Machine Learning Foundation Nanodegree 2018-2019

Project 3: Investigate a Dataset (TMDb Movie Analysis)

Submission by: Aaron Balson Caroltin .J

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I. Introduction

What can we say about the success of a movie before it is released? Are there certain companies (Pixar?) that have found a consistent formula? Given that major films costing over $100 million to produce can still flop, this question is more important than ever to the industry. Film aficionados might have different interests. Can we predict which films will be highly rated, whether or not they are a commercial success?

This dataset under investigation is a sub-set / kaggle version of TMDb movies with about 10K movies (rows) and 21 attributes (columns). It is a great place to start digging in to perform exploratory data analysis with data on the plot, cast, crew, budget, and revenues of several thousand films.

Questions we will try answer

1. Top 5 movies with most budget, revenue, profit
2. Find which genres are behind successful movies
3. Find profitable movie release trend
4. Find profitable movie runtime strategy

In [340]:
```
# All imports

import pandas as pd
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
% matplotlib inline
```

II. Data Wrangling

(i) General Properties

In [341]:
```
# Load Movie data
data = pd.read_csv('tmdb-movies.csv')

# Shape, Size, Dim and Structure of data
print('Data Shape (rows, cols):', data.shape)
print('Data Size (rows x cols):', data.size)
print('Data Dimensions:', data.ndim)

print('Data Structure:')
data.info()

# Display first 5 rows
data.head()
```

```
Data Shape (rows, cols): (10866, 21)
Data Size (rows x cols): 228186
Data Dimensions: 2
Data Structure:
<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
```

Out[341]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www.jurassicworld.com/	Colin Trevorrow	The
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.madmaxmovie.com/	George Miller	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke	
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	http://www.starwars.com/films/star-wars-episod...	J.J. Abrams	ger
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	http://www.furious7.com/	James Wan	Ven Hit

5 rows × 21 columns

In [342]:
```
# Additional observations

print('popularity (min, max) =', data['popularity'].min(), data['popularity'].max())
print('vote_count (min, max) =', data['vote_count'].min(), data['vote_count'].max())
print('vote_average (min, max) =', data['vote_average'].min(), data['vote_average'].max())
print('runtime (min, max) =', data['runtime'].min(), data['runtime'].max())
print('revenue (min, max) =', data['revenue'].min(), data['revenue'].max())
```

```
popularity (min, max) = 6.500000000000001e-05 32.985763
vote_count (min, max) = 10 9767
vote_average (min, max) = 1.5 9.2
runtime (min, max) = 0 900
revenue (min, max) = 0 2781505847
```

In [343]:
```
# finding the movies with longest runtime, most popular
print('Most Runtime:')
data.loc[data['runtime'].idxmax()]
```

```
Most Runtime:
```

Out[343]:

id	125336
imdb_id	tt2044056
popularity	0.006925
budget	0
revenue	0
original_title	The Story of Film: An Odyssey
cast	Mark Cousins|Jean-Michel Frodon|Cari Beauchamp...
homepage	http://www.channel4.com/programmes/the-story-o...
director	Mark Cousins
tagline	NaN
keywords	cinema|nouvelle vague|hindi cinema|cinema novo...
overview	The Story of Film: An Odyssey, written and dir...
runtime	900
genres	Documentary
production_companies	NaN
release_date	9/3/11
vote_count	14
vote_average	9.2
release_year	2011
budget_adj	0
revenue_adj	0

```
Name: 3894, dtype: object
```

In [344]:
```
print('Most Popular:')
data.loc[data['popularity'].idxmax()]
```

```
Most Popular:
```

Out[344]:

id	135397
imdb_id	tt0369610
popularity	32.9858
budget	150000000
revenue	1513528810
original_title	Jurassic World
cast	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
homepage	http://www.jurassicworld.com/
director	Colin Trevorrow
tagline	The park is open.
keywords	monster|dna|tyrannosaurus rex|velociraptor|island
overview	Twenty-two years after the events of Jurassic ...
runtime	124
genres	Action|Adventure|Science Fiction|Thriller
production_companies	Universal Studios|Amblin Entertainment|Legenda...
release_date	6/9/15
vote_count	5562
vote_average	6.5
release_year	2015
budget_adj	1.38e+08
revenue_adj	1.39245e+09

```
Name: 0, dtype: object
```

Initial Observations:

1. All monetary columns are assumed to be of $USD
2. Popularity column (range: 6.5 - 32) is assumed to be of some derived column based on vote_average (range: 0 - 10) and vote_count columns so we will only carry popularity column forward.
3. Film duration (runtime) seems to be in minutes (with an outlier of 900 minutes for British documentary film The Story of Film: An Odyssey which was targeted to TVs than Theatres).
4. Some movies have co-directors, multiple genres, production companies (Piped) but we will assume those combinations to be of seperate and distinct value in those columns (we could have performed one-hot encoding based on questions we seek to answer but we won't be doing it for this analysis)

(ii) Data Cleaning

In [345]:
```
print("Cols before removal:", data.shape[1])

# Dropping columns not required for further analysis
cols_to_delete=[ 'id', 'imdb_id', 'homepage', 'tagline', 'keywords', 'overview', 'production_companies',
                 'vote_count', 'vote_average', 'budget_adj', 'revenue_adj']
data.drop(cols_to_delete,axis=1, inplace=True)

# change date columns to datetime
data.release_date = pd.to_datetime(data['release_date'])

print("Cols after removal:", data.shape[1])
```

```
Cols before removal: 21
Cols after removal: 10
```

In [346]:
```
print("Rows before duplicates removal:", data.shape[0])

# Dropping duplicate rows
data.drop_duplicates(keep ='first', inplace=True)

print("Rows after duplicates removal:", data.shape[0])
```

```
Rows before duplicates removal: 10866
Rows after duplicates removal: 10865
```

In [347]:
```
print("Count of null values in each column:")

# check columns with null values
data.isnull().sum()
```

```
Count of null values in each column:
```

Out[347]:
```
popularity         0
budget             0
revenue            0
original_title     0
cast              76
director          44
runtime            0
genres            23
release_date       0
release_year       0
dtype: int64
```

In [348]:
```
print("Rows before null handling:", data.shape[0])

# Remove rows with "null" director column
data.dropna(subset=['director'], inplace=True)

# Replace "null" with "NA" for cast, genres columns
data["cast"].fillna("NA", inplace = True)
data["genres"].fillna("NA", inplace = True)

print("Rows after null handling:", data.shape[0])
```

```
Rows before null handling: 10865
Rows after null handling: 10821
```

In [349]:
```
print("Rows before zero handling", data.shape[0])

# remove zero budget & zero revenue movies
cond1 = data['budget'] != 0
cond2 = data['revenue'] != 0
data_nonzero = data[cond1 & cond2]
#data.drop(data[cond1 & cond2].index, inplace=True)

print("Rows after zero handling", data_nonzero.shape[0])

print('Finalized dataset:')
data.head()
```

```
Rows before zero handling 10821
Rows after zero handling 3853
Finalized dataset:
```

Out[349]:

	popularity	budget	revenue	original_title	cast	director	runtime	genres	release_date	release_year
0	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller	2015-06-09	2015
1	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	120	Action|Adventure|Science Fiction|Thriller	2015-05-13	2015
2	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	119	Adventure|Science Fiction|Thriller	2015-03-18	2015
3	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy	2015-12-15	2015
4	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	137	Action|Crime|Thriller	2015-04-01	2015

III. Exploratory Data Analysis

Research Question 1 (Top 5 movies with most budget, revenue, profit)

In [350]:
```
# Finding top 5 movies with highest budget
print('Highest budget movies:')
data_nonzero.nlargest(5, 'budget')[['budget', 'original_title', 'release_year']]
```

```
Highest budget movies:
```

Out[350]:

	budget	original_title	release_year
2244	425000000	The Warrior's Way	2010
3375	380000000	Pirates of the Caribbean: On Stranger Tides	2011
7387	300000000	Pirates of the Caribbean: At World's End	2007
14	280000000	Avengers: Age of Ultron	2015
6570	270000000	Superman Returns	2006

In [351]:
```
# Finding top 5 movies with highest revenue
print('Highest revenue movies:')
data_nonzero.nlargest(5, 'revenue')[['revenue', 'original_title', 'release_year']]
```

```
Highest revenue movies:
```

Out[351]:

	revenue	original_title	release_year
1386	2781505847	Avatar	2009
3	2068178225	Star Wars: The Force Awakens	2015
5231	1845034188	Titanic	1997
4361	1519557910	The Avengers	2012
0	1513528810	Jurassic World	2015

In [352]:
```
# Finding top 5 movies with highest profit

data_nonzero['profit'] = pd.to_numeric(data_nonzero['revenue'] - data_nonzero['budget'])
#data_nonzero.assign(profit=data_nonzero.revenue - data_nonzero.budget)
#data_nonzero['profit'] = data_nonzero['profit'].astype(int)
#data_nonzero['profit'] = data_nonzero['profit'].apply(lambda x: '{:.2f}'.format(x))
#data_nonzero['profit'] = pd.to_numeric(data_nonzero['profit'])
#data_nonzero['profit'] = data_nonzero['profit'].apply(pd.to_numeric, downcast='float', errors='coerce')

print('Highest profit movies:')
data_nonzero.nlargest(5, 'profit')[['profit', 'original_title', 'release_year']]

#data_nonzero.info()
```

```
Highest profit movies:

C:\Program Files (x86)\Microsoft Visual Studio\Shared\Anaconda3_64\lib\site-packages\ipykernel_launcher.py:3: SettingWithCopyWarning:
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/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[352]:

	profit	original_title	release_year
1386	2544505847	Avatar	2009
3	1868178225	Star Wars: The Force Awakens	2015
5231	1645034188	Titanic	1997
0	1363528810	Jurassic World	2015
4	1316249360	Furious 7	2015

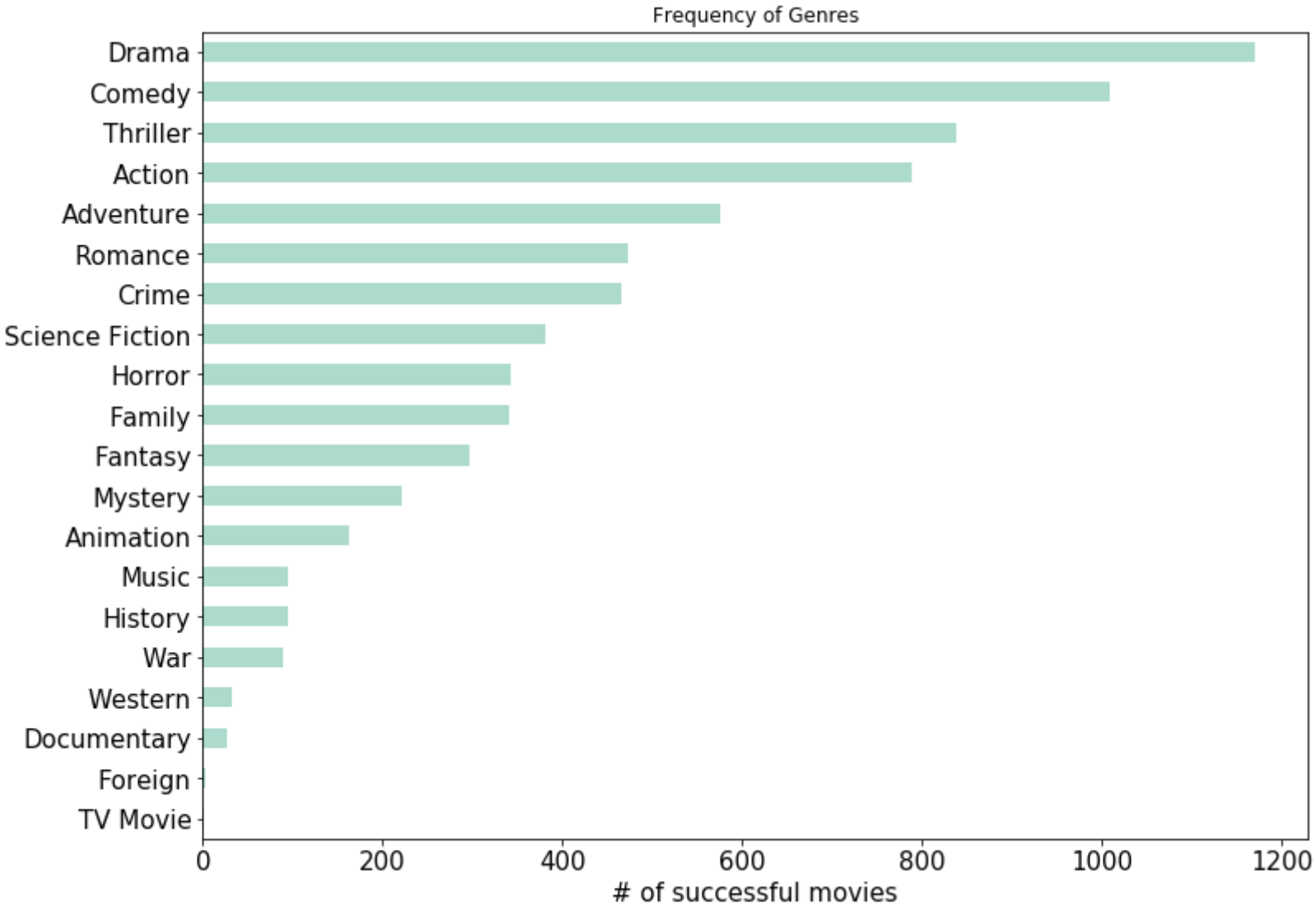
Observation: The top 5 list seems to be in align with the popularity of these movies and hence i will agree on the list.

Research Question 2 (Find which genres are behind successful movies)

In [353]:

```
# Helper functions
def get_series_count(df, column, ascend):
    """ Get the split based on | and returns entries in the series """
    df_temp = df[column].str.cat(sep = '|')
    df_temp = pd.Series(df_temp.split('|'))
    series = df_temp.value_counts(ascending = ascend)

    return series

#get genres for successful movies (profit > 0)
profit_data = data_nonzero[data_nonzero['profit'] > 0]
genres = get_series_count(profit_data, 'genres', ascend=False)

print('Profitable movies:', profit_data['profit'].count())
print('Successful genres:')
print(genres)

#show best genres from top to bottom on a horizontal bar chart
genres.sort_values(ascending = True, inplace = True)
crt = genres.plot.barh(color = '#acdacd', fontsize = 15)

#title, label, figure size
crt.set(title = 'Frequency of Genres')
crt.set_xlabel('# of successful movies', color = 'black', fontsize = '15')
crt.figure.set_size_inches(12, 9)

plt.show()
```

```
Profitable movies: 2777
Successful genres:
Drama              1171
Comedy             1009
Thriller            839
Action              788
Adventure           575
Romance             473
Crime               465
Science Fiction     382
Horror              343
Family              340
Fantasy             296
Mystery             222
Animation           162
Music                94
History              94
War                  89
Western              33
Documentary          26
Foreign               3
TV Movie              1
dtype: int64
```



Observation: I can agree on the top 5 genres however the database is more inclined towards hollywood / english viewers and hence the culture, age of viewers have to be taken into account.

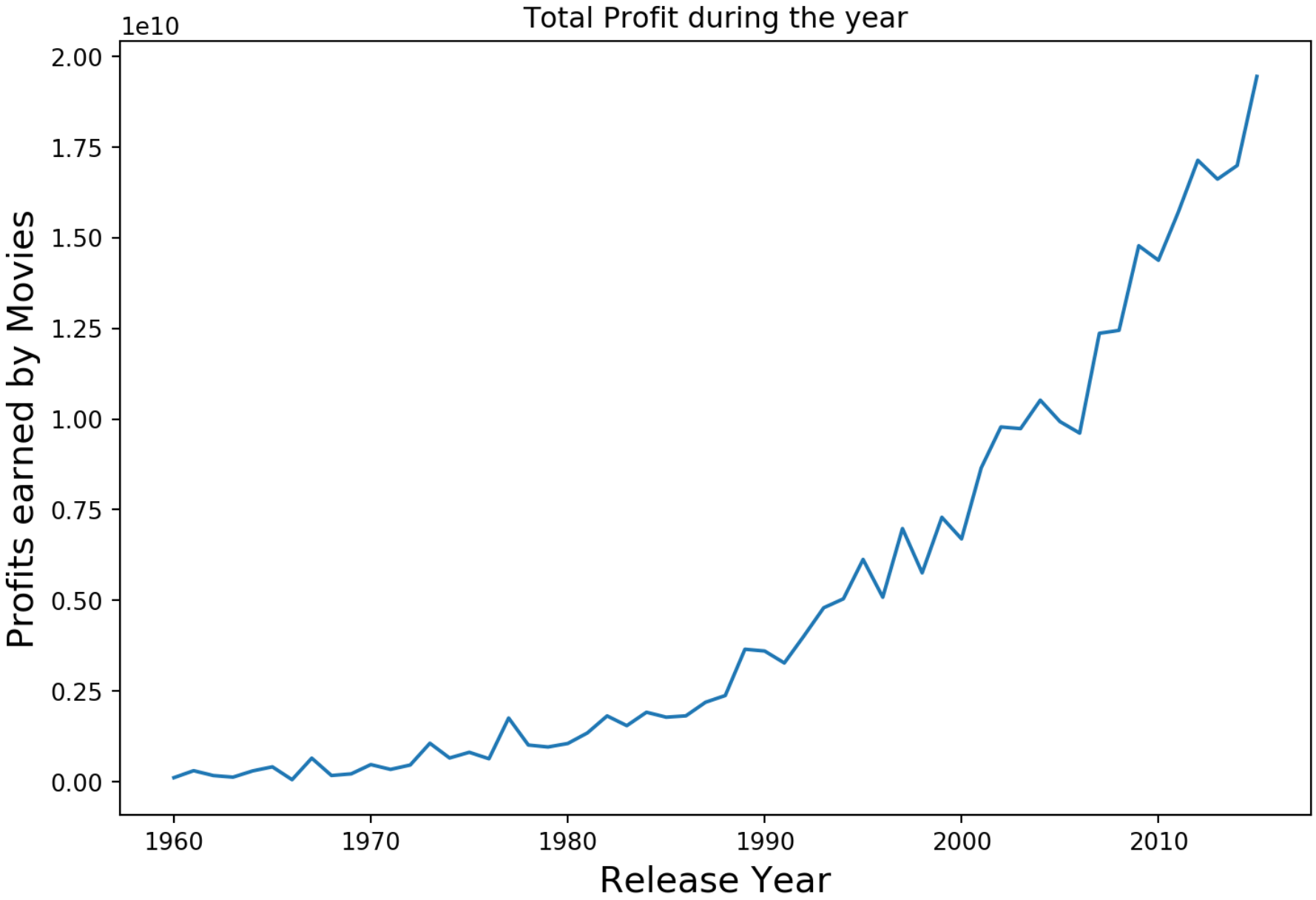
Research Question 3 (Find profitable movie release trend)

In [354]:
```
# Find total yearly profit from all profitted movies and based on release_year
total_yearly_profit = profit_data.groupby('release_year')['profit'].sum()
#print(total_yearly_profit)
total_yearly_profit.describe()
```

Out[354]:
```
count    5.600000e+01
mean     5.121541e+09
std      5.554346e+09
min      5.246869e+07
25%      6.496452e+08
50%      2.281079e+09
75%      8.892808e+09
max      1.944833e+10
Name: profit, dtype: float64
```

In [355]:

```
# plot line graph to describe the trend
plt.figure(figsize=(9,6), dpi = 190)

#set axis, labels, title
plt.xlabel('Release Year', fontsize = 15)
plt.ylabel('Profits earned by Movies', fontsize = 15)
plt.title('Total Profit during the year')

#plot & show

plt.plot(total_yearly_profit)
plt.show()
```


Total Profit during the year
1e10
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Profits earned by Movies
1960
1970
1980
1990
2000
2010
Release Year

Observation: based on single-variable (1d) and multiple-variable (2d) explorations, the reason we are seeing an upward trend for # of successful movies released can be attributed to the increased professionalism in the highly competitive movie making field. Technology also plays major role in making a movie hit. Viewership has increased since the age of internet as well.

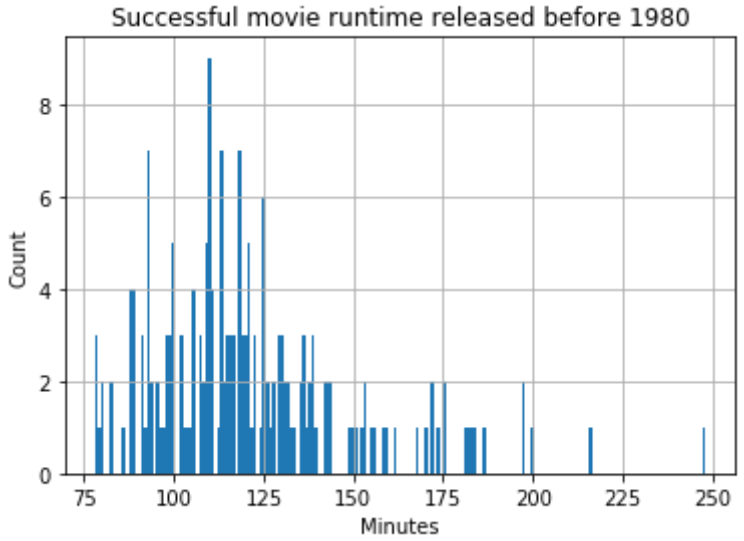
Research Question 4 (Find profitable movie runtime strategy)

In [356]:
```
# describe the runtime (minutes)

profit_data['runtime'].describe()
```

Out[356]:
```
count    2777.000000
mean      110.159165
std        20.113490
min        26.000000
25%        96.000000
50%       106.000000
75%       121.000000
max       248.000000
Name: runtime, dtype: float64
```

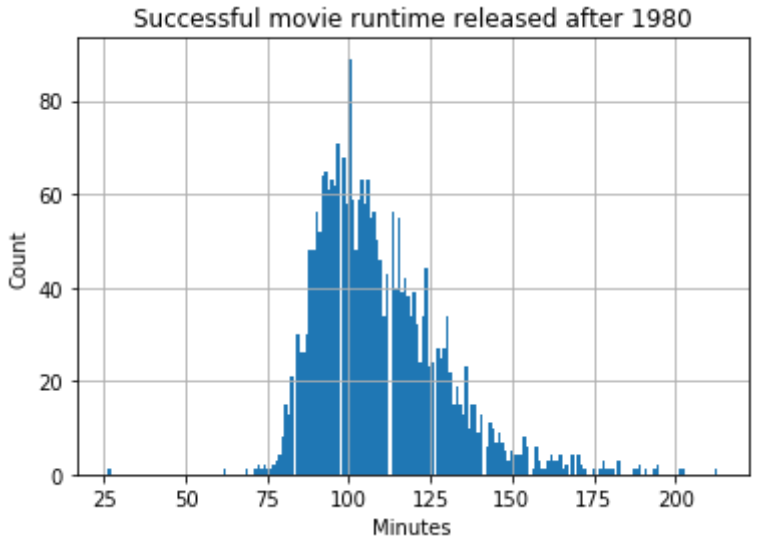
In [357]:
```
# Movie runtime for profitable movies
profit_data['runtime'][profit_data['release_year'] < 1980].hist(bins=200);
plt.xlabel('Minutes')
plt.ylabel('Count')
plt.title('Successful movie runtime released before 1980')
```

Out[357]:
```
Text(0.5,1,'Successful movie runtime released before 1980')
```



In [358]:
```
profit_data['runtime'][profit_data['release_year'] >= 1980].hist(bins=200);
plt.xlabel('Minutes')
plt.ylabel('Count')
plt.title('Successful movie runtime released after 1980')
```

Out[358]:
```
Text(0.5,1,'Successful movie runtime released after 1980')
```



Observation: based on single-variable (1d) and multiple-variable (2d) explorations, the sweet spot seems to be around 90-110 minutes mark (mean = 110.159165).
Irrespective of older or newer movies, people wish to get entertained for about the same time (boredom threshold)

IV. Conclusions

It is found that for a movie to be hit, it has to be around 110 minutes long, be in any one of these genres (Drama, Comedy, Thriller, Action, Adventure). Ofcourse, it needs the correct timing of the public as well the cast & crew performance. Only 2777 movies were profitable but it could be attributed to lack of accurate budget or revenue data out of 3843 datapoints we started with (having non-zero budget, revenue). Also we are unaware of how the popularity was derived as different audience can provide different ratings yet, only same type of audience usually get to vote mostly (internet savvy and/or young) so it can skew such datasets collected via online. Overall, it was an interesting project and entertaining experience, will surely look deeply into the dataset in future for different ideas.

References:

https://medium.com/dunder-data/selecting-subsets-of-data-in-pandas-39e811c81a0c (https://medium.com/dunder-data/selecting-subsets-of-data-in-pandas-39e811c81a0c) https://pandas.pydata.org/pandas-docs (https://pandas.pydata.org/pandas-docs)