tmdb-movies

March 24, 2025

1 Project: Investigate a Dataset - [Movie Data]

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Introduction

1.1.1 Dataset Description

This data set contains information about movies, including user ratings and revenue. ### Question(s) for Analysis which genres are the most popular ?
which genres have highest budget per movie?
which genres have highest revenue per movie ?
which years have the most popular movies ?
which year did producers spend the most on the industry?
which year did producers got the highest revenue?
which production companies have the highest budgets per movie ?
which production companies have the highest revenue per movie ?
do movies with the highest popularity have the highest budget ?
do movies with the highest popularity have the highest revenue ?
do movies with the highest budget have the highest revenue ?

```
In [ ]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        #importing the libraries
```

Data Wrangling started by uploading the data and then used some functions to get some information before the claening like .shape , .describe() and .info()

```
In [ ]: df = pd.read_csv('tmdb-movies.csv')
        #uploading the data set
```

```
In [ ]: df.shape
        df.describe()
        df.info()
        #getting information about the dataframe to get reddy for cleaning
```

```
<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 [ ]: df

Out[ ]:

	id	imdb_id	popularity	budget	revenue	\
0	135397	tt0369610	32.985763	150000000	1513528810	
1	76341	tt1392190	28.419936	150000000	378436354	
2	262500	tt2908446	13.112507	110000000	295238201	
3	140607	tt2488496	11.173104	200000000	2068178225	
4	168259	tt2820852	9.335014	190000000	1506249360	
...	...	...	...	...	...	
10861	21	tt0060371	0.080598	0	0	
10862	20379	tt0060472	0.065543	0	0	
10863	39768	tt0060161	0.065141	0	0	
10864	21449	tt0061177	0.064317	0	0	
10865	22293	tt0060666	0.035919	19000	0	

	original_title	\
0	Jurassic World	
1	Mad Max: Fury Road	

```
2                        Insurgent
3      Star Wars: The Force Awakens
4                        Furious 7
...                            ...
10861            The Endless Summer
10862                   Grand Prix
10863             Beregis Avtomobilya
10864          What's Up, Tiger Lily?
10865       Manos: The Hands of Fate

                                                    cast  \
0      Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1      Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2      Shailene Woodley|Theo James|Kate Winslet|Ansel...
3      Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4      Vin Diesel|Paul Walker|Jason Statham|Michelle ...
...                                                  ...
10861  Michael Hynson|Robert August|Lord 'Tally Ho' B...
10862  James Garner|Eva Marie Saint|Yves Montand|Tosh...
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...
10864  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...
10865  Harold P. Warren|Tom Neyman|John Reynolds|Dian...

                                                homepage            director  \
0                        http://www.jurassicworld.com/     Colin Trevorrow
1                          http://www.madmaxmovie.com/       George Miller
2         http://www.thedivergentseries.movie/#insurgent    Robert Schwentke
3      http://www.starwars.com/films/star-wars-episod...         J.J. Abrams
4                             http://www.furious7.com/           James Wan
...                                                  ...                 ...
10861                                                NaN         Bruce Brown
10862                                                NaN  John Frankenheimer
10863                                                NaN      Eldar Ryazanov
10864                                                NaN         Woody Allen
10865                                                NaN    Harold P. Warren

                                                 tagline  ...  \
0                                   The park is open.  ...
1                                  What a Lovely Day.  ...
2                              One Choice Can Destroy You  ...
3                          Every generation has a story.  ...
4                                   Vengeance Hits Home  ...
...                                                  ...  ...
10861                                                NaN  ...
10862  Cinerama sweeps YOU into a drama of speed and ...  ...
10863                                                NaN  ...
10864                             WOODY ALLEN STRIKES BACK!  ...
10865       It's Shocking! It's Beyond Your Imagination!  ...
```

```
                                            overview runtime  \
0      Twenty-two years after the events of Jurassic ...     124
1      An apocalyptic story set in the furthest reach...     120
2      Beatrice Prior must confront her inner demons ...     119
3      Thirty years after defeating the Galactic Empi...     136
4      Deckard Shaw seeks revenge against Dominic Tor...     137
...                                                  ...     ...
10861  The Endless Summer, by Bruce Brown, is one of ...      95
10862  Grand Prix driver Pete Aron is fired by his te...     176
10863  An insurance agent who moonlights as a carthie...      94
10864  In comic Woody Allen's film debut, he took the...      80
10865  A family gets lost on the road and stumbles up...      74

                                      genres  \
0      Action|Adventure|Science Fiction|Thriller
1      Action|Adventure|Science Fiction|Thriller
2             Adventure|Science Fiction|Thriller
3       Action|Adventure|Science Fiction|Fantasy
4                          Action|Crime|Thriller
...                                          ...
10861                                Documentary
10862                     Action|Adventure|Drama
10863                             Mystery|Comedy
10864                              Action|Comedy
10865                                     Horror

                                  production_companies release_date  \
0      Universal Studios|Amblin Entertainment|Legenda...       6/9/15
1      Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15
2      Summit Entertainment|Mandeville Films|Red Wago...      3/18/15
3              Lucasfilm|Truenorth Productions|Bad Robot     12/15/15
4      Universal Pictures|Original Film|Media Rights ...       4/1/15
...                                                  ...          ...
10861                                  Bruce Brown Films      6/15/66
10862  Cherokee Productions|Joel Productions|Douglas ...     12/21/66
10863                                            Mosfilm       1/1/66
10864                           Benedict Pictures Corp.       11/2/66
10865                                          Norm-Iris     11/15/66

      vote_count  vote_average  release_year    budget_adj   revenue_adj
0           5562           6.5          2015  1.379999e+08  1.392446e+09
1           6185           7.1          2015  1.379999e+08  3.481613e+08
2           2480           6.3          2015  1.012000e+08  2.716190e+08
3           5292           7.5          2015  1.839999e+08  1.902723e+09
4           2947           7.3          2015  1.747999e+08  1.385749e+09
...          ...           ...           ...           ...           ...
10861         11           7.4          1966  0.000000e+00  0.000000e+00
```

```
10862          20            5.7           1966   0.000000e+00   0.000000e+00
10863          11            6.5           1966   0.000000e+00   0.000000e+00
10864          22            5.4           1966   0.000000e+00   0.000000e+00
10865          15            1.5           1966   1.276423e+05   0.000000e+00

[10866 rows x 21 columns]
```

1.1.2 Data Cleaning

there is some null data in some columns we do not need so we will remove them by .dropna function

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

```
Out[ ]: 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
```

since we do not need the imdb_id,cast,homepage,director,tagline,keywords,overview we will drop the columns since we do need the production_companies and genres we will drop the null rows only

```
In [ ]: df.dropna(subset=['genres'], inplace=True)
        df.dropna(subset=['production_companies'], inplace=True)
        df.isnull().sum()
        #droping the null rows
```

```
Out[ ]: id                         0
        imdb_id                    4
```

```
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      35
homepage                7169
director                  20
tagline                 2170
keywords                1125
overview                   1
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
```

In [ ]:
```
df.dropna(inplace=True, axis=1)
#droping the null columns
```

In [ ]:
```
# Split the 'genres' column by '|' and create a list of genres for each row
df['genres'] = df['genres'].astype(str).str.split('|')

# Explode the 'genres' column to create new rows for each genre
df = df.explode('genres', ignore_index=True)

# Now 'df' will have individual genres in separate rows
df
```

Out[ ]:
```
           id  popularity     budget     revenue          original_title  \
0      135397   32.985763  150000000  1513528810          Jurassic World
1      135397   32.985763  150000000  1513528810          Jurassic World
2      135397   32.985763  150000000  1513528810          Jurassic World
3      135397   32.985763  150000000  1513528810          Jurassic World
4       76341   28.419936  150000000   378436354      Mad Max: Fury Road
...       ...         ...        ...         ...                     ...
24757   39768    0.065141          0           0      Beregis Avtomobilya
24758   39768    0.065141          0           0      Beregis Avtomobilya
24759   21449    0.064317          0           0    What's Up, Tiger Lily?
24760   21449    0.064317          0           0    What's Up, Tiger Lily?
24761   22293    0.035919      19000           0  Manos: The Hands of Fate

       runtime          genres  \
0          124          Action
```

```
1          124        Adventure
2          124  Science Fiction
3          124         Thriller
4          120           Action
...        ...              ...
24757       94          Mystery
24758       94           Comedy
24759       80           Action
24760       80           Comedy
24761       74           Horror

                                   production_companies release_date  \
0      Universal Studios|Amblin Entertainment|Legenda...       6/9/15
1      Universal Studios|Amblin Entertainment|Legenda...       6/9/15
2      Universal Studios|Amblin Entertainment|Legenda...       6/9/15
3      Universal Studios|Amblin Entertainment|Legenda...       6/9/15
4      Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15
...                                                  ...          ...
24757                                           Mosfilm       1/1/66
24758                                           Mosfilm       1/1/66
24759                             Benedict Pictures Corp.      11/2/66
24760                             Benedict Pictures Corp.      11/2/66
24761                                         Norm-Iris     11/15/66

       vote_count  vote_average  release_year    budget_adj   revenue_adj
0            5562           6.5          2015  1.379999e+08  1.392446e+09
1            5562           6.5          2015  1.379999e+08  1.392446e+09
2            5562           6.5          2015  1.379999e+08  1.392446e+09
3            5562           6.5          2015  1.379999e+08  1.392446e+09
4            6185           7.1          2015  1.379999e+08  3.481613e+08
...           ...           ...           ...           ...           ...
24757          11           6.5          1966  0.000000e+00  0.000000e+00
24758          11           6.5          1966  0.000000e+00  0.000000e+00
24759          22           5.4          1966  0.000000e+00  0.000000e+00
24760          22           5.4          1966  0.000000e+00  0.000000e+00
24761          15           1.5          1966  1.276423e+05  0.000000e+00

[24762 rows x 14 columns]
```

In [ ]:
```python
# Split the 'production_companies' column by '|' and create a list of production_compani
df['production_companies'] = df['production_companies'].str.split('|')

# Explode the 'production_companies' column to create new rows for each production_compa
df = df.explode('production_companies', ignore_index=True)

# Now 'df' will have individual production_companies in separate rows
df
```

Out[ ]:
```
             id  popularity     budget     revenue          original_title  \
```

```
0      135397  32.985763  150000000  1513528810            Jurassic World
1      135397  32.985763  150000000  1513528810            Jurassic World
2      135397  32.985763  150000000  1513528810            Jurassic World
3      135397  32.985763  150000000  1513528810            Jurassic World
4      135397  32.985763  150000000  1513528810            Jurassic World
...       ...        ...        ...         ...                       ...
59101   39768   0.065141          0           0       Beregis Avtomobilya
59102   39768   0.065141          0           0       Beregis Avtomobilya
59103   21449   0.064317          0           0    What's Up, Tiger Lily?
59104   21449   0.064317          0           0    What's Up, Tiger Lily?
59105   22293   0.035919      19000           0  Manos: The Hands of Fate

       runtime   genres     production_companies release_date  vote_count  \
0          124   Action        Universal Studios       6/9/15        5562
1          124   Action     Amblin Entertainment       6/9/15        5562
2          124   Action        Legendary Pictures       6/9/15        5562
3          124   Action  Fuji Television Network       6/9/15        5562
4          124   Action                   Dentsu       6/9/15        5562
...        ...      ...                      ...          ...         ...
59101       94  Mystery                  Mosfilm       1/1/66          11
59102       94   Comedy                  Mosfilm       1/1/66          11
59103       80   Action  Benedict Pictures Corp.      11/2/66          22
59104       80   Comedy  Benedict Pictures Corp.      11/2/66          22
59105       74   Horror                Norm-Iris     11/15/66          15

       vote_average  release_year    budget_adj   revenue_adj
0               6.5          2015  1.379999e+08  1.392446e+09
1               6.5          2015  1.379999e+08  1.392446e+09
2               6.5          2015  1.379999e+08  1.392446e+09
3               6.5          2015  1.379999e+08  1.392446e+09
4               6.5          2015  1.379999e+08  1.392446e+09
...             ...           ...           ...           ...
59101           6.5          1966  0.000000e+00  0.000000e+00
59102           6.5          1966  0.000000e+00  0.000000e+00
59103           5.4          1966  0.000000e+00  0.000000e+00
59104           5.4          1966  0.000000e+00  0.000000e+00
59105           1.5          1966  1.276423e+05  0.000000e+00

[59106 rows x 14 columns]
```

In [ ]:
```
df.shape
df.describe()
df.info()
#getting information about the dataframe after the cleaning
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59106 entries, 0 to 59105
Data columns (total 14 columns):
```

```
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    59106 non-null  int64
 1   popularity            59106 non-null  float64
 2   budget                59106 non-null  int64
 3   revenue               59106 non-null  int64
 4   original_title        59106 non-null  object
 5   runtime               59106 non-null  int64
 6   genres                59106 non-null  object
 7   production_companies  59106 non-null  object
 8   release_date          59106 non-null  object
 9   vote_count            59106 non-null  int64
 10  vote_average          59106 non-null  float64
 11  release_year          59106 non-null  int64
 12  budget_adj            59106 non-null  float64
 13  revenue_adj           59106 non-null  float64
dtypes: float64(4), int64(6), object(4)
memory usage: 6.3+ MB
```

Exploratory Data Analysis here we will start looking for answers to our questions and visualize our findings

1.1.3 Research Question 1

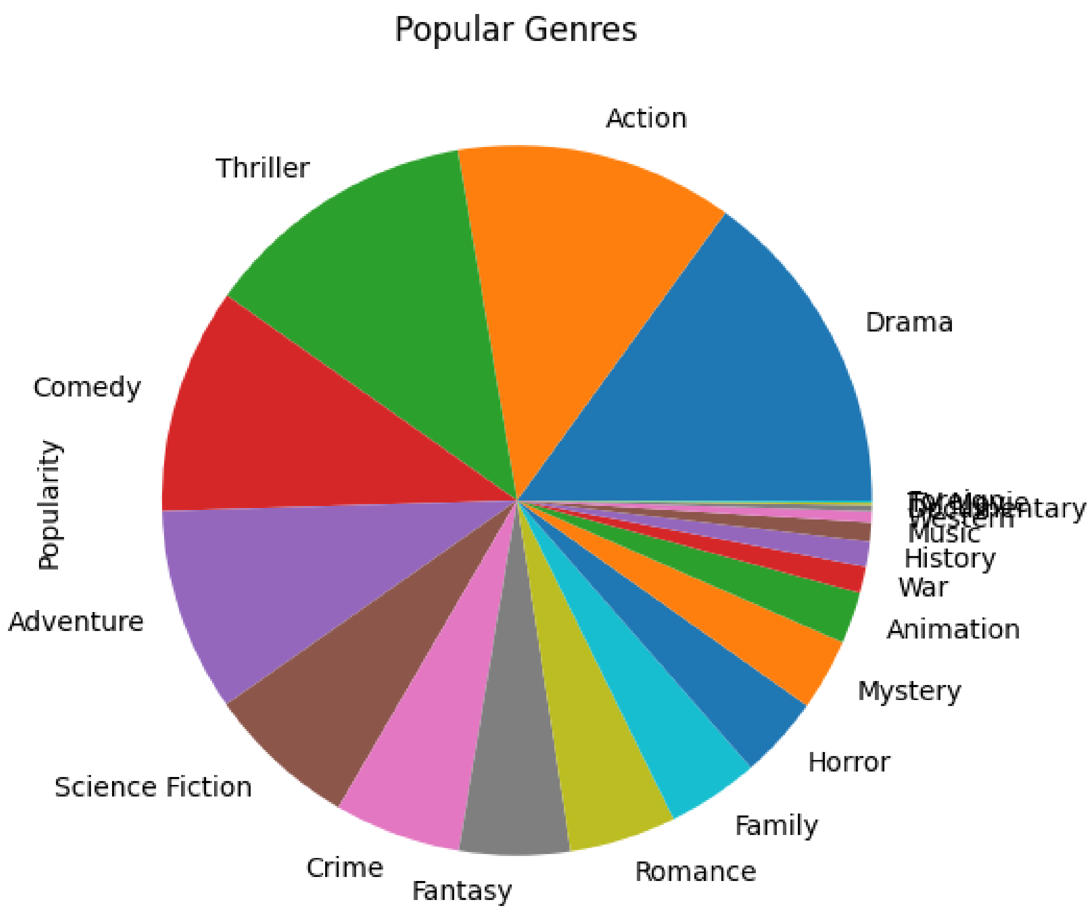
which genres are the most popular ?

```
In [ ]: df_genre_popularity = df.groupby("genres")["popularity"].sum().sort_values(ascending=Fal
        df_genre_popularity.head(10)
```

```
Out[ ]: genres
        Drama              7814.842026
        Action             6572.372664
        Thriller           6525.689730
        Comedy             5341.906805
        Adventure          4810.922986
        Science Fiction    3576.980895
        Crime              2998.036809
        Fantasy            2619.511075
        Romance            2523.121314
        Family             2169.184101
        Name: popularity, dtype: float64
```

```
In [ ]: df_genre_popularity.plot(kind='pie', figsize=(10, 6), xlabel='genres'.title(), ylabel='p
```

```
Out[ ]: <Axes: title={'center': 'Popular Genres'}, ylabel='Popularity'>
```



1.1.4 Research answer 1

drama is the most popular genre

1.1.5 Research Question 2 (which genres have highest budget per movie ?)

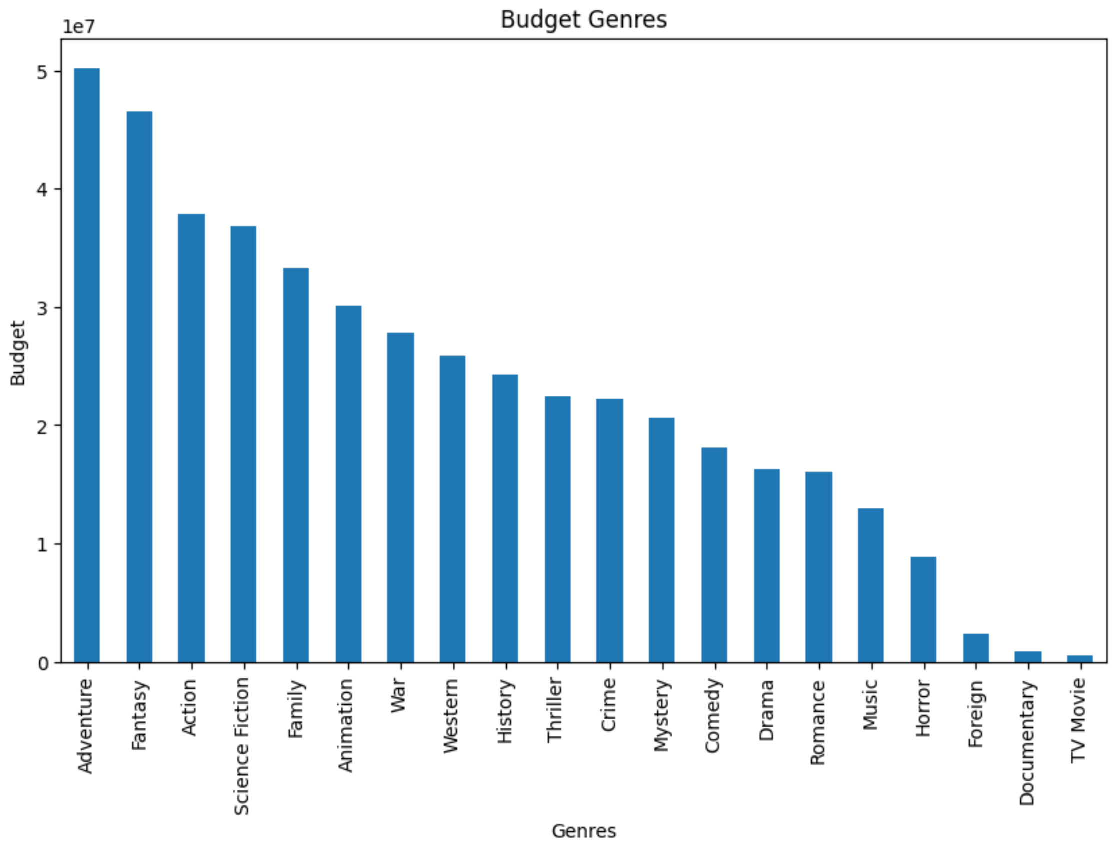
```
In [ ]: df_genre_budget = df.groupby("genres")["budget"].mean().sort_values(ascending=False)
        df_genre_budget.head(10)
```

```
Out[ ]: genres
        Adventure          5.021855e+07
        Fantasy            4.655165e+07
        Action             3.787147e+07
        Science Fiction    3.685623e+07
        Family             3.332051e+07
        Animation          3.011515e+07
        War                2.777379e+07
        Western            2.581750e+07
```

```
History            2.425800e+07
Thriller           2.247848e+07
Name: budget, dtype: float64
```

In [ ]:
```
df_genre_budget.plot(kind='bar', figsize=(10, 6), xlabel='genres'.title(), ylabel='budge
```

Out[ ]:
```
<Axes: title={'center': 'Budget Genres'}, xlabel='Genres', ylabel='Budget'>
```



1.1.6 Research answer 2

Adventure movies have the highest budget per movie

1.1.7 Research Question 3 (which genres have highest revenue per movie ?)

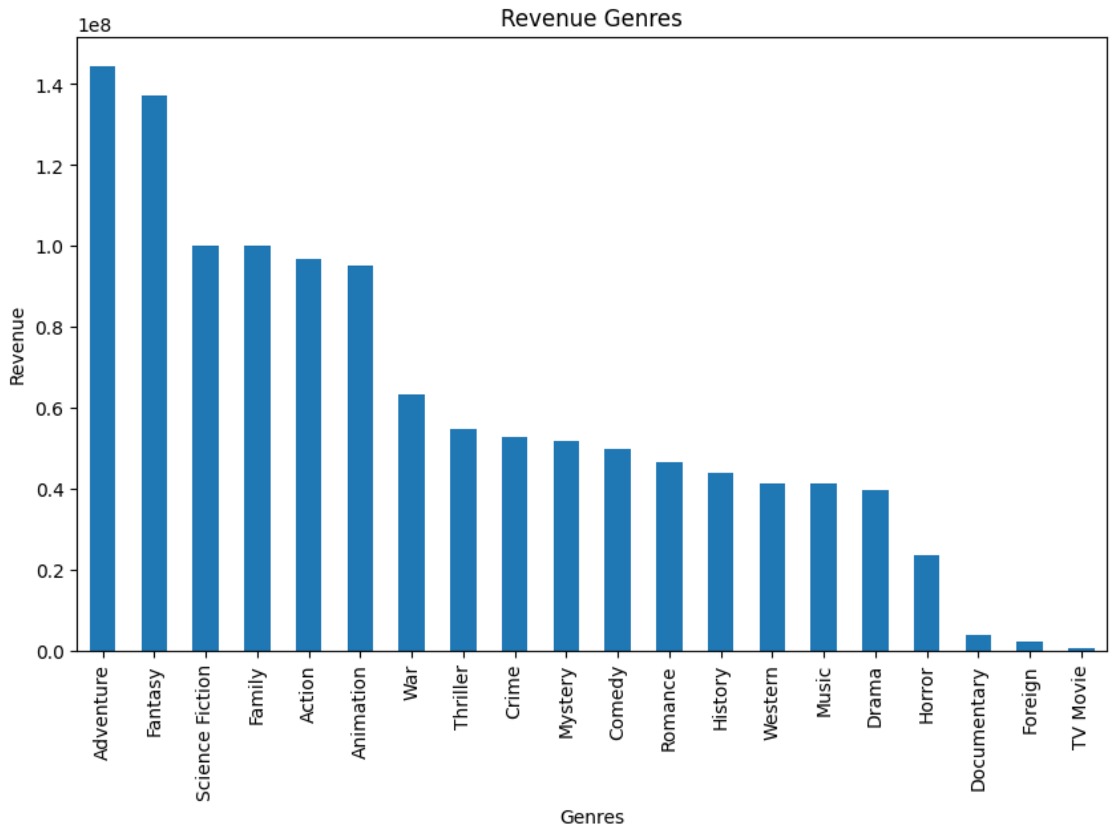
In [ ]:
```
df_genre_revenue = df.groupby("genres")["revenue"].mean().sort_values(ascending=False)
df_genre_revenue.head(10)
```

Out[ ]:
```
genres
Adventure          1.445267e+08
Fantasy            1.370131e+08
Science Fiction    1.002094e+08
```

```
Family            1.000402e+08
Action            9.680103e+07
Animation         9.505797e+07
War               6.340809e+07
Thriller          5.461271e+07
Crime             5.263668e+07
Mystery           5.163316e+07
Name: revenue, dtype: float64
```

```
In [ ]: df_genre_revenue.plot(kind='bar', figsize=(10, 6), xlabel='genres'.title(), ylabel='reve
```

```
Out[ ]: <Axes: title={'center': 'Revenue Genres'}, xlabel='Genres', ylabel='Revenue'>
```



1.1.8 Research answer 3

Adventure movies have the highest revenue per movie

1.1.9 Research Question 4

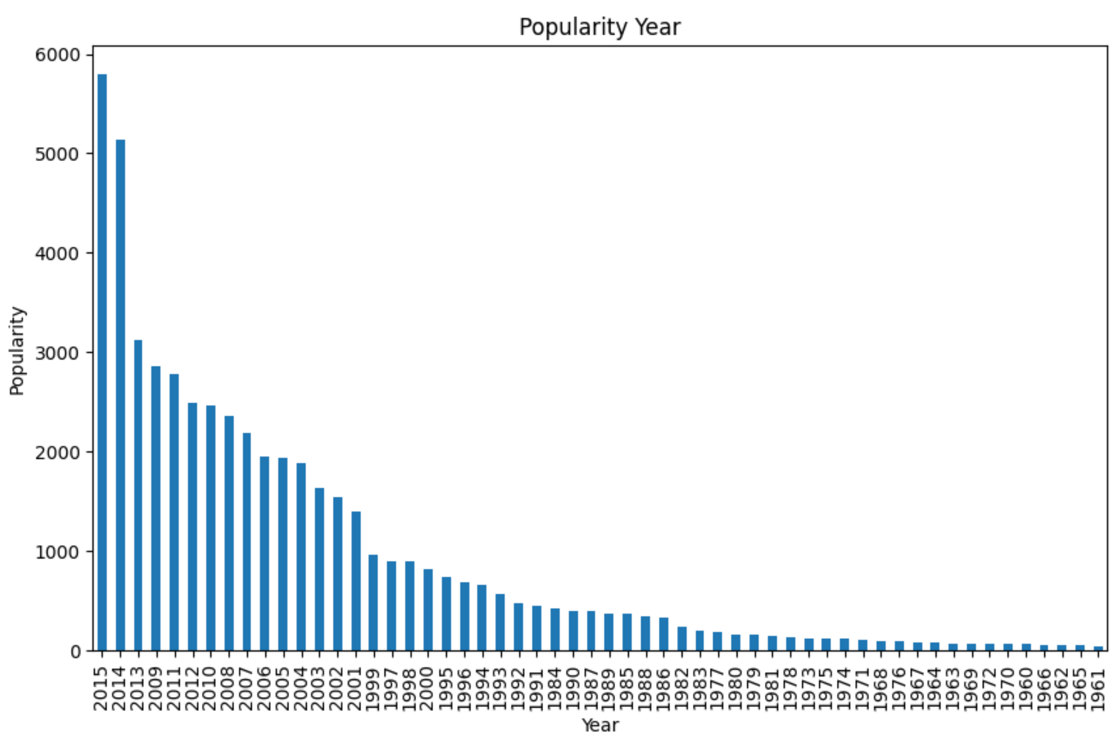
which years have the most popular movies ?

```
In [ ]: df_popularity_year = df.groupby("release_year")["popularity"].sum().sort_values(ascendin
        df_popularity_year.head(10)
```

```
Out[ ]: release_year
        2015    5793.022445
        2014    5140.525794
        2013    3122.444155
        2009    2857.544036
        2011    2780.155537
        2012    2493.082382
        2010    2463.081794
        2008    2353.623409
        2007    2191.089700
        2006    1957.926434
        Name: popularity, dtype: float64
```

```
In [ ]: df_popularity_year.plot(kind='bar', figsize=(10, 6), xlabel='year'.title(), ylabel='popu
```

```
Out[ ]: <Axes: title={'center': 'Popularity Year'}, xlabel='Year', ylabel='Popularity'>
```



1.1.10 Research answer 4

2015 movies are the most popular

1.1.11 Research Question 5

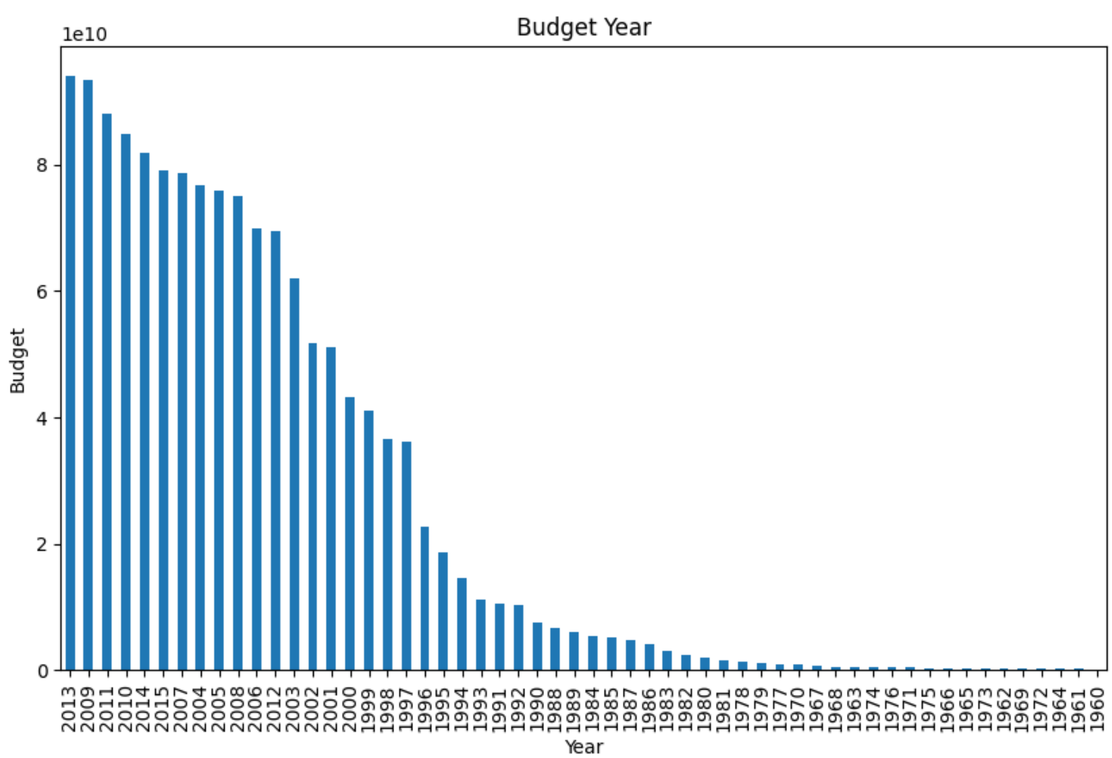
which year did producers spend the most on the industry?

In [ ]:
```
df_budget_year = df.groupby("release_year")["budget"].sum().sort_values(ascending=False)
df_budget_year.head(10)
```

Out[ ]:
```
release_year
2013    93988237332
2009    93465491843
2011    87982276769
2010    84933481817
2014    81908299473
2015    78992210351
2007    78632622880
2004    76689052360
2005    75811162162
2008    74961750224
Name: budget, dtype: int64
```

In [ ]:
```
df_budget_year.plot(kind='bar', figsize=(10, 6), xlabel='year'.title(), ylabel='budget'.
```

Out[ ]:
```
<Axes: title={'center': 'Budget Year'}, xlabel='Year', ylabel='Budget'>
```



1.1.12 Research answer 5

2013 movies have the highest budget

1.1.13 Research Question 6

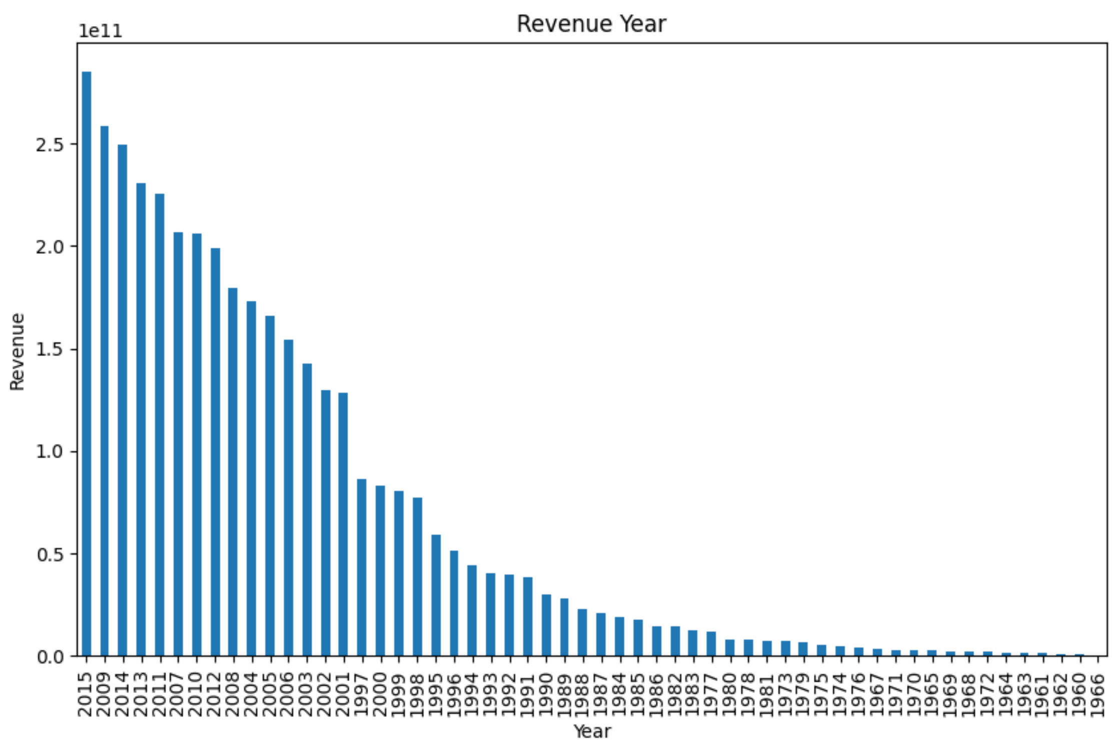
which year did producers got the highest revenue?

```
In [ ]: df_revenue_year = df.groupby("release_year")["revenue"].sum().sort_values(ascending=Fals
        df_revenue_year.head(10)
```

```
Out[ ]: release_year
        2015    284999455620
        2009    258562769207
        2014    249613696849
        2013    230477302486
        2011    225450339042
        2007    206858050627
        2010    206267555113
        2012    198882231945
        2008    179438478334
        2004    173124776931
        Name: revenue, dtype: int64
```

```
In [ ]: df_revenue_year.plot(kind='bar', figsize=(10, 6), xlabel='year'.title(), ylabel='revenue
```

```
Out[ ]: <Axes: title={'center': 'Revenue Year'}, xlabel='Year', ylabel='Revenue'>
```



1.1.14 Research answer 6

2015 movies have the highest revenue

1.1.15 Research Question 7

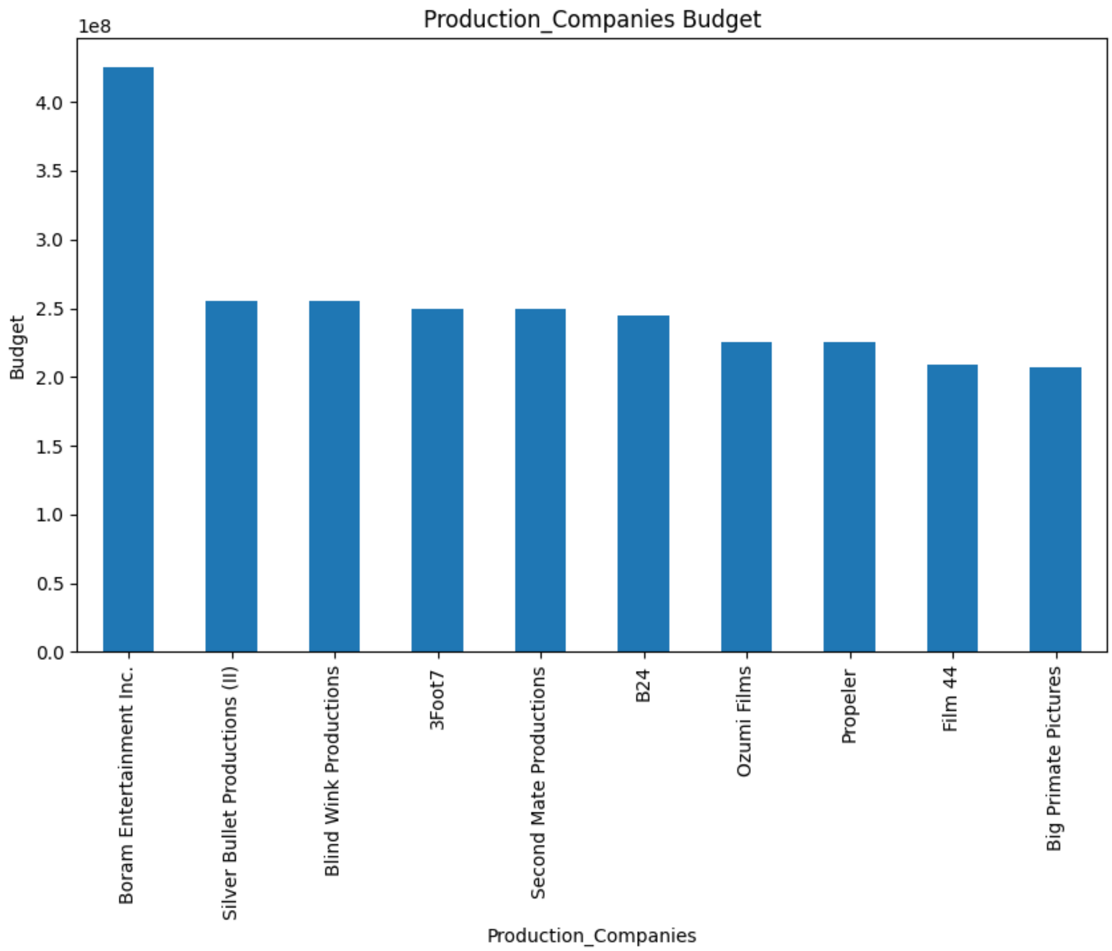
which production companies have the highest budgets per movie ?

```
In [ ]: df_production_companies_budget = df.groupby("production_companies")["budget"].mean().sor
        df_production_companies_budget.head(10)
```

```
Out[ ]: production_companies
        Boram Entertainment Inc.          425000000.0
        Silver Bullet Productions (II)    255000000.0
        Blind Wink Productions            255000000.0
        3Foot7                            250000000.0
        Second Mate Productions           250000000.0
        B24                               245000000.0
        Ozumi Films                       225000000.0
        Propeler                          225000000.0
        Film 44                           209000000.0
        Big Primate Pictures              207000000.0
        Name: budget, dtype: float64
```

```
In [ ]: df_production_companies_budget.head(10).plot(kind='bar', figsize=(10, 6), xlabel='produc
```

```
Out[ ]: <Axes: title={'center': 'Production_Companies Budget'}, xlabel='Production_Companies', y
```



1.1.16 Research answer 7

Boram Entertainment Inc. have the highest budget per movie

1.1.17 Research Question 8

which production companies have the highest revenue per movie ?

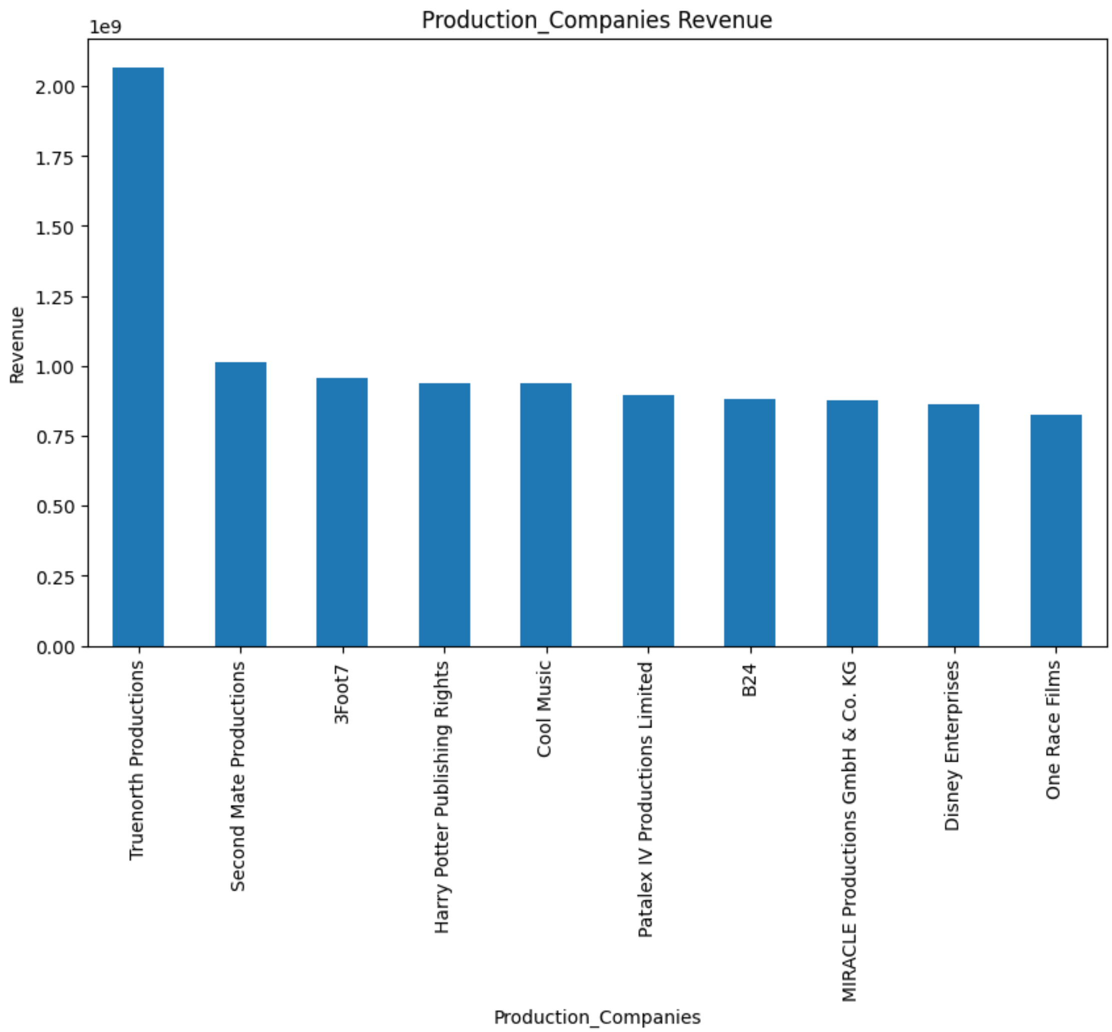
```
In [ ]: df_production_companies_revenue = df.groupby("production_companies")["revenue"].mean().s
        df_production_companies_revenue.head(10)
```

```
Out[ ]: production_companies
        Truenorth Productions              2.068178e+09
        Second Mate Productions            1.013330e+09
        3Foot7                             9.551198e+08
        Harry Potter Publishing Rights     9.382127e+08
        Cool Music                         9.382127e+08
        Patalex IV Productions Limited     8.959210e+08
```

```
B24                                      8.806746e+08
MIRACLE Productions GmbH & Co. KG        8.766885e+08
Disney Enterprises                       8.646260e+08
One Race Films                           8.233230e+08
Name: revenue, dtype: float64
```

In [ ]:
```
df_production_companies_revenue.head(10).plot(kind='bar', figsize=(10, 6), xlabel='produ
```

Out[ ]:
```
<Axes: title={'center': 'Production_Companies Revenue'}, xlabel='Production_Companies',
```



1.1.18 Research answer 8

Truenorth Productions have the highest revenue per movie

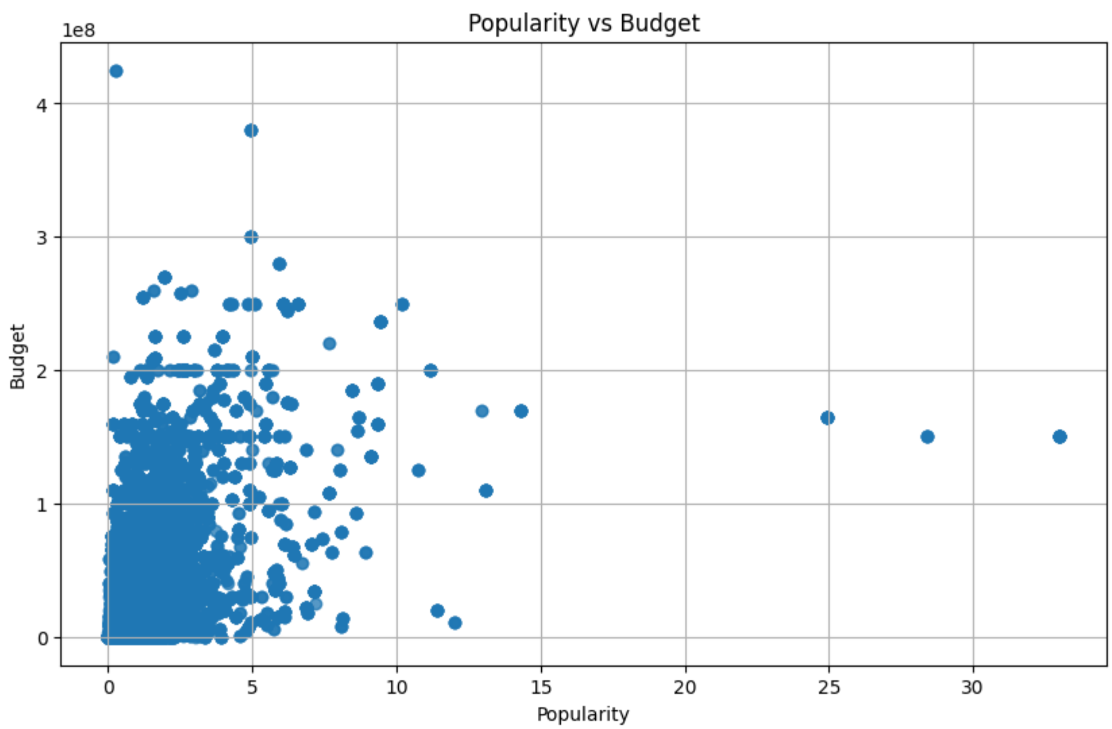
1.1.19 Research Question 9

do movies with the highest popularity have the highest budget ?

In [ ]:
```
df_popularity_budget = df.groupby("popularity")["budget"].mean().sort_values(ascending=F
df_popularity_budget.head(10)
```

Out[ ]:
```
popularity
0.250540    425000000.0
4.955130    380000000.0
4.965391    300000000.0
5.944927    280000000.0
1.957331    270000000.0
1.588457    260000000.0
2.865684    260000000.0
2.520912    258000000.0
1.214510    255000000.0
5.076472    250000000.0
Name: budget, dtype: float64
```

In [ ]:
```
plt.figure(figsize=(10, 6))
plt.scatter(df['popularity'], df['budget'], alpha=0.5)
plt.title('Popularity vs Budget')
plt.xlabel('Popularity')
plt.ylabel('Budget')
plt.grid(True)
plt.show()
```



1.1.20 Research answer 9

No Clear Correlation: The scatter plot shows a dispersed distribution of points, suggesting there isn't a strong linear correlation between popularity and budget. Some High-Budget, High-Popularity Movies: While there's no clear overall correlation, there are some movies with high popularity that also have a high budget. These appear as points in the upper-right quadrant of the scatter plot. Many Low-Budget, High-Popularity Movies: There are many movies with high popularity that have a relatively low budget, indicated by points in the upper-left quadrant of the scatter plot.

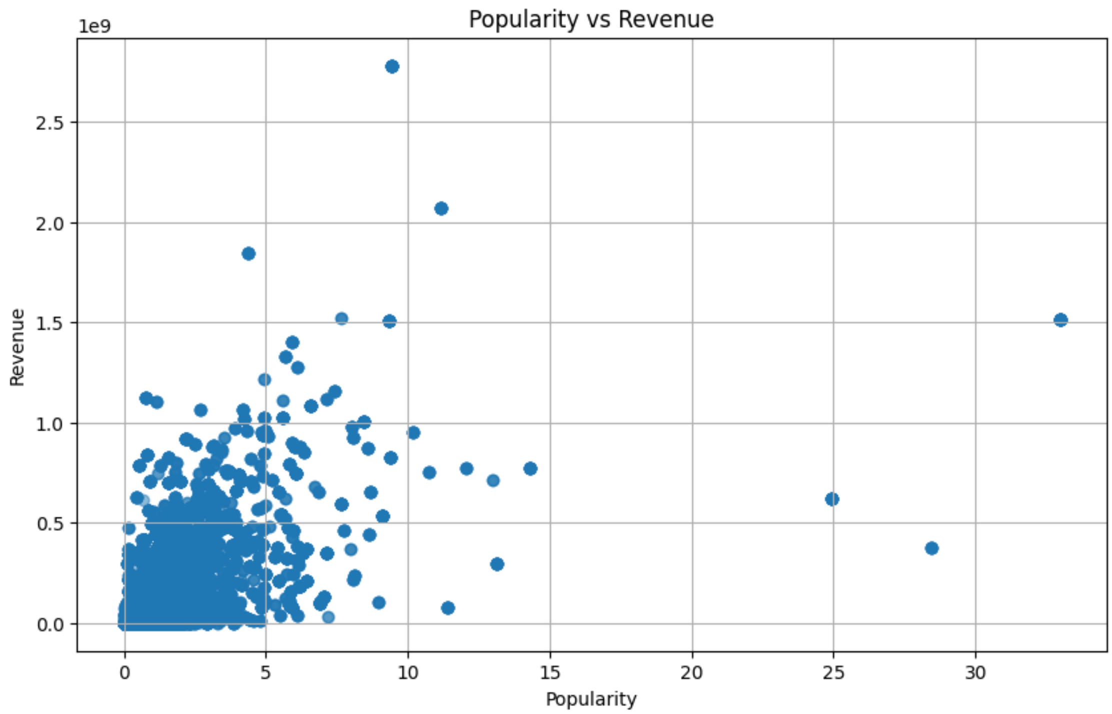
1.1.21 Research Question 10

do movies with the highest popularity have the highest revenue ?

```
In [ ]: df_popularity_revenue = df.groupby("popularity")["revenue"].mean().sort_values(ascending
        df_popularity_revenue.head(10)
```

```
Out[ ]: popularity
        9.432768     2.781506e+09
        11.173104    2.068178e+09
        4.355219     1.845034e+09
        7.637767     1.519558e+09
        32.985763    1.513529e+09
        9.335014     1.506249e+09
        5.944927     1.405036e+09
        5.711315     1.327818e+09
        6.112766     1.274219e+09
        4.946136     1.215440e+09
        Name: revenue, dtype: float64
```

```
In [ ]: plt.figure(figsize=(10, 6))
        plt.scatter(df['popularity'], df['revenue'], alpha=0.5)
        plt.title('Popularity vs Revenue')
        plt.xlabel('Popularity')
        plt.ylabel('Revenue')
        plt.grid(True)
        plt.show()
```



1.1.22 Research answer 10

there is positive correlation between revenue and popularity but there is some out layers

1.1.23 Research Question 11

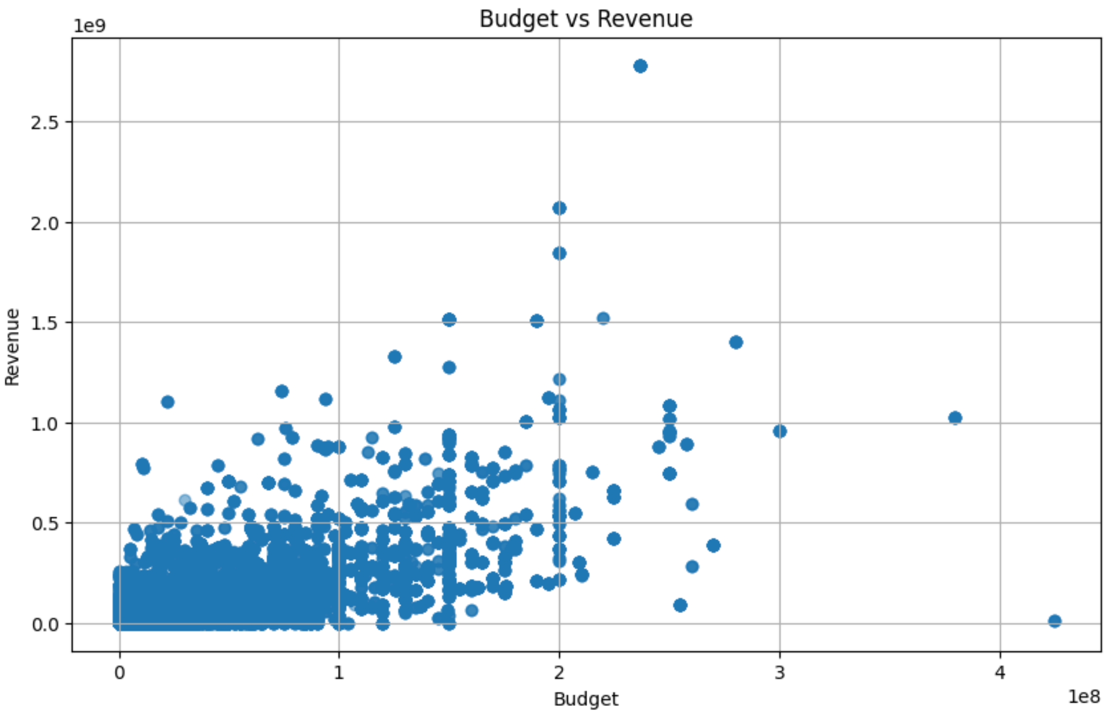
do movies with the highest budget have the highest revenue ?

```
In [ ]: df_budget_revenue = df.groupby("budget")["revenue"].sum().sort_values(ascending=False)
        df_budget_revenue.head(10)
```

```
Out[ ]: budget
        150000000    248128906532
        200000000    150071307707
        100000000    118913338914
        60000000     115088156383
        40000000     113640953341
        50000000     104617314644
        70000000     104164184364
        0            100495277688
        80000000      95493968599
        130000000     90733466321
        Name: revenue, dtype: int64
```

In [ ]:

```
plt.figure(figsize=(10, 6))
plt.scatter(df['budget'], df['revenue'], alpha=0.5)
plt.title('Budget vs Revenue')
plt.xlabel('Budget')
plt.ylabel('Revenue')
plt.grid(True)
plt.show()
```



1.1.24 Research answer 11

there is positive correlation between revenue and budget but there is some out layers
Conclusions This project analyzed tmdb movies data The analysis revealed that:

```
<li>drama is the most popular genre
<li>Adventure movies have the highest budget per movie and the highest revenue per movie
<li>2015 movies are the most popular and have the highest revenue
<li>2013 movies have the highest budget
<li>Boram Entertainment Inc. have the highest budget per movie
<li>Truenorth Productions have the highest revenue per movie
<li>No Clear Correlation between popularity and budget
<li>there is positive correlation between revenue and popularity but there is some out layers
<li>there is positive correlation between revenue and budget but there is some out layers
```

1.2 Limitations

The dataset initially contained null values in several columns. Although rows with null values in crucial columns like 'genres' and 'production_companies' were removed, the remaining dataset may have missing data in other columns. This could impact the analysis, potentially leading to biased or incomplete results.

This dataset focuses on movies and their associated information like revenue, budget, and popularity. But there could be other important factors for a comprehensive analysis that are not included, such as:

Critical Acclaim: Information on movie reviews, awards or ratings from critics are not present. This could affect understanding the relationship between critical acclaim and commercial success.

Audience Reception: Detailed data on audience reviews, social media sentiment, or viewership statistics is not included, limiting the depth of audience analysis.

Marketing and Distribution: Details about the marketing strategies and distribution channels used for movies are missing, preventing investigation into these aspects.