Final Project Submission

Please fill out:

- Student name: Greg Osborne
- Student pace: part time
- Scheduled project review date/time: May 20th 2:00 pm CT
- Instructor name: Claude Fried
- Blog post URL: [https://medium.com/@gregosborne (https://medium.com/@gregosborne)](https://medium.com/@gregosborne)

Business Case

Microsoft's strong representation in the fields of personal computing, business computing, and interactive entertainment needs to expand into other forms of popular media to stay competitive and attract new customers. Microsoft wishes to investigate the best way to expand into the blockbuster movie industry.

To break in to this business, Microsoft faces competition from the five titans of the film industry:

1. Walt Disney/20th Century Fox
2. Warner Brothers
3. Sony/Columbia
4. Universal Studios
5. Paramount Pictures

Microsoft commissioned Data Science firm FurPig Inc. to recommend best practices to succeed in this new initiative.

FurPig Inc. assigned Data Scientist Greg Osborne (me) to the project.

Microsoft provided me with a zip file containing database information detailing several different characteristics from thousands of films. My job is to go through the data and make the best recomendations based on three buisness questions.

Dependent Variable

There are two reasons for this initiative:

1. Make a profit on the films
2. Build a reputation with the public of quality entertainment for Microsoft's brand

Microsoft is not looking to create fodder for the pretentious crowd, generating buzz at film festivals and ignored by the public upon wider release. Microsoft wants its new movie brand—Working title: XBoxOffice—to be recognized by as many people as possible.

Since this is new a initiative for Microsoft, and the whole point is getting as many people to see these films as possible, the driving metric for our analysis will be box office dollars, because that's the metric that's closest to ticket sales.

Our dependent variable will be box office dollars.

Independent Variables

Microsoft contracted FurPig to select three independent variables—that is, three decisions that Microsoft would have complete control over during the selection of which films to produce—and see how changing these three variables yields different box office revenue.

How can we change these variables to make make box office revenue as large as possible?

The three variables selected by FurPig are:

1. Genre
2. Release month
3. Creative Personnel (Writer, Director, Producer, Actor, Actress)

Business Questions

Greg selected the following business questions:

1. What genres of film produce the highest box office revenue?
2. What is the best month to release a film to generate the most revenue?
3. What writers, directors, producers, actors and actresses have the highest revenue earning potential?

Python Libraries

The first thing I'll do is import the libraries I need for this project.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import shutil
import sqlite3
import seaborn as sns
import matplotlib.patches as mpatches
pd.set_option("display.max_columns", None)
```

Data Importation

Now, I'll import the data I was given in the zip file

In [2]:
```
ls zippedData
```

```
 Volume in drive C is OS
 Volume Serial Number is 4EE7-277F

 Directory of C:\Users\g_osb\Clones\Phase1\dsc-phase-1-project-v2-4\zippedData

05/19/2022  01:15 PM    <DIR>          .
06/08/2022  07:58 PM    <DIR>          ..
05/08/2022  11:01 PM            53,544 bom.movie_gross.csv.gz
05/08/2022  11:01 PM        67,149,708 im.db.zip
05/08/2022  11:01 PM           107,563 movie_data_erd.jpeg
05/08/2022  11:01 PM           498,202 rt.movie_info.tsv.gz
05/08/2022  11:01 PM         3,402,194 rt.reviews.tsv.gz
05/08/2022  11:01 PM           827,840 tmdb.movies.csv.gz
05/08/2022  11:01 PM           153,218 tn.movie_budgets.csv.gz
               7 File(s)     72,192,269 bytes
               2 Dir(s)  408,193,974,272 bytes free
```

I'm going to convert each csv file into a pandas database. There are five csv files to convert.

In [3]:
```
bom = pd.read_csv('C:/Users/g_osb/Clones/Phase1/dsc-phase-1-project-v2-4/zippedData/bom.mov
rt_info = pd.read_csv('C:/Users/g_osb/Clones/Phase1/dsc-phase-1-project-v2-4/zippedData/rt
rt_reviews = pd.read_csv('C:/Users/g_osb/Clones/Phase1/dsc-phase-1-project-v2-4/zippedData/
tmdb = pd.read_csv('C:/Users/g_osb/Clones/Phase1/dsc-phase-1-project-v2-4/zippedData/tmdb.r
tn = pd.read_csv('C:/Users/g_osb/Clones/Phase1/dsc-phase-1-project-v2-4/zippedData/tn.movie
```

The remaining zip file needs to be unzipped. It contains a a SQL file, which needs to be connected to python so I can run SQL queries.

In [4]:
```
#unzip the zip file
shutil.unpack_archive("C:/Users/g_osb/Clones/Phase1/dsc-phase-1-project-v2-4/zippedData/im
```

The SQL file is named im.db. Connecting it to Python

In [5]:
```
conn = sqlite3.connect('im.db')
cur = conn.cursor()
```

Next, I'll run a script that sets up printing the table names, then I'll print the table names

In [6]:
```
%%script sqlite3 im.db --out tables
.tables
.quit
```

In [7]:
```
#Now listing the tables
print(tables)
```

```
directors      movie_akas     movie_ratings  principals
known_for      movie_basics   persons        writers
```

I will now convert each of the SQL tables to a pandas data frame and preview the data. Then I checked each table for fully duplicated rows, and deleted the duplicates. If a table had no duplicates, I deleted the check.

In [8]:
```
imdb_directors = pd.read_sql("""
SELECT *
FROM directors
;
""",conn)

imdb_directors.drop(imdb_directors[imdb_directors.duplicated()].index, inplace=True)
imdb_directors
```

Out[8]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0462036	nm1940585
2	tt0835418	nm0151540
4	tt0878654	nm0089502
5	tt0878654	nm2291498
...	...	...
291169	tt8999974	nm10122357
291170	tt9001390	nm6711477
291171	tt9001494	nm10123242
291172	tt9001494	nm10123248
291173	tt9004986	nm4993825

163535 rows × 2 columns

In [9]:
```
imdb_movie_akas = pd.read_sql("""
SELECT *
FROM movie_akas
;
""",conn)
imdb_movie_akas
```

Out[9]:

	movie_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	None	None	0.0
1	tt0369610	11	Jurashikku warudo	JP	None	imdbDisplay	None	0.0
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	None	imdbDisplay	None	0.0
3	tt0369610	13	O Mundo dos Dinossauros	BR	None	None	short title	0.0
4	tt0369610	14	Jurassic World	FR	None	imdbDisplay	None	0.0
...	...	...	...	...	...	...	...	...
331698	tt9827784	2	Sayonara kuchibiru	None	None	original	None	1.0
331699	tt9827784	3	Farewell Song	XWW	en	imdbDisplay	None	0.0
331700	tt9880178	1	La atención	None	None	original	None	1.0
331701	tt9880178	2	La atención	ES	None	None	None	0.0
331702	tt9880178	3	The Attention	XWW	en	imdbDisplay	None	0.0

331703 rows × 8 columns

In [10]:
```python
imdb_movie_ratings = pd.read_sql("""
SELECT *
FROM movie_ratings
;
""",conn)
imdb_movie_ratings
```

Out[10]:

	movie_id	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
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [11]:
```python
imdb_principals = pd.read_sql("""
SELECT *
FROM principals
;
""",conn)
imdb_principals
```

Out[11]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]
1	tt0111414	2	nm0398271	director	None	None
2	tt0111414	3	nm3739909	producer	producer	None
3	tt0323808	10	nm0059247	editor	None	None
4	tt0323808	1	nm3579312	actress	None	["Beth Boothby"]
...	...	...	...	...	...	...
1028181	tt9692684	1	nm0186469	actor	None	["Ebenezer Scrooge"]
1028182	tt9692684	2	nm4929530	self	None	["Herself","Regan"]
1028183	tt9692684	3	nm10441594	director	None	None
1028184	tt9692684	4	nm6009913	writer	writer	None
1028185	tt9692684	5	nm10441595	producer	producer	None

1028186 rows × 6 columns

In [12]:
```
imdb_known_for = pd.read_sql("""
SELECT *
FROM known_for
;
""",conn)
imdb_known_for
```

Out[12]:

	person_id	movie_id
0	nm0061671	tt0837562
1	nm0061671	tt2398241
2	nm0061671	tt0844471
3	nm0061671	tt0118553
4	nm0061865	tt0896534
...	...	...
1638255	nm9990690	tt9090932
1638256	nm9990690	tt8737130
1638257	nm9991320	tt8734436
1638258	nm9991320	tt9615610
1638259	nm9993380	tt8743182

1638260 rows × 2 columns

In [13]:
```
imdb_movie_basics = pd.read_sql("""
SELECT *
FROM movie_basics
;
""",conn)
imdb_movie_basics
```

Out[13]:

	movie_id	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
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	None
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 6 columns

In [14]:
```
imdb_persons = pd.read_sql("""
SELECT *
FROM persons
;
""",conn)
imdb_persons
```

Out[14]:

	person_id	primary_name	birth_year	death_year	primary_profession
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,producer
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_department
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,writer
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_department
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorator
...	...	...	...	...	...
606643	nm9990381	Susan Grobes	NaN	NaN	actress
606644	nm9990690	Joo Yeon So	NaN	NaN	actress
606645	nm9991320	Madeline Smith	NaN	NaN	actress
606646	nm9991786	Michelle Modigliani	NaN	NaN	producer
606647	nm9993380	Pegasus Envoyé	NaN	NaN	director,actor,writer

606648 rows × 5 columns

In [15]:
```
imdb_writers = pd.read_sql("""
SELECT *
FROM writers
;
""",conn)
imdb_writers.drop(imdb_writers[imdb_writers.duplicated()].index, inplace=True)
imdb_writers
```

Out[15]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0438973	nm0175726
2	tt0438973	nm1802864
3	tt0462036	nm1940585
4	tt0835418	nm0310087
...	...	...
255868	tt8999892	nm10122246
255869	tt8999974	nm10122357
255870	tt9001390	nm6711477
255871	tt9004986	nm4993825
255872	tt9010172	nm8352242

178352 rows × 2 columns

A personal test of the provided database

As a fun exercise, I decided to look for Sanford Gibbons, my friend's Uncle.

In [16]:
```
pd.read_sql("""
SELECT *
FROM persons
WHERE primary_name LIKE '%Gibbons%';
""",conn)
```

Out[16]:

	person_id	primary_name	birth_year	death_year	primary_profession
0	nm0316584	Patrick D. Gibbons	NaN	NaN	assistant_director,producer,miscellaneous
1	nm0316554	Greg Gibbons	NaN	NaN	animation_department,visual_effects,art_director
2	nm0316596	Sanford Gibbons	1933.0	2018.0	actor
3	nm1733301	Dave Gibbons	1949.0	NaN	writer,art_department,producer
4	nm0316531	Billy Gibbons	1949.0	NaN	soundtrack,actor,composer
5	nm2524514	Matt Gibbons	NaN	NaN	actor,writer,director
6	nm1644817	Tyler Gibbons	NaN	NaN	composer,sound_department,soundtrack
7	nm3453179	Pete Gibbons	NaN	NaN	producer
8	nm1668151	Neil Gibbons	NaN	NaN	writer,producer,director
9	nm2971362	Tony Gibbons	1983.0	NaN	actor
10	nm1668152	Rob Gibbons	NaN	NaN	writer,producer,director
11	nm1766037	Michael Gibbons	NaN	NaN	None
12	nm3202120	Lauren Gibbons	NaN	NaN	actress
13	nm4752963	Sally Fitzgibbons	NaN	NaN	None
14	nm3501059	Marlon Gibbons	NaN	NaN	composer,soundtrack
15	nm4613842	Richard Fitzgibbons	NaN	NaN	None
16	nm4548984	Darryn Gibbons	NaN	NaN	actor,writer,director
17	nm3106632	Derek Gibbons	NaN	NaN	actor,producer,director
18	nm4313499	Anthony Gibbons	NaN	NaN	cinematographer
19	nm5854730	Anthony Gibbons	NaN	NaN	actor
20	nm3180477	Michael Gibbons	NaN	NaN	actor
21	nm5785553	Tom Gibbons	NaN	NaN	cinematographer
22	nm4425737	Brendan Gibbons	NaN	NaN	director,writer,producer
23	nm5258424	Maurine Gibbons	NaN	NaN	miscellaneous,actress,writer
24	nm4882012	Akil Gibbons	NaN	NaN	producer,miscellaneous,camera_department
25	nm5903645	Kendyl Gibbons	NaN	NaN	None
26	nm5532424	Brendon Gibbons	NaN	NaN	None
27	nm4958141	Philip Gibbons	NaN	NaN	writer,director,producer
28	nm5964883	Matthew Gibbons	NaN	NaN	sound_department,camera_department,editor
29	nm6367107	John Carroll-Gibbons	NaN	NaN	editor,visual_effects,editorial_department
30	nm9242691	Mark Gibbons	NaN	NaN	actor

Sure enough, Sanford's person_id is nm0316596. Let's see what films Sanford Gibbons has listed in this database.

In [17]:
```
pd.read_sql("""
SELECT *
FROM principals
JOIN movie_basics
    USING(movie_id)
WHERE person_id LIKE 'nm0316596';
""",conn)
```

Out[17]:

	movie_id	ordering	person_id	category	job	characters	primary_title	original_title	start_year	runtime_
0	tt5607782	4	nm0316596	actor	None	["Father James Burk"]	The Covenant	The Covenant	2017	

Data Cleaning / Merging of tables

After previewing all the data provided, I decided on these three business questions (printed above):

1. What genres of film produce the highest box office revenue?
2. What is the best month to release a film in to generate the most revenue?
3. What writers, directors, producers, actors and actresses have the highest revenue earning potential?

For these three questions, I don't need to utilize the information from Rotten Tomatoes. That database does not have any movie titles that can be matched to the other databases. It is primarily internet user film ratings, which is not being considered by my three business questions.

Instead, I will join the remaining four databases together: Box Office Mojo, IMDB, The Numbers, and The Movie Database. I will only keep the films that exist in each database provided. First, I'll start with merging Box Office Mojo and the Internet Movie Database.

After reviewing the data, I found a strange mistake in Box Office Mojo's date for a 2012 movie titled Upside Down. It's date is listed 2013. This caused the data to be inconsistent with other databases. I could just delete it, but, after finding the error, it's just as easy to correct it.

In [18]:
```
bom.at[1298,'year'] = 2012
bom.iloc[1298]['year']
```

Out[18]: 2012

In [19]:
```
#Merging bom and imdb
movies_analyzed = pd.merge(bom,imdb_movie_basics, how='inner',left_on='title', right_on='or
movies_analyzed
```

Out[19]:

	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	original_title	start_year
0	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy Story 3	2010
1	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	Inception	2010
2	Shrek Forever After	P/DW	238700000.0	513900000	2010	tt0892791	Shrek Forever After	Shrek Forever After	2010
3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	tt1325004	The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	2010
4	Iron Man 2	Par.	312400000.0	311500000	2010	tt1228705	Iron Man 2	Iron Man 2	2010
...	...	...	...	...	...	...	...	...	...
2771	The Escape	IFC	14000.0	NaN	2018	tt6069126	The Escape	The Escape	2017
2772	Souvenir	Strand	11400.0	NaN	2018	tt2387692	Souvenir	Souvenir	2016
2773	Souvenir	Strand	11400.0	NaN	2018	tt2389092	Souvenir	Souvenir	2014
2774	Souvenir	Strand	11400.0	NaN	2018	tt3478898	Souvenir	Souvenir	2014
2775	An Actor Prepares	Grav.	1700.0	NaN	2018	tt5718046	An Actor Prepares	An Actor Prepares	2018

2776 rows × 11 columns

I will check for inconsitent debut year information between these two database and drop any films with mistakes.

In [20]:
```
movies_to_drop = movies_analyzed[movies_analyzed['title'].duplicated()]
movies_to_drop.drop(movies_to_drop[(movies_to_drop['year'] == movies_to_drop['start_year']]
movies_analyzed.drop(movies_to_drop.index, inplace=True)
movies_analyzed.drop(movies_analyzed[(movies_analyzed['year'] != movies_analyzed['start_yea
bom_and_imdb = movies_analyzed.reset_index()
bom_and_imdb
```

```
C:\Users\g_osb\anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:4163: Sett
ingWithCopyWarning:
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 (https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  return super().drop(
```

Out[20]:

	index	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	original_title	sta
0	0	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy Story 3	
1	1	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	Inception	
2	2	Shrek Forever After	P/DW	238700000.0	513900000	2010	tt0892791	Shrek Forever After	Shrek Forever After	
3	3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	tt1325004	The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	
4	4	Iron Man 2	Par.	312400000.0	311500000	2010	tt1228705	Iron Man 2	Iron Man 2	
...	...	...	...	...	...	...	...	...	...	
1662	2756	The House That Jack Built	IFC	88000.0	NaN	2018	tt4003440	The House That Jack Built	The House That Jack Built	
1663	2761	Helicopter Eela	Eros	72000.0	NaN	2018	tt8427036	Helicopter Eela	Helicopter Eela	
1664	2765	Oolong Courtyard	CL	37700.0	NaN	2018	tt8549902	Oolong Courtyard: KungFu School	Oolong Courtyard	
1665	2768	The Workshop	Strand	22100.0	NaN	2018	tt7405478	The Workshop	The Workshop	
1666	2775	An Actor Prepares	Grav.	1700.0	NaN	2018	tt5718046	An Actor Prepares	An Actor Prepares	

1667 rows × 12 columns

I'm now going to merge in The Movie Database columns. To do that, I need to rename some of the columns so I can tell where each column came from after the merge.

In [21]:
```
tmdb.rename(columns = {'Unnamed: 0':'tmdb_index','original_title':'tmdb_original_title','t
```

Now I have to fix another error in the film Upside Down.

In [22]:
```
tmdb.at[7969,'tmdb_release_date'] = '2012-08-31'
```

Now I'm going convert the release dates to release years, in integers, in a new column. This will allow me to merge and compare with the IMDB and Box Office Mojo data.

In [23]:
```
tmdb['tmdb_year'] = tmdb['tmdb_release_date'].map(lambda x : x[0:4])
tmdb['tmdb_year'] = tmdb['tmdb_year'].astype(int)
```

Merging the previously merged dataframe of IMDB and Box Office Mojo data with the tmdb dataframe. I'll now refer to this database as movies_analyzed.

In [24]:
```
movies_analyzed = pd.merge(bom_and_imdb,tmdb, how='inner',left_on='title', right_on='tmdb_t
movies_analyzed
```

Out[24]:

	index	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	original_title	sta
0	0	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy Story 3	
1	1	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	Inception	
2	2	Shrek Forever After	P/DW	238700000.0	513900000	2010	tt0892791	Shrek Forever After	Shrek Forever After	
3	3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	tt1325004	The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	
4	4	Iron Man 2	Par.	312400000.0	311500000	2010	tt1228705	Iron Man 2	Iron Man 2	
...	...	...	...	...	...	...	...	...	...	
1770	2739	The Guardians	MBox	177000.0	NaN	2018	tt8150132	The Guardians	The Guardians	
1771	2742	Museo	Vita.	149000.0	NaN	2018	tt4958448	Museo	Museo	
1772	2756	The House That Jack Built	IFC	88000.0	NaN	2018	tt4003440	The House That Jack Built	The House That Jack Built	
1773	2756	The House That Jack Built	IFC	88000.0	NaN	2018	tt4003440	The House That Jack Built	The House That Jack Built	
1774	2775	An Actor Prepares	Grav.	1700.0	NaN	2018	tt5718046	An Actor Prepares	An Actor Prepares	

1775 rows × 23 columns

Once again, I will check for inconsitent debut year information and drop any films with mistakes.

In [25]:

```
movies_to_drop = movies_analyzed[movies_analyzed['title'].duplicated()]
movies_to_drop.drop(movies_to_drop[(movies_to_drop['year'] == movies_to_drop['tmdb_year'])]
movies_analyzed.drop(movies_to_drop.index, inplace=True)
movies_analyzed.drop(movies_analyzed[(movies_analyzed['year'] != movies_analyzed['tmdb_yea
bom_imdb_and_tmdb = movies_analyzed.reset_index()
bom_imdb_and_tmdb
```

```
C:\Users\g_osb\anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:4163: Sett
ingWithCopyWarning:
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 (https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  return super().drop(
```

Out[25]:

	level_0	index	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	origin
0	0	0	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy
1	1	1	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	In
2	2	2	Shrek Forever After	P/DW	238700000.0	513900000	2010	tt0892791	Shrek Forever After	Forev
3	3	3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	tt1325004	The Twilight Saga: Eclipse	The '
4	4	4	Iron Man 2	Par.	312400000.0	311500000	2010	tt1228705	Iron Man 2	Iron
...	...	...	...	...	...	...	...	...	...	
1631	1767	2731	Time Freak	Grindstone	10000.0	256000	2018	tt6769280	Time Freak	Time
1632	1768	2732	What They Had	BST	260000.0	NaN	2018	tt6662736	What They Had	Wha
1633	1771	2742	Museo	Vita.	149000.0	NaN	2018	tt4958448	Museo	
1634	1773	2756	The House That Jack Built	IFC	88000.0	NaN	2018	tt4003440	The House That Jack Built	The Th
1635	1774	2775	An Actor Prepares	Grav.	1700.0	NaN	2018	tt5718046	An Actor Prepares	A Pr

1636 rows × 24 columns

Now I'll merge The Numbers into my movies_analyzed dataframe. First I need to edit The Numbers database so I can merge it with movies_analyzed easily. Like earlier, I'll start by editing the column names.

In [26]:
```
tn.rename(columns = {'id':'tn_id','movie':'tn_title','domestic_gross':'tn_domestic_gross',
```

Now I'll fix yet another error in the film Upside Down.

In [27]:
```
tn.at[1203,'tn_release_date'] = 'Aug 31 2012'
```

Now, similarly to earlier, I'll convert the dates to the release year as an integer in new column.

In [28]:
```
tn['tn_year'] = tn['tn_release_date'].map(lambda x : x[-4:])
tn['tn_year'] = tn['tn_year'].astype(int)
```

Now, I'll merge the movies_analyzed dataframe with the newly formatted The Numbers dataframe.

In [29]:
```
movies_analyzed = pd.merge(bom_imdb_and_tmdb,tn, how='inner',left_on='title', right_on='tn_
movies_analyzed
```

Out[29]:

	level_0	index	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	origi
0	0	0	Toy Story 3	BV	415000000.0	652000000	2010	tt0435761	Toy Story 3	Toy
1	1	1	Inception	WB	292600000.0	535700000	2010	tt1375666	Inception	Ir
2	2	2	Shrek Forever After	P/DW	238700000.0	513900000	2010	tt0892791	Shrek Forever After	Forev
3	3	3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000	2010	tt1325004	The Twilight Saga: Eclipse	The
4	4	4	Iron Man 2	Par.	312400000.0	311500000	2010	tt1228705	Iron Man 2	Iro
...	...	...	...	...	...	...	...	...	...	
1157	1741	2682	Suspiria	Amazon	2500000.0	5400000	2018	tt1034415	Suspiria	
1158	1743	2686	The Hurricane Heist	ENTMP	6100000.0	NaN	2018	tt5360952	The Hurricane Heist	H
1159	1745	2688	Destroyer	Annapurna	1500000.0	4000000	2018	tt7137380	Destroyer	D
1160	1749	2694	Gotti	VE	4300000.0	NaN	2018	tt1801552	Gotti	
1161	1759	2710	Mandy	RLJ	1200000.0	NaN	2018	tt6998518	Mandy	

1162 rows × 31 columns

Once again, I'll drop mistakes based on inconsistent years released data.

In [30]:
```
movies_to_drop = movies_analyzed[movies_analyzed['title'].duplicated()]
movies_to_drop.drop(movies_to_drop[(movies_to_drop['year'] == movies_to_drop['tn_year'])].i
movies_analyzed.drop(movies_to_drop.index, inplace=True)
movies_analyzed.drop(movies_analyzed[(movies_analyzed['year'] != movies_analyzed['tn_year']
```

```
C:\Users\g_osb\anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:4163: Sett
ingWithCopyWarning:
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 (https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  return super().drop(
```

Later on in this document, I learned that there are duplicate rows I need to drop. These are minor quirks of the merged dataframes. To do this, I need to create a dataframe with just these values, and preserve the index numbers from movies_analyzed. I'll also create three new columns, duped_title, duped_year and drop. If both the name and year are the same, I'll drop the second of the two rows.

First I'll set the max rows to none so I can review all of the duplicates, then create the new columns.

In [31]:
```
pd.set_option("display.max_rows", None, "display.max_columns", None)

duplicated_titles = movies_analyzed[movies_analyzed['movie_id'].duplicated(keep=False)].so
duplicated_titles = duplicated_titles.iloc[:,1:].reset_index()
duplicated_titles['duped_title'] = duplicated_titles['movie_id'].duplicated()
duplicated_titles['duped_year'] = duplicated_titles['year'].duplicated().astype(bool)
duplicated_titles['drop'] = False

for x in range(len(duplicated_titles)):
    if (duplicated_titles['duped_title'][x] == True and duplicated_titles['duped_year'][x]
        duplicated_titles['drop'][x] = True


duplicated_titles
```

```
<ipython-input-31-f397c46beca5>:11: 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/use
r_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  duplicated_titles['drop'][x] = True
```

Resetting the max rows

In [32]:
```
pd.set_option("display.max_rows", 60, "display.max_columns", None)
```

Now, I'll drop the duplicated rows and check to see if there are any duplicated movie titles.

In [33]:
```
duplicated_titles.drop(duplicated_titles[duplicated_titles['drop'] == False].index, inplace
movies_analyzed.drop(duplicated_titles['level_0'], inplace=True)

movies_analyzed['title'].duplicated().sum()
```

Out[33]:
```
23
```

Funny enough, there are twenty three pairs, or 46 films, that have the same title, were released the same year, but yet have different runtimes and different entries on IMDB. These need to be removed selectively. First, I'll look at the 46 films.

In [34]:
```
test = movies_analyzed[movies_analyzed['title'].duplicated(keep=False)].sort_values('title
test
```

Out[34]:

	title	studio	year	movie_id	runtime_minutes	genres
207	Abduction	LGF	2011	tt1600195	106.0	Action,Mystery,Thriller
208	Abduction	LGF	2011	tt2447982	84.0	Horror,Thriller
614	Addicted	LGF	2014	tt3435418	97.0	Documentary,Music
613	Addicted	LGF	2014	tt2205401	106.0	Drama,Thriller
607	Big Eyes	Wein.	2014	tt4317898	NaN	Documentary
606	Big Eyes	Wein.	2014	tt1126590	106.0	Biography,Crime,Drama
53	Burlesque	SGem	2010	tt1126591	119.0	Drama,Music,Musical
54	Burlesque	SGem	2010	tt1586713	NaN	Drama
962	Coco	BV	2017	tt2380307	105.0	Adventure,Animation,Comedy
963	Coco	BV	2017	tt7002100	98.0	Horror
111	Cyrus	FoxS	2010	tt1327709	87.0	Crime,Horror,Mystery
112	Cyrus	FoxS	2010	tt1336617	91.0	Comedy,Drama,Romance
942	Denial	BST	2016	tt4645330	109.0	Biography,Drama
943	Denial	BST	2016	tt5897002	93.0	Documentary
737	Legend	Uni.	2015	tt3381068	94.0	Horror
739	Legend	Uni.	2015	tt3569230	132.0	Biography,Crime,Drama
848	Lights Out	WB (NL)	2016	tt5328340	90.0	Documentary
847	Lights Out	WB (NL)	2016	tt4786282	81.0	Drama,Horror,Mystery
686	Sisters	Uni.	2015	tt1850457	118.0	Comedy
687	Sisters	Uni.	2015	tt4793074	53.0	Biography,Documentary,Music
698	Spotlight	ORF	2015	tt7785302	99.0	Drama
696	Spotlight	ORF	2015	tt1895587	129.0	Crime,Drama
1055	Stronger	RAtt.	2017	tt3881784	119.0	Biography,Drama
1056	Stronger	RAtt.	2017	tt5738152	125.0	Drama
187	The Artist	Wein.	2011	tt1825978	100.0	Thriller
186	The Artist	Wein.	2011	tt1655442	100.0	Comedy,Drama,Romance
41	The Bounty Hunter	Sony	2010	tt1038919	110.0	Action,Comedy,Romance
42	The Bounty Hunter	Sony	2010	tt1472211	NaN	None
898	The Forest	Focus	2016	tt3387542	93.0	Horror,Mystery,Thriller
901	The Forest	Focus	2016	tt4982356	109.0	Drama,Fantasy,Horror
729	The Night Before	Sony	2015	tt6353886	86.0	Documentary
726	The Night Before	Sony	2015	tt3530002	101.0	Adventure,Comedy,Fantasy
138	The Tempest	Mira.	2010	tt1683003	131.0	Drama
137	The Tempest	Mira.	2010	tt1274300	110.0	Comedy,Drama,Fantasy

	title	studio	year	movie_id	runtime_minutes	genres
695	The Visit	Uni.	2015	tt3833746	83.0	Documentary
693	The Visit	Uni.	2015	tt3567288	94.0	Horror,Mystery,Thriller
721	The Walk	TriS	2015	tt3488710	123.0	Adventure,Biography,Drama
720	The Walk	TriS	2015	tt2159988	89.0	Crime,Thriller
1065	The Wall	RAtt.	2017	tt7578246	NaN	Documentary
1064	The Wall	RAtt.	2017	tt6845582	5.0	Documentary
1063	The Wall	RAtt.	2017	tt4218696	88.0	Action,Drama,Thriller
1114	Truth or Dare	Uni.	2018	tt6869948	92.0	Comedy,Drama,Romance
1113	Truth or Dare	Uni.	2018	tt6772950	100.0	Horror,Thriller
510	Upside Down	MNE	2012	tt1374992	109.0	Drama,Fantasy,Romance
511	Upside Down	MNE	2012	tt2105043	81.0	Drama

Now, I'll check which ones to pick and which to drop. I'll choose which one to keep by identifying the film that matches the data in the other databases.

In [35]:
```
#These are the IMDB movie_id numbers for the films that need to be deleted.
imposter_films = ['tt2447982', 'tt3435418', 'tt4317898', 'tt1586713',
                  'tt7002100', 'tt1327709', 'tt5897002', 'tt3381068',
                  'tt5328340', 'tt4793074', 'tt7785302', 'tt5738152',
                  'tt1825978', 'tt1472211', 'tt4982356', 'tt6353886',
                  'tt1683003', 'tt3833746', 'tt2159988', 'tt7578246',
                  'tt6845582', 'tt6869948', 'tt2105043']

#I'll test to make sure dropping these films will leave me with the ones I want to keep.
to_drop = test[test['movie_id'].isin(imposter_films)].index
test.drop(to_drop, inplace=True)
test.sort_values('title')
```

Out[35]:

	title	studio	year	movie_id	runtime_minutes	genres
207	Abduction	LGF	2011	tt1600195	106.0	Action,Mystery,Thriller
613	Addicted	LGF	2014	tt2205401	106.0	Drama,Thriller
606	Big Eyes	Wein.	2014	tt1126590	106.0	Biography,Crime,Drama
53	Burlesque	SGem	2010	tt1126591	119.0	Drama,Music,Musical
962	Coco	BV	2017	tt2380307	105.0	Adventure,Animation,Comedy
112	Cyrus	FoxS	2010	tt1336617	91.0	Comedy,Drama,Romance
942	Denial	BST	2016	tt4645330	109.0	Biography,Drama
739	Legend	Uni.	2015	tt3569230	132.0	Biography,Crime,Drama
847	Lights Out	WB (NL)	2016	tt4786282	81.0	Drama,Horror,Mystery
686	Sisters	Uni.	2015	tt1850457	118.0	Comedy
696	Spotlight	ORF	2015	tt1895587	129.0	Crime,Drama
1055	Stronger	RAtt.	2017	tt3881784	119.0	Biography,Drama
186	The Artist	Wein.	2011	tt1655442	100.0	Comedy,Drama,Romance
41	The Bounty Hunter	Sony	2010	tt1038919	110.0	Action,Comedy,Romance
898	The Forest	Focus	2016	tt3387542	93.0	Horror,Mystery,Thriller
726	The Night Before	Sony	2015	tt3530002	101.0	Adventure,Comedy,Fantasy
137	The Tempest	Mira.	2010	tt1274300	110.0	Comedy,Drama,Fantasy
693	The Visit	Uni.	2015	tt3567288	94.0	Horror,Mystery,Thriller
721	The Walk	TriS	2015	tt3488710	123.0	Adventure,Biography,Drama
1063	The Wall	RAtt.	2017	tt4218696	88.0	Action,Drama,Thriller
1113	Truth or Dare	Uni.	2018	tt6772950	100.0	Horror,Thriller
510	Upside Down	MNE	2012	tt1374992	109.0	Drama,Fantasy,Romance

The remaining films match all of the databases' entries. Now I'll perform the same action on movies_analyzed.

In [36]:
```
movies_analyzed.drop(to_drop, inplace=True)
```

Now that I've merged all the data together and deleted duplicates and bad entries, I'll rename our database to mark where we are.

In [37]:
```
dataset = movies_analyzed.copy()
```

Now I'll convert the the money in string format into integers.

In [38]:
```
dataset['tn_worldwide_gross'] = dataset['tn_worldwide_gross'].str.replace(',', '')
dataset['tn_worldwide_gross'] = dataset['tn_worldwide_gross'].str.replace('$', '').astype(i
dataset['tn_domestic_gross'] = dataset['tn_domestic_gross'].str.replace(',', '')
dataset['tn_domestic_gross'] = dataset['tn_domestic_gross'].str.replace('$', '').astype(in
dataset['production_budget'] = dataset['production_budget'].str.replace(',', '')
dataset['production_budget'] = dataset['production_budget'].str.replace('$', '').astype(in
dataset[['tn_worldwide_gross', 'tn_domestic_gross', 'production_budget']]
```

Out[38]:

	tn_worldwide_gross	tn_domestic_gross	production_budget
0	1068879522	415004880	200000000
1	835524642	292576195	160000000
2	756244673	238736787	165000000
3	706102828	300531751	68000000
4	621156389	312433331	170000000
...	...	...	...
1157	7034615	2483472	20000000
1158	30963684	6115824	40000000
1159	3681096	1533324	9000000
1160	6089100	4286367	10000000
1161	1427656	1214525	6000000

Reformatting a few numbers in the foreign_gross column.

In [39]:
```
dataset['foreign_gross'] = dataset['foreign_gross'].str.replace(',', '')
```

I want to compare the numbers between the Box Office Mojo domestic_gross column with the box office totals from The Numbers dataset. However, the Box Office Mojo data is missing some values, so I'll fill those in with the data from The Numbers. Then, I'll see if anything is missing from the Box Office Mojo domestic_gross column.

In [40]:
```
dataset['domestic_gross'] = dataset['domestic_gross'].fillna(dataset['tn_domestic_gross'])
dataset['domestic_gross'] = dataset['domestic_gross'].round(decimals=0).astype(int)
dataset['foreign_gross'] = dataset['foreign_gross'].fillna(dataset['tn_worldwide_gross']).a
dataset['foreign_gross'] = dataset['foreign_gross'].round(decimals=0).astype(int)

dataset.isna().sum()
```

Out[40]:
```
level_0                 0
index                   0
title                   0
studio                  0
domestic_gross          0
foreign_gross           0
year                    0
movie_id                0
primary_title           0
original_title          0
start_year              0
runtime_minutes         0
genres                  0
tmdb_index              0
genre_ids               0
tmdb_id                 0
original_language       0
tmdb_original_title     0
popularity              0
tmdb_release_date       0
tmdb_title              0
vote_average            0
vote_count              0
tmdb_year               0
tn_id                   0
tn_release_date         0
tn_title                0
production_budget       0
tn_domestic_gross       0
tn_worldwide_gross      0
tn_year                 0
dtype: int64
```

I need to convert runtime_minutes to an integer because every number in the column is a whole number.

In [41]:
```
dataset['runtime_minutes'] = dataset['runtime_minutes'].astype(int)
```

I need to split out the imdb genre list into separate columns.

In [42]:
```
dataset['imdb_genre_lst'] = dataset['genres'].str.split(',')
dataset['imdb_genre_1'] = dataset['imdb_genre_lst'].apply(lambda x : x[0])
dataset['imdb_genre_2'] = dataset['imdb_genre_lst'].apply(lambda x : x[1] if len(x)>=2 els
dataset['imdb_genre_3'] = dataset['imdb_genre_lst'].apply(lambda x : x[2] if len(x)==3 els
dataset[['imdb_genre_1','imdb_genre_2','imdb_genre_3','imdb_genre_lst']]
```

Out[42]:

	imdb_genre_1	imdb_genre_2	imdb_genre_3	imdb_genre_lst
0	Adventure	Animation	Comedy	[Adventure, Animation, Comedy]
1	Action	Adventure	Sci-Fi	[Action, Adventure, Sci-Fi]
2	Adventure	Animation	Comedy	[Adventure, Animation, Comedy]
3	Adventure	Drama	Fantasy	[Adventure, Drama, Fantasy]
4	Action	Adventure	Sci-Fi	[Action, Adventure, Sci-Fi]
...	...	...	...	...
1157	Fantasy	Horror	Mystery	[Fantasy, Horror, Mystery]
1158	Action	Adventure	Crime	[Action, Adventure, Crime]
1159	Action	Crime	Drama	[Action, Crime, Drama]
1160	Biography	Crime	Drama	[Biography, Crime, Drama]
1161	Action	Fantasy	Horror	[Action, Fantasy, Horror]

I will analyze what the movie release months yield the highest revenue, so I will isolate this info from the TN data. For organizational purposes, I'll also store this info as an integer from 1–12.

In [43]:
```
dataset['tn_release_month'] = dataset['tn_release_date'].str[0:3]
dataset[['tn_release_date','tn_release_month']]
```

Out[43]:

	tn_release_date	tn_release_month
0	Jun 18, 2010	Jun
1	Jul 16, 2010	Jul
2	May 21, 2010	May
3	Jun 30, 2010	Jun
4	May 7, 2010	May
...	...	...
1157	Oct 26, 2018	Oct
1158	Mar 9, 2018	Mar
1159	Dec 25, 2018	Dec
1160	Jun 15, 2018	Jun
1161	Sep 14, 2018	Sep

1008 rows × 2 columns

In [44]:
```
dataset['tn_num_month'] = dataset['tn_release_month'].map(lambda x :
                                                          1 if x == 'Jan' else
                                                          2 if x == 'Feb' else
                                                          3 if x == 'Mar' else
                                                          4 if x == 'Apr' else
                                                          5 if x == 'May' else
                                                          6 if x == 'Jun' else
                                                          7 if x == 'Jul' else
                                                          8 if x == 'Aug' else
                                                          9 if x == 'Sep' else
                                                          10 if x == 'Oct' else
                                                          11 if x == 'Nov' else
                                                          12 if x == 'Dec' else
                                                          'error')
```

I need to check to see if my conversions performed correctly. So, I'll compare the value counts for both columns.

In [45]:
```
print(dataset['tn_release_month'].value_counts())
print()
print(dataset['tn_num_month'].value_counts())
```

```
Nov    120
Oct    104
Dec    103
Sep     96
Jul     95
Jun     88
Aug     87
Mar     78
May     67
Feb     61
Apr     55
Jan     54
Name: tn_release_month, dtype: int64

11    120
10    104
12    103
9      96
7      95
```

The numbers are consistent.

Now I need to compare the Box Office Mojo box office totals to the TN totals. The BOM data separated domestic and foreign totals, while the TN data combined foreign and domestic as worldwide gross. So, I'll make a column of TN foreign gross, and I'll see how the totals of domestic and foreign compare. Once that's done, I'll print the top five columns of the data, and decide on how to proceed from there.

In [46]:
```
dataset['tn_foreign_gross'] = dataset['tn_worldwide_gross'] - dataset['tn_domestic_gross']

comparison = dataset.copy()
comparison['bom_minus_tn_foreign'] = comparison['foreign_gross'] - comparison['tn_foreign_g
comparison['bom_minus_tn_domestic'] = comparison['domestic_gross'] - comparison['tn_domest

comparison[['title','domestic_gross', 'foreign_gross','tn_domestic_gross','tn_worldwide_gr
```

Out[46]:

	title	domestic_gross	foreign_gross	tn_domestic_gross	tn_worldwide_gross	tn_foreign_gross	bom
1074	Avengers: Infinity War	678800000	1370	678815482	2048134200	1369318718	
953	The Fate of the Furious	226000000	1010	225764765	1234846267	1009081502	
636	Jurassic World	652300000	1019	652270625	1648854864	996584239	
45	Dear John	80000000	35000000	80014842	142033509	62018667	
293	Wreck-It Ralph	189400000	281800000	189412677	496511521	307098844	

I was planning on further analysis to see which database provided the best revenue information, but I think I found what I'm looking for in the table above. According to BOM, Avengers Infinity War, Jurassic World, and Fate of the Furious—some of the most profitable film franchises of all time—each made barely over $1000 at the foreign box office. That is not right, so we will rely on the TN database.

I looked for ways to decode the tmdb genre_id categories, but I could not find a simple way to do it. Since IMDB gives up to three genres per film, we'll just use those definitions for any genre comparisons. It's important to note that the genres listed for imdb are in alphabetical order, not order of significance.

In light of this, I'm removing the tmdb genre_id column.

Also, there are a lot of extraneous columns in my dataset, so I'll select the columns that are relevant from this point forward and delete the rest. Then I'll look at the top 30 highest grossing films worldwide to see if I like the data left.

In [47]:
```
dataset = dataset[[
                    #bom
                    'title', 'studio','year',
                    #imdb
                    'movie_id', 'runtime_minutes','imdb_genre_1',
                    'imdb_genre_2', 'imdb_genre_3',
                    #tmdb
                    'tmdb_index', 'tmdb_id','original_language','popularity',
                    'tmdb_release_date','vote_average','vote_count',
                    #tn
                    'tn_release_month', 'tn_num_month', 'production_budget',
                    'tn_domestic_gross', 'tn_foreign_gross',
                    'tn_worldwide_gross']]

dataset.sort_values('tn_worldwide_gross', ascending = 0).head(30)
```

Out[47]:

	title	studio	year	movie_id	runtime_minutes	imdb_genre_1	imdb_genre_2	imdb_genre_3	tmc
1074	Avengers: Infinity War	BV	2018	tt4154756	149	Action	Adventure	Sci-Fi	
636	Jurassic World	Uni.	2015	tt0369610	124	Action	Adventure	Sci-Fi	
637	Avengers: Age of Ultron	BV	2015	tt2395427	141	Action	Adventure	Sci-Fi	
1075	Black Panther	BV	2018	tt1825683	134	Action	Adventure	Sci-Fi	
1076	Jurassic World: Fallen Kingdom	Uni.	2018	tt4881806	128	Action	Adventure	Sci-Fi	
401	Frozen	BV	2013	tt2294629	102	Adventure	Animation	Comedy	
1077	Incredibles 2	BV	2018	tt3606756	118	Action	Adventure	Animation	
953	The Fate of the Furious	Uni.	2017	tt4630562	136	Action	Crime	Thriller	
638	Minions	Uni.	2015	tt2293640	91	Adventure	Animation	Comedy	
1078	Aquaman	WB	2018	tt1477834	143	Action	Adventure	Fantasy	
798	Captain America: Civil War	BV	2016	tt3498820	147	Action	Adventure	Sci-Fi	
141	Transformers: Dark of the Moon	P/DW	2011	tt1399103	154	Action	Adventure	Sci-Fi	
283	Skyfall	Sony	2012	tt1074638	143	Action	Adventure	Thriller	
519	Transformers: Age of Extinction	Par.	2014	tt2109248	165	Action	Adventure	Sci-Fi	
284	The Dark Knight Rises	WB	2012	tt1345836	164	Action	Thriller	None	
0	Toy Story 3	BV	2010	tt0435761	103	Adventure	Animation	Comedy	
142	Pirates of the Caribbean: On Stranger Tides	BV	2011	tt1298650	136	Action	Adventure	Fantasy	

	title	studio	year	movie_id	runtime_minutes	imdb_genre_1	imdb_genre_2	imdb_genre_3	tmc
954	Despicable Me 3	Uni.	2017	tt3469046	89	Adventure	Animation	Comedy	
799	Finding Dory	BV	2016	tt2277860	97	Adventure	Animation	Comedy	
800	Zootopia	BV	2016	tt2948356	108	Adventure	Animation	Comedy	
285	The Hobbit: An Unexpected Journey	WB (NL)	2012	tt0903624	169	Adventure	Family	Fantasy	
402	Despicable Me 2	Uni.	2013	tt1690953	98	Adventure	Animation	Comedy	
955	Jumanji: Welcome to the Jungle	Sony	2017	tt2283362	119	Action	Adventure	Comedy	
403	The Hobbit: The Desolation of Smaug	WB (NL)	2013	tt1170358	161	Adventure	Fantasy	None	
520	The Hobbit: The Battle of the Five Armies	WB (NL)	2014	tt2310332	144	Adventure	Fantasy	None	
1079	Bohemian Rhapsody	Fox	2018	tt1727824	134	Biography	Drama	Music	
801	The Secret Life of Pets	Uni.	2016	tt2709768	87	Adventure	Animation	Comedy	
957	Spider-Man: Homecoming	Sony	2017	tt2250912	133	Action	Adventure	Sci-Fi	
286	Ice Age: Continental Drift	Fox	2012	tt1667889	88	Adventure	Animation	Comedy	
640	Spectre	Sony	2015	tt2379713	148	Action	Adventure	Thriller	

Now, since my dependent variable is worldwixe box office revenue, I'll add a new column, revenue_rank, and sort the data.

In [48]:
```python
dataset.sort_values('tn_worldwide_gross',ascending=False,inplace=True)
dataset.reset_index(inplace=True)
dataset = dataset.iloc[:,1:]
dataset['revenue_rank'] = dataset.index + 1
cols = ['revenue_rank'] + list(dataset.columns[0:-1])
dataset = dataset[cols]
dataset.head(30)
```

Out[48]:

	revenue_rank	title	studio	year	movie_id	runtime_minutes	imdb_genre_1	imdb_genre_2	imdb_
0	1	Avengers: Infinity War	BV	2018	tt4154756	149	Action	Adventure	
1	2	Jurassic World	Uni.	2015	tt0369610	124	Action	Adventure	
2	3	Avengers: Age of Ultron	BV	2015	tt2395427	141	Action	Adventure	
3	4	Black Panther	BV	2018	tt1825683	134	Action	Adventure	
4	5	Jurassic World: Fallen Kingdom	Uni.	2018	tt4881806	128	Action	Adventure	
5	6	Frozen	BV	2013	tt2294629	102	Adventure	Animation	
6	7	Incredibles 2	BV	2018	tt3606756	118	Action	Adventure	A
7	8	The Fate of the Furious	Uni.	2017	tt4630562	136	Action	Crime	
8	9	Minions	Uni.	2015	tt2293640	91	Adventure	Animation	
9	10	Aquaman	WB	2018	tt1477834	143	Action	Adventure	
10	11	Captain America: Civil War	BV	2016	tt3498820	147	Action	Adventure	
11	12	Transformers: Dark of the Moon	P/DW	2011	tt1399103	154	Action	Adventure	
12	13	Skyfall	Sony	2012	tt1074638	143	Action	Adventure	
13	14	Transformers: Age of Extinction	Par.	2014	tt2109248	165	Action	Adventure	
14	15	The Dark Knight Rises	WB	2012	tt1345836	164	Action	Thriller	
15	16	Toy Story 3	BV	2010	tt0435761	103	Adventure	Animation	
16	17	Pirates of the Caribbean: On Stranger Tides	BV	2011	tt1298650	136	Action	Adventure	
17	18	Despicable Me 3	Uni.	2017	tt3469046	89	Adventure	Animation	
18	19	Finding Dory	BV	2016	tt2277860	97	Adventure	Animation	
19	20	Zootopia	BV	2016	tt2948356	108	Adventure	Animation	
20	21	The Hobbit: An Unexpected Journey	WB (NL)	2012	tt0903624	169	Adventure	Family	

	revenue_rank	title	studio	year	movie_id	runtime_minutes	imdb_genre_1	imdb_genre_2	imdb_
21	22	Despicable Me 2	Uni.	2013	tt1690953	98	Adventure	Animation	
22	23	Jumanji: Welcome to the Jungle	Sony	2017	tt2283362	119	Action	Adventure	
23	24	The Hobbit: The Desolation of Smaug	WB (NL)	2013	tt1170358	161	Adventure	Fantasy	
24	25	The Hobbit: The Battle of the Five Armies	WB (NL)	2014	tt2310332	144	Adventure	Fantasy	
25	26	Bohemian Rhapsody	Fox	2018	tt1727824	134	Biography	Drama	
26	27	The Secret Life of Pets	Uni.	2016	tt2709768	87	Adventure	Animation	
27	28	Spider-Man: Homecoming	Sony	2017	tt2250912	133	Action	Adventure	
28	29	Ice Age: Continental Drift	Fox	2012	tt1667889	88	Adventure	Animation	
29	30	Spectre	Sony	2015	tt2379713	148	Action	Adventure	

There's still a long road ahead. In my dataset, I only have genre and release month information. We don't have anything about personnel. I want to analyze what effects five roles have on revenue production: writers, directors actors, actresses and producers.

There's a lot of personnel info in the IMDB data, but I'm going to stick to the personnel in the principals table. This has the big names in the five roles I will analyze. First, I have to make sense of the data in the principals table, so I'll preview the table.

In [49]:
```
imdb_principals
```

Out[49]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]
1	tt0111414	2	nm0398271	director	None	None
2	tt0111414	3	nm3739909	producer	producer	None
3	tt0323808	10	nm0059247	editor	None	None
4	tt0323808	1	nm3579312	actress	None	["Beth Boothby"]
...	...	...	...	...	...	...
1028181	tt9692684	1	nm0186469	actor	None	["Ebenezer Scrooge"]
1028182	tt9692684	2	nm4929530	self	None	["Herself","Regan"]
1028183	tt9692684	3	nm10441594	director	None	None
1028184	tt9692684	4	nm6009913	writer	writer	None
1028185	tt9692684	5	nm10441595	producer	producer	None

1028186 rows × 6 columns

First, I'll cull the principals table to include only the films from my dataset. Then, I'll run the value_counts method on the results to make sure I have the same number of movies in my dataset, 1008.

In [50]:
```
imdb_principals_dataset = imdb_principals[imdb_principals['movie_id'].isin(dataset['movie_i
imdb_principals_dataset['movie_id'].value_counts()
```

Out[50]:
```
tt0993842    10
tt3799694    10
tt3606888    10
tt2283362    10
tt1528100    10
             ..
tt2243537     9
tt3707106     9
tt0873886     8
tt1508675     8
tt7535780     3
Name: movie_id, Length: 1008, dtype: int64
```

I now have the right number of films and the big names attached to them, but I don't want all the names. I just want the names of people from those five categories I'm analyzing (writer, director, actor, actress, producer). I'll see what values are available in the category column.

In [51]:
```
imdb_principals_dataset['category'].value_counts()
```

Out[51]:
```
actor                  2525
writer                 2027
producer               2005
actress                1484
director               1083
composer                472
cinematographer         277
editor                  130
production_designer      38
self                     15
archive_footage           1
archive_sound             1
Name: category, dtype: int64
```

I will cull this to include only the categories I'm analyzing.

In [52]:
```
categories = ['writer', 'director', 'actor', 'actress', 'producer']

imdb_principals_dataset = imdb_principals_dataset[imdb_principals_dataset['category'].isin
imdb_principals_dataset['category'].value_counts()
```

Out[52]:
```
actor       2525
writer      2027
producer    2005
actress     1484
director    1083
Name: category, dtype: int64
```

Now, I'm curious if each movie has at least one of each category. I want to keep actors and actresses separate for later analysis, but for this analysis, I'll combine the two categories into an actorsneutral column. I'll need to check this more than once without editing any paramenters within, so I'll create a function without a parameter call.

In [53]:
```
def missing_categories():
    movies_that_include_writer_director_producer_actorsneutral = []

    categories_no_actors = ['writer', 'director', 'producer']

    for x in categories_no_actors:
        movies_that_include_writer_director_producer_actorsneutral.append(
            len(imdb_principals_dataset[imdb_principals_dataset['category']
            .isin([x])]['movie_id'].value_counts()))

    movies_that_include_writer_director_producer_actorsneutral.append(
        len(imdb_principals_dataset[imdb_principals_dataset['category']
        .isin(['actor','actress'])]['movie_id'].value_counts()))

    print('Movies with writers: ', movies_that_include_writer_director_producer_actorsneutr
    print('Movies with directors: ', movies_that_include_writer_director_producer_actorsneu
    print('Movies with producers: ', movies_that_include_writer_director_producer_actorsneu
    print('Movies with actors (neutral): ', movies_that_include_writer_director_producer_ac
missing_categories()
```

```
Movies with writers:  864
Movies with directors:  980
Movies with producers:  895
Movies with actors (neutral):  1005
```

There are movies in this database with no actors listed. Well, that makes it clear that there are some gaps in the IMDB principals table. I will attempt to fill them in with information from the other IMDB tables. First, I'll see which movies don't have writers.

In [54]:
```
writer = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['writer'])]['mov
no_writer = imdb_principals_dataset[~imdb_principals_dataset['movie_id'].isin(writer).value
no_writer_list = no_writer['movie_id'].unique()
print('There are ' + str(len(no_writer_list)) + ' films missing a writer credit.')
print(no_writer_list)
```

```
There are 144 films missing a writer credit.
['tt0475290' 'tt1403241' 'tt1605783' 'tt1666186' 'tt2083355' 'tt1675192'
 'tt1527186' 'tt1602613' 'tt2215719' 'tt2235108' 'tt1336617' 'tt1650062'
 'tt2184339' 'tt1441326' 'tt0873886' 'tt1213663' 'tt1508675' 'tt1229340'
 'tt1243974' 'tt1549572' 'tt1645080' 'tt1719071' 'tt1764183' 'tt0466893'
 'tt1470827' 'tt1623288' 'tt1702443' 'tt1126591' 'tt1065073' 'tt1535108'
 'tt1535612' 'tt1540133' 'tt1617661' 'tt1020558' 'tt1092026' 'tt0878835'
 'tt1433822' 'tt1421051' 'tt1555064' 'tt2076220' 'tt1869716' 'tt1313092'
 'tt1220634' 'tt1602620' 'tt1615147' 'tt1931533' 'tt1235170' 'tt1182350'
 'tt2170593' 'tt1560747' 'tt1684628' 'tt1853728' 'tt1859650' 'tt1307068'
 'tt2194499' 'tt0872230' 'tt1570989' 'tt1763303' 'tt1316616' 'tt1800246'
 'tt2042568' 'tt2388637' 'tt2334873' 'tt1478964' 'tt1971352' 'tt2229499'
 'tt2401878' 'tt1637688' 'tt1855199' 'tt0938283' 'tt1920849' 'tt1840417'
 'tt1375666' 'tt1710396' 'tt1772288' 'tt1431181' 'tt1655442' 'tt1781827'
 'tt2309260' 'tt1195478' 'tt1333125' 'tt1171222' 'tt2103254' 'tt0478304'
 'tt1878870' 'tt1276104' 'tt1659337' 'tt1855325' 'tt2872718' 'tt3470600'
 'tt3312830' 'tt2334649' 'tt2387433' 'tt3099498' 'tt2690138' 'tt2937898'
 'tt2473794' 'tt3707106' 'tt3850214' 'tt3152624' 'tt2975578' 'tt3783958'
 'tt3606756' 'tt2361509' 'tt2994190' 'tt3760922' 'tt2390361' 'tt2609912'
 'tt2784678' 'tt2884206' 'tt2582802' 'tt2321549' 'tt3460252' 'tt3721936'
 'tt2649554' 'tt3567288' 'tt2872732' 'tt4034228' 'tt4094724' 'tt4925292'
 'tt6000478' 'tt3890160' 'tt5027774' 'tt5052448' 'tt4034354' 'tt5834262'
 'tt5013056' 'tt6265828' 'tt6288250' 'tt5726086' 'tt6791096' 'tt4651520'
 'tt4649416' 'tt5619332' 'tt5758778' 'tt5721088' 'tt4669986' 'tt4761916'
 'tt4624424' 'tt5719700' 'tt7784604' 'tt6499752' 'tt6359956' 'tt6266538']
```

Now I'll do the same for directors.

In [55]:
```
director = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['director'])]
no_director = imdb_principals_dataset[~imdb_principals_dataset['movie_id'].isin(director).
no_director_list = no_director['movie_id'].unique()
print('There are ' + str(len(no_director_list)) + ' films missing a director.')
print(no_director_list)
```

```
There are 28 films missing a director.
['tt1205537' 'tt1258972' 'tt1562568' 'tt1320253' 'tt1637725' 'tt1321860'
 'tt1235170' 'tt1583420' 'tt2177771' 'tt0840361' 'tt1024648' 'tt1859650'
 'tt1570989' 'tt0359950' 'tt2398231' 'tt2229499' 'tt1124035' 'tt1608290'
 'tt1630036' 'tt3707106' 'tt3521126' 'tt2784678' 'tt2637276' 'tt2671706'
 'tt2870708' 'tt6644200' 'tt5619332' 'tt7959026']
```

Now, I'll check if any of these films are listed in the IMDB writers and directors tables.

In [56]:
```
additional_writers = imdb_writers[imdb_writers['movie_id'].isin(no_writer_list)]
additional_writers['movie_id'].value_counts()
```

Out[56]:
```
tt1333125    20
tt4651520     2
tt1666186     2
tt5619332     2
tt1195478     2
             ..
tt1235170     1
tt5721088     1
tt2609912     1
tt1535612     1
tt1684628     1
Name: movie_id, Length: 142, dtype: int64
```

In [57]:
```
additional_directors = imdb_directors[imdb_directors['movie_id'].isin(no_director_list)]
additional_directors['movie_id'].value_counts()
```

Out[57]:
```
tt6644200    1
tt2229499    1
tt1630036    1
tt1321860    1
tt0840361    1
tt2177771    1
tt1608290    1
tt1124035    1
tt1583420    1
tt1235170    1
tt2870708    1
tt1859650    1
tt1570989    1
tt3707106    1
tt7959026    1
tt2671706    1
tt1258972    1
tt1205537    1
tt3521126    1
tt2637276    1
tt5619332    1
tt1320253    1
tt2784678    1
tt0359950    1
tt1024648    1
tt2398231    1
tt1562568    1
tt1637725    1
Name: movie_id, dtype: int64
```

I can now fill in missing data for 142 missing writers and 28 missing directors into our dataset.

To add this data, I first need to add the column "category" to both of these new dataframes, and use the column to assign the correct category label for both writer and director. Then, I'll just add these new rows to the imdb principles dataset. It's important to note that this new information is missing the data listed in the ordering, job and characters columns. This is not a problem since I'm not going to use these columns for my analysis.

In [58]:
```
additional_writers['category'] = 'writer'
additional_directors['category'] = 'director'

#Adding them to the dataset
imdb_principals_dataset = imdb_principals_dataset.append(additional_writers)
imdb_principals_dataset = imdb_principals_dataset.append(additional_directors)
imdb_principals_dataset
```

```
<ipython-input-58-e6c173939bf1>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  additional_writers['category'] = 'writer'
<ipython-input-58-e6c173939bf1>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  additional_directors['category'] = 'director'
```

Out[58]:

	movie_id	ordering	person_id	category	job	characters
37	tt0475290	1.0	nm0000982	actor	None	["Eddie Mannix"]
38	tt0475290	2.0	nm0000123	actor	None	["Baird Whitlock"]
39	tt0475290	3.0	nm2403277	actor	None	["Hobie Doyle"]
40	tt0475290	4.0	nm0000146	actor	None	["Laurence Laurentz"]
41	tt0475290	5.0	nm0001053	director	None	None
...	...	...	...	...	...	...
231826	tt1235170	NaN	nm0432380	director	NaN	NaN
252452	tt1320253	NaN	nm0000230	director	NaN	NaN
271231	tt7959026	NaN	nm0000142	director	NaN	NaN
281388	tt0359950	NaN	nm0001774	director	NaN	NaN
282970	tt2398231	NaN	nm0000169	director	NaN	NaN

9333 rows × 6 columns

Now I'll rerun the missing_categories function to see if the changes are implemented.

In [59]:
```
missing_categories()
```

```
Movies with writers:  1006
Movies with directors:  1008
Movies with producers:  895
Movies with actors (neutral):  1005
```

I still am missing two writers and a few actors, but I successfully filled in a lot of writers and directors. I could complete both the writers and actors categories by using Google to look up the writers for the two movies missing that info, and do the same for actors/actresses for the three movies missing that info.

To start, I'll make a pair of dataframes that ony include the imdb movie_id for the movies with missing writers and actors.

In [60]:
```
#A dataframe with one row per film to compare with dataframes that are missing data.
films_in_dataset = imdb_principals_dataset[~imdb_principals_dataset['movie_id'].duplicated(

#Now, I'll create a a pair of dataframes of movies with no writer or actorneutral.
films_with_writers = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['wri
films_with_writers = films_with_writers[~films_with_writers.duplicated()]
no_writer = films_in_dataset[~films_in_dataset.isin(films_with_writers.tolist())]

films_with_actor = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['actor
films_with_actor = films_with_actor[~films_with_actor.duplicated()]
no_actor = films_in_dataset[~films_in_dataset.isin(films_with_actor.tolist())]
```

Now I'll print two dataframes that give us the movie titles for the movie_ids missing writers and actors that we just extracted.

Movies with missing writers information

In [61]:
```
dataset[dataset['movie_id'].isin(no_writer.tolist())]
```

Out[61]:

	revenue_rank	title	studio	year	movie_id	runtime_minutes	imdb_genre_1	imdb_genre_2	imdb_genr
433	434	Justin Bieber: Never Say Never	Par.	2011	tt1702443	105	Documentary	Music	No
727	728	Katy Perry: Part of Me	Par.	2012	tt2215719	93	Documentary	Music	No

Movies missing actor information

In [62]:
```
dataset[dataset['movie_id'].isin(no_actor.tolist())]
```

Out[62]:

	revenue_rank	title	studio	year	movie_id	runtime_minutes	imdb_genre_1	imdb_genre_2	imdb_genr
433	434	Justin Bieber: Never Say Never	Par.	2011	tt1702443	105	Documentary	Music	No
727	728	Katy Perry: Part of Me	Par.	2012	tt2215719	93	Documentary	Music	No
895	896	Inside Job	SPC	2010	tt1645089	109	Crime	Documentary	No

Interesting. The two films without writers are concert films, so they certainly don't need writers. They do, however, have stars. So I'll add both Katy Perry and Justin Bieber as an actor/actress to those films.

Inside Job has an A-list hollywood actor as a narrator, so I'll add him as an actor too.

In [63]:
```
movie_id_name_job = pd.DataFrame({'movie_id': ['tt1645089', 'tt1702443', 'tt2215719'],
                                   'person_id': None,
                                   'category': ['actor', 'actor', 'actress'],
                                   'name': ['Matt Damon', 'Justin Bieber', 'Katy Perry']})

movie_id_name_job['person_id'] = movie_id_name_job['name'].map(
    lambda x : imdb_persons[imdb_persons['primary_name'].str.contains(x)]['person_id'].iloc

imdb_principals_dataset = imdb_principals_dataset.append(movie_id_name_job.iloc[:,0:3])

print('Additional Actors')
print(movie_id_name_job)
print()

missing_categories()
```

```
Additional Actors
    movie_id  person_id category           name
0  tt1645089  nm0000354    actor     Matt Damon
1  tt1702443  nm3595501    actor  Justin Bieber
2  tt2215719  nm2953537  actress     Katy Perry

Movies with writers:  1006
Movies with directors:  1008
Movies with producers:  895
Movies with actors (neutral):  1008
```

I don't want to look up each film missing a producer, but I might be able to find some producer information in the dataset I have. There are some people listed as producers in the job category. It's possible someone is labeled as a producer in the job column and as something else in the category column.

First, I'll make a list of the films missing a producer credit.

In [64]:
```
producer = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['producer'])]
no_producer = imdb_principals_dataset[~imdb_principals_dataset['movie_id'].isin(producer).v
no_producer_list = no_producer['movie_id'].unique()
print('There are ' + str(len(no_producer_list)) + ' films missing a producer.')
print(no_producer_list)
```

```
There are 113 films missing a producer.
['tt1228705' 'tt2015381' 'tt2096673' 'tt1772341' 'tt1872181' 'tt0974015'
 'tt1961175' 'tt0892791' 'tt1402488' 'tt0948470' 'tt1075747' 'tt1999890'
 'tt0451279' 'tt1508675' 'tt2247476' 'tt1152822' 'tt1843866' 'tt2267968'
 'tt2279373' 'tt1302067' 'tt1985966' 'tt0881320' 'tt1365519' 'tt1487931'
 'tt2006295' 'tt0808510' 'tt0816711' 'tt1436562' 'tt1628841' 'tt1469304'
 'tt1572315' 'tt1860357' 'tt0478970' 'tt1319716' 'tt1790886' 'tt2243537'
 'tt1809398' 'tt2025690' 'tt2096672' 'tt1449283' 'tt1602620' 'tt1279935'
 'tt2294449' 'tt0800369' 'tt0892769' 'tt1196141' 'tt1198101' 'tt0963966'
 'tt1298650' 'tt1591479' 'tt1679335' 'tt0471042' 'tt0472181' 'tt2177771'
 'tt1587310' 'tt0787474' 'tt0864835' 'tt1397280' 'tt1911658' 'tt2176013'
 'tt1790809' 'tt1596346' 'tt2245084' 'tt2250912' 'tt1877832' 'tt1477834'
 'tt2017020' 'tt1621039' 'tt0837562' 'tt1277953' 'tt1711525' 'tt1981115'
 'tt2234155' 'tt2379713' 'tt1333125' 'tt2296777' 'tt0448694' 'tt1630036'
 'tt2283362' 'tt0790736' 'tt0848537' 'tt1979388' 'tt3501632' 'tt2828996'
 'tt2975590' 'tt3606752' 'tt3707106' 'tt2316204' 'tt3300542' 'tt2473510'
 'tt3385516' 'tt3832914' 'tt3498820' 'tt2910274' 'tt2948356' 'tt4154756'
 'tt2660888' 'tt3522806' 'tt3411444' 'tt3731562' 'tt2692250' 'tt2357291'
 'tt3521164' 'tt4849438' 'tt3416828' 'tt4667094' 'tt3922818' 'tt4981636'
 'tt4871980' 'tt5095030' 'tt6182908' 'tt6306064' 'tt7535780']
```

Now we need to look for producers in imdb_principals_dataset to see if there is anyone listed as a producer for the film in the job column but not in the category column.

In [65]:
```
additional_producers = imdb_principals[imdb_principals['movie_id'].isin(imdb_principals_dat
producer_in_job = additional_producers[additional_producers['job'].isin(['producer'])]
print('There are', len(producer_in_job), 'people with a job listed as producer.')
print('Now to see what they are listed as in the category column')
producer_in_job['category'].value_counts()
```

```
There are 2002 people with a job listed as producer.
Now to see what they are listed as in the category column
```

Out[65]:
```
producer    2002
Name: category, dtype: int64
```

It is with a heavy heart that I conclude that there is no missing producer information in this dataset. I'll have to run my analysis on this data as it is.

Now I'll add the names of the people to the imdb principals database.

In [66]:
```python
imdb_principals_dataset = pd.merge(imdb_principals_dataset,imdb_persons[['person_id','prima
imdb_principals_dataset
```

Out[66]:

	movie_id	ordering	person_id	category	job	characters	primary_name	death_year
0	tt0475290	1.0	nm0000982	actor	None	["Eddie Mannix"]	Josh Brolin	NaN
1	tt1075747	1.0	nm0000982	actor	None	["Jonah Hex"]	Josh Brolin	NaN
2	tt1182350	3.0	nm0000982	actor	None	["Roy"]	Josh Brolin	NaN
3	tt1403865	4.0	nm0000982	actor	None	["Tom Chaney"]	Josh Brolin	NaN
4	tt3397884	2.0	nm0000982	actor	None	["Matt Graver"]	Josh Brolin	NaN
...	...	...	...	...	...	...	...	...
9331	tt1333125	NaN	nm0765563	writer	NaN	NaN	Olle Sarri	NaN
9332	tt1333125	NaN	nm1856892	writer	NaN	NaN	Jacob Fleisher	NaN
9333	tt1333125	NaN	nm0698119	writer	NaN	NaN	Greg Pritikin	NaN
9334	tt1333125	NaN	nm2695453	writer	NaN	NaN	Steve Baker	NaN
9335	tt1702443	NaN	nm3595501	actor	NaN	NaN	Justin Bieber	NaN

9336 rows × 8 columns

When I analyze the different personnel in this dataset, I'll need a dataframe for each type of personnel analyzed. I'll create these now.

In [67]:
```
writers = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['writer'])]
directors = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['director'])]
producers = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['producer'])]
actors = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['actor'])]
actresses = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['actress'])]
actorsneutral = imdb_principals_dataset[imdb_principals_dataset['category'].isin(['actor',

#Resetting the index and sorting them.
writers.sort_values('movie_id',inplace=True)
writers.reset_index(inplace=True)
directors.sort_values('movie_id',inplace=True)
directors.reset_index(inplace=True)
producers.sort_values('movie_id',inplace=True)
producers.reset_index(inplace=True)
actors.sort_values('movie_id',inplace=True)
actors.reset_index(inplace=True)
actresses.sort_values('movie_id',inplace=True)
actresses.reset_index(inplace=True)
actorsneutral.sort_values('movie_id',inplace=True)
actorsneutral.reset_index(inplace=True)
```

```
<ipython-input-67-6f20f1fc4bd5>:9: 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/use
r_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  writers.sort_values('movie_id',inplace=True)
<ipython-input-67-6f20f1fc4bd5>:11: 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/use
r_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  directors.sort_values('movie_id',inplace=True)
<ipython-input-67-6f20f1fc4bd5>:13: 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/use
r_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas
```

Business Questions (Reprise)

Now, I can finally move on to the real work: Answering my 3 business questions:

1. What genres of film produce the highest box office revenue?
2. What is the best month to release a film in to generate the most revenue?
3. What writers, directors, producers, actors and actresses have the highest revenue earning potential?

Question 1

Question 1: What genres of film produce the highest box office revenue?

I'll start by generating a list of all the various genres available in the dataset. I should note that the genre columns 1, 2, and 3 are in alphabetical order per film. Each film can have one, two or three genres.

I will count the genres for more than one set of data, so I'll define a function that can do this with a dataframe parameter.

In [68]:

```python
def genre_counts(df):

    #Counting the genres listed in each of the three columns
    genre_col1_count = df['imdb_genre_1'].value_counts()
    genre_col2_count = df['imdb_genre_2'].value_counts()
    genre_col3_count = df['imdb_genre_3'].value_counts()

    #Merging the three dataframes with the genre value counts
    temp = genre_col1_count.append(genre_col2_count.append(genre_col3_count))

    #This will be a dictionary that adds the genre counts together
    genre_count = {}

    for i in range(len(temp)):
        #The index of temp is the genre name
        key = temp.index[i]
        #The value of the single cell in the row is the count of films
        #in that genre in its respective column
        value = temp[i]
        #This tests to see if the genre (key)already has a value in the
        #dictionary. If it doesn't, it creates one.
        if key not in genre_count:
            genre_count[key] = value
        #If it does, then it adds the new value to the existing value.
        else:
            genre_count[key] = int(genre_count[key] + value)

    #Finally, this creates the dataframe to return.
    genre_count_df = pd.DataFrame.from_dict(genre_count,orient = 'index')
    genre_count_df.rename(columns = {0:'count'},inplace=True)
    genre_count_df.sort_values('count', ascending=False,inplace=True)
    return genre_count_df
dataset_genre_counts = genre_counts(dataset)
dataset_genre_counts
```

Out[68]:

	count
Drama	494
Comedy	378
Action	319
Adventure	271
Thriller	176
Crime	156
Romance	140
Biography	103
Horror	103
Sci-Fi	94
Fantasy	88
Animation	82
Mystery	80
Family	66

	count
Music	29
History	29
Sport	20
Documentary	7
War	7
Western	6
Musical	3

So Drama, Comedy, Action and Adventure are the four most numerous genres in the dataset.

There are many factors that make a successful movie. We all know that bad movies exist in all genres. There are superhero films that are among the best selling films ever made, like Avengers Endgame, and superhero films that are so poorly executed that the public is barely aware of them, like The Specials. Therefore, it would be foolish to take an average of all the films in each genre and declaring the highest average as the most successful genre. It would much more valuable to select a list of the best performing films in our dataset and analyzing what genres are represented in those films.

To do this, I'll set a revenue-earned threshold. If I set it to 490 million dollars or above, I'll get exactly 100 films, making percentages effortless to calculate. This number is so close to 500 million, I'll refer to these films as half-billion dollar films.

In [69]:
```
revenue_threshold = 490000000
cols = ['revenue_rank', 'title', 'studio', 'year', 'runtime_minutes',
        'imdb_genre_1', 'imdb_genre_2', 'imdb_genre_3', 'tn_worldwide_gross']
half_billion = dataset[dataset['tn_worldwide_gross'].map(lambda x :
                                    True if x>=revenue_threshold else False)]
half_billion[cols]
```

Out[69]:

	revenue_rank	title	studio	year	runtime_minutes	imdb_genre_1	imdb_genre_2	imdb_genre_3	tn_w
0	1	Avengers: Infinity War	BV	2018	149	Action	Adventure	Sci-Fi	
1	2	Jurassic World	Uni.	2015	124	Action	Adventure	Sci-Fi	
2	3	Avengers: Age of Ultron	BV	2015	141	Action	Adventure	Sci-Fi	
3	4	Black Panther	BV	2018	134	Action	Adventure	Sci-Fi	
4	5	Jurassic World: Fallen Kingdom	Uni.	2018	128	Action	Adventure	Sci-Fi	
...	...	...	...	...	...	...	...	...	
95	96	The Boss Baby	Fox	2017	97	Adventure	Animation	Comedy	
96	97	Dunkirk	WB	2017	106	Action	Drama	History	
97	98	Wreck-It Ralph	BV	2012	101	Adventure	Animation	Comedy	
98	99	How to Train Your Dragon	P/DW	2010	98	Action	Adventure	Animation	
99	100	Rio 2	Fox	2014	101	Adventure	Animation	Comedy	

100 rows × 9 columns

Of these 100 films, I'll see what genres are represented.

In [70]:
```
half_billion_counts = genre_counts(half_billion)
half_billion_counts = half_billion_counts.reset_index()
half_billion_counts
```

Out[70]:

	index	count
0	Adventure	86
1	Action	61
2	Comedy	34
3	Animation	33
4	Sci-Fi	27
5	Fantasy	17
6	Drama	10
7	Thriller	8
8	Family	5
9	Horror	3
10	Biography	3
11	Crime	3
12	Mystery	1
13	Romance	1
14	Music	1
15	History	1

From this, I can see that the most numerous genres are Adventure, Action, Comedy, Animation, and Sci-Fi.

It's important that I define what these genre definitions mean to IMDB, which is where I got the genre information. The data below is copied straight from IMDB's website. In order of popularity:

Adventure: Should contain numerous consecutive and inter-related scenes of characters participating in hazardous or exciting experiences for a specific goal. Often include searches or expeditions for lost continents and exotic locales, characters embarking in treasure hunt or heroic journeys, travels, and quests for the unknown. Not to be confused with Action, and should only sometimes be supplied with it. Subjective. Examples: The Goonies (1985) |The Lord of The Rings: The Fellowship of the Ring (2001) | Life of Pi (2012)

Action: Should contain numerous scenes where action is spectacular and usually destructive. Often includes non-stop motion, high energy physical stunts, chases, battles, and destructive crises (floods, explosions, natural disasters, fires, etc.) Note: if a movie contains just one action scene (even if prolonged, i.e. airplane-accident) it does not qualify. Subjective. Examples: Die Hard (1988) |The Avengers (2012) | Wonder Woman (2019)

Comedy: Virtually all scenes should contain characters participating in humorous or comedic experiences. The comedy can be exclusively for the viewer, at the expense of the characters in the title, or be shared with them. Please submit qualifying keywords to better describe the humor (i.e. spoof, parody, irony, slapstick, satire, black-comedy etc). If the title does not conform to the 'virtually all scenes' guideline then please do not add the comedy genre; instead, submit the same keyword variations described above to signify the comedic elements of the title. Subjective. Examples: Some Like it Hot (1959) |When Harry Met Sally... (1989) | Bridesmaids (2011)

Animation: Over 75% of the title's running time should have scenes that are wholly, or part-animated. Any form of animation is acceptable, e.g., hand-drawn, computer-generated, stop-motion, etc. Puppetry does not count as animation, unless a form of animation such as stop-motion is also applied. Incidental animated sequences should be indicated with the keywords part-animated or animated-sequence instead. Although the overwhelming majority of video games are a form of animation it's okay to forgo this genre when adding them as this is implied by the title type. Objective. Examples: Spirited Away (2001) |The Lion King (1994) | "The Simpsons" (1987)

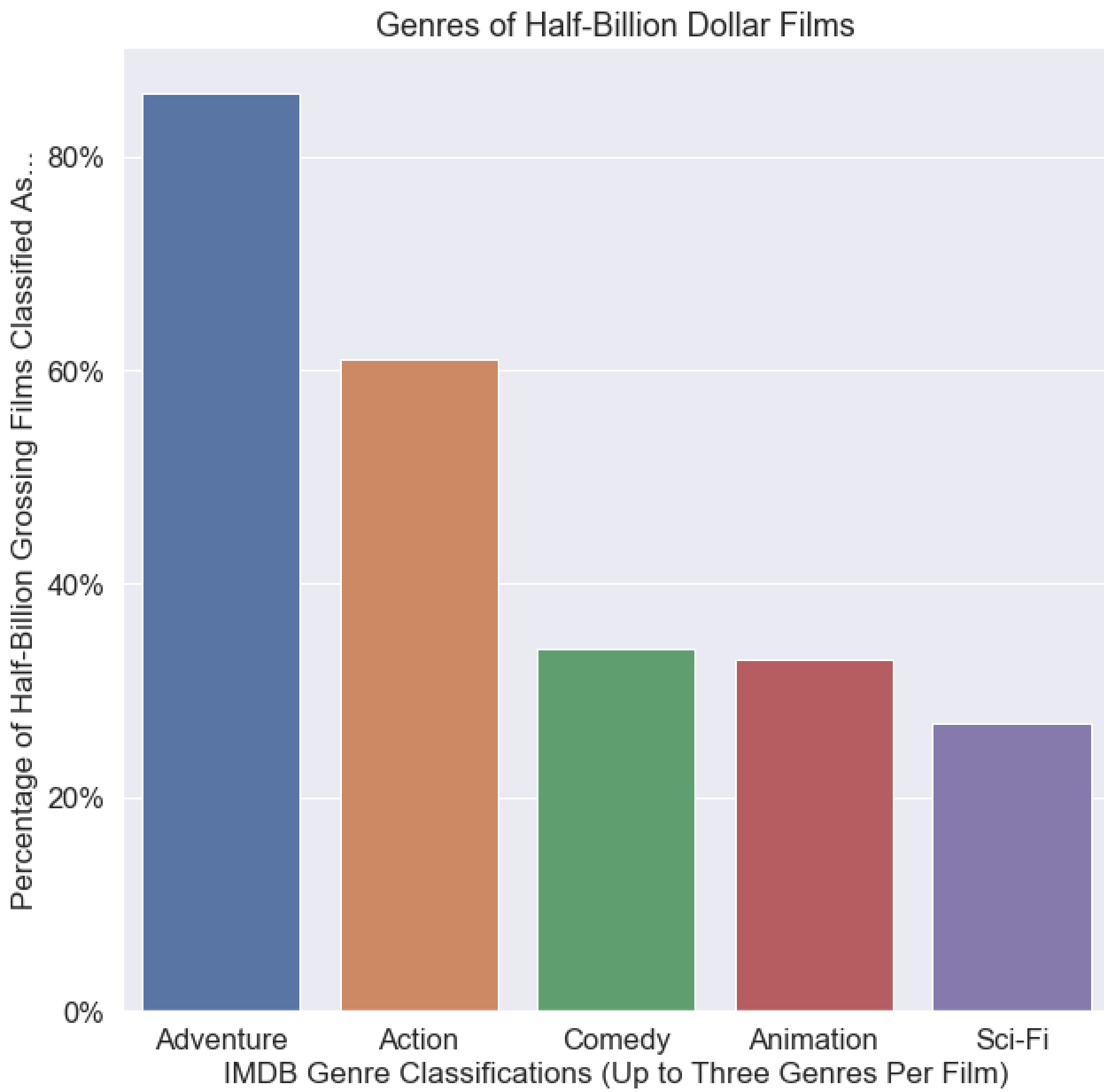
Sci-Fi: Numerous scenes, and/or the entire background for the setting of the narrative, should be based on speculative scientific discoveries or developments, environmental changes, space travel, or life on other planets. Subjective. Examples: Star Wars (1977) |The Matrix (1999) | Alien (1979)

Graphic 1

For this graphic I want to show what genres are the most numerous in the films of our dataset that reach half a billion dollars. I'll use a bar chart to do this.

In [71]:
```
half_billion_counts_percent = half_billion_counts.copy()
genres, percent = half_billion_counts_percent.columns

half_billion_counts_percent[percent] = half_billion_counts_percent[percent]/len(half_billi

plt.figure(figsize=(10, 10))
sns.set(font_scale = 1.5)

xlabel = 'IMDB Genre Classifications (Up to Three Genres Per Film)'
ylabel = 'Percentage of Half-Billion Grossing Films Classified As...'
graphic_title = 'Genres of Half-Billion Dollar Films'

q1_ax = sns.barplot(y=percent,x=genres, data=half_billion_counts_percent.head())

#Formatting
q1_ax.set_xlabel(xlabel, fontsize = 17)
q1_ax.set_ylabel(ylabel, fontsize = 17)
q1_ax.set(title=graphic_title)
current_values = q1_ax.get_yticks()

q1_ax.set_yticklabels(['{:,.0%}'.format(x) for x in current_values]);
```

```
<ipython-input-71-4cc507009cee>:21: UserWarning: FixedFormatter should only be used toget
her with FixedLocator
  q1_ax.set_yticklabels(['{:,.0%}'.format(x) for x in current_values]);
```



The results show that over half of the half-billion grossing films included the genres action and adventure.

Question 1 Answered?

Question 1: What genres of film produce the highest box office revenue?

My analysis has answered this question as well as it can be, however the question itself has flaws. By IMDB's own admission, most film genres are subjective. What one person finds funny, another might find disturbing. What one person finds adventurous, another finds timid. But if we accept the widely understood definitions of these classifications, then the analysis is sound. Action and adventure films do the best at the box office.

To parse genre considerations beyond generalities is an exercise in art criticism, not business analysis.

Question 2

Question 2: What is the best month to release a film in to generate the most revenue?

This question requires far less analysis. I'd like to look at it in two different ways. The first will be a histogram to see what months the half-billion grossing movies were released in. The second is a simple average of worldwide gross of all the films in the dataset binned by month.

I'll count the films by release month in two different dataframes, so first I'll define a function that performs this.

In [72]:
```
def release_month_count(df,div,sig):
    rt = df.groupby('tn_release_month')['tn_num_month','tn_domestic_gross',
                                        'tn_foreign_gross',
                                        'tn_worldwide_gross'].mean()

    #These two rows will be used in the next graphic
    #Count the total films in each month
    rt['count'] = df.groupby('tn_release_month')['title'].count()
    #Lets reduce the significant digits to make the graph more readable.
    #We'll go with millions of dollars.
    rt['count_percent'] = (rt['count']/len(df)).round(decimals=sig+2)


    cols = ['tn_domestic_gross','tn_foreign_gross','tn_worldwide_gross']

    rt[cols[0:3]] = ((rt[cols[0:3]]/div).round()).astype(int)
    rt.sort_values('tn_num_month',inplace=True)
    rt.reset_index(inplace=True)
    rt.drop(columns='tn_num_month',inplace=True)
    return rt

#The last two columns are not relevant to this graphic, so I'll skip them.
binned_by_month = release_month_count(dataset,1000000,1).iloc[:,0:4]
binned_by_month
```

```
<ipython-input-72-0f1e97393514>:2: FutureWarning: Indexing with multiple keys (implicitly
converted to a tuple of keys) will be deprecated, use a list instead.
  rt = df.groupby('tn_release_month')['tn_num_month','tn_domestic_gross',
```

Out[72]:

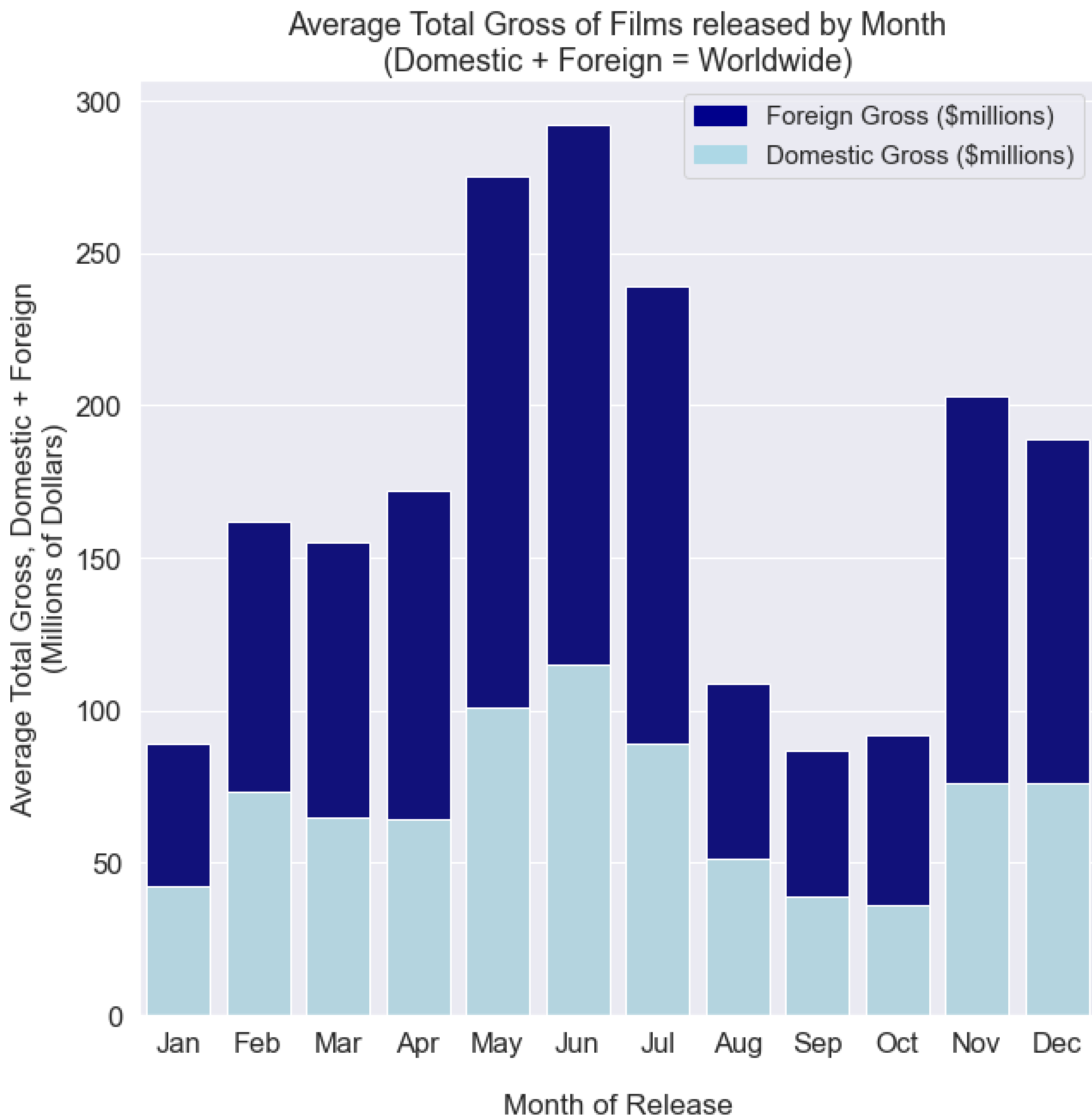
	tn_release_month	tn_domestic_gross	tn_foreign_gross	tn_worldwide_gross
0	Jan	42	47	89
1	Feb	73	89	162
2	Mar	65	89	155
3	Apr	64	108	172
4	May	101	174	275
5	Jun	115	177	292
6	Jul	89	150	239
7	Aug	51	58	109
8	Sep	39	48	87
9	Oct	36	57	92
10	Nov	76	127	203
11	Dec	76	113	189

This shows that the biggest money makers of the year are released in the summer months of May, June and

July.

Graphic 2

In [73]:
```
#Shorthand for the column names
mon, dom, fgn, wor = binned_by_month.columns

#Labels
title = "Average Total Gross of Films released by Month\n(Domestic + Foreign = Worldwide)"
xlabel = '\nMonth of Release'
ylabel = 'Average Total Gross, Domestic + Foreign\n(Millions of Dollars)'

# set the figure size
plt.figure(figsize=(10, 10))

# top bar → take only worldwide values from the data
total = binned_by_month[[mon,wor]]

# bar chart 1 → top bars (group of worldwide total)
q2_ax1 = sns.barplot(x=mon,  y=wor, data=total, color='darkblue')

# bottom bar → take only domestic values from the data
domestic = binned_by_month[[mon,dom,wor]]

# bar chart 2 → bottom bars (group of domestic)
q2_ax2 = sns.barplot(x=mon, y=dom, data=domestic, estimator=sum, ci=None,  color='lightblue

# add legend
top_bar = mpatches.Patch(color='darkblue', label='Foreign Gross ($millions)')
bottom_bar = mpatches.Patch(color='lightblue', label='Domestic Gross ($millions)')
plt.legend(handles=[top_bar, bottom_bar], fontsize = 15)
q2_ax1.set_xlabel(xlabel, fontsize = 17)
q2_ax1.set_ylabel(ylabel, fontsize = 17)
q2_ax1.set(title=title)

# show the graph
plt.show()
```



The graph shows foreign and domestic, which add together to get the worldwide gross.

There are two seasons a year that offer the greatest revenue potential for a movie release:

1. May–July
2. November–December.

Now I'm going to show how many of the half a billion films were released for each month of the year.

Even though we've used all bar charts so far, this plot should also be a bar chart because it fits the data.

In [74]:
```
binned_by_month_half_billion = release_month_count(half_billion,1000000,0)[['tn_release_mon
binned_by_month_half_billion
```

```
<ipython-input-72-0f1e97393514>:2: FutureWarning: Indexing with multiple keys (implicitly converted to a tuple of keys) will be deprecated, use a list instead.
  rt = df.groupby('tn_release_month')['tn_num_month','tn_domestic_gross',
```

Out[74]:

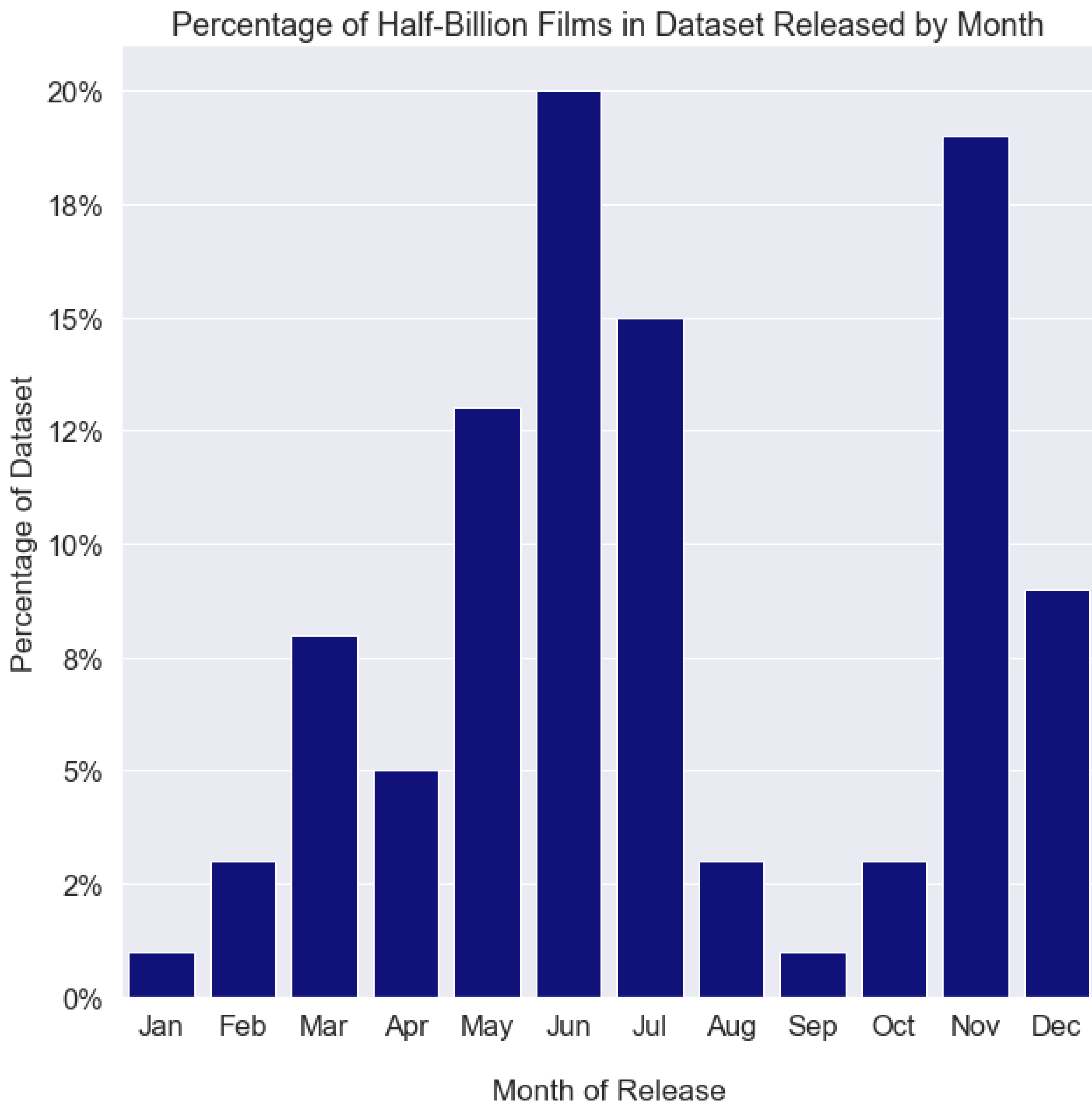
	tn_release_month	count_percent
0	Jan	0.01
1	Feb	0.03
2	Mar	0.08
3	Apr	0.05
4	May	0.13
5	Jun	0.20
6	Jul	0.15
7	Aug	0.03
8	Sep	0.01
9	Oct	0.03
10	Nov	0.19
11	Dec	0.09

Graphic 3

In [75]:

```
#Shorthand for column names
mon, per = binned_by_month_half_billion.columns

#Labels
title = "Percentage of Half-Billion Films in Dataset Released by Month"
xlabel = '\nMonth of Release'
ylabel = 'Percentage of Dataset'

# set the figure size
plt.figure(figsize=(10, 10))

# bar chart 1 → top bars (group of worldwide total)
q2_ax2 = sns.barplot(x=mon,  y=per, data=binned_by_month_half_billion, color='darkblue')

#Formatting
q2_ax2.set_xlabel(xlabel, fontsize = 17)
q2_ax2.set_ylabel(ylabel, fontsize = 17)
q2_ax2.set(title=title)
current_values = q2_ax2.get_yticks()
q2_ax2.set_yticklabels(['{:,.0%}'.format(x) for x in current_values]);

# show the graph
plt.show();
```

```
<ipython-input-75-0c81eb6accd6>:20: UserWarning: FixedFormatter should only be used toget
her with FixedLocator
  q2_ax2.set_yticklabels(['{:,.0%}'.format(x) for x in current_values]);
```



The half-billion dollar films follow the same release season trends.

However, it's worth noting that there are films that made half a billion dollars that were released during the slowest months of the year. So it is possible to make half a billion even in off season months.

Question 2 Answered?

Question 2: What is the best month to release a film to generate the most revenue?

The business question has been answered as well as it can be with the data given, however, more analysis needs to be done to choose a release date for a film.

This question ignores a lot of outside factors regarding release dates. A more thorough analysis would be to separate the films by week instead of month, but even that doesn't go far enough. There are so many events that occur outside of a regular calendar year. It could be that a popular video game was released one week, so people stayed home rather than pay for a film. Also, choosing a release date needs to consider what the competition is doing. We don't want to release a movie that targets the same audience as a Marvel film the same week a Marvel film debuts.

Question 3

Question 3: What writers, directors, producers, actors and actresses have the highest revenue earning potential?

To answer this question, once again, I need to answer it two ways. The first is which category is most consistent, writer, director, producer or actor. Then, I can list the top ten talent with the highest revenue yield in each category.

The writers job has a lot of bad information in it. It contains people who get credit for creating characters that are featured in the mega popular superhero films, but the character creaters didn't write the movie at all. Unfortunatley, there's no way to isolate the screenwriters, so instead I'll just take people who have at least three films on their resume. I'll do this for all creatives.

So, I'll add a column that I'll use to count the films a person has worked on, and then use that to filter the data.

In [76]:
```
def counting_films(df):
    new = df.groupby('person_id')['movie_id','primary_name'].count()
    new.rename(columns = {'movie_id' :'film_count'}, inplace=True)
    df = pd.merge(df,new['film_count'], how='inner',left_on='person_id', right_on='person_i
    return df

writers = counting_films(writers)
directors = counting_films(directors)
producers = counting_films(producers)
actors = counting_films(actors)
actresses = counting_films(actresses)
actorsneutral = counting_films(actorsneutral)
writers
```

```
<ipython-input-76-bfdda0a7229d>:2: FutureWarning: Indexing with multiple keys (implicitly converted to a tuple of keys) will be deprecated, use a list instead.
  new = df.groupby('person_id')['movie_id','primary_name'].count()
```

Out[76]:

	index	movie_id	ordering	person_id	category	job	characters	primary_name	death_year	film
0	6787	tt0359950	6.0	nm0862122	writer	based on the short story by	None	James Thurber	1961.0	
1	6784	tt0359950	5.0	nm0175726	writer	screenplay by	None	Steve Conrad	NaN	
2	6785	tt2358925	6.0	nm0175726	writer	written by	None	Steve Conrad	NaN	
3	6786	tt2543472	6.0	nm0175726	writer	screenplay by	None	Steve Conrad	NaN	
4	1898	tt0365907	6.0	nm0088747	writer	based on the novel by	None	Lawrence Block	NaN	
...	...	...	...	...	...	...	...	...	...	
2203	9258	tt7349662	9.0	nm9259302	writer	based on the book by	None	Ron Stallworth	NaN	
2204	9310	tt7388562	6.0	nm3885256	writer	None	None	Terence Berden	NaN	
2205	9293	tt7535780	3.0	nm0434525	writer	short story	None	Franz Kafka	1924.0	
2206	9240	tt7784604	NaN	nm4170048	writer	NaN	NaN	Ari Aster	NaN	
2207	9274	tt7959026	5.0	nm10095627	writer	inspired by the New York Times Magazine Articl...	None	Sam Dolnick	NaN	

2208 rows × 10 columns

Now I need to add the film grossing information to that personnel data.

```
In [77]: def add_movie_stats(org,cls,div):
             new = pd.merge(org,dataset[cls+['movie_id']], how='inner',left_on='movie_id', right_on=
             new[cls] = (new[cls]/div).round(0)
             return new

         cols = ['tn_worldwide_gross']
         divisor = 1000000
         writers = add_movie_stats(writers,cols,divisor)
         directors = add_movie_stats(directors,cols,divisor)
         producers = add_movie_stats(producers,cols,divisor)
         actors  = add_movie_stats(actors,cols,divisor)
         actresses = add_movie_stats(actresses,cols,divisor)
         actorsneutral = add_movie_stats(actorsneutral,cols,divisor)
```

We can't hire dead people, so let's get them out of the dataset.

```
In [78]: writers_alive = writers[writers['death_year'].isna()]
         directors_alive = directors[directors['death_year'].isna()]
         producers_alive = producers[producers['death_year'].isna()]
         actors_alive = actors[actors['death_year'].isna()]
         actresses_alive = actresses[actresses['death_year'].isna()]
         actorsneutral_alive = actorsneutral[actorsneutral['death_year'].isna()]
```

Now I need to see how the top creatives' averages differ.

```
In [79]: def top(df,floor,num,label):
             new = df[df['film_count'].map(lambda x : True if x>=floor else False)]
             tops = new.groupby('primary_name')[['tn_worldwide_gross']].mean().sort_values('tn_worl
             tops['tn_worldwide_gross'] = tops['tn_worldwide_gross'].round(0).astype(int)
             last = pd.merge(tops,df[['primary_name','film_count']], how='left',left_on='primary_nar
             last.rename(columns={'primary_name':label+"'s name",'tn_worldwide_gross' : label+"'s Gi
             last = last[~last.duplicated()].reset_index(drop=True)
             return last.reset_index()

         #Here I define the minimum number of films a creative must have credited to
         #them in order to be included in the dataset.
         the_floor = 3
         #This variable decides the number of creatives analyzed for each category.
         the_top = 50

         writers_top = top(writers_alive,the_floor,the_top,'Writer')
         directors_top = top(directors_alive,the_floor,the_top,'Director')
         producers_top = top(producers_alive,the_floor,the_top,'Producer')
         actors_top = top(actors_alive,the_floor,the_top,'Actor')
         actresses_top = top(actresses_alive,the_floor,the_top,'Actress')
         actorsneutral_top = top(actorsneutral_alive,the_floor,the_top,'(Gender Inclusive) Actor')
```

Now I'll put the various averages into a single table.

In [80]:
```python
#Since each dataframe I'm merging has exactly 50 rows, we can merge by index.
def merging(df1,df2):
    tem = pd.merge(df1,df2,how='inner',left_on='index',right_on='index')
    return tem

#Now I'll merge all six dataframes together so I can perform calculations
#on all three at once.
temp1 = merging(writers_top,directors_top)
temp2 = merging(producers_top,actors_top)
temp3 = merging(actresses_top,actorsneutral_top)
temp4 = merging(temp1,temp2)
all_creatives = merging(temp4,temp3)

#This defines which rows I need for the graphic
des_rows = ["Writer's Gross","Director's Gross","Producer's Gross",
            "Actor's Gross","Actress's Gross",
            "(Gender Inclusive) Actor's Gross"]

#Now I'll average all the totals together
all_creatives_average = pd.DataFrame(all_creatives[des_rows].mean()
                                     .round(0).astype(int))
all_creatives_average.reset_index(inplace=True)
all_creatives_average.rename(columns={'index':'Creative Jobs',
                                      0:"Top "+str(the_top)+
                                      " Average gross ($MM)"},inplace=True)
all_creatives_average
```

Out[80]:

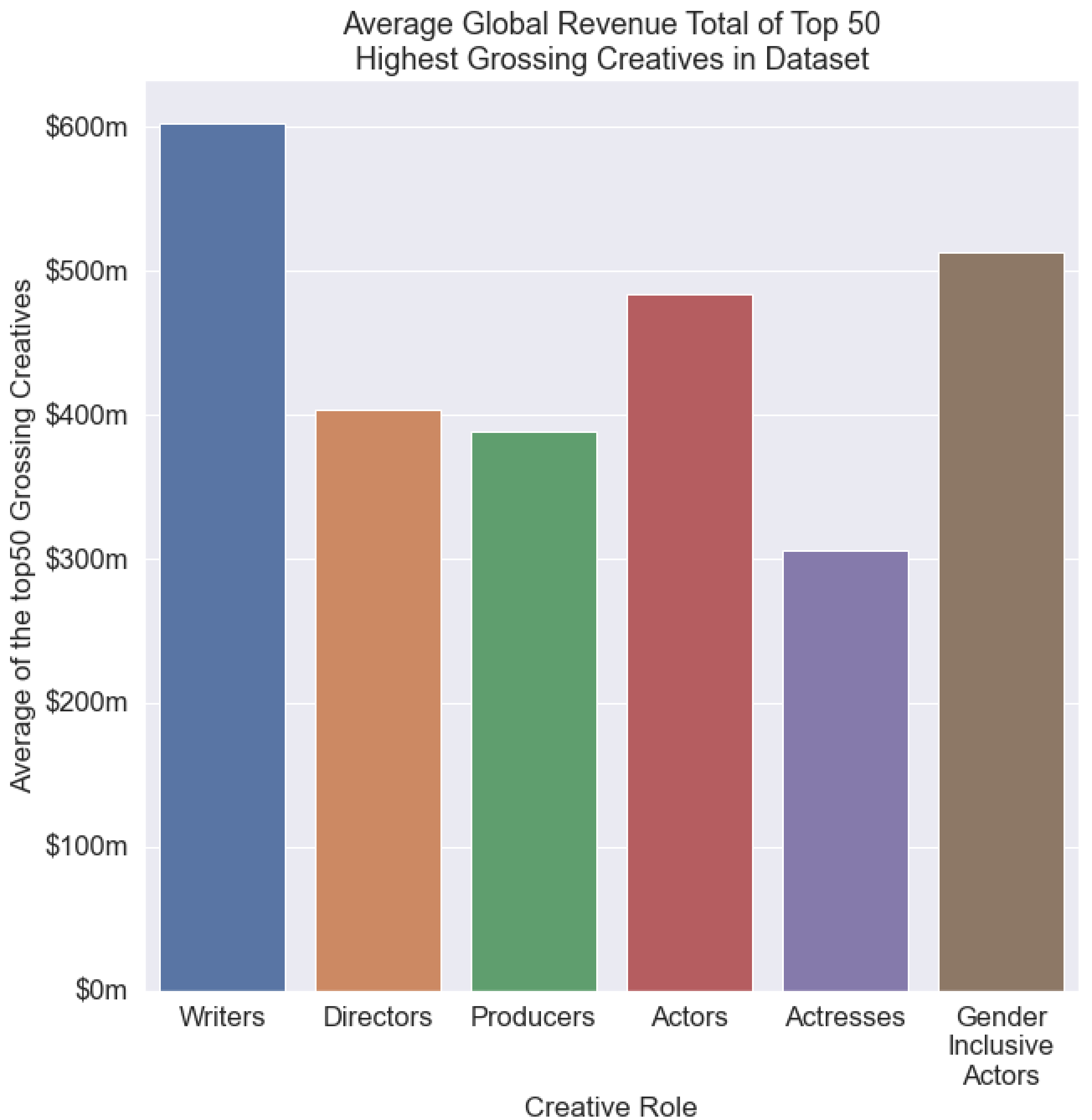
	Creative Jobs	Top 50 Average gross ($MM)
0	Writer's Gross	603
1	Director's Gross	403
2	Producer's Gross	388
3	Actor's Gross	484
4	Actress's Gross	306
5	(Gender Inclusive) Actor's Gross	513

Graphic 4

Now for the graphic

In [81]:
```python
#Shorthand column labels
job, grs = all_creatives_average.columns

#Copy so I can change the dataframe just for this graphic
creatives_gross_graphic = all_creatives_average.copy()

#Labels (abb is abbreviated)
abb_rows = ['Writers','Directors','Producers','Actors',
            'Actresses','Gender\nInclusive\nActors']
#This for loop and corresponding dataframe command labels the graphic
#as specified above
row_change = {}
for i in range(len(des_rows)):
    row_change[des_rows[i]]=abb_rows[i]
creatives_gross_graphic['Creative Jobs'] = creatives_gross_graphic['Creative Jobs'].map(lam

#More labeling
xlabel = "Creative Role"
ylabel = "Average of the top" +str(the_top)+" Grossing Creatives"
title = "Average Global Revenue Total of Top " +str(the_top)+"\nHighest Grossing Creatives

#Setting the plot size
plt.figure(figsize=(10, 10))
sns.set(font_scale = 1.5)

#Creating the plot
q3_ax = sns.barplot(y=grs,x=job, data=creatives_gross_graphic)

#Formatting
q3_ax.set_xlabel(xlabel, fontsize = 17)
q3_ax.set_ylabel(ylabel, fontsize = 17)
q3_ax.set(title=title)
current_values = q3_ax.get_yticks()
current_values[:]=current_values[:]
q3_ax.set_yticklabels(['${:.0f}m'.format(x) for x in current_values]);
```

```
<ipython-input-81-f88ff65a17e8>:35: UserWarning: FixedFormatter should only be used toget
her with FixedLocator
  q3_ax.set_yticklabels(['${:.0f}m'.format(x) for x in current_values]);
```



According to the data, writers and actors have the largest impact on a film's total gross. So I'd recommend hiring some big names in those two categories. Despite the data, I highly reccomend pay equality between actors and actresses. We cannot make popular movies without actresses. We should pay them well. Also, if it gets out that your film studio does not have pay equality between men and women, the public will not be happy.

Anyway, with this in mind, I'll list the top ten highest grossing creatives in the categories of writers, actors and actresses.

Graphic 5

In [82]:
```python
all_creatives.rename(columns = {'index':'Rank'},inplace=True)
all_creatives['Rank'] = all_creatives['Rank'] + 1
top_ten = all_creatives[["Rank","Writer's name","Actor's name","Actress's name"]].head(10)
top_ten
```

Out[82]:

	Rank	Writer's name	Actor's name	Actress's name
0	1	Guillermo del Toro	Richard Armitage	Sandra Bullock
1	2	Christopher Markus	Ian McKellen	Bryce Dallas Howard
2	3	Stephen McFeely	Robert Downey Jr.	Evangeline Lilly
3	4	Derek Connolly	Chris Evans	Scarlett Johansson
4	5	David S. Goyer	Chris Pratt	Eloise Mumford
5	6	Chris McKenna	Chris Hemsworth	Anne Hathaway
6	7	Erik Sommers	Benjamin Bratt	Holly Hunter
7	8	Philippa Boyens	Andy Serkis	Judi Dench
8	9	Fran Walsh	Mark Ruffalo	Angelina Jolie
9	10	Suzanne Collins	Martin Freeman	Emily Mortimer

These are the highest earning writers, actors and actresses in our dataset.

It's worth notnig that each film project has different factors for choosing the right creatives. You cannot just pick a few of the names at the top and expect a smash success.

Question 3 Answered?

Question 3: What writers, directors, producers, actors and actresses have the highest revenue earning potential?

Similar to month, there are many other factors to consider when hiring writers and actors. For starters, is someone who pays to go see Hobbit 2: Desolation of Smaug really going because Evangeline Lilly is in the film, or are they going to see a fantasy adventure film set in the same world as the Lord of the Rings films they saw when they were eleven? Considering how much pull a writer or actor has on an audience has its natural limits.

That being said, we do know which creatives had starring roles in the highest grossing films, but we don't know how prominent a role the actors played in the film, or how the marketing pushed each film.

We do know which creatives had starring roles in the highest grossing films, but we don't know how prominent a role the actors played in the film, or how the marketing advertised each film. Was the film billed as the latest thriller from Steven Spielberg, the latest Star Wars Movie, or Angelina Jolie's role of her career?

We know which people were attached to the highest-grossing films ever released, but we don't know how much draw their names had to the audience.

Conclusion

The analysis I’ve done leads to these three conclusions:

1. The public likes action and adventure films.
2. The best release windows are May–July and November–December.
3. Writers and actors are the best creative personnel to increase a films revenue potential.

This analysis is limited by time and budget. There are many other factors to consider when trying to launch a film business. Some areas to consider looking into before producing a film are:

1. How much do existing franchises influence the public’s film choices?
2. If existing film franchises have a lot of draw, does the public have the appetite for more after they’ve already spent a lot of time and money on the existing franchises?
3. Should Microsoft find an existing property and option it for film or start new?
4. Is streaming a better option for building the brand and generating revenue?
5. Should Microsoft purchase one of the big studios instead of entering the competition?

I think more time spent in answering the questions above would go a long way in helping Microsoft be successful with their film aspirations.