Phase 2 Project Submission

Please fill out:

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- Student pace: self paced
- Scheduled project review date/time: 1/10/25 @ 3:00pm
- Instructor name: Brandon Collins
- Blog post URL: https://dev.to/connoranastasio/the-birthday-paradox-a-statistical-breakdown-and-how-it-relates-to-online-security-52ac

Blockbusters at the Box Office: Investment Analysis

Overview

This project focuses on generating statistical insights for movies. Here we are advising a brand new movie studio on how they can begin generating profit. Our analysis will examine movie genres, distribution areas, runtimes, ratings, and budgets to make informed suggestions on what is most likely to succeed.

Business Problem

Your company now sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of your company's new movie studio can use to help decide what type of films to create.

Data Understanding

Our analysis will focus on certain aspects of movies by utilizing data from various sources:

IMDB: user ratings and movie genres (data/im.db)
Rotten Tomatoes: runtime information (data/rt.movie_info.tsv)
The Numbers: movie budgets (data/tn.movie_budgets.csv)

We will use these data to gain insight into the following questions:

"Which genres are the highest rated?"
"How important is a worldwide release for revenue compared to only domestic?"
"Is there a relationship between movie length and revenue?"

Data Preparation

Let's begin by setting up what we will need for our analysis.

In [1]:
```
#import our libraries and modules
import sqlite3
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import figure
from matplotlib.ticker import StrMethodFormatter
%matplotlib inline

# set float to 2 decimal places
pd.set_option('display.float_format', lambda x: '%.2f' % x)
```

Data Cleaning

Rotten Tomatoes Dataset

In [2]:
```
movie_info_df = pd.read_csv('data/rt.movie_info.tsv', sep='\t')
movie_info_df.head()
```

Out[2]:

	id	synopsis	rating	genre	director	writer	thea
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	O
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	De
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	

We only need the "box_office", "genre" and "runtime" columns from this dataset. Let's clean those up and drop the others.

In [3]:

```
#make a copy of our dataframe for cleaning
movie_info_df_copy = movie_info_df.copy()
runtime_df = movie_info_df_copy
runtime_df
```

Out[3]:

	id	synopsis	rating	genre	director	
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Ti
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	Cronenbe
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison .
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Attanasio|M C
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles (
...	...	...	...	...	...	
1555	1996	Forget terrorists or hijackers -- there's a ha...	R	Action and Adventure|Horror|Mystery and Suspense	NaN	
1556	1997	The popular Saturday Night Live sketch was exp...	PG	Comedy|Science Fiction and Fantasy	Steve Barron	Terry Turn Da Aykroyd|
1557	1998	Based on a novel by Richard Powell, when the l...	G	Classics|Comedy|Drama|Musical and Performing Arts	Gordon Douglas	
1558	1999	The Sandlot is a coming-of-age story about a g...	PG	Comedy|Drama|Kids and Family|Sports and Fitness	David Mickey Evans	David Evans|
1559	2000	Suspended from the force, Paris cop Hubert is ...	R	Action and Adventure|Art House and Internation...	NaN	Luc I

1560 rows × 12 columns

In [4]:
```
# drop unnecessary columns; ignore errors if code is re-run
runtime_df.drop(['synopsis', 'rating', 'writer', 'theater_date', 'dvd_date',
                axis=1, inplace=True, errors='ignore')

# drop null values from box office, genre, runtime columns
runtime_df.dropna(subset=['box_office'], inplace=True)
runtime_df.dropna(subset=['runtime'], inplace=True)
runtime_df.dropna(subset=['genre'], inplace=True)

# strip 'minutes' from rows in runtime
runtime_df['runtime']= runtime_df['runtime'].str.strip(' minutes')
runtime_df['runtime'] = (runtime_df['runtime'].astype(int))

#remove commas from box_office and convert to float
runtime_df["box_office"] = runtime_df["box_office"].str.replace(',', '')
runtime_df
```

Out[4]:

	genre	box_office	runtime
1	Drama|Science Fiction and Fantasy	600000	108
6	Comedy	41032915	82
7	Drama	224114	123
8	Drama	134904	117
15	Comedy|Drama|Mystery and Suspense	1039869	108
...	...	...	...
1541	Action and Adventure|Science Fiction and Fantasy	25335935	119
1542	Comedy|Drama	1416189	129
1545	Horror|Mystery and Suspense	59371	98
1546	Art House and International|Comedy|Drama	794306	97
1555	Action and Adventure|Horror|Mystery and Suspense	33886034	106

338 rows × 3 columns

Movie Budgets

In [5]:
```
budgets_df = pd.read_csv('data/tn.movie_budgets.csv')
budgets_df
```

Out[5]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_g
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721
...	...	...	...	...	...	
5777	78	Dec 31, 2018	Red 11	$7,000	$0	
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181

5782 rows × 6 columns

Let's drop "release_date" and reformat the budget and gross columns.

In [6]:

```
# Drop release_date column

cleaned_budgets_df = budgets_df.drop(columns=['release_date'])
cleaned_budgets_df
```

Out[6]:

	id	movie	production_budget	domestic_gross	worldwide_gross
0	1	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...	...	...
5777	78	Red 11	$7,000	$0	$0
5778	79	Following	$6,000	$48,482	$240,495
5779	80	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	A Plague So Pleasant	$1,400	$0	$0
5781	82	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 5 columns

In [7]:

```
# Remove currency signs and commas from row entries; cast the columns as int
cleaned_budgets_df['domestic_gross'] = cleaned_budgets_df['domestic_gross'].

cleaned_budgets_df['worldwide_gross'] = cleaned_budgets_df['worldwide_gross'

cleaned_budgets_df['production_budget'] = cleaned_budgets_df['production_buc
```

In [8]:

```
#sort largest gross is shown first
cleaned_budgets_df.sort_values('worldwide_gross', ascending=False)

cleaned_budgets_df
```

Out[8]:

	id	movie	production_budget	domestic_gross	worldwide_gross
0	1	Avatar	425000000	760507625	2776345279
1	2	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Dark Phoenix	350000000	42762350	149762350
3	4	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
...	...	...	...	...	...
5777	78	Red 11	7000	0	0
5778	79	Following	6000	48482	240495
5779	80	Return to the Land of Wonders	5000	1338	1338
5780	81	A Plague So Pleasant	1400	0	0
5781	82	My Date With Drew	1100	181041	181041

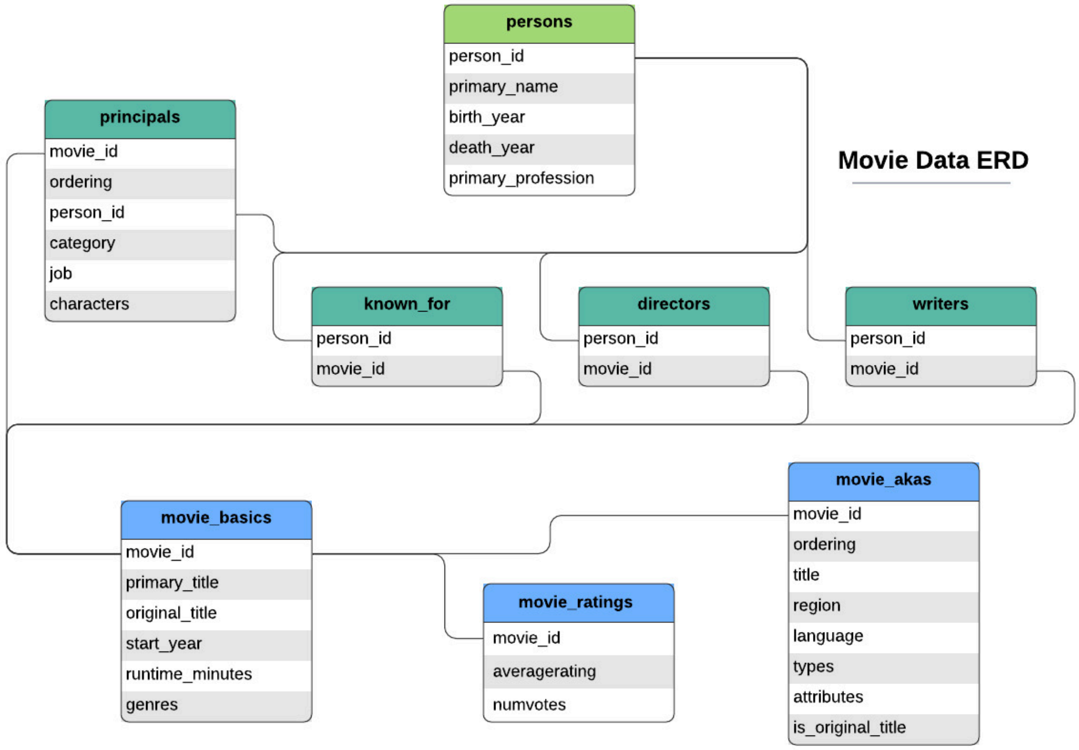
5782 rows × 5 columns

IMDB database

Since im.db is a .db (SQL relational database) file, we will be using pandas and sqlite3 to work with it. Let's first create a connection:

In [9]:

```
# Load the SQLite database
db_path = 'data/im.db'
conn = sqlite3.connect(db_path)
curr = conn.cursor
```



The tables we will be focusing on are movie_basics and movie_ratings. Let's explore them now and clean as needed so they are ready to be joined later.

In [10]:
```
#examine movie_basics
movie_basics = pd.read_sql_query("SELECT * FROM movie_basics;", conn)
movie_basics.head()
```

Out[10]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	
0	tt0063540	Sunghursh	Sunghursh	2013	175.00	Action,Crim
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.00	Biograph
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.00	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comed
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.00	Comedy,Drama,

In [11]:
```
movie_basics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   movie_id         146144 non-null  object
 1   primary_title    146144 non-null  object
 2   original_title   146123 non-null  object
 3   start_year       146144 non-null  int64
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [12]:

```
# examine movie_ratings
ratings_df = pd.read_sql("""SELECT * FROM movie_ratings;""", conn)

ratings_df.head()
```

Out[12]:

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

In [13]:

```
ratings_df.describe()
```

Out[13]:

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

Data Engineering

Budgets

Let's add two columns to our budgets dataframe for net profit from domestic and worldwide gross, respectively:

In [14]:
```
#Create net profit columns to show domestic and worldwide net profits
cleaned_budgets_df['domestic_profit'] = cleaned_budgets_df['domestic_gross']
cleaned_budgets_df['worldwide_profit'] = cleaned_budgets_df['worldwide_gross

#Keep in Descending order
cleaned_budgets_df.sort_values('worldwide_profit', ascending=False)
```

Out[14]:

	id	movie	production_budget	domestic_gross	worldwide_gross	domesti
0	1	Avatar	425000000	760507625	2776345279	335
42	43	Titanic	200000000	659363944	2208208395	459
6	7	Avengers: Infinity War	300000000	678815482	2048134200	378
5	6	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220	630
33	34	Jurassic World	215000000	652270625	1648854864	437
...	...	...	...	...	...	
352	53	Town & Country	105000000	6712451	10364769	-98
341	42	Men in Black: International	110000000	3100000	3100000	-106
193	94	Mars Needs Moms	150000000	21392758	39549758	-128
194	95	Moonfall	150000000	0	0	-150
2	3	Dark Phoenix	350000000	42762350	149762350	-307

5782 rows × 7 columns

SQL Database: Genres and Ratings Join

Let's join the "movie_basics" and "movie_ratings" on their shared primary key "movie_id" to create a new dataframe to work with:

In [15]:
```
#joining movie_basics table that contains movie_id and genres and the movie_
ratings_genres = pd.read_sql("""
    SELECT mb.movie_id AS Movie_ID,
    mb.primary_title AS Title,
    mb.start_year AS Year,
```

```
    mb.genres AS Genre,
    mr.averagerating AS Rating,
    mr.numvotes AS Votes
        FROM movie_basics AS mb
            JOIN movie_ratings AS mr
                 ON mb.movie_id = mr.movie_id
""", conn)

#Ensure "Rating" column is numeric
ratings_genres['Rating'] = pd.to_numeric(ratings_genres['Rating'], errors='c
ratings_genres
```

Out[15]:

	Movie_ID	Title	Year	Genre	Rating	Votes
0	tt0063540	Sunghursh	2013	Action,Crime,Drama	7.00	77
1	tt0066787	One Day Before the Rainy Season	2019	Biography,Drama	7.20	43
2	tt0069049	The Other Side of the Wind	2018	Drama	6.90	4517
3	tt0069204	Sabse Bada Sukh	2018	Comedy,Drama	6.10	13
4	tt0100275	The Wandering Soap Opera	2017	Comedy,Drama,Fantasy	6.50	119
...	...	...	...	...	...	...
73851	tt9913084	Diabolik sono io	2019	Documentary	6.20	6
73852	tt9914286	Sokagin Çocuklari	2019	Drama,Family	8.70	136
73853	tt9914642	Albatross	2017	Documentary	8.50	8
73854	tt9914942	La vida sense la Sara Amat	2019	None	6.60	5
73855	tt9916160	Drømmeland	2019	Documentary	6.50	11

73856 rows × 6 columns

In [16]:
```
ratings_genres.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Movie_ID  73856 non-null  object 
 1   Title     73856 non-null  object 
 2   Year      73856 non-null  int64  
 3   Genre     73052 non-null  object 
 4   Rating    73856 non-null  float64
 5   Votes     73856 non-null  int64  
dtypes: float64(1), int64(2), object(3)
memory usage: 3.4+ MB
```

It looks like there are some nulls in Genre. Let's drop them as there are relatively few:

In [17]:
```
ratings_genres.isna().sum()
```

Out[17]:
```
Movie_ID      0
Title         0
Year          0
Genre       804
Rating        0
Votes         0
dtype: int64
```

In [18]:
```
#Drop null Genre values
ratings_genres = ratings_genres.dropna(subset=['Genre'])

ratings_genres.isna().sum()
```

Out[18]:
```
Movie_ID    0
Title       0
Year        0
Genre       0
Rating      0
Votes       0
dtype: int64
```

In [19]:
```
#Confirm Years are all in range 2010-2019
ratings_genres.groupby('Year').count()
```

Out[19]:

	Movie_ID	Title	Genre	Rating	Votes
Year					
2010	6701	6701	6701	6701	6701
2011	7274	7274	7274	7274	7274
2012	7602	7602	7602	7602	7602
2013	7905	7905	7905	7905	7905
2014	8269	8269	8269	8269	8269
2015	8405	8405	8405	8405	8405
2016	8613	8613	8613	8613	8613
2017	8638	8638	8638	8638	8638
2018	7476	7476	7476	7476	7476
2019	2169	2169	2169	2169	2169

In [20]:
```
#let's convert year back to a string
ratings_genres.loc[:, 'Year'] = ratings_genres['Year'].astype(str)
```

Many movies have multiple genres, but the number of genres is inconsistent throughout. We also don't want to weigh one genre more than the others per movie. One approach to handling this is use .explode(); this will allow us to count each of a movie's genres separately. Unfortunately this will count individual movies multiple times, but it is a useful tradeoff for having a more accurate view of genre ratings.

In [21]:
```
ratings_genres.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 73052 entries, 0 to 73855
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Movie_ID  73052 non-null  object 
 1   Title     73052 non-null  object 
 2   Year      73052 non-null  object 
 3   Genre     73052 non-null  object 
 4   Rating    73052 non-null  float64
 5   Votes     73052 non-null  int64  
dtypes: float64(1), int64(1), object(4)
memory usage: 3.9+ MB
```

In [22]:
```
#convert column to string
ratings_genres.loc[:, 'Genre'] = ratings_genres['Genre'].astype(str)

# split column into lists
ratings_genres.loc[:, 'Genre'] = ratings_genres['Genre'].str.split(',')

# .explode() creates new rows for each genre
ratings_genres_exploded = ratings_genres.explode('Genre')

ratings_genres_exploded
```

Out[22]:

	Movie_ID	Title	Year	Genre	Rating	Votes
0	tt0063540	Sunghursh	2013	Action	7.00	77
0	tt0063540	Sunghursh	2013	Crime	7.00	77
0	tt0063540	Sunghursh	2013	Drama	7.00	77
1	tt0066787	One Day Before the Rainy Season	2019	Biography	7.20	43
1	tt0066787	One Day Before the Rainy Season	2019	Drama	7.20	43
...	...	...	...	...	...	...
73851	tt9913084	Diabolik sono io	2019	Documentary	6.20	6
73852	tt9914286	Sokagin Çocuklari	2019	Drama	8.70	136
73852	tt9914286	Sokagin Çocuklari	2019	Family	8.70	136
73853	tt9914642	Albatross	2017	Documentary	8.50	8
73855	tt9916160	Drømmeland	2019	Documentary	6.50	11

128490 rows × 6 columns

In [23]:
```
print(ratings_genres_exploded.dtypes)
```

```
Movie_ID     object
Title        object
Year         object
Genre        object
Rating      float64
Votes         int64
dtype: object
```

In [24]:
```
# Converting the 'Rating' column  to a numeric data type using the 'pd.to_nu
# The 'errors='coerce'' argument ensures that any values in the 'Rating' col

#ratings_genres_exploded['Rating'] = pd.to_numeric(ratings_genres['ratings_g
```

In [25]:
```
# groupby Genre and show mean Genre score for entries. sort genres by averag
avg_rating = ratings_genres_exploded.groupby('Genre').agg({'Rating': 'mean'}
avg_rating
```

Out[25]:

Genre	Rating
Short	8.80
Documentary	7.33
Game-Show	7.30
News	7.27
Biography	7.16
Music	7.09
History	7.04
Sport	6.96
War	6.58
Reality-TV	6.50
Musical	6.50
Drama	6.40
Family	6.39
Animation	6.25
Adventure	6.20
Romance	6.15
Crime	6.12
Comedy	6.00
Mystery	5.92
Fantasy	5.92
Western	5.87
Action	5.81
Thriller	5.64
Sci-Fi	5.49
Horror	5.00
Adult	3.77

In [26]:

```
#let's look at number of movies per genre
genre_count = ratings_genres_exploded.groupby('Genre')['Movie_ID'].count()
avg_rating['count'] = genre_count
avg_rating
```

Out[26]:

Genre	Rating	count
Short	8.80	1
Documentary	7.33	17753
Game-Show	7.30	2
News	7.27	579
Biography	7.16	3809
Music	7.09	1968
History	7.04	2825
Sport	6.96	1179
War	6.58	853
Reality-TV	6.50	17
Musical	6.50	721
Drama	6.40	30788
Family	6.39	3412
Animation	6.25	1743
Adventure	6.20	3817
Romance	6.15	6589
Crime	6.12	4611
Comedy	6.00	17290
Mystery	5.92	3039
Fantasy	5.92	2126
Western	5.87	280
Action	5.81	6988
Thriller	5.64	8217
Sci-Fi	5.49	2206
Horror	5.00	7674
Adult	3.77	3

We should limit this to genres with at least 150 movie representations to have a more useful analysis.

In [27]:

```
#ignore genres with < 150 movies
```

```
avg_rating_150 = avg_rating.loc[avg_rating['count'] > 150].sort_values(by='R
avg_rating_150
```

Out[27]:

Genre	Rating	count
Documentary	7.33	17753
News	7.27	579
Biography	7.16	3809
Music	7.09	1968
History	7.04	2825
Sport	6.96	1179
War	6.58	853
Musical	6.50	721
Drama	6.40	30788
Family	6.39	3412
Animation	6.25	1743
Adventure	6.20	3817
Romance	6.15	6589
Crime	6.12	4611
Comedy	6.00	17290
Mystery	5.92	3039
Fantasy	5.92	2126
Western	5.87	280
Action	5.81	6988
Thriller	5.64	8217
Sci-Fi	5.49	2206
Horror	5.00	7674

Runtimes and profits

Let's look at runtimes and compare them to profits

In [28]:
```
runtime_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 338 entries, 1 to 1555
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   genre       338 non-null    object
 1   box_office  338 non-null    object
 2   runtime     338 non-null    int64 
dtypes: int64(1), object(2)
memory usage: 10.6+ KB
```

In [29]:

```
runtime_df
```

Out[29]:

	genre	box_office	runtime
1	Drama|Science Fiction and Fantasy	600000	108
6	Comedy	41032915	82
7	Drama	224114	123
8	Drama	134904	117
15	Comedy|Drama|Mystery and Suspense	1039869	108
...	...	...	...
1541	Action and Adventure|Science Fiction and Fantasy	25335935	119
1542	Comedy|Drama	1416189	129
1545	Horror|Mystery and Suspense	59371	98
1546	Art House and International|Comedy|Drama	794306	97
1555	Action and Adventure|Horror|Mystery and Suspense	33886034	106

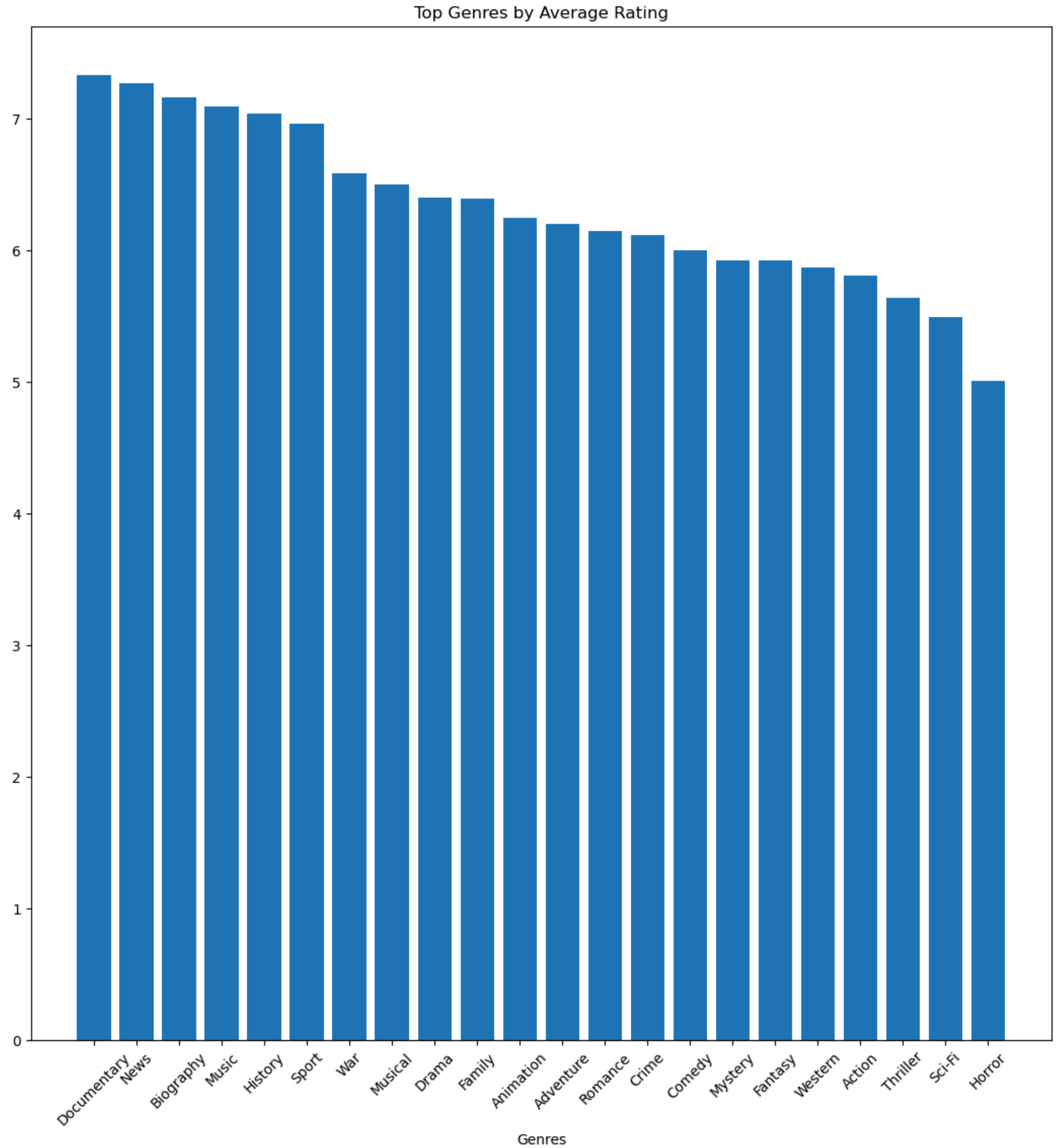
338 rows × 3 columns

Results

Most Popular Genres

In [30]:

```
figure, ax = plt.subplots(figsize=(13, 13))
ax.bar(x = avg_rating_150.index , height = avg_rating_150['Rating'],)
ax.set_title('Top Genres by Average Rating')
ax.set_xlabel('Genres')

plt.xticks(rotation = 45 )

plt.savefig('images/top_genres.png', dpi=300);
```

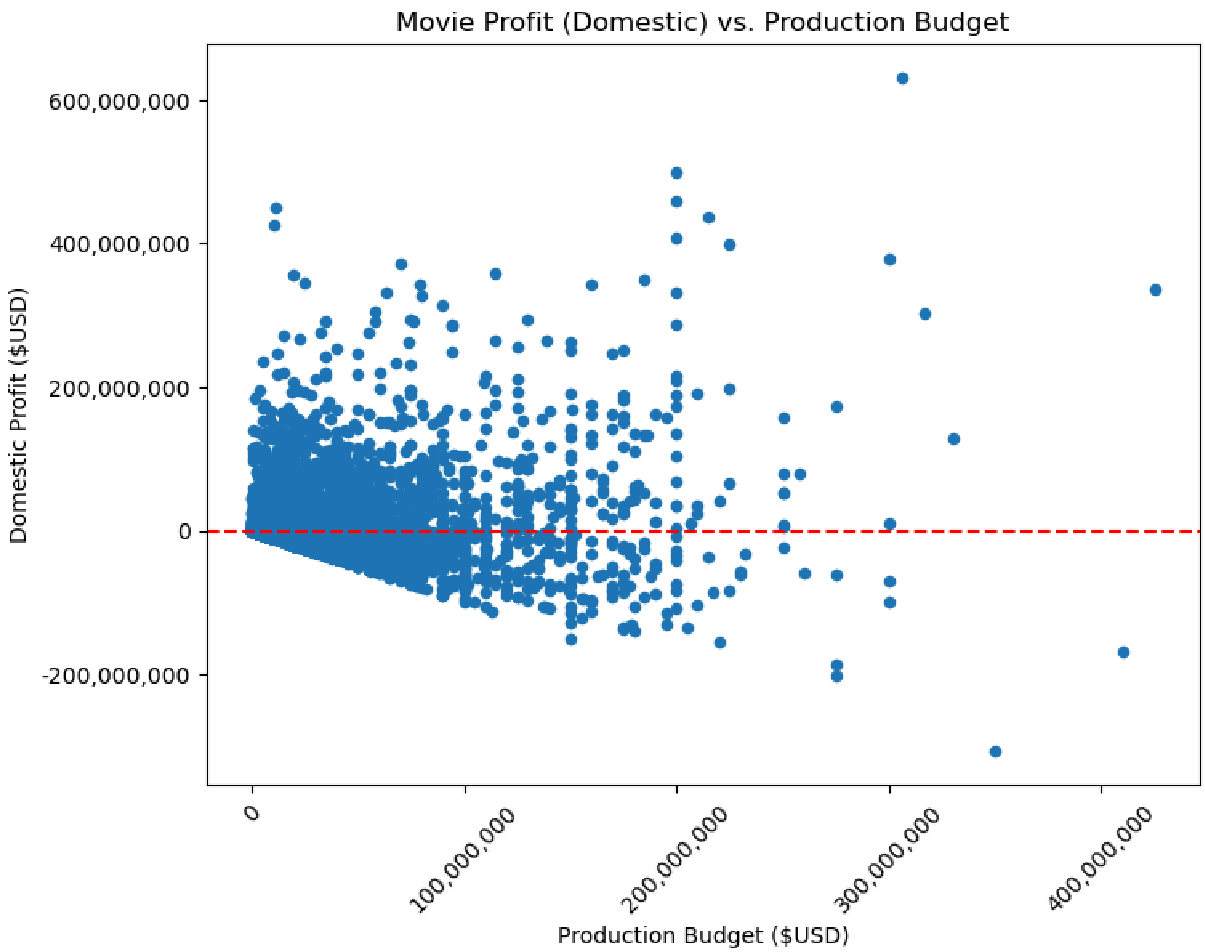


We can see here that the top genres are: Documentary, News, Biography, Music, and History. Making content that falls into these categories will be more likely to be well received.

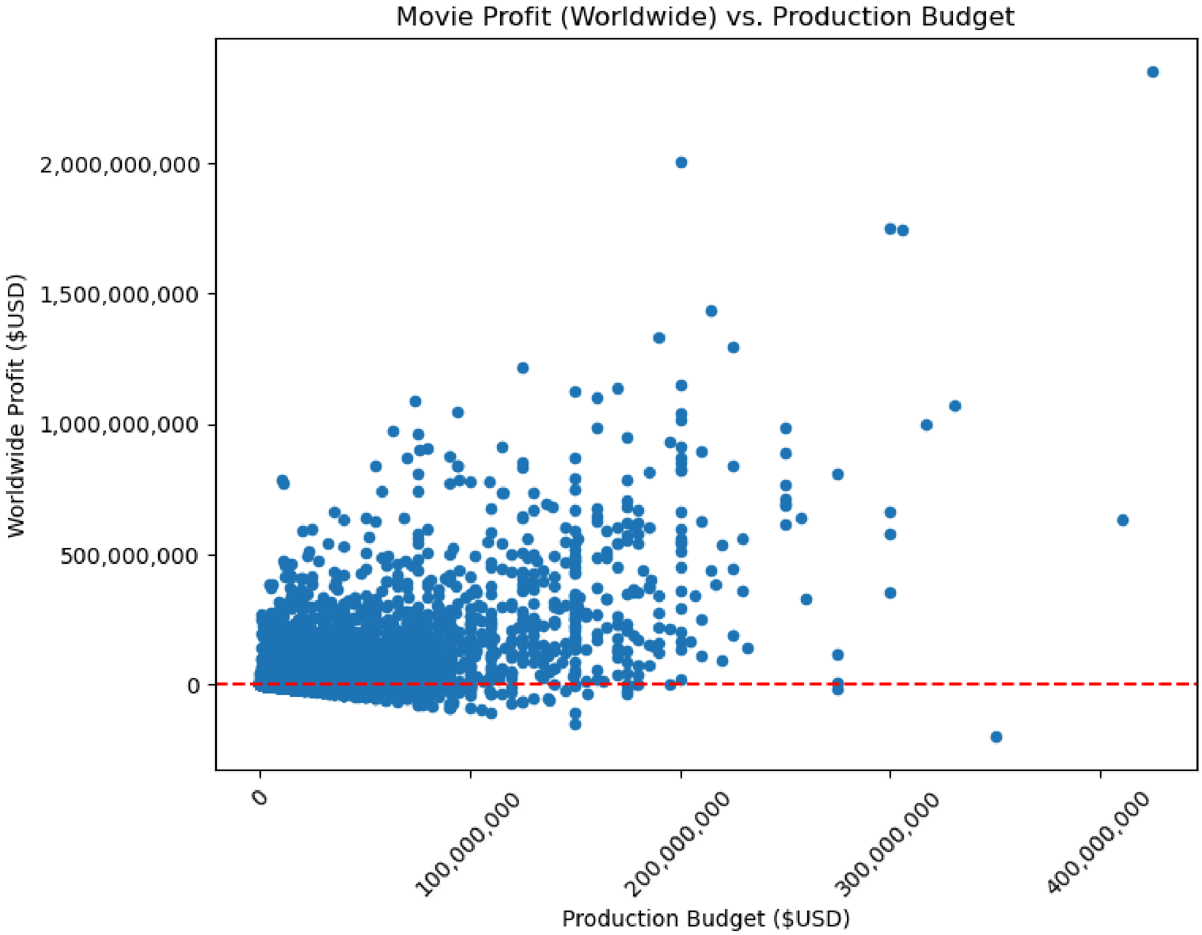
Worldwide Releases are Important

In [31]:
```
#Plot Domestic Profit vs Production Budget
cleaned_budgets_df.plot(x='production_budget', y='domestic_profit', kind='sc

plt.xticks(rotation=45)

plt.xlabel('Production Budget ($USD)')
plt.ylabel('Domestic Profit ($USD)')
plt.title('Movie Profit (Domestic) vs. Production Budget')
```

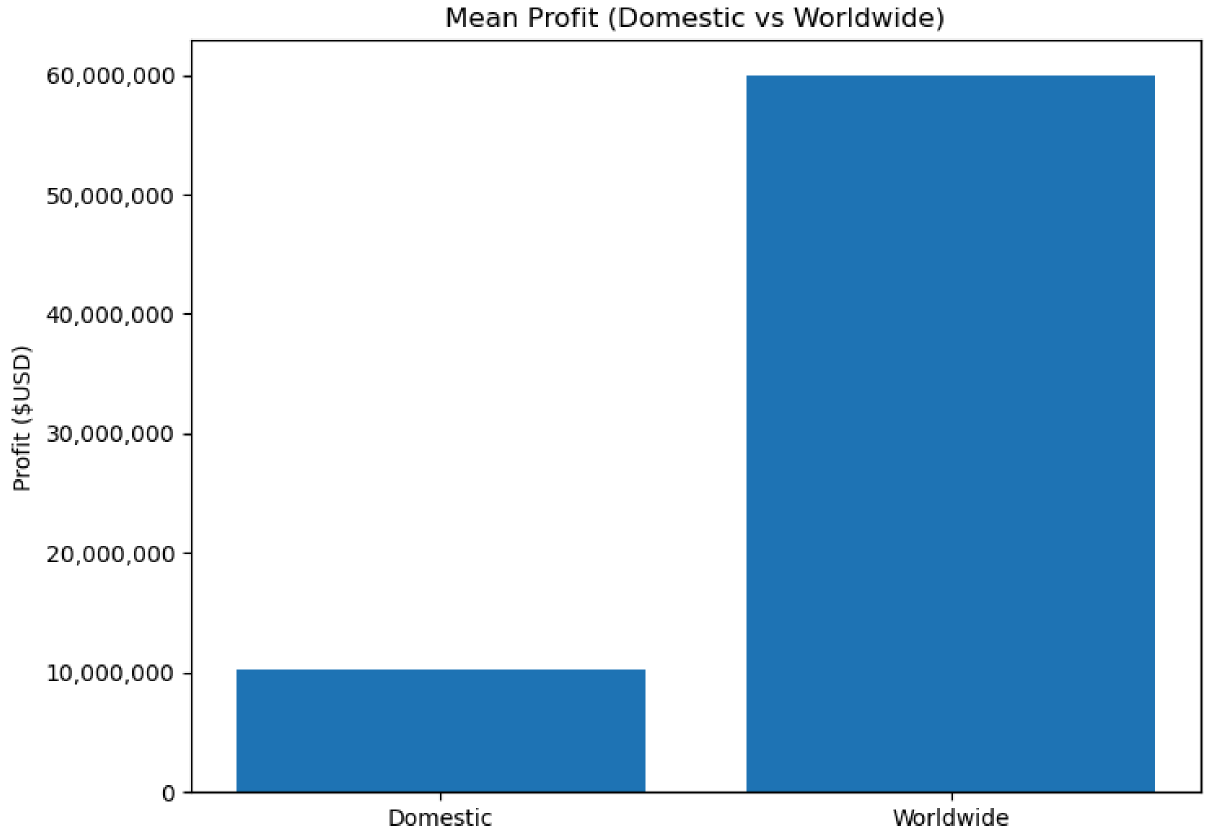
```
plt.ticklabel_format(style='plain', axis='both', useMathText=True)
plt.axhline(y=0, color='red', linestyle='--')

plt.gca().get_xaxis().set_major_formatter(plt.FuncFormatter(lambda x, _: f"{
plt.gca().get_yaxis().set_major_formatter(plt.FuncFormatter(lambda x, _: f"{
```



In [32]:
```
#Plot Worldwide Profit vs Production Budget
cleaned_budgets_df.plot(x='production_budget', y='worldwide_profit', kind='s

plt.xticks(rotation=45)

plt.xlabel('Production Budget ($USD)')
plt.ylabel('Worldwide Profit ($USD)')
plt.title('Movie Profit (Worldwide) vs. Production Budget')

plt.ticklabel_format(style='plain', axis='both', useMathText=True)
plt.axhline(y=0, color='red', linestyle='--')

plt.gca().get_xaxis().set_major_formatter(plt.FuncFormatter(lambda x, _: f"{
plt.gca().get_yaxis().set_major_formatter(plt.FuncFormatter(lambda x, _: f"{
```



In [33]:
```
#calculate mean domestic and worldwide profits
mean_domestic = cleaned_budgets_df['domestic_profit'].mean()
mean_worldwide = cleaned_budgets_df['worldwide_profit'].mean()

fig, ax = plt.subplots(figsize=(8, 6))

# Plot Average profit
ax.bar(['Domestic', 'Worldwide'], [mean_domestic, mean_worldwide])

# Set the title and labels
ax.set_title('Mean Profit (Domestic vs Worldwide)')
ax.set_ylabel('Profit ($USD)')

# Format the y-axis to show full numbers
plt.gca().get_yaxis().set_major_formatter(plt.FuncFormatter(lambda x, _: f"{
```

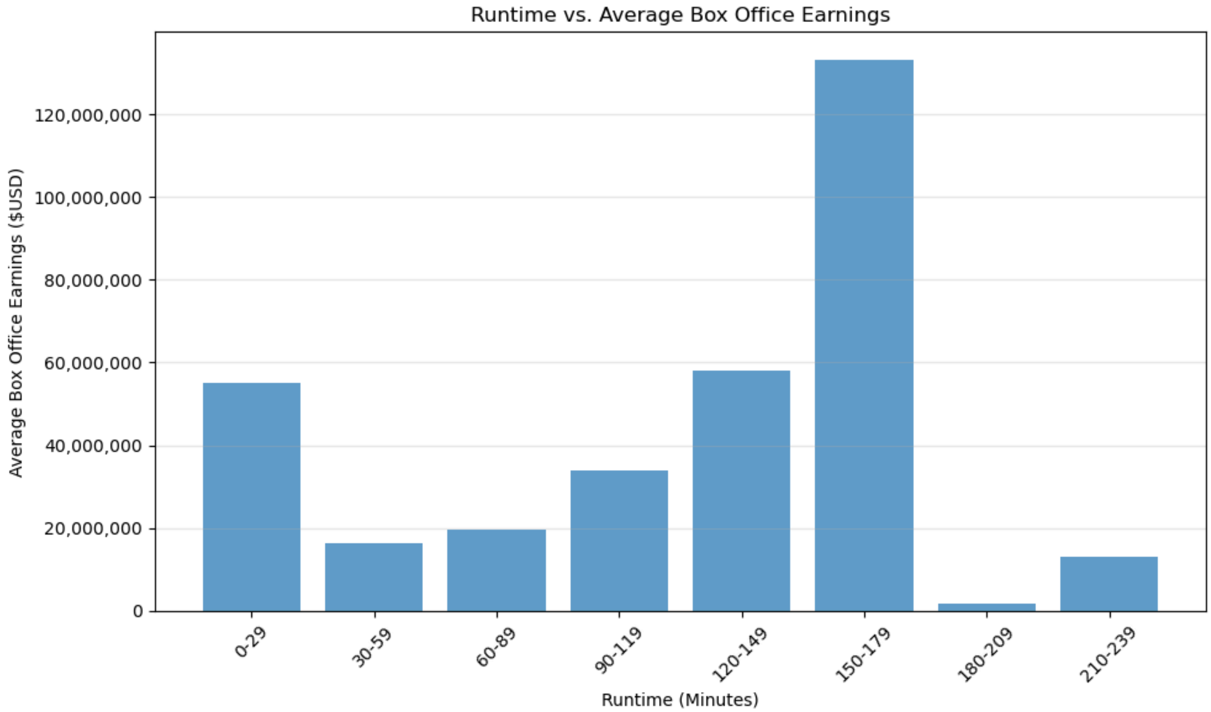


From these modelings, it is clear that worldwide releases are imperative to maximize profit and have a higher chance of continued success.

Runtime: Not too short, not too long

In [34]:
```
# Convert 'box_office' to numeric
runtime_df['box_office'] = pd.to_numeric(runtime_df['box_office'], errors='c

# Bin the runtime into chunks of 30 minutes
bins_30 = range(0, runtime_df['runtime'].max() + 30, 30)
labels_30 = [f"{b}-{b+29}" for b in bins_30[:-1]]
runtime_df['runtime_bin_30'] = pd.cut(runtime_df['runtime'], bins=bins_30, l

# Aggregate box office profits by 30-minute bins
runtime_boxoffice_30 = runtime_df.groupby('runtime_bin_30', observed=False)[

# Bar graph of runtime in 30 minute bins vs box office profits
plt.figure(figsize=(10, 6))
plt.bar(runtime_boxoffice_30['runtime_bin_30'], runtime_boxoffice_30['box_of
plt.title('Runtime vs. Average Box Office Earnings')
plt.xlabel('Runtime (Minutes)')
plt.ylabel('Average Box Office Earnings ($USD)')
plt.xticks(rotation=45)

# Format the y-axis to show full numbers
plt.gca().get_yaxis().set_major_formatter(plt.FuncFormatter(lambda x, _: f"{

plt.grid(axis='y', alpha=0.3)
```

```
plt.tight_layout()
plt.show()
```



It appears that movies with a runtime between 2.5 and 3 hours earn significantly more at the Box Office than movies with other runtimes.

Conclusion

The highest rated genres are Documentary, News, Biography, Music, and History, followed by Sport, War, Musical, Drama, and Family. Based on our analysis, we recommend these as projects for consideration.

Worldwide releases are crucial to our bottom line. Movies released eworldwide earn on averqge $50MM more than those only released domestically. Making content geared towards a worldwide release and inclusive of international markets should be a top priority.

We should focus on "shorts" of less than 30 minutes in length and movies between 2-3hrs in length, as these lengths have been shown to average the highest returns.

Next Steps

While Genre is a good measure of reception, it doesn't necessarily equate to profit. It is possible that movies with terrible ratings gross highly, but we did not have enough information to examine this. Additionally, it could be useful to look at movies from before 2010 to see if there are any trends in which genres are most popular throughout history. I am also unsure if the budgets were adjusted for inflation, but this may not be an issue because of the recency of the years involved.