Final Project Submission

Please fill out:

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- Student pace: self paced
- Scheduled project review date/time: July 1, 2022
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- Blog post URL: http://dmvinedata.com/blog/

Microsoft Movie Studio Analysis

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Overview

This analysis directs Microsoft's potential studio head with actionable insights for their movie studio development. These recommendations are determined from insights from box office movie "Ratings" and depends on other attributes such as "Genre", "Directors" and "Movie Budget" data. The datasets given were filtered to analyze movies and their associated attributes that have a minimum "8/10" ("B") rating. The analysis observed and extracted patterns from data of some of the "best" movies.

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."

Ref: Phase 1 Project Description, 2022

Microsoft is in competition with current major studios who have been in business for many years and already have a wealth of experience. The questions driving the analysis, support Microsoft making choices based on direct data output from their competition as well as potential growth areas that may be overlooked. The analysis questions and main variable of success were chosen with the mindset that Microsoft is a major tech company that has influence and skillsets in other areas of tech. This analysis is for a movie studio which is a part of of a greater ecosystem.

Data Understanding

Box office related datasets (SQL and CSV) with the box office movie target "Rating" variable and associated independent "Genre, Director and Budget" variable information were taken from IMBD and the-numbers.

In [1]:
```
#Import libraries

import pandas as pd
import numpy as np
import sqlite3
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
%matplotlib inline
```

In [2]:
```
#Connecting with databases
conn = sqlite3.connect('data/im.db')
```

In [3]:
```
#View the list of tables in the database

df = pd.read_sql("""
SELECT name
FROM sqlite_master
WHERE type = 'table';""", conn)
df
```

Out[3]:

	name
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers
8	new_directors

IMBD Tables Used:

- **movie_basics**
  - The movie_basics dataset describes just over 146,000 movies with their associated genres, years.
- **movie_ratings**
  - The movie_ratings dataset describes 73,856 movie'saverage rating (from average ratings that range from "1" to "10") and the number of votes the average is calculated (ranging from "5" to "1.84 Mil").
- **directors**
  - The directors dataset describes 291,174 movies and their associated director's id.
- **persons**

- The persons dataset describes 606,648 people and their associated movie related profession(s).

IMBD Table: movie_basics

In [4]:
```
#Looking at movie_basic table
q_basics = '''
SELECT
    *
FROM movie_basics;
'''
MovBasics_df = pd.read_sql(q_basics, conn)
#What does the dataset include?
MovBasics_df.head()
```

Out[4]:

	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

In [5]:
```
MovBasics_df.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 [6]:
```
MovBasics_df["genres"].value_counts()
```

Out[6]:
```
Documentary                     32185
Drama                           21486
Comedy                           9177
Horror                           4372
Comedy,Drama                     3519
                                ...
Family,Fantasy,Western              1
Animation,Horror,Romance            1
Music,Musical,Reality-TV            1
Action,Horror,Music                 1
```

```
Documentary,Mystery,Romance        1
Name: genres, Length: 1085, dtype: int64
```

In [7]:
```
MovBasics_df.isna().sum()
```

Out[7]:
```
movie_id               0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [8]:
```
#Looking to see if there are any duplicates
q_basics = '''
SELECT
    movie_id,
    start_year,
    primary_title,
    genres,
    COUNT(*) AS CNT
FROM movie_basics
GROUP BY movie_id
HAVING COUNT(*) > 1
ORDER BY movie_id;
'''

MovBasics_df = pd.read_sql(q_basics, conn)
#Displays if there are duplicate movies
MovBasics_df
```

Out[8]:

movie_id	start_year	primary_title	genres	CNT

IMBD Table: movie_ratings

The average movie ratings are directly dependent on the "numvotes" column.

In [9]:
```
#Looking at movie_ratings table
q_basics = '''
SELECT
    *
FROM movie_ratings;'''

MovRatings_df = pd.read_sql(q_basics, conn)
MovRatings_df.head()
```

Out[9]:

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

In [10]:
```
MovRatings_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   movie_id       73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

In [11]:
```
MovRatings_df.describe()
```

Out[11]:

	averagerating	numvotes
count	73856.000000	7.385600e+04
mean	6.332729	3.523662e+03
std	1.474978	3.029402e+04
min	1.000000	5.000000e+00
25%	5.500000	1.400000e+01
50%	6.500000	4.900000e+01
75%	7.400000	2.820000e+02
max	10.000000	1.841066e+06

In [12]:
```
MovRatings_df.isna().sum()
```

Out[12]:
```
movie_id         0
averagerating    0
numvotes         0
dtype: int64
```

IMBD Table: directors

Multiple duplicates are found and need to be removed

In [13]:
```
#Looking at directors table
q_basics = '''
SELECT
    *
FROM directors;'''

MovDirID_df = pd.read_sql(q_basics, conn)
MovDirID_df.head(10)
```

Out[13]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0462036	nm1940585
2	tt0835418	nm0151540
3	tt0835418	nm0151540
4	tt0878654	nm0089502
5	tt0878654	nm2291498

	movie_id	person_id
6	tt0878654	nm2292011
7	tt0879859	nm2416460
8	tt0996958	nm2286991
9	tt0996958	nm2286991

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 291174 entries, 0 to 291173
Data columns (total 2 columns):
 #   Column     Non-Null Count   Dtype 
---  ------     --------------   ----- 
 0   movie_id   291174 non-null  object
 1   person_id  291174 non-null  object
dtypes: object(2)
memory usage: 4.4+ MB
```

In [15]:
```
MovDirID_df.describe()
```

Out[15]:

	movie_id	person_id
count	291174	291174
unique	140417	109253
top	tt4050462	nm6935209
freq	3818	238

In [16]:
```
MovDirID_df.isna().sum()
```

Out[16]:
```
movie_id     0
person_id    0
dtype: int64
```

IMBD Table: persons

In [17]:
```
#Looking at persons table for id and name
q_basics = '''
SELECT
    *
FROM persons;'''

MovDir_df = pd.read_sql(q_basics, conn)
MovDir_df.head()
```

Out[17]:

	person_id	primary_name	birth_year	death_year	primary_profe
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,pro
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_depar
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_depar

	person_id	primary_name	birth_year	death_year	primary_profe
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_dec

In [18]:
```
MovDir_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 606648 entries, 0 to 606647
Data columns (total 5 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   person_id           606648 non-null  object 
 1   primary_name        606648 non-null  object 
 2   birth_year          82736 non-null   float64
 3   death_year          6783 non-null    float64
 4   primary_profession  555308 non-null  object 
dtypes: float64(2), object(3)
memory usage: 23.1+ MB
```

In [19]:
```
MovDir_df["primary_name"].isna().sum()
```

Out[19]: 0

Budget CSV:

movie_budgets

- This dataset describes the movie budget and movie gross from 5782 movies. The movie name values are the only link to joining with other movie datasets. This can potentially be a single point of failure or limitation in the data analysis.

In [20]:
```
#Import CSV to a dataframe
Bud_df = pd.read_csv('data/movie_budgets.csv')
Bud_df.head()
```

Out[20]:

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

In [21]:
```
#Note that the production_budget is a string and not a number
Bud_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
```

```
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

Data Preparation

Data Cleaning

Merge movie_basic and movie_ratings on their shared movie_id primary key.

In [22]:
```
#Joining movie_basics and ratings
qB1 = """
SELECT
    movie_id,
    start_year,
    primary_title,
    genres,
    averagerating,
    numvotes
FROM movie_basics
JOIN movie_ratings
    USING (movie_id)
GROUP BY movie_id
ORDER BY numvotes DESC, averagerating
;
"""
Genre_Ratings= pd.read_sql(qB1,conn)
```

In [23]:
```
movieG_df = pd.DataFrame(Genre_Ratings)
movieG_df.head()
```

Out[23]:

	movie_id	start_year	primary_title	genres	averagerating	numvotes
0	tt1375666	2010	Inception	Action,Adventure,Sci-Fi	8.8	1841066
1	tt1345836	2012	The Dark Knight Rises	Action,Thriller	8.4	1387769
2	tt0816692	2014	Interstellar	Adventure,Drama,Sci-Fi	8.6	1299334
3	tt1853728	2012	Django Unchained	Drama,Western	8.4	1211405
4	tt0848228	2012	The Avengers	Action,Adventure,Sci-Fi	8.1	1183655

Split genres on seperate rows

Ref: Split Values on Rows on Stackoverflow By Dan Allen Jun, 2013

In [24]:
```
#Spliting the genres into sep rows by ",". This will help support a cleaner anal
s = movieG_df["genres"].str.split(",").apply(pd.Series, 1).stack()
s.index = s.index.droplevel(-1) # align index
```

```
s.name = "genres" #name to join on
s.head()
```

Out[24]:
```
0       Action
0    Adventure
0       Sci-Fi
1       Action
1     Thriller
Name: genres, dtype: object
```

In [25]:
```
#delete old dataframe column with multiple values
del movieG_df["genres"]
```

In [26]:
```
#making it equal to the new dataframe
movieG1_df = movieG_df.join(s)
movieG1_df.head()
```

Out[26]:

	movie_id	start_year	primary_title	averagerating	numvotes	genres
0	tt1375666	2010	Inception	8.8	1841066	Action
0	tt1375666	2010	Inception	8.8	1841066	Adventure
0	tt1375666	2010	Inception	8.8	1841066	Sci-Fi
1	tt1345836	2012	The Dark Knight Rises	8.4	1387769	Action
1	tt1345836	2012	The Dark Knight Rises	8.4	1387769	Thriller

Missing Values

Drop missing values from dataframe.

Depending on the amount of missing data the missing rows will be dropped or filled in. If there is a negligent amount compared to the entire dataset, the data will be dropped.

In [27]:
```
#Determine if there are missing data
movieG1_df["genres"].isna().sum()
```

Out[27]: 804

In [28]:
```
#Checking to see if any ratings values have missing data
movieG_df["averagerating"].isna().sum()
```

Out[28]: 0

In [29]:
```
#drop missing values since it is determined to be negligent to the number of val
movieG1_df = movieG1_df.dropna()
```

Check similar genre values to see if any could be merged into one. This can be based on the similarity to the

In [30]:
```
movieG1_df["genres"].unique()
```

Out[30]:
```
array(['Action', 'Adventure', 'Sci-Fi', 'Thriller', 'Drama', 'Western',
       'Biography', 'Crime', 'Mystery', 'Comedy', 'Fantasy', 'Family',
       'Animation', 'Romance', 'Music', 'History', 'Horror', 'Sport',
       'War', 'Musical', 'Documentary', 'News', 'Game-Show', 'Reality-TV',
       'Adult', 'Short'], dtype=object)
```

In [31]:
```
#Checking genres values movies to see if they are compatible to be merged
genCat = movieG1_df.loc[(movieG1_df["genres"] == "Music") | (movieG1_df["genres"
genCat.head(20)
```

Out[31]:

	movie_id	start_year	primary_title	averagerating	numvotes	genres
33	tt2582802	2014	Whiplash	8.5	616916	Music
88	tt3783958	2016	La La Land	8.0	436070	Music
141	tt1727824	2018	Bohemian Rhapsody	8.0	345466	Music
184	tt1707386	2012	Les Misérables	7.6	285971	Musical
209	tt1981677	2012	Pitch Perfect	7.2	256565	Music
218	tt1517451	2018	A Star Is Born	7.8	249245	Music
230	tt2771200	2017	Beauty and the Beast	7.2	238325	Musical
307	tt1485796	2017	The Greatest Showman	7.6	199663	Musical
390	tt1226229	2010	Get Him to the Greek	6.4	161653	Music
473	tt2848292	2015	Pitch Perfect 2	6.4	130692	Music
476	tt1980929	2013	Begin Again	7.4	129884	Music
500	tt2042568	2013	Inside Llewyn Davis	7.5	123759	Music
556	tt0475290	2016	Hail, Caesar!	6.3	111422	Music
569	tt1355630	2014	If I Stay	6.8	107625	Music
678	tt4062536	2015	Green Room	7.0	90773	Music
703	tt6412452	2018	The Ballad of Buster Scruggs	7.3	87418	Musical
778	tt1859650	2012	To Rome with Love	6.3	79381	Music
811	tt1702443	2011	Justin Bieber: Never Say Never	1.6	74978	Music
813	tt1294226	2010	The Last Song	6.0	74914	Music
817	tt3544112	2016	Sing Street	8.0	74651	Music

In [32]:
```
movieG1_df["genres"].describe()
```

Out[32]:
```
count      128490
unique         26
top         Drama
freq        30788
Name: genres, dtype: object
```

The "Music" and "Musical" values have enough similarities where we can merge them. There isn't a clear distinction between them.

In [33]:
```
# Rename values in genre to match
movieG1_df["genres"].replace("Musical","Music", inplace = True)
```

Checking the statistical measures of the number of votes. I want to consider the average ratings that were made from a certain amount of votes. The mean number will be considered.

In [34]:
```
#Check the mean amount of votes given.
movieG1_df.describe()
```

Out[34]:

	start_year	averagerating	numvotes
count	128490.000000	128490.000000	1.284900e+05
mean	2014.221021	6.302146	5.337769e+03
std	2.579176	1.457744	3.808942e+04
min	2010.000000	1.000000	5.000000e+00
25%	2012.000000	5.400000	1.600000e+01
50%	2014.000000	6.400000	6.600000e+01
75%	2016.000000	7.300000	4.290000e+02
max	2019.000000	10.000000	1.841066e+06

Filter Ratings

Use data that is filtered by an average rating with a minimum value of "8" and with a minimum numvotes of the mean (5337). Rationale: The analysis goal was to extract patterns from some of the "best" movies. An "8/10" rating is equivalent to a "B" rating. I am confident that "8/10" rating will be a good rating even in the midst of other dataset sources (e.g. Rottentomatoes). Using the mean numvotes filters out a lot of lower outliers produced high rating values. The ratings used to be more credible.

In [35]:

```
#Filters future dataset for a certain averagerating and numvote values
g = movieG1_df.loc[(movieG1_df["averagerating"] >=8) & (movieG1_df["numvotes"] >
g.head(25)
```

Out[35]:

	movie_id	start_year	primary_title	averagerating	numvotes	genres
0	tt1375666	2010	Inception	8.8	1841066	Action
0	tt1375666	2010	Inception	8.8	1841066	Adventure
0	tt1375666	2010	Inception	8.8	1841066	Sci-Fi
1	tt1345836	2012	The Dark Knight Rises	8.4	1387769	Action
1	tt1345836	2012	The Dark Knight Rises	8.4	1387769	Thriller
2	tt0816692	2014	Interstellar	8.6	1299334	Adventure
2	tt0816692	2014	Interstellar	8.6	1299334	Drama
2	tt0816692	2014	Interstellar	8.6	1299334	Sci-Fi
3	tt1853728	2012	Django Unchained	8.4	1211405	Drama
3	tt1853728	2012	Django Unchained	8.4	1211405	Western
4	tt0848228	2012	The Avengers	8.1	1183655	Action
4	tt0848228	2012	The Avengers	8.1	1183655	Adventure
4	tt0848228	2012	The Avengers	8.1	1183655	Sci-Fi
5	tt0993846	2013	The Wolf of Wall Street	8.2	1035358	Biography
5	tt0993846	2013	The Wolf of Wall Street	8.2	1035358	Crime

	movie_id	start_year	primary_title	averagerating	numvotes	genres
5	tt0993846	2013	The Wolf of Wall Street	8.2	1035358	Drama
6	tt1130884	2010	Shutter Island	8.1	1005960	Mystery
6	tt1130884	2010	Shutter Island	8.1	1005960	Thriller
7	tt2015381	2014	Guardians of the Galaxy	8.1	948394	Action
7	tt2015381	2014	Guardians of the Galaxy	8.1	948394	Adventure
7	tt2015381	2014	Guardians of the Galaxy	8.1	948394	Comedy
8	tt1431045	2016	Deadpool	8.0	820847	Action
8	tt1431045	2016	Deadpool	8.0	820847	Adventure
8	tt1431045	2016	Deadpool	8.0	820847	Comedy
10	tt2488496	2015	Star Wars: Episode VII - The Force Awakens	8.0	784780	Action

In [36]:

```
#View filtered data statisics with
g.describe()
```

Out[36]:

	start_year	averagerating	numvotes
count	522.000000	522.000000	5.220000e+02
mean	2014.348659	8.251533	1.818726e+05
std	2.487027	0.285624	3.110069e+05
min	2010.000000	8.000000	5.406000e+03
25%	2013.000000	8.100000	9.988000e+03
50%	2014.000000	8.200000	2.937300e+04
75%	2016.000000	8.300000	1.816010e+05
max	2019.000000	9.700000	1.841066e+06

Remove Duplicates rows from Directors table

In [37]:

```
#Database querying through SQL
from pandasql import sqldf
pysqldf = lambda q: sqldf(q, globals())
```

In [38]:

```
#Checking Duplicates in directors table
q = """
SELECT
*,
COUNT (*) AS CNT
FROM directors
GROUP BY movie_id, person_id
HAVING CNT >1;
"""
Dir_Dup = pd.read_sql(q,conn)
Dir_Dup
```

Out[38]:

	movie_id	person_id	CNT
0	tt0063540	nm0712540	4
1	tt0069049	nm0000080	2
2	tt0100275	nm0749914	2
3	tt0100275	nm0765384	2
4	tt0146592	nm1030585	2
...	...	...	...
54672	tt9916538	nm8185151	3
54673	tt9916622	nm9272490	2
54674	tt9916622	nm9272491	2
54675	tt9916754	nm8349149	2
54676	tt9916754	nm9272490	2

54677 rows × 3 columns

Ref: Remove Duplicates By Database Star

In [39]:

```
#Create a new table with no duplicates
#This is commented out now because table exists already
#If table does not exist, remove comments below

#q = """
#CREATE TABLE new_directors AS
#SELECT
#    movie_id,
#    person_id
#FROM directors
#GROUP BY movie_id, person_id ;
#"""
#pd.read_sql(q,conn)
```

In [40]:

```
#Checking Duplicates in new table
q = """
SELECT
*,
COUNT (*) AS CNT
FROM new_directors
GROUP BY movie_id, person_id
HAVING CNT >1;
"""
newD_Dup = pd.read_sql(q,conn)
newD_Dup
```

Out[40]:

movie_id	person_id	CNT

In [41]:

```
#Code to drop tables if wanting to run code again

#q = """

#DROP TABLE im.new_directors;"""
```

```
#pd.read_sql(q,conn)
```

In [43]:

```
#Joining of several tables to get movie id and their director
qD = """
SELECT
    movie_id,
    primary_name AS Director
FROM movie_basics
JOIN movie_ratings
    USING (movie_id)
JOIN new_directors
    USING (movie_id)
JOIN persons
    USING(person_id);
"""
Dir_Sql = pd.read_sql(qD,conn)

movieD2_df = pd.DataFrame(Dir_Sql)
movieD2_df
```

Out[43]:

	movie_id	Director
0	tt0063540	Harnam Singh Rawail
1	tt0066787	Mani Kaul
2	tt0069049	Orson Welles
3	tt0069204	Hrishikesh Mukherjee
4	tt0100275	Raoul Ruiz
...	...	...
86025	tt9913084	Giancarlo Soldi
86026	tt9914286	Ahmet Faik Akinci
86027	tt9914642	Chris Jordan
86028	tt9914942	Laura Jou
86029	tt9916160	Joost van der Wiel

86030 rows × 2 columns

In [44]:

```
#Import Budget CSV in
Bud_df = pd.read_csv('data/movie_budgets.csv')
Bud_df.head()
Bud_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
```

```
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

Clean the production budget column. Convert to type int

In [45]:
```
#Remove necessary characters from string to prepare for conversion
Bud_df["production_budget"]=Bud_df["production_budget"].str.strip("$")
Bud_df["production_budget"]=Bud_df["production_budget"].str.replace(",", "")
```

In [46]:
```
#Convert Budget from string to int necessary
Bud_df["production_budget"]=Bud_df["production_budget"].astype(int)
Bud_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   int64
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(2), object(4)
memory usage: 271.2+ KB
```

In [47]:
```
#Join this table with Bud_df table - 599 Rows
q = """
SELECT
   averagerating,
   numvotes,
   movie_id,
   genres,
   Director,
   primary_title
FROM g
JOIN movieD2_df
    USING (movie_id);
"""
BudMovie = pysqldf(q)
BudMovie
```

Out[47]:

	averagerating	numvotes	movie_id	genres	Director	primary_title
0	8.8	1841066	tt1375666	Action	Christopher Nolan	Inception
1	8.8	1841066	tt1375666	Adventure	Christopher Nolan	Inception
2	8.8	1841066	tt1375666	Sci-Fi	Christopher Nolan	Inception
3	8.4	1387769	tt1345836	Action	Christopher Nolan	The Dark Knight Rises
4	8.4	1387769	tt1345836	Thriller	Christopher Nolan	The Dark Knight Rises
...	...	...	...	...	...	...
594	8.1	5406	tt1572781	Animation	Yasuhiro Takemoto	The Disappearance of Haruhi Suzumiya

	averagerating	numvotes	movie_id	genres	Director	primary_title
595	8.1	5406	tt1572781	Comedy	Tatsuya Ishihara	The Disappearance of Haruhi Suzumiya
596	8.1	5406	tt1572781	Comedy	Yasuhiro Takemoto	The Disappearance of Haruhi Suzumiya
597	8.1	5406	tt1572781	Drama	Tatsuya Ishihara	The Disappearance of Haruhi Suzumiya
598	8.1	5406	tt1572781	Drama	Yasuhiro Takemoto	The Disappearance of Haruhi Suzumiya

599 rows × 6 columns

The budget data came from a different source than the baseic movie data. The tables can be joined on the name of the movie which are both strings. These two attributes make the join very error prone. From the original 5782 rows from the budget table, the join dropped the instances to 173. This is over 400 rows less than the IMDB movie and director joined table.

In [48]:
```
#Join the tables
#Joining by names narrowed the list to 173 entries
q = """
SELECT
*
FROM BudMovie AS bm
JOIN Bud_df bd
    ON bm.primary_title = bd.movie;
"""
bud_join= pysqldf(q)
bud_join.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 173 entries, 0 to 172
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   averagerating      173 non-null    float64
 1   numvotes           173 non-null    int64  
 2   movie_id           173 non-null    object 
 3   genres             173 non-null    object 
 4   Director           173 non-null    object 
 5   primary_title      173 non-null    object 
 6   id                 173 non-null    int64  
 7   release_date       173 non-null    object 
 8   movie              173 non-null    object 
 9   production_budget  173 non-null    int64  
 10  domestic_gross     173 non-null    object 
 11  worldwide_gross    173 non-null    object 
dtypes: float64(1), int64(3), object(8)
memory usage: 16.3+ KB
```

Analysis

Count the number of movies each genre has with min a rating of "8" and min 5337 votes. Look at genres with high ratings and a large amount of votes - subjective but insightful Look at genres with not a lot of movies for potentia cases

Genre Questions:

- What are the top rated genres?
  Consider the number of votes to determine he average.

- What is the number of movies each genre contain.

In [49]:
```
#Genres and Ratings
mC ="""
SELECT
    genres,
    COUNT (movie_id) AS MCNT,
    ROUND (AVG(numvotes), 0) as Avg_Votes,
    ROUND (AVG(averagerating), 1) as Avg_Rating
FROM g
GROUP BY genres
ORDER BY  MCNT DESC;
"""
MovieCount = pysqldf(mC)
MovieCount
```

Out[49]:

	genres	MCNT	Avg_Votes	Avg_Rating
0	Drama	124	156815.0	8.3
1	Action	52	253171.0	8.3
2	Documentary	44	19787.0	8.3
3	Crime	43	93765.0	8.3
4	Comedy	37	177859.0	8.2
5	Thriller	36	166739.0	8.2
6	Biography	34	193086.0	8.2
7	Adventure	33	451840.0	8.2
8	Animation	19	160027.0	8.2
9	Mystery	17	185083.0	8.3
10	Music	15	110056.0	8.3
11	History	13	131130.0	8.3
12	Sci-Fi	12	744291.0	8.3
13	Romance	10	71304.0	8.3
14	War	8	43235.0	8.5
15	Fantasy	8	227803.0	8.2
16	Sport	7	80928.0	8.2
17	Family	4	40070.0	8.1
18	Horror	3	13840.0	8.2
19	News	2	15556.0	8.2
20	Western	1	1211405.0	8.4

Director Questions:

- How many different type of genres does each director have?
- How many movies does each director have?
- Which directors does each genre have movies in?
- Who are the top 20 directors that have more than 2 movies with top ratings?

The filtered (averagerating and numvotes) dataframe "g" will be used throughout the queries.

In [50]:
```
#Number of Directors in each genre
q = """SELECT
   genres,
   COUNT (Director) AS DirCount
FROM g
JOIN movieD2_df
    USING (movie_id)
GROUP BY genres
ORDER BY DirCount DESC;
"""
Gen_Dir_Count = pysqldf(q)
Gen_Dir_Count
```

Out[50]:

	genres	DirCount
0	Drama	134
1	Action	58
2	Documentary	53
3	Crime	47
4	Adventure	44
5	Comedy	43
6	Biography	40
7	Thriller	37
8	Animation	28
9	Music	18
10	Mystery	17
11	History	15
12	Sci-Fi	14
13	Romance	10
14	Fantasy	10
15	Sport	9
16	War	8
17	Horror	5
18	News	4
19	Family	4
20	Western	1

In [51]:
```
#Director and Distinct Movie Count & Genre Count
q = """
SELECT
    director,
    COUNT ( DISTINCT movie_id) AS Movie_Count,
    COUNT (DISTINCT  genres) AS Genre_Count
FROM g
JOIN movieD2_df
    USING (movie_id)
GROUP BY director
ORDER BY Movie_Count DESC;
"""

Dir_Mov_Gen_Count = pysqldf(q)
Dir_Mov_Gen_Count
```

Out[51]:

	Director	Movie_Count	Genre_Count
0	Martin Scorsese	3	7
1	Denis Villeneuve	3	5
2	Christopher Nolan	3	5
3	Zoya Akhtar	2	3
4	Sukumar	2	4
...	...	...	...
211	Advait Chandan	1	2
212	Adrian Molina	1	3
213	Aditya Dhar	1	3
214	Adesh Prasad	1	3
215	A.R. Murugadoss	1	2

216 rows × 3 columns

Want to look at directors who have done more than one movie. This looks at their experience and versatility.

In [52]:
```
#Specific genres for Directors that have more one move
q = """
SELECT
    director,
    genres
FROM g
JOIN movieD2_df
    USING (movie_id)
GROUP BY director, genres
HAVING COUNT ( DISTINCT movie_id) > 1
ORDER BY genres;
"""

Dir_Gen = pysqldf(q)
Dir_Gen
```

Out[52]:

	Director	genres
0	Anthony Russo	Action
1	Christopher Nolan	Action
2	Joe Russo	Action
3	S.S. Rajamouli	Action
4	Sukumar	Action
5	Anthony Russo	Adventure
6	Christopher Nolan	Adventure
7	Dragan Bjelogrlic	Adventure
8	Joe Russo	Adventure
9	Lee Unkrich	Adventure
10	Lee Unkrich	Animation
11	Martin Scorsese	Biography
12	Dragan Bjelogrlic	Comedy
13	Lee Unkrich	Comedy
14	Anurag Kashyap	Crime
15	Joshua Oppenheimer	Documentary
16	Alper Caglar	Drama
17	Anand Gandhi	Drama
18	Can Ulkay	Drama
19	Damien Chazelle	Drama
20	Denis Villeneuve	Drama
21	Nuri Bilge Ceylan	Drama
22	Quentin Tarantino	Drama
23	S.S. Rajamouli	Drama
24	Stephen Chbosky	Drama
25	Zoya Akhtar	Drama
26	Damien Chazelle	Music
27	Denis Villeneuve	Mystery
28	Sujoy Ghosh	Mystery
29	Anthony Russo	Sci-Fi
30	Christopher Nolan	Sci-Fi
31	Joe Russo	Sci-Fi
32	Neeraj Pandey	Thriller

In [53]:

```
#Genres with their Average Rating and Average votes & associated directors
q = """
```

```
SELECT
    genres,
    ROUND (AVG(numvotes), 0) as Avg_Votes,
    ROUND (AVG(averagerating), 1) as Avg_Rating,
    COUNT(Director) AS Dir_Count
FROM g
JOIN movieD2_df
    USING (movie_id)

WHERE director IN (SELECT
    director
FROM g
JOIN movieD2_df
    USING (movie_id)
GROUP BY director
HAVING COUNT ( DISTINCT movie_id )  > 1)

GROUP BY genres
ORDER BY Dir_Count DESC, genres ASC

"""

Dir_Gen_C = pysqldf(q)
Dir_Gen_C
```

Out[53]:

	genres	Avg_Votes	Avg_Rating	Dir_Count
0	Drama	235838.0	8.3	30
1	Action	434326.0	8.5	15
2	Adventure	581501.0	8.4	12
3	Comedy	193201.0	8.4	8
4	Crime	217793.0	8.2	8
5	Mystery	269043.0	8.1	8
6	Sci-Fi	795105.0	8.5	8
7	Thriller	325420.0	8.1	8
8	Biography	235866.0	8.2	6
9	Music	239015.0	8.2	6
10	Documentary	16883.0	8.2	3
11	War	83822.0	8.8	3
12	Animation	479706.0	8.4	2
13	History	18453.0	8.5	2
14	Horror	9872.0	8.2	2
15	Family	111632.0	8.0	1
16	Fantasy	14128.0	8.3	1
17	Western	1211405.0	8.4	1

Budget Questions:

- How does the different dataset impact the findings?
- What types of movies have the highest, medium and lowest budgets?
- Which directors and genres are associated with the highest budgets? Patterns?

In [54]:
```
#Refine the joined budget list.
#Look to see if the top genres are top and if the same directors for the same mo
q ="""
SELECT
    movie_id,
    movie,
    Director,
    genres,
    averagerating,
    numvotes,
    production_budget AS pbud

FROM bud_join
ORDER BY pbud DESC;
"""
budget_df= pysqldf(q)
budget_df
```

Out[54]:

	movie_id	movie	Director	genres	averagerating	numvotes	pbud
0	tt4154756	Avengers: Infinity War	Anthony Russo	Action	8.5	670926	300000000
1	tt4154756	Avengers: Infinity War	Joe Russo	Action	8.5	670926	300000000
2	tt4154756	Avengers: Infinity War	Anthony Russo	Adventure	8.5	670926	300000000
3	tt4154756	Avengers: Infinity War	Joe Russo	Adventure	8.5	670926	300000000
4	tt4154756	Avengers: Infinity War	Anthony Russo	Sci-Fi	8.5	670926	300000000
...	...	...	...	...	...	...	...
168	tt2375605	The Act of Killing	Christine Cynn	Crime	8.2	31115	1000000
169	tt2375605	The Act of Killing	Joshua Oppenheimer	Crime	8.2	31115	1000000
170	tt2375605	The Act of Killing	Anonymous	Documentary	8.2	31115	1000000
171	tt2375605	The Act of Killing	Christine Cynn	Documentary	8.2	31115	1000000
172	tt2375605	The Act of Killing	Joshua Oppenheimer	Documentary	8.2	31115	1000000

173 rows × 7 columns

In [55]:
```
#Look at average budget for genres
q ="""
SELECT
    genres,
```

```
    ROUND (AVG(pbud), 0) as Avg_pbud,
    COUNT (genres) AS Gen_COUNT
FROM budget_df
GROUP BY genres

;
"""
budA_Gen_df= pysqldf(q)
budA_Gen_df
```

Out[55]:

	genres	Avg_pbud	Gen_COUNT
0	Action	122227273.0	22
1	Adventure	146557692.0	26
2	Animation	134500000.0	13
3	Biography	41136364.0	11
4	Comedy	118928571.0	14
5	Crime	23777778.0	9
6	Documentary	1771429.0	7
7	Drama	39854286.0	35
8	Family	20000000.0	1
9	History	15850000.0	4
10	Music	20575000.0	4
11	Mystery	75760000.0	5
12	Romance	23000000.0	1
13	Sci-Fi	166916667.0	12
14	Sport	25000000.0	1
15	Thriller	76166667.0	6
16	War	6800000.0	1
17	Western	100000000.0	1

Data Analysis

The data is modeled using scatter plots and colormaps. This modeling method allowed the use of 3 main variables depending. I could show the correlation between two independent variables as well as the a Rating (using color) on each visual.

The initial plan was to use a different type of graph for the different independent variables. Because of complexity and the ability to show the correlation between more than two variables a scatter plot with a colormap was used each time.

The three main independent variables chosen where "Genre, Director & Budget". When looking through the data, other variables impacted the interpretation of this data in relation to the Rating (e.g. number of votes).

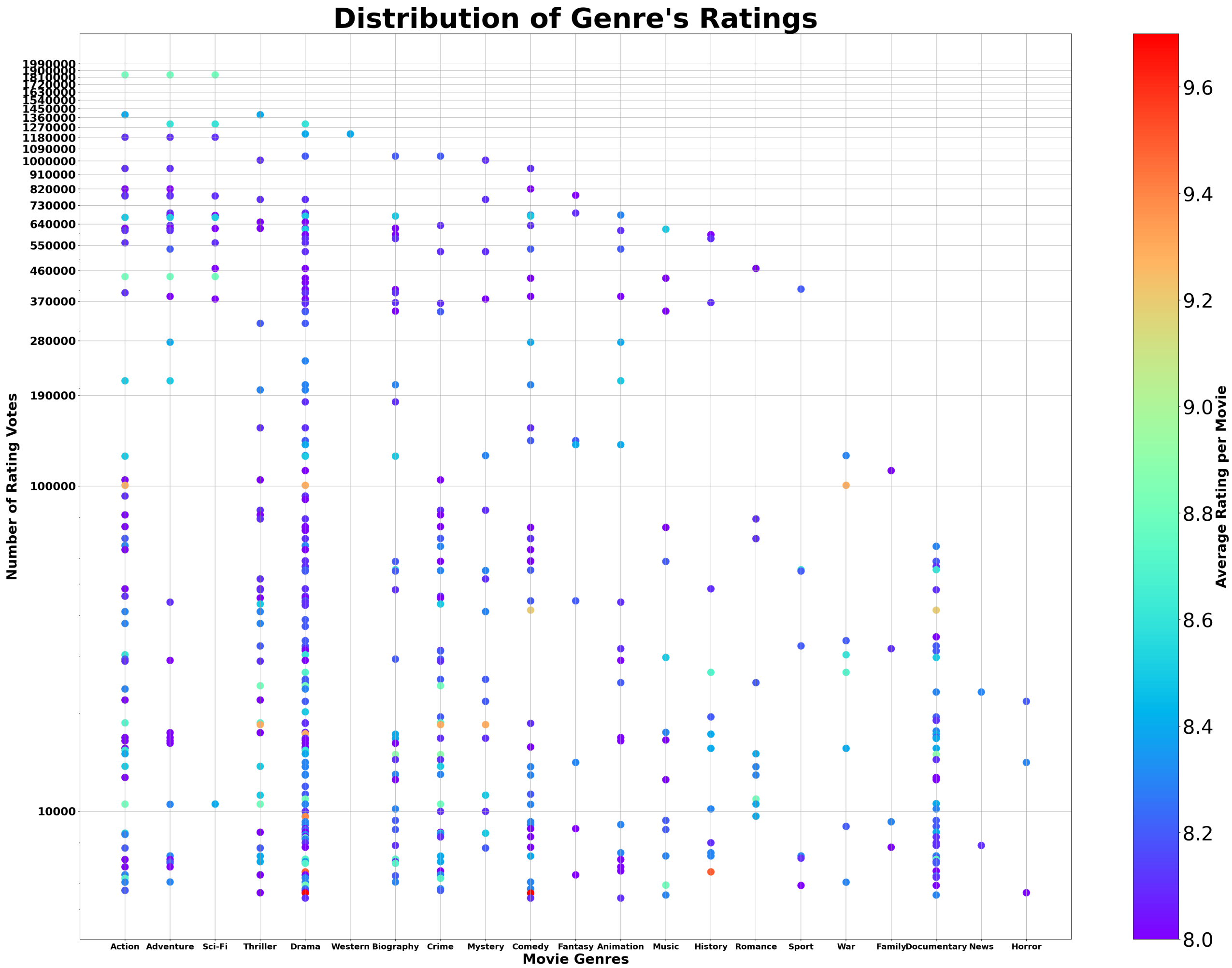
Ref:Austin Animal Center Needs Project Example

```
#Create Plot
fig, genre_rating_ax = plt.subplots(ncols = 1, nrows = 1, figsize=(40, 30))
g.plot.scatter(x = "genres", y = "numvotes", c = "averagerating", fontsize = 15, s = 150, cmap = "rainbow",colorbar
genre_rating_ax.set_yscale('log', subs = [2,3,4,5,6,8])

cbar = plt.colorbar(orientation = "vertical")
cbar.set_label(label = "Trial Error", Size = 20)
```

Genre Analysis

In [56]:

```
#Create Plot
plt.figure(figsize=(40,30), dpi = 150, facecolor = "white" )

#g is the dataframe
plt.scatter(x = g["genres"], y = g["numvotes"], c = g["averagerating"], s = 150,
plt.yscale('log', subs = [2,3,4,5,6,8])

#ticks
plt.xticks(fontsize = 14.75, fontweight = "bold")
yl = np.arange(10000,2000000, step=90000)
plt.yticks(ticks = yl, labels = yl, fontsize = 20, fontweight = "bold")


#Colorbar
cbar = plt.colorbar(orientation = "vertical")
cbar.set_label(label = "Average Rating per Movie", size = 25, fontweight = "bold
cbar.ax.tick_params(labelsize=35)

#Background
plt.grid()




#Set titles
plt.title("Distribution of Genre's Ratings", fontsize=50, fontweight = "bold")
plt.ylabel('Number of Rating Votes', fontsize=25, fontweight = "bold")
plt.xlabel('Movie Genres', fontsize=25, fontweight = "bold")


#Save image in folder
plt.savefig("images/genre_ratings.png", dpi=200)
```



Director Analysis

In [57]:

```
#Table for plotting Top Directs more than 1 movie and genre by ratings
#Using only top genres with most directors Dir_Gen_C

q = """
SELECT
    director,
    genres,
    ROUND (AVG(numvotes), 0) as Avg_Votes,
    ROUND (AVG(averagerating), 1) as Avg_Rating
FROM g
JOIN movieD2_df
    USING (movie_id)

WHERE director IN (SELECT
    director
FROM g
JOIN movieD2_df
    USING (movie_id)
GROUP BY director
HAVING COUNT ( DISTINCT movie_id )  > 1)
AND genres IN (
SELECT
    genres
FROM Dir_Gen_C)
GROUP BY genres, director
```

```
ORDER BY Avg_Rating DESC, Director

"""

Dir_Plot_df = pysqldf(q)
Dir_Plot_df
```

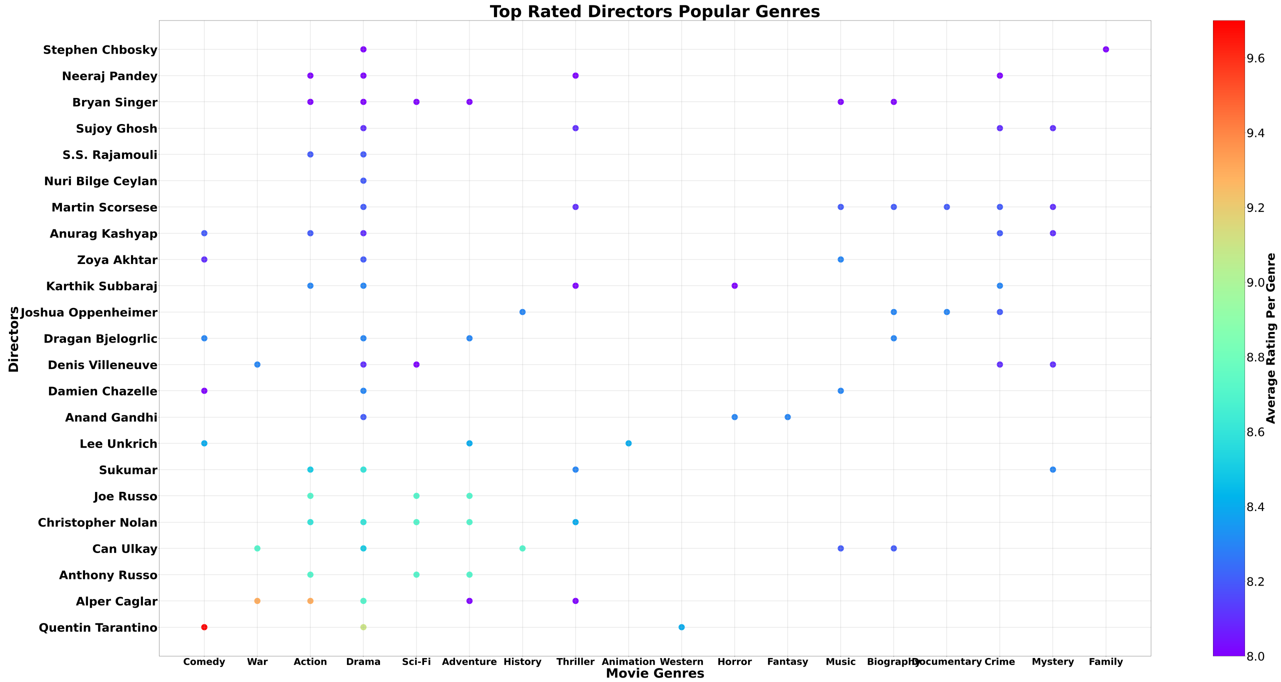
Out[57]:

	Director	genres	Avg_Votes	Avg_Rating
0	Quentin Tarantino	Comedy	5600.0	9.7
1	Alper Caglar	War	100568.0	9.3
2	Alper Caglar	Action	100568.0	9.3
3	Quentin Tarantino	Drama	608503.0	9.1
4	Alper Caglar	Drama	59006.0	8.7
...	...	...	...	...
84	Neeraj Pandey	Drama	45299.0	8.0
85	Neeraj Pandey	Crime	45299.0	8.0
86	Neeraj Pandey	Action	48318.0	8.0
87	Stephen Chbosky	Family	111632.0	8.0
88	Stephen Chbosky	Drama	267152.0	8.0

89 rows × 4 columns

In [58]:

```
#Create Plot
figure(figsize=(95,50), dpi = 150, facecolor = "white")

#Dir_Plot_df is the dataframe
plt.scatter(x = Dir_Plot_df["genres"], y = Dir_Plot_df["Director"], c = Dir_Plot

#ticks
plt.xticks(fontsize = 40, fontweight = "bold")
plt.yticks(fontsize = 50, fontweight = "bold")


#Colorbar
cbar = plt.colorbar(orientation = "vertical")
cbar.set_label(label = "Average Rating Per Genre", size = 50, fontweight = "bold
cbar.ax.tick_params(labelsize=50)

#Set titles
plt.title("Top Rated Directors Popular Genres", fontsize=70, fontweight = "bold"
plt.ylabel('Directors', fontsize=55, fontweight = "bold")
plt.xlabel('Movie Genres', fontsize=55, fontweight = "bold")

plt.grid()
#Save image in folder
plt.savefig("images/genre_ratings_Director.png", dpi=200)
```



Budget Analysis

In [59]:
```
#Searching from directors identified in other data with budget data
#Look at top 5-10 Directors and the movies
q = """
SELECT
    director,
    movie,
    genres,
    pbud
FROM budget_df
WHERE director IN
    (SELECT
        director
    FROM Dir_Plot_df)

"""
BudDir_df= pysqldf(q)
BudDir_df.head()
```

Out[59]:

	Director	movie	genres	pbud
0	Anthony Russo	Avengers: Infinity War	Action	300000000
1	Joe Russo	Avengers: Infinity War	Action	300000000
2	Anthony Russo	Avengers: Infinity War	Adventure	300000000
3	Joe Russo	Avengers: Infinity War	Adventure	300000000
4	Anthony Russo	Avengers: Infinity War	Sci-Fi	300000000

In [60]:
```
#Plot the genres by the budget
q ="""
SELECT
    movie_id,
    genres,
    averagerating,
```

```
    pbud
FROM budget_df
GROUP by movie_id, genres
ORDER BY pbud DESC
;
"""

budGen_df= pysqldf(q)
budGen_df
```

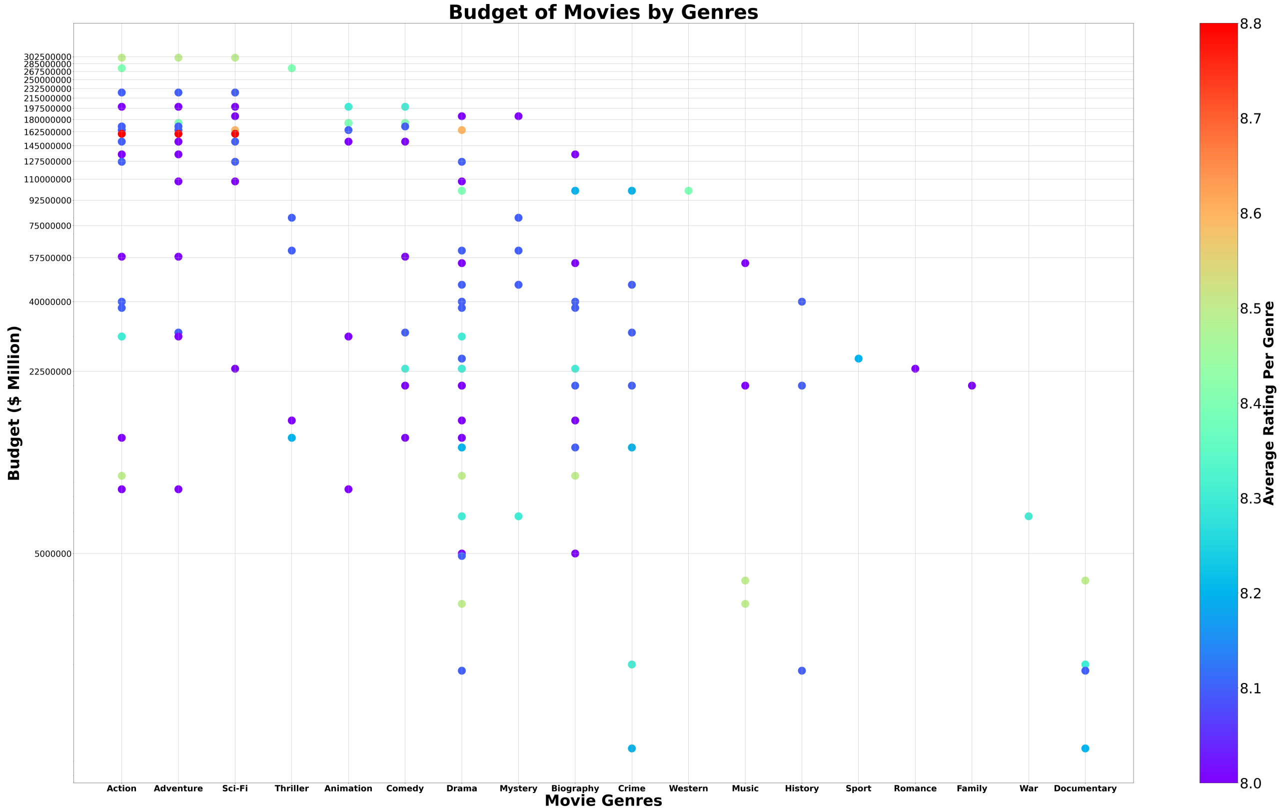
Out[60]:

	movie_id	genres	averagerating	pbud
0	tt4154756	Action	8.5	300000000
1	tt4154756	Adventure	8.5	300000000
2	tt4154756	Sci-Fi	8.5	300000000
3	tt1345836	Action	8.4	275000000
4	tt1345836	Thriller	8.4	275000000
...	...	...	...	...
137	tt2486682	Documentary	8.1	1900000
138	tt2486682	Drama	8.1	1900000
139	tt2486682	History	8.1	1900000
140	tt2375605	Crime	8.2	1000000
141	tt2375605	Documentary	8.2	1000000

142 rows × 4 columns

In [61]:

```
#Create Plot
figure(figsize=(85,50), dpi = 150, facecolor = "white")

#Dir_Plot_df is the dataframe
plt.scatter(x = budGen_df["genres"], y = budGen_df["pbud"], c = budGen_df["avera
plt.yscale('log' )

#ticks
plt.xticks(fontsize = 30, fontweight = "bold")
yl = np.arange(5000000, 310000000, step =17500000)
plt.yticks(yl,yl, fontsize = 30)


#Colorbar
cbar = plt.colorbar(orientation = "vertical")
cbar.set_label(label = "Average Rating Per Genre", size = 50, fontweight = "bold
cbar.ax.tick_params(labelsize=50)

#Set titles
plt.title("Budget of Movies by Genres", fontsize=70, fontweight = "bold")
plt.ylabel('Budget ($ Million)', fontsize=55, fontweight = "bold")
plt.xlabel('Movie Genres', fontsize=55, fontweight = "bold")

plt.grid()
#Save image in folder
plt.savefig("images/genre_ratings_Budget.png", dpi=200)
```



Analysis Evaluation

Thoughts on the interpretation and confidence of the results:

1. The results are interpreted by looking at common patterns and questions asked of the data related to the target variable and the specific independent variables.

2. The results can generalize as more questions are asked of the data. More parameters would be need to analyzed and more specific genre analysis would be helpful.

3. I am confident that the analysis will benefit the current business problem at hand by extracting and reviewing the similar patterns from semi recent data. The data sources are from some of the popular and widely used sites. It may not be complete, but will be a good intial start.

Conclusions

As a for profit company, high revenue is always a goal. The "rating" was chosen as a target variable because it can help support the goal of revenue, but also provide other insights that can be further explored and explained. The following are recommendations for Microsoft from the analysis:

1. Invest in at least one of high budget films in the category of "Action, Adventure or Sci-Fi".

- If the action is taken, I highly recommend the one of the Russo brothers or Christopher Nolan directs this movie. They have some of the highest raitings in these categories

multiple times.
- Movie studios may have major movies that they can be associated with. If Microsoft wants to establish themself in the industry they need one (or more) as well.
- These directors are not only famous but have the movie ratings to prove it. The movies they directed in the mentioned genres had some of the highest number of votes. This is not a direct causation to movie gross, but it is correlated. However, having people watch the move in theatres is a good goal, but Microsoft you ultimately want people engaged in the brand. The high number of votes is a datapoint showing the people who view these type of movies can possibly be engaged with the movie brand online regardless of their view of the specific movie. Their engagement opens the oppurtunity for more areas of Microsoft engagement (e.g. games, advertisments, software, metaverse)

2. Invest in multiple movies in "Drama, Documentary and/or Crime". If one genre, choose "Drama". These types of movies are popular and lower cost risk.

- From the movies that had at least a 8/10 averagerating, dramas ranked first(124/173 movies), 3rd was documentaries (53/173 movies) and 4th crime (50/173 movies).
- All three of these genres were across the spectrum in terms of budget and the number of votes for the rating.
- Most of the directors who had multiple movies credits had a movie categorized as "Drama."
- "Documentaries and Crime" genres don't have the average number of voters as high as the "Action, Adventure and Sci-Fi". This may indicate Documentaries and Crime genres had a core fanbase that supports these movies. Therefore "Documentaries and Crime" may ultimately do the best on other platforms.

3. For the *intial* start of the movie studio, *DO NOT* invest resources in genres focused on "Family, Sports or News". These are higher risk due to lack of highly rated rates compared to the other genres.

- There is a substantially lower level of movies in these genres "Family (4) and Sports (9) and News (4)"
- Their budgets are a lot lower overall and pose a risk in the number of viewers leading to engagement and profit.
- A lot of multi movie directors do not work in this genre.
- The low amount of budgets, ratings, ratings and directors, increase the risk of their reception compared to other genres.

Limitations and Improvements

The following are analysis limitations and analysis future analysis ideas for Microsoft:

1. Microsoft needs to understand and communicate their constraints and vision for their movie experience. The results given were focused only a few parameters. For more fidelity, the recommendation is to add parameters and/or dive deeper into some of the recommendation's patterns. I would add parameters such as regions where the movive plays as well as languagess. These can give more information and nuances as to where to place theatres and certain movies

2. The data analysis was limited in term of the the methods, scope of the analysis and data parameter tuning. The problem given was a one paragraph statement. In a usual business analysis case, there would be more iterative communication with the stakeholder to clarify assumptions, considerations and the specific problem need. Even if Microsoft doesn't know the exact problem, continous communication would refine the vision, values, and initial needs. This analysis was an intial low fidelity partial solution to the problem.

3. Future impovements:

- Add more parameters to analysis (e.g. region, language). These can give more information and nuances such as where to place theatres and certain movies from the the genre recommendations.
- Use the recommendations and do more detailed work into the genres (causality and correlation).
- Analyze the combinations of genres with respect to the target variable and independent variables. For example, movies that were categorized as "Comedy and Animation or Sci-Fi" had higher budgets than "Comedies" that were not.
- Research more on Microsoft's current technical ecosystem and their holistic vision as a company. The protential movie studio is a part of a great system and it is impairative this node harmonizes with the rest of the ecosystem. For example, Microsoft recently invested millions of dollars into the metaverse. The movie studio and the metaverse have many connection points (e.g. brands, storylines, characters, stakeholders). Understanding these points, can help scope and clarify the analysis entities area for a better outcome.

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