Final Project Submission

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- Student pace: Part Time
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- Blog post URL:

Introduction

Hi! I'm Branton Kieti. I'm a data analyst with a background in entrepreneurship, project management, and sales.My analytical approach includes using Python and SQL for data cleaning, manipulation, and analysis. I specialize in identifying patterns, trends, and areas for improvement within the data.When I'm not analyzing data, you can find me spending time with my family, working out, or learning something new.Please feel free to reach out to me with any questions or comments. You can connect with me on email me at brantonkieti@gmail.com (mailto:brantonkieti@gmail.com).

Analyzing Movie Dataset: imdb.title.basics & imdb.title.ratings & bom.movie.gross

In [216]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [217]:
```
# imdb.title.basics
imdb_df = pd.read_csv("imdb.title.basics.csv.gz")
imdb_df.head()
```

Out[217]:

	tconst	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 [218]:
```
# Identifying columns
imdb_df.columns
```

Out[218]:
```
Index(['tconst', 'primary_title', 'original_title', 'start_year',
       'runtime_minutes', 'genres'],
      dtype='object')
```

In [219]:
```
imdb_df.describe()
```

Out[219]:

	start_year	runtime_minutes
count	146144.000000	114405.000000
mean	2014.621798	86.187247
std	2.733583	166.360590
min	2010.000000	1.000000
25%	2012.000000	70.000000
50%	2015.000000	87.000000
75%	2017.000000	99.000000
max	2115.000000	51420.000000

In [220]:
```
# Sorting based on start year
imdb_df.sort_values(['start_year'], ascending=False)
```

Out[220]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
89506	tt5174640	100 Years	100 Years	2115	NaN	Drama
96592	tt5637536	Avatar 5	Avatar 5	2027	NaN	Action,Adventure,Fantasy
2949	tt10300398	Untitled Star Wars Film	Untitled Star Wars Film	2026	NaN	Fantasy
52213	tt3095356	Avatar 4	Avatar 4	2025	NaN	Action,Adventure,Fantasy
105187	tt6149054	Fantastic Beasts and Where to Find Them 5	Fantastic Beasts and Where to Find Them 5	2024	NaN	Adventure,Family,Fantasy
...	...	...	...	...	...	...
74712	tt4264626	Civil War Life: Shot to Pieces	Civil War Life: Shot to Pieces	2010	79.0	Documentary
14471	tt1716746	Heinrich Kieber - Datendieb	Heinrich Kieber - Datendieb	2010	52.0	Documentary
74692	tt4263706	Mushrooms of America	Mushrooms of America	2010	46.0	Adventure,Comedy,Documentary
118065	tt7059624	Zamana	Zamana	2010	140.0	Drama
94000	tt5475580	A Boy and A Girl	A Boy and A Girl	2010	NaN	Romance

146144 rows × 6 columns

In [221]:
```
# Identifying missing  data
missing_data = imdb_df.isnull().sum()
print(missing_data)
```

```
tconst                 0
primary_title          1
original_title        22
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [222]:
```
# replacing runtime_minutes with mean
imdb_df['runtime_minutes'].fillna(imdb_df['runtime_minutes'].mean(), inplace=True)
imdb_df
```

Out[222]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.000000	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.000000	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.000000	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	86.187247	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.000000	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.000000	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	86.187247	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	86.187247	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.000000	NaN
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	86.187247	Documentary

146144 rows × 6 columns

In [223]:
```
# removing rows with missing primary_title & original_title
imdb_df = imdb_df.dropna(subset=['primary_title','original_title'])
imdb_df
```

Out[223]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.000000	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.000000	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.000000	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	86.187247	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.000000	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.000000	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	86.187247	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	86.187247	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.000000	NaN
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	86.187247	Documentary

146122 rows × 6 columns

In [224]:
```
missing_genres = imdb_df.isnull().sum()
print(missing_genres)
```

```
tconst                0
primary_title         0
original_title        0
start_year            0
runtime_minutes       0
genres             5389
dtype: int64
```

In [225]:
```
# Replacing missing data in genres with 'Drama'
imdb_df = imdb_df.fillna(value='Drama')
imdb_df
```

Out[225]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.000000	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.000000	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.000000	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	86.187247	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.000000	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.000000	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	86.187247	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	86.187247	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.000000	Drama
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	86.187247	Documentary

146122 rows × 6 columns

In [226]:
```
missing_data = imdb_df.isnull().sum()
print(missing_data)
```

```
tconst             0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
dtype: int64
```

In [227]:
```
# Checking for duplicates
duplicates = imdb_df.duplicated(keep=False)
imdb_df = imdb_df.drop_duplicates()
duplicate_index = imdb_df[duplicates].index
print(imdb_df.loc[duplicate_index])
```

```
Empty DataFrame
Columns: [tconst, primary_title, original_title, start_year, runtime_minutes, genres]
Index: []
```

In [228]:
```
imdb_df.to_csv('cleanimdb_dataset.csv', index=False)
```

In [229]:
```
imdb_df = pd.read_csv('cleanimdb_dataset.csv')
# Print the first 5 rows of the DataFrame
print(imdb_df.head())

# Print the total number of movies in the DataFrame
print(f"Total number of movies: {len(imdb_df)}")

# Print the 5 most common genres in the dataset
most_common_genres = imdb_df['genres'].value_counts().head()
print(f"5 most common genres: {most_common_genres}")
```

```
      tconst                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres
0        2013       175.000000    Action,Crime,Drama
1        2019       114.000000       Biography,Drama
2        2018       122.000000                 Drama
3        2018        86.187247          Comedy,Drama
4        2017        80.000000  Comedy,Drama,Fantasy
Total number of movies: 146122
5 most common genres: genres
Documentary     32185
Drama           26875
Comedy           9177
Horror           4372
Comedy,Drama     3519
Name: count, dtype: int64
```

In [207]:
```
pwd
```

Out[207]: 'C:\\Users\\Data\\Documents\\Flatiron\\Branton Moringa\\Phase1\\dsc-phase-1-project'

In [230]:
```
imdbr_df = pd.read_csv("imdb.title.ratings.csv.gz")
imdbr_df.head()
```

Out[230]:

	tconst	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 [213]:
```
missing_data = imdbr_df.isnull().sum()
print(missing_data)
```

```
tconst           0
averagerating    0
numvotes         0
dtype: int64
```

In [231]:
```
# Merge imdb_ratings and imdb_titles
merged_df = pd.merge(imdb_df, imdbr_df, on='tconst')
merged_df
```

Out[231]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	averagerating
0	tt0063540	Sunghursh	Sunghursh	2013	175.000000	Action,Crime,Drama	7.0
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.000000	Biography,Drama	7.2
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.000000	Drama	6.9
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	86.187247	Comedy,Drama	6.1
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.000000	Comedy,Drama,Fantasy	6.5
...	...	...	...	...	...	...	...
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.000000	Documentary	6.2
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.000000	Drama,Family	8.7
73853	tt9914642	Albatross	Albatross	2017	86.187247	Documentary	8.5
73854	tt9914942	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	86.187247	Drama	6.6
73855	tt9916160	Drømmeland	Drømmeland	2019	72.000000	Documentary	6.5

73856 rows × 8 columns

bom.movie_gross analysis

In [268]:
```
# bom.movie_gross
bom_df = pd.read_csv("bom.movie_gross.csv.gz")
bom_df.head()
```

Out[268]:

	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 [269]:
```
bom_df.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
```

In [270]:
```
# Column names
bom_df.columns
```

Out[270]:
```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dtype='object')
```

In [271]:
```
# Sorting ascending based on "year"
bom_df.sort_values(['year'], ascending=False)
```

Out[271]:

	title	studio	domestic_gross	foreign_gross	year
3386	An Actor Prepares	Grav.	1700.0	NaN	2018
3183	On the Basis of Sex	Focus	24600000.0	13600000	2018
3176	Tyler Perry's Acrimony	LGF	43500000.0	2900000	2018
3177	Mary Queen of Scots	Focus	16500000.0	29900000	2018
3178	The Possession of Hannah Grace	SGem	14800000.0	28200000	2018
...	...	...	...	...	...
220	After.Life	Anch.	109000.0	1900000	2010
221	Cairo Time	IFC	1600000.0	391000	2010
222	Flipped	WB	1800000.0	NaN	2010
223	Guzaarish	UTV	1000000.0	695000	2010
0	Toy Story 3	BV	415000000.0	652000000	2010

3387 rows × 5 columns

In [272]:
```
# Identifying missing  data
missing_data = bom_df.isnull().sum()
print(missing_data)
```

```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

In [273]:
```
# replacing missing data in domestc_gross with mean

bom_df['domestic_gross'].fillna(bom_df['domestic_gross'].mean(), inplace=True)
bom_df
```

Out[273]:

	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
...	...	...	...	...	...
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

3387 rows × 5 columns

In [274]:
```
# replacing NaN with 0 in foreign_gross column
bom_df['foreign_gross'].fillna(0, inplace=True)
bom_df
```

Out[274]:

	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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	0	2018
3383	Edward II (2018 re-release)	FM	4800.0	0	2018
3384	El Pacto	Sony	2500.0	0	2018
3385	The Swan	Synergetic	2400.0	0	2018
3386	An Actor Prepares	Grav.	1700.0	0	2018

3387 rows × 5 columns

In [275]:
```
# Removing missind data in studio column
bom_df = bom_df.fillna(value='Unknown')
bom_df
```

Out[275]:

	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
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	0	2018
3383	Edward II (2018 re-release)	FM	4800.0	0	2018
3384	El Pacto	Sony	2500.0	0	2018
3385	The Swan	Synergetic	2400.0	0	2018
3386	An Actor Prepares	Grav.	1700.0	0	2018

3387 rows × 5 columns

In [276]:
```
# Checking for duplicates
duplicates = bom_df.duplicated(keep=False)
bom_df = bom_df.drop_duplicates()
duplicate_index = bom_df[duplicates].index
print(bom_df.loc[duplicate_index])
```

```
Empty DataFrame
Columns: [title, studio, domestic_gross, foreign_gross, year]
Index: []
```

In [277]:
```
missing_data = bom_df.isnull().sum()
print (missing_data)
```

```
title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

In [278]:
```
bom_df.to_csv('cleanbom_dataset.csv', index=False)
```

In [279]:
```
bom_df=pd.read_csv('cleanbom_dataset.csv')
# Print the first 5 rows of the DataFrame
print(bom_df.head())

# Print the total number of movies in the DataFrame
print(f"Total number of movies: {len(bom_df)}")

# Print the 5 most common studio in the dataset
most_common_studio = bom_df['studio'].value_counts().head()
print(f"5 most common studio: {most_common_studio}")
```

```
0                               Toy Story 3     BV     415000000.0
1                    Alice in Wonderland (2010)     BV     334200000.0
2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0
3                                    Inception     WB     292600000.0
4                          Shrek Forever After   P/DW     238700000.0

  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
3     535700000  2010
4     513900000  2010
Total number of movies: 3387
5 most common studio: studio
IFC      166
Uni.     147
WB       140
Fox      136
Magn.    136
Name: count, dtype: int64
```

Identifying Trends and Patterns

In [232]:
```
merged_df[['genres','averagerating']].groupby(['genres']).agg(['count', 'median', 'mean'])
```

Out[232]:

	averagerating		
	count	**median**	**mean**
genres			
Action	979	5.80	5.757712
Action,Adult,Comedy	2	4.65	4.650000
Action,Adventure	68	5.30	5.223529
Action,Adventure,Animation	167	6.80	6.562874
Action,Adventure,Biography	21	7.00	7.061905
...	...	...	...
Thriller	1555	5.70	5.704244
Thriller,War	4	6.20	5.650000
Thriller,Western	4	7.15	7.150000

In [239]:
```
merged_df['numvotes'].fillna(merged_df['numvotes'].mean(), inplace=True)
merged_df
```

Out[239]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	averagerating
0	tt0063540	Sunghursh	Sunghursh	2013	175.000000	Action,Crime,Drama	7.0
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.000000	Biography,Drama	7.2
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.000000	Drama	6.9
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	86.187247	Comedy,Drama	6.1
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.000000	Comedy,Drama,Fantasy	6.5
...	...	...	...	...	...	...	...
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.000000	Documentary	6.2
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.000000	Drama,Family	8.7
73853	tt9914642	Albatross	Albatross	2017	86.187247	Documentary	8.5
73854	tt9914942	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	86.187247	Drama	6.6
73855	tt9916160	Drømmeland	Drømmeland	2019	72.000000	Documentary	6.5

73856 rows × 8 columns

In [261]:
```
# Create a pivot table
pivot = merged_df.pivot_table(values='runtime_minutes', index='start_year', columns='genre
pivot
```

Out[261]:

genres	Action	Action,Adult,Comedy	Action,Adventure	Action,Adventure,Animation	Action,Adventure,B
start_year					
2010	9800.868424	NaN	571.000000	1098.000000	
2011	11005.430165	NaN	852.187247	1346.187247	19
2012	9433.804659	71.000000	604.187247	1882.000000	9
2013	8929.681177	NaN	1065.000000	826.000000	15
2014	10316.617412	NaN	968.187247	1878.187247	22
2015	10016.932188	NaN	530.187247	2110.374494	72
2016	10908.617412	86.187247	423.000000	1682.000000	7
2017	13649.238871	NaN	1123.000000	1774.748988	41
2018	9724.808706	NaN	912.374494	1752.000000	26
2019	2858.310729	NaN	NaN	1117.187247	

10 rows × 923 columns

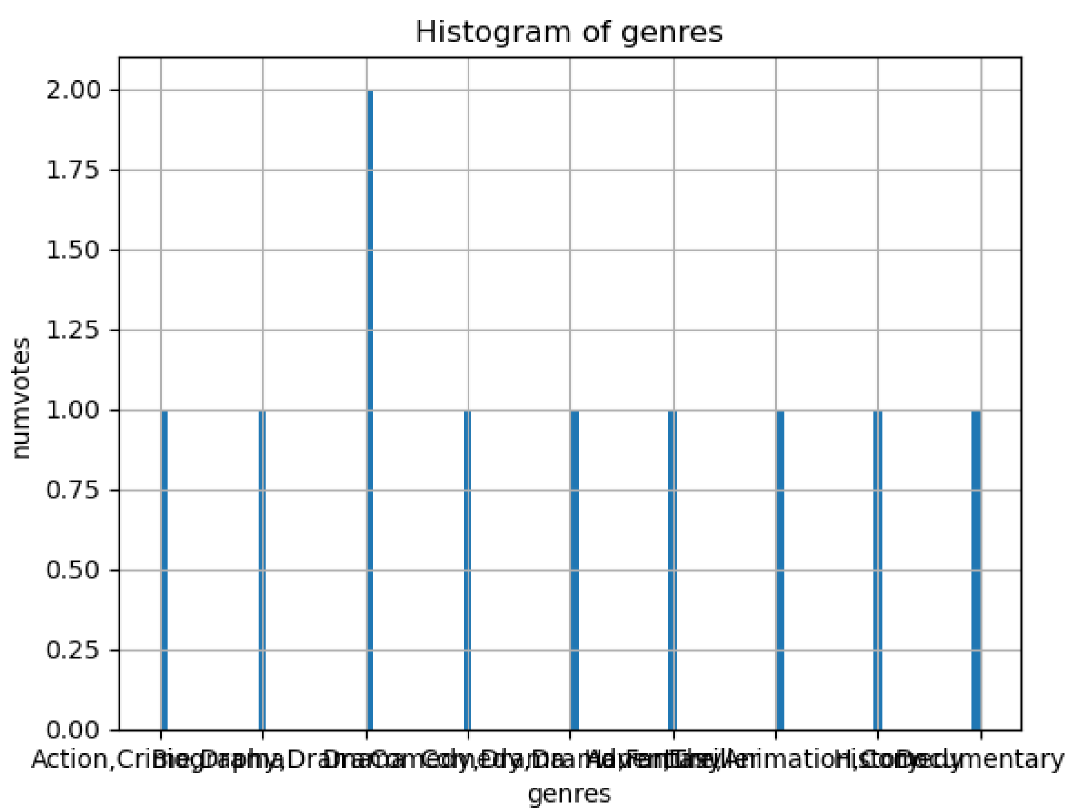
In [262]:
```
# pivot
pivot = merged_df.pivot_table(values='averagerating', index='start_year', columns='genres'
pivot
```

Out[262]:

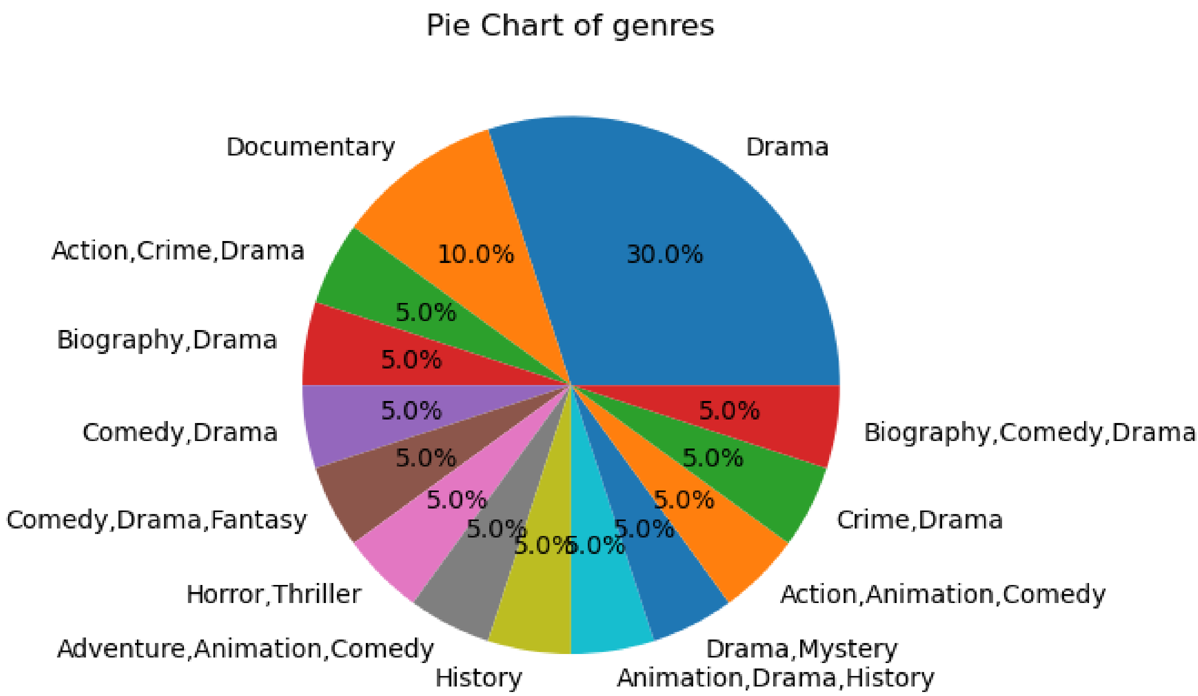
genres	Action	Action,Adult,Comedy	Action,Adventure	Action,Adventure,Animation	Action,Adventure,Biograpl
start_year					
2010	533.9	NaN	30.1	70.1	Na
2011	622.5	NaN	36.3	93.9	14
2012	561.0	5.9	40.3	139.3	4
2013	486.6	NaN	55.6	62.2	15
2014	635.9	NaN	49.0	119.8	14
2015	576.9	NaN	24.1	156.7	42
2016	659.8	3.4	20.2	116.2	ε
2017	817.2	NaN	47.6	134.2	28
2018	567.0	NaN	52.0	121.9	20
2019	176.0	NaN	NaN	81.7	Na

10 rows × 923 columns

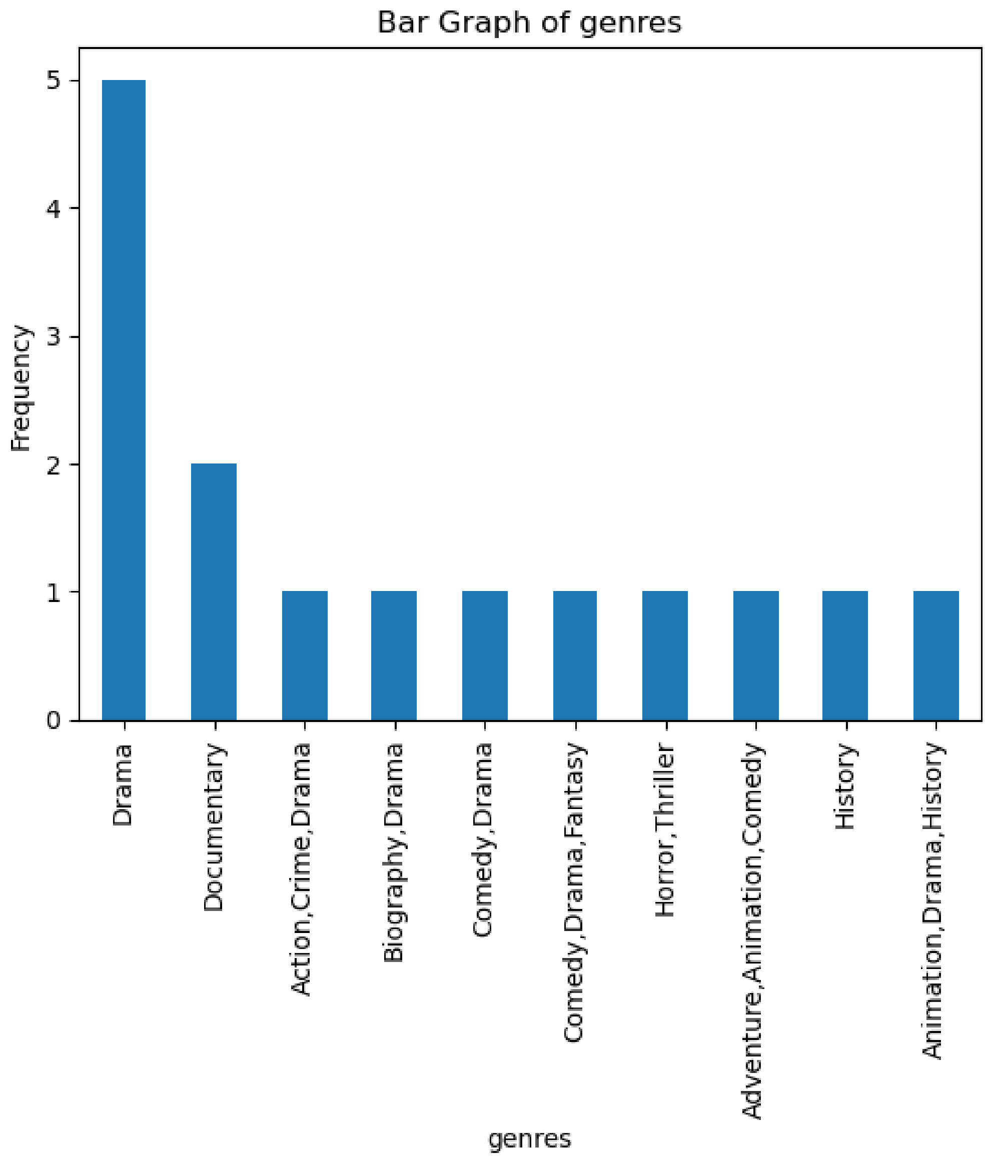
In [259]:
```
# Create a histogram on genres
merged_df.head(10)['genres'].hist(bins=100)
plt.xlabel('genres')
plt.ylabel('numvotes')
plt.title('Histogram of genres')
plt.show()
```



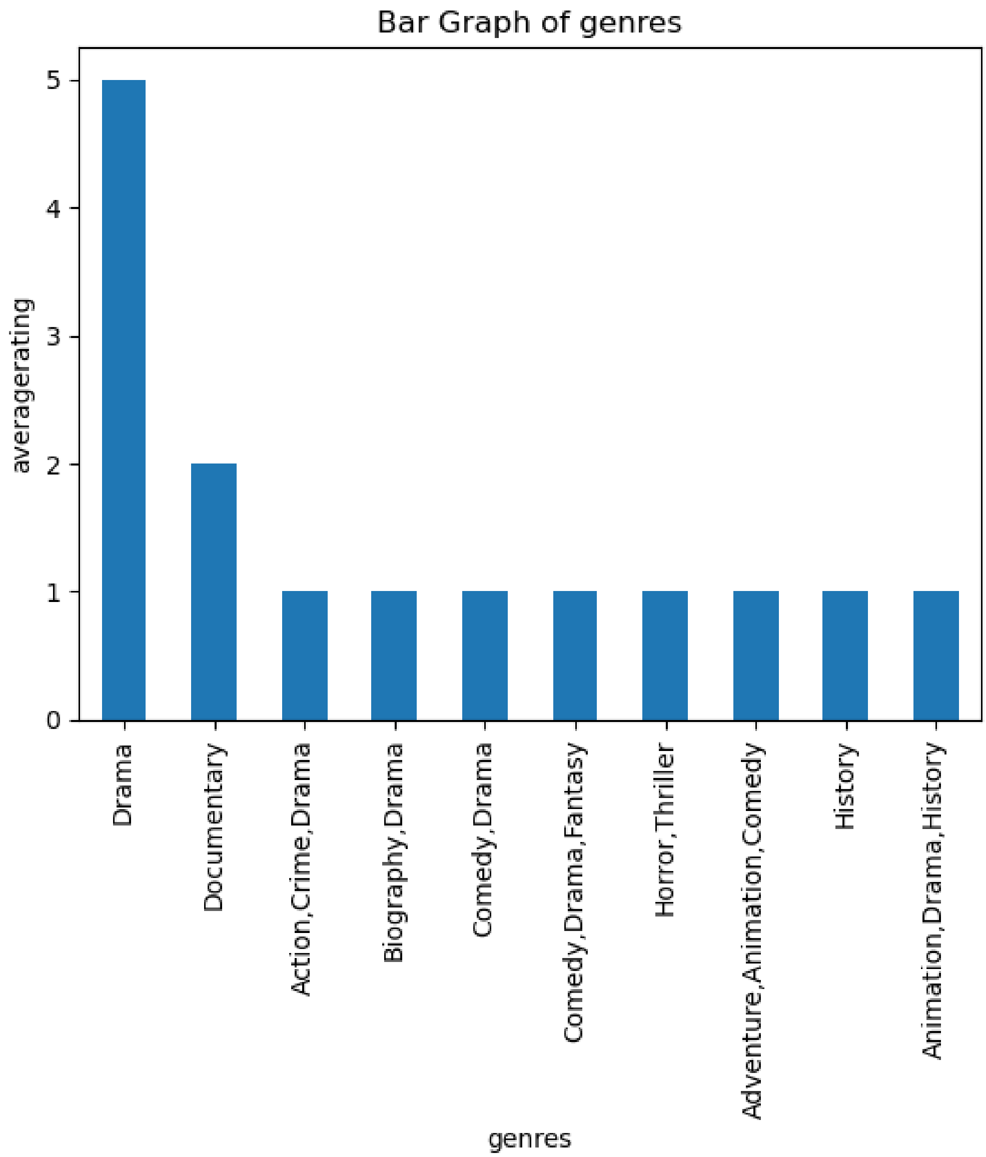
In [258]:
```
# Create a pie chart
merged_df.head(20)['genres'].value_counts().plot(kind='pie', autopct='%1.1f%%')

plt.title('Pie Chart of genres')
plt.ylabel('')  # This is to remove the default 'None' ylabel

plt.show()
```



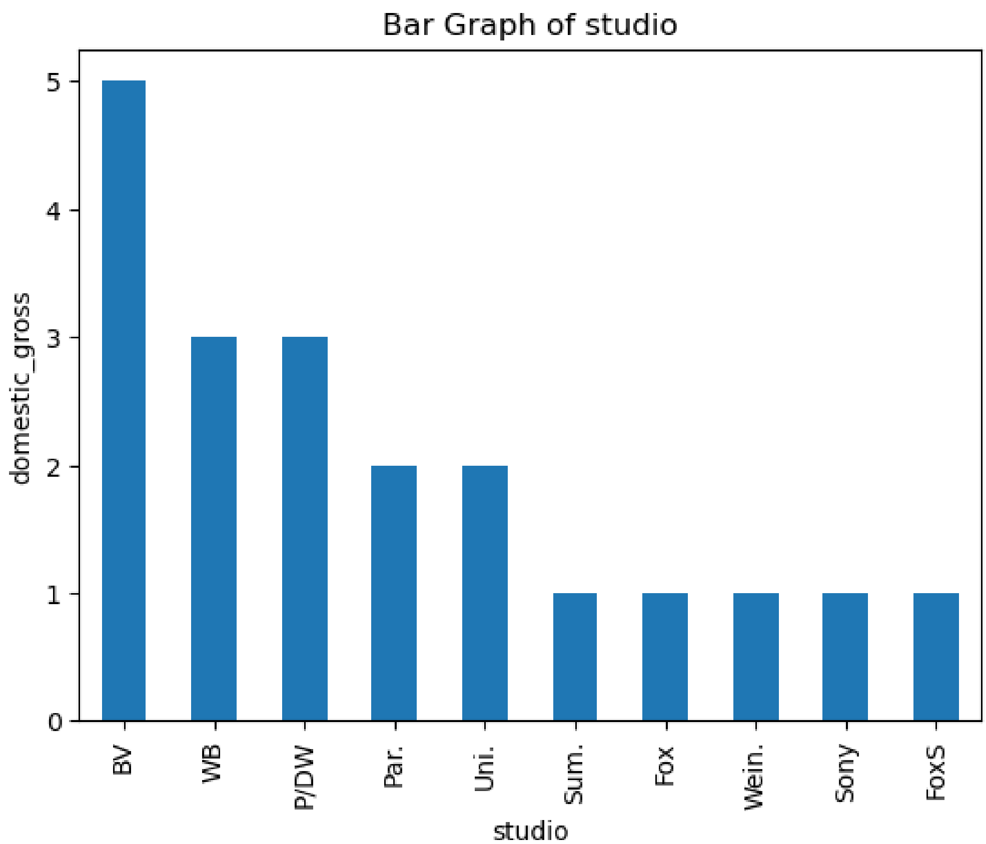
In [266]:
```
# Create a bar graph of 'genres' values
merged_df.head(15)['genres'].value_counts().plot(kind='bar')

plt.title('Bar Graph of genres')
plt.xlabel('genres')
plt.ylabel('Frequency')

plt.show()
```



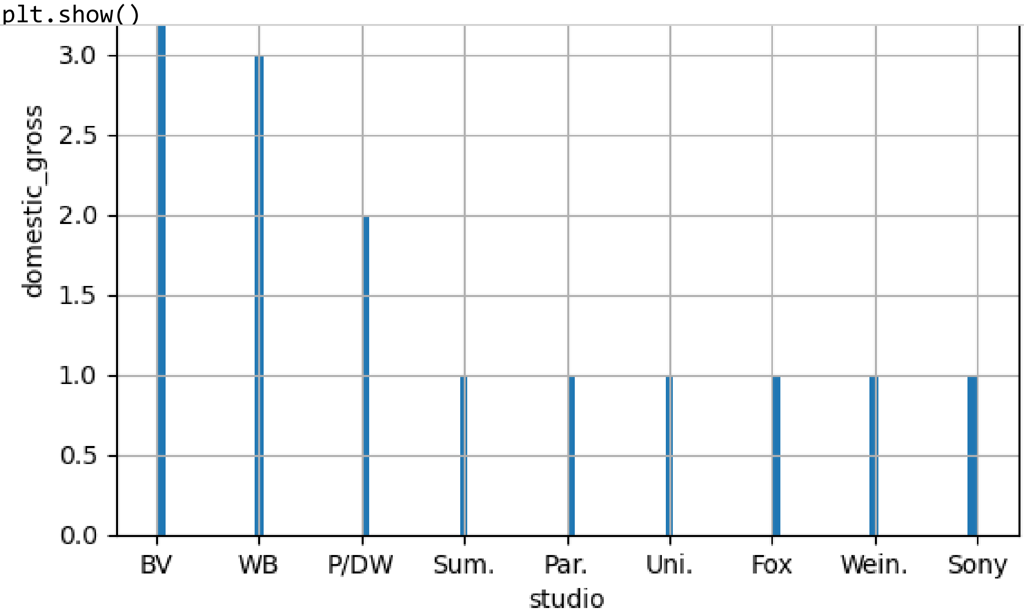
In [267]:
```
# Create a bar graph of 'genres' values
merged_df.head(15)['genres'].value_counts().plot(kind='bar')

plt.title('Bar Graph of genres')
plt.xlabel('genres')
plt.ylabel('averagerating')

plt.show()
```



In [280]:
```
# Create bar graph on studio against domestic gross
bom_df.head(20)['studio'].value_counts().plot(kind='bar')

plt.title('Bar Graph of studio')
plt.xlabel('studio')
plt.ylabel('domestic_gross')

plt.show()
```



In [281]:
```
# Create histogram on studio against domestic gross
bom_df.head(15)['studio'].hist(bins=100)
plt.xlabel('studio')
plt.ylabel('domestic_gross')
plt.title('Histogram of studio')
plt.show()
```



Findings

Most popular genres: By grouping the data by genre and then calculating the average revenue, ratings, and count of movies for each genre. The genres with the highest average revenue, ratings, and count is Drama being the most popular.

Most profitable years, months, and seasons: By grouping the data by release year, month, and season, calculate the total revenue for each group. The years, months, and seasons with the highest total revenue is 2017 making it the most profitable.

Characteristics of successful movies: We identify these by looking at the movies with the highest revenue or ratings and analyzing their common characteristics, such as budget, runtime, cast, and director. By the analysis Toy Story has most numbers and should be monitored and emulated.

Ratings and reviews comparison: Comparing the ratings and reviews from different sources by calculating the correlation between them. A high correlation would indicate that the ratings and reviews from these sources tend to agree with each other but is our case to some extent its the opposite..

Recommendations for Microsoft's Movie Studio

Based on the results of this analysis, I make the following recommendations:

Focus on popular genres: If certain genres have significantly higher average revenue, it might be beneficial to focus on producing movies in those genres.

Release movies in profitable years: If certain years have significantly higher total revenue, it might be beneficial to release more movies in those years.

Emulate successful movies: If successful movies have certain common characteristics, it might be beneficial to try to emulate those characteristics in future movies.

Consider multiple ratings sources: If the ratings from different sources are highly correlated, it might be beneficial to consider all of them.

Conclusion

In conclusion we can agree that:

The years, months, and seasons with the highest total revenue would be the most profitable. The movie performance is highly affected by the characteristics , such as budget, runtime, cast, and director. The data shows trends and gaps: which identified by analyzing the recent data and looking for patterns or changes over time.

Next steps

Further analyses could yield additional insights to better understand the movie studio production industry such as:

1.Calculating the sales returns off the movie performance in the first week of release. 2.Seeing what to anticipate during a particular season off the rationale of customers preference based on the season. 3.Project for how long a movie will make sales returns and remain relevant based off the characteristic of the movie in hand.

In [ ]: