Recomendation System

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Overview

I am looking at movie recommendations for users based on movies that they have currently rated.

Data Understanding

The data is from the MovieLens dataset from the GroupLens research lab at the University of Minnesota.

In [42]:

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from collections import defaultdict
from surprise import Dataset, Reader
from surprise.prediction_algorithms import SVD
from surprise.prediction_algorithms import KNNWithMeans, KNNBasic, SVDpp, KNNBaseline
from surprise import accuracy
from surprise.model_selection import cross_validate, train_test_split, GridSearchCV


links = pd.read_csv('links.csv')
movies = pd.read_csv('movies.csv')
ratings = pd.read_csv('ratings.csv')
tags = pd.read_csv('tags.csv')
```

In [2]:

```
links.head()
```

Out[2]:

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0

In [3]:

```
movies.head()
```

Out[3]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [4]:

```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   movieId  9742 non-null   int64 
 1   title    9742 non-null   object
 2   genres   9742 non-null   object
dtypes: int64(1), object(2)
memory usage: 228.5+ KB
```

In [5]:

```
movies['genres'].value_counts()
```

Out[5]:

```
Drama                                           1053
Comedy                                           946
Comedy|Drama                                     435
Comedy|Romance                                   363
Drama|Romance                                    349
                                                ... 
Action|Adventure|Drama|Romance|Thriller|Western    1
Adventure|Animation|Children|Musical|Western       1
Action|Fantasy|Mystery                             1
Adventure|Documentary|Western                      1
Adventure|Mystery|Thriller                         1
Name: genres, Length: 951, dtype: int64
```

In [6]:

```
ratings.head()
```

Out[6]:

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

In [7]:

```
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   userId     100836 non-null  int64  
 1   movieId    100836 non-null  int64  
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64  
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
```

In [8]:

```
tags.head()
```

Out[8]:

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200

In [9]:

```
tags['tag'].value_counts()
```

Out[9]:

```
In Netflix queue     131
atmospheric           36
thought-provoking     24
superhero             24
surreal               23
                    ...
con artists            1
gintama                1
space station          1
Michigan               1
Animation              1
Name: tag, Length: 1589, dtype: int64
```

In [10]:

```
tags.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3683 entries, 0 to 3682
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   userId     3683 non-null   int64
 1   movieId    3683 non-null   int64
 2   tag        3683 non-null   object
 3   timestamp  3683 non-null   int64
dtypes: int64(3), object(1)
memory usage: 115.2+ KB
```

In [11]:

```
ratings = ratings.drop(columns='timestamp')
ratings.head()
```

Out[11]:

	userId	movieId	rating
0	1	1	4.0
1	1	3	4.0
2	1	6	4.0
3	1	47	5.0
4	1	50	5.0

In [12]:

```
print('Number of Users: ', len(ratings['userId'].unique()))
print('Number of Movies: ', len(ratings['movieId'].unique()))
```

```
Number of Users:  610
Number of Movies:  9724
```

In [13]:

```
ratings['movieId'].value_counts()
```

Out[13]:

```
356       329
318       317
296       307
593       279
2571      278
         ...
5986        1
100304      1
34800       1
83976       1
8196        1
Name: movieId, Length: 9724, dtype: int64
```

In [14]:

```
ratings['rating'].value_counts()
```

Out[14]:

```
4.0    26818
3.0    20047
5.0    13211
3.5    13136
4.5     8551
2.0     7551
2.5     5550
1.0     2811
1.5     1791
0.5     1370
Name: rating, dtype: int64
```

In [15]:

```
ratings
```

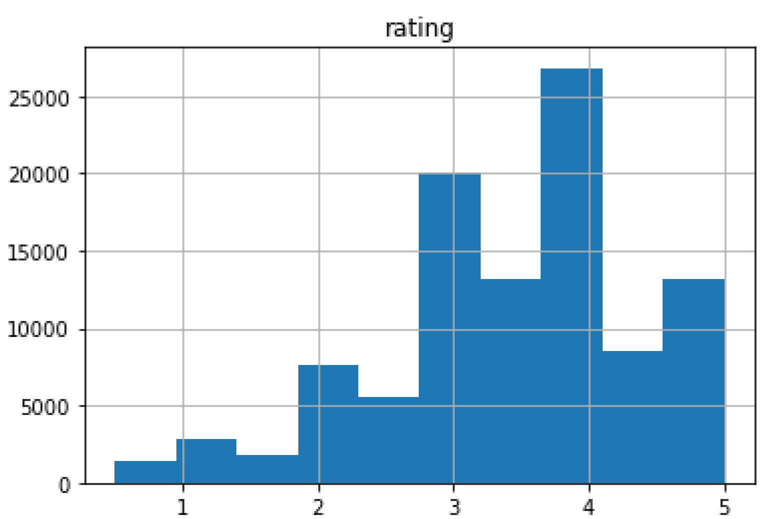
Out[15]:

	userId	movieId	rating
0	1	1	4.0
1	1	3	4.0
2	1	6	4.0
3	1	47	5.0
4	1	50	5.0
...	...	...	...
100831	610	166534	4.0
100832	610	168248	5.0
100833	610	168250	5.0
100834	610	168252	5.0
100835	610	170875	3.0

100836 rows × 3 columns

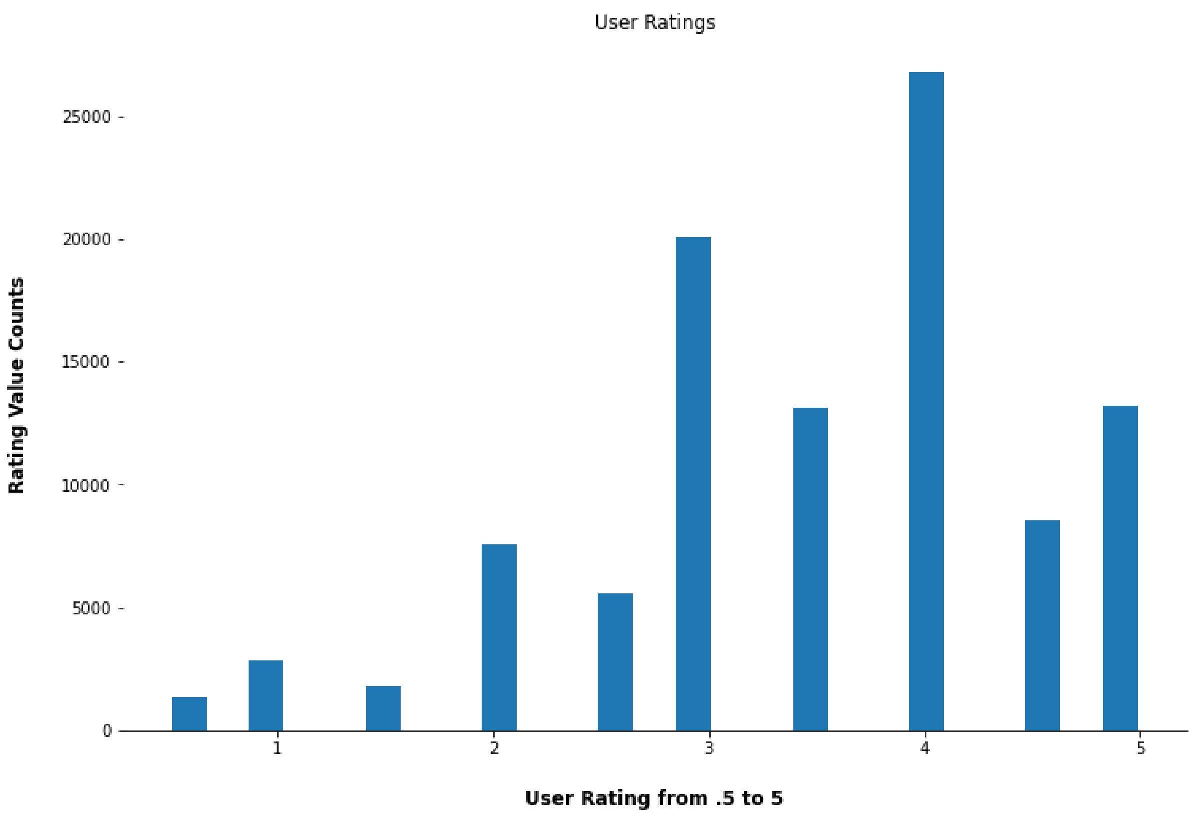
In [16]:

```
ratings.hist(column='rating');
```



In [17]:

```
ax = ratings.hist(column='rating', bins=25, grid=False, figsize=(12,8), zorder=2, rwidth=
0.9)

ax = ax[0]
for x in ax:

    # Despine
    x.spines['right'].set_visible(False)
    x.spines['top'].set_visible(False)
    x.spines['left'].set_visible(False)


    # Set title
    x.set_title("User Ratings")

    # Set x-axis label
    x.set_xlabel("User Rating from .5 to 5", labelpad=20, weight='bold', size=12)

    # Set y-axis label
    x.set_ylabel("Rating Value Counts", labelpad=20, weight='bold', size=12)
```



In [18]:

```
tags = tags.drop(columns='timestamp')
tags.head()
```

Out[18]:

	userId	movieId	tag
0	2	60756	funny
1	2	60756	Highly quotable
2	2	60756	will ferrell
3	2	89774	Boxing story
4	2	89774	MMA

In [19]:

```
print('Number of Users: ', len(tags['userId'].unique()))
```

```
Number of Users:  58
```

In [20]:

```
movie_rate = pd.merge(ratings, movies, on="movieId")
movie_rate.head()
```

Out[20]:

	userId	movieId	rating	title	genres
0	1	1	4.0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	5	1	4.0	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2	7	1	4.5	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
3	15	1	2.5	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
4	17	1	4.5	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy

Fitting and evalutating models

In [21]:

```
data = Dataset.load_builtin('ml-100k')

data
```

Out[21]:

```
<surprise.dataset.DatasetAutoFolds at 0x28387163370>
```

In [22]:

```
reader = Reader()
data = Dataset.load_from_df(ratings,reader)
```

In [23]:

```
dataset = data.build_full_trainset()
print('Number of users: ', dataset.n_users, '\n')
print('Number of items: ', dataset.n_items)
```

```
Number of users:  610

Number of items:  9724
```

In [24]:

```
svd = SVD()

cross_validate(svd, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
```

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std     
RMSE (testset)    0.8735  0.8705  0.8695  0.8707  0.8807  0.8730  0.0041  
MAE (testset)     0.6675  0.6697  0.6697  0.6686  0.6769  0.6705  0.0033  
Fit time          3.67    3.78    3.75    3.59    3.63    3.68    0.07    
Test time         0.17    0.13    0.12    0.17    0.17    0.15    0.02    
```

Out[24]:

```
{'test_rmse': array([0.87347809, 0.87048712, 0.86954418, 0.87073821, 0.880720
04]),
 'test_mae': array([0.6675004 , 0.66968616, 0.66969037, 0.66860142, 0.6769417
7]),
 'fit_time': (3.6692898273468018,
  3.777430295944214,
  3.752838611602783,
  3.5866305828094482,
  3.6307055950164795),
 'test_time': (0.17322015762329102,
  0.1282846927642822З,
  0.12024235725402832,
  0.17186403274536133,
  0.1718614101409912)}
```

In [25]:

```
knn_basic = KNNBasic(sim_options={'name':'pearson', 'user_based':True})
cv_knn_basic = cross_validate(knn_basic, data, n_jobs=-1)
```

In [26]:

```
for i in cv_knn_basic.items():
    print(i)
print('-----------------------')
print(np.mean(cv_knn_basic['test_rmse']))
```

```
('test_rmse', array([0.96556751, 0.97925263, 0.96494013, 0.97764695, 0.970280
02]))
('test_mae', array([0.74597448, 0.75468261, 0.74364708, 0.75579282, 0.7509554
8]))
('fit_time', (0.8944814205169678, 1.0350899696350098, 1.143585443496704, 0.99
60765838623047, 0.9640946388244629))
('test_time', (1.8693113327026367, 2.0274808406829834, 1.50346040725708, 1.55
03294467926025, 1.683650255203247))
-----------------------
0.971537448339444
```

In [27]:

```
knn_baseline = KNNBaseline(sim_options={'name':'pearson', 'user_based':True})
cv_knn_baseline = cross_validate(knn_baseline,data)
```

```
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson similarity matrix...
Done computing similarity matrix.
```

In [28]:

```
for i in cv_knn_baseline.items():
    print(i)

np.mean(cv_knn_baseline['test_rmse'])
```

```
('test_rmse', array([0.86492046, 0.88268782, 0.87804768, 0.87600864, 0.878932
54]))
('test_mae', array([0.66166239, 0.67564623, 0.67143513, 0.67168009, 0.6649395
1]))
('fit_time', (0.7305805683135986, 0.7280683517456055, 0.7347829341888428, 0.7
352149486541748, 0.8651642799377441))
('test_time', (1.6508536338806152, 1.6394004821777344, 1.6811461448669434, 1.
8070271015167236, 1.9446942806243896))
```

Out[28]:

```
0.8761194301708752
```

In [29]:

```
train, test = train_test_split(data, test_size=.2)
```

Based on the results, the best model is SVD.

In [32]:

```
svd = SVD(n_factors= 50, reg_all=0.05)
svd.fit(dataset)
```

Out[32]:

```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x2838361a9a0>
```

In [41]:

```
svd.predict(2,500)
```

Out[41]:

```
Prediction(uid=2, iid=500, r_ui=None, est=3.599943785478982, details={'was_im
possible': False})
```

In [36]:

```
def movie_rater(movie_df,num, genre=None):
    userID = 1000
    rating_list = []
    while num > 0:
        if genre:
            movie = movie_df[movies['genres'].str.contains(genre)].sample(1)
        else:
            movie = movies.sample(1)
        print(movie)
        rating = input('How do you rate this movie on a scale of 1-5, press n if you have
 not seen :\n')
        if rating == 'n':
            continue
        else:
            rating_one_movie = {'userId':userID,'movieId':movie['movieId'].values[0],'rati
ng':rating}
            rating_list.append(rating_one_movie)
            num -= 1
    return rating_list
```

In [37]:

```
user_rating = movie_rater(movies, 4, 'Comedy')
```

```
      movieId                  title  genres
2338     3096  My Man Godfrey (1957)  Comedy

     movieId                                           title  \
924     1223  Grand Day Out with Wallace and Gromit, A (1989)

                                          genres
924  Adventure|Animation|Children|Comedy|Sci-Fi

     movieId             title                                    genres
337      380  True Lies (1994)  Action|Adventure|Comedy|Romance|Thriller

      movieId                          title        genres
4120     5912  Hit the Bank (Vabank) (1981)  Comedy|Crime

      movieId                  title          genres
7758    91337  Play the Game (2009)  Comedy|Romance

      movieId                       title  genres
6222    45726  You, Me and Dupree (2006)  Comedy

      movieId                  title                 genres
7981    96655  Robot & Frank (2012)  Comedy|Drama|Sci-Fi

      movieId                        title          genres
2132     2837  Bedrooms & Hallways (1998)  Comedy|Romance

      movieId                           title        genres
2926     3925  Stranger Than Paradise (1984)  Comedy|Drama

      movieId                          title                        genres
8462   112460  Planes: Fire & Rescue (2014)  Adventure|Animation|Comedy

      movieId        title                 genres
5506    26422  Hair (1979)  Comedy|Drama|Musical

     movieId         title        genres
164      194  Smoke (1995)  Comedy|Drama

      movieId           title          genres
3687     5077  Cousins (1989)  Comedy|Romance

      movieId                                              title  genres
2094     2788  Monty Python's And Now for Something Completel...  Comedy

      movieId                                  title           genres
7962    96283  Diary of a Wimpy Kid: Dog Days (2012)  Children|Comedy

      movieId                           title  genres
7019    68444  Great Buck Howard, The (2008)  Comedy

      movieId                          title        genres
3628     4979  Royal Tenenbaums, The (2001)  Comedy|Drama

      movieId                            title        genres
6206    45440  Art School Confidential (2006)  Comedy|Drama

     movieId                title                             genres
870     1151  Lesson Faust (1994)  Animation|Comedy|Drama|Fantasy
```

```
      movieId                 title             genres
6738    59143  Super High Me (2007)  Comedy|Documentary

      movieId                   title  genres
2441     3254  Wayne's World 2 (1993)  Comedy
```

In [38]:

```
user_rating
```

Out[38]:

```
[{'userId': 1000, 'movieId': 380, 'rating': '3'},
 {'userId': 1000, 'movieId': 45726, 'rating': '1'},
 {'userId': 1000, 'movieId': 2788, 'rating': '5'},
 {'userId': 1000, 'movieId': 3254, 'rating': '2'}]
```

In [39]:

```
new_ratings_df = ratings.append(user_rating,ignore_index=True)
new_data = Dataset.load_from_df(new_ratings_df,reader)
```

In [40]:

```
dataset = data.build_full_trainset()
print('Number of users: ', dataset.n_users, '\n')
print('Number of items: ', dataset.n_items)
```

```
Number of users:  610

Number of items:  9724
```

Recommendations for the new user

In [44]:

```
svd_ = SVD(n_factors= 50, reg_all=0.05)
svd_.fit(new_data.build_full_trainset())
```

Out[44]:

```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x2838361deb0>
```

In [46]:

```
list_of_movies = []
for m_id in ratings['movieId'].unique():
    list_of_movies.append( (m_id,svd_.predict(1000,m_id)[3]))
```

In [47]:

```
ranked_movies = sorted(list_of_movies, key=lambda x:x[1], reverse=True)
```

In [53]:

```
def recommended_movies(user_ratings,movie_title_df,n):
        for idx, rec in enumerate(user_ratings):
            title = movie_title_df.loc[movie_title_df['movieId'] == int(rec[0])]['title']
            print('Recommendation # ', idx+1, ': ', title, '\n')
            n-= 1
            if n == 0:
                break

recommended_movies(ranked_movies,movies,10)
```

```
Recommendation #  1 :  277    Shawshank Redemption, The (1994)
Name: title, dtype: object

Recommendation #  2 :  906    Lawrence of Arabia (1962)
Name: title, dtype: object

Recommendation #  3 :  966    Manchurian Candidate, The (1962)
Name: title, dtype: object

Recommendation #  4 :  922    Godfather: Part II, The (1974)
Name: title, dtype: object

Recommendation #  5 :  659    Godfather, The (1972)
Name: title, dtype: object

Recommendation #  6 :  9618    Three Billboards Outside Ebbing, Missouri (201
7)
Name: title, dtype: object

Recommendation #  7 :  6016    Kiss Kiss Bang Bang (2005)
Name: title, dtype: object

Recommendation #  8 :  2094    Monty Python's And Now for Something Complete
l...
Name: title, dtype: object

Recommendation #  9 :  6153    Thank You for Smoking (2006)
Name: title, dtype: object

Recommendation #  10 :  2226    Fight Club (1999)
Name: title, dtype: object
```

In [ ]: