Project 01: Amazon Project.

Submitted By Mr. Vivek Gautam in October 2020

Building user-based recommendation model for Amazon. 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:

1- Which movies have maximum views/ratings? 2-What is the average rating for each movie? Define the top 5 movies with the maximum ratings. 3-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]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [8]:

```
amazon=pd.read_csv(r'D:\Data_Science_Data\Amazon_Movies and TV Ratings.csv')
amazon
```

Out[8]:

	user_id	Movie1	Movie2	Movie3	Movie4	Movie5	Movie6	Movie7	Movie8
0	A3R5OBKS7OM2IR	5.0	5.0	NaN	NaN	NaN	NaN	NaN	NaN
1	AH3QC2PC1VTGP	NaN	NaN	2.0	NaN	NaN	NaN	NaN	NaN
2	A3LKP6WPMP9UKX	NaN	NaN	NaN	5.0	NaN	NaN	NaN	NaN
3	AVIY68KEPQ5ZD	NaN	NaN	NaN	5.0	NaN	NaN	NaN	NaN
4	A1CV1WROP5KTTW	NaN	NaN	NaN	NaN	5.0	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...
4843	A1IMQ9WMFYKWH5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4844	A1KLIKPUF5E88I	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4845	A5HG6WFZLO10D	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4846	A3UU690TWXCG1X	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4847	AI4J762YI6S06	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

4848 rows × 207 columns

In [7]:

```
amazon.keys()
```

Out[7]:

```
Index(['user_id', 'Movie1', 'Movie2', 'Movie3', 'Movie4', 'Movie5', 'Movie
6',
       'Movie7', 'Movie8', 'Movie9',
       ...
       'Movie197', 'Movie198', 'Movie199', 'Movie200', 'Movie201', 'Movie20
2',
       'Movie203', 'Movie204', 'Movie205', 'Movie206'],
      dtype='object', length=207)
```

summarize on amazon data

In [9]:

```
amazon.shape
```

Out[9]:

```
(4848, 207)
```

In [10]:

```
amazon.isnull().sum()
```

Out[10]:

```
user_id        0
Movie1      4847
Movie2      4847
Movie3      4847
Movie4      4846
            ...
Movie202    4842
Movie203    4847
Movie204    4840
Movie205    4813
Movie206    4835
Length: 207, dtype: int64
```

In [11]:

```
amazon.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4848 entries, 0 to 4847
Columns: 207 entries, user_id to Movie206
dtypes: float64(206), object(1)
memory usage: 7.7+ MB
```

In [12]:

```
amazon.describe()
```

Out[12]:

	Movie1	Movie2	Movie3	Movie4	Movie5	Movie6	Movie7	Movie8	Movie9	Movie10
count	1.0	1.0	1.0	2.0	29.000000	1.0	1.0	1.0	1.0	1.0
mean	5.0	5.0	2.0	5.0	4.103448	4.0	5.0	5.0	5.0	5.0
std	NaN	NaN	NaN	0.0	1.496301	NaN	NaN	NaN	NaN	NaN
min	5.0	5.0	2.0	5.0	1.000000	4.0	5.0	5.0	5.0	5.0
25%	5.0	5.0	2.0	5.0	4.000000	4.0	5.0	5.0	5.0	5.0
50%	5.0	5.0	2.0	5.0	5.000000	4.0	5.0	5.0	5.0	5.0
75%	5.0	5.0	2.0	5.0	5.000000	4.0	5.0	5.0	5.0	5.0
max	5.0	5.0	2.0	5.0	5.000000	4.0	5.0	5.0	5.0	5.0

8 rows × 206 columns

In [13]:

```
amazon.describe().T
```

Out[13]:

	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

quest 1:find out movies having maximum numbers of rating

In [14]:

```
amazon_count=amazon.describe()[:1].T
amazon_count
```

Out[14]:

	count
Movie1	1.0
Movie2	1.0
Movie3	1.0
Movie4	2.0
Movie5	29.0
...	...
Movie202	6.0
Movie203	1.0
Movie204	8.0
Movie205	35.0
Movie206	13.0

206 rows × 1 columns

In [15]:

```
amazon_count.sort_values('count',ascending=False).head()
```

Out[15]:

	count
Movie127	2313.0
Movie140	578.0
Movie16	320.0
Movie103	272.0
Movie29	243.0

In [16]:

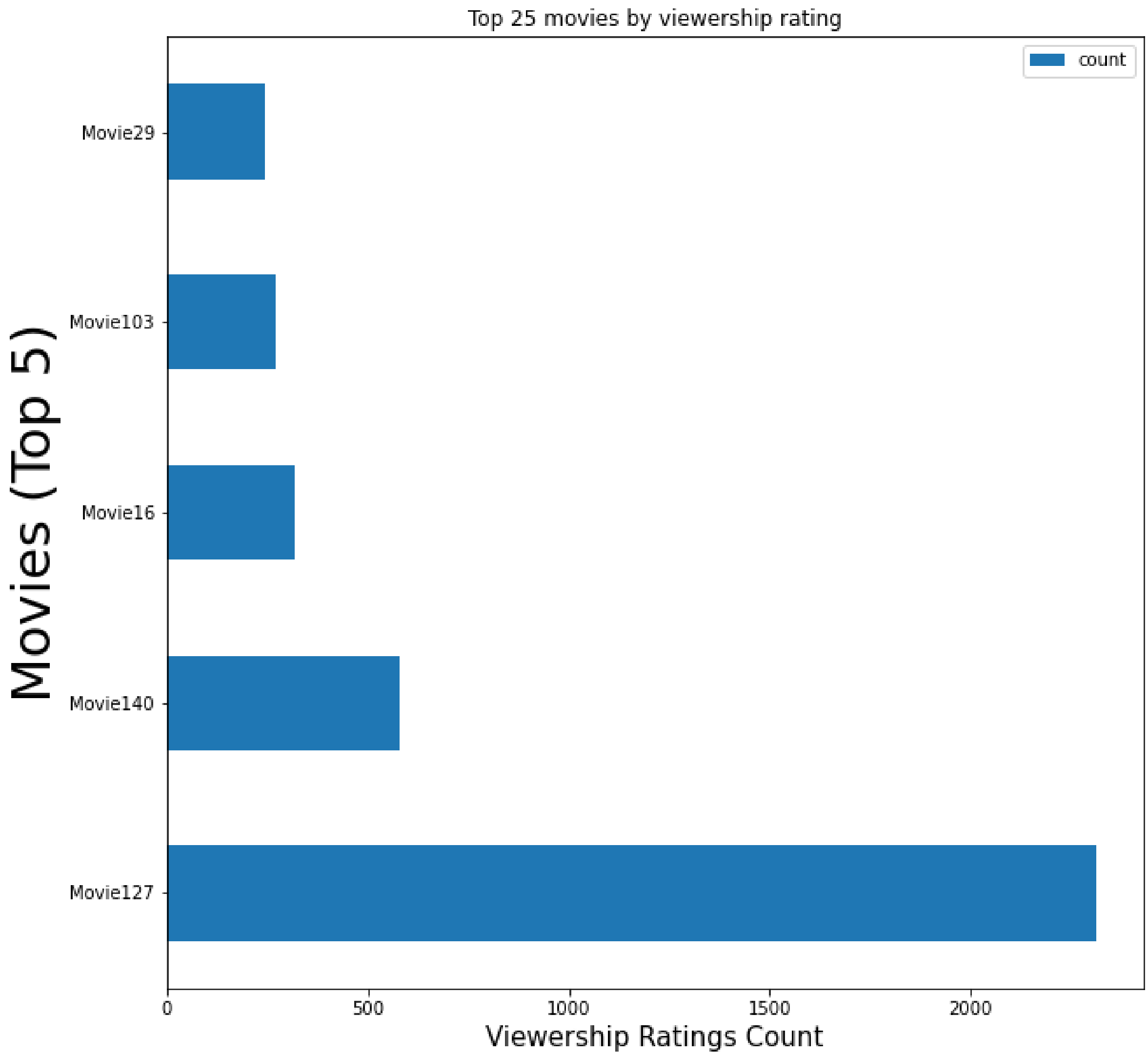
```
top5_movies=amazon_count.sort_values('count',ascending=False)[:5]
top5_movies
```

Out[16]:

	count
Movie127	2313.0
Movie140	578.0
Movie16	320.0
Movie103	272.0
Movie29	243.0

In [17]:

```
top5_movies.plot(kind='barh',alpha=1,figsize=(10,10))
plt.xlabel("Viewership Ratings Count",size=15)
plt.ylabel("Movies (Top 5)",size=30)
plt.title("Top 25 movies by viewership rating")
plt.show()
```



quest2: find out the average rating of all the movies

In [18]:

```
amazon_mean=amazon.describe()[1:2].T
```

In [19]:

```
amazon_mean
```

Out[19]:

	mean
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

206 rows × 1 columns

quest 2.1: top 5 movies with the maximum rating

In [20]:

```
amazon_mean.sort_values('mean',ascending=False).head()
```

Out[20]:

	mean
Movie1	5.0
Movie66	5.0
Movie76	5.0
Movie75	5.0
Movie74	5.0

quest3: top 5 movies with the least audience.

In [21]:

```
amazon_count.sort_values('count',ascending=True)[:5]
```

Out[21]:

	count
Movie1	1.0
Movie71	1.0
Movie145	1.0
Movie69	1.0
Movie68	1.0

In [22]:

```
top5_least_audience=amazon_count.sort_values('count',ascending=True)[:5]
```

In [23]:

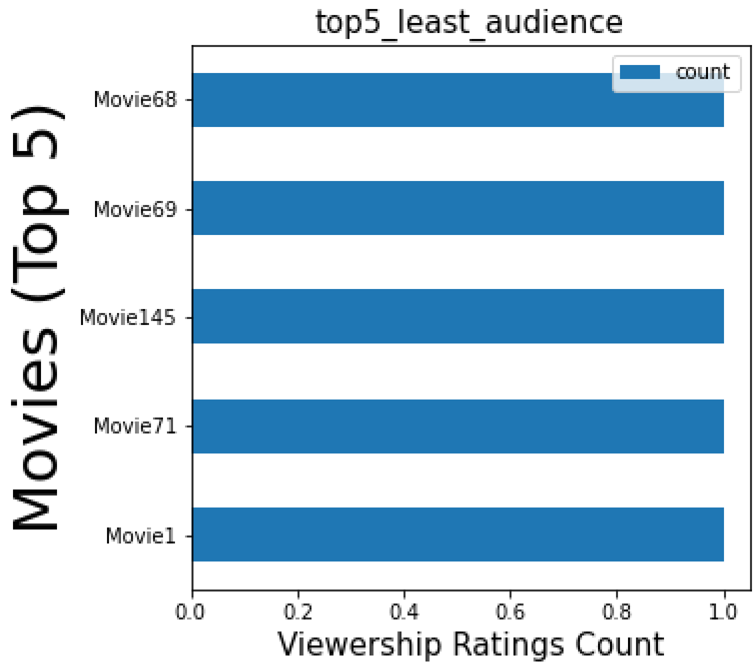
```
top5_least_audience
```

Out[23]:

	count
Movie1	1.0
Movie71	1.0
Movie145	1.0
Movie69	1.0
Movie68	1.0

In [24]:

```
top5_least_audience.plot(kind='barh',alpha=1,figsize=(5,5))
plt.xlabel("Viewership Ratings Count",size=15)
plt.ylabel("Movies (Top 5)",size=30)
plt.title("top5_least_audience",size=15)
plt.show()
```



In [26]:

```
amazon_df=amazon.set_index('user_id').fillna(0)
amazon_df
```

Out[26]:

	Movie1	Movie2	Movie3	Movie4	Movie5	Movie6	Movie7	Movie8	Movie9
user_id									
A3R5OBKS7OM2IR	5.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
AH3QC2PC1VTGP	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.(
A3LKP6WPMP9UKX	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	0.(
AVIY68KEPQ5ZD	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	0.(
A1CV1WROP5KTTW	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.(
...	...	...	...	...	...	...	...	...	..
A1IMQ9WMFYKWH5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A1KLIKPUF5E88I	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A5HG6WFZLO10D	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A3UU690TWXCG1X	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
AI4J762YI6S06	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(

4848 rows × 206 columns

lets find out the user user correlation

In [28]:

```
from scipy.spatial.distance import cosine
from sklearn.metrics import pairwise_distances

#Pairwise distance only accept Matrix object


user_corr = 1 - pairwise_distances( amazon_df, metric="correlation" )


ratings_matrix = pd.DataFrame( user_corr )
ratings_matrix
```

Out[28]:

	0	1	2	3	4	5	6	7	
0	1.000000	-0.006915	-0.006915	-0.006915	-0.006915	-0.006915	-0.006915	-0.006915	-0.(
1	-0.006915	1.000000	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.(
2	-0.006915	-0.004878	1.000000	1.000000	-0.004878	-0.004878	-0.004878	-0.004878	-0.(
3	-0.006915	-0.004878	1.000000	1.000000	-0.004878	-0.004878	-0.004878	-0.004878	-0.(
4	-0.006915	-0.004878	-0.004878	-0.004878	1.000000	1.000000	1.000000	1.000000	1.(
...	...	...	...	...	...	...	...	...	
4843	-0.006915	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.(
4844	-0.006915	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.(
4845	-0.006915	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.(
4846	-0.006915	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.(
4847	-0.006915	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.004878	-0.(

4848 rows × 4848 columns

In [29]:

```
ratings_matrix.index=amazon.user_id.unique()
ratings_matrix.columns=amazon.user_id.unique()
```

In [31]:

```
ratings_matrix
```

Out[31]:

	A3R5OBKS7OM2IR	AH3QC2PC1VTGP	A3LKP6WPMP9UKX	AVIY68KEPQ5ZI
A3R5OBKS7OM2IR	0.000000	-0.006915	-0.006915	-0.00691
AH3QC2PC1VTGP	-0.006915	0.000000	-0.004878	-0.00487
A3LKP6WPMP9UKX	-0.006915	-0.004878	0.000000	1.00000
AVIY68KEPQ5ZD	-0.006915	-0.004878	1.000000	0.00000
A1CV1WROP5KTTW	-0.006915	-0.004878	-0.004878	-0.00487
...	...	...	...	..
A1IMQ9WMFYKWH5	-0.006915	-0.004878	-0.004878	-0.00487
A1KLIKPUF5E88I	-0.006915	-0.004878	-0.004878	-0.00487
A5HG6WFZLO10D	-0.006915	-0.004878	-0.004878	-0.00487
A3UU690TWXCG1X	-0.006915	-0.004878	-0.004878	-0.00487
AI4J762YI6S06	-0.006915	-0.004878	-0.004878	-0.00487

4848 rows × 4848 columns

In [32]:

```
np.fill_diagonal(user_corr,0)
```

In [33]:

```
ratings_matrix
```

Out[33]:

	A3R5OBKS7OM2IR	AH3QC2PC1VTGP	A3LKP6WPMP9UKX	AVIY68KEPQ
A3R5OBKS7OM2IR	0.000000	-0.006915	-0.006915	-0.006
AH3QC2PC1VTGP	-0.006915	0.000000	-0.004878	-0.004
A3LKP6WPMP9UKX	-0.006915	-0.004878	0.000000	1.000
AVIY68KEPQ5ZD	-0.006915	-0.004878	1.000000	0.000
A1CV1WROP5KTTW	-0.006915	-0.004878	-0.004878	-0.004
...	...	...	...	
A1IMQ9WMFYKWH5	-0.006915	-0.004878	-0.004878	-0.004
A1KLIKPUF5E88I	-0.006915	-0.004878	-0.004878	-0.004
A5HG6WFZLO10D	-0.006915	-0.004878	-0.004878	-0.004
A3UU690TWXCG1X	-0.006915	-0.004878	-0.004878	-0.004
AI4J762YI6S06	-0.006915	-0.004878	-0.004878	-0.004

4848 rows × 4848 columns

lets find out the corelation between movies

Let's choose two movies: movie2 and movie4¶

Now lets grab the user ratings for those two movies:

In [35]:

```
Movie2_user_ratings = amazon_df['Movie2']
Movie4_user_ratings = amazon_df['Movie4']
Movie2_user_ratings.head(20)
```

Out[35]:

```
user_id
A3R5OBKS7OM2IR    5.0
AH3QC2PC1VTGP     0.0
A3LKP6WPMP9UKX    0.0
AVIY68KEPQ5ZD     0.0
A1CV1WROP5KTTW    0.0
AP57WZ2X4G0AA     0.0
A3NMBJ2LCRCATT    0.0
A5Y15SAOMX6XA     0.0
A3P671HJ32TCSF    0.0
A3VCKTRD24BG7K    0.0
ANF0AGIV0JCH2     0.0
A3LDEBLV6MVUBE    0.0
A1R2XZWQ6NM5M1    0.0
A36L1XGA5AQIJY    0.0
A2HWI21H23GDS4    0.0
A1DNYFL3RSXRMO    0.0
A39VF226GBM1JH    0.0
ASB0E2O2FLNA7     0.0
A19E15Y9V09CVJ    0.0
A3K979KQ7K0S5K    0.0
Name: Movie2, dtype: float64
```

In [36]:

```
Movie4_user_ratings.head()
```

Out[36]:

```
user_id
A3R5OBKS7OM2IR    0.0
AH3QC2PC1VTGP     0.0
A3LKP6WPMP9UKX    5.0
AVIY68KEPQ5ZD     5.0
A1CV1WROP5KTTW    0.0
Name: Movie4, dtype: float64
```

In [37]:

```
similar_to_Movie2 = amazon_df.corrwith(Movie2_user_ratings)
similar_to_Movie4 = amazon_df.corrwith(Movie4_user_ratings)
```

this is the correlation for movie2

In [38]:

```
print('the reference movie title based on which recommendations are to be made:' )
corr_Movie2 = pd.DataFrame(similar_to_Movie2,columns=['correlation with movie4'])
corr_Movie2.dropna(inplace=True)
corr_Movie2.head(20)
```

```
the reference movie title based on which recommendations are to be made:
```

Out[38]:

	correlation with movie4
Movie1	1.000000
Movie2	1.000000
Movie3	-0.000206
Movie4	-0.000292
Movie5	-0.001049
Movie6	-0.000206
Movie7	-0.000206
Movie8	-0.000206
Movie9	-0.000206
Movie10	-0.000206
Movie11	-0.000292
Movie12	-0.000462
Movie13	-0.000206
Movie14	-0.000206
Movie15	-0.000206
Movie16	-0.003757
Movie17	-0.000206
Movie18	-0.000206
Movie19	-0.000268
Movie20	-0.000206

this is the correlation for movie4

In [41]:

```
print('the reference movie title based on which recommendations are to be made:' )
corr_Movie4 = pd.DataFrame(similar_to_Movie4,columns=['correlation with movie4'])
corr_Movie4.dropna(inplace=True)
corr_Movie4.head(20)
```

```
the reference movie title based on which recommendations are to be made:
```

Out[41]:

	correlation with movie4
Movie1	-0.000292
Movie2	-0.000292
Movie3	-0.000292
Movie4	1.000000
Movie5	-0.001483
Movie6	-0.000292
Movie7	-0.000292
Movie8	-0.000292
Movie9	-0.000292
Movie10	-0.000292
Movie11	-0.000413
Movie12	-0.000653
Movie13	-0.000292
Movie14	-0.000292
Movie15	-0.000292
Movie16	-0.005313
Movie17	-0.000292
Movie18	-0.000292
Movie19	-0.000379
Movie20	-0.000292

**End*