Microsoft's Foray Into the Movie World

Flatiron School Data Science project

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- **Pace:** Flex, 20 weeks

Overview

This project analyzes data about the ratings and popularity of movies to make recommendations to Microsoft, which intends to launch its own movie studio. As a newcomer to the scene, Microsoft has asked for recommendations on what types of movies perform well among audiences. I have available to me movie datasets from Box Office Mojo, IMDb, Rotten Tomatoes, The Movie Database, and The Numbers. I derive my conclusions mainly from the **IMDb datasets**, which contain information about movies from 2010 to 2019, including, genres, average user rating, and the number of users who voted on each movie. As a result of the analysis, I was able to distill 10 well-peforming genres for Microsoft to focus on, as well as make recommendations about how much of its budget it should focus on 1) comedies and 2) animated movies.

Business Problem

Measuing success: A first instict might be to analyze the types of movies that have the highest return-on-investment at the box office. However, in the streaming age, that might not be the best measure of success. Popular movies are increasingly being released directly to streaming services, and the COVID-19 pandemic has dissuaded many people from going to the theaters anymore. A better measure of success would be the number of people that will actually watch the movie. Whether Microsoft plans to sell its movies to distributors like Netflix or spin up its own streaming service to host the films, it needs to determine what kinds of movies are going to attract the most viewers in numbers.

I use the **number of votes a movie has received** on IMDb as an analogue for the number of viewers. The votes may be negative or positive, but we can infer that a vote means someone actually watched the film. Using this metric, I attempt to answer these questions:

- Which 10 genres tend to perform best?
- How much of Microsoft's budget should it focus on making comedies?
- How much fo Microsoft's budget should it focus on making animated movies?

Data Understanding

IMDb is one of the most popular websites for basic facts about movies and TV shows, as well as user reviews. It claims to have nearly 600,000 movies listed and is ranked 75th in in global internet engagement.

The data I've been provided is housed in a SQL file, from which I primarily use two tables:

- `movie_basics`: Contains information about each movie's name, release year, runtime, and genres.
- `movie_ratings`: Contains a weighted average of all the individual user ratings and the number of votes a movie has received.

More information here.

The two tables have a shared column `movie_id`, which is a unique identifier for each movie. I plan to group movies by genre to to see each genre's average rating and and average number of votes.

In [1]:

```
# Importing necessary libraries
```

```
import pandas as pd
import numpy as np
import sqlite3
import matplotlib.pyplot as plt
import seaborn as sns
import zipfile
%matplotlib inline
```

In [2]:

```
! ls zippedData
```

```
bom.movie_gross.csv.gz
im.db
im.db.zip
rt.movie_info.tsv.gz
rt.reviews.tsv.gz
tmdb.movies.csv.gz
tn.movie_budgets.csv.gz
```

Data Preparation

Exloring the SQL database for IMDb

In [3]:

```
with zipfile.ZipFile('zippedData/im.db.zip') as my_zip:
    zipfile.ZipFile.extractall(my_zip, path='ZippedData')

# Created a new file called im.db
# Added the file to .gitignore because it's too big to upload to GitHub
```

In [4]:

```
con = sqlite3.connect('zippedData/im.db')
```

In [5]:

```
pd.read_sql("""
SELECT *
FROM sqlite_schema
WHERE type='table'
""", con)
```

Out[5]:

	type	name	tbl_name	rootpage	sql
0	table	movie_basics	movie_basics	2	CREATE TABLE "movie_basics" (\n"movie_id" TEXT...
1	table	directors	directors	3	CREATE TABLE "directors" (\n"movie_id" TEXT,\n...
2	table	known_for	known_for	4	CREATE TABLE "known_for" (\n"person_id" TEXT,\...
3	table	movie_akas	movie_akas	5	CREATE TABLE "movie_akas" (\n"movie_id" TEXT,\...
4	table	movie_ratings	movie_ratings	6	CREATE TABLE "movie_ratings" (\n"movie_id" TEX...
5	table	persons	persons	7	CREATE TABLE "persons" (\n"person_id" TEXT,\n ...
6	table	principals	principals	8	CREATE TABLE "principals" (\n"movie_id" TEXT,\...
7	table	writers	writers	9	CREATE TABLE "writers" (\n"movie_id" TEXT,\n ...

Merging the IMDb `movie_basics` and `movie_ratings` files:

In [6]:

```
movies_w_ratings_imdb = pd.read_sql("""
```

```
movies_w_ratings_imdb = pd.read_sql("""
SELECT * FROM movie_basics
LEFT JOIN movie_ratings
    USING(movie_id)
""" , con)
```

In [7]:

```
# Preivew the resulting DataFrame
movies_w_ratings_imdb.head()
```

Out[7]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77.0
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43.0
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	6.9	4517.0
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	13.0
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	119.0

In [8]:

```
movies_w_ratings_imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 8 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   movie_id         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 
 6   averagerating    73856 non-null   float64
 7   numvotes         73856 non-null   float64
dtypes: float64(3), int64(1), object(4)
memory usage: 8.9+ MB
```

In [9]:

```
# Calculating the number of null values

movies_w_ratings_imdb.isna().sum()
```

Out[9]:

```
movie_id               0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
averagerating      72288
numvotes           72288
dtype: int64
```

In [10]:

```
# Seeing the proportion of rows with null values

movies_w_ratings_imdb.isna().sum()/len(movies_w_ratings_imdb)
```

Out[10]:

```
movie_id           0.000000
primary_title      0.000000
original_title     0.000144
start_year         0.000000
runtime_minutes    0.217176
genres             0.037005
averagerating      0.494635
numvotes           0.494635
dtype: float64
```

There are several columns with null data to contend with.

Let's start with the `averagerating` and `numvotes` columns.

In [11]:

```
# Confirming that the two columns are null in all the same rows

movies_w_ratings_imdb.isna()['averagerating'].equals(movies_w_ratings_imdb.isna()['numvo
tes'])
```

Out[11]:

```
True
```

Below, we view a sample of the titles where there are no ratings or votes.

They appear to be mostly niche titles, many with missing runtimes or runtimes under one hour. They are not representative of the content Microsoft wants to promote as it debuts its streaming service.

Although they make up about half the dataset, we are not likely to derive any meaningful insight from these titles. Keeping them would disrupt our analysis and there's no value we can replace them with. For these reasons we'll drop these rows. Fortunately, our dataset will still have about 70,000 entries to work with.

In [12]:

```
NaN_movies_w_ratings_imdb = movies_w_ratings_imdb[
    movies_w_ratings_imdb['numvotes'].isna()
    ]
```

In [13]:

```
NaN_movies_w_ratings_imdb.head()
```

Out[13]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
5	tt0111414	A Thin Life	A Thin Life	2018	75.0	Comedy	NaN	NaN
8	tt0139613	O Silêncio	O Silêncio	2012	NaN	Documentary,History	NaN	NaN
9	tt0144449	Nema aviona za Zagreb	Nema aviona za Zagreb	2012	82.0	Biography	NaN	NaN
16	tt0187902	How Huang Fei-hong Rescued the Orphan from the...	How Huang Fei-hong Rescued the Orphan from the...	2011	NaN	None	NaN	NaN
25	tt0262759	Seven Jews from My Class	Siedmiu Zydów z mojej klasy	2018	40.0	Documentary	NaN	NaN

In [14]:

```
# Dropping titles with no votes or rating
```

```
movies_w_ratings_imdb.dropna(subset=['numvotes'], inplace=True)
```

In [15]:

```
# confirming that this worked for both the numvotes and averagerating columns:

print('Number of null ratings:',
      movies_w_ratings_imdb['averagerating'].isnull().sum()
     )

print('Number of null vote counts:',
      movies_w_ratings_imdb['numvotes'].isnull().sum()
     )
```

```
Number of null ratings: 0
Number of null vote counts: 0
```

In [16]:

```
# Reminding myself of the basic info in the dataset
movies_w_ratings_imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73856 entries, 0 to 146134
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   movie_id         73856 non-null  object
 1   primary_title    73856 non-null  object
 2   original_title   73856 non-null  object
 3   start_year       73856 non-null  int64
 4   runtime_minutes  66236 non-null  float64
 5   genres           73052 non-null  object
 6   averagerating    73856 non-null  float64
 7   numvotes         73856 non-null  float64
dtypes: float64(3), int64(1), object(4)
memory usage: 5.1+ MB
```

In [17]:

```
movies_w_ratings_imdb.isna().sum()/len(movies_w_ratings_imdb)
```

Out[17]:

```
movie_id           0.000000
primary_title      0.000000
original_title     0.000000
start_year         0.000000
runtime_minutes    0.103174
genres             0.010886
averagerating      0.000000
numvotes           0.000000
dtype: float64
```

In the remaining dataset, about 1 percent of the titles are missing genres.

Since genres are going to be central to our recommendations, I'll drop those rows, too.

In [18]:

```
# Dropping titles with no genres listed.

movies_w_ratings_imdb.dropna(subset=['genres'], inplace=True)
```

Dealing with duplicates

In [19]:

```
movies_w_ratings_imdb.duplicated().sum()
```

Out[19]:

```
0
```

In [20]:

```
movies_w_ratings_imdb.duplicated(subset='original_title').sum()
```

Out[20]:

```
2707
```

There are more than 2,700 movies with the same name. But that doesn't mean they're duplicates. It could just be a coincidence.

Let's see if there are movies with the same name, runtime, and year.

In [21]:

```
movies_w_ratings_imdb[
    movies_w_ratings_imdb.duplicated(
        subset=['original_title',
                'runtime_minutes',
                'start_year'
               ]
    )
]
```

Out[21]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating
2658	tt10275936	Raggarjävlar (Swedish Greasers)	Raggarjävlar (Swedish Greasers)	2019	70.0	Documentary	6.9
11830	tt1644694	The Gift	The Gift	2010	NaN	Animation,Drama	5.9
12984	tt1674217	Transit	Transit	2010	80.0	Biography,Documentary,Family	6.7
19111	tt1825978	The Artist	The Artist	2011	100.0	Thriller	6.8
23887	tt1967651	Unconditional Love	Unconditional	2012	92.0	Drama,Thriller	5.6
24139	tt1977822	Inside	Inside	2012	85.0	Horror	4.0
33380	tt2246595	Blood Money	Blood Money	2012	109.0	Action,Drama,Thriller	5.2
37698	tt2363471	The Summit	The Summit	2012	95.0	Adventure,Documentary	6.9
47280	tt2805202	Rise of the Undead	Rise of the Undead	2013	70.0	Action	4.2
50941	tt3019098	The Last Act	The Last Act	2012	NaN	Thriller	5.7
72877	tt4156972	Opening Night	Opening Night	2016	90.0	Comedy,Musical	6.3
80877	tt4649330	Eso que llaman amor	Eso que llaman amor	2015	NaN	Drama	6.7
88715	tt5136180	A Courtship	A Courtship	2015	71.0	Documentary	6.3
103321	tt6052236	The Wonderful Digby	The Wonderful Digby	2016	82.0	Biography,Documentary,Music	7.7
103646	tt6073736	Almost Dead	Almost Dead	2016	85.0	Horror	1.9
109186	tt6417762	Happy New Year	Happy New Year	2017	NaN	Drama,Romance	7.4
116144	tt6896536	Foxtrot	Foxtrot	2017	113.0	Drama	7.4
140322	tt9097086	Together	Together	2018	84.0	Drama	7.2

We should delete the duplicates, but we should keep the version with the higher vote count, as it's the version that IMDb users will more likely come across.

In [22]:

```
# Sorting the dataset by vote count

movies_w_ratings_imdb.sort_values(
    by='numvotes',
    ascending=False,
    inplace=True
)
```

In [23]:

```
# Dropping the duplicates

movies_w_ratings_imdb.drop_duplicates(
    subset=[
        'original_title',
        'runtime_minutes',
        'start_year'
    ],
    inplace=True,
    keep='first'
)
```

In [24]:

```
movies_w_ratings_imdb.head()
```

Out[24]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
7066	tt1375666	Inception	Inception	2010	148.0	Action,Adventure,Sci-Fi	8.8	1841066.0
6900	tt1345836	The Dark Knight Rises	The Dark Knight Rises	2012	164.0	Action,Thriller	8.4	1387769.0
311	tt0816692	Interstellar	Interstellar	2014	169.0	Adventure,Drama,Sci-Fi	8.6	1299334.0
20342	tt1853728	Django Unchained	Django Unchained	2012	165.0	Drama,Western	8.4	1211405.0
356	tt0848228	The Avengers	The Avengers	2012	143.0	Action,Adventure,Sci-Fi	8.1	1183655.0

Dealing with the `genres column`:

The values in the genres column contain multiple genres separated by a comma. I'll need to split them up them somehow.

I can use the `df.explode()` method to separate them. But first I'll need to convert the value from a string to an list.

In [25]:

```
# Creating a new dataframe because I may want to use this one in a later analysis.

clean_genres = movies_w_ratings_imdb.copy()
```

In [26]:

```
# Changing each entry in 'genres' from a string into a list

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

In [27]:

```
clean_genres.head(3)
```

Out[27]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
7066	tt1375666	Inception	Inception	2010	148.0	[Action, Adventure, Sci-Fi]	8.8	1841066.0
6900	tt1345836	The Dark Knight Rises	The Dark Knight Rises	2012	164.0	[Action, Thriller]	8.4	1387769.0
311	tt0816692	Interstellar	Interstellar	2014	169.0	[Adventure, Drama, Sci-Fi]	8.6	1299334.0

In [28]:

```
# Creating a list of all unique genres, now that we can iterate through them.

genres_all = set()
genres_column = clean_genres['genres']

for glist in genres_column:
    for g in glist:
        genres_all.add(g)
```

In [29]:

```
print(f'There are {len(genres_all)} genres in our IMDb dataset. They are:\n\n {genres_all
}.')
```

```
There are 26 genres in our IMDb dataset. They are:

 {'Adult', 'Music', 'War', 'Mystery', 'Short', 'Biography', 'Animation', 'Reality-TV', 'F
antasy', 'Action', 'Thriller', 'Family', 'Horror', 'Documentary', 'News', 'Sport', 'Sci-F
i', 'Adventure', 'Drama', 'Musical', 'History', 'Romance', 'Game-Show', 'Crime', 'Western
', 'Comedy'}.
```

Creating a new dataset where the genres are separated

In [30]:

```
# Using df.explode() to split each row so that it has a singular genre.

expl_clean_genres = clean_genres.explode('genres')
```

In [31]:

```
expl_clean_genres.head()
```

Out[31]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
7066	tt1375666	Inception	Inception	2010	148.0	Action	8.8	1841066.0
7066	tt1375666	Inception	Inception	2010	148.0	Adventure	8.8	1841066.0
7066	tt1375666	Inception	Inception	2010	148.0	Sci-Fi	8.8	1841066.0
6900	tt1345836	The Dark Knight Rises	The Dark Knight Rises	2012	164.0	Action	8.4	1387769.0
6900	tt1345836	The Dark Knight Rises	The Dark Knight Rises	2012	164.0	Thriller	8.4	1387769.0

In [32]:

```
expl_clean_genres['genres'].value_counts()
```

Out[32]:

```
Drama            30784
Documentary      17748
Comedy           17289
Thriller          8212
Horror            7672
Action            6986
Romance           6586
Crime             4610
Adventure         3817
Biography         3807
Family            3411
Mystery           3038
History           2825
Sci-Fi            2206
Fantasy           2126
Music             1967
Animation         1742
Sport             1179
War                853
Musical            721
News               579
Western            280
Reality-TV          17
Adult                3
Game-Show            2
Short                1
Name: genres, dtype: int64
```

Dropping titles in noisy genres

There are four genres with particularly low counts. They might introduce noise our analysis when we take the average of `numvotes` and `averagerating` by genre later on. Additionally, they're not traditional movie genres. It's best to drop those genres:

- **Reality-TV**
- **Adult**
- **Game-Show**
- **Short**

In [33]:

```
# Gathering together the 'movie_id' for each entry in these four genres.

titles_in_noisy_genres = (
    expl_clean_genres[expl_clean_genres['genres'].isin([
        'Game-Show', 'Short', 'Adult','Reality-TV'
    ])]['movie_id']
)
```

Below, I us `df.drop()` to get rid of entries with the genres listed above I do this in a *for loop* so that it gets applied to all three versions of our dataframe that we might still use going forward:

- `movies_w_ratings_imdb`
- `clean_genres`
- `expl_clean_genres`

In [34]:

```
# I used this as a model to make sure the operation works, befor doing it inplace.

# clean_genres.drop(index=clean_genres[clean_genres['movie_id'].isin(titles_in_noisy_genr
es)].index)
```

In [35]:

In [35]:

```
for dataset in [clean_genres, expl_clean_genres, movies_w_ratings_imdb]:
    dataset.drop(
        index=dataset[
            dataset['movie_id'].isin(titles_in_noisy_genres)
        ].index,
        inplace=True)
```

In [36]:

```
# Confirming that this worked

expl_clean_genres['genres'].value_counts()
```

Out[36]:

```
Drama          30779
Documentary    17738
Comedy         17285
Thriller        8211
Horror          7671
Action          6984
Romance         6586
Crime           4610
Adventure       3815
Biography       3806
Family          3411
Mystery         3038
History         2824
Sci-Fi          2206
Fantasy         2126
Music           1966
Animation       1742
Sport           1179
War              853
Musical          721
News             578
Western          280
Name: genres, dtype: int64
```

Measuring Success

I plan to use rating and number of votes as indicators of success. In the streaming age, these metrics are are arguably better indicators of a movie's popularity (and therefore incentive to subscribe to streaming service) as opposed to box office revenue and ROI.

Here, I start to explore the distributrions of `averagerating` and `numvotes`.

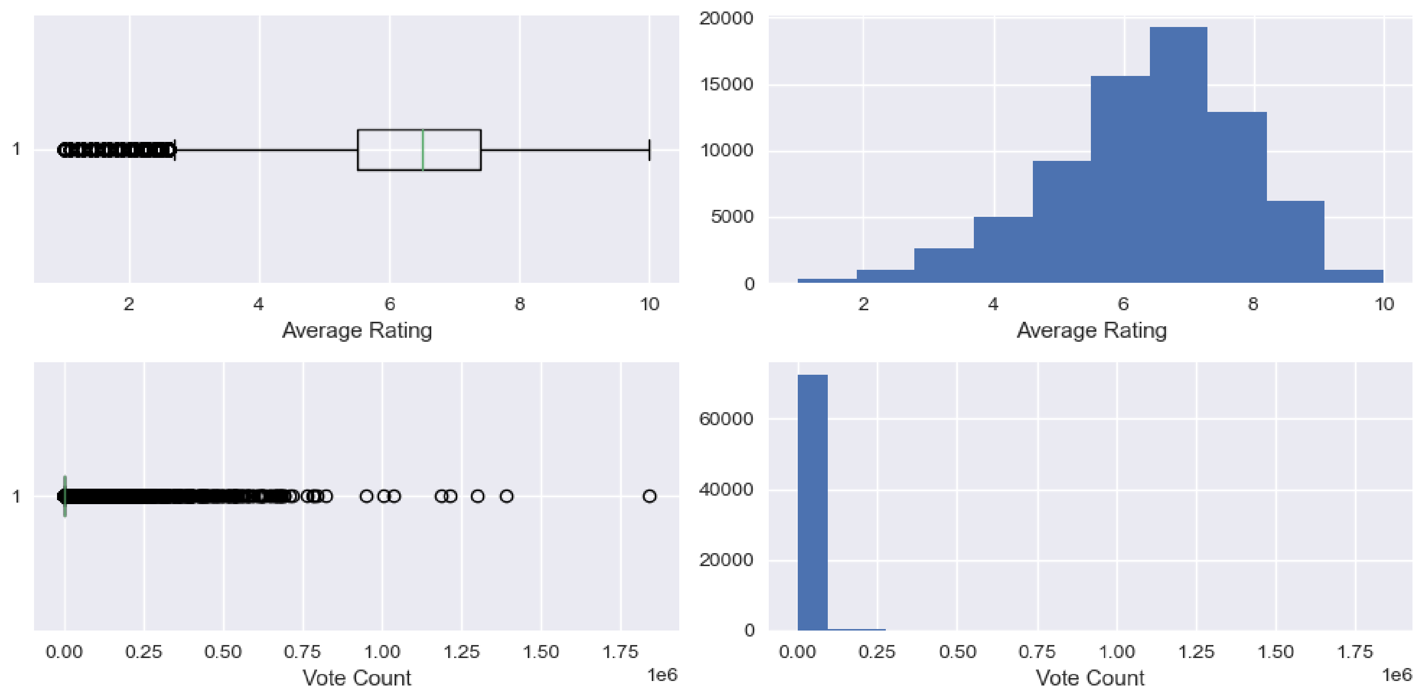
In [37]:

```
plt.rcdefaults()
plt.style.use('seaborn')
```

In [38]:

```
fig, ((ax_rating_box, ax_rating_hist), (ax_votes_box, ax_votes_hist)) = plt.subplots(
    nrows=2, ncols=2, figsize=(10,5))

# Top row
ax_rating_box.boxplot(movies_w_ratings_imdb['averagerating'], vert=False, )
ax_rating_box.set_xlabel('Average Rating')

ax_rating_hist.hist(movies_w_ratings_imdb['averagerating'])
ax_rating_hist.set_xlabel('Average Rating')

###

# Bottom row
```

```python
ax_votes_box.boxplot(movies_w_ratings_imdb['numvotes'], vert=False)
ax_votes_box.set_xlabel('Vote Count')

ax_votes_hist.hist(movies_w_ratings_imdb['numvotes'], bins=20)
ax_votes_hist.set_xlabel('Vote Count')

plt.tight_layout(pad=1)
plt.savefig('./images/dist1.png', dpi=150);
```



The distribution of vote counts is clearly very skewed.

There's a disproportionate number of titles with low vote counts.

Taking a look at these titles.

In [39]:

```python
mean_votes = movies_w_ratings_imdb['numvotes'].mean()
mean_votes
```

Out[39]:

```
3564.0968895098
```

In [40]:

```python
median_votes = movies_w_ratings_imdb['numvotes'].median()
median_votes
```

Out[40]:

```
51.0
```

In [41]:

```python
q90_votes = movies_w_ratings_imdb['numvotes'].quantile(.90)
q90_votes
```

Out[41]:

```
1621.0
```

In [42]:

```python
# Taking a look at the bottom 90 percent of movies
# in terms of number of votes

movies_w_ratings_imdb.query(f"numvotes < {q90_votes}").sample(10)
```

Out[42]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvote
83551	tt4828062	Hush	Hush	2015	100.0	Documentary	4.8	13
54369	tt3198000	Teleios	Teleios	2017	89.0	Drama,Sci-Fi	4.5	1318
1192	tt10092770	Pocong the Origin	Pocong the Origin	2019	90.0	Horror	5.9	34
32972	tt2235164	Lullaby Ride	Nachtlärm	2012	94.0	Drama	5.6	117
43851	tt2611378	Bà nôi	Bà nôi	2013	85.0	Documentary,Drama,Family	6.8	15
24892	tt1998400	The Adored	The Adored	2012	91.0	Drama,Mystery,Romance	3.9	122
48806	tt2907640	L.DK	L.DK	2014	NaN	Drama,Romance	6.4	851
75085	tt4287344	72 Hours: A Brooklyn Love Story?	72 Hours: A Brooklyn Love Story?	2016	78.0	Drama	6.5	17
68189	tt3880898	Gekijouban Sekaiichi hatsukoi: Yokozawa Takafu...	Gekijouban Sekaiichi hatsukoi: Yokozawa Takafu...	2014	50.0	Animation,Romance	7.9	195
48803	tt2907394	Samir Abu el-Nil	Samir Abu el-Nil	2013	109.0	Comedy	4.4	224

This is *most* of our current dataset. But again, we don't want niche, lesser-known titles to pollute our conclusions. The reality is that in the film industry, a ton of content is made, and only a select few enter the cultural zeitgeist. We want our analysis to be based on the most well-known movies, not the long tail of niche movies. A client like Microsoft will want to model its movie business on titles that have broad appeal or are at least well-known.

Below, we drop all movies from our current datasets except those whose number of votes is in the top 10 percent.

In [43]:

```
for dataset in [
    clean_genres,
    expl_clean_genres,
    movies_w_ratings_imdb
]:
    dataset.drop(
        index=dataset.query(f"numvotes < {q90_votes}").index,
        inplace=True
    )
```

In [44]:

```
movies_w_ratings_imdb.shape
```

Out[44]:

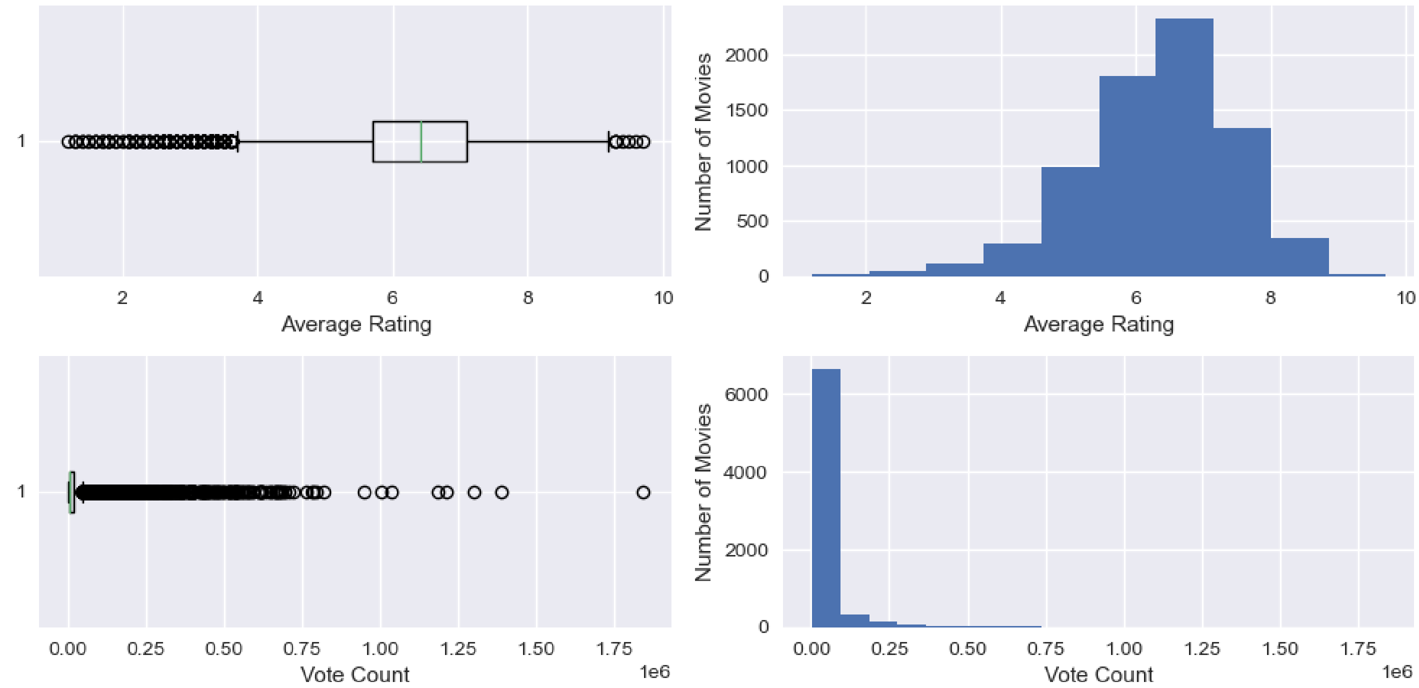
```
(7304, 8)
```

We are left with a dataset with 7,304 movies. Let's look at those distributions again.

In [45]:

```
fig, ((ax_rating_box, ax_rating_hist), (ax_votes_box, ax_votes_hist)) = plt.subplots(
    nrows=2, ncols=2, figsize=(10,5))

# Top row
ax_rating_box.boxplot(movies_w_ratings_imdb['averagerating'], vert=False, )
ax_rating_box.set_xlabel('Average Rating')
```

```python
ax_rating_hist.hist(movies_w_ratings_imdb['averagerating'])
ax_rating_hist.set_xlabel('Average Rating')
ax_rating_hist.set_ylabel('Number of Movies')

###

# Bottom row
ax_votes_box.boxplot(movies_w_ratings_imdb['numvotes'], vert=False)
ax_votes_box.set_xlabel('Vote Count')

ax_votes_hist.hist(movies_w_ratings_imdb['numvotes'], bins=20)
ax_votes_hist.set_xlabel('Vote Count')
ax_votes_hist.set_ylabel('Number of Movies')

plt.tight_layout(pad=1)
plt.savefig('./images/dist2.png', dpi=150);
```



This *slightly* improved the workability of these distributions, but they're still skewed, even after we dumped most of the dataset. This is going to be impossible to avoid due to the massive amount of content out there.

Now, let's see what kind of relationship there is between number of votes and rating.

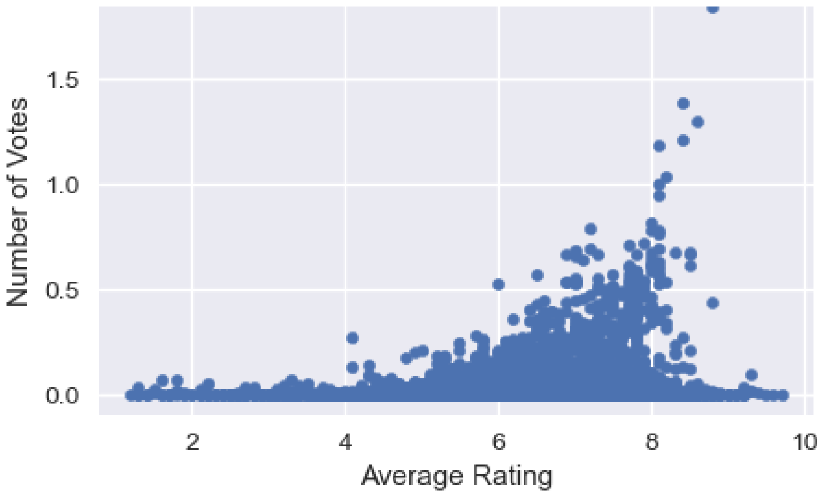
In [46]:

```python
print('Correlation between number of votes and average rating: {}'.format(
    np.corrcoef(
        movies_w_ratings_imdb['numvotes'],
        movies_w_ratings_imdb['averagerating'])[0,1]
))
```

```
Correlation between number of votes and average rating: 0.2126063733913749
```

In [47]:

```python
movies_w_ratings_imdb.plot(
    kind='scatter',
    x='averagerating', y='numvotes',
    figsize=(5,3),
    xlabel='Average Rating',
    ylabel='Number of Votes',
    title='Relationship between average rating and number of votes \n',
);
```



There's a positive relationship between average rating and number of votes.

I am inferring that a higher number of votes means that more people have seen the movie, regardless of the actual rating they voted for. I am also assuming that that Microsoft wants to make movies that are **more likely to be seen**, regardless of whether or not they're critically acclaimed.

Therefore, our measure of success will be number of votes.

In choosing this as our measure of success, we are reassured that that metric is associated with a higher rating anyway.

Because the distributions are skewed, we'll use median to measure the average.

Question 1:

What are the top 10 genres Microsoft should focus on?

Below, we group movies by genre and see the medians of `numvotes` for each genre.

In [48]:

```
# Pivot table showing the means of averagerating and numvotes.

pivot_genres = pd.pivot_table(
    data=expl_clean_genres,
    values='numvotes',
    index='genres',
    aggfunc=np.median
).sort_values(by='numvotes', ascending=False).reset_index()

pivot_genres
```

Out[48]:

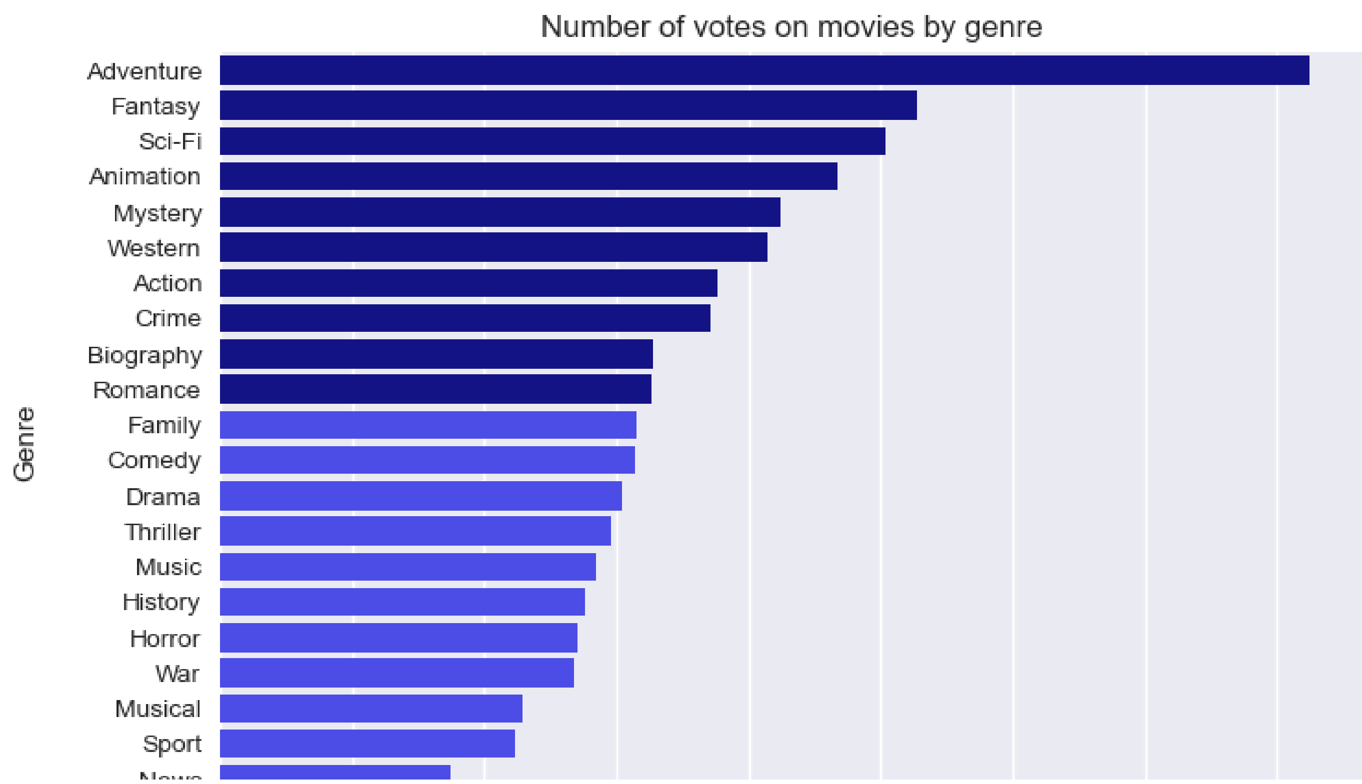
	genres	numvotes
0	Adventure	16484.0
1	Fantasy	10546.0
2	Sci-Fi	10067.0
3	Animation	9354.0
4	Mystery	8494.0
5	Western	8284.5
6	Action	7543.5
7	Crime	7414.0
8	Biography	6560.0

	genres	numvotes
9	Romance	6540.5
10	Family	6322.0
11	Comedy	6293.0
12	Drama	6081.5
13	Thriller	5920.5
14	Music	5695.0
15	History	5536.0
16	Horror	5415.0
17	War	5347.5
18	Musical	4583.0
19	Sport	4454.0
20	News	3477.0
21	Documentary	3442.0

Now that we finally have aggregate measures based on genres, we can analyze which genres are most successful.

In [49]:

```
values = pivot_genres['numvotes']
labels = pivot_genres['genres']

genres_barplot = sns.barplot(
    x=values,
    y=labels,
    orient='h',
#     palette='crest_r'
    palette=['#000099' if (x > values[10]) else '#3333ff' for x in values]
    )

genres_barplot.set(
    xlabel='Average number of votes on IMDb',
    ylabel='Genre',
    title ='Number of votes on movies by genre'
    );

plt.savefig('./images/top_genres', dpi=150)
```



In [50]:

```
print('The top 10 genres in terms of average number of votes on IMDb are:')
print()
for g in pivot_genres.iloc[:10]['genres']:
    print(g)
```

```
The top 10 genres in terms of average number of votes on IMDb are:

Adventure
Fantasy
Sci-Fi
Animation
Mystery
Western
Action
Crime
Biography
Romance
```

The genres listed above are the best performing on IMDb.

That doesn't mean these genres perform well on their own. It's important to remember that we split up the genres before we did this analysis. That means a sci-fi movie that is also a comedy movie might also perform well.

Conclusion 1: Microsoft should focus on movies that include combinations of the following genres:

- **Adventure**
- **Fantasy**
- **Sci-Fi**
- **Animation**
- **Mystery**
- **Western**
- **Action**
- **Crime**
- **Biography**
- **Romance**

Question 2

Among the top 25 percent of movies (in terms of number of votes), what proportion are comedies?

Comedy fans might be dismayed by our first conclusion. Comedy is a major genre that got wiped out due to the statistical analysis. But wat can we learn from comedies that are among the most successful movies?

We'll be working with our `clean_genres` dataset moving forward.

In [51]:

```
# Adding a column to clean_genres with a boolean value
# based on whether the movie is a comedy or not
```

```python
clean_genres['is_comedy'] = ['Comedy' in row for row in clean_genres['genres']]
```

In [52]:

```python
clean_genres.sample(5)
```

Out[52]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	is_comed
6581	tt1316540	The Turin Horse	A torinói ló	2011	155.0	[Drama]	7.8	13459.0	Fals
49641	tt2950236	The Living	The Living	2014	89.0	[Crime, Drama, Mystery]	6.2	1957.0	Fals
117753	tt7027278	Kedarnath	Kedarnath	2018	116.0	[Drama, Romance]	6.0	4189.0	Fals
28575	tt2104994	Steve Jobs: The Lost Interview	Steve Jobs: The Lost Interview	2012	70.0	[Documentary]	8.0	1676.0	Fals
6199	tt1261954	Take Me Home	Take Me Home	2011	97.0	[Comedy, Romance]	6.8	6922.0	Tru

In [53]:

```python
# Finding the 75th percentile of the number of votes per movie

q75_clean_genres = clean_genres['numvotes'].quantile(.75)
q75_clean_genres
```

Out[53]:

19707.5

In [54]:

```python
# Making a sub-dataframe containing the top quarter of movies by number of votes

top25_clean_genres = clean_genres.query(f"numvotes >= {q75_clean_genres}")
top25_clean_genres.sample(5)
```

Out[54]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	is_comedy
216	tt0491152	Something Borrowed	Something Borrowed	2011	112.0	[Comedy, Drama, Romance]	5.9	54314.0	True
447	tt0914863	Unthinkable	Unthinkable	2010	97.0	[Crime, Drama, Thriller]	7.1	80152.0	False
326	tt0829150	Dracula Untold	Dracula Untold	2014	92.0	[Action, Drama, Fantasy]	6.3	164829.0	False
50819	tt3011894	Wild Tales	Relatos salvajes	2014	122.0	[Comedy, Drama, Thriller]	8.1	151123.0	True
16525	tt1763303	The First Time	The First Time	2012	95.0	[Comedy, Drama, Romance]	6.9	62589.0	True

In [55]:

```python
# Of the top 25%, how many movies are comedies?

comedy_breakdown = top25_clean_genres['is_comedy'].value_counts()
```

```
comedy_breakdown
```

Out[55]:

```
False    1210
True      616
Name: is_comedy, dtype: int64
```

In [56]:

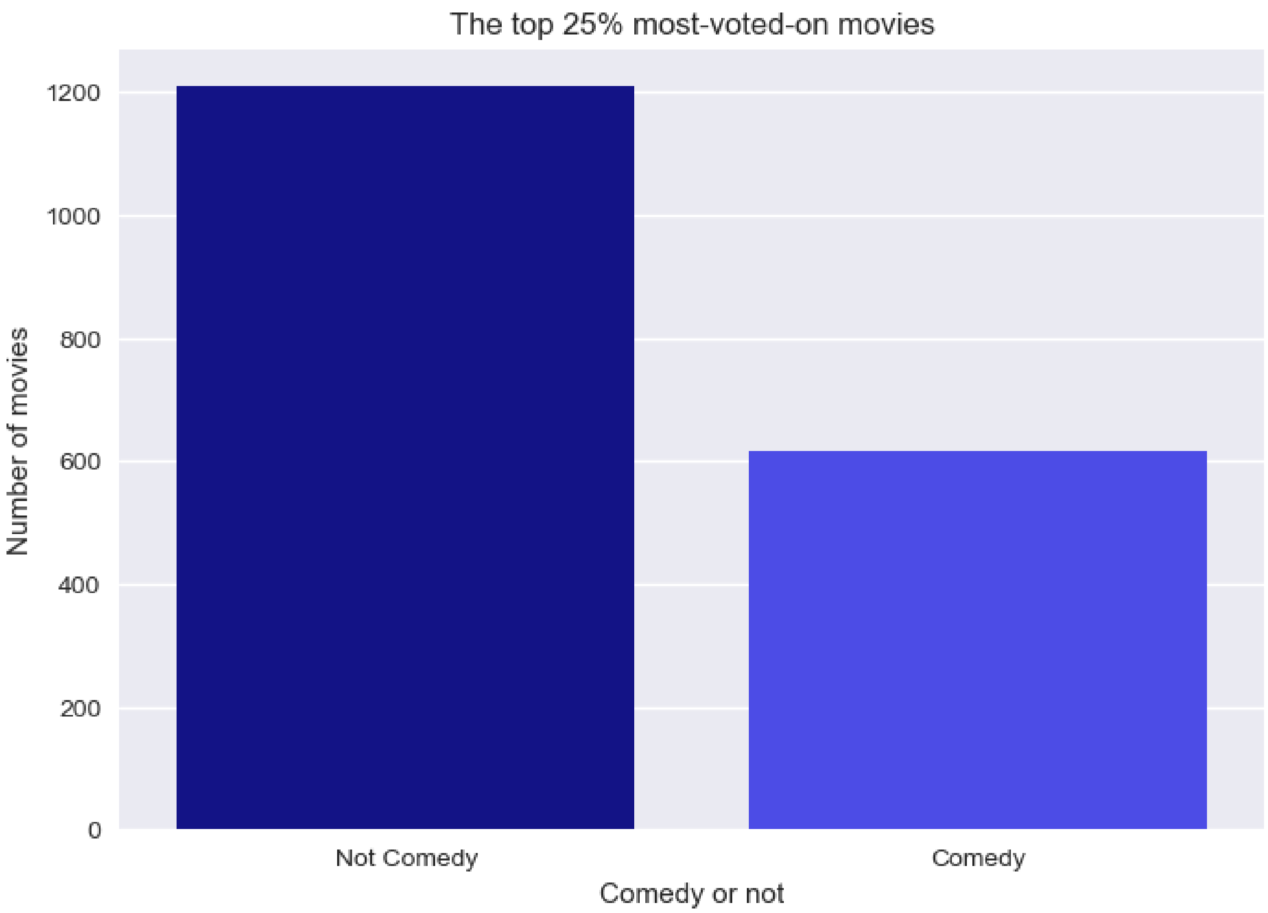
```
comedy_breakdown_norm = top25_clean_genres['is_comedy'].value_counts(normalize=True)
comedy_breakdown_norm
```

Out[56]:

```
False    0.662651
True     0.337349
Name: is_comedy, dtype: float64
```

In [57]:

```
values = comedy_breakdown.values
labels = comedy_breakdown.index

comedy_plot = sns.barplot(
    x=labels,
    y=values,
    palette=['#000099' if x == False else '#3333ff' for x in labels]
    ).set(
    xlabel='Comedy or not',
    ylabel='Number of movies',
    xticklabels=['Not Comedy', 'Comedy'],
    title='The top 25% most-voted-on movies'
)

plt.savefig('./images/comedies', dpi=150)
```



Of the top 25% best-performing movies in our dataset, 616 out of 1,826, or 33.73%, are comedies.

Conclusion 2: **Microsoft should focus about a third of its efforts (in terms of budget or number of movies) on**

making comedic movies.

Question 3:

Along the same lines as Question 2:

Among the top 25 percent of movies (in terms of number of votes), what proportion are animated?

Repeating the process above for animated movies.

In [58]:

```
clean_genres['is_animated'] = ['Animation' in row for row in clean_genres['genres']]
```

In [59]:

```
q75_clean_genres = clean_genres['numvotes'].quantile(.75)
```

In [60]:

```
top25_clean_genres = clean_genres.query(f"numvotes >= {q75_clean_genres}")
```

In [61]:

```
animated_breakdown = top25_clean_genres['is_animated'].value_counts()
animated_breakdown
```

Out[61]:

```
False    1718
True      108
Name: is_animated, dtype: int64
```

In [62]:

```
animated_breakdown_norm = top25_clean_genres['is_animated'].value_counts(normalize=True)
animated_breakdown_norm
```

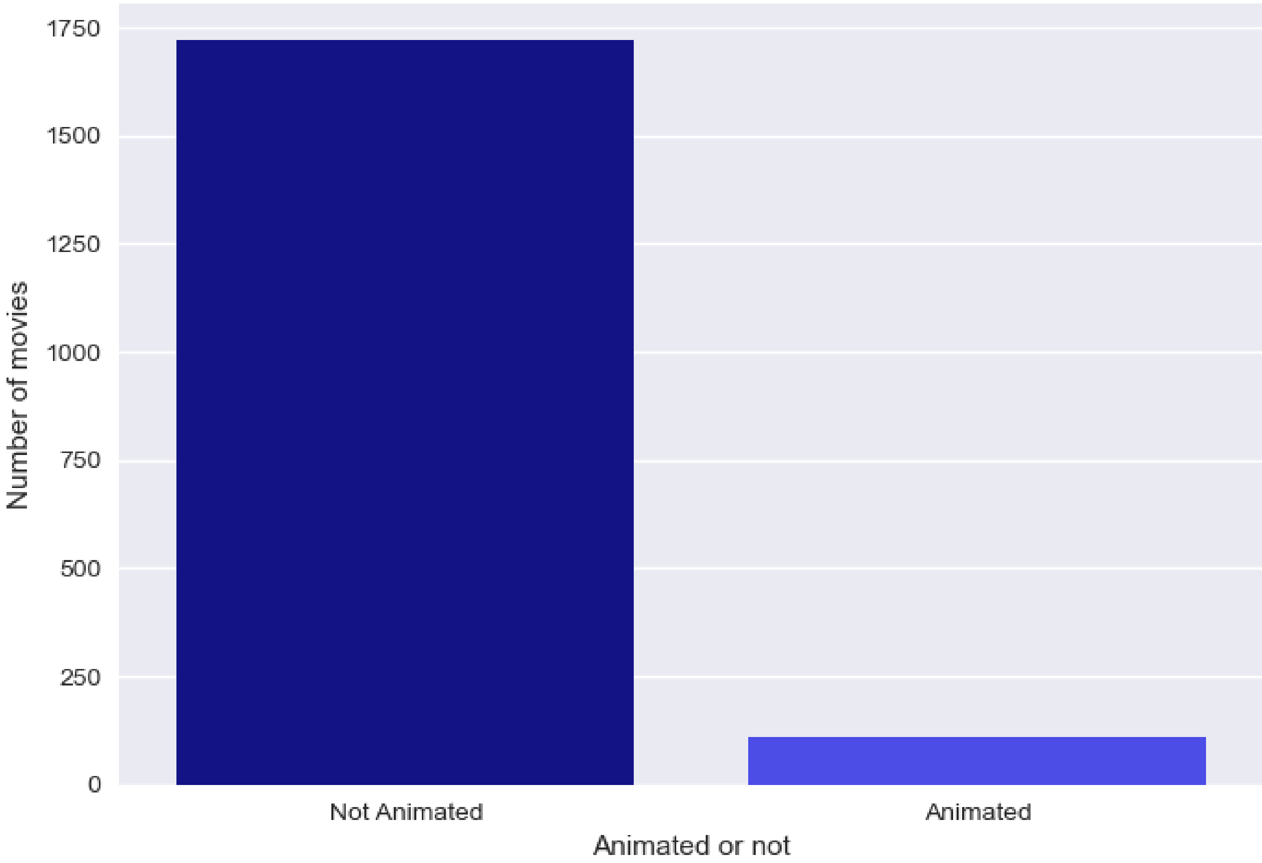
Out[62]:

```
False    0.940854
True     0.059146
Name: is_animated, dtype: float64
```

In [63]:

```
values = animated_breakdown.values
labels = animated_breakdown.index

animated_plot = sns.barplot(
    x=labels,
    y=values,
    palette=['#000099' if x == False else '#3333ff' for x in labels]
    ).set(
    xlabel='Animated or not',
    ylabel='Number of movies',
    xticklabels=['Not Animated', 'Animated'],
    title='The top 25% most-voted-on movies'
)
plt.savefig('./images/animated', dpi=150)
```

The top 25% most-voted-on movies



Of the top 25% best-performing movies in our dataset, 108 out of 1,826, or 5.91%, are animated.

Conclusion 3: **Microsoft should focus about 6 percent of its efforts (in terms of budget or number of movies) on making animated movies.**

Recommendations

In this analysis I attemped to determine the most successful movie genres as well as what proportions of movies are comedies or animated. I arrived at three recommendations for what kinds of movies Microsoft should make:

1. Microsoft should focus its efforts on movies with some combination of these genres:

```
- Adventure
- Fantasy
- Sci-Fi
- Animation
- Mystery
- Western
- Action
- Crime
- Biography
- Romance
```

2. Microsoft should focus about a third of its efforts (in terms of budget or number of movies) on comedy movies.

3. Microsoft should focus about 6 percent of its efforts (in terms of budget or number of movies) on animated movies.