Santander Value Prediction Plot

by Ning Liu, Yilin Liu

In [33]:
```
import numpy as np
import pandas as pd
from sklearn import model_selection
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.preprocessing import normalize
import lightgbm as lgb
import random
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
random.seed(2018)
```

```
/Users/yilinliu/anaconda3/lib/python3.7/site-packages/lightgbm/__ini
t__.py:46: UserWarning:

Starting from version 2.2.1, the library file in distribution wheels
for macOS is built by the Apple Clang (Xcode_9.4.1) compiler.
This means that in case of installing LightGBM from PyPI via the ``p
ip install lightgbm`` command, you don't need to install the gcc com
piler anymore.
Instead of that, you need to install the OpenMP library, which is re
quired for running LightGBM on the system with the Apple Clang compi
ler.
You can install the OpenMP library by the following command: ``brew
install libomp``.
```

1. Load train and test data

In [34]:
```
trainRaw = pd.read_csv('./data/train.csv')
testRaw = pd.read_csv('./data/test.csv')
train = trainRaw.drop(["ID", "target"], axis=1)
target = np.log1p(trainRaw["target"].values)
test = testRaw.drop(["ID"], axis=1)
```

2. Remove some constant and duplicate data

In [35]:
```
#remove constant
colsToRemove = []
for col in train.columns:
    if train[col].std() == 0:
        colsToRemove.append(col)

train.drop(colsToRemove, axis=1, inplace=True)
test.drop(colsToRemove, axis=1, inplace=True)

#remove duplicate
colsToRemove = []
colsScaned = []
dupList = {}
columns = train.columns
for i in range(len(columns)-1):
    v = train[columns[i]].values
    dupCols = []
    for j in range(i+1,len(columns)):
        if np.array_equal(v, train[columns[j]].values):
            colsToRemove.append(columns[j])
            if columns[j] not in colsScaned:
                dupCols.append(columns[j])
                colsScaned.append(columns[j])
                dupList[columns[i]] = dupCols
train.drop(colsToRemove, axis=1, inplace=True)
test.drop(colsToRemove, axis=1, inplace=True)

print("After remove Constant and Dup Train set size: {}".format(train.
shape))
print("After remove Constant and Dup Test set size: {}".format(test.sh
ape))
```

```
After remove Constant and Dup Train set size: (4459, 4730)
After remove Constant and Dup Test set size: (49342, 4730)
```

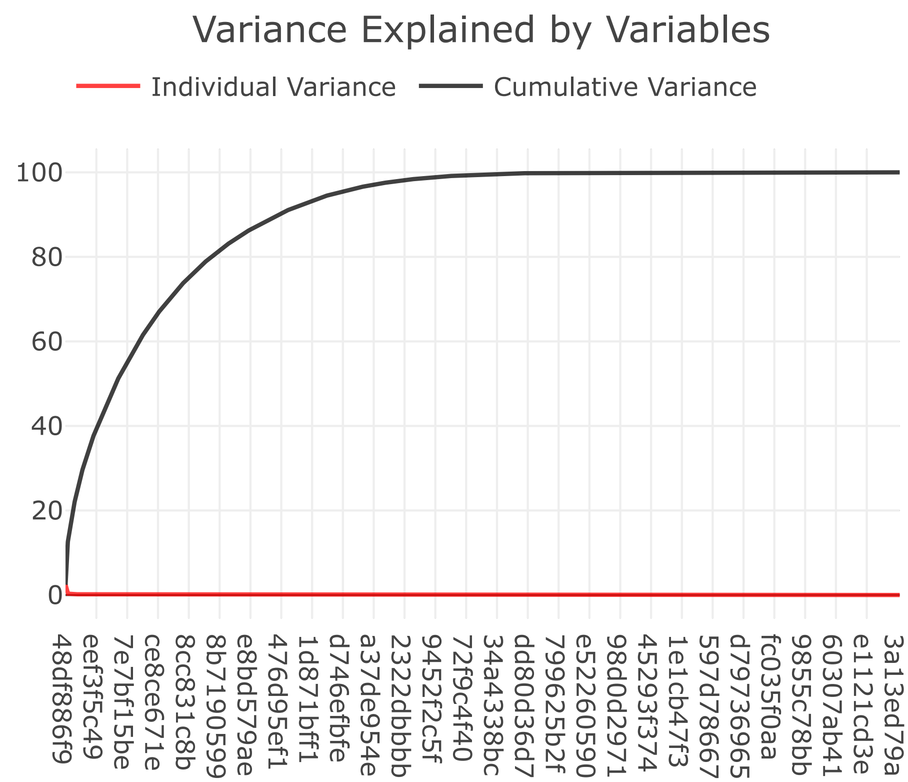
3. Perform feature learning

In [36]:
```
def addSumZeros(train, test, features):
    flist = [x for x in train.columns if not x in ['ID','target']]
    if 'SumZeros' in features:
        train.insert(1, 'SumZeros', (train[flist] == 0).astype(int).su
m(axis=1))
        test.insert(1, 'SumZeros', (test[flist] == 0).astype(int).sum(
axis=1))
    flist = [x for x in train.columns if not x in ['ID','target']]
    return train, test

def addSumValues(train, test, features):
    flist = [x for x in train.columns if not x in ['ID','target']]
    if 'SumValues' in features:
        train.insert(1, 'SumValues', (train[flist] != 0).astype(int).s
um(axis=1))
        test.insert(1, 'SumValues', (test[flist] != 0).astype(int).sum
(axis=1))
    flist = [x for x in train.columns if not x in ['ID','target']]
    return train, test

def addOtherAgg(train, test, features):
    flist = [x for x in train.columns if not x in ['ID','target','SumZ
eros','SumValues']]
    if 'OtherAgg' in features:
        train['Mean']   = train[flist].mean(axis=1)
        train['Median'] = train[flist].median(axis=1)
        train['Mode']   = train[flist].mode(axis=1)
        train['Max']    = train[flist].max(axis=1)
        train['Var']    = train[flist].var(axis=1)
        train['Std']    = train[flist].std(axis=1)

        test['Mean']   = test[flist].mean(axis=1)
        test['Median'] = test[flist].median(axis=1)
        test['Mode']   = test[flist].mode(axis=1)
        test['Max']    = test[flist].max(axis=1)
        test['Var']    = test[flist].var(axis=1)
        test['Std']    = test[flist].std(axis=1)
    flist = [x for x in train.columns if not x in ['ID','target','SumZ
eros','SumValues']]

    return train, test

train, test = addSumZeros(train, test, ['SumZeros'])
train, test = addSumValues(train, test, ['SumValues'])
train, test = addOtherAgg(train, test, ['OtherAgg'])
```

Draw variance plot

In [37]:

```
#plot for variance
import matplotlib.pyplot as plt
import plotly.graph_objs as go
from plotly.offline import init_notebook_mode, iplot
from sklearn.preprocessing import StandardScaler
init_notebook_mode(connected=True)
# Calculating Eigenvectors and eigenvalues
standardized_train = StandardScaler().fit_transform(train.values)
mean_vec = np.mean(standardized_train, axis=0)
cov_matrix = np.cov(standardized_train.T)
eig_vals, eig_vecs = np.linalg.eig(cov_matrix)
eig_pairs = [ (np.abs(eig_vals[i]),eig_vecs[:,i]) for i in range(len(e
ig_vals))]
eig_pairs.sort(key = lambda x: x[0], reverse= True)
tot = sum(eig_vals)
# Individual explained variance
var_exp = [(i/tot)*100 for i in sorted(eig_vals, reverse=True)]
var_exp_real = [v.real for v in var_exp]
# Cumulative explained variance
cum_var_exp = np.cumsum(var_exp)
cum_exp_real = [v.real for v in cum_var_exp]
trace1 = go.Scatter(x=train.columns, y=var_exp_real, name="Individual
Variance", opacity=0.75, marker=dict(color="red"))
trace2 = go.Scatter(x=train.columns, y=cum_exp_real, name="Cumulative
Variance", opacity=0.75, marker=dict(color="black"))
layout = dict(height=400, title='Variance Explained by Variables', leg
end=dict(orientation="h", x=0, y=1.2));
fig = go.Figure(data=[trace1, trace2], layout=layout);
iplot(fig);
```



In [38]:
```
#Perform k means
flist_kmeans = []
flist = [x for x in train.columns if not x in ['ID','target']]
for ncl in range(2,11):
    cls = KMeans(n_clusters=ncl)
    cls.fit_predict(train[flist].values)
    train['kmeans_cluster_'+str(ncl)] = cls.predict(train[flist].value
s)
    test['kmeans_cluster_'+str(ncl)] = cls.predict(test[flist].values)
```

In [39]:
```
#Perform PCA
n_components = 20
flist_pca = []
pca = PCA(n_components=n_components)
flist = [x for x in train.columns if not x in ['ID','target']]
train_projected = pca.fit_transform(normalize(train[flist], axis=0))
test_projected = pca.transform(normalize(test[flist], axis=0))
for npca in range(0, n_components):
    train.insert(1, 'PCA_'+str(npca+1), train_projected[:, npca])
    test.insert(1, 'PCA_'+str(npca+1), test_projected[:, npca])
```

Draw PCA plot

In [40]:

```
#draw PCA plot
import plotly.graph_objs as go
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
def plot_3_components(x_trans, title):
    trace = go.Scatter3d(x=x_trans[:,0], y=x_trans[:,1], z = x_trans[:
,2],
                          mode = 'markers', showlegend = False,
                          marker = dict(size = 8, color=x_trans[:,1],
                          line = dict(width = 1, color = '#f7f4f4'), o
pacity = 0.5))
    layout = go.Layout(title = title, showlegend= True)
    fig = dict(data=[trace], layout=layout)
    iplot(fig)
plot_3_components(train_projected, 'First Three Component of PCA')
```

First Three Component of PCA

Run model

In [41]:
```
def run_lgb(train_X, train_y, val_X, val_y, test_X):
    params = {
        "objective" : "regression",
        "metric" : "rmse",
        "num_leaves" : 30,
        "learning_rate" : 0.01,
        "bagging_fraction" : 0.7,
        "feature_fraction" : 0.7,
        "bagging_frequency" : 5,
        "bagging_seed" : 2018,
        "verbosity" : -1
    }

    lgtrain = lgb.Dataset(train_X, label=train_y)
    lgval = lgb.Dataset(val_X, label=val_y)
    evals_result = {}
    model = lgb.train(params, lgtrain, 1000, valid_sets=[lgtrain, lgva
l], early_stopping_rounds=100,
                          verbose_eval=200, evals_result=evals_result)
    pred_test_y = model.predict(test_X, num_iteration=model.best_itera
tion)
    return pred_test_y, model, evals_result
```

In [42]:
```
# Training LGB
seeds = [42, 2018]
pred_test_full_seed = 0
for seed in seeds:
    kf = model_selection.KFold(n_splits=5, shuffle=True, random_state=
seed)
    pred_test_full = 0
    for dev_index, val_index in kf.split(train):
        dev_X, val_X = train.loc[dev_index,:], train.loc[val_index,:]
        dev_y, val_y = target[dev_index], target[val_index]
        pred_test, model, evals_result = run_lgb(dev_X, dev_y, val_X,
val_y, test)
        pred_test_full += pred_test
    pred_test_full /= 5.
    pred_test_full = np.expm1(pred_test_full)
    pred_test_full_seed += pred_test_full
pred_test_full_seed /= np.float(len(seeds))
print("LightGBM Training Completed!!!")
```

```
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.19687        valid_1's rmse: 1.37702
[400]   training's rmse: 1.01183        valid_1's rmse: 1.36497
[600]   training's rmse: 0.896778       valid_1's rmse: 1.36336
Early stopping, best iteration is:
[592]   training's rmse: 0.900839       valid_1's rmse: 1.36293
Training until validation scores don't improve for 100 rounds.
```

```
[200]   training's rmse: 1.1841 valid_1's rmse: 1.42404
[400]   training's rmse: 0.999223       valid_1's rmse: 1.39722
Early stopping, best iteration is:
[425]   training's rmse: 0.982307       valid_1's rmse: 1.39663
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.19315        valid_1's rmse: 1.41858
[400]   training's rmse: 1.00958        valid_1's rmse: 1.40267
Early stopping, best iteration is:
[416]   training's rmse: 0.998965       valid_1's rmse: 1.40213
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.19581        valid_1's rmse: 1.4072
[400]   training's rmse: 1.01631        valid_1's rmse: 1.37626
[600]   training's rmse: 0.904801       valid_1's rmse: 1.37277
[800]   training's rmse: 0.818532       valid_1's rmse: 1.37288
Early stopping, best iteration is:
[712]   training's rmse: 0.853768       valid_1's rmse: 1.37218
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.1973 valid_1's rmse: 1.36789
[400]   training's rmse: 1.01271        valid_1's rmse: 1.34901
Early stopping, best iteration is:
[364]   training's rmse: 1.03823        valid_1's rmse: 1.34837
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.19319        valid_1's rmse: 1.39006
[400]   training's rmse: 1.00802        valid_1's rmse: 1.36154
Early stopping, best iteration is:
[487]   training's rmse: 0.953766       valid_1's rmse: 1.36003
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.17885        valid_1's rmse: 1.47467
[400]   training's rmse: 0.997238       valid_1's rmse: 1.4574
[600]   training's rmse: 0.883592       valid_1's rmse: 1.4575
Early stopping, best iteration is:
[549]   training's rmse: 0.909437       valid_1's rmse: 1.45583
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.19335        valid_1's rmse: 1.38986
[400]   training's rmse: 1.0118 valid_1's rmse: 1.36534
[600]   training's rmse: 0.897281       valid_1's rmse: 1.3615
Early stopping, best iteration is:
[537]   training's rmse: 0.930082       valid_1's rmse: 1.36114
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.19914        valid_1's rmse: 1.374
[400]   training's rmse: 1.01488        valid_1's rmse: 1.34672
[600]   training's rmse: 0.900099       valid_1's rmse: 1.34472
Early stopping, best iteration is:
[526]   training's rmse: 0.938417       valid_1's rmse: 1.34325
Training until validation scores don't improve for 100 rounds.
[200]   training's rmse: 1.20032        valid_1's rmse: 1.36213
[400]   training's rmse: 1.01468        valid_1's rmse: 1.35351
Early stopping, best iteration is:
[342]   training's rmse: 1.05776        valid_1's rmse: 1.35285
LightGBM Training Completed!!!
```

In [43]:

```
# feature importance
print("Features Importance")
gain = model.feature_importance('gain')
featureimp = pd.DataFrame({'feature':model.feature_name(),
                   'split':model.feature_importance('split'),
                   'gain':100 * gain / gain.sum()}).sort_values('gain'
, ascending=False)
```

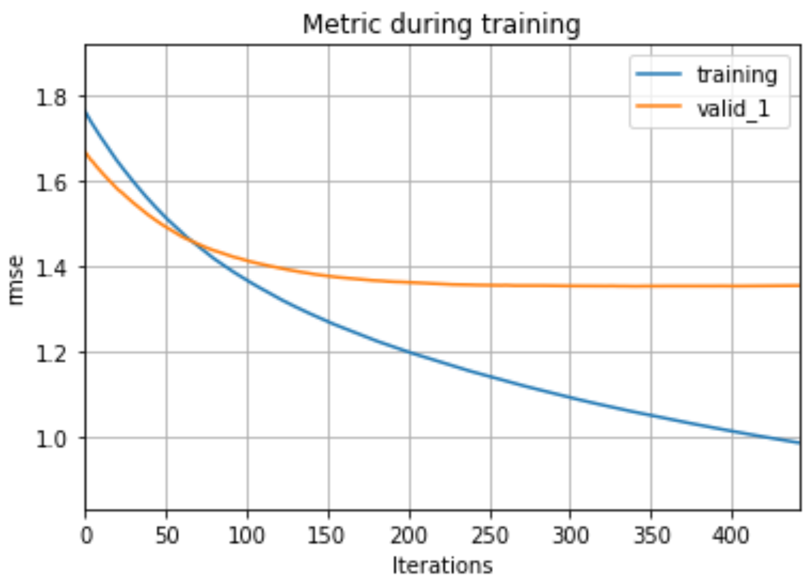
```
Features Importance
```

Draw Top 15 important features and write to aubmission

In [44]:

```
print(featureimp[:15])
_ = lgb.plot_metric(evals_result)

# write to submission
sub = pd.read_csv('./data/sample_submission.csv')
sub["target"] = pred_test_full_seed
sub.to_csv('submission.csv', index=False)
```

	feature	split	gain
4755	Max	248	10.730597
21	SumValues	625	8.761306
20	PCA_1	400	8.404264
4756	Var	155	5.489110
4153	f190486d6	183	5.428505
22	SumZeros	249	4.149135
15	PCA_6	232	3.563886
4752	Mean	249	2.853419
4757	Std	48	1.933355
2400	58e2e02e6	98	1.602898
19	PCA_2	172	1.549771
18	PCA_3	126	1.265547
10	PCA_11	79	1.101662
1572	26ab20ff9	63	0.824005
14	PCA_7	122	0.817456



In [ ]: