Movie Analysis

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Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. You are charged with exploring what types of films are currently doing the best at the box office. You must then translate those findings into actionable insights that the head of Microsoft's new movie studio can use to help decide what type of films to create.

Questions to consider:

- What are the most popular genres?
- How should we budget?
- What genres are most profitable?

Using info from IMDB, Rotten Tomatoes, etc, let's figure out with data what will play into "success"!

Data Understanding

Let's take a look at the given movie datasets from the ZippedData directory.

Movie datasets from:

- IMDB
- Box Office Mojo
- Rotten Tomatoes
- TheMovieDB
- The Numbers

In [1]:
```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
from matplotlib import pyplot

%matplotlib inline
```

IMDB data

In [2]:
```
title_basics = pd.read_csv('zippedData/imdb.title.basics.csv.gz')
title_basics.head()
```

Out[2]:

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

In [3]:
```
title_ratings = pd.read_csv('zippedData/imdb.title.ratings.csv.gz')
title_ratings.head()
```

Out[3]:

	tconst	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

Thoughts: These two IMDB tables may be good to look for genres and ratings. We should merge the two tables into one.

Box Office Mojo

In [4]:
```
movie_gross = pd.read_csv('zippedData/bom.movie_gross.csv.gz')
movie_gross.head()
```

Out[4]:

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

Thoughts: This table may be good to look for gross profits.

Rotten Tomatoes data

In [5]:
```
rt_movie_info_df=pd.read_csv('zippedData/rt.movie_info.tsv.gz', delimiter='\t', h
rt_movie_info_df.head()
```

Out[5]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Se
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	J
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	A
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Au
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	

In [6]:
```
rt_reviews_df=pd.read_csv('zippedData/rt.reviews.tsv.gz',delimiter='\t',header=0,
rt_reviews_df.head()
```

Out[6]:

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

Thoughts: Let's not use the data from Rotten Tomatoes. There are no given datasets that will give us a title.

The Movie Database data

In [7]:
```
tmdb_df = pd.read_csv('zippedData/tmdb.movies.csv.gz')
tmdb_df.head()
```

Out[7]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception

Thoughts: Let's not use the data from The Movie Database. There are no given datasets that will give us genre_ids.

The Numbers data

In [8]:
```
movie_budgets = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
movie_budgets.head()
```

Out[8]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

Thoughts: This dataset has production budget, domestic/worldwide gross.

Data Preparation

Having looked at the data available to us, let's prep the data to answer the questions we previously set.

- What are the most popular genres?
- How should we budget?
- What genres are most profitable?

IMDB Data

- We need to merge data from tables using the primary key of 'tconst'
- Clean data for duplicates and NaN items
- We need to separate and create new columns, or create list with genres options for each movie

In [9]:
```
# Merging datasets using primary key of 'tconst'
imdb_df = title_basics.merge(title_ratings, how="inner", on='tconst')
```

In [10]:
```
# Let's split the string of genres into a searchable list
length = range(len(imdb_df['genres']))
for i in length:
    if type(imdb_df.loc[i,'genres']) == str:
        imdb_df.at[i, 'genres'] = imdb_df.loc[i, 'genres'].split(',')
    else:
        continue
imdb_df
```

Out[10]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	averagerati
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	[Action, Crime, Drama]	
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	[Biography, Drama]	
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	[Drama]	
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	[Comedy, Drama]	
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	[Comedy, Drama, Fantasy]	
...	...	...	...	...	...	...	
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.0	[Documentary]	
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	[Drama, Family]	
73853	tt9914642	Albatross	Albatross	2017	NaN	[Documentary]	
73854	tt9914942	La vida sense la Sara Amat	La vida sense la Sara Amat	2019	NaN	NaN	
73855	tt9916160	Drømmeland	Drømmeland	2019	72.0	[Documentary]	

73856 rows × 8 columns

In [11]:
```
# Checking for missing data
imdb_df.isna().sum()
```

Out[11]:
```
tconst                0
primary_title         0
original_title        0
start_year            0
runtime_minutes    7620
genres              804
averagerating         0
numvotes              0
dtype: int64
```

In [12]:
```
# Missing data in runtime_minutes and genres. We probably want to remove items wi
imdb_df.dropna(subset=['genres'], inplace=True)
```

In [13]:
```
# We do not need the 'runtime_minutes' that is missing values in our data set. Wi
imdb_df.drop(['runtime_minutes'],axis=1, inplace=True)
```

In [14]:
```
imdb_df.rename(columns={"averagerating":"avg_rating","numvotes":"num_votes"},inpl
```

In [15]:
```
# Setting index to tconst
imdb_df.set_index('tconst',inplace=True)
```

In [16]:
```
# Check again for missing data items
print(imdb_df.isna().sum())

# Final check on dataset
imdb_df
```

```
primary_title     0
original_title    0
start_year        0
genres            0
avg_rating        0
num_votes         0
dtype: int64
```

Out[16]:

	primary_title	original_title	start_year	genres	avg_rating	num_votes
tconst						
tt0063540	Sunghursh	Sunghursh	2013	[Action, Crime, Drama]	7.0	77
tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	[Biography, Drama]	7.2	43
tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	[Drama]	6.9	4517
tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	[Comedy, Drama]	6.1	13
tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	[Comedy, Drama, Fantasy]	6.5	119
...	...	...	...	...	...	...
tt9913056	Swarm Season	Swarm Season	2019	[Documentary]	6.2	5
tt9913084	Diabolik sono io	Diabolik sono io	2019	[Documentary]	6.2	6
tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	[Drama, Family]	8.7	136
tt9914642	Albatross	Albatross	2017	[Documentary]	8.5	8
tt9916160	Drømmeland	Drømmeland	2019	[Documentary]	6.5	11

73052 rows × 6 columns

Box Office Mojo Data:

- Clean data for duplicates and NaN items
- Changing data types for gross

In [17]:
```
# Check for data types and missing data
display(movie_gross.head())
display(movie_gross.info())
movie_gross.isna().sum()
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

```
None
```

Out[17]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

In [18]:
```
# We do not need the 'studio' that is missing values in our data set. Will drop c
movie_gross.drop(['studio'],axis=1, inplace=True)
```

In [19]:
```
# Replace zero values for gross values with 0
movie_gross['domestic_gross'] = movie_gross['domestic_gross'].fillna(0)
movie_gross['foreign_gross'] = movie_gross['foreign_gross'].fillna(0)
```

In [20]:
```
# Checking again for missing data
display(movie_gross.isna().sum())
display(movie_gross.info())
```

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

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   domestic_gross  3387 non-null   float64
 2   foreign_gross   3387 non-null   object 
 3   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(2)
memory usage: 106.0+ KB


None
```

There must still be a string as foreign gross is still an object after the NaN values were replaced.

In [21]:
```
# Creating a function to change money strings to a usable float.
def change_money(money):
    if type(money) == str:
        money = money.replace("$","").replace(",","")
        money = float(money) #changing to float in case of cents
        return money
    else:
        return money
```

In [22]:
```
# Let's change the string to a float using the change_money function:
movie_gross['foreign_gross'] = movie_gross.apply(lambda x: change_money(x['foreig
movie_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   domestic_gross  3387 non-null   float64
 2   foreign_gross   3387 non-null   float64
 3   year            3387 non-null   int64  
dtypes: float64(2), int64(1), object(1)
memory usage: 106.0+ KB
```

In [23]:
```
# Adding a column for worldwide gross
movie_gross['worldwide_gross'] = movie_gross['domestic_gross'] + movie_gross['for
movie_gross
```

Out[23]:

	title	domestic_gross	foreign_gross	year	worldwide_gross
0	Toy Story 3	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	238700000.0	513900000.0	2010	7.526000e+08
...	...	...	...	...	...
3382	The Quake	6200.0	0.0	2018	6.200000e+03
3383	Edward II (2018 re-release)	4800.0	0.0	2018	4.800000e+03
3384	El Pacto	2500.0	0.0	2018	2.500000e+03
3385	The Swan	2400.0	0.0	2018	2.400000e+03
3386	An Actor Prepares	1700.0	0.0	2018	1.700000e+03

3387 rows × 5 columns

The Numbers Data:

- Using the titles, budget, and gross values
- Clean data for duplicates and NaN items
- Changing data types for gross

In [24]:
```
# Check for data types and missing data
display(movie_budgets.head())
display(movie_budgets.info())
movie_budgets.isna().sum()
```

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
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              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

```
None
```

Out[24]:
```
id                   0
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

In [25]:
```
# Adjust the values of dataframe to floats
movie_budgets['production_budget'] = movie_budgets.apply(lambda x: change_money(x
movie_budgets['domestic_gross'] = movie_budgets.apply(lambda x: change_money(x['d
movie_budgets['worldwide_gross'] = movie_budgets.apply(lambda x: change_money(x['
display(movie_budgets.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
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              5782 non-null   object 
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
dtypes: float64(3), int64(1), object(2)
memory usage: 271.2+ KB

None
```

In [26]:
```
# Final check
movie_budgets
```

Out[26]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000.0	760507625.0	2.776345e+09
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09
2	3	Jun 7, 2019	Dark Phoenix	350000000.0	42762350.0	1.497624e+08
3	4	May 1, 2015	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000.0	0.0	0.000000e+00
5778	79	Apr 2, 1999	Following	6000.0	48482.0	2.404950e+05
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000.0	1338.0	1.338000e+03
5780	81	Sep 29, 2015	A Plague So Pleasant	1400.0	0.0	0.000000e+00
5781	82	Aug 5, 2005	My Date With Drew	1100.0	181041.0	1.810410e+05

5782 rows × 6 columns

Data Modeling

The data is now ready to go. Let's analyze and model the data to answer the questions we previously set.

- What are the most popular genres?
- What genres are most profitable?
- How should we budget?

What are the most popular genres?

Let's analyze the IMDB data to find out.

In [27]:
```
# Analysis on ratings of movies
imdb_df['avg_rating'].describe()
imdb_df
```

Out[27]:

	primary_title	original_title	start_year	genres	avg_rating	num_votes
tconst						
tt0063540	Sunghursh	Sunghursh	2013	[Action, Crime, Drama]	7.0	77
tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	[Biography, Drama]	7.2	43
tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	[Drama]	6.9	4517
tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	[Comedy, Drama]	6.1	13
tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	[Comedy, Drama, Fantasy]	6.5	119
...	...	...	...	...	...	...
tt9913056	Swarm Season	Swarm Season	2019	[Documentary]	6.2	5
tt9913084	Diabolik sono io	Diabolik sono io	2019	[Documentary]	6.2	6
tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	[Drama, Family]	8.7	136
tt9914642	Albatross	Albatross	2017	[Documentary]	8.5	8
tt9916160	Drømmeland	Drømmeland	2019	[Documentary]	6.5	11

73052 rows × 6 columns

In [28]:
```
# Using the explode function, create a separate table for each genre to stand out
genre_title = imdb_df['genres'].explode().to_frame()
genre_title
```

Out[28]:

	genres
tconst	
tt0063540	Action
tt0063540	Crime
tt0063540	Drama
tt0066787	Biography
tt0066787	Drama
...	...
tt9913084	Documentary
tt9914286	Drama
tt9914286	Family
tt9914642	Documentary
tt9916160	Documentary

128490 rows × 1 columns

In [29]:
```python
# We can merge with the original table to get a line for each genre.
genre_rating = genre_title.merge(imdb_df, on='tconst')
genre_rating
```

Out[29]:

tconst	genres_x	primary_title	original_title	start_year	genres_y	avg_rating	num_votes
tt0063540	Action	Sunghursh	Sunghursh	2013	[Action, Crime, Drama]	7.0	77
tt0063540	Crime	Sunghursh	Sunghursh	2013	[Action, Crime, Drama]	7.0	77
tt0063540	Drama	Sunghursh	Sunghursh	2013	[Action, Crime, Drama]	7.0	77
tt0066787	Biography	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	[Biography, Drama]	7.2	43
tt0066787	Drama	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	[Biography, Drama]	7.2	43
...	...	...	...	...	...	...	...
tt9913084	Documentary	Diabolik sono io	Diabolik sono io	2019	[Documentary]	6.2	6
tt9914286	Drama	Sokagin Çocuklari	Sokagin Çocuklari	2019	[Drama, Family]	8.7	136
tt9914286	Family	Sokagin Çocuklari	Sokagin Çocuklari	2019	[Drama, Family]	8.7	136
tt9914642	Documentary	Albatross	Albatross	2017	[Documentary]	8.5	8
tt9916160	Documentary	Drømmeland	Drømmeland	2019	[Documentary]	6.5	11

128490 rows × 7 columns

In [30]:
```python
# Dropping the duplicate genre table as it is redundant now.
genre_rating.drop('genres_y', axis=1, inplace=True)
```

In [31]:
```
# Renaming genre column name back to how it was
genre_rating.rename(columns={"genres_x":"genres"},inplace=True)
genre_rating
```

Out[31]:

tconst	genres	primary_title	original_title	start_year	avg_rating	num_votes
tt0063540	Action	Sunghursh	Sunghursh	2013	7.0	77
tt0063540	Crime	Sunghursh	Sunghursh	2013	7.0	77
tt0063540	Drama	Sunghursh	Sunghursh	2013	7.0	77
tt0066787	Biography	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	7.2	43
tt0066787	Drama	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	7.2	43
...	...	...	...	...	...	...
tt9913084	Documentary	Diabolik sono io	Diabolik sono io	2019	6.2	6
tt9914286	Drama	Sokagin Çocuklari	Sokagin Çocuklari	2019	8.7	136
tt9914286	Family	Sokagin Çocuklari	Sokagin Çocuklari	2019	8.7	136
tt9914642	Documentary	Albatross	Albatross	2017	8.5	8
tt9916160	Documentary	Drømmeland	Drømmeland	2019	6.5	11

128490 rows × 6 columns

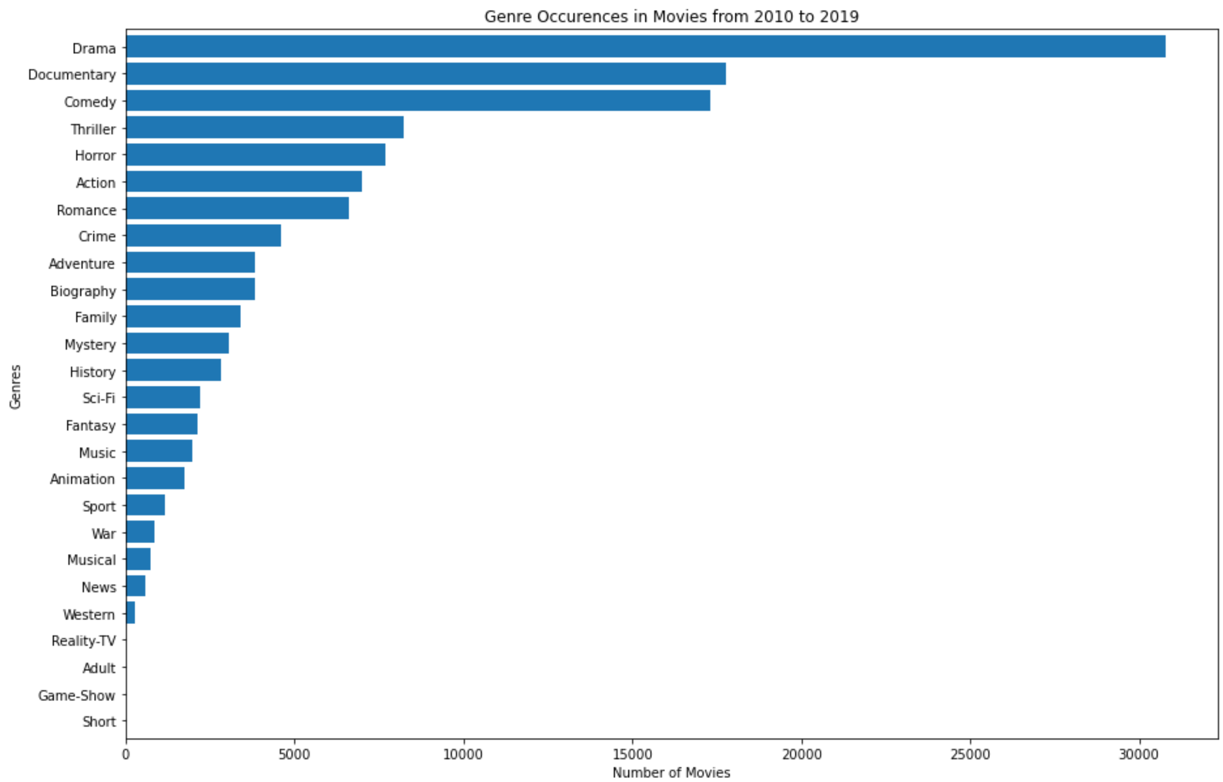
Number of Genre Occurences in Movies

Let's check how often genres occur within the movie landscape. We can visualize this now!

In [32]:
```
genre_rating['genres'].value_counts().sort_values()
```

Out[32]:
```
Short              1
Game-Show          2
Adult              3
Reality-TV        17
Western          280
News             579
Musical          721
War              853
Sport           1179
Animation       1743
Music           1968
Fantasy         2126
Sci-Fi          2206
History         2825
Mystery         3039
Family          3412
Biography       3809
Adventure       3817
Crime           4611
Romance         6589
Action          6988
Horror          7674
Thriller        8217
Comedy         17290
Documentary    17753
Drama          30788
Name: genres, dtype: int64
```

In [33]:
```
fig, ax = plt.subplots(figsize=(15, 10))
ax = genre_rating['genres'].value_counts().sort_values().plot(kind='barh', width=
ax.set_title("Genre Occurences in Movies from 2010 to 2019")
ax.set_ylabel("Genres")
ax.set_xlabel("Number of Movies");
```



We can see that the following movie genres populate the market by far over the past 10 years:

- **Drama**
- **Documentary**
- **Comedy**
- **Thriller**

These list of genres could be good or bad for us to use for Microsoft's movies. We will need to use the popularity of the movies to best gauge what the viewers **ACTUALLY** enjoy.

Average Reviews per Genre

Let's get the average movie scores per movie genre. This will help us get a better grasp of how viewers rate genres.

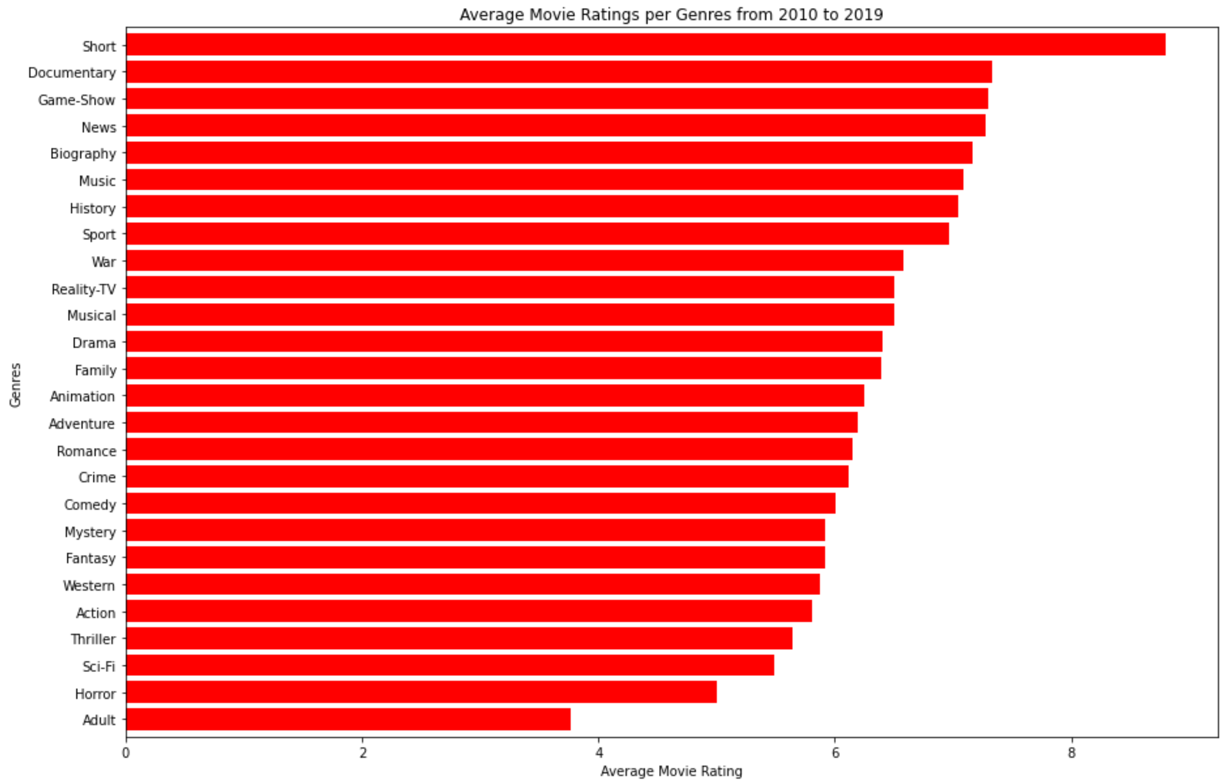
In [34]:
```
genre_rating.groupby(['genres'])['avg_rating'].mean().sort_values()
```

Out[34]:
```
genres
Adult          3.766667
Horror         5.003440
Sci-Fi         5.489755
Thriller       5.639114
Action         5.810361
Western        5.868214
Fantasy        5.919473
Mystery        5.920401
Comedy         6.002689
Crime          6.115441
Romance        6.146608
Adventure      6.196201
Animation      6.248308
Family         6.394725
Drama          6.401559
Musical        6.498336
Reality-TV     6.500000
War            6.584291
Sport          6.961493
History        7.040956
Music          7.091972
Biography      7.162274
News           7.271330
Game-Show      7.300000
Documentary    7.332090
Short          8.800000
Name: avg_rating, dtype: float64
```

In [35]:
```
# Median Score of all genres: Best comparison as there appears to be outliers (Ac
genre_rating.groupby(['genres'])['avg_rating'].mean().sort_values().median()
```

Out[35]:
```
6.32151600876796
```

In [36]:
```
fig, ax = plt.subplots(figsize=(15, 10))
ax = genre_rating.groupby(['genres'])['avg_rating'].mean().sort_values().plot(kir
ax.set_title("Average Movie Ratings per Genres from 2010 to 2019")
ax.set_ylabel("Genres")
ax.set_xlabel("Average Movie Rating");
```



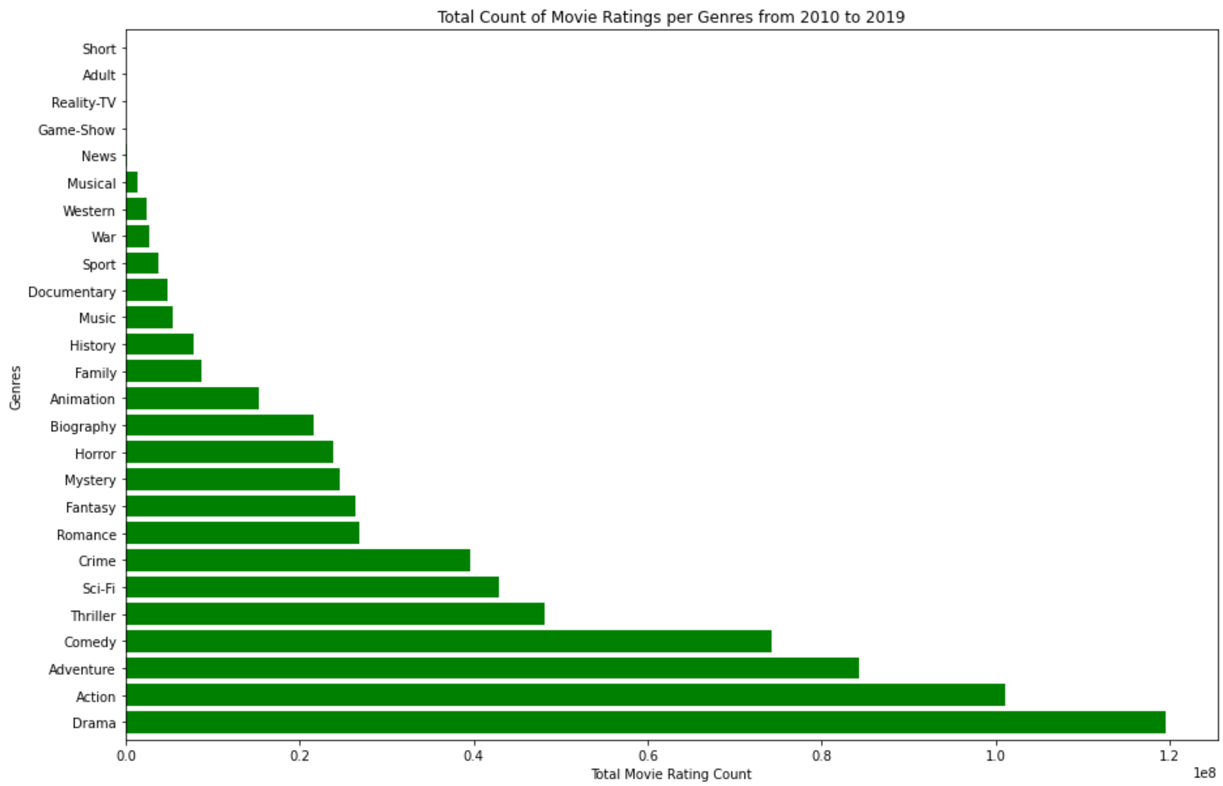
Interesting. We see that Short, Documentary, and Game-Show has the highest Average Movie Ratings. We saw in the previous genre occurence graph that these two genres are some of the least common.

Could something be wrong here? Let's take a look at the total number of votes for each genre.

In [37]:
```
genre_rating.groupby(['genres'])['num_votes'].sum().sort_values()
```

Out[37]:
```
genres
Short                  8
Adult                164
Reality-TV           459
Game-Show           3469
News              123319
Musical          1387965
Western          2452376
War              2684725
Sport            3755824
Documentary      4739345
Music            5453369
History          7843349
Family           8636710
Animation       15353302
Biography       21609446
Horror          23884695
Mystery         24657286
Fantasy         26335704
Romance         26913873
Crime           39631356
Sci-Fi          42960289
Thriller        48155313
Comedy          74305805
Adventure       84232589
Action         101161682
Drama          119567500
Name: num_votes, dtype: int64
```

In [38]:
```
fig, ax = plt.subplots(figsize=(15, 10))
ax = genre_rating.groupby(['genres'])['num_votes'].sum().sort_values(ascending=Fa
ax.set_title("Total Count of Movie Ratings per Genres from 2010 to 2019")
ax.set_ylabel("Genres")
ax.set_xlabel("Total Movie Rating Count");
```



There are much fewer movie review ratings for genres like Short and Game-show. The few number of votes may be driving the average movie score for the genre to be higher or lower than normal.

It may be safer to go with movie genres that have a solid number of movie occurences and vote counts and an average movie score close to the score median **6.32**.

Genres that stand out with this in mind are the following:

- Documentary (Average Movie score = **7.33**, Movie Occurences = **17,753**, Vote Count = **4,739,345**)
- Biography (Average Movie score = **7.16**, Movie Occurences = **3,809**, Vote Count = **21,609,446**)
- Drama (Average Movie score = **6.40**, Movie Occurences = **30,788**, Vote Count = **119,567,500**)
- Animation (Average Movie score = **6.25**, Movie Occurences = **1,743**, Vote Count = **15,353,302**)
- Adventure (Average Movie score = **6.20**, Movie Occurences = **3,817**, Vote Count = **84,232,589**)

What genres are most profitable?

Let's visualize genre to gross using BOM and Numbers dataset

In [39]:
```
display(movie_gross.info())
display(movie_gross.head())
movie_gross.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   title            3387 non-null   object
 1   domestic_gross   3387 non-null   float64
 2   foreign_gross    3387 non-null   float64
 3   year             3387 non-null   int64
 4   worldwide_gross  3387 non-null   float64
dtypes: float64(3), int64(1), object(1)
memory usage: 132.4+ KB

None
```

	title	domestic_gross	foreign_gross	year	worldwide_gross
0	Toy Story 3	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	238700000.0	513900000.0	2010	7.526000e+08

Out[39]:

	domestic_gross	foreign_gross	year	worldwide_gross
count	3.387000e+03	3.387000e+03	3387.000000	3.387000e+03
mean	2.850821e+07	4.502979e+07	2013.958075	7.353800e+07
std	6.675575e+07	1.126843e+08	2.478141	1.705091e+08
min	0.000000e+00	0.000000e+00	2010.000000	1.000000e+02
25%	1.115000e+05	0.000000e+00	2012.000000	2.740000e+05
50%	1.300000e+06	1.500000e+06	2014.000000	5.475000e+06
75%	2.750000e+07	2.915000e+07	2016.000000	6.135000e+07
max	9.367000e+08	9.605000e+08	2018.000000	1.518900e+09

In [40]:
```
# Merge genre and gross tables (based on movie title) to relate the gross values
bom_df = genre_rating.merge(movie_gross, left_on="primary_title", right_on="title
bom_df
```

Out[40]:

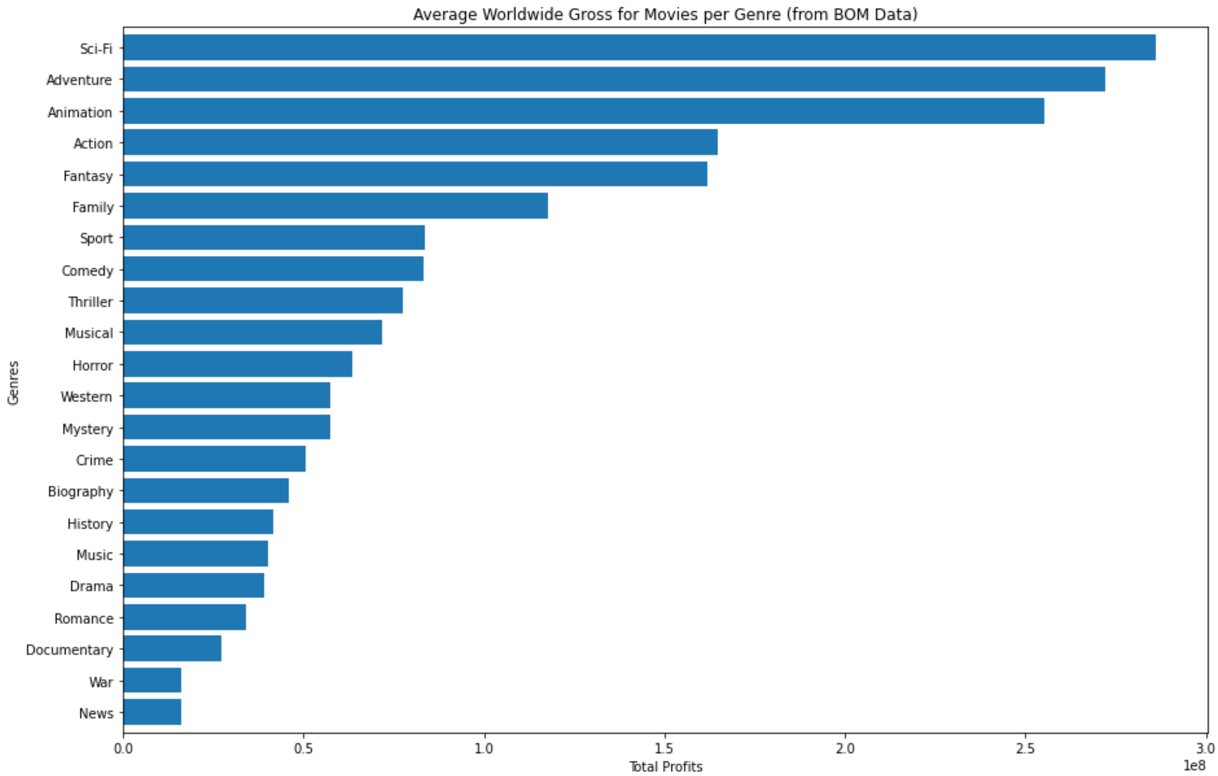
	genres	primary_title	original_title	start_year	avg_rating	num_votes	title	domes
0	Action	Wazir	Wazir	2016	7.1	15378	Wazir	
1	Crime	Wazir	Wazir	2016	7.1	15378	Wazir	
2	Drama	Wazir	Wazir	2016	7.1	15378	Wazir	
3	Adventure	On the Road	On the Road	2012	6.1	37886	On the Road	
4	Drama	On the Road	On the Road	2012	6.1	37886	On the Road	
...	...	...	...	...	...	...	...	
6973	Drama	Helicopter Eela	Helicopter Eela	2018	5.4	673	Helicopter Eela	
6974	Drama	Last Letter	Ni hao, Zhihua	2018	6.4	322	Last Letter	
6975	Romance	Last Letter	Ni hao, Zhihua	2018	6.4	322	Last Letter	
6976	Documentary	Burn the Stage: The Movie	Burn the Stage: The Movie	2018	8.8	2067	Burn the Stage: The Movie	
6977	Music	Burn the Stage: The Movie	Burn the Stage: The Movie	2018	8.8	2067	Burn the Stage: The Movie	

6978 rows × 11 columns

In [41]:
```
# Worldwide Gross per Genre
bom_df.groupby(['genres'])['worldwide_gross'].mean().sort_values()
```

Out[41]:
```
genres
News           1.621035e+07
War            1.630128e+07
Documentary    2.740189e+07
Romance        3.416476e+07
Drama          3.919474e+07
Music          4.028660e+07
History        4.162610e+07
Biography      4.596821e+07
Crime          5.071587e+07
Mystery        5.740066e+07
Western        5.748127e+07
Horror         6.341629e+07
Musical        7.176503e+07
Thriller       7.739527e+07
Comedy         8.331336e+07
Sport          8.365973e+07
Family         1.178723e+08
Fantasy        1.619324e+08
Action         1.646636e+08
Animation      2.552529e+08
Adventure      2.721899e+08
Sci-Fi         2.861222e+08
Name: worldwide_gross, dtype: float64
```

In [42]:
```
fig, ax = plt.subplots(figsize=(15, 10))
ax = bom_df.groupby(['genres'])['worldwide_gross'].mean().sort_values().plot(kind
ax.set_title("Average Worldwide Gross for Movies per Genre (from BOM Data)")
ax.set_ylabel("Genres")
ax.set_xlabel("Total Profits");
```



The most profitable genres by a large margin appear to be the following:

- **Sci-Fi**
- **Adventure**
- **Animation**

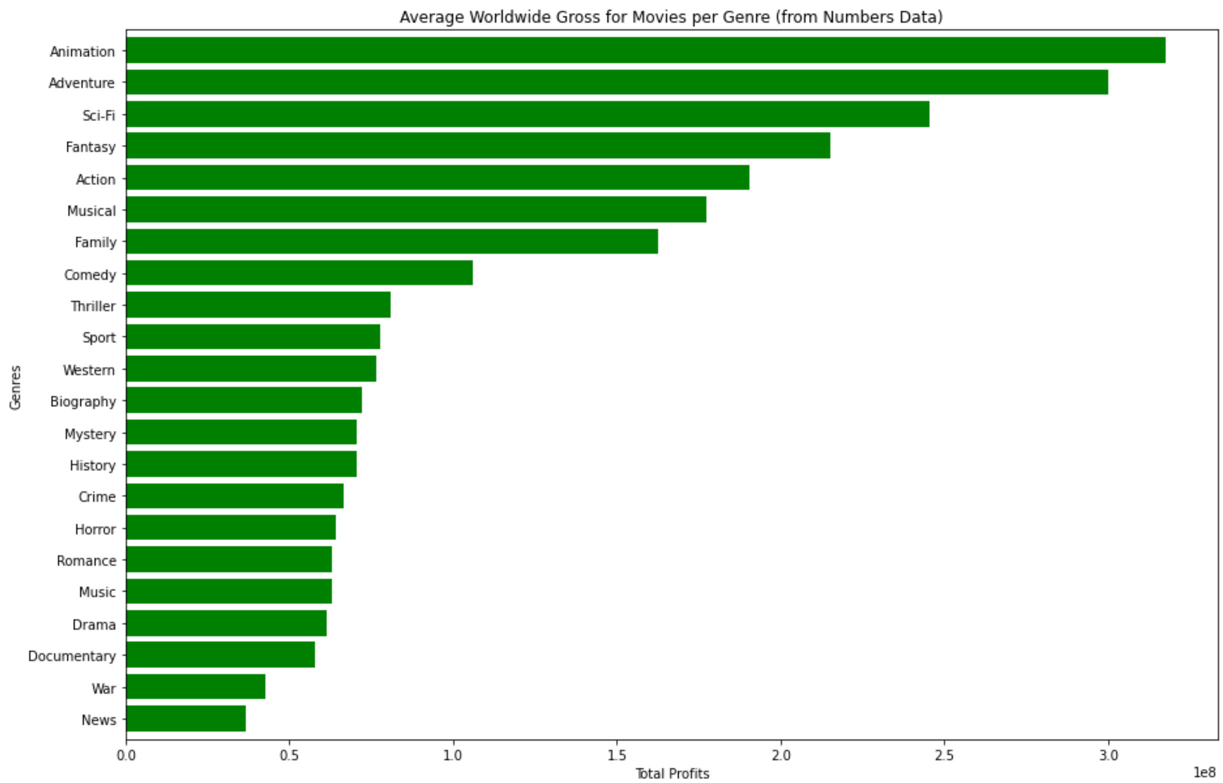
Let's see if movie profits from **The Numbers** dataset display similar results.

In [43]:
```
num_df = genre_rating.merge(movie_budgets, left_on="primary_title", right_on="mov
num_df.head()
```

Out[43]:

	genres	primary_title	original_title	start_year	avg_rating	num_votes	id	release_date	m
0	Action	Foodfight!	Foodfight!	2012	1.9	8248	26	Dec 31, 2012	Food
1	Animation	Foodfight!	Foodfight!	2012	1.9	8248	26	Dec 31, 2012	Food
2	Comedy	Foodfight!	Foodfight!	2012	1.9	8248	26	Dec 31, 2012	Food
3	Adventure	On the Road	On the Road	2012	6.1	37886	17	Mar 22, 2013	O F
4	Drama	On the Road	On the Road	2012	6.1	37886	17	Mar 22, 2013	O F

In [44]:
```
fig, ax = plt.subplots(figsize=(15, 10))
ax = num_df.groupby(['genres'])['worldwide_gross'].mean().sort_values().plot(kinc
ax.set_title("Average Worldwide Gross for Movies per Genre (from Numbers Data)")
ax.set_ylabel("Genres")
ax.set_xlabel("Total Profits");
```



Once again, the most profitable genres by a large margin appear to be the following:

- **Sci-Fi**
- **Adventure**
- **Animation**

The best direction for Microsoft may be to use these genres for its upcoming movie.

How should we budget?

Let's check the relationship between budget and profit of movies using The Numbers dataset.

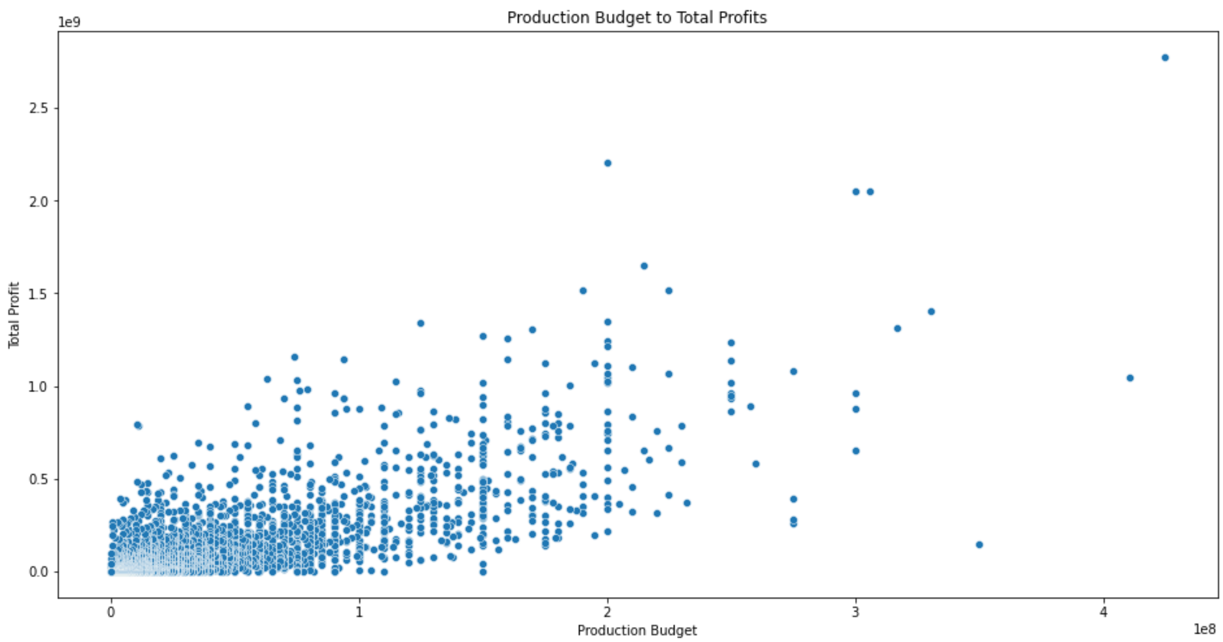
In [45]:
```
movie_budgets.describe()
```

Out[45]:

	id	production_budget	domestic_gross	worldwide_gross
count	5782.000000	5.782000e+03	5.782000e+03	5.782000e+03
mean	50.372363	3.158776e+07	4.187333e+07	9.148746e+07
std	28.821076	4.181208e+07	6.824060e+07	1.747200e+08
min	1.000000	1.100000e+03	0.000000e+00	0.000000e+00
25%	25.000000	5.000000e+06	1.429534e+06	4.125415e+06
50%	50.000000	1.700000e+07	1.722594e+07	2.798445e+07
75%	75.000000	4.000000e+07	5.234866e+07	9.764584e+07
max	100.000000	4.250000e+08	9.366622e+08	2.776345e+09

In [46]:
```
# Budget vs Profit
fig, ax = pyplot.subplots(figsize=(16,8))
sns.scatterplot(data=movie_budgets, x="production_budget", y="worldwide_gross");
ax.set_title('Production Budget to Total Profits')
ax.set_xlabel('Production Budget')
ax.set_ylabel('Total Profit')
```

Out[46]:
```
Text(0, 0.5, 'Total Profit')
```



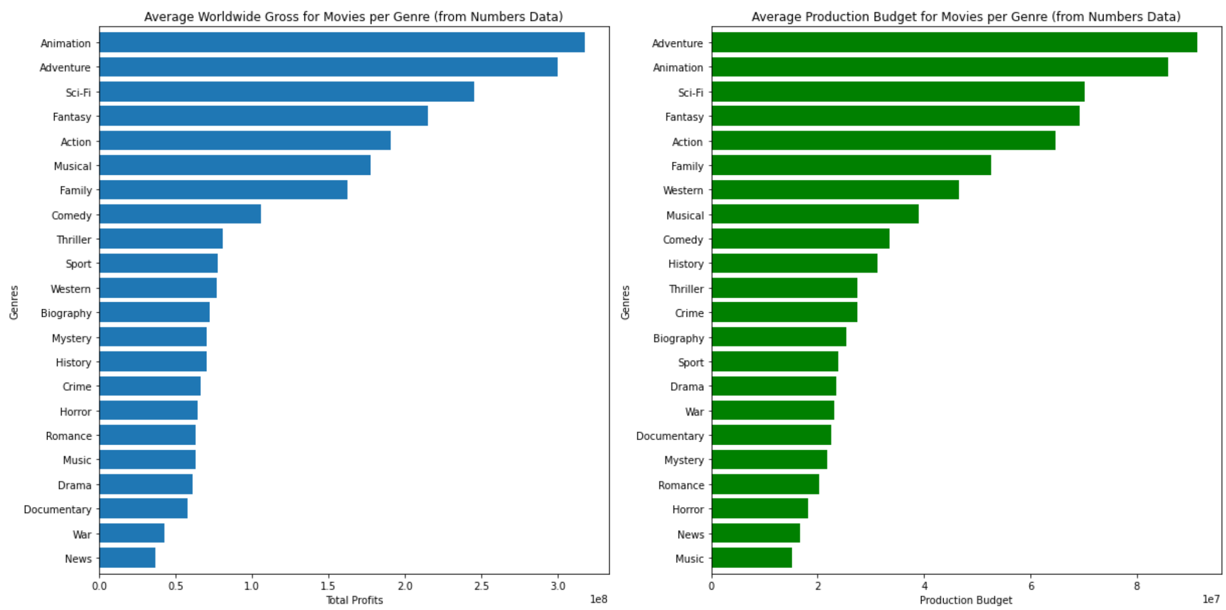
There is a **positive correlation** between movie production budget and profits gained(domestic + worldwide).

We can expect a higher budget will yield higher profits.

Now let's visualize the profits and budgets per genre.

In [47]:
```
# Plotting average of gross and budget
plt.figure(figsize=(20,10))
ax1 = plt.subplot(1,2,1)
num_df.groupby(['genres'])['worldwide_gross'].mean().sort_values().plot(kind='bar
ax1.set_title("Average Worldwide Gross for Movies per Genre (from Numbers Data)")
ax1.set_ylabel("Genres")
ax1.set_xlabel("Total Profits");

ax2 = plt.subplot(1,2,2)
num_df.groupby(['genres'])['production_budget'].mean().sort_values().plot(kind='b
ax2.set_title("Average Production Budget for Movies per Genre (from Numbers Data)
ax2.set_ylabel("Genres")
ax2.set_xlabel("Production Budget");
```



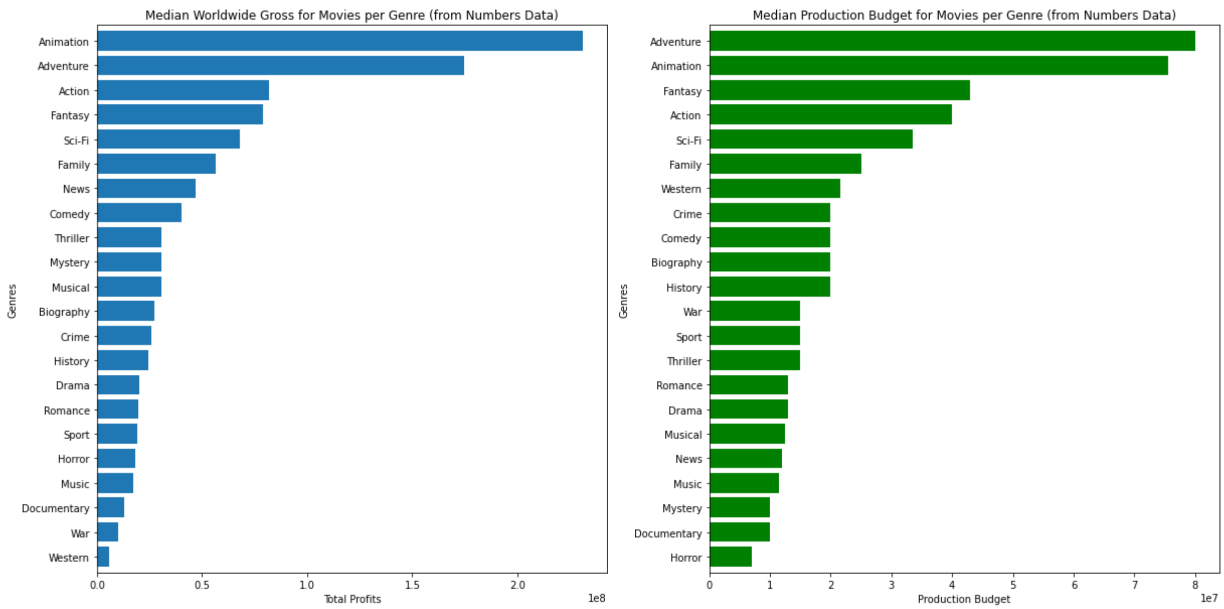
The Top 4 genres are:

- Animation
- Adventure
- Sci-Fi
- Fantasy

We need to visualize the mean and median to see if there is an outlier that may be elevating a genre.

In [48]:
```
# Plotting median of gross and budget
plt.figure(figsize=(20,10))
ax1 = plt.subplot(1,2,1)
num_df.groupby(['genres'])['worldwide_gross'].median().sort_values().plot(kind='b
ax1.set_title("Median Worldwide Gross for Movies per Genre (from Numbers Data)")
ax1.set_ylabel("Genres")
ax1.set_xlabel("Total Profits");

ax2 = plt.subplot(1,2,2)
num_df.groupby(['genres'])['production_budget'].median().sort_values().plot(kind=
ax2.set_title("Median Production Budget for Movies per Genre (from Numbers Data)'
ax2.set_ylabel("Genres")
ax2.set_xlabel("Production Budget");
```



The Top 4 genres are:

- Animation
- Adventure
- Action
- Fantasy

There appears to have been an outlier success Sci-Fi movie that was raising the average production budget and gross for Sci-Fi.

Conclusions

The analysis of the movie datasets resulted in the following answers to the initial questions:

- **What are the most popular genres?**
  The stand-out genres were:
  - **Documentary**
  - **Biography**
  - **Drama**
  - **Animation**
  - **Adventure**
- **What genres are most profitable?**
  The most profitable genres were:
  - **Animation**
  - **Adventure**
  - **Sci-fi**
- **How should we budget?**
  A larger budget will likely lead to a larger profit margin.
  The following genres that exemplified this were:
  - **Animation**
  - **Adventure**
  - **Action**
  - **Fantasy**

The analysis leads to the following recommendations for Microsoft's new studio:

- **The studio should focus on a movie with the Animation, Adventure, and Sci-Fi genres.**
  These genres displayed the highest likelihood for popularity and profitability based on the visualizations
- **The studio should aim for a larger production budget**
  A larger production budget will likely result in a much greater gross profit.

Next Steps:

Further analyses of the movie datasets could yield additional insights to studio recommendations:

- **Best genres for lower budget movies**
- **Predicting changes in viewer taste over time**
- **Best possible budget limit for future films**