Project: TMDB 500 movies analysis (Investigate a Dataset)

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Introduction

The TMDb movie data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue. i am analyzing this data as part of my data analyts nanodegree on udacity.com. The data set include data points such as user ratings, cast , directors, genre, revenue and so much more.

Some Percrularities of the data set

- Certain columns, like 'cast' and 'genres', contain multiple values separated by pipe (|) characters.
- There are some odd characters in the 'cast' column. Don't worry about cleaning them. You can leave them as is.
- The final two columns ending with "_adj" show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation overtime.

Questions for Analysis

Some Questions i would like to answer in my analysis include

- Which genres are most popular from year to year?
- What kinds of properties are associated with movies that have high revenues?
- what movies have the highest profit?
- what is the highest revenue generating genre?

In [52]:
```
#importing libraries
import os
import csv
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

%matplotlib inline
```

Data Wrangling

In this section, I will Load the data and print out a few lines, Perform operations to inspect data types and look for instances of missing or possibly errant data.

> **Tip**: In this section of the report, i will load in the data, check for cleanliness, and then trim and clean your dataset for analysis.

General Properties

In [3]:
```
# Reading in the data
movie_df = pd.read_csv('tmdb-movies.csv')

# Making a copy of the dataset
df = movie_df.copy()

# Loading the fist five rows in the dataset
df.head()
```

Out[3]:

	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...
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...

5 rows × 21 columns

Data Cleaning

Columns of the dataset

In [4]:
```
# Observing the columns in the dataset
for i in df.columns:
    print(i)
```

```
id
imdb_id
popularity
budget
revenue
original_title
cast
homepage
director
tagline
keywords
overview
runtime
genres
production_companies
release_date
vote_count
vote_average
release_year
budget_adj
revenue_adj
```

- The id and imdb_id columns both serve the same purpose, hence I will be dropping one of them (imdb_id)
- The homepage, tagline, keywords, overview columns are not necessary for analysis and would be dropped
- No currency was specified for the budget, revenue, budget_adj and revenue_adj columns, hence I would be using the US Dollar.

In [5]:
```
# Dropping unnecessary columns from the dataset
df.drop(['imdb_id', 'homepage', 'tagline', 'keywords', 'overview'], axis=1,
```

Dimension of the dataset

In [6]:
```
# Checking the dimension of the data after dropping the columns
df.shape
```

Out[6]:
```
(10866, 16)
```

- There are 10,866 rows and 16 columns in the dataset

Duplicated values

In [7]:
```
# Checking for duplicated values
df.duplicated().sum()
```

Out[7]:
```
1
```

- There is a duplicated row in the dataset

In [8]:
```
# Dropping the duplicated row
df.drop_duplicates(subset=None, keep='first', inplace=True)
```

In [9]:
```
# confirming that there is no duplicated rows for Quality assurance
df.duplicated().sum()
```

Out[9]:
```
0
```

Null Values

In [10]:
```
# Checking for null values
df.isnull().sum()
```

Out[10]:
```
id                         0
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
director                  44
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
```

There are null values in the following columns:

- cast
- director
- genres
- production_companies

In order not to lose vital information that may be contained in these rows, I would be replacing the null values with 'Unknown'

In [11]:
```
#changing null values to unknown
df.fillna('Unknown', inplace=True)
```

In [13]:
```
# # confirming that there are no more null values for Quality assurance
df.isnull().sum()
```

Out[13]:
```
id                      0
popularity              0
budget                  0
revenue                 0
original_title          0
cast                    0
director                0
runtime                 0
genres                  0
production_companies    0
release_date            0
vote_count              0
vote_average            0
release_year            0
budget_adj              0
revenue_adj             0
dtype: int64
```

Checking data types

In [14]:
```
# Checking to ensure that the data types are cast correctly
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 16 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                  10865 non-null  object 
 6   director              10865 non-null  object 
 7   runtime               10865 non-null  int64  
 8   genres                10865 non-null  object 
 9   production_companies  10865 non-null  object 
 10  release_date          10865 non-null  object 
 11  vote_count            10865 non-null  int64  
 12  vote_average          10865 non-null  float64
 13  release_year          10865 non-null  int64  
 14  budget_adj            10865 non-null  float64
 15  revenue_adj           10865 non-null  float64
dtypes: float64(4), int64(6), object(6)
memory usage: 1.4+ MB
```

- The release date is cast as an object (string), hence I would be changing it to the datetime format

In [15]:
```
#changing release date to datetime format
df['release_date'] = pd.to_datetime(df['release_date'])
```

In [17]:
```
# checking that the release date is now in datetime format
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 16 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                  10865 non-null  object
 6   director              10865 non-null  object
 7   runtime               10865 non-null  int64
 8   genres                10865 non-null  object
 9   production_companies  10865 non-null  object
 10  release_date          10865 non-null  datetime64[ns]
 11  vote_count            10865 non-null  int64
 12  vote_average          10865 non-null  float64
 13  release_year          10865 non-null  int64
 14  budget_adj            10865 non-null  float64
 15  revenue_adj           10865 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(5)
memory usage: 1.4+ MB
```

Empty values

Empty strings(objects) in a dataset will not be represented as null values in pandas. It is important to check for them separately.

In [18]:
```
# Checking for empty values in the dataset
for i in df.columns:
    for row, value in enumerate(df[i]):
        if value == ' ':
            print(f'Empty value found on row: {row}')
```

- No empty values found in the dataset

In [19]:
```
# viewing cleaned and Final dataset
df.head()
```

Out[19]:

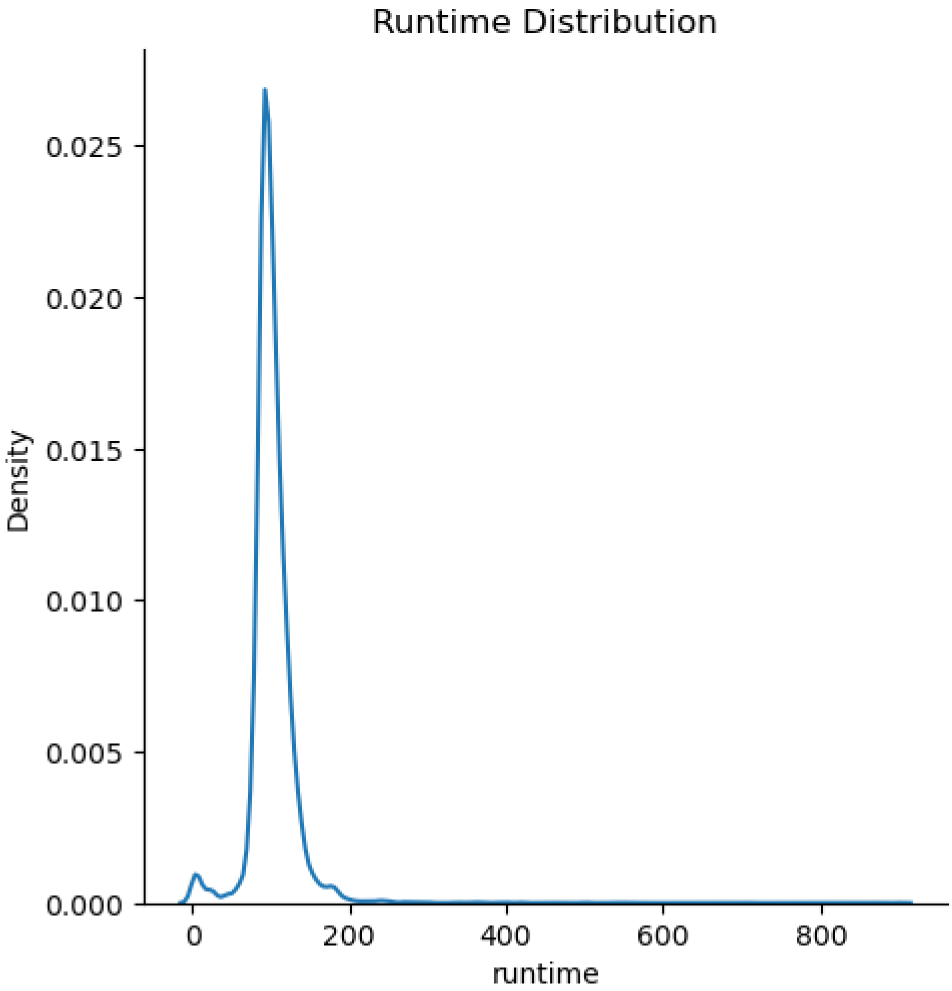
	id	popularity	budget	revenue	original_title	cast	director	r
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	
1	76341	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	
2	262500	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	
3	140607	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	
4	168259	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	

Exploratory Data Analysis

Research Question 1: What is the runtime distribution of the data set?

In [27]:

```
#checking the runtime distribution of the datasetbn
sns.displot(data=df, x='runtime', kind='kde')
plt.title('Runtime Distribution');
```



- The above plot is right skewed. This shows that most movies have a runtime of between 0 - 200 mins

Research Question 2: Which genres are most popular from year to year?

In [29]:
```
df_genres = df['genres'].value_counts().reset_index()
df_genres.head(20)
```

Out[29]:

	index	genres
0	Comedy	712
1	Drama	712
2	Documentary	312
3	Drama|Romance	289
4	Comedy|Drama	280
5	Comedy|Romance	268
6	Horror|Thriller	259
7	Horror	253
8	Comedy|Drama|Romance	222
9	Drama|Thriller	138
10	Comedy|Family	102
11	Action|Thriller	101
12	Thriller	93
13	Drama|Comedy	92
14	Animation|Family	90
15	Crime|Drama|Thriller	81
16	Crime|Drama	74
17	Comedy|Horror	72
18	Drama|Comedy|Romance	64
19	Action	63

The most popular genres are:

- Comedy
- Drama
- Documentary
- Drama|Romance
- Comedy|Drama

Research Question 3: What kinds of properties are associated with movies that have high revenues?

In [30]:

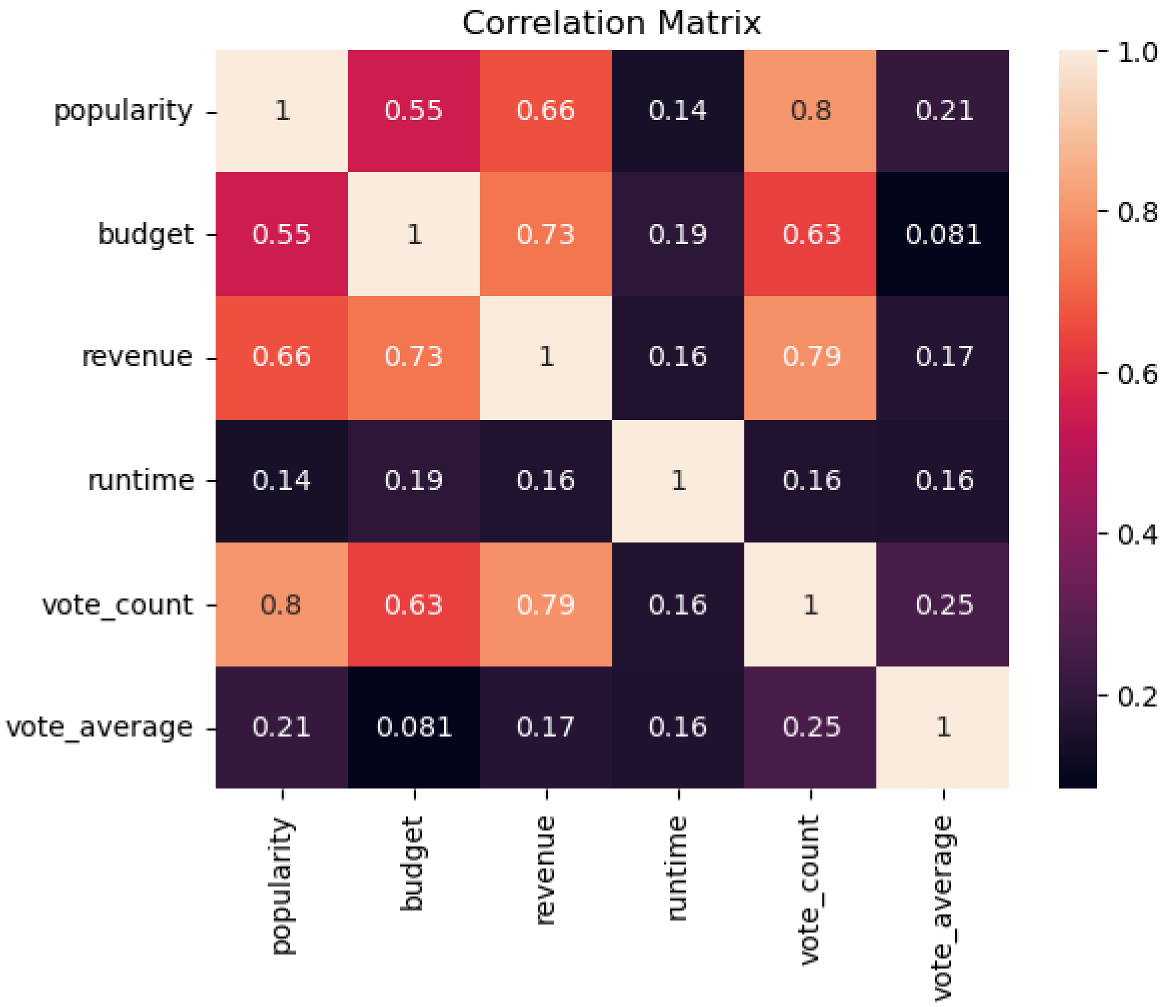
```
# Getting the numerical columns in the dataset
numerical_df = df.select_dtypes(exclude ='object')

# Dropping 'budget_adj' and 'revenue_adj' columns as they basically are the
# Also dropping 'release_date' as it is not an integer or a float, as well a
numerical_df.drop(['id', 'release_date', 'release_year', 'budget_adj', 'reve
numerical_df.head()
```

Out[30]:

	popularity	budget	revenue	runtime	vote_count	vote_average
0	32.985763	150000000	1513528810	124	5562	6.5
1	28.419936	150000000	378436354	120	6185	7.1
2	13.112507	110000000	295238201	119	2480	6.3
3	11.173104	200000000	2068178225	136	5292	7.5
4	9.335014	190000000	1506249360	137	2947	7.3

In [31]:

```
# Plotting the correlation matrix
plt.figure(dpi=100)
sns.heatmap(numerical_df.corr(), annot = True)
plt.title('Correlation Matrix');
```



From the correlation matrix above, the following can be observed:

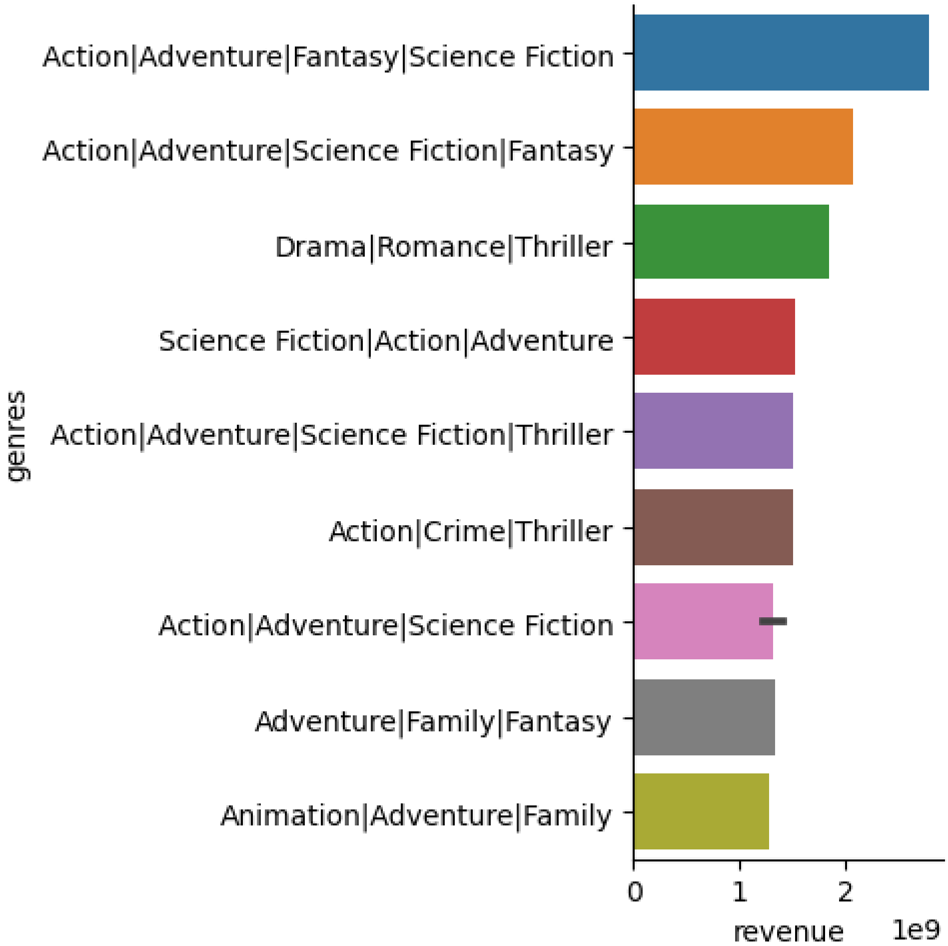
- Popularity is highly correlated with vote_count. This means that higher vote counts are found among more popular movies.
- Budget is highly correlated with revenue. This means that the higher a movie's budget, the more likely it is to generate a higher revenue.
- Revenue is highly correlated to vote_count. This makes sense because vote_count is highly correlated with popularity and by extension revenue would more likely be higher among popular movies.

Therefore, movies that have high revenues have higher vote_counts, higher budgets and higher popularity

Research Question 4: - what is the highest revenue generating genre?

In [33]:
```
# Top 10 genres by revenue
revenue_df = df.nlargest(10, ['revenue'])
```

In [36]:
```
sns.catplot(data=revenue_df, x= 'revenue' , y= 'genres' , kind='bar');
```



From here we can see that a movie with genre mixing is the most popular genre by revenue

Research Question 5: What movies have the highest profit?

In [37]:
```
# Creating a new column called 'profit'
df['profit'] = df['revenue'] - df['budget']
```

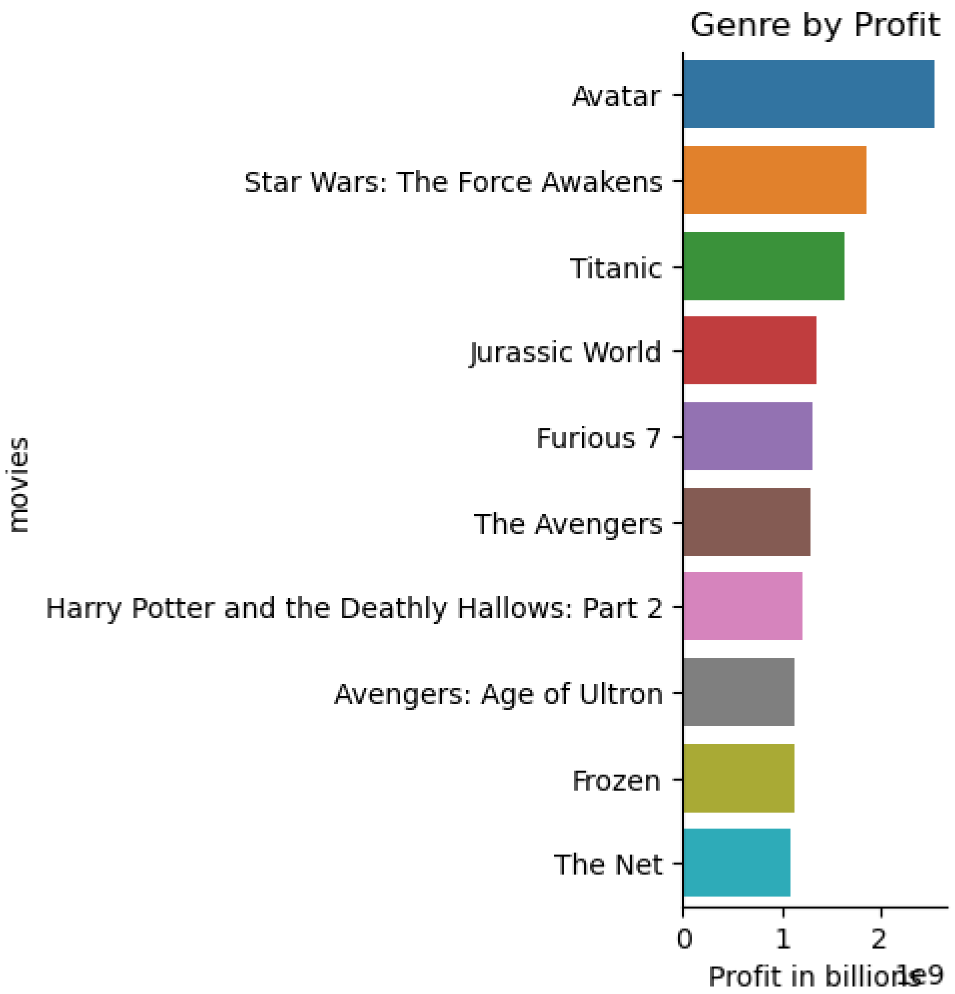
In [38]:
```
# Getting the top 10 genres by profit
profit_df = df.nlargest(10, ['profit'])
profit_df.head()
```

Out[38]:

	id	popularity	budget	revenue	original_title	cast	directo
1386	19995	9.432768	237000000	2781505847	Avatar	Sam Worthington|Zoe Saldana|Sigourney Weaver|S...	Jame Camero
3	140607	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.. Abram
5231	597	4.355219	200000000	1845034188	Titanic	Kate Winslet|Leonardo DiCaprio|Frances Fisher|...	Jame Camero
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Coli Trevorro
4	168259	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	Jame Wa

In [48]:

```
sns.catplot(data=profit_df, x='profit', y='original_title', kind='bar');
plt.title('Genre by Profit')
plt.xlabel('Profit in billions')
plt.ylabel('movies');
```



From here we can see that avatar is the most popular movie making over 2.5B revenue.

Conclusions

From this data set, starting with the correlation matrix above, the following can be observed:

- Popularity is highly correlated with vote_count. This means that higher vote counts are found among more popular movies.
- Budget is highly correlated with revenue. This means that the higher a movie's budget, the more likely it is to generate a higher revenue.
- Revenue is highly correlated to vote_count. This makes sense because vote_count is highly correlated with popularity and by extension revenue would more likely be higher among popular movies.

Therefore, movies that have high revenues have higher vote_counts, higher budgets and higher popularity

I analyzed the top 10 genres, average runtime, the most popular generes and top profit generating movie

Avatar movie stood out as the top profit and revenue generating movie which i thought was interesting as comedy was the most popular genre.

Lastly, it looks like high budget also creates a likelihood of high revenues. This is probably because the high budget allows filmmakers to get the best actors and the best equipment and props to make the movie very good.

Limitations

There were a lot of mixed genre movies which toped the revue chart which made it difficult to obtain the single toping genre from the data set.

Submitting my Project

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

In [ ]: