Zee_Recommend

December 26, 2023

[1]:
```
# import sys
# !{sys.executable} -m pip install pandas
# !{sys.executable} -m pip install sklearn

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
df_movies=pd.read_csv('/home/csc/my_first_environment/Zee_recommendation/
 ↪zee-movies.dat', sep="::
 ↪",names=["MovieID","Title","Genres"],engine='python',encoding='latin-1',header=None,skiprow
df_movies.head()
```

[2]:

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

[3]:
```
df_ratings=pd.read_csv('/home/csc/my_first_environment/Zee_recommendation/
 ↪zee-ratings.dat', sep="::
 ↪",names=["UserID","MovieID","Rating","Timestamp"],engine='python',encoding='latin-1',header
df_ratings.head()
```

[3]:

	UserID	MovieID	Rating	Timestamp
0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

[5]:
```
print(f'Movie dataframe Shape {df_movies.shape}')
print(f'Ratings dataframe Shape {df_ratings.shape}')
print(f'Users dataframe Shape {df_users.shape}')
```

```
Movie dataframe Shape (3883, 3)
Ratings dataframe Shape (1000209, 4)
Users dataframe Shape (6040, 5)
```

[6]:
```
dfmovieratings=df_movies.merge(df_ratings,on='MovieID',how='inner')
dfmovieratings.shape
```

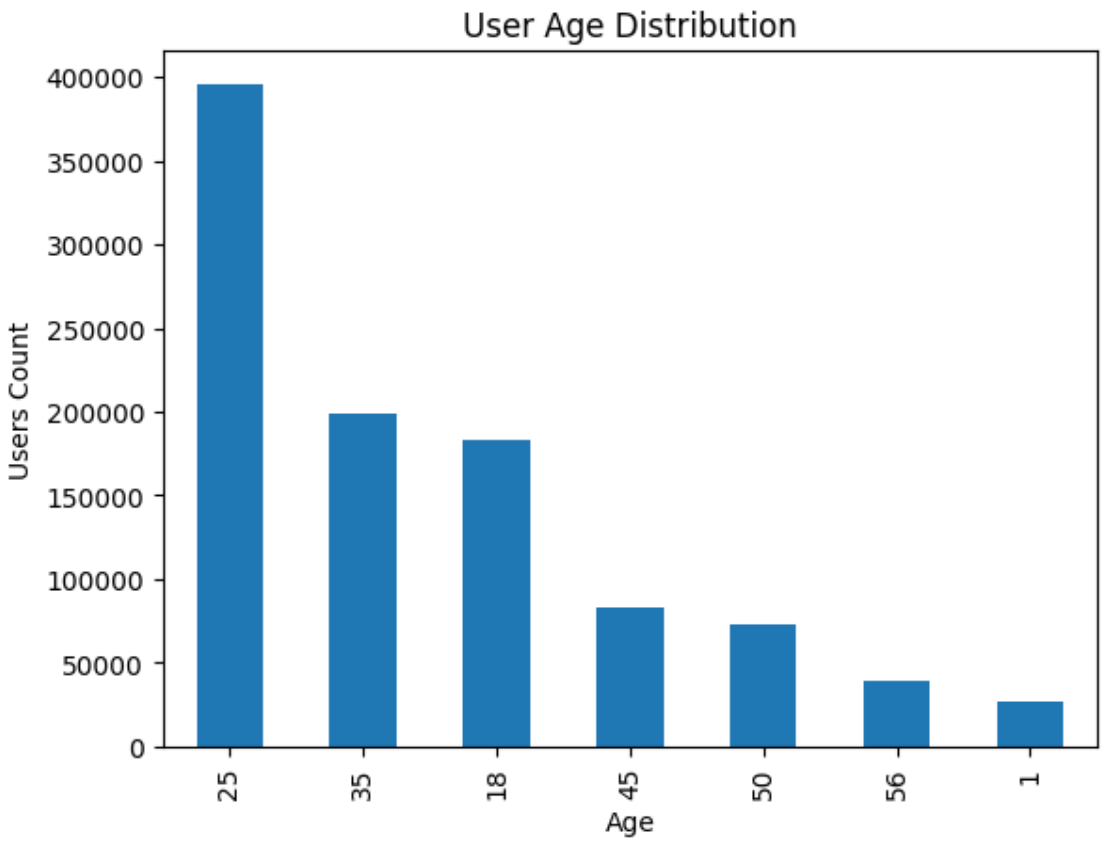
[6]:
```
(1000209, 6)
```

[7]:
```
dfMaster = dfmovieratings.merge(df_users,on="UserID",how='inner')
dfMaster.head()
```

[7]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	1	10	48067
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351	F	1	10	48067
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760	F	1	10	48067
4	527	Schindler's List (1993)	Drama|War	1	5	978824195	F	1	10	48067

[8]:
```
dfMaster['Age'].value_counts().plot(kind='bar')
plt.xlabel("Age")
plt.title("User Age Distribution")
plt.ylabel('Users Count')
plt.show()
```



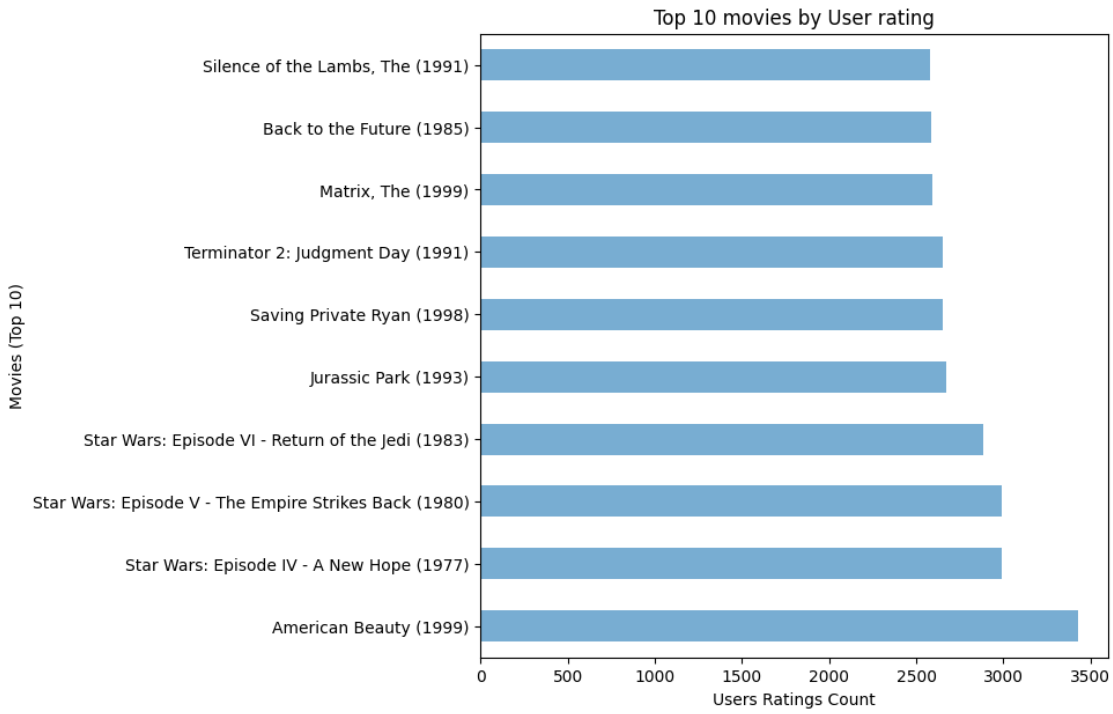
[9]:
```
dfMaster['Age'].value_counts()/ len(dfMaster) * 100
```

[9]:
```
Age
25    39.547335
35    19.896142
18    18.349765
45     8.361552
50     7.247485
56     3.877190
1      2.720531
Name: count, dtype: float64
```

Observations Here we can see thet 20% users are below 25 yrs of age. Age group 25-34 contains around 40% of users. 90% users are below 50 yrs of age.

[11]:
```
top10=dfMaster.groupby('Title').size().sort_values(ascending=False)[:10]
top10.plot(kind='barh',alpha=0.6,figsize=(7,7))
plt.xlabel("Users Ratings Count")
plt.ylabel("Movies (Top 10)")
plt.title("Top 10 movies by User rating")
```

```
plt.show()
```



The movie with maximum no. of ratings is American Beauty.

[12]:
```
top5profession=dfMaster.groupby('Occupation').size().
 ↪sort_values(ascending=False)[:5]
top5profession
# top5profession.plot(kind='barh',alpha=0.6,figsize=(7,7))
# plt.xlabel("Users Ratings Count")
# plt.ylabel("Movies (Top 25)")
# plt.title("Top 25 movies by User rating")
# plt.show()
```

[12]:
```
Occupation
4     131032
0     130499
7     105425
1      85351
17     72816
dtype: int64
```

Observation 1)college/grad student watch the most number of movies 2)Other category people stand next to college grads

[13]:
```
topGender=dfMaster.groupby('Gender').size().sort_values(ascending=False)[:5]
topGender
```

[13]:
```
Gender
M    753769
F    246440
dtype: int64
```

Observation Most of rating is given Male

[14]:
```
dfMaster['Timestamp'] = pd.to_datetime(dfMaster['Timestamp'], unit='s')
dfMaster['Year'] = dfMaster['Timestamp'].dt.year
dfMaster.drop(columns='Timestamp',inplace=True)
```

[15]:
```
dfMaster
```

[15]:

	MovieID	Title	Genres	UserID	Rating	Gender	Age	Occupation	Zip-code	Year
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	F	1	10	48067	2001
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	F	1	10	48067	2001
2	150	Apollo 13 (1995)	Drama	1	5	F	1	10	48067	2000
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	F	1	10	48067	2000
4	527	Schindler's List (1993)	Drama|War	1	5	F	1	10	48067	2000
…	…	…	…	…	…	…	…	…	…	…
1000204	3513	Rules of Engagement (2000)	Drama|Thriller	5727	4	M	25	10	48067	2001
1000205	3535	American Psycho (2000)	Comedy|Horror|Thriller	5727	2	M	25	10	48067	2001
1000206	3536	Keeping the Faith (2000)	Comedy|Romance	5727	5	M	25	10	48067	2000
1000207	3555	U-571 (2000)	Action|Thriller	5727	3	M	25	10	48067	2000
1000208	3578	Gladiator (2000)	Action|Drama	5727	5	M	25	10	48067	2000

```
4                 10    48067  2001
…               …       …   …
1000204           4     92843  2000
1000205           4     92843  2000
1000206           4     92843  2000
1000207           4     92843  2000
1000208           4     92843  2000

[1000209 rows x 10 columns]
```

[16]:
```
dfMaster['Year'].value_counts()
```

[16]:
```
Year
2000    904757
2001     68058
2002     24046
2003      3348
Name: count, dtype: int64
```

Observation

2000 Year as highest Rating

[59]:
```
from sklearn.metrics.pairwise import cosine_similarity
# Creating a pivot table of movie titles & user id and imputing the NaN values
movie_ratings = dfMaster.pivot_table(index='UserID', columns='Title',␣
 ↪values='Rating', fill_value=0)

# Assuming 'Liar Liar (1997)' has MovieID 123
liar_liar_ratings = movie_ratings['Liar Liar (1997)']

# Reshape both arrays to have the same number of features (columns)
liar_liar_ratings_reshaped = liar_liar_ratings.values.reshape(1, -1)

movie_ratings_reshaped = movie_ratings.T.values

# Calculate Cosine Similarity
similarities = cosine_similarity(movie_ratings_reshaped,␣
 ↪liar_liar_ratings_reshaped)

# Get the indices of movies similar to 'Liar Liar'
similar_movies_indices = similarities.argsort(axis=0)[:-4:-1].flatten()

#Get the titles of the top 3 similar movies
top_similar_movies = movie_ratings.columns[similar_movies_indices]

print("Top 3 movies similar to 'Liar Liar':")
```

```
print(top_similar_movies)
```

```
Top 3 movies similar to 'Liar Liar':
Index(['Liar Liar (1997)', 'Mrs. Doubtfire (1993)',
       'Ace Ventura: Pet Detective (1994)'],
      dtype='object', name='Title')
```

[64]:
```
from sklearn.metrics.pairwise import pairwise_distances

# Creating a pivot table of movie titles & user id and imputing the NaN values
movie_ratings = dfMaster.pivot_table(index='UserID', columns='Title',␣
 ↪values='Rating', fill_value=0)

# Calculate the Pearson Correlation
item_correlation = 1 - pairwise_distances(movie_ratings.T, metric='correlation')

# Convert the NumPy array to a Pandas DataFrame
item_correlation_df = pd.DataFrame(item_correlation, columns=movie_ratings.
 ↪columns, index=movie_ratings.columns)

# Write the DataFrame to a CSV file
item_correlation_df.to_csv('item_correlation.csv')

# Function to get top N similar movies based on Pearson Correlation
def get_top_similar_movies(movie_title, n=5):
    movie_idx = movie_ratings.columns.get_loc(movie_title)
    similar_scores = item_correlation[movie_idx]
    top_similar_movies = np.argsort(similar_scores)[::-1][:n]
    return movie_ratings.columns[top_similar_movies]

# Example: Get top 5 movies similar to 'Liar Liar (1997)'
movie_title = 'Liar Liar (1997)'
top_similar_movies = get_top_similar_movies(movie_title, n=5)

print(f"\nTop 5 movies similar to '{movie_title}':")
print(top_similar_movies)
```

```
(3706,)

Top 5 movies similar to 'Liar Liar (1997)':
Index(['Liar Liar (1997)', 'Mrs. Doubtfire (1993)', 'Dumb & Dumber (1994)',
       'Ace Ventura: Pet Detective (1994)', 'Home Alone (1990)'],
      dtype='object', name='Title')
```

[31]:
```
import pandas as pd
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.neighbors import NearestNeighbors
```

```python
# Assuming your DataFrame is named dfMaster
# Replace 'your_file_path.csv' with the actual path to your dataset
# dfMaster = pd.read_csv('your_file_path.csv')

# Creating a pivot table of movie titles & user id and imputing the NaN values
movie_ratings = dfMaster.pivot_table(index='UserID', columns='Title',␣
 ↪values='Rating', fill_value=0)

# Calculate the Cosine Similarity
item_similarity_matrix = cosine_similarity(movie_ratings.T)

# Print the item similarity matrix
print("\nItem Similarity Matrix:")
print(item_similarity_matrix)

# Create a Nearest Neighbors model
nn_model = NearestNeighbors(metric='cosine', algorithm='brute')
nn_model.fit(movie_ratings.T)

# Function to get top N similar movies using Nearest Neighbors and Cosine␣
 ↪Similarity
def get_top_similar_movies_nn(movie_title, n=5):
    movie_idx = movie_ratings.columns.get_loc(movie_title)
    _, indices = nn_model.kneighbors([movie_ratings.T.iloc[movie_idx]],␣
 ↪n_neighbors=n+1)
    top_similar_movies = movie_ratings.columns[indices.flatten()][1:]
    return top_similar_movies

# Example: Get top 5 movies similar to 'Liar Liar (1997)' using Nearest␣
 ↪Neighbors and Cosine Similarity
movie_title = 'Liar Liar (1997)'
top_similar_movies_nn = get_top_similar_movies_nn(movie_title, n=5)

print(f"\nTop 5 movies similar to '{movie_title}' using Nearest Neighbors and␣
 ↪Cosine Similarity:")
print(top_similar_movies_nn)
```

```
Item Similarity Matrix:
[[1.         0.07235746 0.03701053 … 0.         0.12024178 0.02700277]
 [0.07235746 1.         0.11528952 … 0.         0.         0.07780705]
 [0.03701053 0.11528952 1.         … 0.         0.04752635 0.0632837 ]
 …
 [0.         0.         0.         … 1.         0.         0.04564448]
 [0.12024178 0.         0.04752635 … 0.         1.         0.04433508]
 [0.02700277 0.07780705 0.0632837  … 0.04564448 0.04433508 1.        ]]
```

```
Top 5 movies similar to 'Liar Liar (1997)' using Nearest Neighbors and Cosine
Similarity:
Index(['Mrs. Doubtfire (1993)', 'Ace Ventura: Pet Detective (1994)',
       'Dumb & Dumber (1994)', 'Home Alone (1990)', 'Wayne's World (1992)'],
      dtype='object', name='Title')

/home/csc/my_first_environment/lib/python3.10/site-
packages/sklearn/utils/extmath.py:193: RuntimeWarning: invalid value encountered
in matmul
  ret = a @ b
```

[68]:
```python
from surprise import Dataset, Reader
from surprise.model_selection import train_test_split
from surprise import SVD
from surprise import accuracy
import matplotlib.pyplot as plt
import seaborn as sns



# Define a Reader object
reader = Reader(rating_scale=(1, 5))

# Load the data into the Surprise Dataset
data = Dataset.load_from_df(dfMaster[['UserID', 'Title', 'Rating']], reader)

# Split the data into train and test sets
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)

# Create and train the SVD model
model = SVD()
model.fit(trainset)

# Make predictions on the test set
predictions = model.test(testset)

# Evaluate the model using RMSE and MAPE
rmse = accuracy.rmse(predictions)
mae_value = accuracy.mae(predictions)
mape = mae_value / 5.0 * 100

print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Mean Absolute Percentage Error (MAPE): {mape}")


liar_liar_internal_id = trainset.to_inner_iid('Liar Liar (1997)')
```

```python
# Get the latent factors for 'Liar Liar (1997)'
liar_liar_embedding = model.qi[liar_liar_internal_id]

# Find movies similar to 'Liar Liar' based on embeddings
similar_movies_indices = (model.qi @ liar_liar_embedding.T).argsort(axis=0)[::
 ↪-1].flatten()

# Print the top 5 movies similar to 'Liar Liar'
top_similar_movies = dfMaster['Title'].iloc[similar_movies_indices[1:6]]
print("\nTop 5 movies similar to 'Liar Liar (1997)' based on embeddings:")
print(top_similar_movies)
```

```
RMSE: 0.8753
MAE:  0.6873
Root Mean Squared Error (RMSE): 0.8753499629703873
Mean Absolute Percentage Error (MAPE): 13.746726792931169

Top 5 movies similar to 'Liar Liar (1997)' based on embeddings:
1201         Lethal Weapon 2 (1989)
997     Prince of Egypt, The (1998)
935       Driving Miss Daisy (1989)
1446      Lawrence of Arabia (1962)
718          Man on the Moon (1999)
Name: Title, dtype: object
```