Project Title

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Overview

Microsoft is investigating the feasability of a new movie studio and as part of this analysis want to explore the types of films that are doing well at the box office.

Business Problem

In order to identify the best type films for Microsoft to produce we need to analyse the characteristics of a successful film for the business. Key indicators of success for business is revenue and return on investment (ROI).

To carry this out we chose to analyse the 10 largest grossing studios to see what genres, run times and ratings drove revenue and ROI.

Data Understanding

The data used for analysis in this project came from 3 sources:

- Imdb contains genre, run time and ratings data
- The Numbers contains revenue and budget data per movie
- Box office movies contains studio data

The analysis followed the following parameters:

- Top 10 studios by Gross Revenue
- Movies released from 2010 onwards

This decision was taking primarily to have the most current information and to reduce any outlying data from smaller studios.

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]:

```
# Import IMDB
imdb_title_basics_df = pd.read_csv('zippedData/imdb.title.basics.csv.gz')
imdb_ratings_df = pd.read_csv('zippedData/imdb.title.ratings.csv.gz')

# Import Box Office Mojo
bom_gross_df = pd.read_csv('zippedData/bom.movie_gross.csv.gz')

# The Numbers
the_numbers_df = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')

```

In [3]:

```
imdb_title_basics_df
```

Out[3]:

	tconst	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
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	NaN
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 6 columns

In [4]:

```
imdb_ratings_df
```

Out[4]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [5]:

```
bom_gross_df
```

Out[5]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

In [6]:

```
bom_gross_df.dtypes
```

Out[6]:

```
title              object
studio             object
domestic_gross    float64
foreign_gross      object
year                int64
dtype: object
```

In [7]:

```
the_numbers_df
```

Out[7]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 6 columns

In [8]:

```
the_numbers_df.dtypes
```

Out[8]:

```
id                    int64
release_date         object
movie                object
production_budget    object
domestic_gross       object
worldwide_gross      object
dtype: object
```

Find top 10 studios by Gross Revenue

Joining the BOM and the numbers together to get financial data by studio and then filtering down to the top 10 studios so as to have a list to reference for analysis.

In [9]:

```
#Creating a function to convert strings to Integers to facilitate calculations
def tidy_nums(column_head):

        the_numbers_df[column_head].replace(',','', regex=True, inplace=True)
        the_numbers_df[column_head] = the_numbers_df[column_head].map(lambda x:
                                                    int(x.replace('$','')))
        return the_numbers_df
```

In [10]:

```
#Run function
tidy_nums('production_budget')
tidy_nums('domestic_gross')
tidy_nums('worldwide_gross')
```

Out[10]:

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
2	3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
3	4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	7000	0	0
5778	79	Apr 2, 1999	Following	6000	48482	240495
5779	80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338
5780	81	Sep 29, 2015	A Plague So Pleasant	1400	0	0
5781	82	Aug 5, 2005	My Date With Drew	1100	181041	181041

5782 rows × 6 columns

In [11]:

```
# Changing to date to facilitate selection of year
the_numbers_df['year'] = pd.DatetimeIndex(the_numbers_df['release_date']).year
```

In [12]:

```
#Covert $ to millions for visualisations
the_numbers_df['Budget $M'] = the_numbers_df['production_budget']/1000000
the_numbers_df['Revenue $M'] = the_numbers_df['worldwide_gross']/1000000
the_numbers_df['ROI $M'] = the_numbers_df['Revenue $M'] - the_numbers_df['Budget $M']
```

In [13]:

```
# Drop Unecessary Columns
the_numbers_df = the_numbers_df.drop(['id','release_date', 'production_budget', 'domestic_gross', 'worldwide_gross'], axis=1)

```

In [14]:

```
# Only looking at current box office figures so we going to take from 2010 onwards
the_numbers_df = the_numbers_df[(the_numbers_df['year'] >= 2010)]
the_numbers_df
```

Out[14]:

	movie	year	Budget $M	Revenue $M	ROI $M
1	Pirates of the Caribbean: On Stranger Tides	2011	410.6000	1045.663875	635.063875
2	Dark Phoenix	2019	350.0000	149.762350	-200.237650
3	Avengers: Age of Ultron	2015	330.6000	1403.013963	1072.413963
4	Star Wars Ep. VIII: The Last Jedi	2017	317.0000	1316.721747	999.721747
5	Star Wars Ep. VII: The Force Awakens	2015	306.0000	2053.311220	1747.311220
...	...	...	...	...	...
5761	Stories of Our Lives	2014	0.0150	0.000000	-0.015000
5771	Family Motocross	2015	0.0100	0.000000	-0.010000
5772	Newlyweds	2012	0.0090	0.004584	-0.004416
5777	Red 11	2018	0.0070	0.000000	-0.007000
5780	A Plague So Pleasant	2015	0.0014	0.000000	-0.001400

2194 rows × 5 columns

In [15]:

```
#Getting a sample to duplicate names to see if there is a pattern
the_numbers_df['movie'].value_counts().head(5)
```

Out[15]:

```
Robin Hood    2
Snitch        2
Trance        2
The Square    2
Kynodontas    1
Name: movie, dtype: int64
```

In [16]:

```
# Checking duplicates to see if they are remakes. Mulitple years for the movie are a good indication.
duplicates = the_numbers_df.apply(lambda row: row[the_numbers_df['movie'].isin(['Robin Hood', 'Trance', 'The Square', 'Snitch'])]
duplicates = duplicates.sort_values('movie', ascending = True)
duplicates
#Robin hood looks like a remake with the rest having two entries. Only 3 movies out of a data set of 2194 wont skew results
```

Out[16]:

	movie	year	Budget $M	Revenue $M	ROI $M
38	Robin Hood	2010	210.00	322.459006	112.459006
408	Robin Hood	2018	99.00	84.747441	-14.252559
3025	Snitch	2013	15.00	57.907734	42.907734
5351	Snitch	2012	0.85	0.000000	-0.850000
5009	The Square	2010	1.90	0.740932	-1.159068
5099	The Square	2013	1.50	0.176262	-1.323738
2970	Trance	2013	16.00	22.594052	6.594052
5330	Trance	2012	0.95	0.000000	-0.950000

In [17]:

```
#Joining BOM studio data to The Numbers
return_by_studio = pd.merge(left=the_numbers_df, right=bom_gross_df, how="left", left_on=['movie'], right_on=['title'])
return_by_studio
```

Out[17]:

	movie	year_x	Budget $M	Revenue $M	ROI $M	title	studio	domestic_gross	foreign_gross	year_y
0	Pirates of the Caribbean: On Stranger Tides	2011	410.6000	1045.663875	635.063875	Pirates of the Caribbean: On Stranger Tides	BV	241100000.0	804600000	2011.0
1	Dark Phoenix	2019	350.0000	149.762350	-200.237650	NaN	NaN	NaN	NaN	NaN
2	Avengers: Age of Ultron	2015	330.6000	1403.013963	1072.413963	Avengers: Age of Ultron	BV	459000000.0	946400000	2015.0
3	Star Wars Ep. VIII: The Last Jedi	2017	317.0000	1316.721747	999.721747	NaN	NaN	NaN	NaN	NaN
4	Star Wars Ep. VII: The Force Awakens	2015	306.0000	2053.311220	1747.311220	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...
2189	Stories of Our Lives	2014	0.0150	0.000000	-0.015000	NaN	NaN	NaN	NaN	NaN
2190	Family Motocross	2015	0.0100	0.000000	-0.010000	NaN	NaN	NaN	NaN	NaN
2191	Newlyweds	2012	0.0090	0.004584	-0.004416	NaN	NaN	NaN	NaN	NaN
2192	Red 11	2018	0.0070	0.000000	-0.007000	NaN	NaN	NaN	NaN	NaN
2193	A Plague So Pleasant	2015	0.0014	0.000000	-0.001400	NaN	NaN	NaN	NaN	NaN

2194 rows × 10 columns

In [18]:

```
# Drop NAs
return_by_studio.dropna(inplace=True)
```

In [19]:

```
#Remove excess columns
return_by_studio = return_by_studio.drop(['domestic_gross', 'foreign_gross', 'year_y'], axis=1)
```

In [20]:

```
#Group return dataframe by studio to get $ per studio
top10_profit = return_by_studio.groupby(return_by_studio['studio']).sum()
top10_profit
```

Out[20]:

studio	year_x	Budget $M	Revenue $M	ROI $M
3D	2010	5.0	16.515203	11.515203
A24	22170	106.5	355.829992	249.329992
ATO	2010	12.5	2.272186	-10.227814
Affirm	4035	7.0	31.471492	24.471492
Amazon	2018	20.0	7.034615	-12.965385
...	...	...	...	...
W/Dim.	16096	192.5	608.851922	416.351922
WB	199365	8125.0	22163.568959	14038.568959
WB (NL)	72508	2133.6	8520.176106	6386.576106
Wein.	76505	788.0	2785.327163	1997.327163
Yash	4029	35.0	84.713401	49.713401

78 rows × 4 columns

In [21]:

```
#Sort List by highest ROI$
top10_ROI = top10_profit.sort_values('ROI $M', ascending = False).iloc[:10]
top10_ROI
```

Out[21]:

studio	year_x	Budget $M	Revenue $M	ROI $M
BV	140978	9426.80000	33262.637282	23835.837282
Uni.	233621	6572.70000	27305.781963	20733.081963
Fox	215470	7614.00000	26422.455030	18808.455030
WB	199365	8125.00000	22163.568959	14038.568959
Sony	146994	5042.50000	17510.994901	12468.494901
Par.	142974	4722.00000	14321.640964	9599.640964
WB (NL)	72508	2133.60000	8520.176106	6386.576106
LGF	108737	2002.78765	6841.461823	4838.674173
P/DW	20109	1334.00000	5078.027601	3744.027601
LG/S	54381	1537.50000	3678.991779	2141.491779

In [22]:

```
# Resetting the index
df_list=top10_ROI.reset_index()
```

In [23]:

```
# Passing the studios to a list and printing for reference
top10_list = df_list['studio'].tolist()
top10_list
```

Out[23]:

```
['BV', 'Uni.', 'Fox', 'WB', 'Sony', 'Par.', 'WB (NL)', 'LGF', 'P/DW', 'LG/S']
```

Genres by Gross Revenue

Joined the two IMBD databases together to provide a dataframe of non financial data. Matched the financial data from Dataframes created above to calculate the genres with the highest gross revenue.

In [24]:

```
#Merge Imdb basics with ratings to Link Title with genre and dropping NaNs
imdb_merge = pd.merge(left=imdb_title_basics_df,right=imdb_ratings_df, on='tconst', how='inner')
imdb_merge = imdb_merge.dropna()
imdb_merge
```

Out[24]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	6.9	4517
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	119
6	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	8.1	263
...	...	...	...	...	...	...	...	...
73849	tt9911774	Padmavyuhathile Abhimanyu	Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365
73850	tt9913056	Swarm Season	Swarm Season	2019	86.0	Documentary	6.2	5
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.0	Documentary	6.2	6
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	Drama,Family	8.7	136
73855	tt9916160	Drømmeland	Drømmeland	2019	72.0	Documentary	6.5	11

65720 rows × 8 columns

In [25]:

```
#Merge Imdb basics with ratings to Link Title with genre and dropping NaNs
imdb_merge = pd.merge(left=imdb_title_basics_df,right=imdb_ratings_df, on='tconst', how='inner')
imdb_merge = imdb_merge.dropna()
imdb_merge
```

Out[25]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	6.9	4517
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	119
6	tt0137204	Joe Finds Grace	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	8.1	263
...	...	...	...	...	...	...	...	...
73849	tt9911774	Padmavyuhathile Abhimanyu	Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365
73850	tt9913056	Swarm Season	Swarm Season	2019	86.0	Documentary	6.2	5
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.0	Documentary	6.2	6
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	Drama,Family	8.7	136
73855	tt9916160	Drømmeland	Drømmeland	2019	72.0	Documentary	6.5	11

65720 rows × 8 columns

In [26]:

```
#Looking at the data there is more one genre category per movie. Using explode to break up genre of a particular movie
imdb_merge['genres'] = imdb_merge['genres'].apply(lambda x: x.split(','))
imdb_merge = imdb_merge.explode('genres')
imdb_merge
```

Out[26]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action	7.0	77
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Crime	7.0	77
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Drama	7.0	77
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography	7.2	43
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Drama	7.2	43
...	...	...	...	...	...	...	...	...
73850	tt9913056	Swarm Season	Swarm Season	2019	86.0	Documentary	6.2	5
73851	tt9913084	Diabolik sono io	Diabolik sono io	2019	75.0	Documentary	6.2	6
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	Drama	8.7	136
73852	tt9914286	Sokagin Çocuklari	Sokagin Çocuklari	2019	98.0	Family	8.7	136
73855	tt9916160	Drømmeland	Drømmeland	2019	72.0	Documentary	6.5	11

118437 rows × 8 columns

In [27]:

```
#Merging with return_bystudio so we can map a movies to a studio and also provide financial data
movie_by_studio = pd.merge(left=imdb_merge,right=return_by_studio, left_on='primary_title', right_on='movie', how='inner')
movie_by_studio
```

Out[27]:

	tconst	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	movie	year_x	Budget $M	Revenue $M
0	tt0337692	On the Road	On the Road	2012	124.0	Adventure	6.1	37886	On the Road	2013	25.0	9.313302
1	tt0337692	On the Road	On the Road	2012	124.0	Drama	6.1	37886	On the Road	2013	25.0	9.313302
2	tt0337692	On the Road	On the Road	2012	124.0	Romance	6.1	37886	On the Road	2013	25.0	9.313302
3	tt4339118	On the Road	On the Road	2014	89.0	Drama	6.0	6	On the Road	2013	25.0	9.313302
4	tt5647250	On the Road	On the Road	2016	121.0	Drama	5.7	127	On the Road	2013	25.0	9.313302
...	...	...	...	...	...	...	...	...	...	...	...	...
2914	tt7401588	Instant Family	Instant Family	2018	118.0	Comedy	7.4	46728	Instant Family	2018	48.0	119.736188
2915	tt7401588	Instant Family	Instant Family	2018	118.0	Drama	7.4	46728	Instant Family	2018	48.0	119.736188
2916	tt7784604	Hereditary	Hereditary	2018	127.0	Drama	7.3	151571	Hereditary	2018	10.0	70.133905
2917	tt7784604	Hereditary	Hereditary	2018	127.0	Horror	7.3	151571	Hereditary	2018	10.0	70.133905
2918	tt7784604	Hereditary	Hereditary	2018	127.0	Mystery	7.3	151571	Hereditary	2018	10.0	70.133905

2919 rows × 15 columns

In [28]:

```
# Filter to top ten studios
movie_by_studio = movie_by_studio[movie_by_studio['studio'].isin(top10_list)]
```

In [29]:

```
#Removing unecessary columns
movie_by_studio = movie_by_studio.drop(['tconst','original_title', 'movie', 'year_x', 'start_year', 'numvotes', 'year_x'], axis=1
```

In [30]:

```
# Get the Revenue by Genre
return_by_genre = movie_by_studio.groupby(movie_by_studio['genres']).sum()
return_by_genre= return_by_genre.sort_values('ROI $M', ascending = False).iloc[:10]
return_by_genre
```

Out[30]:

genres	runtime_minutes	averagerating	Budget $M	Revenue $M	ROI $M
Adventure	27318.0	1580.5	30758.80000	105443.425859	74684.625859
Action	30814.0	1722.3	28160.20000	90040.864953	61880.664953
Comedy	28352.0	1727.4	16341.20000	59049.735535	42708.535535
Sci-Fi	9536.0	523.2	9836.80000	38077.845112	28241.045112
Drama	30554.0	1761.6	12994.48765	39871.832584	26877.344934
Animation	7313.0	515.8	8614.50000	35105.574914	26491.074914
Thriller	13575.0	776.1	6704.07530	25979.503405	19275.428105
Fantasy	7101.0	385.7	7390.00000	21240.199943	13850.199943
Crime	10504.0	600.2	4710.50000	14659.193795	9948.693795
Horror	7009.0	421.0	2256.90000	10855.806614	8598.906614

In [31]:

```
#Set up a new dataframe with a reset index to enable a bar chart
return_by_genre_graphs=return_by_genre.reset_index()
```

Average ROI v Average Budget

Group up the average financial data per movie.

In [32]:

```
#Group by studio to get the average budget, revenue and calculate ROI
average_by_genre = movie_by_studio.groupby(movie_by_studio['genres']).mean()
average_by_genre['ROI%'] = (average_by_genre['ROI $M']/average_by_genre['Revenue $M'])*100

```

In [33]:

```
#Select the top 10 genres
average_by_genre = average_by_genre.sort_values('Revenue $M', ascending = False).iloc[:10]
```

In [34]:

```
#Setting up DF to graph
average_by_genre_graphs=average_by_genre.reset_index()
```

Leading Studios by Run Time

Providing a count of the run time for the histogram below

In [35]:

```
#Access Movie Studio to get run times and reverse the multiple entries from the explode
runtime_analysis = movie_by_studio.drop_duplicates(subset='primary_title', keep="last")
```

In [36]:

```
#Setting up dataframe for a graph
run_time_analysis_graph = runtime_analysis.reset_index()
```

In [37]:

```
#Calculating ROI% per movie for Run Time
movie_by_studio['ROI%'] = (movie_by_studio['ROI $M']/movie_by_studio['Revenue $M'])*100
```

Rating Analysis

Dropping duplicates from the earlier dataframe to analyse the ratings for those titles greater than 75%

In [38]:

```
#Bringing Movie by Studio into a new DF and dropping duplicates
rating_analysis = movie_by_studio.drop_duplicates(subset='primary_title', keep="last")
```

In [39]:

```
#Only want to look at ROI for movies greater than 75%
rating_analysis = rating_analysis.loc[(rating_analysis['ROI%'] >= 75)]
```

In [40]:

```
#Setting up a dataframe for graph
rating_analysis_graph=rating_analysis.reset_index()
```

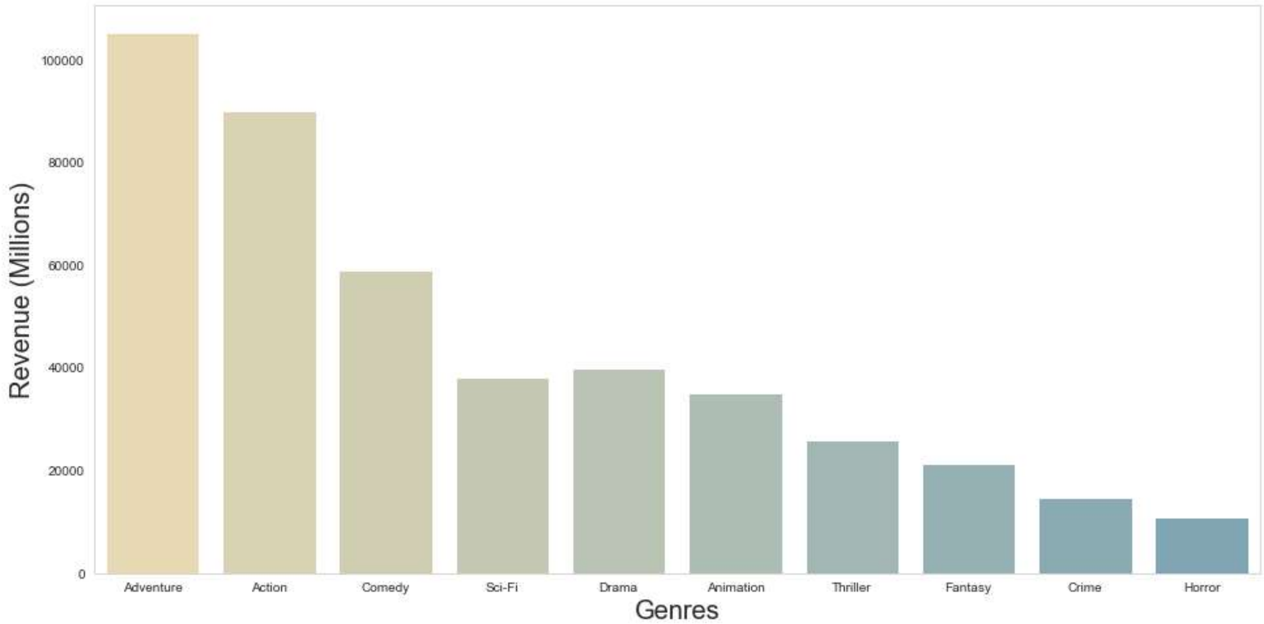
Genres by Gross Revenue Graph

This data was chosen to support the indentification of the most popular type of movies using gross revenue as the main indicator.

In [41]:

```
sns.set_style("whitegrid", {'axes.grid' : False})
plt.figure(figsize = (16,8))
a= sns.barplot(data=return_by_genre_graphs, x='genres',y= 'Revenue $M', palette="blend:#EDA,#7AB")
plt.xlabel('Genres', size=20)
plt.ylabel('Revenue (Millions)', size=20);


```



Average ROI v Average Budget Scatterplot

The data chosen around this was based on a ROI calcultion and is used to highlight the recommendation around categories of movie outside those that are the top earning that would support a higher ROI. It is based on the averages per movie for the top 10 studios.

In [42]:

```
#plot scatter plot: ROI by Production Budget
plt.figure(figsize = (8,8))
p= sns.scatterplot(data=average_by_genre_graphs,
                x='ROI%',
                y='Budget $M',
                size='Revenue $M',
                sizes=(200, 800), hue= 'Revenue $M', palette="rocket")
plt.legend(title='Average Revenue per Movie (Millions)', bbox_to_anchor=(1.45, -0.05), loc="lower right", frameon=True, fontsize
plt.xlabel("Average Return on Investment %", size=20)
plt.ylabel('Average Budget per Movie (Millions)', size=20)
#sns.set(font_scale =1.15)
plt.rcParams["axes.labelsize"] = 20
for i, txt in enumerate(average_by_genre_graphs['genres']):
    plt.annotate(txt,(average_by_genre_graphs['ROI%'][i]+.04, average_by_genre_graphs['Budget $M'][i]-.06), size='medium', color=

```

Runtime Analysis Histogram

This a count of run times for the top 10 studios to support the recommendation around optimal movie run length.

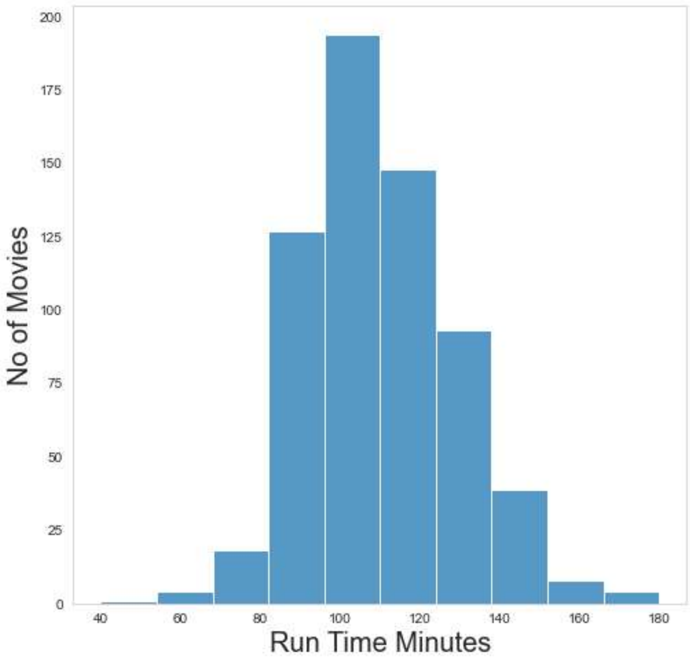
In [43]:

```
plt.figure(figsize = (8,8))
sns.histplot(data=run_time_analysis_graph, x="runtime_minutes", bins=10)
plt.xlabel("Run Time Minutes", size=20)
plt.ylabel('No of Movies', size=20)

```

Out[43]:

```
Text(0, 0.5, 'No of Movies')
```



ROI v Rating

Compares ratings from IMDB to ROI to assess the relationship between ROI and rating.

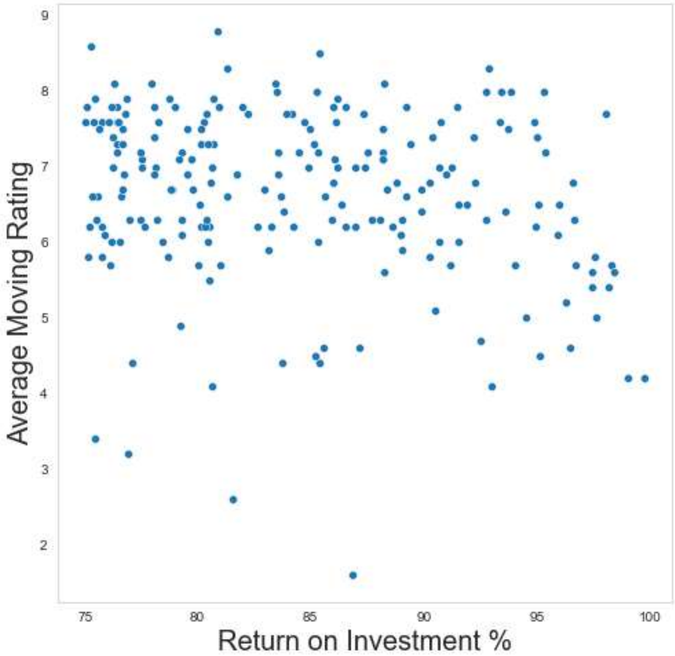
In [44]:

```
plt.figure(figsize = (8,8))
sns.scatterplot(data=rating_analysis_graph, x="ROI%", y="averagerating")
plt.xlabel("Return on Investment %", size=20)
plt.ylabel('Average Moving Rating', size=20)

```

Out[44]:

```
Text(0, 0.5, 'Average Moving Rating')
```



Evaluation

The analysis indentifies the ROI per movie within the leading categories that will drive good returns while maintaining a high level of gross revenue.

As per the ROI v Rating comparison further anlaysis could be undertaken to see which directors and producers drive high ratings so they could be targeted to lead projects in the future.

Conclusions

To pursue a strategy of both high revenue and ROI movies Microsoft should concentrate on the Animation, Sci-Fi and Comedy genres.

For the Animation and Sci-Fi genres production budgets should be between 110M and 130M. Movies in the Comedy could be produced at around 60M

Run time should be between 90-100 Minutes

Further analysis should be undertaken on the directors and actors that drive ratings as this can have a positive impact on movie ROI.