Final Project Submission

Please fill out:

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- Student pace: Part time
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

Overview

Microsoft Movie Studio plans to produce films in genres that resonate with audiences, based on current box office trends. To inform decision-making, an analysis of the most recent movies will be done, focusing on the budget to produce the movies and the money they generate.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
```

Understanding The Data

In [27]:
```
# load data
# df2 = pd.read_csv("C:/Users/Hp/Phase1_Project/dsc-phase-1-project/Dat
# df3 = pd.read_csv("C:/Users/Hp/Phase1_Project/dsc-phase-1-project/Dat
df = pd.read_csv("C:/Users/Hp/Phase1_Project/dsc-phase-1-project/DataSe

```

tn.movie_budgets

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

Out[28]:

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

In [29]:
```
1 df.tail()
```

Out[29]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
78	Dec 31, 2018	Red 11	$7,000	$0	$0
79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

In [30]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   object
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   object
dtypes: object(5)
memory usage: 271.0+ KB
```

In [262]:

```
# sort table by date: latest to earliest by first converting release_da
df["release_date"] = pd.to_datetime(df["release_date"])
date_sorted = df.sort_values(by="release_date", ascending=False)
date_sorted.head(50)
```

Out[262]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
95	2020-12-31	Moonfall	$150,000,000	$0	$0
6	2020-12-31	Hannibal the Conqueror	$50,000,000	$0	$0
36	2020-02-21	Call of the Wild	$82,000,000	$0	$0
81	2019-12-31	Army of the Dead	$90,000,000	$0	$0
16	2019-12-31	Eli	$11,000,000	$0	$0
72	2019-12-31	355	$75,000,000	$0	$0
44	2019-12-31	Down Under Cover	$40,000,000	$0	$0
30	2019-12-31	Reagan	$25,000,000	$0	$0
13	2019-12-31	Rogue City	$13,000,000	$0	$0
8	2019-11-22	The Rhythm Section	$50,000,000	$0	$0
53	2019-11-08	Midway	$59,500,000	$0	$0
7	2019-11-08	Arctic Dogs	$50,000,000	$0	$0
30	2019-09-30	Unhinged	$29,000,000	$0	$0
9	2019-09-20	Ad Astra	$49,800,000	$0	$0
43	2019-09-13	The Goldfinch	$40,000,000	$0	$0
71	2019-08-30	PLAYMOBIL	$75,000,000	$0	$0
64	2019-08-14	Blinded by the Light	$15,000,000	$0	$0
16	2019-07-12	Crawl	$17,000,000	$0	$0
39	2019-06-21	Kursk	$40,000,000	$0	$4,212,799
48	2019-06-21	Burn Your Maps	$8,000,000	$0	$0
42	2019-06-14	Men in Black: International	$110,000,000	$3,100,000	$3,100,000
98	2019-06-14	Shaft	$30,000,000	$600,000	$600,000
3	2019-06-07	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
35	2019-06-07	Late Night	$4,000,000	$246,305	$246,305
81	2019-06-07	The Secret Life of Pets 2	$80,000,000	$63,795,655	$113,351,496
71	2019-05-31	Rocketman	$41,000,000	$57,342,725	$108,642,725
25	2019-05-31	Godzilla: King of the Monsters	$170,000,000	$85,576,941	$299,276,941
66	2019-05-31	MA	$5,000,000	$36,049,540	$44,300,625
13	2019-05-24	BrightBurn	$7,000,000	$16,794,432	$27,989,498
81	2019-05-24	Aladdin	$182,000,000	$246,734,314	$619,234,314
96	2019-05-17	The Sun is Also a Star	$9,000,000	$4,950,029	$5,434,029
81	2019-05-17	John Wick: Chapter 3 â□□ Parabellum	$40,000,000	$141,744,320	$256,498,033
26	2019-05-10	The Professor and the Madman	$25,000,000	$0	$5,227,233

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
76	2019-05-10	PokÃ©mon: Detective Pikachu	$150,000,000	$139,507,806	$411,258,433
16	2019-05-03	El Chicano	$8,000,000	$700,261	$700,261
75	2019-05-03	Long Shot	$40,000,000	$30,202,860	$43,711,031
6	2019-05-03	UglyDolls	$45,000,000	$19,894,664	$24,644,664
72	2019-05-03	The Intruder	$8,000,000	$35,095,904	$36,005,871
38	2019-04-23	Living Dark: The Story of Ted the Caver	$1,750,000	$0	$0
77	2019-04-12	Hellboy	$50,000,000	$21,903,748	$40,725,492
61	2019-04-05	Pet Sematary	$21,000,000	$54,724,696	$109,501,146
34	2019-04-05	The Best of Enemies	$10,000,000	$10,205,616	$10,205,616
97	2019-04-05	Shazam!	$85,000,000	$139,606,856	$362,899,733
22	2019-03-29	Dumbo	$170,000,000	$113,883,318	$345,004,422
33	2019-03-29	Unplanned	$6,000,000	$18,107,621	$18,107,621
88	2019-03-22	Us	$20,000,000	$175,006,930	$254,210,310
94	2019-03-15	Wonder Park	$100,000,000	$45,216,793	$115,149,422
97	2019-03-15	Captive State	$25,000,000	$5,958,315	$8,993,300
91	2019-03-15	Five Feet Apart	$7,000,000	$45,729,221	$80,504,421
96	2019-03-08	Captain Marvel	$175,000,000	$426,525,952	$1,123,061,550

Observation

Based on the 50 most recent movies; from 2020, more than 20 of them do not have a domestic_gross or worldwide gross. We can assume, either the movie was not released or the data was simply not filled. We will drop these rows.

- Most of the movies made a profit(ROI), so we can find out how much they made.

Cleaning & Organizing data.

In [32]:
```
1 date_sorted.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5782 entries, 95 to 78
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype         
---  ------             --------------  -----         
 0   release_date       5782 non-null   datetime64[ns]
 1   movie              5782 non-null   object        
 2   production_budget  5782 non-null   object        
 3   domestic_gross     5782 non-null   object        
 4   worldwide_gross    5782 non-null   object        
dtypes: datetime64[ns](1), object(4)
memory usage: 271.0+ KB
```

In [40]:
```
# convert currency columns to int, removing $ and , on the figures.
# domestic_gross
date_sorted['production_budget'] = date_sorted['production_budget'].str
date_sorted['production_budget'] = date_sorted['production_budget'].str
date_sorted['production_budget'] = date_sorted['production_budget'].ast
```

In [33]:
```
# domestic_gross
date_sorted['domestic_gross'] = date_sorted['domestic_gross'].str.repla
date_sorted['domestic_gross'] = date_sorted['domestic_gross'].str.repla
```

In [34]:
```
# worldwide_gross
date_sorted['worldwide_gross'] = date_sorted['worldwide_gross'].str.rep
date_sorted['worldwide_gross'] = date_sorted['worldwide_gross'].str.rep
```

In [41]:
```
# convert the gross columns to int
date_sorted['domestic_gross'] = date_sorted['domestic_gross'].astype('i
date_sorted['worldwide_gross'] = date_sorted['worldwide_gross'].astype(
date_sorted.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5234 entries, 42 to 78
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype         
---  ------             --------------  -----         
 0   release_date       5234 non-null   datetime64[ns]
 1   movie              5234 non-null   object        
 2   production_budget  5234 non-null   int64         
 3   domestic_gross     5234 non-null   int64         
 4   worldwide_gross    5234 non-null   int64         
dtypes: datetime64[ns](1), int64(3), object(1)
memory usage: 245.3+ KB
```

In [278]:
```
# drop rows with 0 as the domestic_gross and worldwide_gross
date_sorted = date_sorted[date_sorted !=0].dropna()
```

Analysis

We use the 50 most recent movies for our analyis. We can see our data mainly has movies from early 2018 and mid 2019 movies. Our goal is to get the highest grossing movies

In [51]:

```
# Movies and their Return On Investment(ROI)
# Add column for ROI.
roi = date_sorted['domestic_gross'] + date_sorted['worldwide_gross'] -d
date_sorted['roi'] = roi

date_sorted.head(50)
```

Out[51]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
42	2019-06-14	Men in Black: International	110000000	3100000	3100000	-103800
98	2019-06-14	Shaft	30000000	600000	600000	-28800
3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	-157475
35	2019-06-07	Late Night	4000000	246305	246305	-3507
81	2019-06-07	The Secret Life of Pets 2	80000000	63795655	113351496	97147
71	2019-05-31	Rocketman	41000000	57342725	108642725	124985
25	2019-05-31	Godzilla: King of the Monsters	170000000	85576941	299276941	214853
66	2019-05-31	MA	5000000	36049540	44300625	75350
13	2019-05-24	BrightBurn	7000000	16794432	27989498	37783
81	2019-05-24	Aladdin	182000000	246734314	619234314	683968
96	2019-05-17	The Sun is Also a Star	9000000	4950029	5434029	1384
81	2019-05-17	John Wick: Chapter 3 â□□ Parabellum	40000000	141744320	256498033	358242
76	2019-05-10	PokÃ©mon: Detective Pikachu	150000000	139507806	411258433	400766
16	2019-05-03	El Chicano	8000000	700261	700261	-6599
75	2019-05-03	Long Shot	40000000	30202860	43711031	33913
6	2019-05-03	UglyDolls	45000000	19894664	24644664	-460
72	2019-05-03	The Intruder	8000000	35095904	36005871	63101
77	2019-04-12	Hellboy	50000000	21903748	40725492	12629
61	2019-04-05	Pet Sematary	21000000	54724696	109501146	143225
34	2019-04-05	The Best of Enemies	10000000	10205616	10205616	10411
97	2019-04-05	Shazam!	85000000	139606856	362899733	417506
22	2019-03-29	Dumbo	170000000	113883318	345004422	288887
33	2019-03-29	Unplanned	6000000	18107621	18107621	30215
88	2019-03-22	Us	20000000	175006930	254210310	409217
94	2019-03-15	Wonder Park	100000000	45216793	115149422	60366
97	2019-03-15	Captive State	25000000	5958315	8993300	-10048
91	2019-03-15	Five Feet Apart	7000000	45729221	80504421	119233

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
96	2019-03-08	Captain Marvel	175000000	426525952	1123061550	1374587
56	2019-02-22	How to Train Your Dragon: The Hidden World	129000000	160791800	519258283	551050
86	2019-02-14	Fighting With My Family	11000000	22958583	39049922	51008
24	2019-02-14	Alita: Battle Angel	170000000	85710210	402976036	318686
78	2019-02-13	Happy Death Day 2U	9000000	28051045	64179495	83230
30	2019-02-13	Isnâ□□t it Romantic	31000000	48791187	48791187	66582
8	2019-02-08	The LEGO Movie 2: The Second Part	99000000	105806508	190325698	197132
21	2019-02-08	What Men Want	20000000	54611903	69911903	104523
23	2019-02-08	Cold Pursuit	60000000	32138862	62599159	34738
36	2019-02-08	The Prodigy	6000000	14856291	19789712	28646
81	2019-02-01	Miss Bala	15000000	14998027	15362298	15360
55	2019-01-25	The Kid Who Would Be King	59000000	16790790	28348446	-13860
93	2019-01-25	Serenity	25000000	8547045	11367029	-5085
100	2019-01-18	Glass	20000000	111035005	245303505	336338
36	2019-01-16	Dragon Ball Super: Broly	8500000	30376755	122747755	144624
85	2019-01-11	The Upside	37500000	108235497	119024536	189760
41	2019-01-11	A Dogâ□□s Way Home	61000000	41952715	81149689	62102
5	2018-12-25	Destroyer	9000000	1533324	3681096	-3785
100	2018-12-25	Vice	60000000	47836282	70883171	58719
81	2018-12-25	On the Basis of Sex	20000000	24622687	38073377	42696
58	2018-12-25	Holmes & Watson	42000000	30568743	41926605	30495
36	2018-12-21	Aquaman	160000000	335061807	1146894640	1321956
83	2018-12-21	Second Act	15700000	39282227	63288854	86871

In [59]:
```
# 'date_sorted' with only 50 most recent movies to work with.
date_sorted = date_sorted.iloc[:50, :]
len(date_sorted)
```

Out[59]: 50

In [271]:
```
# sorted table by roi
roi_sorted = date_sorted.sort_values(by=['roi'], ascending=False)
roi_sorted.head()
```

Out[271]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	roi
96	2019-03-08	Captain Marvel	175000000	426525952	1123061550	1374587502
36	2018-12-21	Aquaman	160000000	335061807	1146894640	1321956447
81	2019-05-24	Aladdin	182000000	246734314	619234314	683968628
56	2019-02-22	How to Train Your Dragon: The Hidden World	129000000	160791800	519258283	551050083
97	2019-04-05	Shazam!	85000000	139606856	362899733	417506589

In [80]:
```
# to confirm the top figure is correct
print('Highest ROI is:', date_sorted['roi'].max())
```

```
Highest ROI is: 1374587502
```

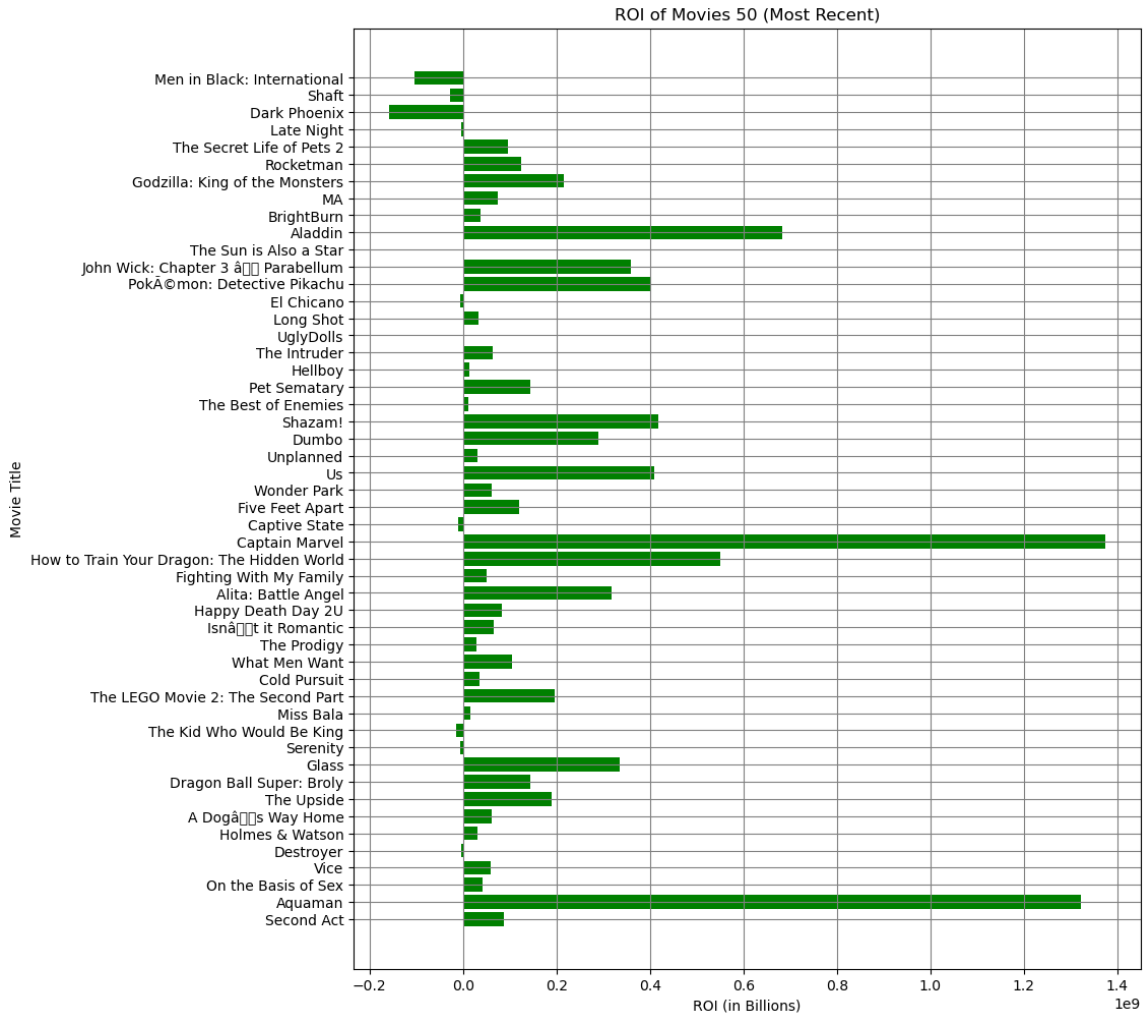
We can see that some movies made a loss. This could be due to reasons like;

- lack of proper marketing
- audience not recieving the movie as expected.
- not enough budget to produce a quality movie.

We focus on the highest grossing only. Those that had a high ROI maybe due to proper marketing or having well known actors/actresses as casts. We can have a bargraph represent all this data visually for 50 most recent movies.

In [78]:

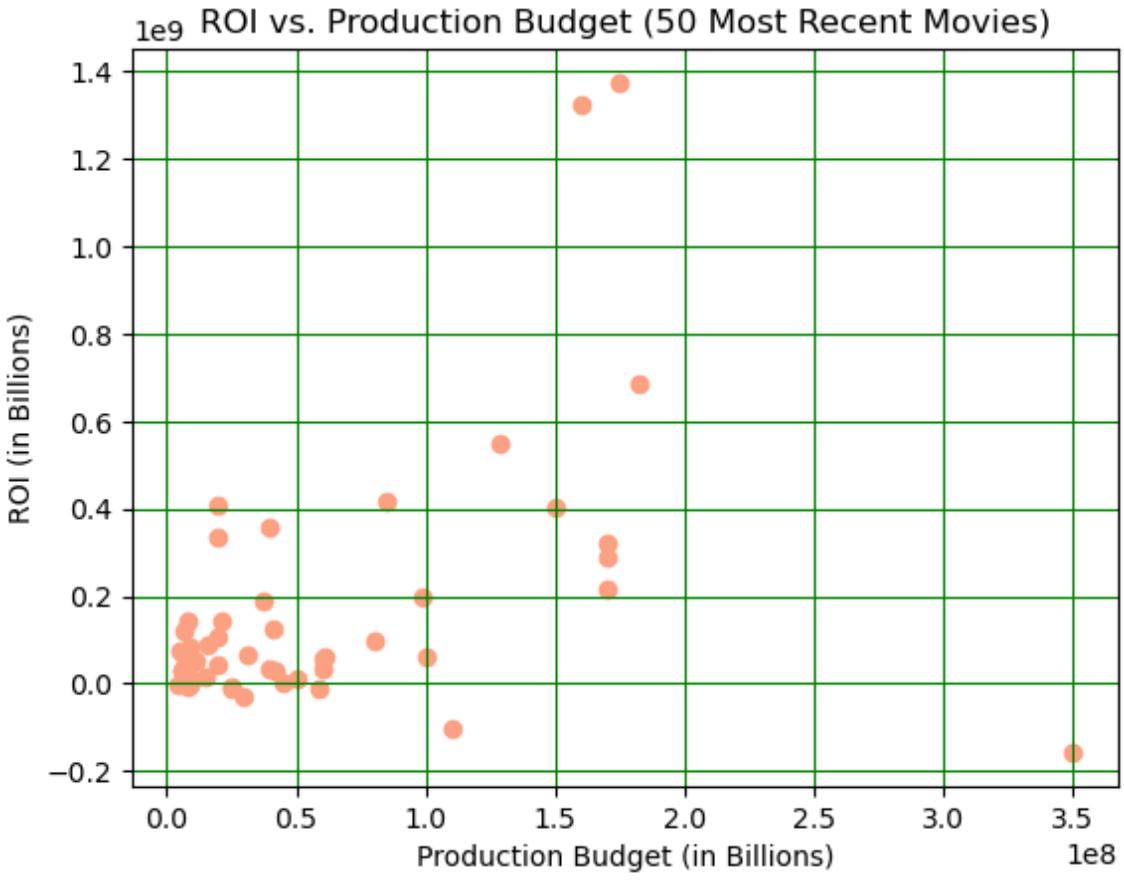
```
# bar graph roi vs movies
# Take the first 50 rows of the DataFrame
date_sorted = date_sorted[:50]

# Sort the DataFrame by date in descending order
date_sorted = date_sorted.sort_values(by=['release_date'], ascending=Tr

# Extract the ROI values from the DataFrame
roi = date_sorted['roi'].to_numpy()

# Extract the movie titles from the DataFrame
movie_titles = date_sorted['movie'].to_numpy()

# Create a horizontal bar graph
fig, ax = plt.subplots(figsize=(10, 12))
plt.barh(movie_titles, roi, color='green')
ax.grid(axis='both', color='grey')

# Set the title and labels for the graph
plt.title('ROI of Movies 50 (Most Recent)')
plt.xlabel('ROI (in Billions)')
plt.ylabel('Movie Title')

# ax.set_xlim(0, 4)
plt.show()
```



From the chart:

- 'Men in Black: International', which made a loss, is the most recent and 'Second Act' being the earliest.
- In this chart, those with roi above 1 Billion were mainly the superhero movies. We can

In [70]:
```
# Scatterplot- roi vs production budget
# Create a scatter plot
import seaborn as sns
sns.set_palette(sns.color_palette("Reds", 2))

# Create a scatter plot
plt.scatter(date_sorted['production_budget'], date_sorted['roi'])
plt.grid(which='both', color='Green')

# Label the axes
plt.xlabel('Production Budget (in Billions)')
plt.ylabel('ROI (in Billions)')

# Title the chart
plt.title('ROI vs. Production Budget (50 Most Recent Movies)')

# Show the plot
plt.show()
```



Conclusion

A quick view shows that the the high production budget generally yielded the high ROI in the sample movies. A lot of movies with production budget below 1 billion yielded an ROI less than a billion, with exceptions. Not to ignore the movie that had about 3.5 billion production

budget but made a loss. A possible reason for this would be poor marketing, or not being

Dataset - tmdb.movies.csv

In [81]:
```
df2 = pd.read_csv("C:/Users/Hp/Phase1_Project/dsc-phase-1-project/DataS
df2.head()
```

Out[81]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

In [82]:
```
# To get years recorded
df2['release_date'].unique()
```

Out[82]:
```
array(['2010-11-19', '2010-03-26', '2010-05-07', ..., '2018-05-08',
       '2018-08-02', '2018-05-26'], dtype=object)
```

In [83]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   genre_ids          26517 non-null  object 
 1   id                 26517 non-null  int64  
 2   original_language  26517 non-null  object 
 3   original_title     26517 non-null  object 
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  object 
 6   title              26517 non-null  object 
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(2), object(5)
memory usage: 2.0+ MB
```

Cleaning df2

To add a new column 'genres', representing the genre_ids

In [84]:
```
# convert 'release_date' to datetime
df2['release_date'] = pd.to_datetime(df2['release_date'])
df2['release_date'].info()
```

```
<class 'pandas.core.series.Series'>
Index: 26517 entries, 0 to 26516
Series name: release_date
Non-Null Count  Dtype
--------------  -----
26517 non-null  datetime64[ns]
dtypes: datetime64[ns](1)
memory usage: 414.3 KB
```

In [203]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 26517 entries, 0 to 26516
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   genre_ids          26517 non-null  object
 1   id                 26517 non-null  int64
 2   original_language  26517 non-null  object
 3   original_title     26517 non-null  object
 4   popularity         26517 non-null  float64
 5   release_date       26517 non-null  datetime64[ns]
 6   title              26517 non-null  object
 7   vote_average       26517 non-null  float64
 8   vote_count         26517 non-null  int64
dtypes: datetime64[ns](1), float64(2), int64(2), object(4)
memory usage: 2.0+ MB
```

In [87]:
```
df2.head()
```

Out[87]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

Since thecolumns have the right datatypes to work with, we can analyse.

Sorting

We can have a new dataframe, 'df2_year_sorted', that contains 50 most recent movies.

In [269]:
```
# Sort by year, to get the most recent movies
df2_year_sorted = df2.sort_values(by='release_date', ascending=False)
df2_year_sorted = df2_year_sorted.head(50)
df2_year_sorted.head()
```

Out[269]:

	genre_ids	id	original_language	original_title	popularity	release_date	title
26057	[27, 80, 80, 80, 80, 80]	570704	en	Murdery Christmas	0.840	2020-12-25	Murdery Christmas
24265	[10749, 18]	428836	en	Ophelia	8.715	2019-06-28	Ophelia
24892	[99]	541577	en	This Changes Everything	3.955	2019-06-28	This Changes Everything
24819	[18]	481880	en	Trial by Fire	4.480	2019-05-17	Trial by Fire
24297	[18]	415085	en	All Creatures Here Below	8.316	2019-05-17	All Creatures Here Below

We can have a new dataframe, 'df2_popularity_sorted', that contains the same movies, but sorted by popularity, from the 'df2_year_sorted'

In [268]:
```
# Movie with highest popularity value
df2_popularity_sorted = df2_year_sorted.sort_values(by='popularity', as
df2_popularity_sorted.head()
```

Out[268]:

	genre_ids	id	original_language	original_title	popularity	release_date	title
23930	[80, 53, 35, 18, 9648]	396461	en	Under the Silver Lake	17.182	2019-04-19	Under the Silver Lake
23945	[18, 27]	507076	fr	Climax	16.574	2019-03-01	Climax
23947	[80, 28, 53]	438674	en	Dragged Across Concrete	16.389	2019-03-22	Dragged Across Concrete
24003	[18, 9648, 53]	411144	en	We Have Always Lived in the Castle	14.028	2019-05-17	We Have Always Lived in the Castle
24084	[53, 18]	500904	en	A Vigilante	11.743	2019-03-29	A Vigilante

In [216]:
```
print('Maximum popularity value:', df2_popularity_sorted['popularity'].
print('Minimum popularity value:', df2_popularity_sorted['popularity'].
print('Average popularity value:', df2_popularity_sorted['popularity'].
```

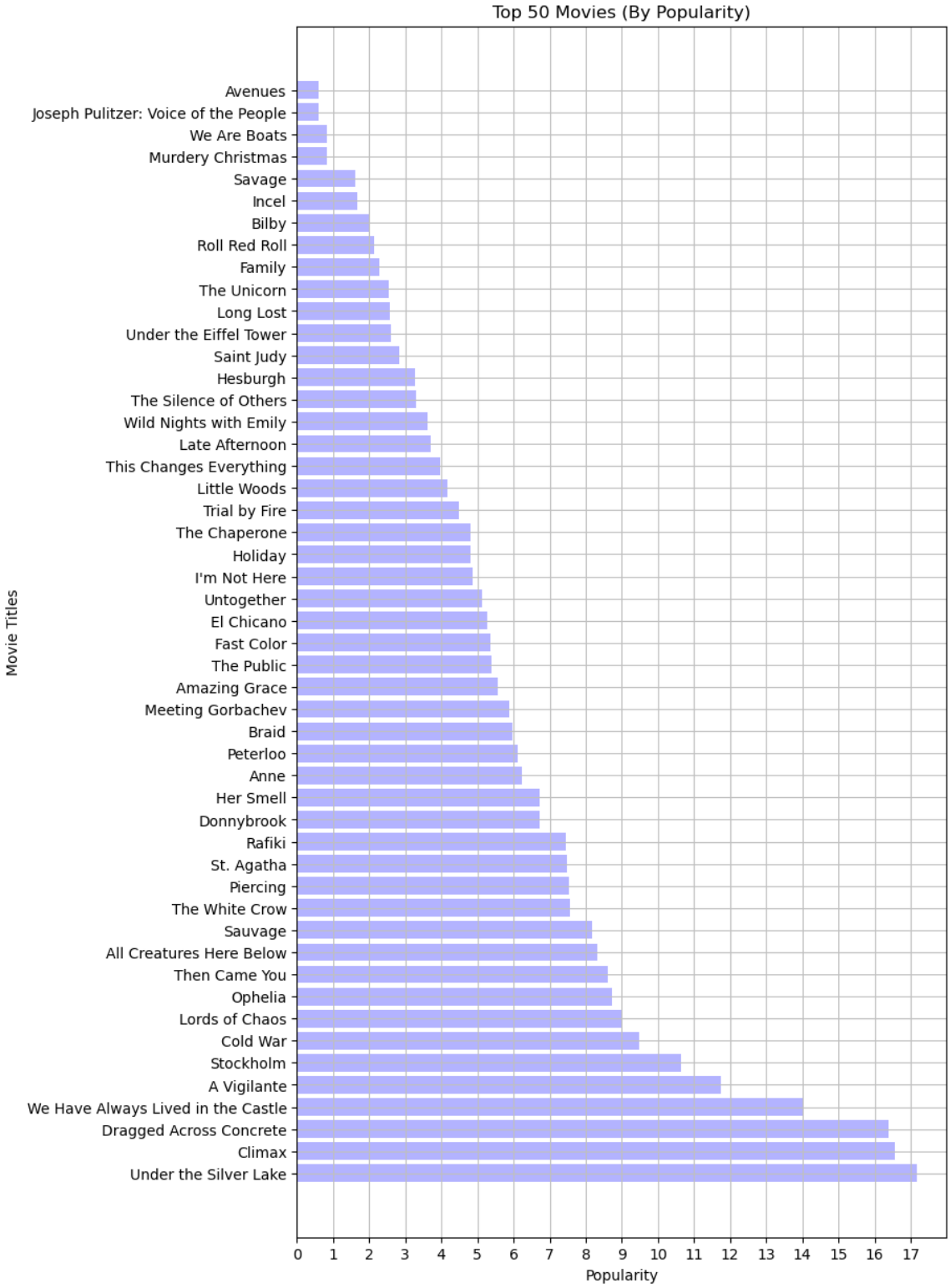
```
Maximum popularity value: 17.182
Minimum popularity value: 0.6
Average popularity value: 5.946840000000001
```

The vote_average values do not necessarily mean the movie was well recieved. This could be influenced by factors like the few viewers who watched it and ended up loving the movies. A lot of these viewers may not have voted.

The popularity values could be more valuable in this case, as they may give a better impression of how the movies were recieved in terms of size of the traget audience.

In [217]:

```
# plotting a graph showing popularity of the 50 movies

# Select the first 50 rows
# Create the bar chart

plt.figure(figsize=(8, 15))

faded_blue = (0.7, 0.7, 1.0)
plt.grid(which='both', color=faded_blue)
plt.barh(df2_popularity_sorted['title'], df2_popularity_sorted['popular

plt.xlim(0, 18)
plt.xticks(range(0, 18, 1))


plt.grid(which='both', color='silver')

# Set the labels and title
plt.xlabel('Popularity')
plt.ylabel('Movie Titles')
plt.title('Top 50 Movies (By Popularity)')

# Show the plot
plt.show()
```



- Maximum popularity value: 17.182
- Minimum popularity value: 0.6
- Average popularity value: 5.946840000000001

Almost half were above the 5.9 average popularity value. We can go ahead and get the movies with a popularity above the average mark, then get the most common genres in that group.

Getting the most common genres for movies above popularity-average

Having a dictionary of genres repsented by the genre id from;
https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee
(https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)

In [299]:
```
# movie id keys
movie_genre
```

Out[299]:
```
{28: 'Action',
 12: 'Adventure',
 16: 'Animation',
 35: 'Comedy',
 80: 'Crime',
 99: 'Documentary',
 18: 'Drama',
 10751: 'Family',
 14: 'Fantasy',
 36: 'History',
 27: 'Horror',
 10402: 'Music',
 9648: 'Mystery',
 10749: 'Romance',
 878: 'Science Fiction',
 10770: 'TV Movie',
 53: 'Thriller',
 10752: 'War',
 37: 'Western'}
```

In [220]:
```
# Data frame representing the movies above average popularity value 'to
top_popular = df2_popularity_sorted[df2_popularity_sorted['popularity']
top_popular
print(f'There are {len(top_popular)} movies above average population va
```

```
There are 21 movies above average population value
```

To now check the genres that these moves represent..

In [267]:
```
top_popular.head()
```

Out[267]:

	genre_ids	id	original_language	original_title	popularity	release_date	title
23930	[80, 53, 35, 18, 9648]	396461	en	Under the Silver Lake	17.182	2019-04-19	Under the Silver Lake
23945	[18, 27]	507076	fr	Climax	16.574	2019-03-01	Climax
23947	[80, 28, 53]	438674	en	Dragged Across Concrete	16.389	2019-03-22	Dragged Across Concrete
24003	[18, 9648, 53]	411144	en	We Have Always Lived in the Castle	14.028	2019-05-17	We Have Always Lived in the Castle
24084	[53, 18]	500904	en	A Vigilante	11.743	2019-03-29	A Vigilante

In [266]:
```
# List of genre_ids in the top_popular dataframe
genre_list = list(top_popular['genre_ids'])
print(genre_list)
```

```
['[80, 53, 35, 18, 9648]', '[18, 27]', '[80, 28, 53]', '[18, 9648, 53]',
'[53, 18]', '[18, 80, 35]', '[18, 10749, 10402]', '[18, 27, 53, 35]', '[10
749, 18]', '[18, 12, 35]', '[18]', '[18]', '[18]', '[53, 27]', '[27]', '[1
8, 10749]', '[18, 80]', '[18, 10402]', '[27]', '[36, 18]', '[53, 18, 27]']
```

In [265]:
```
# These are the genre id in the top_popular movies.
key_list = []
for i in genre_list:
    key_list.append([int(x) for x in i[1:-1].split(',')])
print(key_list)
```

```
[[80, 53, 35, 18, 9648], [18, 27], [80, 28, 53], [18, 9648, 53], [53, 18],
[18, 80, 35], [18, 10749, 10402], [18, 27, 53, 35], [10749, 18], [18, 12,
35], [18], [18], [18], [53, 27], [27], [18, 10749], [18, 80], [18, 10402],
[27], [36, 18], [53, 18, 27]]
```

In [235]:
```
# To create new list that has all key values.
movie_keys = []
for i in key_list:
    for j in i:
        movie_keys.append(j)

print(movie_keys)
print()
print(f'There are {len(movie_keys)} keys in total')
```

```
[80, 53, 35, 18, 9648, 18, 27, 80, 28, 53, 18, 9648, 53, 53, 18, 18, 80, 3
5, 18, 10749, 10402, 18, 27, 53, 35, 10749, 18, 18, 12, 35, 18, 18, 18, 5
3, 27, 27, 18, 10749, 18, 80, 18, 10402, 27, 36, 18, 53, 18, 27]

There are 48 keys in total
```

Having a dictionary of genres repsented by the genre id from;
https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee
(https://www.themoviedb.org/talk/5daf6eb0ae36680011d7e6ee)

In [449]:
```
1 movie_genre
```

Out[449]:
```
{28: 'Action',
 12: 'Adventure',
 16: 'Animation',
 35: 'Comedy',
 80: 'Crime',
 99: 'Documentary',
 18: 'Drama',
 10751: 'Family',
 14: 'Fantasy',
 36: 'History',
 27: 'Horror',
 10402: 'Music',
 9648: 'Mystery',
 10749: 'Romance',
 878: 'Science Fiction',
 10770: 'TV Movie',
 53: 'Thriller',
 10752: 'War',
 37: 'Western'}
```

In [240]:
```
1  # Create a new list to store the movie values
2  movie_value = []
3
4  # Iterate over list3 and assign the corresponding value from the dictio
5  for element in movie_keys:
6      if element in movie_genre:
7          movie_value.append(movie_genre[element])
8      else:
9          movie_value.append(element)
10
11 # Print the new list
12 print(movie_value)
13 print()
14 print(f'There are {len(movie_value)} values in total')
```

```
['Crime', 'Thriller', 'Comedy', 'Drama', 'Mystery', 'Drama', 'Horror', 'Cr
ime', 'Action', 'Thriller', 'Drama', 'Mystery', 'Thriller', 'Thriller', 'D
rama', 'Drama', 'Crime', 'Comedy', 'Drama', 'Romance', 'Music', 'Drama',
'Horror', 'Thriller', 'Comedy', 'Romance', 'Drama', 'Drama', 'Adventure',
'Comedy', 'Drama', 'Drama', 'Drama', 'Thriller', 'Horror', 'Horror', 'Dram
a', 'Romance', 'Drama', 'Crime', 'Drama', 'Music', 'Horror', 'History', 'D
rama', 'Thriller', 'Drama', 'Horror']

There are 48 values in total
```

In [248]:
```
genre_names = set(movie_value)
genre_names = list(genre_names)
genre_names
```

Out[248]:
```
['Romance',
 'Adventure',
 'Mystery',
 'Horror',
 'Thriller',
 'Crime',
 'Drama',
 'Comedy',
 'Action',
 'History',
 'Music']
```

We have the genres in the movies that are above the popularity average. We can go ahead and see the most common occuring genres

In [241]:
```
# Create a dictionary to store the count of each element in the movie_v
movie_value_counts = {}

# Iterate over the movie_value list and increment the count for each el
for element in movie_value:
    if element in movie_value_counts:
        movie_value_counts[element] += 1
    else:
        movie_value_counts[element] = 1

# Print the count of each element in the dictionary
for element, count in movie_value_counts.items():
    print(f'{element}: {count}')
```

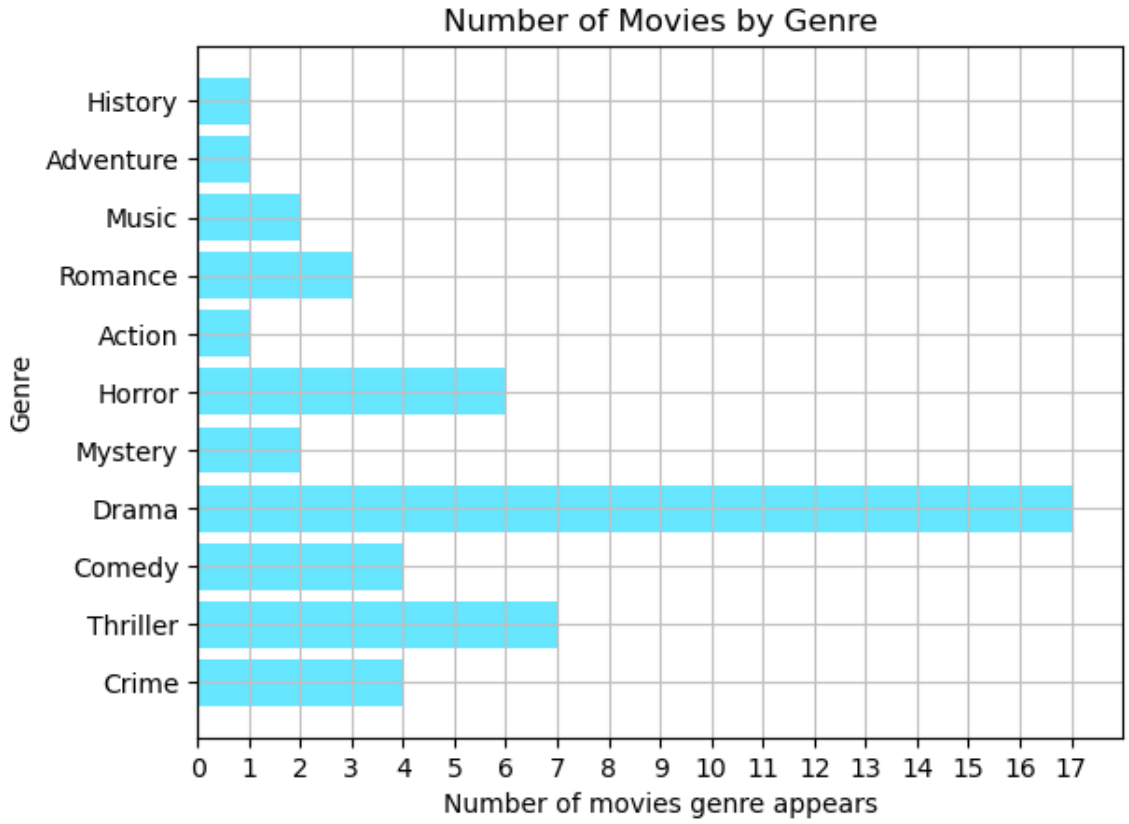
```
Crime: 4
Thriller: 7
Comedy: 4
Drama: 17
Mystery: 2
Horror: 6
Action: 1
Romance: 3
Music: 2
Adventure: 1
History: 1
```

In [254]:
```
movie_value_counts
```

Out[254]:
```
{'Crime': 4,
 'Thriller': 7,
 'Comedy': 4,
 'Drama': 17,
 'Mystery': 2,
 'Horror': 6,
 'Action': 1,
 'Romance': 3,
 'Music': 2,
 'Adventure': 1,
 'History': 1}
```

The count shows the number of times the genre appeared in these 21 movies. In other words, the number of movies that had the genre as part of the style it incorporated.

In [264]:
```
# plotting graph -- Genre vs counts
genres = list(movie_value_counts.keys())
counts = list(movie_value_counts.values())
cyan = (0.4, 0.9, 1)

plt.barh(genres, counts, color=cyan)
plt.xlim(0, 18)
plt.xticks(range(0, 18, 1))


plt.grid(which='both', color='silver')

plt.xlabel('Number of movies genre appears')
plt.ylabel('Genre')
plt.title('Number of Movies by Genre')
plt.show()
# We cannot sirt by counts, since we are using a dict.
```



Summary

Conclusion

Based on the grossing, most movies generally did not have a production budget higher than 1 billion, the ROI was also not more than that figure. A lot of them had a production budget of less than $500,000,000, with the ROI being in the same ballpark. The top genre whose style is most commonly used in the most popular movies is Drama, followed by thriller and Horror.

Recommendations

These are the recommendations on what to focus on, especially for a start up studio.

1. Focus on the Drama and Thriller genres as they are the top genres consumed. This will heavily influence the popularity of the movie.
2. Focus on high production quality, which translates to having a sufficient budget, this is about $500,000,000.
3. While making these movies, consider the international audience, as the make up for most of the ROI. English language movies are the most consumed movies. This is to be considered during cast selection.

A further analysis could give even more insights to improve movie production quality and increase in a positive reception by audience. Factors like;

- cast members and directors
- Marketing strategies

In [ ]:
```
1
```