

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.googlea%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



Importing libraries :

In [0]:

```
!pip install matplotlib==3.1.0
```

In [8]:

```
import matplotlib
matplotlib.__version__
```

Out[8]:

'3.1.0'

In [0]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
import gc
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline

from sklearn import linear_model
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV, train_test_split
from sklearn import preprocessing # KBinsDiscretizer
```

```

from sklearn import preprocessing # StandardScaler
from sklearn import metrics
from joblib import parallel_backend
import scipy.stats as st
import xgboost as xgb
import lightgbm as lgb
from prettytable import PrettyTable

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

```

Util Functions :

In [0]:

```

def auc_plot(c, tr, cv, param):
    plt.figure(figsize=(20, 6))
    plt.plot(c, tr, label='Train AUC')
    plt.plot(c, cv, label='CV AUC')
    plt.scatter(c, tr, label='Train AUC points')
    plt.scatter(c, cv, label='CV AUC points')
    plt.legend()
    plt.xlabel("{} : hyperparameter".format(param))
    plt.ylabel("AUC")
    plt.title("AUC plots for Train vs CV")
    plt.grid()
    plt.show()

def roc_plot(tr_fpr, tr_tpr, te_fpr, te_tpr):
    plt.plot(tr_fpr, tr_tpr, label="Train AUC = {}".format(metrics.auc(tr_fpr, tr_tpr)))
    plt.plot(te_fpr, te_tpr, label="Test AUC = {}".format(metrics.auc(te_fpr, te_tpr)))
    plt.legend()
    plt.xlabel("FPR")
    plt.ylabel("TPR")
    plt.title("ROC Curve")
    plt.grid()
    plt.show()

def plotTrainVsCV_AUC(search, subplots, figsize, idx, cols):
    # Print seaborn heatmaps in subplots: https://stackoverflow.com/a/42712772/9079093
    figure, axes = plt.subplots(*subplots, figsize=figsize)
    # Using grid search parameters for heatmap : https://stackoverflow.com/a/48792210/9079093
    # Print values in seaborn heatmap without scientific notation: https://stackoverflow.com/a/29648332/9079093
    g1 = sns.heatmap(pd.pivot_table(pd.DataFrame(search.cv_results_), values='mean_train_score', index=idx, columns=cols),\
        annot=True, annot_kws={"size": 13}, cmap='Oranges', fmt='.2g', ax=axes[0], xticklabels=True, yticklabels=True)
    g1.set_title('Train AUC Heat Map plot')
    g1.set_ylabel(idx)
    g1.set_xlabel(cols)

    g2 = sns.heatmap(pd.pivot_table(pd.DataFrame(search.cv_results_), values='mean_test_score', index=idx, columns=cols),\
        annot=True, annot_kws={"size": 13}, cmap=None, fmt='.2g', ax=axes[1], xticklabels=True, yticklabels=True)

```

```

g2.set_title('CV AUC Heat Map plot')
g2.set_ylabel(idx)
g2.set_xlabel(cols)

plt.subplots_adjust(hspace=.3)
plt.show()

def predict(proba, threshold, fpr, tpr, dtyp):
    t = threshold[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
    print("The maximum value of {} tpr*(1-fpr) is {} for threshold {}".format(dtyp, max(tpr*(1-fpr)), np.round(t,3)), '\n')

    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)

    return predictions

def printConfusionMatrix(y_tr, y_te, y_tr_pred, y_te_pred, tr_thresh, te_thresh, tr_fpr, tr_tpr, te_fpr, te_tpr):
    # Print seaborn heatmaps in subplots: https://stackoverflow.com/a/42712772/9079093
    figure, axes = plt.subplots(1,2, figsize=(15,5))
    # Print values in seaborn heatmap without scientific notation: https://stackoverflow.com/a/29648332/9079093
    g1 = sns.heatmap(metrics.confusion_matrix(y_tr, predict(y_tr_pred, tr_thresh, tr_fpr, tr_tpr, 'Train')), \
                    annot=True, annot_kws={"size": 16}, cmap='Oranges', fmt='g', ax=axes[0])
    g1.set_title('Train confusion matrix')
    g1.set_xlabel('Predicted Value')
    g1.set_ylabel('Actual Value')

    g2 = sns.heatmap(metrics.confusion_matrix(y_te, predict(y_te_pred, te_thresh, te_fpr, te_tpr, 'Test')), \
                    annot=True, annot_kws={"size": 16}, cmap='Purples', fmt='g', ax=axes[1])
    g2.set_title('Test confusion matrix')
    g2.set_xlabel('Predicted Value')
    g2.set_ylabel('Actual Value')

    plt.subplots_adjust(top=.9, wspace=.5, hspace=.5)
    plt.show()

```

Reading the Data :

In [5]:

```

df_train = pd.read_csv('drive/My Drive/CoLab/CustomTransactionPrediction/train.csv')
df_train.head()

```

Out[5]:

	ID-code	target	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	...
0	train_0	0	8.9255	6.7863	11.9081	5.0930	11.4607	9.2834	5.1187	18.6266	4.9200	5.7470	2.9252	3.1821	14.0137	0.5745	8.7989	14.5691	5.7487	-7.2393	4.2840	30.7133	10.5350	1...
1	train_1	0	11.5006	4.1473	13.8588	5.3890	12.3622	7.0433	5.6208	16.5338	3.1468	8.0851	0.4032	8.0585	14.0239	8.4135	5.4345	13.7003	13.8275	15.5849	7.8000	28.5708	3.4287	...
2	train_2	0	8.6093	2.7457	12.0805	7.8928	10.5825	9.0837	6.9427	14.6155	4.9193	5.9525	0.3249	11.2648	14.1929	7.3124	7.5244	14.6472	7.6782	-1.7395	4.7011	20.4775	17.7559	1...
3	train_3	0	11.0604	2.1518	8.9522	7.1957	12.5846	1.8361	5.8428	14.9250	5.8609	8.2450	2.3061	2.8102	13.8463	11.9704	6.4569	14.8372	10.7430	-0.4299	15.9426	13.7257	20.3010	1...
4	train_4	0	9.8369	1.4834	12.8746	6.6375	12.2772	2.4486	5.9405	19.2514	6.2654	7.6784	9.4458	12.1419	13.8481	7.8895	7.7894	15.0553	8.4871	-3.0680	6.5263	11.3152	21.4246	1...

5 rows × 202 columns



In [0]:

```
df_test = pd.read_csv('drive/My Drive/CoLab/CustomTransactionPrediction/test.csv')
df_test.head()
```

High level statistics:

In [0]:

```
print('Total Datapoints:',df_train.shape[0],\
      '\nTotal Features:',df_train.shape[1],'\n')

print('Some of the Features:')
for idx, col in enumerate(df_train.columns[1::20]):
    print(idx+1,':',col)
```

Total Datapoints: 200000

Total Features: 202

Some of the Features:

```
1 : target
2 : var_19
3 : var_39
4 : var_59
5 : var_79
6 : var_99
7 : var_119
8 : var_139
9 : var_159
10 : var_179
11 : var_199
```

In [0]:

```
print('Number of classes:', df_train.target.unique().size, '\n')

print('DataPoints per class:')
print(df_train.target.value_counts())
```

Number of classes: 2

DataPoints per class:

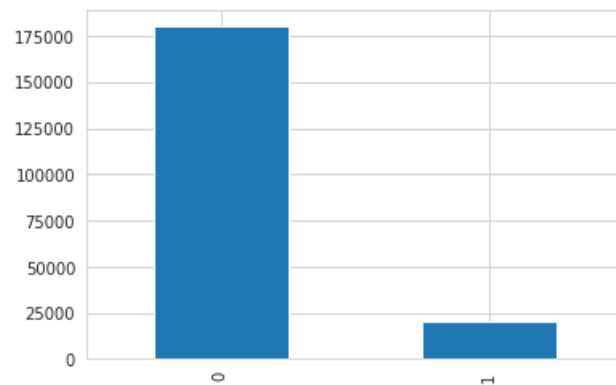
0 179902

1 20098

Name: target, dtype: int64

In [0]:

```
df_train['target'].value_counts().plot.bar()
plt.show()
```



In [0]:

```
if not (df_train.isnull().sum() > 0).any():
    print('No missing Values in the Training Data.')
else:
    print('Missing value features of Training Data :')
    print(df_train.columns[ df_train.isnull().sum() > 0 ])
```

No missing Values in the Training Data.

In [0]:

```
if not (df_test.isnull().sum() > 0).any():
```

```
print('No missing Values in the Test Data.')
else:
    print('Missing value features of Test Data :')
    print(df_test.columns[ df_test.isnull().sum() > 0 ])
```

No missing Values in the Test Data.

In [0]:

```
df_train['target'].value_counts()/df_train.shape[0]*100.
```

Out[0]:

```
0    89.951
1    10.049
Name: target, dtype: float64
```

- Based on the # data points per class we can observe that it's a highly imbalanced dataset.
 - Class_1 : 10%
 - Class_0 : 90%

EDA

Objective :

To identify if a customer will make a specific transaction or not in the future, irrespective of the amount of money transacted. The data provided here has the same structure as the real data we have available to solve this problem.

In [0]:

```
# Let's consider some of the features for the EDA part as there are 200 features and each is numeric.

eda_features = df_train.columns[2::20]
eda_features
```

Out[0]:

```
Index(['var_0', 'var_20', 'var_40', 'var_60', 'var_80', 'var_100', 'var_120',
      'var_140', 'var_160', 'var_180'],
      dtype='object')
```

In [0]:

```
# Since all the required features are numeric we are excluding the non-numeric features and the target which is to be predicted.
```

```
df_train[df.columns.difference(['target'])].describe(exclude=['object'])
```

Out[0]:

	var_0	var_1	var_10	var_100	var_101	var_102	var_103	var_104	var_105	var_106	var_107	var_108	var
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.00
mean	10.679914	-1.627622	0.394340	-6.600518	13.413526	22.294908	1.568393	11.509834	4.244744	8.617657	17.796266	14.224435	18.45
std	3.040051	4.050044	5.500793	9.181683	4.950537	8.628179	0.185020	1.970520	0.855698	1.894899	7.604723	0.171091	4.35
min	0.408400	-15.043400	-20.731300	-39.179100	0.075700	-7.382900	0.979300	4.084600	0.715300	0.942400	-5.898000	13.729000	5.76
25%	8.453850	-4.740025	-3.594950	-13.198700	9.639800	16.047975	1.428900	10.097900	3.639600	7.282300	12.168075	14.098900	15.10
50%	10.524750	-1.608050	0.487300	-6.401500	13.380850	22.306850	1.566000	11.497950	4.224500	8.605150	17.573200	14.226600	18.28
75%	12.758200	1.358625	4.382925	0.132100	17.250225	28.682225	1.705400	12.902100	4.822200	9.928900	23.348600	14.361800	21.85
max	20.315000	10.376800	18.670200	25.140900	28.459400	51.326500	2.188700	19.020600	7.169200	15.307400	46.379500	14.743000	32.05

8 rows × 200 columns

In [0]:

```
df_test.describe()
```

Out[0]:

	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
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.00
mean	10.658737	-1.624244	10.707452	6.788214	11.076399	-5.050558	5.415164	16.529143	0.277135	7.569407	0.371335	-3.268551	14.02
std	3.036716	4.040509	2.633888	2.052724	1.616456	7.869293	0.864686	3.424482	3.333375	1.231865	5.508661	5.961443	0.19
min	0.188700	-15.043400	2.355200	-0.022400	5.484400	-27.767000	2.216400	5.713700	-9.956000	4.243300	-22.672400	-25.811800	13.42
25%	8.442975	-4.700125	8.735600	5.230500	9.891075	-11.201400	4.772600	13.933900	-2.303900	6.623800	-3.626000	-7.522000	13.89
50%	10.513800	-1.590500	10.560700	6.822350	11.099750	-4.834100	5.391600	16.422700	0.372000	7.632000	0.491850	-3.314950	14.02
75%	12.739600	1.343400	12.495025	8.327600	12.253400	0.942575	6.005800	19.094550	2.930025	8.584825	4.362400	0.832525	14.16
max	22.323400	9.385100	18.714100	13.142000	16.037100	17.253700	8.302500	28.292800	9.665500	11.003600	20.214500	16.771300	14.68

8 rows × 200 columns

- The Mean and Spread for some of the features differ a lot between the train and test data.

In [0]:

```
sns.set_style('whitegrid')
```

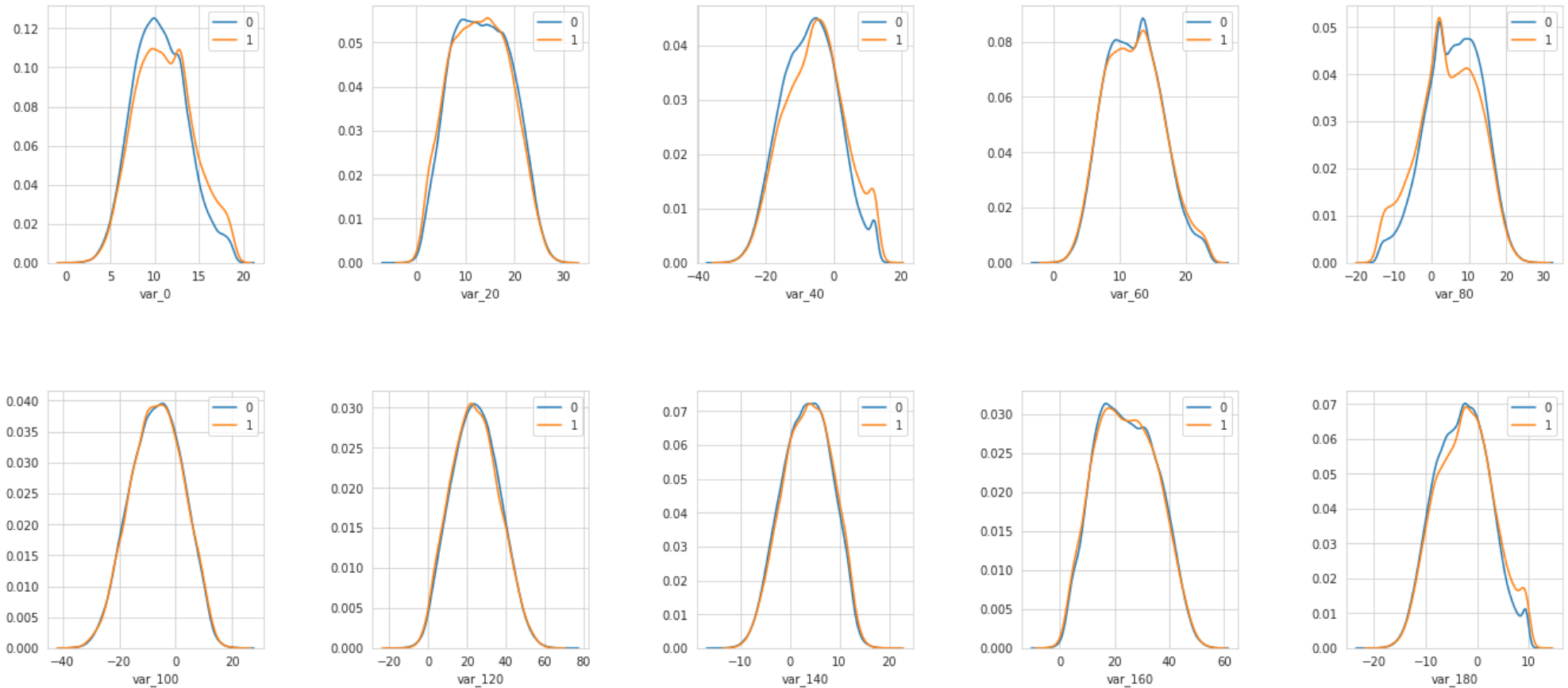
```
In [0]:
```

```
figure, axes = plt.subplots(2, 5, figsize=(23,10))
axes = axes.flatten()

df_train_0 = df_train[df_train.target == 0]
df_train_1 = df_train[df_train.target == 1]

for idx, feat in enumerate(eda_features):
    sns.kdeplot(df_train_0[feat], ax=axes[idx], label='0')
    sns.kdeplot(df_train_1[feat], ax=axes[idx], label='1').set_xlabel(feat)

plt.subplots_adjust(hspace=.5, wspace=.5)
plt.show()
plt.close()
```

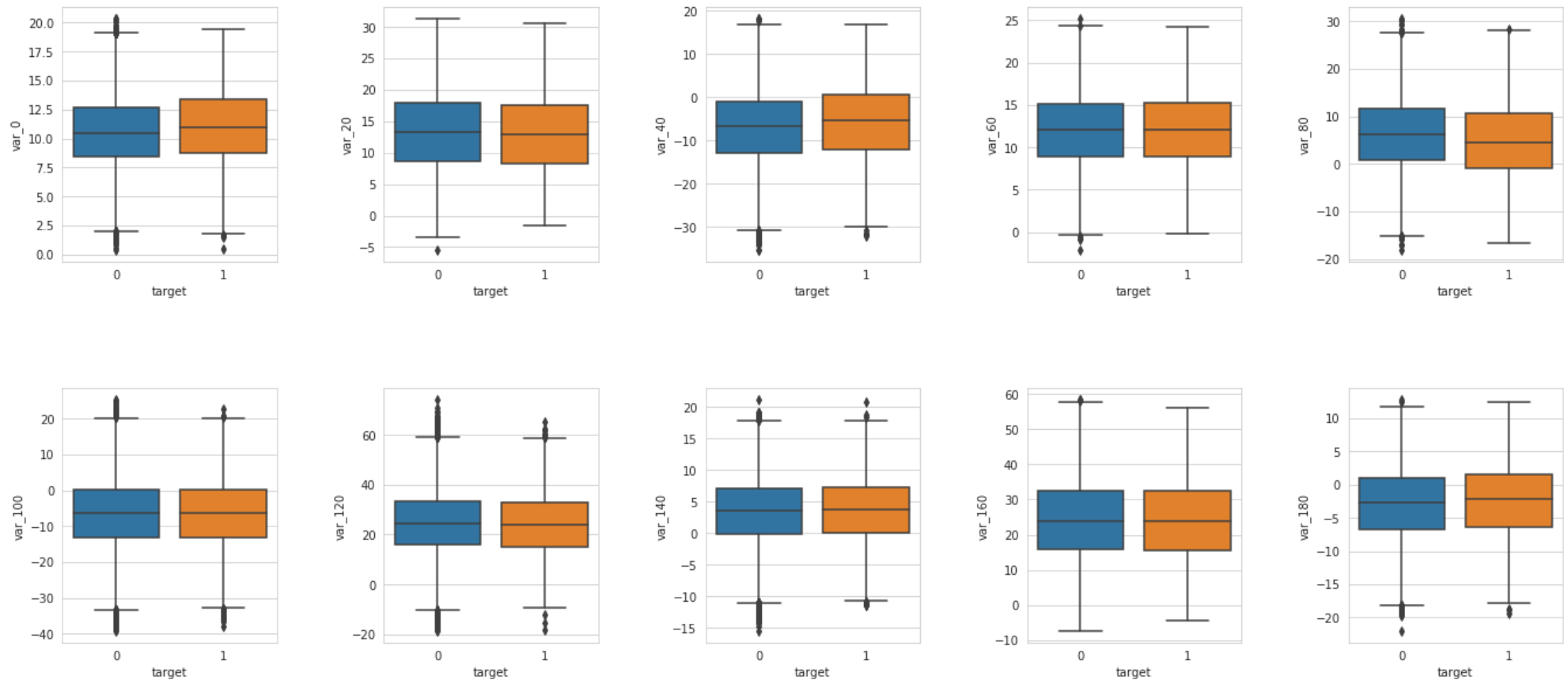


In [0]:

```
#Box Plots and whiskers
figure, axes = plt.subplots(2, 5, figsize=(23,10))
axes = axes.flatten()

for idx, col in enumerate(eda_features):
    sns.boxplot(x='target', y=col, data=df_train, ax=axes[idx])

plt.subplots_adjust(wspace=.5, hspace=.5)
plt.show()
plt.close()
```



In [0]:

```
# # Violin Plots
# figure, axes = plt.subplots(2, 5, figsize=(23, 10))
```

```
# axes = axes.flatten()

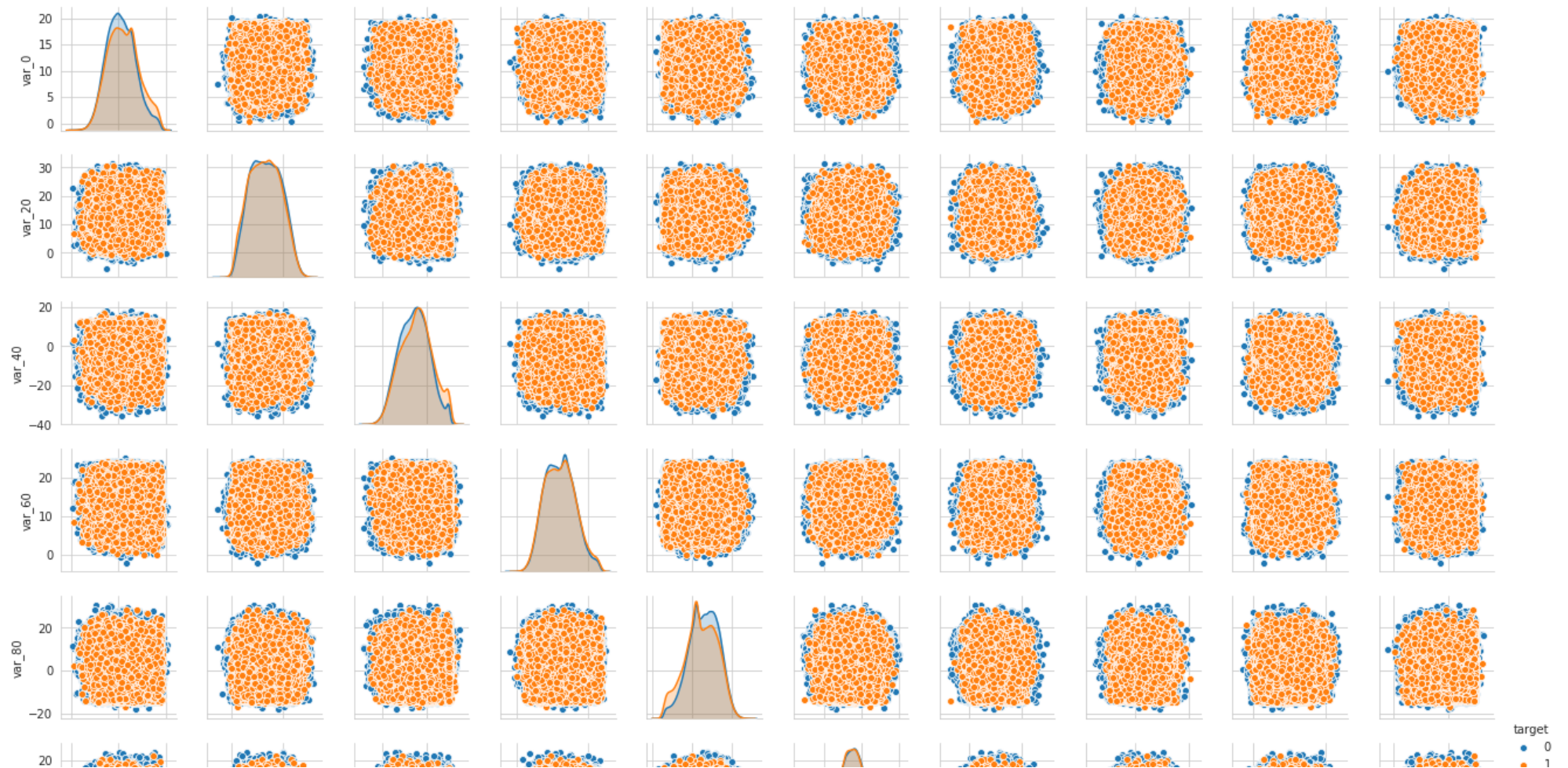
# for idx, col in enumerate(eda_features):
#     sns.violinplot(x='target', y=col, data=df_train, size=8, ax=axes[idx])

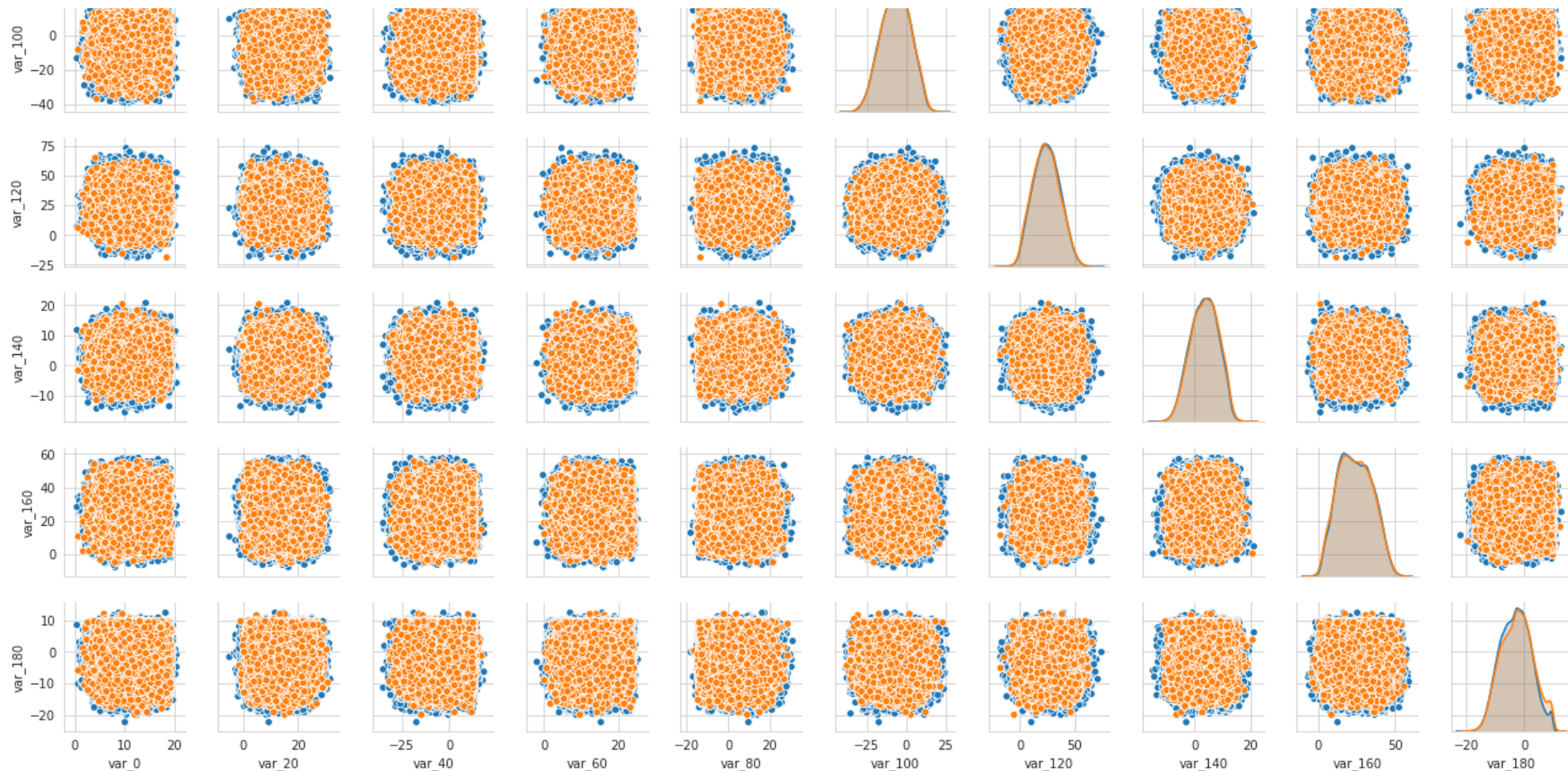
# plt.subplots_adjust(wspace=.5, hspace=.5)
# plt.show()
# plt.close()
```

In [0]:

```
sns.pairplot(df_train[eda_features + ['target']], vars=eda_features, hue='target', height=1.8)

plt.show()
```





- It's hard to separate the classes using the linear models as we can see from the pair plots of the features, almost all of them overlap.
- Most of the features are Gaussian distributed except for some like var_0, var_20, var_40, var_60, var_80 and so on with some bumps on left or right of mean value.

In [0]:

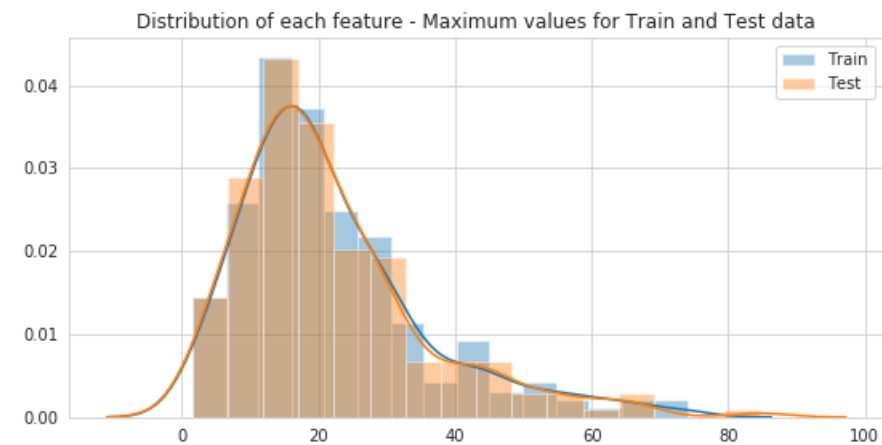
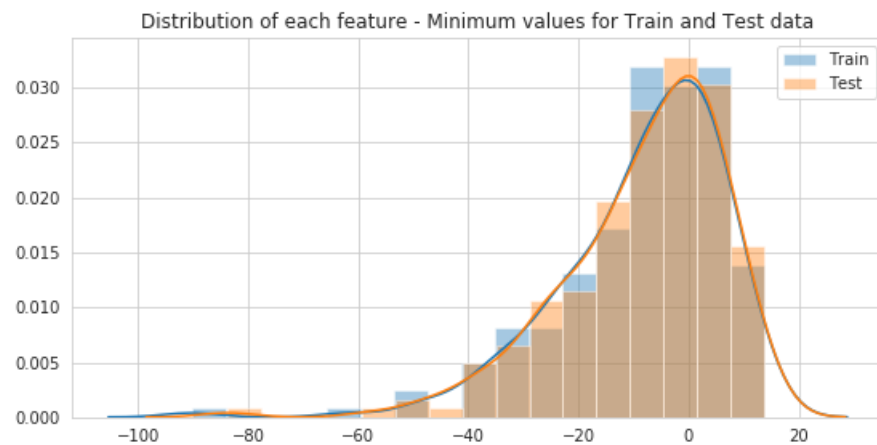
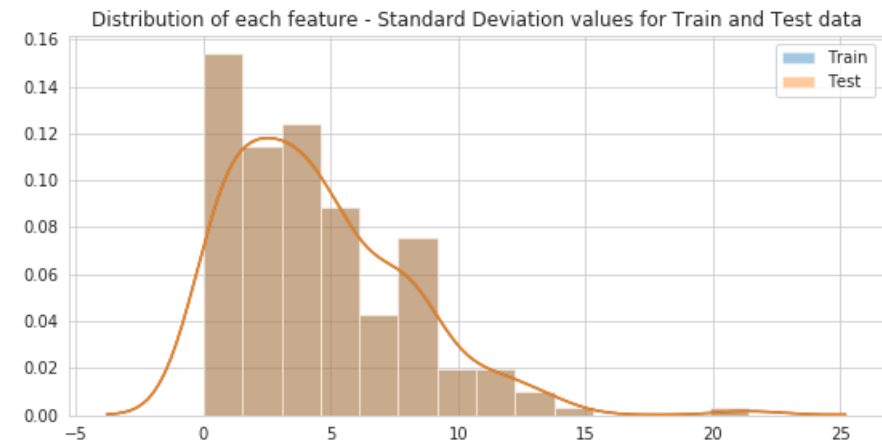
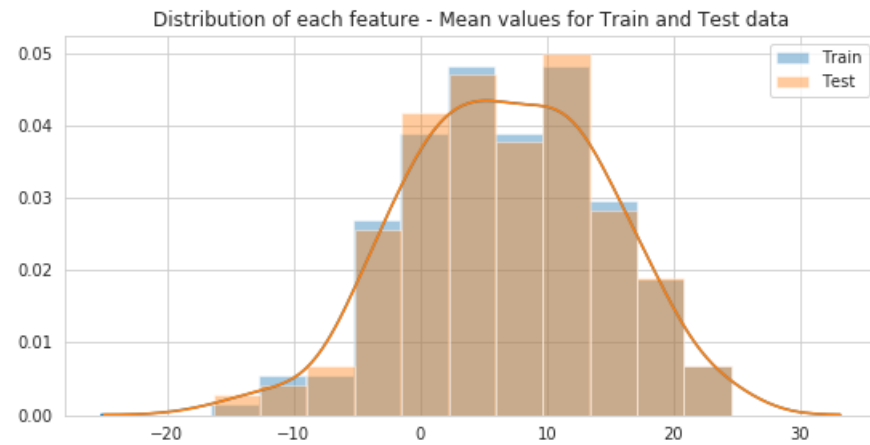
```
plots = ['Mean', 'Standard Deviation', 'Minimum', 'Maximum']
plot_funcs = [np.mean, np.std, np.min, np.max]

figure, axes = plt.subplots(2, 2, figsize=(20, 10))
axes = axes.flatten()

for idx, (stat, func) in enumerate(zip(plots, plot_funcs)):
    sns.distplot(df_train[df_train.columns.difference(['target', 'ID_code'])].apply(func, label='Train', ax=axes[idx])
    sns.distplot(df_test[df_test.columns.difference(['target', 'ID_code'])].apply(func, label='Test', ax=axes[idx])
    axes[idx].set_title('Distribution of each feature - {} values for Train and Test data'.format(stat))
```

```
axes[idx].legend()

plt.subplots_adjust(hspace=.3)
plt.show()
```



- We can see that the train and test data come from almost similar distributions based on mean, standard deviation, minimum and maximum values plots for each feature.

In [0]:

```
df_train_0 = df_train[df_train.target == 0][df_train.columns.difference(['target', 'ID_code'])]
df_train_1 = df_train[df_train.target == 1][df_train.columns.difference(['target', 'ID_code'])]

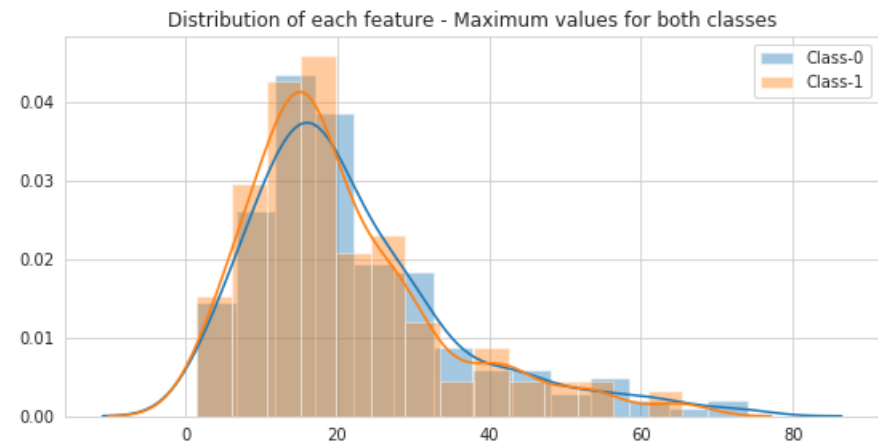
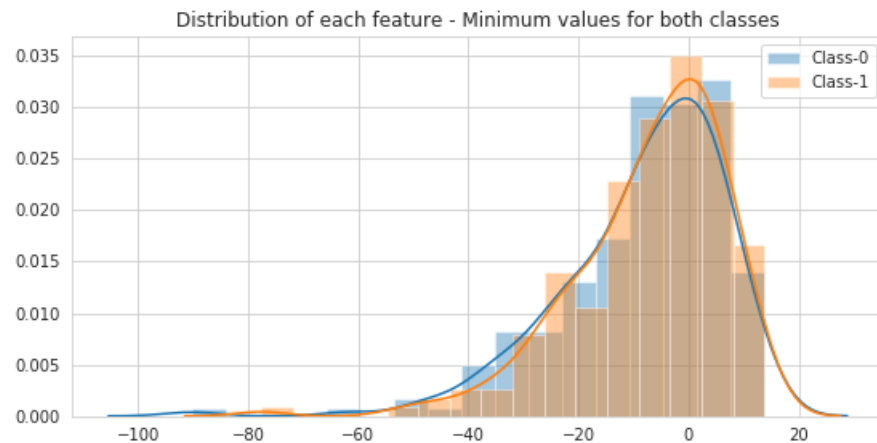
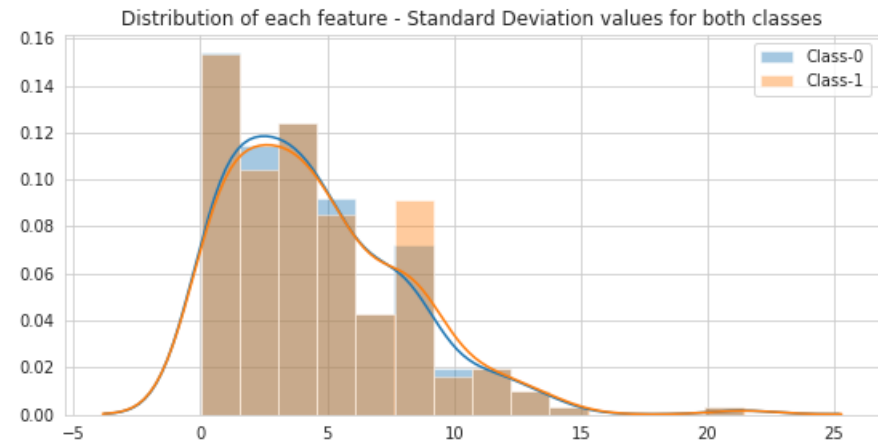
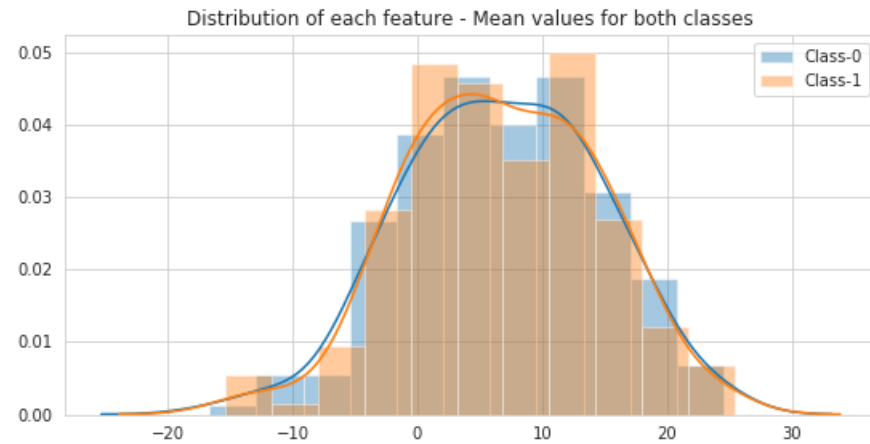
figure, axes = plt.subplots(2, 2, figsize=(20, 10))
axes = axes.flatten()
```

```

for idx, (stat, func) in enumerate(zip(plots, plot_funcs)):
    sns.distplot(df_train_0.apply(func), label='Class-0', ax=axes[idx])
    sns.distplot(df_train_1.apply(func), label='Class-1', ax=axes[idx])
    axes[idx].set_title('Distribution of each feature - {} values for both classes'.format(stat))
    axes[idx].legend()

plt.subplots_adjust(hspace=.3)
plt.show()

```



In [0]:

```

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

train_scaled = StandardScaler().fit_transform(df_train[df_train.columns.difference(['target', 'TD code'])])

```

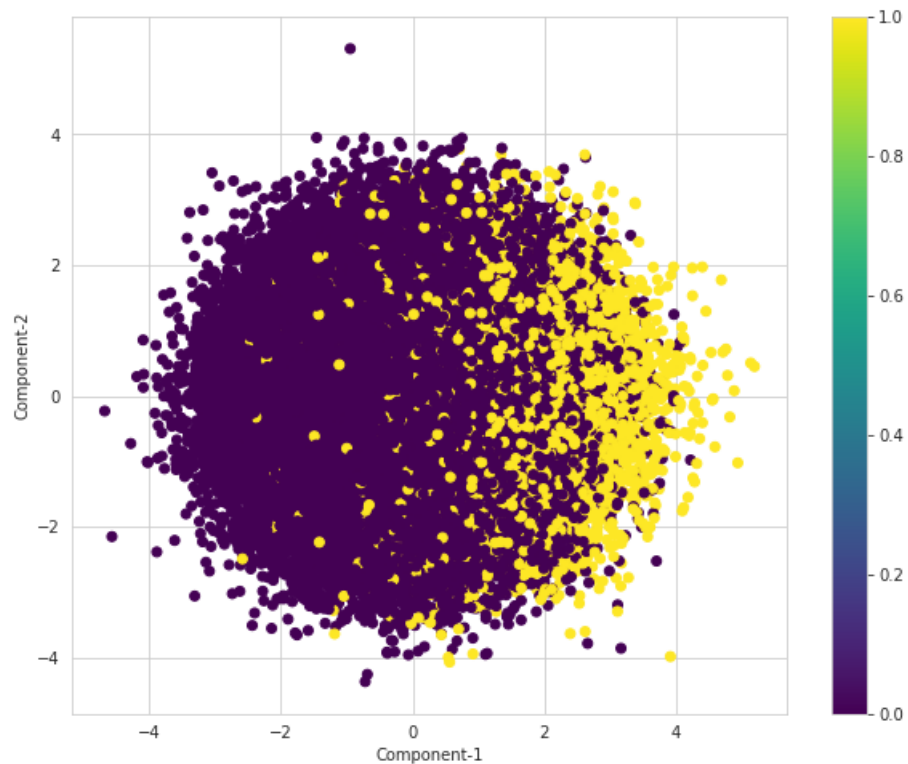


```
PCA_train = PCA(n_components=2).fit_transform(train_scaled)
```

In [0]:

```
plt.figure(figsize=(10, 8))
plt.scatter(PCA_train[:, 0], PCA_train[:, 1], c=df_train.target.values, cmap='viridis',)

plt.xlabel('Component-1')
plt.ylabel('Component-2')
plt.colorbar()
plt.show()
```

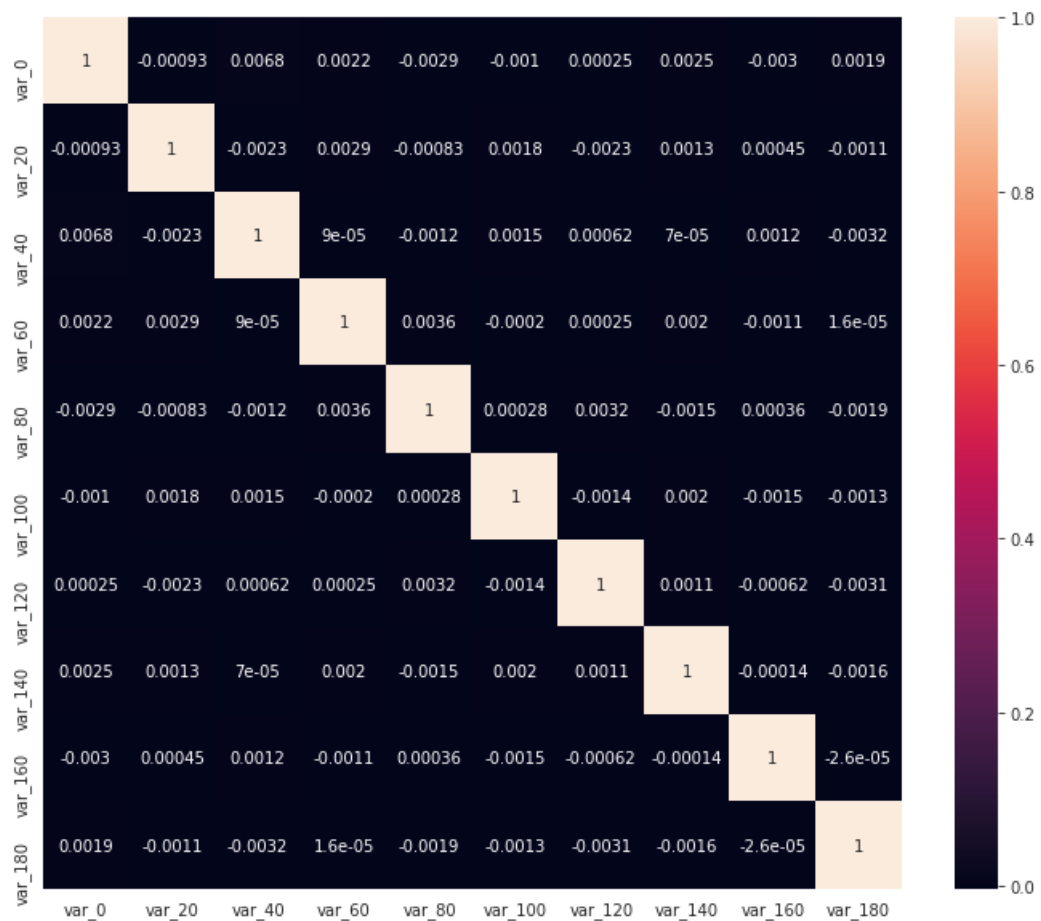


- Even with the PCA the datapoints for both classes are almost overlapping that doesn't seems meaningful.

In [0]:

```
corr = df_train[eda_features].corr()
plt.figure(figsize=(12, 10))
```

```
sns.heatmap(corr, annot=True) # Correlation heatmap for choosen EDA features.
plt.show()
```



In [0]:

```
corr = df_train[df_train.columns.difference(['ID_code', 'target'])].corr()
corr = corr.abs().unstack().sort_values(ascending=False).reset_index()
corr = corr[corr['level_0'] != corr['level_1']]
corr.columns = ['Feature_1', 'Feature_2', 'Correlation']

corr.head(10) # Top 10 correlated features.
```

Out[0]:

Feature_1	Feature_2	Correlation
-----------	-----------	-------------

	Feature_1	Feature_2	Correlation
200	var_39	var_26	0.009844
201	var_26	var_139	0.009844
202	var_53	var_148	0.009788
203	var_148	var_53	0.009788
204	var_81	var_165	0.009714
205	var_165	var_81	0.009714
206	var_81	var_174	0.009490
207	var_174	var_81	0.009490
208	var_183	var_189	0.009359
209	var_189	var_183	0.009359

In [0]:

```
corr.tail(10) # Least 10 correlated features.
```

Out[0]:

	Feature_1	Feature_2	Correlation
39990	var_100	var_177	3.116544e-07
39991	var_177	var_100	3.116544e-07
39992	var_27	var_144	1.772502e-07
39993	var_144	var_27	1.772502e-07
39994	var_126	var_109	1.313947e-07
39995	var_109	var_126	1.313947e-07
39996	var_6	var_173	5.942735e-08
39997	var_173	var_6	5.942735e-08
39998	var_75	var_191	2.703975e-08
39999	var_191	var_75	2.703975e-08

- The correlation between the pair of features is less which implies features are independent.

Basic Features :

In [7]:

```
features = df_train.columns.difference(['ID_code', 'target'])
```



```

feat_names = ['mean', 'std', 'max', 'min', 'median']
feat_funcs = [np.mean, np.std, np.max, np.min, np.median]

for feat, func in tqdm(zip(feat_names, feat_funcs)):
    df_train[feat] = df_train[features].apply(func, axis=1)
    df_test[feat] = df_test[features].apply(func, axis=1)

```

5it [01:24, 17.99s/it]

In [0]:

```
df_train[feat_names].head()
```

Out[0]:

	mean	std	max	min	median
0	7.281591	9.308182	43.1127	-21.4494	6.77040
1	7.076818	10.310257	40.5632	-47.3797	7.22315
2	6.204483	8.731476	33.8820	-22.4038	5.89940
3	6.441160	9.570048	38.1015	-35.1659	6.70260
4	6.771155	11.258868	41.1037	-65.4863	6.94735

In [0]:

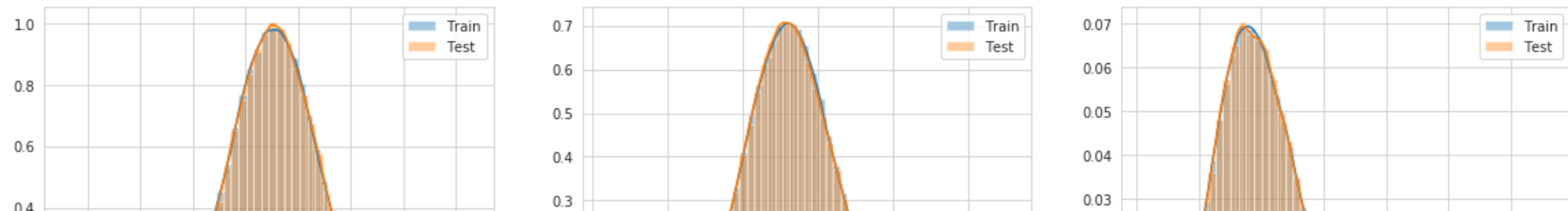
```

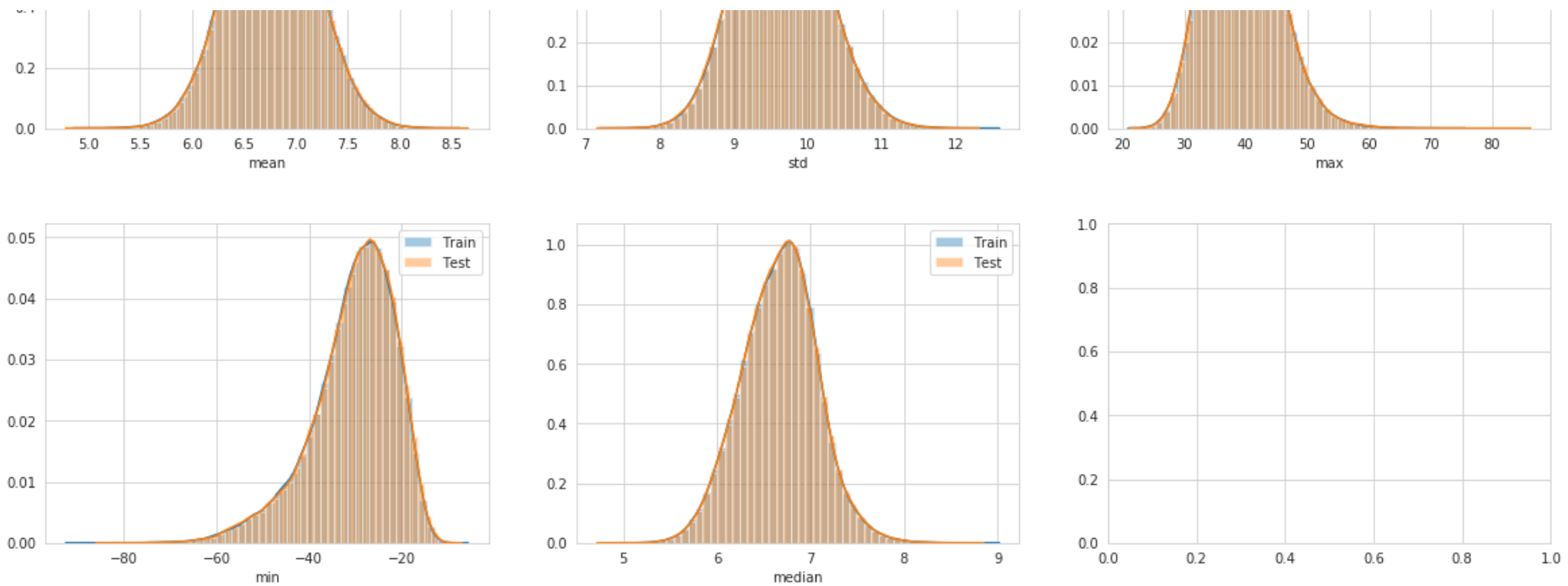
figure, axes = plt.subplots(2, 3, figsize=(20,10))
axes = axes.flatten()

for idx, feat in enumerate(feat_names):
    sns.distplot(df_train[feat], ax=axes[idx], label='Train')
    sns.distplot(df_test[feat], ax=axes[idx], label='Test').set_xlabel(feat)
    axes[idx].legend()

plt.subplots_adjust(hspace=.3)
plt.show()

```





- The basic features seems to follow the gaussian distribution.

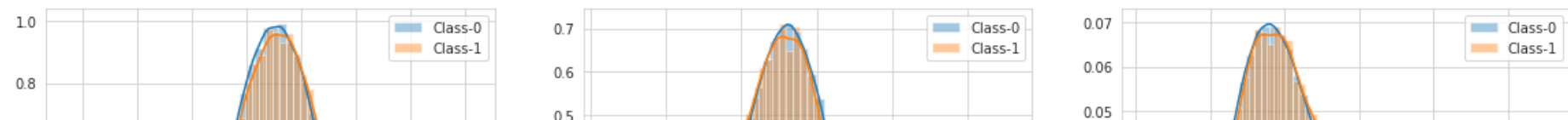
In [0]:

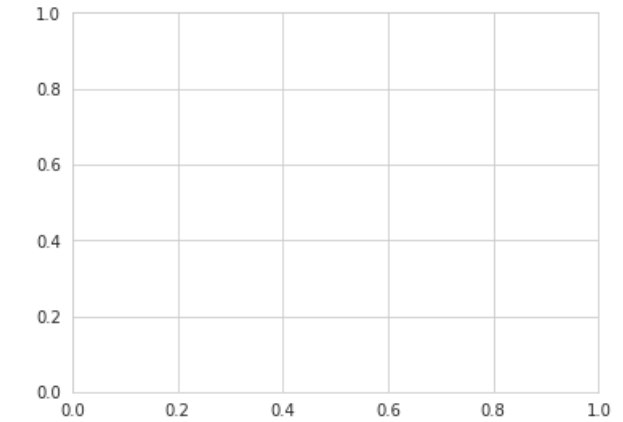
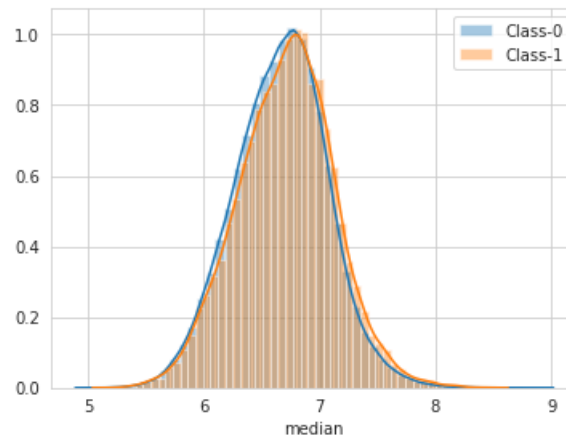
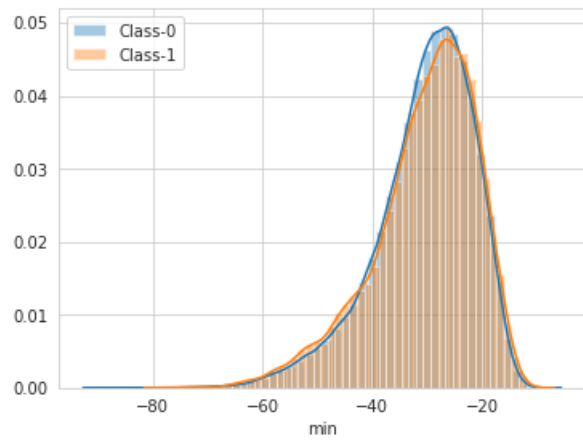
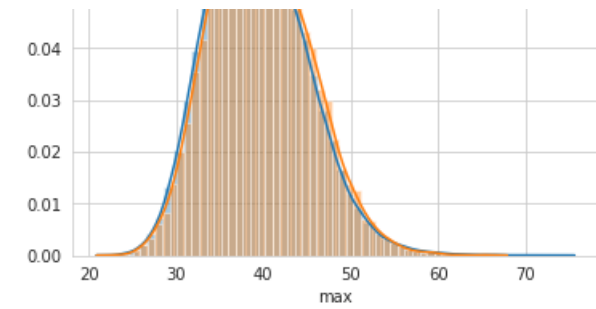
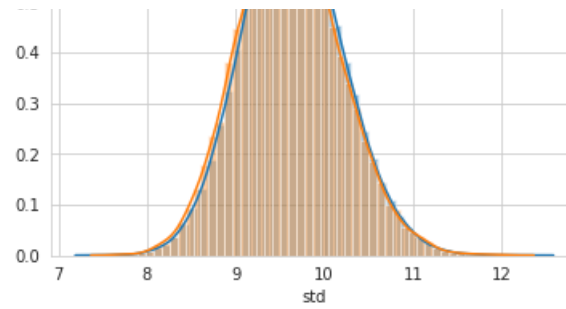
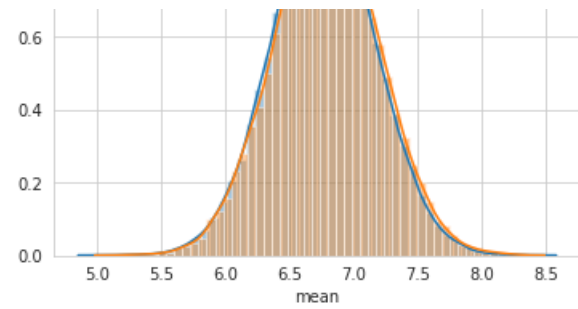
```
df_train_0 = df_train[df_train.target == 0][feat_names]
df_train_1 = df_train[df_train.target == 1][feat_names]

figure, axes = plt.subplots(2, 3, figsize=(20,10))
axes = axes.flatten()

for idx, feat in enumerate(feat_names):
    sns.distplot(df_train_0[feat], ax=axes[idx], label='Class-0')
    sns.distplot(df_train_1[feat], ax=axes[idx], label='Class-1').set_xlabel(feat)
    axes[idx].legend()

plt.subplots_adjust(hspace=.3)
plt.show()
```





Modelling [1] - w/ basic features.

In [0]:

```
X = df_train[df_train.columns.difference(['ID_code', 'target'])]
y = df_train.target.values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random_state=23, stratify=y)

pt_1 = PrettyTable()
pt_1.field_names = ['Model', 'Hyper Parameters', 'Train AUC', 'Test AUC']
```

Logistic Regression(LR) :

RandomSearch :

In [0]:

```
In [0]:
```

```
clf = linear_model.SGDClassifier('log', n_jobs=-1, class_weight='balanced')

params = dict(alpha=st.uniform(.00001, .01))
search = RandomizedSearchCV(clf, params, scoring='roc_auc', n_jobs=-1, verbose=10, return_train_score=True, cv=3)
```

```
In [0]:
```

```
with parallel_backend('threading'):
    search.fit(X_train, y_train)
```

Fitting 3 folds for each of 10 candidates, totalling 30 fits

[CV] alpha=0.004119678779936287

[CV] alpha=0.004119678779936287

[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 2 concurrent workers.

[CV] alpha=0.004119678779936287, score=(train=0.859, test=0.855), total= 22.7s

[CV] alpha=0.004119678779936287

[Parallel(n_jobs=-1)]: Done 1 tasks | elapsed: 22.9s

[CV] alpha=0.004119678779936287, score=(train=0.857, test=0.855), total= 25.5s

[CV] alpha=0.0020817756520198705

[CV] alpha=0.004119678779936287, score=(train=0.859, test=0.853), total= 23.8s

[CV] alpha=0.0020817756520198705

[CV] alpha=0.0020817756520198705, score=(train=0.857, test=0.857), total= 37.7s

[CV] alpha=0.0020817756520198705

[Parallel(n_jobs=-1)]: Done 4 tasks | elapsed: 1.1min

[CV] alpha=0.0020817756520198705, score=(train=0.860, test=0.855), total= 34.2s

[CV] alpha=0.006450444852612077

[CV] alpha=0.0020817756520198705, score=(train=0.856, test=0.851), total= 30.3s

[CV] alpha=0.006450444852612077

[CV] alpha=0.006450444852612077, score=(train=0.857, test=0.854), total= 19.0s

[CV] alpha=0.006450444852612077

[CV] alpha=0.006450444852612077, score=(train=0.858, test=0.854), total= 19.8s

[CV] alpha=0.003828692542999418

[CV] alpha=0.006450444852612077, score=(train=0.860, test=0.856), total= 16.3s

[CV] alpha=0.003828692542999418

[Parallel(n_jobs=-1)]: Done 9 tasks | elapsed: 1.9min

[CV] alpha=0.003828692542999418, score=(train=0.857, test=0.853), total= 22.7s

[CV] alpha=0.003828692542999418

```
[CV] alpha=0.003828692542999418, score=(train=0.858, test=0.857), total= 26.4s
[CV] alpha=0.008794147947487162 .....
[CV] alpha=0.008794147947487162, score=(train=0.857, test=0.855), total= 16.3s
[CV] alpha=0.008794147947487162 .....
[CV] alpha=0.003828692542999418, score=(train=0.859, test=0.855), total= 24.1s
[CV] alpha=0.008794147947487162 .....
[CV] alpha=0.008794147947487162, score=(train=0.860, test=0.857), total= 21.1s
[CV] alpha=0.001390875693309549 .....
```

[Parallel(n_jobs=-1)]: Done 14 tasks | elapsed: 3.0min

```
[CV] alpha=0.008794147947487162, score=(train=0.859, test=0.853), total= 15.4s
[CV] alpha=0.001390875693309549 .....
[CV] alpha=0.001390875693309549, score=(train=0.859, test=0.855), total= 33.9s
[CV] alpha=0.001390875693309549 .....
[CV] alpha=0.001390875693309549, score=(train=0.856, test=0.854), total= 40.3s
[CV] alpha=0.006254124023839812 .....
[CV] alpha=0.006254124023839812, score=(train=0.855, test=0.853), total= 17.0s
[CV] alpha=0.006254124023839812 .....
[CV] alpha=0.001390875693309549, score=(train=0.857, test=0.853), total= 35.8s
[CV] alpha=0.006254124023839812 .....
[CV] alpha=0.006254124023839812, score=(train=0.859, test=0.855), total= 20.1s
[CV] alpha=0.006669809715255771 .....
[CV] alpha=0.006254124023839812, score=(train=0.859, test=0.855), total= 21.0s
[CV] alpha=0.006669809715255771 .....
```

[Parallel(n_jobs=-1)]: Done 21 tasks | elapsed: 4.5min

```
[CV] alpha=0.006669809715255771, score=(train=0.859, test=0.857), total= 20.5s
[CV] alpha=0.006669809715255771 .....
[CV] alpha=0.006669809715255771, score=(train=0.858, test=0.854), total= 16.6s
[CV] alpha=0.005264553242148463 .....
[CV] alpha=0.006669809715255771, score=(train=0.859, test=0.853), total= 19.4s
[CV] alpha=0.005264553242148463 .....
[CV] alpha=0.005264553242148463, score=(train=0.861, test=0.860), total= 22.0s
[CV] alpha=0.005264553242148463 .....
[CV] alpha=0.005264553242148463, score=(train=0.860, test=0.856), total= 23.3s
[CV] alpha=0.005229899758690161 .....
[CV] alpha=0.005264553242148463, score=(train=0.858, test=0.856), total= 17.2s
[CV] alpha=0.005229899758690161 .....
[CV] alpha=0.005229899758690161, score=(train=0.857, test=0.854), total= 22.7s
[CV] alpha=0.005229899758690161 .....
[CV] alpha=0.005229899758690161, score=(train=0.861, test=0.858), total= 20.8s
[CV] alpha=0.005229899758690161, score=(train=0.858, test=0.854), total= 15.3s
```

[Parallel(n_jobs=-1)]: Done 30 out of 30 | elapsed: 6.0min finished

In [0]:

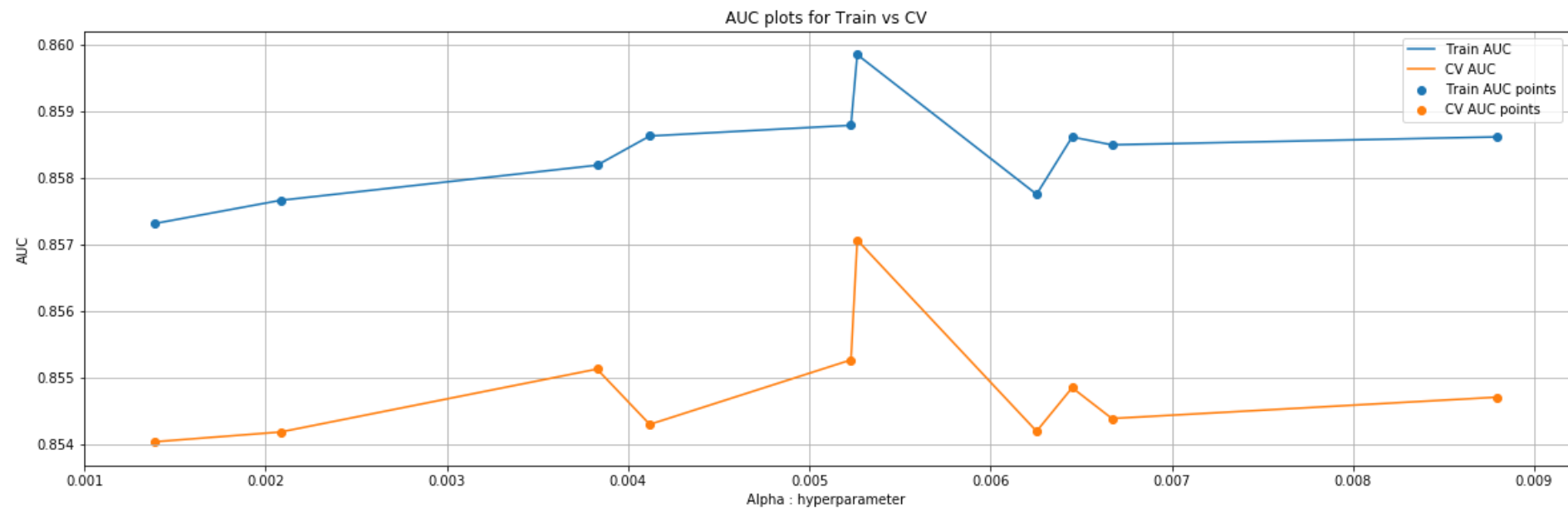
```
search.best_params_
```

```
Out[0]:  
{'alpha': 0.005264553242148463}
```

```
In [0]:  
res = pd.DataFrame(search.cv_results_)
```

```
In [0]:  
idxs = np.argsort(res.param_alpha.values.astype('float64'))
```

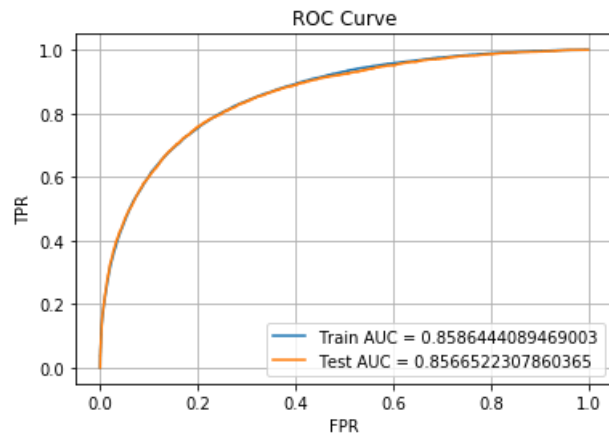
```
In [0]:  
auc_plot(res.param_alpha.values.astype('float64')[idxs],\  
         res.mean_train_score.values[idxs], res.mean_test_score.values[idxs], 'Alpha')
```



```
In [0]:  
y_train_pred = search.best_estimator_.predict_proba(X_train)[: ,1]  
y_test_pred = search.best_estimator_.predict_proba(X_test)[: ,1]
```

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)
```



GridSearch :

In [0]:

```
clf = linear_model.SGDClassifier('log', n_jobs=-1, class_weight='balanced')

params = dict(alpha=[.00001, .0001, .001, .01, .1, 1, 10])
search = GridSearchCV(clf, params, scoring='roc_auc', n_jobs=-1, verbose=10, return_train_score=True, cv=3)
```

In [0]:

```
with parallel_backend('threading'):
    search.fit(X_train, y_train)
```

Fitting 3 folds for each of 7 candidates, totalling 21 fits

```
[CV] alpha=1e-05 .....
[CV] alpha=1e-05 .....
```

[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 2 concurrent workers.

```
[CV] ..... alpha=1e-05, score=(train=0.841, test=0.838), total= 44.7s
[CV] alpha=1e-05 .....
```

```
[Parallel(n_jobs=-1)]: Done    1 tasks      | elapsed:   44.8s
```

```
[CV] ..... alpha=1e-05, score=(train=0.836, test=0.834), total=  48.6s
[CV] alpha=0.0001 .....
[CV] .... alpha=0.0001, score=(train=0.845, test=0.845), total=  49.0s
[CV] alpha=0.0001 .....
[CV] ..... alpha=1e-05, score=(train=0.836, test=0.834), total=  53.7s
[CV] alpha=0.0001 .....
```

```
[Parallel(n_jobs=-1)]: Done    4 tasks      | elapsed:   1.6min
```

```
[CV] .... alpha=0.0001, score=(train=0.835, test=0.835), total=  38.9s
[CV] alpha=0.001 .....
[CV] .... alpha=0.0001, score=(train=0.843, test=0.840), total=  55.8s
[CV] alpha=0.001 .....
[CV] ..... alpha=0.001, score=(train=0.851, test=0.848), total=  43.2s
[CV] alpha=0.001 .....
[CV] ..... alpha=0.001, score=(train=0.858, test=0.854), total=  49.4s
[CV] alpha=0.01 .....
[CV] ..... alpha=0.01, score=(train=0.858, test=0.856), total=  16.0s
[CV] alpha=0.01 .....
```

```
[Parallel(n_jobs=-1)]: Done    9 tasks      | elapsed:   3.7min
```

```
[CV] ..... alpha=0.001, score=(train=0.850, test=0.849), total=  38.9s
[CV] alpha=0.01 .....
[CV] ..... alpha=0.01, score=(train=0.859, test=0.854), total=  14.8s
[CV] alpha=0.1 .....
[CV] ..... alpha=0.01, score=(train=0.860, test=0.857), total=  17.4s
[CV] alpha=0.1 .....
[CV] ..... alpha=0.1, score=(train=0.848, test=0.846), total=   5.6s
[CV] alpha=0.1 .....
[CV] ..... alpha=0.1, score=(train=0.848, test=0.846), total=   5.3s
[CV] alpha=1 .....
```

```
[Parallel(n_jobs=-1)]: Done   14 tasks      | elapsed:   4.0min
```

```
[CV] ..... alpha=1, score=(train=0.830, test=0.829), total=   2.5s
[CV] alpha=1 .....
[CV] ..... alpha=0.1, score=(train=0.849, test=0.843), total=   5.4s
[CV] alpha=1 .....
[CV] ..... alpha=1, score=(train=0.831, test=0.827), total=   2.6s
[CV] alpha=10 .....
[CV] ..... alpha=1, score=(train=0.831, test=0.827), total=   2.4s
[CV] alpha=10 .....
[CV] ..... alpha=10, score=(train=0.796, test=0.795), total=   1.8s
[CV] alpha=10 .....
[CV] ..... alpha=10, score=(train=0.796, test=0.791), total=   1.9s
[CV] ..... alpha=10, score=(train=0.797, test=0.796), total=   1.6s
```



```
[CV] ..... alpha=10, score=(train=0.797, test=0.790), total= 1.05
```

```
[Parallel(n_jobs=-1)]: Done 21 out of 21 | elapsed: 4.2min remaining: 0.0s  
[Parallel(n_jobs=-1)]: Done 21 out of 21 | elapsed: 4.2min finished
```

In [0]:

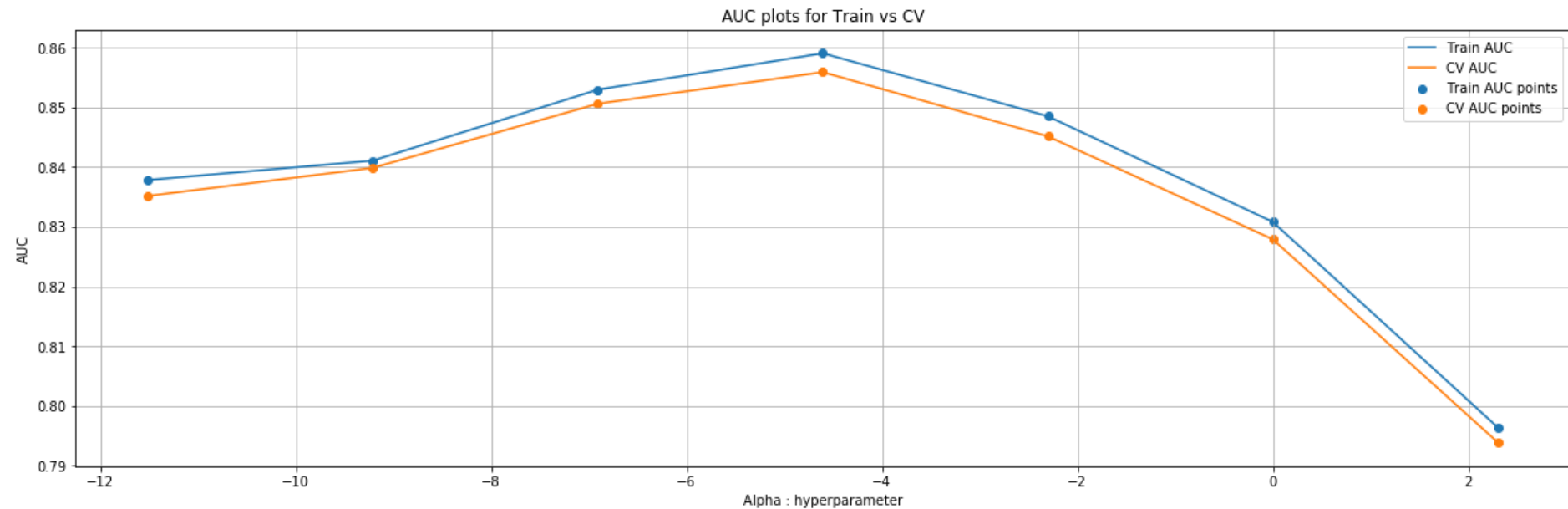
```
search.best_params_
```

Out[0]:

```
{'alpha': 0.01}
```

In [0]:

```
res = pd.DataFrame(search.cv_results_)  
  
auc_plot(np.log(res.param_alpha.values.astype('float64')),\  
         res.mean_train_score.values, res.mean_test_score.values, 'Alpha')
```

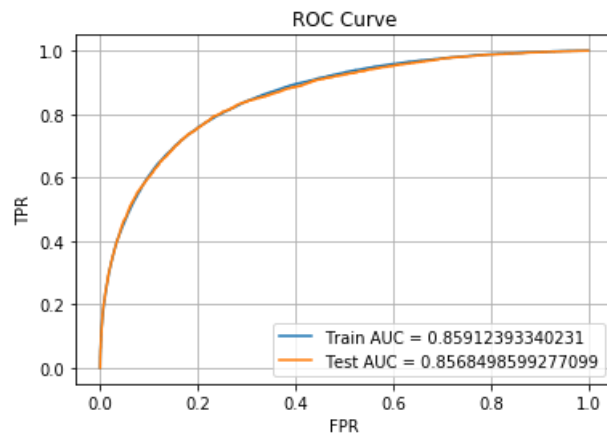


In [0]:

```
y_train_pred = search.best_estimator_.predict_proba(X_train)[: ,1]  
y_test_pred = search.best_estimator_.predict_proba(X_test)[: ,1]
```

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)
```



In [0]:

```
pt_1 = PrettyTable()
pt_1.field_names = ['Model', 'Hyper Paramters', 'Train AUC', 'Test AUC']

pt_1.add_row(['Logistic Regression', 'alpha = 0.01', np.round(.85912393340231, 3), np.round(.8568498599277099, 3)])
```

- The results were almost similar with simple SGD based Logistic Regression with test **AUROC** of ".856" .

Random Forest

In [0]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [0]:

```
clf = RandomForestClassifier(class_weight='balanced', n_jobs=-1, oob_score=True)

params = dict(max_depth=[5, 8, 10], n_estimators=[25, 50, 100], min_samples_split=[5, 10, 100])

search = GridSearchCV(clf, params, scoring='roc_auc', n_jobs=-1, verbose=10, return_train_score=True, cv=2)
```

In [0]:

```
with parallel_backend('threading'):  
    search.fit(X_train, y_train)
```

Fitting 2 folds for each of 27 candidates, totalling 54 fits

[CV] max_depth=5, min_samples_split=5, n_estimators=25[CV] max_depth=5, min_samples_split=5, n_estimators=25

[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 2 concurrent workers.

[CV] max_depth=5, min_samples_split=5, n_estimators=25, score=(train=0.810, test=0.770), total= 1.0min

[CV] max_depth=5, min_samples_split=5, n_estimators=25, score=(train=0.796, test=0.759), total= 1.0min

/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.

warn("Some inputs do not have OOB scores. "

/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide

predictions[k].sum(axis=1)[: , np.newaxis])

/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.

warn("Some inputs do not have OOB scores. "

/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide

predictions[k].sum(axis=1)[: , np.newaxis])

[CV] max_depth=5, min_samples_split=5, n_estimators=25, score=(train=0.790, test=0.752), total= 1.0min

[CV] max_depth=5, min_samples_split=5, n_estimators=50

[Parallel(n_jobs=-1)]: Done 1 tasks | elapsed: 1.0min

[CV] max_depth=5, min_samples_split=5, n_estimators=25, score=(train=0.802, test=0.760), total= 1.0min

[CV] max_depth=5, min_samples_split=5, n_estimators=50

[CV] max_depth=5, min_samples_split=5, n_estimators=50, score=(train=0.821, test=0.781), total= 1.4min

[CV] max_depth=5, min_samples_split=5, n_estimators=100

[CV] max_depth=5, min_samples_split=5, n_estimators=50, score=(train=0.807, test=0.771), total= 1.4min

[CV] max_depth=5, min_samples_split=5, n_estimators=100

[Parallel(n_jobs=-1)]: Done 4 tasks | elapsed: 2.4min

[CV] max_depth=15, min_samples_split=5, n_estimators=150, score=(train=1.000, test=0.774), total= 6.9min

[CV] max_depth=15, min_samples_split=5, n_estimators=150, score=(train=1.000, test=0.770), total= 7.2min

[CV] max_depth=5, min_samples_split=5, n_estimators=100, score=(train=0.834, test=0.794), total= 2.0min

[CV] max_depth=5, min_samples_split=10, n_estimators=25

[CV] max_depth=5, min_samples_split=5, n_estimators=100, score=(train=0.824, test=0.783), total= 2.0min

[CV] max_depth=5, min_samples_split=10, n_estimators=25

/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
  warn("Some inputs do not have OOB scores. ")
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
  predictions[k].sum(axis=1)[:, np.newaxis])
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
  warn("Some inputs do not have OOB scores. ")
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
  predictions[k].sum(axis=1)[:, np.newaxis])
```

```
[CV] max_depth=5, min_samples_split=10, n_estimators=25, score=(train=0.798, test=0.759), total= 20.7s
[CV] max_depth=5, min_samples_split=10, n_estimators=50 .....
[CV] max_depth=5, min_samples_split=10, n_estimators=25, score=(train=0.811, test=0.773), total= 20.8s
[CV] max_depth=5, min_samples_split=10, n_estimators=50 .....
[CV] max_depth=5, min_samples_split=10, n_estimators=50, score=(train=0.814, test=0.773), total= 40.6s
[CV] max_depth=5, min_samples_split=10, n_estimators=100 .....
```

```
[Parallel(n_jobs=-1)]: Done 9 tasks | elapsed: 5.5min
```

```
[CV] max_depth=5, min_samples_split=10, n_estimators=50, score=(train=0.821, test=0.781), total= 40.7s
[CV] max_depth=5, min_samples_split=10, n_estimators=100 .....
[CV] max_depth=5, min_samples_split=10, n_estimators=100, score=(train=0.830, test=0.790), total= 1.3min
[CV] max_depth=5, min_samples_split=100, n_estimators=25 .....
[CV] max_depth=5, min_samples_split=10, n_estimators=100, score=(train=0.825, test=0.786), total= 1.3min
[CV] max_depth=5, min_samples_split=100, n_estimators=25 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
  warn("Some inputs do not have OOB scores. ")
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
  predictions[k].sum(axis=1)[:, np.newaxis])
```

```
[CV] max_depth=5, min_samples_split=100, n_estimators=25, score=(train=0.795, test=0.760), total= 20.2s
[CV] max_depth=5, min_samples_split=100, n_estimators=50 .....
[CV] max_depth=5, min_samples_split=100, n_estimators=25, score=(train=0.796, test=0.760), total= 20.2s
[CV] max_depth=5, min_samples_split=100, n_estimators=50 .....
```

```
[Parallel(n_jobs=-1)]: Done 14 tasks | elapsed: 7.2min
```

```
[CV] max_depth=5, min_samples_split=100, n_estimators=50, score=(train=0.814, test=0.780), total= 40.2s
[CV] max_depth=5, min_samples_split=100, n_estimators=100 .....
[CV] max_depth=5, min_samples_split=100, n_estimators=50, score=(train=0.819, test=0.780), total= 40.3s
[CV] max_depth=5, min_samples_split=100, n_estimators=100 .....
[CV] max_depth=5, min_samples_split=100, n_estimators=100, score=(train=0.822, test=0.785), total= 1.3min
[CV] max_depth=8, min_samples_split=5, n_estimators=25 .....
[CV] max_depth=5, min_samples_split=100, n_estimators=100, score=(train=0.826, test=0.787), total= 1.3min
[CV] max_depth=8, min_samples_split=5, n_estimators=25 .....
[CV] max_depth=8, min_samples_split=5, n_estimators=25, score=(train=0.886, test=0.758), total= 30.6s
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=50 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.
```

```
    warn("Some inputs do not have OOB scores. "
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide  
    predictions[k].sum(axis=1)[: , np.newaxis])
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=25, score=(train=0.876, test=0.758), total= 30.8s
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=50 .....
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=50, score=(train=0.899, test=0.783), total= 1.0min
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=100 .....
```

```
[Parallel(n_jobs=-1)]: Done 21 tasks      | elapsed: 10.8min
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=50, score=(train=0.898, test=0.786), total= 1.0min
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=100 .....
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=100, score=(train=0.909, test=0.796), total= 2.0min
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=25 .....
```

```
[CV] max_depth=8, min_samples_split=5, n_estimators=100, score=(train=0.910, test=0.796), total= 2.0min
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=25 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.
```

```
    warn("Some inputs do not have OOB scores. "
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide  
    predictions[k].sum(axis=1)[: , np.newaxis])
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=25, score=(train=0.877, test=0.758), total= 30.5s
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=50 .....
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=25, score=(train=0.880, test=0.766), total= 30.8s
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=50 .....
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=50, score=(train=0.904, test=0.784), total= 1.0min
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=100 .....
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=50, score=(train=0.903, test=0.786), total= 1.0min
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=100 .....
```

```
[Parallel(n_jobs=-1)]: Done 28 tasks      | elapsed: 14.5min
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=100, score=(train=0.908, test=0.796), total= 2.0min
```

```
[CV] max_depth=8, min_samples_split=100, n_estimators=25 .....
```

```
[CV] max_depth=8, min_samples_split=10, n_estimators=100, score=(train=0.911, test=0.796), total= 2.1min
```

```
[CV] max_depth=8, min_samples_split=100, n_estimators=25 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few trees were used to compute any reliable oob estimates.
```

```
    warn("Some inputs do not have OOB scores. "
```

```
Warning: Some inputs do not have OOB scores.
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
  predictions[k].sum(axis=1)[: , np.newaxis])
```

```
[CV] max_depth=8, min_samples_split=100, n_estimators=25, score=(train=0.877, test=0.782), total= 29.6s
[CV] max_depth=8, min_samples_split=100, n_estimators=50 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
```

```
  warn("Some inputs do not have OOB scores. "
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
  predictions[k].sum(axis=1)[: , np.newaxis])
```

```
[CV] max_depth=8, min_samples_split=100, n_estimators=25, score=(train=0.870, test=0.769), total= 30.9s
[CV] max_depth=8, min_samples_split=100, n_estimators=50 .....
[CV] max_depth=8, min_samples_split=100, n_estimators=50, score=(train=0.892, test=0.796), total= 1.0min
[CV] max_depth=8, min_samples_split=100, n_estimators=100 .....
[CV] max_depth=8, min_samples_split=100, n_estimators=50, score=(train=0.884, test=0.788), total= 1.0min
[CV] max_depth=8, min_samples_split=100, n_estimators=100 .....
[CV] max_depth=8, min_samples_split=100, n_estimators=100, score=(train=0.896, test=0.804), total= 2.0min
[CV] max_depth=10, min_samples_split=5, n_estimators=25 .....
[CV] max_depth=8, min_samples_split=100, n_estimators=100, score=(train=0.899, test=0.805), total= 2.0min
[CV] max_depth=10, min_samples_split=5, n_estimators=25 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
```

```
  warn("Some inputs do not have OOB scores. "
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
  predictions[k].sum(axis=1)[: , np.newaxis])
```

```
[CV] max_depth=10, min_samples_split=5, n_estimators=25, score=(train=0.941, test=0.743), total= 34.7s
[CV] max_depth=10, min_samples_split=5, n_estimators=50 .....
```

```
[Parallel(n_jobs=-1)]: Done 37 tasks | elapsed: 20.6min
```

```
[CV] max_depth=10, min_samples_split=5, n_estimators=25, score=(train=0.944, test=0.743), total= 36.8s
[CV] max_depth=10, min_samples_split=5, n_estimators=50 .....
[CV] max_depth=10, min_samples_split=5, n_estimators=50, score=(train=0.958, test=0.770), total= 1.2min
[CV] max_depth=10, min_samples_split=5, n_estimators=100 .....
[CV] max_depth=10, min_samples_split=5, n_estimators=50, score=(train=0.961, test=0.776), total= 1.2min
[CV] max_depth=10, min_samples_split=5, n_estimators=100 .....
[CV] max_depth=10, min_samples_split=5, n_estimators=100, score=(train=0.969, test=0.792), total= 2.5min
[CV] max_depth=10, min_samples_split=10, n_estimators=25 .....
[CV] max_depth=10, min_samples_split=5, n_estimators=100, score=(train=0.964, test=0.793), total= 2.5min
[CV] max_depth=10, min_samples_split=10, n_estimators=25 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
```

```
warn("Some inputs do not have OOB scores. "
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
predictions[k].sum(axis=1)[:, np.newaxis])
```

```
[CV] max_depth=10, min_samples_split=10, n_estimators=25, score=(train=0.943, test=0.747), total= 34.8s
[CV] max_depth=10, min_samples_split=10, n_estimators=50 .....
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:460: UserWarning: Some inputs do not have OOB scores. This probably means too few
trees were used to compute any reliable oob estimates.
warn("Some inputs do not have OOB scores. "
/usr/local/lib/python3.6/dist-packages/sklearn/ensemble/forest.py:465: RuntimeWarning: invalid value encountered in true_divide
predictions[k].sum(axis=1)[:, np.newaxis])
```

```
[CV] max_depth=10, min_samples_split=10, n_estimators=25, score=(train=0.938, test=0.744), total= 37.4s
[CV] max_depth=10, min_samples_split=10, n_estimators=50 .....
```

```
[CV] max_depth=10, min_samples_split=10, n_estimators=50, score=(train=0.956, test=0.778), total= 1.2min
[CV] max_depth=10, min_samples_split=10, n_estimators=100 .....
```

```
[CV] max_depth=10, min_samples_split=10, n_estimators=50, score=(train=0.952, test=0.773), total= 1.2min
[CV] max_depth=10, min_samples_split=10, n_estimators=100 .....
```

```
[Parallel(n_jobs=-1)]: Done 46 tasks | elapsed: 26.5min
```

```
[CV] max_depth=10, min_samples_split=10, n_estimators=100, score=(train=0.968, test=0.792), total= 2.4min
[CV] max_depth=10, min_samples_split=100, n_estimators=25 .....
```

```
[CV] max_depth=10, min_samples_split=10, n_estimators=100, score=(train=0.968, test=0.795), total= 2.5min
[CV] max_depth=10, min_samples_split=100, n_estimators=25 .....
```

```
[CV] max_depth=10, min_samples_split=100, n_estimators=25, score=(train=0.917, test=0.775), total= 34.6s
[CV] max_depth=10, min_samples_split=100, n_estimators=50 .....
```

```
[CV] max_depth=10, min_samples_split=100, n_estimators=25, score=(train=0.908, test=0.775), total= 36.9s
[CV] max_depth=10, min_samples_split=100, n_estimators=50 .....
```

```
[CV] max_depth=10, min_samples_split=100, n_estimators=50, score=(train=0.934, test=0.798), total= 1.2min
[CV] max_depth=10, min_samples_split=100, n_estimators=100 .....
```

```
[CV] max_depth=10, min_samples_split=100, n_estimators=50, score=(train=0.933, test=0.796), total= 1.2min
[CV] max_depth=10, min_samples_split=100, n_estimators=100 .....
```

```
[CV] max_depth=10, min_samples_split=100, n_estimators=100, score=(train=0.941, test=0.810), total= 2.4min
[CV] max_depth=10, min_samples_split=100, n_estimators=100, score=(train=0.939, test=0.809), total= 2.3min
```

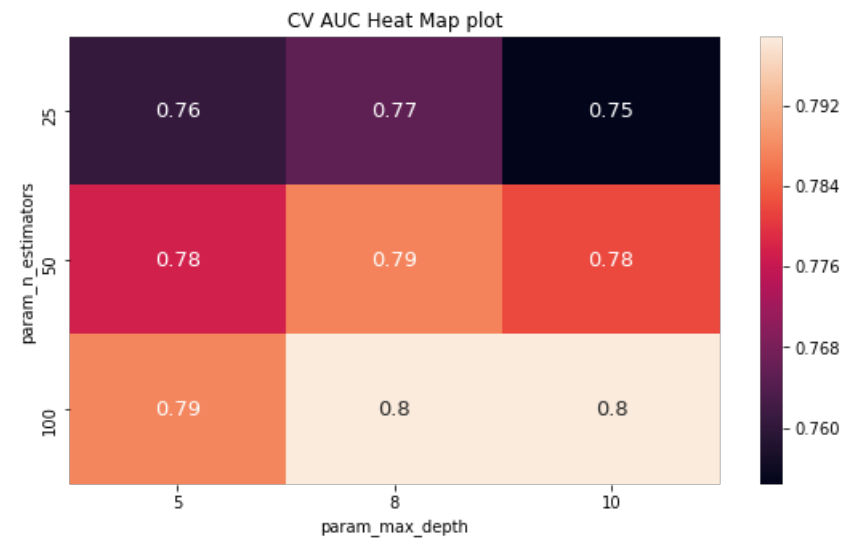
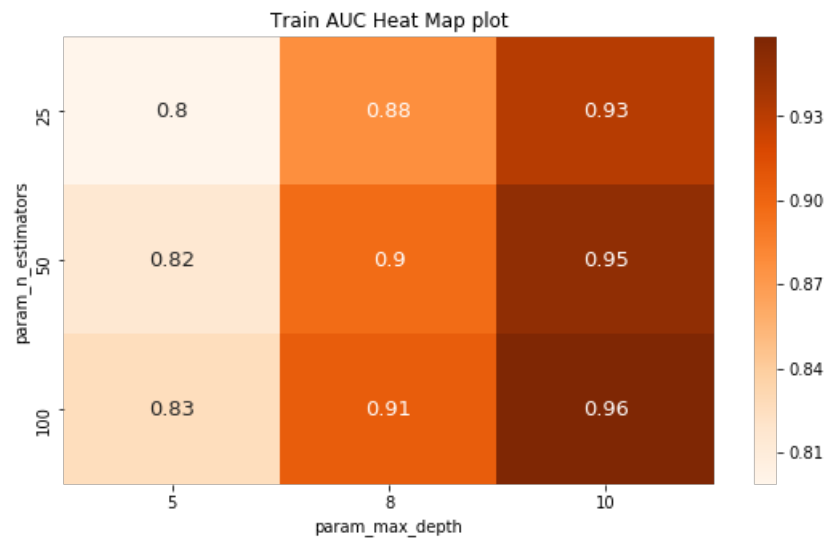
```
[Parallel(n_jobs=-1)]: Done 54 out of 54 | elapsed: 33.1min finished
```

```
In [0]:
```

```
res = pd.DataFrame(search.cv_results_)
```

```
In [0]:
```

```
plotTrainVsCV_AUC(search, subplots=(1, 2), figsize=(20, 5) idx='param_n_estimators', cols='param_max_depth')
```

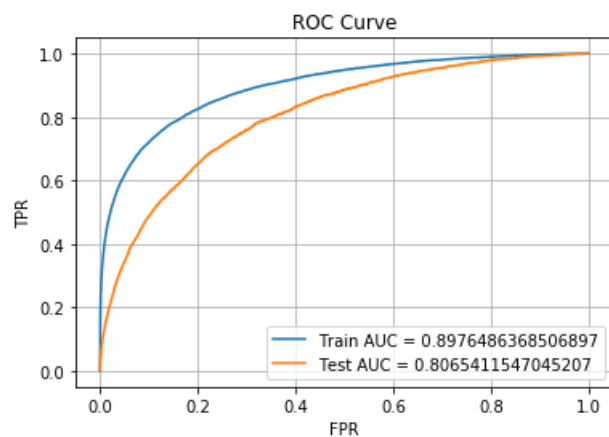


In [0]:

```
y_train_pred = search.best_estimator_.predict_proba(X_train)[: ,1]
y_test_pred = search.best_estimator_.predict_proba(X_test)[: ,1]

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)
```



- Tried Decision Tree and Random Forest but didn't gave better results as both were completely over-fitting on training data even with the various hyper parameters

- Grid Search, Tree and Random Forest didn't gave better results as best were completely over fitting on training data even with the various hyper parameters.

In [0]:

```
pt_1.add_row(['', '', '', ''])
pt_1.add_row(['Random Forest', 'Max_depth = 8, n_estimators = 100',\
              np.round(.8976486368506897, 3), np.round(.8065411547045207, 3)])
```

XGBOOST

In [0]:

```
one_to_left = st.beta(10, 1)
from_zero_positive = st.expon(0, 50)

params = {
    "n_estimators": st.randint(3, 200),
    "max_depth": st.randint(3, 10),
    "learning_rate": st.uniform(0.001, 0.1),
    "colsample_bytree": one_to_left,
    "subsample": one_to_left,
    "gamma": st.uniform(0, 10),
    "reg_lambda": st.uniform(0.001, 0.1),
    "min_child_weight": from_zero_positive,
}

search = RandomizedSearchCV(xgb.XGBClassifier(eval_metric='auc', objective='binary:logistic', n_jobs=-1, tree_method='auto'),\
                             params, scoring='roc_auc', n_jobs=-1, verbose=10, return_train_score=True, cv=2)
```

In [0]:

```
with parallel_backend('multiprocessing'):
    search.fit(X_train, y_train)
```

Fitting 2 folds for each of 10 candidates, totalling 20 fits

[Parallel(n_jobs=-1)]: Using backend MultiprocessingBackend with 2 concurrent workers.

```
[CV] colsample_bytree=0.892207906442659, gamma=1.7488800353518186, learning_rate=0.06747751081039131, max_depth=8,
min_child_weight=21.851606190465088, n_estimators=93, reg_lambda=0.08253053315245326, subsample=0.9226774110370277
[CV] colsample_bytree=0.892207906442659, gamma=1.7488800353518186, learning_rate=0.06747751081039131, max_depth=8,
min_child_weight=21.851606190465088, n_estimators=93, reg_lambda=0.08253053315245326, subsample=0.9226774110370277
[CV] colsample_bytree=0.892207906442659, gamma=1.7488800353518186, learning_rate=0.06747751081039131, max_depth=8,
min_child_weight=21.851606190465088, n_estimators=93, reg_lambda=0.08253053315245326, subsample=0.9226774110370277, score=(train=0.954,
test=0.849), total= 7.8min
[CV] colsample_bytree=0.892207906442659, gamma=1.7488800353518186, learning_rate=0.06747751081039131, max_depth=8,
min_child_weight=21.851606190465088, n_estimators=93, reg_lambda=0.08253053315245326, subsample=0.9226774110370277, score=(train=0.956,
test=0.849), total= 7.8min
```

test=0.824), total= 3.3min

[CV] colsample_bytree=0.8554388572158456, gamma=1.2808291901922786, learning_rate=0.06480135327008976, max_depth=4, min_child_weight=63.22383782769299, n_estimators=91, reg_lambda=0.016279529095083668, subsample=0.6932577829777565
[CV] colsample_bytree=0.8554388572158456, gamma=1.2808291901922786, learning_rate=0.06480135327008976, max_depth=4, min_child_weight=63.22383782769299, n_estimators=91, reg_lambda=0.016279529095083668, subsample=0.6932577829777565

[Parallel(n_jobs=-1)]: Done 1 tasks | elapsed: 7.8min

[CV] colsample_bytree=0.8554388572158456, gamma=1.2808291901922786, learning_rate=0.06480135327008976, max_depth=4, min_child_weight=63.22383782769299, n_estimators=91, reg_lambda=0.016279529095083668, subsample=0.6932577829777565, score=(train=0.860, test=0.824), total= 3.3min

[CV] colsample_bytree=0.9644454614980406, gamma=6.075913532620509, learning_rate=0.002032830201545121, max_depth=7, min_child_weight=55.72368578803438, n_estimators=68, reg_lambda=0.0358647229261306, subsample=0.9921905942236565

[CV] colsample_bytree=0.8554388572158456, gamma=1.2808291901922786, learning_rate=0.06480135327008976, max_depth=4, min_child_weight=63.22383782769299, n_estimators=91, reg_lambda=0.016279529095083668, subsample=0.6932577829777565, score=(train=0.860, test=0.820), total= 3.3min

[CV] colsample_bytree=0.9644454614980406, gamma=6.075913532620509, learning_rate=0.002032830201545121, max_depth=7, min_child_weight=55.72368578803438, n_estimators=68, reg_lambda=0.0358647229261306, subsample=0.9921905942236565

[Parallel(n_jobs=-1)]: Done 4 tasks | elapsed: 11.1min

[CV] colsample_bytree=0.9644454614980406, gamma=6.075913532620509, learning_rate=0.002032830201545121, max_depth=7, min_child_weight=55.72368578803438, n_estimators=68, reg_lambda=0.0358647229261306, subsample=0.9921905942236565, score=(train=0.732, test=0.698), total= 5.2min

[CV] colsample_bytree=0.9552976445386667, gamma=8.070588074129297, learning_rate=0.03867883887926241, max_depth=4, min_child_weight=38.298202983871086, n_estimators=120, reg_lambda=0.03309635037246653, subsample=0.9746209401382341

[CV] colsample_bytree=0.9644454614980406, gamma=6.075913532620509, learning_rate=0.002032830201545121, max_depth=7, min_child_weight=55.72368578803438, n_estimators=68, reg_lambda=0.0358647229261306, subsample=0.9921905942236565, score=(train=0.732, test=0.697), total= 5.3min

[CV] colsample_bytree=0.9552976445386667, gamma=8.070588074129297, learning_rate=0.03867883887926241, max_depth=4, min_child_weight=38.298202983871086, n_estimators=120, reg_lambda=0.03309635037246653, subsample=0.9746209401382341

[CV] colsample_bytree=0.9552976445386667, gamma=8.070588074129297, learning_rate=0.03867883887926241, max_depth=4, min_child_weight=38.298202983871086, n_estimators=120, reg_lambda=0.03309635037246653, subsample=0.9746209401382341, score=(train=0.852, test=0.805), total= 5.3min

[CV] colsample_bytree=0.9760882562642434, gamma=7.33899070008214, learning_rate=0.07511994983852938, max_depth=6, min_child_weight=52.05549446335297, n_estimators=16, reg_lambda=0.016381614223396755, subsample=0.9846398442555937

[CV] colsample_bytree=0.9552976445386667, gamma=8.070588074129297, learning_rate=0.03867883887926241, max_depth=4, min_child_weight=38.298202983871086, n_estimators=120, reg_lambda=0.03309635037246653, subsample=0.9746209401382341, score=(train=0.852, test=0.803), total= 5.3min

[CV] colsample_bytree=0.9760882562642434, gamma=7.33899070008214, learning_rate=0.07511994983852938, max_depth=6, min_child_weight=52.05549446335297, n_estimators=16, reg_lambda=0.016381614223396755, subsample=0.9846398442555937

[CV] colsample_bytree=0.9760882562642434, gamma=7.33899070008214, learning_rate=0.07511994983852938, max_depth=6, min_child_weight=52.05549446335297, n_estimators=16, reg_lambda=0.016381614223396755, subsample=0.9846398442555937, score=(train=0.779, test=0.734), total= 1.1min

[CV] colsample_bytree=0.9392374918228288, gamma=1.2976168531850774, learning_rate=0.0033690080424075832, max_depth=9, min_child_weight=121.04345829562762, n_estimators=189, reg_lambda=0.0017891873407416261, subsample=0.8649567989813004

[Parallel(n_jobs=-1)]: Done 9 tasks | elapsed: 22.8min

[CV] colsample_bytree=0.9760882562642434, gamma=7.33899070008214, learning_rate=0.07511994983852938, max_depth=6

```
[CV] colsample_bytree=0.9760882562642434, gamma=1.33899070008214, learning_rate=0.07511994983852938, max_depth=6,
min_child_weight=52.05549446335297, n_estimators=16, reg_lambda=0.016381614223396755, subsample=0.9846398442555937, score=(train=0.777,
test=0.731), total= 1.1min
[CV] colsample_bytree=0.9392374918228288, gamma=1.2976168531850774, learning_rate=0.0033690080424075832, max_depth=9,
min_child_weight=121.04345829562762, n_estimators=189, reg_lambda=0.0017891873407416261, subsample=0.8649567989813004
[CV] colsample_bytree=0.9392374918228288, gamma=1.2976168531850774, learning_rate=0.0033690080424075832, max_depth=9,
min_child_weight=121.04345829562762, n_estimators=189, reg_lambda=0.0017891873407416261, subsample=0.8649567989813004, score=(train=0.795,
test=0.748), total=16.8min
[CV] colsample_bytree=0.9905388970901187, gamma=0.9553491010166437, learning_rate=0.08297699202864298, max_depth=7,
min_child_weight=33.349588022354965, n_estimators=39, reg_lambda=0.09579148177344904, subsample=0.9969684752561796
[CV] colsample_bytree=0.9392374918228288, gamma=1.2976168531850774, learning_rate=0.0033690080424075832, max_depth=9,
min_child_weight=121.04345829562762, n_estimators=189, reg_lambda=0.0017891873407416261, subsample=0.8649567989813004, score=(train=0.794,
test=0.746), total=16.8min
[CV] colsample_bytree=0.9905388970901187, gamma=0.9553491010166437, learning_rate=0.08297699202864298, max_depth=7,
min_child_weight=33.349588022354965, n_estimators=39, reg_lambda=0.09579148177344904, subsample=0.9969684752561796
[CV] colsample_bytree=0.9905388970901187, gamma=0.9553491010166437, learning_rate=0.08297699202864298, max_depth=7,
min_child_weight=33.349588022354965, n_estimators=39, reg_lambda=0.09579148177344904, subsample=0.9969684752561796, score=(train=0.880,
test=0.804), total= 3.2min
[CV] colsample_bytree=0.6822568644110761, gamma=0.21387817694568323, learning_rate=0.06766228327528674, max_depth=5,
min_child_weight=17.747049596571745, n_estimators=42, reg_lambda=0.055513040244731464, subsample=0.9330200170360701
[CV] colsample_bytree=0.9905388970901187, gamma=0.9553491010166437, learning_rate=0.08297699202864298, max_depth=7,
min_child_weight=33.349588022354965, n_estimators=39, reg_lambda=0.09579148177344904, subsample=0.9969684752561796, score=(train=0.878,
test=0.800), total= 3.2min
[CV] colsample_bytree=0.6822568644110761, gamma=0.21387817694568323, learning_rate=0.06766228327528674, max_depth=5,
min_child_weight=17.747049596571745, n_estimators=42, reg_lambda=0.055513040244731464, subsample=0.9330200170360701
```

[Parallel(n_jobs=-1)]: Done 14 tasks | elapsed: 42.9min

```
[CV] colsample_bytree=0.6822568644110761, gamma=0.21387817694568323, learning_rate=0.06766228327528674, max_depth=5,
min_child_weight=17.747049596571745, n_estimators=42, reg_lambda=0.055513040244731464, subsample=0.9330200170360701, score=(train=0.833,
test=0.779), total= 1.7min
[CV] colsample_bytree=0.9086723055091218, gamma=0.21216894437701028, learning_rate=0.07222791991688925, max_depth=9,
min_child_weight=37.48636405680028, n_estimators=181, reg_lambda=0.014456759006000242, subsample=0.7045874614416053
[CV] colsample_bytree=0.6822568644110761, gamma=0.21387817694568323, learning_rate=0.06766228327528674, max_depth=5,
min_child_weight=17.747049596571745, n_estimators=42, reg_lambda=0.055513040244731464, subsample=0.9330200170360701, score=(train=0.836,
test=0.785), total= 1.7min
[CV] colsample_bytree=0.9086723055091218, gamma=0.21216894437701028, learning_rate=0.07222791991688925, max_depth=9,
min_child_weight=37.48636405680028, n_estimators=181, reg_lambda=0.014456759006000242, subsample=0.7045874614416053
[CV] colsample_bytree=0.9086723055091218, gamma=0.21216894437701028, learning_rate=0.07222791991688925, max_depth=9,
min_child_weight=37.48636405680028, n_estimators=181, reg_lambda=0.014456759006000242, subsample=0.7045874614416053, score=(train=0.971,
test=0.877), total=14.6min
[CV] colsample_bytree=0.8760430563901844, gamma=8.437628384358698, learning_rate=0.02274271827471186, max_depth=6,
min_child_weight=41.31544825645659, n_estimators=157, reg_lambda=0.031149218614658903, subsample=0.9020335523195462
[CV] colsample_bytree=0.9086723055091218, gamma=0.21216894437701028, learning_rate=0.07222791991688925, max_depth=9,
min_child_weight=37.48636405680028, n_estimators=181, reg_lambda=0.014456759006000242, subsample=0.7045874614416053, score=(train=0.972,
test=0.876), total=14.7min
[CV] colsample_bytree=0.8760430563901844, gamma=8.437628384358698, learning_rate=0.02274271827471186, max_depth=6,
min_child_weight=41.31544825645659, n_estimators=157, reg_lambda=0.031149218614658903, subsample=0.9020335523195462
[CV] colsample_bytree=0.8760430563901844, gamma=8.437628384358698, learning_rate=0.02274271827471186, max_depth=6,
min_child_weight=41.31544825645659, n_estimators=157, reg_lambda=0.031149218614658903, subsample=0.9020335523195462, score=(train=0.874,
test=0.812), total= 9.1min
[CV] colsample_bytree=0.8760430563901844, gamma=8.437628384358698, learning_rate=0.02274271827471186, max_depth=6,
```

```
min_child_weight=41.31544825645659, n_estimators=157, reg_lambda=0.031149218614658903, subsample=0.9020335523195462, score=(train=0.872, test=0.809), total= 9.1min
```

```
[Parallel(n_jobs=-1)]: Done 20 out of 20 | elapsed: 68.4min remaining: 0.0s  
[Parallel(n_jobs=-1)]: Done 20 out of 20 | elapsed: 68.4min finished
```

In [0]:

```
search.best_params_
```

Out[0]:

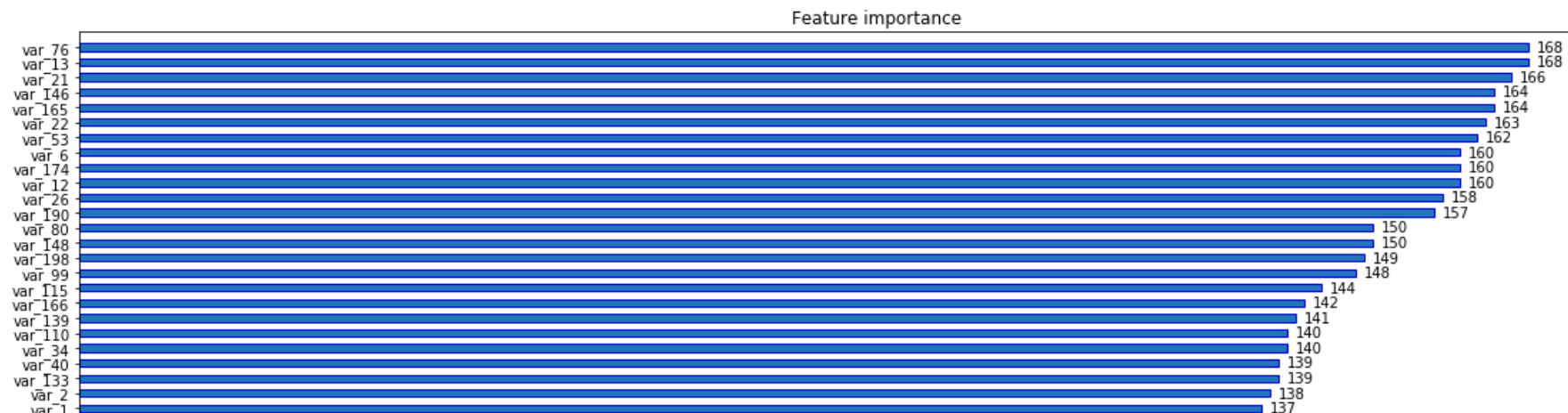
```
{'colsample_bytree': 0.9086723055091218,  
 'gamma': 0.21216894437701028,  
 'learning_rate': 0.07222791991688925,  
 'max_depth': 9,  
 'min_child_weight': 37.48636405680028,  
 'n_estimators': 181,  
 'reg_lambda': 0.014456759006000242,  
 'subsample': 0.7045874614416053}
```

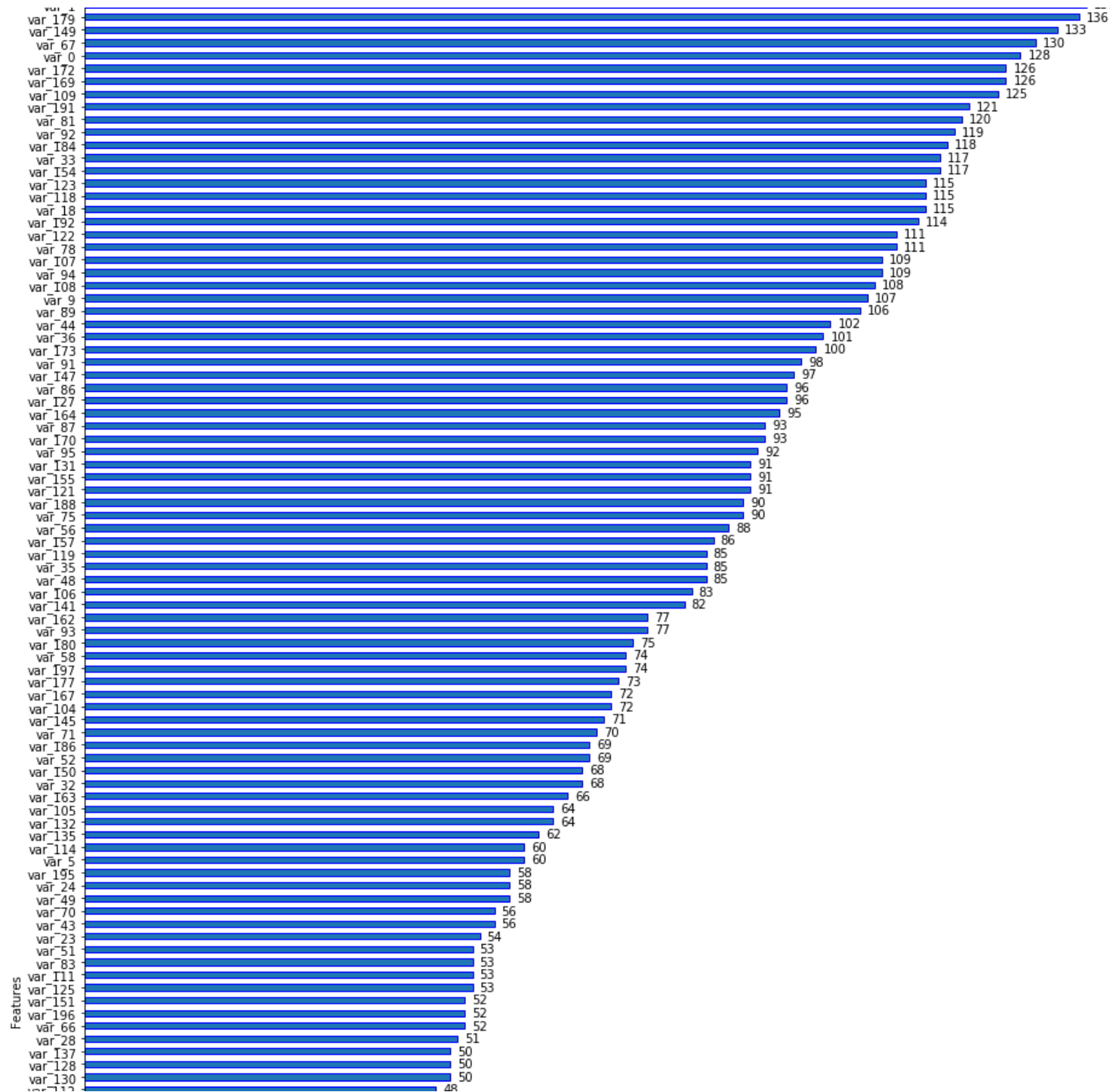
In [0]:

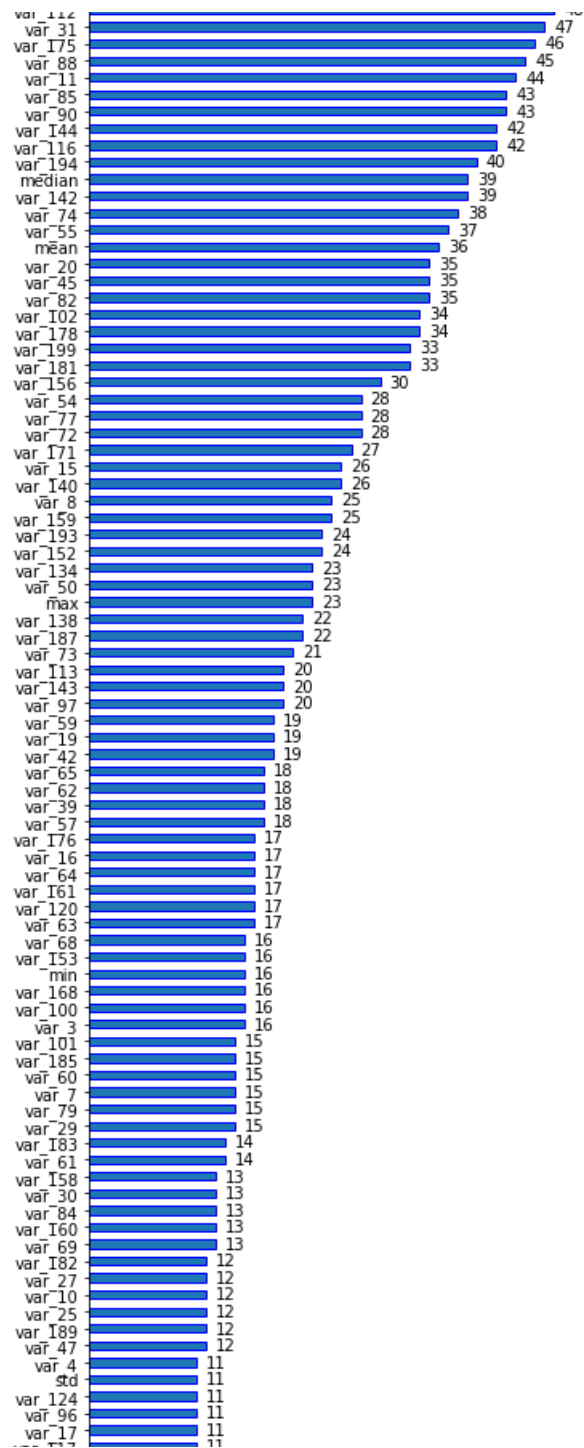
```
xgb.plot_importance?
```

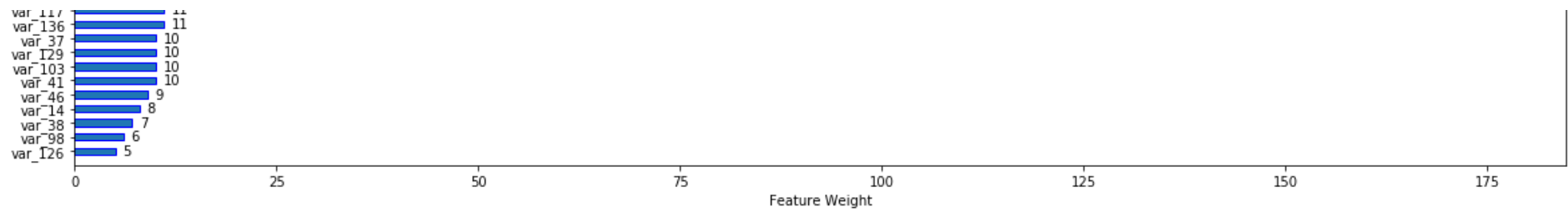
In [0]:

```
plt.figure(figsize=(20, 40))  
xgb.plot_importance(search.best_estimator_, plt.gca(), grid=False, height=.4, edgecolor='blue', xlabel='Feature Weight')  
plt.show()
```







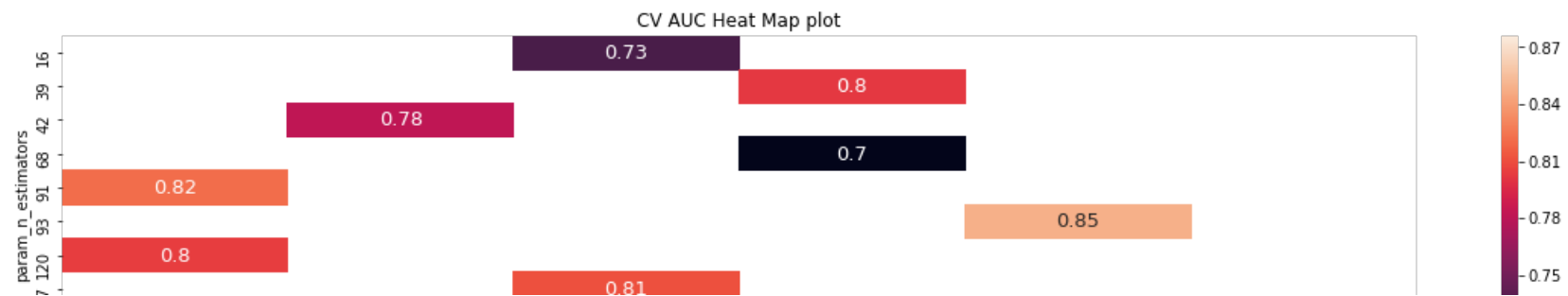
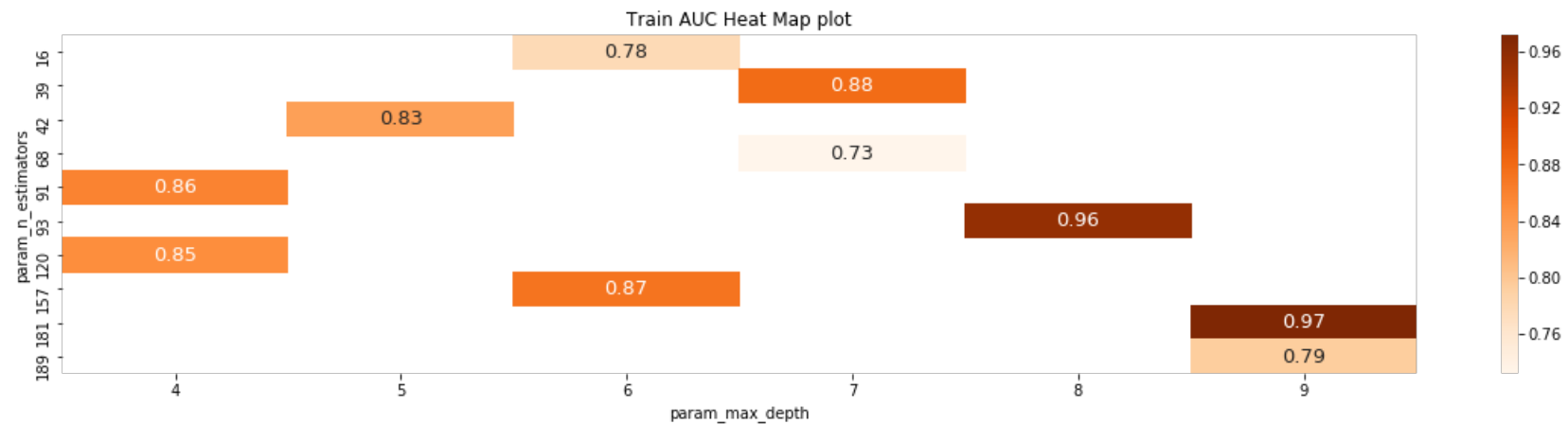


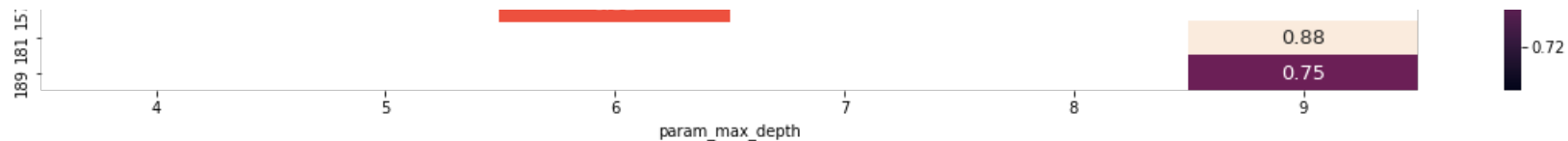
In [0]:

```
res = pd.DataFrame(search.cv_results_)
res
```

In [0]:

```
plotTrainVsCV_AUC(search, subplots=(2, 1), figsize=(20, 10), idx='param_n_estimators', cols='param_max_depth')
```



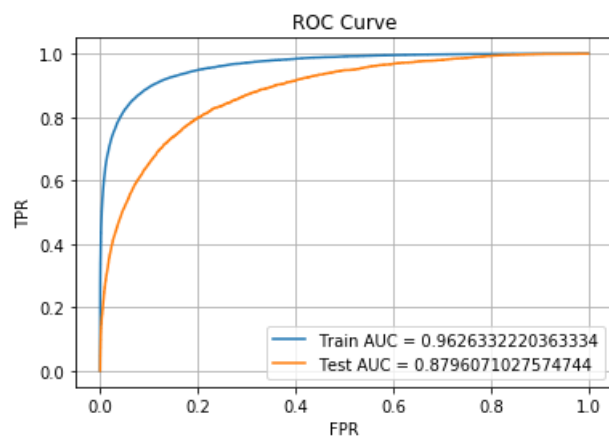


In [0]:

```
y_train_pred = search.best_estimator_.predict_proba(X_train)[:,-1]
y_test_pred = search.best_estimator_.predict_proba(X_test)[:,-1]

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)
```



In [0]:

```
pt_1.add_row(['', '', '', ''])
pt_1.add_row(['XGBoost', 'Max_depth = 9, n_estimators = 181', \
              np.round(.9626332220363334, 3), np.round(.8796071027574744, 3)])
```

Light GBM

In [0]:

```
one_to_left = st.beta(10, 1)
from_zero_positive = st.expon(0, 50)

params = {
    "max_depth": 10,
    "min_child_weight": 100,
    "num_leaves": 200,
```



```

    "num_leaves": st.randint(100, 200),
    "min_data_in_leaf": st.randint(50, 100),
    "max_depth": st.randint(5, 10),
    "learning_rate": st.uniform(0.001, 0.1),
    "colsample_bytree": one_to_left,
    # "subsample": one_to_left,
    "reg_lambda": st.uniform(0.0001, 0.1),
    "reg_alpha": st.uniform(0.0001, 0.01),
    "max_bin": st.randint(67, 100),
}

search = RandomizedSearchCV(lgb.LGBMClassifier(objective='binary', n_jobs=-1), params, n_iter=20,\
                             scoring='roc_auc', n_jobs=-1, verbose=10, return_train_score=True, cv=2, error_score='raise')

```

In [0]:

```

# with parallel backend('multiprocessing'):
search.fit(X_train, y_train, eval_metric='auc')

```

Fitting 2 folds for each of 20 candidates, totalling 40 fits

```

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:   28.9s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:   56.3s
/usr/local/lib/python3.6/dist-packages/joblib/externals/loky/process_executor.py:706: UserWarning: A worker stopped while some jobs were given to
the executor. This can be caused by a too short worker timeout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done    9 tasks      | elapsed:   2.2min
[Parallel(n_jobs=-1)]: Done   14 tasks      | elapsed:   2.9min
[Parallel(n_jobs=-1)]: Done   21 tasks      | elapsed:   4.6min
[Parallel(n_jobs=-1)]: Done   28 tasks      | elapsed:   6.1min
[Parallel(n_jobs=-1)]: Done   37 tasks      | elapsed:   8.6min
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:   9.2min finished

```

Out[0]:

```

RandomizedSearchCV(cv=2, error_score='raise',
                   estimator=LGBMClassifier(boosting_type='gbdt',
                                           class_weight=None,
                                           colsample_bytree=1.0,
                                           importance_type='split',
                                           learning_rate=0.1, max_depth=-1,
                                           min_child_samples=20,
                                           min_child_weight=0.001,
                                           min_split_gain=0.0,
                                           n_estimators=100, n_jobs=-1,
                                           num_leaves=31, objective='binary',
                                           random_state=None, reg_alpha=0.0,
                                           reg_lambda=...
                   'min_data_in_leaf': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f3329cf7b00>,
                   'num_leaves': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f332b899ac8>

```

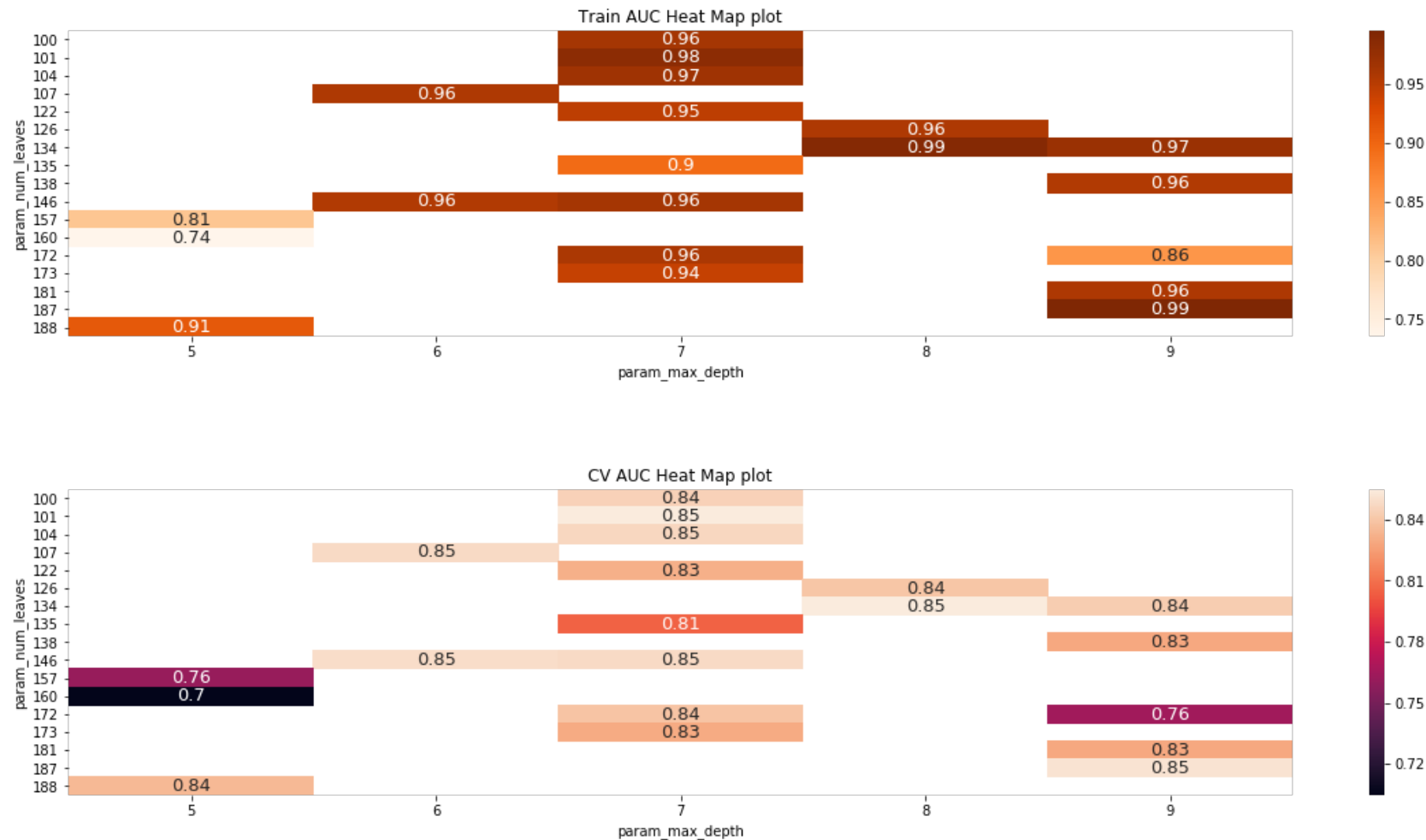
```

num_leaves : <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f332b079ac0>,
'reg_alpha': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f3329d008d0>,
'reg_lambda': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f3329d00668>},
pre_dispatch='2*n_jobs', random_state=None, refit=True,
return_train_score=True, scoring='roc_auc', verbose=10)

```

In [0]:

```
plotTrainVsCV_AUC(search, (2,1), (20, 10), idx='param_num_leaves', cols='param_max_depth')
```



In [0]:

```
y_train_pred = search.best_estimator_.predict_proba(X_train)[: ,1]
```

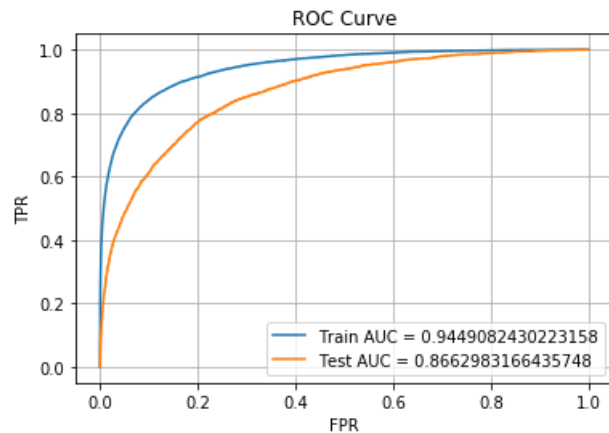
```

y_test_pred = search.best_estimator_.predict_proba(X_test)[:,-1]

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)

```



In [0]:

```

pt_1.add_row(['', '', '', ''])
pt_1.add_row(['Light GBM', 'Max_depth = 6, num_leaves = 181', \
              np.round(.9449082430223158, 3), np.round(.8662983166435748, 3)])

```

New Features

Type - 1 | Count Features :

In [0]:

```

total_vars = X_train.columns.difference(['mean', 'std', 'max', 'min', 'median']).size

X_train_cnt = np.zeros((len(X_train), total_vars * 4))
X_test_cnt = np.zeros((len(X_test), total_vars * 4))

for j in tqdm(range(total_vars)):
    for i in range(1, 4):
        x = np.round(X_train.iloc[:, j], i+1)
        dic = pd.value_counts(x)
        missedValue = dic.idxmax() #np.median(dic.index)
        dic = dic.to_dict()
        X_train_cnt[:, i*4 + i] = pd.Series(x).map(dic)

```

```

X_train_cnt[:, j*4 + 1] = pd.Series(x).map(dic)
X_test_cnt[:, j*4 + i] = pd.Series(np.round(X_test.iloc[:, j], i+1)).map(lambda p: dic.get(p, missedValue))

x = X_train.iloc[:, j]
dic = pd.value_counts(x)
missedValue = dic.idxmax() #np.median(dic.index)
dic = dic.to_dict()

X_train_cnt[:, j*4] = pd.Series(x).map(dic)
X_test_cnt[:, j*4] = pd.Series(X_test.iloc[:, j]).map(lambda p: dic.get(p, missedValue))

X_train_basic_feats = X_train[['mean', 'std', 'max', 'min', 'median']].copy()
X_test_basic_feats = X_test[['mean', 'std', 'max', 'min', 'median']].copy()

X_train_raw = X_train[X_train.columns.difference(['mean', 'std', 'max', 'min', 'median'])].copy()
X_test_raw = X_test[X_test.columns.difference(['mean', 'std', 'max', 'min', 'median'])].copy()

X_train_new_feats = np.zeros((len(X_train_raw), total_vars * 5))
X_test_new_feats = np.zeros((len(X_test_raw), total_vars * 5))

# raw + count of rounded feature
old_cols = X_train_raw.columns
new_cols = list()

for idx in tqdm(range(total_vars)):
    X_train_new_feats[:, 5*idx] = X_train_raw.iloc[:, idx]
    new_cols.extend([old_cols[idx], '{}_count'.format(old_cols[idx])])

    X_train_new_feats[:, 5*idx+1:5*idx+5] = X_train_cnt[:, 4*idx:4*idx+4]
    new_cols.extend(['{}_roundedTo_{}'.format(old_cols[idx], rnd) for rnd in range(2, 5)])

    X_test_new_feats[:, 5*idx] = X_test_raw.iloc[:, idx]
    X_test_new_feats[:, 5*idx+1:5*idx+5] = X_test_cnt[:, 4*idx:4*idx+4]

X_train_new_feats = pd.DataFrame(X_train_new_feats, columns=new_cols)
X_test_new_feats = pd.DataFrame(X_test_new_feats, columns=new_cols)

del X_train_cnt, X_test_cnt, X_train_raw, X_test_raw; gc.collect()

```

```

100%|██████████| 200/200 [01:53<00:00, 2.19it/s]
100%|██████████| 200/200 [00:05<00:00, 36.48it/s]

```

Out[0]:

0

In [0]:

```

basic_feats_also = str(input('Do you want to use basic features also (y/n) : ')) == 'y'

X_tr = pd.concat([X_train_new_feats.reset_index(drop=True), X_train_basic_feats.reset_index(drop=True)],\

```

```
axis=1, sort=False) if basic_feats_also else x_train_new_feats
X_te = pd.concat([X_test_new_feats.reset_index(drop=True), X_test_basic_feats.reset_index(drop=True)],\
axis=1, sort=False) if basic_feats_also else X_test_new_feats
```

Do you want to use basic features also (y/n) : n

In [0]:

```
X_tr.shape, X_te.shape
```

Out[0]:

```
((160000, 1000), (40000, 1000))
```

In [0]:

```
y_train.shape, y_test.shape
```

Out[0]:

```
((160000,), (40000,))
```

Type - 2 | Rounded features :

In [13]:

```
X_tr_2 = X_train[X_train.columns.difference(['mean', 'std', 'max', 'min', 'median'])].copy()
X_te_2 = X_test[X_test.columns.difference(['mean', 'std', 'max', 'min', 'median'])].copy()
```

```
for feature in tqdm(X_tr_2.columns):
    X_tr_2[feature+'_r2'] = np.round(X_tr_2[feature], 2)
    X_tr_2[feature+'_r1'] = np.round(X_tr_2[feature], 1)

    X_te_2[feature+'_r2'] = np.round(X_te_2[feature], 2)
    X_te_2[feature+'_r1'] = np.round(X_te_2[feature], 1)
```

100%|██████████| 200/200 [00:02<00:00, 69.28it/s]

In [14]:

```
basic_feats_also = str(input('Do you want to use basic features also (y/n) : ')) == 'y'

X_tr_2 = pd.concat([X_tr_2.reset_index(drop=True),\
                    X_train[['mean', 'std', 'max', 'min', 'median']].copy().reset_index(drop=True)],\
axis=1, sort=False) if basic_feats_also else X_train_new_feats
X_te_2 = pd.concat([X_te_2.reset_index(drop=True),\
```

```
X_test[['mean', 'std', 'max', 'min', 'median']].copy().reset_index(drop=True),\
axis=1, sort=False) if basic_feats_also else X_test_new_feats
```

Do you want to use basic features also (y/n) : y

Modelling [2] - w/ new[, basic] features.

In [0]:

```
pt_2 = PrettyTable()
pt_2.field_names = ['Model', 'Hyper Parameters', 'Train AUC', 'Test AUC']
```

Logistic Regression :

In [0]:

```
clf = linear_model.LogisticRegression(penalty='elasticnet', n_jobs=-1, class_weight='balanced', solver='saga', fit_intercept=False)

params = dict(C=(.0001, .001, .01, .1), max_iter=st.randint(800, 1000), l1_ratio=st.uniform(.15, .5))
search = RandomizedSearchCV(clf, params, scoring='roc_auc', n_jobs=-1, verbose=10, return_train_score=True, cv=2, n_iter=20)
```

In [0]:

```
with parallel_backend('multiprocessing'):
    search.fit(scaler.fit_transform(X_tr), y_train)
```

Fitting 2 folds for each of 20 candidates, totalling 40 fits

[Parallel(n_jobs=-1)]: Using backend MultiprocessingBackend with 4 concurrent workers.

```
[CV] C=0.0001, l1_ratio=0.40540059812874696, max_iter=849 .....
[CV] C=0.0001, l1_ratio=0.40540059812874696, max_iter=849 .....
[CV] C=0.01, l1_ratio=0.28284730554247794, max_iter=902 .....
[CV] C=0.01, l1_ratio=0.28284730554247794, max_iter=902 .....
[CV] C=0.0001, l1_ratio=0.40540059812874696, max_iter=849, score=(train=0.649, test=0.641), total= 45.6s
[CV] C=0.1, l1_ratio=0.6347826726244412, max_iter=841 .....
[CV] C=0.0001, l1_ratio=0.40540059812874696, max_iter=849, score=(train=0.639, test=0.639), total= 47.8s
[CV] C=0.1, l1_ratio=0.6347826726244412, max_iter=841 .....
[CV] C=0.01, l1_ratio=0.28284730554247794, max_iter=902, score=(train=0.893, test=0.877), total= 1.3min
[CV] C=0.001, l1_ratio=0.5839910295748246, max_iter=923 .....
[CV] C=0.01, l1_ratio=0.28284730554247794, max_iter=902, score=(train=0.891, test=0.879), total= 1.9min
[CV] C=0.001, l1_ratio=0.5839910295748246, max_iter=923 .....
[CV] C=0.1, l1_ratio=0.6347826726244412, max_iter=841, score=(train=0.892, test=0.878), total= 1.2min
[CV] C=0.0001, l1_ratio=0.5667287045097704, max_iter=900 .....
```

[Parallel(n_jobs=-1)]: Done 5 tasks | elapsed: 2.0min

```
[CV] C=0.1, l1_ratio=0.6347826726244412, max_iter=841, score=(train=0.893, test=0.876), total= 1.3min
[CV] C=0.0001, l1_ratio=0.5667287045097704, max_iter=900 .....
[CV] C=0.001, l1_ratio=0.5839910295748246, max_iter=923, score=(train=0.873, test=0.869), total= 56.2s
[CV] C=0.01, l1_ratio=0.45957488288800297, max_iter=943 .....
[CV] C=0.0001, l1_ratio=0.5667287045097704, max_iter=900, score=(train=0.500, test=0.500), total= 24.7s
[CV] C=0.01, l1_ratio=0.45957488288800297, max_iter=943 .....
[CV] C=0.0001, l1_ratio=0.5667287045097704, max_iter=900, score=(train=0.500, test=0.500), total= 26.5s
[CV] C=0.1, l1_ratio=0.5933255298866175, max_iter=863 .....
[CV] C=0.001, l1_ratio=0.5839910295748246, max_iter=923, score=(train=0.875, test=0.867), total= 52.3s
[CV] C=0.1, l1_ratio=0.5933255298866175, max_iter=863 .....
```

[Parallel(n_jobs=-1)]: Done 10 tasks | elapsed: 2.8min

```
[CV] C=0.01, l1_ratio=0.45957488288800297, max_iter=943, score=(train=0.890, test=0.880), total= 1.2min
[CV] C=0.001, l1_ratio=0.2894029134510545, max_iter=802 .....
[CV] C=0.01, l1_ratio=0.45957488288800297, max_iter=943, score=(train=0.892, test=0.877), total= 1.2min
[CV] C=0.001, l1_ratio=0.2894029134510545, max_iter=802 .....
[CV] C=0.1, l1_ratio=0.5933255298866175, max_iter=863, score=(train=0.892, test=0.878), total= 1.2min
[CV] C=0.1, l1_ratio=0.22196647609466505, max_iter=946 .....
[CV] C=0.1, l1_ratio=0.5933255298866175, max_iter=863, score=(train=0.893, test=0.876), total= 1.3min
[CV] C=0.1, l1_ratio=0.22196647609466505, max_iter=946 .....
[CV] C=0.001, l1_ratio=0.2894029134510545, max_iter=802, score=(train=0.883, test=0.877), total= 55.2s
[CV] C=0.0001, l1_ratio=0.4202726590010638, max_iter=871 .....
[CV] C=0.001, l1_ratio=0.2894029134510545, max_iter=802, score=(train=0.885, test=0.875), total= 55.9s
[CV] C=0.0001, l1_ratio=0.4202726590010638, max_iter=871 .....
[CV] C=0.0001, l1_ratio=0.4202726590010638, max_iter=871, score=(train=0.624, test=0.625), total= 43.8s
[CV] C=0.001, l1_ratio=0.1545037567823819, max_iter=898 .....
```

[Parallel(n_jobs=-1)]: Done 17 tasks | elapsed: 5.0min

```
[CV] C=0.1, l1_ratio=0.22196647609466505, max_iter=946, score=(train=0.892, test=0.878), total= 1.3min
[CV] C=0.001, l1_ratio=0.1545037567823819, max_iter=898 .....
[CV] C=0.0001, l1_ratio=0.4202726590010638, max_iter=871, score=(train=0.632, test=0.624), total= 44.0s
[CV] C=0.01, l1_ratio=0.5816246884542369, max_iter=883 .....
[CV] C=0.001, l1_ratio=0.1545037567823819, max_iter=898, score=(train=0.887, test=0.879), total= 59.0s
[CV] C=0.01, l1_ratio=0.5816246884542369, max_iter=883 .....
[CV] C=0.001, l1_ratio=0.1545037567823819, max_iter=898, score=(train=0.889, test=0.877), total= 1.1min
[CV] C=0.001, l1_ratio=0.3932018575524343, max_iter=921 .....
[CV] C=0.01, l1_ratio=0.5816246884542369, max_iter=883, score=(train=0.890, test=0.880), total= 1.1min
[CV] C=0.001, l1_ratio=0.3932018575524343, max_iter=921 .....
[CV] C=0.1, l1_ratio=0.22196647609466505, max_iter=946, score=(train=0.893, test=0.876), total= 2.2min
[CV] C=0.1, l1_ratio=0.45391957123442916, max_iter=983 .....
[CV] C=0.001, l1_ratio=0.3932018575524343, max_iter=921, score=(train=0.880, test=0.875), total= 53.0s
[CV] C=0.1, l1_ratio=0.45391957123442916, max_iter=983 .....
```

[Parallel(n_jobs=-1)]: Done 24 tasks | elapsed: 7.1min

```
[CV] C=0.001, l1_ratio=0.3932018575524343, max_iter=921, score=(train=0.882, test=0.873), total= 58.0s
[CV] C=0.001, l1_ratio=0.35302373545693966, max_iter=882 .....
[CV] C=0.01, l1_ratio=0.5816246884542369, max_iter=883, score=(train=0.892, test=0.877), total= 1.3min
[CV] C=0.001, l1_ratio=0.35302373545693966, max_iter=882 .....
[CV] C=0.1, l1_ratio=0.45391957123442916, max_iter=983, score=(train=0.892, test=0.878), total= 1.2min
[CV] C=0.0001, l1_ratio=0.5563723898738865, max_iter=974 .....
[CV] C=0.0001, l1_ratio=0.5563723898738865, max_iter=974, score=(train=0.500, test=0.500), total= 25.7s
[CV] C=0.0001, l1_ratio=0.5563723898738865, max_iter=974 .....
[CV] C=0.001, l1_ratio=0.35302373545693966, max_iter=882, score=(train=0.881, test=0.876), total= 55.3s
[CV] C=0.0001, l1_ratio=0.5447952733137348, max_iter=862 .....
[CV] C=0.001, l1_ratio=0.35302373545693966, max_iter=882, score=(train=0.883, test=0.874), total= 57.3s
[CV] C=0.0001, l1_ratio=0.5447952733137348, max_iter=862 .....
[CV] C=0.1, l1_ratio=0.45391957123442916, max_iter=983, score=(train=0.893, test=0.876), total= 1.3min
[CV] C=0.001, l1_ratio=0.4740555376479476, max_iter=834 .....
[CV] C=0.0001, l1_ratio=0.5563723898738865, max_iter=974, score=(train=0.500, test=0.500), total= 23.9s
[CV] C=0.001, l1_ratio=0.4740555376479476, max_iter=834 .....
[CV] C=0.0001, l1_ratio=0.5447952733137348, max_iter=862, score=(train=0.500, test=0.500), total= 28.5s
[CV] C=0.01, l1_ratio=0.4964518773723896, max_iter=951 .....
```

```
[Parallel(n_jobs=-1)]: Done 33 tasks | elapsed: 8.8min
```

```
[CV] C=0.0001, l1_ratio=0.5447952733137348, max_iter=862, score=(train=0.570, test=0.564), total= 49.5s
[CV] C=0.01, l1_ratio=0.4964518773723896, max_iter=951 .....
[CV] C=0.001, l1_ratio=0.4740555376479476, max_iter=834, score=(train=0.877, test=0.872), total= 54.3s
[CV] C=0.1, l1_ratio=0.5723260976994545, max_iter=901 .....
[CV] C=0.001, l1_ratio=0.4740555376479476, max_iter=834, score=(train=0.879, test=0.870), total= 55.7s
[CV] C=0.1, l1_ratio=0.5723260976994545, max_iter=901 .....
[CV] C=0.01, l1_ratio=0.4964518773723896, max_iter=951, score=(train=0.890, test=0.880), total= 1.1min
[CV] C=0.01, l1_ratio=0.4964518773723896, max_iter=951, score=(train=0.892, test=0.877), total= 1.1min
```

```
[Parallel(n_jobs=-1)]: Done 38 out of 40 | elapsed: 10.3min remaining: 32.5s
```

```
[CV] C=0.1, l1_ratio=0.5723260976994545, max_iter=901, score=(train=0.892, test=0.878), total= 1.1min
[CV] C=0.1, l1_ratio=0.5723260976994545, max_iter=901, score=(train=0.893, test=0.876), total= 1.1min
```

```
[Parallel(n_jobs=-1)]: Done 40 out of 40 | elapsed: 10.5min finished
```

```
In [0]:
```

```
search.best_params_
```

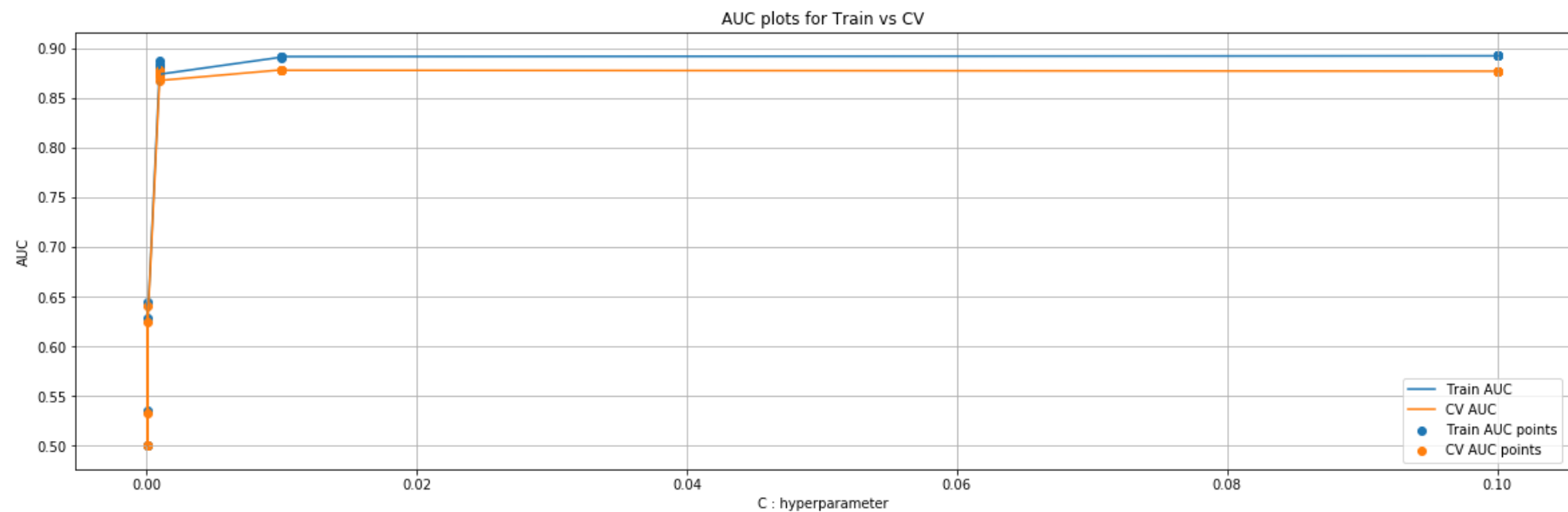
```
Out[0]:
```

```
{'C': 0.01, 'l1_ratio': 0.5816246884542369, 'max_iter': 883}
```


In [0]:

```
res = pd.DataFrame(search.cv_results_)
idxs = np.argsort(res.param_C.values.astype('float64'))

auc_plot(res.param_C.values.astype('float64')[idxs], res.mean_train_score.values[idxs], res.mean_test_score.values[idxs], 'C')
```

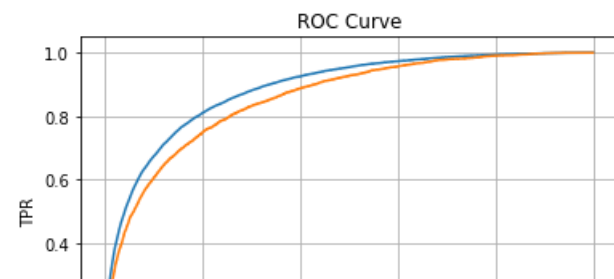


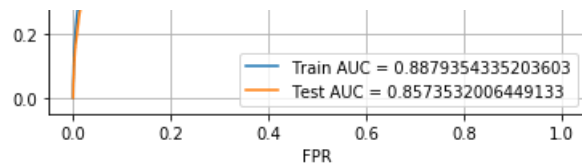
In [0]:

```
y_train_pred = search.best_estimator_.predict_proba(scaler.transform(X_tr))[:,1]
y_test_pred = search.best_estimator_.predict_proba(scaler.transform(X_te))[:,1]

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)
```





In [0]:

```
pt_2.add_row(['Logistic Regression', 'C = 0.01, l1_ratio = 0.5816246884542369, max_iter = 883',\
            np.round(.887993, 3), np.round(.857353, 3)])
```

XGBoost :

In [0]:

```
# https://github.com/dmlc/xgboost/blob/master/demo/kaggle-higgs/higgs-numpy.py

weight = (X_train.var_76 * float(X_test.shape[0]) / len(y_train))

sum_wpos = sum( weight.iloc[i] for i in range(len(y_train)) if y_train[i] )
sum_wneg = sum( weight.iloc[i] for i in range(len(y_train)) if not y_train[i] )
```

In [0]:

```
xgb.XGBClassifier?
```

In [0]:

```
# https://xgboost.readthedocs.io/en/latest/tutorials/param_tuning.html

one_to_left = st.beta(5, 1)
from_zero_positive = st.expon(0, 50)

params = {
    "n_estimators": st.randint(100, 123),
    "max_depth": st.randint(2, 5),
    "colsample_bytree": one_to_left,
    "subsample": one_to_left,
    "gamma": st.uniform(0, 10),
    "reg_lambda": (.001, .01, .1),
    "reg_alpha": (.001, .01, .1),
    "min_child_weight": from_zero_positive,
    "learning_rate": (.01, .1)
}

search = RandomizedSearchCV(xgb.XGBClassifier(max_delta_step=10, eval_metric='auc', objective='binary:logistic',\
n_jobs=-1, scale_pos_weight=sum_wneg/sum_wpos, num_boost_round=100000), \
```

```
n_jobs=-1, scale_pos_weight=sum_wneg/sum_wpos, num_boost_round=10000, \
params, scoring='roc_auc', n_jobs=-1, verbose=23, return_train_score=True, cv=2)
```

In [19]:

```
with parallel_backend('threading'):
    search.fit(X_tr_2, y_train)
```

Fitting 2 folds for each of 10 candidates, totalling 20 fits

```
[CV] colsample_bytree=0.9795385580301809, gamma=7.48368178462424, learning_rate=0.1, max_depth=3, min_child_weight=26.306065256124405, n_estimators=116, reg_alpha=0.01, reg_lambda=0.01, subsample=0.8693109798363479 [CV] colsample_bytree=0.9795385580301809, gamma=7.48368178462424, learning_rate=0.1, max_depth=3, min_child_weight=26.306065256124405, n_estimators=116, reg_alpha=0.01, reg_lambda=0.01, subsample=0.8693109798363479 [CV] colsample_bytree=0.981991935471296, gamma=3.133728648190235, learning_rate=0.01, max_depth=2, min_child_weight=6.56542037919276, n_estimators=122, reg_alpha=0.01, reg_lambda=0.01, subsample=0.9185191139938026 [CV] colsample_bytree=0.981991935471296, gamma=3.133728648190235, learning_rate=0.01, max_depth=2, min_child_weight=6.56542037919276, n_estimators=122, reg_alpha=0.01, reg_lambda=0.01, subsample=0.9185191139938026
```

◀ ▶

[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent workers.

```
[CV] colsample_bytree=0.981991935471296, gamma=3.133728648190235, learning_rate=0.01, max_depth=2, min_child_weight=6.56542037919276, n_estimators=122, reg_alpha=0.01, reg_lambda=0.01, subsample=0.9185191139938026, score=(train=0.702, test=0.690), total= 6.4min [CV] colsample_bytree=0.7306922599120634, gamma=8.954793152617174, learning_rate=0.1, max_depth=3, min_child_weight=86.38868548503523, n_estimators=122, reg_alpha=0.1, reg_lambda=0.001, subsample=0.5839620442647151
```

[Parallel(n_jobs=-1)]: Done 1 tasks | elapsed: 6.5min

```
[CV] colsample_bytree=0.981991935471296, gamma=3.133728648190235, learning_rate=0.01, max_depth=2, min_child_weight=6.56542037919276, n_estimators=122, reg_alpha=0.01, reg_lambda=0.01, subsample=0.9185191139938026, score=(train=0.712, test=0.696), total= 6.4min [CV] colsample_bytree=0.7306922599120634, gamma=8.954793152617174, learning_rate=0.1, max_depth=3, min_child_weight=86.38868548503523, n_estimators=122, reg_alpha=0.1, reg_lambda=0.001, subsample=0.5839620442647151
```

[Parallel(n_jobs=-1)]: Done 2 tasks | elapsed: 6.5min

```
[CV] colsample_bytree=0.9795385580301809, gamma=7.48368178462424, learning_rate=0.1, max_depth=3, min_child_weight=26.306065256124405, n_estimators=116, reg_alpha=0.01, reg_lambda=0.01, subsample=0.8693109798363479, score=(train=0.885, test=0.840), total= 8.8min [CV] colsample_bytree=0.97312978438908, gamma=5.242335416132442, learning_rate=0.1, max_depth=2, min_child_weight=104.78643562746936, n_estimators=116, reg_alpha=0.01, reg_lambda=0.001, subsample=0.9904962826855939
```

◀ ▶

[Parallel(n_jobs=-1)]: Done 3 tasks | elapsed: 8.8min

```
[CV] colsample_bytree=0.9795385580301809, gamma=7.48368178462424, learning_rate=0.1, max_depth=3, min_child_weight=26.306065256124405, n_estimators=116, reg_alpha=0.01, reg_lambda=0.01, subsample=0.8693109798363479, score=(train=0.885, test=0.838), total= 8.8min [CV] colsample_bytree=0.97312978438908, gamma=5.242335416132442, learning_rate=0.1, max_depth=2, min_child_weight=104.78643562746936, n_estimators=116, reg_alpha=0.01, reg_lambda=0.001, subsample=0.9904962826855939
```

n_estimators=116, reg_alpha=0.01, reg_lambda=0.001, subsample=0.9904962826855939

[Parallel(n_jobs=-1)]: Done 4 tasks | elapsed: 8.9min

[CV] colsample_bytree=0.7306922599120634, gamma=8.954793152617174, learning_rate=0.1, max_depth=3, min_child_weight=86.38868548503523, n_estimators=122, reg_alpha=0.1, reg_lambda=0.001, subsample=0.5839620442647151, score=(train=0.885, test=0.845), total= 6.6min

[CV] colsample_bytree=0.964207487966292, gamma=0.7612741260974909, learning_rate=0.1, max_depth=3, min_child_weight=81.85692285482902, n_estimators=103, reg_alpha=0.001, reg_lambda=0.001, subsample=0.7881643463534637

[Parallel(n_jobs=-1)]: Done 5 tasks | elapsed: 13.1min

[CV] colsample_bytree=0.7306922599120634, gamma=8.954793152617174, learning_rate=0.1, max_depth=3, min_child_weight=86.38868548503523, n_estimators=122, reg_alpha=0.1, reg_lambda=0.001, subsample=0.5839620442647151, score=(train=0.885, test=0.843), total= 6.6min

[CV] colsample_bytree=0.964207487966292, gamma=0.7612741260974909, learning_rate=0.1, max_depth=3, min_child_weight=81.85692285482902, n_estimators=103, reg_alpha=0.001, reg_lambda=0.001, subsample=0.7881643463534637

[Parallel(n_jobs=-1)]: Done 6 tasks | elapsed: 13.2min

[CV] colsample_bytree=0.97312978438908, gamma=5.242335416132442, learning_rate=0.1, max_depth=2, min_child_weight=104.78643562746936, n_estimators=116, reg_alpha=0.01, reg_lambda=0.001, subsample=0.9904962826855939, score=(train=0.851, test=0.825), total= 6.1min

[CV] colsample_bytree=0.7768314957295858, gamma=2.246418634135564, learning_rate=0.1, max_depth=4, min_child_weight=19.924485703424306, n_estimators=105, reg_alpha=0.1, reg_lambda=0.01, subsample=0.7651510127958602

[Parallel(n_jobs=-1)]: Done 7 tasks | elapsed: 14.9min

[CV] colsample_bytree=0.97312978438908, gamma=5.242335416132442, learning_rate=0.1, max_depth=2, min_child_weight=104.78643562746936, n_estimators=116, reg_alpha=0.01, reg_lambda=0.001, subsample=0.9904962826855939, score=(train=0.850, test=0.820), total= 6.0min

[CV] colsample_bytree=0.7768314957295858, gamma=2.246418634135564, learning_rate=0.1, max_depth=4, min_child_weight=19.924485703424306, n_estimators=105, reg_alpha=0.1, reg_lambda=0.01, subsample=0.7651510127958602

[Parallel(n_jobs=-1)]: Done 8 tasks | elapsed: 15.0min

[CV] colsample_bytree=0.964207487966292, gamma=0.7612741260974909, learning_rate=0.1, max_depth=3, min_child_weight=81.85692285482902, n_estimators=103, reg_alpha=0.001, reg_lambda=0.001, subsample=0.7881643463534637, score=(train=0.878, test=0.837), total= 7.5min

[CV] colsample_bytree=0.8619262389413318, gamma=4.074731259525173, learning_rate=0.01, max_depth=4, min_child_weight=50.30903142680757, n_estimators=117, reg_alpha=0.01, reg_lambda=0.1, subsample=0.9138171108843222

[Parallel(n_jobs=-1)]: Done 9 tasks | elapsed: 20.7min

[CV] colsample_bytree=0.964207487966292, gamma=0.7612741260974909, learning_rate=0.1, max_depth=3, min_child_weight=81.85692285482902, n_estimators=103, reg_alpha=0.001, reg_lambda=0.001, subsample=0.7881643463534637, score=(train=0.878, test=0.835), total= 7.5min

[CV] colsample_bytree=0.8619262389413318, gamma=4.074731259525173, learning_rate=0.01, max_depth=4, min_child_weight=50.30903142680757, n_estimators=117, reg_alpha=0.01, reg_lambda=0.1, subsample=0.9138171108843222

[Parallel(n_jobs=-1)]: Done 10 tasks | elapsed: 20.7min

```
[CV] colsample_bytree=0.7768314957295858, gamma=2.246418634135564, learning_rate=0.1, max_depth=4, min_child_weight=19.924485703424306,
n_estimators=105, reg_alpha=0.1, reg_lambda=0.01, subsample=0.7651510127958602, score=(train=0.912, test=0.845), total= 8.4min
[CV] colsample_bytree=0.6594019736141953, gamma=2.6035533500979504, learning_rate=0.01, max_depth=4, min_child_weight=61.193191400991445,
n_estimators=116, reg_alpha=0.001, reg_lambda=0.1, subsample=0.6278599077588631
```

```
[Parallel(n_jobs=-1)]: Done 11 tasks | elapsed: 23.4min
```

```
[CV] colsample_bytree=0.7768314957295858, gamma=2.246418634135564, learning_rate=0.1, max_depth=4, min_child_weight=19.924485703424306,
n_estimators=105, reg_alpha=0.1, reg_lambda=0.01, subsample=0.7651510127958602, score=(train=0.911, test=0.843), total= 8.4min
[CV] colsample_bytree=0.6594019736141953, gamma=2.6035533500979504, learning_rate=0.01, max_depth=4, min_child_weight=61.193191400991445,
n_estimators=116, reg_alpha=0.001, reg_lambda=0.1, subsample=0.6278599077588631
```

```
[Parallel(n_jobs=-1)]: Done 12 tasks | elapsed: 23.4min
```

```
[CV] colsample_bytree=0.6594019736141953, gamma=2.6035533500979504, learning_rate=0.01, max_depth=4, min_child_weight=61.193191400991445,
n_estimators=116, reg_alpha=0.001, reg_lambda=0.1, subsample=0.6278599077588631, score=(train=0.773, test=0.743), total= 7.6min
[CV] colsample_bytree=0.9074312279518009, gamma=8.441913379007856, learning_rate=0.01, max_depth=2, min_child_weight=22.495303701236598,
n_estimators=118, reg_alpha=0.01, reg_lambda=0.01, subsample=0.955217118357863
```

```
[Parallel(n_jobs=-1)]: Done 13 tasks | elapsed: 31.1min
```

```
[CV] colsample_bytree=0.6594019736141953, gamma=2.6035533500979504, learning_rate=0.01, max_depth=4, min_child_weight=61.193191400991445,
n_estimators=116, reg_alpha=0.001, reg_lambda=0.1, subsample=0.6278599077588631, score=(train=0.778, test=0.744), total= 7.7min
[CV] colsample_bytree=0.9074312279518009, gamma=8.441913379007856, learning_rate=0.01, max_depth=2, min_child_weight=22.495303701236598,
n_estimators=118, reg_alpha=0.01, reg_lambda=0.01, subsample=0.955217118357863
```

```
[Parallel(n_jobs=-1)]: Done 14 out of 20 | elapsed: 31.2min remaining: 13.4min
```

```
[CV] colsample_bytree=0.8619262389413318, gamma=4.074731259525173, learning_rate=0.01, max_depth=4, min_child_weight=50.30903142680757,
n_estimators=117, reg_alpha=0.01, reg_lambda=0.1, subsample=0.9138171108843222, score=(train=0.769, test=0.737), total=10.5min
[CV] colsample_bytree=0.8705828787827952, gamma=6.169139480861725, learning_rate=0.01, max_depth=4, min_child_weight=74.85042440808952,
n_estimators=112, reg_alpha=0.1, reg_lambda=0.01, subsample=0.48538140978171307
```

```
[Parallel(n_jobs=-1)]: Done 15 out of 20 | elapsed: 31.3min remaining: 10.4min
```

```
[CV] colsample_bytree=0.8619262389413318, gamma=4.074731259525173, learning_rate=0.01, max_depth=4, min_child_weight=50.30903142680757,
n_estimators=117, reg_alpha=0.01, reg_lambda=0.1, subsample=0.9138171108843222, score=(train=0.774, test=0.737), total=10.5min
[CV] colsample_bytree=0.8705828787827952, gamma=6.169139480861725, learning_rate=0.01, max_depth=4, min_child_weight=74.85042440808952,
n_estimators=112, reg_alpha=0.1, reg_lambda=0.01, subsample=0.48538140978171307
```

```
[Parallel(n_jobs=-1)]: Done 16 out of 20 | elapsed: 31.3min remaining: 7.8min
```

```
[CV] colsample_bytree=0.9074312279518009, gamma=8.441913379007856, learning_rate=0.01, max_depth=2, min_child_weight=22.495303701236598,
```

n_estimators=118, reg_alpha=0.01, reg_lambda=0.01, subsample=0.955217118357863, score=(train=0.700, test=0.689), total= 5.8min

[Parallel(n_jobs=-1)]: Done 17 out of 20 | elapsed: 36.9min remaining: 6.5min

[CV] colsample_bytree=0.9074312279518009, gamma=8.441913379007856, learning_rate=0.01, max_depth=2, min_child_weight=22.495303701236598, n_estimators=118, reg_alpha=0.01, reg_lambda=0.01, subsample=0.955217118357863, score=(train=0.708, test=0.692), total= 5.8min

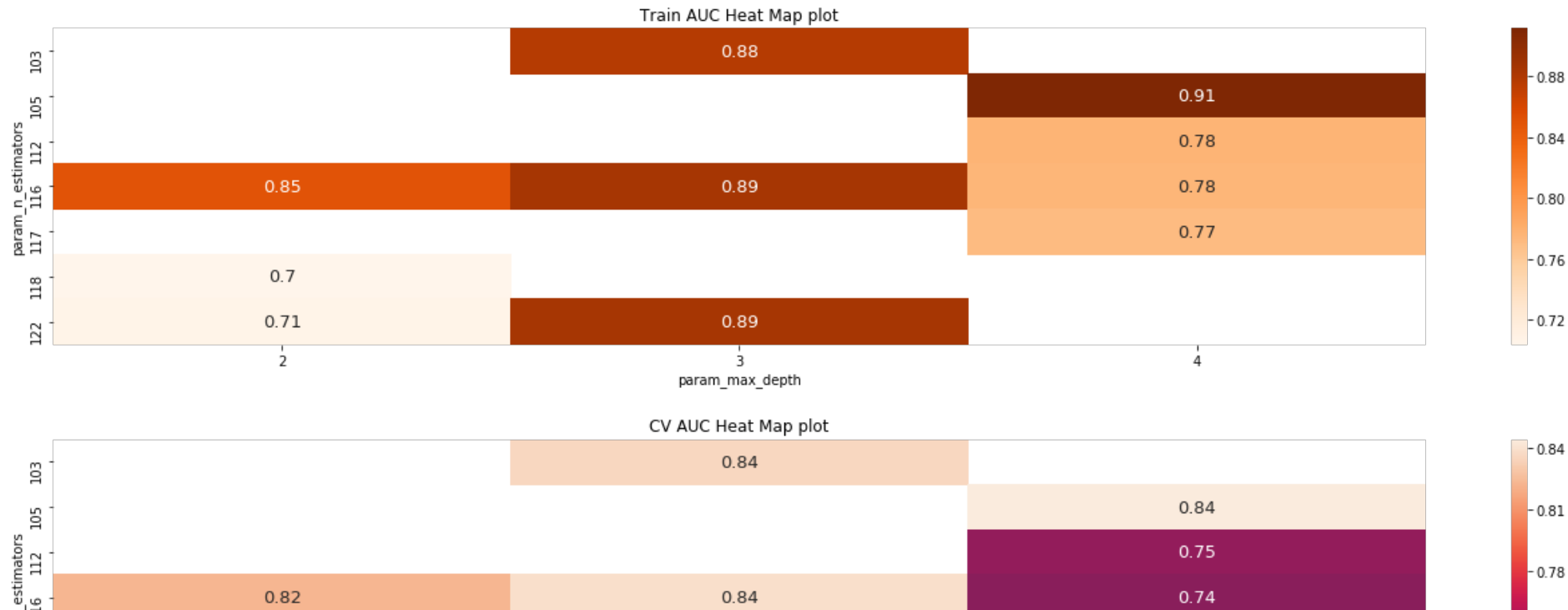
[Parallel(n_jobs=-1)]: Done 18 out of 20 | elapsed: 37.0min remaining: 4.1min

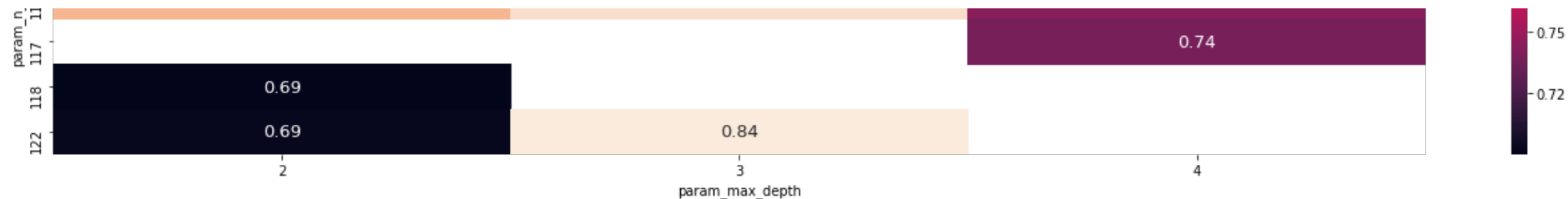
[CV] colsample_bytree=0.8705828787827952, gamma=6.169139480861725, learning_rate=0.01, max_depth=4, min_child_weight=74.85042440808952, n_estimators=112, reg_alpha=0.1, reg_lambda=0.01, subsample=0.48538140978171307, score=(train=0.776, test=0.748), total= 7.3min
[CV] colsample_bytree=0.8705828787827952, gamma=6.169139480861725, learning_rate=0.01, max_depth=4, min_child_weight=74.85042440808952, n_estimators=112, reg_alpha=0.1, reg_lambda=0.01, subsample=0.48538140978171307, score=(train=0.779, test=0.745), total= 7.3min

[Parallel(n_jobs=-1)]: Done 20 out of 20 | elapsed: 38.6min remaining: 0.0s
[Parallel(n_jobs=-1)]: Done 20 out of 20 | elapsed: 38.6min finished

In [20]:

```
plotTrainVsCV_AUC(search, subplots=(2, 1), figsize=(23, 10), idx='param_n_estimators', cols='param_max_depth')
```





In [23]:

```
search.best_params
```

Out[23]:

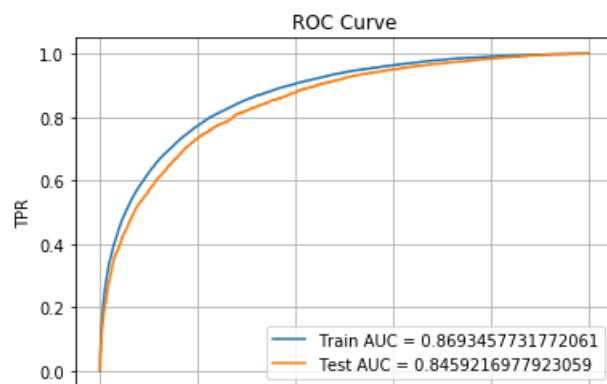
```
{'colsample_bytree': 0.7306922599120634,
 'gamma': 8.954793152617174,
 'learning_rate': 0.1,
 'max_depth': 3,
 'min_child_weight': 86.38868548503523,
 'n_estimators': 122,
 'reg_alpha': 0.1,
 'reg_lambda': 0.001,
 'subsample': 0.5839620442647151}
```

In [21]:

```
y_train_pred = search.best_estimator_.predict_proba(X_tr_2)[:,-1]
y_test_pred = search.best_estimator_.predict_proba(X_te_2)[:,-1]

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)
```




```

    "learning_rate": (0.01, 0.1),
    "reg_lambda": (0.001, 0.01, 0.1),
    "reg_alpha": (0.001, 0.01, 0.1),
    "max_bin": st.randint(67, 100),
    "min_gain_to_split": st.uniform(0, 10)
}

search = RandomizedSearchCV(lgb.LGBMClassifier(objective='binary', n_jobs=-1, min_sum_hessian_in_leaf=10., bagging_freq=5, bagging_fraction=0.4, boost_from_average=False, \
                                     feature_fraction=0.05, num_round=100000), \
                           params, n_iter=10, scoring='roc_auc', verbose=10, return_train_score=True, cv=2, error_score='raise')

```

In [26]:

```

# with parallel_backend('multiprocessing'):
search.fit(X_tr_2, y_train, eval_metric='auc')

```

Fitting 2 folds for each of 10 candidates, totalling 20 fits

[CV] learning_rate=0.1, max_bin=79, max_depth=5, min_data_in_leaf=80, min_gain_to_split=5.756727905110919, num_leaves=45, reg_alpha=0.1, reg_lambda=0.01

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[CV] learning_rate=0.1, max_bin=79, max_depth=5, min_data_in_leaf=80, min_gain_to_split=5.756727905110919, num_leaves=45, reg_alpha=0.1, reg_lambda=0.01, score=(train=0.946, test=0.890), total= 3.6min
[CV] learning_rate=0.1, max_bin=79, max_depth=5, min_data_in_leaf=80, min_gain_to_split=5.756727905110919, num_leaves=45, reg_alpha=0.1, reg_lambda=0.01

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 3.6min remaining: 0.0s

[CV] learning_rate=0.1, max_bin=79, max_depth=5, min_data_in_leaf=80, min_gain_to_split=5.756727905110919, num_leaves=45, reg_alpha=0.1, reg_lambda=0.01, score=(train=0.949, test=0.888), total= 3.6min
[CV] learning_rate=0.1, max_bin=79, max_depth=6, min_data_in_leaf=91, min_gain_to_split=2.15719108068663, num_leaves=43, reg_alpha=0.01, reg_lambda=0.001

[Parallel(n_jobs=1)]: Done 2 out of 2 | elapsed: 7.3min remaining: 0.0s

[CV] learning_rate=0.1, max_bin=79, max_depth=6, min_data_in_leaf=91, min_gain_to_split=2.15719108068663, num_leaves=43, reg_alpha=0.01, reg_lambda=0.001, score=(train=0.999, test=0.873), total= 4.3min
[CV] learning_rate=0.1, max_bin=79, max_depth=6, min_data_in_leaf=91, min_gain_to_split=2.15719108068663, num_leaves=43, reg_alpha=0.01, reg_lambda=0.001

[Parallel(n_jobs=1)]: Done 3 out of 3 | elapsed: 11.9min remaining: 0.0s

[CV] learning_rate=0.1, max_bin=79, max_depth=6, min_data_in_leaf=91, min_gain_to_split=2.15719108068663, num_leaves=43, reg_alpha=0.01, reg_lambda=0.001, score=(train=0.999, test=0.872), total= 4.3min

[CV] learning_rate=0.1, max_bin=81, max_depth=6, min_data_in_leaf=86, min_gain_to_split=6.340819585601512, num_leaves=62, reg_alpha=0.001, reg_lambda=0.01

[Parallel(n_jobs=1)]: Done 4 out of 4 | elapsed: 16.5min remaining: 0.0s

[CV] learning_rate=0.1, max_bin=81, max_depth=6, min_data_in_leaf=86, min_gain_to_split=6.340819585601512, num_leaves=62, reg_alpha=0.001, reg_lambda=0.01, score=(train=0.942, test=0.891), total= 3.5min

[CV] learning_rate=0.1, max_bin=81, max_depth=6, min_data_in_leaf=86, min_gain_to_split=6.340819585601512, num_leaves=62, reg_alpha=0.001, reg_lambda=0.01

[Parallel(n_jobs=1)]: Done 5 out of 5 | elapsed: 20.1min remaining: 0.0s

[CV] learning_rate=0.1, max_bin=81, max_depth=6, min_data_in_leaf=86, min_gain_to_split=6.340819585601512, num_leaves=62, reg_alpha=0.001, reg_lambda=0.01, score=(train=0.944, test=0.890), total= 3.5min

[CV] learning_rate=0.01, max_bin=96, max_depth=2, min_data_in_leaf=88, min_gain_to_split=4.431550819941017, num_leaves=73, reg_alpha=0.001, reg_lambda=0.01

[Parallel(n_jobs=1)]: Done 6 out of 6 | elapsed: 23.7min remaining: 0.0s

[CV] learning_rate=0.01, max_bin=96, max_depth=2, min_data_in_leaf=88, min_gain_to_split=4.431550819941017, num_leaves=73, reg_alpha=0.001, reg_lambda=0.01, score=(train=0.964, test=0.891), total=10.0min

[CV] learning_rate=0.01, max_bin=96, max_depth=2, min_data_in_leaf=88, min_gain_to_split=4.431550819941017, num_leaves=73, reg_alpha=0.001, reg_lambda=0.01

[Parallel(n_jobs=1)]: Done 7 out of 7 | elapsed: 35.7min remaining: 0.0s

[CV] learning_rate=0.01, max_bin=96, max_depth=2, min_data_in_leaf=88, min_gain_to_split=4.431550819941017, num_leaves=73, reg_alpha=0.001, reg_lambda=0.01, score=(train=0.965, test=0.888), total= 9.6min

[CV] learning_rate=0.1, max_bin=96, max_depth=6, min_data_in_leaf=89, min_gain_to_split=2.1284522761940607, num_leaves=31, reg_alpha=0.001, reg_lambda=0.01

[Parallel(n_jobs=1)]: Done 8 out of 8 | elapsed: 47.5min remaining: 0.0s

[CV] learning_rate=0.1, max_bin=96, max_depth=6, min_data_in_leaf=89, min_gain_to_split=2.1284522761940607, num_leaves=31, reg_alpha=0.001, reg_lambda=0.01, score=(train=0.999, test=0.874), total= 4.1min

[CV] learning_rate=0.1, max_bin=96, max_depth=6, min_data_in_leaf=89, min_gain_to_split=2.1284522761940607, num_leaves=31, reg_alpha=0.001, reg_lambda=0.01

[Parallel(n_jobs=1)]: Done 9 out of 9 | elapsed: 51.8min remaining: 0.0s

[CV] learning_rate=0.1, max_bin=96, max_depth=6, min_data_in_leaf=89, min_gain_to_split=2.1284522761940607, num_leaves=31, reg_alpha=0.001, reg_lambda=0.01, score=(train=0.999, test=0.872), total= 4.4min

[CV] learning_rate=0.1, max_bin=79, max_depth=5, min_data_in_leaf=84, min_gain_to_split=6.486166274120549, num_leaves=57, reg_alpha=0.1, reg_lambda=0.01

[CV] learning_rate=0.1, max_bin=79, max_depth=5, min_data_in_leaf=84, min_gain_to_split=6.486166274120549, num_leaves=57, reg_alpha=0.1,

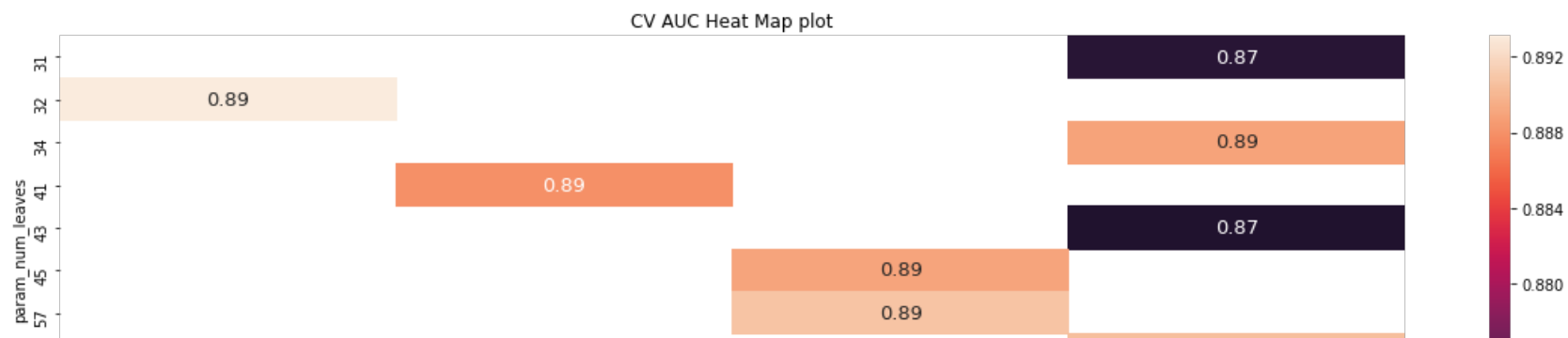
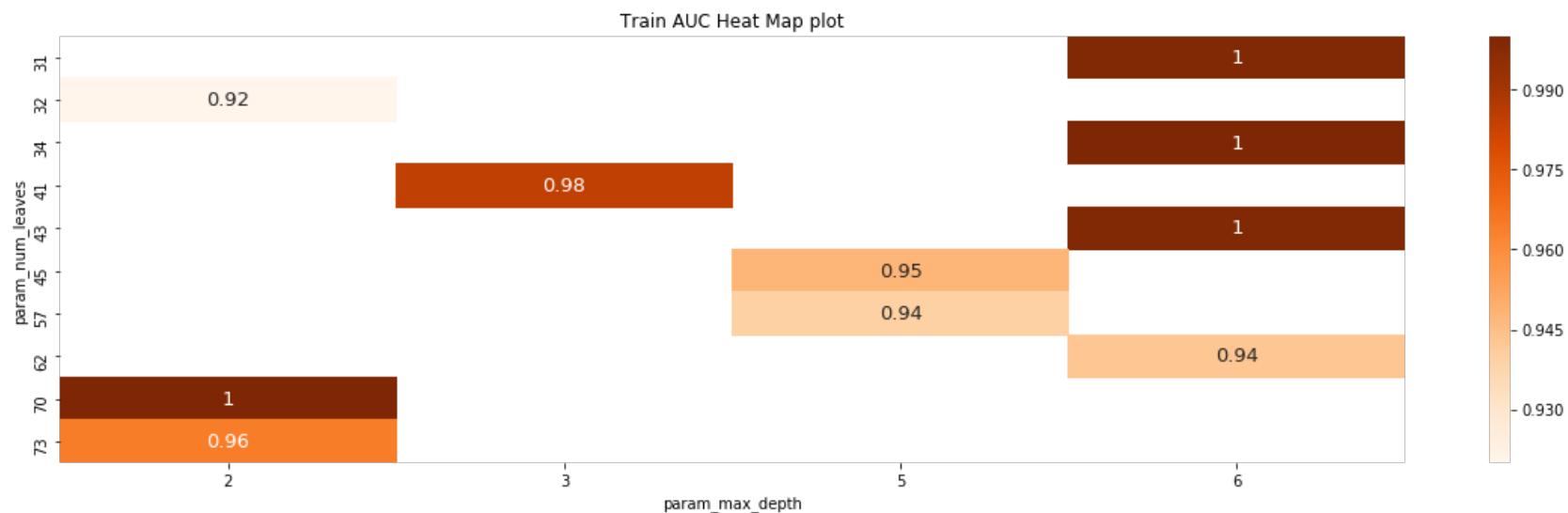

```

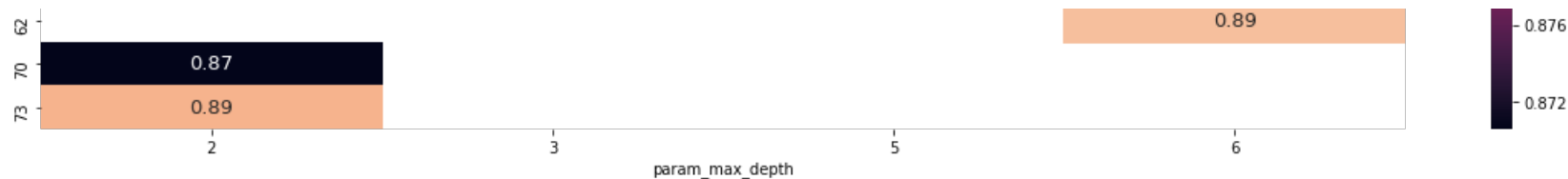
min_child_samples=20,
min_child_weight=0.001,
min_split_gain=0.0,
min_sum_hessian_in_l...
'min_data_in_leaf': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f49c029ddd8>,
'min_gain_to_split': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f49c03c92e8>,
'num_leaves': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f49c029da90>,
'reg_alpha': (0.001, 0.01, 0.1),
'reg_lambda': (0.001, 0.01, 0.1)},
pre_dispatch='2*n_jobs', random_state=None, refit=True,
return_train_score=True, scoring='roc_auc', verbose=10)

```

In [27]:

```
plotTrainVsCV_AUC(search, (2,1), (20, 12), idx='param_num_leaves', cols='param_max_depth')
```





In [30]:

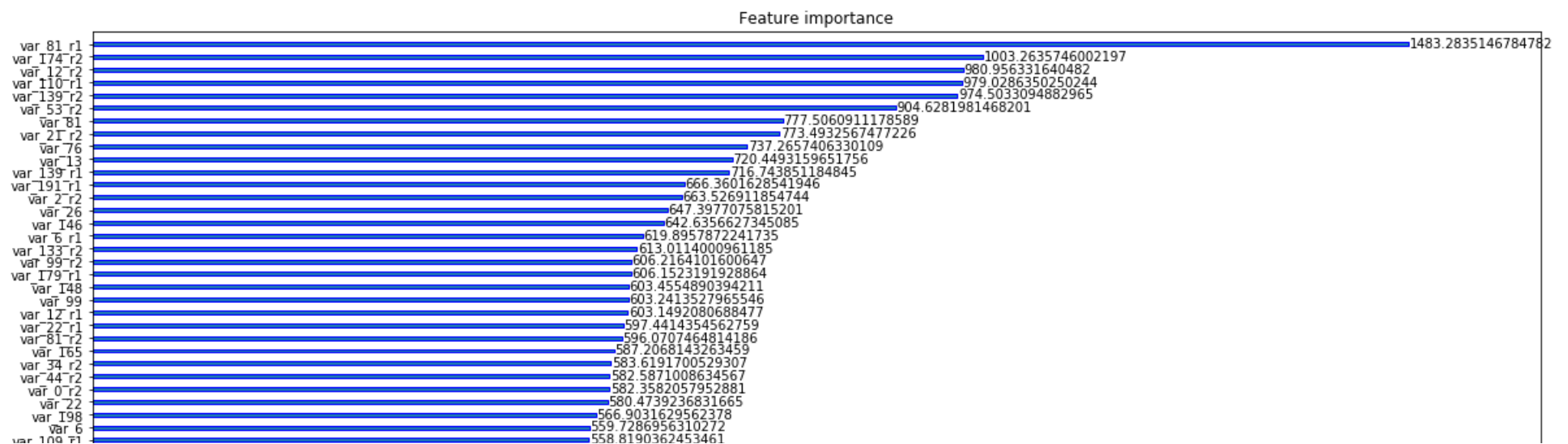
```
search.best_params_
```

Out[30]:

```
{'learning_rate': 0.1,
 'max_bin': 96,
 'max_depth': 2,
 'min_data_in_leaf': 97,
 'min_gain_to_split': 9.293773454804837,
 'num_leaves': 32,
 'reg_alpha': 0.001,
 'reg_lambda': 0.01}
```

In [62]:

```
plt.figure(figsize=(20, 100))
lgb.plot_importance(search.best_estimator_, plt.gca(), grid=False, height=.3, edgecolor='blue',\
                    xlabel='Feature Gain', importance_type='gain')
plt.show()
```



var_94_r2	556.9637405872345
var_26_r2	540.7585518360138
var_40_r2	536.1647257804871
var_166	533.8835045099258
var_53	526.0109502077103
var_139	524.9135451316833
var_108_r2	512.5582256615162
var_80_r2	509.85350036621094
var_26_r1	503.56735467910767
var_78_r2	502.8131255507469
var_80_r1	500.59571611881256
var_166_r2	481.1874795258045
var_190_r1	477.37646222114563
var_0_r1	475.90139269828796
var_76_r2	470.68807773292065
var_164_r2	468.0940878391266
var_108	463.10081082582474
var_12	454.4277993738651
var_110	436.1697564125061
var_94	435.52111491560936
var_92_r2	432.9482145309448
var_146_r1	431.17621541023254
var_53_r1	429.66220819950104
var_6_r2	429.17968702316284
var_166_r1	426.9596860408783
var_109	422.42173290252686
var_174_r1	420.2967780828476
var_133	418.07808381319046
var_165_r1	408.4020302295685
var_169	404.12203991413116
var_44	402.6453881263733
var_190	400.31897170841694
var_78_r1	392.4868114590645
var_146_r2	389.51567965745926
var_18_r1	388.27435398101807
var_89_r2	382.467188000679
var_33_r2	373.45688462257385
var_80	372.76819448452443
var_121_r2	369.39714354276657
var_34	369.15735456347466
var_177_r2	368.73451709747314
var_1_r1	368.2355651855469
var_22_r2	365.165301322937
var_9_r2	363.3715465068817
var_149	362.67470014095306
var_169_r1	359.0918762087822
var_67_r2	355.5495710968971
var_170_r1	355.01714277267456
var_184_r1	353.5151402950287
var_33_r1	353.4653008580208
var_107_r2	351.2331585884094
var_184	351.20506793260574
var_91_r2	350.3860149383545
var_110_r2	340.9974006798599
var_198_r2	338.53313010931015
var_9	336.598849773407
var_188_r1	335.5065517425537
var_177_r1	335.33237540721893
var_179_r2	332.6957525610924
var_2	329.00223183631897
var_170_r2	326.57808113098145
var_123_r2	323.91275453567505
var_119	318.5421048104763
var_147_r1	318.19001841545105
var_198_r1	313.2654882669449
var_115_r1	312.3299674987793
var_154	311.9235579967499
var_127_r1	304.8484605550766
var_13_r1	302.46701860427856
var_115	295.90830278396606
var_95_r2	295.6078462600708
var_92	294.4336233139038
var_164	293.0517385005951
var_1_r2	290.8819988965988
var_1	290.6616052389145
var_154_r1	289.8452498316765
var_2_r1	289.62840712070465
var_78	289.4562611579895
var_86	287.6656322479248
var_109_r2	285.28543615341187
var_179	283.5749843120575
var_92_r1	282.71763394773006
var_180_r2	280.3788344860077
var_145_r1	273.1136820614338
var_148_r1	263.2487154006958
var_192_r1	254.6277039051056
var_75	253.5707504749298
var_40	253.5676367878914
var_190_r2	252.46839714050293
var_122_r1	251.89576768875122
var_40_r1	250.9215407371521

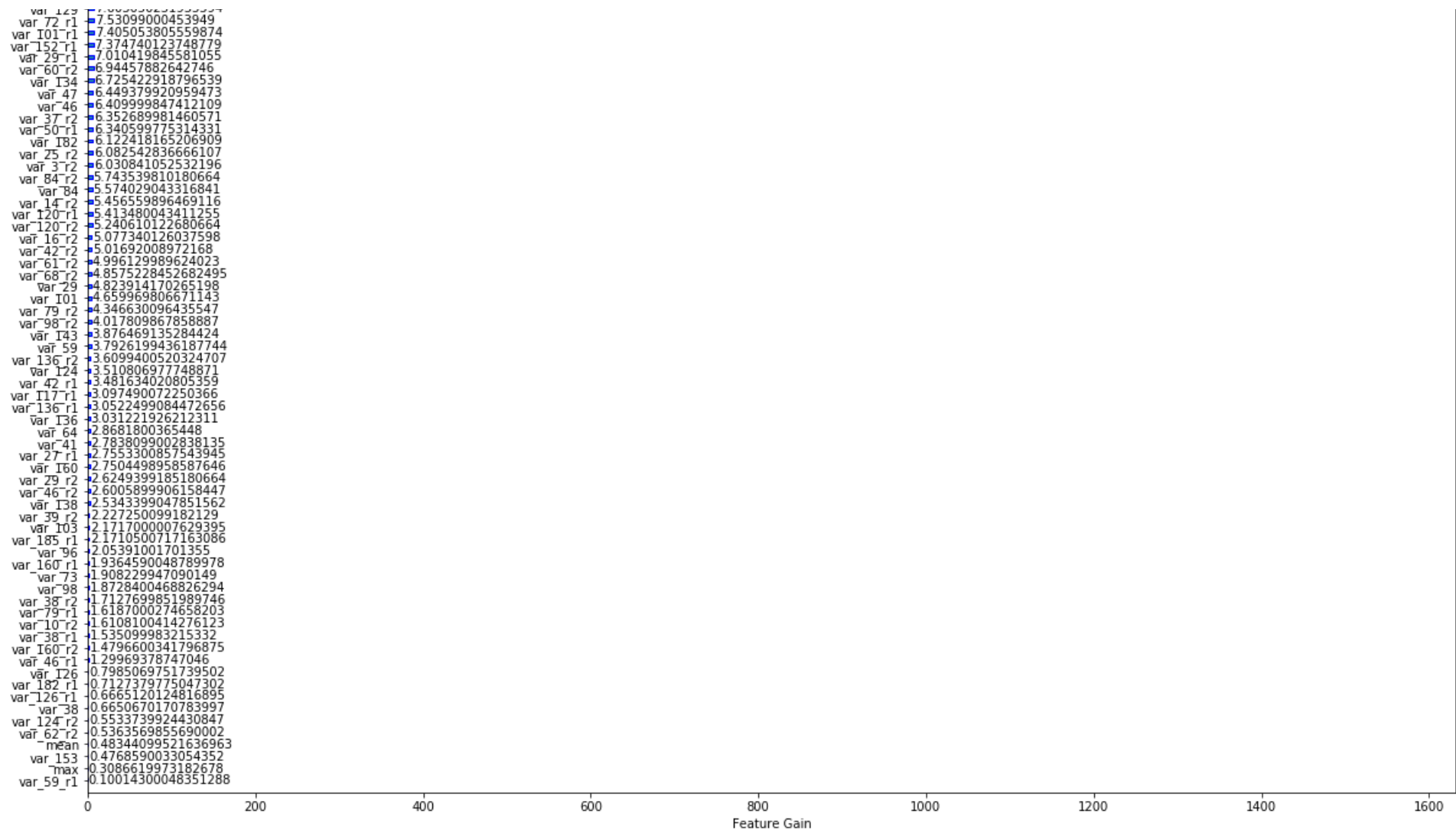
var_170	249.1699564754963
var_163	248.71934127807617
var_172	247.01787835359573
var_95_r1	244.83138218522072
var_118_r2	242.17288041114807
var_148_r2	241.9368682652712
var_165_r2	240.36931574344635
var_197_r2	240.278635263443
var_106_r2	240.20376658439636
var_154_r2	239.24360489845276
var_35_r2	237.5154384970665
var_21	236.90656512975693
var_127_r2	235.32168233394623
var_173_r1	233.96670268848538
var_122	229.87637102603912
var_123_r1	229.80555486679077
var_115_r2	229.78149420022964
var_180_r1	222.16989767551422
var_141	220.27092278003693
var_21_r1	219.4546645283699
var_149_r2	213.8707855939865
var_184_r2	213.46256923675537
var_76_r1	212.9328215122223
var_121	211.65391474962234
var_133_r1	211.19714605808258
var_118_r1	208.17970514297485
var_87	204.08771362900734
var_173	202.07119172811508
var_86_r1	201.89045271277428
var_33	201.83771687746048
var_36_r1	201.83531045913696
var_155_r1	200.660742521286
var_135_r2	200.4347062110901
var_18_r2	200.27512443065643
var_162	197.79110193252563
var_5_r2	197.6023581624031
var_164_r1	197.55503034591675
var_56_r1	195.87259481847286
var_157_r1	194.33429998159409
var_75_r1	191.89724814891815
var_147	188.8607755303383
var_162_r2	188.34573698043823
var_172_r2	187.1928609609604
var_36_r2	186.06934189796448
var_49_r1	184.8076102733612
var_32	183.7007876811549
var_122_r2	181.15560901165009
var_71_r2	180.64578771591187
var_93	179.42154741287231
var_173_r2	178.7367537021637
var_186	178.46141577512026
var_94_r1	177.1163814663887
var_192	174.2059714794159
var_128	173.0475020557642
var_67	170.94679355621338
var_130_r2	170.11635875701904
var_188	169.7858486175537
var_18	169.2144787311554
var_155_r2	167.85162490606308
var_192_r2	162.4272165298462
var_91	161.6324992775917
var_131_r2	160.72012740373611
var_150_r1	160.61209350824356
var_130	159.7265629172325
var_34_r1	158.77294224500656
var_35_r1	156.60370922088623
var_111	155.22294767200947
var_197_r1	153.13075184822083
var_0	153.1016821116209
var_157_r2	149.85442996025085
var_191	149.62077808380127
var_87_r2	147.90847897529602
var_56_r2	147.26486015319824
var_51_r1	147.1840961277485
var_121_r1	146.19964241981506
var_174	146.0626624301076
var_107	145.52548962831497
var_169_r2	144.6094079545784
var_86_r2	144.5985494852066
var_149_r1	141.38901031017303
var_125	138.6440184339881
var_131	137.73805034160614
var_56	137.00462439656258
var_123	136.33691024780273
var_172_r1	135.3073811531067
var_13_r2	134.25062208948657
var_106	133.9901626110077
var_44_r1	133.32749950885773
var_89_r1	131.09998161811382
var_151	129.8420181274414
var_166_r1	128.77157747066498

var_172_r1	128.12905222177505
var_5	127.48407729528844
var_32_r2	127.03726105391979
var_5_r1	125.14178228378296
var_48_r2	124.91010993719101
var_51_r2	124.87282931804657
var_93_r2	124.75474571436644
var_82_r1	124.23970770835876
var_177	123.67181766033173
var_155	123.53988867319107
var_67_r1	123.3283234834671
var_141_r2	120.70903015136719
var_111_r2	118.97615273296833
var_186_r2	118.33571696281433
var_99_r1	117.81040000915527
var_191_r2	117.27293992042542
var_167_r2	116.67534148693085
var_43	115.76733994483948
var_114	115.64649939537048
var_107_r1	115.12785053253174
var_71	114.95912927389145
var_105_r2	113.9918992370367
var_137	113.39760184288025
var_167_r1	110.88831049203873
var_151_r1	110.82242953777313
var_196_r1	110.20278739929199
var_85_r2	110.0612123310566
var_125_r2	109.42323064804077
var_89	107.12097942829132
var_58_r1	106.46422731876373
var_132_r1	106.18482041358948
var_24_r1	105.86531090736389
var_188_r2	105.396599650383
var_48	103.64380133152008
var_197	100.85279858112335
var_195_r2	100.19020891189575
var_52_r1	99.99805709719658
var_23	99.83214826136827
var_141_r1	99.60552144050598
var_163_r2	98.55936908721924
var_194_r1	97.3594001531601
var_150_r2	96.32316136360168
var_130_r1	95.53905242681503
var_114_r2	95.09249067306519
var_116_r1	94.3465805053711
var_114_r1	92.85462671518326
var_112	92.03960132598877
var_9_r1	91.38598775863647
var_20_r1	91.08643698692322
var_28	89.8343816101551
var_118	89.23413014411926
var_112_r1	88.51081842184067
var_70_r2	87.39289128780365
var_145	86.96111035346985
var_75_r2	86.30511206388474
var_70_r1	85.75560212135315
var_51	85.66692066192627
var_167	85.55473899841309
var_24	85.12090873718262
var_175_r1	85.00720989704132
var_102_r1	84.50357937812805
var_83	84.15380835533142
var_66	84.00885045528412
var_28_r1	82.8863000869751
var_58_r2	82.32683789730072
var_125_r1	81.53288102149963
var_144_r2	81.50030052661896
var_23_r2	80.9423816204071
var_55_r1	80.30776888132095
var_132	80.20202112197876
var_199	80.09373092651367
var_162_r1	79.51211071014404
var_49_r2	79.17926144599915
var_90_r1	78.8737211227417
var_137_r1	78.81406655907631
var_150	77.52337944507599
var_52	77.24759984016418
var_49	76.76957893371582
var_112_r2	76.50605905056
var_104_r1	76.3929193019867
var_36	75.39267086982727
var_157	75.32687997817993
var_132_r2	74.97945004701614
var_134_r1	74.33635950088501
var_43_r1	73.69708120822906
var_106_r1	73.56552493572235
var_90_r2	71.8326494621277
var_48_r1	71.58482050895691
var_85_r1	70.83020615577698
var_83_r2	69.82772481441498
var_147_r2	69.14709008216858

Features

var_21_r2	68.48893976211548
var_156_r2	67.7740170955658
-var_45	66.43888926506042
var_52_r2	66.34191083908081
var_24_r2	65.64849676191807
var_31_r1	64.67239189147949
var_151_r2	63.42201268672943
var_195	63.22908961772919
var_97_r2	63.06106925010681
var_156	63.0099983215332
var_163_r1	62.72488534450531
var_93_r1	62.599640130996704
var_104	62.374793231487274
var_74_r2	62.06243419647217
var_175	61.845449447631836
var_45_r1	61.27382040023804
var_193_r2	60.80415246449411
-var_95	60.431740045547485
var_35	60.24540042877197
var_135_r1	59.94133960455656
var_145_r2	59.26669979095459
var_32_r1	59.17906045913696
var_104_r2	59.13499999046326
var_116_r2	58.90983986854553
var_119_r2	58.38493895530701
var_144_r1	57.85086005926132
var_83_r1	57.441699504852295
var_196	57.11380345374346
var_43_r2	55.73171067237854
var_137_r2	55.30083155632019
var_128_r1	54.824020862579346
var_62_r1	53.87110295891762
var_199_r1	53.10415029525757
var_105	52.59596449136734
var_20	51.61511039733887
var_196_r2	51.122278571128845
-var_58	50.68263077735901
var_23_r1	50.6735897064209
var_178_r1	50.48275029659271
-var_88	50.41913056373596
var_50	49.271270513534546
var_127	48.21622025966644
var_119_r1	47.67727613449097
var_180	47.662259578704834
var_87_r1	47.63144016265869
var_11_r1	46.762839794158936
var_168_r1	45.547319531440735
var_187	45.252320289611816
var_11_r2	44.50764870643616
var_138_r2	44.40985918045044
var_135	44.35316555202007
var_8	43.39235019683838
var_85	43.12946057319641
var_11	42.96828031539917
var_193_r1	42.690850615501404
var_128_r2	42.61226975917816
var_131_r1	42.44452929496765
var_142	42.243149638175964
var_142_r2	41.511550426483154
var_168	40.50506925582886
var_15_r2	40.429009675979614
var_66_r2	40.24562072753906
var_116	40.183701038360596
var_31	39.37689971923828
var_77_r1	38.98450970649719
var_194	38.72412967681885
var_88_r2	37.47800821065903
-var_3	37.1693696975708
var_68	36.88407039642334
var_8_r1	36.87950223684311
var_199_r2	36.83099031448364
var_108_r1	36.37936043739319
var_102_r2	36.223960280418396
var_181	35.17061126232147
var_70	34.19751000404358
var_138_r1	34.10675758123398
-var_77	33.49901008605957
var_82_r2	32.815470576286316
var_178	32.79961621761322
var_175_r2	32.31449073553085
var_140_r1	32.24362726509571
var_171_r1	31.68263006210327
var_152_r2	31.27275061607361
std	30.534739792346954
var_66_r1	30.006699085235596
var_74_r1	29.445277214050293
median	29.407612144947052
var_54	29.054514199495316
var_105_r1	28.562979698181152
var_193	27.79826021194458
var_77_r2	27.634730110168457
var_66_r1	

var_55_r2	27.532390117645264
var_63_r2	27.405786961317062
var_69_r2	27.27226960659027
var_91_r1	27.11603021621704
var_194_r2	26.846639752388
var_54_r2	26.667489767074585
var_54_r1	26.47509002685547
var_186_r1	26.224831461906433
var_57	26.19958996772766
var_45_r2	25.42628026008606
var_156_r1	25.330950260162354
var_187_r1	24.965855214744806
var_113_r1	24.797169148921967
var_61	24.73486065864563
var_143_r1	24.67559051513672
var_113_r2	24.44711485505104
var_25	24.339500427246094
var_171_r2	23.78552007675171
var_97_r1	23.48861026763916
var_8_r2	23.30532994866371
var_187_r2	22.915729999542236
var_88_r1	22.877708230167627
var_20_r2	22.873239636421204
var_71_r1	22.656479835510254
var_4_r1	22.525870323181152
var_143_r2	22.05776023864746
var_142_r1	21.83076000213623
var_57_r2	21.219655960798264
var_72_r2	20.756102204322815
var_90	20.475979804992676
var_74	19.243520259857178
var_3_r1	19.224290251731873
var_134_r2	19.154069900512695
var_159_r1	19.13116955757141
var_64_r1	18.9623062312603
var_181_r1	18.633569464087486
var_178_r2	18.478822946548462
var_60_r1	18.287110209465027
var_176	17.992100596427917
var_50_r2	17.91514015197754
var_37_r1	17.660368591547012
var_55	17.625839948654175
var_28_r2	17.39963048696518
var_168_r2	17.04518985748291
var_15	16.35330079495907
var_144	16.324759483337402
var_97	15.815430164337158
var_140	15.812930345535278
var_61_r1	15.408140063285828
var_4_r2	15.400540113449097
var_82	15.359994411468506
var_4	15.344800472259521
var_189_r2	15.065060019493103
var_15_r1	14.682305872440338
var_101_r2	14.582570314407349
var_72	14.473740100860596
var_181_r2	14.367660284042358
var_171	14.353876650333405
var_113	13.768283247947693
var_16_r1	12.648499488830566
var_19	12.31565997004509
var_64_r2	11.941399574279785
var_59_r2	11.891049981117249
min	11.745559692382812
var_102	11.455499649047852
var_65	11.443639993667603
var_63_r1	11.233974933624268
var_60	11.215749859809875
var_140_r2	11.031369805335999
var_14_r1	10.978609800338745
var_159_r2	10.93529987335205
var_19_r1	10.736100196838379
var_152	10.578300476074219
var_153_r1	10.532600402832031
var_120	9.906049966812134
var_159	9.566500067710876
var_73_r2	9.559209823608398
var_27_r2	9.364969968795776
var_153_r2	9.006579875946045
var_65_r1	8.9757399559021
var_16	8.889770030975342
var_19_r2	8.579850196838379
var_69	8.530179977416992
var_189	8.471030235290527
var_65_r2	8.421059608459473
var_63	8.21517014503479
var_161	8.193869590759277
var_129_r2	8.182149887084961
var_73_r1	7.875024974346161
var_14	7.635739803314209
var_73	7.6030502211933544

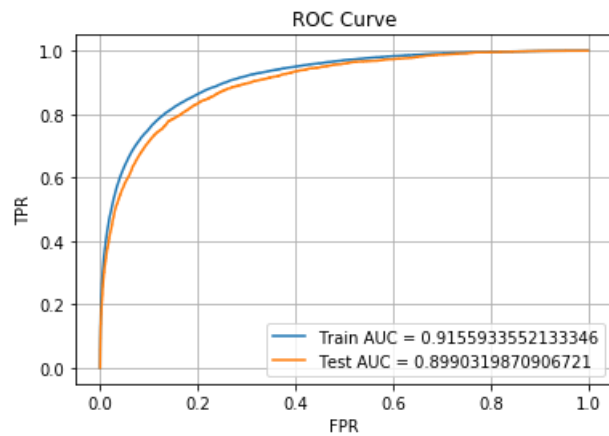


In [28]:

```
y_train_pred = search.best_estimator_.predict_proba(X_tr_2)[: ,1]
y_test_pred = search.best_estimator_.predict_proba(X_te_2)[: ,1]

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

roc_plot(train_fpr, train_tpr, test_fpr, test_tpr)
```



In [0]:

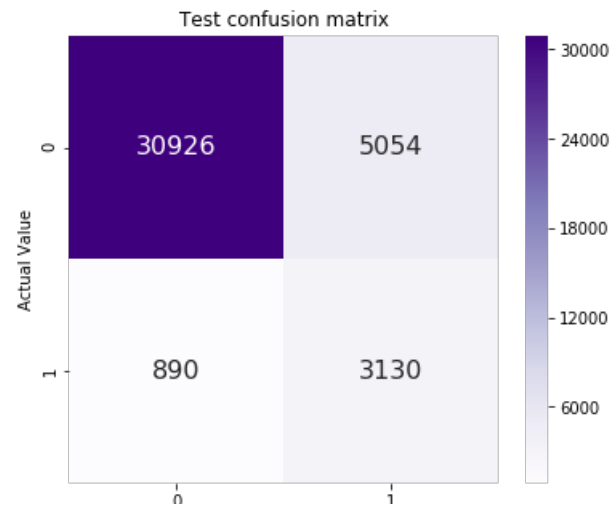
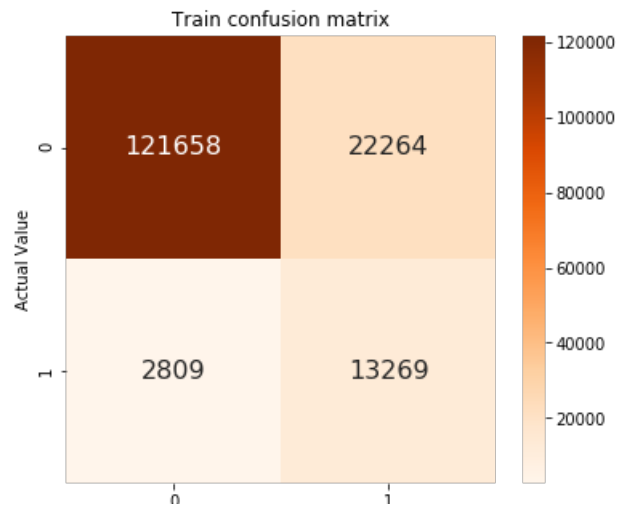
```
pt_2.add_row(['', '', '', ''])
pt_2.add_row(['Light GBM', 'Max_depth = 2, num_leaves = 32', np.round(.9155933, 2), np.round(.89903198, 2)])
```

In [31]:

```
printConfusionMatrix(y_train, y_test, y_train_pred, y_test_pred, tr_thresholds, te_thresholds, train_fpr, train_tpr, test_fpr, test_tpr)
```

The maximum value of Train $tpr \cdot (1 - fpr)$ is 0.69762117902598 for threshold 0.116

The maximum value of Test $tpr \cdot (1 - fpr)$ is 0.6692384381593975 for threshold 0.128



Comparision of Models :

In [80]:

```
print('Modelling With the basic features (mean, std, median, min, max) :')
print(pt_1)
```

Modelling With the basic features (mean, std, median, min, max) :

Model	Hyper Parameters	Train AUC	Test AUC
Logistic Regression	alpha = 0.01	0.859	0.857
Random Forest	Max_depth = 8, n_estimators = 100	0.898	0.807
XGBoost	Max_depth = 9, n_estimators = 181	0.963	0.88
Light GBM	Max_depth = 6, num_leaves = 181	0.945	0.866

In [78]:

```
print('Modelling With the new features(rounding floats) :')
print(pt_2)
```

Modelling With the new features(rounding floats) :

Model	Hyper Parameters	Train AUC	Test AUC
Logistic Regression	C = 0.01, l1_ratio = 0.5816246884542369, max_iter = 883	0.888	0.857
XGBoost	Max_depth = 3, n_estimators = 122	0.869	0.846
Light GBM	Max_depth = 2, num_leaves = 32	0.92	0.9

References :

[1] <https://www.kaggle.com/c/santander-customer-transaction-prediction/discussion/89034#latest-548982>

[2] <https://www.kaggle.com/c/santander-customer-transaction-prediction/discussion/89003#latest-638601>

[3] <https://www.kaggle.com/c/santander-customer-transaction-prediction/discussion/88939#latest-637010>

Light GBM :

[1] <https://www.analyticsvidhya.com/blog/2017/06/which-algorithm-takes-the-crown-light-gbm-vs-xgboost/>

[2] <https://lightgbm.readthedocs.io/en/latest/Python-API.html#>

[3] <https://lightgbm.readthedocs.io/en/latest/Parameters-Tuning.html>

[4] <https://www.kaggle.com/roydatascience/eda-pca-simple-lgbm-on-kfold-technique>

Steps followed :

1. Collected the data from the kaggle website of the competition Santander customer transaction prediction (classification) dataset. The performance metric used for the classification task is **Area Under ROC**.
2. Performed the data cleaning, processing checking for unknown values, filling the missing values. But found that dataset is complete without any missing values, that made the preprocessing simple.
3. Then performed the high level analysis of the dataset like,
 - No. of Datapoints,
 - No. of unique class labels and
 - No. of datapoints per unique class label.
4. Found that the dataset is highly imbalanced with no. of datapoints per class,
 - **Class - 1 (Customers who made txn) : 10%**
 - **Class - 0 (Customers who didn't made txn) : 90%**
5. Performed the EDA on the raw features associated with the dataset and found that features are independent of each other. Written some of my observations inline in the EDA.
6. Applied the dimensionality reduction using the PCA to 2 dimensions and plotted the same. It's hard in separating the classes using linear models as both were completely overlapping.
7. Then I've added the basic features such as mean, standard deviation, median, minimum, maximum of 200 numerical features per data point.
8. Made the train and test split of ratio 80 : 20. Used the train data with the basic features for modelling - I.
9. The basic features gave a reasonable **AUROC** of around **0.85** using the Logistic Regression, Random Forest, XGBoost and Light GBM with hyperparameter tuning. Performed hyperparameter tuning for all the models using RandomizedSearch Cross-Validation.
10. Referring to some of the kaggle discussions I've come across and learnt a new boosting algorithm **Light Gradient boosted Machines(LGBM)** which does splitting leaf-wise instead of depth-wise and gave better predictions than XGBoost.
11. Now I wanted to increase **AUROC** a bit further and gone through some of the kaggle discussions that I referred above. Added some of the count and rounding features for each raw feature as per the discussions.
12. Did the modelling - II with these new count, round features and performed the hyperparameter tuning with previous LR, XGBoost, LGBM.
13. The overfitting problem seems to be reduced for all the models with the new count, round features.
14. LGBM seems to be outperform the other models without overfitting to the training data with the new count, round features which gave an **AUROC** of,
 - Train data -> 0.92.
 - Test data -> 0.9.
15. plotted the feature importance for the LGBM and found that the round features contributed most at each split.
16. Finally compared the all the models for basic and the round features in a table with their train and test **AUROC** and hyperparameters.