dsc-phase1-project-final

April 1, 2021

1 Getting Started in the Movie Industry

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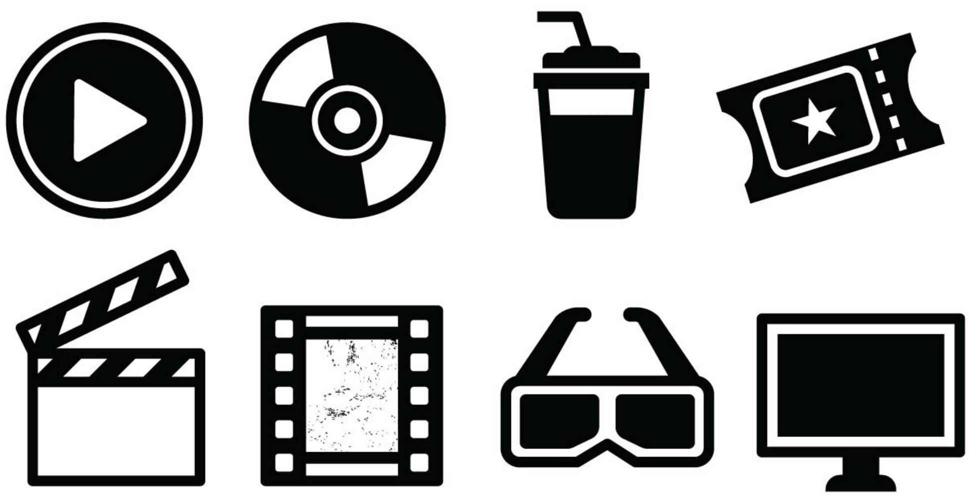


Dvd Vectors by Vecteezy

1.1 Overview

This analysis focuses on an exploration of data tables from IMDB and The Numbers. We will walk through high-level exploratory data analysis to preview what data we have to work with, data cleansing to ensure that our data is accurate, feature engineering to calculate useful metrics based on the provided data and visualization to effectively explain what aspects of film-making Microsoft should focus on as it embarks on a journey to find success in the film industry. The results from this analysis show that overall, Musicals tend to perform well, but of course there are multiple other factors to keep in consideration.

1.2 Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. The goal of this analysis is to explore what types of films are currently doing the best at the box office and translate those findings into actionable insights that the head of Microsoft's new movie studio can use to help decide what type of films to create. For this analysis, we will focus on the following questions:

1. What genres of movie are likely to succeed?
2. What genres cost more to produce?
3. How does production budget affect the success of a movie?

1.3 Data Understanding

In this analysis, we will be exploring datasets from IMDB and The Numbers. We can obtain information regarding movie titles, release years, genres, budget, and ratings from IMDB, and financial data from The Numbers.

To create an optimal basis for analysis, we will restrict movie releases from 2015 to 2019. Because movie preferences change with social context over generations, this will ensure that we have a dataset of movies that are relevant in this time period. By setting an upper limit for movie releases at 2019, we also eliminate any unusual data that has been impacted by COVID-19 restrictions. It is safe to make this assumption, since we are seeing more states open up restrictions with the decline of COVID-19 cases.

We will also be focusing on financial information within the US, since it would be best for a new film studio to focus on a specific audience as opposed to a worldwide audience.

1.3.1 Previewing the Data Tables

[1]:
```
# Import standard packages.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.ticker import FuncFormatter

%matplotlib inline
```

*include a note regarding how i chose my datasets

[2]:
```
# Load and preview data files for ratings and revenue.

imdb_title_basics_df = pd.read_csv('zippedData/imdb.title.basics.csv.gz')
imdb_title_ratings_df = pd.read_csv('zippedData/imdb.title.ratings.csv.gz')
budgets_df = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')

display(imdb_title_basics_df.head(),
        imdb_title_ratings_df.head(),
```

```
        budgets_df.head())
```

```
      tconst                    primary_title              original_title  \
0  tt0063540                        Sunghursh                   Sunghursh
1  tt0066787  One Day Before the Rainy Season             Ashad Ka Ek Din
2  tt0069049       The Other Side of the Wind  The Other Side of the Wind
3  tt0069204                  Sabse Bada Sukh             Sabse Bada Sukh
4  tt0100275         The Wandering Soap Opera       La Telenovela Errante

   start_year  runtime_minutes                genres
0        2013            175.0    Action,Crime,Drama
1        2019            114.0       Biography,Drama
2        2018            122.0                 Drama
3        2018              NaN          Comedy,Drama
4        2017             80.0  Comedy,Drama,Fantasy

       tconst  averagerating  numvotes
0  tt10356526            8.3        31
1  tt10384606            8.9       559
2   tt1042974            6.4        20
3   tt1043726            4.2     50352
4   tt1060240            6.5        21

   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

1.3.2 Previewing the Data Types

[3]:
```
# Display data types of each column in each table

display(imdb_title_basics_df.info(),
        imdb_title_ratings_df.info(),
        budgets_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
```

```
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   tconst           146144 non-null  object
 1   primary_title    146144 non-null  object
 2   original_title   146123 non-null  object
 3   start_year       146144 non-null  int64
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   tconst         73856 non-null  object
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB

None

None

None
```

1.4 Data Preparation

Because the provided tables currently do not have much meaning by themselves, we need to address missing and duplicated data, and we also need to merge the tables in a way that preserves the accuracy of the data.

1.4.1 Merging IMDB Data

We begin by merging the two datasets pulled from IMDB on their common id key labeled "tconst" and addressing missing values for genres and average rating, which are both criteria that will be importance in our final analysis.

[4]:
```
# Merge imdb tables to pair movie titles with their ratings.

imdb_df = imdb_title_basics_df.merge(imdb_title_ratings_df, how='right',
                                      on='tconst')

print("number of rows:", len(imdb_df))
display(imdb_df.head())
```

```
number of rows: 73856

       tconst           primary_title          original_title  start_year  \
0  tt10356526         Laiye Je Yaarian        Laiye Je Yaarian        2019
1  tt10384606               Borderless              Borderless        2019
2   tt1042974               Just Inès               Just Inès        2010
3   tt1043726  The Legend of Hercules  The Legend of Hercules        2014
4   tt1060240               Até Onde?               Até Onde?        2011

   runtime_minutes                    genres  averagerating  numvotes
0            117.0                   Romance            8.3        31
1             87.0               Documentary            8.9       559
2             90.0                     Drama            6.4        20
3             99.0  Action,Adventure,Fantasy            4.2     50352
4             73.0         Mystery,Thriller            6.5        21
```

[5]:
```
imdb_df.isna().sum()
```

[5]:
```
tconst                0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres              804
averagerating         0
numvotes              0
dtype: int64
```

[6]:
```
# Fill missing genres with 'None' and filter out rows that are missing
# averagerating.

imdb_df['genres'].fillna('None', inplace=True)
imdb_df = imdb_df[imdb_df['averagerating'].notna()]
```

1.4.2 Converting Data Types

We want to ensure that our movie titles from the IMDB dataset match with the correct titles from the The Numbers dataset, so we will eventually merge them on the movie title and year. Before we can do so, we need to convert the date information provided in The Numbers dataset into a type and format that matches the date information from IMDB.

[7]:
```
# Convert release date to show year only as int type.

budgets_df['release_date'] = budgets_df['release_date'].str[-4:].astype(int)
```

We also need to format the dollar amounts in order to be able to correctly graph the financial data.

[8]:
```
# Remove commas from dollar amounts.

budgets_df['production_budget'] = budgets_df['production_budget'] \
                                  .replace(',', '', regex = True)
budgets_df['domestic_gross'] = budgets_df['domestic_gross'] \
                               .replace(',', '', regex = True)
budgets_df['worldwide_gross'] = budgets_df['worldwide_gross'] \
                                .replace(',', '', regex = True)

# Remove $ sign and convert to int type.

budgets_df['production_budget'] = budgets_df['production_budget'] \
                                  .str[1:].astype(int)
budgets_df['domestic_gross'] = budgets_df['domestic_gross'] \
                               .str[1:].astype(int)
budgets_df['worldwide_gross'] = budgets_df['worldwide_gross'].str[1:] \
                                .astype(int)

budgets_df.head()
```

[8]:
```
   id  release_date                                        movie  \
0   1          2009                                       Avatar
1   2          2011  Pirates of the Caribbean: On Stranger Tides
2   3          2019                                 Dark Phoenix
3   4          2015                      Avengers: Age of Ultron
4   5          2017            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross  worldwide_gross
0          425000000       760507625       2776345279
1          410600000       241063875       1045663875
2          350000000        42762350        149762350
3          330600000       459005868       1403013963
4          317000000       620181382       1316721747
```

1.4.3 Dropping Unnecessary Columns

Since we will be focusing on domestic gross, we will drop worldwide gross data as well as any other unnecessary columns from our financial table.

[9]:
```
budgets_df.drop(columns=['id', 'worldwide_gross'], inplace=True)
```

[10]:
```
# Drop columns 'id' and 'worldwide_gross' which will not be used for analysis.

# del budgets_df['id']
# del budgets_df['worldwide_gross']
budgets_df.head()
```

[10]:
```
   release_date                                        movie  \
0          2009                                       Avatar
1          2011  Pirates of the Caribbean: On Stranger Tides
2          2019                                 Dark Phoenix
3          2015                      Avengers: Age of Ultron
4          2017            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross
0          425000000       760507625
1          410600000       241063875
2          350000000        42762350
3          330600000       459005868
4          317000000       620181382
```

1.4.4 Dropping Missing Data Entries

We then need to address any rows where we have missing data for domestic gross.

[11]:
```
# Replace all 0 values for domestic gross with NaN.

budgets_df['domestic_gross'] = budgets_df['domestic_gross'] \
                                        .map(lambda x: np.nan if x==0 else x)
```

[12]:
```
# Return only rows where 'domestic_gross' is NOT NaN.

budgets_df = budgets_df[budgets_df['domestic_gross'].notna()]
```

1.4.5 Merging Basic Movie Data with Financial Data

This is where we will combine our IMDB dataset, where we have our genre and average rating data, with our The Numbers dataset which includes all of our financial data. In order to ensure that we are not incorrectly merging our financial data on different movies that have the same title, we will use the release year in conjunction with the title in our merge. We also want to make sure to keep only titles that have financial data, hence we will merge left onto our financial table.

[13]:
```
# Join financial data from tn_movie_budgets with title and rating date
# from imdb_df.

merged_df = budgets_df.merge(imdb_df, how='left', left_on=['movie', \
```

```
                                                        'release_date'], \
                             right_on=['original_title', 'start_year'])

merged_df.head()
```

[13]:

```
   release_date                                        movie  \
0          2009                                       Avatar
1          2011  Pirates of the Caribbean: On Stranger Tides
2          2019                                 Dark Phoenix
3          2015                      Avengers: Age of Ultron
4          2017            Star Wars Ep. VIII: The Last Jedi

   production_budget  domestic_gross     tconst  \
0          425000000     760507625.0        NaN
1          410600000     241063875.0  tt1298650
2          350000000      42762350.0  tt6565702
3          330600000     459005868.0  tt2395427
4          317000000     620181382.0        NaN

                                 primary_title  \
0                                          NaN
1  Pirates of the Caribbean: On Stranger Tides
2                                 Dark Phoenix
3                      Avengers: Age of Ultron
4                                          NaN

                                original_title  start_year  runtime_minutes  \
0                                          NaN         NaN              NaN
1  Pirates of the Caribbean: On Stranger Tides      2011.0            136.0
2                                 Dark Phoenix      2019.0            113.0
3                      Avengers: Age of Ultron      2015.0            141.0
4                                          NaN         NaN              NaN

                     genres  averagerating  numvotes
0                       NaN            NaN       NaN
1  Action,Adventure,Fantasy            6.6  447624.0
2   Action,Adventure,Sci-Fi            6.0   24451.0
3   Action,Adventure,Sci-Fi            7.3  665594.0
4                       NaN            NaN       NaN
```

[14]:

```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5258 entries, 0 to 5257
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
```

```
 0   release_date       5258 non-null   int64
 1   movie              5258 non-null   object
 2   production_budget  5258 non-null   int64
 3   domestic_gross     5258 non-null   float64
 4   tconst             1330 non-null   object
 5   primary_title      1330 non-null   object
 6   original_title     1330 non-null   object
 7   start_year         1330 non-null   float64
 8   runtime_minutes    1325 non-null   float64
 9   genres             1330 non-null   object
 10  averagerating      1330 non-null   float64
 11  numvotes           1330 non-null   float64
dtypes: float64(5), int64(2), object(5)
memory usage: 534.0+ KB
```

1.4.6 Checking for Missing Rating Data

Since it is possible that there was no matching data for each of the entries provided in the financial table, we need to remove any rows that do not have basic movie information data being matched from the IMDB dataset.

[15]:

```
# Filter for rows that are not missing rating data.

merged_df = merged_df[merged_df['averagerating'].notna()] \
                                                .sort_values('release_date')

merged_df.head()
```

[15]:

```
      release_date                       movie  production_budget  \
2530          2010                   You Again           20000000
2501          2010               Vampires Suck           20000000
2467          2010  Why Did I Get Married Too?           20000000
2466          2010               The Last Song           20000000
2449          2010                  Jackass 3D           20000000

      domestic_gross     tconst               primary_title  \
2530      25702053.0  tt1414382                   You Again
2501      36661504.0  tt1666186               Vampires Suck
2467      60095852.0  tt1391137  Why Did I Get Married Too?
2466      62950384.0  tt1294226               The Last Song
2449     117229692.0  tt1116184                  Jackass 3D

                  original_title  start_year  runtime_minutes  \
2530                   You Again      2010.0            105.0
2501               Vampires Suck      2010.0             82.0
2467  Why Did I Get Married Too?      2010.0            121.0
2466               The Last Song      2010.0            107.0
2449                  Jackass 3D      2010.0             95.0
```

```
                      genres  averagerating  numvotes
2530     Comedy,Family,Romance            5.8   46690.0
2501                    Comedy            3.4   43984.0
2467      Comedy,Drama,Romance            4.6    8653.0
2466       Drama,Music,Romance            6.0   74914.0
2449  Action,Comedy,Documentary           7.0   53289.0
```

1.4.7 Checking and Dropping Duplicates

It is necessary to check for duplicates rows where movie and release date are matching. In order to prevent financial data from being matched with incorrect movies with the same title, we will drop the duplicates which have a lower number of rating votes.

[16]:
```
# Drop duplicates based on movie title and release year

merged_df[merged_df.duplicated(subset=['movie', 'release_date'],
                               keep=False)].head()
```

[16]:
```
      release_date              movie  production_budget  domestic_gross  \
2654          2010        The Tempest           20000000        277943.0
2653          2010        The Tempest           20000000        277943.0
1263          2010  The Bounty Hunter           45000000      67061228.0
1262          2010  The Bounty Hunter           45000000      67061228.0
1017          2010          Burlesque           55000000      39440655.0

         tconst      primary_title     original_title  start_year  \
2654  tt1683003        The Tempest        The Tempest      2010.0
2653  tt1274300        The Tempest        The Tempest      2010.0
1263  tt1472211  The Bounty Hunter  The Bounty Hunter      2010.0
1262  tt1038919  The Bounty Hunter  The Bounty Hunter      2010.0
1017  tt1586713          Burlesque          Burlesque      2010.0

      runtime_minutes                  genres  averagerating  numvotes
2654            131.0                   Drama            7.8      94.0
2653            110.0    Comedy,Drama,Fantasy            5.4    7073.0
1263              NaN                    None            6.3      29.0
1262            110.0  Action,Comedy,Romance            5.6  112444.0
1017              NaN                   Drama            7.0      45.0
```

[17]:
```
# Sort values by number of votes in preparation of dropping duplicates with
# lower vote count

merged_df.sort_values('numvotes', ascending=False, inplace=True)

# Drop duplicated movie with lower vote count
```

```
merged_df.drop_duplicates(subset=['movie', 'release_date'], inplace=True)

merged_df.head()
```

[17]:

```
     release_date                movie  production_budget  domestic_gross  \
139          2010            Inception          160000000     292576195.0
10           2012  The Dark Knight Rises          275000000     448139099.0
133          2014         Interstellar          165000000     188017894.0
369          2012      Django Unchained          100000000     162805434.0
26           2012         The Avengers          225000000     623279547.0

        tconst          primary_title         original_title  start_year  \
139  tt1375666              Inception              Inception      2010.0
10   tt1345836  The Dark Knight Rises  The Dark Knight Rises      2012.0
133  tt0816692           Interstellar           Interstellar      2014.0
369  tt1853728       Django Unchained       Django Unchained      2012.0
26   tt0848228           The Avengers           The Avengers      2012.0

     runtime_minutes                    genres  averagerating   numvotes
139            148.0  Action,Adventure,Sci-Fi            8.8  1841066.0
10             164.0          Action,Thriller            8.4  1387769.0
133            169.0   Adventure,Drama,Sci-Fi            8.6  1299334.0
369            165.0            Drama,Western            8.4  1211405.0
26             143.0  Action,Adventure,Sci-Fi            8.1  1183655.0
```

[18]:

```
# Verifying that duplicates have been eliminated.

len(merged_df[merged_df.duplicated(subset=['movie', 'release_date'], \
                                   keep=False)])
```

[18]: 0

1.4.8 Restricting Data to Relevant Years

[19]:

```
# Restrict to last 5 years to keep focus on recent movies, but
# exclude 2020 due to covid impact.

merged_df = merged_df[(merged_df['release_date'] >= 2015) & \
                      (merged_df['release_date'] <= 2019)] \
                      .sort_values('release_date')
```

1.4.9 Feature Engineering

Because our one of our KPIs is percentage profit, we need to create a column that displays this calculation from the domestic gross and production budget columns. The specific formula we will use to calculate percentage profit is $((Domestic Gross - ProductionBudget) / Production Budget) * 100 $.

[20]:
```python
# Create column for % profit based on the formula:
# (domestic_gross - production_budget) / production_buget

merged_df['% profit'] = ((merged_df['domestic_gross'] \
                        - merged_df['production_budget']) \
                        / merged_df['production_budget']) * 100
```

1.5 Data Analysis

[21]:
```python
# Set theme and style for plots.
sns.set_theme('talk')
sns.set_style('darkgrid')
```

1.5.1 FuncFormatter

Before we plot our visualizations, we will define a function to transform our dollar amounts into easier-to-read dollar amounts in millions.

[22]:
```python
# Define function for displaying large dollar amounts in millions.

def millions(x, pos):
    """Source: https://stackoverflow.com/questions/61330427/
 ↪set-y-axis-in-millions"""
    'The two args are the value and tick position'
    return '%1.0fM' % (x * 1e-6)

formatter = FuncFormatter(millions)
```

We have thoroughly prepared our data for visualization, and we can now return to our three questions for analysis:

1. What genres of movie are likely to succeed?
2. What genres cost more to produce?
3. How does production budget affect the success of a movie?

We will now proceed to plot our data to help us get a better sense of how each of these criteria translate to a movie's success.

1.5.2 Genre vs. Movie Success

To examine which genres have the highest KPIs, we will use bar plots. This enables us to clearly see the aggregate median values for each of our genres.

General Genre Data

[23]:
```python
# Split and explode entries to show one genre per row with repeated titles
# where necessary.

merged_df['genre_list'] = merged_df['genres'].str.split(',')
```

```python
exploded_df = merged_df.explode('genre_list')

exploded_df.head()
```

[23]:

```
      release_date                                movie  production_budget  \
1657          2015                           Concussion           35000000
1657          2015                           Concussion           35000000
1657          2015                           Concussion           35000000
3470          2015  The Second Best Exotic Marigold Hotel           10000000
3470          2015  The Second Best Exotic Marigold Hotel           10000000

      domestic_gross     tconst                          primary_title  \
1657      34531832.0  tt3322364                             Concussion
1657      34531832.0  tt3322364                             Concussion
1657      34531832.0  tt3322364                             Concussion
3470      33078266.0  tt2555736  The Second Best Exotic Marigold Hotel
3470      33078266.0  tt2555736  The Second Best Exotic Marigold Hotel

                             original_title  start_year  runtime_minutes  \
1657                             Concussion      2015.0            123.0
1657                             Concussion      2015.0            123.0
1657                             Concussion      2015.0            123.0
3470  The Second Best Exotic Marigold Hotel      2015.0            122.0
3470  The Second Best Exotic Marigold Hotel      2015.0            122.0

                        genres  averagerating  numvotes    % profit genre_list
1657  Biography,Drama,Sport            7.1   77576.0   -1.337623  Biography
1657  Biography,Drama,Sport            7.1   77576.0   -1.337623      Drama
1657  Biography,Drama,Sport            7.1   77576.0   -1.337623      Sport
3470           Comedy,Drama            6.6   28931.0  230.782660     Comedy
3470           Comedy,Drama            6.6   28931.0  230.782660      Drama
```

Genre vs. Rating

[24]:

```python
# Group by genre and calculate aggregate median sorted by rating
# and return top 10 genres.

genre_rating_df = exploded_df.groupby('genre_list') \
                             .median()[['averagerating','% profit']] \
                             .sort_values('averagerating', ascending=False) \
                             .head(10)
genre_rating_df.reset_index(inplace=True)

genre_rating_df
```

[24]:

```
  genre_list  averagerating    % profit
0    Musical           7.40  161.278340
```

```
1      History           7.20    2.056160
2        Sport           7.10   -1.337623
3    Biography           7.10   -5.573207
4      Western           6.90    3.814061
5        Drama           6.80   10.429731
6       Family           6.65   13.786461
7    Animation           6.60   23.805229
8        Music           6.55   38.294300
9  Documentary           6.50   -4.756800
```

Genre vs. Percent Profit

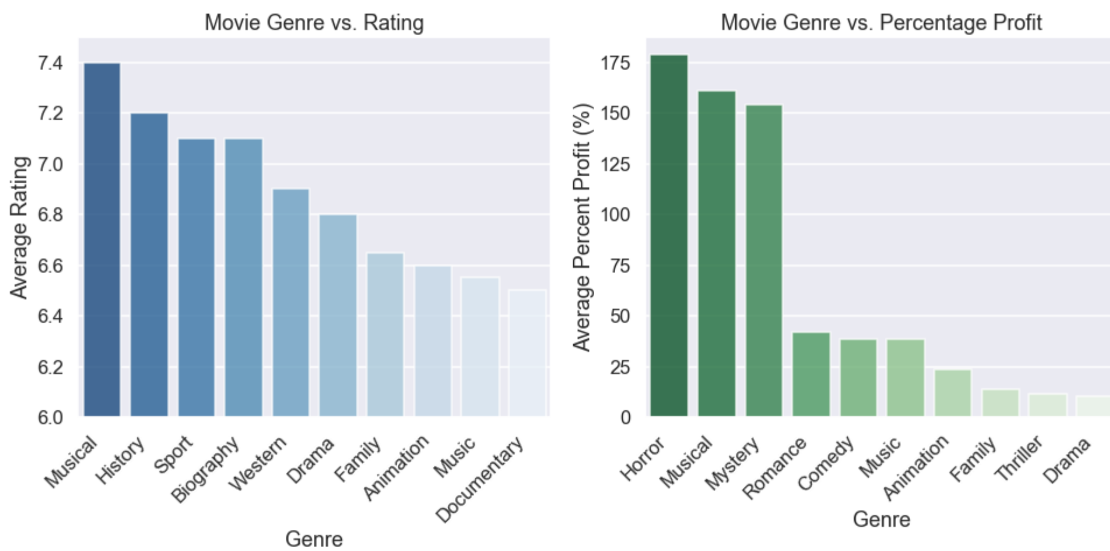
[25]:
```
# Group by genre and calculate aggregate median sorted by % profit.

genre_profit_df = exploded_df.groupby('genre_list') \
                             .median()[['averagerating','% profit']] \
                             .sort_values('% profit', ascending=False) \
                             .head(10)

genre_profit_df.reset_index(inplace=True)
genre_profit_df
```

[25]:
```
  genre_list  averagerating    % profit
0     Horror           5.80  178.555945
1    Musical           7.40  161.278340
2    Mystery           6.15  153.931679
3    Romance           6.40   42.099253
4     Comedy           6.30   38.617048
5      Music           6.55   38.294300
6  Animation           6.60   23.805229
7     Family           6.65   13.786461
8   Thriller           6.10   11.716700
9      Drama           6.80   10.429731
```

Plotting Genre vs. Success

[26]:
```
# Plot genre vs averagerating on bar plot

fig, axes = plt.subplots(ncols=2, figsize=(16,6))

sns.barplot(data=genre_rating_df,
    x="genre_list", y="averagerating",
    ax=axes[0], palette='Blues_r', alpha=0.8)

axes[0].set_ylim([6, 7.5])

axes[0].set_title('Movie Genre vs. Rating')
axes[0].set_xlabel('Genre')
```

```
axes[0].set_ylabel('Average Rating')
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=45, ha='right')

# Plot genre vs average percentage profit on a bar plot

sns.barplot(data=genre_profit_df,
    x="genre_list", y="% profit",
    ax=axes[1], palette='Greens_r', alpha=.8)

axes[1].set_title('Movie Genre vs. Percentage Profit')
axes[1].set_xlabel('Genre')
axes[1].set_ylabel('Average Percent Profit (%)')
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, ha='right');
```



What genres of movie are likely to succeed? Our bar plot indicates that Musicals have a tendency to receive higher ratings with non-fictional genres including History, Biography and Sports following closely behind.

However, the most profitable genres by far appear to be Horror, Musicals, and Mystery.

The Musical genre appears to be a top performer in both cases, but otherwise, genre choice will depend on whether Microsoft's goal is to build a reputation for building good movies, or if it is purely to maximize profits in the most efficient use of its budget.

1.5.3 Genre vs. Production Costs

To examine which genres have the highest mean production costs, we will use bar plots. This plot will indicate clearly which genres on average cost the most to produce.

Genre vs Average Production Cost

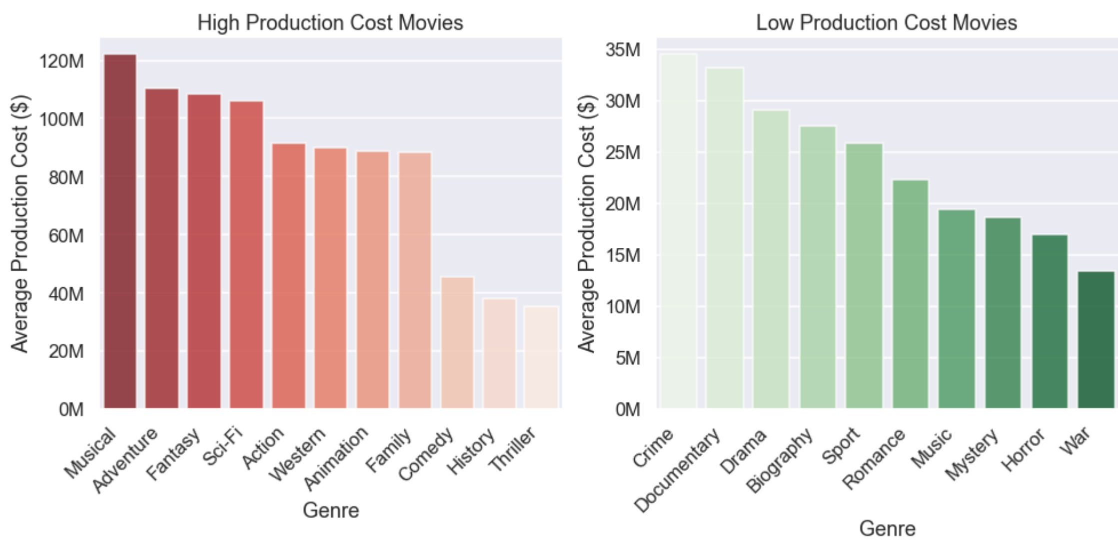
[27]:
```python
# Group by genre and calculate aggregate median sorted by production budget.
# Then create a high budget and low budget table.

high_budget_df = exploded_df.groupby('genre_list') \
                            .mean()[['production_budget']] \
                            .sort_values('production_budget', \
                                         ascending=False) \
                            .head(11)
high_budget_df.reset_index(inplace=True)
high_budget_df = high_budget_df[high_budget_df['genre_list'] != 'None']

low_budget_df = exploded_df.groupby('genre_list') \
                           .mean()[['production_budget']] \
                           .sort_values('production_budget', \
                                        ascending=False) \
                           .tail(10)
low_budget_df.reset_index(inplace=True)
low_budget_df = low_budget_df[low_budget_df['genre_list'] != 'None']

display(high_budget_df, low_budget_df)
```

	genre_list	production_budget
0	Musical	1.220000e+08
1	Adventure	1.102115e+08
2	Fantasy	1.086174e+08
3	Sci-Fi	1.059534e+08
4	Action	9.139595e+07
5	Western	9.000000e+07
6	Animation	8.890217e+07
7	Family	8.851333e+07
8	Comedy	4.551694e+07
9	History	3.823600e+07
10	Thriller	3.542267e+07

	genre_list	production_budget
0	Crime	3.451084e+07
1	Documentary	3.321000e+07
2	Drama	2.907010e+07
3	Biography	2.760667e+07
4	Sport	2.593333e+07
5	Romance	2.232653e+07
6	Music	1.945000e+07
7	Mystery	1.868558e+07
8	Horror	1.697647e+07
9	War	1.340000e+07

Plotting Genre vs. Production Budget

[28]:
```python
#Plot highest costing movies

fig, axes = plt.subplots(ncols=2, figsize=(16,6))

sns.barplot(data=high_budget_df,
    x="genre_list", y="production_budget",
    ax=axes[0], palette='Reds_r', alpha=.8)

axes[0].set_title('High Production Cost Movies')
axes[0].set_xlabel('Genre')
axes[0].set_ylabel('Average Production Cost ($)')
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=45, ha='right')
axes[0].yaxis.set_major_formatter(formatter)

# Plot lowest costing movies

sns.barplot(data=low_budget_df,
    x="genre_list", y="production_budget",
    ax=axes[1], palette='Greens', alpha=.8)

axes[1].set_title('Low Production Cost Movies')
axes[1].set_xlabel('Genre')
axes[1].set_ylabel('Average Production Cost ($)')
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, ha='right')
axes[1].yaxis.set_major_formatter(formatter);
```



What genres cost the most and least to produce? Musicals are by far the most costly genre of movie to produce, followed by Fantasy, Sci-Fi and Adventure. The lowest costing genres are War, Horror and Mystery.

1.5.4 Production Budget vs. Percentage Profit

Now that we have an idea of the impact of genre choice, we can begin to look at how production budget affects movie success.

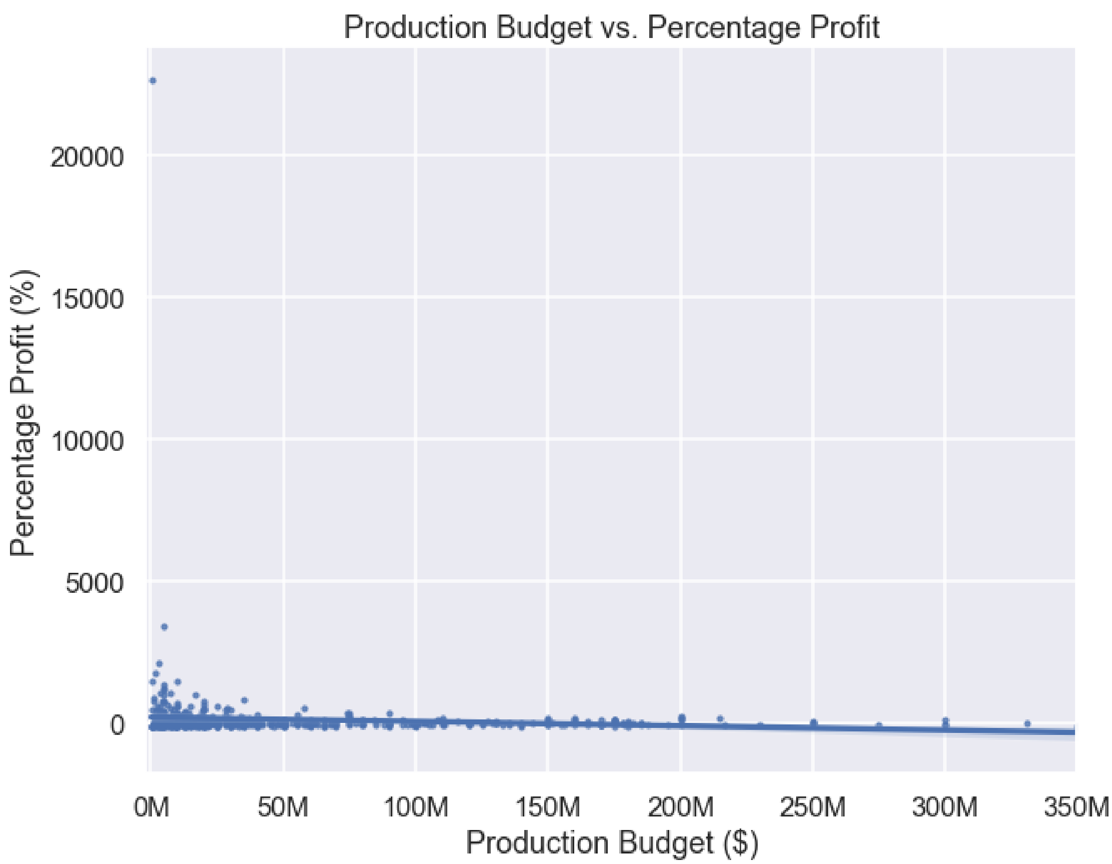
Production Budget Data

[29]:
```
# Create a copy of the dataframe to be used in our analysis of
# budget vs. rating and budget vs. percent profit.

financial_df = merged_df
financial_df.head()
```

[29]:
```
      release_date                               movie  production_budget  \
1657          2015                          Concussion           35000000
3470          2015  The Second Best Exotic Marigold Hotel         10000000
1710          2015                 Unfinished Business           35000000
1163          2015                        Run All Night           50000000
1540          2015               Paul Blart: Mall Cop 2           38000000

      domestic_gross     tconst                        primary_title  \
1657      34531832.0  tt3322364                           Concussion
3470      33078266.0  tt2555736  The Second Best Exotic Marigold Hotel
1710      10219501.0  tt2358925                  Unfinished Business
1163      26461644.0  tt2199571                        Run All Night
1540      71091594.0  tt3450650               Paul Blart: Mall Cop 2

                             original_title  start_year  runtime_minutes  \
1657                             Concussion      2015.0            123.0
3470  The Second Best Exotic Marigold Hotel      2015.0            122.0
1710                    Unfinished Business      2015.0             91.0
1163                          Run All Night      2015.0            114.0
1540                 Paul Blart: Mall Cop 2      2015.0             94.0

                    genres  averagerating  numvotes    % profit  \
1657  Biography,Drama,Sport            7.1   77576.0   -1.337623
3470           Comedy,Drama            6.6   28931.0  230.782660
1710           Comedy,Drama            5.4   29004.0  -70.801426
1163  Action,Drama,Thriller            6.6   94131.0  -47.076712
1540    Action,Comedy,Crime            4.4   30828.0   87.083142

                     genre_list
1657  [Biography, Drama, Sport]
3470            [Comedy, Drama]
1710            [Comedy, Drama]
1163  [Action, Drama, Thriller]
1540    [Action, Comedy, Crime]
```

Plotting Production Budget vs. Success

[30]:
```
# Plot budget vs % profit on regression scatter plot

fig, ax = plt.subplots(figsize=(10,8))
sns.regplot(x="production_budget", y="% profit",
            data=financial_df, ax=ax, fit_reg=True, scatter_kws={'s':10})

ax.set_xlim([-2000000, 350000000])
ax.set_title('Production Budget vs. Percentage Profit')
ax.set_xlabel('Production Budget ($)')
ax.set_ylabel('Percentage Profit (%)')
ax.xaxis.set_major_formatter(formatter);
```

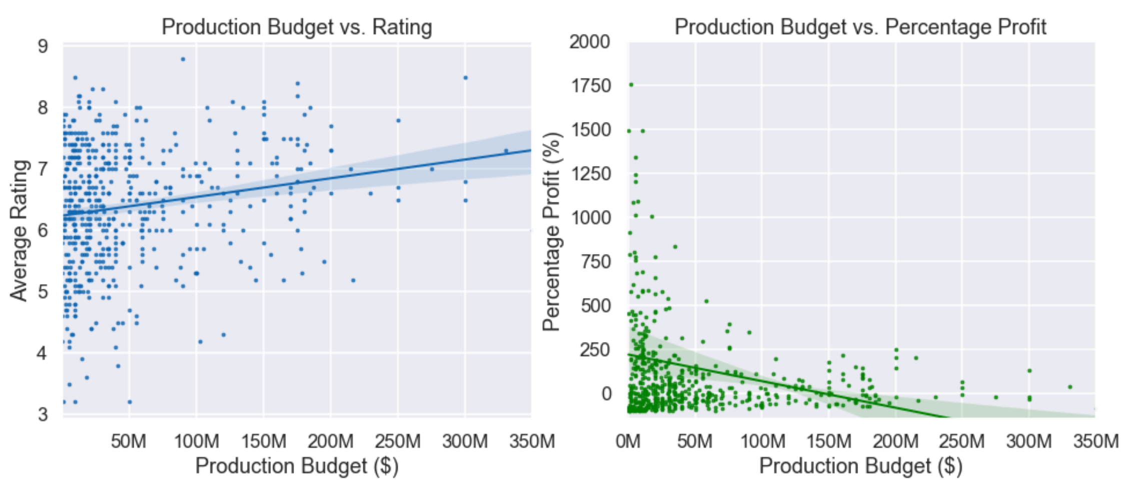


1.5.5 Production Budget vs. Movie Success

We can see above that due to extreme outliers, our regression plot is distorted, showing a large cluster of points below 2,000% profit. Hence, we will restrict the y-axis to more clearly show our data points and regression line.

In this situation, it is appropriate to use a regression plot to display a marker for each of our movies, showing the relationship between each movie's production budget and its respective KPI.

[31]:
```python
# Plot budget vs averagerating on regression scatter plot

fig, axes = plt.subplots(ncols=2, figsize=(16,6))
sns.regplot(x="production_budget", y="averagerating", color='#1167b1',
            line_kws={"lw":2}, scatter_kws={'s':7}, data=financial_df,
            fit_reg=True, ax=axes[0])

axes[0].set_title('Production Budget vs. Rating')
axes[0].set_xlabel('Production Budget ($)')
axes[0].set_ylabel('Average Rating')
axes[0].xaxis.set_major_formatter(formatter)


# Plot and zoom in to budget vs percent profit to examine regression
# without severe outliers

sns.regplot(x="production_budget", y="% profit", color='green',
            line_kws={"lw":2}, data=financial_df, ax=axes[1],
            fit_reg=True, scatter_kws={'s':7})
axes[1].set_ylim([-150, 2000])
axes[1].set_xlim([-2000000, 350000000])

axes[1].set_title('Production Budget vs. Percentage Profit')
axes[1].set_xlabel('Production Budget ($)')
axes[1].set_ylabel('Percentage Profit (%)')
axes[1].xaxis.set_major_formatter(formatter);
```



How does production budget affect the success of a movie? We can see in our regression plot that as production budget increases, there is a positive trend in average rating. Conversely, we can see that profit percentages tend to decrease with larger budget movies.

In this case, it is important to note that the margin of error is skewed on the extremes of the budget. There are a much higher number of samples that are low budget, and fewer samples that are high budget.

Therefore, we can tell that a **higher budget is more likely to receive a higher rating, while likely to return a lower profit percentage**, but movie budget is not a definitive indicator of how successful a movie will be.

This plot gives us enough information now to make a conclusion on what Microsoft should keep in mind when creating its first films.

1.6 Evaluation

1.7 Conclusions

There is no clear-cut formula to creating a successful movie, and there will always be exceptions, even though a certain movie might not seem to fit criteria that have had a track record of success.

Horror and Mystery movies only require a low production budget, but have a track record of receiving high profit percentages. If profit percentage is a priority for Microsoft, either of these genres would be a good pick.

However, with the above analysis, we can see that although Musicals cost the most to produce, they do have a tendency to perform well as opposed to other genres. More specifically, Musicals were likely to receive better ratings, as well as have a higher profit percentage.

Under the assumption that production budget is not a major concern for Microsoft, we can conclude that it would be a safe choice to create movies under the Musical genre, despite the slightly negative correlation between production budget and profit percentage. By focusing on receiving higher ratings, Microsoft would be able to earn a strong reputation within the film industry, allowing it to more effectively market its future productions.

Some questions to consider for further analysis include the following:

1. What would be the most efficient allocation of production budget between cast, directors and writers and does how does this apply to the most successful genres? This would include an analysis of how much impact each of these roles tend to have on a genre's success.
2. Does the provided analysis apply when considering worldwide gross as opposed to just domestic gross? Although it would be best to start off focusing on a smaller audience, it could be in Microsoft's best interest to eventually increase production to a worldwide scale.

1.8 Appendix

1.8.1 Runtime vs. Movie Success

Another potentially useful metric to keep in mind is the movie runtime. This was not included as a main part of the analysis, since it is not as closely related to the other questions of analysis which dealt more with the impact of genre selection.

However, there does seem to be some correlation between runtime and production budget. As we increase both budget and runtime, they both tend to result in a higher rating but a lower profit percentage. It is also intuitive that longer movies cost more to produce due to the amount of additional editing time and wages that would need to be paid.

Runtime Data

[32]:
```
# Eliminate entries  missing data in 'runtime_minutes' to create
# runtime dataframe.

runtime_df = merged_df[merged_df['runtime_minutes'].notna()]
runtime_df
```

[32]:
```
      release_date                                         movie  \
1657          2015                                    Concussion
3470          2015        The Second Best Exotic Marigold Hotel
1710          2015                           Unfinished Business
1163          2015                                 Run All Night
1540          2015                          Paul Blart: Mall Cop 2
…              …                                            …
256           2019  How to Train Your Dragon: The Hidden World
125           2019                          Alita: Battle Angel
3009          2019                                     Miss Bala
395           2019                                   Wonder Park
1462          2019                                     Long Shot

      production_budget  domestic_gross     tconst  \
1657           35000000      34531832.0  tt3322364
3470           10000000      33078266.0  tt2555736
1710           35000000      10219501.0  tt2358925
1163           50000000      26461644.0  tt2199571
1540           38000000      71091594.0  tt3450650
…                   …              …        …
256           129000000     160791800.0  tt2386490
125           170000000      85710210.0  tt0437086
3009           15000000      14998027.0  tt5941692
395           100000000      45216793.0  tt6428676
1462           40000000      30202860.0  tt2139881

                                    primary_title  \
1657                                   Concussion
3470        The Second Best Exotic Marigold Hotel
1710                          Unfinished Business
1163                                Run All Night
1540                         Paul Blart: Mall Cop 2
…                                             …
256   How to Train Your Dragon: The Hidden World
125                           Alita: Battle Angel
3009                                    Miss Bala
395                                   Wonder Park
1462                                    Long Shot

                                   original_title  start_year  runtime_minutes  \
```

```
1657                                       Concussion     2015.0             123.0
3470         The Second Best Exotic Marigold Hotel     2015.0             122.0
1710                              Unfinished Business     2015.0              91.0
1163                                    Run All Night     2015.0             114.0
1540                              Paul Blart: Mall Cop 2     2015.0              94.0
…                                                   …          …                 …
256   How to Train Your Dragon: The Hidden World     2019.0             104.0
125                                Alita: Battle Angel     2019.0             122.0
3009                                        Miss Bala     2019.0             104.0
395                                       Wonder Park     2019.0              85.0
1462                                        Long Shot     2019.0             125.0

                           genres  averagerating  numvotes    % profit  \
1657       Biography,Drama,Sport            7.1   77576.0   -1.337623
3470                Comedy,Drama            6.6   28931.0  230.782660
1710                Comedy,Drama            5.4   29004.0  -70.801426
1163       Action,Drama,Thriller            6.6   94131.0  -47.076712
1540         Action,Comedy,Crime            4.4   30828.0   87.083142
…                             …              …         …          …
256   Action,Adventure,Animation            7.6   60769.0   24.644806
125      Action,Adventure,Sci-Fi            7.5   88207.0  -49.582229
3009          Action,Crime,Drama            5.5    3738.0   -0.013153
395   Adventure,Animation,Comedy            5.7    3091.0  -54.783207
1462              Comedy,Romance            7.2   12814.0  -24.492850

                           genre_list
1657       [Biography, Drama, Sport]
3470                 [Comedy, Drama]
1710                 [Comedy, Drama]
1163       [Action, Drama, Thriller]
1540         [Action, Comedy, Crime]
…                                   …
256   [Action, Adventure, Animation]
125      [Action, Adventure, Sci-Fi]
3009          [Action, Crime, Drama]
395   [Adventure, Animation, Comedy]
1462               [Comedy, Romance]

[546 rows x 14 columns]
```

[33]:

```
# Group by runtime_minutes in order and calculate aggregate median for
# all columns.

runtime_df = runtime_df.sort_values('runtime_minutes')

runtime_df.head()
```

[33]:
```
      release_date            movie  production_budget  domestic_gross  \
193           2017   The Great Wall          150000000      45157105.0
5157          2015    The Overnight             200000       1109808.0
3613          2016            Kicks           10000000        150191.0
4090          2016       Lights Out            5000000      67268835.0
5196          2015      The Gallows             100000      22764410.0

         tconst   primary_title  original_title  start_year  runtime_minutes  \
193   tt7535780  The Great Wall  The Great Wall      2017.0             72.0
5157  tt3844362   The Overnight   The Overnight      2015.0             79.0
3613  tt4254584           Kicks           Kicks      2016.0             80.0
4090  tt4786282      Lights Out      Lights Out      2016.0             81.0
5196  tt2309260     The Gallows     The Gallows      2015.0             81.0

                        genres  averagerating  numvotes      % profit  \
193                Documentary            6.5      24.0    -69.895263
5157            Comedy,Mystery            6.1   14828.0    454.904000
3613           Adventure,Drama            6.3    3789.0    -98.498090
4090       Drama,Horror,Mystery            6.3  100650.0   1245.376700
5196   Horror,Mystery,Thriller            4.2   17763.0  22664.410000

                        genre_list
193                  [Documentary]
5157             [Comedy, Mystery]
3613            [Adventure, Drama]
4090      [Drama, Horror, Mystery]
5196   [Horror, Mystery, Thriller]
```

Runtime vs Movie Success To identify the relationship between runtime and movie success, we have used a regression plot to display a marker for each of the movies with an appropriate regression line for each KPI.

[34]:
```python
# Plot runtime minutes vs averagerating on regression scatter plot

fig, axes = plt.subplots(ncols=2, figsize=(16,6))

sns.regplot(x="runtime_minutes", y="averagerating", color='#1167b1',
            data=runtime_df, ax=axes[0], fit_reg=True, scatter_kws={'s':5},
            line_kws={"lw":2})

axes[0].set_title('Runtime vs. Rating')
axes[0].set_xlabel('Runtime (minutes)')
axes[0].set_ylabel('Average Rating')

# Plot runtime minutes vs percent profit on regression scatter plot

sns.regplot(x="runtime_minutes", y="% profit", color='green',
```

```
             data=runtime_df, ax=axes[1], fit_reg=True, scatter_kws={'s':5},
             line_kws={"lw":1})

axes[1].set_title('Runtime vs. Percentage Profit')
axes[1].set_xlabel('Runtime (minutes)')
axes[1].set_ylabel('Percentage Profit (%)')
axes[1].set_ylim([-150, 2000])

plt.tight_layout();
```