Project: Investigate a Dataset - TMDB Movie Data

Introduction

The information about 10,000 movies in this data set comes from The Movie Database (TMDB). There are 21 columns in the data set and they are:

1. id - unique ID for each row
2. imdb_id - the ID of the movie in IMDB
3. popularity - popularity rating
4. budget - budget of the movie in dollars
5. revenue - revenue of the movie in dollars
6. original_title - title of the movie
7. cast - cast in the movie
8. homepage - homepage of the movie
9. director - director of the movie
10. tagline - tagline of the movie
11. keywords - words to describe the movie
12. overview - general review of the movie
13. runtime - duration of the movie
14. genres - genre/s of the movie
15. production_companies - company that manages the movie
16. release_date - release date of the movie
17. vote_count - vote count of the movie
18. vote_average - average vote of the movie
19. release_year - release year of the movie
20. budget_adj - budget in terms of 2010 dollars
21. revenue_adj - revenue in terms of 2010 dollars

Questions (5)

1. Is the budget of movies getting higher or lower or staying the same over time?
   1B. Did movies with higher runtime have a bigger budget?
2. What is the relationship between years and the amount of movies?
   2B. What is the relationship between months and the amount of movies?
3. What movie has the largest earned revenue? The least?
4. What is the most popular genre?
5. What is the average runtime of all the movies?

In [1]:
```
#packages that I plan on using
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import csv
```

Data Wrangling

In [2]:
```
#loading the data and printing out a few rows
film_dt = pd.read_csv('tmdb-movies.csv')
film_dt.head(3)
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://ww
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentser

3 rows × 21 columns

In [3]:
```
#examining all the columns' data types
film_dt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                      10866 non-null int64
imdb_id                 10856 non-null object
popularity              10866 non-null float64
budget                  10866 non-null int64
revenue                 10866 non-null int64
original_title          10866 non-null object
cast                    10790 non-null object
homepage                2936 non-null object
director                10822 non-null object
tagline                 8042 non-null object
keywords                9373 non-null object
overview                10862 non-null object
runtime                 10866 non-null int64
genres                  10843 non-null object
production_companies    9836 non-null object
release_date            10866 non-null object
vote_count              10866 non-null int64
vote_average            10866 non-null float64
release_year            10866 non-null int64
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

In [4]:
```
#describing the data
film_dt.describe()
```

Out[4]:

	id	popularity	budget	revenue	runtime	vote_count	vote_average
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000000
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974922
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935142
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500000
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400000
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200000

Dropping columns that are not needed in the analysis

In [5]:
```
#dropping columns for readability
dropped_columns = ["id","imdb_id","cast","homepage","tagline","keywords","overview"]
film_dt.drop(dropped_columns, inplace=True, axis=1)
```

In [6]:
```
#checking to see if there are any duplicates in the data
sum(film_dt.duplicated())
```
Out[6]: 1

Dropping any duplicates

In [7]:
```
#dropping duplicates
film_dt.drop_duplicates(inplace=True)
```

In [8]:
```
#checking to see if there are any duplicates in the data
sum(film_dt.duplicated())
```
Out[8]: 0

Converting the column 'release_date' type to date

In [9]:
```
#converting the column 'release_date' type to date
film_dt["release_date"] = pd.to_datetime(film_dt["release_date"])
```

Replacing all values of 0 with NaN

In [10]:
```
#replacing all values of 0 with NaN
film_dt = film_dt.replace(0, np.nan)
```

Dropping all the null values from the data

In [11]:
```
#dropping the null values
film_dt = film_dt.dropna()
```

Converting the columns 'budget' and 'revenue' types to int

In [12]:
```
#converting the columns 'budget' and 'revenue' to int
type_change = ['budget', 'revenue']
#changing data type
film_dt[type_change] = film_dt[type_change].applymap(np.int64)
```

In [13]:
```
#checking if the all the conversions have taken effect
film_dt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3807 entries, 0 to 10848
Data columns (total 14 columns):
popularity              3807 non-null float64
budget                  3807 non-null int64
revenue                 3807 non-null int64
original_title          3807 non-null object
director                3807 non-null object
runtime                 3807 non-null float64
genres                  3807 non-null object
production_companies    3807 non-null object
release_date            3807 non-null datetime64[ns]
vote_count              3807 non-null int64
vote_average            3807 non-null float64
release_year            3807 non-null int64
budget_adj              3807 non-null float64
revenue_adj             3807 non-null float64
dtypes: datetime64[ns](1), float64(5), int64(4), object(4)
memory usage: 446.1+ KB
```

The Cleaning Process Summary

- I dropped the columns "id", "imdb_id", "cast", "homepage", "tagline", "keywords", and "overview" since I won't be using them for data analysis.
- I dropped any duplicate rows.
- I changed the "release_date" column's data type from string to date.
- I dropped the null or 0 values from the data.
- I changed the "budget" and "revenue" columns' data types from float to int.

Exploratory Data Analysis

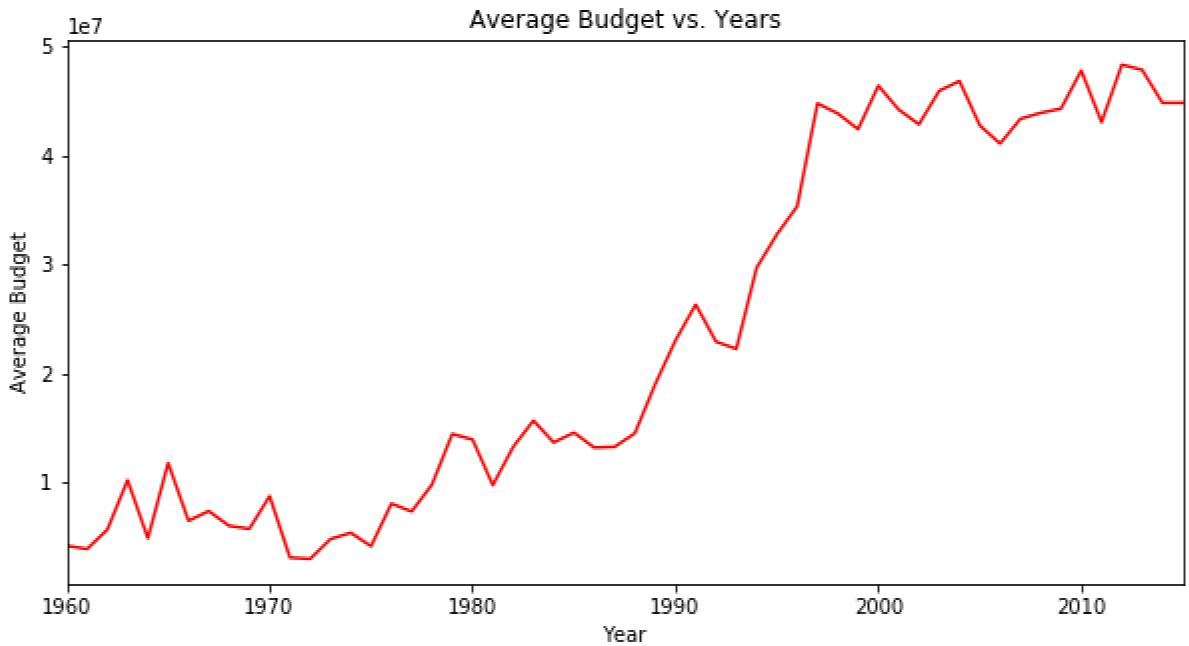
Research Question 1: Is the budget of movies getting higher or lower or staying the same overtime?

In [14]:
```
#function that calculates the mean for the 2nd column(c2) and groupby by the first colum
n(c1)
def average_groupby(c1, c2):
    average_groupby_data = film_dt.groupby(c1)[c2].mean()
    return average_groupby_data
```

In [15]:
```
#calling the average_groupby function with release_year and budget arguments
yr_budget_average = average_groupby('release_year','budget')

#plotting the relationship between release_year and budget using a line graph
yr_budget_average.plot(kind = 'line', color = 'red', figsize = (10,5))
plt.xlabel('Year')
plt.ylabel('Average Budget')
plt.title('Average Budget vs. Years')
```

Out[15]:
```
Text(0.5,1,'Average Budget vs. Years')
```



The average budget has increased significantly from 1960 to 2015. The 2010s have the biggest average budget to produce movies while the 1960s have the lowest. It is worth noting that there is a huge increase of budget between 1990 and 2000.

Research Question 1B: Did movies with higher runtime have a bigger budget?

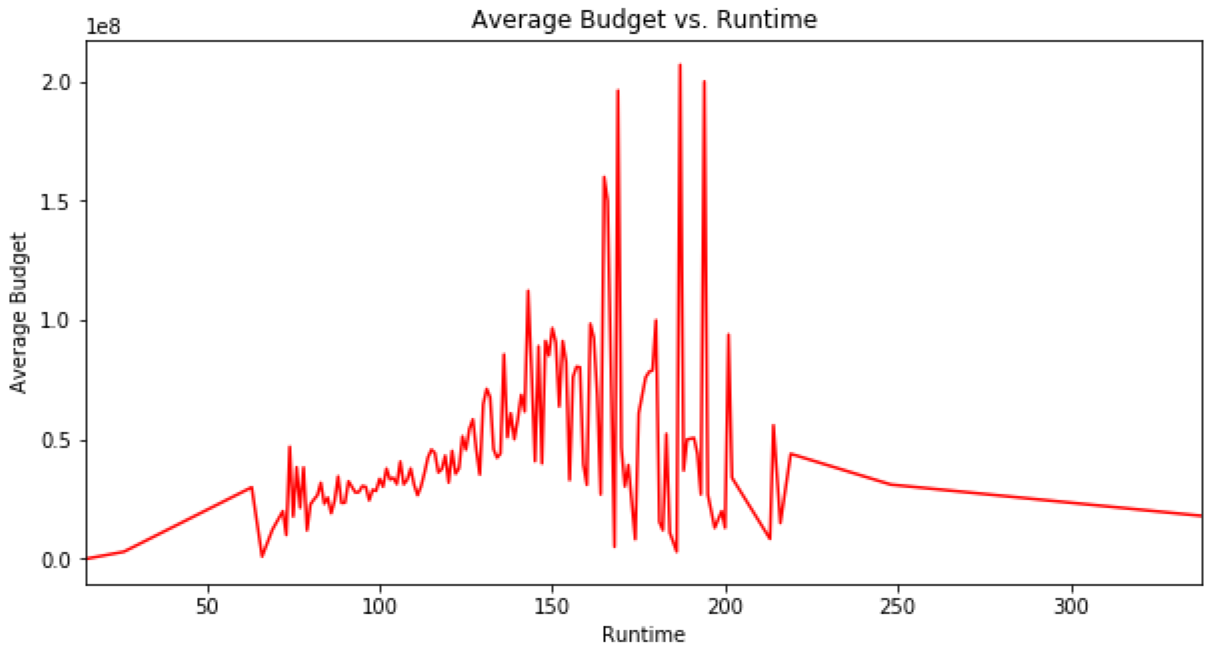
In [16]:

```
#calling the average_groupby function with runtime and budget arguments
runtime_budget_average = average_groupby('runtime','budget')

#plotting the relationship between runtime and budget using a line graph
runtime_budget_average.plot(kind = 'line', color = 'red', figsize = (10,5))
plt.xlabel('Runtime')
plt.ylabel('Average Budget')
plt.title('Average Budget vs. Runtime')
```

Out[16]:

```
Text(0.5,1,'Average Budget vs. Runtime')
```



On average, films that have a runtime between 150 and 200 have a bigger budget than films whose runtimes are less than 150 or more than 200.

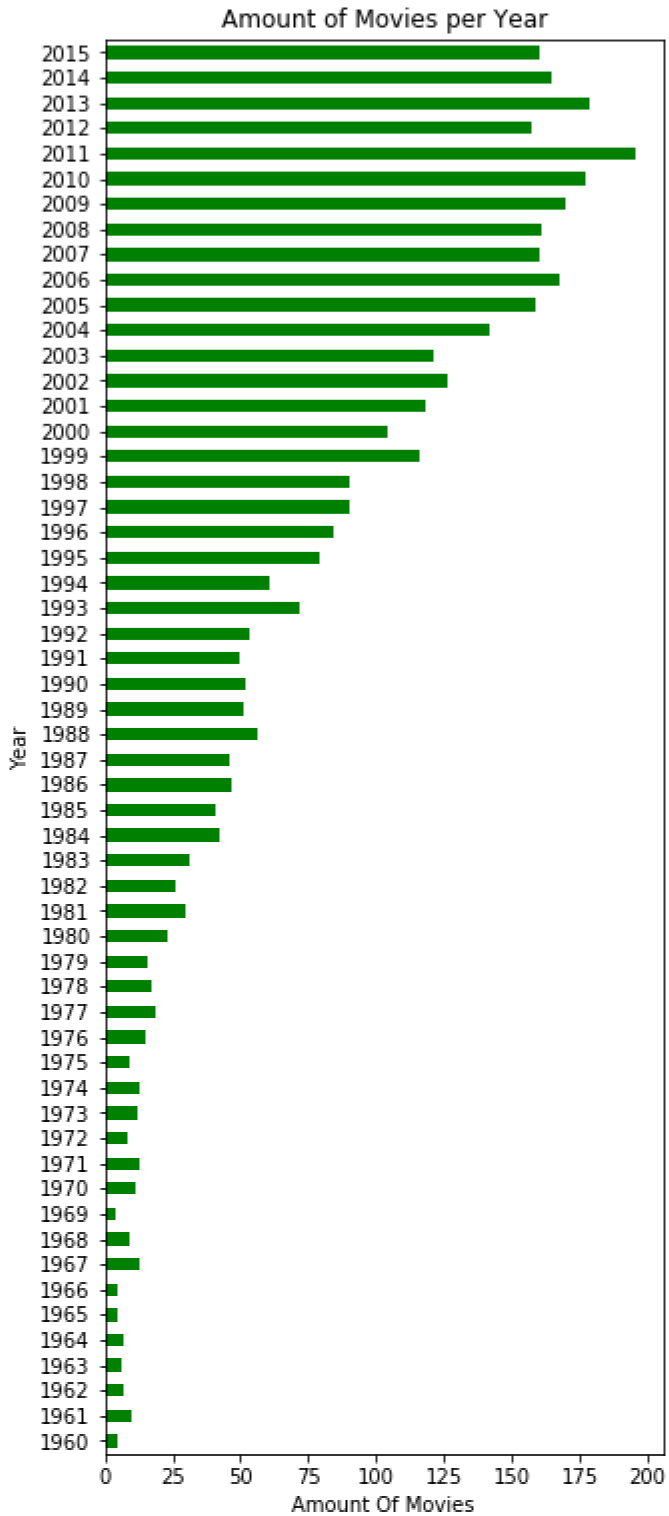
Research Question 2: What is the relationship between years and the amount of movies?

In [17]:

```
#counting the amount of movies per year and then sorting the result
yr_movies_total = film_dt['release_year'].value_counts().sort_index()

#plotting the relationship between release_year and the amount of movies using a horizon
tal bar graph
yr_movies_total.plot(kind = 'barh', color = 'green', figsize = (5,13))
plt.xlabel('Amount Of Movies')
plt.ylabel('Year')
plt.title('Amount of Movies per Year')
```

Out[17]: Text(0.5,1,'Amount of Movies per Year')



The number of movies released has increased significantly from 1960 to 2015. The year 2011 has released the most movies while the year 1969 has released the fewest. It is worth noting that 2011 alone has released more movies than the entire '60s and '70s combined.

Research Question 2B: What is the relationship between months and the amount of movies?

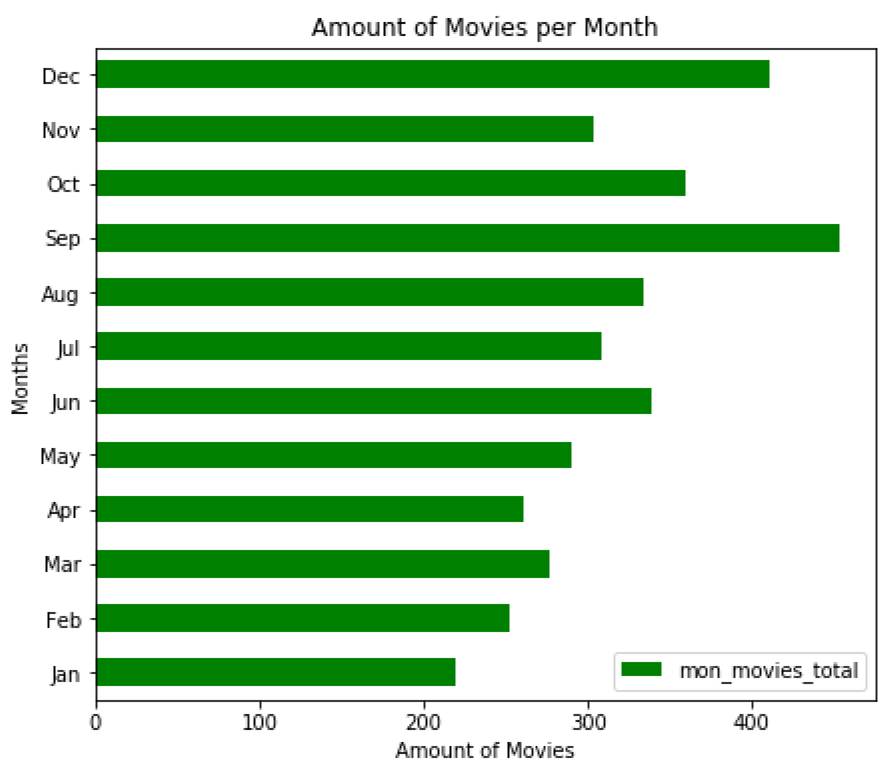
In [18]:
```
#outputting the total number of movies released in each month in all of the years
mon_movies_total = film_dt['release_date'].dt.month.value_counts().sort_index()
mon_movies_total
```

Out[18]:
```
1     219
2     252
3     277
4     261
5     290
6     339
7     308
8     334
9     453
10    360
11    303
12    411
Name: release_date, dtype: int64
```

In [19]:
```
#setting up the months
mon = ['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']
mon_movies_total = pd.DataFrame(mon_movies_total)
mon_movies_total['month'] = mon
mon_movies_total.rename(columns = {'release_date':'mon_movies_total'}, inplace = True)

#plotting the relationship between months and the amount of movies using a horizontal ba
r graph
mon_movies_total.plot(x = 'month', kind = 'barh', color = 'green', figsize = (7,6))
plt.xlabel('Amount of Movies')
plt.ylabel('Months')
plt.title('Amount of Movies per Month')
```

Out[19]:
```
Text(0.5,1,'Amount of Movies per Month')
```



The month of September has released the most movies while the month of January has released the fewest. The top 3 highest months are September, December, and October.

Research Question 3: What movie has the largest earned revenue? The least?

In [20]:
```python
#function that finds the maximum and the minimum value
def max_min(x):
    #using the function 'idmin' to find the index of the lowest value.
    idx_min = film_dt[x].idxmin()
    #using the function 'idmax' to find the index of highest value.
    idx_max = film_dt[x].idxmax()
    high = pd.DataFrame(film_dt.loc[idx_max,:])
    low = pd.DataFrame(film_dt.loc[idx_min,:])

    return pd.concat([high,low], axis = 1)
```

In [21]:
```python
max_min('revenue')
```

Out[21]:

	1386	5067
popularity	9.43277	0.462609
budget	237000000	6000000
revenue	2781505847	2
original_title	Avatar	Shattered Glass
director	James Cameron	Billy Ray
runtime	162	94
genres	Action|Adventure|Fantasy|Science Fiction	Drama|History
production_companies	Ingenious Film Partners|Twentieth Century Fox ...	Lions Gate Films|Cruise/Wagner Productions|Bau...
release_date	2009-12-10 00:00:00	2003-11-14 00:00:00
vote_count	8458	46
vote_average	7.1	6.4
release_year	2009	2003
budget_adj	2.40887e+08	7.11212e+06
revenue_adj	2.82712e+09	2.37071

The film that has the highest earned revenue is "Avatar" with a value of 2.7 Billion Dollars, while the film that has the lowest earned revenue is "Shattered Glass" with a value of 2 Dollars.

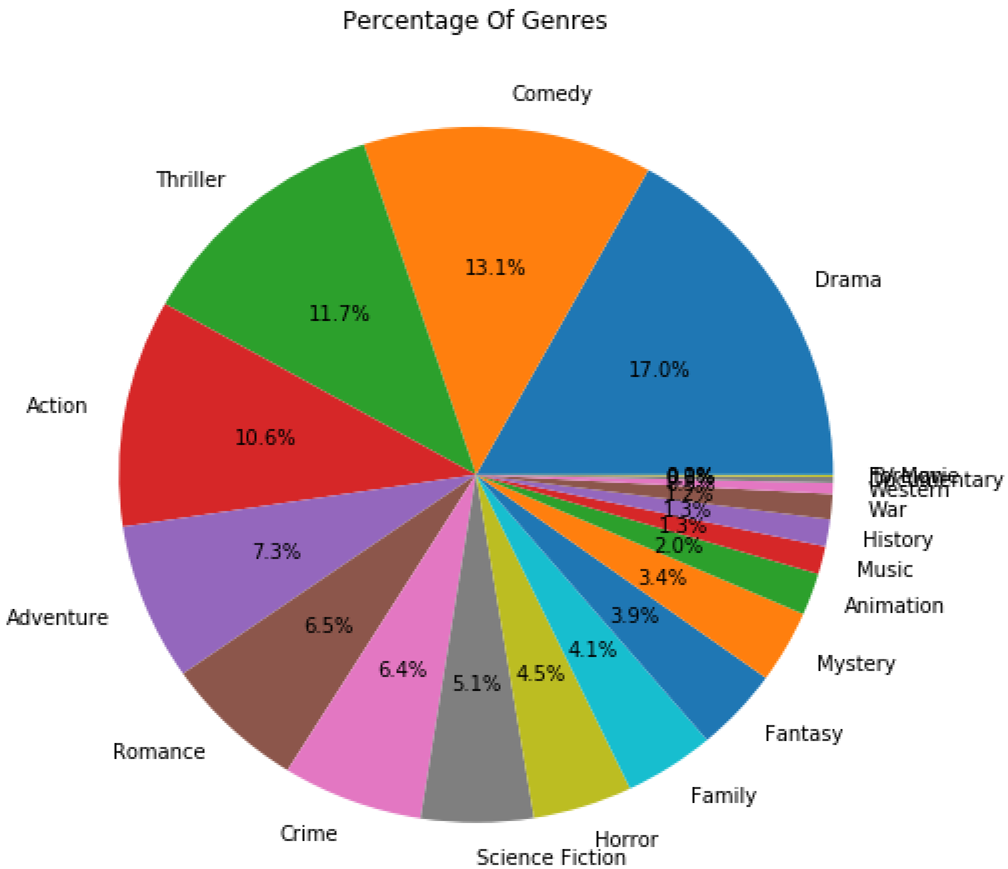
Research Question 4: What is the most popular genre?

In [22]:
```python
#function that separates the data in genres column since there are multiple genre value
s, and counts the number of movies in each genre
def spt_count(c):
    spt_data = pd.Series(film_dt[c].str.cat(sep = '|').split('|'))

    tot_data = spt_data.value_counts(ascending=False)
    return tot_data
```

In [23]:
```python
# Plotting the relationship between genres and amount of movies using a pie chart.
spt_count('genres').plot(kind = 'pie', figsize = (8,8), autopct = '%1.1f%%')
plt.title('Percentage Of Genres')
plt.ylabel('')
```

Out[23]: `Text(0,0.5,'')`



The most popular genre in the film industry from 1960 to 2015 is Drama. Drama takes up about 17% of the pie chart. The next three highest genres are Comedy, Thriller, and Action, respectively. Adding the four aforementioned genres takes up about half of the pie chart.

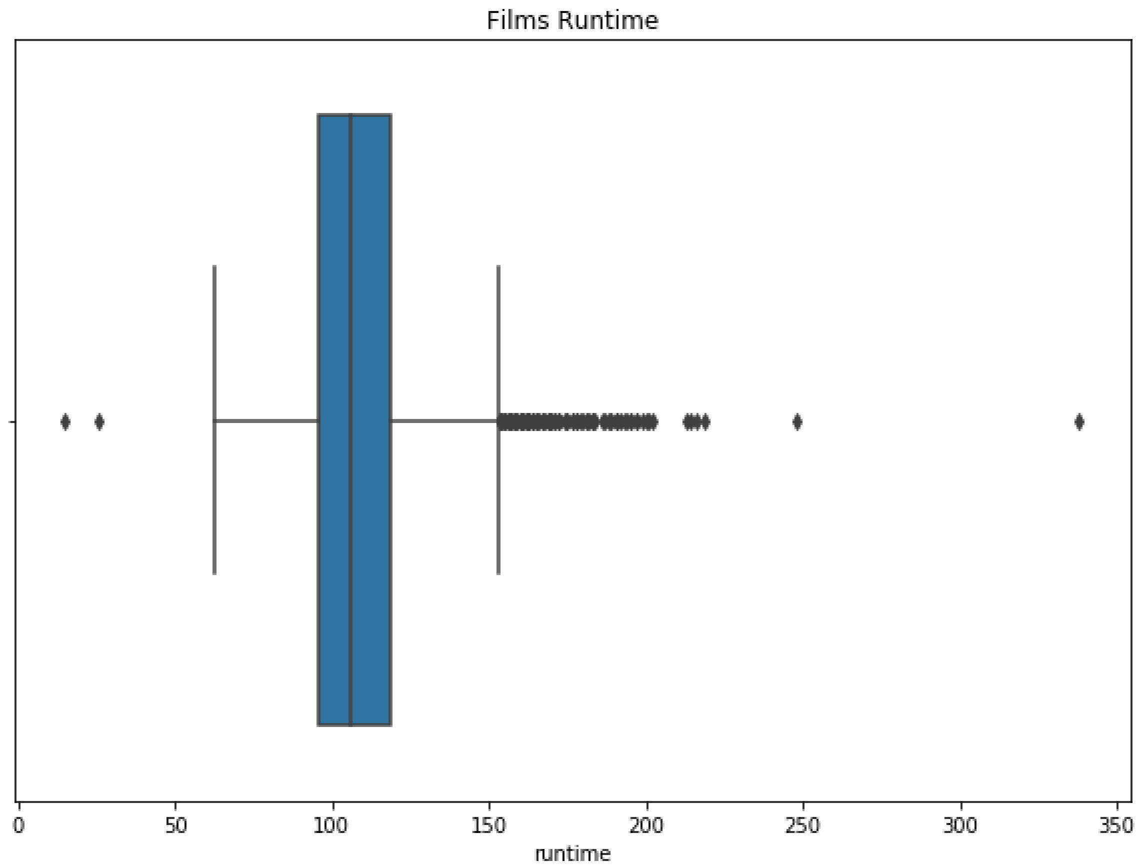
Research Question 5: What is the average runtime of all the movies?

In [24]:
```python
#function that calculates the mean for the column (c1)
def average_col(c1):
    return film_dt[c1].mean()

#calling the average_col function with runtime argument
average_col('runtime')
```

Out[24]: `109.35093249277647`

In [25]:
```
#Plotting the average runtime using boxplot
plt.figure(figsize = (10,7))
sns.boxplot(film_dt['runtime'])
plt.title('Films Runtime')
plt.show()
```



The average duration of all the movies is 109 minutes. The lowest duration is about 15 minutes while the highest duration is about 340 minutes.

Conclusions

1. The first question "Is the budget of movies getting higher or lower or staying the same over time?" has shown predictable results. Looking at the line graph, we can see the average budget to produce films is increasing over time. There is also a significant difference between the budget of films made in the 1960s and the budget of films made in the 2010s.

> 1B. The question "Did movies with higher runtime have a bigger budget" has shown surprising results. Looking at the line graph, we can see that movies with a runtime between 150 and 200 have a bigger budget than movies with a runtime that fall outside of that range.

1. In the second question "What is the relationship between years and the amount of movies?" the number of movies released has increased significantly from the year 1960 to 2015. It's also worth noting that the year 2011 alone has released more movies than the entire 1960s and 1970s combined.

> 2B. In the question "what is the relationship between months and the amount of movies?" the month of September has released the most movies, followed by December and October. It's interesting that there is a greater number of movies that is released in the fall season than in any season.

1. In the third question "What movie has the largest earned revenue? The least?" Avatar has the highest earned revenue with a value of 2.7 Billion Dollars, while Shattered Glass has the lowest earned revenue with a value of 2 Dollars.

1. In the fourth question "What is the most popular genre?" Drama is the most popular genre in the film industry from 1960 to 2015, followed by Comedy, Thriller, and Action. These four genres take up about 50% of the pie chart.

1. In the fifth question "What is the average runtime of all the movies?" the answer is 109 minutes. The highest duration is about 340 minutes while the lowest duration is about 15 minutes.

Limitations

Due to missing values, we had to delete many rows in the data, which ultimately affected our overall results. We also altered the datatypes of some columns in the data. Additionally, we are not certain if the TMDB data included some of the popular movies from all over the world.

In [ ]:

```

```