Final Project Submission

Please fill out:

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- Student pace: full time
- Scheduled project review date/time: 12/03/2023
- Instructor name: William Okomba
- Blog post URL:

In [1]:

```
# NumPy for numerical analysis
import numpy as np

# Pandas for data analysis
import pandas as pd

# Matplotlib.pyplot, Seaborn, and Plotly.express for data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Sqlite3 for database management
import sqlite3
```

In [2]:

```
#Load the data
# Function is created to load the data
def load_data(path, data_format):

    # if statement used to differentiate data format. Checks if data is in 'csv'
    if data_format.lower() == 'csv':
        data = pd.read_csv(path, compression='gzip') # 'compression' parameter us
    # elif statement used to check if data is in 'db' format
    elif data_format.lower() == 'db':
        conn = sqlite3.connect(path) # returns a Connection object that we will u
        return conn
    # else statement returns an error if the data format is not recognized
    else:
        raise ValueError('Data format not recognized')

    return data # returns the DataFrame under the variable name 'data'
```

Dataset 1: Movie Budgets

In [3]:

```
# Load the movie budgets as a pandas DataFrame and assign it to the variable 'mov
movie_budgets_df = load_data('zippedData/tn.movie_budgets.csv.gz', 'csv')

# Preview the first few rows of the 'movie_budgets_df' DataFrame
movie_budgets_df.head()
```

Out[3]:

	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 [4]:

```
# General description of the 'movie_budgets_df' data
movie_budgets_df.info()
```

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

Dataset2 IMDB

In [5]:

```
# Load the imdb data into a DataFrame which returns a Connection object
conn = load_data('/home/james/.cache/.fr-taQ7Ts/im.db', 'db')

# View the tables within the idmb database as a DataFrame
imdb_tables = pd.read_sql("""SELECT name FROM sqlite_master WHERE type = 'table';
imdb_tables
```

Out[5]:

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

In [6]:

```
# Preview the tables of interest in the IMDB data
movie_basics_df = pd.read_sql("""
                        SELECT *
                          FROM  movie_basics AS mb """, conn)

movie_basics_df.head()
```

Out[6]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

In [7]:

```
movie_basics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [8]:

```
# Preview the tables of interest in the IMDB data
persons_df = pd.read_sql("""
                      SELECT *
                        FROM  persons
                      ;
                      """, conn)

persons_df.head()
```

Out[8]:

	person_id	primary_name	birth_year	death_year	primary_pro
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,production_manager,p
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_department,sound_dep
2	nm0062070	Bruce Baum	NaN	NaN	miscellaneous,act
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematographer,art_dep
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_department,set_d

In [9]:

```
persons_df.info()
```

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

In [10]:

```
# Preview the tables of interest in the IMDB data
movie_ratings_df = pd.read_sql("""
                      SELECT *
                        FROM  movie_ratings
                      ;
                      """, conn)

movie_ratings_df.head()
```

Out[10]:

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

In [11]:

```
movie_ratings_df.info()
```

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

In [12]:

```
movie_akas_df = pd.read_sql("""
                      SELECT *
                        FROM  movie_akas
                      ;
                      """, conn)

movie_akas_df.head()
```

Out[12]:

	movie_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	None	None	0.0
1	tt0369610	11	Jurashikku warudo	JP	None	imdbDisplay	None	0.0
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	None	imdbDisplay	None	0.0
3	tt0369610	13	O Mundo dos Dinossauros	BR	None	None	short title	0.0
4	tt0369610	14	Jurassic World	FR	None	imdbDisplay	None	0.0

In [13]:

```
movie_akas_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 331703 entries, 0 to 331702
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   movie_id           331703 non-null  object 
 1   ordering           331703 non-null  int64  
 2   title              331703 non-null  object 
 3   region             278410 non-null  object 
 4   language           41715 non-null   object 
 5   types              168447 non-null  object 
 6   attributes         14925 non-null   object 
 7   is_original_title  331678 non-null  float64
dtypes: float64(1), int64(1), object(6)
memory usage: 20.2+ MB
```

In [14]:

```
#Read directors table
directors_df = pd.read_sql("""
                      SELECT DISTINCT *
                        FROM  directors
                      ;
                      """, conn)
```

In [15]:

```
#Read writers table
writers_df = pd.read_sql("""
SELECT *
FROM writers
;
""", conn)
```

In [16]:

```
# Close the connection to the IMDB database
conn.close()
```

Data Cleaning

We must first identify and clean the pertinent data that will be utilized to compute the RoI based on the performance criteria we are using to identify the best-performing movies at the box office. Also, the business issue is attempting to identify the categories of movies that are now doing the best business; hence, we will focus our investigation on movies that have been published during the last ten years.

In [17]:

```
# Limit the analysis to films that have been released within the past 10 years
movie_budgets_df = movie_budgets_df[movie_budgets_df['release_date'].apply(lambda

movie_budgets_df # Preview the updated 'movie_budgets_df' DataFrame
```

Out[17]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
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
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	$306,000,000	$936,662,225	$2,053,311,220
6	7	Apr 27, 2018	Avengers: Infinity War	$300,000,000	$678,815,482	$2,048,134,200
...	...	...	...	...	...	...
5761	62	Dec 31, 2014	Stories of Our Lives	$15,000	$0	$0
5771	72	May 19, 2015	Family Motocross	$10,000	$0	$0
5772	73	Jan 13, 2012	Newlyweds	$9,000	$4,584	$4,584
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0

1666 rows × 6 columns

In [18]:

```
# Define a function to convert the production_budget, domestic_gross, and worldwi
def convert_to_numeric(df, column):
    df[column] = pd.to_numeric(df[column].str.replace(",", "").str.replace("$", "

    return df

convert_to_numeric(movie_budgets_df, 'production_budget') # convert the productio
convert_to_numeric(movie_budgets_df, 'domestic_gross') # convert the domestic_gro
convert_to_numeric(movie_budgets_df, 'worldwide_gross') # convert the worldwide_g

movie_budgets_df # Preview the updated 'movie_budgets_df' DataFrame
```

Out[18]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220
6	7	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2048134200
...	...	...	...	...	...	...
5761	62	Dec 31, 2014	Stories of Our Lives	15000	0	0
5771	72	May 19, 2015	Family Motocross	10000	0	0
5772	73	Jan 13, 2012	Newlyweds	9000	4584	4584
5777	78	Dec 31, 2018	Red 11	7000	0	0
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0

1666 rows × 6 columns

In [19]:

```
# Find the Top 200 films with the worldwide gross
movie_budgets_df = movie_budgets_df.sort_values(by='worldwide_gross', ascending=F
movie_budgets_df # Preview the updated 'movie_budgets_df' DataFrame
```

Out[19]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220
6	7	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2048134200
33	34	Jun 12, 2015	Jurassic World	215000000	652270625	1648854864
66	67	Apr 3, 2015	Furious 7	190000000	353007020	1518722794
26	27	May 4, 2012	The Avengers	225000000	623279547	1517935897
...	...	...	...	...	...	...
327	28	Dec 21, 2016	Passengers	110000000	100014699	302239672
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941
698	99	Jun 8, 2018	Oceanâ¯s 8	70000000	140218711	297115976
329	30	Sep 30, 2016	Miss Peregrineâ¯s Home for Peculiar Children	110000000	87242834	295986876
321	22	Mar 20, 2015	The Divergent Series: Insurgent	110000000	130179072	295075882

200 rows × 6 columns

In [20]:

```
#Create a new column called 'RoI' that calculates the return on investment (RoI)
# The formula for calculating RoI is to divide the film’s box office earnings by
movie_budgets_df['RoI'] = movie_budgets_df['worldwide_gross'] / movie_budgets_df[

movie_budgets_df # Preview the updated 'movie_budgets_df' DataFrame
```

Out[20]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
5	6	Dec 18, 2015	Star Wars Ep. VII: The Force Awakens	306000000	936662225	2053311220	67
6	7	Apr 27, 2018	Avengers: Infinity War	300000000	678815482	2048134200	68
33	34	Jun 12, 2015	Jurassic World	215000000	652270625	1648854864	76
66	67	Apr 3, 2015	Furious 7	190000000	353007020	1518722794	79
26	27	May 4, 2012	The Avengers	225000000	623279547	1517935897	67
...	...	...	...	...	...	...	
327	28	Dec 21, 2016	Passengers	110000000	100014699	302239672	27
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941	17
698	99	Jun 8, 2018	Oceanâ¯s 8	70000000	140218711	297115976	42
329	30	Sep 30, 2016	Miss Peregrineâ¯s Home for Peculiar Children	110000000	87242834	295986876	26
321	22	Mar 20, 2015	The Divergent Series: Insurgent	110000000	130179072	295075882	26

200 rows × 7 columns

In [21]:

```
# Sort the DataFrame according to the 'RoI' column
movie_budgets_df = movie_budgets_df.sort_values(by='RoI', ascending=False)

movie_budgets_df # Preview the updated 'movie_budgets_df' DataFrame
```

Out[21]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
3517	18	May 25, 2012	Les Intouchables	10800000	13182281	484873045	44
3342	43	Jun 6, 2014	The Fault in Our Stars	12000000	124872350	307166834	25
2491	92	Dec 9, 2016	La La Land	20000000	151101803	426351163	21
3001	2	Aug 11, 2017	Annabelle: Creation	15000000	102092201	305384865	20
1623	24	Sep 8, 2017	It	35000000	327481748	697457969	19
...	...	...	...	...	...	...	
78	79	Jul 22, 2016	Star Trek Beyond	185000000	158848340	335802233	1
72	73	Nov 25, 2015	The Good Dinosaur	187500000	123087120	333771037	1
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941	1
11	12	May 25, 2018	Solo: A Star Wars Story	275000000	213767512	393151347	1
31	32	May 18, 2012	Battleship	220000000	65233400	313477717	1

200 rows × 7 columns

For this stage of data preparation, we shall be looking to integrate the key features of the top performing films into one dataset if possible. These features include Genre, Runtime (Length), Director(s) & Writer(s), Cast, Gross Revenue, Rating, and Production Budget.

In [22]:

```
# Identify a unique column within the 'movie_budgets_df' DataFrame that can be us
print(f"The release_date column has {len(movie_budgets_df.release_date.unique())}
print(f"The movie column has {len(movie_budgets_df.movie.unique())} unique values
```

```
The release_date column has 178 unique values
The movie column has 200 unique values
```

In [23]:

```
# We shall be using either the original_title/primary_title column to join the tw
 
# Try joining the 'movie_budgets_df' and 'movie_titles_df' DataFrames on the 'ori
option_1 = movie_budgets_df.join(movie_basics_df.set_index('original_title'), on=
print(option_1.info())

# Try joining the 'movie_budgets_df' and 'movie_titles_df' DataFrames on the 'pri
option_2 = movie_budgets_df.join(movie_basics_df.set_index('primary_title'), on='
print(option_2.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 222 entries, 3342 to 31
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 222 non-null    int64  
 1   release_date       222 non-null    object 
 2   movie              222 non-null    object 
 3   production_budget  222 non-null    int64  
 4   domestic_gross     222 non-null    int64  
 5   worldwide_gross    222 non-null    int64  
 6   RoI                222 non-null    float64
 7   movie_id           222 non-null    object 
 8   primary_title      222 non-null    object 
 9   start_year         222 non-null    int64  
 10  runtime_minutes    211 non-null    float64
 11  genres             219 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 22.5+ KB
None
<class 'pandas.core.frame.DataFrame'>
Int64Index: 235 entries, 3342 to 31
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 235 non-null    int64  
 1   release_date       235 non-null    object 
 2   movie              235 non-null    object 
 3   production_budget  235 non-null    int64  
 4   domestic_gross     235 non-null    int64  
 5   worldwide_gross    235 non-null    int64  
 6   RoI                235 non-null    float64
 7   movie_id           235 non-null    object 
 8   original_title     235 non-null    object 
 9   start_year         235 non-null    int64  
 10  runtime_minutes    224 non-null    float64
 11  genres             232 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 23.9+ KB
None
```

As there appears to be a one-to-many link between both selections, more than 200 films have been returned in the combined DataFrame. This makes sense because movies have been known to share names. The first step in resolving this issue is to remove all movies from the'movie basics df' DataFrame that are older than ten years. As a result, there will be fewer instances of a movie with the same name as another movie.

In [24]:

```
# Drop the films in the 'movie_basics_df' that are older than 10 years
movie_basics_df = movie_basics_df[movie_basics_df['start_year'] >= 2012]

movie_basics_df # Preview the updated 'movie_basics_df' DataFrame
```

Out[24]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	gen
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Dra
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Dra
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Dra
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Dra
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fant
...	...	...	...	...	...	
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Dra
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Document
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Come
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	No
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Document

121395 rows × 6 columns

We now assess if our one-to-many relationships have decreased as a result.

In [25]:

```
option_1 = movie_budgets_df.join(movie_basics_df.set_index('original_title'), on=
print(option_1.info())

option_2 = movie_budgets_df.join(movie_basics_df.set_index('primary_title'), on='
print(option_2.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 213 entries, 3342 to 31
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 213 non-null    int64
 1   release_date       213 non-null    object
 2   movie              213 non-null    object
 3   production_budget  213 non-null    int64
 4   domestic_gross     213 non-null    int64
 5   worldwide_gross    213 non-null    int64
 6   RoI                213 non-null    float64
 7   movie_id           213 non-null    object
 8   primary_title      213 non-null    object
 9   start_year         213 non-null    int64
 10  runtime_minutes    204 non-null    float64
 11  genres             211 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 21.6+ KB
None
<class 'pandas.core.frame.DataFrame'>
Int64Index: 221 entries, 3342 to 31
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 221 non-null    int64
 1   release_date       221 non-null    object
 2   movie              221 non-null    object
 3   production_budget  221 non-null    int64
 4   domestic_gross     221 non-null    int64
 5   worldwide_gross    221 non-null    int64
 6   RoI                221 non-null    float64
 7   movie_id           221 non-null    object
 8   original_title     221 non-null    object
 9   start_year         221 non-null    int64
 10  runtime_minutes    212 non-null    float64
 11  genres             219 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 22.4+ KB
None
```

We can observe that the one-to-many linkages have somewhat decreased as a result. There is still some cleaning to be done, though. We'll try to connect using the "original title" column based on the two join choices. The work of reducing the data to the Top 200 movies will be made easier by the missing values in the 'runtime minutes' column and the reduced number of duplicate records.

In [26]:

```
# Join the 'movie_budgets_df' and 'movie_titles_df' DataFrames on the 'original_t
top_movies_df = movie_budgets_df.join(movie_basics_df.set_index('original_title')

top_movies_df # Preview the updated 'top_movies_df' DataFrame
```

Out[26]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
3342	43	Jun 6, 2014	The Fault in Our Stars	12000000	124872350	307166834	255
2491	92	Dec 9, 2016	La La Land	20000000	151101803	426351163	213
3001	2	Aug 11, 2017	Annabelle: Creation	15000000	102092201	305384865	203
1623	24	Sep 8, 2017	It	35000000	327481748	697457969	199
2865	66	Apr 6, 2018	A Quiet Place	17000000	188024361	334522294	196
...	...	...	...	...	...	...	
78	79	Jul 22, 2016	Star Trek Beyond	185000000	158848340	335802233	18
72	73	Nov 25, 2015	The Good Dinosaur	187500000	123087120	333771037	17
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941	17
11	12	May 25, 2018	Solo: A Star Wars Story	275000000	213767512	393151347	14
31	32	May 18, 2012	Battleship	220000000	65233400	313477717	14

213 rows × 12 columns

In [27]:

```
# Drop records that are missing 'runtime_minutes' values
top_movies_df = top_movies_df.dropna(subset=['runtime_minutes'])

top_movies_df # Preview the updated 'top_movies_df' DataFrame
```

Out[27]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
3342	43	Jun 6, 2014	The Fault in Our Stars	12000000	124872350	307166834	255
2491	92	Dec 9, 2016	La La Land	20000000	151101803	426351163	213
3001	2	Aug 11, 2017	Annabelle: Creation	15000000	102092201	305384865	203
1623	24	Sep 8, 2017	It	35000000	327481748	697457969	199
2865	66	Apr 6, 2018	A Quiet Place	17000000	188024361	334522294	196
...	...	...	...	...	...	...	
78	79	Jul 22, 2016	Star Trek Beyond	185000000	158848340	335802233	18
72	73	Nov 25, 2015	The Good Dinosaur	187500000	123087120	333771037	17
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941	17
11	12	May 25, 2018	Solo: A Star Wars Story	275000000	213767512	393151347	14
31	32	May 18, 2012	Battleship	220000000	65233400	313477717	14

204 rows × 12 columns

The DataFrame has been reduced to 204 entries at this point. We will contrast the year value in the "release date" column with the "start year" field in order to eliminate the erroneous duplicate records. Records that return contradictory values will be discarded.

In [28]:

```
# Create a new column called 'release_year' that extracts the year from the 'rele
top_movies_df['release_year'] = top_movies_df['release_date'].apply(lambda x: int


#Compare the 'release_year' column to the 'start_year' column. Drop the conflicti
top_movies_df = top_movies_df.loc[top_movies_df['release_year'] == top_movies_df[

top_movies_df # Preview the updated 'top_movies_df' DataFrame
```

```
<ipython-input-28-21391e8ecdab>: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/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  top_movies_df['release_year'] = top_movies_df['release_date'].appl
y(lambda x: int(x.split(" ")[-1]))
```

Out[28]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
3342	43	Jun 6, 2014	The Fault in Our Stars	12000000	124872350	307166834	255
2491	92	Dec 9, 2016	La La Land	20000000	151101803	426351163	213
3001	2	Aug 11, 2017	Annabelle: Creation	15000000	102092201	305384865	203
1623	24	Sep 8, 2017	It	35000000	327481748	697457969	199
2865	66	Apr 6, 2018	A Quiet Place	17000000	188024361	334522294	196
...	...	...	...	...	...	...	
78	79	Jul 22, 2016	Star Trek Beyond	185000000	158848340	335802233	18
72	73	Nov 25, 2015	The Good Dinosaur	187500000	123087120	333771037	17
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941	17
11	12	May 25, 2018	Solo: A Star Wars Story	275000000	213767512	393151347	14
31	32	May 18, 2012	Battleship	220000000	65233400	313477717	14

174 rows × 13 columns

In [29]:

```
len(top_movies_df['movie'].unique()) # Identify the number of movie titles in the
```

Out[29]:

```
170
```

The DataFrame's size has been drastically decreased. This suggests that we may have deleted any outdated entries. There may be up to 4 duplicate entries that need to be examined now that the DataFrame is reduced to 174 records and there are 170 unique movie titles.

In [30]:

```
# Identify the titles of the duplicate movie titles
duplicate_movie_titles = top_movies_df[top_movies_df.duplicated(subset='movie')].
print(f"{len(duplicate_movie_titles)} duplicate title(s)") # identify number of d

# Identify the movie ids of the unique movie titles
duplicate_movie_ids = top_movies_df[top_movies_df.duplicated(subset='movie_id')].
print(f"{len(duplicate_movie_ids)} duplicate id(s)") # identify number of duplica
```

```
3 duplicate title(s)
0 duplicate id(s)
```

In [31]:

```
# Examine the records that belong to the specified set of movies
top_movies_df[top_movies_df.movie.isin(duplicate_movie_titles)]
```

Out[31]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
412	13	Mar 13, 2015	Cinderella	95000000	201151353	534551353	562.6
412	13	Mar 13, 2015	Cinderella	95000000	201151353	534551353	562.6
101	2	Nov 22, 2017	Coco	175000000	209726015	798008101	456.0
101	2	Nov 22, 2017	Coco	175000000	209726015	798008101	456.0
243	44	Mar 27, 2015	Home	130000000	177397510	385997896	296.9
243	44	Mar 27, 2015	Home	130000000	177397510	385997896	296.9
243	44	Mar 27, 2015	Home	130000000	177397510	385997896	296.9

We have identified the records that are duplicated. Before we can decide which records to drop, we will need to integrate more features into our top_movies_df DataFrame.

In [32]:

```
# Join the 'movie_ratings_df' to the 'top_movies_df' DataFrame on the 'movie_id'
top_movies_df = top_movies_df.join(movie_ratings_df.set_index('movie_id'), on='mo

top_movies_df # Preview the updated 'top_movies_df' DataFrame
```

Out[32]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
3342	43	Jun 6, 2014	The Fault in Our Stars	12000000	124872350	307166834	255
2491	92	Dec 9, 2016	La La Land	20000000	151101803	426351163	213
3001	2	Aug 11, 2017	Annabelle: Creation	15000000	102092201	305384865	203
1623	24	Sep 8, 2017	It	35000000	327481748	697457969	199
2865	66	Apr 6, 2018	A Quiet Place	17000000	188024361	334522294	196
...	...	...	...	...	...	...	
78	79	Jul 22, 2016	Star Trek Beyond	185000000	158848340	335802233	18
72	73	Nov 25, 2015	The Good Dinosaur	187500000	123087120	333771037	17
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941	17
11	12	May 25, 2018	Solo: A Star Wars Story	275000000	213767512	393151347	14
31	32	May 18, 2012	Battleship	220000000	65233400	313477717	14

171 rows × 15 columns

In [33]:

```
# Identify the titles of the duplicate movie titles
duplicate_movie_titles = set(top_movies_df[top_movies_df.duplicated(subset='movie
print(f"{len(duplicate_movie_titles)} duplicate movie title(s)") # identify numbe
```

```
1 duplicate movie title(s)
```

In [34]:

```
# Examine the records that belong to the specified set of movies
top_movies_df[top_movies_df.movie.isin(duplicate_movie_titles)]
```

Out[34]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	R
101	2	Nov 22, 2017	Coco	175000000	209726015	798008101	456.0046
101	2	Nov 22, 2017	Coco	175000000	209726015	798008101	456.0046

As there is no certain method to determine which of the two records' data is accurate, it is preferable to drop them both rather than run the chance of having inaccurate data.

In [35]:

```
# Drop records that have 'Coco' as the movie title
top_movies_df.drop(top_movies_df[top_movies_df['movie'] == 'Coco'].index, inplace

top_movies_df # Preview the updated 'top_movies_df' DataFrame
```

Out[35]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	
3342	43	Jun 6, 2014	The Fault in Our Stars	12000000	124872350	307166834	255
2491	92	Dec 9, 2016	La La Land	20000000	151101803	426351163	213
3001	2	Aug 11, 2017	Annabelle: Creation	15000000	102092201	305384865	203
1623	24	Sep 8, 2017	It	35000000	327481748	697457969	199
2865	66	Apr 6, 2018	A Quiet Place	17000000	188024361	334522294	196
...	...	...	...	...	...	...	
78	79	Jul 22, 2016	Star Trek Beyond	185000000	158848340	335802233	18
72	73	Nov 25, 2015	The Good Dinosaur	187500000	123087120	333771037	17
124	25	May 31, 2019	Godzilla: King of the Monsters	170000000	85576941	299276941	17
11	12	May 25, 2018	Solo: A Star Wars Story	275000000	213767512	393151347	14
31	32	May 18, 2012	Battleship	220000000	65233400	313477717	14

169 rows × 15 columns

Now that we don't have any duplicate data, we can begin structuring the DataFrame and cleaning it up by removing the unnecessary columns. The following columns will be removed: 'id', 'domestic_gross', 'primary_title', 'start_year', 'release_year', and 'numvotes'

In [36]:

```
# Drop the 'id', 'domestic_gross', 'primary_title', 'start_year', 'release_year',
top_movies_df.drop(columns=['id', 'domestic_gross', 'primary_title', 'start_year'

top_movies_df # Preview the updated 'top_movies_df' DataFrame
```

Out[36]:

	release_date	movie	production_budget	worldwide_gross	RoI	movie_id	r
3342	Jun 6, 2014	The Fault in Our Stars	12000000	307166834	2559.723617	tt2582846	
2491	Dec 9, 2016	La La Land	20000000	426351163	2131.755815	tt3783958	
3001	Aug 11, 2017	Annabelle: Creation	15000000	305384865	2035.899100	tt5140878	
1623	Sep 8, 2017	It	35000000	697457969	1992.737054	tt1396484	
2865	Apr 6, 2018	A Quiet Place	17000000	334522294	1967.778200	tt6644200	
...	...	...	...	...	...	...	
78	Jul 22, 2016	Star Trek Beyond	185000000	335802233	181.514721	tt2660888	
72	Nov 25, 2015	The Good Dinosaur	187500000	333771037	178.011220	tt1979388	
124	May 31, 2019	Godzilla: King of the Monsters	170000000	299276941	176.045259	tt3741700	
11	May 25, 2018	Solo: A Star Wars Story	275000000	393151347	142.964126	tt3778644	
31	May 18, 2012	Battleship	220000000	313477717	142.489871	tt1440129	

169 rows × 9 columns

In [37]:

```
# Reset the index of the 'top_movies_df' DataFrame
top_movies_df.set_index('movie_id', inplace=True)
top_movies_df.reset_index(inplace=True)
top_movies_df
```

Out[37]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	ru
0	tt2582846	Jun 6, 2014	The Fault in Our Stars	12000000	307166834	2559.723617	
1	tt3783958	Dec 9, 2016	La La Land	20000000	426351163	2131.755815	
2	tt5140878	Aug 11, 2017	Annabelle: Creation	15000000	305384865	2035.899100	
3	tt1396484	Sep 8, 2017	It	35000000	697457969	1992.737054	
4	tt6644200	Apr 6, 2018	A Quiet Place	17000000	334522294	1967.778200	
...	...	...	...	...	...	...	
164	tt2660888	Jul 22, 2016	Star Trek Beyond	185000000	335802233	181.514721	
165	tt1979388	Nov 25, 2015	The Good Dinosaur	187500000	333771037	178.011220	
166	tt3741700	May 31, 2019	Godzilla: King of the Monsters	170000000	299276941	176.045259	
167	tt3778644	May 25, 2018	Solo: A Star Wars Story	275000000	393151347	142.964126	
168	tt1440129	May 18, 2012	Battleship	220000000	313477717	142.489871	

169 rows × 9 columns

In [38]:

```
# Convert the 'release_date' column to a datetime object
top_movies_df['release_date'] = pd.to_datetime(top_movies_df['release_date'], for
```

In [39]:

```
top_movies_df
```

Out[39]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	ru
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	
2	tt5140878	2017-08-11	Annabelle: Creation	15000000	305384865	2035.899100	
3	tt1396484	2017-09-08	It	35000000	697457969	1992.737054	
4	tt6644200	2018-04-06	A Quiet Place	17000000	334522294	1967.778200	
...	...	...	...	...	...	...	
164	tt2660888	2016-07-22	Star Trek Beyond	185000000	335802233	181.514721	
165	tt1979388	2015-11-25	The Good Dinosaur	187500000	333771037	178.011220	
166	tt3741700	2019-05-31	Godzilla: King of the Monsters	170000000	299276941	176.045259	
167	tt3778644	2018-05-25	Solo: A Star Wars Story	275000000	393151347	142.964126	
168	tt1440129	2012-05-18	Battleship	220000000	313477717	142.489871	

169 rows × 9 columns

In [40]:

```
# General overview of the numeric data in the 'top_movies_df' DataFrame
top_movies_df.describe()
```

Out[40]:

	production_budget	worldwide_gross	RoI	runtime_minutes	averagerating
count	1.690000e+02	1.690000e+02	169.000000	169.000000	169.000000
mean	1.402728e+08	6.186634e+08	555.407647	119.224852	6.966864
std	6.460577e+07	3.102610e+08	415.318136	20.310309	0.825323
min	1.200000e+07	2.992769e+08	142.489871	72.000000	4.100000
25%	9.200000e+07	3.713506e+08	304.796374	102.000000	6.500000
50%	1.450000e+08	5.295307e+08	414.780490	118.000000	7.000000
75%	1.800000e+08	7.665751e+08	641.749457	133.000000	7.600000
max	3.306000e+08	2.048134e+09	2559.723617	180.000000	8.600000

Data Analysis and Visualization

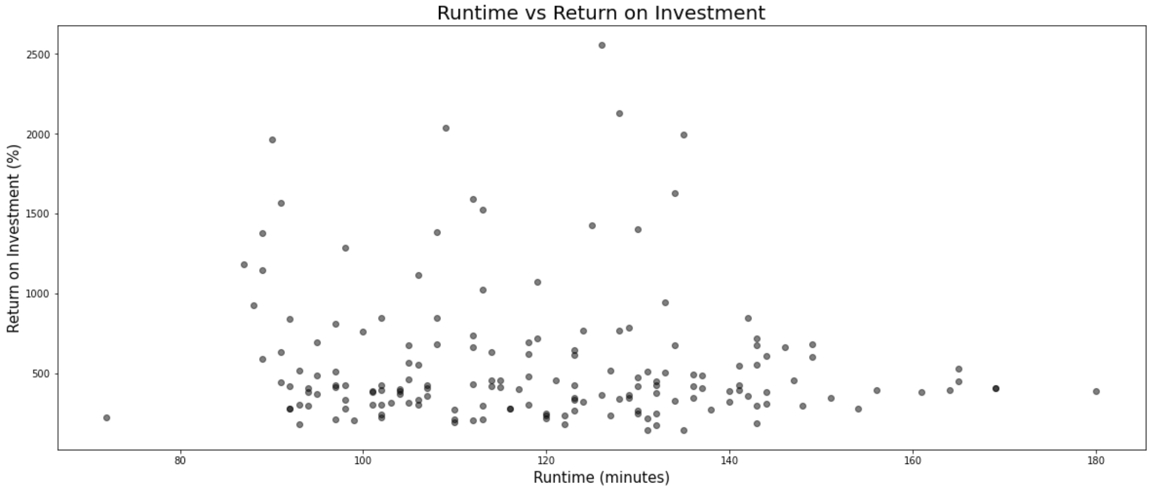
Exploring relationships in the previously provided data is the main goal of the analysis phase. We'll examine the connections between the many elements of a film and its return on investment.

1. Runtime

To illustrate the link between "runtime_minutes" and "RoI," we will create a scatter plot.

In [41]:

```
fig, ax = plt.subplots(figsize=(20,8))

ax.scatter(top_movies_df['runtime_minutes'], top_movies_df['RoI'], c='black', alp
ax.set_xlabel('Runtime (minutes)', fontsize=15)
ax.set_ylabel('Return on Investment (%)', fontsize=15)
ax.set_title('Runtime vs Return on Investment', fontsize=20);
```



In [42]:

```
# Evalulate the Pearson correlation coefficient between the 'runtime_minutes' and
np.corrcoef(top_movies_df['runtime_minutes'], top_movies_df['RoI'])[0,1]
```

Out[42]:

```
-0.09673399075691598
```

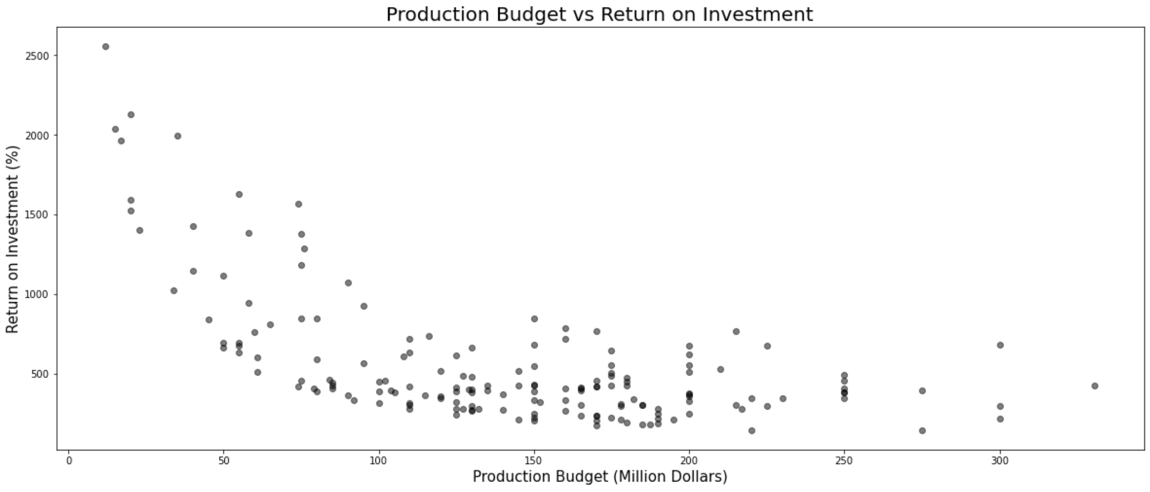
We can observe from the scatter figure above that there is no clear correlation between runtime and ROI. In addition, the correlation coefficient is closer to zero when we examine the Pearson correlation coefficient. This implies that a movie's length has no bearing on its return on investment.

2.Production Budget

We are going to plot a scatter plot to visualize the relationship between the 'production_budget' and 'RoI'.

In [43]:

```
fig, ax = plt.subplots(figsize=(20,8))

ax.scatter(top_movies_df['production_budget']*(10**(-6)), top_movies_df['RoI'], c
ax.set_xlabel('Production Budget (Million Dollars)', fontsize=15)
ax.set_ylabel('Return on Investment (%)', fontsize=15)
ax.set_title('Production Budget vs Return on Investment', fontsize=20);
```



In [44]:

```
# Evaluate the Pearson correlation coefficient between the 'production_budget' an
np.corrcoef(top_movies_df['production_budget'], top_movies_df['RoI'])[0,1]
```

Out[44]:

```
-0.6014369562247762
```

We can observe from the scatter plot above that there is a bad association between the RoI and the production budget. This connection is not linear, though. The correlation is highly negative between 0 and 100 million dollars. The return on investment and the budget have no discernible relationship between 100 and 300 million dollars, though. According to the Pearson correlation coefficient, there is a substantially negative link between the production budget and the return on investment (-0.6).

3. Release Date

We shall be looking to see if there is a relationship between the release date and the RoI.

Month

In order to see the link between the month of release and the average RoI, we will first concentrate on the month in which the movies were released.

In [45]:

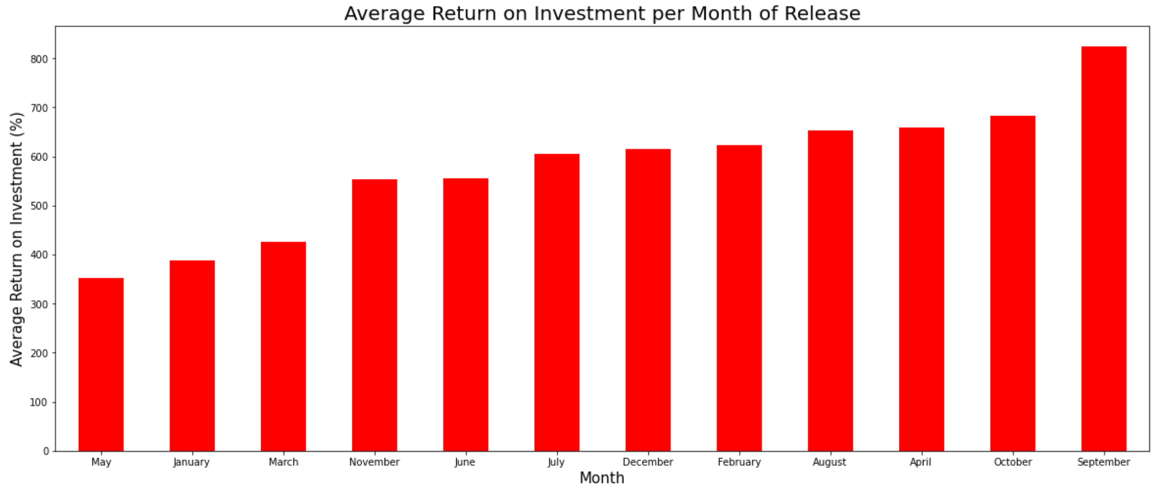
```
# Create a new column that contains the month that the movies were released
release_time_df = top_movies_df.copy()
release_time_df['release_month'] = release_time_df["release_date"].dt.strftime('%

release_time_df.head() # Preview the updated 'release_time_df' DataFrame
```

Out[45]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	runt
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	
2	tt5140878	2017-08-11	Annabelle: Creation	15000000	305384865	2035.899100	
3	tt1396484	2017-09-08	It	35000000	697457969	1992.737054	
4	tt6644200	2018-04-06	A Quiet Place	17000000	334522294	1967.778200	

In [46]:

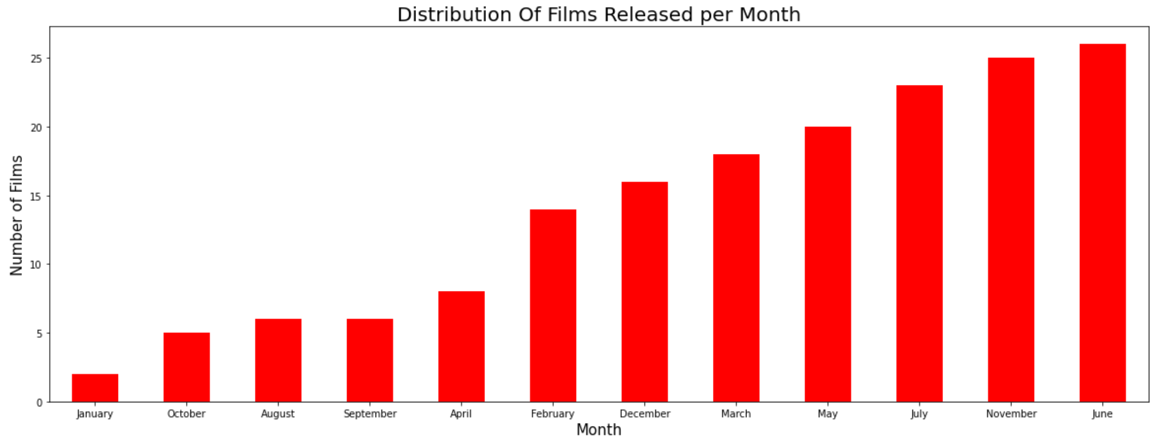
```
# Create a plot that shows average return on investment (RoI) by month
fig, ax = plt.subplots(figsize=(20,8))
release_time_df.groupby('release_month')['RoI'].mean().sort_values().plot(kind='b
ax.set_xlabel('Month', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Average Return on Investment (%)', fontsize=15)
ax.set_title('Average Return on Investment per Month of Release', fontsize=20);
```



Compared to movies made in other months, those that are released in September and October (the fall season) appear to have a better average return on investment. Nevertheless, we also need to consider how many movies are released each month.

In [47]:

```
# Create a plot that shows the number of films released each month
fig, ax = plt.subplots(figsize=(20,7))
release_time_df.groupby('release_month')['movie'].count().sort_values().plot(kind
ax.set_xlabel('Month', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Number of Films', fontsize=15)
ax.set_title('Distribution Of Films Released per Month', fontsize=20);
```



From the 'Number of Films Released per Month' plot above, We can observe that there are not always an equal amount of movies released each month. This may explain why months with fewer films categorized under them, like September and October, have better average returns on investment than the other months.

Season

We are now going to look at the seasons that the films were released and plot a bar plot to visualize the average RoI per season.

In [48]:

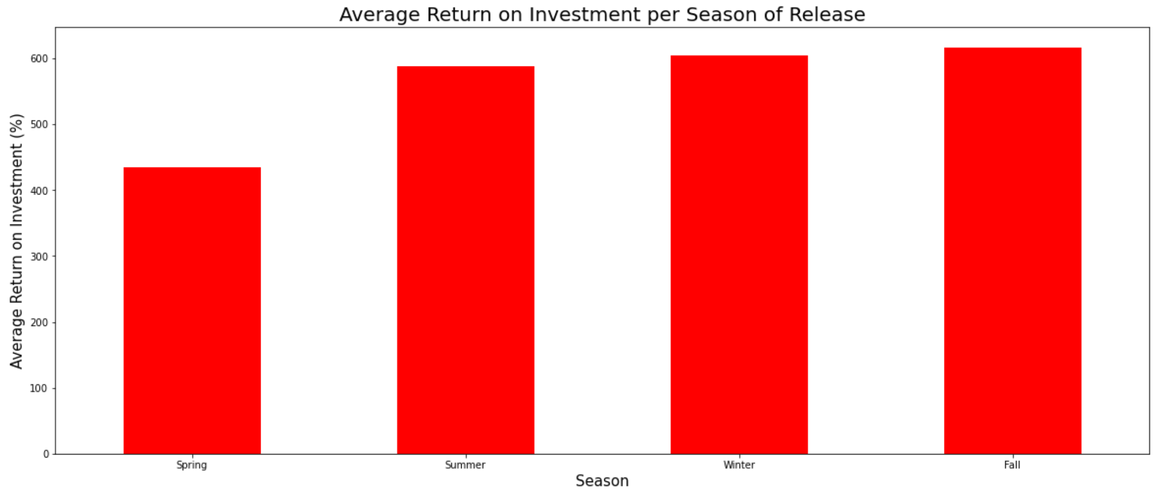
```
# Create a dictionary that maps months to their season
seasons = {'January':'Winter',
           'February':'Winter',
           'March':'Spring',
           'April':'Spring',
           'May':'Spring',
           'June':'Summer',
           'July':'Summer',
           'August':'Summer',
           'September':'Fall',
           'October':'Fall',
           'November':'Fall',
           'December':'Winter'}

# Create a new column that contains the season that the movie was released in
release_time_df['release_season'] = release_time_df['release_month'].map(seasons)

release_time_df.head() # Preview the updated 'release_time_df' DataFrame
```

Out[48]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	runt
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	
2	tt5140878	2017-08-11	Annabelle: Creation	15000000	305384865	2035.899100	
3	tt1396484	2017-09-08	It	35000000	697457969	1992.737054	
4	tt6644200	2018-04-06	A Quiet Place	17000000	334522294	1967.778200	

In [49]:

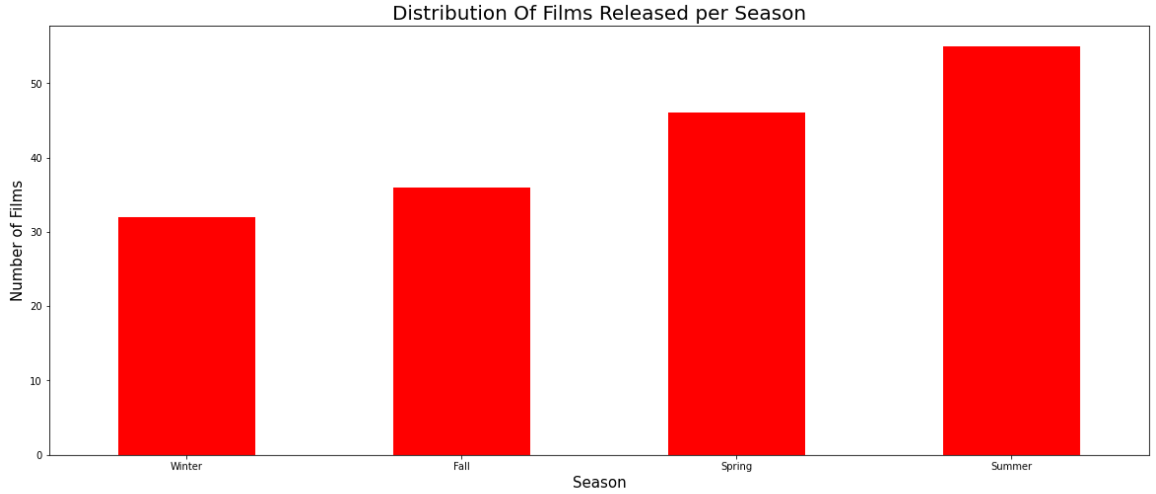
```
# Create a plot that shows average return on investment (RoI) by season
fig, ax = plt.subplots(figsize=(20,8))

release_time_df.groupby('release_season')['RoI'].mean().sort_values().plot(kind='
ax.set_xlabel('Season', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Average Return on Investment (%)', fontsize=15)
ax.set_title('Average Return on Investment per Season of Release', fontsize=20);
```



The bar graph above demonstrates that fall movie releases have the highest average return on investment. Winter, Summer, and Spring all follow it closely. Before drawing any conclusions, though, it is important to consider how many movies are released each season.

In [50]:

```
# Create a plot that shows the number of films released each season
fig, ax = plt.subplots(figsize=(20,8))

release_time_df.groupby('release_season')['movie'].count().sort_values().plot(kin
ax.set_xlabel('Season', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Number of Films', fontsize=15)
ax.set_title('Distribution Of Films Released per Season', fontsize=20);
```



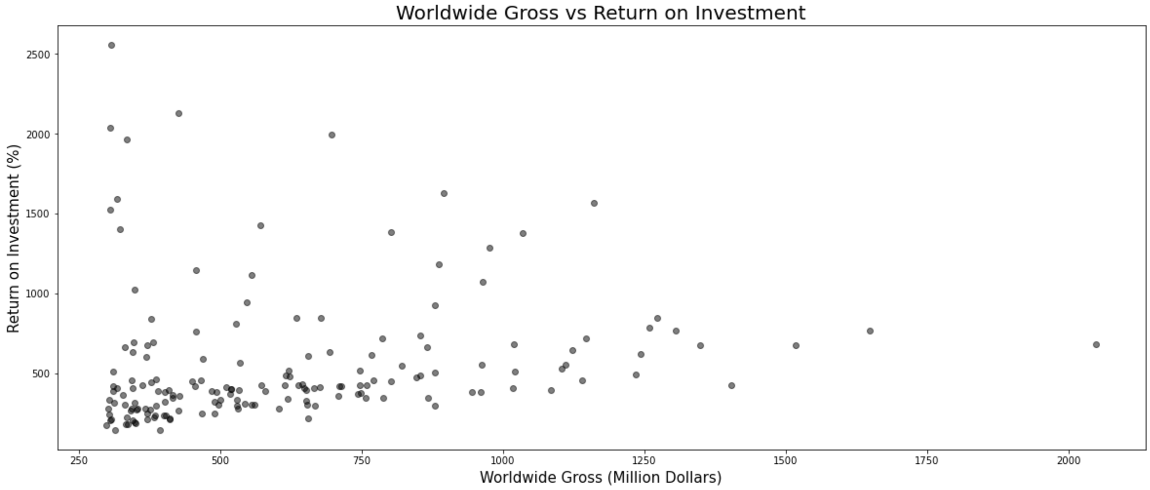
We can see from the "Number of Films Released Per Season" figure above that the number of films released each season is distributed quite evenly. Even though there are more movies made in the summer, the average return on investment is not the lowest; rather, it is equivalent to the average return on investment for the best season (fall). This shows that the summer may be the ideal time to release a movie.

4. Worlwide Gross

We are going to plot a scatter plot to visualize the relationship between the 'worldwide_gross' and 'RoI'.

In [51]:

```
# Create a scatter plot to visualize worldwide gross vs RoI
fig, ax = plt.subplots(figsize=(20,8))

ax.scatter(top_movies_df['worldwide_gross']*(10**(-6)), top_movies_df['RoI'], c='
ax.set_xlabel('Worldwide Gross (Million Dollars)', fontsize=15)
ax.set_ylabel('Return on Investment (%)', fontsize=15)
ax.set_title('Worldwide Gross vs Return on Investment', fontsize=20);
```



In [52]:

```
# We can also look at the Pearson correlation coefficient between the 'worldwide_
np.corrcoef(top_movies_df['worldwide_gross'], top_movies_df['RoI'])[0,1]
```

Out[52]:

```
0.1511294766315755
```

From the scatter plot above, there is no distinct relationship between the worldwide gross and the RoI. Looking at the Pearson correlation coefficient, we see that the correlation coefficient (0.15) is closer to 0 therefore suggesting that the worldwide gross of a film has no impact on its RoI.

5. Genre

We are going to plot a barchart to visualize the relationship between the 'genre' and average 'RoI' for that genre. However, before we can plot, the genre column needs to normalized.

In [53]:

```
# Assign the top_movies_df DataFrame to a new variable called 'genre_analysis_df'
genre_analysis_df = top_movies_df.copy()
genre_analysis_df['genres'] = genre_analysis_df.genres.apply(lambda x: x.split(',

genre_analysis_df = genre_analysis_df.explode('genres') # Normalize the 'genres'

genre_analysis_df.head() # Preview the first few records of the 'genre_analysis_d
```

Out[53]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	runtime_
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	

In [54]:

```
genre_analysis_df.genres.unique() # Identify the unique genres in the 'genre_anal
```

Out[54]:

```
array(['Drama', 'Romance', 'Comedy', 'Music', 'Horror', 'Mystery',
       'Thriller', 'Sci-Fi', 'Biography', 'Adventure', 'Animation',
       'Family', 'Action', 'Fantasy', 'Musical', 'Crime', 'Western',
       'History', 'War', 'Documentary'], dtype=object)
```

In [55]:

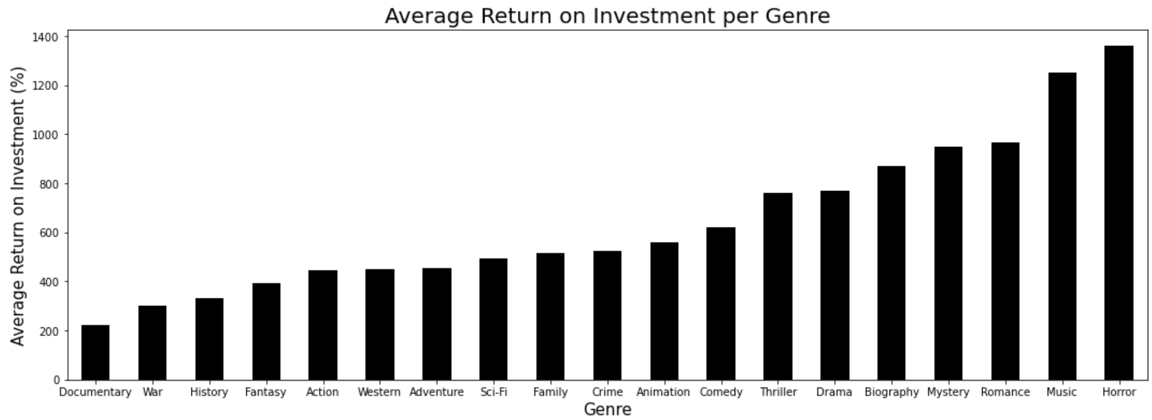
```
# Identify the records that belong to the 'Musical' genre an convert them to 'Mus
genre_analysis_df.loc[genre_analysis_df['genres'] == 'Musical', 'genres'] = 'Musi

genre_analysis_df.genres.unique() # Check if the unique genres have been updated
```

Out[55]:

```
array(['Drama', 'Romance', 'Comedy', 'Music', 'Horror', 'Mystery',
       'Thriller', 'Sci-Fi', 'Biography', 'Adventure', 'Animation',
       'Family', 'Action', 'Fantasy', 'Crime', 'Western', 'History',
       'War', 'Documentary'], dtype=object)
```

In [56]:

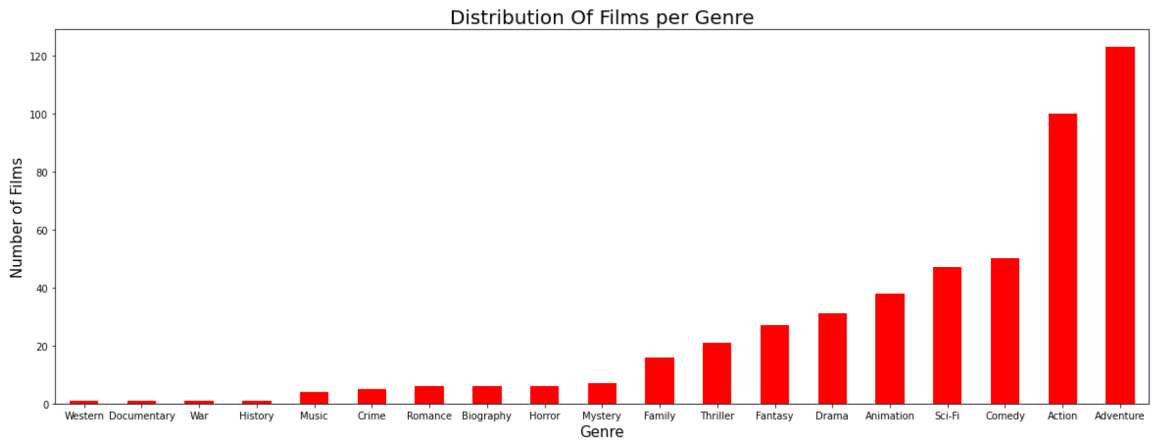
```
# Create a plot that shows average return on investment (RoI) by genre
fig, ax = plt.subplots(figsize=(18,6))

genre_analysis_df.groupby('genres')['RoI'].mean().sort_values().plot(kind='bar',c
ax.set_xlabel('Genre', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Average Return on Investment (%)', fontsize=15)
ax.set_title('Average Return on Investment per Genre', fontsize=20);
```



The "Horror" and "Music" genres have better average returns on investment than other genres, as can be shown. However, before drawing any conclusions, it is important to comprehend the quantity of films released in each genre and evaluate the distribution of films by genre.

In [57]:

```
# Create a plot that counts the number of movies by genre
fig, ax = plt.subplots(figsize=(13,7))

genre_analysis_df.groupby('genres')['movie'].count().sort_values().plot(kind='bar
ax.set_xlabel('Genre', fontsize=15)
plt.xticks(rotation=0)
ax.set_ylabel('Number of Films', fontsize=15)
ax.set_title('Distribution Of Films per Genre', fontsize=20);
```



We can observe from the plot above that the dataset's distribution of films by genre is not uniform. We must thus consider the fact that the 'Horror' and 'Music' genres have a greater average return on investment since there are fewer movies that fall into those categories. But, it's crucial to remember that the majority of the Top 200 Highest Grossing Films—originally chosen—were Adventure and Action movies. This shows that the most profitable genres for movies on average are adventure and action.

6. Directors

We are going to plot a barchart to visualize the relationship between directors and average RoI for the films. We first need to create a new DataFrame that contains the movies and their director information.

In [58]:

```
# Create a copy of the 'top_movies_df' DataFrame to a new variable called 'direct
director_analysis_df = top_movies_df.copy()

# Join the directors_df DataFrame to the top_movies_df DataFrame and assign it to
director_analysis_df = director_analysis_df.join(directors_df.set_index('movie_id

# Join the persons_df DataFrame to the director_analysis_df DataFrame so that we
director_analysis_df = director_analysis_df.join(persons_df.set_index('person_id'
director_analysis_df # Preview the updated 'director_analysis_df' DataFrame
```

Out[58]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	ru
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	
2	tt5140878	2017-08-11	Annabelle: Creation	15000000	305384865	2035.899100	
74	tt0448115	2019-04-05	Shazam!	85000000	362899733	426.940862	
3	tt1396484	2017-09-08	It	35000000	697457969	1992.737054	
...	...	...	...	...	...	...	
164	tt2660888	2016-07-22	Star Trek Beyond	185000000	335802233	181.514721	
165	tt1979388	2015-11-25	The Good Dinosaur	187500000	333771037	178.011220	
166	tt3741700	2019-05-31	Godzilla: King of the Monsters	170000000	299276941	176.045259	
167	tt3778644	2018-05-25	Solo: A Star Wars Story	275000000	393151347	142.964126	
168	tt1440129	2012-05-18	Battleship	220000000	313477717	142.489871	

202 rows × 14 columns

In [59]:

```
# Check if any records have directors that have passed on. If so, drop the record
director_analysis_df[director_analysis_df['death_year'].notna()]
```

Out[59]:

movie_id	release_date	movie	production_budget	worldwide_gross	RoI	runtime_minutes

In [60]:

```
# Directors with more than one film will give the 'person_id' column duplicates.
director_ids = director_analysis_df[director_analysis_df.duplicated(subset='perso

# Update the 'director_analysis_df' DataFrame to only include directors with mult
director_analysis_df = director_analysis_df[director_analysis_df['person_id'].isi
director_analysis_df # Preview the updated 'director_analysis_df' DataFrame
```

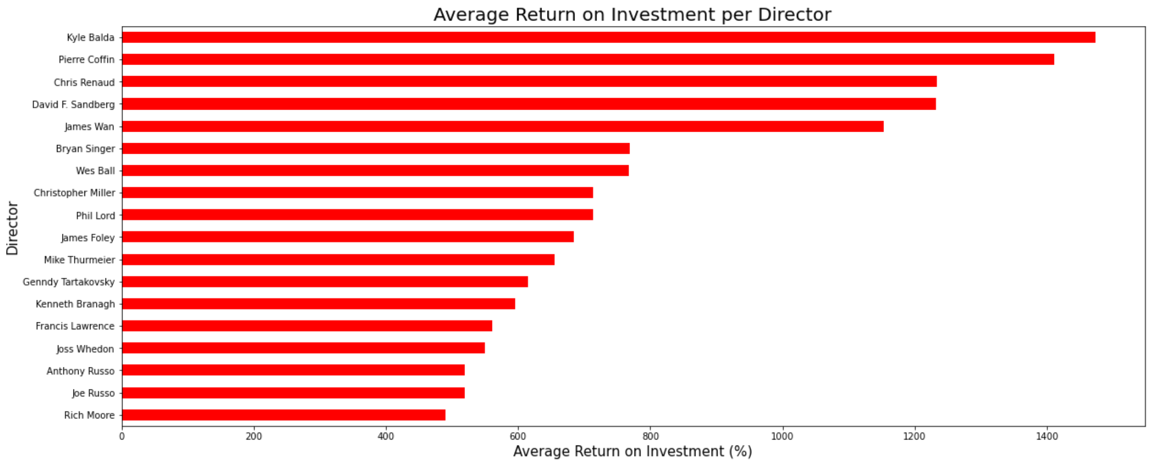
Out[60]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	r
2	tt5140878	2017-08-11	Annabelle: Creation	15000000	305384865	2035.899100	
74	tt0448115	2019-04-05	Shazam!	85000000	362899733	426.940862	
5	tt1727824	2018-11-02	Bohemian Rhapsody	55000000	894985342	1627.246076	
106	tt1877832	2014-05-23	X-Men: Days of Future Past	200000000	747862775	373.931388	
126	tt3385516	2016-05-27	X-Men: Apocalypse	178000000	542537546	304.796374	
...	...	...	...	...	...	...	
112	tt1872181	2014-05-02	The Amazing Spider-Man 2	200000000	708996336	354.498168	
115	tt0948470	2012-07-03	The Amazing Spider-Man	220000000	757890267	344.495576	
113	tt2975590	2016-03-25	Batman v Superman: Dawn of Justice	250000000	867500281	347.000112	
134	tt0770828	2013-06-14	Man of Steel	225000000	667999518	296.888675	
155	tt0974015	2017-11-17	Justice League	300000000	655945209	218.648403	

87 rows × 14 columns

In [61]:

```
# Plot a bar chart that shows the average film (RoI) per director for the top 20
fig, ax = plt.subplots(figsize=(20,8))

director_analysis_df.groupby('primary_name')['RoI'].mean().sort_values(ascending=
ax.set_ylabel('Director', fontsize=15)
ax.set_xlabel('Average Return on Investment (%)', fontsize=15)
ax.set_title('Average Return on Investment per Director', fontsize=20);
```



The top 5 directors with a highest average return on investment are: Kyle Balda, Pierre Coffin, Chris Rennaud, David F. Sandberg, and James Wan.

7. Writers

We are going to plot a barchart to visualize the relationship between writers and average RoI for the films. We first need to create a new DataFrame that contains the movies and their actor information.

In [62]:

```
# Create a copy of the 'top_movies_df' DataFrame to a new variable called 'writer_
writer_analysis_df = top_movies_df.copy()

# Join the top_movies_df DataFrame to the writer_analysis_df DataFrame
writer_analysis_df = writer_analysis_df.join(writers_df.set_index('movie_id'), on=

# Join the persons_df DataFrame to the writer_analysis_df DataFrame so that we ca
writer_analysis_df = writer_analysis_df.join(persons_df.set_index('person_id'), o
writer_analysis_df # Preview the updated 'writer_analysis_df' DataFrame
```

Out[62]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	ru
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
0	tt2582846	2014-06-06	The Fault in Our Stars	12000000	307166834	2559.723617	
1	tt3783958	2016-12-09	La La Land	20000000	426351163	2131.755815	
2	tt5140878	2017-08-11	Annabelle: Creation	15000000	305384865	2035.899100	
...	...	...	...	...	...	...	
165	tt1979388	2015-11-25	The Good Dinosaur	187500000	333771037	178.011220	
166	tt3741700	2019-05-31	Godzilla: King of the Monsters	170000000	299276941	176.045259	
167	tt3778644	2018-05-25	Solo: A Star Wars Story	275000000	393151347	142.964126	
167	tt3778644	2018-05-25	Solo: A Star Wars Story	275000000	393151347	142.964126	
167	tt3778644	2018-05-25	Solo: A Star Wars Story	275000000	393151347	142.964126	

862 rows × 14 columns

In [63]:

```
# Writers with more than one film will give the 'person_id' column duplicates. Th
writer_ids = writer_analysis_df[writer_analysis_df.duplicated(subset='person_id')

# Update the 'writer_analysis_df' DataFrame to only include writers with multiple
writer_analysis_df = writer_analysis_df[writer_analysis_df['person_id'].isin(writ
writer_analysis_df # Preview the updated 'director_analysis_df' DataFrame
```

Out[63]:

	movie_id	release_date	movie	production_budget	worldwide_gross	RoI	ru
2	tt5140878	2017-08-11	Annabelle: Creation	15000000	305384865	2035.899100	
3	tt1396484	2017-09-08	It	35000000	697457969	1992.737054	
7	tt2293640	2015-07-10	Minions	74000000	1160336173	1568.021855	
7	tt2293640	2015-07-10	Minions	74000000	1160336173	1568.021855	
14	tt2709768	2016-07-08	The Secret Life of Pets	75000000	886750534	1182.334045	
...	...	...	...	...	...	...	
164	tt2660888	2016-07-22	Star Trek Beyond	185000000	335802233	181.514721	
148	tt1623205	2013-03-08	Oz the Great and Powerful	200000000	490359051	245.179525	
157	tt1446192	2012-11-21	Rise of the Guardians	145000000	306900902	211.655794	
158	tt2345759	2017-06-09	The Mummy	195000000	409953905	210.232772	
159	tt1631867	2014-06-06	Edge of Tomorrow	178000000	370541256	208.169245	

601 rows × 14 columns

In [64]:

```
# Plot a bar chart that shows the average film (RoI) per writer for the top 20 wr
fig, ax = plt.subplots(figsize=(20,8))

writer_analysis_df.groupby('primary_name')['RoI'].mean().sort_values(ascending=Fa
ax.set_ylabel('Writer', fontsize=15)
ax.set_xlabel('Average Return on Investment (%)', fontsize=15)
ax.set_title('Average Return on Investment per Writer', fontsize=20);
```

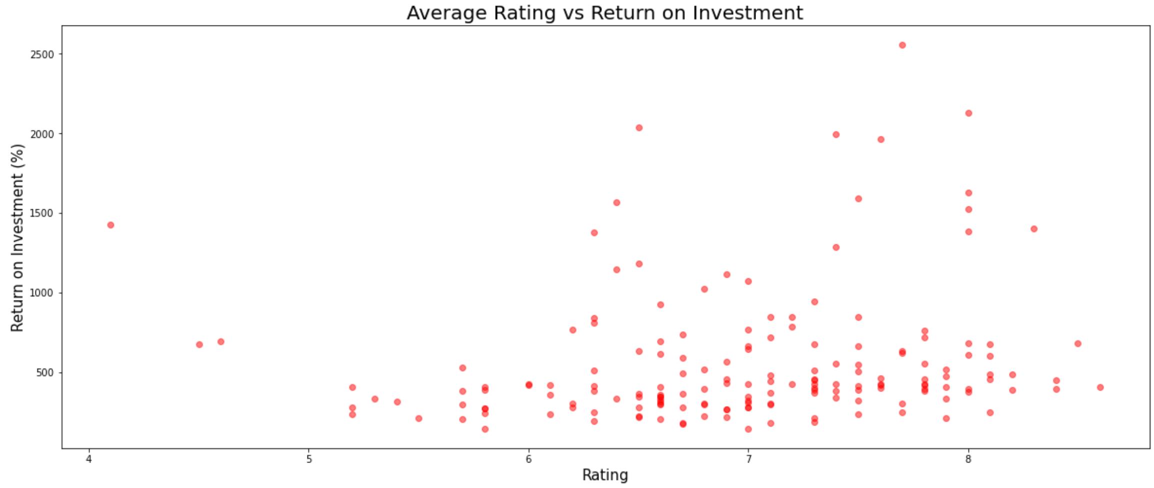
With an average RoI that is about 50% higher than the second-best writer, Brian Lynch, Gary Dauberman has the greatest average RoI among the writers.

8. Rating

The film's rating is the position it received from the public on a scale from 0 to 10. To see how the "rating" and the "RoI" relate to one another, we will create a scatter plot. We want to know what people think of these top-performing movies and whether or not that indicates that the movie is excellent.

In [65]:

```
# Plot a scatter plot that shows the relationship between RoI and rating
fig, ax = plt.subplots(figsize=(20,8))

ax.scatter(top_movies_df['averagerating'], top_movies_df['RoI'], alpha=0.5, color
ax.set_xlabel('Rating', fontsize=15)
ax.set_ylabel('Return on Investment (%)', fontsize=15)
ax.set_title('Average Rating vs Return on Investment', fontsize=20);
```



In [66]:

```
# Evaluate the Pearson correlation coefficient between the 'averagerating' and 'R
np.corrcoef(top_movies_df['averagerating'], top_movies_df['RoI'])[0,1]
```

Out[66]:

```
0.15197381428774626
```

It is challenging to discern any clear link between the rating and the RoI from the scatter plot. There is, in fact, no association between a film's rating and its return on investment (RoI), as shown by the Pearson correlation coefficient's value of 0.15, which is closer to 0.

Conclusion and Recommendations

1. The Runtime of a film has no impact on its box office performance.
2. The Production Budget of a film has a modereately negative correlation with its return on investment.
3. The Worldwide Gross of a film has no impact on its return on investment.
4. Movies released in the Summer are more likely to yield a higher return on investment. Whilst September (Fall) had the best average return on investment, the quantity of films released was much smaller than other months. As a result, it would not have been a reliable indicator of the best time to release a movie.
5. 'Horror' and 'Music' genres are more likely to have a higher return on investment.. It is however important to note that 'Action' and 'Adventure' films are the top most grossing.
6. Films directed by Kyle Balda, Pierre Coffin, Chris Rennaud, David F. Sandberg, and James Wan produce the highest return on investment.
7. Films written by Gary Dauberman produce the highest return on investment.
8. Success of a film is not determinant on the films rating