
Capstone Project - Solution

Overview

If you are planning on going out to see a movie, how well can you trust online reviews and ratings? *Especially* if the same company showing the rating *also* makes money by selling movie tickets. Do they have a bias towards rating movies higher than they should be rated?

Goal:

Your goal is to complete the tasks below based off the 538 article and see if you reach a similar conclusion. You will need to use your pandas and visualization skills to determine if Fandango's ratings in 2015 had a bias towards rating movies better to sell more tickets.

Complete the tasks written in bold.

Part One: Understanding the Background and Data

TASK: Read this article: Be Suspicious Of Online Movie Ratings, Especially Fandango's

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TASK: After reading the article, read these two tables giving an overview of the two .csv files we will be working with:

The Data

This is the data behind the story Be Suspicious Of Online Movie Ratings, Especially Fandango's openly available on 538's github: https://github.com/fivethirtyeight/data. There are two csv files, one with Fandango Stars and Displayed Ratings, and the other with aggregate data for movie ratings from other sites, like Metacritic,IMDB, and Rotten Tomatoes.

all_sites_scores.csv

`all_sites_scores.csv` contains every film that has a Rotten Tomatoes rating, a RT User rating, a Metacritic score, a Metacritic User score, and IMDb score, and at least 30 fan reviews on Fandango. The data from Fandango was pulled on Aug. 24, 2015.

Column	Definition
FILM	The film in question
RottenTomatoes	The Rotten Tomatoes Tomatometer score for the film
RottenTomatoes_User	The Rotten Tomatoes user score for the film
Metacritic	The Metacritic critic score for the film
Metacritic_User	The Metacritic user score for the film
IMDB	The IMDb user score for the film
Metacritic_user_vote_count	The number of user votes the film had on Metacritic
IMDB_user_vote_count	The number of user votes the film had on IMDb

----

fandango_scape.csv

`fandango_scrape.csv` contains every film 538 pulled from Fandango.

Column	Definiton
FILM	The movie
STARS	Number of stars presented on Fandango.com
RATING	The Fandango ratingValue for the film, as pulled from the HTML of each page. This is the actual average score the movie obtained.
VOTES	number of people who had reviewed the film at the time we pulled it.

TASK: Import any libraries you think you will use:

```
# IMPORT HERE!
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Part Two: Exploring Fandango Displayed Scores versus True User Ratings

Let's first explore the Fandango ratings to see if our analysis agrees with the article's conclusion.

TASK: Run the cell below to read in the fandango_scrape.csv file

```
fandango = pd.read_csv("fandango_scrape.csv")
```

TASK: Explore the DataFrame Properties and Head.

```
fandango.head()
```

```
                             FILM  STARS  RATING  VOTES
0  Fifty Shades of Grey (2015)    4.0     3.9  34846
1        Jurassic World (2015)    4.5     4.5  34390
2       American Sniper (2015)    5.0     4.8  34085
3             Furious 7 (2015)    5.0     4.8  33538
4            Inside Out (2015)    4.5     4.5  15749
```

```
fandango.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 504 entries, 0 to 503
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   FILM    504 non-null    object
 1   STARS   504 non-null    float64
 2   RATING  504 non-null    float64
 3   VOTES   504 non-null    int64
dtypes: float64(2), int64(1), object(1)
memory usage: 15.9+ KB
```

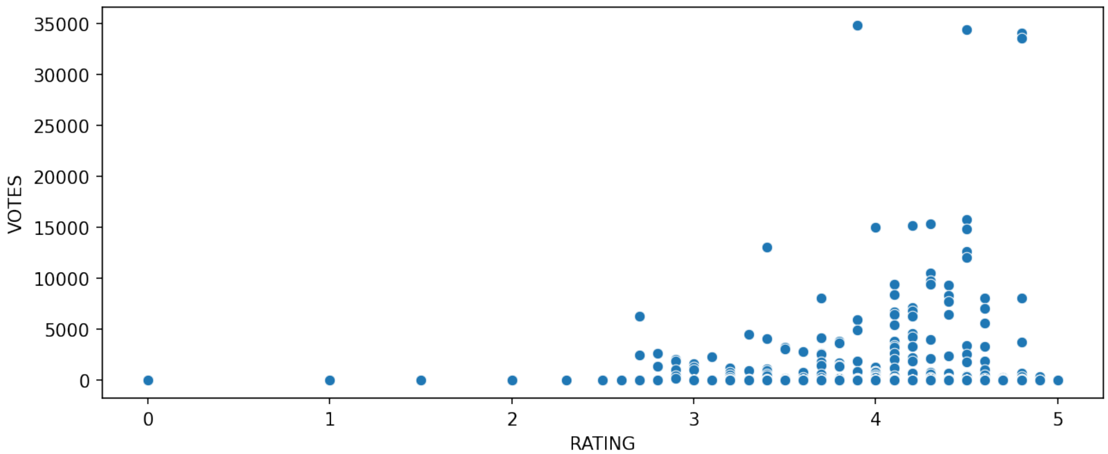
```
fandango.describe()
```

```
            STARS      RATING         VOTES
count  504.000000  504.000000    504.000000
mean     3.558532    3.375794   1147.863095
std      1.563133    1.491223   3830.583136
min      0.000000    0.000000      0.000000
25%      3.500000    3.100000      3.000000
50%      4.000000    3.800000     18.500000
75%      4.500000    4.300000    189.750000
max      5.000000    5.000000  34846.000000
```

TASK: Let's explore the relationship between popularity of a film and its rating. Create a scatterplot showing the relationship between rating and votes. Feel free to edit visual styling to your preference.

```
# CODE HERE
```

```
plt.figure(figsize=(10,4),dpi=150)
sns.scatterplot(data=fandango,x='RATING',y='VOTES');
```



TASK: Calculate the correlation between the columns:

```
# CODE HERE
```

```
fandango.corr()
```

	STARS	RATING	VOTES
STARS	1.000000	0.994696	0.164218
RATING	0.994696	1.000000	0.163764
VOTES	0.164218	0.163764	1.000000

TASK: Assuming that every row in the FILM title column has the same format:

```
Film Title Name (Year)
```

Create a new column that is able to strip the year from the title strings and set this new column as YEAR

```
# CODE HERE
```

```
fandango['YEAR'] = fandango['FILM'].apply(lambda
title:title.split('(')[-1])
```

```
fandango
```

	FILM	STARS	RATING	VOTES	YEAR
0	Fifty Shades of Grey (2015)	4.0	3.9	34846	2015)
1	Jurassic World (2015)	4.5	4.5	34390	2015)
2	American Sniper (2015)	5.0	4.8	34085	2015)
3	Furious 7 (2015)	5.0	4.8	33538	2015)
4	Inside Out (2015)	4.5	4.5	15749	2015)
..	...	...	...	...	...
499	Valiyavan (2015)	0.0	0.0	0	2015)
500	WWE SummerSlam 2015 (2015)	0.0	0.0	0	2015)
501	Yagavarayinum Naa Kaakka (2015)	0.0	0.0	0	2015)
502	Yesterday, Today and Tomorrow (1964)	0.0	0.0	0	1964)
503	Zarafa (2012)	0.0	0.0	0	2012)

```
[504 rows x 5 columns]
```

TASK: How many movies are in the Fandango DataFrame per year?

```
#CODE HERE
```

```
fandango['YEAR'].value_counts()
```

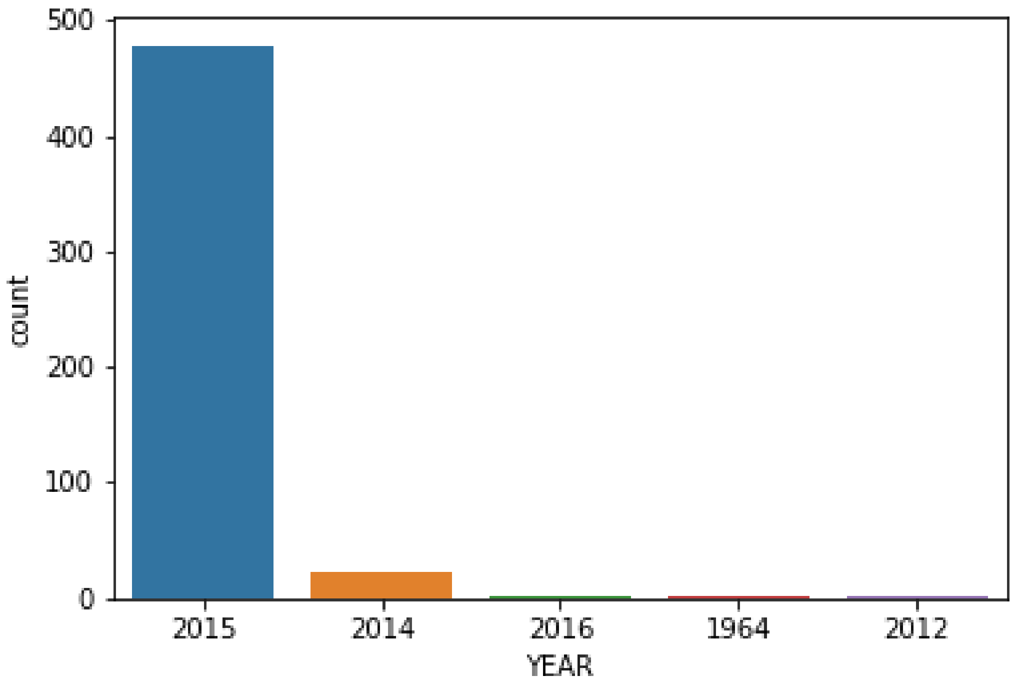
```
2015)    478
2014)     23
2016)      1
1964)      1
2012)      1
Name: YEAR, dtype: int64
```

TASK: Visualize the count of movies per year with a plot:

```
#CODE HERE
```

```
sns.countplot(data=fandango,x='YEAR')
```

```
<AxesSubplot:xlabel='YEAR', ylabel='count'>
```



TASK: What are the 10 movies with the highest number of votes?

```
#CODE HERE
```

```
fandango.nlargest(10,'VOTES')
```

```
                                             FILM  STARS  RATING
VOTES  \
0                      Fifty Shades of Grey (2015)    4.0     3.9
34846
1                            Jurassic World (2015)    4.5     4.5
34390
2                           American Sniper (2015)    5.0     4.8
34085
3                                 Furious 7 (2015)    5.0     4.8
33538
4                                Inside Out (2015)    4.5     4.5
15749
5  The Hobbit: The Battle of the Five Armies (2014)    4.5     4.3
15337
6               Kingsman: The Secret Service (2015)    4.5     4.2
15205
7                                   Minions (2015)    4.0     4.0
14998
8                   Avengers: Age of Ultron (2015)    5.0     4.5
14846
9                            Into the Woods (2014)    3.5     3.4
13055

   YEAR
0  2015
1  2015
2  2015
3  2015
4  2015
5  2014
6  2015
7  2015
8  2015
9  2014
```

TASK: How many movies have zero votes?

```
#CODE HERE

no_votes = fandango['VOTES']==0
no_votes.sum()
```

```
69
```

TASK: Create DataFrame of only reviewed films by removing any films that have zero votes.

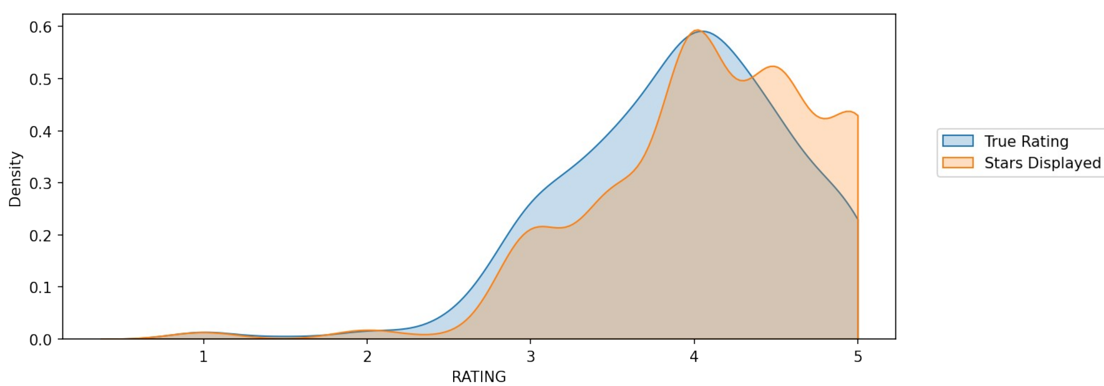
```
#CODE HERE

fan_reviewed = fandango[fandango['VOTES']>0]
```

As noted in the article, due to HTML and star rating displays, the true user rating may be slightly different than the rating shown to a user. Let's visualize this difference in distributions.

TASK: Create a KDE plot (or multiple kdeplots) that displays the distribution of ratings that are displayed (STARS) versus what the true rating was from votes (RATING). Clip the KDEs to 0-5.

```
#CODE HERE

plt.figure(figsize=(10,4),dpi=150)
sns.kdeplot(data=fan_reviewed,x='RATING',clip=[0,5],fill=True,label='T
rue Rating')
sns.kdeplot(data=fan_reviewed,x='STARS',clip=[0,5],fill=True,label='St
ars Displayed')

plt.legend(loc=(1.05,0.5))
```

```
<matplotlib.legend.Legend at 0x1aa0110cdc8>
```



TASK: Let's now actually quantify this discrepancy. Create a new column of the different between STARS displayed versus true RATING. Calculate this difference with STARS-RATING and round these differences to the nearest decimal point.

```
#CODE HERE

fan_reviewed["STARS_DIFF"] = fan_reviewed['STARS'] -
fan_reviewed['RATING']
fan_reviewed['STARS_DIFF'] = fan_reviewed['STARS_DIFF'].round(2)

fan_reviewed
```

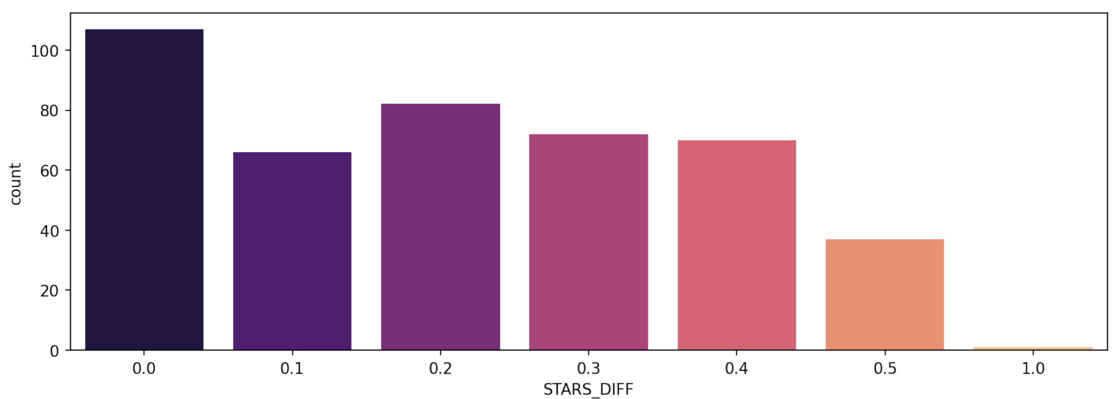
```
                            FILM  STARS  RATING  VOTES  YEAR
STARS_DIFF
0    Fifty Shades of Grey (2015)    4.0     3.9  34846  2015
0.1
1          Jurassic World (2015)    4.5     4.5  34390  2015
0.0
2         American Sniper (2015)    5.0     4.8  34085  2015
```

```
0.2
3               Furious 7 (2015)    5.0     4.8  33538  2015
0.2
4              Inside Out (2015)    4.5     4.5  15749  2015
0.0
..                           ...    ...     ...    ...   ...         .
..
430      That Sugar Film (2015)    5.0     5.0      1  2015
0.0
431          The Intern (2015)    5.0     5.0      1  2015
0.0
432       The Park Bench (2015)    5.0     5.0      1  2015
0.0
433        The Wanted 18 (2015)    5.0     5.0      1  2015
0.0
434      Z For Zachariah (2015)    5.0     5.0      1  2015
0.0

[435 rows x 6 columns]
```

TASK: Create a count plot to display the number of times a certain difference occurs:

```
#CODE HERE

plt.figure(figsize=(12,4),dpi=150)
sns.countplot(data=fan_reviewed,x='STARS_DIFF',palette='magma')
```

```
<AxesSubplot:xlabel='STARS_DIFF', ylabel='count'>
```



TASK: We can see from the plot that one movie was displaying over a 1 star difference than its true rating! What movie had this close to 1 star differential?

```
#CODE HERE

fan_reviewed[fan_reviewed['STARS_DIFF'] == 1]
```

```
                 FILM  STARS  RATING  VOTES  YEAR  STARS_DIFF
381  Turbo Kid (2015)    5.0     4.0      2  2015         1.0
```

Part Three: Comparison of Fandango Ratings to Other Sites

Let's now compare the scores from Fandango to other movies sites and see how they compare.

TASK: Read in the "all_sites_scores.csv" file by running the cell below

```
all_sites = pd.read_csv("all_sites_scores.csv")
```

TASK: Explore the DataFrame columns, info, description.

```
all_sites.head()
```

```
                             FILM  RottenTomatoes  RottenTomatoes_User  \
0  Avengers: Age of Ultron (2015)              74                   86   
1               Cinderella (2015)              85                   80   
2                  Ant-Man (2015)              80                   90   
3          Do You Believe? (2015)              18                   84   
4   Hot Tub Time Machine 2 (2015)              14                   28   

   Metacritic  Metacritic_User  IMDB  Metacritic_user_vote_count  \
0          66              7.1   7.8                        1330   
1          67              7.5   7.1                         249   
2          64              8.1   7.8                         627   
3          22              4.7   5.4                          31   
4          29              3.4   5.1                          88   

   IMDB_user_vote_count  
0                271107  
1                 65709  
2                103660  
3                  3136  
4                 19560  
```

```
all_sites.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146 entries, 0 to 145
Data columns (total 8 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   FILM                        146 non-null    object 
 1   RottenTomatoes              146 non-null    int64  
```

```
 2   RottenTomatoes_User         146 non-null    int64
 3   Metacritic                  146 non-null    int64
 4   Metacritic_User             146 non-null    float64
 5   IMDB                        146 non-null    float64
 6   Metacritic_user_vote_count  146 non-null    int64
 7   IMDB_user_vote_count        146 non-null    int64
dtypes: float64(2), int64(5), object(1)
memory usage: 9.2+ KB
```

```
all_sites.describe()
```

```
       RottenTomatoes  RottenTomatoes_User  Metacritic
Metacritic_User  \
count      146.000000           146.000000  146.000000
146.000000
mean        60.849315            63.876712   58.808219
6.519178
std         30.168799            20.024430   19.517389
1.510712
min          5.000000            20.000000   13.000000
2.400000
25%         31.250000            50.000000   43.500000
5.700000
50%         63.500000            66.500000   59.000000
6.850000
75%         89.000000            81.000000   75.000000
7.500000
max        100.000000            94.000000   94.000000
9.600000

             IMDB  Metacritic_user_vote_count  IMDB_user_vote_count
count  146.000000                  146.000000            146.000000
mean     6.736986                  185.705479          42846.205479
std      0.958736                  316.606515          67406.509171
min      4.000000                    4.000000            243.000000
25%      6.300000                   33.250000           5627.000000
50%      6.900000                   72.500000          19103.000000
75%      7.400000                  168.500000          45185.750000
max      8.600000                 2375.000000         334164.000000
```

Rotten Tomatoes

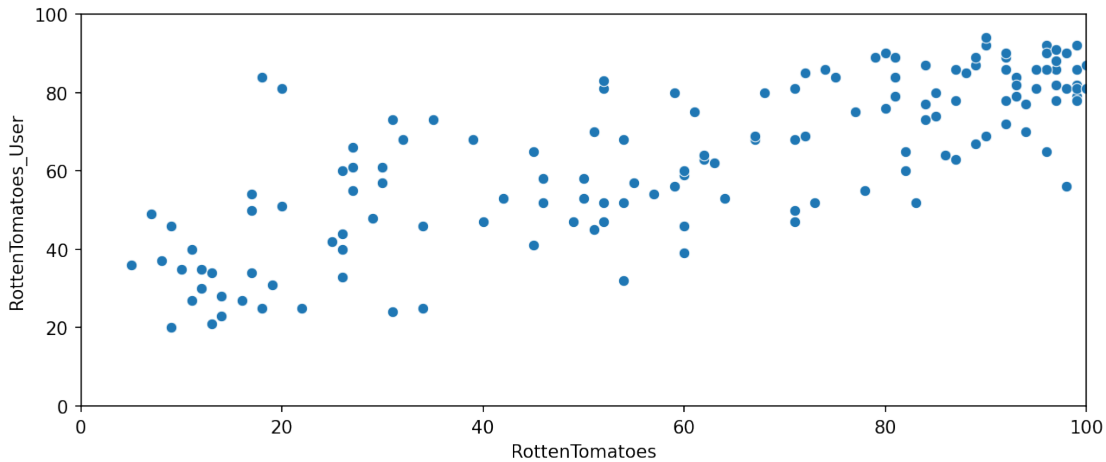
Let's first take a look at Rotten Tomatoes. RT has two sets of reviews, their critics reviews (ratings published by official critics) and user reviews.

TASK: Create a scatterplot exploring the relationship between RT Critic reviews and RT User reviews.

```
# CODE HERE
```

```
plt.figure(figsize=(10,4),dpi=150)
sns.scatterplot(data=all_sites,x='RottenTomatoes',y='RottenTomatoes_User')
plt.xlim(0,100)
plt.ylim(0,100)
```

```
(0.0, 100.0)
```



Let's quantify this difference by comparing the critics ratings and the RT User ratings. We will calculate this with RottenTomatoes-RottenTomatoes_User. Note: Rotten_Diff here is Critics - User Score. So values closer to 0 means aggrement between Critics and Users. Larger positive values means critics rated much higher than users. Larger negative values means users rated much higher than critics.

TASK: Create a new column based off the difference between critics ratings and users ratings for Rotten Tomatoes. Calculate this with RottenTomatoes-RottenTomatoes_User

```
#CODE HERE
```

```
all_sites['Rotten_Diff']  = all_sites['RottenTomatoes'] - all_sites['RottenTomatoes_User']
```

Let's now compare the overall mean difference. Since we're dealing with differences that could be negative or positive, first take the absolute value of all the differences, then take the mean. This would report back on average to absolute difference between the critics rating versus the user rating.

TASK: Calculate the Mean Absolute Difference between RT scores and RT User scores as described above.

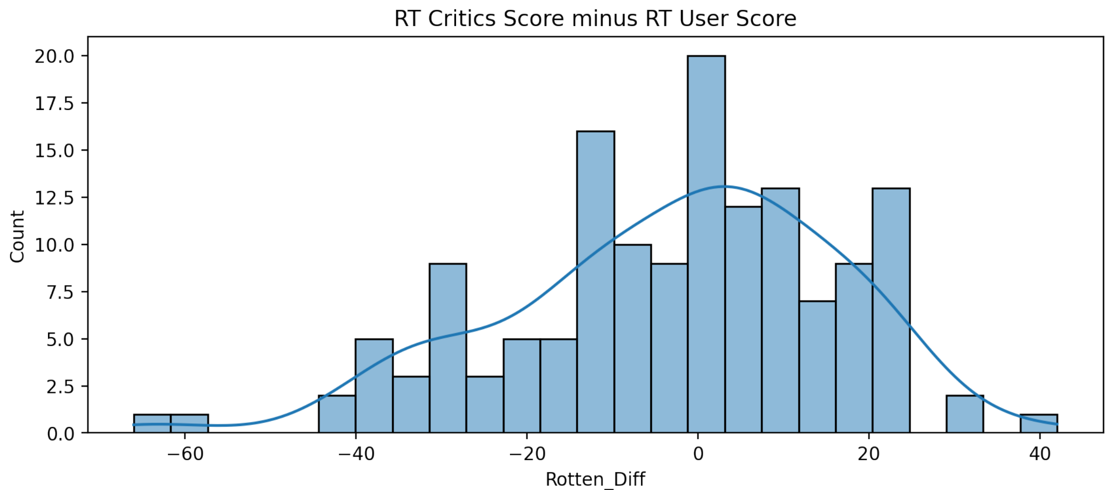
```
# CODE HERE
```

```
all_sites['Rotten_Diff'].apply(abs).mean()
```

```
15.095890410958905
```

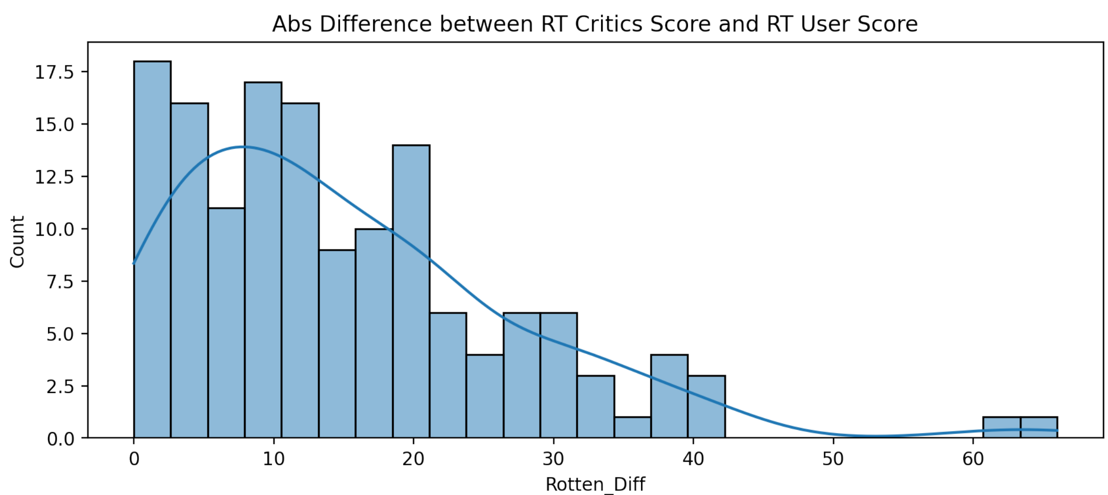
TASK: Plot the distribution of the differences between RT Critics Score and RT User Score. There should be negative values in this distribution plot. Feel free to use KDE or Histograms to display this distribution.

```
#CODE HERE

plt.figure(figsize=(10,4),dpi=200)
sns.histplot(data=all_sites,x='Rotten_Diff',kde=True,bins=25)
plt.title("RT Critics Score minus RT User Score");
```



TASK: Now create a distribution showing the *absolute value* difference between Critics and Users on Rotten Tomatoes.

```
#CODE HERE

plt.figure(figsize=(10,4),dpi=200)
sns.histplot(x=all_sites['Rotten_Diff'].apply(abs),bins=25,kde=True)
plt.title("Abs Difference between RT Critics Score and RT User
Score");
```



Let's find out which movies are causing the largest differences. First, show the top 5 movies with the largest *negative* difference between Users and RT critics. Since we calculated the difference as Critics Rating - Users Rating, then large negative values imply the users rated the movie much higher on average than the critics did.

TASK: What are the top 5 movies users rated higher than critics on average:

```
# CODE HERE
```

```
print("Users Love but Critics Hate")
all_sites.nsmallest(5,'Rotten_Diff')[['FILM','Rotten_Diff']]
```

```
Users Love but Critics Hate
```

	FILM	Rotten_Diff
3	Do You Believe? (2015)	-66
85	Little Boy (2015)	-61
105	Hitman: Agent 47 (2015)	-42
134	The Longest Ride (2015)	-42
125	The Wedding Ringer (2015)	-39

TASK: Now show the top 5 movies critics scores higher than users on average.

```
# CODE HERE
```

```
print("Critics love, but Users Hate")
all_sites.nlargest(5,'Rotten_Diff')[['FILM','Rotten_Diff']]
```

```
Critics love, but Users Hate
```

	FILM	Rotten_Diff
69	Mr. Turner (2014)	42
112	It Follows (2015)	31
115	While We're Young (2015)	31
37	Welcome to Me (2015)	24
40	I'll See You In My Dreams (2015)	24

MetaCritic

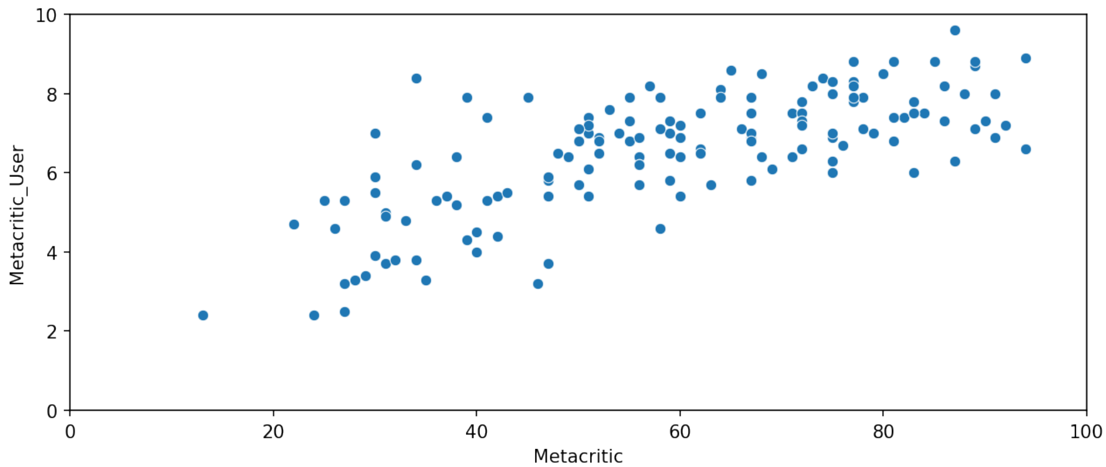
Now let's take a quick look at the ratings from MetaCritic. Metacritic also shows an average user rating versus their official displayed rating.

TASK: Display a scatterplot of the Metacritic Rating versus the Metacritic User rating.

```
# CODE HERE
```

```
plt.figure(figsize=(10,4),dpi=150)
sns.scatterplot(data=all_sites,x='Metacritic',y='Metacritic_User')
plt.xlim(0,100)
plt.ylim(0,10)
```

```
(0.0, 10.0)
```



IMBD

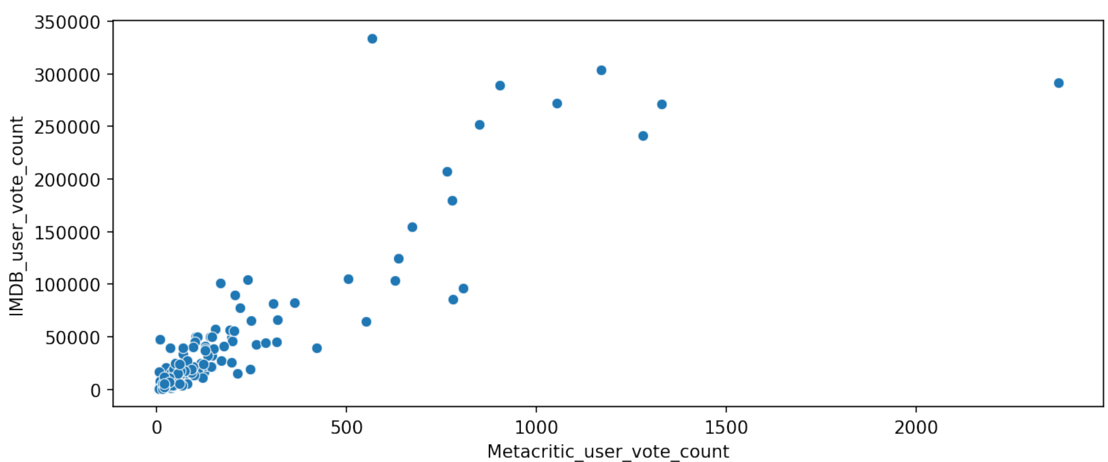
Finally let's explore IMDB. Notice that both Metacritic and IMDB report back vote counts. Let's analyze the most popular movies.

TASK: Create a scatterplot for the relationship between vote counts on MetaCritic versus vote counts on IMDB.

```
#CODE HERE
```

```
plt.figure(figsize=(10,4),dpi=150)
sns.scatterplot(data=all_sites,x='Metacritic_user_vote_count',y='IMDB_user_vote_count')
```

```
<AxesSubplot:xlabel='Metacritic_user_vote_count',
ylabel='IMDB_user_vote_count'>
```



Notice there are two outliers here. The movie with the highest vote count on IMDB only has about 500 Metacritic ratings. What is this movie?

TASK: What movie has the highest IMDB user vote count?

```python
#CODE HERE
```

```python
all_sites.nlargest(1,'IMDB_user_vote_count')
```

```
                          FILM  RottenTomatoes  RottenTomatoes_User  \
14  The Imitation Game (2014)              90                   92   

    Metacritic  Metacritic_User  IMDB  Metacritic_user_vote_count  \
14          73              8.2   8.1                         566   

    IMDB_user_vote_count  Rotten_Diff  
14                334164           -2  
```

TASK: What movie has the highest Metacritic User Vote count?

```python
#CODE HERE
```

```python
all_sites.nlargest(1,'Metacritic_user_vote_count')
```

```
                          FILM  RottenTomatoes  RottenTomatoes_User  \
88  Mad Max: Fury Road (2015)              97                   88   

    Metacritic  Metacritic_User  IMDB  Metacritic_user_vote_count  \
88          89              8.7   8.3                        2375   

    IMDB_user_vote_count  Rotten_Diff  
88                292023            9  
```

Fandago Scores vs. All Sites

Finally let's begin to explore whether or not Fandango artificially displays higher ratings than warranted to boost ticket sales.

TASK: Combine the Fandango Table with the All Sites table. Not every movie in the Fandango table is in the All Sites table, since some Fandango movies have very little or no reviews. We only want to compare movies that are in both DataFrames, so do an *inner* merge to merge together both DataFrames based on the FILM columns.

```python
#CODE HERE
```

```python
df = pd.merge(fandango,all_sites,on='FILM',how='inner')
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 145 entries, 0 to 144
Data columns (total 13 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   FILM                        145 non-null    object 
 1   STARS                       145 non-null    float64
 2   RATING                      145 non-null    float64
```

```
 3   VOTES                        145 non-null    int64
 4   YEAR                         145 non-null    object
 5   RottenTomatoes               145 non-null    int64
 6   RottenTomatoes_User          145 non-null    int64
 7   Metacritic                   145 non-null    int64
 8   Metacritic_User              145 non-null    float64
 9   IMDB                         145 non-null    float64
 10  Metacritic_user_vote_count   145 non-null    int64
 11  IMDB_user_vote_count         145 non-null    int64
 12  Rotten_Diff                  145 non-null    int64
dtypes: float64(4), int64(7), object(2)
memory usage: 15.9+ KB
```

```
df.head()
```

```
                          FILM  STARS  RATING  VOTES  YEAR
RottenTomatoes  \
0  Fifty Shades of Grey (2015)    4.0     3.9  34846  2015
25
1        Jurassic World (2015)    4.5     4.5  34390  2015
71
2       American Sniper (2015)    5.0     4.8  34085  2015
72
3             Furious 7 (2015)    5.0     4.8  33538  2015
81
4            Inside Out (2015)    4.5     4.5  15749  2015
98

   RottenTomatoes_User  Metacritic  Metacritic_User  IMDB  \
0                   42          46              3.2   4.2
1                   81          59              7.0   7.3
2                   85          72              6.6   7.4
3                   84          67              6.8   7.4
4                   90          94              8.9   8.6

   Metacritic_user_vote_count  IMDB_user_vote_count  Rotten_Diff
0                         778                179506          -17
1                        1281                241807          -10
2                         850                251856          -13
3                         764                207211           -3
4                         807                 96252            8
```

Normalize columns to Fandango STARS and RATINGS 0-5

Notice that RT,Metacritic, and IMDB don't use a score between 0-5 stars like Fandango does. In order to do a fair comparison, we need to *normalize* these values so they all fall between 0-5 stars and the relationship between reviews stays the same.

TASK: Create new normalized columns for all ratings so they match up within the 0-5 star range shown on Fandango. There are many ways to do this.

Hint link: https://stackoverflow.com/questions/26414913/normalize-columns-of-pandas-data-frame

Easier Hint:

Keep in mind, a simple way to convert ratings:

- 100/20 = 5
- 10/2 = 5

```
# CODE HERE

# Dont run this cell multiple times, otherwise you keep dividing!
df['RT_Norm'] = np.round(df['RottenTomatoes']/20,1)
df['RTU_Norm'] =  np.round(df['RottenTomatoes_User']/20,1)

# Dont run this cell multiple times, otherwise you keep dividing!
df['Meta_Norm'] =  np.round(df['Metacritic']/20,1)
df['Meta_U_Norm'] =  np.round(df['Metacritic_User']/2,1)

# Dont run this cell multiple times, otherwise you keep dividing!
df['IMDB_Norm'] = np.round(df['IMDB']/2,1)

df.head()
```

```
                             FILM  STARS  RATING  VOTES  YEAR
RottenTomatoes  \
0  Fifty Shades of Grey (2015)    4.0     3.9  34846  2015
25
1        Jurassic World (2015)    4.5     4.5  34390  2015
71
2       American Sniper (2015)    5.0     4.8  34085  2015
72
3             Furious 7 (2015)    5.0     4.8  33538  2015
81
4            Inside Out (2015)    4.5     4.5  15749  2015
98

   RottenTomatoes_User  Metacritic  Metacritic_User  IMDB  \
0                   42          46              3.2   4.2
1                   81          59              7.0   7.3
2                   85          72              6.6   7.4
3                   84          67              6.8   7.4
4                   90          94              8.9   8.6

   Metacritic_user_vote_count  IMDB_user_vote_count  Rotten_Diff
RT_Norm  \
0                         778                179506          -17
1.2
1                        1281                241807          -10
3.6
2                         850                251856          -13
```

```
3.6
3                          764                  207211           -3
4.0
4                          807                   96252            8
4.9

   RTU_Norm  Meta_Norm  Meta_U_Norm  IMDB_Norm
0       2.1        2.3          1.6        2.1
1       4.0        3.0          3.5        3.6
2       4.2        3.6          3.3        3.7
3       4.2        3.4          3.4        3.7
4       4.5        4.7          4.4        4.3
```

TASK: Now create a norm_scores DataFrame that only contains the normalizes ratings. Include both STARS and RATING from the original Fandango table.

```
#CODE HERE

norm_scores =
df[['STARS','RATING','RT_Norm','RTU_Norm','Meta_Norm','Meta_U_Norm','IMDB_Norm']]

norm_scores.head()
```

	STARS	RATING	RT_Norm	RTU_Norm	Meta_Norm	Meta_U_Norm	IMDB_Norm
0	4.0	3.9	1.2	2.1	2.3	1.6	2.1
1	4.5	4.5	3.6	4.0	3.0	3.5	3.6
2	5.0	4.8	3.6	4.2	3.6	3.3	3.7
3	5.0	4.8	4.0	4.2	3.4	3.4	3.7
4	4.5	4.5	4.9	4.5	4.7	4.4	4.3

Comparing Distribution of Scores Across Sites

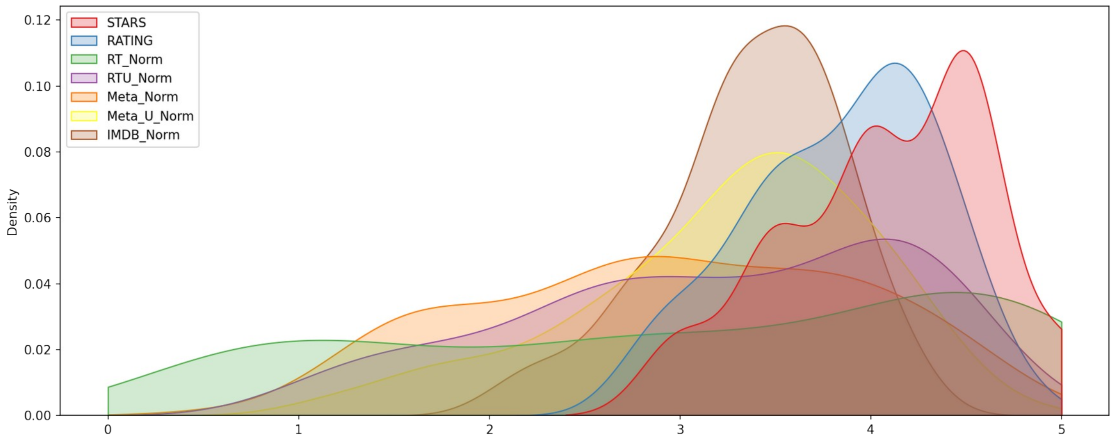
Now the moment of truth! Does Fandango display abnormally high ratings? We already know it pushs displayed RATING higher than STARS, but are the ratings themselves higher than average?

TASK: Create a plot comparing the distributions of normalized ratings across all sites. There are many ways to do this, but explore the Seaborn KDEplot docs for some simple ways to quickly show this. Don't worry if your plot format does not look exactly the same as ours, as long as the differences in distribution are clear.

Quick Note if you have issues moving the legend for a seaborn kdeplot: https://github.com/mwaskom/seaborn/issues/2280

```
#CODE HERE

def move_legend(ax, new_loc, **kws):
    old_legend = ax.legend_
    handles = old_legend.legendHandles
    labels = [t.get_text() for t in old_legend.get_texts()]
```

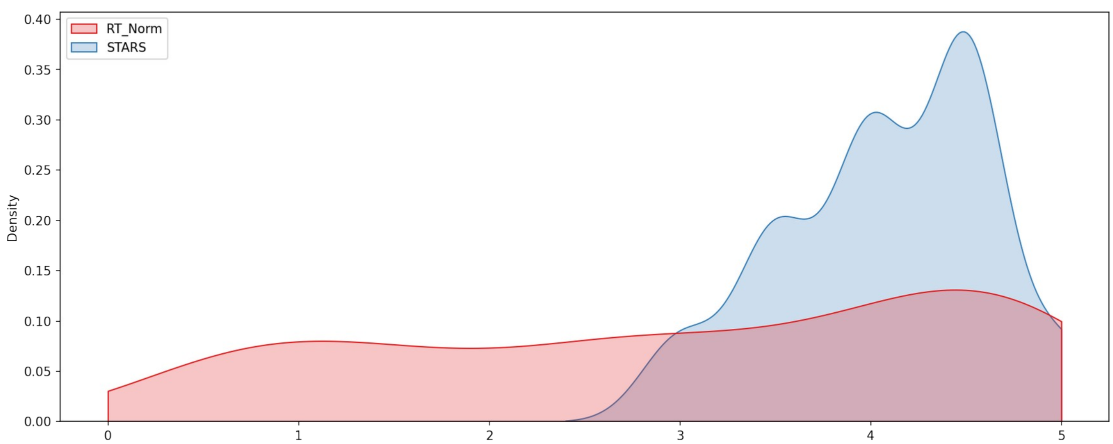
```
    title = old_legend.get_title().get_text()
    ax.legend(handles, labels, loc=new_loc, title=title, **kws)

fig, ax = plt.subplots(figsize=(15,6),dpi=150)
sns.kdeplot(data=norm_scores,clip=[0,5],shade=True,palette='Set1',ax=ax)
move_legend(ax, "upper left")
```



Clearly Fandango has an uneven distribution. We can also see that RT critics have the most uniform distribution. Let's directly compare these two.

TASK: Create a KDE plot that compare the distribution of RT critic ratings against the STARS displayed by Fandango.

```
#CODE HERE

fig, ax = plt.subplots(figsize=(15,6),dpi=150)
sns.kdeplot(data=norm_scores[['RT_Norm','STARS']],clip=[0,5],shade=True,palette='Set1',ax=ax)
move_legend(ax, "upper left")
```

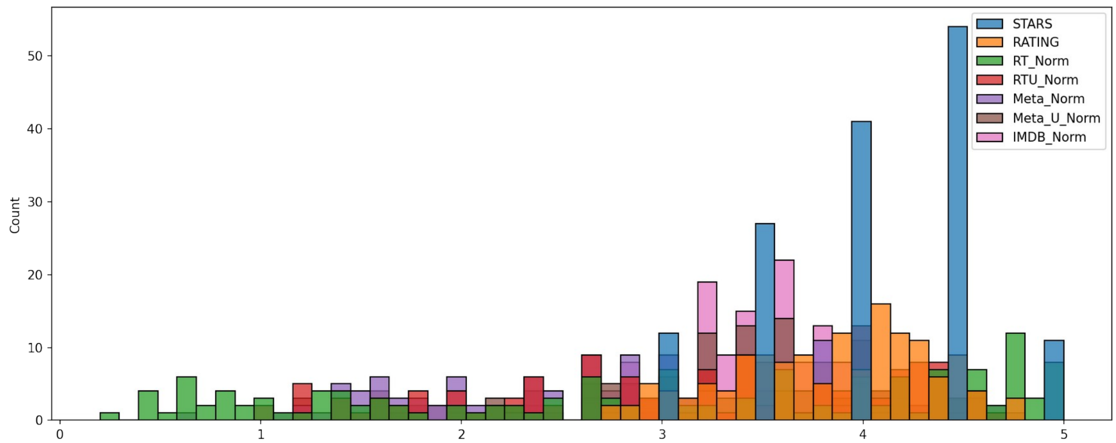


OPTIONAL TASK: Create a histplot comparing all normalized scores.

```
#CODE HERE
```

```
plt.subplots(figsize=(15,6),dpi=150)
sns.histplot(norm_scores,bins=50)
```

```
<AxesSubplot:ylabel='Count'>
```



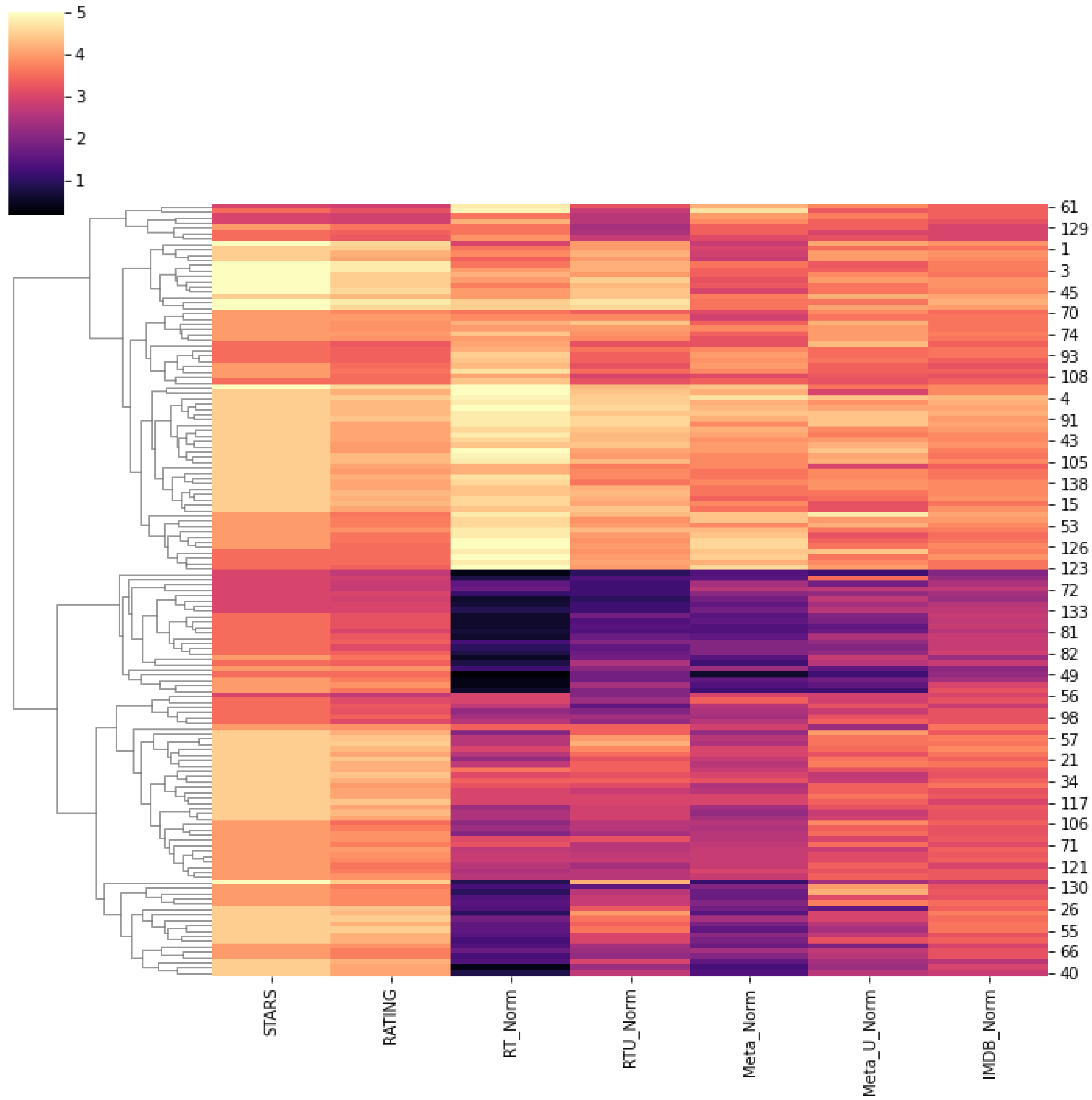
How are the worst movies rated across all platforms?

TASK: Create a clustermap visualization of all normalized scores. Note the differences in ratings, highly rated movies should be clustered together versus poorly rated movies. Note: This clustermap does not need to have the FILM titles as the index, feel free to drop it for the clustermap.

```
# CODE HERE
```

```
sns.clustermap(norm_scores,cmap='magma',col_cluster=False)
```

```
<seaborn.matrix.ClusterGrid at 0x1aa7cb2b548>
```



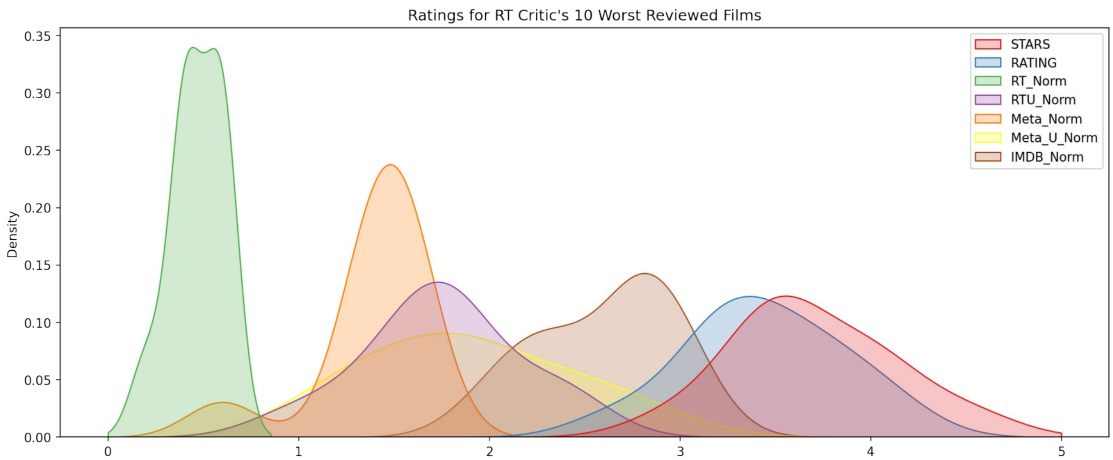
TASK: Clearly Fandango is rating movies much higher than other sites, especially considering that it is then displaying a rounded up version of the rating. Let's examine the top 10 worst movies. Based off the Rotten Tomatoes Critic Ratings, what are the top 10 lowest rated movies? What are the normalized scores across all platforms for these movies? You may need to add the FILM column back in to your DataFrame of normalized scores to see the results.

```
# CODE HERE

norm_films =
df[['STARS','RATING','RT_Norm','RTU_Norm','Meta_Norm','Meta_U_Norm','I
MDB_Norm','FILM']]

norm_films.nsmallest(10,'RT_Norm')

    STARS  RATING  RT_Norm  RTU_Norm  Meta_Norm  Meta_U_Norm
IMDB_Norm  \
```

```
49    3.5     3.5       0.2        1.8         0.6            1.2
2.2
25    4.5     4.1       0.4        2.3         1.3            2.3
3.0
28    3.0     2.7       0.4        1.0         1.4            1.2
2.0
54    4.0     3.7       0.4        1.8         1.6            1.8
2.4
84    4.0     3.9       0.4        2.4         1.4            1.6
3.0
50    4.0     3.6       0.5        1.8         1.5            2.8
2.3
77    3.5     3.2       0.6        1.8         1.5            2.0
2.8
78    3.5     3.2       0.6        1.5         1.4            1.6
2.8
83    3.5     3.3       0.6        1.7         1.6            2.5
2.8
87    3.5     3.2       0.6        1.4         1.6            1.9
2.7

                             FILM
49  Paul Blart: Mall Cop 2 (2015)
25                Taken 3 (2015)
28         Fantastic Four (2015)
54            Hot Pursuit (2015)
84        Hitman: Agent 47 (2015)
50       The Boy Next Door (2015)
77            Seventh Son (2015)
78              Mortdecai (2015)
83             Sinister 2 (2015)
87     Unfinished Business (2015)
```

FINAL TASK: Visualize the distribution of ratings across all sites for the top 10 worst movies.

```
# CODE HERE

print('\n\n')
plt.figure(figsize=(15,6),dpi=150)
worst_films = norm_films.nsmallest(10,'RT_Norm').drop('FILM',axis=1)
sns.kdeplot(data=worst_films,clip=[0,5],shade=True,palette='Set1')
plt.title("Ratings for RT Critic's 10 Worst Reviewed Films");
```



Final thoughts: Wow! Fandango is showing around 3-4 star ratings for films that are clearly bad! Notice the biggest offender, Taken 3!. Fandango is displaying 4.5 stars on their site for a film with an average rating of 1.86 across the other platforms!

```
norm_films.iloc[25]
```

```
STARS                         4.5
RATING                        4.1
RT_Norm                       0.4
RTU_Norm                      2.3
Meta_Norm                     1.3
Meta_U_Norm                   2.3
IMDB_Norm                       3
FILM             Taken 3 (2015)
Name: 25, dtype: object
```

```
0.4+2.3+1.3+2.3+3
```

```
9.3
```

```
9.3/5
```

```
1.86
```
