Project: Investigating TMDb movie Dataset

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Introduction

The data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue. Movie datasets can help us determine the best directors in the industry, understand cultural influence by language, predict movie earnings, create movie recommendation services and so on. Some of the questions we might ask after exploring this data set are as follows:

- What are the 5 most popular movie genres??
- What movie genre receives the highest average rating??
- Do movies with higher budget receive a better rating??
- What properties are associated with movies that have high revenues?
- What are the top 10 most profitable movies???
- Which directors have been consistent with producing top rated movies in the past decade??

Data Wrangling

Data wrangling refers to a variety of processes designed to transform raw data into more readily used formats. The exact methods differ from project to project depending on the data you're leveraging and the goal you're trying to achieve. In this section of the report, we will load in the data, check for cleanliness, and then trim and clean the dataset for analysis.

Gathering the data

In [1]:
```
# import the necessary librarries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
# Load your data
df = pd.read_csv('tmdb-movies.csv')
```

Assessing the data

In [3]:
```
# display the first five rows of the dataframe
df.head(5)
```

Out[3]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline	...	overview	runtime	genre
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www.jurassicworld.com/	Colin Trevorrow	The park is open.	...	Twenty-two years after the events of Jurassic ...	124	Action|Adventure|Scienc Fiction|Thrill
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.madmaxmovie.com/	George Miller	What a Lovely Day.	...	An apocalyptic story set in the furthest reach...	120	Action|Adventure|Scienc Fiction|Thrill
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke	One Choice Can Destroy You	...	Beatrice Prior must confront her inner demons ...	119	Adventure|Scienc Fiction|Thrill
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	http://www.starwars.com/films/star-wars-episod...	J.J. Abrams	Every generation has a story.	...	Thirty years after defeating the Galactic Empi...	136	Action|Adventure|Scienc Fiction|Fantas
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	http://www.furious7.com/	James Wan	Vengeance Hits Home	...	Deckard Shaw seeks revenge against Dominic Tor...	137	Action|Crime|Thrill

5 rows × 21 columns

In [4]:
```
# print information about the dataframe including the index dtype and columns, non-null values and memory usage
df.info()

# get the dimensionality of the dataframe (i.e no of rows x no of columns)
df.shape
```

```
<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
```

Out[4]: (10866, 21)

In [5]:
```
# get number of duplicate rows
sum(df.duplicated())
```

Out[5]: 1

In [6]:
```
# get descriptive statistics of the dataframe
df.describe()
```

Out[6]:

	id	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000000	10866.000000	1.086600e+04	1.086600e+04
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974922	2001.322658	1.755104e+07	5.136436e+07
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935142	12.812941	3.430616e+07	1.446325e+08
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400000	1995.000000	0.000000e+00	0.000000e+00
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000000	2006.000000	0.000000e+00	0.000000e+00
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600000	2011.000000	2.085325e+07	3.369710e+07
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

Cleaning the data

After assessing the data, we realized that our dataset contains duplicates, missing values, incorrect datatypes and several columns that will be irrelevant to our analysis. In this section of the report, we will be using different techniques yo clran our data

In [7]:
```
# Drop columns that won't be used in our analysis
df.drop(columns = ['id', 'imdb_id', 'cast', 'homepage', 'tagline', 'keywords', 'overview', 'production_companies',
                   'release_date', 'budget_adj', 'revenue_adj'], inplace=True)

# rearrange the columns
df = df.reindex(columns=['original_title', 'director', 'genres', 'runtime', 'release_year', 'popularity',
                         'vote_average', 'vote_count', 'budget', 'revenue'])

# print out a few lines of the updated dataframe
df.head()
```

Out[7]:

	original_title	director	genres	runtime	release_year	popularity	vote_average	vote_count	budget	revenue
0	Jurassic World	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	124	2015	32.985763	6.5	5562	150000000	1513528810
1	Mad Max: Fury Road	George Miller	Action|Adventure|Science Fiction|Thriller	120	2015	28.419936	7.1	6185	150000000	378436354
2	Insurgent	Robert Schwentke	Adventure|Science Fiction|Thriller	119	2015	13.112507	6.3	2480	110000000	295238201
3	Star Wars: The Force Awakens	J.J. Abrams	Action|Adventure|Science Fiction|Fantasy	136	2015	11.173104	7.5	5292	200000000	2068178225
4	Furious 7	James Wan	Action|Crime|Thriller	137	2015	9.335014	7.3	2947	190000000	1506249360

In [ ]:
```
# Drop the missing value at genres columns
df.dropna(subset=['genres'], how='any', inplace=True)
```

In [8]:
```
#remove duplicates
df.drop_duplicates(subset=['original_title'], keep='first', inplace=True)

# check number of duplicate rows
sum(df.duplicated())
```

Out[8]: 0

Exploratory Data Analysis

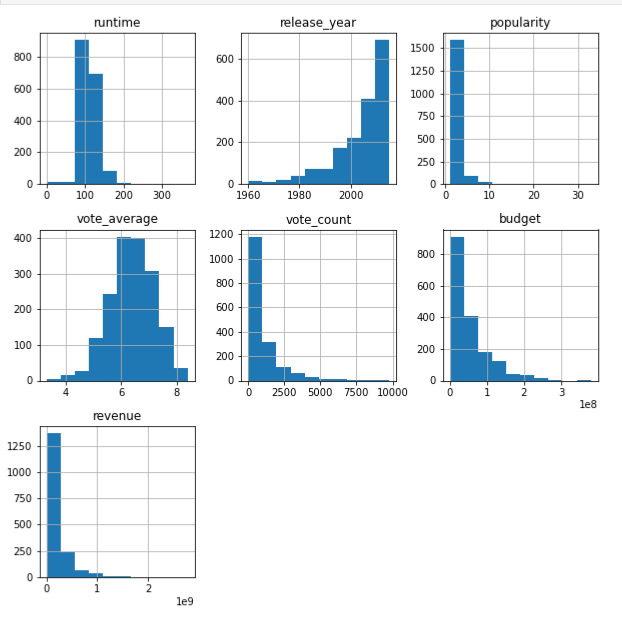
What are the top 10 most popular movie genres??

To get the top 5 most popular genres, we have to get the most popular movie genres from year to year and then count. But how do we classify a movie as popular or not? From the summary statistics, 75 percent of the movies in the dataset have a popularity of approximately 0.71 or less. Let's consider movies that are very popular as movies with popularity greater than or equal to 1.

Notice that each movie has more than one genre. Choosing one genre from each movie would bring bias to our analysis. Therefore we have to consider all the genres to find the most popular genres.

In [9]:
```
# convert the elements in the 'genres' column from a string to a list
df.genres = df.genres.str.split('|')
```

In [10]:
```
# get movies that have popularities greater than or equal to 1
df_very_popular = df.query('popularity >= 1')

# plot histogram of the different variable in the dataframe
df_very_popular.hist(figsize=(10, 10));
```



In [11]:
```
# use the explode() function to convert each list-like element of the 'genres' column into a row.
df_very_popular = df_very_popular.explode('genres')

# reset the index of the dataframe
df_very_popular.reset_index(drop=True, inplace=True)
```

In [12]:
```
# create a function to highlight the genres column
def highlight_col(x):
    return np.full((x.shape), 'background-color: yellow')

# display the first five rows of the exploded dataframe
df_very_popular.head(5).style.apply(highlight_col, axis=0, subset="genres")
```

Out[12]:

	original_title	director	genres	runtime	release_year	popularity	vote_average	vote_count	budget	revenue
0	Jurassic World	Colin Trevorrow	Action	124	2015	32.985763	6.500000	5562	150000000	1513528810
1	Jurassic World	Colin Trevorrow	Adventure	124	2015	32.985763	6.500000	5562	150000000	1513528810
2	Jurassic World	Colin Trevorrow	Science Fiction	124	2015	32.985763	6.500000	5562	150000000	1513528810
3	Jurassic World	Colin Trevorrow	Thriller	124	2015	32.985763	6.500000	5562	150000000	1513528810
4	Mad Max: Fury Road	George Miller	Action	120	2015	28.419936	7.100000	6185	150000000	378436354

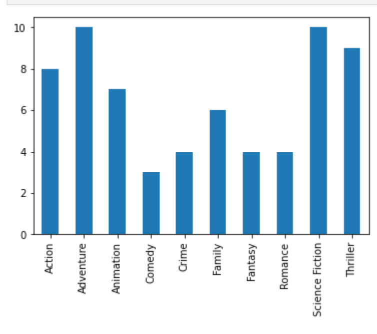
In [13]:
```
# Let's find the mean popularity of each movie genre according to their release year.
df_mean_popular = df_very_popular.groupby(['release_year', 'genres'],  as_index=False)['popularity'].mean()
```

In [14]:
```
# get the indices of the dataframe with the highest mean for each year.
idx = df_mean_popular.groupby(['release_year'])['popularity'].transform(max) == df_mean_popular['popularity']

# create a dataframe for most popular genres
df_most_popular = df_mean_popular[idx]

# display the first five rows of the dataframe
df_most_popular.head(5)
```

Out[14]:

	release_year	genres	popularity
0	1960	Action	1.872132
1	1960	Adventure	1.872132
2	1960	Western	1.872132
3	1961	Adventure	2.631987
4	1961	Animation	2.631987

In [15]:
```
# rank top 10 most popular genres from highest to lowest count
df_most_popular['genres'].value_counts().nlargest(10).sort_index(ascending=True).plot(kind='bar');
```



What is the genre that receives the highest average rating??

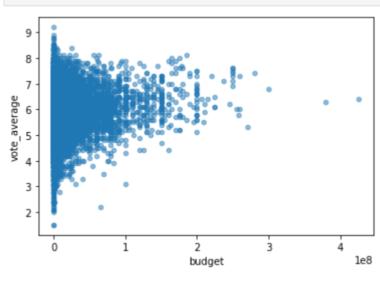
In [16]:
```
# use the explode() function to convert each list-like element of the 'genres' column into a row.
df_genres = df.explode('genres')
```

In [17]:
```
# find the highest mean rating according to genre
df_genres.groupby(['genres'])['vote_average'].mean().nlargest(1)
```

Out[17]:
```
genres
Documentary    6.904678
Name: vote_average, dtype: float64
```

Do movies with higher budget receive a better rating??

In [18]:
```
df.plot.scatter(x="budget", y="vote_average", alpha=0.5);
```



In [19]:
```
# find the correlation between the bugdet column and the vote_average column
df['budget'].corr(df['vote_average'])
```

Out[19]: 0.08385428495191345

From the scatterplot and with a correlation coefficient less than 0.1, we can suggest that movies with higher budget do not necessarily receive better ratings

What properties are associated with movies that have high revenues?

In [20]:
```
# calculate the net profit
profit = df['revenue'] - df['budget']

# create profit column in the dataframe
df['profit'] = profit

# find the correlation between the revenue and other variables
df[['popularity', 'vote_average', 'budget', 'revenue', 'profit']].corr()
```

Out[20]:

	popularity	vote_average	budget	revenue	profit
popularity	1.000000	0.208749	0.544877	0.661999	0.627368
vote_average	0.208749	1.000000	0.083854	0.173435	0.183285
budget	0.544877	0.083854	1.000000	0.735011	0.569641
revenue	0.661999	0.173435	0.735011	1.000000	0.975982
profit	0.627368	0.183285	0.569641	0.975982	1.000000

Correlation coefficients whose magnitude are between 0.7 and 0.9 indicate variables which can be considered highly correlated. Although, it should be noted that correlation does not imply causation. From the figure above, we can suggest that high revenue movies come with higher bugdget, higher profit, and higher popularity

What are the top 10 most profitable movies???

In [21]:
```
# calculate the Return On Investment (ROI)
df['ROI'] = df['profit'] / df['budget']

# sort the dataframe by net profit from highest to lowest
df_profitable = df.sort_values(by=['profit'], ascending=False)

# display the first ten rows of the dataframe
df_profitable.head(10)
```

Out[21]:

	original_title	director	genres	runtime	release_year	popularity	vote_average	vote_count	budget	revenue	profit	ROI
1386	Avatar	James Cameron	[Action, Adventure, Fantasy, Science Fiction]	162	2009	9.432768	7.1	8458	237000000	2781505847	2544505847	10.736312
3	Star Wars: The Force Awakens	J.J. Abrams	[Action, Adventure, Science Fiction, Fantasy]	136	2015	11.173104	7.5	5292	200000000	2068178225	1868178225	9.340891
5231	Titanic	James Cameron	[Drama, Romance, Thriller]	194	1997	4.355219	7.3	4654	200000000	1845034188	1645034188	8.225171
0	Jurassic World	Colin Trevorrow	[Action, Adventure, Science Fiction, Thriller]	124	2015	32.985763	6.5	5562	150000000	1513528810	1363528810	9.090192
4	Furious 7	James Wan	[Action, Crime, Thriller]	137	2015	9.335014	7.3	2947	190000000	1506249360	1316249360	6.927628
4361	The Avengers	Joss Whedon	[Science Fiction, Action, Adventure]	143	2012	7.637767	7.3	8903	220000000	1519557910	1299557910	5.907081
3374	Harry Potter and the Deathly Hallows: Part 2	David Yates	[Adventure, Family, Fantasy]	130	2011	5.711315	7.7	3750	125000000	1327817822	1202817822	9.622543
14	Avengers: Age of Ultron	Joss Whedon	[Action, Adventure, Science Fiction]	141	2015	5.944927	7.4	4304	280000000	1405035767	1125035767	4.017985
8094	The Net	Irwin Winkler	[Crime, Drama, Mystery, Thriller, Action]	114	1995	1.136610	5.6	201	22000000	1106279658	1084279658	49.285439
8	Minions	Kyle Balda|Pierre Coffin	[Family, Animation, Adventure, Comedy]	91	2015	7.404165	6.5	2893	74000000	1156730962	1082730962	14.631499

Which directors has been consistent with producing top rated movies in the past decade??

How do we classify a movie as "top rated"? From the summary statistics, 75 percent of the movies in the dataset have a popularity of approximately 6.6 or less. Let's consider movies as "top rated" if they have a rating of 7 and above.

In [22]:
```
df_top_rated = df.query('vote_average >= 7 & release_year >=  release_year.max() - 10')
```

In [23]:
```
df_top_rated.director.value_counts().nlargest(10)
```

Out[23]:
```
Wes Anderson         7
Christopher Nolan    6
Joss Whedon          5
Martin Scorsese      5
Shannon Hartman      4
David Yates          4
Tom Hooper           4
Matthew Vaughn       4
Louis C.K.           4
Jay Oliva            4
Name: director, dtype: int64
```

Limitations to our dataset

- Lack of information on how the vote_average was calculated
- The missing values in the data may affect our accuracy of analysis

Conclusions

From our analysis, we see that movies with higher revenues will most likely require higher budget. Production companies will require higher bugdget to produce high-quality movies that will generate higher profit. We can see the return on investments from some of the most profitable movies are 4 up to 49 times their budget. If we intend to produce a movie, it will be wise to hire directors like **Christopher Nolan** who have been consistent with creating top rated movies in the past deacade.