Phase 1 Project

1. Business Understanding

The head of Microsoft needs to know what types of films are trending so that they can be at the top of the game when opening their new movie studio

Some of the questions to be answer

1. What are the top 5 genres currently trending?
2. What genres generate the highest gross
3. What is the average time of movies?

2. Data Understanding

Understanding bom.movie_gross.csv data

In [1]:
```
import pandas as pd

bom_movie_gross_df = pd.read_csv('data/bom.movie_gross.csv/bom.movie_gross.csv') # R
```

In [2]:
```
bom_movie_gross_df.head()
```

Out[2]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [3]:
```
bom_movie_gross_df.info
```

Out[3]:
```
<bound method DataFrame.info of                                                 title
studio  domestic_gross  \
0                                     Toy Story 3          BV     415000000.0
1                       Alice in Wonderland (2010)          BV     334200000.0
2     Harry Potter and the Deathly Hallows Part 1          WB     296000000.0
3                                       Inception          WB     292600000.0
4                              Shrek Forever After        P/DW     238700000.0
...                                            ...         ...             ...
3382                                  The Quake       Magn.          6200.0
3383                Edward II (2018 re-release)          FM          4800.0
3384                                   El Pacto        Sony          2500.0
3385                                   The Swan  Synergetic          2400.0
3386                            An Actor Prepares       Grav.          1700.0

     foreign_gross  year
0        652000000  2010
1        691300000  2010
2        664300000  2010
3        535700000  2010
4        513900000  2010
...            ...   ...
3382           NaN  2018
```

```
3383           NaN  2018
3384           NaN  2018
3385           NaN  2018
3386           NaN  2018

[3387 rows x 5 columns]>
```

In [4]:
```
bom_movie_gross_df.columns
```

Out[4]:
```
Index(['title', 'studio', 'domestic_gross', 'foreign_gross', 'year'], dtype='object')
```

In [5]:
```
bom_movie_gross_df.describe()
```

Out[5]:

	domestic_gross	year
count	3.359000e+03	3387.000000
mean	2.874585e+07	2013.958075
std	6.698250e+07	2.478141
min	1.000000e+02	2010.000000
25%	1.200000e+05	2012.000000
50%	1.400000e+06	2014.000000
75%	2.790000e+07	2016.000000
max	9.367000e+08	2018.000000

Understanding im.db data

In [6]:
```
import sqlite3
conn = sqlite3.connect('data/im.db/im.db')
```

In [7]:
```
query = "SELECT name FROM sqlite_master WHERE type='table';"
imdb_tables = pd.read_sql(query, conn)
imdb_tables
```

Out[7]:

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

In [8]:
```
for imdb_table_name in imdb_tables['name']:
    cursor = conn.cursor()
    query = f"SELECT * FROM {imdb_table_name} LIMIT 5;"
    cursor.execute(query) # helps execute and retrieve data
    imdb_data_df = pd.DataFrame(cursor.fetchall(), columns=[col[0] for col in cursor
    print(f"Table: {imdb_table_name}")
    print(imdb_data_df)
    print("-" * 50)
```

```
Table: movie_basics
    movie_id                    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
--------------------------------------------------
Table: directors
    movie_id  person_id
0  tt0285252  nm0899854
1  tt0462036  nm1940585
2  tt0835418  nm0151540
3  tt0835418  nm0151540
4  tt0878654  nm0089502
--------------------------------------------------
Table: known_for
   person_id   movie_id
0  nm0061671  tt0837562
1  nm0061671  tt2398241
2  nm0061671  tt0844471
3  nm0061671  tt0118553
4  nm0061865  tt0896534
--------------------------------------------------
Table: movie_akas
    movie_id  ordering                                      title region  \
0  tt0369610        10                          Джурасик свят     BG
1  tt0369610        11                       Jurashikku warudo     JP
2  tt0369610        12  Jurassic World: O Mundo dos Dinossauros     BR
3  tt0369610        13                  O Mundo dos Dinossauros     BR
4  tt0369610        14                           Jurassic World     FR

  language        types   attributes  is_original_title
0       bg         None         None                0.0
1     None  imdbDisplay         None                0.0
2     None  imdbDisplay         None                0.0
3     None         None  short title                0.0
4     None  imdbDisplay         None                0.0
--------------------------------------------------
Table: movie_ratings
     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
--------------------------------------------------
Table: persons
   person_id       primary_name birth_year death_year  \
0  nm0061671  Mary Ellen Bauder       None       None
1  nm0061865       Joseph Bauer       None       None
2  nm0062070         Bruce Baum       None       None
3  nm0062195       Axel Baumann       None       None
4  nm0062798        Pete Baxter       None       None

                            primary_profession
0         miscellaneous,production_manager,producer
1        composer,music_department,sound_department
2                       miscellaneous,actor,writer
3  camera_department,cinematographer,art_department
4  production_designer,art_department,set_decorator
--------------------------------------------------
```

```
Table: principals
    movie_id  ordering  person_id  category       job        characters
0  tt0111414         1  nm0246005     actor      None       ["The Man"]
1  tt0111414         2  nm0398271  director      None              None
2  tt0111414         3  nm3739909  producer  producer              None
3  tt0323808        10  nm0059247    editor      None              None
4  tt0323808         1  nm3579312   actress      None  ["Beth Boothby"]
--------------------------------------------------
Table: writers
    movie_id  person_id
0  tt0285252  nm0899854
1  tt0438973  nm0175726
2  tt0438973  nm1802864
3  tt0462036  nm1940585
4  tt0835418  nm0310087
--------------------------------------------------
```

Focusing on two tables movie_basics and movie_ratings because movie basics shows the different types of genres as well as the runtimes and movie_ratings shows the average ratings

In [9]:
```
table_names = ['movie_ratings', 'movie_basics']
for table_name in table_names:
    query = f"SELECT * FROM {table_name} LIMIT 5;"
    cursor = conn.cursor()
    cursor.execute(query)

    # Fetch the im.db data and load into a DataFrame
    imdb_df = pd.DataFrame(cursor.fetchall(), columns=[col[0] for col in cursor.desc

    print(f"Table: {table_name}")
    print(imdb_df)
    print("-" * 50)
```

```
Table: movie_ratings
     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
--------------------------------------------------
Table: movie_basics
    movie_id                    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
--------------------------------------------------
```

3. Data Preparation

After understanding the bom_movie_gross.csv data, I decided to check for missing or inconsistent values in the data. I have created a function which checks for missing values in both the bom.movie_gross_df and the imdb_df Dataframes

In [10]:
```
def print_missing_values(dataframe):
    missing_value_total = dataframe.isnull().sum()
    print(missing_value_total)
```

In [11]:
```
print_missing_values(bom_movie_gross_df)
```

```
title               0
studio              5
domestic_gross     28
foreign_gross    1350
year                0
dtype: int64
```

I realized that foreign gross has a high number of missing values so I made the decision to add zeros to all the rows that had a null value. I made the assumption that those particular movies did not receive any foreign_gross that year. I also made the decision to fill the studio missing valuse with 'Not Available' just to indicate that there was no information for those studio names I also filled the domestic_gross with zeros to indicated that those movies did not receive any domestic_gross

In [12]:
```
def fill_missing_values(dataframe, column, fill_value):
    dataframe[column] = dataframe[column].fillna(fill_value)
    return dataframe
```

In [13]:
```
bom_movie_gross_df = fill_missing_values(bom_movie_gross_df, 'foreign_gross', 0)
bom_movie_gross_df = fill_missing_values(bom_movie_gross_df, 'studio', 'Not Availabl
bom_movie_gross_df = fill_missing_values(bom_movie_gross_df, 'domestic_gross', 0)

print("Updated DataFrame:")
print(bom_movie_gross_df)
```

```
Updated DataFrame:
                                          title      studio  domestic_gross  \
0                                 Toy Story 3          BV     415000000.0
1                   Alice in Wonderland (2010)          BV     334200000.0
2     Harry Potter and the Deathly Hallows Part 1          WB     296000000.0
3                                     Inception          WB     292600000.0
4                         Shrek Forever After        P/DW     238700000.0
...                                       ...         ...             ...
3382                              The Quake       Magn.           6200.0
3383                  Edward II (2018 re-release)          FM          4800.0
3384                                El Pacto        Sony          2500.0
3385                                The Swan  Synergetic          2400.0
3386                          An Actor Prepares       Grav.          1700.0

     foreign_gross  year
0        652000000  2010
1        691300000  2010
2        664300000  2010
3        535700000  2010
4        513900000  2010
...            ...   ...
3382             0  2018
3383             0  2018
3384             0  2018
3385             0  2018
3386             0  2018

[3387 rows x 5 columns]
```

In [14]:
```
print_missing_values(bom_movie_gross_df)
```

```
title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

After understanding the imdb data, I decided to check for missing values in the tables of movie_basics and movie_ratings.

In [15]:
```
print_missing_values(imdb_df)
```

```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    1
genres             0
dtype: int64
```

I realized that runtime_minutes has one row that has a missing value so i decided to drop that row

In [16]:
```
imdb_df = imdb_df.dropna(subset=['runtime_minutes'])
```

In [17]:
```
print_missing_values(imdb_df)
```

```
movie_id           0
primary_title      0
original_title     0
start_year         0
runtime_minutes    0
genres             0
dtype: int64
```

4. Data Analysis

Here I am doing my analysis on of the questions set in the Business Understanding:

1. What are the top 5 genres currently trending?

- The data being used in this analysis is the im.db where I'll be using the two tables prepared above; movie_basics and movie_ratings
- Joined the two tables movie_basics and movie_ratings based on the movie_id key

In [18]:
```
query = '''SELECT mb.movie_id, mb.primary_title, mb.genres, mr.averagerating, mr.num
            FROM movie_basics AS mb
            JOIN movie_ratings AS mr
            ON mb.movie_id = mr.movie_id'''


combined_movie_df = pd.read_sql(query, conn)
conn.close()

print('Combined DataFrame')
print(combined_movie_df.head())
```

```
Combined DataFrame
    movie_id                    primary_title                genres  \
0  tt0063540                        Sunghursh    Action,Crime,Drama
1  tt0066787  One Day Before the Rainy Season       Biography,Drama
2  tt0069049       The Other Side of the Wind                Drama
3  tt0069204                  Sabse Bada Sukh          Comedy,Drama
4  tt0100275         The Wandering Soap Opera  Comedy,Drama,Fantasy

   averagerating  numvotes
0            7.0        77
1            7.2        43
2            6.9      4517
3            6.1        13
4            6.5       119
```

- Since the genres are stored as a list of many genres in a row, it is necessary to split them into individual rows
- I will also group the Combined DataFrame by genre and calculate the average ratings of each genre as well as the total number of votes
- Then sort to get the top 5 genres by average ratings and the top 5 genres by total number of votes
- The results indicate that the top 5 genres by average ratings include: Short, Documentary, Game-Show, News, Biography, while the top 5 genres by total number of votes include: Drama, Action, Adventure, Comedy, Thriller.

In [19]:
```
combined_movie_df['genres'] = combined_movie_df['genres'].str.split(',')
combined_movie_df = combined_movie_df.explode('genres')

genre_stats = combined_movie_df.groupby('genres').agg({
    'averagerating': 'mean',
    'numvotes': 'sum'
}).reset_index()

# Sorting by average ratings and by total number of votes to get the top 5 genres in
top_genres_by_rating = genre_stats.sort_values(by='averagerating', ascending=False).
top_genres_by_votes = genre_stats.sort_values(by='numvotes', ascending=False).head(5

print("\nTop 5 Genres by Average Rating:")
print(top_genres_by_rating)

print("\nTop 5 Genres by Total Number of Votes:")
print(top_genres_by_votes)
```

```
Top 5 Genres by Average Rating:
         genres  averagerating  numvotes
21        Short       8.800000         8
7   Documentary       7.332090   4739345
11    Game-Show       7.300000      3469
17         News       7.271330    123319
4     Biography       7.162274  21609446

Top 5 Genres by Total Number of Votes:
       genres  averagerating   numvotes
8       Drama       6.401559  119567500
0      Action       5.810361  101161682
2   Adventure       6.196201   84232589
5      Comedy       6.002689   74305805
23   Thriller       5.639114   48155313
```

1. What genres generate the highest gross?

- The data being used is a combination of bom.movie_gross.csv data and the im.db data.

- The reason for the merged DataFrames is because the imdb_df contains the list genres while the bom_movie_gross_df contains the domestic and foreign gross data.
- I am merging the two dataframes using the primary key title and primary_title respectively. This is after I saw those that both columns don't have missing values as well as both columns are unique to the whole table.
- From the results its evident that the highest domestic gross is 415000000.0 while foreign gross is 652000000.0
- We can also see that the top 5 highest generating genres is: Action, Adventure, Animation, Biography and Comedy

In [20]:
```
# Merge the datasets
merged_df = pd.merge(bom_movie_gross_df, combined_movie_df, left_on='title', right_o

# Split genres and explode the DataFrame
merged_df['genres'] = merged_df['genres'].str.split(',')
exploded_df = merged_df.explode('genres')

# Convert foreign_gross to string, remove commas, and convert to float
exploded_df['foreign_gross'] = exploded_df['foreign_gross'].astype(str).str.replace(
exploded_df['foreign_gross'] = exploded_df['foreign_gross'].replace('', 0).fillna(0)

print("\nCleaned DataFrame:")
display(exploded_df.head())

# Calculate total gross for each genre
exploded_df['total_gross'] = exploded_df['domestic_gross'] + exploded_df['foreign_gr
genre_gross = exploded_df.groupby('genres')['total_gross'].sum().reset_index()

print("\nTotal Gross by Genre DataFrame:")
display(genre_gross.head())

genre_gross = genre_gross.sort_values(by='total_gross', ascending=False)
```

Cleaned DataFrame:

	title	studio	domestic_gross	foreign_gross	year	movie_id	primary_title	genres	averag
0	Toy Story 3	BV	415000000.0	652000000.0	2010	tt0435761	Toy Story 3	Adventure	
1	Toy Story 3	BV	415000000.0	652000000.0	2010	tt0435761	Toy Story 3	Animation	
2	Toy Story 3	BV	415000000.0	652000000.0	2010	tt0435761	Toy Story 3	Comedy	
3	Inception	WB	292600000.0	535700000.0	2010	tt1375666	Inception	Action	
4	Inception	WB	292600000.0	535700000.0	2010	tt1375666	Inception	Adventure	

Total Gross by Genre DataFrame:

	genres	total_gross
0	Action	1.063727e+11
1	Adventure	1.194914e+11
2	Animation	3.879844e+10
3	Biography	1.310094e+10
4	Comedy	7.714817e+10

1. What is the average time of movies?

- Using the start_year column and runtime_minutes column of the imdb_df dataframe I calculated the mean runtime for each year.
- This is so that I can understand what is the average runtime_minutes in each year. 2013 recorded the highest runtime_minutes of around 175.0 min while the lowest recorded runtime_minutes is 80 in 2017.
- I also calcultated the 25th and the 75th percentile of the runtime_minutes where majority of movies fall which is 105.5 mins and 135.25 mins.
- On average, movies should have runtime_minutes of 122.75 mins

In [21]:
```
# Calculate the average runtime for each year
average_runtime_per_year = imdb_df.groupby('start_year')['runtime_minutes'].mean()

# overall average runtime
overall_average_runtime = imdb_df['runtime_minutes'].mean()

# Determine the range of runtimes where the majority of movies fall
common_runtime_range = (imdb_df['runtime_minutes'].quantile(0.25), imdb_df['runtime_

# Calculate lowest and highest runtimes
lowest_runtime = imdb_df['runtime_minutes'].min()
highest_runtime = imdb_df['runtime_minutes'].max()

print("Average Movie Runtime by Year:")
print(average_runtime_per_year)
print("\nOverall Average Runtime of movies:", overall_average_runtime, "minutes")
print("\nCommon Runtime Range (25th to 75th percentile):", common_runtime_range, "mi
print("\nLowest Runtime :", lowest_runtime, "minutes")
print("\nHighest Runtime :", highest_runtime, "minutes")
```

```
Average Movie Runtime by Year:
start_year
2013    175.0
2017     80.0
2018    122.0
2019    114.0
Name: runtime_minutes, dtype: float64

Overall Average Runtime of movies: 122.75 minutes

Common Runtime Range (25th to 75th percentile): (105.5, 135.25) minutes

Lowest Runtime : 80.0 minutes

Highest Runtime : 175.0 minutes
```

5. Visualization

The visualization below showcases two bar graphs in one figure: Top 5 genres by Average Rating and Top 5 Genres by Total Number of Votes.

- From the visualizations below it is easier to get insights of the top 5 genres that consumers love from the Top 5 genres by Total Number of Votes graph.

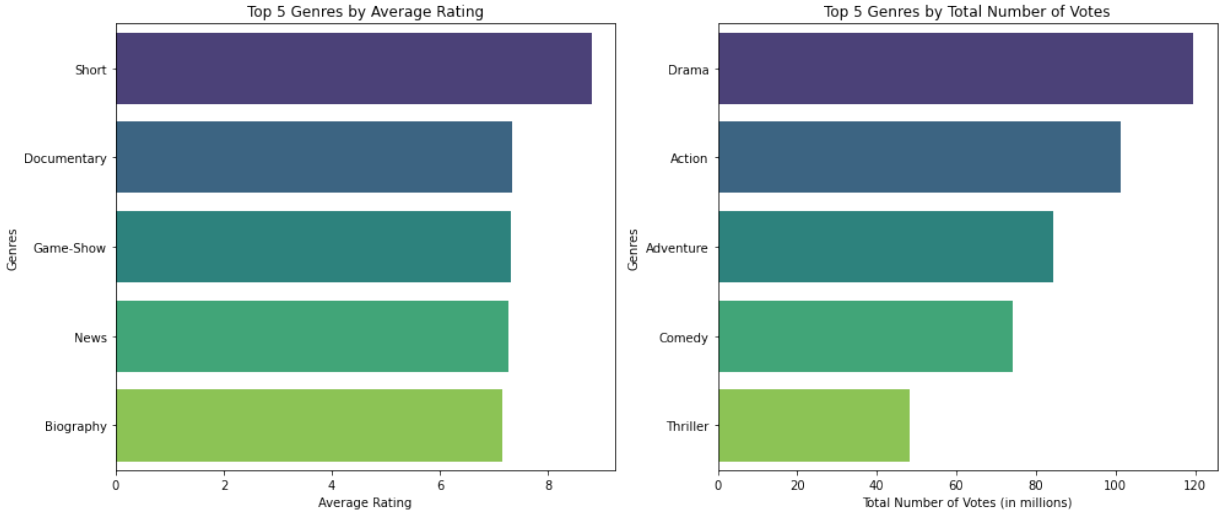
In [22]:
```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

plt.figure(figsize=(14, 6))

# Bar plot for Top 5 Genres by Average Rating
plt.subplot(1, 2, 1)
sns.barplot(x='averagerating', y='genres', data=top_genres_by_rating, palette='virid
plt.title('Top 5 Genres by Average Rating')
plt.xlabel('Average Rating')
plt.ylabel('Genres')

# Bar plot for Top 5 Genres by Total Number of Votes
plt.subplot(1, 2, 2)
top_genres_by_votes['numvotes'] = top_genres_by_votes['numvotes'] / 1e6  # Convert t
sns.barplot(x='numvotes', y='genres', data=top_genres_by_votes, palette='viridis')
plt.title('Top 5 Genres by Total Number of Votes')
plt.xlabel('Total Number of Votes (in millions)')
plt.ylabel('Genres')

plt.tight_layout()
plt.show()
```

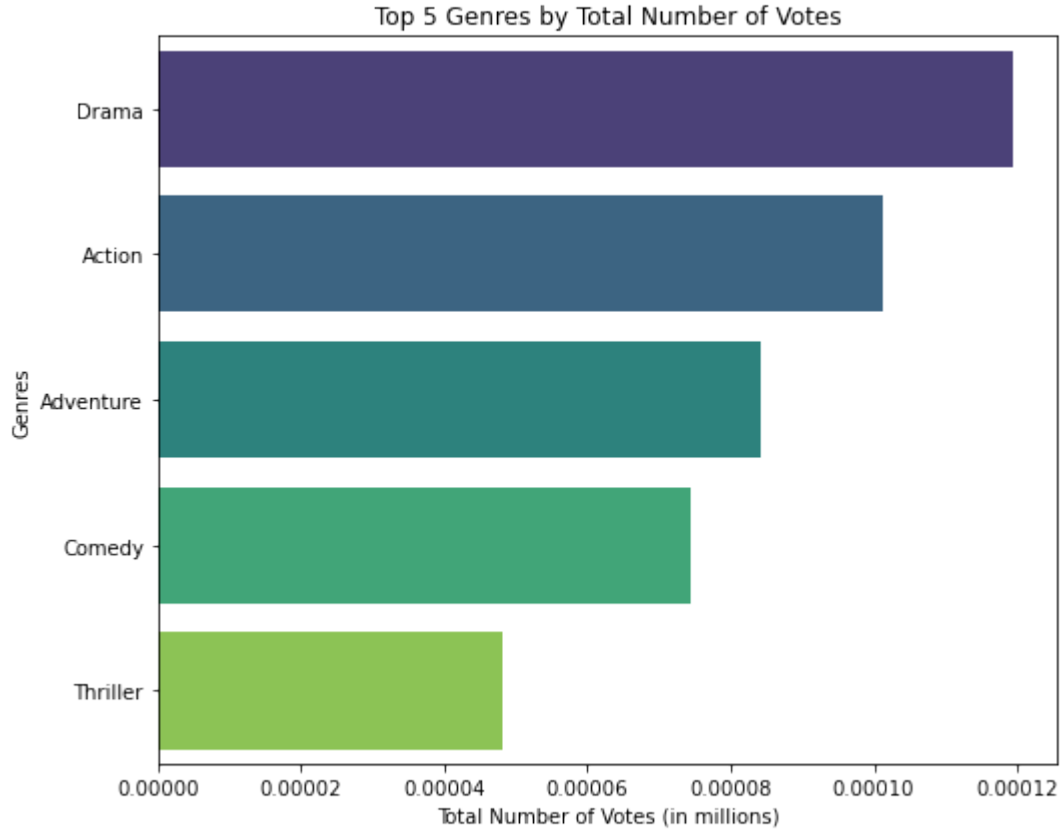


- Focusing on the Top 5 Genres by Total Number of Votes we can see that Drama has the highest number of votes with around 120 million votes followed by Action, Adventure,Comedy and Thriller.
- This means that Drama has the highest user favourite.

In [23]:
```
plt.figure(figsize=(14, 6))

# Bar plot for Top 5 Genres by Total Number of Votes
plt.subplot(1, 2, 2)
top_genres_by_votes['numvotes'] = top_genres_by_votes['numvotes'] / 1e6  # Convert t
sns.barplot(x='numvotes', y='genres', data=top_genres_by_votes, palette='viridis')
plt.title('Top 5 Genres by Total Number of Votes')
plt.xlabel('Total Number of Votes (in millions)')
plt.ylabel('Genres')


plt.tight_layout()
plt.show()
```



The below bar graph showcases the list of genres from the highest generating gross to the genres with the lowest generating gross.

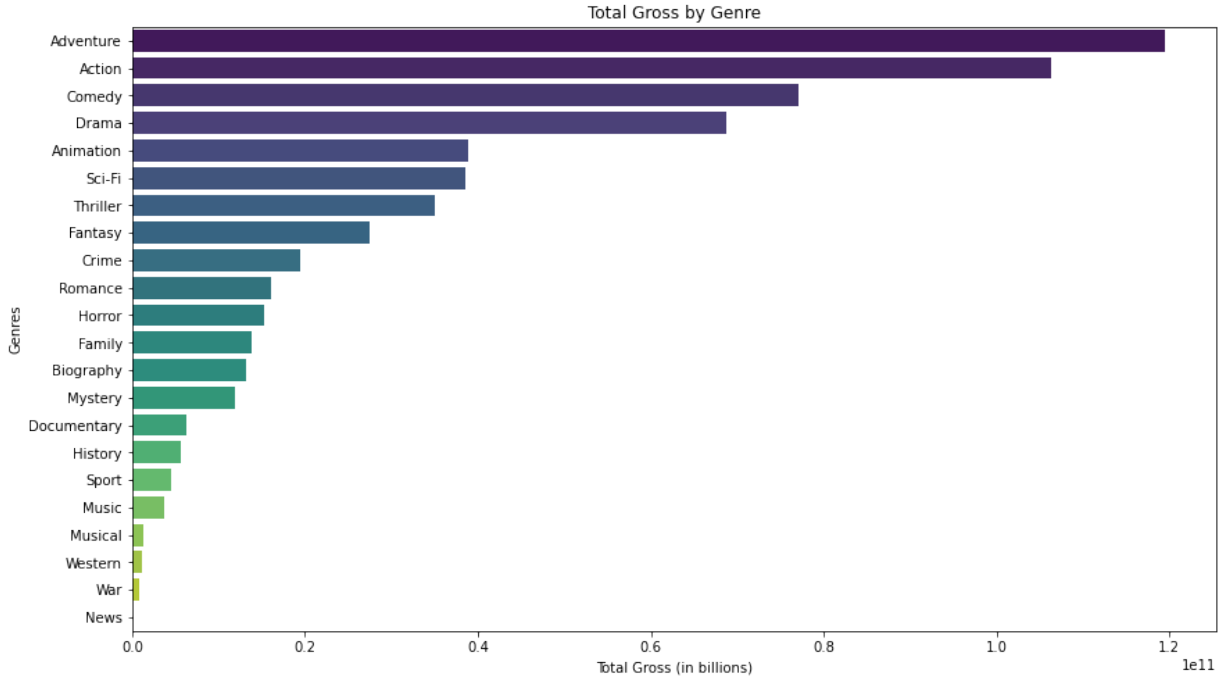
- From the bar graph it is evident that Adventure genre has the highest generating total gross of 1.2 Billion. The other four highest generating gross as follows in Action, Comedy, Drama and Animation.
- The lowest generating genres is Musical, Western, War and News.

In [24]:
```
plt.figure(figsize=(14, 8))

sns.barplot(x='total_gross', y='genres', data=genre_gross, palette='viridis')

plt.title('Total Gross by Genre')
plt.xlabel('Total Gross (in billions)')
plt.ylabel('Genres')

plt.show()
```



The graph below showcases the highest, lowest, average as well as the range of recommended movie runtimes using a combination of area plot and line plot.

- I chose the combination of the two because with the line plot it precisely shows you the exact figure of the runtime_minutes, in this case it shows the highest runtime as 175.0 mins, the average as 122.75 minutes and the lowest as 80.0 mins. The box plot helps show the range of most movie runtime produced, meaning it will be ideal to stick within this range when creating movies.

In [25]:
```
plt.figure(figsize=(12, 6))

# Plot the overall average runtime
plt.axhline(y=overall_average_runtime, color='green', linestyle='--', label=f'Overal

# area plot for the common runtime range
plt.fill_between([min(imdb_df['start_year']), max(imdb_df['start_year'])], common_ru
 label='Recommended movie runtime range')

plt.text(min(imdb_df['start_year']) + 0.1, overall_average_runtime + 5, f'Overall Av
 color='green')
```

```
plt.text(min(imdb_df['start_year']) + 0.1, lowest_runtime + 5, f'Lowest: {lowest_run
plt.text(min(imdb_df['start_year']) + 0.1, highest_runtime - 10, f'Highest: {highest


plt.axhline(y=lowest_runtime, color='blue', linestyle='--')
plt.axhline(y=highest_runtime, color='red', linestyle='--')

plt.xlabel('Year')
plt.ylabel('Runtime (minutes)')
plt.title('Recommended Average Movie Runtime')

plt.legend()

plt.grid(axis='y')
plt.show()
```