# 1 Introduction and Business Understanding

In this project, we will be looking at movie datasets in order to give recommendations to Microsoft's new movie studio.

Entertainment is a huge, global market. According to [Forbes (https://www.forbes.com/sites/rosaescandon/2020/03/12/the-film-industry-made-a-record-breaking-100-billion-last-year/?sh=5404bc6634cd)](https://www.forbes.com/sites/rosaescandon/2020/03/12/the-film-industry-made-a-record-breaking-100-billion-last-year/?sh=5404bc6634cd), the film industry made over 100 billion dollars in 2019. While that is a significant chunk of change, there is also a significant overhead in creating entertainment content. It is important for fledgling movie studios to research what type of content does well, so that they can use this information as a guide to replicate that success. As Microsoft is interested in making movies, the following project will focus on that component of the entertainment industry.

## 1.1 Data

In order to glean information relevant to movie-making we will be looking at two datasets from https://www.imdb.com/ (https://www.imdb.com/) and https://www.boxofficemojo.com/ (https://www.boxofficemojo.com/).

- IMDB stands for Internet Movie Database and is one of the most popular and comprehensive internet sources for movie and entertainment data. The dataset we are working with focuses on information about movies - the producers, the genres, the actors, the movies ratings, ect.
- Box Office Mojo is a site that tracks box-office revenue, and the data set we will be using from them contains this information.

By using these two datasets together, we can extract if certain aspects of a movie lead to higher box-office revenue, which is an industry standard for movie success.

**Limitations**

This data is only on movies, thus it can not be extrapolated to the entire entertainment industry. Additionally, as the dataset only contains the total gross, it will not include the costs of creating the movies. Finally, the dataset only looks at box office revenue, which means that the total revenue (from streaming sites or other sources) may be higher.

## 1.2 Objectives

- Import datasets and do an initial viewing.
- Ask some relevant questions!
- Find answers to those questions, and do some analysis.
- Conclusion.

# 2 Method

## 2.1 Data Preparation

First we are going to import some required packages needed to process the data. Then we will connect to our datasets and take a peek inside.

In [1]:

```
# found this here: https://jupyter-contrib-nbextensions.readthedocs.io/en/
!pip install autopep8
```

```
Requirement already satisfied: autopep8 in c:\users\15164\anaconda3\envs\
learn-env\lib\site-packages (1.6.0)
Requirement already satisfied: toml in c:\users\15164\anaconda3\envs\lear
n-env\lib\site-packages (from autopep8) (0.10.2)
Requirement already satisfied: pycodestyle>=2.8.0 in c:\users\15164\anaco
nda3\envs\learn-env\lib\site-packages (from autopep8) (2.8.0)
```

In [2]:

```
# importing required packages
import warnings
import zipfile
import seaborn as sns
import sqlite3 as sql
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
warnings.filterwarnings("ignore")
```

In [3]:

```
# unzip data - code from https://docs.python.org/3/library/zipfile.html
with zipfile.ZipFile('zipped_data/im.db.zip', 'r') as zip_ref:
    zip_ref.extractall('data')
```

### 2.1.1 IMDB Dataset

In [4]:

```
# create connection to the database and cursor object:
conn = sql.connect('data/im.db')
cur = conn.cursor()

# find table names
cur.execute(""" SELECT name
                FROM sqlite_master
                WHERE type = 'table';""")

# fetch the result and store it in table_names
table_names = cur.fetchall()
table_names
```

Out[4]:

```
[('movie_basics',),
 ('directors',),
 ('known_for',),
 ('movie_akas',),
 ('movie_ratings',),
```

Above we see 8 tables names - lets look into those tables now.

For the `movie_basics` table:

In [5]:

```
# creating movie_basics dataframe
imbd_movie_basics = pd.read_sql("""
                                SELECT *
                                FROM movie_basics;
                                """, conn)

imbd_movie_basics
```

Out[5]:

| | movie_id | primary_title | original_title | start_year | runtime_minutes | ge |
|---|---|---|---|---|---|---|
| **0** | tt0063540 | Sunghursh | Sunghursh | 2013 | 175.0 | Action,Crime,D |
| **1** | tt0066787 | One Day Before the Rainy Season | Ashad Ka Ek Din | 2019 | 114.0 | Biography,D |
| **2** | tt0069049 | The Other Side of the Wind | The Other Side of the Wind | 2018 | 122.0 | D |
| **3** | tt0069204 | Sabse Bada Sukh | Sabse Bada Sukh | 2018 | NaN | Comedy,D |
| **4** | tt0100275 | The Wandering Soap Opera | La Telenovela Errante | 2017 | 80.0 | Comedy,Drama,Fa |
| **...** | ... | ... | ... | ... | ... | |
| **146139** | tt9916538 | Kuambil Lagi Hatiku | Kuambil Lagi Hatiku | 2019 | 123.0 | D |
| **146140** | tt9916622 | Rodolpho Teóphilo - O Legado de um Pioneiro | Rodolpho Teóphilo - O Legado de um Pioneiro | 2015 | NaN | Docume |
| **146141** | tt9916706 | Dankyavar Danka | Dankyavar Danka | 2013 | NaN | Co |
| **146142** | tt9916730 | 6 Gunn | 6 Gunn | 2017 | 116.0 | I |
| **146143** | tt9916754 | Chico Albuquerque - Revelações | Chico Albuquerque - Revelações | 2013 | NaN | Docume |

146144 rows × 6 columns

For the `directors` table:

In [6]:
```
# creating a dataframe for the directors table
imbd_directors = pd.read_sql("""
                                SELECT *
                                FROM directors;
                                """, conn)

imbd_directors
```

Out[6]:

| | movie_id | person_id |
|---|---|---|
| **0** | tt0285252 | nm0899854 |
| **1** | tt0462036 | nm1940585 |
| **2** | tt0835418 | nm0151540 |
| **3** | tt0835418 | nm0151540 |
| **4** | tt0878654 | nm0089502 |
| **...** | ... | ... |
| **291169** | tt8999974 | nm10122357 |
| **291170** | tt9001390 | nm6711477 |
| **291171** | tt9001494 | nm10123242 |
| **291172** | tt9001494 | nm10123248 |
| **291173** | tt9004986 | nm4993825 |

291174 rows × 2 columns

For the `known_for` table:

In [7]:
```
# getting data and creating the dataframe for the known_for table
imbd_known_for = pd.read_sql("""
                                SELECT *
                                FROM known_for;
                                """, conn)
imbd_known_for
```

Out[7]:

| | person_id | movie_id |
|---|---|---|
| **0** | nm0061671 | tt0837562 |
| **1** | nm0061671 | tt2398241 |
| **2** | nm0061671 | tt0844471 |
| **3** | nm0061671 | tt0118553 |
| **4** | nm0061865 | tt0896534 |
| **...** | ... | ... |
| **1638255** | nm9990690 | tt9090932 |
| **1638256** | nm9990690 | tt8737130 |
| **1638257** | nm9991320 | tt8734436 |

| | person_id | movie_id |
|---|---|---|
| **1638258** | nm9991320 | tt9615610 |
| **1638259** | nm9993380 | tt8743182 |

For the `movie_akas` table:

In [8]:
```
# creating the dataframe for the movie_akas table
imbd_movie_akas = pd.read_sql("""
                                SELECT *
                                FROM movie_akas;
                                """, conn)
imbd_movie_akas
```

Out[8]:

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

331703 rows × 8 columns

For the `movie_ratings` table:

In [9]:
```
# creating the dataframe for the movie_ratings table
imbd_movie_ratings = pd.read_sql("""
                                SELECT *
                                FROM movie_ratings;
                                """, conn)
imbd_movie_ratings
```

Out[9]:

| | 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 |

For the `persons` table:

In [10]:
```
# creating the dataframe for the persons table
imbd_persons = pd.read_sql("""
                                SELECT *
                                FROM persons;
                                """, conn)
imbd_persons
```

Out[10]:

| | person_id | primary_name | birth_year | death_year | prim |
|---|---|---|---|---|---|
| **0** | nm0061671 | Mary Ellen Bauder | NaN | NaN | miscellaneous,production_m |
| **1** | nm0061865 | Joseph Bauer | NaN | NaN | composer,music_department,so |
| **2** | nm0062070 | Bruce Baum | NaN | NaN | miscellan |
| **3** | nm0062195 | Axel Baumann | NaN | NaN | camera_department,cinematographe |
| **4** | nm0062798 | Pete Baxter | NaN | NaN | production_designer,art_departme |
| **...** | ... | ... | ... | ... | |
| **606643** | nm9990381 | Susan Grobes | NaN | NaN | |
| **606644** | nm9990690 | Joo Yeon So | NaN | NaN | |
| **606645** | nm9991320 | Madeline Smith | NaN | NaN | |

| | person_id | primary_name | birth_year | death_year | prim |
|---|---|---|---|---|---|
| **606646** | nm9991786 | Michelle Modigliani | NaN | NaN | |
| **606647** | nm9993380 | Pegasus Envoyé | NaN | NaN | dir |

For the `principals` table:

In [11]:
```
# creating the dataframe for the principals table
imbd_principals = pd.read_sql("""
                                SELECT *
                                FROM principals;
                                """, conn)
imbd_principals
```

Out[11]:

| | 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"] |
| **...** | ... | ... | ... | ... | ... | ... |
| **1028181** | tt9692684 | 1 | nm0186469 | actor | None | ["Ebenezer Scrooge"] |
| **1028182** | tt9692684 | 2 | nm4929530 | self | None | ["Herself","Regan"] |
| **1028183** | tt9692684 | 3 | nm10441594 | director | None | None |
| **1028184** | tt9692684 | 4 | nm6009913 | writer | writer | None |
| **1028185** | tt9692684 | 5 | nm10441595 | producer | producer | None |

1028186 rows × 6 columns

For the `writers` table:

In [12]:
```
# creating the dataframe for the writers table
imbd_writers = pd.read_sql("""
                                SELECT *
                                FROM writers;
                                """, conn)
imbd_writers
```

Out[12]:

| | movie_id | person_id |
|---|---|---|
| **0** | tt0285252 | nm0899854 |
| **1** | tt0438973 | nm0175726 |
| **2** | tt0438973 | nm1802864 |
| **3** | tt0462036 | nm1940585 |

| | movie_id | person_id |
|---|---|---|
| **4** | tt0835418 | nm0310087 |
| **...** | ... | ... |
| **255868** | tt8999892 | nm10122246 |
| **255869** | tt8999974 | nm10122357 |
| **255870** | tt9001390 | nm6711477 |
| **255871** | tt9004986 | nm4993825 |
| **255872** | tt9010172 | nm8352242 |

### 2.1.2 Box Office Mojo (BOM) Dataset

First we are going to read and create the BOM dataframe. Then we will clean it a little, and check the column value types for the BOM dataset ( `bom_df` ).

In [13]:

```
# reaing the data and checking the columns data types
bom_df = pd.read_csv('zipped_data/bom.movie_gross (1).csv.gz')
print(bom_df.dtypes)

# getting rid of commas before we make the transformation
bom_df['foreign_gross'] = bom_df['foreign_gross'].str.replace(',', '')

# transforming the string object into a float
bom_df = bom_df.astype({'foreign_gross': np.float})

# checking to see if it worked
print(bom_df.dtypes)

# check to see number of NaN values in `foreign_gross`
print(
    f"Number of null values in 'foreign_gross' column :{bom_df['foreign_gr

# check to see number of NaN values in `title`
print(
    f"Number of null values in 'title' column :{bom_df['title'].isnull().s

# drop rows with NaN values in `foreign_gross`
bom_df.dropna(subset=['foreign_gross'], inplace=True)

# check for NaN values in `foreign_gross`
print(
    f"Number of null values in 'foreign_gross' column after cleaning :{bom_
```

```
title              object
studio             object
domestic_gross    float64
foreign_gross      object
year                int64
dtype: object
title              object
```

In [14]:

```
# cleaned dataset!
bom_df
```

Out[14]:

| | title | studio | domestic_gross | foreign_gross | year |
|---|---|---|---|---|---|
| **0** | Toy Story 3 | BV | 415000000.0 | 652000000.0 | 2010 |
| **1** | Alice in Wonderland (2010) | BV | 334200000.0 | 691300000.0 | 2010 |
| **2** | Harry Potter and the Deathly Hallows Part 1 | WB | 296000000.0 | 664300000.0 | 2010 |
| **3** | Inception | WB | 292600000.0 | 535700000.0 | 2010 |
| **4** | Shrek Forever After | P/DW | 238700000.0 | 513900000.0 | 2010 |
| **...** | ... | ... | ... | ... | ... |
| **3275** | I Still See You | LGF | 1400.0 | 1500000.0 | 2018 |
| **3286** | The Catcher Was a Spy | IFC | 725000.0 | 229000.0 | 2018 |
| **3309** | Time Freak | Grindstone | 10000.0 | 256000.0 | 2018 |
| **3342** | Reign of Judges: Title of Liberty - Concept Short | Darin Southa | 93200.0 | 5200.0 | 2018 |
| **3353** | Antonio Lopez 1970: Sex Fashion & Disco | FM | 43200.0 | 30000.0 | 2018 |

2037 rows × 5 columns

## 2.2 Questions about the Data and Data Analysis

- Do certain genres result in higher grossing films?
- Is there a relationship between specific actors and higher grossing films?
- Do movies with higher average ratings result in higher grossing films?

You may have noticed that all these questions are related to the gross of the movies. That's because in order for Microsoft's new movie studio to flourish, it needs to be able to make money, as usually production costs for movies are not cheap. Hopefully, after answering these questions we will have some recommendations for Microsoft in order to direct them on how to make high-grossing, successful films!

### 2.2.1 Do certain genres result in higher grossing films?

In order to answer this question we need to make sure our data types are the way we want them.

Lets start by saving `bom_df` in a SQLite database, so that we can then use SQLite to join and query the `bom_df` data set and the `imbd_movie_basics` data set.

In [15]:
```
bom_df.to_sql('bom_df', conn)
```

Now we can query `bom_df` using SQLite.

In [16]:
```
pd.read_sql("""
                SELECT *
                FROM bom_df;
                """, conn)
```

Out[16]:

| | index | title | studio | domestic_gross | foreign_gross | year |
|---|---|---|---|---|---|---|
| **0** | 0 | Toy Story 3 | BV | 415000000.0 | 652000000.0 | 2010 |
| **1** | 1 | Alice in Wonderland (2010) | BV | 334200000.0 | 691300000.0 | 2010 |
| **2** | 2 | Harry Potter and the Deathly Hallows Part 1 | WB | 296000000.0 | 664300000.0 | 2010 |
| **3** | 3 | Inception | WB | 292600000.0 | 535700000.0 | 2010 |
| **4** | 4 | Shrek Forever After | P/DW | 238700000.0 | 513900000.0 | 2010 |
| **...** | ... | ... | ... | ... | ... | ... |
| **2032** | 3275 | I Still See You | LGF | 1400.0 | 1500000.0 | 2018 |
| **2033** | 3286 | The Catcher Was a Spy | IFC | 725000.0 | 229000.0 | 2018 |
| **2034** | 3309 | Time Freak | Grindstone | 10000.0 | 256000.0 | 2018 |
| **2035** | 3342 | Reign of Judges: Title of Liberty - Concept Short | Darin Southa | 93200.0 | 5200.0 | 2018 |
| **2036** | 3353 | Antonio Lopez 1970: Sex Fashion & Disco | FM | 43200.0 | 30000.0 | 2018 |

2037 rows × 6 columns

Now we're going to join the two tables based on movie title and year.

In [17]:
```
# we don't need the movie_id column for the first question, but we will in
bom_movie_basics_joined = pd.read_sql('''
    SELECT bom_df.title, bom_df.foreign_gross, movie_basics.genres, bom_df
    FROM bom_df
        INNER JOIN movie_basics
            /* Joining on title and year, so as to have the most accurate 
        ON bom_df.title=movie_basics.original_title AND bom_df.year=movie_
    ORDER BY foreign_gross DESC;
''', conn)
bom_movie_basics_joined
```

Out[17]:

| title | foreign_gross | genres | year | movie_id |
|---|---|---|---|---|

| | title | foreign_gross | genres | year | movie_id |
|---|---|---|---|---|---|
| **0** | Avengers: Age of Ultron | 946400000.0 | Action,Adventure,Sci-Fi | 2015 | tt2395427 |
| **1** | Jurassic World: Fallen Kingdom | 891800000.0 | Action,Adventure,Sci-Fi | 2018 | tt4881806 |
| **2** | Frozen | 875700000.0 | Adventure,Animation,Comedy | 2013 | tt2294629 |
| **3** | Transformers: Age of Extinction | 858600000.0 | Action,Adventure,Sci-Fi | 2014 | tt2109248 |
| **4** | Minions | 823400000.0 | Adventure,Animation,Comedy | 2015 | tt2293640 |
| **...** | ... | ... | ... | ... | ... |
| **1194** | Client 9: The Rise and Fall of Eliot Spitzer | 3500.0 | Documentary | 2010 | tt1638362 |
| **1195** | Avengers: Infinity War | 1369.5 | Action,Adventure,Sci-Fi | 2018 | tt4154756 |

In [18]:
```
bom_movie_basics_joined[bom_movie_basics_joined["title"].duplicated()]
```

Out[18]:

| | title | foreign_gross | genres | year | movie_id |
|---|---|---|---|---|---|
| **25** | Coco | 597400000.0 | Horror | 2017 | tt7002100 |
| **333** | The Artist | 88800000.0 | Thriller | 2011 | tt1825978 |
| **356** | Lights Out | 81600000.0 | Documentary | 2016 | tt5328340 |
| **388** | The Bounty Hunter | 69300000.0 | None | 2010 | tt1472211 |
| **451** | Abduction | 54000000.0 | Horror,Thriller | 2011 | tt2447982 |
| **454** | Truth or Dare | 53900000.0 | Comedy,Drama,Romance | 2018 | tt6869948 |
| **461** | Spotlight | 53200000.0 | Drama | 2015 | tt7785302 |
| **477** | The Walk | 51000000.0 | Adventure,Biography,Drama | 2015 | tt3488710 |
| **482** | Burlesque | 50100000.0 | Drama | 2010 | tt1586713 |
| **534** | Legend | 41100000.0 | Biography,Crime,Drama | 2015 | tt3569230 |
| **578** | The Visit | 33200000.0 | Documentary | 2015 | tt3833746 |
| **733** | Sisters | 18000000.0 | Biography,Documentary,Music | 2015 | tt4793074 |
| **776** | Big Eyes | 14800000.0 | Documentary | 2014 | tt4317898 |
| **811** | Sleepless | 12100000.0 | Drama,War | 2017 | tt4388844 |
| **831** | The Forest | 11000000.0 | Drama,Fantasy,Horror | 2016 | tt4982356 |
| **858** | The Night Before | 9300000.0 | Documentary | 2015 | tt6353886 |
| **915** | Gone | 6400000.0 | Drama | 2012 | tt2230954 |
| **981** | Stronger | 4200000.0 | Drama | 2017 | tt5738152 |
| **1019** | The Wall | 2700000.0 | Documentary | 2017 | tt6845582 |
| **1020** | The Wall | 2700000.0 | Documentary | 2017 | tt7578246 |
| **1024** | Cyrus | 2500000.0 | Comedy,Drama,Romance | 2010 | tt1336617 |
| **1160** | I'm Still Here | 160000.0 | None | 2010 | tt1701997 |
| **1178** | The Tempest | 68700.0 | Drama | 2010 | tt1683003 |

We can use `.shape` to find the number of duplicated rows:

In [19]:
```
bom_movie_basics_joined[bom_movie_basics_joined["title"].duplicated()].sha
```

Out[19]:
```
(23, 5)
```

So we have 1199 rows in our complete joined file, and 23 duplicated rows within that. Accounting for the duplication, that means that around 46 lines are doubled. 46/1299 equals to a bit less than 4%. Since it's impossible without incorperating more data to tell these duplicated movies apart (and make sure the right profits/genres are ascribed to the right movie), I'm going to delete all of them from our dataset.

In [20]:

```
bom_movie_basics_joined.drop_duplicates(
    subset=['title', 'year'], keep=False, inplace=True)
bom_movie_basics_joined
```

Out[20]:

| | title | foreign_gross | genres | year | movie_id |
|---|---|---|---|---|---|
| **0** | Avengers: Age of Ultron | 946400000.0 | Action,Adventure,Sci-Fi | 2015 | tt2395427 |
| **1** | Jurassic World: Fallen Kingdom | 891800000.0 | Action,Adventure,Sci-Fi | 2018 | tt4881806 |
| **2** | Frozen | 875700000.0 | Adventure,Animation,Comedy | 2013 | tt2294629 |
| **3** | Transformers: Age of Extinction | 858600000.0 | Action,Adventure,Sci-Fi | 2014 | tt2109248 |
| **4** | Minions | 823400000.0 | Adventure,Animation,Comedy | 2015 | tt2293640 |
| **...** | ... | ... | ... | ... | ... |
| **1194** | Client 9: The Rise and Fall of Eliot Spitzer | 3500.0 | Documentary | 2010 | tt1638362 |
| **1195** | Avengers: Infinity War | 1369.5 | Action,Adventure,Sci-Fi | 2018 | tt4154756 |
| **1196** | Jurassic World | 1019.4 | Action,Adventure,Sci-Fi | 2015 | tt0369610 |
| **1197** | The Fate of the Furious | 1010.0 | Action,Crime,Thriller | 2017 | tt4630562 |
| **1198** | Chasing Mavericks | 600.0 | Biography,Drama,Sport | 2012 | tt1629757 |

1154 rows × 5 columns

Okay! Now we have our cleaned data, leaving us with a dataset of 1154 movies, with their foreign gross, the genres associated with them, the year they were released, and the movie ID.

Lets get back to our original question; Do certain genres result in higher grossing films? In order to look at this, we will need to seperate the listed genres.

In [21]:

```
bom_movie_basics_joined['genres'] = bom_movie_basics_joined['genres'].str.
    pat=',')
bom_movie_basics_exploded = bom_movie_basics_joined.explode(
    'genres', ignore_index=True)
```

Now lets take a look at our data:

In [22]:

```
print(bom_movie_basics_exploded.dtypes)
bom_movie_basics_exploded
```

```
title             object
foreign_gross    float64
genres            object
year               int64
movie_id          object
dtype: object
```

Out[22]:

| title | foreign_gross | genres | year | movie_id |
|---|---|---|---|---|

| | title | foreign_gross | genres | year | movie_id |
|---|---|---|---|---|---|
| **0** | Avengers: Age of Ultron | 946400000.0 | Action | 2015 | tt2395427 |
| **1** | Avengers: Age of Ultron | 946400000.0 | Adventure | 2015 | tt2395427 |
| **2** | Avengers: Age of Ultron | 946400000.0 | Sci-Fi | 2015 | tt2395427 |
| **3** | Jurassic World: Fallen Kingdom | 891800000.0 | Action | 2018 | tt4881806 |
| **4** | Jurassic World: Fallen Kingdom | 891800000.0 | Adventure | 2018 | tt4881806 |
| **...** | ... | ... | ... | ... | ... |
| **2990** | The Fate of the Furious | 1010.0 | Crime | 2017 | tt4630562 |
| **2991** | The Fate of the Furious | 1010.0 | Thriller | 2017 | tt4630562 |
| **2992** | Chasing Mavericks | 600.0 | Biography | 2012 | tt1629757 |
| **2993** | Chasing Mavericks | 600.0 | Drama | 2012 | tt1629757 |
| **2994** | Chasing Mavericks | 600.0 | Sport | 2012 | tt1629757 |

Okay! So now we have a full workable list of the movies and their genres. Let's find the average amount each genre made in the dataset.

We are using the average here, as the dataset is fairly large (2995 movies) and so we are not as concerned about outliers skewing the data.

In [23]:

```
bom_movie_basics_exploded_avg = bom_movie_basics_exploded.groupby(
    ['genres']).foreign_gross.mean().reset_index()
bom_movie_basics_exploded_avg
```

Out[23]:

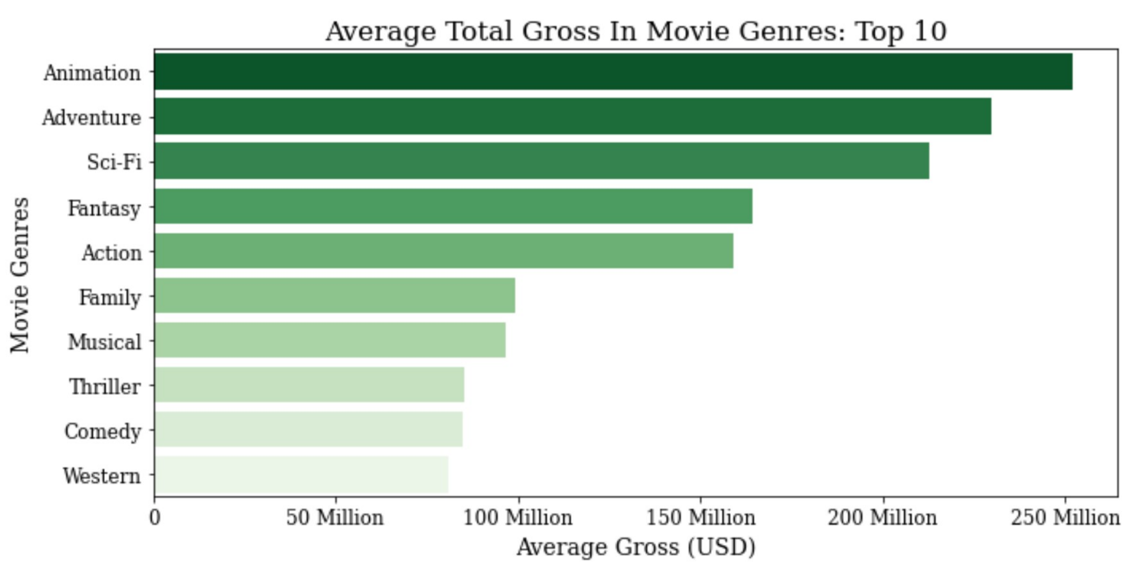
| | genres | foreign_gross |
|---|---|---|
| **0** | Action | 1.591982e+08 |
| **1** | Adventure | 2.297876e+08 |
| **2** | Animation | 2.518275e+08 |
| **3** | Biography | 4.951967e+07 |
| **4** | Comedy | 8.502199e+07 |
| **5** | Crime | 4.157536e+07 |
| **6** | Documentary | 1.201011e+07 |
| **7** | Drama | 4.738446e+07 |
| **8** | Family | 9.907607e+07 |
| **9** | Fantasy | 1.643918e+08 |
| **10** | History | 5.273703e+07 |
| **11** | Horror | 5.869045e+07 |
| **12** | Music | 5.320197e+07 |
| **13** | Musical | 9.681422e+07 |
| **14** | Mystery | 6.290475e+07 |

| | genres | foreign_gross |
|---|---|---|
| 15 | Romance | 3.829549e+07 |
| 16 | Sci-Fi | 2.127523e+08 |
| 17 | Sport | 2.323193e+07 |
| 18 | Thriller | 8.521993e+07 |
| 19 | War | 2.391725e+07 |

#### 2.2.1.1 Visualization: Average Total Gross In Movie Genres: Top 10

In [24]:

```
# setting universal font type for this and future graphs - from :https://d
plt.rcParams.update({'font.family': 'serif'})

# specify size of plot
fig, ax = plt.subplots(figsize=(10, 5))

# create bar plot of top 10 grossing genres
sns.barplot(data=bom_movie_basics_exploded_avg.sort_values(by='foreign_gro
            x='foreign_gross',
            y='genres',
            ci=None,
            palette='Greens_r')

# lable and define fontsize for main and axes titles
plt.xlabel('Average Gross (USD)', fontsize=14)
plt.ylabel('Movie Genres', fontsize=14)
plt.title('Average Total Gross In Movie Genres: Top 10', fontsize=17)
plt.tick_params(axis='both', which='major', labelsize=12)

# set x-axes tick labels
ax.set_xticklabels(['0', '50 Million', '100 Million',
                   '150 Million', '200 Million', '250 Million'])

# get rid of scientific notation
plt.tight_layout()
plt.show()
```



#### 2.2.1.2 Business recommendation: Do certain genres result in higher grossing films?

Based on the above graph, we see that there are genres that have on average higher grossing films

The top 5 genres according to the above graph are:

- **animation**
- **adventure**
- **sci-fi**
- **fantasy**
- **action**

As such, I would advise Microsoft to focus on these 5 genres in their initial films for their new movie studio. Many of these genres can and do overlap in films, so it may be best to focus on animated movies with sub-genres of adventure, sci-fi, fantasy, or action.

### 2.2.2 Is there a relationship between specific actors and higher grossing films?

In order to answer this question, we are going to have to create a cohesive data set where we have the actors, the various films they acted in, and the total amount the movies made once they were put out.

To do this, lets create an inner join between `bom_df` , `movie_basics` , `principles` , and `persons` .

In [25]:

```
join_actors_gross = pd.read_sql("""
    SELECT bom.foreign_gross, bas.genres, per.person_id,  per.primary_name
    FROM bom_df AS bom
            /*joining bom_df and movie_basics*/
        INNER JOIN
        movie_basics AS bas
        ON bom.title=bas.original_title AND bom.year=bas.start_year
            /*joining pricipals to dataset*/
        INNER JOIN
        principals AS pri
        ON bas.movie_id=pri.movie_id
            /*joining persons to dataset*/
        INNER JOIN
        persons AS per
        ON pri.person_id=per.person_id
            WHERE category='actor' OR 'actress'
    ORDER BY foreign_gross DESC;
    """, conn)

join_actors_gross
```

Out[25]:

| | foreign_gross | genres | person_id | primary_name |
|---|---|---|---|---|
| **0** | 946400000.0 | Action,Adventure,Sci-Fi | nm0000375 | Robert Downey Jr. |
| **1** | 946400000.0 | Action,Adventure,Sci-Fi | nm0262635 | Chris Evans |
| **2** | 946400000.0 | Action,Adventure,Sci-Fi | nm0749263 | Mark Ruffalo |
| **3** | 946400000.0 | Action,Adventure,Sci-Fi | nm1165110 | Chris Hemsworth |
| **4** | 891800000.0 | Action,Adventure,Sci-Fi | nm0695435 | Chris Pratt |
| **...** | ... | ... | ... | ... |
| **2913** | 1010.0 | Action,Crime,Thriller | nm0004874 | Vin Diesel |
| **2914** | 1010.0 | Action,Crime,Thriller | nm0005458 | Jason Statham |
| **2915** | 1010.0 | Action,Crime,Thriller | nm0425005 | Dwayne Johnson |
| **2916** | 600.0 | Biography,Drama,Sport | nm4103976 | Jonny Weston |
| **2917** | 600.0 | Biography,Drama,Sport | nm0124930 | Gerard Butler |

2918 rows × 4 columns

In [26]:
```
# checking for null values - you can run this if you want, but there are n
# print(pd.isnull(join_actors_gross['person_id']).values.sum())
# pd.isnull(join_actors_gross['primary_name']).values.sum()
```

Okay! Let's try to make a data set where we have the median foreign gross per movie that the actors/actresses appeared in.

We're using the median here as there may be actors who worked in only a few movies, and we want the data to be more resistant to outliers.

The total number of actors in this dataset is 1411.

In [27]:
```
median_foreign_gross_per_actor = join_actors_gross.groupby(
    ['person_id', 'primary_name'], as_index=False).median()
median_foreign_gross_per_actor
```

Out[27]:

| | person_id | primary_name | foreign_gross |
|---|---|---|---|
| **0** | nm0000092 | John Cleese | 11722000.0 |
| **1** | nm0000093 | Brad Pitt | 63200000.0 |
| **2** | nm0000095 | Woody Allen | 56600000.0 |
| **3** | nm0000100 | Rowan Atkinson | 153150000.0 |
| **4** | nm0000101 | Dan Aykroyd | 101300000.0 |
| **...** | ... | ... | ... |
| **1407** | nm9061885 | Gonzalo Moreno | 597400000.0 |
| **1408** | nm9061887 | Leolo Moulin | 597400000.0 |
| **1409** | nm9133740 | Huck Milner | 634200000.0 |
| **1410** | nm9377852 | Yugesh Anil | 600000.0 |

| | person_id | primary_name | foreign_gross |
|---|---|---|---|
| **1411** | nm9501548 | Robert Jon Mello | 8100000.0 |

In [28]:

```
# checking for duplicate rows
median_foreign_gross_per_actor[median_foreign_gross_per_actor['primary_nam
)]
```

Out[28]:

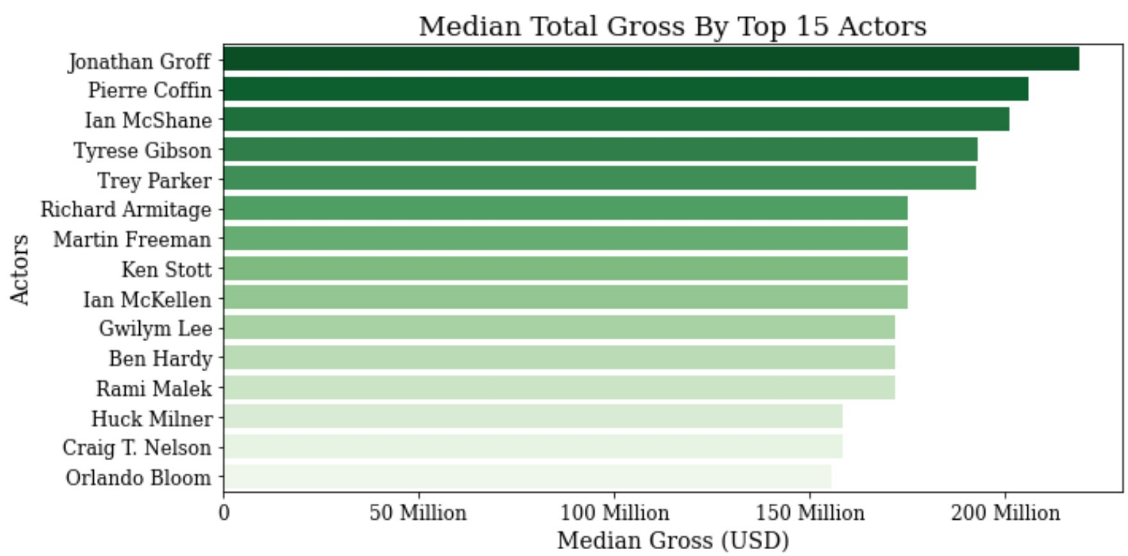
| person_id | primary_name | foreign_gross |
|---|---|---|

Woohoo! There are no duplicate rows, so we can use `median_foreign_gross_per_actor` to create our next graph. For this question, our final dataset has 1412 actors, along with their names, ID numbers, and their median foreign gross.

#### 2.2.2.1 Visualization: Median Total Gross By Top 15 Actors

In [29]:

```
# our data for this graph
top15_med_gross_actor = median_foreign_gross_per_actor.sort_values(
    by='foreign_gross', ascending=False).head(15)

# specify size of plot
fig, ax = plt.subplots(figsize=(10, 5))

# create bar plot
sns.barplot(data=top15_med_gross_actor,
            x='foreign_gross',
            y='primary_name',
            ci=None,
            palette='Greens_r')

# lable and define fontsize for main and axes titles
plt.xlabel('Median Gross (USD)', fontsize=14)
plt.ylabel('Actors', fontsize=14)
plt.title('Median Total Gross By Top 15 Actors', fontsize=17)
plt.tick_params(axis='both', which='major', labelsize=12)

# set x-axes tick labels
ax.set_xticklabels(['0', '50 Million', '100 Million',
                   '150 Million', '200 Million', '250 Million'])

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




#### 2.2.2.2 Business recommendation: Is there a relationship between specific actors and higher grossing films?

At a glance, we do see that there is a significant difference between the median gross of films with different actors. Surprisingly, there are only a few household names in the final 15. This may relate back to our previous finding, which is that animated films are the highest grossing movie genre. In animated films, one doesn't see the actors' faces, and as such may be more 'anonymous' and unknown to the average movie watcher. On a separate note, it is surprising that this list is composed only of men.

Before, the analysis seemed to indicate that animated films are a direction for Microsoft's new movie studio to check out. Let's see if any of the top 15 actors were involved in animated films

In [30]:
```
top15_in_animation = []
for name, gross, genres in zip(join_actors_gross['primary_name'], join_act
    if genres is not None and 'Animation' in genres:
        top15_in_animation.append([name, gross, genres, True])
    else:
        top15_in_animation.append([name, gross, genres, False])


top15_in_animation = pd.DataFrame(
    top15_in_animation, columns=['name', 'gross', 'genres', 'Is Animation 
top15_in_animation.groupby(['name'], as_index=False).median().sort_values(
    by='gross', ascending=False).head(15)
```

Out[30]:

| | name | gross | Is Animation in Genres |
|---|---|---|---|
| **697** | Jonathan Groff | 875700000.0 | 1.0 |
| **1033** | Pierre Coffin | 823400000.0 | 1.0 |
| **516** | Ian McShane | 804600000.0 | 0.0 |
| **1348** | Tyrese Gibson | 771400000.0 | 0.0 |
| **1339** | Trey Parker | 770200000.0 | 1.0 |
| **1071** | Richard Armitage | 700900000.0 | 0.0 |
| **845** | Martin Freeman | 700450000.0 | 0.0 |
| **515** | Ian McKellen | 700000000.0 | 0.0 |
| **749** | Ken Stott | 700000000.0 | 0.0 |
| **1050** | Rami Malek | 687200000.0 | 0.0 |
| **486** | Gwilym Lee | 687200000.0 | 0.0 |
| **119** | Ben Hardy | 687200000.0 | 0.0 |
| **277** | Craig T. Nelson | 634200000.0 | 1.0 |
| **505** | Huck Milner | 634200000.0 | 1.0 |
| **991** | Orlando Bloom | 622300000.0 | 0.0 |

We see above that 5/15 were in at least one animated film - around 30%. It might be worth further analysis to see if any of these actors are a good fit Microsofts upcoming movies.

### 2.2.3 Do movies with higher average ratings result in higher grossing films?

Our final question! Let's look at the datset where we had the `averagerating` data again:

In [31]:
```
imbd_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

Okay! Let's do some inner joins so we can get the total gross and the average ratings.

In [32]:

```
join_ratings_gross = pd.read_sql("""
    SELECT bom.foreign_gross, ratings.averagerating
    FROM bom_df AS bom
            /*joining bom_df and movie_basics*/
        INNER JOIN
        movie_basics AS bas
        ON bom.title=bas.original_title AND bom.year=bas.start_year
            /*joining movie_ratings to dataset*/
        INNER JOIN
        movie_ratings AS ratings
        ON ratings.movie_id=bas.movie_id;
        """, conn)
join_ratings_gross
```

Out[32]:

| | foreign_gross | averagerating |
|---|---|---|
| 0 | 652000000.0 | 8.3 |
| 1 | 535700000.0 | 8.8 |
| 2 | 513900000.0 | 6.3 |
| 3 | 398000000.0 | 5.0 |
| 4 | 311500000.0 | 7.0 |
| ... | ... | ... |
| 1185 | 1200000.0 | 6.2 |
| 1186 | 2000000.0 | 6.9 |
| 1187 | 1500000.0 | 5.7 |
| 1188 | 229000.0 | 6.2 |

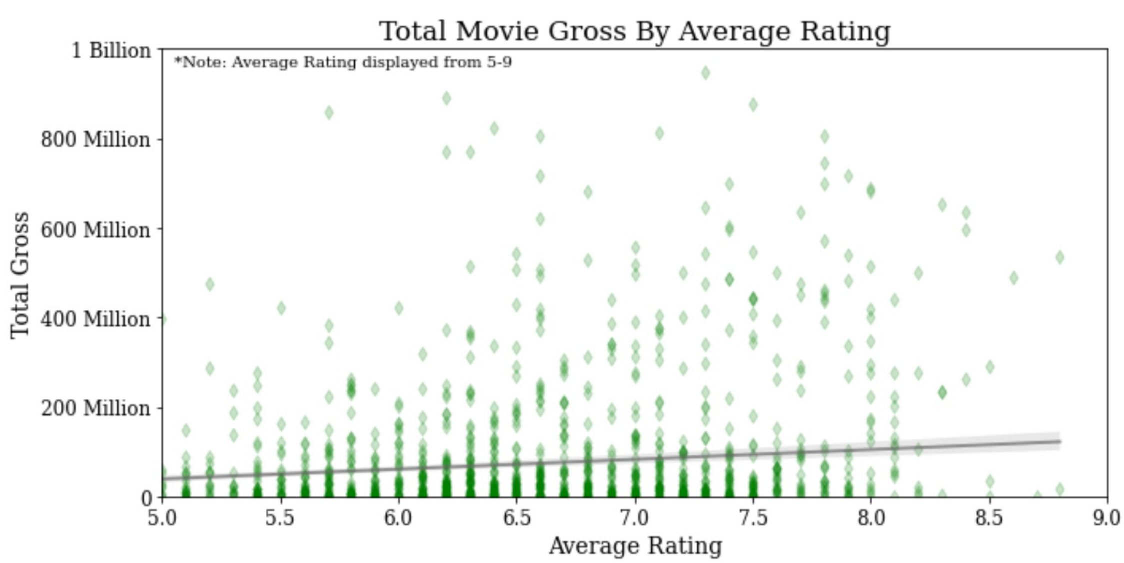
| | foreign_gross | averagerating |
|---|---|---|
| **1189** | 256000.0 | 5.7 |

#### 2.2.3.1 Visualization: Total Movie Gross By Average Rating

Our final dataset for this question has 1190 average ratings, each representing a specific movie, and also contains the foreign gross for each film.

In [33]:

```
# save our dataframe as we want it
sorted_join_ratings_gross = join_ratings_gross.sort_values(
    by='foreign_gross', ascending=False)

# specify size of plot
fig, ax = plt.subplots(figsize=(10, 5))

# set axis ticks and labels
    # found inspiration for the following two lines of code from Kimberly
plt.gca().set(xlim=(5, 9))
plt.gca().set(ylim=(0, 1000000000))
ax.set_yticklabels(['0', '200 Million', '400 Million',
                   '600 Million', '800 Million', '1 Billion'])
plt.tick_params(axis='both', which='major', labelsize=12)

# add regression line - seaborn documentation:https://seaborn.pydata.org/g
sns.regplot(sorted_join_ratings_gross.averagerating, sorted_join_ratings_g
            scatter_kws={'color': 'g', 'alpha': 0.2}, line_kws={'color': '
            robust=True)

# specifiy axis and title labels
plt.title('Total Movie Gross By Average Rating', fontsize=17)
plt.xlabel('Average Rating', fontsize=14)
plt.ylabel('Total Gross', fontsize=14)

# adding note that x axis starts at 5
plt.text(5.05, 960000000, '*Note: Average Rating displayed from 5-9')


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



#### 2.2.3.2 Business recommendation: Do movies with higher average ratings result in higher grossing films?

Hmm, it doesn't seem like there is a strong correlation between these ratings and the total gross. Let's check Pearson's correlation, and see if there is a significant correlation

In [34]:
```
# pearsons correlation
sorted_join_ratings_gross.corr()
```

Out[34]:

| | foreign_gross | averagerating |
|---|---|---|
| **foreign_gross** | 1.000000 | 0.237023 |
| **averagerating** | 0.237023 | 1.000000 |

Anything under .25 is considered no correlation - so while there is a very, very slight positive correlation between ratings and total gross, it's not significant. Based on these results, one may conclude that you don't have to make amazing movies in order to end up with financially successful movies.

# 3 Conclusion

In summation, the three recommendations coming out of this analysis are:

- The data indicates that there are specific genres that in the past have (on average) done very well. In particular, animation seems to have high on-average box office returns. As such, I would recommend that Microsoft focus its initial film-making energies on animated films, with sub-genres of adventure, scifi, and fantasy.
- There are actors that have a high median total foreign gross. These actors should be further analyzed when the movie making process is farther along to see if they would be a good fit in any of the initial films. It should be noted that 5/15 of the actors (33.3%) have worked on at least one animation film, and as such these actors should especially be noted for possible future films.
- Finally, it seems that there is no significant correlation between film ratings and box office success - as such it is important to note that the quality of the movie has little to no bearing on a movie's box office success. In short, it's okay to skimp on film quality to a certain extent.

Initially focusing on animated films will enable the studio to step into a lucrative movie genre. Similarly, casting actors with a high median total gross will hopefully engender similar results - particularly actors with prior experience in animated films. Finally, it is worthwhile to note that movies do not have to be exceptional to do well, which should be kept in mind if and when costs need to be cut.