At Santander our mission is to help people and businesses prosper. We are always looking for ways to help our customers understand their financial health and identify which products and services might help them achieve their monetary goals.

Our data science team is continually challenging our machine learning algorithms, working with the global data science community to make sure we can more accurately identify new ways to solve our most common challenge, binary classification problems such as: is a customer satisfied? Will a customer buy this product? Can a customer pay this loan?

In this challenge, we invite Kagglers to help us identify which customers will make a specific transaction in the future, irrespective of the amount of money transacted. The data provided for this competition has the same structure as the real data we have available to solve this problem.

Source:[https://www.kaggle.com/c/santander-customer-transaction-prediction (https://www.kaggle.com/c/santander-customer-transaction-prediction)](https://www.kaggle.com/c/santander-customer-transaction-prediction)

Reference:[https://www.kaggle.com/gpreda/santander-eda-and-prediction (https://www.kaggle.com/gpreda/santander-eda-and-prediction)](https://www.kaggle.com/gpreda/santander-eda-and-prediction) \ [https://www.kaggle.com/jiweiliu/lgb-2-leaves-augment (https://www.kaggle.com/jiweiliu/lgb-2-leaves-augment)](https://www.kaggle.com/jiweiliu/lgb-2-leaves-augment) \ [https://www.kaggle.com/sicongfang/eda-feature-engineering (https://www.kaggle.com/sicongfang/eda-feature-engineering)](https://www.kaggle.com/sicongfang/eda-feature-engineering) \ [https://www.kaggle.com/titericz/single-model-using-only-train-counts-information (https://www.kaggle.com/titericz/single-model-using-only-train-counts-information)](https://www.kaggle.com/titericz/single-model-using-only-train-counts-information)

metric used = auc(since data is not balanced)

Note: Here i am working only on train data dropping the labels for test as aaic team used to work for better visualization

importing the necessary libraries

In [0]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns              #For plots
import warnings
with warnings.catch_warnings():
    warnings.simplefilter("ignore")

%matplotlib inline
```

In [0]:
```
train = pd.read_csv("/content/train.csv.zip")
test = pd.read_csv("/content/test.csv.zip")
```

In [0]:
```
train.shape, test.shape
```

Out[0]:
```
((200000, 202), (200000, 201))
```

As we can see from above that train and test, both contains 0.2 million rows.

In [0]:
```
train.head(5)
```

Out[0]:

	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8
0	train_0	0	8.9255	-6.7863	11.9081	5.0930	11.4607	-9.2834	5.1187	18.6266	-4.9200
1	train_1	0	11.5006	-4.1473	13.8588	5.3890	12.3622	7.0433	5.6208	16.5338	3.1468
2	train_2	0	8.6093	-2.7457	12.0805	7.8928	10.5825	-9.0837	6.9427	14.6155	-4.9193
3	train_3	0	11.0604	-2.1518	8.9522	7.1957	12.5846	-1.8361	5.8428	14.9250	-5.8609
4	train_4	0	9.8369	-1.4834	12.8746	6.6375	12.2772	2.4486	5.9405	19.2514	6.2654

5 rows × 202 columns

In [0]:
```
test.head(5)
```

Out[0]:

	ID_code	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8	var_9
0	test_0	11.0656	7.7798	12.9536	9.4292	11.4327	-2.3805	5.8493	18.2675	2.1337	8.8100
1	test_1	8.5304	1.2543	11.3047	5.1858	9.1974	-4.0117	6.0196	18.6316	-4.4131	5.9739
2	test_2	5.4827	-10.3581	10.1407	7.0479	10.2628	9.8052	4.8950	20.2537	1.5233	8.3442
3	test_3	8.5374	-1.3222	12.0220	6.5749	8.8458	3.1744	4.9397	20.5660	3.3755	7.4578
4	test_4	11.7058	-0.1327	14.1295	7.7506	9.1035	-8.5848	6.8595	10.6048	2.9890	7.1437

5 rows × 201 columns

In [0]:
```
#target = train["target"]
```

In [0]:
```
#train = train.drop(["target"], axis=1)
```

Checking missing values if any

In [0]:
```
train.isnull().sum()
```

Out[0]:
```
ID_code    0
target     0
var_0      0
var_1      0
var_2      0
var_3      0
var_4      0
var_5      0
var_6      0
var_7      0
var_8      0
var_9      0
var_10     0
var_11     0
var_12     0
var_13     0
var_14     0
var_15     0
var_16     0
var_17     0
var_18     0
var_19     0
var_20     0
var_21     0
var_22     0
var_23     0
var_24     0
var_25     0
var_26     0
var_27     0
          ..
var_170    0
var_171    0
var_172    0
var_173    0
var_174    0
var_175    0
var_176    0
var_177    0
var_178    0
var_179    0
var_180    0
var_181    0
var_182    0
var_183    0
var_184    0
var_185    0
var_186    0
var_187    0
var_188    0
var_189    0
var_190    0
var_191    0
var_192    0
var_193    0
var_194    0
var_195    0
```

```
var_196    0
var_197    0
var_198    0
var_199    0
Length: 202, dtype: int64
```

we can see that there is no null value in train

In [0]:
```
test.isnull().sum()
```

```
Out[0]: ID_code     0
        var_0       0
        var_1       0
        var_2       0
        var_3       0
        var_4       0
        var_5       0
        var_6       0
        var_7       0
        var_8       0
        var_9       0
        var_10      0
        var_11      0
        var_12      0
        var_13      0
        var_14      0
        var_15      0
        var_16      0
        var_17      0
        var_18      0
        var_19      0
        var_20      0
        var_21      0
        var_22      0
        var_23      0
        var_24      0
        var_25      0
        var_26      0
        var_27      0
        var_28      0
                   ..
        var_170     0
        var_171     0
        var_172     0
        var_173     0
        var_174     0
        var_175     0
        var_176     0
        var_177     0
        var_178     0
        var_179     0
        var_180     0
        var_181     0
        var_182     0
        var_183     0
        var_184     0
        var_185     0
        var_186     0
        var_187     0
        var_188     0
        var_189     0
        var_190     0
        var_191     0
        var_192     0
        var_193     0
        var_194     0
        var_195     0
```

```
var_196     0
var_197     0
var_198     0
var_199     0
Length: 201, dtype: int64
```

We can see that there is no null values in test data

Lets describe train

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

Out[0]:

	target	var_0	var_1	var_2	var_3	var_
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.00000
mean	0.100490	10.679914	-1.627622	10.715192	6.796529	11.07833
std	0.300653	3.040051	4.050044	2.640894	2.043319	1.62315
min	0.000000	0.408400	-15.043400	2.117100	-0.040200	5.07480
25%	0.000000	8.453850	-4.740025	8.722475	5.254075	9.88317
50%	0.000000	10.524750	-1.608050	10.580000	6.825000	11.10825
75%	0.000000	12.758200	1.358625	12.516700	8.324100	12.26112
max	1.000000	20.315000	10.376800	19.353000	13.188300	16.67140

8 rows × 201 columns

Lets describe test

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

Out[0]:

	var_0	var_1	var_2	var_3	var_4	var_
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.00000
mean	10.658737	-1.624244	10.707452	6.788214	11.076399	-5.05055
std	3.036716	4.040509	2.633888	2.052724	1.616456	7.86929
min	0.188700	-15.043400	2.355200	-0.022400	5.484400	-27.76700
25%	8.442975	-4.700125	8.735600	5.230500	9.891075	-11.20140
50%	10.513800	-1.590500	10.560700	6.822350	11.099750	-4.83410
75%	12.739600	1.343400	12.495025	8.327600	12.253400	0.94257
max	22.323400	9.385100	18.714100	13.142000	16.037100	17.25370

8 rows × 200 columns

from this train_vis we are going to visualize 11 features as pair plot because visualizing all at one takes a lot of time

In [0]:
```
train_vis = train.iloc[:, 1:13]
```

In [0]:
```
train_vis.head(2)
```

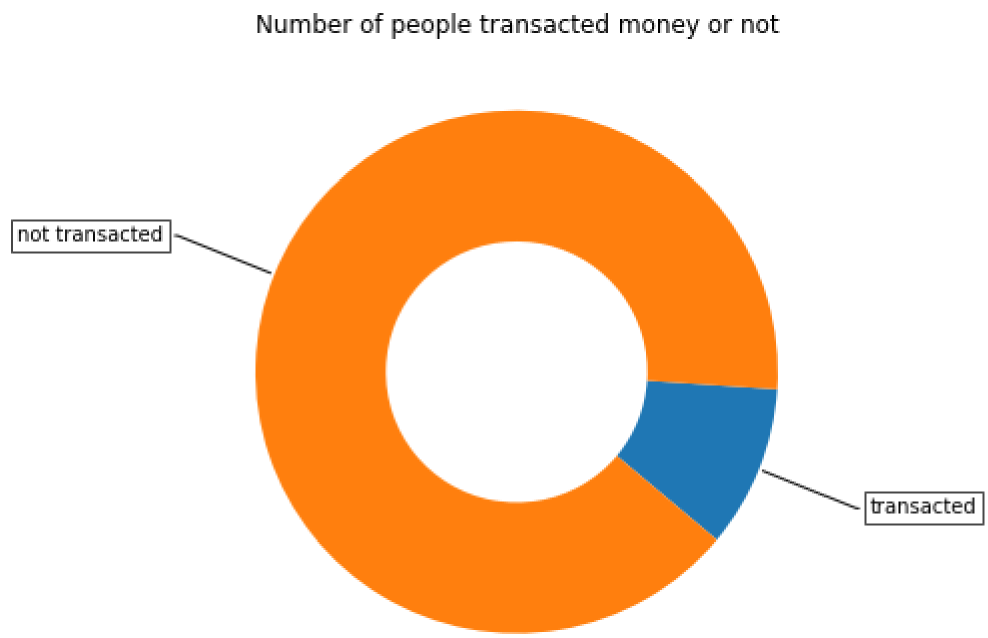
Out[0]:

	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8	var_9	v
0	0	8.9255	-6.7863	11.9081	5.093	11.4607	-9.2834	5.1187	18.6266	-4.9200	5.7470	2
1	0	11.5006	-4.1473	13.8588	5.389	12.3622	7.0433	5.6208	16.5338	3.1468	8.0851	-(

Data Analysis on train data

In [0]:
```
# PROVIDE CITATIONS TO YOUR CODE IF YOU TAKE IT FROM ANOTHER WEBSITE.
# https://matplotlib.org/gallery/pie_and_polar_charts/pie_and_donut_labe
ls.html#sphx-glr-gallery-pie-and-polar-charts-pie-and-donut-labels-py


y_value_counts = train['target'].value_counts()
print("Number of people transacted the money in future ", y_value_counts
[1], ", (", (y_value_counts[1]/(y_value_counts[1]+y_value_counts[0]))*10
0,"%)")
print("Number of people not transacted the money in future  ", y_value_c
ounts[0], ", (", (y_value_counts[0]/(y_value_counts[1]+y_value_counts[0
]))*100,"%)")
#above codes will give the%age of approved and not approved project

fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(aspect="equal"))
recipe = ["transacted", "not transacted"]

data = [y_value_counts[1], y_value_counts[0]]

wedges, texts = ax.pie(data, wedgeprops=dict(width=0.5), startangle=-40)

bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
kw = dict(xycoords='data', textcoords='data', arrowprops=dict(arrowstyle
="-"),
          bbox=bbox_props, zorder=0, va="center")

for i, p in enumerate(wedges):
    ang = (p.theta2 - p.theta1)/2. + p.theta1
    y = np.sin(np.deg2rad(ang))
    x = np.cos(np.deg2rad(ang))
    horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
    connectionstyle = "angle,angleA=0,angleB={}".format(ang)
    kw["arrowprops"].update({"connectionstyle": connectionstyle})
    ax.annotate(recipe[i], xy=(x, y), xytext=(1.35*np.sign(x), 1.4*y),
                horizontalalignment=horizontalalignment, **kw)

ax.set_title("Number of people transacted money or not")

plt.show()
```

```
Number of people transacted the money in future  20098 , ( 10.049 %)
Number of people not transacted the money in future   179902 , ( 89.951
00000000001 %)
```



So from the above plot we can observe that the number of people transected the money os about 10% of the total data only.\ *this is a purely imbalanced data.*

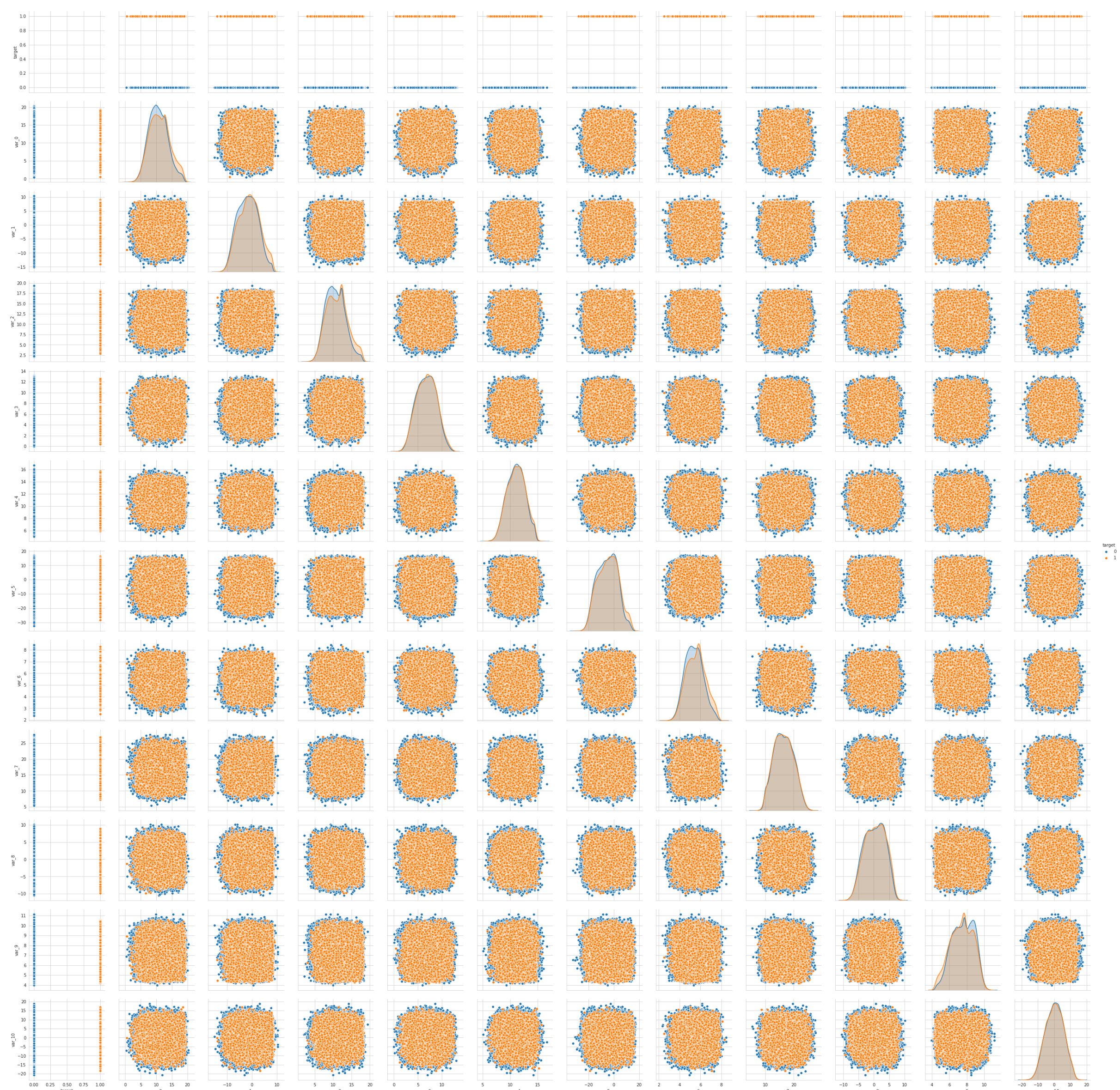
Visualising with all the features is quite difficult so I am choosing 10 var columns to visualise as pair plot

PAIR PLOT only for first 10 var_0 to var_10

we can visualize relationship between two varioables with this

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.pairplot.html
plt.close()  #Closing all open window
sns.set_style("whitegrid");
sns.pairplot(train_vis, hue="target", height=3);
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/nonparametric/kde.p
y:487: RuntimeWarning: invalid value encountered in true_divide
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
/usr/local/lib/python3.6/dist-packages/statsmodels/nonparametric/kdetoo
ls.py:34: RuntimeWarning: invalid value encountered in double_scalars
  FAC1 = 2*(np.pi*bw/RANGE)**2
```



from this few features only we can see that both traget is easily seperable using any of the two features.
although the data is imbalanced but easily seperable

Pdf for all features

https://www.kaggle.com/gpreda/santander-eda-and-prediction (https://www.kaggle.com/gpreda/santander-eda-and-prediction)

In [0]:
```
def plot_feature_distribution(df1, df2, label1, label2, features):
    i = 0
    sns.set_style('whitegrid')
    plt.figure()
    fig, ax = plt.subplots(10,10,figsize=(18,22))

    for feature in features:
        i += 1
        plt.subplot(10,10,i)
        sns.distplot(df1[feature], hist=False,label=label1)
        sns.distplot(df2[feature], hist=False,label=label2)
        plt.xlabel(feature, fontsize=9)
        locs, labels = plt.xticks()
        plt.tick_params(axis='x', which='major', labelsize=6, pad=-6)
        plt.tick_params(axis='y', which='major', labelsize=6)
    plt.show();
```

first 100

here I am distributing dataset label wise

In [0]:
```
t0 = train.loc[train['target'] == 0]
t1 = train.loc[train['target'] == 1]
```

In [0]:
```
features = train.columns.values[2:102]
plot_feature_distribution(t0, t1, '0', '1', features)
```

<Figure size 432x288 with 0 Axes>

from features 100 -200

In [0]:
```
features = train.columns.values[102:202]
plot_feature_distribution(t0, t1, '0', '1', features)
```

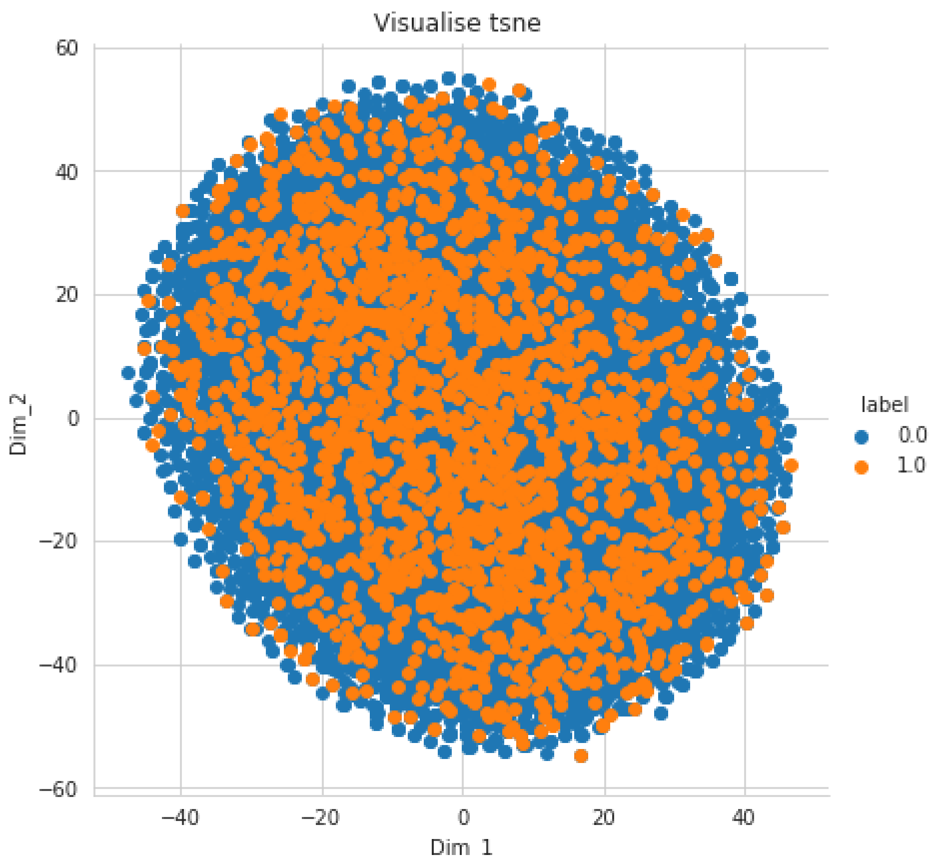
```
<Figure size 432x288 with 0 Axes>
```

As we can see from above pdf that there is a lot of different distribution\ and for most of the data where label=1 and label=0 follows same distribution\ var_10 ,var_11, var_8, var_65, var_84 ect. follows same distribution like gaussian\ var_70, var_60, var_85 ect follows similar distribution\ var_80, var_86 etc follows similar distribution.\ similarly we can see from feature 102 to 202.

Visualising by tsne

In [0]:
```
train_5000 = train.head(20000)
y =train_5000["target"]
x = train_5000.iloc[:,2:202].values
```

In [0]:
```
# https://github.com/pavlin-policar/fastTSNE you can try this also, this
version is little faster than sklearn
#reference: aaic tsne
import numpy as np
from sklearn.manifold import TSNE
from sklearn import datasets
import pandas as pd
import matplotlib.pyplot as plt


tsne = TSNE(n_components=2, perplexity=30, learning_rate=200)

X_embedding = tsne.fit_transform(x)
# if x is a sparse matrix you need to pass it as X_embedding = tsne.fit_
transform(x.toarray()) , .toarray() will convert the sparse matrix into
 dense matrix

for_tsne = np.vstack((X_embedding.T, y)).T#y.reshape(-1,1)
for_tsne_df = pd.DataFrame(data=for_tsne, columns=['Dim_1','Dim_2','labe
l'])
# Ploting the result of tsne
sns.FacetGrid(for_tsne_df, hue="label", height=6).map(plt.scatter, 'Dim_
1', 'Dim_2').add_legend()
plt.title("Visualise tsne ")
plt.show()
```



from the above tsne plot we can see that label 1 is not much seperable when we visualise it in 2d plot

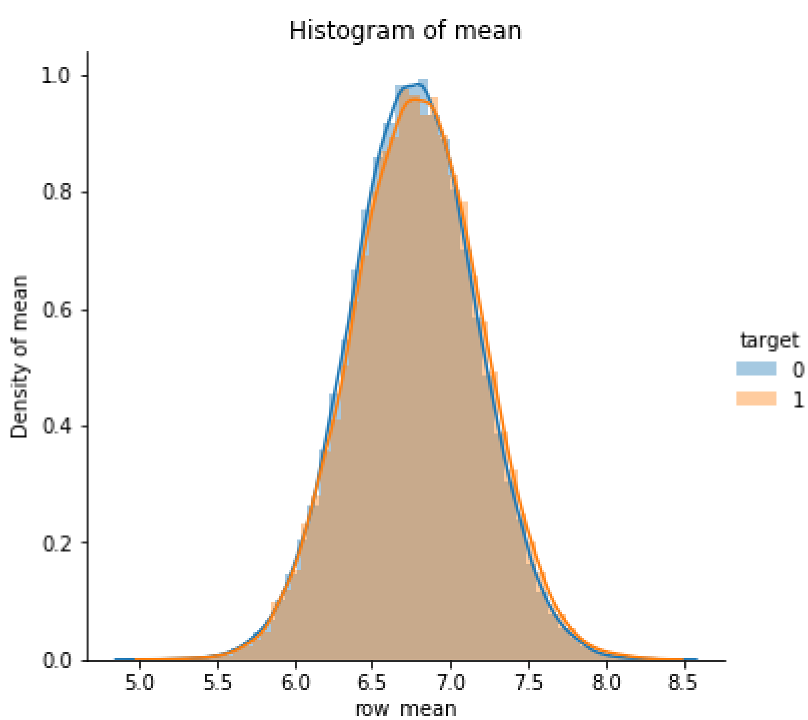
Visualizing mean, median, std, kurtosis, skew, add, min, max, moving average of train and simultaneously doing feature engineering

In [0]:
```
features_train = train.columns.values[2:202]
features_test = test.columns.values[1:201]
row_mean_train = train[features_train].mean(axis=1)
train["row_mean"] =row_mean_train
row_mean_test = test[features_test].mean(axis=1)
test["row_mean"] = row_mean_test
```

Pdf gives the probabily of points lying in a certain range

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
             .map(sns.distplot, "row_mean")\
             .add_legend()
plt.title("Histogram of mean")
plt.ylabel("Density of mean")
plt.plot()
```

Out[0]: []



from the above pdf we can say that when mean>6.2 and mean<7 then it is clear that probability of target=1 is high.

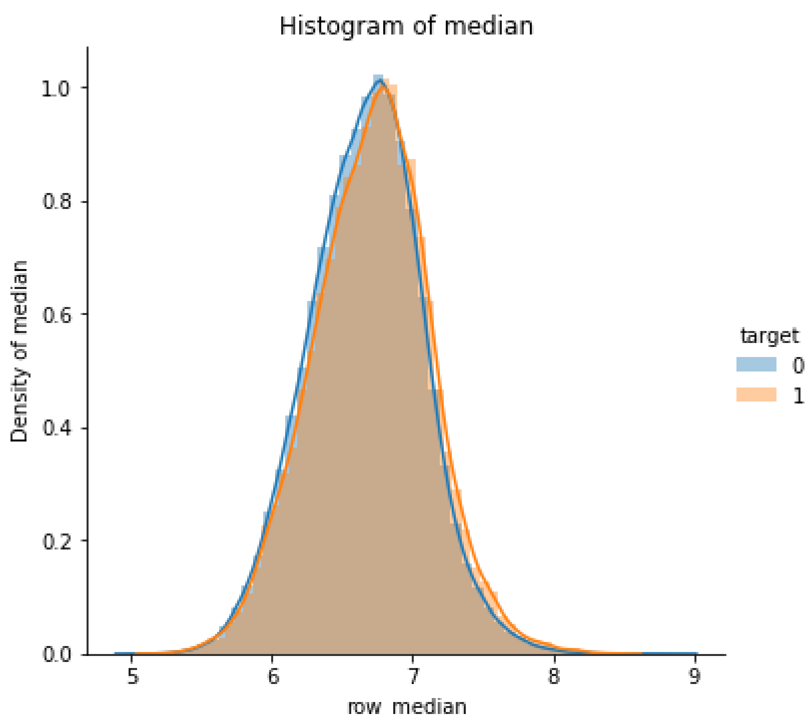
adding median

In [0]:
```
#reference : aaic haberman
```

In [0]:
```
row_median_train = train[features_train].median(axis=1)
train["row_median"] =row_median_train
row_median_test = test[features_test].median(axis=1)
test["row_median"] = row_median_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
             .map(sns.distplot, "row_median")\
             .add_legend()
plt.title("Histogram of median")
plt.ylabel("Density of median")
plt.plot()
```

Out[0]: []



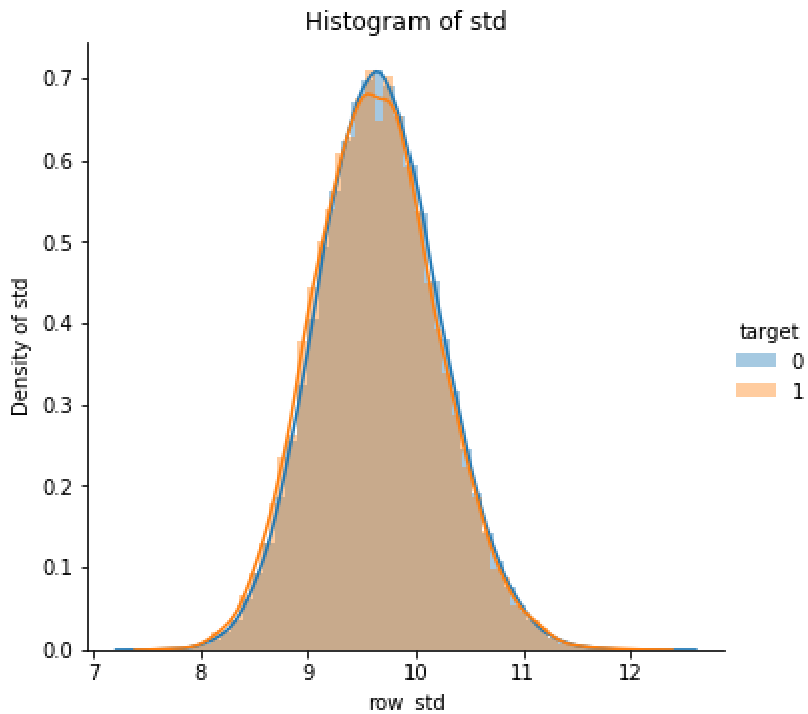
from the above pdf we can see that when median>6 and median<7 , the probability of target==1 is high

std

In [0]:
```
row_std_train = train[features_train].std(axis=1)
train["row_std"] =row_std_train
row_std_test = test[features_test].std(axis=1)
test["row_std"] = row_std_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
             .map(sns.distplot, "row_std")\
             .add_legend()
plt.title("Histogram of std")
plt.ylabel("Density of std")
plt.plot()
```

Out[0]: []



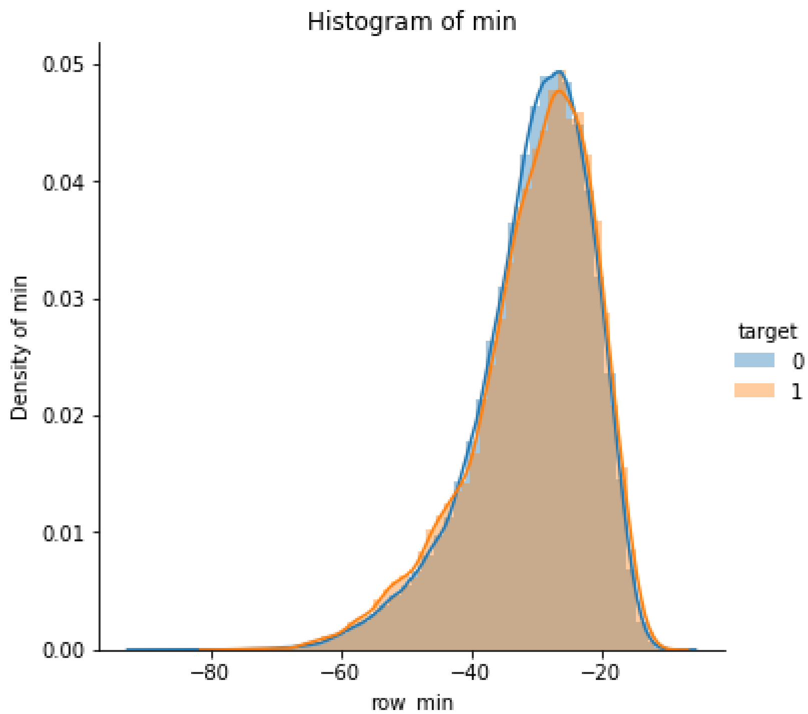
it is clear from the above pdf that when std>9.2 and std<10.2 probability of target==1 is high.

min

In [0]:
```
row_min_train = train[features_train].min(axis=1)
train["row_min"] =row_min_train
row_min_test = test[features_test].min(axis=1)
test["row_min"] = row_min_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
              .map(sns.distplot, "row_min")\
              .add_legend()
plt.title("Histogram of min")
plt.ylabel("Density of min")
plt.plot()
```

Out[0]: []



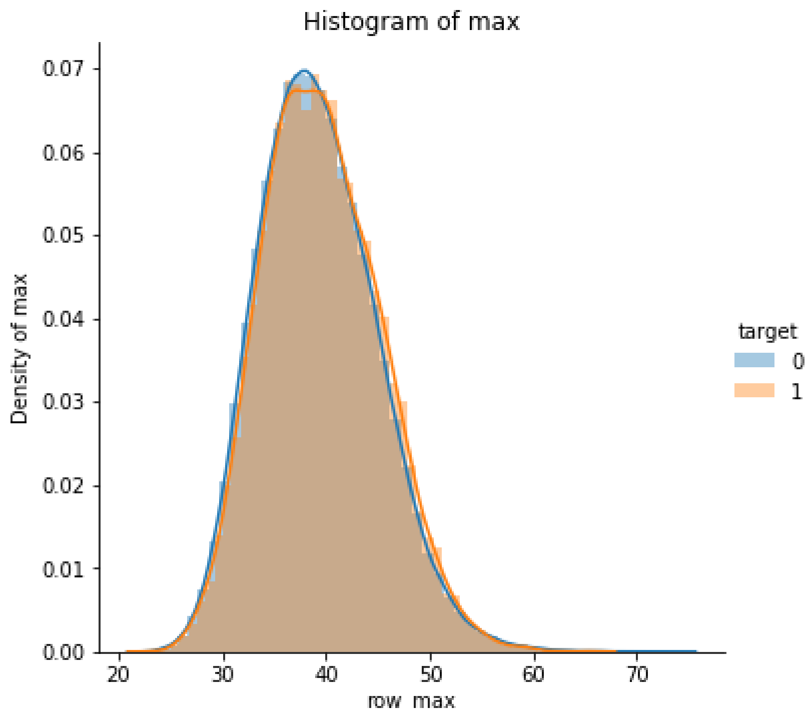
it is clear from the above pdf that when min<-20 and min>-50 probability of target==1 is high

max

In [0]:
```
row_max_train = train[features_train].max(axis=1)
train["row_max"] =row_max_train
row_max_test = test[features_test].max(axis=1)
test["row_max"] = row_max_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
              .map(sns.distplot, "row_max")\
              .add_legend()
plt.title("Histogram of max")
plt.ylabel("Density of max")
plt.plot()
```

Out[0]: []



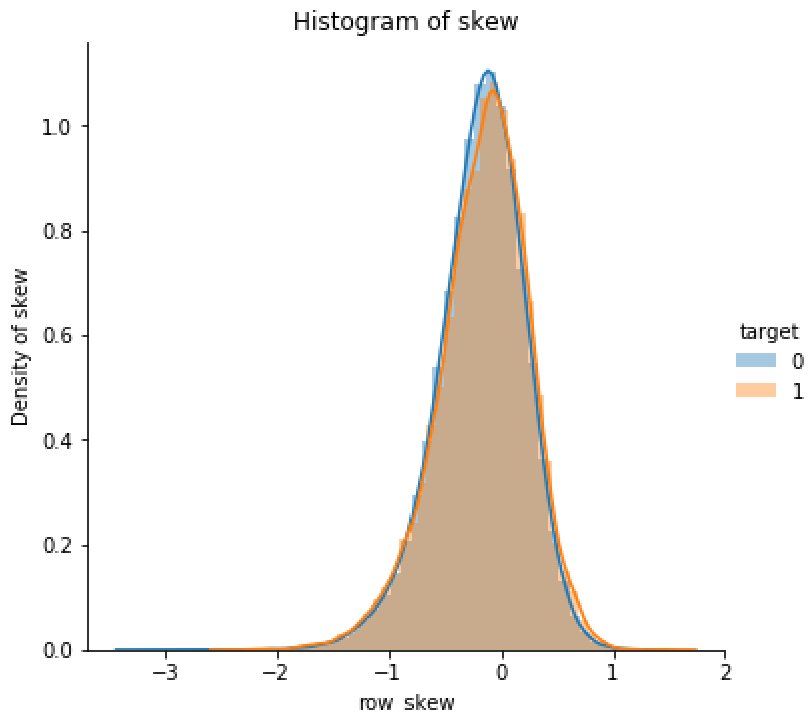
it is clear from the above pdf that when max>35 and min<45 probability of target==1 is high

Skew

In [0]:
```
row_skew_train = train[features_train].skew(axis=1)
train["row_skew"] =row_skew_train
row_skew_test = test[features_test].skew(axis=1)
test["row_skew"] = row_skew_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
             .map(sns.distplot, "row_skew")\
             .add_legend()
plt.title("Histogram of skew")
plt.ylabel("Density of skew")
plt.plot()
```

Out[0]: []

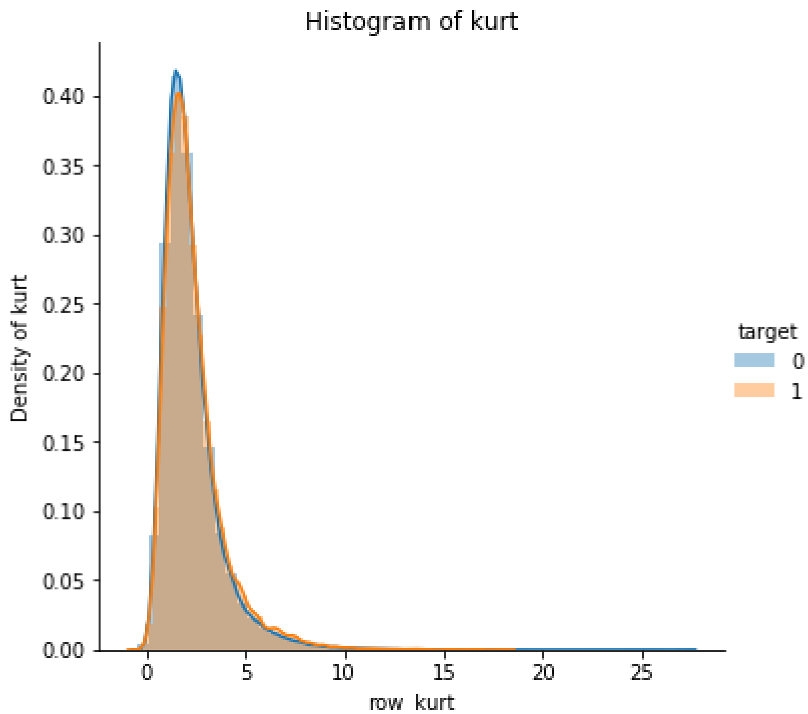


kurtosis

In [0]:
```
row_kurt_train = train[features_train].kurtosis(axis=1)
train["row_kurt"] =row_kurt_train
row_kurt_test = test[features_test].kurtosis(axis=1)
test["row_kurt"] = row_kurt_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
             .map(sns.distplot, "row_kurt")\
             .add_legend()
plt.title("Histogram of kurt")
plt.ylabel("Density of kurt")
plt.plot()
```

Out[0]: []



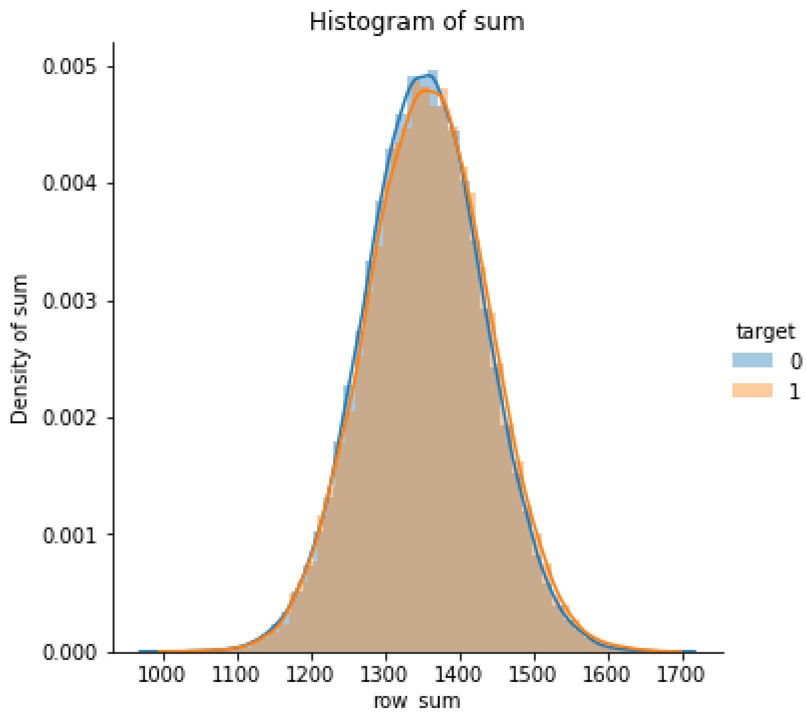
it is clear from the above pdf that when kurt>2 and kurt<4 probability of target==1 is high

sum

In [0]:
```
row_sum_train = train[features_train].sum(axis=1)
train["row_sum"] =row_sum_train
row_sum_test = test[features_test].sum(axis=1)
test["row_sum"] = row_sum_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
sns.FacetGrid(train, hue = "target", height = 5)\
             .map(sns.distplot, "row_sum")\
             .add_legend()
plt.title("Histogram of sum")
plt.ylabel("Density of sum")
plt.plot()
```

Out[0]: []



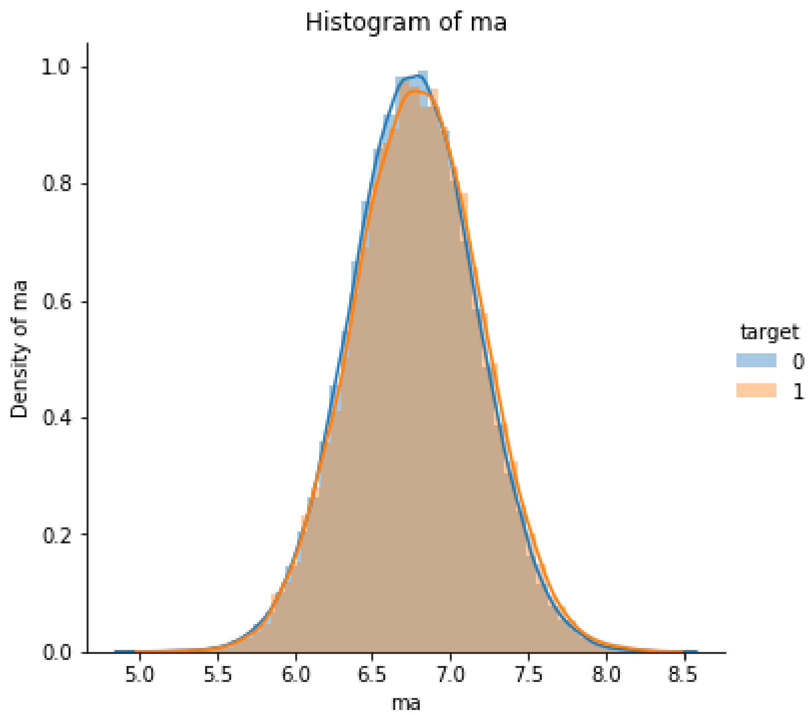
it is clear from the above pdf that when sum>1250 and sum<1450 probability of target==1 is high

moving sum mean

In [0]:
```
#https://www.kaggle.com/hjd810/keras-lgbm-aug-feature-eng-sampling-predi
ction
row_ma_train = train[features_train].apply(lambda x: np.ma.average(x), a
xis=1)
train["ma"] = row_ma_train
row_ma_test = test[features_test].apply(lambda x: np.ma.average(x), axis
=1)
test["ma"] = row_ma_test
```

In [0]:
```
#https://seaborn.pydata.org/generated/seaborn.distplot.html
#https://docs.scipy.org/doc/numpy/reference/generated/numpy.ma.average.h
tml
sns.FacetGrid(train, hue = "target", height = 5)\
              .map(sns.distplot, "ma")\
              .add_legend()
plt.title("Histogram of ma")
plt.ylabel("Density of ma")
plt.plot()
```

Out[0]: []



it is clear from the above pdf that when ma>6.2 and ma<7 probability of target==1 is high

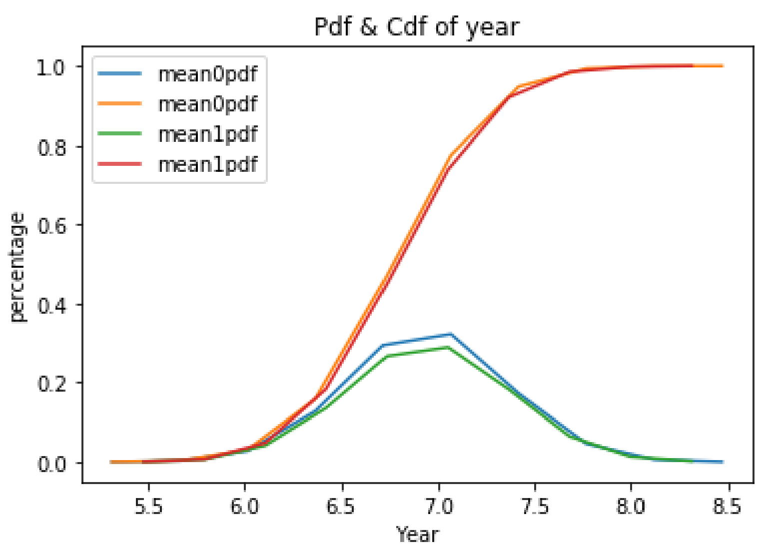
Pdf and cdf using kde(Kernal Distribution Estimation)

In [0]:
```
t0 = train.loc[train['target'] == 0]
t1 = train.loc[train['target'] == 1]
```

In [0]:
```
#reference: aaic haberman
counts, bin_edges=np.histogram(t0["row_mean"], bins=10, density=True)
pdf=counts/(sum(counts))
print(pdf);    #this will return 10 values
print(bin_edges);  #this will return 11 values
cdf=np.cumsum(pdf)
plt.plot(bin_edges[1:], pdf, label="mean0pdf");
plt.plot(bin_edges[1:], cdf, label="mean0pdf");

counts, bin_edges=np.histogram(t1["row_mean"], bins=10, density=True)
pdf=counts/(sum(counts))
print(pdf);    #this will return 10 values
print(bin_edges);  #this will return 11 values
cdf=np.cumsum(pdf)
plt.plot(bin_edges[1:], pdf, label="mean1pdf");
plt.plot(bin_edges[1:], cdf, label="mean1pdf");
plt.legend()
plt.title("Pdf & Cdf of year")
plt.xlabel("Year")
plt.ylabel("percentage")
```

```
[1.50081711e-04 2.89046259e-03 2.75650076e-02 1.28225367e-01
 2.94043424e-01 3.22197641e-01 1.72721815e-01 4.59361208e-02
 5.89765539e-03 3.72424987e-04]
[4.9633175  5.31394435 5.6645712  6.01519805 6.3658249  6.71645175
 7.0670786  7.41770545 7.7683323  8.11895915 8.469586  ]
[0.00059707 0.00597074 0.04094935 0.13598368 0.26639467 0.2887352
 0.18260523 0.06398647 0.01293661 0.00184098]
[5.1600995 5.4754376 5.7907757 6.1061138 6.4214519 6.73679   7.0521281
 7.3674662 7.6828043 7.9981424 8.3134805]
```

Out[0]: Text(0, 0.5, 'percentage')

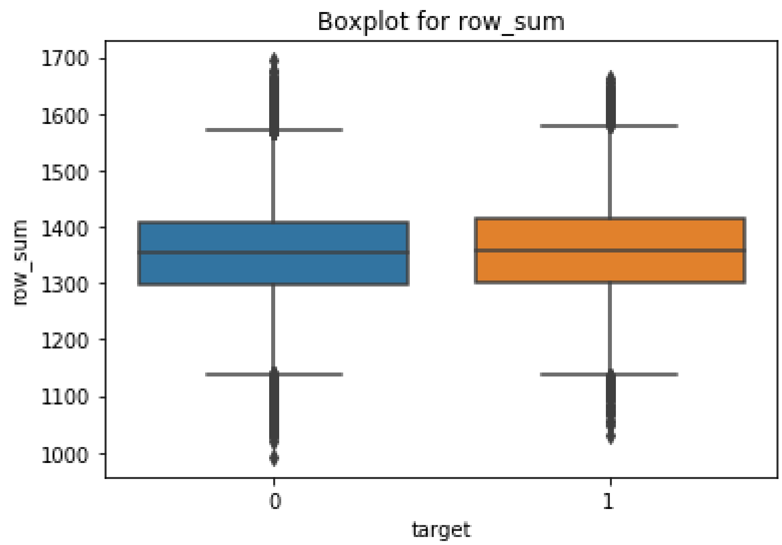


from the above pdf and cdf we can say that 90 % of data lie below 7.5

Box_plot

In [0]:
```
#reference aaic haberman
sns.boxplot(x="target", y="row_sum", data=train)
plt.title("Boxplot for row_sum")
plt.plot()
```

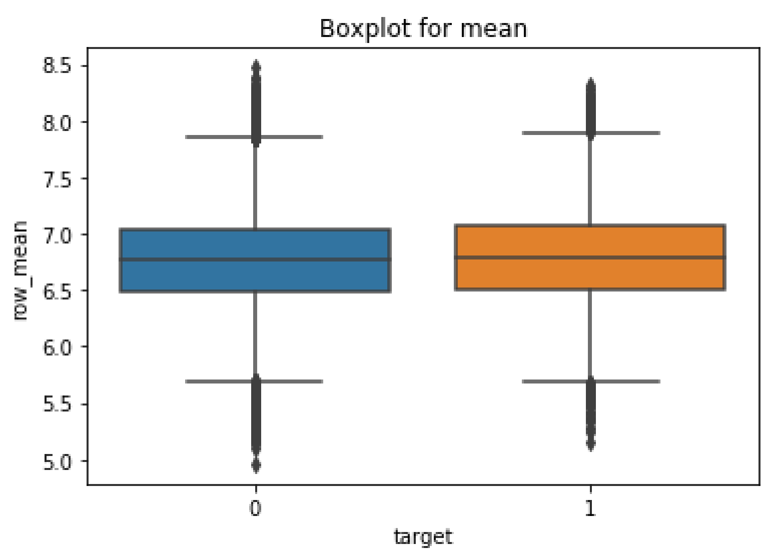
Out[0]: []



distribution according to box plot is also same.

In [0]:
```
sns.boxplot(x="target", y="row_mean", data=train)
plt.title("Boxplot for mean")
plt.plot()
```

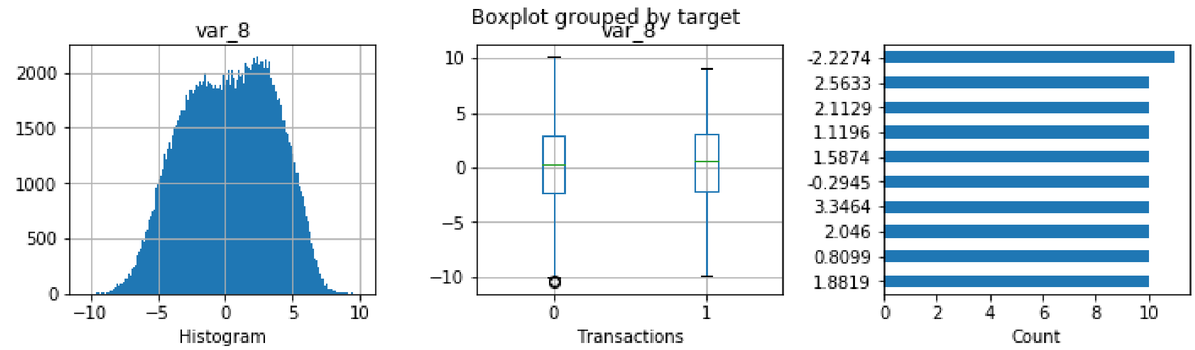
Out[0]: []

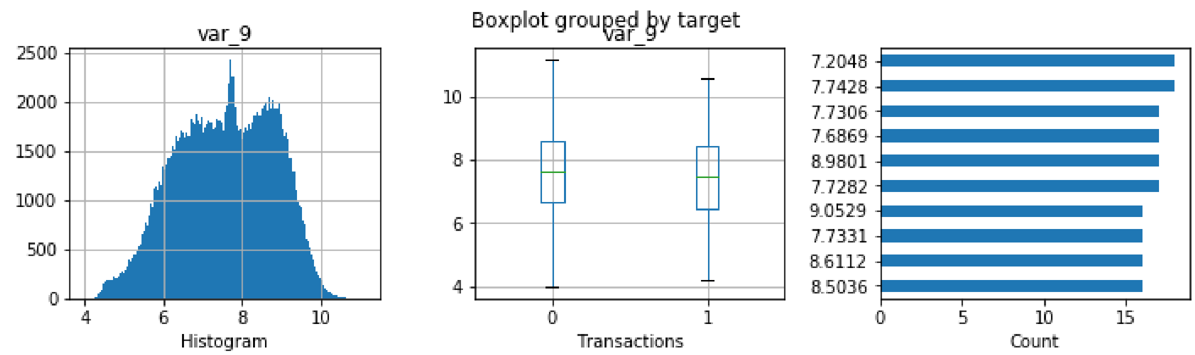


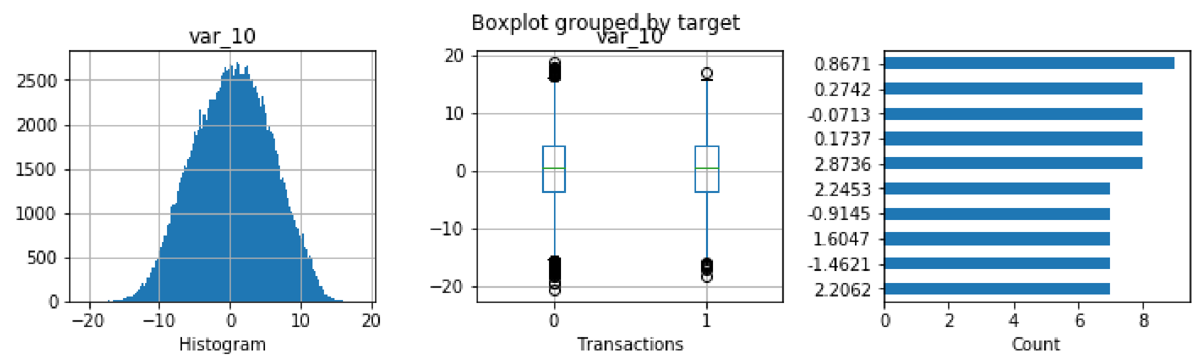
Visualize var_13 to var_17

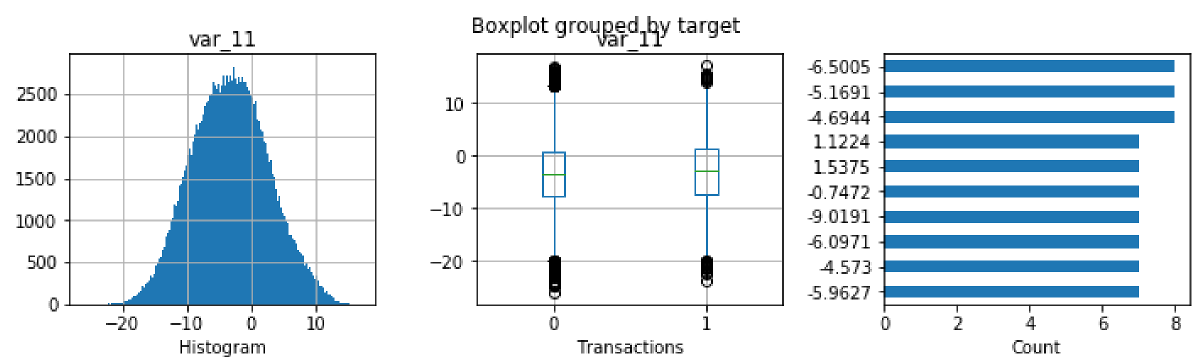
In [0]:
```
#create a function which makes the plot:
#https://www.kaggle.com/sicongfang/eda-feature-engineering
from matplotlib.ticker import FormatStrFormatter
def visualize_numeric(ax1, ax2, ax3, df, col, target):
    #plot histogram:
    df.hist(column=col,ax=ax1,bins=200)
    ax1.set_xlabel('Histogram')

    #plot box-whiskers:
    df.boxplot(column=col,by=target,ax=ax2)
    ax2.set_xlabel('Transactions')

    #plot top 10 counts:
    cnt = df[col].value_counts().sort_values(ascending=False)
    cnt.head(10).plot(kind='barh',ax=ax3)
    ax3.invert_yaxis()  # labels read top-to-bottom
#     ax3.yaxis.set_major_formatter(FormatStrFormatter('%.2f')) #somehow
not working
    ax3.set_xlabel('Count')
```

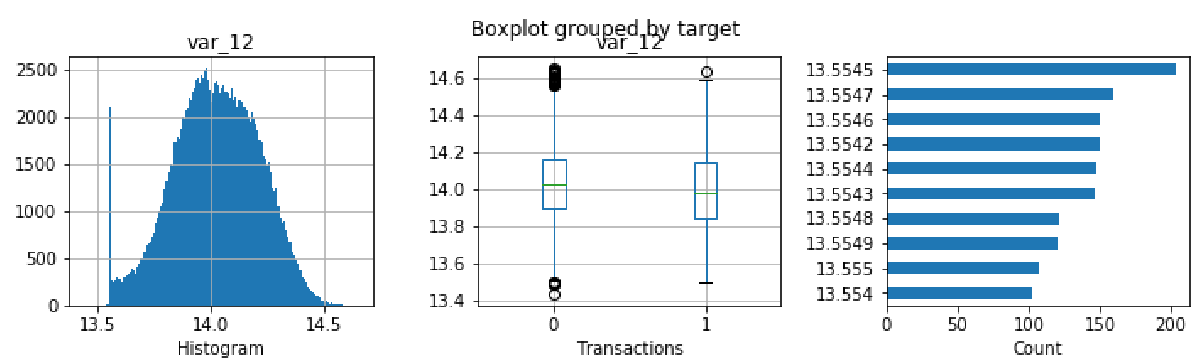
In [0]:
```
##https://www.kaggle.com/sicongfang/eda-feature-engineering
for col in list(train.columns[10:20]):
    fig, axes = plt.subplots(1, 3,figsize=(10,3))
    ax11 = plt.subplot(1, 3, 1)
    ax21 = plt.subplot(1, 3, 2)
    ax31 = plt.subplot(1, 3, 3)
    fig.suptitle('Feature: %s'%col,fontsize=5)
    visualize_numeric(ax11,ax21,ax31,train,col,'target')
    plt.tight_layout()
```

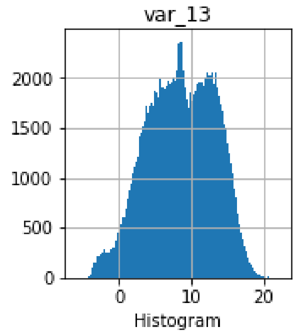

var_8
Histogram
Boxplot grouped by target
var_8
Transactions
-2.2274
2.5633
2.1129
1.1196
1.5874
-0.2945
3.3464
2.046
0.8099
1.8819
Count

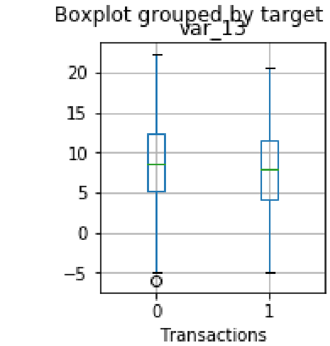

var_9
Histogram
Boxplot grouped by target
var_9
Transactions
7.2048
7.7428
7.7306
7.6869
8.9801
7.7282
9.0529
7.7331
8.6112
8.5036
Count

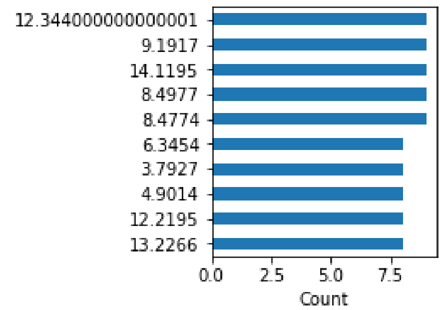

var_10
Histogram
Boxplot grouped by target
var_10
Transactions
0.8671
0.2742
-0.0713
0.1737
2.8736
2.2453
-0.9145
1.6047
-1.4621
2.2062
Count

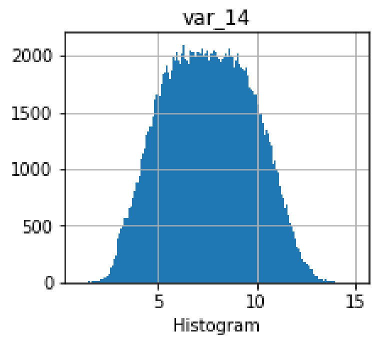

var_11
Histogram
Boxplot grouped by target
var_11
Transactions
-6.5005
-5.1691
-4.6944
1.1224
1.5375
-0.7472
-9.0191
-6.0971
-4.573
-5.9627
Count

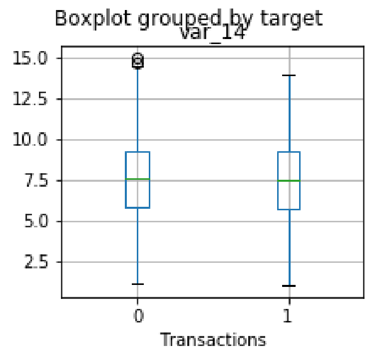

var_12
Histogram
Boxplot grouped by target
var_12
Transactions
13.5545
13.5547
13.5546
13.5542
13.5544
13.5543
13.5548
13.5549
13.555
13.554
Count

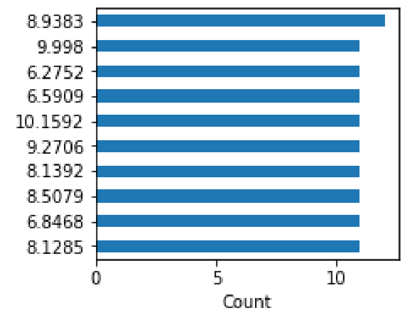

var_13
Histogram

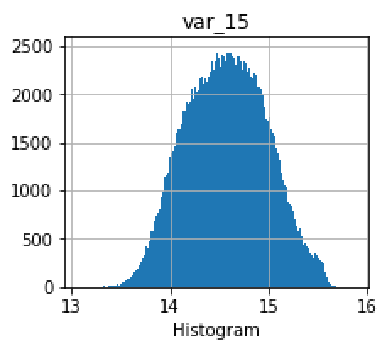

Boxplot grouped by target
var_13
Transactions

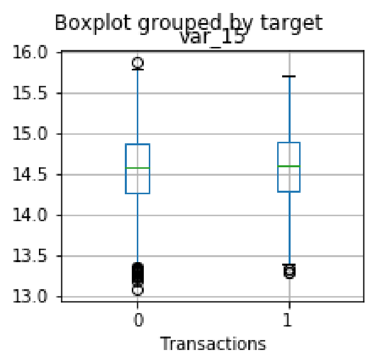

12.344000000000001
9.1917
14.1195
8.4977
8.4774
6.3454
3.7927
4.9014
12.2195
13.2266
Count

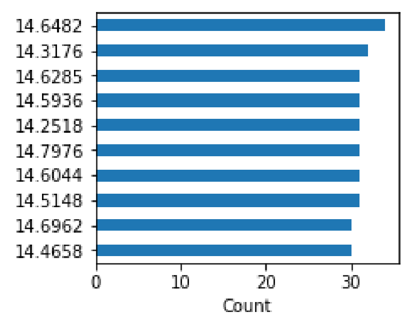

var_14
Histogram

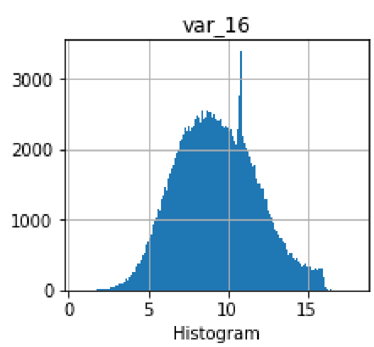

Boxplot grouped by target
var_14
Transactions

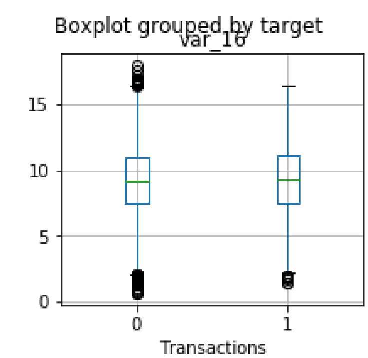

8.9383
9.998
6.2752
6.5909
10.1592
9.2706
8.1392
8.5079
6.8468
8.1285
Count

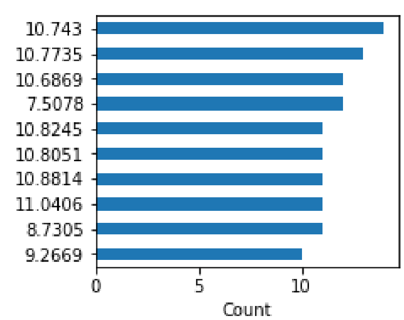

var_15
Histogram

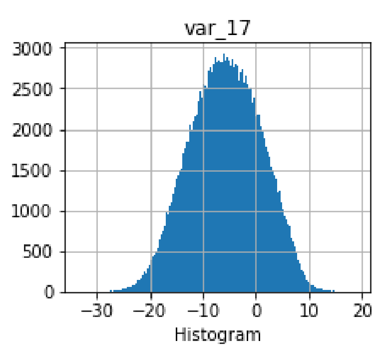

Boxplot grouped by target
var_15
Transactions

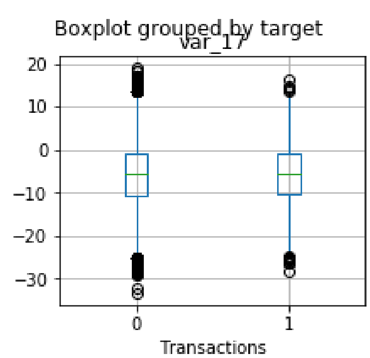

14.6482
14.3176
14.6285
14.5936
14.2518
14.7976
14.6044
14.5148
14.6962
14.4658
Count

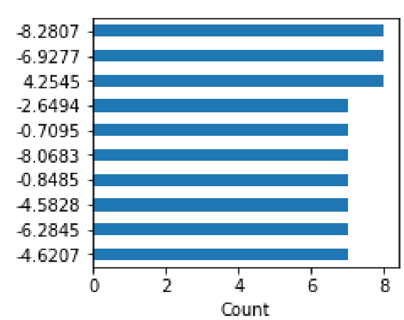

var_16
Histogram


Boxplot grouped by target
var_16
Transactions


10.743
10.7735
10.6869
7.5078
10.8245
10.8051
10.8814
11.0406
8.7305
9.2669
Count


var_17
Histogram


Boxplot grouped by target
var_17
Transactions


-8.2807
-6.9277
4.2545
-2.6494
-0.7095
-8.0683
-0.8485
-4.5828
-6.2845
-4.6207
Count

->from the above we can conclude that data follows different distribution\ ->from the boxplot we can assume that for var_11 50% of its values lies with -8 to 0. and for for var_10 50% of its value lie within -5 to 5 and like wise for others we can conclude from boxplot\ ->from the above count plot we can see that maximum number of count of some particular value is variable in nature.

In [0]:
```
train.head(2)
```

Out[0]:

	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8
0	train_0	0	8.9255	-6.7863	11.9081	5.093	11.4607	-9.2834	5.1187	18.6266	-4.9200
1	train_1	0	11.5006	-4.1473	13.8588	5.389	12.3622	7.0433	5.6208	16.5338	3.1468

2 rows × 211 columns

In [0]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive
```

Now saving all the feature engineered data to train_santander.csv

In [0]:
```
train.to_csv("/content/drive/My Drive/train_santander.csv")
```

In [0]:
```
test.to_csv("/content/drive/My Drive/test_santander.csv")
```

importing necessary libraries

In [0]:
```
import pandas as pd
import matplotlib.pyplot as plt
import re
import time
import warnings
import numpy as np
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics.classification import accuracy_score, log_loss
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import SGDClassifier
from imblearn.over_sampling import SMOTE
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
import math
from sklearn.metrics import normalized_mutual_info_score
from sklearn.ensemble import RandomForestClassifier
warnings.filterwarnings("ignore")

from mlxtend.classifier import StackingClassifier

from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
```

working only on train datasets just to see how well my model is doing.

In [0]:
```
train = pd.read_csv("/content/drive/My Drive/train_santander.csv")
#test = pd.read_csv("/content/drive/My Drive/test_santander.csv")
```

In [0]:
```
train.head(2)
```

Out[0]:

	Unnamed: 0	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_
0	0	train_0	0	8.9255	-6.7863	11.9081	5.093	11.4607	-9.2834	5.1187	18.626
1	1	train_1	0	11.5006	-4.1473	13.8588	5.389	12.3622	7.0433	5.6208	16.533

2 rows × 212 columns

as we can see from above that I have successfully added feature engineered features in train data

In [0]:
```
#target values
target = train["target"].values
```

In [0]:
```
#imp features from column 3 to 212
train = train.iloc[:,3:212]
```

In [0]:
```
train.shape
```

Out[0]:
```
(200000, 209)
```

Dividing train into train and test

In [0]:
```
#https://scikit-learn.org/stable/modules/generated/sklearn.model_selecti
on.train_test_split.html
from sklearn.model_selection import train_test_split
train, test, y_train, y_test = train_test_split(train, target, test_size
=0.4)
```

In [0]:
```
train.head(2)
```

Out[0]:

	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8	var_9	va
41283	10.9731	-4.6904	12.0139	6.7342	10.7631	-7.8887	6.4342	14.6397	4.5487	6.4155	6.
110029	9.8618	-7.5704	11.2805	7.8334	12.9967	6.8037	5.5669	17.9570	-3.5852	6.2679	-0.

2 rows × 209 columns

In [0]:
```
test.head(2)
```

Out[0]:

	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	var_8	var_9	var
52412	6.3458	-5.5601	12.5416	5.1773	11.0935	-7.9247	7.5710	13.7295	-4.5946	6.7022	2.8
10937	10.3105	-5.4767	11.2129	3.9750	11.2268	2.2041	4.6284	11.6618	1.9519	7.8688	-2.9

2 rows × 209 columns

In [0]:
```
#https://stackoverflow.com/questions/26414913/normalize-columns-of-panda
s-data-frame
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
scaler = scaler.fit(train)
train = scaler.transform(train)
test = scaler.transform(test)
```

Now applying different ML algorithms

Logistic

Defining necessary functions.

In [0]:
```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probabi
lity estimates of the positive class
    # not the predicted outputs

    y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041
 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

    return y_data_pred
```

In [0]:
```
#From facebook recommendation applied this code is taken and modified ac
cording to use
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    TN = C[0,0]
    FP = C[0,1]
    FN = C[1,0]
    TP = C[1,1]
    print("True Positive",TP)
    print("False Negative",FN)
    print("False Positive",FP)
    print("True Negative",TN)



    A =(((C.T)/(C.sum(axis=1))).T)

    B =(C/C.sum(axis=0))
    plt.figure(figsize=(30,6))

    labels = [0,1]
    # representing A in heatmap format
    cmap=sns.light_palette("Navy", as_cmap=True)#https://stackoverflow.c
om/questions/37902459/seaborn-color-palette-as-matplotlib-colormap
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels,
yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")


    plt.show()
```

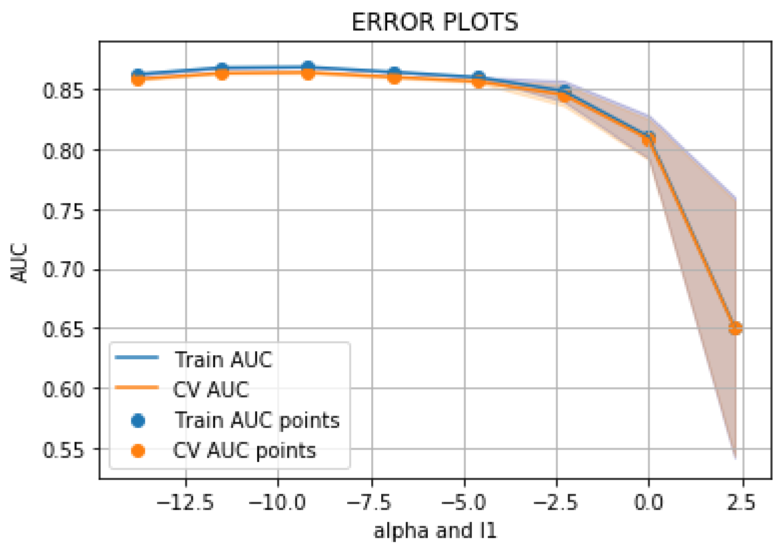
In [0]:
```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def predict(proba, threshould, fpr, tpr):

    t = threshould[np.argmax(tpr*(1-fpr))]

    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is v
ery high

    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for thr
eshold", np.round(t,3))
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

In [0]:
```
#As mentioned in logistic regression assignment I am changing alpha to l
og to plot a goog graph
import numpy as np
def log_alpha(al):
    alpha=[]
    for i in al:
        a=np.log(i)
        alpha.append(a)
    return alpha
```

Logistic Regression

In [0]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_select
ion.GridSearchCV.html
# https://scikit-learn.org/stable/modules/generated/sklearn.linear_mode
l.SGDClassifier.html
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier
from sklearn.metrics import roc_auc_score

lg = SGDClassifier(loss='log', class_weight='balanced', penalty="l2")
alpha=[0.000001, 0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
parameters = {'alpha':alpha}
clf = GridSearchCV(lg, parameters, cv=3, scoring='roc_auc', n_jobs=-1, r
eturn_train_score=True,)
clf.fit(train, y_train)

print("Model with best parameters :\n",clf.best_estimator_)

alpha = log_alpha(alpha)


best_alpha = clf.best_estimator_.alpha
#best_split = clf.best_estimator_.min_samples_split

print(best_alpha)
#print(best_split)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']

plt.plot(alpha, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/40
84039
plt.gca().fill_between(alpha,train_auc - train_auc_std,train_auc + train
_auc_std,alpha=0.2,color='darkblue')

plt.plot(alpha, cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/40
84039
plt.gca().fill_between(alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alp
ha=0.2,color='darkorange')

plt.scatter(alpha, train_auc, label='Train AUC points')
plt.scatter(alpha, cv_auc, label='CV AUC points')


plt.legend()
plt.xlabel("alpha and l1")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

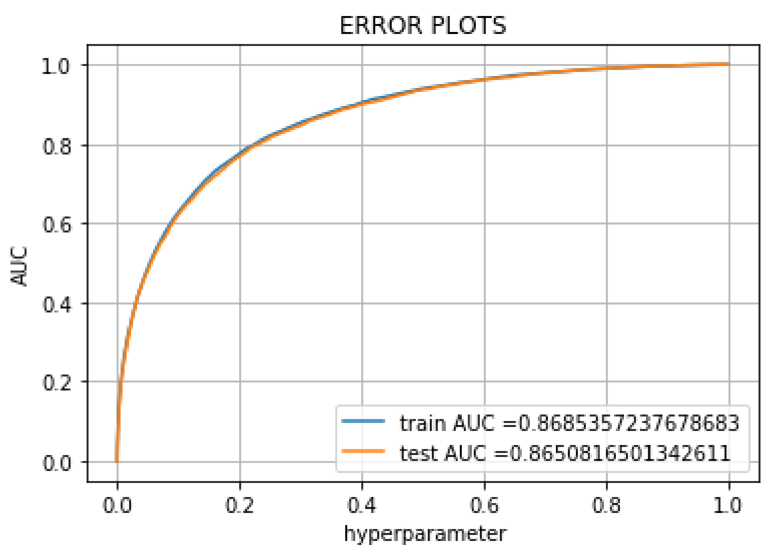
```
Model with best parameters :
 SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercep
t=True,
              l1_ratio=0.15, learning_rate='optimal', loss='log', max_i
ter=1000,
              n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.
5,
              random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
0.0001
```



From the above plot it is clearly visible that when alpha=0.0001 we have maximum auc.

Making final models with best alpha and penalty

In [0]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
from sklearn.calibration import CalibratedClassifierCV

lg = SGDClassifier(loss='log', alpha=best_alpha, penalty="l2", class_weight="balanced")
#lg.fit(train_1, project_data_y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

sig_clf = CalibratedClassifierCV(lg, method="isotonic")
lg = sig_clf.fit(train, y_train)


y_train_pred = lg.predict_proba(train)[:,1]
y_test_pred = lg.predict_proba(test)[:,1]

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

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(" hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

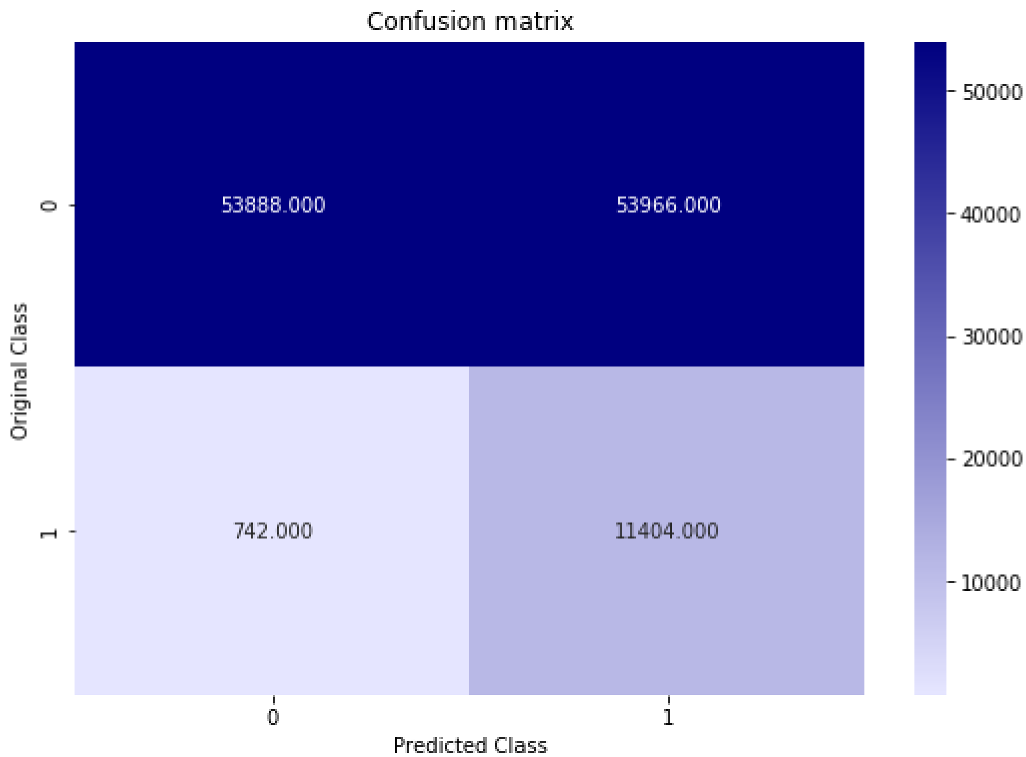


So the maximum auc here is 0.865

Confusion Matrix with using map

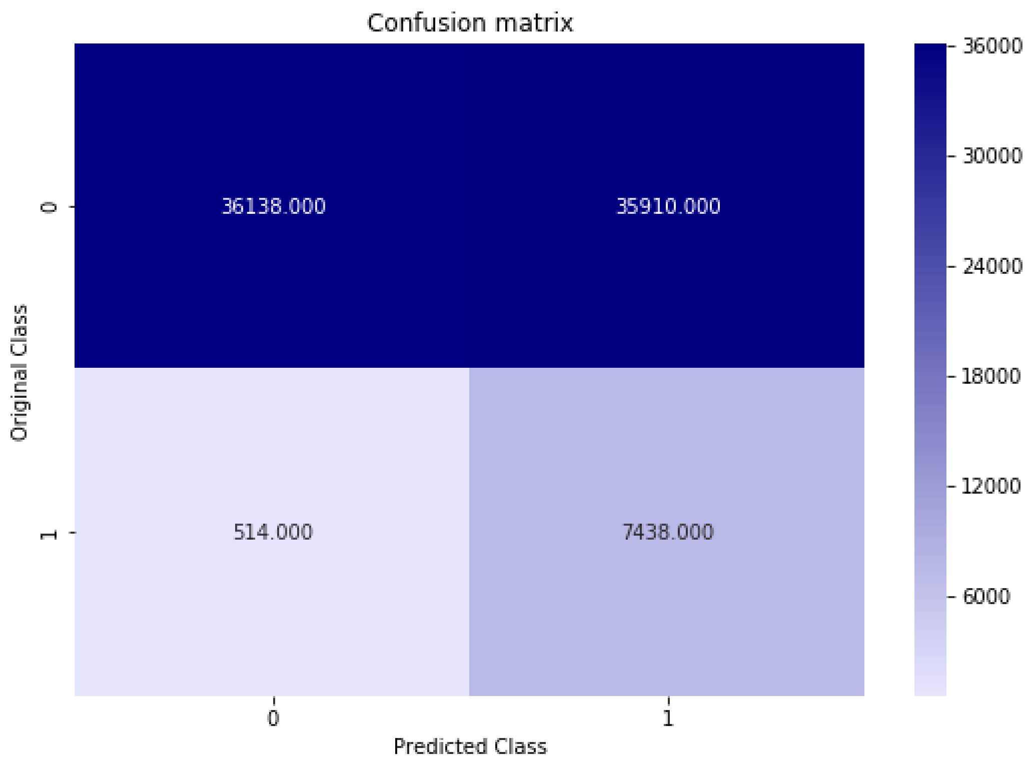
In [0]:
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,predict(y_train_pred, tr_thresholds, train
_fpr, train_fpr))
```

```
Train confusion_matrix
the maximum value of tpr*(1-fpr) 0.24999986924548293 for threshold 0.03
3
True Positive 11404
False Negative 742
False Positive 53966
True Negative 53888
```



In [0]:
```
print('Test confusion_matrix')
plot_confusion_matrix(y_test,predict(y_test_pred, tr_thresholds, train_f
pr, train_fpr))
```

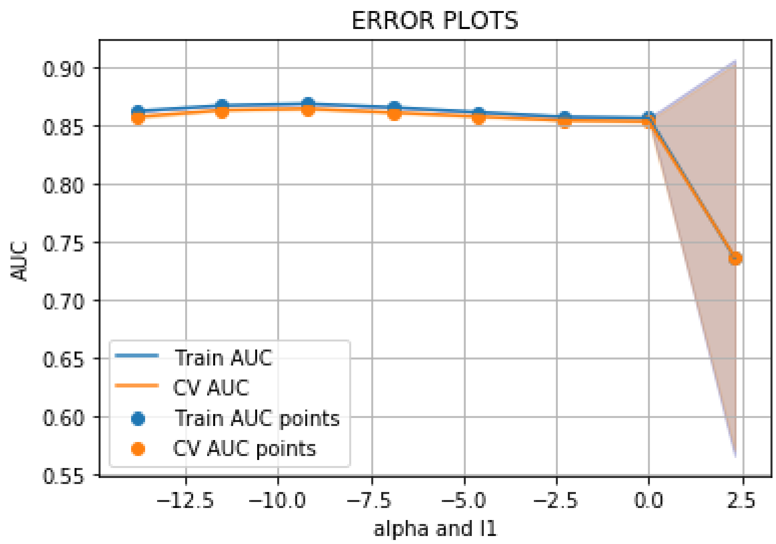
```
Test confusion_matrix
the maximum value of tpr*(1-fpr) 0.24999986924548293 for threshold 0.03
3
True Positive 7438
False Negative 514
False Positive 35910
True Negative 36138
```



SVM

In [0]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_select
ion.GridSearchCV.html
# https://scikit-learn.org/stable/modules/generated/sklearn.linear_mode
l.SGDClassifier.html
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import SGDClassifier
from sklearn.metrics import roc_auc_score

svm = SGDClassifier(loss='hinge', class_weight='balanced', penalty="l2")
alpha=[0.000001, 0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
parameters = {'alpha':alpha}
clf = GridSearchCV(svm, parameters, cv=3, scoring='roc_auc', n_jobs=-1,
return_train_score=True,)
clf.fit(train, y_train)

print("Model with best parameters :\n",clf.best_estimator_)

alpha = log_alpha(alpha)


best_alpha = clf.best_estimator_.alpha
#best_split = clf.best_estimator_.min_samples_split

print(best_alpha)
#print(best_split)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']

plt.plot(alpha, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/40
84039
plt.gca().fill_between(alpha,train_auc - train_auc_std,train_auc + train
_auc_std,alpha=0.2,color='darkblue')

plt.plot(alpha, cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/40
84039
plt.gca().fill_between(alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alp
ha=0.2,color='darkorange')

plt.scatter(alpha, train_auc, label='Train AUC points')
plt.scatter(alpha, cv_auc, label='CV AUC points')


plt.legend()
plt.xlabel("alpha and l1")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

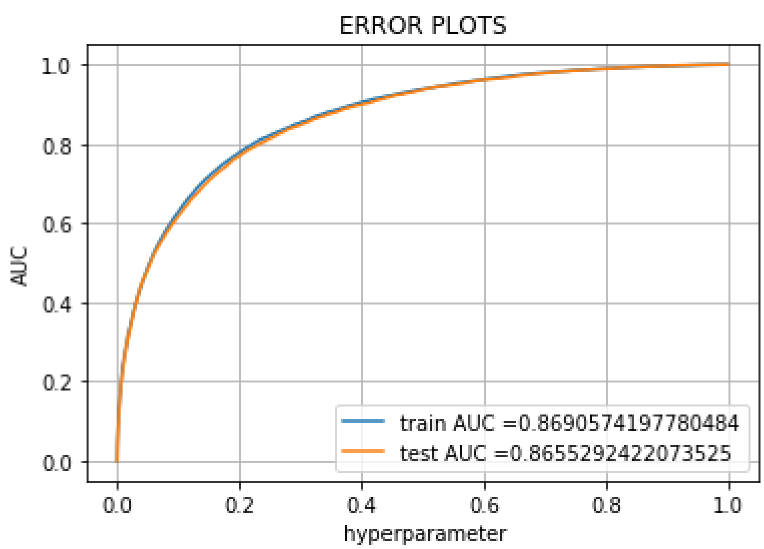
```
Model with best parameters :
 SGDClassifier(alpha=0.0001, average=False, class_weight='balanced',
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercep
t=True,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty
='l2',
              power_t=0.5, random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
0.0001
```



from the above auc plot it is clearly visible that when auc alpha = 0.0001 , we have maximum auc

Making final models with best alpha and penalty

In [0]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
from sklearn.calibration import CalibratedClassifierCV

svm = SGDClassifier(loss='hinge', alpha=best_alpha, penalty="l2", class_weight="balanced")
#svm.fit(train_1, project_data_y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

sig_clf = CalibratedClassifierCV(svm, method="isotonic")
svm = sig_clf.fit(train, y_train)


y_train_pred = svm.predict_proba(train)[:,1]
y_test_pred = svm.predict_proba(test)[:,1]

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

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(" hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

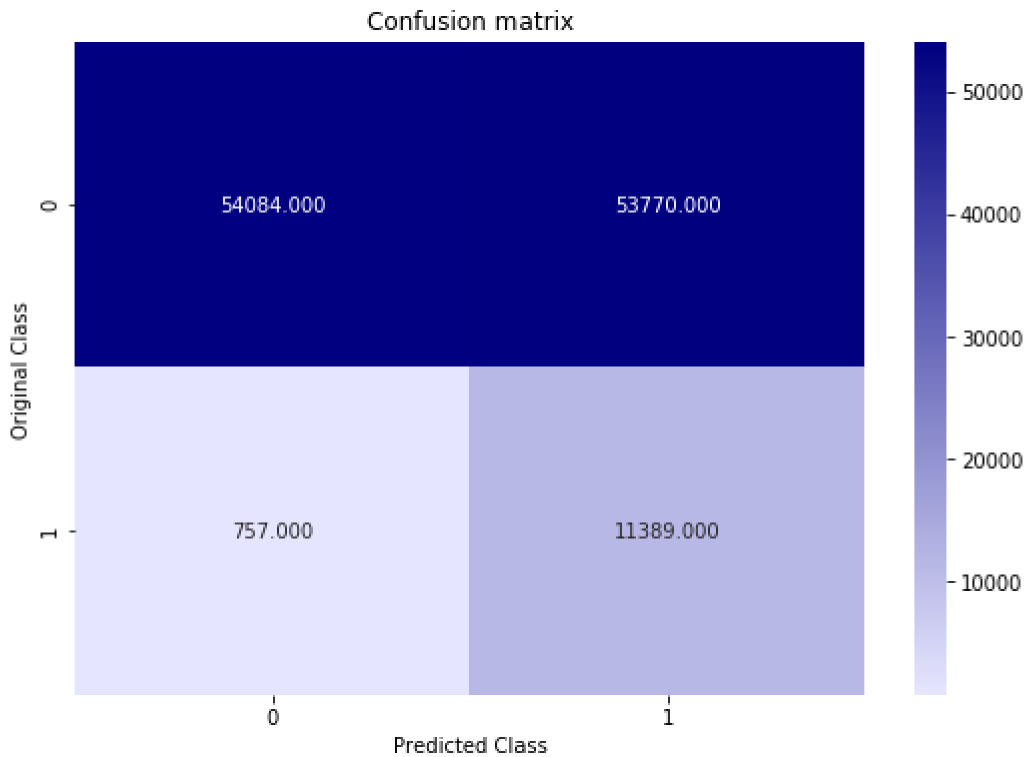


so from the above plot we can see tha test auc is 0.865

Confusion Matrix with using map

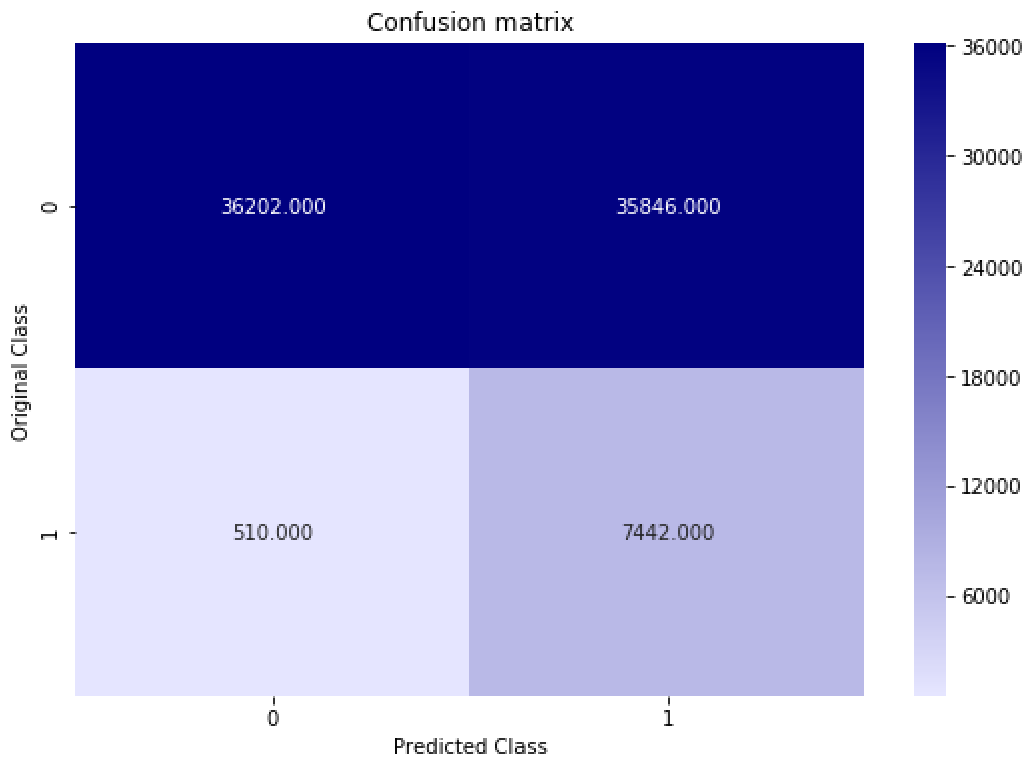
In [0]:
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,predict(y_train_pred, tr_thresholds, train
_fpr, train_fpr))
```

```
Train confusion_matrix
the maximum value of tpr*(1-fpr) 0.24999788102032108 for threshold 0.03
1
True Positive 11389
False Negative 757
False Positive 53770
True Negative 54084
```



In [0]:
```
print('Test confusion_matrix')
plot_confusion_matrix(y_test,predict(y_test_pred, tr_thresholds, train_f
pr, train_fpr))
```

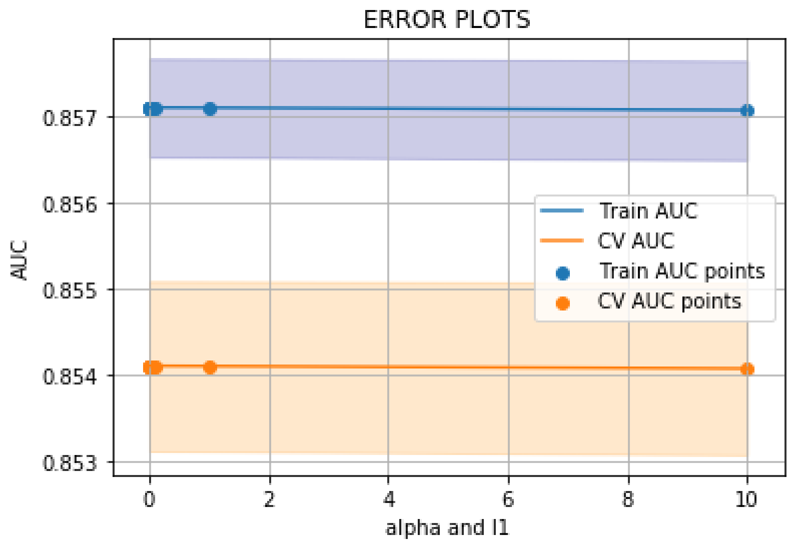
```
Test confusion_matrix
the maximum value of tpr*(1-fpr) 0.24999788102032108 for threshold 0.03
1
True Positive 7442
False Negative 510
False Positive 35846
True Negative 36202
```



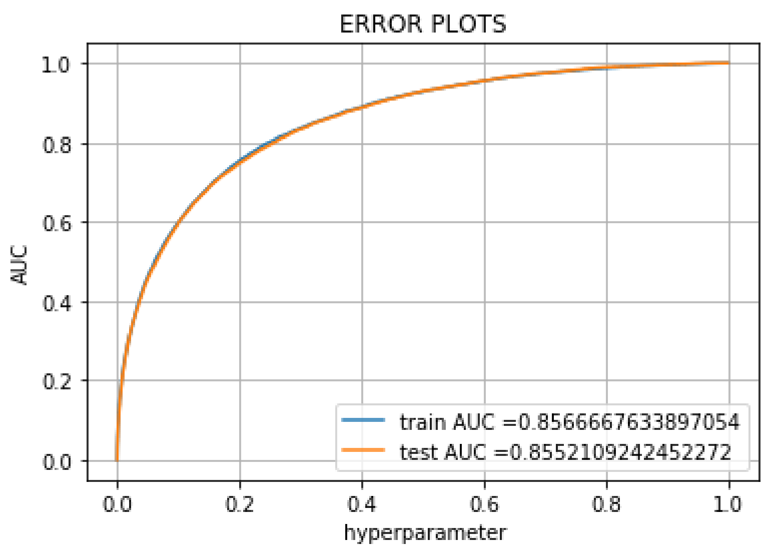
Naive Bayes

In [0]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_select
ion.GridSearchCV.html
#https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.M
ultinomialNB.html
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
naive = MultinomialNB(fit_prior=False)
alpha=[0.000001, 0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
parameters = {'alpha':alpha}
clf = GridSearchCV(naive, parameters, cv=3, scoring='roc_auc', return_tr
ain_score=True)
clf.fit(train, y_train)

print("Model with best parameters :\n",clf.best_estimator_)

train_auc= list(clf.cv_results_['mean_train_score'])
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = list(clf.cv_results_['mean_test_score'])
cv_auc_std= clf.cv_results_['std_test_score']

best_alpha=clf.best_estimator_.alpha

alpha = log_alpha(alpha)

plt.plot(alpha, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/40
84039
plt.gca().fill_between(alpha,train_auc - train_auc_std,train_auc + train
_auc_std,alpha=0.2,color='darkblue')

plt.plot(alpha, cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/40
84039
plt.gca().fill_between(alpha,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alp
ha=0.2,color='darkorange')

plt.scatter(alpha, train_auc, label='Train AUC points')
plt.scatter(alpha, cv_auc, label='CV AUC points')


plt.legend()
plt.xlabel("alpha and l1")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

```
Model with best parameters :
 MultinomialNB(alpha=1e-05, class_prior=None, fit_prior=False)
```



In [0]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc

naive = MultinomialNB(alpha=best_alpha, fit_prior=False)
naive.fit(train, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

y_train_pred = naive.predict_proba(train)[:,1]
y_test_pred = naive.predict_proba(test)[:,1]

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

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(" hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

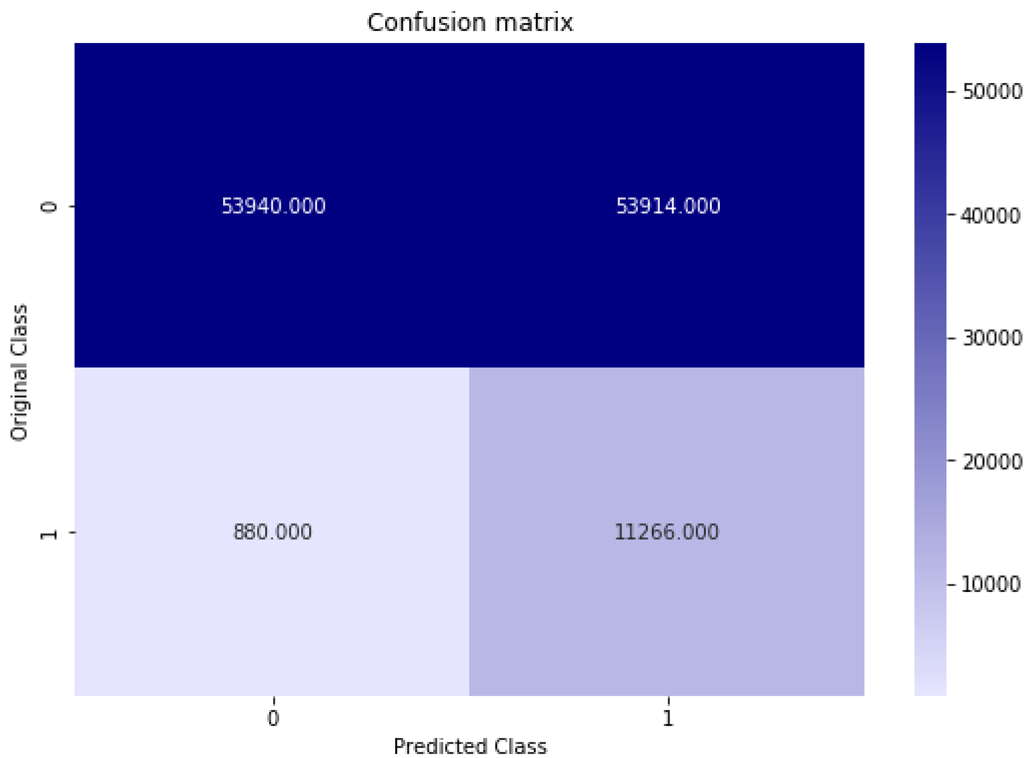


from the above plot we can say that test auc is 0.855

Confusion Matrix using heat map

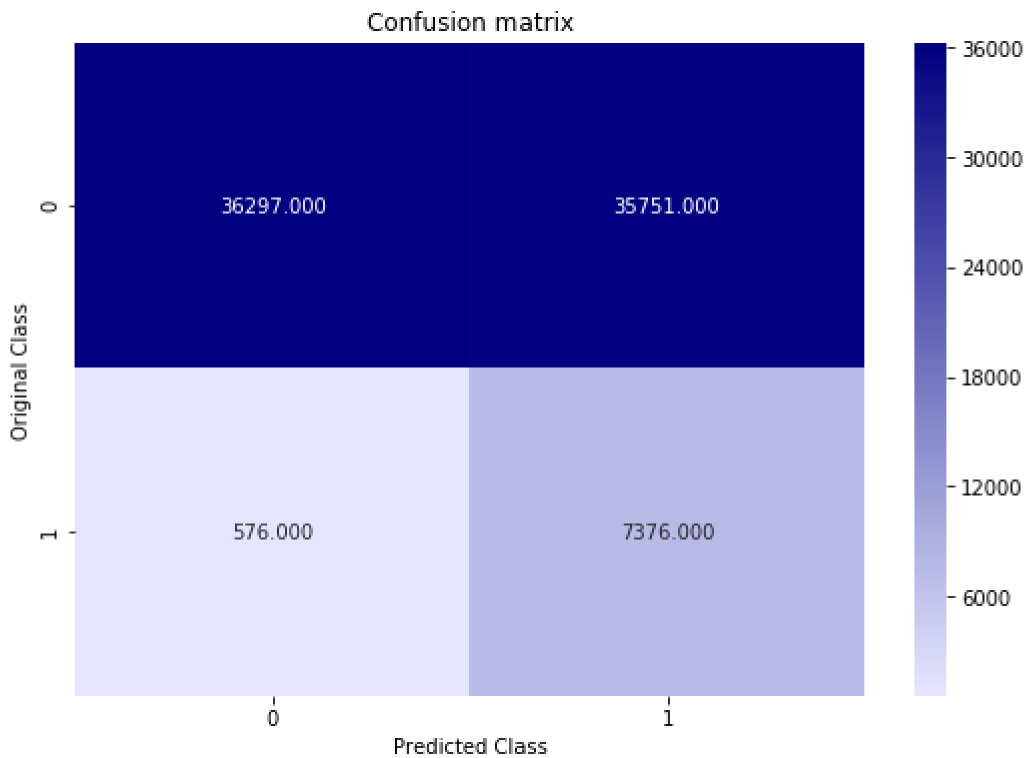
In [0]:
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,predict(y_train_pred, tr_thresholds, train_fpr, train_fpr))
```

```
Train confusion_matrix
the maximum value of tpr*(1-fpr) 0.2499999854717203 for threshold 0.486
True Positive 11266
False Negative 880
False Positive 53914
True Negative 53940
```



In [0]:
```
print('Test confusion_matrix')
plot_confusion_matrix(y_test,predict(y_test_pred, tr_thresholds, train_f
pr, train_fpr))
```

```
Test confusion_matrix
the maximum value of tpr*(1-fpr) 0.2499999854717203 for threshold 0.486
True Positive 7376
False Negative 576
False Positive 35751
True Negative 36297
```



Light GbM

[https://www.kaggle.com/gpreda/santander-eda-and-prediction (https://www.kaggle.com/gpreda/santander-eda-and-prediction)](https://www.kaggle.com/gpreda/santander-eda-and-prediction)

In [0]:
```
train = pd.read_csv("/content/drive/My Drive/train_santander.csv")
```

In [0]:
```
from sklearn.model_selection import train_test_split
train, test, y_train, y_test = train_test_split(train, target, test_size
=0.4)
```

In [0]:
```
#taking all the columns except idcode, target, unnamed0
features = [c for c in train.columns if c not in ['ID_code', 'target',"U
nnamed:0"]]
target = train['target']
```

importing necessary libraries

In [0]:
```
import gc
import os
import logging
import datetime
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
import lightgbm as lgb
from tqdm import tqdm_notebook
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.model_selection import StratifiedKFold
warnings.filterwarnings('ignore')
```

In [0]:
```
#setting parameters
param = {
    'bagging_freq': 5,
    'bagging_fraction': 0.4,
    'boost_from_average':'false',
    'boost': 'gbdt',
    'feature_fraction': 0.05,
    'learning_rate': 0.01,
    '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]:
```
#making 10 folds
folds = StratifiedKFold(n_splits=10, shuffle=False, random_state=44000)
oof = np.zeros(len(train))
predictions = np.zeros(len(test))
feature_importance_df = pd.DataFrame()

for fold_, (trn_idx, val_idx) in enumerate(folds.split(train.values, tar
get)):
    print("Fold {}".format(fold_))
    trn_data = lgb.Dataset(train.iloc[trn_idx][features], label=target.i
loc[trn_idx])
    val_data = lgb.Dataset(train.iloc[val_idx][features], label=target.i
loc[val_idx])

    num_round = 1000000
    clf = lgb.train(param, trn_data, num_round, valid_sets = [trn_data,
val_data], verbose_eval=1000, early_stopping_rounds = 3000)
    oof[val_idx] = clf.predict(train.iloc[val_idx][features], num_iterat
ion=clf.best_iteration)

    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_impor
tance_df], axis=0)

    predictions += clf.predict(test[features], num_iteration=clf.best_it
eration) / folds.n_splits

print("CV score: {:<8.5f}".format(roc_auc_score(target, oof)))
```

```
Fold 0
Training until validation scores don't improve for 3000 rounds.
[1000]	training's auc: 0.91012	valid_1's auc: 0.891048
[2000]	training's auc: 0.922393	valid_1's auc: 0.898032
[3000]	training's auc: 0.93073	valid_1's auc: 0.90145
[4000]	training's auc: 0.93779	valid_1's auc: 0.902904
[5000]	training's auc: 0.943841	valid_1's auc: 0.903862
[6000]	training's auc: 0.949329	valid_1's auc: 0.904328
[7000]	training's auc: 0.954276	valid_1's auc: 0.904513
[8000]	training's auc: 0.95882	valid_1's auc: 0.904236
[9000]	training's auc: 0.963171	valid_1's auc: 0.903923
Early stopping, best iteration is:
[6543]	training's auc: 0.952048	valid_1's auc: 0.904637
Fold 1
Training until validation scores don't improve for 3000 rounds.
[1000]	training's auc: 0.910776	valid_1's auc: 0.87999
[2000]	training's auc: 0.923381	valid_1's auc: 0.887051
[3000]	training's auc: 0.931882	valid_1's auc: 0.889855
[4000]	training's auc: 0.938715	valid_1's auc: 0.891421
[5000]	training's auc: 0.944728	valid_1's auc: 0.891751
[6000]	training's auc: 0.950076	valid_1's auc: 0.892179
[7000]	training's auc: 0.954983	valid_1's auc: 0.8922
[8000]	training's auc: 0.959543	valid_1's auc: 0.891963
[9000]	training's auc: 0.963822	valid_1's auc: 0.891783
Early stopping, best iteration is:
[6800]	training's auc: 0.954026	valid_1's auc: 0.892395
Fold 2
Training until validation scores don't improve for 3000 rounds.
[1000]	training's auc: 0.910917	valid_1's auc: 0.880874
[2000]	training's auc: 0.92327	valid_1's auc: 0.888438
[3000]	training's auc: 0.931566	valid_1's auc: 0.892268
[4000]	training's auc: 0.938475	valid_1's auc: 0.893897
[5000]	training's auc: 0.944514	valid_1's auc: 0.895186
[6000]	training's auc: 0.949925	valid_1's auc: 0.895621
[7000]	training's auc: 0.954805	valid_1's auc: 0.896052
[8000]	training's auc: 0.95937	valid_1's auc: 0.896057
[9000]	training's auc: 0.963674	valid_1's auc: 0.895937
[10000]	training's auc: 0.967612	valid_1's auc: 0.895907
Early stopping, best iteration is:
[7218]	training's auc: 0.955811	valid_1's auc: 0.896161
Fold 3
Training until validation scores don't improve for 3000 rounds.
[1000]	training's auc: 0.910332	valid_1's auc: 0.886326
[2000]	training's auc: 0.922851	valid_1's auc: 0.893769
[3000]	training's auc: 0.931158	valid_1's auc: 0.896971
[4000]	training's auc: 0.938053	valid_1's auc: 0.898329
[5000]	training's auc: 0.944101	valid_1's auc: 0.899213
[6000]	training's auc: 0.949485	valid_1's auc: 0.899612
[7000]	training's auc: 0.954551	valid_1's auc: 0.899746
[8000]	training's auc: 0.959176	valid_1's auc: 0.899663
[9000]	training's auc: 0.963421	valid_1's auc: 0.899466
Early stopping, best iteration is:
[6659]	training's auc: 0.952844	valid_1's auc: 0.899818
Fold 4
Training until validation scores don't improve for 3000 rounds.
[1000]	training's auc: 0.910884	valid_1's auc: 0.876176
[2000]	training's auc: 0.923198	valid_1's auc: 0.885391
```

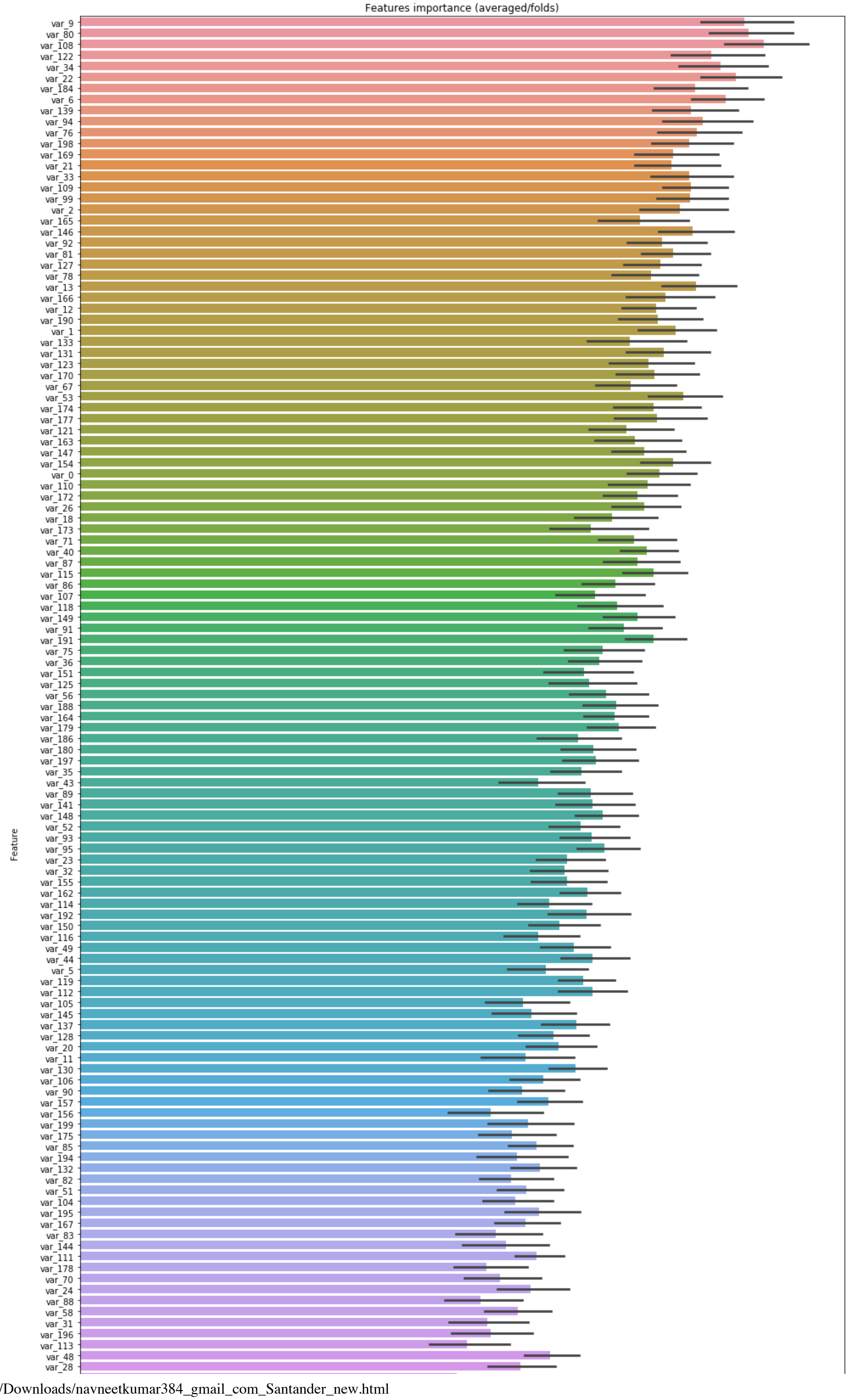
```
[3000]  training's auc: 0.931728        valid_1's auc: 0.889177
[4000]  training's auc: 0.938842        valid_1's auc: 0.891406
[5000]  training's auc: 0.944914        valid_1's auc: 0.891953
[6000]  training's auc: 0.950405        valid_1's auc: 0.892415
[7000]  training's auc: 0.95528 valid_1's auc: 0.892463
[8000]  training's auc: 0.959821        valid_1's auc: 0.892343
[9000]  training's auc: 0.964021        valid_1's auc: 0.892289
Early stopping, best iteration is:
[6249]  training's auc: 0.951663        valid_1's auc: 0.89256
Fold 5
Training until validation scores don't improve for 3000 rounds.
[1000]  training's auc: 0.910378        valid_1's auc: 0.885394
[2000]  training's auc: 0.922775        valid_1's auc: 0.893774
[3000]  training's auc: 0.931203        valid_1's auc: 0.896869
[4000]  training's auc: 0.938301        valid_1's auc: 0.898908
[5000]  training's auc: 0.94434 valid_1's auc: 0.900033
[6000]  training's auc: 0.949729        valid_1's auc: 0.900666
[7000]  training's auc: 0.954701        valid_1's auc: 0.900446
[8000]  training's auc: 0.959163        valid_1's auc: 0.900884
[9000]  training's auc: 0.963404        valid_1's auc: 0.900944
[10000] training's auc: 0.967309        valid_1's auc: 0.900969
[11000] training's auc: 0.970908        valid_1's auc: 0.900706
[12000] training's auc: 0.974286        valid_1's auc: 0.900744
Early stopping, best iteration is:
[9622]  training's auc: 0.965848        valid_1's auc: 0.901077
Fold 6
Training until validation scores don't improve for 3000 rounds.
[1000]  training's auc: 0.910555        valid_1's auc: 0.884567
[2000]  training's auc: 0.922579        valid_1's auc: 0.892911
[3000]  training's auc: 0.930862        valid_1's auc: 0.896466
[4000]  training's auc: 0.93785 valid_1's auc: 0.898559
[5000]  training's auc: 0.943937        valid_1's auc: 0.899583
[6000]  training's auc: 0.94941 valid_1's auc: 0.899824
[7000]  training's auc: 0.954497        valid_1's auc: 0.900188
[8000]  training's auc: 0.95906 valid_1's auc: 0.900387
[9000]  training's auc: 0.963334        valid_1's auc: 0.900317
[10000] training's auc: 0.967349        valid_1's auc: 0.900313
[11000] training's auc: 0.971038        valid_1's auc: 0.900474
Early stopping, best iteration is:
[8219]  training's auc: 0.960043        valid_1's auc: 0.900503
Fold 7
Training until validation scores don't improve for 3000 rounds.
[1000]  training's auc: 0.910169        valid_1's auc: 0.888964
[2000]  training's auc: 0.922202        valid_1's auc: 0.894795
[3000]  training's auc: 0.93062 valid_1's auc: 0.898717
[4000]  training's auc: 0.937701        valid_1's auc: 0.901172
[5000]  training's auc: 0.94373 valid_1's auc: 0.90236
[6000]  training's auc: 0.949189        valid_1's auc: 0.903216
[7000]  training's auc: 0.954234        valid_1's auc: 0.903715
[8000]  training's auc: 0.958932        valid_1's auc: 0.903623
[9000]  training's auc: 0.963206        valid_1's auc: 0.903486
[10000] training's auc: 0.96721 valid_1's auc: 0.903111
Early stopping, best iteration is:
[7110]  training's auc: 0.954745        valid_1's auc: 0.903751
Fold 8
Training until validation scores don't improve for 3000 rounds.
[1000]  training's auc: 0.910458        valid_1's auc: 0.884755
```

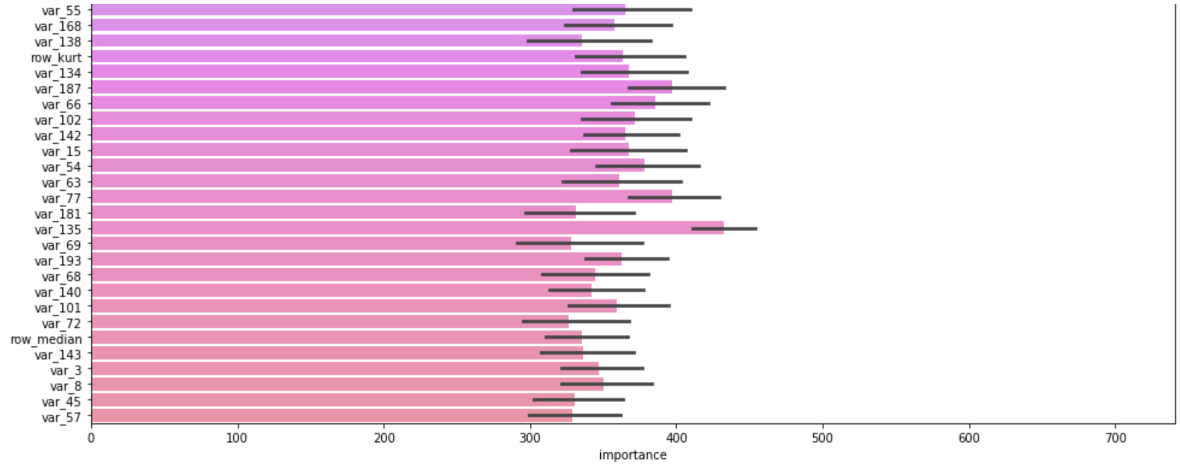
```
[2000]	training's auc: 0.922732	valid_1's auc: 0.892515
[3000]	training's auc: 0.931118	valid_1's auc: 0.895593
[4000]	training's auc: 0.938013	valid_1's auc: 0.898047
[5000]	training's auc: 0.944101	valid_1's auc: 0.899248
[6000]	training's auc: 0.949529	valid_1's auc: 0.899813
[7000]	training's auc: 0.954588	valid_1's auc: 0.900217
[8000]	training's auc: 0.95922	valid_1's auc: 0.900048
[9000]	training's auc: 0.963411	valid_1's auc: 0.900011
Early stopping, best iteration is:
[6848]	training's auc: 0.953842	valid_1's auc: 0.900337
Fold 9
Training until validation scores don't improve for 3000 rounds.
[1000]	training's auc: 0.910958	valid_1's auc: 0.880668
[2000]	training's auc: 0.923063	valid_1's auc: 0.887606
[3000]	training's auc: 0.931616	valid_1's auc: 0.890702
[4000]	training's auc: 0.938643	valid_1's auc: 0.892194
[5000]	training's auc: 0.944671	valid_1's auc: 0.89263
[6000]	training's auc: 0.950148	valid_1's auc: 0.892885
[7000]	training's auc: 0.955041	valid_1's auc: 0.892787
[8000]	training's auc: 0.959587	valid_1's auc: 0.893121
[9000]	training's auc: 0.963853	valid_1's auc: 0.892884
[10000]	training's auc: 0.967755	valid_1's auc: 0.893041
[11000]	training's auc: 0.971413	valid_1's auc: 0.89268
Early stopping, best iteration is:
[8175]	training's auc: 0.960348	valid_1's auc: 0.893211
CV score: 0.89830
```

from the above we can say taht lightgbm has performed well than all the other models. auc reaching to 0.90

Important features in decending order.

In [0]:
```
cols = (feature_importance_df[["Feature", "importance"]]
        .groupby("Feature")
        .mean()
        .sort_values(by="importance", ascending=False)[:150].index)
best_features = feature_importance_df.loc[feature_importance_df.Feature.
isin(cols)]

plt.figure(figsize=(14,28))
#plotting a bar plot where y represents features and x represents its im
portance.
sns.barplot(x="importance", y="Feature", data=best_features.sort_values(
by="importance",ascending=False))
plt.title('Features importance (averaged/folds)')
plt.tight_layout()
plt.savefig('FI.png')
```


Features importance (averaged/folds)
Feature
var_9
var_80
var_108
var_122
var_34
var_22
var_184
var_6
var_139
var_94
var_76
var_198
var_169
var_21
var_33
var_109
var_99
var_2
var_165
var_146
var_92
var_81
var_127
var_78
var_13
var_166
var_12
var_190
var_1
var_133
var_131
var_123
var_170
var_67
var_53
var_174
var_177
var_121
var_163
var_147
var_154
var_0
var_110
var_172
var_26
var_18
var_173
var_71
var_40
var_87
var_115
var_86
var_107
var_118
var_149
var_91
var_191
var_75
var_36
var_151
var_125
var_56
var_188
var_164
var_179
var_186
var_180
var_197
var_35
var_43
var_89
var_141
var_148
var_52
var_93
var_95
var_23
var_32
var_155
var_162
var_114
var_192
var_150
var_116
var_49
var_44
var_5
var_119
var_112
var_105
var_145
var_137
var_128
var_20
var_11
var_130
var_106
var_90
var_157
var_156
var_199
var_175
var_85
var_194
var_132
var_82
var_51
var_104
var_195
var_167
var_83
var_144
var_111
var_178
var_70
var_24
var_88
var_58
var_31
var_196
var_113
var_48
var_28



PrettyTable

In [0]:
```
#http://zetcode.com/python/prettytable/
from prettytable import PrettyTable

x = PrettyTable()
x.field_names =["Models","Test auc"]
x.add_row(["Logistic ",0.865])
x.add_row(["SVM ",0.865])
x.add_row(["Naive ",0.85])
x.add_row(["LightGbm",0.90])

print(x)
```

```
+-----------+----------+
|   Models  | Test auc |
+-----------+----------+
| Logistic  |  0.865   |
|    SVM    |  0.865   |
|   Naive   |   0.85   |
|  LightGbm |   0.9    |
+-----------+----------+
```

Final model with full dataset with submission.

importing dataset from drive.

In [0]:
```
train = pd.read_csv("/content/drive/My Drive/train_santander.csv")
test = pd.read_csv("/content/drive/My Drive/test_santander.csv")
```

In [0]:
```
train.head(2)
```

Out[0]:

	Unnamed: 0	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_
0	0	train_0	0	8.9255	-6.7863	11.9081	5.093	11.4607	-9.2834	5.1187	18.626
1	1	train_1	0	11.5006	-4.1473	13.8588	5.389	12.3622	7.0433	5.6208	16.533

2 rows × 212 columns

In [0]:
```
test.head(2)
```

Out[0]:

	Unnamed: 0	ID_code	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	va
0	0	test_0	11.0656	7.7798	12.9536	9.4292	11.4327	-2.3805	5.8493	18.2675	2.13
1	1	test_1	8.5304	1.2543	11.3047	5.1858	9.1974	-4.0117	6.0196	18.6316	-4.41

2 rows × 211 columns

Credit: [https://www.kaggle.com/titericz/single-model-using-only-train-counts-information (https://www.kaggle.com/titericz/single-model-using-only-train-counts-information)](https://www.kaggle.com/titericz/single-model-using-only-train-counts-information)

I thought of trying magic as done in other kernels but this kernal was much more interesting\ because in this values_count() is used in a simple and more readable way.\ leaderboard score after implementing this.

Public: 0.91497\ Private: 0.91433

---

taking only those features whose name starts with var, like var_0, var_1 etc.

In [0]:
```
features = [x for x in train.columns if x.startswith("var")]
```

In [0]:
```
#https://www.kaggle.com/titericz/single-model-using-only-train-counts-information
```

np.corrcoef return Pearson product-moment correlation coefficients and if it is less than zero then reverse the value of train and test.

In [0]:
```
#Reverse some features.
#Not really necessary for LGB, but helps a little
#https://docs.scipy.org/doc/numpy/reference/generated/numpy.corrcoef.htm
l
for var in features:
    if np.corrcoef( train['target'], train[var] )[1][0] < 0:
        train[var] = train[var] * -1
        test[var]  = test[var]  * -1
```

value_counts() counts the number of time a variable has occured\ once we got the value count then we put that into a dictionary with\ keys as variabe and values as number of count.

In [0]:
```
#count train values to split Rare/NonRare values
var_stats = {}
for var in features:
    var_stats[var] = train[var].value_counts()
```

printing the top 10 counts of var_0

In [0]:
```
var_stats["var_0"].head(10)
```

Out[0]:
```
13.0656    11
8.6649     11
10.6829    11
11.9590    10
8.9425     10
10.7369    10
12.9271    10
9.5114     10
10.9468    10
8.9129     10
Name: var_0, dtype: int64
```

Defining the functions

1. logit() which gives the difference of log(p) and log(1-p)\ 2. var_to_features which creates a new dataframe\ and of shape(200000,4) and coulmn name as var, hist, feature it and var_rank

In [0]:
```
def logit(p):
    return np.log(p) - np.log(1 - p)

def var_to_feat(vr, var_stats, feat_id ):
    new_df = pd.DataFrame()
    new_df["var"] = vr.values
    new_df["hist"] = pd.Series(vr).map(var_stats)
    new_df["feature_id"] = feat_id
    new_df["var_rank"] = new_df["var"].rank()/200000.
    #print(new_df.shape)
    return new_df.values
```

creating a target of shape (40000000,) i.e 4 crores

In [0]:
```
TARGET = np.array( list(train['target'].values) * 200 )
TARGET.shape
```

Out[0]:
```
(40000000,)
```

In [0]:
```
TARGET
```

Out[0]:
```
array([0, 0, 0, ..., 0, 0, 0])
```

Train

here the idea is appending each 200000 rors 200 times that makes is 4 crore rows and predicting for each individually and then reshaping back to (200000, 200)

In [0]:
```
#initializing a empty list named TRAIN
TRAIN = []
#initializing an empty dictionary var_mean
#this will contain mean value of counts
var_mean = {}
#this will contain variance of counts
#initializing an empty dictionary var_var
var_var  = {}
for var in features:
    #for all column in features
    #this below tmp wii be of shape (200000,4)
    tmp = var_to_feat(train[var], var_stats[var], int(var[4:]) )
    #putting mean of var with column as keys and mean with values.
    var_mean[var] = np.mean(tmp[:,0])
    #putting variance of var with column as keys and mean with values.
    var_var[var]  = np.var(tmp[:,0])
    #normalizing all tmp and putting that in tmp again
    tmp[:,0] = (tmp[:,0]-var_mean[var])/var_var[var]
    #appending everything in train
    TRAIN.append( tmp )
#this will stack in vertically
TRAIN = np.vstack( TRAIN )
#taking target values
target = train['target'].values
#deleting train
del train
#garbaze collector deallocates the space
#https://www.geeksforgeeks.org/garbage-collection-python/
_=gc.collect()

print( TRAIN.shape, len( TARGET ) )
```

```
(40000000, 4) 40000000
```

we can see there are 4 column in train

In [0]:
```
TRAIN[0,:]
```

Out[0]:
```
array([-0.1898334,  6.        ,  0.        ,  0.3043175])
```

Light gbm

choosing the best parameters

In [0]:
```
#https://medium.com/@pushkarmandot/https-medium-com-pushkarmandot-what-i
s-lightgbm-how-to-implement-it-how-to-fine-tune-the-parameters-60347819b
7fc
# https://www.kaggle.com/titericz/single-model-using-only-train-counts-i
nformation
model = lgb.LGBMClassifier(**{
     'learning_rate': 0.03,
     'num_leaves': 31,
     'max_bin': 1023,
     'min_child_samples': 1000,
     'feature_fraction': 1.0,
     'bagging_freq': 1,
     'bagging_fraction': 0.85,
     'objective': 'binary',
     'n_jobs': -1,
     'n_estimators':200,})
```

Training the model

In [0]:
```
#taking a total of 10 folds
NFOLDS = 10
predtrain = np.zeros( len(TARGET) )
MODELS = []
skf = StratifiedKFold(n_splits=NFOLDS, shuffle=True, random_state=11111)
for fold_, (train_indexes, valid_indexes) in enumerate(skf.split(TRAIN,
TARGET)):
    print('Fold:', fold_ )
    model = model.fit( TRAIN[train_indexes], TARGET[train_indexes],
                      eval_set = (TRAIN[valid_indexes], TARGET[valid_ind
exes]),
                      verbose = 100,
                      eval_metric='auc',
                      early_stopping_rounds=20,
                      categorical_feature = [2] )
    MODELS.append( model )
    predtrain[valid_indexes] = model.predict_proba( TRAIN[valid_indexes]
)[:,1]

#Reshape to original format 200k x 200
pred = np.reshape( predtrain , (200000,200) , order='F' )
#Use logit for better performance
print( NFOLDS,'-Fold CV AUC:',roc_auc_score( target, np.mean( logit(pred
),axis=1)  ) )
_=gc.collect()
```

```
Fold: 0
Training until validation scores don't improve for 20 rounds.
Early stopping, best iteration is:
[72]	valid_0's auc: 0.528425 valid_0's binary_logloss: 0.325237
Fold: 1
Training until validation scores don't improve for 20 rounds.
[100]	valid_0's auc: 0.528451 valid_0's binary_logloss: 0.325221
Early stopping, best iteration is:
[138]	valid_0's auc: 0.528489 valid_0's binary_logloss: 0.325215
Fold: 2
Training until validation scores don't improve for 20 rounds.
[100]	valid_0's auc: 0.529245 valid_0's binary_logloss: 0.325213
Early stopping, best iteration is:
[96]	valid_0's auc: 0.529258 valid_0's binary_logloss: 0.325214
Fold: 3
Training until validation scores don't improve for 20 rounds.
[100]	valid_0's auc: 0.527479 valid_0's binary_logloss: 0.325254
Early stopping, best iteration is:
[107]	valid_0's auc: 0.527492 valid_0's binary_logloss: 0.325252
Fold: 4
Training until validation scores don't improve for 20 rounds.
[100]	valid_0's auc: 0.528375 valid_0's binary_logloss: 0.325214
Early stopping, best iteration is:
[101]	valid_0's auc: 0.528383 valid_0's binary_logloss: 0.325214
Fold: 5
Training until validation scores don't improve for 20 rounds.
[100]	valid_0's auc: 0.527999 valid_0's binary_logloss: 0.325232
Early stopping, best iteration is:
[140]	valid_0's auc: 0.528042 valid_0's binary_logloss: 0.325226
Fold: 6
Training until validation scores don't improve for 20 rounds.
Early stopping, best iteration is:
[78]	valid_0's auc: 0.528153 valid_0's binary_logloss: 0.325266
Fold: 7
Training until validation scores don't improve for 20 rounds.
[100]	valid_0's auc: 0.528773 valid_0's binary_logloss: 0.325249
Early stopping, best iteration is:
[112]	valid_0's auc: 0.528792 valid_0's binary_logloss: 0.325246
Fold: 8
Training until validation scores don't improve for 20 rounds.
Early stopping, best iteration is:
[68]	valid_0's auc: 0.527847 valid_0's binary_logloss: 0.325268
Fold: 9
Training until validation scores don't improve for 20 rounds.
Early stopping, best iteration is:
[78]	valid_0's auc: 0.528205 valid_0's binary_logloss: 0.325253
10 -Fold CV AUC: 0.9167636465611065
```

as we can see that maximum auc we can attain with 10 folds is 0.9167

Test prediction and submission.

In [0]:

```
#initialising arrays of 2 lack rows and 200 columns with zero values
ypred = np.zeros( (200000,200) )
for feat,var in enumerate(features):
    #build dataset
    tmp = var_to_feat(test[var], var_stats[var], int(var[4:]) )
    #Standard Scale feature according train statistics
    tmp[:,0] = (tmp[:,0]-var_mean[var])/var_var[var]
    tmp[:,1] = tmp[:,1] + 1
    #Write 1 to frequency of values not seem in trainset
    tmp[ np.isnan(tmp) ] = 1
    #Predict testset for N folds
    for model_id in range(NFOLDS):
        model = MODELS[model_id]
        ypred[:,feat] += model.predict_proba( tmp )[:,1] / NFOLDS
#making final prediction with mean of logit.
ypred = np.mean( logit(ypred), axis=1 )

#Submission and finally taking its rank and normalizing it.
sub = test[['ID_code']]
sub['target'] = ypred
sub['target'] = sub['target'].rank() / 200000.
sub.to_csv('santander_good.csv', index=False)
print( sub.head(4) )
```

```
  ID_code    target
0  test_0  0.873200
1  test_1  0.915495
2  test_2  0.876500
3  test_3  0.875915
```

Conclusion:

Lightgbm is giving best results than any other models.\ final auc on test is greater than 0.91

Steps Done:

1. Importing the necessary libraries.
2. Visualizing the train and test data.
3. Checking for null values in train and test data if any.
4. Describing the data 5.Since pairplot for all the data was not possible so I did it for random 10 data
5. Analysis of train data where we find out that data is purely unbaanced.
6. Visualizing the pair plots.
7. Pdf for all the features from 2 to 202(here we find out that there is some corelations between some of the data.)
8. Visualising by tsne.
9. Visualizing mean.
10. visualising median
11. visualising dtd
12. visualising min
13. visualising max
14. visualising kurtosis
15. visualizing skew
16. visualising moving average.
17. Visualizing by kde
18. Visualizing by boxplot
19. puting all the features to to dataframe.
20. importing necessary libraries
21. importing the new train data.
22. Splitting data into train and test.
23. Applying different models like naive bayes, logistic regression, svm, lightgbm
24. Feature importance