```
In [0]: |!pip install -U -q PyDrive
        from pydrive.auth import GoogleAuth
        from pydrive.drive import GoogleDrive
        from google.colab import auth
        from oauth2client.client import GoogleCredentials
        # Authenticate and create the PyDrive client.
        auth.authenticate user()
        gauth = GoogleAuth()
        gauth.credentials = GoogleCredentials.get application default()
        drive = GoogleDrive(gauth)
        id1='1lmufFI9aDOcTLyigjJVhOspYM7olhbH1'
        downloaded1 = drive.CreateFile({'id': id1})
        downloaded1.GetContentFile('orange small train.data')
        id2='1J4ePx792hvmcgjACwUI0dokrOnmMd96P'
        downloaded1 = drive.CreateFile({'id': id2})
        downloaded1.GetContentFile('orange small train churn.labels')
In [0]:
        import pandas as pd
        import matplotlib.pyplot as plt
In [0]: train=pd.read csv('orange small train.data',sep='\t')
In [0]: train['churn']=pd.read csv('orange small train churn.labels',header=None)
        train['appetency']=pd.read csv('orange small train appetency.labels',header=None)
        train['upselling']=pd.read csv('orange small train upselling.labels',header=None)
```

```
In [239]:
           train.head(5)
Out[239]:
               Var1 Var2 Var3
                              Var4
                                   Var5
                                          Var6
                                               Var7
                                                     Var8
                                                          Var9
                                                                Var10
                                                                      Var11
                                                                            Var12
                                                                                   Var13
                                                                                         Var14
                                                                                               Var15
                                                                                                     Var16
                                                                                                            Var17
                                                                                                                  Var18
                                                                                                                        Var19
                                                                                                                               Var20
                                                                                                                                     Var21
                    NaN
                                   NaN
                                         1526.0
                                                 7.0
                                                     NaN
                                                          NaN
                                                                 NaN
                                                                       NaN
                                                                             NaN
                                                                                   184.0
                                                                                          NaN
                                                                                                 NaN
                                                                                                       NaN
                                                                                                             NaN
                                                                                                                   NaN
                                                                                                                         NaN
                                                                                                                                NaN
                                                                                                                                      464.0
              NaN
                         NaN
                              NaN
                                          525.0
                                                                                                                                      168.0
               NaN
                    NaN
                         NaN
                              NaN
                                    NaN
                                                 0.0
                                                     NaN
                                                          NaN
                                                                 NaN
                                                                       NaN
                                                                             NaN
                                                                                     0.0
                                                                                          NaN
                                                                                                 NaN
                                                                                                       NaN
                                                                                                             NaN
                                                                                                                   NaN
                                                                                                                         NaN
                                                                                                                                NaN
                                                                                                                                     1212.0
              NaN
                    NaN
                         NaN
                              NaN
                                   NaN
                                         5236.0
                                                 7.0
                                                     NaN
                                                          NaN
                                                                 NaN
                                                                       NaN
                                                                             NaN
                                                                                   904.0
                                                                                          NaN
                                                                                                NaN
                                                                                                       NaN
                                                                                                             NaN
                                                                                                                   NaN
                                                                                                                         NaN
                                                                                                                                NaN
               NaN
                    NaN
                         NaN
                              NaN
                                    NaN
                                           NaN
                                                 0.0
                                                     NaN
                                                          NaN
                                                                 NaN
                                                                       NaN
                                                                             NaN
                                                                                     0.0
                                                                                          NaN
                                                                                                NaN
                                                                                                       NaN
                                                                                                             NaN
                                                                                                                   NaN
                                                                                                                         NaN
                                                                                                                                NaN
                                                                                                                                       NaN
                                        1029.0
                                                                             NaN 3216.0
                                                                                                                                       64.0
                   NaN NaN NaN NaN
                                                 7.0
                                                     NaN NaN
                                                                 NaN
                                                                       NaN
                                                                                          NaN
                                                                                                NaN
                                                                                                       NaN
                                                                                                             NaN
                                                                                                                   NaN
                                                                                                                         NaN
                                                                                                                                NaN
           5 rows × 233 columns
           x=train.isnull().sum()/train.shape[0]
In [240]:
           plt.hist(x)
Out[240]:
           (array([ 31., 38.,
                                  1.,
                                        0.,
                                               2.,
                                                            0.,
                                                                         0., 154.]),
                                                     5.,
            array([0., 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]),
            <a list of 10 Patch objects>)
            160
            140
            120
            100
             80
             60
             40
```

Here we have many columns which has all values Null so we will be removing those values . Around 28 columns only ehich have no null values and

0.0

0.2

0.4

0.6

0.8

1.0

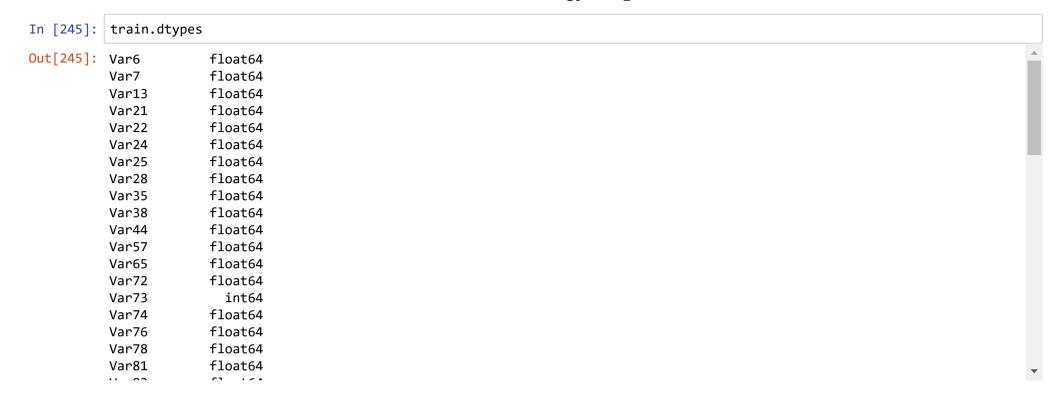
20

154 columns which have all null values

```
In [241]: train.shape
Out[241]: (50000, 233)

Removing the columns whose null values are more than 80%
In [0]: columns= [cols for cols in train if train[cols].isnull().sum()/train.shape[0] > 0.50]

Dropping Those columns
In [0]: train.drop(columns,axis=1,inplace =True)
In [244]: len(train.columns)
Out[244]: 72
```



```
In [246]: train['Var192'].value_counts()
Out[246]: qFpmfo8zhV
                         385
           DHeq9ayfAo
                         384
           zKnr4RXktW
                         380
           8I1r4RXXnK
                         379
           HYTrjIK12c
                         379
           751r4RXktW
                         377
           1GdOj1KXzC
                         376
           2jirEyXktW
                         373
           CxSr4RXktW
                         369
           oyGrjIXt5a
                         368
           vAsgUHXM47
                         368
           hSogUHXZeb
                         367
           vAsTmBfHUn
                         363
           ZSNrjIX0Db
                         362
           dRavyx7ejg
                         360
           xearjIX0Db
                         352
           avkq9ayfAo
                         351
           wRXmfo875g
                         349
           LDPvyx7IEC
                         348
           columns which have Object Datatype
           cols=[col for col in train if train[col].dtype=='0']
  In [0]:
           #Columns with categories / different values less than 500 is used so that we can covert it into one hot or something like
           cols new=[i for i in cols if train[i].nunique() < 500]</pre>
  In [0]: train cat=train[cols new]
  In [0]:
```

Handling missing categorical values

```
In [249]: train_cat.isnull().sum()
           train_cat['Var192'].value_counts()
Out[249]: qFpmfo8zhV
                         385
           DHeq9ayfAo
                         384
           zKnr4RXktW
                         380
           8I1r4RXXnK
                         379
           HYTrjIK12c
                         379
           751r4RXktW
                         377
           1GdOj1KXzC
                         376
                         373
           2jirEyXktW
           CxSr4RXktW
                         369
           oyGrjIXt5a
                         368
           vAsgUHXM47
                         368
           hSogUHXZeb
                         367
           vAsTmBfHUn
                         363
           ZSNrjIX0Db
                         362
           dRavyx7ejg
                         360
           xearjIX0Db
                         352
           avkq9ayfAo
                         351
           wRXmfo875g
                         349
          LDPvyx7IEC
                         348
             T-00 01 1
```

```
In [250]: train_cat['Var223']
Out[250]: 0
                    jySVZN10Jy
                    LM81689q0p
                    jySVZN10Jy
           2
           3
                    LM81689q0p
                    LM81689q0p
           4
           5
                    LM81689q0p
                    LM81689q0p
           7
                           NaN
           8
                    jySVZN10Jy
                    LM81689q0p
           9
           10
                    LM81689q0p
                    LM81689q0p
           11
           12
                    LM81689q0p
           13
                    LM81689q0p
                    LM81689q0p
           14
           15
                    LM81689q0p
           16
                    jySVZN10Jy
           17
                    LM81689q0p
           18
                    jySVZN10Jy
```

After checking the columns Var192 and Var223 we noticed to handle the missing values we have use ffill because we cannot replace by maximum number of occured.

```
In [0]: train_cat=train_cat.ffill(axis=0)
```

In [252]: train cat.isnull().sum()

0

Out[252]: Var192

```
Var193
                     0
           Var195
                     0
           Var196
                     0
           Var197
                     0
           Var203
                     0
           Var204
           Var205
                     0
           Var206
                     0
           Var207
                     0
           Var208
                     0
           Var210
           Var211
                     0
           Var212
           Var218
                     0
           Var219
                     0
           Var221
                     0
           Var223
                     0
           Var226
           Var227
                     0
           Var228
                     0
           dtype: int64
           So no Null values we have till now in categorical columns
  In [0]: train num=train.drop(cols,axis=1)
In [254]: train num.columns
Out[254]: Index(['Var6', 'Var7', 'Var13', 'Var21', 'Var22', 'Var24', 'Var25', 'Var28',
                  'Var35', 'Var38', 'Var44', 'Var57', 'Var65', 'Var72', 'Var73', 'Var74',
                  'Var76', 'Var78', 'Var81', 'Var83', 'Var85', 'Var94', 'Var109',
                  'Var112', 'Var113', 'Var119', 'Var123', 'Var125', 'Var126', 'Var132',
                  'Var133', 'Var134', 'Var140', 'Var143', 'Var144', 'Var149', 'Var153',
                  'Var160', 'Var163', 'Var173', 'Var181', 'churn', 'appetency',
                  'upselling'],
                 dtype='object')
```

```
In [0]:
          train_num.isnull().sum()
In [255]:
Out[255]: Var6
                         5529
                         5539
           Var7
          Var13
                         5539
          Var21
                         5529
           Var22
                         5009
          Var24
                         7230
          Var25
                         5009
          Var28
                         5011
          Var35
                         5009
          Var38
                         5009
          Var44
                         5009
          Var57
                            0
          Var65
                         5539
           Var72
                        22380
          Var73
                            0
           Var74
                         5539
          Var76
                         5009
          Var78
                         5009
           Var81
                         5529
                         ----
  In [0]:
          for i in train num.columns:
               train num[i].fillna(train num[i].mean(),inplace=True)
In [257]:
          print(train_cat.shape)
           print(train num.shape)
           (50000, 21)
           (50000, 44)
          train_final=pd.concat([train_num,train_cat],axis=1)
  In [0]:
  In [0]:
```

Predicting Class change

```
In [0]: | train_final['churn']=(train_final['churn']+1)/2
           train_final['appetency']=(train_final['appetency']+1)/2
           train final['upselling']=(train final['upselling']+1)/2
  In [0]: train final['churn']=train final['churn'].astype('int')
           train final['appetency']=train final['appetency'].astype('int')
           train final['upselling']=train final['upselling'].astype('int')
  In [0]: trai,tes = train test split(train final,test size=0.2)
  In [0]: from sklearn.model selection import train test split
           X train = trai.drop(['churn', 'appetency', 'upselling'], axis=1)
           X test = tes.drop(['churn', 'appetency', 'upselling'], axis=1)
           y train
                       = trai['churn']
                       = tes['churn']
           y test
           y train app = trai['appetency']
           y test app = tes['appetency']
           y train up = trai['upselling']
           y test up = tes['upselling']
  In [0]:
In [263]: X test.shape
Out[263]: (10000, 62)
          ##Categorical features
           We have 21 categorical features so if we assume on an average if each columncorreponds to 100 features so maximum features will be 2100. Not
           Bad:)
  In [0]:
          from sklearn.preprocessing import LabelEncoder,OneHotEncoder
           import bisect
           from scipy.sparse import hstack
```

```
In [266]:
          #https://stackoverflow.com/questions/40321232/handling-unknown-values-for-label-encoding
          le=LabelEncoder()
          X train['Var192']=le.fit transform(X train['Var192'])
          X test['Var192'] = X test['Var192'].map(lambda s: 'other' if s not in le.classes else s)
          le classes = le.classes .tolist()
          bisect.insort left(le classes, 'other')
          le.classes = le classes
          X test['Var192']=le.transform(X test['Var192'])
          ohe=OneHotEncoder(handle unknown='ignore')
          X tr = ohe.fit transform(X train['Var192'].values.reshape(-1,1))
          X te = ohe.transform(X test['Var192'].values.reshape(-1,1))
          flag=0
          for i in train cat.columns:
            if (flag!=0):
                  le = LabelEncoder()
                  X train[i]=le.fit transform(X train[i])
                  X test[i] = X test[i].map(lambda s: 'other' if s not in le.classes else s)
                  le classes = le.classes .tolist()
                  bisect.insort left(le classes, 'other')
                  le.classes = le classes
                  X test[i]=le.transform(X test[i])
                  ohe=OneHotEncoder(handle unknown='ignore')
                  print(i)
                  X tri = ohe.fit transform(X train[i].values.reshape(-1,1))
                  X tei = ohe.transform(X test[i].values.reshape(-1,1))
                  X tr=hstack((X tr,X tri))
                  X te=hstack((X te,X tei))
            flag=1
```

```
Var193
Var195
Var196
Var197
Var203
Var204
```

```
Var205
Var206
Var207
Var208
Var210
Var211
Var212
Var218
Var219
Var221
Var223
Var223
Var226
Var227
```

### GridSearch

```
In [0]: from sklearn.model_selection import GridSearchCV
    from sklearn.naive_bayes import MultinomialNB
    model=MultinomialNB()
    para = {'alpha':[0.0001,0.001,0.01,1,10,100,1000,10000]}
    clf = GridSearchCV(model, para, cv=5, scoring='roc_auc',return_train_score=True)
    clf.fit(X_tr, y_train)
    train_auc= clf.cv_results_['mean_train_score']
    cv_auc = clf.cv_results_['mean_test_score']
    ...
```

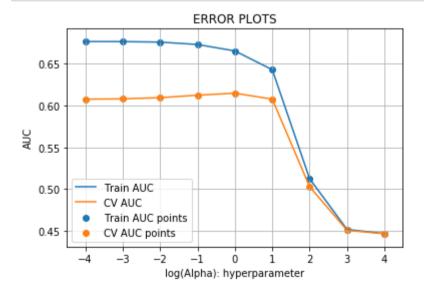
```
In [0]: from xgboost import XGBClassifier
model=XGBClassifier(n_estimators=100,max_depth=2,class_weight='balanced')
model.fit(X_tr, y_train)

y_test_pred = model.predict_proba(X_te)
roc_auc_score(y_test, y_test_pred[:,1])
```

## Out[60]: 0.6197069181951065

```
In [0]: from sklearn.ensemble import ExtraTreesClassifier, RandomForestClassifier, GradientBoostingClassifier
    from xgboost import XGBClassifier
    model=RandomForestClassifier(n_estimators = 100, random_state = 0)
    model.fit(X_tr, y_train)
    y_test_pred = model.predict_proba(X_te)
    roc_auc_score(y_test, y_test_pred[:,1])
```

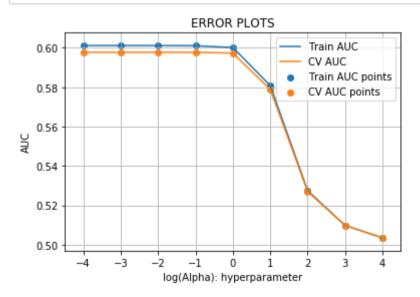
### Out[66]: 0.5378825184819434



##Numerical Features

```
In [0]: from sklearn.preprocessing import MinMaxScaler
           for i in train num.columns:
            if i!='churn':
              if i!='appetency':
                if i!='upselling':
                    m = MinMaxScaler()
                    X train[i]=m.fit transform(X train[i].values.reshape(-1,1))
                    X test[i]=m.transform(X test[i].values.reshape(-1,1))
          cols=[i for i in train cat.columns if i not in ['churn','appetency','upselling']]
          X tr num=X train.drop(cols,axis=1)
          X te num=X test.drop(cols,axis=1)
In [269]: | X_tr_num.columns
Out[269]: Index(['Var6', 'Var7', 'Var13', 'Var21', 'Var22', 'Var24', 'Var25', 'Var28',
                  'Var35', 'Var38', 'Var44', 'Var57', 'Var65', 'Var72', 'Var73', 'Var74',
                  'Var76', 'Var78', 'Var81', 'Var83', 'Var85', 'Var94', 'Var109',
                  'Var112', 'Var113', 'Var119', 'Var123', 'Var125', 'Var126', 'Var132',
                  'Var133', 'Var134', 'Var140', 'Var143', 'Var144', 'Var149', 'Var153',
                  'Var160', 'Var163', 'Var173', 'Var181'],
                dtvpe='object')
 In [69]: from sklearn.ensemble import ExtraTreesClassifier, RandomForestClassifier, GradientBoostingClassifier
          from sklearn.metrics import roc auc score
          from xgboost import XGBClassifier
          model=XGBClassifier(n estimators = 100, max depth=2, random state = 0)
          model.fit(X tr num, y train)
          y test pred = model.predict proba(X te num)
          roc auc score(y test, y test pred[:,1])
 Out[69]: 0.7186206592728834
```

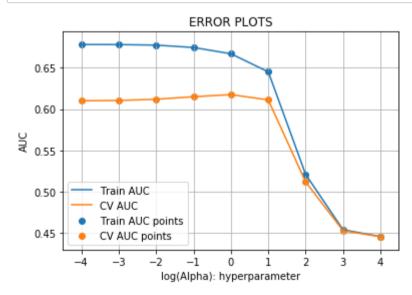
localhost:8888/notebooks/AI/CS1/utkarsh.alok01%40gmail.com 27.ipynb



# **Categorical + Numerical**

```
In [0]: X_tr_final = hstack((X_tr_num, X_tr))
X_te_final = hstack((X_te_num, X_te))
```

```
In [0]: from sklearn.model selection import GridSearchCV
       from sklearn.naive bayes import MultinomialNB
       model=MultinomialNB()
       clf = GridSearchCV(model, para, cv=5, scoring='roc auc',return train score=True)
       clf.fit(X tr final, y train)
       train auc= clf.cv results ['mean train score']
       cv auc = clf.cv results ['mean test score']
       from math import log
       plt.plot([log(y,10) for y in Alpha], train auc, label='Train AUC')
       plt.plot([log(y,10) for y in Alpha], cv auc, label='CV AUC')
       plt.scatter([log(y,10) for y in Alpha], train_auc, label='Train AUC points')
       plt.scatter([log(v,10) for v in Alpha], cv auc, label='CV AUC points')
       plt.legend()
       plt.xlabel("log(Alpha): hyperparameter")
       plt.ylabel("AUC")
       plt.title("ERROR PLOTS")
       plt.grid()
       plt.show()
```



```
In [0]: from sklearn.tree import DecisionTreeClassifier
    from sklearn.model_selection import GridSearchCV

model=DecisionTreeClassifier(criterion='gini', splitter='random')

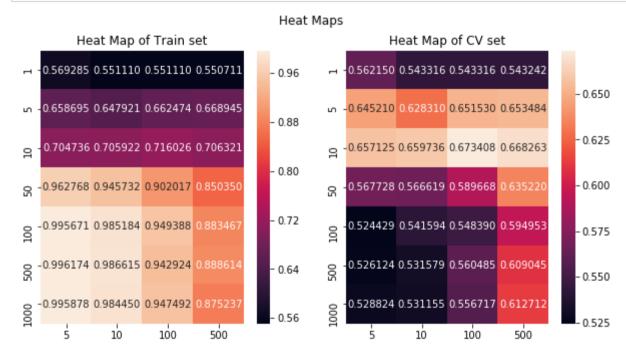
para = {'max_depth':[1, 5, 10, 50, 100, 500,1000], 'min_samples_split':[5, 10, 100, 500]}

clf = GridSearchCV(model, para, cv=3, scoring='roc_auc',return_train_score=True,verbose=2,n_jobs=40)
    clf.fit(X_tr_final, y_train)
    train_auc= clf.cv_results_['mean_train_score']
    cv_auc = clf.cv_results_['mean_test_score']
```

Fitting 3 folds for each of 28 candidates, totalling 84 fits

```
[Parallel(n_jobs=40)]: Using backend LokyBackend with 40 concurrent workers. [Parallel(n_jobs=40)]: Done 48 out of 84 | elapsed: 4.0min remaining: 3.0min [Parallel(n_jobs=40)]: Done 84 out of 84 | elapsed: 5.2min finished
```

```
In [0]: import seaborn as sns
import numpy as np
fig, (left, right) = plt.subplots(ncols=2, figsize=(10, 5))
t_auc=np.array(train_auc).reshape(7,4)
a=sns.heatmap(t_auc,annot=True,fmt="f",xticklabels=min_split, yticklabels=Depth,ax=left)
left.set_title('Heat Map of Train set')
c_auc=np.array(cv_auc).reshape(7,4)
b=sns.heatmap(c_auc,annot=True,fmt="f",xticklabels=min_split, yticklabels=Depth,ax=right)
right.set_title('Heat Map of CV set')
fig.suptitle("Heat Maps")
plt.show()
```



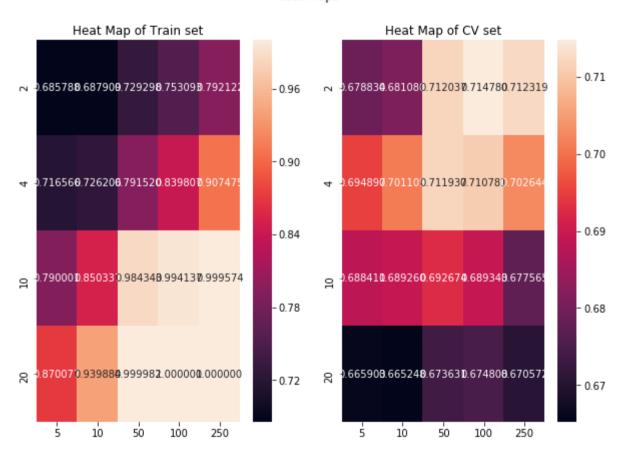
```
In [0]: from xgboost import XGBClassifier
    parameters = {'n_estimators':[5,10,50,100,250] , 'max_depth' :[2,4,10,20]}
    xb1=XGBClassifier(class_weight='balanced')
    clf1=GridSearchCV(xb1,parameters,cv=2,scoring='roc_auc',return_train_score=True,verbose=10,n_jobs=40)
    clf1.fit(X_tr_final,y_train)
    train_auc= clf1.cv_results_['mean_train_score']
    cv_auc = clf1.cv_results_['mean_test_score']
```

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

```
[Parallel(n jobs=40)]: Using backend LokyBackend with 40 concurrent workers.
[Parallel(n jobs=40)]: Done 1 tasks
                                           elapsed:
                                                     11.1s
[Parallel(n jobs=40)]: Done
                            6 out of 40 |
                                           elapsed:
                                                     49.3s remaining: 4.7min
[Parallel(n jobs=40)]: Done 11 out of 40 |
                                           elapsed: 1.4min remaining: 3.7min
[Parallel(n jobs=40)]: Done 16 out of 40 |
                                           elapsed: 1.8min remaining:
                                                                       2.6min
[Parallel(n jobs=40)]: Done 21 out of 40 | elapsed: 2.5min remaining: 2.3min
[Parallel(n jobs=40)]: Done 26 out of 40 |
                                           elapsed: 3.3min remaining: 1.8min
[Parallel(n jobs=40)]: Done 31 out of 40 |
                                           elapsed: 5.0min remaining: 1.4min
[Parallel(n jobs=40)]: Done 36 out of 40 |
                                           elapsed: 6.8min remaining:
                                                                        45.2s
[Parallel(n jobs=40)]: Done 40 out of 40 |
                                           elapsed: 8.2min finished
```

```
In [0]: fig, (left, right) = plt.subplots(ncols=2, figsize=(10, 7))
    t_auc=np.array(train_auc).reshape(4,5)
    a=sns.heatmap(t_auc,annot=True,fmt="f",xticklabels=parameters['n_estimators'], yticklabels=parameters['max_depth'],ax=lef
    left.set_title('Heat Map of Train set')
    c_auc=np.array(cv_auc).reshape(4,5)
    b=sns.heatmap(c_auc,annot=True,fmt="f",xticklabels=parameters['n_estimators'], yticklabels=parameters['max_depth'],ax=rig
    right.set_title('Heat Map of CV set')
    fig.suptitle("Heat Maps")
    plt.show()
```

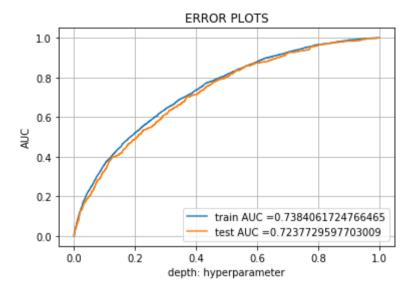
#### Heat Maps



```
In [0]: def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs
    y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
        # we will be predicting for the last data points
        y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

return y_data_pred
```

```
In [0]: from sklearn.metrics import roc curve,auc
        best esti=100
        best depth=2
        xg4=XGBClassifier(n estimators=best esti,max depth=best depth,n jobs=-1,class weight='balanced')
        xg4.fit(X tr final, y train)
        y train pred = batch predict(xg4,X tr final.tocsr())
        v test pred = batch predict(xg4,X te final.tocsr())
        train fpr, train tpr, tr thresholds = roc curve(y train, y train pred)
        test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
        plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
        plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
        plt.legend()
        plt.xlabel("depth: hyperparameter")
        plt.ylabel("AUC")
        plt.title("ERROR PLOTS")
        plt.grid()
        plt.show()
        #Credits:AppliedaAIcourse.com
        from sklearn.metrics import confusion matrix
        def predict(proba, threshould, fpr, tpr):
          t = threshould[np.argmax(fpr*(1-tpr))]
          # (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)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))
          predictions = []
          for i in proba:
            if i>=t:
              predictions.append(1)
            else:
              predictions.append(0)
            return predictions
```



```
In [0]: from sklearn.ensemble import ExtraTreesClassifier, RandomForestClassifier, GradientBoostingClassifier
    from xgboost import XGBClassifier
    model=XGBClassifier(n_estimators = 100,max_depth=2, random_state = 0)
    model.fit(X_tr_final, y_train)
    y_test_pred = model.predict_proba(X_te_final)
    roc_auc_score(y_test, y_test_pred[:,1])
```

Out[72]: 0.7265878086083746

In [273]:

Out[273]: 0.8251691343843911

In [92]: from sklearn.metrics import accuracy\_score
 y\_test\_pred = model.predict(X\_te)
 accuracy\_score(y\_test, y\_test\_pred)

Out[92]: 0.9265

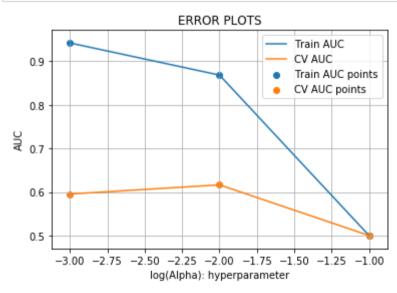
Out[76]: 0.7096949951205049

```
In [0]: from sklearn.neural network import MLPClassifier
        mlp = MLPClassifier(
             hidden layer sizes=(1024, 256, 64, 16),
             activation="relu",
            max iter=int(1e+3),
             early stopping=True,
            validation fraction=0.2,
            n iter no change=50,
            random state=2,
            verbose=True,
        mlp.fit(X tr final, y train)
        y test pred = mlp.predict proba(X te final)
        Iteration 1, loss = 0.27214162
        Validation score: 0.926375
        Iteration 2, loss = 0.24798246
        Validation score: 0.926375
        Iteration 3, loss = 0.24047966
        Validation score: 0.926375
        Iteration 4, loss = 0.22143650
        Validation score: 0.922125
        Iteration 5, loss = 0.18512248
        Validation score: 0.905875
        Iteration 6, loss = 0.14387142
        Validation score: 0.903375
        Iteration 7, loss = 0.10792924
        Validation score: 0.899750
        Iteration 8, loss = 0.07846820
        Validation score: 0.894750
        Iteration 9, loss = 0.06431966
        Validation score: 0.902125
        Iteration 10, loss = 0.05080494
        .. ... ..
In [0]: from sklearn.metrics import roc_auc_score
        roc_auc_score(y_test, y_test_pred[:,1])
```

Out[44]: 0.626717914277289

```
In [0]: X tr final.shape
Out[78]: (40000, 1010)
         ##MLP Classifier
         Upsampling the data
In [0]:
 In [0]: from sklearn.neural network import MLPClassifier
         from sklearn.model selection import GridSearchCV
         from sklearn.metrics import auc
         model=MLPClassifier(hidden layer sizes=(130,75,50,30,10),batch size=500,max iter=500)
         para = {'learning rate init':[0.1,0.01,0.001]}
         clf = GridSearchCV(model, para, cv=3, scoring='roc auc', return train score=True, verbose=2, n jobs=40)
         clf.fit(X tr num, y train)
         train auc= clf.cv results ['mean train score']
         cv auc = clf.cv results ['mean test score']
         Fitting 3 folds for each of 3 candidates, totalling 9 fits
         [Parallel(n jobs=40)]: Using backend LokyBackend with 40 concurrent workers.
         [Parallel(n jobs=40)]: Done 5 out of 9 | elapsed: 9.4min remaining: 7.5min
         [Parallel(n jobs=40)]: Done 9 out of 9 | elapsed: 10.9min finished
In [0]: cv_auc
Out[64]: array([0.5
                          , 0.61635579, 0.59532081])
```

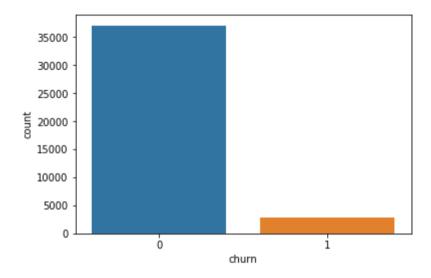
```
In [0]: from math import log
lr=[0.1,0.01,0.001]
    plt.plot([log(y,10) for y in lr], train_auc, label='Train AUC')
    plt.plot([log(y,10) for y in lr], cv_auc, label='CV AUC')
    plt.scatter([log(y,10) for y in lr], train_auc, label='Train AUC points')
    plt.scatter([log(y,10) for y in lr], cv_auc, label='CV AUC points')
    plt.legend()
    plt.xlabel("log(Alpha): hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.grid()
    plt.show()
```



## Upsampling the data

```
In [0]: import matplotlib.pyplot as plt
import seaborn as sns
sns.countplot(y_train)
```

Out[74]: <matplotlib.axes. subplots.AxesSubplot at 0x7feb09bd1080>



```
In [0]: from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=2)
X_tr_num_res, y_tr_num_res = sm.fit_sample(X_tr_num, y_train.ravel())
```

```
In [0]: from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=2)
X_te_num_res, y_te_num_res = sm.fit_sample(X_te_num, y_test.ravel())
```

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

Out[86]: (18444, 41)

```
In [0]: from sklearn.neural network import MLPClassifier
         from sklearn.model selection import GridSearchCV
         from sklearn.metrics import auc
         model=MLPClassifier(hidden layer sizes=(130,75,50,30,10),batch size=500,max iter=500)
         para = {'learning rate init':[0.01]}
         clf = GridSearchCV(model, para,cv=3,scoring='roc auc',return train score=True,verbose=2,n jobs=40)
         clf.fit(X te num res, y te num res)
         train auc= clf.cv results ['mean train score']
         cv auc = clf.cv results ['mean test score']
In [0]:
In [0]: clf.cv results
         print("train AUC", train auc)
 In [0]:
         print("CV AUC",cv auc)
         train AUC [0.9954992]
         CV AUC [0.95130601]
In [0]: from sklearn.metrics import roc curve, auc
         model=MLPClassifier(hidden layer sizes=(130,75,50,30,10),learning_rate_init=0.01,batch_size=500,max_iter=500)
         model.fit(X tr num res, y tr num res)
Out[88]: MLPClassifier(activation='relu', alpha=0.0001, batch size=500, beta 1=0.9,
                       beta 2=0.999, early stopping=False, epsilon=1e-08,
                       hidden layer sizes=(130, 75, 50, 30, 10),
                       learning_rate='constant', learning_rate_init=0.01, max iter=500,
                       momentum=0.9, n iter no change=10, nesterovs momentum=True,
                       power t=0.5, random state=None, shuffle=True, solver='adam',
                       tol=0.0001, validation fraction=0.1, verbose=False,
                       warm start=False)
```

```
In [0]: y_test_pred= model.predict_proba(X_te_num)
roc_auc_score(y_test, y_test_pred[:,1])
```

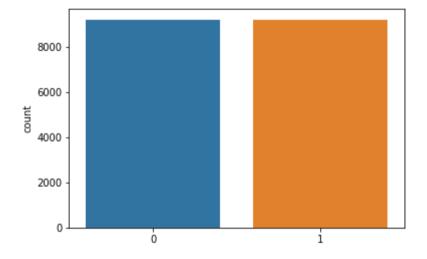
Out[89]: 0.6012187799489206

```
In [0]: from sklearn.metrics import roc_auc_score
roc_auc_score(y_te_num_res, y_test_pred[:,1])
```

Out[80]: 0.7601658899745692

```
In [0]: import matplotlib.pyplot as plt
import seaborn as sns
sns.countplot(y_te_num_res)
```

Out[73]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7feb09c73e10>



```
In [0]: len(X_te_num_res)
    len(y_te_num_res)
    len(y_test_pred)
```

Out[50]: 25992

Upsampling:

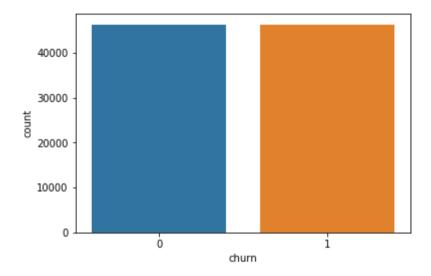
```
In [0]:
        cols=[i for i in train_cat.columns]
        data=train_final.drop(cols,axis=1)
In [0]:
        import seaborn as sns
In [0]:
        sns.countplot(data['churn'],hue=data['churn'])
         plt.show()
                                                        churn
            40000
            30000
          count
            20000
           10000
                                     churn
In [0]:
        data 0 = data[data['churn']==0]
         data_1 = data[data['churn']==1]
In [0]: from sklearn.utils import resample
         data 1 upsampled = resample(data 1,replace=True,n samples=data 0.shape[0],random state=50)
        print(data_1_upsampled.shape)
In [0]:
         print(data 0.shape)
         (46328, 42)
```

(46328, 42)

```
In [0]: final_sampled_data=pd.concat([data_1_upsampled,data_0])
    final_sampled_data.shape
```

Out[54]: (92656, 42)

In [0]: sns.countplot(final\_sampled\_data['churn'])
 plt.show()



```
In [0]: from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(final_sampled_data.drop(['churn'],axis=1),final_sampled_data['churn'],test
```

```
In [0]: from sklearn.preprocessing import MinMaxScaler

for i in X_train.columns:
    if i!='churn':

        m = MinMaxScaler()
        X_train[i]=m.fit_transform(X_train[i].values.reshape(-1,1))
        X_test[i]=m.transform(X_test[i].values.reshape(-1,1))
```

```
In [0]: from sklearn.neural network import MLPClassifier
        from sklearn.model selection import GridSearchCV
        from sklearn.metrics import auc
        model=MLPClassifier(hidden layer sizes=(130,75,10,2),batch size=100,max iter=500)
        para = {'learning rate init':[0.001]}
        clf = GridSearchCV(model, para,cv=3,scoring='roc auc',return train score=True,verbose=2,n jobs=3)
        clf.fit(X train, y train)
        train auc= clf.cv results ['mean train score']
        cv auc = clf.cv results ['mean test score']
        Fitting 3 folds for each of 1 candidates, totalling 3 fits
        [Parallel(n jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
        [Parallel(n jobs=3)]: Done 3 out of 3 | elapsed: 46.7min finished
In [0]: #This I ran Initially without normalizing the data and the result was devastating.
        #print("Train AUC:",train auc)
        #print("CV AUC : ",cv auc)
        Train AUC: [0.50000675]
        CV AUC : [0.50001349]
In [0]: print("Train AUC:",train auc)
        print("CV AUC : ",cv auc)
        Train AUC: [0.78453373]
        CV AUC : [0.75162872]
```

# Test sample without upsampling

```
In [0]: from sklearn.neural_network import MLPClassifier
    from sklearn.model_selection import GridSearchCV
    from sklearn.metrics import auc
```

```
In [0]: from sklearn.model_selection import train_test_split
    data_train,data_test=train_test_split(data,test_size=0.2)
```

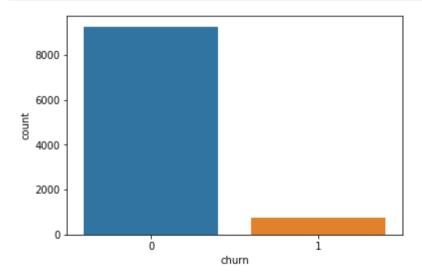
```
data 0 = data train[data train['churn']==0]
In [0]:
        data 1 = data train[data train['churn']==1]
        from sklearn.utils import resample
        data 1 upsampled = resample(data 1,replace=True,n samples=data 0.shape[0],random state=50)
        final sampled data=pd.concat([data 1 upsampled,data 0])
        final sampled data.shape
        X train = final sampled data.drop(['churn'],axis=1)
        y train = final sampled data['churn']
        X test = data test.drop(['churn'],axis=1)
        y test = data test['churn']
        from sklearn.preprocessing import MinMaxScaler
        for i in X train.columns:
          if i!='churn':
                m = MinMaxScaler()
                X train[i]=m.fit transform(X train[i].values.reshape(-1,1))
                X test[i]=m.transform(X test[i].values.reshape(-1,1))
        from sklearn.metrics import roc curve,auc
        from sklearn.metrics import roc auc score
        model=MLPClassifier(hidden layer sizes=(130,75,50,30,10),learning rate init=0.001,batch size=100,max iter=500)
        model.fit(X train, y train)
        y test pred = model.predict proba(X test)
        roc auc score(y test, y test pred[:,1])
```

Out[70]: 0.5966307119499122

```
In [0]:
         model=MLPClassifier(hidden layer sizes=(1024,256,64,10),learning rate init=0.01,early stopping=True,batch size=100,max it
         model.fit(X train, y train)
Out[74]: MLPClassifier(activation='relu', alpha=0.0001, batch size=100, beta 1=0.9,
                       beta 2=0.999, early stopping=True, epsilon=1e-08,
                       hidden layer sizes=(1024, 256, 64, 10), learning rate='constant',
                       learning rate init=0.01, max iter=500, momentum=0.9,
                       n iter no change=10, nesterovs momentum=True, power t=0.5,
                       random state=None, shuffle=True, solver='adam', tol=0.0001,
                       validation fraction=0.1, verbose=False, warm start=False)
In [0]: y test pred = model.predict proba(X test)
         roc auc score(y test, y test pred[:,1])
```

Out[76]: 0.6390448526368927

In [0]: sns.countplot(y test) plt.show()



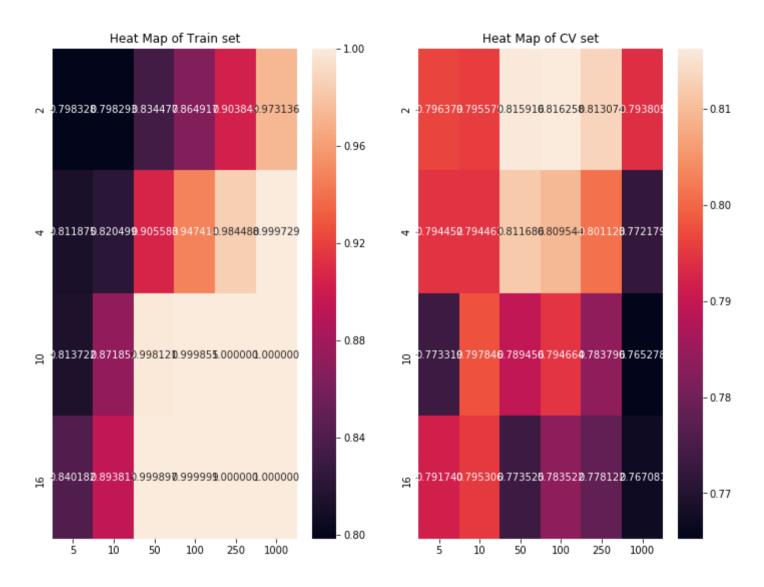
# **XGBClassifier**

```
In [0]: from xgboost import XGBClassifier
          model=XGBClassifier(n estimators=500,max depth=2,class weight='balanced')
          model.fit(X train, y train)
          v test pred = model.predict(X test)
          roc auc score(y test, y test pred)
 Out[73]: 0.6571282069853994
 In [0]:
          ##Appetency
          from xgboost import XGBClassifier
In [275]:
          from sklearn.model selection import GridSearchCV
          parameters = {'n estimators':[5,10,50,100,250,1000] , 'max depth' :[2,4,10,16]}
          xb1=XGBClassifier(class weight='balanced')
          clf1=GridSearchCV(xb1,parameters,cv=2,scoring='roc auc',return train score=True,verbose=10,n jobs=40)
          clf1.fit(X tr final,y train app)
          train auc= clf1.cv results ['mean train score']
          cv auc = clf1.cv results ['mean test score']
          Fitting 2 folds for each of 24 candidates, totalling 48 fits
          [Parallel(n jobs=40)]: Using backend LokyBackend with 40 concurrent workers.
          [Parallel(n jobs=40)]: Done 4 out of 48 | elapsed:
                                                               22.0s remaining: 4.0min
          [Parallel(n jobs=40)]: Done 9 out of 48 | elapsed: 1.2min remaining: 5.2min
          [Parallel(n jobs=40)]: Done 14 out of 48 | elapsed: 2.5min remaining: 6.0min
          [Parallel(n jobs=40)]: Done 19 out of 48 | elapsed: 2.6min remaining: 3.9min
          [Parallel(n jobs=40)]: Done 24 out of 48 |
                                                      elapsed: 3.9min remaining: 3.9min
          [Parallel(n jobs=40)]: Done 29 out of 48 | elapsed: 6.1min remaining: 4.0min
          [Parallel(n jobs=40)]: Done 34 out of 48 |
                                                      elapsed: 7.3min remaining: 3.0min
                                                      elapsed: 11.3min remaining: 2.6min
          [Parallel(n jobs=40)]: Done 39 out of 48 |
          [Parallel(n jobs=40)]: Done 44 out of 48 | elapsed: 13.6min remaining: 1.2min
          [Parallel(n jobs=40)]: Done 48 out of 48 | elapsed: 17.9min finished
```

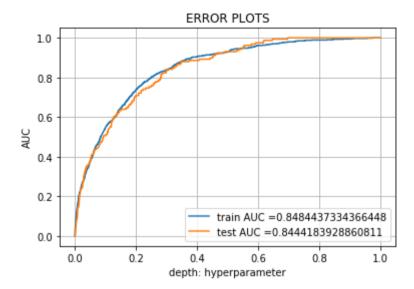
```
In [276]: import numpy as np
import seaborn as sns
fig, (left, right) = plt.subplots(ncols=2, figsize=(12, 9))
t_auc=np.array(train_auc).reshape(4,6)
a=sns.heatmap(t_auc,annot=True,fmt="f",xticklabels=parameters['n_estimators'], yticklabels=parameters['max_depth'],ax=lef
left.set_title('Heat Map of Train set')
c_auc=np.array(cv_auc).reshape(4,6)
b=sns.heatmap(c_auc,annot=True,fmt="f",xticklabels=parameters['n_estimators'], yticklabels=parameters['max_depth'],ax=rig

right.set_title('Heat Map of CV set')
fig.suptitle("Heat Maps")
plt.show()
```

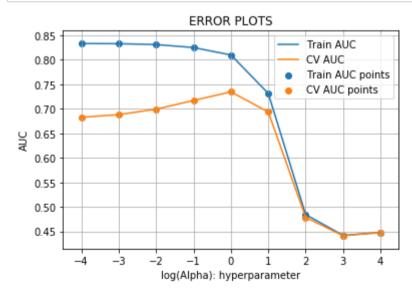
#### Heat Maps



```
In [279]: from sklearn.metrics import roc curve, auc
          best esti=100
          best depth=2
          xg4=XGBClassifier(n estimators=best esti,max depth=best depth,n jobs=10,class weight='balanced')
          xg4.fit(X tr final, v train app)
          y train pred = batch predict(xg4,X tr final.tocsr())
          v test pred = batch predict(xg4,X te final.tocsr())
          train fpr, train tpr, tr thresholds = roc_curve(y_train_app, y_train_pred)
          test fpr, test tpr, te thresholds = roc curve(y test app, y test pred)
          plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
          plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
          plt.legend()
          plt.xlabel("depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.grid()
           plt.show()
          #Credits:AppliedaAIcourse.com
          from sklearn.metrics import confusion matrix
          def predict(proba, threshould, fpr, tpr):
            t = threshould[np.argmax(fpr*(1-tpr))]
            # (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)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))
            predictions = []
            for i in proba:
              if i>=t:
                predictions.append(1)
              else:
                 predictions.append(0)
              return predictions
```



```
In [274]:
         from sklearn.model selection import GridSearchCV
         from sklearn.naive bayes import MultinomialNB
         model=MultinomialNB()
         clf = GridSearchCV(model, para, cv=5, scoring='roc auc',return train score=True)
         clf.fit(X tr final, y train app)
         train auc= clf.cv results ['mean train score']
         cv auc = clf.cv results ['mean test score']
         from math import log
         plt.plot([log(y,10) for y in Alpha], train auc, label='Train AUC')
         plt.plot([log(y,10) for y in Alpha], cv auc, label='CV AUC')
         plt.scatter([log(y,10) for y in Alpha], train auc, label='Train AUC points')
         plt.scatter([log(v,10) for v in Alpha], cv auc, label='CV AUC points')
         plt.legend()
         plt.xlabel("log(Alpha): hyperparameter")
         plt.ylabel("AUC")
         plt.title("ERROR PLOTS")
         plt.grid()
         plt.show()
```



```
In [0]: import seaborn as sns
import numpy as np
fig, (left, right) = plt.subplots(ncols=2, figsize=(12, 9))
t_auc=np.array(train_auc).reshape(7,4)
a=sns.heatmap(t_auc,annot=True,fmt="f",xticklabels=min_split, yticklabels=Depth,ax=left)
left.set_title('Heat Map of Train set')
c_auc=np.array(cv_auc).reshape(7,4)
b=sns.heatmap(c_auc,annot=True,fmt="f",xticklabels=min_split, yticklabels=Depth,ax=right)
right.set_title('Heat Map of CV set')
fig.suptitle("Heat Maps")
plt.show()
```

### In [0]:

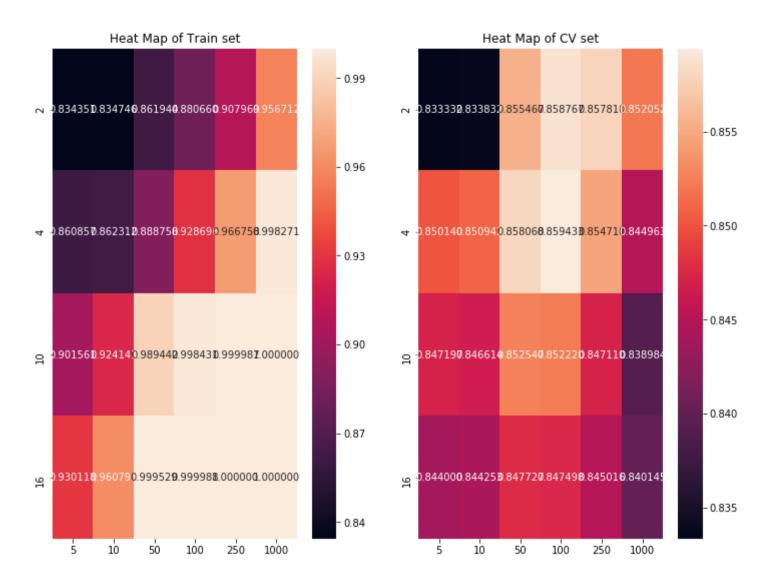
##Upselling

```
In [280]:
          from xgboost import XGBClassifier
          from sklearn.model selection import GridSearchCV
          parameters = {'n estimators':[5,10,50,100,250,1000], 'max depth':[2,4,10,16]}
          xb1=XGBClassifier(class weight='balanced')
          clf1=GridSearchCV(xb1,parameters,cv=2,scoring='roc auc',return train score=True,verbose=10,n jobs=40)
          clf1.fit(X tr final,y train up)
          train auc= clf1.cv results ['mean train score']
          cv auc = clf1.cv results ['mean test score']
          import numpy as np
          import seaborn as sns
          fig, (left, right) = plt.subplots(ncols=2, figsize=(12, 9))
          t auc=np.array(train auc).reshape(4,6)
          a=sns.heatmap(t auc,annot=True,fmt="f",xticklabels=parameters['n estimators'], yticklabels=parameters['max depth'],ax=lef
          left.set title('Heat Map of Train set')
          c auc=np.array(cv auc).reshape(4,6)
          b=sns.heatmap(c auc,annot=True,fmt="f",xticklabels=parameters['n estimators'], yticklabels=parameters['max depth'],ax=rig
          right.set title('Heat Map of CV set')
          fig.suptitle("Heat Maps")
          plt.show()
```

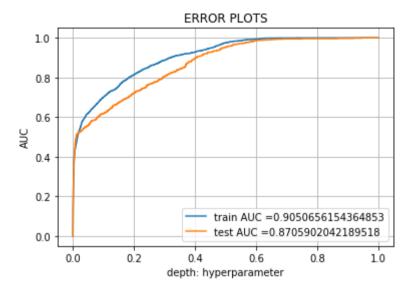
Fitting 2 folds for each of 24 candidates, totalling 48 fits

```
[Parallel(n jobs=40)]: Using backend LokyBackend with 40 concurrent workers.
[Parallel(n jobs=40)]: Done 4 out of 48 | elapsed:
                                                    30.2s remaining: 5.5min
[Parallel(n jobs=40)]: Done 9 out of 48
                                          elapsed: 1.5min remaining: 6.4min
[Parallel(n jobs=40)]: Done 14 out of 48 | elapsed: 1.9min remaining: 4.7min
[Parallel(n jobs=40)]: Done 19 out of 48 | elapsed: 2.8min remaining: 4.2min
[Parallel(n jobs=40)]: Done 24 out of 48 | elapsed: 4.1min remaining: 4.1min
                                          elapsed: 6.6min remaining: 4.3min
[Parallel(n jobs=40)]: Done 29 out of 48 |
[Parallel(n jobs=40)]: Done 34 out of 48 |
                                          elapsed: 7.6min remaining: 3.1min
[Parallel(n jobs=40)]: Done 39 out of 48 |
                                          elapsed: 11.9min remaining: 2.7min
[Parallel(n jobs=40)]: Done 44 out of 48 | elapsed: 14.5min remaining: 1.3min
[Parallel(n jobs=40)]: Done 48 out of 48
                                          elapsed: 21.0min finished
```

#### Heat Maps



```
In [282]: from sklearn.metrics import roc curve, auc
           best esti=100
          best depth=4
          xg4=XGBClassifier(n estimators=best esti,max depth=best depth,n jobs=10,class weight='balanced')
          xg4.fit(X tr final, y train up)
          y train pred = batch predict(xg4,X tr final.tocsr())
          v test pred = batch predict(xg4,X te final.tocsr())
          train fpr, train tpr, tr thresholds = roc_curve(y_train_up, y_train_pred)
          test fpr, test tpr, te thresholds = roc curve(y test up, y test pred)
          plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
          plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
          plt.legend()
          plt.xlabel("depth: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.grid()
           plt.show()
          #Credits:AppliedaAIcourse.com
          from sklearn.metrics import confusion matrix
          def predict(proba, threshould, fpr, tpr):
            t = threshould[np.argmax(fpr*(1-tpr))]
            # (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)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))
            predictions = []
            for i in proba:
              if i>=t:
                predictions.append(1)
              else:
                 predictions.append(0)
              return predictions
```



## In [0]:

#### ##Conclusion: Final

We can see that using upsampling on the data both train ans the test an implemeting the MLP Classifier We are getting the good auc score around 0.95. But using upsampling only for train set model overfits in train data.

Till now the best model is XGBClassifier with n\_iteration = 100 and depth = 2 which is giving a AUC score of 0.72 for churn It is cross validated and an tested on test data.

For Appetency XGBClassifier is best model AUC=0.84

For Upsampling XGBClassifier is best model AUC=0.87

and overall AUC =0.81

```
In [289]: #Conclusion for CHURN
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Algorithm", "AUC","Remarks"]
x.add_row(["Multinomial NB/Baseline Model ", 0.62,"Good"])
x.add_row(["DecisionTreeClassifier ", 0.67,"Good"])
x.add_row(["XGBClassifierClassifier", 0.72,"Best - Class Weight is Balanced"])
x.add_row(["Upsampling/ MLPClassifier /SMOTE", 0.71,'Same as XGBClassifier without upsampling'])
x.add_row(["Upsampling/ MLPClassifier /SMOTE/On Train Data", 0.60,'Bad/ Overfitting'])
x.add_row(["Upsampling/ MLPClassifier /Upsampling", 0.90,'Good but data is upsampled'])
x.add_row(["Upsampling/ MLPClassifier /Upsampling/On Train Data", 0.60,'Overfitting'])
print(x)
```

Algorithm	+   AUC	Remarks	
Multinomial NB/Baseline Model	0.62	Good	
DecisionTreeClassifier	0.67	Good	
XGBClassifierClassifier	0.72	Best - Class Weight is Balanced	
Upsampling/ MLPClassifier /SMOTE	0.71	Same as XGBClassifier without upsampling	
Upsampling/ MLPClassifier /SMOTE/On Train Data	0.6	Bad/ Overfitting	
Upsampling/ MLPClassifier /Upsampling	0.9	Good but data is upsampled	
Upsampling/ MLPClassifier /Upsampling/On Train Data	0.6	Overfitting	
Upsampling/ MLPClassifier /Upsampling	0.9	Good but data is upsampled	

After seeing the data Appetency and Upselling follows the same path but giving better results on XGBClassifier.

```
In [295]: from prettytable import PrettyTable
    x = PrettyTable()
    x.field_names = ["Estimator","Model" ,"AUC"]
    x.add_row(["Churn", "XGBClassifier n_iter=100, depth=2", 0.72])
    x.add_row(["Appetency", "XGBClassifier n_iter=100, depth=2", 0.84])
    x.add_row(["Upsampling","XGBClassifier n_iter=100, depth=4", 0.87])
    x.add_row(["Total", "Overall", 0.81])
    print(x)
```

Estimator   Model   AUC   +	+	LL	
Appetency   XGBClassifier n_iter=100, depth=2   0.84   Upsampling   XGBClassifier n_iter=100, depth=4   0.87	Estimator	Model	AUC
	Appetency Upsampling	XGBClassifier n_iter=100, depth=2 XGBClassifier n_iter=100, depth=4	0.84     0.87