In [302]:
```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
```

In [3]:
```
unames = ['user_id', 'gender', 'age', 'occupation', 'zip']
users = pd.read_table('ml-1m/users.dat', sep='::', header=None, names=

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

mnames = ['movie_id', 'title', 'genres']
movies = pd.read_table('ml-1m/movies.dat', sep='::', header=None, name
```

In [4]:
```
display(users.head(2))
display(ratings.head(2))
display(movies.head(2))
```

	user_id	gender	age	occupation	zip
0	1	F	1	10	48067
1	2	M	56	16	70072

	user_id	movie_id	rating	timestamp
0	1	1193	5	978300760
1	1	661	3	978302109

	movie_id	title	genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy

Question 1:

An aggregate of movie ratings by men of age above 25 for each particular genre, e.g., Action, Adventure, Drama, Science Fiction, ... Note, Action|Drama|Thriller' is not considered a unique genre. The movie that has a genre like this belongs to all three genres.

- step 1: check how many unique genre we have

In [5]:
```
movies["genres"].value_counts()
```

Out[5]:
```
Drama                                  843
Comedy                                 521
Horror                                 178
Comedy|Drama                           162
Comedy|Romance                         142
                                      ...
Action|Comedy|Crime|Horror|Thriller      1
Action|Drama|Thriller|War                1
Action|Adventure|Children's              1
Action|Adventure|Children's|Fantasy      1
Adventure|Crime|Sci-Fi|Thriller          1
Name: genres, Length: 301, dtype: int64
```

- step 2: what is the longest genre group?

In [7]:
```
movies["genres"].str.count("\|").max()
```

Out[7]:
```
5
```

- step3, we need to create 6 more columns to hold those genres

In [8]:
```
def assignCol(data, index):
    if index >= len(data):
        return np.nan
    else: return data[index]
```

In [9]:
```
# declare a new dataframe to backup, called df_movie
df_movie = movies.copy()
```

In [16]:
```
df_movie["genres_A"] = df_movie["genres"].str.split("|").apply(lambda
df_movie["genres_B"] = df_movie["genres"].str.split("|").apply(lambda
df_movie["genres_C"] = df_movie["genres"].str.split("|").apply(lambda
df_movie["genres_D"] = df_movie["genres"].str.split("|").apply(lambda
df_movie["genres_E"] = df_movie["genres"].str.split("|").apply(lambda
df_movie["genres_F"] = df_movie["genres"].str.split("|").apply(lambda
```

In [22]:
```
# df_moive sample looks like beneath
df_movie.loc[[4,2,0,47,69,1187]]
```

Out[22]:

	movie_id	title	genres	genres_A	genres_B	genres_
4	5	Father of the Bride Part II (1995)	Comedy	Comedy	NaN	Na
2	3	Grumpier Old Men (1995)	Comedy|Romance	Comedy	Romance	Na
0	1	Toy Story (1995)	Animation|Children's|Comedy	Animation	Children's	Come
47	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	Animation	Children's	Music
69	70	From Dusk Till Dawn (1996)	Action|Comedy|Crime|Horror|Thriller	Action	Comedy	Crin
1187	1205	Transformers: The Movie, The (1986)	Action|Animation|Children's|Sci-Fi|Thriller|War	Action	Animation	Childrer

- step 4, melt genresA - genresF in to one column and dropna

In [27]:
```
movie_melt = df_movie.drop(columns = "genres")\
                    .melt(var_name = "original columns", value_name =
                         value_vars=["genres_A", "genres_B","genres_
                         id_vars = ["movie_id", "title"])\
                    .drop(columns = "original columns")\
                    .dropna()
movie_melt
```

Out[27]:

	movie_id	title	genres
0	1	Toy Story (1995)	Animation
1	2	Jumanji (1995)	Adventure
2	3	Grumpier Old Men (1995)	Comedy
3	4	Waiting to Exhale (1995)	Comedy
4	5	Father of the Bride Part II (1995)	Comedy
...	...	...	...
17517	2054	Honey, I Shrunk the Kids (1989)	Sci-Fi
17543	2080	Lady and the Tramp (1955)	Romance
17544	2081	Little Mermaid, The (1989)	Romance
17785	2322	Soldier (1998)	War
20602	1205	Transformers: The Movie, The (1986)	War

6408 rows × 3 columns

- step 5 confirm that the movie_melt dataframe has the same length as required

In [48]:
```
def confirm_df_length():
    length_list = []
    # 6 genres in the movie
    genres6 = movies[movies["genres"].str.count("\|") == 5].shape[0]
    # 5 genres in the movie
    genres5 = movies[movies["genres"].str.count("\|") == 4].shape[0]
    # 6 genres in the movie
    genres4 = movies[movies["genres"].str.count("\|") == 3].shape[0]
    # 6 genres in the movie
    genres3 = movies[movies["genres"].str.count("\|") == 2].shape[0]
    # 6 genres in the movie
    genres2 = movies[movies["genres"].str.count("\|") == 1].shape[0]
    # 6 genres in the movie
    genres1 = movies[movies["genres"].str.count("\|") == 0].shape[0]

    length_list.append(6 * genres6)
    length_list.append(5 * genres5)
    length_list.append(4 * genres4)
    length_list.append(3 * genres3)
    length_list.append(2 * genres2)
    length_list.append(1 * genres1)

    for i in range(6,0,-1):
        print(f"we have {length_list[6-i]//i} movies with {i}'s genres
    print("total number of genres is", sum(length_list))
    return sum(length_list)
```

In [49]:
```
assert confirm_df_length() == movie_melt.shape[0]
```

```
we have 1 movies with 6's genres
we have 14 movies with 5's genres
we have 100 movies with 4's genres
we have 421 movies with 3's genres
we have 1322 movies with 2's genres
we have 2025 movies with 1's genres
total number of genres is 6408
```

- step6 create a df holds the value of men whoes age is above 25

In [51]:
```
df_men_over25 = users.copy()
df_men_over25 = df_men_over25[(df_men_over25["gender"] == "M") & (df_m
display(df_men_over25.shape)
df_men_over25.sample(5)
```

(1844, 5)

Out[51]:

	user_id	gender	age	occupation	zip
4825	4826	M	45	12	55436
55	56	M	35	20	60440
3997	3998	M	45	0	74354
5195	5196	M	56	7	20814
2331	2332	M	56	14	01545

In [58]:
```
men_25_merge_3_df = movie_melt.merge(ratings, left_on = "movie_id", ri
                                     .merge(df_men_over25, left_on = "user_ic
men_25_merge_3_df
```

Out[58]:

	movie_id	title	genres	user_id	rating	timestamp	gender	age	occupatior
0	1	Toy Story (1995)	Animation	23	4	978463614	M	35	(
1	1	Toy Story (1995)	Children's	23	4	978463614	M	35	(
2	1	Toy Story (1995)	Comedy	23	4	978463614	M	35	(
3	2	Jumanji (1995)	Adventure	23	2	978461604	M	35	(
4	2	Jumanji (1995)	Children's	23	2	978461604	M	35	(
...	...	...	...	...	...	...	...	...	..
612990	3176	Talented Mr. Ripley, The (1999)	Drama	5145	4	962028914	M	35	7
612991	3176	Talented Mr. Ripley, The (1999)	Mystery	5145	4	962028914	M	35	7
612992	3176	Talented Mr. Ripley, The (1999)	Thriller	5145	4	962028914	M	35	7
612993	3742	Battleship Potemkin, The (Bronenosets Potyomki...	Drama	5145	5	962028814	M	35	7
612994	3742	Battleship Potemkin, The (Bronenosets Potyomki...	War	5145	5	962028814	M	35	7

612995 rows × 10 columns

In [63]:
```
men_25_merge_3_df[men_25_merge_3_df["user_id"] == 23]
```

Out[63]:

	movie_id	title	genres	user_id	rating	timestamp	gender	age	occupation	
0	1	Toy Story (1995)	Animation	23	4	978463614	M	35	0	90(
1	1	Toy Story (1995)	Children's	23	4	978463614	M	35	0	90(
2	1	Toy Story (1995)	Comedy	23	4	978463614	M	35	0	90(
3	2	Jumanji (1995)	Adventure	23	2	978461604	M	35	0	90(
4	2	Jumanji (1995)	Children's	23	2	978461604	M	35	0	90(
...	...	...	...	...	...	...	...	...	...	
742	3877	Supergirl (1984)	Fantasy	23	1	978461689	M	35	0	90(
743	3920	Faraway, So Close (In Weiter Ferne, So Nah!) (...	Drama	23	2	978461308	M	35	0	90(
744	3920	Faraway, So Close (In Weiter Ferne, So Nah!) (...	Fantasy	23	2	978461308	M	35	0	90(
745	3952	Contender, The (2000)	Drama	23	4	978461000	M	35	0	90(
746	3952	Contender, The (2000)	Thriller	23	4	978461000	M	35	0	90(

747 rows × 10 columns

In [67]:
```
men_25_merge_3_df.groupby("genres")\
                 .describe()["rating"]\
                 .sort_values("count", ascending = False)
```

Out[67]:

genres	count	mean	std	min	25%	50%	75%	max
Drama	107794.0	3.812309	1.000675	1.0	3.0	4.0	5.0	5.0
Comedy	95836.0	3.565456	1.082492	1.0	3.0	4.0	4.0	5.0
Action	76448.0	3.554547	1.080126	1.0	3.0	4.0	4.0	5.0
Thriller	54883.0	3.644025	1.051257	1.0	3.0	4.0	4.0	5.0
Sci-Fi	49518.0	3.509693	1.115381	1.0	3.0	4.0	4.0	5.0
Adventure	39923.0	3.538637	1.078655	1.0	3.0	4.0	4.0	5.0
Romance	39747.0	3.659748	1.027161	1.0	3.0	4.0	4.0	5.0
War	24391.0	3.940634	1.008249	1.0	3.0	4.0	5.0	5.0
Crime	22545.0	3.764249	1.016280	1.0	3.0	4.0	5.0	5.0
Horror	22303.0	3.241089	1.219419	1.0	2.0	3.0	4.0	5.0
Children's	17540.0	3.475314	1.109345	1.0	3.0	4.0	4.0	5.0
Mystery	12919.0	3.759347	1.023142	1.0	3.0	4.0	5.0	5.0
Musical	11973.0	3.700242	1.059583	1.0	3.0	4.0	5.0	5.0
Animation	9866.0	3.721569	1.036493	1.0	3.0	4.0	5.0	5.0
Fantasy	9539.0	3.490408	1.090758	1.0	3.0	4.0	4.0	5.0
Western	8583.0	3.708494	1.050721	1.0	3.0	4.0	4.0	5.0
Film-Noir	6838.0	4.117140	0.883036	1.0	4.0	4.0	5.0	5.0
Documentary	2349.0	3.950192	1.006616	1.0	3.0	4.0	5.0	5.0

Question II

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

In [91]:
```
merge_all_three_tables = movies.merge(ratings, on = "movie_id")\
                              .merge(users, on="user_id")
merge_all_three_tables
```

Out[91]:

	movie_id	title	genres	user_id	rating	timestamp
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351
2	150	Apollo 13 (1995)	Drama	1	5	978301777
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760
4	527	Schindler's List (1993)	Drama|War	1	5	978824195
...	...	...	...	...	...	...
1000204	3513	Rules of Engagement (2000)	Drama|Thriller	5727	4	958489970
1000205	3535	American Psycho (2000)	Comedy|Horror|Thriller	5727	2	958489970
1000206	3536	Keeping the Faith (2000)	Comedy|Romance	5727	5	958489902
1000207	3555	U-571 (2000)	Action|Thriller	5727	3	958490699
1000208	3578	Gladiator (2000)	Action|Drama	5727	5	958490171

1000209 rows × 10 columns

In [92]:
```
merge_all_three_tables.groupby("title")\
                      .count()[["rating"]]\
                      .sort_values("rating", ascending= False)\
                      .head()
```

Out[92]:

title	rating
American Beauty (1999)	3428
Star Wars: Episode IV - A New Hope (1977)	2991
Star Wars: Episode V - The Empire Strikes Back (1980)	2990
Star Wars: Episode VI - Return of the Jedi (1983)	2883
Jurassic Park (1993)	2672

Question III

Average movie ratings between users of different age groups (<18, 18-30, 30-50, 50-70, 70>)

In [118]:
```
merge_all_three_tables["age_group"] = pd.cut(merge_all_three_tables["a
                                             labels = ["less than 18",
```

In [119]:
```
merge_all_three_tables
```

Out[119]:

	movie_id	title	genres	user_id	rating	timestamp
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351
2	150	Apollo 13 (1995)	Drama	1	5	978301777
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760
4	527	Schindler's List (1993)	Drama|War	1	5	978824195
...	...	...	...	...	...	...
1000204	3513	Rules of Engagement (2000)	Drama|Thriller	5727	4	958489970
1000205	3535	American Psycho (2000)	Comedy|Horror|Thriller	5727	2	958489970
1000206	3536	Keeping the Faith (2000)	Comedy|Romance	5727	5	958489902
1000207	3555	U-571 (2000)	Action|Thriller	5727	3	958490699
1000208	3578	Gladiator (2000)	Action|Drama	5727	5	958490171

1000209 rows × 11 columns

In [127]:
```
merge_all_three_tables.groupby("age_group")\
                      .mean()[["rating"]]\
                      .rename(columns = {"rating": "Average Movie Rati
                      .fillna("Data not covered")
```

Out[127]:

	Average Movie Ratings
age_group	
less than 18	3.54952
18 - 29	3.533299
30 - 49	3.62405
50 - 69	3.732677
greater than 69	Data not covered

Question IV

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.

- pick movie name `Apollo 13` which was shown on year 2000

In [147]:
```
merge_all_three_tables["date"] = pd.to_datetime(merge_all_three_tables
```

In [170]:
```
apollo13 = merge_all_three_tables[merge_all_three_tables["title"] == "
apollo13.head(2)
```

Out[170]:

	movie_id	title	genres	user_id	rating	timestamp	gender	age	occupation	zip	ag
2	150	Apollo 13 (1995)	Drama	1	5	978301777	F	1	10	48067	
139	150	Apollo 13 (1995)	Drama	8	4	978230611	M	25	12	11413	

In [178]:
```
merge_all_three_tables_2000 = merge_all_three_tables[merge_all_three_t
```

In [180]:
```
merge_all_three_tables_2000["age_group"] = pd.cut(merge_all_three_tabl
                                                  [0,18,45,100],
                                                  labels=["a) under 18
merge_all_three_tables_2000["year"] = merge_all_three_tables_2000["dat
```

In [181]:
```
merge_all_three_tables_2000.sample(5)
```

Out[181]:

	movie_id	title	genres	user_id	rating	timestamp
432510	2099	Song of the South (1946)	Adventure|Animation|Children's|Musical	4438	3	965098514
390010	3699	Starman (1984)	Adventure|Drama|Romance|Sci-Fi	4016	3	965529227
71640	750	Dr. Strangelove or: How I Learned to Stop Worr...	Sci-Fi|War	801	4	975469694
941108	1620	Kiss the Girls (1997)	Crime|Drama|Thriller	5895	2	957462368
294936	2369	Desperately Seeking Susan (1985)	Comedy|Romance	3196	1	968637962

In [224]:
```
unique_film_2000_by_age = merge_all_three_tables_2000.groupby(["year",
                                                         .apply(lambda x:
                                                         .to_frame()\
                                                         .rename(columns =

unique_film_2000_by_age
```

Out[224]:

year	age_group	No. unique movies rating by age group
2000	**a) under 18**	3379
	b) 19 - 45	3581
	c) above 45	3288

Question V

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, i.e. with the same rating. Demonstrate that your function works.

In [276]:
```
merge_all_three_tables
```

Out[276]:

	movie_id	title	genres	user_id	rating	timestamp
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	978824351
2	150	Apollo 13 (1995)	Drama	1	5	978301777
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantasy|Sci-Fi	1	4	978300760
4	527	Schindler's List (1993)	Drama|War	1	5	978824195
...	...	...	...	...	...	...
1000204	3513	Rules of Engagement (2000)	Drama|Thriller	5727	4	958489970
1000205	3535	American Psycho (2000)	Comedy|Horror|Thriller	5727	2	958489970
1000206	3536	Keeping the Faith (2000)	Comedy|Romance	5727	5	958489902
1000207	3555	U-571 (2000)	Action|Thriller	5727	3	958490699
1000208	3578	Gladiator (2000)	Action|Drama	5727	5	958490171

1000209 rows × 12 columns

In [278]:
```
def same_rating_like_given_movie(user_id:int, movie_id:int)->list:
    movie_group_for_user = merge_all_three_tables[merge_all_three_tabl
    rating = movie_group_for_user[movie_group_for_user["movie_id"] ==
    if len(rating) == 0:
        return "Sorry there is no other movies match your search"
    else: rating = rating.values[0]

    result = movie_group_for_user[movie_group_for_user["rating"] == ra

    return result["title"].tolist()
```

In [279]:
```
same_rating_like_given_movie(1, 1)
```

Out[279]:
```
['Toy Story (1995)',
 'Pocahontas (1995)',
 'Apollo 13 (1995)',
 "Schindler's List (1993)",
 'Beauty and the Beast (1991)',
 'Cinderella (1950)',
 'Mary Poppins (1964)',
 'Dumbo (1941)',
 'Sound of Music, The (1965)',
 "One Flew Over the Cuckoo's Nest (1975)",
 'Back to the Future (1985)',
 'Ben-Hur (1959)',
 'Last Days of Disco, The (1998)',
 'Rain Man (1988)',
 'Saving Private Ryan (1998)',
 "Bug's Life, A (1998)",
 'Christmas Story, A (1983)',
 'Awakenings (1990)']
```

In [280]:
```
same_rating_like_given_movie(5727, 3578)
```

Out[280]:
```
['Red Violin, The (Le Violon rouge) (1998)',
 'Arlington Road (1999)',
 'Thomas Crown Affair, The (1999)',
 'American Beauty (1999)',
 'Toy Story 2 (1999)',
 'Whole Nine Yards, The (2000)',
 'Erin Brockovich (2000)',
 'Keeping the Faith (2000)',
 'Gladiator (2000)']
```

In [281]:
```
same_rating_like_given_movie(99999, 99999)
```

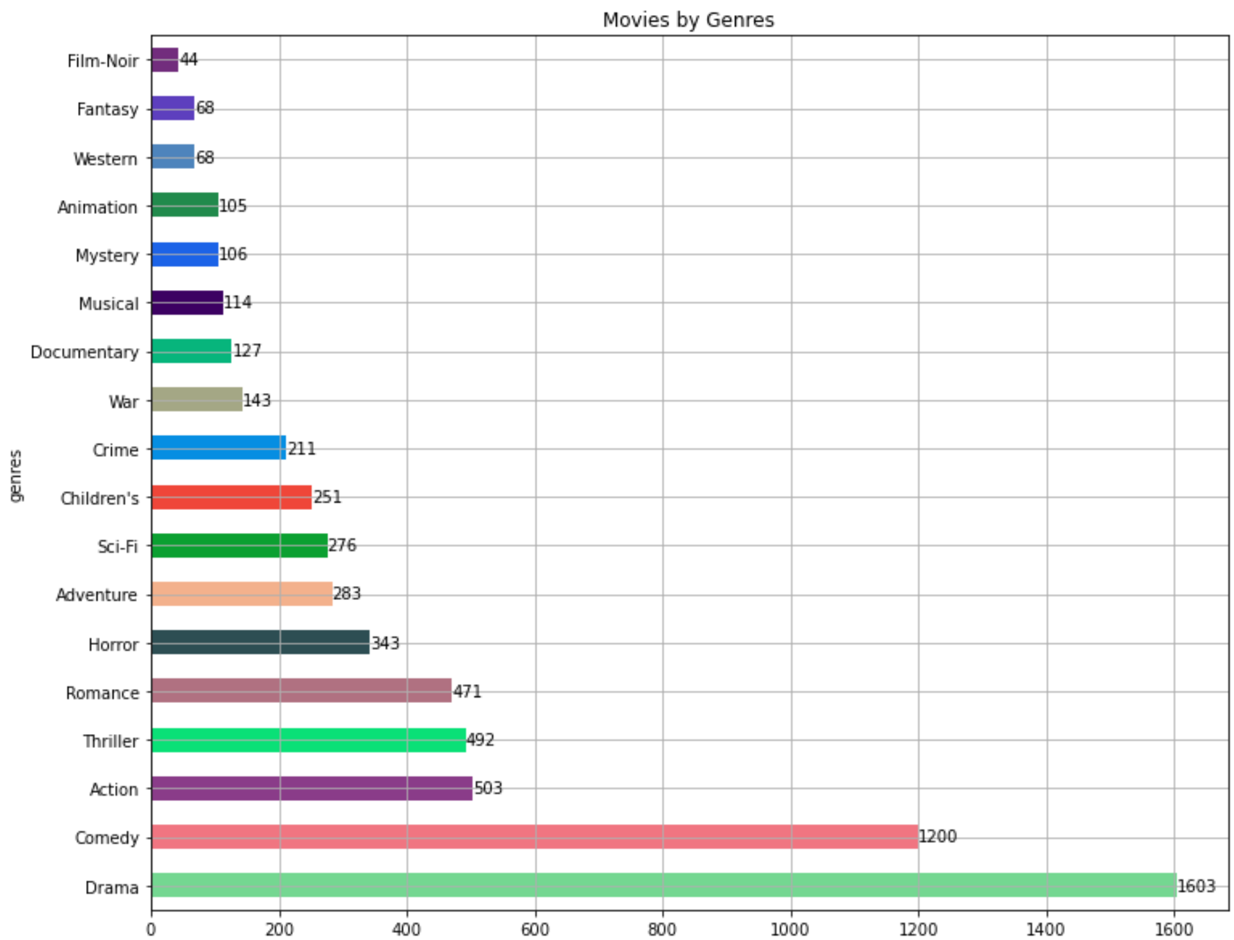
Out[281]:
```
'Sorry there is no other movies match your search'
```

Q6

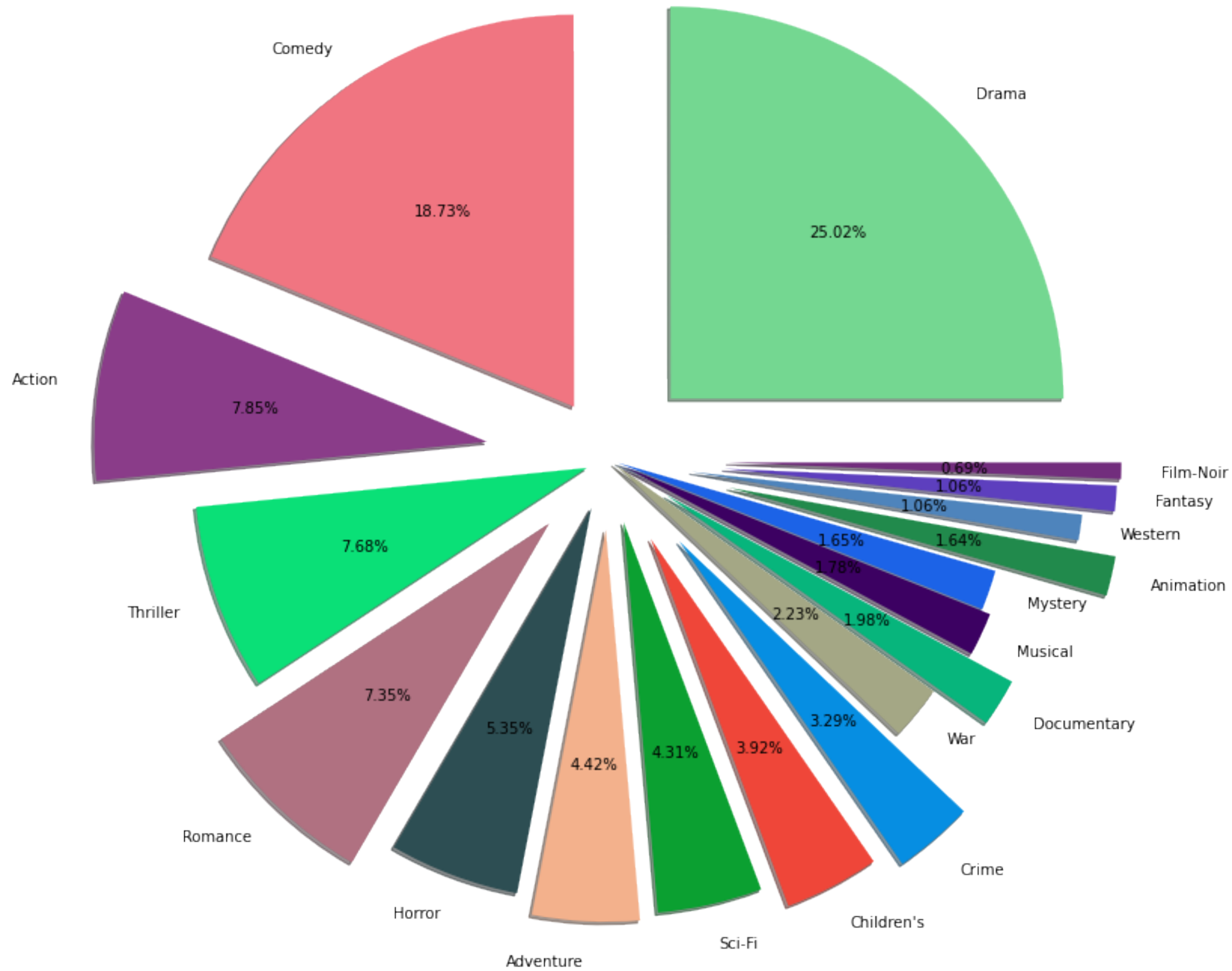
Some other statistic, figure, aggregate, or plot that you created using this dataset, along with a short description of what interesting observations you derived from it.

In [290]:
```
colors = ["#" + "".join([random.choice("0123456789ABCDEF") for j in ra
```

In [303]:
```
plot1 = movie_melt.value_counts("genres")\
                  .plot(kind = "barh", figsize=(12,10),color = colors,
                       title = "Movies by Genres")
plot1.bar_label(plot1.containers[0])
plt.show()
```



In [320]:
```
plot2 = movie_melt.value_counts("genres")\
                    .plot(kind = "pie", radius = 3, label = "",
                          explode = [random.random() for i in range(18)]
                          colors = colors, autopct = "%1.2f%%")
```



In [350]:
```
movie_melt.value_counts("genres")
```

Out[350]:
```
genres
Drama          1603
Comedy         1200
Action          503
Thriller        492
Romance         471
Horror          343
Adventure       283
Sci-Fi          276
Children's      251
Crime           211
War             143
Documentary     127
Musical         114
Mystery         106
Animation       105
Western          68
Fantasy          68
Film-Noir        44
dtype: int64
```

In [352]:
```
movies.value_counts("genres")
```

Out[352]:
```
genres
Drama                                   843
Comedy                                  521
Horror                                  178
Comedy|Drama                            162
Comedy|Romance                          142
                                       ... 
Animation|Children's|Drama|Fantasy        1
Animation|Children's|Fantasy|War          1
Animation|Children's|Musical|Romance      1
Animation|Mystery                         1
Animation|Children's|Fantasy|Musical      1
Length: 301, dtype: int64
```

In [353]:
```
men_25_merge_3_df.groupby("genres")\
                .describe()["rating"]\
                .sort_values("count", ascending = False)
```

Out[353]:

genres	count	mean	std	min	25%	50%	75%	max
Drama	107794.0	3.812309	1.000675	1.0	3.0	4.0	5.0	5.0
Comedy	95836.0	3.565456	1.082492	1.0	3.0	4.0	4.0	5.0
Action	76448.0	3.554547	1.080126	1.0	3.0	4.0	4.0	5.0
Thriller	54883.0	3.644025	1.051257	1.0	3.0	4.0	4.0	5.0
Sci-Fi	49518.0	3.509693	1.115381	1.0	3.0	4.0	4.0	5.0
Adventure	39923.0	3.538637	1.078655	1.0	3.0	4.0	4.0	5.0
Romance	39747.0	3.659748	1.027161	1.0	3.0	4.0	4.0	5.0
War	24391.0	3.940634	1.008249	1.0	3.0	4.0	5.0	5.0
Crime	22545.0	3.764249	1.016280	1.0	3.0	4.0	5.0	5.0
Horror	22303.0	3.241089	1.219419	1.0	2.0	3.0	4.0	5.0
Children's	17540.0	3.475314	1.109345	1.0	3.0	4.0	4.0	5.0
Mystery	12919.0	3.759347	1.023142	1.0	3.0	4.0	5.0	5.0
Musical	11973.0	3.700242	1.059583	1.0	3.0	4.0	5.0	5.0
Animation	9866.0	3.721569	1.036493	1.0	3.0	4.0	5.0	5.0
Fantasy	9539.0	3.490408	1.090758	1.0	3.0	4.0	4.0	5.0
Western	8583.0	3.708494	1.050721	1.0	3.0	4.0	4.0	5.0
Film-Noir	6838.0	4.117140	0.883036	1.0	4.0	4.0	5.0	5.0
Documentary	2349.0	3.950192	1.006616	1.0	3.0	4.0	5.0	5.0

In [354]:
```
merge_all_three_tables.groupby("title")\
                      .count()[["rating"]]\
                      .sort_values("rating", ascending= False)\
                      .head()
```

Out[354]:

title	rating
American Beauty (1999)	3428
Star Wars: Episode IV - A New Hope (1977)	2991
Star Wars: Episode V - The Empire Strikes Back (1980)	2990
Star Wars: Episode VI - Return of the Jedi (1983)	2883
Jurassic Park (1993)	2672

Observations:

- The original movies has `301` different genres while most of them are composite genres like `Animation|Children's|Drama|Fantasy` , however when I used `melt` function or `pivot` function to transform one columns to multiple columns and stack them together, I found there are only 18 unique genres
- Genre prefered by group men age above 25
  - Originally I thought men above 25 may like `war` or `Adventure` genres, but by analysing data through this dataset it shows men prefer `Drama` which is far away from my prediction.
  - Meanwhile, I found men over 25 don't prefer `Animation and Fantasy` which is similar like I thougth,
  - Last the least popular type is `Documentary`
- StarWars is the most famous topic because within the top 5 movies by rating, 3 of them are Star Wars