Netflix Movie Recommendation System

1. Business Problem

1.1 Problem Description

Netflix is a online repository where we can watch videos, movies, documentaries etc. Netflix is all about connecting people to the movies they love. To help customers find those movies, they developed world-class movie recommendation system: CinematchSM (Cinematch system is internally built by Netflix). Its job is to predict whether someone will enjoy a movie based on how much they liked or disliked other movies. Netflix use those predictions to make personal movie recommendations based on each customer’s unique tastes. And while **Cinematch** is doing pretty well, it can always be made better.
Metric used is RMSE - Root Mean Squared Error

Now there are a lot of interesting alternative approaches to how Cinematch works that netflix haven’t tried. Some are described in the literature, some aren’t. We’re curious whether any of these can beat Cinematch by making better predictions. Because, frankly, if there is a much better approach it could make a big difference to our customers and our business.

Credits: https://www.netflixprize.com/rules.html

1.2 Problem Statement

Netflix provided a lot of anonymous rating data, and a prediction accuracy bar that is 10% better than what Cinematch can do on the same training data set. (Accuracy is a measurement of how closely predicted ratings of movies match subsequent actual ratings.)

1.3 Sources

- https://www.netflixprize.com/rules.html
- https://www.kaggle.com/netflix-inc/netflix-prize-data
- Netflix blog: https://medium.com/netflix-techblog/netflix-recommendations-beyond-the-5-stars-part-1-55838468f429 (very nice blog)
- surprise library: http://surpriselib.com/ (we use many models from this library)
- surprise library doc: http://surprise.readthedocs.io/en/stable/getting_started.html (we use many models from this library)
- installing surprise: https://github.com/NicolasHug/Surprise#installation
- Research paper: http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf (most of our work was inspired by this paper)
- SVD Decomposition : https://www.youtube.com/watch?v=P5mlg91as1c

1.4 Real world/Business Objectives and constraints

Objectives:

1. Predict the rating that a user would give to a movie that he/she has not yet rated.
2. Minimize the difference between predicted rating given by algorithm and actual rating given by user (RMSE and MAPE).
3. RMSE - Root Mean Squared Error , MAPE - Mean Absolute Percentage Error.
4. Rating values will be between 1 to 5.
5. This case study is like regression problem and we can pose it as both, regression problem as it has rating(class Y) values from 1 to 5 and can also pose as a recommendation problem as we are trying to recommend movie Mj to a user Ui.

Constraints:

1. Some form of interpretability. We should understand why the model is recomending particular movie, and user also should understand why they are being recommended a movie. This is important constraint.

1. We may think that low-latency should be there for this recommendation , but netflix does not compute the movie recommendations right at the moment when the user logs-in. It will pre-compute all these movie recommendations for every user and put these recommendations in hash table or look-up table.
2. As soon as the user log-in, it will show the pre-computed movie recommendations to the user . As many users watch minimum number of movies a day, netflix can take hours and compute the movie recommendations for each day, and show to the users when they log-in.
3. So these recommendations are good and so there is no explicit low latency requirement as recomendations can be pre-computed and there is no need to compute in milli-sec.

2. Machine Learning Problem

2.1 Data

2.1.1 Data Overview

Get the data from : https://www.kaggle.com/netflix-inc/netflix-prize-data/data

Data files :

- combined_data_1.txt
- combined_data_2.txt
- combined_data_3.txt
- combined_data_4.txt
- movie_titles.csv -- It has movie id and movie name


```
The first line of each file [combined_data_1.txt, combined_data_2.txt, combined
_data_3.txt, combined_data_4.txt] contains the movie id followed by a colon. Ea
ch subsequent line in the file corresponds to a rating from a customer and its
date in the following format:

CustomerID,Rating,Date

MovieIDs range from 1 to 17770 sequentially.
CustomerIDs range from 1 to 2649429, with gaps. There are 480189 unique users.
Ratings are on a five star (integral) scale from 1 to 5.
Dates have the format YYYY-MM-DD.
```

2.1.2 Example Data point

Format

Movie id

- Customer/User id , movie rating(1 to 5) , movie watched date (yyyy-mm-dd).
- This format is there for every movie.

```
1:
1488844,3,2005-09-06
822109,5,2005-05-13
885013,4,2005-10-19
30878,4,2005-12-26
823519,3,2004-05-03
893988,3,2005-11-17
124105,4,2004-08-05
1248029,3,2004-04-22
1842128,4,2004-05-09
2238063,3,2005-05-11
1503895,4,2005-05-19
2207774,5,2005-06-06
2590061,3,2004-08-12
2442,3,2004-04-14
543865,4,2004-05-28
1209119,4,2004-03-23
804919,4,2004-06-10
1086807,3,2004-12-28
1711859,4,2005-05-08
372233,5,2005-11-23
1080361,3,2005-03-28
1245640,3,2005-12-19
558634,4,2004-12-14
2165002,4,2004-04-06
1181550,3,2004-02-01
1227322,4,2004-02-06
427928,4,2004-02-26
814701,5,2005-09-29
808731,4,2005-10-31
662870,5,2005-08-24
337541,5,2005-03-23
786312,3,2004-11-16
```

2.2 Mapping the real world problem to a Machine Learning Problem

2.2.1 Type of Machine Learning Problem

1. For a given movie and user we need to predict the rating would be given by him/her to the movie.
2. The given problem is a Recommendation problem . There are multiple approaches for this problem like similarity based approaches like user-user similarity , item-item similarity ,etc. , Matrix Factorization approaches
3. It can also seen as a Regression problem. As ratings rij's are values between 1 to 5 . These are Yi's. And we can get Xi's from the recommendation system matrix dataset of movies and users.
4. So we will use concepts from recommendation and matrix factorixation like SVD, User-user similarity, movie-movie similarity and concepts of regression like XGBoost

2.2.2 Performance metric

- Mean Absolute Percentage Error: https://en.wikipedia.org/wiki/Mean_absolute_percentage_error
- Root Mean Square Error: https://en.wikipedia.org/wiki/Root-mean-square_deviation

2.2.3 Machine Learning Objective and Constraints

Main objective is :-

1. Minimize RMSE - Root Mean Squared Error
2. Try to provide some interpretability (understanding of why model gave particular recommendations).

Importing libraries

In [1]:
```
# 'datetime' is just to know how much time will it take to run this entire ipy
thon notebook
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
from sklearn.metrics import mean_squared_error

from surprise import Reader, Dataset
import scipy
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
from surprise import BaselineOnly
from surprise import KNNBaseline
from surprise import SVD
from surprise import SVDpp
```

3. Exploratory Data Analysis

3.1 Preprocessing

3.1.1 Converting / Merging whole data in 4 files to required format: u_i, m_j, r_ij

1. Each row will have - User id (Ui), Movie id (Mj), Rating (rij) User gave on Movie , Date of this rating.
2. We create a CSV file table with these 4 columns

In [3]:
```
# this tells how much time did it take to complete execution of below steps. i
t is like start of timer
start = datetime.now()
if not os.path.isfile('total_data.csv'):
    # Create a file 'data.csv' before reading it
    # Read all the files in netflix and store them in one big file('data.csv')
    # We re reading from each of the four files and appendig each rating to a
 global file 'train.csv'
    data = open('total_data.csv', mode='w')

    row = list()
    # reading each of the 4 files and converting to the format we want
    files=['combined_data_1.txt','combined_data_2.txt',
           'combined_data_3.txt','combined_data_4.txt']
    for file in files:
        print("Reading ratings from {}...".format(file))
        with open(file) as f:
            for line in f:
                del row[:] # you don't have to do this.
                line = line.strip()
                if line.endswith(':'):
                    # All below are ratings for this movie, until another movi
e appears.
                    movie_id = line.replace(':', '')
                else:
                    row = [x for x in line.split(',')]
                    row.insert(0, movie_id)
                    data.write(','.join(row))
                    data.write('\n')
        print("Done.\n")
    data.close()
print('Time taken :', datetime.now() - start)   # end of timer. current time -
start time = time taken to run this.
```

```
Time taken : 0:00:00.000382
```

In [4]:
```
print("creating the dataframe from data.csv file..")
df = pd.read_csv('total_data.csv', sep=',',
                       names=['movie', 'user','rating','date'])
df.date = pd.to_datetime(df.date)
print('Done.\n')

# we are arranging the ratings according to time.
print('Sorting the dataframe by date..') # sorting in increasing order of date
df.sort_values(by='date', inplace=True)
print('Done..')
```

```
creating the dataframe from data.csv file..
Done.

Sorting the dataframe by date..
Done..
```

In [5]:
```
# date is in increasing order.
df.head()
```

Out[5]:

	movie	user	rating	date
56431994	10341	510180	4	1999-11-11
9056171	1798	510180	5	1999-11-11
58698779	10774	510180	3	1999-11-11
48101611	8651	510180	2	1999-11-11
81893208	14660	510180	2	1999-11-11

In [6]:
```
# 50% is the median rating which is 4.
df.describe()['rating']
```

Out[6]:
```
count    1.004805e+08
mean     3.604290e+00
std      1.085219e+00
min      1.000000e+00
25%      3.000000e+00
50%      4.000000e+00
75%      4.000000e+00
max      5.000000e+00
Name: rating, dtype: float64
```

3.1.2 Checking for NaN values

In [7]:
```
# just to make sure that all Nan (Not a Number values) containing rows are del
eted..
print("No of Nan values in our dataframe : ", sum(df.isnull().any()))
```

```
No of Nan values in our dataframe :  0
```

3.1.3 Removing Duplicates

In [8]:
```
# now dataframe format is - [Mj, Ui, rij(rating given by user i to a movie j),
date]
# checking for duplicates
dup_bool = df.duplicated(['movie','user','rating'])
dups = sum(dup_bool) # by considering all columns..( including timestamp)
print("There are {} duplicate rating entries in the data..".format(dups))
```

```
There are 0 duplicate rating entries in the data..
```

3.1.4 Basic Statistics (#Ratings, #Users, and #Movies)

In [9]:
```
# printing total data in csv file.  It is in format of  - Movie id(Mj), User i
d(Ui), Rating(rij), Date .
# Data is sorted in In ascending order of date where olderst date at the first
and newest date at the bottom
print("Total data ")
print("-"*50)
print("\nTotal no of ratings :",df.shape[0])
print("Total No of Users   :", len(np.unique(df.user)))
print("Total No of movies  :", len(np.unique(df.movie)))
```

```
Total data
--------------------------------------------------

Total no of ratings : 100480507
Total No of Users   : 480189
Total No of movies  : 17770
```

3.2 Spliting data into Train and Test(80:20)

1. There is temporal structure to the data. Data till today/all the historical data till current time is taken to train the model and the model is deployed into production to-night.
2. From tomorrow the model starts predicting the ratings will be given by any new user on any new movie.
3. Since there is temporal nature to the data, we can split the data temporally , according to date which is already sorted. First 80% data according to date is taken as train data and bottom 20% is test data. This creates the temporal nature of splitting the data.

In [10]:
```
if not os.path.isfile('train.csv'):
    # create the dataframe and store it in the disk for offline purposes..
    # First 80% data is train data and stored as csv file
    df.iloc[:int(df.shape[0]*0.80)].to_csv("train.csv", index=False)

if not os.path.isfile('test.csv'):
    # create the dataframe and store it in the disk for offline purposes..
    # Bottom 20% of rows/data is test data and stored as test.csv file
    df.iloc[int(df.shape[0]*0.80):].to_csv("test.csv", index=False)

train_df = pd.read_csv("train.csv", parse_dates=['date'])
test_df = pd.read_csv("test.csv")
```

3.2.1 Basic Statistics in Train data (#Ratings, #Users, and #Movies) after splitting

In [11]:
```
# total 100 million rating are divided into 80 million train data and 20 milli
on test data
# movies = train_df.movie.value_counts()
# users = train_df.user.value_counts()
print("Training data ")
print("-"*50)
print("\nTotal no of ratings :",train_df.shape[0])
print("Total No of Users   :", len(np.unique(train_df.user)))
print("Total No of movies  :", len(np.unique(train_df.movie)))
```

```
Training data
--------------------------------------------------

Total no of ratings : 80384405
Total No of Users   : 405041
Total No of movies  : 17424
```

3.2.2 Basic Statistics in Test data (#Ratings, #Users, and #Movies) after splitting

In [12]:
```
print("Test data ")
print("-"*50)
print("\nTotal no of ratings :",test_df.shape[0])
print("Total No of Users   :", len(np.unique(test_df.user)))
print("Total No of movies  :", len(np.unique(test_df.movie)))
```

```
Test data
--------------------------------------------------

Total no of ratings : 20096102
Total No of Users   : 349312
Total No of movies  : 17757
```

3.3 Exploratory Data Analysis on Train data

In [13]:
```
# method to make y-axis more readable
def human(num, units = 'M'):
    units = units.lower()
    num = float(num)
    if units == 'k':
        return str(num/10**3) + " K"
    elif units == 'm':
        return str(num/10**6) + " M"
    elif units == 'b':
        return str(num/10**9) +  " B"
```

3.3.1 Distribution of ratings

In [26]:
```
# typically ratings are higher not lower
%matplotlib inline
fig, ax = plt.subplots()
plt.title('Distribution of ratings over Training dataset', fontsize=15)
sns.countplot(train_df.rating)
ax.set_yticklabels([human(item, 'M') for item in ax.get_yticks()])
ax.set_ylabel('No. of Ratings(Millions)')

plt.show()
```

Add new column (week day) to the data set for analysis.

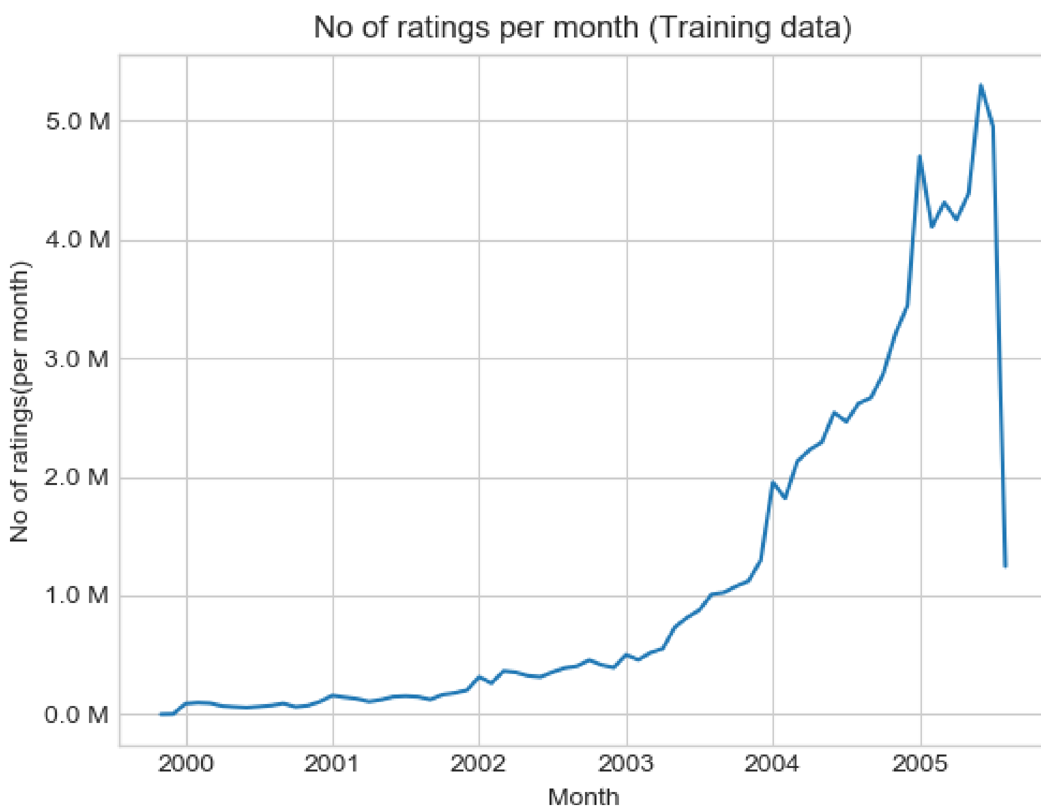
In [14]:
```
# It is used to skip the warning ''SettingWithCopyWarning''..
pd.options.mode.chained_assignment = None  # default='warn'

train_df['day_of_week'] = train_df.date.dt.weekday_name

train_df.tail()
```

Out[14]:

	movie	user	rating	date	day_of_week
80384400	12074	2033618	4	2005-08-08	Monday
80384401	862	1797061	3	2005-08-08	Monday
80384402	10986	1498715	5	2005-08-08	Monday
80384403	14861	500016	4	2005-08-08	Monday
80384404	5926	1044015	5	2005-08-08	Monday

3.3.2 Number of Ratings per a month

In [16]:
```
ax = train_df.resample('m', on='date')['rating'].count().plot()
ax.set_title('No of ratings per month (Training data)')
plt.xlabel('Month')
plt.ylabel('No of ratings(per month)')
ax.set_yticklabels([human(item, 'M') for item in ax.get_yticks()])
plt.show()
```



Observations: -

1. Till Jan 2003 , there were less ratings and after 2003 till 2004 ratings increased massively and there is massive growth in netflix over the months. This observation is on train data.

3.3.3 Analysis on the Ratings given by user

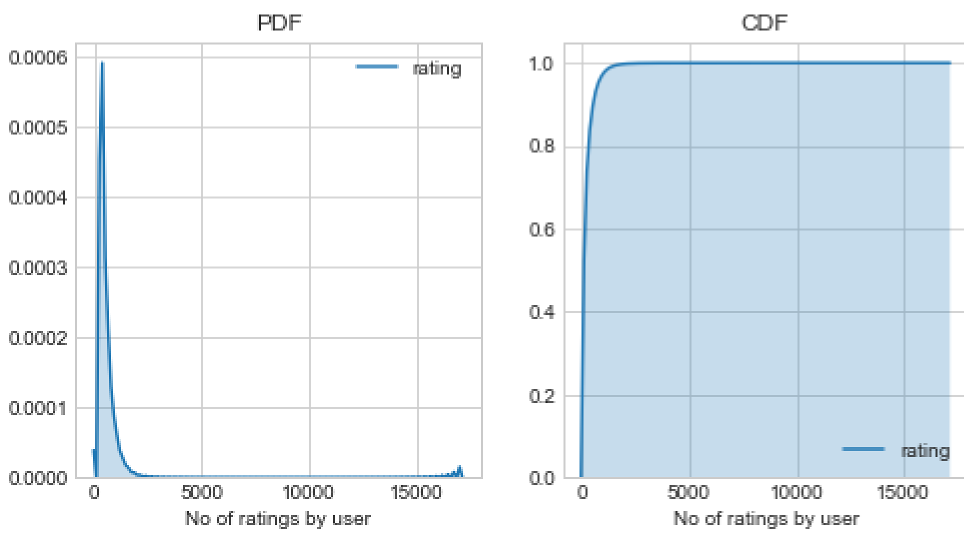
In [15]:
```
# Number of ratings given by a particular user  / number of movies rated by a
 user.
no_of_rated_movies_per_user = train_df.groupby(by='user')['rating'].count().so
rt_values(ascending=False)

no_of_rated_movies_per_user.head()
```

Out[15]:
```
user
305344     17112
2439493    15896
387418     15402
1639792     9767
1461435     9447
Name: rating, dtype: int64
```

Plotting PDF and CDF of number of movies ratings per user

In [19]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

In [20]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

fig = plt.figure(figsize=plt.figaspect(.5))

ax1 = plt.subplot(121)
sns.kdeplot(no_of_rated_movies_per_user, shade=True, ax=ax1)
plt.xlabel('No of ratings by user')
plt.title("PDF")

ax2 = plt.subplot(122)
sns.kdeplot(no_of_rated_movies_per_user, shade=True, cumulative=True,ax=ax2)
plt.xlabel('No of ratings by user')
plt.title('CDF')

plt.show()
```



Observation:-

1. In PDF ,most people give very few ratings and very few users are giving lots of ratings.
2. In CDF , we can see that 90% of people give very few ratings

Getting percentiles / Quantiles of number of ratings per user

In [16]:
```
# Checking percentile of number of ratings per user
no_of_rated_movies_per_user.describe()
```

Out[16]:
```
count    405041.000000
mean        198.459921
std         290.793238
min           1.000000
25%          34.000000
50%          89.000000
75%         245.000000
max       17112.000000
Name: rating, dtype: float64
```

Observation:-

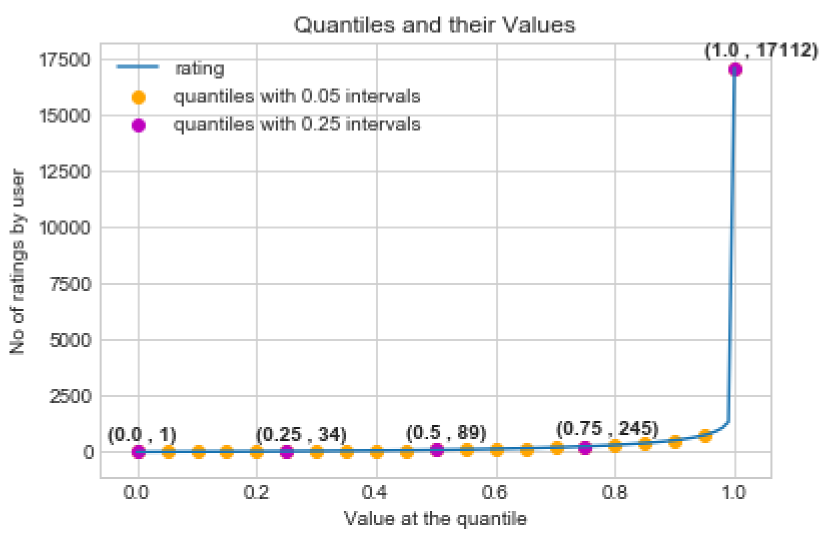
1. Mean/ Average number of movies rated by a user is 198 .
2. Minimum number of movies rated by a user is 1
3. Maximum number of movies rated by a user is 17112
4. Median number of movies rated by a user is 89, which is 50% of customers have rated more than 89 movies.

> *There, is something interesting going on with the quantiles..*

In [17]:
```
quantiles = no_of_rated_movies_per_user.quantile(np.arange(0,1.01,0.01), inter
polation='higher')
```

Plotting Quantiles and their Values

In [23]:
```
# Plotting Quantiles and their Values to get clear understanding of values/rat
ings between 75% and 100%
plt.title("Quantiles and their Values")
quantiles.plot()
# quantiles with 0.05 difference
plt.scatter(x=quantiles.index[::5], y=quantiles.values[::5], c='orange', label
="quantiles with 0.05 intervals")
# quantiles with 0.25 difference
plt.scatter(x=quantiles.index[::25], y=quantiles.values[::25], c='m', label =
"quantiles with 0.25 intervals")
plt.ylabel('No of ratings by user')
plt.xlabel('Value at the quantile')
plt.legend(loc='best')

# annotate the 25th, 50th, 75th and 100th percentile values....
for x,y in zip(quantiles.index[::25], quantiles[::25]):
    plt.annotate(s="({} , {})".format(x,y), xy=(x,y), xytext=(x-0.05, y+500)
                ,fontweight='bold')


plt.show()
```



In [18]:
```
# Percentile values
quantiles[::5]
```

Out[18]:
```
0.00        1
0.05        7
0.10       15
0.15       21
0.20       27
0.25       34
0.30       41
0.35       50
0.40       60
0.45       73
0.50       89
0.55      109
0.60      133
0.65      163
0.70      199
0.75      245
0.80      307
0.85      392
0.90      520
0.95      749
1.00    17112
Name: rating, dtype: int64
```

Observation:-

1. From the above values, we can observe that there are 5% users who rated more than 749 movies which is a lot of ratings .
2. 50% of users rated more than 89 movies, and 50% of users rated less than or equal to 89 movies.
3. 90% of users rated 15 and more than 15 movies

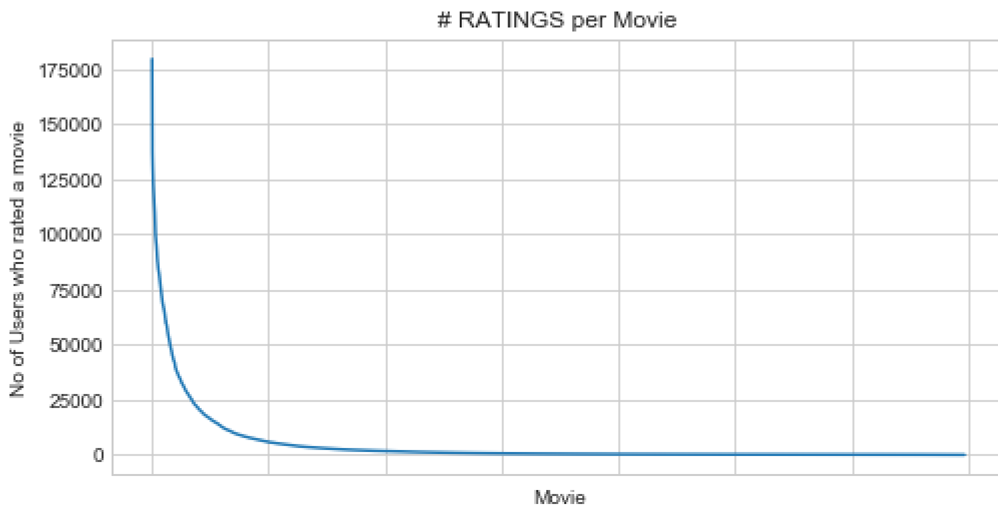
how many ratings at the last 5% of all ratings??

In [19]:
```
print('\n No of ratings at last 5 percentile : {}\n'.format(sum(no_of_rated_mo
vies_per_user>= 749)) )
```

```
 No of ratings at last 5 percentile : 20305
```

3.3.4 Analysis of ratings of a movie given by a user

In [26]:
```
no_of_ratings_per_movie = train_df.groupby(by='movie')['rating'].count().sort_values(ascending=False)

fig = plt.figure(figsize=plt.figaspect(.5))
ax = plt.gca()
plt.plot(no_of_ratings_per_movie.values)
plt.title('# RATINGS per Movie')
plt.xlabel('Movie')
plt.ylabel('No of Users who rated a movie')
ax.set_xticklabels([])

plt.show()
```

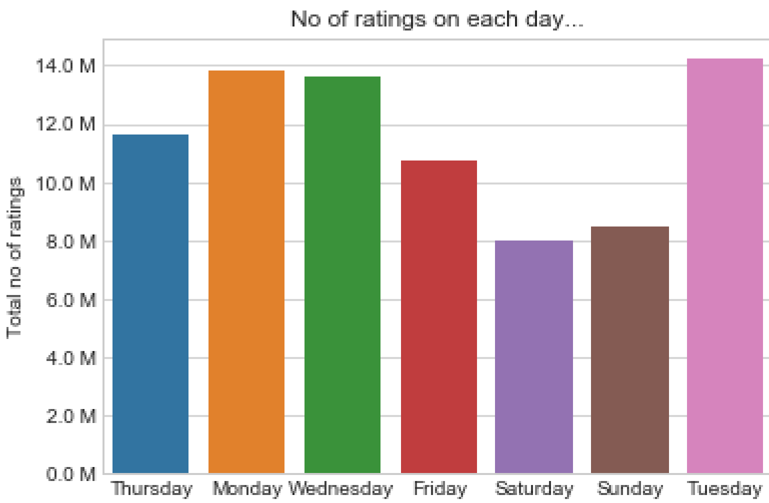


- **It is very skewed.. just like nunmber of ratings given per user.**

```
- There are some movies (which are very popular) which are rated by huge number of users.

- But most of the movies(like 90%) got some hundereds of ratings by fewer people.
```

3.3.5 Number of ratings on each day of the week

In [27]:
```
# Plot to see whether number of ratings differ by a day
fig, ax = plt.subplots()
sns.countplot(x='day_of_week', data=train_df, ax=ax)
plt.title('No of ratings on each day...')
plt.ylabel('Total no of ratings')
plt.xlabel('')
ax.set_yticklabels([human(item, 'M') for item in ax.get_yticks()])
plt.show()
```

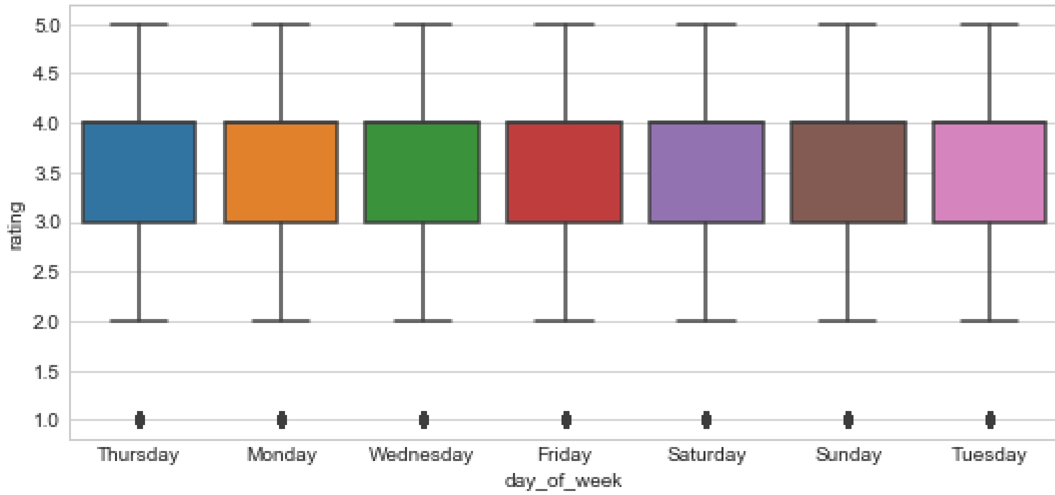


Observation:-

1. There are fewer ratings on weekends Saturday and Sunday and there are more ratings on Tuesday followed by Monday.

Plotting the boxplot to check if the day of week is an important feature to predict the ratings

In [28]:
```
start = datetime.now()
fig = plt.figure(figsize=plt.figaspect(.45))
sns.boxplot(y='rating', x='day_of_week', data=train_df)
plt.show()
print(datetime.now() - start)
```




```
0:00:39.413397
```

Observation:-

1. As all the boxplots are aligned in similar manner, there is no much information in this plot.
2. This shows that day of week is not a very good predictor to predict the rating would a person give for a movie based on day of week.

Average rating for each day of week given by users

In [20]:
```
avg_week_df = train_df.groupby(by=['day_of_week'])['rating'].mean()
print(" AVerage ratings")
print("-"*30)
print(avg_week_df)
print("\n")
```

```
 AVerage ratings
------------------------------
day_of_week
Friday       3.585274
Monday       3.577250
Saturday     3.591791
Sunday       3.594144
Thursday     3.582463
Tuesday      3.574438
Wednesday    3.583751
Name: rating, dtype: float64
```

Observation:-

1. By these average ratings we can observe that most of the ratings are very close for all days around 3.5 with very small deviation.
2. So day of week is not very important factor. So we can drop this feature from the data table. It is like a experiment to see whether the feature day of week important or not.

In ML and Data science most of the experiments around 90% of them fail and only 10% get succeed .

3.3.6 Creating sparse matrix from data frame

`![data_c.jpg](attachment:data_c.jpg)` `![arrow.jpg](attachment:arrow.jpg)` `![data_sparse_c.jpg](attachment:data_sparse_c.jpg)`

3.3.6.1 Creating sparse matrix from train data frame

1. We are converting a dataframe into a matrix with users and movies. Each row corresponds to a user and each column corresponds to a movie.
2. Each user will not rate all the movies, they only rate some subset of movies. We are converting a dataframe into a sparse matrix .
3. To convert anything into a sparse matrix, in scipy there is a function called csr_matrix to create a sparse matrix .
4. csr_matrix is Compressed Sparse Row matrix. This matrix is very large and it is computationaly very high as there are many null entries.
5. The csr_matrix of scipy does not use entire data in the matrix, it optimizes the matrix and uses only non-zero/non-null entries of matrix.
6. So we are creating sparse matrices of train and test data using csr_matrix of scipy.

Creating sparse matrix from train data frame

In [21]:
```
start = datetime.now()
if os.path.isfile('train_sparse_matrix.npz'):
    print("It is present in your pwd, getting it from disk....")
    # just get it from the disk instead of computing it
    train_sparse_matrix = sparse.load_npz('train_sparse_matrix.npz')
    print("DONE..")
else:
    print("We are creating sparse_matrix from the dataframe..")
    # create sparse_matrix and store it for after usage.
    # csr_matrix(data_values, (row_index, col_index), shape_of_matrix)
    # It should be in such a way that, MATRIX[row, col] = data
    train_sparse_matrix = sparse.csr_matrix((train_df.rating.values, (train_df
.user.values,
                                              train_df.movie.values)),)

    print('Done. It\'s shape is : (user, movie) : ',train_sparse_matrix.shape)
    print('Saving it into disk for furthur usage..')
    # save it into disk
    sparse.save_npz("train_sparse_matrix.npz", train_sparse_matrix)
    print('Done..\n')

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

```
It is present in your pwd, getting it from disk....
DONE..
0:00:04.332904
```

The Sparsity of Train Sparse Matrix

In [22]:
```
us,mv = train_sparse_matrix.shape
elem = train_sparse_matrix.count_nonzero()

# 99.89% of cells in train sparse matrix are non-existent or null values. Ther
e are no ratings given by any user
print("Sparsity Of Train matrix : {} % ".format(  (1-(elem/(us*mv))) * 100) )
```

```
Sparsity Of Train matrix : 99.8292709259195 %
```

3.3.6.2 Creating sparse matrix from test data frame

In [23]:
```
start = datetime.now()
if os.path.isfile('test_sparse_matrix.npz'):
    print("It is present in your pwd, getting it from disk....")
    # just get it from the disk instead of computing it
    test_sparse_matrix = sparse.load_npz('test_sparse_matrix.npz')
    print("DONE..")
else:
    print("We are creating sparse_matrix from the dataframe..")
    # create sparse_matrix and store it for after usage.
    # csr_matrix(data_values, (row_index, col_index), shape_of_matrix)
    # It should be in such a way that, MATRIX[row, col] = data
    test_sparse_matrix = sparse.csr_matrix((test_df.rating.values, (test_df.us
er.values,
                                               test_df.movie.values)))

    print('Done. It\'s shape is : (user, movie) : ',test_sparse_matrix.shape)
    print('Saving it into disk for furthur usage..')
    # save it into disk
    sparse.save_npz("test_sparse_matrix.npz", test_sparse_matrix)
    print('Done..\n')

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

```
It is present in your pwd, getting it from disk....
DONE..
0:00:01.270394
```

The Sparsity of Test data Matrix

In [24]:
```
us,mv = test_sparse_matrix.shape
elem = test_sparse_matrix.count_nonzero()

print("Sparsity Of Test matrix : {} % ".format(  (1-(elem/(us*mv))) * 100) )
```

```
Sparsity Of Test matrix : 99.95731772988694 %
```

Observation:-

1. There is extremely sparsity of data in both train and test matrices , over 99% of points have no ratings and are empty.

3.3.7 Finding Global average of all movie ratings, Average rating per user, and Average rating per movie

1. Each row represents a user , each column is a movie.
2. First global mean we want to compute is the mean of all ratings. We take all the cells which have a non-null value. This tells us what is the mean/Average rating given by any netflix user on any given movie.
3. We have seen that the Median of number of ratings given by a user is 89, so in a row we can find good number of ratings.
4. Next we compute user averages , where each row of users in matrix is taken and average of all values is computed. This tells us whether the user typically gives high rating or low rating.
5. Next we compute movie averages. we take each column of movies and compute average of all values in that column, and we get movie average rating.
6. Both user averages and movie averages are vectors where for each user we get a average rating and for every movie we get movie average.
7. Global mean is a single value and is represented as 'Mu'.
8. User average tells us about the user behaviour, whether they are critical or liniant. Movie average tells whether the movie is hit or not. These 2 averages are important.

In [25]:
```
# get the user averages in dictionary (key: user_id/movie_id, value: avg ratin
g)
# function get_average_ratings computes the averages and puts it into a dictio
nary

def get_average_ratings(sparse_matrix, of_users):

    # average ratings of user/axes
    ax = 1 if of_users else 0 # 1 - User axes,0 - Movie axes

    # ".A1" is for converting Column_Matrix to 1-D numpy array
    sum_of_ratings = sparse_matrix.sum(axis=ax).A1
    # Boolean matrix of ratings ( whether a user rated that movie or not)
    is_rated = sparse_matrix!=0
    # no of ratings that each user OR movie..
    no_of_ratings = is_rated.sum(axis=ax).A1

    # max_user  and max_movie ids in sparse matrix
    u,m = sparse_matrix.shape
    # creae a dictonary of users and their average ratigns..
    average_ratings = { i : sum_of_ratings[i]/no_of_ratings[i]
                                 for i in range(u if of_users else m)
                                    if no_of_ratings[i] !=0}

    # return that dictionary of average ratings
    return average_ratings
```

3.3.7.1 finding global average of all movie ratings

In [26]:
```
train_averages = dict()
# get the global average of ratings in our train set.
train_global_average = train_sparse_matrix.sum()/train_sparse_matrix.count_non
zero()
train_averages['global'] = train_global_average
train_averages
```

Out[26]:
```
{'global': 3.582890686321557}
```

3.3.7.2 finding average rating per user

In [27]:
```
train_averages['user'] = get_average_ratings(train_sparse_matrix, of_users=Tru
e)
print('\nAverage rating of user 10 :',train_averages['user'][10])
```

```
Average rating of user 10 : 3.3781094527363185
```

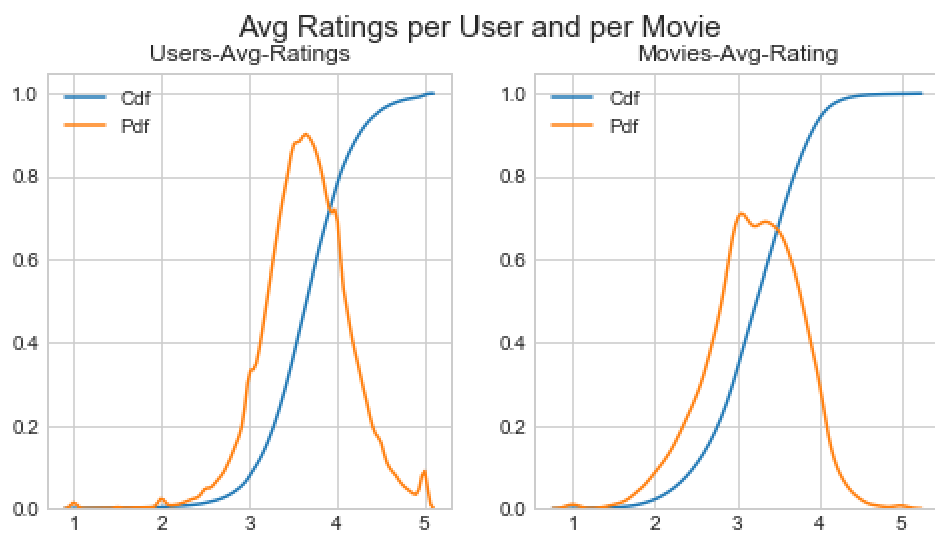
3.3.7.3 finding average rating per movie

In [28]:
```
train_averages['movie'] =  get_average_ratings(train_sparse_matrix, of_users=F
alse)
print('\n AVerage rating of movie 15 :',train_averages['movie'][15])
```

```
 AVerage rating of movie 15 : 3.3038461538461537
```

3.3.7.4 PDF's & CDF's of Avg.Ratings of Users & Movies (In Train Data)

In [29]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

start = datetime.now()
# draw pdfs for average rating per user and average
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=plt.figaspect(.5))
fig.suptitle('Avg Ratings per User and per Movie', fontsize=15)

ax1.set_title('Users-Avg-Ratings')
# get the list of average user ratings from the averages dictionary..
user_averages = [rat for rat in train_averages['user'].values()]
sns.distplot(user_averages, ax=ax1, hist=False,
             kde_kws=dict(cumulative=True), label='Cdf')
sns.distplot(user_averages, ax=ax1, hist=False,label='Pdf')

ax2.set_title('Movies-Avg-Rating')
# get the list of movie_average_ratings from the dictionary..
movie_averages = [rat for rat in train_averages['movie'].values()]
sns.distplot(movie_averages, ax=ax2, hist=False,
             kde_kws=dict(cumulative=True), label='Cdf')
sns.distplot(movie_averages, ax=ax2, hist=False, label='Pdf')

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




```
0:01:24.087875
```

3.3.8 Cold Start problem

1. This is the important problem in recommender systems. We have sliced/divided data over time into train data-80% and test data-20%.
2. There may be some users and some movies which are present in test data and not training data. There will be some new users and new movies created in test data time, for whom there is no data in training data set . This is called cold start problem.

3.3.8.1 Cold Start problem with Users

In [29]:
```
total_users = len(np.unique(df.user))
users_train = len(train_averages['user'])
new_users = total_users - users_train

print('\nTotal number of Users  :', total_users)
print('\nNumber of Users in Train data :', users_train)
print("\nNo of Users that didn't appear in train data: {}({} %) \n ".format(ne
w_users,
                                                                        np.rou
nd((new_users/total_users)*100, 2)))
```

```
Total number of Users  : 480189

Number of Users in Train data : 405041

No of Users that didn't appear in train data: 75148(15.65 %)
```

Observation:-

1. Total number of users inluding train and test data is 480189 , of which 405041 users are present in trian and test data.
2. There are 75148 users (which is 15% of total users) who are present only in test data and not present in train data and there is no rating of them in past.
3. So from the above observations we say see that , 15% of users in test data do not have any rating that they provided in training data.
4. Here in case of users, cold start problem is severe.

> We might have to handle **new users** (***75148***) who didn't appear in train data.

3.3.8.2 Cold Start problem with Movies

In [30]:
```
total_movies = len(np.unique(df.movie))
movies_train = len(train_averages['movie'])
new_movies = total_movies - movies_train

print('\nTotal number of Movies  :', total_movies)
print('\nNumber of Users in Train data :', movies_train)
print("\nNo of Movies that didn't appear in train data: {}({} %) \n ".format(n
ew_movies,
                                                                        np.rou
nd((new_movies/total_movies)*100, 2)))
```

```
Total number of Movies  : 17770

Number of Users in Train data : 17424

No of Movies that didn't appear in train data: 346(1.95 %)
```

Observation:-

1. There are total of 17770 movies in train and test data. Out of which only 346 movies are only present in test data and not in train data. This is 1.9% movies of total movies do not have correspoinding rating in training data.
2. Here cold start problem is not severe in case of movies.

> We might have to handle **346 movies** (small comparatively) in test data

3.4 Computing Similarity matrices

3.4.1 Computing User-User Similarity matrix

1. Calculating User User Similarity_Matrix is **not very easy**(*unless you have huge Computing Power and lots of time*) because of number of. usersbeing lare.
    - You can try if you want to. Your system could crash or the program stops with **Memory Error**
2. Each column is a movie and each row corresponds to a user.
3. We can find user-user similarity by doing cosine similary between the users. User similarity matrix is a symmetric matrix. Each row and column corresponds to a user . There will be cosine similirites of users in the matrix.
4. This similairty matrix is not sparse as we can compute similarity for every pair of users . It is only symmetric in nature where Sim_ij = Sim_ji. So we need to compute 82 billion dot products , it is very expensive

3.4.2 Computing Movie-Movie Similarity matrix

1. Each movie vectors are very large, each of this vector is extremely sparse.
2. Movie similaritymatrix gives similarity between the movies using cosine similarity. This matrix is symmetric and dense

In [31]:
```
start = datetime.now()
if not os.path.isfile('m_m_sim_sparse.npz'):
    print("It seems you don't have that file. Computing movie_movie similarit
y...")
    start = datetime.now()
    m_m_sim_sparse = cosine_similarity(X=train_sparse_matrix.T, dense_output=F
alse)
    print("Done..")
    # store this sparse matrix in disk before using it. For future purposes.
    print("Saving it to disk without the need of re-computing it again.. ")
    sparse.save_npz("m_m_sim_sparse.npz", m_m_sim_sparse)
    print("Done..")
else:
    print("It is there, We will get it.")
    m_m_sim_sparse = sparse.load_npz("m_m_sim_sparse.npz")
    print("Done ...")

print("It's a ",m_m_sim_sparse.shape," dimensional matrix")

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

```
It is there, We will get it.
Done ...
It's a  (17771, 17771)  dimensional matrix
0:00:31.887204
```

In [32]:
```
m_m_sim_sparse.shape
```

Out[32]:
```
(17771, 17771)
```

- Even though we have similarity measure of each movie, with all other movies, We generally don't care much about least similar movies.
- Most of the times, only top_xxx similar items matters. It may be 10 or 100.
- We take only those top similar movie ratings and store them in a saperate dictionary, where key is movie and value is a dictionary , we use dictionary of dictionaries

In [33]:
```
movie_ids = np.unique(m_m_sim_sparse.nonzero()[1])
```

In [34]:
```
start = datetime.now()
similar_movies = dict()
for movie in movie_ids:
    # get the top similar movies and store them in the dictionary
    sim_movies = m_m_sim_sparse[movie].toarray().ravel().argsort()[::-1][1:]
    similar_movies[movie] = sim_movies[:100]
print(datetime.now() - start)

# just testing similar movies for movie_15
similar_movies[15]
```

```
0:00:31.211036
```

Out[34]:
```
array([ 8279,  8013, 16528,  5927, 13105, 12049,  4424, 10193, 17590,
        4549,  3755,   590, 14059, 15144, 15054,  9584,  9071,  6349,
       16402,  3973,  1720,  5370, 16309,  9376,  6116,  4706,  2818,
         778, 15331,  1416, 12979, 17139, 17710,  5452,  2534,   164,
       15188,  8323,  2450, 16331,  9566, 15301, 13213, 14308, 15984,
       10597,  6426,  5500,  7068,  7328,  5720,  9802,   376, 13013,
        8003, 10199,  3338, 15390,  9688, 16455, 11730,  4513,   598,
       12762,  2187,   509,  5865,  9166, 17115, 16334,  1942,  7282,
       17584,  4376,  8988,  8873,  5921,  2716, 14679, 11947, 11981,
        4649,   565, 12954, 10788, 10220, 10963,  9427,  1690,  5107,
        7859,  5969,  1510,  2429,   847,  7845,  6410, 13931,  9840,
        3706])
```

3.4.3 Finding most similar movies using similarity matrix

Does Similarity really works as the way we expected...?
Let's pick some random movie and check for its similar movies....

In [35]:
```
# First Let's load the movie details into soe dataframe..
# movie details are in 'netflix/movie_titles.csv'

movie_titles = pd.read_csv("movie_titles.csv", sep=',', header = None,
                           names=['movie_id', 'year_of_release', 'title'], ver
bose=True,
                      index_col = 'movie_id', encoding = "ISO-8859-1")

movie_titles.head()
```

```
Tokenization took: 22.63 ms
Type conversion took: 11.07 ms
Parser memory cleanup took: 0.01 ms
```

Out[35]:

movie_id	year_of_release	title
1	2003.0	Dinosaur Planet
2	2004.0	Isle of Man TT 2004 Review
3	1997.0	Character
4	1994.0	Paula Abdul's Get Up & Dance
5	2004.0	The Rise and Fall of ECW

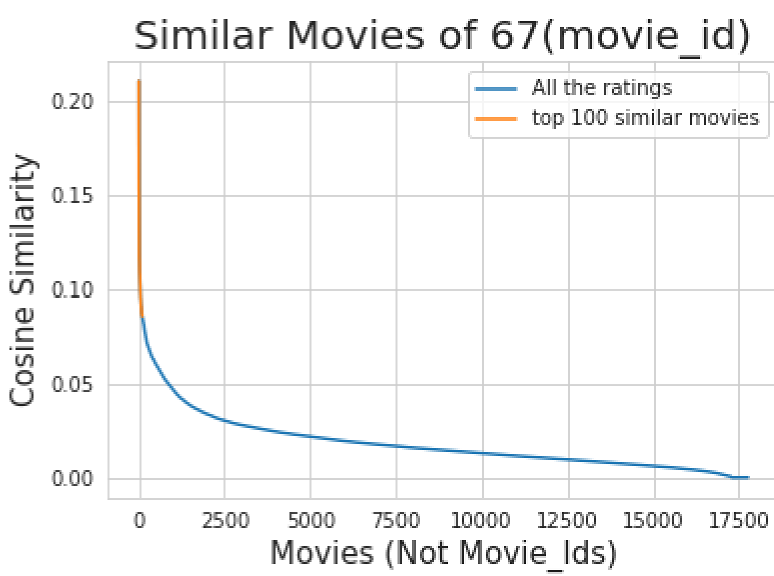
Similar Movies for 'Vampire Journals'

In [36]:
```
mv_id = 67

print("\nMovie ----->",movie_titles.loc[mv_id].values[1])

print("\nIt has {} Ratings from users.".format(train_sparse_matrix[:,mv_id].ge
tnnz()))

print("\nWe have {} movies which are similarto this  and we will get only top
 most..".format(m_m_sim_sparse[:,mv_id].getnnz()))
```

```
Movie -----> Vampire Journals

It has 270 Ratings from users.

We have 17284 movies which are similarto this  and we will get only top mos
t..
```

In [37]:
```
similarities = m_m_sim_sparse[mv_id].toarray().ravel()

similar_indices = similarities.argsort()[::-1][1:]

similarities[similar_indices]

sim_indices = similarities.argsort()[::-1][1:] # It will sort and reverse the
 array and ignore its similarity (ie.,1)
                                               # and return its indices(movie_
ids)
```

In [38]:
```
%matplotlib inline
plt.plot(similarities[sim_indices], label='All the ratings')
plt.plot(similarities[sim_indices[:100]], label='top 100 similar movies')
plt.title("Similar Movies of {}(movie_id)".format(mv_id), fontsize=20)
plt.xlabel("Movies (Not Movie_Ids)", fontsize=15)
plt.ylabel("Cosine Similarity",fontsize=15)
plt.legend()
plt.show()
```



Observation:-

1. The top similar movie to vampire journal has similarity value of 0.23 and 100th siimilarity of 0.08 approx
2. Orange line represents similarity values of the top 100 movies to vampire journals.

Top 10 similar movies

In [38]:
```
movie_titles.loc[sim_indices[:10]]
```

Out[38]:

movie_id	year_of_release	title
323	1999.0	Modern Vampires
4044	1998.0	Subspecies 4: Bloodstorm
1688	1993.0	To Sleep With a Vampire
13962	2001.0	Dracula: The Dark Prince
12053	1993.0	Dracula Rising
16279	2002.0	Vampires: Los Muertos
4667	1996.0	Vampirella
1900	1997.0	Club Vampire
13873	2001.0	The Breed
15867	2003.0	Dracula II: Ascension

Observation:-

1. We got these similar movies names list just by computing movie-movie similarity using cosine similarity.

> Similarly, we can ***find similar users*** and compare how similar they are.

4. Machine Learning Models

1. Here we use both regression and recommendation systems ideas.
2. Our task is, given User Ui, and Movie Mj, we have to predict rating rij. Xi = {Ui,Mj} this is input and Yi = rij is output. We pose this as regression problem.
3. Based on input we can get features like, user-user similarity and movie-movie similarity, average rating given by user to a movie etc.

   #### Surprise library:-
4. It is one of the best library for recommender systems in python. It is very compatibale with python and it works very well for this case study.
5. It has algorithms like baseline algorithms, neighbourhood method and matrix factorization methods like SVD, SVD++, NMF(Non Negative Matrix Factorization). It has built-in cosine similarities
6. SurPRISE - Simple Python Recommendation System Engine

Model 1:-

1. On the feature set 1 which have 13 hand-crafted characters , we build/train the XGBoost Regessor with RMSE as loss function. We have to minimise the RMSE. This is first model and we don't use Surprise library here.

Model 2 :-

1. We use Surprise library here and there are many models in surprise library like Baseline model, KNN Model, Knn model with item-item similarity.
2. Given user and movie, the baseline model predicts a rating rij, and we use this rating output from this model as a feature . Now we have first 13 features + this 1 feature from baseline model from surprise library. So total 14 features.
3. Using these 14 features, then we train the model with XGBoost with 14 features. This is model 2.

Model 3:-

1. Now we compute Knn model with user user similarity and this output will become the 15th / 3rd set of feature. Then we compute surprise with item item similarity and get the output as feature 16 or feature set 4.

SO set 1 features - 13 hand-crafted characters set 2 - Output of baseline model set 3 - output of KNN model with user-user similarity set 4 - output of KNN model with item-item/movie-movie similarity

Now final model we get is XGBoost with feature sets 1,2,3,4

1. We get Feature set 5 by using surprise library with Matrix Factorization SVD . Output of SVD is the feature set 5.
2. We get feature set 6 by using SVD++ . It is output of SVD++.
3. So we use the outputs of all models of Surprise .Total there are 6 feature sets.
4. Now by taking all these 6 feature sets as input Xi and we build 2 more XGBoost models and get Yi which is the rating given by a user to a movie.

In [39]:
```
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 It will create
        and store the sampled sparse matrix in the path specified.
    """

    # 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), le
n(movies)))
    print("Original Matrix : Ratings -- {}\n".format(len(ratings)))

    # 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=False)
    sample_movies = np.random.choice(movies, no_movies, replace=False)
    # get the boolean mask or these sampled_items in originl row/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], (row_ind[mask], c
ol_ind[mask])),
                                             shape=(max(sample_users)+1, max(s
ample_movies)+1))

    if verbose:
        print("Sampled Matrix : (users, movies) -- ({} {})".format(len(sample_
users), len(sample_movies)))
        print("Sampled Matrix : Ratings --", format(ratings[mask].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

Taking sample of 25k Users and 3k movies for Train data

In [40]:
```
start = datetime.now()
path = "sample_train_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_train_sparse_matrix = sparse.load_npz(path)
    print("DONE..")
else:
    # get 25k users and 3k movies from available data
    sample_train_sparse_matrix = get_sample_sparse_matrix(train_sparse_matrix,
no_users=25000, no_movies=3000,
                                             path = path)

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

```
It is present in your pwd, getting it from disk....
DONE..
0:00:00.075931
```

4.1.2 Build sample test data from the test data

Taking sample of 10k Users and 1k movies for Test data

In [41]:
```
start = datetime.now()

path = "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 10k users and 1000 movies from available data
    sample_test_sparse_matrix = get_sample_sparse_matrix(test_sparse_matrix, n
o_users=10000, no_movies=1000,
                                                 path = path)
print(datetime.now() - start)
```

```
It is present in your pwd, getting it from disk....
DONE..
0:00:00.042622
```

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

In [42]:
```
sample_train_averages = dict()
```

4.2.1 Finding Global Average of all movie ratings

In [43]:
```
# get the global average of ratings in our train set.
global_average = sample_train_sparse_matrix.sum()/sample_train_sparse_matrix.c
ount_nonzero()
sample_train_averages['global'] = global_average
sample_train_averages
```

Out[43]:
```
{'global': 3.581679377504138}
```

4.2.2 Finding Average rating per User

In [46]:
```
sample_train_averages['user'] = get_average_ratings(sample_train_sparse_matrix
, of_users=True)
print('\nAverage rating of user 1515220 :',sample_train_averages['user'][15152
20])
```

```
Average rating of user 1515220 : 3.9655172413793105
```

4.2.3 Finding Average rating per Movie

In [47]:
```
sample_train_averages['movie'] =  get_average_ratings(sample_train_sparse_matr
ix, of_users=False)
print('\n AVerage rating of movie 15153 :',sample_train_averages['movie'][1515
3])
```

```
 AVerage rating of movie 15153 : 2.6458333333333335
```

4.3 Featurizing data

In [48]:
```
print('\n No of ratings in Our Sampled train matrix is : {}\n'.format(sample_t
rain_sparse_matrix.count_nonzero()))
print('\n No of ratings in Our Sampled test  matrix is : {}\n'.format(sample_t
est_sparse_matrix.count_nonzero()))
```

```
 No of ratings in Our Sampled train matrix is : 129286


 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 [49]:
```
# get users, movies and ratings from our samples train sparse matrix
sample_train_users, sample_train_movies, sample_train_ratings = sparse.find(sa
mple_train_sparse_matrix)
```

In [50]:
```
############################################################
# It took me almost 10 hours to prepare this train dataset.#
# 'sample/small/reg_train.csv'
############################################################
start = datetime.now()
if os.path.isfile('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_ra
tings)))
    with open('reg_train.csv', mode='w') as reg_data_file:
        count = 0
        for (user, movie, rating)  in zip(sample_train_users, sample_train_mov
ies, sample_train_ratings):
            st = datetime.now()
        #     print(user, movie)
            #--------------------- Ratings of "movie" by similar users of "use
r" ---------------------
            # compute the similar Users of the "user"
            user_sim = cosine_similarity(sample_train_sparse_matrix[user], sam
ple_train_sparse_matrix).ravel()
            top_sim_users = user_sim.argsort()[::-1][1:] # we are ignoring 'Th
e 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].toa
rray().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 "mo
vie" ---------------------
            # 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].toa
rray().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_movies
            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 pair...
            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)
```

```
File already exists you don't have to prepare again...
0:00:00.000709
```

Reading from the file to make a Train_dataframe

In [51]:

```
reg_train = pd.read_csv('reg_train.csv', names = ['user', 'movie', 'GAvg', 'su
r1', 'sur2', 'sur3', 'sur4', 'sur5','smr1', 'smr2', 'smr3', 'smr4', 'smr5', 'U
Avg', 'MAvg', 'rating'], header=None)
reg_train.head()
```

Out[51]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	
0	53406	33	3.581679	4.0	5.0	5.0	4.0	1.0	5.0	2.0	5.0	3.0	1.0	3.37
1	99540	33	3.581679	5.0	5.0	5.0	4.0	5.0	3.0	4.0	4.0	3.0	5.0	3.55
2	99865	33	3.581679	5.0	5.0	4.0	5.0	3.0	5.0	4.0	4.0	5.0	4.0	3.71
3	101620	33	3.581679	2.0	3.0	5.0	5.0	4.0	4.0	3.0	3.0	4.0	5.0	3.58
4	112974	33	3.581679	5.0	5.0	5.0	5.0	5.0	3.0	5.0	5.0	5.0	3.0	3.75

- **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..) sur1 - similar user 1
- **Similar movies rated by this user**:
  - smr1, smr2, smr3, smr4, smr5 (top 5 similar movies rated by this user..) smr1 - similar movie rated 1
- **UAvg** : User's Average rating
- **MAvg** : Average rating of this movie
- **rating** : Rating of this movie by this user.

Given user Ui, movie Mj, rating rij, we have to convert it into a regression problem. Steps for this are:-

1. Using Ui and Mj data, we compute a vector of features Xij and rating rij becomes Yij. Now the dataset is {Xij, Yij}

There are 13 features

1. Global Average 2,3,4,5,6 - top 5 similar users rated the movie 7,8,9,10,11 - top 5 similar movies rated by the user
2. User Average
3. Movie Average

All these 13 features becomes Xij feature vector

When we compute similar users on test data, we have to compare with training data similar users . We cannot use test data for feature engineering

If a user is in test data and is not present in train data , which is a cold start problem, then we give all the 'sur' ratings to 0 ,as the user is new and there are no similar users. Same for movies data also.

4.3.1.2 Featurizing test data

In [52]:
```
# get users, movies and ratings from the Sampled Test
sample_test_users, sample_test_movies, sample_test_ratings = sparse.find(sampl
e_test_sparse_matrix)
```

In [53]:
```
sample_train_averages['global']
```

Out[53]: 3.581679377504138

In [54]:
```
start = datetime.now()

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

    print('preparing {} tuples for the dataset..\n'.format(len(sample_test_rat
ings)))
    with open('reg_test.csv', mode='w') as reg_data_file:
        count = 0
        for (user, movie, rating)  in zip(sample_test_users, sample_test_movie
s, sample_test_ratings):
            st = datetime.now()

        #--------------------- Ratings of "movie" by similar users of "user" -
--------------------
            #print(user, movie)
            try:
                # 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'][m
ovie]]*(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 gi
ven user for top similar movies...
                ########## Cold STart Problem ##########
                top_sim_users_ratings.extend([sample_train_averages['global']]
*(5 - len(top_sim_users_ratings)))
                #print(top_sim_users_ratings)
            except:
                print(user, movie)
                # we just want KeyErrors to be resolved. Not every Exceptio
n...
                raise



            #--------------------- Ratings by "user"  to similar movies of "mo
vie" ---------------------
            try:
                # compute the similar movies of the "movie"
                movie_sim = cosine_similarity(sample_train_sparse_matrix[:,mov
ie].T, sample_train_sparse_matrix.T).ravel()
                top_sim_movies = movie_sim.argsort()[::-1][1:] # we are ignori
ng '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'][u
ser]]*(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_averages['global'
]]*(5-len(top_sim_movies_ratings)))
                    #print(top_sim_movies_ratings)
                except :
                    raise

                #-----------------prepare the row to be stores in a file----------
-------#
                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_movies
                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 pair...
                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 [55]:
```
reg_test_df = pd.read_csv('reg_test.csv', names = ['user', 'movie', 'GAvg', 's
ur1', 'sur2', 'sur3', 'sur4', 'sur5',
                                                          'smr1', 'smr2', 'smr
3', 'smr4', 'smr5',
                                                          'UAvg', 'MAvg', 'rat
ing'], header=None)
reg_test_df.head(4)
```

Out[55]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sı
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581
2	1737912	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581
3	1849204	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581

- **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

Surprise uses a data format internally tto make execution of these algorithms fast to train

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 (http://surprise.readthedocs.io/en/stable/getting_started.html#load-dom-dataframe-py)

Surprise reader quickly reads the data from pandas dataframe or a file and trasform it internally into a format it wants

In [56]:

```
# 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))

# Giving the train dataframe to the surprise and converting into train_data wh
ich is a surprise variable
# in which all training data stored
train_data = Dataset.load_from_df(reg_train[['user', 'movie', 'rating']], read
er)

# build the trainset from train_data.., 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)

In [57]:

```
# test dataframes is converted into a testset that surprise needs
testset = list(zip(reg_test_df.user.values, reg_test_df.movie.values, reg_test
_df.rating.values))
testset[:3]
```

Out[57]:

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

4.4 Applying Machine Learning models

Applying XGBoost on 13 features.

- 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 [58]:
```
models_evaluation_train = dict()
models_evaluation_test = dict()

models_evaluation_train, models_evaluation_test
```

Out[58]:
```
({}, {})
```

> **Utility functions for running regression models**

In [59]:
```
# there are 2 error metrics - RMSE , MAPE
# to get rmse and mape given actual and predicted ratings rij's..
def get_error_metrics(y_true, y_pred):
    rmse = np.sqrt(np.mean([ (y_true[i] - y_pred[i])**2 for i in range(len(y_p
red)) ]))
    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, 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.... evaluate the model
    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.values, y_pred=y_te
st_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 [60]:
```
# it is just to makesure that all of our algorithms should produce same result
s
# 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

##############################################################################
####
# 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 other is for test
        Each of them have 3 key-value pairs, which specify ''rmse'', ''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
    st = datetime.now()
    print('Training the model...')
    algo.fit(trainset)
    print('Done. time taken : {} \n'.format(datetime.now()-st))

    # ---------------- Evaluating train data--------------------#
    st = datetime.now()
```

```
    print('Evaluating the model with train data..')
    # get the train predictions (list of prediction class inside Surprise)
    train_preds = algo.test(trainset.build_testset())
    # get predicted ratings from the train predictions..
    train_actual_ratings, train_pred_ratings = get_ratings(train_preds)
    # get ''rmse'' and ''mape'' from the train predictions.
    train_rmse, train_mape = get_errors(train_preds)
    print('time taken : {}'.format(datetime.now()-st))

    if verbose:
        print('-'*15)
        print('Train Data')
        print('-'*15)
        print("RMSE : {}\n\nMAPE : {}\n".format(train_rmse, train_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---------------#
    st = datetime.now()
    print('\nEvaluating for 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_preds)
    # get error metrics from the predicted and actual ratings
    test_rmse, test_mape = get_errors(test_preds)
    print('time taken : {}'.format(datetime.now()-st))

    if verbose:
        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

    print('\n'+'-'*45)
    print('Total time taken to run this algorithm :', datetime.now() - start)

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

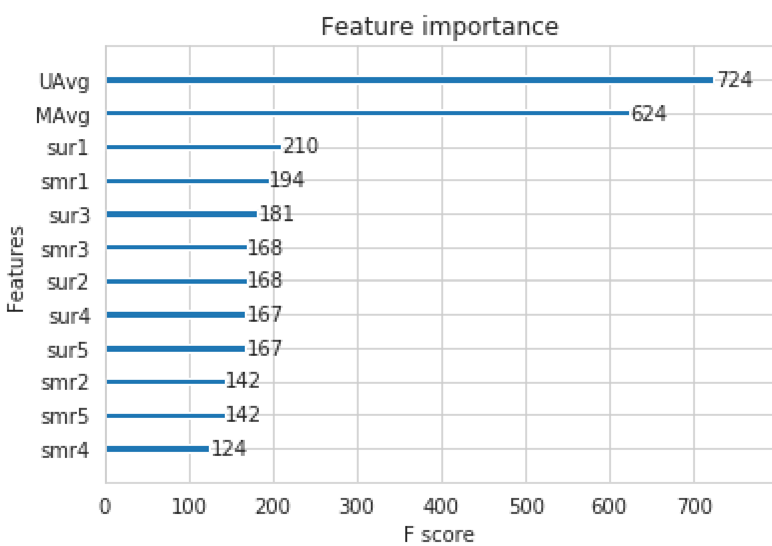
4.4.1 XGBoost with initial 13 features

In [61]:
```
# https://xgboost.readthedocs.io/en/latest/python/python_api.html
# 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']
```

In [62]:
```
import xgboost as xgb
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

params = {'n_estimators': [16, 32, 64, 80, 100], 'max_depth': [3, 5, 7, 9]}

first_xgb = xgb.XGBRegressor(silent=True, n_jobs=13, random_state=15)
xgb_model = GridSearchCV(first_xgb, params, scoring = 'neg_mean_squared_error'
, n_jobs = -1, cv=3)
xgb_model.fit(x_train, y_train)

print("Model with best parameters is :\n", xgb_model.best_estimator_)

optimal_n_estimators =  xgb_model.best_estimator_.n_estimators
print("The optimal value of n_estimators is :", optimal_n_estimators)

optimal_max_depth = xgb_model.best_estimator_.max_depth
print("The optimal value of max_depth is:", optimal_max_depth)

xgb_optimal = xgb.XGBRegressor(n_estimators = optimal_n_estimators, max_depth
= optimal_max_depth)

# fitting the optimal model on train data
xgb_optimal.fit(x_train, y_train)

# from the trained model, get the predictions.... evaluate the model on train
 data
print('Evaluating the model with TRAIN data...')
train_pred = xgb_optimal.predict(x_train)
# get the rmse and mape of train data...
rmse_train, mape_train = get_error_metrics(y_train.values, train_pred)
# store the results in train_results dictionary..
train_results = {'rmse': rmse_train, 'mape' : mape_train, 'predictions' : trai
n_pred}
print('\nTRAIN DATA')
print('-'*30)
print('RMSE : ', rmse_train)
print('MAPE : ', mape_train)

#######################################
# get the test data predictions and compute rmse and mape
print('Evaluating Test data')
# predict the response
test_pred = xgb_optimal.predict(x_test)
# get the rmse and mape of test data..
rmse_test, mape_test = get_error_metrics(y_true=y_test.values, y_pred = test_p
red)
# store them in test results dictionary.
test_results = {'rmse': rmse_test, 'mape' : mape_test, 'predictions': test_pre
d}
print('\nTEST DATA')
print('-'*30)
print('RMSE : ', rmse_test)
print('MAPE : ', mape_test)
```

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

xgb.plot_importance(xgb_optimal)
plt.show()

print("Time Taken:{}".format(datetime.now()-start))
```

```
Model with best parameters is :
 XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, importance_type='gain',
       learning_rate=0.1, max_delta_step=0, max_depth=5,
       min_child_weight=1, missing=None, n_estimators=100, n_jobs=13,
       nthread=None, objective='reg:linear', random_state=15, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
The optimal value of n_estimators is : 100
The optimal value of max_depth is: 5
Evaluating the model with TRAIN data...

TRAIN DATA
------------------------------
RMSE :  0.8346452174223339
MAPE :  24.751039447859068
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.0755881866540673
MAPE :  34.55557960993355
```




```
Time Taken:0:06:05.766319
```

Observation:-

1. Test RMSE for this model is 1.0755 , as we training the model on sample data of 25k users and 3k movies. But if we train on entire data then the results will be much better and RMSE value will be reduced further.
2. From the above plot,we can see, the most important feature in predicting the rating(rij) that user Ui would give on Movie Mj, is the User Average (UAvg).
3. The relative difference between the values/scores of features matter here.
4. 2nd important feature is Movie Mj avg.
5. Next we get similar user rating(sur) and similar movie rating(smr)

4.4.2 Suprise BaselineModel

Predicted_rating : (baseline prediction)

```
-  http://surprise.readthedocs.io/en/stable/basic_algorithms.html#surprise.predicti
on_algorithms.baseline_only.BaselineOnly
```

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

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

r_ui^ : rating that the user u gave on item i (item is movie in this case). This is predicted value.

1. In actual data ,we have user, movie and rating r_ui . Now the model predicts rating r_ui^
2. so predicted value r_ui^ is called b_ui , b is baseline . It is a baseline model.
3. So the above equation says, it predicts the predicted rating r_ui^ as sum of global mean (mu) and bias for each user and item(movie). mu is constant (like 3.5), it is the average of all ratings in training data.
4. We have to compute user and item bias .
5. Here user bias is like user mean and item/movie bias is like movie mean in 13 features where we explicitly cmputed it. But in this case there is no explicitly computing these ,we only compute global average explicitly.
6. These biases will be estimated by solving optimization problem, like Least squares problem .

Optimization function (Least Squares Problem)

```
- http://surprise.readthedocs.io/en/stable/prediction_algorithms.html#baselines-est
imates-configuration
```

r_ui^ = mu + b_u + b_i

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

1. In this problem we have to minimmize the difference between actual rating (r_ui) and predicted rating(r_ui^), given biases . Mu is fixed as global average . and add L2 regularizer.
2. So this problem is, minimize b_u and b_i over all possible values of r_ui (r_ui - r_ui^) + Lamda. regularization . This is standard Least squares optimization problem.
3. We can solve this problem with SGD

In [63]:
```
# options are to specify.., how to compute those user and item biases
bsl_options = {'method': 'sgd',
               'learning_rate': .001
               }
# we use BaselineOnly model with SGD as optimizer
bsl_algo = BaselineOnly(bsl_options=bsl_options)
# run this algorithm.., It will return the train and test results..
bsl_train_results, bsl_test_results = run_surprise(bsl_algo, trainset, testset
, verbose=True)


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

```
Training the model...
Estimating biases using sgd...
Done. time taken : 0:00:00.811972

Evaluating the model with train data..
time taken : 0:00:01.262837
---------------
Train Data
---------------
RMSE : 0.9347153928678286

MAPE : 29.389572652358183

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.078190
---------------
Test Data
---------------
RMSE : 1.0730330260516174

MAPE : 35.04995544572911

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:00:02.154054
```

Observation:-

1. We got the training data RMSE of 0.93 and test data RMSE of 1.0730. We only consider test data RMSE.
2. If there is much difference between both train and test error/RMSE, then the model is overfitting. But in above Baseline model there is no much difference between them, so model is not overfitting .
3. In XGBoost model with 13 features , we got test error of 1.075, this baseline model has 1.073 , which is slightly better

4.4.3 XGBoost with initial 13 features + Surprise Baseline predictor

1. To the 13 features , we add a 14th feature which is a predicted value of a baseline model (bslpr)
2. Given Ui and Mj and baseline model, then it returns a rating as output which is baseline model predicted value and make it as a 14th feature and apply XGBoost on all these 14 features.
3. So the output we get from surprise models, we make them as features to XGBoost model .

Updating Train Data

In [64]:
```
# add our baseline_predicted value as our feature..
reg_train['bslpr'] = models_evaluation_train['bsl_algo']['predictions']
reg_train.head(2)
```

Out[64]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	U
0	53406	33	3.581679	4.0	5.0	5.0	4.0	1.0	5.0	2.0	5.0	3.0	1.0	3.370
1	99540	33	3.581679	5.0	5.0	5.0	4.0	5.0	3.0	4.0	4.0	3.0	5.0	3.555

Updating Test Data

In [65]:
```
# add that baseline predicted ratings with Surprise to the test data as well
reg_test_df['bslpr']  = models_evaluation_test['bsl_algo']['predictions']

reg_test_df.head(2)
```

Out[65]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.5816
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.5816

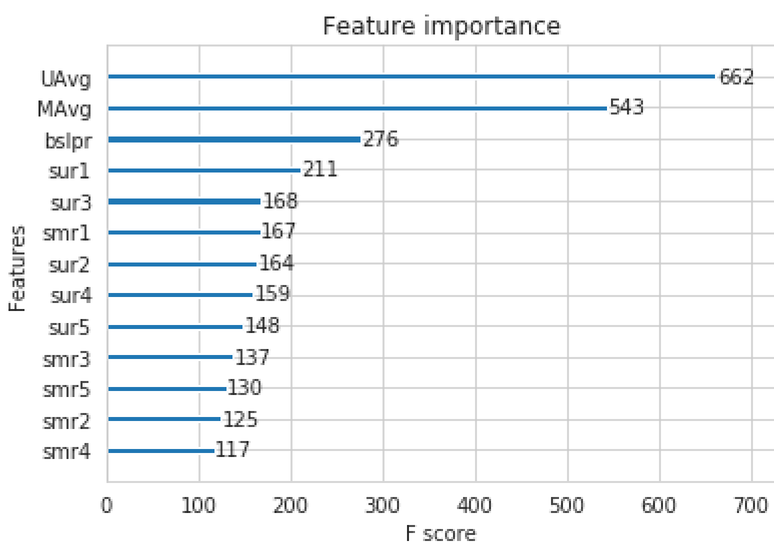
Training the Model

In [66]:
```
# 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']
```

In [67]:
```
import xgboost as xgb
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

params = {'n_estimators': [16, 32, 64, 80, 100], 'max_depth': [3, 5, 7, 9]}

sur_xgb = xgb.XGBRegressor(silent=True, n_jobs=13, random_state=15)
xgb_sbl = GridSearchCV(sur_xgb, params, scoring = 'neg_mean_squared_error', n_
jobs = -1, cv=3)
xgb_sbl.fit(x_train, y_train)

print("Model with best parameters is :\n", xgb_sbl.best_estimator_)

optimal_n_estimators =  xgb_sbl.best_estimator_.n_estimators
print("The optimal value of n_estimators is :", optimal_n_estimators)

optimal_max_depth = xgb_sbl.best_estimator_.max_depth
print("The optimal value of max_depth is:", optimal_max_depth)

xgb_sbl_optimal = xgb.XGBRegressor(n_estimators = optimal_n_estimators, max_de
pth = optimal_max_depth)

# fitting the optimal model on train data
xgb_sbl_optimal.fit(x_train, y_train)

# from the trained model, get the predictions.... evaluate the model on train
 data
print('Evaluating the model with TRAIN data...')
train_pred = xgb_sbl_optimal.predict(x_train)
# get the rmse and mape of train data...
rmse_train, mape_train = get_error_metrics(y_train.values, train_pred)
# store the results in train_results dictionary..
train_results = {'rmse': rmse_train, 'mape' : mape_train, 'predictions' : trai
n_pred}
print('\nTRAIN DATA')
print('-'*30)
print('RMSE : ', rmse_train)
print('MAPE : ', mape_train)

#######################################
# get the test data predictions and compute rmse and mape
print('Evaluating Test data')
# predict the response
test_pred = xgb_sbl_optimal.predict(x_test)
# get the rmse and mape of test data..
rmse_test, mape_test = get_error_metrics(y_true=y_test.values, y_pred = test_p
red)
# store them in test results dictionary.
test_results = {'rmse': rmse_test, 'mape' : mape_test, 'predictions': test_pre
d}
print('\nTEST DATA')
print('-'*30)
print('RMSE : ', rmse_test)
print('MAPE : ', mape_test)
```

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

xgb.plot_importance(xgb_sbl_optimal)
plt.show()

print("Time Taken:{}".format(datetime.now()-start))
```

```
Model with best parameters is :
 XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, importance_type='gain',
       learning_rate=0.1, max_delta_step=0, max_depth=5,
       min_child_weight=1, missing=None, n_estimators=100, n_jobs=13,
       nthread=None, objective='reg:linear', random_state=15, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
The optimal value of n_estimators is : 100
The optimal value of max_depth is: 5
Evaluating the model with TRAIN data...

TRAIN DATA
------------------------------
RMSE :  0.8347924892733507
MAPE :  24.766660508668497
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.0755535872144923
MAPE :  34.56640790617408
```




```
Time Taken:0:24:18.995085
```

Observation:-

1. F Score means Feature Score.

4.4.4 Surprise KNNBaseline predictor

- KNN BASELINE
  - http://surprise.readthedocs.io/en/stable/knn_inspired.html#surprise.prediction_algorithms.knns.KNNBasel (http://surprise.readthedocs.io/en/stable/knn_inspired.html#surprise.prediction_algorithms.knns.KNNBase

- PEARSON_BASELINE SIMILARITY
  - http://surprise.readthedocs.io/en/stable/similarities.html#surprise.similarities.pearson_baseline (http://surprise.readthedocs.io/en/stable/similarities.html#surprise.similarities.pearson_baseline)

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

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

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

- $\boldsymbol{b_{ui}}$ - *Baseline prediction* of (user,movie) rating
- $\boldsymbol{N_i^k(u)}$ - Set of **K similar** users (neighbours) of **user (u)** who rated **movie(i)**
- *sim (u, v)* - **Similarity** between users **u and v**
  - Generally, similarity value can be computed with 2 methods - 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)
  - shrunk comes from the word shrinkage , which is like laplace smoothing

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

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

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

4.4.4.1 Surprise KNNBaseline with user user similarities

In [68]:
```
# we specify , how to compute similarities and what to consider with sim_optio
ns to our algorithm
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 values.
bsl_options = {'method': 'sgd'}

# k = 40 means 40 nearest neighbors
knn_bsl_u = KNNBaseline(k=40, sim_options = sim_options, bsl_options = bsl_opt
ions)
knn_bsl_u_train_results, knn_bsl_u_test_results = run_surprise(knn_bsl_u, trai
nset, testset, verbose=True)

# Just store these error metrics in our models_evaluation datastructure
# knn_bsl_u = knn baseline user-user similarity
models_evaluation_train['knn_bsl_u'] = knn_bsl_u_train_results
models_evaluation_test['knn_bsl_u'] = knn_bsl_u_test_results
```

```
Training the model...
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
Done. time taken : 0:00:35.315680

Evaluating the model with train data..
time taken : 0:01:44.465502
---------------
Train Data
---------------
RMSE : 0.33642097416508826

MAPE : 9.145093375416348

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.082533
---------------
Test Data
---------------
RMSE : 1.0726493739667242

MAPE : 35.02094499698424

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:02:19.864556
```

Observations:-

1. As the train model and test model RMSE has much difference, we can do hyperparameter tuning with hyperparameters like shrinkage, min_support and k, using grid serach / random , we can improve test error.

4.4.4.2 Surprise KNNBaseline with movie movie similarities

In [69]:
```
# we specify , how to compute similarities and what to consider with sim_optio
ns to our algorithm

# 'user_based' : Fals => this considers the similarities of movies instead of
 users
# taking 2 nearest neighbors --  min_support: 2
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 values.
bsl_options = {'method': 'sgd'}

# nearest neighbors = 40
knn_bsl_m = KNNBaseline(k=40, sim_options = sim_options, bsl_options = bsl_opt
ions)

knn_bsl_m_train_results, knn_bsl_m_test_results = run_surprise(knn_bsl_m, trai
nset, testset, verbose=True)

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

```
Training the model...
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
Done. time taken : 0:00:01.047015

Evaluating the model with train data..
time taken : 0:00:10.449413
---------------
Train Data
---------------
RMSE : 0.32584796251610554

MAPE : 8.447062581998374

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.080761
---------------
Test Data
---------------
RMSE : 1.072758832653683

MAPE : 35.02269653015042

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:00:11.578099
```

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 [70]:
```
# 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)
```

Out[70]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	U
0	53406	33	3.581679	4.0	5.0	5.0	4.0	1.0	5.0	2.0	5.0	3.0	1.0	3.370
1	99540	33	3.581679	5.0	5.0	5.0	4.0	5.0	3.0	4.0	4.0	3.0	5.0	3.555

Preparing Test data

In [71]:
```
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)
```

Out[71]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.5816
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.5816

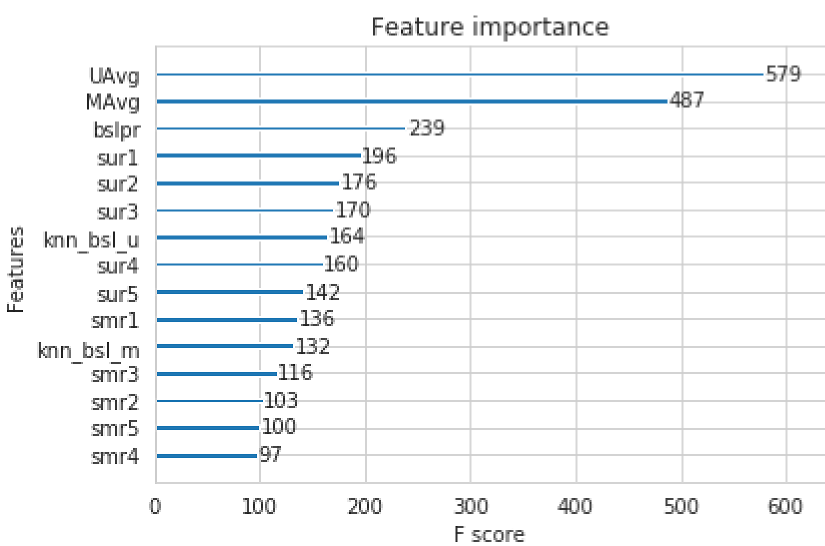
Training the model

In [72]:
```
# prepare the train data....
x_train = reg_train.drop(['user', 'movie', 'rating'], axis=1)
y_train = reg_train['rating']

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

In [73]:
```
import xgboost as xgb
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

params = {'n_estimators': [16, 32, 64, 80, 100], 'max_depth': [3, 5, 7, 9]}

knn_xgb = xgb.XGBRegressor(silent=True, n_jobs=13, random_state=15)
xgb_sbl_knn = GridSearchCV(knn_xgb, params, scoring = 'neg_mean_squared_error'
, n_jobs = -1, cv=3)
xgb_sbl_knn.fit(x_train, y_train)

print("Model with best parameters is :\n", xgb_sbl_knn.best_estimator_)

optimal_n_estimators =  xgb_sbl_knn.best_estimator_.n_estimators
print("The optimal value of n_estimators is :", optimal_n_estimators)

optimal_max_depth = xgb_sbl_knn.best_estimator_.max_depth
print("The optimal value of max_depth is:", optimal_max_depth)

xgb_sbl_knn_optimal = xgb.XGBRegressor(n_estimators = optimal_n_estimators, ma
x_depth = optimal_max_depth)

# fitting the optimal model on train data
xgb_sbl_knn_optimal.fit(x_train, y_train)

# from the trained model, get the predictions.... evaluate the model on train
 data
print('Evaluating the model with TRAIN data...')
train_pred = xgb_sbl_knn_optimal.predict(x_train)
# get the rmse and mape of train data...
rmse_train, mape_train = get_error_metrics(y_train.values, train_pred)
# store the results in train_results dictionary..
train_results = {'rmse': rmse_train, 'mape' : mape_train, 'predictions' : trai
n_pred}
print('\nTRAIN DATA')
print('-'*30)
print('RMSE : ', rmse_train)
print('MAPE : ', mape_train)

#######################################
# get the test data predictions and compute rmse and mape
print('Evaluating Test data')
# predict the response
test_pred = xgb_sbl_knn_optimal.predict(x_test)
# get the rmse and mape of test data..
rmse_test, mape_test = get_error_metrics(y_true=y_test.values, y_pred = test_p
red)
# store them in test results dictionary.
test_results = {'rmse': rmse_test, 'mape' : mape_test, 'predictions': test_pre
d}
print('\nTEST DATA')
print('-'*30)
print('RMSE : ', rmse_test)
print('MAPE : ', mape_test)
```

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

xgb.plot_importance(xgb_sbl_knn_optimal)
plt.show()

print("Time Taken:{}".format(datetime.now()-start))
```

```
Model with best parameters is :
 XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, importance_type='gain',
       learning_rate=0.1, max_delta_step=0, max_depth=5,
       min_child_weight=1, missing=None, n_estimators=100, n_jobs=13,
       nthread=None, objective='reg:linear', random_state=15, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
The optimal value of n_estimators is : 100
The optimal value of max_depth is: 5
Evaluating the model with TRAIN data...

TRAIN DATA
------------------------------
RMSE :  0.8347193192795542
MAPE :  24.77271608838077
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.0754488117769814
MAPE :  34.57388916971077
```




```
Time Taken:0:45:11.862591
```

Observation:-

Till now we have done 13 handcrafted features , surprise baseline predictors, KNN baseline model with users , KNN baseline model with movies. Now we have to do matrix factorizations like SVD, SVD++. Surprise library has matrix factorization techniques.

4.4.6 Matrix Factorization Techniques

4.4.6.1 SVD Matrix Factorization User Movie intractions

http://surprise.readthedocs.io/en/stable/matrix_factorization.html#surprise.prediction_algorithms.matrix_factorizatic (http://surprise.readthedocs.io/en/stable/matrix_factorization.html#surprise.prediction_algorithms.matrix_factorizati

- 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
```

- q_i^T p_u - is the Matrix Factorization part. To compute Matrix Factorization , there are multiple ways. 1. SVD , 2. NMF

1. Here q_i and p_u is vector where there is no need of all the elements of it to be positive /there is no non-negative constraint. So it is not NMF. We can solve it using SVD.

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

In [74]:
```
# initiallize the model
# n_factors=100 is the 'K' which is a hyperparameter
svd = SVD(n_factors=100, biased=True, random_state=15, verbose=True)
svd_train_results, svd_test_results = run_surprise(svd, trainset, testset, ver
bose=True)

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

```
Training the model...
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
Done. time taken : 0:00:07.896170

Evaluating the model with train data..
time taken : 0:00:01.384968
---------------
Train Data
---------------
RMSE : 0.6574721240954099

MAPE : 19.704901088660474

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.078622
---------------
Test Data
---------------
RMSE : 1.0726046873826458

MAPE : 35.01953535988152

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:00:09.360622
```

Observation:-

1. We got less test RMSE of 1.072 which is less when compared to all the models till now. So this is basic SVD model with Baseline.

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

This is also called as SVDpp or SVD++

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

- $\boldsymbol{I_u}$ --- the set of all items rated by user u
- $\boldsymbol{y_j}$ --- 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 [75]:
```
# initiallize the model , n_factors is 'K' which is dimensions
svdpp = SVDpp(n_factors=50, random_state=15, verbose=True)
svdpp_train_results, svdpp_test_results = run_surprise(svdpp, trainset, testse
t, 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
```

```
Training the model...
 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
Done. time taken : 0:02:05.415920

Evaluating the model with train data..
time taken : 0:00:06.835009
---------------
Train Data
---------------
RMSE : 0.6032438403305899

MAPE : 17.49285063490268

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.079524
---------------
Test Data
---------------
RMSE : 1.0728491944183447

MAPE : 35.03817913919887

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:02:12.331551
```

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

In Matrix Factorization , we have seen 2 techniques - SVD and SVD++

Preparing Train data

In [76]:
```
# 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']['predictions']

reg_train.head(2)
```

Out[76]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	...	smr4	smr5	UAvg
0	53406	33	3.581679	4.0	5.0	5.0	4.0	1.0	5.0	2.0	...	3.0	1.0	3.37037(
1	99540	33	3.581679	5.0	5.0	5.0	4.0	5.0	3.0	4.0	...	3.0	5.0	3.55555(

2 rows × 21 columns

Preparing Test data

In [77]:
```
reg_test_df['svd'] = models_evaluation_test['svd']['predictions']
reg_test_df['svdpp'] = models_evaluation_test['svdpp']['predictions']

reg_test_df.head(2)
```

Out[77]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.5816
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.5816

2 rows × 21 columns

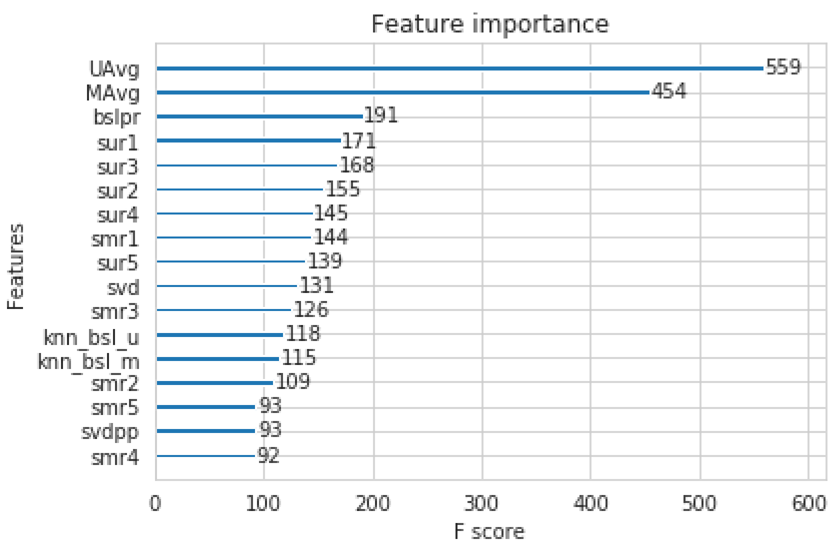
Training the model - XgBoost with 13 features + Surprise Baseline + Surprise KNNbaseline + MF Techniques

In [78]:
```
# 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']
```

In [79]:
```
import xgboost as xgb
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

params = {'n_estimators': [16, 32, 64, 80, 100], 'max_depth': [3, 5, 7, 9]}

final_xgb = xgb.XGBRegressor(silent=True, n_jobs=13, random_state=15)
xgb_svdpp = GridSearchCV(final_xgb, params, scoring = 'neg_mean_squared_error'
, n_jobs = -1, cv=3)
xgb_svdpp.fit(x_train, y_train)

print("Model with best parameters is :\n", xgb_svdpp.best_estimator_)

optimal_n_estimators =  xgb_svdpp.best_estimator_.n_estimators
print("The optimal value of n_estimators is :", optimal_n_estimators)

optimal_max_depth = xgb_svdpp.best_estimator_.max_depth
print("The optimal value of max_depth is:", optimal_max_depth)

xgb_svdpp_optimal = xgb.XGBRegressor(n_estimators = optimal_n_estimators, max_
depth = optimal_max_depth)

# fitting the optimal model on train data
xgb_svdpp_optimal.fit(x_train, y_train)

# from the trained model, get the predictions.... evaluate the model on train
 data
print('Evaluating the model with TRAIN data...')
train_pred = xgb_svdpp_optimal.predict(x_train)
# get the rmse and mape of train data...
rmse_train, mape_train = get_error_metrics(y_train.values, train_pred)
# store the results in train_results dictionary..
train_results = {'rmse': rmse_train, 'mape' : mape_train, 'predictions' : trai
n_pred}
print('\nTRAIN DATA')
print('-'*30)
print('RMSE : ', rmse_train)
print('MAPE : ', mape_train)

#######################################
# get the test data predictions and compute rmse and mape
print('--'*30)
print('Evaluating Test data')
# predict the response
test_pred = xgb_svdpp_optimal.predict(x_test)
# get the rmse and mape of test data..
rmse_test, mape_test = get_error_metrics(y_true=y_test.values, y_pred = test_p
red)
# store them in test results dictionary.
test_results = {'rmse': rmse_test, 'mape' : mape_test, 'predictions': test_pre
d}
print('\nTEST DATA')
print('-'*30)
print('RMSE : ', rmse_test)
print('MAPE : ', mape_test)
```

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

xgb.plot_importance(xgb_svdpp_optimal)
plt.show()

print("Time Taken:{}".format(datetime.now()-start))
```

```
Model with best parameters is :
 XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, importance_type='gain',
       learning_rate=0.1, max_delta_step=0, max_depth=5,
       min_child_weight=1, missing=None, n_estimators=100, n_jobs=13,
       nthread=None, objective='reg:linear', random_state=15, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
The optimal value of n_estimators is : 100
The optimal value of max_depth is: 5
Evaluating the model with TRAIN data...

TRAIN DATA
------------------------------
RMSE :  0.8338467813405877
MAPE :  24.745181265602316
------------------------------------------------------------
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.077182757447147
MAPE :  34.41750848790213
```




```
Time Taken:1:34:00.060354
```

4.4.8 XgBoost with Surprise Baseline + Surprise KNNbaseline + MF Techniques

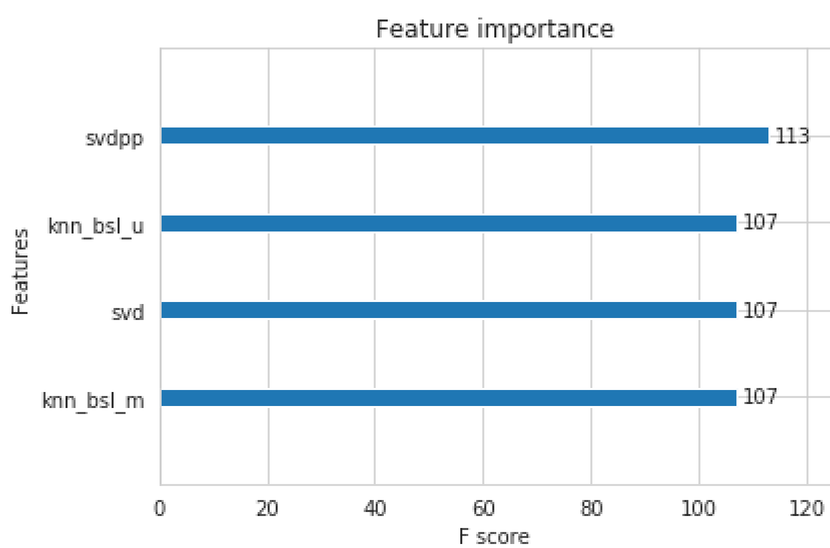
We removed 13 features here

In [80]:
```
# prepare train data , svdpp - svd++
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']
```

In [81]:
```
import xgboost as xgb
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

params = {'n_estimators': [16, 32, 64, 80, 100], 'max_depth': [3, 5, 7, 9]}

xgb_model = xgb.XGBRegressor(silent=True, n_jobs=13, random_state=15)
xgb_nofeatures = GridSearchCV(xgb_model, params, scoring = 'neg_mean_squared_e
rror', n_jobs = -1, cv=3)
xgb_nofeatures.fit(x_train, y_train)

print("Model with best parameters is :\n", xgb_nofeatures.best_estimator_)

optimal_n_estimators =  xgb_nofeatures.best_estimator_.n_estimators
print("The optimal value of n_estimators is :", optimal_n_estimators)

optimal_max_depth = xgb_nofeatures.best_estimator_.max_depth
print("The optimal value of max_depth is:", optimal_max_depth)

xgb_nofeatures_optimal = xgb.XGBRegressor(n_estimators = optimal_n_estimators,
max_depth = optimal_max_depth)

# fitting the optimal model on train data
xgb_nofeatures_optimal.fit(x_train, y_train)

# from the trained model, get the predictions.... evaluate the model on train
 data
print('Evaluating the model with TRAIN data...')
train_pred = xgb_nofeatures_optimal.predict(x_train)
# get the rmse and mape of train data...
rmse_train, mape_train = get_error_metrics(y_train.values, train_pred)
# store the results in train_results dictionary..
train_results = {'rmse': rmse_train, 'mape' : mape_train, 'predictions' : trai
n_pred}
print('\nTRAIN DATA')
print('-'*30)
print('RMSE : ', rmse_train)
print('MAPE : ', mape_train)

#######################################
# get the test data predictions and compute rmse and mape
print('--'*30)
print('Evaluating Test data')
# predict the response
test_pred = xgb_nofeatures_optimal.predict(x_test)
# get the rmse and mape of test data..
rmse_test, mape_test = get_error_metrics(y_true=y_test.values, y_pred = test_p
red)
# store them in test results dictionary.
test_results = {'rmse': rmse_test, 'mape' : mape_test, 'predictions': test_pre
d}
print('\nTEST DATA')
print('-'*30)
print('RMSE : ', rmse_test)
print('MAPE : ', mape_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_nofeatures_optimal)
plt.show()

print("Time Taken:{}".format(datetime.now()-start))
```

```
Model with best parameters is :
 XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, importance_type='gain',
       learning_rate=0.1, max_delta_step=0, max_depth=3,
       min_child_weight=1, missing=None, n_estimators=64, n_jobs=13,
       nthread=None, objective='reg:linear', random_state=15, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
The optimal value of n_estimators is : 64
The optimal value of max_depth is: 3
Evaluating the model with TRAIN data...

TRAIN DATA
------------------------------
RMSE :  1.0743221721956466
MAPE :  35.26360668366878
------------------------------------------------------------
Evaluating Test data

TEST DATA
------------------------------
RMSE :  1.0753442199902932
MAPE :  35.05268362328282
```




```
Time Taken:1:45:13.663355
```

Observation:-

1. With this final model by removing 13 features, we got almost equal feature importance for SVDpp, SVD, Knn baseline with Users and Knn baseline with Movies.
2. By this we can understand that all the 4 features are important in this model.

4.5 Comparision between all models

In [84]:
```
# Saving our TEST_RESULTS into a dataframe
if not os.path.isfile('small_sample_results.csv'):
    data = open('small_sample_results.csv', mode='w')
pd.DataFrame(models_evaluation_test).to_csv('small_sample_results.csv')
models = pd.read_csv('small_sample_results.csv', index_col=0)
models.loc['rmse'].sort_values()
```

Out[84]:
```
svd                1.0726046873826458
knn_bsl_u          1.0726493739667242
knn_bsl_m           1.072758832653683
svdpp              1.0728491944183447
bsl_algo           1.0730330260516174
xgb_all_models     1.0753442199902932
xgb_knn_bsl        1.0754488117769814
xgb_bsl            1.0755535872144923
first_algo         1.0755881866540673
xgb_final           1.077182757447147
Name: rmse, dtype: object
```

Observation:-

1. I sorted the models in increasing order of Test RMSE. The lower the RMSE, the better the model is. The above results are after hyperparameter tuning of XGBoost models.
2. Best model is SVD model with low Test RMSE of 1.0726.

4.6 Models Summarization

In [98]:
```
from pandas import DataFrame
Netflix = {'Model':['XGBoost_13 (first_algo)','Surprise Baseline(bsl_algo)','X
GB_13_BSL','KNN_BSL_User','KNN_BSL_Movie',
                    'XGB_13_BSL_KNN','SVD','SVDpp','XGB_13_BSL_KNN_MF (xgb_fin
al)','XGB_BSL_KNN_MF (xgb_all_models)'],
                    'Optimal n_estimators':['100','','100','','','100','','',
'100','64'],
                    'Optimal max_depth':['5','','5','','','5','','','5','3'],
                    'Train RMSE':['0.834','0.934','0.834','0.336','0.325','0.8
34','0.657','0.603','0.833','1.074'],
                    'Test RMSE':['1.0755','1.0730','1.0755','1.0726','1.0727',
'1.0754','1.0726','1.0728','1.0771','1.0753']}
```

In [99]:
```
Final_conclusions = DataFrame(Netflix)
Final_conclusions
```

Out[99]:

	Model	Optimal max_depth	Optimal n_estimators	Test RMSE	Train RMSE
0	XGBoost_13 (first_algo)	5	100	1.0755	0.834
1	Surprise Baseline(bsl_algo)			1.0730	0.934
2	XGB_13_BSL	5	100	1.0755	0.834
3	KNN_BSL_User			1.0726	0.336
4	KNN_BSL_Movie			1.0727	0.325
5	XGB_13_BSL_KNN	5	100	1.0754	0.834
6	SVD			1.0726	0.657
7	SVDpp			1.0728	0.603
8	XGB_13_BSL_KNN_MF (xgb_final)	5	100	1.0771	0.833
9	XGB_BSL_KNN_MF (xgb_all_models)	3	64	1.0753	1.074

4.7 Conclusions:-

By using 25k Users and 3k Movies data, I trained different models like XGBoost 13 features, Surprise baseline, XGBoost 13 features with baseline, Surprise Baseline KNN with User and Movie, XGBoost 13 features with baseline and KNN, Matrix Factorization techniques like SVD, SVDpp, XGBoost 13 features with baseline,KNN,MF techniques and finally XGBoost with baseline,KNN,MF techniques by removing 13 features.

From the above results, we can observe that,

1. The best model is SVD model with low Test RMSE of 1.0726.
2. xgb_final model which is XgBoost model 13 features + Surprise Baseline + Surprise KNNbaseline + MF Techniques has high Test RMSE of 1.0771.
3. I had done Hyperparameter tuning on all XGBoost models with hyperparameters like n_estimators and max_depth.
4. After hyperparameter tuning of XGBoost models, XGBoost model with baseline + KNN + MF techniques and without 13 features(XGB_BSL_KNN_MF) has given Test RMSE of 1.0753 which is low as compared to other tuned XGBoost models.
5. I also observed that, XGBoost model with baseline + KNN + MF techniques without 13 features gave low Test RMSE than XGBoost with 13 features + baseline + KNN + MF techniques.

```
In [ ]:
```