

## 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> (<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.netflixprize.com/rules.html>)

- <https://www.kaggle.com/netflix-inc/netflix-prize-data> (<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> (<https://medium.com/netflix-techblog/netflix-recommendations-beyond-the-5-stars-part-1-55838468f429>) (very nice blog)
- surprise library: <http://surpriselib.com/> (<http://surpriselib.com/>) (we use many models from this library)
- surprise library doc: [http://surprise.readthedocs.io/en/stable/getting\\_started.html](http://surprise.readthedocs.io/en/stable/getting_started.html) ([http://surprise.readthedocs.io/en/stable/getting\\_started.html](http://surprise.readthedocs.io/en/stable/getting_started.html)) (we use many models from this library)
- installing surprise: <https://github.com/NicolasHug/ Surprise#installation> (<https://github.com/NicolasHug/ Surprise#installation>)
- Research paper: <http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf> (<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> (<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 has 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> (<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. Each 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](https://en.wikipedia.org/wiki/Mean_absolute_percentage_error)  
([https://en.wikipedia.org/wiki/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](https://en.wikipedia.org/wiki/Root-mean-square_deviation) ([https://en.wikipedia.org/wiki/Root-mean-square\\_deviation](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 [1]:

```
# this is just to know how much time will it take to run this entire ipython notebook
from datetime import datetime
# globalstart = datetime.now()
import pandas as pd
import numpy as np
import matplotlib
matplotlib.use('nbagg')

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

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

from sklearn.decomposition import TruncatedSVD
from sklearn.metrics.pairwise import cosine_similarity
import random
```

## 3. Exploratory Data Analysis

### 3.1 Preprocessing

#### 3.1.1 Converting / Merging whole data to required format: $u_i$ , $m_j$ , $r_{ij}$

In [0]:

```

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 appending each rating to a global file
    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.txt']
    for file in files:
        print("Reading ratings from {}".format(file))
        with open(file) as f:
            for line in f:
                del row[:] # you don't have to do this.
                line = line.strip()
                if line.endswith(':'):
                    # All below are ratings for this movie, until another movie 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)

```

Reading ratings from data\_folder/combined\_data\_1.txt...  
Done.

Reading ratings from data\_folder/combined\_data\_2.txt...  
Done.

Reading ratings from data\_folder/combined\_data\_3.txt...  
Done.

Reading ratings from data\_folder/combined\_data\_4.txt...  
Done.

Time taken : 0:05:03.705966

In [0]:

```
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 [0]:

df.head()

Out[14]:

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

In [0]:

df.describe()['rating']

Out[7]:

```
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 [0]:

```
# 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 [0]:

```
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 [0]:

```
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 Splitting data into Train and Test(80:20)

In [0]:

```
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 [0]:

```
# 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 [0]:

```
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 [0]:

```
# 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"
```

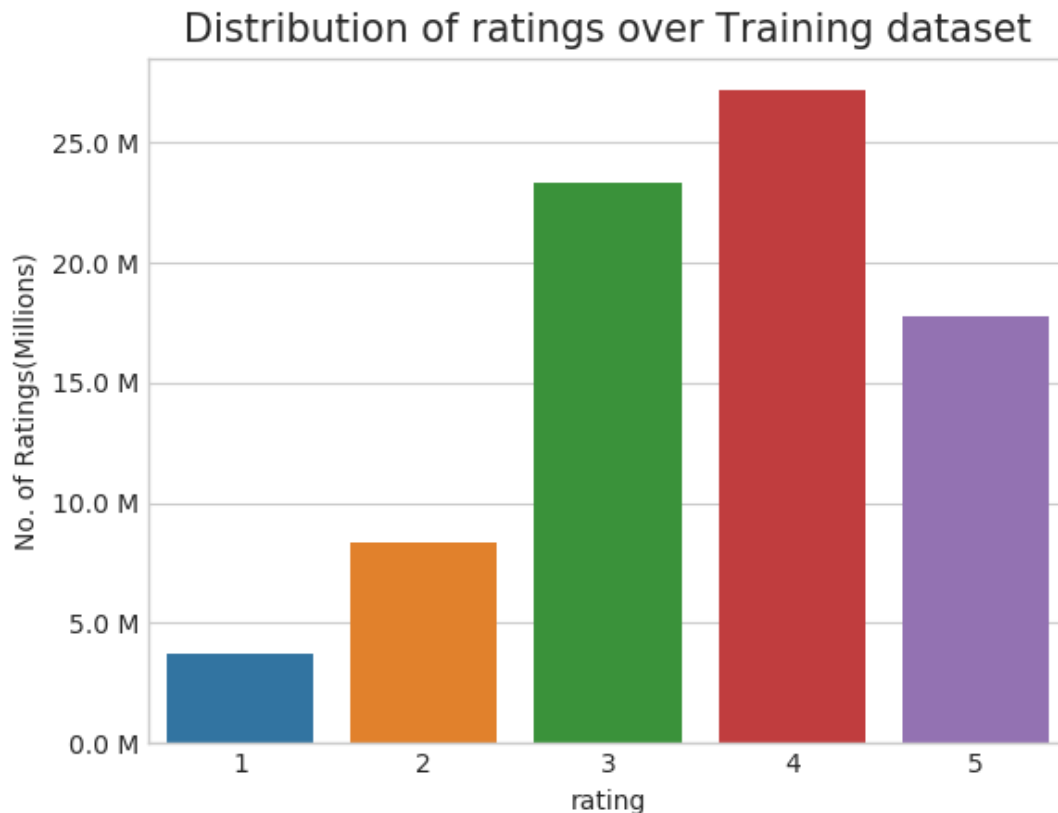
### 3.3.1 Distribution of ratings

In [0]:

```
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()
```

<IPython.core.display.Javascript object>



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

In [0]:

```
# It is used to skip the warning ''SettingWithCopyWarning' '..  
pd.options.mode.chained_assignment = None # default='warn'  
  
train_df['day_of_week'] = train_df.date.dt.weekday_name  
  
train_df.tail()
```

Out[17]:

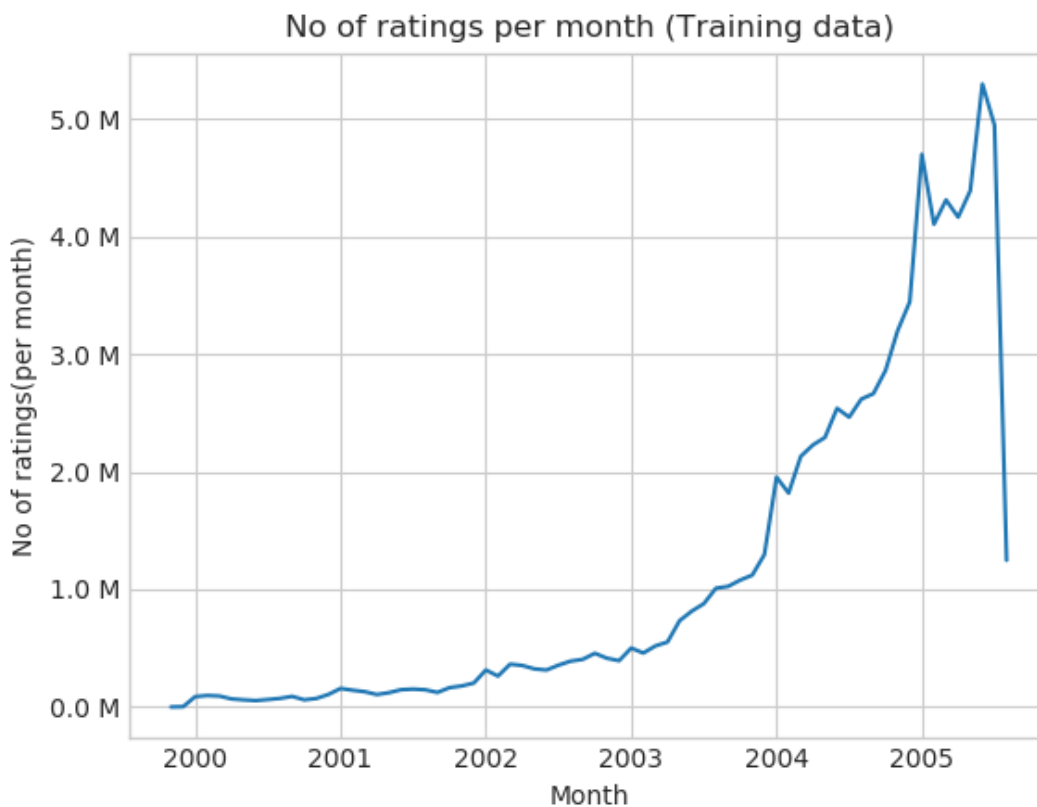
	movie	user	rating	date	day_of_week
<b>80384400</b>	12074	2033618	4	2005-08-08	Monday
<b>80384401</b>	862	1797061	3	2005-08-08	Monday
<b>80384402</b>	10986	1498715	5	2005-08-08	Monday
<b>80384403</b>	14861	500016	4	2005-08-08	Monday
<b>80384404</b>	5926	1044015	5	2005-08-08	Monday

### 3.3.2 Number of Ratings per a month

In [0]:

```
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()
```

&lt;IPython.core.display.Javascript object&gt;



### 3.3.3 Analysis on the Ratings given by user

In [0]:

```
no_of_rated_movies_per_user = train_df.groupby(by='user')['rating'].count().sort_values(asc
no_of_rated_movies_per_user.head()
```

Out[20]:

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

In [0]:

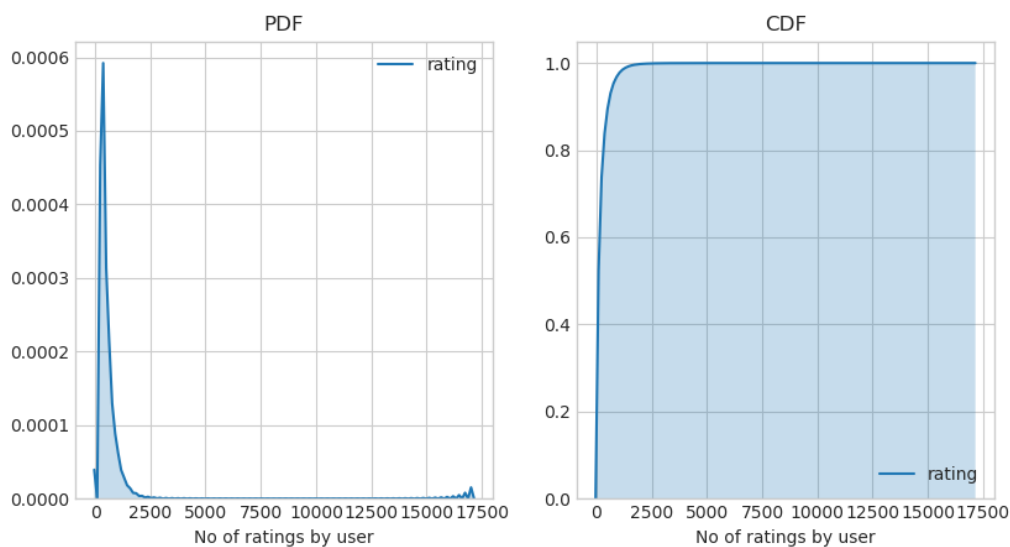
```
fig = plt.figure(figsize=plt.figaspect(.5))

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()
```

&lt;IPython.core.display.Javascript object&gt;



In [0]:

```
no_of Rated_movies_per_user.describe()
```

Out[22]:

```
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 [0]:

```
quantiles = no_of_rated_movies_per_user.quantile(np.arange(0,1.01,0.01), interpolation='high')
```

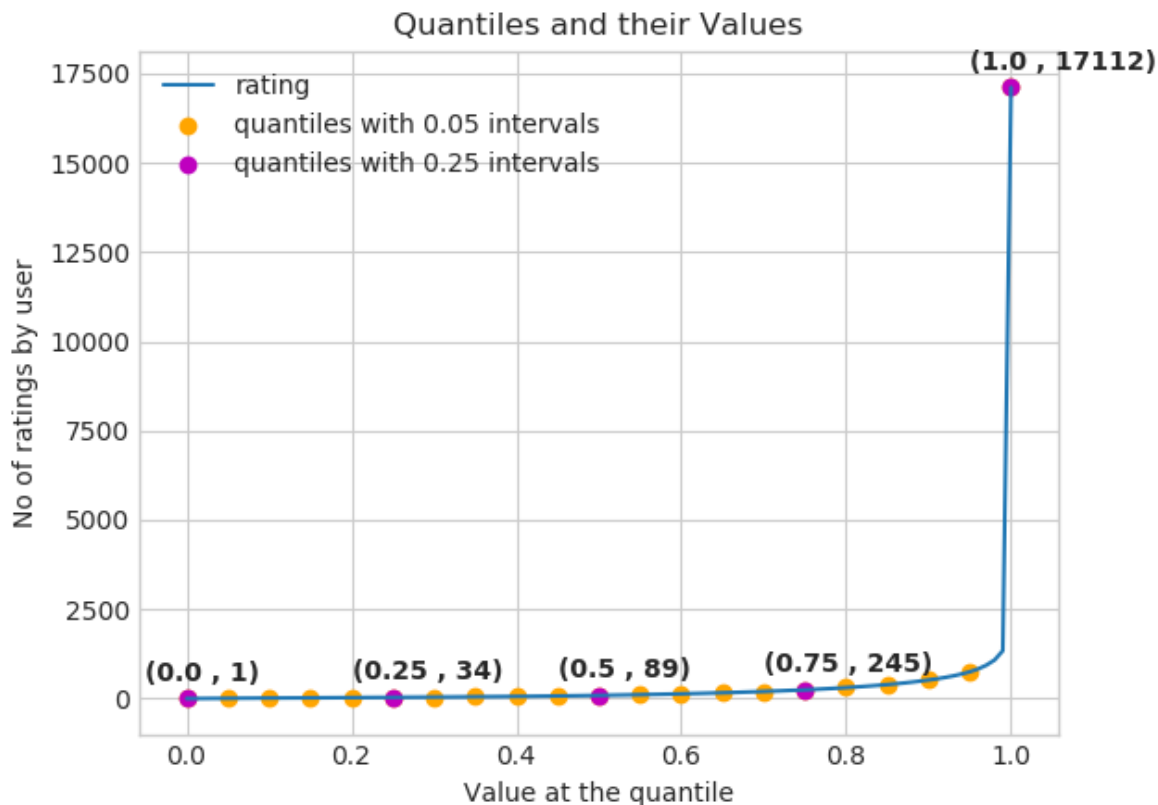
In [0]:

```
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 w
# quantiles with 0.25 difference
plt.scatter(x=quantiles.index[::25], y=quantiles.values[::25], c='m', label = "quantiles wi
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()
```

&lt;IPython.core.display.Javascript object&gt;



In [0]:

```
quantiles[:,5]
```

Out[25]:

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 [0]:

```
print('\n No of ratings at last 5 percentile : {}'.format(sum(no_of Rated_Movies_per_User
```

No of ratings at last 5 percentile : 20305

### 3.3.4 Analysis of ratings of a movie given by a user

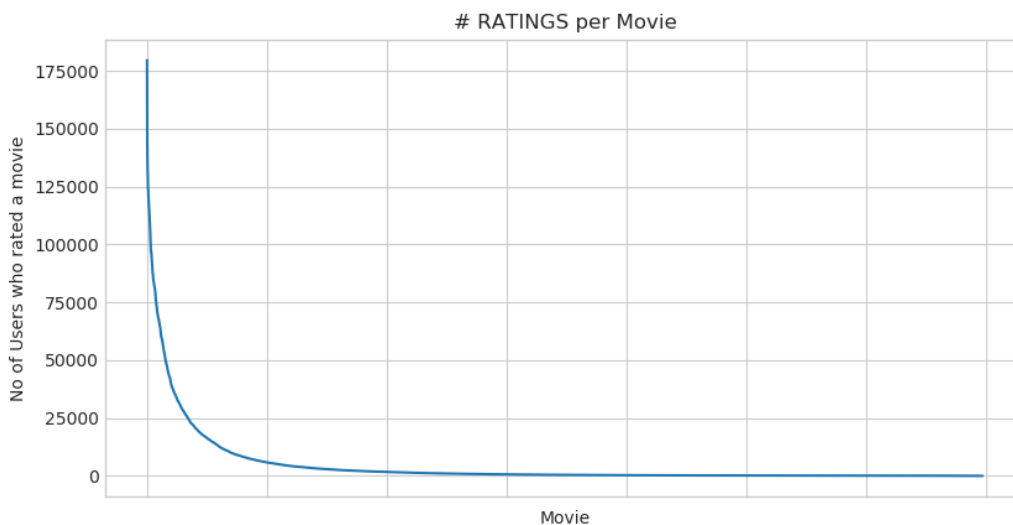
In [0]:

```
no_of_ratings_per_movie = train_df.groupby(by='movie')['rating'].count().sort_values(ascending=True)

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()
```

<IPython.core.display.Javascript object>



- **It is very skewed.. just like numnber 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.

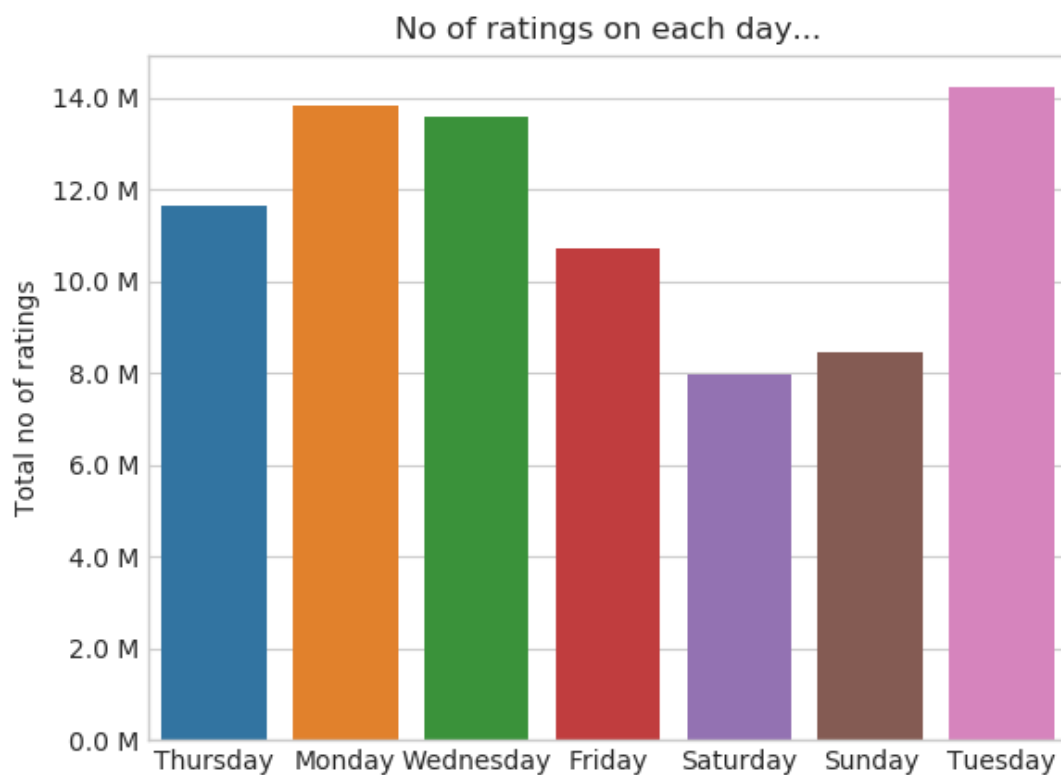


### 3.3.5 Number of ratings on each day of the week

In [0]:

```
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()
```

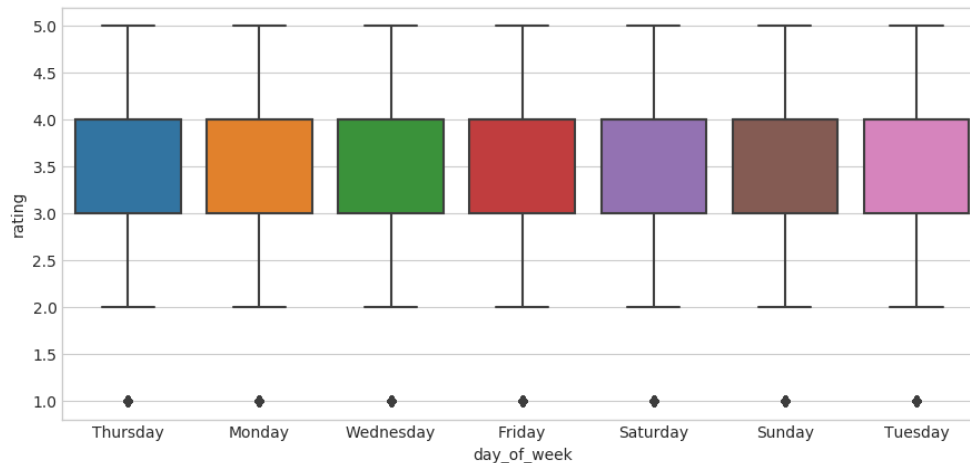
<IPython.core.display.Javascript object>



In [0]:

```
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)
```

&lt;IPython.core.display.Javascript object&gt;



0:01:10.003761

In [0]:

```
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

MOVIE_ID	USER_ID	RATING
1	1	3
2	1	4
3	1	2
3	2	1
4	2	4
8	2	2
1	3	3
7	3	1
10	3	5



	1	2	3	4	5	6	7	8	9	10	(movie)
1	3	4	2	-	-	-	-	-	-	-	
2	-	-	1	4	-	-	-	-	-	-	
3	3	-	-	-	-	-	1	-	-	5	
(user)											

### 3.3.6.1 Creating sparse matrix from train data frame

In [0]:

```
train_sparse_matrix = sparse.csr_matrix((train_df.rating.values, ()))
```

In [0]:

```
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)
```

```
We are creating sparse_matrix from the dataframe..
Done. It's shape is : (user, movie) : (2649430, 17771)
Saving it into disk for furthur usage..
Done..
```

```
0:01:13.804969
```

### The Sparsity of Train Sparse Matrix

In [0]:

```
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 [0]:

```
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.user.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)
```

We are creating sparse\_matrix from the dataframe..  
 Done. It's shape is : (user, movie) : (2649430, 17771)  
 Saving it into disk for furthur usage..  
 Done..

0:00:18.566120

### The Sparsity of Test data Matrix

In [0]:

```
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 [11]:

```
# get the user averages in dictionary (key: user_id/movie_id, value: avg rating)

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)
    isRated = sparse_matrix!=0
    # no of ratings that each user OR movie..
    no_of_ratings = isRated.sum(axis=ax).A1

    # max_user and max_movie ids in sparse matrix
    u,m = sparse_matrix.shape
    # create a dictionary of users and their average ratings..
    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 [0]:

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

Out[36]:

```
{'global': 3.582890686321557}
```

### 3.3.7.2 finding average rating per user

In [0]:

```
train_averages['user'] = get_average_ratings(train_sparse_matrix, of_users=True)
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 [0]:

```
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 [0]:

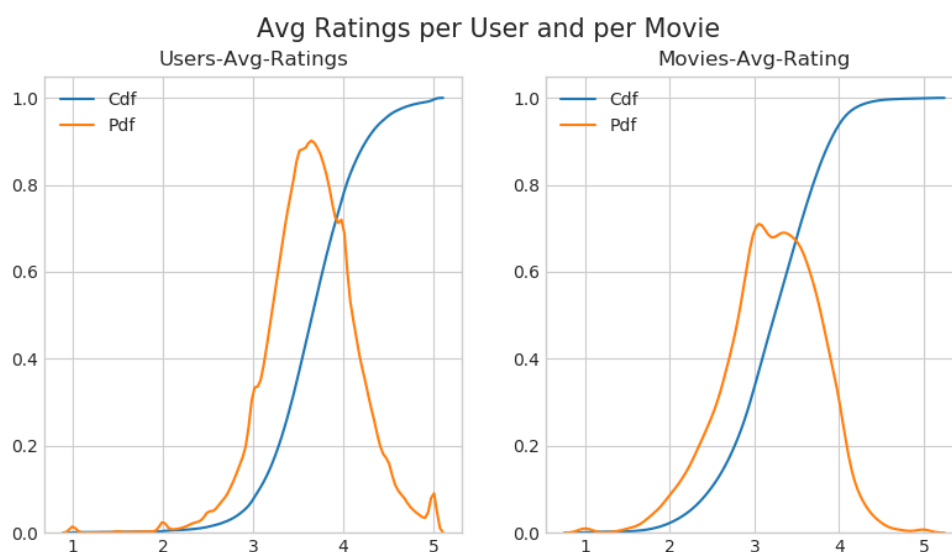
```
start = datetime.now()
# draw pdfs for average rating per user and average
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=plt.figaspect(.5))
fig.suptitle('Avg Ratings per User and per Movie', fontsize=15)

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)
```

<IPython.core.display.Javascript object>



0:00:35.003443

### 3.3.8 Cold Start problem

### 3.3.8.1 Cold Start problem with Users

In [0]:

```
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(new_users,
                                                                              np.round((new_users
```

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 test data.

### 3.3.8.2 Cold Start problem with Movies

In [0]:

```
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(new_movies,
                                                                              np.round((new_movie
```

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. users being large.

- 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 [0]:

```

from sklearn.metrics.pairwise import cosine_similarity

def compute_user_similarity(sparse_matrix, compute_for_few=False, top = 100, verbose=False,
                           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 sparse 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).ravel()
        # 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_users)), time_

```

In [0]:

```

start = datetime.now()
u_u_sim_sparse, _ = compute_user_similarity(train_sparse_matrix, compute_for_few=True, top
                                             verbose=True)
print("-"*100)
print("Time taken :",datetime.now()-start)

```

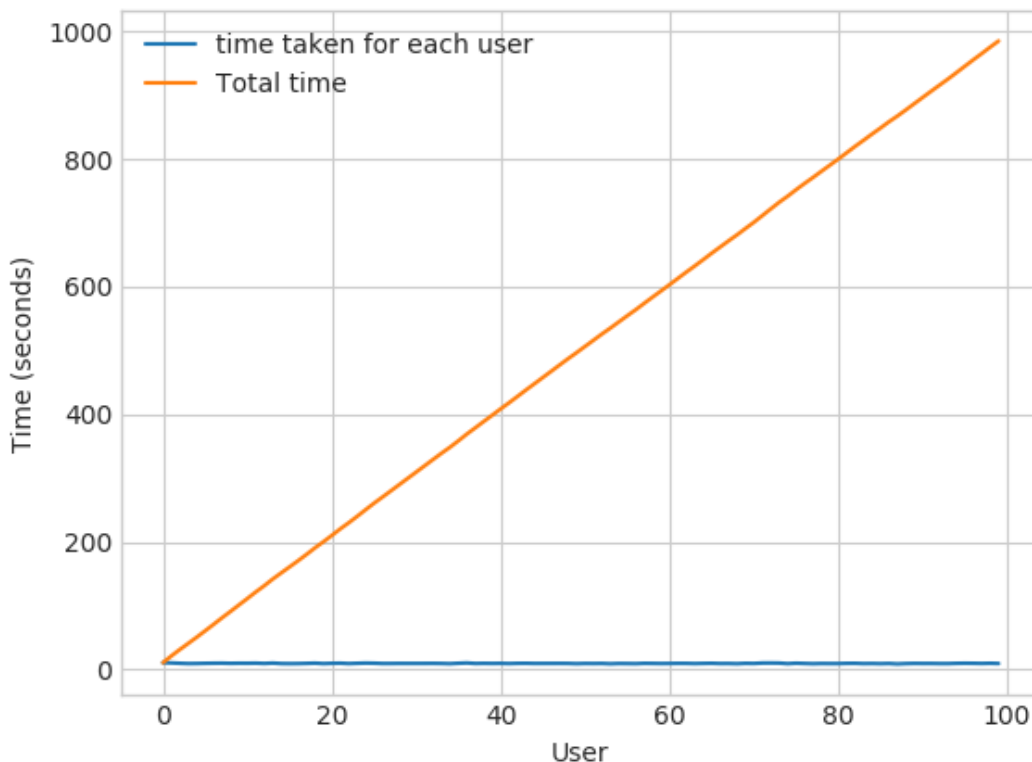
Computing top 100 similarities for each user..

```

computing done for 20 users [ time elapsed : 0:03:20.300488 ]
computing done for 40 users [ time elapsed : 0:06:38.518391 ]
computing done for 60 users [ time elapsed : 0:09:53.143126 ]
computing done for 80 users [ time elapsed : 0:13:10.080447 ]
computing done for 100 users [ time elapsed : 0:16:24.711032 ]
Creating Sparse matrix from the computed similarities

```

<IPython.core.display.Javascript object>



Time taken : 0:16:33.618931

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

- We have **405,041 users** in our 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.
- $405041 \times 8.88 = 3596764.08 \text{ sec} = 59946.068 \text{ min} = 999.101133333 \text{ hours} = 41.629213889 \text{ days}$ .
  - Even if we run on 4 cores parallely (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 solver.
netflix_svd = TruncatedSVD(n_components=500, algorithm='randomized', random_state=15)
trunc_svd = netflix_svd.fit_transform(train_sparse_matrix)

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

0:29:07.069783

Here,

- $\Sigma \leftarrow (\text{netflix\_svd.singular\_values\_})$
- $V^T \leftarrow (\text{netflix\_svd.components\_})$
- $U$  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)
# annotate 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')

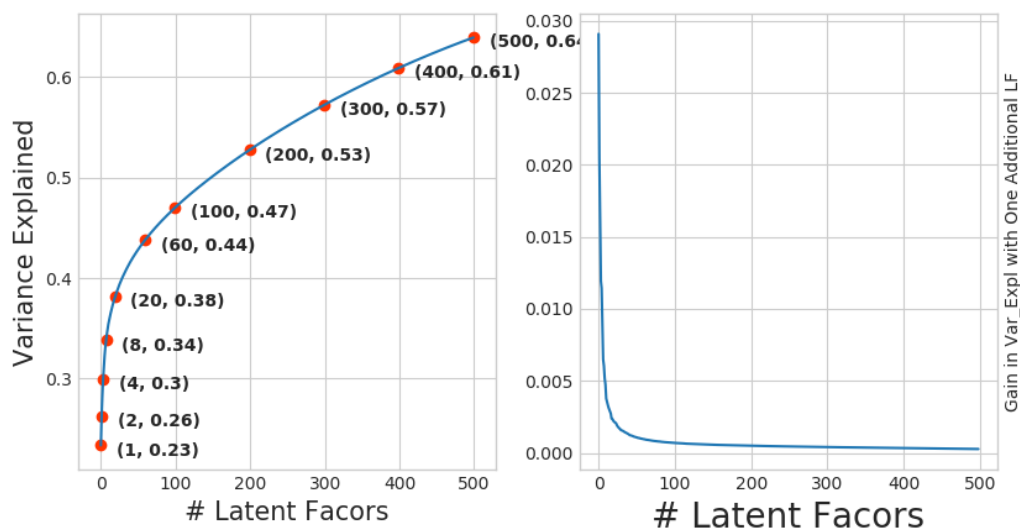
change_in_expl_var = [expl_var[i+1] - expl_var[i] for i in range(len(expl_var)-1)]
ax2.plot(change_in_expl_var)

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()

```

&lt;IPython.core.display.Javascript object&gt;



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[53]:

```
(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 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[55]:

```
(2649430, 500)
```

In [0]:

```

start = datetime.now()
trunc_u_u_sim_matrix, _ = compute_user_similarity(trunc_sparse_matrix, compute_for_few=True,
                                                  verb_for_n_rows=10)
print("-"*50)
print("time:",datetime.now()-start)

```

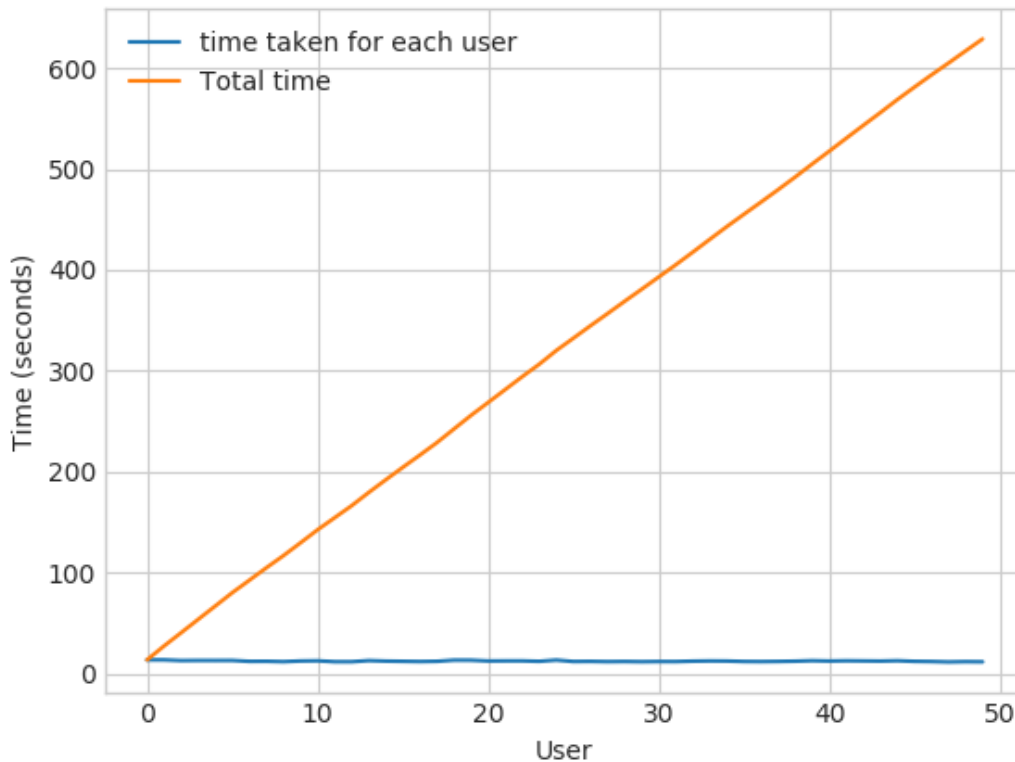
Computing top 50 similarities for each user..

```

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

```

<IPython.core.display.Javascript object>



-----  
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 similar 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 parallely (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, whenever 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, and add this to our datastructure, so that we can just access it(similar users) without 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 computed a long time ago. Because user preferences changes over time. If we could maintain in 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 [0]:

```

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 similarity...")
    start = datetime.now()
    m_m_sim_sparse = cosine_similarity(X=train_sparse_matrix.T, dense_output=False)
    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 seems you don't have that file. Computing movie\_movie similarity...  
 Done..  
 Saving it to disk without the need of re-computing it again..  
 Done..  
 It's a (17771, 17771) dimensional matrix  
 0:10:02.736054

In [0]:

```
m_m_sim_sparse.shape
```

Out[59]:

```
(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 [0]:

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

In [0]:

```

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]

```

0:00:33.411700

Out[62]:

```

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

```

### 3.4.3 Finding most similar movies using similarity matrix

**Does Similarity really works as the way we expected...?**

*Let's pick some random movie and check for its similar movies....*

In [0]:

```
# First Let's Load the movie details into soe dataframe..
# movie details are in 'netflix/movie_titles.csv'

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

movie_titles.head()
```

Tokenization took: 4.50 ms

Type conversion took: 165.72 ms

Parser memory cleanup took: 0.01 ms

Out[64]:

	year_of_release	title
movie_id		
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 [0]:

```
mv_id = 67

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

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

print("\nWe have {} movies which are similarto this and we will get only top most..".format(
```

Movie -----&gt; Vampire Journals

It has 270 Ratings from users.

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

In [0]:

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

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

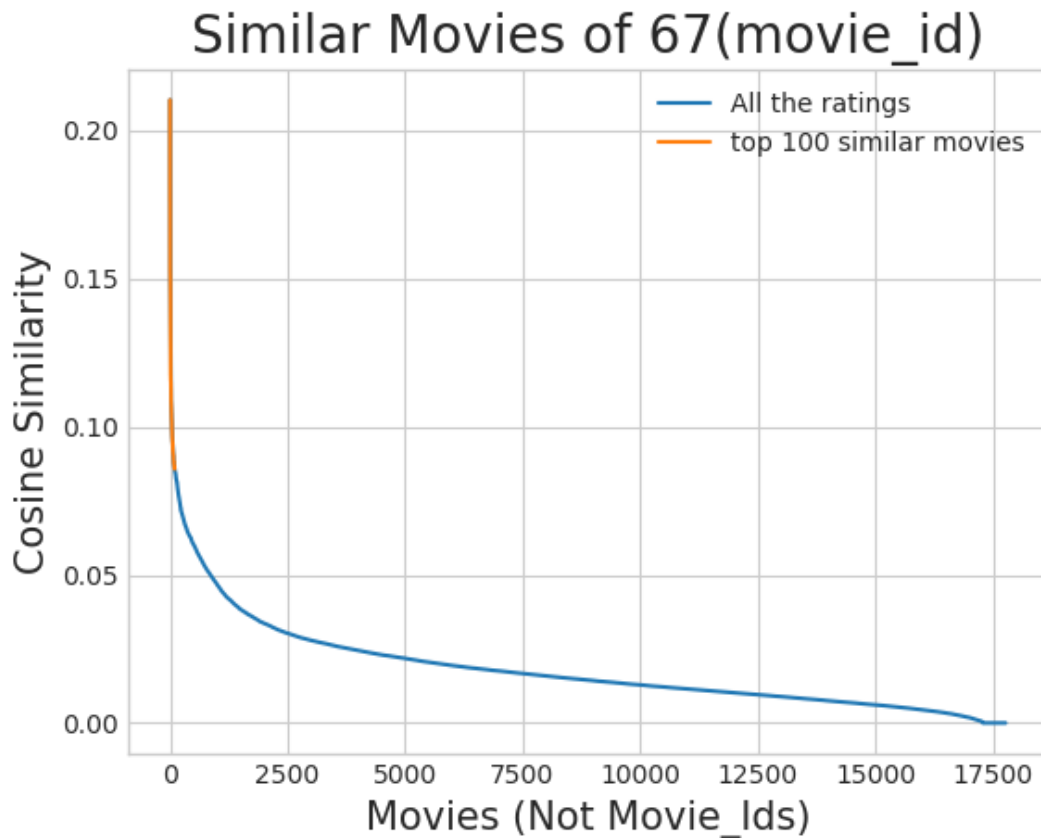
similarities[similar_indices]

sim_indices = similarities.argsort()[::-1][1:] # It will sort and reverse the array and ign
# and return its indices(movie_ids)
```

In [0]:

```
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()
```

<IPython.core.display.Javascript object>



**Top 10 similar movies**

In [0]:

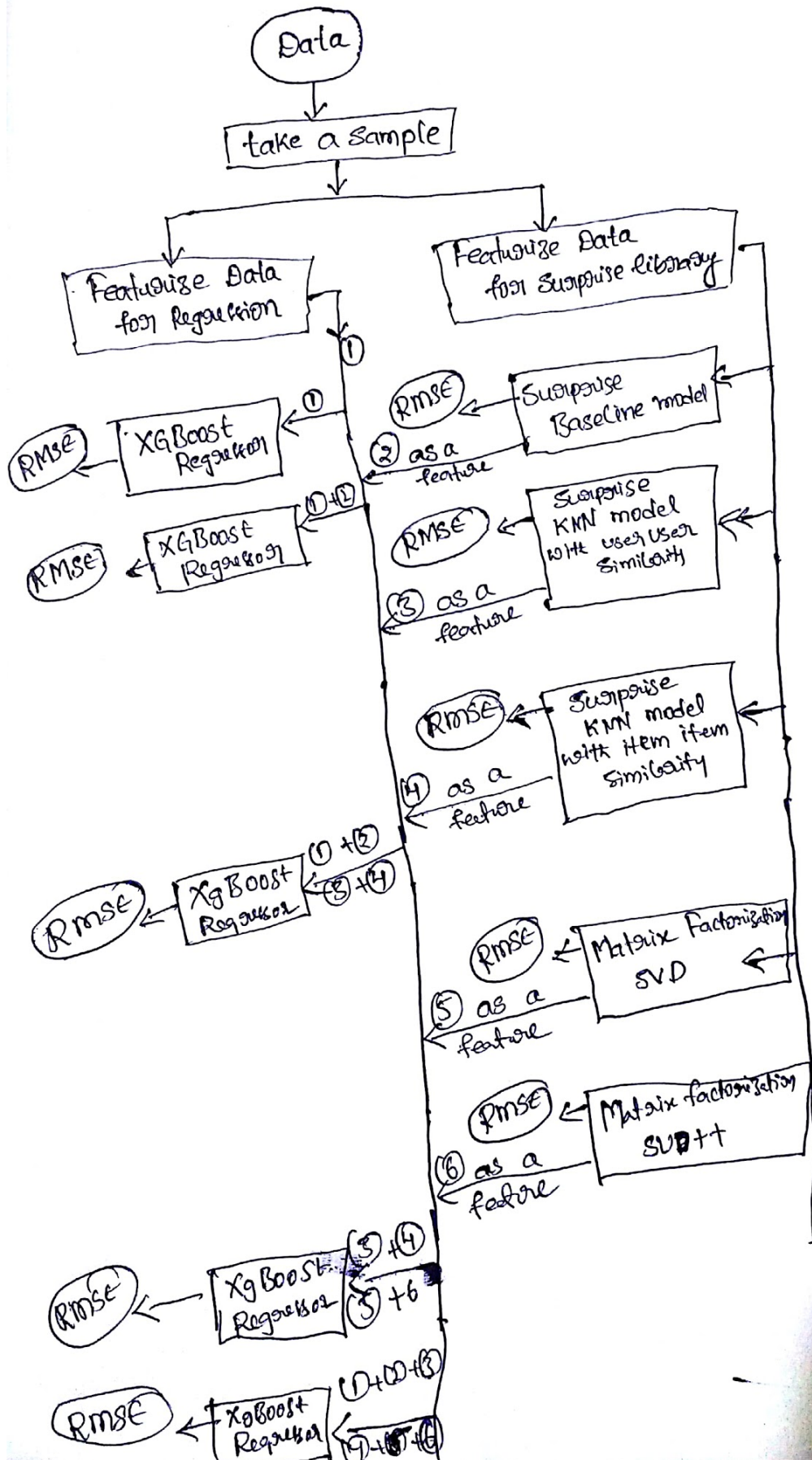
```
movie_titles.loc[sim_indices[:10]]
```

Out[68]:

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

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

## 4. Machine Learning Models



In [2]:

```
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), len(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], col_ind[mask])),
                                              shape=(max(sample_users)+1, max(sample_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 [3]:

```
from scipy import sparse
train_sparse_matrix = sparse.load_npz('data/train_sparse_matrix.npz')
test_sparse_matrix = sparse.load_npz('data/test_sparse_matrix.npz')
```

In [5]:

```

start = datetime.now()
path = "data/sample/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,
                                                         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..

0:00:58.267618

### 4.1.2 Build sample test data from the test data

In [7]:

```

start = datetime.now()

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

print(datetime.now() - start)

```

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

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

0:00:14.364561

## 4.2 Finding Global Average of all movie ratings, Average rating



## per User, and Average rating per Movie (from sampled train)

In [9]:

```
sample_train_averages = dict()
```

### 4.2.1 Finding Global Average of all movie ratings

In [10]:

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

Out[10]:

```
{'global': 3.5875813607223455}
```

### 4.2.2 Finding Average rating per User

In [12]:

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

Average rating of user 1515220 : 3.923076923076923

### 4.2.3 Finding Average rating per Movie

In [13]:

```
sample_train_averages['movie'] = get_average_ratings(sample_train_sparse_matrix, of_movies=True)  
print('\n AVerage rating of movie 15153 :',sample_train_averages['movie'][15153])
```

Average rating of movie 15153 : 2.752

## 4.3 Featurizing data

In [14]:

```
print('\n No of ratings in Our Sampled train matrix is : {}'.format(sample_train_sparse_m
print('\n No of ratings in Our Sampled test  matrix is : {}'.format(sample_test_sparse_ma
```

No of ratings in Our Sampled train matrix is : 856986

No of ratings in Our Sampled test matrix is : 7333

## 4.3.1 Featurizing data for regression problem

### 4.3.1.1 Featurizing train data

In [15]:

```
# get users, movies and ratings from our samples train sparse matrix
sample_train_users, sample_train_movies, sample_train_ratings = sparse.find(sample_train_sp
```

In [ ]:

```
#####
# It took me almost 10 hours to prepare this train dataset.#
#####
start = datetime.now()
if os.path.isfile('data/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('data/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[sample_train_movies])
            top_sim_users = user_sim.argsort()[::-1][1:] # we are ignoring 'The User' from the list
            # 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[sample_train_users])
            top_sim_movies = movie_sim.argsort()[::-1][1:] # we are ignoring 'The User' from the list
            # 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----- 1:16:49.029051
Done for 20000 rows----- 2:34:12.438039
Done for 30000 rows----- 3:53:42.805636
Done for 40000 rows----- 5:14:23.759578
Done for 50000 rows----- 6:35:57.537216
Done for 60000 rows----- 7:59:10.794613
Done for 70000 rows----- 9:20:59.092061
Done for 80000 rows----- 10:42:09.472652
Done for 90000 rows----- 12:03:27.660913
Done for 100000 rows----- 13:25:33.432221
Done for 110000 rows----- 14:46:53.750178
Done for 120000 rows----- 16:08:03.858680
Done for 130000 rows----- 17:27:23.950198
Done for 140000 rows----- 18:46:51.920474
Done for 160000 rows----- 21:27:38.827946
Done for 170000 rows----- 22:48:07.712119
Done for 180000 rows----- 1 day, 0:09:01.255080
Done for 190000 rows----- 1 day, 1:30:20.305161
Done for 200000 rows----- 1 day, 2:51:27.292072
Done for 210000 rows----- 1 day, 4:11:30.695628
Done for 220000 rows----- 1 day, 5:31:21.970785
Done for 230000 rows----- 1 day, 6:51:38.170238
Done for 240000 rows----- 1 day, 8:11:15.870969
Done for 250000 rows----- 1 day, 9:30:49.705279
Done for 260000 rows----- 1 day, 10:51:12.131510
Done for 270000 rows----- 1 day, 12:11:15.170048
Done for 280000 rows----- 1 day, 13:31:34.890438
Done for 290000 rows----- 1 day, 14:51:58.825148
Done for 300000 rows----- 1 day, 16:12:50.290461
Done for 310000 rows----- 1 day, 17:32:34.247814
Done for 320000 rows----- 1 day, 18:52:35.629456
Done for 330000 rows----- 1 day, 20:13:05.652020
Done for 340000 rows----- 1 day, 21:33:22.821100
Done for 350000 rows----- 1 day, 22:53:40.562024
Done for 360000 rows----- 2 days, 0:14:05.088183
Done for 370000 rows----- 2 days, 1:33:32.469408
Done for 380000 rows----- 2 days, 2:52:33.157338
Done for 390000 rows----- 2 days, 4:11:35.802499
Done for 400000 rows----- 2 days, 5:31:14.887313
Done for 410000 rows----- 2 days, 6:50:53.396729
Done for 490000 rows----- 2 days, 17:24:45.602650
Done for 500000 rows----- 2 days, 18:41:16.942381
Done for 510000 rows----- 2 days, 19:57:12.945898
Done for 520000 rows----- 2 days, 21:14:00.568283
Done for 530000 rows----- 2 days, 22:30:44.893863
Done for 540000 rows----- 2 days, 23:46:50.767463
Done for 550000 rows----- 3 days, 1:03:22.270534
Done for 560000 rows----- 3 days, 2:19:19.628573
Done for 570000 rows----- 3 days, 3:35:28.722468
```

## Reading from the file to make a Train\_dataframe

In [2]:

```
reg_train = pd.read_csv('data/reg_train.csv', names = ['user', 'movie', 'GAvg', 'sur1', 'sur2', 'sur3', 'sur4', 'sur5', 'smr1', 'smr2', 'smr3', 'smr4', 'smr5'])
reg_train.head()
```

Out[2]:

	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	3.8
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	2.6
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	3.7
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	3.8
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	4.0

In [3]:

```
reg_train.shape
```

Out[3]:

```
(856986, 16)
```

- **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 [18]:

```
# get users, movies and ratings from the Sampled Test
sample_test_users, sample_test_movies, sample_test_ratings = sparse.find(sample_test_sparse)
```

In [19]:

```
sample_train_averages['global']
```

Out[19]:

3.5875813607223455

In [0]:

```
start = datetime.now()

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

    print('preparing {} tuples for the dataset..\\n'.format(len(sample_test_ratings)))
    with open('sample/small/reg_test.csv', mode='w') as reg_data_file:
        count = 0
        for (user, movie, rating) in zip(sample_test_users, sample_test_movies, 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[sample_test_movies])
                top_sim_users = user_sim.argsort()[::-1][1:] # we are ignoring 'The User' first
                # 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="--")

            except (IndexError, KeyError):
                # It is a new User or new Movie or there are no ratings for given user for
                ##### 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 Exception...
                raise

            #----- Ratings by "user" to similar movies of "movie" -----
            try:
                # compute the similar movies of the "movie"
                movie_sim = cosine_similarity(sample_train_sparse_matrix[:,movie].T, sample_train_sparse_matrix[sample_test_users,:].T)
                top_sim_movies = movie_sim.argsort()[::-1][1:] # we are ignoring 'The User' first
                # 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)
            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 7333 tuples for the dataset..

```

Done for 1000 rows----- 0:04:29.293783
Done for 2000 rows----- 0:08:57.208002
Done for 3000 rows----- 0:13:30.333223
Done for 4000 rows----- 0:18:04.050813
Done for 5000 rows----- 0:22:38.671673
Done for 6000 rows----- 0:27:09.697009
Done for 7000 rows----- 0:31:41.933568
0:33:12.529731

```

**Reading from the file to make a test dataframe**



In [4]:

```
reg_test_df = pd.read_csv('data/reg_test.csv', names = ['user', 'movie', 'GAvg', 'sur1', 's
               'smr1', 'smr2', 'smr3', 'smr4', '
               'UAvg', 'MAvg', 'rating'], header
reg_test_df.head(4)
```

Out[4]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	UAvg	MAvg	rating
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679
2	1737912	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679
3	1849204	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679

In [5]:

```
reg_test_df.shape
```

Out[5]:

(7333, 16)

- **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 [6]:

```
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 separate 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)  
[\(http://surprise.readthedocs.io/en/stable/getting\\_started.html#load-dom-dataframe-py\)](http://surprise.readthedocs.io/en/stable/getting_started.html#load-dom-dataframe-py)

In [7]:

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

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

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

#### 4.3.2.2 Transforming test data

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

In [8]:

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

Out[8]:

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

## 4.4 Applying Machine Learning models

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

**keys** : model names(string)

**value**: dict(**key** : metric, **value** : value )

In [9]:

```
models_evaluation_train = dict()  
models_evaluation_test = dict()  
  
models_evaluation_train, models_evaluation_test
```

Out[9]:

({}, {})

**Utility functions for running regression models**

In [10]:

```

# 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_pred)) ]))
    mape = np.mean(np.abs( (y_true - y_pred)/y_true )) * 100
    return rmse, mape

#####
#####
def run_xgboost(algo, x_train, y_train, x_test, y_test, 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 : {}'.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_test_pred)
    # store them in our test results dictionary.
    test_results = {'rmse': rmse_test,
                    'mape' : mape_test,
                    'predictions':y_test_pred}

    if verbose:
        print('\nTEST DATA')
        print('-'*30)
        print('RMSE : ', rmse_test)
        print('MAPE : ', mape_test)

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

```

Utility functions for Surprise modes

In [11]:

```
# it is just to make sure that all of our algorithms should produce same results
# everytime they run...

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

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

    return actual, pred

#####
# get 'rmse' and 'mape' , given list of prediction objects
#####
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 [12]:

```
import xgboost as xgb
```

In [13]:

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

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



In [41]:

```

from sklearn.model_selection import RandomizedSearchCV

clf = xgb.XGBRegressor()
params = {
    'n_estimators': [200, 400, 600, 800],
    'max_depth': [5, 10, 50, 100]
}

random_search = RandomizedSearchCV(clf, params, cv=2, scoring='neg_mean_squared_error', n_j
random_search.fit(x_train, y_train)

```

Fitting 2 folds for each of 10 candidates, totalling 20 fits

[Parallel(n\_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.  
/opt/anaconda3/lib/python3.7/site-packages/sklearn/externals/joblib/external  
s/loky/process\_executor.py:706: UserWarning: A worker stopped while some job  
s were given to the executor. This can be caused by a too short worker timeo  
ut or by a memory leak.

"timeout or by a memory leak.", UserWarning  
/opt/anaconda3/lib/python3.7/site-packages/sklearn/externals/joblib/external  
s/loky/process\_executor.py:706: UserWarning: A worker stopped while some job  
s were given to the executor. This can be caused by a too short worker timeo  
ut or by a memory leak.

"timeout or by a memory leak.", UserWarning  
/opt/anaconda3/lib/python3.7/site-packages/sklearn/externals/joblib/external  
s/loky/process\_executor.py:706: UserWarning: A worker stopped while some job  
s were given to the executor. This can be caused by a too short worker timeo  
ut or by a memory leak.

"timeout or by a memory leak.", UserWarning  
/opt/anaconda3/lib/python3.7/site-packages/sklearn/externals/joblib/external  
s/loky/process\_executor.py:706: UserWarning: A worker stopped while some job  
s were given to the executor. This can be caused by a too short worker timeo  
ut or by a memory leak.

"timeout or by a memory leak.", UserWarning  
/opt/anaconda3/lib/python3.7/site-packages/sklearn/externals/joblib/external  
s/loky/process\_executor.py:706: UserWarning: A worker stopped while some job  
s were given to the executor. This can be caused by a too short worker timeo  
ut or by a memory leak.

"timeout or by a memory leak.", UserWarning  
/opt/anaconda3/lib/python3.7/site-packages/sklearn/externals/joblib/external  
s/loky/process\_executor.py:706: UserWarning: A worker stopped while some job  
s were given to the executor. This can be caused by a too short worker timeo  
ut or by a memory leak.

"timeout or by a memory leak.", UserWarning

[Parallel(n\_jobs=-1)]: Done 20 out of 20 | elapsed: 277.2min finished  
/opt/anaconda3/lib/python3.7/site-packages/xgboost/core.py:587: FutureWarnin  
g: Series.base is deprecated and will be removed in a future version

if getattr(data, 'base', None) is not None and \  
/opt/anaconda3/lib/python3.7/site-packages/xgboost/core.py:588: FutureWarnin  
g: Series.base is deprecated and will be removed in a future version  
data.base is not None and isinstance(data, np.ndarray) \

Out[41]:

```

RandomizedSearchCV(cv=2, error_score='raise-deprecating',
    estimator=XGBRegressor(base_score=0.5, booster='gbtree', colsamp
le_bylevel=1,
    colsample_bytree=1, gamma=0, importance_type='gain',
    learning_rate=0.1, max_delta_step=0, max_depth=3,

```

```

min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
nthread=None, objective='reg:linear', random_state=0, reg_alpha=0,
reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
subsample=1),
    fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
    param_distributions={'n_estimators': [200, 400, 600, 800], 'max_
depth': [5, 10, 50, 100]},
    pre_dispatch='2*n_jobs', random_state=None, refit=True,
    return_train_score='warn', scoring='neg_mean_squared_error',
    verbose=2)

```

In [43]:

```

best = random_search.best_params_
best

```

Out[43]:

```
{'n_estimators': 400, 'max_depth': 5}
```

In [ ]:

```

import warnings
warnings.filterwarnings('ignore')

```

In [14]:

```

# initialize Our first XGBoost model...
first_xgb = xgb.XGBRegressor(
    silent=False,
    n_jobs=13,
    random_state=15,
    max_depth=5,
    n_estimators=400)
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

```

Training the model..

Done. Time taken : 0:02:44.205843

Done

Evaluating the model with TRAIN data...

Evaluating Test data

TEST DATA

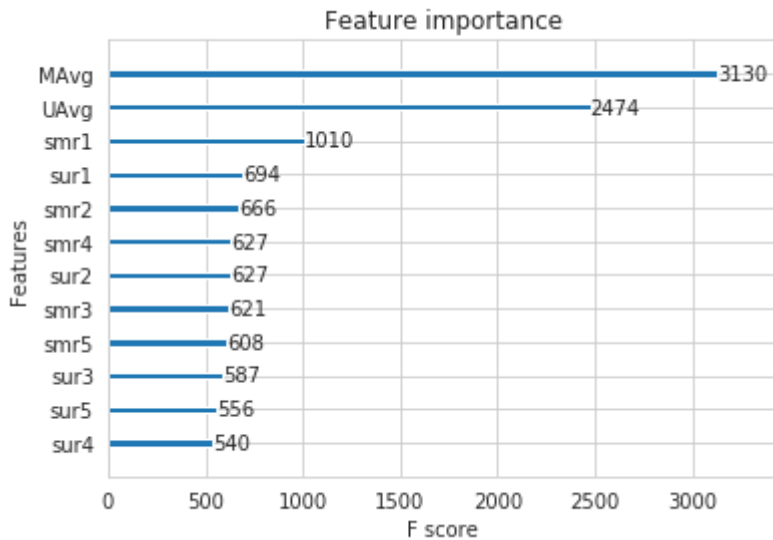
```

-----
RMSE :  1.0865153626345139
MAPE :  33.89009055329852

```

In [15]:

```
%matplotlib inline
xgb.plot_importance(first_xgb)
plt.show()
```



#### 4.4.2 Surprise BaselineModel

In [16]:

```
from surprise import BaselineOnly
```

**Predicted\_rating : ( baseline prediction )**

- [http://surprise.readthedocs.io/en/stable/basic\\_algorithms.html#surprise.prediction\\_algorithms.baseline\\_only.BaselineOnly](http://surprise.readthedocs.io/en/stable/basic_algorithms.html#surprise.prediction_algorithms.baseline_only.BaselineOnly)

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

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

**Optimization function ( Least Squares Problem )**

- [http://surprise.readthedocs.io/en/stable/prediction\\_algorithms.html#baselines-estimates-configuration](http://surprise.readthedocs.io/en/stable/prediction_algorithms.html#baselines-estimates-configuration)

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

In [17]:

```
# 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 : 0:00:08.871894

Evaluating the model with train data..

time taken : 0:00:08.886171

-----

Train Data

-----

RMSE : 0.9220478981418425

MAPE : 28.6415868708249

adding train results in the dictionary..

Evaluating for test data...

time taken : 0:00:00.070902

-----

Test Data

-----

RMSE : 1.0655294354066949

MAPE : 34.406634720551914

storing the test results in test dictionary...

-----

Total time taken to run this algorithm : 0:00:17.830414

### 4.4.3 XGBoost with initial 13 features + Surprise Baseline predictor

#### Updating Train Data

In [18]:

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

Out[18]:

	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	3.8
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	2.6

## Updating Test Data

In [19]:

```
# 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[19]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679

In [20]:

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

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

In [55]:

```
clf = xgb.XGBRegressor()
params = {
    'n_estimators': [200, 400, 600],
    'max_depth': [5, 10, 50]
}

random_search = RandomizedSearchCV(clf, params, cv=2, scoring='neg_mean_squared_error', n_j
random_search.fit(x_train, y_train)
```

Out[55]:

```
RandomizedSearchCV(cv=2, error_score='raise-deprecating',
    estimator=XGBRegressor(base_score=0.5, booster='gbtree', colsample
_bylevel=1,
    colsample_bytree=1, gamma=0, importance_type='gain',
    learning_rate=0.1, max_delta_step=0, max_depth=3,
    min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
    nthread=None, objective='reg:linear', random_state=0, reg_alpha=0,
    reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
    subsample=1),
    fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
    param_distributions={'n_estimators': [200, 400, 600], 'max_depth':
[5, 10, 50]},
    pre_dispatch='2*n_jobs', random_state=None, refit=True,
    return_train_score='warn', scoring='neg_mean_squared_error',
    verbose=0)
```

In [57]:

```
best = random_search.best_params_
best
```

Out[57]:

```
{'n_estimators': 200, 'max_depth': 5}
```

In [21]:

```

xgb_bsl = xgb.XGBRegressor(
    silent=False,
    n_jobs=13,
    random_state=15,
    max_depth=5,
    n_estimators=200)
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 : 0:02:04.502770

Done

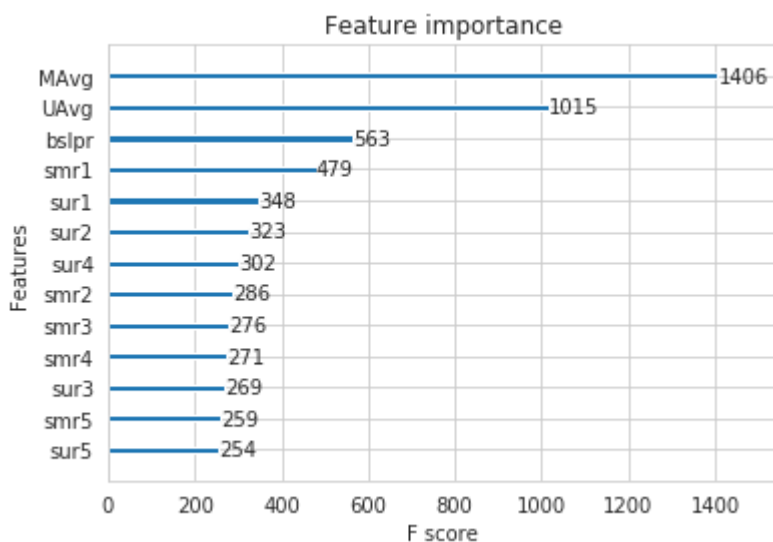
Evaluating the model with TRAIN data...

Evaluating Test data

TEST DATA

RMSE : 1.0804996202827688

MAPE : 34.198448940853496



#### 4.4.4 Surprise KNNBaseline predictor

In [22]:

```
from surprise import KNNBaseline
```

- KNN BASELINE

- [http://surprise.readthedocs.io/en/stable/knn\\_inspired.html#surprise.prediction\\_algorithms.knns.KNNBaseline](http://surprise.readthedocs.io/en/stable/knn_inspired.html#surprise.prediction_algorithms.knns.KNNBaseline) ([http://surprise.readthedocs.io/en/stable/knn\\_inspired.html#surprise.prediction\\_algorithms.knns.KNNBaseline](http://surprise.readthedocs.io/en/stable/knn_inspired.html#surprise.prediction_algorithms.knns.KNNBaseline))

- 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)  
([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 \_ )

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

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

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

- \_Notations follows same as above (user user based predicted rating ) \_

#### 4.4.4.1 Surprise KNNBaseline with user user similarities



In [23]:

```
# we specify , how to compute similarities and what to consider with sim_options to our alg
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 value
bsl_options = {'method': 'sgd'}

knn_bsl_u = KNNBaseline(k=40, sim_options = sim_options, bsl_options = bsl_options)
knn_bsl_u_train_results, knn_bsl_u_test_results = run_surprise(knn_bsl_u, trainset, testset)

# 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 : 0:07:55.836114

Evaluating the model with train data..  
 time taken : 0:30:56.991033

-----  
 Train Data

-----  
 RMSE : 0.4536279292470732

MAPE : 12.840252350475915

adding train results in the dictionary..

Evaluating for test data...  
 time taken : 0:00:00.136871

-----  
 Test Data

-----  
 RMSE : 1.0651583775048283

MAPE : 34.3955649993566

storing the test results in test dictionary...

-----  
 Total time taken to run this algorithm : 0:38:52.964901

#### 4.4.4.2 Surprise KNNBaseline with movie movie similarities

In [24]:

```
# we specify , how to compute similarities and what to consider with sim_options to our alg
# '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 value
bsl_options = {'method': 'sgd'}

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

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

# 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 : 0:00:18.199058
```

```
Evaluating the model with train data..
time taken : 0:02:10.828492
```

```
-----
Train Data
```

```
-----
RMSE : 0.5038994796517224
```

```
MAPE : 14.168515366483724
```

```
adding train results in the dictionary..
```

```
Evaluating for test data...
time taken : 0:00:00.078447
```

```
-----
Test Data
```

```
-----
RMSE : 1.066111028261093
```

```
MAPE : 34.41196670639251
```

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

```
-----
Total time taken to run this algorithm : 0:02:29.107807
```

#### 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 [25]:

```
# 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[25]:

	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	3.8
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	2.6

### Preparing Test data

In [26]:

```
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[26]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679

In [27]:

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

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

In [29]:

```

from sklearn.model_selection import RandomizedSearchCV

clf = xgb.XGBRegressor()
params = {
    'n_estimators': [200, 400, 600, 800],
    'max_depth': [5, 10, 50, 100]
}

random_search = RandomizedSearchCV(clf, params, cv=2, scoring='neg_mean_squared_error', n_j
random_search.fit(x_train, y_train)

```

Out[29]:

```

RandomizedSearchCV(cv=2, error_score='raise-deprecating',
    estimator=XGBRegressor(base_score=0.5, booster='gbtree', colsample
_bylevel=1,
    colsample_bytree=1, gamma=0, importance_type='gain',
    learning_rate=0.1, max_delta_step=0, max_depth=3,
    min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
    nthread=None, objective='reg:linear', random_state=0, reg_alpha=0,
    reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
    subsample=1),
    fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
    param_distributions={'n_estimators': [200, 400, 600, 800], 'max_de
pth': [5, 10, 50, 100]},
    pre_dispatch='2*n_jobs', random_state=None, refit=True,
    return_train_score='warn', scoring='neg_mean_squared_error',
    verbose=0)

```

In [30]:

```

best = random_search.best_params_
best

```

Out[30]:

```
{'n_estimators': 400, 'max_depth': 5}
```

In [31]:

```
# declare the model
xgb_knn_bsl = xgb.XGBRegressor(
    n_jobs=10,
    random_state=15,
    max_depth=5,
    n_estimators=400)
train_results, test_results = run_xgboost(xgb_knn_bsl, x_train, y_train, x_test, 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 : 0:03:57.622260

Done

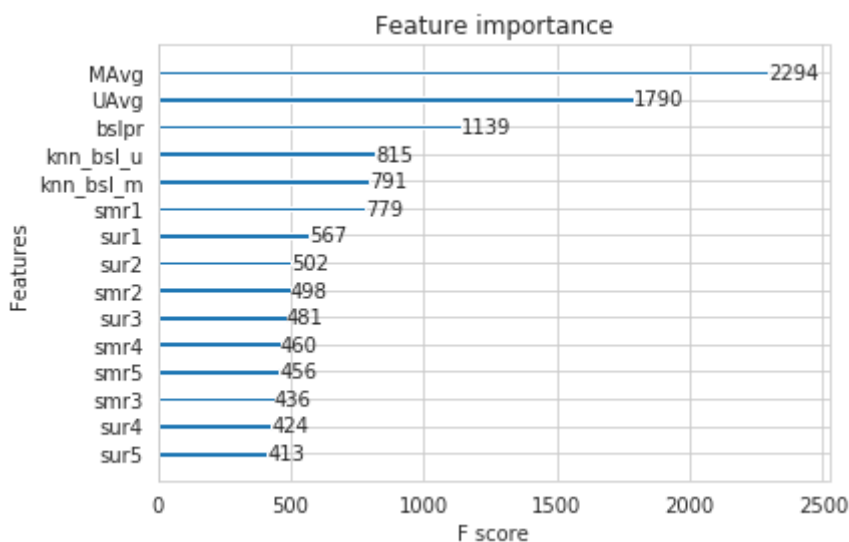
Evaluating the model with TRAIN data...

Evaluating Test data

TEST DATA

-----  
RMSE : 1.0893322610406004

MAPE : 33.777668189664304



## 4.4.6 Matrix Factorization Techniques

### 4.4.6.1 SVD Matrix Factorization User Movie intractions

In [32]:

```
from surprise import SVD
```

[http://surprise.readthedocs.io/en/stable/matrix\\_factorization.html#surprise.prediction\\_algorithms.matrix\\_factorization](http://surprise.readthedocs.io/en/stable/matrix_factorization.html#surprise.prediction_algorithms.matrix_factorization)  
[http://surprise.readthedocs.io/en/stable/matrix\\_factorization.html#surprise.prediction\\_algorithms.matrix\\_factorization](http://surprise.readthedocs.io/en/stable/matrix_factorization.html#surprise.prediction_algorithms.matrix_factorization)

- **Predicted Rating :**

- - $\hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u$ 
    - $q_i$  - Representation of item(movie) in latent factor space
    - $p_u$  - 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) ([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)**

- - $\sum_{r_{ui} \in R_{train}} (r_{ui} - \hat{r}_{ui})^2 + \lambda (b_i^2 + b_u^2 + \|q_i\|^2 + \|p_u\|^2)$

In [33]:

```
# initialize 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, verbose=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 : 0:00:50.921064

Evaluating the model with train data..

time taken : 0:00:10.037977

-----

Train Data

-----

RMSE : 0.6746731413267192

MAPE : 20.05479554670084

adding train results in the dictionary..

Evaluating for test data...

time taken : 0:00:00.073041

-----

Test Data

-----

RMSE : 1.06539583258785

MAPE : 34.26066030096141

storing the test results in test dictionary...

-----

Total time taken to run this algorithm : 0:01:01.033284

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

In [34]:

```
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 :**

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

- $I_u$  --- 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)**

$$\sum_{r_{ui} \in R_{train}} (r_{ui} - \hat{r}_{ui})^2 + \lambda (b_i^2 + b_u^2 + \|q_i\|^2 + \|p_u\|^2 + \|y_j\|^2)$$



In [35]:

```
# initialize the model
svdpp = SVDpp(n_factors=50, random_state=15, verbose=True)
svdpp_train_results, svdpp_test_results = run_surprise(svdpp, trainset, testset, verbose=True)

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

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 : 0:36:26.824021

Evaluating the model with train data..

time taken : 0:01:34.600753

-----

Train Data

-----

RMSE : 0.6641918784333875

MAPE : 19.24213231265533

adding train results in the dictionary..

Evaluating for test data...

time taken : 0:00:00.080597

-----

Test Data

-----

RMSE : 1.0664479484659375

MAPE : 34.15617562453539

storing the test results in test dictionary...

-----

Total time taken to run this algorithm : 0:38:01.506353

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

### Preparing Train data

In [36]:

```
# 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[36]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	...	smr4	smr5	U/
0	174683	10	3.587581	5.0	5.0	3.0	4.0	4.0	3.0	5.0	...	3.0	2.0	3.882
1	233949	10	3.587581	4.0	4.0	5.0	1.0	3.0	2.0	3.0	...	3.0	3.0	2.692

2 rows × 21 columns

### Preparing Test data

In [37]:

```
reg_test_df['svd'] = models_evaluation_test['svd']['predictions']
reg_test_df['svdpp'] = models_evaluation_test['svdpp']['predictions']

reg_test_df.head(2)
```

Out[37]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	si
0	808635	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581
1	941866	71	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581679	3.581

2 rows × 21 columns

In [38]:

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

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

In [41]:

```
clf = xgb.XGBRegressor()
params = {
    'n_estimators': [200, 400, 600, 800],
    'max_depth': [5, 10, 50, 100]
}

random_search = RandomizedSearchCV(clf, params, cv=2, scoring='neg_mean_squared_error', n_j
random_search.fit(x_train, y_train)
```

Out[41]:

```
RandomizedSearchCV(cv=2, error_score='raise-deprecating',
    estimator=XGBRegressor(base_score=0.5, booster='gbtree', colsample
_bylevel=1,
    colsample_bytree=1, gamma=0, importance_type='gain',
    learning_rate=0.1, max_delta_step=0, max_depth=3,
    min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
    nthread=None, objective='reg:linear', random_state=0, reg_alpha=0,
    reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
    subsample=1),
    fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
    param_distributions={'n_estimators': [200, 400, 600, 800], 'max_de
pth': [5, 10, 50, 100]},
    pre_dispatch='2*n_jobs', random_state=None, refit=True,
    return_train_score='warn', scoring='neg_mean_squared_error',
    verbose=0)
```

In [42]:

```
best = random_search.best_params_
best
```

Out[42]:

```
{'n_estimators': 200, 'max_depth': 5}
```

In [43]:

```
xgb_final = xgb.XGBRegressor(
    n_jobs=10,
    random_state=15,
    max_depth=5,
    n_estimators=200)
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 : 0:02:08.197637

Done

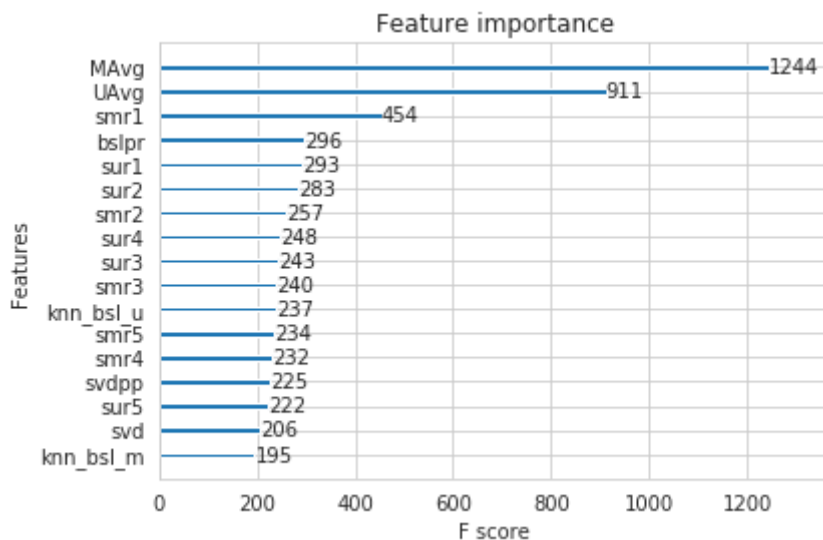
Evaluating the model with TRAIN data...

Evaluating Test data

TEST DATA

RMSE : 1.096271036373701

MAPE : 33.51852070424193



#### 4.4.8 XgBoost with Surprise Baseline + Surprise KNNbaseline + MF Techniques

In [44]:

```
# 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']
```

In [45]:

```
clf = xgb.XGBRegressor()
params = {
    'n_estimators': [200, 400, 600, 800],
    'max_depth': [5, 10, 50, 100]
}

random_search = RandomizedSearchCV(clf, params, cv=2, scoring='neg_mean_squared_error', n_j
random_search.fit(x_train, y_train)
```

Out[45]:

```
RandomizedSearchCV(cv=2, error_score='raise-deprecating',
    estimator=XGBRegressor(base_score=0.5, booster='gbtree', colsample
_bylevel=1,
    colsample_bytree=1, gamma=0, importance_type='gain',
    learning_rate=0.1, max_delta_step=0, max_depth=3,
    min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
    nthread=None, objective='reg:linear', random_state=0, reg_alpha=0,
    reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
    subsample=1),
    fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
    param_distributions={'n_estimators': [200, 400, 600, 800], 'max_de
pth': [5, 10, 50, 100]},
    pre_dispatch='2*n_jobs', random_state=None, refit=True,
    return_train_score='warn', scoring='neg_mean_squared_error',
    verbose=0)
```

In [46]:

```
best = random_search.best_params_
best
```

Out[46]:

```
{'n_estimators': 400, 'max_depth': 5}
```

In [47]:

```
xgb_all_models = xgb.XGBRegressor(  
    n_jobs=10,  
    random_state=15,  
    max_depth=5,  
    n_estimators=400)  
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 : 0:03:33.496765

Done

Evaluating the model with TRAIN data...

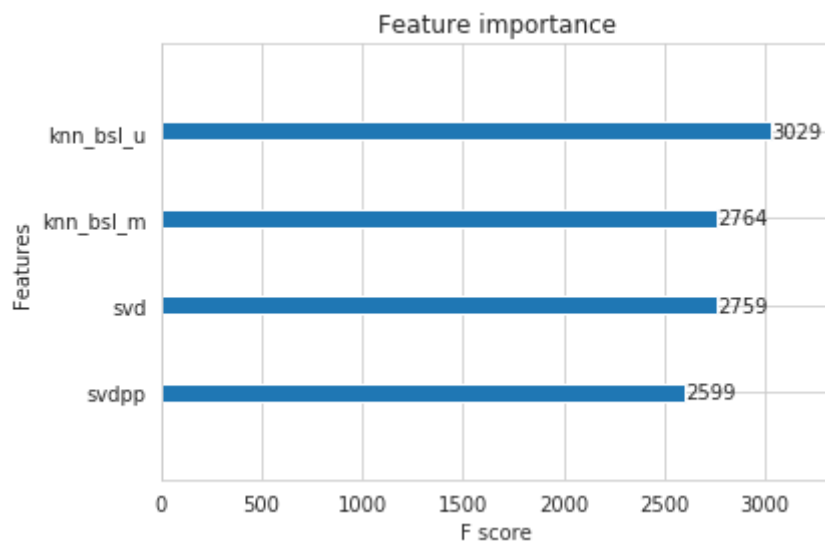
Evaluating Test data

TEST DATA

-----

RMSE : 1.0750049828399206

MAPE : 35.21017222134837



## 4.5 Comparision between all models

In [48]:

```
# Saving our TEST_RESULTS into a dataframe so that you don't have to run it again
pd.DataFrame(models_evaluation_test).to_csv('data/results.csv')
models = pd.read_csv('data/results.csv', index_col=0)
models.loc['rmse'].sort_values()
```

Out[48]:

```
knn_bsl_u      1.0651583775048283
svd            1.06539583258785
bsl_algo      1.0655294354066949
knn_bsl_m      1.066111028261093
svdpp         1.0664479484659375
xgb_all_models 1.0750049828399206
xgb_bsl       1.0804996202827688
first_algo     1.0865153626345139
xgb_knn_bsl    1.0893322610406004
xgb_final     1.096271036373701
Name: rmse, dtype: object
```

### Steps followed:

- Loaded dataset and performed basic statistics.
- Performed EDA, data preprocessing.
- Computed similarity matrices(User-User, Movie-Movie).
- Featurized data for regression problem.
- Transformed data for Surprise models.
- Applied Machine Learning Models:
  - XGBoost with initial 13 features.
  - XGBoost with initial 13 features + Surprise Baseline predictor.
  - XGBoost with initial 13 features + Surprise Baseline Predictor + KNNBaseline predictor
  - XGBoost with 13 features + Surprise Baseline + Surprise KNNbaseline + MF Techniques.
  - XGBoost with Surprise Baseline + Surprise KNNbaseline + MF Techniques.
- Applied Surprise Models:
  - Surprise Baseline Model.
  - Surprise KNNBaseline Model(User-User, Movie-Movie).
  - SVD Matrix Factorization.
  - SVDpp Matrix Factorization.
- Model Comparision.