# Microsoft Movie Industry Analysis

## Author: Jonah Devoy

## Overview

For my exploratory data analysis project, I have been tasked with using exploratory data analysis to generate insights for business stakeholders. My goal for this project was to investigate what genre of films is the most profitable and deliver these findings to Microsoft's new movie studio executives. The analysis results, shown by visualizations and descriptive statistics revealed the most profitable movie genres and recommended the best directors to hire for each genre. Microsoft's new movie studio can use my report to produce movies that accumulate the highest profit and tailor those movies to specific genres and what directors are the best to use for each of those selected genres.

## Business Problem

It was brought to my attention that Microsoft has noticed other big enterprises creating original video content and they would like to enter the exciting world of movie-making with their new movie studio. One problem is that Microsoft is uncertain of where to start. I have been recruited with exploring what types of films Microsofts new movie studio should produce to be successful. Using my findings I transformed those results into actionable insights so that Microsoft's new movie studio will have direction to be profitable. To aid Microsofts studio, I looked at the highest-profiting genre of movies, which genre of movies should be produced, and what directors to use for the selected genres. The three factors I based my analysis on are:

- What movie genres produce the highest profits?
- What movie genres should be produced to avoid competition?
- What director should be hired to produce their movies?

# Data Understanding

I used two data sources for my analysis to determine the best recommendations for Microsofts new movie studio.

- tn.movie_budgets.csv: This compressed csv was extracted from the zipped data folder provided in the dsc-phase-1-project-v2-4.git Github repository located at https://github.com/learn-co-curriculum/dsc-phase-1-project-v2-4.git (https://github.com/learn-co-curriculum/dsc-phase-1-project-v2-4.git). I forked the repository and extracted all the files to my local machine where I could work on the tn.movie_budgets.csv on my local machine's Jupyter Notebook.
- imdb_top_1000.csv: This data set is taken from Kaggles EDA on IMDB Movies Dataset located at https://www.kaggle.com/code/harshitshankhdhar/eda-on-imdb-movies-dataset/notebook (https://www.kaggle.com/code/harshitshankhdhar/eda-on-imdb-movies-dataset/notebook). I downloaded the data to my local machine and moved the csv file to the zipped data folder with the rest of the given csv files. I chose to utilize this data set because of the information it gave such as movie directors, top four stars per movie, and gross income of the movie.

# Data Preparation

In [1]:
```
# Importing the proper packages to prepare my data for analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from ast import literal_eval
from collections import Counter
```

In [2]:
```
he data file path
ad_csv('/Users/jdapeman/Documents/Flatiron/Microsoft_Movie_Analysis/pha
```

In [3]:
```
data.head()
```

Out[3]:

| itle | Released_Year | Certificate | Runtime | Genre | IMDB_Rating | Overview | Meta_score | Direc |
|---|---|---|---|---|---|---|---|---|
| The hank tion | 1994 | A | 142 min | Drama | 9.3 | Two imprisoned men bond over a number of years... | 80.0 | Fr Darab |
| The ther | 1972 | A | 175 min | Crime, Drama | 9.2 | An organized crime dynasty's aging patriarch t... | 100.0 | Frar F Copp |
| )ark iight | 2008 | UA | 152 min | Action, Crime, Drama | 9.0 | When the menace known as the Joker wreaks havo... | 84.0 | Christop Nc |
| The her: art II | 1974 | A | 202 min | Crime, Drama | 9.0 | The early life and career of Vito Corleone in ... | 90.0 | Frar F Copp |
| ngry Men | 1957 | U | 96 min | Crime, Drama | 9.0 | A jury holdout attempts to prevent a miscarria... | 96.0 | Sid Lu |

## Renaming the column titles and droping column Poster_Link and Overview

## data columns key:

- Movie_Title: Name of the movie
- Year_released: Year at which that movie released
- Certificate_Grade: Certificate earned by that movie
- Runtime: Total runtime of the movie
- Genre: Genre of the movie
- IMDB_Rating: Rating of the movie at IMDB site
- Meta_score: Score earned by the movie
- Director: Name of the Director
- Star1,2,3,4: Name of the Stars
- Vote_Count: Total number of votes
- Gross: Money earned by that movie

In [4]:
```
data.rename(columns={"Series_Title": "Movie_Title", "Released_Year": "
"Certificate": "Certificate_Grade", "No_of_Votes": "Vote_Count"}, inpl
```

In [5]:
```
# Removing unecessary columns
data = data.drop('Poster_Link', axis=1)
data = data.drop('Overview', axis=1)
```

In [6]:
```
data.head()
```

Out[6]:

| | Movie_Title | Year_released | Certificate_Grade | Runtime | Genre | IMDB_Rating | Meta_score |
|---|---|---|---|---|---|---|---|
| **0** | The Shawshank Redemption | 1994 | A | 142 min | Drama | 9.3 | 80.0 |
| **1** | The Godfather | 1972 | A | 175 min | Crime, Drama | 9.2 | 100.0 |
| **2** | The Dark Knight | 2008 | UA | 152 min | Action, Crime, Drama | 9.0 | 84.0 |
| **3** | The Godfather: Part II | 1974 | A | 202 min | Crime, Drama | 9.0 | 90.0 |
| **4** | 12 Angry Men | 1957 | U | 96 min | Crime, Drama | 9.0 | 96.0 |

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Movie_Title        1000 non-null   object 
 1   Year_released      1000 non-null   object 
 2   Certificate_Grade  899 non-null    object 
 3   Runtime            1000 non-null   object 
 4   Genre              1000 non-null   object 
 5   IMDB_Rating        1000 non-null   float64
 6   Meta_score         843 non-null    float64
 7   Director           1000 non-null   object 
 8   Star1              1000 non-null   object 
 9   Star2              1000 non-null   object 
 10  Star3              1000 non-null   object 
 11  Star4              1000 non-null   object 
 12  Vote_Count         1000 non-null   int64  
 13  Gross              831 non-null    object 
dtypes: float64(2), int64(1), object(11)
memory usage: 109.5+ KB
```

In [8]:
```
# Changing the 'Gross' column datatype from a object to an int64 and N
data['Gross'] = data['Gross'].str.replace(',', '')
data['Gross'] = data['Gross'].replace(np.nan, 0)
data['Gross'] = data['Gross'].astype('int64')
```

In [9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Movie_Title        1000 non-null   object 
 1   Year_released      1000 non-null   object 
 2   Certificate_Grade  899 non-null    object 
 3   Runtime            1000 non-null   object 
 4   Genre              1000 non-null   object 
 5   IMDB_Rating        1000 non-null   float64
 6   Meta_score         843 non-null    float64
 7   Director           1000 non-null   object 
 8   Star1              1000 non-null   object 
 9   Star2              1000 non-null   object 
 10  Star3              1000 non-null   object 
 11  Star4              1000 non-null   object 
 12  Vote_Count         1000 non-null   int64  
 13  Gross              1000 non-null   int64  
dtypes: float64(2), int64(2), object(10)
memory usage: 109.5+ KB
```

In [10]:
```
# Here I replaced all 'Gross' values equaling zero with the median gro
# because there were only 169 0 values and imputating the median is mo
# the mean.

data['Gross'].median()
```

Out[10]:
```
10702751.5
```

In [11]:
```
data.loc[data['Gross'] == 0, 'Gross'] = 10702752
```

In [12]:
```
data.sort_values(by=['Movie_Title'], inplace=True)
```

In [13]:
```
data.head()
```

Out[13]:

| | Movie_Title | Year_released | Certificate_Grade | Runtime | Genre | IMDB_Rating | Meta_sc |
|---|---|---|---|---|---|---|---|
| **754** | (500) Days of Summer | 2009 | UA | 95 min | Comedy, Drama, Romance | 7.7 | 7 |
| **4** | 12 Angry Men | 1957 | U | 96 min | Crime, Drama | 9.0 | 9 |
| **215** | 12 Years a Slave | 2013 | A | 134 min | Biography, Drama, History | 8.1 | 9 |
| **84** | 1917 | 2019 | R | 119 min | Drama, Thriller, War | 8.3 | 7 |
| **114** | 2001: A Space Odyssey | 1968 | U | 149 min | Adventure, Sci-Fi | 8.3 | 8 |

In [14]:
```
# I imported data from tn.movie_budgets.csv specifically for the 'proc
df_budgets = pd.read_csv('/Users/jdapeman/Documents/Flatiron/Microsoft
```

In [15]:
```
# Sorting values by movie name and renaming the column 'movie' to matc
df_budgets.sort_values(by=['movie'], inplace=True)
df_budgets.rename(columns = {'movie' : 'Movie_Title'}, inplace=True)
```

In [16]:
```
df_budgets.head()
```

Out[16]:

| | id | release_date | Movie_Title | production_budget | domestic_gross | worldwide_gross |
|---|---|---|---|---|---|---|
| **5115** | 16 | Nov 20, 2015 | #Horror | $1,500,000 | $0 | $0 |
| **3954** | 55 | Jul 17, 2009 | (500) Days of Summer | $7,500,000 | $32,425,665 | $34,439,060 |
| **4253** | 54 | Mar 11, 2016 | 10 Cloverfield Lane | $5,000,000 | $72,082,999 | $108,286,422 |
| **3447** | 48 | Nov 11, 2015 | 10 Days in a Madhouse | $12,000,000 | $14,616 | $14,616 |
| **3262** | 63 | Mar 31, 1999 | 10 Things I Hate About You | $13,000,000 | $38,177,966 | $60,413,950 |

In [17]:
```
# Math operations cannot be done on the prodcution_budget, domestic_gr
# they are strings. Here I stripped them of $ and thier commas, allowi
# string to an int
df_budgets['production_budget'] = df_budgets['production_budget'].str.
df_budgets['production_budget'] = df_budgets['production_budget'].str.
df_budgets['production_budget'] = df_budgets['production_budget'].asty
```

```
/var/folders/yd/tybxdv4901xbv_l8x4p1g7tm0000gn/T/ipykernel_5588/15976
61293.py:4: FutureWarning: The default value of regex will change fro
m True to False in a future version. In addition, single character re
gular expressions will *not* be treated as literal strings when regex
=True.
  df_budgets['production_budget'] = df_budgets['production_budget'].s
tr.replace(r'$', '')
```

In [18]:
```
df_budgets['domestic_gross'] = df_budgets['domestic_gross'].str.replac
df_budgets['domestic_gross'] = df_budgets['domestic_gross'].str.replac
df_budgets['domestic_gross'] = df_budgets['domestic_gross'].astype(int
```

```
/var/folders/yd/tybxdv4901xbv_l8x4p1g7tm0000gn/T/ipykernel_5588/35447
28917.py:1: FutureWarning: The default value of regex will change fro
m True to False in a future version. In addition, single character re
gular expressions will *not* be treated as literal strings when regex
=True.
  df_budgets['domestic_gross'] = df_budgets['domestic_gross'].str.rep
lace(r'$', '')
```

In [19]:
```
df_budgets['worldwide_gross'] = df_budgets['worldwide_gross'].str.repl
df_budgets['worldwide_gross'] = df_budgets['worldwide_gross'].str.repl
df_budgets['worldwide_gross'] = df_budgets['worldwide_gross'].astype(i
```

```
/var/folders/yd/tybxdv4901xbv_l8x4p1g7tm0000gn/T/ipykernel_5588/18869
19089.py:1: FutureWarning: The default value of regex will change fro
m True to False in a future version. In addition, single character re
gular expressions will *not* be treated as literal strings when regex
=True.
  df_budgets['worldwide_gross'] = df_budgets['worldwide_gross'].str.r
eplace(r'$', '')
```

In [20]:
```
df_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 5115 to 2701
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   Movie_Title        5782 non-null   object
 3   production_budget  5782 non-null   int64 
 4   domestic_gross     5782 non-null   int64 
 5   worldwide_gross    5782 non-null   int64 
dtypes: int64(4), object(2)
memory usage: 316.2+ KB
```

In [21]:
```
# I combined the two dataframes, data and df_budgets. For my perameter
# 'Movie_title' because I wanted to keep the titles from both data set
profit_per_cat_data = pd.merge(data, df_budgets, left_on = 'Movie_Titl
profit_per_cat_data.head()
```

Out[21]:

| | Movie_Title | Year_released | Certificate_Grade | Runtime | Genre | IMDB_Rating | Meta_score |
|---|---|---|---|---|---|---|---|
| **0** | (500) Days of Summer | 2009 | UA | 95 min | Comedy, Drama, Romance | 7.7 | 76.( |
| **1** | 12 Angry Men | 1957 | U | 96 min | Crime, Drama | 9.0 | 96.( |
| **2** | 12 Years a Slave | 2013 | A | 134 min | Biography, Drama, History | 8.1 | 96.( |
| **3** | 2001: A Space Odyssey | 1968 | U | 149 min | Adventure, Sci-Fi | 8.3 | 84.( |
| **4** | 21 Grams | 2003 | UA | 124 min | Crime, Drama, Thriller | 7.6 | 70.( |

In [22]:
```
profit_per_cat_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 521 entries, 0 to 520
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Movie_Title        521 non-null    object
 1   Year_released      521 non-null    object
 2   Certificate_Grade  511 non-null    object
 3   Runtime            521 non-null    object
 4   Genre              521 non-null    object
 5   IMDB_Rating        521 non-null    float64
 6   Meta_score         503 non-null    float64
 7   Director           521 non-null    object
 8   Star1              521 non-null    object
 9   Star2              521 non-null    object
 10  Star3              521 non-null    object
 11  Star4              521 non-null    object
 12  Vote_Count         521 non-null    int64
 13  Gross              521 non-null    int64
 14  id                 521 non-null    int64
 15  release_date       521 non-null    object
 16  production_budget  521 non-null    int64
 17  domestic_gross     521 non-null    int64
 18  worldwide_gross    521 non-null    int64
dtypes: float64(2), int64(6), object(11)
memory usage: 81.4+ KB
```

In [23]:
```
# Dropping rows with zero value for 'domestic_gross'. There are five z
profit_per_cat_data = profit_per_cat_data[profit_per_cat_data['domesti
```

In [24]:
```
# I created a column titled 'Total_Domestic_Gross', consisting of the
# 'domestic_gross' columns
profit_per_cat_data['Total_Domestic_Gross'] = (profit_per_cat_data['Gr
profit_per_cat_data.head()
```

Out[24]:

| | Movie_Title | Year_released | Certificate_Grade | Runtime | Genre | IMDB_Rating | Meta_score |
|---|---|---|---|---|---|---|---|
| 0 | (500) Days of Summer | 2009 | UA | 95 min | Comedy, Drama, Romance | 7.7 | 76.( |
| 2 | 12 Years a Slave | 2013 | A | 134 min | Biography, Drama, History | 8.1 | 96.( |
| 3 | 2001: A Space Odyssey | 1968 | U | 149 min | Adventure, Sci-Fi | 8.3 | 84.( |
| 4 | 21 Grams | 2003 | UA | 124 min | Crime, Drama, Thriller | 7.6 | 70.( |
| 5 | 25th Hour | 2002 | R | 135 min | Drama | 7.6 | 68.( |

In [25]:
```
# From here I dropped the Gross, domestic_gross, and id columns
profit_per_cat_data = profit_per_cat_data.drop('Gross', axis=1)
```

In [26]:
```
profit_per_cat_data = profit_per_cat_data.drop('domestic_gross', axis=
```

In [27]:
```
profit_per_cat_data = profit_per_cat_data.drop('id', axis=1)
```

In [28]:
```
profit_per_cat_data.columns
```

Out[28]:
```
Index(['Movie_Title', 'Year_released', 'Certificate_Grade', 'Runtime'
, 'Genre',
       'IMDB_Rating', 'Meta_score', 'Director', 'Star1', 'Star2', 'St
ar3',
       'Star4', 'Vote_Count', 'release_date', 'production_budget',
       'worldwide_gross', 'Total_Domestic_Gross'],
      dtype='object')
```

In [29]:
```
# Now we can make a profit column
profit_per_cat_data['Profit'] = profit_per_cat_data['worldwide_gross']
```

In [30]:
```
profit_per_cat_data.columns
```

Out[30]:
```
Index(['Movie_Title', 'Year_released', 'Certificate_Grade', 'Runtime'
, 'Genre',
       'IMDB_Rating', 'Meta_score', 'Director', 'Star1', 'Star2', 'St
ar3',
       'Star4', 'Vote_Count', 'release_date', 'production_budget',
       'worldwide_gross', 'Total_Domestic_Gross', 'Profit'],
      dtype='object')
```

In [31]:
```
# Seperating the genre types in the 'Genre' column
profit_per_cat_data['Genre'] = profit_per_cat_data['Genre'].str.strip(
```

In [33]:
```
profit_per_cat_data = profit_per_cat_data.explode('Genre')
```

In [34]:
```
profit_per_cat_data.head()
```

Out[34]:

| | Movie_Title | Year_released | Certificate_Grade | Runtime | Genre | IMDB_Rating | Meta_score |
|---|---|---|---|---|---|---|---|
| **0** | (500) Days of Summer | 2009 | UA | 95 min | Comedy | 7.7 | 76.0 |
| **0** | (500) Days of Summer | 2009 | UA | 95 min | Drama | 7.7 | 76.0 |
| **0** | (500) Days of Summer | 2009 | UA | 95 min | Romance | 7.7 | 76.0 |
| **2** | 12 Years a Slave | 2013 | A | 134 min | Biography | 8.1 | 96.0 |
| **2** | 12 Years a Slave | 2013 | A | 134 min | Drama | 8.1 | 96.0 |

In [35]:
```
profit_per_cat_data['Genre'].value_counts()
```

Out[35]:
```
 Drama        208
Drama         138
Action        106
 Adventure     89
 Thriller      73
Comedy         60
 Sci-Fi        58
Biography      56
 Romance       54
Adventure      49
Crime          48
 Comedy        47
 Crime         42
Animation      41
 Mystery       38
 Fantasy       31
 Family        30
 History       29
 War           21
 Sport         15
 Music         12
Horror         12
 Biography     11
 Action        10
 Western       10
 Horror         9
 Musical        7
 Film-Noir      4
Mystery         3
Western         2
Family          1
Name: Genre, dtype: int64
```

In [44]:
```
# There are double counts of genres becasue of whitespace attached to
profit_per_cat_data['Genre'] = profit_per_cat_data['Genre'].str.strip(
```

In [45]:
```
profit_per_cat_data['Genre'].value_counts()
```

Out[45]:
```
Drama          346
Adventure      138
Action         116
Comedy         107
Crime           90
Thriller        73
Biography       67
Sci-Fi          58
Romance         54
Mystery         41
Animation       41
Fantasy         31
Family          31
History         29
Horror          21
War             21
Sport           15
Music           12
Western         12
Musical          7
Film-Noir        4
Name: Genre, dtype: int64
```

In [69]:
```
# There is a 'PG' value in the 'Year_relesed' column for the movie Apo
# change the year from a string to an integer.
profit_per_cat_data.loc[profit_per_cat_data['Year_released'] == 'PG',
```

In [71]:
```
profit_per_cat_data[profit_per_cat_data['Year_released'] == 'PG'].valu
```

Out[71]:
```
Series([], dtype: int64)
```

In [72]:
```
profit_per_cat_data['Year_released'] = profit_per_cat_data['Year_relea
```

In [73]:
```
# Finding what movies are relased after 1999
saturation_data = profit_per_cat_data[profit_per_cat_data['Year_releas
```

In [74]:
```
saturation_data_v2 = saturation_data[['Year_released', 'Genre']].copy(
```

In [75]:
```
saturation_data_v2
```

Out[75]:

| | Year_released | Genre |
|---|---|---|
| **0** | 2009 | Comedy |
| **0** | 2009 | Drama |
| **0** | 2009 | Romance |
| **2** | 2013 | Biography |
| **2** | 2013 | Drama |
| **...** | ... | ... |
| **518** | 2016 | Adventure |
| **518** | 2016 | Comedy |
| **520** | 2006 | Drama |
| **520** | 2006 | Thriller |
| **520** | 2006 | War |

716 rows × 2 columns

In [82]:
```
# Creating a table of the top 5 profiable movies to check for oversatu
saturation_data_v3 = saturation_data_v2[(saturation_data_v2['Genre'] =
                  (saturation_data_v2['Genre'] == "Family") | (saturat
                  (saturation_data_v2['Genre'] == "Animation")]
```

In [95]:
```
saturation_data_v3
```

Out[95]:

| | Year_released | Genre |
|---|---|---|
| **6** | 2006 | Action |
| **7** | 2007 | Action |
| **15** | 2013 | Fantasy |
| **23** | 2000 | Adventure |
| **32** | 2006 | Action |
| **...** | ... | ... |
| **514** | 2014 | Adventure |
| **517** | 2009 | Adventure |
| **517** | 2009 | Fantasy |
| **518** | 2016 | Animation |
| **518** | 2016 | Adventure |

211 rows × 2 columns

In [190]:
```
#Top directors for movies after the 21st century
directors = profit_per_cat_data[profit_per_cat_data['Year_released'] >
```

In [191]:
```
directors_v2 = directors[['Year_released', 'Genre', 'Director', 'Profi
```

In [192]:
```
directors_v3 = directors_v2[(directors_v2['Genre'] == "Adventure") | (
                  (directors_v2['Genre'] == "Family") | (directors_v2[
                  (directors_v2['Genre'] == "Animation")]
```

In [193]:
```
directors_v3
```

Out[193]:

| | Year_released | Genre | Director | Profit |
|---|---|---|---|---|
| **6** | 2006 | Action | Zack Snyder | 394161935 |
| **7** | 2007 | Action | James Mangold | 23171825 |
| **15** | 2013 | Fantasy | Richard Curtis | 77309178 |
| **23** | 2000 | Adventure | Cameron Crowe | -12628809 |
| **32** | 2006 | Action | Mel Gibson | 81032272 |
| **...** | ... | ... | ... | ... |
| **514** | 2014 | Adventure | Bryan Singer | 547862775 |
| **517** | 2009 | Adventure | Ruben Fleischer | 78636596 |
| **517** | 2009 | Fantasy | Ruben Fleischer | 78636596 |
| **518** | 2016 | Animation | Byron Howard | 869429616 |
| **518** | 2016 | Adventure | Byron Howard | 869429616 |

211 rows × 4 columns

In [ ]:
```
b = directors_v3[directors_v3['Genre'] == 'Action']
```

In [238]:
```
b_v2 = b.sort_values(ascending=False, by=['Profit']).head()
```

In [239]:
```
b_v2
```

Out[239]:

| | Year_released | Genre | Director | Profit |
|---|---|---|---|---|
| **37** | 2009 | Action | James Cameron | 2351345279 |
| **38** | 2018 | Action | Anthony Russo | 1748134200 |
| **374** | 2012 | Action | Joss Whedon | 1292935897 |
| **438** | 2003 | Action | Peter Jackson | 1047403341 |
| **207** | 2018 | Action | Brad Bird | 1042520711 |

In [243]:
```
c = directors_v3[directors_v3['Genre'] == 'Adventure']
```

In [244]:
```
c_v2 = c.sort_values(ascending=False, by=['Profit']).head()
```

In [245]:
```
c_v2
```

Out[245]:

| | Year_released | Genre | Director | Profit |
|---|---|---|---|---|
| **37** | 2009 | Adventure | James Cameron | 2351345279 |
| **38** | 2018 | Adventure | Anthony Russo | 1748134200 |
| **374** | 2012 | Adventure | Joss Whedon | 1292935897 |
| **438** | 2003 | Adventure | Peter Jackson | 1047403341 |
| **207** | 2018 | Adventure | Brad Bird | 1042520711 |

In [246]:
```
d = directors_v3[directors_v3['Genre'] == 'Family']
```

In [247]:
```
d_v2 = d.sort_values(ascending=False, by=['Profit']).head()
```

In [248]:
```
d_v2
```

Out[248]:

| | Year_released | Genre | Director | Profit |
|---|---|---|---|---|
| **185** | 2005 | Family | Mike Newell | 747099794 |
| **186** | 2009 | Family | David Yates | 685213767 |
| **187** | 2004 | Family | Alfonso Cuarón | 666907323 |
| **94** | 2017 | Family | Lee Unkrich | 623008101 |
| **512** | 2017 | Family | Stephen Chbosky | 284604712 |

In [249]:
```
e = directors_v3[directors_v3['Genre'] == 'Fantasy']
e_v2 = e.sort_values(ascending=False, by=['Profit']).head()
e_v2
```

Out[249]:

| | Year_released | Genre | Director | Profit |
|---|---|---|---|---|
| **37** | 2009 | Fantasy | James Cameron | 2351345279 |
| **417** | 2012 | Fantasy | Peter Jackson | 767003568 |
| **185** | 2005 | Fantasy | Mike Newell | 747099794 |
| **418** | 2013 | Fantasy | Peter Jackson | 710366855 |
| **187** | 2004 | Fantasy | Alfonso Cuarón | 666907323 |

In [250]:
```
f = directors_v3[directors_v3['Genre'] == 'Animation']
f_v2 = f.sort_values(ascending=False, by=['Profit']).head()
f_v2
```

Out[250]:

| | Year_released | Genre | Director | Profit |
|---|---|---|---|---|
| **207** | 2018 | Animation | Brad Bird | 1042520711 |
| **518** | 2016 | Animation | Byron Howard | 869429616 |
| **495** | 2010 | Animation | Lee Unkrich | 868879522 |
| **147** | 2003 | Animation | Andrew Stanton | 842429370 |
| **211** | 2015 | Animation | Pete Docter | 679235992 |

In [251]:
```
to_concat = [b_v2, c_v2, d_v2, e_v2, f_v2]
new_director_list = pd.concat(to_concat)
```

In [252]:
```
new_director_list
```

Out[252]:

| | Year_released | Genre | Director | Profit |
|---|---|---|---|---|
| **37** | 2009 | Action | James Cameron | 2351345279 |
| **38** | 2018 | Action | Anthony Russo | 1748134200 |
| **374** | 2012 | Action | Joss Whedon | 1292935897 |
| **438** | 2003 | Action | Peter Jackson | 1047403341 |
| **207** | 2018 | Action | Brad Bird | 1042520711 |
| **37** | 2009 | Adventure | James Cameron | 2351345279 |
| **38** | 2018 | Adventure | Anthony Russo | 1748134200 |
| **374** | 2012 | Adventure | Joss Whedon | 1292935897 |
| **438** | 2003 | Adventure | Peter Jackson | 1047403341 |
| **207** | 2018 | Adventure | Brad Bird | 1042520711 |
| **185** | 2005 | Family | Mike Newell | 747099794 |
| **186** | 2009 | Family | David Yates | 685213767 |
| **187** | 2004 | Family | Alfonso Cuarón | 666907323 |
| **94** | 2017 | Family | Lee Unkrich | 623008101 |
| **512** | 2017 | Family | Stephen Chbosky | 284604712 |
| **37** | 2009 | Fantasy | James Cameron | 2351345279 |
| **417** | 2012 | Fantasy | Peter Jackson | 767003568 |
| **185** | 2005 | Fantasy | Mike Newell | 747099794 |
| **418** | 2013 | Fantasy | Peter Jackson | 710366855 |
| **187** | 2004 | Fantasy | Alfonso Cuarón | 666907323 |
| **207** | 2018 | Animation | Brad Bird | 1042520711 |
| **518** | 2016 | Animation | Byron Howard | 869429616 |
| **495** | 2010 | Animation | Lee Unkrich | 868879522 |
| **147** | 2003 | Animation | Andrew Stanton | 842429370 |
| **211** | 2015 | Animation | Pete Docter | 679235992 |

In [269]:
```
#Profitability of top 5 movies
top_5_profits = profit_per_cat_data[(profit_per_cat_data['Genre'] == "
                    (profit_per_cat_data['Genre'] == "Family") | (profit
                    (profit_per_cat_data['Genre'] == "Animation")]
```

In [271]:
```
top_5_profits.head()
```

Out[271]:

| | Movie_Title | Year_released | Certificate_Grade | Runtime | Genre | IMDB_Rating | Meta_scor |
|---|---|---|---|---|---|---|---|
| **3** | 2001: A Space Odyssey | 1968 | U | 149 min | Adventure | 8.3 | 84. |
| **6** | 300 | 2006 | A | 117 min | Action | 7.6 | 52. |
| **7** | 3:10 to Yuma | 2007 | A | 122 min | Action | 7.7 | 76. |
| **10** | A Christmas Story | 1983 | U | 93 min | Family | 7.9 | 77. |
| **15** | About Time | 2013 | R | 123 min | Fantasy | 7.8 | 55. |

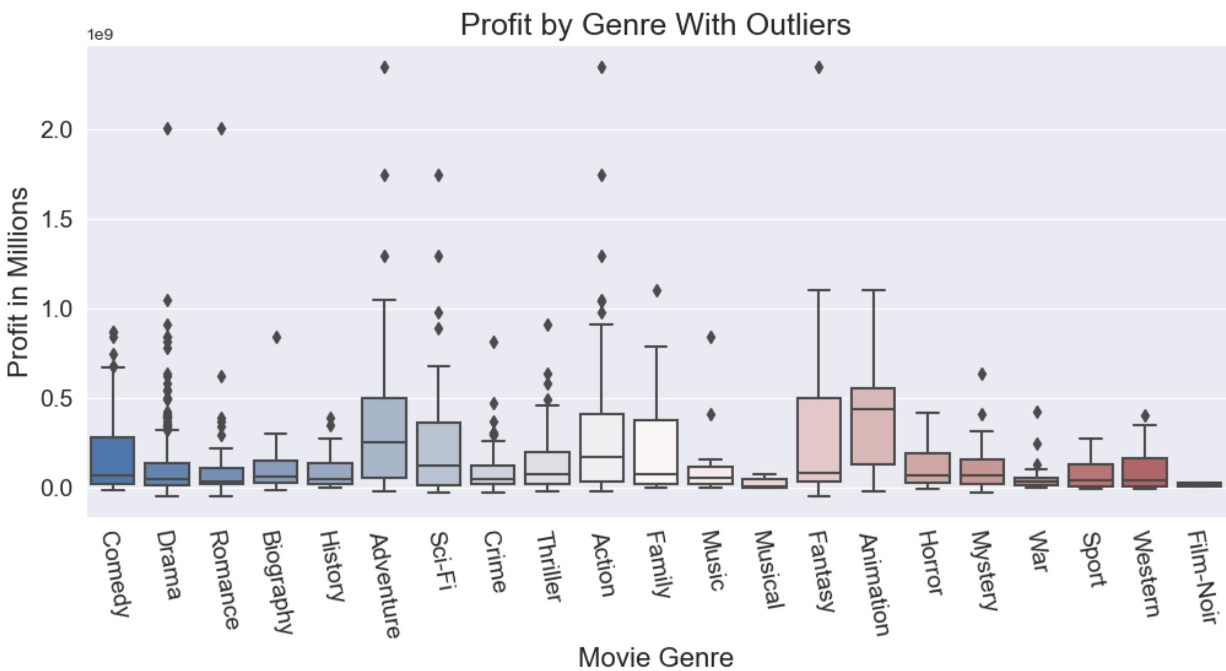
# Data Analysis

After all the data has been assembled I plotted my visualizations to determine the relationships between the elements I was investigating and their relationships. Below are the visual descriptions of my three key questions:

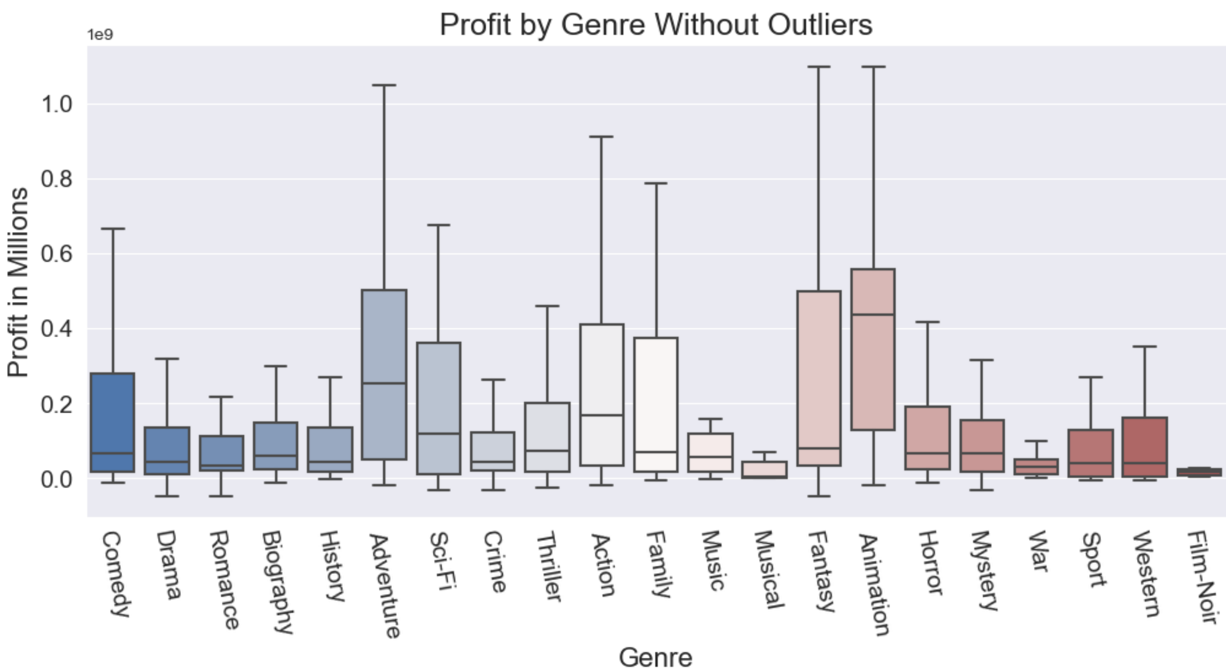
- What movie genres produce the highest profits?
- What movie genres should be produced to avoid competition?
- What director should be hired to produce their movies?

# Which genre of movies genreates the highest profit?

In [47]:
```
plt.figure(figsize=(12,5))
sns.set_style('darkgrid')
sns.boxplot(x='Genre', y='Profit', data=profit_per_cat_data, palette='
plt.xticks(rotation=-80)
plt.ylabel('Profit in Millions', fontsize=16)
plt.xlabel('Movie Genre', fontsize = 16)
plt.title('Profit by Genre With Outliers', fontsize = 18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14);
```



In [48]:
```
plt.figure(figsize=(12,5))
sns.set_style('darkgrid')
sns.boxplot(x='Genre', y='Profit', data=profit_per_cat_data, showflier
plt.xticks(rotation=-80)
plt.ylabel('Profit in Millions', fontsize=16)
plt.xlabel('Genre', fontsize = 16)
plt.title('Profit by Genre Without Outliers', fontsize = 18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14);
```



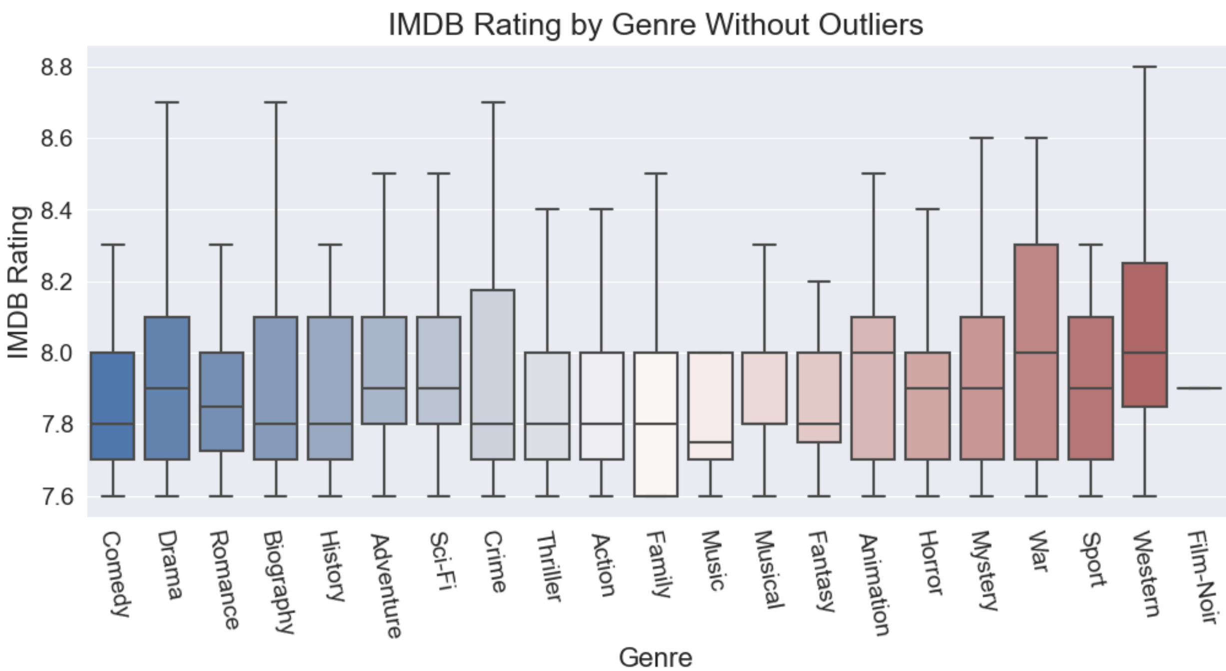
In [272]:
```
plt.figure(figsize=(12,5))
sns.set_style('darkgrid')
sns.boxplot(x='Genre', y='Profit', data=top_5_profits, palette='vlag')
plt.xticks(rotation=-80)
plt.ylabel('Profit in Millions', fontsize=16)
plt.xlabel('Movie Genre', fontsize = 16)
plt.title('Profit by Genre With Outliers', fontsize = 18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14);
```

In [273]:
```
plt.figure(figsize=(12,5))
sns.set_style('darkgrid')
sns.boxplot(x='Genre', y='Profit', data=top_5_profits, showfliers=Fals
plt.xticks(rotation=-80)
plt.ylabel('Profit in Millions', fontsize=16)
plt.xlabel('Genre', fontsize = 16)
plt.title('Profit by Genre Without Outliers', fontsize = 18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14);
```

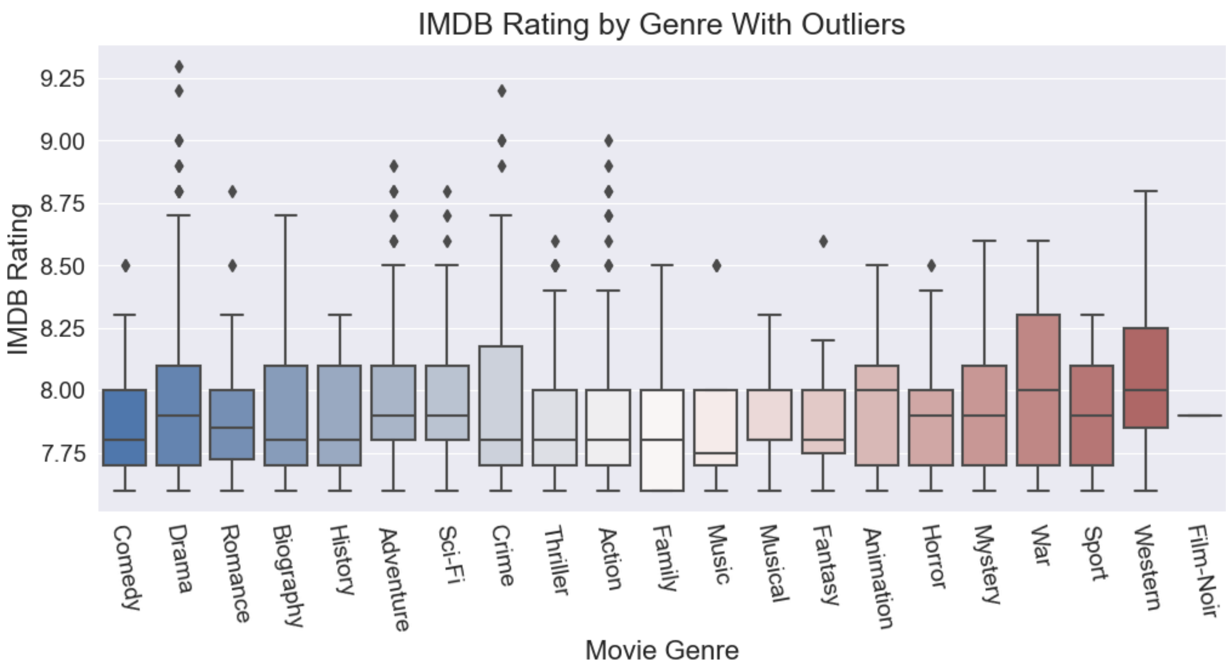

**The results indicate that the highest proffiting genres are Adventure, Action, Family, Fantasy and Animation.**

**Lets take a quick look at IMDB rating for the movie genres.**

In [60]:
```
plt.figure(figsize=(12,5))
sns.set_style('darkgrid')
sns.boxplot(x='Genre', y='IMDB_Rating', data=profit_per_cat_data, show
plt.xticks(rotation=-80)
plt.ylabel('IMDB Rating', fontsize=16)
plt.xlabel('Genre', fontsize = 16)
plt.title('IMDB Rating by Genre Without Outliers', fontsize = 18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14);
```



In [61]:
```
plt.figure(figsize=(12,5))
sns.set_style('darkgrid')
sns.boxplot(x='Genre', y='IMDB_Rating', data=profit_per_cat_data, pale
plt.xticks(rotation=-80)
plt.ylabel('IMDB Rating', fontsize=16)
plt.xlabel('Movie Genre', fontsize = 16)
plt.title('IMDB Rating by Genre With Outliers', fontsize = 18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14);
```

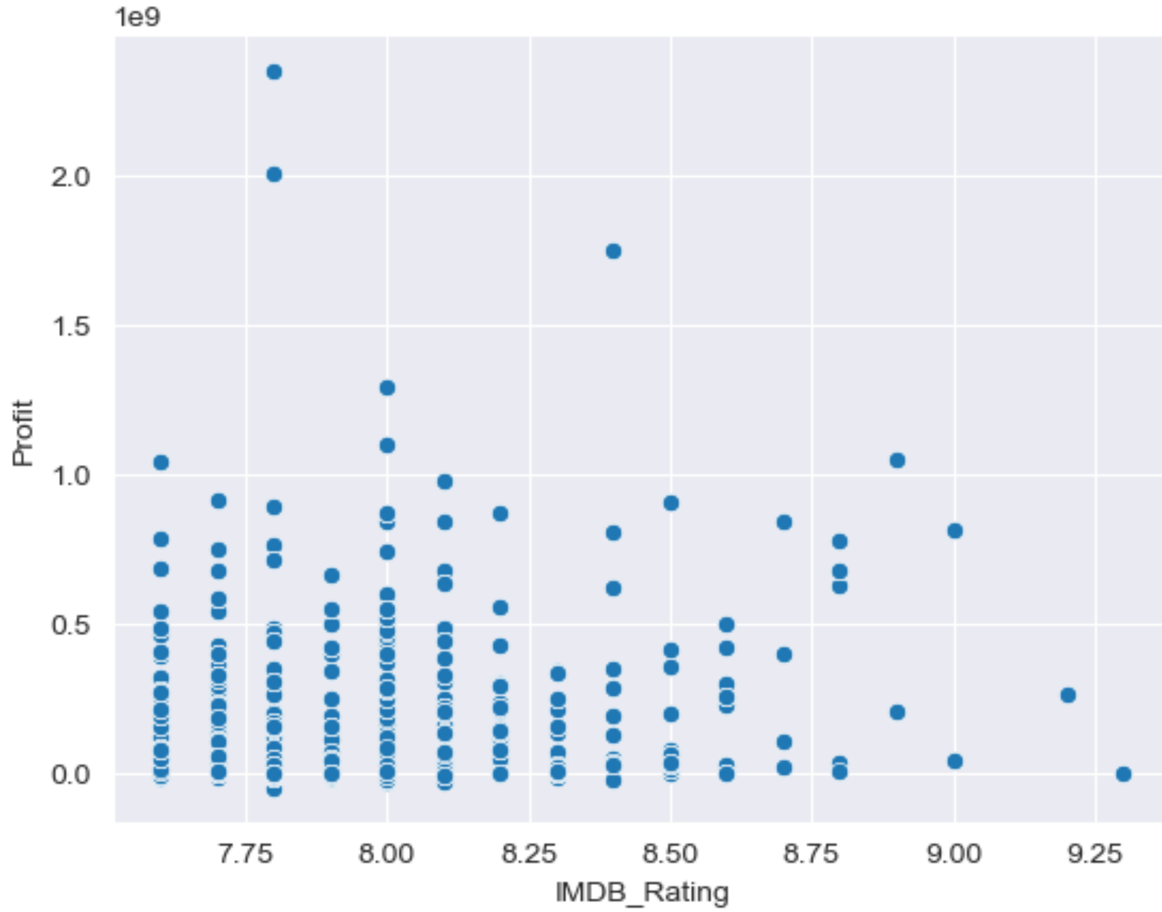



## Is there any correlation between IMDB rating and Proffitability?

In [63]:
```
correlation_data = profit_per_cat_data[['Profit', 'IMDB_Rating']].copy
```

In [64]:
```
sns.scatterplot(data = correlation_data, x = 'IMDB_Rating', y = 'Profi
```

Out[64]: <Axes: xlabel='IMDB_Rating', ylabel='Profit'>




In [65]:
```
correlation_data.corr()
```

Out[65]:

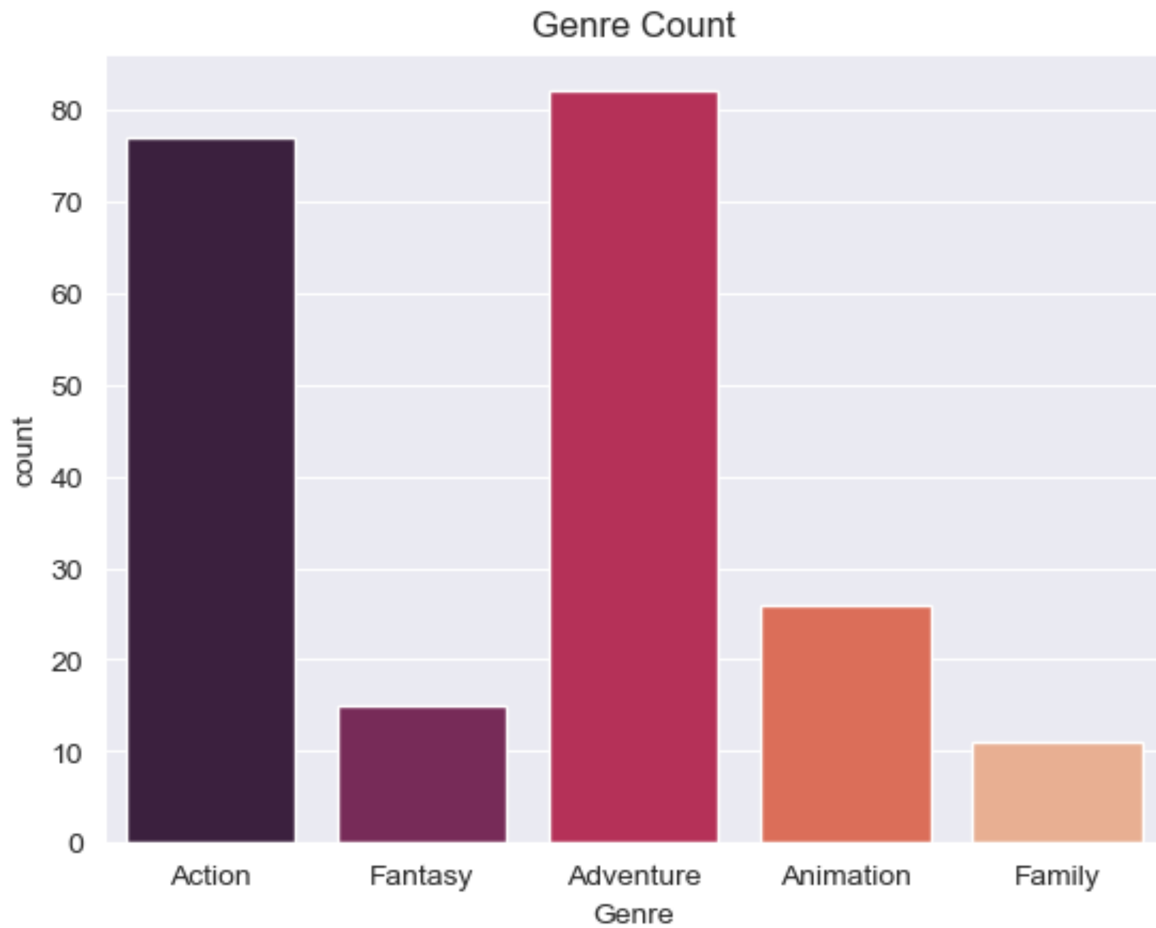
| | Profit | IMDB_Rating |
|---|---|---|
| **Profit** | 1.000000 | 0.163062 |
| **IMDB_Rating** | 0.163062 | 1.000000 |

### From the results there seems to be little correlation between IMDB ratings and profit.

## Which of the 5 most popular genre of movies would stand out against competeing movie types?

In [114]:
```
sns.countplot(x=saturation_data_v3['Genre'], palette='rocket').set_tit
```

Out[114]:
```
Text(0.5, 1.0, 'Genre Count')
```




**The results indicate that Action and Adventure are genres relased often in the 21st century. Fantasy**

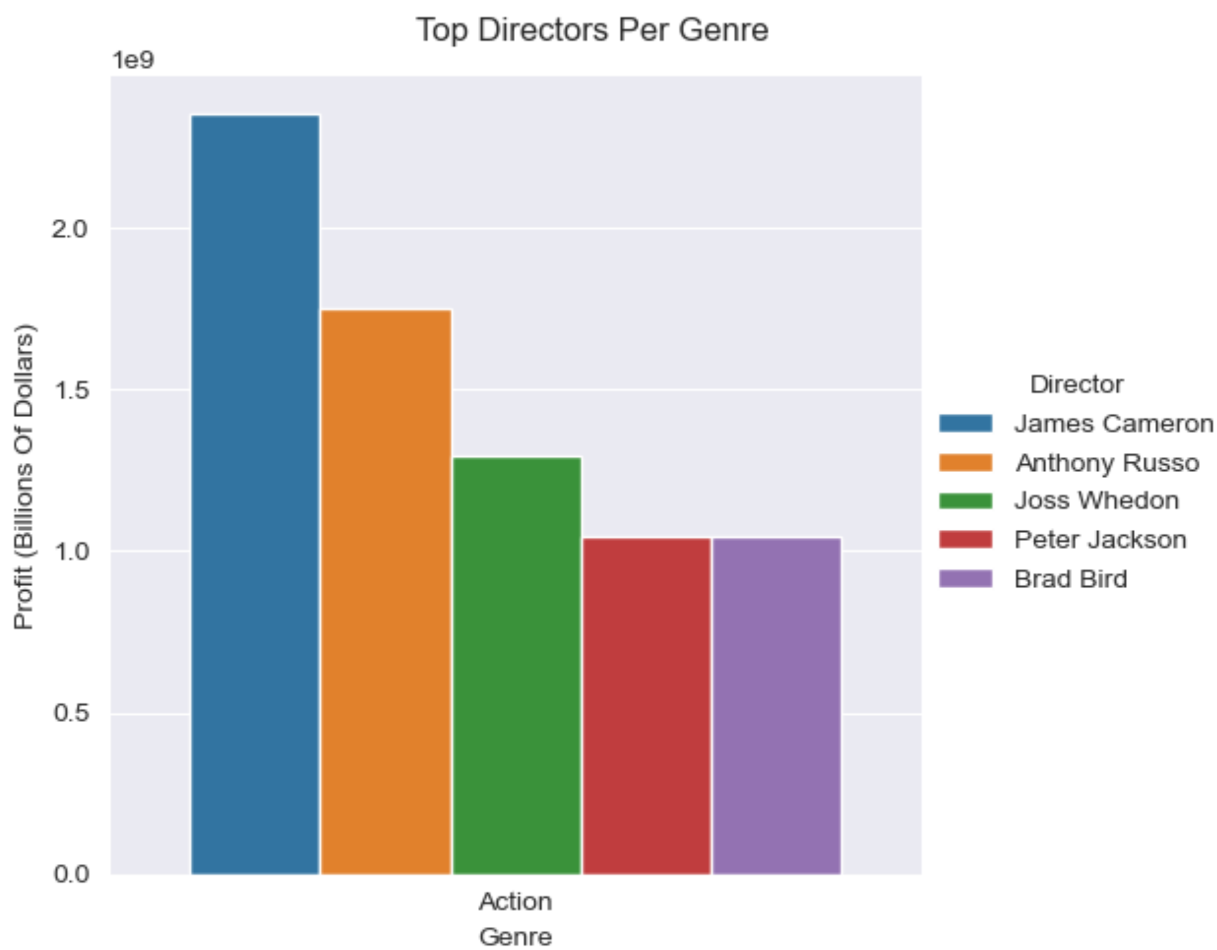
**Animation and Family are genred that are not oversaturated in the market.**

## Who are the top five directors to hire for action, fantasy, adventure, animation, and

## family movies?

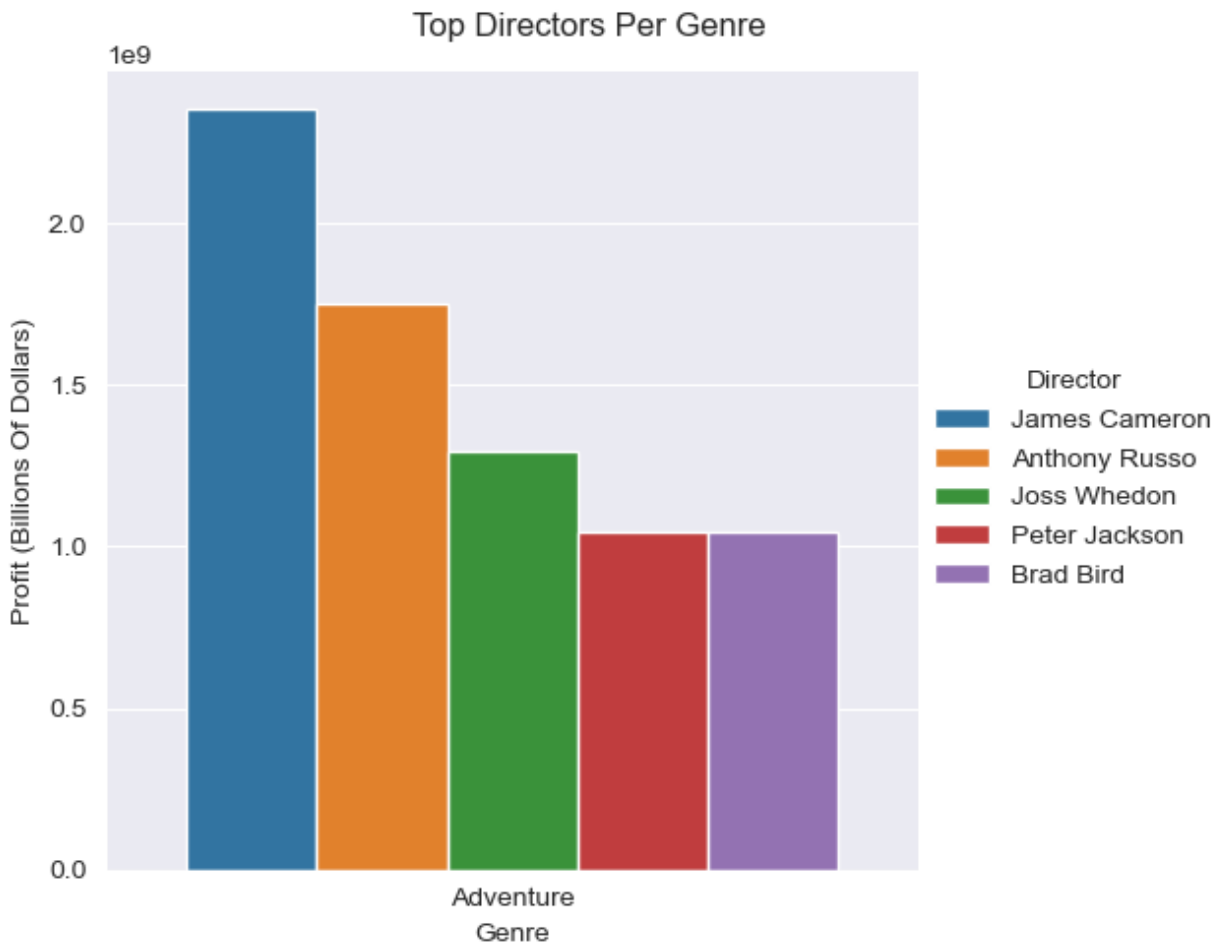
In [262]:
```
cat = sns.catplot(data=b_v2, x='Genre', y='Profit', hue='Director', ki
cat.fig.subplots_adjust(top=0.92)
cat.fig.suptitle('Top Directors Per Genre')
cat.set_ylabels('Profit (Billions Of Dollars)')

plt.show()
```



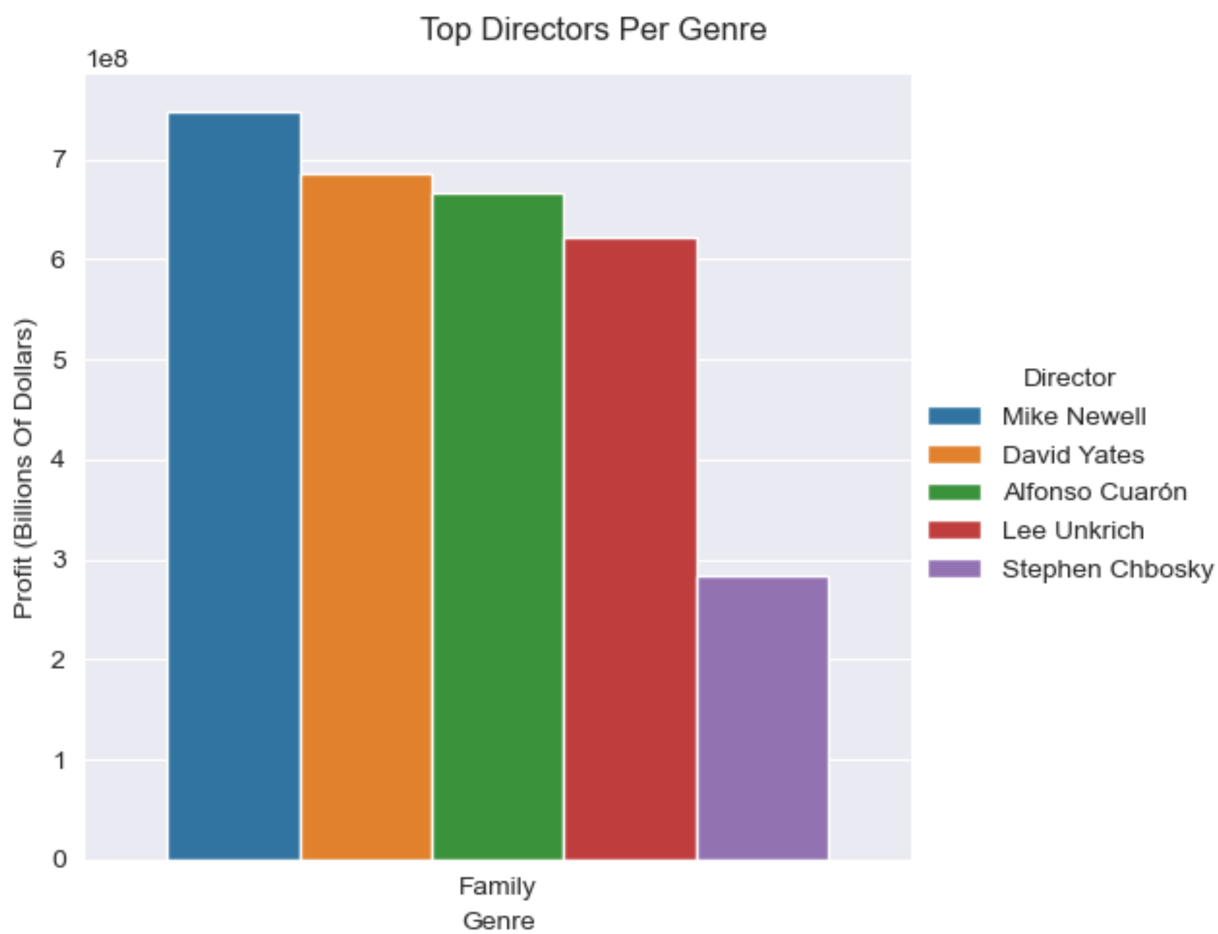
In [263]:
```
cat = sns.catplot(data=c_v2, x='Genre', y='Profit', hue='Director', ki
cat.fig.subplots_adjust(top=0.92)
cat.fig.suptitle('Top Directors Per Genre')
cat.set_ylabels('Profit (Billions Of Dollars)')

plt.show()
```



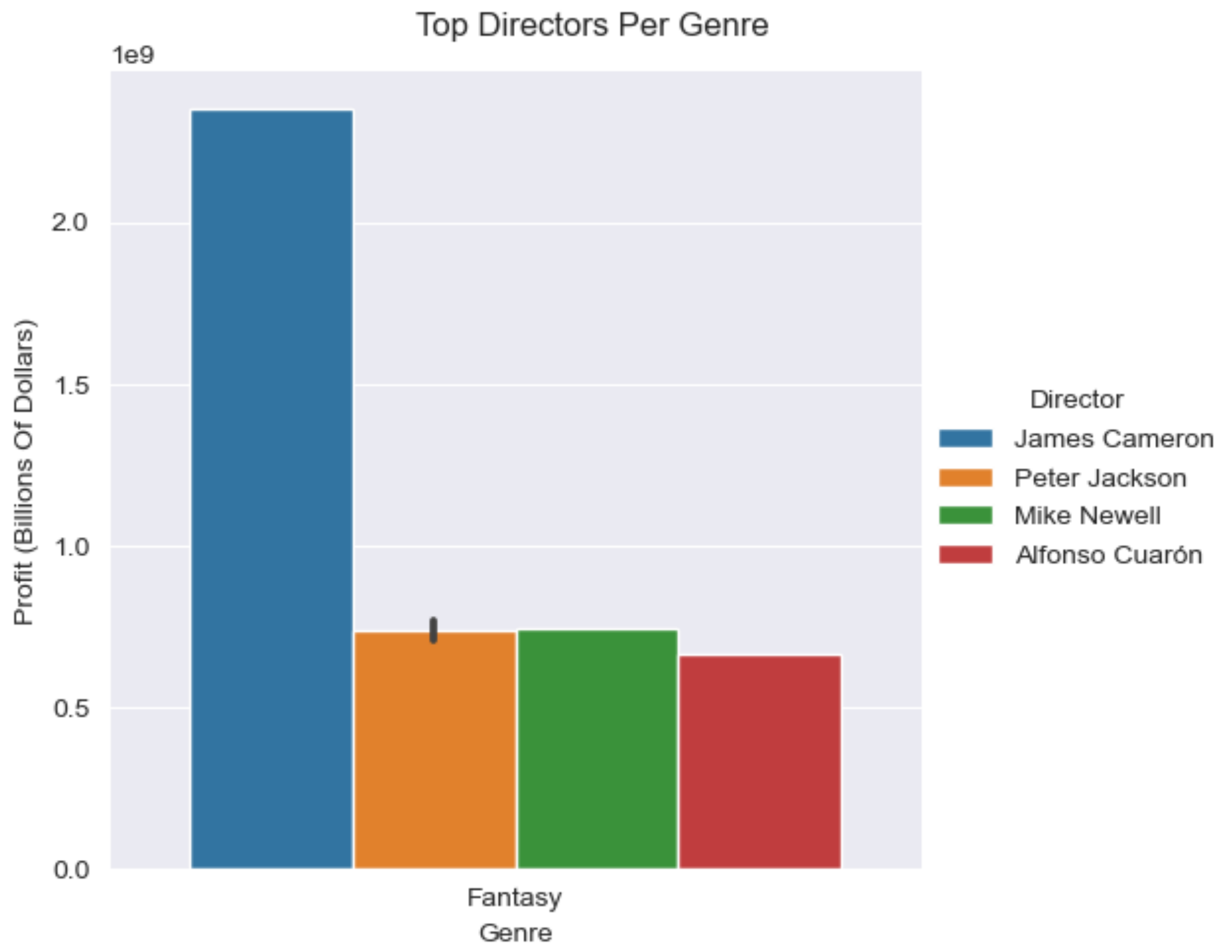
In [264]:
```
cat = sns.catplot(data=d_v2, x='Genre', y='Profit', hue='Director', ki
cat.fig.subplots_adjust(top=0.92)
cat.fig.suptitle('Top Directors Per Genre')
cat.set_ylabels('Profit (Billions Of Dollars)')

plt.show()
```



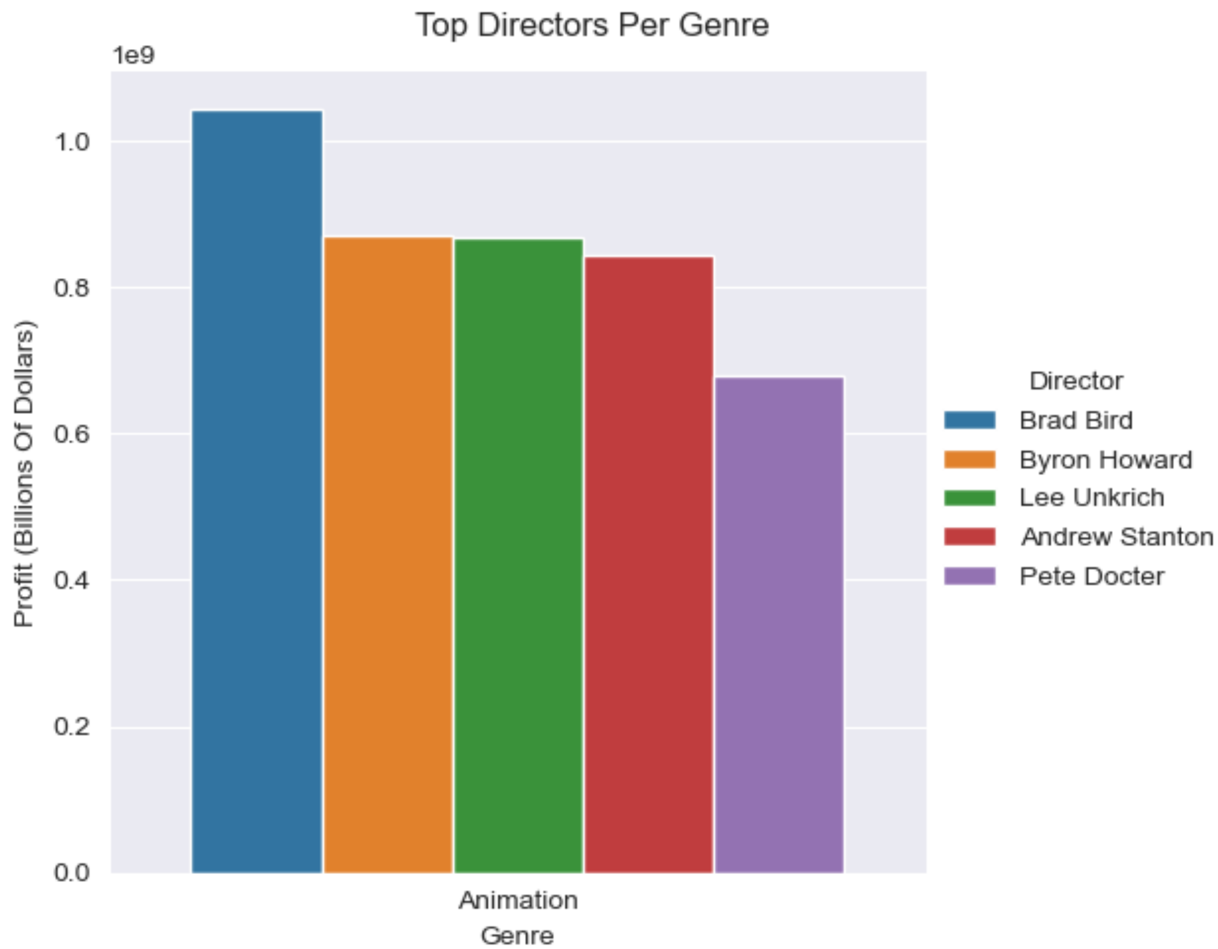
In [265]:
```
cat = sns.catplot(data=e_v2, x='Genre', y='Profit', hue='Director', ki
cat.fig.subplots_adjust(top=0.92)
cat.fig.suptitle('Top Directors Per Genre')
cat.set_ylabels('Profit (Billions Of Dollars)')

plt.show()
```



In [266]:
```
cat = sns.catplot(data=f_v2, x='Genre', y='Profit', hue='Director', ki
cat.fig.subplots_adjust(top=0.92)
cat.fig.suptitle('Top Directors Per Genre')
cat.set_ylabels('Profit (Billions Of Dollars)')

plt.show()
```




### The findings indicate that for action, fantasy and adventure movies James Cameron should be hired as director. For Animation movies Brad Bird should be hired, and for Family movies Microsoft should recruit Mike Newell

# Conclusion

### I would suggest that Microsoft the following types of movies.

Movie Option #1

- A fantasy movie directed by James Cameron.
- Potential profit of $2,351,345,279

Movie Option #2

- A animation movie directed by Brad Bird.
- Potential profit of $1,042,520,711

Movie Option #3

- A family movie directed by Mike Newell.
- Potential profit of $747,099,794

In [ ]:

```

```