Assignment2

September 29, 2023

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

1 Data & Setup

- First I am loading `movies.dat` & `user_ratedmovies.dat` into memory for further analyses. If I felt need to use some additional data, I will load that as the need be.
  - In the further questions, it was asked to rated for *mean rating given to a movie by MovieLens users* and from the data set it was not clear, which coulmn would correspond to the this rating.
  - Therefore after reading the readme.txt, so I am assuming, `user_ratedmovies.dat` represents the MovieLens user ratings. I can take average of these ratings for each movie
- I loaded this dataset from `.dat` file using refrence given in Missing Data code files as I wasn't sure how to load and parse the `.dat` file.
- Once the data is loaded, I am using the `describe()` method on the DataFrame to extract some initial information

[2]:
```
df_movies = pd.read_table('movies.dat', sep='\t', na_values=['\\N'],␣
↪encoding='latin1', low_memory=False)
df_ml_ratings = pd.read_table('user_ratedmovies.dat', sep='\t',␣
↪na_values=['\\N'], encoding='latin1', low_memory=False)

# to make a uniform column name for movie id across all data set
df_movies.rename(columns={"id": "movieID"}, inplace=True)

df_avg_ml_rating = df_ml_ratings.groupby('movieID')['rating'].mean().
↪reset_index()
df_avg_ml_rating.rename(columns={'rating':'rtMlUserMeanRating'}, inplace= True)

# Left join MovieLens to movies datafream.
df_movies = df_movies.merge(df_avg_ml_rating, how='left', on='movieID')

df_movies.describe().transpose()
```

[2]:

	count	mean	std	min
movieID	10197.0	12852.741002	17431.004896	1.0
imdbID	10197.0	202188.472002	207128.724821	439.0
year	10197.0	1988.251643	18.688734	1903.0
rtAllCriticsRating	9967.0	5.139300	2.598048	0.0
rtAllCriticsNumReviews	9967.0	42.822414	50.561048	0.0
rtAllCriticsNumFresh	9967.0	25.817698	35.221036	0.0
rtAllCriticsNumRotten	9967.0	17.004716	26.200666	0.0
rtAllCriticsScore	9967.0	56.705127	32.784319	0.0
rtTopCriticsRating	9967.0	2.773874	3.139613	0.0
rtTopCriticsNumReviews	9967.0	9.754891	12.148680	0.0
rtTopCriticsNumFresh	9967.0	5.455302	8.181109	0.0
rtTopCriticsNumRotten	9967.0	4.299589	6.826212	0.0
rtTopCriticsScore	9967.0	41.611518	38.773000	0.0
rtAudienceRating	9967.0	2.497652	1.542419	0.0
rtAudienceNumRatings	9967.0	15781.439149	63716.849495	0.0
rtAudienceScore	9967.0	48.340925	32.699404	0.0
rtMlUserMeanRating	10109.0	3.213406	0.640538	0.5

	25%	50%	75%	max
movieID	2780.000000	5421.000000	8664.000000	65133.0
imdbID	82200.000000	113057.000000	281724.000000	1349938.0
year	1981.000000	1995.000000	2002.000000	2011.0
rtAllCriticsRating	4.000000	5.800000	7.000000	9.6
rtAllCriticsNumReviews	8.000000	22.000000	56.000000	281.0
rtAllCriticsNumFresh	4.000000	12.000000	33.000000	265.0
rtAllCriticsNumRotten	1.000000	5.000000	19.000000	171.0
rtAllCriticsScore	30.000000	63.000000	86.000000	100.0
rtTopCriticsRating	0.000000	0.000000	5.900000	10.0
rtTopCriticsNumReviews	1.000000	4.000000	16.000000	48.0
rtTopCriticsNumFresh	0.000000	2.000000	7.000000	42.0
rtTopCriticsNumRotten	0.000000	1.000000	5.000000	38.0
rtTopCriticsScore	0.000000	38.000000	80.000000	100.0
rtAudienceRating	0.000000	3.200000	3.600000	5.0
rtAudienceNumRatings	0.000000	1445.000000	8865.500000	1768593.0
rtAudienceScore	0.000000	57.000000	76.000000	100.0
rtMlUserMeanRating	2.851293	3.312415	3.681452	5.0

- As can be seen from above output, we have **10,197** entires for `imdbID` however only **9,967** for RottenTomato entries. Let's see if we have any missing values for `rtID` and corresponding columns
- Further, in subsequent questions, we are intersted in ratings `rtAllCriticsRating`, `rtTopCriticsRating`, `rtAudienceRating`, & `rtMlUserMeanRating` so I will be working with these ratings only in next lines of code

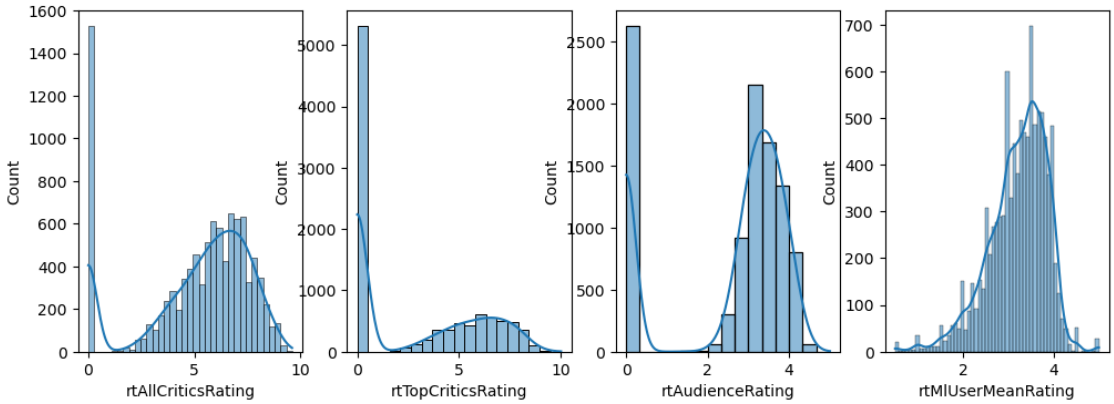
[3]:

```
rating_col_interested = ['rtAllCriticsRating', 'rtTopCriticsRating',␣
 ↪'rtAudienceRating', 'rtMlUserMeanRating']
```

[4]:
```python
# Numerical and Graphical distribution of the ratings interested

fig, axes = plt.subplots(1, len(rating_col_interested), figsize=(12, 4))

for i in range(len(rating_col_interested)):
    print(f'Numerical Distribution of ratings -> {rating_col_interested[i]}')
    print(df_movies[rating_col_interested[i]].describe())
    print('='*100)
    sns.histplot(x=rating_col_interested[i], ax = axes[i], data = df_movies,␣
 ↪kde = True)
plt.show()
```

```
Numerical Distribution of ratings -> rtAllCriticsRating
count    9967.000000
mean        5.139300
std         2.598048
min         0.000000
25%         4.000000
50%         5.800000
75%         7.000000
max         9.600000
Name: rtAllCriticsRating, dtype: float64
================================================================================
====================
Numerical Distribution of ratings -> rtTopCriticsRating
count    9967.000000
mean        2.773874
std         3.139613
min         0.000000
25%         0.000000
50%         0.000000
75%         5.900000
max        10.000000
Name: rtTopCriticsRating, dtype: float64
================================================================================
====================
Numerical Distribution of ratings -> rtAudienceRating
count    9967.000000
mean        2.497652
std         1.542419
min         0.000000
25%         0.000000
50%         3.200000
75%         3.600000
max         5.000000
Name: rtAudienceRating, dtype: float64
================================================================================
====================
```

```
Numerical Distribution of ratings -> rtMlUserMeanRating
count    10109.000000
mean         3.213406
std          0.640538
min          0.500000
25%          2.851293
50%          3.312415
75%          3.681452
max          5.000000
Name: rtMlUserMeanRating, dtype: float64
================================================================================
====================
```



- As can be seen from the above distributions, all these ratings are not normally distrbuted. Infact it seems, **0** rating has the most number of entries.
- Also, as explained in the Missing Data, 0 rating for RottenTomatoes doesn't mean anything as ratings are scaled from 1-10.
- Therefore, we can assume these **0** rated entries as missing data and can replace that missing data with proper np.nan in pandas

[5]:
```
# replace missing data 0 with proper nan
for i in range(len(rating_col_interested)):
    df_movies.loc[df_movies[rating_col_interested[i]] == 0,␣
 ↪rating_col_interested[i]] = np.nan
```

- This distribution is acceptable and seems reasonable as well as we have missing value rather than errorenous data(**0** rating)
- Now, if we think of filling missing values, one possible way is to check if the missing rating movies have any number of users to give a rating. If not, then that rating can actually have a 0 value.
  - I can fill these no rating available missing values with 0, however, that can impact our paired T-tests and further descriptive analyses.
  - So, in order to do a non-biased analyses, I am skipping to fill any further missing value

[6]:
```
df_rating_describe = df_movies[rating_col_interested].describe().transpose()
total_rt_entires = len(df_movies)
df_rating_describe['% missing'] = (total_rt_entires -␣
 ↪df_rating_describe['count'])*100/total_rt_entires
df_rating_describe
```

[6]:
```
                       count      mean       std  min       25%       50%  \
rtAllCriticsRating    8441.0  6.068404  1.526898  1.2  5.000000  6.200000
rtTopCriticsRating    4662.0  5.930330  1.534093  1.6  4.800000  6.100000
rtAudienceRating      7345.0  3.389258  0.454034  1.5  3.100000  3.400000
rtMlUserMeanRating   10109.0  3.213406  0.640538  0.5  2.851293  3.312415

                          75%   max  % missing
rtAllCriticsRating   7.200000   9.6  17.220751
rtTopCriticsRating   7.100000  10.0  54.280671
rtAudienceRating     3.700000   5.0  27.969010
rtMlUserMeanRating   3.681452   5.0   0.862999
```

2 Comparing Ratings

1. **Numerical and Graphical Distribution comparison for critic ratings (All Critics and Top Critics), the Audience Rating**
   - There are significant number of movies for which no review is available for each of the category, however, `rtTopCriticsRating` and `rtAudienceRating` have the most number of movies for which number of reviews are 0
   - The distribution for `rtAllCriticsRating` and `rtAudienceRating` is *right skewed* however for `rtTopCriticsRating` is left skewed

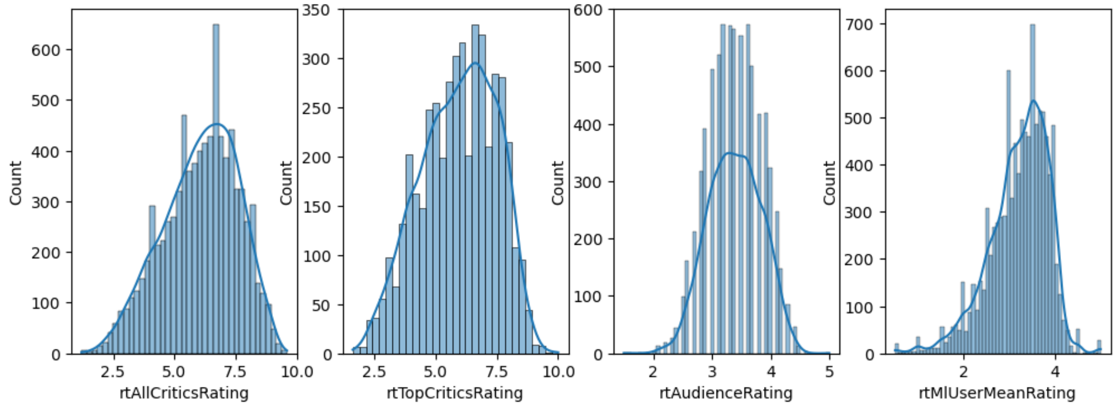
   - `rtAllCriticsRating` in this category, only 25% of the movies have received a rating greater than or equal to 7.1 and 50% movies recieved rating less than or equal to 6.
   - `rtTopCriticsRating` The top 25% of the movies have received a rating greater than or equal to 6.6, lower than `rtAllCriticsRating`, and 50% movies recieved rating less than or equal to 4.7, again lower than `rtAllCriticsRating`.
   - `rtAudienceRating` Top 25% movies have recieved a rating higher than 3.6 with a maximum rating of 5. It seems like this rating is on the scale of 1-5.
   - `rtMlUserMeanRating` as like `rtAudienceRating`, it seems like this rating is on the same scale of 1-5. The top 25% movies have a rating higher than 3.68 with a maximum rating of 5.

[7]:
```
# Let's re visualize that data
fig, axes = plt.subplots(1, len(rating_col_interested), figsize=(12, 4))

for i in range(len(rating_col_interested)):
    print(f'Numerical Distribution of ratings -> {rating_col_interested[i]}')
    print(df_movies[rating_col_interested[i]].describe())
    print('='*100)
```

```
    sns.histplot(x=rating_col_interested[i], ax = axes[i], data = df_movies,␣
 ↪kde = True)
plt.show()
```

```
Numerical Distribution of ratings -> rtAllCriticsRating
count    8441.000000
mean        6.068404
std         1.526898
min         1.200000
25%         5.000000
50%         6.200000
75%         7.200000
max         9.600000
Name: rtAllCriticsRating, dtype: float64
================================================================================
====================
Numerical Distribution of ratings -> rtTopCriticsRating
count    4662.000000
mean        5.930330
std         1.534093
min         1.600000
25%         4.800000
50%         6.100000
75%         7.100000
max        10.000000
Name: rtTopCriticsRating, dtype: float64
================================================================================
====================
Numerical Distribution of ratings -> rtAudienceRating
count    7345.000000
mean        3.389258
std         0.454034
min         1.500000
25%         3.100000
50%         3.400000
75%         3.700000
max         5.000000
Name: rtAudienceRating, dtype: float64
================================================================================
====================
Numerical Distribution of ratings -> rtMlUserMeanRating
count    10109.000000
mean         3.213406
std          0.640538
min          0.500000
25%          2.851293
50%          3.312415
75%          3.681452
```

```
max           5.000000
Name: rtMlUserMeanRating, dtype: float64
================================================================================
====================
```



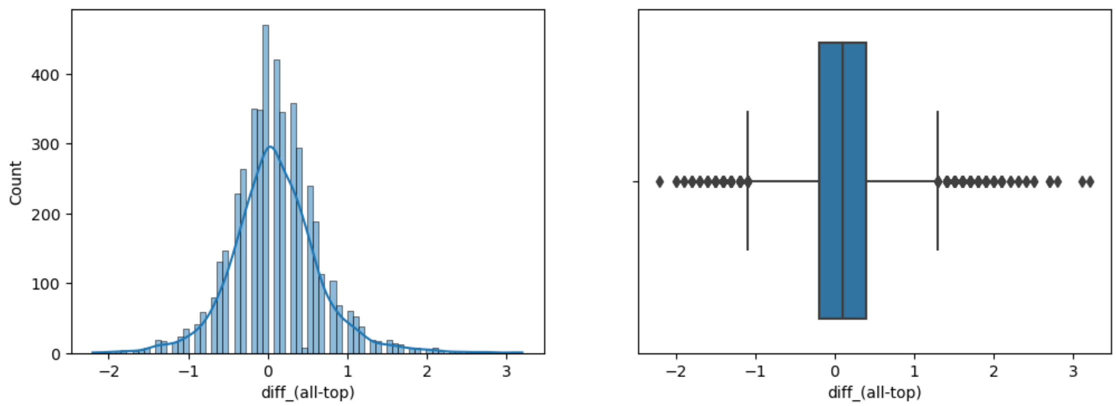
2. **Describe the distribution of the difference between the All Critics and Top Critics ratings for movies where both are defined, both numerically and graphically.**

   - It seems like `rtAllCriticsRating` ratings are generally higher than `rtTopCriticsRating` implying Top Critics seems to be conservative in giving ratings.
   - From the distribution, we can see, on an average, the rating given by `rtAllCriticsRating` user is higher by **0.09** and 50% of the movies rated by both, have always `rtAllCriticsRating` higher ratings compared to `rtTopCriticsRating`

[8]:
```
mask_all = df_movies['rtAllCriticsRating'].isna()
mask_top = df_movies['rtTopCriticsRating'].isna()

df_all_top_rating = df_movies[(~mask_all) & (~mask_top)][['rtAllCriticsRating',␣
↪'rtTopCriticsRating']].copy()
df_all_top_rating['diff_(all-top)'] = df_all_top_rating['rtAllCriticsRating'] -␣
↪df_all_top_rating['rtTopCriticsRating']

print('Numerical Distribution of ratings -> diff_(all-top)')
print(df_all_top_rating['diff_(all-top)'].describe())
print('='*100)

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

sns.histplot(x='diff_(all-top)', data = df_all_top_rating, kde = True,␣
↪ax=axes[0])

sns.boxplot(x='diff_(all-top)', data = df_all_top_rating, ax=axes[1])
```

```
plt.show()
```

```
Numerical Distribution of ratings -> diff_(all-top)
count    4662.000000
mean        0.094123
std         0.549673
min        -2.200000
25%        -0.200000
50%         0.100000
75%         0.400000
max         3.200000
Name: diff_(all-top), dtype: float64
================================================================================
====================
```



3. **Paired T-tests** 3.1. **Between the ratings given to movies by all critics and those given by top critics**
   - I used a significance level of 5% to do the paired T-test
   - From the *paired T-test* it's clear that these 2 ratings are very much different.

[9]:
```
# Null Hypothese -> There is no significance difference between␣
↪'rtAllCriticsRating' and 'rtTopCriticsRating'
# Alternate Hypo -> There is significant difference between␣
↪'rtAllCriticsRating' and 'rtTopCriticsRating'
t_statistic, p_value = stats.ttest_rel(df_all_top_rating['rtAllCriticsRating'],
                                       df_all_top_rating['rtTopCriticsRating']
                                      )

# Print the results
print("Paired T-Test Results:")
print(f"T-statistic: {t_statistic}")
print(f"P-value: {p_value}")
```

```
# Interpret the results
alpha = 0.05  # Significance level
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant difference␣
 ↪between 'rtAllCriticsRating' and 'rtTopCriticsRating'")
else:
    print("Fail to reject the null hypothesis: There is no significant␣
 ↪difference between 'rtAllCriticsRating' and 'rtTopCriticsRating'")
```

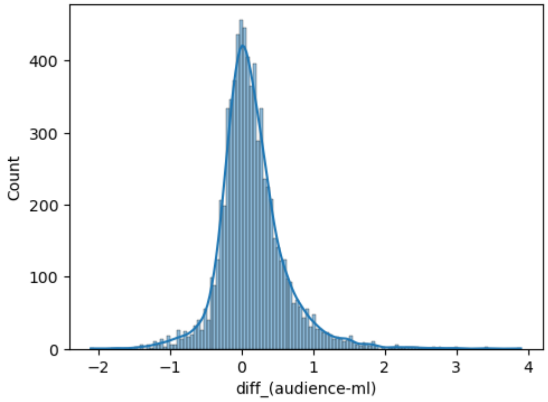
```
Paired T-Test Results:
T-statistic: 11.691646881769833
P-value: 3.813058893006197e-31
Reject the null hypothesis: There is a significant difference between
'rtAllCriticsRating' and 'rtTopCriticsRating'
```

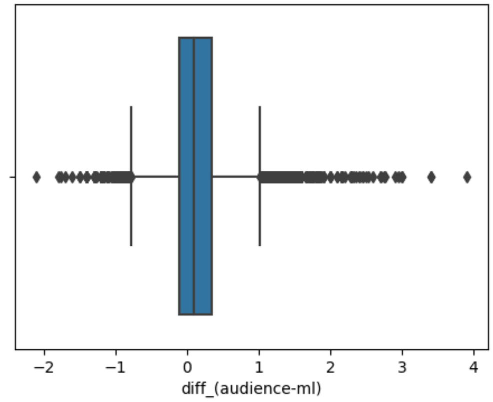
3. **Paird T-tests** 3.1. **Between average audience rating RottenTomatoes users give to a movie and the mean rating MovieLens users**
    - Since these both ratings are on the same scale and thus are compareable.
    - I will compare the ratings where the data is available for both ratings only
    - I used a significance level of 5% to do the paired T-test
    - From the *paired T-test* it's clear that these 2 ratings are very much different.

[10]:
```
mask_audience = df_movies['rtAudienceRating'].isna()
mask_ml_users = df_movies['rtMlUserMeanRating'].isna()

df_both_avail = df_movies[(~mask_audience) & (~mask_ml_users)].copy()

df_both_avail['diff_(audience-ml)'] = df_both_avail['rtAudienceRating'] -␣
 ↪df_both_avail['rtMlUserMeanRating']

print('Numerical Distribution of ratings -> diff_(audience-ml)')
print(df_both_avail['diff_(audience-ml)'].describe())
print('='*100)

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

sns.histplot(x='diff_(audience-ml)', data = df_both_avail, kde = True,␣
 ↪ax=axes[0])

sns.boxplot(x='diff_(audience-ml)', data = df_both_avail, ax=axes[1])
plt.show()


# Null Hypothese -> There is no significance difference between␣
 ↪'rtAudienceRating' and 'rtMlUserMeanRating'
# Alternate Hypo -> There is significant difference between 'rtAudienceRating'␣
 ↪and 'rtMlUserMeanRating'
t_statistic, p_value = stats.ttest_rel(df_both_avail['rtAudienceRating'],
```

```
                                        df_both_avail['rtMlUserMeanRating']
                                       )

# Print the results
print("Paired T-Test Results:")
print(f"T-statistic: {t_statistic}")
print(f"P-value: {p_value}")

# Interpret the results
alpha = 0.05  # Significance level
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant difference␣
 ↪between 'rtAudienceRating' and 'rtMlUserMeanRating'")
else:
    print("Fail to reject the null hypothesis: There is no significant␣
 ↪difference between 'rtAudienceRating' and 'rtMlUserMeanRating'")
```

```
Numerical Distribution of ratings -> diff_(audience-ml)
count    7314.000000
mean        0.148691
std         0.457967
min        -2.100000
25%        -0.106454
50%         0.091838
75%         0.343147
max         3.900000
Name: diff_(audience-ml), dtype: float64
================================================================================
====================
```






```
Paired T-Test Results:
T-statistic: 27.76689581170543
P-value: 2.0388425974633915e-161
```

```
Reject the null hypothesis: There is a significant difference between
'rtAudienceRating' and 'rtMlUserMeanRating'
```

3 Confidence Intervals

[11]:
```
df_genres = pd.read_table('movie_genres.dat', sep='\t', na_values=['\\N'],␣
↪encoding='latin1', low_memory=False)

# Merge ratings with genres
df_genres = df_genres.merge(df_movies, on='movieID')
```

[12]:
```
df_ci = df_genres.groupby('genre').agg({'rtAllCriticsRating':
                                                              ␣
↪['count','min','max','median','mean','std']}
                                       ).reset_index().copy()
df_ci.columns = df_ci.columns.droplevel(level=0)
df_ci.rename(columns={'':'genre'}, inplace=True)
```

1. **For each of the 20 genres, compute the mean and a 95% confidence interval for the all-critic ratings using the standard error method. Show the results as a data frame sorted by decreasing mean (look up the sort_values method in Pandas). Does it look like the top two genres have different mean critic ratings? Does it look like the top and bottom genres have different mean critic ratings? Defend your answers using the confidence intervals.**

Below is the sorted dataframe for all 20 genres showing confidence interevals and corresponding standard errors. The dataframe is sorted by `mean` value in a decresing order.

`The top two genres have different mean critic ratings?` Indeed the top 2 genres (Film-Noir, Documentary) have different critics rating, as the mean rating for **Film-Noir** will be between 7.48 and 7.03 however for Documentary it can be 7.23 and 7.03. These ranges are quite different hence the top 2 genres have different mean critic ratings.

`Bottom genres have different mean critic ratings` as like top 2 rated genres, the bottom 2 genres also don't have same mean critic ratings.

[13]:
```
col_mean = ('mean')
col_std = ('std')
col_count = ('count')
z_value = 1.96 # for 95% confidence interval

df_ci['std_error'] = df_ci[col_std]/ np.sqrt(df_ci[col_count])
df_ci['ci_higher'] = df_ci[col_mean] + z_value*df_ci['std_error']
df_ci['ci_lower'] = df_ci[col_mean] - z_value*df_ci['std_error']
df_ci = df_ci.sort_values(by=col_mean, ascending= False)

df_ci
```

[13]:

	genre	count	min	max	median	mean	std	std_error
9	Film-Noir	127	3.7	9.3	7.60	7.253543	1.273527	0.113007
6	Documentary	334	2.6	9.1	7.30	7.129641	0.979147	0.053577
11	IMAX	16	5.9	8.4	7.00	6.950000	0.747440	0.186860
18	War	388	1.9	9.2	6.90	6.753351	1.354775	0.068778
19	Western	193	1.8	9.0	6.70	6.613472	1.394007	0.100343
12	Musical	347	2.3	9.4	6.70	6.483573	1.319328	0.070825
7	Drama	4306	1.9	9.6	6.60	6.462657	1.337138	0.020377
2	Animation	235	3.0	9.1	6.40	6.343404	1.393417	0.090897
13	Mystery	434	1.9	9.4	6.40	6.228571	1.488513	0.071451
14	Romance	1427	1.9	9.5	6.30	6.194744	1.432974	0.037934
5	Crime	943	2.0	9.3	6.30	6.161612	1.494892	0.048680
8	Fantasy	458	2.0	9.5	6.00	6.023362	1.577800	0.073726
1	Adventure	817	1.6	9.2	6.10	5.952876	1.519157	0.053149
17	Thriller	1452	1.7	9.3	6.00	5.856680	1.503450	0.039455
3	Children	442	1.9	9.2	5.85	5.779864	1.532010	0.072870
4	Comedy	3030	1.2	9.5	5.80	5.732409	1.546115	0.028088
0	Action	1192	1.4	9.2	5.60	5.574497	1.560583	0.045201
15	Sci-Fi	571	1.3	8.9	5.60	5.567601	1.554942	0.065072
10	Horror	784	1.2	9.2	5.50	5.471046	1.601864	0.057209
16	Short	0	NaN	NaN	NaN	NaN	NaN	NaN

	ci_higher	ci_lower
9	7.475038	7.032049
6	7.234651	7.024631
11	7.316246	6.583754
18	6.888156	6.618545
19	6.810143	6.416800
12	6.622391	6.344756
7	6.502596	6.422718
2	6.521561	6.165247
13	6.368615	6.088528
14	6.269094	6.120394
5	6.257025	6.066198
8	6.167865	5.878860
1	6.057048	5.848705
17	5.934013	5.779348
3	5.922690	5.637039
4	5.787462	5.677357
0	5.663091	5.485903
15	5.695142	5.440059
10	5.583176	5.358915
16	NaN	NaN

2. **For each of the 20 genres, compute the mean and a 95% bootstrapped confidence interval for the mean all-critic rating. Show the result in a table. Does this look the same as the standard error CIs?**

- I used the same code available in PenguinSamples.ipynb to do the bootstrap.
- The CIs computed using Standard Error and Bootstrap are not exactly the same for all genres.

[14]:
```
rng = np.random.default_rng(20200913)

def boot_mean_estimate(vals, nboot=10000):
    obs = vals.dropna()  # ignore missing values
    mean = obs.mean()
    n = obs.count()

    if n == 0:
        return pd.Series({
            'mean_bootstrap': np.nan,
            'ci_bootstrap_lower': np.nan,
            'ci_bootstrap_higher': np.nan
        })

    boot_means = [np.mean(rng.choice(obs, size=n)) for i in range(nboot)]
    ci_low, ci_high = np.quantile(boot_means, [0.025, 0.975])
    return pd.Series({
        'mean_bootstrap': mean,
        'ci_bootstrap_lower': ci_low,
        'ci_bootstrap_higher': ci_high
    })


df_bootstrap = df_genres.groupby('genre')['rtAllCriticsRating'].
 ↪apply(boot_mean_estimate).unstack().reset_index()

df_ci = df_ci.merge(df_bootstrap, on = 'genre')
df_ci = df_ci.sort_values(by=col_mean, ascending= False)
df_ci['is_CIs_same'] = (df_ci['ci_higher'] == df_ci['ci_bootstrap_higher']) &␣
 ↪(df_ci['ci_lower'] == df_ci['ci_bootstrap_lower'])
df_ci
```

[14]:

	genre	count	min	max	median	mean	std	std_error	\
0	Film-Noir	127	3.7	9.3	7.60	7.253543	1.273527	0.113007	
1	Documentary	334	2.6	9.1	7.30	7.129641	0.979147	0.053577	
2	IMAX	16	5.9	8.4	7.00	6.950000	0.747440	0.186860	
3	War	388	1.9	9.2	6.90	6.753351	1.354775	0.068778	
4	Western	193	1.8	9.0	6.70	6.613472	1.394007	0.100343	
5	Musical	347	2.3	9.4	6.70	6.483573	1.319328	0.070825	
6	Drama	4306	1.9	9.6	6.60	6.462657	1.337138	0.020377	
7	Animation	235	3.0	9.1	6.40	6.343404	1.393417	0.090897	
8	Mystery	434	1.9	9.4	6.40	6.228571	1.488513	0.071451	
9	Romance	1427	1.9	9.5	6.30	6.194744	1.432974	0.037934	

10	Crime	943	2.0	9.3	6.30	6.161612	1.494892	0.048680
11	Fantasy	458	2.0	9.5	6.00	6.023362	1.577800	0.073726
12	Adventure	817	1.6	9.2	6.10	5.952876	1.519157	0.053149
13	Thriller	1452	1.7	9.3	6.00	5.856680	1.503450	0.039455
14	Children	442	1.9	9.2	5.85	5.779864	1.532010	0.072870
15	Comedy	3030	1.2	9.5	5.80	5.732409	1.546115	0.028088
16	Action	1192	1.4	9.2	5.60	5.574497	1.560583	0.045201
17	Sci-Fi	571	1.3	8.9	5.60	5.567601	1.554942	0.065072
18	Horror	784	1.2	9.2	5.50	5.471046	1.601864	0.057209
19	Short	0	NaN	NaN	NaN	NaN	NaN	NaN

	ci_higher	ci_lower	mean_bootstrap	ci_bootstrap_lower	\
0	7.475038	7.032049	7.253543	7.029921	
1	7.234651	7.024631	7.129641	7.020951	
2	7.316246	6.583754	6.950000	6.606250	
3	6.888156	6.618545	6.753351	6.618557	
4	6.810143	6.416800	6.613472	6.412435	
5	6.622391	6.344756	6.483573	6.345814	
6	6.502596	6.422718	6.462657	6.422734	
7	6.521561	6.165247	6.343404	6.167660	
8	6.368615	6.088528	6.228571	6.088249	
9	6.269094	6.120394	6.194744	6.119690	
10	6.257025	6.066198	6.161612	6.067017	
11	6.167865	5.878860	6.023362	5.879907	
12	6.057048	5.848705	5.952876	5.847858	
13	5.934013	5.779348	5.856680	5.779475	
14	5.922690	5.637039	5.779864	5.635294	
15	5.787462	5.677357	5.732409	5.677855	
16	5.663091	5.485903	5.574497	5.487408	
17	5.695142	5.440059	5.567601	5.438529	
18	5.583176	5.358915	5.471046	5.356626	
19	NaN	NaN	NaN	NaN	

	ci_bootstrap_higher	is_CIs_same
0	7.467717	False
1	7.235030	False
2	7.306250	False
3	6.887113	False
4	6.805699	False
5	6.621909	False
6	6.502323	False
7	6.519574	False
8	6.367972	False
9	6.270922	False
10	6.256734	False
11	6.170311	False
12	6.056429	False

```
13           5.934160        False
14           5.919457        False
15           5.786272        False
16           5.662334        False
17           5.694225        False
18           5.583039        False
19                NaN        False
```

4 Popularity and Bootstraps

1. **Test the null hypothesis that action movies and documentaries have the same median number of ratings using a bootstrapped p-value. Does your test accept or reject the null? What are the median number of ratings for movies in each of these genres?**
   - We accept the null hypotheses based on bootstrapped p-value

[15]:
```
df_movie_user_count = df_ml_ratings.groupby('movieID')['userID'].count().
 ↪reset_index()
df_movie_user_count.rename(columns={'userID':'numRatings'}, inplace=True)
df_movie_user_count = df_movie_user_count.merge(df_genres[['movieID','genre']],␣
 ↪on='movieID')
df_action = df_movie_user_count[df_movie_user_count['genre'] == 'Action'].copy()
df_doc = df_movie_user_count[df_movie_user_count['genre'] == 'Documentary'].
 ↪copy()
```

[16]:
```
# Calculate the observed difference in median ratings
observed_difference = np.median(df_action['numRatings']) - np.
 ↪median(df_doc['numRatings'])

# Number of bootstrap samples
num_samples = 10000

# Initialize an empty array to store bootstrap differences
bootstrap_differences = np.empty(num_samples)

# Perform bootstrapping
for i in range(num_samples):
    # Randomly sample with replacement from both genres
    action_sample = np.random.choice(df_action['numRatings'],␣
 ↪len(df_action['numRatings']), replace=True)
    documentary_sample = np.random.choice(df_doc['numRatings'],␣
 ↪len(df_doc['numRatings']), replace=True)

    # Calculate the difference in medians for this sample
    bootstrap_differences[i] = np.median(action_sample) - np.
 ↪median(documentary_sample)
```

```python
# Calculate the p-value
p_value = np.mean(bootstrap_differences >= observed_difference)

alpha = 0.05  # Set your significance level
if p_value < alpha:
    result = "Reject the null hypothesis"
else:
    result = "Accept the null hypothesis"

# Calculate the median number of ratings for each genre
median_ratings_action = np.median(df_action['numRatings'])
median_ratings_documentary = np.median(df_doc['numRatings'])

# Print results
print(f"Observed Difference in Median Ratings: {observed_difference}")
print(f"Bootstrapped p-value: {p_value}")
print(f"Result: {result}")
print(f"Median Ratings for Action Movies: {median_ratings_action}")
print(f"Median Ratings for Documentaries: {median_ratings_documentary}")
```

```
Observed Difference in Median Ratings: 44.5
Bootstrapped p-value: 0.4756
Result: Accept the null hypothesis
Median Ratings for Action Movies: 56.0
Median Ratings for Documentaries: 11.5
```

2. **What if you use the # of audience ratings from RottenTomatoes instead of the # of MovieLens ratings?**
   - The results are same even if we use # of audience ratings

[17]:
```python
df_aud = df_genres[['movieID','genre']].
 ↪merge(df_movies[['movieID','rtAudienceNumRatings']], on='movieID').copy()
df_aud.dropna(inplace=True)
df_action = df_aud[df_aud['genre'] == 'Action'].copy()
df_doc = df_aud[df_aud['genre'] == 'Documentary'].copy()

# Calculate the observed difference in median ratings
observed_difference = np.median(df_action['rtAudienceNumRatings']) - np.
 ↪median(df_doc['rtAudienceNumRatings'])

# Number of bootstrap samples
num_samples = 10000

# Initialize an empty array to store bootstrap differences
bootstrap_differences = np.empty(num_samples)

# Perform bootstrapping
```

```
for i in range(num_samples):
    # Randomly sample with replacement from both genres
    action_sample = np.random.choice(df_action['rtAudienceNumRatings'],␣
↪len(df_action['rtAudienceNumRatings']), replace=True)
    documentary_sample = np.random.choice(df_doc['rtAudienceNumRatings'],␣
↪len(df_doc['rtAudienceNumRatings']), replace=True)

    # Calculate the difference in medians for this sample
    bootstrap_differences[i] = np.median(action_sample) - np.
↪median(documentary_sample)

# Calculate the p-value
p_value = np.mean(bootstrap_differences >= observed_difference)

alpha = 0.05  # Set your significance level
if p_value < alpha:
    result = "Reject the null hypothesis"
else:
    result = "Accept the null hypothesis"

# Calculate the median number of ratings for each genre
median_ratings_action = np.median(df_action['rtAudienceNumRatings'])
median_ratings_documentary = np.median(df_doc['rtAudienceNumRatings'])

# Print results
print(f"Observed Difference in Median Ratings: {observed_difference}")
print(f"Bootstrapped p-value: {p_value}")
print(f"Result: {result}")
print(f"Median Ratings for Action Movies: {median_ratings_action}")
print(f"Median Ratings for Documentaries: {median_ratings_documentary}")
```

```
Observed Difference in Median Ratings: 4866.0
Bootstrapped p-value: 0.4981
Result: Accept the null hypothesis
Median Ratings for Action Movies: 5353.0
Median Ratings for Documentaries: 487.0
```

3. **Compare the mean of the critic ratings (using the All Critics ratings from Rotten Tomatoes) between action and documentary movies. Is there a difference? Test the difference with both the bootstrap and an approprate t-test.**

   - Based on the rating `rtAllCriticsRating`, on average, action movies in the sample received a critic rating of approximately 5.57 & documentary movies 7.13
   - The very small p-value indicates that there is strong evidence to suggest that the difference in mean critic ratings between action and documentary movies is statistically significant. In other words, it's highly unlikely that the observed difference in mean ratings occurred by chance.
   - The CI suggests that, with 95% confidence, the true difference in mean critic ratings

between action and documentary movies is likely to be somewhere between -1.69271119 and -1.42091679.
- Since this interval does not include zero, it further supports the conclusion that there is a significant difference in mean critic ratings between the two types of movies.

[18]:
```
df_aud = df_genres[['movieID','genre']].
 ↪merge(df_movies[['movieID','rtAllCriticsRating']], on='movieID').copy()
df_aud.dropna(inplace=True)
df_action = df_aud[df_aud['genre'] == 'Action'].copy()
df_doc = df_aud[df_aud['genre'] == 'Documentary'].copy()

# Calculate the means of critic ratings for each group
mean_action = np.mean(df_action['rtAllCriticsRating'])
mean_documentary = np.mean(df_doc['rtAllCriticsRating'])

# Perform a two-sample t-test
t_stat, p_value = stats.ttest_ind(df_action['rtAllCriticsRating'],␣
 ↪df_doc['rtAllCriticsRating'])

# Bootstrap resampling
n_bootstrap = 10000
bootstrap_means_diff = np.zeros(n_bootstrap)

for i in range(n_bootstrap):
    action_sample = np.random.choice(df_action['rtAllCriticsRating'],␣
 ↪len(df_action['rtAllCriticsRating']), replace=True)
    documentary_sample = np.random.choice(df_doc['rtAllCriticsRating'],␣
 ↪len(df_doc['rtAllCriticsRating']), replace=True)
    bootstrap_means_diff[i] = np.mean(action_sample) - np.
 ↪mean(documentary_sample)

# Calculate a 95% confidence interval for the bootstrap mean difference
confidence_interval = np.percentile(bootstrap_means_diff, [2.5, 97.5])

# Print the results
print(f"Mean Critic Rating for Action Movies: {mean_action}")
print(f"Mean Critic Rating for Documentary Movies: {mean_documentary}")
print(f"Two-sample t-test p-value: {p_value}")
print(f"95% Confidence Interval for Bootstrap Mean Difference:␣
 ↪{confidence_interval}")
```

```
Mean Critic Rating for Action Movies: 5.5744966442953015
Mean Critic Rating for Documentary Movies: 7.129640718562875
Two-sample t-test p-value: 3.0246362376002706e-61
95% Confidence Interval for Bootstrap Mean Difference: [-1.68944429 -1.41795421]
```

5 Reflection

- **Learnings**
  - I first learned the concept of descriptive statistics and how to read the visualization graphs. I learnt to perform different tests, such as `paird T-test`, `Bootstrap p-value` etc., and how to use these tests to make conclusions about data.
    - Like using `paird T-test` I was able to comment whether ratings *rtAllCriticsRating* and *rtTopCriticsRating* are same or different.
  - I also learnt how to calculate the Confidence Intervals using both `Standaed Error` and `Bootstrap`. From this I think `Bootstrap` is a better method to compute the CIs as we are taking samples with replacement and using that sample means to get the qunatile ranges which seems more robust than `Standaed Error`.
  - It helped in my critical thinking as I was asked to defend my answers using confidence intervals and statistical tests. This process encouraged critical thinking and helped me interpret the results in the context of the data.

Other than these learings, I learned in general about movie ratings, what different ratings mean and how do these differ from one another. Another thing I enjoyed doing this is helping on my python programming skills and using math in python coding. So overall a great learning from this assignment :)