ISE529 - Final Project

Santander Customer Transaction Prediction

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```
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Preface

Below is our work for the "Santander Customer Transaction Prediction" Competition on Kaggle. Our work is divided into three major portions; Data Exploration, Data Preprocessing, and Data Modeling.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix
```

In [2]:
```
data_train = pd.read_csv('train.csv')
data_test = pd.read_csv('test1.csv')
```

In [3]:
```
from sklearn.model_selection import KFold, cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from lightgbm import LGBMClassifier
import lightgbm as lgb
```

In [4]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from xgboost import XGBClassifier
from sklearn.utils import resample
from sklearn.preprocessing import QuantileTransformer
```

In [5]:
```
from sklearn.metrics import make_scorer, accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score, roc_curve
```

In [6]:
```
import keras
from keras.models import Sequential
from keras.layers import Dense
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
```

```
Using TensorFlow backend.
```

Data Exploration

We begin this project by first exploring our data to ensure it is suitable for modeling.

First we visualize the data with a simple head call. Here we can see that each identity has an identifying 'ID_code', a response variable of 'target', and 200 features (var_0 to var_199).

In [7]:
```
data_train.head()
```

Out[7]:

	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	...	var_
0	train_0	0	8.9255	-6.7863	11.9081	5.0930	11.4607	-9.2834	5.1187	18.6266	...	4.4
1	train_1	0	11.5006	-4.1473	13.8588	5.3890	12.3622	7.0433	5.6208	16.5338	...	7.6
2	train_2	0	8.6093	-2.7457	12.0805	7.8928	10.5825	-9.0837	6.9427	14.6155	...	2.9
3	train_3	0	11.0604	-2.1518	8.9522	7.1957	12.5846	-1.8361	5.8428	14.9250	...	4.4
4	train_4	0	9.8369	-1.4834	12.8746	6.6375	12.2772	2.4486	5.9405	19.2514	...	-1.4

5 rows × 202 columns

In [8]:
```
data_train.describe()
```

Out[8]:

	target	var_0	var_1	var_2	var_3	var_
count	200000.000000	200000.000000	200000.000000	200000.000000	200000.000000	200000.0000(
mean	0.100490	10.679914	-1.627622	10.715192	6.796529	11.0783:
std	0.300653	3.040051	4.050044	2.640894	2.043319	1.6231!
min	0.000000	0.408400	-15.043400	2.117100	-0.040200	5.0748(
25%	0.000000	8.453850	-4.740025	8.722475	5.254075	9.8831
50%	0.000000	10.524750	-1.608050	10.580000	6.825000	11.1082!
75%	0.000000	12.758200	1.358625	12.516700	8.324100	12.2611:
max	1.000000	20.315000	10.376800	19.353000	13.188300	16.6714(

8 rows × 201 columns

Then we confirm that our response is binary. And check to see the shape of our data finding 200,000 rows.

```
In [9]: data_train['target'].unique()
Out[9]: array([0, 1])
```

```
In [85]: data_train.shape
Out[85]: (200000, 210)
```

```
In [87]: data_test.shape # Does not have target value row
Out[87]: (200000, 209)
```

Now we check for missing and duplicate values. None were found.

```
In [86]: data_train.isnull().sum().sum()
Out[86]: 0
```

```
In [88]: data_test.isnull().sum().sum()
Out[88]: 0
```

```
In [89]: data_train.duplicated().sum()
Out[89]: 0
```

```
In [90]: data_test.duplicated().sum()
Out[90]: 0
```

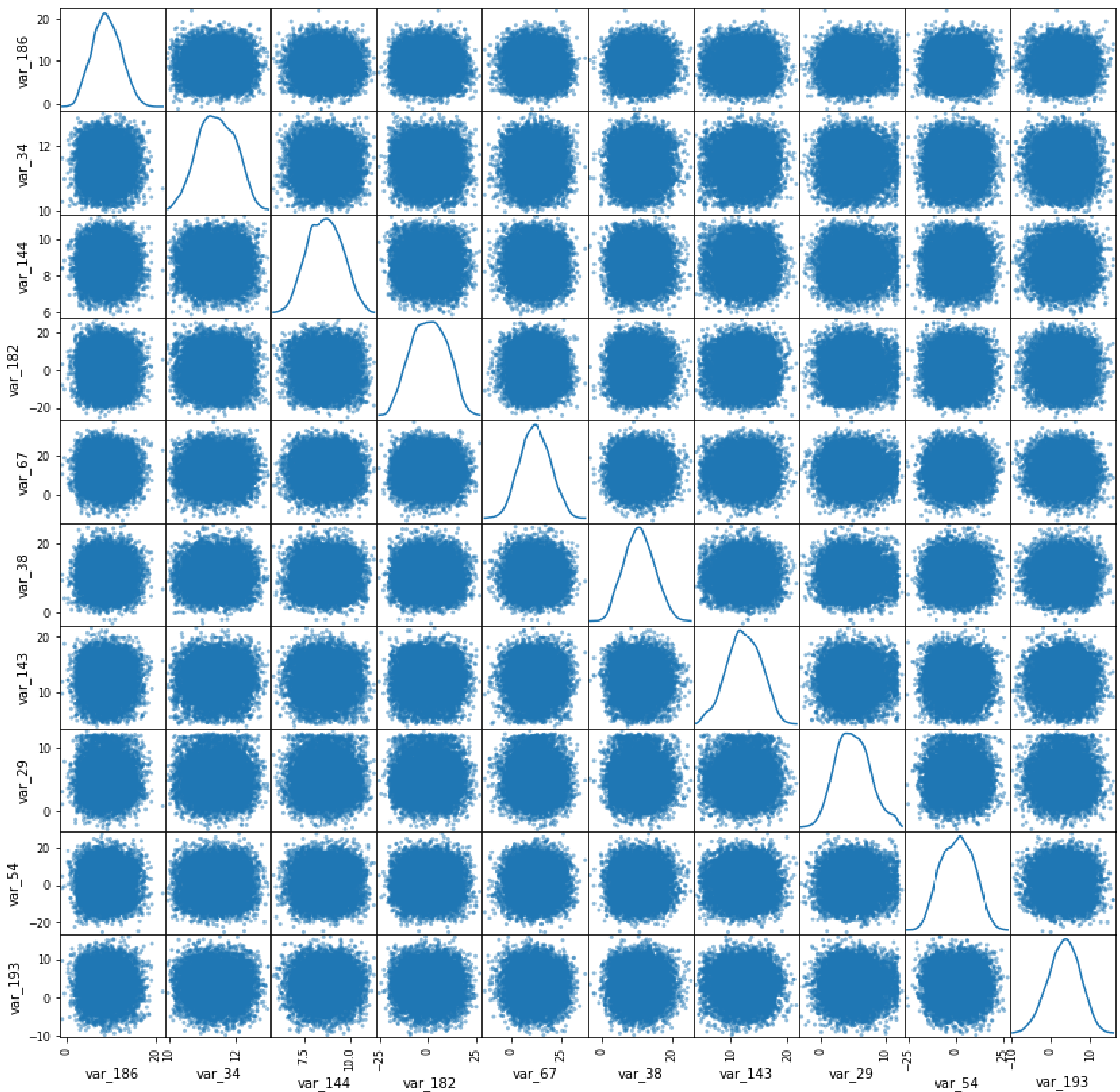
Next we search our data to see if there is any correlation between our data to see its effect on our future models. We first pull a random assortment of features to visualize the correlations. We then search for the maximum correlations. The maximum value is .009844, which shows that there is very little correlation between our feature set.

In [91]:
```
feature = data_train[2:].columns
random_feature = np.random.choice(feature, size=10, replace=False)
data_train[random_feature][::20].corr()
```

Out[91]:

	var_186	var_34	var_144	var_182	var_67	var_38	var_143	var_29	
var_186	1.000000	-0.006536	-0.006844	-0.009555	-0.003563	-0.005402	-0.008140	0.001525	-
var_34	-0.006536	1.000000	-0.004898	-0.007816	0.019814	0.009537	0.024916	-0.002942	
var_144	-0.006844	-0.004898	1.000000	-0.015985	0.008164	0.002632	0.004429	0.008370	
var_182	-0.009555	-0.007816	-0.015985	1.000000	0.017996	-0.002752	0.004099	0.006980	-
var_67	-0.003563	0.019814	0.008164	0.017996	1.000000	-0.011002	0.017284	-0.010370	
var_38	-0.005402	0.009537	0.002632	-0.002752	-0.011002	1.000000	-0.009415	0.001689	
var_143	-0.008140	0.024916	0.004429	0.004099	0.017284	-0.009415	1.000000	0.006824	-
var_29	0.001525	-0.002942	0.008370	0.006980	-0.010370	0.001689	0.006824	1.000000	
var_54	-0.002247	0.000259	0.010917	-0.007889	0.013309	0.017797	-0.005035	0.008258	
var_193	0.002442	-0.019912	0.003093	-0.005964	-0.019874	-0.007272	0.003488	-0.011328	-

In [92]:
```
scatter_matrix(data_train[random_feature][::20], diagonal= 'kde',figsize=(14,14));
```



We then search for the maximum correlations. The maximum value is .009844, which shows that there is very little correlation between our feature set.

In [13]:
```
correlations = data_train.drop(columns=['ID_code','target']).corr()\
              .abs().unstack().sort_values(kind="quicksort").reset_index()
correlations = correlations[correlations['level_0'] != correlations['level_1'
]]
correlations.tail(10)
```

Out[13]:

	level_0	level_1	0
39790	var_183	var_189	0.009359
39791	var_189	var_183	0.009359
39792	var_174	var_81	0.009490
39793	var_81	var_174	0.009490
39794	var_81	var_165	0.009714
39795	var_165	var_81	0.009714
39796	var_53	var_148	0.009788
39797	var_148	var_53	0.009788
39798	var_26	var_139	0.009844
39799	var_139	var_26	0.009844

Data Preprocessing

Feature Engineering

From research through participants notebooks we found that some feature engineering will assist in our prediction. Our goal for this portion is to utilize all 200 features to create 8 new features based on their combined statistical information

In [14]:
```
%%time
idx = features = data_train.columns.values[2:202]
for df in [data_train, data_test]:
    df['sum'] = df[idx].sum(axis=1)
    df['min'] = df[idx].min(axis=1)
    df['max'] = df[idx].max(axis=1)
    df['mean'] = df[idx].mean(axis=1)
    df['std'] = df[idx].std(axis=1)
    df['skew'] = df[idx].skew(axis=1)
    df['kurt'] = df[idx].kurtosis(axis=1)
    df['med'] = df[idx].median(axis=1)
```

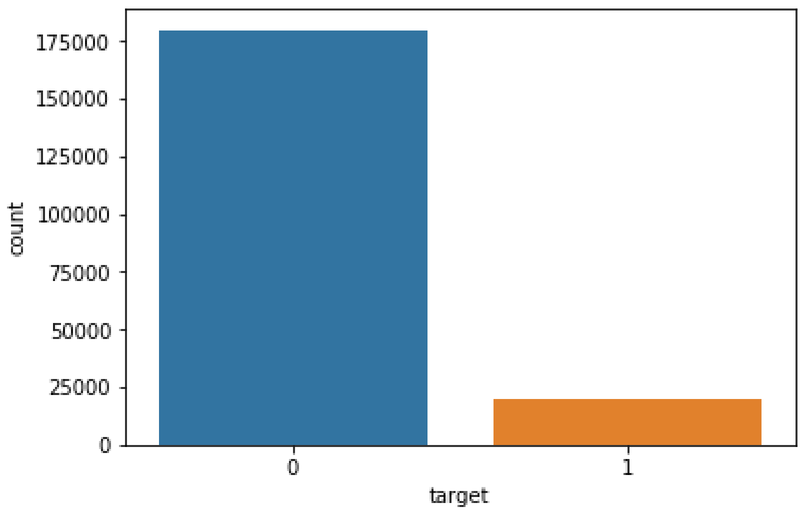
```
CPU times: user 13 s, sys: 9.3 s, total: 22.3 s
Wall time: 16 s
```

Data Balancing

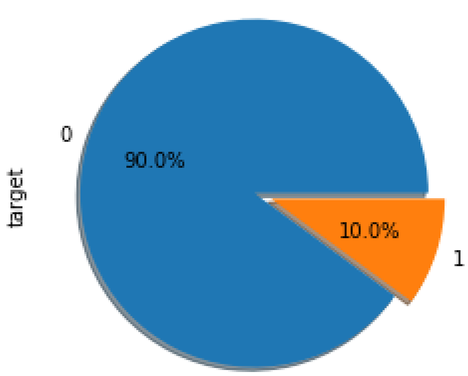
Now we'll address our dataset's unbalance. Here we want to create our data set in such a way that

Now we check the distribution between Target 0 and Target 1 to see how well balanced our provided dataset is. We can see that only about 10% of our data is in the Target 1 category. This is highly unbalanced, and we saw during our initial trials that it led to very poorly performing models that tended to predict Target 0 more often.

In [10]:
```
sns.countplot(data_train['target'])
plt.show()
```



In [11]:
```
data_train['target'].value_counts().plot.pie(explode=[0,0.1],autopct='%1.1f%%'
,
                                              shadow=True)
plt.show()
```



In [16]:
```
# Balancing method found at https://elitedatascience.com/imbalanced-classes
# Separate majority and minority classes
df_one = data_train[data_train.target==1]
df_zero = data_train[data_train.target==0]

# down sample majority class
df_zero_down_sampled = resample(df_zero,
                                 replace=True,      # sample with replacement
                                 n_samples=20098,    # to match majority class
                                 random_state=42) # reproducible results

# Combine minority class with down sampled majority class
df_down_sampled = pd.concat([df_one, df_zero_upsampled])

# Display new class counts
df_down_sampled.target.value_counts()
```

Out[16]:
```
1    20098
0    20098
Name: target, dtype: int64
```

Now that our data is balanced we will convert it to into our X and y's respective Train and Test sets.

In [17]:
```
y = df_down_sampled.target
X = df_down_sampled.drop(columns=['target','ID_code'])
```

In [18]:
```
X_pred = data_test.drop(columns=['ID_code'])
```

In [19]:
```
#kfold = KFold(n_splits = 5, random_state=1)
```

In [20]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size = .9,
                                                     test_size =.1)
```

Normalization

Now we normalize the data. We used three transformers and checked their performance. StandardScaler performed the best between itself, MinMaxScaler, QuantileTransformer.

In [21]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_pred = scaler.transform(X_pred)
```

In [22]:
```
#scaler = MinMaxScaler()
#X_train = scaler.fit_transform(X_train)
#X_test = scaler.transform(X_test)
#X_pred = scaler.transform(X_pred)
```

In [23]:
```
#scaler = QuantileTransformer(n_quantiles=10, random_state=0)
#X_train = scaler.fit_transform(X_train)
#X_test = scaler.transform(X_test)
#X_pred = scaler.transform(X_pred)
```

Principle Component Analysis

We attempted to use PCA to transform our data set. However, using the full data set proved to perform better in the end.

In [24]:
```
#pca = PCA(0.50).fit(X_train)
#pca.n_components_
```

In [25]:
```
#X_train_comp = pca.transform(X_train)
#X_test_comp = pca.transform(X_test)
```

Data Modeling

Initial Analysis

We initially tested various models with untuned hyper-parameters to see the general performance of the different

In [26]:
```
models = []
models.append(('LR',LogisticRegression(solver='liblinear')))
models.append(('LDA',LinearDiscriminantAnalysis()))
models.append(('KNN',KNeighborsClassifier()))
models.append(('Tree',DecisionTreeClassifier()))
models.append(('NB',GaussianNB())) # No additional tuning required
models.append(('SVM',SVC(kernel='rbf',gamma=1)))
models.append(('RF',RandomForestClassifier()))
models.append(('XGB',XGBClassifier()))
models.append(('GBM',LGBMClassifier()))
```

In [27]:
```
names = []
results = []
means = []
sdevs = []
scoring = 'accuracy'
```

In [28]:
```
for name, model in models:
    model.fit(X_train, y_train)
    means.append(model.score(X_test, y_test))
    #sdevs.append(cv_results.std())
    names.append(name)
```

```
/home/ec2-user/anaconda3/envs/amazonei_tensorflow_p36/lib/python3.6/site-pack
ages/sklearn/discriminant_analysis.py:388: UserWarning: Variables are colline
ar.
  warnings.warn("Variables are collinear.")
/home/ec2-user/anaconda3/envs/amazonei_tensorflow_p36/lib/python3.6/site-pack
ages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of n_es
timators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

In [29]:
```
df1 = pd.DataFrame()
df1['name'] = names
df1['accuracy'] = means
#df1['accuracy_std_dev'] = sdevs
df1
```

Out[29]:

	name	accuracy
0	LR	0.784328
1	LDA	0.785572
2	KNN	0.564428
3	Tree	0.597512
4	NB	0.797512
5	SVM	0.549005
6	RF	0.654478
7	XGB	0.736318
8	GBM	0.784080

Here we see the most promising models include Logistic Regression, Linear Discriminant Analysis, Naive Bayes, XGBoost, and Light GMB. Next we'll check the performance of a generic neural network.

In [30]:
```
model = Sequential()
model.add(Dense(128,kernel_initializer = 'uniform', activation = 'relu',
                input_shape=(208,)))
model.add(Dense(128,kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(64,kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(1,kernel_initializer = 'uniform', activation = 'sigmoid'))

model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'
])
```

```
WARNING:tensorflow:From /home/ec2-user/anaconda3/envs/amazonei_tensorflow_p3
6/lib/python3.6/site-packages/tensorflow/python/ops/resource_variable_ops.py:
435: colocate_with (from tensorflow.python.framework.ops) is deprecated and w
ill be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
```

In [ ]:
```
model.fit(X_train,y_train,epochs=20,batch_size=1, verbose=0)
```

In [41]:
```
model.evaluate(X_test,y_test,verbose=0)
```

Out[41]:
```
[2.6477809452891945, 0.7139303684234619]
```

This neural network after 20 epochs ranks 6th of our initial models. The 20th epoch resulted in the following loss and accuracy scores; loss: 0.0536 - accuracy: 0.9824. As it is such a time intensive model, we will focus on other models before revisiting the neural network.

Data Tuning

We now move to tuning our models. With a dataset this size, we found that tuning took a significant amount of time. This limited us from fully tuning all models, but instead focusing on the models with highest potential.

Gaussian Naive Bayes

In [44]:
```
m0 = GaussianNB() # No Tuning Required
m0.fit(X_train, y_train)
m0.score(X_test, y_test)
```

Out[44]: 0.7975124378109453

In [45]:
```
yproba1 = m0.predict_proba(X_test)
```

In [46]:
```
y_proba1 = yproba1[:,1]
fpr1, tpr1, thresholds1 = roc_curve(y_test,y_proba1)

df1 = pd.DataFrame()
df1['fpr'] = fpr1
df1['tpr'] = tpr1
df1['threshold'] = thresholds1
```

In [47]:
```
auc1 = roc_auc_score(y_test,y_proba1)
auc1
```

Out[47]: 0.8747632474968342

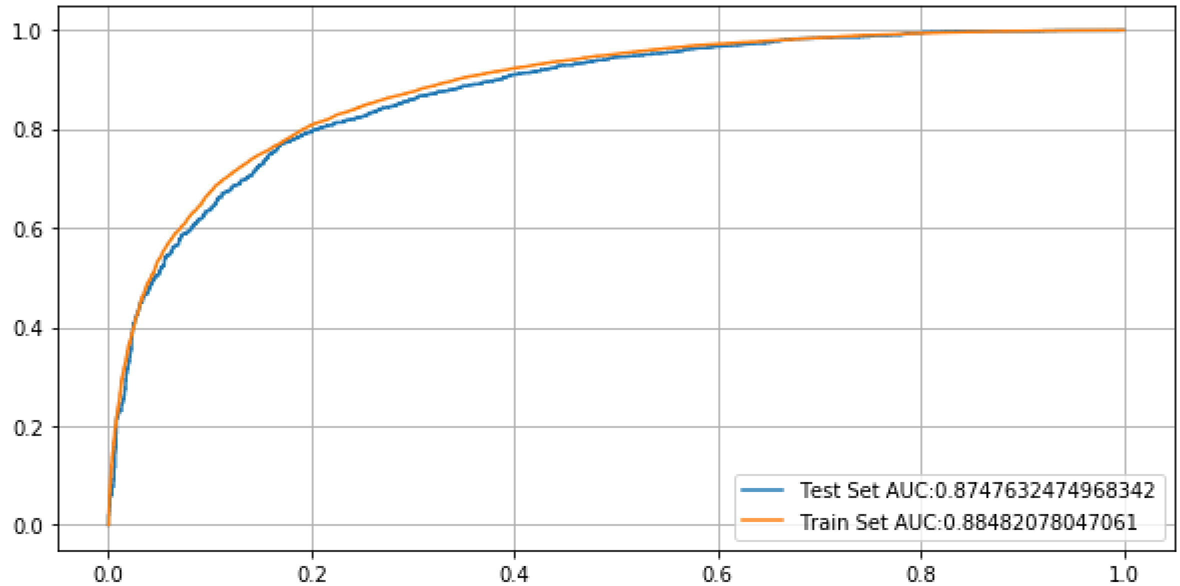
In [49]:
```
yproba2 = m0.predict_proba(X_train)
```

In [50]:
```
y_proba2 = yproba2[:,1]
fpr2, tpr2, thresholds2 = roc_curve(y_train,y_proba2)

df1 = pd.DataFrame()
df1['fpr'] = fpr2
df1['tpr'] = tpr2
df1['threshold'] = thresholds2

auc2 = roc_auc_score(y_train,y_proba2)
```

In [51]:
```
plt.figure(figsize=(10,5))
plt.plot(fpr1,tpr1,label='Test Set AUC:'+str(auc1))
plt.plot(fpr2,tpr2,label='Train Set AUC:'+str(auc2))
plt.legend(loc=4)
plt.grid()
```



Logistic Regression

In [52]:
```
# Choose the type of classifier.
clf = LogisticRegression()

# Choose some parameter combinations to try
parameters = {'penalty': ['l1', 'l2'],
              'C':  np.logspace(-4, 4, 20),
              'solver': ['liblinear'],
             }

# Type of scoring used to compare parameter combinations
acc_scorer = make_scorer(accuracy_score)

# Run the grid search
grid_obj = GridSearchCV(clf, parameters, scoring=acc_scorer)
grid_obj = grid_obj.fit(X_train, y_train)

# Set the clf to the best combination of parameters
m1 = grid_obj.best_estimator_

# Fit the best algorithm to the data.
m1.fit(X_train, y_train)
```

```
/home/ec2-user/anaconda3/envs/amazonei_tensorflow_p36/lib/python3.6/site-pack
ages/sklearn/model_selection/_split.py:2053: FutureWarning: You should specif
y a value for 'cv' instead of relying on the default value. The default value
will change from 3 to 5 in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

Out[52]:
```
LogisticRegression(C=0.23357214690901212, class_weight=None, dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [53]:
```
m1.score(X_test,y_test)
```

Out[53]:
```
0.7843283582089552
```

In [54]:
```
yproba1 = m1.predict_proba(X_test)
```

In [55]:
```
y_proba1 = yproba1[:,1]
fpr1, tpr1, thresholds1 = roc_curve(y_test,y_proba1)

df1 = pd.DataFrame()
df1['fpr'] = fpr1
df1['tpr'] = tpr1
df1['threshold'] = thresholds1
```

In [56]:
```
auc1 = roc_auc_score(y_test,y_proba1)
auc1
```

Out[56]:
```
0.8617194592983711
```

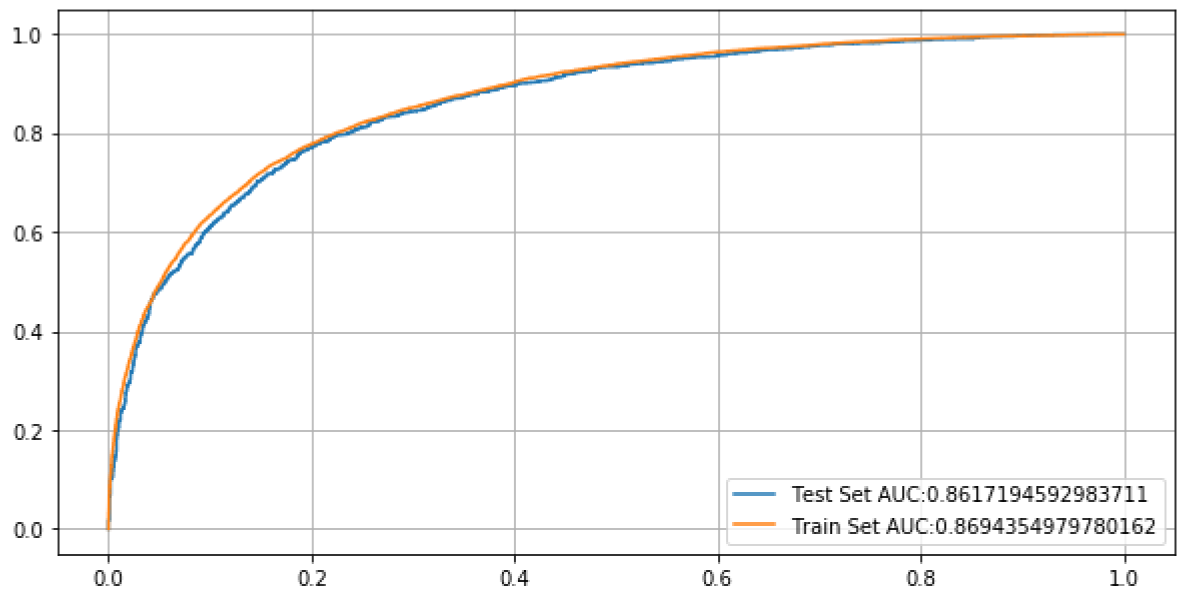
In [58]:
```
yproba2 = m1.predict_proba(X_train)
```

In [59]:
```
y_proba2 = yproba2[:,1]
fpr2, tpr2, thresholds2 = roc_curve(y_train,y_proba2)

df1 = pd.DataFrame()
df1['fpr'] = fpr2
df1['tpr'] = tpr2
df1['threshold'] = thresholds2

auc2 = roc_auc_score(y_train,y_proba2)
```

In [60]:
```
plt.figure(figsize=(10,5))
plt.plot(fpr1,tpr1,label='Test Set AUC:'+str(auc1))
plt.plot(fpr2,tpr2,label='Train Set AUC:'+str(auc2))
plt.legend(loc=4)
plt.grid()
```



Our logistic regression remains relatively unchanged after tuning.

Linear Discriminant Analysis

In [ ]:
```
# Choose the type of classifier.
clf = LinearDiscriminantAnalysis()

# Choose some parameter combinations to try
parameters = {'solver': ['svd','lsqr'],
              'n_components': [5,10,100,None],
             }

# Type of scoring used to compare parameter combinations
acc_scorer = make_scorer(accuracy_score)

# Run the grid search
grid_obj = GridSearchCV(clf, parameters, scoring=acc_scorer)
grid_obj = grid_obj.fit(X_train, y_train)

# Set the clf to the best combination of parameters
m2 = grid_obj.best_estimator_

# Fit the best algorithm to the data.
m2.fit(X_train, y_train)
```

In [62]:
```
m2.score(X_test,y_test)
```

Out[62]:
```
0.7855721393034826
```

In [63]:
```
yproba1 = m2.predict_proba(X_test)
```

In [64]:
```
y_proba1 = yproba1[:,1]
fpr1, tpr1, thresholds1 = roc_curve(y_test,y_proba1)

df1 = pd.DataFrame()
df1['fpr'] = fpr1
df1['tpr'] = tpr1
df1['threshold'] = thresholds1
```

In [65]:
```
auc1 = roc_auc_score(y_test,y_proba1)
auc1
```

Out[65]:
```
0.8616508963675014
```

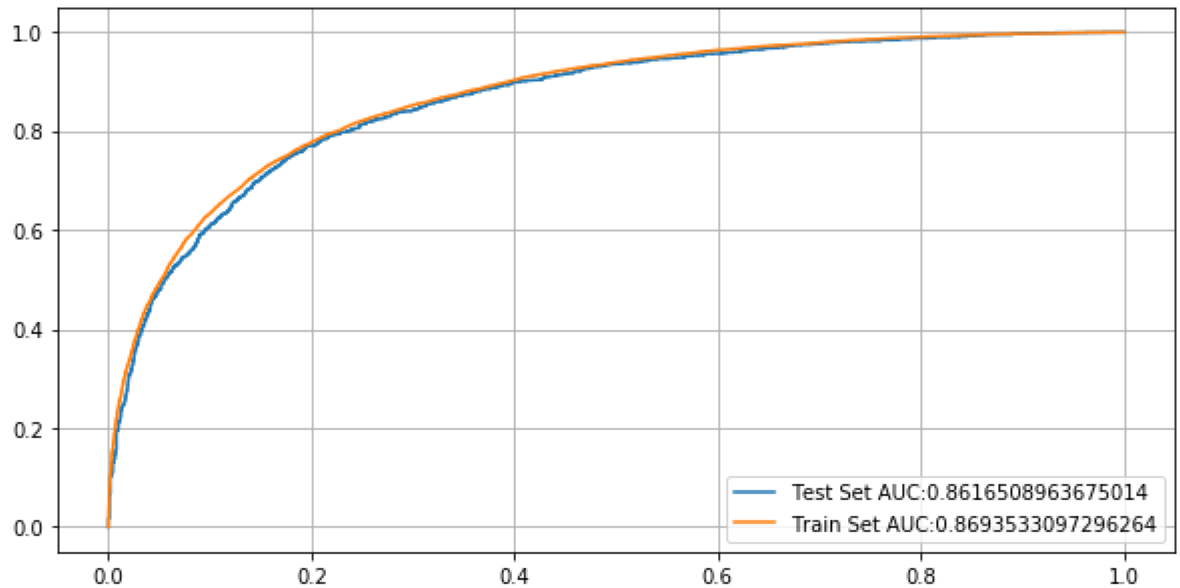
In [66]:
```
yproba2 = m2.predict_proba(X_train)
```

In [67]:
```
y_proba2 = yproba2[:,1]
fpr2, tpr2, thresholds2 = roc_curve(y_train,y_proba2)

df1 = pd.DataFrame()
df1['fpr'] = fpr2
df1['tpr'] = tpr2
df1['threshold'] = thresholds2

auc2 = roc_auc_score(y_train,y_proba2)
```

In [68]:
```
plt.figure(figsize=(10,5))
plt.plot(fpr1,tpr1,label='Test Set AUC:'+str(auc1))
plt.plot(fpr2,tpr2,label='Train Set AUC:'+str(auc2))
plt.legend(loc=4)
plt.grid()
```



Another slight improvement from tuning; however, still no significant increase.

Extreme Gradient Boost

Now we move on to our XGBoost. This model has potential; however, it was a challenge to train it due to the time requirements to run through our data set. We used the highspeed computing available from Amazon Web Services' SageMaker console, but still saw our ensemble models taking a significant amount of time to run (hours for anything greater than a 6 parameter, 3 fold GridSearch).

We attempted tune with smaller batches, using PCA to limit the features, and used a hypopt function to train without kfolds. But all of those methods left us with degraded results. In the end, our model performed better with more limited tuning while compared to the entire balanced dataset.

In [69]:
```
%%time
# Choose the type of classifier.
clf = XGBClassifier()

# Choose some parameter combinations to try
parameters = {'n_estimators': [100, 500],
              'max_depth': [2],
              'learning_rate': [.1]
             }

# Type of scoring used to compare parameter combinations
acc_scorer = make_scorer(accuracy_score)

# Run the grid search
grid_obj = GridSearchCV(clf, parameters, scoring=acc_scorer, cv=3)
grid_obj = grid_obj.fit(X_train, y_train)

# Set the clf to the best combination of parameters
m3 = grid_obj.best_estimator_

# Fit the best algorithm to the data.
m3.fit(X_train, y_train)
```

```
CPU times: user 12min 25s, sys: 0 ns, total: 12min 25s
Wall time: 12min 25s
```

In [71]:
```
m3.score(X_test,y_test)
```

Out[71]:
```
0.7925373134328358
```

In [72]:
```
yproba1 = m3.predict_proba(X_test)
```

In [73]:
```
y_proba1 = yproba1[:,1]
fpr1, tpr1, thresholds1 = roc_curve(y_test,y_proba1)

df1 = pd.DataFrame()
df1['fpr'] = fpr1
df1['tpr'] = tpr1
df1['threshold'] = thresholds1
```

In [74]:
```
auc1 = roc_auc_score(y_test,y_proba1)
auc1
```

Out[74]:
```
0.868544193635578
```

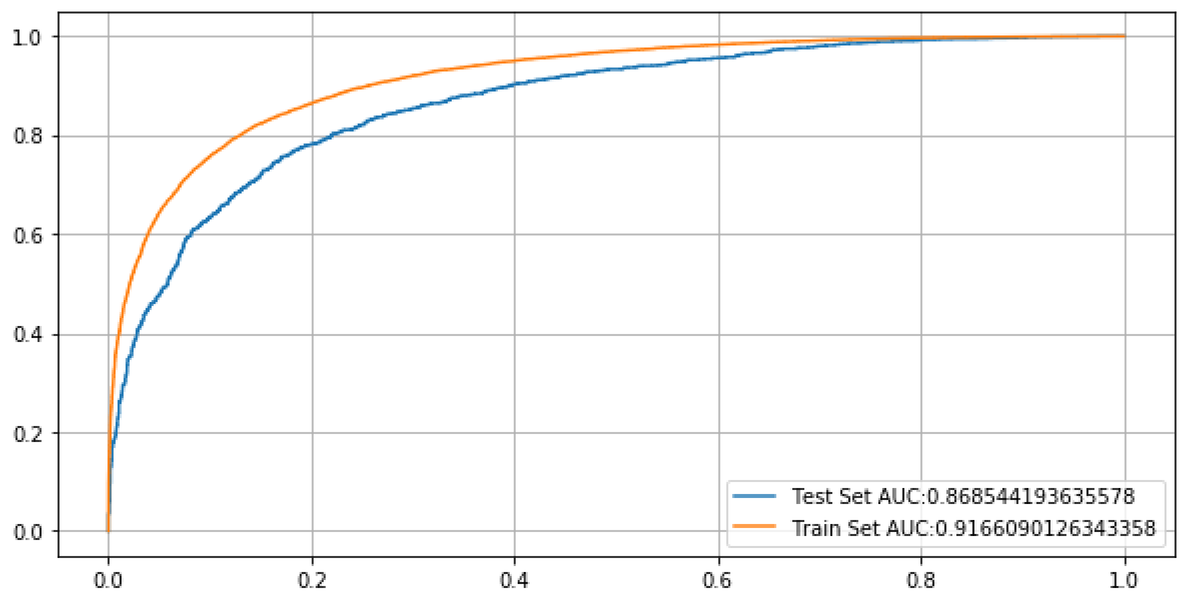
In [75]:
```
yproba2 = m3.predict_proba(X_train)
```

In [76]:
```
y_proba2 = yproba2[:,1]
fpr2, tpr2, thresholds2 = roc_curve(y_train,y_proba2)

df1 = pd.DataFrame()
df1['fpr'] = fpr2
df1['tpr'] = tpr2
df1['threshold'] = thresholds2

auc2 = roc_auc_score(y_train,y_proba2)
```

In [77]:
```
plt.figure(figsize=(10,5))
plt.plot(fpr1,tpr1,label='Test Set AUC:'+str(auc1))
plt.plot(fpr2,tpr2,label='Train Set AUC:'+str(auc2))
plt.legend(loc=4)
plt.grid()
```



We see an improvement of almost 6 percent with our tuned model placing XGBoost as our current top model. However, despite the tuning we are still performing relatively poorly compared to the other competitors. To improve our performance further we moved onto the Light GMB Model

Light GMB Model - Final Submission

So far our efforts have resulted in small improvements. To increase these, we researched the notebooks of past competitors to find methods that can help us improve our scores from high 70s/low 80s to high 80s/low 90s. The most beneficial Jupyter Notebook we utilized was "Santander Magic LGB 0.901" by Nanashi, which introduced a better approach "Light Gradient Boost Model" that results in a significantly increased score.

In [78]:
```
from numba import jit
```

In [79]:
```
@jit
def augment(x,y,t=2):
    xs,xn = [],[]
    for i in range(t):
        mask = y>0
        x1 = x[mask].copy()
        ids = np.arange(x1.shape[0])
        for c in range(x1.shape[1]):
            np.random.shuffle(ids)
            x1[:,c] = x1[ids][:,c]
        xs.append(x1)

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

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

In [80]:
```
param = {
    'bagging_freq': 5,
    'bagging_fraction': 0.335,
    'boost_from_average':'false',
    'boost': 'gbdt',
    'feature_fraction': 0.041,
    'learning_rate': 0.0083,
    'max_depth': -1,
    'metric':'auc',
    'min_data_in_leaf': 80,
    'min_sum_hessian_in_leaf': 10.0,
    'num_leaves': 13,
    'num_threads': 8,
    'tree_learner': 'serial',
    'objective': 'binary',
    'verbosity': -1
}
```

In [81]:
```
#kfold = 15
#folds = StratifiedKFold(n_splits=kfold, shuffle=False, random_state=44000)
num_folds = 11
features = [c for c in df_down_sampled.columns if c not in ['ID_code', 'targe
t']]

folds = KFold(n_splits=num_folds, random_state=2319)
oof = np.zeros(len(df_down_sampled))
getVal = np.zeros(len(df_upsampled))
predictions = np.zeros(200000)
feature_importance_df = pd.DataFrame()
```

In [ ]:
```
test = data_test.iloc[:,1::]
for fold_, (trn_idx, val_idx) in enumerate(folds.split(df_down_sampled.values,
                                                      df_down_sampled.values
)):

    X_train, y_train = df_down_sampled.iloc[trn_idx][features], \
                       df_down_sampled.target.iloc[trn_idx]
    X_valid, y_valid = df_down_sampled.iloc[val_idx][features], \
                       df_down_sampled.target.iloc[val_idx]

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

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

    clf = lgb.train(param, trn_data, 1000000, valid_sets = [trn_data, val_data
],
                    verbose_eval=5000, early_stopping_rounds = 4000)
    oof[val_idx] = clf.predict(df_down_sampled.iloc[val_idx][features],
                               num_iteration=clf.best_iteration)
    getVal[val_idx]+= clf.predict(df_down_sampled.iloc[val_idx][features],
                                  num_iteration=clf.best_iteration) / folds.n_
splits

    fold_importance_df = pd.DataFrame()
    fold_importance_df["feature"] = features
    fold_importance_df["importance"] = clf.feature_importance()
    fold_importance_df["fold"] = fold_ + 1
    feature_importance_df = pd.concat([feature_importance_df, fold_importance_
df], axis=0)

    predictions += clf.predict(test[features],
                               num_iteration=clf.best_iteration) / folds.n_spl
its;
```

One fold results shown here to save space

Early stopping, best iteration is:

[16750] training's auc: 0.960467 test's auc: 0.901262

As can be seen this model has the highest AUC across the test set of our models. We now submit our predictions to Kaggle.

In [84]:
```
sub6 = pd.DataFrame({"ID_code":data_test["ID_code"].values})
sub6["target"] = predictions
sub6.to_csv("sub6.csv", index=False)
```

This allowed us to create a tuned Light GBM model to increase our Kaggle score to ***89.73%***. This score falls within the middle of the competition submissions. With the highest score on the leader board being 92.6%.