Final Project Submission

Please fill out:

Student name: DIANA MBUVIStudent pace: PART TIME

import pandas as pd import numpy as np import matplotlib.pyplot as plt %matplotlib inline

Importing the data

UNDERSTANDING THE DATA

#reading the data from a csv file

Out[251]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
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	[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	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186
26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-10-13	Laboratory Conditions	0.0	1
26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-05-01	_EXHIBIT_84xxx_	0.0	1
26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-10-01	The Last One	0.0	1
26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-06-22	Trailer Made	0.0	1
26516	[53, 27]	309885	en	The Church	0.600	2018-10-05	The Church	0.0	1

In [251]: df=pd.read_csv('C:/Users/Lenovo/Desktop/Phase_one_project/dsc-phase-1-project/zippedData/tmdb.movies.csv', in

26517 rows × 9 columns

In [252]: df1=pd.read_csv('C:/Users/Lenovo/Desktop/Phase_one_project/dsc-phase-1-project/zippedData/tn.movie_budgets.csv
df1
#reading the data from a csv file

Out[252]:

	release_date	movie	production_budget	domestic_gross	worldwide_gross
id					
1	Dec 18, 2009	Avatar	\$425,000,000	\$760,507,625	\$2,776,345,279
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	\$410,600,000	\$241,063,875	\$1,045,663,875
3	Jun 7, 2019	Dark Phoenix	\$350,000,000	\$42,762,350	\$149,762,350
4	May 1, 2015	Avengers: Age of Ultron	\$330,600,000	\$459,005,868	\$1,403,013,963
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	\$317,000,000	\$620,181,382	\$1,316,721,747
78	Dec 31, 2018	Red 11	\$7,000	\$0	\$0
79	Apr 2, 1999	Following	\$6,000	\$48,482	\$240,495
80	Jul 13, 2005	Return to the Land of Wonders	\$5,000	\$1,338	\$1,338
81	Sep 29, 2015	A Plague So Pleasant	\$1,400	\$0	\$0
82	Aug 5, 2005	My Date With Drew	\$1,100	\$181,041	\$181,041

5782 rows × 5 columns

```
In [255]: # Convert 'release_date' to datetime type
    df['release_date'] = pd.to_datetime(df['release_date'])
    df1['release_date'] = pd.to_datetime(df1['release_date'])

# Merge the dataframes based on 'release_date' and 'original_title'
    df2= pd.merge(df, df1, left_on=['release_date', 'original_title'], right_on=['release_date', 'movie'], how='in
    # Display the merged dataframe
    df2
```

Out[255]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count	movie	prodi
0	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610	How to Train Your Dragon	
1	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368	Iron Man 2	
2	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	
1396	[53, 18, 27]	510284	en	Braid	5.972	2019-02-01	Braid	6.4	18	Braid	
1397	[18, 10752]	514407	en	Indivisible	5.599	2018-10-26	Indivisible	5.4	13	Indivisible	
1398	[18, 28, 80]	547590	en	El Chicano	5.274	2019-05-03	EI Chicano	9.0	1	El Chicano	
1399	[18, 35, 28, 80]	506971	ur	Teefa in Trouble	4.486	2018-07-20	Teefa in Trouble	7.6	11	Teefa in Trouble	
1400	[28, 12, 16]	332718	en	Bilal: A New Breed of Hero	2.707	2018-02-02	Bilal: A New Breed of Hero	6.8	54	Bilal: A New Breed of Hero	
1401	rowe x 13 c	olumno									

1401 rows × 13 columns

In [256]: df2.head() #getting the first 5 rows of the data

Out[256]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count	movie	production
0	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610	How to Train Your Dragon	\$165 ₃
1	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368	Iron Man 2	\$170
2	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	\$30,
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	\$30,
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	\$160
4											•

```
In [257]: df2.info() #gives information about the data set
           <class 'pandas.core.frame.DataFrame'>
           Int64Index: 1401 entries, 0 to 1400
           Data columns (total 13 columns):
               Column
                                    Non-Null Count Dtype
           ---
                -----
            0
                                    1401 non-null
                                                     object
                genre_ids
            1
                id
                                    1401 non-null
                                                     int64
            2
                original_language
                                    1401 non-null
                                                     object
            3
                original_title
                                    1401 non-null
                                                     object
            4
                                    1401 non-null
                                                     float64
                popularity
                release_date
                                    1401 non-null
                                                     datetime64[ns]
            6
                title
                                    1401 non-null
                                                     object
            7
                vote_average
                                    1401 non-null
                                                    float64
            8
                vote_count
                                    1401 non-null
                                                     int64
            9
                movie
                                    1401 non-null
                                                     object
            10
                production_budget 1401 non-null
                                                     object
            11 domestic_gross
                                    1401 non-null
                                                     object
            12 worldwide_gross
                                    1401 non-null
                                                    object
           dtypes: datetime64[ns](1), float64(2), int64(2), object(8)
           memory usage: 153.2+ KB
In [258]: df2.dtypes #getting the type of data
Out[258]: genre_ids
                                         object
           id
                                          int64
           original_language
                                         object
           original_title
                                         object
                                        float64
           popularity
           release_date
                                 datetime64[ns]
           title
                                         object
           vote_average
                                        float64
           vote_count
                                          int64
           movie
                                         object
           production_budget
                                         object
           domestic_gross
                                         object
           worldwide gross
                                         object
           dtype: object
In [259]: df2.describe() #describes the data
Out[259]:
                           id
                                popularity
                                         vote average
                                                        vote count
                   1401.000000
                               1401.000000
                                           1401.000000
                                                       1401.000000
           count
            mean
                 202685.153462
                                 13.346337
                                              6.346824
                                                       2243.757316
                                 8.051220
                                                       2993.835538
                 138350.904263
                                              0.865988
              std
             min
                     95.000000
                                 0.600000
                                              3.000000
                                                          1.000000
             25%
                  68728.000000
                                 8.459000
                                              5.800000
                                                        373.000000
                 205584.000000
                                 11.546000
                                              6.400000
                                                       1097.000000
             50%
```

323676.000000

max 547590.000000

75%

16.302000

80.773000

6.900000

2817.000000

9.000000 22186.000000

```
In [260]: df2.isna().sum() #gives the number of empty values per column
```

```
Out[260]: genre_ids
                               0
          id
          original_language
                               0
          original_title
          popularity
                               0
                               0
          release_date
          title
                               0
          vote_average
                               0
          vote_count
                               0
          movie
                               0
          production_budget
          domestic_gross
                               0
          worldwide_gross
                               0
```

dtype: int64

There were no missing values in the columns.

```
In [261]: df2.isna().sum().sum() #gives number of empty values in entires data
```

Out[261]: 0

There were no missing values.

```
In [262]: duplicate_rows= df2[df2.duplicated()] #checking for duplicated rows
duplicate_rows
```

Out[262]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count	movie	pr
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	
86	[18, 10749]	46705	en	Blue Valentine	8.994	2010-12-29	Blue Valentine	6.9	1677	Blue Valentine	
112	[35, 18]	46829	en	Barney's Version	7.357	2011-01-14	Barney's Version	7.2	210	Barney's Version	
131	[18]	59728	en	The 5th Quarter	2.142	2011-03-25	The 5th Quarter	4.7	15	The 5th Quarter	
145	[18, 36, 10752]	387	de	Das Boot	16.554	1982-02-10	Das Boot	8.1	981	Das Boot	
1248	[35, 18, 878]	301337	en	Downsizing	10.682	2017-12-22	Downsizing	5.1	1887	Downsizing	
1257	[18, 12]	407890	en	Lean on Pete	9.307	2018-04-06	Lean on Pete	6.9	133	Lean on Pete	
1263	[18]	300687	en	Same Kind of Different as Me	8.756	2017-10-20	Same Kind of Different as Me	6.8	103	Same Kind of Different as Me	
1266	[28, 35]	398177	en	Just Getting Started	8.459	2017-12-08	Just Getting Started	4.9	94	Just Getting Started	
1272	[18]	392982	en	Marshall	7.879	2017-10-13	Marshall	7.3	257	Marshall	
130 rc	ows × 13 co	lumns									•

title vote average vote count

In [263]: df2=df2.drop_duplicates() #displays data after dropping duplicated rows
df2

id original language original title popularity release date

Out[263]:

aonro ide

14, 12, 10751]	10191					How to			114-	
		en	How to Train Your Dragon	28.734	2010-03-26	Train Your Dragon	7.7	7610	How to Train Your Dragon	
12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368	Iron Man 2	
16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	
3, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	
28, 12, 1, 878]	19995	en	Avatar	26.526	2009-12-18	Avatar	7.4	18676	Avatar	
53, 18, 27]	510284	en	Braid	5.972	2019-02-01	Braid	6.4	18	Braid	
[18, 10752]	514407	en	Indivisible	5.599	2018-10-26	Indivisible	5.4	13	Indivisible	
18, 28, 80]	547590	en	El Chicano	5.274	2019-05-03	El Chicano	9.0	1	El Chicano	
18, 35, 28, 80]	506971	ur	Teefa in Trouble	4.486	2018-07-20	Teefa in Trouble	7.6	11	Teefa in Trouble	
28, 12, 16]	332718	en	Bilal: A New Breed of Hero	2.707	2018-02-02	Bilal: A New Breed of Hero	6.8	54	Bilal: A New Breed of Hero	
1 3 2 1 1 1 2	16, 35, 18, 12] 28, 12, 4, 878] 53, 18, 27] [18, 28, 80] [18, 35, 88]	16, 35, 862 18, 878, 27205 18, 12, 19995 19, 18, 18, 510284 19, 18, 28, 514407 18, 28, 80, 547590 18, 35, 506971	16, 35, 862 en 18, 878, 27205 en 18, 12, 19995 en 10, 878, 510284 en 11, 10, 10, 10, 10, 10, 10, 10, 10, 10,	16, 35, 10751] 862 en Toy Story 18, 878, 12] 27205 en Inception 18, 12, 19995 en Avatar 18, 18, 27, 510284 en Braid 18, 28, 27, 514407 en Indivisible 18, 28, 28, 28, 547590 en El Chicano 18, 35, 506971 ur Teefa in Trouble 18, 12, 15, 332718 en Braid en Braid	16, 35, 10751] 862 en Toy Story 28.005 18, 878, 12] 27205 en Inception 27.920 18, 12, 1, 19995 en Avatar 26.526 18, 12, 1, 19995 en Braid 5.972 13, 18, 27, 27, 510284 en Braid 5.972 18, 28, 28, 80, 547590 en El Chicano 5.274 18, 35, 88, 80, 506971 ur Teefa in Trouble 4.486 18, 12, 16, 332718 Bilal: A New Breed of 2.707	16, 35, 10751] 862 en Toy Story 28.005 1995-11-22 18, 878, 12] 27205 en Inception 27.920 2010-07-16 18, 12, 1, 878] 19995 en Avatar 26.526 2009-12-18 13, 18, 27] 510284 en Braid 5.972 2019-02-01 [18, 28, 28, 31407 en Indivisible 5.599 2018-10-26 18, 28, 80, 547590 en El Chicano 5.274 2019-05-03 18, 35, 80, 80, 80, 80, 80, 80, 80, 80, 80, 80	16, 35, 10751] 862 en Toy Story 28.005 1995-11-22 Toy Story 3, 878, 12, 12, 18, 878] 27205 en Inception 27.920 2010-07-16 Inception 28, 12, 12, 18, 1878] 19995 en Avatar 26.526 2009-12-18 Avatar <	16, 35, 10751] 862 en Toy Story 28.005 1995-11-22 Toy Story 7.9 3, 878, 12, 12, 18, 878] 27205 en Inception 27.920 2010-07-16 Inception 8.3 28, 12, 18, 878] 19995 en Avatar 26.526 2009-12-18 Avatar 7.4 10, 878] 510284 en Braid 5.972 2019-02-01 Braid 6.4 18, 28, 28, 80, 547590 en Indivisible 5.599 2018-10-26 Indivisible 5.4 18, 38, 80, 506971 ur Teefa in Trouble 4.486 2018-07-20 Teefa in Trouble 7.6 18, 12, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16	10751 862	16, 35, 10751] 862 en Toy Story 28.005 1995-11-22 Toy Story 7.9 10174 Toy Story 3, 878, 12] 27205 en Inception 27.920 2010-07-16 Inception 8.3 22186 Inception 12] en Avatar 26.526 2009-12-18 Avatar 7.4 18676 Avatar 1.4, 878] 19995 en Avatar 26.526 2009-12-18 Avatar 7.4 18676 Avatar 1.5, 878] 510284 en Braid 5.972 2019-02-01 Braid 6.4 18 Braid 16, 16, 16, 16, 16, 16, 16, 16, 16, 16,

In [264]: vote_count = df2['vote_count'].max() #checking the highest number of votes
vote_count

Out[264]: 22186

In [265]: average_vote_count = df2['vote_count'].mean() #getting the mean of the vote count
average_vote_count

Out[265]: 2164.369000786782

In [266]: mode_vote_count = df2['vote_count'].mode() #getting the mode of the vote count
mode_vote_count

Out[266]: 0 6

Name: vote_count, dtype: int64

In [267]: median_vote_count = df2['vote_count'].median() #getting the median of the vote count
median_vote_count

Out[267]: 1058.0

In [268]: df2 = df2[df2['vote_count'] >= 1058] #dropping the rows with an average vote count less than 1058
df2.reset_index(drop=True, inplace=True)
df2

Out[268]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count	movie	produc
0	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610	How to Train Your Dragon	4
1	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368	Iron Man 2	9
2	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	
3	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	\$
4	[28, 12, 14, 878]	19995	en	Avatar	26.526	2009-12-18	Avatar	7.4	18676	Avatar	\$
631	[9648, 27, 53]	406563	en	Insidious: The Last Key	16.017	2018-01-05	Insidious: The Last Key	6.1	1306	Insidious: The Last Key	
632	[35, 18, 10749]	449176	en	Love, Simon	15.608	2018-03-16	Love, Simon	8.2	3165	Love, Simon	
633	[53, 27]	460019	en	Truth or Dare	14.354	2018-04-13	Truth or Dare	6.0	2005	Truth or Dare	
634	[10752, 18, 36, 28]	429351	en	12 Strong	13.183	2018-01-19	12 Strong	5.6	1312	12 Strong	
635	[12, 878, 10751, 14]	407451	en	A Wrinkle in Time	12.529	2018-03-09	A Wrinkle in Time	5.0	1073	A Wrinkle in Time	\$
636 r	ows × 13 c	olumns									

In [269]: vote_average = df2['vote_average'].max() #the highest vote average
vote_average

Out[269]: 8.4

In [270]: df2_sort = df2.sort_values(by=['vote_average'], ascending=True) #sorting to get the least vote_average
df2_sort

Out[270]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count	movie	produ
93	[35]	71880	en	Jack and Jill	11.277	2011-11-11	Jack and Jill	4.1	1124	Jack and Jill	
420	[53]	241251	en	The Boy Next Door	7.062	2015-01-23	The Boy Next Door	4.4	1382	The Boy Next Door	
375	[28, 12, 878]	166424	en	Fantastic Four	16.360	2015-08-07	Fantastic Four	4.4	3837	Fantastic Four	
233	[35]	87818	en	Movie 43	12.813	2013-01-25	Movie 43	4.4	1332	Movie 43	
15	[28, 12, 10751, 14]	10196	en	The Last Airbender	16.595	2010-07-01	The Last Airbender	4.6	2143	The Last Airbender	
590	[18, 35]	490132	en	Green Book	36.284	2018-11-16	Green Book	8.3	3499	Green Book	
579	[12, 28, 14]	299536	en	Avengers: Infinity War	80.773	2018-04-27	Avengers: Infinity War	8.3	13948	Avengers: Infinity War	
3	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	
270	[18, 10402]	244786	en	Whiplash	28.784	2014-10-10	Whiplash	8.4	7908	Whiplash	
131	[18, 80]	311	en	Once Upon a Time in America	17.717	1984-06-01	Once Upon a Time in America	8.4	2243	Once Upon a Time in America	
636 r	ows × 13 c	olumns									

4

In [271]: df2_sort = df2.sort_values(by=['vote_average'], ascending=False) #sorting values from the highest vote average
df2_sort

Out[271]:

[18, 80]	311		0			_				
	311	en	Once Upon a Time in America	17.717	1984-06-01	Once Upon a Time in America	8.4	2243	Once Upon a Time in America	
[18, 10402]	244786	en	Whiplash	28.784	2014-10-10	Whiplash	8.4	7908	Whiplash	
[12, 28, 14]	299536	en	Avengers: Infinity War	80.773	2018-04-27	Avengers: Infinity War	8.3	13948	Avengers: Infinity War	
[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	
[18, 35]	490132	en	Green Book	36.284	2018-11-16	Green Book	8.3	3499	Green Book	
[28, 12, 10751, 14]	10196	en	The Last Airbender	16.595	2010-07-01	The Last Airbender	4.6	2143	The Last Airbender	
[28, 12, 878]	166424	en	Fantastic Four	16.360	2015-08-07	Fantastic Four	4.4	3837	Fantastic Four	
[53]	241251	en	The Boy Next Door	7.062	2015-01-23	The Boy Next Door	4.4	1382	The Boy Next Door	
[35]	87818	en	Movie 43	12.813	2013-01-25	Movie 43	4.4	1332	Movie 43	
[35]	71880	en	Jack and Jill	11.277	2011-11-11	Jack and Jill	4.1	1124	Jack and Jill	
1	10402] [12, 28, 14] [28, 878, 12] [18, 35] [28, 12, 0751, 14] [28, 12, 878] [53]	10402] 244786 [12, 28, 299536] [28, 878, 27205] [18, 35] 490132	10402] 244788 en [12, 28, 14] 299536 en [28, 878, 27205 en [18, 35] 490132 en [28, 12, 0751, 14] 10196 en [28, 12, 878] 166424 en [53] 241251 en [35] 87818 en	10402] 244766 en Willplash [12, 28, 12, 0751, 14] 299536 en Avengers: Infinity War [28, 878, 12] 27205 en Inception [18, 35] 490132 en Green Book [28, 12, 0751, 14] 10196 en The Last Airbender [28, 12, 878] 166424 en Fantastic Four [53] 241251 en The Boy Next Door [35] 87818 en Movie 43	10402] 244766 en Wiliplash 26.764 [12, 28, 12] 299536 en Avengers: Infinity War 80.773 [28, 878, 12] 27205 en Inception 27.920 [18, 35] 490132 en Green Book 36.284 [28, 12, 0751, 14] 10196 en The Last Airbender 16.595 [28, 12, 878] 166424 en Fantastic Four 16.360 [53] 241251 en The Boy Next Door 7.062 [35] 87818 en Movie 43 12.813	10402] 244766 ell Wilipiasi 28.784 2014-10-10 [12, 28, 299536 en Avengers: Infinity War 80.773 2018-04-27 [28, 878, 12] 27205 en Inception 27.920 2010-07-16 [18, 35] 490132 en Green Book 36.284 2018-11-16 [28, 12, 0751, 14] 10196 en The Last Airbender 16.595 2010-07-01 [28, 12, 878] 166424 en Fantastic Four 16.360 2015-08-07 [53] 241251 en The Boy Next Door 7.062 2015-01-23 [35] 87818 en Movie 43 12.813 2013-01-25	10402 244786	10402] 244765 ell Wilipiasi 26.764 2014-10-10 Wilipiasi 6.4 [12, 28, 12, 0751, 14] 10196 en Fantastic Four The Boy Next Door [35] 87818 en Movie 43 12.813 2013-01-25 Movie 43 4.4	10402] 244786 ell Wilipiasii 28.784 2014-10-10 Wilipiasii 0.4 7906 [12, 28, 14] 299536 en Avengers: Infinity War 80.773 2018-04-27 Infinity War 8.3 13948 [28, 878, 12] 27205 en Inception 27.920 2010-07-16 Inception 8.3 22186 [18, 35] 490132 en Green Book 36.284 2018-11-16 Green Book 8.3 3499	10402 244766 ell Whiplash 28.764 2014-10-10 Whiplash 8.4 7906 Whiplash 1212 28, 299536 en Avengers: Infinity War 80.773 2018-04-27 Infinity 8.3 13948 Infinity War 128, 878, 129 27205 en Inception 27.920 2010-07-16 Inception 8.3 22186 Inception 18, 35 490132 en Green Book 36.284 2018-11-16 Green Book 8.3 3499 Green Book 36.284 2018-11-16 Green

```
In [272]: # Convert columns to numeric for calculations
          df2['worldwide_gross'] = pd.to_numeric(df2['worldwide_gross'].str.replace('$', '').str.replace(',', ''))
          df2['production_budget'] = pd.to_numeric(df2['production_budget'].str.replace('$', '').str.replace(',',
          df2['domestic_gross'] = pd.to_numeric(df2['domestic_gross'].str.replace('$', '').str.replace(',', ''))
          # df2['production budget'] = pd.to numeric(df2['production budget'].str.replace('$', '')
          # Calculate domestic ROI
          df2['domestic_roi'] = ((df2['domestic_gross'] - df2['production_budget']) / df2['production_budget']) * 100
          # Calculate worldwide ROI
          df2['worldwide_roi'] = ((df2['worldwide_gross'] - df2['production_budget']) / df2['production_budget']) * 100
          # Display the dataset with the calculated ROI
          df2[['original title', 'production budget', 'worldwide gross', 'worldwide roi', 'domestic roi']]
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel_14264\1942295363.py:2: FutureWarning: The default value of rege
          x will change from True to False in a future version. In addition, single character regular expressions will
          *not* be treated as literal strings when regex=True.
            df2['worldwide_gross'] = pd.to_numeric(df2['worldwide_gross'].str.replace('$', '').str.replace(',', ''))
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel_14264\1942295363.py:2: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
          Try using .loc[row indexer,col indexer] = value instead
          See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
          returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return
          ing-a-view-versus-a-copy)
            df2['worldwide gross'] = pd.to numeric(df2['worldwide gross'].str.replace('$', '').str.replace(',', ''))
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel_14264\1942295363.py:3: FutureWarning: The default value of rege
          x will change from True to False in a future version. In addition, single character regular expressions will
          *not* be treated as literal strings when regex=True.
            df2['production budget'] = pd.to numeric(df2['production_budget'].str.replace('$', '').str.replace(',',
          ''))
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel_14264\1942295363.py:3: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
          Try using .loc[row indexer,col indexer] = value instead
          See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
          returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return
          ing-a-view-versus-a-copy)
            df2['production budget'] = pd.to numeric(df2['production budget'].str.replace('$', '').str.replace(',',
          ''))
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel 14264\1942295363.py:4: FutureWarning: The default value of rege
          x will change from True to False in a future version. In addition, single character regular expressions will
          *not* be treated as literal strings when regex=True.
            df2['domestic_gross'] = pd.to_numeric(df2['domestic_gross'].str.replace('$', '').str.replace(',', ''))
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel 14264\1942295363.py:4: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
          Try using .loc[row_indexer,col_indexer] = value instead
          See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
          returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#return
          ing-a-view-versus-a-copy)
            df2['domestic_gross'] = pd.to_numeric(df2['domestic_gross'].str.replace('$', '').str.replace(',', ''))
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel_14264\1942295363.py:8: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
          Try using .loc[row_indexer,col_indexer] = value instead
          See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
          returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return
          ing-a-view-versus-a-copy)
            df2['domestic_roi'] = ((df2['domestic_gross'] - df2['production_budget']) / df2['production_budget']) * 10
          C:\Users\Lenovo\AppData\Local\Temp\ipykernel_14264\1942295363.py:11: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
          Try using .loc[row_indexer,col_indexer] = value instead
          See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
          returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#return
          ing-a-view-versus-a-copy)
            df2['worldwide_roi'] = ((df2['worldwide_gross'] - df2['production_budget']) / df2['production_budget']) *
          100
```

Out[272]:

	original_title	production_budget	worldwide_gross	worldwide_roi	domestic_roi
0	How to Train Your Dragon	165000000	494870992	199.921813	31.867413
1	Iron Man 2	170000000	621156389	265.386111	83.784312
2	Toy Story	30000000	364545516	1115.151720	539.320777
3	Inception	160000000	835524642	422.202901	82.860122
4	Avatar	425000000	2776345279	553.257713	78.942971
631	Insidious: The Last Key	10000000	167885588	1578.855880	577.453300
632	Love, Simon	10000000	65520633	555.206330	308.263410
633	Truth or Dare	3500000	95127344	2617.924114	1083.171857
634	12 Strong	35000000	71118378	103.195366	30.913466
635	A Wrinkle in Time	103000000	133401882	29.516390	-2.447953

636 rows × 5 columns

In [273]: df2 #checking the data

Out[273]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count	movie	produc
0	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610	How to Train Your Dragon	
1	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368	Iron Man 2	
2	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174	Toy Story	
3	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	
4	[28, 12, 14, 878]	19995	en	Avatar	26.526	2009-12-18	Avatar	7.4	18676	Avatar	
631	[9648, 27, 53]	406563	en	Insidious: The Last Key	16.017	2018-01-05	Insidious: The Last Key	6.1	1306	Insidious: The Last Key	
632	[35, 18, 10749]	449176	en	Love, Simon	15.608	2018-03-16	Love, Simon	8.2	3165	Love, Simon	
633	[53, 27]	460019	en	Truth or Dare	14.354	2018-04-13	Truth or Dare	6.0	2005	Truth or Dare	
634	[10752, 18, 36, 28]	429351	en	12 Strong	13.183	2018-01-19	12 Strong	5.6	1312	12 Strong	
635	[12, 878, 10751, 14]	407451	en	A Wrinkle in Time	12.529	2018-03-09	A Wrinkle in Time	5.0	1073	A Wrinkle in Time	
636 r	ows × 15 c	olumns									

Out[274]:

233 15 ₁₀ 590	[35] [53] [28, 12, 878]	71880 241251	en	Jack and Jill	11.277	2011-11-11	Jack and Jill	4.1	1124	Jack and Jill	
375 233 15 ₁₀ 	[28, 12,	241251	en	TI . D						JIII	
233 15 ₁₀ 590				The Boy Next Door	7.062	2015-01-23	The Boy Next Door	4.4	1382	The Boy Next Door	
15 ₁₀ 590		166424	en	Fantastic Four	16.360	2015-08-07	Fantastic Four	4.4	3837	Fantastic Four	
 590	[35]	87818	en	Movie 43	12.813	2013-01-25	Movie 43	4.4	1332	Movie 43	
590	[28, 12, 0751, 14]	10196	en	The Last Airbender	16.595	2010-07-01	The Last Airbender	4.6	2143	The Last Airbender	
	[18, 35]	490132	en	Green Book	36.284	2018-11-16	Green Book	8.3	3499	Green Book	
579	[12, 28, 14]	299536	en	Avengers: Infinity War	80.773	2018-04-27	Avengers: Infinity War	8.3	13948	Avengers: Infinity War	
3 [3	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186	Inception	
270	[18, 10402]	244786	en	Whiplash	28.784	2014-10-10	Whiplash	8.4	7908	Whiplash	
131	[18, 80]	311	en	Once Upon a Time in America	17.717	1984-06-01	Once Upon a Time in America	8.4	2243	Once Upon a Time in America	
636 rows		olumns									

In [275]: sort_popularity = df2.sort_values(by=['popularity'], ascending=True) #sorting the data by popularity
sort_popularity

Out[275]:

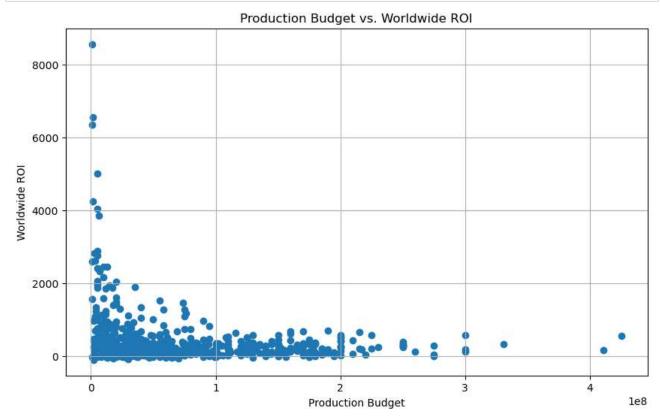
	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count	movie	prod
259	[35]	116741	en	The Internship	0.600	2013-06-07	The Internship	6.2	2631	The Internship	
51	[28, 12, 27, 878]	35791	en	Resident Evil: Afterlife	0.667	2010-09-10	Resident Evil: Afterlife	5.9	2119	Resident Evil: Afterlife	
578	[28, 27, 878]	173897	en	Resident Evil: The Final Chapter	0.844	2017-01-27	Resident Evil: The Final Chapter	5.9	1859	Resident Evil: The Final Chapter	
183	[28, 27, 878]	71679	en	Resident Evil: Retribution	1.325	2012-09-14	Resident Evil: Retribution	5.7	2321	Resident Evil: Retribution	
115	[28, 878, 12]	49538	en	X-Men: First Class	1.447	2011-06-03	X-Men: First Class	7.2	8211	X-Men: First Class	
262	[28, 878, 12]	118340	en	Guardians of the Galaxy	49.606	2014-08-01	Guardians of the Galaxy	7.9	17958	Guardians of the Galaxy	
116	[878, 28, 12]	24428	en	The Avengers	50.289	2012-05-04	The Avengers	7.6	19673	The Avengers	
261	[28, 12, 14]	122917	en	The Hobbit: The Battle of the Five Armies	53.783	2014-12-17	The Hobbit: The Battle of the Five Armies	7.3	8392	The Hobbit: The Battle of the Five Armies	
260	[28, 53]	245891	en	John Wick	78.123	2014-10-24	John Wick	7.2	10081	John Wick	
579	[12, 28, 14]	299536	en	Avengers: Infinity War	80.773	2018-04-27	Avengers: Infinity War	8.3	13948	Avengers: Infinity War	
636 r	ows × 15 c	olumns									>

DATA VISUALIZATION

The graphical representation of the data. Scatter plots were used for this analysis.

SCATTER PLOT

```
In [276]: plt.figure(figsize=(10, 6))
    plt.scatter(production_budget, worldwide_roi, marker='o')
    plt.title('Production Budget vs. Worldwide ROI')
    plt.xlabel('Production Budget')
    plt.ylabel('Worldwide ROI')
    plt.grid(True)
    plt.show()
```

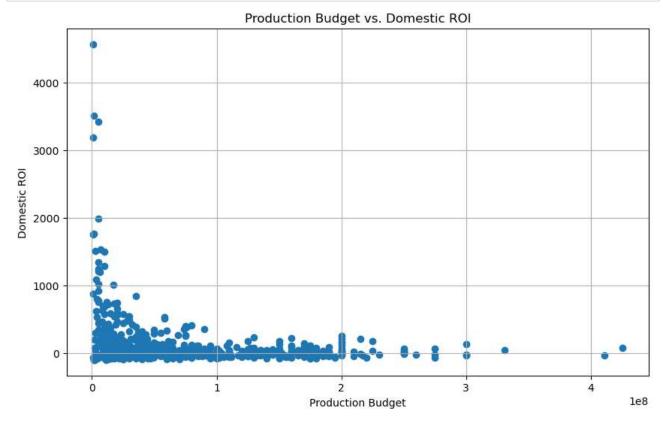


This scatter plot shows a positive correlation between the two variables, suggesting that films with higher production budgets tend to have higher worldwide ROI. However, there is also a lot of variation in the data, suggesting that other factors also influence worldwide ROI

```
In [277]:
# Extract the 'domestic_roi' and 'production_budget' columns
domestic_roi = df2['domestic_roi']
production_budget = df2['production_budget']

# Create a scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(production_budget, domestic_roi, marker='o')
plt.title('Production Budget vs. Domestic ROI')
plt.xlabel('Production Budget')
plt.ylabel('Domestic ROI')
plt.grid(True)

# Show the scatter plot
plt.show()
```

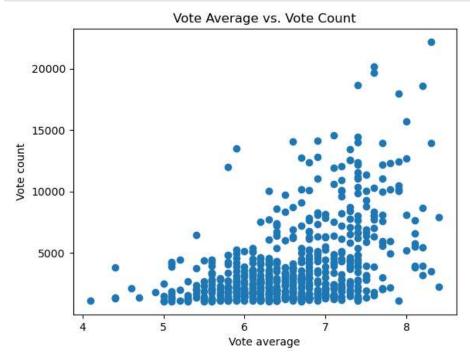


```
In [278]: vote_average = df2['vote_average']
    vote_count = df2['vote_count']

# Create a scatter plot
    plt.scatter(vote_average, vote_count, marker='o')

# Add Labels and a title
    plt.xlabel('Vote average')
    plt.ylabel('Vote count')
    plt.title('Vote Average vs. Vote Count')

# Show the plot
    plt.show()
```



This scatter plot shows a positive correlation between the two variables, suggesting that films with higher vote averages tend to also have higher vote counts. However, there are some outliers, such as films that were less popular with the general public but were popular with a small group of critics.

```
In [279]: domestic_gross = df2['domestic_gross']
           worldwide_gross = df2['worldwide_gross']
           # Create a scatter plot
           plt.scatter(domestic_gross, worldwide_gross, marker='o')
           # Add Labels and a title
           plt.xlabel('Domestic gross')
           plt.ylabel('Worldwide gross')
           plt.title('Domestic Gross vs. Worldwide Gross')
           # Show the plot
           plt.show()
               2.0
            Worldwide gross
               1.5
               1.0
               0.5
               0.0
                                                               5
                                      2
                                              3
                                                       4
                                                                       6
                                              Domestic gross
                                                                                    1e8
```

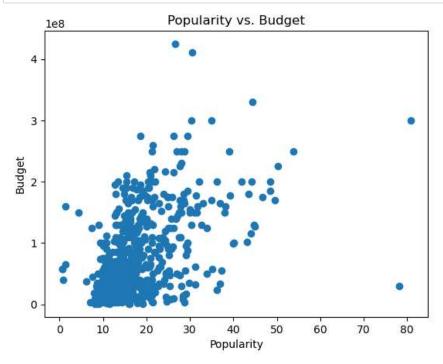
This scatter plot shows a strong correlation between the two variables, suggesting that films with higher domestic gross tend to also have higher worldwide gross. However, there are some outliers, such as films that were more popular in international markets than in the domestic market.

```
In [280]:
# Extract the popularity and budget variables
popularity = df2['popularity']
budget = df2['production_budget']

# Create a scatter plot
plt.scatter(popularity, budget, marker='o')

# Add labels and a title
plt.xlabel('Popularity')
plt.ylabel('Budget')
plt.title('Popularity vs. Budget')

# Show the plot
plt.show()
```



The scatter plot shows that movies with a higher production budget are more popular