> **Tip**: Welcome to the Investigate a Dataset project! You will find tips in quoted sections like this to help organize your approach to your investigation. Once you complete this project, remove these **Tip** sections from your report before submission. First things first, you might want to double-click this Markdown cell and change the title so that it reflects your dataset and investigation.

Project: Investigate a Dataset - [Dataset-name]

Table of Contents

Introduction

Dataset Description

I chose the TMDB movie data set for my data analysis because I'm interested in movies. This data set contains information about 10,000 movies collected from the Movie Database (TMDb), including user reviews and revenue.

> **TMDB**
>
> - rows = 10866
> - columns = 21

Question(s) for Analysis

1. Which director produces most movies?
2. Which actor has starred in the most movies?
3. Which most genres are represented in the movies?
4. What is the most popular genre from year to year?
5. Does popularity have an impact on profit?
6. Which films are the most profitable, which has the highest turnover rate and which is the most popular?

In [1]:
```
# Use this cell to set up import statements for all of the packages that you
#   plan to use.

# Remember to include a 'magic word' so that your visualizations are plotted
#   inline with the notebook. See this page for more:
#   http://ipython.readthedocs.io/en/stable/interactive/magics.html
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Data Wrangling

> **Tip**: In this section of the report, you will load in the data, check for cleanliness, and then trim and clean your dataset for analysis. Make sure that you **document your data cleaning steps in mark-down cells precisely and justify your cleaning decisions.**

General Properties

> **Tip**: You should *not* perform too many operations in each cell. Create cells freely to explore your data. One option that you can take with this project is to do a lot of explorations in an initial notebook. These don't have to be organized, but make sure you use enough comments to understand the purpose of each code cell. Then, after you're done with your analysis, create a duplicate notebook where you will trim the excess and organize your steps so that you have a flowing, cohesive report.

In [2]:

```
# Load your data and print out a few lines. Perform operations to inspect data
#   types and look for instances of missing or possibly errant data.
df=pd.read_csv('tmdb-movies.csv')
df.head()
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://ww
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentser
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	http://www.starwars.
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	http:,

5 rows × 21 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10866 non-null  int64
 1   imdb_id               10856 non-null  object
```

```
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64
 4   revenue               10866 non-null  int64
 5   original_title        10866 non-null  object
 6   cast                  10790 non-null  object
 7   homepage              2936 non-null   object
 8   director              10822 non-null  object
 9   tagline               8042 non-null   object
 10  keywords              9373 non-null   object
 11  overview              10862 non-null  object
 12  runtime               10866 non-null  int64
 13  genres                10843 non-null  object
 14  production_companies  9836 non-null   object
 15  release_date          10866 non-null  object
 16  vote_count            10866 non-null  int64
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

In [4]:

```
df.describe()
```

Out[4]:

	id	popularity	budget	revenue	runtime	vote_count	vote_average	relea
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000000	1086
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974922	2001
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935142	12
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500000	196
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400000	199
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000000	200
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600000	2011
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200000	201

In [5]:

```
df.isnull().sum()
```

Out[5]:

```
id                         0
imdb_id                   10
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
homepage                7930
director                  44
tagline                 2824
keywords                1493
overview                   4
runtime                    0
genres                    23
production_companies    1030
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj                 0
revenue_adj                0
dtype: int64
```

Data Cleaning

> **Tip**: Make sure that you keep your reader informed on the steps that you are taking in your investigation. Follow every code cell, or every set of related code cells, with a markdown cell to describe to the reader what was found in the preceding cell(s). Try to make it so that the reader can then understand what they will be seeing in the following cell(s).

1) Remove duplicate rows from the data set

In [6]:
```
# Check of duplicated
print(df.duplicated().sum())
```

```
1
```

In [7]:
```
# Which data set is duplicate
df[df.duplicated()].head()
```

Out[7]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline
2090	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	NaN	Dwight H. Little	Survival is no game

1 rows × 21 columns

In [8]:
```
# visual check: whether different data is included
df[df['id'] == 42194].head()
```

Out[8]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline
2089	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	NaN	Dwight H. Little	Survival is no game
2090	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	NaN	Dwight H. Little	Survival is no game

2 rows × 21 columns

In [9]:
```
# Data is the same, delete a record
df.drop_duplicates(inplace=True)
```

In [10]:
```
# Verifying implementation
print(df.duplicated().sum())
```

```
0
```

2) Change the date/time format

In [11]:

```
# Change from string format to datetime format
df['release_date']=pd.to_datetime(df['release_date'])
df['release_date'].head()
```

Out[11]:

```
0    2015-06-09
1    2015-05-13
2    2015-03-18
3    2015-12-15
4    2015-04-01
Name: release_date, dtype: datetime64[ns]
```

3) Remove unnecessary columns

In [12]:

```
# Delete unnecessary columns based on the questions
df.drop(['imdb_id', 'homepage', 'tagline', 'keywords', 'overview', 'runtime', 'production_compa
```

In [13]:

```
# Verifying implementation
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              10865 non-null  int64
 1   popularity      10865 non-null  float64
 2   budget          10865 non-null  int64
 3   revenue         10865 non-null  int64
 4   original_title  10865 non-null  object
 5   cast            10789 non-null  object
 6   director        10821 non-null  object
 7   genres          10842 non-null  object
 8   release_date    10865 non-null  datetime64[ns]
 9   vote_count      10865 non-null  int64
 10  vote_average    10865 non-null  float64
 11  release_year    10865 non-null  int64
dtypes: datetime64[ns](1), float64(2), int64(5), object(4)
memory usage: 1.1+ MB
```

4) Save this data in a new file

In [14]:

```
# save the new data frame in "tmdb_clean.csv"
df.to_csv('tmdb_clean.csv', index=False, encoding = 'utf-8')
```

In [15]:

```
# Check after saving, loading the file
df = pd.read_csv('tmdb_clean.csv')
```

Exploratory Data Analysis

> **Tip**: Now that you've trimmed and cleaned your data, you're ready to move on to exploration. **Compute statistics** and **create visualizations** with the goal of addressing the research questions that you posed in the Introduction section. You should compute the relevant statistics throughout the analysis when an inference is made about the data. Note that at least two or more kinds of plots should be created as part of the exploration, and you must compare and show trends in the varied visualizations.
>
> **Tip**: - Investigate the stated question(s) from multiple angles. It is recommended that you be systematic with your approach. Look at one variable at a time, and then follow it up by looking at relationships between variables. You should explore at least three variables in relation to the

> primary question. This can be an exploratory relationship between three variables of interest, or looking at how two independent variables relate to a single dependent variable of interest. Lastly, you should perform both single-variable (1d) and multiple-variable (2d) explorations.

Question 1: Which director produces most movies?

In [16]:

```
# The 10 director with the most movies
df['director'].value_counts().head(n=10)
```

Out[16]:

```
Woody Allen          45
Clint Eastwood       34
Martin Scorsese      29
Steven Spielberg     29
Ridley Scott         23
Steven Soderbergh    22
Ron Howard           22
Joel Schumacher      21
Brian De Palma       20
Tim Burton           19
Name: director, dtype: int64
```

Answer 1: Woody Allen produces most movies

Question 2: Which actor has starred in the most movies?

In [17]:

```
# Actors are included in the “cast” column
df['cast'].value_counts().head(n=10)
```

Out[17]:

```
Louis C.K.                                                                 6
William Shatner|Leonard Nimoy|DeForest Kelley|James Doohan|George Takei    5
Bill Burr                                                                  4
George Carlin                                                              3
Pierre Coffin                                                              3
Jim Jefferies                                                              3
Jennifer Lawrence|Josh Hutcherson|Liam Hemsworth|Woody Harrelson|Elizabeth Banks    3
Chris Wedge                                                                3
Zac Efron|Vanessa Hudgens|Ashley Tisdale|Lucas Grabeel|Corbin Bleu         3
Aziz Ansari                                                                3
Name: cast, dtype: int64
```

In [18]:

```
# function to split the string and return the count of each data set.
def split(x):
    # Concatenate all rows of the data set
    split_plot = df[x].str.cat(sep = '|')
    split = pd.Series(split_plot.split('|'))
    # Count every data set and return.
    info = split.value_counts(ascending=False)
    return info
```

In [19]:

```
# Call the function "Split" to display the actor
df_actor = split('cast')
print(df_actor)
```

```
Robert De Niro       72
Samuel L. Jackson    71
Bruce Willis         62
Nicolas Cage         61
Michael Caine        53
                     ..
Asen Asenov           1
Joe Quesada           1
Andy Milonakis        1
```

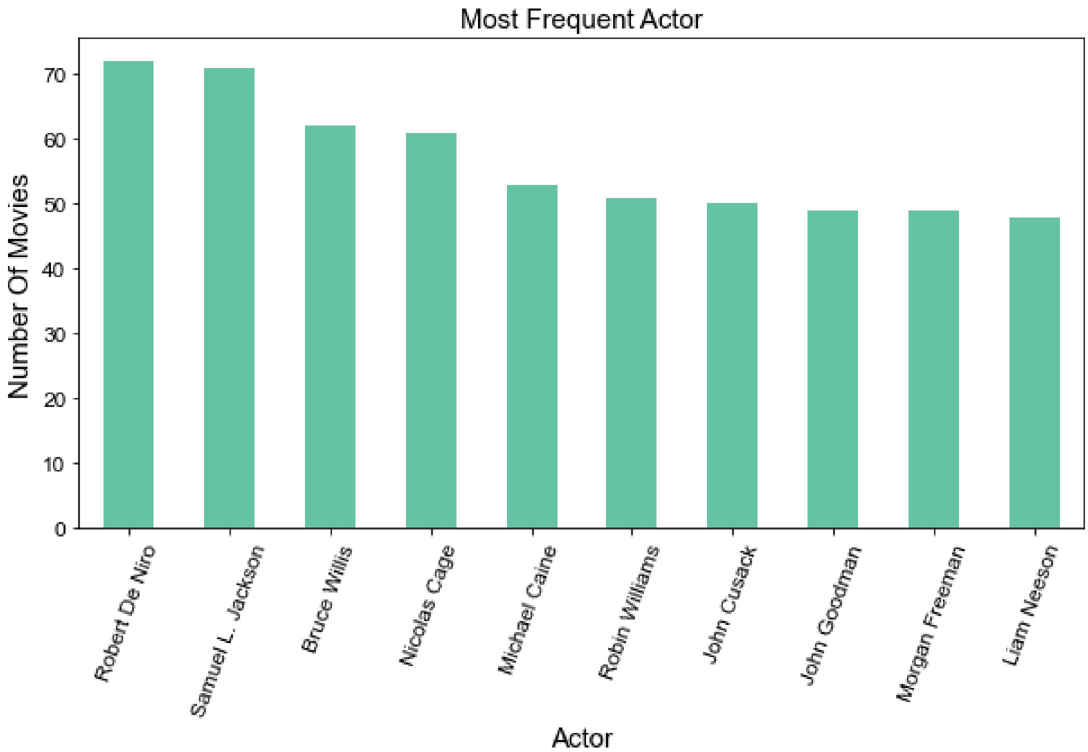
```
Samantha Cope          1
Stephanie Nielson      1
Length: 19026, dtype: int64
```

Answer 2 is presented in a graphical form

In [20]:

```python
#plot the bar plot.
df_actor.iloc[:10].plot.bar(figsize=(10,5),colormap= 'Set2',fontsize=12)

#setup the title and the labels of the plot.
plt.title("Most Frequent Actor",fontsize=15)
plt.xticks(rotation = 70)
plt.xlabel('Actor',fontsize=15)
plt.ylabel("Number Of Movies",fontsize= 15)
sns.set_style("white")
```



Answer 2: Robert De Niro has starred in the most movies, but Samuel L. Jackson is right behind him.

Question 3: Which most genres are represented in the movies?

In [21]:

```python
# Call the function "Split" to display the genres
df_genres = split('genres')
print(df_genres)
```

```
Drama              4760
Comedy             3793
Thriller           2907
Action             2384
Romance            1712
Horror             1637
Adventure          1471
Crime              1354
Family             1231
Science Fiction    1229
Fantasy             916
Mystery             810
Animation           699
```

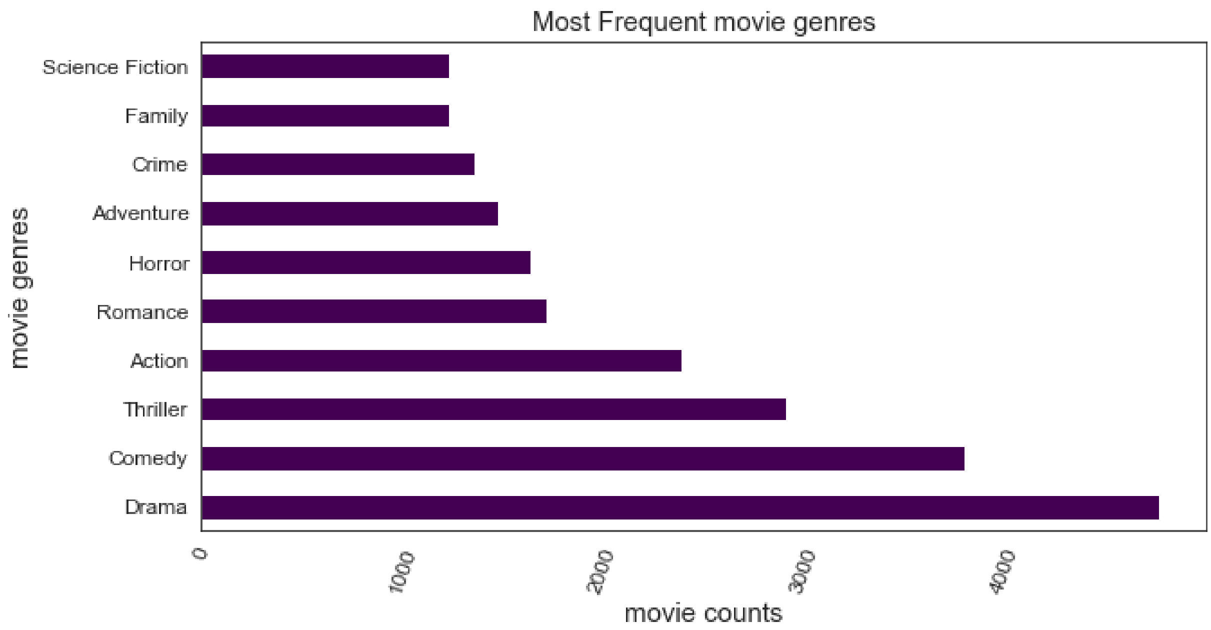
```
Documentary        520
Music              408
History            334
War                270
Foreign            188
TV Movie           167
Western            165
dtype: int64
```

Answer 3 is presented in a graphical form

In [22]:

```
#plot the bar plot.
df_genres.iloc[:10].plot.barh(figsize=(10,5),colormap= 'viridis',fontsize=12)

#setup the title and the labels of the plot.
plt.title("Most Frequent movie genres",fontsize=15)
plt.xticks(rotation = 70)
plt.xlabel('movie counts',fontsize=15)
plt.ylabel("movie genres",fontsize= 15)
sns.set_style("white")
```



Answer 3: Drama is the most genres are represented in the movies

---

Question 4: What is the most popular genre from year to year?

In [23]:

```
# copy a new dataframe
df_g = df.copy()
#convert genres datatype to string
df_g.genres = df_g.genres.astype('str')
```

In [24]:

```
# split the genres string
df_g.genres = df_g.genres.str.split('|')
```

In [25]:

```
# Verifying implementation
df_g.head(1)
```

Out[25]:

	id	popularity	budget	revenue	original_title	cast	director	genres	release_date	vo
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce	Colin Trevorrow	[Action, Adventure,	2015-06-09	

	id	popularity	budget	revenue	original_title	cast	director	genres	release_date	vo
						Dallas Howard|Irrfan Khan|Vi...		Science Fiction, Thriller]		

In [26]:
```
# creategenre list( create each row for each gen) using explode
df_g = df_g.explode('genres')
```

In [27]:
```
# Verifying implementation
df_g.head(1)
```

Out[27]:

	id	popularity	budget	revenue	original_title	cast	director	genres	release_date	vote_c
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action	2015-06-09	

In [28]:
```
# groupby year again and get the largest value
df_g.groupby(['release_year','genres'])['popularity'].mean().groupby(level='release_year').nlar
```

Out[28]:
```
release_year  release_year  genres
1960          1960          Thriller           0.811910
1961          1961          Animation          2.631987
1962          1962          Adventure          0.942513
1963          1963          Animation          2.180410
1964          1964          War                0.930959
1965          1965          Music              0.968850
1966          1966          Animation          0.585717
1967          1967          Animation          1.348805
1968          1968          Mystery            1.519456
1969          1969          Crime              0.948020
1970          1970          Animation          1.127719
1971          1971          Family             1.530722
1972          1972          Crime              1.072768
1973          1973          Animation          0.956526
1974          1974          Mystery            0.702035
1975          1975          Adventure          0.880297
1976          1976          Crime              0.707249
1977          1977          Action             1.419319
1978          1978          Music              0.679805
1979          1979          Action             1.410014
1980          1980          Science Fiction    0.897143
1981          1981          Adventure          0.875815
1982          1982          War                1.143182
1983          1983          Adventure          0.900596
1984          1984          Family             0.823924
1985          1985          Family             0.924311
1986          1986          Adventure          0.798935
1987          1987          History            0.815643
1988          1988          Action             0.599017
1989          1989          Animation          1.177585
1990          1990          Adventure          0.801768
1991          1991          Animation          1.665002
1992          1992          Animation          1.286893
1993          1993          Fantasy            0.918601
1994          1994          Crime              1.297888
1995          1995          Animation          1.467780
1996          1996          Crime              0.976838
1997          1997          Science Fiction    1.140241
1998          1998          War                1.246619
1999          1999          Adventure          1.012306
2000          2000          Adventure          0.854593
```

```
2001          2001          Fantasy          1.565260
2002          2002          Fantasy          1.430465
2003          2003          Fantasy          1.747524
2004          2004          Fantasy          1.320568
2005          2005          Fantasy          1.117732
2006          2006          Fantasy          1.023134
2007          2007          Fantasy          0.957349
2008          2008          Adventure        1.008385
2009          2009          Adventure        1.138422
2010          2010          Adventure        1.360319
2011          2011          Western          1.175800
2012          2012          Western          1.732778
2013          2013          Adventure        1.260832
2014          2014          Adventure        2.430526
2015          2015          Adventure        3.283786
Name: popularity, dtype: float64
```

In [29]:

```
# tidy up the data by removing extra row index by reset index
df_g = df_g.groupby(['release_year','genres'])['popularity'].mean().groupby(level='release_year
```

In [30]:

```
# Verifying implementation
df_g.head()
```

Out[30]:

```
release_year  genres
1960          Thriller     0.811910
1961          Animation    2.631987
1962          Adventure    0.942513
1963          Animation    2.180410
1964          War          0.930959
Name: popularity, dtype: float64
```

In [31]:

```
# change the pandas series to pandas dataframe
df_g = df_g.reset_index()
```

In [32]:

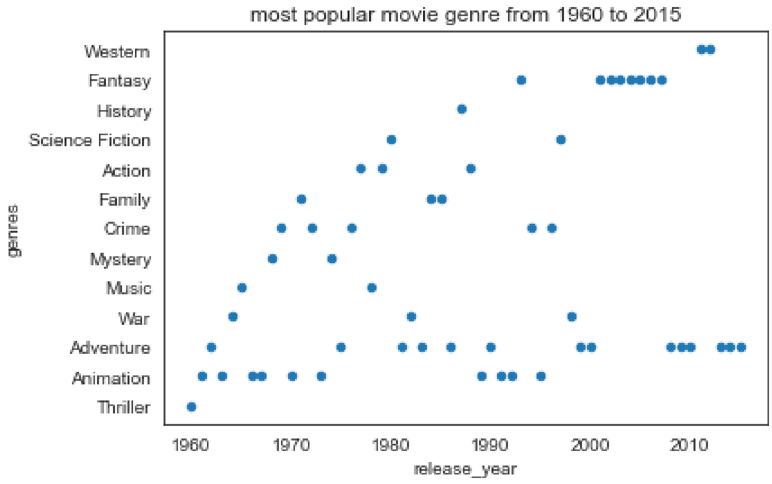
```
# Verifying implementation
df_g.head()
```

Out[32]:

	release_year	genres	popularity
0	1960	Thriller	0.811910
1	1961	Animation	2.631987
2	1962	Adventure	0.942513
3	1963	Animation	2.180410
4	1964	War	0.930959

In [33]:

```
# Create a chart
df_g.plot(x='release_year', y='genres', kind='scatter', title = 'most popular movie genre from
```



Answer 4:

- It is a trend for the last 20 years to see that the most profitable genres are “fantasy” and “adventure.”
- In previous years before 2000, the spectrum was even wider.
- If I were a director I would probably make a movie that includes these two genres

---

Question 5: Does popularity have an impact on profit?

In [34]:

```
# Caldulation: profit value
df['profit'] = df['revenue'] - df['budget']
```

In [35]:

```
# create a Regression Plot
ax = sns.regplot(x=df['popularity'],y=df['profit'],color='c')

#setup the title and the labels of the scatter plot.
ax.set_title("Popularity vs Profit",fontsize=13)
ax.set_xlabel("Popularity",fontsize=12)
ax.set_ylabel("Profit",fontsize=12)

#setup the figure size.
sns.set(rc={'figure.figsize':(6,4)})
sns.set_style("whitegrid")

#find the correlation between them.
data_corr = df.corr()

print(data_corr.loc['popularity','profit'])
```

```
0.6289972839642584
```

Answer 5:

> - The presentation shows us that popularity and profit correlate positively (0.61).
> - This means that movies that are highly popular tend to generate high profits.
> - But in addition to profit, I also wanted to look at the return on sales (ROI).

Question 6: Which films are the most profitable, which has the highest Return of Investment (ROI) and which is the most popular?

In [36]:

```
# Caldulation: Return of Sales (ROI)
df['ROI'] = df['profit'] / df['budget']
```

In [37]:

```
# Create the required data set
df_m = df.groupby(['original_title', 'popularity','release_year', 'revenue','budget','profit'])

# top 10 movies with most profitable
df_m = df_m.reset_index().sort_values(by='profit', ascending=False)[:10]
df_m [:10]
```

Out[37]:

	original_title	popularity	release_year	revenue	budget	profit	ROI
836	Avatar	9.432768	2009	2781505847	237000000	2544505847	10.736312
7571	Star Wars: The Force Awakens	11.173104	2015	2068178225	200000000	1868178225	9.340891
9995	Titanic	4.355219	1997	1845034188	200000000	1645034188	8.225171
4553	Jurassic World	32.985763	2015	1513528810	150000000	1363528810	9.090192
3301	Furious 7	9.335014	2015	1506249360	190000000	1316249360	6.927628
8058	The Avengers	7.637767	2012	1519557910	220000000	1299557910	5.907081
3701	Harry Potter and the Deathly Hallows: Part 2	5.711315	2011	1327817822	125000000	1202817822	9.622543
838	Avengers: Age of Ultron	5.944927	2015	1405035767	280000000	1125035767	4.017985
3282	Frozen	6.112766	2013	1274219009	150000000	1124219009	7.494793
9192	The Net	1.136610	1995	1106279658	22000000	1084279658	49.285439

Answer 6.1: Avatar is the most profitable movie, but does not have the highest ROI.

In [38]:

```
# top 10 movies with highest ROI
df_m_R = df_m.sort_values(by='ROI', ascending=False)
df_m_R [:10]
```

Out[38]:

	original_title	popularity	release_year	revenue	budget	profit	ROI
9192	The Net	1.136610	1995	1106279658	22000000	1084279658	49.285439
836	Avatar	9.432768	2009	2781505847	237000000	2544505847	10.736312
3701	Harry Potter and the Deathly Hallows: Part 2	5.711315	2011	1327817822	125000000	1202817822	9.622543
7571	Star Wars: The Force Awakens	11.173104	2015	2068178225	200000000	1868178225	9.340891
4553	Jurassic World	32.985763	2015	1513528810	150000000	1363528810	9.090192
9995	Titanic	4.355219	1997	1845034188	200000000	1645034188	8.225171
3282	Frozen	6.112766	2013	1274219009	150000000	1124219009	7.494793

	original_title	popularity	release_year	revenue	budget	profit	ROI
3301	Furious 7	9.335014	2015	1506249360	190000000	1316249360	6.927628
8058	The Avengers	7.637767	2012	1519557910	220000000	1299557910	5.907081
838	Avengers: Age of Ultron	5.944927	2015	1405035767	280000000	1125035767	4.017985

Answer 6.2: "The Net" has the highest ROI, although this is very low in popularity

In [39]:

```
# top 10 movies with highest popularity
df_m_P = df_m.sort_values(by='popularity', ascending=False)
df_m_P [:10]
```

Out[39]:

	original_title	popularity	release_year	revenue	budget	profit	ROI
4553	Jurassic World	32.985763	2015	1513528810	150000000	1363528810	9.090192
7571	Star Wars: The Force Awakens	11.173104	2015	2068178225	200000000	1868178225	9.340891
836	Avatar	9.432768	2009	2781505847	237000000	2544505847	10.736312
3301	Furious 7	9.335014	2015	1506249360	190000000	1316249360	6.927628
8058	The Avengers	7.637767	2012	1519557910	220000000	1299557910	5.907081
3282	Frozen	6.112766	2013	1274219009	150000000	1124219009	7.494793
838	Avengers: Age of Ultron	5.944927	2015	1405035767	280000000	1125035767	4.017985
3701	Harry Potter and the Deathly Hallows: Part 2	5.711315	2011	1327817822	125000000	1202817822	9.622543
9995	Titanic	4.355219	1997	1845034188	200000000	1645034188	8.225171
9192	The Net	1.136610	1995	1106279658	22000000	1084279658	49.285439

Answer 6.3: "Jurassic World" Is the most popular movie

Conclusions

> There are 20 unique movie genres, but drama is the genre that is showing an increasing trend in recent years. It also shows that more “fantasy” and ”adventure” films have been made in recent years.
>
> This data set is very rich in information. However, some data sets have zero values, which I would also like to have used for further analysis, e.g. keywords. This is because zero values would lead to incorrect results in the correlation diagrams and the calculation. Therefore, data cleansing is a necessary part before starting to examine the data set. Furthermore, it was also difficult to have double values in the actors or genres columns
>
> I've seen that there is a positive correlation between profitability and popularity. However, I was surprised that the movie with the highest ROI was one of the less popular films.

Submitting your Project

> **Tip**: Before you submit your project, you need to create a .html or .pdf version of this notebook in the workspace here. To do that, run the code cell below. If it worked correctly, you should get a return code of 0, and you should see the generated .html file in the workspace directory (click on the orange Jupyter icon in the upper left).

> **Tip**: Alternatively, you can download this report as .html via the **File** > **Download as** submenu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.
>
> **Tip**: Once you've done this, you can submit your project by clicking on the "Submit Project" button in the lower right here. This will create and submit a zip file with this .ipynb doc and the .html or .pdf version you created. Congratulations!

In [ ]:

```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```