Netflix Movie Recommendation System

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



from google.colab import drive
drive.mount('/content/gdrive')

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
import warnings
warnings.filterwarnings('ignore')
from datetime import datetime
from scipy import sparse
import dask.dataframe as dd
import dask.bag as db
from dask.delayed import delayed
dir_path = '/content/gdrive/My Drive/netflix/'
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.decomposition import TruncatedSVD
!pip install --upgrade surprise
from surprise import Reader, Dataset
import xgboost as xgb
from surprise import BaselineOnly, KNNBaseline , SVD, SVDpp
```

```
Looking in indexes: <a href="https://pypi.org/simple">https://us-python.pkg.dev/colab-wheels/public/simple/</a>
Collecting surprise

Downloading surprise-0.1-py2.py3-none-any.whl (1.8 kB)

Collecting scikit-surprise (from surprise)

Downloading scikit-surprise-1.1.3.tar.gz (771 kB)

772.0/772.0 kB 42.4 MB/s eta 0:00:00

Preparing metadata (setup.py) ... done

Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-surprise->surprise) (1.2.0)

Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-surprise->surprise) (1.22.4)

Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-surprise->surprise) (1.10.1)

Building wheels for collected packages: scikit-surprise

Building wheel for scikit-surprise (setup.py) ... done

Created wheel for scikit-surprise: filename=scikit_surprise-1.1.3-cp310-cp310-linux_x86_64.whl size=3095482 sha256=0756c9f43640d3

Stored in directory: /root/.cache/pip/wheels/a5/ca/a8/4e28def53797fdc4363ca4af740db15a9c2f1595ebc51fb445

Successfully built scikit-surprise

Installing collected packages: scikit-surprise, surprise

Successfully installed scikit-surprise-1.1.3 surprise-0.1
```

```
start_time = datetime.now()
if not os.path.isfile(dir_path + 'netflix_data.csv'):
    data = open(dir_path + 'netflix_data.csv', mode='w')
    row = []
```

```
dir_path + 'combined_data_1.txt',
             dir_path + 'combined_data_2.txt',
             dir_path + 'combined_data_3.txt',
             dir_path + 'combined_data_4.txt'
     for file in files:
         print("Reading the file {}...".format(file))
         with open(file) as f:
             for line in f:
                 del row[:]
                 line = line.strip()
                 if line.endswith(':'):
                      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...")
    data.close()
print("Time Taken =" ,datetime.now()-start_time )
     Time Taken = 0:00:00.002004
df = pd.read_csv(dir_path + 'netflix_data.csv')
df.shape
     (100480506, 4)
# Only run this block when you dont have sorted data by 'time'.
if not os.path.isfile(dir_path + "netflix_sorted_data"):
    start_time = datetime.now()
    # creating the dataframe with 4 columns; namely 'movies_id','customer','rating','date'.
    print("Creating the dataframe")
    df = pd.read_csv(dir_path + "netflix_data.csv", sep=',', names=['movies_id','customer','rating','date'])
    # Checking the null value and then delete them if any.
    print("Checking Null values")
    print("Number of nan values: ",sum(df.isnull().any()))
    df = df.dropna(axis=0, inplace= False)
    # Checking the duplicate entries and remove them.
    dups_bool = df.duplicated(['movies_id','customer','rating'])
    dups = sum(dups_bool)
    print("Total number of duplicate entries: {}".format(dups))
    df = df.drop_duplicates()
    # Sorting the dataframe by date column.
    print("Sorting the dataframe")
    df = df.sort_values(by='date', inplace=False)
    print("Done")
    print("Saving... Please wait")
    df.to_csv(dir_path + "netflix_sorted_data", index=False)
    print("Saved")
    print("Time Taken: ", datetime.now()-start_time)
    df = pd.read_csv(dir_path + 'netflix_sorted_data', sep=',' )
print("Total number of ratings in whole dataset: ", df.shape[0])
print("Total number of Users in whole dataset: ", len(np.unique(df.customer)))
print("Total number of Movies in whole dataset: ",len(np.unique(df.movies_id)))
      Total number of ratings in whole dataset: 100480507
df.customer.describe()
               1.004805e+08
     count
               1.322489e+06
     mean
               7.645368e+05
               6.000000e+00
               6.611980e+05
               1.319012e+06
               1.984455e+06
               2.649429e+06
      Name: customer, dtype: float64
```

files = [

```
df.rating.describe()

count 1.004805e+08
mean 3.604290e+00
std 1.085219e+00
min 1.00000e+00
25% 3.000000e+00
50% 4.00000e+00
75% 4.00000e+00
max 5.000000e+00
Name: rating, dtype: float64
```

Spliting the data into Train, Cross Validate and Test dataset.

```
#saving the datasets and loading them.
start = datetime.now()
if not os.path.isfile(dir_path + "train.csv"):
    df.iloc[:int(df.shape[0]*0.6)].to_csv(dir_path + "train.csv")

if not os.path.isfile(dir_path + "cv.csv"):
    df.iloc[int(df.shape[0]*0.6):int(df.shape[0]*0.8)].to_csv(dir_path + "cv.csv")

if not os.path.isfile(dir_path + "test.csv"):
    df.iloc[int(df.shape[0]*0.8):].to_csv(dir_path + "test.csv")
print("Time Taken: ",datetime.now()-start)

train_df = pd.read_csv(dir_path + "train.csv", parse_dates=['date'])
cv_df = pd.read_csv(dir_path + "cv.csv", parse_dates=['date'])
test_df = pd.read_csv(dir_path + "test.csv", parse_dates=['date'])
print("Datasets loaded successfully.")
```

Time Taken: 0:00:00.001880

Statistic on dataset

```
# This block tells you no. of datapoints in a dataset ,no. of rating, no. of unique users and movies
print("Train Dataset")
print("-"*50)
print("\nNumber of ratings: {}".format(train_df.rating.shape[0]))
print("Number of users: {}".format(len(np.unique(train_df.customer))))
print("Number of movies: {}".format(len(np.unique(train_df.movies_id))))
print("\n")
print("Cross Validate Dataset")
print("-"*50)
print("Number of datapoints: ",cv_df.shape[0],"(", np.round((cv_df.shape[0]/(train_df.shape[0]+cv_df.shape[0])+test_df.shape[0]))*100), 3, and a substitute of datapoints: ",cv_df.shape[0],"(", np.round((cv_df.shape[0]/(train_df.shape[0]+cv_df.shape[0]))*100), 3, and a substitute of datapoints of datap
print("\nNumber of ratings: {}".format(cv_df.rating.shape[0]))
print("Number of users: {}".format(len(np.unique(cv_df.customer))))
print("Number of movies: {}".format(len(np.unique(cv_df.movies_id))))
print("\n")
print("Test Dataset")
print("-"*50)
print("Number of datapoints: ",test\_df.shape[0],"(", np.round((test\_df.shape[0]/(train\_df.shape[0]+cv\_df.shape[0])+test\_df.shape[0]))*100 \\
print("\nNumber of ratings: {}".format(test_df.rating.shape[0]))
print("Number of users: {}".format(len(np.unique(test_df.customer))))
print("Number of movies: {}".format(len(np.unique(test_df.movies_id))))
```

```
Train Dataset

Number of datapoints: 60288304 (60.0 3 % )

Number of ratings: 60288304

Number of users: 328767

Number of movies: 16464

Cross Validate Dataset

Number of datapoints: 20096101 (20.0 3 % )

Number of ratings: 20096101

Number of users: 327155

Number of movies: 17386

Test Dataset

Number of datapoints: 20096102 (20.0 3 % )
```

```
Number of users: 349312
Number of movies: 17757

def human(num , units = 'M'):
    units = units.lower()
    num = float(num)
    if units == 'k':
        return str(num/10**3) + 'K'
    if units == 'm':
        return str(num/10**6) + 'M'
    if units == 'b':
        return str(num/10**9) + 'B'
```

print("Occurance of each rating in train dataset.\n")
train_df.rating.value_counts()

Occurance of each rating in train dataset.

```
4 20394785
3 17726270
5 12650808
2 6595195
1 2921246
Name: rating, dtype: int64
```

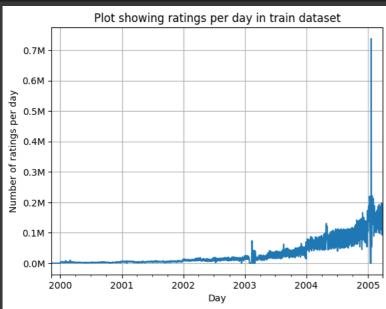
Number of ratings: 20096102

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

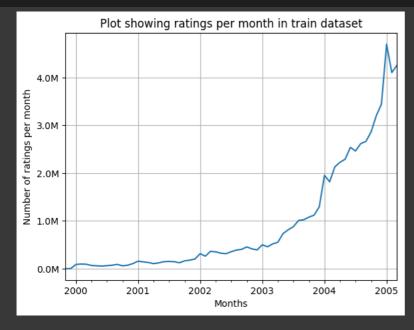


pd.options.mode.chained_assignment = None train_df['days_of_week'] = train_df.date.dt.day_name() train_df.tail(10)

```
60288294
ax = train_df.resample('d' , on='date')['rating'].count().plot()
ax.set_yticklabels([human(item,'M') for item in ax.get_yticks()])
ax.set_title("Plot showing ratings per day in train dataset")
plt.xlabel("Day")
plt.ylabel("Number of ratings per day")
plt.grid()
plt.show()
```



```
ax = train_df.resample('m' , on='date')['rating'].count().plot()
ax.set_yticklabels([human(item,'M') for item in ax.get_yticks()])
ax.set_title("Plot showing ratings per month in train dataset")
plt.xlabel("Months")
plt.ylabel("Number of ratings per month")
plt.grid()
plt.show()
```



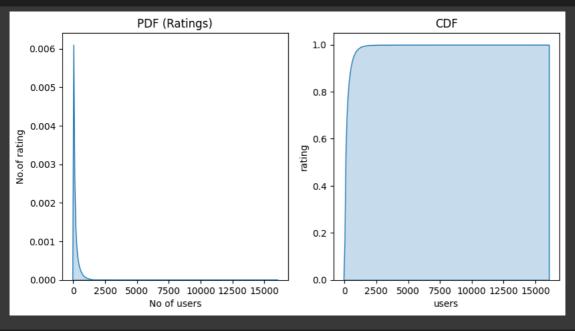
```
print("Number of ratings given by top 5 users.")
no_of_rating_per_user = train_df.groupby(by='customer')['rating'].count().sort_values(ascending = False)
no_of_rating_per_user.head()
     Number of ratings given by top 5 users.
     2439493
```

387418 9748 1932594

Name: rating, dtype: int64

```
fig = plt.figure(figsize = plt.figaspect(.5))
ax1 = plt.subplot(1,2,1)
plt.title("PDF (Ratings)")
plt.xlabel("No of users")
plt.ylabel("No.of rating")
sns.kdeplot(no_of_rating_per_user, ax=ax1,shade= True)

ax2= plt.subplot(1,2,2)
plt.title("CDF")
plt.xlabel('users')
plt.ylabel('rating')
sns.kdeplot(no_of_rating_per_user,cumulative = True, ax = ax2, shade = True)
plt.show()
```



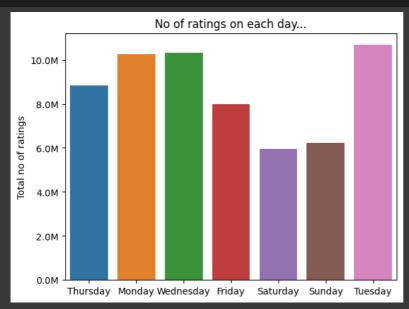
no_of_rating_per_user.describe()

```
count 328767.0000000
mean 183.376993
std 276.787794
min 1.000000
25% 26.000000
50% 81.000000
75% 226.000000
max 15998.000000
Name: rating, dtype: float64
```

```
quantiles = no_of_rating_per_user.quantile(np.arange(0,1.01,0.01), interpolation = 'higher')
quantiles.plot()
plt.title("Quantiles and their values")
plt.xlabel("Values of quantile")
plt.ylabel("No of rating given by user")
# quantiles with 0.05 intervals
plt.scatter(x=quantiles.index[::5], y=quantiles.values[::5], color='red',label= "quantiles with 0.05 intervals")
# quantiles with 0.25 intervals
plt.scatter(x=quantiles.index[::25], y=quantiles.values[::25],color='green',label='quantiles with 0.25 intervals')
plt.legend(loc = 'best')
for x,y in zip(quantiles.index[::25], quantiles.values[::25]):
  ''' s="({} , {})".format(x, y) sets the content of the annotation to a formatted string that includes the values of x and y.
      For example, if x is 0.25 and y is 500, the annotation will display "(0.25, 500)".
      xy=(x, y) specifies the coordinates on the plot where the annotation arrow will point to. It corresponds to the x and y values
      obtained from the quantiles array.
      xytext=(x-0.05, y+500) sets the coordinates where the annotation text will be placed. It determines the position of the text
      relative to the annotation point. In this case, x-0.05 shifts the text slightly to the left of the annotation point, and y+500
      moves the text upward.''
 plt.annotate(text="(\{\},\{\})".format(x,y), xy=(x,y), xytext=(x-0.08,y+400))
```

```
Quantiles and their values
                                                                             (1.0,15998)
         16000
                        rating
                        quantiles with 0.05 intervals
         14000
                        quantiles with 0.25 intervals
      No of rating given by user 10000 8000 8000 4000
print("Quantiles of ratings from 1 to 100 with interval of 5")
quantiles[::5]
     Quantiles of ratings from 1 to 100 with interval of 5
     0.00
     0.05
     0.30
     0.40
     0.45
     0.50
     0.60
0.65
                149
     0.80
     0.85
     0.90
     0.95
     1.00
     Name: rating, dtype: int64
print("No of ratinga at last 5 percentile: ",sum(no_of_rating_per_user>707))
     No of ratinga at last 5 percentile: 16419
no_of_movies_per_rate = train_df.groupby(by ='movies_id')['rating'].count().sort_values(ascending=False)
fig = plt.figure(figsize=plt.figaspect(.5))
ax = plt.gca() #Get Current Axes
plt.plot(no_of_movies_per_rate.values)
plt.title("Plot showing movies that have higher ratings")
plt.xlabel("Movies")
plt.ylabel("Ratings")
ax.set_xticklabels([])
plt.show()
```

```
fig, ax = plt.subplots()
sns.countplot(x='days_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()
```



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

```
Average ratings

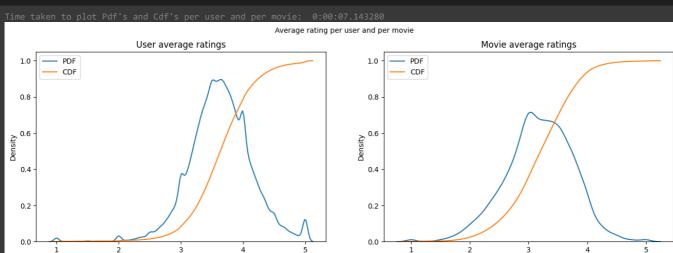
days_of_week
Friday 3.551549
Monday 3.547009
Saturday 3.559087
Sunday 3.562834
Thursday 3.551846
Tuesday 3.542370
Wednesday 3.554788
Name: rating, dtype: float64
```

tr_us,tr_mv = train_sparse_matrix.shape
tr_element = train_sparse_matrix.count_nonzero()

```
start = datetime.now()
if os.path.isfile(dir_path + 'train_sparse_matrix.npz'):
   print("It is present in your netflix folder on google drive, getting it from drive....")
    # just get it from the disk instead of computing it
    train_sparse_matrix = sparse.load_npz(dir_path + '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.customer.values,train_df.movie.values)),)
    print('Saving it into disk for furthur usage..')
    # save it into disk
    sparse.save_npz(dir_path + "train_sparse_matrix.npz", train_sparse_matrix)
    print('Done..\n')
print('It\'s shape is : (user, movie) : ',train_sparse_matrix.shape)
print(datetime.now() - start)
     It is present in your netflix folder on google drive, getting it from drive....
     DONE..
     It's shape is : (user, movie) : (2649430, 17771)
     0:00:05.400190
```

```
print("Sparsity \ Of \ Train \ matrix : \ \{\} \ \% \ ".format( \ (1-(tr\_element/(tr\_us*tr\_mv)))) \ * \ 100) \ )
     Sparsity Of Train matrix : 99.87195319390865 %
start = datetime.now()
if os.path.isfile(dir_path + 'cv_sparse_matrix.npz'):
    print("It is present in your netflix folder on google drive, getting it from drive....")
    # just get it from the disk instead of computing it
    cv_sparse_matrix = sparse.load_npz(dir_path + 'cv_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
   cv_sparse_matrix = sparse.csr_matrix((cv_df.rating.values, (cv_df.customer.values,cv_df.movie.values)),)
   print('Saving it into disk for furthur usage..')
    # save it into disk
    sparse.save_npz(dir_path + "cv_sparse_matrix.npz", cv_sparse_matrix)
    print('Done..\n')
print("It\'s\ shape\ is\ :\ (user,\ movie)\ :\ "\_,cv\_sparse\_matrix.shape)
print(datetime.now() - start)
     It is present in your netflix folder on google drive, getting it from drive....
     DONE.
     It's shape is : (user, movie) : (2649430, 17771)
     0:00:02.386528
cv_us,cv_mv = cv_sparse_matrix.shape
cv_element = cv_sparse_matrix.count_nonzero()
print("Sparsity Of Train matrix : {} % ".format( (1-(tr_element/(cv_us*cv_mv))) * 100) )
     Sparsity Of Train matrix : 99.87195319390865 %
start = datetime.now()
if os.path.isfile(dir_path + 'test_sparse_matrix.npz'):
    print("It is present in your netflix folder on google drive, getting it from drive....")
    # just get it from the disk instead of computing it
    test_sparse_matrix = sparse.load_npz(dir_path + 'test_sparse_matrix.npz')
   print("DONE..")
    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.customer.values,test_df.movie.values)),)
    print('Saving it into disk for furthur usage..')
    # save it into disk
    sparse.save_npz(dir_path + "test_sparse_matrix.npz", test_sparse_matrix)
    print('Done..\n')
print('It\'s shape is : (user, movie) : ',test_sparse_matrix.shape)
print(datetime.now() - start)
     It is present in your netflix folder on google drive, getting it from drive....
     DONE..
     It's shape is : (user, movie) : (2649430, 17771)
     0:00:02.478079
te_us,te_mv = test_sparse_matrix.shape
te_element = test_sparse_matrix.count_nonzero()
print("Sparsity Of Train matrix : {} % ".format( (1-(te_element/(te_us*te_mv))) * 100) )
     Sparsity Of Train matrix : 99.95731772988694 %
def get_average_ratings(sparse_matrix , of_user):
 # chose ax=1 if of_user is True, 0 other wise.
 ax=1 if of_user else 0
 # A1 is used to convert the column matrix into 1-d array.
 # Represents the sum of ratings for that user or movie,
 sum_of_ratings = sparse_matrix.sum(axis=ax).A1
 # Create the boolean matrix denoting whether the user rated the movie or not.
 is_rated = sparse_matrix != 0
 # Represents the number of ratings received by that user or movie.
  no_of_ratings = is_rated.sum(axis=ax).A1
  u, m = sparse_matrix.shape
```

```
# This line of code creates a dictionary where the keys are user or movie IDs, and the values are the corresponding average ratings.
  # The comprehension filters out IDs with zero ratings and calculates the average rating for the remaining IDs by dividing the
  # sum of ratings by the number of ratings.
  average_rating = {i: sum_of_ratings[i] / no_of_ratings[i] for i in range(u if of_user else m) if(no_of_ratings[i] != 0)}
  return average_rating
Global rating for train dataset
train_average = dict()
train_global_rating = train_sparse_matrix.sum()/ train_sparse_matrix.count_nonzero()
train_average['global_rating'] = train_global_rating
     {'global rating': 3.551661131485802}
User rating for train dataset
user_id = 29
train_average['user_rating'] = get_average_ratings(train_sparse_matrix, of_user = True)
if user_id in train_average['user_rating']:
 print("Average rating of User: ",user_id," is ",train_average['user_rating'][user_id])
else:
 print("There is no rating with user_id {}".format(user_id))
     There is no rating with user id 29
user id = 10
# train_average['user_rating'] = get_average_ratings(train_sparse_matrix, of_user = True)
if user_id in train_average['user_rating']:
 print("Average rating of User: ",user_id," is ",train_average['user_rating'][user_id])
  print("There is no rating with user_id {}".format(user_id))
     Average rating of User: 10 is 3.3846153846153846
Movie rating for train dataset
movie_id = 29
train_average['movie_rating'] = get_average_ratings(train_sparse_matrix, of_user = False)
if movie_id in train_average['movie_rating']:
 print("Average rating of Movie: ",movie_id," is ",train_average['movie_rating'][movie_id])
else:
  print("There is no rating with movie_id {}".format(movie_id))
     Average rating of Movie: 29 is 3.5313351498637604
Observation: By this we observe that the movie with id 29 has an not superhit but average.
movie_id = 10
train_average['movie_rating'] = get_average_ratings(train_sparse_matrix, of_user = False)
if movie_id in train_average['movie_rating']:
 print("Average rating of Movie: ",movie_id," is ",train_average['movie_rating'][movie_id])
else:
  print("There is no rating with movie_id {}".format(movie_id))
     Average rating of Movie: 10 is 3.193877551020408
```



Cold Start Problem

Cold start problem with users

```
total_user_r = len(np.unique(df['customer']))
user_r = len(train_average['user_rating'])
print("Total number of Users in dataset: ",total_user_r)
print("Number of users present in train dataset: ", user_r)
print("Number of users NOT present in train dataset: ",total_user_r - user_r , ((total_user_r-user_r)/total_user_r)*100, "%")

Total number of Users in dataset: 480189
Number of users present in train dataset: 328767
Number of users NOT present in train dataset: 151422 31.53383355303849 %
```

Cold start problem with movies

```
total_movie_r = len(np.unique(df['movies_id']))
movie_r = len(train_average['movie_rating'])
print("Total number of Movie in dataset: ",total_movie_r)
print("Number of movie present in train dataset: ", movie_r)
print("Number of movie NOT present in train dataset: ",total_movie_r - movie_r , ((total_movie_r-movie_r)/total_user_r)*100, "%")

Total number of Movie in dataset: 17770
Number of movie present in train dataset: 16464
Number of movie NOT present in train dataset: 1306 0.27197624268777504 %

def compute_user_similarity(sparse_matrix, verbose=False, compute_for_few=False, top=100,verbose_for_n_rows=20,draw_time_taken=True):
no_of_user, _ = sparse_matrix.shape
row_ind, col_ind = sparse_matrix.nonzero()
row_ind = sorted(set(row_ind))
time_taken = list()
rows, cols, data = list(), list(), list()
if verbose: print("Computing top {} similar users".format(top))
```

```
start time = datetime.now()
  temp = 0
  for row in row_ind[:top] if compute_for_few else row_ind:
    temp = temp+1
    prev = datetime.now()
    sim = cosine_similarity(sparse_matrix.getrow(row),sparse_matrix).ravel() # (X)^T.X
    top_sim_ind = sim.argsort()[-top:]
    top_sim_val = sim[top_sim_ind]
    rows.extend([row]*top)
    cols.extend(top_sim_ind)
    data.extend(top_sim_val)
    time_taken.append(datetime.now().timestamp() - prev.timestamp())
    # The purpose of this condition is typically to provide periodic progress updates or print intermediate results during a long compute
    if verbose:
      if temp % verbose_for_n_rows == 0 :
       print("Computing done for {} users [time elapsed : {} ]".format(temp, datetime.now() -start_time))
  if verbose: print("Creating sparse matrix from the computes similarities.")
  if draw_time_taken:
      plt.plot(time_taken, label= 'Time taken for each user')
      plt.plot(np.cumsum(time_taken), label = 'Total time taken')
      plt.legend(loc = 'best')
      plt.grid()
      plt.xlabel("Users")
      plt.ylabel("Time taken in seconds")
  return sparse.csr_matrix((data,(rows,cols)) , shape=(no_of_user , no_of_user)), time_taken
start = datetime.now()
u_u_sim, _ =compute_user_similarity(train_sparse_matrix , compute_for_few=True, verbose = True, top=100)
print("*"*100)
print("Time Taken : {}".format(datetime.now()-start))
         250

    Time taken for each user

    Total time taken

         200
      taken in seconds
         150
         100
      Time
          50
           n
                            20
                                        40
                                                    60
                                                                80
                                                                            100
                                            Users
```

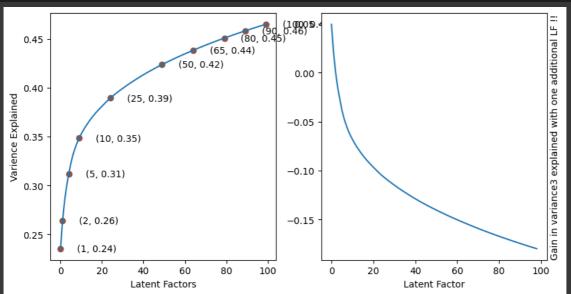
```
start = datetime.now()
svd = TruncatedSVD(n_components= 100, algorithm='randomized', random_state=15)
trunSvd = svd.fit_transform(train_sparse_matrix)
print("Time Taken: ", datetime.now()-start)
```

Time Taken: 0:07:33.430947

Overall, the below code appears to plot the variance explained (expl_var) on the first subplot and the gain in variance explained with one additional latent factor (change_in_expl_var) on the second subplot. Additionally, it adds annotations to specific points on the first subplot to provide additional information about the (latentfactors, expl_var) values at those points.

```
# It returns an array-like object containing the explained variance ratios in descending order.
exp_var = np.cumsum(svd.explained_variance_ratio_)
# This line creates a figure and two subplots arranged horizontally. ax1 and ax2 are the axes objects representing the two subplots.
fig, (ax1,ax2) = plt.subplots(nrows=1, ncols=2, figsize= plt.figaspect(.5))
ax1.set_ylabel("Varience Explained")
ax1.set_xlabel("Latent Factors")
ax1.plot(exp_var)
# Defines a list of indices to annotate on the plot.
index = [1,2,5,10,25,50,65,80,90,100]
\# Plots scatter points on the first subplot at the specified indices, with a custom color.
ax1.scatter(x=[i-1 for i in index], y=exp_var[[i-1 for i in index]], c='#8c564b')
# Annotates text on the plot to label specific points. It iterates over the indices in ind and adds an annotation with the corresponding
for i in index:
 text = "({}, {})".format(i, np.round(exp_var[i-1],2))
 # xytext = used to add annotations to specific points (Position) xytext = (i+7, exp_var[i-1] - 0.003)) play with these value for adjust
 ax1.annotate(text = text, xy = (i-1, exp_var[i-1]), xytext = (i+7, exp_var[i-1] - 0.003))
# Calculates the change in expl_var for each adjacent pair of elements.
change_in_exp_var = [exp_var[1+1] - exp_var[i] for i in range(len(exp_var)-1)]
ax2.plot(change_in_exp_var)
ax2.set_xlabel("Latent Factor")
ax2.set_ylabel("Gain in variance3 explained with one additional LF !!")
ax2.yaxis.set_label_position("right")
plt.show()
```

An attribute that represents the ratio of the explained variance for each latent factor or component obtained from the SVD.



More specifically, expl_var represents the cumulative sum of the explained variance ratios for each latent factor or component. The explained variance ratio quantifies the proportion of the total variance in the data that is explained by each latent factor. By summing up these ratios cumulatively, expl_var provides insight into the cumulative amount of variance explained as more latent factors or components are considered.

For example, if expl_var has values [0.2, 0.4, 0.6, 0.8, 1.0], it means that the first latent factor explains 20% of the total variance, the second latent factor explains an additional 20% (40% in total), the third factor explains another 20% (60% in total), and so on. The final value of 1.0 indicates that all the variance in the data has been accounted for by the latent factors considered.

```
for i in index:

print("For Latent Factor {} , {}% of variance covered.".format(i, np.round(exp_var[i-1]*100, 2)))

For Latent Factor 1 , 23.54% of variance covered.

For Latent Factor 2 , 26.4% of variance covered.

For Latent Factor 5 , 31.17% of variance covered.

For Latent Factor 10 , 34.84% of variance covered.

For Latent Factor 25 , 38.93% of variance covered.

For Latent Factor 50 , 42.36% of variance covered.

For Latent Factor 65 , 43.82% of variance covered.

For Latent Factor 80 , 45.07% of variance covered.

For Latent Factor 90 , 45.8% of variance covered.

For Latent Factor 100 , 46.48% of variance covered.
```

```
start = datetime.now()
trun_matrix = train_sparse_matrix.dot(svd.components_.T)
print("Time taken: {}".format(datetime.now()- start))
     Time taken: 0:00:13.458206
type(trun_matrix) , trun_matrix.shape
     (numpy.ndarray, (2649430, 100))
Double-click (or enter) to edit
if os.path.isfile(dir_path + "trun_sparse_matrix.npz"):
  trun_sparse_matrix = sparse.load_npz(dir_path + "trun_sparse_matrix.npz")
else:
  trun_sparse_matrix = sparse.csr_matrix(trun_matrix)
  sparse.save_npz(dir_path + "trun_sparse_matrix.npz", trun_sparse_matrix)
print("The shape of Truncated SpareseMatrix is : ", trun_sparse_matrix.shape)
     The shape of Truncated SpareseMatrix is : (2649430, 100)
start = datetime.now()
trun_u_u_sim = compute_user_similarity(trun_sparse_matrix, verbose=True, compute_for_few = True, top=100, verbose_for_n_rows=10)
print("*"*100)
print("TimeTaken: ",datetime.now()-start)
         140
                    Time taken for each user
                    Total time taken
         120
        100
      Time taken in seconds
          80
          60
          40
          20
           0
                            20
                                                                 80
                                                                             100
```

TimeTaken: 0:02:26.693408

Movie-Movie Similarity

```
start = datetime.now()
if not os.path.isfile(dir_path + "m_m_similarity_sparse.npz"):
    print("File not forund...")
    for i in range(4):
        print(".")
    print("Wait... We are computing file for you")
    m_m_similarity_sparse = cosine_similarity(train_sparse_matrix.T, dense_output=False)
    print("Computed Successfully")
    print("Saving the file in googledrive under netflix folder. ")
    sparse.save_npz(dir_path + "m_m_similarity_sparse.npz", m_m_similarity_sparse)
    print("Saved Successfully")
```

Users

```
print("Time Taken to compute: ",datetime.now()-start)
else:
  m_m_similarity_sparse = sparse.load_npz(dir_path + "m_m_similarity_sparse.npz")
  print("File loaded successfully")
  print("The shape of movie-movie similarity sparse matrix is: ", m_m_similarity_sparse.shape)
  print("Time Taken to load: ",datetime.now()-start)
      File loaded successfully
      The shape of movie-movie similarity sparse matrix is: (17771, 17771)
      Time Taken to load: 0:00:46.278728
This line of code calculates the similarity scores for the current movie with all other movies, sorts the movies based on similarity (in descending
order), and stores the indices of the most similar movies in the sim_movies array.
movie_ids = np.unique(m_m_similarity_sparse.nonzero()[1])
start = datetime.now()
top sim mvi = dict()
for movie in movie_ids:
  # .toarray() converts the selected row to a dense array format. This step is necessary because the subsequent operations require an arr
  # .ravel() flattens the 2D array to a 1D array, ensuring that the similarity scores are in a one-dimensional format.
  # .argsort() returns the indices that would sort the similarity scores in ascending order. Since we want the most similar movies, we no
  # [::-1] reverses the sorted indices, effectively sorting the similarity scores in descending order.
  # [1:] slices the sorted indices starting from index 1, excluding the first element. This is done to exclude the current movie itself
  similar_movies = m_m_similarity_sparse[movie].toarray().ravel().argsort()[: :-1][1:]
  top_sim_mvi[movie] = similar_movies[:100]
print("Time taken: ",datetime.now()-start)
# checking the top 100 similar movies for movie_id 29
top_sim_mvi[29]
      Time taken: 0:00:29.067522
      array([15405, 8162, 13625, 7843, 12824, 16071, 2513, 6155, 14249, 11533, 9988, 5707, 12067, 5336, 1774, 2561, 1694, 14263, 1460, 10405, 13608, 16033, 8562, 11906, 4599, 10423, 5351,
              6157, 16706, 6072, 5977, 7673, 9581, 11982, 11125, 13863, 11588, 9643, 16250, 7242, 10125, 4366, 12138, 8855, 1234,
              10910, 11058, 11245, 15604, 6005, 5118, 7579, 4219, 10910, 11065, 7808, 2773, 12452, 13620, 14115, 4144, 202, 15872, 3276, 17066, 517, 10846, 10448, 3515, 15625, 15515, 9224, 883, 5400, 14457, 12312, 1364
               9224, 883, 5400, 14457, 12313, 17614, 7972, 14221, 582, 2383, 5016, 709, 5357, 17319, 15628, 7820, 8754, 2493, 632, 14634, 7194, 9355, 16705, 15817, 12389, 13951, 1160,
               17248])
Reading the Movies titles
if os.path.isfile(dir_path + "movie_titles.csv"):
  print("Reading the data from google drive")
  movies_title = pd.read_csv(dir_path + "movie_titles.csv" , sep=',' , header=None, verbose=True,

names=['Movie_id', 'Movie_release_year', 'Movie_title'], index_col='Movie_id', encoding = 'ISO-8859-1')
  print("movie_titles.csv not found kindly go to kaggle and download it.")
movies_title.head()
                   Movie release year
                                                          Dinosaur Planet
           1
                                  2003.0
           3
                                  1997.0
                                                                Character
                                  2004.0
                                                The Rise and Fall of ECW
           5
```

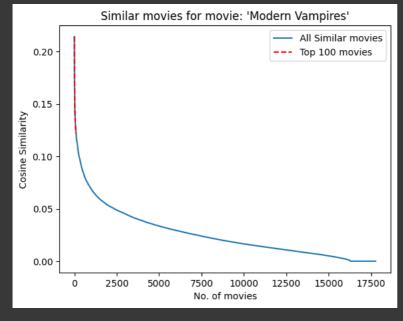
print("The shape of movie-movie similarity sparse matrix is: ", m_m_similarity_sparse.shape)

movies_title[movies_title['Movie_title'] == 'Titanic']

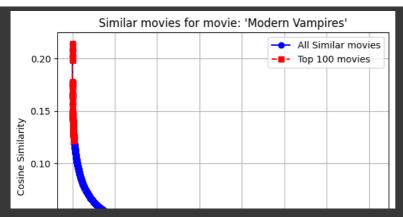
Double-click (or enter) to edit

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

```
mvi_id = 323
plt.plot(similarities[sim_indices], label="All Similar movies", linestyle='solid')
plt.plot(similarities[sim_indices[:100]], label="Top 100 movies", color='red', linestyle='dashed')
plt.xlabel("No. of movies")
plt.ylabel("Cosine Similarity")
plt.title("Similar movies for movie: '{}'".format(movies_title.loc[mvi_id].values[1]))
plt.legend()
plt.show()
```



```
mvi_id = 323
plt.plot(similarities[sim_indices], label="All Similar movies", linestyle='-', marker='o', color='blue')
plt.plot(similarities[sim_indices[:100]], label="Top 100 movies", linestyle='--', marker='s', color='red')
plt.xlabel("No. of movies")
plt.ylabel("Cosine Similarity")
plt.title("Similar movies for movie: '{}'".format(movies_title.loc[mvi_id].values[1]))
plt.legend()
plt.grid()
plt.show()
```



Thig plot will show that the top 100 movies for movie title "Modern Vampires" have 23% to 13% similarities.

print("Top 10 movies similar to ' Modern Vampires'")
movies_title.loc[sim_indices[:10]]

Top 10 movies similar to 'Modern Vampires'

Movie_release_year

Movie_titl

Novie id

Vampirella	1996.0	4667
	2001.0	15237
Vampire Journals	1997.0	67
Vampires: Los Muertos	2002.0	16279
The Breed	2001.0	13873
From Dusk Till Dawn 2: Texas Blood Money	1998.0	4173
Club Vampire	1997.0	1900
Dracula: The Dark Prince	2001.0	13962
Dracula II: Ascension	2003.0	15867
Vampires	1998.0	3496

```
def get_sample_sparse_matrix(sparse_matrix, no_user, no_movie, path ,verbose=True):
  row_index, col_index, rating = sparse.find(sparse_matrix)
  users = np.unique(row_index)
  movies = np.unique(col_index)
  \label{eq:print(shape of matrix before sampling: ({} X {} {})".format(len(users) \ , \ len(movies))) \\
  print("Ratings before sampling: ",len(rating))
  np.random.seed(20)
  sample_users = np.random.choice(users, no_user, replace=False)
  sample_movies= np.random.choice(movies, no_movie , replace=False)
  mask = np.logical_and(np.isin(row_index , sample_users), np.isin(col_index, sample_movies))
  sample_sparse_matrix = sparse.csr_matrix((rating[mask] , (row_index[mask] , col_index[mask])), shape= (max(sample_users)+1, max(sample_
sample_sparse_matrix = sparse.csr_matrix((rating[mask] , (row_index[mask] , col_index[mask])), shape= (max(sample_users)+1, max(sample_users)+1)
  if verbose:
    print("Shape of matrix after sampling: ({{}} X {{}})".format(len(sample\_users), len(sample\_movies)))\\
    print("Ratings after sampling: ",rating[mask].shape[0])
  print("Saving the matrix into drive.")
  sparse.save_npz(path , sample_sparse_matrix)
  if verbose:
    print("Save successfully")
  return sample_sparse_matrix
path = dir_path + "train_sample_sparse_matrix.npz"
```

```
path = dir_path + "train_sample_sparse_matrix.npz"
if not os.path.isfile(path):
    print("Creating the Train sample sparse matrix. \n\n Please Wait")
    train_sample_sparse_matrix = get_sample_sparse_matrix(train_sparse_matrix, no_user = 10000, no_movie=1000, path=path)
else:
    print("Loading the Sample Matrix. \n\n Please Wait")
    train_sample_sparse_matrix = sparse.load_npz(path)
```

Loading the Sample Matrix.

Please Wait

```
path = dir_path + "cv_sample_sparse_matrix.npz"
if not os.path.isfile(path):
 print("Creating the CV sample sparse matrix. \n\n Please Wait")
 cv_sample_sparse_matrix = get_sample_sparse_matrix(cv_sparse_matrix, no_user = 5000, no_movie=500, path=path)
else:
 print("Loading the Sample Matrix. \n\n Please Wait")
 cv sample sparse matrix = sparse.load npz(path)
     Loading the Sample Matrix.
      Please Wait
path = dir_path + "test_sample_sparse_matrix.npz"
if not os.path.isfile(path):
 print("Creating the Test sample sparse matrix. \n\n Please Wait")
  test_sample_sparse_matrix = get_sample_sparse_matrix(test_sparse_matrix, no_user = 5000, no_movie=500, path=path)
else:
 print("Loading the Sample Matrix. \n\n Please Wait")
 test_sample_sparse_matrix = sparse.load_npz(path)
     Loading the Sample Matrix.
      Please Wait
Featurizing
sample_train_dataset = dict()
average_global_rating = train_sample_sparse_matrix.sum() / train_sample_sparse_matrix.count_nonzero()
sample_train_dataset['global'] = average_global_rating
sample_train_dataset
     {'global': 3.545324133472072}
user = 311465
sample_train_dataset['user'] = get_average_ratings(train_sample_sparse_matrix, of_user=True)
print("Average rating of user {} is: {}".format(user,sample_train_dataset['user'][user]))
     Average rating of user 311465 is: 4.0
'''Movie_release_year
                         1964.0
   Movie_title
                        Marnie
   Name: 17109, dtype: object'''
movieid= 17109
sample_train_dataset['movie'] = get_average_ratings(train_sample_sparse_matrix, of_user=False)
print("Average rating for movie '{}' is: {}".format(movies_title.iloc[17109 -1].values[1] ,sample_train_dataset['movie'][movieid] ))
     Average rating for movie 'Marnie' is: 3.4927536231884058
train_sample_user, train_sample_movie,train_sample_rating = sparse.find(train_sparse_matrix)
#user_sim = cosine_similarity(sample_train_sparse_matrix[user], sample_train_sparse_matrix).ravel():
#This line calculates the cosine similarity between the user (represented by the index user) and all other users in the
#sample_train_sparse_matrix. The result is flattened using ravel() to create a 1D array.
# top_sim_users = user_sim.argsort()[::-1][1:]: Here, argsort() sorts the similarity scores in ascending order and returns the indices
# that would sort the array. By using [::-1], it reverses the order, resulting in indices that sort the array in descending order. [1:]
# is used to exclude the first element, which corresponds to the user itself. Thus, top_sim_users contains the indices of users that ar
#top_ratings = sample_train_sparse_matrix[top_sim_users, movie].toarray().ravel(): This line retrieves the ratings of the most similar users.
#for the given movie. It uses the top_sim_users indices and the movie index to access the corresponding ratings from the
#sample_train_sparse_matrix. The toarray() method converts the sparse matrix slice to a dense array, and ravel() flattens it to a 1D arm
#top_sim_users_ratings = list(top_ratings[top_ratings != 0][:5]): Here, top_ratings[top_ratings != 0] filters out any zero ratings from
#the top_ratings array, and [:5] selects at most the first five non-zero ratings. This ensures that we have a maximum of five ratings from
#similar users for the movie.
#top_sim_users_ratings.extend([sample_train_averages['movie'][movie]]*(5 - len(top_sim_users_ratings))): This line extends the
#top_sim_users_ratings list by appending the average rating of the movie (sample_train_averages['movie'][movie])
#repeated 5 - len(top_sim_users_ratings) times. It ensures that if there are fewer than five ratings from similar users, the remaining s
#are filled with the average rating.
start = datetime.now()
if os.path.isfile(dir_path + "train_regression_data.csv"):
 \verb|print("Train Regression Dataset found in the google drive.\nReading...")|\\
  train_regression_data = pd.read_csv(dir_path + "train_regression_data.csv")
 print("Load Successfully and time taken: {}".format(datetime.now()-start))
else:
 print("Preparing {} tuples\nKindly wait...".format(len(train_sample_rating)))
```

```
with open(dir_path + "train_regression_data.csv" , mode = 'w') as train_regression_data_file:
    count = 0
    for user, movie, rating in zip(train sample user, train sample movie, train sample rating):
      st = datetime.now()
      # Finding 5 most similar users.
      user_similarity = cosine_similarity(train_sample_sparse_matrix[user],train_sample_sparse_matrix).ravel()
      top_sim_user = user_similarity.argsort()[::-1][1:]
      # top_sim_user: (2648546,)
      top_rating = train_sample_sparse_matrix[top_sim_user , movie].toarray().ravel()
      top_sim_user_rating = list(top_rating[top_rating != 0][:5])
      top_sim_user_rating.extend([sample_train_dataset['movie'][movie]]* (5- len(top_sim_user_rating)))
      # Finding 5 most similar movies.
      movie_similarity = cosine_similarity(train_sample_sparse_matrix[:,movie].T,train_sample_sparse_matrix.T).ravel()
      top_sim_movies = movie_similarity.argsort()[::-1][1:]
      # top_sim_movies: (17749,)
      top_rating = train_sample_sparse_matrix[ user ,top_sim_movies].toarray().ravel()
      top_sim_movie_rating = list(top_rating[top_rating != 0][:5])
      top_sim_movie_rating.extend([sample_train_dataset['user'][user]]* (5-len(top_sim_movie_rating)))
      # Preparing the row by inserting values.
      row.append(user)
      row.append(movie)
      row.append(sample_train_dataset['global'])
      row.extend(top_sim_user_rating)
      row.extend(top_sim_movie_rating)
      row.append(sample_train_dataset['user'][user])
      row.append(sample_train_dataset['movie'][movie])
      row.append(rating)
      count += 1
      train_regression_data_file.write(','.join(map(str,row)))
      train_regression_data_file.write('\n')
      if count% 10000 == 0:
        print("Done for {} rows and time elapse: {}".format(count,datetime.now()-start))
print("Total time taken: {}".format(datetime.now()-start))
```

- SEARCH STACK OVERFLOW
- 1. The prepare_regression_data function takes three lists as input: train_sample_user, train_sample_movie, and train_sample_rating. These lists represent the user, movie, and rating data, respectively.
- 2. The function first checks if the train_regression_data.csv file already exists. If it does, it reads the file using pd.read_csv and skips the processing step.
- 3. If the train_regression_data.csv file doesn't exist, it proceeds with the data preparation. The function creates a partial function called partial_process_tuple using the partial function from the functools module. This partial function fixes the first three arguments of the partial_process_tuple function, which are user, movie, and rating.
- 4. The partial_process_tuple function performs the data processing for each tuple of user, movie, and rating. It calculates the cosine similarity between the user and all other users (user_similarity) and selects the top similar users (top_sim_users). It then retrieves the ratings of the top similar users for the given movie (top_ratings) and filters out zero ratings. Similarly, it calculates the cosine similarity between the movie and all other movies (movie_similarity) and selects the top similar movies (top_sim_movies). It retrieves the ratings of the top similar movies for the given user and filters out zero ratings.
- 5. The processed values are appended to the row list, which represents a row in the train_regression_data.csv file. The values in the row list are written to the file using the write method.

- 6. The prepare_regression_data function then creates a Pool object, which represents a pool of worker processes. By default, the number of worker processes is determined by the number of CPU cores available.
- 7. The starmap method of the Pool object is used to apply the partial_process function to each tuple of train_sample_user, train_sample_movie, and train_sample_rating. The starmap function distributes the processing of tuples among the worker processes in parallel.
- 8. After the parallel processing is completed, the close method is called on the Pool object to prevent any new tasks from being submitted to the pool. Then, the join method is called to wait for all the worker processes to complete.
- 9. Finally, the total time taken for the data preparation process is printed.

By using parallel processing with the multiprocessing module, the code distributes the processing of tuples across multiple CPU cores, potentially speeding up the overall execution time compared to sequential processing.

```
import os
import pandas as pd
from datetime import datetime
from sklearn.metrics.pairwise import cosine similarity
from functools import partial
from multiprocessing import Pool
def partial_process_tuple(user, movie, rating):
    # Open the file within the process
    with open(dir_path + "train_regression_data.csv", mode='a') as train_regression_data_file:
        # Finding 5 most similar users.
        user_similarity = cosine_similarity(train_sample_sparse_matrix[user], train_sample_sparse_matrix).ravel()
        top_sim_users = user_similarity.argsort()[::-1][1:]
        top_ratings = train_sample_sparse_matrix[top_sim_users, movie].toarray().ravel()
        top_sim_users_ratings = list(top_ratings[top_ratings != 0][:5])
        top_sim_users_ratings.extend([sample_train_dataset['movie'][movie]] * (5 - len(top_sim_users_ratings)))
        # Finding 5 most similar movies.
        movie_similarity = cosine_similarity(train_sample_sparse_matrix[:, movie].T, train_sample_sparse_matrix.T).ravel()
        top_sim_movies = movie_similarity.argsort()[::-1][1:]
        top_ratings = train_sample_sparse_matrix[user, top_sim_movies].toarray().ravel()
        top_sim_movies_ratings = list(top_ratings[top_ratings != 0][:5])
        top_sim_movies_ratings.extend([sample_train_dataset['user'][user]] * (5 - len(top_sim_movies_ratings)))
        # Preparing the row by inserting values.
        row = []
        row.append(user)
        row.append(movie)
        row.append(sample_train_dataset['global'])
        row.extend(top_sim_users_ratings)
        row.extend(top_sim_movies_ratings)
        row.append(sample_train_dataset['user'][user])
        row.append(sample_train_dataset['movie'][movie])
        row.append(rating)
        train_regression_data_file.write(','.join(map(str, row)))
        train_regression_data_file.write('\n')
\tt def\ prepare\_regression\_data(train\_sample\_user,\ train\_sample\_movie,\ train\_sample\_rating):
    if os.path.isfile(dir_path + "train_regression_data.csv"):
        print("Train Regression Dataset found in the Google Drive.\nReading...")
        train_regression_data = pd.read_csv(dir_path + "train_regression_data.csv")
       print("Load Successful and time taken: {}".format(datetime.now() - start))
    else:
        print("Preparing {} tuples\nKindly wait...".format(len(train_sample_rating)))
        # Define the partial function
        partial_process = partial(partial_process_tuple)
        # Create a pool of workers
        pool = Pool()
        # Apply parallel processing
        pool.starmap(partial_process, zip(train_sample_user, train_sample_movie, train_sample_rating))
        pool.close()
        pool.join()
       print("Total time taken: {}".format(datetime.now() - start))
start = datetime.now()
prepare_regression_data(train_sample_user, train_sample_movie, train_sample_rating)
     Preparing 98987 tuples
     Kindly wait...
test_sample_user, test_sample_movie, test_sample_rating = sparse.find(test_sample_sparse_matrix)
start = datetime.now()
if os.path.isfile(dir_path + "test_regression_data.csv"):
 print("Test Regression Data found in google drive.\n reading data...")
  test_regression_data = pd.read_csv(dir_path + "test_regression_data.csv")
 print("Data loading successfully")
else:
 print("Test Regression Data not found in google drive.\nPreparing tuple {}\nKindly Wait...".format(len(test_sample_rating)))
 with open(dir_path + "test_regression_data.csv", mode='w') as regression_data_file:
```

```
for user, movie, rating in zip(test_sample_user, test_sample_movie, test_sample_rating):
      st = datetime.now()
        user similarity = cosine similarity(train sample sparse matrix[user], train sample sparse matrix).ravel()
        top_sim_user = user_similarity.argsort()[::-1][1:]
        top_rating = train_sample_sparse_matrix[top_sim_user, movie].toarray().ravel()
        top_sim_user_rating = list(top_rating[top_rating != 0][:5])
        top_sim_user_rating.extend([sample_train_dataset['movie'][movie]]*(5 - len(top_sim_user_rating)))
      except(IndexError, KeyError):
        top_sim_user_rating.extend([sample_train_dataset['global']] * (5 - len(top_sim_user_rating)))
      except:
       print(user,movie)
        raise
      trv:
        movie_similarity = cosine_similarity(train_sample_sparse_matrix[:,movie].T, train_sample_sparse_matrix.T).ravel()
        top_sim_movie = movie_similarity.argsort()[::-1][1:]
        top_rating = train_sample_sparse_matrix[user, top_sim_movie].toarray().ravel()
        top_sim_movie_rating = list(top_rating[top_rating!= 0][:5])
        top_sim_movie_rating.extend([sample_train_dataset['user'][user]] * (5 - len(top_sim_movie_rating)))
      except(IndexError, KeyError):
        top_sim_movie_rating.extend([sample_train_dataset['global']] * (5- len(top_sim_movie_rating)))
      except:
       print(user,rating)
        raise
      row =[]
      row.append(user)
      row.append(movie)
      row.append(sample_train_dataset['global'])
      row.extend(top_sim_user_rating)
      row.extend(top_sim_movie_rating)
        row.append(sample_train_dataset['user'][user])
      except(KeyError):
        row.append(sample_train_dataset['global'])
      try:
        row.append(sample_train_dataset['movie'][movie])
      except(KeyError):
       row.append(sample train dataset['global'])
      row.append(rating)
      regression_data_file.write(','.join(map(str,row)))
      regression_data_file.write('\n')
      if count%1000 == 0:
  \label{lem:print("Done for {} row... Time elapse {}".format(count, datetime.now()- start))} \\ print("Total time taken {}".format(datetime.now()-start))
     Test Regression Data not found in google drive.
     Preparing tuple 7257
     Kindly Wait...
     Done for 1000 row... Time elapse 0:04:15.966295
     Done for 2000 row... Time elapse 0:08:25.964561
     Done for 3000 row... Time elapse 0:12:32.473567
     Done for 4000 row... Time elapse 0:16:42.830608
     Done for 5000 row... Time elapse 0:20:49.653053
     Done for 6000 row... Time elapse 0:24:59.295137
     Done for 7000 row... Time elapse 0:29:08.424005
     Total time taken 0:30:13.720584
For Cross Validate
cv_sample_user, cv_sample_movie, cv_sample_rating = sparse.find(cv_sample_sparse_matrix)
start = datetime.now()
if os.path.isfile(dir_path + "cv_regression_data.csv"):
  print("CrossValidate Regression Data found in google drive.\n reading data...")
  test_regression_data = pd.read_csv(dir_path + "cv_regression_data.csv")
  print("Data loading successfully")
  print("CrossValidate Regression Data not found in google drive.\nPreparing tuple {}\nKindly Wait...".format(len(cv_sample_rating)))
  with open(dir_path + "cv_regression_data.csv", mode='w') as regression_data_file:
    count = 0
```

```
for user, movie, rating in zip(cv_sample_user, cv_sample_movie, cv_sample_rating):
    st = datetime.now()
      user_similarity = cosine_similarity(train_sample_sparse_matrix[user], train_sample_sparse_matrix).ravel()
      top_sim_user = user_similarity.argsort()[::-1][1:]
      top_rating = train_sample_sparse_matrix[top_sim_user, movie].toarray().ravel()
      top_sim_user_rating = list(top_rating[top_rating != 0][:5])
      top_sim_user_rating.extend([sample_train_dataset['movie'][movie]]*(5 - len(top_sim_user_rating)))
    except(IndexError, KeyError):
      top_sim_user_rating.extend([sample_train_dataset['global']] * (5 - len(top_sim_user_rating)))
    except:
     print(user,movie)
      raise
    try:
      movie_similarity = cosine_similarity(train_sample_sparse_matrix[:,movie].T, train_sample_sparse_matrix.T).ravel()
      top_sim_movie = movie_similarity.argsort()[::-1][1:]
      top_rating = train_sample_sparse_matrix[user, top_sim_movie].toarray().ravel()
      top_sim_movie_rating = list(top_rating[top_rating!= 0][:5])
      top_sim_movie_rating.extend([sample_train_dataset['user'][user]] * (5 - len(top_sim_movie_rating)))
    except(IndexError, KeyError):
      top_sim_movie_rating.extend([sample_train_dataset['global']] * (5- len(top_sim_movie_rating)))
    except:
     print(user,rating)
    row =[]
    row.append(user)
    row.append(movie)
    row.append(sample_train_dataset['global'])
    row.extend(top sim user rating)
    row.extend(top_sim_movie_rating)
      row.append(sample_train_dataset['user'][user])
    except(KeyError):
      row.append(sample_train_dataset['global'])
      row.append(sample_train_dataset['movie'][movie])
    except(KeyError):
     row.append(sample train dataset['global'])
    row.append(rating)
    regression_data_file.write(','.join(map(str,row)))
    regression_data_file.write('\n')
    if count%1000 == 0:
     print("Done for {} row... Time elapse {}".format(count, datetime.now()- start))
print("Total time taken {}".format(datetime.now()-start))
   CrossValidate Regression Data not found in google drive.
   Preparing tuple 11926
   Kindly Wait...
   Done for 1000 row... Time elapse 0:03:58.587465
   Done for 2000 row... Time elapse 0:07:55.910899
   Done for 3000 row... Time elapse 0:11:52.203224
   Done for 4000 row... Time elapse 0:15:43.544197
   Done for 5000 row... Time elapse 0:19:33.789241
   Done for 6000 row... Time elapse 0:23:24.642801
   Done for 7000 row... Time elapse 0:27:13.917863
   Done for 8000 row... Time elapse 0:31:03.895687
   Done for 9000 row... Time elapse 0:34:53.763637
   Done for 10000 row... Time elapse 0:38:43.891820 Done for 11000 row... Time elapse 0:42:30.181282 Total time taken 0:45:57.811517
```

Reading Regression dataset for Train

		movie			sur2		sur4	sur5	smr1	smr2	smr3	smr4	smr5			rating
0	53406	33	3.581679	4.0	5.0	5.0	4.0	1.0	5.0	2.0	5.0	3.0	1.0	3.370370	4.092437	4
1	99540	33	3.581679	5.0	5.0	5.0	4.0	5.0	3.0	4.0	4.0	3.0	5.0	3.555556	4.092437	3
2	99865	33	3.581679	5.0	5.0	4.0	5.0	3.0	5.0	4.0	4.0	5.0	4.0	3.714286	4.092437	5

Reading Regression dataset for CrossValidate

		movie		sur1	sur2		sur4	sur5	smr1	smr2	smr3	smr4	smr5	UAvg
0	543665	91	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
1	1932594	91	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
2	2321468	91	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
3	14936	241	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
4	44518	241	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324

Reading Regression dataset for Test

test_regression_data = pd.read_csv(dir_path + "test_regression_data.csv", names=['user','movie','GAvg', 'sur1','sur2','sur3','sur4','sur3','sur4','sur5','UAvg','MAvg','rating']
test_regression_data.head()

		movie		sur1	sur2		sur4	sur5	smr1	smr2	smr3	smr4	smr5	UAvg
0	256033	24	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
1	1735827	24	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
2	1804811	24	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
3	2485642	24	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324
4	2308181	38	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324	3.545324

Overview of Surprise Library

The Surprise library uses a specific data format called the Surprise Dataset format. This format is designed to facilitate the use of various recommender algorithms provided by the library.

The Surprise Dataset format represents the user-item ratings data in a structured manner that can be easily processed by the library's algorithms. It consists of three main components: users, items, and ratings.

Here's a brief overview of the format:

- 1. Users: Users are identified by unique user IDs. Each user ID corresponds to a set of ratings given by that user.
- 2. Items: Items (or items being recommended) are identified by unique item IDs. Each item ID corresponds to a set of ratings received by
- 3. Ratings: Ratings represent the user-item interactions or preferences. They typically indicate how a user rates or interacts with an item. Ratings can be numerical, binary (e.g., liked/disliked), or explicit/implicit.

The Surprise Dataset format is often constructed using the Dataset class provided by the library. It offers methods like load_from_df, load_from_file, or load_builtin to load data from dataframes, files, or built-in datasets, respectively. These methods convert the data into the Surprise Dataset format.

Once the data is loaded into the Surprise Dataset format, it can be further processed, split into train and test sets, and used as input for training and evaluating recommender algorithms provided by the Surprise library.

```
!pip install surprise
from surprise import Reader, Dataset
reader = Reader(rating_scale=(1,5))
dataset = Dataset.load_from_df(train_regression_data[['user','movie','rating']], reader)
train_set = dataset.build_full_trainset()
```

```
Looking in indexes: <a href="https://pypi.org/simple">https://us-python.pkg.dev/colab-wheels/public/simple/</a>
Requirement already satisfied: surprise in /usr/local/lib/python3.10/dist-packages (0.1)
Requirement already satisfied: scikit-surprise in /usr/local/lib/python3.10/dist-packages (from surprise) (1.1.3)
Requirement already satisfied: joblib=1.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-surprise->surprise) (1.2.0)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-surprise->surprise) (1.2.4)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-surprise->surprise) (1.10.1)

cv_set = list(zip(cv_regression_data.user.values , cv_regression_data.movie.values , cv_regression_data.rating.values))
cv_set[:3]

[(543665, 91, 2), (1932594, 91, 2), (2321468, 91, 5)]

test_set = list(zip(test_regression_data.user.values , test_regression_data.movie.values , test_regression_data.rating.values))
test_set[:3]

[(256033, 24, 4), (1735827, 24, 4), (1804811, 24, 3)]
```

Applying Machine Learning Models

These dictionaries are used as the set of RMSE in Train, cv, test sets for all the machine learning model.

```
train_model_evaluation = {}

cv_model_evaluation = {}

test_model_evaluation = {}

train_model_evaluation, cv_model_evaluation, test_model_evaluation
```

Utility functions for XGBoost Regression

```
def get_error_matrix(y_true, y_predict):
  rmse = np.sqrt(np.mean([ (y_true[i] - y_predict[i])**2 for i in range(len(y_predict))])) # Root Mean Square Error
  mape = np.mean(np.abs((y_true - y_predict)/y_true)) *100 # Mean Absolute Percentage Error
  return rmse , mape
def run_xgboost(algo, x_train, y_train, x_test, y_test, verbose=True):
  train_result = {}
  test_result = {}
  print("Training the model")
  start = datetime.now()
  algo.fit(x_train, y_train , eval_metric = 'rmse')
  print("Done\n Time Taken: ",datetime.now()-start)
  print("Evaluating the model on Train data")
  start = datetime.now()
  y_train_predict = algo.predict(x_train)
  train_rmse, train_mape = get_error_matrix(y_train.values,y_train_predict)
  train_result = { 'rmse': train_rmse ,
                    'mape': train_mape ,
                   'y_predict': y_train_predict}
  print("Evaluating the model on Test data")
  y_test_predict = algo.predict(x_test)
  test_rmse, test_mape = get_error_matrix(y_test, y_test_predict)
  test_result = { 'rmse': test_rmse ,
                  'mape': test_mape ,
                  'y_predict':y_test_predict}
  if verbose:
    print("*"*100)
    print("Train Data")
    print("RMSE: ",train_rmse)
print("MAPE: ",train_mape)
    print("\n")
    print("*"*100)
    print("Test Data")
    print("RMSE: ",test_rmse)
    print("MAPE: ",test_mape)
    return train_result , test_result
```

Utility Function for Surprise Model

```
my_seed = 15
# random.seed(my_seed)
np.random.seed(my_seed)
def get_rating(prediction):
 actual = np.array([pred.r_ui for pred in prediction])
 predict = np.array([pred.est for pred in prediction])
 return actual, predict
def get_errors(prediction, print_them=False):
 actual , predict = get_rating(prediction)
 rmse = np.sqrt(np.mean((predict - actual)**2))
 mape = np.mean(np.abs(predict - actual)/actual)*100
 return rmse , mape
def run_surprise(algo, train_set , test_set, verbose=True):
 start = datetime.now()
 train_result = {}
 test_result = {}
 print("Training the surprise model")
 algo.fit(train_set)
 print("Done\n Time Taken: ",datetime.now()-start)
 # Evaluating Train set
 st = datetime.now()
 print("Evaluting the Train set")
 train_predict = algo.test(train_set.build_testset())
 train_actual_rating , train_predict_rating = get_rating(train_predict)
 train_rmse , train_mape = get_errors(train_predict)
 print("Time Taken: ",datetime.now()-st)
 train_result = { 'rmse': train_rmse,
                   'mape': train_mape,
                   'y_predict': train_predict_rating}
 if verbose:
   print("*"*100)
    print("Train Data")
    print("RMSE: ",train_rmse)
    print("MAPE: ",train_mape)
 # Evaluating Test set
 st = datetime.now()
 print("Evaluting the Test set")
  test_predict = algo.test(test_set)
 test_actual_rating , test_predict_rating = get_rating(test_predict)
 test_rmse , test_mape = get_errors(test_predict)
 print("Time Taken: ",datetime.now()-st)
 test_result = { 'rmse': test_rmse,
                   'mape': test_mape,
                   'y_predict': test_predict_rating}
 if verbose:
   print("*"*100)
   print("Test Data")
   print("RMSE: ",test_rmse)
   print("MAPE: ",test_mape)
 print("\n")
 print("~"*100)
 print("Total Time taken to run the algo: ",datetime.now()-start)
 return train result, test result
```

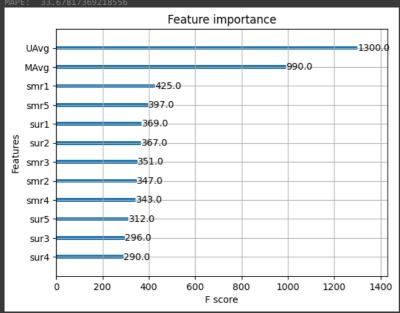
First XGBoost model with 13 handcraft features

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

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

first_xgb = xgb.XGBRegressor(n_job = -1, random_state=15, n_estimator=100, silence= False)
train_result, test_result = run_xgboost(first_xgb, x_train, y_train, x_test, y_test)
train_model_evaluation['first_algo'] = train_result
```

RMSE: 1.2192864215756742



Baseline Surprise model

```
bsl_options = {'method':'sgd', 'learning_rate': 0.001}
bsl_algo = BaselineOnly(bsl_options=bsl_options)
bsl_train_result , bsl_test_result = run_surprise(bsl_algo, train_set, test_set, verbose=True)
train_model_evaluation['bsl_algo'] = train_result
test_model_evaluation['bsl_algo'] = test_result
```

train_regression_data['bslpre'] = train_model_evaluation['bsl_algo']['y_predict'] train_regression_data.head(3) 0 53406 33 3.581679 4.0 5.0 5.0 4.0 1.0 5.0 2.0 5.0 3.0 1.0 3.370370 4.092437 4 3.919560 2 99865 33 3.581679 4.0 5.0 3.0 4.0 4.0 5.0 4.0 3.714286 4.092437 4.376114 5.0 5.0 5.0 test_regression_data['bslpre'] = test_model_evaluation['bsl_algo']['y_predict'] test_regression_data.head(3) 0 256033 24 3.5453241804811 from xgboost.sklearn import XGBRegressor x_train = train_regression_data.drop(['user', 'movie', 'rating'],axis=1) y_train = train_regression_data['rating'] x_test = test_regression_data.drop(['user', 'movie', 'rating'],axis=1) y_test = test_regression_data['rating'] second_xgb = xgb.XGBRegressor(n_job=-1, n_estimator=100, silence=False, random_state=15) train_result, test_result = run_xgboost(second_xgb, x_train, y_train, x_test, y_test) train_model_evaluation['second_xgb_bsl'] = train_result test_model_evaluation['second_xgb_bsl'] = test_result xgb.plot_importance(second_xgb) plt.show() Feature importance bslpre 1739.0 1065.0 UAvg 820.0 MAvg 259.0 sur1 233.0 smr5 226.0 sur5 Features =225.0 smr1 224.0 sur2 223.0 sur3 218.0 sur4 216.0 smr2 207.0 smr3 smr4 195.0

0

250

500

750

1000

F score

1250

1500

1750

Surprise KNN with user-user similarity

```
sim_options = { 'user_based':True, 'shrikage':100, "name":'pearson_baseline', 'min_support':2}
bsl_options = { 'method':'sgd'}
knn_baseline = KNNBaseline(sim_options = sim_options, bsl_options=bsl_options, k=20)
knn_u_bsl_train_result , knn_u_bsl_test_result = run_surprise(knn_baseline, train_set, test_set, verbose=True)
train_model_evaluation['knn_bsl_u'] = knn_u_bsl_train_result
test_model_evaluation['knn_bsl_u'] = knn_u_bsl_test_result
     Training the surprise model
    Estimating biases using sgd...
    Computing the pearson_baseline similarity matrix...
    Done computing similarity matrix.
    Done
     Time Taken: 0:00:14.746729
    Evaluting the Train set
     Time Taken: 0:01:38.492308
     Train Data
    RMSE: 0.2761839099722744
           7.391408141050905
    MAPE:
    Evaluting the Test set
    Time Taken: 0:00:00.055750
                               *************************
    Test Data
    RMSE: 1.1058524900205533
MAPE: 35.840822583307116
     Total Time taken to run the algo: 0:01:53.300548
```

Surprise KNN with item-item similarity model

```
sim_options = { 'user_based':False, 'shrikage':100, "name":'pearson_baseline', 'min_support':2}
bsl_options = { 'method':'sgd'}
knn_baseline = KNNBaseline(sim_options = sim_options, bsl_options=bsl_options, k=20)
knn_m_bsl_train_result , knn_m_bsl_test_result = run_surprise(knn_baseline, train_set, test_set, verbose=True)
train_model_evaluation['knn_bsl_m'] = knn_m_bsl_train_result
test_model_evaluation['knn_bsl_m'] = knn_m_bsl_test_result
     Training the surprise model
     Estimating biases using sgd...
     Computing the pearson_baseline similarity matrix...
     Done computing similarity matrix.
     Done
      Time Taken: 0:00:01.066893
     Evaluting the Train set
     Time Taken: 0:00:08.502476
                               *************************************
     Train Data
     RMSE: 0.3166747918437742
MAPE: 8.234166602083588
     Evaluting the Test set
     Time Taken: 0:00:00.055548
     RMSE: 1.1059045973935064
     MAPE: 35.842238488246274
     Total Time taken to run the algo: 0:00:09.629935
sim_options = { 'user_based':False,
```

```
train_regression_data['knn_bsl_u'] = train_model_evaluation['knn_bsl_u']['y_predict']
train_regression_data['knn_bsl_m'] = train_model_evaluation['knn_bsl_m']['y_predict']
train_regression_data.head(2)
                0 53406
                                                  33 3.581679
                                                                                        4.0
                                                                                                        5.0
                                                                                                                       5.0
                                                                                                                                       4.0
                                                                                                                                                      1.0
                                                                                                                                                                      5.0
                                                                                                                                                                                     2.0
                                                                                                                                                                                                     5.0
                                                                                                                                                                                                                    3.0
                                                                                                                                                                                                                                    1.0 3.370370 4.092437
                                                                                                                                                                                                                                                                                                               4 3.919560
                                                                                                                                                                                                                                                                                                                                                  3.890735
 test_regression_data['knn_bsl_u'] = test_model_evaluation['knn_bsl_u']['y_predict']
test_regression_data['knn_bsl_m'] = test_model_evaluation['knn_bsl_m']['y_predict']
test_regression_data.head(2)
                         256033
                                                       24 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3
x_train = train_regression_data.drop(['user', 'movie', 'rating'], axis=1)
y_train = train_regression_data['rating']
x_test = test_regression_data.drop(['user', 'movie', 'rating'], axis=1)
y_test = test_regression_data['rating']
third_xgb = xgb.XGBRegressor(n_estimator = 100, n_job = -1, silence= False, randon_state=15)
train_result , test_result = run_xgboost(third_xgb, x_train, y_train, x_test, y_test)
train_model_evaluation['xgb_bsl_knn'] = train_result
test_model_evaluation['xgb_bsl_knn'] = test_result
xgb.plot_importance(third_xgb)
plt.show()
```

```
svd = SVD(n_factors = 50, n_epochs = 20, biased= True, random_state= 15, verbose=True)
train_svd_result, test_svd_result = run_surprise(svd, train_set, test_set, verbose=True)
train_model_evaluation['svd'] = train_svd_result
test_model_evaluation['svd'] = test_svd_result
     Training the surprise 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: 0:00:03.823376
    Evaluting the Train set
    Time Taken: 0:00:05.871097
     Train Data
    RMSE: 0.7321358234779256
MAPE: 22.076350745298114
    Evaluting the Test set
    RMSE: 1.1058922174782135
MAPE: 35.83563206357407
    Total Time taken to run the algo: 0:00:09.957217
svdpp = SVDpp(n_factors= 50, n_epochs= 20, random_state= 15, verbose=True)
train_svdpp_result, test_svdpp_result = run_surprise(svdpp, train_set, test_set, verbose= True)
train_model_evaluation['svdpp'] = train_svdpp_result
test_model_evaluation['svdpp'] = test_svdpp_result
Training the surprise 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: 0:00:23.167086
    Evaluting the Train set
    Time Taken: 0:00:10.573294
     Train Data
    RMSE: 0.6032438403305899
    MAPE: 17.49285063490268
     Evaluting the Test set
     Time Taken: 0:00:00.056293
     Test Data
```

RMSE: 1.1059761773758738

```
MAPE: 35.830226335646685
     Total Time taken to run the algo: 0:00:33.805700
XGB with 13 features + bslpre + knn_bsl_u + knn_bsl_m + SVD + SVDPP
train_regression_data['svd'] = train_model_evaluation['svd']['y_predict']
train_regression_data['svdpp'] = train_model_evaluation['svdpp']['y_predict']
train_regression_data.head(2)
                                                                                                                                3.890735
      0 53406
                  33 3 581679
                                 4.0
                                       5.0
                                             5.0
                                                   4.0
                                                         1.0
                                                               5.0
                                                                     2.0
                                                                                3.0
                                                                                     1.0 3.370370 4.092437
                                                                                                                  4 3 919560
test_regression_data['svd'] = test_model_evaluation['svd']['y_predict']
test_regression_data['svdpp'] = test_model_evaluation['svdpp']['y_predict']
test_regression_data.head(2)
                     24 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324 3.545324
         256033
                                                                                                         3.545324 3.545324 3.545324 3.54
x_train = train_regression_data.drop(['user' , 'movie' , 'rating'], axis=1)
y_train = train_regression_data['rating']
x_test = test_regression_data.drop(['user', 'movie', 'rating'], axis = 1)
y_test = test_regression_data['rating']
forth_xgb = xgb.XGBRegressor(n_job=-1, random_state=15)
train_result, test_result = run_xgboost(forth_xgb, x_train, y_train, x_test, y_test)
train_model_evaluation['xgb_bsl_knn_svd_svdpp'] = train_result
test_model_evaluation['xgb_bsl_knn_svd_svdpp'] = test_result
```