Data Analysis on Movie Studios | Lucas Kimball & Eduardo Gonzalez | 9.15.23

Business Problem

We are Consideratum Studios. We've ventured into the movie industry, driven not by financial gain but by our passion for creating exceptional films. Having achieved success in various other ventures, we embark on this cinematic journey with a singular goal – to produce top-tier, award-worthy movies that will stand the test of time.

Our mission is simple: we aspire to become the most decorated studio in the industry. To achieve this, we seek to unravel the secrets behind crafting award-winning films. We're keen to understand what makes a movie truly award-worthy, explore the genres that hold the key to success, and identify the factors that set exceptional movies apart from the rest.

Data Sources

To embark on this exciting quest, we've armed ourselves with a wealth of data from various sources, including:

- Academy Award winners spanning from 1927 to 2015.
- Golden Globe Awards victors from 1944 to 2020.
- Valuable insights from Box Office Mojo.
- IMDb's extensive film database.
- Rotten Tomatoes' critical and audience scores.
- The Movie Database (TMDb) for comprehensive movie information.
- The Numbers, offering insights into movie financials.

Join us on this cinematic exploration as we dive into the data and uncover the ingredients that make movies shine on the silver screen. Let's begin our journey towards creating award-worthy masterpieces!

Import packages and data

In [1]:
```
# Import necessary packages and suppress warnings

import pandas as pd
import sqlite3
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import gzip
```

```
import time
from fuzzywuzzy import fuzz
from fuzzywuzzy import process
warnings.filterwarnings('ignore')
```

Importing the data

In [2]:
```
conn = sqlite3.connect('data/im.db')

movie_gross = pd.read_csv('data/bom.movie_gross.csv.gz')

with gzip.open('data/rt.movie_info.tsv.gz', 'rt', encoding='utf-8') as file:
    movie_info = pd.read_csv(file, delimiter='\t')

with gzip.open('data/rt.reviews.tsv.gz', 'rt') as file:
    reviews = pd.read_csv(file, delimiter='\t')

with gzip.open('data/tmdb.movies.csv.gz') as file:
    tmdb_movies = pd.read_csv(file)

with gzip.open('data/tn.movie_budgets.csv.gz') as file:
    movie_budgets = pd.read_csv(file)

golden_globe_awards = pd.read_csv('data/golden_globe_awards.csv')

academy_awards = pd.read_csv('data/academy_awards.csv')
```

In [3]:
```
#Create a list with the names of the different Datasets to make it easier to co
df_list = ['conn','movie_gross','movie_info','reviews','tmdb_movies','movie_bud
```

Exploring the different Databases

Exploring IMDb

In [4]:
```
pd.read_sql("""SELECT name, sql FROM sqlite_master WHERE type='table';""",conn)
```

Out[4]:

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

In [5]:
```
pd.read_sql("""SELECT * FROM movie_basics LIMIT 2""",conn)
```

Out[5]:

	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 [6]:
```
pd.read_sql("""SELECT * FROM directors LIMIT 2""",conn)
```

Out[6]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0462036	nm1940585

In [7]:
```
pd.read_sql("""SELECT * FROM known_for LIMIT 2""",conn)
```

Out[7]:

	person_id	movie_id
0	nm0061671	tt0837562
1	nm0061671	tt2398241

In [8]:
```
pd.read_sql("""SELECT * FROM movie_akas LIMIT 2""",conn)
```

Out[8]:

	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 [9]:
```
pd.read_sql("""SELECT * FROM movie_ratings LIMIT 2""",conn)
```

Out[9]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559

In [10]:
```
pd.read_sql("""SELECT * FROM persons LIMIT 2""",conn)
```

Out[10]:

	person_id	primary_name	birth_year	death_year	primary_profess
0	nm0061671	Mary Ellen Bauder	None	None	miscellaneous,production_manager,produ
1	nm0061865	Joseph Bauer	None	None	composer,music_department,sound_departm

In [11]:
```
pd.read_sql("""SELECT * FROM principals LIMIT 2""",conn)
```

Out[11]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]
1	tt0111414	2	nm0398271	director	None	None

In [12]:
```
pd.read_sql("""SELECT * FROM writers LIMIT 2""",conn)
```

Out[12]:

	movie_id	person_id
0	tt0285252	nm0899854
1	tt0438973	nm0175726

Based on this preliminary exploration, we can evaluate the content of every table within thew database, creating tin that way one solely chart that will have all we need for further exploration

We're going to evaluate what makes a movie win awards, so let's dive in what we need from each table.

movie_basics: We need the name of the movie, the runtime in minutes thast it playead and the genres, we decided to keep both the primary and the original name, to evaluate later which one is easire to pair the other dataframes with

directors: We're going to add the director of each movie.

known_for: We don't find any relevant information to add.

movie_akas: We don;t find any relevant information to add.

movie_ratings: We might want to see if there's any correlation in the awards and the rating and votes they get.

persons: We need the name of the directors of our movies, We also want to know if the person is still alive

principal: Having found above the relevant information about the directors, we don't need the information about them.

writers: We don't find any relevant information to add.

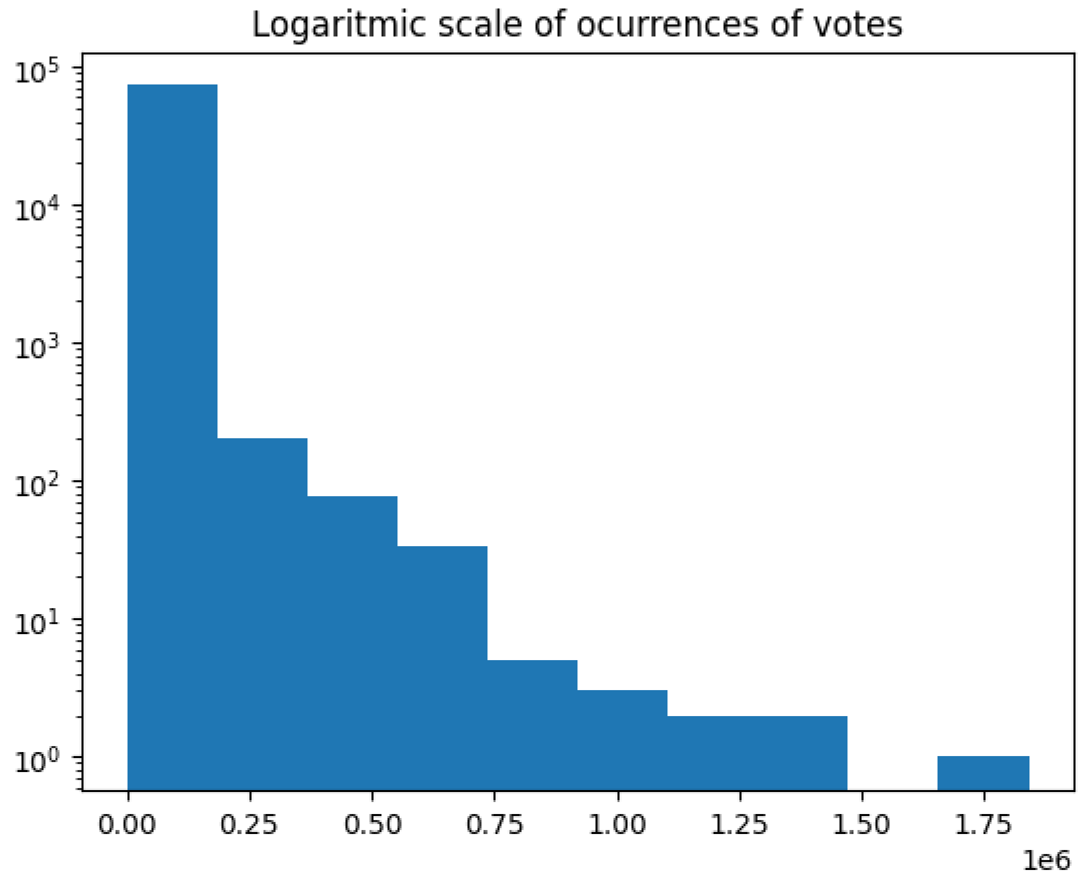
Movie_ratings

We're evaluating if the amount of votes will be a necessary value to keep, we plot an histogram on a logaritmic scale.

In [13]:
```
votes = pd.read_sql("""SELECT * FROM movie_ratings """,conn)['numvotes']
plt.hist(votes, log=True);
plt.title('Logaritmic scale of ocurrences of votes');
```

```
print(f"This Column has a mean of {round(votes.mean(),2)} a median of {votes.me
standard deviation of {round(votes.std(),2)}, is not worth to keep, is far fron
```

```
This Column has a mean of 3523.66 a median of 49.0 and a standard deviation of
30294.02, is not worth to keep, is far from normally distributed
```

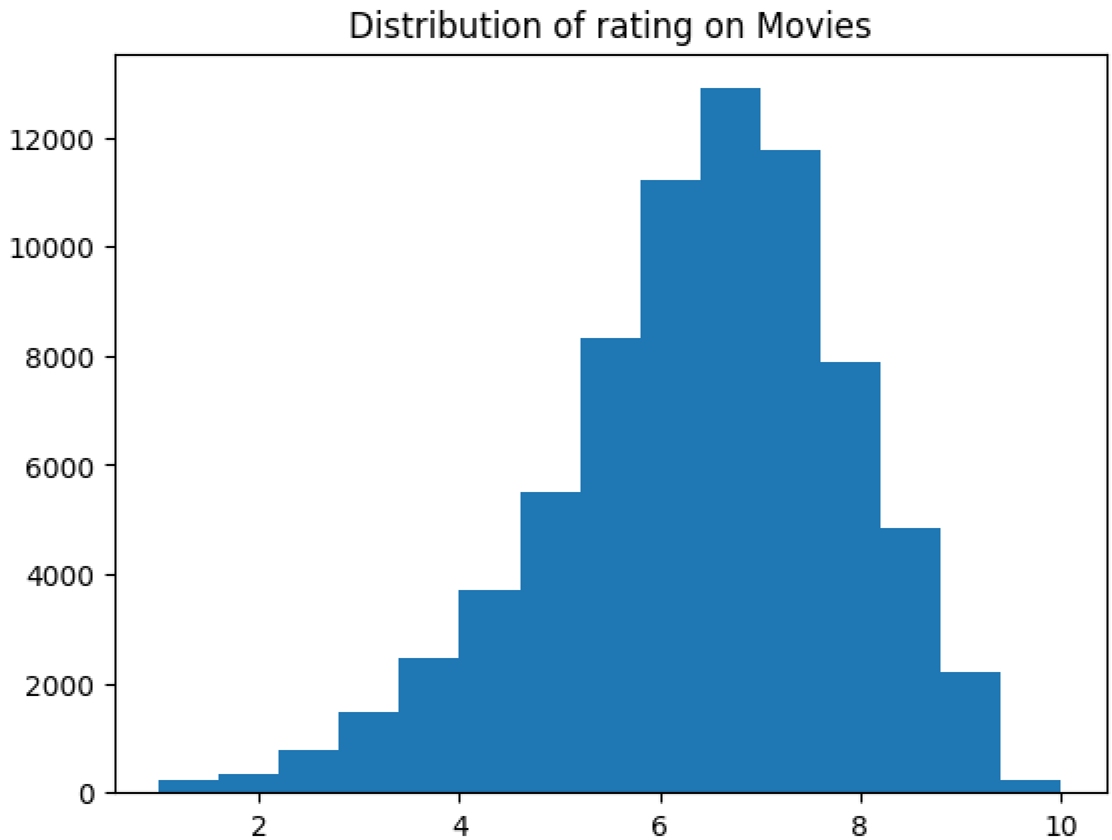


We had to do a logaritmic adjust to evaluate the distribution, because of the big ocurrence of outliers. We decided tro discard this.

Average Rating

Evaluating the distribution.

In [14]:
```
#Plotting the distribution of ratings
rating = pd.read_sql("""SELECT * FROM movie_ratings""",conn)['averagerating']
plt.hist(rating, bins=15);
plt.title('Distribution of rating on Movies');
```



We notice that the average rating has a distribution similar to a normal one, slightly skewed, we're going to keep it for further analysis.

Creating the Query to extract the desired DataFrame

In [15]:
```
#Creating a Query for this database to Extract the Desired Data From it

imdb = pd.read_sql("""
SELECT primary_title, original_title, start_year, runtime_minutes, primary_name
FROM movie_basics
LEFT JOIN directors USING(movie_id)
LEFT JOIN persons USING(person_id)
LEFT JOIN movie_ratings USING(movie_id)
GROUP BY movie_id
""",conn)
```

Genres

As we notice above, the genres column has more than one value per movie, that'd make it hard to analyze going forward. We decided instead to created columns for the different genres and assign a binary value in case the movie falls into that specific genre.

In [16]:
```
#We make sure that every row has a value in the genre column.
imdb = imdb.drop_duplicates(subset=['primary_title'])
imdb['genres'].fillna('No Genre', inplace=True)
# Split the 'genres' column into a list of genres and then explode them into se
imdb['genres'] = imdb['genres'].str.split(',')
```

```
imdb = imdb.explode('genres')
# Create binary indicators for each genre
for genre in imdb['genres'].dropna().unique():
    imdb[genre] = imdb['genres'].str.contains(genre).astype(int)
# Drop the original genres column
imdb.drop(columns=['genres'], inplace=True)
```

That made what we needed, but now we have as many rows per movie as genres they're in, we need to consolidate them

In [17]:
```
# Separate what are "genres column" from "non genres column"
non_genre_columns = ['primary_title', 'original_title','start_year','runtime_mi
genre_columns = imdb.columns.difference(non_genre_columns)
# Group by 'primary_title' and sum the genre columns
genres_consolidated = imdb.groupby('primary_title', as_index=False)[genre_colur

#Merging all the columns together
imdb = pd.merge(imdb[non_genre_columns], genres_consolidated, on='primary_title
#Elimintating duplicates based on primary_title
imdb = imdb.drop_duplicates(subset=['primary_title'])
imdb.reset_index(drop=True, inplace=True)
```

Null values

Different methods were used to fill the null values in our database.

The most important to keep in mind is the averagerating, filled by the median of the values in the column.

In [18]:
```
#If we don't have the original_title, we'll just keep the primary_title.
imdb['original_title'].fillna(imdb['primary_title'], inplace=True)
#For runtime_minutes and death_year, we'll use 0 as a placeholder value
imdb['runtime_minutes'].fillna(0, inplace=True)
imdb['death_year'].fillna(0, inplace=True)
#For directors, we'll replace with 'Unknown'
imdb['director_name'].fillna('Unknown',inplace=True)
#For the averagerating we decided to fill the null values with the median.
imdb['averagerating'].fillna(imdb['averagerating'].median(),inplace=True)
```

Exploring Resulting Data

In [19]:
```
imdb.head()
```

Out[19]:

	primary_title	original_title	start_year	runtime_minutes	director_name	death_year	averag
0	Sunghursh	Sunghursh	2013	175.0	Harnam Singh Rawail	2004.0	
1	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Mani Kaul	2011.0	
2	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Orson Welles	1985.0	
3	Sabse Bada Sukh	Sabse Bada Sukh	2018	0.0	Hrishikesh Mukherjee	2006.0	
4	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Raoul Ruiz	2011.0	

5 rows × 35 columns

In [20]:

```
imdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 136071 entries, 0 to 136070
Data columns (total 35 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   primary_title    136071 non-null  object 
 1   original_title   136071 non-null  object 
 2   start_year       136071 non-null  int64  
 3   runtime_minutes  136071 non-null  float64
 4   director_name    136071 non-null  object 
 5   death_year       136071 non-null  float64
 6   averagerating    136071 non-null  float64
 7   Action           136071 non-null  int32  
 8   Adult            136071 non-null  int32  
 9   Adventure        136071 non-null  int32  
 10  Animation        136071 non-null  int32  
 11  Biography        136071 non-null  int32  
 12  Comedy           136071 non-null  int32  
 13  Crime            136071 non-null  int32  
 14  Documentary      136071 non-null  int32  
 15  Drama            136071 non-null  int32  
 16  Family           136071 non-null  int32  
 17  Fantasy          136071 non-null  int32  
 18  Game-Show        136071 non-null  int32  
 19  History          136071 non-null  int32  
 20  Horror           136071 non-null  int32  
 21  Music            136071 non-null  int32  
 22  Musical          136071 non-null  int32  
 23  Mystery          136071 non-null  int32  
 24  News             136071 non-null  int32  
 25  No Genre         136071 non-null  int32  
 26  Reality-TV       136071 non-null  int32  
 27  Romance          136071 non-null  int32  
 28  Sci-Fi           136071 non-null  int32  
 29  Short            136071 non-null  int32  
 30  Sport            136071 non-null  int32  
 31  Talk-Show        136071 non-null  int32  
 32  Thriller         136071 non-null  int32  
 33  War              136071 non-null  int32  
 34  Western          136071 non-null  int32  
dtypes: float64(3), int32(28), int64(1), object(3)
memory usage: 21.8+ MB
```

In [21]:
```
imdb.describe()
```

Out[21]:

	start_year	runtime_minutes	death_year	averagerating	Action	
count	136071.000000	136071.000000	136071.000000	136071.000000	136071.000000	136071.0
mean	2014.561413	67.518325	12.702317	6.418684	0.070037	0.0
std	2.732568	156.417561	159.460165	1.055786	0.255210	0.0
min	2010.000000	0.000000	0.000000	1.000000	0.000000	0.0
25%	2012.000000	37.000000	0.000000	6.500000	0.000000	0.0
50%	2015.000000	79.000000	0.000000	6.500000	0.000000	0.0
75%	2017.000000	95.000000	0.000000	6.500000	0.000000	0.0
max	2027.000000	51420.000000	2019.000000	10.000000	1.000000	1.0

8 rows × 32 columns

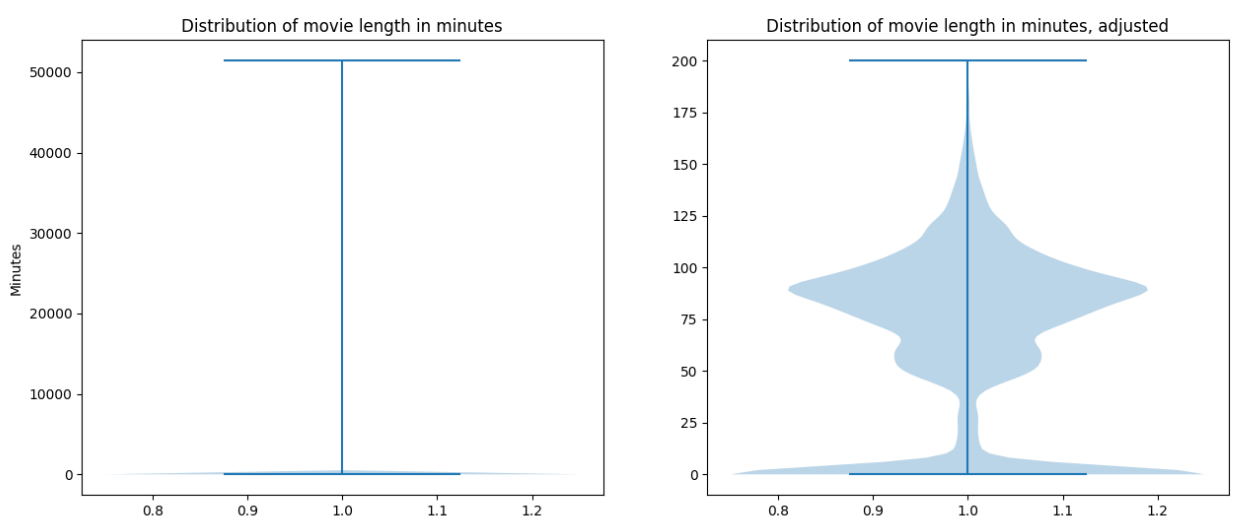
Runtime

We can advert that there are some outliers that won't allow us to visualize the complete data distribution.

We created a threshold to be able to visualize the data properly without the big outliers.

In [22]:

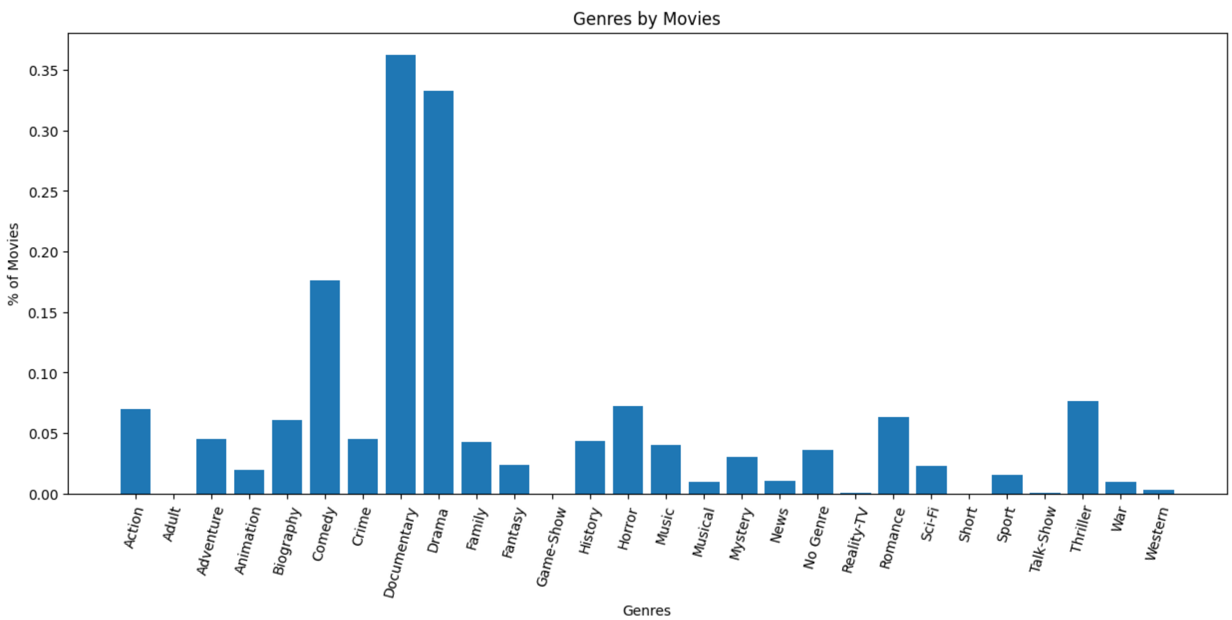
```
fig, (ax1,ax2) = plt.subplots(ncols=2, figsize=(15,6))
ax1.violinplot(imdb['runtime_minutes'])
ax1.set_title('Distribution of movie length in minutes')
ax1.set_ylabel('Minutes');

threshold = 200  # Adjust this threshold based on your data
runtime_with_threshold = [x for x in imdb['runtime_minutes'] if x <= threshold]
ax2.violinplot(runtime_with_threshold)
ax2.set_title('Distribution of movie length in minutes, adjusted');
```



What genres the movies are?

Now we continue to analyze the dataset by vieweing the number of genres ocurrences in the dataset.

In [23]:
```
#Creating a category_columns list
category_columns = ['Action', 'Adult',
        'Adventure', 'Animation', 'Biography', 'Comedy', 'Crime', 'Documentary',
        'Drama', 'Family', 'Fantasy', 'Game-Show', 'History', 'Horror', 'Music',
        'Musical', 'Mystery', 'News', 'No Genre', 'Reality-TV', 'Romance',
        'Sci-Fi', 'Short', 'Sport', 'Talk-Show', 'Thriller', 'War', 'Western']
# Adding the total ocurrence of genre in the dataset
columns_sums = imdb[category_columns].sum()
fig, ax = plt.subplots(figsize=(15,6))

#Plotting the sums divided by the length of the dataset to get the % of ocurre
plt.bar(columns_sums.index, columns_sums/len(imdb))
plt.xticks(rotation=75)
plt.title('Genres by Movies')
plt.xlabel('Genres')
plt.ylabel('% of Movies');
```



As we can see there's a big % of movies that falls in either documentary or drama. We need to keep in mind that some movies might fall into more than once category.

Movie_gross

Since we're going to work only with US based awards, we're going to focus on domestic gross rather than foreign_gross.

We drop all the columns and rows that we don't need or are irrelevant for our analysis.

In [24]:
```
#Dropping unnecessary columns and rows
movie_gross.drop(columns=['studio','year','foreign_gross'],inplace=True)
movie_gross.dropna(axis=0, inplace=True)
```

In [25]:
```
movie_gross.describe()
```

Out[25]:

	domestic_gross
count	3.359000e+03
mean	2.874585e+07
std	6.698250e+07
min	1.000000e+02
25%	1.200000e+05
50%	1.400000e+06
75%	2.790000e+07
max	9.367000e+08

TMDB movies

In [26]:
```
tmdb_movies.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
```

In [27]:
```
tmdb_movies.head()
```

Out[27]:

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

In [28]:

```
#Keeping just the release year instead of the full date
tmdb_movies['release_year'] = tmdb_movies['release_date'].str[:4]
# drop unnecessary columns
tmdb_movies.drop(columns=['Unnamed: 0','original_language','popularity','vote_a
```

Genre unification

In this dataframe, the Genre column was identified just as ids. Founding online a dictionary with the corresponding Genre by map. We're able to replace the numbers by the actual genre name.

After doing this, we found the same issue that on our IMBD database, having the genres combined instead of separated. Therefore, we create a new set of columns for the genres with binary values if the movie belongs to it

In [29]:

```
#Creating the genre dictionary
genre_mapping = {12: 'Adventure',
                 14: 'Fantasy',
                 16: 'Animation',
                 18: 'Drama',
                 27: 'Horror',
                 28: 'Action',
                 35: 'Comedy',
                 36: 'History',
                 37: 'Western',
                 53: 'Thriller',
                 80: 'Crime',
                 99: 'Documentary',
                 9648: 'Mystery',
                 10402: 'Music',
                 10749: 'Romance',
                 10751: 'Family',
                 10752: 'War',
```

```
                 10770: 'TV Movie',
                 878: 'Science Fiction'}

#Creating a function that will substitute the number with the corresponding ge

def map_genre_ids(ids_str):
    ids = eval(ids_str)
    genres = [genre_mapping.get(id, 'Unknown') for id in ids]
    return ','.join(genres)
# Applying function to my data
tmdb_movies['genres'] = tmdb_movies['genre_ids'].apply(map_genre_ids)
tmdb_movies.drop(columns='genre_ids',inplace=True)
#Everything that doesn't have a genre, substitute with 'Unknown'.
tmdb_movies.loc[tmdb_movies['genres'] == '', 'genres'] = 'Unknown'
```

In [30]:
```
#We make sure that every row has a value in the genre column.
tmdb_movies = tmdb_movies.drop_duplicates(subset=['id'])

# Split the 'genres' column into a list of genres and then explode them into se
tmdb_movies['genres'] = tmdb_movies['genres'].str.split(',')

tmdb_movies = tmdb_movies.explode('genres')

# Create binary indicators for each genre
for genre in tmdb_movies['genres'].dropna().unique():
    tmdb_movies[genre] = tmdb_movies['genres'].str.contains(genre).astype(int)
# Drop the original genres column
tmdb_movies.drop(columns=['genres'], inplace=True)

# Separate what are "genres column" from "non genres column"
non_genre_columns = ['id','original_title','title','release_year']
genre_columns = tmdb_movies.columns.difference(non_genre_columns)
# Group by 'primary_title' and sum the genre columns
genres_consolidated = tmdb_movies.groupby('id', as_index=False)[genre_columns].

#Merging all the columns together
tmdb_movies = pd.merge(tmdb_movies[non_genre_columns], genres_consolidated, on=
#Elimintating duplicates based on primary_title
tmdb_movies = tmdb_movies.drop_duplicates(subset=['id'])
tmdb_movies.reset_index(drop=True, inplace=True)
```

In [31]:
```
tmdb_movies['release_year'].value_counts().sort_index(ascending=False)
```

Out[31]:
```
release_year
2020       1
2019      63
2018    2496
2017    2921
2016    2970
        ...
1946       1
1939       1
1936       1
1933       1
1930       1
Name: count, Length: 66, dtype: int64
```

Movie_budgets

In [32]:
```
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   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
```

Adjusting type

As we can see in the information about the movie_budgets data, we have the production_budget, the domestic_Gross and the worldwide_gross as object instead of integers.

We remove some of the characters that will create an issue by transforming the datatype, and afterwards we'll create two new columns to be able to visualize the domestic gross to budget ratio.

In [33]:
```
# Converting columns from string to numeric data types
columns_to_convert = ['worldwide_gross', 'production_budget', 'domestic_gross']
for col in columns_to_convert:
    movie_budgets[col] = pd.to_numeric(movie_budgets[col].str.replace('[$,]',
#creating a new column for worldwide_gross/production_budget measuring the amou
movie_budgets['worldwide_gross/production_budget'] = movie_budgets['worldwide_g
#doing the same but for domestic gross
movie_budgets['domestic_gross/production_budget'] = movie_budgets['domestic_grc
#checking that it worked
movie_budgets.head(1)
```

Out[33]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross	worldwide_g
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279	

Awards Databases

Since we're trying to figure out which movies provide the most awards, we got access to a Database of the golge globe Awards from 1944 to 2020.

We'll try to explore the data to determine which factors make a movie worth of awards

Golden Globes

Exploring the data

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

Out[34]:

	year_film	year_award	ceremony	category	nominee	film	win
0	1943	1944	1	Best Performance by an Actress in a Supporting...	Katina Paxinou	For Whom The Bell Tolls	True
1	1943	1944	1	Best Performance by an Actor in a Supporting R...	Akim Tamiroff	For Whom The Bell Tolls	True
2	1943	1944	1	Best Director - Motion Picture	Henry King	The Song Of Bernadette	True
3	1943	1944	1	Picture	The Song Of Bernadette	NaN	True
4	1943	1944	1	Actress In A Leading Role	Jennifer Jones	The Song Of Bernadette	True

In [35]:
```
golden_globe_awards.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7991 entries, 0 to 7990
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   year_film   7991 non-null   int64 
 1   year_award  7991 non-null   int64 
 2   ceremony    7991 non-null   int64 
 3   category    7991 non-null   object
 4   nominee     7991 non-null   object
 5   film        6191 non-null   object
 6   win         7991 non-null   bool  
dtypes: bool(1), int64(3), object(3)
memory usage: 382.5+ KB
```

Exploring and cleaning

We're going to use information about the winners, so we don't need to keep the people that was just nomineed.

In the exploration, we noticed that when the movie is the "nominee", the 'film' column gets a null value, so in those cases we'll copy the name from nominee into film.

We also remove unnecessary columns.

In [36]:
```
#Keeping only the winners, and dropping unnecessary columns
#When the nominee was the movie itself instead of an specific Crew member, the
# Having the Name of the film in the 'nominee' column. We replace accordingly
golden_globe_awards = golden_globe_awards.loc[golden_globe_awards['win'] == Tru
golden_globe_awards.drop(columns=['year_award','ceremony','win'],inplace=True)
golden_globe_awards['film'] = golden_globe_awards['film'].fillna(golden_globe_a
```

In [37]:
```
golden_globe_awards['category'].value_counts()
```

Out[37]:
```
category
Best Performance by an Actress in a Supporting Role in any Motion Picture    7
9
Best Director - Motion Picture                                               7
7
Best Performance by an Actor in a Supporting Role in any Motion Picture      7
7
Best Performance by an Actress in a Motion Picture - Drama                   7
1
Best Performance by an Actor in a Motion Picture - Drama                     7
1

..
Actress In A Supporting Role - Television Series
1
Actor In A Supporting Role - Television Series
1
Actor In A Television Series - Musical Or Comedy
1
Actor In A Television Series - Drama
1
Television Producer/Director
1
Name: count, Length: 72, dtype: int64
```

Categories

By evaluating the categories for the award, we decided to remove everything related to television shows (Since we're examining movies), and foreign awards, since our analysis is US based.

Also, we're consolidate the categories to make it easier to analyze.

In [38]:
```
#Removing awards not related to US movies
golden_globe_awards = golden_globe_awards[~golden_globe_awards['category'].str.
golden_globe_awards = golden_globe_awards[~golden_globe_awards['category'].str.
```

In [39]:
```
#Creating a category cleaning function
def cat_cleaner(char, cat):
    for i in char:
       golden_globe_awards.loc[golden_globe_awards['category'].str.contains(i,c

#Creating a list that includes certain keywords that give us hints on the cate
soundtrack = ['song','music']
production = ['cinematography','screenplay','song','use of color']
best_actor = ['actor','performance']
directing = ['directing','director']
best_movie = ['picture']
best_actress = ['actress']

#Applying the category function

cat_cleaner(best_actor, 'Best Actor')
cat_cleaner(best_movie, 'Best Picture')
cat_cleaner(soundtrack, 'Soundtrack')
```

```
cat_cleaner(production, 'Production')
cat_cleaner(best_actress, 'Best Actress')
cat_cleaner(directing, 'Best Director')

#Every prize that won't fall in the categories mentioned above will be marked a
golden_globe_awards.loc[((golden_globe_awards['category'] != 'Best Actor') & (g
                         (golden_globe_awards['category'] != 'Soundtrack') & (g
                        (golden_globe_awards['category'] != 'Best Actress') & (
                          'category'] = 'Others'
```

Re-exploring the data

In [40]:
```
golden_globe_awards['category'].value_counts()
```

Out[40]:
```
category
Best Actor      486
Best Picture    429
Others           97
Best Actress     67
Soundtrack       23
Production       14
Name: count, dtype: int64
```

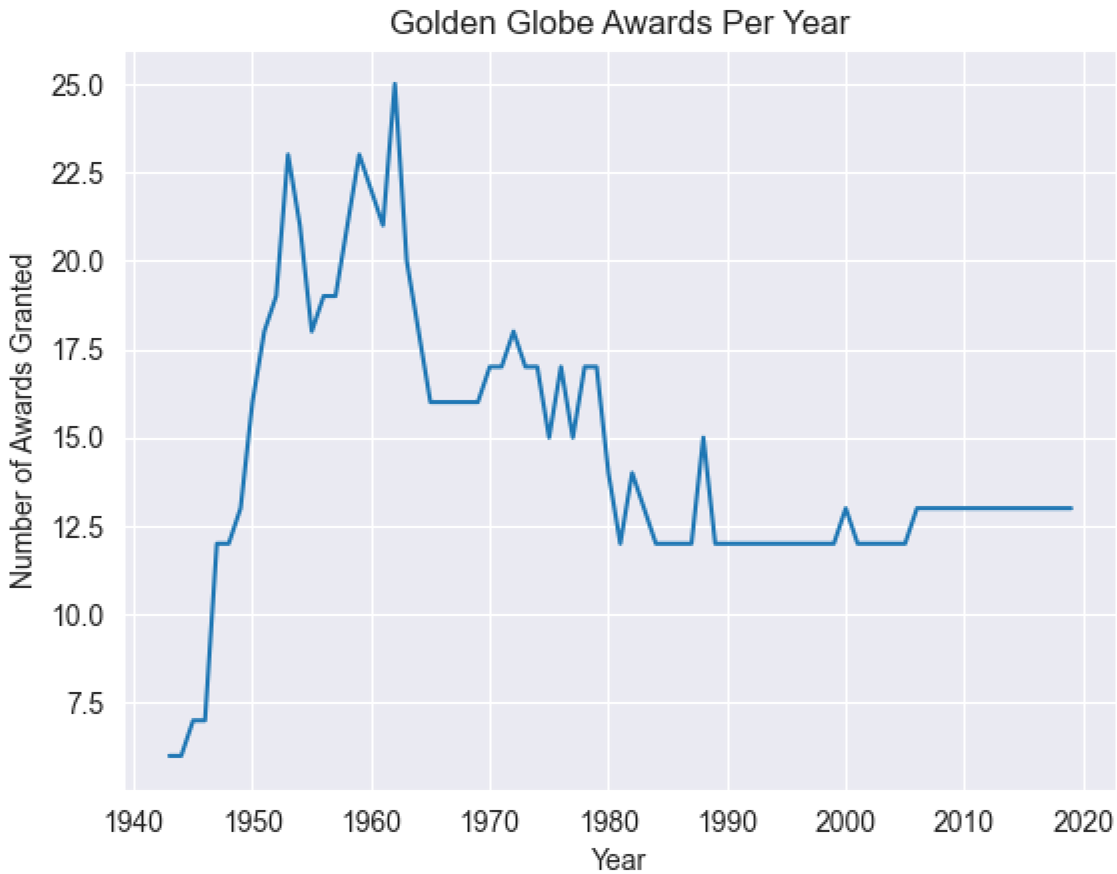
In [41]:
```
golden_globe_awards.head()
```

Out[41]:

	year_film	category	nominee	film
0	1943	Best Actor	Katina Paxinou	For Whom The Bell Tolls
1	1943	Best Actor	Akim Tamiroff	For Whom The Bell Tolls
2	1943	Best Picture	Henry King	The Song Of Bernadette
3	1943	Best Picture	The Song Of Bernadette	The Song Of Bernadette
4	1943	Best Actress	Jennifer Jones	The Song Of Bernadette

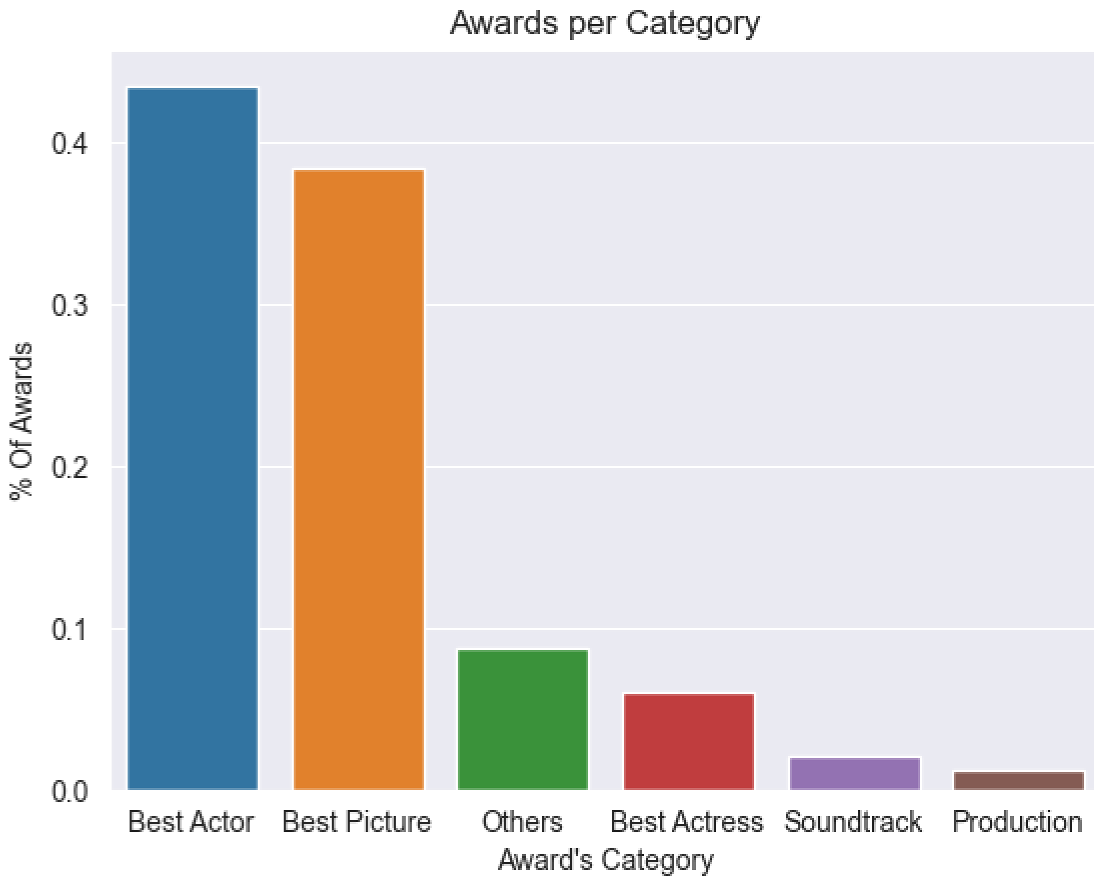
In [42]:
```
yearly = golden_globe_awards.groupby('year_film').count()
```

In [43]:
```
sns.set_style('darkgrid')
sns.lineplot(x = yearly.index, y = yearly['category'])
plt.title('Golden Globe Awards Per Year')
plt.xlabel('Year')
plt.ylabel('Number of Awards Granted');
```



We can see based on the above visualization, that the amount of awards per year has decreasedin comparison with their peak in the sixties, having 'plateau' aroun 1990, where the amount of awards has stayed the same.

In [44]:
```
golden_globe_categories = golden_globe_awards['category'].value_counts(normaliz
sns.barplot(x = golden_globe_categories.index, y = golden_globe_categories)
plt.title('Awards per Category')
plt.xlabel("Award's Category")
plt.ylabel('% Of Awards');
```



In the above barplot, we can see how Best Actor and Best Picture are a big part of the complete set of awards given by the Golden globes over the years

Creating Pivot tables Grouping nominees and films for the Golden Globes

For further analysis, we're creating tables grouped by films and nominees, allowing us to better explore the data.

In [45]:
```
#Creating a Table showing the golden globe awards grouped by film name.
golden_globe_by_film = golden_globe_awards.groupby('film').agg({'year_film': 'f
golden_globe_by_film.columns = ['Name', 'Year', 'Number Of Awards']
#Creating a Table showing the golden globe awards grouped by nominees.
golden_globe_by_nominee = golden_globe_awards.groupby('nominee').agg({'year_fil
golden_globe_by_nominee.columns = ['Nominee', 'Year', 'Number Of Awards']
```

Name matcher

With the new tables that we just created, we can merge them with the IMDb table, to get more insight into the movies that won awards.

Unfortunately, sometimes the names are not exactly the same in different tables, that's why we created a 'name_matcher' function, that allows us to create a similarity score between some names, and if that score is equal or above a threshold, cretaes a tuple with both names and the similarity score, to allow us later to merge them together based on it.

In [46]:
```
#Creating name_matcher function
def name_matcher(list1, list2, threshold):
    pairs = []
    for name1 in list1:
        for name2 in list2:
            similarity_score = fuzz.ratio(name1,name2)
            if similarity_score >= threshold:
                pairs.append((name1, name2, similarity_score))
    return pairs
```

Now that we have the function, we remove spaces and set everything lowercase to make it easiear to match

In [47]:
```
# Remove spaces from movie names and convert to lowercase for easier matching
golden_globe_by_film['Name_formatted'] = golden_globe_by_film['Name'].str.repla
imdb['primary_title_cleaned'] = imdb['primary_title'].str.replace(' ', '').str.
```

In [48]:
```
#Assigning the variable 'pairs' to the name_matcher function, using the names u
# Setting up a threshold of 90
pairs = name_matcher(golden_globe_by_film['Name_formatted'],imdb['primary_title

# Create a DataFrame from the list of matching pairs
pairs_GG_by_film = pd.DataFrame(pairs, columns=[ 'Golden_Globe_name','imdb_name

# Merge the two datasets using the paired Dataframe as a reference for the keys
pairs_GG_by_film = pd.merge(imdb, pairs_GG_by_film, left_on='primary_title_clea
merged_data_GG_by_film = pd.merge(pairs_GG_by_film, golden_globe_by_film, left_
merged_data_GG_by_film.head()
```

Out[48]:

	primary_title	original_title	start_year	runtime_minutes	director_name	death_year	averag
0	Toy Story 3	Toy Story 3	2010	103.0	Lee Unkrich	0.0	
1	Lincoln	Lincoln	2012	150.0	Steven Spielberg	0.0	
2	Life of Pi	Life of Pi	2012	127.0	Ang Lee	0.0	
3	Dallas Buyers Club	Dallas Buyers Club	2013	117.0	Jean-Marc Vallée	0.0	
4	Conan the Barbarian	Conan the Barbarian	2011	113.0	Marcus Nispel	0.0	

5 rows × 43 columns

During the merge, is possible that we see two movies that has the same, or very similar name, but being two actual different movies, in this case we're using the year as a reference. But since there's a chance that a movie get an award the year after it was released, we creates another column with the magnitude of difference between the year of the awards and the year it was released.

Everything above two years is discarded.

In [49]:

```
#creating a new column called year_difference, which will be used for cleaning
merged_data_GG_by_film['year_difference'] = abs(merged_data_GG_by_film['start_y
merged_data_GG_by_film = merged_data_GG_by_film[merged_data_GG_by_film['year_di

merged_data_GG_by_film.head()
```

Out[49]:

	primary_title	original_title	start_year	runtime_minutes	director_name	death_year	averag
0	Toy Story 3	Toy Story 3	2010	103.0	Lee Unkrich	0.0	
1	Lincoln	Lincoln	2012	150.0	Steven Spielberg	0.0	
2	Life of Pi	Life of Pi	2012	127.0	Ang Lee	0.0	
3	Dallas Buyers Club	Dallas Buyers Club	2013	117.0	Jean-Marc Vallée	0.0	
6	How to Train Your Dragon 2	How to Train Your Dragon 2	2014	102.0	Dean DeBlois	0.0	

5 rows × 44 columns

We prepared to do the same with the data of the golden globes by nominees. This is because we might find ocurrences in which the name of the movie was actually in the nominee column.

To make sure that we're keeping all of them, we're merging the imdb database with both grouped tables (by film and by nominee), afterwards we'll concatenate them by rows, and eliminate duplicates, so we can have only one ocurrence per movie.

In [50]:
```
# Remove characters and convert to lowercase using chaining methods
golden_globe_by_nominee['Nominee_formatted'] = (
    golden_globe_by_nominee['Nominee']
    .str.replace(',', '')
    .str.replace(' ', '')
    .str.replace('"', '')
    .str.lower()
)

# Remove characters and convert to lowercase using chaining methods
imdb['primary_title_cleaned'] = (
    imdb['primary_title']
    .str.replace(',', '')
    .str.replace(' ', '')
    .str.replace('"', '')
    .str.lower()
)
```

In [51]:
```
#Applying the name_matcher function to the new datasets we want to merge.
pairs2 = name_matcher(golden_globe_by_nominee['Nominee_formatted'], imdb['prima

# Create a DataFrame from the list of matching pairs
pairs_GG_by_nominee = pd.DataFrame(pairs2, columns=[ 'Golden_Globe_nominee','im


# Merge the two datasets using the paired Dataframe as a reference for the keys
pairs_GG_by_nominee = pd.merge(imdb, pairs_GG_by_nominee, left_on='primary_titl
merged_data_GG_by_nominee = pd.merge(pairs_GG_by_nominee, golden_globe_by_nomin

#creating a new column called year_difference, which will be used for cleaning
merged_data_GG_by_nominee['year_difference'] = abs(merged_data_GG_by_nominee['s
merged_data_GG_by_nominee = merged_data_GG_by_nominee[merged_data_GG_by_nominee

merged_data_GG_by_nominee.head()
```

Out[51]:

	primary_title	original_title	start_year	runtime_minutes	director_name	death_year	averag
0	Toy Story 3	Toy Story 3	2010	103.0	Lee Unkrich	0.0	
2	How to Train Your Dragon 2	How to Train Your Dragon 2	2014	102.0	Dean DeBlois	0.0	
11	Argo	Argo	2012	120.0	Ben Affleck	0.0	
13	Coco	Coco	2018	0.0	Unknown	0.0	
14	Boyhood	Boyhood	2014	165.0	Richard Linklater	0.0	

5 rows × 44 columns

In [52]:
```
# Concatenate the dfs
Golden_Globes_Winners = pd.concat([merged_data_GG_by_film, merged_data_GG_by_no
#reset the index
Golden_Globes_Winners.reset_index(drop=True, inplace=True)
```

```
Golden_Globes_Winners.head()
```

Out[52]:

	primary_title	original_title	start_year	runtime_minutes	director_name	death_year	averag
0	Toy Story 3	Toy Story 3	2010	103.0	Lee Unkrich	0.0	
1	Lincoln	Lincoln	2012	150.0	Steven Spielberg	0.0	
2	Life of Pi	Life of Pi	2012	127.0	Ang Lee	0.0	
3	Dallas Buyers Club	Dallas Buyers Club	2013	117.0	Jean-Marc Vallée	0.0	
4	How to Train Your Dragon 2	How to Train Your Dragon 2	2014	102.0	Dean DeBlois	0.0	

5 rows × 47 columns

In [53]:
```
Golden_Globes_Winners.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85 entries, 0 to 84
Data columns (total 47 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   primary_title         85 non-null     object 
 1   original_title        85 non-null     object 
 2   start_year            85 non-null     int64  
 3   runtime_minutes       85 non-null     float64
 4   director_name         85 non-null     object 
 5   death_year            85 non-null     float64
 6   averagerating         85 non-null     float64
 7   Action                85 non-null     int32  
 8   Adult                 85 non-null     int32  
 9   Adventure             85 non-null     int32  
 10  Animation             85 non-null     int32  
 11  Biography             85 non-null     int32  
 12  Comedy                85 non-null     int32  
 13  Crime                 85 non-null     int32  
 14  Documentary           85 non-null     int32  
 15  Drama                 85 non-null     int32  
 16  Family                85 non-null     int32  
 17  Fantasy               85 non-null     int32  
 18  Game-Show             85 non-null     int32  
 19  History               85 non-null     int32  
 20  Horror                85 non-null     int32  
 21  Music                 85 non-null     int32  
 22  Musical               85 non-null     int32  
 23  Mystery               85 non-null     int32  
 24  News                  85 non-null     int32  
 25  No Genre              85 non-null     int32  
 26  Reality-TV            85 non-null     int32  
 27  Romance               85 non-null     int32  
 28  Sci-Fi                85 non-null     int32  
 29  Short                 85 non-null     int32  
 30  Sport                 85 non-null     int32  
 31  Talk-Show             85 non-null     int32  
 32  Thriller              85 non-null     int32  
 33  War                   85 non-null     int32  
 34  Western               85 non-null     int32  
 35  primary_title_cleaned 85 non-null     object 
 36  Golden_Globe_name     63 non-null     object 
 37  imdb_name             85 non-null     object 
 38  similarity_score      85 non-null     int64  
 39  Name                  63 non-null     object 
 40  Year                  85 non-null     int64  
 41  Number Of Awards      85 non-null     int64  
 42  Name_formatted        63 non-null     object 
 43  year_difference       85 non-null     int64  
 44  Golden_Globe_nominee  22 non-null     object 
 45  Nominee               22 non-null     object 
 46  Nominee_formatted     22 non-null     object 
dtypes: float64(3), int32(28), int64(5), object(11)
memory usage: 22.0+ KB
```

In [54]:

```
#Eliminating unnecessary columns
Golden_Globes_Winners.drop(
    ['start_year',
     'primary_title_cleaned',
     'year_difference',
```

```
    'Nominee_formatted',
    'Name_formatted',
    'Name',
    'death_year',
    'original_title',
    'Golden_Globe_nominee',
    'imdb_name',
    'similarity_score',
    'Nominee',
    'Golden_Globe_name'
    ], axis=1, inplace=True)

Golden_Globes_Winners.drop_duplicates(inplace=True)
Golden_Globes_Winners.head()
```

Out[54]:

	primary_title	runtime_minutes	director_name	averagerating	Action	Adult	Adventure	Ani
0	Toy Story 3	103.0	Lee Unkrich	8.3	0	0	1	
1	Lincoln	150.0	Steven Spielberg	7.4	0	0	0	
2	Life of Pi	127.0	Ang Lee	7.9	0	0	1	
3	Dallas Buyers Club	117.0	Jean-Marc Vallée	8.0	0	0	0	
4	How to Train Your Dragon 2	102.0	Dean DeBlois	7.8	1	0	1	

5 rows × 34 columns

Academy Awards

Exploring the data

In [55]:
```
academy_awards.head()
```

Out[55]:

	Year	Ceremony	Award	Winner	Name	Film
0	1927/1928	1	Actor	NaN	Richard Barthelmess	The Noose
1	1927/1928	1	Actor	1.0	Emil Jannings	The Last Command
2	1927/1928	1	Actress	NaN	Louise Dresser	A Ship Comes In
3	1927/1928	1	Actress	1.0	Janet Gaynor	7th Heaven
4	1927/1928	1	Actress	NaN	Gloria Swanson	Sadie Thompson

In [56]:
```
academy_awards.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9964 entries, 0 to 9963
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Year      9964 non-null   object 
 1   Ceremony  9964 non-null   int64  
 2   Award     9964 non-null   object 
 3   Winner    2321 non-null   float64
 4   Name      9964 non-null   object 
 5   Film      9631 non-null   object 
dtypes: float64(1), int64(1), object(4)
memory usage: 467.2+ KB
```

In [57]:
```
academy_awards.describe(include='all')
```

Out[57]:

	Year	Ceremony	Award	Winner	Name	Film
count	9964	9964.000000	9964	2321.0	9964	9631
unique	88	NaN	114	NaN	5747	6363
top	1942	NaN	Directing	NaN	Meryl Streep	Metro-Goldwyn-Mayer
freq	186	NaN	429	NaN	19	60
mean	NaN	45.471798	NaN	1.0	NaN	NaN
std	NaN	24.841392	NaN	0.0	NaN	NaN
min	NaN	1.000000	NaN	1.0	NaN	NaN
25%	NaN	23.000000	NaN	1.0	NaN	NaN
50%	NaN	44.000000	NaN	1.0	NaN	NaN
75%	NaN	68.000000	NaN	1.0	NaN	NaN
max	NaN	88.000000	NaN	1.0	NaN	NaN

Conditional switching

Some categories, as in the Golden Globes dataset, have the nominee and the film values swapped, we checked the entire database and we found that there are some specific awards and years that have the above-mentioned values swapped.

In [58]:
```
#Creation conditions to swap the film and the name.
condition = ((academy_awards['Year'] == '1929/1930') & ((academy_awards['Award
         | (academy_awards['Award'] == 'Outstanding Production')\
         | (academy_awards['Award'] == 'Sound Recording') | (academy_awards['Aw
#Swapping name and Film
temp = academy_awards.loc[condition, 'Film'].copy()
academy_awards.loc[condition, 'Film'] = academy_awards.loc[condition, 'Name']
academy_awards.loc[condition, 'Name'] = temp

#Creating a list of new awards to switch
awards_switched = [
    'Writing (Adaptation)','Writing (Screenplay, Adapted)','Writing (Screenplay
    'Writing (Screenplay Based on Material Previously Produced or Published)',
    'Writing (Screenplay Based on Material from Another Medium)',
```

```
    'Writing (Screenplay, Based on Material from Another Medium)', 'Animated Fe
    'Writing (Original Screenplay)','Cinematography','Directing','Sound Mixing
    'Sound Editing','Costume Design','Visual Effects','Documentary (Short Subje
    'Makeup and Hairstyling','Music (Original Score)','Best Picture','Productio
    'Short Film (Live Action)','Writing (Screenplay)'
]
#Switching them
condition2 = (academy_awards['Award'].isin(awards_switched)) & (academy_awards[
temp = academy_awards.loc[condition2, 'Film'].copy()
academy_awards.loc[condition2, 'Film'] = academy_awards.loc[condition2, 'Name']
academy_awards.loc[condition2, 'Name'] = temp
```

In [59]:
```
academy_awards.head()
```

Out[59]:

	Year	Ceremony	Award	Winner	Name	Film
0	1927/1928	1	Actor	NaN	Richard Barthelmess	The Noose
1	1927/1928	1	Actor	1.0	Emil Jannings	The Last Command
2	1927/1928	1	Actress	NaN	Louise Dresser	A Ship Comes In
3	1927/1928	1	Actress	1.0	Janet Gaynor	7th Heaven
4	1927/1928	1	Actress	NaN	Gloria Swanson	Sadie Thompson

Unifying award categories

Over the year, the name of the awards has changed in different ways, we consolidate them in order to be able to determine the % of awards given per category

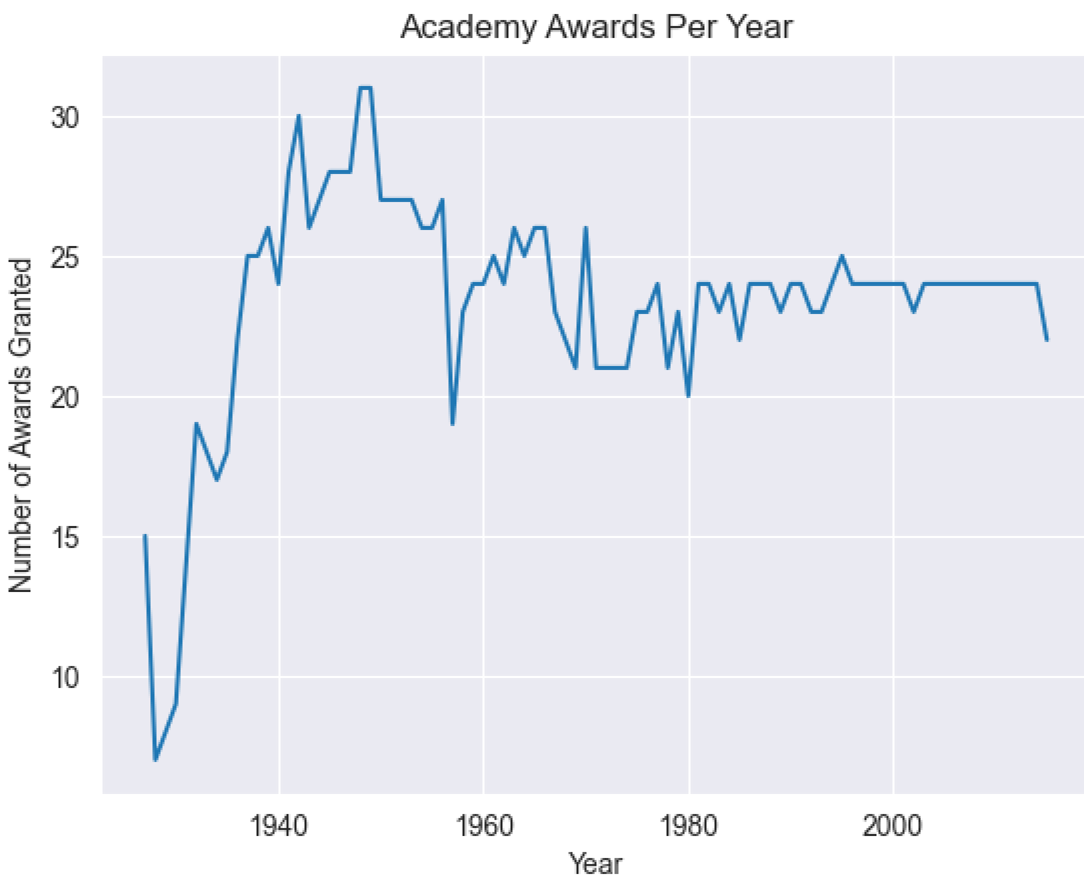
In [60]:
```
#Keeping just the winners. Dropping unnecessary columns and unifying the year c
academy_awards.dropna(subset = 'Winner', axis=0, inplace = True)
academy_awards.drop(columns=['Winner','Ceremony'],inplace=True)
academy_awards['Year'] = academy_awards['Year'].str.slice(0,4).astype(int)
```

In [61]:
```
#Dropping awards that won't be analyzed
academy_awards = academy_awards[~academy_awards['Award'].str.contains('Commenda
academy_awards = academy_awards[~academy_awards['Award'].str.contains('Honorary
academy_awards = academy_awards[~academy_awards['Award'].str.contains('Foreign 
academy_awards = academy_awards[~academy_awards['Award'].str.contains('Humanita
#Creating a category cleaning function and a list that includes certain keyword
def cat_cleaner(char, cat):
    for i in char:
       academy_awards.loc[academy_awards['Award'].str.contains(i,case=False),

best_actress = ['actress']
best_actor = ['actor']
directing = ['directing','director']
music = ['music','sound']
writing  = ['writing']
production = ['dance','art','cinematography','special ach','effects','costume',
overall_movie = ['documentary','short','picture','special award','feature film

#Applying the category cleaner function

cat_cleaner(overall_movie, 'Best Movie')
cat_cleaner(production, 'Production')
```

```
cat_cleaner(music, 'Soundtrack')
cat_cleaner(writing, 'Writing')
cat_cleaner(best_actor, 'Best Actor')
cat_cleaner(best_actress, 'Best Actress')
cat_cleaner(directing, 'Best Director')
```

How many awards have been granted per year?

In [62]:
```
yearly_aa = academy_awards.groupby('Year').count()

sns.set_style('darkgrid')
sns.lineplot(x = yearly_aa.index, y = yearly_aa['Award'])
plt.title('Academy Awards Per Year')
plt.xlabel('Year')
plt.ylabel('Number of Awards Granted');
```



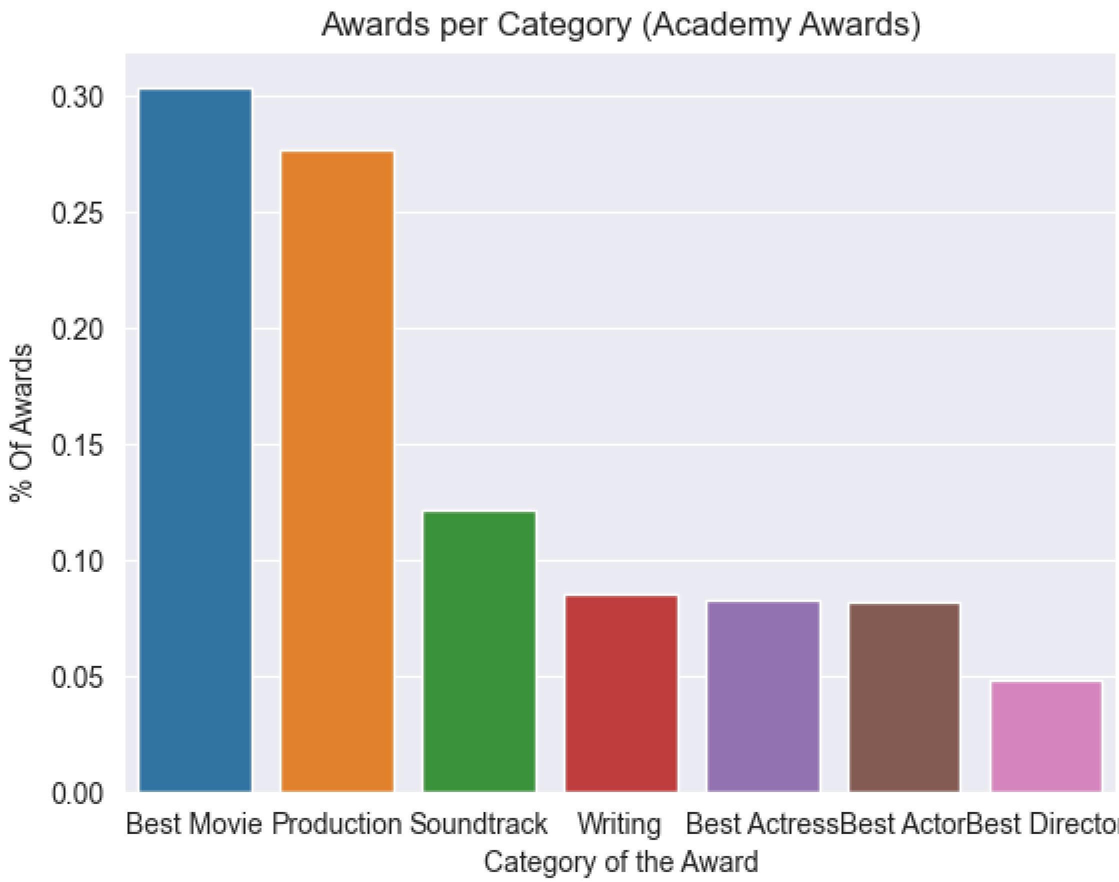
As we can see, even though there was a peak around the 1950s, the amount of awards granted have been always between 20 and 25 for the last 50 years

How is the distribution of prizes per categories?

We saw on the golden globes dataset that the actor played an important role in the amount of awards a movie gets, how's the distribution in the Academy Awards?

In [63]:
```
academy_categories = academy_awards['Award'].value_counts(normalize=True)
sns.barplot(x = academy_categories.index, y = academy_categories)
plt.title('Awards per Category (Academy Awards)')
```

```
plt.xlabel('Category of the Award')
plt.ylabel('% Of Awards');
```



Unlike the Golden Globes, the Academy Awards seems to grant a bigger part of their awards to categories related to the movies, being the actors aorund 16% of the total of awards granted.

Creating Pivot tables Grouping nominees and films for the Academy Awards

As we did for the Golden Globes dataset, to make our analysis easier, we're going to group the Data by film and by nominees. We'll do the merging by both just to make sure that no film ends in the nominee column.

In [64]:
```
#Creating the tables of the Academy Awards grouped by Film and Nominees.

academy_by_film = academy_awards.groupby('Film').agg({'Year': 'first', 'Award':
academy_by_film.columns = ['Film', 'Year', 'Number Of Awards']

academy_by_nominee = academy_awards.groupby('Name').agg({'Year': 'first', 'Awar
academy_by_nominee.columns = ['Name', 'Year', 'Number Of Awards']
```

Pairing the IMDb database and the Academy Awards grouped by Film name

In [65]:
```
# Remove spaces from movie names and convert to lowercase for easier matching
```

```
# Remove characters and convert to lowercase using chaining methods
academy_by_film['Film_formatted'] = (
    academy_by_film['Film']
    .str.replace(',', '')
    .str.replace(' ', '')
    .str.replace('"', '')
    .str.replace("'", '')
    .str.lower()
)

imdb['primary_title_cleaned'] = (
    imdb['primary_title']
    .str.replace(',', '')
    .str.replace(' ', '')
    .str.replace('"', '')
    .str.replace("'", '')
    .str.lower()
)
```

In [66]:
```
#Applying the name_matcher function
pairs3 = name_matcher(academy_by_film['Film_formatted'],imdb['primary_title_cle

# Create a DataFrame from the list of matching pairs
pairs_AA_by_film = pd.DataFrame(pairs3, columns=[ 'Academy_Film','imdb_name',

# Merge the two datasets based on the similarity score threshold
pairs_AA_by_film = pd.merge(imdb, pairs_AA_by_film, left_on='primary_title_clea
merged_data_AA_by_film = pd.merge(pairs_AA_by_film, academy_by_film, left_on='A

#creating a new column called year_difference, which will be used for cleaning
merged_data_AA_by_film['year_difference'] = abs(merged_data_AA_by_film['start_y
merged_data_AA_by_film = merged_data_AA_by_film[merged_data_AA_by_film['year_di

merged_data_AA_by_film.head()
```

Out[66]:

	primary_title	original_title	start_year	runtime_minutes	director_name	death_year	averag
2	Toy Story 3	Toy Story 3	2010	103.0	Lee Unkrich	0.0	
3	Lincoln	Lincoln	2012	150.0	Steven Spielberg	0.0	
4	Lincoln	Lincoln	2012	150.0	Steven Spielberg	0.0	
5	Lincoln	Lincoln	2012	150.0	Steven Spielberg	0.0	
6	Lincoln	Lincoln	2012	150.0	Steven Spielberg	0.0	

5 rows × 44 columns

Pairing the IMDb database and the Academy Awards grouped by Nominees

In [67]:

```
# Remove characters and convert to lowercase using chaining methods
academy_by_nominee['Name_formatted'] = (
    academy_by_nominee['Name']
    .str.replace(',', '')
    .str.replace(' ', '')
    .str.replace('"', '')
    .str.replace('(', '')
    .str.replace(')', '')
    .str.lower()
)

imdb['primary_title_cleaned'] = (
    imdb['primary_title']
    .str.replace(',', '')
    .str.replace(' ', '')
    .str.replace('"', '')
    .str.replace('(', '')
    .str.replace(')', '')
    .str.lower()
)
```

In [68]:

```
#Applying the name_matcher function
pairs4 = name_matcher(academy_by_nominee['Name_formatted'],imdb['primary_title_

# Create a DataFrame from the list of matching pairs
pairs_AA_by_nominee = pd.DataFrame(pairs4, columns=[ 'Academy_nominee','imdb_na

# Merge the two datasets based on the similarity score threshold
pairs_AA_by_nominee = pd.merge(imdb, pairs_AA_by_nominee, left_on='primary_titl
merged_data_AA_by_nominee = pd.merge(pairs_AA_by_nominee, academy_by_nominee, l

#creating a new column called year_difference, which will be used for cleaning
merged_data_AA_by_nominee['year_difference'] = abs(merged_data_AA_by_nominee['s
merged_data_AA_by_nominee = merged_data_AA_by_nominee[merged_data_AA_by_nominee

merged_data_AA_by_nominee.head()
```

Out[68]:

	primary_title	original_title	start_year	runtime_minutes	director_name	death_year	averag
1	The Wolfman	The Wolfman	2010	103.0	Joe Johnston	0.0	
2	Hugo	Hugo	2011	126.0	Martin Scorsese	0.0	
3	The Iron Lady	The Iron Lady	2011	105.0	Phyllida Lloyd	0.0	
8	Alice in Wonderland	Alice in Wonderland	2010	108.0	Tim Burton	0.0	

4 rows × 44 columns

In [69]:

```
# Concatenate the dfs
Academy_Awards_Winners = pd.concat([merged_data_AA_by_film, merged_data_AA_by_n
Academy_Awards_Winners.reset_index(drop=True, inplace=True)
#Dropping Unnecessary columns
```

```
Academy_Awards_Winners.drop(
    ['start_year','primary_title_cleaned','year_difference',
     'Name_formatted','Name','death_year','original_title',
     'Academy_nominee','imdb_name','similarity_score',
     'Academy_Film','Film','Film_formatted',
     ], axis=1, inplace=True)
#Dropping Duplicates
Academy_Awards_Winners.drop_duplicates(inplace=True)
Academy_Awards_Winners.head()
```

Out[69]:

	primary_title	runtime_minutes	director_name	averagerating	Action	Adult	Adventure	Ani
0	Toy Story 3	103.0	Lee Unkrich	8.3	0	0	1	
1	Lincoln	150.0	Steven Spielberg	7.4	0	0	0	
5	Life of Pi	127.0	Ang Lee	7.9	0	0	1	
6	Ex Machina	108.0	Alex Garland	7.7	0	0	0	
7	Dallas Buyers Club	117.0	Jean-Marc Vallée	8.0	0	0	0	

5 rows × 34 columns

We're going to visualize the distribution of the rating of award-winning movies, we'll set a vertical line on the mean of the whole IMDb dataset so we can evaluate how award-winning movies perform against all of them as far as ratings.

Merging Awards Databases with Movie Budgets

In [70]:

```
pairs5 = name_matcher(academy_by_film['Film'],movie_budgets['movie'],92)

# Create a DataFrame from the list of matching pairs
matching_data = pd.DataFrame(pairs5, columns=['aa_name', 'mb_name', 'similarity
# Merge the two datasets based on the similarity score threshold
academy_movie_budgets = pd.merge(academy_by_film, matching_data, left_on='Film
academy_movie_budgets = pd.merge(academy_movie_budgets, movie_budgets, left_on=

academy_movie_budgets.drop(columns=['mb_name','aa_name','similarity_score','id
academy_movie_budgets.drop_duplicates(keep='first',inplace=True)
academy_movie_budgets.head()
```

Out[70]:

	Film	Year	Number Of Awards	production_budget	domestic_gross	worldwide_gross	worldwide_g
0	12 Years a Slave	2013	1	20000000	56671993	181025343	
1	12 Years a Slave	2013	2	20000000	56671993	181025343	
2	20 Feet from Stardom	2013	1	1000000	4946250	5892466	
3	A Beautiful Mind	2001	1	78000000	170708996	317668058	
4	A Beautiful Mind	2001	3	78000000	170708996	317668058	

In [71]:

```
pairs6 = name_matcher(golden_globe_by_film['Name'],movie_budgets['movie'],92)

# Create a DataFrame from the list of matching pairs
matching_data = pd.DataFrame(pairs6, columns=['gg_name', 'mb_name', 'similarity
# Merge the two datasets based on the similarity score threshold
golden_globes_movie_budgets = pd.merge(golden_globe_by_film, matching_data, lef
golden_globes_movie_budgets = pd.merge(golden_globes_movie_budgets, movie_budge

golden_globes_movie_budgets.drop(columns=['mb_name','gg_name','similarity_score
golden_globes_movie_budgets.drop_duplicates(keep='first',inplace=True)
golden_globes_movie_budgets.head()
```

Out[71]:

	Name	Year	Number Of Awards	production_budget	domestic_gross	worldwide_gross	worldwide_
0	12 Years a Slave	2013	1	20000000	56671993	181025343	
1	A Beautiful Mind	2001	4	78000000	170708996	317668058	
2	About Schmidt	2002	2	30000000	65005217	107054484	
3	Adaptation	2002	2	18500000	22498520	32531759	
4	Aladdin	1992	2	182000000	246734314	619234314	

Results

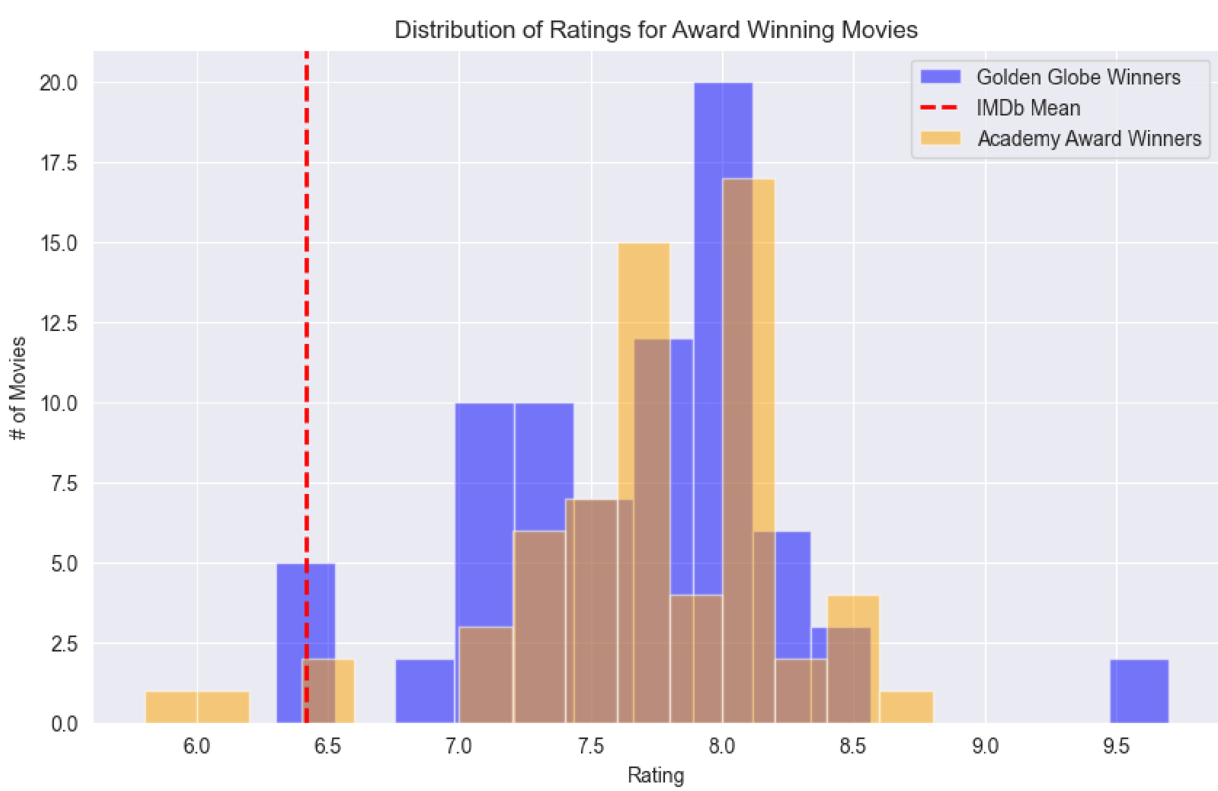
There are a massive number of factors to consider when investigating contribution to the production of an Award Winning movie. We analyzed historical data from the Academy Awards and Golden Globes in search of those characteristics.

Comparing Award Winners with Regular Movies

We'd run a series of plots to visualize the actual difference between award winning movies and the rest of our dataset. One of the first things to evaluate is the ratings, does award winning movies have better average than the rest?

For this, we created a histogram on the ratings of both Academy Awards and Golden Globes and set up a vertical line where the mean of the IMDb database is on the average rating.

In [72]:
```
fig, ax = plt.subplots(figsize=(10, 6))

# Plot histogram for Golden Globe Winning Movies
rating_gg = Golden_Globes_Winners['averagerating']
ax.hist(rating_gg, bins=15, alpha=0.5, color='blue', label='Golden Globe Winne

#Setting a vertical line for the mean of the IMDb movies dataset
ax.axvline(imdb['averagerating'].mean(), color='red', linestyle='dashed', linew

# Plot histogram for Academy Award Winning Movies
rating_aa = Academy_Awards_Winners['averagerating']
ax.hist(rating_aa, bins=15, alpha=0.5, color='orange', label='Academy Award Wi

# Set titles, labels, and legend
ax.set_title('Distribution of Ratings for Award Winning Movies')
ax.set_xlabel('Rating')
ax.set_ylabel('# of Movies')
ax.legend();
```



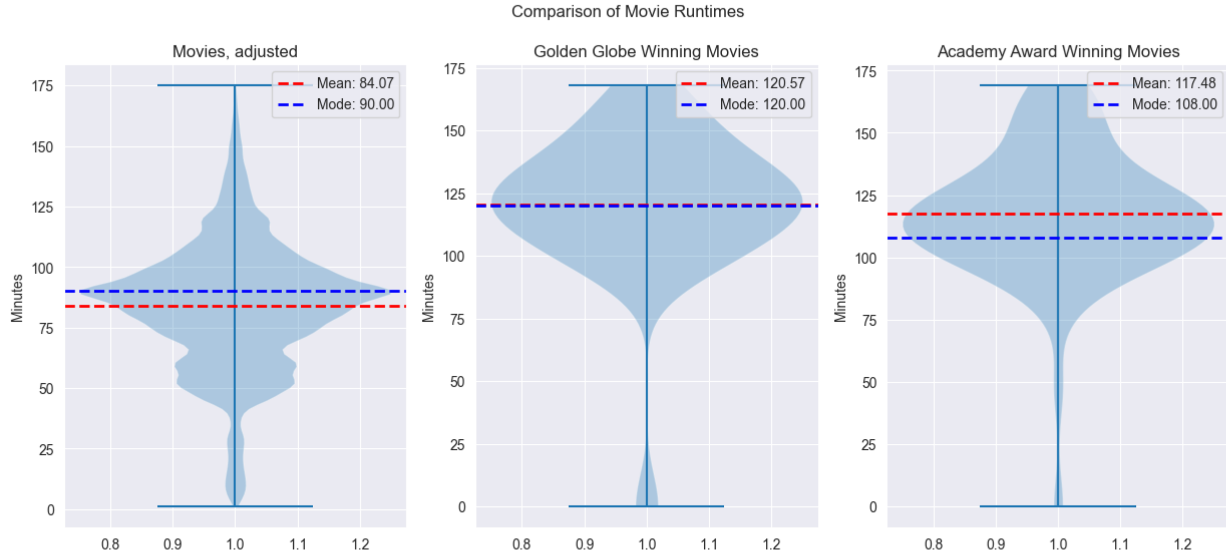
Above we can observe that movies that won awards usually perform better than average as far as ratings.

Does the runtime affects award winning movies?

We want to evaluate if there's any difference between the award-winning movies and the overall population as far as the length of the movie in minutes.

We'll take into consideration the mean and mode of our data for analysis and visualization purposes.

In [73]:
```
#Calculate mean and mode values for each dataset
mean_runtime2 = Golden_Globes_Winners['runtime_minutes'].mean()
mode_runtime2 = Golden_Globes_Winners['runtime_minutes'].mode().iloc[0]

#Creating thresholds to evaluate our movies, and setting up a lower threshold a
upper_threshold = 175
lower_threshold = 0
runtime_with_threshold = [x for x in imdb['runtime_minutes'] if lower_threshol
mean_runtime_adjusted = pd.Series(runtime_with_threshold).mean()  # Convert the

mean_runtime3 = Academy_Awards_Winners['runtime_minutes'].mean()
mode_runtime3 = Academy_Awards_Winners['runtime_minutes'].mode().iloc[0]

#Create subplots
fig, (ax1, ax2, ax3) = plt.subplots(ncols=3, figsize=(15, 6))

#Plot violin plots and add horizontal lines for mean and mode
def add_mean_mode_lines(ax, data, title):
    ax.violinplot(data)
    ax.set_title(title)
    ax.set_ylabel('Minutes')
    mean_value = data.mean()
    mode_value = data.mode().iloc[0]
    ax.axhline(mean_value, color='red', linestyle='dashed', linewidth=2, label=
    ax.axhline(mode_value, color='blue', linestyle='dashed', linewidth=2, label
    ax.legend()

add_mean_mode_lines(ax2, Golden_Globes_Winners['runtime_minutes'], 'Golden Glob
add_mean_mode_lines(ax1, pd.Series(runtime_with_threshold), 'Movies, adjusted')
add_mean_mode_lines(ax3, Academy_Awards_Winners['runtime_minutes'], 'Academy Aw

fig.suptitle('Comparison of Movie Runtimes')
plt.show()
```



There's a clear difference between the length of the overall movies and the award-winning ones. We can see that they're usually longer than the average runtime of the movies.

We found that the distribution of movie runtimes was different between our overall movie dataset and our set of award-winning movies. After filtering out the movies with listed 0-minute runtimes, as well as any movies longer than 175 minutes, we found:

The mean runtime for all movies is 84.07 minutes

The mean runtime for Academy Award-winning movies is 120.57 minutes

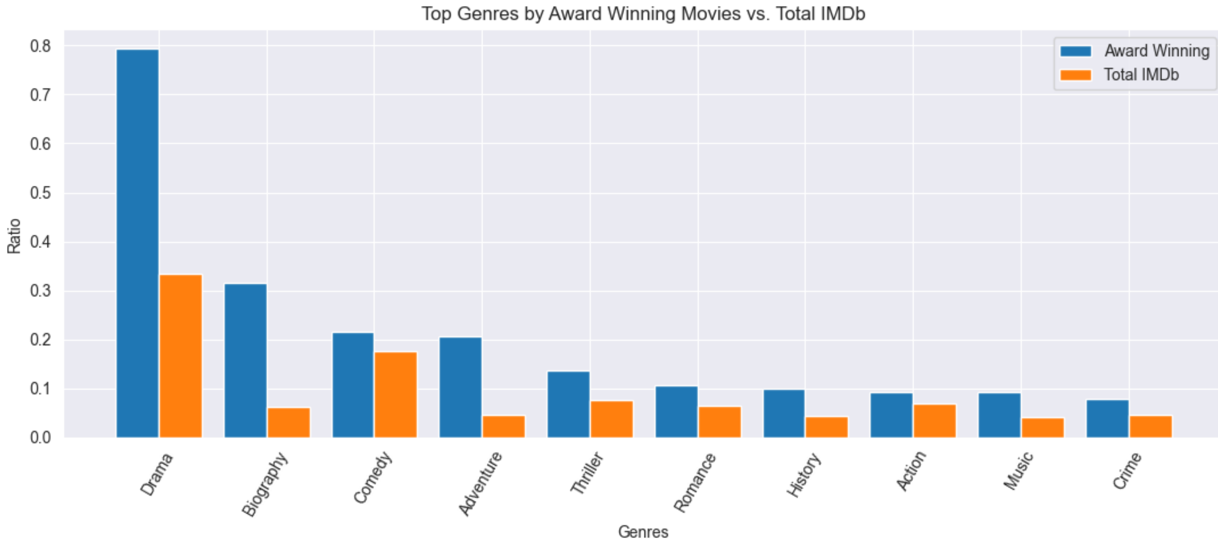
The mean runtime for Golden Globe-winning movies is 117.48 minutes

Genres by Award-winning movies

We looked above the amount of movies that fall into each category (we can't forget that a movie can be in more than one category). Now, we want to see the % of award-winning movies that are part of each individual category, compared to the total movies of the IMDbs dataset. We want to evaluate only the top genres, so we'll keep only the top 10 for visualization purposes.

In [74]:
```
# Creating a list of all the genre-columns
category_columns = ['Action', 'Adult', 'Adventure', 'Animation', 'Biography',
                    'Drama', 'Family', 'Fantasy', 'Game-Show', 'History', 'Horr
                    'News', 'No Genre', 'Reality-TV', 'Romance', 'Sci-Fi', 'Sho
                    'War', 'Western']

# Calculating the total count of movies per each category in both Academy Award
aa_sums = Academy_Awards_Winners[category_columns].sum()
gg_sums = Golden_Globes_Winners[category_columns].sum()

# Getting the total counts of each genre in both datasets
award_winning_sums = aa_sums + gg_sums

# Getting the length of both datasets
size_award_winners = len(Academy_Awards_Winners) + len(Golden_Globes_Winners)
```

```
# Calculate the ratio of award-winning movies to the total
award_winning_ratio = award_winning_sums / size_award_winners

# Calculate the ratio of genres in the entire IMDb database
total_genre_counts = imdb[category_columns].sum()
total_ratio = total_genre_counts / len(imdb)

# Sort the genres by their award-winning ratios
sorted_genre_data = pd.DataFrame({'Genre': award_winning_ratio.index, 'Award_Wi
                                  'Total_Ratio': total_ratio})
sorted_genre_data = sorted_genre_data.sort_values(by='Award_Winning_Ratio', asc

# Number of top genres to keep
top_n_genres = 10

# Select the top N genres by award-winning ratio
top_genres = sorted_genre_data.head(top_n_genres)

# Create a legend for the plot
legend_labels = ['Award Winning', 'Total IMDb']

fig, ax = plt.subplots(figsize=(11, 5))

# Plotting bars for Award Winning and Total IMDb for the top genres
bar_width = 0.4  # Adjust the width of the bars as needed
bar1 = plt.bar(range(len(top_genres)), top_genres['Award_Winning_Ratio'], width
               label=legend_labels[0])
bar2 = plt.bar([x + bar_width for x in range(len(top_genres))],
               top_genres['Total_Ratio'], width=bar_width, label=legend_labels[

# Customize the x-axis labels
plt.xticks([i + bar_width / 2 for i in range(len(top_genres))], top_genres['Gen

plt.title('Top Genres by Award Winning Movies vs. Total IMDb')
plt.xlabel('Genres')
plt.ylabel('Ratio')

# Add a legend
plt.legend()

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



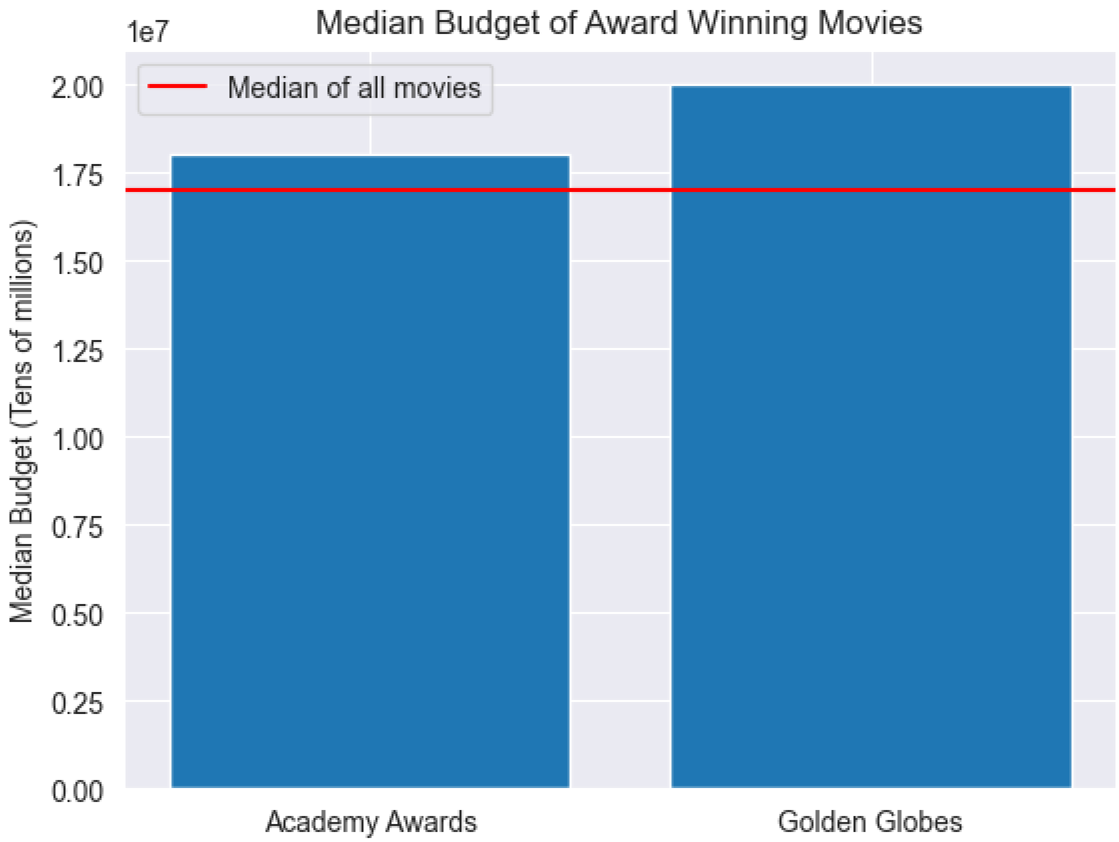
This shows that around 79% of Awards Winning movies have some degree of drama, which is a clear indicator that in order to be more likely to have an award-winning movie, you need to lean into drama.

Budget of award winning movies vs regular movies

We want to know if there's a difference between the median of the movies that are award winners and the median of the movies in general.

To do this we compared the median of the Golden Globe Winners with the median of the Academy Award winners, then we trace a horizontal line showing the median of all the movies.

In [75]:
```
y = [academy_movie_budgets['production_budget'].median(), golden_globes_movie_b
x = ['Academy Awards','Golden Globes']
plt.bar(x=x,height=y)
plt.axhline(y=movie_budgets['production_budget'].median(),color='red',label='Me
plt.legend()
plt.ylabel('Median Budget (Tens of millions)')
plt.title('Median Budget of Award Winning Movies');
```



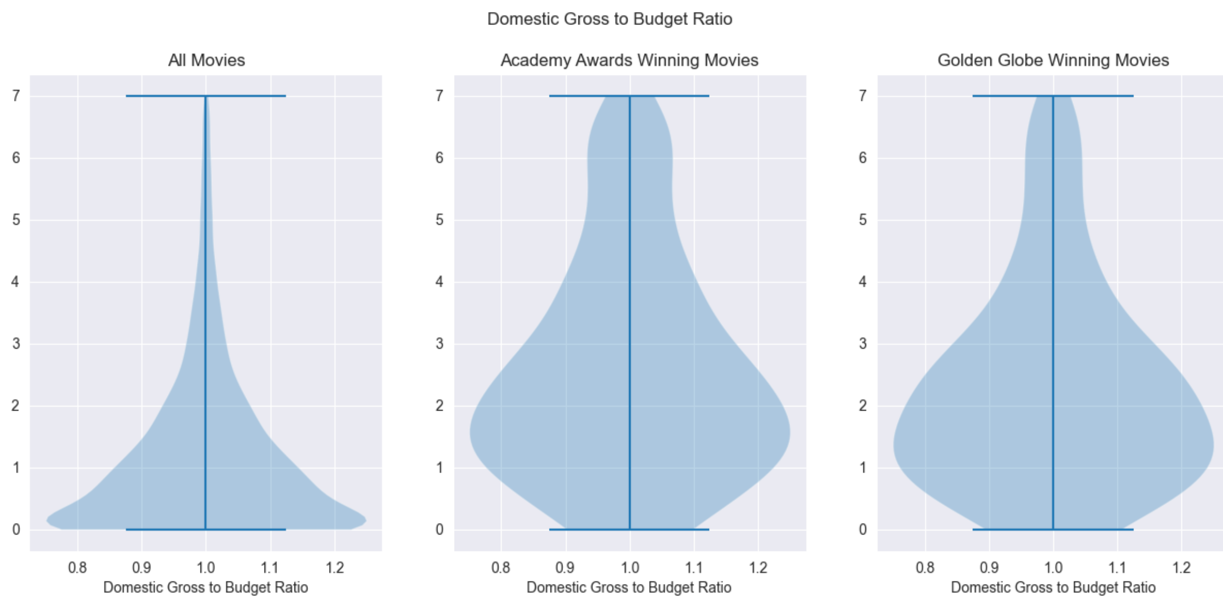
As we can see here, there's not much difference between them. This means that the budget of a movie is not a determinant factor to whether they'll win awards or not.

Domestic Gross to Budget

On the other hand, we want to evaluate how much money movies award movies earn in relation to their budget.

To do that we created a Domestic Gross to budget ratio for regular movies, Academy Award winners, and Golden Globe winners. Setting up a threshold of 7 times to allow a clear visualization.

In [76]:
```
# Setting up the threshold and the values
threshold = 7
domestic_budgets_with_threshold = [x for x in movie_budgets['domestic_gross/pro
gg_with_threshold = [x for x in golden_globes_movie_budgets['domestic_gross/pro
aa_with_threshold = [x for x in academy_movie_budgets['domestic_gross/productio
#Plotting our data
fig, (ax1,ax2,ax3) = plt.subplots(ncols=3, figsize=(15,6))
ax1.violinplot(domestic_budgets_with_threshold)
ax2.violinplot(aa_with_threshold)
ax3.violinplot(gg_with_threshold)
fig.suptitle('Domestic Gross to Budget Ratio')
ax1.set_title('All Movies')
ax2.set_title('Academy Awards Winning Movies')
ax3.set_title('Golden Globe Winning Movies')
ax1.set_xlabel('Domestic Gross to Budget Ratio')
ax2.set_xlabel('Domestic Gross to Budget Ratio')
ax3.set_xlabel('Domestic Gross to Budget Ratio');
```



There's a difference between the Domestic Gross to budget ratio of award winning movies in relation to regular movies.

We can see in this Violin plot that if we achieve the goal of winning awards, the movie will be also financially sustainable.

It seems that most movies that wins awards are above the 1 ratio, which means they break even, with most of them around 1.5.

On the other side, regular movies seems to perform not as good, with the majority of them in our database performing under 0.5 in this rate, meaning that they don't gross even half of their cost.

Finding the right Crew

Directors

Now, we're focusing on finding the adequate people for key positions in the film making process. Our objective is to find a database that has the best directors based on awards and movies directed.

In [77]:
```
#Creating a Genre Column List associated with the IMDb table
genre_columns = ['Action', 'Adult',
        'Adventure', 'Animation', 'Biography', 'Comedy', 'Crime', 'Documentary',
        'Drama', 'Family', 'Fantasy', 'Game-Show', 'History', 'Horror', 'Music',
        'Musical', 'Mystery', 'News', 'No Genre', 'Reality-TV', 'Romance',
        'Sci-Fi', 'Short', 'Sport', 'Talk-Show', 'Thriller', 'War', 'Western']

#Grouping all our director's name on the IMDb database, creating a count of the
#We're also keeping the genres columns to evaluate how many of their movies are
directors = imdb.groupby('director_name').agg({'primary_title':'count', **{col

# Merging that with both the Academy Awards and the Golden Globe dataset, we do
```

```
# Since we're trying to find the director's name, we need perfect matches.
aa_directors = pd.merge(academy_by_nominee, directors, left_on = 'Name', right_
gg_directors = pd.merge(golden_globe_by_nominee, directors, left_on = 'Nominee

#We keep only the most important genres we'd analyze, rename the column to spec
#We do that for both Academy Award Directors and Golden Globe Directors
aa_directors = aa_directors[['Name', 'Number Of Awards', 'primary_title','Adver
aa_directors.rename(columns={'primary_title':'Number of Movies Directed'}, inpl
aa_directors.sort_values(by=['Number Of Awards','Drama'],ascending=False, inpla
aa_directors = aa_directors.head(15)
gg_directors = gg_directors[['Nominee', 'Number Of Awards', 'primary_title','Ac
gg_directors.rename(columns={'primary_title':'Number of Movies Directed','Nomir
gg_directors.sort_values(by=['Number Of Awards','Drama'],ascending=False, inpla
gg_directors = gg_directors.head(15)

#Concatenate both dataframes
best_directors = pd.concat([aa_directors,gg_directors], axis=0)
best_directors.reset_index(drop=True)

#Grouping them by the name, adding up the amount of awards received. Sorting tl
best_directors = best_directors.groupby('Name').agg({'Number Of Awards':'sum',
best_directors.sort_values(['Number Of Awards','Drama'], ascending=False, inpla
```

In [78]:
```
#Create a manual dictionary with all the people in the best_directors dataframe
#We had other people that won awards in other categories and then directed, so
dt_rol = {'John Williams': 'Soundtrack','Clint Eastwood': 'Director','Oliver St

#Add that dictionary into our dataframe as 'Role'
best_directors['Role'] = best_directors.index.map(dt_rol)
```

In [79]:
```
best_directors.head()
```

Out[79]:

Name	Number Of Awards	Number of Movies Directed	Adventure	Biography	Drama	Comedy	Role
John Williams	8	7	0	0	2	3	Soundtrack
Clint Eastwood	7	6	0	5	6	0	Director
Oliver Stone	7	5	0	1	3	0	Director
Dustin Hoffman	6	1	0	0	1	1	Actor
Steven Spielberg	5	9	4	2	5	0	Director

Our top awarded person is neither a director nor an actor, so is someone worth to add to our team for sure.

In [80]:
```
#Find just directors
directors = best_directors.loc[best_directors['Role'] == 'Director']
# Sort them by number of award and tie breaking by number of drama movies direc
directors.sort_values(by=['Number Of Awards','Drama'],ascending=False,inplace=T
```

```
#Showing the top three
directors[['Number Of Awards','Number of Movies Directed']].head(3)
```

Out[80]:

Name	Number Of Awards	Number of Movies Directed
Clint Eastwood	7	6
Oliver Stone	7	5
Steven Spielberg	5	9

Actor and Actress

Now that we found our top three Directors, we'll do the same with actors and actresses.

We'll go back to our Academy Awards and Golden Globe datasets and use the acting awards categories to filter them, and find the most awarded ones

In [81]:

```
#Filter Just best actor and best actress for our Academy Award Database, groupi
academy_actors = academy_awards.loc[(academy_awards['Award'] == 'Best Actor')
academy_actors = academy_actors.groupby('Name').agg({'Year': 'first', 'Award':
academy_actors.columns = ['Name', 'Year', 'Number Of Awards']
#Sorting by number of awards, keeping the top ten.
academy_actors.sort_values(by=['Number Of Awards'], ascending=False, inplace=Tr
top_aa_actors = academy_actors.head(10)

#Applying the same on the Golden globe Database
golden_globe_actors = golden_globe_awards.loc[(golden_globe_awards['category']
golden_globe_actors = golden_globe_actors.groupby('nominee').agg({'year_film':
golden_globe_actors.columns = ['nominee', 'Year', 'Number Of Awards']
golden_globe_actors.sort_values(by=['Number Of Awards'], ascending=False, inpla
top_gg_actors = golden_globe_actors.head(10)
#Renaming the column so is the same on both
top_gg_actors.rename(columns={'nominee':'Name'},inplace=True)
#Concatenating both datasets.

top_actors = pd.concat([top_aa_actors,top_gg_actors], axis=0)
top_actors.reset_index(drop=True)
#Grouping by Name, sort by number of awards
top_actors = top_actors.groupby('Name').sum()
top_actors.sort_values(by='Number Of Awards', ascending=False, inplace=True)
top_actors.reset_index(inplace=True)
#Show name and number of awards of our top 5 actors and actresses
top_actors[['Name','Number Of Awards']].head()
```

Out[81]:

	Name	Number Of Awards
0	Meryl Streep	10
1	Jack Nicholson	9
2	Katharine Hepburn	4
3	Dustin Hoffman	4
4	Tom Hanks	4

We can see how this is our top performing actors and actresses as far as awards won.

By doing a manual research, re realized that Katharine Hepburn died in 2003 and Jack Nicholson is retired, so that will discard them from our recommendations.

Recommendations

- We Recommend that our movie have a certain degree of Drama in it, by the data we saw how relevant the genre is as far as getting award-winning movies.
- A length of around two hours is recommended since the mean of Academy Award winners and Golden Globe winners falls into that category.
- Budget doesn't have to be a primary concern, since it's proven by the data that we don't need to have above-average spending in order to win awards.
- The crew definitely plays an important role in whether a movie can win an award or not. To increase the likelihood of winning an award, we recommend recruiting one of the following directors: Steven Spielberg, Oliver Stone, or Clint Eastwood, the third one is set to retire in 2023, so if we want to include him, we better give him an offer fast. As per actors, the top chosen were: Meryl Streep, Dustin Hoffman, and Tom Hanks.
- John Williams was an outlier on our research, he was so above the rest as far as soundtrack, that he becomes a must when is time to recruit the team for our movie.

Next Steps

- Update our data to include data of the Academy Awards and the Golden Globes after 2015 and 2020, respectively.
- Create an Analysis of the salary and the budget that our studio will need for the making of a potential award-winning movie.
- Create a prediction model that, given a movie, to determine how likely it is for it to win an award.

In [ ]:

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