Exploratory analysys of the movies box offices

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Image: cicnews.com

Overview

During this project, we will be investigating movie datasets using exploratory analysis for the customer, who is new to the movie industry. For the sake of research, we will use the following datasets (with formats):

- The Internet Movie DataBase (IDMB), SQL
- Rotten Tomatoes, TSV
- The Movie DataBase (TMDB), CSV
- The Numbers (TN), CSV
- Box Office Mojo (BOM), CSV

We will employ Pandas, SQLITE3, MatPlotLib, and SeaBorn libraries.

Considering the customer strategy **'Comprehensive Products Revolutionising Services Across Globe'** we choose worldwide box office as the primary metric for measuring films' success as it reflects global audience coverage most unambiguously in the given datasets.

We will research **box offices by month of a film release, box office by genres in two different datasets, trending genres, ROI by genres, and top producers by box offices of films they took part in for the 2010-2018 years**. We choose the latter assuming that the customer may want to consult or hire subject matter experts.

Business Problem

The customer wants to expand and create a movie studio, and the main challenge is that they don't have any expertise in the industry. Our primary goals in this project are generating insight and making further recommendations to the decision-makers.

We assume that before investing in the movie studio, the customer may want to know which genres are trending globally and what are their cummulative box offices, or, in other words, what is the industry size by genres. We also think that the customer, who wants to produce movies by themself, may wish to hire subject matter experts (producers) to reduce potential risks accompanied by entering a highly-competitive industry.

Data Understanding

During the following steps, we will load and expore the datasets we have and decide if data represented in each of them is relevant for our research.

In [1]:
```
# In this section we import necessary libriaries for working with our datasets
import pandas as pd
import sqlite3
import matplotlib.pyplot as plt
import string
import seaborn as sns
import numpy as np
%matplotlib inline
```

In [3]:
```
# Connecting IMDB SQL Dataset
conn=sqlite3.connect('data/im.db')
# Loading Box Office Mojo (BOM) Dataset
df_bom = pd.read_csv('data/bom.movie_gross.csv')
# Loading Rotten Tomatoes Movie Dataset
df_rt_movie = pd.read_csv('data/rt.movie_info.tsv', sep='\t')
# Loading Rotten Tomatoes Review Dataset
df_rt_reviews = pd.read_csv('data/rt.reviews.tsv', sep='\t', encoding='windows-1252')
# Loading The Movie Dataset
df_tmdb = pd.read_csv('data/tmdb.movies.csv')
# Loading The Numbers Dataset
df_budgets = pd.read_csv('data/tn.movie_budgets.csv')
```

In [3]:
```
df_rt_movie.head(2)
```

Out[3]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtime	
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN	104 minutes	
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	Jan 1, 2013	$	600,000	108 minutes	Ent

In this dataset we have genres and box office columns. Next we will check missing values.

In [4]:
```
# Checking number of missing values in 'box_office' column
df_rt_movie['box_office'].isna().sum()
```

Out[4]: 1220

In [5]:
```
# Checking number of missing values in 'genre' column
df_rt_movie['genre'].isna().sum()
```

Out[5]: 8

In [6]:
```
# Retrieving the dataset info
df_rt_movie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            1560 non-null   int64 
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
```

We have about 80% of missing values in the **'box_office'** column, and 8 missing values in **'genre'** column. Next we explore **Box Office Mojo** dataset.

In [7]:
```
#Retrieving the first five records of the Box Office Mojo dataset.
df_bom.head()
```

Out[7]:

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

In [8]:
```
# The Box Office Mojo dataset info
df_bom.info()
```

```
<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
```

Box Office Mojo contains **box office data, movie title, and release year**. Most of the values are present.

In [9]:
```
#Retrieving the first five records of the Rotten Tomatoes Reviews dataset.
df_rt_reviews.head()
```

Out[9]:

	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

In the Rotten Tomato reviews dataset there is nor box office or genre information, neither release date.

In [10]:
```
#Getting the first five records of The Movie DataBase
df_tmdb.head()
```

Out[10]:

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_average	vote_count
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	7.7	10788
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7.7	7610
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6.8	12368
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7.9	10174
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8.3	22186

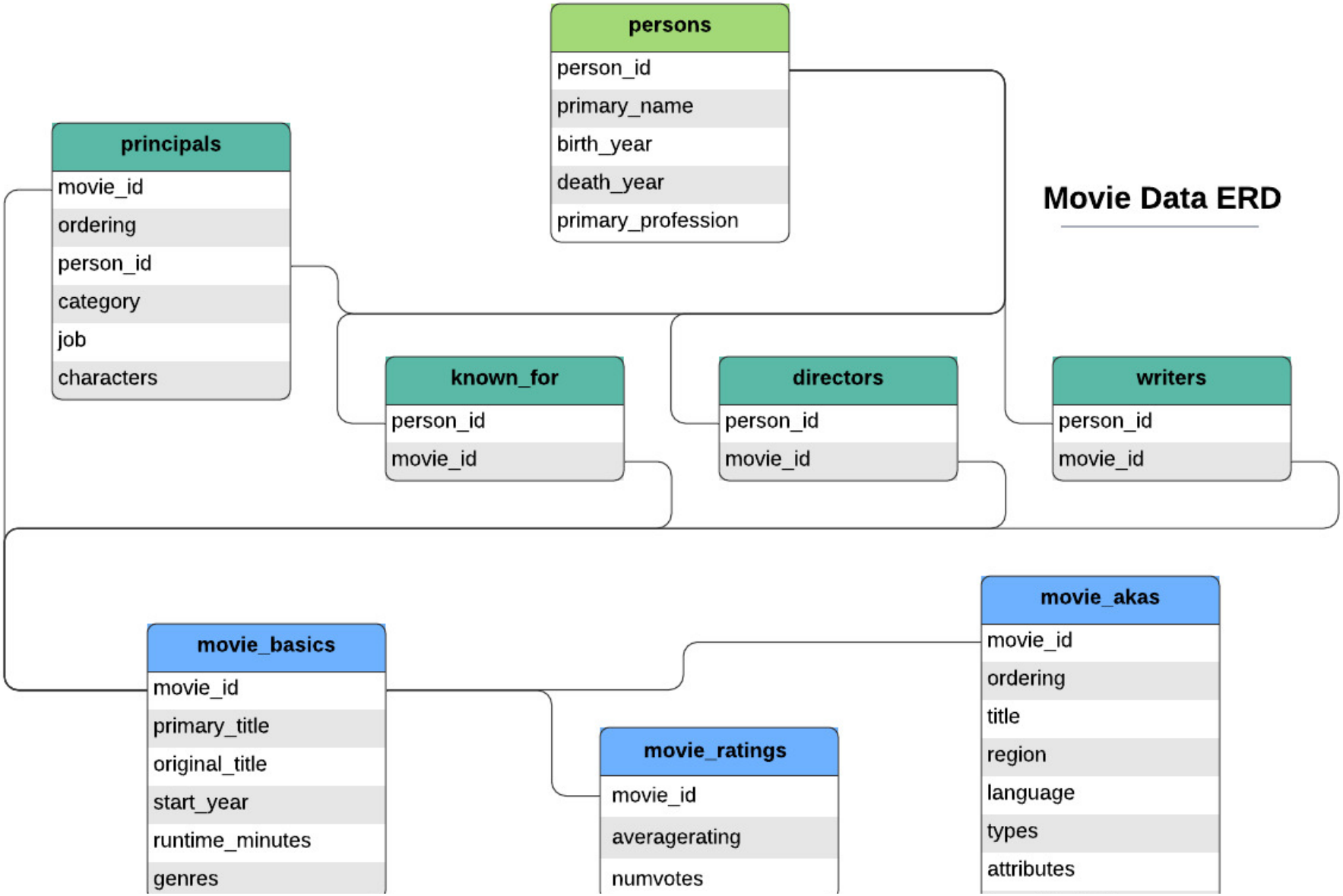
In [11]:
```
#Retrieving the database info
df_tmdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         26517 non-null  int64  
 1   genre_ids          26517 non-null  object 
 2   id                 26517 non-null  int64  
 3   original_language  26517 non-null  object 
 4   original_title     26517 non-null  object 
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object 
 7   title              26517 non-null  object 
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
```

This dataset has the infromation about movies genre represented as numerical 'id' but there is no actual genre name or type. It also does't have any information about box offices.

Exploring IMDB data

The IMDB database represented in SQL format accroding to the provided schema.



For the sake of analysis we will explore **movie_basics**, **movie_akas**, **principals**, and **persons** tables.

In [12]:
```
#Querying 'principals' table
pd.read_sql(""" SELECT * FROM principals WHERE(job='producer') LIMIT 2;

""", conn)
```

Out[12]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	3	nm3739909	producer	producer	None
1	tt0323808	6	nm0811056	producer	producer	None

In [13]:
```
#Querying 'movie_basics' table
pd.read_sql(""" SELECT * FROM movie_basics LIMIT 2;

""", conn)
```

Out[13]:

	movie_id	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

In [14]:
```
#Querying 'persons' table


pd.read_sql(""" SELECT * FROM persons LIMIT 2;

""", conn)
```

Out[14]:

	person_id	primary_name	birth_year	death_year	primary_profession
0	nm0061671	Mary Ellen Bauder	None	None	miscellaneous,production_manager,producer
1	nm0061865	Joseph Bauer	None	None	composer,music_department,sound_department

In [15]:
```
#Querying 'movie_akas' table
pd.read_sql(""" SELECT * FROM movie_akas LIMIT 2;

""", conn)
```

Out[15]:

	movie_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	None	None	0.0
1	tt0369610	11	Jurashikku warudo	JP	None	imdbDisplay	None	0.0

In [16]:
```
#Querying 'known_for' table
pd.read_sql(""" SELECT * FROM known_for LIMIT 2;

""", conn)
```

Out[16]:

	person_id	movie_id
0	nm0061671	tt0837562
1	nm0061671	tt2398241

In [17]:
```
#Retrieving The Numbers database info
df_budgets = pd.read_csv('zippedData/tn.movie_budgets.csv')
df_budgets.head()
```

Out[17]:

	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

In [18]:
```
df_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   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
```

"The Numbers" database has domestc gross and worldwide gross data. There is no mising values.

Conclusions

For future analysis, we will be using **IMDB**, **Rotten Tomatoes Movies**, **The Numbers**.

From the Rotten Tomatoes dataset, we will retrieve information about the most successful genres at the box office. As there is no notation if the box office information in the database regarding domestic or international sales, for analysis on the latter parameter, we will be using **The Numbers** dataset.

We will create a Pandas DatFrame from IMDB with names of producers and movies and merge it with The Numbers database on the movie title. We will plot the trending genres then.

We will not be using **Box Office Mojo** database as it contains about twice less records than **The Numbers**.

Data Cleaning and Visualization

In [19]:
```
# Creating a function for removing punctuation and lowering letters.
def remove_and_lower_punctuations(text):
    for punctuation in string.punctuation:
        text = text.replace(punctuation, '').lower()
    return text
```

Cleaning Rotten Tomato Dataset

In [20]:
```
# Printing the dataset head
df_rt_movie.head(2)
```

Out[20]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtime	
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN	104 minutes	
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	Jan 1, 2013	$	600,000	108 minutes	Ent

In [21]:
```
"""
The 'genre' records are separated with delimiter '|'. There is also more than one genre associated wi
th some
records. We need to split each string first. Then we will use 'explode' method for creating a single
 record for
every genre.
"""
# Spliting records.
df_rt_movie['genre_separated'] = df_rt_movie['genre'].str.split('|')
# Applying 'explode' method
df_rt_movie_expl = df_rt_movie.explode('genre_separated')
df_rt_movie_expl.head(2)
```

Out[21]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date	currency	box_office	runtime	studio	genre
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN	104 minutes	NaN	
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001	NaN	NaN	104 minutes	NaN	

In [22]:
```
# Getting the resulting list of unique genres
df_rt_movie_expl.genre_separated.unique()
```

Out[22]:
```
array(['Action and Adventure', 'Classics', 'Drama',
       'Science Fiction and Fantasy', 'Musical and Performing Arts',
       'Mystery and Suspense', 'Romance', 'Kids and Family', 'Comedy',
       nan, 'Documentary', 'Special Interest',
       'Art House and International', 'Horror', 'Western', 'Television',
       'Sports and Fitness', 'Animation', 'Faith and Spirituality',
       'Cult Movies', 'Anime and Manga', 'Gay and Lesbian'], dtype=object)
```

In [23]:
```
"""
The 'box_office' column contains non-numerical as well as NaN values. We will replace NaN values with
0 (zero)
and then convert to an integer type.
"""
# Replacing NaN with 0
df_rt_movie_expl.box_office.fillna(value=0, inplace=True)
# Replacing non-digit symbols
df_rt_movie_expl['box_office'].replace(to_replace=r'[^0-9.\-]', value=r'', regex=True, inplace=True)
# Converting into 'int64'
df_rt_movie_expl['box_office_int'] = df_rt_movie_expl['box_office'].astype('int64')
```

In [24]:
```
df_rt_movie_expl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3581 entries, 0 to 1559
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   id               3581 non-null   int64 
 1   synopsis         3479 non-null   object
 2   rating           3578 non-null   object
 3   genre            3573 non-null   object
 4   director         3138 non-null   object
 5   writer           2560 non-null   object
 6   theater_date     2872 non-null   object
 7   dvd_date         2872 non-null   object
 8   currency         724 non-null    object
 9   box_office       3581 non-null   object
 10  runtime          3529 non-null   object
 11  studio           1062 non-null   object
 12  genre_separated  3573 non-null   object
 13  box_office_int   3581 non-null   int64 
dtypes: int64(2), object(12)
memory usage: 419.6+ KB
```

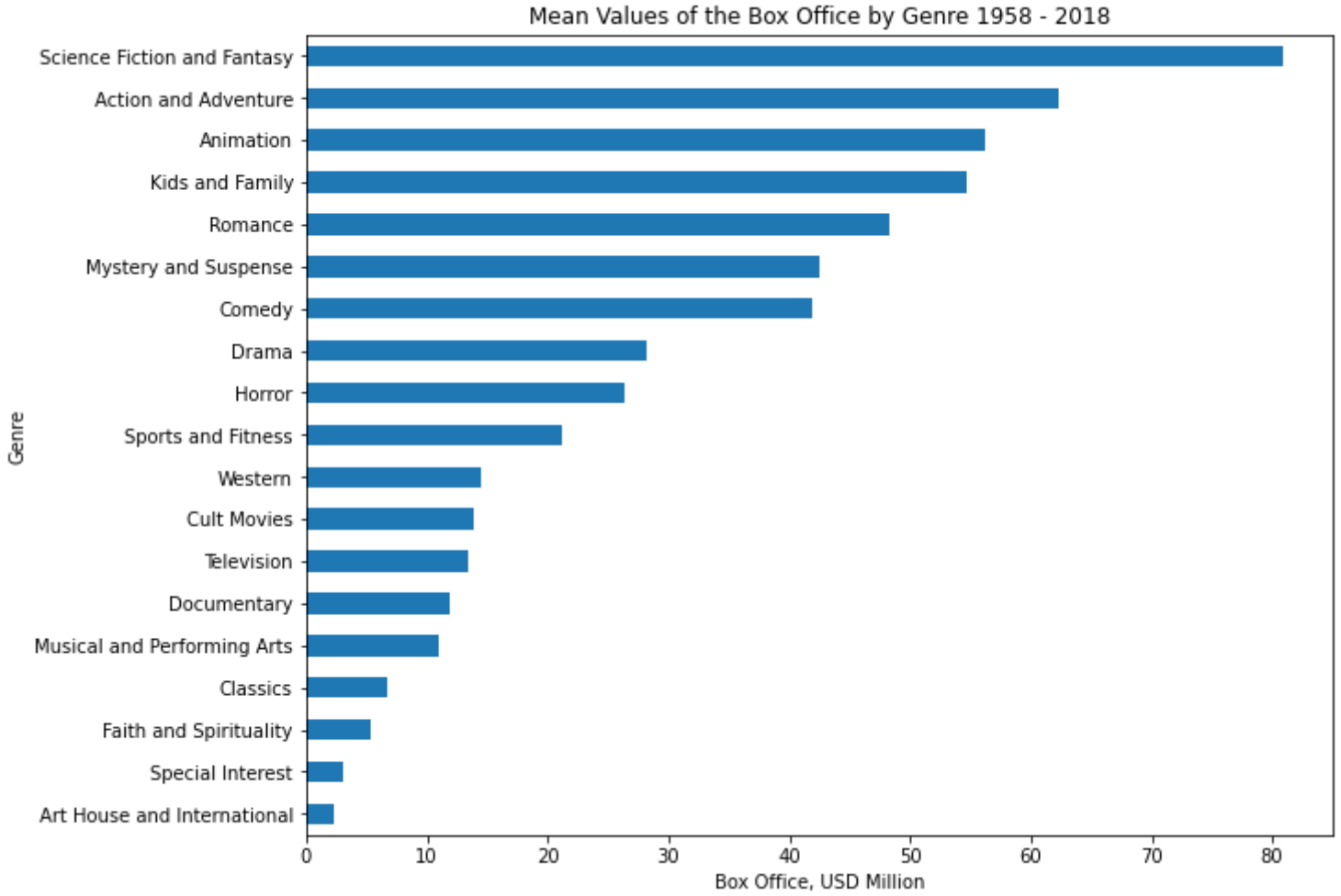
In [25]:
```
# Convert 'genres_separated' to a string for the plotting
df_rt_movie_expl['genre_separated'] = df_rt_movie_expl['genre_separated'].astype('str')
# Replacing 'nan'
df_rt_movie_expl.genre_separated.replace(to_replace='nan', value='Unknown', inplace=True)
```

In [26]:
```
# Creating a new dataset without null values in the 'box_office' column
df_rt_movie_no_null = df_rt_movie_expl[df_rt_movie_expl.box_office_int!=0]
```

In [27]:
```
# Dividing by 1.0 million for better readability and creating a new column
df_rt_movie_no_null['box_off_mill'] = df_rt_movie_no_null['box_office_int']/1000000
```

```
<ipython-input-27-ca34f140bd84>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexi
ng.html#returning-a-view-versus-a-copy
  df_rt_movie_no_null['box_off_mill'] = df_rt_movie_no_null['box_office_int']/1000000
```

In [28]:
```
# Plotting
df_rt_movie_no_null.groupby(
    ['genre_separated'])['box_off_mill'].mean().sort_values(ascending=True).plot.barh(figsize=(10,8))
# Labelling
plt.title('Mean Values of the Box Office by Genre 1958 - 2018')
plt.xlabel('Box Office, USD Million')
plt.ylabel('Genre');
```



Cleaning The Numbers dataset

In [29]:
```
# Replacing non-digit symbols
df_budgets['production_budget'].replace(to_replace=r'[^0-9.\-]', value=r'', regex=True, inplace=True)
df_budgets['domestic_gross'].replace(to_replace=r'[^0-9.\-]', value=r'', regex=True, inplace=True)
df_budgets['worldwide_gross'].replace(to_replace=r'[^0-9.\-]', value=r'', regex=True, inplace=True)
# Converting into 'int64'
df_budgets['production_budget'] = df_budgets['production_budget'].astype('int64')
df_budgets['domestic_gross'] = df_budgets['domestic_gross'].astype('int64')
df_budgets['worldwide_gross'] = df_budgets['worldwide_gross'].astype('int64')

df_budgets.head()
```

Out[29]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

In [30]:
```
df_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   int64 
 4   domestic_gross     5782 non-null   int64 
 5   worldwide_gross    5782 non-null   int64 
dtypes: int64(4), object(2)
memory usage: 271.2+ KB
```

In [31]:
```
df_budgets['total_net'] = df_budgets['worldwide_gross'] - df_budgets['production_budget']
```

In [32]:
```
# Getting production budget mean
df_budgets.production_budget.mean()
```

Out[32]:
```
31587757.0965064
```

In [33]:
```
# # Getting production budget median
df_budgets.production_budget.median()
```

Out[33]:
```
17000000.0
```

In [34]:
```
# Retrieving a movie release month
df_budgets['release_month'] = df_budgets.release_date.map(lambda x: x[:4])
```

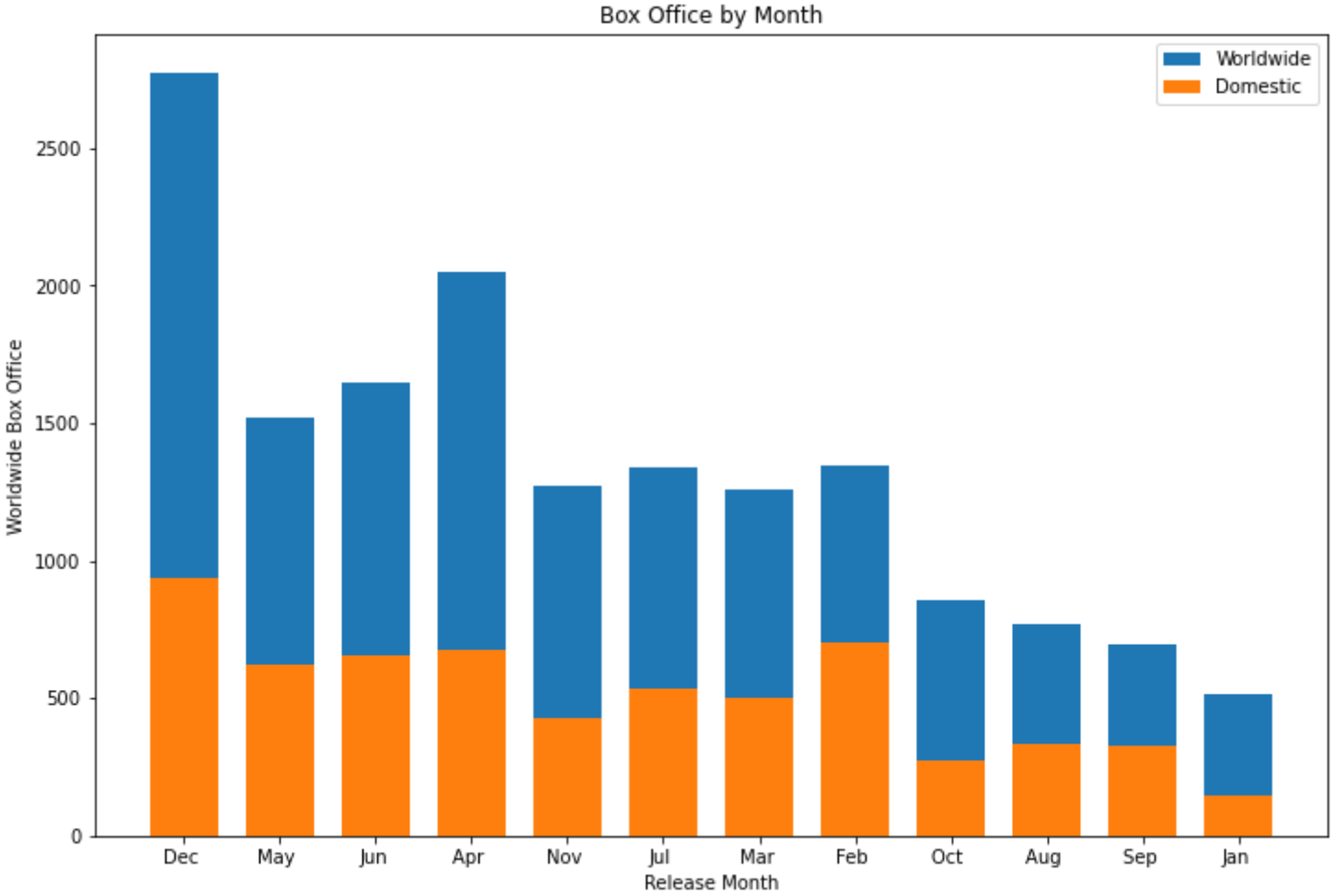
In [35]:
```
df_budgets.head()
```

Out[35]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	total_net	release_month
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	2351345279	Dec
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	635063875	May
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350	-200237650	Jun
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963	1072413963	May
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	999721747	Dec

In [36]:
```
# Dividing by 1.0 million for better readability and creating a new column
df_budgets['worldwide_gross_mill'] = df_budgets['worldwide_gross']/1000000
df_budgets['domestic_gross_mill'] = df_budgets['domestic_gross']/1000000
```

In [37]:
```
# Plotting domestic and worldwide gross by month
fig, ax = plt.subplots(figsize=(12,8))
ax.bar(df_budgets['release_month'], df_budgets['worldwide_gross_mill'], width=0.7)
ax.bar(df_budgets['release_month'], df_budgets['domestic_gross_mill'], width=0.7)
# Add lables
plt.title('Box Office by Month')
plt.xlabel('Release Month')
plt.ylabel('Worldwide Box Office')
ax.legend(('Worldwide', 'Domestic'));
```



Merging IMDB and Budgets databases on movie title

In [38]:
```
# Creating a database containing movies' data grouped by producers of each movie.
df_producers_imdb = pd.read_sql(
""" SELECT primary_name, birth_year, death_year, primary_title, start_year, genres
FROM persons
JOIN principals USING(person_id)
JOIN movie_basics USING(movie_id)
JOIN movie_akas USING(movie_id)
GROUP BY primary_name
HAVING primary_profession LIKE '%producer%'
;

""", conn)
df_producers_imdb.head()
```

Out[38]:

	primary_name	birth_year	death_year	primary_title	start_year	genres
0	'Cousin Brucie' Morrow	1935.0	NaN	Katz's: That's All	2010	Documentary
1	'Freeway' Ricky Ross	1960.0	NaN	How to Make Money Selling Drugs	2012	Crime,Documentary
2	'Om' Rakesh Chaturvedi	NaN	NaN	BHK Bhalla@Halla.Kom	2016	Comedy
3	'Punnagai Poo' Geetha	NaN	NaN	Narthaki	2011	Family
4	50 Cent	1975.0	NaN	Escape Plan	2013	Action,Crime,Mystery

In [39]:
```
df_producers_imdb.count()
```

Out[39]:
```
primary_name     131126
birth_year        22575
death_year         1079
primary_title    131126
start_year       131126
genres           129591
dtype: int64
```

Data cleaning and normalization

During the next step we will normalize data in both databases to prepare it for joining.

In [40]:
```
# Normalizing 'primary_title' column
df_producers_imdb['primary_title'] = df_producers_imdb['primary_title'].apply(remove_and_lower_punctu
ations)

# Normalizing 'movie' column and creating new column 'primary_title'
df_budgets['primary_title'] = df_budgets['movie'].apply(remove_and_lower_punctuations)

# Merging
df_budgets_and_producers_imdb = df_producers_imdb.merge(df_budgets, on='primary_title')
df_budgets_and_producers_imdb.head(2)
```

Out[40]:

	primary_name	birth_year	death_year	primary_title	start_year	genres	id	release_date	movie	production_budget	d
0	50 Cent	1975.0	NaN	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	70000000	
1	Arnold Schwarzenegger	1947.0	NaN	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	70000000	

In [41]:
```
df_budgets_and_producers_imdb.count()
```

Out[41]:
```
primary_name            5849
birth_year              2310
death_year               115
primary_title           5849
start_year              5849
genres                  5817
id                      5849
release_date            5849
movie                   5849
production_budget       5849
domestic_gross          5849
worldwide_gross         5849
total_net               5849
release_month           5849
worldwide_gross_mill    5849
domestic_gross_mill     5849
dtype: int64
```

In [42]:
```
# Create a separate record for each genre
# Splitting
df_budgets_and_producers_imdb['genres_cleaned'] = df_budgets_and_producers_imdb['genres'].str.split(
','')
# Applying the 'explode' method
df_budgets_and_producers_imdb_exploded = df_budgets_and_producers_imdb.explode('genres_cleaned')
df_budgets_and_producers_imdb.head()
```

Out[42]:

	primary_name	birth_year	death_year	primary_title	start_year	genres	id	release_date	movie	production_budget	d
0	50 Cent	1975.0	NaN	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	70000000	
1	Arnold Schwarzenegger	1947.0	NaN	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	70000000	
2	Jason Keller	1968.0	NaN	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	70000000	
3	Remington Chase	NaN	NaN	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	70000000	
4	A. Scott Berg	1949.0	NaN	genius	2016	Biography,Drama	10	Jun 10, 2016	Genius	17000000	

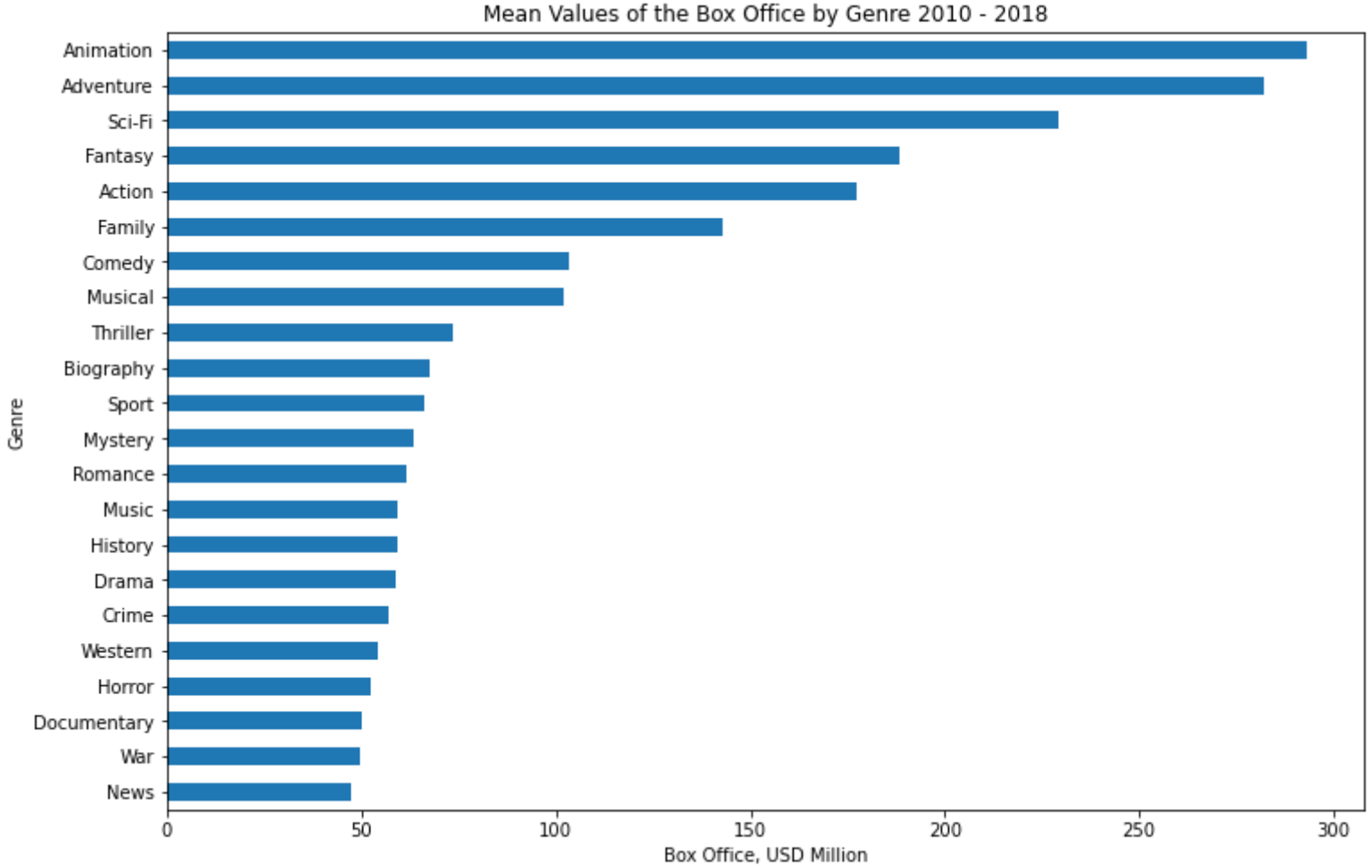
In [43]:
```
# Checking the number of NaN values in genres records
df_budgets_and_producers_imdb_exploded.genres_cleaned.isna().sum()
```

Out[43]:
```
32
```

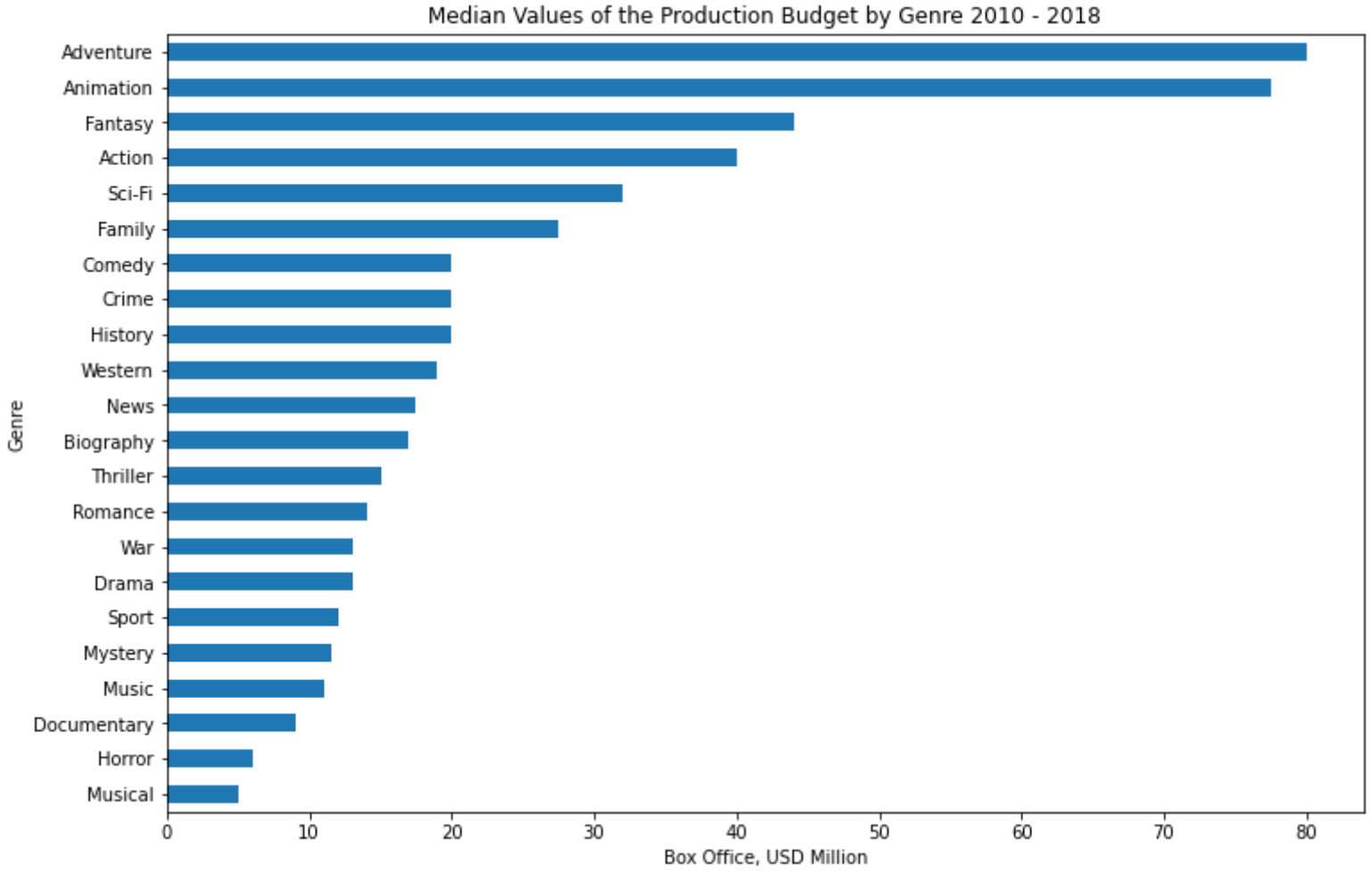
In [44]:
```
# Drop NaN rows
df_budgets_and_producers_imdb_exploded.dropna(subset='genres_cleaned', inplace=True)
df_budgets_and_producers_imdb_exploded.isna().sum()
```

Out[44]:
```
primary_name               0
birth_year              7611
death_year             12996
primary_title              0
start_year                 0
genres                     0
id                         0
release_date               0
movie                      0
production_budget          0
domestic_gross             0
worldwide_gross            0
total_net                  0
release_month              0
worldwide_gross_mill       0
domestic_gross_mill        0
genres_cleaned             0
dtype: int64
```

In [45]:
```
# Plotting mean values of worldwide gross sales by genres
df_budgets_and_producers_imdb_exploded.groupby(
    ['genres_cleaned'])['worldwide_gross_mill'].mean().sort_values(ascending=True).plot.barh(figsize=
(12,8));

# Labelling
plt.title('Mean Values of the Box Office by Genre 2010 - 2018')
plt.xlabel('Box Office, USD Million')
plt.ylabel('Genre');
```



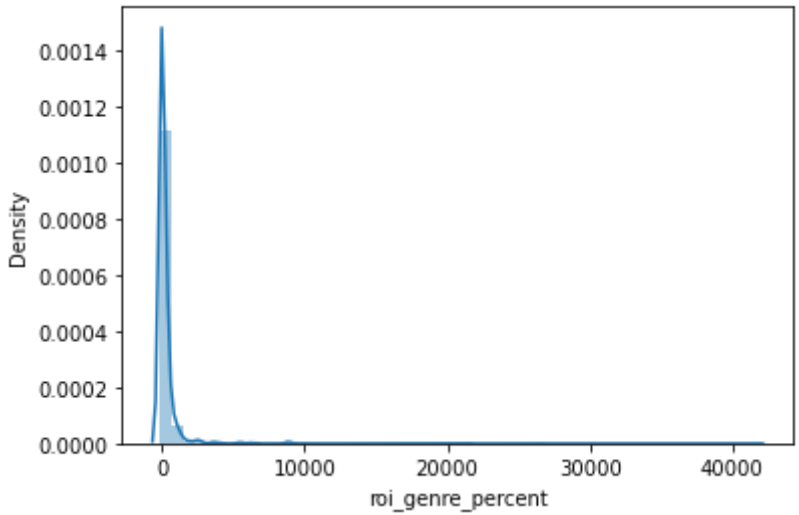
In [46]:
```
# Plotting median values of production budget by genres
# Divide by 1.0 million
df_budgets_and_producers_imdb_exploded['production_budget_mill'] = df_budgets_and_producers_imdb_expl
oded[
    'production_budget']/1000000
# Plot
df_budgets_and_producers_imdb_exploded.groupby(
    ['genres_cleaned'])['production_budget_mill'].median().sort_values(ascending=True).plot.barh(figs
ize=(12,8))

# Labelling
plt.title('Median Values of the Production Budget by Genre 2010 - 2018')
plt.xlabel('Box Office, USD Million')
plt.ylabel('Genre');
```



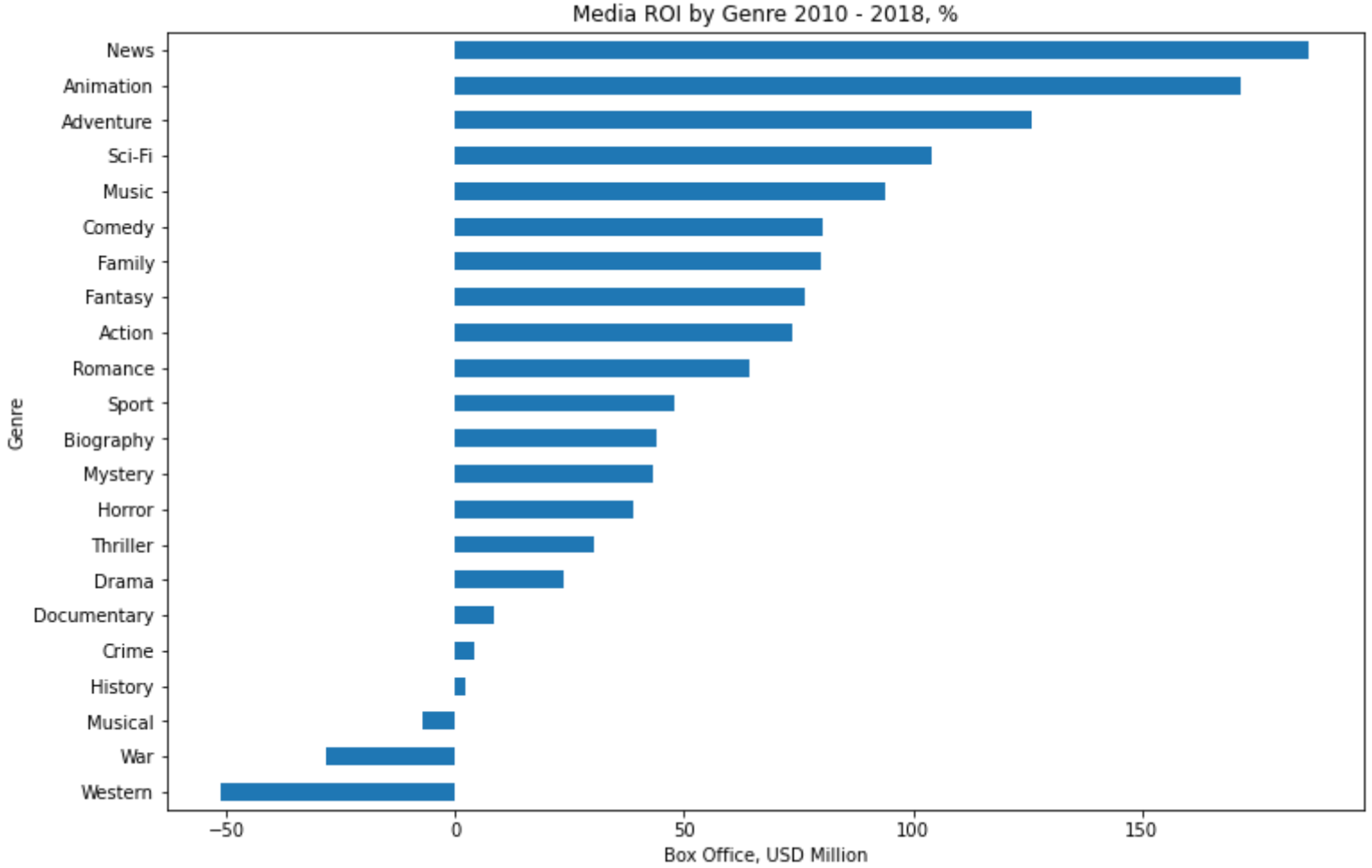
In [47]:
```
# Calculate ROI by genres
df_budgets_and_producers_imdb_exploded['roi_genre_percent'] = ((df_budgets_and_producers_imdb_explode
d[
    'worldwide_gross_mill']-df_budgets_and_producers_imdb_exploded[
    'production_budget_mill'])/df_budgets_and_producers_imdb_exploded[
    'production_budget_mill']*100).round(2)
```

In [48]:
```
# Plotting distribution
sns.distplot(df_budgets_and_producers_imdb_exploded.roi_genre_percent);
```

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarni
ng: `distplot` is a deprecated function and will be removed in a future version. Please adapt your c
ode to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axe
s-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [49]:
```
# Plot ROI by genres
df_budgets_and_producers_imdb_exploded.groupby(
    ['genres_cleaned'])['roi_genre_percent'].median().sort_values(ascending=True).plot.barh(figsize=(
12,8))

# Labelling
plt.title('Media ROI by Genre 2010 - 2018, %')
plt.xlabel('Box Office, USD Million')
plt.ylabel('Genre');
```



In [50]:
```
# Create a DataFrame with mean values for each genre by years
df_imdb_budgets_years_genres = pd.pivot_table(df_budgets_and_producers_imdb_exploded, index='start_year',
                                              columns='genres_cleaned',
                            values='worldwide_gross', aggfunc='mean')
df_imdb_budgets_years_genres
```

Out[50]:

genres_cleaned	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drama	
start_year									
2010	1.371600e+08	2.649303e+08	4.262830e+08	5.225303e+07	9.806388e+07	3.891749e+07	3.713990e+07	7.370377e+07	1.7
2011	1.783031e+08	2.748490e+08	3.399847e+08	1.992523e+07	1.116498e+08	1.085049e+08	6.882746e+07	6.169200e+07	1.1
2012	2.018982e+08	3.688598e+08	2.582620e+08	6.734096e+07	9.026252e+07	3.881978e+07	5.081050e+07	4.834651e+07	2.2
2013	1.588812e+08	2.335612e+08	3.571165e+08	1.440919e+08	9.788852e+07	9.919453e+07	5.673833e+07	7.173324e+07	1.1
2014	1.398867e+08	2.253645e+08	2.112647e+08	5.379416e+07	8.465923e+07	4.900321e+07	2.141317e+07	4.080261e+07	8.9
2015	1.882882e+08	3.345025e+08	1.871761e+08	8.285541e+07	8.882174e+07	2.397161e+07	4.592322e+07	4.294675e+07	9.3
2016	1.917465e+08	2.394168e+08	3.246850e+08	3.332918e+07	1.704600e+08	6.151042e+07	9.913484e+07	7.293978e+07	1.0
2017	2.522327e+08	3.500978e+08	2.936686e+08	9.833773e+07	1.359039e+08	4.719148e+07	5.393617e+07	5.557787e+07	1.1
2018	2.867552e+08	3.396477e+08	3.730657e+08	1.272303e+08	8.207225e+07	3.950002e+07	4.584897e+07	6.927862e+07	3.4
2019	1.241631e+08	2.221529e+08	1.382417e+08	2.176983e+07	1.310488e+08	5.118057e+07	7.397209e+07	2.420568e+07	2.0
2020	NaN	2.744747e+07	NaN	NaN	NaN	4.370000e+07	NaN	2.464874e+07	
2021	5.235400e+07	1.221332e+08	5.799091e+07	NaN	NaN	NaN	NaN	1.958500e+04	

12 rows × 22 columns

In [51]:
```
# Drop rows and column with a vast majority of NaN's and
df_imdb_budgets_years_genres.drop(columns='News', axis=1, inplace=True)
df_imdb_budgets_years_genres.drop(index=[2020,2021, 2019], inplace=True)
```

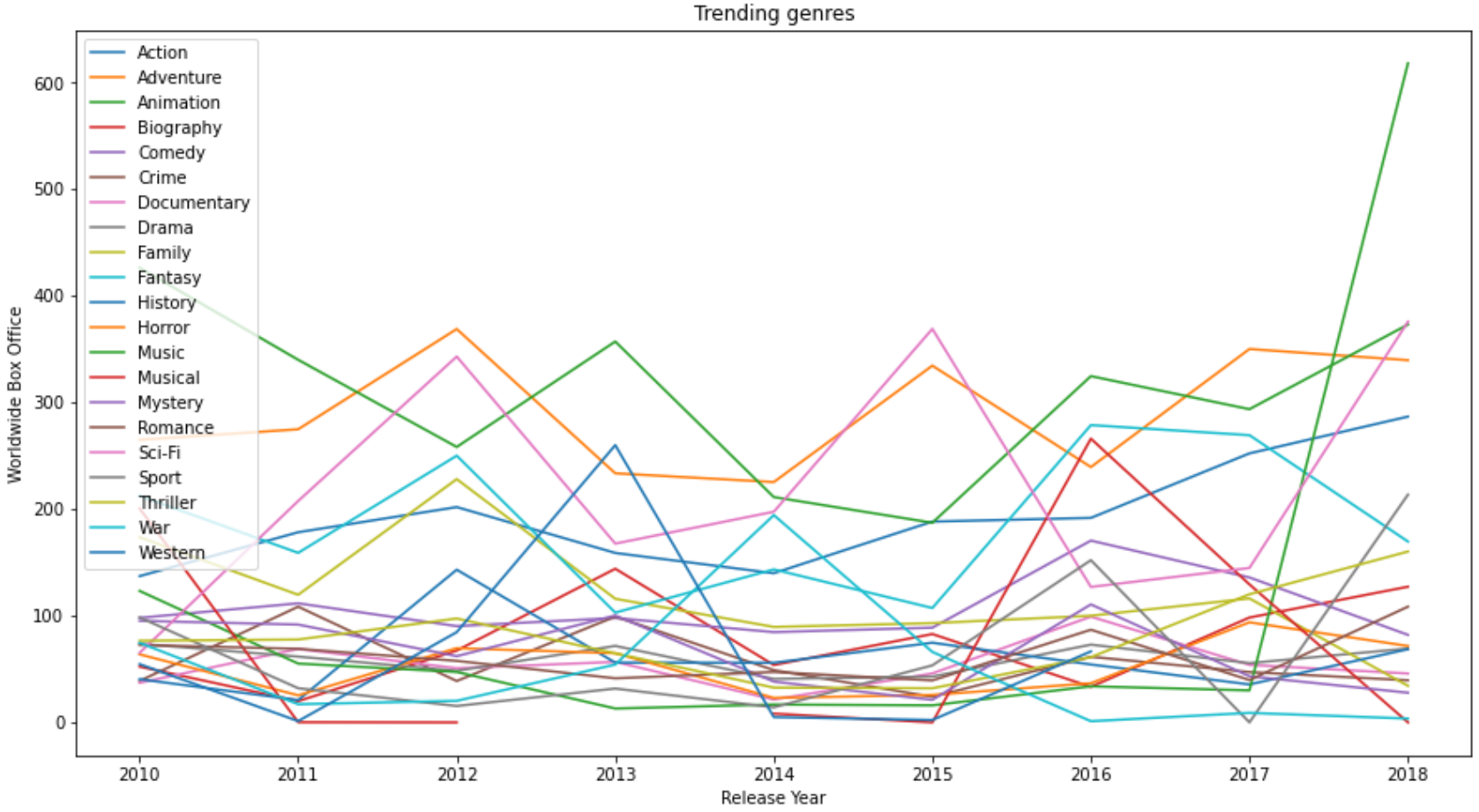
In [52]:
```
# Divide a dataframe by 1.0 million and round up to 3 decimals
df_imdb_budgets_years_genres = df_imdb_budgets_years_genres/1000000
df_imdb_budgets_years_genres.round(decimals=3)
```

Out[52]:

genres_cleaned	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drama	Family	Fantasy	...	Horror	Mu
start_year													
2010	137.160	264.930	426.283	52.253	98.064	38.917	37.140	73.704	173.616	212.502	...	63.787	123.2
2011	178.303	274.849	339.985	19.925	111.650	108.505	68.827	61.692	119.652	158.972	...	25.414	55.1
2012	201.898	368.860	258.262	67.341	90.263	38.820	50.810	48.347	228.109	250.097	...	69.591	47.2
2013	158.881	233.561	357.117	144.092	97.889	99.195	56.738	71.733	115.920	102.921	...	64.875	13.0
2014	139.887	225.365	211.265	53.794	84.659	49.003	21.413	40.803	89.505	143.449	...	22.965	16.7
2015	188.288	334.502	187.176	82.855	88.822	23.972	45.923	42.947	93.059	107.257	...	25.778	15.9
2016	191.746	239.417	324.685	33.329	170.460	61.510	99.135	72.940	100.025	278.771	...	36.716	33.8
2017	252.233	350.098	293.669	98.338	135.904	47.191	53.936	55.578	116.238	269.323	...	93.815	30.0
2018	286.755	339.648	373.066	127.230	82.072	39.500	45.849	69.279	34.304	169.568	...	71.664	618.0

9 rows × 21 columns

In [53]:
```
# Plot genres trends


df_imdb_budgets_years_genres.plot(figsize=(15,8))

# Add lables
plt.title('Trending genres')
plt.xlabel('Release Year')
plt.ylabel('Worldwide Box Office')
plt.legend(loc='upper left');
```



In [54]:
```
# Fill NaN values
df_budgets_and_producers_imdb_exploded.fillna(value='Unknown', inplace=True)
```

In [55]:
```
df_budgets_and_producers_imdb_exploded
```

Out[55]:

	primary_name	birth_year	death_year	primary_title	start_year	genres	id	release_date	movie	production_budg
0	50 Cent	1975.0	Unknown	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	700000
0	50 Cent	1975.0	Unknown	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	700000
0	50 Cent	1975.0	Unknown	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	700000
1	Arnold Schwarzenegger	1947.0	Unknown	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	700000
1	Arnold Schwarzenegger	1947.0	Unknown	escape plan	2013	Action,Crime,Mystery	37	Oct 18, 2013	Escape Plan	700000
...	...	...	...	...	...	...	...	...	...	
5846	Zach Staenberg	1954.0	Unknown	in time	2011	Action,Crime,Drama	74	Oct 28, 2011	In Time	350000
5847	Zanda Senkova	1991.0	Unknown	swingers	2016	Comedy	16	Oct 18, 1996	Swingers	2000
5848	Ákos Varga	Unknown	Unknown	bodom	2014	Horror,Mystery,Thriller	54	Dec 31, 2016	Bodom	12500
5848	Ákos Varga	Unknown	Unknown	bodom	2014	Horror,Mystery,Thriller	54	Dec 31, 2016	Bodom	12500
5848	Ákos Varga	Unknown	Unknown	bodom	2014	Horror,Mystery,Thriller	54	Dec 31, 2016	Bodom	12500

13284 rows × 19 columns

In [56]:
```
# Filter persons who has a death year in the record
df_producers_likely_alive = df_budgets_and_producers_imdb_exploded[
    df_budgets_and_producers_imdb_exploded['death_year']=='Unknown']
```

In [57]:
```
# Select top 3 genres
df_producers_likely_alive_genres = df_producers_likely_alive[
    (df_producers_likely_alive['genres_cleaned']=='Action')
    |(df_producers_likely_alive['genres_cleaned']=='Sci-Fi')
    |(df_producers_likely_alive['genres_cleaned']=='Animation')]
```

In [58]:
```
# Create a table with likely alive persons, working in top 3 genres, aggregated by worldwide gross box offices.
df_producers_likely_alive_genres_piv = pd.pivot_table(df_producers_likely_alive_genres, index='primary_name',
                                                      columns='genres_cleaned',
                            values='worldwide_gross_mill', aggfunc='sum')
```

In [59]:
```
# Retrieving top 10 persons in 'Sci-Fi'
df_producers_likely_alive_genres_piv.sort_values('Sci-Fi', ascending=False).head(10).to_excel('scifi.xlsx')
df_producers_likely_alive_genres_piv.sort_values('Sci-Fi', ascending=False).head(10)
```

Out[59]:

genres_cleaned	Action	Animation	Sci-Fi
primary_name			
Judy Greer	1648.854864	NaN	1648.854864
Derek Connolly	1648.854864	NaN	1648.854864
Colin Trevorrow	1648.854864	NaN	1648.854864
Chris Pratt	1648.854864	NaN	1648.854864
Patrick Crowley	1648.854864	NaN	1648.854864
Amanda Silver	1648.854864	NaN	1648.854864
Rick Jaffa	1648.854864	NaN	1648.854864
Zak Penn	1566.521313	NaN	1566.521313
Seamus McGarvey	1566.521313	NaN	1566.521313
Joss Whedon	1566.521313	NaN	1566.521313

In [60]:
```
# Retrieving top 10 persons in 'Action'
df_producers_likely_alive_genres_piv.sort_values('Action', ascending=False).head(10).to_excel('actio
n.xlsx')
df_producers_likely_alive_genres_piv.sort_values('Action', ascending=False).head(10)
```

Out[60]:

genres_cleaned	Action	Animation	Sci-Fi
primary_name			
Judy Greer	1648.854864	NaN	1648.854864
Chris Pratt	1648.854864	NaN	1648.854864
Rick Jaffa	1648.854864	NaN	1648.854864
Patrick Crowley	1648.854864	NaN	1648.854864
Derek Connolly	1648.854864	NaN	1648.854864
Colin Trevorrow	1648.854864	NaN	1648.854864
Amanda Silver	1648.854864	NaN	1648.854864
Zak Penn	1566.521313	NaN	1566.521313
Scarlett Johansson	1566.521313	NaN	1566.521313
Joss Whedon	1566.521313	NaN	1566.521313

In [61]:
```
# Retrieving top 10 persons in 'Animation'
df_producers_likely_alive_genres_piv.sort_values('Animation', ascending=False).head(10).to_excel('ani
mation.xlsx')
df_producers_likely_alive_genres_piv.sort_values('Animation', ascending=False).head(10)
```

Out[61]:

genres_cleaned	Action	Animation	Sci-Fi
primary_name			
Shane Morris	NaN	1272.469910	NaN
Peter Del Vecho	NaN	1272.469910	NaN
Nicole Paradis Grindle	1242.520711	1242.520711	NaN
Craig T. Nelson	1242.520711	1242.520711	NaN
John Walker	1242.520711	1242.520711	NaN
Tom Hanks	NaN	1068.879522	NaN
Tim Allen	NaN	1068.879522	NaN
John Lasseter	NaN	1068.879522	NaN
Michael Arndt	NaN	1068.879522	NaN
Darla K. Anderson	NaN	1068.879522	NaN

Conclusions

After reviewing and analyzing the data, we can make the following suggestions.

Genres

The genres with the maximum median box offices and return of investments are:

- Action and Adventure;
- Sci-Fi;
- Animation.

The most trending genres are also Sci-Fi, Action, and Animation. The 'News' genre shows the maximum median ROI, but the box office is relatively low.

Release months

According to the maximum box offices by the month of a movie release, the top 3 months are:

- December;
- February;
- April.

Whereas the top worst are:

- August;
- September;
- January.

Producers

The top 10 persons working in either of the three top genres we recommend hiring or consulting with are:

Sci-Fi

Judy Greer	1648.854864	NaN	1648.854864
Derek Connolly	1648.854864	NaN	1648.854864
Colin Trevorrow	1648.854864	NaN	1648.854864
Chris Pratt	1648.854864	NaN	1648.854864
Patrick Crowley	1648.854864	NaN	1648.854864
Amanda Silver	1648.854864	NaN	1648.854864
Rick Jaffa	1648.854864	NaN	1648.854864
Zak Penn	1566.521313	NaN	1566.521313
Seamus McGarvey	1566.521313	NaN	1566.521313
Joss Whedon	1566.521313	NaN	1566.521313

Action

Judy Greer	1648.854864	NaN	1648.854864
Chris Pratt	1648.854864	NaN	1648.854864
Rick Jaffa	1648.854864	NaN	1648.854864
Patrick Crowley	1648.854864	NaN	1648.854864
Derek Connolly	1648.854864	NaN	1648.854864
Colin Trevorrow	1648.854864	NaN	1648.854864
Amanda Silver	1648.854864	NaN	1648.854864
Zak Penn	1566.521313	NaN	1566.521313
Scarlett Johansson	1566.521313	NaN	1566.521313
Joss Whedon	1566.521313	NaN	1566.521313

Animation

Shane Morris	NaN	1272.469910	NaN
Peter Del Vecho	NaN	1272.469910	NaN
Nicole Paradis Grindle	1242.520711	1242.520711	NaN
Craig T. Nelson	1242.520711	1242.520711	NaN
John Walker	1242.520711	1242.520711	NaN
Tom Hanks	NaN	1068.879522	NaN
Tim Allen	NaN	1068.879522	NaN
John Lasseter	NaN	1068.879522	NaN
Michael Arndt	NaN	1068.879522	NaN
Darla K. Anderson	NaN	1068.879522	NaN

Further study

Further study on box offices by region suggested.