example

Project 1: Movie Analysis

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Overview

The Project is the provide business insigts about the recent trends in movie industry to the business stakeholder so that they could enter this new entertainment markert.

The project has utilized public data to analyze movies. Based upon the findings about movie rating and gross revenues etc, recommendatios are given to the stakerholder

Business Problem

Microsoft sees the opportunity of creating original video content and they want to get in the new market. They have decided to create a new movie studio. The current business pain point is that they don't have much information about this new field and do not know what movies to create

The Questions we would like to answer is what movies

Out task is to provide insights about what types of films are currently doing the best

We will explore the data to find out what types of movies are outstandings in the follow areas:

- Popularity of Movie (quantity)
- Movie ratings
- Box office revenues

Data Understanding

We use the public data from IMDB and other sources. These data provivde direction information of our areas of interest. Some targeted quantities are movie ratings and gross box revenues etc.

In [78]:

```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

In [79]:

```
# Here you run your code to explore the data
#### glob module is used to retrieve files/pathnames matching a pattern.

import glob, os
fpath = 'zippedData/'
os.listdir(fpath)
```

Out[79]:

```
['bom.movie_gross.csv.gz',
 'imdb.name.basics.csv.gz',
 'imdb.title.akas.csv.gz',
 'imdb.title.basics.csv.gz',
 'imdb.title.crew.csv.gz',
 'imdb.title.principals.csv.gz',
 'imdb.title.ratings.csv.gz',
 'rt.movie_info.tsv.gz',
 'rt.reviews.tsv.gz',
 'tmdb.movies.csv.gz',
 'tn.movie_budgets.csv.gz']
```

In [80]:

```
query=fpath+'*.gz'

file_list=glob.glob(query)
file_list
```

Out[80]:

```
['zippedData\\bom.movie_gross.csv.gz',
 'zippedData\\imdb.name.basics.csv.gz',
 'zippedData\\imdb.title.akas.csv.gz',
 'zippedData\\imdb.title.basics.csv.gz',
 'zippedData\\imdb.title.crew.csv.gz',
 'zippedData\\imdb.title.principals.csv.gz',
 'zippedData\\imdb.title.ratings.csv.gz',
 'zippedData\\rt.movie_info.tsv.gz',
```

```
 'zippedData\\rt.reviews.tsv.gz',
 'zippedData\\tmdb.movies.csv.gz',
 'zippedData\\tn.movie_budgets.csv.gz']
```

Display and Explore all the datasets

In [81]:

```
tables={}

for file in file_list:
    file_name=file.split('\\')[-1].replace('.','_')
    print('##'*20)
    print(file_name)
    if '.tsv.gz' in file:
        temp_df = pd.read_csv(file, sep='\t', encoding='latin-1')
    else:
        temp_df = pd.read_csv(file)
    display(temp_df.head(), temp_df.tail())
    tables[file_name]=temp_df
```

```
########################################
bom_movie_gross_csv_gz
```

	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

	title	studio	domestic_gross	foreign_gross	year
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

```
########################################
imdb_name_basics_csv_gz
```

	nconst	primary_name	birth_year	death_year	primary_profession	known_for_titles
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,producer	tt0837562,tt2398241,tt0844471,tt0118553
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_department	tt0896534,tt6791238,tt0287072,tt1682940
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,actor,writer	tt1470654,tt0363631,tt0104030,tt0102898
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_department	tt0114371,tt2004304,tt1618448,tt1224387
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_decorator	tt0452644,tt0452692,tt3458030,tt2178256

	nconst	primary_name	birth_year	death_year	primary_profession	known_for_titles
606643	nm9990381	Susan Grobes	NaN	NaN	actress	NaN
606644	nm9990690	Joo Yeon So	NaN	NaN	actress	tt9090932,tt8737130
606645	nm9991320	Madeline Smith	NaN	NaN	actress	tt8734436,tt9615610
606646	nm9991786	Michelle Modigliani	NaN	NaN	producer	NaN
606647	nm9993380	Pegasus Envoyé	NaN	NaN	director,actor,writer	tt8743182

```
########################################
imdb_title_akas_csv_gz
```

	title_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	NaN	NaN	0.0
1	tt0369610	11	Jurashikku warudo	JP	NaN	imdbDisplay	NaN	0.0
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	NaN	imdbDisplay	NaN	0.0
3	tt0369610	13	O Mundo dos Dinossauros	BR	NaN	NaN	short title	0.0
4	tt0369610	14	Jurassic World	FR	NaN	imdbDisplay	NaN	0.0

	title_id	ordering	title	region	language	types	attributes	is_original_title
331698	tt9827784	2	Sayonara kuchibiru	NaN	NaN	original	NaN	1.0
331699	tt9827784	3	Farewell Song	XWW	en	imdbDisplay	NaN	0.0
331700	tt9880178	1	La atención	NaN	NaN	original	NaN	1.0
331701	tt9880178	2	La atención	ES	NaN	NaN	NaN	0.0

	title_id	ordering	title	region	language	types	attributes	is_original_title
331702	tt9880178	3	The Attention	XWW	en	imdbDisplay	NaN	0.0

```
########################################
imdb_title_basics_csv_gz
```

	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

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
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	NaN
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

```
########################################
imdb_title_crew_csv_gz
```

	tconst	directors	writers
0	tt0285252	nm0899854	nm0899854
1	tt0438973	NaN	nm0175726,nm1802864
2	tt0462036	nm1940585	nm1940585
3	tt0835418	nm0151540	nm0310087,nm0841532
4	tt0878654	nm0089502,nm2291498,nm2292011	nm0284943

	tconst	directors	writers

	tconst	directors	writers
146139	tt8999974	nm10122357	nm10122357
146140	tt9001390	nm6711477	nm6711477
146141	tt9001494	nm10123242,nm10123248	NaN
146142	tt9004986	nm4993825	nm4993825
146143	tt9010172	NaN	nm8352242

```
########################################
imdb_title_principals_csv_gz
```

	tconst	ordering	nconst	category	job	characters
0	tt0111414	1	nm0246005	actor	NaN	["The Man"]
1	tt0111414	2	nm0398271	director	NaN	NaN
2	tt0111414	3	nm3739909	producer	producer	NaN
3	tt0323808	10	nm0059247	editor	NaN	NaN
4	tt0323808	1	nm3579312	actress	NaN	["Beth Boothby"]

	tconst	ordering	nconst	category	job	characters
1028181	tt9692684	1	nm0186469	actor	NaN	["Ebenezer Scrooge"]
1028182	tt9692684	2	nm4929530	self	NaN	["Herself","Regan"]
1028183	tt9692684	3	nm10441594	director	NaN	NaN
1028184	tt9692684	4	nm6009913	writer	writer	NaN
1028185	tt9692684	5	nm10441595	producer	producer	NaN

```
########################################
imdb_title_ratings_csv_gz
```

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20

	tconst	averagerating	numvotes
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

	tconst	averagerating	numvotes
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

```
########################################
rt_movie_info_tsv_gz
```

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtime	
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN	104 minutes	
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	Jan 1, 2013	$	600,000	108 minutes	Entert
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000	NaN	NaN	116 minutes	
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Aug 27, 1997	NaN	NaN	128 minutes	

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtime
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	NaN	NaN	NaN	200 minutes

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtime
1555	1996	Forget terrorists or hijackers -- there's a ha...	R	Action and Adventure|Horror|Mystery and Suspense	NaN	NaN	Aug 18, 2006	Jan 2, 2007	$	33,886,034	106 minutes
1556	1997	The popular Saturday Night Live sketch was exp...	PG	Comedy|Science Fiction and Fantasy	Steve Barron	Terry Turner|Tom Davis|Dan Aykroyd|Bonnie Turner	Jul 23, 1993	Apr 17, 2001	NaN	NaN	88 minutes
1557	1998	Based on a novel by Richard Powell, when the l...	G	Classics|Comedy|Drama|Musical and Performing Arts	Gordon Douglas	NaN	Jan 1, 1962	May 11, 2004	NaN	NaN	111 minutes
1558	1999	The Sandlot is a coming-of-age story about a g...	PG	Comedy|Drama|Kids and Family|Sports and Fitness	David Mickey Evans	David Mickey Evans|Robert Gunter	Apr 1, 1993	Jan 29, 2002	NaN	NaN	101 minutes
1559	2000	Suspended from the force, Paris cop Hubert is ...	R	Action and Adventure|Art House and Internation...	NaN	Luc Besson	Sep 27, 2001	Feb 11, 2003	NaN	NaN	94 minutes

```
########################################
rt_reviews_tsv_gz
```

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

	id	review	rating	fresh	critic	top_critic	publisher	date
54427	2000	The real charm of this trifle is the deadpan c...	NaN	fresh	Laura Sinagra	1	Village Voice	September 24, 2002
54428	2000	NaN	1/5	rotten	Michael Szymanski	0	Zap2it.com	September 21, 2005
54429	2000	NaN	2/5	rotten	Emanuel Levy	0	EmanuelLevy.Com	July 17, 2005
54430	2000	NaN	2.5/5	rotten	Christopher Null	0	Filmcritic.com	September 7, 2003
54431	2000	NaN	3/5	fresh	Nicolas Lacroix	0	Showbizz.net	November 12, 2002

```
########################################
tmdb_movies_csv_gz
```

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7.7	10788
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.6	2018-10-13	Laboratory Conditions	0.0	1
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.6	2018-05-01	_EXHIBIT_84xxx_	0.0	1
26514	26514	[14, 28, 12]	381231	en	The Last One	0.6	2018-10-01	The Last One	0.0	1
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.6	2018-06-22	Trailer Made	0.0	1
26516	26516	[53, 27]	309885	en	The Church	0.6	2018-10-05	The Church	0.0	1

```
############################################
tn_movie_budgets_csv_gz
```

	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

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

In [82]:
```
bom_movie_gross_csv_gz=tables['bom_movie_gross_csv_gz'].copy()
bom_movie_gross_csv_gz
```

Out[82]:

	title	studio	domestic_gross	foreign_gross	year

	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 [83]:
```
imdb_title_basics_csv_gz=tables['imdb_title_basics_csv_gz'].copy()
imdb_title_basics_csv_gz
```

Out[83]:

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

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	NaN
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 6 columns

In [84]:
```
imdb_title_ratings_csv_gz=tables['imdb_title_ratings_csv_gz'].copy()
imdb_title_ratings_csv_gz
```

Out[84]:

	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
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [85]:
```
imdb_title_basics_csv_gz.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   tconst           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 [86]:

```
imdb_title_ratings_csv_gz.describe()
```

Out[86]:

	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 [87]:

```
bom_movie_gross_csv_gz.describe()
```

Out[87]:

	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

Data Preparation

We check missing values for data preparation

For the foreign gross column, more than 1/3 of the data are missing. And therefore, we remove this information and focus on the domestic gross

There are only a few records with missing values in domestic gross and studio. These records are dropped.

Distributions of some data are visuzlized

DataFrames are merged together to combination and connect the informaiton

Check Missing Values

For 3 datasets

imdb_title_ratings_csv_gz ; bom_movie_gross_csv_gz ; imdb_title_basics_csv_gz

In [88]:
```
imdb_title_ratings_csv_gz.isnull().sum()
```

Out[88]:
```
tconst           0
averagerating    0
numvotes         0
dtype: int64
```

In [89]:
```
bom_movie_gross_csv_gz.shape
```

Out[89]:
```
(3387, 5)
```

In [90]:
```
bom_movie_gross_csv_gz.isnull().sum()
```

Out[90]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

In [91]:
```
bom_movie_gross_csv_gz.drop(['foreign_gross'], axis=1, inplace=True)
```

Drop missing values

In [92]:
```
bom_movie_gross_csv_gz.dropna(inplace=True)
```

In [93]:
```
bom_movie_gross_csv_gz.shape
```

Out[93]:
```
(3356, 4)
```

In [94]:
```
imdb_title_basics_csv_gz.isnull().sum()
```

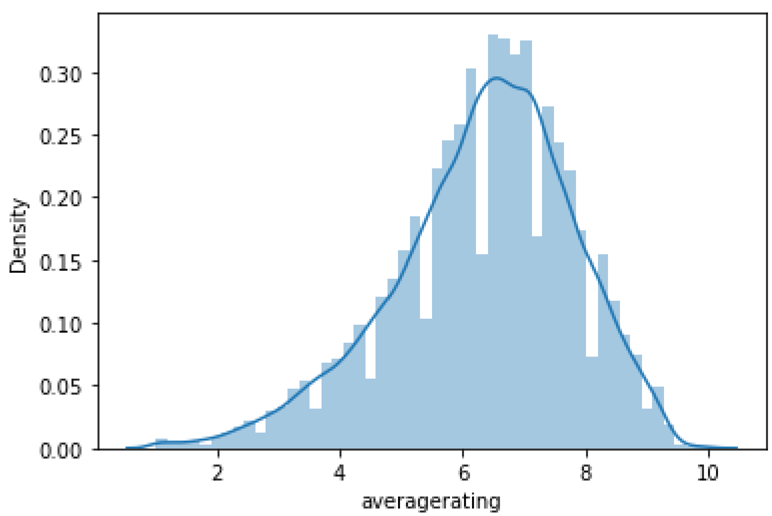
Out[94]:
```
tconst                0
primary_title         0
original_title       21
start_year            0
runtime_minutes   31739
genres             5408
dtype: int64
```

In [95]:
```
imdb_title_basics_csv_gz.drop(['runtime_minutes'], axis=1, inplace=True)
imdb_title_basics_csv_gz.dropna(inplace=True)
```

Check Distributions of 'AverageRating' and 'Domestic Gross'

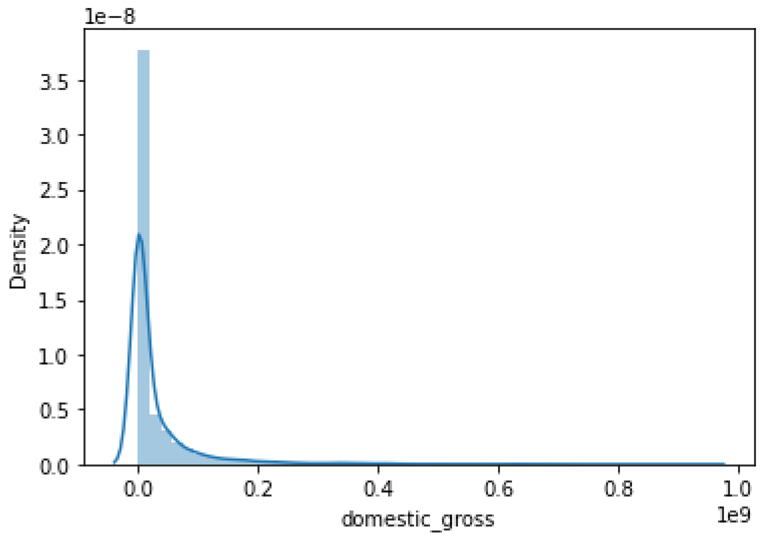
In [96]:
```
sns.distplot(imdb_title_ratings_csv_gz['averagerating'])
```

Out[96]:
```
<AxesSubplot:xlabel='averagerating', ylabel='Density'>
```



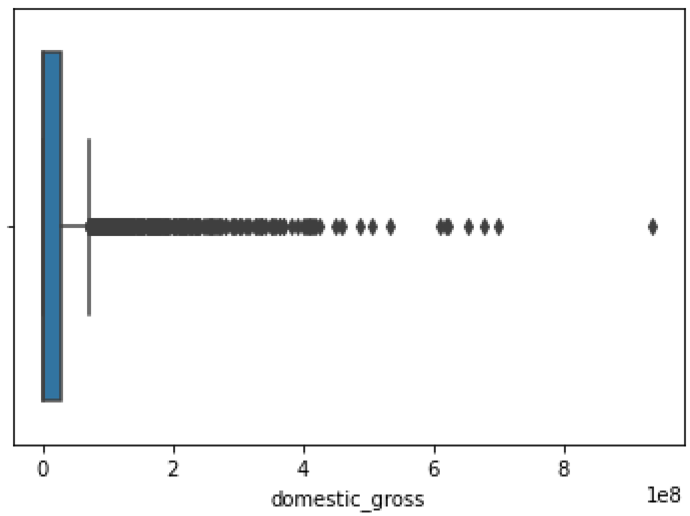
In [97]:
```
sns.distplot(bom_movie_gross_csv_gz['domestic_gross'])
```

Out[97]: <AxesSubplot:xlabel='domestic_gross', ylabel='Density'>



In [98]:
```
sns.boxplot(x=bom_movie_gross_csv_gz['domestic_gross'])
```

Out[98]: <AxesSubplot:xlabel='domestic_gross'>



Merge Datasets to connect the information

In [99]:
```
df_basic_gross = pd.merge(bom_movie_gross_csv_gz,imdb_title_basics_csv_gz,
                          how='inner', left_on='title', right_on='primary_title')
df_basic_gross
```

Out[99]:

	title	studio	domestic_gross	year	tconst	primary_title	original_title	start_year	genres
0	Toy Story 3	BV	415000000.0	2010	tt0435761	Toy Story 3	Toy Story 3	2010	Adventure,Animation,Comedy
1	Inception	WB	292600000.0	2010	tt1375666	Inception	Inception	2010	Action,Adventure,Sci-Fi
2	Shrek Forever After	P/DW	238700000.0	2010	tt0892791	Shrek Forever After	Shrek Forever After	2010	Adventure,Animation,Comedy
3	The Twilight Saga: Eclipse	Sum.	300500000.0	2010	tt1325004	The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	2010	Adventure,Drama,Fantasy
4	Iron Man 2	Par.	312400000.0	2010	tt1228705	Iron Man 2	Iron Man 2	2010	Action,Adventure,Sci-Fi
...	...	...	...	...	...	...	...	...	...
3296	Souvenir	Strand	11400.0	2018	tt2389092	Souvenir	Souvenir	2014	Comedy,Romance
3297	Souvenir	Strand	11400.0	2018	tt3478898	Souvenir	Souvenir	2014	Documentary
3298	Beauty and the Dogs	Osci.	8900.0	2018	tt6776572	Beauty and the Dogs	Aala Kaf Ifrit	2017	Crime,Drama,Thriller
3299	The Quake	Magn.	6200.0	2018	tt6523720	The Quake	Skjelvet	2018	Action,Drama,Thriller
3300	An Actor Prepares	Grav.	1700.0	2018	tt5718046	An Actor Prepares	An Actor Prepares	2018	Comedy

3301 rows × 9 columns

In [100…

```
df_basic_rating= pd.merge(imdb_title_basics_csv_gz,imdb_title_ratings_csv_gz,
                          how='inner', left_on='tconst',right_on='tconst')
df_basic_rating
```

Out[100…

	tconst	primary_title	original_title	start_year	genres	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	Action,Crime,Drama	7.0	77
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	Biography,Drama	7.2	43
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	Drama	6.9	4517
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	Comedy,Drama	6.1	13
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	Comedy,Drama,Fantasy	6.5	119
...	...	...	...	...	...	...	...

	tconst	primary_title	original_title	start_year	genres	averagerating	numvotes
73047	tt9913056	Swarm Season	Swarm Season	2019	Documentary	6.2	5
73048	tt9913084	Diabolik sono io	Diabolik sono io	2019	Documentary	6.2	6
73049	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	Drama,Family	8.7	136
73050	tt9914642	Albatross	Albatross	2017	Documentary	8.5	8
73051	tt9916160	Drømmeland	Drømmeland	2019	Documentary	6.5	11

73052 rows × 7 columns

Data Analysis

In this sections, we analyze what types of movies are the top movies in the following categories:

- Quantity of the movies
- Movie Ratings
- Box office gross revenue

We visuzlize the data and the findings

Count and Visualzie quantity of movies

In [101…

```
gen_split=imdb_title_basics_csv_gz['genres'].str.get_dummies(sep=',').sum()
gen_split
```

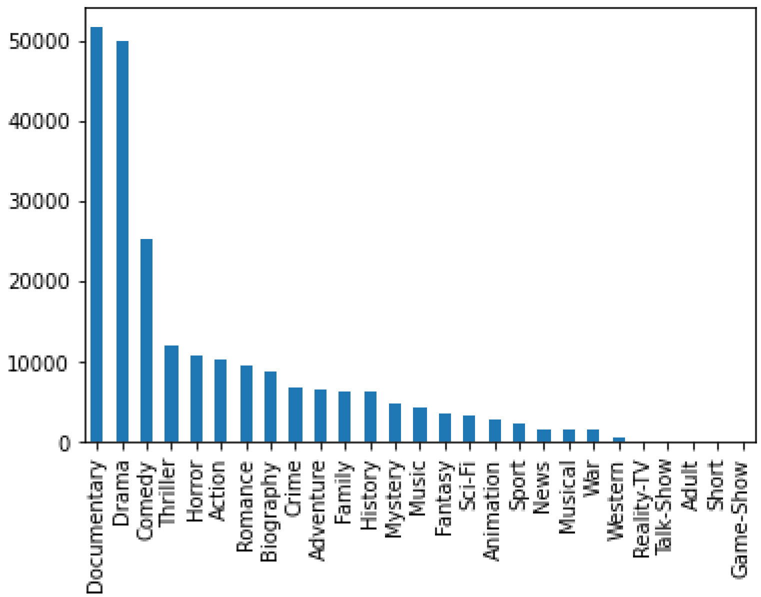
Out[101…

```
Action         10335
Adult             25
Adventure       6464
Animation       2799
Biography       8722
Comedy         25312
Crime           6753
Documentary    51640
Drama          49883
Family          6227
Fantasy         3516
Game-Show          4
History         6225
Horror         10805
```

```
Music           4314
Musical         1430
Mystery         4659
News            1551
Reality-TV        98
Romance         9371
Sci-Fi          3365
Short             11
Sport           2234
Talk-Show         50
Thriller       11883
War             1405
Western          467
dtype: int64
```

In [102…
```
gen_split.sort_values(ascending=False).plot.bar()
```

Out[102…
```
<AxesSubplot:>
```



Top 3 types of movies : Documentary, Drama, Comedy

Analyze Movie Ratings

In [103…
```
df_basic_rating.head()
```

Out[103…

	tconst	primary_title	original_title	start_year	genres	averagerating	numvotes

	tconst	primary_title	original_title	start_year	genres	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	Action,Crime,Drama	7.0	77
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	Biography,Drama	7.2	43
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	Drama	6.9	4517
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	Comedy,Drama	6.1	13
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	Comedy,Drama,Fantasy	6.5	119

In [104…

```
movie_types=df_basic_rating['genres'].str.get_dummies(sep=',').columns
```

In [105…

```
d={}
for movie in movie_types:
    d[movie]=[0, 0]
```

In [106…

```
for i in range(len(df_basic_rating)):
    movie_lst=df_basic_rating.loc[i]['genres'].split(',')
    rating = df_basic_rating.loc[i]['averagerating']
    count = df_basic_rating.loc[i]['numvotes']

    for movie in movie_lst:
        d[movie][0] += rating*count
        d[movie][1] += count
```

In [107…

```
d_rating={movie:round(values[0]/values[1],4) for movie, values in d.items()}
```

In [108…

```
d_rating1={'Type':d_rating.keys(), 'Rating':d_rating.values()}

df_rating=pd.DataFrame(data=d_rating1)
df_rating
```

Out[108…

	Type	Rating
0	Action	6.8874
1	Adult	2.4293
2	Adventure	7.0549
3	Animation	7.2648

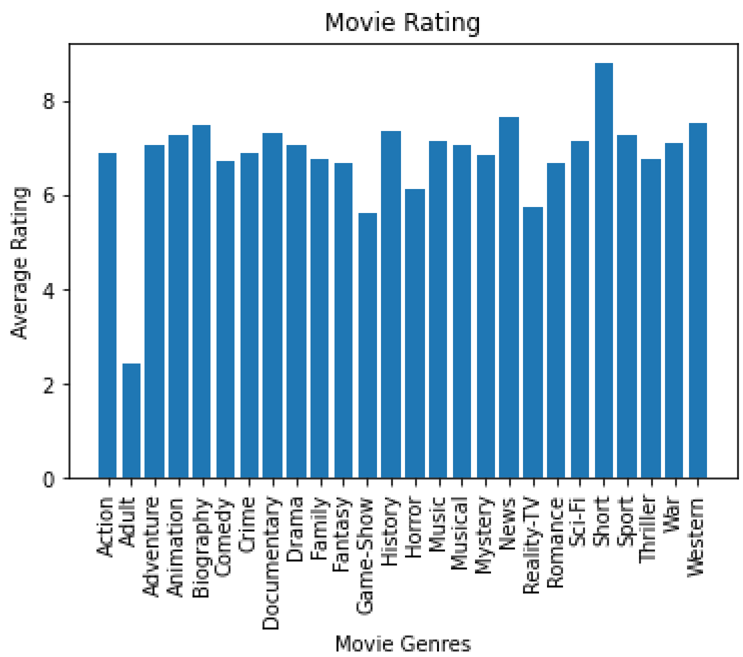
	Type	Rating
4	Biography	7.4748
5	Comedy	6.7232
6	Crime	6.8720
7	Documentary	7.2984
8	Drama	7.0663
9	Family	6.7400
10	Fantasy	6.6870
11	Game-Show	5.6069
12	History	7.3577
13	Horror	6.1279
14	Music	7.1314
15	Musical	7.0642
16	Mystery	6.8620
17	News	7.6399
18	Reality-TV	5.7497
19	Romance	6.6711
20	Sci-Fi	7.1205
21	Short	8.8000
22	Sport	7.2897
23	Thriller	6.7597
24	War	7.0840
25	Western	7.5190

Visuzlize Movie Ratings

In [109…

```
fig, ax = plt.subplots()
ax.bar(df_rating.Type, df_rating.Rating)
```

```
ax.set_xlabel('Movie Genres')
ax.set_ylabel('Average Rating')
ax.set_title('Movie Rating')
ax.tick_params(axis="x", labelrotation=90)
```



Top 3 Movie Rating:

```
"Short" : 8.92
"News"  : 7.64
"Western: 7.51
```

Analyze Movie box office gross

In [110…

```
df_basic_gross.head()
```

Out[110…

	title	studio	domestic_gross	year	tconst	primary_title	original_title	start_year	genres
0	Toy Story 3	BV	415000000.0	2010	tt0435761	Toy Story 3	Toy Story 3	2010	Adventure,Animation,Comedy
1	Inception	WB	292600000.0	2010	tt1375666	Inception	Inception	2010	Action,Adventure,Sci-Fi
2	Shrek Forever After	P/DW	238700000.0	2010	tt0892791	Shrek Forever After	Shrek Forever After	2010	Adventure,Animation,Comedy

	title	studio	domestic_gross	year	tconst	primary_title	original_title	start_year	genres
3	The Twilight Saga: Eclipse	Sum.	300500000.0	2010	tt1325004	The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	2010	Adventure,Drama,Fantasy
4	Iron Man 2	Par.	312400000.0	2010	tt1228705	Iron Man 2	Iron Man 2	2010	Action,Adventure,Sci-Fi

In [111…

```
movie_types=df_basic_rating['genres'].str.get_dummies(sep=',').columns
```

In [112…

```
movie_types
```

Out[112…

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

In [113…

```
d_gross={}
for movie in movie_types:
    d_gross[movie]=[0, 0]
```

In [114…

```
for i in range(len(df_basic_gross)):
    movie_lst=df_basic_gross.loc[i]['genres'].split(',')
    gross = df_basic_gross.loc[i]['domestic_gross']

    for movie in movie_lst:
        d_gross[movie][0] += gross
        d_gross[movie][1] += 1
```

In [115…

```
d_gross_df={movie:round(values[0]/values[1],2) for movie, values
                 in d_gross.items() if values[1]!=0}
```

In [116…

```
d_gross_df1={'Type':d_gross_df.keys(), 'Domestic_Gross':d_gross_df.values()}

df_gross=pd.DataFrame(data=d_gross_df1)
df_gross
```

Out[116…

	Type	Domestic_Gross
0	Action	5.841816e+07
1	Adventure	9.440941e+07

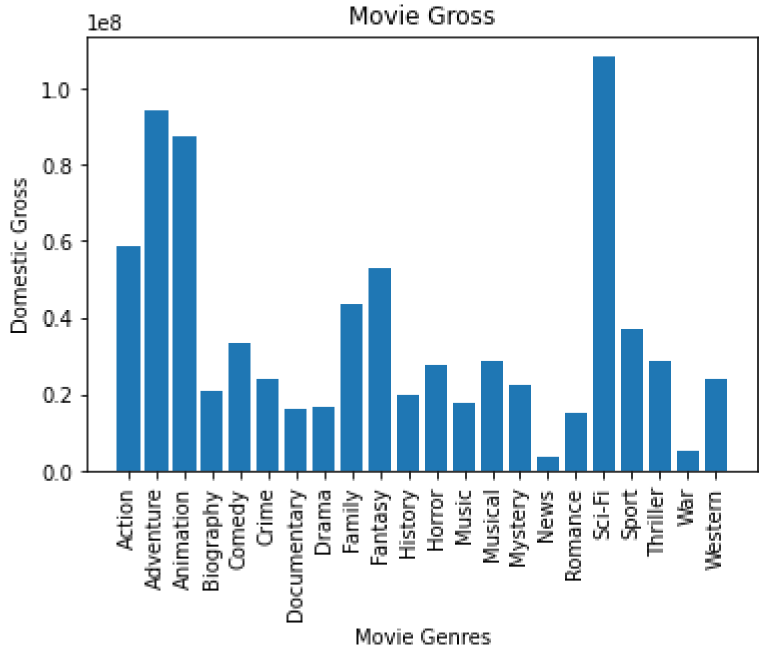
	Type	Domestic_Gross
2	Animation	8.732619e+07
3	Biography	2.098164e+07
4	Comedy	3.378180e+07
5	Crime	2.422938e+07
6	Documentary	1.649487e+07
7	Drama	1.666751e+07
8	Family	4.372936e+07
9	Fantasy	5.277712e+07
10	History	2.002153e+07
11	Horror	2.779874e+07
12	Music	1.767898e+07
13	Musical	2.899244e+07
14	Mystery	2.271399e+07
15	News	3.640900e+06
16	Romance	1.517973e+07
17	Sci-Fi	1.083885e+08
18	Sport	3.723851e+07
19	Thriller	2.896379e+07
20	War	5.309440e+06
21	Western	2.406744e+07

Visualize Movie Box Office

In [117…

```
fig, ax = plt.subplots()
ax.bar(df_gross.Type, df_gross.Domestic_Gross)
ax.set_xlabel('Movie Genres')
ax.set_ylabel('Domestic Gross')
```

```
ax.set_title('Movie Gross')
ax.tick_params(axis="x", labelrotation=90)
```



Top 3 Movie Gross Box Office:

```
"Sci-Fi"     :   1.083885e+08
"Adventure"  :   9.440941e+07
"Animation   :   8.732619e+07
```

Recommendations

3 Recommendations on the the types of movies contents to create:

In terms of quantity, movie rating, movie gross:

- Documentary, Drama, Comedy
- Short, News, Western
- Sci-Fi, Adventure, Animation

Conclusions

The Project has performed analysis on movie datasets. Business insights and recommendations provide guidance to the Microsoft movie studio stakeholder as for what types of movies to create.

Further analysis would generate more insights

```
In [ ]:
```