Project

Using Data Analysis and Data visualization to jump to a conclusion about Fandango's rating of the movies.

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Overview:

In light of recent concerns about biased online movie ratings, is it really worth trusting these ratings at all? After all, the company that produces the rating system also profits from selling movie tickets. Might they be inclined to rate movies higher than they should, in order to boost sales?

Goal:

Based on the article published in FiveThirtyEight, to see if we reach a similar conclusion? We will be using Python, NumPy, Pandas, Matplotlib and Seaborn to analyse the data and determine if Fandango's ratings in 2015 had a bias towards rating movies better to sell more tickets.

Background:

Article-https://fivethirtyeight.com/features/fandango-movies-ratings/ (https://fivethirtyeight.com/features/fandango-movies-ratings/)

Data- https://github.com/fivethirtyeight/data/tree/master/fandango (https://github.com/fivethirtyeight/data/tree/master/fandango)

Project resources and material -www.pieriandata.com (http://www.pieriandata.com)

There are two different types of data here (2 CSV files) - ratings from Fandango Stars and ratings from other sources like like Metacritic,IMDB, and Rotten Tomatoes. Together, they provide a more comprehensive picture of how people are reacting to films.

Part One: Understanding the Data

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. `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.

In [3]:

```
# Importing the important libraries

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 look at the Fandango ratings to see if our analysis agrees with the article's conclusion.

In [4]:

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

In [5]:

```
#Exploring the DataFrame Properties and Head.
fandango.head()
```

Out[5]:

	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

In [6]:

```
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
```

In [7]:

```
fandango.describe()
```

Out[7]:

	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

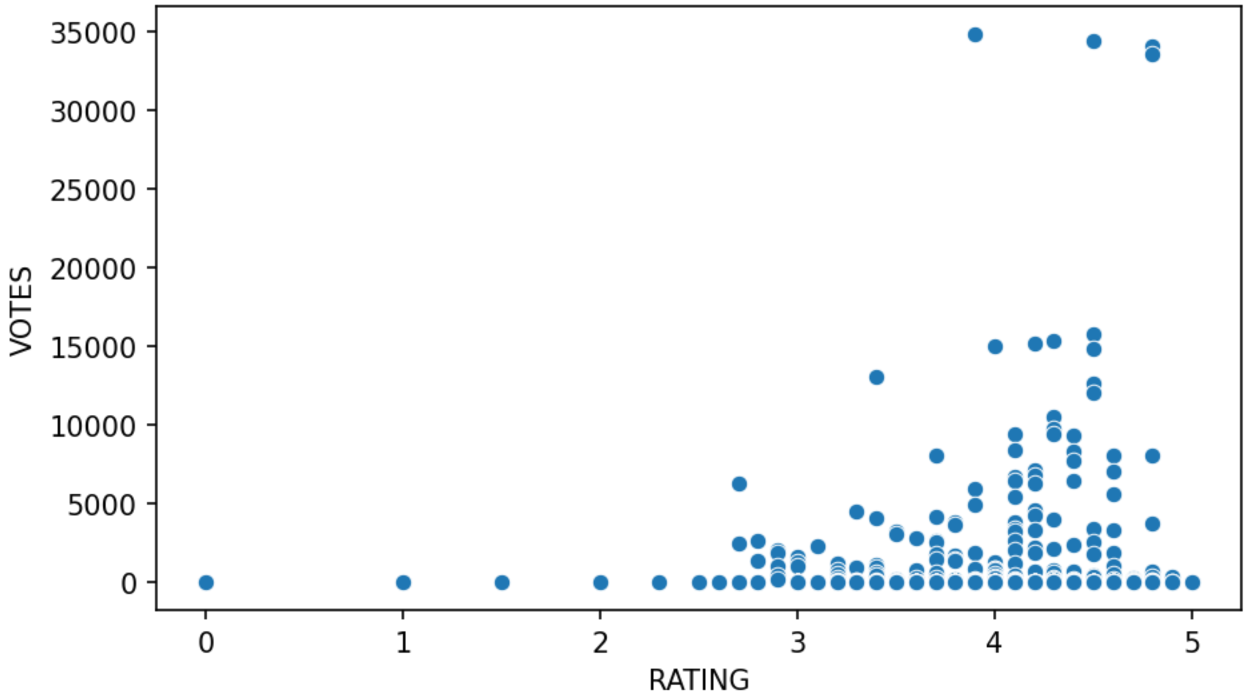
Let's explore the relationship between popularity of a film and its rating by creating a scatterplot showing the relationship between rating and votes.

In [8]:

```
plt.figure(figsize=(7,4),dpi=150)
sns.scatterplot(data=fandango,x='RATING',y='VOTES')
```

Out[8]:

```
<AxesSubplot:xlabel='RATING', ylabel='VOTES'>
```



Calculating the correlation between the columns:

In [9]:

```
fandango.corr()
```

Out[9]:

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

Creating a new column that is able to strip the year from the title strings and set this new column as 'YEAR' as year column was not available.

In [10]:

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

In [12]:

```
fandango['YEAR']
```

Out[12]:

```
0      2015
1      2015
2      2015
3      2015
4      2015
       ...
499    2015
500    2015
501    2015
502    1964
503    2012
Name: YEAR, Length: 504, dtype: object
```

Finding the number of movies per year in Fandango DataFrame

In [13]:

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

Out[13]:

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

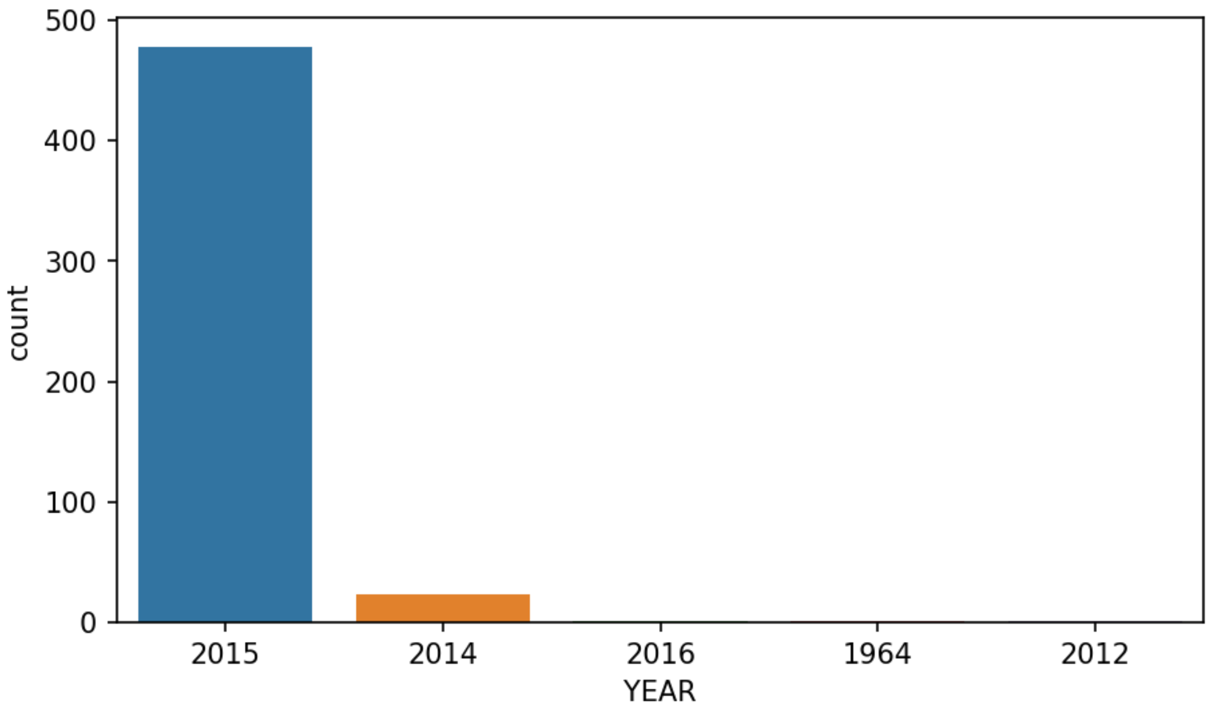
Visualize the count of movies per year with a plot:

In [15]:

```
plt.figure(figsize=(7,4),dpi=150)
sns.countplot(data=fandango,x='YEAR')
```

Out[15]:

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



In [ ]:

```

```

10 movies with the highest number of votes.

In [17]:

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

Out[17]:

	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
5	The Hobbit: The Battle of the Five Armies (2014)	4.5	4.3	15337	2014
6	Kingsman: The Secret Service (2015)	4.5	4.2	15205	2015
7	Minions (2015)	4.0	4.0	14998	2015
8	Avengers: Age of Ultron (2015)	5.0	4.5	14846	2015
9	Into the Woods (2014)	3.5	3.4	13055	2014

In [ ]:

```

```

Number of Movies with zero votes.

In [18]:

```
len(fandango[fandango['VOTES'].values == 0])
```

Out[18]:

69

In [ ]:

```

```

Creating DataFrame of only reviewed films by removing any films that have zero votes

In [19]:

```
df = fandango[fandango['VOTES'].values != 0]
```

In [20]:

```
df
```

Out[20]:

	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
...	...	...	...	...	...
430	That Sugar Film (2015)	5.0	5.0	1	2015
431	The Intern (2015)	5.0	5.0	1	2015
432	The Park Bench (2015)	5.0	5.0	1	2015
433	The Wanted 18 (2015)	5.0	5.0	1	2015
434	Z For Zachariah (2015)	5.0	5.0	1	2015

435 rows × 5 columns

In [ ]:

```

```

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.

Creating KDE plots that displays the distribution of ratings that are displayed (STARS) versus what the true rating was from votes (RATING). Also Clip the KDEs to 0-5 as ratings are between 0-5

In [21]:

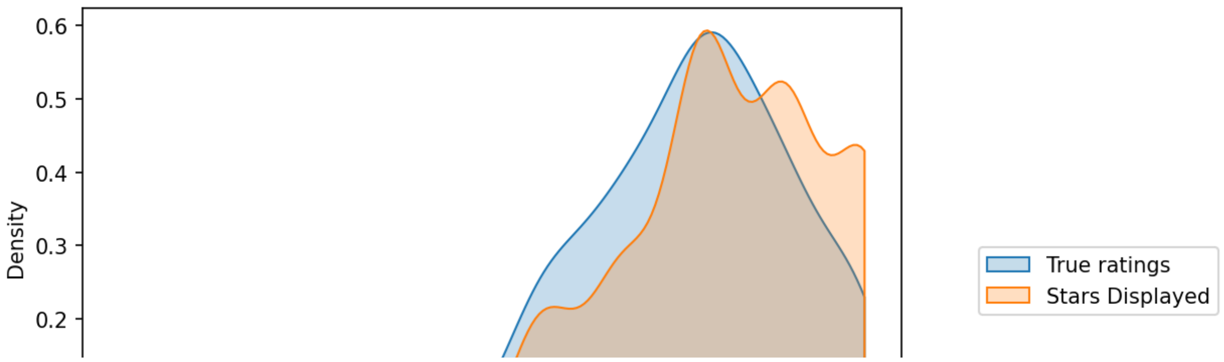
```
plt.figure(figsize=(7,4),dpi=150)

sns.kdeplot(data=df,x='RATING',fill=True,clip=[0,5],legend=True,label='True ratings')
sns.kdeplot(data=df,x='STARS',fill=True,clip=[0,5],legend=True,label='Stars Displayed')

plt.legend(bbox_to_anchor=(1.40,0.5))
```

Out[21]:

```
<matplotlib.legend.Legend at 0x29854f96820>
```



Let's now actually quantify this discrepancy by creating a new column of the difference between STARS displayed versus true RATING(to the nearest decimal point for better readbility)

In [27]:

```
#chained_assignment is None to hide copy warnings
pd.options.mode.chained_assignment = None
df['STARS_DIFF'] = (df['STARS'] - df['RATING']).round(1)
```

In [26]:

```
df
```

Out[26]:

	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 × 6 columns

In [ ]:

```
```

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

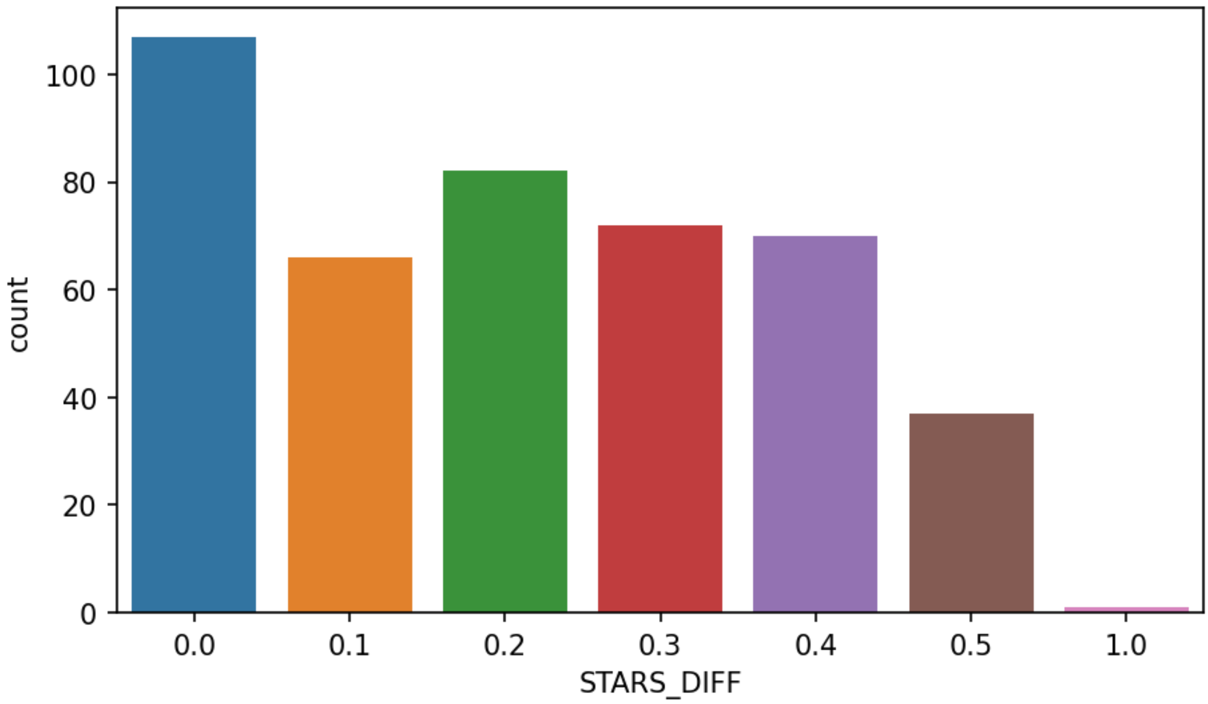
In [28]:

```
plt.figure(figsize=(7,4),dpi=150)

sns.countplot(data=df,x='STARS_DIFF')
```

Out[28]:

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



In [ ]:

We can see from the plot that one movie was displaying over a 1 star difference than its true rating! Let's find out this movie which has close to 1 star difference ?

In [29]:

```
df[df['STARS_DIFF'] == 1]
```

Out[29]:

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

In [ ]:

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.

In [30]:

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

Exploring the DataFrame columns, info, description.

In [31]:

```
all_sites
```

Out[31]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metacritic_user_vote_count	IMDB_user_vote_count
0	Avengers: Age of Ultron (2015)	74	86	66	7.1	7.8	1330	271107
1	Cinderella (2015)	85	80	67	7.5	7.1	249	65709
2	Ant-Man (2015)	80	90	64	8.1	7.8	627	103660
3	Do You Believe? (2015)	18	84	22	4.7	5.4	31	3136
4	Hot Tub Time Machine 2 (2015)	14	28	29	3.4	5.1	88	19560
...	...	...	...	...	...	...	...	...
141	Mr. Holmes (2015)	87	78	67	7.9	7.4	33	7367
142	'71 (2015)	97	82	83	7.5	7.2	60	24116
143	Two Days, One Night (2014)	97	78	89	8.8	7.4	123	24345
144	Gett: The Trial of Viviane Amsalem (2015)	100	81	90	7.3	7.8	19	1955
145	Kumiko, The Treasure Hunter (2015)	87	63	68	6.4	6.7	19	5289

146 rows × 8 columns

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.

Creating a scatterplot exploring the relationship between RT Critic reviews and RT User reviews.

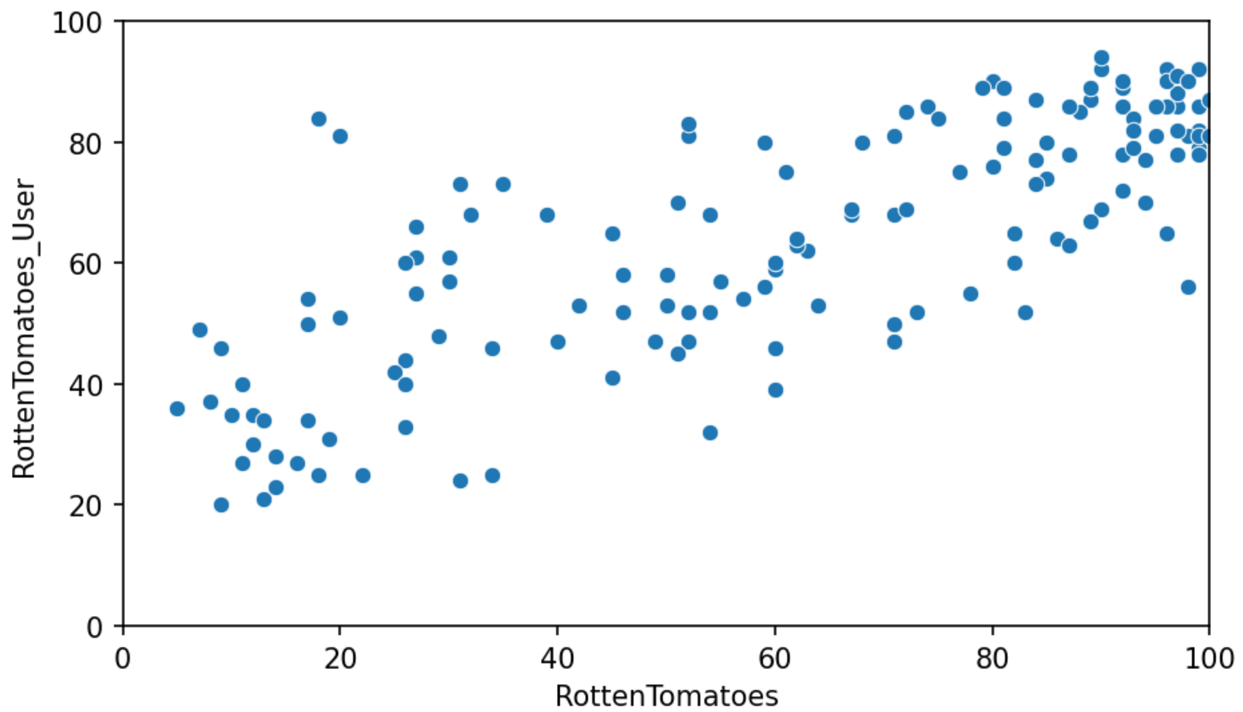
In [32]:

```
plt.figure(figsize=(7,4),dpi=150)

sns.scatterplot(data=all_sites,x='RottenTomatoes',y='RottenTomatoes_User')
plt.xlim(0,100)
plt.ylim(0,100)
```

Out[32]:

```
(0.0, 100.0)
```



Let's now quantify this difference by comparing the critics ratings and the RT User ratings.

We will calculate this with RottenTomatoes-RottenTomatoes_User.The 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.

In [35]:

```
#Creating a new column based off the difference

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

In [34]:

```
all_sites
```

Out[34]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metacritic_user_vote_count	IMDB_user_vote_count	RT_DIFF
0	Avengers: Age of Ultron (2015)	74	86	66	7.1	7.8	1330	271107	-12
1	Cinderella (2015)	85	80	67	7.5	7.1	249	65709	5
2	Ant-Man (2015)	80	90	64	8.1	7.8	627	103660	-10
3	Do You Believe? (2015)	18	84	22	4.7	5.4	31	3136	-66
4	Hot Tub Time Machine 2 (2015)	14	28	29	3.4	5.1	88	19560	-14
...	...	...	...	...	...	...	...	...	...
141	Mr. Holmes (2015)	87	78	67	7.9	7.4	33	7367	9
142	'71 (2015)	97	82	83	7.5	7.2	60	24116	15
143	Two Days, One Night (2014)	97	78	89	8.8	7.4	123	24345	19
144	Gett: The Trial of Viviane Amsalem (2015)	100	81	90	7.3	7.8	19	1955	19
145	Kumiko, The Treasure Hunter (2015)	87	63	68	6.4	6.7	19	5289	24

146 rows × 9 columns

In [ ]:

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.

In [36]:

```
all_sites['RT_DIFF'].abs().mean()
```

Out[36]:

```
15.095890410958905
```

In [ ]:

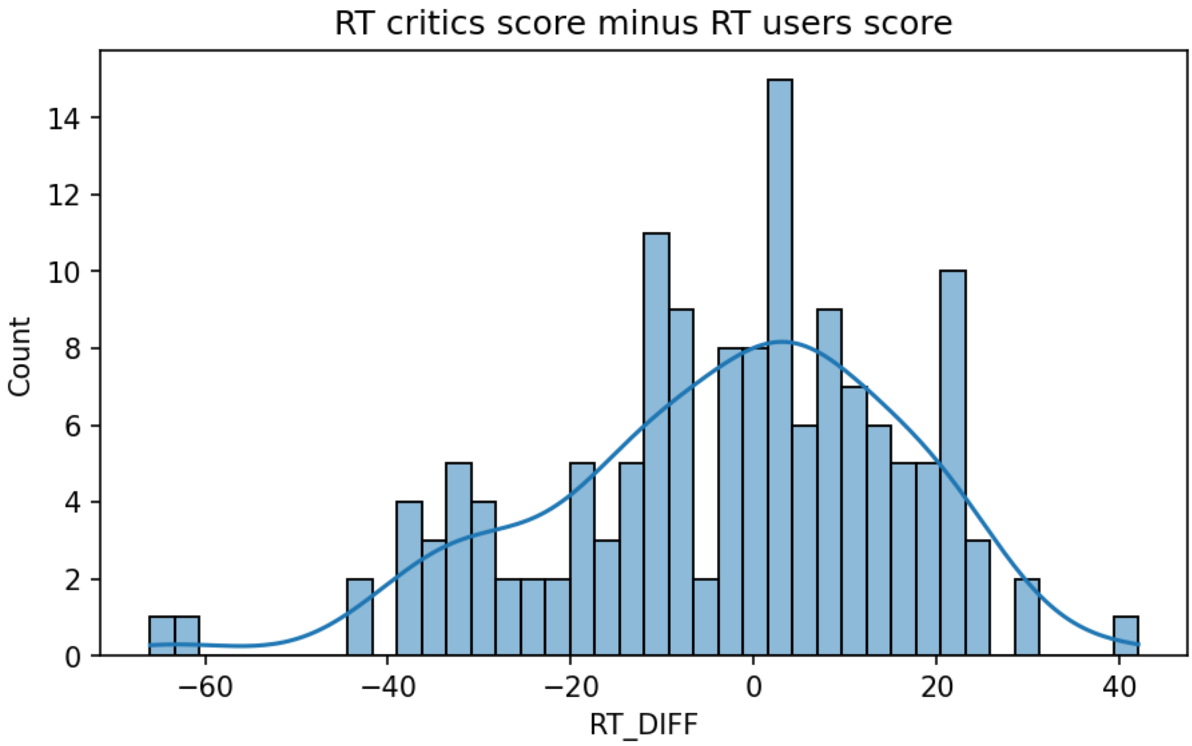
Ploting the distribution of the differences between RT Critics Score and RT User Score.

In [37]:

```
plt.figure(figsize=(7,4),dpi=150)
sns.histplot(data=all_sites,x='RT_DIFF',bins=40,kde=True)
plt.title('RT critics score minus RT users score')
```

Out[37]:

```
Text(0.5, 1.0, 'RT critics score minus RT users score')
```



In [ ]:

```
```

Now creating a distribution showing the absolute value difference between Critics and Users on Rotten Tomatoes.

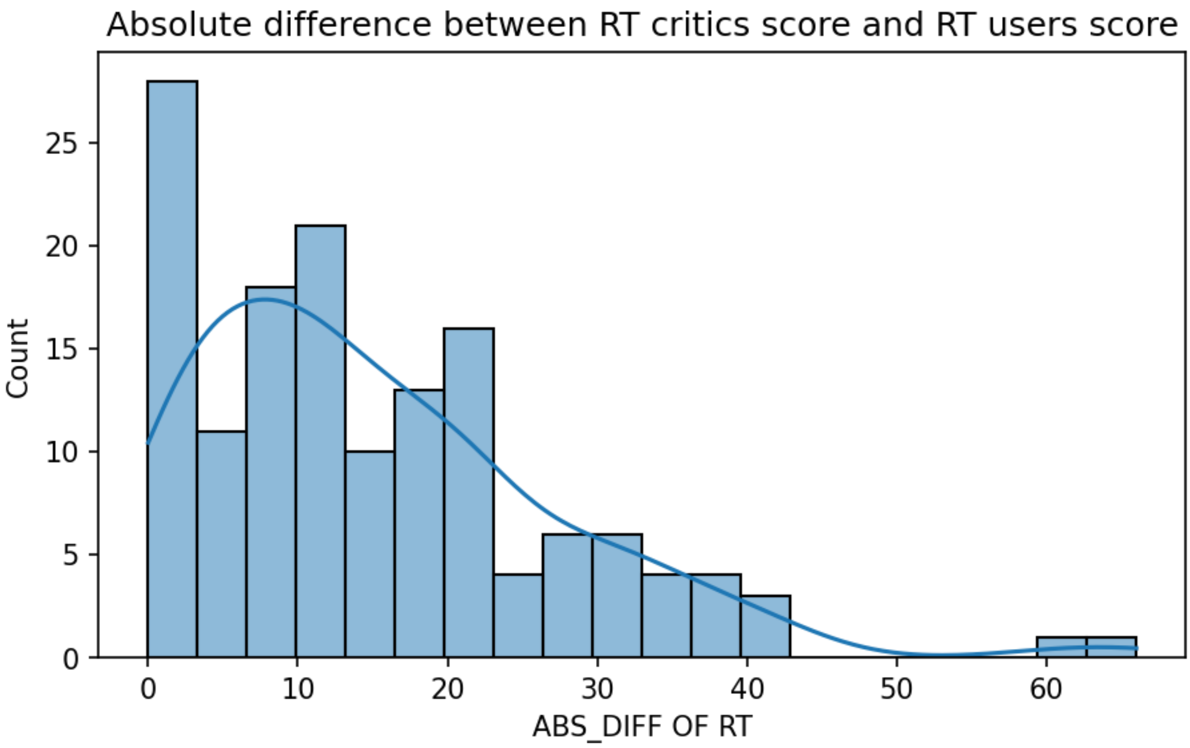
In [38]:

```
all_sites['ABS_DIFF OF RT'] = all_sites['RT_DIFF'].abs()

plt.figure(figsize=(7,4),dpi=150)
sns.histplot(data=all_sites,x='ABS_DIFF OF RT',bins=20,kde=True)
plt.title('Absolute difference between RT critics score and RT users score')
```

Out[38]:

```
Text(0.5, 1.0, 'Absolute difference between RT critics score and RT users score')
```



In [ ]:

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.

In [40]:

```
# Top 5 movies users rated higher than critics on average
all_sites.nsmallest(5,'RT_DIFF')[['FILM','RT_DIFF']]
```

Out[40]:

	FILM	RT_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

In [ ]:

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

In [41]:

```
all_sites.nlargest(5,'RT_DIFF')[['FILM','RT_DIFF']]
```

Out[41]:

	FILM	RT_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

In [ ]:

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.

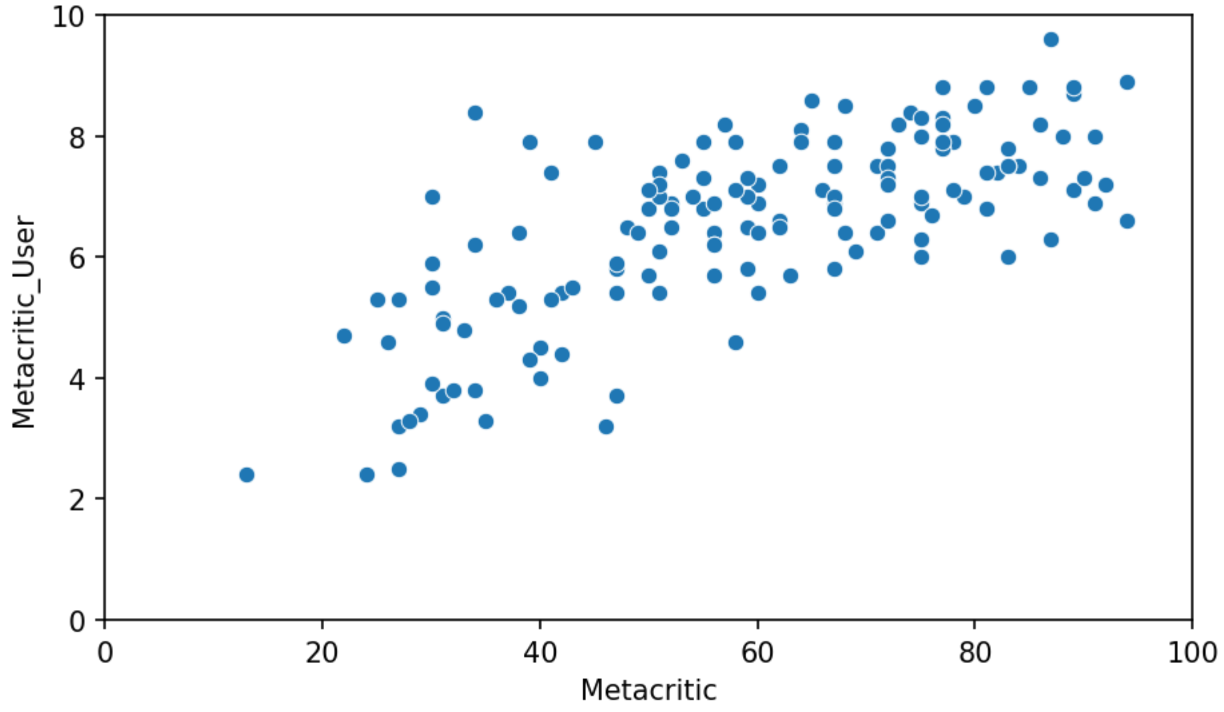
Display a scatterplot of the Metacritic Rating versus the Metacritic User rating.

In [42]:

```
plt.figure(figsize=(7,4),dpi=150)
sns.scatterplot(data=all_sites,x='Metacritic',y='Metacritic_User')
plt.xlim(0,100)
plt.ylim(0,10)
```

Out[42]:

```
(0.0, 10.0)
```



IMDB

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

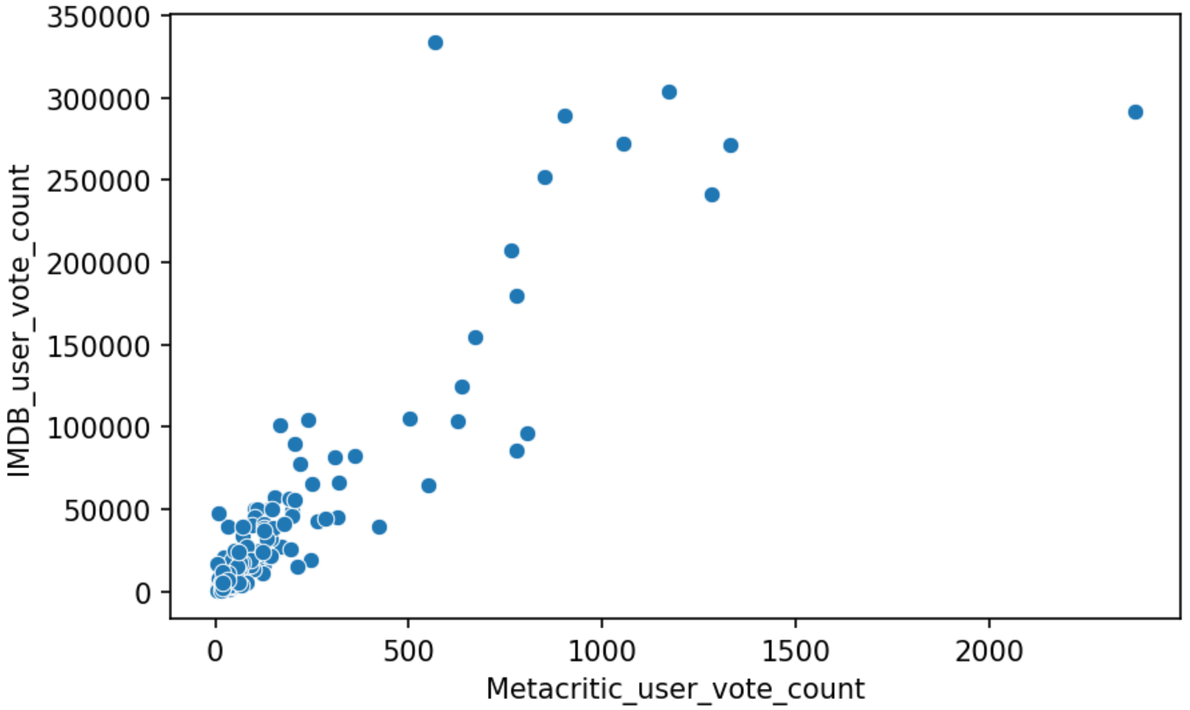
Creating a scatterplot for the relationship between vote counts on MetaCritic versus vote counts on IMDB.

In [46]:

```
plt.figure(figsize=(6.5,4),dpi=150)
sns.scatterplot(data=all_sites,x='Metacritic_user_vote_count',y='IMDB_user_vote_count')
```

Out[46]:

```
&lt;AxesSubplot:xlabel='Metacritic_user_vote_count', ylabel='IMDB_user_vote_count'&gt;
```



Notice there are two outliers here. The movie with the highest vote count on IMDB only has about 500 Metacritic ratings. Let's find out this movie.

In [47]:

```
# movie with highest IMDB user vote count
all_sites.nlargest(1,'IMDB_user_vote_count')
```

Out[47]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metacritic_user_vote_count	IMDB_user_vote_count	RT_DIFF	ABS_ O
14	The Imitation Game (2014)	90	92	73	8.2	8.1	566	334164	-2	

In [ ]:

In [49]:

```
# movie with highest Metacritic User Vote count
all_sites.nlargest(1,'Metacritic_user_vote_count')
```

Out[49]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metacritic_user_vote_count	IMDB_user_vote_count	RT_DIFF	ABS_DI OF
88	Mad Max: Fury Road (2015)	97	88	89	8.7	8.3	2375	292023	9	

In [ ]:

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.

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 with an inner merge,we can merge together both DataFrames based on the FILM columns.

In [50]:

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

In [51]:

```
pd_merged.head()
```

Out[51]:

	FILM	STARS	RATING	VOTES	YEAR	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metacritic_user_vote_count	IMDB_
0	Fifty Shades of Grey (2015)	4.0	3.9	34846	2015	25	42	46	3.2	4.2	778	
1	Jurassic World (2015)	4.5	4.5	34390	2015	71	81	59	7.0	7.3	1281	
2	American Sniper (2015)	5.0	4.8	34085	2015	72	85	72	6.6	7.4	850	
3	Furious 7 (2015)	5.0	4.8	33538	2015	81	84	67	6.8	7.4	764	
4	Inside Out (2015)	4.5	4.5	15749	2015	98	90	94	8.9	8.6	807	

Normalize columns to Fandango STARS and RATINGS 0-5

We noticed 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.

Creating new normalized columns for all ratings so they match up within the 0-5 star range shown on Fandango.

In [53]:

```
# Conversion by dividing the ratings of 100 with 20 and ratings of 10 with 2 to make it a rating out of 5

pd_merged['RT_Norm'] = (pd_merged['RottenTomatoes'] /20).round(1)
pd_merged['RTU_Norm'] = (pd_merged['RottenTomatoes_User'] /20).round(1)
pd_merged['Meta_Norm'] = (pd_merged['Metacritic'] /20).round(1)
pd_merged['Meta_U_Norm'] = (pd_merged['Metacritic_User'] /2).round(1)
pd_merged['IMDB_Norm'] = (pd_merged['IMDB'] /2).round(1)
```

In [55]:

```
pd_merged.head()
```

Out[55]:

	FILM	STARS	RATING	VOTES	YEAR	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metacritic_user_vote_count	IMDB_
0	Fifty Shades of Grey (2015)	4.0	3.9	34846	2015	25	42	46	3.2	4.2	778	
1	Jurassic World (2015)	4.5	4.5	34390	2015	71	81	59	7.0	7.3	1281	
2	American Sniper (2015)	5.0	4.8	34085	2015	72	85	72	6.6	7.4	850	
3	Furious 7 (2015)	5.0	4.8	33538	2015	81	84	67	6.8	7.4	764	
4	Inside Out (2015)	4.5	4.5	15749	2015	98	90	94	8.9	8.6	807	

In [ ]:

```

```

Now creating a norm_scores DataFrame that only contains the normalizes ratings, including both STARS and RATING from the original Fandango table.

In [56]:

```
norm_scores = pd_merged[['STARS','RATING','RT_Norm','RTU_Norm','Meta_Norm','Meta_U_Norm','IMDB_Norm']]
norm_scores.head()
```

Out[56]:

	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

In [ ]:

```

```

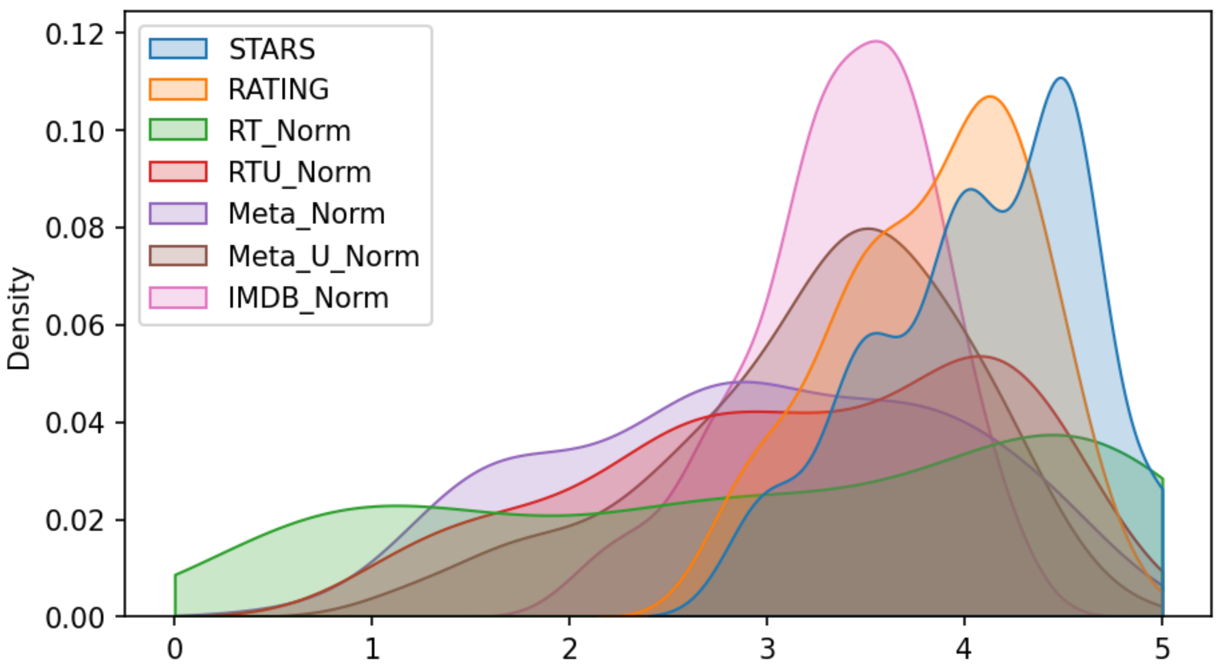
Comparing Distribution of Scores Across Sites

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

Creating a plot comparing the distributions of normalized ratings across all sites.

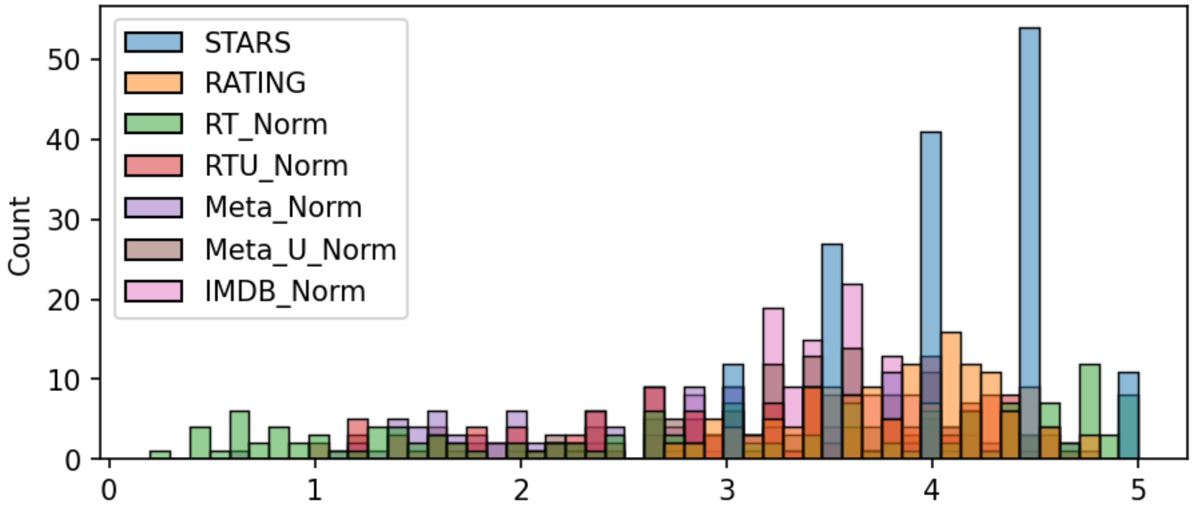
In [57]:

```
plt.figure(figsize=(7,4),dpi=150)
ax = sns.kdeplot(data=norm_scores,fill=True,clip=[0,5])
sns.move_legend(ax, "upper left")
```



In [59]:

```
#Creating a histplot comparing all normalized scores.
plt.figure(figsize=(7,3),dpi=150)
ax = sns.histplot(data=norm_scores,bins=50)
```

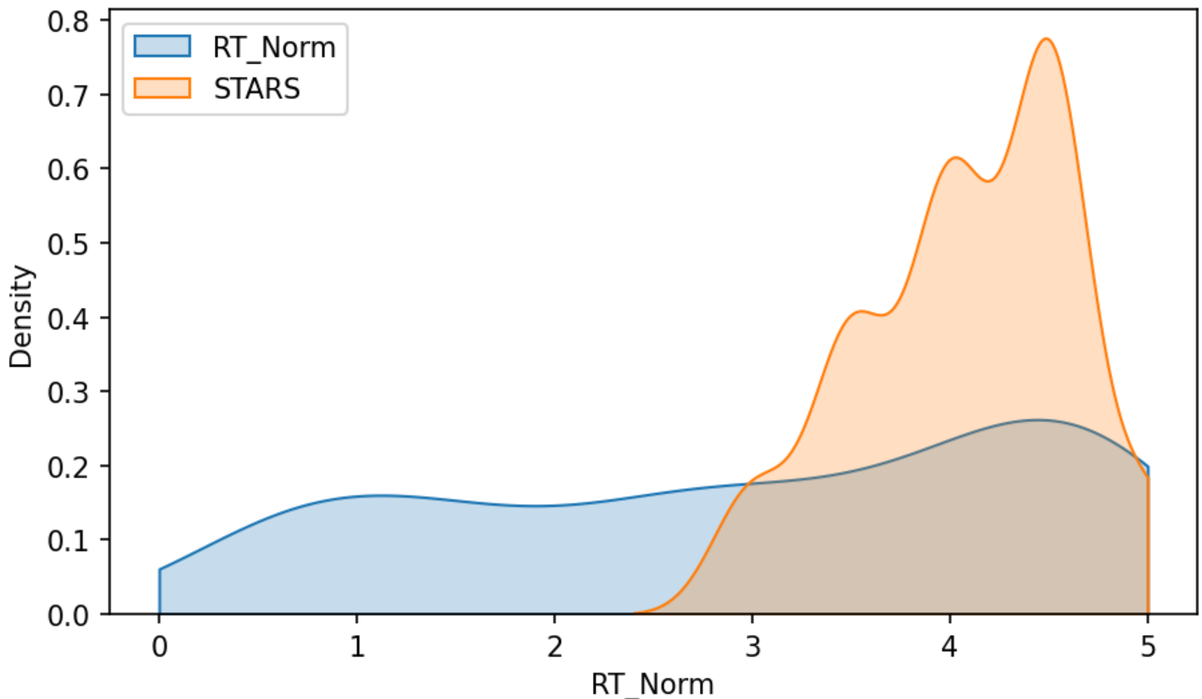


Clearly Fandango has an uneven distribution. We can also see that RT critics have the most uniform distribution. Let's directly compare these two.

In [58]:

```
plt.figure(figsize=(7,4),dpi=150)
ax = sns.kdeplot(data=norm_scores,x='RT_Norm',fill=True,clip=[0,5])
ax = sns.kdeplot(data=norm_scores,x='STARS',fill=True,clip=[0,5])

plt.legend(loc='upper left', labels=['RT_Norm', 'STARS'])
plt.show(ax)
```



In [ ]:

```

```

How are the worst movies rated across all platforms?

Creating a clustermap visualization of all normalized scores. Noting the differences in ratings, highly rated movies are clustered together versus poorly rated movies.

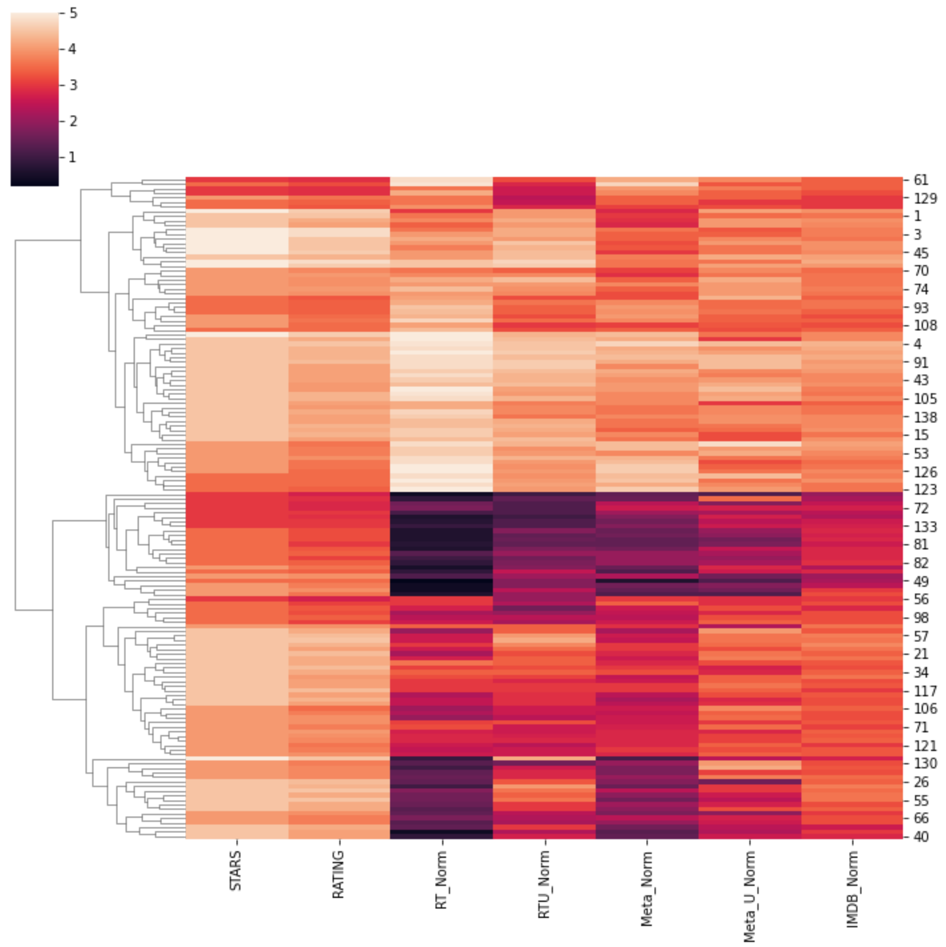
In [60]:

```
plt.figure(figsize=(7,3),dpi=150)
sns.clustermap(data=norm_scores,col_cluster=False)
```

Out[60]:

```
<seaborn.matrix.ClusterGrid at 0x298560f4eb0>
```

```
<Figure size 1050x450 with 0 Axes>
```



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?

In [61]:

```
# adding the FILM column back in to your DataFrame of normalized scores to see the results.
norm_scores['FILM'] = pd_merged['FILM']
norm_scores.head()
```

Out[61]:

	STARS	RATING	RT_Norm	RTU_Norm	Meta_Norm	Meta_U_Norm	IMDB_Norm	FILM
0	4.0	3.9	1.2	2.1	2.3	1.6	2.1	Fifty Shades of Grey (2015)
1	4.5	4.5	3.6	4.0	3.0	3.5	3.6	Jurassic World (2015)
2	5.0	4.8	3.6	4.2	3.6	3.3	3.7	American Sniper (2015)
3	5.0	4.8	4.0	4.2	3.4	3.4	3.7	Furious 7 (2015)
4	4.5	4.5	4.9	4.5	4.7	4.4	4.3	Inside Out (2015)

In [ ]:

```

```

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

In [62]:

```
worst_movies = norm_scores.nsmallest(10,'RT_Norm')
worst_movies
```

Out[62]:

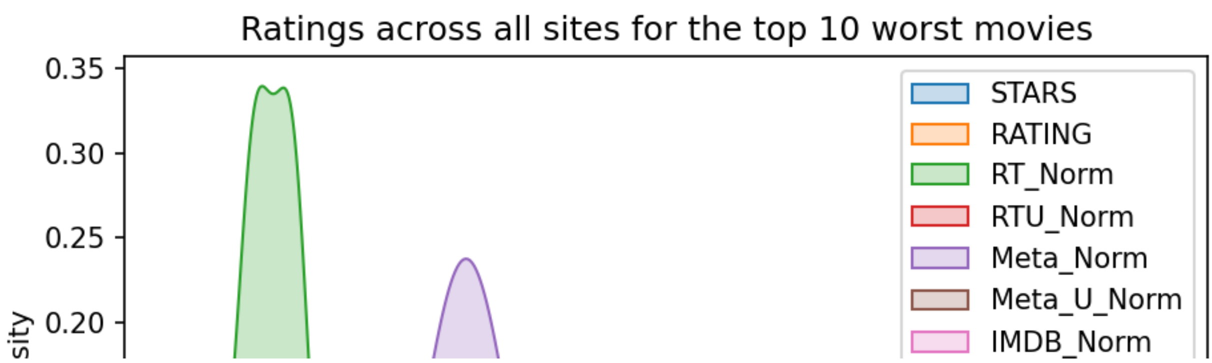
	STARS	RATING	RT_Norm	RTU_Norm	Meta_Norm	Meta_U_Norm	IMDB_Norm	FILM
49	3.5	3.5	0.2	1.8	0.6	1.2	2.2	Paul Blart: Mall Cop 2 (2015)
25	4.5	4.1	0.4	2.3	1.3	2.3	3.0	Taken 3 (2015)
28	3.0	2.7	0.4	1.0	1.4	1.2	2.0	Fantastic Four (2015)
54	4.0	3.7	0.4	1.8	1.6	1.8	2.4	Hot Pursuit (2015)
84	4.0	3.9	0.4	2.4	1.4	1.6	3.0	Hitman: Agent 47 (2015)
50	4.0	3.6	0.5	1.8	1.5	2.8	2.3	The Boy Next Door (2015)
77	3.5	3.2	0.6	1.8	1.5	2.0	2.8	Seventh Son (2015)
78	3.5	3.2	0.6	1.5	1.4	1.6	2.8	Mortdecai (2015)
83	3.5	3.3	0.6	1.7	1.6	2.5	2.8	Sinister 2 (2015)
87	3.5	3.2	0.6	1.4	1.6	1.9	2.7	Unfinished Business (2015)

In [65]:

```
plt.figure(figsize=(7,4),dpi=150)
sns.kdeplot(data=worst_movies,fill=True,clip=(0,5))
plt.title('Ratings across all sites for the top 10 worst movies')
```

Out[65]:

```
Text(0.5, 1.0, 'Ratings across all sites for the top 10 worst movies')
```




```
**Thoughts: Fandango is showing around 3-4 star ratings for films that are clearly bad!**
```

For example take Notice of 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!

In [68]:

```
# avg rating of Taken 3 = (0.4+2.3+1.3+2.3+3)/5 = 1.86 Across all other platforms.
worst_movies[worst_movies['FILM'] == 'Taken 3 (2015)']
```

Out[68]:

	STARS	RATING	RT_Norm	RTU_Norm	Meta_Norm	Meta_U_Norm	IMDB_Norm	FILM
25	4.5	4.1	0.4	2.3	1.3	2.3	3.0	Taken 3 (2015)

Final thoughts: Really ! Fandango is showing around 3-4 star ratings for films that are clearly bad! Notice the biggest offender, [Taken 3! (https://www.youtube.com/watch?v=tJrflmRCHJ0)](https://www.youtube.com/watch?v=tJrflmRCHJ0). Fandango is displaying 4.5 stars on their site for a film with an [average rating of 1.86 (https://en.wikipedia.org/wiki/Taken_3#Critical_response)](https://en.wikipedia.org/wiki/Taken_3#Critical_response) across the other platforms!

Clearly Fandango has a bias towards rating movies higher than they should be rated.