Exploring the MovieLens 1M Dataset

Extrated (and slightly modified) from *Python for Data Analysis (Wes McKinney)*

This dataset contains 1 million ratings collected from 6000 users on 4000 movies, and it is organized into three tables:

- Ratings
- Users
- Movie information

Each table is available as a separate file, each containing a series of rows where columns are separated by *::*

Download the dataset here

This example illustrates a series of interesting things that we can learn from this dataset. Most operations will be performed using the pandas library. For more details, please refer to *Python for Data Analysis - page 26*.

Code -- huiying yu

Let's begin by importing pandas. It is conventional to use *pd* to denote pandas

In [ ]:
```
import pandas as pd
```

Next we will import each of the three tables and assign names to each of the columns:

In [ ]:
```
unames = ['user_id', 'gender', 'age', 'occupation', 'zip']
users = pd.read_table('ml-1m/users.dat', sep='::', header=None, names=unames, engine='python')

rnames = ['user_id', 'movie_id', 'rating', 'timestamp']
ratings = pd.read_table('ml-1m/ratings.dat', sep='::', header=None, names=rnames, engine='python')

mnames = ['movie_id', 'title', 'genres']
movies = pd.read_table('ml-1m/movies.dat', sep='::', header=None, names=mnames, engine='python', encoding='latin1')
```

Let's take a look at the first 5 rows of each table:

In [ ]:
```
users[:5]
```

Out[ ]:

	user_id	gender	age	occupation	zip
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 [ ]:
```
ratings[:5]
```

Out[ ]:

	user_id	movie_id	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 [ ]:
```
movies[:5]
```

Out[ ]:

	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

Having all information spread across different tables makes it much more dificult to analyse the data. Using pandas's merge function, we first merge ratings with users then we merge that result with the movies data. pandas infers which columns to use as the merge (or join) keys based on overlapping names:

In [ ]:
```
data = pd.merge(pd.merge(ratings, users), movies)
```

Below is the first row in that dataset

In [ ]:
```
data.head(1)
```

Out[ ]:

	user_id	movie_id	rating	timestamp	gender	age	occupation	zip	title	genres
0	1	1193	5	978300760	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	Drama

In this form, aggregating the ratings grouped by one or more user or movie characteristics is straightforward once you build some familiarity with pandas. To get mean movie ratings for each film grouped by gender, we can use the pivot_table method:

In [ ]:
```
mean_ratings = data.pivot_table('rating', index='title', columns='gender', aggfunc='mean')
```

In [ ]:
```
mean_ratings[:5]
```

Out[ ]:

gender	F	M
title		
$1,000,000 Duck (1971)	3.375000	2.761905
'Night Mother (1986)	3.388889	3.352941
'Til There Was You (1997)	2.675676	2.733333
'burbs, The (1989)	2.793478	2.962085
...And Justice for All (1979)	3.828571	3.689024

If we wish to only look at movies that received more than a certain number of ratings, we can group them as follows (here using 250 ratings):

In [ ]:
```
ratings_by_title = data.groupby('title').size()
```

In [ ]:
```
ratings_by_title[:5]
```

Out[ ]:
```
title
$1,000,000 Duck (1971)            37
'Night Mother (1986)              70
'Til There Was You (1997)         52
'burbs, The (1989)               303
...And Justice for All (1979)    199
dtype: int64
```

Let's now grab the titles of movies that were rated more than 250 times:

In [ ]:
```
active_titles = ratings_by_title.index[ratings_by_title >= 250]
```

In [ ]:
```
active_titles[:5]
```

Out[ ]:
```
Index([''burbs, The (1989)', '10 Things I Hate About You (1999)',
       '101 Dalmatians (1961)', '101 Dalmatians (1996)',
       '12 Angry Men (1957)'],
      dtype='object', name='title')
```

The index of titles receiving at least 250 ratings can then be used to select rows from mean_ratings above:

In [ ]:
```
mean_ratings = mean_ratings.loc[active_titles]
```

In [ ]:
```
mean_ratings[:5]
```

Out[ ]:

gender	F	M
title		
'burbs, The (1989)	2.793478	2.962085
10 Things I Hate About You (1999)	3.646552	3.311966
101 Dalmatians (1961)	3.791444	3.500000
101 Dalmatians (1996)	3.240000	2.911215
12 Angry Men (1957)	4.184397	4.328421

To see the top films among female viewers, we can sort by the F column in descending order:

In [ ]:
```
top_female_ratings = mean_ratings.sort_values(by='F', ascending=False)
```

In [ ]:
```
top_female_ratings[:10]
```

Out[ ]:

gender	F	M
title		
Close Shave, A (1995)	4.644444	4.473795
Wrong Trousers, The (1993)	4.588235	4.478261
Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)	4.572650	4.464589
Wallace & Gromit: The Best of Aardman Animation (1996)	4.563107	4.385075
Schindler's List (1993)	4.562602	4.491415
Shawshank Redemption, The (1994)	4.539075	4.560625
Grand Day Out, A (1992)	4.537879	4.293255
To Kill a Mockingbird (1962)	4.536667	4.372611
Creature Comforts (1990)	4.513889	4.272277
Usual Suspects, The (1995)	4.513317	4.518248

Likewise, for males:

In [ ]:
```
top_male_ratings = mean_ratings.sort_values(by='M', ascending=False)
```

In [ ]:
```
top_male_ratings[:10]
```

Out[ ]:

gender	F	M
title		
Godfather, The (1972)	4.314700	4.583333
Seven Samurai (The Magnificent Seven) (Shichinin no samurai) (1954)	4.481132	4.576628
Shawshank Redemption, The (1994)	4.539075	4.560625
Raiders of the Lost Ark (1981)	4.332168	4.520597
Usual Suspects, The (1995)	4.513317	4.518248
Star Wars: Episode IV - A New Hope (1977)	4.302937	4.495307
Schindler's List (1993)	4.562602	4.491415
Wrong Trousers, The (1993)	4.588235	4.478261
Close Shave, A (1995)	4.644444	4.473795
Rear Window (1954)	4.484536	4.472991

Suppose you wanted to find the movies that are most divisive between male and female viewers. One way is to add a column to *mean_ratings* containing the difference in means, then sort by that:

In [ ]:
```
mean_ratings['diff'] = mean_ratings['M'] - mean_ratings['F']
```

Sorting by 'diff' gives us the movies with the greatest rating difference and which were preferred by women:

In [ ]:
```
sorted_by_diff = mean_ratings.sort_values(by='diff')
```

In [ ]:
```
sorted_by_diff[:10]
```

Out[ ]:

gender	F	M	diff
title			
Dirty Dancing (1987)	3.790378	2.959596	-0.830782
Jumpin' Jack Flash (1986)	3.254717	2.578358	-0.676359
Grease (1978)	3.975265	3.367041	-0.608224
Little Women (1994)	3.870588	3.321739	-0.548849
Steel Magnolias (1989)	3.901734	3.365957	-0.535777
Anastasia (1997)	3.800000	3.281609	-0.518391
Rocky Horror Picture Show, The (1975)	3.673016	3.160131	-0.512885
Color Purple, The (1985)	4.158192	3.659341	-0.498851
Age of Innocence, The (1993)	3.827068	3.339506	-0.487561
Free Willy (1993)	2.921348	2.438776	-0.482573

Reversing the order of the rows and again slicing off the top 10 rows, we get the movies preferred by men that women didn’t rate highly:

In [ ]:
```
sorted_by_diff[::-1][:10]
```

Out[ ]:

gender	F	M	diff
title			
Good, The Bad and The Ugly, The (1966)	3.494949	4.221300	0.726351
Kentucky Fried Movie, The (1977)	2.878788	3.555147	0.676359
Dumb & Dumber (1994)	2.697987	3.336595	0.638608
Longest Day, The (1962)	3.411765	4.031447	0.619682
Cable Guy, The (1996)	2.250000	2.863787	0.613787
Evil Dead II (Dead By Dawn) (1987)	3.297297	3.909283	0.611985
Hidden, The (1987)	3.137931	3.745098	0.607167
Rocky III (1982)	2.361702	2.943503	0.581801
Caddyshack (1980)	3.396135	3.969737	0.573602
For a Few Dollars More (1965)	3.409091	3.953795	0.544704

Question 1, The mean of movie ratings by men of age above 25 for each particular genre

In [ ]:
```
movie_data = data.copy()
# filter men above 25
movie_data = movie_data[(movie_data["gender"] == "M") & (movie_data["age"] > 25)]

# split genres into list
movie_data["genres"] = movie_data["genres"].str.split('|')
data_exploded = movie_data.explode("genres").reset_index(drop=True)

# get mean ratings for each genre
genre_mean_ratings = data_exploded.groupby("genres")["rating"].mean().reset_index()
genre_mean_ratings
```

Out[ ]:

	genres	rating
0	Action	3.554547
1	Adventure	3.538637
2	Animation	3.721569
3	Children's	3.475314
4	Comedy	3.565456
5	Crime	3.764249
6	Documentary	3.950192
7	Drama	3.812309
8	Fantasy	3.490408
9	Film-Noir	4.117140
10	Horror	3.241089
11	Musical	3.700242
12	Mystery	3.759347
13	Romance	3.659748
14	Sci-Fi	3.509693
15	Thriller	3.644025
16	War	3.940634
17	Western	3.708494

Question 2, The top 5 ranked movies by the most number of ratings (not the highest rating).

In [ ]:
```
# top 5 movies with the most ratings
top_movie_ratings = data.groupby('title')['rating'].count().reset_index()
top_movie_ratings.sort_values('rating', ascending=False).head(5)
```

Out[ ]:

	title	rating
127	American Beauty (1999)	3428
3153	Star Wars: Episode IV - A New Hope (1977)	2991
3154	Star Wars: Episode V - The Empire Strikes Back...	2990
3155	Star Wars: Episode VI - Return of the Jedi (1983)	2883
1789	Jurassic Park (1993)	2672

Question 3, Average movie ratings between users of different age groups (<=18, 19-30, 31-50, 51-70, >=71)

In [ ]:
```
# define age bins and age groups
age_bins = [0, 18, 30, 50, 70, float('inf')]
age_groups = ['<=18', '19-30', '31-50', '51-70', '>=71']
data['age_group'] = pd.cut(data['age'], bins=age_bins, labels=age_groups, right=False)

# get average ratings for each age group
average_ratings = data.groupby('age_group', observed=False).agg({'rating': ['size', 'mean']})
average_ratings
```

Out[ ]:

	rating	
	size	mean
age_group		
<=18	27211	3.549520
19-30	579092	3.533299
31-50	282636	3.624050
51-70	111270	3.732677
>=71	0	NaN

Question 4, Pick a movie of your choice and for all movies of the same year provide a breakdown of the number of unique movies rated by 3 ranges of age of reviewers (a) under 18 (b) 19 to 45 (c) Above 45.

In [ ]:
```
# pick a movie Jueassic Park in year 1993
pick_movie = "Jurassic Park (1993)"
movie_year = int(pick_movie[-5:-1])
same_year = data[data['title'].str.contains(str(movie_year))]
```

```
# conditions for age group
under_18 = same_year[same_year['age'] <= 17]['movie_id'].nunique()
nineteen_to_45 = same_year[(same_year['age'] >= 19) & (same_year['age'] <= 45)]['movie_id'].nunique()
above_45 = same_year[same_year['age'] >= 46]['movie_id'].nunique()

# list of unique movies rated by age group
age_group = pd.DataFrame({
    'age group': ['under 18', '19 to 45', 'above 45'],
    'unique movies rated': [under_18, nineteen_to_45, above_45]
})
age_group
```

Out[ ]:

	age group	unique movies rated
0	under 18	113
1	19 to 45	157
2	above 45	151

Question 5, A function that takes in a user_id and a movie_id, and returns a list of all the other movies that the user rated similarly to the given movie.

In [ ]:

```
def get_similarly_rated_movies(user_id, movie_id):
    # get the rating of the movie by the user
    user_movie_rating = data[(data['user_id'] == user_id) & (data['movie_id'] == movie_id)]['rating'].iloc[0]

    # get all movies rated by the user with the same rating as the movie
    similarly_rated_movies = data[(data['user_id'] == user_id) & (data['rating'] == user_movie_rating)
                                  & (data['movie_id'] != movie_id)][['movie_id', 'title', 'rating']].reset_index(drop

    return similarly_rated_movies

# test user_id is 1, movie_id is 1193, title is One Flew Over the Cuckoo's Nest (1975), rating is 5
user_id = 1
movie_id = 1193
similarly_rated_movies = get_similarly_rated_movies(user_id, movie_id)
similarly_rated_movies
```

Out[ ]:

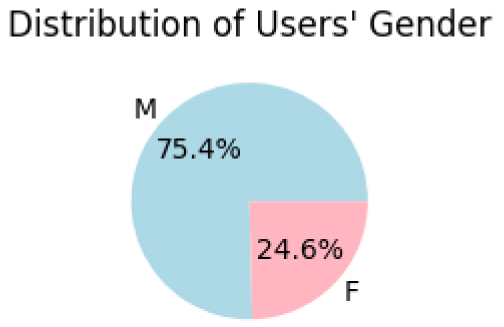
	movie_id	title	rating
0	2355	Bug's Life, A (1998)	5
1	1287	Ben-Hur (1959)	5
2	2804	Christmas Story, A (1983)	5
3	595	Beauty and the Beast (1991)	5
4	1035	Sound of Music, The (1965)	5
5	3105	Awakenings (1990)	5
6	1270	Back to the Future (1985)	5
7	527	Schindler's List (1993)	5
8	48	Pocahontas (1995)	5
9	1836	Last Days of Disco, The (1998)	5
10	1022	Cinderella (1950)	5
11	150	Apollo 13 (1995)	5
12	1	Toy Story (1995)	5
13	1961	Rain Man (1988)	5
14	1028	Mary Poppins (1964)	5
15	1029	Dumbo (1941)	5
16	2028	Saving Private Ryan (1998)	5

Question 6, Some other statistic, figure, aggregate, or plot that you created using this dataset, along with a short description of what interesting observations you derived from it.

A, Distribution of users' gender

In [ ]:

```
import matplotlib.pyplot as plt
gender_distribution = data['gender'].value_counts()

plt.figure(figsize=(4, 2))
gender_distribution.plot(kind='pie', autopct='%1.1f%%', colors=['lightblue', 'lightpink'])
plt.title('Distribution of Users\' Gender')
plt.ylabel('')
plt.tight_layout()
plt.show()
```

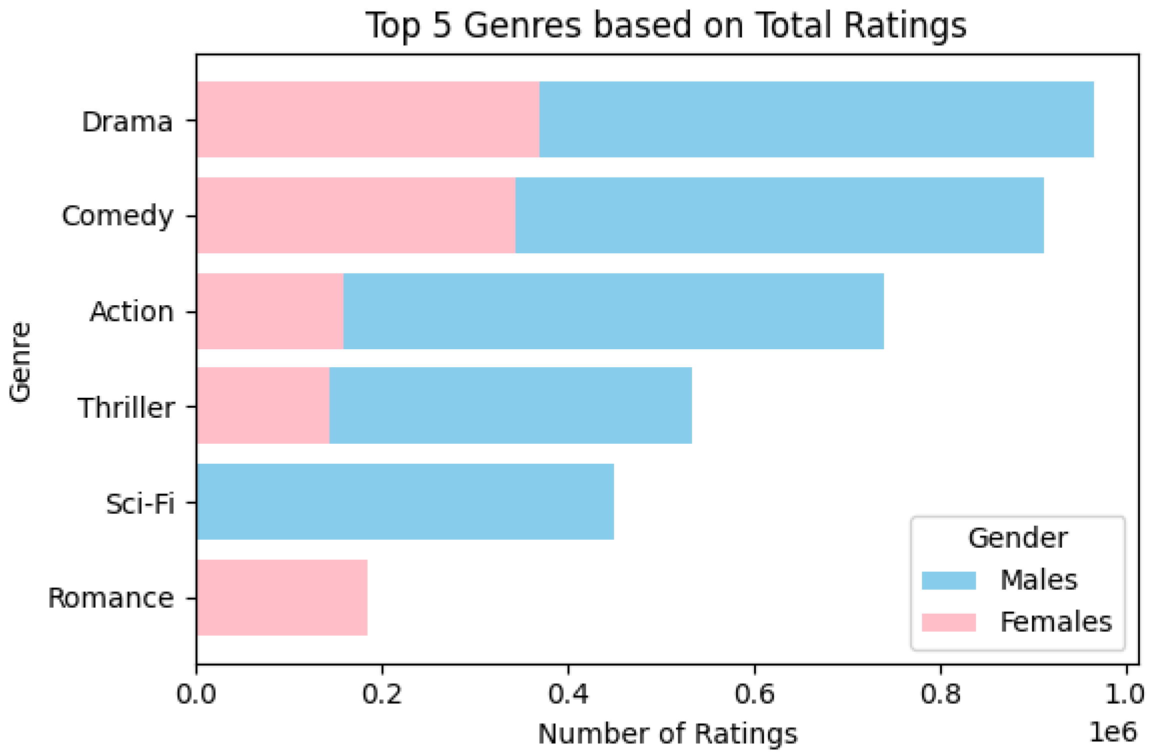


Observations: the pie chart displays a stark gender contrast in the movie dataset, with 75.4% male users and 24.6% female users. This distinction emphasizes the need to cater to a diverse user base for optimal platform engagement.

B, Distribution of Top 5 Genres by Gender based on Total Ratings

In [ ]:
```
movie_data = data.assign(genres=data['genres'].str.split('|')).explode('genres')

# get total ratings for each genre split by gender
genre_ratings = movie_data.groupby(['genres', 'gender'])['rating'].sum().reset_index()
top_genres_male = genre_ratings[genre_ratings['gender'] == 'M'].nlargest(5, 'rating')
top_genres_female = genre_ratings[genre_ratings['gender'] == 'F'].nlargest(5, 'rating')

print("Top 5 Genres for Males based on Total Ratings:")
print(top_genres_male)
print("\nTop 5 Genres for Females based on Total Ratings:")
print(top_genres_female)

plt.figure(figsize=(6, 4))
plt.barh(top_genres_male['genres'], top_genres_male['rating'], color='skyblue', label='Males')
plt.barh(top_genres_female['genres'], top_genres_female['rating'], color='pink', label='Females')
plt.xlabel('Number of Ratings')
plt.ylabel('Genre')
plt.title('Top 5 Genres based on Total Ratings')
plt.legend(title='Gender', loc='lower right')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

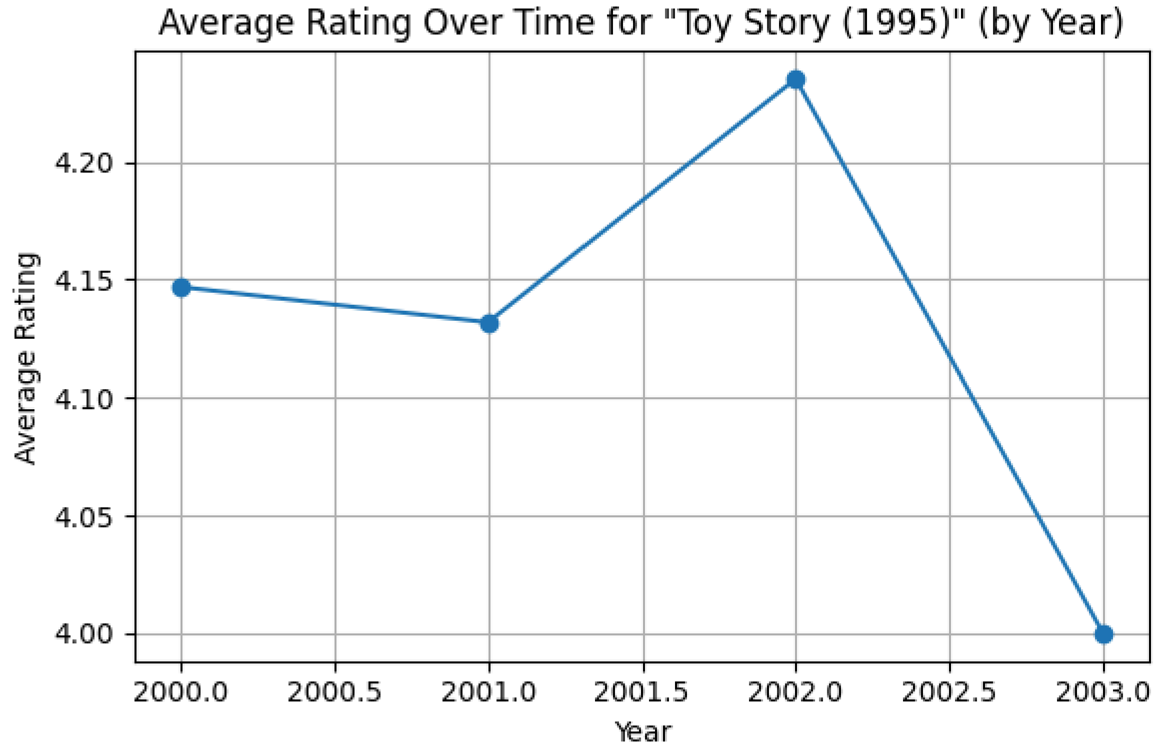
```
Top 5 Genres for Males based on Total Ratings:
      genres gender  rating
15     Drama      M  965663
9     Comedy      M  912036
1     Action      M  739500
31  Thriller      M  533211
29    Sci-Fi      M  450726

Top 5 Genres for Females based on Total Ratings:
      genres gender  rating
14     Drama      F  369611
8     Comedy      F  343874
26   Romance      F  184770
0     Action      F  159330
30  Thriller      F  144035
```



Observations: drama is the top choice for both genders, especially favored by males, while comedy is enjoyed by both but slightly more by males. Action and thriller genres are more popular among males, whereas females show a preference for romance. Sci-fi appeals more to males. These genre preferences highlight diverse interests across genders in the movie-watching experience.

C, Average Ratings Over Time for 'Toy Story (1995)

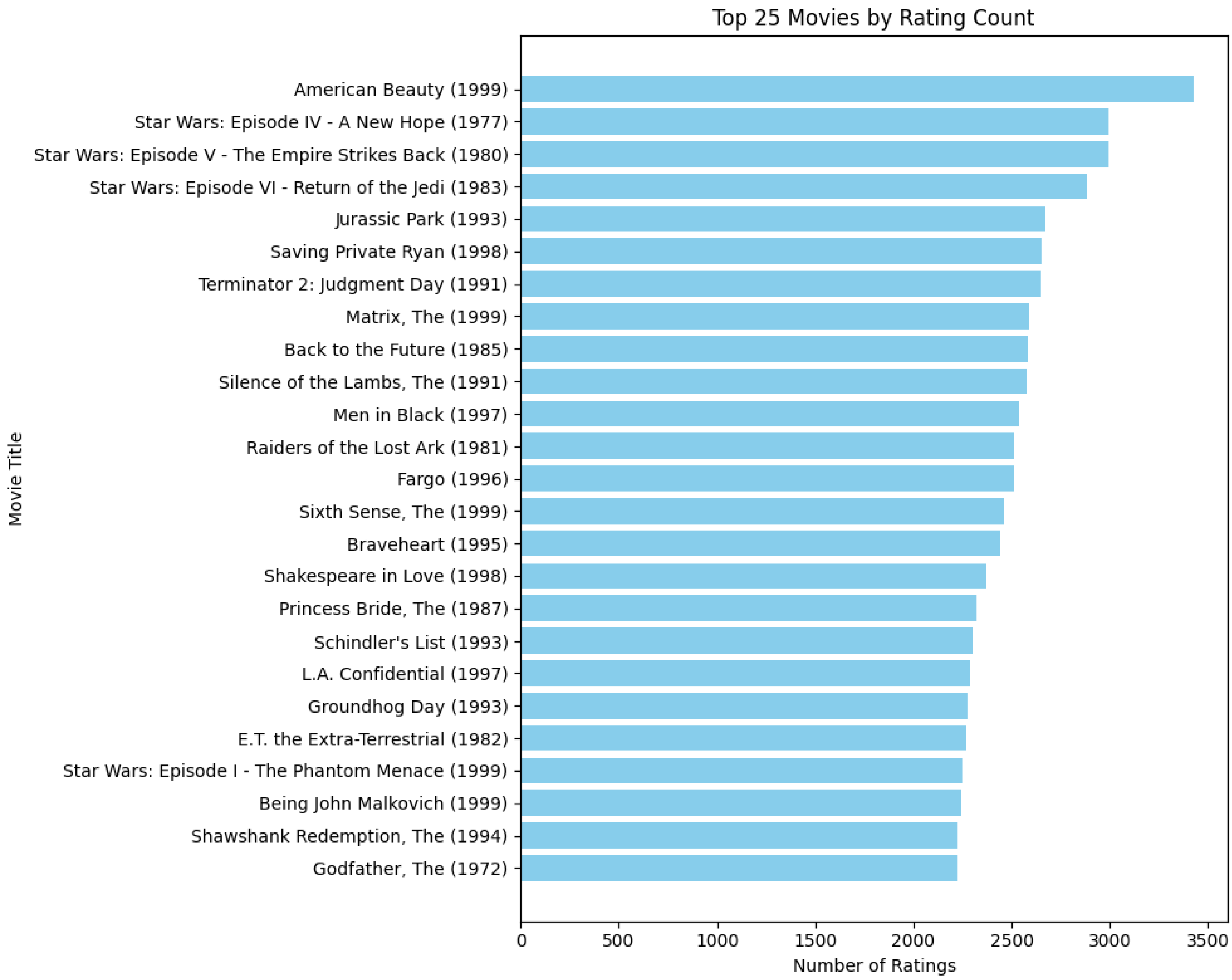
In [ ]:
```
# pick a movie "Toy Story (1995)"
movie_title = "Toy Story (1995)"
movie_ratings = data[data['title'] == movie_title].copy()

# convert timestamp to datetime and extract year
movie_ratings['timestamp'] = pd.to_datetime(movie_ratings['timestamp'], unit='s')
movie_ratings['year'] = movie_ratings['timestamp'].dt.year

avg_rating_per_year = movie_ratings.groupby('year')['rating'].mean().reset_index()

plt.figure(figsize=(6, 4))
plt.plot(avg_rating_per_year['year'], avg_rating_per_year['rating'], marker='o')
plt.xlabel('Year')
plt.ylabel('Average Rating')
plt.title(f'Average Rating Over Time for "{movie_title}" (by Year)')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Observations: from 2000 to 2003, the movie 'Toy Story (1995)' enjoyed consistently high average ratings, with a peak in 2002 at 4.24. Despite a slight dip in 2003, the film maintained a strong average rating of 4.0, reflecting its enduring popularity and positive viewer reception.

D, Top 25 movies by rating count.

In [ ]:
```
# get the total number of ratings for each movie
movie_ratings_count = data.groupby('title')['rating'].count().reset_index()
movie_ratings_count.columns = ['title', 'rating_count']

# get the top 25 movies by rating count
top_movies = movie_ratings_count.nlargest(25, 'rating_count')

plt.figure(figsize=(10, 8))
plt.barh(top_movies['title'], top_movies['rating_count'], color='skyblue')
plt.xlabel('Number of Ratings')
plt.ylabel('Movie Title')
plt.title('Top 25 Movies by Rating Count')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



Observations: the top-rated movies showcase the enduring appeal of "American Beauty" and the "Star Wars" franchise, highlighting their lasting impact on audiences. "Jurassic Park" also stands out as a beloved classic among the top-ranking films, reflecting the timeless popularity of iconic blockbusters.