Final Project Submission

Please fill out:

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- Student pace: full time
- Scheduled project review date/time: 26/08/2022/5:00 p.m
- Instructor name:
- Blog post URL:

Business Understanding

Microsoft is seeking to open up a new movie studio based on its competitors who are all focusing on creating original video content. The role as a data scientist is to review the different types of films and access the film that is doing best at the box office.

Import Libraries

In [5]:

```
import pandas as pd
import numpy as np
import sqlite3
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
```

In [3]:

```
import sqlite3
conn = sqlite3.connect('zippedData/im.db')
imdb_df = pd.read_sql("""SELECT name FROM sqlite_master WHERE type = 'table';""", conn)
imdb_df
```

Out[3]:

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

Data Import

In [239]:

```
!ls ./zippedData
```

```
Project.ipynb
bom.movie_gross.csv
bom.movie_gross.csv.gz
im.db
im.db.zip
rt.movie_info.tsv
rt.movie_info.tsv.gz
rt.reviews.tsv
rt.reviews.tsv.gz
tmdb.movies.csv
tmdb.movies.csv.gz
tn.movie_budgets.csv
tn.movie_budgets.csv.gz
```

In [52]:

```
#Loading Data that we will work with
# IMDB
imdb = pd.read_sql("""
SELECT a.primary_title,
        a.original_title,
        a.start_year,
        a.runtime_minutes,
        a.genres,
        b.averagerating,
        b.numvotes,
        c.person_id,
        d.primary_name

  FROM movie_basics as a
  JOIN movie_ratings as b
    ON b.movie_id = a.movie_id
  JOIN directors as c
    ON b.movie_id = c.movie_id
  JOIN persons as d
    ON c.person_id = d.person_id;
""", conn)
imdb
```

Out[52]:

	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
1	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
2	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
3	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
4	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43
...	...	...	...	...	...	...	...

In [11]:

```
# TheMovieDB
tmdb_movies = pd.read_csv('zippedData/tmdb.movies.csv')

tmdb_movies
```

Out[11]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_d
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07
...	...	...	...	...	...	...	
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05
26514	26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06
26516	26516	[53, 27]	309885	en	The Church	0.600	2018-10

26517 rows × 10 columns

In [12]:

```
# TheNumbers
tn_movie_budgets = pd.read_csv('zippedData/tn.movie_budgets.csv')

tn_movie_budgets
```

Out[12]:

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

5782 rows × 6 columns

In [13]:

```
# Rotten Tomatoes
rt_reviews = pd.read_csv('zippedData/rt.reviews.tsv', sep='\t', encoding= 'unicode_escape')

rt_reviews
```

Out[13]:

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

54432 rows × 8 columns

In [14]:

```
# Rotten Tomatoes
rt_movie_info= pd.read_csv('zippedData/rt.movie_info.tsv', sep='\t')

rt_movie_info
```

Out[14]:

	id	synopsis	rating	genre	director	writer	the
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	C
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Au
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Se
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	D
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	
...	...	...	...	...	...	...	
1555	1996	Forget terrorists or hijackers -- there's a ha...	R	Action and Adventure|Horror|Mystery and Suspense	NaN	NaN	Au
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	Ju
1557	1998	Based on a novel by Richard Powell, when the l...	G	Classics|Comedy|Drama|Musical and Performing Arts	Gordon Douglas	NaN	J
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	A
1559	2000	Suspended from the force, Paris cop Hubert is ...	R	Action and Adventure|Art House and Internation...	NaN	Luc Besson	Se

1560 rows × 12 columns

In [15]:

```
bom_movie_gross = pd.read_csv('zippedData/bom.movie_gross.csv')

bom_movie_gross
```

Out[15]:

	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

Data Exploration

IMDB

In [53]:

```
# first 5 rows of the data
imdb.head()
```

Out[53]:

	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	nu
0	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
1	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
2	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
3	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
4	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	

In [54]:

```
# last 5 rows of the data
imdb.tail()
```

Out[54]:

	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	nu
181382	Albatross	Albatross	2017	NaN	Documentary	8.5	
181383	Albatross	Albatross	2017	NaN	Documentary	8.5	
181384	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	NaN	None	6.6	
181385	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	NaN	None	6.6	
181386	Drømmeland	Drømmeland	2019	72.0	Documentary	6.5	

In [55]:

```
# summary statistics of the data
imdb.describe()
```

Out[55]:

	start_year	runtime_minutes	averagerating	numvotes
count	181387.000000	163584.000000	181387.000000	1.813870e+05
mean	2014.309802	97.789484	6.217683	4.955524e+03
std	2.536111	194.434689	1.388026	3.760931e+04
min	2010.000000	3.000000	1.000000	5.000000e+00
25%	2012.000000	84.000000	5.400000	1.900000e+01
50%	2014.000000	94.000000	6.300000	6.600000e+01
75%	2016.000000	107.000000	7.200000	3.110000e+02
max	2019.000000	51420.000000	10.000000	1.841066e+06

In [56]:

```
#check for missing data
imdb.isnull().sum()
```

Out[56]:

```
primary_title          0
original_title         0
start_year             0
runtime_minutes    17803
genres              1340
averagerating          0
numvotes               0
person_id              0
primary_name           0
dtype: int64
```

In [57]:

```
# check count of the genres
imdb['genres'].value_counts()
```

Out[57]:

```
Drama                          25002
Documentary                    18077
Horror                         13006
Comedy                         12723
Comedy,Drama                    5903
                               ...  
Documentary,News,Romance           1
Drama,Family,Western               1
Action,Crime,Western               1
Action,Music                       1
History,Romance,War                1
Name: genres, Length: 921, dtype: int64
```

In [58]:

```
# check the original_title duplicates
imdb['original_title'].value_counts()
```

Out[58]:

```
World of Death           3818
Our Footloose Remake     2397
50 Kisses                2392
60 Seconds to Die        2013
Our RoboCop Remake       1770
                         ... 
Run This Town               1
Pelo malo                   1
Inkaar                      1
Almost Married              1
L'armée du salut            1
Name: original_title, Length: 70387, dtype: int64
```

In [59]:

```
#check the other details of a duplicated title
imdb[imdb['original_title'] == 'Lucky']
```

Out[59]:

	primary_title	original_title	start_year	runtime_minutes	genres	averag
2511	Lucky	Lucky	2010	87.0	Documentary	
7693	Lucky	Lucky	2011	103.0	Comedy	
7694	Lucky	Lucky	2011	103.0	Comedy	
18111	Lucky	Lucky	2011	100.0	Drama	
27272	Lucky	Lucky	2011	98.0	Comedy,Drama,Romance	
27273	Lucky	Lucky	2011	98.0	Comedy,Drama,Romance	
60030	Lucky	Lucky	2014	72.0	Biography,Documentary	
82305	Lucky	Lucky	2012	148.0	Comedy,Romance	
87378	Lucky	Lucky	2012	132.0	Comedy	
101770	Lucky	Lucky	2016	89.0	Action,Crime,Drama	
146902	Lucky	Lucky	2017	88.0	Comedy,Drama	
146903	Lucky	Lucky	2017	88.0	Comedy,Drama	

The Movie DB

In [27]:

```
# first 5 rows of the data
tmdb_movies.head()
```

Out[27]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	t
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Ha Po and Deat Hallo Pa
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	Hov Tr Y Drag
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron M
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	St
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Incept

In [37]:

```
# last 5 rows of the data
tmdb_movies.tail()
```

Out[37]:

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

In [38]:

```
# summary statistics of the data
tmdb_movies.describe()
```

Out[38]:

	Unnamed: 0	id	popularity	vote_average	vote_count
count	26517.00000	26517.000000	26517.000000	26517.000000	26517.000000
mean	13258.00000	295050.153260	3.130912	5.991281	194.224837
std	7654.94288	153661.615648	4.355229	1.852946	960.961095
min	0.00000	27.000000	0.600000	0.000000	1.000000
25%	6629.00000	157851.000000	0.600000	5.000000	2.000000
50%	13258.00000	309581.000000	1.374000	6.000000	5.000000
75%	19887.00000	419542.000000	3.694000	7.000000	28.000000
max	26516.00000	608444.000000	80.773000	10.000000	22186.000000

In [32]:

```
#check for missing data
tmdb_movies.isnull().sum()
```

Out[32]:

```
Unnamed: 0           0
genre_ids            0
id                   0
original_language    0
original_title       0
popularity           0
release_date         0
title                0
vote_average         0
vote_count           0
dtype: int64
```

In [34]:

```
# check the original_title duplicates
tmdb_movies['original_title'].value_counts()
```

Out[34]:

```
Eden                                          7
Home                                          6
Truth or Dare                                 5
Lucky                                         5
Aftermath                                     5
                                             ..
Life According to Sam                         1
Chicago Cubs: The Heart and Soul of Chicago   1
The Space Invaders: In Search of Lost Time    1
Guidance                                      1
Sham love Series - Stop That Wedding          1
Name: original_title, Length: 24835, dtype: int64
```

In [36]:

```
#check the other details of a duplicated title
tmdb_movies[tmdb_movies['original_title'] == 'Eden']
```

Out[36]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date
5493	5493	[18]	96599	en	Eden	6.877	2012-03-11
11604	11604	[18, 10402]	283330	en	Eden	5.373	2015-06-19
13854	13854	[]	446332	en	Eden	0.600	2014-10-04
14748	14748	[18, 10402]	283330	en	Eden	5.373	2015-06-19
14989	14989	[53, 18]	360339	en	Eden	3.061	2015-09-18
18019	18019	[18, 10402]	283330	en	Eden	5.373	2015-06-19
26506	26506	[]	561861	en	Eden	0.600	2018-11-25

Box Office Mojo

In [47]:

```
# first 5 rows of the data
bom_movie_gross.head()
```

Out[47]:

	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 [48]:

```
# last 5 rows of the data
bom_movie_gross.tail()
```

Out[48]:

	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

In [49]:

```
# summary statistics of the data
bom_movie_gross.describe()
```

Out[49]:

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

In [50]:

```
#check for missing data
bom_movie_gross.isnull().sum()
```

Out[50]:

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

In [66]:

```
# check the original_title duplicates
bom_movie_gross['title'].value_counts()
```

Out[66]:

```
Bluebeard                                       2
Armadillo                                       1
Forgiveness of Blood                            1
A Pigeon Sat on a Branch Reflecting on Existence    1
The Greatest (2010)                             1
                                               ..
Joe (2014)                                      1
It Comes At Night                               1
The Boy and the Beast                           1
Love & Mercy                                    1
The Past                                        1
Name: title, Length: 3386, dtype: int64
```

In [68]:

```
#check the other details of a duplicated title
bom_movie_gross[bom_movie_gross['title'] == 'Bluebeard']
```

Out[68]:

	title	studio	domestic_gross	foreign_gross	year
317	Bluebeard	Strand	33500.0	5200	2010
3045	Bluebeard	WGUSA	43100.0	NaN	2017

Rotten Tomatoes

In [39]:

```
# first 5 rows of the data
rt_movie_info.head()
```

Out[39]:

	id	synopsis	rating	genre	director	writer	theater_date
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971
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
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN

In [40]:

```
# last 5 rows of the data
rt_movie_info.tail()
```

Out[40]:

	id	synopsis	rating	genre	director	writer	theater_d
1555	1996	Forget terrorists or hijackers -- there's a ha...	R	Action and Adventure|Horror|Mystery and Suspense	NaN	NaN	Aug 18, 2(
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, 1!
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, 1!
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, 1!
1559	2000	Suspended from the force, Paris cop Hubert is ...	R	Action and Adventure|Art House and Internation...	NaN	Luc Besson	Sep 27, 2(

In [41]:

```
# summary statistics of the data
rt_movie_info.describe()
```

Out[41]:

	id
count	1560.000000
mean	1007.303846
std	579.164527
min	1.000000
25%	504.750000
50%	1007.500000
75%	1503.250000
max	2000.000000

In [42]:

```
#check for missing data
rt_movie_info.isnull().sum()
```

Out[42]:

```
id                 0
synopsis          62
rating             3
genre              8
director         199
writer           449
theater_date     359
dvd_date         359
currency        1220
box_office      1220
runtime           30
studio          1066
dtype: int64
```

The Numbers

In [60]:

```
# first 5 rows of the data
tn_movie_budgets.head()
```

Out[60]:

	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 [61]:

```
# last 5 rows of the data
tn_movie_budgets.tail()
```

Out[61]:

	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 [62]:

```
# summary statistics of the data
tn_movie_budgets.describe()
```

Out[62]:

	id
count	5782.000000
mean	50.372363
std	28.821076
min	1.000000
25%	25.000000
50%	50.000000
75%	75.000000
max	100.000000

In [63]:

```
#check for missing data
tn_movie_budgets.isnull().sum()
```

Out[63]:

```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

In [64]:

```
# check the original_title duplicates
tn_movie_budgets['movie'].value_counts()
```

Out[64]:

```
King Kong                     3
Home                          3
Halloween                     3
The Great Gatsby              2
Left Behind                   2
                             ..
House of Flying Daggers       1
Beyond the Valley of the Dolls    1
Something's Gotta Give        1
Mirror Mirror                 1
The Specials                  1
Name: movie, Length: 5698, dtype: int64
```

In [65]:

```
#check the other details of a duplicated title
tn_movie_budgets[tn_movie_budgets['movie'] == 'King Kong']
```

Out[65]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
39	40	Dec 14, 2005	King Kong	$207,000,000	$218,080,025	$550,517,357
2374	75	Dec 17, 1976	King Kong	$23,000,000	$52,614,445	$90,614,445
5396	97	Apr 7, 1933	King Kong	$672,000	$10,000,000	$10,000,650

Data Exploration & Analysis

IMDB

- popular genres
- top 10 movies in top 10 genres
- number of movies released over the years
- distribution of ratings
- Top directors of the top 10 genres

1. Popular Genres

In [71]:

```
imdb = imdb.iloc[: , 1:]
imdb.head()
```

Out[71]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	pers
0	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	nm07
1	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	nm07
2	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	nm07
3	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	nm07
4	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43	nm0(

In [149]:

```
#top 10 genres based on the movie count
pop_genres = imdb['genres'].value_counts()
pop_genres.head(10)
```

Out[149]:

```
Drama                       25002
Documentary                 18077
Horror                      13006
Comedy                      12723
Comedy,Drama                 5903
Comedy,Horror,Sci-Fi         4059
Comedy,Horror                3814
Comedy,Drama,Romance         3360
Drama,Romance                3117
Comedy,Drama,Music           2726
Name: genres, dtype: int64
```

In [72]:

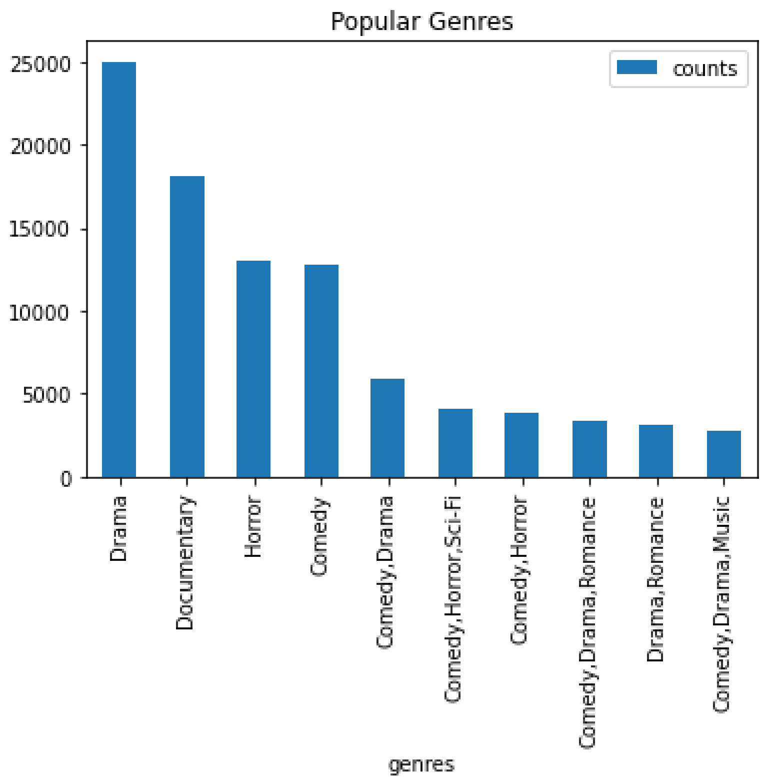
```
pop_genres = imdb['genres'].value_counts().rename_axis('genres').reset_index(name='counts')
top_genres = pop_genres.iloc[:10]
```

In [73]:

```
top_genres.plot.bar(x = 'genres', title = 'Popular Genres')
```

Out[73]:

```
<AxesSubplot:title={'center':'Popular Genres'}, xlabel='genres'>
```



In [74]:

```
#ranking movies in each genre
imdb['rank'] = imdb.groupby(["genres"])["averagerating"].rank("dense", ascending=False)
imdb.head(20)
```

Out[74]:

	original_title	start_year	runtime_minutes	genres	averagerating	num
0	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
1	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
2	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
3	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	
4	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	
5	The Other Side of the Wind	2018	122.0	Drama	6.9	
6	The Other Side of the Wind	2018	122.0	Drama	6.9	
7	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	
8	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	
9	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	
10	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	
11	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	
12	Bigfoot	2017	NaN	Horror,Thriller	4.1	
13	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	8.1	
14	Pál Adrienn	2010	136.0	Drama	6.8	
15	Pál Adrienn	2010	136.0	Drama	6.8	
16	Oda az igazság	2010	100.0	History	4.6	
17	Cooper and Hemingway: The True Gen	2013	180.0	Documentary	7.6	
18	A zöld sárkány gyermekei	2010	89.0	Drama	6.9	

	original_title	start_year	runtime_minutes	genres	averagerating	num
19	A zöld sárkány gyermekei	2010	89.0	Drama	6.9	

1.2 Top 10 movies in the 5 Popular Genres

1.2.1 Drama

In [75]:

```
#drama
drama = imdb[imdb['genres'] == 'Drama'].sort_values('rank', ascending = True)
drama
```

Out[75]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_i
130423	Dog Days in the Heartland	2017	NaN	Drama	10.0	5	nm689356
180215	Gini Helida Kathe	2019	138.0	Drama	9.9	417	nm1036956
176738	Eghantham	2018	125.0	Drama	9.7	639	nm998266
176902	Gangter in Morteni	2017	69.0	Drama	9.6	98	nm1000512
166084	Taawdo the Sunlight	2017	98.0	Drama	9.5	70	nm923176
...	...	...	...	...	...	...	.
13306	Hito no sabaku	2010	121.0	Drama	1.0	449	nm382795
13307	Hito no sabaku	2010	121.0	Drama	1.0	449	nm382795
139235	Sakura saku	2017	NaN	Drama	1.0	20	nm308795
13302	Hito no sabaku	2010	121.0	Drama	1.0	449	nm382783
13317	Hito no sabaku	2010	121.0	Drama	1.0	449	nm382936

25002 rows × 9 columns

In [108]:

```
top_drama = drama.iloc[:10]
top_drama
```

Out[108]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_i
130423	Dog Days in the Heartland	2017	NaN	Drama	10.0	5	nm689356
180215	Gini Helida Kathe	2019	138.0	Drama	9.9	417	nm1036956
176738	Eghantham	2018	125.0	Drama	9.7	639	nm998266
176902	Gangter in Morteni	2017	69.0	Drama	9.6	98	nm1000512
166084	Taawdo the Sunlight	2017	98.0	Drama	9.5	70	nm923176
171130	Never-Ending Road	2017	111.0	Drama	9.5	84	nm015166
170395	Peranbu	2018	147.0	Drama	9.4	9629	nm359149
179863	Got my Hustle Up	2018	NaN	Drama	9.4	24	nm1029869
170396	Peranbu	2018	147.0	Drama	9.4	9629	nm359149
170397	Peranbu	2018	147.0	Drama	9.4	9629	nm604168

1.2.2 Documentary

In [76]:

```
#documentary
documentary = imdb[imdb['genres'] == 'Documentary'].sort_values('rank', ascending = True)
documentary
```

Out[76]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	per
139115	Atlas Mountain: Barbary Macaques - Childcaring...	2015	59.0	Documentary	10.0	5	nm4
180724	Renegade	2019	NaN	Documentary	10.0	20	nm3
176787	Pick It Up! - Ska in the '90s	2019	99.0	Documentary	10.0	5	nm4
162633	A Dedicated Life: Phoebe Brand Beyond the Group	2015	93.0	Documentary	10.0	5	nm2
1585	Exteriores: Mulheres Brasileiras na Diplomacia	2018	52.0	Documentary	10.0	5	nm10
...	...	...	...	...	...	...	
40618	Ramo Trip	2012	119.0	Documentary	1.0	439	nm4
40614	Ramo Trip	2012	119.0	Documentary	1.0	439	nm4
40615	Ramo Trip	2012	119.0	Documentary	1.0	439	nm4
40604	Ramo Trip	2012	119.0	Documentary	1.0	439	nm0
40608	Ramo Trip	2012	119.0	Documentary	1.0	439	nm4

18077 rows × 9 columns

In [77]:

```
top_documentary = drama.iloc[:10]
top_documentary
```

Out[77]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_i
130423	Dog Days in the Heartland	2017	NaN	Drama	10.0	5	nm689356
180215	Gini Helida Kathe	2019	138.0	Drama	9.9	417	nm1036956
176738	Eghantham	2018	125.0	Drama	9.7	639	nm998266
176902	Gangter in Morteni	2017	69.0	Drama	9.6	98	nm1000512
166084	Taawdo the Sunlight	2017	98.0	Drama	9.5	70	nm923176
171130	Never-Ending Road	2017	111.0	Drama	9.5	84	nm015166
170395	Peranbu	2018	147.0	Drama	9.4	9629	nm359149
179863	Got my Hustle Up	2018	NaN	Drama	9.4	24	nm1029869
170396	Peranbu	2018	147.0	Drama	9.4	9629	nm359149
170397	Peranbu	2018	147.0	Drama	9.4	9629	nm604168

1.2.3 Horror

In [80]:

```
#horror
horror = imdb[imdb['genres'] == 'Horror'].sort_values('rank', ascending = True)
horror
```

Out[80]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_i
1501	Ragmork	2019	86.0	Horror	9.2	6	nm419148
148679	Las Reglas de la Ruina	2018	90.0	Horror	9.2	41	nm398626
1866	Chinnada Gombe	2018	110.0	Horror	9.1	40	nm1071010
139037	Body Farm	2018	NaN	Horror	9.0	5	nm280389
139038	Body Farm	2018	NaN	Horror	9.0	5	nm304659
...	...	...	...	...	...	...	.
149363	Desu foresuto kyofu no mori 5	2016	65.0	Horror	1.0	230	nm790776
149364	Desu foresuto kyofu no mori 5	2016	65.0	Horror	1.0	230	nm790776
149595	Death Forest 4	2016	70.0	Horror	1.0	230	nm519385
96958	Tôkyô Densetsu: Yuganda Ikei Toshi	2014	66.0	Horror	1.0	6	nm148085
149359	Desu foresuto kyofu no mori 5	2016	65.0	Horror	1.0	230	nm220375

13006 rows × 9 columns

In [81]:

```
top_horror = horror.iloc[:10]
top_horror
```

Out[81]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_i
1501	Ragmork	2019	86.0	Horror	9.2	6	nm419148
148679	Las Reglas de la Ruina	2018	90.0	Horror	9.2	41	nm398626
1866	Chinnada Gombe	2018	110.0	Horror	9.1	40	nm1071010
139037	Body Farm	2018	NaN	Horror	9.0	5	nm280389
139038	Body Farm	2018	NaN	Horror	9.0	5	nm304659
158025	Here Be Dragons	2018	70.0	Horror	8.8	8	nm512690
1771	Shed	2019	82.0	Horror	8.8	8	nm312797
161531	Dark Ditties Presents 'Mrs Wiltshire'	2018	67.0	Horror	8.8	10	nm456380
161532	Dark Ditties Presents 'Mrs Wiltshire'	2018	67.0	Horror	8.8	10	nm456380
161533	Dark Ditties Presents 'Mrs Wiltshire'	2018	67.0	Horror	8.8	10	nm732477

1.2.4 Comedy

In [83]:

```
#comedy
comedy = imdb[imdb['genres'] == 'Comedy'].sort_values('rank', ascending = True)
comedy
```

Out[83]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_
180680	Yeh Suhaagraat Impossible	2019	92.0	Comedy	9.6	624	nm104362
178989	Postal	2019	77.0	Comedy	9.3	10	nm54628
175419	Babysplitters	2019	119.0	Comedy	9.3	77	nm11536
137307	Oporuka	2015	68.0	Comedy	9.2	23	nm77945
179504	Sakala Kalasala	2019	132.0	Comedy	9.2	767	nm32737
...	...	...	...	...	...	...	
59757	Momok jangan cari pasal!	2012	85.0	Comedy	1.0	5	nm11054
38971	Seikai gûdo mooningu!!	2010	81.0	Comedy	1.0	429	nm44071
147213	Utsuroi no hyôhonbako	2016	95.0	Comedy	1.0	205	nm52924
160651	Jak se mori revizori	2018	NaN	Comedy	1.0	5	nm60089
39951	Yûyami Daria	2011	70.0	Comedy	1.0	127	nm30879

12723 rows × 9 columns

In [84]:

```
top_comedy = comedy.iloc[:10]
top_comedy
```

Out[84]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_
180680	Yeh Suhaagraat Impossible	2019	92.0	Comedy	9.6	624	nm104362
178989	Postal	2019	77.0	Comedy	9.3	10	nm54628
175419	Babysplitters	2019	119.0	Comedy	9.3	77	nm11536
137307	Oporuka	2015	68.0	Comedy	9.2	23	nm77945
179504	Sakala Kalasala	2019	132.0	Comedy	9.2	767	nm32737
179505	Sakala Kalasala	2019	132.0	Comedy	9.2	767	nm32737
36561	Argyle	2011	45.0	Comedy	9.2	6	nm17142
36562	Argyle	2011	45.0	Comedy	9.2	6	nm17142
137308	Oporuka	2015	68.0	Comedy	9.2	23	nm77945
162289	Deany Bean is Dead	2018	84.0	Comedy	9.2	16	nm04710

1.2.5 Comedy, Drama

In [137]:

```
#comedy,drama
comedy_drama = imdb[imdb['genres'] == 'Comedy,Drama'].sort_values('rank', ascending = True)
comedy_drama
```

Out[137]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	p
164323	Once Upon a Time ... in Hollywood	2019	159.0	Comedy,Drama	9.7	5600	nm
161920	Erra Buss	2014	140.0	Comedy,Drama	9.2	516	nm
33252	Remembering Erik Lowhouse	2019	49.0	Comedy,Drama	9.2	5	nm
101083	Lights Camera Bullshit	2014	95.0	Comedy,Drama	9.2	11	nm
171161	Fall Semester	2017	86.0	Comedy,Drama	9.2	13	nm
...	...	...	...	...	...	...	
131231	Pure Hearts: Into Chinese Showbiz	2015	96.0	Comedy,Drama	1.0	453	nm
113835	Mr. Home	2014	70.0	Comedy,Drama	1.0	126	nm
113836	Mr. Home	2014	70.0	Comedy,Drama	1.0	126	nm
113852	Mr. Home	2014	70.0	Comedy,Drama	1.0	126	nm
113855	Mr. Home	2014	70.0	Comedy,Drama	1.0	126	nm

5903 rows × 9 columns

In [116]:

```
top_comedy_drama = drama.iloc[:10]
top_comedy_drama
```

Out[116]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	person_i
130423	Dog Days in the Heartland	2017	NaN	Drama	10.0	5	nm689356
180215	Gini Helida Kathe	2019	138.0	Drama	9.9	417	nm1036956
176738	Eghantham	2018	125.0	Drama	9.7	639	nm998266
176902	Gangter in Morteni	2017	69.0	Drama	9.6	98	nm1000512
166084	Taawdo the Sunlight	2017	98.0	Drama	9.5	70	nm923176
171130	Never-Ending Road	2017	111.0	Drama	9.5	84	nm015166
170395	Peranbu	2018	147.0	Drama	9.4	9629	nm359149
179863	Got my Hustle Up	2018	NaN	Drama	9.4	24	nm1029869
170396	Peranbu	2018	147.0	Drama	9.4	9629	nm359149
170397	Peranbu	2018	147.0	Drama	9.4	9629	nm604168

2. Top Directors

In [100]:

```
# top drama directors based on number of movies produced

drama_directors = drama['primary_name'].value_counts().rename_axis('name').reset_index(name
drama_directors.head(10)
```

Out[100]:

	name	counts
0	Xavier Agudo	26
1	Adam Ruszkowski	24
2	Wi Ding Ho	24
3	Nicolas Fogliarini	24
4	Prashant Sehgal	24
5	Sabine Sebaaly	24
6	Craig Lines	24
7	Ian Bonner	24
8	Nicole Sylvester	24
9	Vishesh Mankal	24

In [102]:

```
# top documentary directors based on number of movies produced

documentary_directors = documentary['primary_name'].value_counts().rename_axis('name').rese
documentary_directors.head(10)
```

Out[102]:

	name	counts
0	Daniel Ramírez	39
1	Pietro Marcello	33
2	Guido Lombardi	32
3	Bruno Oliviero	29
4	Gianluca Loffredo	28
5	Luca Martusciello	27
6	Fabio Mollo	27
7	Stefano Martone	27
8	Nicolangelo Gelormini	27
9	Mario F. Martone	27

In [103]:

```
# top horror directors based on number of movies produced

horror_directors = horror['primary_name'].value_counts().rename_axis('name').reset_index(na
horror_directors.head(10)
```

Out[103]:

	name	counts
0	Tony Newton	138
1	Sam Mason-Bell	122
2	Jason Impey	113
3	Martin Sonntag	92
4	Dustin Ferguson	92
5	Richard Chandler	85
6	Hunter Johnson	77
7	Michael J. Epstein	77
8	Kieran Johnston	77
9	Sophia Cacciola	76

In [105]:

```
# top comedy directors based on number of movies produced

comedy_directors = comedy['primary_name'].value_counts().rename_axis('name').reset_index(na
comedy_directors.head(10)
```

Out[105]:

	name	counts
0	Neri Parenti	35
1	Dmitriy Kiselev	34
2	Fausto Brizzi	32
3	Timur Bekmambetov	29
4	Smeep Kang	27
5	Yaroslav Chevazhevskiy	25
6	Stefan Nieuwoudt	25
7	Aleksandr Voytinskiy	23
8	Ignas Jonynas	23
9	Dmitriy Dyachenko	23

In [106]:

```
# top comedy,drama directors based on number of movies produced

comedy_drama_directors = comedy_drama['primary_name'].value_counts().rename_axis('name').re
comedy_drama_directors.head(10)
```

Out[106]:

	name	counts
0	Ram	2
1	Arsel Arumugam	1
2	Chad Carpenter	1
3	Anjana Krishnakumar	1
4	Chi-Yung Chang	1
5	Colonelu Morteni	1
6	Vijay Suthar	1
7	Nagaraja Uppunda	1
8	Jason Dbks Hampton	1

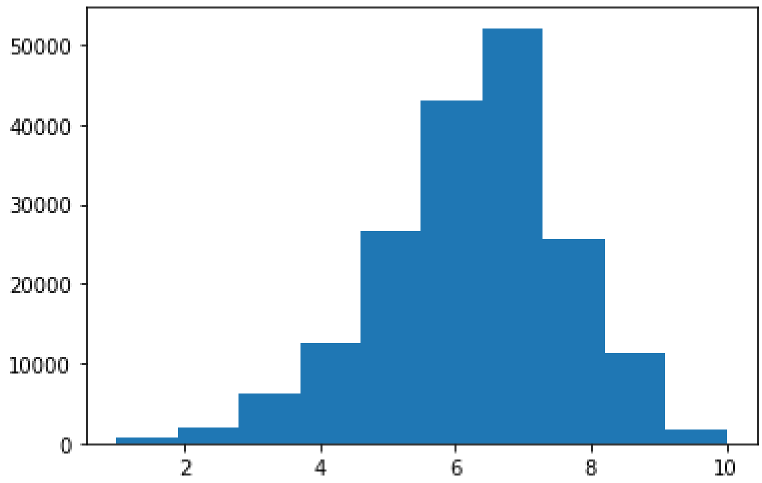
3. Distribution of Averaging ratings

In [150]:

```
#imdb rating distribution
plt.hist(imdb['averagerating'])
```

Out[150]:

```
(array([  736.,  1861.,  6188., 12508., 26726., 42899., 52098., 25550.,
        11227.,  1594.]),
 array([ 1. ,  1.9,  2.8,  3.7,  4.6,  5.5,  6.4,  7.3,  8.2,  9.1, 10. ]),
 <BarContainer object of 10 artists>)
```

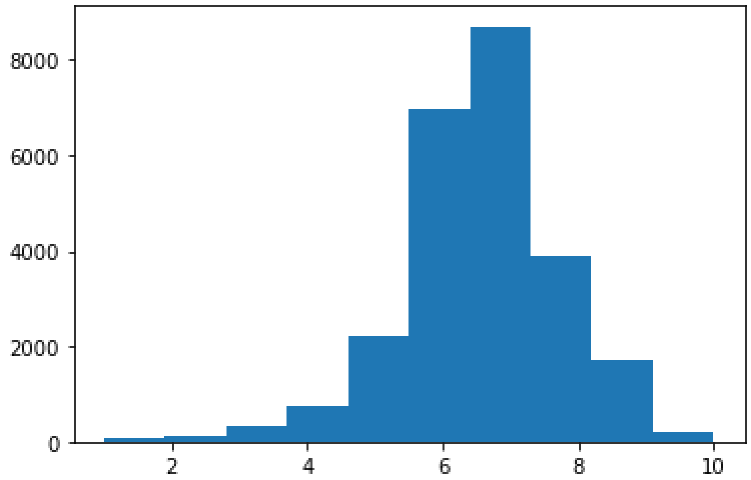


In [110]:

```
# Average drama rating distribution
plt.hist(drama['averagerating'])
```

Out[110]:

```
(array([  90.,  128.,  344.,  736., 2228., 6961., 8697., 3907., 1713.,
         198.]),
 array([ 1. ,  1.9,  2.8,  3.7,  4.6,  5.5,  6.4,  7.3,  8.2,  9.1, 10. ]),
 <BarContainer object of 10 artists>)
```

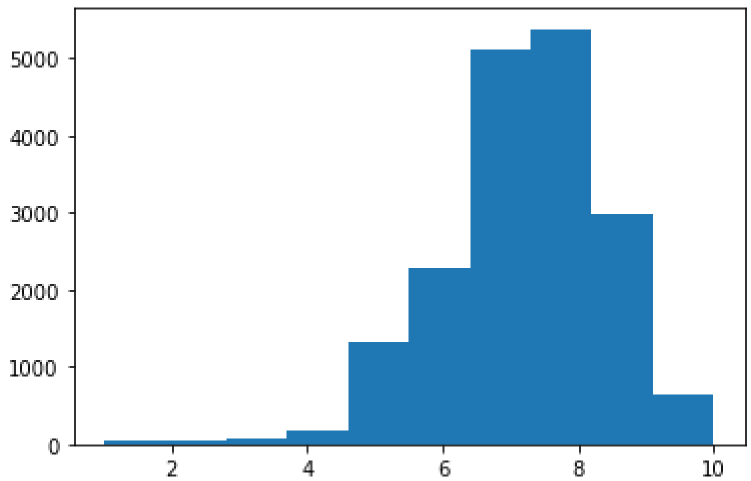


In [111]:

```
# Average rating distribution
plt.hist(documentary['averagerating'])
```

Out[111]:

```
(array([  42.,   42.,   70.,  186., 1321., 2293., 5103., 5382., 2990.,
         648.]),
 array([ 1. ,  1.9,  2.8,  3.7,  4.6,  5.5,  6.4,  7.3,  8.2,  9.1, 10. ]),
 <BarContainer object of 10 artists>)
```

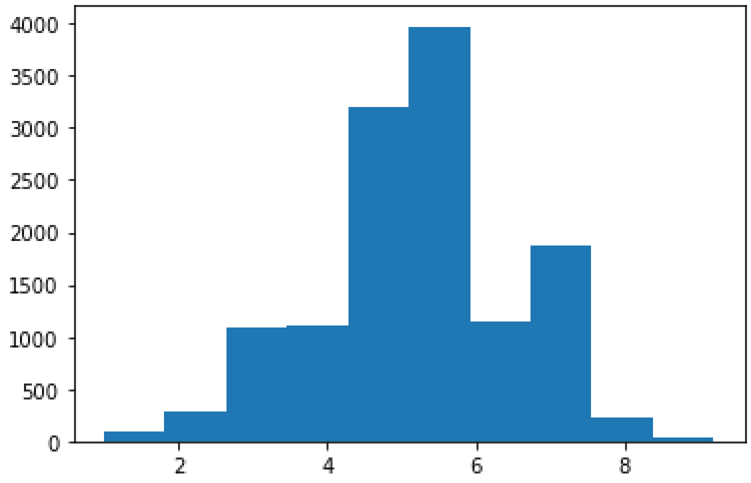


In [112]:

```
# Average rating distribution
plt.hist(horror['averagerating'])
```

Out[112]:

```
(array([  97.,  275., 1087., 1116., 3195., 3973., 1143., 1868.,  219.,
          33.]),
 array([1.  , 1.82, 2.64, 3.46, 4.28, 5.1 , 5.92, 6.74, 7.56, 8.38, 9.2 ]),
 <BarContainer object of 10 artists>)
```

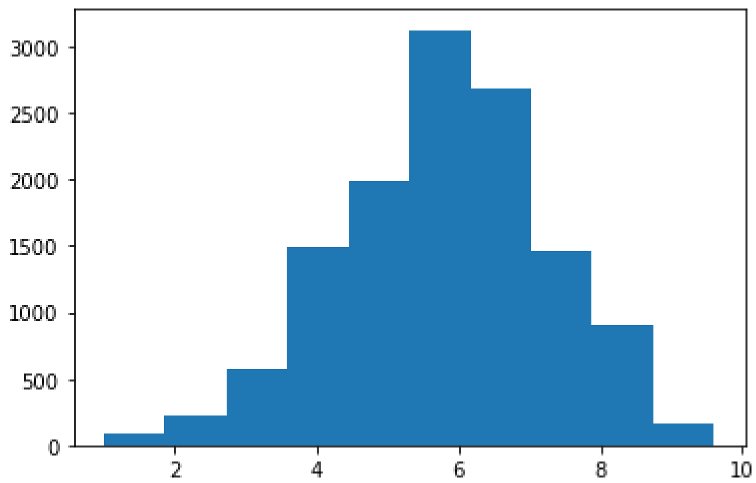


In [113]:

```
# Average rating distribution
plt.hist(comedy['averagerating'])
```

Out[113]:

```
(array([  84.,  228.,  568., 1491., 1995., 3127., 2689., 1469.,  902.,
         170.]),
 array([1.  , 1.86, 2.72, 3.58, 4.44, 5.3 , 6.16, 7.02, 7.88, 8.74, 9.6 ]),
 <BarContainer object of 10 artists>)
```

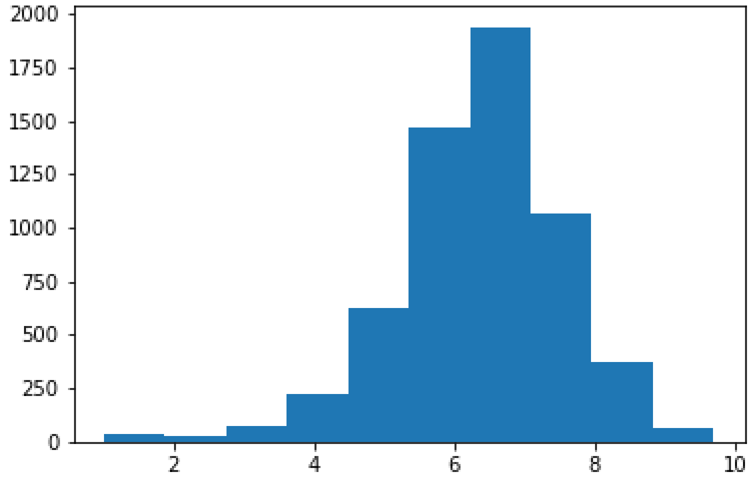


In [117]:

```
# Average rating distribution
plt.hist(comedy_drama['averagerating'])
```

Out[117]:

```
(array([  40.,   30.,   75.,  219.,  629., 1470., 1938., 1063.,  373.,
          66.]),
 array([1.  , 1.87, 2.74, 3.61, 4.48, 5.35, 6.22, 7.09, 7.96, 8.83, 9.7 ]),
 <BarContainer object of 10 artists>)
```



4. Number of movies per year

In [168]:

```
# num of movies

years = imdb['start_year'].value_counts().rename_axis('years').reset_index(name='counts')
years
```

Out[168]:

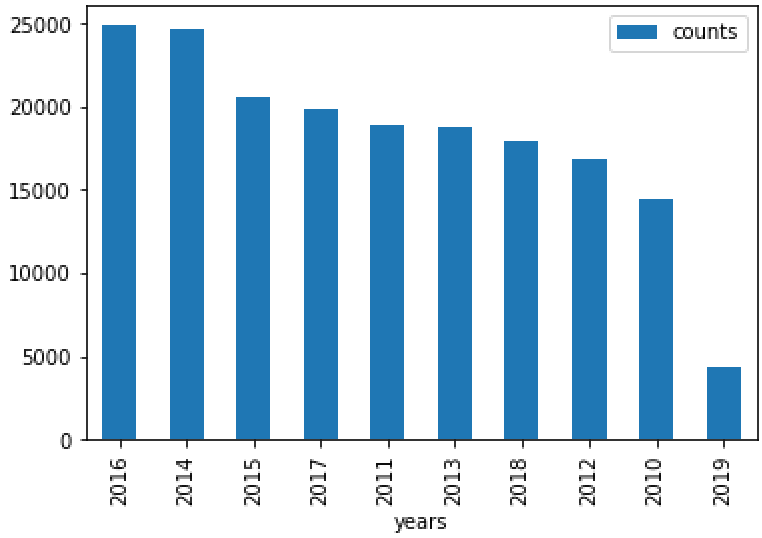
	years	counts
0	2016	24890
1	2014	24651
2	2015	20635
3	2017	19814
4	2011	18902
5	2013	18747
6	2018	17905
7	2012	16917
8	2010	14514
9	2019	4412

In [169]:

```
years.plot.bar(x = 'years')
```

Out[169]:

```
<AxesSubplot:xlabel='years'>
```



5. Top 10 Directors

In [138]:

```
imdb['primary_name'].value_counts()
```

Out[138]:

```
Tony Newton            217
Jason Impey            180
Shane Ryan             177
Ruben Rodriguez        150
Martin Sonntag         135
                      ... 
Jens Dahl                1
David J. Greenberg       1
Elizabeth Wood           1
Russell Whaley           1
Rajan Kumar Patel        1
Name: primary_name, Length: 56742, dtype: int64
```

In [129]:

```
# num of movies each director

movie_dir = imdb['primary_name'].value_counts().rename_axis('name').reset_index(name='count
movie_dir
```

Out[129]:

	name	counts
0	Tony Newton	217
1	Jason Impey	180
2	Shane Ryan	177
3	Ruben Rodriguez	150
4	Martin Sonntag	135
...	...	...
56737	Jens Dahl	1
56738	David J. Greenberg	1
56739	Elizabeth Wood	1
56740	Russell Whaley	1
56741	Rajan Kumar Patel	1

56742 rows × 2 columns

In [130]:

```
top_dir = movie_dir.iloc[:10]
top_dir
```

Out[130]:

	name	counts
0	Tony Newton	217
1	Jason Impey	180
2	Shane Ryan	177
3	Ruben Rodriguez	150
4	Martin Sonntag	135
5	Sam Mason-Bell	130
6	Gav Chuckie Steel	119
7	Corey Norman	114
8	Dustin Ferguson	106
9	R.J. Wilson	100