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

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.a

Enter your authorization code:
··········
Mounted at /content/drive
```

```
#IMPORTING THE DATA FROM THE DATASETS.
import pandas as pd
import numpy as np
import csv
import matplotlib.pyplot as plt
from skimage import data, io, filters
# Import the necessary modules and libraries
import numpy as np
from sklearn.tree import DecisionTreeRegressor
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold


path_users = "/content/drive/My Drive/ML Project /users.dat"
path_ratings = "/content/drive/My Drive/ML Project /ratings.dat"
path_movies = "/content/drive/My Drive/ML Project /movies.dat"
```

Data Preparation

```
AGES = { 1: "Under 18", 18: "18-24", 25: "25-34", 35: "35-44", 45: "45-49", 50: "50-55", 56: "56+" }
OCCUPATIONS = { 0: "other or not specified", 1: "academic/educator", 2: "artist", 3: "clerical/admin",
                4: "college/grad student", 5: "customer service", 6: "doctor/health care",
                7: "executive/managerial", 8: "farmer", 9: "homemaker", 10: "K-12 student", 11: "lawyer",
                12: "programmer", 13: "retired", 14: "sales/marketing", 15: "scientist", 16: "self-employed",
```

```
                17: "technician/engineer", 18: "tradesman/craftsman", 19: "unemployed", 20: "writer" }

ratings = pd.read_csv(path_ratings,sep = '::', engine='python', names=['user_id', 'movie_id', 'rating', 'timestamp'])
max_userid = ratings['user_id'].drop_duplicates().max()
# Set max_movieid to the maximum movie_id in the ratings
max_movieid = ratings['movie_id'].drop_duplicates().max()

# Process ratings dataframe for Keras Deep Learning model
# Add user_emb_id column whose values == user_id - 1
ratings['user_emb_id'] = ratings['user_id'] - 1
# Add movie_emb_id column whose values == movie_id - 1
ratings['movie_emb_id'] = ratings['movie_id'] - 1

users = pd.read_csv(path_users,
                    sep='::',
                    engine='python',
                    names=['user_id', 'gender', 'age', 'occupation', 'zipcode'])
users['age_desc'] = users['age'].apply(lambda x: AGES[x])
users['occ_desc'] = users['occupation'].apply(lambda x: OCCUPATIONS[x])

movies = pd.read_csv(path_movies,sep='::',
                     engine ='python',
                     names = ['movie_id', 'title', 'genres'])

dataset = pd.merge(pd.merge(movies,ratings),users)

```

EXPLORATION

```
#computing the number of unique users and movies in this dataset:
noOfUsers = ratings.user_id.unique().shape[0]
noOfMovies = ratings.movie_id.unique().shape[0]
print("The no. of unique users is : {0}\nThe no. of unique movies is: {1}".format(noOfUsers,noOfMovies))
```

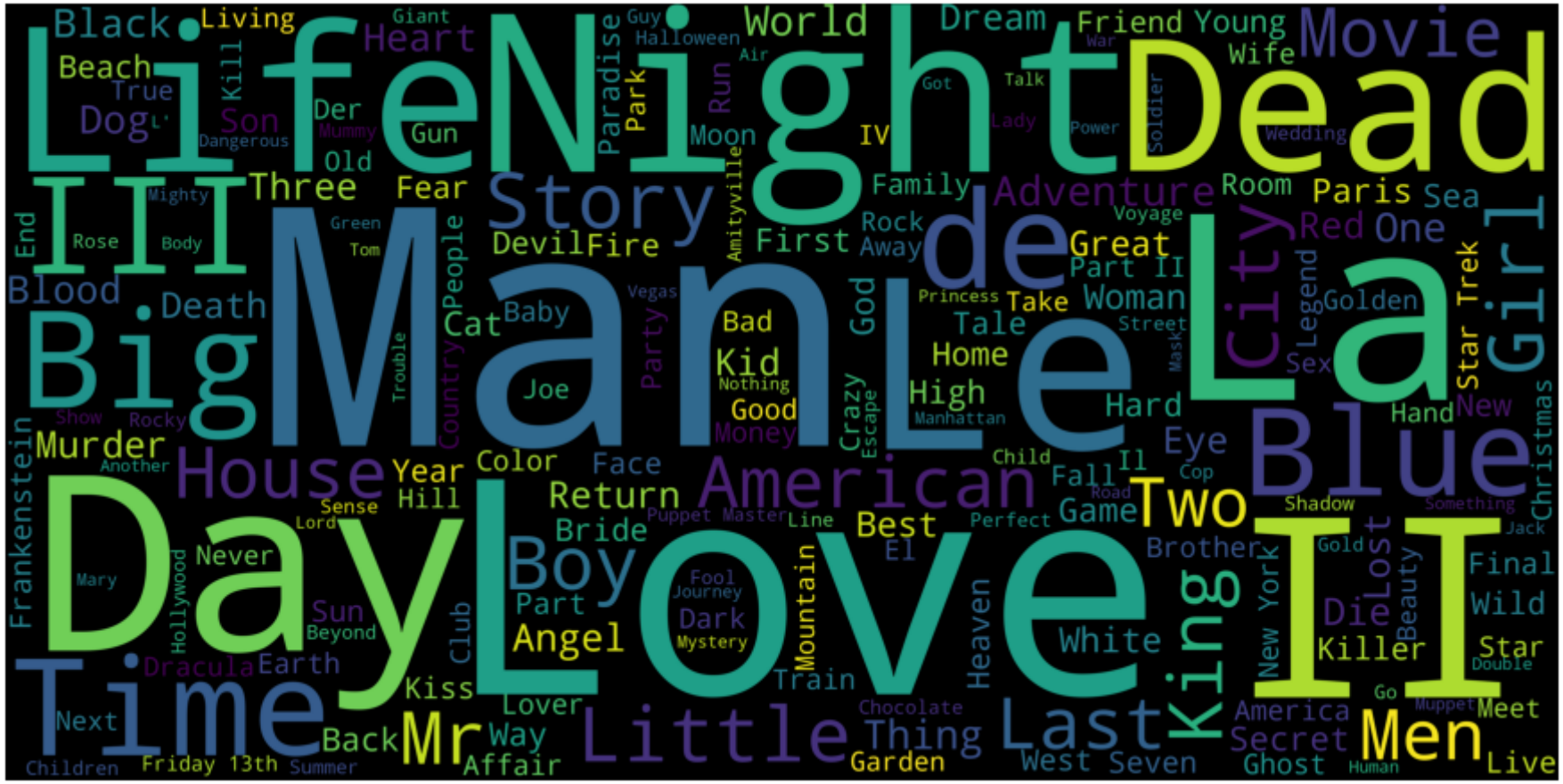
```
The no. of unique users is : 6040
The no. of unique movies is: 3706
```

```
print(users.info())
print(users.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   user_id     6040 non-null   int64 
 1   gender      6040 non-null   object
 2   age         6040 non-null   int64 
 3   occupation  6040 non-null   int64 
 4   zipcode     6040 non-null   object
 5   age_desc    6040 non-null   object
 6   occ_desc    6040 non-null   object
dtypes: int64(3), object(4)
memory usage: 330.4+ KB
None
   user_id gender  age  occupation zipcode  age_desc              occ_desc
0        1      F    1          10   48067  Under 18          K-12 student
1        2      M   56          16   70072       56+         self-employed
2        3      M   25          15   55117     25-34             scientist
3        4      M   45           7   02460     45-49  executive/managerial
4        5      M   25          20   55455     25-34                writer
```

```
import wordcloud
from wordcloud import WordCloud, STOPWORDS

movies['title'] = movies['title'].fillna("").astype('str')
title_list = ' '.join(movies['title'])
title_cloud = WordCloud(stopwords=STOPWORDS, height=2000, width=4000).generate(title_list)

plt.figure(figsize=(16,8))
plt.axis('off')
plt.imshow(title_cloud)
```

```
11 plt.show()
```

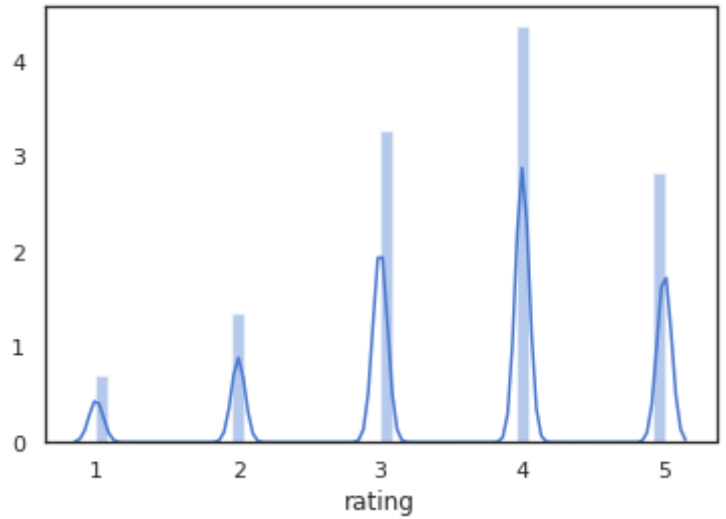



```
1 import seaborn as sns
2 import pandas.util.testing as tm
3 ratings['rating'].describe()
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use t
  import pandas.util.testing as tm
count    1.000209e+06
mean     3.581564e+00
std      1.117102e+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
```

```
1 sns.set(style="white", palette="muted", color_codes=True)
2 sns.distplot(ratings['rating'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb783d2e0f0>
```




```
1 dataset[['title','genres','rating']].sort_values('rating', ascending=False).head(20)
```

	title	genres	rating
0	Toy Story (1995)	Animation|Children's|Comedy	5
489283	American Beauty (1999)	Comedy|Drama	5
489259	Election (1999)	Comedy	5
489257	Matrix, The (1999)	Action|Sci-Fi|Thriller	5
489256	Dead Ringers (1988)	Drama|Thriller	5
489237	Rushmore (1998)	Comedy	5
489236	Simple Plan, A (1998)	Crime|Thriller	5
489226	Hands on a Hard Body (1996)	Documentary	5
489224	Pleasantville (1998)	Comedy	5
489212	Say Anything... (1989)	Comedy|Drama|Romance	5
489207	Beetlejuice (1988)	Comedy|Fantasy	5
489190	Roger & Me (1989)	Comedy|Documentary	5
489172	Buffalo 66 (1998)	Action|Comedy|Drama	5
489171	Out of Sight (1998)	Action|Crime|Romance	5
489170	I Went Down (1997)	Action|Comedy|Crime	5
489168	Opposite of Sex, The (1998)	Comedy|Drama	5
489157	Good Will Hunting (1997)	Drama	5
489152	Fast, Cheap & Out of Control (1997)	Documentary	5
489149	L.A. Confidential (1997)	Crime|Film-Noir|Mystery|Thriller	5
489145	Contact (1997)	Drama|Sci-Fi	5

```
1 count = [0,0,0,0,0]
```

```
count = [0,0,0,0,0]
for i in dataset['rating']:
  count[i-1] = count[i-1]+1

print("USER RATINGS\n_____________")
print("\n1 Star:{0}\n2 Star:{1}\n3 Star:{2}\n4 Star:{3}\n5 Star:{4}\n_____________\nTotal:{5} ratings".
      format(count[0],count[1],count[2],count[3],count[4],sum(count)))
```

```
USER RATINGS
_____________

1 Star:56174
2 Star:107557
3 Star:261197
4 Star:348971
5 Star:226310
_____________
Total:1000209 ratings
```

```
genre_labels = set()
for s in movies['genres'].str.split('|').values:
    genre_labels = genre_labels.union(set(s))

def count_word(dataset, ref_col, census):
    keyword_count = dict()
    for s in census:
        keyword_count[s] = 0
    for census_keywords in dataset[ref_col].str.split('|'):
        if type(census_keywords) == float and pd.isnull(census_keywords):
            continue
        for s in [s for s in census_keywords if s in census]:
            if pd.notnull(s):
                keyword_count[s] += 1
    keyword_occurences = []
    for k,v in keyword_count.items():
        keyword_occurences.append([k,v])
    keyword_occurences.sort(key = lambda x:x[1], reverse = True)
    return keyword_occurences, keyword_count
```

```
keyword_occurences, dum = count_word(movies, 'genres', genre_labels)
print("Movie\t\tNumber of Entries\n---------\t---------- ")
keyword_occurences = np.array(keyword_occurences)
for i in range (len(keyword_occurences)):
  print("{0}\t\t\t{1}\n".format(keyword_occurences[i][0],keyword_occurences[i][1]).ljust(10))
```

Movie	Number of Entries
Drama	1603
Comedy	1200
Action	503
Thriller	492
Romance	471
Horror	343
Adventure	283
Sci-Fi	276
Children's	251
Crime	211
War	143
Documentary	127
Musical	114
Mystery	106
Animation	105
Western	68
Fantasy	68
Film-Noir	44

Data pre-processing

```
# Creating a train, test and validation dataset
import pandas as pd
from sklearn import datasets, linear_model
from sklearn.model_selection import train_test_split

data_train, data_test = train_test_split(ratings, test_size=0.2)
data_test, data_valid = train_test_split(ratings, test_size = 0.5)
```

```
# Fill NaN values in user_id and movie_id column with 0
ratings['user_id'] = ratings['user_id'].fillna(0)
ratings['movie_id'] = ratings['movie_id'].fillna(0)

# Replace NaN values in rating column with average of all values
ratings['rating'] = ratings['rating'].fillna(ratings['rating'].mean())
print(ratings.info())
data_subset = ratings.sample(frac= 0.02)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 6 columns):
 #   Column        Non-Null Count    Dtype
---  ------        --------------    -----
 0   user_id       1000209 non-null  int64
 1   movie_id      1000209 non-null  int64
 2   rating        1000209 non-null  int64
 3   timestamp     1000209 non-null  int64
 4   user_emb_id   1000209 non-null  int64
 5   movie_emb_id  1000209 non-null  int64
dtypes: int64(6)
memory usage: 45.8 MB
None
```

```
ratings = ratings.drop(labels=[ 'user_emb_id',
```

```
'movie_emb_id'],axis =1)
```

```
dataset_in = dataset.drop(labels=['title', 'genres','user_emb_id', 'movie_emb_id', 'gender','age_desc','occ_desc','zipcode'],axis=
```

```
# Convert titles to string value
dataset['title'] = dataset['title'].fillna("").astype('str')
# Convert genres to string value
dataset['genres'] = dataset['genres'].fillna("").astype('str')
# Convert occupation description to string value
dataset['occ_desc'] = dataset['occ_desc'].fillna("").astype('str')
```

```
from sklearn.feature_extraction.text import TfidfVectorizer

tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='english')
tfidf_matrix_genres = tf.fit_transform(dataset['genres'])
print(tfidf_matrix_genres.shape)

tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='english')
tfidf_matrix_occ = tf.fit_transform(dataset['occ_desc'])
print(tfidf_matrix_occ.shape)

tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='english')
tfidf_matrix_title = tf.fit_transform(dataset['occ_desc'])
print(tfidf_matrix_title.shape)
```

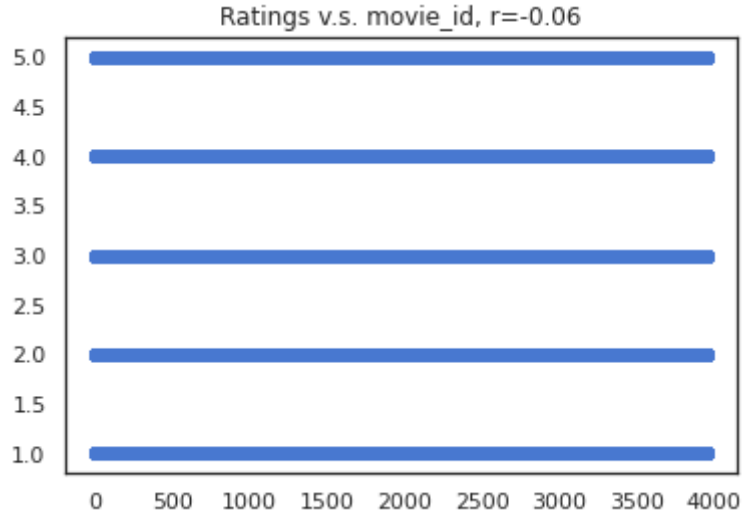
```
(1000209, 127)
(1000209, 46)
(1000209, 46)
```

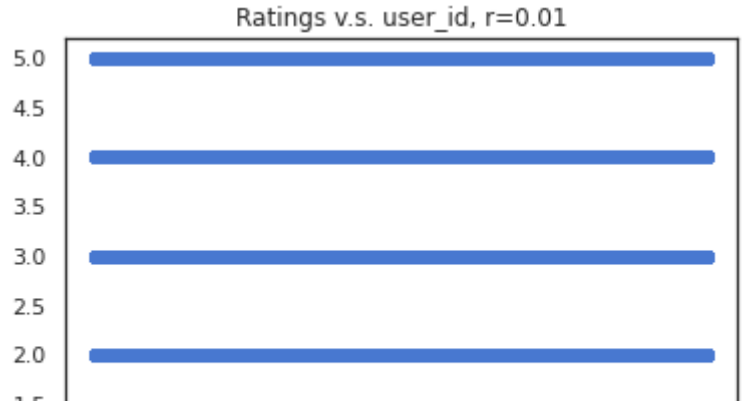
```
#pearson's r between features vs ratings
from scipy.stats import pearsonr

print(dataset_in)
dataset_in = dataset_in.drop(labels=['rating'],axis=1)
target = dataset.rating
for i in dataset_in.columns:
  plt.scatter(dataset_in[i],target)
```

```
plt.scatter(dataset_in[i],target)
corr,p = pearsonr(dataset_in[i],target)
plt.title("Ratings v.s. " + i + ", r=" + str(format(corr, '.2f')))
plt.show()
```

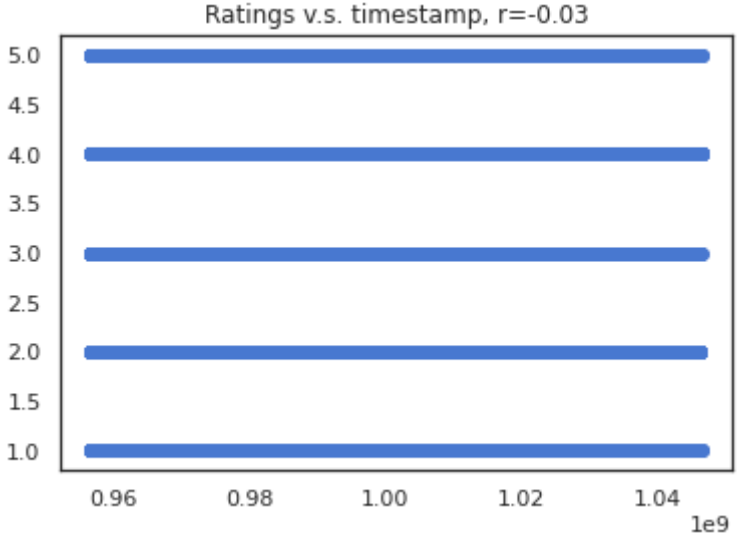
	movie_id	user_id	rating	timestamp	age	occupation
0	1	1	5	978824268	1	10
1	48	1	5	978824351	1	10
2	150	1	5	978301777	1	10
3	260	1	4	978300760	1	10
4	527	1	5	978824195	1	10
...	...	...	...	...	...	...
1000204	3513	5727	4	958489970	25	4
1000205	3535	5727	2	958489970	25	4
1000206	3536	5727	5	958489902	25	4
1000207	3555	5727	3	958490699	25	4
1000208	3578	5727	5	958490171	25	4

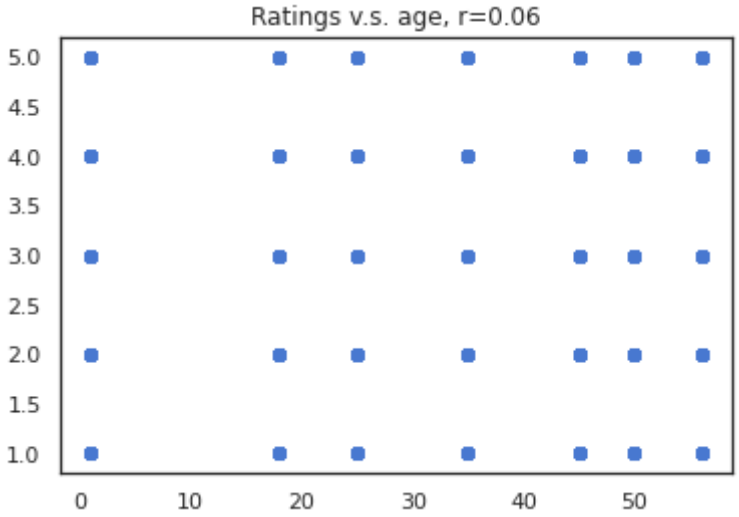
[1000209 rows x 6 columns]

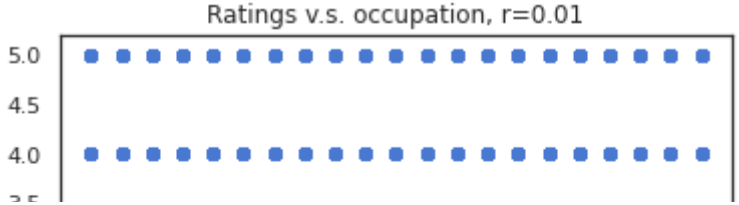


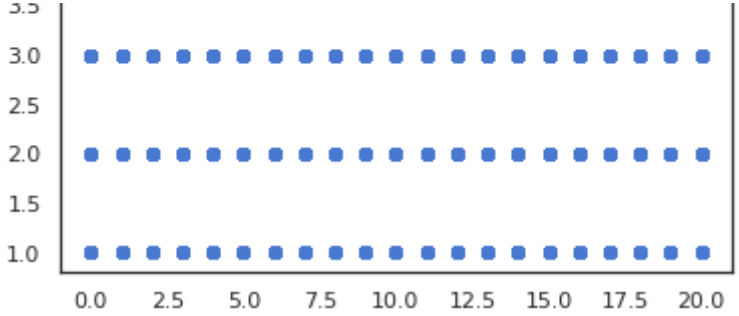



1.5
1.0
0
1000
2000
3000
4000
5000
6000


Ratings v.s. timestamp, r=-0.03
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.96
0.98
1.00
1.02
1.04
1e9


Ratings v.s. age, r=0.06
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
10
20
30
40
50


Ratings v.s. occupation, r=0.01
5.0
4.5
4.0




```
for i in dataset_in.columns:
  for j in dataset_in.columns:
    corr, p = pearsonr(dataset_in[i], dataset_in[j])
    print(format(corr, '.2f'), end = ',')
  print()

```

```
1.00,-0.02,0.04,0.03,0.01,
-0.02,1.00,-0.49,0.03,-0.03,
0.04,-0.49,1.00,-0.06,0.02,
0.03,0.03,-0.06,1.00,0.08,
0.01,-0.03,0.02,0.08,1.00,
```

```
data_train, data_test, target_train, target_test = train_test_split(dataset_in,target, test_size=0.2)
data_test, data_valid, target_test, target_valid = train_test_split(data_test,target_test,test_size = 0.5)
```

```
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge

lr = LinearRegression()
lr.fit(data_train,target_train)

train_score, train_score_p = pearsonr(lr.predict(data_train),target_train)
print("r=" + format(train_score, '.2f') + ", p=" + format(train_score_p, '.2f'))

test_score, test_score_p = pearsonr(lr.predict(data_test),target_test)
print("r=" + format(test_score, '.2f') + ", p=" + format(test_score_p, '.2f'))
```

```
r=0.09, p=0.00
r=0.09, p=0.00
```

```
# Randomly sample 1% of the ratings dataset
small_data = dataset_in.sample(frac=0.02)
# Check the sample info
print(small_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20004 entries, 671785 to 527272
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   movie_id    20004 non-null  int64
 1   user_id     20004 non-null  int64
 2   timestamp   20004 non-null  int64
 3   age         20004 non-null  int64
 4   occupation  20004 non-null  int64
dtypes: int64(5)
memory usage: 937.7 KB
None
```

```
data_train, data_test= train_test_split(small_data, test_size=0.2)
# data_test, data_valid= train_test_split(data_test, test_size = 0.5)
```

```
# Create two user-item matrices, one for training and another for testing
train_data_matrix = np.array(data_train.drop(labels=['age', 'occupation'],axis=1))
test_data_matrix = np.array(data_test.drop(labels=['age', 'occupation'],axis=1))

# Check their shape
print(train_data_matrix.shape)
print(test_data_matrix.shape)
```

```
(16003, 3)
(4001, 3)
```

```
from sklearn.metrics.pairwise import pairwise_distances
```

```
# Item Similarity Matrix
item_correlation = 1 - pairwise_distances(train_data_matrix.T, metric='correlation')
item_correlation[np.isnan(item_correlation)] = 0
print(item_correlation)
```

```
[[ 1.         -0.01479626  0.03406019]
 [-0.01479626  1.         -0.48371933]
 [ 0.03406019 -0.48371933  1.        ]]
```

```
# Function to predict ratings
def predict(ratings, similarity):
    pred = ratings.dot(similarity) / np.array([np.abs(similarity).sum(axis=1)])
    return pred
```

```
from sklearn.metrics import mean_squared_error
from math import sqrt

# Function to calculate RMSE
def rmse(pred, actual):
    # Ignore nonzero terms.
    pred = pred[actual.nonzero()].flatten()
    actual = actual[actual.nonzero()].flatten()
    return sqrt(mean_squared_error(pred, actual))
```

```
item_prediction = predict(train_data_matrix, item_correlation)
```

```
# RMSE on the test data
print('Item-based CF RMSE: ' + str(rmse(item_prediction, test_data_matrix)))
```

```
Item-based CF RMSE: 264455589.246584
```

```
# RMSE on the train data
print('Item-based CF RMSE: ' + str(rmse(item_prediction, train_data_matrix)))
```

```
Item-based CF RMSE: 264269704.02283144
```

PCA Implementation

```
Ratings = ratings.pivot(index = 'user_id', columns ='movie_id', values = 'rating').fillna(0)
```

```
# Data_Preprocessing for zero mean
R = Ratings.to_numpy()
user_ratings_mean = np.mean(R, axis = 1)
Ratings_demeaned = R - user_ratings_mean.reshape(-1, 1)
```

```
from numpy import mean
from numpy import cov
from numpy.linalg import eig

V = cov(Ratings_demeaned.T)
values, vectors = eig(V)
new_vectors=np.argsort(values)[-50:]
new_values = []
Vt = []
U = []

for i in new_vectors:
  new_values.append(values[i])
  Vt.append(vectors[i])
  U.append(R.T[i])
sigma= np.diag(new_values)

Vt = np.array(Vt)
U = np.array(U)
P = np.dot(np.dot(U.T, sigma), Vt)
P = P + user_ratings_mean.reshape(-1, 1)
P = pd.DataFrame(P, columns = Ratings.columns)
P.head()
```

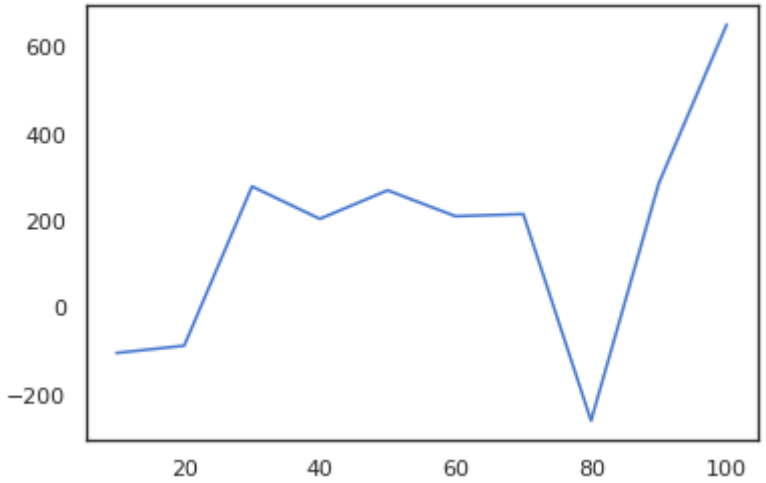
movie_id	1	2	3	4	5	6
0	-54.567852+0.000000j	15.089488+0.000000j	28.505553+0.000000j	48.413456+0.000000j	47.102674+0.000000j	51.276238+0.000000j
1	-0.210675+0.000000j	0.192335+0.000000j	0.314633+0.000000j	-0.025535+0.000000j	-0.025579+0.000000j	0.014184+0.000000j
2	0.053697+0.000000j	0.053697+0.000000j	0.053697+0.000000j	0.053697+0.000000j	0.053697+0.000000j	0.053697+0.000000j
3	0.023745+0.000000j	0.023745+0.000000j	0.023745+0.000000j	0.023745+0.000000j	0.023745+0.000000j	0.023745+0.000000j
4	-7.530086+0.000000j	0.809984+0.000000j	6.014066+0.000000j	-9.423351+0.000000j	0.393749+0.000000j	1.785977+0.000000j

5 rows × 3706 columns

```
# SVD for dimensionality reduction
sigma_list = []
U_list = []
Vt_list = []
for i in range (1,11):
  from scipy.sparse.linalg import svds
  U, sigma, Vt = svds(Ratings_demeaned, k=i*10)
  sigma_list.append(sigma)
  U_list.append(U)
  Vt_list.append(Vt)
s= []
for i in range(len(sigma_list)):
  Lambda_d_sum = sum(sum(U_list[i]))
  Lambda_k_sum = sum(sigma_list[i])
  sk = Lambda_k_sum/Lambda_d_sum
  s.append(sk)


```

```
k =[10,20,30,40,50,60,70,80,90,100]
plt.plot(k,s)
```

```
[<matplotlib.lines.Line2D at 0x7fb7921a35c0>]
```




```
def reconstruct_data(U,sigma,Vt):
  sigma = np.diag(sigma)
  all_user_predicted_ratings = np.dot(np.dot(U, sigma), Vt) + user_ratings_mean.reshape(-1, 1)
  preds = pd.DataFrame(all_user_predicted_ratings, columns = Ratings.columns)
```

```
sigma = np.diag(sigma)
```

```
all_user_predicted_ratings = np.dot(np.dot(U, sigma), Vt) + user_ratings_mean.reshape(-1, 1)
```

```
preds = pd.DataFrame(all_user_predicted_ratings, columns = Ratings.columns)
```

```
preds.head()
```

movie_id	1	2	3	4	5	6	7	8	9	10	11	1
0	5.157608	0.184833	0.348341	-0.022609	0.139622	-0.156937	-0.061122	0.072117	0.018278	-0.372566	-0.275992	-0.06915
1	0.557186	0.296927	0.078853	-0.013888	0.028675	1.092160	-0.054492	0.114191	0.090106	1.695371	0.611882	0.08798
2	2.176318	0.396428	0.302057	-0.117164	-0.006330	0.077833	0.000836	0.064654	-0.018309	1.062417	-0.231946	0.04593
3	0.194185	0.155507	0.046863	0.047477	-0.014495	0.247765	-0.057580	-0.006338	0.007387	-0.423240	-0.267654	0.00019

```
1 ratings.head()
```

	user_id	movie_id	rating	timestamp	user_emb_id	movie_emb_id
0	1	1193	5	978300760	0	1192
1	1	661	3	978302109	0	660
2	1	914	3	978301968	0	913
3	1	3408	4	978300275	0	3407
4	1	2355	5	978824291	0	2354

```
1 def recommend_movies(predictions, userID, movies, original_ratings, num_recommendations):
2
3     # Get and sort the user's predictions
4     user_row_number = userID - 1 # User ID starts at 1, not 0
5     sorted_user_predictions = preds.iloc[user_row_number].sort_values(ascending=False)
6
7     # Get the user's data and merge in the movie information.
8     user_data = original_ratings[original_ratings.user_id == (userID)]
9     #adding information about the movie. This is not part of the prediction just for visualisation
10    user_full = (user_data.merge(movies, how = 'left', left_on = 'movie_id', right_on = 'movie_id').
11                     sort_values(['rating'], ascending=False)
12                 )
13
14    print('User {0} has already rated {1} movies.'.format(userID, user_full.shape[0]))
15    print('Recommending highest {0} predicted ratings movies not already rated.'.format(num_recommendations))
16
```

```
    # Recommend the highest predicted rating movies that the user hasn't seen yet.
    recommendations = (movies[~movies['movie_id'].isin(user_full['movie_id'])].
         merge(pd.DataFrame(sorted_user_predictions).reset_index(), how = 'left',
               left_on = 'movie_id',
               right_on = 'movie_id').
         rename(columns = {user_row_number: 'Predictions'}).
         sort_values('Predictions', ascending = False).
                       iloc[:num_recommendations, :-1]
                      )

    return user_full, recommendations
```

```
already_rated, predictions = recommend_movies(preds, 65, movies, ratings, 50)
```

```
User 65 has already rated 121 movies.
Recommending highest 50 predicted ratings movies not already rated.
```

```
already_rated.head(10)
```

	user_id	movie_id	rating	timestamp	user_emb_id	movie_emb_id	title	genres
120	65	1246	5	987383453	64	1245	Dead Poets Society (1989)	Drama
100	65	1124	5	983853171	64	1123	On Golden Pond (1981)	Drama
54	65	3252	5	977888608	64	3251	Scent of a Woman (1992)	Drama
53	65	1573	5	986615241	64	1572	Face/Off (1997)	Action|Sci-Fi|Thriller
94	65	500	5	977888587	64	499	Mrs. Doubtfire (1993)	Comedy
51	65	969	5	986615227	64	968	African Queen, The (1951)	Action|Adventure|Romance|War
95	65	1036	5	986615095	64	1035	Die Hard (1988)	Action|Thriller

```
1 predictions.head(50)
```

3397	3578	Gladiator (2000)	Action|Drama
2485	2640	Superman (1978)	Action|Adventure|Sci-Fi
1866	2002	Lethal Weapon 3 (1992)	Action|Comedy|Crime|Drama
3232	3408	Erin Brockovich (2000)	Drama
8	11	American President, The (1995)	Comedy|Drama|Romance
2260	2405	Jewel of the Nile, The (1985)	Action|Adventure|Comedy|Romance
569	589	Terminator 2: Judgment Day (1991)	Action|Sci-Fi|Thriller
3638	3827	Space Cowboys (2000)	Action|Sci-Fi
1176	1234	Sting, The (1973)	Comedy|Crime
353	364	Lion King, The (1994)	Animation|Children's|Musical
3264	3441	Red Dawn (1984)	Action|War
3272	3450	Grumpy Old Men (1993)	Comedy
2719	2881	Double Jeopardy (1999)	Action|Thriller
154	161	Crimson Tide (1995)	Drama|Thriller|War
57	62	Mr. Holland's Opus (1995)	Drama
2915	3082	World Is Not Enough, The (1999)	Action|Thriller
2158	2302	My Cousin Vinny (1992)	Comedy
1212	1275	Highlander (1986)	Action|Adventure
1077	1127	Abyss, The (1989)	Action|Adventure|Sci-Fi|Thriller
1488	1584	Contact (1997)	Drama|Sci-Fi
1745	1876	Deep Impact (1998)	Action|Drama|Sci-Fi|Thriller
1047	1092	Basic Instinct (1992)	Mystery|Thriller
1577	1682	Truman Show, The (1998)	Drama

2275	2424	You've Got Mail (1998)	Comedy|Romance
2934	3101	Fatal Attraction (1987)	Thriller
3188	3363	American Graffiti (1973)	Comedy|Drama
2822	2985	Robocop (1987)	Action|Crime|Sci-Fi
2632	2791	Airplane! (1980)	Comedy
887	924	2001: A Space Odyssey (1968)	Drama|Mystery|Sci-Fi|Thriller
283	292	Outbreak (1995)	Action|Drama|Thriller
43	47	Seven (Se7en) (1995)	Crime|Thriller
459	474	In the Line of Fire (1993)	Action|Thriller

```python
#Evaluation of the model
from surprise import SVD
from surprise import Dataset, Reader
from surprise.model_selection import cross_validate

reader = Reader()

# Load the movielens-100k dataset (download it if needed),
data = Dataset.load_from_df(ratings[['user_id', 'movie_id', 'rating']], reader)

# We'll use the famous SVD algorithm.
algo = SVD()

# Run 5-fold cross-validation and print results
cross_validate(algo, data, measures=['RMSE'], cv=5, verbose=True)
```

```
Evaluating RMSE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std     
RMSE (testset)    0.8753  0.8748  0.8714  0.8723  0.8741  0.8736  0.0015  
Fit time          59.14   59.48   59.90   57.42   58.90   58.97   0.85    
Test time         2.76    2.99    2.78    2.45    2.76    2.75    0.17    
{'fit_time': (59.143911838531494,
  59.48141026496887,
  59.902074337005615,
  57.41506791114807,
  58.90307545661926),
 'test_rmse': array([0.87532321, 0.87482425, 0.87136265, 0.87230161, 0.87410427]),
 'test_time': (2.758392333984375,
  2.9852092266082764,
  2.7836737632751465,
  2.4511756896972656,
  2.761986017227173)}
```