1 Jumpstarting Microsoft's New Film Department ¶

2 Overview

This project analyzes film data provided by [IMDB (https://www.imdb.com/)](https://www.imdb.com/), [Rotten Tomatoes (https://www.rottentomatoes.com/)](https://www.rottentomatoes.com/), & [The Numbers (https://www.the-numbers.com/)](https://www.the-numbers.com/). Through the following analysis, I draw connections between responses to a film (box office performance & viewer favorability) and essential film features, such as its total runtime, primary genre and budget size.

3 Business Problem

Microsoft has recently decided to create a new movie studio, but as a company they are completely new to movie making. Thus, they are in need of a data-driven analysis to provide some insight on what kinds of movies will perform well & earn lots if made.

4 Data Preparation

4.1 Importing Libraries & Datasets

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

In [2]:
```
csv_files = glob("zippedData/*.csv.gz")
```

In [3]:
```
csv_files_dict = {}
for filename in csv_files:
    filename_cleaned = os.path.basename(filename).replace(".csv.gz", "").re
    filename_df = pd.read_csv(filename, index_col = 0)
    csv_files_dict[filename_cleaned] = filename_df
```

In [4]:
```
csv_files_dict.keys()
```

Out[4]:
```
dict_keys(['imdb_title_crew', 'tmdb_movies', 'imdb_title_akas', 'imdb_tit
le_ratings', 'imdb_name_basics', 'imdb_title_basics', 'tn_movie_budgets',
'bom_movie_gross', 'imdb_title_principals'])
```

In [5]:
```
title_basics_df = csv_files_dict['imdb_title_basics']
title_ratings_df = csv_files_dict['imdb_title_ratings']
movie_budgets_df = csv_files_dict['tn_movie_budgets']
```

In [6]:
```
rt_reviews_df = pd.read_csv("zippedData/rt.reviews.tsv.gz", delimiter = '\t
rt_info_df = pd.read_csv("zippedData/rt.movie_info.tsv.gz", delimiter = '\t
```

Now, I examine each of the DataFrames, both to inspect the data types and to search for any abnormalities such as null values.

In [7]:
```
movie_budgets_df.shape
```

Out[7]:
```
(5782, 5)
```

In [8]:
```
movie_budgets_df.isna().sum() / len(movie_budgets_df)
```

Out[8]:
```
release_date         0.0
movie                0.0
production_budget    0.0
domestic_gross       0.0
worldwide_gross      0.0
dtype: float64
```

In [9]:
```
for col in movie_budgets_df:
    print(f"Currently checking values from col: {col}")
    print(f"Top 5 values:\n{movie_budgets_df[col].value_counts(normalize =
    print("------------------------------")
```

```
Currently checking values from col: release_date
Top 5 values:
Dec 31, 2014    0.004151
Dec 31, 2015    0.003978
Dec 31, 2010    0.002594
Dec 31, 2008    0.002421
Dec 31, 2012    0.002248
Name: release_date, dtype: float64
------------------------------
Currently checking values from col: movie
Top 5 values:
Home          0.000519
King Kong     0.000519
Halloween     0.000519
Cat People    0.000346
The Fog       0.000346
Name: movie, dtype: float64
------------------------------
Currently checking values from col: production_budget
Top 5 values:
$20,000,000    0.039952
$10,000,000    0.036666
$30,000,000    0.030612
$15,000,000    0.029920
$25,000,000    0.029575
Name: production_budget, dtype: float64
------------------------------
Currently checking values from col: domestic_gross
Top 5 values:
$0             0.094777
$8,000,000     0.001557
$2,000,000     0.001211
$7,000,000     0.001211
$10,000,000    0.001038
Name: domestic_gross, dtype: float64
------------------------------
Currently checking values from col: worldwide_gross
Top 5 values:
$0            0.063473
$8,000,000    0.001557
$2,000,000    0.001038
$7,000,000    0.001038
$4,000,000    0.000692
Name: worldwide_gross, dtype: float64
------------------------------
```

In [10]:
```
title_basics_df.shape
```

Out[10]:
```
(146144, 5)
```

In [11]:
```
title_basics_df.isna().sum() / len(title_basics_df)
```

Out[11]:
```
primary_title      0.000000
original_title     0.000144
start_year         0.000000
runtime_minutes    0.217176
genres             0.037005
dtype: float64
```

In [12]:
```
for col in title_basics_df:
    print(f"Currently checking values from col: {col}")
    print(f"Top 5 values:\n{title_basics_df[col].value_counts(normalize = T
    print("------------------------------")
```

```
Currently checking values from col: primary_title
Top 5 values:
The Return    0.000137
Broken        0.000137
Homecoming    0.000109
Alone         0.000109
Name: primary_title, dtype: float64
------------------------------
Currently checking values from col: original_title
Top 5 values:
Home          0.000123
The Return    0.000116
Alone         0.000089
The Gift      0.000089
Name: original_title, dtype: float64
------------------------------
Currently checking values from col: start_year
Top 5 values:
2016    0.118185
2018    0.115290
2015    0.111144
2014    0.106669
Name: start_year, dtype: float64
------------------------------
Currently checking values from col: runtime_minutes
Top 5 values:
Series([], Name: runtime_minutes, dtype: float64)
------------------------------
Currently checking values from col: genres
Top 5 values:
Drama           0.152669
Comedy          0.065207
Horror          0.031065
Comedy,Drama    0.025004
Name: genres, dtype: float64
------------------------------
```

In [13]:
```
title_ratings_df.shape
```

Out[13]:
```
(73856, 2)
```

In [14]:
```
title_ratings_df.isna().sum() / len(title_ratings_df)
```

Out[14]:
```
averagerating    0.0
numvotes         0.0
dtype: float64
```

In [15]:
```
for col in title_ratings_df:
    print(f"Currently checking values from col: {col}")
    print(f"Top 5 values:\n{title_ratings_df[col].value_counts(normalize =
    print("------------------------------")
```

```
Currently checking values from col: averagerating
Top 5 values:
Series([], Name: averagerating, dtype: float64)
------------------------------
Currently checking values from col: numvotes
Top 5 values:
5    0.036544
7    0.033525
8    0.029341
9    0.026118
Name: numvotes, dtype: float64
------------------------------
```

In [16]:
```
rt_info_df.shape
```

Out[16]:
```
(1560, 12)
```

In [17]:
```
rt_info_df.isna().sum() / len(rt_info_df)
```

Out[17]:
```
id              0.000000
synopsis        0.039744
rating          0.001923
genre           0.005128
director        0.127564
writer          0.287821
theater_date    0.230128
dvd_date        0.230128
currency        0.782051
box_office      0.782051
runtime         0.019231
studio          0.683333
dtype: float64
```

In [18]:
```
for col in rt_info_df.drop(columns='synopsis'):
    print(f"Currently checking values from col: {col}")
    print(f"Top 5 values:\n{rt_info_df[col].value_counts(normalize = True)[
    print("------------------------------")
```

```
Currently checking values from col: id
Top 5 values:
2000    0.000641
697     0.000641
673     0.000641
674     0.000641
675     0.000641
Name: id, dtype: float64
------------------------------
Currently checking values from col: rating
Top 5 values:
R        0.334618
NR       0.323057
PG       0.154143
PG-13    0.150931
G        0.036609
Name: rating, dtype: float64
------------------------------
Currently checking values from col: genre
Top 5 values:
Drama                                0.097294
Comedy                               0.070876
Comedy|Drama                         0.051546
Drama|Mystery and Suspense           0.043170
Art House and International|Drama    0.039948
Name: genre, dtype: float64
------------------------------
Currently checking values from col: director
Top 5 values:
Steven Spielberg    0.007348
Clint Eastwood      0.005878
William Beaudine    0.002939
Yimou Zhang         0.002939
Bruce Beresford     0.002939
Name: director, dtype: float64
------------------------------
Currently checking values from col: writer
Top 5 values:
Woody Allen           0.0036
Hong Sang-soo         0.0027
John Hughes           0.0027
Jim Jarmusch          0.0027
Sylvester Stallone    0.0027
Name: writer, dtype: float64
------------------------------
Currently checking values from col: theater_date
Top 5 values:
Jan 1, 1987    0.006661
Jan 1, 1994    0.004163
Jan 1, 1973    0.003331
Jun 1, 1990    0.003331
Jan 1, 1966    0.003331
```

```
Name: theater_date, dtype: float64
------------------------------
Currently checking values from col: dvd_date
Top 5 values:
Jun 1, 2004     0.009159
Sep 3, 2002     0.005828
Nov 6, 2001     0.005828
Aug 27, 1997    0.004996
Sep 2, 2003     0.004996
Name: dvd_date, dtype: float64
------------------------------
Currently checking values from col: currency
Top 5 values:
$    1.0
Name: currency, dtype: float64
------------------------------
Currently checking values from col: box_office
Top 5 values:
32,000,000    0.005882
200,000       0.005882
600,000       0.005882
20,900,803    0.005882
25,957,696    0.002941
Name: box_office, dtype: float64
------------------------------
Currently checking values from col: runtime
Top 5 values:
90 minutes     0.047059
95 minutes     0.043137
100 minutes    0.033333
93 minutes     0.030719
96 minutes     0.028105
Name: runtime, dtype: float64
------------------------------
Currently checking values from col: studio
Top 5 values:
Universal Pictures         0.070850
Paramount Pictures         0.054656
20th Century Fox           0.052632
Sony Pictures Classics     0.044534
Warner Bros. Pictures      0.042510
Name: studio, dtype: float64
------------------------------
```

In [19]:

```
rt_reviews_df.shape
```

Out[19]:

```
(54432, 8)
```

In [20]:
```
rt_reviews_df.isna().sum() / len(rt_reviews_df)
```

Out[20]:
```
id            0.000000
review        0.102201
rating        0.248328
fresh         0.000000
critic        0.050007
top_critic    0.000000
publisher     0.005677
date          0.000000
dtype: float64
```

In [21]:
```
for col in rt_reviews_df.drop(columns='review'):
    print(f"Currently checking values from col: {col}")
    print(f"Top 5 values:\n{rt_reviews_df[col].value_counts(normalize = Tru
    print("------------------------------")
```

```
Currently checking values from col: id
Top 5 values:
782     0.006210
1067    0.005052
1525    0.004813
1777    0.004777
1083    0.004777
Name: id, dtype: float64
------------------------------
Currently checking values from col: rating
Top 5 values:
3/5    0.105756
4/5    0.089747
3/4    0.087425
2/5    0.077233
2/4    0.066284
Name: rating, dtype: float64
------------------------------
Currently checking values from col: fresh
Top 5 values:
fresh     0.606904
rotten    0.393096
Name: fresh, dtype: float64
------------------------------
Currently checking values from col: critic
Top 5 values:
Emanuel Levy       0.011506
Roger Ebert        0.008915
Dennis Schwartz    0.007987
Nell Minow         0.007194
Frank Swietek      0.006730
Name: critic, dtype: float64
------------------------------
Currently checking values from col: top_critic
Top 5 values:
0    0.759406
1    0.240594
Name: top_critic, dtype: float64
------------------------------
Currently checking values from col: publisher
Top 5 values:
eFilmCritic.com         0.012435
EmanuelLevy.Com         0.010920
New York Times          0.010901
Washington Post         0.010439
Entertainment Weekly    0.009996
Name: publisher, dtype: float64
------------------------------
Currently checking values from col: date
Top 5 values:
January 1, 2000     0.079053
May 20, 2003        0.003711
```

```
December 6, 2005     0.003325
September 7, 2011    0.002278
July 26, 2002        0.002223
Name: date, dtype: float64
------------------------------
```

4.2 Basic Data Cleaning

Both the **title_basics_df** & **rt_reviews_df** DataFrames have columns (*runtime_minutes* & *reviews*, respectively) containing large chunks of missing values -- about 20% of entries for both.

Additionally, each DataFrame has tens or hundreds of thousands of elements, so both are sufficiently large even after I drop all null values.

In [22]:
```
title_basics_df.dropna(inplace=True)
```

In [23]:
```
title_basics_df.shape
```

Out[23]:
```
(112232, 5)
```

In [24]:
```
title_basics_df.isna().sum() / len(title_basics_df)
```

Out[24]:
```
primary_title      0.0
original_title     0.0
start_year         0.0
runtime_minutes    0.0
genres             0.0
dtype: float64
```

In [25]:
```
rt_reviews_df.dropna(inplace=True)
```

In [26]:
```
rt_reviews_df.shape
```

Out[26]:
```
(33988, 8)
```

In [27]:
```
rt_reviews_df.isna().sum() / len(rt_reviews_df)
```

Out[27]:
```
id            0.0
review        0.0
rating        0.0
fresh         0.0
critic        0.0
top_critic    0.0
publisher     0.0
date          0.0
dtype: float64
```

The columns for *budget* and both *gross* values are not stored as numerical data in the **movie_budgets_df** DataFrame, which will cause issues for analysis.

In [28]:
```
movie_budgets_df.head()
```

Out[28]:

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

I remove the dollar signs and commas from each column before converting their data types to 'integer'.

In [29]:
```
def convert_money_int(df, col):
    df[col] = df[col].str.replace("$","").str.replace(",","").astype(int)
    return df
```

In [30]:
```
cols_to_convert = ['production_budget', 'domestic_gross', 'worldwide_gross'
for col in cols_to_convert:
    movie_budgets_df = convert_money_int(movie_budgets_df, col)
```

In [31]:
```
movie_budgets_df.head()
```

Out[31]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross
id					
1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

5 Analysis

5.1 Movie Genre

Using IMDB's data, I explore the link between a movie's primary genre and its worldwide financial performance. This begins with creating new columns for global net gross, release year & return on investment as a percentage.

In [32]:
```
movie_budgets_df['net_world'] = movie_budgets_df['worldwide_gross'] - movie
```

In [33]:
```
movie_budgets_df['year'] = pd.to_datetime(movie_budgets_df['release_date'])
```

In [34]:
```
movie_budgets_df['roi_%'] = (movie_budgets_df['net_world'] / movie_budgets_
```

In [35]:
```
movie_budgets_df.head()
```

Out[35]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	net_wo
1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	23513
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	6350
3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-2002
4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	10724
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	9997

I merge DataFrames from IMDB & The Numbers into the new **gross_by_genre_df** and remove duplicate entries.

In [36]:
```
gross_by_genre_df = pd.merge(movie_budgets_df, title_basics_df, left_on = [
                             right_on = ['primary_title', 'start_year'],
                             how = 'inner')
gross_by_genre_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1519 entries, 0 to 1518
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   release_date       1519 non-null   object
 1   movie              1519 non-null   object
 2   production_budget  1519 non-null   int64
 3   domestic_gross     1519 non-null   int64
 4   worldwide_gross    1519 non-null   int64
 5   net_world          1519 non-null   int64
 6   year               1519 non-null   int64
 7   roi_%              1519 non-null   float64
 8   primary_title      1519 non-null   object
 9   original_title     1519 non-null   object
 10  start_year         1519 non-null   int64
 11  runtime_minutes    1519 non-null   float64
 12  genres             1519 non-null   object
dtypes: float64(2), int64(6), object(5)
memory usage: 166.1+ KB
```

In [37]:
```
gross_by_genre_df.isna().sum() / len(gross_by_genre_df)
```

Out[37]:
```
release_date         0.0
movie                0.0
production_budget    0.0
domestic_gross       0.0
worldwide_gross      0.0
net_world            0.0
year                 0.0
roi_%                0.0
primary_title        0.0
original_title       0.0
start_year           0.0
runtime_minutes      0.0
genres               0.0
dtype: float64
```

In [38]:
```
gross_by_genre_df.drop_duplicates(subset=['release_date', 'movie'], inplace
gross_by_genre_df.shape
```

Out[38]:
```
(1470, 13)
```

This process appears to have spotted 49 duplicate entries and dropped all of them. Now, I examine the *genres* column to see if it's currently usable for creating a plot.

In [39]:
```
gross_by_genre_df.genres
```

Out[39]:
```
0         Action,Adventure,Fantasy
1          Action,Adventure,Sci-Fi
2          Action,Adventure,Sci-Fi
3          Action,Adventure,Sci-Fi
4         Action,Adventure,Fantasy
                    ...
1514                         Drama
1515       Horror,Mystery,Thriller
1516          Crime,Drama,Thriller
1517         Drama,Horror,Thriller
1518                         Drama
Name: genres, Length: 1470, dtype: object
```

I create a new *genres_split* column, where each element contains a film's given genres separated within a list.

In [40]:
```
gross_by_genre_df['genres_split'] = gross_by_genre_df['genres'].map(lambda
gross_by_genre_df.head()
```

Out[40]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross	net_worl
0	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	635063
1	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-200237
2	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	1072413
3	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2048134200	1748134
4	Nov 17, 2017	Justice League	300000000	229024295	655945209	355945

It is now easy to create specific columns for a film's primary & secondary genres. I am working under the assumption that IMDB has listed the genres for each film in order of relevance.

After that is done, I drop unnecessary columns and check for any ROI outliers that might distort my attempts at visualizations.

In [41]:
```
gross_by_genre_df['genre1'] = gross_by_genre_df['genres_split'].map(lambda
```

In [42]:
```
y = 'NA'
gross_by_genre_df['genre2'] = gross_by_genre_df['genres_split'].map(lambda
```

In [43]:
```
to_drop = ['primary_title', 'original_title', 'start_year',
            'genres', 'genres_split', 'release_date']
gross_by_genre_df.drop(columns = to_drop, inplace=True)
```

In [44]:
```
gross_by_genre_df.sort_values(by='roi_%', ascending=False).head()
```

Out[44]:

	movie	production_budget	domestic_gross	worldwide_gross	net_world	year
1494	The Gallows	100000	22764410	41656474	41556474	2015
1400	The Devil Inside	1000000	53262945	101759490	100759490	2012
1281	Paranormal Activity 2	3000000	84752907	177512032	174512032	2010
1189	Get Out	5000000	176040665	255367951	250367951	2017
1375	Moonlight	1500000	27854931	65245512	63745512	2016

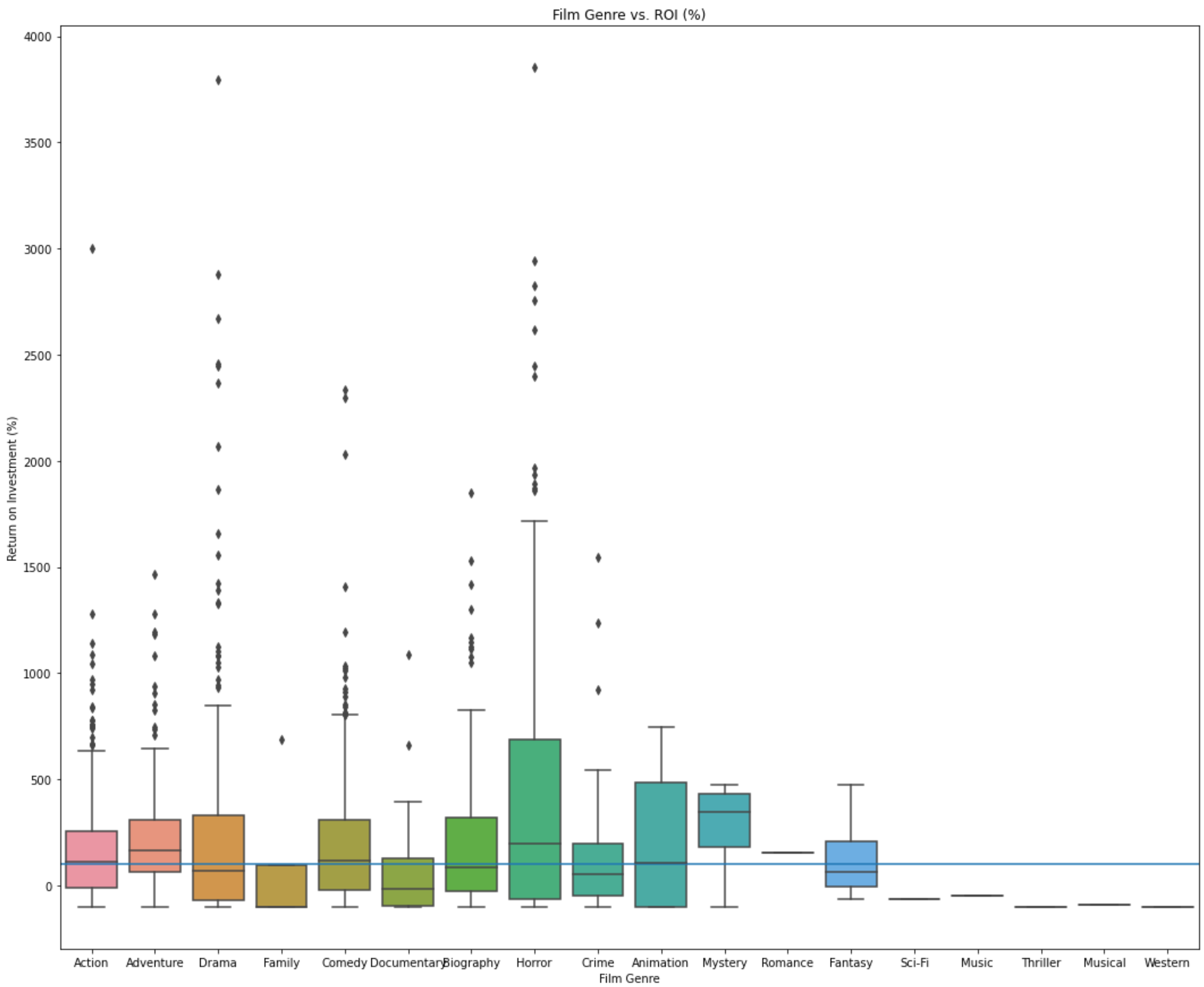
In [45]:
```
df1 = gross_by_genre_df[(np.abs(stats.zscore(gross_by_genre_df['roi_%'])) <
```

Now I am ready to visualize the data.

In [46]:
```
fig, ax = plt.subplots(figsize=(18,15))

sns.boxplot(x='genre1', y='roi_%', data=df1, ax=ax)
ax.axhline(y=100)
ax.set_title('Film Genre vs. ROI (%)')
ax.set_xlabel('Film Genre')
ax.set_ylabel('Return on Investment (%)')

plt.savefig("roigenrebox.png")
plt.show()
```



In the boxplot above, I added a horizontal line at the y-value of 100% ROI. This marker indicates the point where a film has earned double its production budget.

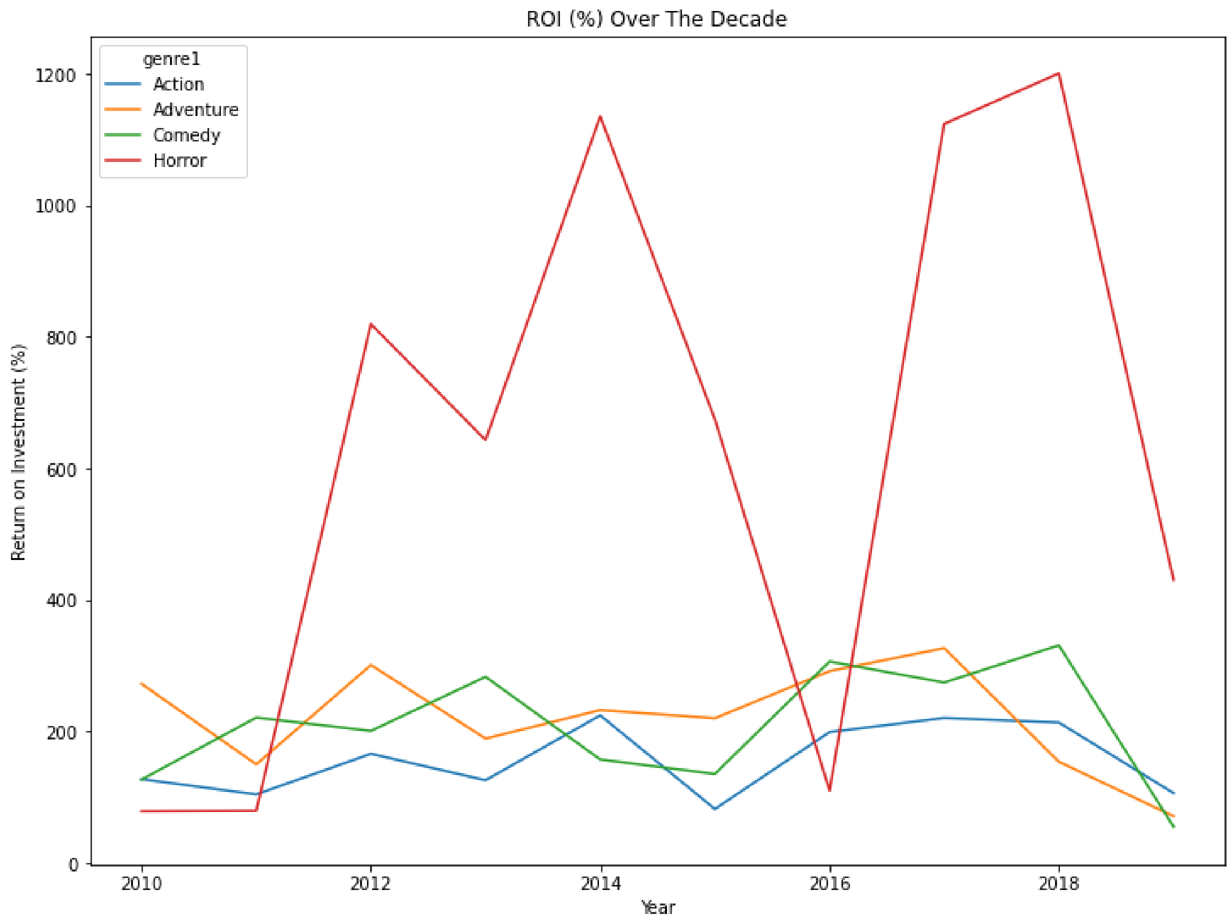
The primary genres of Action, Adventure, Comedy, Horror, Animation & Mystery all have median ROI levels above the 100% threshold. The best looking genres with numerous entries, however, seem to be Action, Adventure, Comedy & Horror, so I will explore the ROI trends for each of these genres further.

In [47]:
```
df1 = df1[(df1.genre1 == 'Adventure') | (df1.genre1 == 'Comedy') |
          (df1.genre1 == 'Horror') | (df1.genre1 == 'Action')]
```

In [48]:
```
fig, ax = plt.subplots(figsize=(12,9))

sns.lineplot(x='year', y='roi_%', data=df1, hue='genre1', ci=None, ax=ax)
ax.set_title('ROI (%) Over The Decade')
ax.set_xlabel('Year')
ax.set_ylabel('Return on Investment (%)')

plt.savefig("timeroi.png")
plt.show()
```



It seems as though the advent of streaming has been negatively impacting overall film profitability over the last couple of years, as every genres' ROI percentage has trended downwards since 2018.

Looking at the trends pre-2018, however, reveals that Action, Comedy & Horror movies have made noticeable gains from the beginning of the decade. Action seems to have the most stable, subtle growth, and Comedy has had some noticeable oscillations in profitability. Horror, however, has by far the most erratic jumps up and down in its return on investment.

Adventure has ROI shifts similar to those of Comedy, but overall seems to be trending downwards over the decade, even before 2018.

Based on these figures, I would recommend that Microsoft begin their venture by focusing on primary genres of Action, Comedy & Horror. They should keep in mind, too, that Action might be the most dependable of the three profit-wise.

5.2 Production Budget

The production budgets of films listed by The Numbers have a mean of ~32 million dollars and a median of 17 million dollars. This discrepency makes it evident that there is significant skew in the budgets.

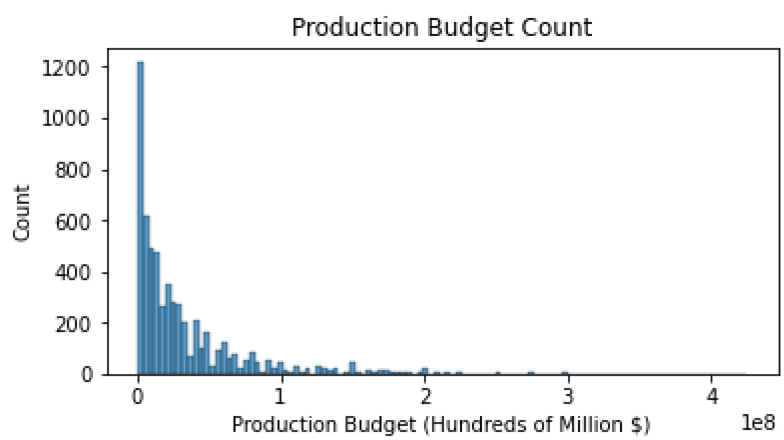
In [49]:
```
movie_budgets_df['production_budget'].describe()
```

Out[49]:
```
count    5.782000e+03
mean     3.158776e+07
std      4.181208e+07
min      1.100000e+03
25%      5.000000e+06
50%      1.700000e+07
75%      4.000000e+07
max      4.250000e+08
Name: production_budget, dtype: float64
```

In [50]:
```
plt.figure(figsize=(6,3))
sns.histplot(data=movie_budgets_df['production_budget'])

plt.title('Production Budget Count')
plt.xlabel('Production Budget (Hundreds of Million $)')

plt.savefig("budgetcount.png")
```



It is now especially clear that the collection of budgets is both skewed and enormously wide-ranging. In other words, a single plot that captures every value won't be particularly insightful. Instead, I divide the budgets into different ranges before observing the financial performance of each group.

The most sensible way to categorize production budgets is by using the quantiles shown above. This provides 4 distinct budget tiers -- High Budget, Medium-Low Budget, Medium-High Budget and High Budget.

In [51]:
```
bins = [0, 5000000, 17000000, 40000000, np.inf]
names = ['Low', 'MedLo', 'MedHi', 'High']
```

In [52]:
```
movie_budgets_df['budget_tier'] = pd.cut(movie_budgets_df['production_budge
```

In [53]:
```
movie_budgets_df.head()
```

Out[53]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross	net_wo
id						
1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	235134
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	63506
3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-20023
4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	107241
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	99972

I inspect the ROI values from **movie_budgets_df** to see, like in the last analysis, if any outliers exist and need to be dropped.

In [54]:
```
print(movie_budgets_df.sort_values(by='roi_%', ascending=False).head())
```

```
    release_date                      movie  production_budget  domestic_gr
oss  \
id
46  Jun 30, 1972               Deep Throat              25000         45000
000
14  Mar 21, 1980                   Mad Max             200000          8750
000
93  Sep 25, 2009       Paranormal Activity             450000        107918
810
80  Jul 10, 2015               The Gallows             100000         22764
410
7   Jul 14, 1999  The Blair Witch Project             600000        140539
099

    worldwide_gross  net_world  year          roi_% budget_tier
id
46         45000000   44975000  1972  179900.000000         Low
14         99750000   99550000  1980   49775.000000         Low
93        194183034  193733034  2009   43051.785333         Low
80         41656474   41556474  2015   41556.474000         Low
7         248300000  247700000  1999   41283.333333         Low
```

In [55]:
```
print('Mean:', movie_budgets_df['roi_%'].mean())
print('Standard Dev:', movie_budgets_df['roi_%'].std())
print('Upper Outliers Above:', movie_budgets_df['roi_%'].mean() + 3*(movie_
```

```
Mean: 380.01613657949645
Standard Dev: 2953.0282308933056
Upper Outliers Above: 9239.100829259412
```

In [56]:
```
movie_budgets_df = movie_budgets_df[movie_budgets_df['roi_%'] <= 9239.1]
print(movie_budgets_df.sort_values(by='roi_%', ascending=False).head())
```

```
    release_date           movie  production_budget  domestic_gross  \
id
76  Feb 15, 1950      Cinderella            2900000        85000000
7   Nov 19, 1925  The Big Parade             245000        11000000
60  Apr 23, 2009            Home             500000           15433
57  Oct 29, 2004             Saw            1200000        55968727
26  Apr 15, 1983   The Evil Dead             375000         2400000

    worldwide_gross  net_world  year        roi_% budget_tier
id
76        263591415  260691415  1950  8989.359138         Low
7          22000000   21755000  1925  8879.591837         Low
60         44793168   44293168  2009  8858.633600         Low
57        103880027  102680027  2004  8556.668917         Low
26         29400000   29025000  1983  7740.000000         Low
```

The median ROI from each group indicates that the high-budget films (at least 40 million dollars) have the highest relative payoff.

In [57]:
```
movie_budgets_df.groupby('budget_tier')['roi_%'].median()
```

Out[57]:
```
budget_tier
Low       -12.972350
MedLo      65.099995
MedHi      66.240468
High      117.279631
Name: roi_%, dtype: float64
```

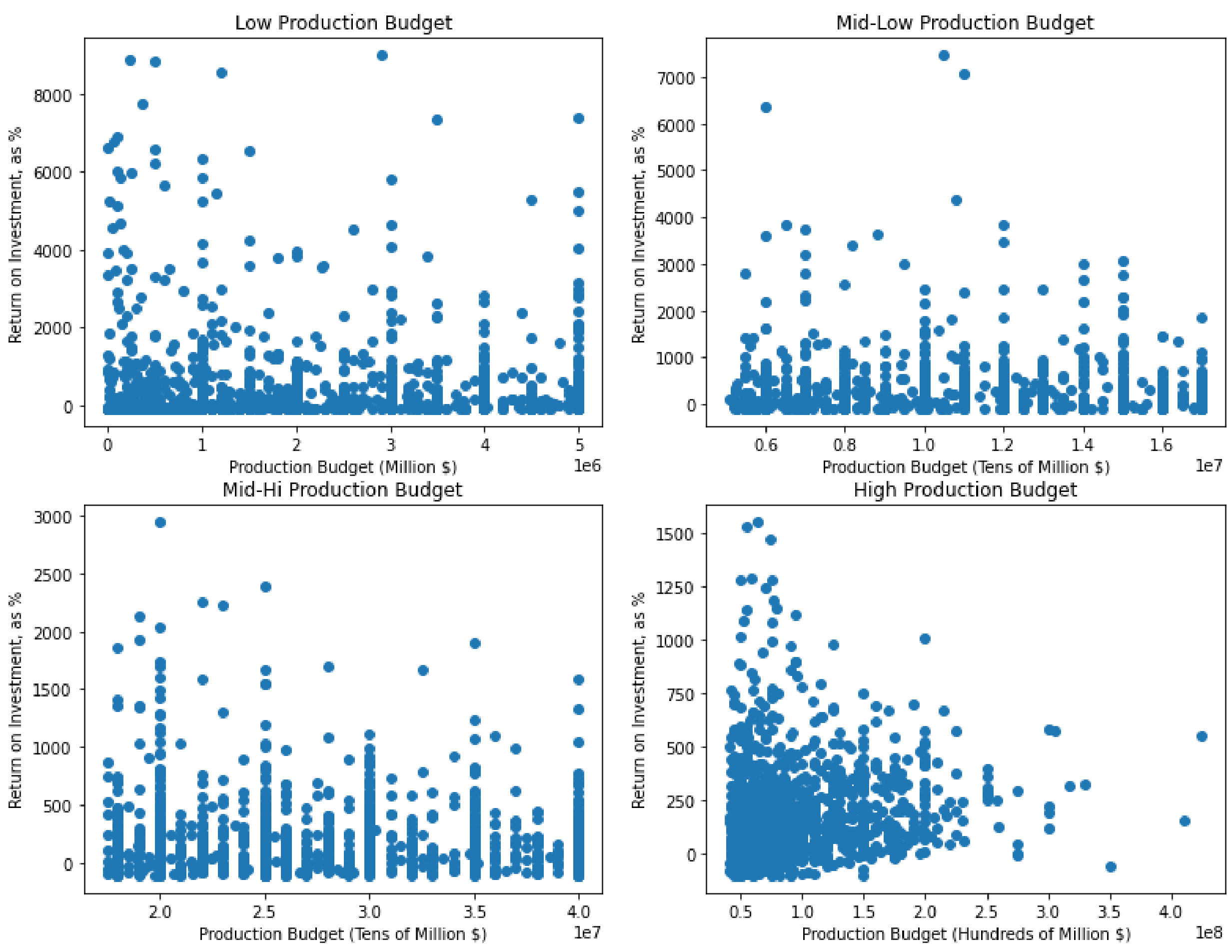
In [58]:
```
low_df = movie_budgets_df[movie_budgets_df['budget_tier']=='Low']
medlo_df = movie_budgets_df[movie_budgets_df['budget_tier']=='MedLo']
medhi_df = movie_budgets_df[movie_budgets_df['budget_tier']=='MedHi']
high_df = movie_budgets_df[movie_budgets_df['budget_tier']=='High']
```

In [59]:
```
tier_list = [low_df, medlo_df, medhi_df, high_df]
low_df.name = "Low Production Budget"
medlo_df.name = "Mid-Low Production Budget"
medhi_df.name = "Mid-Hi Production Budget"
high_df.name = "High Production Budget"
```

In [60]:
```
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(13,10))

for (i, j) in zip(ax.flatten(), tier_list):
    i.scatter(x= j["production_budget"],
              y= j["roi_%"])
    i.set_title(j.name)
    i.set_ylabel('Return on Investment, as %')
    if j['production_budget'].mean() <= 10000000:
        i.set_xlabel('Production Budget (Million $)')
    elif j['production_budget'].mean() <= 50000000:
        i.set_xlabel('Production Budget (Tens of Million $)')
    else:
        i.set_xlabel('Production Budget (Hundreds of Million $)')

plt.savefig("budgetvsroi.png")
plt.show()
```



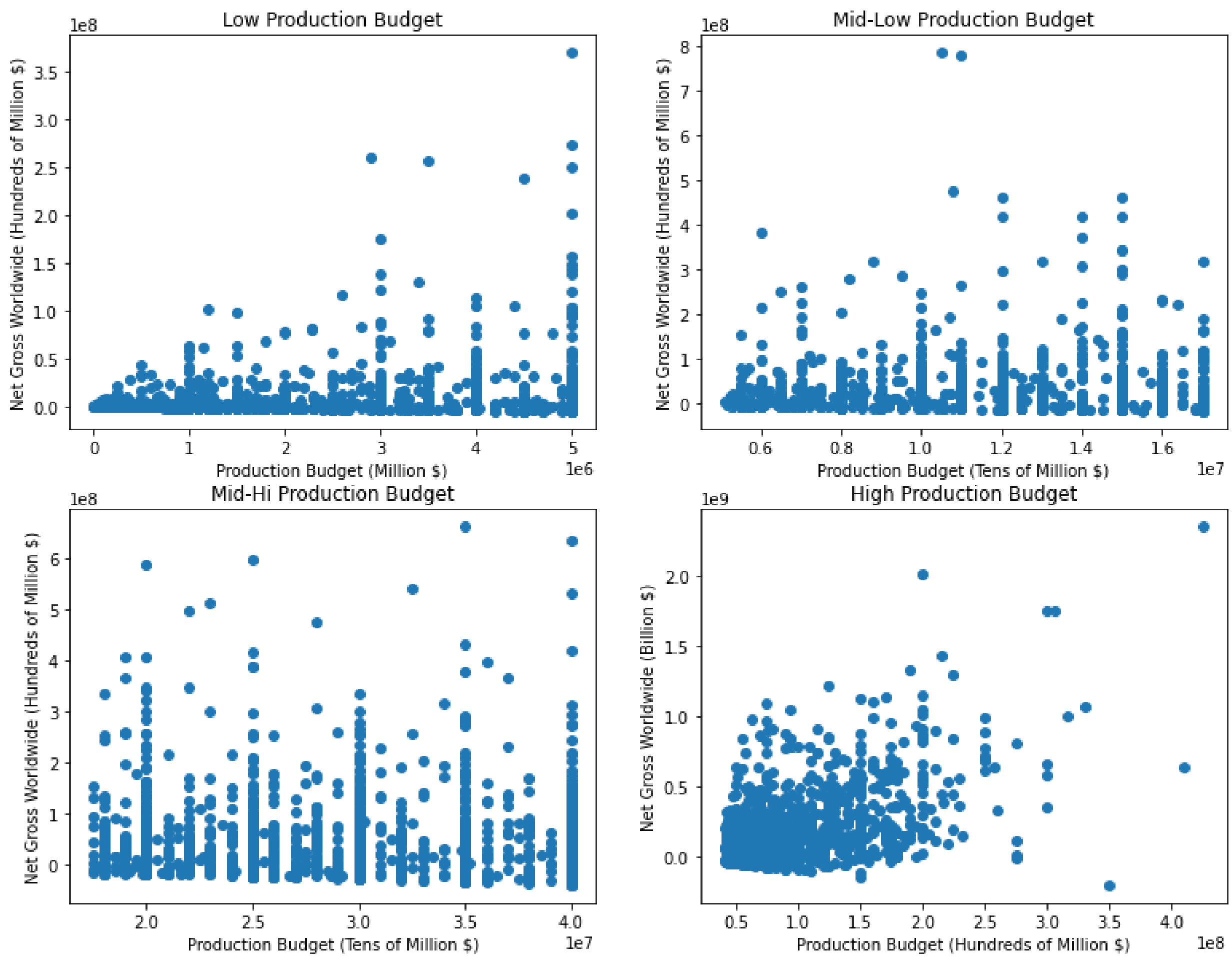
(Note that the above plots have different scales for measuring production budget & ROI. Check the axis labels for more detail.)

These plots indicate that there is only a positive correlation between budget & ROI for high budget films. I look at the relationship between budget and global net gross, a more concrete figure, to confirm my conclusion.

In [61]:
```
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(13,10))

for (i, j) in zip(ax.flatten(), tier_list):
    i.scatter(x= j["production_budget"],
              y= j["net_world"])
    i.set_title(j.name)
    if j['production_budget'].mean() <= 10000000:
        i.set_xlabel('Production Budget (Million $)')
        i.set_ylabel('Net Gross Worldwide (Hundreds of Million $)')
    elif j['production_budget'].mean() <= 50000000:
        i.set_xlabel('Production Budget (Tens of Million $)')
        i.set_ylabel('Net Gross Worldwide (Hundreds of Million $)')
    else:
        i.set_xlabel('Production Budget (Hundreds of Million $)')
        i.set_ylabel('Net Gross Worldwide (Billion $)')

plt.savefig("budgetvsnet.png")
plt.show()
```



These plots further cement my previous interpretation: films with high budgets (40 million USD or more) have by far the most predictable correlation between budget and net financial gain.

5.3 Movie Runtime

I see if a film's runtime affects how positively the audience & critics respond to the film.

5.3.1 First, I inspect ratings_basics_df, which is both IMDB DataFrames merged into one that can display runtime and audience ratings.

In [62]:
```
ratings_basics_df = pd.merge(title_basics_df, title_ratings_df, on='tconst'
ratings_basics_df.head()
```

Out[62]:

	primary_title	original_title	start_year	runtime_minutes	genres
tconst					
tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Dram
tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Dram
tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Dram
tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantas
tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comed

In [63]:
```
ratings_basics_df.drop(columns=['original_title', 'genres'], inplace=True)
ratings_basics_df.drop_duplicates(subset=['primary_title', 'start_year'], i
```

I want to see whether the relationship between runtime and aggregate audience rating is affected at all by the number of votes in a rating. So, as with the previous question, I split the number of votes into four distinct categories by quantile value.

In [64]:
```
ratings_basics_df['numvotes'].describe()
```

Out[64]:
```
count    6.523600e+04
mean     3.968060e+03
std      3.216720e+04
min      5.000000e+00
25%      1.600000e+01
50%      6.200000e+01
75%      3.530000e+02
max      1.841066e+06
Name: numvotes, dtype: float64
```

In [65]:
```
bins2 = [0, 16, 62, 353, np.inf]
names2 = ['LoVotes', 'MedLoVotes', 'MedHiVotes', 'HighVotes']

ratings_basics_df['numvotes_tier'] = pd.cut(ratings_basics_df['numvotes'],
```

In [66]:
```
print('DataFrame Dimensions:', ratings_basics_df.shape)
print(ratings_basics_df.head())
```

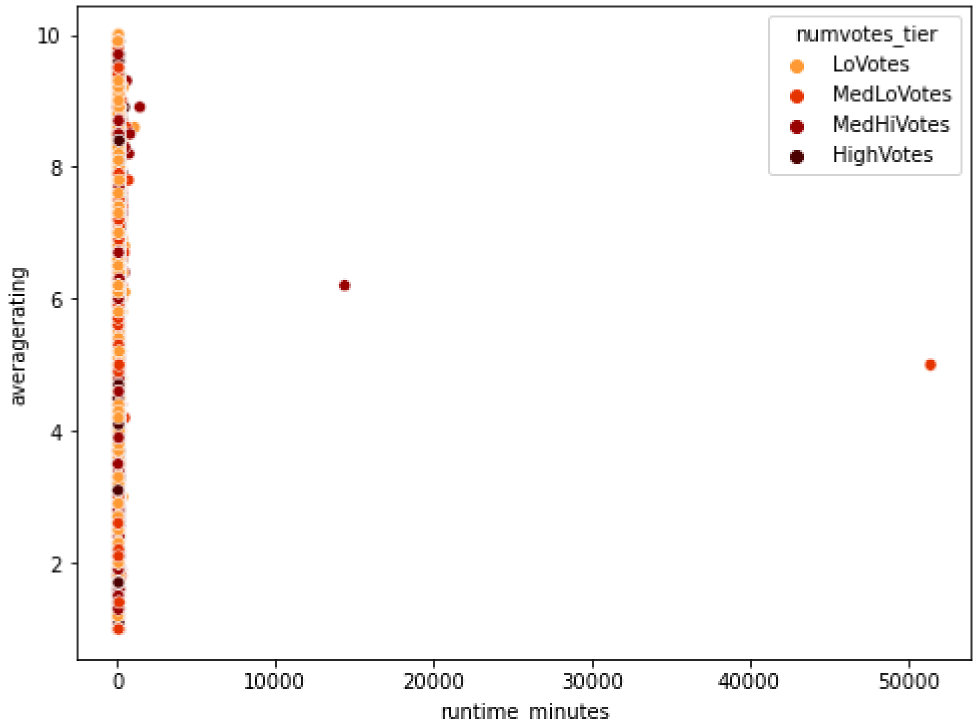
```
DataFrame Dimensions: (65236, 6)
                             primary_title  start_year  runtime_minutes  \
tconst
tt0063540                        Sunghursh        2013            175.0
tt0066787  One Day Before the Rainy Season        2019            114.0
tt0069049       The Other Side of the Wind        2018            122.0
tt0100275         The Wandering Soap Opera        2017             80.0
tt0137204                  Joe Finds Grace        2017             83.0

           averagerating  numvotes numvotes_tier
tconst
tt0063540            7.0        77    MedHiVotes
tt0066787            7.2        43    MedLoVotes
tt0069049            6.9      4517     HighVotes
tt0100275            6.5       119    MedHiVotes
tt0137204            8.1       263    MedHiVotes
```

I now try making a visual plotting the runtime vs. audience rating, colored by how many votes were cast for the film's rating.

In [67]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(data = ratings_basics_df,
                x='runtime_minutes',
                y='averagerating',
                hue='numvotes_tier',
                palette='gist_heat_r'
                )
```

Out[67]:
```
<AxesSubplot:xlabel='runtime_minutes', ylabel='averagerating'>
```



The plot makes it obvious that there are harmful outliers in the film runtime. I elminiate these through filtering **ratings_basics_df**.

In [68]:
```
ratings_basics_df['runtime_minutes'].describe()
```

Out[68]:
```
count    65236.000000
mean        94.738595
std        210.141817
min          3.000000
25%         81.000000
50%         91.000000
75%        104.000000
max      51420.000000
Name: runtime_minutes, dtype: float64
```

In [69]:
```
runtime = ratings_basics_df['runtime_minutes']
runtime_cleaned_df = ratings_basics_df[runtime < (runtime.mean() + 3*runtim
print(runtime_cleaned_df.sort_values(by='runtime_minutes', ascending=False)
```

```
                                              primary_title  start_year  \
tconst
tt2261469                              Double Fine Adventure        2015
tt5374716                                  Chamisso's Shadow        2016
tt5375100                                       Paint Drying        2016
tt8690764  Silence not silence, red not red, live not live        2018
tt3984388                                           Close Up        2012

           runtime_minutes  averagerating  numvotes numvotes_tier
tconst
tt2261469            724.0            8.5        59    MedLoVotes
tt5374716            720.0            7.8        19    MedLoVotes
tt5375100            607.0            9.3       218    MedHiVotes
tt8690764            601.0            8.6        22    MedLoVotes
tt3984388            500.0            6.1        13       LoVotes
```

This helps make the data more plottable. But a look at the new descriptive statistics lets me know that there is still at least one more outlier in need of elimination (see *mean*, *std* & *max* below).

In [70]:
```
runtime_cleaned_df['runtime_minutes'].describe()
```

Out[70]:
```
count    65230.000000
mean        93.675502
std         24.136521
min          3.000000
25%         81.000000
50%         91.000000
75%        104.000000
max        724.000000
Name: runtime_minutes, dtype: float64
```

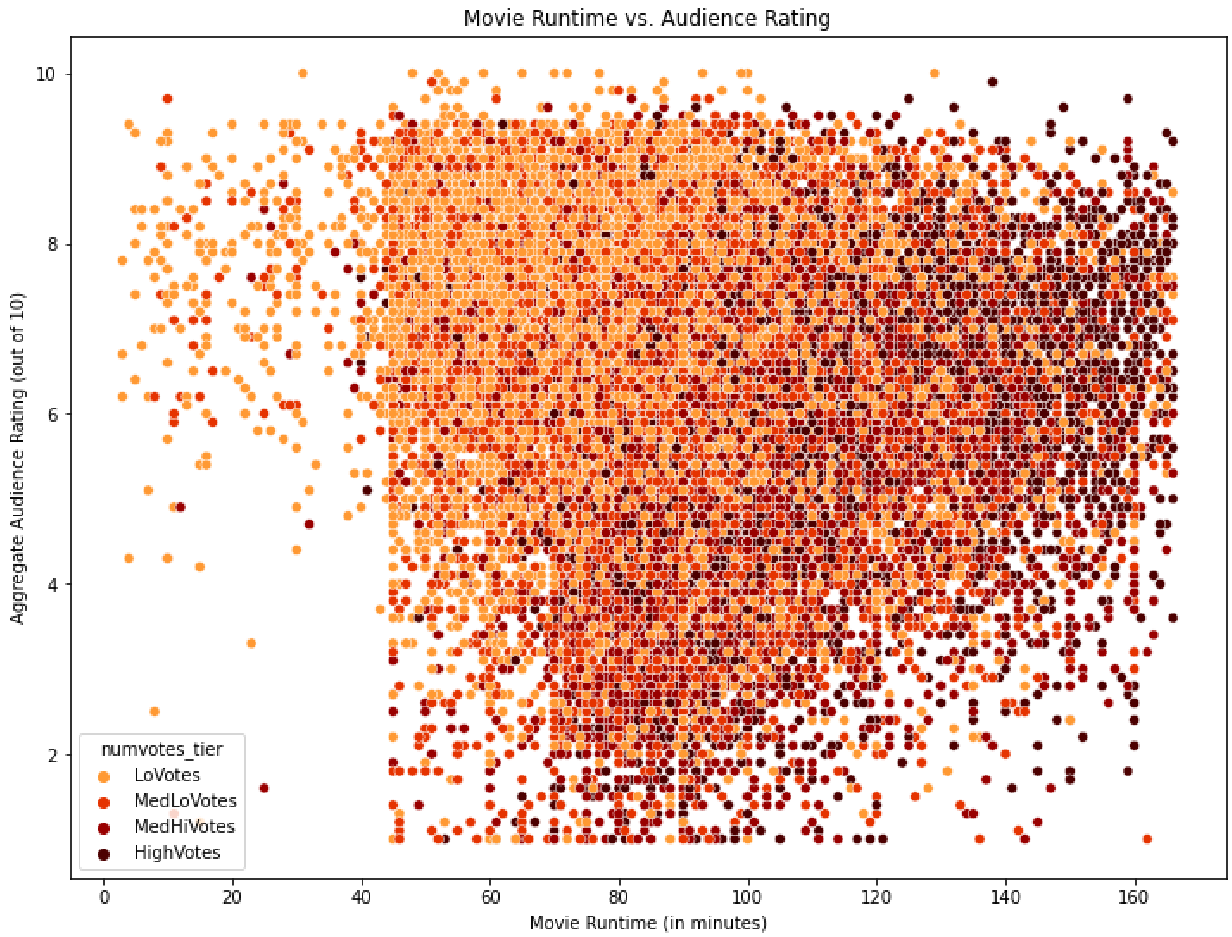
In [71]:
```
runtime2 = runtime_cleaned_df['runtime_minutes']
runtime_cleaned_df = runtime_cleaned_df[runtime2 < (runtime2.mean() + 3*run
print(runtime_cleaned_df.sort_values(by='runtime_minutes', ascending=False)
```

```
                                 primary_title  start_year  runtime_minutes  \
tconst
tt7757972                            Saakshyam        2018            166.0
tt2309600                             Singam 2        2013            166.0
tt2579680                            100% Love        2012            166.0
tt2956300  ABCD: American-Born Confused Desi        2013            166.0
tt2320312        Idiot: I Do Ishq Only Tumse        2012            166.0

           averagerating  numvotes numvotes_tier
tconst
tt7757972            5.3       262    MedHiVotes
tt2309600            6.3      5046     HighVotes
tt2579680            6.0       296    MedHiVotes
tt2956300            6.7      2141     HighVotes
tt2320312            6.0        10       LoVotes
```

In [72]:
```
plt.figure(figsize=(12,9))
sns.scatterplot(data = runtime_cleaned_df,
                x='runtime_minutes',
                y='averagerating',
                hue='numvotes_tier',
                palette='gist_heat_r'
                )
plt.title('Movie Runtime vs. Audience Rating')
plt.xlabel('Movie Runtime (in minutes)')
plt.ylabel('Aggregate Audience Rating (out of 10)')

plt.savefig("runtimeratingtier.png")
```

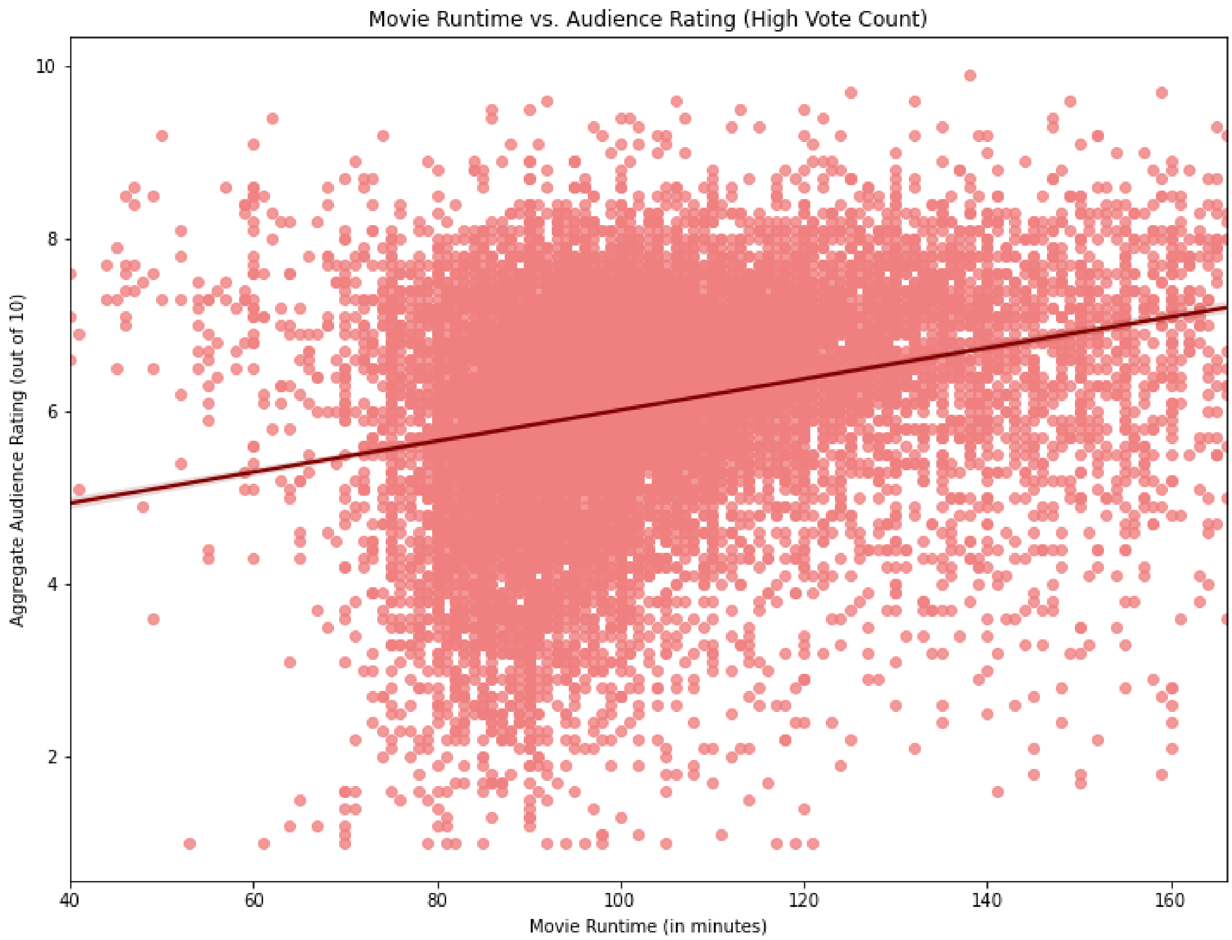


The scatter plot is significantly improved, but it is now clear that using all categories of *numvotes_tier* introduces too much noise. I switch to a regplot only using ratings with a "high" number of votes. Of the four categories, it is clearly the closest to representing the actual audience response.

In [73]:
```
fig, ax = plt.subplots(figsize=(12,9))

ax.set_title('Movie Runtime vs. Audience Rating (High Vote Count)')
sns.regplot(x='runtime_minutes', y='averagerating',
            data=runtime_cleaned_df[runtime_cleaned_df['numvotes_tier'] ==
            ax=ax,
            color='lightcoral',
            line_kws={'color':'maroon'},
            fit_reg=True)
ax.set_xlabel('Movie Runtime (in minutes)')
ax.set_ylabel('Aggregate Audience Rating (out of 10)')

plt.savefig("runtimerating.png")
```



This plot suggests a positive relationship between runtime & audience response, especially from the 90 minute runtime onwards. The films with the highest rating floor that still have tight clustering appear around 110-120 minutes.

5.3.2 Next, I inspect review scores from Rotten Tomatoes.

I combine the two Rotten Tomatoes DataFrames into one that give both a film's runtime and its review score. But first, I notice that **rt_reviews_df**'s *rating* column has scores of differing metrics.

In [74]:
```
rt_reviews_df.head()
```

Out[74]:

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
6	3	Quickly grows repetitive and tiresome, meander...	C	rotten	Eric D. Snider	0	EricDSnider.com	July 17, 2013
7	3	Cronenberg is not a director to be daunted by ...	2/5	rotten	Matt Kelemen	0	Las Vegas CityLife	April 21, 2013
11	3	While not one of Cronenberg's stronger films, ...	B-	fresh	Emanuel Levy	0	EmanuelLevy.Com	February 3, 2013
12	3	Robert Pattinson works mighty hard to make Cos...	2/4	rotten	Christian Toto	0	Big Hollywood	January 15, 2013

In [75]:
```python
rt_reviews_df['rating'].unique()
```

Out[75]:
```
array(['3/5', 'C', '2/5', 'B-', '2/4', 'B', '3/4', '4/5', '4/4', '6/10',
       '1/4', '8', '2.5/4', '4/10', '2.0/5', '3/10', '7/10', 'A-', '5/5',
       'F', '3.5/4', 'D+', '1.5/4', '3.5/5', '8/10', 'B+', '9/10',
       '2.5/5', '7.5/10', '5.5/10', 'C-', '1.5/5', '1/5', '5/10', 'C+',
       '0/5', '6', '0.5/4', 'D', '3.1/5', '3/6', '0/4', '2/10', '7', '3',
       'A+', 'A', '4.5/5', '4.0/4', '9.5/10', '2.5', '2.1/2', '6.5/10',
       '3.7/5', '8.4/10', '9', '1', '7.2/10', '2.2/5', '0.5/10', '5',
'0',
       '2', '1/10', '4.5', '7.7', '5.0/5', '8.5/10', '3.0/5', '0.5/5',
       '1.5/10', '3.0/4', '2.3/10', '4.5/10', '4/6', '3.5', '8.6/10',
       '6/8', 'D-', '2.0/4', '2.7', '4.2/10', '5.8', '4', '7.1/10',
       '3.5/10', '5.8/10', '4.0/5', '0/10', '5.0/10', '5.9/10', '2.4/5',
       '1.9/5', '4.9', '7.4/10', '1.5', '2.3/4', '8.8/10', '4.0/10',
       '2.2', '3.8/10', '6.8/10', '7.3', '7.0/10', '3.2', '4.2', '8.4',
       '5.5/5', '6.3/10', '7.6/10', '8.1/10', '3.6/5', '2/6', '7.7/10',
       '1.8', '8.9/10', '8.9', '8.2/10', '8.3/10', '2.6/6', '4.1/10',
       '2.5/10', 'F+', '6.0/10', '1.0/4', '7.9/10', '8.7/10', '4.3/10',
       '9.6/10', '9.0/10', '4.0', '7.9', '6.7', '8.0/10', '9.2/10', '5.
2',
       '5.9', '3.7', '4.7', '6.2/10', '1/6', '8.2', '2.6/5', '3.4', '9.
7',
       '3.3/5', '3.8/5', '1/2', '7.4', '4.8', '1.6/5', '2/2', '1-5',
       '1.0', '4.3/5', '5/6', '9.2', '2.7/5', '4.9/10', '3.0', '3.1',
       '7.8/10', 'F-', '2.3/5', '3.0/10', '3/2', '7.8', '4.2/5', '9.0',
       '7.3/10', '4.4/5', '6.9/10', '0/6', 'T', '6.2', '3.3', '9.8',
       '8.5', '1.0/5', '4.1', '7.1', '3 1/2'], dtype=object)
```

The single number scores and letter grades like 'T' are too vague to be useful and must be dropped. After drops are made, I convert the letter-grade & fraction scores into one standard percent score that doesn't exceed a grade of 100.

In [76]:
```python
for (index, rating) in rt_reviews_df['rating'].items():
    if '/' not in rating:
        if (rating.isupper() == False):
            rt_reviews_df.drop(index, inplace=True)
        elif rating == 'T':
            rt_reviews_df.drop(index, inplace=True)
        else:
            continue
    elif ' ' in rating:
            rt_reviews_df.drop(index, inplace=True)
    else:
        continue
```

In [77]:
```python
letter_grade_dict = {'A+': 98,'A': 95,'A-': 92,'B+': 88,'B': 85,'B-': 82,
                     'C+': 78,'C': 75,'C-': 72,'D+': 68,'D': 65,'D-': 62,
                     'F+': 58,'F': 55,'F-': 52}
```

In [78]:
```
def score_convert(score):
    if '/' in score:
        fract = score.split('/')
        score = float(fract[0]) * (100.0/float(fract[1]))
    elif score.isupper() == True:
        score = letter_grade_dict[score]
    return score
```

In [79]:
```
rt_reviews_df['rating'] = rt_reviews_df['rating'].map(lambda x: score_conve
rt_reviews_df = rt_reviews_df[rt_reviews_df['rating'] <=100]
```

In [80]:
```
rt_reviews_df['rating'].unique()
```

Out[80]:
```
array([ 60.        ,  75.        ,  40.        ,  82.        ,
        50.        ,  85.        ,  80.        , 100.        ,
        25.        ,  62.5       ,  30.        ,  70.        ,
        92.        ,  55.        ,  87.5       ,  68.        ,
        37.5       ,  88.        ,  90.        ,  72.        ,
        20.        ,  78.        ,   0.        ,  12.5       ,
        65.        ,  62.        ,  98.        ,  95.        ,
        74.        ,  84.        ,  44.        ,   5.        ,
        10.        ,  15.        ,  23.        ,  45.        ,
        66.66666667,  86.        ,  42.        ,  71.        ,
        35.        ,  58.        ,  59.        ,  48.        ,
        38.        ,  57.5       ,  63.        ,  76.        ,
        81.        ,  33.33333333,  77.        ,  89.        ,
        83.        ,  43.33333333,  41.        ,  79.        ,
        87.        ,  43.        ,  96.        ,  16.66666667,
        52.        ,  66.        ,  32.        ,  83.33333333,
        54.        ,  49.        ,  46.        ,  73.        ,
        69.        ])
```

The two DataFrames **rt_reviews_df** & **rt_info_df** are almost ready to be joined. Before that is done, though, I change the name of the (audience) *rating* column in **rt_reviews_df** to avoid confusion with the (MPA content) *rating* column from **rt_info_df**.

In [81]:
```
rt_reviews_df = rt_reviews_df.rename(columns={'rating': 'score'})
```

In [82]:
```
info_reviews_df = pd.merge(rt_reviews_df, rt_info_df, on = ['id'], how = 'l
```

In [83]:
```
info_reviews_df.head()
```

Out[83]:

	id	review	score	fresh	critic	top_critic	publisher	date	synopsi
0	3	A distinctly gallows take on contemporary fina...	60.0	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018	New Y City, r too-dista future: F
1	3	Quickly grows repetitive and tiresome, meander...	75.0	rotten	Eric D. Snider	0	EricDSnider.com	July 17, 2013	New Y City, r too-dista future: F
2	3	Cronenberg is not a director to be daunted by ...	40.0	rotten	Matt Kelemen	0	Las Vegas CityLife	April 21, 2013	New Y City, r too-dista future: F
3	3	While not one of Cronenberg's stronger films, ...	82.0	fresh	Emanuel Levy	0	EmanuelLevy.Com	February 3, 2013	New Y City, r too-dista future: F
4	3	Robert Pattinson works mighty hard to make Cos...	50.0	rotten	Christian Toto	0	Big Hollywood	January 15, 2013	New Y City, r too-dista future: F

In [84]:
```
cols_to_drop = ['review','fresh','top_critic','date','synopsis','rating',
                'genre','theater_date','dvd_date','studio']
info_reviews_df.drop(columns=cols_to_drop, inplace=True)
info_reviews_df.head()
```

Out[84]:

	id	score	critic	publisher	director	writer	currency	box_office
0	3	60.0	PJ Nabarro	Patrick Nabarro	David Cronenberg	David Cronenberg|Don DeLillo	$	600,000
1	3	75.0	Eric D. Snider	EricDSnider.com	David Cronenberg	David Cronenberg|Don DeLillo	$	600,000
2	3	40.0	Matt Kelemen	Las Vegas CityLife	David Cronenberg	David Cronenberg|Don DeLillo	$	600,000
3	3	82.0	Emanuel Levy	EmanuelLevy.Com	David Cronenberg	David Cronenberg|Don DeLillo	$	600,000
4	3	50.0	Christian Toto	Big Hollywood	David Cronenberg	David Cronenberg|Don DeLillo	$	600,000

In [85]:
```
print(info_reviews_df.shape)
print(info_reviews_df.isna().sum() / len(info_reviews_df))
```

```
(33334, 9)
id            0.000000
score         0.000000
critic        0.000000
publisher     0.000000
director      0.104698
writer        0.170817
currency      0.303444
box_office    0.303444
runtime       0.017100
dtype: float64
```

In [86]:
```
info_reviews_df.runtime.unique()
```

Out[86]:
```
array(['108 minutes', '116 minutes', '128 minutes', '95 minutes',
       '82 minutes', '123 minutes', '117 minutes', nan, '90 minutes',
       '97 minutes', '106 minutes', '129 minutes', '98 minutes',
       '127 minutes', '96 minutes', '114 minutes', '110 minutes',
       '75 minutes', '92 minutes', '91 minutes', '100 minutes',
       '99 minutes', '103 minutes', '142 minutes', '119 minutes',
       '122 minutes', '86 minutes', '93 minutes', '111 minutes',
       '89 minutes', '115 minutes', '107 minutes', '165 minutes',
       '113 minutes', '118 minutes', '102 minutes', '101 minutes',
       '135 minutes', '109 minutes', '70 minutes', '124 minutes',
       '105 minutes', '134 minutes', '87 minutes', '188 minutes',
       '104 minutes', '126 minutes', '63 minutes', '132 minutes',
       '137 minutes', '79 minutes', '65 minutes', '147 minutes',
       '171 minutes', '59 minutes', '80 minutes', '94 minutes',
       '88 minutes', '81 minutes', '85 minutes', '130 minutes',
       '143 minutes', '133 minutes', '52 minutes', '83 minutes',
       '121 minutes', '146 minutes', '196 minutes', '78 minutes',
       '120 minutes', '69 minutes', '125 minutes', '153 minutes',
       '145 minutes', '76 minutes', '179 minutes', '64 minutes',
       '138 minutes', '84 minutes', '174 minutes', '144 minutes',
       '184 minutes', '148 minutes', '71 minutes', '358 minutes',
       '67 minutes', '60 minutes', '155 minutes', '150 minutes',
       '164 minutes', '154 minutes', '166 minutes', '140 minutes',
       '112 minutes', '167 minutes', '156 minutes', '170 minutes',
       '205 minutes', '159 minutes', '157 minutes', '136 minutes',
       '58 minutes', '149 minutes', '139 minutes', '161 minutes',
       '56 minutes', '141 minutes', '131 minutes', '229 minutes',
       '180 minutes', '158 minutes', '73 minutes'], dtype=object)
```

I cannot work mathematically or visually with these runtimes as strings, so I remove the "minutes" portion of the string and convert the column to type int. Additionally, I spot a null "nan" label, so any null values from the column must be dropped.

In [87]:
```
info_reviews_df.dropna(subset=['runtime'], inplace=True)
info_reviews_df.runtime = info_reviews_df.runtime.str.replace(' minutes', '
info_reviews_df.dtypes
```

Out[87]:
```
id              int64
score         float64
critic         object
publisher      object
director       object
writer         object
currency       object
box_office     object
runtime         int64
dtype: object
```

Because the last collection of runtimes had obvious outliers, I inspect the description of this collection as a precaution to ensure that, at the very least, the max value doesn't sit over 3 standard deviations away from the mean runtime.

In [88]:
```
info_reviews_df['runtime'].describe()
```

Out[88]:
```
count    32764.00000
mean       110.43679
std         20.87213
min         52.00000
25%         96.00000
50%        108.00000
75%        119.00000
max        358.00000
Name: runtime, dtype: float64
```

In [89]:
```
runtime3 = info_reviews_df['runtime']
info_reviews_df = info_reviews_df[runtime3 < (runtime3.mean() + 3*runtime3.
print(info_reviews_df.describe())
```

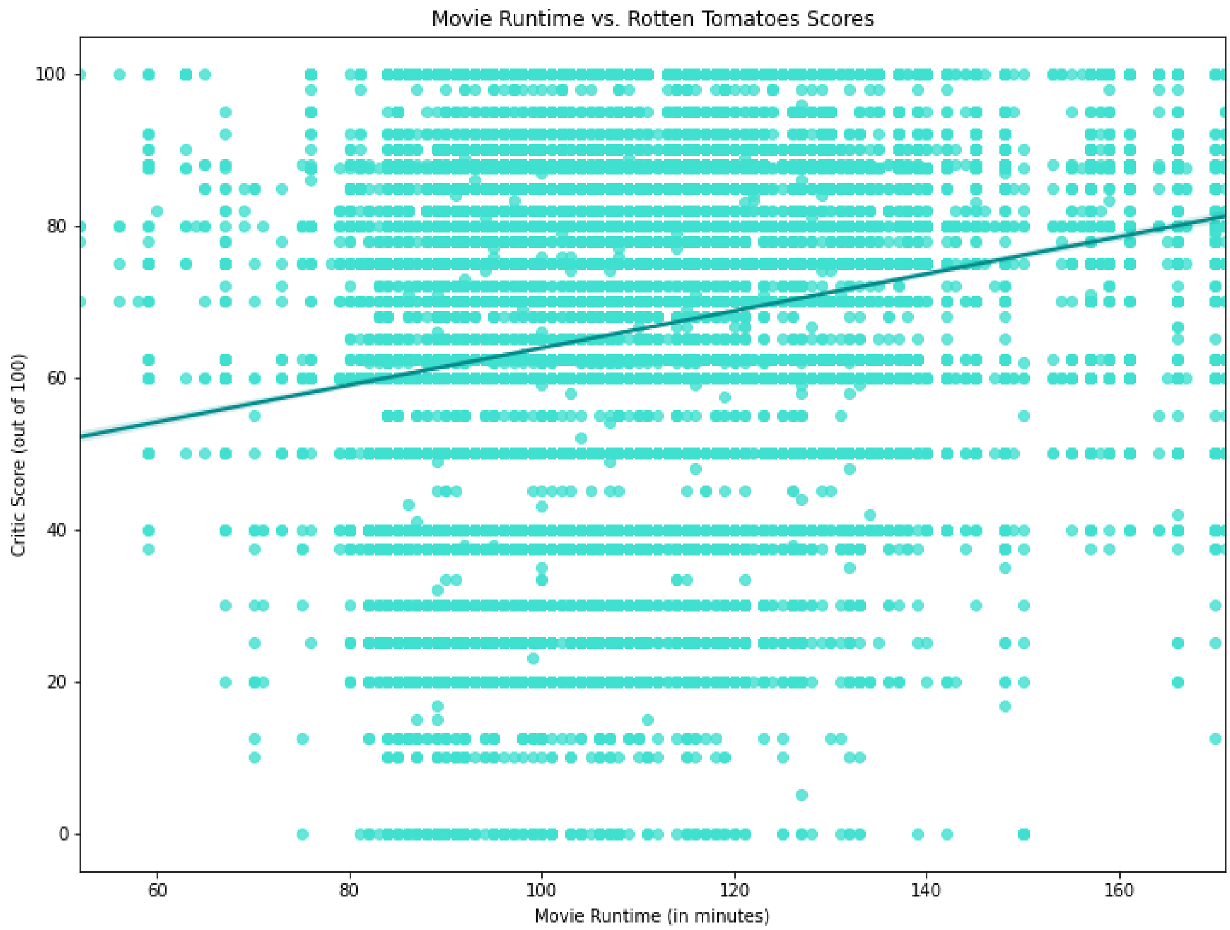
```
                 id         score       runtime
count  32529.000000  32529.000000  32529.000000
mean    1047.001014     66.197065    109.581174
std      585.095333     20.914943     17.630648
min        3.000000      0.000000     52.000000
25%      554.000000     50.000000     96.000000
50%     1083.000000     70.000000    108.000000
75%     1545.000000     80.000000    119.000000
max     2000.000000    100.000000    171.000000
```

Now that the outliers have been filtered out, I am ready to put the plot together.

In [90]:
```
fig, ax = plt.subplots(figsize=(12,9))

ax.set_title('Movie Runtime vs. Rotten Tomatoes Scores')
sns.regplot(x='runtime', y='score',
            data=info_reviews_df,
            ax=ax,
            color='turquoise',
            line_kws={'color':'darkcyan'},
            fit_reg=True)
ax.set_xlabel('Movie Runtime (in minutes)')
ax.set_ylabel('Critic Score (out of 100)')

plt.savefig("runtimescore.png")
```



This dataset allows for each film to have multiple scores associated with it, making the plot a little more tricky to navigate, but nonetheless informative. Overall, there seems to be a slight positive correlation between runtime and critic score.

The higher (60%+) critic scores seem to cluster most tightly between runtimes of 80 & 140 minutes, further solidifying the runtime range previously explored.

6 Conclusions

My analysis leads to the following recommendations for Microsoft as they begin their venture into film:

- **Focus primarily on creating Action, Comedy or Horror films before determining where to branch out.** Not only do these genres have some of the most impressive returns on investment, but each genre's profitability has grown, with varying stability, over most of the last decade. Action movies seem to be the safest bet of the three with regards to profit.
- **Ensure a positive return on investment by making as many high-budget films (at least 40 million USD) as possible.** Only at these large budget levels does there seem to be a positive correlation between the money put into making a film and its relative financial gains. Microsoft is also in the unique position of being able to pay for big budgets from the start.
- **Gain favorability with audiences & critics by releasing movies that run between 100 & 120 minutes.** Looking at the responses provided by IMDB and Rotten Tomatoes, it seems apparent that the films with tightly clustered positive scores and relatively low amounts of negative reactions have runtimes in this range. Additionally, there does appear to be positive correlation between runtime and response, so do not be afraid to test the upper limits of acceptable runtimes.

7 Next Steps

Given the necessary time, additional analysis could provide insight on questions such as:

- Which experienced studios could Microsoft benefit from a partnership with?
- Which screenwriters make the most profitable scripts?
- Which release months or seasons are best for a film's financial performance?

In [ ]: