Assignment

1.Instead of using 10K users and 1K movies to train the above models, use 25K users and 3K movies (or more) to train all of the above models. Report the RMSE and MAPE on the test data using larger amount of data and provide a comparison between various models as shown above.

NOTE: Please be patient as some of the code snippets make take many hours to compelte execution.

2.Tune hyperparamters of all the Xgboost models above to improve the RMSE.

```
In [1]: # this is just to know how much time will it take to run this e
        ntire ipython notebook

        import warnings
        warnings.filterwarnings("ignore")

        from datetime import datetime
        # globalstart = datetime.now()
        import pandas as pd
        import numpy as np
        import matplotlib
        matplotlib.use('nbagg')

        import matplotlib.pyplot as plt
        plt.rcParams.update({'figure.max_open_warning': 0})

        import seaborn as sns
        sns.set_style('whitegrid')
        import os
        from scipy import sparse
        from scipy.sparse import csr_matrix

        from sklearn.decomposition import TruncatedSVD
        from sklearn.metrics.pairwise import cosine_similarity
        import random
        import xgboost as xgb
        from sklearn.metrics import mean_squared_error
        from math import sqrt
```

Assignment

1. Using only 25k users and 3k movies/items for traning because of computational constrain

2. Hypertuning all the Xgboost models and few Surprise Models as well

4. Machine Learning Models

Continue ...

In [3]:
```
def get_sample_sparse_matrix(sparse_matrix, no_users, no_movies
, path, verbose = True):
    """
        It will get it from the ''path'' if it is present  or I
t will create
        and store the sampled sparse matrix in the path specifi
ed.
    """

    # get (row, col) and (rating) tuple from sparse_matrix...
    row_ind, col_ind, ratings = sparse.find(sparse_matrix)
    users = np.unique(row_ind)
    movies = np.unique(col_ind)

    print("Original Matrix : (users, movies) -- ({} {})".format
(len(users), len(movies)))
    print("Original Matrix : Ratings -- {}\n".format(len(rating
s)))

    # It just to make sure to get same sample everytime we run
 this program..
    # and pick without replacement....
    np.random.seed(15)
    sample_users = np.random.choice(users, no_users, replace=Fa
lse)
    sample_movies = np.random.choice(movies, no_movies, replace
=False)
    # get the boolean mask or these sampled_items in originl ro
w/col_inds..
    mask = np.logical_and( np.isin(row_ind, sample_users),
                      np.isin(col_ind, sample_movies) )

    sample_sparse_matrix = sparse.csr_matrix((ratings[mask], (r
ow_ind[mask], col_ind[mask])),
                                             shape=(max(sample_
users)+1, max(sample_movies)+1))

    if verbose:
        print("Sampled Matrix : (users, movies) -- ({} {})".for
mat(len(sample_users), len(sample_movies)))
        print("Sampled Matrix : Ratings --", format(ratings[mas
k].shape[0]))

    print('Saving it into disk for furthur usage..')
    # save it into disk
    sparse.save_npz(path, sample_sparse_matrix)
    if verbose:
            print('Done..\n')

    return sample_sparse_matrix
```

4.1 Sampling Data

4.1.1 Build sample train data from the train data

In [11]:
```
start = datetime.now()
path = "sample/small/sample_train_sparse_matrix.npz"
if os.path.isfile(path):
    print("It is present in your pwd, getting it from disk...."
```

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```
    # just get it from the disk instead of computing it
    sample_train_sparse_matrix = sparse.load_npz(path)
    print("DONE..")
else:
    # get 10k users and 1k movies from available data
    sample_train_sparse_matrix = get_sample_sparse_matrix(train
_sparse_matrix, no_users=22000, no_movies=3000,
                                             path = path)

print(datetime.now() - start)
```

```
It is present in your pwd, getting it from disk....
DONE..
0:00:00.122776
```

4.1.2 Build sample test data from the test data

In [9]:
```
start = datetime.now()

path = "sample/small/sample_test_sparse_matrix.npz"
if os.path.isfile(path):
    print("It is present in your pwd, getting it from disk...."
)
    # just get it from the disk instead of computing it
    sample_test_sparse_matrix = sparse.load_npz(path)
    print("DONE..")
else:
    # get 5k users and 500 movies from available data
    sample_test_sparse_matrix = get_sample_sparse_matrix(test_s
parse_matrix, no_users=5000, no_movies=500,
                                                 path = "sampl
e/small/sample_test_sparse_matrix.npz")
print(datetime.now() - start)
```

```
Original Matrix : (users, movies) -- (349312 17757)
Original Matrix : Ratings -- 20096102

Sampled Matrix : (users, movies) -- (5000 500)
Sampled Matrix : Ratings -- 7333
Saving it into disk for furthur usage..
Done..

0:00:12.608737
```

4.2 Finding Global Average of all movie ratings, Average rating per User, and Average rating per Movie (from sampled train)

In [3]:
```
sample_train_averages = dict()
```

4.2.1 Finding Global Average of all movie ratings

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```
In [17]: # get the global average of ratings in our train set.
         global_average = sample_train_sparse_matrix.sum()/sample_train_
         sparse_matrix.count_nonzero()
         sample_train_averages['global'] = global_average
         sample_train_averages
```

```
{'global': 3.586696968854172}
```

4.2.2 Finding Average rating per User

```
In [18]: sample_train_averages['user'] = get_average_ratings(sample_trai
         n_sparse_matrix, of_users=True)
         print('\nAverage rating of user 1515220 :',sample_train_average
         s['user'][1515220])
```

```
Average rating of user 1515220 : 3.923076923076923
```

4.2.3 Finding Average rating per Movie

```
In [19]: sample_train_averages['movie'] =  get_average_ratings(sample_tr
         ain_sparse_matrix, of_users=False)
         print('\n AVerage rating of movie 15153 :',sample_train_average
         s['movie'][15153])
```

```
 AVerage rating of movie 15153 : 2.765217391304348
```

4.3 Featurizing data

```
In [12]: print('\n No of ratings in Our Sampled train matrix is : {}\n'.
         format(sample_train_sparse_matrix.count_nonzero()))
         print('\n No of ratings in Our Sampled test  matrix is : {}\n'.
         format(sample_test_sparse_matrix.count_nonzero()))
```

```
 No of ratings in Our Sampled train matrix is : 755061


 No of ratings in Our Sampled test  matrix is : 7333
```

4.3.1 Featurizing data for regression problem

4.3.1.1 Featurizing train data

```
In [16]: # get users, movies and ratings from our samples train sparse m
         atrix
         sample_train_users, sample_train_movies, sample_train_ratings =
         sparse.find(sample_train_sparse_matrix)
```

```
In [17]: ############################################################
         # It took me almost 10 hours to prepare this train dataset.#
         ############################################################
Loading [MathJax]/jax/output/HTML-CSS/jax.js = datetime.now()
```

```python
if os.path.isfile('sample/small/reg_train.csv'):
    print("File already exists you don't have to prepare again..." )
else:
    print('preparing {} tuples for the dataset..\n'.format(len(sample_train_ratings)))
    with open('sample/small/reg_train.csv', mode='w') as reg_data_file:
        count = 0
        for (user, movie, rating)  in zip(sample_train_users, sample_train_movies, sample_train_ratings):
            st = datetime.now()
        #     print(user, movie)    
            #--------------------- Ratings of "movie" by similar users of "user" ---------------------
            # compute the similar Users of the "user"        
            user_sim = cosine_similarity(sample_train_sparse_matrix[user], sample_train_sparse_matrix).ravel()
            top_sim_users = user_sim.argsort()[::-1][1:] # we are ignoring 'The User' from its similar users.
            # get the ratings of most similar users for this movie
            top_ratings = sample_train_sparse_matrix[top_sim_users, movie].toarray().ravel()
            # we will make it's length "5" by adding movie averages to .
            top_sim_users_ratings = list(top_ratings[top_ratings != 0][:5])
            top_sim_users_ratings.extend([sample_train_averages['movie'][movie]]*(5 - len(top_sim_users_ratings)))
        #     print(top_sim_users_ratings, end=" ")    


            #--------------------- Ratings by "user"  to similar movies of "movie" ---------------------
            # compute the similar movies of the "movie"        
            movie_sim = cosine_similarity(sample_train_sparse_matrix[:,movie].T, sample_train_sparse_matrix.T).ravel()
            top_sim_movies = movie_sim.argsort()[::-1][1:] # we are ignoring 'The User' from its similar users.
            # get the ratings of most similar movie rated by this user..
            top_ratings = sample_train_sparse_matrix[user, top_sim_movies].toarray().ravel()
            # we will make it's length "5" by adding user averages to.
            top_sim_movies_ratings = list(top_ratings[top_ratings != 0][:5])
            top_sim_movies_ratings.extend([sample_train_averages['user'][user]]*(5-len(top_sim_movies_ratings))) 
        #     print(top_sim_movies_ratings, end=" : -- ")

            #-----------------prepare the row to be stores in a file-----------------#
            row = list()
            row.append(user)
            row.append(movie)
            # Now add the other features to this data...
            row.append(sample_train_averages['global']) # first feature
            # next 5 features are similar_users "movie" ratings
            row.extend(top_sim_users_ratings)
            # next 5 features are "user" ratings for similar_mo
vies
            row.extend(top_sim_movies_ratings)
            # Avg_user rating
            row.append(sample_train_averages['user'][user])
            # Avg_movie rating
            row.append(sample_train_averages['movie'][movie])

            # finalley, The actual Rating of this user-movie pa
ir...
            row.append(rating)
            count = count + 1

            # add rows to the file opened..
            reg_data_file.write(','.join(map(str, row)))
            reg_data_file.write('\n')
            if (count)%10000 == 0:
                # print(','.join(map(str, row)))
                print("Done for {} rows----- {}".format(count,
datetime.now() - start))


print(datetime.now() - start)
```

```
preparing 755061 tuples for the dataset..

Done for 10000 rows----- 1:31:55.562553
Done for 20000 rows----- 3:03:55.813751
Done for 30000 rows----- 4:52:51.163289
Done for 40000 rows----- 6:48:27.670960
Done for 50000 rows----- 8:31:22.057444
Done for 60000 rows----- 10:29:45.204598
Done for 70000 rows----- 12:42:53.474772
Done for 80000 rows----- 19:16:34.746836
Done for 90000 rows----- 20:57:54.954084
Done for 100000 rows----- 23:05:00.660495
Done for 110000 rows----- 1 day, 0:44:25.305511
Done for 120000 rows----- 1 day, 2:24:54.052441
Done for 130000 rows----- 1 day, 4:09:57.957780
Done for 140000 rows----- 1 day, 6:24:05.590037
Done for 150000 rows----- 1 day, 8:15:33.424803
Done for 160000 rows----- 1 day, 10:22:33.311227
Done for 170000 rows----- 1 day, 12:00:51.903907
Done for 180000 rows----- 1 day, 13:36:37.739632
Done for 190000 rows----- 1 day, 15:11:58.748821
Done for 200000 rows----- 1 day, 16:47:38.990989
Done for 210000 rows----- 1 day, 18:21:25.305253
Done for 220000 rows----- 1 day, 20:07:23.720122
Done for 230000 rows----- 1 day, 22:10:30.176990
Done for 240000 rows----- 1 day, 23:59:05.521467
Done for 250000 rows----- 2 days, 2:12:09.694986
Done for 260000 rows----- 2 days, 5:28:44.009471
Done for 270000 rows----- 2 days, 7:04:23.454643
Done for 280000 rows----- 2 days, 9:08:45.214563
Done for 290000 rows----- 2 days, 10:53:30.018186
```

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```
Done for 300000 rows----- 2 days, 12:28:16.470219
Done for 310000 rows----- 2 days, 14:03:13.686340
Done for 320000 rows----- 2 days, 15:38:27.715425
Done for 330000 rows----- 2 days, 17:22:32.457171
Done for 340000 rows----- 2 days, 19:31:30.399766
Done for 350000 rows----- 2 days, 21:13:48.695508
Done for 360000 rows----- 2 days, 23:14:58.683335
Done for 370000 rows----- 3 days, 1:16:19.698199
Done for 380000 rows----- 3 days, 3:05:25.189972
Done for 390000 rows----- 3 days, 5:17:52.183447
Done for 400000 rows----- 3 days, 7:00:02.195518
Done for 410000 rows----- 3 days, 8:48:58.109100
Done for 420000 rows----- 3 days, 10:47:52.133506
Done for 430000 rows----- 3 days, 12:20:08.363889
Done for 440000 rows----- 3 days, 13:49:26.960257
Done for 450000 rows----- 3 days, 15:22:53.372306
Done for 460000 rows----- 3 days, 16:56:54.539723
Done for 470000 rows----- 3 days, 18:55:26.674520
Done for 480000 rows----- 3 days, 21:07:34.134569
Done for 490000 rows----- 3 days, 22:54:26.326606
Done for 500000 rows----- 4 days, 0:41:37.618221
Done for 510000 rows----- 4 days, 2:29:53.846479
Done for 520000 rows----- 4 days, 4:42:26.969426
Done for 530000 rows----- 4 days, 6:45:34.720070
Done for 540000 rows----- 4 days, 8:32:10.284825
Done for 550000 rows----- 4 days, 10:06:51.206291
Done for 560000 rows----- 4 days, 11:41:07.756233
Done for 570000 rows----- 4 days, 13:15:21.381377
Done for 580000 rows----- 4 days, 14:49:53.291097
Done for 590000 rows----- 4 days, 16:24:19.248694
Done for 600000 rows----- 4 days, 18:23:45.432014
Done for 610000 rows----- 4 days, 20:30:10.094573
Done for 620000 rows----- 4 days, 22:16:14.588154
Done for 630000 rows----- 4 days, 23:56:31.349335
Done for 640000 rows----- 5 days, 2:05:39.961697
Done for 650000 rows----- 5 days, 3:38:12.901471
Done for 660000 rows----- 5 days, 5:40:28.541694
Done for 670000 rows----- 5 days, 7:16:34.925528
Done for 680000 rows----- 5 days, 9:22:23.893797
Done for 690000 rows----- 5 days, 11:00:49.380512
Done for 700000 rows----- 5 days, 12:31:59.920691
Done for 710000 rows----- 5 days, 14:03:10.448798
Done for 720000 rows----- 5 days, 15:35:03.811425
Done for 730000 rows----- 5 days, 17:06:51.818248
Done for 740000 rows----- 5 days, 19:03:12.615211
Done for 750000 rows----- 5 days, 20:41:22.338858
5 days, 21:47:29.292160
```

Reading from the file to make a Train_dataframe

```
In [3]: reg_train = pd.read_csv('sample/small/reg_train.csv', names = [
        ', 'movie', 'GAvg', 'sur1', 'sur2', 'sur3', 'sur4', 'sur5'
,'smr1', 'smr2', 'smr3', 'smr4', 'smr5', 'UAvg', 'MAvg', 'ratin
g'], header=None)
reg_train.head()
```

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	174683	10	3.586697	5.0	5.0	3.0	4.0	4.0	3.0	5.0
1	233949	10	3.586697	4.0	4.0	5.0	1.0	5.0	2.0	3.0
2	555770	10	3.586697	4.0	5.0	4.0	5.0	3.0	4.0	2.0
3	767518	10	3.586697	5.0	4.0	4.0	3.0	4.0	5.0	5.0
4	894393	10	3.586697	3.0	5.0	4.0	4.0	5.0	4.0	4.0

- **GAvg** : Average rating of all the ratings
- **Similar users rating of this movie**:
  - sur1, sur2, sur3, sur4, sur5 (top 5 similar users who rated that movie..)
- **Similar movies rated by this user**:
  - smr1, smr2, smr3, smr4, smr5 (top 5 similar movies rated by this movie..)
- **UAvg** : User's Average rating
- **MAvg** : Average rating of this movie
- **rating** : Rating of this movie by this user.

4.3.1.2 Featurizing test data

```
In [ ]: # get users, movies and ratings from the Sampled Test
        sample_test_users, sample_test_movies, sample_test_ratings = sp
        arse.find(sample_test_sparse_matrix)
```

```
In [20]: sample_train_averages['global']
```

```
3.586696968854172
```

```
In [22]: start = datetime.now()

         if os.path.isfile('sample/small/reg_test.csv'):
             print("It is already created...")
         else:

             print('preparing {} tuples for the dataset..\n'.format(len(
         sample_test_ratings)))
             with open('sample/small/reg_test.csv', mode='w') as reg_dat
         a_file:
                 count = 0
                 for (user, movie, rating)  in zip(sample_test_users, sa
         mple_test_movies, sample_test_ratings):
                     st = datetime.now()

                 #--------------------- Ratings of "movie" by similar us
         ers of "user" ---------------------
                     #print(user, movie)
```

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```
            try:
                # compute the similar Users of the "user"
                user_sim = cosine_similarity(sample_train_spars
e_matrix[user], sample_train_sparse_matrix).ravel()
                top_sim_users = user_sim.argsort()[::-1][1:] #
 we are ignoring 'The User' from its similar users.
                # get the ratings of most similar users for thi
s movie
                top_ratings = sample_train_sparse_matrix[top_si
m_users, movie].toarray().ravel()
                # we will make it's length "5" by adding movie
 averages to .
                top_sim_users_ratings = list(top_ratings[top_ra
tings != 0][:5])
                top_sim_users_ratings.extend([sample_train_aver
ages['movie'][movie]]*(5 - len(top_sim_users_ratings)))
                # print(top_sim_users_ratings, end="--")

            except (IndexError, KeyError):
                # It is a new User or new Movie or there are no
ratings for given user for top similar movies...
                ########## Cold STart Problem ##########
                top_sim_users_ratings.extend([sample_train_aver
ages['global']]*(5 - len(top_sim_users_ratings)))
                #print(top_sim_users_ratings)
            except:
                print(user, movie)
                # we just want KeyErrors to be resolved. Not ev
ery Exception...
                raise



            #--------------------- Ratings by "user"  to simila
r movies of "movie" ---------------------
            try:
                # compute the similar movies of the "movie"
                movie_sim = cosine_similarity(sample_train_spar
se_matrix[:,movie].T, sample_train_sparse_matrix.T).ravel()
                top_sim_movies = movie_sim.argsort()[::-1][1:]
# we are ignoring 'The User' from its similar users.
                # get the ratings of most similar movie rated b
y this user..
                top_ratings = sample_train_sparse_matrix[user,
top_sim_movies].toarray().ravel()
                # we will make it's length "5" by adding user a
verages to.
                top_sim_movies_ratings = list(top_ratings[top_r
atings != 0][:5])
                top_sim_movies_ratings.extend([sample_train_ave
rages['user'][user]]*(5-len(top_sim_movies_ratings)))
                #print(top_sim_movies_ratings)
            except (IndexError, KeyError):
                #print(top_sim_movies_ratings, end=" : -- ")
                top_sim_movies_ratings.extend([sample_train_ave
rages['global']]*(5-len(top_sim_movies_ratings)))
                #print(top_sim_movies_ratings)
            except :
                raise

            #-----------------prepare the row to be stores in a
      -----------------#
```

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```
                row = list()
                # add usser and movie name first
                row.append(user)
                row.append(movie)
                row.append(sample_train_averages['global']) # first
feature
                #print(row)
                # next 5 features are similar_users "movie" ratings
                row.extend(top_sim_users_ratings)
                #print(row)
                # next 5 features are "user" ratings for similar_mo
vies
                row.extend(top_sim_movies_ratings)
                #print(row)
                # Avg_user rating
                try:
                    row.append(sample_train_averages['user'][user])
                except KeyError:
                    row.append(sample_train_averages['global'])
                except:
                    raise
                #print(row)
                # Avg_movie rating
                try:
                    row.append(sample_train_averages['movie'][movie
])
                except KeyError:
                    row.append(sample_train_averages['global'])
                except:
                    raise
                #print(row)
                # finalley, The actual Rating of this user-movie pa
ir...
                row.append(rating)
                #print(row)
                count = count + 1

                # add rows to the file opened..
                reg_data_file.write(','.join(map(str, row)))
                #print(','.join(map(str, row)))
                reg_data_file.write('\n')
                if (count)%1000 == 0:
                    #print(','.join(map(str, row)))
                    print("Done for {} rows----- {}".format(count,
datetime.now() - start))
    print("",datetime.now() - start)
```

```
It is already created...
```

Reading from the file to make a test dataframe

In [2]:
```
reg_test_df = pd.read_csv('sample/small/reg_test.csv', names =
['user', 'movie', 'GAvg', 'sur1', 'sur2', 'sur3', 'sur4', 'sur
5',
                                                          'smr
1', 'smr2', 'smr3', 'smr4', 'smr5',
                                                          'UAv
g', 'MAvg', 'rating'], header=None)
reg_test_df.head(4)
```

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	user	movie	GAvg	sur1	sur2	sur3	sur4	
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5
2	1737912	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5
3	1849204	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5

- **GAvg** : Average rating of all the ratings
- **Similar users rating of this movie**:
  - sur1, sur2, sur3, sur4, sur5 (top 5 simiular users who rated that movie..)
- **Similar movies rated by this user**:
  - smr1, smr2, smr3, smr4, smr5 (top 5 simiular movies rated by this movie..)
- **UAvg** : User AVerage rating
- **MAvg** : Average rating of this movie
- **rating** : Rating of this movie by this user.

4.3.2 Transforming data for Surprise models

In [4]:
```
from surprise import Reader, Dataset
```

4.3.2.1 Transforming train data

- We can't give raw data (movie, user, rating) to train the model in Surprise library.
- They have a saperate format for TRAIN and TEST data, which will be useful for training the models like SVD, KNNBaseLineOnly....etc..,in Surprise.
- We can form the trainset from a file, or from a Pandas DataFrame. http://surprise.readthedocs.io/en/stable/getting_started.html#load-dom-dataframe-py

In [5]:
```
# It is to specify how to read the dataframe.
# for our dataframe, we don't have to specify anything extra..
reader = Reader(rating_scale=(1,5))

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

# build the trainset from traindata.., It is of dataset format
 from surprise library..
trainset = train_data.build_full_trainset()
```

4.3.2.2 Transforming test data

- Testset is just a list of (user, movie, rating) tuples. (Order in the tuple is impotant)

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```
In [6]: testset = list(zip(reg_test_df.user.values, reg_test_df.movie.v
alues, reg_test_df.rating.values))
testset[:3]
```

```
[(808635, 71, 5), (941866, 71, 4), (1737912, 71, 3)]
```

4.4 Applying Machine Learning models

- Global dictionary that stores rmse and mape for all the models....
    - It stores the metrics in a dictionary of dictionaries

> **keys** : model names(string)
>
> **value**: dict(**key** : metric, **value** : value)

```
In [7]: models_evaluation_train = dict()
models_evaluation_test = dict()

models_evaluation_train, models_evaluation_test
```

```
({}, {})
```

> **Utility functions for running regression models**

```
In [8]: # to get rmse and mape given actual and predicted ratings..
def get_error_metrics(y_true, y_pred):
    rmse = np.sqrt(np.mean([ (y_true[i] - y_pred[i])**2 for i i
n range(len(y_pred)) ]))
    mape = np.mean(np.abs( (y_true - y_pred)/y_true )) * 100
    return rmse, mape

################################################################
####
################################################################
####
def run_xgboost(algo,  x_train, y_train, x_test, y_test, verbos
e=True):
    """
    It will return train_results and test_results
    """

    # dictionaries for storing train and test results
    train_results = dict()
    test_results = dict()


    # fit the model
    print('Training the model..')
    start =datetime.now()
    algo.fit(x_train, y_train, eval_metric = 'rmse')
    print('Done. Time taken : {}\n'.format(datetime.now()-start
    print('Done \n')

    # from the trained model, get the predictions....
    print('Evaluating the model with TRAIN data...')
    start =datetime.now()
    y_train_pred = algo.predict(x_train)
    # get the rmse and mape of train data...
    rmse_train, mape_train = get_error_metrics(y_train.values,
y_train_pred)

    # store the results in train_results dictionary..
    train_results = {'rmse': rmse_train,
                    'mape' : mape_train,
                    'predictions' : y_train_pred}

    #######################################
    # get the test data predictions and compute rmse and mape
    print('Evaluating Test data')
    y_test_pred = algo.predict(x_test)
    rmse_test, mape_test = get_error_metrics(y_true=y_test.valu
es, y_pred=y_test_pred)
    # store them in our test results dictionary.
    test_results = {'rmse': rmse_test,
                    'mape' : mape_test,
                    'predictions':y_test_pred}
    if verbose:
        print('\nTEST DATA')
        print('-'*30)
        print('RMSE : ', rmse_test)
        print('MAPE : ', mape_test)

    # return these train and test results...
    return train_results, test_results


# utility function for hypeparameter tuning
def run_xgboost_hyperparameter_tune(algo,  x_train, y_train, x_
test, y_test, verbose=True):
    """
    It will return train_results and test_results
    """

    # dictionaries for storing train and test results
    train_results = dict()
    test_results = dict()


    # fit the model
    print('Training the model..')
    start =datetime.now()
    algo.fit(x_train, y_train, eval_metric = 'rmse')
    print('Done. Time taken : {}\n'.format(datetime.now()-start
))
    print('Done \n')

    # from the trained model, get the predictions....
    print('Evaluating the model with TRAIN data...')
    start =datetime.now()
    y_train_pred = algo.predict(x_train)
    # get the rmse and mape of train data...
    rmse_train, mape_train = get_error_metrics(y_train.values,
```
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```
in_pred)
```

```
    # store the results in train_results dictionary..
    train_results = {'rmse': rmse_train,
                    'mape' : mape_train,
                    'predictions' : y_train_pred}

    #######################################
    # get the test data predictions and compute rmse and mape
    print('Evaluating Test data')
    y_test_pred = algo.predict(x_test)
    rmse_test, mape_test = get_error_metrics(y_true=y_test.valu
es, y_pred=y_test_pred)
    # store them in our test results dictionary.
    test_results = {'rmse': rmse_test,
                    'mape' : mape_test,
                    'predictions':y_test_pred}
    if verbose:
        print('\nTEST DATA')
        print('-'*30)
        print('RMSE : ', rmse_test)
        print('MAPE : ', mape_test)

    # return these train and test results...
    return train_results, test_results
```

Utility functions for Surprise modes

In [9]:
```
# it is just to makesure that all of our algorithms should prod
uce same results
# everytime they run...

my_seed = 15
random.seed(my_seed)
np.random.seed(my_seed)

##########################################################
# get  (actual_list , predicted_list) ratings given list
# of predictions (prediction is a class in Surprise).
##########################################################
def get_ratings(predictions):
    actual = np.array([pred.r_ui for pred in predictions])
    pred = np.array([pred.est for pred in predictions])

    return actual, pred

################################################################
#
# get ''rmse'' and ''mape'' , given list of prediction objecs
################################################################
#
def get_errors(predictions, print_them=False):

    actual, pred = get_ratings(predictions)
    rmse = np.sqrt(np.mean((pred - actual)**2))
    mape = np.mean(np.abs(pred - actual)/actual)

    return rmse, mape*100
```

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```
#################################################################
###################
# It will return predicted ratings, rmse and mape of both train
and test data   #
#################################################################
###################
def run_surprise(algo, trainset, testset, verbose=True):
    '''
        return train_dict, test_dict

        It returns two dictionaries, one for train and the othe
r is for test
        Each of them have 3 key-value pairs, which specify ''rm
se'', ''mape'', and ''predicted ratings''.
    '''
    start = datetime.now()
    # dictionaries that stores metrics for train and test..
    train = dict()
    test = dict()

    # train the algorithm with the trainset
    algo.fit(trainset)

    # ---------------- Evaluating train data--------------------
-#
    st = datetime.now()
    # get the train predictions (list of prediction class insid
e Surprise)
    train_preds = algo.test(trainset.build_testset())
    # get predicted ratings from the train predictions..
    train_actual_ratings, train_pred_ratings = get_ratings(trai
n_preds)
    # get ''rmse'' and ''mape'' from the train predictions.
    train_rmse, train_mape = get_errors(train_preds)


    if verbose:
        print('-'*15)
        print('Train Data')
        print('-'*15)
        print("RMSE : {}\n\nMAPE : {}\n".format(train_rmse, tra
in_mape))

    #store them in the train dictionary
    if verbose:
        print('adding train results in the dictionary..')
    train['rmse'] = train_rmse
    train['mape'] = train_mape
    train['predictions'] = train_pred_ratings

    #------------ Evaluating Test data---------------#

    # get the predictions( list of prediction classes) of test
 data
    test_preds = algo.test(testset)
    # get the predicted ratings from the list of predictions
    test_actual_ratings, test_pred_ratings = get_ratings(test_p
reds)
    # get error metrics from the predicted and actual ratings
    test_rmse, test_mape = get_errors(test_preds)

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```

```
            print('-'*15)
            print('Test Data')
            print('-'*15)
            print("RMSE : {}\n\nMAPE : {}\n".format(test_rmse, test
_mape))
        # store them in test dictionary
        if verbose:
            print('storing the test results in test dictionary...')
        test['rmse'] = test_rmse
        test['mape'] = test_mape
        test['predictions'] = test_pred_ratings


        # return two dictionaries train and test
        return train, test
```

4.4.1 XGBoost with initial 13 features

Hyperparameter tuning

In [ ]:
```
from sklearn.model_selection import RandomizedSearchCV

# prepare Train data
x_train = reg_train.drop(['user','movie','rating'], axis=1)
y_train = reg_train['rating']

# Prepare Test data
x_test = reg_test_df.drop(['user','movie','rating'], axis=1)
y_test = reg_test_df['rating']


depth=[3,5,10,25,30,35]
learning_rate= [0.01,0.03,0.05,0.1,0.5,1]
n_estimators= [25,50,100,150,200]

param={"max_depth":depth,"learning_rate":learning_rate,"n_estim
ators":n_estimators}


xgb_model=xgb.XGBRegressor(max_depth=3,learning_rate=0.1, n_est
imators=100)

start =datetime.now()
# fit the model
print('Training the model..')
rscv=RandomizedSearchCV( estimator=xgb_model,param_distribution
s=param,scoring='neg_mean_squared_error',n_jobs=-2)
rscv.fit(x_train, y_train)
print('Done. Time taken : {}\n'.format(datetime.now()-start))
print('Done \n')
```

In [14]:
```
# best RMSE score
np.sqrt(-rscv.best_score_)
```

```
0.8625960428242238
```

In [16]:
```
# best esitmator
rscv.best_estimator_
```

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```
XGBRegressor(base_score=0.5, booster='gbtree', colsampl
e_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, ga
mma=0,
             importance_type='gain', learning_rate=0.0
5, max_delta_step=0,
             max_depth=5, min_child_weight=1, missing=N
one, n_estimators=150,
             n_jobs=1, nthread=None, objective='reg:lin
ear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weigh
t=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [18]:
```
rscv.best_params_
```

```
{'n_estimators': 150, 'max_depth': 5, 'learning_rate':
0.05}
```

Traning with best hyperparameter

In [10]:
```
# traning using best hyperparameter
print("best_hyperparameter:",{'n_estimators': 150, 'max_depth':
5, 'learning_rate': 0.05},"\n\n")


# prepare train data
x_train = reg_train.drop(['user', 'movie','rating'], axis=1)
y_train = reg_train['rating']

# Prepare Test data
x_test = reg_test_df.drop(['user','movie','rating'], axis=1)
y_test = reg_test_df['rating']


xgb_model=xgb.XGBRegressor(base_score=0.5, booster='gbtree', co
lsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.05, max_de
lta_step=0,
             max_depth=5, min_child_weight=1, missing=None, n_e
stimators=150,
             n_jobs=1, nthread=None, objective='reg:linear', ra
ndom_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, see
d=None,
             silent=None, subsample=1, verbosity=1)


train_results, test_results = run_xgboost_hyperparameter_tune(x
gb_model, x_train, y_train, x_test, y_test,verbose=1)

# Just store these error metrics in our models_evaluation datas
tructure
models_evaluation_train['initial 13 features'] = train_results
models_evaluation_test['initial 13 features'] = test_results
```

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```
xgb.plot_importance(xgb_model)
plt.show()
```

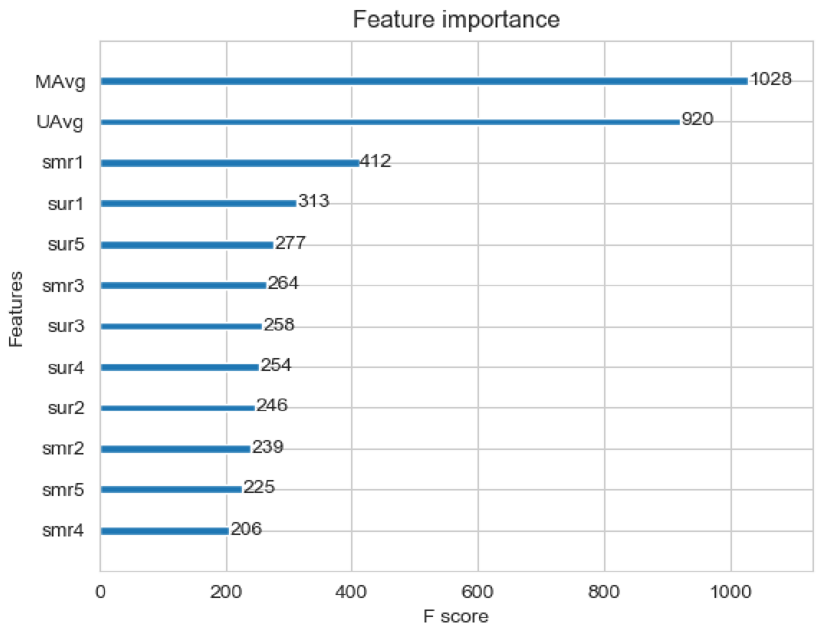
```
best_hyperparameter: {'n_estimators': 150, 'max_depth':
5, 'learning_rate': 0.05}


Training the model..
[21:16:58] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:01:20.348063

Done

Evaluating the model with TRAIN data...
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.0750789121096134
MAPE :  34.61955182638714
```



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4.4.2 Suprise BaselineModel

```
In [12]: from surprise import BaselineOnly
```

Predicted_rating : (baseline prediction)

> \- http://surprise.readthedocs.io/en/stable/basic_algorithms.html#surprise.prediction_algorithms.baseline_only.BaselineOnly

> $$\hat{r}_{ui} = b_{ui} = \mu + b_u + b_i$$

- $\boldsymbol{\mu}$: Average of all trainings in training data.
- $\boldsymbol{b}_u$: User bias
- $\boldsymbol{b}_i$: Item bias (movie biases)

Optimization function (Least Squares Problem)

> \- http://surprise.readthedocs.io/en/stable/prediction_algorithms.html#baselines-estimates-configuration

> $$\sum_{r_{ui} \in R_{train}} \left(r_{ui} - (\mu + b_u + b_i)\right)^2 + \lambda \left(b_u^2 + b_i^2\right). \text{ [mimimize } b_u, b_i]$$

Method : "als"

```
In [48]: # creating hyperparameter alias

         options=[]

         epoch=[10,20,30,50]
         n_user=[2,5,10,12,15]
         n_item=[2,5,10,12,15]


         for ep in epoch:
             for user in n_user:
                 for item in n_item:
                     options.append({'method': 'als',
                                     'n_epochs': ep,
                                     'reg_u': item,
```

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```
                              'reg_i': user
                              })

#example
print("bsl_option 1: ",options[0])
```

```
bsl_option 1:  {'method': 'als', 'n_epochs': 10, 'reg_
u': 2, 'reg_i': 2}
```

In [67]:
```
# Traning
train_rmse=[]
train_mape=[]
test_rmse=[]
test_mape=[]

for idx,param in enumerate(options):

    bsl_algo = BaselineOnly(bsl_options=param)
    # run this algorithm.., It will return the train and test r
esults..
    print("index =",idx+1," out of" ,len(options), "completed")
    bsl_train_results, bsl_test_results = run_surprise(bsl_algo
, trainset, testset, verbose=False)

    # Just store these error metrics in our models_evaluation d
atastructure
    train_rmse.append(bsl_train_results['rmse'])
    train_mape.append(bsl_train_results['mape'])

    test_rmse.append(bsl_test_results['rmse'])
    test_mape.append(bsl_test_results['mape'])
```

```
index = 1  out of 100 completed
Estimating biases using als...
index = 2  out of 100 completed
Estimating biases using als...
index = 3  out of 100 completed
Estimating biases using als...
index = 4  out of 100 completed
Estimating biases using als...
index = 5  out of 100 completed
Estimating biases using als...
index = 6  out of 100 completed
Estimating biases using als...
index = 7  out of 100 completed
Estimating biases using als...
index = 8  out of 100 completed
Estimating biases using als...

index = 9  out of 100 completed
Estimating biases using als...
index = 10  out of 100 completed
Estimating biases using als...
index = 11  out of 100 completed
Estimating biases using als...
```

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```
index = 12  out of 100 completed
Estimating biases using als...
index = 13  out of 100 completed
Estimating biases using als...
index = 14  out of 100 completed
Estimating biases using als...
index = 15  out of 100 completed
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index = 19  out of 100 completed
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index = 32  out of 100 completed
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Estimating biases using als...

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Estimating biases using als...
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timating biases using als...
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index = 38  out of 100 completed
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index = 63  out of 100 completed
  timating biases using als...
```

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```
index = 64  out of 100 completed
Estimating biases using als...
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Estimating biases using als...

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Estimating biases using als...
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Estimating biases using als...
index = 89  out of 100 completed
  timating biases using als...
```

```
index = 90  out of 100 completed
Estimating biases using als...
index = 91  out of 100 completed
Estimating biases using als...
index = 92  out of 100 completed
Estimating biases using als...
index = 93  out of 100 completed
Estimating biases using als...
index = 94  out of 100 completed
Estimating biases using als...
index = 95  out of 100 completed
Estimating biases using als...
index = 96  out of 100 completed
Estimating biases using als...
index = 97  out of 100 completed
Estimating biases using als...
index = 98  out of 100 completed
Estimating biases using als...
index = 99  out of 100 completed
Estimating biases using als...
index = 100  out of 100 completed
Estimating biases using als...
```

In [68]:
```
# storing reults of all the hyperparameter
result=pd.DataFrame({"param": options,"train_rmse":train_rmse,
"train_mape":train_mape,"test_rmse":test_rmse,"test_mape":test_
mape })
result
```

	param	train_rmse	train_mape	test_rmse	test_mape
0	{'method': 'als', 'n_epochs': 10, 'reg_u': 2, ...	0.896630	27.336924	1.067473	34.228577
1	{'method': 'als', 'n_epochs': 10, 'reg_u': 5, ...	0.899705	27.537338	1.067179	34.252275
2	{'method': 'als', 'n_epochs': 10, 'reg_u': 10,...	0.904128	27.785690	1.067003	34.273143
3	{'method': 'als', 'n_epochs': 10, 'reg_u': 12,...	0.905696	27.867779	1.066971	34.278442
4	{'method': 'als', 'n_epochs': 10, 'reg_u': 15,...	0.907880	27.978513	1.066943	34.285001
...	...	...	...	...	...
95	{'method': 'als', 'n_epochs': 50, 'reg_u': 2, ...	0.898681	27.506804	1.066728	34.354359
96	{'method': 'als', 'n_epochs': 50, 'reg_u': 5, ...	0.901799	27.718905	1.066425	34.319823
97	{'method': 'als', 'n_epochs': 50, 'reg_u': 10,...	0.906238	27.971642	1.066298	34.308159

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98	{'method': 'als', 'n_epochs': 50, 'reg_u': 12,...	0.907808	28.054399	1.066284	34.307193
99	{'method': 'als', 'n_epochs': 50, 'reg_u': 15,...	0.909992	28.165872	1.066279	34.307098

100 rows × 5 columns

```
In [69]: best_result=result[result["test_mape"]==min(result["test_mape"
         ])]
         print(f"best parameter: {best_result['param'][0]}")
         print(f"best RMSE_score: {best_result['test_rmse'][0]}")
         print(f"best MAPE_score: {best_result['test_mape'][0]}")
```

```
best parameter: {'method': 'als', 'n_epochs': 10, 'reg_
u': 2, 'reg_i': 2}
best RMSE_score: 1.0674729813270976
best MAPE_score: 34.22857744546804
```

Traning with best hyperparameter

```
In [14]: # traning using best hyperparameter

         print("traning using optimal hyperparameter: {'method': 'als',
          'n_epochs': 10, 'reg_u': 2, 'reg_i': 2} \n\n")

         bsl_algo = BaselineOnly( bsl_options={'method': 'als', 'n_epoch
         s': 10, 'reg_u': 2, 'reg_i': 2})

         # run this algorithm.., It will return the train and test resul
         ts..
         bsl_train_results, bsl_test_results = run_surprise(bsl_algo, tr
         ainset, testset, verbose=True)

         # Just store these error metrics in our models_evaluation datas
         tructure
         models_evaluation_train['bsl_algo'] = bsl_train_results
         models_evaluation_test['bsl_algo'] = bsl_test_results
```

```
traning using optimal hyperparameter: {'method': 'als',
'n_epochs': 10, 'reg_u': 2, 'reg_i': 2}


Estimating biases using als...
---------------
Train Data
---------------
RMSE : 0.8966304838554658

MAPE : 27.336923805931296

adding train results in the dictionary..
---------------
Test Data
---------------
```

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```
RMSE : 1.0674729813270976

MAPE : 34.22857744546804

storing the test results in test dictionary...
```

4.4.3 XGBoost with initial 13 features + Surprise Baseline predictor

Updating Train Data

```
In [15]: # add our baseline_predicted value as our feature..
         reg_train['bslpr'] = models_evaluation_train['bsl_algo']['predi
         ctions']
         reg_train.head(2)
```

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	174683	10	3.586697	5.0	5.0	3.0	4.0	4.0	3.0	5.0
1	233949	10	3.586697	4.0	4.0	5.0	1.0	5.0	2.0	3.0

Updating Test Data

```
In [16]: # add that baseline predicted ratings with Surprise to the test
         data as well
         reg_test_df['bslpr']  = models_evaluation_test['bsl_algo']['pre
         dictions']

         reg_test_df.head(5)
```

	user	movie	GAvg	sur1	sur2	sur3	sur4	
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5
2	1737912	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5
3	1849204	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.5
4	28572	111	3.581679	3.581679	3.581679	3.581679	3.581679	3.5

Finding best hyperparameter

```
In [103]: from sklearn.model_selection import RandomizedSearchCV

          # prepare Train data
          x_train = reg_train.drop(['user','movie','rating'], axis=1)
          y_train = reg_train['rating']

          # Prepare Test data
          x_test = reg_test_df.drop(['user','movie','rating'], axis=1)
          y_test = reg_test_df['rating']


          depth=[3,5,10,25,30,35]
          learning_rate= [0.01,0.03,0.05,0.1,0.5,1]
          n_estimators= [25,50,100,150,200]
```

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```
param={"max_depth":depth,"learning_rate":learning_rate,"n_estim
ators":n_estimators}


xgb_model=xgb.XGBRegressor(max_depth=3,learning_rate=0.1, n_est
imators=100)

start =datetime.now()
# fit the model
print('Training the model..')
rscv=RandomizedSearchCV( estimator=xgb_model,param_distribution
s=param,scoring='neg_mean_squared_error',n_jobs=-2)
rscv.fit(x_train, y_train)
print('Done. Time taken : {}\n'.format(datetime.now()-start))
print('Done \n')
```

```
Training the model..
[18:10:22] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:19:07.183473

Done
```

```
In [104]: # best RMSE score
np.sqrt(-rscv.best_score_)
```

```
0.862558929050448
```

```
In [105]: # best esitmator
rscv.best_estimator_
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsampl
e_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, ga
mma=0,
             importance_type='gain', learning_rate=0.0
5, max_delta_step=0,
             max_depth=5, min_child_weight=1, missing=N
one, n_estimators=150,
             n_jobs=1, nthread=None, objective='reg:lin
ear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weigh
t=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

```
In [106]: rscv.best_params_
```

```
{'n_estimators': 150, 'max_depth': 5, 'learning_rate':
0.05}
```

Loading [MathJax]/jax/output/HTML-CSS/jax.js

Traning with best hyperparameter

```
In [55]: # traning using best hyperparameter
print("traning using best_hyperparameter:{'n_estimators': 150,
 'max_depth': 5, 'learning_rate': 0.05}\n\n")


# prepare train data
x_train = reg_train.drop(['user', 'movie','rating'], axis=1)
y_train = reg_train['rating']

# Prepare Test data
x_test = reg_test_df.drop(['user','movie','rating'], axis=1)
y_test = reg_test_df['rating']


xgb_model=xgb.XGBRegressor(base_score=0.5, booster='gbtree', co
lsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.05, max_de
lta_step=0,
             max_depth=5, min_child_weight=1, missing=None, n_e
stimators=150,
             n_jobs=1, nthread=None, objective='reg:linear', ra
ndom_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, see
d=None,
             silent=None, subsample=1, verbosity=1)

train_results, test_results = run_xgboost_hyperparameter_tune(x
gb_model, x_train, y_train, x_test, y_test,verbose=1)

# Just store these error metrics in our models_evaluation datas
tructure
models_evaluation_train['13 features+bsl_m'] = train_results
models_evaluation_test['13 features+bsl_m'] = test_results

xgb.plot_importance(xgb_model)
plt.show()
```

```
traning using best_hyperparameter:{'n_estimators': 150,
'max_depth': 5, 'learning_rate': 0.05}



Training the model..
[19:50:27] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:02:08.409808

Done

Evaluating the model with TRAIN data...
Evaluating Test data

TEST DATA
------------------------------
```

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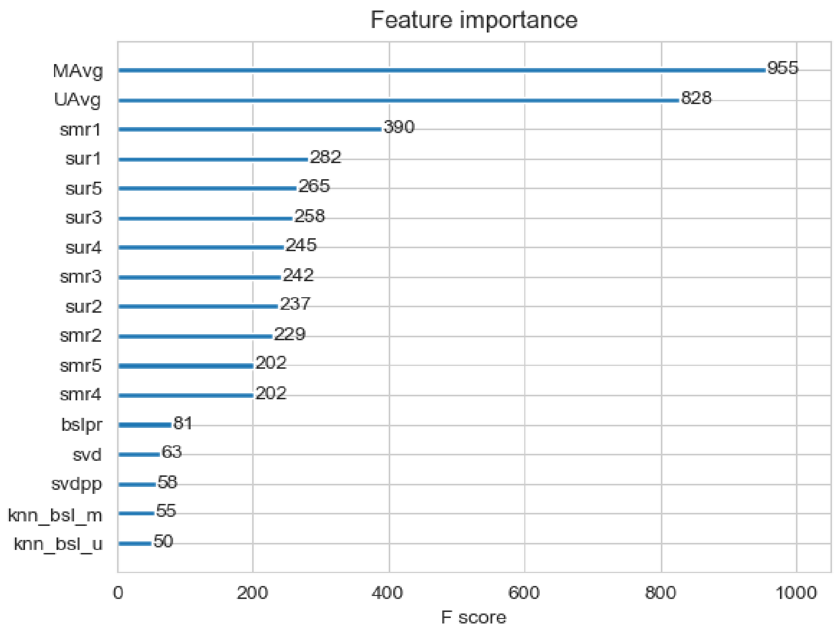
```
RMSE :   1.0749056674390538
MAPE :   34.63908028573338
```



4.4.4 Surprise KNNBaseline predictor

```
In [20]: from surprise import KNNBaseline
```

- KNN BASELINE
  - http://surprise.readthedocs.io/en/stable/knn_inspired.html#surp

- PEARSON_BASELINE SIMILARITY
  - http://surprise.readthedocs.io/en/stable/similarities.html#surpris

- SHRINKAGE
  - *2.2 Neighborhood Models* in http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf

- **predicted Rating** : (***based on User-User similarity***)

$$\hat{r}_{ui} = b_{ui} + \frac{\sum\limits_{v \in N_i^k(u)} \text{sim}(u, v) \cdot (r_{vi} - b_{vi})}{\sum\limits_{v \in N_i^k(u)} \text{sim}(u, v)}$$

- $\boldsymbol{b_{ui}}$ - *Baseline prediction* of (user,movie) rating
- $\boldsymbol{N_i^k(u)}$ - Set of **K similar** users (neighbours) of **user (u)** who rated **movie(i)**

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- *sim (u, v)* - **Similarity** between users **u and v**
  - Generally, it will be cosine similarity or Pearson correlation coefficient.
  - But we use **shrunk Pearson-baseline correlation coefficient**, which is based on the pearsonBaseline similarity (we take base line predictions instead of mean rating of user/item)

- **Predicted rating** (based on Item Item similarity):

$$\hat{r}_{ui} = b_{ui} + \frac{\sum\limits_{j \in N_u^k(i)} \text{sim}(i,j) \cdot (r_{uj} - b_{uj})}{\sum\limits_{j \in N_u^k(j)} \text{sim}(i,j)}$$

  - ***Notations follows same as above (user user based predicted rating)***

4.4.4.1 Surprise KNNBaseline with user user similarities

Hyperparameter Tuning

```
In [145]: # we specify , how to compute similarities and what to consider
with sim_options to our algorithm
# Traning
train_rmse=[]
train_mape=[]
test_rmse=[]
test_mape=[]


k_range=[10,20,30,40,50]

for i in tqdm(range(len(k_range))):

    sim_options = {'user_based' : True,
                   'name': 'pearson_baseline',
                   'shrinkage': 100,
                   'min_support': 2
                  }
    # we keep other parameters like regularization parameter an
d learning_rate as default values.
    bsl_options = {'method': 'sgd'}

    knn_bsl_u = KNNBaseline(k=k_range[i], sim_options = sim_opt
ions, bsl_options = bsl_options)

    knn_bsl_u_train_results, knn_bsl_u_test_results = run_surpr
ise(knn_bsl_u, trainset, testset, verbose=False)
    # run this algorithm.., It will return the train and test r
esults..
    print("index =",i+1," out of" ,len(options), "completed")

    # Just store these error metrics in our models_evaluation d
atastructure
    train_rmse.append(knn_bsl_u_train_results['rmse'])
    train_mape.append(knn_bsl_u_train_results['mape'])
```

Loading [MathJax]/jax/output/HTML-CSS/jax.js

```
    test_rmse.append(knn_bsl_u_test_results['rmse'])
    test_mape.append(knn_bsl_u_test_results['mape'])
```

```
  0%|
| 0/5 [00:00<?, ?it/s]


Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
index = 2  out of 105 completed



 20%|████████
| 1/5 [18:59<1:15:59, 1139.96s/it]


Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
index = 2  out of 105 completed



 40%|████████████████▌
| 2/5 [38:29<57:26, 1148.73s/it]


Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
index = 2  out of 105 completed



 60%|████████████████████████▉
| 3/5 [58:19<38:42, 1161.35s/it]


Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
index = 2  out of 105 completed



 80%|█████████████████████████
███████                | 4/5 [1:18:44<19:40, 1180.
24s/it]


Estimating biases using sgd...
```

```
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
index = 2  out of 105 completed


100%|████████████████████████████████████████████████████████████
██████████████████████████████████| 5/5 [1:39:35<00:00, 1195.
10s/it]
```

```
In [146]: # storing reults of all the hyperparameter
          result_knn_baseline=pd.DataFrame({"k": k_range,"train_rmse":tra
          in_rmse,"train_mape":train_mape,"test_rmse":test_rmse,"test_map
          e":test_mape })
          result_knn_baseline
```

	k	train_rmse	train_mape	test_rmse	test_mape
0	10	0.314136	8.613099	1.065704	34.439241
1	20	0.390270	10.909957	1.065758	34.440028
2	30	0.428351	12.073307	1.065712	34.441516
3	40	0.452366	12.810295	1.065735	34.443225
4	50	0.469137	13.327551	1.065755	34.443847

```
In [147]: best_result=result_knn_baseline[result_knn_baseline["test_mape"
          ]==min(result_knn_baseline["test_mape"])]
          print(f"best k: {result_knn_baseline['k'][0]}")
          print(f"best RMSE_score: {result_knn_baseline['test_rmse'][0]}"
          )
          print(f"best MAPE_score: {result_knn_baseline['test_mape'][0]}"
          )
```

```
best k: 10
best RMSE_score: 1.0657042125048963
best MAPE_score: 34.439241286194736
```

Traning Using best Hyperparameter

```
In [21]: # we specify , how to compute similarities and what to consider
         with sim_options to our algorithm
         sim_options = {'user_based' : True,
                        'name': 'pearson_baseline',
                        'shrinkage': 100,
                        'min_support': 2
                       }
         # we keep other parameters like regularization parameter and le
         arning_rate as default values.
         bsl_options = {'method': 'sgd'}

         knn_bsl_u = KNNBaseline(k=10, sim_options = sim_options, bsl_op
         tions = bsl_options)
         knn_bsl_u_train_results, knn_bsl_u_test_results = run_surprise(
         knn_bsl_u, trainset, testset, verbose=True)

         # Just store these error metrics in our models_evaluation datas
         ure
```

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```
models_evaluation_train['knn_bsl_u'] = knn_bsl_u_train_results
models_evaluation_test['knn_bsl_u'] = knn_bsl_u_test_results
```

```
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
---------------
Train Data
---------------
RMSE : 0.3141357816682863

MAPE : 8.613099315403797

adding train results in the dictionary..
---------------
Test Data
---------------
RMSE : 1.0657042125048963

MAPE : 34.439241286194736

storing the test results in test dictionary...
```

4.4.4.2 Surprise KNNBaseline with movie movie similarities

In [22]:
```
# we specify , how to compute similarities and what to consider
with sim_options to our algorithm

# 'user_based' : Fals => this considers the similarities of mov
ies instead of users

sim_options = {'user_based' : False,
               'name': 'pearson_baseline',
               'shrinkage': 100,
               'min_support': 2
              }
# we keep other parameters like regularization parameter and le
arning_rate as default values.
bsl_options = {'method': 'sgd'}


knn_bsl_m = KNNBaseline(k=40, sim_options = sim_options, bsl_op
tions = bsl_options)

knn_bsl_m_train_results, knn_bsl_m_test_results = run_surprise(
knn_bsl_m, trainset, testset, verbose=True)

# Just store these error metrics in our models_evaluation datas
tructure
models_evaluation_train['knn_bsl_m'] = knn_bsl_m_train_results
models_evaluation_test['knn_bsl_m'] = knn_bsl_m_test_results
```

```
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
---------------
```

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```
Train Data
---------------
RMSE : 0.50085847421266

MAPE : 14.072064728120523

adding train results in the dictionary..
---------------
Test Data
---------------
RMSE : 1.066402047909581

MAPE : 34.45353435356671

storing the test results in test dictionary...
```

4.4.5 XGBoost with initial 13 features + Surprise Baseline predictor + KNNBaseline predictor

- First we will run XGBoost with predictions from both KNN's (that uses User_User and Item_Item similarities along with our previous features.
- Then we will run XGBoost with just predictions form both knn models and preditions from our baseline model.

Preparing Train data

In [23]:
```python
# add the predicted values from both knns to this dataframe
reg_train['knn_bsl_u'] = models_evaluation_train['knn_bsl_u'][
'predictions']
reg_train['knn_bsl_m'] = models_evaluation_train['knn_bsl_m'][
'predictions']


reg_train.head(2)
```

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	174683	10	3.586697	5.0	5.0	3.0	4.0	4.0	3.0	5.0
1	233949	10	3.586697	4.0	4.0	5.0	1.0	5.0	2.0	3.0

Preparing Test data

In [24]:
```python
reg_test_df['knn_bsl_u'] = models_evaluation_test['knn_bsl_u'][
'predictions']
reg_test_df['knn_bsl_m'] = models_evaluation_test['knn_bsl_m'][
'predictions']


reg_test_df.head(2)
```

	user	movie	GAvg	sur1	sur2	sur3	sur4	
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.58
1	41866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.58

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```
In [25]: # pickle saving

         import pickle
         '''file = open('reg_update_train.pkl', 'wb')
         pickle.dump(reg_train, file)

         import pickle
         file = open('reg_update_test.pkl', 'wb')
         pickle.dump(reg_test_df, file)
         '''

         file = open('reg_update_train.pkl', 'rb')
         reg_train=pickle.load(file)

         file = open('reg_update_test.pkl', 'rb')
         reg_test_df=pickle.load(file)
```

Hyperparameter Tuning

```
In [156]: from sklearn.model_selection import RandomizedSearchCV

          # prepare Train data
          x_train = reg_train.drop(['user','movie','rating'], axis=1)
          y_train = reg_train['rating']

          # Prepare Test data
          x_test = reg_test_df.drop(['user','movie','rating'], axis=1)
          y_test = reg_test_df['rating']


          depth=[3,5,10,25,30,35]
          learning_rate= [0.01,0.03,0.05,0.1,0.5,1]
          n_estimators= [25,50,100,150,200]

          param={"max_depth":depth,"learning_rate":learning_rate,"n_estim
          ators":n_estimators}


          xgb_model=xgb.XGBRegressor(max_depth=3,learning_rate=0.1, n_est
          imators=100)

          start =datetime.now()
          # fit the model
          print('Training the model..')
          rscv=RandomizedSearchCV( estimator=xgb_model,param_distribution
          s=param,scoring='neg_mean_squared_error',n_jobs=-2)
          rscv.fit(x_train, y_train)
          print('Done. Time taken : {}\n'.format(datetime.now()-start))
          print('Done \n')
```

```
Training the model..
[22:08:58] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:29:53.364050
```

```
Done
```

```
In [157]: # best RMSE score
np.sqrt(-rscv.best_score_)
```

```
0.8629562063851135
```

```
In [158]: # best esitmator
rscv.best_estimator_
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsampl
e_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, ga
mma=0,
             importance_type='gain', learning_rate=0.0
5, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=
None, n_estimators=200,
             n_jobs=1, nthread=None, objective='reg:lin
ear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weigh
t=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

```
In [159]: rscv.best_params_
```

```
{'n_estimators': 200, 'max_depth': 10, 'learning_rate':
0.05}
```

Traning using best hyperparameter

```
In [57]: # traning using best hyperparameter
print("traning using best_hyperparameter:{'n_estimators': 200,
 'max_depth': 10, 'learning_rate': 0.05}\n\n")


# prepare train data
x_train = reg_train.drop(['user', 'movie','rating'], axis=1)
y_train = reg_train['rating']

# Prepare Test data
x_test = reg_test_df.drop(['user','movie','rating'], axis=1)
y_test = reg_test_df['rating']


xgb_model=xgb.XGBRegressor(base_score=0.5, booster='gbtree', co
lsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.05, max_de
lta_step=0,
             max_depth=10, min_child_weight=1, missing=None, n_
estimators=200,
             n_jobs=1, nthread=None, objective='reg:linear', ra
```

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```
ndom_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, see
d=None,
             silent=None, subsample=1, verbosity=1)

train_results, test_results = run_xgboost_hyperparameter_tune(x
gb_model, x_train, y_train, x_test, y_test,verbose=1)

# Just store these error metrics in our models_evaluation datas
tructure
models_evaluation_train['13 features+bsl_m+knn_bsl_m'] = train_
results
models_evaluation_test['13 features+bsl_m+knn_bsl_m'] = test_re
sults

xgb.plot_importance(xgb_model)
plt.show()
```

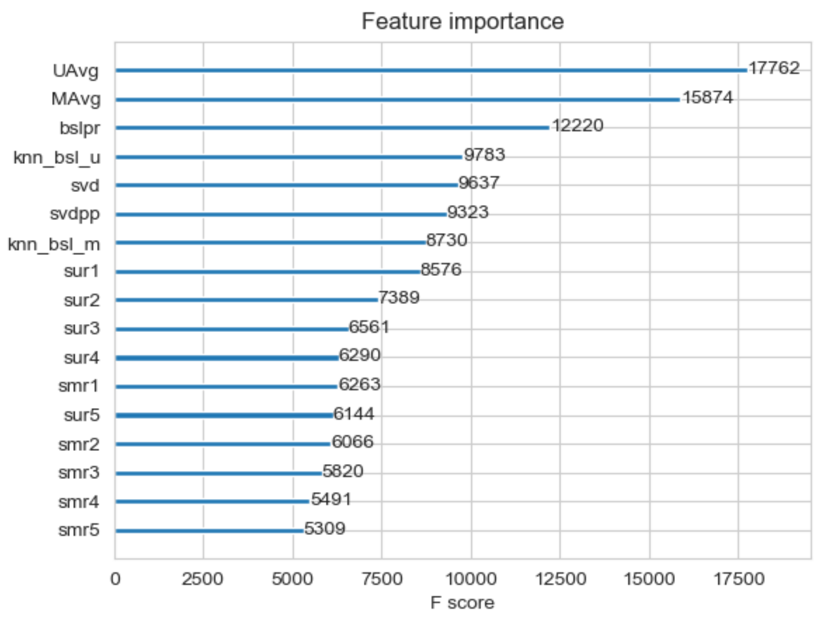
```
traning using best_hyperparameter:{'n_estimators': 200,
'max_depth': 10, 'learning_rate': 0.05}


Training the model..
[19:53:12] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:05:56.092928

Done

Evaluating the model with TRAIN data...
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.1491717436917956
MAPE :  32.22357687735982
```



4.4.6 Matrix Factorization Techniques

4.4.6.1 SVD Matrix Factorization User Movie intractions

```
In [30]: from surprise import SVD
```

http://surprise.readthedocs.io/en/stable/matrix_factorization.html#surpris

- Predicted Rating :

> - $ \large \hat r_{ui} = \mu + b_u + b_i + q_i^Tp_u $
>
>   - $\pmb q_i$ - Representation of item(movie) in latent factor space
>
>   - $\pmb p_u$ - Representation of user in new latent factor space

- A BASIC MATRIX FACTORIZATION MODEL in https://datajobs.com/data-science-repo/Recommender-Systems-[Netflix].pdf

- Optimization problem with user item interactions and regularization (to avoid overfitting)

> - $\large \sum_{r_{ui} \in R_{train}} \left (r_{ui} - \hat{r}_{ui} \right)^2 +

\lambda\left(b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2\right) $

Loading [MathJax]/jax/output/HTML-CSS/jax.js

```
In [31]: # initiallize the model
svd = SVD(n_factors=100, biased=True, random_state=15, verbose=
True)
svd_train_results, svd_test_results = run_surprise(svd, trainse
t, testset, verbose=True)

# Just store these error metrics in our models_evaluation datas
tructure
models_evaluation_train['svd'] = svd_train_results
models_evaluation_test['svd'] = svd_test_results
```

```
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
---------------
Train Data
---------------
RMSE : 0.6724095459788582

MAPE : 20.00557612865896

adding train results in the dictionary..
---------------
Test Data
---------------
RMSE : 1.0658291640505728

MAPE : 34.32164154476558

storing the test results in test dictionary...
```

4.4.6.2 SVD Matrix Factorization with implicit feedback from user (user rated movies)

```
In [32]: from surprise import SVDpp
```

Loading [MathJax]/jax/output/HTML-CSS/jax.js

- -----> 2.5 Implicit Feedback in http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf

- Predicted Rating :

> - $ \large \hat{r}_{ui} = \mu + b_u + b_i + q_i^T\left(p_u + |I_u|^{-\frac{1}{2}} \sum_{j \in I_u}y_j\right) $

- I_u --- the set of all items rated by user u
- y_j --- Our new set of item factors that capture implicit ratings.

- Optimization problem with user item interactions and regularization (to avoid overfitting)

> - $ \large \sum_{r_{ui} \in R_{train}} \left(r_{ui} - \hat{r}_{ui} \right)^2 +

\lambda\left(b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2 + ||y_j||^2\right) $

```
In [33]: # initiallize the model
svdpp = SVDpp(n_factors=50, random_state=15, verbose=True)
svdpp_train_results, svdpp_test_results = run_surprise(svdpp, trainset, testset, verbose=True)

# Just store these error metrics in our models_evaluation datastructure
models_evaluation_train['svdpp'] = svdpp_train_results
models_evaluation_test['svdpp'] = svdpp_test_results
```

```
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
```

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```
 processing epoch 17
 processing epoch 18
 processing epoch 19
---------------
Train Data
---------------
RMSE : 0.6630297928023139

MAPE : 19.2061856855646

adding train results in the dictionary..
---------------
Test Data
---------------
RMSE : 1.0665294257919915

MAPE : 34.20534945513256

storing the test results in test dictionary...
```

4.4.7 XgBoost with 13 features + Surprise Baseline + Surprise KNNbaseline + MF Techniques

Preparing Train data

In [34]:
```
# add the predicted values from both knns to this dataframe
reg_train['svd'] = models_evaluation_train['svd']['predictions'
]
reg_train['svdpp'] = models_evaluation_train['svdpp']['predicti
ons']

reg_train.head(2)
```

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	174683	10	3.586697	5.0	5.0	3.0	4.0	4.0	3.0	5.0
1	233949	10	3.586697	4.0	4.0	5.0	1.0	5.0	2.0	3.0

2 rows × 21 columns

Preparing Test data

In [35]:
```
reg_test_df['svd'] = models_evaluation_test['svd']['prediction
s']
reg_test_df['svdpp'] = models_evaluation_test['svdpp']['predict
ions']

reg_test_df.head(2)
```

	user	movie	GAvg	sur1	sur2	sur3	sur4
	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.58

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1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.58

2 rows × 21 columns

In [36]:
```
# pickle saving

"""import pickle
file = open('reg_update_train.pkl', 'wb')
pickle.dump(reg_train, file)

import pickle
file = open('reg_update_test.pkl', 'wb')
pickle.dump(reg_test_df, file)
"""

file = open('reg_update_train.pkl', 'rb')
reg_train=pickle.load(file)

file = open('reg_update_test.pkl', 'rb')
reg_test_df=pickle.load(file)
```

HyperParameter Tuning usning RandomSearchCV

In [37]:
```
from sklearn.model_selection import RandomizedSearchCV

# prepare Train data
x_train = reg_train.drop(['user','movie','rating'], axis=1)
y_train = reg_train['rating']

# Prepare Test data
x_test = reg_test_df.drop(['user','movie','rating'], axis=1)
y_test = reg_test_df['rating']


depth=[3,5,10,25,30,35]
learning_rate= [0.01,0.03,0.05,0.1,0.5,1]
n_estimators= [25,50,100,150,200]

param={"max_depth":depth,"learning_rate":learning_rate,"n_estim
ators":n_estimators}


xgb_model=xgb.XGBRegressor(max_depth=3,learning_rate=0.1, n_est
imators=100)

start =datetime.now()
# fit the model
print('Training the model..')
rscv=RandomizedSearchCV( estimator=xgb_model,param_distribution
s=param,scoring='neg_mean_squared_error',n_jobs=-2)
rscv.fit(x_train, y_train)
print('Done. Time taken : {}\n'.format(datetime.now()-start))
print('Done \n')
```

```
Training the model..
[17:58:55] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
t is now deprecated in favor of reg:squarederror.
```

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```
Done. Time taken : 0:27:01.263794

Done
```

```
In [38]: # best RMSE score
         np.sqrt(-rscv.best_score_)
```

```
0.8626559746121821
```

```
In [23]: # best esitmator
         rscv.best_estimator_
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsampl
e_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, ga
mma=0,
             importance_type='gain', learning_rate=0.0
5, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=
None, n_estimators=200,
             n_jobs=1, nthread=None, objective='reg:lin
ear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weigh
t=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

```
In [39]: rscv.best_params_
```

```
{'n_estimators': 150, 'max_depth': 5, 'learning_rate':
0.05}
```

Traning with best hyperparameter

```
In [40]: # prepare x_train and y_train
         x_train = reg_train.drop(['user', 'movie', 'rating',], axis=1)
         y_train = reg_train['rating']

         # prepare test data
         x_test = reg_test_df.drop(['user', 'movie', 'rating'], axis=1)
         y_test = reg_test_df['rating']



         xgb_final = rscv.best_estimator_

         train_results, test_results = run_xgboost(xgb_final, x_train, y
         _train, x_test, y_test)

         # store the results in models_evaluations dictionaries
         models_evaluation_train['xgb_final'] = train_results
         models_evaluation_test['xgb_final'] = test_results
```

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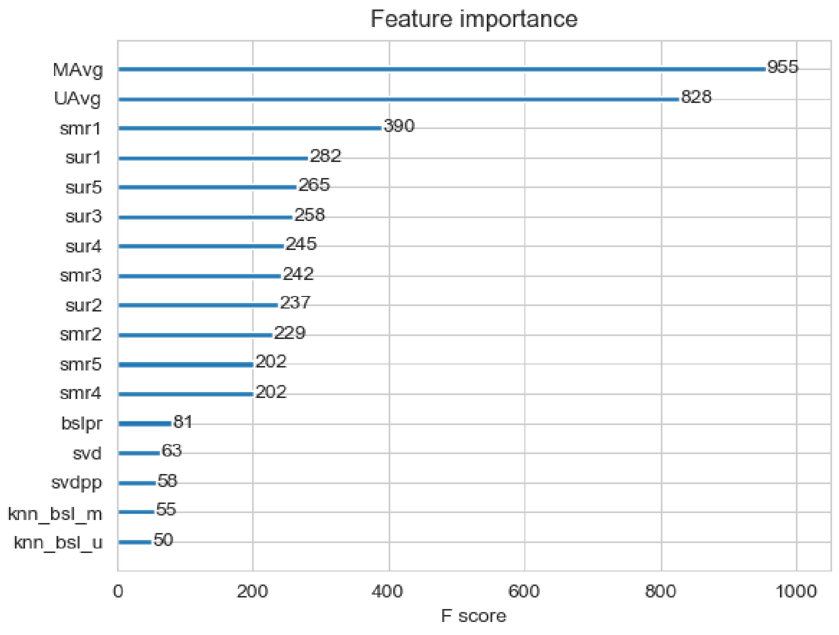
```
xgb.plot_importance(xgb_final)
plt.show()
```

```
Training the model..
[18:01:04] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:02:09.770045

Done

Evaluating the model with TRAIN data...
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.0749056674390538
MAPE :  34.63908028573338
```



4.4.8 XgBoost with Surprise Baseline + Surprise KNNbaseline + MF Techniques

Hyperparameter Tuning

In [41]:
```
from sklearn.model_selection import RandomizedSearchCV

# prepare Train data
x_train = reg_train[['knn_bsl_u', 'knn_bsl_m', 'svd', 'svdpp']]
y_train = reg_train['rating']

# test data
x_test = reg_test_df[['knn_bsl_u', 'knn_bsl_m', 'svd', 'svdpp'
```

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```
y_test = reg_test_df['rating']


depth=[3,5,10,25,30,35]
learning_rate= [0.01,0.03,0.05,0.1,0.5,1]
n_estimators= [25,50,100,150,200]

param={"max_depth":depth,"learning_rate":learning_rate,"n_estim
ators":n_estimators}


xgb_model=xgb.XGBRegressor(max_depth=3,learning_rate=0.1, n_est
imators=100)

start =datetime.now()
# fit the model
print('Training the model..')
rscv=RandomizedSearchCV( estimator=xgb_model,param_distribution
s=param,scoring='neg_mean_squared_error',n_jobs=-2)
rscv.fit(x_train, y_train)
print('Done. Time taken : {}\n'.format(datetime.now()-start))
print('Done \n')
```

```
Training the model..
[18:15:16] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:12:44.939846

Done
```

```
In [42]: # best RMSE score
         np.sqrt(-rscv.best_score_)
```

```
1.083152058523289
```

```
In [43]: # best esitmator
         rscv.best_estimator_
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsampl
e_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, ga
mma=0,
             importance_type='gain', learning_rate=0.0
5, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=N
one, n_estimators=200,
             n_jobs=1, nthread=None, objective='reg:lin
ear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weigh
t=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

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```
best_params_
```

```
{'n_estimators': 200, 'max_depth': 3, 'learning_rate':
0.05}
```

Traning using optimal hyperparameter

```
In [45]: # prepare train data
         x_train = reg_train[['knn_bsl_u', 'knn_bsl_m', 'svd', 'svdpp']]
         y_train = reg_train['rating']

         # test data
         x_test = reg_test_df[['knn_bsl_u', 'knn_bsl_m', 'svd', 'svdpp'
         ]]
         y_test = reg_test_df['rating']


         xgb_all_models = rscv.best_estimator_
         train_results, test_results = run_xgboost(xgb_all_models, x_tra
         in, y_train, x_test, y_test)

         # store the results in models_evaluations dictionaries
         models_evaluation_train['xgb_all_models'] = train_results
         models_evaluation_test['xgb_all_models'] = test_results

         xgb.plot_importance(xgb_all_models)
         plt.show()
```

```
Training the model..
[18:16:05] WARNING: C:/Jenkins/workspace/xgboost-win64_r
elease_0.90/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
Done. Time taken : 0:00:49.278826

Done

Evaluating the model with TRAIN data...
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.075420477871072
MAPE :  35.21831995221971
```

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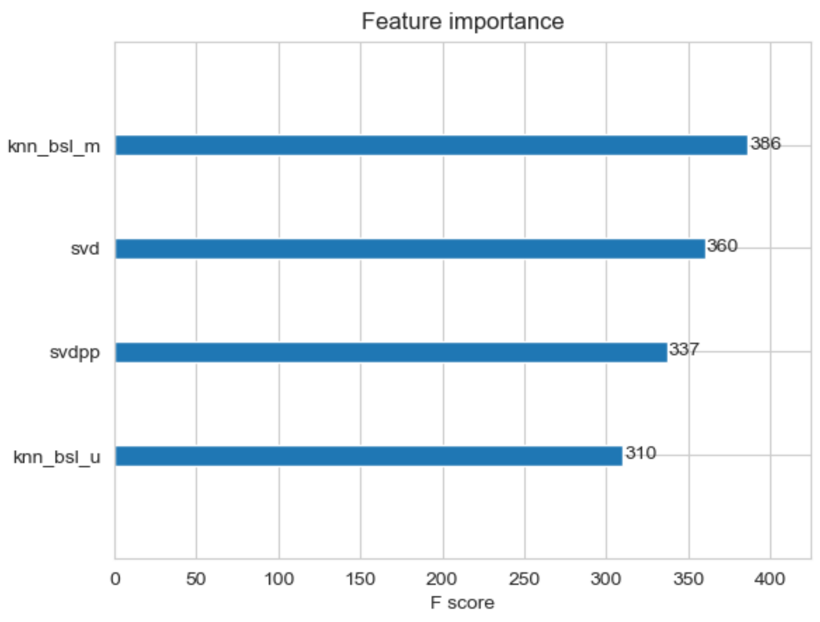

4.5 Comparision between all models

4.5.1 Before Hypertuning

```
In [91]: # Saving our TEST_RESULTS into a dataframe so that you don't ha
         ve to run it again
         models = pd.read_csv('sample/small/small_sample_results.csv', i
         ndex_col=0)
```

```
In [105]: models.T[["rmse",'mape']].sort_values(by='rmse')
```

	rmse	mape
knn_bsl_u	1.0657348797314812	34.44322466866583
svd	1.0658291640505728	34.32164154476558
bsl_algo	1.0659638954236386	34.43052499512186
knn_bsl_m	1.066402047909581	34.45353435356671
svdpp	1.0665294257919915	34.20534945513256
first_algo	1.0731831625477235	34.93936012439215
xgb_bsl	1.0731848133115496	34.93942495443435
xgb_knn_bsl	1.0731848133115496	34.93942495443435
xgb_final	1.0731851944485837	34.939430765230185
xgb_all_models	1.0753710007379194	35.2152699422574

1.5.2 After Hypertuning

```
In [106]: # Saving our TEST_RESULTS into a dataframe so that you don't ha
          ve to run it again
          pd.DataFrame(models_evaluation_test).to_csv('sample/small/small
          _sample_results_new.csv')
```

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```
models_new = pd.read_csv('sample/small/small_sample_results_ne
w.csv', index_col=0)
```

```
In [116]: (models_new.iloc[:2].T.sort_values(by='rmse'))
```

	rmse	mape
knn_bsl_u	1.0657042125048963	34.439241286194736
svd	1.0658291640505728	34.32164154476558
knn_bsl_m	1.066402047909581	34.45353435356671
svdpp	1.0665294257919915	34.20534945513256
bsl_algo	1.0674729813270976	34.22857744546804
xgb_final	1.0749056674390538	34.63908028573338
initial 13 features	1.0749056674390538	34.63908028573338
13 features+bsl_m	1.0749056674390538	34.63908028573338
xgb_all_models	1.075420477871072	35.21831995221971
13 features+bsl_m+knn_bsl_m	1.1491717436917956	32.22357687735982

Observation:

There is very slight improvement is RMSE after hypertuning. This could be because of choosing only 25k user and 3k movies_item as traning data.

END :)

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