Microsoft Movie Analysis

Authors: Anh Luong

Overview

This project analyses what types of films are currently performing the best at the box office. Descriptive analysis of current films provide insights to help Microsoft's new movie studio decide what type of films to create.

Business Problem

Summary of the business problem:

1. What are the best selling genres of all time?

We will look at the best selling genres by total sales and averaged sales since released as there are movies that was released many years ago. This will tell us not only the most popular genres, but also the most profitability genres as it keeps generate sales in many years after release. The data to be looked at will be: genres, total sales and averaged sales.

2. What genres are highly rated with the most rating received?

By answering this question, Microsoft can chose to make a movie that is not only well received by the public but also from professional movie critics. This will potentially allow Microsoft to build up its reputation in the film industry. The data will be looked at are: genres, rating, number of votes and sales.

3. What are the best selling genres recently?

This is to find out what are the viewers' preferred genres recently. This recommendation will help Microsoft to make a film that is most likely attractive to viewers now. The data will be looked at are: Sales, Genres and Year.

Data Understanding

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

%matplotlib inline
```

In [2]:
```
# Load and Understand each dataset
sales = pd.read_csv('zippedData/bom.movie_gross.csv.gz')
titles=pd.read_csv('zippedData/imdb.title.basics.csv.gz')
ratings=pd.read_csv('zippedData/imdb.title.ratings.csv.gz')
pd.options.display.float_format = '{:,.0f}'.format
```

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

Out[3]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415,000,000	652000000	2010
1	Alice in Wonderland (2010)	BV	334,200,000	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296,000,000	664300000	2010
3	Inception	WB	292,600,000	535700000	2010
4	Shrek Forever After	P/DW	238,700,000	513900000	2010

In [4]:
```
sales.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
```

In [5]:
```
sales.nunique()
```

Out[5]:
```
title             3386
studio             257
domestic_gross    1797
foreign_gross     1204
year                 9
dtype: int64
```

In [6]:
```
sales.isna().sum()
```

Out[6]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

In [7]:
```
titles.head()
```

Out[7]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80	Comedy,Drama,Fantasy

In [8]:
```
titles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   tconst           146144 non-null  object 
 1   primary_title    146144 non-null  object 
 2   original_title   146123 non-null  object 
 3   start_year       146144 non-null  int64  
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

In [9]:
```
titles.nunique()
```

Out[9]:
```
tconst             146144
primary_title      136071
original_title     137773
start_year             19
runtime_minutes       367
genres               1085
dtype: int64
```

In [10]:
```
titles.isna().sum()
```

Out[10]:
```
tconst                 0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

In [11]:
```
ratings.head()
```

Out[11]:

	tconst	averagerating	numvotes
0	tt10356526	8	31
1	tt10384606	9	559
2	tt1042974	6	20
3	tt1043726	4	50352
4	tt1060240	6	21

In [12]:
```
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   tconst         73856 non-null  object 
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64  
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

In [13]:
```
ratings.nunique()
```

Out[13]:
```
tconst           73856
averagerating       91
numvotes          7349
dtype: int64
```

In [14]:
```
ratings.isna().sum()
```

Out[14]:
```
tconst           0
averagerating    0
numvotes         0
dtype: int64
```

Data Preparation

In [15]:
```
#Cleaning up the sales data
#replace NAN value and convert to the right data type
sales["foreign_gross"] = sales["foreign_gross"].fillna(0)
sales['domestic_gross'] = sales['domestic_gross'].astype(float)
sales['foreign_gross'] = sales['foreign_gross'].replace(',','', regex=True).astype(float)
sales.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   3387 non-null   float64
 4   year            3387 non-null   int64  
dtypes: float64(2), int64(1), object(2)
memory usage: 132.4+ KB
```

In [16]:
```
# add columns to calculate average of domestic and foreign sales per year
sales['age']=[2022] - sales.loc[:,"year"]
sales['age']=sales['age'].astype(float)

sales['total sales']=sales.loc[:,"domestic_gross"] + sales.loc[:,"foreign_gross"]
sales['total sales']=sales['total sales'].astype(float)
```

In [17]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 7 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   3387 non-null   float64
 4   year            3387 non-null   int64  
 5   age             3387 non-null   float64
 6   total sales     3359 non-null   float64
dtypes: float64(4), int64(1), object(2)
memory usage: 185.4+ KB
```

In [18]:
```
sales.head()
```

Out[18]:

	title	studio	domestic_gross	foreign_gross	year	age	total sales
0	Toy Story 3	BV	415,000,000	652,000,000	2010	12	1,067,000,000
1	Alice in Wonderland (2010)	BV	334,200,000	691,300,000	2010	12	1,025,500,000
2	Harry Potter and the Deathly Hallows Part 1	WB	296,000,000	664,300,000	2010	12	960,300,000
3	Inception	WB	292,600,000	535,700,000	2010	12	828,300,000
4	Shrek Forever After	P/DW	238,700,000	513,900,000	2010	12	752,600,000

In [19]:
```
sales['avg_sales']=sales.loc[:,"total sales"]/sales.loc[:,"age"]
```

In [20]:
```
sales.head()
```

Out[20]:

	title	studio	domestic_gross	foreign_gross	year	age	total sales	avg_sales
0	Toy Story 3	BV	415,000,000	652,000,000	2010	12	1,067,000,000	88,916,667
1	Alice in Wonderland (2010)	BV	334,200,000	691,300,000	2010	12	1,025,500,000	85,458,333
2	Harry Potter and the Deathly Hallows Part 1	WB	296,000,000	664,300,000	2010	12	960,300,000	80,025,000
3	Inception	WB	292,600,000	535,700,000	2010	12	828,300,000	69,025,000
4	Shrek Forever After	P/DW	238,700,000	513,900,000	2010	12	752,600,000	62,716,667

In [21]:
```
sales.drop(sales.iloc[:, 1:6], inplace=True, axis=1)
```

In [22]:
```
sales.head()
```

Out[22]:

	title	total sales	avg_sales
0	Toy Story 3	1,067,000,000	88,916,667
1	Alice in Wonderland (2010)	1,025,500,000	85,458,333
2	Harry Potter and the Deathly Hallows Part 1	960,300,000	80,025,000
3	Inception	828,300,000	69,025,000
4	Shrek Forever After	752,600,000	62,716,667

In [23]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   title        3387 non-null   object 
 1   total sales  3359 non-null   float64
 2   avg_sales    3359 non-null   float64
dtypes: float64(2), object(1)
memory usage: 79.5+ KB
```

In [24]:
```
titles.head()
```

Out[24]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	nan	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80	Comedy,Drama,Fantasy

In [25]:
```
#rename and drop unnessary columns
titles.drop(titles.iloc[:, 2:3], inplace=True, axis=1)
titles.rename(columns = {'tconst':'ID'}, inplace = True)
titles.rename(columns = {'primary_title':'title'}, inplace = True)
titles.rename(columns = {'start_year':'year'}, inplace = True)
titles.head()
```

Out[25]:

	ID	title	year	runtime_minutes	genres
0	tt0063540	Sunghursh	2013	175	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	2019	114	Biography,Drama
2	tt0069049	The Other Side of the Wind	2018	122	Drama
3	tt0069204	Sabse Bada Sukh	2018	nan	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	2017	80	Comedy,Drama,Fantasy

In [26]:
```
titles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 5 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   ID               146144 non-null  object 
 1   title            146144 non-null  object 
 2   year             146144 non-null  int64  
 3   runtime_minutes  114405 non-null  float64
 4   genres           140736 non-null  object 
dtypes: float64(1), int64(1), object(3)
memory usage: 5.6+ MB
```

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

Out[27]:

	tconst	averagerating	numvotes
0	tt10356526	8	31
1	tt10384606	9	559
2	tt1042974	6	20
3	tt1043726	4	50352
4	tt1060240	6	21

In [28]:
```
#rename and drop unnessary columns
ratings.rename(columns = {'tconst':'ID'}, inplace = True)
ratings.rename(columns = {'averagerating':'avg_rating'}, inplace = True)
ratings.rename(columns = {'numvotes':'no_votes'}, inplace = True)
ratings.head()
```

Out[28]:

	ID	avg_rating	no_votes
0	tt10356526	8	31
1	tt10384606	9	559
2	tt1042974	6	20
3	tt1043726	4	50352
4	tt1060240	6	21

In [29]:
```
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   ID          73856 non-null  object
 1   avg_rating  73856 non-null  float64
 2   no_votes    73856 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
```

In [30]:
```
ratings.describe()
```

Out[30]:

	avg_rating	no_votes
count	73,856	73,856
mean	6	3,524
std	1	30,294
min	1	5
25%	6	14
50%	6	49
75%	7	282
max	10	1,841,066

In [31]:
```
#create a summary table that contains all neccessary information.
titles_ratings = pd.merge(titles,
                          ratings,
                              on=['ID'],
                              how='left')
```

In [32]:
```
titles_ratings.head()
```

Out[32]:

	ID	title	year	runtime_minutes	genres	avg_rating	no_votes
0	tt0063540	Sunghursh	2013	175	Action,Crime,Drama	7	77
1	tt0066787	One Day Before the Rainy Season	2019	114	Biography,Drama	7	43
2	tt0069049	The Other Side of the Wind	2018	122	Drama	7	4,517
3	tt0069204	Sabse Bada Sukh	2018	nan	Comedy,Drama	6	13
4	tt0100275	The Wandering Soap Opera	2017	80	Comedy,Drama,Fantasy	6	119

In [33]:
```
sales.head()
```

Out[33]:

	title	total sales	avg_sales
0	Toy Story 3	1,067,000,000	88,916,667
1	Alice in Wonderland (2010)	1,025,500,000	85,458,333
2	Harry Potter and the Deathly Hallows Part 1	960,300,000	80,025,000
3	Inception	828,300,000	69,025,000
4	Shrek Forever After	752,600,000	62,716,667

In [34]:
```
#create a summary table that contains all neccessary information.
titles_ratings_sales=pd.merge(titles_ratings, sales,
                              on=['title'],
                              how='left')
```

In [35]:
```
#check results:
titles_ratings_sales.head()
```

Out[35]:

	ID	title	year	runtime_minutes	genres	avg_rating	no_votes	total sales	avg_sales
0	tt0063540	Sunghursh	2013	175	Action,Crime,Drama	7	77	nan	nan
1	tt0066787	One Day Before the Rainy Season	2019	114	Biography,Drama	7	43	nan	nan
2	tt0069049	The Other Side of the Wind	2018	122	Drama	7	4,517	nan	nan
3	tt0069204	Sabse Bada Sukh	2018	nan	Comedy,Drama	6	13	nan	nan
4	tt0100275	The Wandering Soap Opera	2017	80	Comedy,Drama,Fantasy	6	119	nan	nan

In [36]:
```
titles_ratings_sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 146146 entries, 0 to 146145
Data columns (total 9 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   ID               146146 non-null  object
 1   title            146146 non-null  object
 2   year             146146 non-null  int64
 3   runtime_minutes  114407 non-null  float64
 4   genres           140738 non-null  object
 5   avg_rating       73858 non-null   float64
 6   no_votes         73858 non-null   float64
 7   total sales      3342 non-null    float64
 8   avg_sales        3342 non-null    float64
dtypes: float64(5), int64(1), object(3)
memory usage: 11.2+ MB
```

Data Modeling and Evaluation

1. What are the best selling genres of all time?

In [37]:
```
#Create new dataframe:

Genres_df=titles_ratings_sales[['genres','total sales', 'avg_sales']].copy()
Genres_df.dropna(inplace=True)
Genres_df.groupby('genres')
Genres_df.groupby(Genres_df['genres'])
Genres_df.head()
```

Out[37]:

	genres	total sales	avg_sales
38	Action,Crime,Drama	1,100,000	183,333
48	Adventure,Drama,Romance	8,744,000	874,400
54	Adventure,Comedy,Drama	188,100,000	20,900,000
58	Action,Crime,Drama	53,200,000	6,650,000
60	Action,Adventure,Sci-Fi	652,301,019	93,185,860

In [38]:
```
Top_10_bytotal = Genres_df.groupby('genres').sum().sort_values(by="total sales",ascending=False).head(10)
```

In [39]:
```
Top_10_bytotal
```

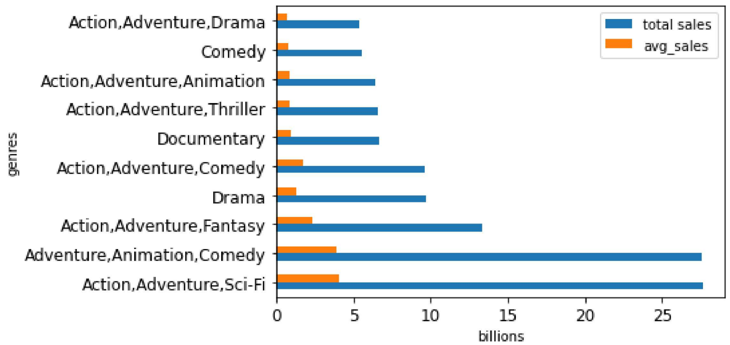
Out[39]:

genres	total sales	avg_sales
Action,Adventure,Sci-Fi	27,636,102,388	4,079,057,082
Adventure,Animation,Comedy	27,607,332,597	3,879,035,962
Action,Adventure,Fantasy	13,314,887,000	2,318,437,551
Drama	9,705,685,196	1,278,078,355
Action,Adventure,Comedy	9,666,672,299	1,753,394,320
Documentary	6,670,552,396	918,880,416
Action,Adventure,Thriller	6,600,098,000	899,998,869
Action,Adventure,Animation	6,454,160,400	899,124,031
Comedy	5,513,496,099	752,689,767
Action,Adventure,Drama	5,359,704,799	728,890,930

In [40]:
```
import matplotlib.ticker as ticker
ax=Top_10_bytotal.plot(kind="barh", fontsize=12)
current_values = plt.gca().get_xticks()

scale_x = 1e9
ticks_x = ticker.FuncFormatter(lambda y, pos: '{0:g}'.format(y/scale_x))
ax.xaxis.set_major_formatter(ticks_x)
ax.set_xlabel('billions')
```

Out[40]:
```
Text(0.5, 0, 'billions')
```



Recommendation 1:

```
The top 2 best selling genres based on both total and averaged sales are
    1 - Action, Adventure and Scifi
    2 - Action, Animation and Comedy
```

It is worth noting that Action and Adventure genres appear in all 6 out 10 genres. It is recommended that a film with a mix genre of at least Action and Adventure will most likely to be performing well in the box office.

2. What genres are highly rated with the most rating received?

In [41]:
```
#create new dataframe:

AvgRatings_df= titles_ratings_sales[['genres','avg_rating']].copy()
AvgRatings_df.dropna(inplace=True)
AvgRatings_df_2=AvgRatings_df.groupby('genres').mean().sort_values(by="avg_rating",ascending=False)
AvgRatings_df_2.head()
```

Out[41]:

genres	avg_rating
Comedy,Documentary,Fantasy	9
Documentary,Family,Musical	9
History,Sport	9
Music,Mystery	9
Game-Show	9

In [42]:
```
Votes_df= titles_ratings_sales[['genres', 'no_votes']].copy()
Votes_df.dropna(inplace=True)
Votes_df_2=Votes_df.groupby('genres').sum().sort_values(by="no_votes",ascending=False)
Votes_df_2.head(10)
```

Out[42]:

genres	no_votes
Action,Adventure,Sci-Fi	23,023,248
Action,Adventure,Fantasy	9,658,883
Adventure,Animation,Comedy	8,687,435
Drama	8,395,521
Comedy,Drama,Romance	7,665,463
Action,Adventure,Comedy	7,256,686
Comedy	6,832,037
Comedy,Drama	6,462,839
Action,Crime,Drama	5,563,553
Drama,Romance	5,542,760

In [43]:
```
#create a dataframe for top 10 genres that are highly rated with the most rating received:
genres_ratings=pd.merge(AvgRatings_df_2, Votes_df_2,
                              on=['genres'],
                              how='left')
genres_ratings.describe()
```

Out[43]:

	avg_rating	no_votes
count	923	923
mean	6	281,934
std	1	1,191,639
min	1	5
25%	6	166
50%	6	2,389
75%	7	51,818
max	9	23,023,248

In [44]:
```
#see what genres receives the most number votes and what are the rating
genres_ratings.sort_values(by="no_votes",ascending=False).head(10)
```

Out[44]:

genres	avg_rating	no_votes
Action,Adventure,Sci-Fi	6	23,023,248
Action,Adventure,Fantasy	5	9,658,883
Adventure,Animation,Comedy	6	8,687,435
Drama	6	8,395,521
Comedy,Drama,Romance	6	7,665,463
Action,Adventure,Comedy	6	7,256,686
Comedy	6	6,832,037
Comedy,Drama	6	6,462,839
Action,Crime,Drama	6	5,563,553
Drama,Romance	6	5,542,760

The table shows that even though the top ten genres receives the most votes, but do not recessarily receive the highest rating. The rating is average. None of the top 10 most voted genres receive a rating of 7 which is considered above average.

In [45]:
```
#now we want to sort out genres that receives at least 1 million votes with a rating of at least 6.5.
votes_over_1mil = genres_ratings[genres_ratings['no_votes']> 1000000]
highly_rated=votes_over_1mil[votes_over_1mil['avg_rating']>= 6.5]
highly_rated.sort_values(by="no_votes",ascending=False).head(10)
```

Out[45]:

genres	avg_rating	no_votes
Action,Adventure,Animation	7	3,570,543
Biography,Drama,History	7	3,502,843
Biography,Drama	7	2,694,678
Biography,Crime,Drama	7	2,491,084
Biography,Comedy,Drama	7	2,418,463
Biography,Drama,Thriller	7	1,859,152
Documentary	7	1,785,513
Action,Biography,Drama	7	1,510,436
Biography,Drama,Sport	7	1,432,227
Action,Drama,History	7	1,124,245

The above shows that Action, Adventure and Animation receives the most critiics reviews, suggesting that it is quite popular among the film critics.

Now, we would like to find out if the highly rated genres by critics are also doing well in terms of sales:

In [46]:
```
#create new data frame

highly_rated_sales = pd.merge( highly_rated,Genres_df,
                              on=['genres'],
                              how='left')
highly_rated_sales.drop(highly_rated_sales.iloc[:, 1:3], inplace=True, axis=1)
highly_rated_sales.groupby('genres').sum().sort_values(by="total sales",ascending=False).head(10)
highly_rated_sales2=highly_rated_sales.groupby('genres').sum().sort_values(by="total sales",ascending=False).head(10)
```

In [47]:
```
highly_rated_sales2
```

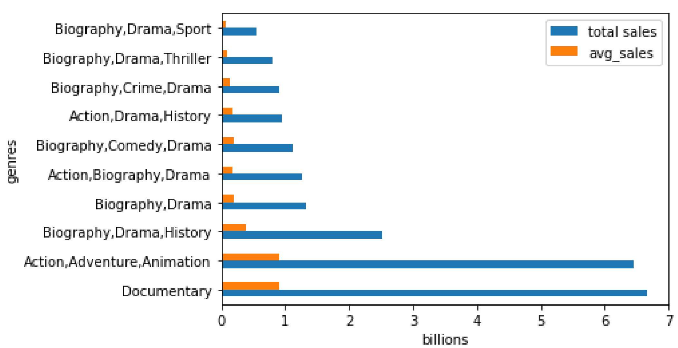
Out[47]:

genres	total sales	avg_sales
Documentary	6,670,552,396	918,880,416
Action,Adventure,Animation	6,454,160,400	899,124,031
Biography,Drama,History	2,520,359,399	379,434,181
Biography,Drama	1,334,131,099	187,036,867
Action,Biography,Drama	1,256,488,900	174,417,353
Biography,Comedy,Drama	1,125,083,600	202,817,471
Action,Drama,History	944,747,300	182,873,550
Biography,Crime,Drama	912,358,200	129,128,717
Biography,Drama,Thriller	806,888,000	101,284,439
Biography,Drama,Sport	563,121,600	64,648,889

In [48]:
```
import matplotlib.ticker as ticker
graph2 = highly_rated_sales2.plot.barh()
current_values = plt.gca().get_xticks()

scale_x = 1e9
ticks_x = ticker.FuncFormatter(lambda y, pos: '{0:g}'.format(y/scale_x))
graph2.xaxis.set_major_formatter(ticks_x)
graph2.set_xlabel('billions')
```

Out[48]: Text(0.5, 0, 'billions')



Action, Adventure and Animation is still performing well in term of sales. Whilst Documentory did not receive as much traction with the film critics, it is still highly rated and generate the most sales out of the top 10 highly rated genres. Biography and Drama appear in 7 out the top 10 highly rated genres.

What are the best selling genres recently?

In [49]:
```
# best selling or rating by year (grouped)
titles_ratings_sales.head()
```

Out[49]:

	ID	title	year	runtime_minutes	genres	avg_rating	no_votes	total sales	avg_sales
0	tt0063540	Sunghursh	2013	175	Action,Crime,Drama	7	77	nan	nan
1	tt0066787	One Day Before the Rainy Season	2019	114	Biography,Drama	7	43	nan	nan
2	tt0069049	The Other Side of the Wind	2018	122	Drama	7	4,517	nan	nan
3	tt0069204	Sabse Bada Sukh	2018	nan	Comedy,Drama	6	13	nan	nan
4	tt0100275	The Wandering Soap Opera	2017	80	Comedy,Drama,Fantasy	6	119	nan	nan

In [50]:
```
#create new dataframe for analysis:
sales_by_year = titles_ratings_sales[['year','genres','total sales']].copy()
sales_by_year.dropna(inplace=True)
sales_by_year.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3302 entries, 38 to 146080
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   year         3302 non-null   int64  
 1   genres       3302 non-null   object 
 2   total sales  3302 non-null   float64
dtypes: float64(1), int64(1), object(1)
memory usage: 103.2+ KB
```

In [51]:
```
sales_by_year
```

Out[51]:

	year	genres	total sales
38	2016	Action,Crime,Drama	1,100,000
48	2012	Adventure,Drama,Romance	8,744,000
54	2013	Adventure,Comedy,Drama	188,100,000
58	2014	Action,Crime,Drama	53,200,000
60	2015	Action,Adventure,Sci-Fi	652,301,019
...	...	...	...
145431	2019	Drama	14,900,000
145505	2018	Drama	22,800
145666	2019	Action,Drama	105,000,000
145702	2019	Crime	613,000
146080	2019	Documentary	167,800,000

3302 rows × 3 columns

In [52]:
```
sales_by_year2=sales_by_year.groupby(['year', 'genres']).sum().reset_index()
sales_by_year2
```

Out[52]:

	year	genres	total sales
0	2010	Action	26,417,500
1	2010	Action,Adventure,Animation	635,000,000
2	2010	Action,Adventure,Crime	30,757,000
3	2010	Action,Adventure,Drama	503,492,600
4	2010	Action,Adventure,Family	535,000,000
...	...	...	...
1155	2019	History	34,700,000
1156	2019	Horror	113,200,000
1157	2019	Horror,Thriller	343,000
1158	2019	Thriller	60,917,500
1159	2020	Drama	76,900

1160 rows × 3 columns

In [53]:
```
sales_by_year2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1160 entries, 0 to 1159
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   year         1160 non-null   int64
 1   genres       1160 non-null   object
 2   total sales  1160 non-null   float64
dtypes: float64(1), int64(1), object(1)
memory usage: 27.3+ KB
```

In [54]:
```
sales_by_year3=sales_by_year2.sort_values(by="total sales",ascending=False).groupby('year').head(1).sort_values(by="year",ascending=False)
sales_by_year3
```

Out[54]:

	year	genres	total sales
1159	2020	Drama	76,900
1135	2019	Action	306,700,000
1048	2018	Action,Adventure,Sci-Fi	4,386,201,370
920	2017	Action,Adventure,Fantasy	4,513,100,000
825	2016	Adventure,Animation,Comedy	4,780,699,999
664	2015	Action,Adventure,Sci-Fi	3,366,401,019
526	2014	Action,Adventure,Sci-Fi	4,030,400,000
397	2013	Action,Adventure,Sci-Fi	4,803,500,000
302	2012	Adventure,Animation,Comedy	2,881,170,200
171	2011	Adventure,Animation,Comedy	2,737,471,700
32	2010	Adventure,Animation,Comedy	2,663,400,000

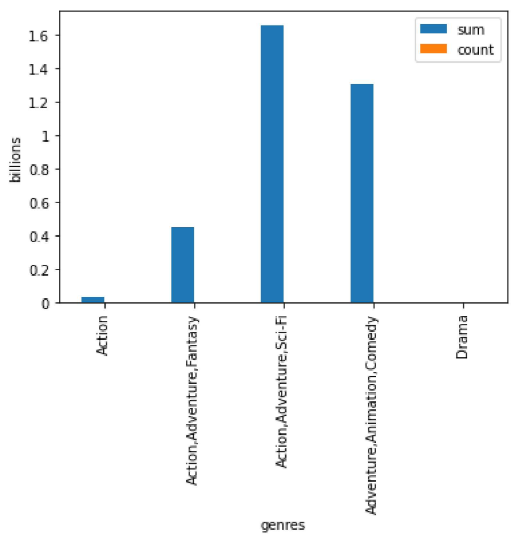
In [55]:
```
sales_by_year4=sales_by_year3.groupby('genres').agg({'total sales': ['sum', 'count']}).reset_index()
sales_by_year4
```

Out[55]:

	genres	total sales	
		sum	count
0	Action	306,700,000	1
1	Action,Adventure,Fantasy	4,513,100,000	1
2	Action,Adventure,Sci-Fi	16,586,502,389	4
3	Adventure,Animation,Comedy	13,062,741,899	4
4	Drama	76,900	1

In [56]:
```
graph3= sales_by_year4.plot.bar(x='genres', y='total sales')
scale_y = 1e10
ticks_y = ticker.FuncFormatter(lambda x, pos: '{0:g}'.format(x/scale_y))
graph3.yaxis.set_major_formatter(ticks_y)
graph3.set_ylabel('billions')
plt.xticks(rotation=90)
```

Out[56]:
```
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'Action'),
  Text(1, 0, 'Action,Adventure,Fantasy'),
  Text(2, 0, 'Action,Adventure,Sci-Fi'),
  Text(3, 0, 'Adventure,Animation,Comedy'),
  Text(4, 0, 'Drama')])
```



'Action,Adventure,Sci-Fiz' and 'Adventure,Animation,Comedy' are most popular genres which generated $16 and$13 billions in sales revnue respectively in the last 10 years.

2019 and 2020 best selling genres appear to be Action and Drama respectively. However, the sales revenue is much lower compared to the previous year. Viewers film preferences may have changed in the last two year or the data may be incomplete.

Limitation

It is worth noting that sales data is a lot smaller compared to rating data i.e. Sales dataset contains ~3300 movies whilst the rating dataset has more than 70,00 movies. The above data analysis is mainly based on sales, therefore, further data collection is highly recommended to further understand the trend.

The analysis has also not considered the cost to make different type of genres which plays a major role in terms of profit.

Conclusions

Despite of the limitation stated above, the recommendations are:

From a sales perspective, the top 2 best selling genres based on both total and averaged sales are 1 - Action, Adventure and Scifi 2 - Action, Animation and Comedy

It is worth noting that Action and Adventure genres appear in all 7 out of Top 10 selling genres of all time. It is recommended that a film with a mix genre of at least Action and Adventure will most likely to be performing well in the box office.

In terms of ratings, 'Action, Adventure and Animation' performs well the most among the highly rated movies. Whilst Documentory did not receive as much traction from the film critics, it is still highly rated and generate the most sales out of the top 10 highly rated genres. Biography and Drama appear in 7 out the top 10 highly rated genres with a good sales performance.

Lastly, 'Action,Adventure,Sci-Fi' and 'Adventure,Animation,Comedy' are most popular genres which generated $16 and$13 billions in sales revnue respectively in the last 10 years.

Next step, the business should look to obtain a larger dataset for sales, especially for 2019 and 2020 datasets and ensure that the datasets are up to date and complete. Furthermore, cost should also be a key factor for consideration as it can be more costly to create film in Action, Animiation or Scifi genres than Drama or Documentary. It may be more profitable make Drama or Documentary if they can generate a good volumn of sales, which may not be as much as Action, Animation or Scifi.

In [ ]:

```

```