Netflix_Models_MAPE

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)
```

```
2019-06-25 10:36:20.107312 Training Stage ...
Estimating biases using sgd...
2019-06-25 10:36:27.842645 Training Stage Done !!!
2019-06-25 10:36:27.842908 Test Stage ...
2019-06-25 10:36:29.007775 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)
```

```
2019-06-25 10:36:30.523481 Training Stage ...
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
2019-06-25 11:04:15.379397 Training Stage Done !!!
2019-06-25 11:04:15.395576 Test Stage ...
2019-06-25 11:06:17.264291 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)
```

```
2019-06-25 11:06:31.133016 Training Stage ...
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
2019-06-25 11:07:55.231868 Training Stage Done !!!
2019-06-25 11:07:55.231948 Test Stage ...
2019-06-25 11:08:03.424434 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)
```

```
2019-06-25 11:08:05.272483 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
2019-06-25 11:08:44.433132 Training Stage Done !!!
2019-06-25 11:08:44.433227 Test Stage ...
2019-06-25 11:08:46.039565 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)
```

```
2019-06-25 11:08:47.677612 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
2019-06-25 11:34:40.168822 Training Stage Done !!!
2019-06-25 11:34:40.168915 Test Stage ...
2019-06-25 11:34:47.404024 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 = 'MAPE'

             # 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)
```

```
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()
```

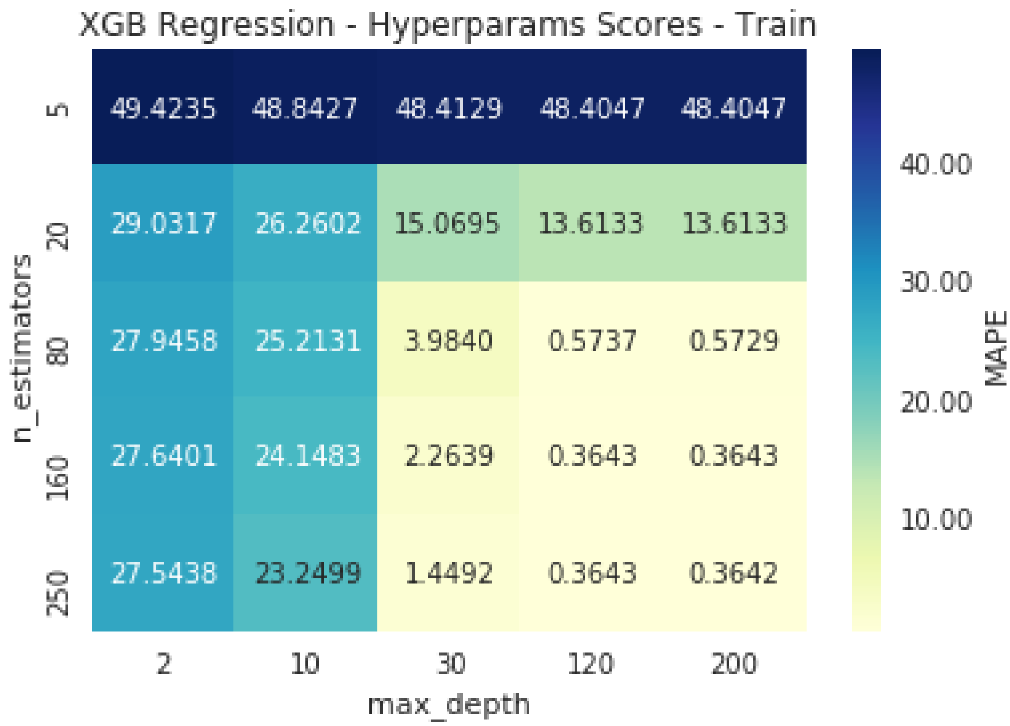
```
        else:
            print(grid_info_df)

        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
```

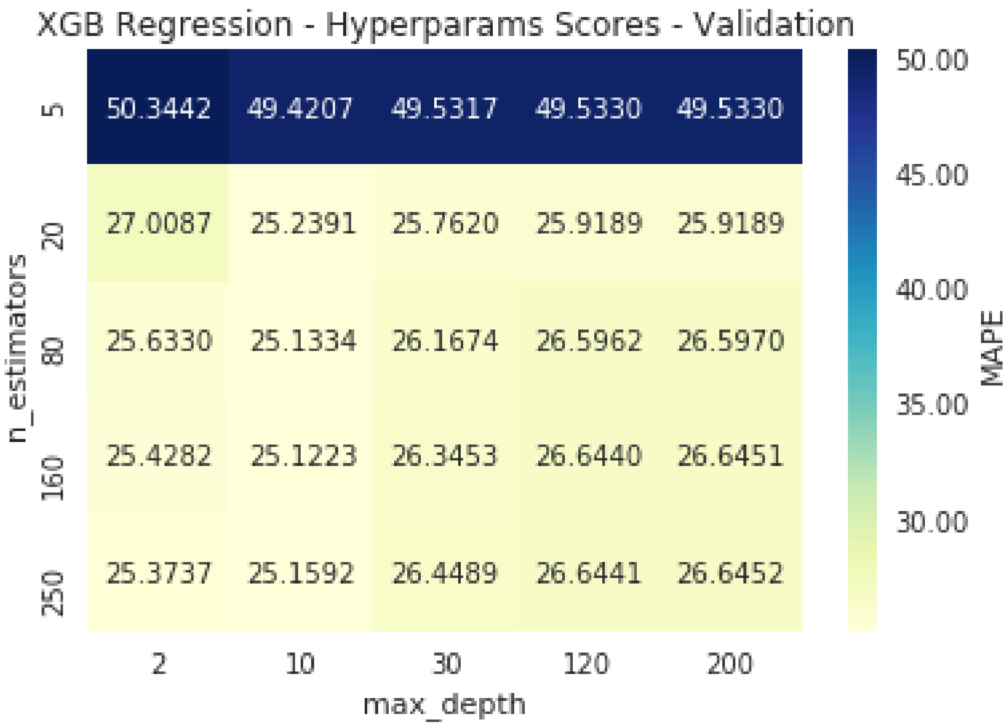
5.1 B1) XGB with First 13 Features

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')
```

```
2019-06-25 11:34:50.414381  Hyperparam Tuning of XGB started
```


XGB Regression - Hyperparams Scores - Train
49.4235
48.8427
48.4129
48.4047
48.4047
29.0317
26.2602
15.0695
13.6133
13.6133
27.9458
25.2131
3.9840
0.5737
0.5729
27.6401
24.1483
2.2639
0.3643
0.3643
27.5438
23.2499
1.4492
0.3643
0.3642
5
20
80
160
250
n_estimators
2
10
30
120
200
max_depth
40.00
30.00
20.00
10.00
MAPE




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 160} Best Train Score:  24.14833654959
2019-06-25 16:10:02.010315  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()
```

```
2019-06-25 16:10:02.517546  Training of XGB started
2019-06-25 16:12:55.171481  Training of XGB completed
```

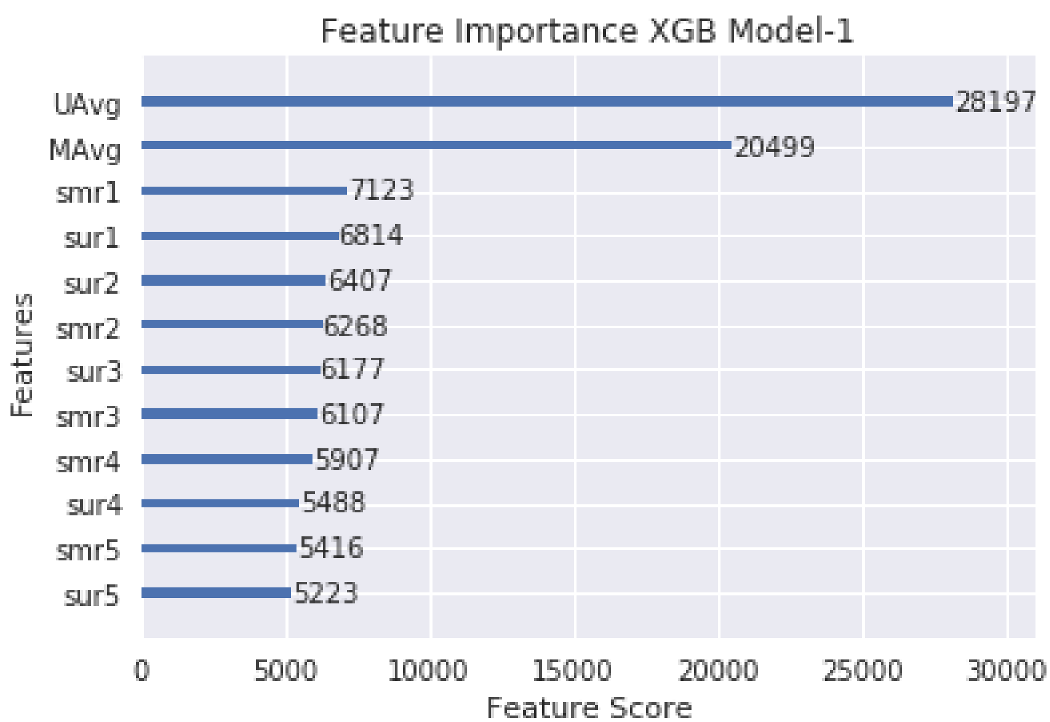
5.1.3 Step 3 : Evaluate model

```
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:0.651300          MAPE:24.019100
Test -> MSE:1.148000          MAPE:32.749500
```

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

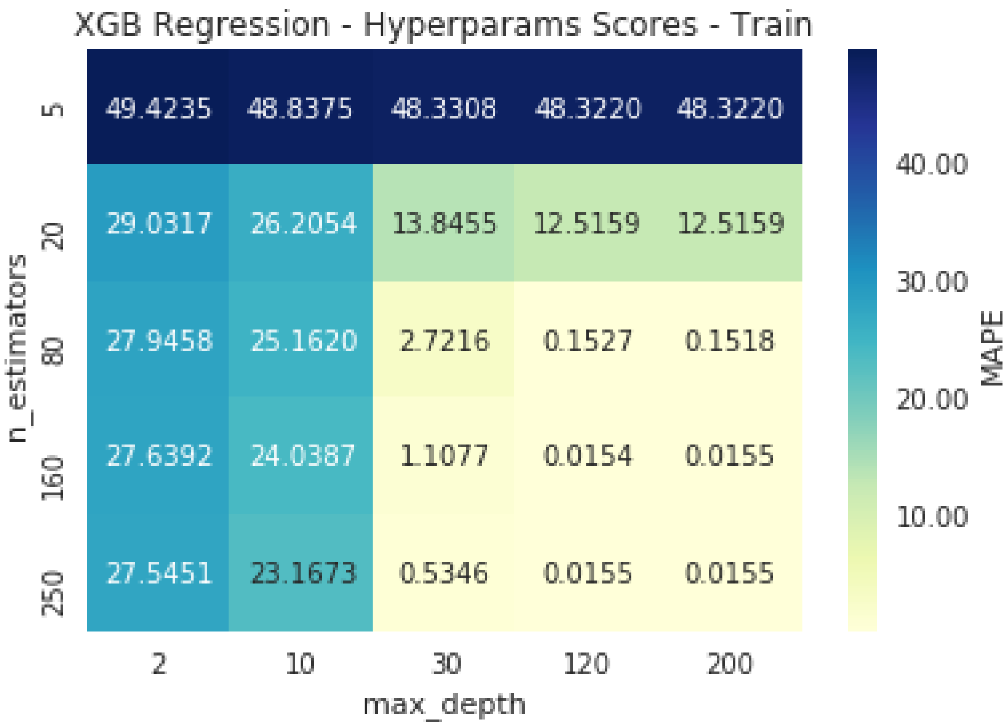
In [29]:
```
# Surprise baseline model predictions
X_train['F_BaselineOnly'] = results_dict_bsl['train']['predictions']
X_test['F_BaselineOnly'] = results_dict_bsl['test']['predictions']
X_test.head()
```

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
```

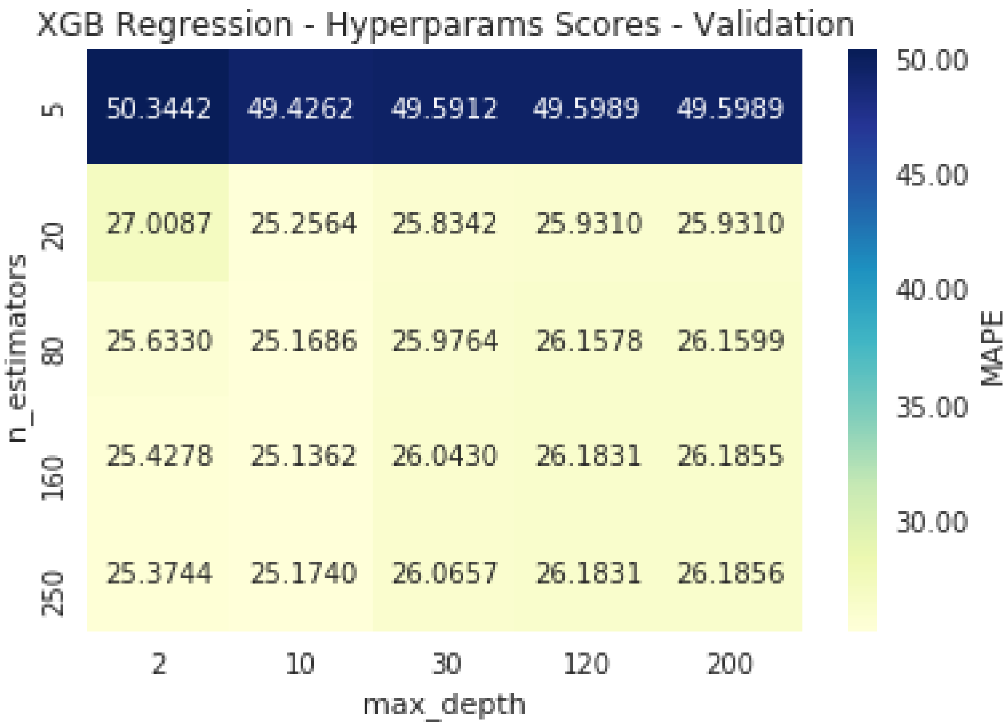
5.3.2 Step 1. Find best hyperparameter

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')
```

```
2019-06-25 16:13:13.338634  Hyperparam Tuning of XGB started
```



XGB Regression - Hyperparams Scores - Train
49.4235
48.8375
48.3308
48.3220
48.3220
29.0317
26.2054
13.8455
12.5159
12.5159
27.9458
25.1620
2.7216
0.1527
0.1518
27.6392
24.0387
1.1077
0.0154
0.0155
27.5451
23.1673
0.5346
0.0155
0.0155
n_estimators
5
20
80
160
250
max_depth
2
10
30
120
200
MAPE
40.00
30.00
20.00
10.00




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 160} Best Train Score:  24.03871814409
2019-06-25 21:23:07.745464  Hyperparam Tuning of XGB completed
```

In [31]:
```
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]:
```
# 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()
```

```
2019-06-25 21:23:10.089463   Training of XGB started
2019-06-25 21:26:30.019260   Training of XGB completed
```

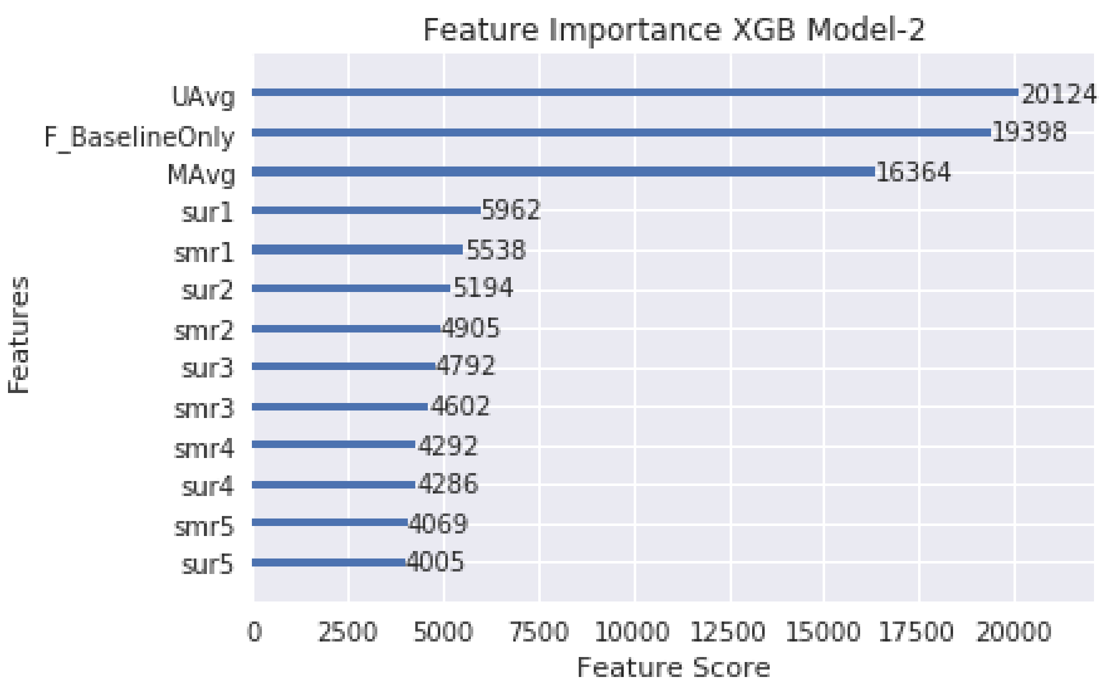
5.3.4 Step 3 : Evaluate model

```
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:0.649600          MAPE:24.008800
Test -> MSE:1.141800          MAPE:32.713600
```

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']
```

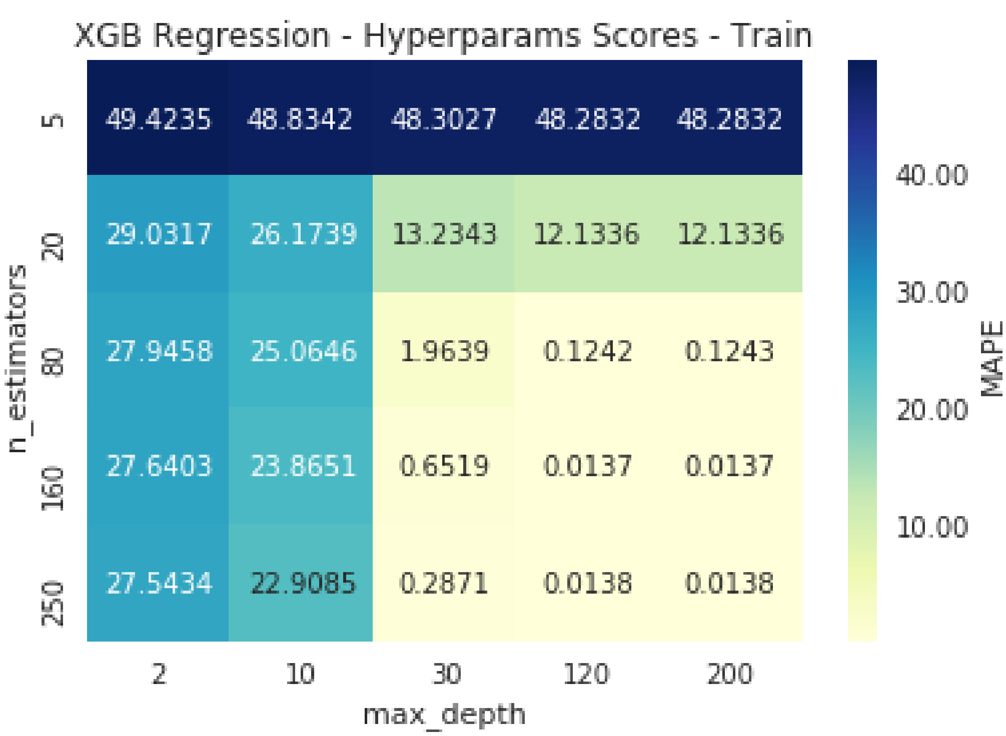
```
X_test['F_KNN_Baseline'] = results_dict_knn_bsl_m['test']['predictions']
X_test.head()
```

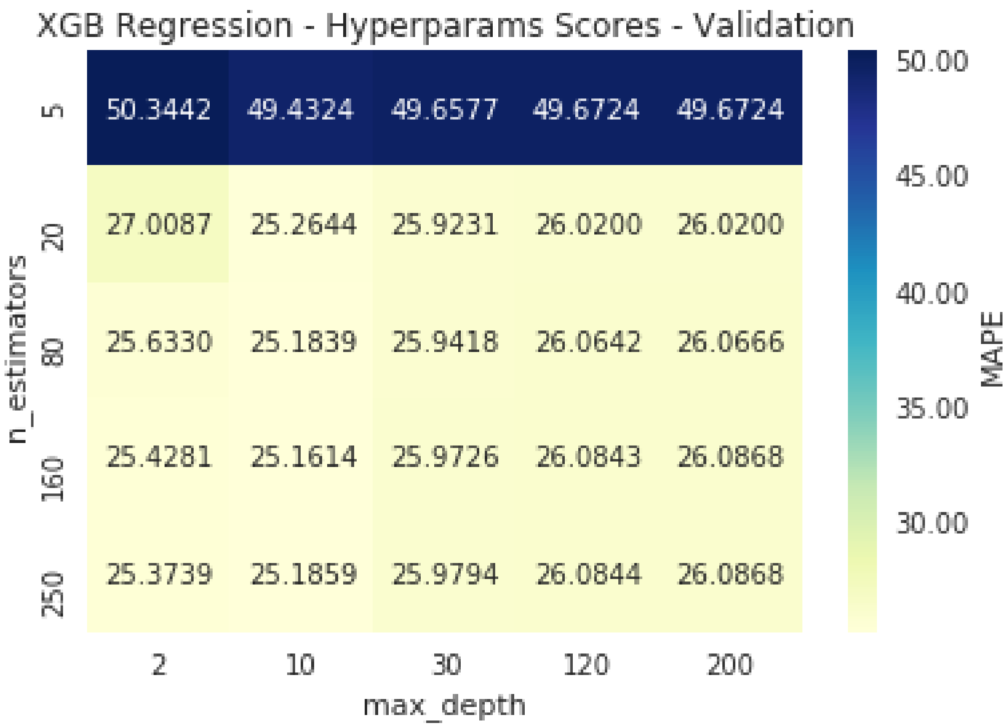
Out[35]:
```
   sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
2   4.0   4.0   4.0   5.0   4.0   5.0   2.0   2.0   5.0   2.0  2.978261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

```
2019-06-25 21:26:47.122800  Hyperparam Tuning of XGB started
```






```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 160} Best Train Score:  23.86511166890
2019-06-26 02:46:49.042587  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()
```

```
2019-06-26 02:46:51.286078  Training of XGB started
2019-06-26 02:50:40.667285  Training of XGB completed
```

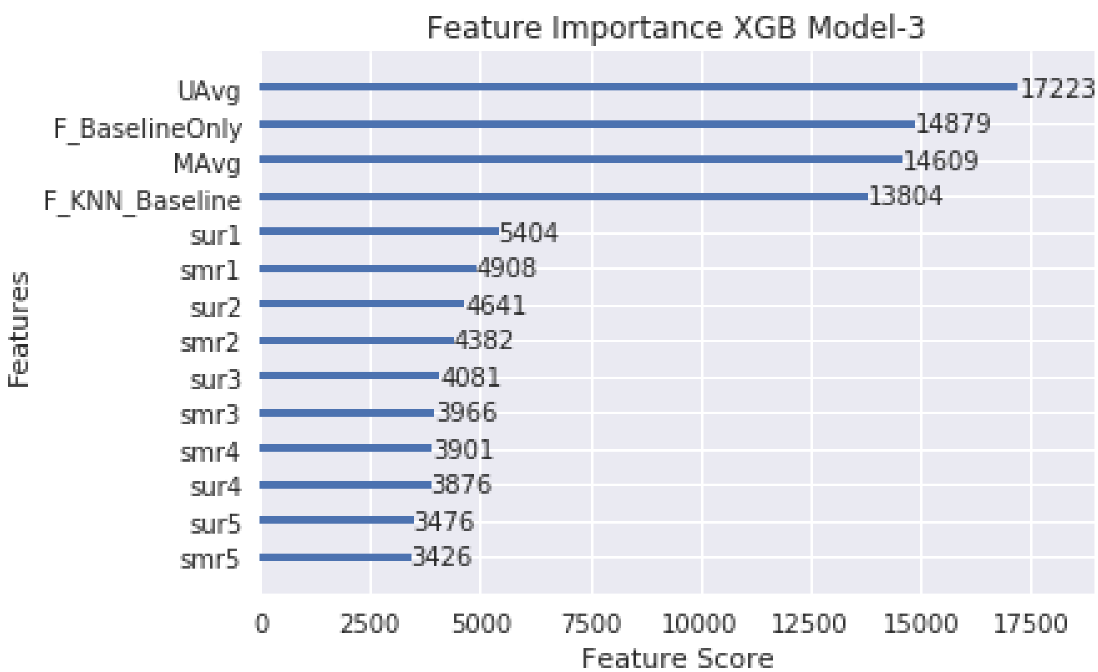
5.5.4 Step 3 : Evaluate model

```
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:0.646500          MAPE:23.951900
Test -> MSE:1.143700          MAPE:32.750300
```

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

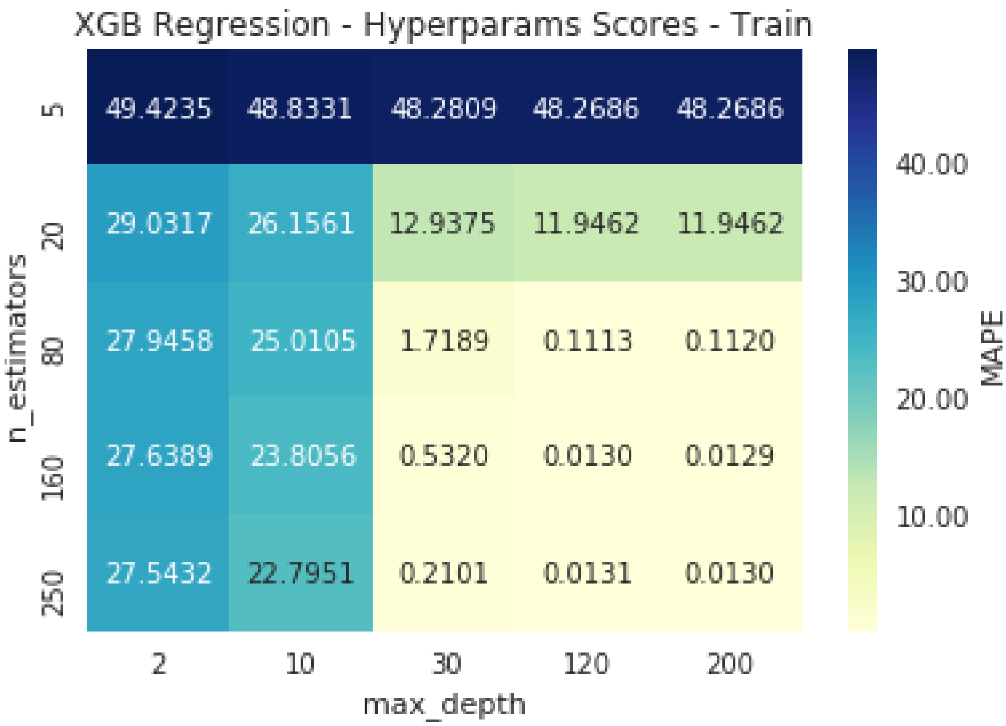
```
In [41]: # Surprise baseline model predictions
         X_train['F_SVD'] = results_dict_svd['train']['predictions']
         X_test['F_SVD'] = results_dict_svd['test']['predictions']
         X_test.head()
```

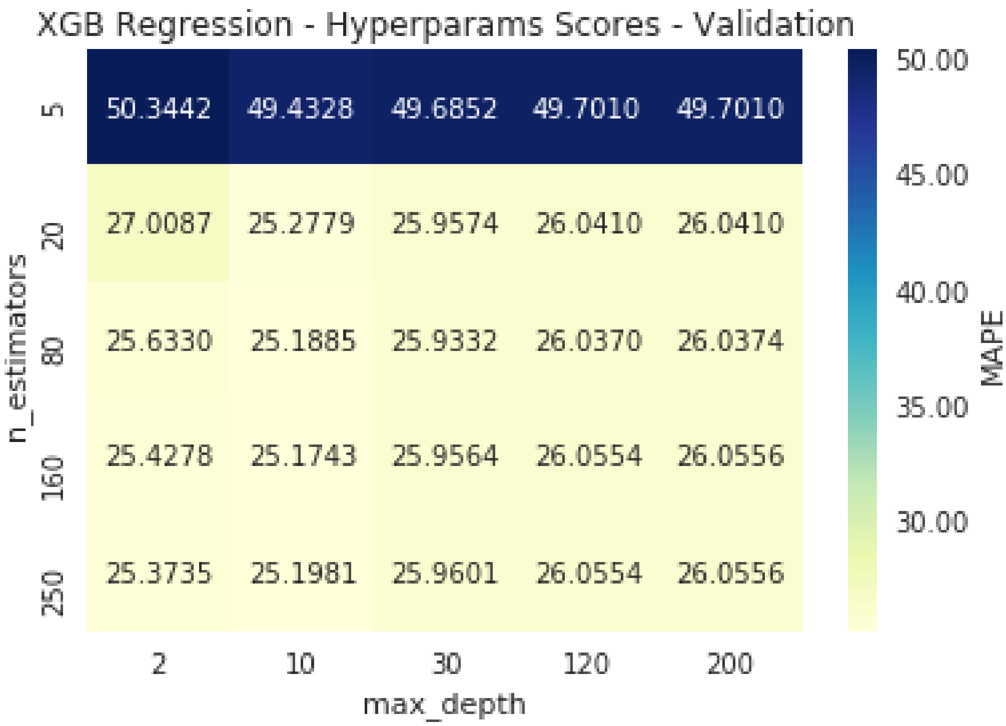
```
Out[41]:    sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
         0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
         1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
         2   4.0   4.0   4.0   5.0   4.0   5.0   2.0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

```
2019-06-26 02:50:59.575304  Hyperparam Tuning of XGB started
```


XGB Regression - Hyperparams Scores - Train
49.4235
48.8331
48.2809
48.2686
48.2686
29.0317
26.1561
12.9375
11.9462
11.9462
27.9458
25.0105
1.7189
0.1113
0.1120
27.6389
23.8056
0.5320
0.0130
0.0129
27.5432
22.7951
0.2101
0.0131
0.0130
n_estimators
5
20
80
160
250
max_depth
2
10
30
120
200
MAPE
40.00
30.00
20.00
10.00




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 160} Best Train Score:  23.80555868148
2019-06-26 08:28:27.502578  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]:
```python
# 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()
```

```
2019-06-26 08:28:29.759600  Training of XGB started
2019-06-26 08:32:50.148239  Training of XGB completed
```

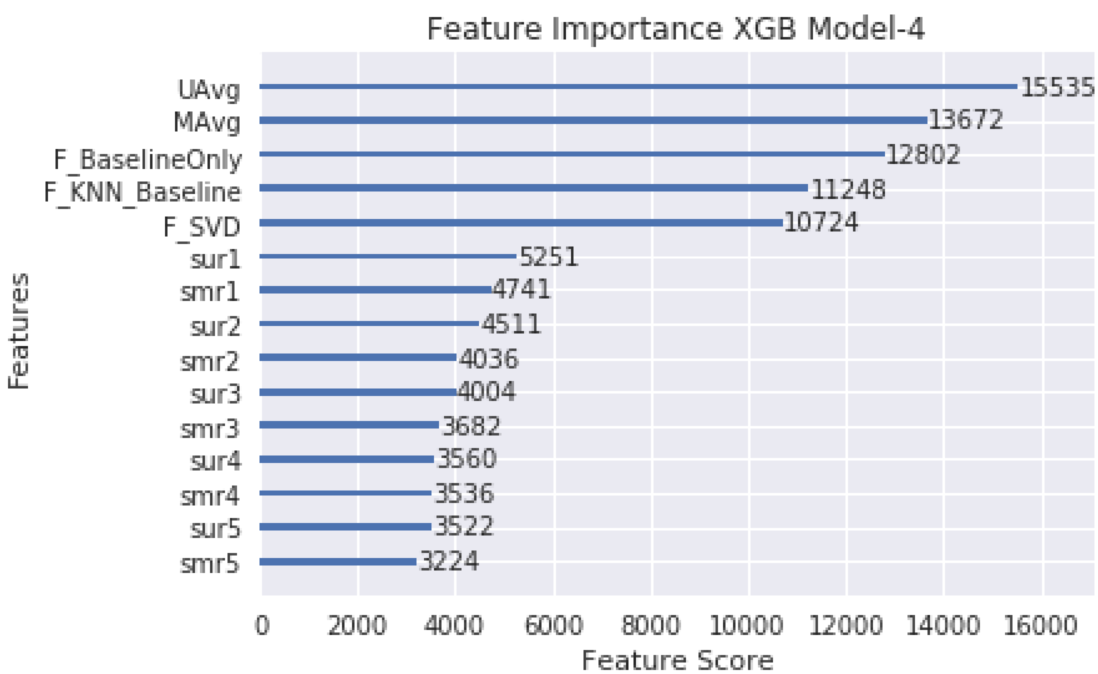
5.7.4 Step 3 : Evaluate model

```
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:0.643700          MAPE:23.901200
Test -> MSE:1.142700          MAPE:32.731100
```

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

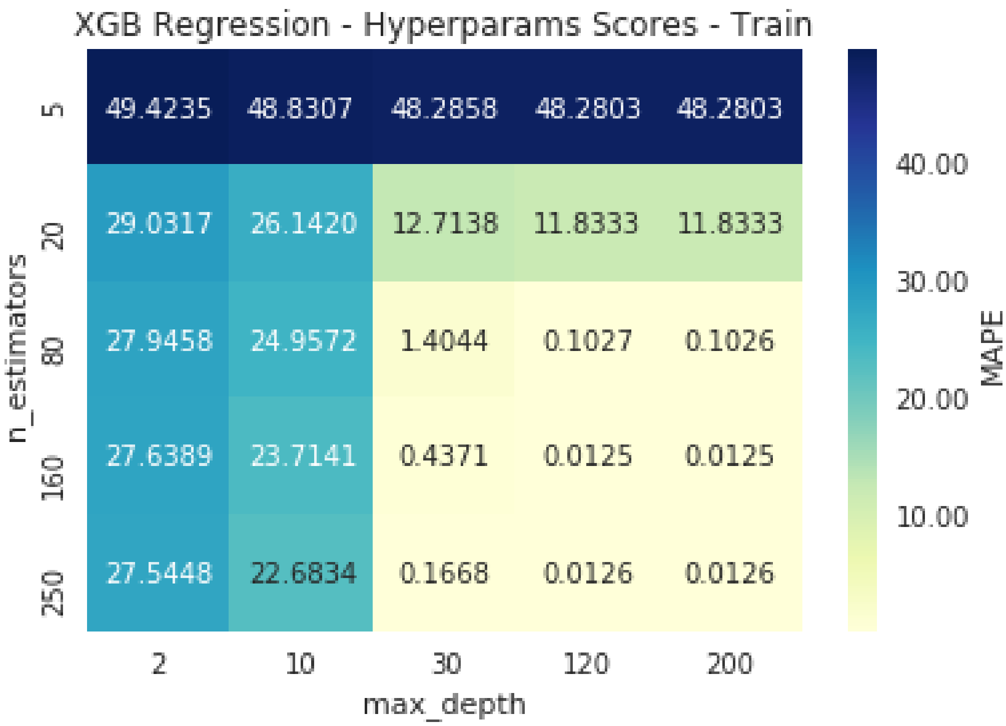
In [47]:
```
# Surprise baseline model predictions
X_train['F_SVDpp'] = results_dict_svdpp['train']['predictions']
X_test['F_SVDpp'] = results_dict_svdpp['test']['predictions']
X_test.head()
```

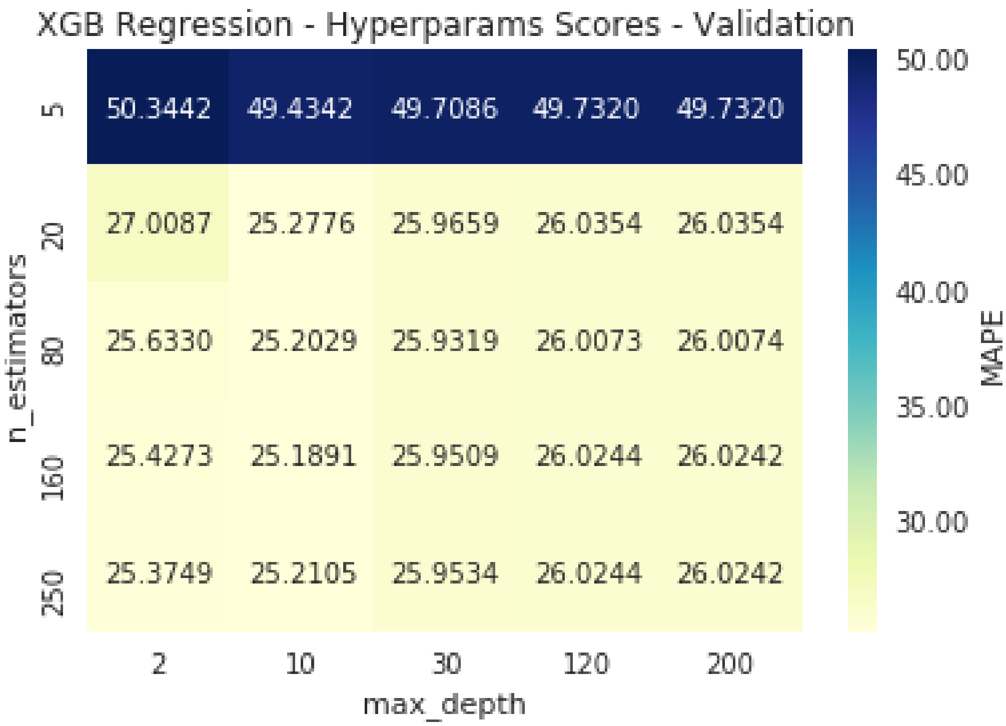
Out[47]:
```
   sur1  sur2  sur3  sur4  sur5  smr1  smr2  smr3  smr4  smr5      UAvg  \
0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0   3.0  3.500000
1   3.0   3.0   3.0   3.0   3.0   3.0   2.0   2.0   2.0   2.0  2.978261
2   4.0   4.0   4.0   5.0   4.0   5.0   2.0   2.0   5.0   2.0  2.978261
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')
```

```
2019-06-26 08:33:09.068359  Hyperparam Tuning of XGB started
```


XGB Regression - Hyperparams Scores - Train
49.4235
48.8307
48.2858
48.2803
48.2803
29.0317
26.1420
12.7138
11.8333
11.8333
27.9458
24.9572
1.4044
0.1027
0.1026
27.6389
23.7141
0.4371
0.0125
0.0125
27.5448
22.6834
0.1668
0.0126
0.0126
n_estimators
5
20
80
160
250
max_depth
2
10
30
120
200
MAPE
40.00
30.00
20.00
10.00




```
Best hyperparam value:  {'max_depth': 10, 'n_estimators': 160} Best Train Score:  23.71405859788
2019-06-26 14:32:35.548926  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()
```

```
2019-06-26 14:32:37.800396  Training of XGB started
2019-06-26 14:37:32.455250  Training of XGB completed
```

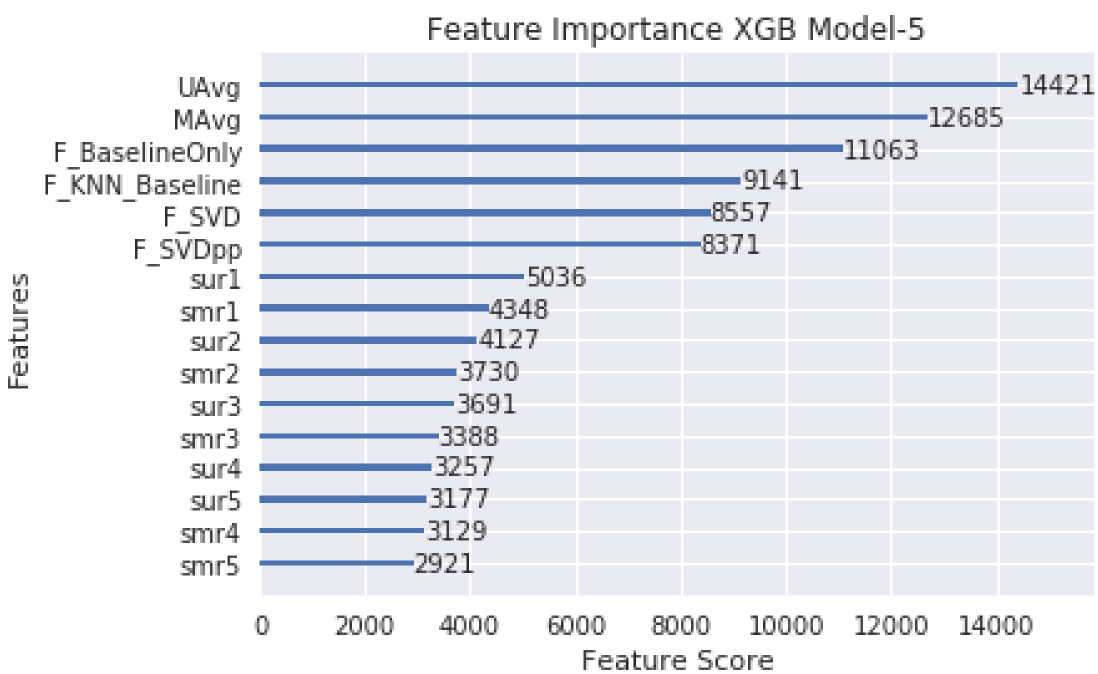
5.9.4 Step 3 : Evaluate model

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:0.644500          MAPE:23.926400
Test -> MSE:1.142200          MAPE:32.738500
```

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)
```

```
+------------------------------------------------------------------------------------------------
|                                            Movie Ratings Results Summary
+--------------+----------------------+------------+-----------+----------+------------+-------
|    Model     |      Hyperparam      | # Features | Train MSE | Test MSE | Train MAPE | Test M
+--------------+----------------------+------------+-----------+----------+------------+-------
| BaselineOnly |          --          |     13     |   0.8615  |  1.0458  |  28.8726   |  32.11
| KNN Baseline |          --          |     13     |   0.2478  |  1.0643  |  14.0426   |  31.72
|     SVD      |          --          |     13     |   0.4543  |  1.0334  |  20.0957   |  31.38
|    SVDpp     |          --          |     13     |   0.4364  |  1.0355  |  19.3678   |  31.12
|     XGB      |   {'max_depth': 10   |     13     |   0.6513  |  1.148   |  24.0191   |  32.74
|              | 'n_estimators': 160} |            |           |          |            |
|     XGB      |   {'max_depth': 10   |     14     |   0.6496  |  1.1418  |  24.0088   |  32.71
|              | 'n_estimators': 160} |            |           |          |            |
|     XGB      |   {'max_depth': 10   |     15     |   0.6465  |  1.1437  |  23.9519   |  32.75
|              | 'n_estimators': 160} |            |           |          |            |
|     XGB      |   {'max_depth': 10   |     16     |   0.6437  |  1.1427  |  23.9012   |  32.73
|              | 'n_estimators': 160} |            |           |          |            |
|     XGB      |   {'max_depth': 10   |     17     |   0.6445  |  1.1422  |  23.9264   |  32.73
|              | 'n_estimators': 160} |            |           |          |            |
+--------------+----------------------+------------+-----------+----------+------------+-------
```

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 MAPE value obatined is 31.1285 from baseline SVDpp
The best XGB model gave 32.7136 MAPE with 14 features dataset
More feature engineering can be done to improve XGB models output further
Other models can be tried instead of XGB models