1. Business Problem

1.1 Problem Description

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. 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.

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 ahs not yet rated.
2. Minimize the difference between predicted and actual rating (RMSE and MAPE)

Constraints:

1. Some form of interpretability.

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


```
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 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

```
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
1133214,4,2004-03-07
1537427,4,2004-03-29
1209954,5,2005-05-09
2381599,3,2005-09-12
525356,2,2004-07-11
1910569,4,2004-04-12
2263586,4,2004-08-20
2421815,2,2004-02-26
1009622,1,2005-01-19
1481961,2,2005-05-24
401047,4,2005-06-03
2179073,3,2004-08-29
1434636,3,2004-05-01
93986,5,2005-10-06
```

```
1308744,5,2005-10-29
2647871,4,2005-12-30
1905581,5,2005-08-16
2508819,3,2004-05-18
1578279,1,2005-05-19
1159695,4,2005-02-15
2588432,3,2005-03-31
2423091,3,2005-09-12
470232,4,2004-04-08
2148699,2,2004-06-05
1342007,3,2004-07-16
466135,4,2004-07-13
2472440,3,2005-08-13
1283744,3,2004-04-17
1927580,4,2004-11-08
716874,5,2005-05-06
4326,4,2005-10-29
```

2.2 Mapping the real world problem to a Machine Learning Problem

2.2.1 Type of Machine Learning Problem

```
For a given movie and user we need to predict the rating would be given by him/her
to the movie.
The given problem is a Recommendation problem
It can also seen as a Regression problem
```

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

1. Minimize RMSE.
2. Try to provide some interpretability.

In [162]:
```
# this is just to know how much time will it take to run this entire ipython n
otebook
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})
from sklearn.model_selection import RandomizedSearchCV
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
```

3. Exploratory Data Analysis

3.1 Preprocessing

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

In [163]:
```
start = datetime.now()
if not os.path.isfile('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('data.csv', mode='w')

    row = list()
    files=['data_folder/combined_data_1.txt','data_folder/combined_data_2.txt'
,
           'data_folder/combined_data_3.txt', 'data_folder/combined_data_4.tx
t']
    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)
```

```
Time taken : 0:00:00.002981
```

In [164]:
```
print("creating the dataframe from data.csv file..")
df = pd.read_csv('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..')
df.sort_values(by='date', inplace=True)
print('Done..')
```

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

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

In [165]:
```
df.head()
```

Out[165]:

	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 [166]:
```
df.describe()['rating']
```

Out[166]:
```
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 [6]:
```
# just to make sure that all Nan containing rows are deleted..
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 [7]:
```
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 [8]:
```
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)

In [9]:
```
if not os.path.isfile('train.csv'):
    # create the dataframe and store it in the disk for offline purposes..
    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..
    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)

In [10]:
```
# 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)

In [11]:
```
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)))
```

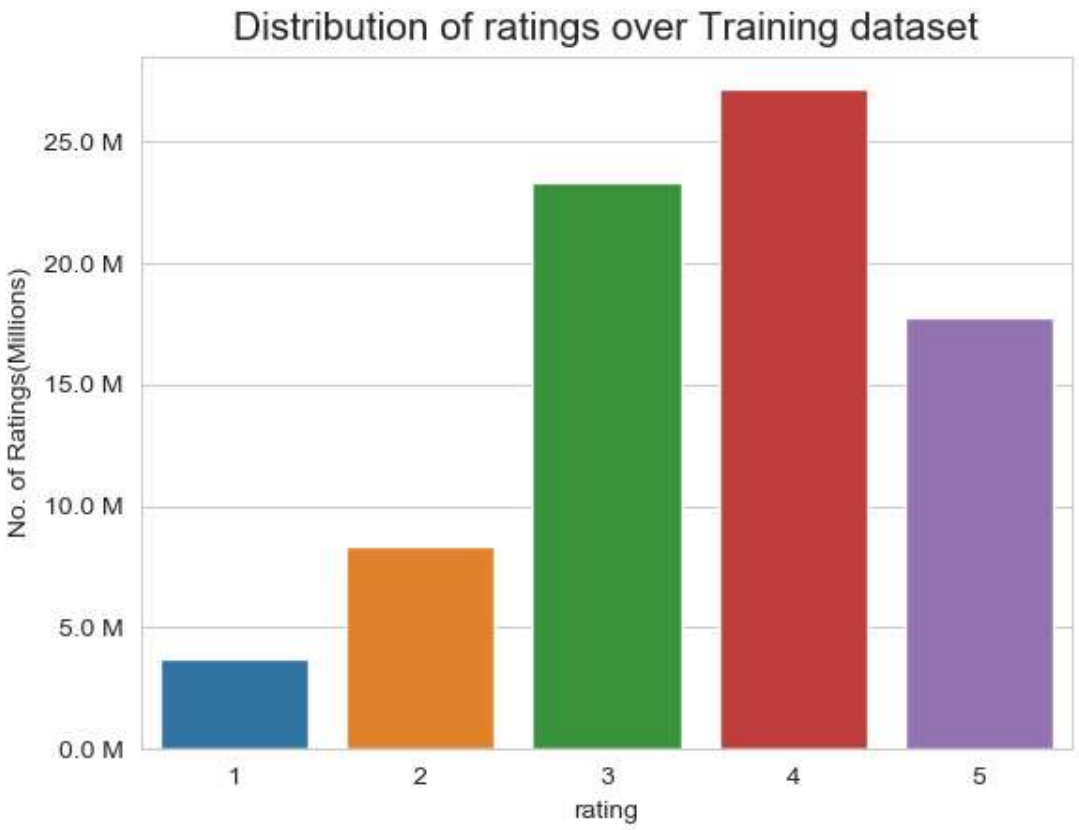
```
Test data
--------------------------------------------------

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

3.3 Exploratory Data Analysis on Train data

In [12]:
```
# 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 [16]:
```
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.

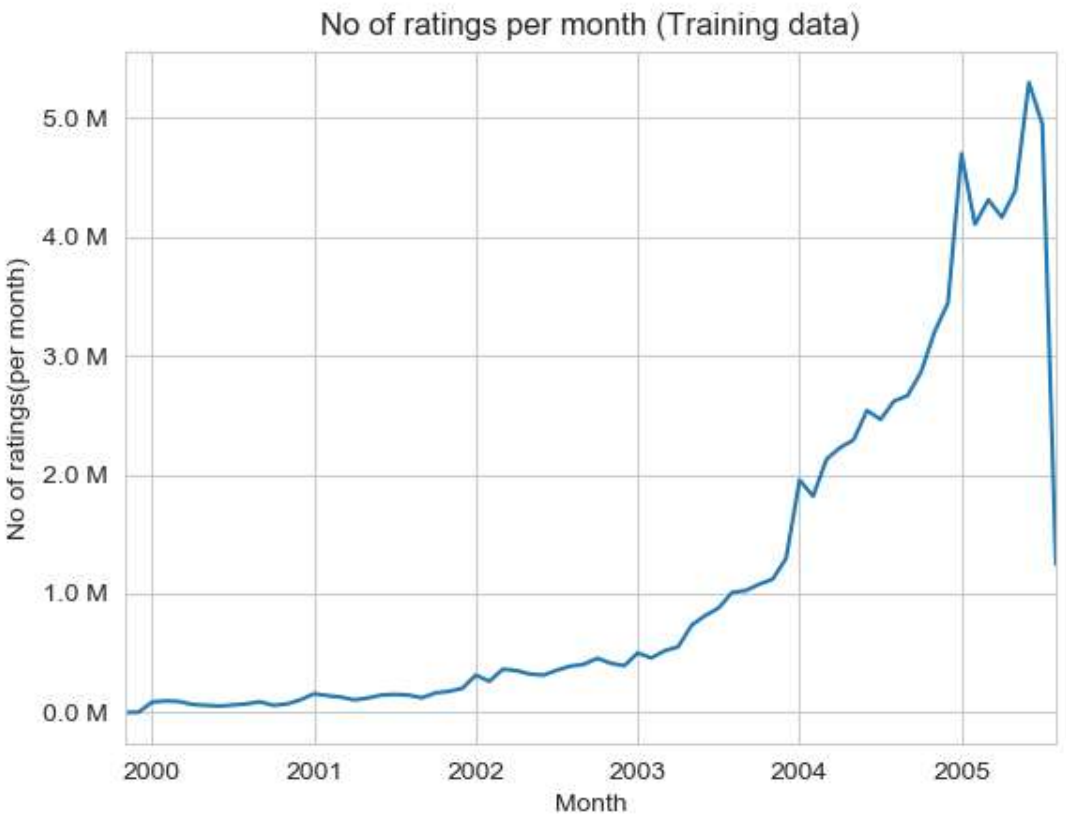
In [19]:
```
# It is used to skip the warning ''SettingWithCopyWarning''..
pd.options.mode.chained_assignment = None  # default='warn'

train_df['day_of_week'] = train_df.date.dt.day_name()

train_df.tail()
```

Out[19]:

	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 [21]:
```
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()
```

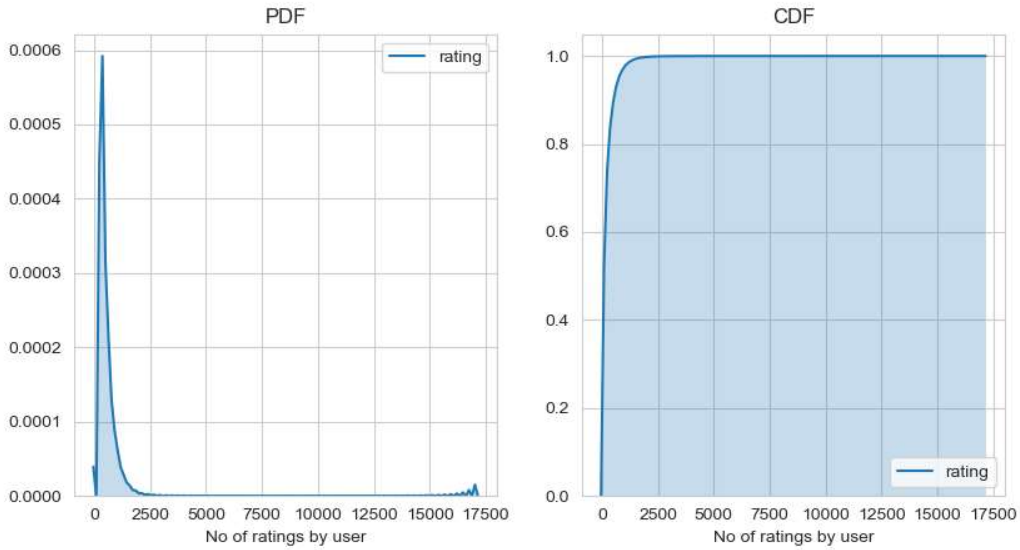


3.3.3 Analysis on the Ratings given by user

In [22]:
```
no_of_rated_movies_per_user = train_df.groupby(by='user')['rating'].count().sort_values(ascending=False)

no_of_rated_movies_per_user.head()
```

Out[22]:
```
user
305344     17112
2439493    15896
387418     15402
1639792     9767
1461435     9447
Name: rating, dtype: int64
```

In [23]:
```
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()
```



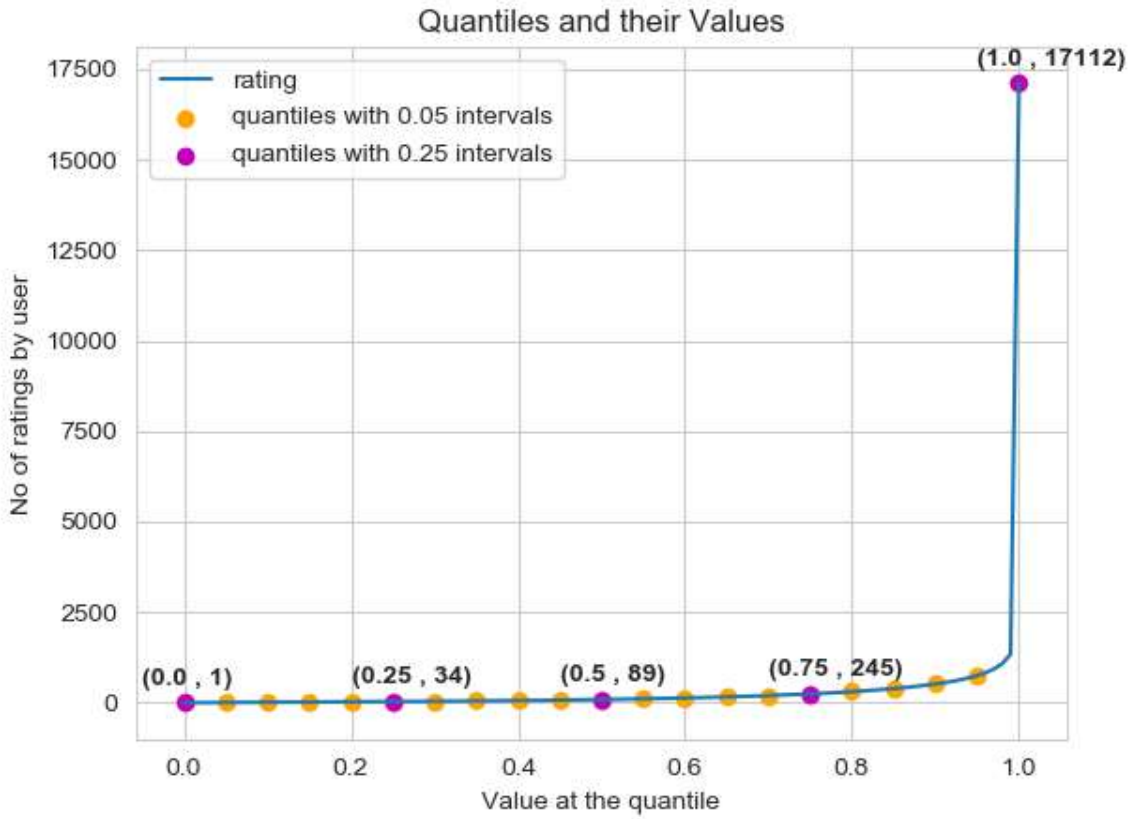
In [24]:
```
no_of_rated_movies_per_user.describe()
```

Out[24]:
```
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
```

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

In [25]:
```
quantiles = no_of_rated_movies_per_user.quantile(np.arange(0,1.01,0.01), interpolation='higher')
```

In [26]:
```
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 [27]:
```
quantiles[::5]
```

Out[27]:
```
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
```

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

In [28]:
```
print('\n No of ratings at last 5 percentile : {}\n'.format(sum(no_of_rated_movies_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 [29]:
```
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()
```

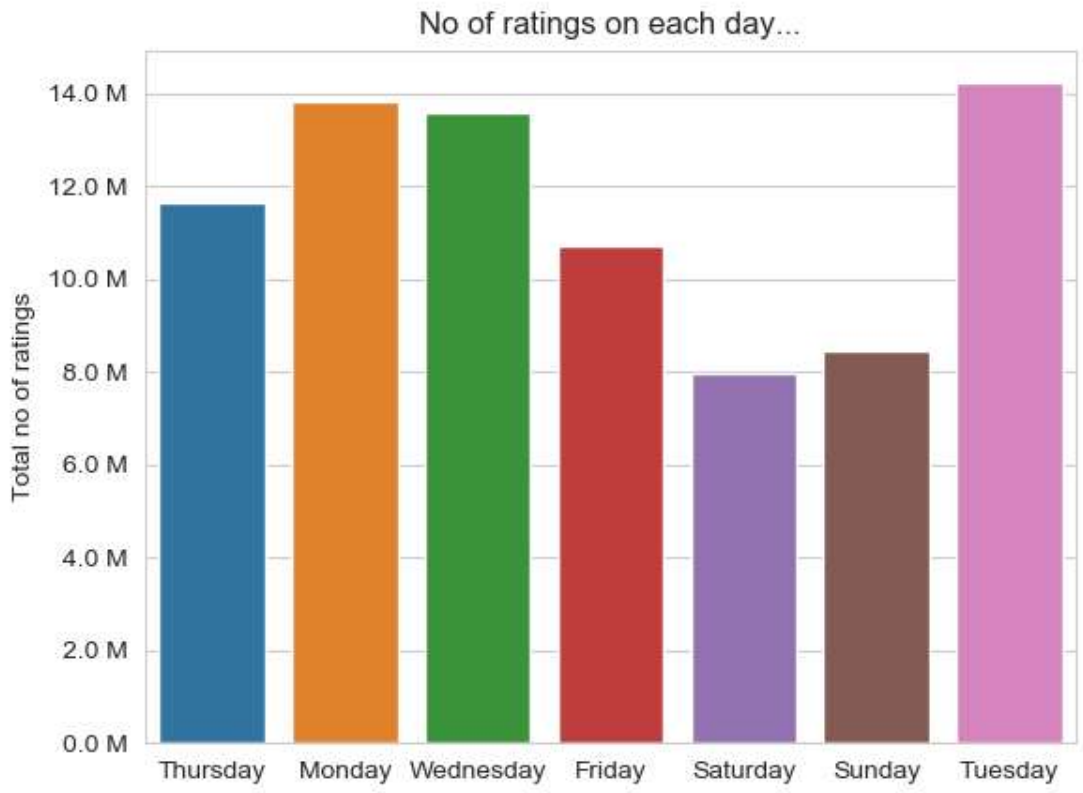
- **It is very skewed.. just like nunmber of ratings given per user.**

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

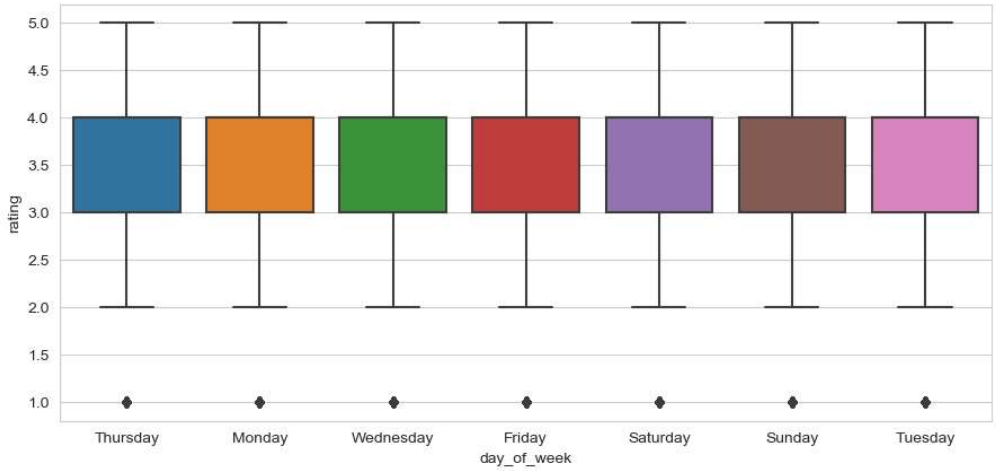
  - But most of the movies(like 90%) got some hundereds of ratings.

3.3.5 Number of ratings on each day of the week

In [30]:
```
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()
```



In [31]:
```
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)
```

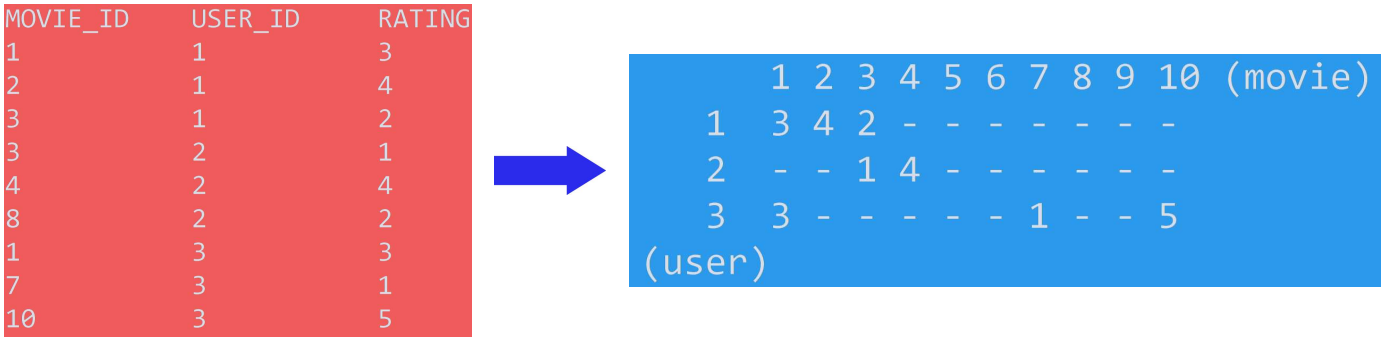



```
0:00:14.574874
```

In [32]:
```
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
```

3.3.6 Creating sparse matrix from data frame



3.3.6.1 Creating sparse matrix from train data frame

In [2]:
```
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..
0:00:02.640000
```

The Sparsity of Train Sparse Matrix

In [3]:
```
us,mv = train_sparse_matrix.shape
elem = train_sparse_matrix.count_nonzero()

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 [4]:
```
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..
0:00:00.700000
```

The Sparsity of Test data Matrix

In [5]:
```
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 %
```

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

In [6]:
```
# get the user averages in dictionary (key: user_id/movie_id, value: avg ratin
g)

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 [7]:
```
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[7]:
```
{'global': 3.582890686321557}
```

3.3.7.2 finding average rating per user

In [8]:
```
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
```

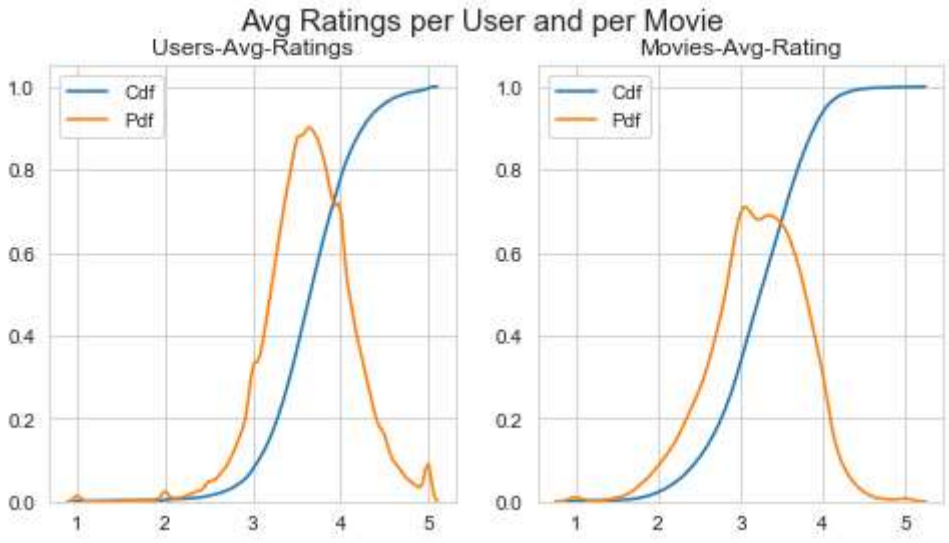
3.3.7.3 finding average rating per movie

In [9]:
```
train_averages['movie'] =  get_average_ratings(train_sparse_matrix, of_users=False)
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 [10]:
```
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)
```




```
0:00:47.269033
```

3.3.8 Cold Start problem

3.3.8.1 Cold Start problem with Users

In [167]:
```
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 %)
```

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 [168]:
```
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 %)
```

> 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**

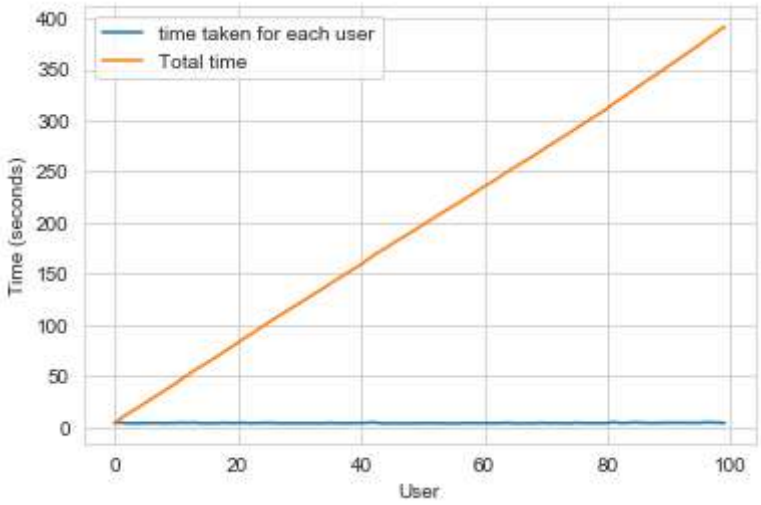
3.4.1.1 Trying with all dimensions (17k dimensions per user)

In [169]:
```
from sklearn.metrics.pairwise import cosine_similarity


def compute_user_similarity(sparse_matrix, compute_for_few=False, top = 100, v
erbose=False, verb_for_n_rows = 20,
                            draw_time_taken=True):
    no_of_users, _ = sparse_matrix.shape
    # get the indices of  non zero rows(users) from our sparse matrix
    row_ind, col_ind = sparse_matrix.nonzero()
    row_ind = sorted(set(row_ind)) # we don't have to
    time_taken = list() #  time taken for finding similar users for an user..

    # we create rows, cols, and data lists.., which can be used to create spar
se matrices
    rows, cols, data = list(), list(), list()
    if verbose: print("Computing top",top,"similarities for each user..")

    start = datetime.now()
    temp = 0

    for row in row_ind[:top] if compute_for_few else row_ind:
        temp = temp+1
        prev = datetime.now()

        # get the similarity row for this user with all other users
        sim = cosine_similarity(sparse_matrix.getrow(row), sparse_matrix).rave
l()
        # We will get only the top ''top'' most similar users and ignore rest
 of them..
        top_sim_ind = sim.argsort()[-top:]
        top_sim_val = sim[top_sim_ind]

        # add them to our rows, cols and data
        rows.extend([row]*top)
        cols.extend(top_sim_ind)
        data.extend(top_sim_val)
        time_taken.append(datetime.now().timestamp() - prev.timestamp())
        if verbose:
            if temp%verb_for_n_rows == 0:
                print("computing done for {} users [  time elapsed : {}  ]"
                      .format(temp, datetime.now()-start))


    # lets create sparse matrix out of these and return it
    if verbose: print('Creating Sparse matrix from the computed similarities')
    #return rows, cols, data

    if draw_time_taken:
        plt.plot(time_taken, label = 'time taken for each user')
        plt.plot(np.cumsum(time_taken), label='Total time')
        plt.legend(loc='best')
        plt.xlabel('User')
        plt.ylabel('Time (seconds)')
        plt.show()
```

```
    return sparse.csr_matrix((data, (rows, cols)), shape=(no_of_users, no_of_u
sers)), time_taken
```

In [170]:
```
start = datetime.now()
u_u_sim_sparse, _ = compute_user_similarity(train_sparse_matrix, compute_for_f
ew=True, top = 100,
                                            verbose=True)
print("-"*100)
print("Time taken :",datetime.now()-start)
```

```
Computing top 100 similarities for each user..
computing done for 20 users [  time elapsed : 0:01:18.450499  ]
computing done for 40 users [  time elapsed : 0:02:35.401576  ]
computing done for 60 users [  time elapsed : 0:03:51.450631  ]
computing done for 80 users [  time elapsed : 0:05:07.976630  ]
computing done for 100 users [  time elapsed : 0:06:31.801715  ]
Creating Sparse matrix from the computed similarities
```




```
------------------------------------------------------------------------------
-----------------------
Time taken : 0:06:43.386180
```

3.4.1.2 Trying with reduced dimensions (Using TruncatedSVD for dimensionality reduction of user vector)

- We have **405,041 users** in out training set and computing similarities between them..(**17K dimensional vector..**) is time consuming..
- From above plot, It took roughly **8.88 sec** for computing simlilar users for **one user**
- We have **405,041 users** with us in training set.
- $405041 \times 8.88 = 3596764.08 \text{ sec} = 59946.068 \text{ min} = 999.101133333 \text{ hours} = 41.629213889 \text{ day}$
  - Even if we run on 4 cores parallelly (a typical system now a days), It will still take almost **10 and 1/2** days.

  IDEA: Instead, we will try to reduce the dimentsions using SVD, so that **it might** speed up the process...

In [0]:
```
from datetime import datetime
from sklearn.decomposition import TruncatedSVD

start = datetime.now()

# initilaize the algorithm with some parameters..
# All of them are default except n_components. n_itr is for Randomized SVD sol
ver.
netflix_svd = TruncatedSVD(n_components=500, algorithm='randomized', random_st
ate=15)
trunc_svd = netflix_svd.fit_transform(train_sparse_matrix)

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

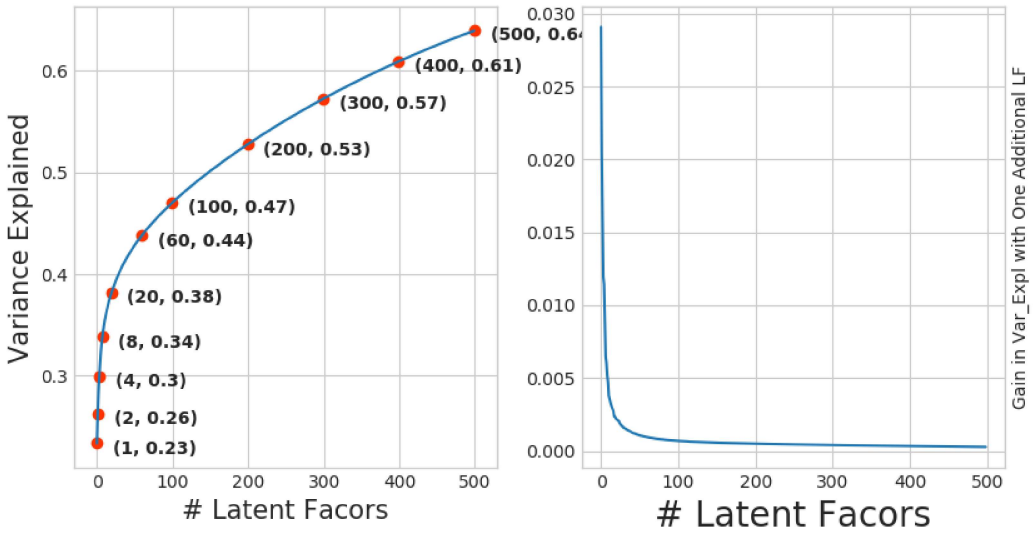
```
0:29:07.069783
```

Here,

- $\sum \longleftarrow$ (netflix_svd.**singular_values_**)
- $V^T \longleftarrow$ (netflix_svd.**components_**)
- U is not returned. instead **Projection_of_X** onto the new vectorspace is returned.
- It uses **randomized svd** internally, which returns **All 3 of them saperately**. Use that instead..

In [0]:
```
expl_var = np.cumsum(netflix_svd.explained_variance_ratio_)
```

In [0]:
```
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=plt.figaspect(.5))

ax1.set_ylabel("Variance Explained", fontsize=15)
ax1.set_xlabel("# Latent Facors", fontsize=15)
ax1.plot(expl_var)
# annote some (latentfactors, expl_var) to make it clear
ind = [1, 2,4,8,20, 60, 100, 200, 300, 400, 500]
ax1.scatter(x = [i-1 for i in ind], y = expl_var[[i-1 for i in ind]], c='#ff3300')
for i in ind:
    ax1.annotate(s ="({}, {})".format(i,  np.round(expl_var[i-1], 2)), xy=(i-1, expl_var[i-1]),
                 xytext = ( i+20, expl_var[i-1] - 0.01), fontweight='bold')

change_in_expl_var = [expl_var[i+1] - expl_var[i] for i in range(len(expl_var)-1)]
ax2.plot(change_in_expl_var)



ax2.set_ylabel("Gain in Var_Expl with One Additional LF", fontsize=10)
ax2.yaxis.set_label_position("right")
ax2.set_xlabel("# Latent Facors", fontsize=20)

plt.show()
```



In [0]:
```
for i in ind:
    print("({}, {})".format(i, np.round(expl_var[i-1], 2)))
```

```
(1, 0.23)
(2, 0.26)
(4, 0.3)
(8, 0.34)
(20, 0.38)
(60, 0.44)
(100, 0.47)
(200, 0.53)
(300, 0.57)
(400, 0.61)
(500, 0.64)
```

> I think 500 dimensions is good enough

- By just taking **(20 to 30)** latent factors, explained variance that we could get is **20 %**.
- To take it to **60%**, we have to take **almost 400 latent factors**. It is not fare.

- It basically is the **gain of variance explained**, if we ***add one additional latent factor to it.***

- By adding one by one latent factore too it, the **_gain in expained variance** with that addition is decreasing. (Obviously, because they are sorted that way).
- ***LHS Graph***:
  - **x** --- (No of latent factos),
  - **y** --- (The variance explained by taking x latent factors)

- **More decrease in the line (RHS graph)** :
  - We are getting more expained variance than before.
- **Less decrease in that line (RHS graph)** :
  - We are not getting benifitted from adding latent factor furthur. This is what is shown in the plots.

- ***RHS Graph***:
  - **x** --- (No of latent factors),
  - **y** --- (Gain n Expl_Var by taking one additional latent factor)

In [0]:
```
# Let's project our Original U_M matrix into into 500 Dimensional space...
start = datetime.now()
trunc_matrix = train_sparse_matrix.dot(netflix_svd.components_.T)
print(datetime.now()- start)
```

```
0:00:45.670265
```

In [0]:
```
type(trunc_matrix), trunc_matrix.shape
```

Out[0]:
```
(numpy.ndarray, (2649430, 500))
```

- Let's convert this to actual sparse matrix and store it for future purposes

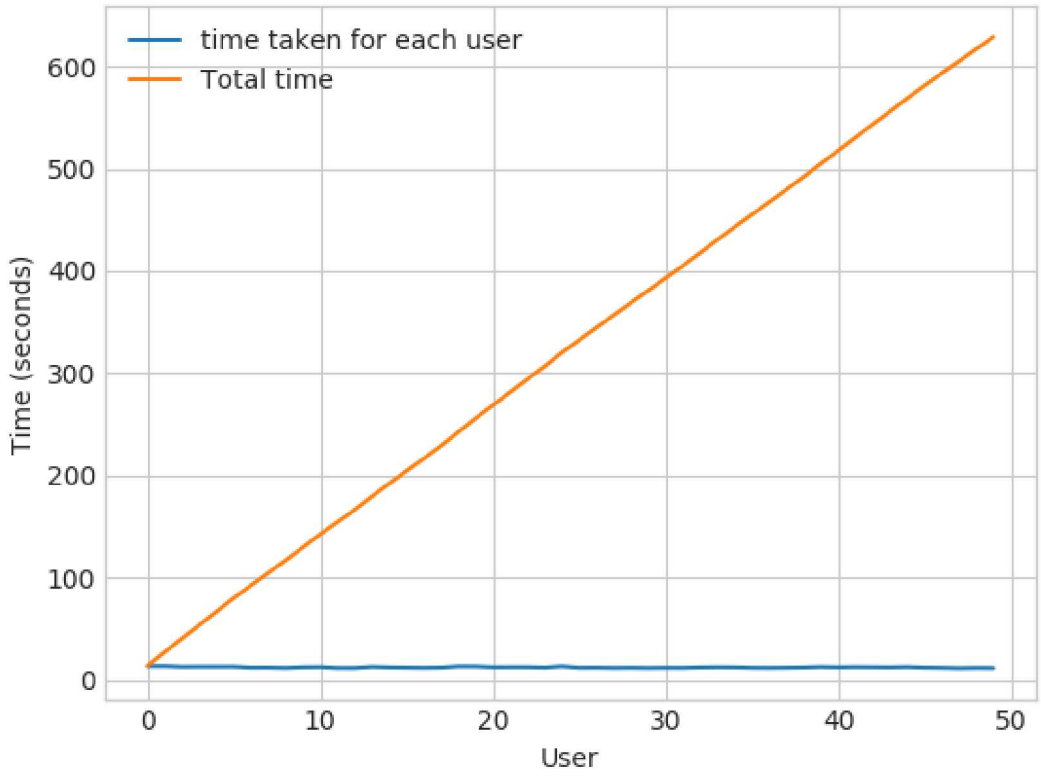
In [0]:
```
if not os.path.isfile('trunc_sparse_matrix.npz'):
    # create that sparse sparse matrix
    trunc_sparse_matrix = sparse.csr_matrix(trunc_matrix)
    # Save this truncated sparse matrix for later usage..
    sparse.save_npz('trunc_sparse_matrix', trunc_sparse_matrix)
else:
    trunc_sparse_matrix = sparse.load_npz('trunc_sparse_matrix.npz')
```

In [0]:
```
trunc_sparse_matrix.shape
```

Out[0]:
```
(2649430, 500)
```

In [0]:
```
start = datetime.now()
trunc_u_u_sim_matrix, _ = compute_user_similarity(trunc_sparse_matrix, compute
_for_few=True, top=50, verbose=True,
                                                   verb_for_n_rows=10)
print("-"*50)
print("time:",datetime.now()-start)
```

```
Computing top 50 similarities for each user..
computing done for 10 users [  time elapsed : 0:02:09.746324  ]
computing done for 20 users [  time elapsed : 0:04:16.017768  ]
computing done for 30 users [  time elapsed : 0:06:20.861163  ]
computing done for 40 users [  time elapsed : 0:08:24.933316  ]
computing done for 50 users [  time elapsed : 0:10:28.861485  ]
Creating Sparse matrix from the computed similarities
```




```
--------------------------------------------------
time: 0:10:52.658092
```

: This is taking more time for each user than Original one.

- from above plot, It took almost **12.18** for computing simlilar users for **one user**
- We have **405041 users** with us in training set.
- $405041 \times 12.18 ==== 4933399.38 \text{ sec} ==== 82223.323 \text{ min} ==== 1370.388716667 \text{ hours} =$
  - Even we run on 4 cores parallelly (a typical system now a days), It will still take almost **(14 - 15)** days.

- **Why did this happen...??**

```
- Just think about it. It's not that difficult.
```

----------*(sparse & dense.....get it ??)*----------

Is there any other way to compute user user similarity..??

-An alternative is to compute similar users for a particular user, whenenver required (**ie., Run time**)

```
- We maintain a binary Vector for users, which tells us whether we already computed
or not..
- ***If not*** :
    - Compute top (let's just say, 1000) most similar users for this given user, an
d add this to our datastructure, so that we can just access it(similar users) witho
ut recomputing it again.
    -
- ***If It is already Computed***:
    - Just get it directly from our datastructure, which has that information.
    - In production time, We might have to recompute similarities, if it is compute
d a long time ago. Because user preferences changes over time. If we could maintain
some kind of Timer, which when expires, we have to update it ( recompute it ).
    -
- ***Which datastructure to use:***
    - It is purely implementation dependant.
    - One simple method is to maintain a **Dictionary Of Dictionaries**.
        -
        - **key    :** _userid_
        - __value__: _Again a dictionary_
            - __key__  : _Similar User_
            - __value__: _Similarity Value_
```

3.4.2 Computing Movie-Movie Similarity matrix

In [171]:
```
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
0:00:18.500970
```

In [172]:
```
m_m_sim_sparse.shape
```

Out[172]:
```
(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.

In [173]:
```
movie_ids = np.unique(m_m_sim_sparse.nonzero()[1])
```

In [174]:
```
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]
```

```
0:00:27.224472
```

Out[174]:
```
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], dtype=int64)
```

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 [175]:
```
# 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: 3.00 ms
Type conversion took: 15.00 ms
Parser memory cleanup took: 0.00 ms
```

Out[175]:

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

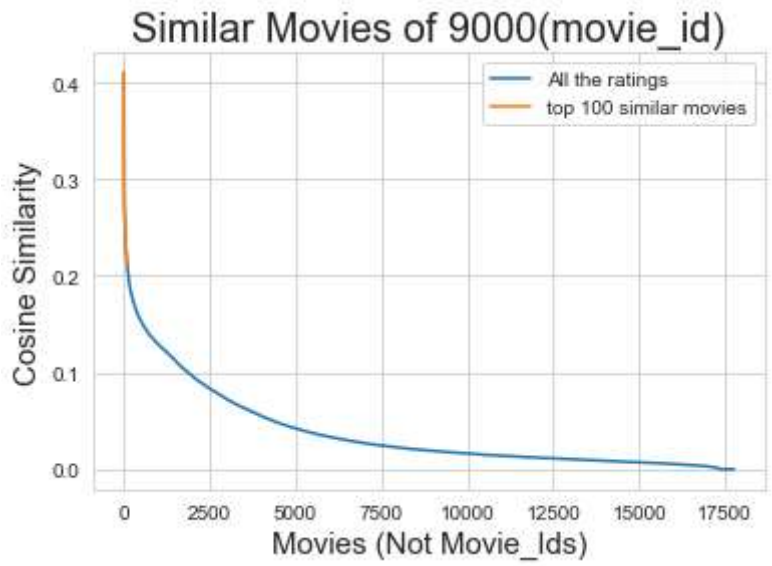
Similar Movies for 'Vampire Journals'

In [176]:
```
mv_id = 9000

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 -----> Homeward Bound 2: Lost in San Francisco

It has 4862 Ratings from users.

We have 17350 movies which are similarto this  and we will get only top mos
t..
```

In [177]:
```
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 [178]:
```
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()
```



Top 10 similar movies

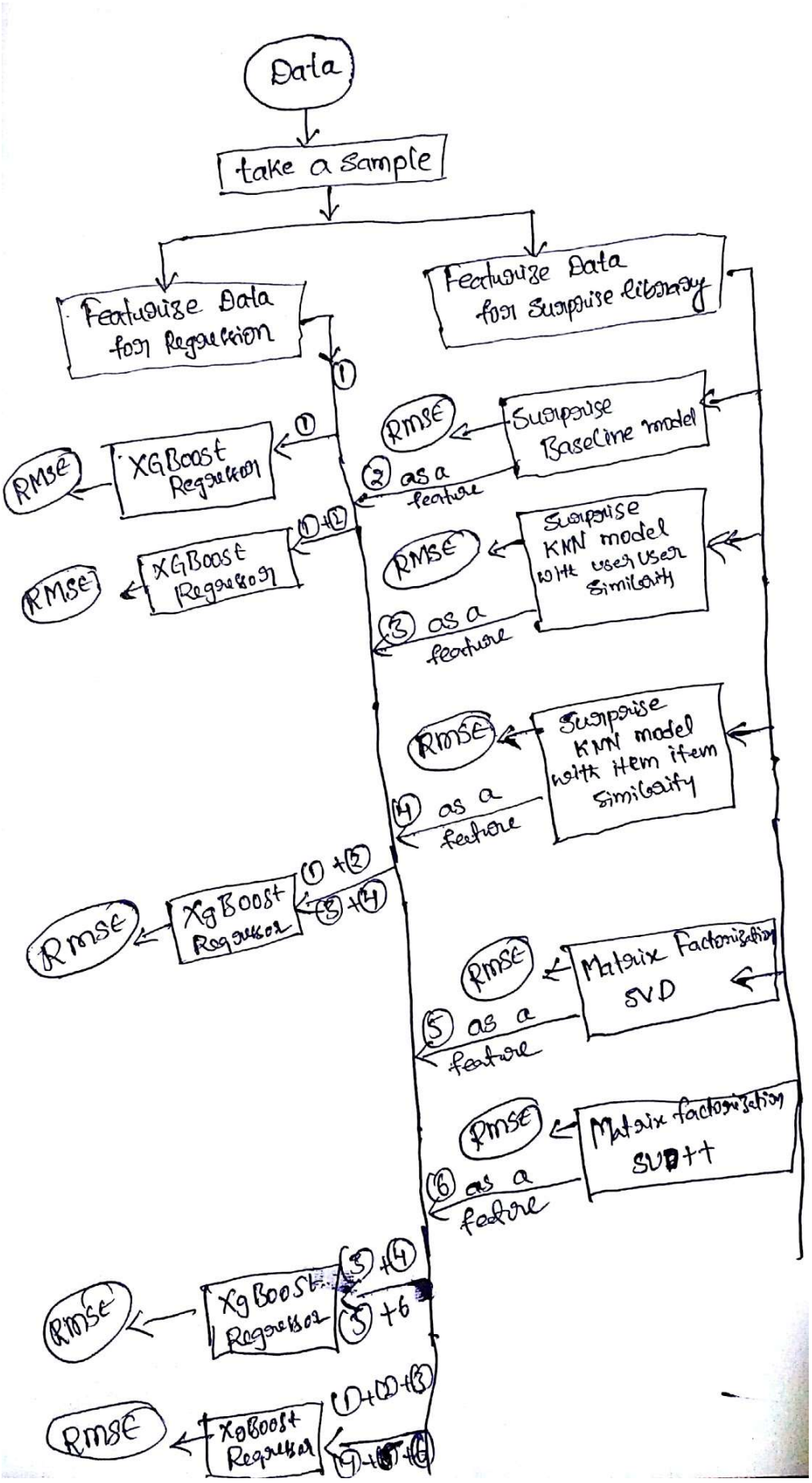
In [179]:
```
movie_titles.loc[sim_indices[:10]]
```

Out[179]:

movie_id	year_of_release	title
9757	1993.0	Homeward Bound: The Incredible Journey
8518	1997.0	Air Bud
17133	1989.0	All Dogs Go to Heaven
15616	1996.0	All Dogs Go to Heaven 2
14564	1995.0	Balto
12002	1988.0	Oliver & Company
16755	1994.0	Andre
17624	1995.0	Free Willy 2: The Adventure Home
6961	1997.0	George of the Jungle
2153	1993.0	Free Willy

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

4. Machine Learning Models


Data
take a sample
Featurize Data for Regression
Featurize Data for Surprise library
XGBoost Regressor
RMSE
Surprise Baseline model
as a feature
XGBoost Regressor
Surprise KNN model with user user Similarity
Surprise KNN model with item item Similarity
XgBoost Regressor
Matrix Factorization SVD
Matrix factorization SVD++
XgBoost Regressor
XgBoost Regressor

In [78]:
```
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

In [79]:
```
start = datetime.now()
path = "sample/small/sample_train_sparse_matrix.npz"
if os.path.isfile(path):
    print("It is present in your pwd, getting it from disk....")
    # 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)
```

```
Original Matrix : (users, movies) -- (405041 17424)
Original Matrix : Ratings -- 80384405

Sampled Matrix : (users, movies) -- (25000 3000)
Sampled Matrix : Ratings -- 856986
Saving it into disk for furthur usage..
Done..

0:00:46.098948
```

4.1.2 Build sample test data from the test data

In [80]:
```
start = datetime.now()

path = "sample/small/sample_test_sparse_matrix.npz"
if os.path.isfile(path):
    print("It is present in your pwd, getting it from disk....")
    # just get it from the disk instead of computing it
    sample_test_sparse_matrix = sparse.load_npz(path)
    print("DONE..")
else:
    # get 10k users and 1k movies from available data
    sample_test_sparse_matrix = get_sample_sparse_matrix(test_sparse_matrix, n
o_users=10000, no_movies=1000,
                                                         path = "sample/small/sample_t
est_sparse_matrix.npz")
print(datetime.now() - start)
```

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

Sampled Matrix : (users, movies) -- (10000 1000)
Sampled Matrix : Ratings -- 36017
Saving it into disk for furthur usage..
Done..

0:00:10.385000
```

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

In [81]:
```
sample_train_averages = dict()
```

4.2.1 Finding Global Average of all movie ratings

In [82]:
```
# 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[82]:
```
{'global': 3.5875813607223455}
```

4.2.2 Finding Average rating per User

In [83]:
```
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 : 3.923076923076923
```

4.2.3 Finding Average rating per Movie

In [84]:
```
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 : 2.752
```

4.3 Featurizing data

In [85]:
```
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 : 856986


 No of ratings in Our Sampled test  matrix is : 36017
```

4.3.1 Featurizing data for regression problem

4.3.1.1 Featurizing train data

In [86]:
```
# 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 [87]:
```
############################################################
# It took me almost 10 hours to prepare this train dataset.#
############################################################
start = datetime.now()
if os.path.isfile('sample/small/reg_train.csv'):
    print("File already exists you don't have to prepare again..." )
else:
    print('preparing {} tuples for the dataset..\n'.format(len(sample_train_ratings)))
    with open('sample/small/reg_train.csv', mode='w') as reg_data_file:
        count = 0
        for (user, movie, rating)  in zip(sample_train_users, sample_train_movies, sample_train_ratings):
            st = datetime.now()
        #     print(user, movie)
            #-------------------- Ratings of "movie" by similar users of "user" ---------------------
            # compute the similar Users of the "user"
            user_sim = cosine_similarity(sample_train_sparse_matrix[user], sample_train_sparse_matrix).ravel()
            top_sim_users = user_sim.argsort()[::-1][1:] # we are ignoring 'The User' from its similar users.
            # get the ratings of most similar users for this movie
            top_ratings = sample_train_sparse_matrix[top_sim_users, movie].toarray().ravel()
            # we will make it's length "5" by adding movie averages to .
            top_sim_users_ratings = list(top_ratings[top_ratings != 0][:5])
            top_sim_users_ratings.extend([sample_train_averages['movie'][movie]]*(5 - len(top_sim_users_ratings)))
        #     print(top_sim_users_ratings, end=" ")


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

            #-----------------prepare the row to be stores in a file-------------------#
            row = list()
            row.append(user)
            row.append(movie)
            # Now add the other features to this data...
            row.append(sample_train_averages['global']) # first feature
            # next 5 features are similar_users "movie" ratings
```

```
            row.extend(top_sim_users_ratings)
            # next 5 features are "user" ratings for similar_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)
```

```
preparing 856986 tuples for the dataset..

Done for 10000 rows----- 1:02:37.252114
Done for 20000 rows----- 2:03:33.408226
Done for 30000 rows----- 3:05:16.000813
Done for 40000 rows----- 4:05:23.624308
Done for 50000 rows----- 5:06:55.358537
Done for 60000 rows----- 6:09:14.692507
Done for 70000 rows----- 7:12:56.104668
Done for 80000 rows----- 8:15:22.583661
Done for 90000 rows----- 9:16:50.563794
Done for 100000 rows----- 10:16:55.222617
Done for 110000 rows----- 11:20:22.857586
Done for 120000 rows----- 12:24:48.423667
Done for 130000 rows----- 13:30:48.197755
Done for 140000 rows----- 14:34:41.450557
Done for 150000 rows----- 15:36:43.159556
Done for 160000 rows----- 16:35:17.991554
Done for 170000 rows----- 17:33:55.543556
Done for 180000 rows----- 18:32:32.857556
Done for 190000 rows----- 19:31:38.486362
Done for 200000 rows----- 20:30:55.230270
Done for 210000 rows----- 21:29:53.598263
Done for 220000 rows----- 22:29:09.727263
Done for 230000 rows----- 23:32:10.135827
Done for 240000 rows----- 1 day, 0:34:49.742880
Done for 250000 rows----- 1 day, 1:34:50.234186
Done for 260000 rows----- 1 day, 2:32:52.327774
Done for 270000 rows----- 1 day, 3:34:36.690716
Done for 280000 rows----- 1 day, 4:38:22.690982
Done for 290000 rows----- 1 day, 5:39:31.204413
Done for 300000 rows----- 1 day, 6:39:34.921076
Done for 310000 rows----- 1 day, 7:41:46.147480
Done for 320000 rows----- 1 day, 8:42:51.325970
Done for 330000 rows----- 1 day, 9:43:31.547422
Done for 340000 rows----- 1 day, 10:47:58.661567
Done for 350000 rows----- 1 day, 11:52:04.383011
Done for 360000 rows----- 1 day, 12:51:45.447139
Done for 370000 rows----- 1 day, 13:48:57.773139
Done for 380000 rows----- 1 day, 14:46:10.905140
Done for 390000 rows----- 1 day, 15:43:20.806889
Done for 400000 rows----- 1 day, 16:40:30.308889
Done for 410000 rows----- 1 day, 17:37:32.498889
Done for 420000 rows----- 1 day, 18:34:42.482889
Done for 430000 rows----- 1 day, 19:31:56.071889
Done for 440000 rows----- 1 day, 20:29:08.559263
Done for 450000 rows----- 1 day, 21:26:16.005263
Done for 460000 rows----- 1 day, 22:23:20.889908
Done for 470000 rows----- 1 day, 23:20:21.085901
Done for 480000 rows----- 2 days, 0:17:15.173874
Done for 490000 rows----- 2 days, 1:16:19.127012
Done for 500000 rows----- 2 days, 2:17:30.816867
Done for 510000 rows----- 2 days, 3:21:57.326715
Done for 520000 rows----- 2 days, 4:25:54.788256
Done for 530000 rows----- 2 days, 5:31:16.393744
Done for 540000 rows----- 2 days, 6:36:00.303501
Done for 550000 rows----- 2 days, 7:40:51.770621
```

```
Done for 560000 rows----- 2 days, 8:45:34.840507
Done for 570000 rows----- 2 days, 9:49:34.995140
Done for 580000 rows----- 2 days, 10:54:35.326400
Done for 590000 rows----- 2 days, 11:58:07.671004
Done for 600000 rows----- 2 days, 13:02:03.217236
Done for 610000 rows----- 2 days, 14:01:25.172262
Done for 620000 rows----- 2 days, 15:00:41.176228
Done for 630000 rows----- 2 days, 16:00:03.002259
Done for 640000 rows----- 2 days, 16:59:20.578259
Done for 650000 rows----- 2 days, 17:58:33.712225
Done for 660000 rows----- 2 days, 18:57:57.484259
Done for 670000 rows----- 2 days, 19:57:22.569267
Done for 680000 rows----- 2 days, 20:57:24.748223
Done for 690000 rows----- 2 days, 21:57:16.177635
Done for 700000 rows----- 2 days, 22:58:29.398698
Done for 710000 rows----- 3 days, 0:02:04.655256
Done for 720000 rows----- 3 days, 1:04:18.237304
Done for 730000 rows----- 3 days, 2:05:08.664725
Done for 740000 rows----- 3 days, 3:09:21.943090
Done for 750000 rows----- 3 days, 4:12:46.237487
Done for 760000 rows----- 3 days, 5:13:28.722571
Done for 770000 rows----- 3 days, 6:14:10.105661
Done for 780000 rows----- 3 days, 7:15:43.282137
Done for 790000 rows----- 3 days, 8:18:33.096722
Done for 800000 rows----- 3 days, 9:21:12.983567
Done for 810000 rows----- 3 days, 10:25:23.531617
Done for 820000 rows----- 3 days, 11:30:51.013856
Done for 830000 rows----- 3 days, 12:34:14.091720
Done for 840000 rows----- 3 days, 13:31:30.700850
Done for 850000 rows----- 3 days, 14:28:36.046833
3 days, 15:08:32.599875
```

Reading from the file to make a Train_dataframe

In [93]:
```
reg_train = pd.read_csv('sample/small/reg_train.csv', names = ['user', 'movie'
, 'GAvg', 'sur1', 'sur2', 'sur3', 'sur4', 'sur5','smr1', 'smr2', 'smr3', 'smr
4', 'smr5', 'UAvg', 'MAvg', 'rating'], header=None)
reg_train.head()
```

Out[93]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	
0	174683	10	3.587581	5.0	5.0	3.0	4.0	4.0	3.0	5.0	4.0	3.0	2.0	3.88
1	233949	10	3.587581	4.0	4.0	5.0	1.0	3.0	2.0	3.0	2.0	3.0	3.0	2.69
2	555770	10	3.587581	4.0	5.0	4.0	4.0	5.0	4.0	2.0	5.0	4.0	4.0	3.79
3	767518	10	3.587581	2.0	5.0	4.0	4.0	3.0	5.0	5.0	4.0	4.0	3.0	3.88
4	894393	10	3.587581	3.0	5.0	4.0	4.0	3.0	4.0	4.0	4.0	4.0	4.0	4.00

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

4.3.1.2 Featurizing test data

In [90]:
```
# 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 [91]:
```
sample_train_averages['global']
```

Out[91]: 3.5875813607223455

In [92]:
```
start = datetime.now()

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

    print('preparing {} tuples for the dataset..\n'.format(len(sample_test_rat
ings)))
    with open('sample/small/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)
```

```
preparing 36017 tuples for the dataset..

Done for 1000 rows----- 0:05:29.634052
Done for 2000 rows----- 0:11:00.982051
Done for 3000 rows----- 0:16:30.608057
Done for 4000 rows----- 0:22:01.578052
Done for 5000 rows----- 0:27:31.873999
Done for 6000 rows----- 0:33:02.999054
Done for 7000 rows----- 0:38:32.532000
Done for 8000 rows----- 0:44:03.443060
Done for 9000 rows----- 0:49:36.415000
Done for 10000 rows----- 0:55:11.402962
Done for 11000 rows----- 1:00:43.763961
Done for 12000 rows----- 1:06:15.565972
Done for 13000 rows----- 1:11:46.002933
Done for 14000 rows----- 1:17:16.320967
Done for 15000 rows----- 1:22:46.290957
Done for 16000 rows----- 1:28:15.904958
Done for 17000 rows----- 1:33:45.629961
Done for 18000 rows----- 1:39:13.374935
Done for 19000 rows----- 1:44:42.868962
Done for 20000 rows----- 1:50:12.111957
Done for 21000 rows----- 1:55:39.785958
Done for 22000 rows----- 2:01:09.120905
Done for 23000 rows----- 2:06:39.287906
Done for 24000 rows----- 2:12:09.174961
Done for 25000 rows----- 2:17:35.679906
Done for 26000 rows----- 2:23:03.196906
Done for 27000 rows----- 2:28:32.089906
Done for 28000 rows----- 2:34:00.028961
Done for 29000 rows----- 2:39:28.492906
Done for 30000 rows----- 2:44:57.779961
Done for 31000 rows----- 2:50:28.813906
Done for 32000 rows----- 2:55:56.792934
Done for 33000 rows----- 3:01:25.581906
Done for 34000 rows----- 3:06:52.225962
Done for 35000 rows----- 3:12:19.514906
Done for 36000 rows----- 3:17:46.919964
 3:17:52.309906
```

Reading from the file to make a test dataframe

In [94]:
```
reg_test_df = pd.read_csv('sample/small/reg_test.csv', names = ['user', 'movie', 'GAvg', 'sur1', 'sur2', 'sur3', 'sur4', 'sur5',
                                                                'smr1', 'smr2', 'smr3', 'smr4', 'smr5',
                                                                'UAvg', 'MAvg', 'rating'], header=None)
reg_test_df.head(4)
```

Out[94]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sr
0	808635	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875
1	898730	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875
2	941866	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875
3	1280761	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875

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

4.3.2 Transforming data for Surprise models

In [95]:
```
from surprise import Reader, Dataset
```

4.3.2.1 Transforming train data

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

In [96]:
```
# It is to specify how to read the dataframe.
# for our dataframe, we don't have to specify anything extra..
reader = Reader(rating_scale=(1,5))

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

# build the trainset from traindata.., It is of dataset format from surprise l
ibrary..
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 [98]:
```
testset = list(zip(reg_test_df.user.values, reg_test_df.movie.values, reg_test
_df.rating.values))
testset[:3]
```

Out[98]:
```
[(808635, 71, 5), (898730, 71, 3), (941866, 71, 4)]
```

4.4 Applying Machine Learning models

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

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

In [99]:
```
models_evaluation_train = dict()
models_evaluation_test = dict()

models_evaluation_train, models_evaluation_test
```

Out[99]:
```
({}, {})
```

Utility functions for running regression models

In [100]:
```
# to get rmse and mape given actual and predicted ratings..
def get_error_metrics(y_true, y_pred):
    rmse = np.sqrt(np.mean([ (y_true[i] - y_pred[i])**2 for i 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....
    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 [101]:
```
# 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()
```

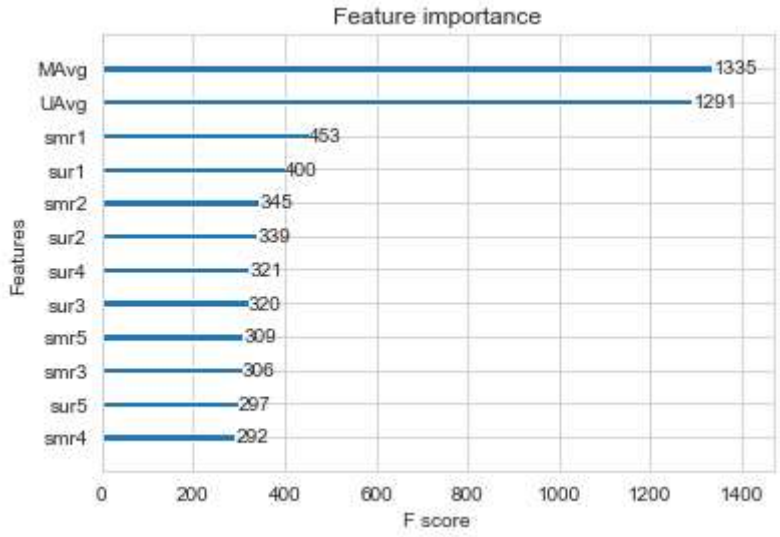
```
    print('Evaluating the model with train data..')
    # get the train predictions (list of prediction class inside Surprise)
    train_preds = algo.test(trainset.build_testset())
    # get predicted ratings from the train predictions..
    train_actual_ratings, train_pred_ratings = get_ratings(train_preds)
    # 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 [102]:
```
import xgboost as xgb
```

In [103]:
```
# 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']

# initialize Our first XGBoost model...
first_xgb = xgb.XGBRegressor(silent=False, n_jobs=13, random_state=15, n_estim
ators=100)
train_results, test_results = run_xgboost(first_xgb, x_train, y_train, x_test,
y_test)

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

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

```
Training the model..
Done. Time taken : 0:00:26.599959

Done

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

TEST DATA
------------------------------
RMSE :  1.1309760133947593
MAPE :  34.35794050637289
```



Hyperparameter tuning of XG Boost

In [107]:
```
%%time
# 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']




paramss = {"n_estimators":[600,900,1100,1400],
           "max_depth": [2,4,6,8],
           'learning_rate':[0.01,0.1,1]
          }


clf = xgb.XGBRegressor(random_state=25,n_jobs=-1)

random_clf = RandomizedSearchCV(clf, param_distributions=paramss,
                                n_iter=3,cv=5,random_state=25, verbose=3,n_
jobs=-1)

random_clf.fit(x_train,y_train)
random_clf.best_params_
```

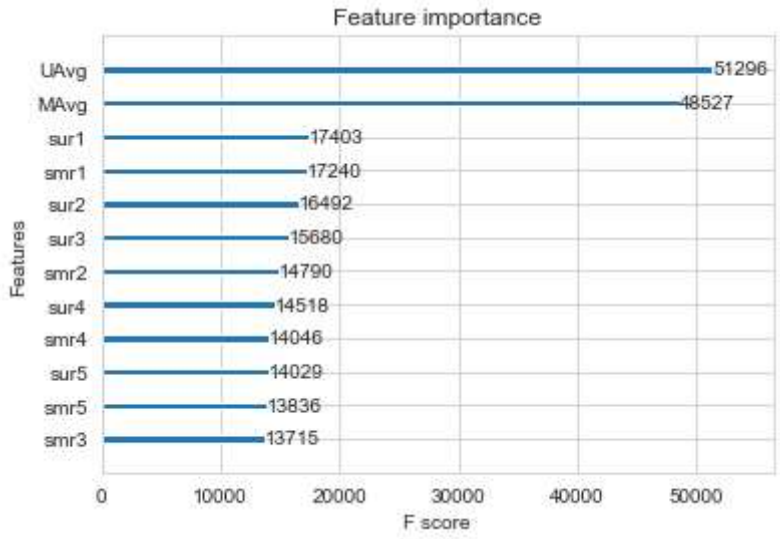
```
Fitting 5 folds for each of 3 candidates, totalling 15 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   4 out of  15 | elapsed: 42.3min remaining: 116.
3min
[Parallel(n_jobs=-1)]: Done  10 out of  15 | elapsed: 50.7min remaining: 25.3
min
[Parallel(n_jobs=-1)]: Done  15 out of  15 | elapsed: 54.3min finished

Wall time: 1h 1min 21s
```

Out[107]:
```
{'n_estimators': 1100, 'max_depth': 8, 'learning_rate': 0.01}
```

Running model with tuned XG Boost

In [108]:
```
# initialize Our first XGBoost model...
first_xgb = xgb.XGBRegressor(silent=False, n_jobs=-1, random_state=15,
                             max_depth = 8,
                             learning_rate = 0.01,
                             n_estimators=1100)
train_results, test_results = run_xgboost(first_xgb, x_train, y_train, x_test,
y_test)

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

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

```
Training the model..
Done. Time taken : 0:07:10.913707

Done

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

TEST DATA
------------------------------
RMSE :  1.1132864575141992
MAPE :  34.76736812027518
```



4.4.2 Suprise BaselineModel

In [109]:
```
from surprise import BaselineOnly
```

Predicted_rating : (baseline prediction)

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

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

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

Optimization function (Least Squares Problem)

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

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

In [110]:
```
# options are to specify.., how to compute those user and item biases
bsl_options = {'method': 'sgd',
               'learning_rate': .001
               }
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 : 0:00:04.406000

Evaluating the model with train data..
time taken : 0:00:05.626036
---------------
Train Data
---------------
RMSE : 0.9220478981418425

MAPE : 28.6415868708249

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.240997
---------------
Test Data
---------------
RMSE : 1.0926308758324264

MAPE : 35.929512482685944

storing the test results in test dictionary...

------------------------------------------
Total time taken to run this algorithm : 0:00:10.274033
```

4.4.3 XGBoost with initial 13 features + Surprise Baseline predictor

Updating Train Data

In [111]:
```
# add our baseline_predicted value as our feature..
reg_train['bslpr'] = models_evaluation_train['bsl_algo']['predictions']
reg_train.head(2)
```

Out[111]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	
0	174683	10	3.587581	5.0	5.0	3.0	4.0	4.0	3.0	5.0	4.0	3.0	2.0	3.88
1	233949	10	3.587581	4.0	4.0	5.0	1.0	3.0	2.0	3.0	2.0	3.0	3.0	2.69

Updating Test Data

In [112]:
```
# 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[112]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	808635	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875
1	898730	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875

Tunning Hyperparameters of XG Boost

In [113]:
```
%%time
# 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']




paramss = {"n_estimators":[600,900,1100,1400],
           "max_depth": [2,4,6,8],
           'learning_rate':[0.01,0.1,1]
          }


clf = xgb.XGBRegressor(random_state=25,n_jobs=-1)

random_clf = RandomizedSearchCV(clf, param_distributions=paramss,
                                n_iter=3,cv=5,random_state=25, verbose=3,n_
jobs=-1)

random_clf.fit(x_train,y_train)
random_clf.best_params_
```

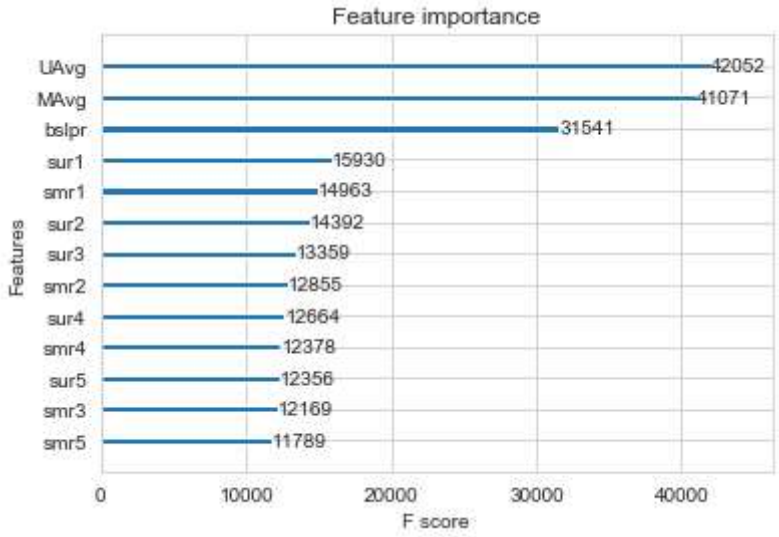
```
Fitting 5 folds for each of 3 candidates, totalling 15 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   4 out of  15 | elapsed: 53.0min remaining: 145.
7min
[Parallel(n_jobs=-1)]: Done  10 out of  15 | elapsed: 62.4min remaining: 31.2
min
[Parallel(n_jobs=-1)]: Done  15 out of  15 | elapsed: 66.6min finished

Wall time: 1h 17min 50s
```

Out[113]:
```
{'n_estimators': 1100, 'max_depth': 8, 'learning_rate': 0.01}
```

Running model with Tuned XG Boost

In [114]:
```
# initialize Our first XGBoost model...
xgb_bsl = xgb.XGBRegressor(silent=False, n_jobs=-1, random_state=15,
                           max_depth = 8,
                           learning_rate = 0.01,
                           n_estimators=1100)
train_results, test_results = run_xgboost(xgb_bsl, x_train, y_train, x_test, y
_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_bsl)
plt.show()
```

```
Training the model..
Done. Time taken : 0:11:10.541997

Done

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

TEST DATA
------------------------------
RMSE :  1.1101635923935806
MAPE :  34.907060380518224
```



4.4.4 Surprise KNNBaseline predictor

In [115]:
```
from surprise import KNNBaseline
```

- 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***)

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

- $\boldsymbol{b_{ui}}$ - *Baseline prediction* of (user,movie) rating
- $\boldsymbol{N_i^k(u)}$ - Set of **K similar** users (neighbours) of **user (u)** who rated **movie(i)**
- *sim (u, v)* - **Similarity** between users **u and v**
  - Generally, it will be cosine similarity or Pearson correlation coefficient.
  - But we use **shrunk Pearson-baseline correlation coefficient**, which is based on the pearsonBaseline similarity (we take base line predictions instead of mean rating of user/item)

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

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

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

4.4.4.1 Surprise KNNBaseline with user user similarities

In [116]:
```
# 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'}

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
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 : 0:14:21.187110

Evaluating the model with train data..
time taken : 0:19:00.421353
---------------
Train Data
---------------
RMSE : 0.4536279292470732

MAPE : 12.840252350475915

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.587967
---------------
Test Data
---------------
RMSE : 1.0934889652441049

MAPE : 35.95037412142581

storing the test results in test dictionary...

------------------------------------------
Total time taken to run this algorithm : 0:33:22.212431
```

4.4.4.2 Surprise KNNBaseline with movie movie similarities

In [117]:
```
# 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

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'}


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 : 0:00:16.431003

Evaluating the model with train data..
time taken : 0:01:43.332710
---------------
Train Data
---------------
RMSE : 0.5038994796517224

MAPE : 14.168515366483724

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.260944
---------------
Test Data
---------------
RMSE : 1.0939686125271795

MAPE : 35.96478484010793

storing the test results in test dictionary...

------------------------------------------------
Total time taken to run this algorithm : 0:02:00.024657
```

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 [118]:
```
# 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[118]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	
0	174683	10	3.587581	5.0	5.0	3.0	4.0	4.0	3.0	5.0	4.0	3.0	2.0	3.88
1	233949	10	3.587581	4.0	4.0	5.0	1.0	3.0	2.0	3.0	2.0	3.0	3.0	2.69

Preparing Test data

In [119]:
```
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[119]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	808635	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875
1	898730	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875

Tuning Hyperparameters of XG Boost

In [120]:
```
%%time
# 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']




paramss = {"n_estimators":[600,900,1100,1400],
           "max_depth": [2,4,6,8,10],
           'learning_rate':[0.01,0.1,1]
          }


clf = xgb.XGBRegressor(random_state=25,n_jobs=-1)

random_clf = RandomizedSearchCV(clf, param_distributions=paramss,
                                n_iter=3,cv=5,random_state=25, verbose=3,n_
jobs=-1)

random_clf.fit(x_train,y_train)
random_clf.best_params_
```

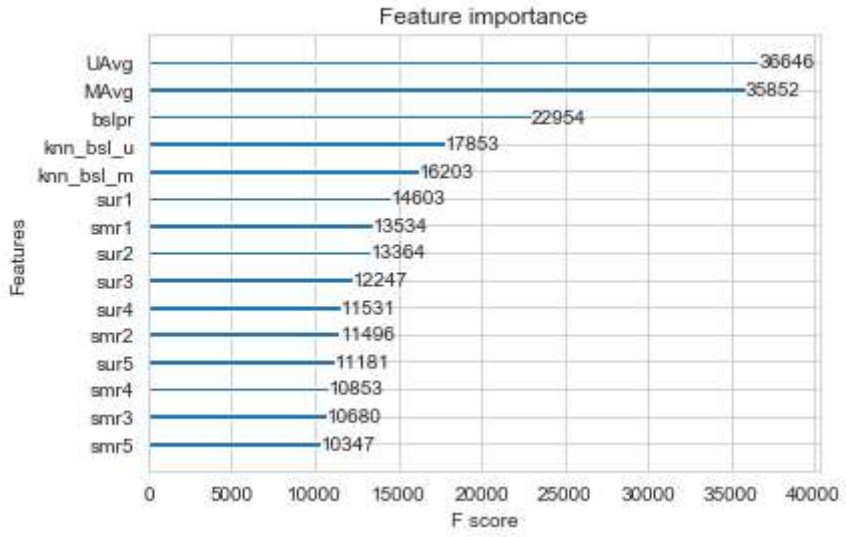
```
Fitting 5 folds for each of 3 candidates, totalling 15 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   4 out of  15 | elapsed: 70.3min remaining: 193.
3min
[Parallel(n_jobs=-1)]: Done  10 out of  15 | elapsed: 81.8min remaining: 40.9
min
[Parallel(n_jobs=-1)]: Done  15 out of  15 | elapsed: 87.3min finished

Wall time: 1h 40min 27s
```

Out[120]:
```
{'n_estimators': 1100, 'max_depth': 8, 'learning_rate': 0.01}
```

Running model with tuned XG Boost

In [121]:
```
# declare the model
xgb_knn_bsl = xgb.XGBRegressor(n_jobs=10, random_state=15,
                               max_depth = 8,
                              learning_rate = 0.01,
                              n_estimators=1100)
train_results, test_results = run_xgboost(xgb_knn_bsl, x_train, y_train, x_tes
t, y_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_knn_bsl)
plt.show()
```

```
Training the model..
Done. Time taken : 0:11:04.058093

Done

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

TEST DATA
------------------------------
RMSE :  1.1110244693719702
MAPE :  34.84884167446569
```



4.4.6 Matrix Factorization Techniques

4.4.6.1 SVD Matrix Factorization User Movie intractions

In [122]:
```
from surprise import SVD
```

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

- 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 [123]:
```
# initiallize the model
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 : 0:00:37.766031

Evaluating the model with train data..
time taken : 0:00:06.468022
---------------
Train Data
---------------
RMSE : 0.6746731413267192

MAPE : 20.05479554670084

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.502002
---------------
Test Data
---------------
RMSE : 1.0928020848745568

MAPE : 35.853854694602624

storing the test results in test dictionary...

------------------------------------------
Total time taken to run this algorithm : 0:00:44.738001
```

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

In [124]:
```
from surprise import SVDpp
```

- -----> 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) $

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

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

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

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

In [125]:
```
# initiallize the model
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 : 0:27:02.218688

Evaluating the model with train data..
time taken : 0:01:07.105948
---------------
Train Data
---------------
RMSE : 0.6641918784333875

MAPE : 19.24213231265533

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:00.227010
---------------
Test Data
---------------
RMSE : 1.0935512303051578

MAPE : 35.790700741972806

storing the test results in test dictionary...

------------------------------------------
Total time taken to run this algorithm : 0:28:09.551646
```

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

Preparing Train data

In [126]:
```
# 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[126]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	...	smr4	smr5	UAv
0	174683	10	3.587581	5.0	5.0	3.0	4.0	4.0	3.0	5.0	...	3.0	2.0	3.88235
1	233949	10	3.587581	4.0	4.0	5.0	1.0	3.0	2.0	3.0	...	3.0	3.0	2.69230

2 rows × 21 columns

Preparing Test data

In [127]:
```
reg_test_df['svd'] = models_evaluation_test['svd']['predictions']
reg_test_df['svdpp'] = models_evaluation_test['svdpp']['predictions']

reg_test_df.head(2)
```

Out[127]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	sm
0	808635	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875
1	898730	71	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.5875

2 rows × 21 columns

Tuning Hyperparameters of XG Boost

In [128]:
```
%%time
# 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']




paramss = {"n_estimators":[600,900,1100,1400],
           "max_depth": [2,4,6,8,10],
           'learning_rate':[0.01,0.1,1]
          }


clf = xgb.XGBRegressor(random_state=25,n_jobs=-1)

random_clf = RandomizedSearchCV(clf, param_distributions=paramss,
                                n_iter=3,cv=5,random_state=25, verbose=3,n_
jobs=-1)

random_clf.fit(x_train,y_train)
random_clf.best_params_
```

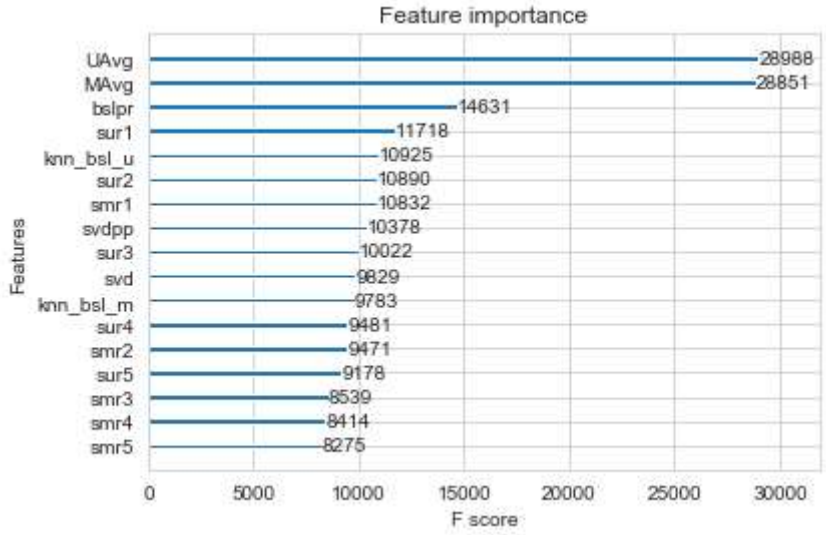
```
Fitting 5 folds for each of 3 candidates, totalling 15 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   4 out of  15 | elapsed: 56.1min remaining: 154.
4min
[Parallel(n_jobs=-1)]: Done  10 out of  15 | elapsed: 114.0min remaining: 57.
0min
[Parallel(n_jobs=-1)]: Done  15 out of  15 | elapsed: 126.2min finished

Wall time: 2h 15min 24s
```

Out[128]:
```
{'n_estimators': 900, 'max_depth': 8, 'learning_rate': 0.01}
```

Running model with tuned XG boost

In [130]:
```
xgb_final = xgb.XGBRegressor(n_jobs=10, random_state=15,
                                  max_depth = 8,
                                learning_rate = 0.01,
                                n_estimators=900)
train_results, test_results = run_xgboost(xgb_final, x_train, y_train, x_test,
y_test)

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


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

```
Training the model..
Done. Time taken : 0:09:28.634158

Done

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

TEST DATA
------------------------------
RMSE :  1.1071051610102167
MAPE :  34.98777552065433
```



4.4.8 XgBoost with Surprise Baseline + Surprise KNNbaseline + MF Techniques

In [71]:
```
reg_train
```

Out[71]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	...	smr4	smr5
0	53406	33	3.581679	4.0	5.0	5.0	4.0	1.0	5.0	2.0	...	3.0	1.0
1	99540	33	3.581679	5.0	5.0	5.0	4.0	5.0	3.0	4.0	...	3.0	5.0
2	99865	33	3.581679	5.0	5.0	4.0	5.0	3.0	5.0	4.0	...	5.0	4.0
3	101620	33	3.581679	2.0	3.0	5.0	5.0	4.0	4.0	3.0	...	4.0	5.0
4	112974	33	3.581679	5.0	5.0	5.0	5.0	5.0	3.0	5.0	...	5.0	3.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
129281	2585154	17723	3.581679	3.0	3.0	4.0	4.0	4.0	3.0	5.0	...	5.0	4.0
129282	2604824	17723	3.581679	5.0	3.0	4.0	2.0	3.0	3.0	4.0	...	5.0	3.0
129283	2622281	17723	3.581679	4.0	3.0	3.0	5.0	3.0	3.0	3.0	...	3.0	2.0
129284	2627366	17723	3.581679	4.0	3.0	4.0	3.0	3.0	4.0	3.0	...	3.0	4.0
129285	2629799	17723	3.581679	3.0	4.0	4.0	5.0	5.0	4.0	3.0	...	4.0	3.0

129286 rows × 21 columns

Tuning Hyperparameters of XG Boost

In [131]:
```
# prepare train data
x_train = reg_train[['knn_bsl_u', 'knn_bsl_m', 'svd', 'svdpp']]
y_train = reg_train['rating']

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




paramss = {"n_estimators":[800,900,1100,1400],
           "max_depth": [2,4,6,8],
           'learning_rate':[0.1,0.01,1]
          }


clf = xgb.XGBRegressor(random_state=25,n_jobs=-1)

random_clf = RandomizedSearchCV(clf, param_distributions=paramss,
                                n_iter=3,cv=3,random_state=25, verbose=3,n_
jobs=-1)

random_clf.fit(x_train,y_train)
random_clf.best_params_
```

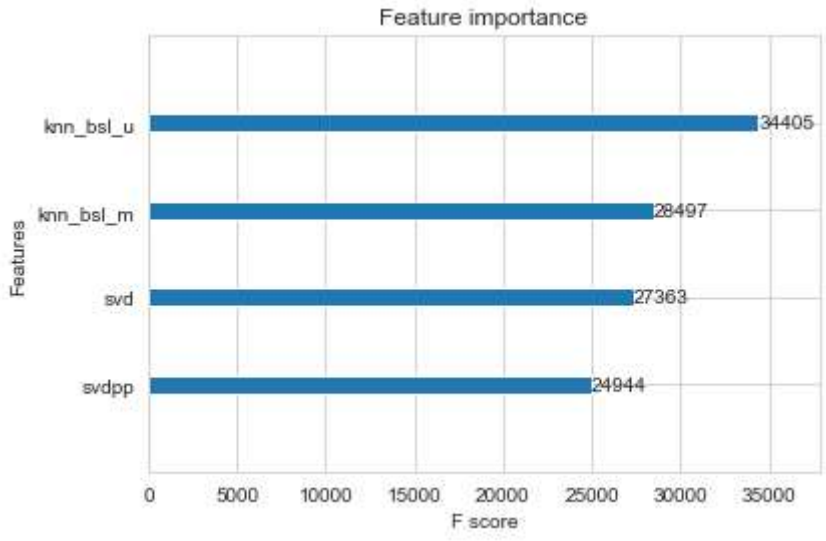
```
C:\Users\snake\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:281: UserWarning: The total space of parameters 2 is smaller than n_iter=3.
Running 2 iterations. For exhaustive searches, use GridSearchCV.
  % (grid_size, self.n_iter, grid_size), UserWarning)
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.

Fitting 3 folds for each of 2 candidates, totalling 6 fits

[Parallel(n_jobs=-1)]: Done   4 out of   6 | elapsed: 24.3min remaining: 12.1
min
[Parallel(n_jobs=-1)]: Done   6 out of   6 | elapsed: 24.4min finished
```

Out[131]:
```
{'n_estimators': 1100, 'max_depth': 8, 'learning_rate': 0.01}
```

Running model with tuned XG boost

In [132]:
```
xgb_all_models = xgb.XGBRegressor(n_jobs=10, random_state=15,
                                  max_depth = 8,
                                learning_rate = 0.01,
                                n_estimators=900)
train_results, test_results = run_xgboost(xgb_all_models, x_train, y_train, x_
test, y_test)

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

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

```
Training the model..
Done. Time taken : 0:06:43.417710

Done

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

TEST DATA
------------------------------
RMSE :  1.1022810628457278
MAPE :  36.47368360091552
```



4.5 Conclusion

In [137]:
```
# Saving our TEST_RESULTS into a dataframe so that you don't have to run it ag
ain
pd.DataFrame(models_evaluation_test).to_csv('sample/small/small_sample_result
s.csv')
models = pd.read_csv('sample/small/small_sample_results.csv', index_col=0)
models.loc['rmse'].sort_values()
```

Out[137]:
```
bsl_algo          1.0926308758324264
svd               1.0928020848745568
knn_bsl_u         1.0934889652441049
svdpp             1.0935512303051578
knn_bsl_m         1.0939686125271795
xgb_all_models    1.1022810628457278
xgb_final         1.1071051610102167
xgb_bsl           1.1101635923935806
xgb_knn_bsl       1.1110244693719702
first_algo        1.1132864575141992
Name: rmse, dtype: object
```

In [144]:
```
models.columns
```

Out[144]:
```
Index(['first_algo', 'bsl_algo', 'xgb_bsl', 'knn_bsl_u', 'knn_bsl_m',
       'xgb_knn_bsl', 'svd', 'svdpp', 'xgb_final', 'xgb_all_models'],
      dtype='object')
```

In [155]:
```
test_rmse = ['1.1132864575141992', '1.0926308758324264', '1.1101635923935806',
       '1.0934889652441049', '1.0939686125271795', '1.1110244693719702',
       '1.0928020848745568', '1.0935512303051578', '1.1071051610102167',
       '1.1022810628457278']

test_mape = ['34.76736812027518', '35.929512482685944', '34.907060380518224',
       '35.95037412142581', '35.96478484010793', '34.84884167446569',
       '35.853854694602624', '35.790700741972806', '34.98777552065433',
       '36.47368360091552']

features = [ 'XGBoost with Basic initial 13 features',
            'Suprise BaselineModel',
            'XGBoost with Basic initial 13 features + Surprise Baseline predic
tor',
            'Surprise KNNBaseline with user user similarities',
            'Surprise KNNBaseline with movie movie similarities',
            'XGBoost with Basic initial 13 features + Surprise Baseline predic
tor + KNNBaseline predictor',
            'SVD Matrix Factorization User Movie intractions',
            'SVD Matrix Factorization with implicit feedback from user ( user
 rated movies ) ',
            'XGBoost with Basic 13 features + Surprise Baseline + Surprise KNN
baseline + MF Techniques ',
            'XGBoost with Surprise Baseline + Surprise KNNbaseline + MF Techni
ques'
]



CSI="\x1B["
print(CSI+"31;40m" + "                                                All XGBoost Mod
els are tuned                                    " + CSI + "0m")
data = { 'Models with featurization': features,'Test RMSE' : test_rmse, 'Test
 MAPE' : test_mape}
dfff = pd.DataFrame(data)
dfff.style.set_properties(**{'background-color': 'black',
                             'color': 'lawngreen',
                             'border-color': 'white'})
```

```
All XGBoost Models are tuned
```

Out[155]:

	Models with featurization	Test RMSE	Test MAPE
0	XGBoost with Basic initial 13 features	1.1132864575141992	34.76736812027518
1	Suprise BaselineModel	1.0926308758324264	35.929512482685944
2	XGBoost with Basic initial 13 features + Surprise Baseline predictor	1.1101635923935806	34.907060380518224
3	Surprise KNNBaseline with user user similarities	1.0934889652441049	35.95037412142581
4	Surprise KNNBaseline with movie movie similarities	1.0939686125271795	35.96478484010793
5	XGBoost with Basic initial 13 features + Surprise Baseline predictor + KNNBaseline predictor	1.1110244693719702	34.84884167446569
6	SVD Matrix Factorization User Movie intractions	1.0928020848745568	35.853854694602624
7	SVD Matrix Factorization with implicit feedback from user (user rated movies)	1.0935512303051578	35.790700741972806
8	XGBoost with Basic 13 features + Surprise Baseline + Surprise KNNbaseline + MF Techniques	1.1071051610102167	34.98777552065433
9	XGBoost with Surprise Baseline + Surprise KNNbaseline + MF Techniques	1.1022810628457278	36.47368360091552

Basic Surprise Models have low rmse and are working better than XGBoost models

Took 4 days to run whole notebook