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 determine if Fandango's ratings in 2015 had a bias towards rating movies better to sell more tickets.

Part One: Understanding the Background and Data

TASK: Read this article: [Be Suspicious Of Online Movie Ratings, Especially Fandango's (http://fivethirtyeight.com/features/fandango-movies-ratings/)](http://fivethirtyeight.com/features/fandango-movies-ratings/)

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 (http://fivethirtyeight.com/features/fandango-movies-ratings/)](http://fivethirtyeight.com/features/fandango-movies-ratings/) openly available on 538's github: [https://github.com/fivethirtyeight/data (https://github.com/fivethirtyeight/data)](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

In [1]:

```
# Importing basic libraries

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

Exploring Fandango Displayed Scores versus True User Ratings

In [2]:

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

In [3]:

```
fandango.head()
```

Out[3]:

	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 [4]:

```
fandango.tail()
```

Out[4]:

	FILM	STARS	RATING	VOTES
499	Valiyavan (2015)	0.0	0.0	0
500	WWE SummerSlam 2015 (2015)	0.0	0.0	0
501	Yagavarayinum Naa Kaakka (2015)	0.0	0.0	0
502	Yesterday, Today and Tomorrow (1964)	0.0	0.0	0
503	Zarafa (2012)	0.0	0.0	0

In [5]:

```
fandango.sample(5)
```

Out[5]:

	FILM	STARS	RATING	VOTES
436	7 Minutes (2015)	0.0	0.0	0
464	La passion d'Augustine (2015)	0.0	0.0	0
99	American Ultra (2015)	4.0	3.7	638
117	What We Do in the Shadows (2015)	4.5	4.3	259
486	Set Fire to the Stars (2015)	0.0	0.0	0

In [6]:

```
fandango.shape
```

Out[6]:

```
(504, 4)
```

In [7]:

```
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 [8]:

```
fandango.describe()
```

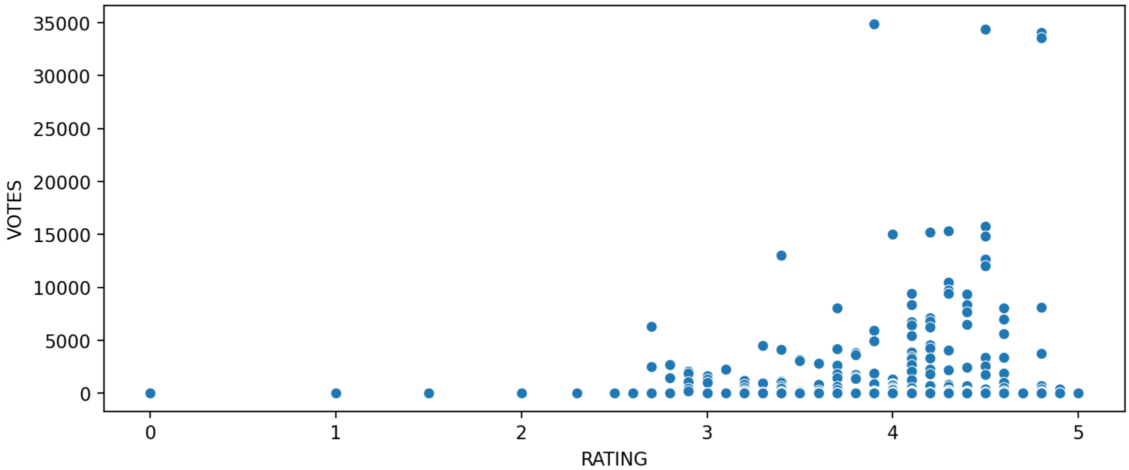
Out[8]:

	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.

In [9]:

```
plt.figure(figsize=(10,4),dpi=200)

sns.scatterplot(data=fandango,x='RATING',y='VOTES');
```



Calculating the correlation between the columns

In [10]:

```
fandango.corr()
```

```
C:\Users\vijay\AppData\Local\Temp\ipykernel_13280\1316820973.py:1: FutureW
arning: The default value of numeric_only in DataFrame.corr is deprecated.
In a future version, it will default to False. Select only valid columns o
r specify the value of numeric_only to silence this warning.
  fandango.corr()
```

Out[10]:

	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

In [11]:

```
year = 'Film Title Name (Year)'
```

In [12]:

```
year.split('(')[-1].replace(')','')
```

Out[12]:

```
'Year'
```

In [13]:

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

In [14]:

```
fandango.head()
```

Out[14]:

	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

In [15]:

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

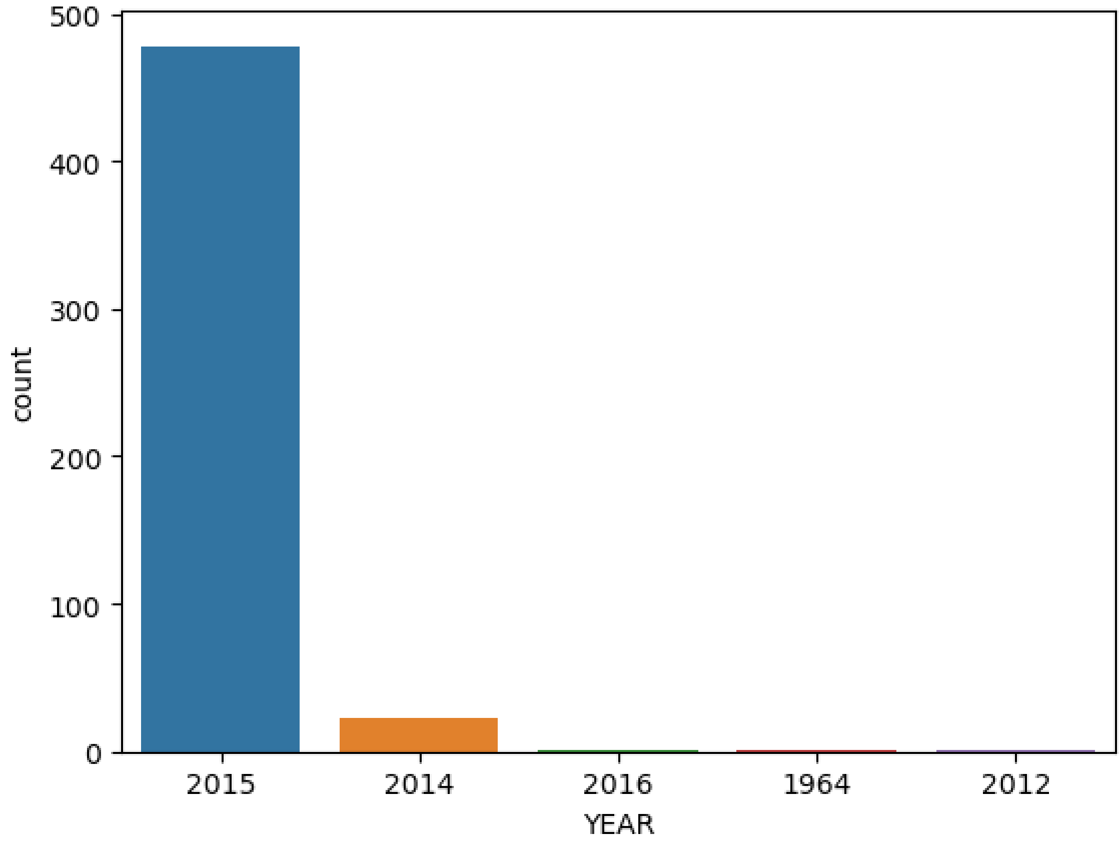
Out[15]:

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

Visualizing the count of movies per year with a plot

In [16]:

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



Top 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

How many movies have zero votes

In [18]:

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

Out[18]:

69

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

In [19]:

```
fandango1 = fandango[fandango['VOTES'] > 0]
```

In [20]:

```
fandango1
```

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

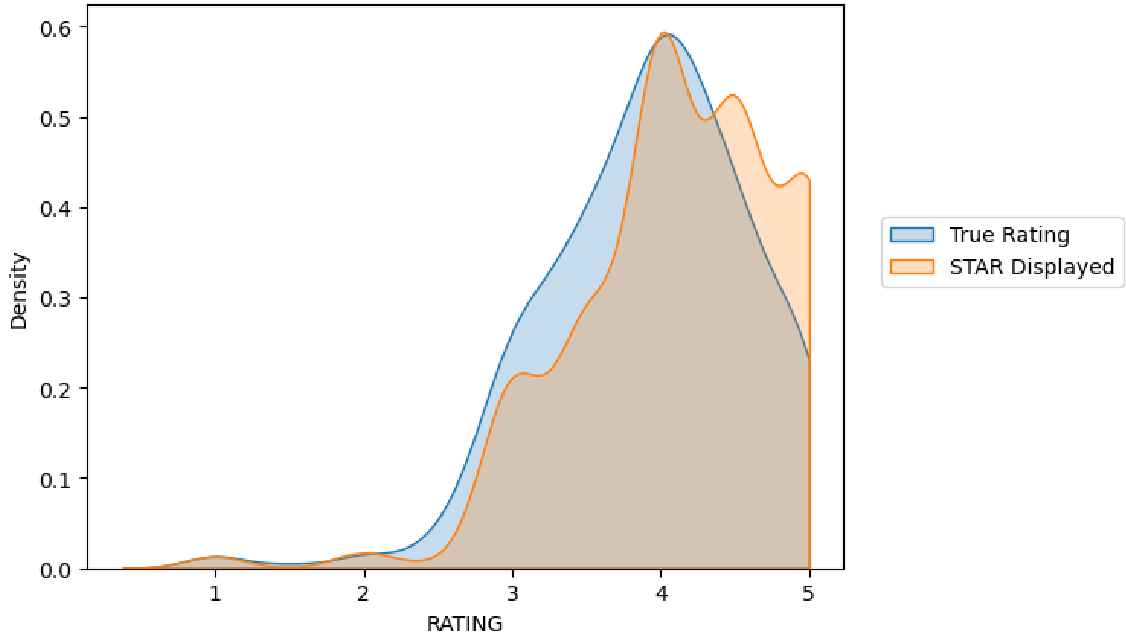
Creating a KDE plot that displays the distribution of ratings that are displayed (STARS) versus what the true rating was from votes (RATING)

In [21]:

```
sns.kdeplot(data=fandango1,x='RATING',clip=[0,5],fill=True,label='True Rating');
sns.kdeplot(data=fandango1,x='STARS',clip=[0,5],fill=True,label='STAR Displayed');
plt.legend(loc=(1.05,0.5))
```

Out[21]:

```
<matplotlib.legend.Legend at 0x1c8305c7ee0>
```



Creating a new column of the difference between STARS displayed versus true RATING.

In [22]:

```
fandango1['STARS_DIFF'] = fandango1['STARS'] - fandango1['RATING']
```

```
C:\Users\vijay\AppData\Local\Temp\ipykernel_13280\1283554698.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://
pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
view-versus-a-copy)
  fandango1['STARS_DIFF'] = fandango1['STARS'] - fandango1['RATING']
```

In [23]:

```
fandango1['STARS_DIFF'] = fandango1['STARS_DIFF'].round(2)
```

```
C:\Users\vijay\AppData\Local\Temp\ipykernel_13280\2622306232.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://
pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
view-versus-a-copy)
  fandango1['STARS_DIFF'] = fandango1['STARS_DIFF'].round(2)
```

In [24]:

```
fandango1.head()
```

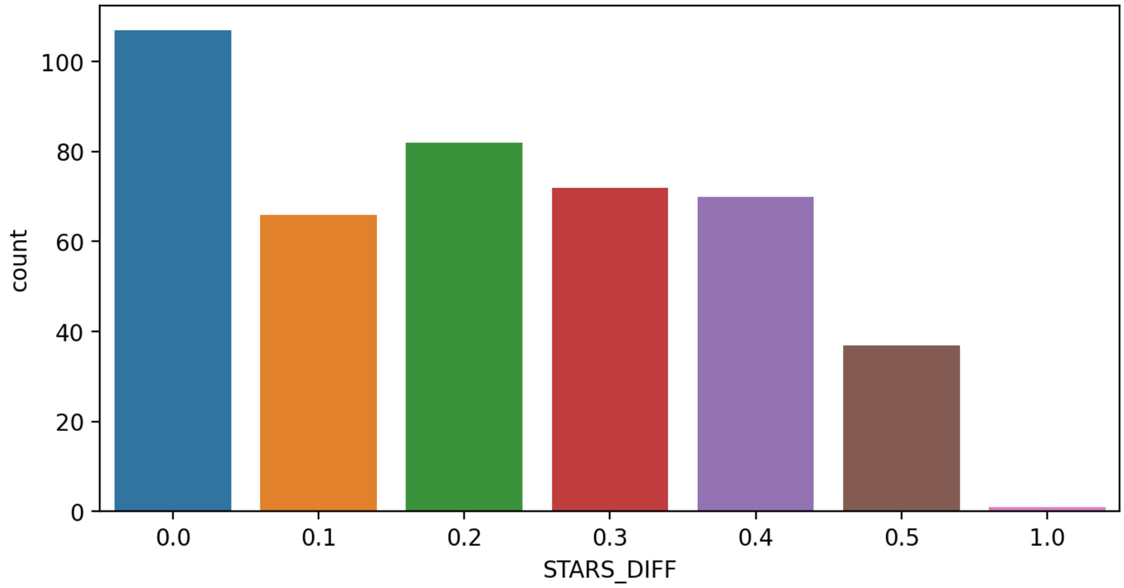
Out[24]:

	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

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

In [25]:

```
plt.figure(figsize=(8,4),dpi=200)
sns.countplot(data=fandango1, x='STARS_DIFF');
```



We can see from the plot that one movie was displaying over a 1 star difference than its true rating!

In [26]:

```
fandango1[fandango1['STARS_DIFF'] == 1.0]
```

Out[26]:

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

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

In [27]:

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

In [28]:

```
all_sites.head()
```

Out[28]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Meta
0	Avengers: Age of Ultron (2015)	74	86	66	7.1	7.8	
1	Cinderella (2015)	85	80	67	7.5	7.1	
2	Ant-Man (2015)	80	90	64	8.1	7.8	
3	Do You Believe? (2015)	18	84	22	4.7	5.4	
4	Hot Tub Time Machine 2 (2015)	14	28	29	3.4	5.1	

In [29]:

```
all_sites.tail()
```

Out[29]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Met
141	Mr. Holmes (2015)	87	78	67	7.9	7.4	
142	'71 (2015)	97	82	83	7.5	7.2	
143	Two Days, One Night (2014)	97	78	89	8.8	7.4	
144	Gett: The Trial of Viviane Amsalem (2015)	100	81	90	7.3	7.8	
145	Kumiko, The Treasure Hunter (2015)	87	63	68	6.4	6.7	

In [30]:

```
all_sites.sample(5)
```

Out[30]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metac
34	Aloha (2015)	19	31	40	4.0	5.5	
32	The Hunting Ground (2015)	92	72	77	7.8	7.5	
27	Still Alice (2015)	88	85	72	7.8	7.5	
38	Saint Laurent (2015)	51	45	52	6.8	6.3	
8	Shaun the Sheep Movie (2015)	99	82	81	8.8	7.4	

In [31]:

```
all_sites.shape
```

Out[31]:

```
(146, 8)
```

In [32]:

```
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
```

In [33]:

```
all_sites.describe()
```

Out[33]:

	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Meta
count	146.000000	146.000000	146.000000	146.000000	146.000000	
mean	60.849315	63.876712	58.808219	6.519178	6.736986	
std	30.168799	20.024430	19.517389	1.510712	0.958736	
min	5.000000	20.000000	13.000000	2.400000	4.000000	
25%	31.250000	50.000000	43.500000	5.700000	6.300000	
50%	63.500000	66.500000	59.000000	6.850000	6.900000	
75%	89.000000	81.000000	75.000000	7.500000	7.400000	
max	100.000000	94.000000	94.000000	9.600000	8.600000	

In [34]:

```
all_sites.isna().sum()
```

Out[34]:

```
FILM                          0
RottenTomatoes                0
RottenTomatoes_User           0
Metacritic                    0
Metacritic_User               0
IMDB                          0
Metacritic_user_vote_count    0
IMDB_user_vote_count          0
dtype: int64
```

Rotten Tomatoes

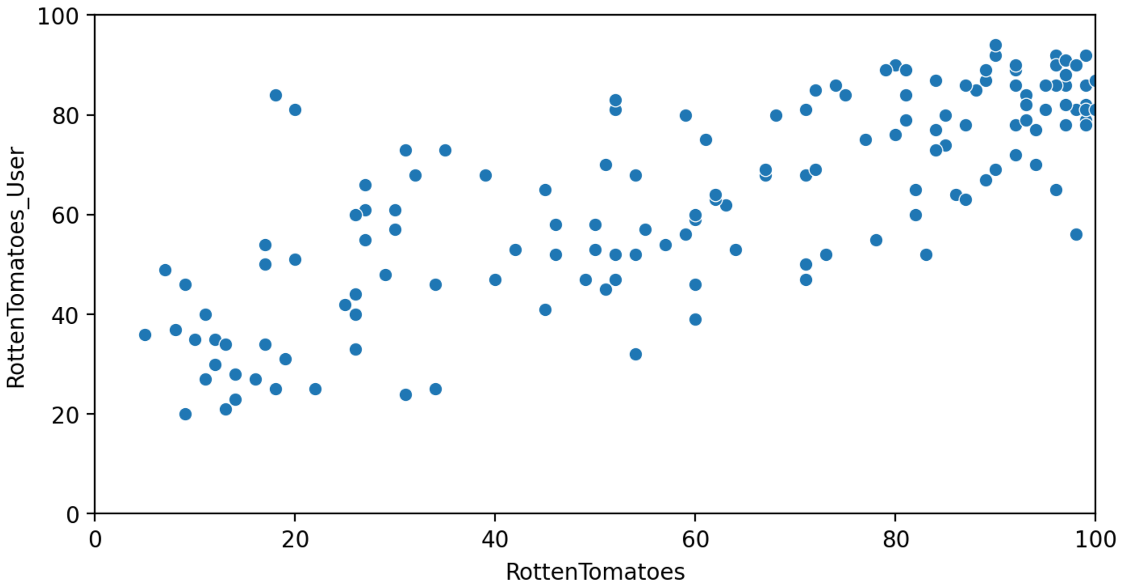
Let's first take a look at Rotten Tomatoes. RT has two sets of reviews, their critics reviews (ratings published by official critics) and user reviews.

In [35]:

```
plt.figure(figsize=(8,4),dpi=200)
sns.scatterplot(data=all_sites, x='RottenTomatoes', y='RottenTomatoes_User')
plt.xlim(0,100)
plt.ylim(0,100)
```

Out[35]:

```
(0.0, 100.0)
```



Creating a new column based off the difference between critics ratings and users ratings for Rotten Tomatoes.

In [36]:

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

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.

In [37]:

```
all_sites.head()
```

Out[37]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Meta
0	Avengers: Age of Ultron (2015)	74	86	66	7.1	7.8	
1	Cinderella (2015)	85	80	67	7.5	7.1	
2	Ant-Man (2015)	80	90	64	8.1	7.8	
3	Do You Believe? (2015)	18	84	22	4.7	5.4	
4	Hot Tub Time Machine 2 (2015)	14	28	29	3.4	5.1	

Let's now compare the overall mean difference

In [38]:

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

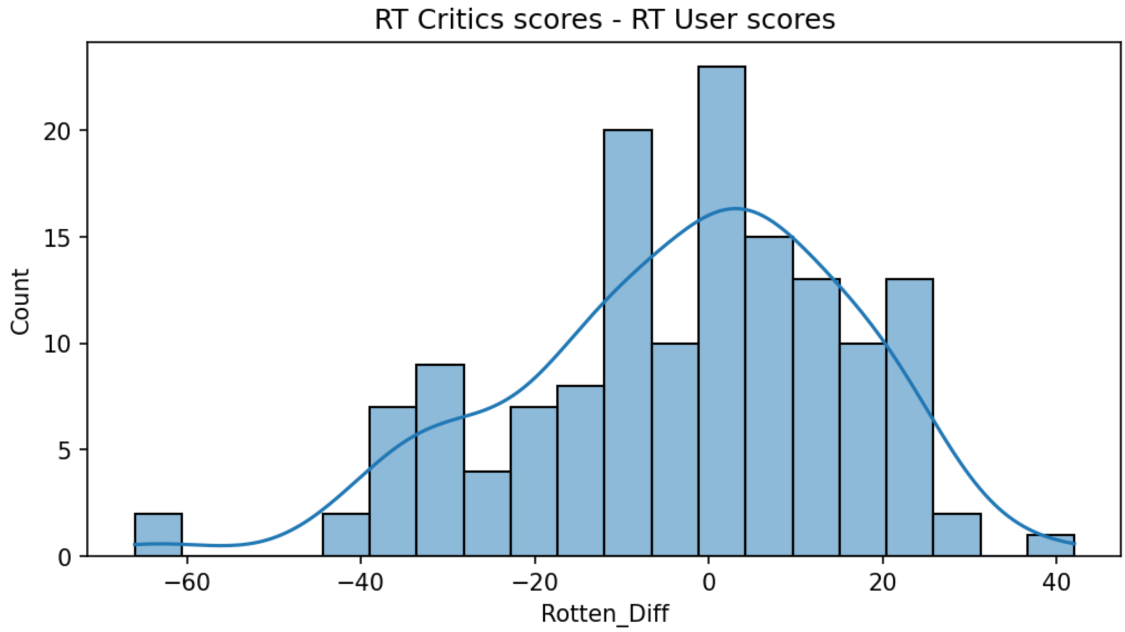
Out[38]:

```
15.095890410958905
```

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

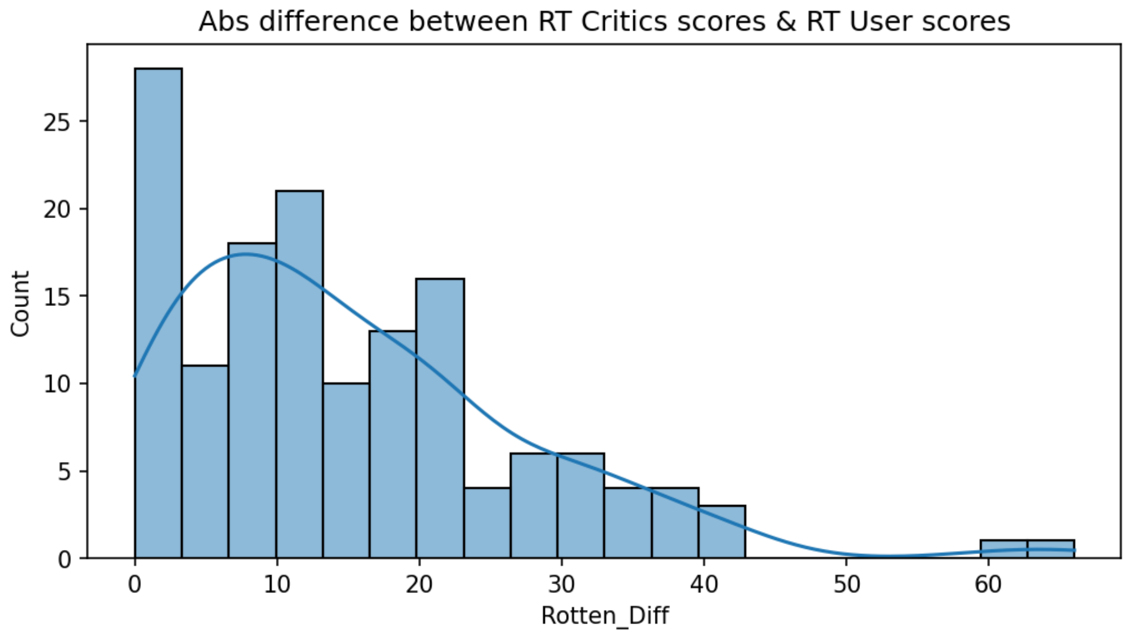
In [39]:

```
plt.figure(figsize=(8,4),dpi=150)

sns.histplot(data=all_sites, x='Rotten_Diff',bins=20, kde=True)
plt.title('RT Critics scores - RT User scores');
```



In [40]:

```
plt.figure(figsize=(8,4),dpi=150)

sns.histplot(data=all_sites, x=all_sites['Rotten_Diff'].apply(abs),bins=20, kde=True)
plt.title('Abs difference between RT Critics scores & RT User scores');
```



Let's find out which movies are causing the largest differences.

Top 5 movies users rated higher than critics on average

In [41]:

```
all_sites.nsmallest(5,'Rotten_Diff')['FILM']
```

Out[41]:

```
3          Do You Believe? (2015)
85              Little Boy (2015)
105      Hitman: Agent 47 (2015)
134      The Longest Ride (2015)
125    The Wedding Ringer (2015)
Name: FILM, dtype: object
```

Top 5 movies critics scores higher than users on average.

In [42]:

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

Out[42]:

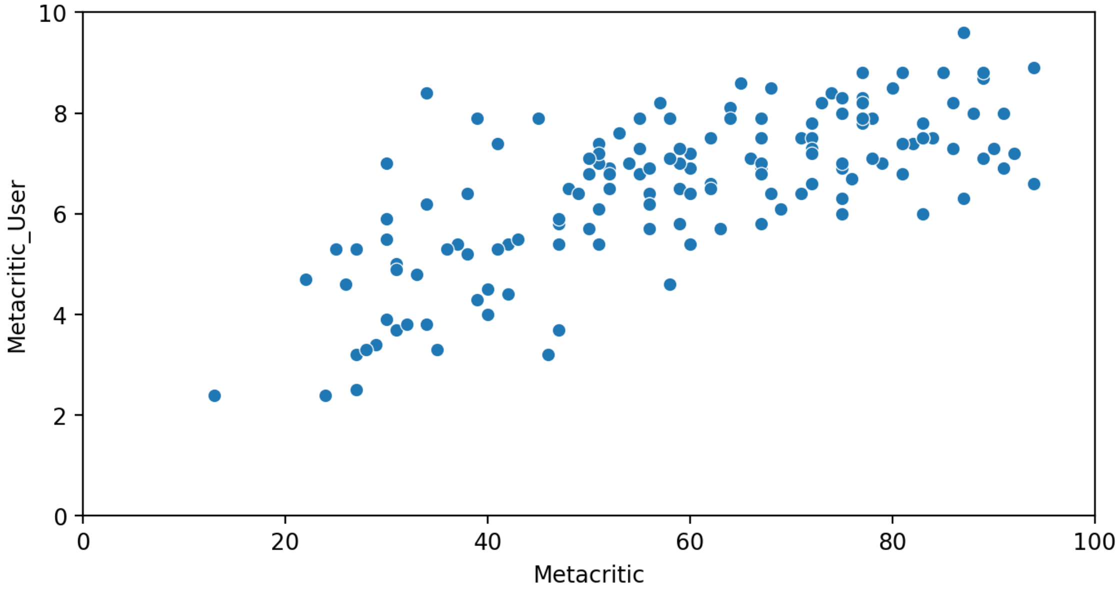
```
69                    Mr. Turner (2014)
112                   It Follows (2015)
115            While We're Young (2015)
37                 Welcome to Me (2015)
40     I'll See You In My Dreams (2015)
Name: FILM, dtype: object
```

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.

In [43]:

```
plt.figure(figsize=(8,4),dpi=200)
sns.scatterplot(data=all_sites, x='Metacritic', y='Metacritic_User')
plt.xlim(0,100)
plt.ylim(0,10);
```

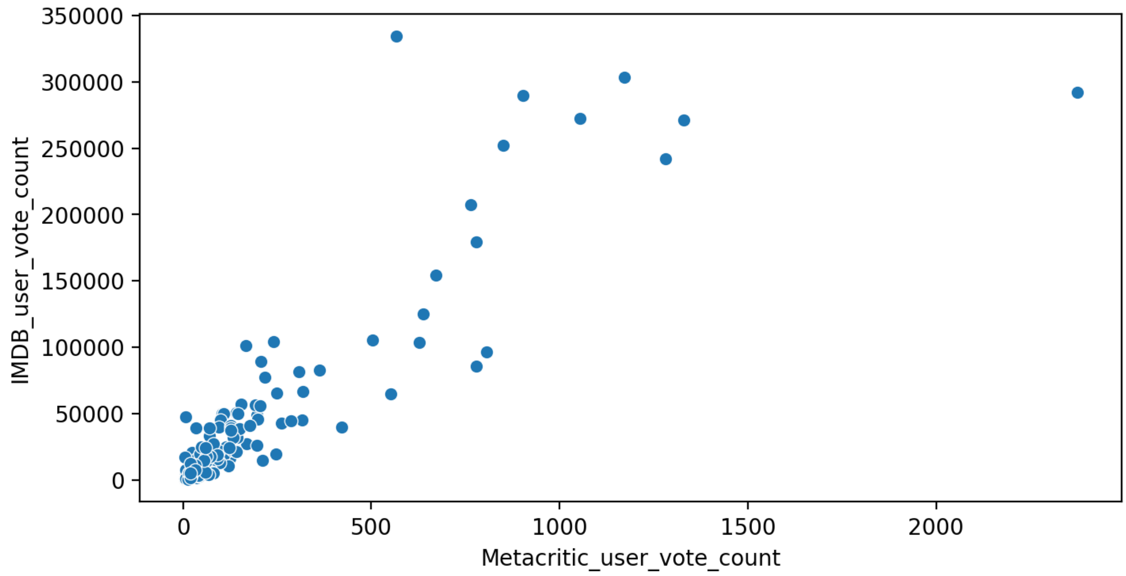


IMDB

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

In [44]:

```
plt.figure(figsize=(8,4),dpi=200)
sns.scatterplot(data=all_sites, y='IMDB_user_vote_count', x='Metacritic_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?

Let's find the movie which has the highest IMDB user vote count.

In [45]:

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

Out[45]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metac
14	The Imitation Game (2014)	90	92	73	8.2	8.1	

Let's find the movie which has the highest Metacritic user vote count.

In [46]:

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

Out[46]:

	FILM	RottenTomatoes	RottenTomatoes_User	Metacritic	Metacritic_User	IMDB	Metacri
88	Mad Max: Fury Road (2015)	97	88	89	8.7	8.3	

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.

Combining the Fandango Table with the All Sites table.

In [47]:

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

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

In [48]:

```
df.head()
```

Out[48]:

	FILM	STARS	RATING	VOTES	YEAR	RottenTomatoes	RottenTomatoes_User	Metacr
0	Fifty Shades of Grey (2015)	4.0	3.9	34846	2015	25	42	
1	Jurassic World (2015)	4.5	4.5	34390	2015	71	81	
2	American Sniper (2015)	5.0	4.8	34085	2015	72	85	
3	Furious 7 (2015)	5.0	4.8	33538	2015	81	84	
4	Inside Out (2015)	4.5	4.5	15749	2015	98	90	

In [49]:

```
df.shape
```

Out[49]:

```
(145, 13)
```

In [50]:

```
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
```

In [51]:

```
df.describe().T
```

Out[51]:

	count	mean	std	min	25%	50%	75
STARS	145.0	4.086207	0.541169	3.0	3.5	4.0	4
RATING	145.0	3.841379	0.502437	2.7	3.5	3.9	4
VOTES	145.0	3817.696552	6368.668671	35.0	218.0	1430.0	4279
RottenTomatoes	145.0	60.634483	30.161098	5.0	31.0	63.0	89
RottenTomatoes_User	145.0	63.696552	19.974749	20.0	50.0	66.0	81
Metacritic	145.0	58.696552	19.538183	13.0	43.0	59.0	75
Metacritic_User	145.0	6.508966	1.510883	2.4	5.7	6.8	7
IMDB	145.0	6.729655	0.957944	4.0	6.3	6.9	7
Metacritic_user_vote_count	145.0	184.489655	317.361740	4.0	33.0	72.0	167
IMDB_user_vote_count	145.0	42572.186207	67558.506121	243.0	5626.0	18986.0	44711
Rotten_Diff	145.0	-3.062069	19.218488	-66.0	-14.0	0.0	11

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.

Keep in mind, a simple way to convert ratings:

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

In [52]:

```
df['RT_Norm'] = np.round(df['RottenTomatoes'] / 20,1)
df['RT_User_Norm'] = np.round(df['RottenTomatoes_User'] / 20,1)
```

In [53]:

```
df['Meta_Norm'] = np.round(df['Metacritic'] / 20,1)
df['Meta_User_Norm'] = np.round(df['Metacritic_User'] / 2,1)
```

In [54]:

```
df['IMDB_Norm'] = np.round(df['IMDB'] / 2,1)
```

In [55]:

```
df.head()
```

Out[55]:

	FILM	STARS	RATING	VOTES	YEAR	RottenTomatoes	RottenTomatoes_User	Metacr
0	Fifty Shades of Grey (2015)	4.0	3.9	34846	2015	25	42	
1	Jurassic World (2015)	4.5	4.5	34390	2015	71	81	
2	American Sniper (2015)	5.0	4.8	34085	2015	72	85	
3	Furious 7 (2015)	5.0	4.8	33538	2015	81	84	
4	Inside Out (2015)	4.5	4.5	15749	2015	98	90	

Creating a new DataFrame that only contains the normalizes ratings. Include both STARS and RATING from the original Fandango table.

In [56]:

```
df.columns
```

Out[56]:

```
Index(['FILM', 'STARS', 'RATING', 'VOTES', 'YEAR', 'RottenTomatoes',
       'RottenTomatoes_User', 'Metacritic', 'Metacritic_User', 'IMDB',
       'Metacritic_user_vote_count', 'IMDB_user_vote_count', 'Rotten_Dif
f',
       'RT_Norm', 'RT_User_Norm', 'Meta_Norm', 'Meta_User_Norm', 'IMDB_Nor
m'],
      dtype='object')
```

In [57]:

```
norm_scores = df[['STARS', 'RATING','RT_Norm', 'RT_User_Norm', 'Meta_Norm', 'Meta_User_N
```

In [58]:

```
norm_scores.head()
```

Out[58]:

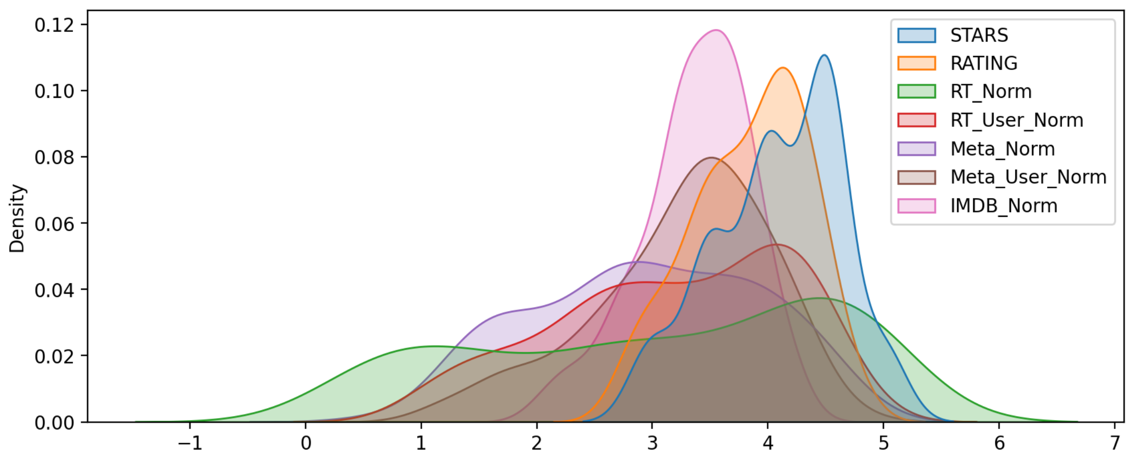
	STARS	RATING	RT_Norm	RT_User_Norm	Meta_Norm	Meta_User_Norm	IMDB_Norm
0	4.0	3.9	1.2	2.1	2.3	1.6	2.1
1	4.5	4.5	3.6	4.0	3.0	3.5	3.6
2	5.0	4.8	3.6	4.2	3.6	3.3	3.7
3	5.0	4.8	4.0	4.2	3.4	3.4	3.7
4	4.5	4.5	4.9	4.5	4.7	4.4	4.3

Comparing Distribution of Scores Across Sites

Comparing the distributions of normalized ratings across all sites.

In [59]:

```
plt.figure(figsize=(10,4),dpi=200)
sns.kdeplot(data=norm_scores,fill=True);
```

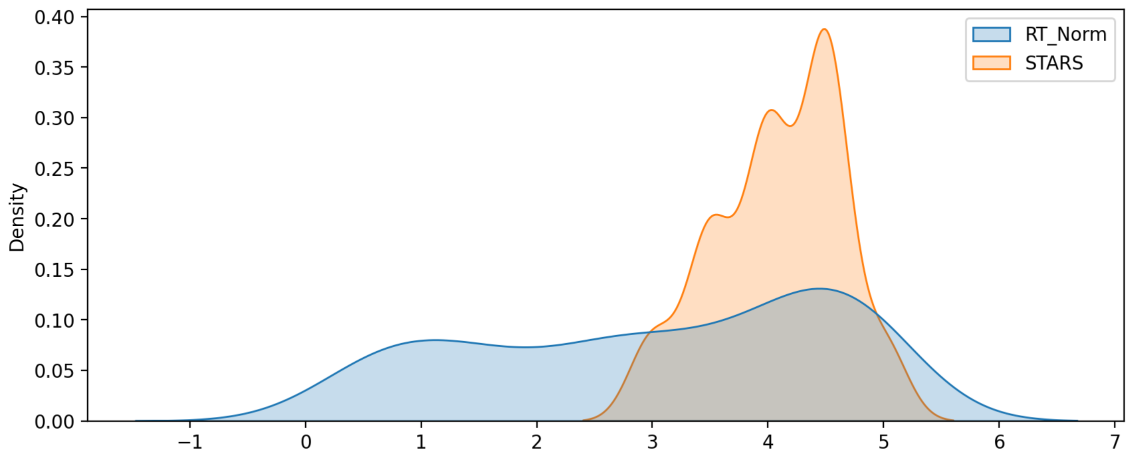


Clearly Fandango has an uneven distribution. We can also see that RT critics have the most uniform distribution. Let's directly compare these two.

Comparing the distribution of RT critic ratings against the STARS displayed by Fandango.

In [60]:

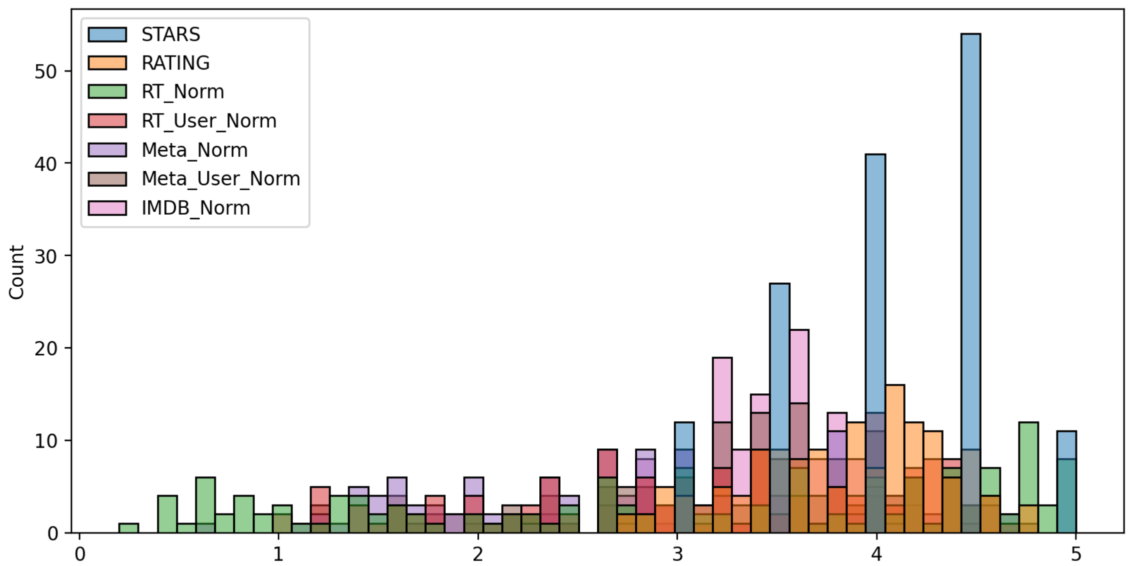
```
plt.figure(figsize=(10,4),dpi=200)
sns.kdeplot(data=norm_scores[['RT_Norm','STARS']],fill=True);
```



Creating a histplot comparing all normalized scores.

In [61]:

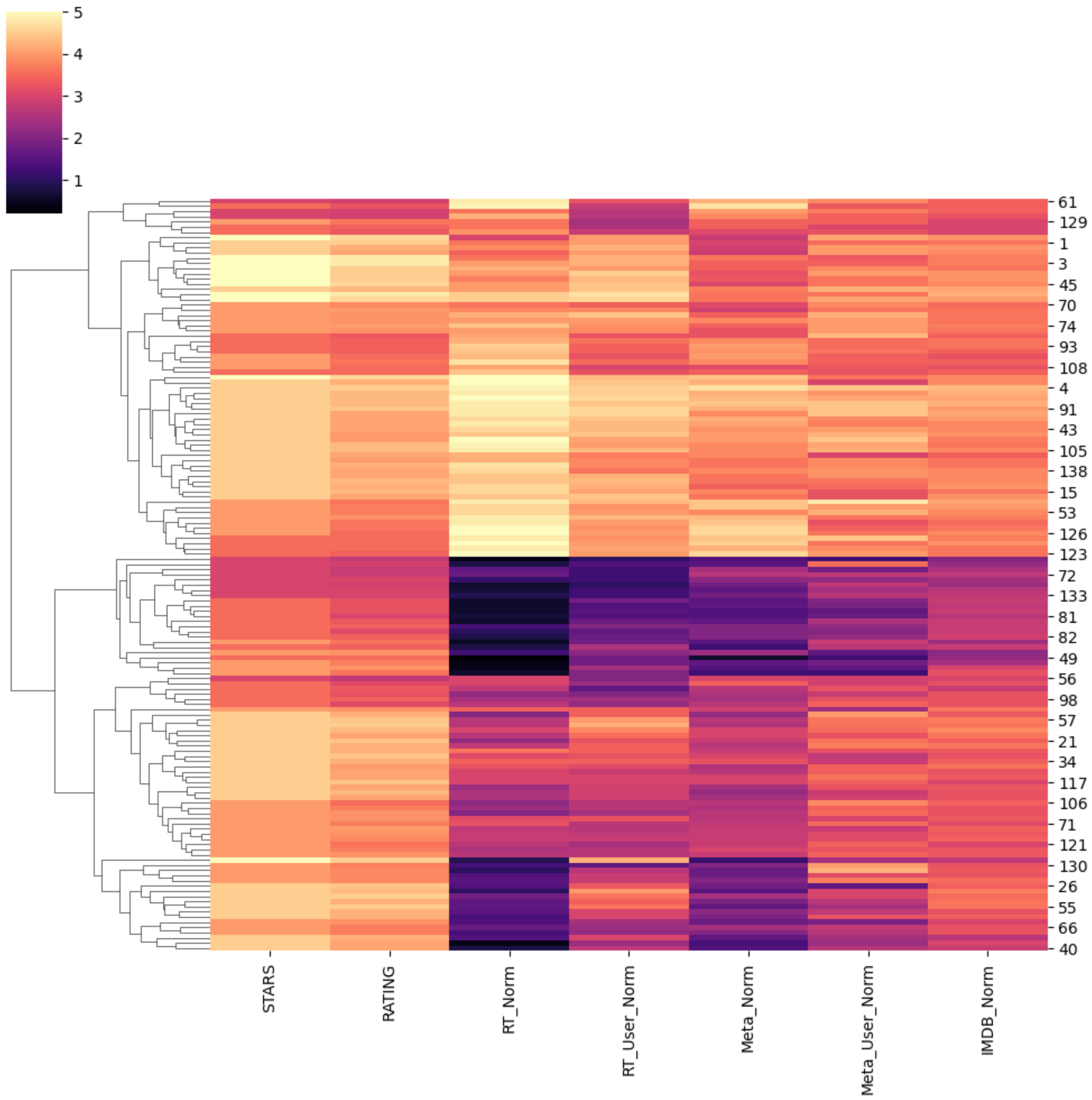
```
plt.figure(figsize=(10,5),dpi=200)
sns.histplot(data=norm_scores,fill=True,bins=50);
```



Let's find out the worst movies rated across all platforms.

In [62]:

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



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 [63]:

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

In [64]:

```
worst_films
```

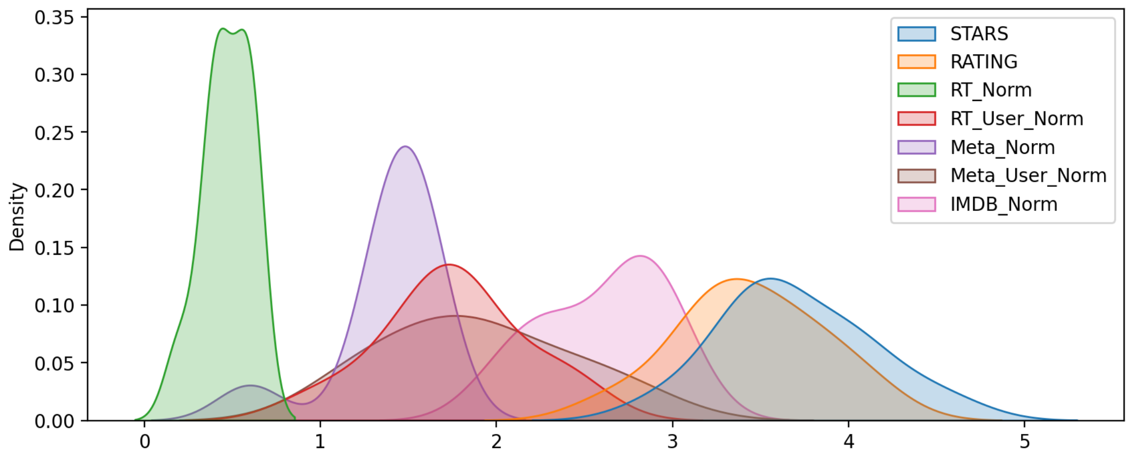
Out[64]:

	STARS	RATING	RT_Norm	RT_User_Norm	Meta_Norm	Meta_User_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

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

In [65]:

```
plt.figure(figsize=(10,4),dpi=200)
sns.kdeplot(data=worst_films,fill=True);
```



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!

In [66]:

```
df.iloc[25]
```

Out[66]:

```
FILM                            Taken 3 (2015)
STARS                                      4.5
RATING                                     4.1
VOTES                                     6757
YEAR                                      2015
RottenTomatoes                               9
RottenTomatoes_User                         46
Metacritic                                  26
Metacritic_User                            4.6
IMDB                                       6.1
Metacritic_user_vote_count                 240
IMDB_user_vote_count                    104235
Rotten_Diff                                -37
RT_Norm                                    0.4
RT_User_Norm                               2.3
Meta_Norm                                  1.3
Meta_User_Norm                             2.3
IMDB_Norm                                  3.0
Name: 25, dtype: object
```

In [67]:

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

Out[67]:

```
9.3
```

In [68]:

```
9.3/5
```

Out[68]:

```
1.86
```