Microsoft Movie Studios

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Overview

Microsoft is creating a new movie studio and is inquiring about what types of films are currently doing the best at the box office. The datasets used in answering the business problem are from various movie websites and contain box office information. Methods used were exploratory data analysis, data cleaning, and data manipulation. The data shows that the highest grossing genre of films are Adventure, Action, and Comedy. The highest grossing time of the year for movie releases is May. There is also a positive correlation between a film's production budget and its profits. Ideally, we should make it a priority to hire Christopher Nolan as film director.

Business Problem

Microsoft 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 Microsoft's new movie studio can use to help decide what type of films to create.

Questions to consider:

1. What are the highest grossing genre of movies?
2. What time of the year is best to release a movie?
3. Is there a correlation between budget and profit?
4. Who are fan favorite directors that we should look to hire?

These questions were considered in order to maximize studio success. Profits are one marker of a film's success, telling us whether or not the film was financially worth pursuing. Finding out whether a large budget is favorable will aid the studio into making informed decisions. Data on the highest grossing genres will help Microsoft Studios narrow down on what type of films to invest in. The release window also influences a film's success. It's key that the studio releases it at a time where the most people will go see it. Finally, it's important to choose a proven visionary for the director's chair.

Data Understanding

Note that this data may not reflect the most up-to-date box office information.

1) im.db.zip

```
A zipped SQLite database containing movie data from the website Inter
net Movie Data Base. There is information on genre, online user vote
s, average user ratings, roles of people involved in the film etc...
The most relevant tables are movie_basics and movie_ratings.
```

2) bom.movie_gross.csv.gz

```
A compressed CSV file containing box office data from the website Box
Office Mojo.  Domestic and Foreign Gross are the
most relevant features.
```

3) tn.movie_budgets.csv.gz

In [1]:
```
##Import Standard Packages
import pandas as pd
import numpy as np
import sqlite3
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

1. What are the highest grossing genres of movies?

Connect to the IMDB database

In [2]:
```
# unzip the imdb database file
import zipfile
with zipfile.ZipFile('zippedData/im.db.zip', 'r') as zip_ref:
    zip_ref.extractall('zippedData')
```

In [3]:
```
# make a connection with the IMDB DATABASE using SQLite3
conn = sqlite3.connect('zippedData/im.db')
```

In [4]:
```
# set up a cursor in order to browse through the database.
# A cursor object is what can actually execute SQL commands. You create it by

cur = conn.cursor()

# This is a special query for finding the table names.
cur.execute("""SELECT name FROM sqlite_master WHERE type = 'table';""")
```

Out[4]:
```
<sqlite3.Cursor at 0x2bd741fe180>
```

In [5]:
```
# Use the fetchall method to find out the table names
# Fetch the result and store it in table_names
table_names = cur.fetchall()
table_names
```

Out[5]:
```
[('movie_basics',),
 ('directors',),
 ('known_for',),
 ('movie_akas',),
 ('movie_ratings',),
 ('persons',),
 ('principals',),
 ('writers',)]
```

In [6]:
```
# use the pd.read_sql function to generate a dataframe
pd.read_sql("SELECT * FROM movie_basics;", conn)
```

Out[6]:

	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 [7]:
```
# generate movie ratings table
pd.read_sql("SELECT * FROM movie_ratings ORDER BY movie_id;", conn)
```

Out[7]:

	movie_id	averagerating	numvotes
0	tt0063540	7.0	77
1	tt0066787	7.2	43
2	tt0069049	6.9	4517
3	tt0069204	6.1	13
4	tt0100275	6.5	119
...	...	...	...
73851	tt9913084	6.2	6
73852	tt9914286	8.7	136
73853	tt9914642	8.5	8
73854	tt9914942	6.6	5
73855	tt9916160	6.5	11

73856 rows × 3 columns

Join Tables

In [8]:
```
# select relevant columns and join tables using a shared column

# filter out lesser popular titles

s = """
SELECT primary_title, runtime_minutes, genres, averagerating, numvotes
FROM movie_basics
JOIN movie_ratings
USING(movie_id)
WHERE numvotes > 62500
ORDER BY numvotes DESC
;
"""
# make imdb dataframe
imdb = pd.read_sql(s, conn)
```

In [9]:
```
#use exploratory data analysis
imdb.head(20)
```

Out[9]:

	primary_title	runtime_minutes	genres	averagerating	numvotes
0	Inception	148.0	Action,Adventure,Sci-Fi	8.8	1841066
1	The Dark Knight Rises	164.0	Action,Thriller	8.4	1387769
2	Interstellar	169.0	Adventure,Drama,Sci-Fi	8.6	1299334
3	Django Unchained	165.0	Drama,Western	8.4	1211405
4	The Avengers	143.0	Action,Adventure,Sci-Fi	8.1	1183655
5	The Wolf of Wall Street	180.0	Biography,Crime,Drama	8.2	1035358
6	Shutter Island	138.0	Mystery,Thriller	8.1	1005960
7	Guardians of the Galaxy	121.0	Action,Adventure,Comedy	8.1	948394
8	Deadpool	108.0	Action,Adventure,Comedy	8.0	820847
9	The Hunger Games	142.0	Action,Adventure,Sci-Fi	7.2	795227
10	Star Wars: Episode VII - The Force Awakens	136.0	Action,Adventure,Fantasy	8.0	784780
11	Mad Max: Fury Road	120.0	Action,Adventure,Sci-Fi	8.1	780910
12	Gone Girl	149.0	Drama,Mystery,Thriller	8.1	761592
13	The Hobbit: An Unexpected Journey	169.0	Adventure,Family,Fantasy	7.9	719629
14	Gravity	91.0	Drama,Sci-Fi,Thriller	7.7	710018
15	Iron Man 3	130.0	Action,Adventure,Sci-Fi	7.2	692794
16	Harry Potter and the Deathly Hallows: Part 2	130.0	Adventure,Drama,Fantasy	8.1	691835
17	Thor	115.0	Action,Adventure,Fantasy	7.0	683264
18	Toy Story 3	103.0	Adventure,Animation,Comedy	8.3	682218
19	The Martian	144.0	Adventure,Drama,Sci-Fi	8.0	680116

In [10]:
```
# .info provides a useful overview of the data
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 925 entries, 0 to 924
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   primary_title    925 non-null    object 
 1   runtime_minutes  925 non-null    float64
 2   genres           925 non-null    object 
 3   averagerating    925 non-null    float64
 4   numvotes         925 non-null    int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 36.3+ KB
```

In [11]:
```
# .describe() calculates the basic summary statistics for each column
imdb.describe()
```

Out[11]:

	runtime_minutes	averagerating	numvotes
count	925.000000	925.000000	9.250000e+02
mean	113.921081	6.808757	2.017624e+05
std	18.854227	0.835132	1.785720e+05
min	80.000000	1.600000	6.258900e+04
25%	101.000000	6.300000	8.846900e+04
50%	111.000000	6.800000	1.364470e+05
75%	124.000000	7.400000	2.377200e+05
max	321.000000	9.300000	1.841066e+06

Box Office Mojo Database

In [12]:
```
# Import the file
bom = pd.read_csv("zippedData/bom.movie_gross.csv.gz")
bom.head()
```

Out[12]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [13]:
```
bom.describe()
```

Out[13]:

	domestic_gross	year
count	3.359000e+03	3387.000000
mean	2.874585e+07	2013.958075
std	6.698250e+07	2.478141
min	1.000000e+02	2010.000000
25%	1.200000e+05	2012.000000
50%	1.400000e+06	2014.000000
75%	2.790000e+07	2016.000000
max	9.367000e+08	2018.000000

In [14]:
```
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

The dtype for the foreign_gross column is a string, we have to change this into either a float or integer. When we use the astype function we encounter the following errors:

bom['foreign_gross'].astype(float) Gives Error: could not convert string to float: '1,131.6'

bom['foreign_gross'].astype(int) Gives Error: cannot convert float NaN to integer

In [15]:
```
# sorting the values by domestic gross, we see that the foreign gross is off f
bom.sort_values(by=['domestic_gross'],ascending=False)
```

Out[15]:

	title	studio	domestic_gross	foreign_gross	year
1872	Star Wars: The Force Awakens	BV	936700000.0	1,131.6	2015
3080	Black Panther	BV	700100000.0	646900000	2018
3079	Avengers: Infinity War	BV	678800000.0	1,369.5	2018
1873	Jurassic World	Uni.	652300000.0	1,019.4	2015
727	Marvel's The Avengers	BV	623400000.0	895500000	2012
...	...	...	...	...	...
1975	Surprise - Journey To The West	AR	NaN	49600000	2015
2392	Finding Mr. Right 2	CL	NaN	114700000	2016
2468	Solace	LGP	NaN	22400000	2016
2595	Viral	W/Dim.	NaN	552000	2016
2825	Secret Superstar	NaN	NaN	122000000	2017

3387 rows × 5 columns

In [16]:
```
# sorting the values by foreign gross, we see that the top 5 results are popul
bom.sort_values(by=['foreign_gross'])
```

Out[16]:

	title	studio	domestic_gross	foreign_gross	year
2760	The Fate of the Furious	Uni.	226000000.0	1,010.0	2017
1873	Jurassic World	Uni.	652300000.0	1,019.4	2015
1872	Star Wars: The Force Awakens	BV	936700000.0	1,131.6	2015
1874	Furious 7	Uni.	353000000.0	1,163.0	2015
3079	Avengers: Infinity War	BV	678800000.0	1,369.5	2018
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

In [17]:
```
# REPLACE the incorrect values with more realistic ones.  The five entries wer
bom['foreign_gross'] = bom['foreign_gross'].replace(['1,010.0','1,019.4','1,13
```

In [18]:
```
#check to see if the values changed
bom.sort_values(by=['domestic_gross'],ascending=False)
```

Out[18]:

	title	studio	domestic_gross	foreign_gross	year
1872	Star Wars: The Force Awakens	BV	936700000.0	1131000000	2015
3080	Black Panther	BV	700100000.0	646900000	2018
3079	Avengers: Infinity War	BV	678800000.0	1369000000	2018
1873	Jurassic World	Uni.	652300000.0	1019000000	2015
727	Marvel's The Avengers	BV	623400000.0	895500000	2012
...	...	...	...	...	...
1975	Surprise - Journey To The West	AR	NaN	49600000	2015
2392	Finding Mr. Right 2	CL	NaN	114700000	2016
2468	Solace	LGP	NaN	22400000	2016
2595	Viral	W/Dim.	NaN	552000	2016
2825	Secret Superstar	NaN	NaN	122000000	2017

Data Preparation

Drop Rows

In order to find the highest total grossing movies we need both domestic and foreign gross values. Films with missing values in either gross column should be droppped:

In [19]:
```
# drop rows with missing gross values
bom.dropna(inplace=True)
```

In [20]:
```
# check to see if changes were made
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2007 entries, 0 to 3353
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           2007 non-null   object 
 1   studio          2007 non-null   object 
 2   domestic_gross  2007 non-null   float64
 3   foreign_gross   2007 non-null   object 
 4   year            2007 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 94.1+ KB
```

The 'foreign_gross' column has the dtype 'object'. We need to change this into a numerical dtype, preferably to integer in order to make the values easier to read. Change the 'domestic_gross' dtype to integer as well.

In [21]:
```
# convert 'domestic gross' column from float to integer
bom['domestic_gross'] = bom['domestic_gross'].astype(int)
```

In [22]:
```
# convert 'foreign gross' column from object to integer
bom['foreign_gross'] = bom['foreign_gross'].astype(int)
```

In [23]:
```
# check to see if changes were made
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2007 entries, 0 to 3353
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   title           2007 non-null   object
 1   studio          2007 non-null   object
 2   domestic_gross  2007 non-null   int32 
 3   foreign_gross   2007 non-null   int32 
 4   year            2007 non-null   int64 
dtypes: int32(2), int64(1), object(2)
memory usage: 78.4+ KB
```

Create New Column

We will create a new column called 'total_gross' which combines both foreign and domestic grosses.

In [24]:
```
# create a total_gross column
bom['total_gross'] = bom['domestic_gross'] + bom['foreign_gross']
```

In [25]:
```
# look at values by total gross
bom.sort_values(by=['total_gross'],ascending=False)
```

Out[25]:

	title	studio	domestic_gross	foreign_gross	year	total_gross
1872	Star Wars: The Force Awakens	BV	936700000	1131000000	2015	2067700000
3079	Avengers: Infinity War	BV	678800000	1369000000	2018	2047800000
1873	Jurassic World	Uni.	652300000	1019000000	2015	1671300000
727	Marvel's The Avengers	BV	623400000	895500000	2012	1518900000
1874	Furious 7	Uni.	353000000	1163000000	2015	1516000000
...	...	...	...	...	...	...
711	I'm Glad My Mother is Alive	Strand	8700	13200	2011	21900
322	The Thorn in the Heart	Osci.	7400	10500	2010	17900
1110	Cirkus Columbia	Strand	3500	9500	2012	13000
715	Aurora	CGld	5700	5100	2011	10800
721	To Die Like a Man	Strand	4000	900	2011	4900

2007 rows × 6 columns

Drop Columns

In [26]:
```
# movie studio and year are irrelevant to our current question and can be drop
bom = bom.drop(['studio', 'year'], axis=1)
```

In [27]:
```
bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2007 entries, 0 to 3353
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   title           2007 non-null   object
 1   domestic_gross  2007 non-null   int32 
 2   foreign_gross   2007 non-null   int32 
 3   total_gross     2007 non-null   int32 
dtypes: int32(3), object(1)
memory usage: 54.9+ KB
```

In [28]:
```
bom.describe()
```

Out[28]:

	domestic_gross	foreign_gross	total_gross
count	2.007000e+03	2.007000e+03	2.007000e+03
mean	4.701984e+07	7.862646e+07	1.256463e+08
std	8.162689e+07	1.480804e+08	2.211996e+08
min	4.000000e+02	6.000000e+02	4.900000e+03
25%	6.700000e+05	4.000000e+06	8.239000e+06
50%	1.670000e+07	1.970000e+07	4.240000e+07
75%	5.605000e+07	7.775000e+07	1.337500e+08
max	9.367000e+08	1.369000e+09	2.067700e+09

Joining Dataframes

In [29]:
```
# set the bom index to 'title'
bom.set_index('title', inplace=True)
```

In [30]:
```
bom
```

Out[30]:

	domestic_gross	foreign_gross	total_gross
title			
Toy Story 3	415000000	652000000	1067000000
Alice in Wonderland (2010)	334200000	691300000	1025500000
Harry Potter and the Deathly Hallows Part 1	296000000	664300000	960300000
Inception	292600000	535700000	828300000
Shrek Forever After	238700000	513900000	752600000
...	...	...	...
I Still See You	1400	1500000	1501400
The Catcher Was a Spy	725000	229000	954000
Time Freak	10000	256000	266000
Reign of Judges: Title of Liberty - Concept Short	93200	5200	98400
Antonio Lopez 1970: Sex Fashion & Disco	43200	30000	73200

2007 rows × 3 columns

In [31]:
```
#set the imdb index to 'primary_title'
imdb.set_index('primary_title', inplace=True)
```

In [32]:
```
imdb
```

Out[32]:

primary_title	runtime_minutes	genres	averagerating	numvotes
Inception	148.0	Action,Adventure,Sci-Fi	8.8	1841066
The Dark Knight Rises	164.0	Action,Thriller	8.4	1387769
Interstellar	169.0	Adventure,Drama,Sci-Fi	8.6	1299334
Django Unchained	165.0	Drama,Western	8.4	1211405
The Avengers	143.0	Action,Adventure,Sci-Fi	8.1	1183655
...	...	...	...	...
The Death of Stalin	107.0	Comedy,Drama,History	7.2	63156
Europa Report	90.0	Drama,Mystery,Sci-Fi	6.4	62994
Underworld: Blood Wars	91.0	Action,Adventure,Fantasy	5.8	62942
To All the Boys I've Loved Before	99.0	Drama,Romance	7.3	62683
The First Time	95.0	Comedy,Drama,Romance	6.9	62589

925 rows × 4 columns

In [33]:
```
# join the two dataframes using an inner join
joined_df = imdb.join(bom, how='inner')

joined_df
```

Out[33]:

	runtime_minutes	genres	averagerating	numvotes	domestic_gr
Inception	148.0	Action,Adventure,Sci-Fi	8.8	1841066	292600
The Dark Knight Rises	164.0	Action,Thriller	8.4	1387769	448100
Interstellar	169.0	Adventure,Drama,Sci-Fi	8.6	1299334	188000
Django Unchained	165.0	Drama,Western	8.4	1211405	162800
The Wolf of Wall Street	180.0	Biography,Crime,Drama	8.2	1035358	116900
...	...	...	...	...	
Act of Valor	110.0	Action,Adventure,Drama	6.5	63787	70000
Trollhunter	103.0	Drama,Fantasy,Horror	7.0	63470	253
Trolls	92.0	Adventure,Animation,Comedy	6.5	63295	153700
The Death of Stalin	107.0	Comedy,Drama,History	7.2	63156	8000
Underworld: Blood Wars	91.0	Action,Adventure,Fantasy	5.8	62942	30400

716 rows × 7 columns

In [34]:
```python
# sort values by gross
joined_df.sort_values(by=['total_gross'], ascending=False).head(20)
```

Out[34]:

	runtime_minutes	genres	averagerating	numvotes	domestic_
Avengers: Infinity War	149.0	Action,Adventure,Sci-Fi	8.5	670926	6788
Jurassic World	124.0	Action,Adventure,Sci-Fi	7.0	539338	6523
Furious 7	137.0	Action,Crime,Thriller	7.2	335074	3530
Avengers: Age of Ultron	141.0	Action,Adventure,Sci-Fi	7.3	665594	4590
Black Panther	134.0	Action,Adventure,Sci-Fi	7.3	516148	7001
Star Wars: The Last Jedi	152.0	Action,Adventure,Fantasy	7.1	462903	6202
Jurassic World: Fallen Kingdom	128.0	Action,Adventure,Sci-Fi	6.2	219125	4177
Frozen	102.0	Adventure,Animation,Comedy	7.5	516998	4007
Incredibles 2	118.0	Action,Adventure,Animation	7.7	203510	6086
The Fate of the Furious	136.0	Action,Crime,Thriller	6.7	179774	2260
Iron Man 3	130.0	Action,Adventure,Sci-Fi	7.2	692794	4090
Minions	91.0	Adventure,Animation,Comedy	6.4	193917	3360
Captain America: Civil War	147.0	Action,Adventure,Sci-Fi	7.8	583507	4081
Aquaman	143.0	Action,Adventure,Fantasy	7.1	263328	3351
Transformers: Dark of the Moon	154.0	Action,Adventure,Sci-Fi	6.2	366409	3524
Skyfall	143.0	Action,Adventure,Thriller	7.8	592221	3044
Transformers: Age of Extinction	165.0	Action,Adventure,Sci-Fi	5.7	283486	2454
The Dark Knight Rises	164.0	Action,Thriller	8.4	1387769	4481
Toy Story 3	103.0	Adventure,Animation,Comedy	8.3	682218	4150
Rogue One: A Star Wars Story	133.0	Action,Adventure,Sci-Fi	7.8	478592	5322

In [35]:
```
# filter movies containing the genre 'Action'
action = joined_df['genres'].str.contains('Action')

# Add the sum of the total gross of action films
joined_df.loc[action, ['total_gross']].sum()
```

Out[35]:
```
total_gross    98800274995
dtype: int64
```

In [36]:
```
# repeat for other genres
adventure = joined_df['genres'].str.contains('Adventure')

joined_df.loc[adventure, ['total_gross']].sum()
```

Out[36]:
```
total_gross    106667023996
dtype: int64
```

In [37]:
```
scifi = joined_df['genres'].str.contains('Sci-Fi')

joined_df.loc[scifi, ['total_gross']].sum()
```

Out[37]:
```
total_gross    39209814999
dtype: int64
```

In [38]:
```
comedy = joined_df['genres'].str.contains('Comedy')

joined_df.loc[comedy, ['total_gross']].sum()
```

Out[38]:
```
total_gross    53519643196
dtype: int64
```

In [39]:
```
drama = joined_df['genres'].str.contains('Drama')

joined_df.loc[drama, ['total_gross']].sum()
```

Out[39]:
```
total_gross    41214138496
dtype: int64
```

In [40]:
```
romance = joined_df['genres'].str.contains('Romance')

joined_df.loc[romance, ['total_gross']].sum()
```

Out[40]:
```
total_gross    8803926798
dtype: int64
```

In [41]:
```
fantasy = joined_df['genres'].str.contains('Fantasy')

joined_df.loc[fantasy, ['total_gross']].sum()
```

Out[41]:
```
total_gross    23548531999
dtype: int64
```

In [42]:
```
crime = joined_df['genres'].str.contains('Crime')

joined_df.loc[crime, ['total_gross']].sum()
```

Out[42]:
```
total_gross    16300406499
dtype: int64
```

In [43]:
```
music = joined_df['genres'].str.contains('Music')

joined_df.loc[music, ['total_gross']].sum()
```

Out[43]:
```
total_gross    2990600000
dtype: int64
```

In [44]:
```
thriller = joined_df['genres'].str.contains('Thriller')

joined_df.loc[thriller, ['total_gross']].sum()
```

Out[44]:
```
total_gross    28418320598
dtype: int64
```

In [45]:
```
animation = joined_df['genres'].str.contains('Animation')

joined_df.loc[animation, ['total_gross']].sum()
```

Out[45]:
```
total_gross    30561400000
dtype: int64
```

In [46]:
```
history = joined_df['genres'].str.contains('History')

joined_df.loc[history, ['total_gross']].sum()
```

Out[46]:
```
total_gross    3518600000
dtype: int64
```

In [47]:
```
horror = joined_df['genres'].str.contains('Horror')

joined_df.loc[horror, ['total_gross']].sum()
```

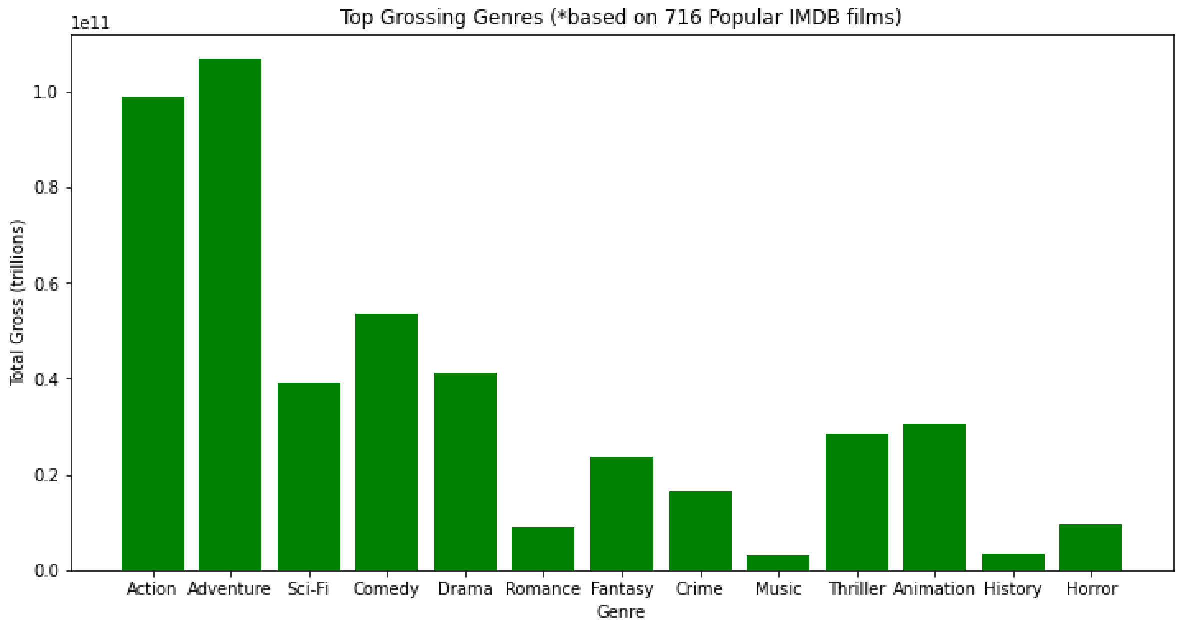
Out[47]:
```
total_gross    9474700600
dtype: int64
```

In [48]:
```
#plot the total gross values by genre
height = [98800274995,106667023996,39209814999,53519643196, 41214138496,880392
x = range(13)
labels = ['Action', 'Adventure', 'Sci-Fi', 'Comedy', 'Drama', 'Romance', 'Fant

# Create the plot
fig, ax = plt.subplots(figsize=(12, 6))

# Plot vertical bars of fixed width by passing x and height values to .bar() f
ax.bar(x, height, tick_label=labels, color='green')

# Give a title to the bar graph and label the axes
ax.set_title("Top Grossing Genres (*based on 716 Popular IMDB films)")
ax.set_ylabel("Total Gross (trillions)")
ax.set_xlabel("Genre");
```



The top grossing genres are Adventure, Action, and Comedy. The former two genres do exceptionally well at the box office.

2. What time of the year is best to release a movie?

The Numbers Database

In [49]:
```
# Load up the third dataframe, THE NUMBERS, with Pandas.
numbers = pd.read_csv("zippedData/tn.movie_budgets.csv.gz")
numbers
```

Out[49]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495

Drop Columns

The 'id' column is not necessary. We can also drop 'domestic_gross', we do not need it for this inquiry.

In [50]:
```
# drop the 'id' column and 'domestic_gross'
numbers = numbers.drop(['id', 'domestic_gross'], axis=1)
```

In [51]:
```
# set the index to the 'movie' column
numbers.set_index('movie', inplace=True)
```

In [52]:
```
# preview the dataset
numbers.head()
```

Out[52]:

movie	release_date	production_budget	worldwide_gross
Avatar	Dec 18, 2009	$425,000,000	$2,776,345,279
Pirates of the Caribbean: On Stranger Tides	May 20, 2011	$410,600,000	$1,045,663,875
Dark Phoenix	Jun 7, 2019	$350,000,000	$149,762,350
Avengers: Age of Ultron	May 1, 2015	$330,600,000	$1,403,013,963
Star Wars Ep. VIII: The Last Jedi	Dec 15, 2017	$317,000,000	$1,316,721,747

In [53]:
```
numbers.describe()
```

Out[53]:

	release_date	production_budget	worldwide_gross
count	5782	5782	5782
unique	2418	509	5356
top	Dec 31, 2014	$20,000,000	$0
freq	24	231	367

In [54]:
```
numbers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5782 entries, Avatar to My Date With Drew
Data columns (total 3 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   release_date       5782 non-null   object
 1   production_budget  5782 non-null   object
 2   worldwide_gross    5782 non-null   object
dtypes: object(3)
memory usage: 180.7+ KB
```

Notice that the columns are all in string form. This is going to be changed.

In [55]:
```
# change 'release_date' values into datetime objects
numbers['release_date'] = pd.to_datetime(numbers['release_date'])
```

In [56]:
```
numbers.head()
```

Out[56]:

movie	release_date	production_budget	worldwide_gross
Avatar	2009-12-18	$425,000,000	$2,776,345,279
Pirates of the Caribbean: On Stranger Tides	2011-05-20	$410,600,000	$1,045,663,875
Dark Phoenix	2019-06-07	$350,000,000	$149,762,350
Avengers: Age of Ultron	2015-05-01	$330,600,000	$1,403,013,963
Star Wars Ep. VIII: The Last Jedi	2017-12-15	$317,000,000	$1,316,721,747

In [57]:
```
# convert production_budget column into a float. Replace commas and $ signs to
numbers['production_budget']= numbers['production_budget'].apply(lambda x: x.r
```

In [58]:
```
# convert worldwide_gross column into a float. Replace commas and $ signs to a
numbers['worldwide_gross']= numbers['worldwide_gross'].apply(lambda x: x.repla
```

In [59]:
```
numbers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5782 entries, Avatar to My Date With Drew
Data columns (total 3 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   release_date       5782 non-null   datetime64[ns]
 1   production_budget  5782 non-null   float64
 2   worldwide_gross    5782 non-null   float64
dtypes: datetime64[ns](1), float64(2)
memory usage: 180.7+ KB
```

In [60]:
```
# make a new 'release month' column by extracting the numeric month from the a
numbers['release_month'] = numbers['release_date'].dt.month
```

In [61]:
```
numbers
```

Out[61]:

movie	release_date	production_budget	worldwide_gross	release_month
Avatar	2009-12-18	425000000.0	2.776345e+09	12
Pirates of the Caribbean: On Stranger Tides	2011-05-20	410600000.0	1.045664e+09	5
Dark Phoenix	2019-06-07	350000000.0	1.497624e+08	6
Avengers: Age of Ultron	2015-05-01	330600000.0	1.403014e+09	5
Star Wars Ep. VIII: The Last Jedi	2017-12-15	317000000.0	1.316722e+09	12
...	...	...	...	...
Red 11	2018-12-31	7000.0	0.000000e+00	12
Following	1999-04-02	6000.0	2.404950e+05	4
Return to the Land of Wonders	2005-07-13	5000.0	1.338000e+03	7
A Plague So Pleasant	2015-09-29	1400.0	0.000000e+00	9
My Date With Drew	2005-08-05	1100.0	1.810410e+05	8

5782 rows × 4 columns

In [62]:
```
# filter the releases by month and get the mean worldwide gross for each month
Jan = numbers.loc[numbers['release_month'] == 1]

Jan['worldwide_gross'].mean()
```

Out[62]: 46563824.023054756

In [63]:
```
# repeat for the subsequent months
Feb = numbers.loc[numbers['release_month'] == 2]

Feb['worldwide_gross'].mean()
```

Out[63]: 71544525.81887755

In [64]:
```
Mar = numbers.loc[numbers['release_month'] == 3]

Mar['worldwide_gross'].mean()
```

Out[64]: 80633371.12978724

In [65]:
```
Apr = numbers.loc[numbers['release_month'] == 4]

Apr['worldwide_gross'].mean()
```

Out[65]: 59920258.56828194

In [66]:
```
May = numbers.loc[numbers['release_month'] == 5]
May['worldwide_gross'].mean()
```
Out[66]: 162268003.96805897

In [67]:
```
June = numbers.loc[numbers['release_month'] == 6]
June['worldwide_gross'].mean()
```
Out[67]: 142523030.59916493

In [68]:
```
July = numbers.loc[numbers['release_month'] == 7]
July['worldwide_gross'].mean()
```
Out[68]: 140963614.66590908

In [69]:
```
Aug = numbers.loc[numbers['release_month'] == 8]
Aug['worldwide_gross'].mean()
```
Out[69]: 60978411.048387095

In [70]:
```
Sep = numbers.loc[numbers['release_month'] == 9]
Sep['worldwide_gross'].mean()
```
Out[70]: 46693687.19269777

In [71]:
```
Oct = numbers.loc[numbers['release_month'] == 10]
Oct['worldwide_gross'].mean()
```
Out[71]: 49464561.72251309

In [72]:
```
Nov = numbers.loc[numbers['release_month'] == 11]
Nov['worldwide_gross'].mean()
```
Out[72]: 135741626.89711934

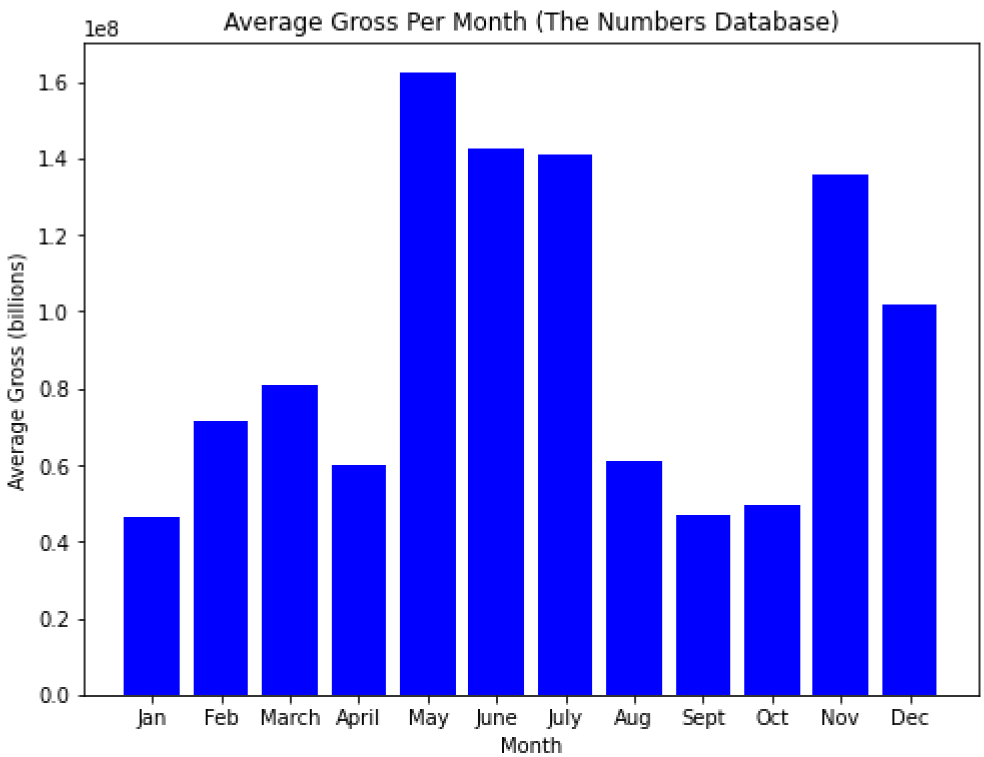
In [73]:
```
Dec = numbers.loc[numbers['release_month'] == 12]
Dec['worldwide_gross'].mean()
```
Out[73]: 101693170.67516778

In [74]:
```
# plot the average box office gross per month
height = [46563824.023054756,71544525.81887755,80633371.12978724,59920258.5682
x = range(12)
labels = ['Jan', 'Feb', 'March', 'April', 'May', 'June', 'July', 'Aug', 'Sept'

# Create the plot
fig, ax = plt.subplots(figsize=(8, 6))

# Plot vertical bars of fixed width by passing x and height values to .bar() f
ax.bar(x, height, tick_label=labels, color= 'blue')

# Give a title to the bar graph and label the axes
ax.set_title("Average Gross Per Month (The Numbers Database)")
ax.set_ylabel("Average Gross (billions)")
ax.set_xlabel("Month");
```



There is a tremendous spike in box office sales during May, June, and July. A May release is preferable, so that any hit movie has the potential to sustain a box office presence throughout the summer. There's also another jump in gross during November and December.

3. What is the correlation between budget and return on investment?

In [75]:
```
# make a new column, "profit"
numbers['profit'] = numbers['worldwide_gross'] - numbers['production_budget']
```

In [76]:
```
numbers.head()
```

Out[76]:

movie	release_date	production_budget	worldwide_gross	release_month	profit
Avatar	2009-12-18	425000000.0	2.776345e+09	12	2.351345e+09
Pirates of the Caribbean: On Stranger Tides	2011-05-20	410600000.0	1.045664e+09	5	6.350639e+08
Dark Phoenix	2019-06-07	350000000.0	1.497624e+08	6	-2.002376e+08
Avengers: Age of Ultron	2015-05-01	330600000.0	1.403014e+09	5	1.072414e+09
Star Wars Ep. VIII: The Last Jedi	2017-12-15	317000000.0	1.316722e+09	12	9.997217e+08

In [77]:
```
# sort values by 'profit'
numbers.sort_values(by=['profit'], ascending=False).head(20)
```

Out[77]:

movie	release_date	production_budget	worldwide_gross	release_month	profit
Avatar	2009-12-18	425000000.0	2.776345e+09	12	2.351345e+09
Titanic	1997-12-19	200000000.0	2.208208e+09	12	2.008208e+09
Avengers: Infinity War	2018-04-27	300000000.0	2.048134e+09	4	1.748134e+09
Star Wars Ep. VII: The Force Awakens	2015-12-18	306000000.0	2.053311e+09	12	1.747311e+09
Jurassic World	2015-06-12	215000000.0	1.648855e+09	6	1.433855e+09
Furious 7	2015-04-03	190000000.0	1.518723e+09	4	1.328723e+09

In [78]:
```
numbers.describe()
```

Out[78]:

	production_budget	worldwide_gross	release_month	profit
count	5.782000e+03	5.782000e+03	5782.000000	5.782000e+03
mean	3.158776e+07	9.148746e+07	7.050675	5.989970e+07
std	4.181208e+07	1.747200e+08	3.480147	1.460889e+08
min	1.100000e+03	0.000000e+00	1.000000	-2.002376e+08
25%	5.000000e+06	4.125415e+06	4.000000	-2.189071e+06
50%	1.700000e+07	2.798445e+07	7.000000	8.550286e+06
75%	4.000000e+07	9.764584e+07	10.000000	6.096850e+07
max	4.250000e+08	2.776345e+09	12.000000	2.351345e+09

In [79]:
```
numbers.sort_values(by=['production_budget'], ascending=False).head(20)
```

Out[79]:

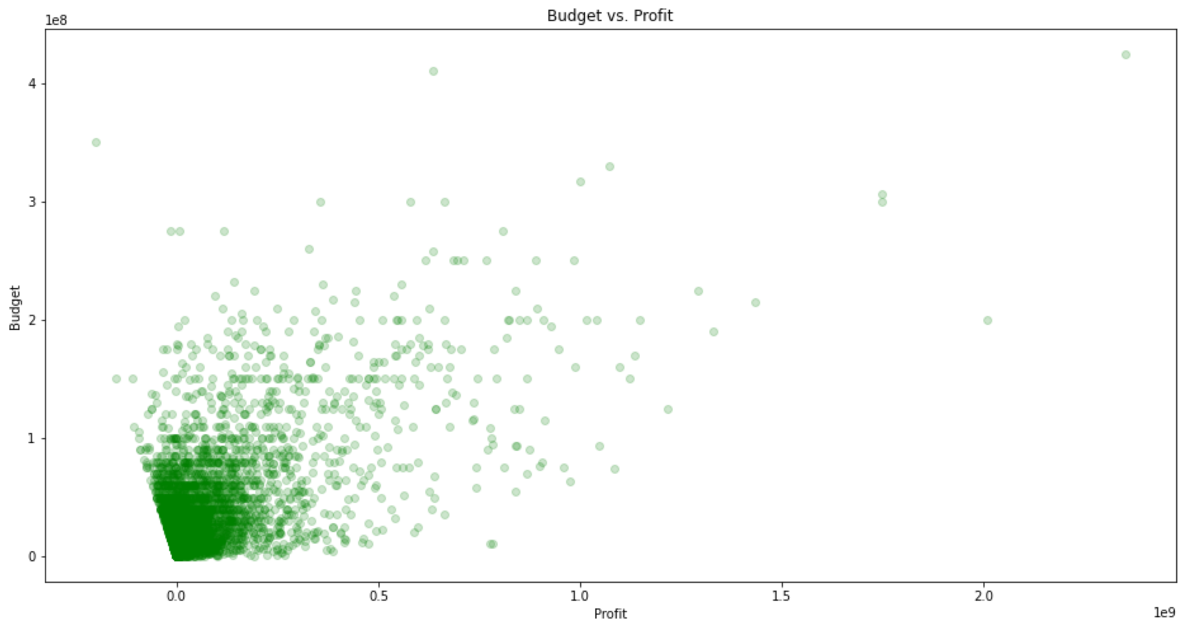
movie	release_date	production_budget	worldwide_gross	release_month	profit
Avatar	2009-12-18	425000000.0	2.776345e+09	12	2.351345e+09
Pirates of the Caribbean: On Stranger Tides	2011-05-20	410600000.0	1.045664e+09	5	6.350639e+08
Dark Phoenix	2019-06-07	350000000.0	1.497624e+08	6	-2.002376e+08
Avengers: Age of Ultron	2015-05-01	330600000.0	1.403014e+09	5	1.072414e+09
Star Wars Ep. VIII: The Last Jedi	2017-12-15	317000000.0	1.316722e+09	12	9.997217e+08
Star Wars Ep. VII: The Force Awakens	2015-12-18	306000000.0	2.053311e+09	12	1.747311e+09
Avengers: Infinity War	2018-04-27	300000000.0	2.048134e+09	4	1.748134e+09
Pirates of the Caribbean: At Worldâ□□s End	2007-05-24	300000000.0	9.634204e+08	5	6.634204e+08
Justice League	2017-11-17	300000000.0	6.559452e+08	11	3.559452e+08
Spectre	2015-11-06	300000000.0	8.796209e+08	11	5.796209e+08
The Dark Knight Rises	2012-07-20	275000000.0	1.084439e+09	7	8.094391e+08
Solo: A Star Wars Story	2018-05-25	275000000.0	3.931513e+08	5	1.181513e+08
The Lone Ranger	2013-07-02	275000000.0	2.600021e+08	7	-1.499788e+07
John Carter	2012-03-09	275000000.0	2.827781e+08	3	7.778100e+06
Tangled	2010-11-24	260000000.0	5.864772e+08	11	3.264772e+08
Spider-Man 3	2007-05-04	258000000.0	8.948602e+08	5	6.368602e+08
Batman v Superman: Dawn of Justice	2016-03-25	250000000.0	8.675003e+08	3	6.175003e+08
The Hobbit: An Unexpected Journey	2012-12-14	250000000.0	1.017004e+09	12	7.670036e+08

	release_date	production_budget	worldwide_gross	release_month	profit
movie					
Harry Potter and the Half-Blood Prince	2009-07-15	250000000.0	9.352138e+08	7	6.852138e+08
The Hobbit: The Desolation of Smaug	2013-12-13	250000000.0	9.603669e+08	12	7.103669e+08

In [80]:
```
# make scatter plot of budget and profit
fig, ax = plt.subplots(figsize=(16, 8))

ax.scatter(
    x=numbers['profit'],
    y=numbers['production_budget'],
    alpha=0.2,
    color='green')

ax.set_xlabel("Profit")
ax.set_ylabel("Budget")
ax.set_title("Budget vs. Profit");
```



In [81]:
```
#calculate correlation coefficient
np.corrcoef(numbers['profit'], numbers['production_budget'])
```

Out[81]:
```
array([[1.        , 0.60875215],
       [0.60875215, 1.        ]])
```

There is a strong correlation between production budget and return on investment. This means we are likely to turn a profit with our project and should be liberal with our spending. The mean production budget is $31,587,760. We can go well above that with our budget.

4. Who are some fan-favorite directors that we should look to hire?

IMDB Database

In [82]:
```
# show directors with popular movies that are rated 7.5+

d = """
SELECT primary_title, runtime_minutes, genres, category, primary_name, average
FROM principals
JOIN movie_ratings
USING (movie_id)
JOIN movie_basics
USING (movie_id)
JOIN persons
USING (person_id)
WHERE category = "director" AND averagerating >= 7.5
AND numvotes > 63000
ORDER BY numvotes DESC;
"""
imdb2 = pd.read_sql(d, conn)
```

In [83]:
```
imdb2.head()
```

Out[83]:

	primary_title	runtime_minutes	genres	category	primary_name	averagerating	r
0	Inception	148.0	Action,Adventure,Sci-Fi	director	Christopher Nolan	8.8	
1	The Dark Knight Rises	164.0	Action,Thriller	director	Christopher Nolan	8.4	
2	Interstellar	169.0	Adventure,Drama,Sci-Fi	director	Christopher Nolan	8.6	
3	Django Unchained	165.0	Drama,Western	director	Quentin Tarantino	8.4	
4	The Avengers	143.0	Action,Adventure,Sci-Fi	director	Joss Whedon	8.1	

In [84]:
```
# value count of directors with popular films
imdb2['primary_name'].value_counts().head(10)
```

Out[84]:
```
Denis Villeneuve         5
Christopher Nolan        4
Anthony Russo            4
Joe Russo                4
Wes Anderson             3
Martin Scorsese          3
Matthew Vaughn           3
David Fincher            3
Alejandro G. Iñárritu    3
David Yates              2
Name: primary_name, dtype: int64
```

In [85]:
```
# set imdb2 index to 'primary_title'
imdb2.set_index('primary_title', inplace=True)
```

Join databases

In [86]:
```
# join imdb2 with bom, with a left join so that we get all the directors' film
directors_df = imdb2.join(bom, how='left')
```

In [87]:
```
directors_df
```

Out[87]:

	runtime_minutes	genres	category	primary_name	averagerating
12 Years a Slave	134.0	Biography,Drama,History	director	Steve McQueen	8.1
127 Hours	94.0	Adventure,Biography,Drama	director	Danny Boyle	7.6
42	128.0	Biography,Drama,Sport	director	Brian Helgeland	7.5
50/50	100.0	Comedy,Drama,Romance	director	Jonathan Levine	7.7
A Monster Calls	108.0	Animation,Drama,Fantasy	director	J.A. Bayona	7.5
...	...	...	...	...	...
X-Men: First Class	131.0	Action,Adventure,Sci-Fi	director	Matthew Vaughn	7.7
Your Name.	106.0	Animation,Drama,Fantasy	director	Makoto Shinkai	8.4
Zootopia	108.0	Adventure,Animation,Comedy	director	Byron Howard	8.0
Zootopia	108.0	Adventure,Animation,Comedy	director	Rich Moore	8.0
Zootopia	108.0	Adventure,Animation,Comedy	director	Jared Bush	8.0

229 rows × 9 columns

In [88]:
```
# sort by numvotes
directors_df.sort_values(by=['numvotes'],ascending=False).head(60)
```

Out[88]:

	runtime_minutes	genres	category	primary_name	averager
Inception	148.0	Action,Adventure,Sci-Fi	director	Christopher Nolan	
The Dark Knight Rises	164.0	Action,Thriller	director	Christopher Nolan	
Interstellar	169.0	Adventure,Drama,Sci-Fi	director	Christopher Nolan	
Django Unchained	165.0	Drama,Western	director	Quentin Tarantino	
The Avengers	143.0	Action,Adventure,Sci-Fi	director	Joss Whedon	
The Wolf of Wall Street	180.0	Biography,Crime,Drama	director	Martin Scorsese	
Shutter Island	138.0	Mystery,Thriller	director	Martin Scorsese	

In [89]:
```
# filter rows for only Christopher Nolan films
CN = directors_df.loc[directors_df['primary_name'] == 'Christopher Nolan']
CN
```

Out[89]:

	runtime_minutes	genres	category	primary_name	averagerating	numv
Dunkirk	106.0	Action,Drama,History	director	Christopher Nolan	7.9	466
Inception	148.0	Action,Adventure,Sci-Fi	director	Christopher Nolan	8.8	1841
Interstellar	169.0	Adventure,Drama,Sci-Fi	director	Christopher Nolan	8.6	1299
The Dark Knight Rises	164.0	Action,Thriller	director	Christopher Nolan	8.4	1387

In [90]:
```
CN.describe()

# AVERAGE Rating 8.425
```

Out[90]:

	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_gross	total_gro
count	4.000000	4.000000	4.000000e+00	4.000000e+00	4.000000e+00	4.000000e+
mean	146.750000	8.425000	1.248687e+06	2.791750e+08	4.997750e+08	7.789500e+
std	28.605069	0.386221	5.728622e+05	1.229385e+08	1.246391e+08	2.385668e+
min	106.000000	7.900000	4.665800e+05	1.880000e+08	3.372000e+08	5.252000e+
25%	137.500000	8.275000	1.091146e+06	1.880000e+08	4.513500e+08	6.393500e+
50%	156.000000	8.500000	1.343552e+06	2.403000e+08	5.125500e+08	7.528500e+
75%	165.250000	8.650000	1.501093e+06	3.314750e+08	5.609750e+08	8.924500e+
max	169.000000	8.800000	1.841066e+06	4.481000e+08	6.368000e+08	1.084900e+

In [91]:
```
CN['numvotes'].sum()
# NUMVOTES 4994749
# AVG TOTAL GROSS $778,950,000
```

Out[91]: 4994749

In [92]:
```
# filter rows for only Denis Villeneuve films
DV = directors_df.loc[directors_df['primary_name'] == 'Denis Villeneuve']
DV
```

Out[92]:

	runtime_minutes	genres	category	primary_name	averagerating	numvot
Arrival	116.0	Drama,Mystery,Sci-Fi	director	Denis Villeneuve	7.9	5154
Blade Runner 2049	164.0	Drama,Mystery,Sci-Fi	director	Denis Villeneuve	8.0	3762
Incendies	131.0	Drama,Mystery,War	director	Denis Villeneuve	8.3	1241
Prisoners	153.0	Crime,Drama,Mystery	director	Denis Villeneuve	8.1	5262
Sicario	121.0	Action,Crime,Drama	director	Denis Villeneuve	7.6	3285

In [93]:
```
DV['numvotes'].sum()
# NUMVOTES 1870701
```

Out[93]: 1870701

In [94]:
```
DV.describe()

# AVERAGE Rating 7.98
# NUMVOTES 1870701
# Avg Total Gross $167,400,000
```

Out[94]:

	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_gross	total_gr
count	5.000000	5.000000	5.000000	4.000000e+00	4.000000e+00	4.000000e
mean	137.000000	7.980000	374140.200000	7.512500e+07	9.227500e+07	1.674000e
std	20.724382	0.258844	164086.363128	2.535224e+07	5.669270e+07	7.872475e
min	116.000000	7.600000	124156.000000	4.690000e+07	3.800000e+07	8.490000e
25%	121.000000	7.900000	328548.000000	5.747500e+07	5.532500e+07	1.128000e
50%	131.000000	8.000000	376241.000000	7.655000e+07	8.195000e+07	1.627000e
75%	153.000000	8.100000	515483.000000	9.420000e+07	1.189000e+08	2.173000e
max	164.000000	8.300000	526273.000000	1.005000e+08	1.672000e+08	2.593000e

In [95]:
```
# filter rows for only Russo Brothers films
RU = directors_df.loc[directors_df['primary_name'] == 'Anthony Russo']
RU
```

Out[95]:

	runtime_minutes	genres	category	primary_name	averagerating	numvo
Avengers: Endgame	181.0	Action,Adventure,Sci-Fi	director	Anthony Russo	8.8	441
Avengers: Infinity War	149.0	Action,Adventure,Sci-Fi	director	Anthony Russo	8.5	670
Captain America: Civil War	147.0	Action,Adventure,Sci-Fi	director	Anthony Russo	7.8	583
Captain America: The Winter Soldier	136.0	Action,Adventure,Sci-Fi	director	Anthony Russo	7.8	666

In [96]:
```
RU['numvotes'].sum()
# NUMVOTES 2361820
```

Out[96]: 2361820

In [97]:
```
RU.describe()
# AVERAGE Rating 8.225
# NUMVOTES 2361820
# AVG TOTAL GROSS $1,305,133,000
```

Out[97]:

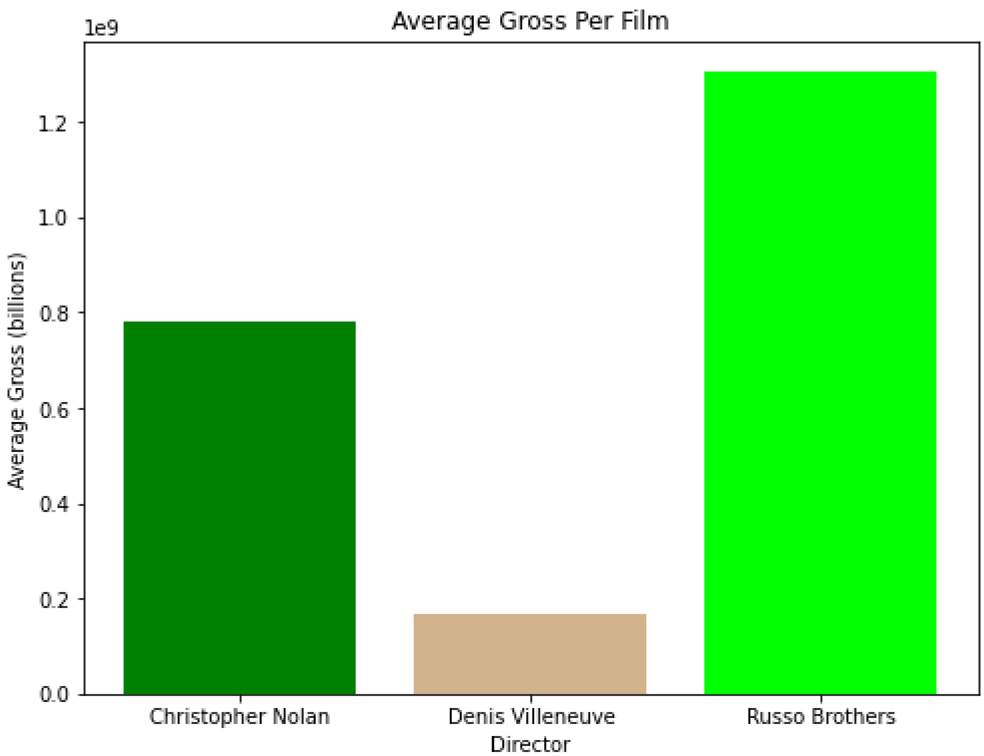
	runtime_minutes	averagerating	numvotes	domestic_gross	foreign_gross	total_gr
count	4.000000	4.0000	4.000000	3.000000e+00	3.000000e+00	3.000000e
mean	153.250000	8.2250	590455.000000	4.489000e+08	8.562333e+08	1.305133e
std	19.362765	0.5058	107339.809568	2.124588e+08	4.672514e+08	6.795922e
min	136.000000	7.8000	441135.000000	2.598000e+08	4.545000e+08	7.143000e
25%	144.250000	7.8000	547914.000000	3.339500e+08	5.998500e+08	9.338000e
50%	148.000000	8.1500	624879.500000	4.081000e+08	7.452000e+08	1.153300e
75%	157.000000	8.5750	667420.500000	5.434500e+08	1.057100e+09	1.600550e
max	181.000000	8.8000	670926.000000	6.788000e+08	1.369000e+09	2.047800e

In [98]:
```
# plot the average box office gross per film by director
height = [7.789500e+08,1.674000e+08,1.305133e+09]
x = range(3)
labels = ['Christopher Nolan', 'Denis Villeneuve', 'Russo Brothers']

# Create the plot
fig, ax = plt.subplots(figsize=(8, 6))

# Plot vertical bars of fixed width by passing x and height values to .bar() f
ax.bar(x, height, tick_label=labels, color=['green','tan','lime'])

# Give a title to the bar graph and label the axes
ax.set_title("Average Gross Per Film")
ax.set_ylabel("Average Gross (billions)")
ax.set_xlabel("Director");
```



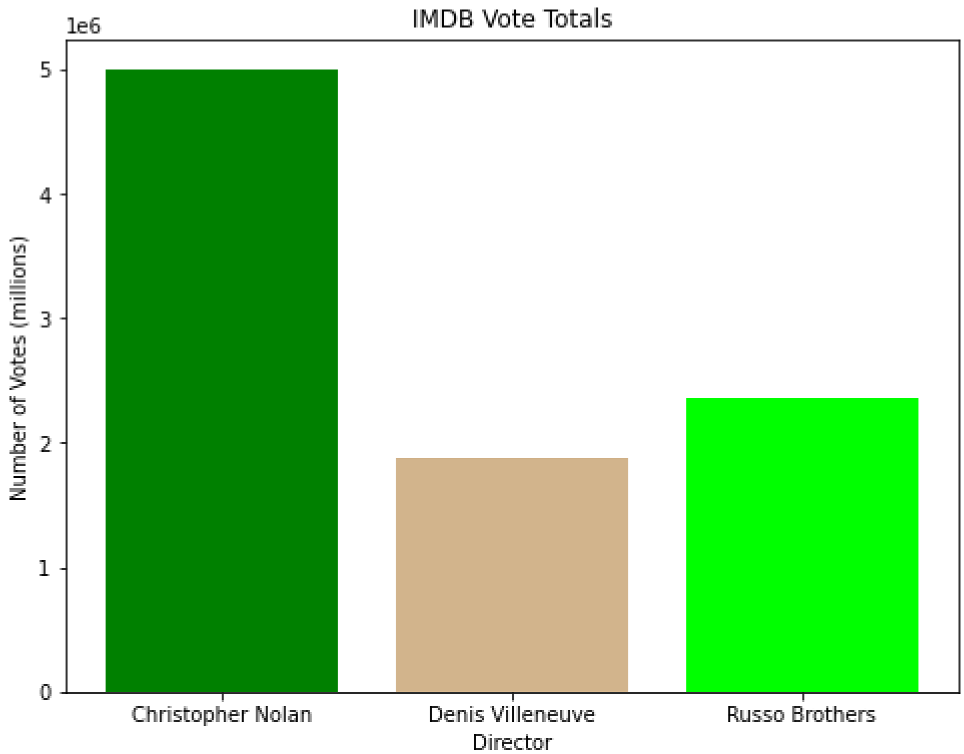
Though the four Russo Brothers films are the highest grossing, they are all in the same genre and are Marvel Superhero films, backed by Disney. They have the advantage of being sequels to films that are a part of a popular franchise, using established comic book source material. As a new studio Microsoft is unlikely to replicate the Russo Brothers' success without Marvel licensing.

In [99]:
```
# plot the number of IMDB votes by director
height = [CN['numvotes'].sum(),DV['numvotes'].sum(),RU['numvotes'].sum()]
x = range(3)
labels = ['Christopher Nolan', 'Denis Villeneuve', 'Russo Brothers']

# Create the plot
fig, ax = plt.subplots(figsize=(8, 6))

# Plot vertical bars of fixed width by passing x and height values to .bar() f
ax.bar(x, height, tick_label=labels, color=['green','tan','lime'])

# Give a title to the bar graph and label the axes
ax.set_title("IMDB Vote Totals")
ax.set_ylabel("Number of Votes (millions)")
ax.set_xlabel("Director");
```



Christopher Nolan is a more ideal director. Nolan's filmography is more versatile, spanning six genres. He has seen success both with (Batman films) and without licensed material. According to IMDB, fans are more engaged with Nolan's films compared to other directors. The top 3 voted films of all time, Inception, The Dark Knight Rises, and Interstellar, are all Christopher Nolan films. He also has the highest average rating for his popular films- averaging an 8.425, compared to Villeneuve's 7.98 and the Russo Brothers 8.225.

Conclusions

I recommend that Microsoft Studios collaborate with Christopher Nolan and release a big budget film that is, at minumum, heavy on action & adventure. The film should aim for a May release so that it can benefit from the summer box office boom.

Still, there are some reasons that this recommendation may not fully solve the business problem. Depending on what competing studios are doing, the release window may be overcrowded by other films. The analysis also doesn't make predictions farther out into the future. Older films will probably have less online engagement on IMDB compared to modern ones. Further, having additional data available would aid Microsoft into making better informed decisions. It would be helpful to have the following data in the future: movie streaming numbers, digital purchase and rental sales, VHS and DVD sales, and data during the pandemic and the post-pandemic recovery period