Analysis of Movie Data

Questions to be answered

1. Is there any correlation between critic and user ratings with box office results in the U.S.?

1. Which genres of film resulted in the greatest box office success?

1. Does MPAA rating affect the box office?

1. How does the month of release affect box office results?

1. Does runtime affect box office results?

In [1]:
```
#Import Dependancies
%matplotlib inline
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.api as sm
import datetime as dt
import seaborn as sns ; sns.set()
from matplotlib.ticker import PercentFormatter
```

In [2]:
```
#Import the data
movies = pd.read_csv('Movie_Data.csv')
movies.head()
```

Out[2]:

	IMDb ID	Title	Runtime (mins)	Year	Genres	Release Date	IMDb Rating	Metascore	Rating	Box C
0	tt1872181	The Amazing Spider-Man 2	142	2014	Action, Adventure, Sci-Fi	4/10/2014	6.6	53	PG-13	18327
1	tt1323594	Despicable Me	95	2010	Animation, Comedy, Family, Fantasy	6/20/2010	7.7	72	PG	25147
2	tt1375670	Grown Ups	102	2010	Comedy	6/24/2010	6.0	30	PG-13	16200
3	tt0892769	How to Train Your Dragon	98	2010	Animation, Action, Adventure, Family, Fantasy	3/18/2010	8.1	74	PG	21690
4	tt1375666	Inception	148	2010	Action, Adventure, Sci-Fi, Thriller	7/8/2010	8.8	74	PG-13	29256

1. Analysis of Critics and User Rating

We want to see whether user rating (represented by IMDB rating) and critics rating (represented by the metascore) are significantly different for the films

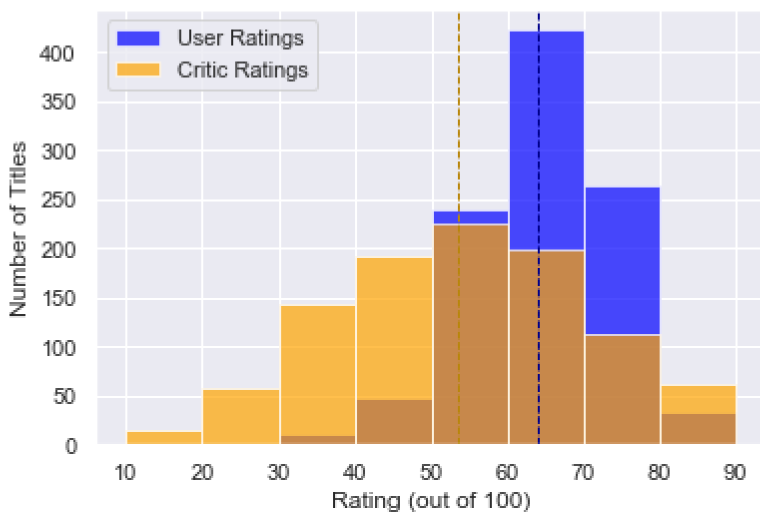
If so, we want to see how the scores influence the box office return.

This will allow us to determine which score, if any, to target in the creation of our movie

Testing Differences

First, lets visualize the differences by displaying them as histograms

In [3]:
```
#Plot the histogram of the IMDb Rating to represent the user ratings
#Values are multiplied by 10 to show them on the same scale as the metascore
plt.hist(movies['IMDb Rating'] * 10, bins=[10, 20, 30, 40, 50 , 60, 70, 80, 90
], label='User Ratings', alpha=0.7, color='blue')
plt.axvline(movies['IMDb Rating'].mean() * 10, color='darkblue', linestyle='da
shed', linewidth=1)

#Plot the histogram of the Metacritic Rating to represent the critic rating ra
tings
plt.hist(movies['Metascore'], bins=[10, 20, 30, 40, 50 , 60, 70, 80, 90], labe
l='Critic Ratings', alpha=0.7, color='orange')
plt.axvline(movies['Metascore'].mean(), color='darkgoldenrod', linestyle='dash
ed', linewidth=1)
plt.legend()
plt.xlabel('Rating (out of 100)')
plt.ylabel('Number of Titles')

plt.savefig("Analysis Charts/1. Critic and User Rating/Rating_Histogram.png")

plt.show()
```



Observations

Looking at the histograms, we can see the average User score is higher than the average critic's score.

Most of the user ratings fall between 50 and 70, whereas the critics ratings are much more widely distributed

Next, let's test to ensure the two are statistically different. We will be using a 2-sample T-test with a confidence level of 95% to make our determination

The hypothesis we are testing is the the two scores are different

The null hypothis is that the two score are the same

In [4]:
```
p_value = stats.ttest_ind(movies['IMDb Rating'] * 10, movies['Metascore'], equ
al_var=False)

print(f"The P value = {p_value[1]}")
```

```
The P value = 3.64643515520769e-62
```

Observations

Since the P value is less than 5%, we need to reject the null hypothosis that the two scores are the same

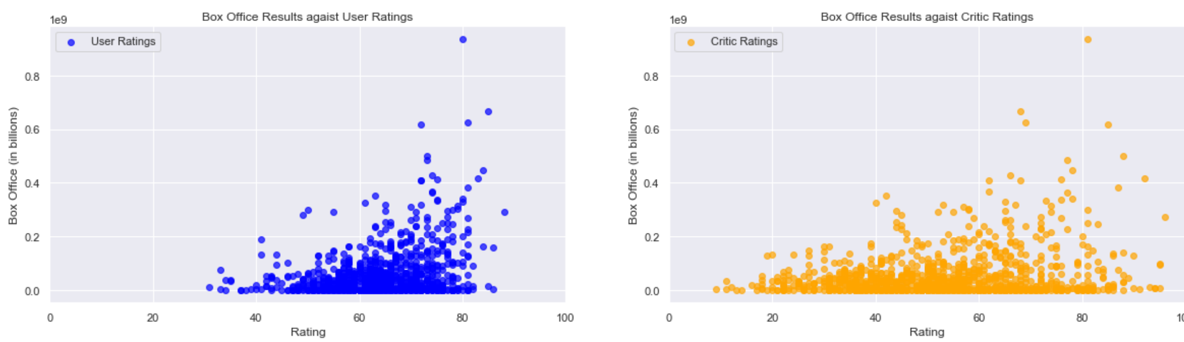
Now that we know the scores are different, let's visualized how the box office returns change given a change in each of the scores.

We can do this by using scatterplots. Again, the need to multipy the IMDb score by 10 to set the axis to be the same.

In [5]:
```
movies['Box Office'].max()
```

Out[5]:
```
936658640
```

In [6]:
```
f = plt.figure(figsize=(20,5))

ax = plt.subplot(1,2,1)
ax.scatter(movies['IMDb Rating'] * 10, movies['Box Office'], label='User Ratin
gs', alpha=0.7, color='blue')

ax2 = plt.subplot(1,2,2)
ax2.scatter(movies['Metascore'],movies['Box Office'], label='Critic Ratings',
alpha=0.7, color='orange', )

ax.legend()
ax2.set_xbound(0,100)
ax.set_xbound(0,100)
ax2.legend()
ax.set_xlabel('Rating')
ax2.set_xlabel('Rating')
ax.set_ylabel('Box Office (in billions)')
ax2.set_ylabel('Box Office (in billions)')
ax.set_title('Box Office Results agaist User Ratings')
ax2.set_title('Box Office Results agaist Critic Ratings')

plt.savefig("Analysis Charts/1. Critic and User Rating/Rating_Scatter.png")

plt.show()
```



Observations

As expected from the histogram, the critics ratings are have a much wider distribution than the User ratings

There are a large number of movies that, regardless of the rating, have very low box office numbers.

Although the correlation appears weak it does seem like the higher the rating is, there are more high box office movies there are

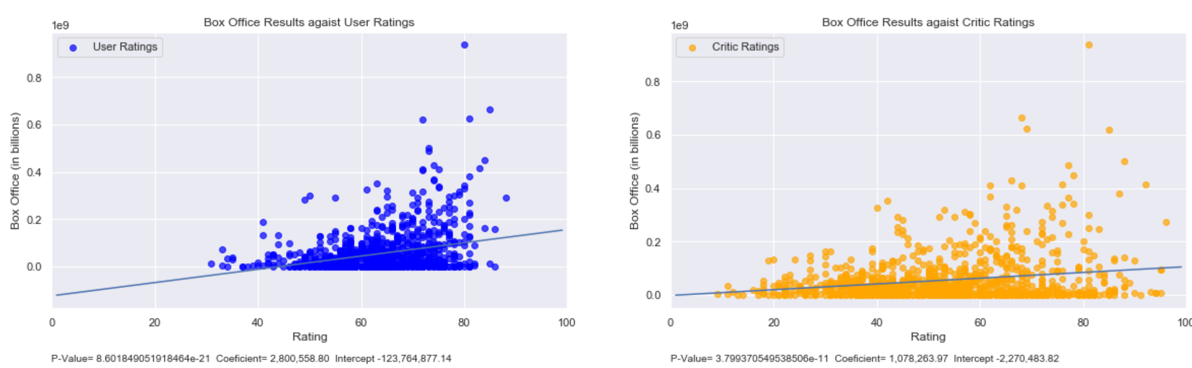
The variables seem to be highly correlated

Now we're going to test the observation made in the scatter plots by using a regression analysis for each to see if the trend is satistically significant

In [7]:
```
regress_user = stats.linregress(movies['IMDb Rating'] * 10, movies['Box Offic
e'])

regress_user
```

Out[7]:
```
LinregressResult(slope=2800558.7969714804, intercept=-123764877.13609344, rva
lue=0.28739826331757057, pvalue=8.601849051918464e-21, stderr=292959.39635618
84)
```

In [8]:
```
f = plt.figure(figsize=(20,5))
x = np.arange(1, 100, 1)
regress_user = stats.linregress(movies['IMDb Rating'] * 10, movies['Box Offic
e'])
regress_critic = stats.linregress(movies['Metascore'], movies['Box Office'])

ax = plt.subplot(1,2,1)
ax.scatter(movies['IMDb Rating'] * 10, movies['Box Office'], label='User Ratin
gs', alpha=0.7, color='blue')
ax.plot(x, x * regress_user[0] + regress_user[1])

ax2 = plt.subplot(1,2,2)
ax2.scatter(movies['Metascore'],movies['Box Office'], label='Critic Ratings',
alpha=0.7, color='orange', )
ax2.plot(x, x * regress_critic[0] + regress_critic[1])

ax.legend()
ax2.set_xbound(0,100)
ax.set_xbound(0,100)
ax2.legend()
ax.set_xlabel('Rating')
ax2.set_xlabel('Rating')
ax.set_ylabel('Box Office (in billions)')
ax2.set_ylabel('Box Office (in billions)')
ax.set_title('Box Office Results agaist User Ratings')
ax2.set_title('Box Office Results agaist Critic Ratings')
ax.text(0, -4 * 100000000, 'P-Value= ' + str(regress_user[3]) + '  Coeficient=
' + "{:,.2f}".format(regress_user[0]) + '  Intercept ' + "{:,.2f}".format(regr
ess_user[1]))
ax2.text(0, -2.5 * 100000000, 'P-Value= ' + str(regress_critic[3]) + '  Coefic
ient= ' + "{:,.2f}".format(regress_critic[0]) + '  Intercept ' + "{:,.2f}".for
mat(regress_critic[1]))

plt.savefig("Analysis Charts/1. Critic and User Rating/Rating_LR.png")

plt.show()
```



Observations

Simple linear regression for each of the variables show that, independantly, they are both significant

Since both are independantly significant and they appear to be correlated, let's set up a multiple linear regression analysis to determine if they are both still significant together

In [9]:
```
X = movies[['IMDb Rating', 'Metascore']]
y = movies['Box Office']

X = sm.add_constant(X)
est = sm.OLS(y, X).fit()

est.summary()
```

Out[9]:

OLS Regression Results

Dep. Variable:	Box Office	**R-squared:**	0.083
Model:	OLS	**Adj. R-squared:**	0.081
Method:	Least Squares	**F-statistic:**	45.70
Date:	Thu, 07 Mar 2019	**Prob (F-statistic):**	9.92e-20
Time:	21:55:13	**Log-Likelihood:**	-20004.
No. Observations:	1017	**AIC:**	4.001e+04
Df Residuals:	1014	**BIC:**	4.003e+04
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.263e+08	2.05e+07	-6.146	0.000	-1.67e+08	-8.59e+07
IMDb Rating	2.901e+07	4.34e+06	6.692	0.000	2.05e+07	3.75e+07
Metascore	-7.349e+04	2.34e+05	-0.315	0.753	-5.32e+05	3.85e+05

Omnibus:	719.680	**Durbin-Watson:**	1.370
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	12911.763
Skew:	3.047	**Prob(JB):**	0.00
Kurtosis:	19.357	**Cond. No.**	446.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Observations

After including both variables in the model, we can see that the critic's ratings (Metascore) is no longer significant.

Even though user rating is found to be significant, this modle only has an adjusted R-squared of 0.081, meaning that only 8.3% of the variability is explained by the model.

As such, we should try to maximize the user rating of our film.

---

2. Analysis of Genres

We want to see whether the genres between movies have an affect on average box office earnings.

If so, we want to see which genres lead to the biggest earnings.

This will allow us to narrow down which genres are most popular.

In [10]:
```
# File to Load
movie_data = "Movie_Data.csv"

# Read the Movie Data
movie = pd.read_csv('Movie_Data.csv')

# Display the data table for preview
movie.head()
```

Out[10]:

	IMDb ID	Title	Runtime (mins)	Year	Genres	Release Date	IMDb Rating	Metascore	Rating	Box C
0	tt1872181	The Amazing Spider-Man 2	142	2014	Action, Adventure, Sci-Fi	4/10/2014	6.6	53	PG-13	18327
1	tt1323594	Despicable Me	95	2010	Animation, Comedy, Family, Fantasy	6/20/2010	7.7	72	PG	25147
2	tt1375670	Grown Ups	102	2010	Comedy	6/24/2010	6.0	30	PG-13	16200
3	tt0892769	How to Train Your Dragon	98	2010	Animation, Action, Adventure, Family, Fantasy	3/18/2010	8.1	74	PG	21690
4	tt1375666	Inception	148	2010	Action, Adventure, Sci-Fi, Thriller	7/8/2010	8.8	74	PG-13	29256

In [11]:
```
#Extract relevant columns
movie = movie[['Genres', 'Box Office', 'Year']]
movie.head()
```

Out[11]:

	Genres	Box Office	Year
0	Action, Adventure, Sci-Fi	183277573	2014
1	Animation, Comedy, Family, Fantasy	251476985	2010
2	Comedy	162001186	2010
3	Animation, Action, Adventure, Family, Fantasy	216900000	2010
4	Action, Adventure, Sci-Fi, Thriller	292568851	2010

In [12]:
```
# Create a genre set containing genre types
# Split genres in Genres column using a delimeter
# Looping statement and add genre to the genre set unless already present
genre_set = set()
for row in movie['Genres'].str.split(", "):
    for genre in row:
        if genre not in genre_set:
            genre_set.add(genre)
```

In [13]:
```
# A list containing genres
genre_set = list(genre_set)
```

In [14]:
```
# Create box office success list; y-value
# Looping statement and mean of each genre
averages_list = []
for genre in genre_set:
    mask = movie["Genres"].str.contains(f'{genre}')==True
    avg = movie[mask]["Box Office"].mean()
    averages_list.append(avg)
```

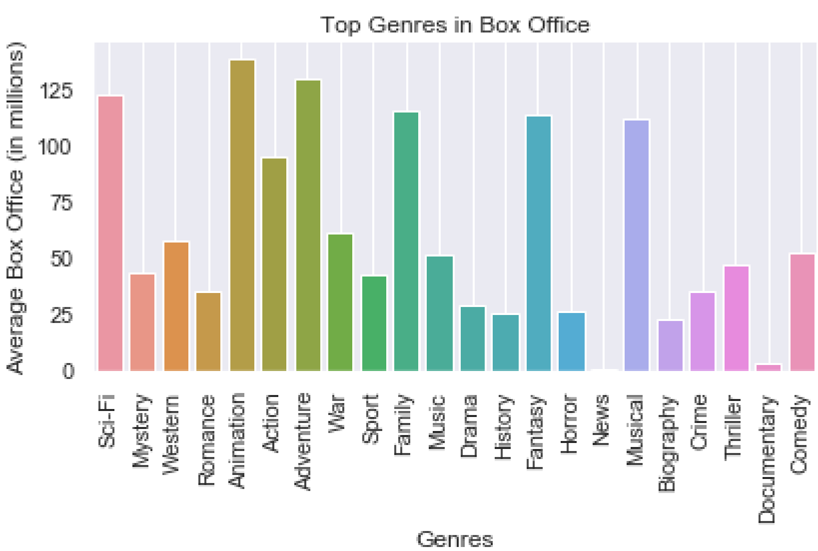
In [15]:
```
# Covert Box Office to millions
averages_list = [x/1000000 for x in averages_list]
averages_list
```

Out[15]:
```
[122.88188585526316,
 42.86875228703704,
 57.635095642857145,
 35.24443222767857,
 138.4912569032258,
 95.066479,
 129.59390039215688,
 61.16326675,
 42.21486465384615,
 115.78014762727273,
 51.67360983636364,
 29.383784037313433,
 25.05508141860465,
 113.4111595549133,
 26.34676623214286,
 0.061153,
 111.68704716666667,
 22.54826979761905,
 35.3096476626506,
 46.52079175884245,
 2.98926508,
 52.621246884514434]
```

In [16]:
```
# Show Genres; x-value
genre_set
```

Out[16]:
```
['Sci-Fi',
 'Mystery',
 'Western',
 'Romance',
 'Animation',
 'Action',
 'Adventure',
 'War',
 'Sport',
 'Family',
 'Music',
 'Drama',
 'History',
 'Fantasy',
 'Horror',
 'News',
 'Musical',
 'Biography',
 'Crime',
 'Thriller',
 'Documentary',
 'Comedy']
```

In [17]:
```
# Bar Chart to identify top Genres
sns.barplot(genre_set, averages_list)
sns.despine()
plt.xticks(rotation=90);

# Add labels to the x and y axes
plt.title("Top Genres in Box Office")
plt.xlabel("Genres")
plt.ylabel("Average Box Office (in millions)")

# Set your grid
plt.grid()

# Tight Layout
plt.tight_layout()

# Save the plot and display it
plt.savefig("Analysis Charts/2. Genres/Top_Genres.png")

# Show figure
plt.show()
```



Genre success over time with a line graph

In [18]:
```
# Create data frame for all animation genre in Genres column
Animation = movie[movie["Genres"].str.contains("Animation")]
Animation.head()
```

Out[18]:

	Genres	Box Office	Year
1	Animation, Comedy, Family, Fantasy	251476985	2010
3	Animation, Action, Adventure, Family, Fantasy	216900000	2010
10	Animation, Adventure, Comedy, Family, Fantasy	414984497	2010
26	Animation, Adventure, Comedy, Family, Fantasy	237282182	2012
40	Animation, Comedy, Family, Fantasy	148280635	2012

In [19]:
```
# Average Box Office per year for Animation genre
animation2010 = Animation["Box Office"][Animation["Year"] == 2010].mean()
animation2011 = Animation["Box Office"][Animation["Year"] == 2011].mean()
animation2012 = Animation["Box Office"][Animation["Year"] == 2012].mean()
animation2013 = Animation["Box Office"][Animation["Year"] == 2013].mean()
animation2014 = Animation["Box Office"][Animation["Year"] == 2014].mean()
animation2015 = Animation["Box Office"][Animation["Year"] == 2015].mean()
animation2016 = Animation["Box Office"][Animation["Year"] == 2016].mean()
```

In [20]:
```
# Create data frame for all adventure genre in Genres column
Adventure = movie[movie["Genres"].str.contains("Adventure")]
Adventure.head()
```

Out[20]:

	Genres	Box Office	Year
0	Action, Adventure, Sci-Fi	183277573	2014
3	Animation, Action, Adventure, Family, Fantasy	216900000	2010
4	Action, Adventure, Sci-Fi, Thriller	292568851	2010
5	Action, Adventure, Sci-Fi	312057433	2010
9	Action, Adventure, Fantasy, Sci-Fi	172051787	2010

In [21]:
```
# Average Box Office per year for adventure genre
adventure2010 = Adventure["Box Office"][Adventure["Year"] == 2010].mean()
adventure2011 = Adventure["Box Office"][Adventure["Year"] == 2011].mean()
adventure2012 = Adventure["Box Office"][Adventure["Year"] == 2012].mean()
adventure2013 = Adventure["Box Office"][Adventure["Year"] == 2013].mean()
adventure2014 = Adventure["Box Office"][Adventure["Year"] == 2014].mean()
adventure2015 = Adventure["Box Office"][Adventure["Year"] == 2015].mean()
adventure2016 = Adventure["Box Office"][Adventure["Year"] == 2016].mean()
```

In [22]:
```
# Create data frame for all Sci-Fi genre in Genres column
SciFi = movie[movie["Genres"].str.contains("Sci-Fi")]
SciFi.head()
```

Out[22]:

	Genres	Box Office	Year
0	Action, Adventure, Sci-Fi	183277573	2014
4	Action, Adventure, Sci-Fi, Thriller	292568851	2010
5	Action, Adventure, Sci-Fi	312057433	2010
9	Action, Adventure, Fantasy, Sci-Fi	172051787	2010
14	Mystery, Sci-Fi, Thriller	79230923	2011

In [23]:
```
# Average Box Office per year for scifi genre
scifi2010 = SciFi["Box Office"][SciFi["Year"] == 2010].mean()
scifi2011 = SciFi["Box Office"][SciFi["Year"] == 2011].mean()
scifi2012 = SciFi["Box Office"][SciFi["Year"] == 2012].mean()
scifi2013 = SciFi["Box Office"][SciFi["Year"] == 2013].mean()
scifi2014 = SciFi["Box Office"][SciFi["Year"] == 2014].mean()
scifi2015 = SciFi["Box Office"][SciFi["Year"] == 2016].mean()
scifi2016 = SciFi["Box Office"][SciFi["Year"] == 2016].mean()
```

In [24]:
```
# Create data frame for all Family genre in Genres column
Family = movie[movie["Genres"].str.contains("Family")]
Family.head()
```

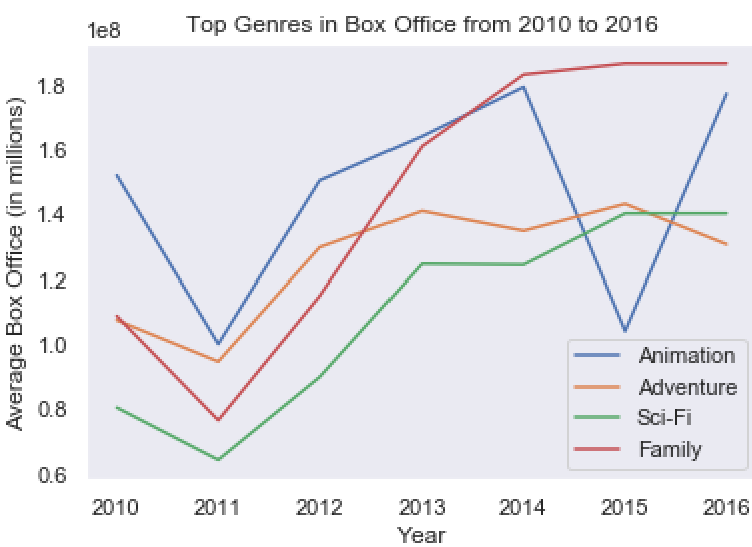
Out[24]:

	Genres	Box Office	Year
1	Animation, Comedy, Family, Fantasy	251476985	2010
3	Animation, Action, Adventure, Family, Fantasy	216900000	2010
10	Animation, Adventure, Comedy, Family, Fantasy	414984497	2010
26	Animation, Adventure, Comedy, Family, Fantasy	237282182	2012
39	Adventure, Family, Fantasy	303001229	2012

In [25]:
```
# Average Box Office per year for Animation genre
family2010 = Family["Box Office"][Family["Year"] == 2010].mean()
family2011 = Family["Box Office"][Family["Year"] == 2011].mean()
family2012 = Family["Box Office"][Family["Year"] == 2012].mean()
family2013 = Family["Box Office"][Family["Year"] == 2013].mean()
family2014 = Family["Box Office"][Family["Year"] == 2014].mean()
family2015 = Family["Box Office"][Family["Year"] == 2016].mean()
family2016 = Family["Box Office"][Family["Year"] == 2016].mean()
```

In [26]:
```
# Define x and y values
Years = ['2010', '2011', '2012', '2013', '2014', '2015', '2016']
animation_list = [animation2010, animation2011, animation2012, animation2013,
animation2014, animation2015, animation2016]
adventure_list = [adventure2010, adventure2011, adventure2012, adventure2013,
adventure2014, adventure2015, adventure2016]
scifi_list = [scifi2010, scifi2011, scifi2012, scifi2013, scifi2014, scifi2015
, scifi2016]
family_list = [family2010, family2011, family2012, family2013, family2014, fam
ily2015, family2016]
```

In [27]:
```
# Line chart to identify top Genres over Years
sns.lineplot(x= Years, y= animation_list, label = "Animation")
sns.lineplot(x= Years, y=adventure_list, label = "Adventure")
sns.lineplot(x= Years, y=scifi_list, label = "Sci-Fi")
sns.lineplot(x= Years, y=family_list, label = "Family")

# Add labels to the x and y axes
plt.title("Top Genres in Box Office from 2010 to 2016")
plt.xlabel("Year")
plt.ylabel("Average Box Office (in millions)")

# Set your grid
plt.grid()

# Save the plot and display it
plt.savefig("Analysis Charts/2. Genres/Top_Genres_Years.png")

# Show figure
plt.show()
```



Observations

1) The top four genres based on box office revenue were animation, adventure, sci-fi, and fantasy.

2) Animation has the lowest box office revenue in 2015 compared to the other top genres.

3) Family genre has the lowest box office revenue compared to the other top genres, but it did had a gradual incline in revenue over the years.

Highlight

Although animation was the top genre with the highest box office revenue between 2010 to 2016, it had the lowest box office revenue in 2015 compared to the other top genres.

---

3. Analysis of MPAA Rating

We want to see whether MPAA rating has an affect on the average box office.

If so, we want to see which ratings have the best and worst outcomes.

This will help determine how graphic users prefer their movies to be.

In [28]:
```
#Read clean data
movies = pd.read_csv("Movie_Data.csv")
movies.head()
```

Out[28]:

	IMDb ID	Title	Runtime (mins)	Year	Genres	Release Date	IMDb Rating	Metascore	Rating	Box C
0	tt1872181	The Amazing Spider-Man 2	142	2014	Action, Adventure, Sci-Fi	4/10/2014	6.6	53	PG-13	18327
1	tt1323594	Despicable Me	95	2010	Animation, Comedy, Family, Fantasy	6/20/2010	7.7	72	PG	25147
2	tt1375670	Grown Ups	102	2010	Comedy	6/24/2010	6.0	30	PG-13	1620C
3	tt0892769	How to Train Your Dragon	98	2010	Animation, Action, Adventure, Family, Fantasy	3/18/2010	8.1	74	PG	21690
4	tt1375666	Inception	148	2010	Action, Adventure, Sci-Fi, Thriller	7/8/2010	8.8	74	PG-13	29256

In [29]:
```
#Extract relevant columns
mpaa_df = movies[['Rating','Box Office']]
mpaa_df.head()
```

Out[29]:

	Rating	Box Office
0	PG-13	183277573
1	PG	251476985
2	PG-13	162001186
3	PG	216900000
4	PG-13	292568851

In [30]:
```
#Create x value
ratings = []
for rating in mpaa_df['Rating']:
    if rating not in ratings:
        ratings.append(rating)

ratings
```

Out[30]:
```
['PG-13', 'PG', 'R', 'G', 'NC-17', 'Not Rated']
```

In [31]:
```
#Create y value
df0 = mpaa_df[mpaa_df['Rating'] == ratings[0]].mean()
df1 = mpaa_df[mpaa_df['Rating'] == ratings[1]].mean()
df2 = mpaa_df[mpaa_df['Rating'] == ratings[2]].mean()
df3 = mpaa_df[mpaa_df['Rating'] == ratings[3]].mean()
df4 = mpaa_df[mpaa_df['Rating'] == ratings[4]].mean()
df5 = mpaa_df[mpaa_df['Rating'] == ratings[5]].mean()

average_box_office = [df0[0],df1[0],df2[0],df3[0],df4[0], df5[0]]
average_box_office = [x/1000000 for x in average_box_office]
average_box_office
```

Out[31]:
```
[81.4896013923077,
 91.66613701587302,
 26.064236822072075,
 120.3966333076923,
 2.971782,
 0.2227295348837209]
```

In [32]:
```
# x and y values as a df
data = pd.DataFrame({"Rating":ratings,"Average Box Office (millions)":average_
box_office})
data
```

Out[32]:

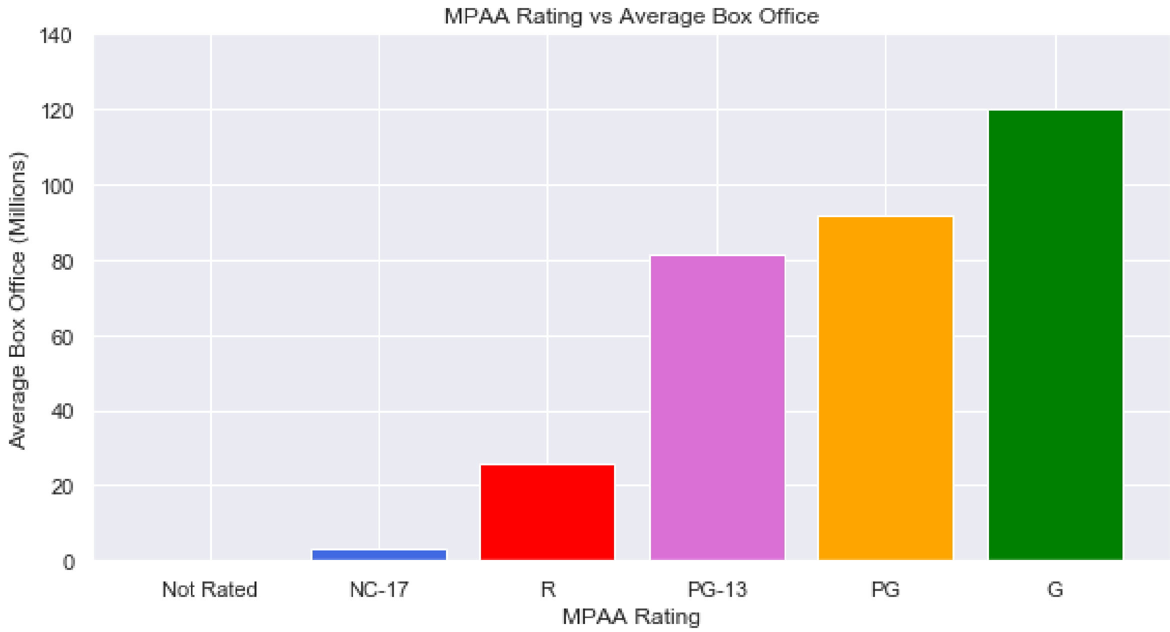
	Rating	Average Box Office (millions)
0	PG-13	81.489601
1	PG	91.666137
2	R	26.064237
3	G	120.396633
4	NC-17	2.971782
5	Not Rated	0.222730

In [33]:
```
# sort data
average_box = sorted(data['Average Box Office (millions)'])

ratings = ratings
ratings = ['Not Rated','NC-17','R','PG-13','PG','G']
sorted_data = pd.DataFrame({"Rating":ratings,
                            "Average Box Office (millions)":average_box
})
sorted_data
```

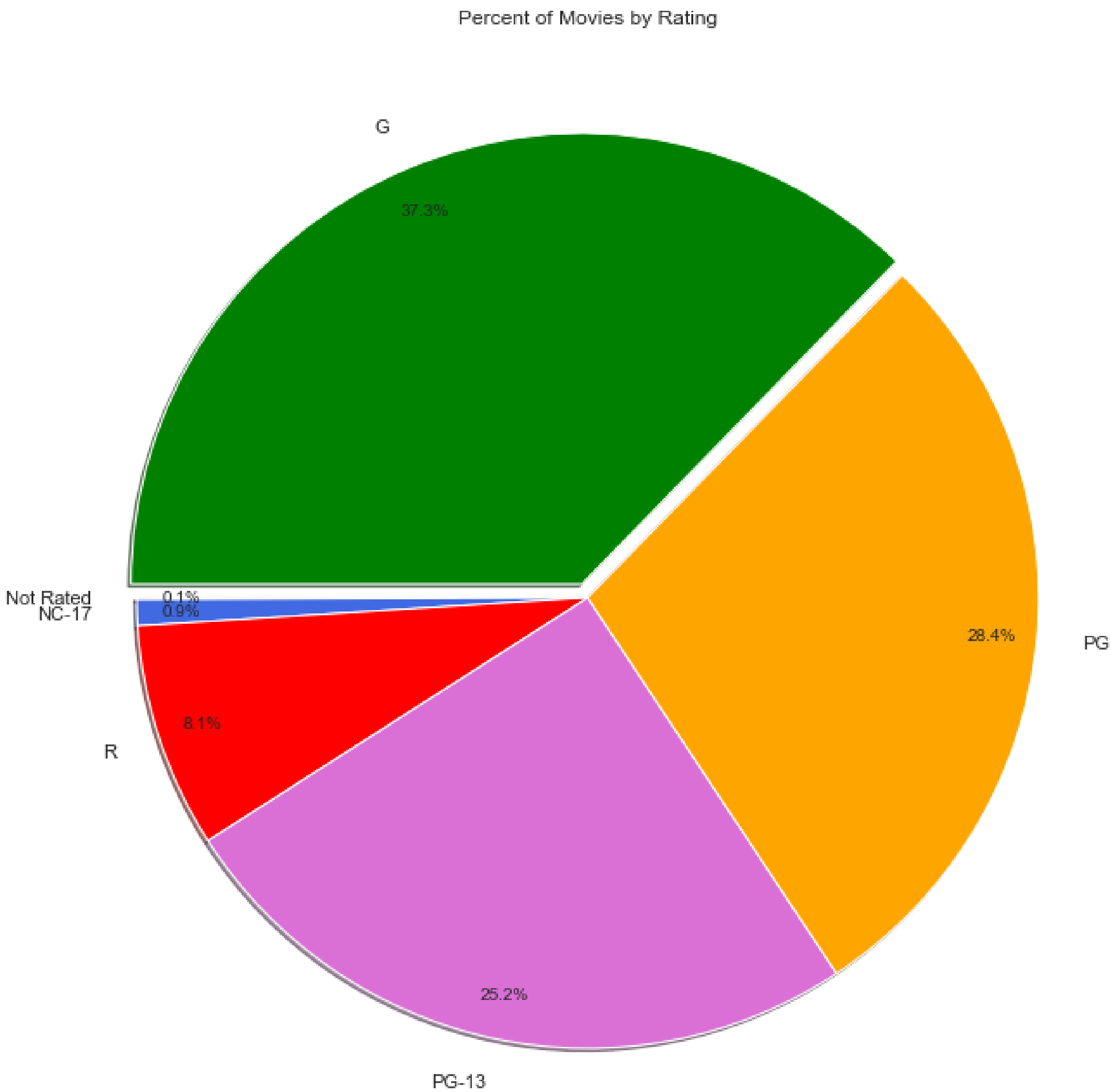
Out[33]:

	Rating	Average Box Office (millions)
0	Not Rated	0.222730
1	NC-17	2.971782
2	R	26.064237
3	PG-13	81.489601
4	PG	91.666137
5	G	120.396633

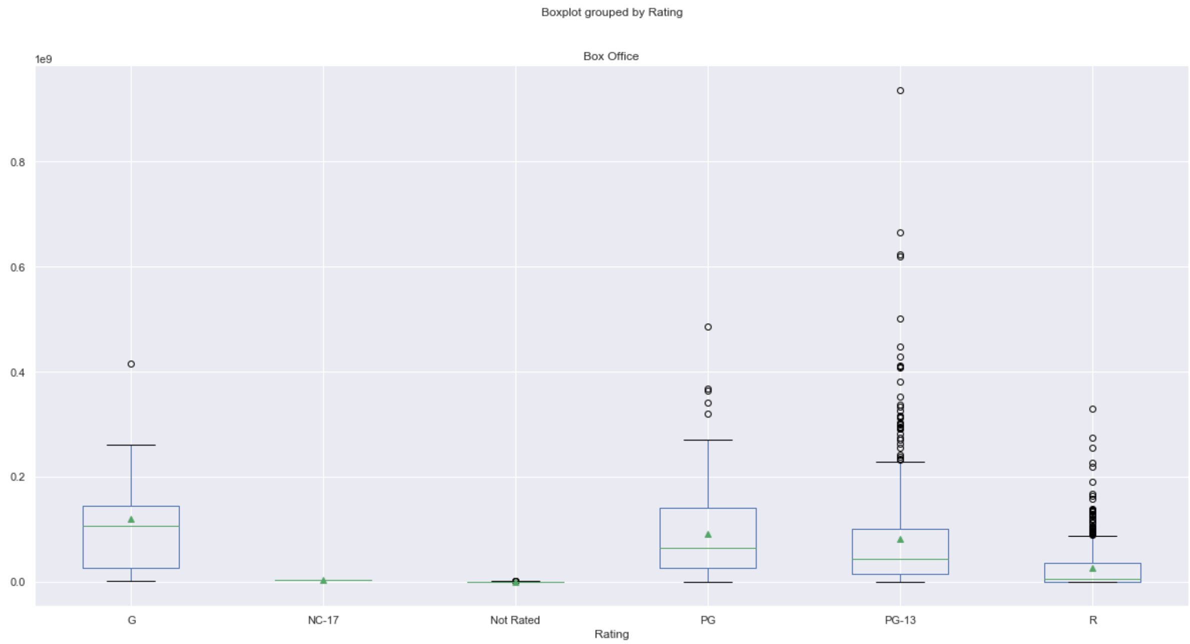
In [34]:
```
# bar chart showing relation
plt.figure(figsize=(10,5))
color=['maroon', 'royalblue', 'red','orchid','orange','green']
plt.bar(sorted_data['Rating'], sorted_data['Average Box Office (millions)'], c
olor=color,align='center')
plt.ylim(0, 140)
plt.xlabel("MPAA Rating")
plt.ylabel("Average Box Office (Millions)")
plt.title("MPAA Rating vs Average Box Office")

# Save image
plt.savefig("Analysis Charts/3. MPAA/MPAA_bar.png")

plt.show()
```



In [35]:
```
# pie chart showing relation
explode = [0,0,0,0,0,0.1]
colors = ['maroon', 'royalblue', 'red','orchid','orange','green']
plt.pie(sorted_data['Average Box Office (millions)'],labels=sorted_data['Rating'],colors=colors,explode=explode,autopct="%1.1f%%",shadow=True,pctdistance=0.9,radius=3,startangle=180)
plt.title("Percent of Movies by Rating",y=2)

# Save image
plt.savefig("Analysis Charts/3. MPAA/MPAA_pie.png", bbox_inches='tight')

plt.show()
```



In [36]:
```
# Box plot
mpaa_df.boxplot("Box Office", by="Rating", figsize=(20, 10),showmeans=True)

# Save image
plt.savefig("Analysis Charts/3. MPAA/MPAA_box.png")

plt.show()
```



In [37]:
```
# ANOVA test
group1 = mpaa_df[mpaa_df["Rating"] == 'Not Rated']["Box Office"]
group2 = mpaa_df[mpaa_df["Rating"] == 'NC-17']["Box Office"]
group3 = mpaa_df[mpaa_df["Rating"] == 'R']["Box Office"]
group4 = mpaa_df[mpaa_df["Rating"] == 'PG-13']["Box Office"]
group5 = mpaa_df[mpaa_df["Rating"] == 'PG']["Box Office"]
group6 = mpaa_df[mpaa_df["Rating"] == 'G']["Box Office"]

stats.f_oneway(group1, group2, group3, group4, group5, group6)
```

Out[37]:
```
F_onewayResult(statistic=29.37724940787404, pvalue=6.545578428438524e-28)
```

Observation

- Based on the data, on average, G movies bring in the most box office revenue
- It appears that PG-13 rated movies have the movies with the highest earnings. However it also must have a lot of poorly performing movies as well, bringing the average down.
- R rated movies only has 8.1% of the average revenue, likely because of a more narrow audience.
- Using the ANOVA test, the pvalue is less than 0.05. The test is significant.

---

4. Analysis of Box Office Results by Month of Release

We want to see if there is a correlation between the money a movie makes at the box office and when the movie is released.

This will allow us to determine which the best time of year to release a movie.

In [38]:
```
#Read clean data
movies = pd.read_csv("Movie_Data.csv")
movies.head()
```

Out[38]:

	IMDb ID	Title	Runtime (mins)	Year	Genres	Release Date	IMDb Rating	Metascore	Rating	Box C
0	tt1872181	The Amazing Spider-Man 2	142	2014	Action, Adventure, Sci-Fi	4/10/2014	6.6	53	PG-13	18327
1	tt1323594	Despicable Me	95	2010	Animation, Comedy, Family, Fantasy	6/20/2010	7.7	72	PG	25147
2	tt1375670	Grown Ups	102	2010	Comedy	6/24/2010	6.0	30	PG-13	1620C
3	tt0892769	How to Train Your Dragon	98	2010	Animation, Action, Adventure, Family, Fantasy	3/18/2010	8.1	74	PG	21690
4	tt1375666	Inception	148	2010	Action, Adventure, Sci-Fi, Thriller	7/8/2010	8.8	74	PG-13	29256

In [39]:
```
#Extract relevant columns
release = movies[['Title','Release Date','Box Office']]
release.head()
```

Out[39]:

	Title	Release Date	Box Office
0	The Amazing Spider-Man 2	4/10/2014	183277573
1	Despicable Me	6/20/2010	251476985
2	Grown Ups	6/24/2010	162001186
3	How to Train Your Dragon	3/18/2010	216900000
4	Inception	7/8/2010	292568851

In [40]:
```
# Convert release date to datetime
release['Release Date'] =  pd.to_datetime(release['Release Date'])
release.head()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
```

Out[40]:

	Title	Release Date	Box Office
0	The Amazing Spider-Man 2	2014-04-10	183277573
1	Despicable Me	2010-06-20	251476985
2	Grown Ups	2010-06-24	162001186
3	How to Train Your Dragon	2010-03-18	216900000
4	Inception	2010-07-08	292568851

In [41]:
```
# Add column for month of release
months = []
for date in release['Release Date']:
    months.append(date.month)
release['Release Month'] = months
release.head()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  """
```

Out[41]:

	Title	Release Date	Box Office	Release Month
0	The Amazing Spider-Man 2	2014-04-10	183277573	4
1	Despicable Me	2010-06-20	251476985	6
2	Grown Ups	2010-06-24	162001186	6
3	How to Train Your Dragon	2010-03-18	216900000	3
4	Inception	2010-07-08	292568851	7

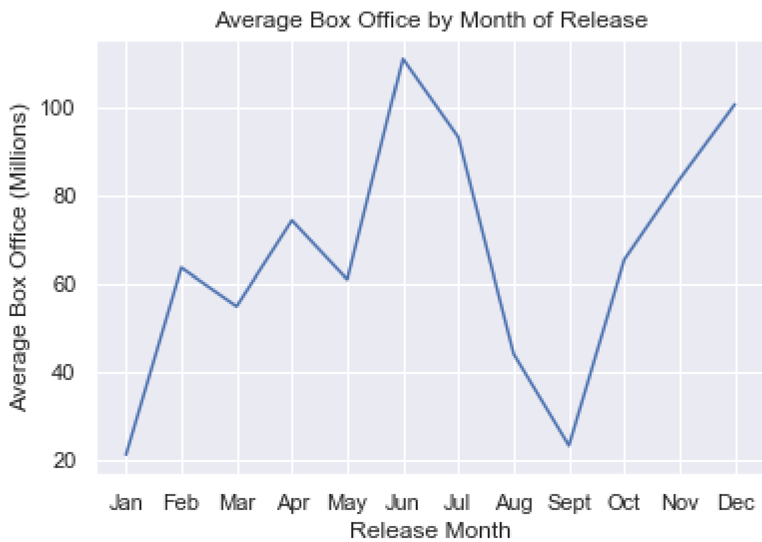
In [42]:
```
# Average Box Office per month
Jan = release['Box Office'][release['Release Month'] == 1].mean()
Feb = release['Box Office'][release['Release Month'] == 2].mean()
Mar = release['Box Office'][release['Release Month'] == 3].mean()
Apr = release['Box Office'][release['Release Month'] == 4].mean()
May = release['Box Office'][release['Release Month'] == 5].mean()
Jun = release['Box Office'][release['Release Month'] == 6].mean()
Jul = release['Box Office'][release['Release Month'] == 7].mean()
Aug = release['Box Office'][release['Release Month'] == 8].mean()
Sept = release['Box Office'][release['Release Month'] == 9].mean()
Oct = release['Box Office'][release['Release Month'] == 10].mean()
Nov = release['Box Office'][release['Release Month'] == 11].mean()
Dec = release['Box Office'][release['Release Month'] == 12].mean()
```

In [43]:
```
# df for x and y
release_df = pd.DataFrame({"Month":['Jan','Feb','Mar','Apr','May','Jun','Jul',
'Aug','Sept','Oct','Nov','Dec'],
                          "Average Box Office (millions)":[Jan,Feb,Mar,Apr,May
,Jun,Jul,Aug,Sept,Oct,Nov,Dec]})
release_df['Average Box Office (millions)'] = release_df['Average Box Office
 (millions)']/1000000
release_df
```

Out[43]:

	Month	Average Box Office (millions)
0	Jan	21.135935
1	Feb	63.600268
2	Mar	54.834767
3	Apr	74.316960
4	May	60.912100
5	Jun	111.011569
6	Jul	93.221184
7	Aug	44.072004
8	Sept	23.217586
9	Oct	65.371941
10	Nov	83.642154
11	Dec	100.694448

In [44]:
```
# line plot to show box office relation to months
plt.plot(release_df['Month'],release_df['Average Box Office (millions)'])
plt.xlabel("Release Month")
plt.ylabel("Average Box Office (Millions)")
plt.title("Average Box Office by Month of Release")

# Save image
plt.savefig("Analysis Charts/4. Release Month/monthly_line.png")

plt.show()
```

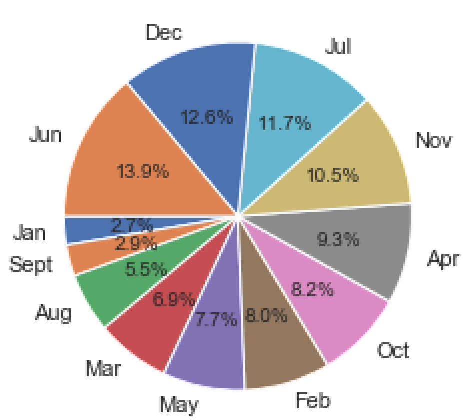


In [45]:
```
# sort data
sorted(release_df['Average Box Office (millions)'])

sorted_release = pd.DataFrame({'Month':['Jan', 'Sept', 'Aug', 'Mar', 'May', 'F
eb', 'Oct', 'Apr', 'Nov', 'Jul', 'Dec', 'Jun'],
                               'Average Box Office (millions)':sorted(release_
df['Average Box Office (millions)'])
                              })
sorted_release
```

Out[45]:

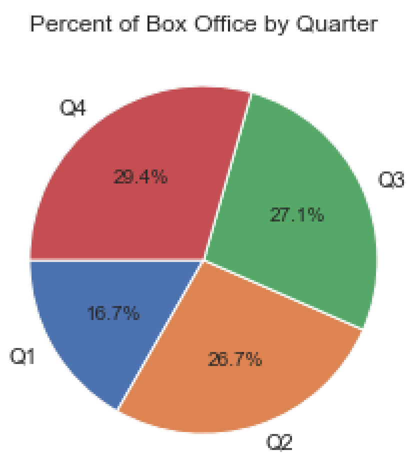
	Month	Average Box Office (millions)
0	Jan	21.135935
1	Sept	23.217586
2	Aug	44.072004
3	Mar	54.834767
4	May	60.912100
5	Feb	63.600268
6	Oct	65.371941
7	Apr	74.316960
8	Nov	83.642154
9	Jul	93.221184
10	Dec	100.694448
11	Jun	111.011569

In [46]:
```
# pie chart percentage per month
plt.pie(sorted_release['Average Box Office (millions)'],labels=sorted_release[
'Month'],autopct="%1.1f%%",startangle=180)

# Save image
plt.savefig("Analysis Charts/4. Release Month/monthly_pie.png")

plt.show()
```



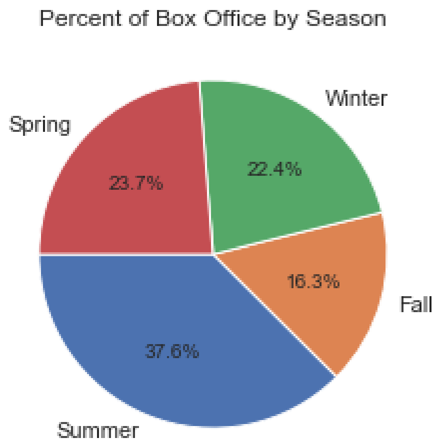
In [47]:
```
# pie chart by quarter
q1 = release_df['Average Box Office (millions)'][0:2].sum()
q2 = release_df['Average Box Office (millions)'][3:5].sum()
q3 = release_df['Average Box Office (millions)'][6:8].sum()
q4 = release_df['Average Box Office (millions)'][9:11].sum()
labels = ['Q1','Q2','Q3','Q4']
size = [q1, q2, q3, q4]
```

In [48]:
```
plt.pie(size,labels=labels,autopct="%1.1f%%",startangle=180)
plt.title("Percent of Box Office by Quarter")

# Save image
plt.savefig("Analysis Charts/4. Release Month/quarterly_pie.png")

plt.show()
```



In [49]:
```
# Pie chart by Season
summer = release_df['Average Box Office (millions)'][5:7].sum()
fall = release_df['Average Box Office (millions)'][8:10].sum()
winter = release_df['Average Box Office (millions)'][0:1].sum()
winter = winter + release_df['Average Box Office (millions)'][11].sum()
spring = release_df['Average Box Office (millions)'][2:4].sum()

labels = ['Summer','Fall','Winter','Spring']
size = [summer, fall, winter, spring]
```

In [50]:
```
plt.pie(size,labels=labels,autopct="%1.1f%%",startangle=180)
plt.title("Percent of Box Office by Season")

# Save image
plt.savefig("Analysis Charts/4. Release Month/season_pie.png")

plt.show()
```



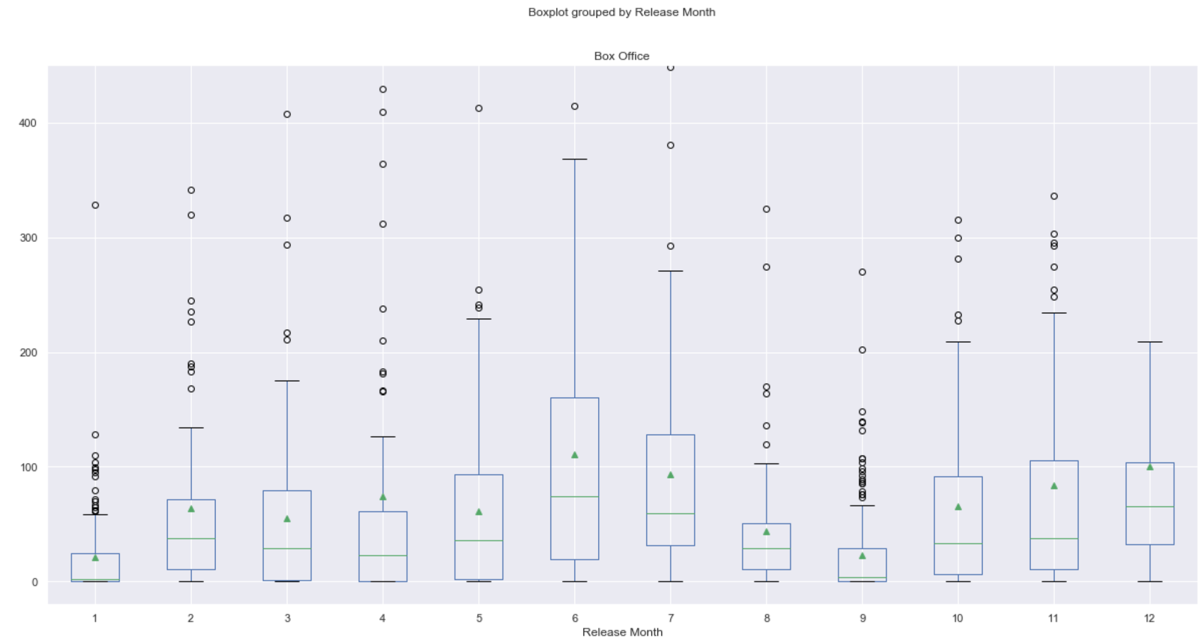
In [51]:
```
# box plot
box = release[['Box Office','Release Month']]
box['Box Office'] = box['Box Office']/1000000
box.head()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

Out[51]:

	Box Office	Release Month
0	183.277573	4
1	251.476985	6
2	162.001186	6
3	216.900000	3
4	292.568851	7

In [52]:
```
box.boxplot("Box Office", by="Release Month", figsize=(20, 10),showmeans=True)
plt.ylim(-20, 450)

# Save image
plt.savefig("Analysis Charts/4. Release Month/monthly_box.png")

plt.show()
```



In [53]:
```
# ANOVA test
Jan = release['Box Office'][release['Release Month'] == 1]
Feb = release['Box Office'][release['Release Month'] == 2]
Mar = release['Box Office'][release['Release Month'] == 3]
Apr = release['Box Office'][release['Release Month'] == 4]
May = release['Box Office'][release['Release Month'] == 5]
Jun = release['Box Office'][release['Release Month'] == 6]
Jul = release['Box Office'][release['Release Month'] == 7]
Aug = release['Box Office'][release['Release Month'] == 8]
Sept = release['Box Office'][release['Release Month'] == 9]
Oct = release['Box Office'][release['Release Month'] == 10]
Nov = release['Box Office'][release['Release Month'] == 11]
Dec = release['Box Office'][release['Release Month'] == 12]


stats.f_oneway(Jan,Feb,Mar,Apr,May,Jun,Jul,Aug,Sept,Oct,Nov,Dec)
```

Out[53]:
```
F_onewayResult(statistic=10.874730742925472, pvalue=3.6178800066850965e-19)
```

Observation

- Box Office earnings peak in the Summer as well as the holiday season.
- 48.7% of Box Office earnings are from 4 months (June, July, November, December) in these peak times.
- Box Office earnings dip in the few months after each of these peak seasons, like in January and September.
- Quarter 1 is the slowest, only representing 16.7% of yearly Box Office earnings.
- The other quarters have their own slow months as well, but the peak months within them keep their earning up.
- After doing an ANOVA test, the pvalue is less than 0.05 so, this test is significant.

---

5. Does runtime have an affect the box office results?

We want to see whether runtime significantly effects box office results and whether there is a point where the movies runtime starts to negatively effect the box office results.

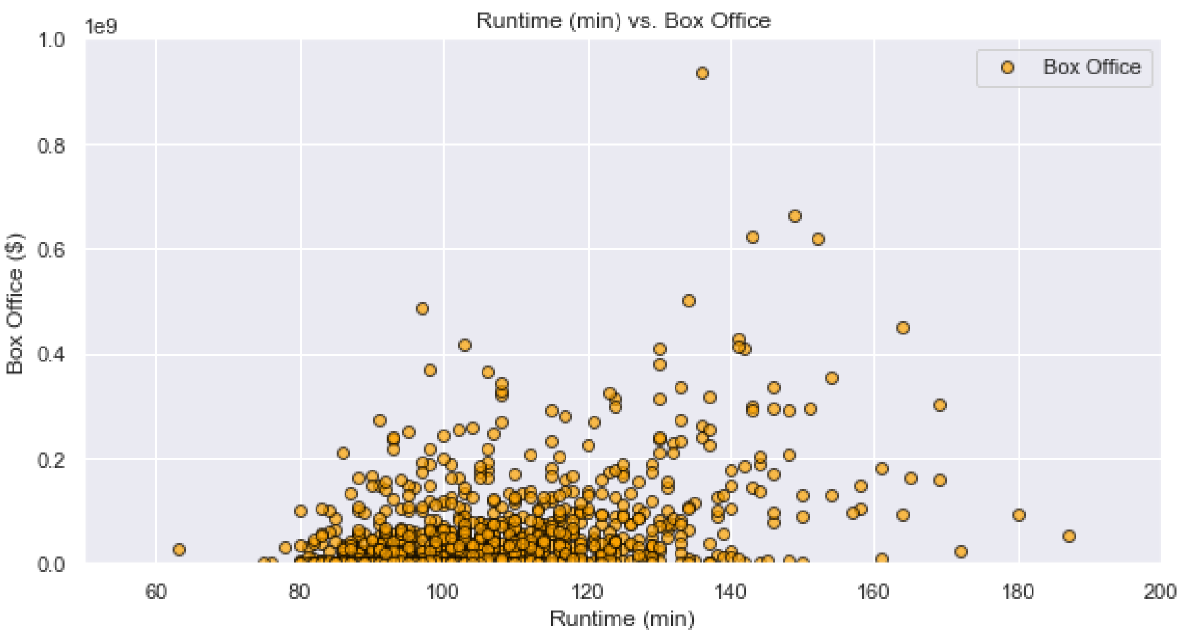
This will allow us to determine the optimal runtime to maximize the box office return.

In [54]:
```
#Read csv with proper encoding
path = "Movie_Data.csv"
movies_runtime = pd.read_csv(path, encoding='latin1')
movies_runtime.head()
```

Out[54]:

	IMDb ID	Title	Runtime (mins)	Year	Genres	Release Date	IMDb Rating	Metascore	Rating	Box C
0	tt1872181	The Amazing Spider-Man 2	142	2014	Action, Adventure, Sci-Fi	4/10/2014	6.6	53	PG-13	18327
1	tt1323594	Despicable Me	95	2010	Animation, Comedy, Family, Fantasy	6/20/2010	7.7	72	PG	25147
2	tt1375670	Grown Ups	102	2010	Comedy	6/24/2010	6.0	30	PG-13	16200
3	tt0892769	How to Train Your Dragon	98	2010	Animation, Action, Adventure, Family, Fantasy	3/18/2010	8.1	74	PG	21690
4	tt1375666	Inception	148	2010	Action, Adventure, Sci-Fi, Thriller	7/8/2010	8.8	74	PG-13	29256

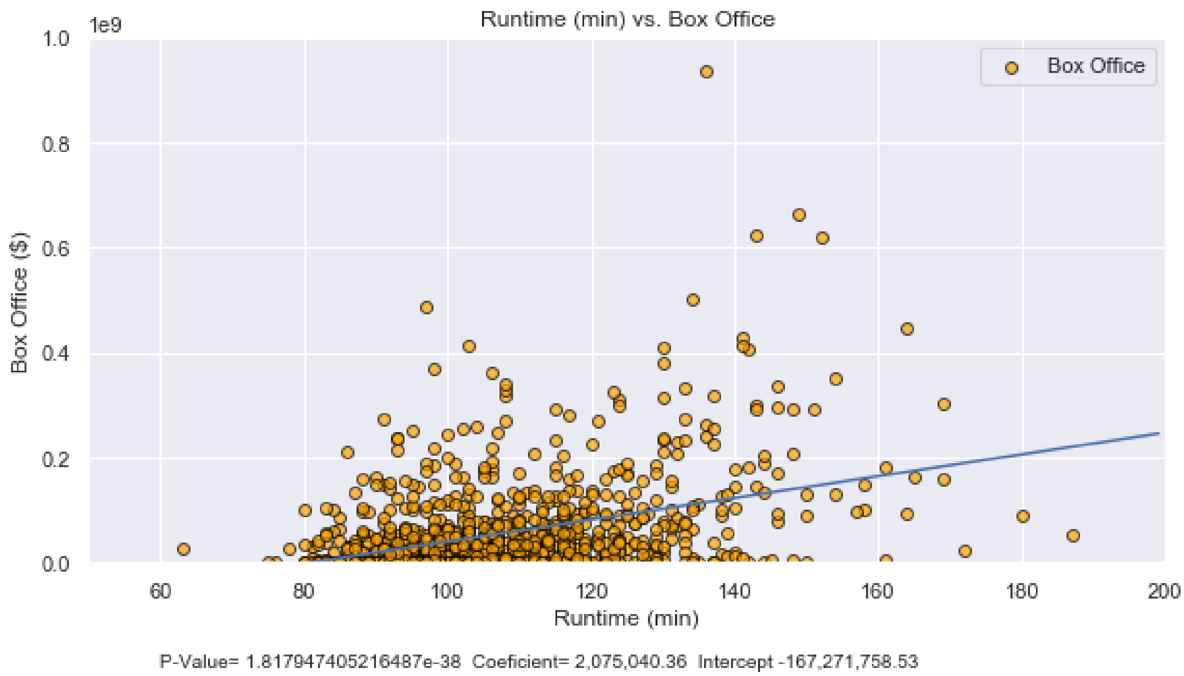
In [55]:
```
# Create a scatterplot for Runtime vs Box Office
plt.figure(figsize=(10,5))
plt.scatter((movies_runtime["Runtime (mins)"]), movies_runtime["Box Office"],
            marker = "o", color ="orange", alpha = 0.7, edgecolor ="black")
plt.title("Runtime (min) vs. Box Office")
plt.xlabel("Runtime (min)")
plt.ylabel("Box Office ($)")
plt.xlim(50, 200)
plt.ylim(0, 1000000000)
plt.grid(True)
plt.legend()
plt.savefig("Analysis Charts/5. Runtime/Runtime_vs_Box_Office_scatter.png")
plt.show()
```



Observations

From the scatter plot, it can be determined that a large number of movies make less than $100 millions with runtimes ranging from 80 minutes to 180 minutes. This shows that a majority of movies fail to produce at the box office no matter what the runtimes are. However, it does appear that there is a weak correlation between runtime and box office given that the plot shows that as runtime increases, box office results increases as well. This will be further investigated below.

In [56]:
```
# Linear Regression
x = np.arange(1, 200, 1)
regress_runtime = stats.linregress(movies_runtime['Runtime (mins)'], movies_runtime['Box Office'])
plt.figure(figsize=(10,5))
plt.scatter((movies_runtime["Runtime (mins)"]), movies_runtime["Box Office"],
            marker = "o", color ="orange", alpha = 0.7, edgecolor ="black")
plt.title("Runtime (min) vs. Box Office")
plt.xlabel("Runtime (min)")
plt.ylabel("Box Office ($)")
plt.xlim(50, 200)
plt.ylim(0, 1000000000)
plt.grid(True)
plt.text(60, -2 * 100000000, 'P-Value= ' + str(regress_runtime[3]) + '  Coefficient= ' + "{:,.2f}".format(regress_runtime[0]) + '  Intercept ' + "{:,.2f}".format(regress_runtime[1]))
plt.legend()
plt.plot(x, x * regress_runtime[0] + regress_runtime[1])


plt.savefig("Analysis Charts/5. Runtime/Runtime_vs_Box_Office_scatter_regression.png")
plt.show()
```

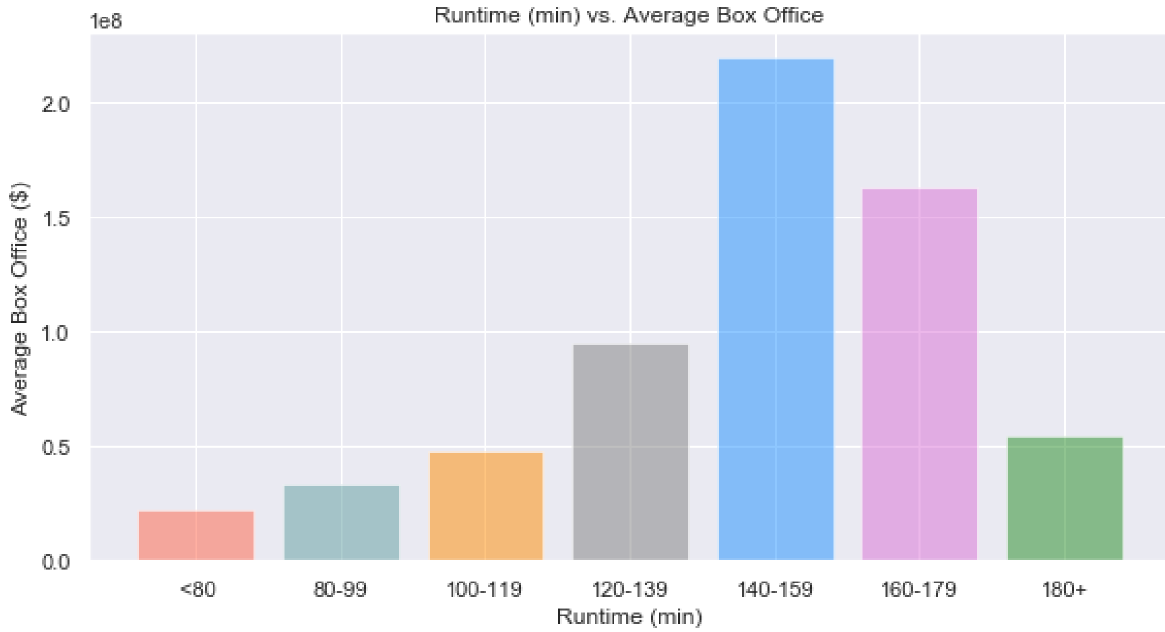


Observations

From looking at the scatter plot earlier, it was determined that it appeared that there was some correlation between runtime and box office. After running a simple linear regression and calculating a p-value of 1.81 e-38, it can be concluded that there is a relationship and that box office results increase as runtime increases. This conclusion has to have limits since there has to be a point that the movie would be too long for movie viewers to sit through, an observation on runtimes versus the average box office was done below.

In [57]:
```
# Create bar chart with ranges of runtimes vs Box Office
bins = [0, 80, 100, 120, 140, 160, 180, 200]

# Create names for the bins
group_names = [" <80", "80-99", "100-119", "120-139", "140-159", "160-179", "1
80+" ]

# Create a DataFrame
movies_runtime["Runtime (mins)"] = pd.cut(movies_runtime["Runtime (mins)"], bi
ns, labels = group_names)
movies_runtime_groupby = movies_runtime["Runtime (mins)"]

# Create a DataFrame to specific format for bar chart.
movies_runtime_groupby_df = pd.DataFrame(movies_runtime_groupby)
movies_runtime_join_df = movies_runtime_groupby_df.merge(movies_runtime, on='R
untime (mins)', how='right')
movies_runtime_join_df.drop_duplicates(subset=None, keep="first", inplace=True
)
movies_runtime_final_df = movies_runtime_join_df[["Runtime (mins)", "Box Offic
e"]]
groupby_run = movies_runtime_final_df["Box Office"].groupby(movies_runtime_fin
al_df["Runtime (mins)"])
movies_runtime_mean_df = pd.DataFrame(groupby_run.mean())
movies_runtime_mean_df = movies_runtime_mean_df.reset_index()
```

In [58]:
```
# Bar chart
plt.figure(figsize=(10,5))
color=['tomato', 'cadetblue', 'darkorange','grey','dodgerblue','orchid', 'fore
stgreen']
plt.bar(movies_runtime_mean_df["Runtime (mins)"], movies_runtime_mean_df["Box
 Office"],
        color = color, alpha = 0.5, align = "center")
plt.title("Runtime (min) vs. Average Box Office")
plt.xlabel("Runtime (min)")
plt.ylabel("Average Box Office ($)")
plt.savefig("Analysis Charts/5. Runtime/Runtime_vs_Box_Office_Bar.png")
plt.show()
```



Observations

The conclusion from the scatter plot and regression analysis showed that the box office results will increase with runtime. However, it did not specify when that relationship would breakdown. From the bar graph, the runtime that produced the highest average box office results were between 140-159 minutes. This appears to be the point where the runtime will adversely effect the box office results. The ideal runtime to maximize box office returns would therefore be between 140-159 minutes in length.

In [ ]: