In [133]:

```
#https://github.com/SRIRAM777/Netflix-Movie-Recommendation-System/blob/master/Netflix_Movie_Recommender_System_Sriram2.ipynb
```

Netfilx Prize

1. Business Problem

1.1 Problem Description

Netflix is all about connecting people to the movies they love. To help customers find those movies, they developed world-class movie recommendation system: CinematchSM. Its job is to predict whether someone will enjoy a movie based on how much they liked or disliked other movies. Netflix use those predictions to make personal movie recommendations based on each customer's unique tastes. And while **Cinematch** is doing pretty well, it can always be made better.

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

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

1.2 Problem Statement

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

1.3 Sources

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

paper)
- SVD Decomposition : https://www.youtube.com/watch?v=P5mlg91as1c

1.4 Real world/Business Objectives and constraints

Objectives:

1. Predict the rating that a user would give to a movie that he ahs not yet rated.
2. Minimize the difference between predicted and actual rating (RMSE and MAPE)

Constraints:

1. Some form of interpretability.

2. Machine Learning Problem

2.1 Data

2.1.1 Data Overview

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

Data files :

- combined_data_1.txt
- combined_data_2.txt
- combined_data_3.txt
- combined_data_4.txt
- movie_titles.csv

```
The first line of each file [combined_data_1.txt, combined_data_2.txt, combined_data_3.txt,
combined_data_4.txt] contains the movie id followed by a colon. 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
- Root Mean Square Error: https://en.wikipedia.org/wiki/Root-mean-square_deviation

2.2.3 Machine Learning Objective and Constraints

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

In [4]:

```
# 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

from sklearn.metrics import mean_squared_error
from surprise.model_selection import GridSearchCV
from tqdm import tqdm
```

3. Exploratory Data Analysis

3.1 Preprocessing

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

In [5]:

```
start = datetime.now()
if not os.path.isfile('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/data.csv'):
    # Create a file 'data.csv' before reading it
    # Read all the files in netflix and store them in one big file('data.csv')
    # We re reading from each of the four files and appendig each rating to a global file
'train.csv'
    data = open('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/data.csv', mode='w')

    row = list()
    files=['E:/BOOKS NEW/Cases datasets/4. Netflix Prize/combined_data_1.txt','E:/BOOKS NEW/Cases
datasets/4. Netflix Prize/combined_data_2.txt',
           'E:/BOOKS NEW/Cases datasets/4. Netflix Prize/combined_data_3.txt','E:/BOOKS NEW/Cases
datasets/4. Netflix Prize/combined_data_4.txt']
    for file in tqdm(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)
```

```
Time taken : 0:00:00.000998
```

In [6]:

```
print("creating the dataframe from data.csv file..")
df = pd.read_csv('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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 [7]:

```
df.head()
```

Out[7]:

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

In [8]:

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

Out[8]:

```
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 [9]:

```
# 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 [10]:

```
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)

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

In [11]:

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

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

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

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

In [12]:

```
if not os.path.isfile('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/train.csv'):
    # create the dataframe and store it in the disk for offline purposes..
    df.iloc[:int(df.shape[0]*0.80)].to_csv("E:/BOOKS NEW/Cases datasets/4. Netflix
Prize/train.csv", index=False)

if not os.path.isfile('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/test.csv'):
    # create the dataframe and store it in the disk for offline purposes..
    df.iloc[int(df.shape[0]*0.80):].to_csv("E:/BOOKS NEW/Cases datasets/4. Netflix Prize/test.csv",
index=False)

train_df = pd.read_csv("E:/BOOKS NEW/Cases datasets/4. Netflix Prize/train.csv",
parse_dates=['date'])
test_df = pd.read_csv("E:/BOOKS NEW/Cases datasets/4. Netflix Prize/test.csv")
```

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

In [13]:

```
# 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 [14]:

```
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 [15]:

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

3.3.1 Distribution of ratings

In [16]:

```
fig, ax = plt.subplots()
plt.title('Distribution of ratings over Training dataset', fontsize=15)
sns.countplot(train_df.rating)
ax.set_yticklabels([human(item, 'M') for item in ax.get_yticks()])
ax.set_ylabel('No. of Ratings(Millions)')

plt.show()
```

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

In [17]:

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

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

train_df.tail()
```

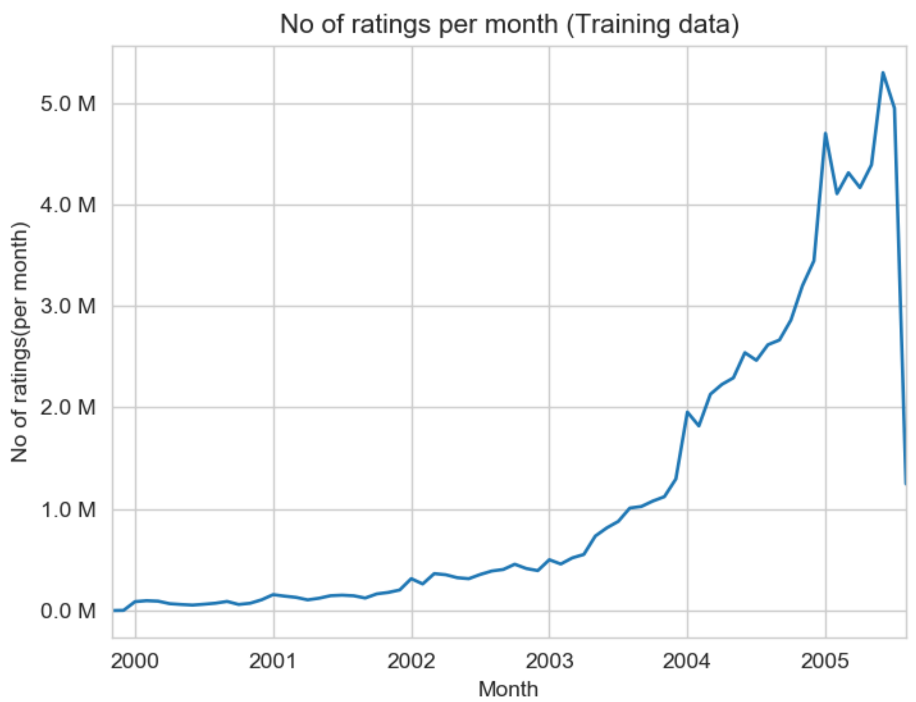
Out[17]:

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

3.3.2 Number of Ratings per a month

In [18]:

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



3.3.3 Analysis on the Ratings given by user

In [19]:

```
no_of_rated_movies_per_user = train_df.groupby(by='user')['rating'].count().sort_values(ascending=F
alse)

no_of_rated_movies_per_user.head()
```

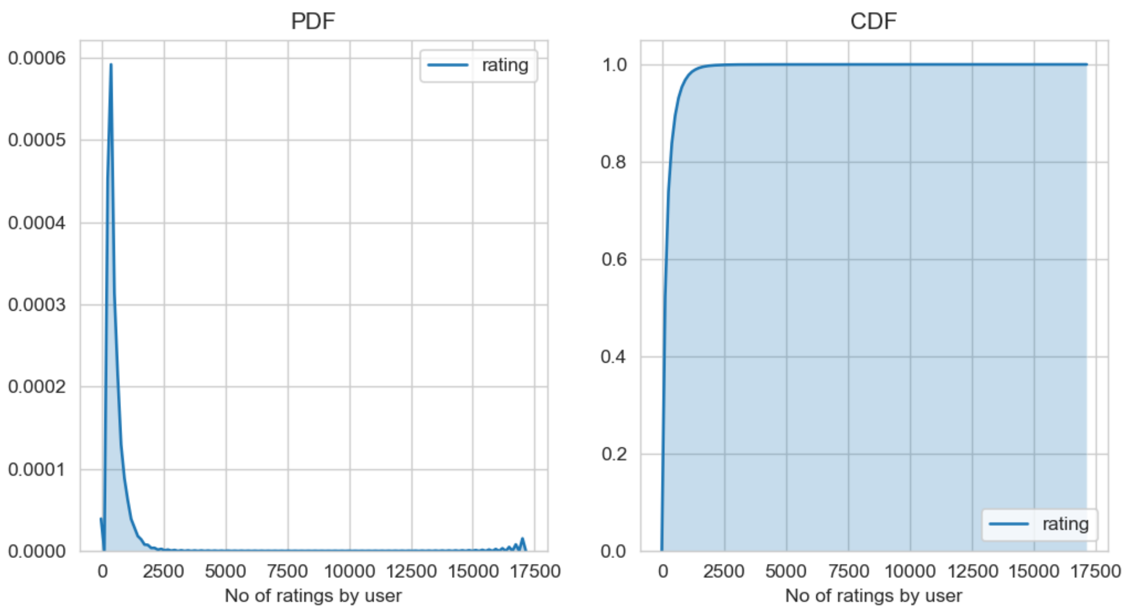
Out[19]:

```
user
305344     17112
2439493    15896
387418     15402
1639792     9767
1461435     9447
```

```
Name: rating, dtype: int64
```

In [20]:

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

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

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

plt.show()
```



In [21]:

```python
no_of_rated_movies_per_user.describe()
```

Out[21]:

```
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..*

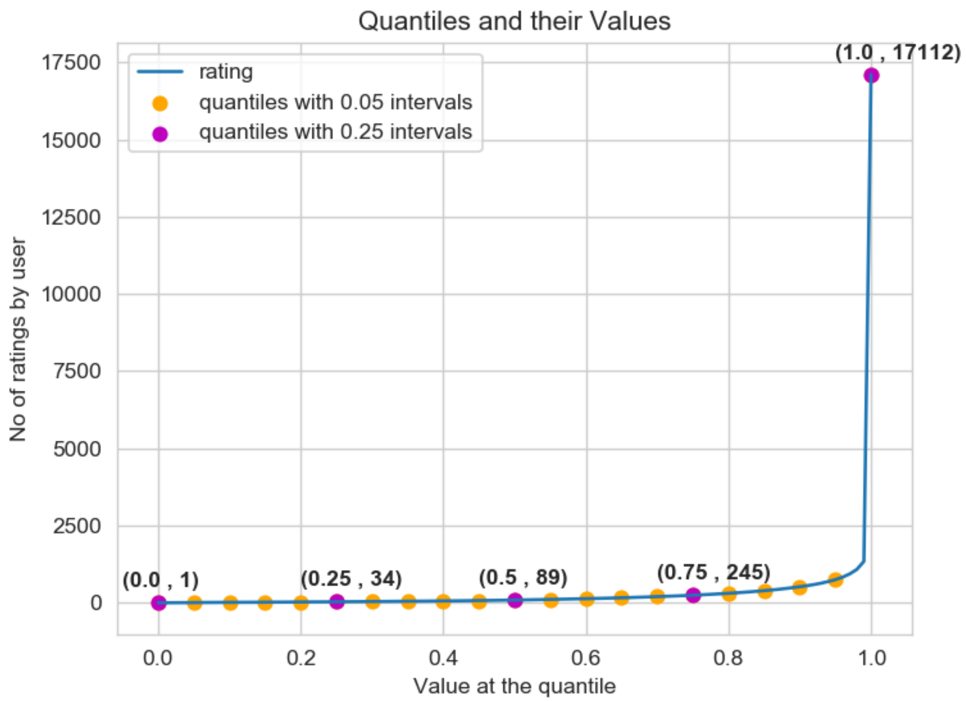
In [22]:

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

In [23]:

```python
plt.title("Quantiles and their Values")
```

```
plt.title('Quantiles and their Values')
quantiles.plot()
# quantiles with 0.05 difference
plt.scatter(x=quantiles.index[::5], y=quantiles.values[::5], c='orange', label="quantiles with 0.05
intervals")
# quantiles with 0.25 difference
plt.scatter(x=quantiles.index[::25], y=quantiles.values[::25], c='m', label = "quantiles with 0.25
intervals")
plt.ylabel('No of ratings by user')
plt.xlabel('Value at the quantile')
plt.legend(loc='best')

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


plt.show()
```



In [24]:

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

Out[24]:

```
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 [25]:

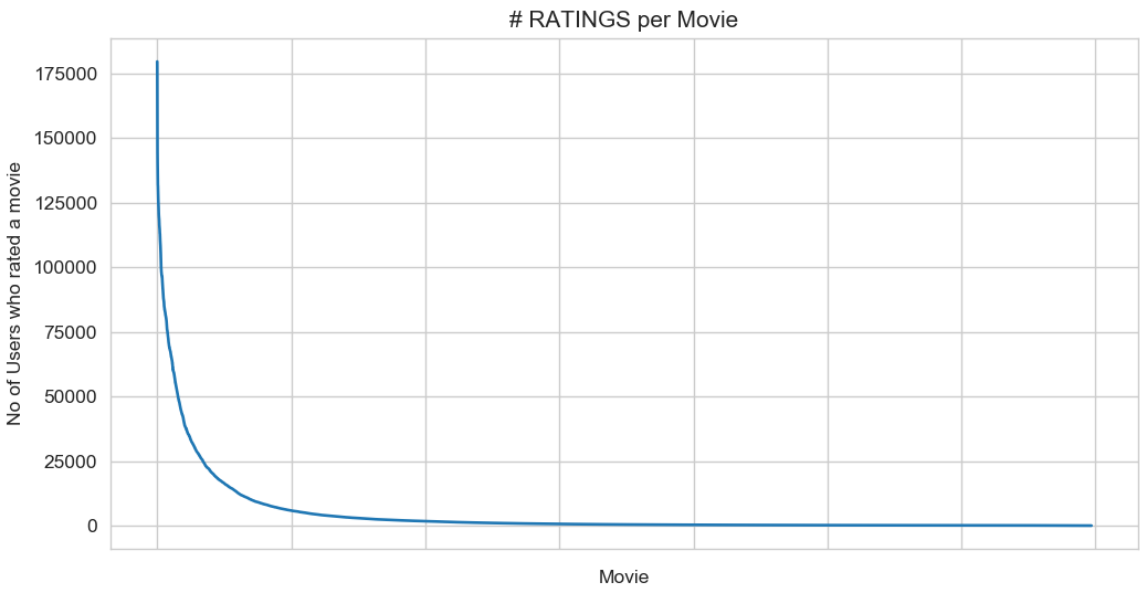
```
print('\n No of ratings at last 5 percentile : {}\n'.format(sum(no_of_rated_movies_per_user>= 749)
) )
```

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

3.3.4 Analysis of ratings of a movie given by a user

In [26]:

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

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

plt.show()
```



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

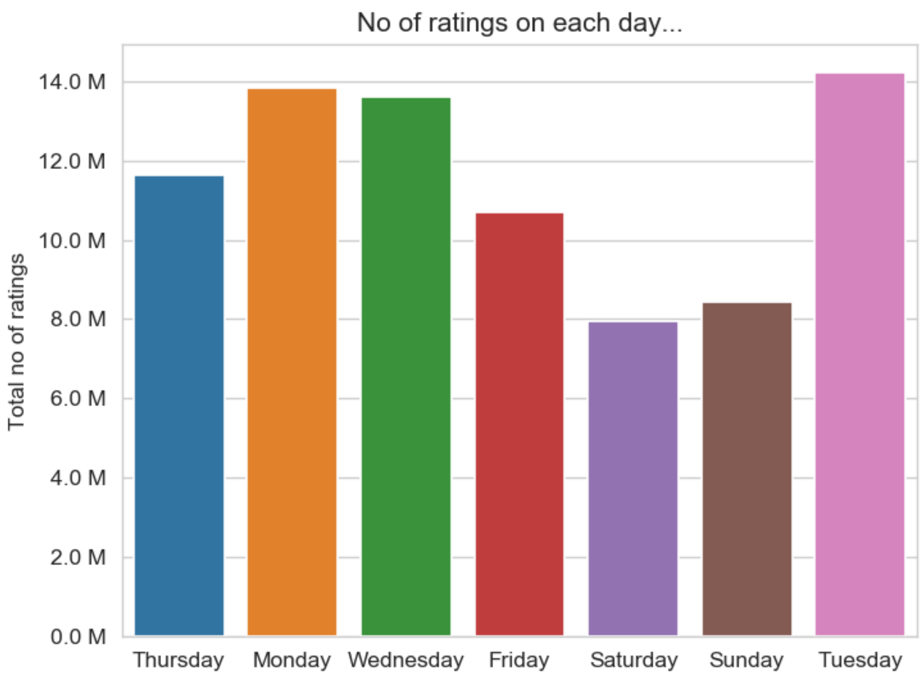
```
- There are some movies (which are very popular) which are rated by huge number of users.

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

3.3.5 Number of ratings on each day of the week

In [27]:

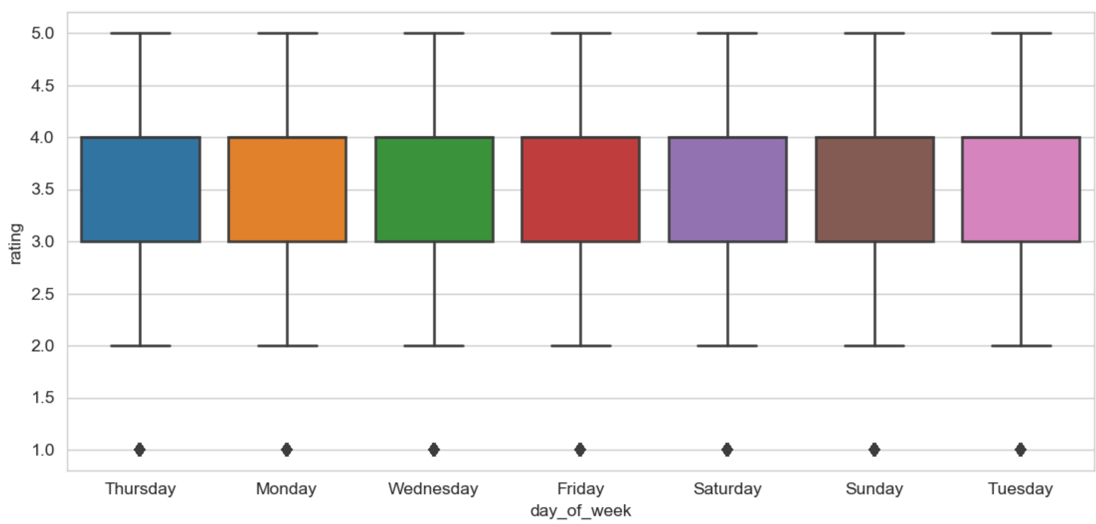
```
fig, ax = plt.subplots()
```

```
fig, ax = plt.subplots()
sns.countplot(x='day_of_week', data=train_df, ax=ax)
plt.title('No of ratings on each day...')
plt.ylabel('Total no of ratings')
plt.xlabel('')
ax.set_yticklabels([human(item, 'M') for item in ax.get_yticks()])
plt.show()
```



In [28]:

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



0:00:13.058641

In [29]:

```
avg_week_df = train_df.groupby(by=['day_of_week'])['rating'].mean()
```

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

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

3.3.6 Creating sparse matrix from data frame

3.3.6.1 Creating sparse matrix from train data frame

In [30]:

```
start = datetime.now()
if os.path.isfile('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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('E:/BOOKS NEW/Cases datasets/4. Netflix 
Prize/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("E:/BOOKS NEW/Cases datasets/4. Netflix Prize/train_sparse_matrix.npz", 
train_sparse_matrix)
    print('Done..\n')

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

```
It is present in your pwd, getting it from disk....
DONE..
0:00:03.159239
```

The Sparsity of Train Sparse Matrix

In [31]:

```
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

3.3.6.2 Creating sparse matrix from test data frame

In [32]:

```
start = datetime.now()
if os.path.isfile('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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('E:/BOOKS NEW/Cases datasets/4. Netflix
Prize/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("E:/BOOKS NEW/Cases datasets/4. Netflix Prize/test_sparse_matrix.npz",
test_sparse_matrix)
    print('Done..\n')

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

```
It is present in your pwd, getting it from disk....
DONE..
0:00:01.070142
```

The Sparsity of Test data Matrix

In [33]:

```
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 [34]:

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

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

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

3.3.7.1 finding global average of all movie ratings

In [35]:

```
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[35]:

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

3.3.7.2 finding average rating per user

In [36]:

```
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 [37]:

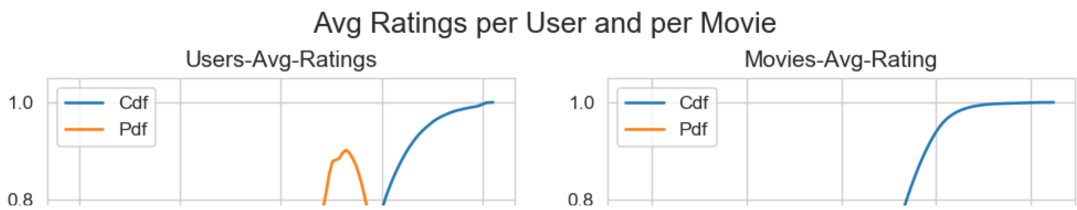
```
train_averages['movie'] =  get_average_ratings(train_sparse_matrix, of_users=False)
print('\n AVerage rating of movie 15 :',train_averages['movie'][15])
```

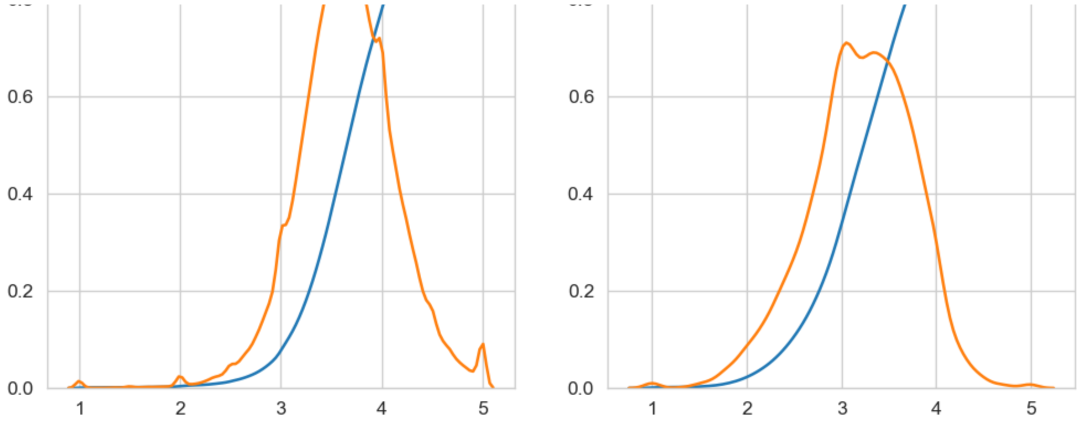
```
 AVerage rating of movie 15 : 3.3038461538461537
```

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

In [38]:

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

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

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

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






```
0:00:51.370271
```

3.3.8 Cold Start problem

3.3.8.1 Cold Start problem with Users

In [39]:

```
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_users)*100, 2)))
```

```
Total number of Users  : 480189

Number of Users in Train data : 405041

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

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

3.3.8.2 Cold Start problem with Movies

In [40]:

```
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_movies/total_movies)*100, 2)))
```

```
Total number of Movies  : 17770

Number of Users in Train data : 17424

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

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

3.4 Computing Similarity matrices

3.4.1 Computing User-User Similarity matrix

1. Calculating User User Similarity_Matrix is **not very easy**(*unless you have huge Computing Power and lots of time*) because of number of. usersbeing lare.

    - You can try if you want to. Your system could crash or the program stops with **Memory Error**

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

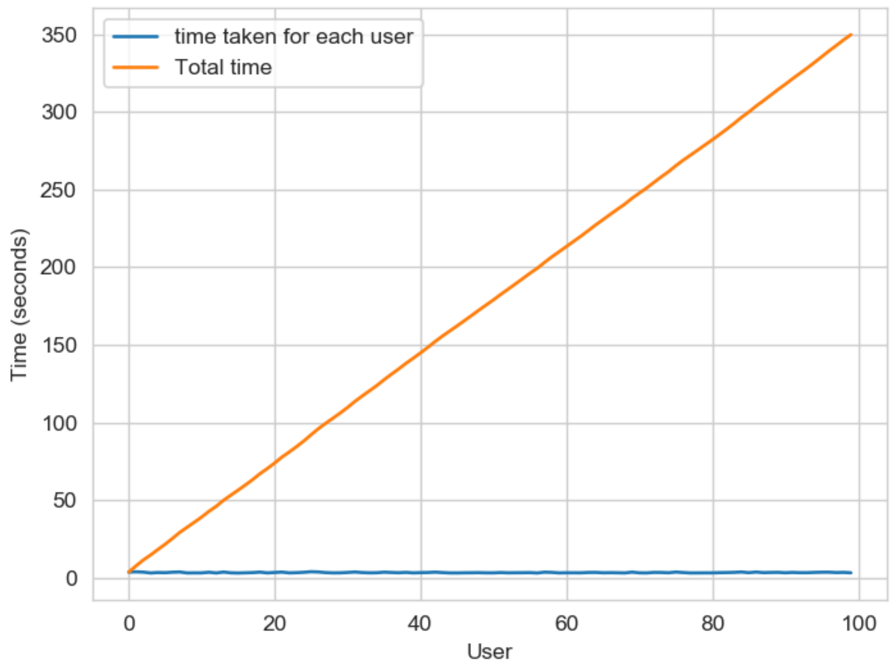
In [41]:

```
from sklearn.metrics.pairwise import cosine_similarity


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

    # we create rows, cols, and data lists.., which can be used to create 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_taken
```

In [42]:

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

```
Computing top 100 similarities for each user..
computing done for 20 users [  time elapsed : 0:01:10.426835  ]
computing done for 40 users [  time elapsed : 0:02:21.420767  ]
computing done for 60 users [  time elapsed : 0:03:29.958355  ]
computing done for 80 users [  time elapsed : 0:04:38.691169  ]
computing done for 100 users [  time elapsed : 0:05:49.646849  ]
Creating Sparse matrix from the computed similarities
```




```
----------------------------------------------------------------------------------------------------
Time taken : 0:05:59.846856
```

In [43]:

```
train_sparse_matrix.get_shape()
```

Out[43]:

```
(2649430, 17771)
```

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

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

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

In [44]:

```
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=100, algorithm='randomized', random_state=15)
trunc_svd = netflix_svd.fit_transform(train_sparse_matrix)

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

```
0:03:21.892719
```

Here,

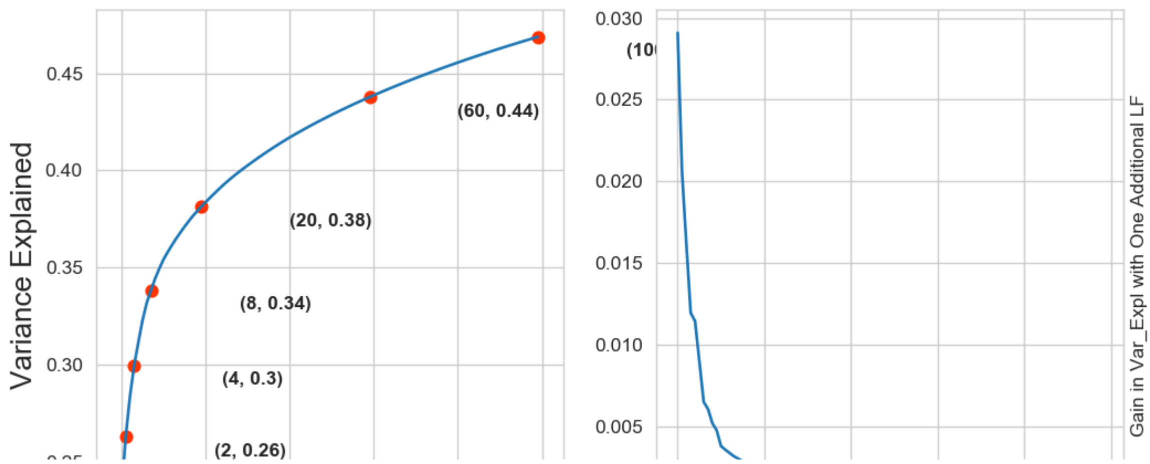
- \sum \longleftarrow (netflix_svd.**singular_values_**)
- \bigvee^T \longleftarrow (netflix_svd.**components_**)
- \bigcup is not returned. instead **Projection_of_X** onto the new vectorspace is returned.
- It uses **randomized svd** internally, which returns **All 3 of them saperately**. Use that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

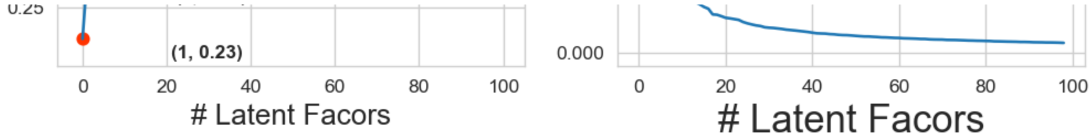
In [45]:

```
expl_var = np.cumsum(netflix_svd.explained_variance_ratio_)
```

In [46]:

```
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=plt.figaspect(.5))

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

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



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

plt.show()
```





In [47]:

```
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)
```

In [48]:

```
# 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)
```

```
0:00:04.534866
```

In [49]:

```
type(trunc_matrix), trunc_matrix.shape
```

Out[49]:

```
(numpy.ndarray, (2649430, 100))
```

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

In [50]:

```
if not os.path.isfile('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/trunc_sparse_matrix.npz'):
    # create that sparse sparse matrix
    trunc_sparse_matrix = sparse.csr_matrix(trunc_matrix)
    # Save this truncated sparse matrix for later usage..
    sparse.save_npz('trunc_sparse_matrix', trunc_sparse_matrix)
else:
    trunc_sparse_matrix = sparse.load_npz('E:/BOOKS NEW/Cases datasets/4. Netflix
Prize/trunc_sparse_matrix.npz')
```

In [51]:

```
trunc_sparse_matrix.shape
```

Out[51]:

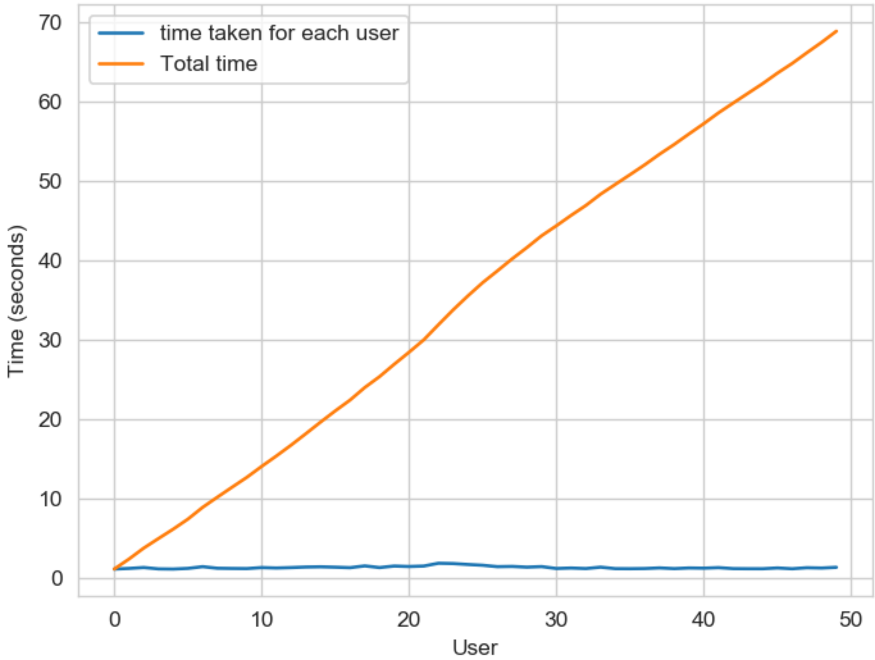
```
(2649430, 100)
```

In [52]:

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

```
Computing top 50 similarities for each user..
computing done for 10 users [  time elapsed : 0:00:12.743978  ]
```

```
computing done for 10 users [  time elapsed : 0:00:12.743978  ]
computing done for 20 users [  time elapsed : 0:00:26.991772  ]
computing done for 30 users [  time elapsed : 0:00:43.180316  ]
computing done for 40 users [  time elapsed : 0:00:56.006417  ]
computing done for 50 users [  time elapsed : 0:01:08.953996  ]
Creating Sparse matrix from the computed similarities
```




```
--------------------------------------------------
time: 0:01:14.095297
```

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

- from above plot, It took almost **12.18** for computing simlilar users for **one user**
- We have **405041 users** with us in training set.
- { 405041 \times 12.18 ==== 4933399.38 \sec } ==== 82223.323 \min ==== 1370.388716667 \text{ hours} ==== 57.099529861 \text{ days}...
  - Even we run on 4 cores parallelly (a typical system now a days), It will still take almost **(14 - 15)** days.
- **Why did this happen...??**

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

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

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

```
- We maintain a binary Vector for users, which tells us whether we already computed or
not..
- ***If not*** :
    - Compute top (let's just say, 1000) most similar users for this given user, 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 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 [53]:

```
start = datetime.now()
if not os.path.isfile('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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("E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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("E:/BOOKS NEW/Cases datasets/4. Netflix
Prize/m_m_sim_sparse.npz")
    print("Done ...")

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

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

```
It is there, We will get it.
Done ...
It's a  (17771, 17771)  dimensional matrix
0:00:31.926998
```

In [54]:

```
m_m_sim_sparse.shape
```

Out[54]:

```
(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 [55]:

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

In [56]:

```
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]
```

```
0:00:24.539848
```

Out[56]:

```
array([ 8279,  8013, 16528,  5927, 13105, 12049,  4424, 10193, 17590,
        4549,  3755,   590, 14059, 15144, 15054,  9584,  9071,  6349,
       16402,  3973,  1720,  5370, 16309,  9376,  6116,  4706,  2818,
         778, 15331,  1416, 12979, 17139, 17710,  5452,  2534,   164,
       15188,  8323,  2450, 16331,  9566, 15301, 13213, 14308, 15984,
       10597,  6426,  5500,  7068,  7328,  5720,  9802,   376, 13013,
        8003, 10199,  3338, 15390,  9688, 16455, 11730,  4513,   598,
       12762,  2187,   509,  5865,  9166, 17115, 16334,  1942,  7282,
       17584,  4376,  8988,  8873,  5921,  2716, 14679, 11947, 11981,
        4649,   565, 12954, 10788, 10220, 10963,  9427,  1690,  5107,
        7859,  5969,  1510,  2429,   847,  7845,  6410, 13931,  9840,
        3706], dtype=int64)
```

3.4.3 Finding most similar movies using similarity matrix

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

In [57]:

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

movie_titles = pd.read_csv("E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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: 4.88 ms
Type conversion took: 19.98 ms
Parser memory cleanup took: 0.00 ms
```

Out[57]:

	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 [58]:

```
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(m_m_s
im_sparse[:,mv_id].getnnz()))
```

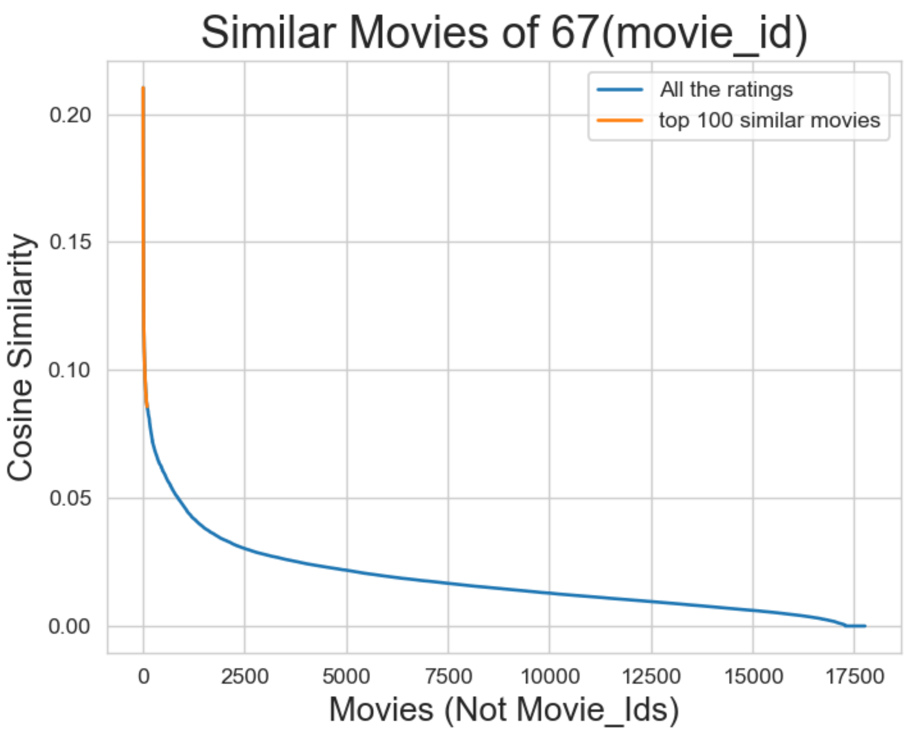
```
Movie -----> Vampire Journals

It has 270 Ratings from users.

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

In [59]:

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

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

similarities[similar_indices]

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

In [60]:

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



Top 10 similar movies

In [61]:

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

Out[61]:

movie_id	year_of_release	title
323	1999.0	Modern Vampires

movie_id	year_of_release	title
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 [62]:

```
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_mc
vies)))
        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
```

Task 1 25k users and 3k movies

4.1 Sampling Data

4.1.1 Build sample train data from the train data

In [70]:

```
start = datetime.now()
path = "E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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 10k users and 1k movies from available data
sample_train_sparse_matrix = get_sample_sparse_matrix(train_sparse_matrix, no_users=10000, no_movie
s=1000,
                                             path = path)

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

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

Sampled Matrix : (users, movies) -- (10000 1000)
Sampled Matrix : Ratings -- 129286
Saving it into disk for furthur usage..
Done..

0:01:10.804951
```

4.1.2 Build sample test data from the test data

In [72]:

```
start = datetime.now()

path = "E:/BOOKS NEW/Cases datasets/4. Netflix Prize/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=25000, no_movies
=3000,
                                                 path = path)
print(datetime.now() - start)
```

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

Sampled Matrix : (users, movies) -- (25000 3000)
Sampled Matrix : Ratings -- 261693
Saving it into disk for furthur usage..
Done..

0:00:13.184578
```

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

In [65]:

```
sample_train_averages = dict()
```

4.2.1 Finding Global Average of all movie ratings

In [66]:

```
# 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[66]:

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

4.2.2 Finding Average rating per User

In [67]:

```
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 [68]:

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

```
 AVerage rating of movie 15153 : 2.752
```

4.3 Featurizing data

In [69]:

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

```
 No of ratings in Our Sampled train matrix is : 856986


 No of ratings in Our Sampled test  matrix is : 261693
```

4.3.1 Featurizing data for regression problem

4.3.1.1 Featurizing train data

In [74]:

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

In [75]:

```
############################################################
# It took me almost 10 hours to prepare this train dataset.#
############################################################
start = datetime.now()
if os.path.isfile('D:/BOOKS NEW/Cases datasets/4. Netflix Prize/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('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/reg_train.csv', mode='w') as
```

```
reg_data_file:
        count = 0
        for (user, movie, rating)  in tqdm(zip(sample_train_users, sample_train_movies,
sample_train_ratings)):
            st = datetime.now()
        #     print(user, movie)
            #--------------------- Ratings of "movie" by similar users of "user" ------------------
--
            # compute the similar Users of the "user"
            user_sim = cosine_similarity(sample_train_sparse_matrix[user],
sample_train_sparse_matrix).ravel()
            top_sim_users = user_sim.argsort()[::-1][1:] # we are ignoring 'The User' from its simi
lar users.
            # get the ratings of most similar users for this movie
            top_ratings = sample_train_sparse_matrix[top_sim_users, movie].toarray().ravel()
            # we will make it's length "5" by adding movie averages to .
            top_sim_users_ratings = list(top_ratings[top_ratings != 0][:5])
            top_sim_users_ratings.extend([sample_train_averages['movie'][movie]]*(5 -
len(top_sim_users_ratings)))
        #     print(top_sim_users_ratings, end=" ")


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

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

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

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


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

```
preparing 129286 tuples for the dataset..
```

```
10000it [1:09:58,  4.23it/s]
```

```
Done for 10000 rows----- 1:10:01.020953
```

```
20000it [1:49:54,  4.61it/s]
```

```
Done for 20000 rows----- 1:49:57.432888
```

```
30000it [2:29:50,  4.65it/s]
```

```
Done for 30000 rows----- 2:29:53.300849
```

```
40000it [3:07:09,  4.59it/s]
```

```
Done for 40000 rows----- 3:07:12.406253
```

```
50000it [3:43:56,  4.71it/s]
```

```
Done for 50000 rows----- 3:43:58.893251
```

```
60000it [4:20:33,  4.69it/s]
```

```
Done for 60000 rows----- 4:20:36.041462
```

```
70000it [4:56:31,  4.66it/s]
```

```
Done for 70000 rows----- 4:56:34.452803
```

```
80000it [5:33:28,  4.60it/s]
```

```
Done for 80000 rows----- 5:33:30.875203
```

```
90000it [6:10:31,  4.71it/s]
```

```
Done for 90000 rows----- 6:10:33.851802
```

```
100000it [6:47:59,  4.70it/s]
```

```
Done for 100000 rows----- 6:48:02.617110
```

```
110000it [7:24:55,  4.53it/s]
```

```
Done for 110000 rows----- 7:24:58.327557
```

```
120000it [8:03:43,  4.68it/s]
```

```
Done for 120000 rows----- 8:03:45.903361
```

```
129286it [8:37:17,  4.17it/s]
```

```
8:37:20.388394
```

In [76]:

```
reg_train = pd.read_csv('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/reg_train.csv', names =
['user', 'movie', 'GAvg', 'sur1', 'sur2', 'sur3', 'sur4', 'sur5','smr1', 'smr2', 'smr3', 'smr4', 'sm
r5', 'UAvg', 'MAvg', 'rating'], header=None)
reg_train.head()
```

Out[76]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	UAvg	MAvg	rating
0	53406	33	3.587581	4.0	5.0	5.0	4.0	1.0	5.0	2.0	5.0	3.0	1.0	3.408333	4.114865	4

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	UAvg	MAvg	rating
1	99540	33	3.587581	5.0	5.0	5.0	4.0	5.0	3.0	4.0	4.0	3.0	5.0	3.142857	4.114865	3
2	99865	33	3.587581	5.0	5.0	4.0	5.0	3.0	5.0	4.0	4.0	5.0	4.0	3.642424	4.114865	5
3	101620	33	3.587581	2.0	3.0	5.0	5.0	4.0	4.0	3.0	3.0	4.0	5.0	3.640777	4.114865	5
4	112974	33	3.587581	5.0	5.0	5.0	5.0	5.0	3.0	5.0	5.0	5.0	3.0	3.809524	4.114865	5

- **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 [161]:

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

In [162]:

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

Out[162]:

```
3.5875813607223455
```

In [166]:

```
start = datetime.now()

if os.path.isfile('D:/BOOKS NEW/Cases datasets/4. Netflix Prize/reg_test.csv'):
    print("It is already created...")
else:

    print('preparing {} tuples for the dataset..\n'.format(len(sample_test_ratings)))
    with open('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/reg_test.csv', mode='w') as
reg_data_file:
        count = 0
        for (user, movie, rating)  in tqdm(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).ravel()
                top_sim_users = user_sim.argsort()[::-1][1:] # we are ignoring 'The User' from its
similar users.
                # get the ratings of most similar users for this movie
                top_ratings = sample_train_sparse_matrix[top_sim_users, movie].toarray().ravel()
                # we will make it's length "5" by adding movie averages to .
                top_sim_users_ratings = list(top_ratings[top_ratings != 0][:5])
                top_sim_users_ratings.extend([sample_train_averages['movie'][movie]]*(5 -
```

```
len(top_sim_users_ratings)))
                # print(top_sim_users_ratings, end="--")

            except (IndexError, KeyError):
                # It is a new User or new Movie or there are no ratings for given user for top simi
lar movies...
                ########## Cold STart Problem ##########
                top_sim_users_ratings.extend([sample_train_averages['global']]*(5 - 
len(top_sim_users_ratings)))
                #print(top_sim_users_ratings)
            except:
                print(user, movie)
                # we just want KeyErrors to be resolved. Not every 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.T).ravel()
                top_sim_movies = movie_sim.argsort()[::-1][1:] # we are ignoring 'The User' from it
s similar users.
                # get the ratings of most similar movie rated by this user..
                top_ratings = sample_train_sparse_matrix[user, top_sim_movies].toarray().ravel()
                # we will make it's length "5" by adding user averages to.
                top_sim_movies_ratings = list(top_ratings[top_ratings != 0][:5])
                top_sim_movies_ratings.extend([sample_train_averages['user']
[user]]*(5-len(top_sim_movies_ratings)))
                #print(top_sim_movies_ratings)
            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)))
```

```python
            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)
```

```
0it [00:00, ?it/s]
```

```
preparing 261693 tuples for the dataset..
```

```
1000it [04:53,  3.40it/s]
```

```
Done for 1000 rows----- 0:04:53.464930
```

```
2000it [09:48,  3.47it/s]
```

```
Done for 2000 rows----- 0:09:48.601744
```

```
3000it [14:44,  3.40it/s]
```

```
Done for 3000 rows----- 0:14:44.218693
```

```
4000it [19:39,  3.40it/s]
```

```
Done for 4000 rows----- 0:19:39.478822
```

```
5000it [24:33,  3.39it/s]
```

```
Done for 5000 rows----- 0:24:34.085708
```

```
6000it [29:28,  3.40it/s]
```

```
Done for 6000 rows----- 0:29:28.973604
```

```
7000it [34:24,  3.37it/s]
```

```
Done for 7000 rows----- 0:34:24.635472
```

```
8000it [39:21,  3.25it/s]
```

```
Done for 8000 rows----- 0:39:21.589929
```

```
9000it [44:13,  3.44it/s]
```

```
Done for 9000 rows----- 0:44:13.288773
```

```
10000it [49:04,  3.46it/s]
```

```
Done for 10000 rows----- 0:49:04.364601
```

```
11000it [53:54,  3.46it/s]
```

```
Done for 11000 rows----- 0:53:54.832275
```

```
12000it [58:45,  3.45it/s]
```

```
Done for 12000 rows----- 0:58:45.522583
```

```
13000it [1:03:36,  3.44it/s]
Done for 13000 rows----- 1:03:36.375005
14000it [1:08:27,  3.43it/s]
Done for 14000 rows----- 1:08:27.266043
15000it [1:13:20,  3.38it/s]
Done for 15000 rows----- 1:13:20.283073
16000it [1:18:12,  3.45it/s]
Done for 16000 rows----- 1:18:12.151280
17000it [1:23:03,  3.43it/s]
Done for 17000 rows----- 1:23:03.948785
18000it [1:27:55,  3.32it/s]
Done for 18000 rows----- 1:27:55.487318
19000it [1:32:47,  3.45it/s]
Done for 19000 rows----- 1:32:47.342975
20000it [1:37:38,  3.43it/s]
Done for 20000 rows----- 1:37:38.742839
21000it [1:42:29,  3.45it/s]
Done for 21000 rows----- 1:42:29.953854
22000it [1:47:22,  3.41it/s]
Done for 22000 rows----- 1:47:22.119719
23000it [1:52:15,  3.43it/s]
Done for 23000 rows----- 1:52:15.972511
24000it [1:57:07,  3.44it/s]
Done for 24000 rows----- 1:57:07.655419
25000it [2:01:59,  3.45it/s]
Done for 25000 rows----- 2:01:59.127206
26000it [2:06:50,  3.45it/s]
Done for 26000 rows----- 2:06:50.569374
27000it [2:11:41,  3.46it/s]
Done for 27000 rows----- 2:11:41.281731
```

```
Done for 27000 rows----- 2:11:41.261751
```

```
28000it [2:16:31,  3.45it/s]
```

```
Done for 28000 rows----- 2:16:32.070315
```

```
29000it [2:21:22,  3.45it/s]
```

```
Done for 29000 rows----- 2:21:22.731873
```

```
30000it [2:26:13,  3.42it/s]
```

```
Done for 30000 rows----- 2:26:13.801031
```

```
31000it [2:31:04,  3.44it/s]
```

```
Done for 31000 rows----- 2:31:04.211714
```

```
32000it [2:35:54,  3.45it/s]
```

```
Done for 32000 rows----- 2:35:54.629199
```

```
33000it [2:40:45,  3.36it/s]
```

```
Done for 33000 rows----- 2:40:46.017475
```

```
34000it [2:45:37,  3.44it/s]
```

```
Done for 34000 rows----- 2:45:37.469295
```

```
35000it [2:50:31,  3.30it/s]
```

```
Done for 35000 rows----- 2:50:31.259988
```

```
36000it [2:55:21,  3.44it/s]
```

```
Done for 36000 rows----- 2:55:21.294695
```

```
37000it [3:00:10,  3.47it/s]
```

```
Done for 37000 rows----- 3:00:10.189563
```

```
38000it [3:04:59,  3.48it/s]
```

```
Done for 38000 rows----- 3:04:59.800652
```

```
39000it [3:09:48,  3.43it/s]
```

```
Done for 39000 rows----- 3:09:48.479069
```

```
40000it [3:14:38,  3.45it/s]
```

```
Done for 40000 rows----- 3:14:38.407004
```

```
41000it [3:19:31,  3.43it/s]
```

```
Done for 41000 rows----- 3:19:31.339908
```

```
42000it [3:24:22,  3.44it/s]
```

```
Done for 42000 rows----- 3:24:22.938259

43000it [3:29:16,  3.47it/s]

Done for 43000 rows----- 3:29:16.502441

44000it [3:34:04,  3.48it/s]

Done for 44000 rows----- 3:34:04.625671

45000it [3:38:52,  3.49it/s]

Done for 45000 rows----- 3:38:52.726520

46000it [3:43:45,  3.43it/s]

Done for 46000 rows----- 3:43:46.046929

47000it [3:48:38,  3.45it/s]

Done for 47000 rows----- 3:48:39.016879

48000it [3:53:29,  3.43it/s]

Done for 48000 rows----- 3:53:30.010534

49000it [3:58:23,  3.46it/s]

Done for 49000 rows----- 3:58:23.867069

50000it [4:03:14,  3.41it/s]

Done for 50000 rows----- 4:03:15.060555

51000it [4:08:06,  3.44it/s]

Done for 51000 rows----- 4:08:06.662502

52000it [4:12:57,  3.45it/s]

Done for 52000 rows----- 4:12:57.262997

53000it [4:17:47,  3.42it/s]

Done for 53000 rows----- 4:17:47.961709

54000it [4:22:38,  3.42it/s]

Done for 54000 rows----- 4:22:38.412703

55000it [4:27:40,  3.40it/s]

Done for 55000 rows----- 4:27:40.097160

56000it [4:32:42,  3.32it/s]

Done for 56000 rows----- 4:32:42.301827
```

```
57000it [4:37:44,  3.34it/s]
```

Done for 57000 rows----- 4:37:44.905550

```
58000it [4:42:48,  3.29it/s]
```

Done for 58000 rows----- 4:42:48.193096

```
59000it [4:47:52,  3.28it/s]
```

Done for 59000 rows----- 4:47:52.706010

```
60000it [4:52:59,  3.30it/s]
```

Done for 60000 rows----- 4:52:59.763658

```
61000it [4:58:06,  3.29it/s]
```

Done for 61000 rows----- 4:58:06.600929

```
62000it [5:03:11,  3.29it/s]
```

Done for 62000 rows----- 5:03:11.764599

```
63000it [5:08:18,  3.35it/s]
```

Done for 63000 rows----- 5:08:18.970442

```
64000it [5:13:58,  3.31it/s]
```

Done for 64000 rows----- 5:13:58.303893

```
65000it [5:19:12,  3.24it/s]
```

Done for 65000 rows----- 5:19:12.375356

```
66000it [5:24:56,  3.21it/s]
```

Done for 66000 rows----- 5:24:56.674799

```
67000it [5:30:24,  3.20it/s]
```

Done for 67000 rows----- 5:30:24.693999

```
68000it [5:35:50,  3.11it/s]
```

Done for 68000 rows----- 5:35:50.436912

```
69000it [5:41:25,  2.10it/s]
```

Done for 69000 rows----- 5:41:25.693648

```
70000it [5:47:01,  1.95it/s]
```

Done for 70000 rows----- 5:47:01.582038

```
71000it [5:53:04,  2.37it/s]
```

```
Done for 71000 rows----- 5:53:04.153760

72000it [5:58:06,  3.37it/s]

Done for 72000 rows----- 5:58:06.620051

73000it [6:03:09,  3.37it/s]

Done for 73000 rows----- 6:03:09.360272

74000it [6:08:12,  3.34it/s]

Done for 74000 rows----- 6:08:12.807577

75000it [6:13:21,  3.35it/s]

Done for 75000 rows----- 6:13:21.484347

76000it [6:18:30,  3.30it/s]

Done for 76000 rows----- 6:18:31.089653

77000it [6:23:58,  3.19it/s]

Done for 77000 rows----- 6:23:59.009509

78000it [6:28:56,  3.44it/s]

Done for 78000 rows----- 6:28:56.242840

79000it [6:33:49,  3.40it/s]

Done for 79000 rows----- 6:33:49.175892

80000it [6:38:44,  3.41it/s]

Done for 80000 rows----- 6:38:44.241490

81000it [6:43:36,  3.42it/s]

Done for 81000 rows----- 6:43:37.006837

82000it [6:48:29,  3.35it/s]

Done for 82000 rows----- 6:48:30.036435

83000it [6:53:22,  3.44it/s]

Done for 83000 rows----- 6:53:22.524687

84000it [6:58:15,  3.39it/s]

Done for 84000 rows----- 6:58:15.275481

85000it [7:03:09,  3.45it/s]

Done for 85000 rows----- 7:03:09.102045
```

```
86000it [7:08:02,  3.35it/s]
```

Done for 86000 rows----- 7:08:02.095156

```
87000it [7:12:54,  3.42it/s]
```

Done for 87000 rows----- 7:12:54.225316

```
88000it [7:17:50,  3.38it/s]
```

Done for 88000 rows----- 7:17:50.447905

```
89000it [7:22:46,  3.42it/s]
```

Done for 89000 rows----- 7:22:46.758285

```
90000it [7:27:46,  3.38it/s]
```

Done for 90000 rows----- 7:27:47.077309

```
91000it [7:32:39,  3.43it/s]
```

Done for 91000 rows----- 7:32:39.989649

```
92000it [7:37:31,  3.42it/s]
```

Done for 92000 rows----- 7:37:32.028351

```
93000it [7:42:24,  3.44it/s]
```

Done for 93000 rows----- 7:42:24.178335

```
94000it [7:47:16,  3.42it/s]
```

Done for 94000 rows----- 7:47:16.628973

```
95000it [7:52:09,  3.42it/s]
```

Done for 95000 rows----- 7:52:09.264853

```
96000it [7:57:02,  3.37it/s]
```

Done for 96000 rows----- 7:57:02.126981

```
97000it [8:01:54,  3.39it/s]
```

Done for 97000 rows----- 8:01:54.681689

```
98000it [8:06:49,  3.41it/s]
```

Done for 98000 rows----- 8:06:50.026485

```
99000it [8:11:45,  3.43it/s]
```

Done for 99000 rows----- 8:11:45.631853

```
100000it [8:16:38,  3.42it/s]
```

```
Done for 100000 rows----- 8:16:38.511992
101000it [8:21:30,  3.43it/s]
Done for 101000 rows----- 8:21:30.979661
102000it [8:26:26,  3.43it/s]
Done for 102000 rows----- 8:26:26.778106
103000it [8:31:18,  3.41it/s]
Done for 103000 rows----- 8:31:18.985415
104000it [8:36:15,  3.42it/s]
Done for 104000 rows----- 8:36:15.496857
105000it [8:41:10,  3.38it/s]
Done for 105000 rows----- 8:41:10.164211
106000it [8:46:03,  3.40it/s]
Done for 106000 rows----- 8:46:03.890931
107000it [8:50:56,  3.40it/s]
Done for 107000 rows----- 8:50:56.687423
108000it [8:55:51,  3.40it/s]
Done for 108000 rows----- 8:55:51.108899
109000it [9:00:44,  3.40it/s]
Done for 109000 rows----- 9:00:44.829513
110000it [9:05:37,  3.43it/s]
Done for 110000 rows----- 9:05:37.154322
111000it [9:10:29,  3.37it/s]
Done for 111000 rows----- 9:10:29.340905
112000it [9:15:21,  3.44it/s]
Done for 112000 rows----- 9:15:21.635337
113000it [9:20:14,  3.42it/s]
Done for 113000 rows----- 9:20:14.408948
114000it [9:25:07,  3.40it/s]
Done for 114000 rows----- 9:25:07.191606
```

```
115000it [9:30:01,  3.31it/s]
```

Done for 115000 rows----- 9:30:02.058844

```
116000it [9:34:55,  3.37it/s]
```

Done for 116000 rows----- 9:34:55.721029

```
117000it [9:39:50,  3.39it/s]
```

Done for 117000 rows----- 9:39:50.242596

```
118000it [9:44:43,  3.42it/s]
```

Done for 118000 rows----- 9:44:43.356112

```
119000it [9:49:35,  3.44it/s]
```

Done for 119000 rows----- 9:49:35.743301

```
120000it [9:54:28,  3.42it/s]
```

Done for 120000 rows----- 9:54:28.438154

```
121000it [9:59:20,  3.42it/s]
```

Done for 121000 rows----- 9:59:20.540480

```
122000it [10:04:12,  3.43it/s]
```

Done for 122000 rows----- 10:04:12.972352

```
123000it [10:09:08,  3.34it/s]
```

Done for 123000 rows----- 10:09:08.372422

```
124000it [10:14:01,  3.36it/s]
```

Done for 124000 rows----- 10:14:01.841111

```
125000it [10:18:54,  3.41it/s]
```

Done for 125000 rows----- 10:18:54.487264

```
126000it [10:23:46,  3.43it/s]
```

Done for 126000 rows----- 10:23:46.534312

```
127000it [10:28:38,  3.43it/s]
```

Done for 127000 rows----- 10:28:38.929714

```
128000it [10:33:30,  3.44it/s]
```

Done for 128000 rows----- 10:33:31.067869

```
129000it [10:38:23,  3.45it/s]
```

```
Done for 129000 rows----- 10:38:23.239037
130000it [10:43:15,  3.43it/s]
Done for 130000 rows----- 10:43:15.203407
131000it [10:48:07,  3.42it/s]
Done for 131000 rows----- 10:48:07.538535
132000it [10:53:00,  3.43it/s]
Done for 132000 rows----- 10:53:00.811187
133000it [10:57:53,  3.41it/s]
Done for 133000 rows----- 10:57:54.032154
134000it [11:02:46,  3.39it/s]
Done for 134000 rows----- 11:02:46.577636
135000it [11:07:38,  3.42it/s]
Done for 135000 rows----- 11:07:38.559340
136000it [11:12:30,  3.44it/s]
Done for 136000 rows----- 11:12:30.591514
137000it [11:17:23,  3.43it/s]
Done for 137000 rows----- 11:17:23.868971
138000it [11:22:16,  3.42it/s]
Done for 138000 rows----- 11:22:16.600186
139000it [11:27:09,  3.43it/s]
Done for 139000 rows----- 11:27:09.120479
140000it [11:32:01,  3.37it/s]
Done for 140000 rows----- 11:32:01.707169
141000it [11:36:54,  3.42it/s]
Done for 141000 rows----- 11:36:54.275629
142000it [11:41:46,  3.43it/s]
Done for 142000 rows----- 11:41:46.517487
143000it [11:46:38,  3.43it/s]
Done for 143000 rows----- 11:46:38.938412
```

```
144000it [11:51:31,  3.41it/s]
```

Done for 144000 rows----- 11:51:31.470209

```
145000it [11:56:23,  3.44it/s]
```

Done for 145000 rows----- 11:56:23.623027

```
146000it [12:01:15,  3.45it/s]
```

Done for 146000 rows----- 12:01:15.962747

```
147000it [12:06:09,  3.39it/s]
```

Done for 147000 rows----- 12:06:10.005158

```
148000it [12:11:04,  3.40it/s]
```

Done for 148000 rows----- 12:11:04.851110

```
149000it [12:15:57,  3.38it/s]
```

Done for 149000 rows----- 12:15:57.439908

```
150000it [12:20:49,  3.41it/s]
```

Done for 150000 rows----- 12:20:49.486580

```
151000it [12:25:41,  3.42it/s]
```

Done for 151000 rows----- 12:25:41.344164

```
152000it [12:30:33,  3.41it/s]
```

Done for 152000 rows----- 12:30:33.446616

```
153000it [12:35:25,  3.42it/s]
```

Done for 153000 rows----- 12:35:25.502790

```
154000it [12:40:16,  3.44it/s]
```

Done for 154000 rows----- 12:40:17.060159

```
155000it [12:45:09,  3.39it/s]
```

Done for 155000 rows----- 12:45:09.380105

```
156000it [12:50:03,  3.38it/s]
```

Done for 156000 rows----- 12:50:03.169450

```
157000it [12:54:56,  3.42it/s]
```

Done for 157000 rows----- 12:54:56.292045

```
158000it [12:59:49,  3.42it/s]
```

```
Done for 158000 rows----- 12:59:49.364752
```

```
159000it [13:04:41,  3.42it/s]
```

```
Done for 159000 rows----- 13:04:41.373079
```

```
160000it [13:09:33,  3.42it/s]
```

```
Done for 160000 rows----- 13:09:33.120014
```

```
161000it [13:14:25,  3.35it/s]
```

```
Done for 161000 rows----- 13:14:25.211756
```

```
162000it [13:19:16,  3.42it/s]
```

```
Done for 162000 rows----- 13:19:16.982297
```

```
163000it [13:24:09,  3.43it/s]
```

```
Done for 163000 rows----- 13:24:09.162576
```

```
164000it [13:29:00,  3.42it/s]
```

```
Done for 164000 rows----- 13:29:01.081600
```

```
165000it [13:33:52,  3.45it/s]
```

```
Done for 165000 rows----- 13:33:52.719062
```

```
166000it [13:38:44,  3.44it/s]
```

```
Done for 166000 rows----- 13:38:44.375970
```

```
167000it [13:43:36,  3.42it/s]
```

```
Done for 167000 rows----- 13:43:36.094554
```

```
168000it [13:48:29,  3.39it/s]
```

```
Done for 168000 rows----- 13:48:29.980487
```

```
169000it [13:53:22,  3.43it/s]
```

```
Done for 169000 rows----- 13:53:22.604000
```

```
170000it [13:58:15,  3.43it/s]
```

```
Done for 170000 rows----- 13:58:15.224715
```

```
171000it [14:03:07,  3.41it/s]
```

```
Done for 171000 rows----- 14:03:08.048575
```

```
172000it [14:08:00,  3.43it/s]
```

```
Done for 172000 rows----- 14:08:00.446758
```

```
173000it [14:12:52,  3.43it/s]

Done for 173000 rows----- 14:12:52.687115

174000it [14:17:45,  3.42it/s]

Done for 174000 rows----- 14:17:45.184900

175000it [14:22:37,  3.42it/s]

Done for 175000 rows----- 14:22:37.603668

176000it [14:27:30,  3.41it/s]

Done for 176000 rows----- 14:27:30.291579

177000it [14:32:22,  3.44it/s]

Done for 177000 rows----- 14:32:22.648379

178000it [14:37:14,  3.43it/s]

Done for 178000 rows----- 14:37:15.011891

179000it [14:42:07,  3.40it/s]

Done for 179000 rows----- 14:42:07.587225

180000it [14:47:00,  3.42it/s]

Done for 180000 rows----- 14:47:00.431228

181000it [14:51:52,  3.43it/s]

Done for 181000 rows----- 14:51:52.925402

182000it [14:56:45,  3.43it/s]

Done for 182000 rows----- 14:56:45.644518

183000it [15:01:38,  3.41it/s]

Done for 183000 rows----- 15:01:38.100103

184000it [15:06:36,  3.27it/s]

Done for 184000 rows----- 15:06:36.461469

185000it [15:11:51,  3.16it/s]

Done for 185000 rows----- 15:11:52.060341

186000it [15:17:08,  3.39it/s]

Done for 186000 rows----- 15:17:08.545541

187000it [15:22:01,  3.33it/s]
```

```
Done for 187000 rows----- 15:22:02.000962
188000it [15:26:54,  3.44it/s]
Done for 188000 rows----- 15:26:55.020582
189000it [15:31:47,  3.41it/s]
Done for 189000 rows----- 15:31:47.932773
190000it [15:36:41,  3.24it/s]
Done for 190000 rows----- 15:36:41.262836
191000it [15:41:34,  3.40it/s]
Done for 191000 rows----- 15:41:34.103007
192000it [15:46:25,  3.41it/s]
Done for 192000 rows----- 15:46:25.779714
193000it [15:51:16,  3.40it/s]
Done for 193000 rows----- 15:51:16.680863
194000it [15:56:06,  3.44it/s]
Done for 194000 rows----- 15:56:06.970081
195000it [16:00:57,  3.45it/s]
Done for 195000 rows----- 16:00:57.550356
196000it [16:05:50,  3.40it/s]
Done for 196000 rows----- 16:05:50.502156
197000it [16:10:42,  3.42it/s]
Done for 197000 rows----- 16:10:42.636496
198000it [16:15:34,  3.41it/s]
Done for 198000 rows----- 16:15:34.977311
199000it [16:20:26,  3.33it/s]
Done for 199000 rows----- 16:20:26.141613
200000it [16:25:17,  3.41it/s]
Done for 200000 rows----- 16:25:17.538653
201000it [16:30:08,  3.45it/s]
Done for 201000 rows----- 16:30:08.381005
```

```
202000it [16:35:01,  3.40it/s]
```

Done for 202000 rows----- 16:35:01.415978

```
203000it [16:39:55,  3.45it/s]
```

Done for 203000 rows----- 16:39:55.794086

```
204000it [16:44:48,  3.45it/s]
```

Done for 204000 rows----- 16:44:48.942577

```
205000it [16:49:52,  3.07it/s]
```

Done for 205000 rows----- 16:49:52.185593

```
206000it [16:54:55,  3.39it/s]
```

Done for 206000 rows----- 16:54:55.615352

```
207000it [16:59:49,  3.40it/s]
```

Done for 207000 rows----- 16:59:50.008275

```
208000it [17:04:43,  3.44it/s]
```

Done for 208000 rows----- 17:04:43.419646

```
209000it [17:09:48,  3.42it/s]
```

Done for 209000 rows----- 17:09:48.435400

```
210000it [17:14:44,  3.30it/s]
```

Done for 210000 rows----- 17:14:44.544595

```
211000it [17:19:49,  3.21it/s]
```

Done for 211000 rows----- 17:19:49.753992

```
212000it [17:24:57,  3.21it/s]
```

Done for 212000 rows----- 17:24:58.068996

```
213000it [17:30:17,  3.37it/s]
```

Done for 213000 rows----- 17:30:17.839548

```
214000it [17:35:42,  3.37it/s]
```

Done for 214000 rows----- 17:35:43.072704

```
215000it [17:40:52,  3.44it/s]
```

Done for 215000 rows----- 17:40:52.555935

```
216000it [17:45:59,  3.35it/s]
```

```
Done for 216000 rows----- 17:45:59.608770

217000it [17:51:03,  3.41it/s]

Done for 217000 rows----- 17:51:03.702365

218000it [17:56:03,  3.16it/s]

Done for 218000 rows----- 17:56:03.110878

219000it [18:01:02,  3.34it/s]

Done for 219000 rows----- 18:01:02.273968

220000it [18:06:11,  3.35it/s]

Done for 220000 rows----- 18:06:12.016550

221000it [18:11:12,  3.23it/s]

Done for 221000 rows----- 18:11:12.430200

222000it [18:16:17,  3.35it/s]

Done for 222000 rows----- 18:16:17.465217

223000it [18:21:36,  2.57it/s]

Done for 223000 rows----- 18:21:36.855689

224000it [18:26:50,  3.37it/s]

Done for 224000 rows----- 18:26:50.555676

225000it [18:31:57,  3.37it/s]

Done for 225000 rows----- 18:31:57.308876

226000it [18:37:36,  3.37it/s]

Done for 226000 rows----- 18:37:36.283731

227000it [18:42:44,  3.26it/s]

Done for 227000 rows----- 18:42:45.077955

228000it [18:47:55,  3.37it/s]

Done for 228000 rows----- 18:47:55.392184

229000it [18:53:12,  2.24it/s]

Done for 229000 rows----- 18:53:12.393034

230000it [18:58:43,  3.04it/s]

Done for 230000 rows----- 18:58:43.764846

231000it [19:04:07,  3.30it/s]
```

```
231000it [19:04:07,  3.30it/s]
```

Done for 231000 rows----- 19:04:07.376235

```
232000it [19:09:20,  3.43it/s]
```

Done for 232000 rows----- 19:09:20.611299

```
233000it [19:14:22,  3.44it/s]
```

Done for 233000 rows----- 19:14:22.913986

```
234000it [19:19:15,  3.44it/s]
```

Done for 234000 rows----- 19:19:15.897526

```
235000it [19:24:07,  3.45it/s]
```

Done for 235000 rows----- 19:24:07.721883

```
236000it [19:28:58,  3.42it/s]
```

Done for 236000 rows----- 19:28:58.903867

```
237000it [19:33:49,  3.46it/s]
```

Done for 237000 rows----- 19:33:49.708762

```
238000it [19:38:40,  3.46it/s]
```

Done for 238000 rows----- 19:38:40.726379

```
239000it [19:43:38,  2.80it/s]
```

Done for 239000 rows----- 19:43:38.964873

```
240000it [19:49:32,  2.52it/s]
```

Done for 240000 rows----- 19:49:33.081988

```
241000it [19:55:37,  2.63it/s]
```

Done for 241000 rows----- 19:55:37.895865

```
242000it [20:01:01,  3.40it/s]
```

Done for 242000 rows----- 20:01:01.266092

```
243000it [20:05:55,  3.43it/s]
```

Done for 243000 rows----- 20:05:55.904452

```
244000it [20:10:47,  3.43it/s]
```

Done for 244000 rows----- 20:10:47.870466

```
245000it [20:15:42,  3.42it/s]
```

Done for 245000 rows----- 20:15:42.300845

```
Done for 245000 rows----- 20:15:42.560645
```

```
246000it [20:20:36,  3.38it/s]
```

```
Done for 246000 rows----- 20:20:36.969552
```

```
247000it [20:25:55,  3.35it/s]
```

```
Done for 247000 rows----- 20:25:55.790999
```

```
248000it [20:31:00,  3.33it/s]
```

```
Done for 248000 rows----- 20:31:00.492151
```

```
249000it [20:35:59,  3.33it/s]
```

```
Done for 249000 rows----- 20:35:59.953941
```

```
250000it [20:40:59,  3.36it/s]
```

```
Done for 250000 rows----- 20:40:59.229624
```

```
251000it [20:46:03,  3.29it/s]
```

```
Done for 251000 rows----- 20:46:03.887515
```

```
252000it [20:51:02,  3.32it/s]
```

```
Done for 252000 rows----- 20:51:02.840776
```

```
253000it [20:56:06,  3.31it/s]
```

```
Done for 253000 rows----- 20:56:06.755399
```

```
254000it [21:01:14,  2.96it/s]
```

```
Done for 254000 rows----- 21:01:14.439829
```

```
255000it [21:06:22,  3.32it/s]
```

```
Done for 255000 rows----- 21:06:22.815774
```

```
256000it [21:11:28,  3.34it/s]
```

```
Done for 256000 rows----- 21:11:28.167842
```

```
257000it [21:16:37,  3.31it/s]
```

```
Done for 257000 rows----- 21:16:37.778363
```

```
258000it [21:21:51,  3.32it/s]
```

```
Done for 258000 rows----- 21:21:51.891161
```

```
259000it [21:27:01,  3.25it/s]
```

```
Done for 259000 rows----- 21:27:01.650732
```

```
260000it [21:32:16,  3.28it/s]
```

```
Done for 260000 rows----- 21:32:16.425876
```

```
261000it [21:37:32,  3.23it/s]
```

```
Done for 261000 rows----- 21:37:32.462460
```

```
261693it [21:41:08,  3.35it/s]
```

```
 21:41:08.631255
```

In [80]:

```
reg_test_df = pd.read_csv('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/reg_test.csv', names =
['user', 'movie', 'GAvg', 'sur1', 'sur2', 'sur3', 'sur4', 'sur5',
                                                          'smr1', 'smr2', 'smr3', 'smr4', 'smr5',
                                                          'UAvg', 'MAvg', 'rating'], header=None)
reg_test_df.head(4)
```

Out[80]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	
0	1129620	2	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58
1	3321	5	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58
2	368977	5	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58
3	508584	5	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58

- **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 [77]:

```
from surprise import Reader, Dataset
```

4.3.2.1 Transforming train data

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

In [78]:

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

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

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

4.3.2.2 Transforming test data

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

In [81]:

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

Out[81]:

```
[(1129620, 2, 3), (3321, 5, 4), (368977, 5, 5)]
```

Task 2 Hyper parameter tuning

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 [82]:

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

models_evaluation_train, models_evaluation_test
```

Out[82]:

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

> **Utility functions for running regression models**

In [87]:

```
from sklearn.model_selection import RandomizedSearchCV
```

In [83]:

```
# 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,param_tuning=True):

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

    if param_tuning:
        params = {
             'learning_rate': [0.01,0.05,0.2,0.3],
             'n_estimators': [50,100,400,800],
             'max_depth': [5, 7,9],
             'colsample_bytree': [0.5, 0.7,1],
        }

        xgb_clf = RandomizedSearchCV(algo, param_distributions=params, verbose=2, n_jobs=-1, cv=2,
                                       scoring=['neg_mean_squared_error', 'neg_mean_absolute_error'
'explained_variance', 'r2'],
                                       refit='neg_mean_squared_error')
        model = xgb_clf

        model.fit(x_train, y_train)

        # Get the training results
        y_train_pred = model.predict(x_train)
        rmse_train, mape_train = get_error_metrics(y_train.values, y_train_pred)
        train_results = {'rmse': rmse_train,'mape' : mape_train,'predictions':y_train_pred}

        # Get the testing results
        y_test_pred = model.predict(x_test)
        rmse_test, mape_test = get_error_metrics(y_test.values, y_test_pred)
        test_results = {'rmse': rmse_test,'mape' : mape_test,'predictions':y_test_pred}

    else:
        model = algo
        model.fit(x_train, y_train, eval_metric='rmse', verbose=True)
        #xgb_model = algo.best_estimator_

        # Get the training results
        y_train_pred = model.predict(x_train)
        rmse_train, mape_train = get_error_metrics(y_train.values, y_train_pred)
        train_results = {'rmse': rmse_train,'mape' : mape_train,'predictions':y_train_pred}

        # Get the testing results
        y_test_pred = model.predict(x_test)
        rmse_test, mape_test = get_error_metrics(y_test.values, y_test_pred)
        test_results = {'rmse': rmse_test,'mape' : mape_test,'predictions':y_test_pred}

    return train_results, test_results,model
```

Utility functions for Surprise modes

In [84]:

```
# it is just to makesure 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])
```

```python
    return actual, pred

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

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

    return rmse, mape*100

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

        It returns two dictionaries, one for train and the other is for test
        Each of them have 3 key-value pairs, which specify ''rmse'', ''mape'', and ''predicted rat
ings''.
    '''
    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 [88]:

```
import xgboost as xgb


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

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

# initialize Our first XGBoost model...
first_xgb = xgb.XGBRegressor(n_jobs=-1, random_state=15)
train_results, test_results,model = run_xgboost(first_xgb, x_train, y_train, x_test, y_test,param_t
uning=True)

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

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   8 out of  20 | elapsed:   13.9s remaining:   20.9s
[Parallel(n_jobs=-1)]: Done  20 out of  20 | elapsed:   52.2s finished
```

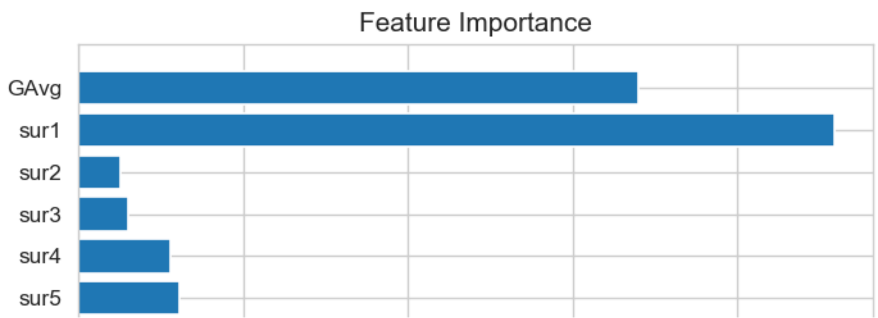
```
[06:17:38] WARNING: src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
```

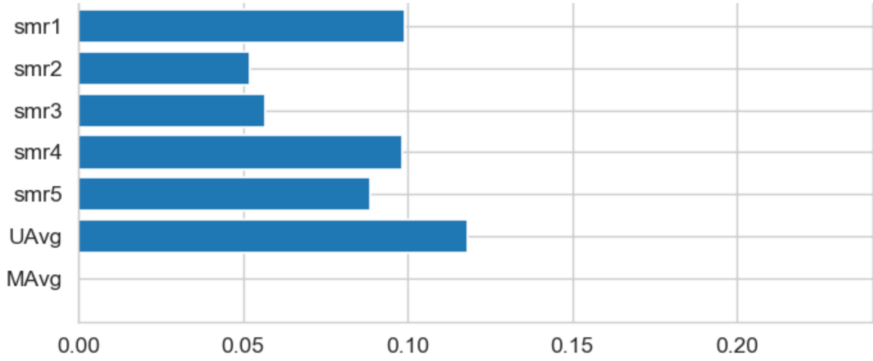
In [89]:

```
model_feat = model.best_estimator_.feature_importances_
index = np.arange(len(model_feat))
```

In [90]:

```
plt.barh(index,model_feat)
plt.yticks(index[::-1],reg_train.columns.drop(['user','movie','rating']).values)
plt.title('Feature Importance')
plt.show()
```





In [91]:

```
print('RMSE of the model ',models_evaluation_test['first_algo']['rmse'])
print('MAPE of the model ',models_evaluation_test['first_algo']['mape'])
```

```
RMSE of the model  1.0834830215885431
MAPE of the model  34.24178377637676
```

In [92]:

```
model.best_estimator_
```

Out[92]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.7, gamma=0,
             importance_type='gain', learning_rate=0.05, max_delta_step=0,
             max_depth=5, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=-1, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

4.4.2 Suprise BaselineModel

In [93]:

```
from surprise import BaselineOnly
```

Predicted_rating : (baseline prediction)

```
-
http://surprise.readthedocs.io/en/stable/basic_algorithms.html#surprise.prediction_algorithm
seline_only.BaselineOnly
```

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

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

Optimization function (Least Squares Problem)

```
- http://surprise.readthedocs.io/en/stable/prediction_algorithms.html#baselines-estimates-c
onfiguration
```

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

In [94]:

```
# 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 : 0:00:00.652221

Evaluating the model with train data..
time taken : 0:00:00.707166
---------------
Train Data
---------------
RMSE : 0.9347153928678286

MAPE : 29.389572652358183

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:01.809161
---------------
Test Data
---------------
RMSE : 1.0870675945776358

MAPE : 34.279025130371885

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:00:03.168548
```

4.4.3 XGBoost with initial 13 features + Surprise Baseline predictor

Updating Train Data

In [95]:

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

Out[95]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	UAvg	MAvg	rating	bslpr
0	53406	33	3.587581	4.0	5.0	5.0	4.0	1.0	5.0	2.0	5.0	3.0	1.0	3.408333	4.114865	4	3.898982
1	99540	33	3.587581	5.0	5.0	5.0	4.0	5.0	3.0	4.0	4.0	3.0	5.0	3.142857	4.114865	3	3.371403

Updating Test Data

In [96]:

```
# 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[96]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	
0	1129620	2	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58
1	3321	5	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58

In [99]:

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

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

# initialize Our first XGBoost model...
xgb_bsl = xgb.XGBRegressor(silent=False, n_jobs=13, random_state=15, n_estimators=100)
train_results, test_results,model = run_xgboost(xgb_bsl, x_train, y_train, x_test, y_test,param_tun
ing=True)
# store the results in models_evaluations dictionaries
models_evaluation_train['xgb_bsl'] = train_results
models_evaluation_test['xgb_bsl'] = test_results
```

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   8 out of  20 | elapsed:   33.2s remaining:   49.8s
[Parallel(n_jobs=-1)]: Done  20 out of  20 | elapsed:  1.1min finished
```

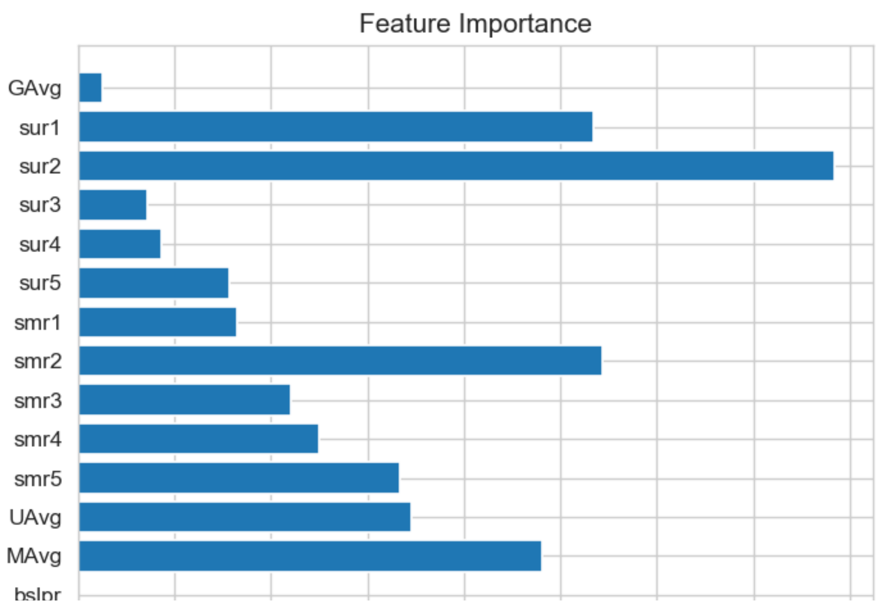
```
[06:26:16] WARNING: src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
```

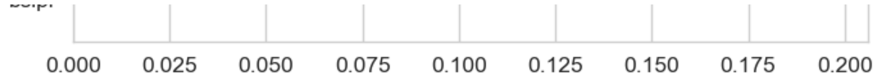
In [100]:

```
model_bsl_feat = model.best_estimator_.feature_importances_
index = np.arange(len(model_bsl_feat))
```

In [101]:

```
plt.barh(index,model_bsl_feat)
plt.yticks(index[::-1],reg_train.columns.drop(['user','movie','rating']).values)
plt.title('Feature Importance')
plt.show()
```





4.4.4 Surprise KNNBaseline predictor

In [103]:

```
from surprise import KNNBaseline
```

- KNN BASELINE
  - 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
  - SHRINKAGE
    - *2.2 Neighborhood Models* in http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf
  - **predicted Rating** : (***based on User-User similarity***)

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

- $\pmb{b_{ui}}$ - *Baseline prediction* of (user,movie) rating
- $\pmb {N_i^k (u)}$ - Set of **K similar** users (neighbours) of **user (u)** who rated **movie(i)**
- *sim (u, v)* - **Similarity** between users **u and v**
  - Generally, it will be cosine similarity or Pearson correlation coefficient.
  - But we use **shrunk Pearson-baseline correlation coefficient**, which is based on the pearsonBaseline similarity (we take base line predictions instead of mean rating of user/item)
- **Predicted rating** (based on Item Item similarity): $\begin{align} \hat{r}_{ui} = b_{ui} + \frac{ \sum\limits_{j \in N^k_u(i)}\text{sim}(i, j) \cdot (r_{uj} - b_{uj})} {\sum\limits_{j \in N^k_u(j)} \text{sim}(i, j)} \end{align}$
  - ***Notations follows same as above (user user based predicted rating)***

4.4.4.1 Surprise KNNBaseline with user user similarities

In [104]:

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

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

# Just store these error metrics in our models_evaluation 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 : 0:00:32.730665

Evaluating the model with train data..
time taken : 0:01:17.252911
---------------
Train Data
---------------
RMSE : 0.33642097416508826

MAPE : 9.145093375416348

adding train results in the dictionary..
```

```
Evaluating for test data...
time taken : 0:00:02.027598
---------------
Test Data
---------------
RMSE : 1.0868930924141922

MAPE : 34.2648242978909

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:01:52.012133
```

4.4.4.2 Surprise KNNBaseline with movie movie similarities

In [105]:

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

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

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

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

```
Training the model...
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
Done. time taken : 0:00:01.110993

Evaluating the model with train data..
time taken : 0:00:07.481591
---------------
Train Data
---------------
RMSE : 0.32584796251610554

MAPE : 8.447062581998374

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:02.021559
---------------
Test Data
---------------
RMSE : 1.0869572969858712

MAPE : 34.26667689410217

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:00:10.615138
```

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 the Train Data

In [106]:

```
# 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[106]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	UAvg	MAvg	rating	bslpr	knn_b
0	53406	33	3.587581	4.0	5.0	5.0	4.0	1.0	5.0	2.0	5.0	3.0	1.0	3.408333	4.114865	4	3.898982	3.9
1	99540	33	3.587581	5.0	5.0	5.0	4.0	5.0	3.0	4.0	4.0	3.0	5.0	3.142857	4.114865	3	3.371403	3.1

Preparing Test data

In [107]:

```
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[107]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	smr3	smr4	smr5	
0	1129620	2	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58
1	3321	5	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.58

In [109]:

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

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

# initialize Our first XGBoost model...
xgb_knn_bsl = xgb.XGBRegressor(silent=False, n_jobs=13, random_state=15, n_estimators=100)
train_results, test_results,model = run_xgboost(xgb_knn_bsl, x_train, y_train, x_test, y_test,param
_tuning=True)
# store the results in models_evaluations dictionaries
models_evaluation_train['xgb_knn_bsl'] = train_results
models_evaluation_test['xgb_knn_bsl'] = test_results
```

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   8 out of  20 | elapsed:   20.3s remaining:   30.5s
[Parallel(n_jobs=-1)]: Done  20 out of  20 | elapsed:  1.2min finished
```

```
[06:36:12] WARNING: src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
```

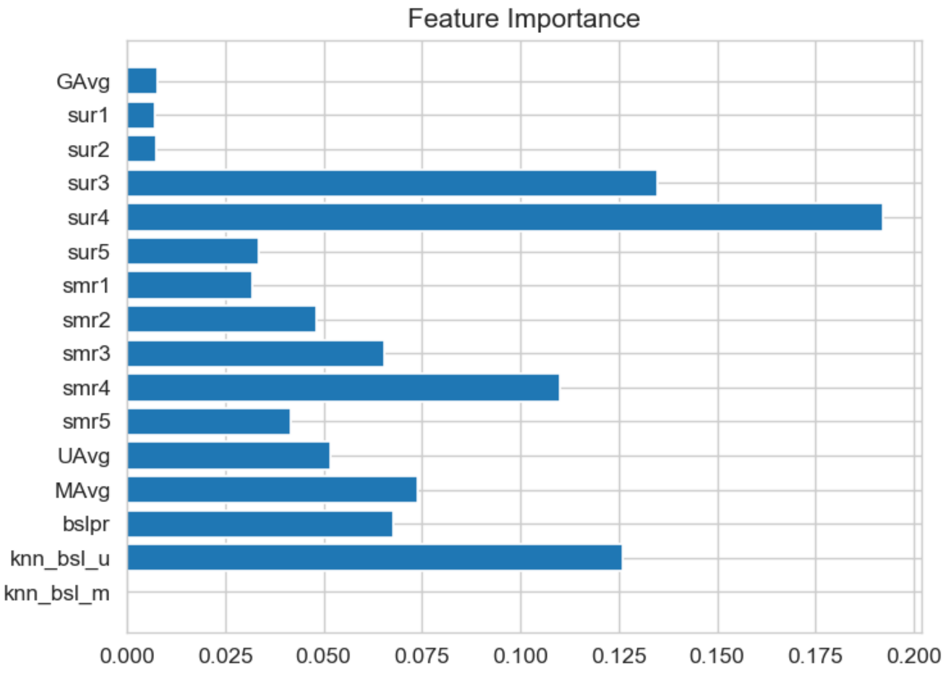
In [110]:

```
model_knn_bsl_feat = model.best_estimator_.feature_importances_
index = np.arange(len(model_knn_bsl_feat))
```

```
index = np.arange(len(model_knn_bsl_feat))
```

In [111]:

```
plt.barh(index,model_knn_bsl_feat)
plt.yticks(index[::-1],reg_train.columns.drop(['user','movie','rating']).values)
plt.title('Feature Importance')
plt.show()
```



In [113]:

```
print('RMSE of the model ',models_evaluation_test['first_algo']['rmse'])
print('MAPE of the model ',models_evaluation_test['first_algo']['mape'])
```

```
RMSE of the model  1.0834830215885431
MAPE of the model  34.24178377637676
```

In [114]:

```
model.best_estimator_
```

Out[114]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.5, gamma=0,
             importance_type='gain', learning_rate=0.05, max_delta_step=0,
             max_depth=7, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=13, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=False, subsample=1, verbosity=1)
```

4.4.6 Matrix Factorization Techniques

4.4.6.1 SVD Matrix Factorization User Movie intractions

In [112]:

```
from surprise import SVD
```

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

- Predicted Rating :

    - $ \large \hat r_{ui} = \mu + b_u + b_i + q_i^Tp_u $

        - $\pmb q_i$ - Representation of item(movie) in latent factor space

        - $\pmb p_u$ - Representation of user in new latent factor space

- A BASIC MATRIX FACTORIZATION MODEL in https://datajobs.com/data-science-repo/Recommender-Systems-[Netflix].pdf
- ## Optimization problem with user item interactions and regularization (to avoid overfitting)
    - \large \sum_{r_{ui} \in R_{train}} \left(r_{ui} - \hat{r}_{ui} \right)^2 + \lambda\left(b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2\right)

In [115]:

```
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)

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 : 0:00:06.270281

Evaluating the model with train data..
time taken : 0:00:01.047138
---------------
Train Data
---------------
RMSE : 0.6574721240954099

MAPE : 19.704901088660478

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:01.903939
---------------
Test Data
---------------
RMSE : 1.086920556350756

MAPE : 34.2640855964798

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:00:09.221358
```

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

In [116]:

```
from surprise import SVDpp
```

- -----> 2.5 Implicit Feedback in http://courses.ischool.berkeley.edu/i290-dm/s11/SECURE/a1-koren.pdf
- ## Predicted Rating :
  - \large \hat{r}_{ui} = \mu + b_u + b_i + q_i^T\left(p_u + |I_u|^{-\frac{1}{2}} \sum_{j \in I_u}y_j\right)
  - \pmb{I_u} --- the set of all items rated by user u
- \pmb{y_j} --- Our new set of item factors that capture implicit ratings.

In [117]:

```
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 : 0:01:33.860101

Evaluating the model with train data..
time taken : 0:00:04.788162
---------------
Train Data
---------------
RMSE : 0.6032438403305899

MAPE : 17.49285063490268

adding train results in the dictionary..

Evaluating for test data...
time taken : 0:00:01.976676
---------------
Test Data
---------------
RMSE : 1.0871683578478946

MAPE : 34.28175061176099

storing the test results in test dictionary...

---------------------------------------------
Total time taken to run this algorithm : 0:01:40.624939
```

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

Preparing Train data

In [118]:

```
# 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[118]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	...	smr4	smr5	UAvg	MAvg	rating	bslpr	knn_bsl_
0	53406	33	3.587581	4.0	5.0	5.0	4.0	1.0	5.0	2.0	...	3.0	1.0	3.408333	4.114865	4	3.898982	3.9300
1	99540	33	3.587581	5.0	5.0	5.0	4.0	5.0	3.0	4.0	...	3.0	5.0	3.142857	4.114865	3	3.371403	3.1773

2 rows × 21 columns

Preparing Test data

In [119]:

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

reg_test_df.head(2)
```

Out[119]:

	user	movie	GAvg	sur1	sur2	sur3	sur4	sur5	smr1	smr2	...	smr4	smr5	UAvg
0	1129620	2	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	...	3.587581	3.587581	3.587581
1	3321	5	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	3.587581	...	3.587581	3.587581	3.587581

2 rows × 21 columns

In [121]:

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

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

xgb_final = xgb.XGBRegressor(silent=False, n_jobs=-1, random_state=15, n_estimators=100)
train_results, test_results,model = run_xgboost(xgb_final, x_train, y_train, x_test, y_test,param_t
uning=True)
# store the results in models_evaluations dictionaries
models_evaluation_train['xgb_final'] = train_results
models_evaluation_test['xgb_final'] = test_results
```

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   8 out of  20 | elapsed:   10.1s remaining:   15.2s
[Parallel(n_jobs=-1)]: Done  20 out of  20 | elapsed:  1.0min finished
```

```
[06:43:15] WARNING: src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
```

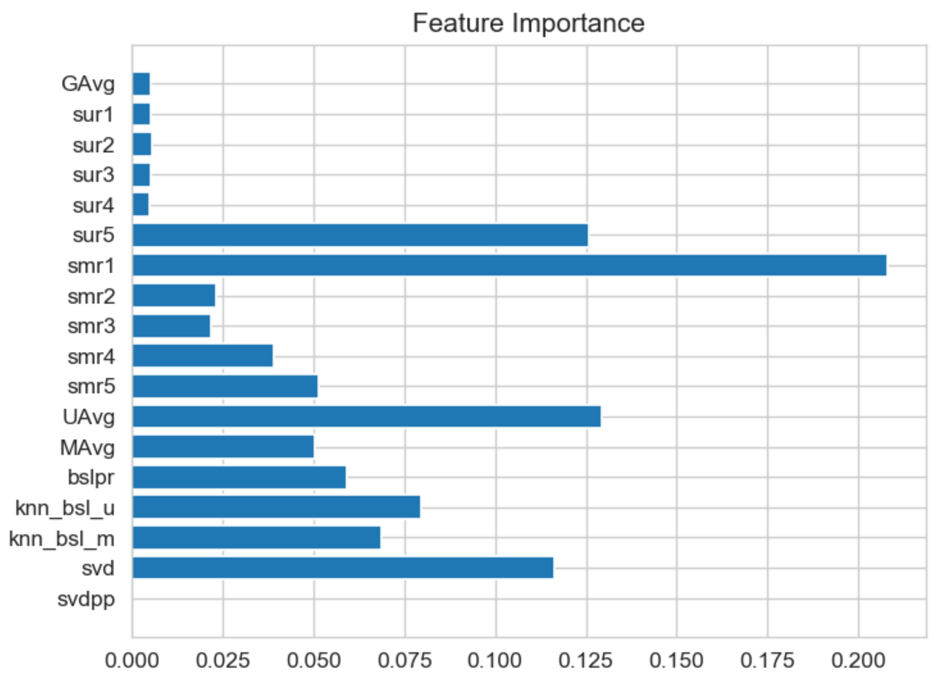
In [122]:

```
model_final = model.best_estimator_.feature_importances_
```

```
index = np.arange(len(model_final))
```

In [123]:

```
plt.barh(index,model_final)
plt.yticks(index[::-1],reg_train.columns.drop(['user','movie','rating']).values)
plt.title('Feature Importance')
plt.show()
```



In [124]:

```
print('RMSE of the model ',models_evaluation_test['first_algo']['rmse'])
print('MAPE of the model ',models_evaluation_test['first_algo']['mape'])
```

```
RMSE of the model  1.0834830215885431
MAPE of the model  34.24178377637676
```

In [125]:

```
model.best_estimator_
```

Out[125]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.5, gamma=0,
             importance_type='gain', learning_rate=0.05, max_delta_step=0,
             max_depth=5, min_child_weight=1, missing=None, n_estimators=400,
             n_jobs=-1, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=False, subsample=1, verbosity=1)
```

4.4.8 XgBoost with Surprise Baseline + Surprise KNNbaseline + MF Techniques

In [127]:

```
x_train = reg_train[['knn_bsl_u', 'knn_bsl_m', 'svd', 'svdpp']]
y_train = reg_train['rating']

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

```
y_test = reg_test_df['rating']

xgb_all_models = xgb.XGBRegressor(silent=False, n_jobs=-1, random_state=15, n_estimators=100)
train_results, test_results,model = run_xgboost(xgb_all_models, x_train, y_train, x_test, y_test,pa
ram_tuning=True)
# store the results in models_evaluations dictionaries
models_evaluation_train['xgb_all_models'] = train_results
models_evaluation_test['xgb_all_models'] = test_results
```

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   8 out of  20 | elapsed:   13.8s remaining:   20.8s
[Parallel(n_jobs=-1)]: Done  20 out of  20 | elapsed:   50.5s finished
```

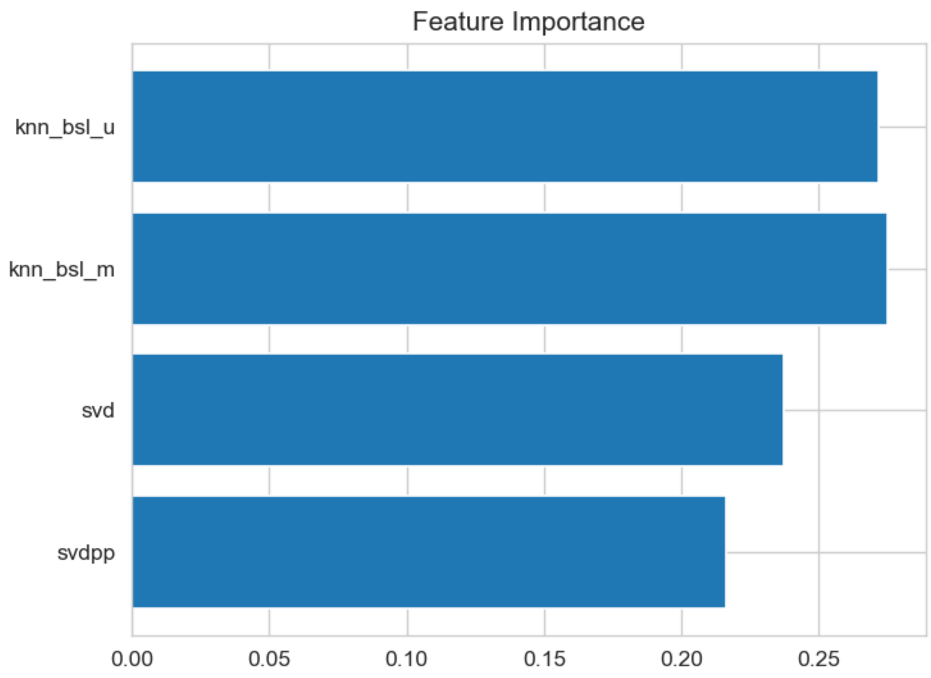
```
[06:45:50] WARNING: src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
```

In [128]:

```
model_final_all = model.best_estimator_.feature_importances_
index = np.arange(len(model_final_all))
```

In [129]:

```
plt.barh(index,model_final_all)
plt.yticks(index[::-1],reg_train[['knn_bsl_u', 'knn_bsl_m', 'svd', 'svdpp']].columns.values)
plt.title('Feature Importance')
plt.show()
```



In [130]:

```
print('RMSE of the model ',models_evaluation_test['first_algo']['rmse'])
print('MAPE of the model ',models_evaluation_test['first_algo']['mape'])
```

```
RMSE of the model  1.0834830215885431
MAPE of the model  34.24178377637676
```

In [131]:

```
model.best_estimator_
```

Out[131]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.05, max_delta_step=0,
             max_depth=7, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=-1, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=False, subsample=1, verbosity=1)
```

4.5 Comparision between all models

In [132]:

```
# Saving our TEST_RESULTS into a dataframe so that you don't have to run it again
pd.DataFrame(models_evaluation_test).to_csv('E:/BOOKS NEW/Cases datasets/4. Netflix
Prize/small_sample_results.csv')
models = pd.read_csv('E:/BOOKS NEW/Cases datasets/4. Netflix Prize/small_sample_results.csv', inde
x_col=0)
models.loc['rmse'].sort_values()
```

Out[132]:

```
first_algo        1.0834830215885431
xgb_bsl           1.0836178316143001
xgb_knn_bsl       1.0836375522231276
xgb_final          1.083769795695866
knn_bsl_u         1.0868930924141922
svd                1.086920556350756
knn_bsl_m         1.0869572969858712
bsl_algo          1.0870675945776358
svdpp             1.0871683578478946
xgb_all_models    1.0930607323920836
Name: rmse, dtype: object
```