Netflix_Models_MSE

June 29, 2019

In [1]:
```
import pandas as pd
import numpy as np
from datetime import datetime
import pickle

import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

In [2]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import train_test_split

# Model evaluation related packages
from sklearn.metrics import make_scorer
from sklearn.metrics import mean_squared_error


# Surprise libray related packages
from surprise import Reader, Dataset
from surprise import BaselineOnly
from surprise import KNNBaseline
from surprise import SVD
from surprise import SVDpp

# XGB Models
from xgboost import XGBRegressor
import xgboost

#
from prettytable import PrettyTable
```

1 Configs

In [3]:
```
sample_size = -1 # set -1 if you want to use full size
```

```
df_train_path = './data/Final_Train.csv'
df_test_path =  './data/Final_Test.csv'
```

2 UTIL functions

```
In [4]: def get_ratings(predictions):

            # get the actual labels
            actual = np.array([pred.r_ui for pred in predictions])

            # get the predicted labels
            pred = np.array([pred.est for pred in predictions])

            return (actual, pred,)
```

```
In [5]: def compute_mape(actual, predicted):

            # compute MAPE error
            try:
                mape = np.mean(abs(actual - predicted)/actual)
            except ZeroDivisionError:
                print('Division by zero error in MAPE')
                mape = np.inf
            except:
                print('Exception in computing MAPE value')
                mape = np.inf

            # get percentage value & return
            return mape * 100
```

```
In [6]: def evaluate_model(model, X, y, prefix=str()):

            # get predicted values
            pred_values = model.predict(X)

            # compute mean squared error
            mse = mean_squared_error(y, pred_values)

            # compute mape
            mape = compute_mape(y, pred_values)

            # round off the value to 4 decimal places
            mse = round(mse, 4)
            mape = round(mape, 4)

            print(prefix + ' -> MSE:%f \t MAPE:%f'%(mse, mape,))

            return (mse, mape,)
```

3 Data

In [7]:
```
# read the dataframes
df_train = pd.read_csv(df_train_path, index_col=False)
df_test = pd.read_csv(df_test_path, index_col=False)

# sort the records by date
df_train['date'] = pd.to_datetime(df_train['date'], format='%Y-%m-%d')
df_test['date'] = pd.to_datetime(df_test['date'], format='%Y-%m-%d')

# sort the datafrmaes in ascending order of timestamp
df_train = df_train.sort_values(['date'], ascending=True)
df_train = df_train.reset_index(drop=True)
df_test = df_test.sort_values(['date'], ascending=True)
df_test = df_test.reset_index(drop=True)

# sample the dataframe
if sample_size > 0:
    df_train = df_train.iloc[0:sample_size,]
    df_test = df_test.iloc[0:sample_size,]

print('Shape of train df :', df_train.shape)
print('Shape of test df :', df_test.shape)
```

```
Shape of train df : (696736, 17)
Shape of test df : (174185, 17)
```

In [8]:
```
df_train.head()
```

Out[8]:
```
         date    user  movie  sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  \
0 1999-11-11  510180   2866     3     3     3     3     3     3     3     5
1 1999-11-11  510180   3870     3     3     1     3     3     3     3     3
2 1999-11-11  510180  14660     3     3     2     1     3     1     3     3
3 1999-11-11  510180  11234     3     3     3     3     3     3     2     3
4 1999-12-06  510180   9536     4     4     4     4     4     3     2     3

   smr4  smr5      Gavg  UAvg      MAvg  rating
0     3     4  3.586035  3.44  3.230769       3
1     3     3  3.586035  3.44  3.145320       2
2     3     4  3.586035  3.44  3.000000       2
3     5     1  3.586035  3.44  3.555556       5
4     2     5  3.586035  3.44  4.000000       5
```

In [9]:
```
df_test.tail()
```

Out[9]:
```
              date     user  movie      sur1      sur2      sur3      sur4  \
174180  2005-12-31  1088143  10729  3.586035  3.586035  3.586035  3.586035
174181  2005-12-31  1427836   6386  3.586035  3.586035  3.586035  3.586035
```

```
174182 2005-12-31  1427836  13651  3.586035  3.586035  3.586035  3.586035
174183 2005-12-31  1427836   2913  3.586035  3.586035  3.586035  3.586035
174184 2005-12-31   239139  12034  3.586035  3.586035  3.586035  3.586035

            sur5      smr1      smr2      smr3      smr4      smr5      Gavg  \
174180  3.586035  4.193548  4.045793  3.968914  3.838843  4.018973  3.586035
174181  3.586035  3.585621  3.409039  3.256491  3.690944  3.823619  3.586035
174182  3.586035  3.409039  3.690944  3.741748  3.765557  3.330142  3.586035
174183  3.586035  4.328924  3.589595  4.145440  3.374704  4.416130  3.586035
174184  3.586035  4.134667  3.645894  3.954266  4.391037  4.128524  3.586035

            UAvg      MAvg  rating
174180  3.586035  3.943820       3
174181  3.586035  3.255159       4
174182  3.586035  3.692144       4
174183  3.586035  4.045169       4
174184  3.586035  4.080811       3
```

In [10]:
```python
# Extract features and labels separately
X_train = df_train.drop(['date', 'user', 'movie', 'Gavg', 'rating'], axis=1)
y_train = df_train['rating']

X_test = df_test.drop(['date', 'user', 'movie', 'Gavg', 'rating'], axis=1)
y_test = df_test['rating']
```

In [11]:
```python
X_test.head()
```

Out[11]:
```
   sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
2   4.0   4.0   4.0   5.0   4.0   5.0   2.0   2.0   5.0   2.0  2.978261
3   3.0   4.0   2.0   3.0   3.0   3.0   4.0   4.0   5.0   4.0  4.000000
4   2.0   3.0   2.0   2.0   2.0   3.0   3.0   3.0   3.0   3.0  3.914894

       MAvg
0  3.409039
1  3.821851
2  4.080811
3  3.617293
4  2.854015
```

4 A) Surprise Library Models

In [12]:
```python
def run_surprise_model(algo, train_df, test_df, verbose=True):
    """
        return train_dict, test_dict

        It returns two dictionaries, one for train and the other is for test
```

```
    Each of them have 3 key-value pairs, which specify ''rmse'', ''mape'', and ''pr
"""

reader = Reader(rating_scale=(1,5))

# create the traindata from the dataframe...
train_data = Dataset.load_from_df(train_df[['user', 'movie', 'rating']], reader)
test_data = Dataset.load_from_df(test_df[['user', 'movie', 'rating']], reader)

# build the trainset from traindata.., It is of dataset format from surprise librar
trainset = train_data.build_full_trainset()
testset = test_data.build_full_trainset()

# dictionaries that stores metrics for train and test..
evaluation_dict = dict()


# ==================== Train Stage ===================================
print(datetime.now(), 'Training Stage ...')
# fit to data
algo.fit(trainset)
# predict on train data set
train_pred_tuples = algo.test(trainset.build_testset())
# get the mean squared error & mape
actual, predicted = get_ratings(train_pred_tuples)
mse = mean_squared_error(actual, predicted)
mape = compute_mape(actual, predicted)

# round off values upto 4 decimal places
mse = round(mse, 4)
mape = round(mape, 4)

evaluation_dict['train'] = {'mse':mse, 'mape':mape, 'predictions':predicted}
print(datetime.now(), 'Training Stage Done !!!')


# ==================== Evaluating Test data =========================

print(datetime.now(), 'Test Stage ...')

# predict on train data set
test_pred_tuples = algo.test(testset.build_testset())
# get the mean squared error & mape
actual, predicted = get_ratings(test_pred_tuples)
mse = mean_squared_error(actual, predicted)
mape = compute_mape(actual, predicted)
```

```
    # round off values upto 4 decimal places
    mse = round(mse, 4)
    mape = round(mape, 4)

    evaluation_dict['test'] = {'mse':mse, 'mape':mape, 'predictions':predicted}
    print(datetime.now(), 'Testing Stage Done !!!')


    print('---------------------- Evaluation results --------------------')
    print('Train data : MSE:%f, MAPE:%f'%(evaluation_dict['train']['mse'],
                                      evaluation_dict['train']['mape'],))
    print('Test data : MSE:%f, MAPE:%f'%(evaluation_dict['test']['mse'],
                                      evaluation_dict['test']['mape'],))

    return evaluation_dict
```

4.1 A1) Surprise BaselineOnly Model

In [13]:
```
# options are to specify.., how to compute those user and item biases
bsl_options = {'method': 'sgd',
               'learning_rate': 0.001
               }
bsl_algo = BaselineOnly(bsl_options=bsl_options)
```

In [14]:
```
results_dict_bsl = run_surprise_model(bsl_algo, df_train, df_test)
```

```
2019-06-27 21:47:45.802968 Training Stage ...
Estimating biases using sgd...
2019-06-27 21:47:51.601480 Training Stage Done !!!
2019-06-27 21:47:51.601552 Test Stage ...
2019-06-27 21:47:52.567338 Testing Stage Done !!!
----------------------- Evaluation results --------------------
Train data : MSE:0.861500, MAPE:28.872600
Test data : MSE:1.045800, MAPE:32.111800
```

4.2 A2) Surprise KNN Base Line Model

In [15]:
```
# we specify , how to compute similarities and what to consider with sim_options to our
sim_options = {'user_based' : True,
               'name': 'pearson_baseline',
               'shrinkage': 100,
               'min_support': 2
              }
# we keep other parameters like regularization parameter and learning_rate as default v
bsl_options = {'method': 'sgd'}

# create model object
knn_bsl_u = KNNBaseline(k=40, sim_options = sim_options, bsl_options = bsl_options)
```

```
In [16]: results_dict_knn_bsl_u = run_surprise_model(knn_bsl_u, df_train, df_test)
```

```
2019-06-27 21:47:53.912091 Training Stage ...
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
2019-06-27 22:08:04.300934 Training Stage Done !!!
2019-06-27 22:08:04.327742 Test Stage ...
2019-06-27 22:09:40.412058 Testing Stage Done !!!
---------------------- Evaluation results --------------------
Train data : MSE:0.201900, MAPE:12.744700
Test data : MSE:1.029900, MAPE:31.580100
```

```
In [17]: sim_options = {'user_based' : False,
                        'name': 'pearson_baseline',
                        'shrinkage': 100,
                        'min_support': 2
                       }
         # we keep other parameters like regularization parameter and learning_rate as default v
         bsl_options = {'method': 'sgd'}

         # create model object
         knn_bsl_m = KNNBaseline(k=40, sim_options = sim_options, bsl_options = bsl_options)
```

```
In [18]: results_dict_knn_bsl_m = run_surprise_model(knn_bsl_m, df_train, df_test)
```

```
2019-06-27 22:09:46.667977 Training Stage ...
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
2019-06-27 22:11:02.344973 Training Stage Done !!!
2019-06-27 22:11:02.345047 Test Stage ...
2019-06-27 22:11:09.673331 Testing Stage Done !!!
---------------------- Evaluation results --------------------
Train data : MSE:0.247800, MAPE:14.042600
Test data : MSE:1.064300, MAPE:31.723400
```

4.3 A3) Surprise Model SVD

```
In [19]: svd = SVD(n_factors=100, biased=True, random_state=15, verbose=True)
```

```
In [20]: results_dict_svd = run_surprise_model(svd, df_train, df_test)
```

```
2019-06-27 22:11:11.190890 Training Stage ...
Processing epoch 0
Processing epoch 1
Processing epoch 2
```

```
Processing epoch 3
Processing epoch 4
Processing epoch 5
Processing epoch 6
Processing epoch 7
Processing epoch 8
Processing epoch 9
Processing epoch 10
Processing epoch 11
Processing epoch 12
Processing epoch 13
Processing epoch 14
Processing epoch 15
Processing epoch 16
Processing epoch 17
Processing epoch 18
Processing epoch 19
2019-06-27 22:11:42.301565 Training Stage Done !!!
2019-06-27 22:11:42.301776 Test Stage ...
2019-06-27 22:11:43.566680 Testing Stage Done !!!
---------------------- Evaluation results --------------------
Train data : MSE:0.454300, MAPE:20.095700
Test data : MSE:1.033400, MAPE:31.385700
```

4.4 A4) Surprise Model SVDpp

```
In [21]: svdpp = SVDpp(n_factors=50, random_state=15, verbose=True)
```

```
In [22]: results_dict_svdpp = run_surprise_model(svdpp, df_train, df_test)
```

```
2019-06-27 22:11:44.993017 Training Stage ...
 processing epoch 0
 processing epoch 1
 processing epoch 2
 processing epoch 3
 processing epoch 4
 processing epoch 5
 processing epoch 6
 processing epoch 7
 processing epoch 8
 processing epoch 9
 processing epoch 10
 processing epoch 11
 processing epoch 12
 processing epoch 13
 processing epoch 14
 processing epoch 15
```

```
 processing epoch 16
 processing epoch 17
 processing epoch 18
 processing epoch 19
2019-06-27 22:30:49.528529 Training Stage Done !!!
2019-06-27 22:30:49.528608 Test Stage ...
2019-06-27 22:30:55.158251 Testing Stage Done !!!
---------------------- Evaluation results --------------------
Train data : MSE:0.436400, MAPE:19.367800
Test data : MSE:1.035500, MAPE:31.128500
```

5 B) XGB Model

```
In [23]: def get_best_hyperparam_XGBRegressor(param_dict, X, y, random_search=False):

             # set the scoring function
             final_scorer = 'MSE'

             # declare a scoring dictionary
             score_dict = {
                 'MAPE': make_scorer(score_func=compute_mape, greater_is_better=False,
                                     needs_proba=False, needs_threshold=False),
                 'MSE' : make_scorer(score_func=mean_squared_error, greater_is_better=False,
                                     needs_proba=False, needs_threshold=False)
             }

              #Declare the metric as  'minimization' or 'maximization'
             optimization_dict = {
                 'MAPE' : 'minimization',
                 'MSE' : 'minimization'
             }

             # Time Series split
             cv_data = TimeSeriesSplit(n_splits=3)

             # ==============================================================================


             # declare model
             model = XGBRegressor()

             if random_search:
                 search_cv = RandomizedSearchCV(estimator=model, param_distribution=param_dict,
                                                cv=cv_data, scoring=score_dict, refit=False,
                                                return_train_score=True, n_iter=6, n_jobs=-1)
```

```python
else:
    # declare grid search CV object
    search_cv = GridSearchCV(estimator=model, param_grid=param_dict, cv=cv_data,
                             scoring=score_dict, refit=False,
                             return_train_score=True, n_jobs=-1)

# fit to the data
search_cv.fit(X, y)


# get total number of param settings
param_list = list(param_dict.keys())
param_field_list = ['param_' + item for item in param_list]

# get list of train metric list
train_metric_list = ['mean_train_' + item for item in score_dict.keys()]
# get list of test metric list
test_metric_list = ['mean_test_' + item for item in score_dict.keys()]

# get number of rows in the search cv data frame
num_rows = len(search_cv.cv_results_['params'])

# create the grid search info df
grid_info_df = pd.DataFrame(search_cv.cv_results_, index=range(num_rows))

# prepare a list of reqired columns
required_columns = ['params'] + param_field_list + train_metric_list + \
                   test_metric_list

# slice the data frame to only required columns
grid_info_df = grid_info_df[required_columns]

# process individual metrics
for metric, optimization in optimization_dict.items():
    if optimization == 'minimization':
        grid_info_df['mean_train_' + metric] *= -1
        grid_info_df['mean_test_' + metric] *= -1

# Find the best hyperparam & its corresponding scores
if optimization_dict[final_scorer] == 'minimization':
    best_hyperparam_record = grid_info_df.loc[grid_info_df[
                              'mean_test_'+ final_scorer].idxmin(),:]
else:
    best_hyperparam_record = grid_info_df.loc[grid_info_df[
                              'mean_test_'+ final_scorer].idxmax(),:]

# best hyperparam & corresponding scores
best_hyperparam = best_hyperparam_record['params']
```

```
best_train_score = best_hyperparam_record['mean_train_'+ final_scorer]
best_validation_score = best_hyperparam_record['mean_test_'+ final_scorer]

# plot the hyper params
if len(param_list) == 1:
    # extract individual fiedls
    x_vals = grid_info_df[param_field_list[0]].tolist()
    y_vals_tr = grid_info_df['mean_train_' + final_scorer].tolist()
    y_vals_val = grid_info_df['mean_test_' + final_scorer].tolist()

    # plot train, validation performances
    plt.plot(x_vals, y_vals_tr, label='Train', color='r', marker='o', linestyle='-'
    plt.plot(x_vals, y_vals_val, label='Validation', color='b', marker='o', linesty
    plt.xlabel('Hyper Params -' + param_list[0])
    plt.ylabel(final_scorer)
    plt.legend()
    plt.title('XGB Regression - Hyperparam Train v/s Validation Scores')
    plt.show()

# Heatmap plot for pair of hyperparam values
elif len(param_list) == 2:
    # get pivoted table
    train_hyp_df = pd.pivot_table(data=grid_info_df, index=param_field_list[0],
                                  columns=param_field_list[1],
                                  values='mean_train_' + final_scorer ,
                                  fill_value=np.inf)
    sns.heatmap(train_hyp_df, annot=True, cmap='YlGnBu', fmt='.4f',
                cbar_kws={'label': final_scorer, 'format':'%.2f'})
    plt.xlabel(param_list[1])
    plt.ylabel(param_list[0])
    plt.title('XGB Regression - Hyperparams Scores - Train')
    plt.show()

    print('\n'*3)

    # Test hyperparam

    # get pivoted table
    train_hyp_df = pd.pivot_table(data=grid_info_df, index=param_field_list[0],
                                  columns=param_field_list[1],
                                  values='mean_test_' + final_scorer, fill_value=np
    sns.heatmap(train_hyp_df, annot=True, cmap='YlGnBu', fmt='.4f',
                cbar_kws={'label': final_scorer, 'format':'%.2f'})
    plt.xlabel(param_list[1])
    plt.ylabel(param_list[0])
    plt.title('XGB Regression - Hyperparams Scores - Validation')
    plt.show()
```

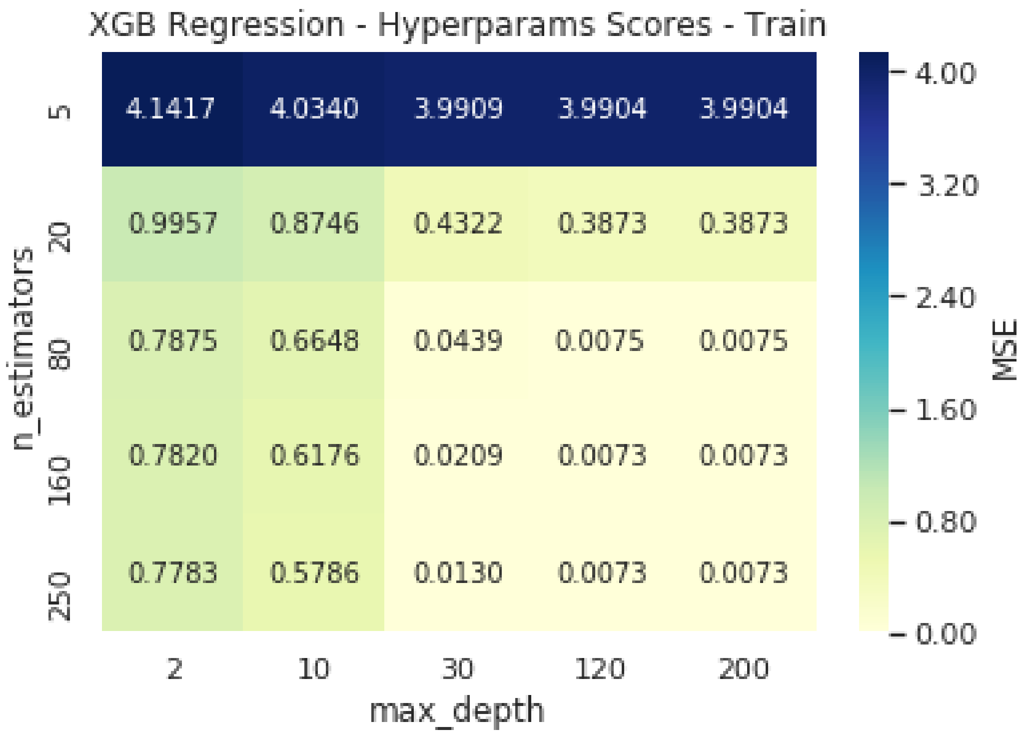
```
        else:
            print(grid_info_df)

        print('Best hyperparam value: ', best_hyperparam, 'Best Train Score: ', best_train_
              'Best Validation Score: ', best_validation_score)


        best_mse_train = best_hyperparam_record['mean_train_MSE']
        best_mse_validation = best_hyperparam_record['mean_test_MSE']

        # return tuple
        ret_tuple = (best_hyperparam, best_train_score, best_validation_score,
                     best_mse_train, best_mse_validation)


        return ret_tuple
```

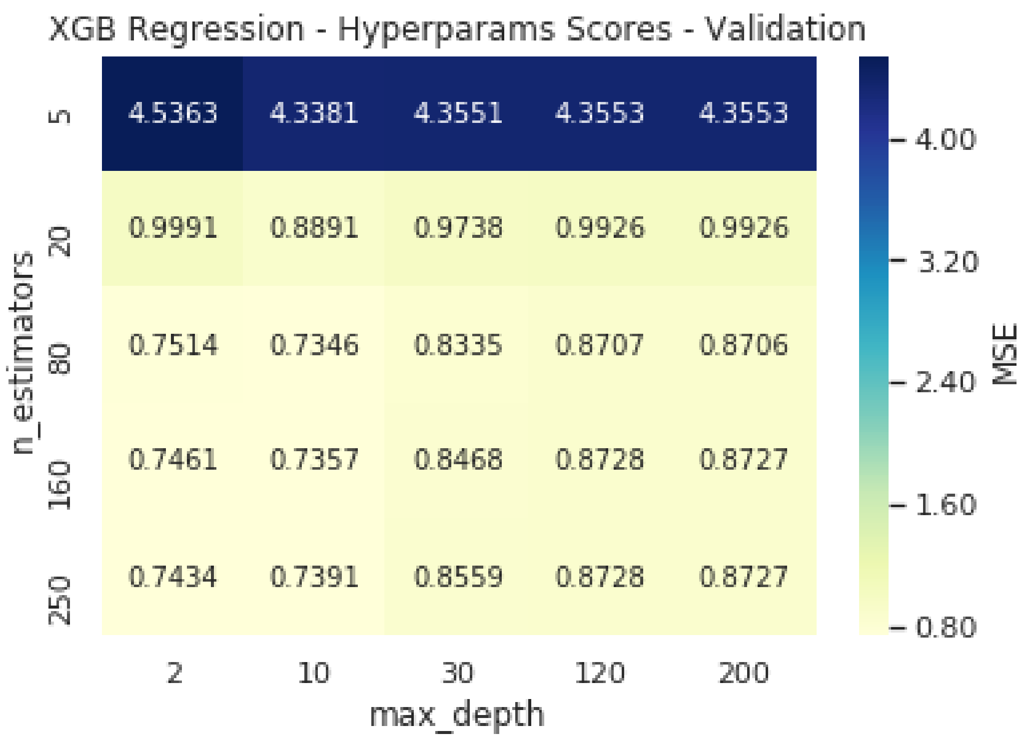
5.1 B1) XGB with First 13 Features

5.1.1 Step 1. Find best hyperparameter

In [24]:
```
param_dict_xgb_1 = {'n_estimators':[5, 20, 80, 160, 250],
                    'max_depth':[2, 10, 30, 120, 200]}

print(datetime.now() ,' Hyperparam Tuning of XGB started')
hyp_tuned_info_xgb_1 = get_best_hyperparam_XGBRegressor(param_dict_xgb_1, X_train, y_tr
print(datetime.now() ,' Hyperparam Tuning of XGB completed')
```

```
2019-06-27 22:30:56.129446  Hyperparam Tuning of XGB started


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
```


XGB Regression - Hyperparams Scores - Train
n_estimators
5
20
80
160
250
max_depth
2
10
30
120
200
4.1417
4.0340
3.9909
3.9904
3.9904
0.9957
0.8746
0.4322
0.3873
0.3873
0.7875
0.6648
0.0439
0.0075
0.0075
0.7820
0.6176
0.0209
0.0073
0.0073
0.7783
0.5786
0.0130
0.0073
0.0073
MSE
4.00
3.20
2.40
1.60
0.80
0.00




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 80} Best Train Score:  0.6648344353398
2019-06-28 01:11:45.565146  Hyperparam Tuning of XGB completed
```

```
In [25]: best_hyp_xgb_1, best_train_score, best_validation_score, best_mse_train, best_mse_valid
```

5.1.2 Step 2 : Train model with best hyperparam

```
In [26]: # declare model
         print(datetime.now() ,' Training of XGB started')
         xgb_model_1 = XGBRegressor(n_estimators=best_hyp_xgb_1['n_estimators'],
                                    max_depth=best_hyp_xgb_1['max_depth'])
         xgb_model_1.fit(X_train, y_train)
         print(datetime.now() ,' Training of XGB completed')

         # save model to disk
         pickle_out = open("./model/xgb_reg1.pkl","wb")
         pickle.dump(xgb_model_1, pickle_out)
         pickle_out.close()
```

```
2019-06-28 01:11:46.056943  Training of XGB started
2019-06-28 01:12:43.748370  Training of XGB completed
```

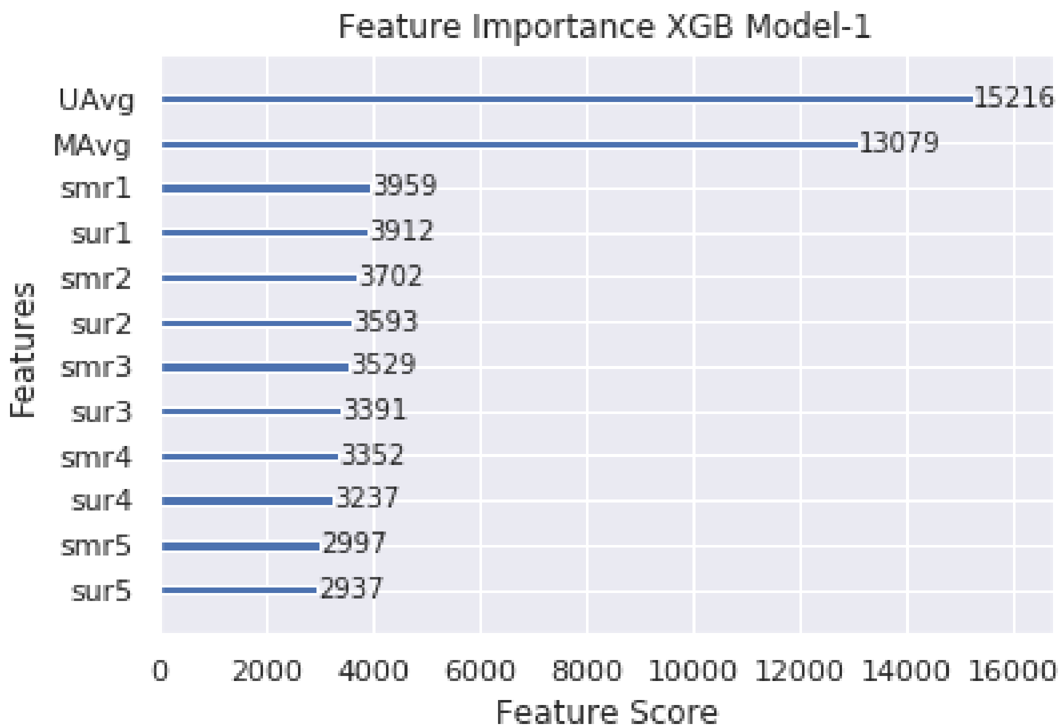
5.1.3 Step 3 : Evaluate model

In [27]:
```
#load model from disk
pickle_in = open("./model/xgb_reg1.pkl","rb")
xgb_model_1 = pickle.load(pickle_in)
pickle_in.close()

# performace of model
train_mse_xgb_1, train_mape_xgb_1 = evaluate_model(xgb_model_1, X_train, y_train, prefi
test_mse_xgb_1, test_mape_xgb_1 = evaluate_model(xgb_model_1, X_test, y_test, prefix='T
```

```
Train -> MSE:0.683000          MAPE:24.706900
Test -> MSE:1.132500          MAPE:32.653800
```

5.2 Plot Feature Importance

In [28]:
```
xgboost.plot_importance(xgb_model_1, title='Feature Importance XGB Model-%d'%(1,),
                        xlabel='Feature Score',)
plt.show()
```



5.3 B2) XGB with 13 features + BaselineOnly feature

5.3.1 Adding the as feature to X_train, X_test

```
In [29]: # Surprise baseline model predictions
         X_train['F_BaselineOnly'] = results_dict_bsl['train']['predictions']
         X_test['F_BaselineOnly'] = results_dict_bsl['test']['predictions']
         X_test.head()
```

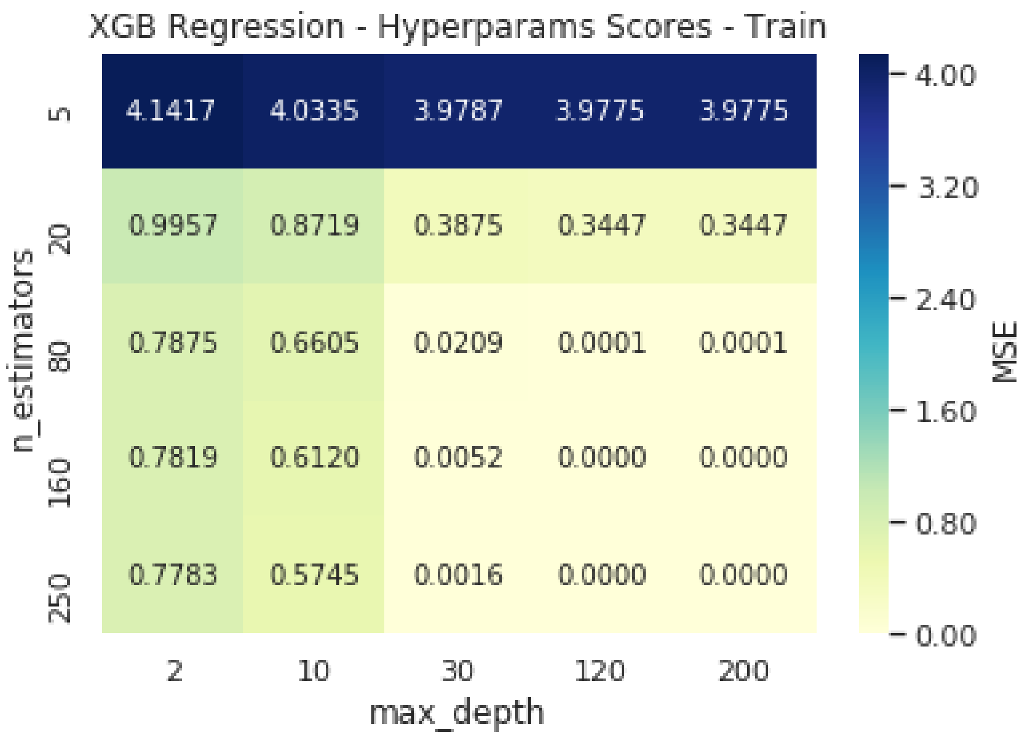
```
Out[29]:    sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
         0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
         1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
         2   4.0   4.0   4.0   5.0   4.0   5.0   2.0   2.0   5.0   2.0  2.978261
         3   3.0   4.0   2.0   3.0   3.0   3.0   4.0   4.0   5.0   4.0  4.000000
         4   2.0   3.0   2.0   2.0   2.0   3.0   3.0   3.0   3.0   3.0  3.914894

                MAvg  F_BaselineOnly
         0  3.409039        3.476408
         1  3.821851        3.822106
         2  4.080811        3.980199
         3  3.617293        4.271171
         4  2.854015        3.377190
```

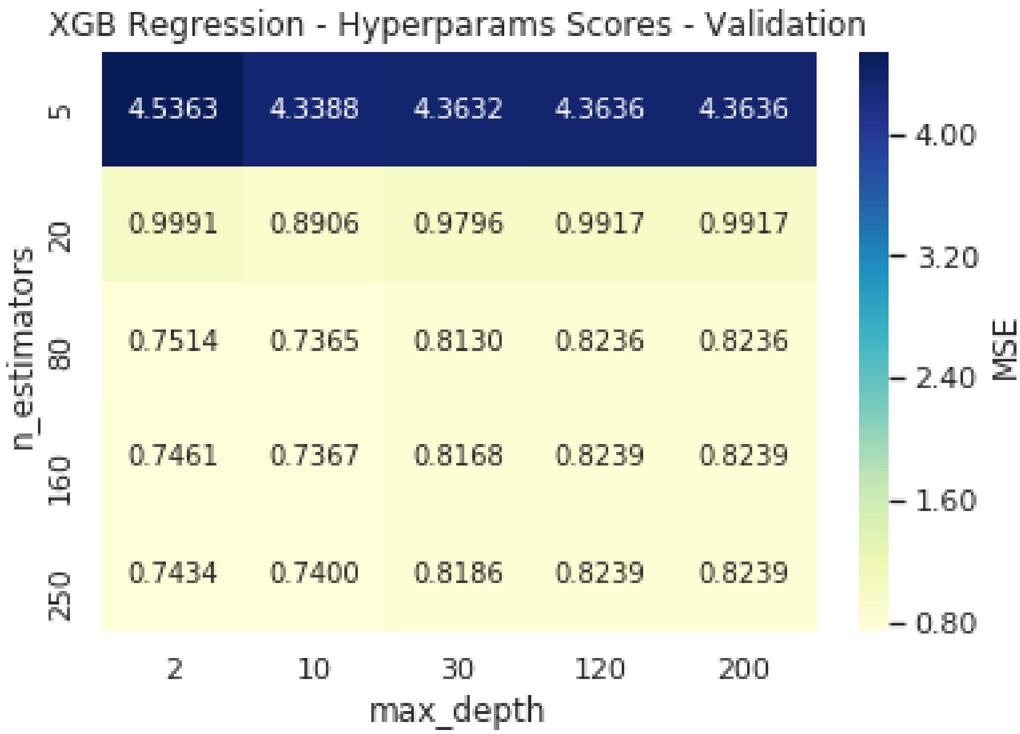
5.3.2 Step 1. Find best hyperparameter

```
In [30]: param_dict_xgb_2 = {'n_estimators':[5, 20, 80, 160, 250],
                             'max_depth':[2, 10, 30, 120, 200]}

         print(datetime.now() ,' Hyperparam Tuning of XGB started')
         hyp_tuned_info_xgb_2 = get_best_hyperparam_XGBRegressor(param_dict_xgb_2, X_train, y_tr
         print(datetime.now() ,' Hyperparam Tuning of XGB completed')
```

```
2019-06-28 01:12:51.123961  Hyperparam Tuning of XGB started


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
```

```
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
```






```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 80} Best Train Score:  0.6604782276809
2019-06-28 04:12:19.131399  Hyperparam Tuning of XGB completed
```

In [31]:
```python
best_hyp_xgb_2, best_train_score, best_validation_score, best_mse_train, best_mse_valid
```

5.3.3 Step 2 : Train model with best hyperparam

In [32]:
```python
# declare model
print(datetime.now() ,'  Training of XGB started')
xgb_model_2 = XGBRegressor(n_estimators=best_hyp_xgb_2['n_estimators'],
                           max_depth=best_hyp_xgb_2['max_depth'])
xgb_model_2.fit(X_train, y_train)
print(datetime.now() ,'  Training of XGB completed')


# save model to disk
pickle_out = open("./model/xgb_reg2.pkl","wb")
pickle.dump(xgb_model_2, pickle_out)
pickle_out.close()
```

```
2019-06-28 04:12:19.449913   Training of XGB started
2019-06-28 04:13:25.657234   Training of XGB completed
```

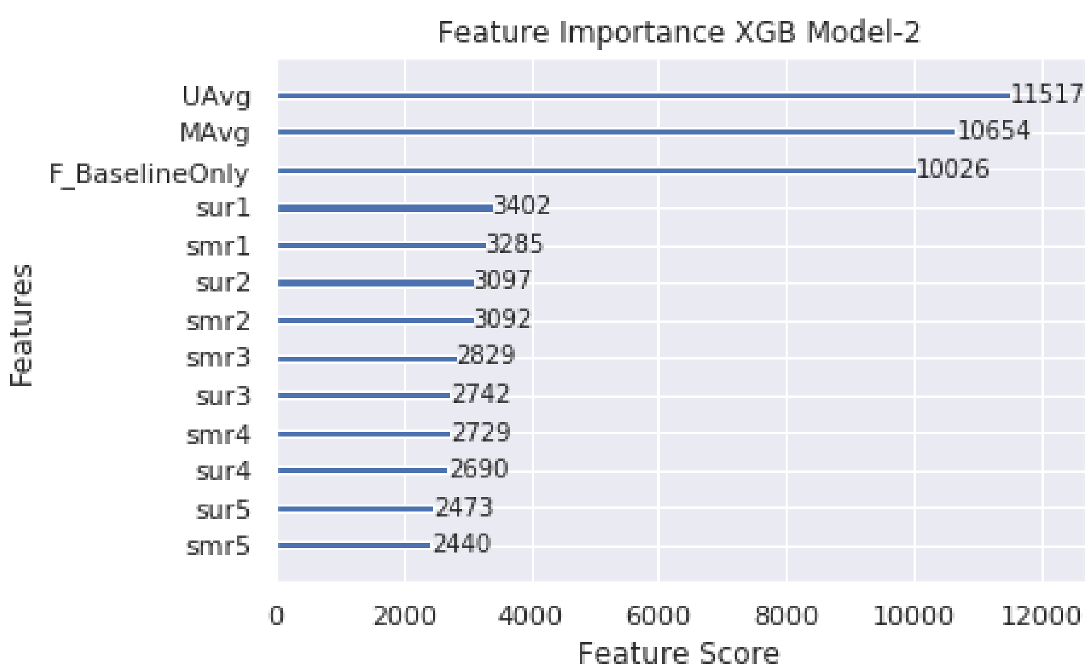
5.3.4 Step 3 : Evaluate model

```
In [33]: #load model from disk
         pickle_in = open("./model/xgb_reg2.pkl","rb")
         xgb_model_2 = pickle.load(pickle_in)
         pickle_in.close()

         # performace of model
         train_mse_xgb_2, train_mape_xgb_2 = evaluate_model(xgb_model_2, X_train, y_train, prefi
         test_mse_xgb_2, test_mape_xgb_2 = evaluate_model(xgb_model_2, X_test, y_test, prefix='T
```

```
Train -> MSE:0.682000          MAPE:24.690700
Test -> MSE:1.133900          MAPE:32.710400
```

5.4 Plot Feature Importance

```
In [34]: xgboost.plot_importance(xgb_model_2, title='Feature Importance XGB Model-%d'%(2,),
                                 xlabel='Feature Score',)
         plt.show()
```



5.5 B3) XGB with 13 features + BaselineOnly + KNN Base Line features

5.5.1 Adding the as feature to X_train, X_test

```
In [35]: # Surprise baseline model predictions
         X_train['F_KNN_Baseline'] = results_dict_knn_bsl_m['train']['predictions']
```

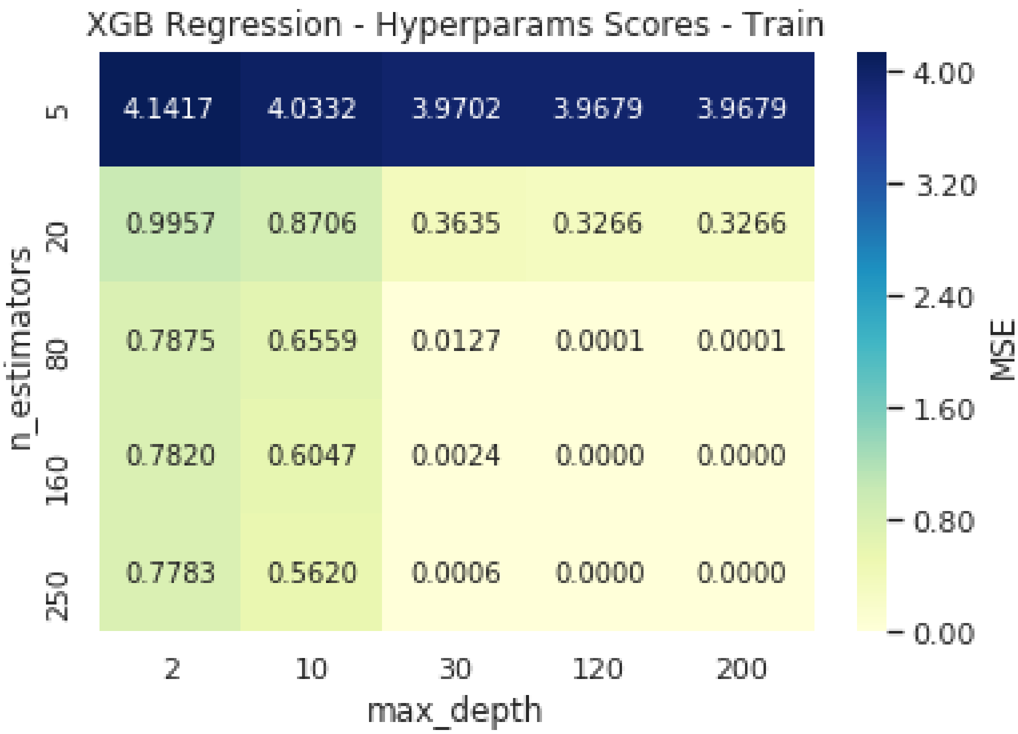
```
X_test['F_KNN_Baseline'] = results_dict_knn_bsl_m['test']['predictions']
X_test.head()
```

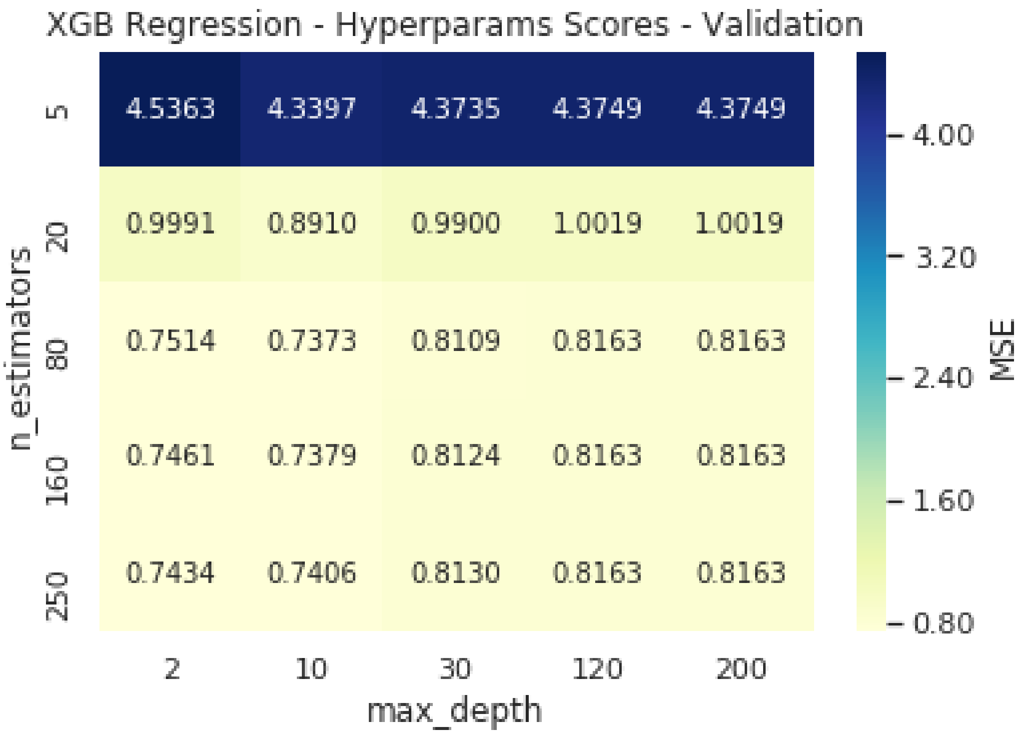
```
Out[35]:    sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
         0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
         1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
         2   4.0   4.0   4.0   5.0   4.0   5.0   2.0   2.0   5.0   2.0  2.978261
         3   3.0   4.0   2.0   3.0   3.0   3.0   4.0   4.0   5.0   4.0  4.000000
         4   2.0   3.0   2.0   2.0   2.0   3.0   3.0   3.0   3.0   3.0  3.914894

                MAvg  F_BaselineOnly  F_KNN_Baseline
         0  3.409039        3.476408        2.285921
         1  3.821851        3.822106        2.570363
         2  4.080811        3.980199        2.702690
         3  3.617293        4.271171        3.074824
         4  2.854015        3.377190        2.192587
```

5.5.2 Step 1. Find best hyperparameter

```
In [36]: param_dict_xgb_3 = {'n_estimators':[5, 20, 80, 160, 250],
                             'max_depth':[2, 10, 30, 120, 200]}

         print(datetime.now() ,' Hyperparam Tuning of XGB started')
         hyp_tuned_info_xgb_3 = get_best_hyperparam_XGBRegressor(param_dict_xgb_3, X_train, y_tr
         print(datetime.now() ,' Hyperparam Tuning of XGB completed')
```

```
2019-06-28 04:13:32.778473  Hyperparam Tuning of XGB started


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
```


XGB Regression - Hyperparams Scores - Train
n_estimators
5
20
80
160
250
max_depth
2
10
30
120
200
4.1417
4.0332
3.9702
3.9679
3.9679
0.9957
0.8706
0.3635
0.3266
0.3266
0.7875
0.6559
0.0127
0.0001
0.0001
0.7820
0.6047
0.0024
0.0000
0.0000
0.7783
0.5620
0.0006
0.0000
0.0000
MSE
4.00
3.20
2.40
1.60
0.80
0.00




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 80} Best Train Score:  0.6559253596523
2019-06-28 07:13:16.234816  Hyperparam Tuning of XGB completed
```

```
In [37]: best_hyp_xgb_3, best_train_score, best_validation_score, best_mse_train, best_mse_valid
```

5.5.3 Step 2 : Train model with best hyperparam

```
In [38]: # declare model
         print(datetime.now() ,' Training of XGB started')
         xgb_model_3 = XGBRegressor(n_estimators=best_hyp_xgb_3['n_estimators'],
                                    max_depth=best_hyp_xgb_3['max_depth'])
         xgb_model_3.fit(X_train, y_train)
         print(datetime.now() ,' Training of XGB completed')

         # save model to disk
         pickle_out = open("./model/xgb_reg3.pkl","wb")
         pickle.dump(xgb_model_3, pickle_out)
         pickle_out.close()
```

```
2019-06-28 07:13:16.845366  Training of XGB started
2019-06-28 07:14:32.608752  Training of XGB completed
```

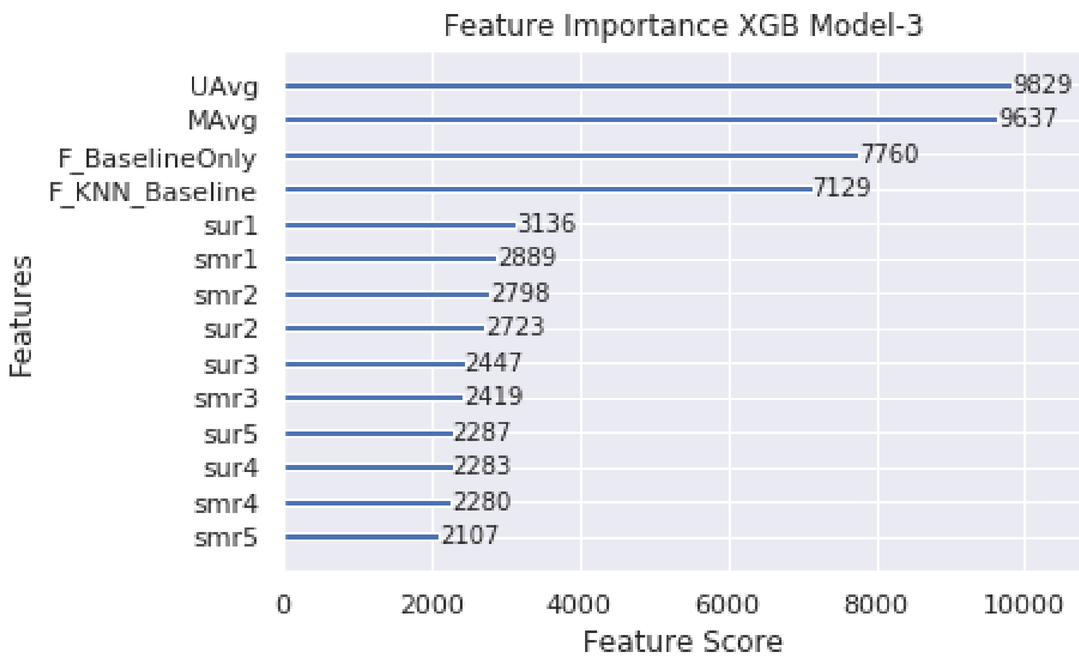
5.5.4 Step 3 : Evaluate model

```
In [39]: #load model from disk
         pickle_in = open("./model/xgb_reg3.pkl","rb")
         xgb_model_3 = pickle.load(pickle_in)
         pickle_in.close()

         # performace of model
         train_mse_xgb_3, train_mape_xgb_3 = evaluate_model(xgb_model_3, X_train, y_train, prefi
         test_mse_xgb_3, test_mape_xgb_3 = evaluate_model(xgb_model_3, X_test, y_test, prefix='T
```

```
Train -> MSE:0.680600          MAPE:24.668100
Test -> MSE:1.131300          MAPE:32.656000
```

5.6 Plot Feature Importance

```
In [40]: xgboost.plot_importance(xgb_model_3, title='Feature Importance XGB Model-%d'%(3,),
                                 xlabel='Feature Score',)
         plt.show()
```



5.7 B4) XGB with 13 features + BaselineOnly + KNN Base Line + SVD Features

5.7.1 Adding the as feature to X_train, X_test

```
In [41]: # Surprise baseline model predictions
         X_train['F_SVD'] = results_dict_svd['train']['predictions']
```

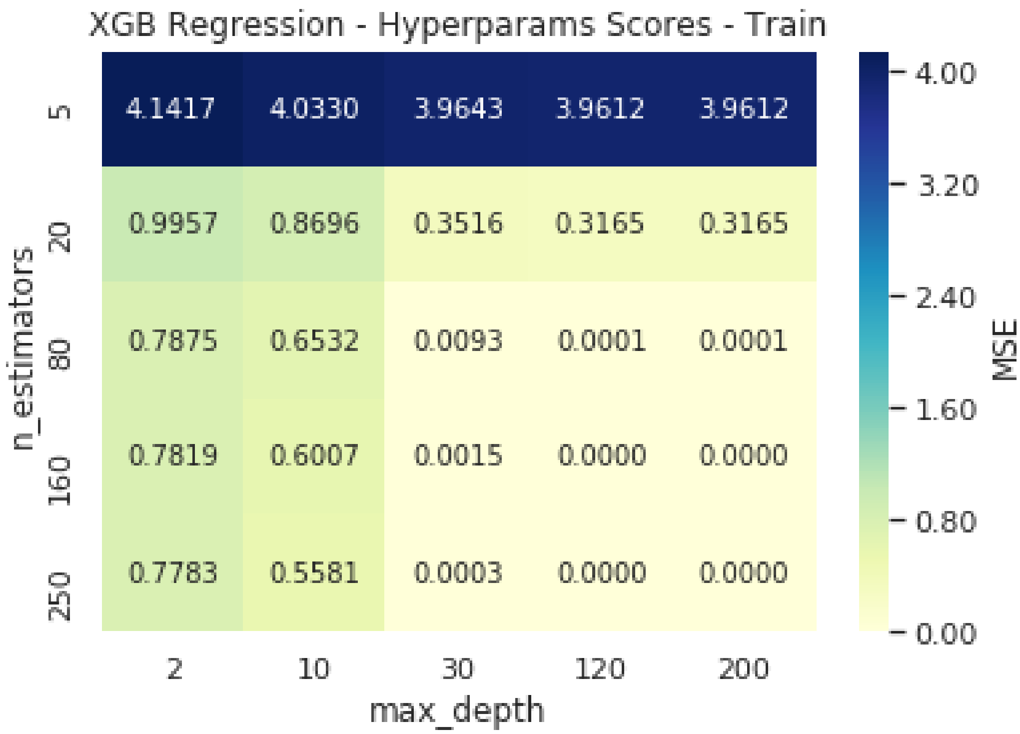
```
X_test['F_SVD'] = results_dict_svd['test']['predictions']
X_test.head()
```

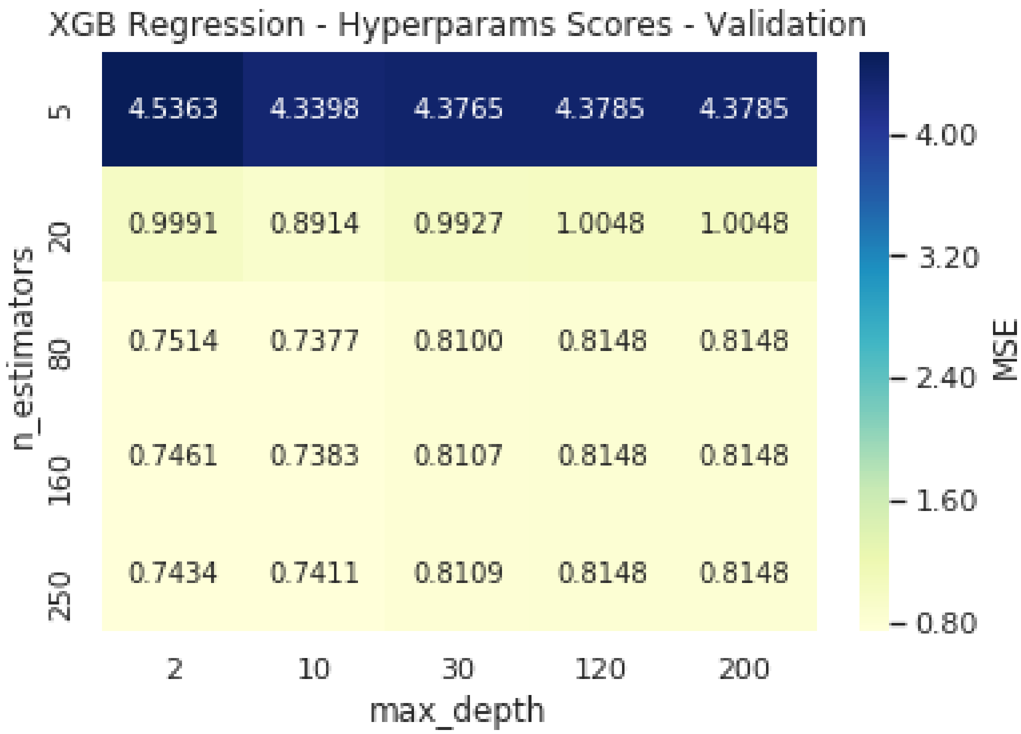
```
Out[41]:    sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
2   4.0   4.0   4.0   5.0   4.0   5.0   2.0   2.0   5.0   2.0  2.978261
3   3.0   4.0   2.0   3.0   3.0   3.0   4.0   4.0   5.0   4.0  4.000000
4   2.0   3.0   2.0   2.0   2.0   3.0   3.0   3.0   3.0   3.0  3.914894

       MAvg  F_BaselineOnly  F_KNN_Baseline     F_SVD
0  3.409039        3.476408        2.285921  3.370094
1  3.821851        3.822106        2.570363  3.803793
2  4.080811        3.980199        2.702690  3.960326
3  3.617293        4.271171        3.074824  4.344987
4  2.854015        3.377190        2.192587  3.003624
```

5.7.2 Step 1. Find best hyperparameter

```
In [42]: param_dict_xgb_4 = {'n_estimators':[5, 20, 80, 160, 250],
                             'max_depth':[2, 10, 30, 120, 200]}

         print(datetime.now() ,' Hyperparam Tuning of XGB started')
         hyp_tuned_info_xgb_4 = get_best_hyperparam_XGBRegressor(param_dict_xgb_4, X_train, y_tr
         print(datetime.now() ,' Hyperparam Tuning of XGB completed')
```

```
2019-06-28 07:14:39.654904  Hyperparam Tuning of XGB started


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
```


XGB Regression - Hyperparams Scores - Train
n_estimators
5
20
80
160
250
max_depth
2
10
30
120
200
4.1417
4.0330
3.9643
3.9612
3.9612
0.9957
0.8696
0.3516
0.3165
0.3165
0.7875
0.6532
0.0093
0.0001
0.0001
0.7819
0.6007
0.0015
0.0000
0.0000
0.7783
0.5581
0.0003
0.0000
0.0000
MSE
4.00
3.20
2.40
1.60
0.80
0.00




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 80} Best Train Score:  0.6531862682743
2019-06-28 10:24:37.293625  Hyperparam Tuning of XGB completed
```

```
In [43]: best_hyp_xgb_4, best_train_score, best_validation_score, best_mse_train, best_mse_valid
```

5.7.3 Step 2 : Train model with best hyperparam

```
In [44]: # declare model
         print(datetime.now() ,' Training of XGB started')
         xgb_model_4 = XGBRegressor(n_estimators=best_hyp_xgb_4['n_estimators'],
                                    max_depth=best_hyp_xgb_4['max_depth'])
         xgb_model_4.fit(X_train, y_train)
         print(datetime.now() ,' Training of XGB completed')

         # save model to disk
         pickle_out = open("./model/xgb_reg4.pkl","wb")
         pickle.dump(xgb_model_4, pickle_out)
         pickle_out.close()
```

```
2019-06-28 10:24:38.041155  Training of XGB started
2019-06-28 10:26:03.313402  Training of XGB completed
```

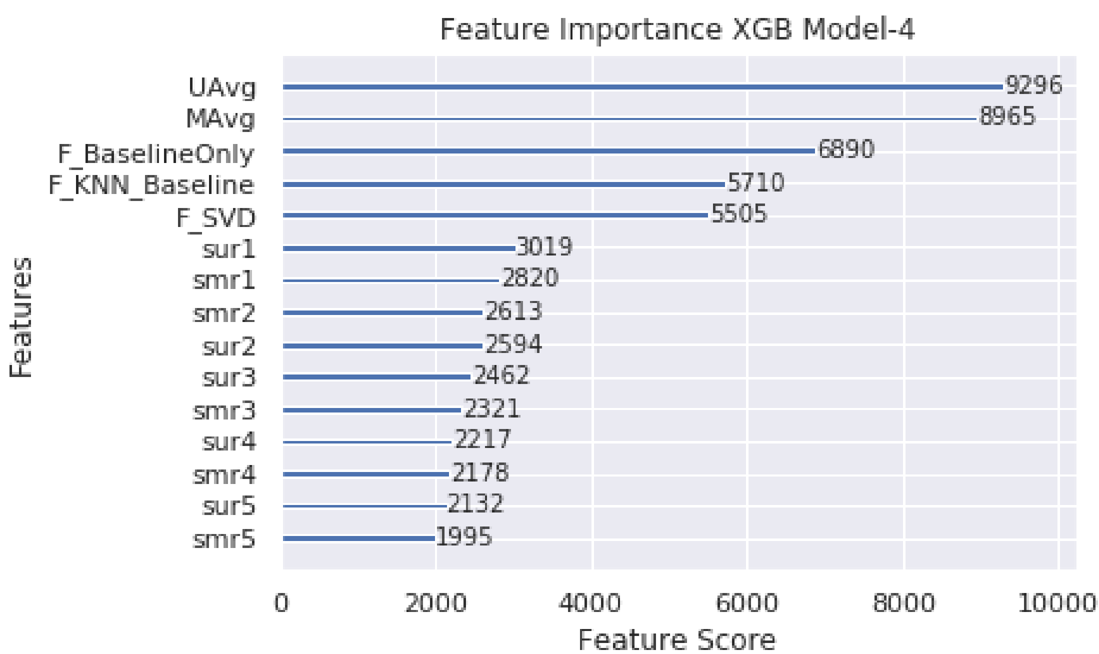
5.7.4 Step 3 : Evaluate model

In [45]:
```
# save model to disk
pickle_in = open("./model/xgb_reg4.pkl","rb")
xgb_model_4 = pickle.load(pickle_in)
pickle_in.close()

# performace of model
train_mse_xgb_4, train_mape_xgb_4 = evaluate_model(xgb_model_4, X_train, y_train, prefi
test_mse_xgb_4, test_mape_xgb_4 = evaluate_model(xgb_model_4, X_test, y_test, prefix='T
```

```
Train -> MSE:0.679200          MAPE:24.643200
Test -> MSE:1.133900          MAPE:32.699500
```

5.8 Plot Feature Importance

In [46]:
```
xgboost.plot_importance(xgb_model_4, title='Feature Importance XGB Model-%d'%(4,),
                        xlabel='Feature Score',)
plt.show()
```



5.9 B5) XGB with 13 features + BaselineOnly + KNN Base Line + SVD + SVDpp features

5.9.1 Adding the as feature to X_train, X_test

In [47]:
```
# Surprise baseline model predictions
X_train['F_SVDpp'] = results_dict_svdpp['train']['predictions']
```

```
X_test['F_SVDpp'] = results_dict_svdpp['test']['predictions']
X_test.head()
```

Out[47]:

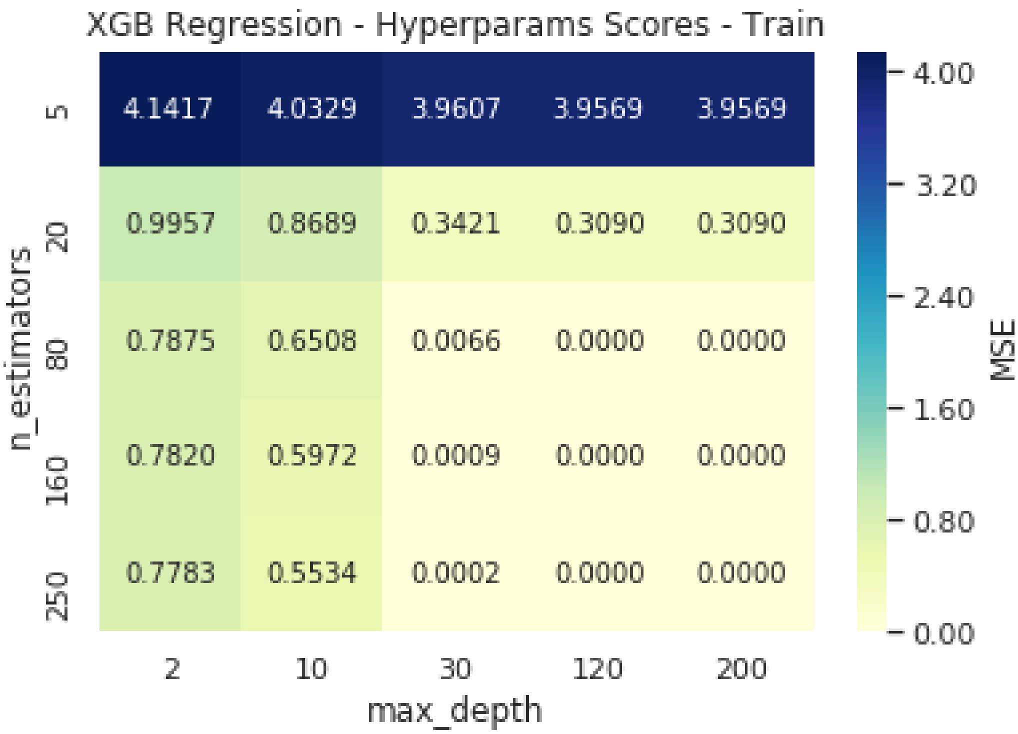
```
   sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
2   4.0   4.0   4.0   5.0   4.0   5.0   2.0   2.0   5.0   2.0  2.978261
3   3.0   4.0   2.0   3.0   3.0   3.0   4.0   4.0   5.0   4.0  4.000000
4   2.0   3.0   2.0   2.0   2.0   3.0   3.0   3.0   3.0   3.0  3.914894

       MAvg  F_BaselineOnly  F_KNN_Baseline     F_SVD   F_SVDpp
0  3.409039        3.476408        2.285921  3.370094  3.391509
1  3.821851        3.822106        2.570363  3.803793  3.559892
2  4.080811        3.980199        2.702690  3.960326  4.114547
3  3.617293        4.271171        3.074824  4.344987  4.131854
4  2.854015        3.377190        2.192587  3.003624  3.194473
```

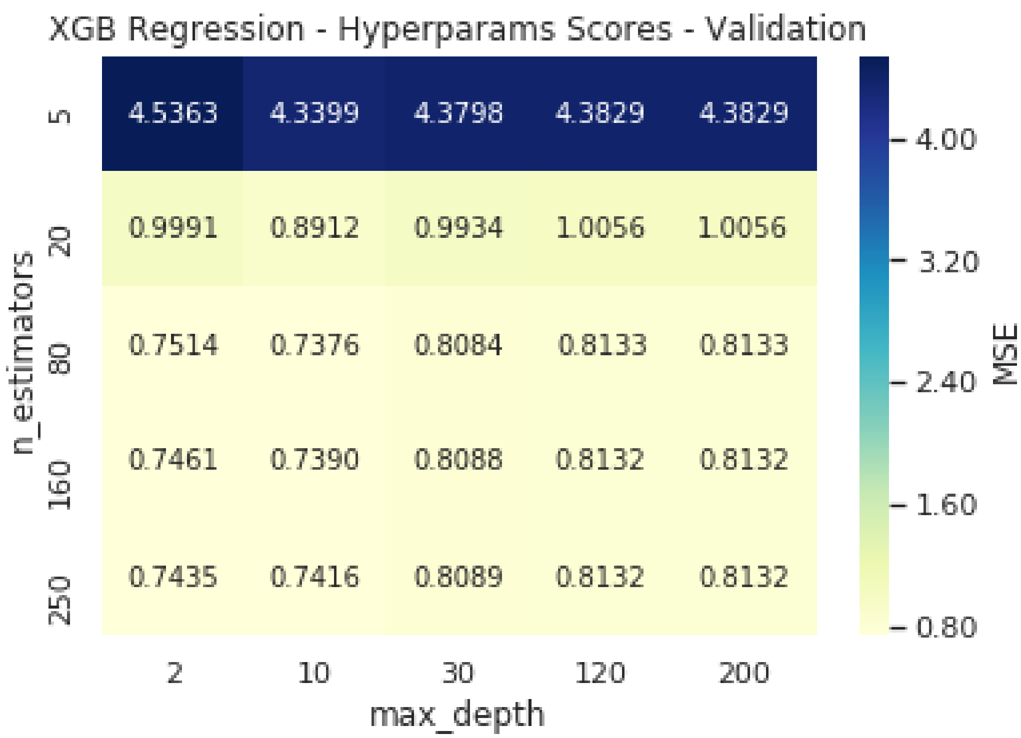
5.9.2 Step 1. Find best hyperparameter

In [48]:

```
param_dict_xgb_5 = {'n_estimators':[5, 20, 80, 160, 250],
                    'max_depth':[2, 10, 30, 120, 200]}

print(datetime.now() ,' Hyperparam Tuning of XGB started')
hyp_tuned_info_xgb_5 = get_best_hyperparam_XGBRegressor(param_dict_xgb_5, X_train,
                                                         y_train)
print(datetime.now() ,' Hyperparam Tuning of XGB completed')
```

```
2019-06-28 10:26:09.912972  Hyperparam Tuning of XGB started


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
```


XGB Regression - Hyperparams Scores - Train
n_estimators
5
20
80
160
250
max_depth
2
10
30
120
200
4.1417
4.0329
3.9607
3.9569
3.9569
0.9957
0.8689
0.3421
0.3090
0.3090
0.7875
0.6508
0.0066
0.0000
0.0000
0.7820
0.5972
0.0009
0.0000
0.0000
0.7783
0.5534
0.0002
0.0000
0.0000
MSE
4.00
3.20
2.40
1.60
0.80
0.00




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 80} Best Train Score:  0.6507868153953
2019-06-28 13:50:52.495515  Hyperparam Tuning of XGB completed
```

```
In [49]: best_hyp_xgb_5, best_train_score, best_validation_score, best_mse_train, best_mse_valid
```

5.9.3 Step 2 : Train model with best hyperparam

```
In [50]: # declare model
         print(datetime.now() ,' Training of XGB started')
         xgb_model_5 = XGBRegressor(n_estimators=best_hyp_xgb_5['n_estimators'],
                                    max_depth=best_hyp_xgb_5['max_depth'])
         xgb_model_5.fit(X_train, y_train)
         print(datetime.now() ,' Training of XGB completed')

         # save model to disk
         pickle_out = open("./model/xgb_reg5.pkl","wb")
         pickle.dump(xgb_model_5, pickle_out)
         pickle_out.close()
```

```
2019-06-28 13:50:52.689561  Training of XGB started
2019-06-28 13:52:32.769833  Training of XGB completed
```

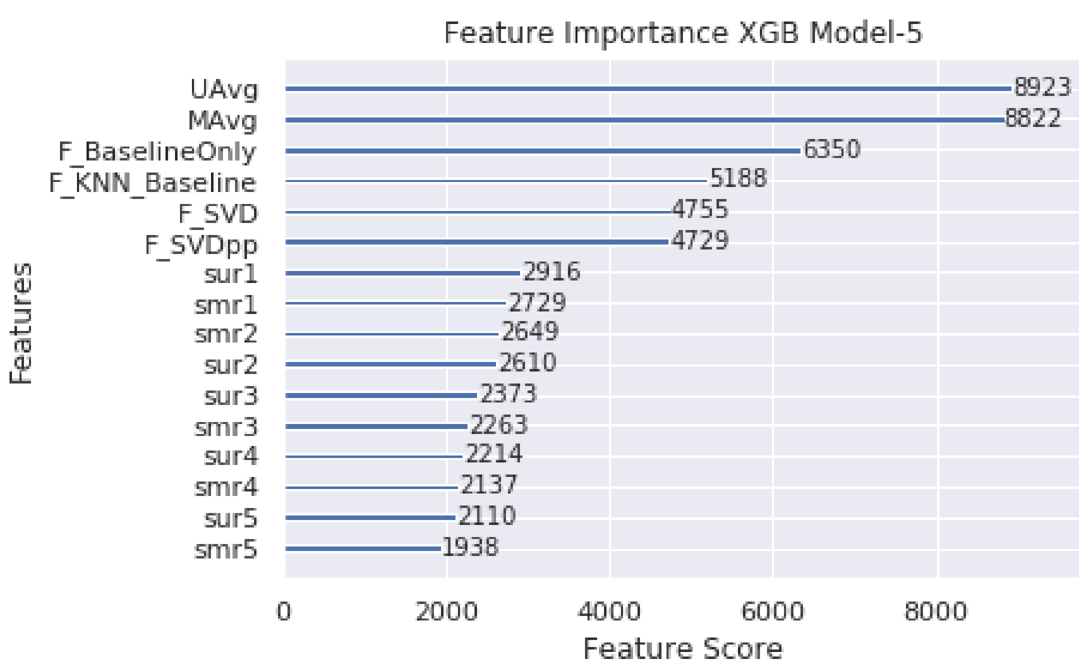
5.9.4 Step 3 : Evaluate model

```
In [51]: #load model from disk
         pickle_in = open("./model/xgb_reg5.pkl","rb")
         xgb_model_5 = pickle.load(pickle_in)
         pickle_in.close()

         # performace of model
         train_mse_xgb_5, train_mape_xgb_5 = evaluate_model(xgb_model_5, X_train,
                                                             y_train, prefix='Train')
         test_mse_xgb_5, test_mape_xgb_5 = evaluate_model(xgb_model_5, X_test,
                                                           y_test, prefix='Test')
```

```
Train -> MSE:0.675800          MAPE:24.578200
Test -> MSE:1.132900          MAPE:32.682500
```

5.10 Plot Feature Importance

```
In [52]: xgboost.plot_importance(xgb_model_5, title='Feature Importance XGB Model-%d'%(5,),
                                  xlabel='Feature Score',)
         plt.show()
```



6 Results

In [53]:
```
Pret_table = PrettyTable()
Pret_table.field_names = ['Model', 'Hyperparam', '# Features', 'Train MSE', 'Test MSE',
                          'Train MAPE', 'Test MAPE']
Pret_table.title = 'Movie Ratings Results Summary'

# surprise model results
Pret_table.add_row(['BaselineOnly', '--', 13 ,
                    results_dict_bsl['train']['mse'],
                    results_dict_bsl['test']['mse'],
                    results_dict_bsl['train']['mape'],
                    results_dict_bsl['test']['mape']])
Pret_table.add_row(['KNN Baseline', '--', 13 ,
                    results_dict_knn_bsl_m['train']['mse'],
                    results_dict_knn_bsl_m['test']['mse'],
                    results_dict_knn_bsl_m['train']['mape'],
                    results_dict_knn_bsl_m['test']['mape']])
Pret_table.add_row(['SVD', '--', 13 ,
                    results_dict_svd['train']['mse'],
                    results_dict_svd['test']['mse'],
                    results_dict_svd['train']['mape'],
                    results_dict_svd['test']['mape']])
Pret_table.add_row(['SVDpp', '--', 13 ,
                    results_dict_svdpp['train']['mse'],
                    results_dict_svdpp['test']['mse'],
                    results_dict_svdpp['train']['mape'],
                    results_dict_svdpp['test']['mape']])

# XGB model results

best_hyp_xgb_1 = '\n'.join(str(best_hyp_xgb_1).split(','))
best_hyp_xgb_2 = '\n'.join(str(best_hyp_xgb_2).split(','))
best_hyp_xgb_3 = '\n'.join(str(best_hyp_xgb_3).split(','))
best_hyp_xgb_4 = '\n'.join(str(best_hyp_xgb_4).split(','))
best_hyp_xgb_5 = '\n'.join(str(best_hyp_xgb_5).split(','))


Pret_table.add_row(['XGB', best_hyp_xgb_1, 13,
                    train_mse_xgb_1, test_mse_xgb_1,
                    train_mape_xgb_1, test_mape_xgb_1])
Pret_table.add_row(['XGB', best_hyp_xgb_2, 14,
                    train_mse_xgb_2, test_mse_xgb_2,
                    train_mape_xgb_2, test_mape_xgb_2])
Pret_table.add_row(['XGB', best_hyp_xgb_3, 15,
                    train_mse_xgb_3, test_mse_xgb_3,
                    train_mape_xgb_3, test_mape_xgb_3])
Pret_table.add_row(['XGB', best_hyp_xgb_4, 16,
```

```
                         train_mse_xgb_4, test_mse_xgb_4,
                         train_mape_xgb_4, test_mape_xgb_4])
Pret_table.add_row(['XGB', best_hyp_xgb_5, 17,
                         train_mse_xgb_5, test_mse_xgb_5,
                         train_mape_xgb_5, test_mape_xgb_5])

#
print(Pret_table)
```

```
+--------------+----------------------+------------+-----------+----------+------------+--------
|    Model     |      Hyperparam      | # Features | Train MSE | Test MSE | Train MAPE | Test MA
+--------------+----------------------+------------+-----------+----------+------------+--------
| BaselineOnly |          --          |     13     |   0.8615  |  1.0458  |  28.8726   |  32.111
| KNN Baseline |          --          |     13     |   0.2478  |  1.0643  |  14.0426   |  31.723
|     SVD      |          --          |     13     |   0.4543  |  1.0334  |  20.0957   |  31.385
|    SVDpp     |          --          |     13     |   0.4364  |  1.0355  |  19.3678   |  31.128
|     XGB      |  {'max_depth': 10    |     13     |   0.683   |  1.1325  |  24.7069   |  32.653
|              | 'n_estimators': 80}  |            |           |          |            |
|     XGB      |  {'max_depth': 10    |     14     |   0.682   |  1.1339  |  24.6907   |  32.710
|              | 'n_estimators': 80}  |            |           |          |            |
|     XGB      |  {'max_depth': 10    |     15     |   0.6806  |  1.1313  |  24.6681   |   32.65
|              | 'n_estimators': 80}  |            |           |          |            |
|     XGB      |  {'max_depth': 10    |     16     |   0.6792  |  1.1339  |  24.6432   |  32.699
|              | 'n_estimators': 80}  |            |           |          |            |
|     XGB      |  {'max_depth': 10    |     17     |   0.6758  |  1.1329  |  24.5782   |  32.682
|              | 'n_estimators': 80}  |            |           |          |            |
+--------------+----------------------+------------+-----------+----------+------------+--------
```

7 Procedure Summary

Surprise library model is used as a baseline model
Multiple datasets are constructed by getting the predictions from surprise libray models
Hyperparameter tuning is done for XGB models on all the datasets created
XGB models are trained with the best hyperparam values
XGB models performace evaluated using the test dataset

8 Conclusion

The best MSE value obatined is 1.0334 from baseline SVD
The best XGB model gave 1.1313 MSE with 15 features dataset
More feature engineering can be done to improve XGB models output further
Other models can be tried instead of XGB models