Data-Driven Insights for a New Movie Studio

PHASE TWO PROJECT - GROUP 3

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1. Project Overview

This project focuses on exploratory data analysis to uncover key insights that will inform the strategy of a newly established movie studio. By analyzing film industry data, the goal is to identify trends that contribute to success in film industry. The findings will provide data-driven recommendations to help the studio make informed decisions about the types of films to produce, increasing the likelihood of financial success. This project uses sqlite3 and Python libraries such as pandas for data manipulation and matplotlib and seaborn for visualization. requires getting an insight into which types of movie genres are successful interms their rating and number of peopel who rated them, that in turn shows us the size of the thier audiens and the profit they can make. It also looked into how runtime of movies, language and region of movies affect their rating and number of votes. The data analysis shows that `Action,Adventure,Sci-Fi` genre has the highest number of votes followed by `Action,Adventure,Fantacy` and `Adventure,Animation,Comedy` genres . `Drama` genre has the highest rating with the highest number of votes followed by `Comedy,Drama` and `Drama,Romance` . This movie genrea are generaly succesful in thier audience size and hence their financial benefit. The data analysis also shows that movies in french language and from US have higher votes and ratings. It also show that runtime of the movies has no effect on the rating and number of votes of movies.

1.1. Business Understanding

1.11.2 Business Problem

A company has decided to create a new movie studio, but they don’t know anything about creating movies. We have been charged with exploring what types of films are currently doing the best at the box office. We must then translate those findings into actionable insights that the head of the company's new movie studio can use to help decide what type of films to create.

1.1.2. Key Business Questions

- Which Movie Genres have the highest average rating?
- Which Movie Genres have the highest Number of votes?
- What impact does the runtime in minutes has on the average rating and votes?

- How does language influence the average rating and total number of voters of movies?
- How does region influence the number of votes and average ratings of movies?

2. Data Understanding

2.1 Data Preprocessing

2.1.1 The Data

To ensure comprehensive analysis of the business problem we retrieved data from the IMDB website (https://www.imdb.com/ (https://www.imdb.com/)). The IMDB dataset has eight tables and for this particular project we will focus on three tables, namely 'movie_basics', 'movie_ratings' and 'movie_akas'. These three tables share a column 'movie_id' which will be our Primary Key. From 'movie_basics' table we focus on 'Genres' and 'Runtime in Minutes' columns. From 'movie_ratings' we focus on 'average ratings' and 'number of votes'and from the 'movie_akas' we focus on 'region' and 'language'. The database consists of information about 331,703 movies with start dates ranging from 2010 to 2025.Two or more tables will be joined using 'movie_id' to access information about the genre, start year, run time, average rating, number of votes, language and region about each movie.

2.1.2. Data Preparation

This entails;

- Importing necessary libraries
- Loading and Accessing of the dataset
- Data Cleaning and preparation which involves: Accessing necessary data for analysis, Handling missing values and Standardizing columns.

2.1.2.1. Importing necessary libraries

In [27]:
```
# importing necessary libraries
import itertools
import numpy as np
import pandas as pd
from numbers import Number
import sqlite3
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
sns.set_style('whitegrid')

import pickle
```

2.1.2.2. Accessing the Database

In [28]:
```
# Connecting to the'im.db' database
conn = sqlite3.connect('im.db')
```

In [29]:
```
#accessing tables in the database
q ='''
SELECT  name
FROM sqlite_master
WHERE type='table';
'''
pd.read_sql(q, conn)
```

Out[29]:

	name
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers

- Our database consists of 8 tables and our project focuses on movie_basics, movie_ratings and movie_akas tables.
- Below, we view the three tables and all their cloumns.

2.1.2.3. Movie_basics table

In [30]:
```
#Viewing columns in the movie_basics table in the database
q = '''
SELECT *
FROM movie_basics;
'''
movie_basics = pd.read_sql(q, conn)
movie_basics
```

Out[30]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	None
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 6 columns

2.1.2.4. Movie_ratings table

In [31]:
```
#Viewing columns in the movie_ratings table from the database
q = '''
SELECT *
FROM movie_ratings;
'''
movie_ratings = pd.read_sql(q, conn)
movie_ratings
```

Out[31]:

	movie_id	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
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

2.1.2.5. Movie_akas table

In [32]:
```
#Viewing columns in the movie_akas table from the database
q = '''
SELECT *
FROM movie_akas;
'''
movie_akas = pd.read_sql(q, conn)
movie_akas
```

Out[32]:

	movie_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	None	None	0.0
1	tt0369610	11	Jurashikku warudo	JP	None	imdbDisplay	None	0.0
2	tt0369610	12	Jurassic World: O Mundo dos Dinossauros	BR	None	imdbDisplay	None	0.0
3	tt0369610	13	O Mundo dos Dinossauros	BR	None	None	short title	0.0
4	tt0369610	14	Jurassic World	FR	None	imdbDisplay	None	0.0
...	...	...	...	...	...	...	...	...
331698	tt9827784	2	Sayonara kuchibiru	None	None	original	None	1.0
331699	tt9827784	3	Farewell Song	XWW	en	imdbDisplay	None	0.0
331700	tt9880178	1	La atención	None	None	original	None	1.0
331701	tt9880178	2	La atención	ES	None	None	None	0.0
331702	tt9880178	3	The Attention	XWW	en	imdbDisplay	None	0.0

331703 rows × 8 columns

- *movie_basics*, *movie_ratings* and *movie_akas* tables consit of 146144, 73855 and 331702 rows or entries of movies respectively
- all tables having *movie_id* as a primary-kay or foriegn-key, having varying number of rows indicates that there may be missing and null values

2.1.3. Viewing missing or null values

In [33]:
```
# viewing null values from momovie_basics table
movie_basics.isnull().sum()
```

Out[33]:
```
movie_id               0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [34]:
```
# viewing null values from momovie_ratings table
movie_ratings.isnull().sum()
```

Out[34]:
```
movie_id         0
averagerating    0
numvotes         0
dtype: int64
```

In [35]:
```
# viewing null values from momovie_akas table
movie_akas.isnull().sum()
```

Out[35]:
```
movie_id                  0
ordering                  0
title                     0
region                53293
language             289988
types                163256
attributes           316778
is_original_title        25
dtype: int64
```

- We notice that there are null values in movie_basics and movie_akas tables.
- Using SQL for data extraction and manupilation, we will be dealing with these missing and null values in the queries we write whenever those columns with the null values are envolved

3. Data Analysis

- We join `movie_basics` and `movie_rating` tables to analyse the rating and total number of votes of movie genres
- we analyse the trend in the rating and number of votes of top rated and voted genres over the years
- we analyse the effect of runtime in minutes, language and region in the rating and number of votes

In [36]:
```
# join movie_basics and movie_ratings tables
# to remove null values - query contains 'genres is not null'
q = """
SELECT movie_id, genres, averagerating, numvotes
FROM movie_basics
   JOIN movie_ratings
   USING(movie_id)
WHERE genres IS NOT NULL
"""
movie_basics_and_ratings = pd.read_sql(q, conn)
movie_basics_and_ratings
```

Out[36]:

	movie_id	genres	averagerating	numvotes
0	tt0063540	Action,Crime,Drama	7.0	77
1	tt0066787	Biography,Drama	7.2	43
2	tt0069049	Drama	6.9	4517
3	tt0069204	Comedy,Drama	6.1	13
4	tt0100275	Comedy,Drama,Fantasy	6.5	119
...	...	...	...	...
73047	tt9913056	Documentary	6.2	5
73048	tt9913084	Documentary	6.2	6
73049	tt9914286	Drama,Family	8.7	136
73050	tt9914642	Documentary	8.5	8
73051	tt9916160	Documentary	6.5	11

73052 rows × 4 columns

- Joined table gives us the rating and number of votes for each rated movie.

3.1. Movie Rating and Number of Votes

3.1.1 Movie Ratings

In [37]:
```
# top 10 movie genres with highest average rating irrespective of their number o
q = """
    SELECT genres, AVG(averagerating) AS Avg_averagerating, SUM(numvotes) AS Tota
      FROM movie_basics
           JOIN movie_ratings
           USING(movie_id)
   GROUP BY genres
  ORDER BY Avg_averagerating DESC, Total_numvotes DESC
     LIMIT 10
    """
genres_top_rate = pd.read_sql(q, conn)
genres_top_rate
```

Out[37]:

	genres	Avg_averagerating	Total_numvotes
0	Comedy,Documentary,Fantasy	9.4	5
1	Documentary,Family,Musical	9.3	19
2	History,Sport	9.2	5
3	Game-Show	9.0	7
4	Music,Mystery	9.0	5
5	Documentary,News,Sport	8.8	25
6	Drama,Fantasy,War	8.8	22
7	Comedy,Drama,Reality-TV	8.8	15
8	Documentary,News,Reality-TV	8.8	8
9	Drama,Short	8.8	8

- These are movie genres with the highest ratings but their votes(number of people who rated them) is very low (5-25)
- These high ratings, with minimum number of voters, are of less or no significance to evaluate success of the movies
- Thus, we evaluate movie success based on number of votes and ratings combined

3.1.2. Genres with highest number of votes and ratings

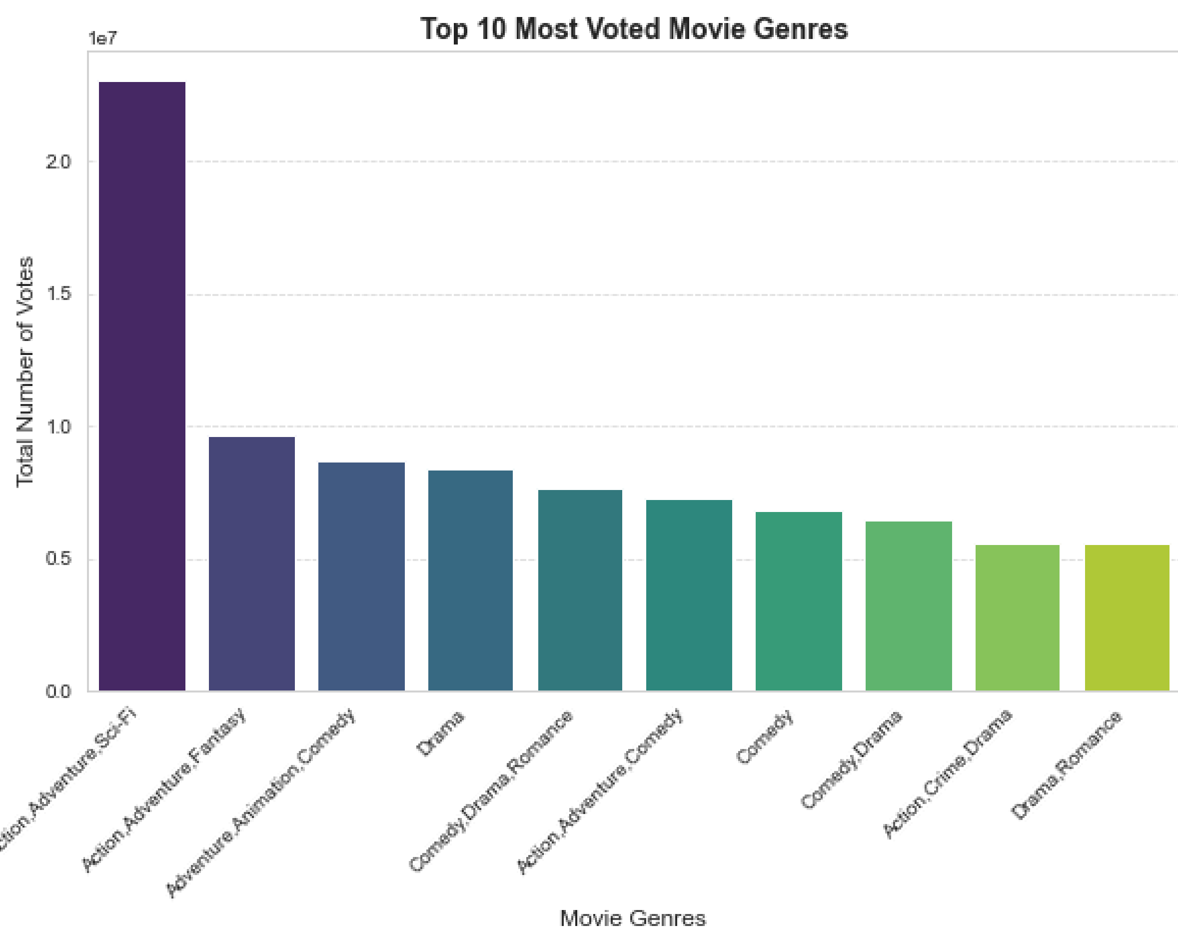
In [38]:
```
# top 10 movie genres with highest number of votes and average rating
q = """
    SELECT genres, SUM(numvotes) AS Total_numvotes, AVG(averagerating) AS Avg_ave
      FROM movie_basics
           JOIN movie_ratings
           USING(movie_id)
  GROUP BY genres
  ORDER BY Total_numvotes DESC, Avg_averagerating DESC
     LIMIT 10
    """
genres_top_vote_and_rate = pd.read_sql(q, conn)
genres_top_vote_and_rate
```

Out[38]:

	genres	Total_numvotes	Avg_averagerating
0	Action,Adventure,Sci-Fi	23023248	5.655906
1	Action,Adventure,Fantasy	9658883	5.371845
2	Adventure,Animation,Comedy	8687435	5.936555
3	Drama	8395521	6.494265
4	Comedy,Drama,Romance	7665463	6.292467
5	Action,Adventure,Comedy	7256686	5.554032
6	Comedy	6832037	5.777998
7	Comedy,Drama	6462839	6.364119
8	Action,Crime,Drama	5563553	5.989146
9	Drama,Romance	5542760	6.294305

3.1.3. Visualization of movie genres with highest number of votes

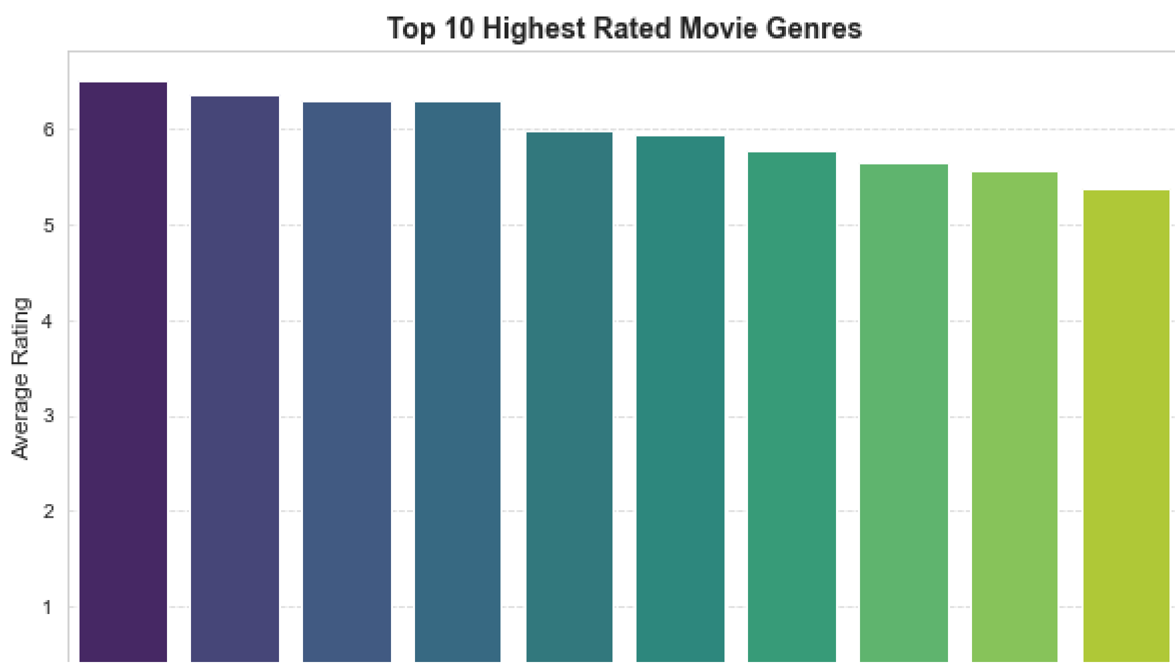
In [39]:
```
# plot bar graph of top ten genres of movies with highest total number of votes
# Set figure size for better visibility
plt.figure(figsize=(10, 6))

# Use a more appealing color palette
sns.barplot(
    x=genres_top_vote_and_rate['genres'],
    y=genres_top_vote_and_rate['Total_numvotes'],
    palette="viridis"
)
# Add labels and title with improved formatting
plt.xlabel('Movie Genres', fontsize=12)
plt.ylabel('Total Number of Votes', fontsize=12)
plt.title('Top 10 Most Voted Movie Genres', fontsize=14, fontweight='bold')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

# Display the grid for better readability
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```



- `Action,Adventure,Sci-Fi` genre has the highest number of votes followed by `Action,Adventure,Fantacy` and `Adventure,Animation,Comedy` genres .
- `Drama,Romance` genre has the lowest votes among the top 10 highest voted.

3.1.4. Visualization of movie genres with highest average ratings

In [40]:
```
# Sort data by average rating in descending order
sorted_data = genres_top_vote_and_rate.sort_values(by='Avg_averagerating', ascend

# Set figure size for better visibility
plt.figure(figsize=(10, 6))

# Use a more appealing color palette
sns.barplot(
    x=sorted_data['genres'],
    y=sorted_data['Avg_averagerating'],
    palette="viridis"
)

# Add labels and title with improved formatting
plt.xlabel('Movie Genres', fontsize=12)
plt.ylabel('Average Rating', fontsize=12)
plt.title('Top 10 Highest Rated Movie Genres', fontsize=14, fontweight='bold')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

# Display the grid for better readability
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```



- `Drama` genre has the highest rating based on the top ten genres with the highest number of votes followed by `Comedy,Drama` and `Drama,Romance`.
- `Action,Adventure,Fantasy` genre has the lowest rating among the top 10 highest rated genres.
- All top 10 genres have ratings in the range between 5.4 and 6.5.

3.2. Movie genre ratings and number of votes over the years

3.2.1. Top five movie genres - votes and ratings over the years

In [41]:
```
# Total number of votes and ratings of top 5 movies over the years
q = """
    SELECT genres, start_year, SUM(numvotes) AS Total_numvotes, AVG(averagerating
      FROM movie_basics
           JOIN movie_ratings
           USING(movie_id)
    WHERE genres IS NOT NULL
  GROUP BY genres, start_year
    HAVING genres == 'Action,Adventure,Sci-Fi' OR genres =='Action,Adventure,Fant
  ORDER BY genres, Total_numvotes DESC;

    """
genres_votes_over_years = pd.read_sql(q, conn)
genres_votes_over_years.head()
```

Out[41]:

	genres	start_year	Total_numvotes	Avg_averagerating
0	Action,Adventure,Fantasy	2017	2171754	5.575000
1	Action,Adventure,Fantasy	2016	2124337	6.292308
2	Action,Adventure,Fantasy	2011	1650970	4.780000
3	Action,Adventure,Fantasy	2015	883563	5.033333
4	Action,Adventure,Fantasy	2010	828729	6.216667

In [42]:
```
## Top Rating movies and their number of votes
```

In [43]:
```
# top 10 movie genres with highest number of votes and average rating
q = """
    SELECT genres, AVG(averagerating) AS Avg_averagerating, SUM(numvotes) AS Tota
      FROM movie_basics
           JOIN movie_ratings
           USING(movie_id)
   GROUP BY genres
  ORDER BY Avg_averagerating DESC, Total_numvotes DESC
     LIMIT 10
    """
genres_top_rate = pd.read_sql(q, conn)
genres_top_rate
```

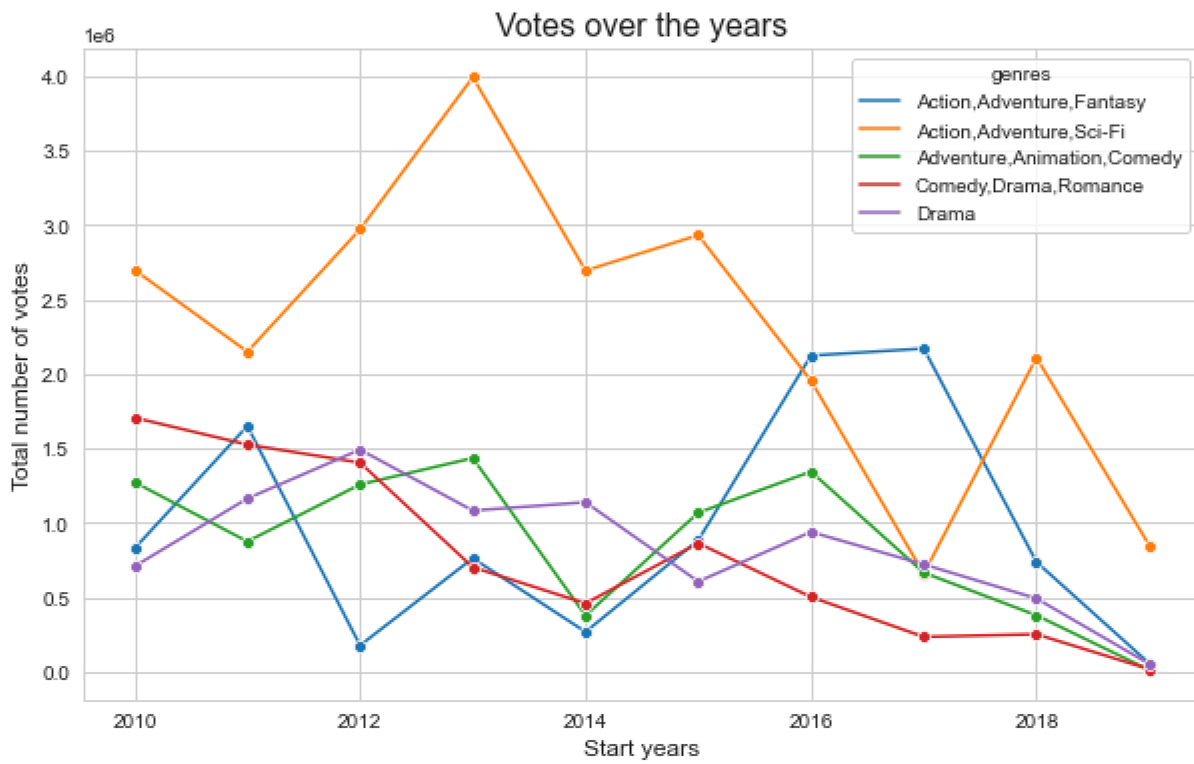
Out[43]:

	genres	Avg_averagerating	Total_numvotes
0	Comedy,Documentary,Fantasy	9.4	5
1	Documentary,Family,Musical	9.3	19
2	History,Sport	9.2	5
3	Game-Show	9.0	7
4	Music,Mystery	9.0	5
5	Documentary,News,Sport	8.8	25
6	Drama,Fantasy,War	8.8	22
7	Comedy,Drama,Reality-TV	8.8	15
8	Documentary,News,Reality-TV	8.8	8
9	Drama,Short	8.8	8

- Genres with highest rating hava th

3.2.2. Visualization of number votes of top five movie genres over time

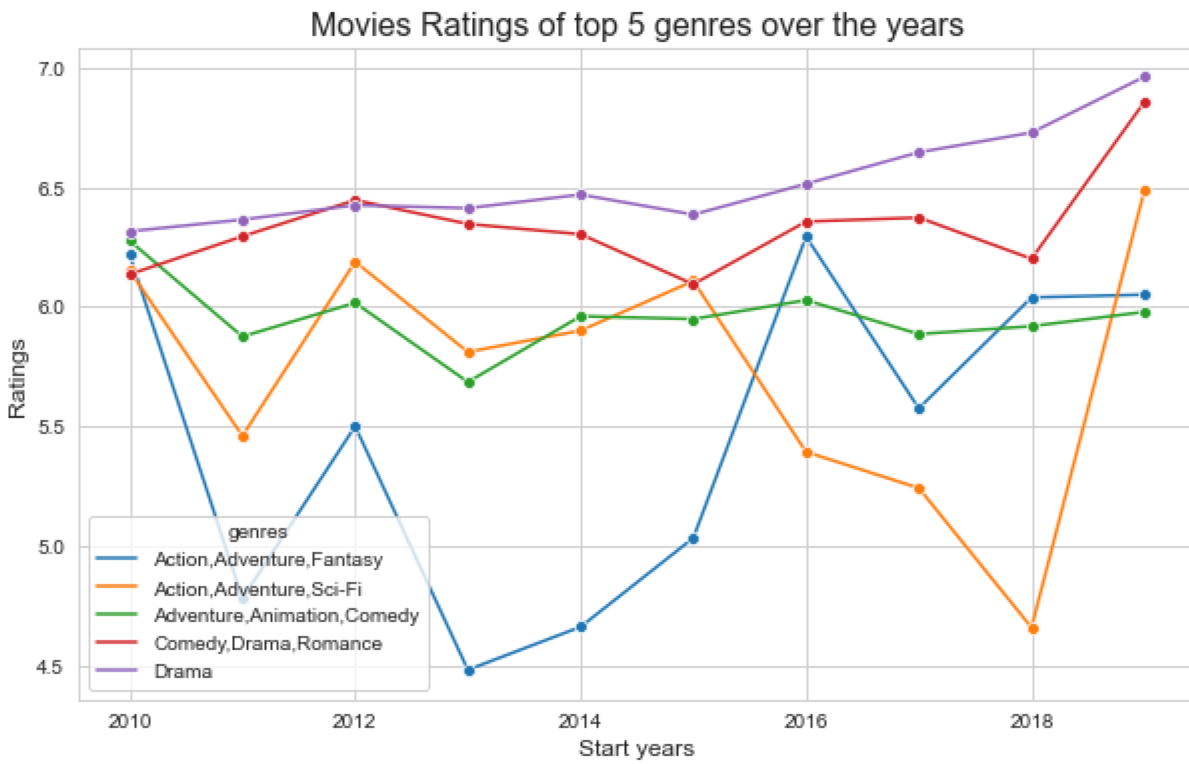
In [44]:
```
# plot top 5 genres and total number of voters over the years
plt.figure(figsize=(10, 6))
sns.lineplot(data= genres_votes_over_years, x='start_year', y='Total_numvotes', h

# Add labels and title with improved formatting
plt.title('Votes over the years', fontsize=16)
plt.xlabel('Start years', fontsize=12)
plt.ylabel('Total number of votes', fontsize=12)
plt.grid(True)
plt.legend(title='genres')
plt.show()
```



- Visualization above displays the total number of votes over the years from the year 2010 to the year 2019. We can observe that number of votes have been decreasing gradually over the years.
- `Action,Adventure,Sci-Fi` genre is with the highest number of votes over the years.

3.2.3. Visualization of average ratings of top five movie genres over the years

In [45]:
```
# plot ratings of top 5 genres over the years
plt.figure(figsize=(10, 6))
sns.lineplot(data= genres_votes_over_years, x='start_year', y='Avg_averagerating'

plt.title('Movies Ratings of top 5 genres over the years', fontsize=16)
plt.xlabel('Start years', fontsize=12)
plt.ylabel('Ratings', fontsize=12)
plt.grid(True)
plt.legend(title='genres')
plt.show()
```



- From the above visualization, we can observe that:
- There is a general trend of increase in the rating of most of the genres.
- `Drama` genre has the highest and increased rating over the years followed by `commedy,Drama,Romance` and `Adventure,Animation,comedy` genres.
- `Action,Adventure,Sci-Fi` and `Action,Adventure,Fantacy` genres had fluctuating ratings over the years.

3.3. Runtime of movies and effect on votes and ratings

In [46]:
```
# check if there is effect of runtime of movies on rating and votes
# join movie_basics and movie_ratings tables
q = """
    SELECT AVG(runtime_minutes) AS Avg_runtime_minutes, SUM(numvotes) AS Total_nu
      FROM movie_basics
           JOIN movie_ratings
           USING(movie_id)
    WHERE runtime_minutes IS NOT NULL
    GROUP BY genres
  ORDER BY Total_numvotes DESC, Avg_rating DESC
    """
movie_runtime = pd.read_sql(q, conn)
movie_runtime
```

Out[46]:

	Avg_runtime_minutes	Total_numvotes	Avg_rating
0	108.569106	23023053	5.668293
1	108.320000	9658805	5.336000
2	88.448718	8687201	5.944444
3	97.633723	8342370	6.485779
4	100.415876	7662618	6.288870
...	...	...	...
902	87.000000	6	2.800000
903	70.000000	5	9.400000
904	74.000000	5	6.400000
905	105.000000	5	6.400000
906	78.000000	5	4.400000

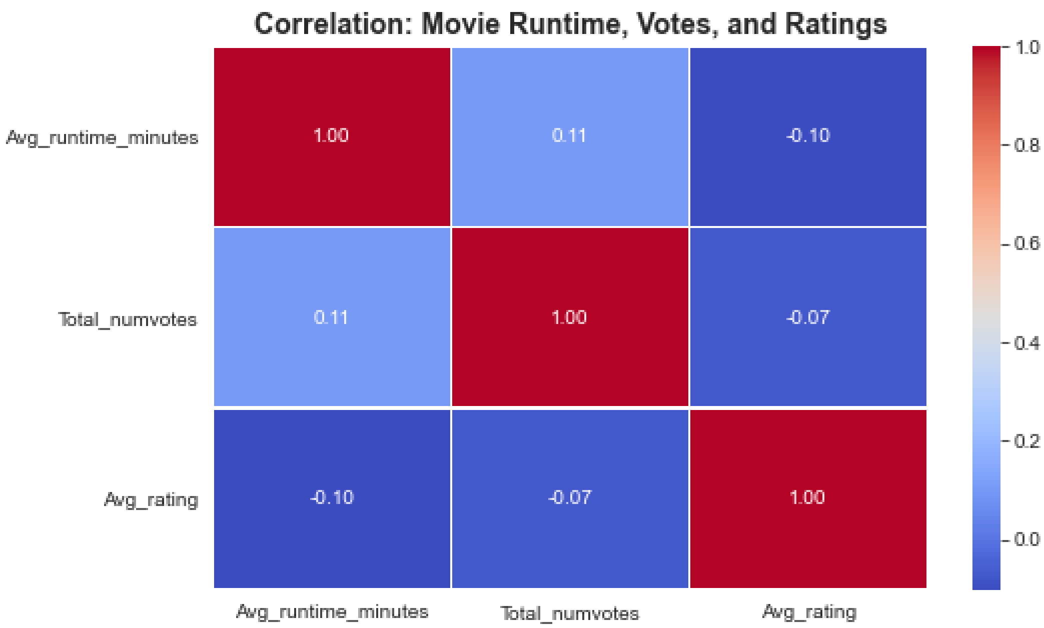
907 rows × 3 columns

- From the above table we can see that the top 10 movie genres with highest votes

  and ratings have an average runtime between 88.4 and 108.6 minutes

3.3.1. Correlation between Average runtime, number of votes and avarage rating

In [47]:
```
# Compute correlation matrix
correlation_matrix = movie_runtime[['Avg_runtime_minutes', 'Total_numvotes', 'Avg

plt.figure(figsize=(8, 5))

# Plot heatmap
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f", linewidth

# Add title
plt.title("Correlation: Movie Runtime, Votes, and Ratings", fontsize=14, fontweig

# Show plot
plt.show()
```



We can observe:

- correlation of 0.11 between the `total number of votes` and `average runtime` which indicates a `weak positive` relationship.
- correlation of -0.07 between the `total number of votes` and `average rating` which indicates a `weak negative` relationship
- correlation of -0.10 between the `average rating` and `average runtime` which indicates a `weak negative` relationship.
- Generally there is a week or correlation between movie runtime and number of votes and ratings.

3.4. Movie languages and ratings and number of votes

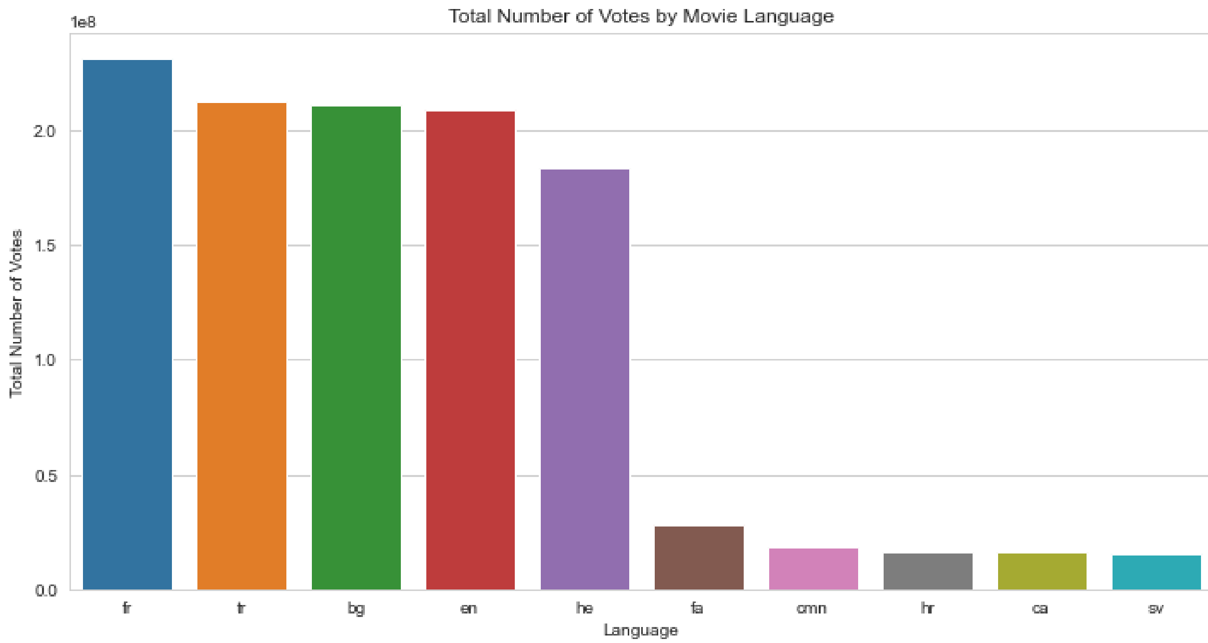
In [48]:
```
# check effect of language on the rating and number of votes of movies
q = '''
SELECT language, SUM(numvotes) AS Total_numvotes, AVG(averagerating) AS Avg_avera
      FROM movie_akas
           JOIN movie_ratings
           USING(movie_id)
     WHERE language IS NOT NULL
  GROUP BY language
  ORDER BY Total_numvotes DESC, Avg_averagerating DESC
  LIMIT 10
'''

movie_language = pd.read_sql(q, conn)
movie_language
```

Out[48]:

	language	Total_numvotes	Avg_averagerating
0	fr	231092513	6.413583
1	tr	212375744	6.179227
2	bg	211275380	6.248951
3	en	209264624	6.269339
4	he	183490289	6.537221
5	fa	28314980	6.166087
6	cmn	18428732	5.834505
7	hr	16425337	5.851701
8	ca	15852436	6.762882
9	sv	15698475	6.811809

3.4.1. Visualization of effect of movie language on rating and total number of voters of movies

In [49]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x='language', y='Total_numvotes', data=movie_language, ci=None)
#plt.xticks(rotation=90)  # Rotate labels for readability
plt.xlabel("Language")
plt.ylabel("Total Number of Votes")
plt.title("Total Number of Votes by Movie Language")
plt.show()
```



- Movies in **French language** have the highest votes followed by **Turkish** and **Bulgarian**.
- We have movies with swedish language with the lowest number of votes.

3.4.2. Chi-square to test if movie language affects ratings

To determine if ratings vary by language, we used Chi-Square Which is designed to test relationships between categorical variables hence great for our task.

Hypothesis testing

Null Hypothesis (H_0):

There is no difference in ratings of movies in different languages.

Alternative Hypothesis (H_1):

There is difference in ratings of movies in different languages.

In [50]:
```
# we use chi-square to test the hypothesis

#import necessary library
from scipy.stats import chi2_contingency

# Categorize ratings
bins = [0, 6.5, 7.5, 10]
labels = ['Low', 'Medium', 'High']
movie_language['Rating_Category'] = pd.cut(movie_language['Avg_averagerating'], b

# Create a contingency table
contingency_table = pd.crosstab(movie_language['language'], movie_language['Ratin

# Perform Chi-Square test
chi2_stat, p_value, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-Square Statistic: {chi2_stat:.2f}, p-value: {p_value:.4f}")
```

```
Chi-Square Statistic: 10.00, p-value: 0.3505
```

- With 95% significance level(alpha = 0.05), since P-value(0.3505) is greater than 0.05, we fail to reject the null hypothesis. This means that the relationship between movie language and ratings is not statistically significant.

3.5. Regions and ratings and number of votes

In [51]:
```
# check effect of region on the rating and number of votes of movies
q = '''
    SELECT region AS movie_region, SUM(numvotes) AS Total_numvotes, AVG(averagera
      FROM movie_ratings
           LEFT JOIN movie_akas
           USING(movie_id)
    WHERE region IS NOT NULL
  GROUP BY region
  ORDER BY Total_numvotes DESC, Avg_averagerating DESC
  LIMIT 10;
'''
movie_region = pd.read_sql(q, conn)
movie_region
```

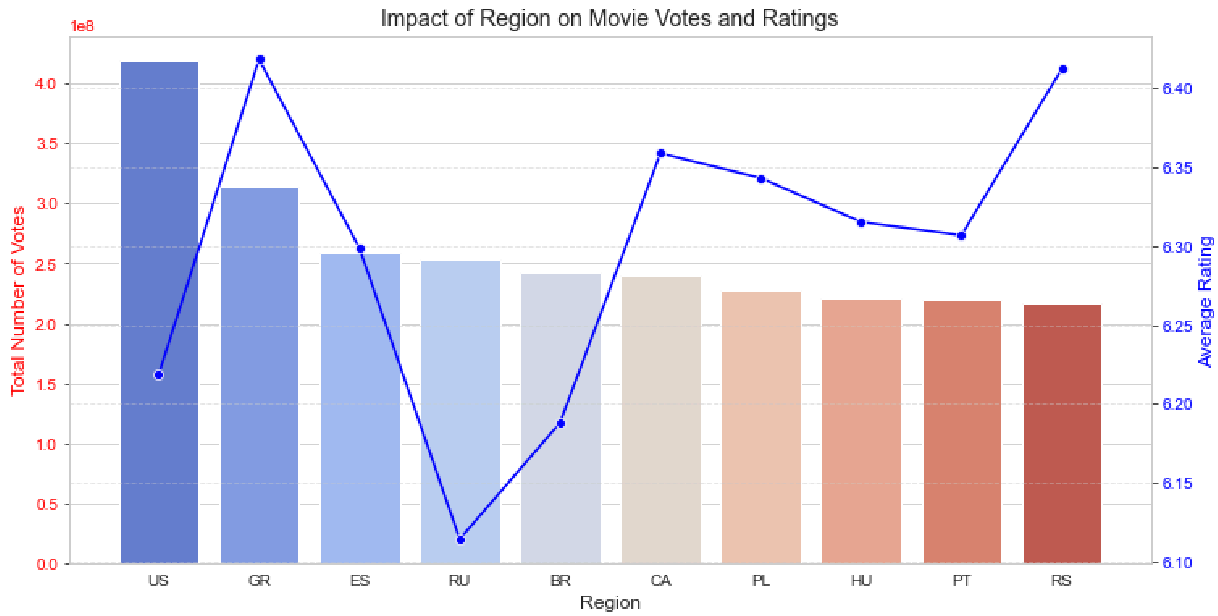
Out[51]:

	movie_region	Total_numvotes	Avg_averagerating
0	US	418957631	6.218606
1	GR	314020162	6.418054
2	ES	259269856	6.298747
3	RU	253657614	6.114330
4	BR	242543329	6.188029
5	CA	240139452	6.358648
6	PL	227107093	6.342997
7	HU	221576907	6.315188
8	PT	219949216	6.306735
9	RS	216622549	6.411964

3.5.1. Visualization of impact of movie region on effect ratingsabs and total number of voters

In [52]:
```
# plot bar graph and line graph on the same axsis to show impact of
# movie region on ratings and total number of votes

plt.figure(figsize=(12, 6))

# Sort data by votes for better visualization
movie_region = movie_region.sort_values(by="Total_numvotes", ascending=False)

# Create a twin-axis plot
fig, ax1 = plt.subplots(figsize=(12, 6))

# Plot total votes (bar chart)
sns.barplot(
    x="movie_region", y="Total_numvotes", data=movie_region, palette="coolwarm",
)
ax1.set_ylabel("Total Number of Votes", color="red", fontsize=12)
ax1.set_xlabel("Region", fontsize=12)
ax1.tick_params(axis="y", labelcolor="red")

# Create a second y-axis for average ratings
ax2 = ax1.twinx()
sns.lineplot(
    x="movie_region", y="Avg_averagerating", data=movie_region, color="blue", mar
)
ax2.set_ylabel("Average Rating", color="blue", fontsize=12)
ax2.tick_params(axis="y", labelcolor="blue")

# Title and layout
plt.title("Impact of Region on Movie Votes and Ratings", fontsize=14)
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.grid(axis="y", linestyle="--", alpha=0.5)
plt.show()
```

```
<Figure size 864x432 with 0 Axes>
```



- From the above visualization we can observe that United states has the highest number of votes and the highest number of rating followed by Greece.
- Russia has the lowest avarage rating.
- Republic of Serbia has the lowest number of votes overal.

4. Analysis Summary

Our analysis process included:

- 1. Exploratory Data Analysis (EDA): We examined various film attributes, such as genres, ratings, votes, languages, and regions, to uncover patterns and trends in the film industry.
- 2. Visualization and Insights: Through data visualization techniques, we identified key findings and trends in the industry, which were then translated into actionable recommendations.
- 3. Statistical Analysis: We applied correlation analysis and hypothesis testing to determine relationships between film attributes such as runtime, language, and popularity.

5. Key Findings

Our analysis revealed several characteristics of films that tend to perform well at the box office:

Genre Trends:

- **Drama** movies have the highest rating among the top ten genres with the highest number of votes, followed by **Comedy,Drama**, and **Drama,Romance**.
- The **Action,Adventure,Sci-Fi** genre has the highest number of votes, followed by **Action,Adventure,Fantasy** and **Adventure,Animation,Comedy**. These genres have a strong audience base, indicating their popularity in mainstream cinema.

Runtime and Popularity:

- There is a very weak positive correlation (0.10) between the total number of votes and average runtime, and very weak negative correlation (-0.07) between average rating and average runtime.
- This suggests that runtime of movies as little or no effect on ratings or number of votes.

Language Preference:

Movies in the French language have received the highest number of votes (231,092,513), followed by Turkish and Bulgarian films. This suggests that French-language films have a wider global reach or a highly engaged audience.

Regional Popularity:

- Movies form United States have the highest number of votes and ratings, reflecting its dominance in global cinema.
- Surprisingly, Greece ranks second, indicating a strong movie-watching culture or high engagement from Greek audiences.

6. Recommendations

Based on our findings, we suggest the following strategies for the studio:

1. Genre Selection for High Engagement

- Focus on producing or promoting Drama, Comedy, and Romance films, as they receive the highest ratings with high number of votes.
- **Action,Adventure,Sci-Fi**, **Action,Adventure,Fantacy** and **Adventure,Animation,Comedy** genres attract the most votes, which inturn means the highest global audience, making them ideal for blockbuster-style films targeting a broad audience.
- Consider blending elements of popular genres (e.g., Action-Drama or Sci-Fi-Romance) to appeal to both high-rating and high-vote segments.

2. Language and Market Expansion

- Given the high number of votes for French, Turkish, and Bulgarian films, production companies should consider dubbing or subtitling in these languages to increase global reach.
- Investing in regional language content can help tap into underrepresented but highly engaged audiences.

3. Target High-Engagement Markets

- The United States leads in votes, making it a key market for movie releases.
- The strong Greek audience engagement suggests opportunities for localized content, marketing campaigns, and regional streaming services.

7. Summary

Our analysis of the movie industry data has provided valuable insights that can guide the strategic decisions of the new movie studio. We identified the most popular genres based on average ratings and total votes, revealing that Drama movies tend to receive the highest ratings, while

Action, Adventure, and Sci-Fi films attract the most votes. Understanding these trends will help the studio choose movie genres that are both critically acclaimed and commercially successful. Additionally, we examined how factors like movie runtime, language, and region impact ratings and votes.

By focusing on high-performing genres and considering factors like language and audience preferences, the new studio can increase its chances of success in a competitive industry