X_trai
        test_fpr, test_tpr, thresholds = roc_curve(y_test, gnb_optimal.predict_proba(X_test)[:
```

```
In [0]: plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```



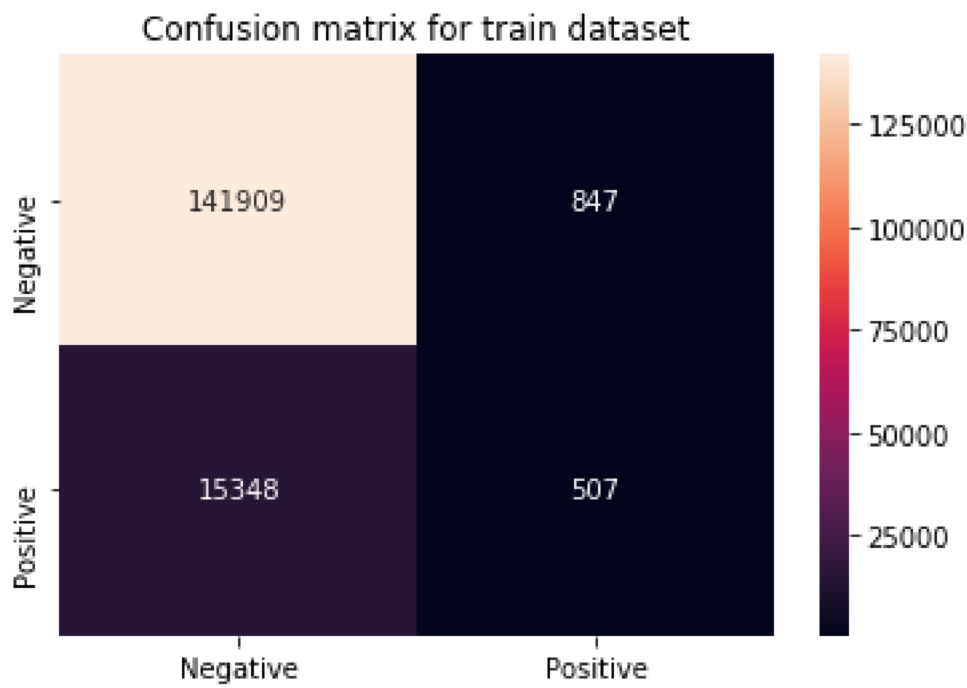
In [0]:
```
pred=gnb_optimal.predict(X_test)
conf_matrix=confusion_matrix(y_test, pred)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for test dataset')
```



In [0]:
```
predictions=gnb_optimal.predict(X_train)
conf_matrix=confusion_matrix(y_train, predictions)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for train dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))

                precision    recall  f1-score   support

negative_class       0.90      0.99      0.95     17836
positive_class       0.39      0.03      0.06      1991

      accuracy                           0.90     19827
     macro avg       0.65      0.51      0.50     19827
  weighted avg       0.85      0.90      0.86     19827
```

The AUC score deteriorated if compared to both the logistic regression models.
8.4.3. On the dataset with original and genetic features.
Preparing the dataset.

```
In [0]: features = train_df_genetic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)

(198264, 400) (198264,)
```

In [0]:
```
X_train, X_CV, y_train, y_CV=train_test_split(features, target, test_size=0.2, random_s
X_CV, X_test, y_CV, y_test=train_test_split(X_CV, y_CV, test_size=0.5, random_state=42)
X_train=np.asarray(X_train)
X_CV=np.asarray(X_CV)
X_test=np.asarray(X_test)
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_CV=sc.transform(X_CV)
X_test=sc.transform(X_test)
print(X_train.shape, y_train.shape)
print(X_CV.shape, y_CV.shape)
print(X_test.shape, y_test.shape)
```

```
(158611, 400) (158611,)
(19826, 400) (19826,)
(19827, 400) (19827,)
```

Finding the suitable hyperparameters for the model.

In [0]:
```
tr_scores=[]
cv_scores=[]
smoothing=[10**-9, 10**-7, 10**-5, 10**-3, 10**-1, 1]
for s in tqdm(smoothing):
  gnb=GaussianNB(var_smoothing=s)
  gnb.fit(X_train, y_train)
  y_train_predict=gnb.predict_proba(X_train)[:,1]
  y_cv_predict=gnb.predict_proba(X_CV)[:,1]
  tr_scores.append(roc_auc_score(y_train, y_train_predict))
  cv_scores.append(roc_auc_score(y_CV, y_cv_predict))
```

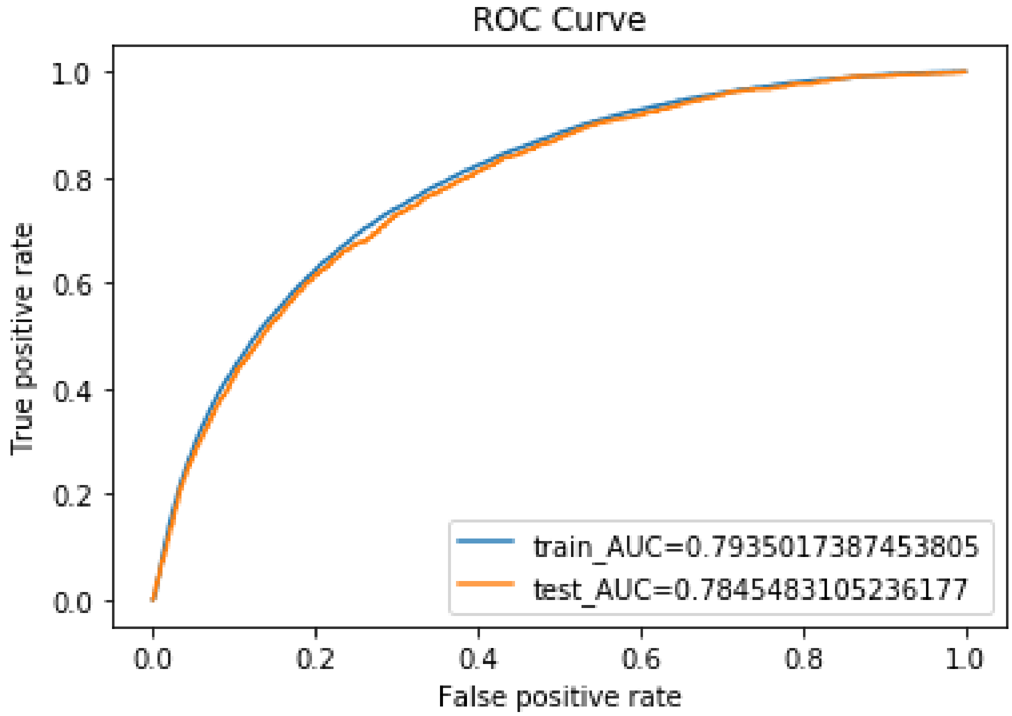
```
100%|| 6/6 [00:12<00:00,  2.08s/it]
```

Running the optimal model and looking at the results.

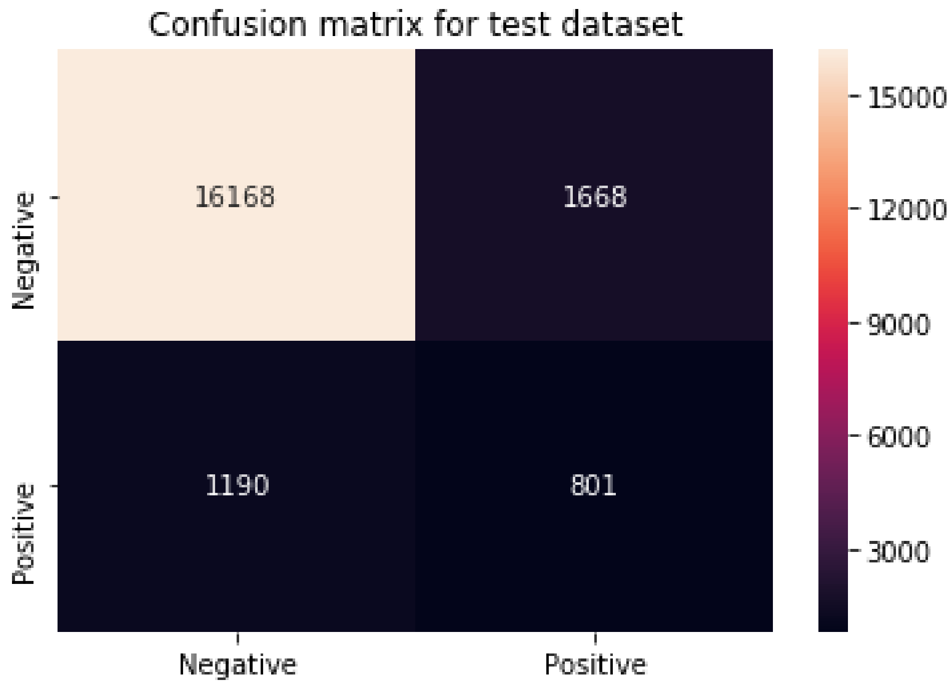
In [0]:
```
optimal=smoothing[cv_scores.index(max(cv_scores))]
```

In [0]:
```
gnb_optimal=GaussianNB(var_smoothing=optimal)

gnb_optimal.fit(X_train, y_train)
train_fpr, train_tpr, thresholds = roc_curve(y_train, gnb_optimal.predict_proba(X_trai
test_fpr, test_tpr, thresholds = roc_curve(y_test, gnb_optimal.predict_proba(X_test)[:
```

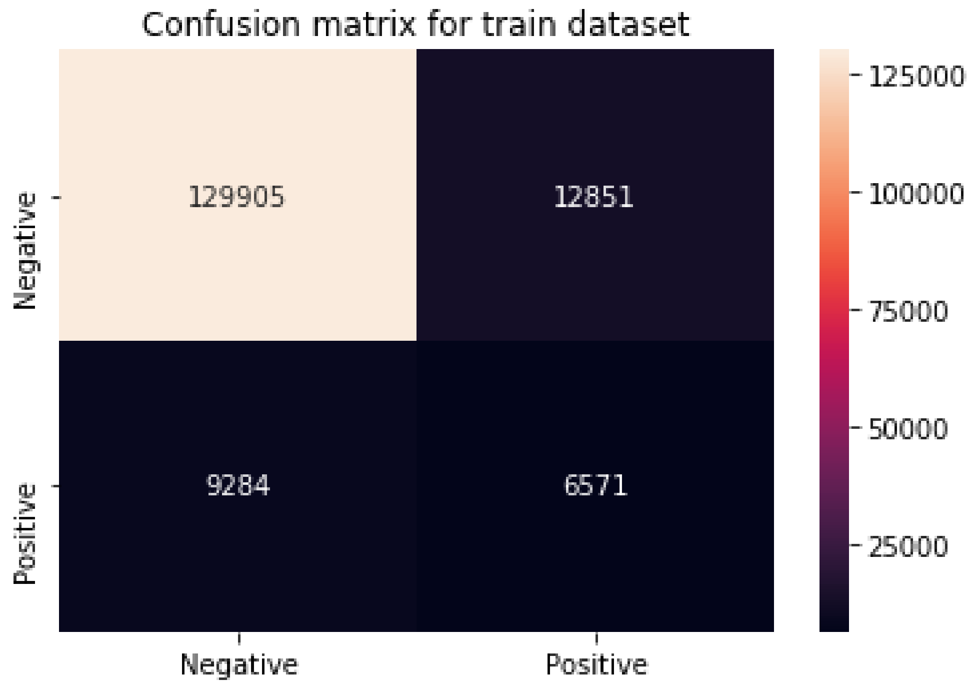
In [0]:
```
plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.title("ROC Curve")
plt.show()
```




```
In [0]: pred=gnb_optimal.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=gnb_optimal.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: target_names=['negative_class', 'positive_class']
        print(classification_report(y_test, pred, target_names=target_names))
```

```
                precision    recall  f1-score   support

negative_class       0.93      0.91      0.92     17836
positive_class       0.32      0.40      0.36      1991

      accuracy                           0.86     19827
     macro avg       0.63      0.65      0.64     19827
  weighted avg       0.87      0.86      0.86     19827
```

Once again it can be seen that the model performance has been deteriorated, thus it can be said that Gaussian Naive Bayes worked best with the original dataset with no added features.

Comparing the results of all the three Gaussian Naive Bayes models.

```
In [6]: x = PrettyTable()
        x.title = 'Results of all the three Gaussian Naive Bayes models.'
        x.field_names = ['Dataset form', 'Test AUC score', 'Train AUC score']
        x.add_row(['Only with original features', 0.89176, 0.88958])
        x.add_row(['With original and basic features', 0.86350, 0.86586 ])
        x.add_row(['With original and genetic features',0.78454, 0.79350])
        print(x)
```

```
+-------------------------------------------------------------------+
|          Results of all the three Gaussian Naive Bayes models.     |
+------------------------------------+----------------+------------------+
|             Dataset form           | Test AUC score | Train AUC score |
+------------------------------------+----------------+------------------+
|     Only with original features    |    0.89176     |     0.88958     |
|   With original and basic features |     0.8635     |     0.86586     |
| With original and genetic features |    0.78454     |      0.7935     |
+------------------------------------+----------------+------------------+
```

8.5. Random Forest Model without Hyperparameter tuning
8.5.1. On the original dataset with no added features.
Preparing the dataset.

```
In [0]: features = train_df.drop(['ID_code','target'],axis=1)
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 200) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
        X_test=np.asarray(X_test)
        sc=StandardScaler()
        X_train=sc.fit_transform(X_train)
        X_test=sc.transform(X_test)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 200) (158611,)
(39653, 200) (39653,)
```

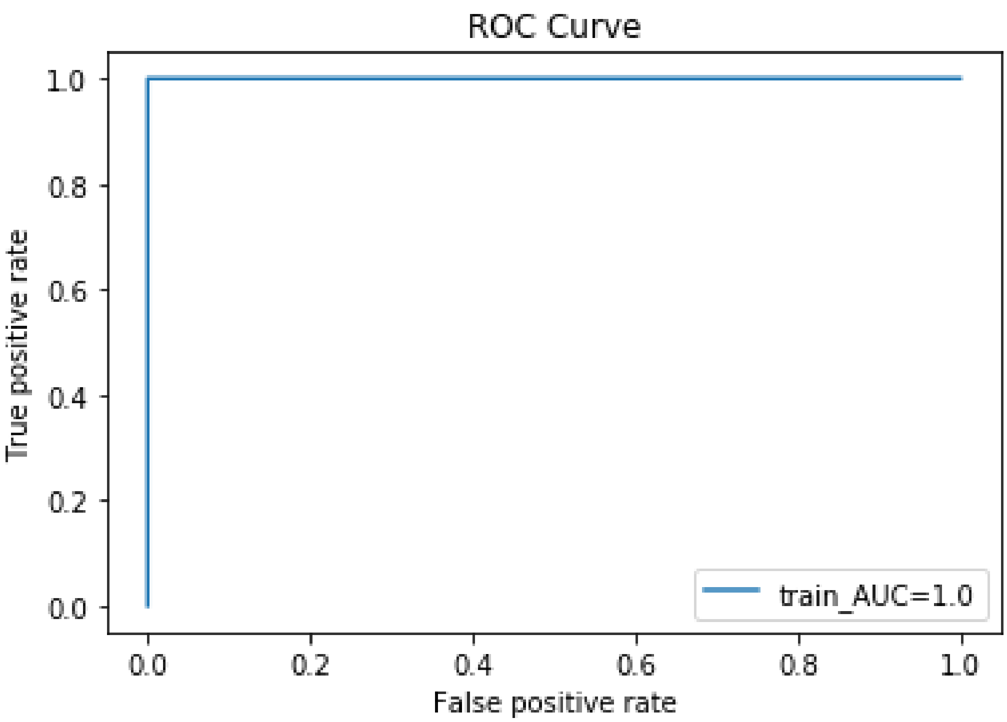
Using only 50 estimators to fit the model and looking the results.

```
In [0]: r_cfl=RandomForestClassifier(n_estimators=50,n_jobs=-1)
        r_cfl.fit(X_train,y_train)
        cal_clf = CalibratedClassifierCV(r_cfl, method="sigmoid")
        cal_clf.fit(X_train, y_train)
```

```
Out[0]: CalibratedClassifierCV(base_estimator=RandomForestClassifier(bootstrap=True,
                                                                     class_weight=None,
                                                                     criterion='gini',
                                                                     max_depth=None,
                                                                     max_features='auto',
                                                                     max_leaf_nodes=None,
                                                                     min_impurity_decrease=0.0
```

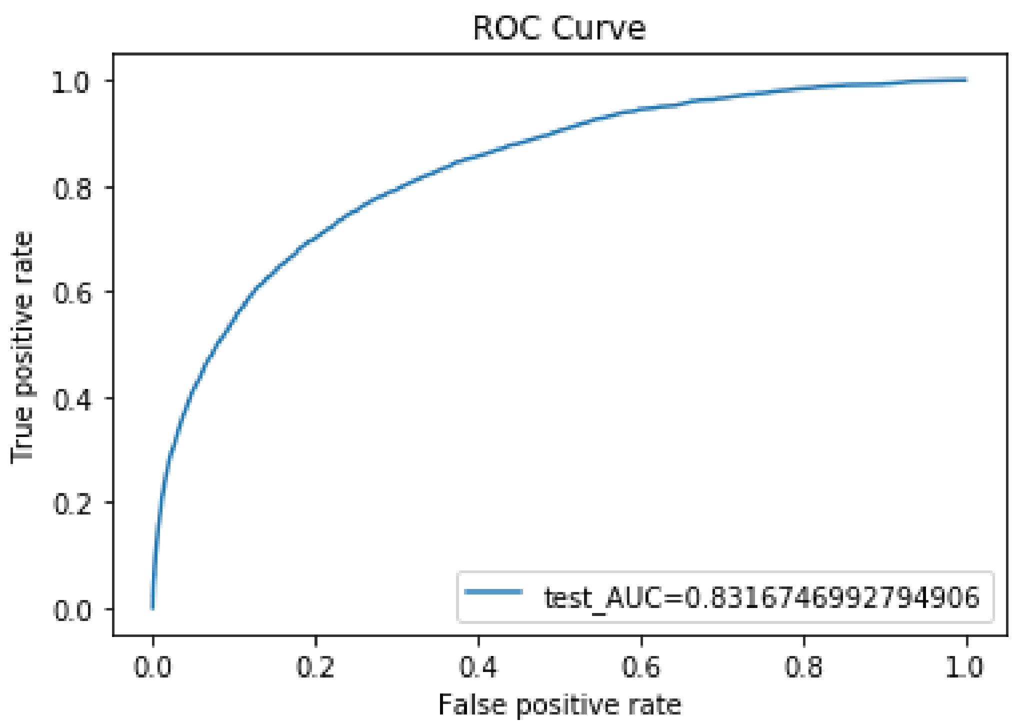
```
                                                                min_impurity_split=None,
                                                                min_samples_leaf=1,
                                                                min_samples_split=2,
                                                                min_weight_fraction_leaf=(
                                                                n_estimators=50,
                                                                n_jobs=-1,
                                                                oob_score=False,
                                                                random_state=None,
                                                                verbose=0,
                                                                warm_start=False),
                                   cv='warn', method='sigmoid')
```

```
In [0]: train_fpr, train_tpr, thresholds=roc_curve(y_train, cal_clf.predict_proba(X_train)[:, 1
        plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```




```
In [0]: test_fpr, test_tpr, thresholds=roc_curve(y_test, cal_clf.predict_proba(X_test)[:, 1])
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
```

```
plt.ylabel("True positive rate")
plt.title("ROC Curve")
plt.show()
```

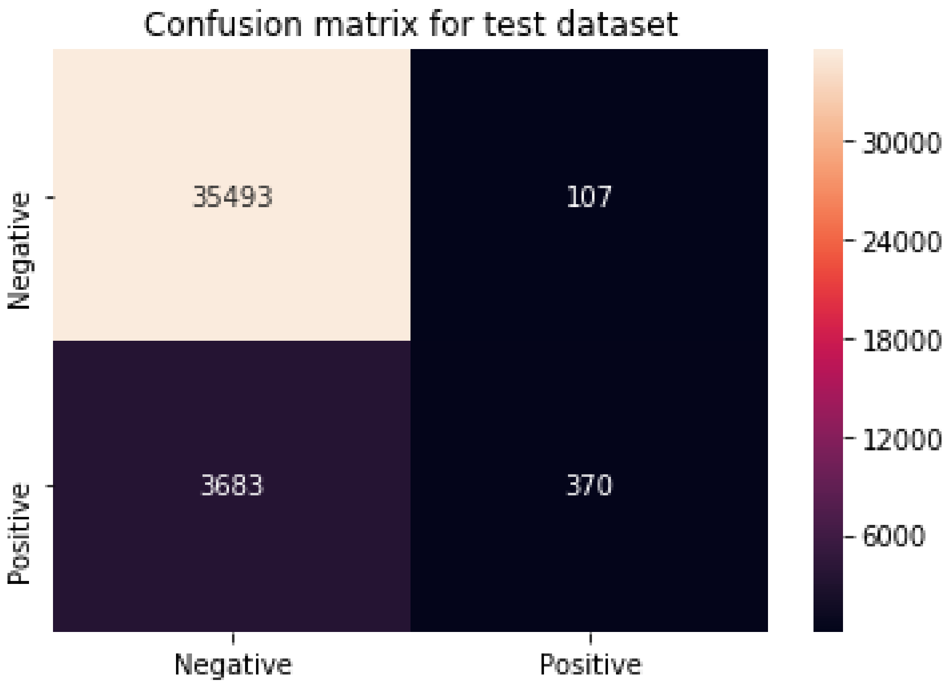



```
In [0]: predict_y = cal_clf.predict_proba(X_train)
        print('Training_ROC Score is :',roc_auc_score(y_train,predict_y[:,1]))
        predict_y = cal_clf.predict_proba(X_test)
        print('Testing_ROC Score is :',roc_auc_score(y_test,predict_y[:,1]))
```

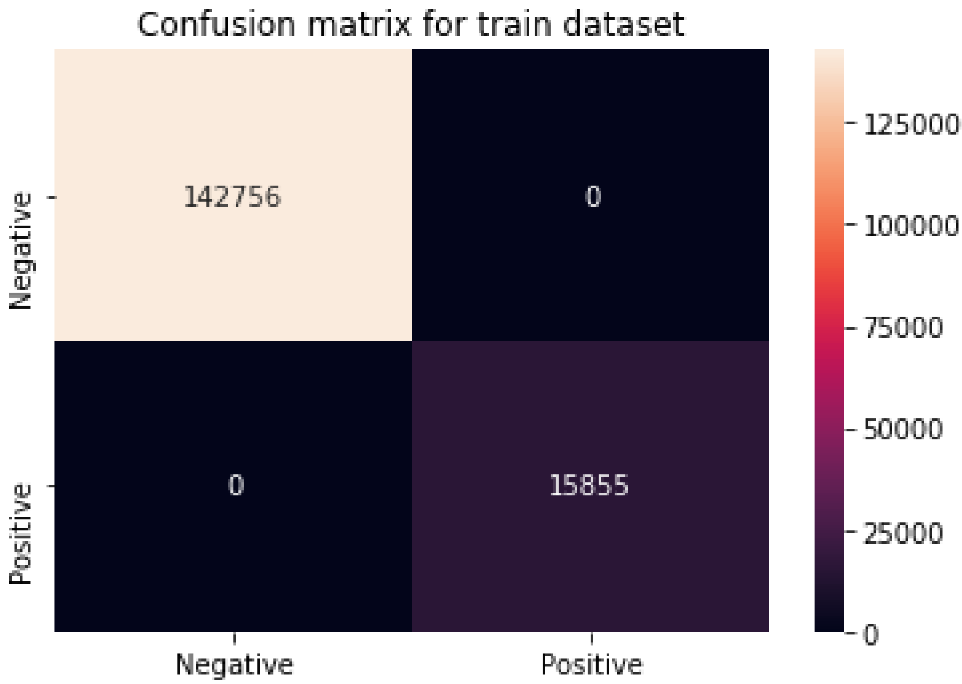
```
Training_ROC Score is : 1.0
Testing_ROC Score is : 0.8316746992794906
```

```
In [0]: pred=cal_clf.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")
```

```
Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```




```
In [0]: predictions=cal_clf.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```



As from the above results, it can clearly be seen that this simple random forest model is overfitting there is a huge difference between the training and testing ROC AUC Score and also in the confusion matrix, we can see in the training matrix there is no false positive's and false negative's but in testing matrix we can see large numbers of false positives. Thus deciding not going further with Random Forest model with other forms of dataset as the original dataset with no added features is overfitting the data.

As it can be seen from the results of Logistic regression, Decision Tree and Gaussian Naive Bayes from the above cells that dataset with genetic features does not provide great improvement in AUC scores and thus running XGBoost on only two forms of dataset, they are:-

- Dataset with only original features.
- Dataset with original and basic features.

8.6. XGBoost Model with Hyperparameter tuning
8.6.1 On original dataset with no added features.
Preparing the dataset.

```
In [0]: features = train_df.drop(['ID_code','target'],axis=1)
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 200) (198264,)
```

```
In [0]: X_train, X_test, y_train, y_test=train_test_split(features, target, test_size=0.2, ranc
        X_train=np.asarray(X_train)
```

```
X_test=np.asarray(X_test)
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(158611, 200) (158611,)
(39653, 200) (39653,)
```

Finding the best hyperparameters for the model.

```
In [0]: model = XGBClassifier(
            eval_metric=["auc"]
        )

        param_grid = {
            "learning_rate": [0.1, 0.01],
            "colsample_bytree": [0.6, 0.8, 1.0],
            "subsample": [0.6, 0.8, 1.0],
            "max_depth": [2, 3, 4],
            "n_estimators": [100, 200, 300, 400],
            "reg_lambda": [1, 1.5, 2],
            "gamma": [0, 0.1, 0.3],
        }

        scoring = {
            'AUC': 'roc_auc',
        }

        # create the Kfold object
        num_folds = 10
        kfold = StratifiedKFold(n_splits=num_folds)
        # create the grid search object
        n_iter=50
        grid = RandomizedSearchCV(
            estimator=model,
            param_distributions=param_grid,
            cv=kfold,
            scoring=scoring,
            n_jobs=-1,
            n_iter=n_iter,
            refit="AUC",
            verbose=1
        )

        grid.fit(X_train,y_train)
        best_clf=grid.best_estimator_
```

```
In [0]: best_clf
```

```
Out[0]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=0.8, eval_metric=['auc'],
                      gamma=0.1, learning_rate=0.1, max_delta_step=0, max_depth=4,
                      min_child_weight=1, missing=None, n_estimators=400, n_jobs=-1,
                      nthread=None, objective='binary:logistic', random_state=0,
                      reg_alpha=0, reg_lambda=2, scale_pos_weight=1, seed=None,
                      silent=None, subsample=0.8, verbose=1, verbosity=1)
```

Fitting the optimal model and looking at the results.

```
In [0]: best_clf=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bytree=0.8, eval_metric=['auc'], gamma=0.1,
                      learning_rate=0.1, max_delta_step=0, max_depth=4,
                      min_child_weight=1, n_estimators=400, n_jobs=-1,
                      nthread=None, objective='binary:logistic', random_state=0,
                      reg_alpha=0, reg_lambda=2, scale_pos_weight=1, seed=None,
                      silent=None, subsample=0.8, verbose=1)
        best_clf.fit(X_train,y_train)
```

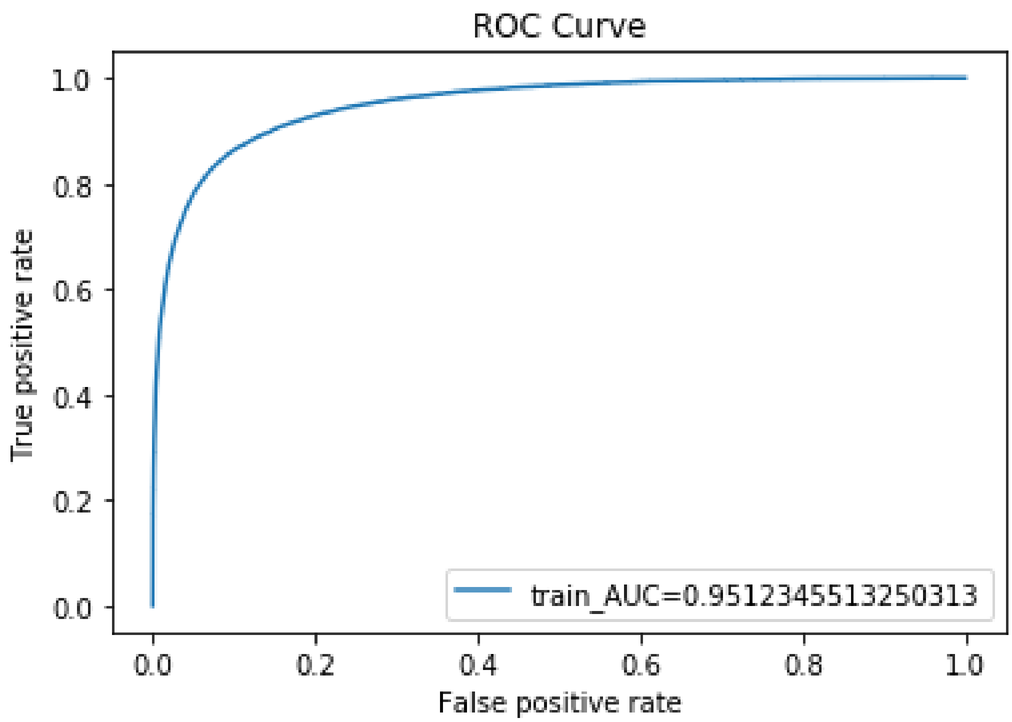
```
Out[0]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=0.8, eval_metric=['auc'],
                      gamma=0.1, learning_rate=0.1, max_delta_step=0, max_depth=4,
                      min_child_weight=1, missing=None, n_estimators=400, n_jobs=-1,
                      nthread=None, objective='binary:logistic', random_state=0,
                      reg_alpha=0, reg_lambda=2, scale_pos_weight=1, seed=None,
                      silent=None, subsample=0.8, verbose=1, verbosity=1)
```

```
In [0]: cal_clf = CalibratedClassifierCV(best_clf, method="sigmoid")
        cal_clf.fit(X_train, y_train)
```

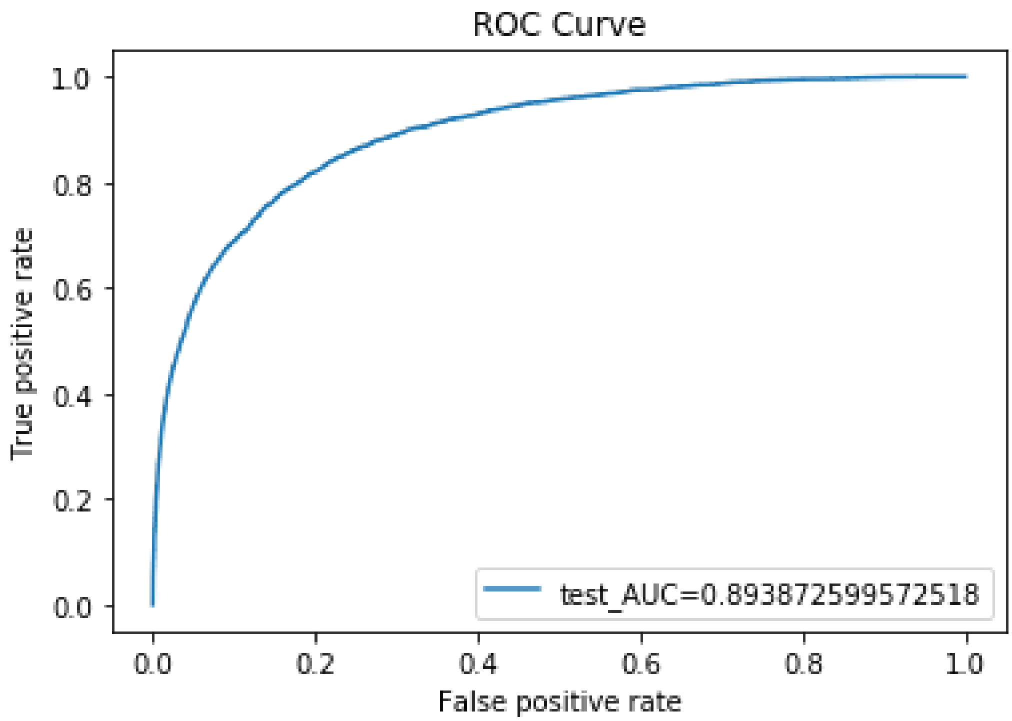
```
Out[0]: CalibratedClassifierCV(base_estimator=XGBClassifier(base_score=0.5,
                                                            booster='gbtree',
                                                            colsample_bylevel=1,
                                                            colsample_bynode=1,
                                                            colsample_bytree=0.8,
                                                            eval_metric=['auc'],
                                                            gamma=0.1,
                                                            learning_rate=0.1,
                                                            max_delta_step=0,
                                                            max_depth=4,
                                                            min_child_weight=1,
                                                            missing=None,
                                                            n_estimators=400, n_jobs=-1,
                                                            nthread=None,
                                                            objective='binary:logistic',
                                                            random_state=0, reg_alpha=0,
                                                            reg_lambda=2,
```

```
                                                          scale_pos_weight=1,
                                                          seed=None, silent=None,
                                                          subsample=0.8, verbose=1,
                                                          verbosity=1),
                                      cv='warn', method='sigmoid')
```

In [0]:
```
train_fpr, train_tpr, thresholds=roc_curve(y_train, cal_clf.predict_proba(X_train)[:, 1
plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
plt.legend()
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.title("ROC Curve")
plt.show()
```



In [0]:
```
test_fpr, test_tpr, thresholds=roc_curve(y_test, cal_clf.predict_proba(X_test)[:, 1])
plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.title("ROC Curve")
plt.show()
```

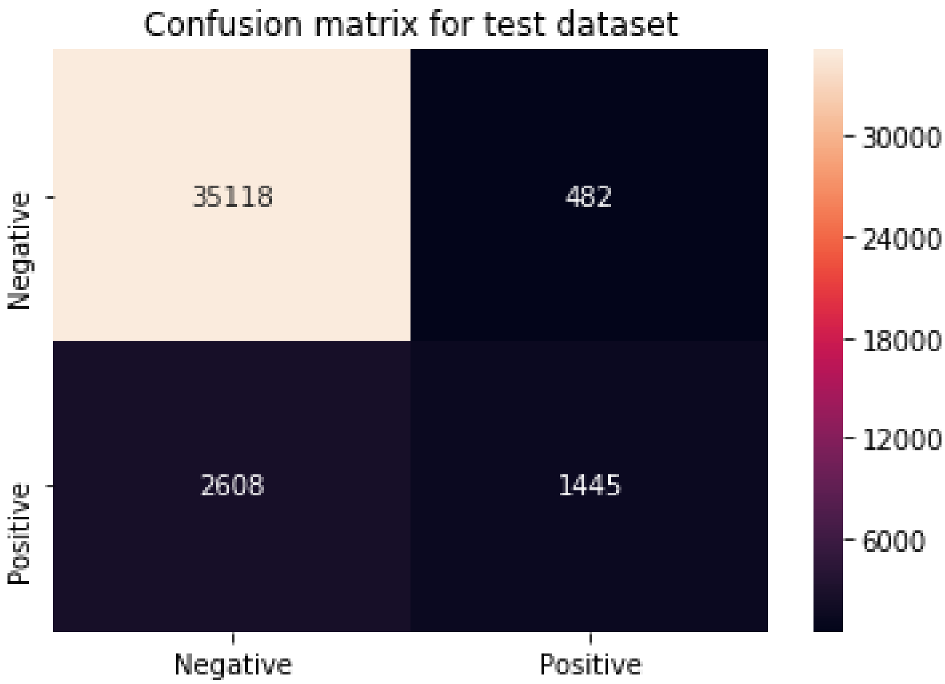


In [0]:
```
predict_y = cal_clf.predict_proba(X_train)
print('Training_ROC Score is :',roc_auc_score(y_train,predict_y[:,1]))
predict_y = cal_clf.predict_proba(X_test)
print('Testing_ROC Score is :',roc_auc_score(y_test,predict_y[:,1]))
```

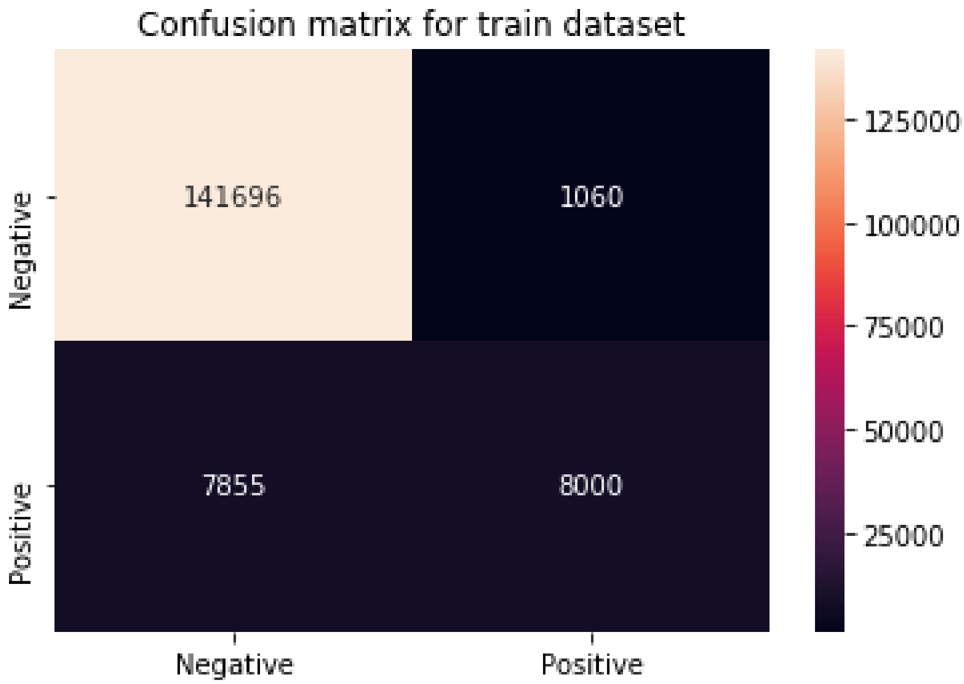
```
Training_ROC Score is : 0.9512345513250313
Testing_ROC Score is : 0.893872599572518
```

In [0]:
```
pred=cal_clf.predict(X_test)
conf_matrix=confusion_matrix(y_test, pred)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for test dataset')
```

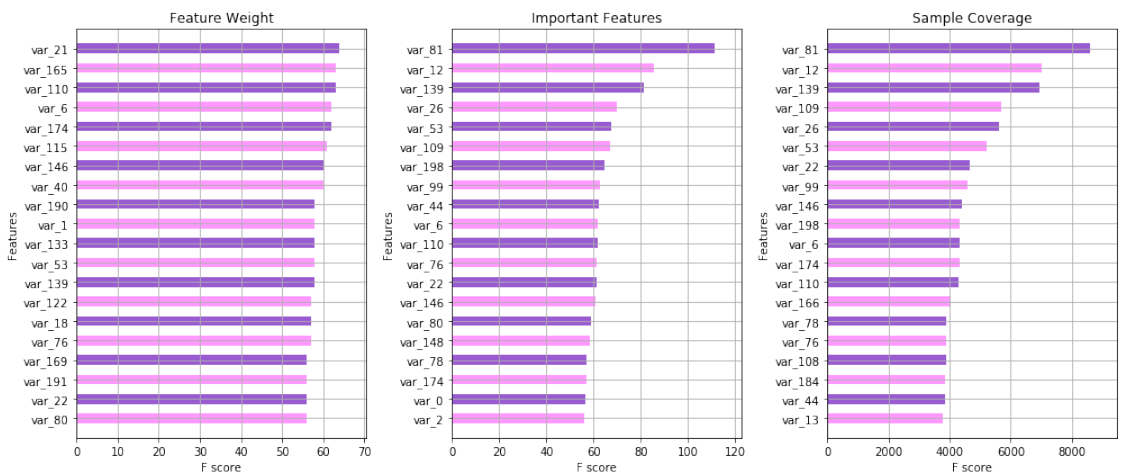



```
In [0]: predictions=cal_clf.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "F
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```



In [0]:
```
#Taken from:- https://towardsdatascience.com/running-xgboost-on-google-colab-free-gpu-
import xgboost as xgb
# store the winning model in a new variable
xgc = best_clf
# saving the feature names to the model
xgc.get_booster().feature_names = list(features.columns)
# Create the feature importances plot
fig, ax = plt.subplots(1, 3, figsize=(14,6))
# plot importances with split mean gain
xgb.plot_importance(
    booster=xgc,
    max_num_features=20,
    importance_type='gain',
    title='Important Features',
    show_values=False,
    height=0.5,
    ax=ax[1],
    color=['#FF99FF','#995BD0']
)
# plot importances with feature weight
xgb.plot_importance(
    booster=xgc,
    max_num_features=20,
    importance_type='weight',
    title='Feature Weight',
```

```
        show_values=False,
        height=0.5,
        ax=ax[0],
        color=['#FF99FF','#995BD0']
    )

    # plot importances with sample coverage
    xgb.plot_importance(
        xgc,
        max_num_features=20,
        importance_type='cover',
        title='Sample Coverage',
        show_values=False,
        height=0.5,
        ax=ax[2],
        color=['#FF99FF','#995BD0']
    )
    plt.tight_layout()
    plt.show()
```



XGBoost model is doing pretty well as compared to the random forest model this is all because of the hyperparameter tuning and cross-validation, now it can be seen that there is difference between training and testing ROC AUC score as it has been decreased from that of Random forest model. In the testing confusion matrix, it can be seen that XGBoost has decreased the false positive's but still there is a chance of improvement as there is no feature engineering involved. The top 20 important features from XGBoost model has been plotted.

8.6.2. On the dataset with original and basic features in addition with class weight balance

Preparing the dataset.

```
In [0]: features = train_df_basic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 408) (198264,)
```

```
In [0]: X_train,X_test,y_train,y_test=train_test_split(features,target,test_size=0.20,stratify=
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(158611, 408) (158611,)
(39653, 408) (39653,)
```

Preparing class weights.

```
In [0]: class_weights = class_weight.compute_class_weight('balanced',
                                                         np.unique(y_train),
                                                         y_train)
```

```
In [0]: w_array = np.ones(y_train.shape[0], dtype = 'float')
        for i, val in enumerate(y_train):
            w_array[i] = class_weights[val-1]
```

Finding the right hyperparameter for the model

```
In [0]: model = XGBClassifier(
            eval_metric=["auc"]
        )

        param_grid = {
            "learning_rate": [0.1, 0.01],
            "colsample_bytree": [0.6, 0.8, 1.0],
            "subsample": [0.6, 0.8, 1.0],
            "max_depth": [2, 3, 4],
            "n_estimators": [100, 200, 300, 400],
            "reg_lambda": [1, 1.5, 2],
            "gamma": [0, 0.1, 0.3],
        }

        scoring = {
            'AUC': 'roc_auc',
        }

        # create the Kfold object
        num_folds = 10
        kfold = StratifiedKFold(n_splits=num_folds)
        # create the grid search object
        n_iter=50
        grid = RandomizedSearchCV(
            estimator=model,
            param_distributions=param_grid,
```

```
            cv=kfold,
            scoring=scoring,
            n_jobs=-1,
            n_iter=n_iter,
            refit="AUC",
            verbose=1
        )

        best_model = grid.fit(X_train,y_train)
        best_clf=grid.best_estimator_
```

In [0]:
```
best_clf
```

Out[0]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, eval_metric=['auc'],
              gamma=0.1, learning_rate=0.1, max_delta_step=0, max_depth=4,
              min_child_weight=1, missing=None, n_estimators=400, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=2, scale_pos_weight=1, seed=None,
              silent=None, subsample=0.8, verbosity=1)
```

Fitting the optimal model and looking at the results.

In [0]:
```
best_clf=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bytree=0.8, eval_metric=['auc'], gamma=0.1,
              learning_rate=0.1, max_delta_step=0, max_depth=4,
              min_child_weight=1,n_estimators=400, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=2, scale_pos_weight=1, seed=None,
              silent=None, subsample=0.8)
best_clf.fit(X_train,y_train,sample_weight=w_array)
```

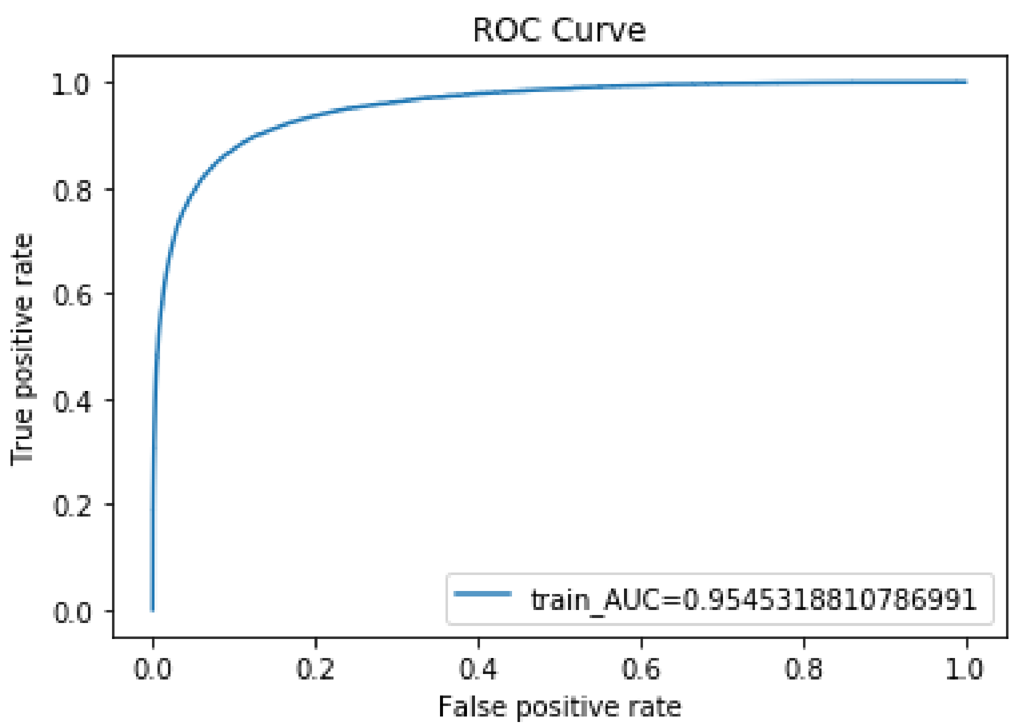
Out[0]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, eval_metric=['auc'],
              gamma=0.1, learning_rate=0.1, max_delta_step=0, max_depth=4,
              min_child_weight=1, missing=None, n_estimators=400, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=2, scale_pos_weight=1, seed=None,
              silent=None, subsample=0.8, verbosity=1)
```

In [0]:
```
cal_clf = CalibratedClassifierCV(best_clf, method="sigmoid")
cal_clf.fit(X_train, y_train)
```

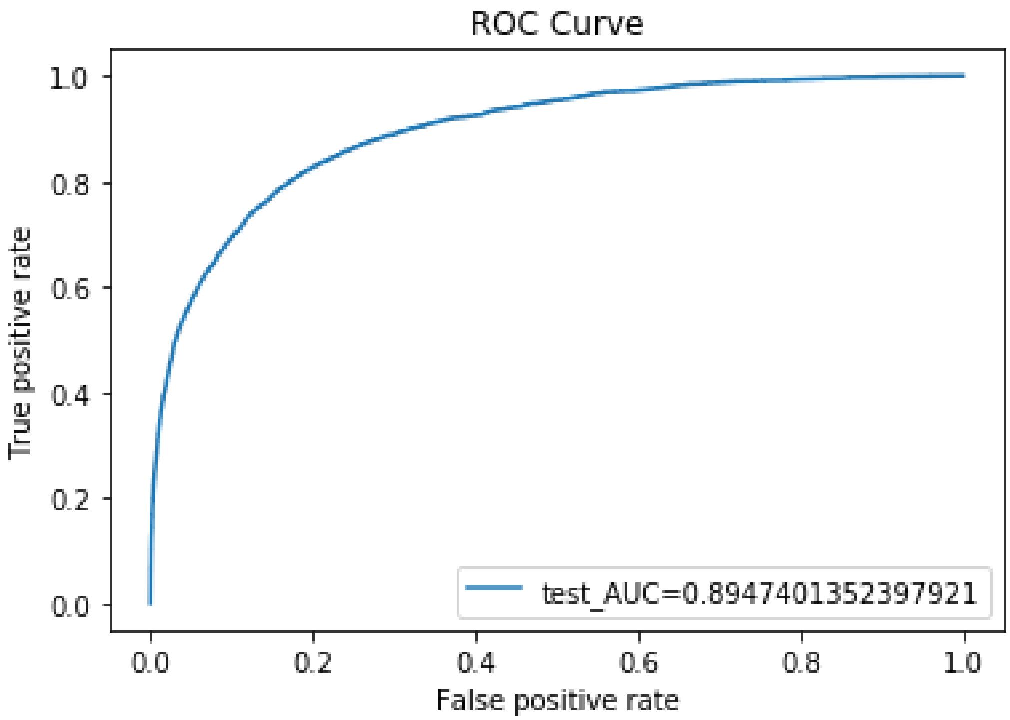
Out[0]:
```
CalibratedClassifierCV(base_estimator=XGBClassifier(base_score=0.5,
                                                    booster='gbtree',
                                                    colsample_bylevel=1,
                                                    colsample_bynode=1,
                                                    colsample_bytree=0.8,
                                                    eval_metric=['auc'],
```

```
                                         gamma=0.1,
                                         learning_rate=0.1,
                                         max_delta_step=0,
                                         max_depth=4,
                                         min_child_weight=1,
                                         missing=None,
                                         n_estimators=400, n_jobs=1,
                                         nthread=None,
                                         objective='binary:logistic',
                                         random_state=0, reg_alpha=0,
                                         reg_lambda=2,
                                         scale_pos_weight=1,
                                         seed=None, silent=None,
                                         subsample=0.8,
                                         verbosity=1),
                          cv='warn', method='sigmoid')
```

In [0]:
```
train_fpr, train_tpr, thresholds=roc_curve(y_train, cal_clf.predict_proba(X_train)[:, 1
plt.plot(train_fpr, train_tpr, label='train_AUC='+str(auc(train_fpr, train_tpr)))
plt.legend()
plt.xlabel("False positive rate")
plt.ylabel("True positive rate")
plt.title("ROC Curve")
plt.show()
```



```
In [0]: test_fpr, test_tpr, thresholds=roc_curve(y_test, cal_clf.predict_proba(X_test)[:, 1])
        plt.plot(test_fpr, test_tpr, label='test_AUC='+str(auc(test_fpr, test_tpr)))
        plt.legend()
        plt.xlabel("False positive rate")
        plt.ylabel("True positive rate")
        plt.title("ROC Curve")
        plt.show()
```

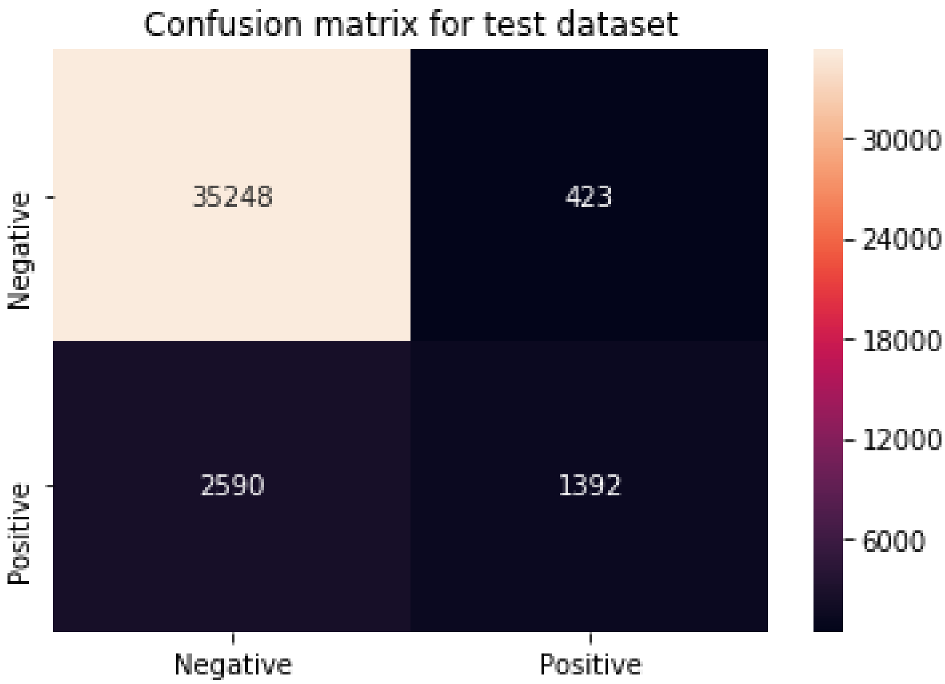



```
In [0]: predict_y = cal_clf.predict_proba(X_train)
        print('Training_ROC Score is :',roc_auc_score(y_train,predict_y[:,1]))
        predict_y = cal_clf.predict_proba(X_test)
        print('Testing_ROC Score is :',roc_auc_score(y_test,predict_y[:,1]))
```

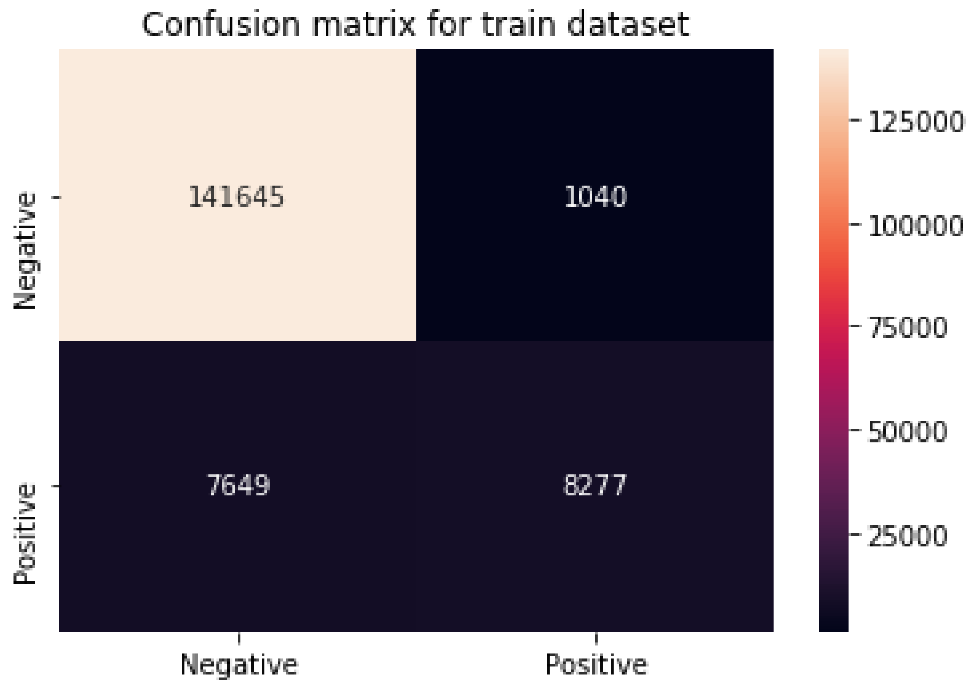
```
Training_ROC Score is : 0.9545318810786991
Testing_ROC Score is : 0.8947401352397921
```

```
In [0]: pred=cal_clf.predict(X_test)
        conf_matrix=confusion_matrix(y_test, pred)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for test dataset")
```

```
Out[0]: Text(0.5, 1, 'Confusion matrix for test dataset')
```

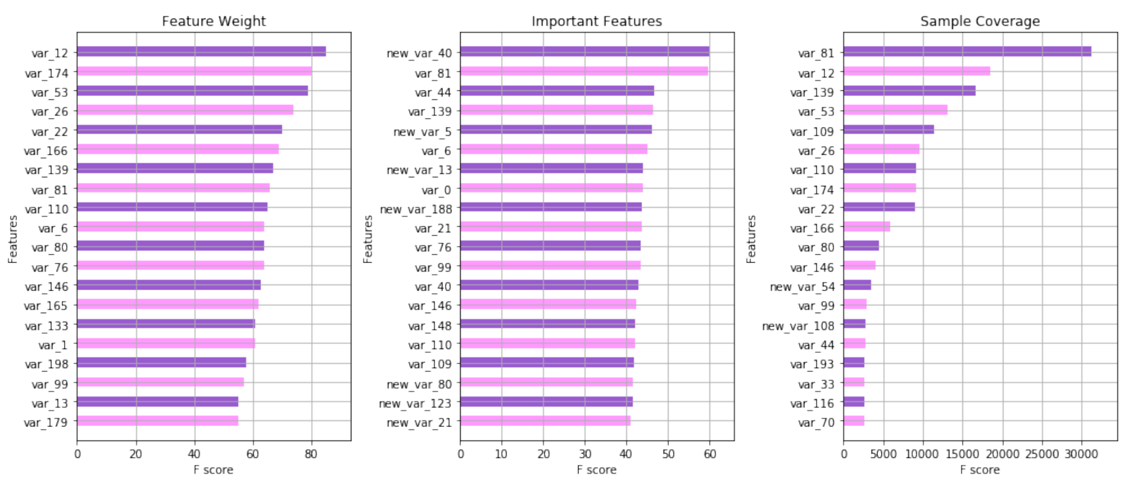



```
In [0]: predictions=cal_clf.predict(X_train)
        conf_matrix=confusion_matrix(y_train, predictions)
        confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
        sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
        plt.title("Confusion matrix for train dataset")

Out[0]: Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: #Taken from:- https://towardsdatascience.com/running-xgboost-on-google-colab-free-gpu-
        import xgboost as xgb
        # store the winning model in a new variable
        xgc = best_clf
        # saving the feature names to the model
        xgc.get_booster().feature_names = list(features.columns)
        # Create the feature importances plot
        fig, ax = plt.subplots(1, 3, figsize=(14,6))
        # plot importances with split mean gain
        xgb.plot_importance(
            booster=xgc,
            max_num_features=20,
            importance_type='gain',
            title='Important Features',
            show_values=False,
            height=0.5,
            ax=ax[1],
            color=['#FF99FF','#995BD0']
        )
        # plot importances with feature weight
        xgb.plot_importance(
            booster=xgc,
            max_num_features=20,
            importance_type='weight',
            title='Feature Weight',
```

```
    show_values=False,
    height=0.5,
    ax=ax[0],
    color=['#FF99FF','#995BD0']
)

# plot importances with sample coverage
xgb.plot_importance(
    xgc,
    max_num_features=20,
    importance_type='cover',
    title='Sample Coverage',
    show_values=False,
    height=0.5,
    ax=ax[2],
    color=['#FF99FF','#995BD0']
)
plt.tight_layout()
plt.show()
```



As it can be seen that there is a slight increase in testing ROC AUC score and also there is not much difference between training and testing ROC AUC Score. From the important feature plot, it can be seen that the new basic features are contributing pretty well in the model.

Comparing the results of the two XGBoost models.

```
In [8]: x = PrettyTable()
        x.title = 'AUC results of the two XGBoost models.'
        x.field_names = ['Dataset form', 'Test AUC score', 'Train AUC score']
        x.add_row(['Only with original features', 0.89387, 0.95123])
        x.add_row(['With original and basic features', 0.89474, 0.95453 ])
        print(x)
```

```
+------------------------------------------------------------------------+
|                 AUC results of the two XGBoost models.                 |
+-----------------------------------+----------------+-----------------+
|            Dataset form           | Test AUC score | Train AUC score |
+-----------------------------------+----------------+-----------------+
|   Only with original features     |    0.89387     |     0.95123     |
| With original and basic features  |    0.89474     |     0.95453     |
+-----------------------------------+----------------+-----------------+
```

8.7. LightGBM Model with Bayesian Optimization and Data Augmentation
Note:- Reference of this section has been taken from https://www.kaggle.com/jiweiliu/lgb-2-leaves-augment
8.7.1 On the dataset with original and basic features.

```
In [0]: features = train_df_basic_f.drop(['ID_code','target'],axis=1)
        features = features.drop([features.columns[0]], axis='columns')
        target = train_df['target']
        print(features.shape, target.shape)
```

```
(198264, 408) (198264,)
```

```
In [0]: X_train_cv,X_test,y_train_cv,y_test=train_test_split(features,target,test_size=0.20,st
        X_train_cv.shape, X_test.shape
```

```
Out[0]: ((158611, 408), (39653, 408))
```

```
In [0]: def augment(x,y,t=2):
            xs,xn = [],[]
            for i in range(t):
                mask = y>0
                x1 = x[mask].copy()
                ids = np.arange(x1.shape[0])
                for c in range(x1.shape[1]):
                    np.random.shuffle(ids)
                    x1[:,c] = x1[ids][:,c]
                xs.append(x1)

            for i in range(t//2):
                mask = y==0
                x1 = x[mask].copy()
                ids = np.arange(x1.shape[0])
                for c in range(x1.shape[1]):
                    np.random.shuffle(ids)
                    x1[:,c] = x1[ids][:,c]
                xn.append(x1)

            xs = np.vstack(xs)
```

```
        xn = np.vstack(xn)
        ys = np.ones(xs.shape[0])
        yn = np.zeros(xn.shape[0])
        x = np.vstack([x,xs,xn])
        y = np.concatenate([y,ys,yn])
        return x,y
```

In [0]:
```
# best parameter after bayesian opitmization
random_state = 42
np.random.seed(random_state)

param = {
    'bagging_freq': 5,
    'bagging_fraction': 0.335,
    'boost_from_average':'false',
    'boost': 'gbdt',
    'feature_fraction': 1.0,
    'learning_rate': 0.0083,
    'max_depth': -1,
    'metric':'auc',
    'min_data_in_leaf': 80,
    'min_sum_hessian_in_leaf': 10.0,
    'num_leaves': 13,
    'num_threads': 8,
    'tree_learner': 'serial',
    'objective': 'binary',
    'verbosity': -1
}
```

In [0]:
```
num_folds = 11
features = [i for i in features.columns ]

folds = KFold(n_splits=num_folds, random_state=random_state)
oof = np.zeros(len(X_train_cv))
getVal = np.zeros(len(X_train_cv))
predictions = np.zeros(len(y_train_cv))
feature_importance_df = pd.DataFrame()

for fold_, (trn_idx, val_idx) in enumerate(folds.split(X_train_cv.values, y_train_cv.va

    X_train, y_train = X_train_cv.iloc[trn_idx][features], y_train_cv.iloc[trn_idx]
    X_valid, y_valid = X_train_cv.iloc[val_idx][features], y_train_cv.iloc[val_idx]

    X_tr, y_tr = augment(X_train.values, y_train.values)
    X_tr = pd.DataFrame(X_tr)

    print("Fold idx:{}".format(fold_ + 1))
    trn_data = lgb.Dataset(X_tr, label=y_tr)
```

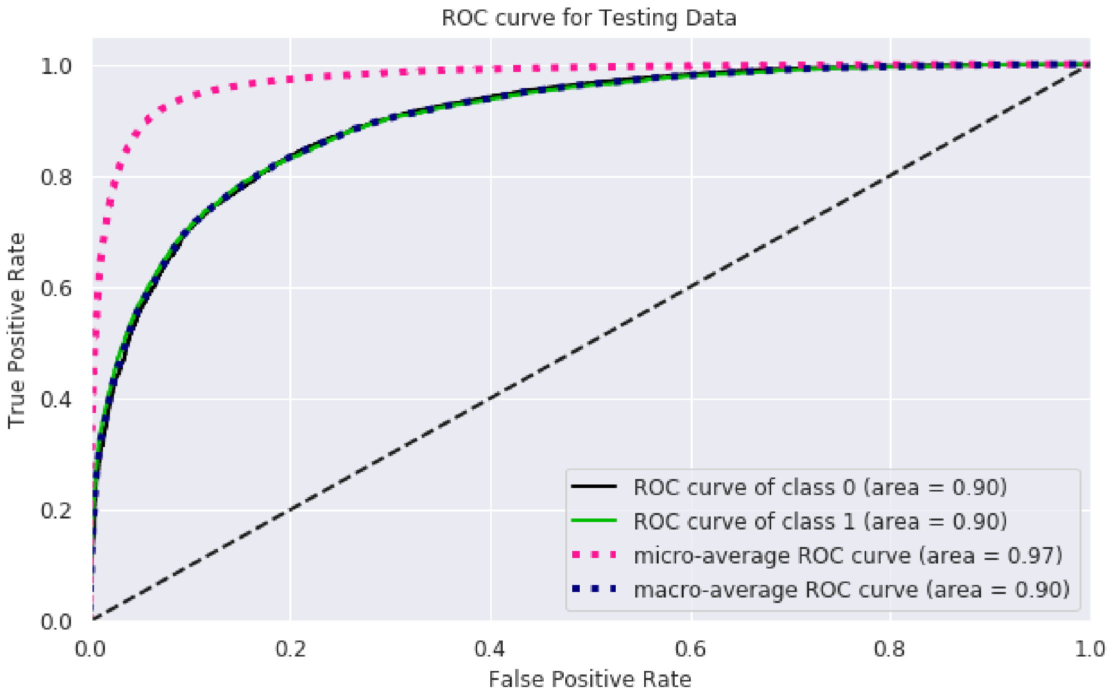
```
            val_data = lgb.Dataset(X_valid, label=y_valid)

            clf = lgb.train(param, trn_data, 1000000, valid_sets = [trn_data, val_data], verbos
            oof[val_idx] = clf.predict(X_train_cv.iloc[val_idx][features], num_iteration=clf.be
            getVal[val_idx]+= clf.predict(X_train_cv.iloc[val_idx][features], num_iteration=cl

            fold_importance_df = pd.DataFrame()
            fold_importance_df["feature"] = features
            fold_importance_df["importance"] = clf.feature_importance()
            fold_importance_df["fold"] = fold_ + 1
            feature_importance_df = pd.concat([feature_importance_df, fold_importance_df], axi

            #predictions += clf.predict(test[features], num_iteration=clf.best_iteration) / fo

        print("\n >> CV score: {:<8.5f}".format(roc_auc_score(y_train_cv, oof)))
```

```
Fold idx:1
Training until validation scores don't improve for 4000 rounds.
[5000]        training's auc: 0.927187        valid_1's auc: 0.892344
[10000]        training's auc: 0.943236        valid_1's auc: 0.89415
Early stopping, best iteration is:
[8056]        training's auc: 0.937726        valid_1's auc: 0.894577
Fold idx:2
Training until validation scores don't improve for 4000 rounds.
[5000]        training's auc: 0.926921        valid_1's auc: 0.894885
[10000]        training's auc: 0.943189        valid_1's auc: 0.897834
[15000]        training's auc: 0.955871        valid_1's auc: 0.896969
Early stopping, best iteration is:
[11179]        training's auc: 0.946399        valid_1's auc: 0.897956
Fold idx:3
Training until validation scores don't improve for 4000 rounds.
[5000]        training's auc: 0.927361        valid_1's auc: 0.897057
[10000]        training's auc: 0.943434        valid_1's auc: 0.90008
Early stopping, best iteration is:
[10935]        training's auc: 0.945939        valid_1's auc: 0.900367
Fold idx:4
Training until validation scores don't improve for 4000 rounds.
[5000]        training's auc: 0.927834        valid_1's auc: 0.895238
[10000]        training's auc: 0.943723        valid_1's auc: 0.897704
Early stopping, best iteration is:
[9848]        training's auc: 0.943327        valid_1's auc: 0.897815
Fold idx:5
Training until validation scores don't improve for 4000 rounds.
[5000]        training's auc: 0.925782        valid_1's auc: 0.902486
[10000]        training's auc: 0.942138        valid_1's auc: 0.903884
Early stopping, best iteration is:
[7935]        training's auc: 0.936177        valid_1's auc: 0.90423
Fold idx:6
```

```
Training until validation scores don't improve for 4000 rounds.
[5000]	training's auc: 0.927236	valid_1's auc: 0.885826
[10000]	training's auc: 0.943271	valid_1's auc: 0.889088
[15000]	training's auc: 0.955893	valid_1's auc: 0.888971
Early stopping, best iteration is:
[13425]	training's auc: 0.952158	valid_1's auc: 0.889448
Fold idx:7
Training until validation scores don't improve for 4000 rounds.
[5000]	training's auc: 0.927251	valid_1's auc: 0.896621
[10000]	training's auc: 0.943424	valid_1's auc: 0.899715
Early stopping, best iteration is:
[9135]	training's auc: 0.941069	valid_1's auc: 0.899805
Fold idx:8
Training until validation scores don't improve for 4000 rounds.
[5000]	training's auc: 0.927237	valid_1's auc: 0.900199
[10000]	training's auc: 0.943178	valid_1's auc: 0.901125
Early stopping, best iteration is:
[7648]	training's auc: 0.936462	valid_1's auc: 0.901593
Fold idx:9
Training until validation scores don't improve for 4000 rounds.
[5000]	training's auc: 0.927042	valid_1's auc: 0.897233
[10000]	training's auc: 0.943119	valid_1's auc: 0.899953
Early stopping, best iteration is:
[9326]	training's auc: 0.941237	valid_1's auc: 0.900031
Fold idx:10
Training until validation scores don't improve for 4000 rounds.
[5000]	training's auc: 0.926877	valid_1's auc: 0.891376
[10000]	training's auc: 0.942999	valid_1's auc: 0.894211
Early stopping, best iteration is:
[10955]	training's auc: 0.945589	valid_1's auc: 0.894403
Fold idx:11
Training until validation scores don't improve for 4000 rounds.
[5000]	training's auc: 0.926765	valid_1's auc: 0.900332
[10000]	training's auc: 0.943014	valid_1's auc: 0.903177
Early stopping, best iteration is:
[8410]	training's auc: 0.938471	valid_1's auc: 0.90335

 >> CV score: 0.89827
```

In [0]:
```python
sns.set(rc={'figure.figsize':(10,6)})
predict_y = clf.predict(X_train_cv)
predict_y_prob=[[abs(1-i),i] for i in predict_y]
skplt.metrics.plot_roc_curve(y_train_cv, predict_y_prob)
plt.title('ROC curve for Training Data')
plt.show()
```

In [0]:
```
predict_y = clf.predict(X_test)
predict_y_prob=[[abs(1-i),i] for i in predict_y]
skplt.metrics.plot_roc_curve(y_test, predict_y_prob)
plt.title('ROC curve for Testing Data')
plt.show()
```

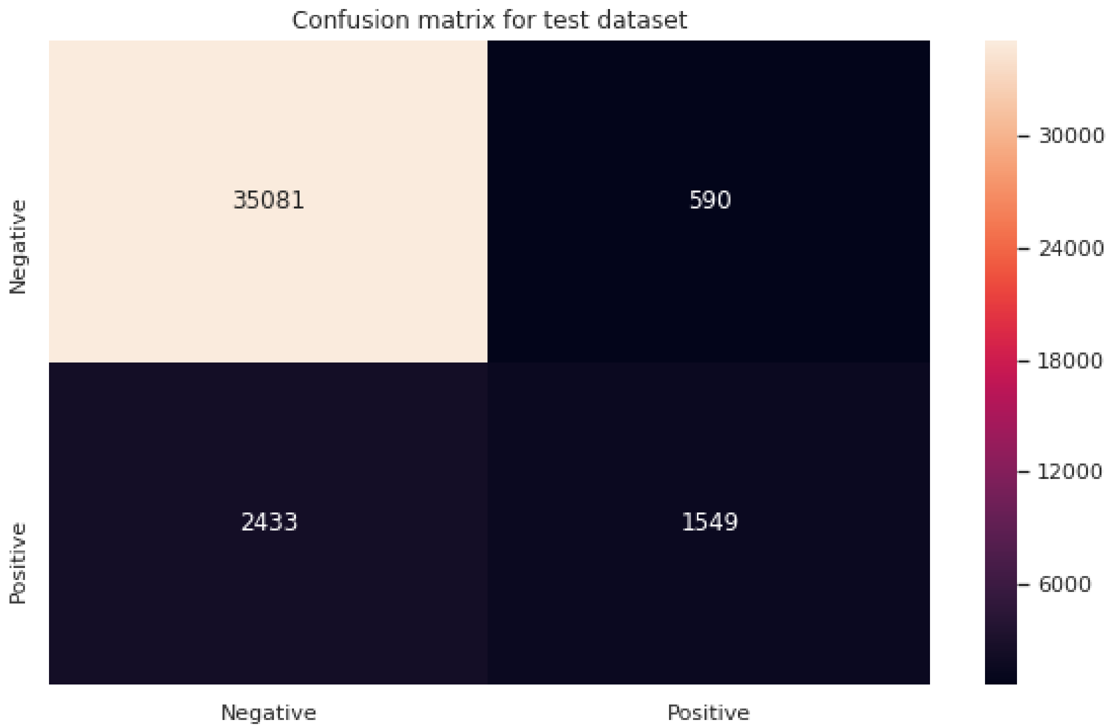


In [0]:
```
predict_y = clf.predict(X_train_cv)
print('Training_ROC Score is :',roc_auc_score(y_train_cv,predict_y))
predict_y = clf.predict(X_test)
print('Testing_ROC Score is :',roc_auc_score(y_test,predict_y))
```

```
Training_ROC Score is : 0.9295086856819318
Testing_ROC Score is : 0.899835028985316
```

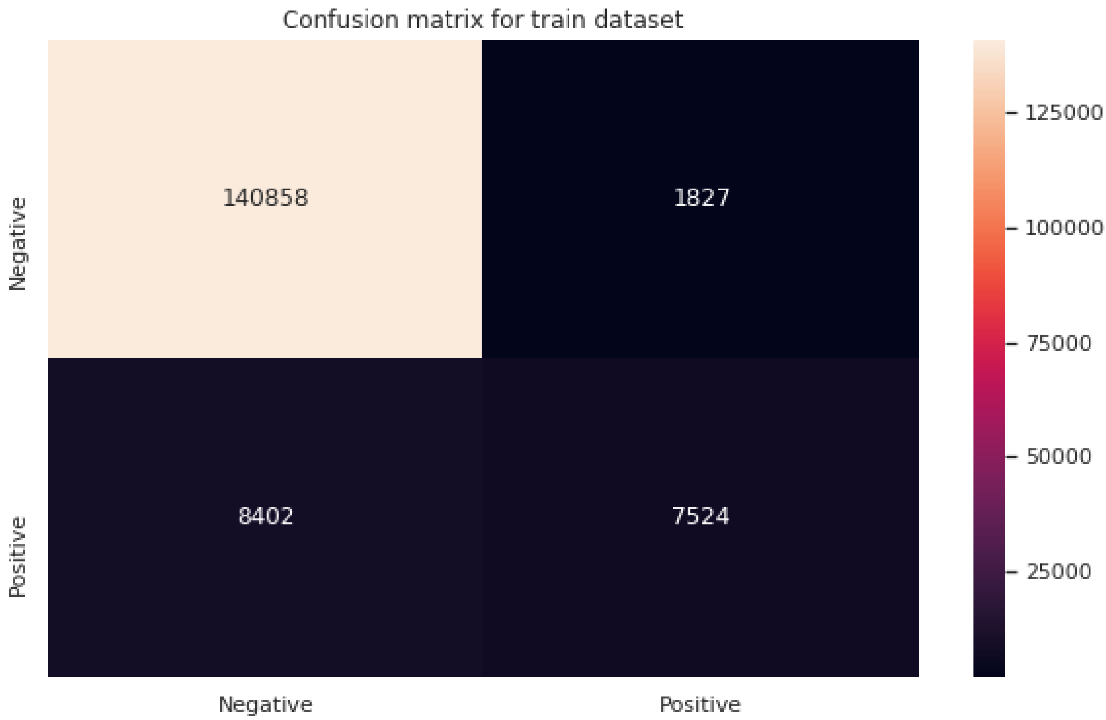
In [0]:
```
pred_test=clf.predict(X_test)
pred_test_v=[1 if i>0.5 else 0 for i in pred_test]
conf_matrix=confusion_matrix(y_test, pred_test_v)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "I
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for test dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for test dataset')
```

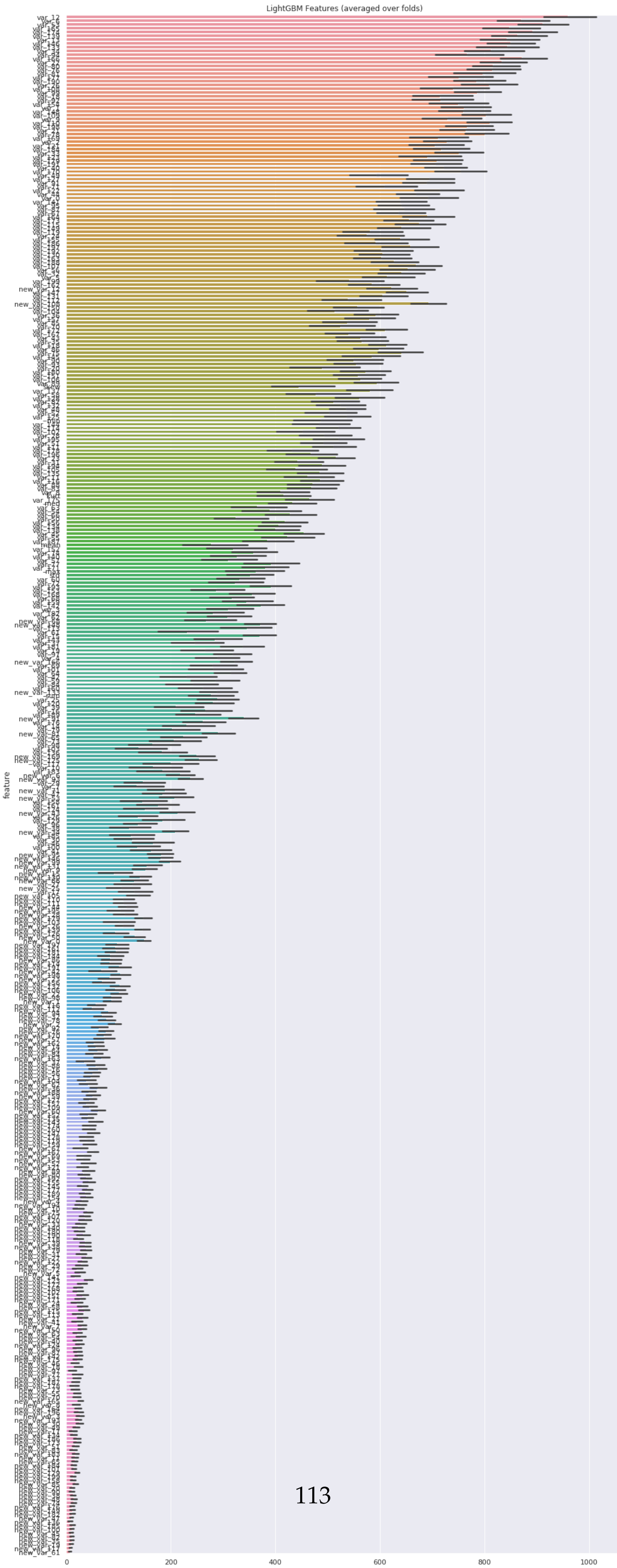


In [0]:
```
pred_train=clf.predict(X_train_cv)
pred_train_v=[1 if i>0.5 else 0 for i in pred_train]
conf_matrix=confusion_matrix(y_train_cv, pred_train_v)
confusion_matrix_df=pd.DataFrame(conf_matrix, ["Negative", "Positive"], ["Negative", "P
sns.heatmap(confusion_matrix_df, annot=True, fmt="g")
plt.title("Confusion matrix for train dataset")
```

Out[0]:
```
Text(0.5, 1, 'Confusion matrix for train dataset')
```




```
In [0]: cols = (feature_importance_df[["feature", "importance"]]
                .groupby("feature")
                .mean()
                .sort_values(by="importance", ascending=False)[:1000].index)
        best_features = feature_importance_df.loc[feature_importance_df.feature.isin(cols)]

        plt.figure(figsize=(14,35))
        sns.barplot(x="importance", y="feature", data=best_features.sort_values(by="importance'
        plt.title('LightGBM Features (averaged over folds)')
        plt.tight_layout()
        plt.savefig('lgbm_importances.png')
```


LightGBM Features (averaged over folds)
feature
importance
0
200
400
600
800
1000

By using LightGBM training and test ROC Scores are very close to each other which shows this model is not overfitting that much and also number of True Positives are highest in LightGBM model which is very good.

8.8. Picking the best machine learning model based on test AUC scores from each of the seven methods that were implemented in the above section and comparing the results.

```
In [18]: x = PrettyTable()
         x.title = 'Comparing the test AUC results of best machine learning model from each of
         x.field_names = ['Sr No.', 'Method', 'Dataset form', 'Test AUC score']
         x.add_row([1, 'Logistic Regression(no class balance)', 'With original and basic featu
         x.add_row([2, 'Logistic Regression(with class balance)', 'With original and basic fea
         x.add_row([3, 'Decision Tree', 'With original and basic features', 0.68157])
         x.add_row([4, 'Gaussian Naive Bayes', 'Only with original features', 0.89176])
         x.add_row([5, 'Random Forest', 'Only with original features', 0.83167])
         x.add_row([6, 'XGBoost', 'With original and basic features', 0.89474])
         x.add_row([7, 'LightGBM', 'With original and basic features', 0.89983])

         print(x)
```

```
+---------------------------------------------------------------------------------------------
|    Comparing the test AUC results of best machine learning model from each of the seven metho
+--------+-----------------------------------------+-----------------------------------+--------
| Sr No. |                 Method                  |            Dataset form           | Test AU
+--------+-----------------------------------------+-----------------------------------+--------
|   1    |  Logistic Regression(no class balance)  | With original and basic features |    0.87
|   2    | Logistic Regression(with class balance) | With original and basic features |     0.8
|   3    |              Decision Tree              | With original and basic features |    0.68
|   4    |           Gaussian Naive Bayes          |   Only with original features    |    0.89
|   5    |              Random Forest              |   Only with original features    |    0.83
|   6    |                 XGBoost                 | With original and basic features |    0.89
|   7    |                 LightGBM                | With original and basic features |    0.89
+--------+-----------------------------------------+-----------------------------------+--------
```

9. Conclusion

- In this case study an anonymized dataset of 200,000 data points with 202 features in which 200 features were numerical was provided to us.
- From EDA it became clear that the data is highly imbalanced, there is no missing value in data, there are very small no. of outliers, there is very low correlation between each features.
- In feature engineering section we devised new features by looking the results obtained from the EDA section and using symbolic regression with the help of python's external library known as 'gplearn'
- After feature engineering the dataset was given three forms, one with only original features, other with basic features which were obtained by using the results of EDA section and last one was with original features with genetic features which was devised using 'gplearn'.

- These three forms of dataset were tested on 4 machine learning models and by analysing the results of these four models it was concluded that genetic features don't help much and thus were dropped from further analysis.
- By analysing the results of the seven models it can be stated that the features which were devised using EDA results were very fruitful because when the best results of the seven models are analysed it can be seen basic features were fruitful in five of them.
- The best result came from the LightGBM Model which shows the power of state of the art bayesian optimization and data augmentation techniques.
- Altough Gaussian Naive Bayes with only original features obtained almost the same result of LightGBM.
- The best train and test AUC scores were 0.929 and 0.899.