Movie Analysis

> Business Problem: Microsoft has decided to create a new movie studio. Microsoft wants to know what types of films are currently doing the best at the box office to help decide what type of films to create.

Load Data and Packages

In [1]:
```
# importing packages
import pandas as pd
# setting pandas display to avoid scientific notation
pd.options.display.float_format = '{:.2f}'.format
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt

%matplotlib inline
```

In [2]:
```
# Load Files into data frames
# Contains movie info and genres imdb's website
df_titles = pd.read_csv('data/imdb.title.basics.csv.gz')
# Contains ratings and numvotes from imbd's website
df_ratings = pd.read_csv('data/imdb.title.ratings.csv.gz')
# Contains budget and revenue info
df_budget = pd.read_csv('data/tn.movie_budgets.csv.gz')
```

Data Exploration

> Explore data in each file. Before we can develop a plan for our analysis we must understand our data. Exploring our data will help us decide what questions we can ask in our analysis and what steps need to be taken to prepare the data for analysis.

- Understand contents of each column
- Understand data types of each column
- Understand basic statistics of each dataframe

In [3]:
```
df_titles.head(14)
```

1	tt0066787	Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy
5	tt0111414	A Thin Life	A Thin Life	2018	75.00	Comedy
6	tt0112502	Bigfoot	Bigfoot	2017	nan	Horror,Thriller
7	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.00	Adventure,Animation,Comedy
8	tt0139613	O Silêncio	O Silêncio	2012	nan	Documentary,History
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.00	Biography

In [4]:
```
df_titles.describe()
```

Out[4]:

	start_year	runtime_minutes
count	146144.00	114405.00
mean	2014.62	86.19
std	2.73	166.36
min	2010.00	1.00
25%	2012.00	70.00
50%	2015.00	87.00
75%	2017.00	99.00
max	2115.00	51420.00

In [5]:
```
df_titles.dtypes
```

Out[5]:
```
tconst             object
primary_title      object
original_title     object
start_year          int64
runtime_minutes   float64
genres             object
dtype: object
```

In [6]:
```
df_ratings.head()
```

Out[6]:

	tconst	averagerating	numvotes
0	tt10356526	8.30	31
1	tt10384606	8.90	559
2	tt1042974	6.40	20
3	tt1043726	4.20	50352
4	tt1060240	6.50	21

In [7]:
```
df_ratings.describe()
```

Out[7]:

	averagerating	numvotes
count	73856.00	73856.00
mean	6.33	3523.66
std	1.47	30294.02
min	1.00	5.00
25%	5.50	14.00
50%	6.50	49.00
75%	7.40	282.00
max	10.00	1841066.00

In [8]:
```
df_ratings.dtypes
```

Out[8]:
```
tconst            object
averagerating    float64
numvotes           int64
dtype: object
```

In [9]:
```
df_budget.head()
```

Out[9]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [10]:
```
df_budget.describe()
```

Out[10]:

	id
count	5782.00
mean	50.37
std	28.82
min	1.00
25%	25.00
50%	50.00
75%	75.00
max	100.00

In [11]:
```
df_budget.dtypes
```

Out[11]:
```
id                   int64
release_date        object
movie               object
production_budget   object
domestic_gross      object
worldwide_gross     object
dtype: object
```

Data Preparation

Preparation to dos:

- df_title
  - Reassign movies to all related genres
- df_ratings
  - Merge df_titles and df_ratings into the same df --> df_imbd
- df_budget
  - Convert budget and gross numbers to float so they can be manipulated as a number
  - Create a profit column
  - Create profit margin column
  - Create separate column for release year
  - Merge df_budget with df_imbd (the merged titles and ratings df)

Future Analysis Goals:

- Avg rating by genre
- Avg # of reviews by genre
- Percent of movie titles produced by genre

- profit by genre
- profit margin by genre

In [12]:
```
#Convert budget and gross columns to floats in df_budget
my_cols = ['production_budget','domestic_gross','worldwide_gross']
for i in my_cols:
    df_budget[i] = df_budget[i].str.replace('$','')\
                               .str.replace(',','')\
                               .astype(float)
#Convert release_date to date
df_budget['release_date'] = pd.to_datetime(df_budget['release_date'])
df_budget
```

Out[12]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	2009-12-18	Avatar	425000000.00	760507625.00	2776345279.00
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.00	241063875.00	1045663875.00
2	3	2019-06-07	Dark Phoenix	350000000.00	42762350.00	149762350.00
3	4	2015-05-01	Avengers: Age of Ultron	330600000.00	459005868.00	1403013963.00
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.00	620181382.00	1316721747.00
...	...	...	...	...	...	...
5777	78	2018-12-31	Red 11	7000.00	0.00	0.00
5778	79	1999-04-02	Following	6000.00	48482.00	240495.00
5779	80	2005-07-13	Return to the Land of Wonders	5000.00	1338.00	1338.00
5780	81	2015-09-29	A Plague So Pleasant	1400.00	0.00	0.00
5781	82	2005-08-05	My Date With Drew	1100.00	181041.00	181041.00

5782 rows × 6 columns

In [13]:
```
#Add worldwide_profit and worldwide_profit_margin cols
df_budget['worldwide_profit'] = df_budget['worldwide_gross'] - df_budget['p
df_budget['worldwide_profit_margin'] = df_budget['worldwide_profit'] / df_b
#Add year col
df_budget['year'] = df_budget['release_date'].dt.year
df_budget
```

Out[13]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	worldwide_
0	1	2009-12-18	Avatar	425000000.00	760507625.00	2776345279.00	2351345
1	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.00	241063875.00	1045663875.00	635063
2	3	2019-06-07	Dark Phoenix	350000000.00	42762350.00	149762350.00	-200237
3	4	2015-05-01	Avengers: Age of Ultron	330600000.00	459005868.00	1403013963.00	1072413
4	5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.00	620181382.00	1316721747.00	999721
...	...	...	...	...	...	...	
5777	78	2018-12-31	Red 11	7000.00	0.00	0.00	-7
5778	79	1999-04-02	Following	6000.00	48482.00	240495.00	234
5779	80	2005-07-13	Return to the Land of Wonders	5000.00	1338.00	1338.00	-3
5780	81	2015-09-29	A Plague So Pleasant	1400.00	0.00	0.00	-1
5781	82	2005-08-05	My Date With Drew	1100.00	181041.00	181041.00	179

5782 rows × 9 columns

In [14]:
```
#Float error when using make_genre_columns function so made sure everything
df_titles['genres'] = df_titles['genres'].astype(str)
```

In [15]:
```
def make_genre_columns(dataframe, genre_col_name='genres', drop_genres_col=
    '''Creates a new DataFrame of a column for each genres from the genres
    Input:
        dataframe: Original DataFrame
        genres_col_name: Name of the column of genres (values look like "Ac
        drop_genres_col: Flag to drop the original genres column
    Returns:
        A copy of the original DataFrame with a column for each genres from
    '''
    ## Get list of unique genres
    # Join all the (unique) genres values into one big string
    list_all_genres = ','.join(dataframe[genre_col_name].unique())
    # Get a set of all unique genres (no duplicates)
    unique_genres = set(list_all_genres.split(','))
    ## Create new columns with the genres & populate with 0 & 1
    # Make a safe copy
    new_dataframe = dataframe.copy(deep=True)
    for genre in unique_genres:
        new_dataframe[genre] = new_dataframe[genre_col_name].map(lambda val
    # Drop the unused `genre_col_name` column
    if drop_genres_col:
        new_dataframe = new_dataframe.drop([genre_col_name], axis=1)
    return new_dataframe
```

In [16]:
```
#Run df_titles through make_genre_columns function
df_titles_new = make_genre_columns(df_titles)
df_titles_new.head()
```

Out[16]:

	tconst	primary_title	original_title	start_year	runtime_minutes	Musical	History	Action	New
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	0	0	1	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	0	0	0	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	0	0	0	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	0	0	0	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	0	0	0	

5 rows × 33 columns

In [17]:
```
#Create a unige list of all genres
list_all_genres = ','.join(df_titles['genres'].unique())
unique_genres = list(set(list_all_genres.split(',')))
print(unique_genres)
```

```
['Musical', 'History', 'Action', 'News', 'Reality-TV', 'Comedy', 'Music',
'Talk-Show', 'Mystery', 'Adventure', 'Game-Show', 'Sci-Fi', 'Horror', 'Sh
ort', 'Crime', 'Documentary', 'Fantasy', 'Animation', 'Thriller', 'Spor
t', 'Biography', 'nan', 'Romance', 'War', 'Western', 'Adult', 'Drama', 'F
amily']
```

In [18]:
```
#Merge df_titles_new with df_ratings
df_imbd = df_titles_new.merge(df_ratings, left_on='tconst', right_on='tcons
df_imbd.head()
```

Out[18]:

	tconst	primary_title	original_title	start_year	runtime_minutes	Musical	History	Action	News
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	0	0	1	0
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	0	0	0	0
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	0	0	0	0
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	0	0	0	0
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	0	0	0	0

5 rows × 35 columns

In [19]:
```
# Merge df_budget with df_imbd
df_imbd_budget = df_budget.merge(df_imbd, left_on=['movie','year'], right_o
)
df_imbd_budget.head()
```

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	worldwide_profi
0	2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.00	241063875.00	1045663875.00	635063875.0(
1	3	2019-06-07	Dark Phoenix	350000000.00	42762350.00	149762350.00	-200237650.0(
2	4	2015-05-01	Avengers: Age of Ultron	330600000.00	459005868.00	1403013963.00	1072413963.0(
3	7	2018-04-27	Avengers: Infinity War	300000000.00	678815482.00	2048134200.00	1748134200.0(
4	9	2017-11-17	Justice League	300000000.00	229024295.00	655945209.00	355945209.0(

5 rows × 44 columns

In [20]:
```
df_imbd.count()
```

Out[20]:
```
tconst             73856
primary_title      73856
original_title     73856
start_year         73856
runtime_minutes    66236
Musical            73856
History            73856
Action             73856
News               73856
Reality-TV         73856
Comedy             73856
Music              73856
Talk-Show          73856
Mystery            73856
Adventure          73856
Game-Show          73856
Sci-Fi             73856
Horror             73856
Short              73856
Crime              73856
Documentary        73856
Fantasy            73856
Animation          73856
Thriller           73856
Sport              73856
Biography          73856
nan                73856
Romance            73856
War                73856
Western            73856
Adult              73856
Drama              73856
Family             73856
averagerating      73856
numvotes           73856
dtype: int64
```

In [21]:
```
df_budget.count()
```

Out[21]:
```
id                      5782
release_date            5782
movie                   5782
production_budget       5782
domestic_gross          5782
worldwide_gross         5782
worldwide_profit        5782
worldwide_profit_margin 5782
year                    5782
dtype: int64
```

In [22]:
```
df_imbd_budget.count()
```

Out[22]:
```
id                        1498
release_date              1498
movie                     1498
production_budget         1498
domestic_gross            1498
worldwide_gross           1498
worldwide_profit          1498
worldwide_profit_margin   1498
year                      1498
tconst                    1498
primary_title             1498
original_title            1498
start_year                1498
runtime_minutes           1490
Musical                   1498
History                   1498
Action                    1498
News                      1498
Reality-TV                1498
Comedy                    1498
Music                     1498
Talk-Show                 1498
Mystery                   1498
Adventure                 1498
Game-Show                 1498
Sci-Fi                    1498
Horror                    1498
Short                     1498
Crime                     1498
Documentary               1498
Fantasy                   1498
Animation                 1498
Thriller                  1498
Sport                     1498
Biography                 1498
nan                       1498
Romance                   1498
War                       1498
Western                   1498
Adult                     1498
Drama                     1498
Family                    1498
averagerating             1498
numvotes                  1498
dtype: int64
```

In [23]:
```
# Number of records lost in df_budget and df_imbd merge
5782 - 1498
```

Out[23]:
```
4284
```

In [24]:
```
# Percent of records lost in df_budget and df_imbd merge
(5782 - 1498)/5782
```

Out[24]:
```
0.7409200968523002
```

Data Analysis

Analysis Goals:

- Avg rating by genre
- Avg # of reviews by genre
- profit by genre
- profit margin by genre

In [25]:
```
# Create a df with summary statistics grouped by genre for percent of title
column_names=['genre','mean_rating', 'count_titles', 'avg_num_votes', 'avg_
my_dict = {}
i = 0
for genre in unique_genres:
    df_genre = df_imbd[df_imbd[genre] == 1]
    m = df_genre['averagerating'].mean()
    c = df_genre['tconst'].count()
    d = df_genre['numvotes'].mean()
    t = df_genre['runtime_minutes'].mean()
    y = df_genre['start_year'].mean()

    my_dict[i] = [genre, m,c,d,t,y]
    i = i +1

print(my_dict)
df_summary = pd.DataFrame.from_dict(my_dict, orient='index',
                        columns=column_names)
```

```
360618202613, 6988, 14476.485689753863, 104.00317611561061, 2014.28191184
88837], 3: ['News', 7.2713298791018985, 579, 212.98618307426597, 78.27130
434782609, 2013.062176165803], 4: ['Reality-TV', 6.499999999999999, 17, 2
7.0, 76.0, 2014.1176470588234], 5: ['Comedy', 6.002689415847302, 17290, 4
297.617408906883, 97.212388810107, 2014.2533256217466], 6: ['Music', 6.93
0521936459925, 2644, 2524.3343419062026, 96.05086136177195, 2013.93645990
92285], 7: ['Talk-Show', nan, 0, nan, nan, nan], 8: ['Mystery', 5.9204014
47844683, 3039, 8113.618295491938, 95.19522326064381, 2014.416913458374
4], 9: ['Adventure', 6.196201205134906, 3817, 22067.74665968038, 93.77133
388566695, 2014.3031176316479], 10: ['Game-Show', 7.3, 2, 1734.5, 117.0,
2015.0], 11: ['Sci-Fi', 5.4897552130552985, 2206, 19474.292384406166, 92.
32666015625, 2014.3458748866726], 12: ['Horror', 5.00344018764659, 7674,
3112.417904612979, 88.57582767095562, 2014.3530101641907], 13: ['Short',
8.8, 1, 8.0, 18.0, 2018.0], 14: ['Crime', 6.115441335935799, 4611, 8594.9
59011060508, 99.50991240202859, 2014.2424636738235], 15: ['Documentary',
7.332090350926571, 17753, 266.96023207345235, 85.76630335505084, 2014.132
6536360052], 16: ['Fantasy', 5.919473189087487, 2126, 12387.443085606774,
96.21381411884205, 2014.309971777987], 17: ['Animation', 6.24830751577740
9, 1743, 8808.549627079748, 85.456346749226, 2014.3666092943201], 18: ['T
```

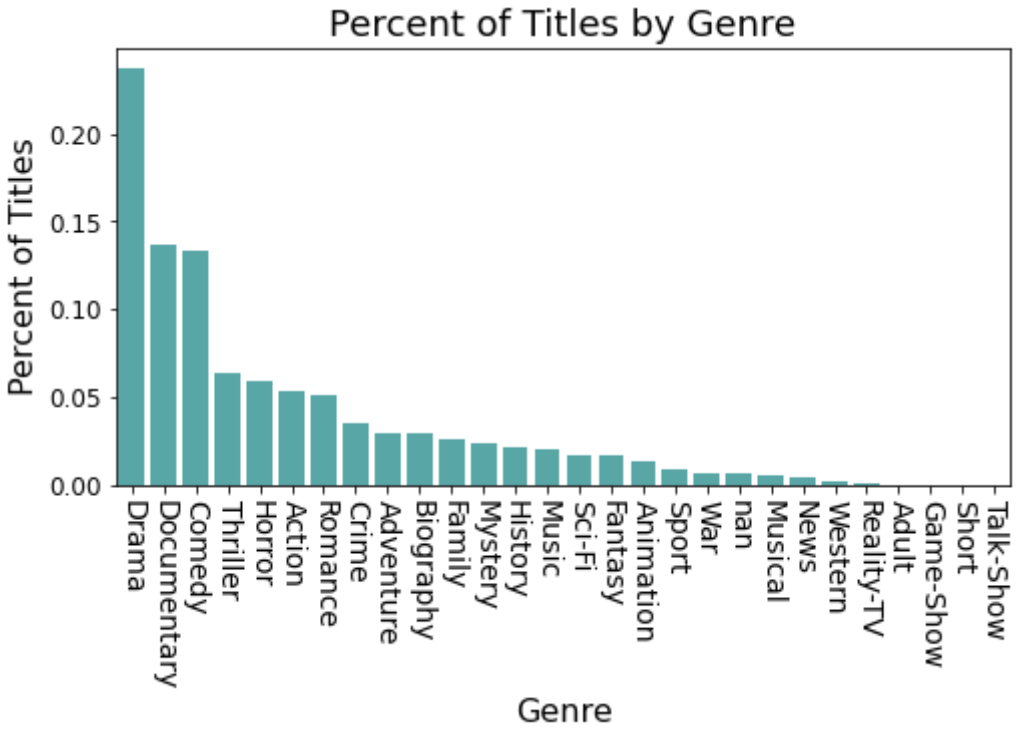
In [26]:
```
# Add percent_titles column
df_summary['percent_titles'] =1.0*df_summary['count_titles']/df_summary['co
```

In [27]:
```
df_summary
```

Out[27]:

	genre	mean_rating	count_titles	avg_num_votes	avg_runtime	avg_year	percent_titles
0	Musical	6.50	721	1925.06	104.37	2014.03	0.01
1	History	7.04	2825	2776.41	92.61	2013.87	0.02
2	Action	5.81	6988	14476.49	104.00	2014.28	0.05
3	News	7.27	579	212.99	78.27	2013.06	0.00
4	Reality-TV	6.50	17	27.00	76.00	2014.12	0.00
5	Comedy	6.00	17290	4297.62	97.21	2014.25	0.13
6	Music	6.93	2644	2524.33	96.05	2013.94	0.02
7	Talk-Show	nan	0	nan	nan	nan	0.00
8	Mystery	5.92	3039	8113.62	95.20	2014.42	0.02
9	Adventure	6.20	3817	22067.75	93.77	2014.30	0.03
10	Game-Show	7.30	2	1734.50	117.00	2015.00	0.00

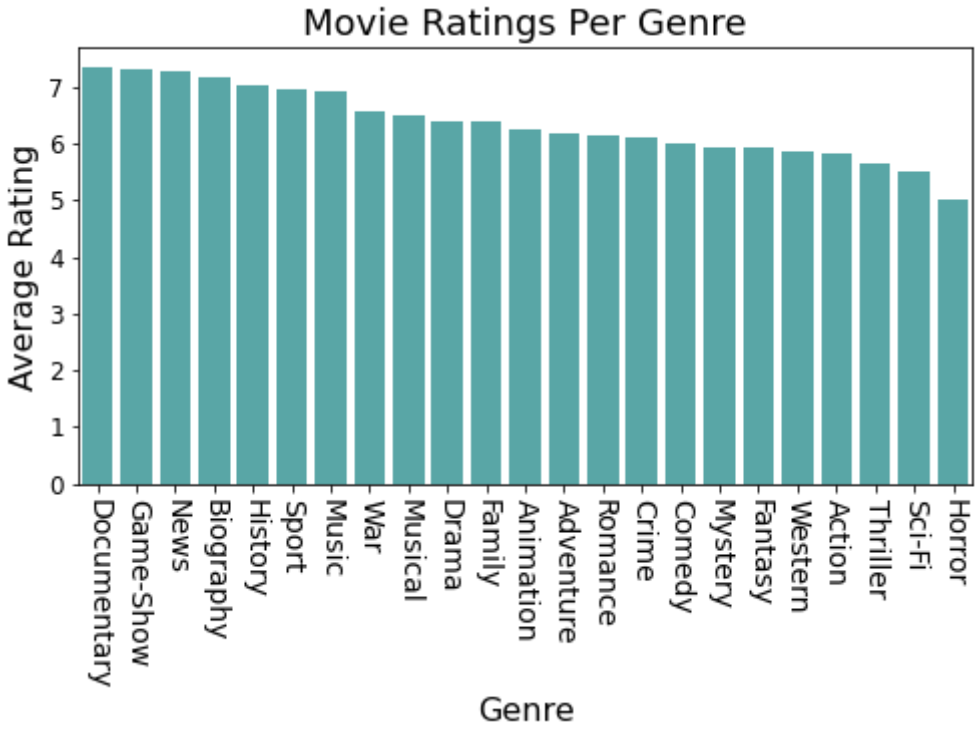
In [28]:
```
#Create visualization for percent of titles by genre
df_graph = df_summary.sort_values(by=['percent_titles'],ascending = False)
plt.figure(figsize=(8,4))
sns.barplot(data=df_graph, x='genre',y='percent_titles', color="aqua", satu
plt.title('Percent of Titles by Genre', fontsize=18)
plt.ylabel('Percent of Titles', fontsize=16)
plt.xlabel('Genre', fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.xticks(rotation=-90);
```



- Genres with most titles:
    1. Drama
    2. Documentary
    3. Comedy

- We can see from our visualization that our competitors primarily produce films associated with the Drama genre. About 24% of all films examined can be associated with the Drama genre. In second and third place are Documentary and Comedy at around 13-14% each. These three genres dominate all other genres; altogether they account for about half of all films produced.

In [29]:
```
#Create a visualization for movie ratings by genre
df_graph = df_summary[df_summary['avg_num_votes']> 100].sort_values(by=['me
plt.figure(figsize=(8,4))
sns.barplot(data=df_graph, x='genre',y='mean_rating', color="aqua", saturat
plt.title('Movie Ratings Per Genre', fontsize=18)
plt.ylabel('Average Rating', fontsize=16)
plt.xlabel('Genre', fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.xticks(rotation=-90);
```



- Genres with highest ratings:
    1. Documentary
    2. Game-show
    3. News
- Viewer ratings per genre are very similar with the exception of a slightly lower rating for Westerns. There could be a selection bias here because only individuals which have already decided they want to watch a certain genre will provide a rating.
- The only top three genre which overlaps with the top 3 produced genres is Documentary.

In [30]:
```
# Create a df with summary statistics grouped by genre for buget, profit, a
column_names_2=['genre','count_of_titles','avg_year',
                'avg_runtime_minutes', 'avg_rating', 'median_production_bud
                'median_worldwide_profit', 'median_worldwide_profit_margin'
my_dict_2 = {}
i = 0
for genre in unique_genres:
    df_genre = df_imbd_budget[df_imbd_budget[genre] == 1]

    my_dict_2[i] = [genre,
                    df_genre['primary_title'].count(),
                    df_genre['start_year'].mean(),
                    df_genre['runtime_minutes'].mean(),
                    df_genre['averagerating'].mean(),
                    df_genre['production_budget'].median(),
                    df_genre['worldwide_profit'].median(),
                    df_genre['worldwide_profit_margin'].median()
                   ]
    i = i +1

print(my_dict_2)
df_summary_2 = pd.DataFrame.from_dict(my_dict_2, orient='index',
                        columns=column_names_2)
```

```
{0: ['Musical', 9, 2012.7777777777778, 115.11111111111111, 6.077777777777
7775, 55000000.0, 35552675.0, 0.3926187161229638], 1: ['History', 39, 201
5.051282051282, 124.12820512820512, 6.946153846153848, 25000000.0, 200449
09.0, 0.4650659499862768], 2: ['Action', 447, 2014.0671140939598, 112.064
8769574944, 6.2436241610738215, 58000000.0, 52737201.0, 0.527534787108576
2], 3: ['News', 0, nan, nan, nan, nan, nan, nan], 4: ['Reality-TV', 0, na
n, nan, nan, nan, nan, nan, nan], 5: ['Comedy', 514, 2013.5875486381324, 102.5
3424657534246, 6.194747081712068, 25500000.0, 29484039.0, 0.5721417910341
198], 6: ['Music', 56, 2013.642857142857, 110.17857142857143, 6.321428571
4285685, 15000000.0, 11938819.5, 0.5418963748040291], 7: ['Talk-Show', 0,
nan, nan, nan, nan, nan, nan, nan], 8: ['Mystery', 126, 2014.126984126984, 10
5.91269841269842, 6.103968253968255, 12000000.0, 33547637.5, 0.6907233771
593373], 9: ['Adventure', 350, 2014.2485714285715, 111.13753581661891, 6.
44257142857143, 100000000.0, 128795727.0, 0.6198683799102109], 10: ['Game
-Show', 0, nan, nan, nan, nan, nan, nan], 11: ['Sci-Fi', 133, 2014.383458
6466166, 114.71428571428571, 6.449624060150375, 80000000.0, 120796009.0,
0.62740262596782], 12: ['Horror', 182, 2014.1153846153845, 97.59890109890
11, 5.460989010989014, 9500000.0, 17966210.5, 0.5946980760717238], 13:
['Short', 0, nan, nan, nan, nan, nan, nan], 14: ['Crime', 234, 2013.93162
3931624, 109.38034188034187, 6.311965811965811, 28000000.0, 13630709.5,
0.385118293897491], 15: ['Documentary', 37, 2013.1351351351352, 83.583333
33333333, 6.8108108108108105, 2000000.0, 1653715.0, 0.27198145591164496],
16: ['Fantasy', 123, 2013.918699186992, 111.17073170731707, 6.10894308943
0891, 60000000.0, 41647574.0, 0.5398502138822221], 17: ['Animation', 101,
2014.1584158415842, 94.53465346534654, 6.519801980198023, 85000000.0, 196
392649.0, 0.6660616782066121], 18: ['Thriller', 263, 2013.809885931559, 1
05.44866920152091, 5.99619771863118, 20000000.0, 26844357.0, 0.5692172404
429768], 19: ['Sport', 34, 2013.9411764705883, 119.70588235294117, 6.8911
76470588235, 17500000.0, 12042788.5, 0.3337962257379088], 20: ['Biograph
y', 133, 2014.8045112781954, 118.46616541353383, 7.029323308270678, 20000
000.0, 17425450.0, 0.4652044166984573], 21: ['nan', 2, 2014.0, nan, 6.949
999999999999, 72000000.0, 38278139.0, 0.25023751755030355], 22: ['Romanc
```

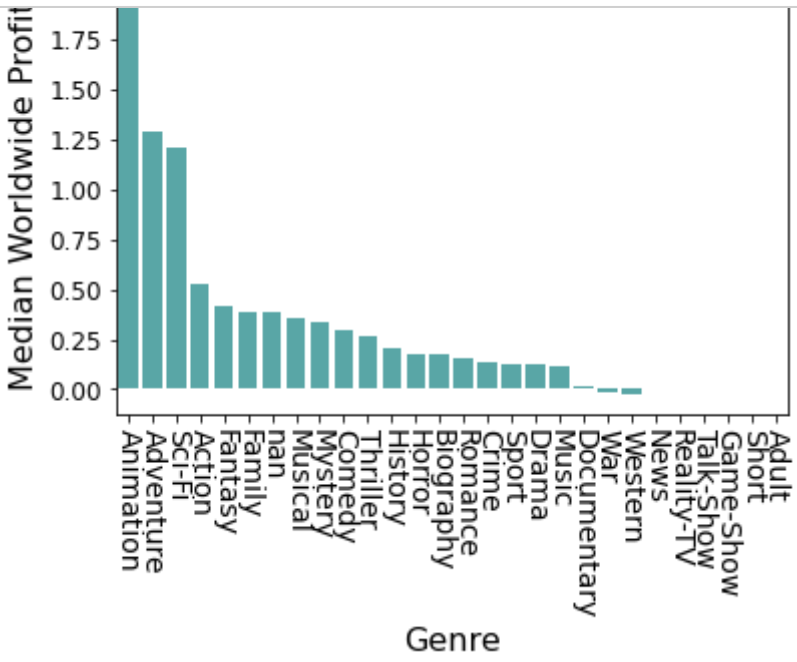
```
e', 188, 2013.0212765957447, 106.03743315508021, 6.310638297872338, 17000
000.0, 15746105.5, 0.5635678973430353], 23: ['War', 17, 2013.588235294117
6, 120.6470588235294, 6.570588235294117, 20000000.0, -1973745.0, -0.19685
765023929672], 24: ['Western', 11, 2012.8181818181818, 115.5454545454545
5, 6.318181818181818, 35000000.0, -2240304.0, -0.9470473695937643], 25:
['Adult', 0, nan, nan, nan, nan, nan, nan], 26: ['Drama', 726, 2013.84022
0385675, 111.4986187845304, 6.540633608815421, 17000000.0, 12036639.0, 0.
43188044303034906], 27: ['Family', 94, 2013.372340425532, 105.88172043010
752, 6.142553191489362, 39500000.0, 38644914.5, 0.499179119549635]}
```

In [31]:
```
# Add percent_titles column
df_summary_2['percent_titles'] =1.0*df_summary_2['count_of_titles']/df_summ
```

In [32]:
```
df_summary_2
```

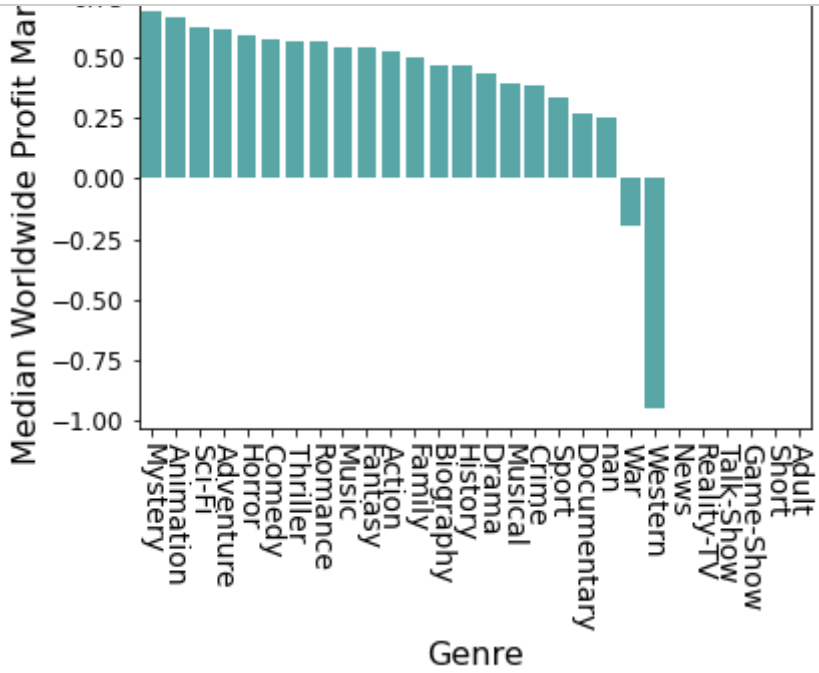
16	Fantasy	123	2013.92	111.17	6.11	60000000.0
17	Animation	101	2014.16	94.53	6.52	85000000.0
18	Thriller	263	2013.81	105.45	6.00	20000000.0
19	Sport	34	2013.94	119.71	6.89	17500000.0
20	Biography	133	2014.80	118.47	7.03	20000000.0
21	nan	2	2014.00	nan	6.95	72000000.0
22	Romance	188	2013.02	106.04	6.31	17000000.0
23	War	17	2013.59	120.65	6.57	20000000.0
24	Western	11	2012.82	115.55	6.32	35000000.0
25	Adult	0	nan	nan	nan	na

In [33]:
```
df_graph = df_summary_2.sort_values(by=['median_worldwide_profit'],ascendin
sns.barplot(data=df_graph, x="genre", y="median_worldwide_profit", color='a
plt.title('Profit per Genre', fontsize=18)
plt.ylabel('Median Worldwide Profit', fontsize=16)
plt.xlabel('Genre', fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.xticks(rotation=-90);
```



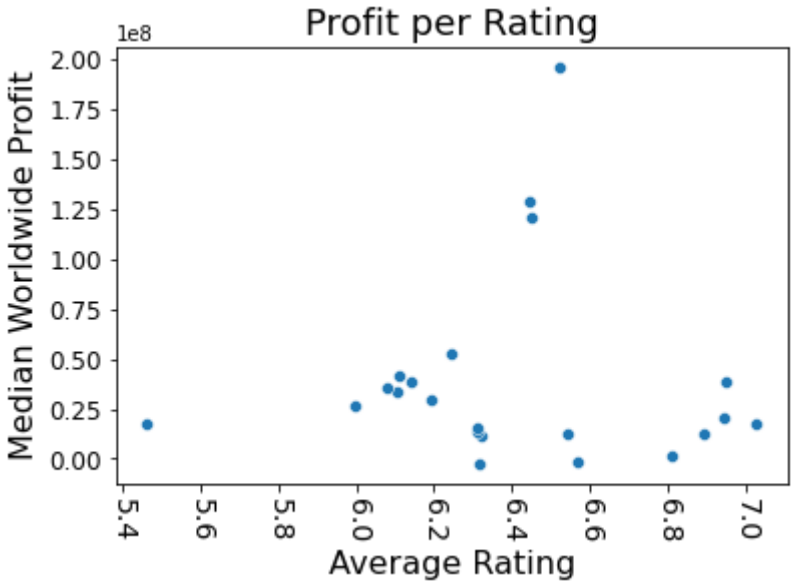
- Do commonly produced genres earn higher profits?
  - Genres with highest ratings:
    1. Documentary
    2. Game-show
    3. News
  - Genres with most profit:
    1. Animation
    2. Adventure
    3. Sci-Fi
- The 3 genres associated with half of all titles produced are nowhere in the top three earning genres.

In [34]:
```
df_graph = df_summary_2.sort_values(by=['median_worldwide_profit_margin'],a
sns.barplot(data=df_graph, x="genre", y="median_worldwide_profit_margin", c
plt.title('Profit Margin per Genre', fontsize=18)
plt.ylabel('Median Worldwide Profit Margin', fontsize=16)
plt.xlabel('Genre', fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.xticks(rotation=-90);
```



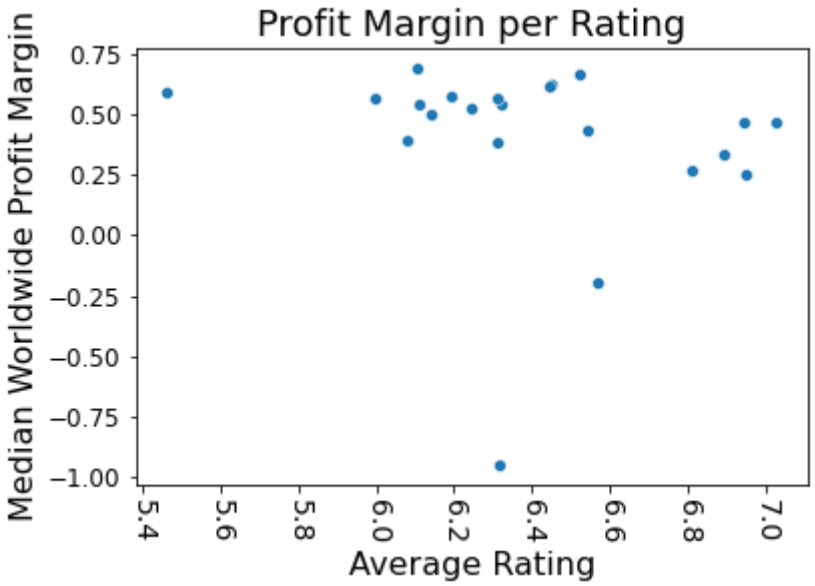
- The 3 genres associated with half of all titles produced are nowhere in the genres which have the best profit margin either.
  - Genres with highest ratings:
    1. Documentary
    2. Game-show
    3. News
  - Genres with most profit margin:
    1. Mystery
    2. Animation
    3. Sci-Fi

In [35]:
```
#Visualize profit per average genre rating
df_graph = df_summary_2.sort_values(by=['avg_rating'],ascending = False)
sns.scatterplot(data=df_graph, x="avg_rating", y="median_worldwide_profit")
#                  color='aqua', saturation=.3)
plt.title('Profit per Rating', fontsize=18)
plt.ylabel('Median Worldwide Profit', fontsize=16)
plt.xlabel('Average Rating', fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.xticks(rotation=-90);
```



- Do highly rated genres earn higher profits?
  - Genres with highest ratings:
    1. Documentary
    2. Game-show
    3. News
  - Genres with most profit:
    1. Animation
    2. Adventure
    3. Sci-Fi
- The 3 genres which received the highest average rating are not part of the top 3 earning genres.

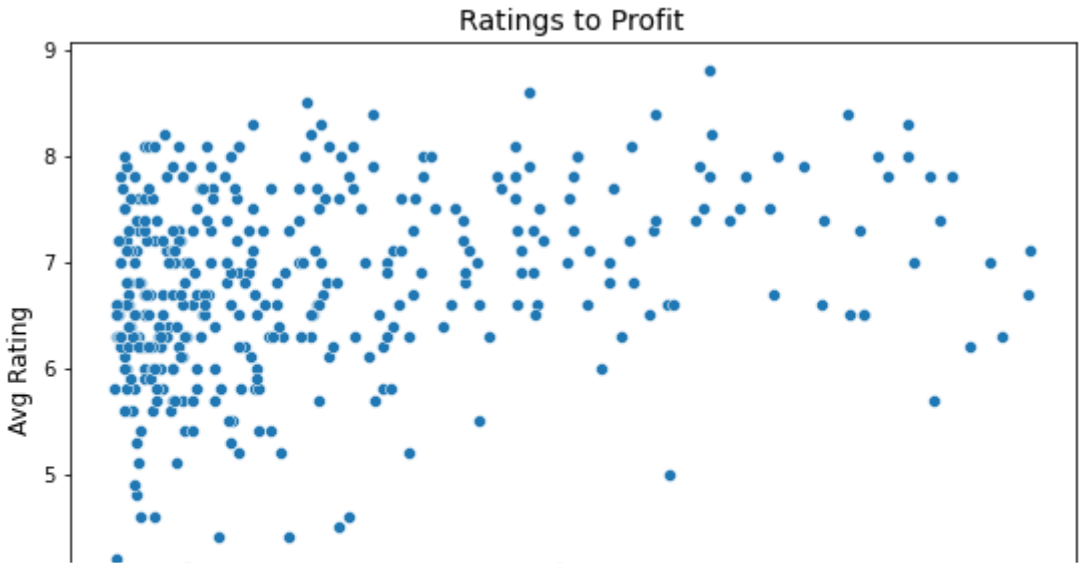
In [36]:
```
#Visualize profit margin vs avegage genre rating
df_graph = df_summary_2.sort_values(by=['avg_rating'],ascending = False)
sns.scatterplot(data=df_graph, x="avg_rating", y="median_worldwide_profit_m
plt.title('Profit Margin per Rating', fontsize=18)
plt.ylabel('Median Worldwide Profit Margin', fontsize=16)
plt.xlabel('Average Rating', fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.xticks(rotation=-90);
```



- Do highly rated genres have better margins?
  - Genres with highest ratings:
    1. Documentary
    2. Game-show
    3. News
  - Genres with most profit margin:
    1. Mystery
    2. Animation
    3. Sci-Fi
- The 3 genres which received the highest average rating are not part of the genres with top 3 margins.

In [37]:
```
# Just because our top 3 didn't align doesn't mean there is no overall patt
# Create scatter visualization for rating vs profit to further visualize co
plt.figure(figsize=(9,6))
plt.title('Ratings to Profit', fontsize=14)
plt.ylabel('Avg Rating', fontsize=12)
plt.xlabel('Median Worldwide Profit', fontsize=12)
plt.xticks(fontsize=14)
sns.scatterplot(data=df_imbd_budget[(df_imbd_budget['worldwide_profit']>100
                                     (df_imbd_budget['worldwide_profit']<100
                                    ], x="worldwide_profit", y="averageratin
```

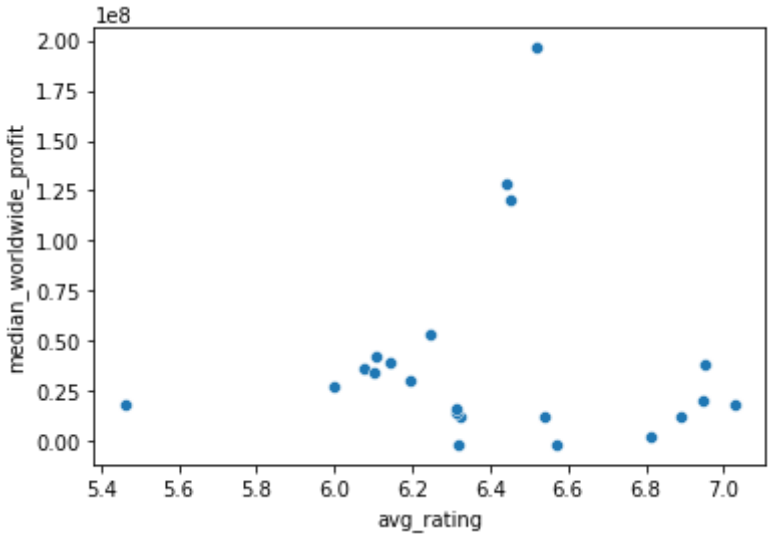
Out[37]:
```
<AxesSubplot:title={'center':'Ratings to Profit'}, xlabel='Median Worldwi
de Profit', ylabel='Avg Rating'>
```



- There doesn't appear to be any correlation between viewer ratings submitted on imbd and profit.
- Further Investigation: Calculate correlation with formula

In [38]:
```
# Additional look at correlation - average ratings by genre vs profit. Ther
sns.scatterplot(data=df_summary_2, x="avg_rating", y="median_worldwide_prof
```

Out[38]: <AxesSubplot:xlabel='avg_rating', ylabel='median_worldwide_profit'>



In [39]:
```
# Create a visualization to show avg rating profit and genre together
plt.figure(figsize=(9,6))
plt.title('Avg Ratings vs Profit', fontsize=15)
plt.ylabel('Median Worldwide Profit', fontsize=14)
plt.xlabel('Avg Ratings', fontsize=14)
plt.xticks(fontsize=14)
sns.scatterplot(data=df_summary_2[df_summary_2['count_of_titles']>100], x="
```

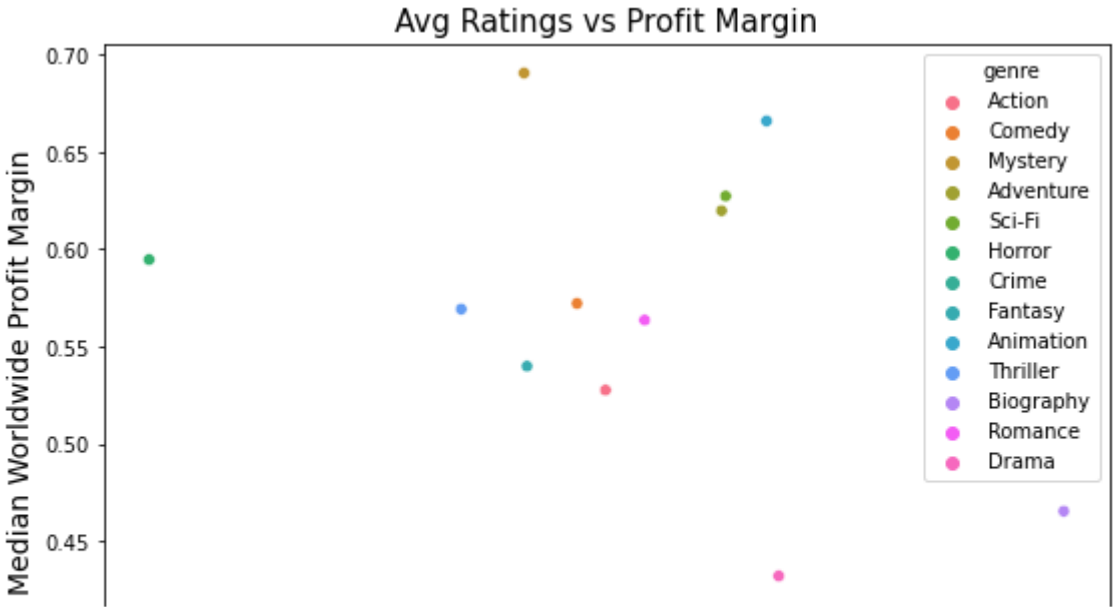
```
s', ylabel='Median Worldwide Profit'>
```

- Genres with most profit:
    1. Animation
    2. Adventure
    3. Sci-Fi

- These three genres stand out in their profits far beyond other genres.
- We can see average ratings by genre are not strongly related to total profits.

In [40]:
```
# Create a visualization to show avg rating profit margin and genre togethe
plt.figure(figsize=(9,6))
plt.title('Avg Ratings vs Profit Margin', fontsize=15)
plt.ylabel('Median Worldwide Profit Margin', fontsize=14)
plt.xlabel('Avg Ratings', fontsize=14)
plt.xticks(fontsize=14)
sns.scatterplot(data=df_summary_2[df_summary_2['count_of_titles']>100], x="
```

```
Ratings', ylabel='Median Worldwide Profit Margin'>
```



- Genres with most profit margin:
  1. Mystery (very low total profits not of interest to Microsoft)
  2. Animation
  3. Sci-Fi
- We can see average ratings by genre are not strongly related to profit margin.

Summary

Data Limitations

- Ratings may not be a strong indicator of global profits however we need to investigate other sources of consumer ratings outside of imdb to confirm.
  - Age distribution of imdb users
  - Country of origin distribution of imdb users
- Percent of titles by genre may not be a strong indicator of global profits however we need to investigate other sources of movies produced outside of imdb to confirm.
  - Country of origin for movie production

Further Investigation

- Find other profit data source to expand to more titles
- Calculate Profit by Runtime
- Calculate Average # of reviews by genre
- Explore data outside of imdb
- Calculate correlation coefficient
- Investigate 74% of records lost in budget to imbd merge
    - Are the sample records representative of all the data?

Conclusions:

- Profits and commonly produced genres: No relationship
- Profits and highly rated genres: No relationship
    - Genres with most profit:
        1. Animation
        2. Adventure
        3. Sci-Fi

Recommendations:

- Don't produce genres commonly produced by competitors. These genres do not correlate to profit.
- Don't produce genres solely based on viewer ratings. These genres do not correlate to profit.
- According to our current findings, Microsoft should invest in producing animation films since they have the best success globally.

Extras

In [41]:
```
# Scatterplot gross revenue vs average rating by genre
sns.scatterplot(data=df_imbd_budget[df_imbd_budget['Animation']==1], x="ave

# sns.scatterplot(data=df_imbd_budget[df_imbd_budget['Documentary']==1], x=
# sns.scatterplot(data=df_imbd_budget[df_imbd_budget['Drama']==1], x="avera
# sns.scatterplot(data=df_imbd_budget[df_imbd_budget['Comedy']==1], x="aver
```

Out[41]: <AxesSubplot:xlabel='averagerating', ylabel='worldwide_gross'>