In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

In [2]:
```python
movies = pd.read_csv('movie.csv')
```

In [3]:
```python
movies.head()
```

Out[3]:

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

In [4]:
```python
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27278 entries, 0 to 27277
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   movieId  27278 non-null  int64 
 1   title    27278 non-null  object
 2   genres   27278 non-null  object
dtypes: int64(1), object(2)
memory usage: 639.5+ KB
```

In [5]:
```python
ratings = pd.read_csv('rating.csv')
```

In [6]:
```python
ratings.head()
```

Out[6]:

	userId	movieId	rating	timestamp
0	1	2	3.5	2005-04-02 23:53:47
1	1	29	3.5	2005-04-02 23:31:16
2	1	32	3.5	2005-04-02 23:33:39
3	1	47	3.5	2005-04-02 23:32:07
4	1	50	3.5	2005-04-02 23:29:40

In [7]:
```python
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000263 entries, 0 to 20000262
Data columns (total 4 columns):
 #   Column     Dtype  
---  ------     -----  
 0   userId     int64  
 1   movieId    int64  
 2   rating     float64
 3   timestamp  object 
dtypes: float64(1), int64(2), object(1)
memory usage: 610.4+ MB
```

In [8]:
```
df = ratings.merge(movies, on="movieId", how="left")
df.head()
```

Out[8]:

	userId	movieId	rating	timestamp	title	gen
0	1	2	3.5	2005-04-02 23:53:47	Jumanji (1995)	Adventure|Children|Fant
1	1	29	3.5	2005-04-02 23:31:16	City of Lost Children, The (Cité des enfants p...	Adventure|Drama|Fantasy|Mystery|
2	1	32	3.5	2005-04-02 23:33:39	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	Mystery|Sci-Fi|Thr
3	1	47	3.5	2005-04-02 23:32:07	Seven (a.k.a. Se7en) (1995)	Mystery|Thr
4	1	50	3.5	2005-04-02 23:29:40	Usual Suspects, The (1995)	Crime|Mystery|Thr

In [9]:
```
import re
df['year'] = df['title'].str.extract(r'\((\d{4})\)').astype(float)
df.head()
```

Out[9]:

	userId	movieId	rating	timestamp	title	gen
0	1	2	3.5	2005-04-02 23:53:47	Jumanji (1995)	Adventure|Children|Fant
1	1	29	3.5	2005-04-02 23:31:16	City of Lost Children, The (Cité des enfants p...	Adventure|Drama|Fantasy|Mystery|
2	1	32	3.5	2005-04-02 23:33:39	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	Mystery|Sci-Fi|Thr
3	1	47	3.5	2005-04-02 23:32:07	Seven (a.k.a. Se7en) (1995)	Mystery|Thr
4	1	50	3.5	2005-04-02 23:29:40	Usual Suspects, The (1995)	Crime|Mystery|Thr

In [10]:

```
df['genres'] = df['genres'].str.split('|')
df.head()
```

Out[10]:

	userId	movieId	rating	timestamp	title	genres	year
0	1	2	3.5	2005-04-02 23:53:47	Jumanji (1995)	[Adventure, Children, Fantasy]	1995.0
1	1	29	3.5	2005-04-02 23:31:16	City of Lost Children, The (Cité des enfants p...	[Adventure, Drama, Fantasy, Mystery, Sci-Fi]	1995.0
2	1	32	3.5	2005-04-02 23:33:39	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	[Mystery, Sci-Fi, Thriller]	1995.0
3	1	47	3.5	2005-04-02 23:32:07	Seven (a.k.a. Se7en) (1995)	[Mystery, Thriller]	1995.0
4	1	50	3.5	2005-04-02 23:29:40	Usual Suspects, The (1995)	[Crime, Mystery, Thriller]	1995.0

In [11]:

```
df.rename(columns={'timestamp':'date'}, inplace=True)
df.head()
```

Out[11]:

	userId	movieId	rating	date	title	genres	year
0	1	2	3.5	2005-04-02 23:53:47	Jumanji (1995)	[Adventure, Children, Fantasy]	1995.0
1	1	29	3.5	2005-04-02 23:31:16	City of Lost Children, The (Cité des enfants p...	[Adventure, Drama, Fantasy, Mystery, Sci-Fi]	1995.0
2	1	32	3.5	2005-04-02 23:33:39	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	[Mystery, Sci-Fi, Thriller]	1995.0
3	1	47	3.5	2005-04-02 23:32:07	Seven (a.k.a. Se7en) (1995)	[Mystery, Thriller]	1995.0
4	1	50	3.5	2005-04-02 23:29:40	Usual Suspects, The (1995)	[Crime, Mystery, Thriller]	1995.0

In [12]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000263 entries, 0 to 20000262
Data columns (total 7 columns):
 #   Column   Dtype  
---  ------   -----  
 0   userId   int64  
 1   movieId  int64  
 2   rating   float64
 3   date     object 
 4   title    object 
 5   genres   object 
 6   year     float64
dtypes: float64(2), int64(2), object(3)
memory usage: 1.0+ GB
```

In [13]:

```
df.isnull().sum()
```

Out[13]:

```
userId       0
movieId      0
rating       0
date         0
title        0
genres       0
year       405
dtype: int64
```

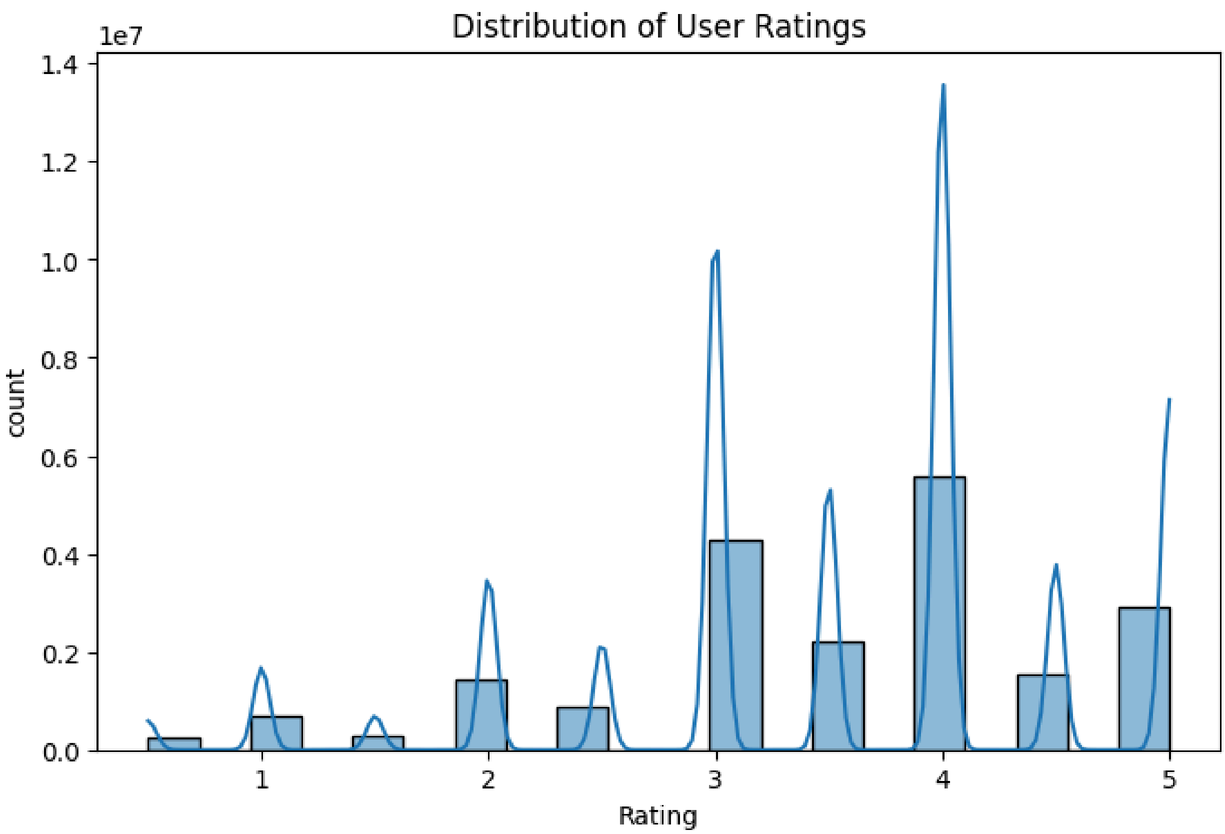
In [16]:

```
df['year'].fillna(df['year'].mode()[0])
df.isnull().sum()
```

Out[16]:
```
userId     0
movieId    0
rating     0
date       0
title      0
genres     0
year       0
dtype: int64
```

In [15]:
```python
movies_df = df.copy()                    #I am Using .copy() for protects the ori
```

In [16]:
```python
plt.figure(figsize=(8,5))
sns.histplot(movies_df['rating'], bins=20, kde=True)
plt.title('Distribution of User Ratings')
plt.xlabel('Rating')
plt.ylabel('count')
plt.show()
```



In [17]:
```python
# The distribution shows that most movie ratings fall between 3.0 and 4.0,
# indicating that users tend to rate movies favorably.
# Extreme ratings (very low or very high) are relatively rare.
# The scientific notation 1e7 on the y-axis represents counts in the scale of
# meaning the dataset contains a large number of total ratings.
```

In [18]:
```python
# The dataset is too large, so I am working with a sample for genre analysis.
# I am running into a MemoryError because exploding the genres column creates
```

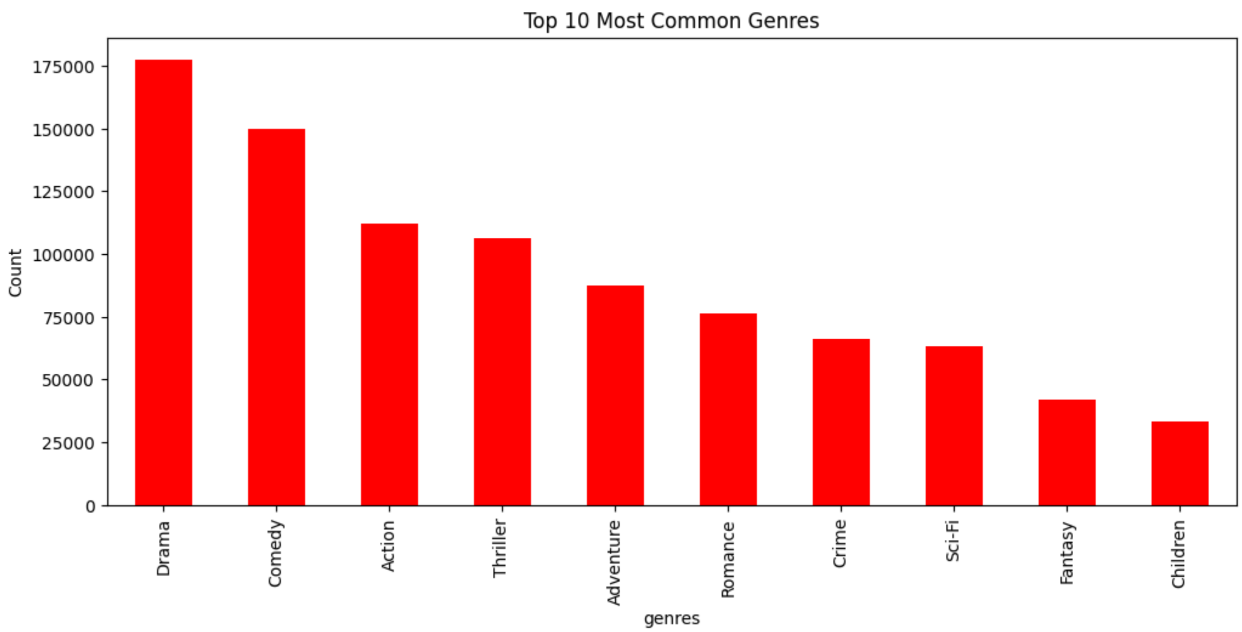
```python
sample_df = movies_df.sample(400_000, random_state=42)
movies_genres = sample_df[['movieId', 'rating', 'genres']].explode('genres')

movies_genres.head()
```

Out[18]:

	movieId	rating	genres
17679788	8360	3.5	Adventure
17679788	8360	3.5	Animation
17679788	8360	3.5	Children
17679788	8360	3.5	Comedy
17679788	8360	3.5	Musical

In [19]:

```python
plt.figure(figsize=(12,5))
movies_genres['genres'].value_counts().head(10).plot(kind="bar",color = 'red')
plt.title("Top 10 Most Common Genres")
plt.ylabel("Count")
plt.show()
```

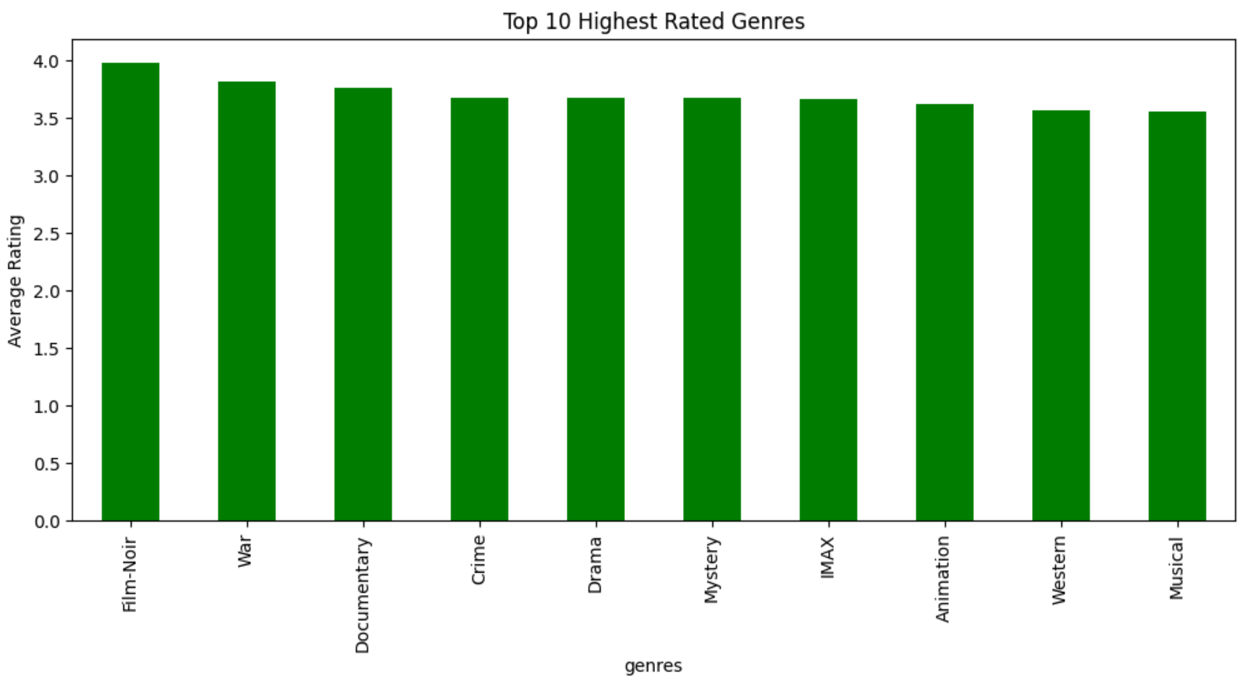


In [20]:

```python
genre_ratings = movies_genres.groupby('genres')['rating'].mean().sort_values(a

genre_ratings.head(10)
```

Out[20]:
```
genres
Film-Noir      3.983699
War            3.815908
Documentary    3.764737
Crime          3.679582
Drama          3.676948
Mystery        3.669854
IMAX           3.665881
Animation      3.616760
Western        3.563012
Musical        3.560036
Name: rating, dtype: float64
```

In [21]:
```
plt.figure(figsize=(12,5))
genre_ratings.head(10).plot(kind='bar', color='green')
plt.title("Top 10 Highest Rated Genres")
plt.ylabel("Average Rating")
plt.show()
```



In [22]:
```
movie_stats = sample_df.groupby('title').agg({
    'rating': 'mean',
    'userId': 'count'
}).rename(columns={'userId': 'rating_count'})

filtered_movies = movie_stats[movie_stats['rating_count']>=50]

top_movies = filtered_movies.sort_values(by='rating', ascending=False).head(10
top_movies
```

Out[22]:

title	rating	rating_count
Shawshank Redemption, The (1994)	4.496828	1261
Usual Suspects, The (1995)	4.378885	933
Double Indemnity (1944)	4.357759	116
Godfather, The (1972)	4.350059	847
Schindler's List (1993)	4.315738	1023
Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)	4.308824	136
Godfather: Part II, The (1974)	4.308608	546
Lives of Others, The (Das leben der Anderen) (2006)	4.297414	116
Big Sleep, The (1946)	4.295918	98
Rear Window (1954)	4.293716	366

In [23]:

```
# Groups movies → calculates their average rating and number of ratings → remc
# sorts them by rating → shows the top 10 highest-rated movies.
```

In [24]:

```
sample_df.head()
```

Out[24]:

	userId	movieId	rating	date	title	genres	year
17679788	122270	8360	3.5	2012-04-22 01:07:04	Shrek 2 (2004)	[Adventure, Animation, Children, Comedy, Music...	2004.0
7106385	49018	32	2.0	2001-09-11 07:50:36	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	[Mystery, Sci-Fi, Thriller]	1995.0
12970708	89527	109374	3.5	2015-01-06 09:26:40	Grand Budapest Hotel, The (2014)	[Comedy, Drama]	2014.0
15426752	106704	1060	3.0	2000-01-22 21:27:57	Swingers (1996)	[Comedy, Drama]	1996.0
6934678	47791	1732	2.0	2006-01-19 15:48:23	Big Lebowski, The (1998)	[Comedy, Crime]	1998.0

In [25]:

```
rating_trend = sample_df.groupby('year')['rating'].mean().reset_index()
```

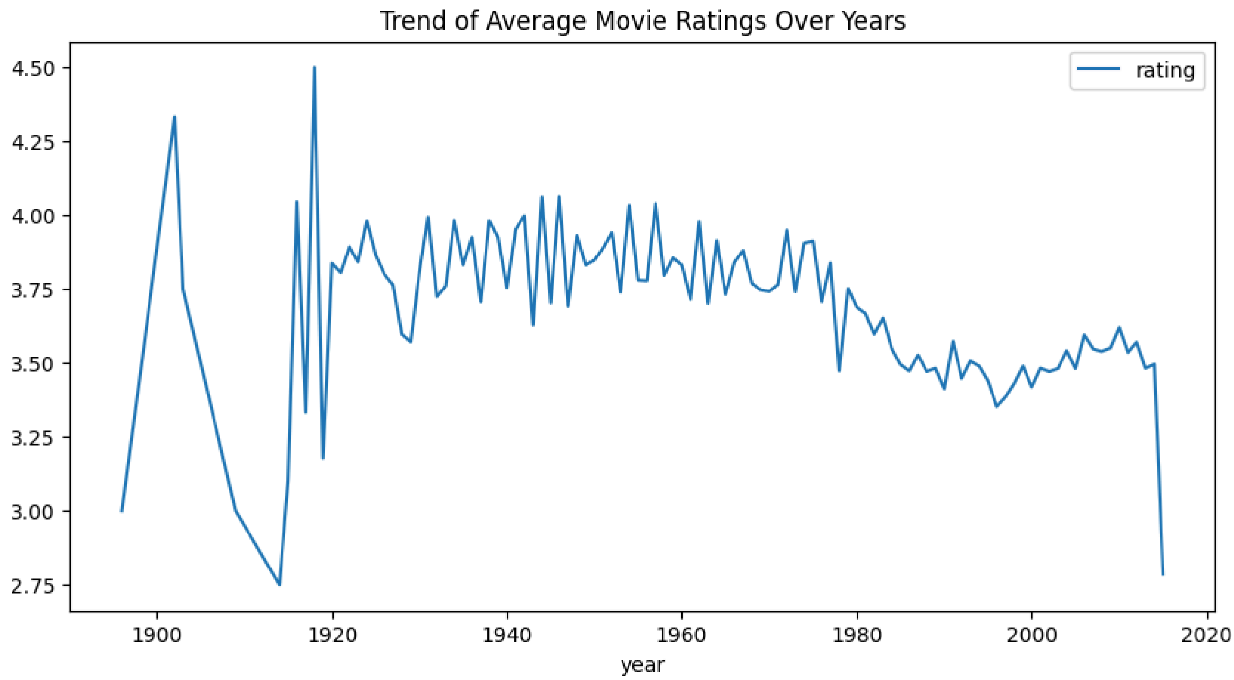
```
rating_trend.head()
```

Out[25]:

	year	rating
0	1896.0	3.000000
1	1902.0	4.333333
2	1903.0	3.750000
3	1909.0	3.000000
4	1914.0	2.750000

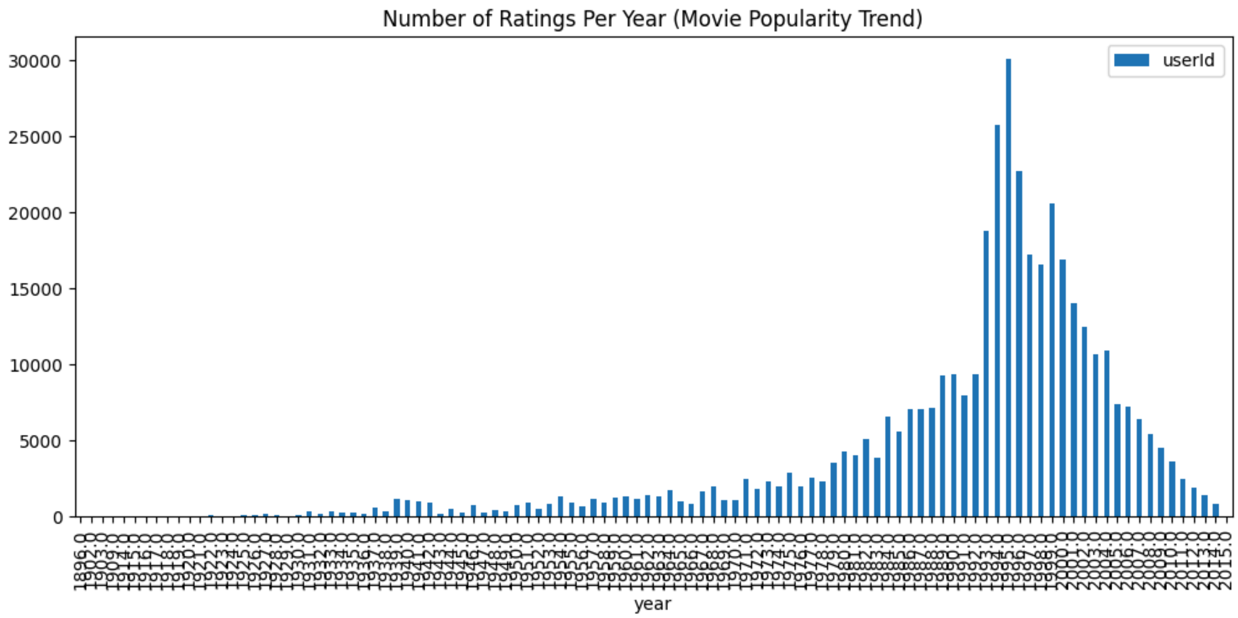
In [26]:
```
rating_trend.plot(x='year', y='rating', kind='line', figsize=(10,5), title='Tr
```

Out[26]:
```
<Axes: title={'center': 'Trend of Average Movie Ratings Over Years'}, xlabe
l='year'>
```



In [27]:
```
popularity_trend = sample_df.groupby('year')['userId'].count().reset_index()

popularity_trend.plot(x='year', y='userId', kind='bar', figsize=(12,5), title=
```

Out[27]:
```
<Axes: title={'center': 'Number of Ratings Per Year (Movie Popularity Tren
d)'}, xlabel='year'>
```

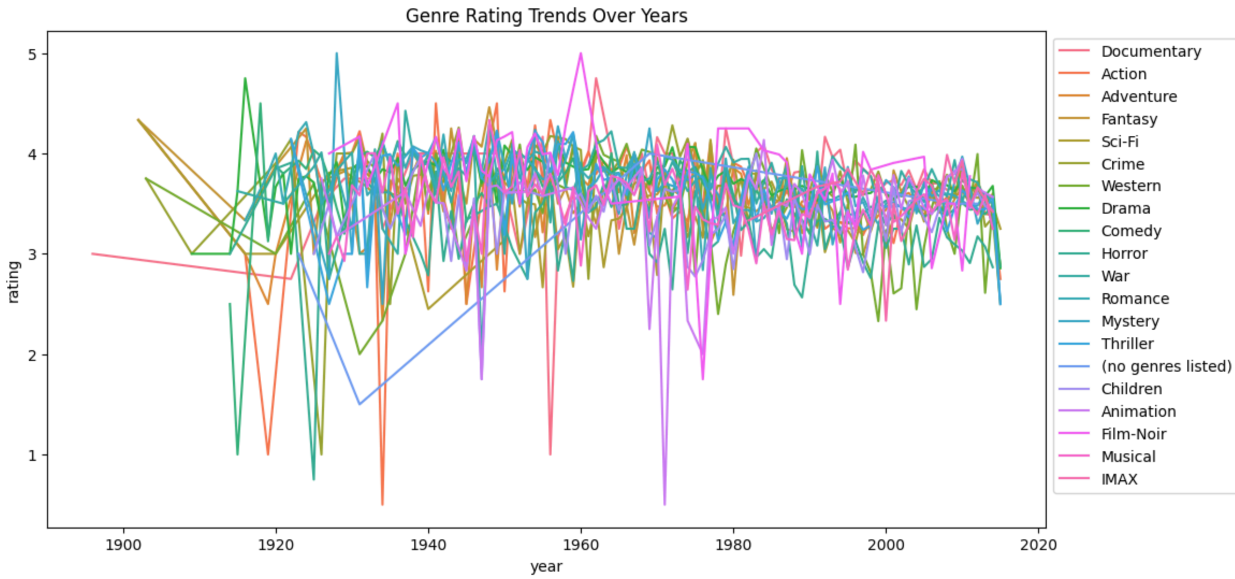


In [28]:
```
genre_year_trend = sample_df.explode('genres').groupby(['year','genres'])['rat
genre_year_trend.head(10)
```

Out[28]:

	year	genres	rating
0	1896.0	Documentary	3.000000
1	1902.0	Action	4.333333
2	1902.0	Adventure	4.333333
3	1902.0	Fantasy	4.333333
4	1902.0	Sci-Fi	4.333333
5	1903.0	Crime	3.750000
6	1903.0	Western	3.750000
7	1909.0	Crime	3.000000
8	1909.0	Drama	3.000000
9	1914.0	Comedy	2.500000

In [29]:
```
plt.figure(figsize=(12,6))
sns.lineplot(data=genre_year_trend, x='year', y='rating', hue='genres')
plt.title("Genre Rating Trends Over Years")
plt.legend(bbox_to_anchor=(1,1))
plt.show()
```



In [30]:
```
movie_year_stats = sample_df.groupby(['title', 'year'])['userId'].count().rese

top_movies = movie_year_stats.sort_values(by='userId', ascending=False).head(1
top_movies
```

Out[30]:

	title	year	userId
8879	Pulp Fiction (1994)	1994.0	1389
4081	Forrest Gump (1994)	1994.0	1287
9956	Silence of the Lambs, The (1991)	1991.0	1264
9849	Shawshank Redemption, The (1994)	1994.0	1261
5991	Jurassic Park (1993)	1993.0	1175
10368	Star Wars: Episode IV - A New Hope (1977)	1977.0	1114
10852	Terminator 2: Judgment Day (1991)	1991.0	1107
7132	Matrix, The (1999)	1999.0	1086
1651	Braveheart (1995)	1995.0	1030
9630	Schindler's List (1993)	1993.0	1023

In [31]:
```
sample_df.head()
```

Out[31]:

	userId	movieId	rating	date	title	genres	year
17679788	122270	8360	3.5	2012-04-22 01:07:04	Shrek 2 (2004)	[Adventure, Animation, Children, Comedy, Music...	2004.0
7106385	49018	32	2.0	2001-09-11 07:50:36	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	[Mystery, Sci-Fi, Thriller]	1995.0
12970708	89527	109374	3.5	2015-01-06 09:26:40	Grand Budapest Hotel, The (2014)	[Comedy, Drama]	2014.0
15426752	106704	1060	3.0	2000-01-22 21:27:57	Swingers (1996)	[Comedy, Drama]	1996.0
6934678	47791	1732	2.0	2006-01-19 15:48:23	Big Lebowski, The (1998)	[Comedy, Crime]	1998.0

In [49]:
```
mr_df = sample_df[['userId', 'movieId', 'rating']].copy()
```

In [50]:
```
mr_df['userId'] = mr_df['userId'].astype('category').cat.codes
mr_df['movieId'] = mr_df['movieId'].astype('category').cat.codes

mr_df.head()
```

Out[50]:

	userId	movieId	rating
17679788	87938	6809	3.5
7106385	35270	31	2.0
12970708	64366	12084	3.5
15426752	76718	981	3.0
6934678	34378	1558	2.0

In [51]:
```
from sklearn.model_selection import train_test_split

x = mr_df[['userId', 'movieId']]
y = mr_df['rating']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, rando
```

In [52]:
```
from sklearn.linear_model import LinearRegression
```

```python
lm = LinearRegression()
lm.fit(x_train, y_train)
```

Out[52]:

▾ LinearRegression

Parameters

	fit_intercept	True
	copy_X	True
	tol	1e-06
	n_jobs	None
	positive	False

In [53]:
```python
y_pred = lm.predict(x_test)
```

In [54]:
```python
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score


rmse = np.sqrt(mean_squared_error(y_test, y_pred))
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("📌 Model Evaluation Results")
print("RMSE:", rmse)
print("MAE:", mae)
print("R2 Score:", r2)
```

```
📌 Model Evaluation Results
RMSE: 1.0540940457331724
MAE: 0.8420110436343979
R2 Score: 0.00024800373574662693
```

In [55]:
```python
from sklearn.linear_model import Ridge

ridge_model = Ridge(alpha=1.0)
ridge_model.fit(x_train, y_train)

ridge_pred = ridge_model.predict(x_test)

rmse_ridge = np.sqrt(mean_squared_error(y_test, ridge_pred))
print("Ridge RMSE:", rmse_ridge)
```

```
Ridge RMSE: 1.0540940457331727
```

In [56]:
```python
from sklearn.linear_model import Lasso

lasso_model = Lasso(alpha=0.001)
lasso_model.fit(x_train, y_train)
```

```
lasso_pred = lasso_model.predict(x_test)

rmse_lasso = np.sqrt(mean_squared_error(y_test, lasso_pred))
print("Lasso RMSE:", rmse_lasso)
```

```
Lasso RMSE: 1.0540940473418565
```

In [57]:
```
models = {
    "Linear Regression": rmse,
    "Ridge Regression": rmse_ridge,
    "Lasso Regression": rmse_lasso
}

models
```

Out[57]:
```
{'Linear Regression': 1.0540940457331724,
 'Ridge Regression': 1.0540940457331727,
 'Lasso Regression': 1.0540940473418565}
```

In [58]:
```
#All three models show almost identical performance.
#This indicates the dataset is simple, the features are not highly correlated,
# let’s upgrade movie rating prediction model with feature engineering + bette
```

In [59]:
```
# Feature Engineering

# Average rating per movie
sample_df['movie_avg_rating'] = sample_df.groupby('movieId')['rating'].transfo

# Average rating per user
sample_df['user_avg_rating'] = sample_df.groupby('userId')['rating'].transform

# Rating count per movie
sample_df['movie_rating_count'] = sample_df.groupby('movieId')['rating'].trans

# Rating count per user
sample_df['user_rating_count'] = sample_df.groupby('userId')['rating'].transfo
```

In [60]:
```
from sklearn.model_selection import train_test_split

features = [
    'userId', 'movieId',
    'movie_avg_rating', 'user_avg_rating',
    'movie_rating_count', 'user_rating_count'
]

X = sample_df[features]
y = sample_df['rating']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

In [61]:
```
from sklearn.preprocessing import OrdinalEncoder

encoder = OrdinalEncoder(
```

```python
    handle_unknown='use_encoded_value',
    unknown_value=-1
)

X_train.loc[:, ['userId','movieId']] = encoder.fit_transform(
    X_train[['userId','movieId']]
)

X_test.loc[:, ['userId','movieId']] = encoder.transform(
    X_test[['userId','movieId']]
)
```

In [62]:

```python
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean_squared_error
import numpy as np

models = {
    "Linear Regression": LinearRegression(),
    "Ridge Regression": Ridge(alpha=1.0),
    "Lasso Regression": Lasso(alpha=0.001)
}

results = {}

for name, model in models.items():
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    results[name] = rmse
```

In [63]:

```python
results
```

Out[63]:

```
{'Linear Regression': 0.7546256717824902,
 'Ridge Regression': 0.7546256943450338,
 'Lasso Regression': 0.7546394173818821}
```