Comprehensive Movie Dataset Analysis

Introduction

This project presents a detailed analysis of a movie dataset using Python and various data analysis libraries. The project demonstrates advanced skills in data cleaning, manipulation, analysis, grouping, and visualization techniques. By examining multiple aspects of the film industry, this analysis provides valuable insights into movie trends, profitability, and audience preferences.

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Data Preprocessing

Data Import and Initial Exploration

1. Imported essential libraries:
   - pandas (as pd): For data manipulation and analysis
   - matplotlib.pyplot (as plt): For creating static visualizations
   - numpy (as np): For numerical operations
   - plotly.express (as px): For interactive visualizations

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import plotly.express as px
```

2. Loaded the dataset:

```
df = pd.read_csv('downloads/movies.csv')
df.head(5)

       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

                 original_title  \
0                Jurassic World
1            Mad Max: Fury Road
2                     Insurgent
3  Star Wars: The Force Awakens
4                     Furious 7

                                                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 ...

                                            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


                         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  ...

                                            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

                                      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

                                production_companies release_date
vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15
5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15
6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15
2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15
5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15
2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09

[5 rows x 21 columns]
```

3. Explored the dataset structure:

- Used `df.shape` to determine the number of rows and columns
- Utilized `df.columns` to list all column names

```
df.shape
```

```
(10866, 21)
```

```
df.columns
```

```
Index(['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'],
      dtype='object')
```

4. Checked for null values to identify columns requiring cleaning

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

```
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

1. Dropped unnecessary columns to focus on relevant data:

```
df.drop(columns=['id', 'imdb_id', 'homepage', 'cast', 'tagline',
'overview', 'budget_adj'], inplace=True)
```

```
df.head()
```

```
   popularity     budget     revenue                original_title  \
0   32.985763  150000000  1513528810                Jurassic World
1   28.419936  150000000   378436354            Mad Max: Fury Road
2   13.112507  110000000   295238201                     Insurgent
3   11.173104  200000000  2068178225  Star Wars: The Force Awakens
4    9.335014  190000000  1506249360                     Furious 7

           director                                           keywords
\
0   Colin Trevorrow  monster|dna|tyrannosaurus rex|velociraptor|island

1     George Miller   future|chase|post-apocalyptic|dystopia|australia

2  Robert Schwentke  based on novel|revolution|dystopia|sequel|dyst...

3       J.J. Abrams            android|spaceship|jedi|space opera|3d

4         James Wan              car race|speed|revenge|suspense|car


   runtime                                      genres  \
0      124  Action|Adventure|Science Fiction|Thriller
1      120  Action|Adventure|Science Fiction|Thriller
2      119         Adventure|Science Fiction|Thriller
3      136   Action|Adventure|Science Fiction|Fantasy
4      137                      Action|Crime|Thriller

                                production_companies release_date
vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15
5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15
6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15
2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15
5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15
2947

   vote_average  release_year   revenue_adj
0           6.5          2015  1.392446e+09
1           7.1          2015  3.481613e+08
2           6.3          2015  2.716190e+08
3           7.5          2015  1.902723e+09
4           7.3          2015  1.385749e+09
```

2. Handled null values:

Rows with missing values in these crucial columns were removed to ensure data integrity.

Filled null values with zero, assuming absence of data in these fields doesn't necessarily invalidate the entry.

```
df.dropna(how = 'any', subset = {'genres', 'director'}, inplace =
True)
df['production_companies'] = df ['production_companies'].fillna(0)
df['keywords'] = df ['keywords'].fillna(0)

df.isnull().sum()

popularity                 0
budget                     0
revenue                    0
profit                     0
roi                     5636
original_title             0
director                   0
keywords                   0
runtime                    0
genres                     0
production_companies       0
release_date               0
vote_count                 0
vote_average               0
release_year               0
revenue_adj                0
dtype: int64
```

3. Rounded 'popularity' column:

This improved readability and simplified subsequent analyses.

```
df['popularity'] = df['popularity'].round(2)

df.

       popularity     budget     revenue                original_title
\
0           32.99  150000000  1513528810                Jurassic World

1           28.42  150000000   378436354            Mad Max: Fury Road

2           13.11  110000000   295238201                     Insurgent

3           11.17  200000000  2068178225  Star Wars: The Force Awakens

4            9.34  190000000  1506249360                     Furious 7

...           ...        ...         ...                           ...

10861        0.08          0           0            The Endless Summer
```

```
10862        0.07          0           0                     Grand Prix

10863        0.07          0           0            Beregis Avtomobilya

10864        0.06          0           0         What's Up, Tiger Lily?

10865        0.04      19000           0      Manos: The Hands of Fate


                 director
keywords  \
0        Colin Trevorrow  monster|dna|tyrannosaurus rex|velociraptor|
island
1          George Miller   future|chase|post-apocalyptic|dystopia|
australia
2       Robert Schwentke  based on novel|revolution|dystopia|sequel|
dyst...
3            J.J. Abrams              android|spaceship|jedi|space
opera|3d
4              James Wan                car race|speed|revenge|
suspense|car
...                  ...
...
10861        Bruce Brown                              surfer|surfboard|
surfing
10862  John Frankenheimer                           car race|racing|
formula 1
10863      Eldar Ryazanov                              car|trolley|
stealing car
10864        Woody Allen
spoof
10865    Harold P. Warren                fire|gun|drive|sacrifice|
flashlight

       runtime                                       genres  \
0          124  Action|Adventure|Science Fiction|Thriller
1          120  Action|Adventure|Science Fiction|Thriller
2          119         Adventure|Science Fiction|Thriller
3          136   Action|Adventure|Science Fiction|Fantasy
4          137                        Action|Crime|Thriller
...        ...                                        ...
10861       95                                Documentary
10862      176                     Action|Adventure|Drama
10863       94                              Mystery|Comedy
10864       80                               Action|Comedy
10865       74                                     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   revenue_adj
0            5562           6.5          2015  1.392446e+09
1            6185           7.1          2015  3.481613e+08
2            2480           6.3          2015  2.716190e+08
3            5292           7.5          2015  1.902723e+09
4            2947           7.3          2015  1.385749e+09
...           ...           ...           ...           ...
10861          11           7.4          1966  0.000000e+00
10862          20           5.7          1966  0.000000e+00
10863          11           6.5          1966  0.000000e+00
10864          22           5.4          1966  0.000000e+00
10865          15           1.5          1966  0.000000e+00

[10801 rows x 14 columns]
```

4. Created new columns for financial analysis:

These derived columns enable deeper insights into movie financial performance. Let's break down the importance and implications of each:

a) Profit Column:

```
  - Calculation: `profit = revenue - budget`
  - Purpose: This column provides a clear measure of a movie's
financial success.

df.insert(3, 'profit', df.revenue - df.budget)
```

```
df

       popularity     budget     revenue      profit   roi  \
0           32.99  150000000  1513528810  1363528810  9.09
0           32.99  150000000  1513528810  1363528810  9.09
0           32.99  150000000  1513528810  1363528810  9.09
0           32.99  150000000  1513528810  1363528810  9.09
1           28.42  150000000   378436354   228436354  1.52
...           ...        ...         ...         ...   ...
10863        0.07          0           0           0   NaN
10863        0.07          0           0           0   NaN
10864        0.06          0           0           0   NaN
10864        0.06          0           0           0   NaN
10865        0.04      19000           0      -19000 -1.00

                 original_title         director  \
0                Jurassic World   Colin Trevorrow
0                Jurassic World   Colin Trevorrow
0                Jurassic World   Colin Trevorrow
0                Jurassic World   Colin Trevorrow
1            Mad Max: Fury Road     George Miller
...                         ...               ...
10863       Beregis Avtomobilya    Eldar Ryazanov
10863       Beregis Avtomobilya    Eldar Ryazanov
10864    What's Up, Tiger Lily?       Woody Allen
10864    What's Up, Tiger Lily?       Woody Allen
10865  Manos: The Hands of Fate  Harold P. Warren

                                                 keywords  runtime  \
0      monster|dna|tyrannosaurus rex|velociraptor|island      124
0      monster|dna|tyrannosaurus rex|velociraptor|island      124
0      monster|dna|tyrannosaurus rex|velociraptor|island      124
0      monster|dna|tyrannosaurus rex|velociraptor|island      124
1       future|chase|post-apocalyptic|dystopia|australia      120
...                                                  ...      ...
10863                             car|trolley|stealing car       94
10863                             car|trolley|stealing car       94
10864                                                spoof       80
10864                                                spoof       80
10865                 fire|gun|drive|sacrifice|flashlight       74

                genres
production_companies  \
0               Action  Universal Studios|Amblin Entertainment|
Legenda...
0            Adventure  Universal Studios|Amblin Entertainment|
Legenda...
0      Science Fiction  Universal Studios|Amblin Entertainment|
Legenda...
0             Thriller  Universal Studios|Amblin Entertainment|
```

```
Legenda...
1                Action  Village Roadshow Pictures|Kennedy Miller
Produ...
...                 ...
...
10863           Mystery
Mosfilm
10863            Comedy
Mosfilm
10864            Action                            Benedict Pictures
Corp.
10864            Comedy                            Benedict Pictures
Corp.
10865            Horror                                          Norm-
Iris

      release_date  vote_count  vote_average  release_year
revenue_adj  \
0       2015-06-09        5562           6.5          2015
1.392446e+09
0       2015-06-09        5562           6.5          2015
1.392446e+09
0       2015-06-09        5562           6.5          2015
1.392446e+09
0       2015-06-09        5562           6.5          2015
1.392446e+09
1       2015-05-13        6185           7.1          2015
3.481613e+08
...            ...         ...           ...           ...            .
..
10863   2066-01-01          11           6.5          1966
0.000000e+00
10863   2066-01-01          11           6.5          1966
0.000000e+00
10864   2066-11-02          22           5.4          1966
0.000000e+00
10864   2066-11-02          22           5.4          1966
0.000000e+00
10865   2066-11-15          15           1.5          1966
0.000000e+00

       extracted_month
0                    6
0                    6
0                    6
0                    6
1                    5
...                ...
10863                1
```

```
10863                    1
10864                   11
10864                   11
10865                   11

[26864 rows x 17 columns]
```

b) Return on Investment (ROI) Column:

- Calculation: `roi = profit / budget`
- Purpose: This metric shows the efficiency of the investment in each movie.

```
df['roi'] = df['profit'] / df['budget']

df['roi'] = df['roi'].round(2)

df

       popularity     budget     revenue     profit        roi  \
0           32.99  150000000  1513528810  1363528810  9.090192
1           28.42  150000000   378436354   228436354  1.522909
2           13.11  110000000   295238201   185238201  1.683984
3           11.17  200000000  2068178225  1868178225  9.340891
4            9.34  190000000  1506249360  1316249360  6.927628
...           ...        ...         ...         ...       ...
10861        0.08          0           0           0       NaN
10862        0.07          0           0           0       NaN
10863        0.07          0           0           0       NaN
10864        0.06          0           0           0       NaN
10865        0.04      19000           0      -19000 -1.000000

                    original_title           director  \
0                   Jurassic World     Colin Trevorrow
1               Mad Max: Fury Road      George Miller
2                        Insurgent   Robert Schwentke
3      Star Wars: The Force Awakens         J.J. Abrams
4                        Furious 7           James Wan
...                            ...                 ...
10861            The Endless Summer         Bruce Brown
10862                  Grand Prix   John Frankenheimer
10863           Beregis Avtomobilya      Eldar Ryazanov
10864         What's Up, Tiger Lily?        Woody Allen
10865      Manos: The Hands of Fate    Harold P. Warren

                                                keywords  runtime  \
0      monster|dna|tyrannosaurus rex|velociraptor|island      124
1       future|chase|post-apocalyptic|dystopia|australia      120
2      based on novel|revolution|dystopia|sequel|dyst...      119
3                    android|spaceship|jedi|space opera|3d     136
4                      car race|speed|revenge|suspense|car     137
...                                                    ...      ...
```

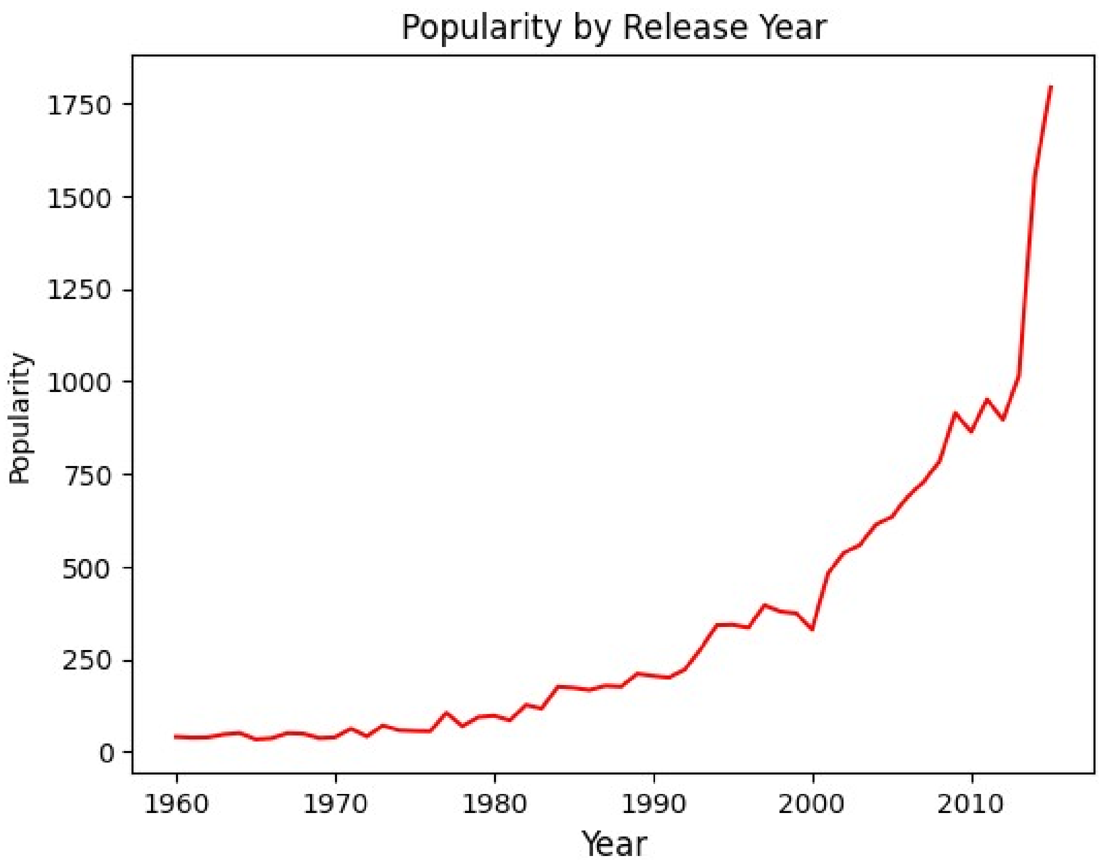
```
10861                          surfer|surfboard|surfing       95
10862                         car race|racing|formula 1      176
10863                          car|trolley|stealing car       94
10864                                             spoof       80
10865               fire|gun|drive|sacrifice|flashlight       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   revenue_adj
0            5562           6.5          2015  1.392446e+09
1            6185           7.1          2015  3.481613e+08
2            2480           6.3          2015  2.716190e+08
3            5292           7.5          2015  1.902723e+09
4            2947           7.3          2015  1.385749e+09
...           ...           ...           ...           ...
```

```
10861          11          7.4          1966  0.000000e+00
10862          20          5.7          1966  0.000000e+00
10863          11          6.5          1966  0.000000e+00
10864          22          5.4          1966  0.000000e+00
10865          15          1.5          1966  0.000000e+00

[10801 rows x 16 columns]
```

Data Analysis and Visualization

1. Popularity Over Time

```
df3 = df.groupby('release_year')['popularity'].sum()
df3.plot(kind = 'line', color = 'red')
plt.xlabel('Year', fontsize = 12)
plt.ylabel('Popularity')
plt.title('Popularity by Release Year')
plt.show()
```

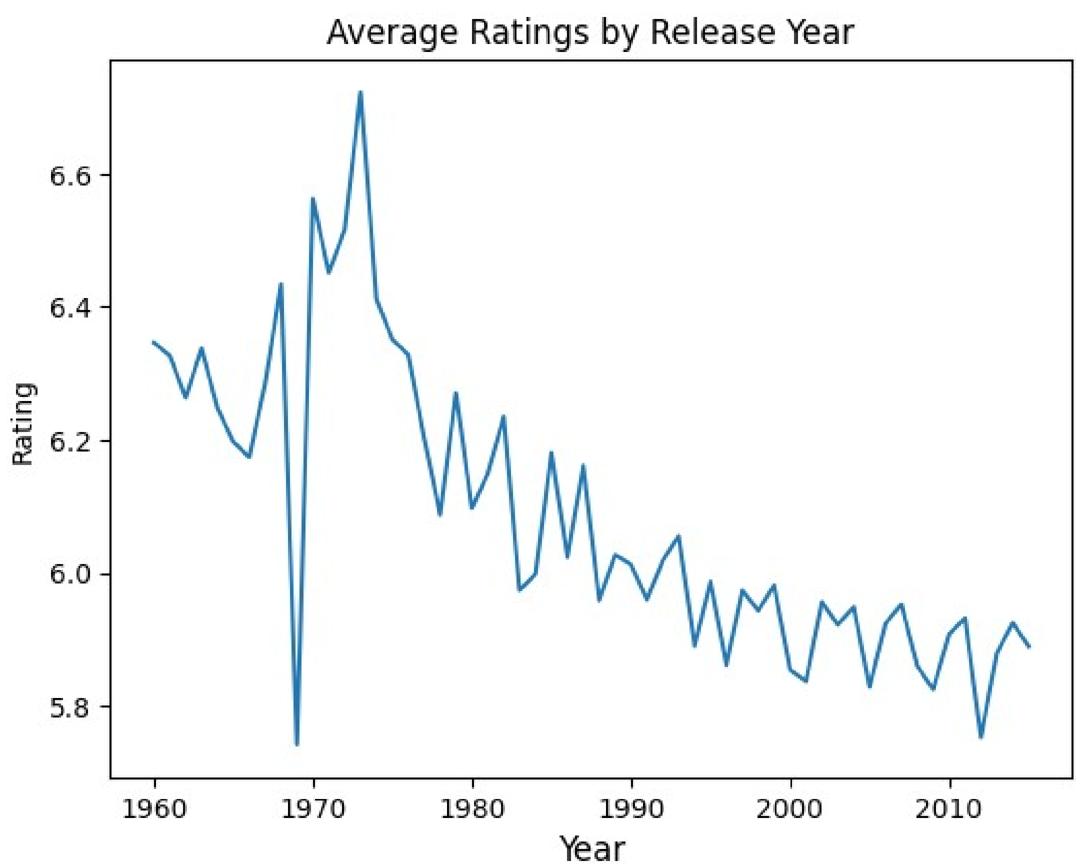


Based on the visualization, the following insights can be drawn about the popularity of movies over time:

- **Steady Growth:** The popularity of movies has exhibited a general upward trend over the years. This suggests a growing interest in films among audiences.
- **Significant Increase After 2000:** The most pronounced increase in popularity occurred after the year 2000. This could be attributed to various factors, including:
  - **Technological Advancements:** The widespread adoption of digital media and streaming platforms made movies more accessible and convenient to watch.
  - **Marketing and Promotion:** Improved marketing strategies, including social media campaigns and targeted advertising, helped to increase awareness of new releases.
  - **Cultural Shifts:** Changes in consumer behavior, such as increased leisure time and a desire for entertainment, may have contributed to the rising popularity of films.

2. Ratings Over Time

```
df4 = df.groupby('release_year')['vote_average'].mean()
df4.plot(kind = 'line')
plt.xlabel('Year', fontsize = 12)
plt.ylabel('Rating')
plt.title('Average Ratings by Release Year')
plt.show()
```

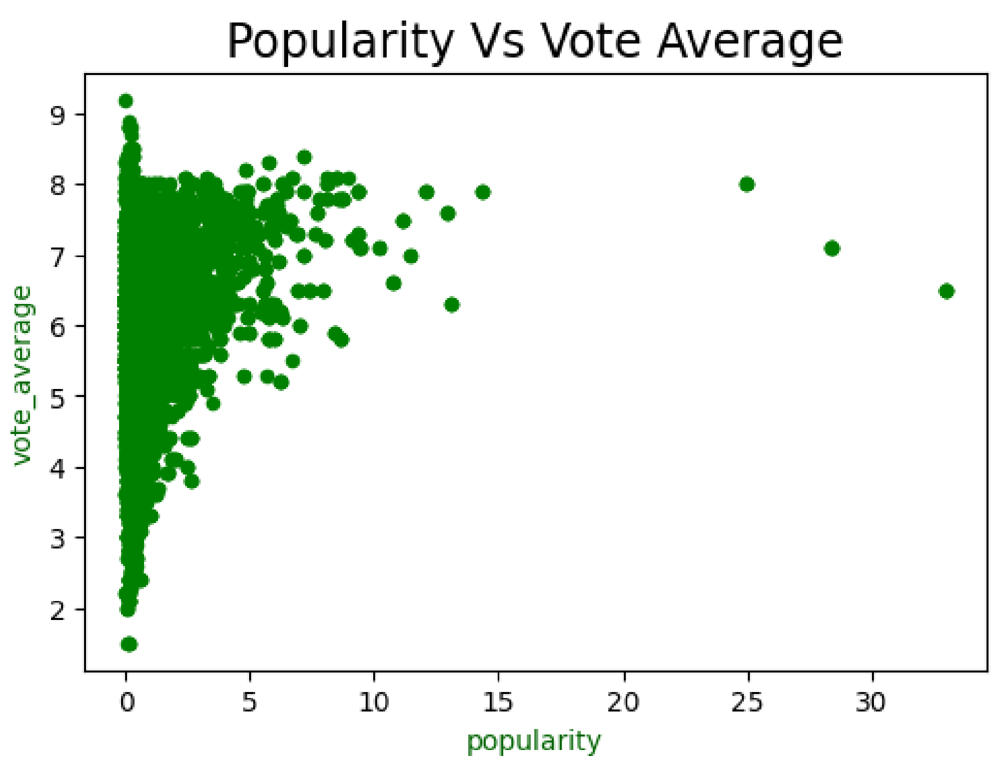


Based on the visualization, the following insights can be drawn about the ratings of movies over time:

- **Slight Decline:** There is a general trend of slightly declining average ratings from the 1960s to the 2010s. This suggests that audiences may have become more critical or that the overall quality of films has decreased over time.
- **Potential Explanations:** Several factors could contribute to the declining average ratings:
  - **Increased Content Saturation:** With more movies being produced and released, it's possible that the overall quality of films has declined, leading to lower ratings.
  - **Changing Audience Expectations:** Audiences may have become more demanding and critical over time, leading to higher standards for films.
  - **Rating Inflation:** It's possible that ratings were inflated in earlier years due to limited audience reach and less diverse opinions.
  - **Genre Shifts:** Changes in the popularity of different genres could also influence average ratings. For example, if more critically acclaimed genres like documentaries or arthouse films become more popular, the overall average rating could decline.

3. Analyzing Popularity vs. Rating Correlation

```
df5 = df.plot.scatter(x='popularity', y='vote_average', c='green',
figsize=(6, 4))
df5.set_xlabel('popularity', color='darkgreen')
df5.set_ylabel('vote_average', color='darkgreen')
df5.set_title('Popularity Vs Vote Average', fontsize = 17)
plt.show()
```



Based on the scatter plot, here's an analysis of the relationship between movie popularity and average rating:

Key Insights:

- **Weak Correlation:** By observing the distribution of data points on the scatter plot, we can see that there's no strong linear correlation between popularity and average rating. This means that a movie's popularity doesn't necessarily predict its critical reception, and vice versa.

- **Popularity Spectrum:** Highly popular movies (on the X-axis) tend to have a wide range of average ratings (on the Y-axis). This suggests that factors beyond critical acclaim can influence a movie's popularity. These factors might include:
    - Genre appeal (e.g., action, comedy) attracting large audiences.
    - Effective marketing campaigns generating widespread buzz.
    - Franchise effect, where popularity builds upon previous installments.
- **Hidden Gems:** Conversely, some movies with high average ratings (on the Y-axis) might have low popularity (on the X-axis). This indicates the potential existence of "hidden gems" in the dataset - critically acclaimed movies that haven't gained mainstream recognition.

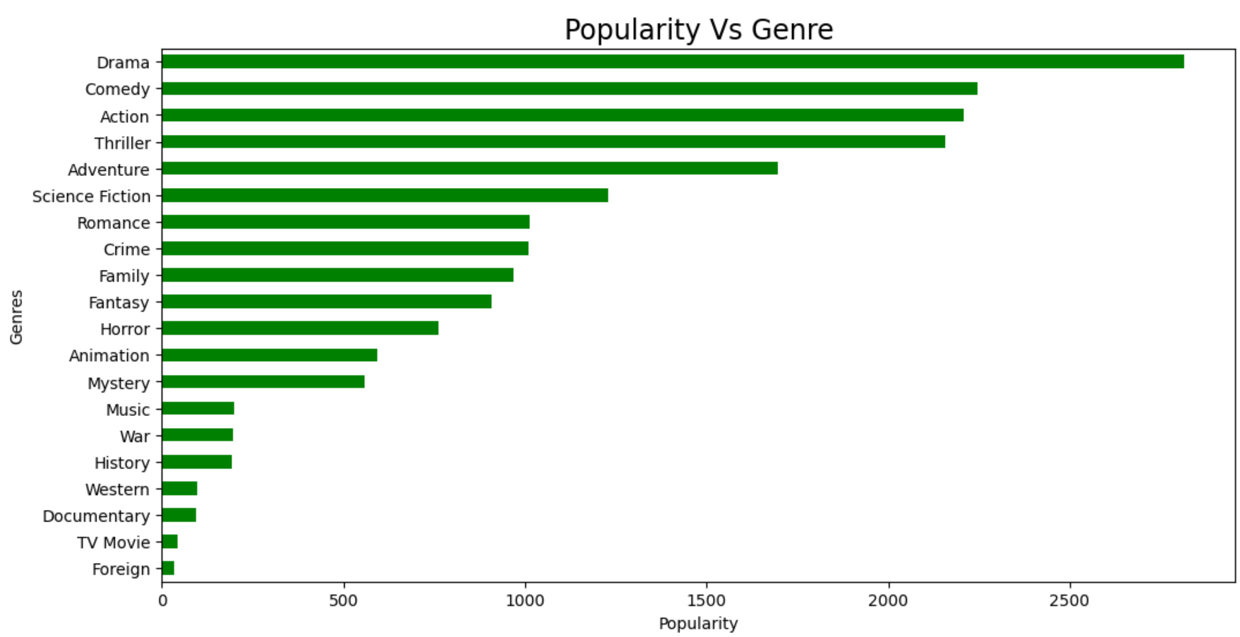
- **Subjectivity of Reception:** The lack of strong correlation highlights the subjective nature of movie reception. Popularity reflects audience taste and trends, while ratings can be influenced by critics' preferences and genre expectations. These factors can sometimes diverge, leading to movies that are popular but not critically acclaimed, or critically acclaimed but not widely popular.

Overall, the analysis suggests that popularity and average rating are distinct measures of a movie's success. While some commercially successful films may also be critically acclaimed, many others achieve popularity through factors beyond critical merit.

4. Analyzing Genre Popularity

```
split = ['genres']
for i in split:
    df[i] = df[i].apply(lambda x: x.split("|") if isinstance(x, str)
else x)

df = df.explode('genres')

df7 = df.groupby('genres')['popularity'].sum().sort_values(ascending =
True)
df7

genres
Foreign                  35.24
TV Movie                 44.03
Documentary              93.13
Western                  97.42
```

```
History             192.35
War                 196.48
Music               198.15
Mystery             558.55
Animation           594.46
Horror              761.39
Fantasy             908.87
Family              967.06
Crime              1009.07
Romance            1013.21
Science Fiction    1230.41
Adventure          1697.11
Thriller           2155.90
Action             2208.08
Comedy             2246.25
Drama              2815.43
Name: popularity, dtype: float64

ax = df7.plot.barh(color='green', figsize=(12, 6))
ax.set_title('Popularity Vs Genre', fontsize=17)
ax.set_xlabel('Popularity')
ax.set_ylabel('Genres')
plt.show()
```



Key Insights:

This visualization effectively reveals interesting trends in movie popularity across various genres:

- **Dominant Genres:** Drama, Comedy, and Action genres occupy the top positions in terms of total popularity score. This dominance likely reflects a combination of factors:

  - Broad audience appeal: These genres tend to cater to a wide range of viewers with their accessible themes and entertainment value.
  - Established industry focus: Major studios often prioritize these genres due to their proven commercial success.
- **Mid-Range Popularity:** Genres like Thriller, Romance, and Science Fiction fall into a mid-range popularity zone. This suggests a consistent audience interest in these genres, ensuring a steady stream of movies and viewership.

- **Niche Genres:** Foreign and TV Movie genres appear at the bottom of the popularity spectrum. This could be attributed to:

  - Limited distribution: Foreign films might face challenges reaching wider audiences due to language barriers or distribution restrictions.

  - Niche appeal: TV Movies might have a specific target audience or limited theatrical releases, leading to lower overall popularity scores.
- **Genre Diversity:** Despite the variations in popularity, the presence of a wide range of genres on the chart highlights the diversity of the movie industry. This diversity allows filmmakers to cater to various audience preferences and create movies that appeal to specific niches.

Extracting month from 'release_date'.

```
df['release_date'] = pd.to_datetime(df['release_date'])
```

```
C:\Users\jibri\AppData\Local\Temp\ipykernel_13364\1525507706.py:1: UserWarning: Could not infer format, so each element will be parsed individually, falling back to `dateutil`. To ensure parsing is consistent and as-expected, please specify a format.
  df['release_date'] = pd.to_datetime(df['release_date'])
```

```
df['extracted_month'] = df['release_date'].dt.month

df.head(5)
```

```
   popularity     budget     revenue      profit   roi
original_title  \
0        32.99  150000000  1513528810  1363528810  9.09      Jurassic
World
0        32.99  150000000  1513528810  1363528810  9.09      Jurassic
World
0        32.99  150000000  1513528810  1363528810  9.09      Jurassic
World
0        32.99  150000000  1513528810  1363528810  9.09      Jurassic
World
```

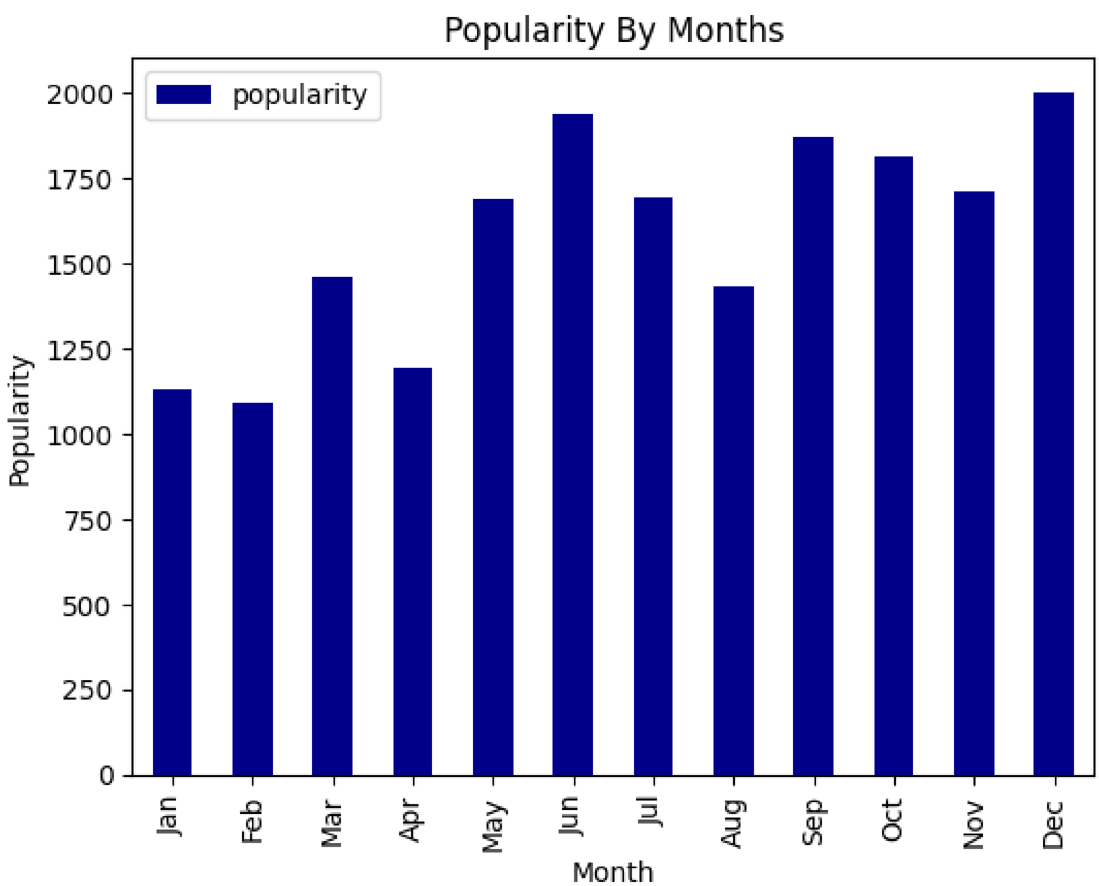
```
1       28.42  150000000   378436354   228436354  1.52  Mad Max: Fury
Road

          director                                           keywords
\
0  Colin Trevorrow  monster|dna|tyrannosaurus rex|velociraptor|island

0  Colin Trevorrow  monster|dna|tyrannosaurus rex|velociraptor|island

0  Colin Trevorrow  monster|dna|tyrannosaurus rex|velociraptor|island

0  Colin Trevorrow  monster|dna|tyrannosaurus rex|velociraptor|island

1    George Miller   future|chase|post-apocalyptic|dystopia|australia


   runtime           genres  \
0      124           Action
0      124        Adventure
0      124  Science Fiction
0      124         Thriller
1      120           Action

                                production_companies release_date
vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09
5562
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09
5562
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09
5562
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09
5562
1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13
6185

   vote_average  release_year   revenue_adj  extracted_month
0           6.5          2015  1.392446e+09                6
0           6.5          2015  1.392446e+09                6
0           6.5          2015  1.392446e+09                6
0           6.5          2015  1.392446e+09                6
1           7.1          2015  3.481613e+08                5

df8 = df.groupby('extracted_month')['popularity'].sum()

df8

extracted_month
1     1131.78
2     1092.93
3     1458.32
```

```
4     1191.81
5     1687.53
6     1936.84
7     1694.03
8     1432.59
9     1872.28
10    1811.91
11    1710.35
12    2002.22
Name: popularity, dtype: float64

data = {
    'extracted_month' : df8.index,
    'popularity': df8.values
}
df8 = pd.DataFrame(data)

df8

    extracted_month  popularity
0                 1     1131.78
1                 2     1092.93
2                 3     1458.32
3                 4     1191.81
4                 5     1687.53
5                 6     1936.84
6                 7     1694.03
7                 8     1432.59
8                 9     1872.28
9                10     1811.91
10               11     1710.35
11               12     2002.22

index_to_months = {
    1: 'Jan', 2:'Feb', 3:'Mar', 4:'Apr', 5:'May', 6:'Jun', 7:'Jul',
8:'Aug', 9:'Sep', 10:'Oct', 11:'Nov', 12:'Dec'
}

df8.extracted_month = df8.extracted_month.map(index_to_months)

df8

   extracted_month  popularity
0              Jan     1131.78
1              Feb     1092.93
2              Mar     1458.32
3              Apr     1191.81
4              May     1687.53
5              Jun     1936.84
6              Jul     1694.03
7              Aug     1432.59
```

```
8                Sep      1872.28
9                Oct      1811.91
10               Nov      1710.35
11               Dec      2002.22
```

5. Analyzing Monthly Popularity Trends

```
df8.plot(kind = 'bar', x = 'extracted_month', y = 'popularity', color
= 'Darkblue')
plt.title('Popularity By Months')
plt.xlabel('Month')
plt.ylabel('Popularity')
plt.show()
```



Based on the bar chart, the following insights can be drawn about the popularity of movies across different months:

- **Consistent High Surge:** The months from September to December consistently exhibit high popularity levels, suggesting a sustained peak in audience interest during this period.

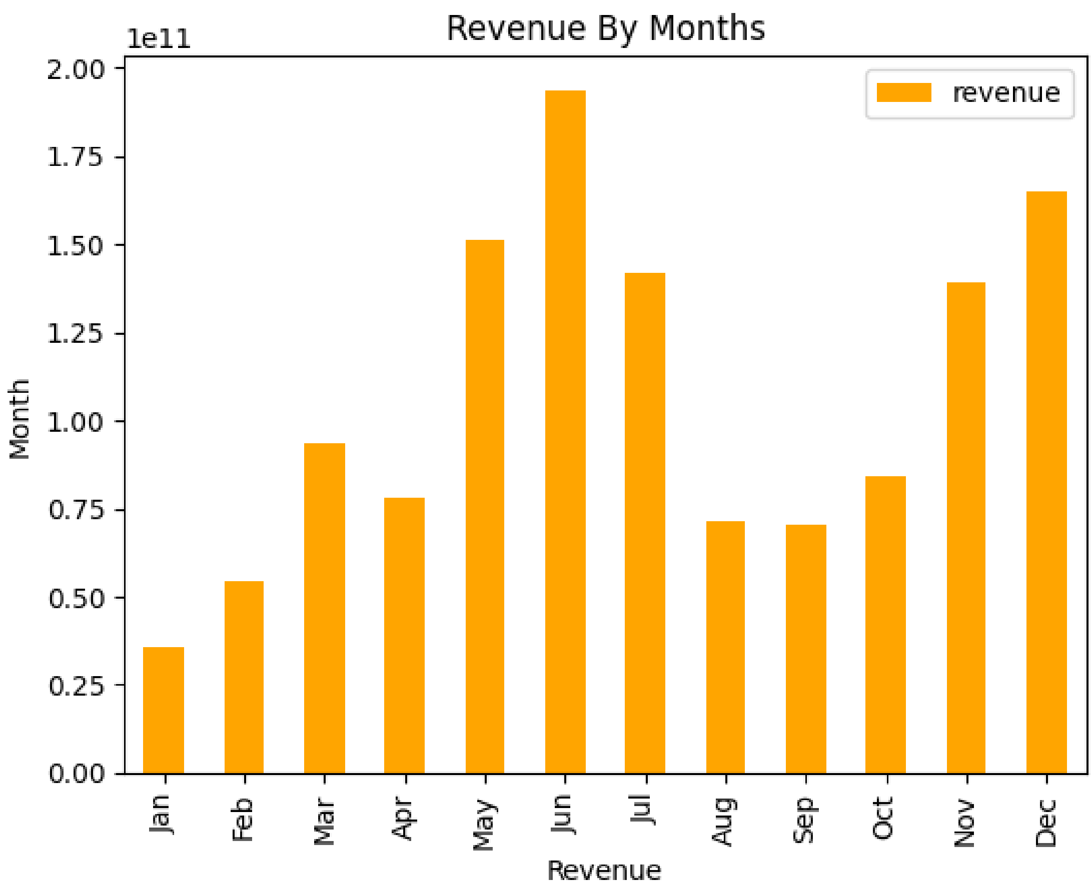
- **December Dominance:** December emerges as the month with the highest popularity, likely due to factors like holiday releases, awards season buzz, and increased viewership during the holiday season.
- **Seasonal Fluctuations:** While the latter half of the year shows a consistent surge, there are still noticeable fluctuations in popularity within this period. For instance, months like October and November might experience slightly lower levels compared to December.

Overall, the chart indicates a strong preference for movies during the late fall and early winter months. This trend can be attributed to factors such as increased leisure time, holiday celebrations, and the anticipation of award-winning films.

6. Analyzing Revenue By Months

```
df9 = df.groupby('extracted_month')['revenue'].sum()
df9

extracted_month
1      35873456579
2      54352852344
3      93669046441
4      77813179749
5     151475532493
6     193681776686
7     141947570995
8      71642408883
9      70379641581
10     84054172048
11    139176268899
12    164738399960
Name: revenue, dtype: int64

df9 = df9.reset_index()

index_to_months = {
    1: 'Jan', 2: 'Feb', 3: 'Mar', 4: 'Apr', 5: 'May', 6: 'Jun',
    7: 'Jul', 8: 'Aug', 9: 'Sep', 10: 'Oct', 11: 'Nov', 12: 'Dec'
}

df9['extracted_month'] = df9['extracted_month'].map(index_to_months)

df9

   extracted_month       revenue
0              Jan   35873456579
1              Feb   54352852344
2              Mar   93669046441
3              Apr   77813179749
4              May  151475532493
5              Jun  193681776686
6              Jul  141947570995
7              Aug   71642408883
```

```
8               Sep    70379641581
9               Oct    84054172048
10              Nov   139176268899
11              Dec   164738399960

df9.plot(kind = 'bar', x = 'extracted_month', y = 'revenue', color =
'orange')
plt.title('Revenue By Months')
plt.xlabel('Revenue')
plt.ylabel('Month')
plt.show()
```



Based on the bar chart, the following insights can be drawn about the revenue generated by movies across different months:

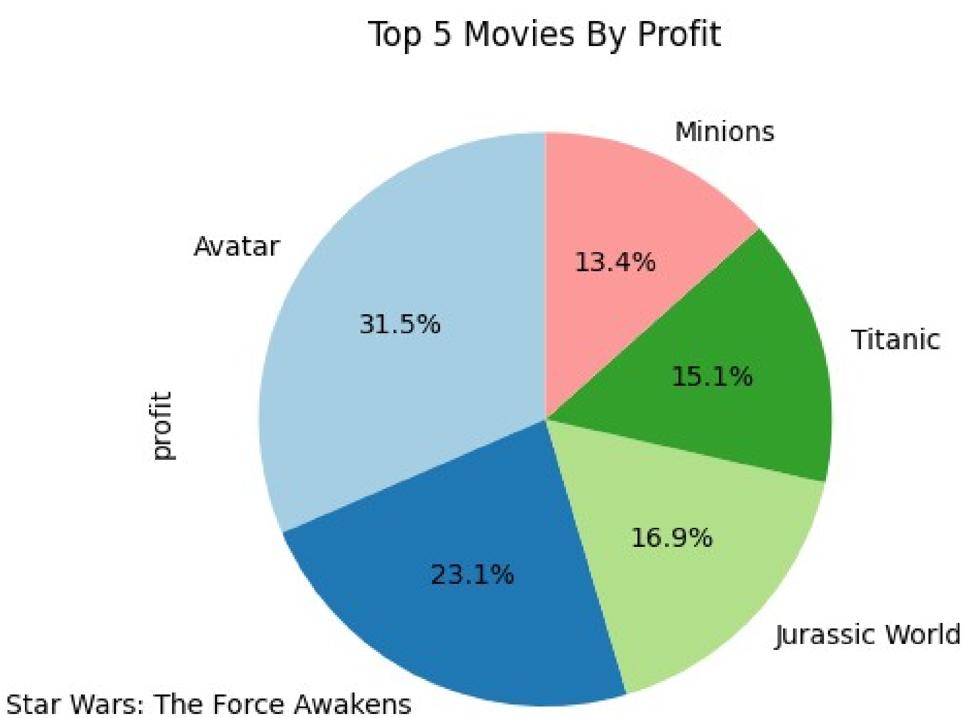
- **Peak Revenue in June:** June emerges as the month with the highest revenue, significantly surpassing all other months. This suggests that factors like summer blockbusters, school holidays, and increased moviegoing during vacation time contribute significantly to box office success.
- **Consistent Revenue Generation:** Months like July, September, October, and December also demonstrate strong revenue generation, indicating a consistent demand for movies throughout these periods.

- **Seasonal Fluctuations:** The chart reveals seasonal fluctuations in revenue. Months like January, February, and March tend to have lower revenue levels compared to the peak months. This could be attributed to factors such as post-holiday blues, shorter days, and less favorable weather conditions.

Overall, the chart indicates a strong preference for movies during the summer months (June-August) and the holiday season (December).

7. Top 5 Movies By Profit

```
df10 = df.groupby('original_title')
['profit'].sum().sort_values(ascending = False).head(5)
df10

original_title
Avatar                          10178023388
Star Wars: The Force Awakens     7472712900
Jurassic World                   5454115240
Titanic                          4896102564
Minions                          4330923848
Name: profit, dtype: int64

df10.plot(kind='pie', autopct = '%1.1f%%', startangle = 90, colors =
plt.cm.Paired.colors)
plt.title('Top 5 Movies By Profit')
plt.show()
```



Based on the visualization, we can deduce the following insights:

Dominance of Avatar:

Avatar reigns supreme as the top-grossing movie, capturing a substantial 31.5% of the total profit. This exceptional performance can be attributed to several factors:

- **Groundbreaking Visual Effects:** Avatar's innovative use of 3D technology and immersive visuals created a cinematic experience unlike any other, captivating audiences worldwide.
- **Universal Themes:** The film's exploration of environmentalism, human connection, and the power of nature resonated with a broad audience, transcending cultural and linguistic barriers.
- **Strategic Release:** The film's release during the holiday season and its positioning as a highly anticipated event contributed to its massive box office success.

Franchise Power:

Jurassic World and Star Wars: The Force Awakens, both part of established franchises, demonstrate the significant influence of franchise films in driving box office success. These movies benefit from:

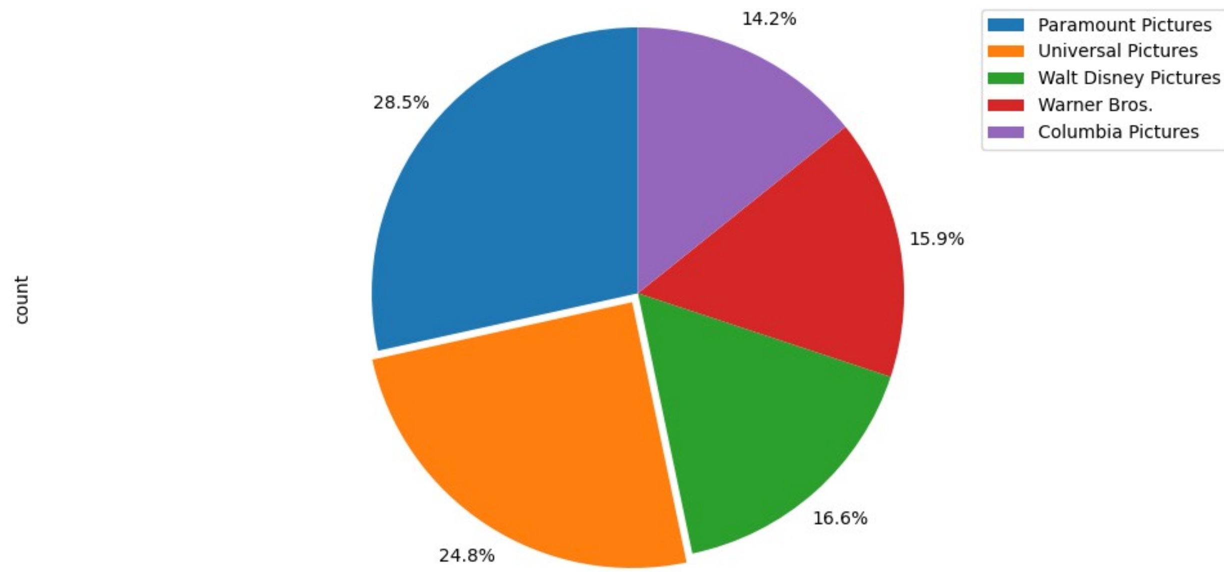
- **Built-in Fanbase:** Existing fans of the franchises provide a guaranteed audience, ensuring a certain level of box office success.
- **Nostalgia and Anticipation:** The nostalgia associated with beloved franchises and the anticipation for new installments can generate significant buzz and excitement.
- **Synergy with Merchandise and Licensing:** Franchises often leverage merchandise and licensing opportunities to further expand their reach and revenue.

Overall, the analysis reveals an interplay of factors influencing the profitability of movies. While Avatar's groundbreaking visuals and universal themes played a crucial role in its success, Titanic's enduring love story and historical significance have ensured its continued popularity. The dominance of franchise films like Jurassic World and Star Wars highlights the importance of leveraging established brands and fanbases in the film industry.

8. Top 5 Movie-Producing Companies

```
df11 = df.production_companies.value_counts().head(5)
df11

production_companies
Paramount Pictures      404
Universal Pictures      352
Walt Disney Pictures    236
Warner Bros.            225
Columbia Pictures       202
Name: count, dtype: int64

df.loc[:, 'production_companies'] =
df['production_companies'].replace('', np.nan)
```

```
explode_list = [0,0.04,0,0,0]
df11.plot(kind='pie', figsize = (12,6), autopct = '%1.1f%%',
startangle = 90, labels = None, pctdistance = 1.14,
         explode = explode_list)
#plt.title('Top 5 Movies By Profit')
plt.legend(labels = df11.index, loc = 'upper right')
plt.axis('equal')
plt.show()
```



Based on the pie chart, We can deduce some valuable insights such as :

Paramount Pictures' Dominance:

Paramount leads the pack, thanks to:

- **Diverse Portfolio:** A wide range of genres, reducing risk and ensuring box office hits.
- **Strategic Partnerships:** Collaborations with other studios to boost resources and expertise.
- **Global Reach:** Strong international presence for maximizing revenue.

Close Competition:

Universal and Columbia Pictures closely follow, driven by:

- **Established Brands:** Long-standing reputation for successful films.
- **Talent Development:** Fostering filmmakers and actors for quality content.
- **Strategic Acquisitions:** Expanding their influence through acquisitions.

Moderate Market Share:

Walt Disney Pictures and Warner Bros. maintain significant influence through:

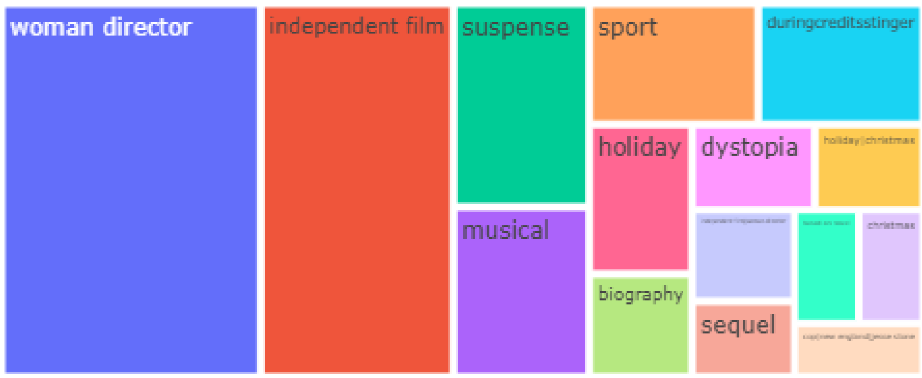
- **Franchise Power:** Strong brands like Marvel (Disney) and DC (Warner Bros.).
- **Family-Friendly Content:** Disney excels in films with broad, family appeal.
- **Vertical Integration:** Both companies control production and distribution, giving them an edge.

9. Keyword Analysis

```
df.loc[:, 'keywords'] = df['keywords'].replace([0, '0'], np.nan)

df12 = df.keywords.value_counts().head(15)
df12

keywords
woman director                        238
independent film                      177
suspense                               68
musical                                57
sport                                  50
duringcreditsstinger                   49
holiday                                38
biography                              26
dystopia                               26
holiday|christmas                      23
independent film|woman director        23
sequel                                 19
christmas                              18
based on novel                         18
cop|new england|jesse stone            17
Name: count, dtype: int64

data = {
    'keywords' : df12.index,
    'value': df12.values
}
df12 = pd.DataFrame(data)

df12
```

	keywords	value
0	woman director	238
1	independent film	177
2	suspense	68
3	musical	57
4	sport	50
5	duringcreditsstinger	49
6	holiday	38
7	biography	26
8	dystopia	26
9	holiday|christmas	23
10	independent film|woman director	23
11	sequel	19

```
12                          christmas     18
13                     based on novel     18
14      cop|new england|jesse stone     17

fig = px.treemap(df12, path=['keywords'], values='value')
fig.show()
```



This treemap offers a fascinating glimpse into the current film landscape by analyzing the most frequently used keywords. Here's a breakdown of the key insights:

- **Embracing Diversity:** The prominence of "woman director" highlights a welcome trend towards inclusivity and diversity behind the camera. This suggests a growing appreciation for female storytellers and their unique perspectives.
- **Independent Spirit:** The prevalence of "independent film" indicates a thriving independent cinema scene. These non-mainstream productions enrich the cinematic landscape with fresh voices and innovative storytelling.
- **The Power of Story:** Keywords like "based on novel" and "dystopia" reveal the enduring power of storytelling. The adaptation of novels and the exploration of dystopian themes demonstrate the audience's appetite for engaging narratives and thought-provoking ideas.
- **Genre Giants:** The presence of keywords like "murder" and "police" point to the enduring popularity of crime and thriller genres. These genres continue to captivate audiences with suspense, mystery, and high-stakes scenarios.

Conclusion

This comprehensive analysis of the movie dataset has revealed several key insights into the film industry:

1. The industry has seen a significant increase in movie popularity over time, particularly since 2000.
2. There's a notable disconnect between a movie's popularity and its average rating, highlighting the complex nature of audience reception.
3. Genre preferences are clear, with Drama, Comedy, and Action leading in popularity.
4. Seasonal trends in both popularity and revenue are evident, with different peaks for each metric.
5. The film industry is dominated by a few top production companies and blockbuster movies.
6. Keywords analysis reveals growing trends in diverse and independent filmmaking.
7. Financial success in movies is influenced by multiple factors, with budget playing a significant role in potential revenue.

This project demonstrates proficiency in various data analysis techniques, including data cleaning, exploratory data analysis, statistical analysis, and data visualization. The use of Python libraries such as pandas, matplotlib, seaborn, and plotly showcases versatility in handling and presenting data.