Amazon user Based Recommendation Model

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`DESCRIPTION`

The dataset provided contains movie reviews given by Amazon customers. Reviews were given between May 1996 and July 2014.

Data Dictionary UserID – 4848 customers who provided a rating for each movie Movie 1 to Movie 206 – 206 movies for which ratings are provided by 4848 distinct users

Data Considerations

- All the users have not watched all the movies and therefore, all movies are not rated. These missing values are represented by NA.
- Ratings are on a scale of -1 to 10 where -1 is the least rating and 10 is the best.

Analysis Task

- Exploratory Data Analysis:

Which movies have maximum views/ratings? What is the average rating for each movie? Define the top 5 movies with the maximum ratings. Define the top 5 movies with the least audience.

- Recommendation Model: Some of the movies hadn't been watched and therefore, are not rated by the users. Netflix would like to take this as an opportunity and build a machine learning recommendation algorithm which provides the ratings for each of the users.

Divide the data into training and test data Build a recommendation model on training data Make predictions on the test data

In [1]:
```
# Importing the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
amz = pd.read_csv("C:/Users/Simeon/Desktop/Amazon movies dataset.csv")
```

Exploratory Data Analysis

In [3]:
```
amz.head()
```

Out[3]:

	user_id	Movie1	Movie2	Movie3	Movie4	Movie5	Movie6	Movie7	Movie8	Movie9	...	Movie197	Movie198	Movie199	Movie2
0	A3R5OBKS7OM2IR	5.0	5.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	Na
1	AH3QC2PC1VTGP	NaN	NaN	2.0	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	Na
2	A3LKP6WPMP9UKX	NaN	NaN	NaN	5.0	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	Na
3	AVIY68KEPQ5ZD	NaN	NaN	NaN	5.0	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	Na
4	A1CV1WROP5KTTW	NaN	NaN	NaN	NaN	5.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	Na

5 rows × 207 columns

In [4]:
```
#checking the shape of the data sets
amz.shape
```

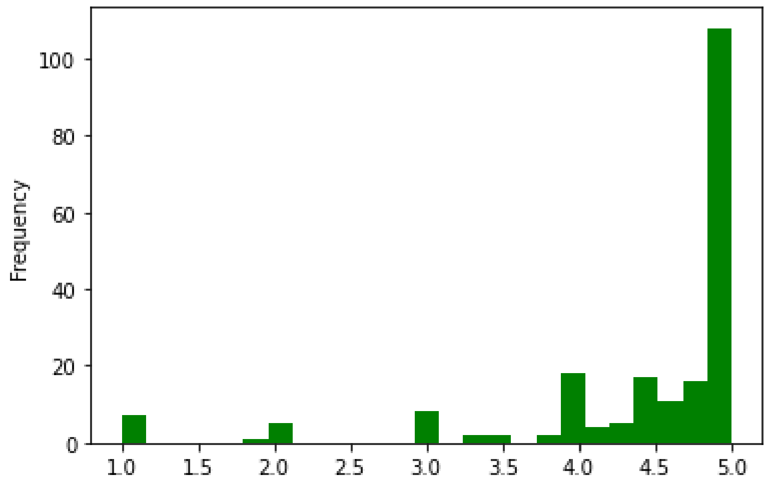
Out[4]: (4848, 207)

In [5]:
```
amz.describe().T
```
Out[5]:

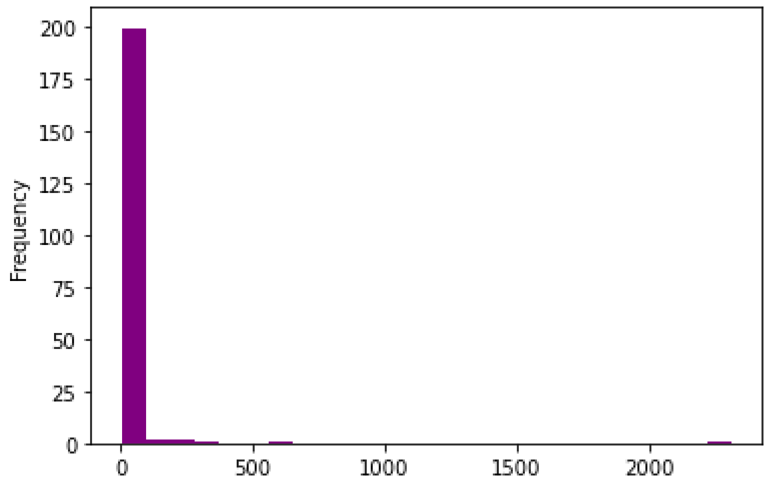
	count	mean	std	min	25%	50%	75%	max
Movie1	1.0	5.000000	NaN	5.0	5.00	5.0	5.0	5.0
Movie2	1.0	5.000000	NaN	5.0	5.00	5.0	5.0	5.0
Movie3	1.0	2.000000	NaN	2.0	2.00	2.0	2.0	2.0
Movie4	2.0	5.000000	0.000000	5.0	5.00	5.0	5.0	5.0
Movie5	29.0	4.103448	1.496301	1.0	4.00	5.0	5.0	5.0
...	...	...	...	...	...	...	...	...
Movie202	6.0	4.333333	1.632993	1.0	5.00	5.0	5.0	5.0
Movie203	1.0	3.000000	NaN	3.0	3.00	3.0	3.0	3.0
Movie204	8.0	4.375000	1.407886	1.0	4.75	5.0	5.0	5.0
Movie205	35.0	4.628571	0.910259	1.0	5.00	5.0	5.0	5.0
Movie206	13.0	4.923077	0.277350	4.0	5.00	5.0	5.0	5.0

206 rows × 8 columns

In [6]:
```
#ploting the mean frequency
amz.describe().T['mean'].plot(bins=25, kind='hist', color = 'green');
```



In [7]:
```
#ploting the count frequency
amz.describe().T['count'].plot(bins=25, kind='hist', color = 'purple');
```



In [8]:
```
# Movie that has maxmium view
amz.describe().T['count'].sort_values(ascending=False)[:1].to_frame()
```
Out[8]:

	count
Movie127	2313.0

In [9]:
```
# Movie that has maxmium ratings
amz.drop('user_id',axis=1).sum().sort_values(ascending=False)[:1].to_frame()
```
Out[9]:

	0
Movie127	9511.0

In [10]:
```
# Average rating of each movie
amz.drop('user_id',axis=1).mean()
```

Out[10]:
```
Movie1      5.000000
Movie2      5.000000
Movie3      2.000000
Movie4      5.000000
Movie5      4.103448
              ...
Movie202    4.333333
Movie203    3.000000
Movie204    4.375000
Movie205    4.628571
Movie206    4.923077
Length: 206, dtype: float64
```

In [11]:
```
#top 5 movies with the maximum rating
amz.drop('user_id',axis=1).mean().sort_values(ascending=False)[0:5].to_frame()
```

Out[11]:

	0
Movie1	5.0
Movie66	5.0
Movie76	5.0
Movie75	5.0
Movie74	5.0

In [12]:
```
# Top 5 movies with least audience
amz.describe().T['count'].sort_values(ascending=True)[:5].to_frame()
```

Out[12]:

	count
Movie1	1.0
Movie71	1.0
Movie145	1.0
Movie69	1.0
Movie68	1.0

User based Model building

In [13]:
```

#importing libiraies for model building
from surprise import Reader
from surprise import Dataset
from surprise import accuracy
from surprise import SVD
from surprise.model_selection import train_test_split
```

In [14]:
```
movie_data = amz.melt(id_vars = amz.columns[0],value_vars=amz.columns[1:],var_name="Movies",value_name="Rating")
movie_data
```

Out[14]:

	user_id	Movies	Rating
0	A3R5OBKS7OM2IR	Movie1	5.0
1	AH3QC2PC1VTGP	Movie1	NaN
2	A3LKP6WPMP9UKX	Movie1	NaN
3	AVIY68KEPQ5ZD	Movie1	NaN
4	A1CV1WROP5KTTW	Movie1	NaN
...	...	...	...
998683	A1IMQ9WMFYKWH5	Movie206	5.0
998684	A1KLIKPUF5E88I	Movie206	5.0
998685	A5HG6WFZLO10D	Movie206	5.0
998686	A3UU690TWXCG1X	Movie206	5.0
998687	AI4J762YI6S06	Movie206	5.0

998688 rows × 3 columns

In [15]:
```
#creating a dataset for training and testing
rd = Reader(rating_scale=(-1,10))
data = Dataset.load_from_df(movie_data.fillna(0),reader=rd)
data
```

Out[15]:
```
<surprise.dataset.DatasetAutoFolds at 0x18052b25e20>
```

In [16]:
```
train_data,test_data = train_test_split(data,test_size=0.20)
```

In [17]:
```
#Using SVD (Singular Value Descomposition)
svd = SVD()
```

In [18]:
```
svd.fit(train_data)
```

Out[18]:
```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x18051fc5490>
```

In [19]:
```
pred = svd.test(test_data)
```

In [20]:
```
accuracy.rmse(pred)
```

```
RMSE: 0.2757
```

Out[20]:
```
0.2756661256276847
```

In [21]:
```
accuracy.mae(pred)
```

```
MAE:  0.0409
```

Out[21]:
```
0.04094988248375935
```

In [22]:
```
u_id='AH3QC2PC1VTGP'
mv = 'Movie206'
r_id = 5.0
svd.predict(u_id, mv, r_ui=r_id, verbose= True)
```

```
user: AH3QC2PC1VTGP item: Movie206   r_ui = 5.00   est = 0.04   {'was_impossible': False}
```

Out[22]:
```
Prediction(uid='AH3QC2PC1VTGP', iid='Movie206', r_ui=5.0, est=0.037522696094773544, details={'was_impossible': Fals
e})
```

In [23]:
```
from surprise.model_selection import cross_validate
```

In [24]:
```
cross_validate(svd, data, measures = ['RMSE', 'MAE'], cv = 3, verbose = True)
```

```
Evaluating RMSE, MAE of algorithm SVD on 3 split(s).

                  Fold 1  Fold 2  Fold 3  Mean    Std
RMSE (testset)    0.2790  0.2831  0.2855  0.2826  0.0027
MAE (testset)     0.0429  0.0429  0.0427  0.0428  0.0001
Fit time          69.14   60.81   74.83   68.26   5.76
Test time         4.99    4.19    8.04    5.74    1.66
```

Out[24]:
```
{'test_rmse': array([0.27903865, 0.28312894, 0.28553412]),
 'test_mae': array([0.04288795, 0.04287469, 0.04269187]),
 'fit_time': (69.14156985282898, 60.80686831474304, 74.82693457603455),
 'test_time': (4.986289978027344, 4.192029714584351, 8.03850531578064)}
```

In [25]:
```
def repeat(ml_type,dframe,min_,max_):
    rd = Reader()
    data = Dataset.load_from_df(dframe,reader=rd)
    print(cross_validate(ml_type, data, measures = ['RMSE', 'MAE'], cv = 3, verbose = True))
    print("#"*10)
    u_id = 'AH3QC2PC1VTGP'
    m_id = 'Movie206'
    ra_u = 5.0
    print(ml_type.predict(u_id,mv,r_ui=ra_u,verbose=True))
    print("#"*10)
    print()
```

In [26]:
```
amz= amz.iloc[:3000, :50]
movie_data = amz.melt(id_vars = amz.columns[0],value_vars=amz.columns[1:],var_name="Movies",value_name="Rating")
```

In [27]:
```
repeat(SVD(),movie_data.fillna(0),-1,10)
repeat(SVD(),movie_data.fillna(movie_data.mean()),-1,10)
repeat(SVD(),movie_data.fillna(movie_data.median()),-1,10)
```

```
Evaluating RMSE, MAE of algorithm SVD on 3 split(s).

                  Fold 1  Fold 2  Fold 3  Mean    Std
RMSE (testset)    1.0271  1.0310  1.0289  1.0290  0.0016
MAE (testset)     1.0116  1.0131  1.0123  1.0123  0.0006
Fit time          11.43   14.13   15.07   13.54   1.54
Test time         0.60    0.69    0.90    0.73    0.12
{'test_rmse': array([1.02705457, 1.03104907, 1.02894154]), 'test_mae': array([1.01163967, 1.01310641, 1.01227078]),
'fit_time': (11.43297553062439, 14.131345510482788, 15.068916320800781), 'test_time': (0.6032133102416992, 0.686423
5401153564, 0.8986828327178955)}
##########
user: AH3QC2PC1VTGP item: Movie206   r_ui = 5.00   est = 1.00   {'was_impossible': False}
user: AH3QC2PC1VTGP item: Movie206   r_ui = 5.00   est = 1.00   {'was_impossible': False}
##########


C:\Users\Public\Documents\Wondershare\CreatorTemp/ipykernel_18212/127061997.py:2: FutureWarning: Dropping of nuisan
ce columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise Ty
peError.  Select only valid columns before calling the reduction.
  repeat(SVD(),movie_data.fillna(movie_data.mean()),-1,10)

Evaluating RMSE, MAE of algorithm SVD on 3 split(s).

                  Fold 1  Fold 2  Fold 3  Mean    Std
RMSE (testset)    0.0510  0.0649  0.0543  0.0567  0.0059
MAE (testset)     0.0076  0.0075  0.0072  0.0074  0.0002
Fit time          8.05    9.37    7.84    8.42    0.68
Test time         1.08    0.45    0.82    0.78    0.26
{'test_rmse': array([0.05096145, 0.06486785, 0.0543207 ]), 'test_mae': array([0.00759636, 0.0074677 , 0.00715425]),
'fit_time': (8.04529333114624, 9.369925260543823, 7.844586133956909), 'test_time': (1.080878496170044, 0.4459848403
930664, 0.8164474964141846)}
##########
user: AH3QC2PC1VTGP item: Movie206   r_ui = 5.00   est = 4.53   {'was_impossible': False}
user: AH3QC2PC1VTGP item: Movie206   r_ui = 5.00   est = 4.53   {'was_impossible': False}
##########


C:\Users\Public\Documents\Wondershare\CreatorTemp/ipykernel_18212/127061997.py:3: FutureWarning: Dropping of nuisan
ce columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise Ty
peError.  Select only valid columns before calling the reduction.
  repeat(SVD(),movie_data.fillna(movie_data.median()),-1,10)

Evaluating RMSE, MAE of algorithm SVD on 3 split(s).

                  Fold 1  Fold 2  Fold 3  Mean    Std
RMSE (testset)    0.0555  0.0687  0.0626  0.0623  0.0054
MAE (testset)     0.0053  0.0051  0.0051  0.0052  0.0001
Fit time          8.25    9.16    7.77    8.39    0.58
Test time         0.47    0.81    0.44    0.57    0.17
{'test_rmse': array([0.05546185, 0.06872768, 0.06259858]), 'test_mae': array([0.00525613, 0.00513913, 0.00508715]),
'fit_time': (8.248005390167236, 9.164777278900146, 7.766745090484619), 'test_time': (0.4727299213409424, 0.81245923
04229736, 0.43959951400756836)}
##########
user: AH3QC2PC1VTGP item: Movie206   r_ui = 5.00   est = 4.92   {'was_impossible': False}
user: AH3QC2PC1VTGP item: Movie206   r_ui = 5.00   est = 4.92   {'was_impossible': False}
##########
```

In [28]:
```
#trying grid search and find optimum hyperparameter value for n_factors
from surprise.model_selection import GridSearchCV
```

In [29]:
```
param_grid = {'n_epochs':[20,30],
             'lr_all':[0.005,0.001],
             'n_factors':[50,100]}
```

In [30]:
```
gs = GridSearchCV(SVD,param_grid,measures=['rmse','mae'],cv=3)
gs.fit(data)
```

In [31]:
```
gs.best_score
```

Out[31]:
```
{'rmse': 0.28011413685252345, 'mae': 0.04127550428050707}
```

In [32]:
```
print(gs.best_score["rmse"])
print(gs.best_params["rmse"])
```

```
0.28011413685252345
{'n_epochs': 30, 'lr_all': 0.005, 'n_factors': 50}
```