In [104…
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
#pd.set_option('display.max_columns', None)
import os

os.environ['PYDEVD_DISABLE_FILE_VALIDATION'] = '1'
```

In [105…
```
df_user = pd.read_table('zee-users.dat', sep='::',engine='python')
```

In [106…
```
df_rating = pd.read_table('zee-ratings.dat', sep='::',engine='python')
```

In [107…
```
df_movies = pd.read_table('zee-movies.dat', sep='::', encoding='latin1',engine='python')
```

In [108…
```
df_movies.head()
```

Out[108]:

	Movie ID	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

In [109…
```
df_rating.head()
```

Out[109]:

	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

In [ ]:
```
```

EDA for Users

In [110…
```
df_user.head()
```

Out[110]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460
4	5	M	25	20	55455

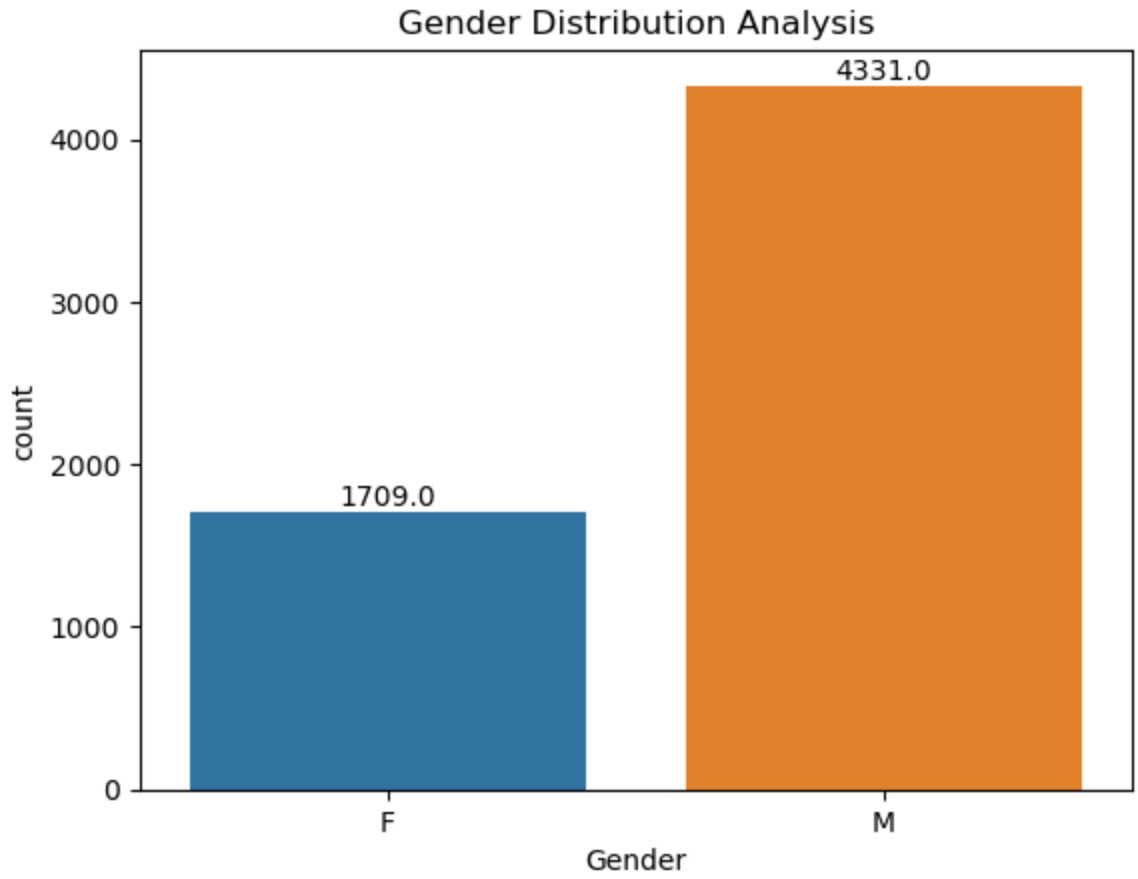
In [111…

```
def user_occupation_preprocessing(val):
    if(val==20):
        return "writer"
    if(val==19):
        return "unemployed"
    if(val==18):
        return "tradesman/craftsman"
    if(val==17):
        return "technician/engineer"
    if(val==16):
        return "self-employed"
    if(val==15):
        return "scientist"
    if(val==14):
        return "sales/marketing"
    if(val==13):
        return "retired"
    if(val==12):
        return "programmer"
    if(val==11):
        return "lawyer"
    if(val==10):
        return "K-12 student"
    if(val==9):
        return "homemaker"
    if(val==8):
        return "farmer"
    if(val==7):
        return "executive/managerial"
    if(val==6):
        return "doctor/health care"
    if(val==5):
        return "customer service"
    if(val==4):
        return "college/grad student"
    if(val==3):
        return "clerical/admin"
    if(val==2):
        return "artist"
    if(val==1):
        return "academic/educator"
    if(val==0):
        return "other/not specified"

def user_age_preprocessing(val):
    if(val==1):
        return "Under 18"
    if(val==18):
        return "18-24"
    if(val==25):
        return "25-34"
    if(val==35):
        return "35-44"
    if(val==45):
        return "45-49"
    if(val==50):
        return "50-55"
    if(val==56):
        return "56+";
```

Univariate Analysis of Gender

In [112…
```
df_user['Age'] = df_user['Age'].apply(user_age_preprocessing)
df_user['Occupation'] = df_user['Occupation'].apply(user_occupation_preprocessing)
```

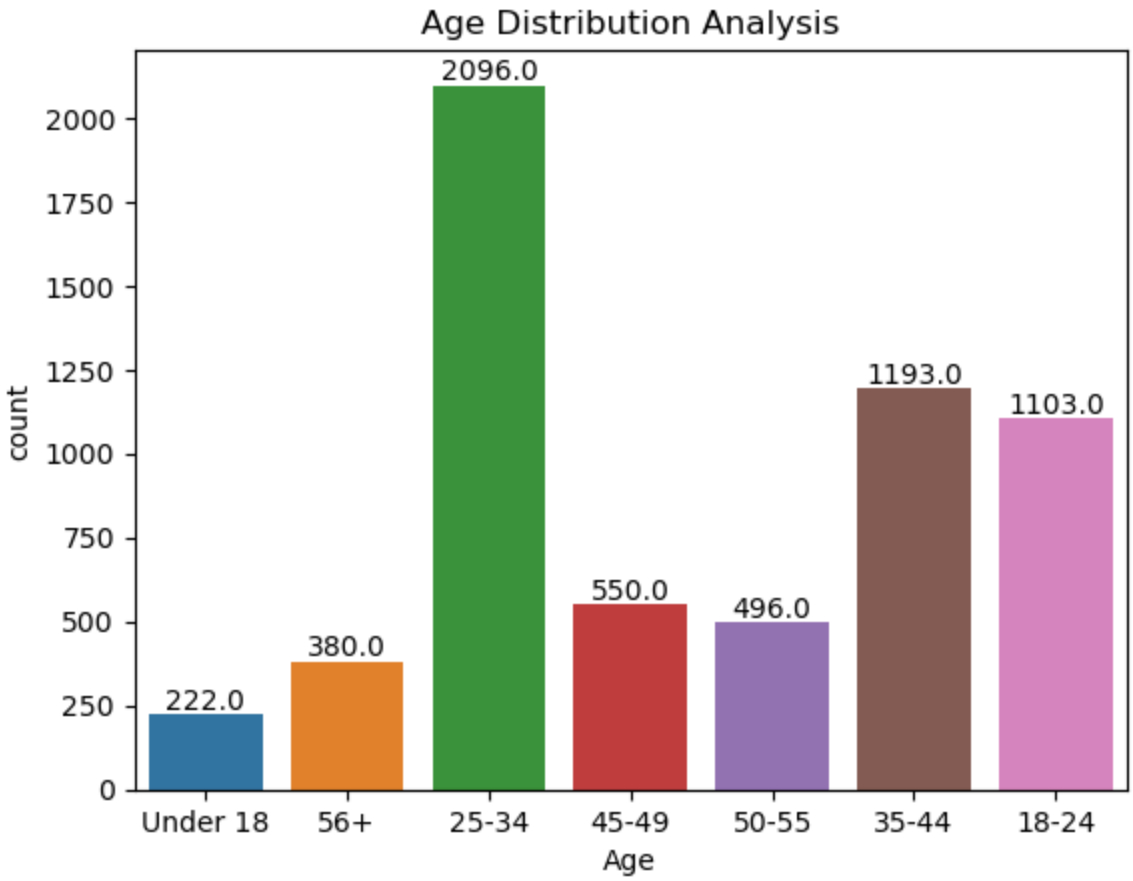
In [113…
```
plt.title('Gender Distribution Analysis')
ax = sns.countplot(data=df_user,x='Gender')

for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')
plt.show()
```

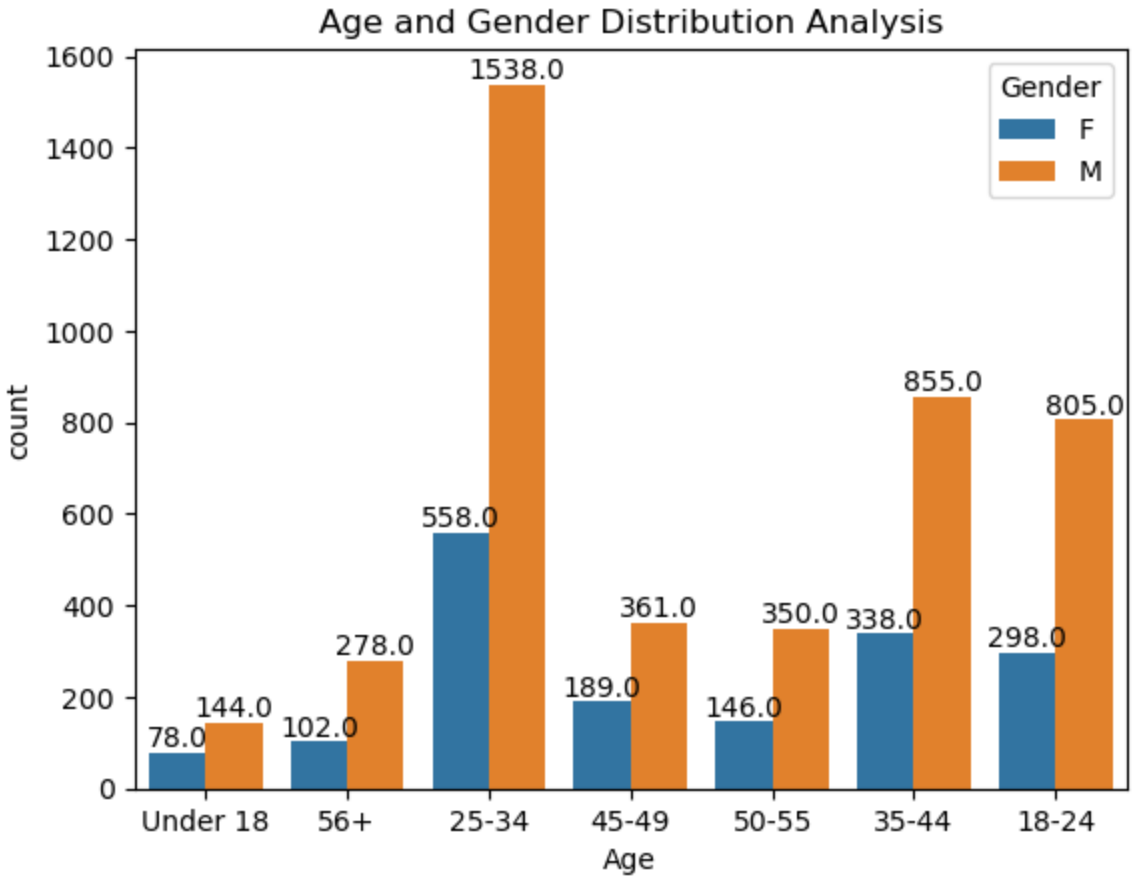


Observation

Male Users are more as compare to Female User

In [114…
```
ax = sns.countplot(data=df_user,x='Age')
plt.title('Age Distribution Analysis')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')
plt.show()

ax = sns.countplot(data=df_user,x='Age',hue='Gender')
plt.title('Age and Gender Distribution Analysis')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

plt.show()
```





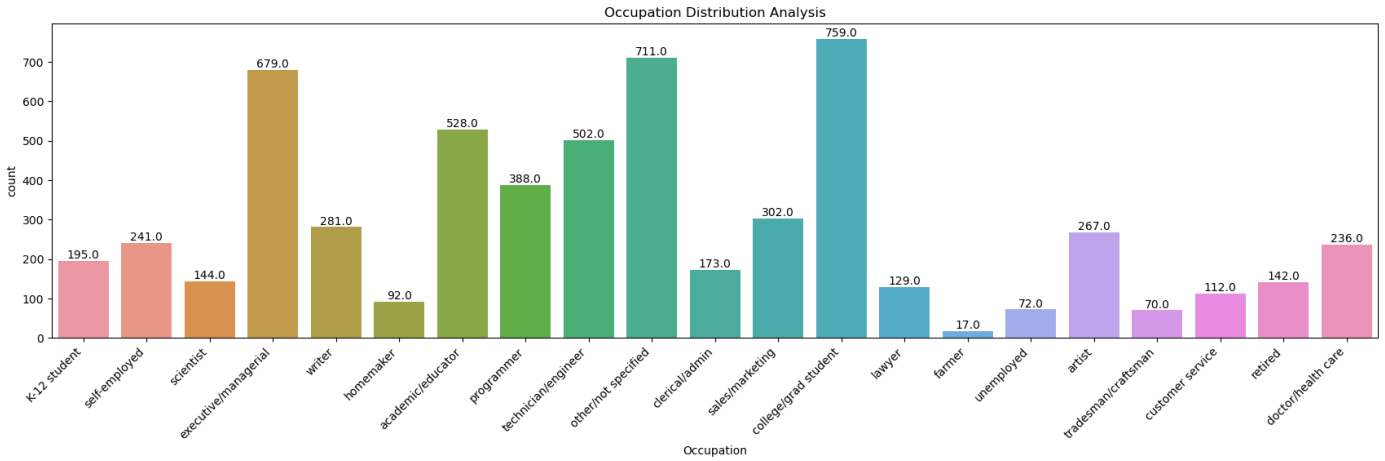
Observation

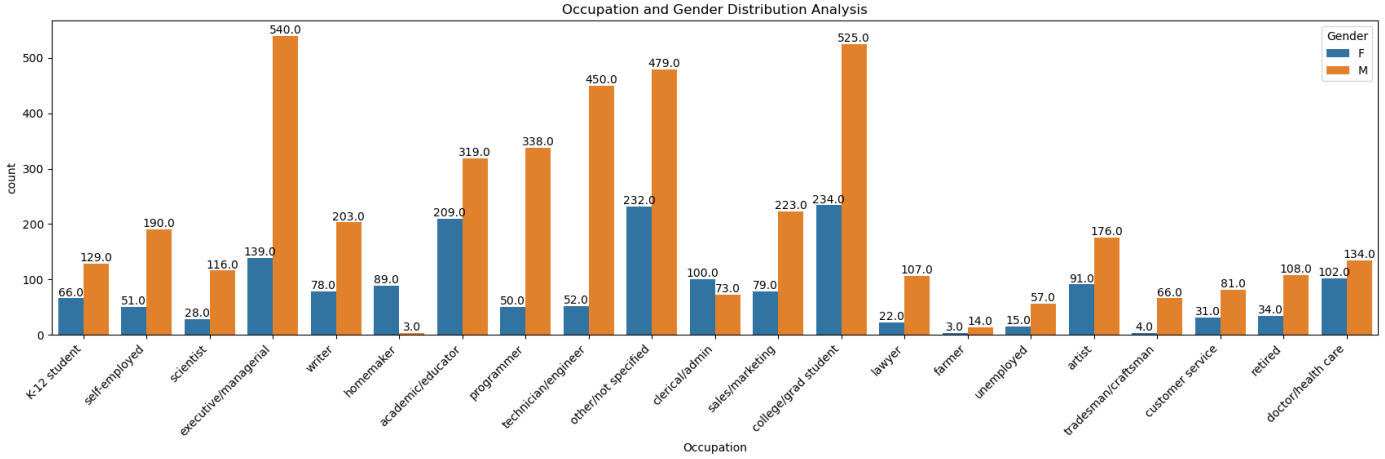
1. It is observed that users of age between 25 to 34 are highly active.
2. It is observed that Male users of age between 25 to 34 are highly active.

3. It is observed that user with age group of 56+ is less.

In [115…

```
plt.figure(figsize=(21, 5))
ax = sns.countplot(data=df_user, x='Occupation')

plt.title('Occupation Distribution Analysis')

# Rotate x-axis labels by 90 degrees
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

# Display the count on top of each bar
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

plt.show()


plt.figure(figsize=(21, 5))
ax = sns.countplot(data=df_user, x='Occupation',hue='Gender')

plt.title('Occupation and Gender Distribution Analysis')

# Rotate x-axis labels by 90 degrees
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

# Display the count on top of each bar
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

plt.show()
```





Observation

1. Homemaker users are less as compare to other occupation users.
2. Every occupation category male users are high except homemaker's.

EDA For Movie data

In [116…
```
df_movies.head()
```

Out[116]:

	Movie ID	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

In [117…
```
len(set(df_movies['Movie ID']))
```

Out[117]:
```
3883
```

In [118…
```
len(set(df_rating['MovieID']))
```

Out[118]:
```
3706
```

In [119…
```
df_rating.head()
```

Out[119]:

	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

In [120…
```
rating_and_movies  = pd.merge(df_rating,df_movies,how='left',left_on='MovieID',right_on=
```

In [121…
```
rating_and_movies.drop('Movie ID',axis=1,inplace=True)
```

In [19]:
```
rating_and_movies.shape
```

Out[19]:
```
(1000209, 6)
```

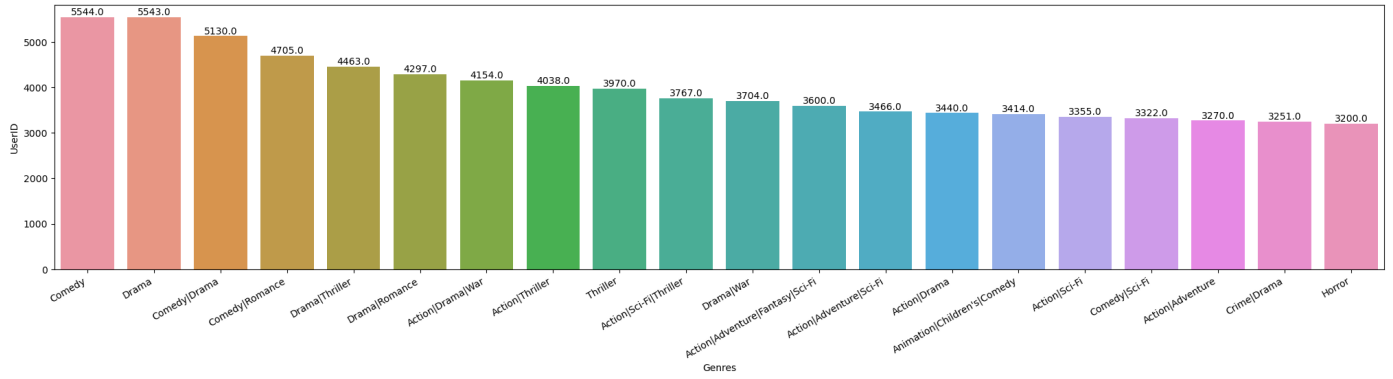
In [20]:
```
rating_and_movies.head()
```

Out[20]:

	UserID	MovieID	Rating	Timestamp	Title	Genres
0	1	1193	5	978300760	One Flew Over the Cuckoo's Nest (1975)	Drama
1	1	661	3	978302109	James and the Giant Peach (1996)	Animation|Children's|Musical
2	1	914	3	978301968	My Fair Lady (1964)	Musical|Romance
3	1	3408	4	978300275	Erin Brockovich (2000)	Drama
4	1	2355	5	978824291	Bug's Life, A (1998)	Animation|Children's|Comedy

In [21]:
```
genre_user_top_20 = rating_and_movies[['Genres','UserID']].groupby(['Genres']).nunique()
```

In [22]:
```
plt.figure(figsize=(25,5))
ax = sns.barplot(data=genre_user_top_20,x='Genres',y='UserID')
ax.set_xticklabels(ax.get_xticklabels(), rotation=30, ha='right')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

plt.show()
```



Observation

1. User Prefer more Movies with comedy genre or amalgamation with comedy genre.
2. Users prefer less movies with action or voilent genre.

In [23]:
```
user_ratings = rating_and_movies[['UserID','Rating']].groupby(['UserID']).mean(['Rating'
```

In [24]:
```
print(f'Max ratings: {user_ratings["Rating"].max()}, Min ratings: {user_ratings["Rating"
```

```
Max ratings: 4.962962962962963, Min ratings: 1.0153846153846153
```

In [25]:
```
df_user.head()
```

Out[25]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	Under 18	K-12 student	48067
1	2	M	56+	self-employed	70072
2	3	M	25-34	scientist	55117
3	4	M	45-49	executive/managerial	02460
4	5	M	25-34	writer	55455

In [26]:
```
df = pd.merge(rating_and_movies,df_user,how='left',left_on='UserID',right_on='UserID')
```

In [27]:
```
df.head()
```

Out[27]:

	UserID	MovieID	Rating	Timestamp	Title	Genres	Gender	Age	Occupation	Zco
0	1	1193	5	978300760	One Flew Over the Cuckoo's Nest (1975)	Drama	F	Under 18	K-12 student	480
1	1	661	3	978302109	James and the Giant Peach (1996)	Animation|Children's|Musical	F	Under 18	K-12 student	480
2	1	914	3	978301968	My Fair Lady (1964)	Musical|Romance	F	Under 18	K-12 student	480
3	1	3408	4	978300275	Erin Brockovich (2000)	Drama	F	Under 18	K-12 student	480
4	1	2355	5	978824291	Bug's Life, A (1998)	Animation|Children's|Comedy	F	Under 18	K-12 student	480

In [28]:
```
df.shape
```

Out[28]:
```
(1000209, 10)
```

Gender Specifics Interest Analysis

In [29]:
```
gender_distribution = df.groupby(['Genres', 'Gender']).size().unstack(fill_value=0)
```

In [30]:
```
#pd.set_option('display.max_rows', None)
gender_distribution
```

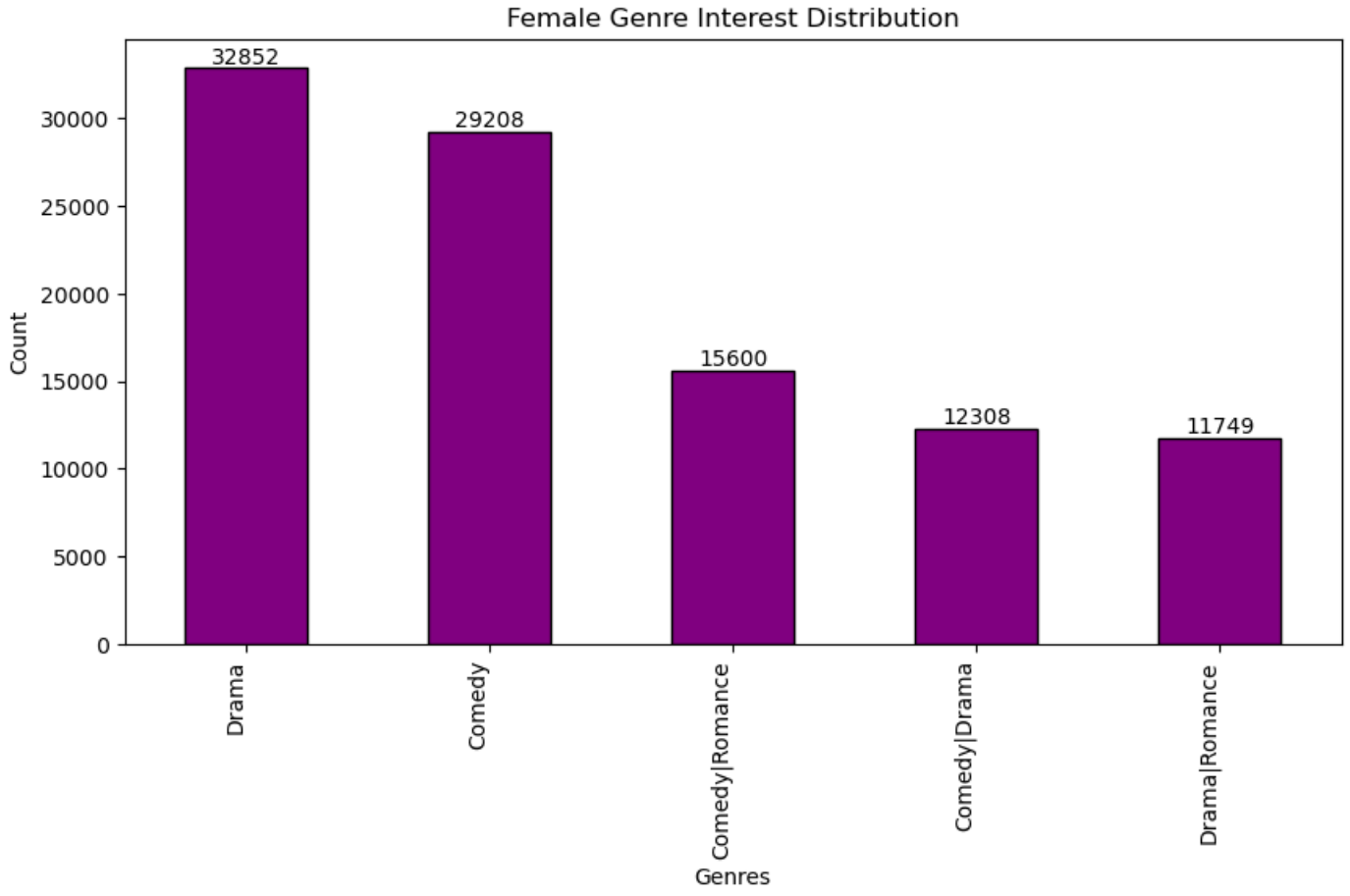
Out[30]:

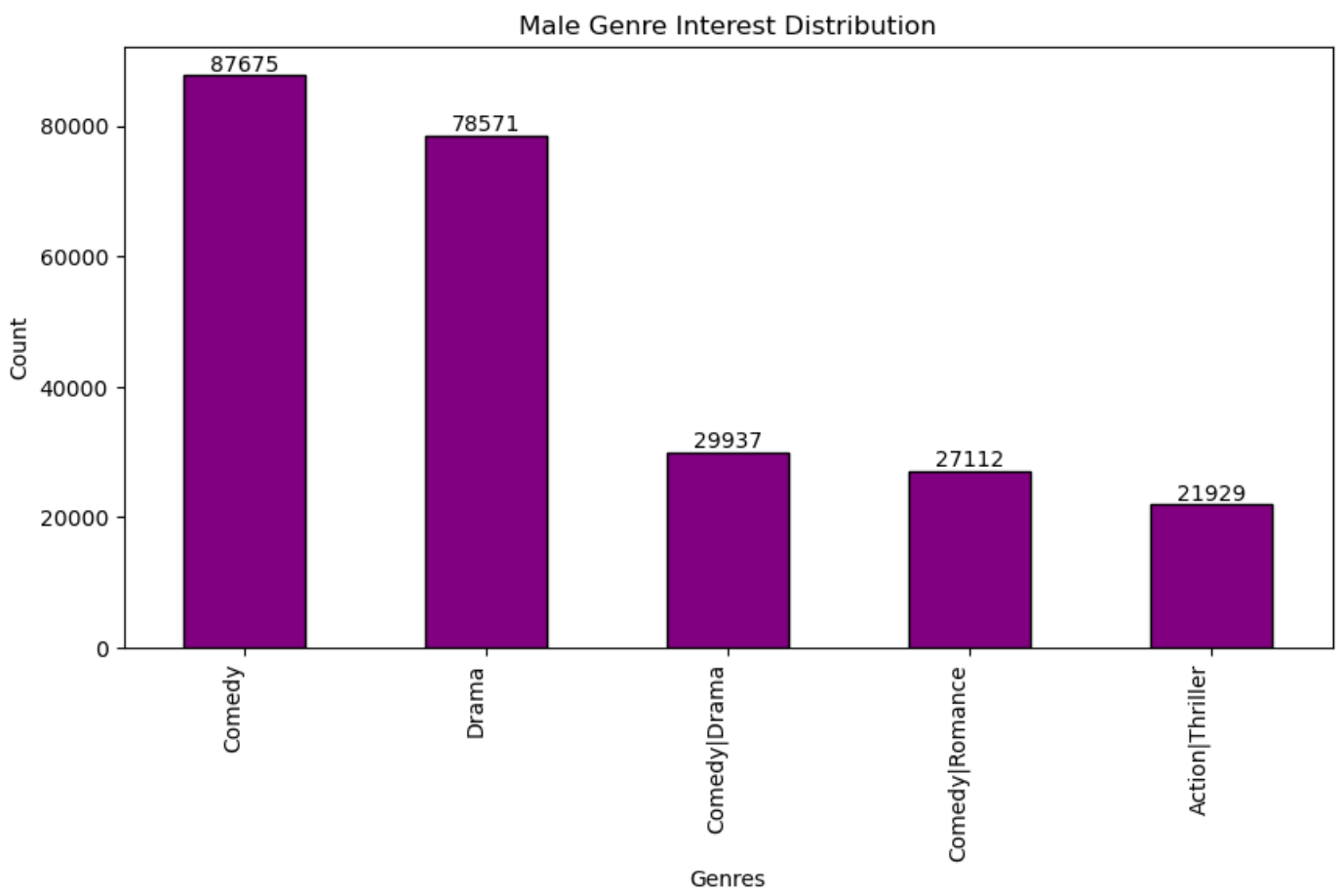
Gender	F	M
Genres		
Action	1611	10700
Action|Adventure	1978	8468
Action|Adventure|Animation	64	281
Action|Adventure|Animation|Children's|Fantasy	41	94
Action|Adventure|Animation|Horror|Sci-Fi	71	547
...	...	...
Sci-Fi|Thriller|War	40	240
Sci-Fi|War	231	1136
Thriller	4312	13539
War	101	890
Western	685	5004

301 rows × 2 columns

In [31]:
```
female_genre_interest = gender_distribution['F'].sort_values(ascending=False)[:5]
male_genre_interest = gender_distribution['M'].sort_values(ascending=False)[:5]
```

In [32]:
```
plt.figure(figsize=(10, 5))
ax = female_genre_interest.plot(kind='bar', color='purple', edgecolor='black')

ax.set_title('Female Genre Interest Distribution')
ax.set_xlabel('Genres')
ax.set_ylabel('Count')
ax.set_xticklabels(ax.get_xticklabels(), rotation=90, ha='right')

for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

plt.show()


plt.figure(figsize=(10, 5))
ax = male_genre_interest.plot(kind='bar', color='purple', edgecolor='black')

ax.set_title('Male Genre Interest Distribution')
ax.set_xlabel('Genres')
ax.set_ylabel('Count')
ax.set_xticklabels(ax.get_xticklabels(), rotation=90, ha='right')

for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 5), textcoords='offset points')

plt.show()
```





Observation

1. Female Population prefer Drama genre more as compare to other genres.
2. Male Population prefer Comedy genre more as compare to other genres.

Age Specific Interest Analysis

In [33]:
```
age_interest_distribution = df.groupby(['Genres','Age']).size().unstack(fill_value=0)
age_interest_distribution
```

Out[33]:

Genres	Age 18-24	25-34	35-44	45-49	50-55	56+	Under 18
Action	2075	5053	2587	952	935	427	282
Action|Adventure	2020	4161	2126	807	727	374	231
Action|Adventure|Animation	104	152	40	13	9	5	22
Action|Adventure|Animation|Children's|Fantasy	34	34	27	7	6	3	24
Action|Adventure|Animation|Horror|Sci-Fi	106	303	145	32	18	4	10
...	...	...	...	...	...	...	...
Sci-Fi|Thriller|War	17	78	74	40	46	22	3
Sci-Fi|War	195	478	291	149	132	87	35
Thriller	2917	7435	3612	1516	1330	644	397
War	81	198	228	156	191	122	15
Western	604	1879	1272	626	791	456	61

301 rows × 7 columns

In [34]:
```
_18_24_values = age_interest_distribution['18-24'].sort_values(ascending=False)[:10]
_25_34_values = age_interest_distribution['25-34'].sort_values(ascending=False)[:10]
_45_49_values = age_interest_distribution['45-49'].sort_values(ascending=False)[:10]
_35_44_values = age_interest_distribution['35-44'].sort_values(ascending=False)[:10]
_50_55_values = age_interest_distribution['50-55'].sort_values(ascending=False)[:10]
_56_plus_values = age_interest_distribution['56+'].sort_values(ascending=False)[:10]
under_18_values = age_interest_distribution['Under 18'].sort_values(ascending=False)[:10
```

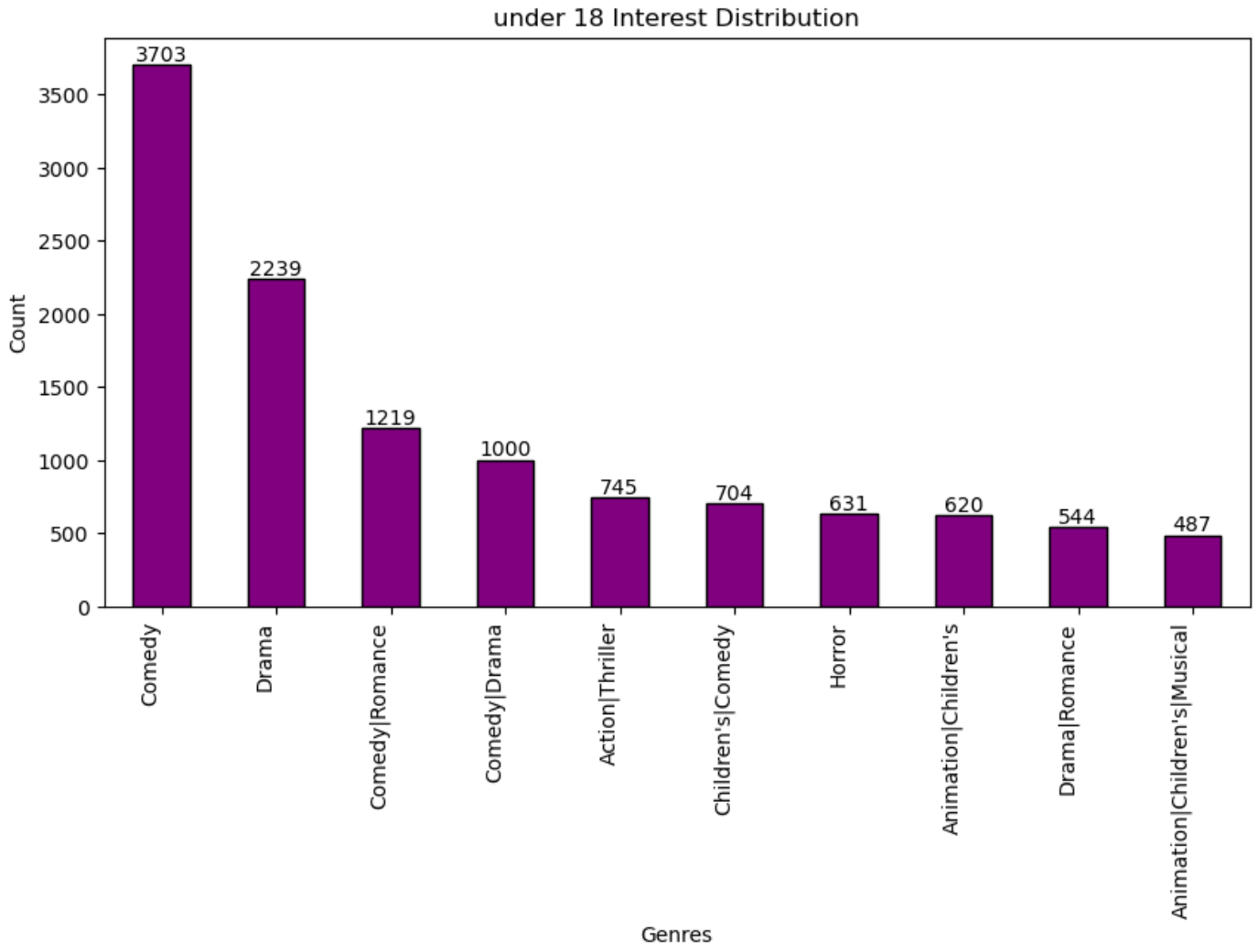
In [ ]:
```
```

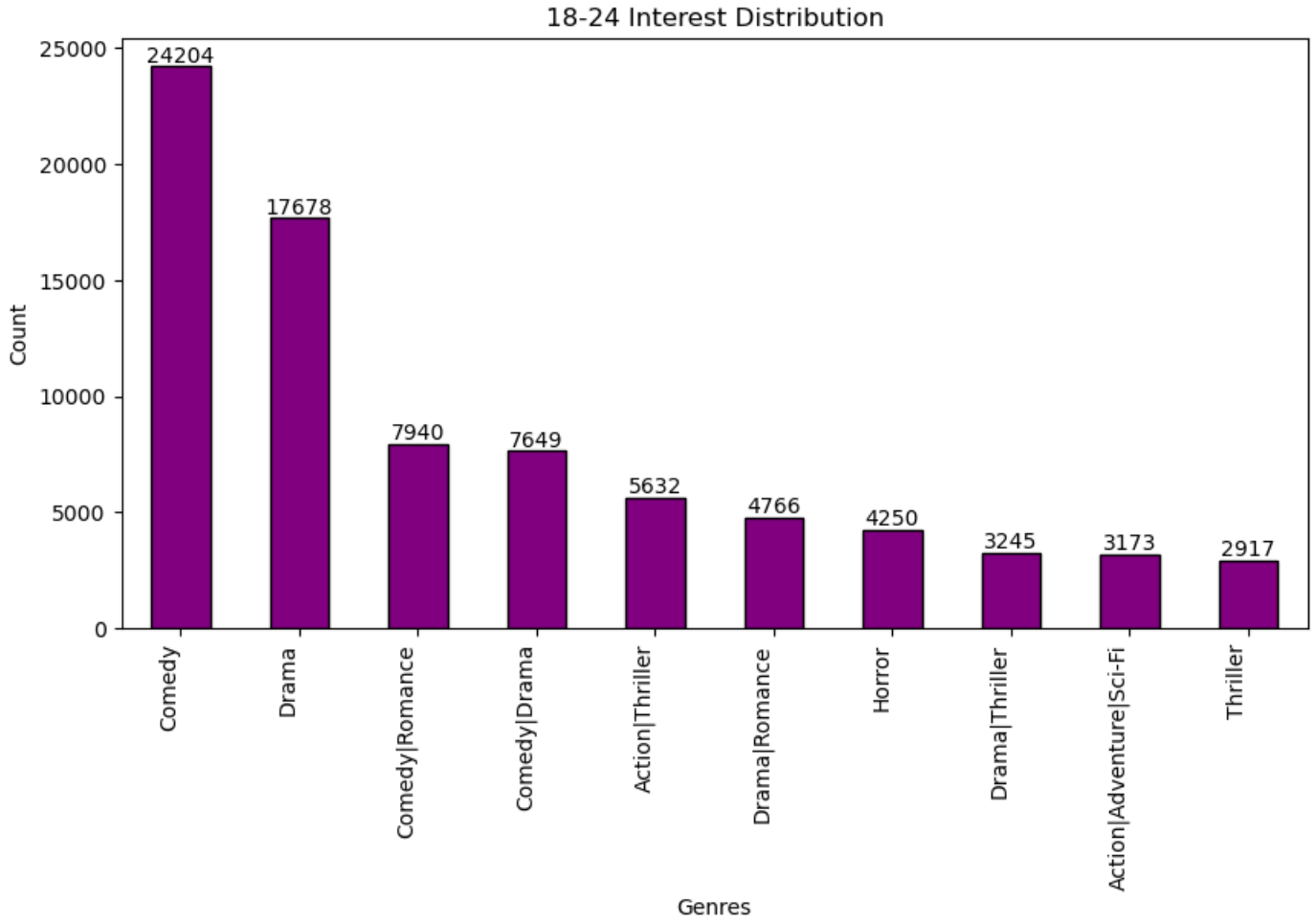
In [35]:
```
def plot_values(vals,kind,title,xlabel,ylabel,color='purple', edgecolor='black'):
    plt.figure(figsize=(10, 5))
    ax = vals.plot(kind=kind,color=color,edgecolor=edgecolor)
    ax.set_title(title)
    ax.set_xlabel(xlabel)
    ax.set_ylabel(ylabel)
    ax.set_xticklabels(ax.get_xticklabels(), rotation=90, ha='right')

    for p in ax.patches:
        ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()
                    ha='center', va='center', xytext=(0, 5), textcoords='offset points')

    plt.show()
```

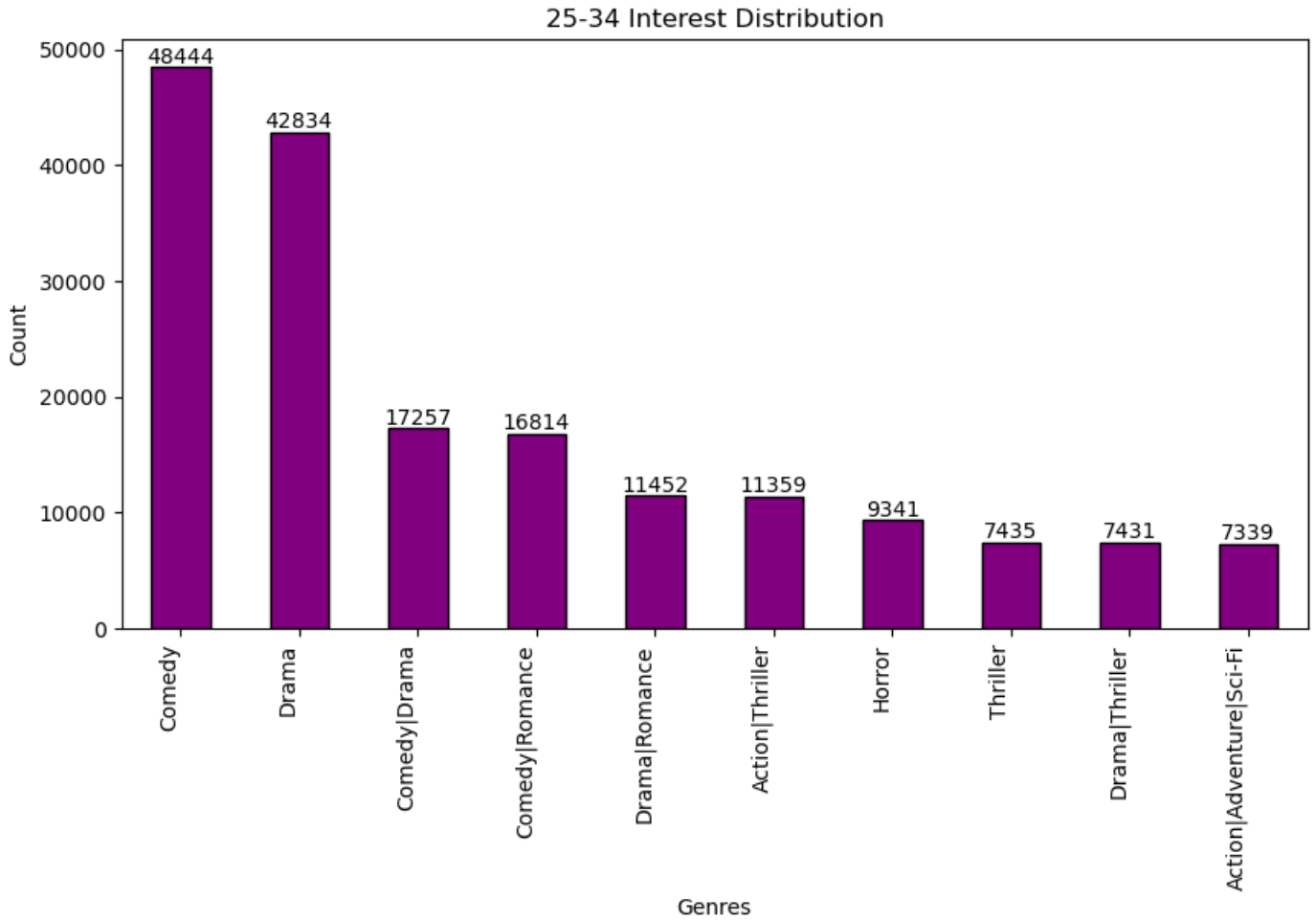
In [ ]:
```
```

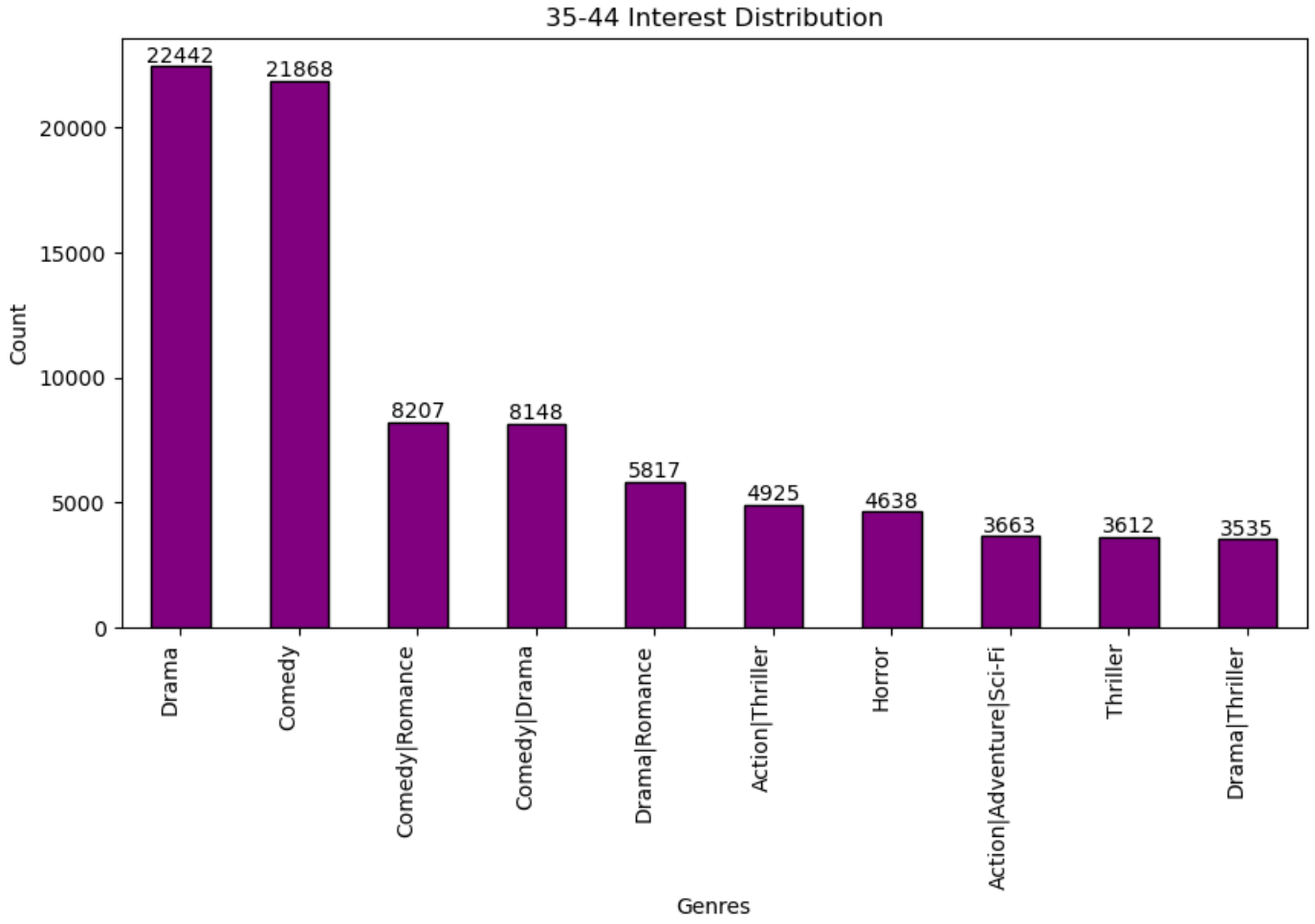
In [36]:
```
plot_values(under_18_values,kind='bar',title='under 18 Interest Distribution',xlabel='Ge

plot_values(_18_24_values,kind='bar',title='18-24 Interest Distribution',xlabel='Genres'

plot_values(_25_34_values,kind='bar',title='25-34 Interest Distribution',xlabel='Genres'

plot_values(_35_44_values,kind='bar',title='35-44 Interest Distribution',xlabel='Genres'

plot_values(_45_49_values,kind='bar',title='45-49 Interest Distribution',xlabel='Genres'

plot_values(_50_55_values,kind='bar',title='50-55 Interest Distribution',xlabel='Genres'
```

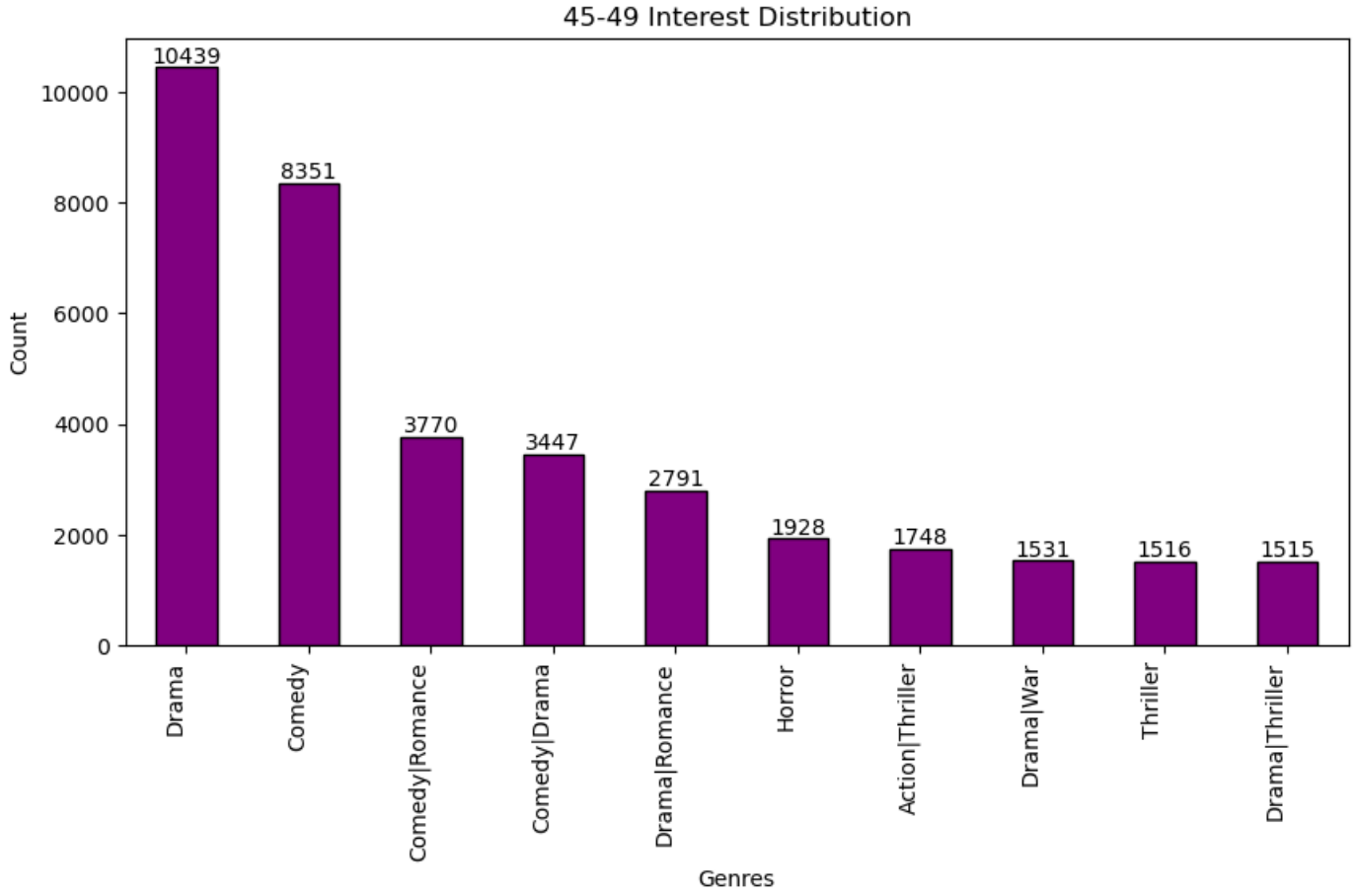
```
plot_values(_56_plus_values,kind='bar',title='56+ Interest Distribution',xlabel='Genres'
```

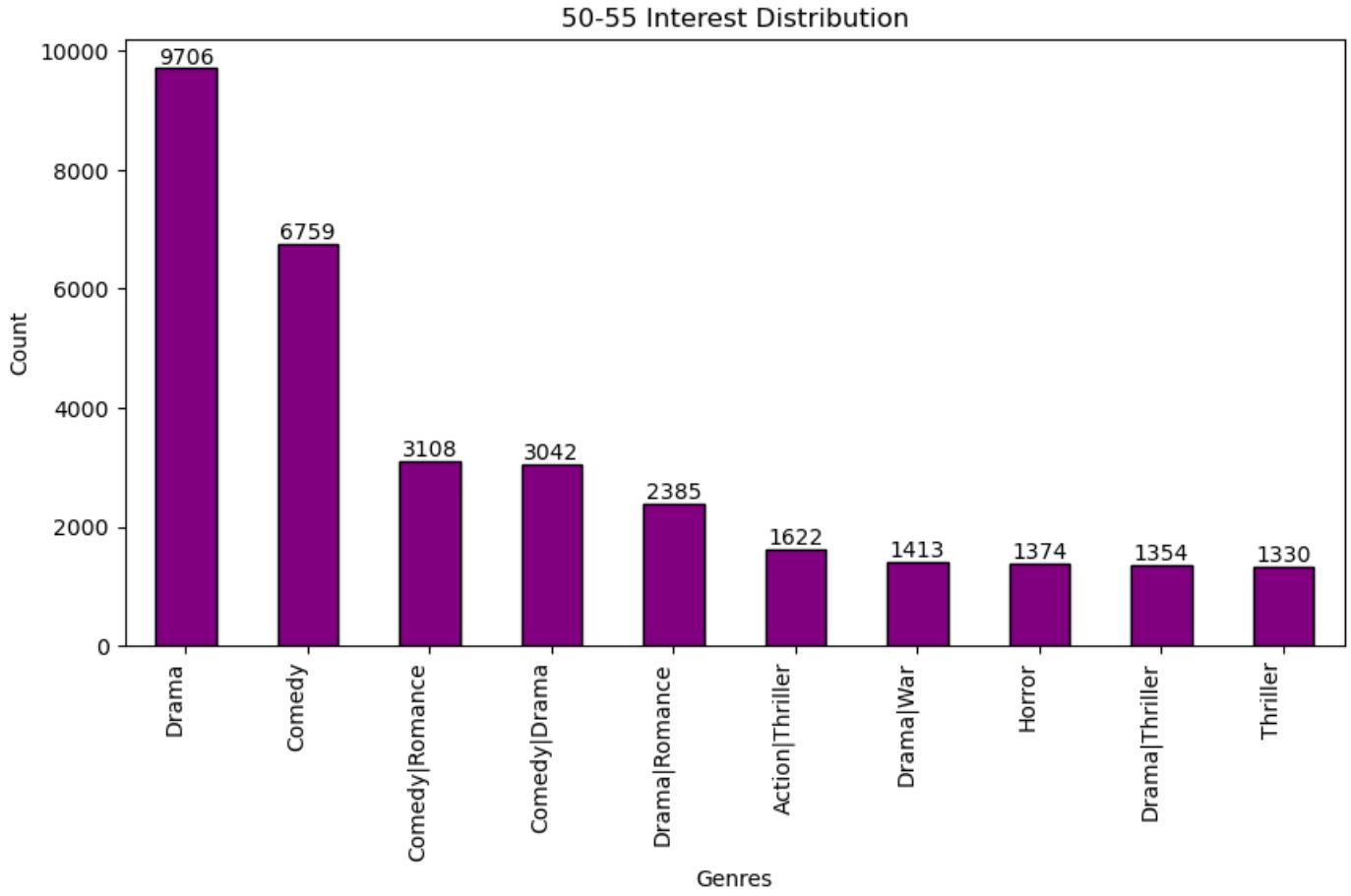


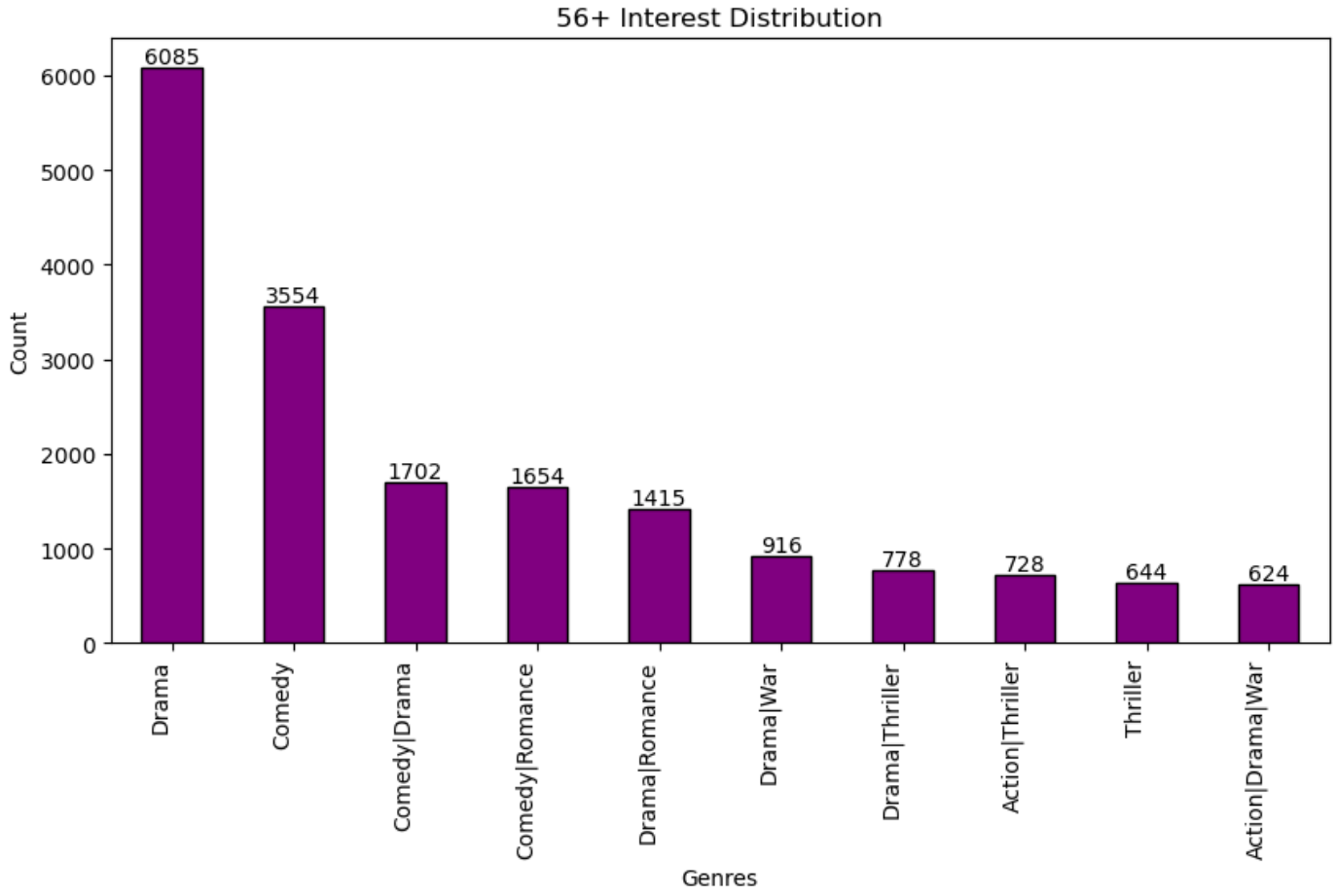












Observation

1. It is observed that user of age between 18 to 35 prefer more Comedy over drama.

2. It is observed that user of age of 35+ prefer more Drama over comedy.

Data Preperation for Recommendation System

In [37]:
```
df_rating.head()
```

Out[37]:

	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

In [38]:
```
df_movies.rename({'Movie ID':'MovieID'},axis=1,inplace=True)
```

In [39]:
```
df_movies.head()
```

Out[39]:

	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

In [40]:
```
movies = df_movies.copy()
```

In [41]:
```
movies['Genres']= movies['Genres'].str.split('|')
movies= movies.explode('Genres')
movies = movies.pivot(index='MovieID',columns='Genres',values='Title')
movies = ~movies.isna()
movies = movies.astype(int)
movies.head()
```

Out[41]:

Genres	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horr
MovieID											
1	0	0	1	1	1	0	0	0	0	0	
2	0	1	0	1	0	0	0	0	1	0	
3	0	0	0	0	1	0	0	0	0	0	
4	0	0	0	0	1	0	0	1	0	0	
5	0	0	0	0	1	0	0	0	0	0	

In [42]:
```
from datetime import datetime
ratings = df_rating.copy()
ratings['hour'] = ratings['Timestamp'].apply(lambda x:datetime.fromtimestamp(x).hour)
ratings.head()
```

Out[42]:

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

In [43]:
```
users = df_user.copy()
```

In [44]:
```
users.head()
```

Out[44]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	Under 18	K-12 student	48067
1	2	M	56+	self-employed	70072
2	3	M	25-34	scientist	55117
3	4	M	45-49	executive/managerial	02460
4	5	M	25-34	writer	55455

In [45]:
```
users = users.merge(ratings.groupby('UserID')['Rating'].mean().reset_index(),on='UserID'
```

In [46]:
```
users = users.merge(ratings.groupby('UserID')['hour'].mean().reset_index(),on='UserID')
```

In [47]:
```
users
```

Out[47]:

	UserID	Gender	Age	Occupation	Zip-code	Rating	hour
0	1	F	Under 18	K-12 student	48067	4.188679	3.792453
1	2	M	56+	self-employed	70072	3.713178	2.968992
2	3	M	25-34	scientist	55117	3.901961	2.215686
3	4	M	45-49	executive/managerial	02460	4.190476	1.000000
4	5	M	25-34	writer	55455	3.146465	11.656566
...	...	...	...	...	...	...	...
6035	6036	F	25-34	scientist	32603	3.302928	10.869369
6036	6037	F	45-49	academic/educator	76006	3.717822	7.000000
6037	6038	F	56+	academic/educator	14706	3.800000	5.550000
6038	6039	F	45-49	other/not specified	01060	3.878049	5.512195
6039	6040	M	25-34	doctor/health care	11106	3.577713	10.826979

6040 rows × 7 columns

In [48]:
```
users.isna().sum()
```

Out[48]:
```
UserID        0
Gender        0
Age           0
Occupation    0
Zip-code      0
Rating        0
hour          0
dtype: int64
```

Preprocessing Users data for recommendation systems and applying Regression technique to predict ratings

In [49]:
```
from sklearn.preprocessing import LabelEncoder,TargetEncoder,StandardScaler
from sklearn.impute import KNNImputer,SimpleImputer
```

In [50]:
```
users['Gender'] = LabelEncoder().fit_transform(users['Gender'])
```

In [51]:
```
def decode_age(age):
    if(age=='18-24'):
        return 18
    if(age=='25-34'):
        return 25
    if(age=='35-44'):
        return 35
    if(age=='45-49'):
        return 45
    if(age=='50-55'):
        return 50
    if(age=='56+'):
        return 56
    if(age=='Under 18'):
        return 1
```

In [52]:
```
users['Age'] = users['Age'].apply(decode_age)
```

In [53]:
```
users.head()
```

Out[53]:

	UserID	Gender	Age	Occupation	Zip-code	Rating	hour
0	1	0	1	K-12 student	48067	4.188679	3.792453
1	2	1	56	self-employed	70072	3.713178	2.968992
2	3	1	25	scientist	55117	3.901961	2.215686
3	4	1	45	executive/managerial	02460	4.190476	1.000000
4	5	1	25	writer	55455	3.146465	11.656566

In [54]:
```
users.drop(['Occupation','Zip-code','Gender','Age'],axis=1,inplace=True)
```

In [55]:
```
users.head()
```

Out[55]:

	UserID	Rating	hour
0	1	4.188679	3.792453
1	2	3.713178	2.968992
2	3	3.901961	2.215686
3	4	4.190476	1.000000
4	5	3.146465	11.656566

In [56]:
```
df_users = users.copy()
```

In [57]:
```
df_users = df_users.set_index('UserID')
```

In [58]:
```
cols = list(df_users.columns)
cols
```

Out[58]:
```
['Rating', 'hour']
```

In [59]:
```
scaler = StandardScaler()
df_users = pd.DataFrame(scaler.fit_transform(df_users),columns=cols,index=df_users.index
```

In [60]:
```
df_users.head()
```

Out[60]:

	Rating	hour
UserID		
1	1.131261	-0.909947
2	0.024380	-1.037952
3	0.463832	-1.155052
4	1.135444	-1.344027
5	-1.294827	0.312509

In [61]:
```
movies
```

Out[61]:

Genres	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horr
MovieID											
1	0	0	1	1	1	0	0	0	0	0	
2	0	1	0	1	0	0	0	0	1	0	
3	0	0	0	0	1	0	0	0	0	0	
4	0	0	0	0	1	0	0	1	0	0	
5	0	0	0	0	1	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	
3948	0	0	0	0	1	0	0	0	0	0	
3949	0	0	0	0	0	0	0	1	0	0	
3950	0	0	0	0	0	0	0	1	0	0	
3951	0	0	0	0	0	0	0	1	0	0	
3952	0	0	0	0	0	0	0	1	0	0	

3883 rows × 18 columns

In [62]:
```
X = pd.DataFrame(ratings[['UserID','MovieID','Rating']].copy())
```

In [63]:
```
X.head()
```

Out[63]:

	UserID	MovieID	Rating
0	1	1193	5
1	1	661	3
2	1	914	3
3	1	3408	4
4	1	2355	5

In [64]:
```
# X = X.merge(df_users.reset_index(),on='UserID',how='right')
# X = X.merge(movies.reset_index(),on='MovieID',how='right')

X = pd.merge(X,df_users.reset_index(),on='UserID',how='right')
X = pd.merge(X,movies.reset_index(),on='MovieID',how='right')
```

In [65]:
```
X.head()
```

Out[65]:

	UserID	MovieID	Rating_x	Rating_y	hour	Action	Adventure	Animation	Children's	Comedy	...	Fant
0	1.0	1	5.0	1.131261	-0.909947	0	0	1	1	1	...	
1	6.0	1	4.0	0.462546	-0.010682	0	0	1	1	1	...	
2	8.0	1	4.0	0.424099	-0.296155	0	0	1	1	1	...	
3	9.0	1	5.0	0.077154	-0.513996	0	0	1	1	1	...	
4	10.0	1	5.0	0.959081	-0.528025	0	0	1	1	1	...	

5 rows × 23 columns

In [66]:
```
X.drop(['UserID','MovieID'],axis=1,inplace=True)
```

In [67]:
```
X.rename({'Rating_x':'ratings','Rating_y':'avg_ratings'},axis=1,inplace=True)
```

In [68]:
```
X.head()
```

Out[68]:

	ratings	avg_ratings	hour	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	...
0	5.0	1.131261	-0.909947	0	0	1	1	1	0	0	...
1	4.0	0.462546	-0.010682	0	0	1	1	1	0	0	...
2	4.0	0.424099	-0.296155	0	0	1	1	1	0	0	...
3	5.0	0.077154	-0.513996	0	0	1	1	1	0	0	...
4	5.0	0.959081	-0.528025	0	0	1	1	1	0	0	...

5 rows × 21 columns

In [69]:
```
X.shape
```

Out[69]:
```
(1000386, 21)
```

In [70]:
```
cols = X.columns
```

In [71]:
```
x = SimpleImputer(strategy='median').fit_transform(X)
```

In [72]:
```
x = pd.DataFrame(x,columns = cols)
x.isna().sum()
```

Out[72]:
```
ratings        0
avg_ratings    0
hour           0
Action         0
Adventure      0
Animation      0
Children's     0
Comedy         0
Crime          0
Documentary    0
Drama          0
Fantasy        0
Film-Noir      0
Horror         0
Musical        0
Mystery        0
Romance        0
Sci-Fi         0
Thriller       0
War            0
Western        0
dtype: int64
```

In [73]:
```
Y = x.pop('ratings')
```

In [74]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
def check_vif(df):
    tmp = df.columns
    df = StandardScaler().fit_transform(df)
    df = pd.DataFrame(df,columns=tmp)
```

```
    vif_df = pd.DataFrame()
    vif_df['Features'] = df.columns
    vif_df["VIF"] = [round(variance_inflation_factor(df.values, i),2) for i in range(len
    return vif_df,df
```

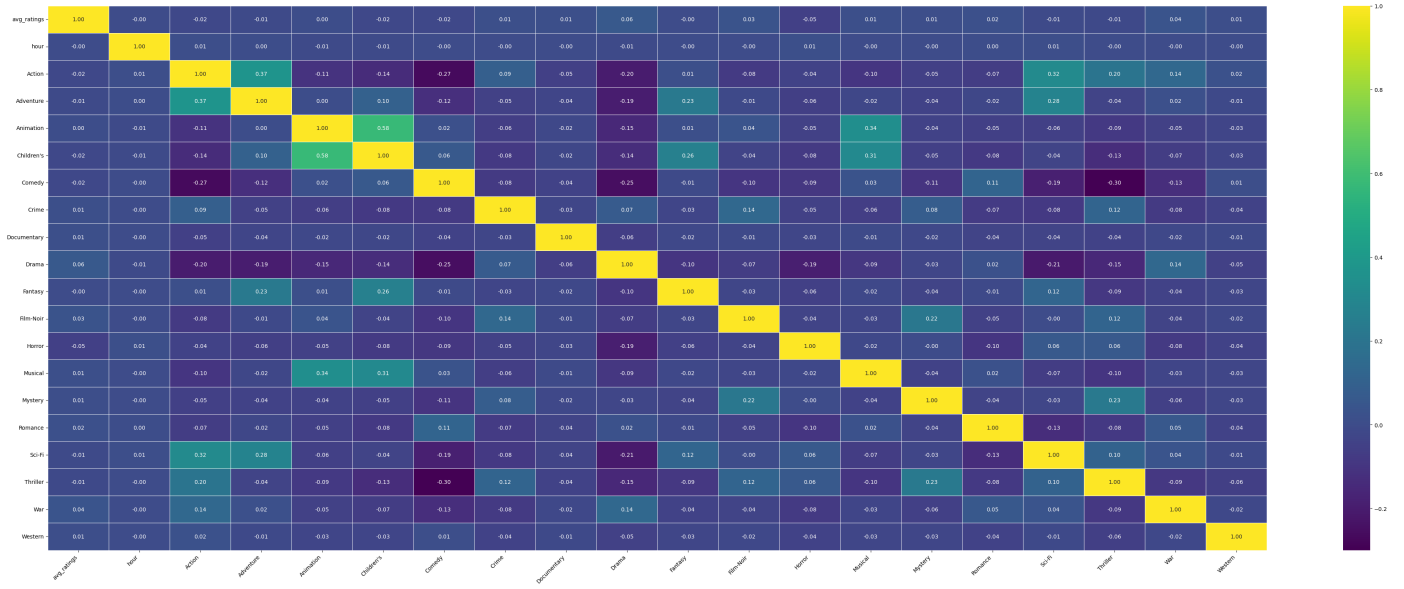
In [75]:
```
vif,data = check_vif(x)
```

In [76]:
```
vif
```

Out[76]:

	Features	VIF
0	avg_ratings	1.01
1	hour	1.00
2	Action	1.56
3	Adventure	1.34
4	Animation	1.65
5	Children's	1.79
6	Comedy	1.58
7	Crime	1.09
8	Documentary	1.05
9	Drama	1.63
10	Fantasy	1.19
11	Film-Noir	1.13
12	Horror	1.17
13	Musical	1.19
14	Mystery	1.12
15	Romance	1.07
16	Sci-Fi	1.27
17	Thriller	1.35
18	War	1.09
19	Western	1.03

In [89]:
```
plt.figure(figsize=(50, 18))

# Create a heatmap of the correlation matrix
heatmap = sns.heatmap(x.corr(), annot=True, cmap='viridis', fmt='.2f', linewidths=.5)

# Rotate x-axis labels for better readability
heatmap.set_xticklabels(heatmap.get_xticklabels(), rotation=45, horizontalalignment='rig
plt.show()
```



In [92]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, Y, test_size=0.50, random_state=0
```

In [ ]:
```
```

In [93]:
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import LinearRegression

model = LinearRegression(n_jobs=-1)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

In [ ]:
```
# from sklearn.metrics import r2_score
```

In [ ]:
```
# r2_score(y_test,y_pred)
```

In [94]:
```
model.score(X_test,y_test)
```

Out[94]:
```
0.17557627239714557
```

In [95]:
```
model.score(X_train,y_train)
```

Out[95]:
```
0.17717080596370405
```

Collaborative filtering technique

In [98]:
```
df_rating.head()
```

Out[98]:

	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

In [99]:
```
user_item_interation_df = df_rating.pivot(index='UserID',columns='MovieID',values='Ratin
```

In [107…
```
user_item_interation_df.head()
```

Out[107]:

MovieID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
UserID																						
1	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0

In [105…
```
user_item_interation_df.shape
```

Out[105]:
```
(6040, 3706)
```

Sparcity Check

In [104…
```
((user_item_interation_df > 0).sum().sum() / (user_item_interation_df.shape[0] * user_it
```

Out[104]:
```
4.468362562231285
```

In [109…
```
# only 4.46 % values are filled
```

In [159…
```
ratings = df_rating[['UserID', 'MovieID', 'Rating']]
ratings.columns = ['UserId', 'ItemId', 'Rating']
```

In [160…
```
ratings
```

Out[160]:

	UserId	ItemId	Rating
0	1	1193	5
1	1	661	3
2	1	914	3
3	1	3408	4
4	1	2355	5
...	...	...	...
1000204	6040	1091	1
1000205	6040	1094	5
1000206	6040	562	5
1000207	6040	1096	4
1000208	6040	1097	4

1000209 rows × 3 columns

In [161…
```
from cmfrec import CMF
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
```

In [164…

```
params = {
    'k': list(range(30,100)),
    'lambda_':np.arange(0, 9, 0.01).tolist(),
    'method' : ['als'],
    'center' : [True,False],
    'niter' : list(range(6,300))

}
grid = RandomizedSearchCV(param_distributions=params,n_jobs=-1,estimator=CMF(),scoring='
```

In [165…

```
grid.fit(ratings)
```

```
C:\Users\gaura\anaconda3\Lib\site-packages\sklearn\model_selection\_search.py:1051: User
Warning: One or more of the test scores are non-finite: [nan nan nan nan nan nan nan nan
nan nan]
  warnings.warn(
```

```
Starting ALS optimization routine

Updating B ... done
Updating A ... done
        Completed ALS iteration  1

Updating B ... done
Updating A ... done
        Completed ALS iteration  2

Updating B ... done
Updating A ... done
        Completed ALS iteration  3

Updating B ... done
Updating A ... done
        Completed ALS iteration  4

Updating B ... done
Updating A ... done
        Completed ALS iteration  5

Updating B ... done
Updating A ... done
        Completed ALS iteration  6

Updating B ... done
Updating A ... done
        Completed ALS iteration  7

Updating B ... done
Updating A ... done
        Completed ALS iteration  8

Updating B ... done
Updating A ... done
        Completed ALS iteration  9

Updating B ... done
Updating A ... done
        Completed ALS iteration 10

Updating B ... done
Updating A ... done
        Completed ALS iteration 11

Updating B ... done
Updating A ... done
        Completed ALS iteration 12

Updating B ... done
Updating A ... done
        Completed ALS iteration 13

Updating B ... done
Updating A ... done
        Completed ALS iteration 14

Updating B ... done
Updating A ... done
        Completed ALS iteration 15

Updating B ... done
Updating A ... done
```

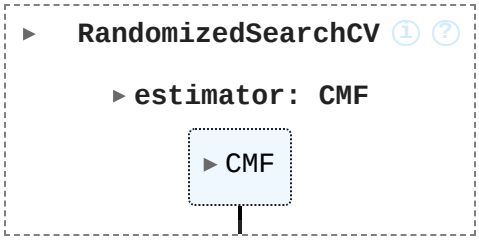
```
        Completed ALS iteration 16

Updating B ... done
Updating A ... done
        Completed ALS iteration 17

Updating B ... done
Updating A ... done
        Completed ALS iteration 18

Updating B ... done
Updating A ... done
        Completed ALS iteration 19

Updating B ... done
Updating A ... done
        Completed ALS iteration 20

Updating B ... done
Updating A ... done
        Completed ALS iteration 21

Updating B ... done
Updating A ... done
        Completed ALS iteration 22

Updating B ... done
Updating A ... done
        Completed ALS iteration 23

Updating B ... done
Updating A ... done
        Completed ALS iteration 24

Updating B ... done
Updating A ... done
        Completed ALS iteration 25

Updating B ... done
Updating A ... done
        Completed ALS iteration 26

Updating B ... done
Updating A ... done
        Completed ALS iteration 27

Updating B ... done
Updating A ... done
        Completed ALS iteration 28

Updating B ... done
Updating A ... done
        Completed ALS iteration 29

Updating B ... done
Updating A ... done
        Completed ALS iteration 30

Updating B ... done
Updating A ... done
        Completed ALS iteration 31

Updating B ... done
Updating A ... done
```

```
        Completed ALS iteration 32

Updating B ... done
Updating A ... done
        Completed ALS iteration 33

Updating B ... done
Updating A ... done
        Completed ALS iteration 34

Updating B ... done
Updating A ... done
        Completed ALS iteration 35

Updating B ... done
Updating A ... done
        Completed ALS iteration 36

Updating B ... done
Updating A ... done
        Completed ALS iteration 37

Updating B ... done
Updating A ... done
        Completed ALS iteration 38

Updating B ... done
Updating A ... done
        Completed ALS iteration 39

Updating B ... done
Updating A ... done
        Completed ALS iteration 40

Updating B ... done
Updating A ... done
        Completed ALS iteration 41

Updating B ... done
Updating A ... done
        Completed ALS iteration 42

Updating B ... done
Updating A ... done
        Completed ALS iteration 43

Updating B ... done
Updating A ... done
        Completed ALS iteration 44

Updating B ... done
Updating A ... done
        Completed ALS iteration 45

Updating B ... done
Updating A ... done
        Completed ALS iteration 46

Updating B ... done
Updating A ... done
        Completed ALS iteration 47

Updating B ... done
Updating A ... done
```

```
        Completed ALS iteration 48

Updating B ... done
Updating A ... done
        Completed ALS iteration 49

Updating B ... done
Updating A ... done
        Completed ALS iteration 50

Updating B ... done
Updating A ... done
        Completed ALS iteration 51

Updating B ... done
Updating A ... done
        Completed ALS iteration 52

Updating B ... done
Updating A ... done
        Completed ALS iteration 53

Updating B ... done
Updating A ... done
        Completed ALS iteration 54

Updating B ... done
Updating A ... done
        Completed ALS iteration 55

Updating B ... done
Updating A ... done
        Completed ALS iteration 56

Updating B ... done
Updating A ... done
        Completed ALS iteration 57

Updating B ... done
Updating A ... done
        Completed ALS iteration 58

Updating B ... done
Updating A ... done
        Completed ALS iteration 59

Updating B ... done
Updating A ... done
        Completed ALS iteration 60

Updating B ... done
Updating A ... done
        Completed ALS iteration 61

Updating B ... done
Updating A ... done
        Completed ALS iteration 62

Updating B ... done
Updating A ... done
        Completed ALS iteration 63

Updating B ... done
Updating A ... done
```

```
        Completed ALS iteration 64

Updating B ... done
Updating A ... done
        Completed ALS iteration 65

Updating B ... done
Updating A ... done
        Completed ALS iteration 66

ALS procedure terminated successfully
```

Out[165]:



In [170…

```
best_estimator = grid.best_estimator_

# Print the best estimator's parameters
print("Best Estimator Parameters:")
print(best_estimator.get_params())
```

```
Best Estimator Parameters:
{'k': 42, 'lambda_': 5.39, 'method': 'als', 'use_cg': True, 'user_bias': True, 'item_bia
s': True, 'center': False, 'add_implicit_features': False, 'scale_lam': False, 'scale_la
m_sideinfo': False, 'scale_bias_const': False, 'k_user': 0, 'k_item': 0, 'k_main': 0, 'w
_main': 1.0, 'w_user': 1.0, 'w_item': 1.0, 'w_implicit': 0.5, 'l1_lambda': 0.0, 'center_
U': True, 'center_I': True, 'maxiter': 800, 'niter': 66, 'parallelize': 'separate', 'cor
r_pairs': 4, 'max_cg_steps': 3, 'precondition_cg': False, 'finalize_chol': True, 'NA_as_
zero': False, 'NA_as_zero_user': False, 'NA_as_zero_item': False, 'nonneg': False, 'nonn
eg_C': False, 'nonneg_D': False, 'max_cd_steps': 100, 'precompute_for_predictions': Tru
e, 'include_all_X': True, 'use_float': True, 'random_state': 1, 'verbose': True, 'print_
every': 10, 'handle_interrupt': True, 'produce_dicts': False, 'nthreads': 12}
```

In [174…

```
model = CMF(k=42,lambda_=5.39,method='als',center=False,niter=66)
```

In [175…

```
model.fit(ratings)
```

```
Starting ALS optimization routine

Updating B ... done
Updating A ... done
        Completed ALS iteration  1

Updating B ... done
Updating A ... done
        Completed ALS iteration  2

Updating B ... done
Updating A ... done
        Completed ALS iteration  3

Updating B ... done
Updating A ... done
        Completed ALS iteration  4

Updating B ... done
Updating A ... done
        Completed ALS iteration  5

Updating B ... done
Updating A ... done
        Completed ALS iteration  6

Updating B ... done
Updating A ... done
        Completed ALS iteration  7

Updating B ... done
Updating A ... done
        Completed ALS iteration  8

Updating B ... done
Updating A ... done
        Completed ALS iteration  9

Updating B ... done
Updating A ... done
        Completed ALS iteration 10

Updating B ... done
Updating A ... done
        Completed ALS iteration 11

Updating B ... done
Updating A ... done
        Completed ALS iteration 12

Updating B ... done
Updating A ... done
        Completed ALS iteration 13

Updating B ... done
Updating A ... done
        Completed ALS iteration 14

Updating B ... done
Updating A ... done
        Completed ALS iteration 15

Updating B ... done
Updating A ... done
```

```
        Completed ALS iteration 16

Updating B ... done
Updating A ... done
        Completed ALS iteration 17

Updating B ... done
Updating A ... done
        Completed ALS iteration 18

Updating B ... done
Updating A ... done
        Completed ALS iteration 19

Updating B ... done
Updating A ... done
        Completed ALS iteration 20

Updating B ... done
Updating A ... done
        Completed ALS iteration 21

Updating B ... done
Updating A ... done
        Completed ALS iteration 22

Updating B ... done
Updating A ... done
        Completed ALS iteration 23

Updating B ... done
Updating A ... done
        Completed ALS iteration 24

Updating B ... done
Updating A ... done
        Completed ALS iteration 25

Updating B ... done
Updating A ... done
        Completed ALS iteration 26

Updating B ... done
Updating A ... done
        Completed ALS iteration 27

Updating B ... done
Updating A ... done
        Completed ALS iteration 28

Updating B ... done
Updating A ... done
        Completed ALS iteration 29

Updating B ... done
Updating A ... done
        Completed ALS iteration 30

Updating B ... done
Updating A ... done
        Completed ALS iteration 31

Updating B ... done
Updating A ... done
```

```
        Completed ALS iteration 32

Updating B ... done
Updating A ... done
        Completed ALS iteration 33

Updating B ... done
Updating A ... done
        Completed ALS iteration 34

Updating B ... done
Updating A ... done
        Completed ALS iteration 35

Updating B ... done
Updating A ... done
        Completed ALS iteration 36

Updating B ... done
Updating A ... done
        Completed ALS iteration 37

Updating B ... done
Updating A ... done
        Completed ALS iteration 38

Updating B ... done
Updating A ... done
        Completed ALS iteration 39

Updating B ... done
Updating A ... done
        Completed ALS iteration 40

Updating B ... done
Updating A ... done
        Completed ALS iteration 41

Updating B ... done
Updating A ... done
        Completed ALS iteration 42

Updating B ... done
Updating A ... done
        Completed ALS iteration 43

Updating B ... done
Updating A ... done
        Completed ALS iteration 44

Updating B ... done
Updating A ... done
        Completed ALS iteration 45

Updating B ... done
Updating A ... done
        Completed ALS iteration 46

Updating B ... done
Updating A ... done
        Completed ALS iteration 47

Updating B ... done
Updating A ... done
```

```
        Completed ALS iteration 48

Updating B ... done
Updating A ... done
        Completed ALS iteration 49

Updating B ... done
Updating A ... done
        Completed ALS iteration 50

Updating B ... done
Updating A ... done
        Completed ALS iteration 51

Updating B ... done
Updating A ... done
        Completed ALS iteration 52

Updating B ... done
Updating A ... done
        Completed ALS iteration 53

Updating B ... done
Updating A ... done
        Completed ALS iteration 54

Updating B ... done
Updating A ... done
        Completed ALS iteration 55

Updating B ... done
Updating A ... done
        Completed ALS iteration 56

Updating B ... done
Updating A ... done
        Completed ALS iteration 57

Updating B ... done
Updating A ... done
        Completed ALS iteration 58

Updating B ... done
Updating A ... done
        Completed ALS iteration 59

Updating B ... done
Updating A ... done
        Completed ALS iteration 60

Updating B ... done
Updating A ... done
        Completed ALS iteration 61

Updating B ... done
Updating A ... done
        Completed ALS iteration 62

Updating B ... done
Updating A ... done
        Completed ALS iteration 63

Updating B ... done
Updating A ... done
```

```
        Completed ALS iteration 64

Updating B ... done
Updating A ... done
        Completed ALS iteration 65

Updating B ... done
Updating A ... done
        Completed ALS iteration 66

ALS procedure terminated successfully
```

Out[175]:
```
 Collective matrix factorization model
 (explicit-feedback variant)
```

In [10]:
```
import pickle
```

In [11]:
```
import joblib

# # Save the model to a file using joblib
# joblib.dump(model, 'recommedation_system.joblib')
model  = joblib.load('recommedation_system.joblib')
```

In [181…
```
user_matrix,item_matrix = model.A_,model.B_
```

In [183…
```
user_matrix.shape,item_matrix.shape
```

Out[183]:
```
 ((6040, 42), (3706, 42))
```

In [35]:
```
from sklearn.metrics import mean_squared_error as mse, root_mean_squared_error as rmse
```

In [187…
```
rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
print(f' MSE : {round(mse(user_item_interation_df.values[user_item_interation_df > 0], r
```

```
 MSE : 3.24
```

In [198…
```
# MSE is not a sole metrics on which we can depend,
# we also need to calculate overlap between recommendations and actual values
```

In [248…
```
# top_items = model.topN(user=1,n=20)
# #df_movies.loc[df_movies.MovieID.isin(top_items)]
# user_movies = df_rating.loc[df_rating['UserID']==1]['MovieID']
# valid_recommendations = set(user_movies).intersection(set(top_items))
# num = set(df_rating.loc[df_rating['UserID']==1].sort_values(['Rating'],ascending=False
# denom = set(valid_recommendations)
# overlap = len(num.intersection(denom))
# num_rec = len(valid_recommendations)
# overlap,num_rec,overlap/num_rec
```

In [247…
```
# top_item = model.topN(user=4,n=10)
# user_movies = df_rating.loc[df['UserID']==4]['MovieID']
# print(user_movies )
# valid_reccomendation = set(user_movies).intersection(set(top_item))
# print(valid_reccomendation)
```

Calculating Overlap

In [14]:
```
def get_over_lap_percentage(df_rating):
    overlap = []
    num_rec = []
```

```
    n=10
    for user in df_rating['UserID'].unique():
        top_item = model.topN(user=user,n=n)
        user_movies = df_rating.loc[df_rating['UserID']==user]['MovieID']
        valid_reccomendation = set(top_item).intersection(set(user_movies))
        overlap_len = len(set(df_rating.loc[df_rating['UserID']==user].sort_values('Rati
        overlap.append(overlap_len)
        num_rec.append(len(valid_reccomendation))
    return overlap,num_rec
```

In [15]:
```
overlap,num_rec = get_over_lap_percentage(df_rating)
```

In [16]:
```
print('avg_perc_overlap:', round(np.array(overlap).mean() / np.array(num_rec).mean(),3))
```

```
avg_perc_overlap: 0.397
```

Calculating K-precision

$$\text{P@K} = \frac{\sum \text{Relevant items in top K recommendations}}{\sum \text{Items in top K recommendations}}$$

In [19]:
```
def get_k_precision(df_rating):
    overlap = []
    for user in df_rating['UserID'].unique():
        topitem = model.topN(user=user,n=100)
        user_interaction_movies = df_rating.loc[df_rating['UserID']==user]['MovieID']
        valid_recommendation = set(topitem).intersection(set(user_interaction_movies))
        relevent_items = df_rating.loc[(df_rating['UserID']==user) & (df_rating['Rating'
    #     print(f'user_id:{user},items : {len(relevent_items)}')
        num = len(set(topitem).intersection(set(relevent_items)))
        denom = len(valid_recommendation)
        try:
            vals = num/denom
        except:
            vals = 0
        overlap.append(vals)
    return overlap
```

In [20]:
```
print('avg_overlap:', np.array(get_k_precision(df_rating)).mean())
```

```
avg_overlap: 0.9845720938762794
```

In [25]:
```
df_rating.head()
```

Out[25]:

	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

In [173…
```
min(df_rating['MovieID'])
```

Out[173]: 1

In [28]:
```
pred = model.predict(df_rating.loc[df_rating['UserID']==2]['UserID'],df_rating.loc[df_ra
```

In [36]:
```
print('RMSE of CMF model : ',rmse(pred,df_rating.loc[df_rating['UserID']==2]['Rating']))
```

```
RMSE of CMF model :  1.2326450052857336
```

Item-Item similarity with Collaborative Filtering using Pearson Correlation

`Steps to proceed`

1. Create a User Item Matrix
2. Create a Correlation matrix which specifies similarity of between Item1 and Item2 Based on user interaction
3. Using Correlation get top 5 similar movies then using those movies recommend movie to all users who have watched parent movie.

In [6]:
```
user_item_matrix = df_rating.pivot(index='UserID',columns='MovieID',values='Rating').fil
```

In [9]:
```
user_item_matrix.head()
```

Out[9]:

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	3950	39
UserID																				
1	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
5	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 3706 columns

In [10]:
```
user_item_matrix_numpy = user_item_matrix.to_numpy()
```

In [11]:
```
user_item_matrix
```

Out[11]:

MovieID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
UserID																						
1	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
6036	0.0	0.0	0.0	2.0	0.0	3.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	3.0	4.0	0.0	0.0	0.0	3.0	0.0
6037	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0
6038	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6039	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6040	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0

6040 rows × 3706 columns

In [12]:
```
user_item_matrix_numpy.shape
```

Out[12]:
```
(6040, 3706)
```

$$R_{\text{centered}}(i,j) = R(i,j) - \bar{R}(i)$$

$$\text{Pearson}(u,v) = \frac{\sum_i (R_{\text{centered}}(u,i) \cdot R_{\text{centered}}(v,i))}{\sqrt{\sum_i (R_{\text{centered}}(u,i))^2} \cdot \sqrt{\sum_i (R_{\text{centered}}(v,i))^2}}$$

In [428…
```
def pearson_correlation(item1,item2):
    common_item = np.where((item1!=0) & (item2!=0))[0]
    if(len(common_item)==0):
        return 0
    else :
        mean_item1 = np.mean(item1[common_item])
        mean_item2 = np.mean(item2[common_item])

        numerator = np.sum((item1[common_item]-mean_item1) * (item2[common_item]-mean_it
        denominator = np.sqrt(np.sum((item1[common_item]-mean_item1)**2) * np.sum((item2

    if(denominator==0):
        return 0
    return numerator/denominator

def pearson_correlation_matrix(user_item_matrix):
    num_movies,num_users = user_item_matrix.shape
    correlation_matrix = np.zeros((num_movies,num_movies))

    for i in range(num_movies):
        for j in range(num_movies):
            correlation_matrix[i,j] = pearson_correlation(user_item_matrix[i,:],user_ite
    return correlation_matrix
```

In [429…
```
correlation_matrix = pearson_correlation_matrix(user_item_matrix_numpy.T)
```

In [430…
```
user_item_matrix[0,:]
```

Out[430]:
```
array([5., 0., 0., ..., 0., 0., 0.])
```

In [431…
```
correlation_matrix.shape
```

Out[431]:
```
(3706, 3706)
```

In [432…
```
item_item_similarity_matrix = pd.DataFrame(correlation_matrix)
```

In [433…
```
item_item_similarity_matrix.head()
```

Out[433]:

	0	1	2	3	4	5	6	7	8	9	...	
0	1.000000	0.187467	0.160649	0.348759	0.156957	0.051097	0.149536	0.151248	-0.039358	0.143598	...	-0.
1	0.187467	1.000000	0.149349	0.057874	0.384293	0.075067	0.251093	0.312949	0.407857	0.254558	...	0.
2	0.160649	0.149349	1.000000	0.261800	0.399532	0.156934	0.220211	0.394405	0.151163	0.269250	...	-0.
3	0.348759	0.057874	0.261800	1.000000	0.401954	-0.012096	0.097271	0.074080	-0.681895	0.010868	...	0.
4	0.156957	0.384293	0.399532	0.401954	1.000000	0.075755	0.276160	0.589313	0.538139	0.241397	...	-0.

5 rows × 3706 columns

In [434…
```
item_item_similarity_matrix = item_item_similarity_matrix.reset_index()
```

In [435…
```
item_item_similarity_matrix
```

Out[435]:

	index	0	1	2	3	4	5	6	7	8	...
0	0	1.000000	0.187467	0.160649	0.348759	0.156957	0.051097	0.149536	0.151248	-0.039358	...
1	1	0.187467	1.000000	0.149349	0.057874	0.384293	0.075067	0.251093	0.312949	0.407857	...
2	2	0.160649	0.149349	1.000000	0.261800	0.399532	0.156934	0.220211	0.394405	0.151163	...
3	3	0.348759	0.057874	0.261800	1.000000	0.401954	-0.012096	0.097271	0.074080	-0.681895	...
4	4	0.156957	0.384293	0.399532	0.401954	1.000000	0.075755	0.276160	0.589313	0.538139	...
...	...	...	...	...	...	...	...	...	...	...	...
3701	3701	0.139323	0.216196	0.314249	0.209258	0.416291	0.096261	0.053806	0.339746	0.020824	...
3702	3702	0.189518	0.082241	0.026743	-0.434783	-0.133077	0.048698	-0.004335	-0.436815	-0.085554	...
3703	3703	0.146536	-0.154672	0.445399	0.500000	0.650000	-0.207339	0.364932	0.943242	0.000000	...
3704	3704	0.324325	-0.353553	0.000000	0.000000	0.000000	-0.156174	0.613155	0.000000	0.000000	...
3705	3705	0.157996	0.073111	0.110024	0.154463	-0.033736	0.072161	-0.035417	-0.140313	-0.203005	...

3706 rows × 3707 columns

In [436…
```
def get_top_five_similar_movie(movie_id):
    """
    This function will get you top 5 similar movies
    """
    tmp = item_item_similarity_matrix.loc[item_item_similarity_matrix['index']==movie_id
    ans= []
    for j in range(tmp.shape[1]-1):
        ans.append((tmp[j][movie_id],j))
    ans.sort(key=lambda x : x[0],reverse=True)
```

```
def get_movie_ids_for_recommendation(movie_id):
    """
    This function will help you to get recommendation movie dictionary
    """
    recommeddation_movie_ids = [x[1]+1 for x in get_top_five_similar_movie(movie_id) if(
    recom_dict = {movie_id:recommeddation_movie_ids}
    return recom_dict

def get_recommendation_dataFrame(recomendation_values):
    """
    This function will create dataframe for recommmendation

    """
    vals = list(recomendation_values.keys())[0]
    vals = {vals:list(df_movies.loc[df_movies['Movie ID'].isin(list(recomendation_values
    return pd.DataFrame(list(vals.items()), columns=['MovieID', 'recommended_movies_name

def movie_recommendation_to_users(df_rating,recommendation_df,recommendation_df_movie_id
    """
    This function will help to return recommendation of similar movies to users.
    """
    tb1 = df_rating.loc[df_rating['MovieID']==recommendation_df_movie_id]
    tb1 = tb1.merge(recommendation_df,how='left',on='MovieID')[['UserID','MovieID','reco
    return tb1
```

Steps used to recommend movies using Item-item similarity matrix

1. Here we are passing movieid to a function named `get_movie_ids_for_recommendation` it will return a dictionary of `{'MovieID':['list of similar movies']}`

1. we are calling function named `get_recommendation_dataFrame` it will return dataframe having movie id with similar movie name.

1. we are calling function named `movie_recommendation_to_users` which will merge the `final_recommendation_using_item_item_similarity_matrix` to all users who have watched `Parent_movie_id`.

In [437…
```
recomendation_values = get_movie_ids_for_recommendation(3)
recommendation_df = get_recommendation_dataFrame(recomendation_values)
final_recommendation_using_item_item_similarity_matrix  = movie_recommendation_to_users(
```

In [438…
```
final_recommendation_using_item_item_similarity_matrix.rename({'MovieID':'Parent_movie_i
```

Recommendation of movies using Item-Item Similarity Matrix

In [439…
```
final_recommendation_using_item_item_similarity_matrix
```

Out[439]:

	UserID	Parent_movie_id	recommended_movies_name
0	26	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
1	45	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
2	62	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
3	137	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
4	153	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
...	...	...	...
473	5972	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
474	6000	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
475	6016	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
476	6025	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...
477	6035	3	[Bed of Roses (1996), Happy Gilmore (1996), Fl...

478 rows × 3 columns

Recommendation system using User-User similarity

`Steps to make user- user similarity based recommendation`

1. Create User-USer similarity matrix using cosine similarity.
2. get top 10 similar users and recommend according to movie watched by similar parent userid

In [9]:
```
from sklearn.metrics.pairwise import cosine_similarity
```

In [10]:
```
user_item_matrix.head()
```

Out[10]:

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	3950	39
UserID																				
1	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
5	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 3706 columns

In [40]:
```
def user_user_similarity_matrix(user_item_matrix):
    user_similarity_matrix = pd.DataFrame(cosine_similarity(user_item_matrix), index=use
    return user_similarity_matrix

# Calculate user-user similarity matrix
user_similarity_matrix = user_user_similarity_matrix(user_item_matrix)
```

In [41]:
```
user_similarity_matrix.head()
```

Out[41]:

UserID	1	2	3	4	5	6	7	8	9	10	...
UserID											
1	1.000000	0.096382	0.120610	0.132455	0.090158	0.179222	0.059678	0.138241	0.226148	0.255288	...
2	0.096382	1.000000	0.151479	0.171176	0.114394	0.100865	0.305787	0.203337	0.190198	0.226861	...
3	0.120610	0.151479	1.000000	0.151227	0.062907	0.074603	0.138332	0.077656	0.126457	0.213655	...
4	0.132455	0.171176	0.151227	1.000000	0.045094	0.013529	0.130339	0.100856	0.093651	0.120738	...
5	0.090158	0.114394	0.062907	0.045094	1.000000	0.047449	0.126257	0.220817	0.261330	0.117052	...

5 rows × 6040 columns

In [42]:
```
user_similarity_matrix.shape
```

Out[42]:
```
(6040, 6040)
```

In [45]:
```
user_similarity_matrix = user_similarity_matrix.reset_index()
```

In [50]:
```
user_similarity_matrix.loc[user_similarity_matrix['UserID']==1]
```

Out[50]:

UserID	UserID	1	2	3	4	5	6	7	8	9	...	603
0	1	1.0	0.096382	0.12061	0.132455	0.090158	0.179222	0.059678	0.138241	0.226148	...	0.17058

1 rows × 6041 columns

In [269…
```
def get_similar_users(user_id):
    tmp = user_similarity_matrix.loc[user_similarity_matrix['UserID']==user_id]
    ans = []
    for i in range(1,tmp.shape[1]):
        ans.append((tmp[i][user_id-1],i))
    ans.sort(reverse=True,key = lambda x : x[0])
    return (ans[1:][:10],user_id)

def get_similar_user_ids(similiar_users):
    users =  [x[1] for x in similiar_users[0]]
    parent_id = similiar_users[1]
    return {parent_id:users}
    #return users

def get_movie_recommendation(similiar_user_ids,user_id):
    tmp = pd.DataFrame(similiar_user_ids).T
    df= pd.DataFrame(tmp.unstack(),columns=['UserIDs']).reset_index()
    df.drop('level_0',axis=1,inplace=True)
    tb1 = rating_and_movies.groupby('UserID')['Title'].agg(list).reset_index()
    vals = tb1.loc[tb1['UserID']==user_id]
    final_ans = pd.merge(df,vals,left_on='level_1',right_on='UserID',how='left')
    final_ans.drop(['level_1','UserID'],axis=1,inplace=True)
    final_ans.rename({'Title':'Recommended Movies'},axis=1,inplace=True)
    return final_ans
```

In [270…
```
similiar_users = get_similar_users(2)
similiar_user_ids = get_similar_user_ids(similiar_users)
similiar_user_ids
```

Out[270]:
```
{2: [3108, 95, 2814, 4601, 2303, 300, 3995, 3361, 4786, 558]}
```

Final User-User similarity based Recommendation

In [271…
```
get_movie_recommendation(similiar_user_ids,2)
```

Out[271]:

	UserIDs	Recommended Movies
0	3108	[Shine (1996), Verdict, The (1982), Shall We D...
1	95	[Shine (1996), Verdict, The (1982), Shall We D...
2	2814	[Shine (1996), Verdict, The (1982), Shall We D...
3	4601	[Shine (1996), Verdict, The (1982), Shall We D...
4	2303	[Shine (1996), Verdict, The (1982), Shall We D...
5	300	[Shine (1996), Verdict, The (1982), Shall We D...
6	3995	[Shine (1996), Verdict, The (1982), Shall We D...
7	3361	[Shine (1996), Verdict, The (1982), Shall We D...
8	4786	[Shine (1996), Verdict, The (1982), Shall We D...
9	558	[Shine (1996), Verdict, The (1982), Shall We D...

In [ ]:
```

```