Final Project Submission

Please fill out:

Student name: Amanda Gaeta

Student pace: part time

Scheduled project review date/time: December 2nd, 2020 at 3pm CST

• Instructor name: Lindsey Berlin

Blog post URL: https://medium.com/@amandabgaeta/why-data-science-d8c6e4645fa5

Introduction

Microsoft wants to start their own movie production studio, but they do not have the movie knowledge that they need to start. This workbook walks through the data analysis used to provide movie landscape knowledge, movie production recommendations, and possible next steps of analysis.

The below uses IMDB and The Numbers data on movies from the 2010s (2010-2019) to answer the following:

- Question 1: What were the top movie genres made in the 2010s?
- Question 2: What is the best month to release a movie for highest worldwide gross?
- Question 3: Of movies that breakeven (ROI >= 1), what genres are most represented?
- Question 4: Based on production budget and average ratings, what genres are the best investments?
- Question 5: For these breakeven movies that fall into these genres, what is the recommended runtime and who are the highest rated directors?

In [1]:

```
#import packages for file import, cleansing and plotting
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set_style(style="whitegrid")
```

Data Source Decisions

Data sources available included:

- IMDB (Internet movie database) information related to films, television programs, home videos, video games, and streaming content online
- Box Office Mojo tracks box office revenue
- Rotten Tomatoes movie reviews from critics and everyday watchers alike, freshness scoe
- The Numbers box office data

IMDB was selected because it was the largest data set with greatest breadth of data. This breadth came in multiple files (in the rawData folder) and was easy to match as all movies have unique ids for most accurate merging. Part of these IMDB files was one specifically on ratings, which made Rotten Tomatoes unecessary especially with less specific ways of matching due to different ids than IMDB. Finally, both The Numbers and Box Office Mojo focus on box office data, but Numbers had more data on more movies including budgets versus gross. Box Office Mojo only provided gross.

Import, join and merge relevant data tables

Start with IMDB files including Title Basics and Title Ratings.

Import Title Basics imdb_tb_df = pd.read_csv('rawData/zippedData/imdb.title.basics.csv.gz') imdb tb df.head()

Out[2]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [3]:

```
# Import Title Ratings
imdb_tr_df = pd.read_csv('rawData/zippedData/imdb.title.ratings.csv.gz')
imdb_tr_df.head()
```

Out[3]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

In [4]:

```
# They are from the same source and have the 'tconst' id to use as a joining reference
# Merging versus joining because ratings is required for the bulk of the analysis
imdb_tb_tr = imdb_tb_df.merge(imdb_tr_df, on='tconst')
```

In [5]:

```
# Check new table, still more than enough data for analysis with 73k
imdb_tb_tr.info()
# Runtime_minutes has many nulls, be aware in further analysis
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 8 columns):
# Column
                   Non-Null Count Dtype
____
                   _____
                   73856 non-null object
0
  tconst
  primary_title 73856 non-null object
1
                   73856 non-null object
2 original_title
                   73856 non-null int64
3
  start_year
4 runtime_minutes 66236 non-null float64
5 genres
                   73052 non-null object
6 averagerating
                  73856 non-null float64
7 numvotes
                  73856 non-null int64
dtypes: float64(2), int64(2), object(4)
memory usage: 5.1+ MB
```

In [6]:

```
# I see genres has some missing values, fill with Unknown for now
imdb_tb_tr['genres'] = imdb_tb_tr['genres'].fillna('Unknown')
```

```
In [7]:
# Preview runtime minutes values to fill nulls
imdb tb tr['runtime minutes']
Out[7]:
        175.0
1
        114.0
2
        122.0
3
         NaN
4
         80.0
73851
        75.0
73852
        98.0
73853
         NaN
73854
         NaN
         72.0
73855
Name: runtime minutes, Length: 73856, dtype: float64
In [8]:
# Fill nulls with 0.0. If doing runtime mins analysis can easily make table that excludes
these
imdb tb tr['runtime minutes'] = imdb tb tr['runtime minutes'].fillna(0.0)
In [9]:
# Check edited table info, nulls populated
imdb tb tr.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 73855
Data columns (total 8 columns):
 #
   Column
                    Non-Null Count Dtype
____
                     _____
0
   tconst
                    73856 non-null object
  primary_title
                    73856 non-null object
1
  original_title 73856 non-null object
 2
3
   start year
                    73856 non-null int64
   runtime_minutes 73856 non-null float64
 4
                    73856 non-null object
 5
   genres
 6 averagerating
                    73856 non-null float64
7 numvotes
                    73856 non-null int64
dtypes: float64(2), int64(2), object(4)
memory usage: 5.1+ MB
```

We are also interested in writer and director analysis for our last question, so import and join IMDB Title Crew to new dataset from above

```
In [10]:
# Import IMDB Title Crew file
imdb_tc_df = pd.read_csv('rawData/zippedData/imdb.title.crew.csv.gz')
# Preview file
imdb_tc_df.head()
```

writers	directors	tconst
nm0899854	nm0899854	0 tt0285252
nm0175726,nm1802864	NaN	1 tt0438973
nm1940585	nm1940585	2 tt0462036
nm0310087,nm0841532	nm0151540	3 tt0835418
nm0284943	nm0089502,nm2291498,nm2292011	4 tt0878654

In [11]:

Out[10]:

```
# Use join as writers and directors will be nice to have
imdb tb tr tc = imdb tb tr.set index('tconst').join(imdb tc df.set index('tconst'))
In [12]:
# Check info on new table to confirm join, good rate of matches especially at director le
ve1
imdb tb tr tc.info()
<class 'pandas.core.frame.DataFrame'>
Index: 73856 entries, tt0063540 to tt9916160
Data columns (total 9 columns):
                      Non-Null Count Dtype
 # Column
 0
   primary_title
                     73856 non-null object
    original_title 73856 non-null object
 1
   start_year
                      73856 non-null int64
   runtime_minutes 73856 non-null float64
                      73856 non-null object
73856 non-null float64
73856 non-null int64
    genres
 5
    averagerating
 6
    numvotes
                      73104 non-null object
 7
    directors
 8
    writers
                      63295 non-null object
dtypes: float64(2), int64(2), object(5)
memory usage: 8.1+ MB
In [13]:
# Post join reset the index
imdb tb tr tc = imdb tb tr tc.reset index()
In [14]:
# Parse out genres into boolean columns for analysis
imdb_tb_tr_tc['genres']
Out[14]:
0
           Action, Crime, Drama
1
              Biography, Drama
2
                        Drama
3
                 Comedy, Drama
4
         Comedy, Drama, Fantasy
                 . . .
73851
                  Documentary
73852
                 Drama, Family
73853
                  Documentary
73854
                      Unknown
                  Documentary
73855
Name: genres, Length: 73856, dtype: object
In [15]:
# Check type
type(imdb tb tr tc['genres'][0])
Out[15]:
str
In [16]:
# Currently strings, need to convert to lists
imdb tb tr tc['genres'] = imdb tb tr tc['genres'].str.split(',')
In [17]:
# Establish variable for Series
imdb genres = imdb tb tr tc['genres']
```

Tn [181:

```
#Establish empyt list to collect all possible genres. These will be made into columns
imdb genres list = []
# Start with rows in index
for row in imdb genres.index:
    # Access the list data type in each row, it will change with every row in the index
    for item in imdb genres[row]:
        # append the genre that is taken as an item from the list within the row and add
it to the genres list
        imdb genres_list.append(item)
# Define a set of the genres list from the above for loop; reassign the genres list varia
ble name to this set
imdb_genres_list = set(imdb_genres_list)
In [19]:
# Check list
imdb_genres_list
Out[19]:
{'Action',
 'Adult',
 'Adventure',
 'Animation',
 'Biography',
 'Comedy',
 'Crime',
 'Documentary',
 'Drama',
 'Family',
 'Fantasy',
 'Game-Show',
 'History',
 'Horror',
 'Music',
 'Musical',
 'Mystery',
 'News',
 'Reality-TV',
 'Romance',
 'Sci-Fi',
 'Short',
 'Sport',
 'Thriller',
 'Unknown',
 'War',
 'Western'}
In [20]:
# Define a new DataFrame for genres to add Boolean columns to
imdb genres = pd.DataFrame(imdb tb tr tc['genres'])
In [21]:
# Preview new DataFrame
imdb\_genres
Out[21]:
                    genres
   0
        [Action, Crime, Drama]
    1
           [Biography, Drama]
```

2

3

[Drama]

[Comedy, Drama]

4 [Oamada Daama Fantana]

4 (Come	eay, prama, Fantasyj genres
•••	
73851	[Documentary]
73852	[Drama, Family]
73853	[Documentary]
73854	[Unknown]
73855	[Documentary]

73856 rows × 1 columns

In [22]:

```
# Use for loop to create columns for each genre in the deduplicated set of genres for the
genres_list
for genre in imdb_genres_list:
    #create a new column in our new DataFrame
    imdb_genres[genre] = 0
```

In [23]:

```
# View DataFrame. Each genre now has its own column
imdb_genres
```

Out[23]:

	genres	Music	War	Reality- TV	Sport	Drama	Adventure	Game- Show	Animation	History	 Horror	Crime	Family
0	[Action, Crime, Drama]	0	0	0	0	0	0	0	0	0	 0	0	0
1	[Biography, Drama]	0	0	0	0	0	0	0	0	0	 0	0	0
2	[Drama]	0	0	0	0	0	0	0	0	0	 0	0	0
3	[Comedy, Drama]	0	0	0	0	0	0	0	0	0	 0	0	0
4	[Comedy, Drama, Fantasy]	0	0	0	0	0	0	0	0	0	 0	0	0
73851	[Documentary]	0	0	0	0	0	0	0	0	0	 0	0	0
73852	[Drama, Family]	0	0	0	0	0	0	0	0	0	 0	0	0
73853	[Documentary]	0	0	0	0	0	0	0	0	0	 0	0	0
73854	[Unknown]	0	0	0	0	0	0	0	0	0	 0	0	0
73855	[Documentary]	0	0	0	0	0	0	0	0	0	 0	0	0

73856 rows × 28 columns

In [24]:

```
for row in imdb_genres.index:
    # Using previous for loop, edit it to access our new DF's column 'genres' THEN the ro
w
    # This will get us to the list of genres in the given row
    for item in imdb_genres['genres'][row]:
        # Then say access the column that matches single genre in that list of genres (it
em) in that row (row)
        imdb_genres[item][row] = 1

<ipython-input-24-e66ac367fcb4>:6: SettingWithCopyWarning:
```

A value is trying to be set on a copy of a slice from a DataFrame

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g uide/indexing.html#returning-a-view-versus-a-copy imdb_genres[item][row] = 1
```

In [25]:

```
# Review table and check work
imdb_genres
```

Out[25]:

	genres	Music	War	Reality- TV	Sport	Drama	Adventure	Game- Show	Animation	History		Horror	Crime	Family
0	[Action, Crime, Drama]	0	0	0	0	1	0	0	0	0		0	1	0
1	[Biography, Drama]	0	0	0	0	1	0	0	0	0		0	0	0
2	[Drama]	0	0	0	0	1	0	0	0	0		0	0	0
3	[Comedy, Drama]	0	0	0	0	1	0	0	0	0		0	0	0
4	[Comedy, Drama, Fantasy]	0	0	0	0	1	0	0	0	0		0	0	0
											•••			
73851	[Documentary]	0	0	0	0	0	0	0	0	0		0	0	0
73852	[Drama, Family]	0	0	0	0	1	0	0	0	0		0	0	1
73853	[Documentary]	0	0	0	0	0	0	0	0	0		0	0	0
73854	[Unknown]	0	0	0	0	0	0	0	0	0		0	0	0
73855	[Documentary]	0	0	0	0	0	0	0	0	0		0	0	0

73856 rows × 28 columns

•

Merge previous IMDB dataset with new genres table

```
In [26]:
```

```
# Same DataFrame length, merge on indices
imdb_with_genre_cols = imdb_tb_tr_tc.merge(imdb_genres, left_index=True, right_index=True)
```

In [27]:

```
# Check new table
imdb_with_genre_cols.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 38 columns):
```

#	Column	Non-Null Count	Dtype
0	tconst	73856 non-null	object
1	primary_title	73856 non-null	object
2	original_title	73856 non-null	object
3	start_year	73856 non-null	int64
4	runtime_minutes	73856 non-null	float64
5	genres_x	73856 non-null	object
6	averagerating	73856 non-null	float64
7	numvotes	73856 non-null	int64
8	directors	73104 non-null	object
9	writers	63295 non-null	object
1 ∩	conrod to	72056 202-211	obicat

```
TO AGUITES À
                    12020 HOH-HATT ONJECT
11 Music 73856 non-null int64
12 War 73856 non-null int64
13 Reality-TV 73856 non-null int64
14 Sport 73856 non-null int64
15 Drama 73856 non-null int64
                       73856 non-null int64
73856 non-null int64
 16 Adventure
 17 Game-Show
                         73856 non-null int64
 18 Animation
                         73856 non-null int64
 19 History
                         73856 non-null int64
 20 Romance
                        73856 non-null int64
73856 non-null int64
 21 Musical
                        73856 non-null int64
 22 News
22 News
23 Mystery
24 Comedy
25 Documentary
26 Fantasy
27 73856 non-null int64
28 73856 non-null int64
73856 non-null int64
73856 non-null int64
                          73856 non-null int64
73856 non-null int64
 28 Horror
 29 Crime
                          73856 non-null int64
                        73856 non-null int64
 30 Family
 31 Unknown
                          73856 non-null int64
 32 Thriller
                        73856 non-null int64
                         73856 non-null int64
 33 Western
                          73856 non-null int64
 34 Action
 35 Short
                          73856 non-null int64
 36 Sci-Fi
                          73856 non-null int64
 37 Biography 73856 non-null int64
dtypes: float64(2), int64(29), object(7)
memory usage: 21.4+ MB
```

Additionally we need financial data where relevant for ROI analysis

Prep The Numbers gross data for merge with IMDB. It has more records than Rotten Tomatoes data and ability to get budget vesus gross for ROI calculation.

Cleaning includes: converting gross data to millions, calculating domestic and foreign gross in mill and percentages, and calculating production ROI

```
In [28]:
```

```
#import file tn.movie_budgets.csv.gz
tn_mb_df = pd.read_csv('rawData/zippedData/tn.movie_budgets.csv.gz')
tn_mb_df.head()
```

Out[28]:

	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 [29]:

```
# Since no way to match via ID, create DIY unique ID via title and year to match on for f
uture join
# First do it for main table that will be joined with imdb_with_genre_cols
imdb_with_genre_cols['title_year'] = imdb_with_genre_cols['primary_title'] + ' ' + imdb_
with_genre_cols['start_year'].astype(str)
```

In [30]:

The Numbers table doesn't have year, so will need to parse out year from release date;

```
test first
tn_mb_df['release_date'][0].split(", ")[1]
Out[30]:
'2009'
In [31]:
tn_mb_df['release_year'] = tn_mb_df['release_date'].map(lambda x: x.split(", ")[1])
In [32]:
# Check work
tn mb df['release year']
Out[32]:
0
        2009
        2011
1
2
        2019
3
        2015
4
        2017
        . . .
5777
        2018
5778
        1999
5779
        2005
        2015
5780
        2005
5781
Name: release year, Length: 5782, dtype: object
In [33]:
# Now can create title and year ID in The Numbers file
tn mb df['title year'] = tn mb df['movie'] + ' ' + tn mb df['release year'].astype(str)
In [34]:
# Check work
tn_mb_df['title_year']
Out[34]:
Ω
                                             Avatar 2009
1
        Pirates of the Caribbean: On Stranger Tides 2011
2
                                       Dark Phoenix 2019
3
                            Avengers: Age of Ultron 2015
4
                  Star Wars Ep. VIII: The Last Jedi 2017
                              . . .
5777
                                             Red 11 2018
                                          Following 1999
5778
5779
                      Return to the Land of Wonders 2005
5780
                               A Plague So Pleasant 2015
5781
                                  My Date With Drew 2005
Name: title year, Length: 5782, dtype: object
In [35]:
# Review The Numbers table info
tn mb df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 8 columns):
 #
   Column
                        Non-Null Count
                                        Dtype
___
                        _____
 0
                        5782 non-null
    id
                                        int64
 1
   release_date
                        5782 non-null
                                       object
 2
   movie
                        5782 non-null object
 3
   production budget 5782 non-null
                                        object
 4
                        5782 non-null
   domestic gross
                                        object
 5
                        5782 non-null
   worldwide gross
                                        object
 6
   release year
                        5782 non-null
                                        object
```

```
In [36]:
# Convert worldwide gross to float
tn mb df['worldwide gross'] = tn mb df['worldwide gross'].str.replace(',','')
tn mb df['worldwide gross'] = tn mb df['worldwide gross'].str.replace('$','').astype(flo
at)
In [37]:
# Create column that converts worldwide gross to millions
tn mb df['worldwide gross in mil'] = round((tn mb df['worldwide gross']/1000000),2)
In [38]:
# Check work
tn_mb_df.head()
Out[38]:
                    movie production_budget domestic_gross worldwide_gross release_year
  id release_date
                                                                                   title_year worldwide_gre
                                                                                     Avatar
                                             $760,507,625
  1 Dec 18, 2009
                               $425,000,000
                                                           2.776345e+09
                                                                             2009
                    Avatar
                                                                                       2009
                  Pirates of
                                                                                   Pirates of
                      the
                                                                                        the
                                                                                  Caribbean:
                 Caribbean:
  2 May 20, 2011
                                                                             2011
                               $410,600,000
                                             $241,063,875
                                                           1.045664e+09
                       On
                                                                                        On
                  Stranger
                                                                                    Stranger
                     Tides
                                                                                  Tides 2011
                                                                                       Dark
                     Dark
                               $350,000,000
                                                           1.497624e+08
                                                                             2019
                                                                                    Phoenix
2
  3
       Jun 7, 2019
                                              $42,762,350
                   Phoenix
                                                                                       2019
                                                                                   Avengers:
                  Avengers:
                                                                                     Age of
      May 1, 2015
                    Age of
                               $330,600,000
                                             $459,005,868
                                                           1.403014e+09
                                                                             2015
                                                                                      Ultron
                    Ultron
                                                                                       2015
                  Star Wars
                                                                                   Star Wars
                   Ep. VIII:
                                                                                    Ep. VIII:
                               $317,000,000
                                             $620,181,382
                                                                             2017
   5 Dec 15, 2017
                                                           1.316722e+09
                   The Last
                                                                                    The Last
                                                                                   Jedi 2017
                      Jedi
In [39]:
# worldwide gross in mil is added and float type
tn mb df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 9 columns):
   Column
                                Non-Null Count
___
     _____
 0
                                 5782 non-null
                                                  int64
1
   release date
                                5782 non-null object
                                                  object
                                 5782 non-null
   movie
                                5782 non-null
   production_budget
                                                   object
                                5782 non-null
                                                  object
   domestic gross
 5
    worldwide_gross
                                5782 non-null
                                                  float64
 6
                                5782 non-null
     release year
                                                   object
 7
                                 5782 non-null
     title year
                                                   object
     worldwide_gross_in_mil 5782 non-null
                                                   float64
dtypes: float64(2), int64(1), object(6)
```

title year

memory usage: 406.7+ KB

In [40]:

dtypes: int64(1), object(7)
memory usage: 361.5+ KB

5782 non-null

object

```
# Convert production_budget to float
tn_mb_df['production_budget'] = tn_mb_df['production_budget'].str.replace(',','')
tn_mb_df['production_budget'] = tn_mb_df['production_budget'].str.replace('$','').astype(
float)
```

In [41]:

```
# Create column that converts production_budget to millions
tn_mb_df['production_budget_in_mil'] = round((tn_mb_df['production_budget']/1000000),2)
tn_mb_df.head()
```

Out[41]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	title_year	worldwide_gr
0	1	Dec 18, 2009	Avatar	425000000.0	\$760,507,625	2.776345e+09	2009	Avatar 2009	
1	2	. May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	\$241,063,875	1.045664e+09	2011	Pirates of the Caribbean: On Stranger Tides 2011	
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	\$42,762,350	1.497624e+08	2019	Dark Phoenix 2019	
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	\$459,005,868	1.403014e+09	2015	Avengers: Age of Ultron 2015	
4	- 5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	\$620,181,382	1.316722e+09	2017	Star Wars Ep. VIII: The Last Jedi 2017	
4									<u> </u>

In [42]:

```
# Create column in The Numbers that calculates ROI of prod budget to worldwide gross (wor
ldwide_gross/production_budget)?
tn_mb_df['prod_budget_ROI'] = tn_mb_df['worldwide_gross_in_mil']/tn_mb_df['production_budget_in_mil']
tn_mb_df.head()
```

Out[42]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	title_year	worldwide_gr
0	1	Dec 18, 2009	Avatar	425000000.0	\$760,507,625	2.776345e+09	2009	Avatar 2009	
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	\$241,063,875	1.045664e+09	2011	Pirates of the Caribbean: On Stranger Tides 2011	
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	\$42,762,350	1.497624e+08	2019	Dark Phoenix 2019	
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	\$459,005,868	1.403014e+09	2015	Avengers: Age of Ultron 2015	
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	\$620,181,382	1.316722e+09	2017	Star Wars Ep. VIII: The Last Jedi 2017	

```
In [43]:
# Check new prod budget ROI numbers
tn mb df['prod budget ROI'].describe()
Out[43]:
        5780.000000
count
mean
                inf
                NaN
std
           0.000000
min
           0.492245
25%
50%
           1.709144
75%
           3.760000
max
                inf
Name: prod budget ROI, dtype: float64
In [44]:
# Found resolution to rid of infs on stackoverflow using np
tn_mb_df['prod_budget_ROI'] = tn_mb_df['prod_budget_ROI'].replace([np.inf, -np.inf], np.
nan)
In [45]:
# Check solution, no more NaN or inf
tn mb df['prod budget ROI'].describe()
Out[45]:
count
        5779.000000
           4.838506
mean
std
          34.340229
min
           0.000000
25%
           0.492183
50%
           1.708889
75%
           3.757857
max
        2250.000000
Name: prod budget ROI, dtype: float64
In [46]:
# Check back on prod budget for nulls
tn mb df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 11 columns):
 #
    Column
                              Non-Null Count Dtype
    _____
                               -----
0
   id
                              5782 non-null int64
                              5782 non-null object
1 release date
 2 movie
                              5782 non-null
                                            object
   production_budget
                              5782 non-null
 3
                                             float64
                              5782 non-null
                                              object
    domestic_gross
   worldwide_gross
 5
                              5782 non-null
                                              float64
 6
    release year
                              5782 non-null
                                             object
                                             object
 7
    title year
                              5782 non-null
 8
    worldwide gross in mil
                              5782 non-null
                                              float64
    production budget in mil 5782 non-null
 9
                                              float64
10 prod budget ROI
                              5779 non-null
                                              float64
dtypes: float64(5), int64(1), object(5)
memory usage: 497.0+ KB
In [47]:
# Fill with median for analysis
tn mb df['prod budget ROI'] = tn mb df['prod budget ROI'].fillna(1.71)
In [48]:
```

```
tn mb df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 11 columns):
   Column
                              Non-Null Count Dtype
                               _____
    _____
 0
   id
                               5782 non-null int64
                              5782 non-null object
 1 release_date
 2 movie
                              5782 non-null object
 3 production_budget
4 domestic_gross
                              5782 non-null float64
                             5782 non-null object float64
 5 worldwide gross
                              5782 non-null object
5782 non-null object
 6
    release year
 7
    title year
 8
    worldwide_gross_in_mil
                              5782 non-null float64
   production budget in mil 5782 non-null float64
 9
10 prod_budget_ROI
                             5782 non-null float64
dtypes: float64(\overline{5}), int64(1), object(5)
memory usage: 497.0+ KB
```

Check that nulls are filled

In [49]:

```
# Convert domestic_gross to float
tn_mb_df['domestic_gross'] = tn_mb_df['domestic_gross'].str.replace(',','')
tn_mb_df['domestic_gross'] = tn_mb_df['domestic_gross'].str.replace('$','').astype(float)
```

In [50]:

```
# Create column that converts domestic_gross to millions
tn_mb_df['domestic_gross_in_mil'] = round((tn_mb_df['domestic_gross']/1000000),2)
tn_mb_df.head()
```

Out[50]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	title_year	worldwide_gr
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2009	Avatar 2009	
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	2011	Pirates of the Caribbean: On Stranger Tides 2011	
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	2019	Dark Phoenix 2019	
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	2015	Avengers: Age of Ultron 2015	
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	2017	Star Wars Ep. VIII: The Last Jedi 2017	
4									D.

In [51]:

```
# Create column for foreign_gross_in_mil
tn_mb_df['foreign_gross_in_mil'] = tn_mb_df['worldwide_gross_in_mil'] - tn_mb_df['domesti
c_gross_in_mil']
tn_mb_df.head()
```

	ıa	release_date	movie	production_budget	aomestic_gross	worlawide_gross	release_year	title_year	worlawiae_gr
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2009	Avatar 2009	
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	2011	Pirates of the Caribbean: On Stranger Tides 2011	
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	2019	Dark Phoenix 2019	
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	2015	Avengers: Age of Ultron 2015	
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	2017	Star Wars Ep. VIII: The Last Jedi 2017	
4					1888				b

In [52]:

```
# Create column for domestic_gross_p and foreign_gross_p
tn_mb_df['domestic_gross_p'] = round((tn_mb_df['domestic_gross_in_mil']/tn_mb_df['worldwi
de_gross_in_mil']), 2)
tn_mb_df['foreign_gross_p'] = round((tn_mb_df['foreign_gross_in_mil']/tn_mb_df['worldwide
_gross_in_mil']), 2)
tn_mb_df.head()
```

Out[52]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	title_year	worldwide_gr
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2009	Avatar 2009	
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	2011	Pirates of the Caribbean: On Stranger Tides 2011	
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	2019	Dark Phoenix 2019	
3	4	M ay 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	2015	Avengers: Age of Ultron 2015	
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	2017	Star Wars Ep. VIII: The Last Jedi 2017	
4)

In [53]:

```
tn_mb_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 15 columns):
```

Column Non-Null Count Dtype
--- 0 id 5782 non-null int64
1 release_date 5782 non-null object

```
movie
                             5/82 non-null
                                           object
   production budget
                             5782 non-null float64
 4 domestic_gross
                            5782 non-null float64
 5 worldwide_gross
                            5782 non-null float64
                                           object
   release_year
                            5782 non-null
 6
7
                                           object
   title year
                            5782 non-null
                                           float64
                            5782 non-null
   worldwide_gross_in mil
 8
    production budget in mil 5782 non-null
9
                                            float64
                                           float64
10 prod_budget_ROI
                             5782 non-null
11 domestic_gross_in_mil
                                           float64
                             5782 non-null
12 foreign_gross_in_mil
                             5782 non-null float64
13 domestic_gross_p
                             5362 non-null float64
                             5362 non-null float64
14 foreign_gross_p
dtypes: float64(10), int64(1), object(4)
memory usage: 677.7+ KB
In [54]:
# Domestic and foreign gross % columns have nulls. Fill with median
tn mb df['domestic gross p'].median()
Out [54]:
0.6
In [55]:
tn mb df['foreign gross p'].median()
Out[55]:
0.4
In [56]:
tn mb df['domestic gross p'] = tn mb df['domestic gross p'].fillna(0.6)
tn mb df['foreign gross p'] = tn mb df['foreign gross p'].fillna(0.4)
In [57]:
# Parse out release month
tn mb df['release month'] = tn mb df['release date'].map(lambda x: x.split(" ")[0])
In [58]:
# Check table, nulls are filled
tn mb df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 16 columns):
 #
   Column
                             Non-Null Count Dtype
   ----
   id
0
                             5782 non-null int64
   release date
                                           object
 1
                             5782 non-null
                                           object
   movie
                             5782 non-null
   production budget
 3
                             5782 non-null float64
 4
   domestic gross
                             5782 non-null float64
 5
   worldwide gross
                             5782 non-null float64
 6
                             5782 non-null object
   release year
7
                            5782 non-null object
   title year
 8 worldwide gross in mil 5782 non-null float64
 9 production budget in mil 5782 non-null float64
10 prod budget ROI
                            5782 non-null float64
11 domestic_gross_in mil
                            5782 non-null float64
                             5782 non-null float64
12 foreign gross in mil
                             5782 non-null float64
13 domestic gross p
14 foreign_gross_p
                             5782 non-null float64
15 release_month
                            5782 non-null object
dtypes: float64(10), int64(1), object(5)
memory usage: 722.9+ KB
```

```
In [59]:
tn_mb_df.head()
```

Out[59]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year	title_year	worldwide_gr
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09	2009	Avatar 2009	
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	2011	Pirates of the Caribbean: On Stranger Tides 2011	
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	2019	Dark Phoenix 2019	
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	2015	Avengers: Age of Ultron 2015	
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	2017	Star Wars Ep. VIII: The Last Jedi 2017	
4					1				Þ

Merge The Numbers and imdb_with_genre_cols using title and year concatenation as unique id

```
In [60]:
```

```
# Merge on title_year by using it as index and joining
imdb_with_genre_cols = imdb_with_genre_cols.set_index('title_year').join(tn_mb_df.set_ind
ex('title_year'))
```

In [61]:

```
# Check new table
imdb_with_genre_cols.info()
```

<class 'pandas.core.frame.DataFrame'>
Index: 73856 entries, !Women Art Revolution 2010 to Šiška Deluxe 2015
Data columns (total 53 columns):

0 tconst 73856 non-null object 1 primary_title 73856 non-null object 2 original_title 73856 non-null object 3 start_year 73856 non-null int64 4 runtime_minutes 73856 non-null float64 5 genres_x 73856 non-null object 6 averagerating 73856 non-null int64 7 numvotes 73104 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null int64 12 War 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	#	Column	Non-Null Count	Dtype
1 primary_title 73856 non-null object 2 original_title 73856 non-null int64 3 start_year 73856 non-null int64 4 runtime_minutes 73856 non-null float64 5 genres_x 73856 non-null object 6 averagerating 73856 non-null int64 7 numvotes 73856 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64		toonst	73856 non-null	object
2 original_title 73856 non-null object 3 start_year 73856 non-null int64 4 runtime_minutes 73856 non-null float64 5 genres_x 73856 non-null object 6 averagerating 73856 non-null int64 7 numvotes 73856 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64				_
3 start_year 73856 non-null int64 4 runtime_minutes 73856 non-null float64 5 genres_x 73856 non-null object 6 averagerating 73856 non-null float64 7 numvotes 73856 non-null int64 8 directors 73104 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64				
4 runtime_minutes 73856 non-null float64 5 genres_x 73856 non-null object 6 averagerating 73856 non-null float64 7 numvotes 73856 non-null int64 8 directors 73104 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64		<u> </u>		_
5 genres_x 73856 non-null object 6 averagerating 73856 non-null float64 7 numvotes 73856 non-null int64 8 directors 73104 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64				
6 averagerating 73856 non-null float64 7 numvotes 73856 non-null int64 8 directors 73104 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null int64 11 Music 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64		_		
7 numvotes 73856 non-null int64 8 directors 73104 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null object 11 Music 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64		-		=
8 directors 73104 non-null object 9 writers 63295 non-null object 10 genres_y 73856 non-null object 11 Music 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64				
9 writers 63295 non-null object 10 genres_y 73856 non-null object 11 Music 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	-			
10 genres_y 73856 non-null object 11 Music 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64				=
11 Music 73856 non-null int64 12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	9	writers	63295 non-null	object
12 War 73856 non-null int64 13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	10	genres_y	73856 non-null	object
13 Reality-TV 73856 non-null int64 14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	11	Music	73856 non-null	int64
14 Sport 73856 non-null int64 15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	12	War	73856 non-null	int64
15 Drama 73856 non-null int64 16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	13	Reality-TV	73856 non-null	int64
16 Adventure 73856 non-null int64 17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	14	Sport	73856 non-null	int64
17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	15	Drama	73856 non-null	int64
17 Game-Show 73856 non-null int64 18 Animation 73856 non-null int64 19 History 73856 non-null int64	16	Adventure	73856 non-null	int64
18 Animation 73856 non-null int64 19 History 73856 non-null int64	17	Game-Show		
19 History 73856 non-null int64				
		_		

```
tall TTnu-uou ococ/
∠∪ Komance
21 Musical
                             73856 non-null int64
22 News
                             73856 non-null int64
23 Mystery
                             73856 non-null int64
24 Comedy
                             73856 non-null int64
25 Documentary
                            73856 non-null int64
26 Fantasy
                            73856 non-null int64
27 Adult
                            73856 non-null int64
28 Horror
                             73856 non-null int64
29 Crime
                             73856 non-null int64
30 Family
                             73856 non-null int64
                             73856 non-null int64
31 Unknown
                             73856 non-null int64
   Thriller
32
                             73856 non-null int64
33 Western
                             73856 non-null int64
 34
    Action
 3.5
    Short
                             73856 non-null int64
 36 Sci-Fi
                             73856 non-null int64
37 Biography
                             73856 non-null int64
38 id
                             1498 non-null float64
39 release_date
                            1498 non-null object
40 movie
                            1498 non-null object
41 production budget
                            1498 non-null float64
42 domestic gross
                            1498 non-null float64
43 worldwide gross
                            1498 non-null float64
44 release year
                            1498 non-null object
45 worldwide_gross_in_mil 1498 non-null float64
46 production_budget_in_mil 1498 non-null float64
                            1498 non-null float64
 47 prod_budget_ROI
48 domestic_gross_in_mil 1498 non-null float64
49 foreign gross_in_mil 1498 non-null float64
50 domestic_gross_p
                             1498 non-null
                                            float64
    foreign_gross_p
                             1498 non-null
51
                                            float64
52 release month
                             1498 non-null object
dtypes: float64(13), int64(29), object(11)
memory usage: 30.4+ MB
In [62]:
# Look at what years are represented in table using IMDB start year (more data available)
; 2010-2019 covered
imdb with genre cols['start year'].astype('int').describe()
Out[62]:
count
       73856.000000
         2014.276132
mean
std
            2.614807
min
         2010.000000
25%
         2012.000000
50%
        2014.000000
75%
        2016.000000
         2019.000000
```

Question 1: What were the top movie genres made in the 2010s?

Name: start year, dtype: float64

In [65]:

```
In [63]:
# Reset the index post merge
imdb_with_genre_cols = imdb_with_genre_cols.reset_index()

In [64]:
imdb_with_genre_cols = imdb_with_genre_cols.drop(labels='Unknown', axis=1)
```

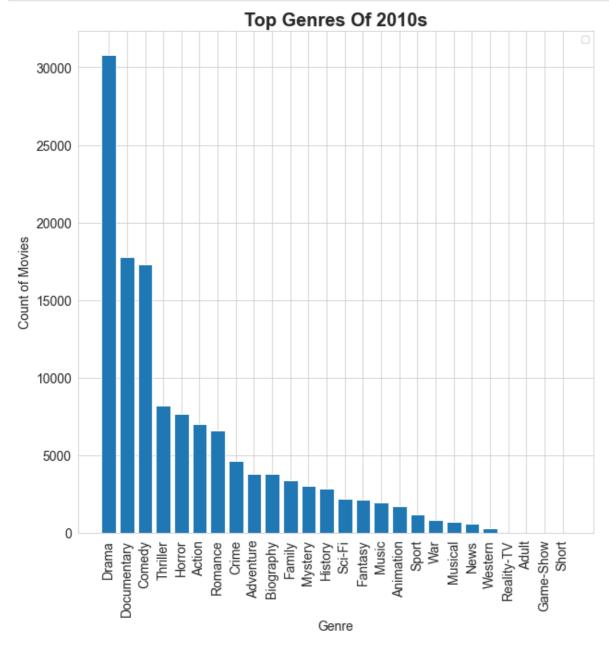
```
# Get list of genre names to create dictionary with count per genre
genre_name_list = list(imdb_with_genre_cols.columns[12:38])
```

```
In [66]:
# Create dictionary using for loop to grab column name as the dict key and sum of each co
lumn as dict value
genre_total_dict = {}
for genre in genre name list:
    genre total dict[genre] = imdb with genre cols[genre].sum()
genre total dict
Out[66]:
{'Music': 1968,
 'War': 853,
 'Reality-TV': 17,
 'Sport': 1179,
 'Drama': 30788,
 'Adventure': 3817,
 'Game-Show': 2,
 'Animation': 1743,
 'History': 2825,
 'Romance': 6589,
 'Musical': 721,
 'News': 579,
 'Mystery': 3039,
 'Comedy': 17290,
 'Documentary': 17753,
 'Fantasy': 2126,
 'Adult': 3,
 'Horror': 7674,
 'Crime': 4611,
 'Family': 3412,
 'Thriller': 8217,
 'Western': 280,
 'Action': 6988,
 'Short': 1,
 'Sci-Fi': 2206,
 'Biography': 3809}
In [67]:
# Sort the dictionary
import operator
sorted_genre_count_dict = dict( sorted(genre total dict.items(), key=operator.itemgetter(
1), reverse=True))
sorted_genre_count_dict
Out[67]:
{'Drama': 30788,
 'Documentary': 17753,
 'Comedy': 17290,
 'Thriller': 8217,
 'Horror': 7674,
 'Action': 6988,
 'Romance': 6589,
 'Crime': 4611,
 'Adventure': 3817,
 'Biography': 3809,
 'Family': 3412,
 'Mystery': 3039,
 'History': 2825,
 'Sci-Fi': 2206,
 'Fantasy': 2126,
 'Music': 1968,
 'Animation': 1743,
 'Sport': 1179,
 'War': 853,
 'Musical': 721,
 'News': 579,
 'Western': 280,
 'Reality-TV': 17,
```

```
'Adult': 3,
'Game-Show': 2,
'Short': 1}
```

In [68]:

```
#Plot, note movies with multiple genres counted once for each genre
plt.figure (figsize=(10,10))
plt.bar(sorted_genre_count_dict.keys(), sorted_genre_count_dict.values())
plt.title('Top Genres Of 2010s', fontsize=20, fontweight="bold")
plt.xlabel('Genre', fontsize=14)
plt.xticks(rotation=90, fontsize=14)
plt.ylabel('Count of Movies', fontsize=14)
plt.yticks(fontsize=14)
plt.legend('')
plt.show()
```



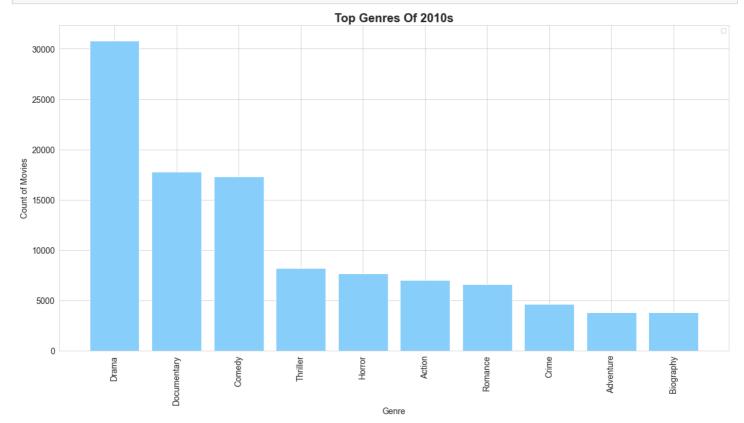
In [69]:

```
# Zoom in on top 10 for presentation
genre_count_dict_zoom = {k: sorted_genre_count_dict[k] for k in list(sorted_genre_count_dict)[:10]}
```

In [70]:

```
# Replot
plt.figure (figsize=(20,10))
plt.bar(genre_count_dict_zoom.keys(), genre_count_dict_zoom.values(), color='lightskyblue
')
```

```
plt.title('Top Genres Of 2010s', fontsize=20, fontweight="bold")
plt.xlabel('Genre', fontsize=14)
plt.xticks(rotation=90, fontsize=14)
plt.ylabel('Count of Movies', fontsize=14)
plt.yticks(fontsize=14)
plt.legend('')
plt.legend('')
plt.savefig("images/1_bar_top_10_genres_2010s_lsb_wide.png")
plt.show()
```



Of movies with financial data, look into production budget versus worldwide gross

```
In [71]:
```

```
# Create DataFrame with records that have production budget ROI data
imdb_all_prod_roi_genres = imdb_with_genre_cols[imdb_with_genre_cols['prod_budget_ROI'].n
otnull()]
```

In [72]:

```
imdb_all_prod_roi_genres.info()
```

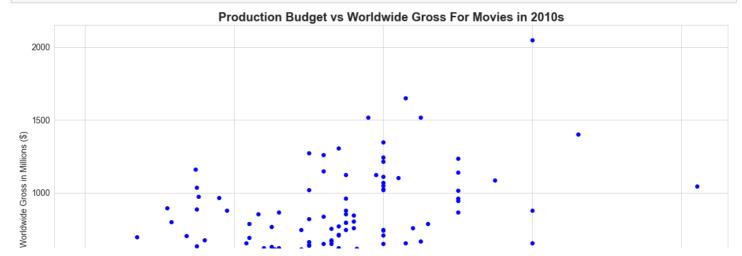
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1498 entries, 18 to 73700
Data columns (total 53 columns):
```

#	Column	Non-Null Count	Dtype
0	title_year	1498 non-null	object
1	tconst	1498 non-null	object
2	primary_title	1498 non-null	object
3	original_title	1498 non-null	object
4	start_year	1498 non-null	int64
5	runtime_minutes	1498 non-null	float64
6	genres_x	1498 non-null	object
7	averagerating	1498 non-null	float64
8	numvotes	1498 non-null	int64
9	directors	1497 non-null	object
10	writers	1480 non-null	object
11	genres_y	1498 non-null	object
12	Music	1498 non-null	int64
13	War	1498 non-null	int64
14	Reality-TV	1498 non-null	int64
15	Snort	1/00 non-null	in+61

```
エン
    PPULL
                             TIOU IIOII IIUTT
                                            TIICOT
 16
    Drama
                             1498 non-null
                                            int64
17
    Adventure
                             1498 non-null
                                            int64
18
    Game-Show
                             1498 non-null
                                            int64
                                           int64
19 Animation
                             1498 non-null
                                           int64
20 History
                             1498 non-null
21 Romance
                             1498 non-null int64
22 Musical
                             1498 non-null
                                           int64
23 News
                             1498 non-null
                                           int64
24 Mystery
                             1498 non-null
25 Comedy
                             1498 non-null
26 Documentary
                             1498 non-null
                                           int64
27 Fantasy
                             1498 non-null
                                            int.64
28 Adult
                             1498 non-null
                                            int64
29 Horror
                             1498 non-null
                                            int64
30 Crime
                             1498 non-null
                                            int64
31 Family
                             1498 non-null
                                            int64
32
    Thriller
                             1498 non-null
                                            int64
33 Western
                             1498 non-null
 34
    Action
                             1498 non-null
                                            int64
                                           int64
 35
    Short
                             1498 non-null
                                           int64
 36
    Sci-Fi
                             1498 non-null
 37 Biography
                             1498 non-null int64
38
   id
                             1498 non-null float64
39 release_date
                             1498 non-null object
40 movie
                             1498 non-null object
41 production budget
                            1498 non-null float64
42 domestic gross
                             1498 non-null float64
43 worldwide_gross
                             1498 non-null float64
44 release year
                             1498 non-null object
45 worldwide_gross_in_mil 1498 non-null float64
46 production_budget_in_mil 1498 non-null
                                           float64
                                           float64
47 prod budget ROI
                             1498 non-null
 48 domestic_gross_in_mil
                            1498 non-null
                                           float64
49 foreign_gross_in_mil
                            1498 non-null
                                           float64
50
    domestic gross p
                             1498 non-null
                                            float64
51
    foreign_gross_p
                             1498 non-null
                                            float64
                             1498 non-null
52 release month
dtypes: float64(13), int64(28), object(12)
memory usage: 632.0+ KB
```

In [73]:

```
# Plot chart prod vs gross for all 2010 movies with financial data from table above
x = imdb_all_prod_roi_genres['production_budget_in_mil']
y = imdb_all_prod_roi_genres['worldwide_gross_in_mil']
plt.figure (figsize=(20,10))
plt.scatter(x, y, color='blue')
plt.title('Production Budget vs Worldwide Gross For Movies in 2010s', fontsize=20, fontwe ight="bold")
plt.xlabel('Production Budget in Millions ($)', fontsize=14)
plt.xticks(fontsize=14)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=14)
plt.yticks(fontsize=14)
plt.savefig("images/additionalViz/scatter_prodbudg_vs_wwgross_2010s_all_fg_wide.png")
plt.show()
```



```
0 100 200 300 400

Production Budget in Millions ($)
```

In [74]:

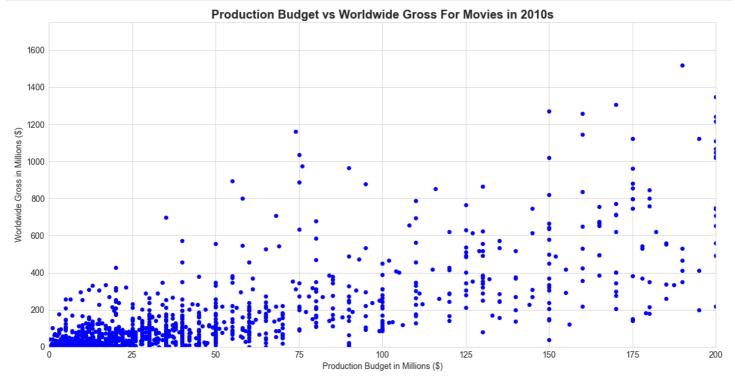
```
len(imdb_all_prod_roi_genres[imdb_all_prod_roi_genres['production_budget_in_mil'] <= 200]
)</pre>
```

Out[74]:

1471

In [75]:

```
# Replot with zoom into production budget up to 200 mil
x = imdb_all_prod_roi_genres['production_budget_in_mil']
y = imdb_all_prod_roi_genres['worldwide_gross_in_mil']
plt.figure (figsize=(20,10))
plt.scatter(x, y, color='blue')
plt.title('Production Budget vs Worldwide Gross For Movies in 2010s', fontsize=20, fontwe ight="bold")
plt.xlabel('Production Budget in Millions ($)', fontsize=14)
plt.xticks(fontsize=14)
plt.xlim(0,200)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=14)
plt.yticks(fontsize=14)
plt.yticks(fontsize=14)
plt.ylim(0,1750)
plt.savefig("images/additionalViz/scatter_prodbudg_vs_wwgross_2010s_200M_fg_wide.png")
plt.show()
```



In [76]:

```
# Get list of genre columns imdb_all_prod_roi_genres.columns[12:38]
```

Out[76]:

```
'Biography'],
dtype='object')
```

In [77]:

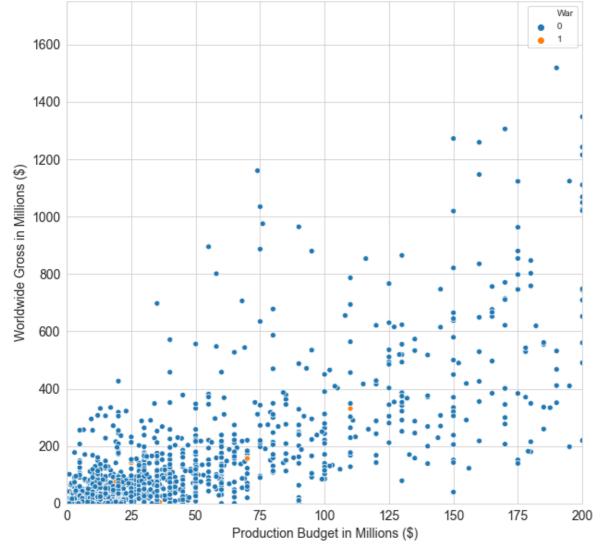
```
# Create list and assign variable name
genre_columns = list(imdb_all_prod_roi_genres.columns[13:38])
```

In [78]:

```
# Use for loop to chart prod budget vs worldwide gross per genre
for genre in genre columns:
   print (genre)
    x = imdb_all_prod_roi_genres['production_budget_in_mil']
    y = imdb_all_prod_roi_genres['worldwide_gross_in_mil']
    plt.figure (figsize=(10,10))
    sns.scatterplot(x, y, hue=imdb all prod roi genres[genre])
   plt.title(f'Production Budget vs Worldwide Gross For {genre} Movies in 2010s', fonts
ize=20, fontweight="bold")
   plt.xlabel('Production Budget in Millions ($)', fontsize=14)
   plt.xlim(0,200)
   plt.xticks(fontsize=14)
   plt.ylabel('Worldwide Gross in Millions ($)', fontsize=14)
    plt.ylim(0,1750)
   plt.yticks(fontsize=14)
    plt.show()
   plt.savefig(f"images/additionalViz/prod budg by gross genre/scatter {genre} prodbudg
vs wwgross 2010s 200M fg.png")
```

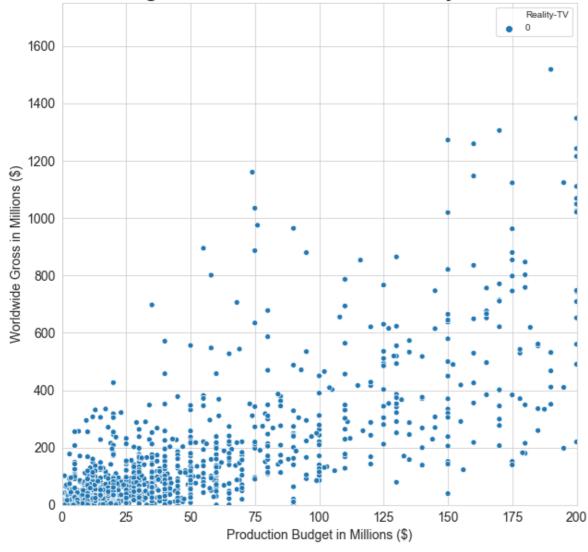
War

Production Budget vs Worldwide Gross For War Movies in 2010s



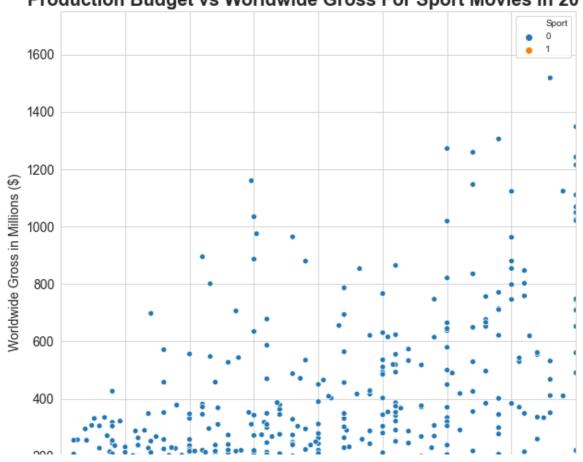
Reality-TV <Figure size 432x288 with 0 Axes>

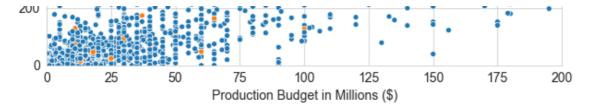
Production Budget vs Worldwide Gross For Reality-TV Movies in 2010s



Sport
<Figure size 432x288 with 0 Axes>



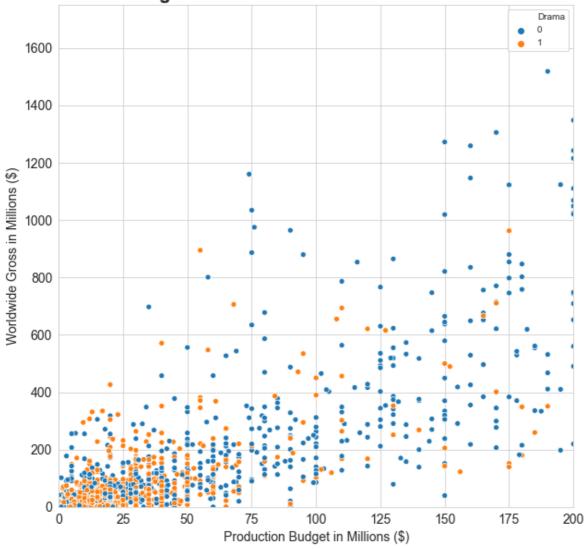




Drama

<Figure size 432x288 with 0 Axes>

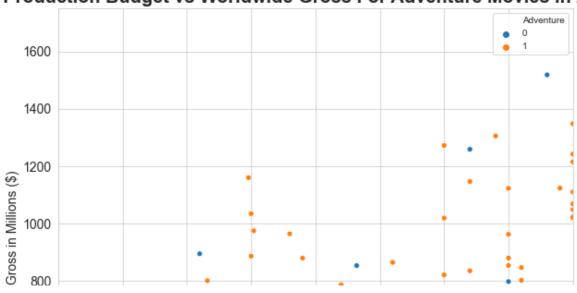


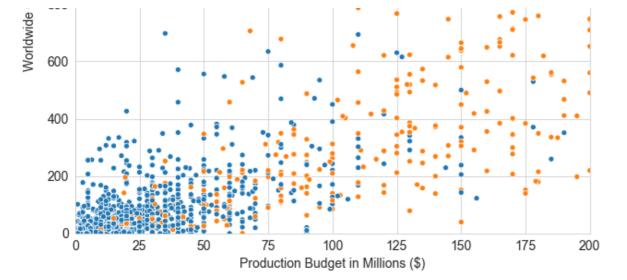


Adventure

<Figure size 432x288 with 0 Axes>

Production Budget vs Worldwide Gross For Adventure Movies in 2010s

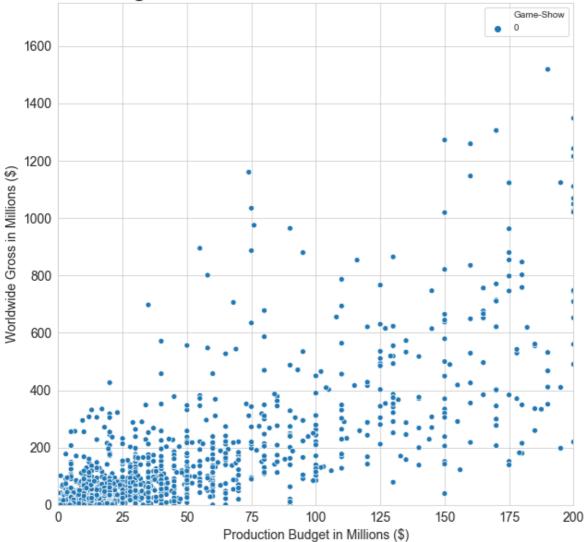




Game-Show

<Figure size 432x288 with 0 Axes>

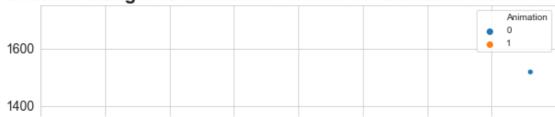
Production Budget vs Worldwide Gross For Game-Show Movies in 2010s

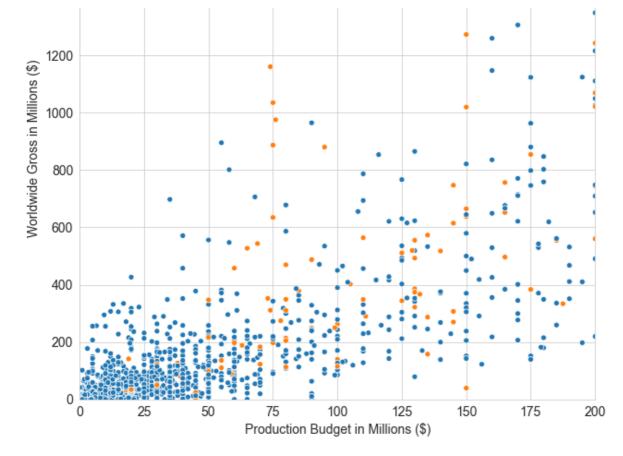


Animation

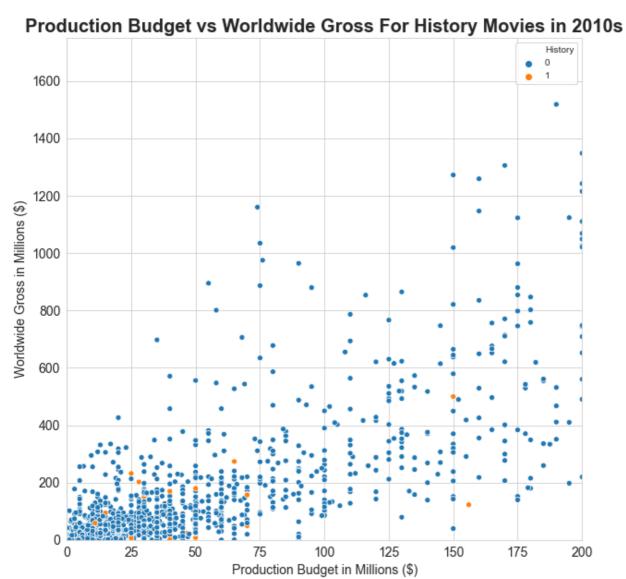
<Figure size 432x288 with 0 Axes>

Production Budget vs Worldwide Gross For Animation Movies in 2010s

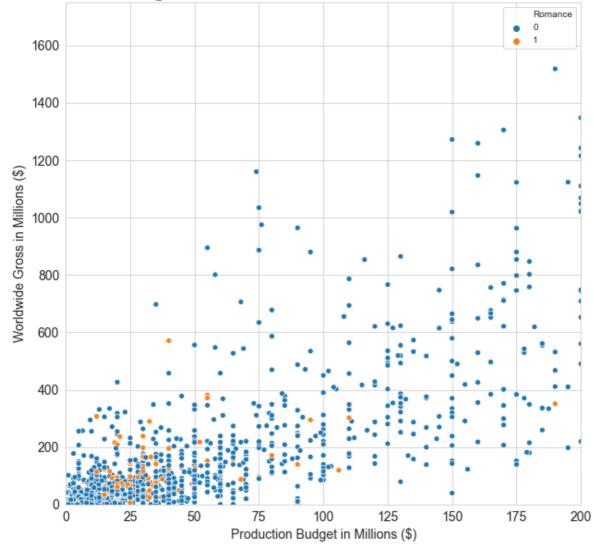




History
<Figure size 432x288 with 0 Axes>

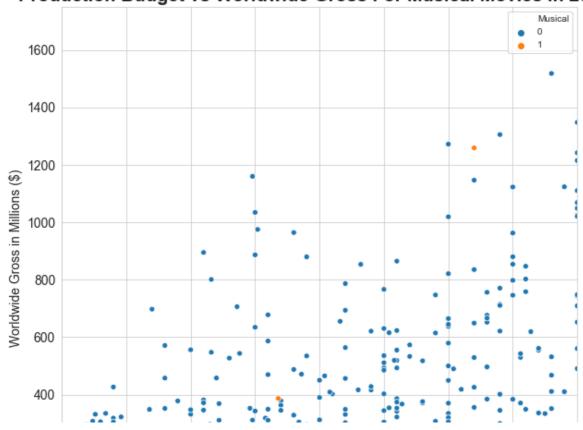


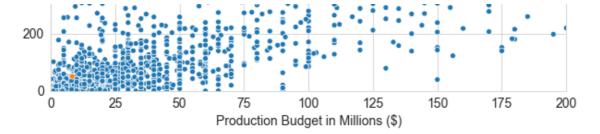
Production Budget vs Worldwide Gross For Romance Movies in 2010s



Musical
<Figure size 432x288 with 0 Axes>

Production Budget vs Worldwide Gross For Musical Movies in 2010s

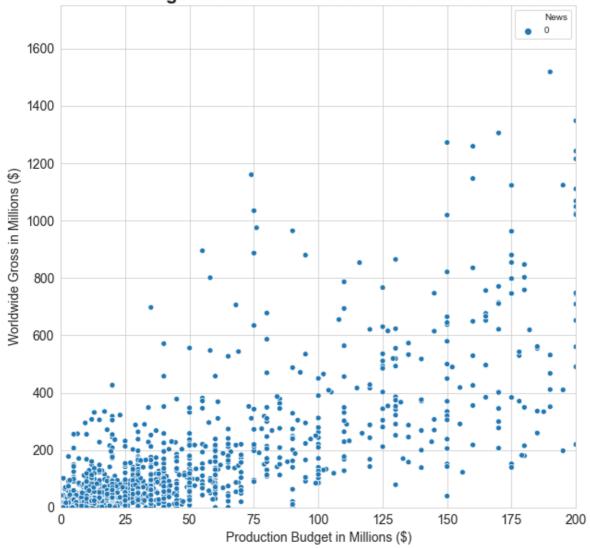




News

<Figure size 432x288 with 0 Axes>

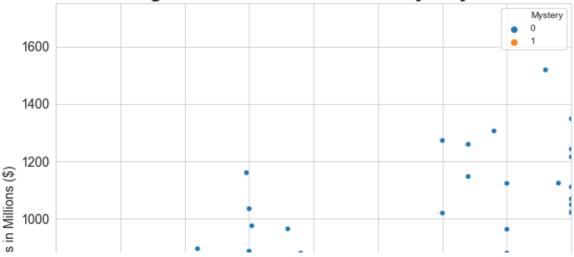
Production Budget vs Worldwide Gross For News Movies in 2010s

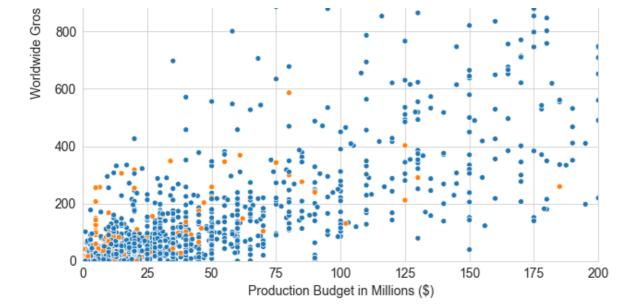


Mystery

<Figure size 432x288 with 0 Axes>

Production Budget vs Worldwide Gross For Mystery Movies in 2010s

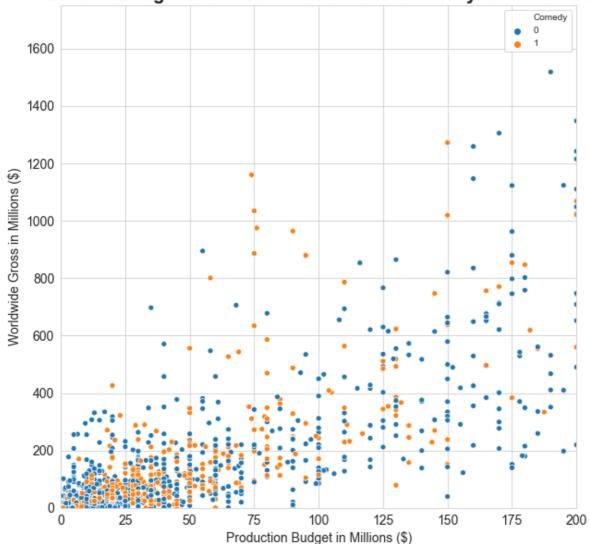




Comedy

<Figure size 432x288 with 0 Axes>

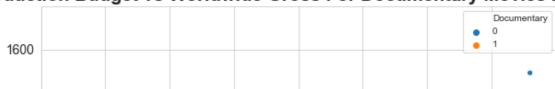
Production Budget vs Worldwide Gross For Comedy Movies in 2010s

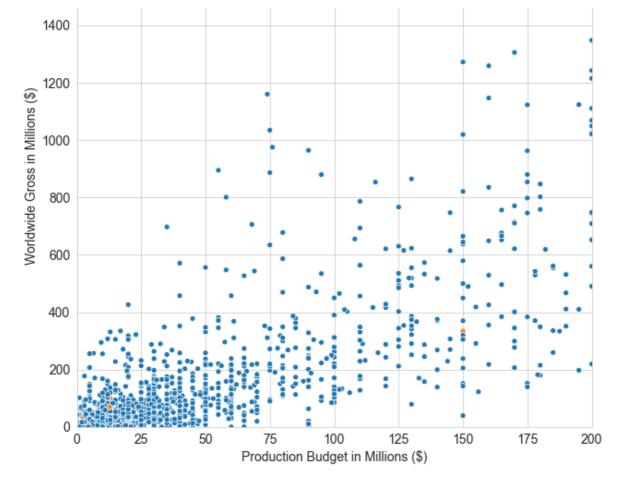


Documentary

<Figure size 432x288 with 0 Axes>

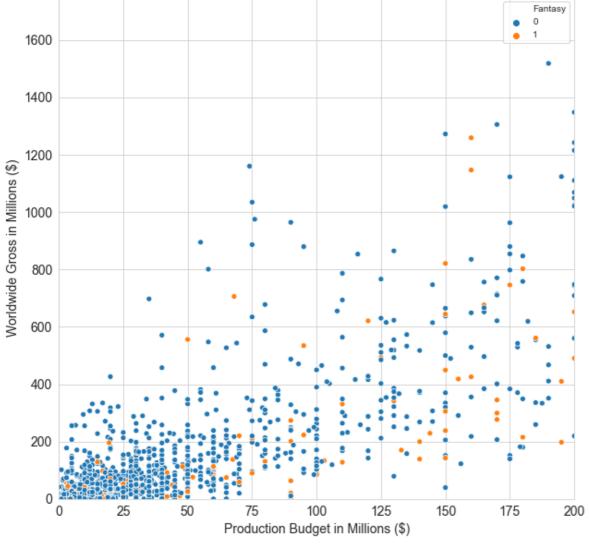
Production Budget vs Worldwide Gross For Documentary Movies in 2010s



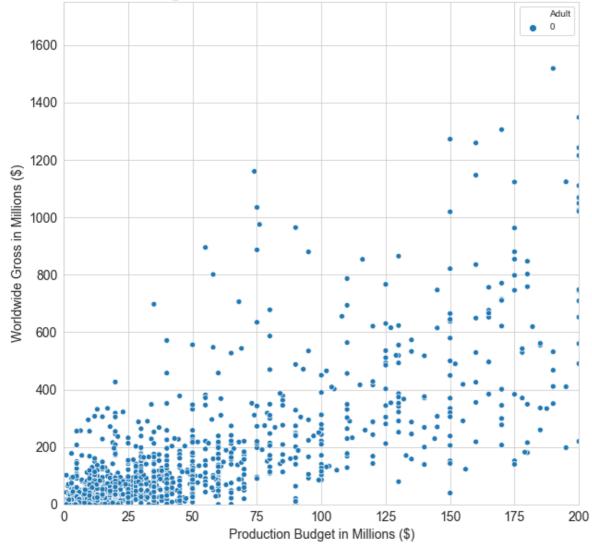


Fantasy
<Figure size 432x288 with 0 Axes>





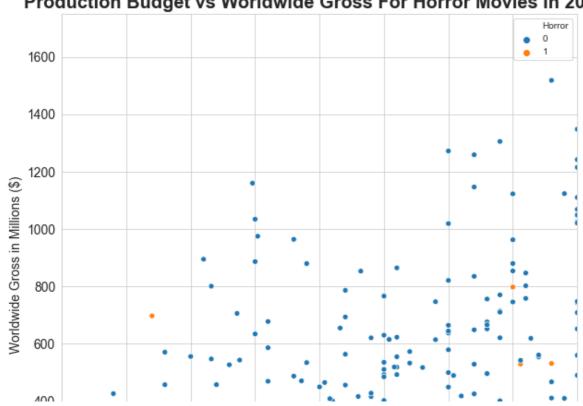
Production Budget vs Worldwide Gross For Adult Movies in 2010s

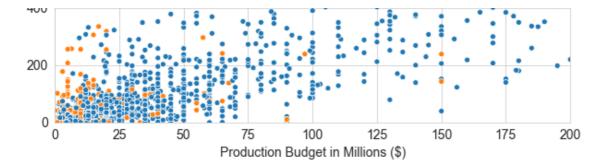


Horror

<Figure size 432x288 with 0 Axes>

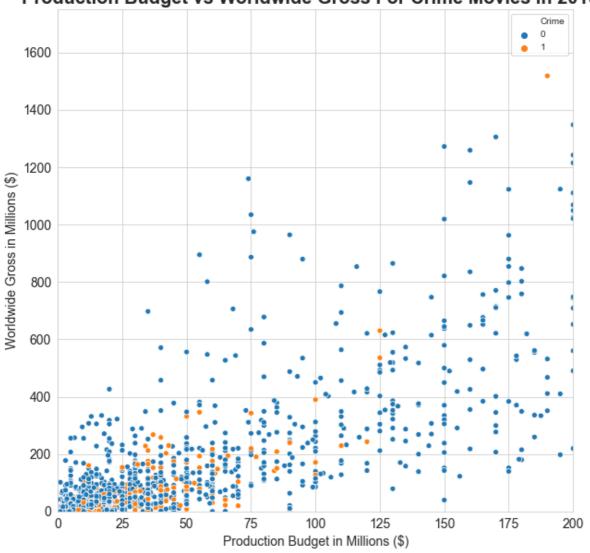
Production Budget vs Worldwide Gross For Horror Movies in 2010s





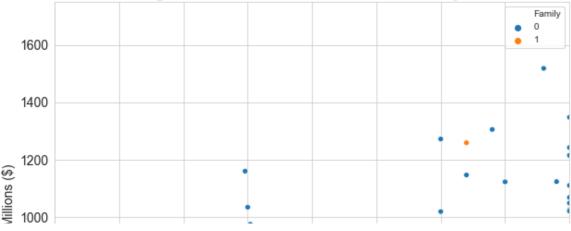
Crime
<Figure size 432x288 with 0 Axes>

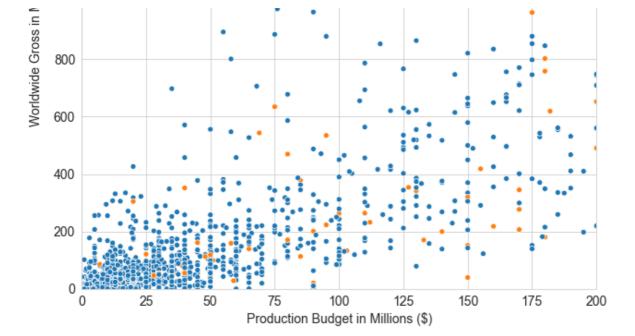
Production Budget vs Worldwide Gross For Crime Movies in 2010s



Family
<Figure size 432x288 with 0 Axes>

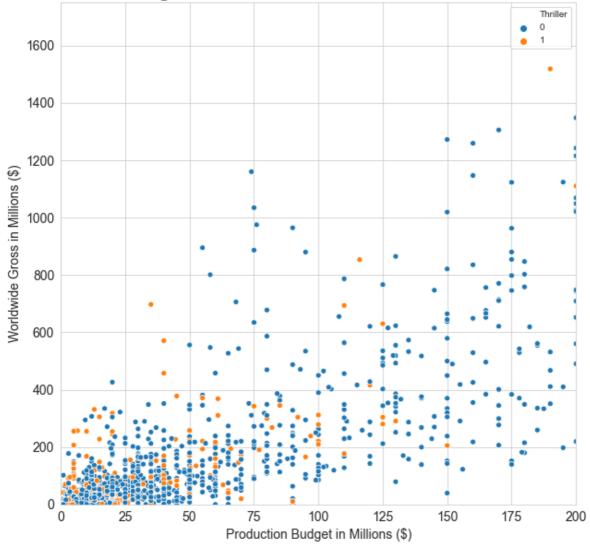
Production Budget vs Worldwide Gross For Family Movies in 2010s





Thriller
<Figure size 432x288 with 0 Axes>

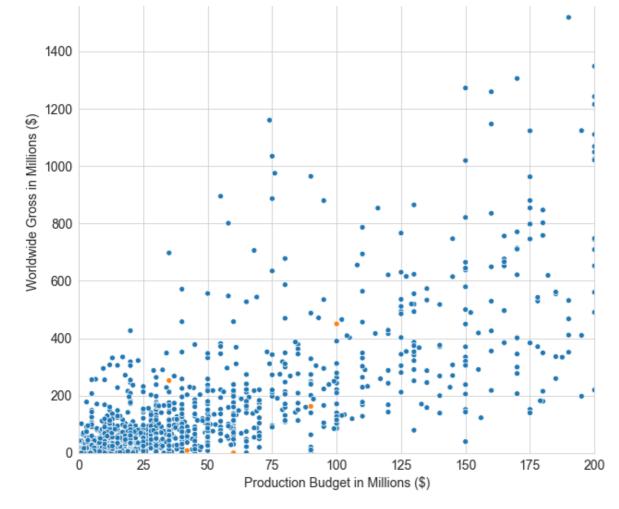
Production Budget vs Worldwide Gross For Thriller Movies in 2010s



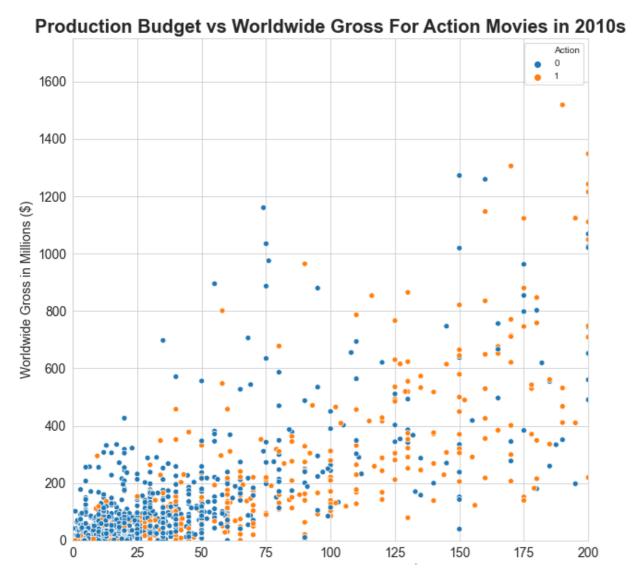
Western
<Figure size 432x288 with 0 Axes>

Production Budget vs Worldwide Gross For Western Movies in 2010s





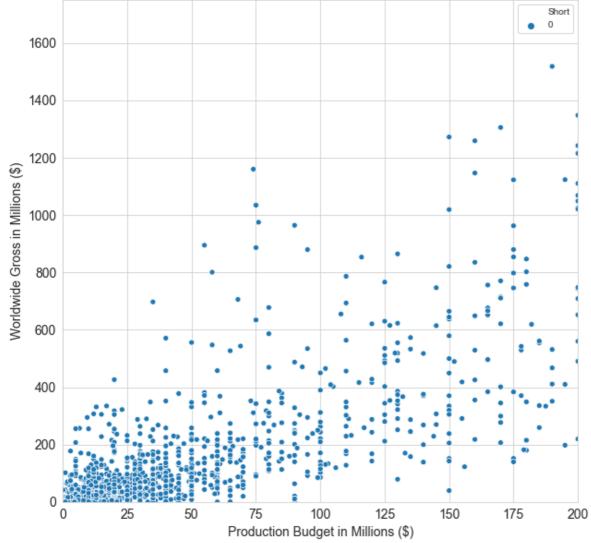
Action
<Figure size 432x288 with 0 Axes>



Short

<Figure size 432x288 with 0 Axes>

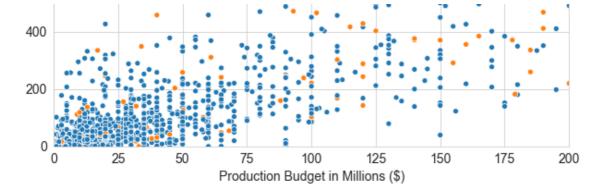




Sci-Fi
<Figure size 432x288 with 0 Axes>

Production Budget vs Worldwide Gross For Sci-Fi Movies in 2010s

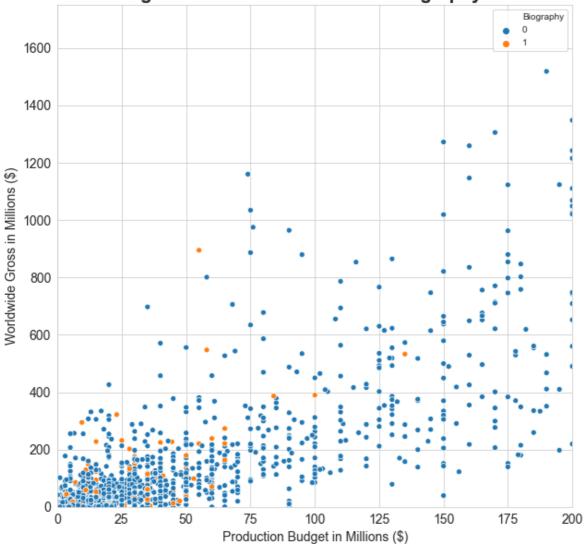




Biography

<Figure size 432x288 with 0 Axes>

Production Budget vs Worldwide Gross For Biography Movies in 2010s



<Figure size 432x288 with 0 Axes>

Question 2: What is the best month to release a movie for highest worldwide gross?

In [79]:

imdb_all_prod_roi_genres.head()

Out[79]:

	title_year	tconst	primary_title	original_title	start_year	runtime_minutes	genres_x	averagerating	numvotes	di
18	#Horror 2015	tt3526286	#Horror	#Horror	2015	101.0	[Crime, Drama, Horror]	3.0	3092	nm0

	title_year	tconst	primary_title	original_title	start_year	runtime_minutes	genres_x IDrama.	averagerating	numvotes	di
168	Cloverfield Lane 2016	tt1179933	Cloverfield Lane	Cloverfield Lane	2016	103.0	Horror, Mystery]	7.2	260383	nm0
170	10 Days in a Madhouse 2015	tt3453052	10 Days in a Madhouse	10 Days in a Madhouse	2015	111.0	[Drama]	6.7	1114	nm0
319	12 Strong 2018	tt1413492	12 Strong	12 Strong	2018	130.0	[Action, Drama, History]	6.6	50155	nm3
321	12 Years a Slave 2013	tt2024544	12 Years a Slave	12 Years a Slave	2013	134.0	[Biography, Drama, History]	8.1	577301	nm2

5 rows × 53 columns

In [80]:

2 - - 2 -

Reset index
imdb_all_prod_roi_genres = imdb_all_prod_roi_genres.reset_index()

In [81]:

View table
imdb_all_prod_roi_genres

4400 E4 aal......

Out[81]:

	index	title_year	tconst	primary_title	original_title	start_year	runtime_minutes	genres_x	averagerating	numvo
0	18	#Horror 2015	tt3526286	#Horror	#Horror	2015	101.0	[Crime, Drama, Horror]	3.0	3
1	168	10 Cloverfield Lane 2016	tt1179933	10 Cloverfield Lane	10 Cloverfield Lane	2016	103.0	[Drama, Horror, Mystery]	7.2	260
2	170	10 Days in a Madhouse 2015	tt3453052	10 Days in a Madhouse	10 Days in a Madhouse	2015	111.0	[Drama]	6.7	1
3	319	12 Strong 2018	tt1413492	12 Strong	12 Strong	2018	130.0	[Action, Drama, History]	6.6	50 ⁻
4	321	12 Years a Slave 2013	tt2024544	12 Years a Slave	12 Years a Slave	2013	134.0	[Biography, Drama, History]	8.1	577:
			•••					•••		
1493	73597	Zookeeper 2011	tt1222817	Zookeeper	Zookeeper	2011	102.0	[Comedy, Family, Romance]	5.2	52:
1494	73598	Zoolander 2 2016	tt1608290	Zoolander 2	Zoolander 2	2016	101.0	[Comedy]	4.7	59!
1495	73608	Zootopia 2016	tt2948356	Zootopia	Zootopia	2016	108.0	[Adventure, Animation, Comedy]	8.0	3834
1496	73625	Zulu 2013	tt2249221	Zulu	Zulu	2013	110.0	[Crime, Drama, Thriller]	6.7	160
1497	73700	xXx: Return of Xander Cage 2017	tt1293847	xXx: Return of Xander Cage	xXx: Return of Xander Cage	2017	107.0	[Action, Adventure, Thriller]	5.2	779

In [82]:

```
# View info
imdb_all_prod_roi_genres.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1498 entries, 0 to 1497
Data columns (total 54 columns):

Data	columns (total 54 columns)) :		
#	Column	Non-l	Null Count	Dtype
0	index	1498	non-null	int64
1	title year		non-null	
2	tconst		non-null	
3	primary title		non-null	-
4	original_title		non-null	=
5	start_year		non-null	
6	runtime_minutes		non-null	
7	genres_x		non-null	
8	averagerating	1498	non-null	float64
9	numvotes	1498	non-null	int64
10	directors	1497	non-null	object
11	writers	1480	non-null	object
12	genres_y		non-null	object
13	Music	1498	non-null	int64
14	War	1498	non-null	int64
15	Reality-TV	1498	non-null	int64
16	Sport	1498	non-null	int64
17	Drama	1498	non-null	int64
18	Adventure	1498	non-null	int64
19	Game-Show	1498	non-null	int.64
20	Animation		non-null	
21	History		non-null	
22	Romance			
23	Musical	1/100	non-null non-null	int 6/
24	News		non-null	int64 int64
25	Mystery		non-null	int64
26	= =	1490	non-null	111111111111111111111111111111111111111
	Comedy		non-null	
27	Documentary			
28	Fantasy		non-null	
29	Adult		non-null	
30	Horror		non-null	
31	Crime		non-null	
32	Family		non-null	
33	Thriller		non-null	
34	Western	1498	non-null	
35	Action	1498	non-null	int64
36	Short	1498	non-null	int64
37	Sci-Fi	1498	non-null	int64
38	Biography	1498	non-null	int64
39	id	1498	non-null	float64
40	release date	1498	non-null	object
41	movie	1498	non-null	object
42	production budget		non-null	float64
43	domestic gross		non-null	float64
44	worldwide gross		non-null	float64
45	release year		non-null	object
46	worldwide gross in mil		non-null	float64
47	production budget in mil		non-null	float64
48	prod budget ROI		non-null	float64
49	domestic_gross_in_mil		non-null	float64
50	foreign_gross_in_mil		non-null	float64
51	domestic_gross_p		non-null	float64
52	foreign_gross_p		non-null	float64
53	release_month		non-null	object
	es: float64(13), int64(29)	, obj	ect(12)	
memoi	ry usage: 632.1+ KB			

```
Out[83]:
       Nov 20, 2015
0
1
       Mar 11, 2016
       Nov 11, 2015
3
       Jan 19, 2018
4
       Oct 18, 2013
       Jul 8, 2011
1493
1494
      Feb 12, 2016
1495
       Mar 4, 2016
1496
      Dec 31, 2013
      Jan 20, 2017
1497
Name: release_date, Length: 1498, dtype: object
In [84]:
# Convert release date values to date time
imdb all prod roi genres['release date'] = pd.to datetime(imdb all prod roi genres['relea
se date'])
In [85]:
# Review new values
imdb all prod roi genres['release date']
Out[85]:
0
      2015-11-20
1
      2016-03-11
2
      2015-11-11
3
      2018-01-19
4
      2013-10-18
          . . .
1493
     2011-07-08
1494
     2016-02-12
1495
     2016-03-04
1496
     2013-12-31
1497
     2017-01-20
Name: release date, Length: 1498, dtype: datetime64[ns]
What is best month to release a movie?
In [86]:
# Pull out month from date time value
imdb all prod roi genres['release month number'] = imdb all prod roi genres['release date
'].dt.month
In [87]:
imdb all prod roi genres['release month number']
Out[87]:
        11
1
        3
2
        11
3
        1
        10
1493
1494
        2
1495
        3
1496
        12
1497
        1
Name: release month number, Length: 1498, dtype: int64
```

Look at release date values

imdb all prod roi genres['release date']

In [88]: imdb_all_prod_roi_genres_mon = imdb_all_prod_roi_genres.groupby(['release_month_number']) ['worldwide_gross_in_mil'].agg(['sum']).reset_index()

In [89]:

```
imdb_all_prod_roi_genres_mon
```

Out[89]:

	release_month_number	sum
0	1	5654.15
1	2	12884.42
2	3	20920.30
3	4	14778.52
4	5	24474.02
5	6	27466.34
6	7	23893.14
7	8	11378.60
8	9	9804.44
9	10	12160.59
10	11	27038.26
11	12	22045.37

In [90]:

```
# Replace release month number with name of month. There's a more efficient way to do thi
for row in imdb all prod roi genres mon.index:
   if imdb all prod roi genres mon['release month number'][row] == 1:
       imdb all prod roi genres mon['release month number'][row] = 'January'
   elif imdb_all_prod_roi_genres mon['release month number'][row] == 2:
       imdb all prod roi genres mon['release month number'][row] = 'February'
   elif imdb all prod roi genres mon['release month number'][row] == 3:
       imdb all prod roi genres mon['release month number'][row] = 'March'
   elif imdb all prod roi genres mon['release month number'][row] == 4:
        imdb_all_prod_roi_genres_mon['release_month_number'][row] = 'April'
   elif imdb all prod roi genres mon['release month number'][row] == 5:
       imdb all prod roi genres mon['release month number'][row] = 'May'
   elif imdb all prod roi genres mon['release month number'][row] == 6:
       imdb all prod roi genres mon['release month number'][row] = 'June'
   elif imdb_all_prod_roi_genres_mon['release_month_number'][row] == 7:
       imdb_all_prod_roi_genres_mon['release_month_number'][row] = 'July'
   elif imdb all prod roi genres mon['release month number'][row] == 8:
       imdb all prod roi genres mon['release month number'][row] = 'August'
   elif imdb all prod roi genres mon['release month number'][row] == 9:
       imdb_all_prod_roi_genres_mon['release_month_number'][row] = 'September'
   elif imdb all prod roi genres mon['release month number'][row] == 10:
       imdb all prod roi genres mon['release month number'][row] = 'October'
   elif imdb_all_prod_roi_genres mon['release month number'][row] == 11:
       imdb_all_prod_roi_genres_mon['release_month_number'][row] = 'November'
   else:
       imdb all prod roi genres mon['release month number'][row] = 'December'
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
  self. setitem with indexer(indexer, value)
<ipython-input-90-8aa5e037843c>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'February'
<ipython-input-90-8aa5e037843c>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb_all_prod_roi_genres_mon['release_month number'][row] = 'March'
<ipython-input-90-8aa5e037843c>:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'April'
<ipython-input-90-8aa5e037843c>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'May'
<ipython-input-90-8aa5e037843c>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb_all_prod_roi_genres_mon['release_month number'][row] = 'June'
<ipython-input-90-8aa5e037843c>:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb_all_prod_roi_genres_mon['release_month_number'][row] = 'July'
<ipython-input-90-8aa5e037843c>:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'August'
<ipython-input-90-8aa5e037843c>:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'September'
<ipython-input-90-8aa5e037843c>:22: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'October'
<ipython-input-90-8aa5e037843c>:24: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'November'
<ipython-input-90-8aa5e037843c>:26: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  imdb all prod roi genres mon['release month number'][row] = 'December'
```

--- (>+)·

Out[91]:

	release_month_number	sum
0	January	5654.15
1	February	12884.42
2	March	20920.30
3	April	14778.52
4	May	24474.02
5	June	27466.34
6	July	23893.14
7	August	11378.60
8	September	9804.44
9	October	12160.59
10	November	27038.26
11	December	22045.37

imdb_all_prod_roi_genres_mon

In [92]:

```
# Rename column release_month_number and sum
imdb_all_prod_roi_genres_mon = imdb_all_prod_roi_genres_mon.rename(columns={"release_month_number": "release_month_name", "sum": "worldwide_gross_in_mil_sum"})
```

In [93]:

```
imdb_all_prod_roi_genres_mon
```

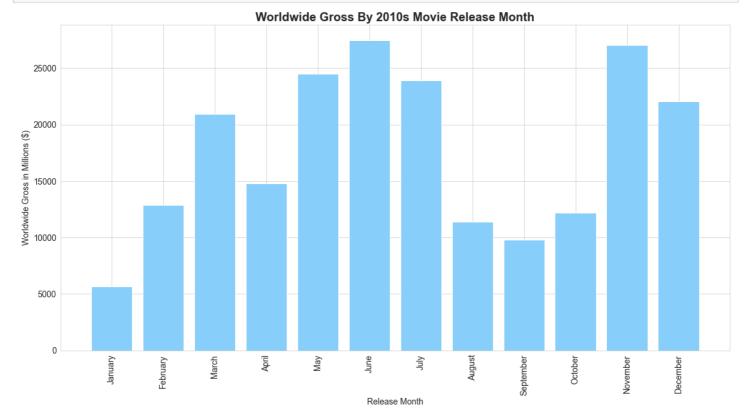
Out[93]:

	release_month_name	worldwide_gross_in_mil_sum
0	January	5654.15
1	February	12884.42
2	March	20920.30
3	April	14778.52
4	May	24474.02
5	June	27466.34
6	July	23893.14
7	August	11378.60
8	September	9804.44
9	October	12160.59
10	November	27038.26
11	December	22045.37

In [94]:

```
x = imdb_all_prod_roi_genres_mon['release_month_name']
y = imdb_all_prod_roi_genres_mon['worldwide_gross_in_mil_sum']
plt.figure (figsize=(20,10))
plt.bar(x, y, color='lightskyblue')
plt.title('Worldwide Gross By 2010s Movie Release Month', fontsize=20, fontweight="bold")
plt.xlabel('Release Month', fontsize=14)
plt.xticks(rotation=90, fontsize=14)
plt.ylabel('Worldwide Gross in Millions ($)', fontsize=14)
```

```
plt.yticks(fontsize=14)
plt.savefig("images/2_bar_release_months_by_wwgross_lsb_wide.png")
plt.show()
# n=1498
```



Learning: June and November are top months for worldwide gross – summer blockbuster, thanksgiving/holiday release

Question 3: Of movies that breakeven (ROI >= 1), what genres are most represented?

```
In [95]:
```

```
# Define new DataFrame with prod_ROI >=1
imdb_prodROI_breakeven = imdb_with_genre_cols[imdb_with_genre_cols['prod_budget_ROI'] >=
1]
```

In [96]:

```
# Check new table; 1049 movies represented imdb_prodROI_breakeven.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1049 entries, 168 to 73700
Data columns (total 53 columns):
```

		- , -	
#	Column	Non-Null Count	Dtype
0	title_year	1049 non-null	object
1	tconst	1049 non-null	object
2	primary title	1049 non-null	object
3	original title	1049 non-null	object
4	start_year	1049 non-null	int64
5	runtime_minutes	1049 non-null	float64
6	genres_x	1049 non-null	object
7	averagerating	1049 non-null	float64
8	numvotes	1049 non-null	int64
9	directors	1048 non-null	object
10	writers	1042 non-null	object
11	genres_y	1049 non-null	object
12	Music	1049 non-null	int64
1.3	War	1049 non-niill	int64

```
14 Reality-TV
                                      1049 non-null
 15 Sport
                                      1049 non-null int64
 16 Drama
                                      1049 non-null
 17 Adventure
                                      1049 non-null int64
 18 Game-Show
                                      1049 non-null int64
 19 Animation
                                      1049 non-null int64
 20 History
21 Romance
                                      1049 non-null int64
                                      1049 non-null int64
 22 Musical
                                      1049 non-null int64
 23 News
                                      1049 non-null int64
 24 Mystery
                                     1049 non-null int64
 25 Comedy
                                     1049 non-null int64
 26 Documentary
                                     1049 non-null int64
 27 Fantasy
                                     1049 non-null int64
 28 Adult
                                     1049 non-null int64
 29 Horror
                                     1049 non-null int64
 30 Crime
                                     1049 non-null int64
                                     1049 non-null int64
 31 Family
 32 Thriller
                                     1049 non-null int64
 33 Western
                                     1049 non-null int64
 34 Action
                                      1049 non-null int64
                                     1049 non-null int64
1049 non-null int64
1049 non-null int64
1049 non-null float64
 35 Short
 36 Sci-Fi
 37 Biography
 38 id
 39 release_date
                                      1049 non-null object
 40 movie
                                     1049 non-null object
                                    1049 non-null float64
41 production_budget 1049 non-null float64
42 domestic_gross 1049 non-null float64
43 worldwide_gross 1049 non-null float64
44 release_year 1049 non-null object
45 worldwide_gross_in_mil 1049 non-null float64
 46 production_budget_in_mil 1049 non-null float64
47 prod_budget_ROI 1049 non-null float64
48 domestic_gross_in_mil 1049 non-null float64
49 foreign_gross_in_mil 1049 non-null float64
50 domestic_gross_p 1049 non-null float64
50 domestic_gross_p 1049 non-null float64
51 foreign_gross_p 1049 non-null float64
52 release_month 1049 non-null object
dtypes: float64(13), int64(28), object(12)
memory usage: 442.5+ KB
In [97]:
```

```
# Create DataFrame for genre ROI analysis
imdb_prodROI_breakeven_genres = imdb_prodROI_breakeven[genre_name_list]
```

In [98]:

```
# Check work
imdb_prodROI_breakeven_genres.info()
```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1049 entries, 168 to 73700
Data columns (total 26 columns):

#	Column	Non-Null Count	Dtype
0	Music	1049 non-null	int64
1	War	1049 non-null	int64
2	Reality-TV	1049 non-null	int64
3	Sport	1049 non-null	int64
4	Drama	1049 non-null	int64
5	Adventure	1049 non-null	int64
6	Game-Show	1049 non-null	int64
7	Animation	1049 non-null	int64
8	History	1049 non-null	int64
9	Romance	1049 non-null	int64
10	Musical	1049 non-null	int64
11	News	1049 non-null	int64
12	Mystery	1049 non-null	int64
13	Comedy	1049 non-null	int64
1 /	Dogumentari	1040 202-211	; ~+ ~ V

```
14 DOCUMENTALY 1049 NON-NULL
                                TIILU4
                 1049 non-null int64
15 Fantasy
16 Adult
                 1049 non-null int64
17 Horror
                 1049 non-null int64
18 Crime
                 1049 non-null int64
19 Family
                 1049 non-null int64
20 Thriller
                1049 non-null int64
21 Western
                 1049 non-null int64
22 Action
                 1049 non-null int64
23 Short
                 1049 non-null
                               int64
24 Sci-Fi
                 1049 non-null
                                int64
25 Biography
                 1049 non-null
                                int64
dtypes: int64(26)
memory usage: 221.3 KB
In [99]:
for genre column in imdb prodROI breakeven genres:
   print(genre column, imdb prodROI breakeven genres[genre column].sum())
Music 36
War 7
Reality-TV 0
Sport 22
Drama 471
Adventure 296
Game-Show 0
Animation 91
History 25
Romance 139
Musical 5
News 0
Mystery 92
Comedy 391
Documentary 22
Fantasy 95
Adult 0
Horror 115
Crime 151
Family 71
Thriller 179
Western 4
Action 326
Short 0
Sci-Fi 102
Biography 88
In [100]:
prodROI genres = []
prodROI counts = []
for genre column in imdb prodROI breakeven genres:
   prodROI genres.append(genre column)
   prodROI counts.append(imdb prodROI breakeven genres[genre column].sum())
In [101]:
prodROI genres
Out[101]:
['Music',
 'War',
 'Reality-TV',
 'Sport',
 'Drama',
 'Adventure',
 'Game-Show',
 'Animation',
 'History',
 'Romance',
 'Musical'
```

```
'News',
 'Mystery',
 'Comedy',
 'Documentary',
 'Fantasy',
 'Adult',
 'Horror',
 'Crime',
 'Family',
 'Thriller',
 'Western',
 'Action',
 'Short',
 'Sci-Fi',
 'Biography']
In [102]:
prodROI counts
Out[102]:
[36,
7,
 Ο,
 22,
 471,
 296,
 Ο,
 91,
25,
 139,
 5,
 0,
 92,
 391,
 22,
 95,
 Ο,
 115,
 151,
 71,
 179,
 4,
 326,
 Ο,
 102,
 88]
In [103]:
# Create DataFrame for plotting
prodROI genre counts = list(zip(prodROI genres, prodROI counts))
# Assign data to tuples.
prodROI_genre_counts
# Create DataFrame
prodROI genre counts = pd.DataFrame(prodROI genre counts, columns = ['genre', 'count'])
prodROI_genre_counts = prodROI_genre_counts.sort_values(by='count', ascending=False)
prodROI genre counts
Out[103]:
         genre count
 4
                471
        Drama
```

.....,

13

22

5

Comedy

Adventure

Action

391

326

296

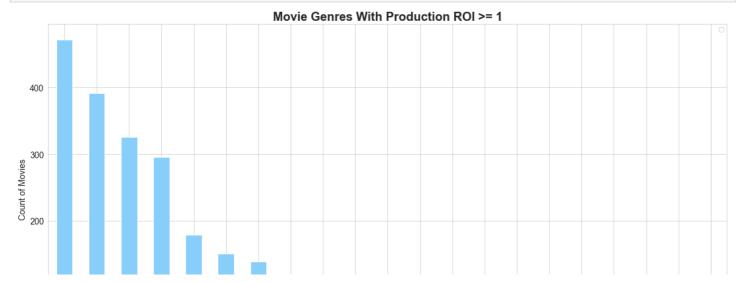
20	T genre Thriller	count
18	Crime	151
9	Romance	139
17	Horror	115
24	Sci-Fi	102
15	Fantasy	95
12	Mystery	92
7	Animation	91
25	Biography	88
19	Family	71
0	Music	36
8	History	25
14	Documentary	22
3	Sport	22
1	War	7
10	Musical	5
21	Western	4
11	News	0
16	Adult	0
6	Game-Show	0
23	Short	0
2	Reality-TV	0

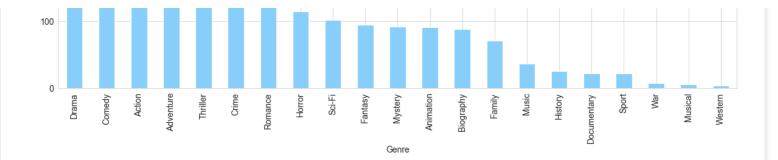
In [104]:

```
# Filter out Unknown genre and any genre with 0 count
prodROI_genre_counts = prodROI_genre_counts[prodROI_genre_counts['count'] >=4]
```

In [105]:

```
# Plot bar chart of top genre counts in the table
prodROI_genre_counts.plot(kind='bar', x='genre', y='count', figsize = (20,10), color='li
ghtskyblue')
plt.title('Movie Genres With Production ROI >= 1', fontsize=20, fontweight="bold")
plt.xlabel('Genre', fontsize=14)
plt.xticks(fontsize=14)
plt.ylabel('Count of Movies', fontsize=14)
plt.yticks(fontsize=14)
plt.legend('')
plt.savefig('images/3_bar_genres_with_roi_breakeven_wide.png')
```





Learning: Of movie genres that make their budget back - Drama, Comedy, Action, Adventure, and Thriller are top 5

Question 4: Based on production budget and average ratings, what genres are the best investments?

```
Explore Drama
In [106]:
# Create DataFrame for Drama records
imdb with genre cols drama = imdb with genre cols[imdb with genre cols['Drama'] == 1]
In [107]:
# Look at stats for prod budget to look at investment needs
imdb with genre cols drama['production budget in mil'].describe()
Out[107]:
         726.000000
count
mean
          26.595771
std
          32.402310
min
          0.020000
25%
          6.125000
50%
          17.000000
75%
          35.000000
         210.000000
Name: production budget in mil, dtype: float64
In [108]:
# What is average rating for Drama movies according to IMDB data
imdb_with_genre_cols_drama['averagerating'].mean()
Out[108]:
6.401559048980189
In [109]:
#Define top genres
imdb genre names = ['Drama', 'Comedy', 'Action', 'Adventure', 'Thriller']
# Create for loop to do the above for each top genre and print results
for genre in imdb genre names:
        print(f"{genre}:")
        genre table = imdb with genre cols[imdb with genre cols[genre] == 1]
        print(f"median production budget: {genre table['production budget in mil'].median
() }")
        print(f"average rating: {(round(genre table['averagerating'].mean(), 1))}")
```

Drama:

Comedy:

median production budget: 17.0

median production budget: 25.5

average rating: 6.4

average rating: 6.0

```
Action:
median production budget: 58.0
average rating: 5.8
Adventure:
median production budget: 100.0
average rating: 6.2
Thriller:
median production budget: 20.0
average rating: 5.6
In [110]:
## Create DF to visualize median production budgets
imdb_genre_names = ["Drama", "Comedy", "Action", "Adventure", "Thriller"]
imdb_genre_budgets = [17.0, 25.5, 58.0, 100.0, 20.0]
# Create DataFrame for plotting
imdb top genre prodbudgmed = list(zip(imdb genre names, imdb genre budgets))
# Assign data to tuples.
imdb_top_genre_prodbudgmed
# Create DF
imdb top genre prodbudgmed = pd.DataFrame(imdb top genre prodbudgmed, columns = ['genre'
, 'median prod budg in mil'])
imdb top genre prodbudgmed
Out[110]:
      genre median_prod_budg_in_mil
O
     Drama
                           17.0
    Comedy
                           25.5
2
     Action
                           58.0
3 Adventure
                          100.0
                           20.0
     Thriller
In [111]:
# Also need average rating, adding on
imdb top genre prodbudgmed['average rating'] = [6.4, 6.0, 5.8, 6.2, 5.6]
In [112]:
# Preview new DataFrame
```

Preview new DataFrame
imdb_top_genre_prodbudgmed

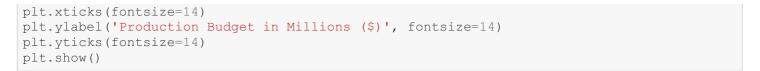
Out[112]:

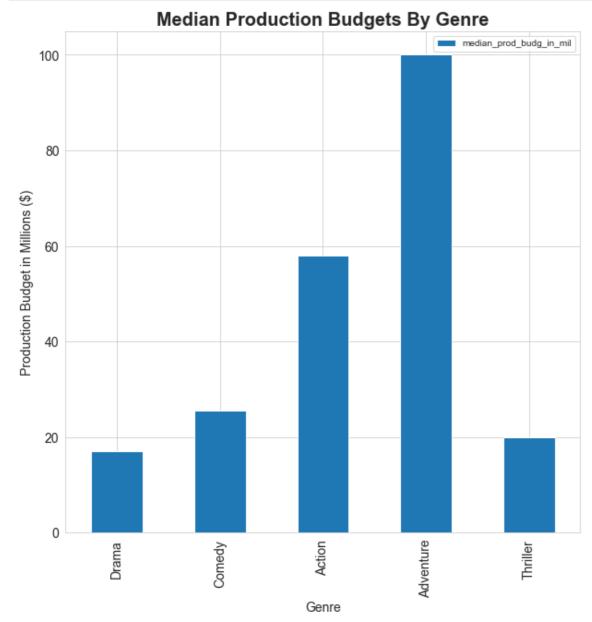
genre median_prod_budg_in_mil average_rating

0	Drama	17.0	6.4
1	Comedy	25.5	6.0
2	Action	58.0	5.8
3	Adventure	100.0	6.2
4	Thriller	20.0	5.6

In [113]:

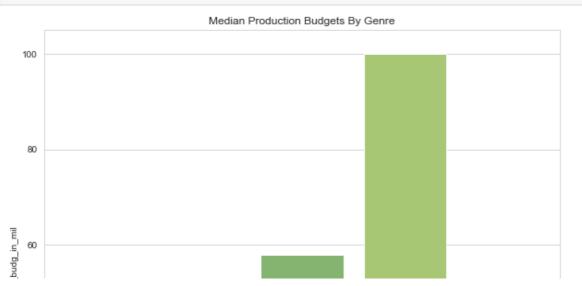
```
# Plot
imdb_top_genre_prodbudgmed.plot(kind='bar', x='genre', y='median_prod_budg_in_mil', figs
ize = (10,10))
plt.title('Median Production Budgets By Genre', fontsize=20, fontweight="bold")
plt.xlabel('Genre', fontsize=14)
```

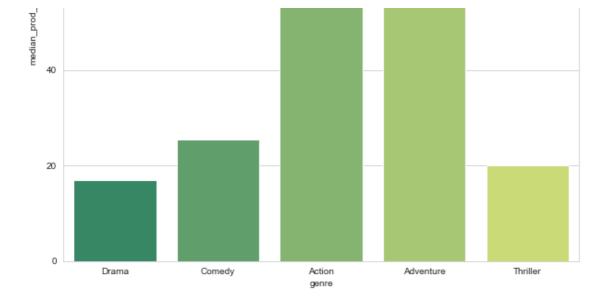




In [114]:

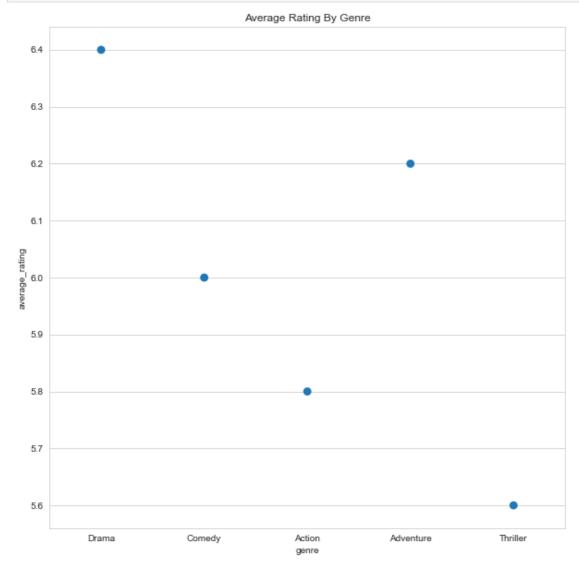
```
# Edit plot - draft for presentation
plt.figure(figsize=(10,10))
plt.title('Median Production Budgets By Genre')
sns.barplot(x='genre', y='median_prod_budg_in_mil', data=imdb_top_genre_prodbudgmed, pal
ette='summer')
plt.show()
```





In [115]:

```
# Plot average ratings
plt.figure(figsize=(10,10))
plt.title('Average Rating By Genre')
sns.pointplot(x='genre', y='average_rating', data=imdb_top_genre_prodbudgmed, join=False)
plt.show()
```

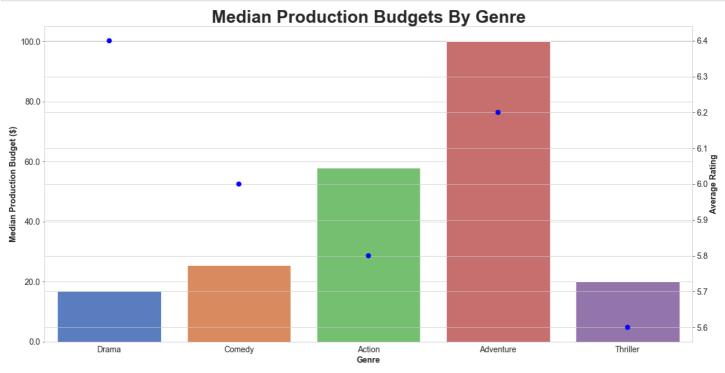


In [116]:

```
len(imdb_top_genre_prodbudgmed)
```

Out[116]:

```
# Create combo chart measuring median Prod Budget ROI by genre with an overlay of average
# Looking for most white space between budget and rating showing that budget was low and
rating was high
fig, ax1 = plt.subplots(figsize=(20,10))
#bar plot creation
ax1.set title('Median Production Budgets By Genre', fontsize=30, fontweight="bold")
sns.barplot(x='genre', y='median prod budg in mil', data=imdb top genre prodbudgmed, pal
ette='muted')
ax1.set xlabel('Genre', fontsize=14, fontweight='bold')
ax1.set xticklabels(ax1.get xticks(), size=14)
ax1.set ylabel('Median Production Budget ($)', fontsize=14, fontweight='bold')
ax1.set yticklabels(ax1.get yticks(), size=14)
ax1.tick params(axis='y')
#specify we want to share the same x-axis
ax2 = ax1.twinx()
#line plot creation
ax2 = sns.pointplot(x='genre', y='average rating', data=imdb top genre prodbudgmed, join
=False, color='blue')
ax2.set ylabel('Average Rating', fontsize=14, fontweight='bold')
ax2.set yticklabels(ax2.get yticks(), size=14)
ax2.tick params(axis='y')
#save plot
plt.savefig("images/4 combo genre prod budg with rating wide.png")
#show plot
plt.show()
```



Learning: Drama in cheapest to produce with highest average rating

Data Review: Drama is cheapest to produce and most likely to return ROI; Comedy is next best Thrillers also less money, but have lowest average rating Drama and Adventure have highest average rating, but Adventure 5.8x more to produce

Business rec: If money is a concern, best investment would be in Dramas. Next best investment would be in Comedy. If up front money is not a concern, then can consider Adventure or Action movies. Adventure is 2x the production budget, so depending on how much budget there is, Action is the more conservative choice of the two.

Question 5: For the breakeven movies that fall into these genres, what is the recommended runtime and who are the highest rated directors?

In [118]:

```
# Create new DataFrame for known Drama Directors
imdb_drama_writ_dir = imdb_with_genre_cols[(imdb_with_genre_cols['Drama'] == 1) & (imdb_with_genre_cols['directors'] != "Unknown")]
```

In [119]:

```
# Check new DataFrame
imdb_drama_writ_dir.info()
```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 30788 entries, 6 to 73855

Data columns (total 53 columns):	
----------------------------------	--

	columns (total 53 columns)		
#	Column	Non-Null Count	Dtype
0	title year	30788 non-null	object
1	tconst	30788 non-null	object
2	primary_title	30788 non-null	object
3	original title	30788 non-null	object
4	start year	30788 non-null	int64
5	runtime minutes	30788 non-null	
6	genres x	30788 non-null	
7	averagerating	30788 non-null	
8	numvotes	30788 non-null	
9	directors	30676 non-null	
10	writers		
		28936 non-null	_
11	genres_y	30788 non-null	_
12	Music	30788 non-null	int64
13	War	30788 non-null	int64
14	Reality-TV	30788 non-null	
15	Sport	30788 non-null	
16	Drama	30788 non-null	
17	Adventure	30788 non-null	int64
18	Game-Show	30788 non-null	
19	Animation	30788 non-null	int64
20	History	30788 non-null	int64
21	Romance	30788 non-null	int64
22	Musical	30788 non-null	int64
23	News	30788 non-null	int64
24	Mystery	30788 non-null	
25	Comedy	30788 non-null	
26	Documentary	30788 non-null	
27	Fantasy	30788 non-null	int64
28	Adult	30788 non-null	int64
29	Horror	30788 non-null	
30	Crime	30788 non-null	
31	Family	30788 non-null	int64
32	Thriller	30788 non-null	
	Western	30788 non-null	
33	Action		
34		30788 non-null	
35	Short	30788 non-null	
36	Sci-Fi	30788 non-null	int64
37	Biography	30788 non-null	int64
38	id	726 non-null	float64
39	release_date	726 non-null	object
40	movie	726 non-null	object
41	production_budget	726 non-null	float64
42	domestic_gross	726 non-null	float64
43	worldwide_gross	726 non-null	float64
44	release_year	726 non-null	object
45	worldwide_gross_in_mil	726 non-null	float64
46	production_budget_in_mil	726 non-null	float64
47	prod_budget_ROI	726 non-null	float64
48	domestic_gross_in_mil	726 non-null	float64
49	foreign gross in mil	726 non-null	float64
50	domestic gross p	726 non-null	float64
51	foreign gross p	726 non-null	float64
52	release month	726 non-null	object
	es: float64(13), int64(28),		J
	ry usage: 12.7+ MB	-	
)		

```
In [120]:
```

```
imdb_drama_writ_dir[imdb_drama_writ_dir['runtime_minutes'] > 0]
```

Out[120]:

	title_year	tconst	primary_title	original_title	start_year	runtime_minutes	genres_x	averagerating	num
6	#BKKY 2016	tt6170868	#BKKY	#BKKY	2016	75.0	[Drama]	7.4	
13	#Ewankosau saranghaeyo 2015	tt4375578	#Ewankosau saranghaeyo	#Ewankosau saranghaeyo	2015	110.0	[Drama]	7.3	
18	#Horror 2015	tt3526286	#Horror	#Horror	2015	101.0	[Crime, Drama, Horror]	3.0	
25	#REALITYHIGH 2017	tt6119504	#REALITYHIGH	#REALITYHIGH	2017	99.0	[Comedy, Drama, Romance]	5.2	
26	#Realmovie 2013	tt3184026	#Realmovie	#Realmovie	2013	62.0	[Drama, Thriller]	5.0	
•••									
73835	Última sesión 2010	tt1754950	Última sesión	Última sesión	2010	90.0	[Drama]	6.2	
73836	Últimos días en La Habana 2016	tt5065762	Últimos días en La Habana	Últimos días en La Habana	2016	93.0	[Drama]	7.2	
73839	Über uns das All 2011	tt1813774	Über uns das All	Über uns das All	2011	88.0	[Drama]	6.7	
73854	ärtico 2014	tt3509772	ärtico	ärtico	2014	78.0	[Drama]	6.6	
73855	Šiška Deluxe 2015	tt4373884	Šiška Deluxe	Siska Deluxe	2015	108.0	[Comedy, Drama]	6.3	

28394 rows × 53 columns

In [121]:

Filter by movies that have enough votes to consider in "top rated" to find top director
s
imdb_drama_writ_dir['numvotes'].describe()

Out[121]:

count3.078800e+04mean3.883575e+03std2.863222e+04min5.000000e+0025%1.700000e+0150%7.100000e+0175%4.120000e+02max1.299334e+06

Name: numvotes, dtype: float64

In [122]:

imdb_drama_writ_dir[imdb_drama_writ_dir['numvotes'] >= (imdb_drama_writ_dir['numvotes'].m
edian())]

Out[122]:

	title_year	tconst	primary_title	original_title	start_year	runtime_minutes	genres_x av
18	#Horror 2015	tt3526286	#Horror	#Horror	2015	101.0	[Crime, Drama, Horror]

25	title_year #RFALITYHIGH 2017	tconst	primary_title #REALITYFIGH	original_title #REALITYFIGH	start_year	runtime_minutes	[Gennedy, Drama	av		
							Romance]			
37	#SquadGoals 2018	tt6540984	#SquadGoals	#SquadGoals	2018	90.0	[Drama, Thriller]			
39	#Stuck 2014	tt2075318	#Stuck	#Stuck	2014	82.0	[Comedy, Drama, Romance]			
41	#TemanTapiMenikah 2018	tt8076266	#TemanTapiMenikah	#TemanTapiMenikah	2018	102.0	[Biography, Drama]			
•••							***			
73837	Únos 2017	tt6602928	Únos	Únos	2017	0.0	[Drama]			
73838	Úsmevy smutných muzu 2018	tt8526824	Úsmevy smutných muzu	Úsmevy smutných muzu	2018	0.0	[Comedy, Drama]			
73839	Über uns das All 2011	tt1813774	Über uns das All	Über uns das All	2011	88.0	[Drama]			
73854	ärtico 2014	tt3509772	ärtico	ärtico	2014	78.0	[Drama]			
73855	Šiška Deluxe 2015	tt4373884	Šiška Deluxe	Siska Deluxe	2015	108.0	[Comedy, Drama]			
45400										
15408 1	rows × 53 columns		1							
).										
In [12	23]:									
				of voter. High mdb drama writ o						
_ mas_	arama_wrre_arr	a	rama_wrre_arr[r	mas_arama_wrre_c	zrr [Tramv	70005] 7 /1	1			
In [12	24]:									
				ting to get top						
imdb_0	drama_writ_dir =	= imdb_d	rama_writ_dir.s	ort_values(by= <mark>'</mark>	averagera	ating', ascen	.ding= Fals	se .		
·										
In [12	25]:									
	<i>k at average ra</i> drama_writ_dir[_	ts rating'].descri	be()						
Out[12	25]:									
count 15408.000000 mean 6.181192 std 1.148144 min 1.000000 25% 5.600000 50% 6.300000 75% 6.900000 max 9.900000 Name: averagerating, dtype: float64										
In [12	26]:									
	ate DataFrame o. ated_imdb_dramas			[imdb_drama_writ	_dir['av	veragerating'] >= 6.18	3]		
In [12	In [127]:									

What is aveage run time
top_rated_imdb_dramas['runtime_minutes'].mean()

Out[127]:

In [128]:

104.36118690313779

```
top_rated_imdb_dramas.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8796 entries, 23916 to 3295
Data columns (total 53 columns):
 # Column
                                Non-Null Count Dtype
    title_year
0
                                 8796 non-null object
   tconst
1
                                8796 non-null object
                               8796 non-null object
 2 primary_title
                              8796 non-null object
8796 non-null int64
3 original_title
 4 start_year
 5 runtime_minutes
                           8796 non-null float64
8796 non-null object
 6 genres x
                           8796 non-null float64
7 averagerating
 8 numvotes
                               8796 non-null int64
                               8782 non-null object
 9 directors
                               8459 non-null object
10 writers
                               8796 non-null object
11 genres_y
12 Music
                               8796 non-null int64
13 War
                               8796 non-null int64
14 Reality-TV
                               8796 non-null int64
15 Sport
                                8796 non-null
                                                 int64
16 Drama
                                8796 non-null
                                8796 non-null int64
 17
    Adventure
                               8796 non-null int64
18
    Game-Show
19 Animation
                               8796 non-null int64
20 History
                               8796 non-null int64
21 Romance
                               8796 non-null int64
                               8796 non-null int64
22 Musical
                               8796 non-null int64
23 News
24 Mystery
                               8796 non-null int64
25 Comedy
                               8796 non-null int64
26 Documentary
                               8796 non-null int64
27 Fantasy
                               8796 non-null int64
                               8796 non-null int64
28 Adult
29 Horror
                               8796 non-null int64
30 Crime
                               8796 non-null int64
31 Family
                               8796 non-null int64
32 Thriller
                                                int64
                               8796 non-null
                                                 int64
 33 Western
                               8796 non-null
 34 Action
                                8796 non-null
                                8796 non-null
 35
    Short
 36
    Sci-Fi
                                8796 non-null int64
 37 Biography
                                8796 non-null int64
                               500 non-null float64
 38 id
39 release_date
                               500 non-null object
 40 movie
                               500 non-null object
41 production_budget 500 non-null float64
42 domestic_gross 500 non-null float64
43 worldwide_gross 500 non-null float64
44 release_year 500 non-null object
45 worldwide_gross_in_mil 500 non-null float64
46 production_budget_in_mil 500 non-null float64
47 prod_budget_ROI 500 non-null float64
48 domestic_gross_in_mil 500 non-null float64
49 foreign_gross_in_mil 500 non-null float64
50 domestic_gross_p 500 non-null float64
51 foreign_gross_p 500 non-null float64
    foreign_gross_p 500 non-null
52 release month
                                                object
dtypes: float64(13), int64(28), object(12)
memory usage: 3.6+ MB
In [129]:
top_rated_imdb_dramas.groupby(['directors']).agg("mean").sort_values(by='averagerating',
ascending=False) .head(5)
```

Out[129]:

directors	start_year	runtime_minutes	averagerating	numvotes	Music	War	Reality-	Sport	Drama	Adventure	•••	produ
nm18369569	2019.0	138.0	9.9	417.0	0.0	0.0	0.0	0.0	1.0	0.0		
nm9982663	2018.0	125.0	9.7	639.0	0.0	0.0	0.0	0.0	1.0	0.0		
nm3123304	2018.0	132.0	9.6	2604.0	0.0	0.0	0.0	0.0	1.0	0.0		
nm1682596	2017.0	87.0	9.6	78.0	1.0	0.0	0.0	0.0	1.0	0.0		
nm10005127	2017.0	69.0	9.6	98.0	0.0	0.0	0.0	0.0	1.0	0.0		

5 rows × 41 columns

In [130]:

top_5_drama_directors = top_rated_imdb_dramas.groupby(['directors']).agg("mean").sort_va
lues(by='averagerating', ascending=False).head(5)

In [131]:

```
top_5_drama_directors.index
```

Out[131]:

Index(['nm10369569', 'nm9982663', 'nm3123304', 'nm1682596', 'nm10005127'], dtype='object'
, name='directors')

In [132]:

```
top_5_drama_directors = top_5_drama_directors.reset_index()
```

In [133]:

```
top_5_drama_directors
```

Out[133]:

	directors	start_year	runtime_minutes	averagerating	numvotes	Music	War	Reality- TV	Sport	Drama	 production_bu
0	nm10369569	2019.0	138.0	9.9	417.0	0.0	0.0	0.0	0.0	1.0	
1	nm9982663	2018.0	125.0	9.7	639.0	0.0	0.0	0.0	0.0	1.0	
2	nm3123304	2018.0	132.0	9.6	2604.0	0.0	0.0	0.0	0.0	1.0	
3	nm1682596	2017.0	87.0	9.6	78.0	1.0	0.0	0.0	0.0	1.0	
4	nm10005127	2017.0	69.0	9.6	98.0	0.0	0.0	0.0	0.0	1.0	

5 rows x 42 columns

In [134]:

```
top_5_drama_directors_ns = top_5_drama_directors['directors']
```

In [135]:

```
top_5_drama_directors_ns = list(top_5_drama_directors_ns)
```

In [136]:

```
# import file imdb.name.basics.csv.gz -- list of imdb people with list of professions
imdb_nb_df = pd.read_csv('rawData/zippedData/imdb.name.basics.csv.gz')
# preview file
imdb_nb_df.head()
```

Out[136]:

```
nconst primary name
Mary Ellen
                        birth_year death_year
                                                                    primary_profession
  nm0061671
                            NaN
                                      NaN
                                                 miscellaneous,production_manager,producer tt0837562,tt2398241
                  Bauder
1 nm0061865
            Joseph Bauer
                            NaN
                                      NaN
                                               composer, music department, sound department tt0896534,tt6791238.
2 nm0062070
              Bruce Baum
                            NaN
                                      NaN
                                                               miscellaneous,actor,writer tt1470654,tt0363631
                    Axel
3 nm0062195
                            NaN
                                      NaN camera_department,cinematographer,art_department tt0114371,tt2004304
                Baumann
4 nm0062798
              Pete Baxter
                            NaN
                                      NaN
                                             production_designer,art_department,set_decorator tt0452644,tt0452692
In [137]:
(imdb nb df[imdb nb df['nconst'] == top 5 drama directors ns[0]])
Out[137]:
          nconst
                    primary_name birth_year death_year primary_profession known_for_titles
85395 nm10369569 Nagaraja Uppunda
                                    NaN
                                              NaN
                                                           director
                                                                           NaN
In [138]:
# Write for loop to find top director names from drama directors list
top 5 drama directors names = []
for director in top 5 drama directors ns:
    for row in imdb nb df.index:
        if imdb nb df['nconst'][row] == director:
             top 5 drama directors names.append(imdb nb df['primary name'][row])
In [139]:
# Check list outcome
top 5 drama directors names
Out[139]:
['Nagaraja Uppunda',
 'Arsel Arumugam',
 'Nikoloz Khomasuridze',
 'Paul Michael Bloodgood',
 'Colonelu Morteni']
In [140]:
# Define function to get top 5 directors names
def top 5 directors names(directors list):
    """Return primary name of director in a list of nm IDs"""
    for director in directors list:
        for row in imdb nb df.index:
             if imdb nb df['nconst'][row] == director:
                 print(imdb nb df['primary name'][row])
In [141]:
#Define top genres
top genres list = ['Drama', 'Comedy', 'Action', 'Adventure', 'Thriller']
# Create for loop to do the above for each top genre and print results
for genre in top genres list:
    print(f"{genre}:")
    genre table = imdb with genre cols[(imdb with genre cols[genre] == 1) & (imdb with g
enre cols['directors'] != "Unknown")]
    print(f"median votes = {genre table['numvotes'].median()}")
    genre table = genre table[genre table['numvotes'] >= (genre table['numvotes'].median
())]
    print(f"average rating = {genre_table['averagerating'].median()}")
    genre table = genre table[genre table['averagerating'] >= (genre table['averagerating'])
```

```
g'].median())]
    genre_table_runtime = genre_table[genre_table['runtime_minutes'] > 0]
    print(f"average runtime = {round(genre table runtime['runtime minutes'].mean(),2)}")
    top_5_genre_directors = genre_table.groupby(['directors']).agg("mean").sort values(b
y='averagerating', ascending=False).head(5)
    top 5 genre directors = top 5 genre directors.reset index()
    top 5 genre directors ns = list(top 5 genre directors['directors'])
    print(top 5 genre directors ns)
    top 5 directors names (top 5 genre directors ns)
Drama:
median votes = 71.0
average rating = 6.3
average runtime = 107.47
['nm10369569', 'nm9982663', 'nm10285722', 'nm1682596', 'nm10005127']
Nagaraja Uppunda
Arsel Arumugam
Sudheer Shanbhogue
Paul Michael Bloodgood
Colonelu Morteni
Comedy:
median votes = 95.0
average rating = 5.8
average runtime = 103.63
['nm0000233', 'nm10285722', 'nm10436203', 'nm9073819', 'nm8589213']
Quentin Tarantino
Sudheer Shanbhogue
Abhinav Thakur
Amr Gamal
Karan R Guliani
Action:
median votes = 170.0
average rating = 5.8
average runtime = 117.65
['nm10466690', 'nm0000233', 'nm9276879', 'nm6442107', 'nm3586222']
Shankar
Quentin Tarantino
Ajay Andrews Nuthakki
Ram Kumar
Thiagarajan Kumararaja
Adventure:
median votes = 111.0
average rating = 6.0
average runtime = 105.66
['nm6748553', 'nm5139001', 'nm1957250, nm1601055', 'nm7186336', 'nm9762716']
Karzan Kardozi
Zolbayar Dorj
Christina Kyi
Matt Horton
Thriller:
median votes = 132.0
average rating = 5.5
average runtime = 107.38
['nm4891543', 'nm2755490', 'nm10079200', 'nm7464139', 'nm6442107']
Shivkumar Parthasarathy
Amitabh Reza Chowdhury
Gvr Vasu
Sushanth Reddy
Ram Kumar
In [142]:
# Look up Adventure directing duo, person 1
(imdb nb df[imdb nb df['nconst'] == 'nm1957250'])
Out[142]:
         nconst primary_name birth_year death_year
                                                              primary profession
```

168298 nm1957250 Kevin NaN NaN camera_department,editor,cinematographer tt1342019,tt4902348,tt41

- 1

In [143]:
Look up Adventure directing duo, person 2
(imdb_nb_df[imdb_nb_df['nconst'] == 'nm1601055'])
Out[143]:

nconst	primary_name	imary_name birth_year death_year primary_profession		known_for_titles	
133586 nm1601055	Zack Bennett	1988.0	NaN	actor,producer,writer	tt1352771,tt4126322,tt0944142,tt1342019

Learning: Movies in top genres should have runtime 1.75-2 hours. Top directors are global names. Research and see if any of interest to partner with for production.

Additional Analysis

. •

There are additional opportunities to continue analysis with the data given. This includes:

- Top writers per top genre (expanding what was done for directors to writers)
- . Highest rated actors in top genres and their known for characters
- What studio Microsoft can model portfolio after

Each of these can help with specific recommendations as Microsoft prepares to take next steps in producing their first movies.