dsc-movie-analysis

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1 Movie Industry Analysis

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1.1 Overview

This project analyzes past movies data to offer strategic business recommendations for a new film studio. We aim to predict the most profitable strategies for film production and release by examining production budgets, gross revenues, net profits, genres, popularity, key staff and release timelines. As result this project provides three business recommendations: what genre should a future movie be, what budget to allocate and when to release it.

1.2 Business Problem

The company is expanding its portfolio by investing in a new film studio. Launching a film studio in today's competitive entertainment industry requires a solid understanding of what drives movie success and attracts audiences. The movie industry is known for its substantial risks and high capital demands. Recent developments in AI have made video content creation faster and more efficient, increasing competition but also opening up new opportunities to enter the market.

Our project aims to analyze various datasets, including past movies' financial results, genre correlations, and movie ratings and popularity. By using data analysis techniques, we seek to gain valuable insights and identify patterns that can help shape the company's film production strategy. The goal is to provide three concrete business recommendations that maximize profitability and lower business risks, ensuring a strong entry into the market.

Questions we tried to answer with analysis: * How should the movie be budgeted? * What genres are most profitable? * When should a movie be released?

1.3 Data Understanding

We used datasets from Rotten Tomatoes, TheMovieDB, Bom Office Mojo, IMDB and The Numbers. Each dataset is of different size and contains different data catecories which might be seen as a limitation. For every question we answer we choose the most relevant dataset or merge some of them together for a fuller picture.

For budget related analysis we used IMDB and The Numbers. TheMovieDD dataset was used to explore movie ratings and popularity.

- One of the main metrics we explored is genre. IMDB defines genre as a category of artistic composition, characterized by similarities in form, style, or subject matter for a piece of content. Reaserch by Mustafa Mahmoud Yousry has shown that genre is the main decision factor for audience when chosing a movie to watch.

- We introduced the Return on Investment (ROI) metric as a standardized criterion to measure the financial success of a movie relative to its investments, as well as calculated movie net profit.
- We calculated Net Profit.

1.4 Data Analysis

[1]:
```
import pandas as pd
import numpy as np
import sqlite3
from scipy import stats
import matplotlib.pyplot as plt
from math import ceil, floor
import seaborn as sns
import tempfile,zipfile
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
```

1.5 A risk analysis of the movie production business

In order to provide any business recommendation, we need to understand how much money it is being bet and how much profit is desired in entering this industry.

Our concept of risk group is then defined: a high risk group is one with a large budget that, if successful, will yield large profit, but if failed, can result in a great loss.

We start by cleaning The Numbers dataset and trying to explain correlations between profit, loss and budget.

[2]:
```
#function for cleaning columns and coverting to integer

def clean_and_convert_to_int(column):
    return column.replace({'\$': '', ',': ''}, regex=True).astype(int)

#function for converting to date type

def convert_to_date(column):
    return pd.to_datetime(column, errors='coerce')

#function to clean object columns

def clean_object(column):
    return column.strip().lower()

def split(column):
```

```
    return column.str.split(',')
```

[3]:
```
#Cleaning The Numbers DF
tn = pd.read_csv('zippedData/tn.movie_budgets.csv')

#Converting strings to int values. Ex: '$1922819' -> 1922819
tn[['production_budget', 'domestic_gross', 'worldwide_gross']] =␣
 ↪tn[['production_budget', 'domestic_gross', 'worldwide_gross']].
 ↪apply(clean_and_convert_to_int)

#Getting release date in timestamp format to get the year
tn[['release_date']] = tn[['release_date']].apply(convert_to_date)
tn['release_year'] = tn['release_date'].dt.year

#id is an internal identifier
tn = tn.drop(columns=['id'])

#Calculating Net Profit. We only regards international success. A lot of movies␣
 ↪have huge budgets and only become profitable internationally
tn['worldwide_net'] = tn['worldwide_gross'] - tn['production_budget']

#Calculating Return Over Investment
tn['ROI'] = (tn['worldwide_net']) / tn['production_budget']

tn = tn[(tn['domestic_gross'] != 0) & (tn['worldwide_gross'] != 0)]
tn = tn[(tn['ROI'] != 0) & (tn['ROI'] != np.inf) & (tn['ROI'] != -np.inf) &␣
 ↪(tn['ROI'] != -100)]
tn = tn.sort_values(by='ROI')

tn
```

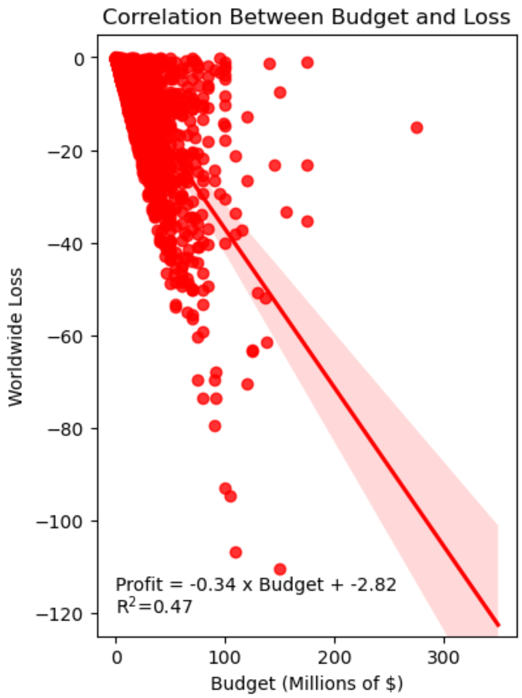
[3]:
```
     release_date                         movie  production_budget  \
4081   2010-05-21              Perrierâ s Bounty          6600000
3818   2015-05-08                     Skin Trade          9000000
2152   1997-08-24  The Grimm Brothers' Snow White        26000000
5027   1993-01-01          Ed and his Dead Mother          1800000
1242   2013-11-01                     Mr. Nobody         46500000
…             …                             …                 …
5406   1999-07-14        The Blair Witch Project            600000
5679   2015-07-10                    The Gallows            100000
5492   2009-09-25             Paranormal Activity            450000
5613   1980-03-21                        Mad Max            200000
5745   1972-06-30                    Deep Throat             25000

      domestic_gross  worldwide_gross  release_year  worldwide_net  \
4081             828              828          2010       -6599172
3818            1242             1242          2015       -8998758
```

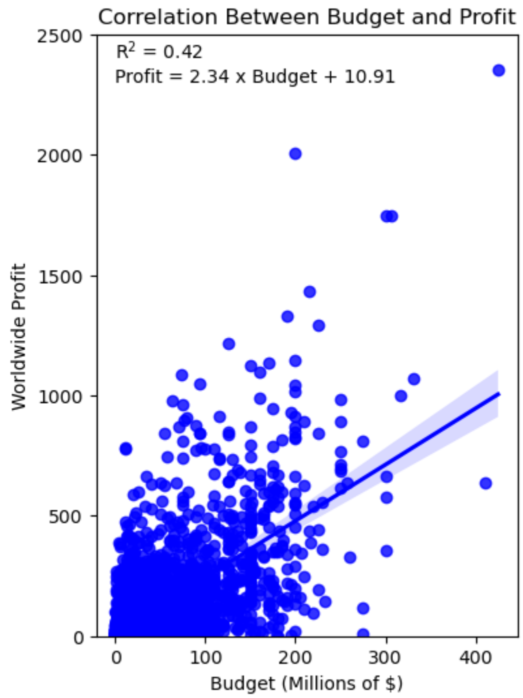
```
2152           5000          5000       1997    -25995000
5027            673           673       1993     -1799327
1242           3622         22254       2013    -46477746
…                 …             …  …        …
5406      140539099     248300000       1999    247700000
5679       22764410      41656474       2015     41556474
5492      107918810     194183034       2009    193733034
5613        8750000      99750000       1980     99550000
5745       45000000      45000000       1972     44975000

              ROI
4081    -0.999875
3818    -0.999862
2152    -0.999808
5027    -0.999626
1242    -0.999521
…             …
5406   412.833333
5679   415.564740
5492   430.517853
5613   497.750000
5745  1799.000000

[5234 rows x 8 columns]
```

[4]:
```python
tn_loss = tn[tn['worldwide_net']<0]
tn_profit = tn[tn['worldwide_net']>0]
```

[5]:
```python
fig,[ax1,ax2] = plt.subplots(ncols=2,figsize=(10,6),gridspec_kw={'wspace':0.4})

p = sns.regplot(x=tn_loss['production_budget']/10**6,y=tn_loss['worldwide_net']/
 ↪10**6,color='r',ax=ax1)
ax1.set_title('Correlation Between Budget and Loss')
ax1.set_xlabel('Budget (Millions of $)')
ax1.set_ylabel('Worldwide Loss')
ax1.set_ylim(-125,5)
slope, intercept, r, p_value1, sterr = stats.linregress(x=p.get_lines()[0].
 ↪get_xdata(),
                                                        y=p.get_lines()[0].
 ↪get_ydata())
X = np.array(tn_loss['production_budget']).reshape(-1, 1)  # Feature
y = np.array(tn_loss['worldwide_net'])  # Target

#Fit linear regression model
model = LinearRegression()
model.fit(X, y)
```

```
#predict and calculate R²
y_pred = model.predict(X)
r2_loss = r2_score(y, y_pred)

#add regression equation to plot
ax1.text(0, -120, f'R$^2$={r2_loss:.02f}')
ax1.text(0, -115, f'Profit = {slope:.02f} x Budget + {intercept:.02f}');

p = sns.regplot(x=tn_profit['production_budget']/
 ↪10**6,y=tn_profit['worldwide_net']/10**6,color='b',ax=ax2)
ax2.set_ylim(0,2500)
ax2.set_title('Correlation Between Budget and Profit')
ax2.set_xlabel('Budget (Millions of $)')
ax2.set_ylabel('Worldwide Profit')
slope, intercept, r2, p_value2, sterr = stats.linregress(x=p.get_lines()[0].
 ↪get_xdata(),
                                                         y=p.get_lines()[0].
 ↪get_ydata())

X = np.array(tn_profit['production_budget']).reshape(-1, 1)  # Feature
y = np.array(tn_profit['worldwide_net'])  # Target

#Fit linear regression model
model = LinearRegression()
model.fit(X, y)

#predict and calculate R²
y_pred = model.predict(X)
r2_profit = r2_score(y, y_pred)
#Add correlation to plot
ax2.text(0, 2400, f'R$^2$ = {r2_profit:.02f}')
ax2.text(0, 2300, f'Profit = {slope:.02f} x Budget + {intercept:.02f}');
# print(p.get_lines()[0].get_ydata(),list(slope*tn_loss['production_budget']/
 ↪10**6)+intercept)
```





Based on the determination that a higher budget does indeed correlate with higher profits and losses, we divide the dataset into 3 groups with same size based on their risk level: - High risk invetsment, higher budget movies that will probably not have a very high ROI but have the chance of making large profit if audiences enjoy it; - Low risk investment, a lower cost that can have a high ROI based on the lower investment; - Medium risk investment, that is just inbetween.

We first filter the dataset starting from 2000 to onli pick up recent trends and calculate the 2 budget thresholds for each group.

[6]:
```
tn_since2000 = tn[pd.to_datetime(tn['release_date']).dt.year>=2000]
tn_since2000
```

[6]:
```
      release_date                 movie  production_budget  domestic_gross  \
4081    2010-05-21      Perrierâ s Bounty            6600000             828
3818    2015-05-08             Skin Trade            9000000            1242
1242    2013-11-01             Mr. Nobody           46500000            3622
5298    2002-12-13         The Jimmy Show            1000000             703
5297    2006-04-21    In Her Line of Fire            1000000             884
…              …                      …                  …               …
5656    2007-05-16                   Once             150000         9445857
5781    2005-08-05      My Date With Drew               1100          181041
5709    2004-05-07          Super Size Me              65000        11529368
5679    2015-07-10            The Gallows             100000        22764410
5492    2009-09-25    Paranormal Activity             450000       107918810
```

```
      worldwide_gross  release_year  worldwide_net         ROI
4081              828          2010       -6599172   -0.999875
3818             1242          2015       -8998758   -0.999862
1242            22254          2013      -46477746   -0.999521
5298              703          2002        -999297   -0.999297
5297              884          2006        -999116   -0.999116
…                 …             …             …          …
5656         23323631          2007       23173631  154.490873
5781           181041          2005         179941  163.582727
5709         22233808          2004       22168808  341.058585
5679         41656474          2015       41556474  415.564740
5492        194183034          2009      193733034  430.517853

[3865 rows x 8 columns]
```

[7]:
```python
# We will work with 2 thresholds for our analysis
budget = tn_since2000['production_budget'].sort_values()
n_budget = len(budget)
threshold_budget_low = budget.iloc[int(n_budget/3)]
threshold_budget_high = budget.iloc[int(2*n_budget/3)]
print(f'The threshold in between low and medium risk is at␣
 ↪${threshold_budget_low/10**6:.02f} \
millions and in between medium and high is ${threshold_budget_high/10**6:0.2f}␣
 ↪millions.')
```

```
The threshold in between low and medium risk is at $11.50 millions and in
between medium and high is $36.00 millions.
```

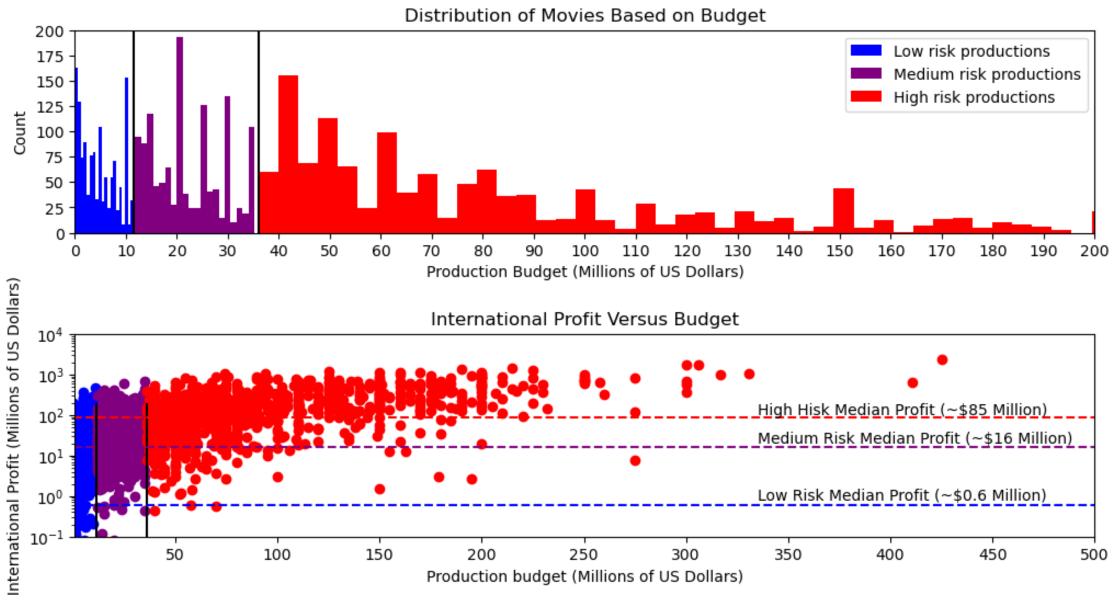
[8]:
```python
tn_low_risk  =␣
 ↪tn_since2000[tn_since2000['production_budget']<=threshold_budget_low]
tn_medium_risk =␣
 ↪tn_since2000[(tn_since2000['production_budget']>threshold_budget_low) &␣
 ↪(tn_since2000['production_budget']<threshold_budget_high)]
tn_high_risk =␣
 ↪tn_since2000[tn_since2000['production_budget']>=threshold_budget_high]
```

[9]:
```python
fig, ax = plt.subplots(nrows=2, figsize=(12,6), gridspec_kw={'hspace': 0.5})
# fig.tight_layout()



median_profit_low = tn_low_risk['worldwide_net'].median()/10**6
median_profit_medium = tn_medium_risk['worldwide_net'].median()/10**6
median_profit_high = tn_high_risk['worldwide_net'].median()/10**6
print(median_profit_low, median_profit_medium, median_profit_high)

ax[0].hist(tn_low_risk['production_budget']/10**6, color='b',bins=20,␣
 ↪label='Low risk productions')
```

```python
ax[0].hist(tn_medium_risk['production_budget']/10**6, color='purple',bins=20, label='Medium risk productions')
ax[0].hist(tn_high_risk['production_budget']/10**6, color='r',bins=100, label='High risk productions');
ax[0].set_yticks(np.arange(0,201,25))
ax[0].set_ylim(0,200)
ax[0].set_xticks(np.arange(0,501,10))
ax[0].set_xlim(0,200)
ax[0].set_xlabel('Production Budget (Millions of US Dollars)')
ax[0].set_ylabel('Count')
ax[0].legend()
ax[0].set_title('Distribution of Movies Based on Budget')
ax[0].vlines(x=threshold_budget_low/10**6,ymin=0,ymax=200,color='black')
# ax[0].text(x=threshold_budget_low/10**6,y=175,s='Median budget')
ax[0].vlines(x=threshold_budget_high/10**6,ymin=0,ymax=200,color='black')
# ax[0].text(x=threshold_budget_high,y=175,s='Median budget')

ax[1].scatter(x=tn_low_risk['production_budget']/10**6, y=tn_low_risk['worldwide_net']/10**6,color='b',label='Low risk productions')
ax[1].scatter(x=tn_medium_risk['production_budget']/10**6, y=tn_medium_risk['worldwide_net']/10**6,color='purple',label='Medium risk productions')
ax[1].scatter(x=tn_high_risk['production_budget']/10**6, y=tn_high_risk['worldwide_net']/10**6, color='r', label='High risk productions')
ax[1].set_title('International Profit Versus Budget')
ax[1].set_xlabel('Production budget (Millions of US Dollars)')
ax[1].set_ylabel('International Profit (Millions of US Dollars)')
ax[1].set_yticks(np.arange(0,1000,25))
ax[1].set_ylim(0.1,10000)
ax[1].set_xticks(np.arange(0,501,50))
ax[1].set_xlim(1,500)
ax[1].vlines(x=threshold_budget_low/10**6,ymin=0,ymax=200,color='black')
ax[1].vlines(x=threshold_budget_high/10**6,ymin=0,ymax=200,color='black')
ax[1].hlines(xmin=0,xmax=500,y=median_profit_low,color='blue', linestyle='dashed')
ax[1].hlines(xmin=0,xmax=500,y=median_profit_medium,color='purple', linestyle='dashed')
ax[1].hlines(xmin=0,xmax=500,y=median_profit_high,color='red', linestyle='dashed')
ax[1].set_yscale('log')
ax[1].text(x=335,y=0.8,s='Low Risk Median Profit (~$0.6 Million)')
ax[1].text(x=335,y=20,s='Medium Risk Median Profit (~$16 Million)')
ax[1].text(x=335,y=100,s='High Hisk Median Profit (~$85 Million)')

# ax[1].text(x=21,y=2000,s='Median Profit for Low Risk Movie')
```

```
0.611615 15.943401 85.08081
```

[9]:
```
Text(335, 100, 'High Hisk Median Profit (~$85 Million)')
```



2 Low Risk - Budget < $11.50 millions

The first thing we need to do is join the table with budgets and profit with the table that contains genres. Genres are in both IMDB and Movie DB meaning that in order to lose the least amount of information, we need to perform joins with different tables, concatenate and remove duplicates.

[10]:
```
tn_low_risk
```

[10]:
```
     release_date                movie  production_budget  domestic_gross  \
4081   2010-05-21    Perrierâ s Bounty           6600000             828
3818   2015-05-08           Skin Trade           9000000            1242
5298   2002-12-13       The Jimmy Show           1000000             703
5297   2006-04-21  In Her Line of Fire           1000000             884
3728   2009-10-16      Janky Promoters          10000000            9069
…             …                    …                …               …
5656   2007-05-16                 Once            150000         9445857
5781   2005-08-05     My Date With Drew             1100          181041
5709   2004-05-07        Super Size Me             65000        11529368
5679   2015-07-10          The Gallows            100000        22764410
5492   2009-09-25  Paranormal Activity            450000       107918810

      worldwide_gross  release_year  worldwide_net        ROI
4081              828          2010       -6599172  -0.999875
```

```
3818              1242          2015      -8998758   -0.999862
5298               703          2002       -999297   -0.999297
5297               884          2006       -999116   -0.999116
3728              9069          2009      -9990931   -0.999093
…                    …             …             …          …
5656          23323631          2007      23173631  154.490873
5781            181041          2005        179941  163.582727
5709          22233808          2004      22168808  341.058585
5679          41656474          2015      41556474  415.564740
5492         194183034          2009     193733034  430.517853

[1289 rows x 8 columns]
```

[11]:
```
# Create a temporary file
with tempfile.NamedTemporaryFile(delete=False) as temp_db:
    # Extract the database file from the zip archive to the temporary file
    with zipfile.ZipFile('zippedData/im.db.zip', 'r') as z:
        with z.open('im.db') as f:
            temp_db.write(f.read())
    temp_db_path = temp_db.name
conn = sqlite3.connect(temp_db_path)

imdb = pd.read_sql(
    """
    SELECT  mb.primary_title AS movie,
            mb.start_year,
            mb.runtime_minutes,
            mb.genres,
            per.primary_name AS director
    FROM movie_basics AS mb
    JOIN movie_akas AS ma
    USING(movie_id)
    JOIN directors AS dir
    USING(movie_id)
    JOIN persons AS per
    USING(person_id)
    GROUP BY movie_id

    """
, conn
)
imdb
```

[11]:
```
                                 movie  start_year  runtime_minutes  \
0                           Sunghursh        2013            175.0
1      One Day Before the Rainy Season        2019            114.0
2           The Other Side of the Wind        2018            122.0
```

```
3                         Sabse Bada Sukh        2018               NaN
4                 The Wandering Soap Opera        2017              80.0
…                                         …         …              …
119436          Padmavyuhathile Abhimanyu        2019             130.0
119437                     Nepal - Homebird        2019              52.0
119438                        A Cherry Tale        2019              85.0
119439                    Vida em Movimento        2019              70.0
119440                        The Rehearsal        2019              51.0

                       genres               director
0          Action,Crime,Drama   Harnam Singh Rawail
1             Biography,Drama             Mani Kaul
2                       Drama          Orson Welles
3                Comedy,Drama  Hrishikesh Mukherjee
4       Comedy,Drama,Fantasy            Raoul Ruiz
…                           …                    …
119436                  Drama       Vineesh Aaradya
119437            Documentary    Andrea Leichtfried
119438            Documentary            Eva Mulvad
119439            Documentary     Eduardo Rajabally
119440                  Drama       Tamar Guimaraes

[119441 rows x 5 columns]
```

[12]:

```
genre_dict = {
    '28': 'Action',
    '12': 'Adventure',
    '16': 'Animation',
    '35': 'Comedy',
    '80': 'Crime',
    '99': 'Documentary',
    '18': 'Drama',
    '10751': 'Family',
    '14': 'Fantasy',
    '36': 'History',
    '27': 'Horror',
    '10402': 'Music',
    '9648': 'Mystery',
    '10749': 'Romance',
    '878': 'Science Fiction',
    '10770': 'TV Movie',
    '53': 'Thriller',
    '10752': 'War',
    '37': 'Western'
}
```

[13]:
```
movie_db = pd.read_csv('zippedData/tmdb.movies.csv')
movie_db['genre_ids'] = movie_db['genre_ids'].replace({'\[': '', '\]': ''},
    regex=True)
movie_db['genre_ids'] = movie_db['genre_ids'].str.split(',')
movie_db = movie_db.explode('genre_ids')
movie_db['genre_ids'] = movie_db['genre_ids'].apply(clean_object)
movie_db['genre_ids'] = movie_db['genre_ids'].map(genre_dict)
movie_db.drop(labels=['Unnamed: 0', 'id', 'original_language', 'popularity',
    'release_date','vote_average', 'vote_count'],axis=1,inplace=True)
movie_db.rename(columns={'title':'movie','genre_ids':'genres'},inplace=True)
movie_db
```

[13]:
```
          genres                               original_title  \
0      Adventure  Harry Potter and the Deathly Hallows: Part 1
0        Fantasy  Harry Potter and the Deathly Hallows: Part 1
0         Family  Harry Potter and the Deathly Hallows: Part 1
1        Fantasy                      How to Train Your Dragon
1      Adventure                      How to Train Your Dragon
…          …                                             …
26515     Family                                  Trailer Made
26515  Adventure                                  Trailer Made
26515     Action                                  Trailer Made
26516   Thriller                                    The Church
26516     Horror                                    The Church

                                              movie
0      Harry Potter and the Deathly Hallows: Part 1
0      Harry Potter and the Deathly Hallows: Part 1
0      Harry Potter and the Deathly Hallows: Part 1
1                          How to Train Your Dragon
1                          How to Train Your Dragon
…                                               …
26515                                  Trailer Made
26515                                  Trailer Made
26515                                  Trailer Made
26516                                    The Church
26516                                    The Church

[47834 rows x 3 columns]
```

[14]:
```
df_lowrisk_merged1 = pd.merge(tn_low_risk,movie_db,how='inner',on='movie')
df_lowrisk_merged1.drop_duplicates(subset=['release_date','genres','movie'],
    inplace=True)
df_lowrisk_merged1.drop('original_title', axis=1, inplace=True)
df_lowrisk_merged1.dropna(subset=['genres', 'worldwide_net',
    'movie','production_budget'],inplace=True)
df_lowrisk_merged1
```

[14]:

```
      release_date            movie  production_budget  domestic_gross  \
0       2015-05-08       Skin Trade            9000000            1242
1       2015-05-08       Skin Trade            9000000            1242
2       2015-05-08       Skin Trade            9000000            1242
4       2018-05-11     Higher Power             500000             528
5       2018-05-11     Higher Power             500000             528
…              …                …                  …              …
1314    2009-04-23             Home             500000           15433
1319    2012-01-06  The Devil Inside            1000000        53262945
1320    2012-01-06  The Devil Inside            1000000        53262945
1321    2015-07-10      The Gallows             100000        22764410
1322    2015-07-10      The Gallows             100000        22764410

      worldwide_gross  release_year  worldwide_net         ROI  \
0                1242          2015       -8998758   -0.999862
1                1242          2015       -8998758   -0.999862
2                1242          2015       -8998758   -0.999862
4                 528          2018        -499472   -0.998944
5                 528          2018        -499472   -0.998944
…                 …             …             …          …
1314         44793168          2009       44293168   88.586336
1319        101759490          2012      100759490  100.759490
1320        101759490          2012      100759490  100.759490
1321         41656474          2015       41556474  415.564740
1322         41656474          2015       41556474  415.564740

               genres
0            Thriller
1              Action
2               Drama
4              Action
5     Science Fiction
…                 …
1314           Horror
1319         Thriller
1320           Horror
1321           Horror
1322         Thriller

[1148 rows x 9 columns]
```

[15]:

```
df_lowrisk_merged2 = pd.merge(left=tn_low_risk,
 ↪right=movie_db,how='inner',left_on='movie', right_on='original_title')
df_lowrisk_merged2.drop_duplicates(subset=['release_date','genres','movie_x'],
 ↪inplace=True)
df_lowrisk_merged2.rename(columns={'movie_x':'movie'},inplace=True)
df_lowrisk_merged2.drop(['original_title', 'movie_y'],axis=1,inplace=True)
```

```
df_lowrisk_merged2.dropna(subset=['genres', 'worldwide_net',␣
 ↪'movie','production_budget'],inplace=True)
df_lowrisk_merged2
```

[15]:

```
     release_date             movie  production_budget  domestic_gross  \
0      2015-05-08        Skin Trade            9000000            1242
1      2015-05-08        Skin Trade            9000000            1242
2      2015-05-08        Skin Trade            9000000            1242
4      2018-05-11      Higher Power             500000             528
5      2018-05-11      Higher Power             500000             528
…             …                 …                  …               …
1296   2009-04-23              Home             500000           15433
1300   2012-01-06   The Devil Inside           1000000        53262945
1301   2012-01-06   The Devil Inside           1000000        53262945
1302   2015-07-10       The Gallows             100000        22764410
1303   2015-07-10       The Gallows             100000        22764410

      worldwide_gross  release_year  worldwide_net         ROI  \
0                1242          2015       -8998758   -0.999862
1                1242          2015       -8998758   -0.999862
2                1242          2015       -8998758   -0.999862
4                 528          2018        -499472   -0.998944
5                 528          2018        -499472   -0.998944
…                   …             …             …          …
1296         44793168          2009       44293168   88.586336
1300        101759490          2012      100759490  100.759490
1301        101759490          2012      100759490  100.759490
1302         41656474          2015       41556474  415.564740
1303         41656474          2015       41556474  415.564740

               genres
0            Thriller
1              Action
2               Drama
4              Action
5     Science Fiction
…                   …
1296            Drama
1300         Thriller
1301           Horror
1302           Horror
1303         Thriller

[1146 rows x 9 columns]
```

[16]:

```python
df_lowrisk_merged3 = pd.merge(tn_low_risk,imdb,how='inner',on='movie')
df_lowrisk_merged3.drop_duplicates(subset=['release_date','movie'],␣
↪inplace=True)
df_lowrisk_merged3.drop(['runtime_minutes', 'start_year','director'], axis=1,␣
↪inplace=True)
df_lowrisk_merged3.dropna(subset=['genres', 'worldwide_net',␣
↪'movie','production_budget'],inplace=True)
df_lowrisk_merged3
```

[16]:

```
    release_date                          movie  production_budget  \
0     2015-05-08                     Skin Trade            9000000
2     2018-05-11                   Higher Power             500000
3     2013-02-22                    Inescapable            4000000
4     2013-04-05 Eddie: The Sleepwalking Cannibal            1400000
5     2012-10-26       The Ghastly Love of Johnny X            2000000
..           …                              …                  …
838   2015-04-17                     Unfriended            1000000
839   2011-04-01                      Insidious            1500000
840   2009-04-23                           Home             500000
860   2012-01-06                The Devil Inside            1000000
861   2015-07-10                    The Gallows             100000

     domestic_gross  worldwide_gross  release_year  worldwide_net         ROI  \
0              1242             1242          2015       -8998758   -0.999862
2               528              528          2018        -499472   -0.998944
3              4327             4327          2013       -3995673   -0.998918
4              1632             1632          2013       -1398368   -0.998834
5              2436             2436          2012       -1997564   -0.998782
..                …                …             …              …           …
838        32789645         64364198          2015       63364198   63.364198
839        54009150         99870886          2011       98370886   65.580591
840           15433         44793168          2009       44293168   88.586336
860        53262945        101759490          2012      100759490  100.759490
861        22764410         41656474          2015       41556474  415.564740

                      genres
0                Documentary
2      Action,Sci-Fi,Thriller
3        Action,Drama,Mystery
4              Comedy,Horror
5      Comedy,Fantasy,Musical
..                         …
838  Horror,Mystery,Thriller
839  Horror,Mystery,Thriller
840                    Drama
860                   Horror
861  Horror,Mystery,Thriller
```

```
[568 rows x 9 columns]
```

We explode the lists with the genres so that movies might be duplicate buteach entry will have a diffrent genre it is part of.

[17]:
```python
df_lowrisk_merged3['genres'] = df_lowrisk_merged3['genres'].str.split(',')
df_lowrisk_merged3 = df_lowrisk_merged3.explode('genres')
# df_lowrisk_merged3['genres'].value_counts()
```

[18]:
```python
df_lowrisk_exploded = pd.
 ↪concat([df_lowrisk_merged1,df_lowrisk_merged2,df_lowrisk_merged3])
df_lowrisk_exploded.drop_duplicates(subset=['release_date','movie','genres'],␣
 ↪inplace=True)
df_lowrisk_exploded['genres'].value_counts()
```

[18]:
```
genres
Drama              413
Comedy             192
Thriller           176
Horror             127
Romance            113
Mystery             96
Crime               84
Action              67
Documentary         66
Biography           52
Science Fiction     40
Fantasy             36
Music               36
Adventure           34
Family              32
Sci-Fi              28
History             27
War                 16
Sport               13
Animation            9
Western              7
Musical              5
Name: count, dtype: int64
```

Finally, we rename same genres written diffrently.

[19]:
```python
df_lowrisk_exploded['genres'].replace(to_replace='Science Fiction',␣
 ↪value='Sci-Fi',inplace=True)
df_lowrisk_exploded['genres'].value_counts()
```

```
/tmp/ipykernel_102626/4107546668.py:1: FutureWarning: A value is trying to be
```

```
set on a copy of a DataFrame or Series through chained assignment using an
inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df_lowrisk_exploded['genres'].replace(to_replace='Science Fiction',
value='Sci-Fi',inplace=True)
```

[19]:
```
genres
Drama          413
Comedy         192
Thriller       176
Horror         127
Romance        113
Mystery         96
Crime           84
Sci-Fi          68
Action          67
Documentary     66
Biography       52
Music           36
Fantasy         36
Adventure       34
Family          32
History         27
War             16
Sport           13
Animation        9
Western          7
Musical          5
Name: count, dtype: int64
```

2.1 Low Risk - Genre

Finally, the dataframe has now all the information from genres and movies we need.

[20]:
```python
df_lowrisk_exploded.groupby('genres')['ROI'].median().
 ↪sort_values(ascending=False).reset_index().head()
```

[20]:
```
    genres       ROI
0   Horror  4.163727
1  Mystery  3.810244
```

```
2     Sci-Fi  1.751043
3    Romance  1.036410
4   Thriller  0.999622
```

[21]:
```
df_lowrisk_exploded.groupby('genres')['worldwide_net'].median().
  ↪sort_values(ascending=False).reset_index().head()
```

[21]:
```
      genres  worldwide_net
0     Horror     15434588.0
1    Mystery     14371155.5
2    Romance      2681937.0
3    Fantasy      2438210.0
4   Thriller      1889796.0
```

Horror and Mystery have very similar ROI's and international profits. In order to determine which is more profitable, we use a t-test.

[22]:
```
mean_horror = 
  ↪df_lowrisk_exploded[df_lowrisk_exploded['genres']=='Horror']['worldwide_net'].
  ↪mean()/10**6
std_horror = 
  ↪df_lowrisk_exploded[df_lowrisk_exploded['genres']=='Horror']['worldwide_net'].
  ↪std()/10**6
n_horror = 
  ↪len(df_lowrisk_exploded[df_lowrisk_exploded['genres']=='Horror']['worldwide_net'])

t_horror_20 = (20-mean_horror)/(std_horror/n_horror**0.5)
t_horror_35 = (35-mean_horror)/(std_horror/n_horror**0.5)
t_horror_50 = (50-mean_horror)/(std_horror/n_horror**0.5)
print(f'T scores for profit of: \n$20 million = {t_horror_20}\n$35 million = 
  ↪{t_horror_35}\n$50 million = {t_horror_50}\n')

prob_horror_20 = 1-stats.t.cdf(t_horror_20,df=n_horror-1)
prob_horror_35 = 1-stats.t.cdf(t_horror_35,df=n_horror-1)
prob_horror_50 = 1-stats.t.cdf(t_horror_50,df=n_horror-1)
print(f'Probability for profit of: \n$20 million = {prob_horror_20}\n$35 
  ↪million = {prob_horror_35}\n$50 million = {prob_horror_50}')

horror_avg_cost = df_lowrisk_exploded[df_lowrisk_exploded['genres'] == 
  ↪'Horror']['production_budget'].mean()
print(f'Average cost of Horror movies below ${threshold_budget_low/10**6:0.2f} 
  ↪million are ${horror_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -3.6017645678829213
$35 million = -0.6797071532264725
$50 million = 2.242350261429976
```

```
Probability for profit of:
$20 million = 0.9997733937949502
$35 million = 0.7510316219789762
$50 million = 0.013343571801237686
Average cost of Horror movies below $11.50 million are $4.51 millions
```

[23]:

```python
mean_mystery = df_lowrisk_exploded[df_lowrisk_exploded['genres']=='Mystery']['worldwide_net'].mean()/10**6
std_mystery = df_lowrisk_exploded[df_lowrisk_exploded['genres']=='Mystery']['worldwide_net'].std()/10**6
n_mystery = len(df_lowrisk_exploded[df_lowrisk_exploded['genres']=='Mystery']['worldwide_net'])

t_mystery_20 = (20-mean_mystery)/(std_mystery/n_mystery**0.5)
t_mystery_35 = (35-mean_mystery)/(std_mystery/n_mystery**0.5)
t_mystery_50 = (50-mean_mystery)/(std_mystery/n_mystery**0.5)
print(f'T scores for profit of: \n$20 million = {t_mystery_20}\n$35 million = {t_mystery_35}\n$50 million = {t_mystery_50}\n')

prob_mystery_20 = 1-stats.t.cdf(t_mystery_20,df=n_mystery-1)
prob_mystery_35 = 1-stats.t.cdf(t_mystery_35,df=n_mystery-1)
prob_mystery_50 = 1-stats.t.cdf(t_mystery_50,df=n_mystery-1)
print(f'Probability for profit f: \n$20 million = {prob_mystery_20}\n$35 million = {prob_mystery_35}\n$50 million = {prob_mystery_50}')

mystery_avg_cost = df_lowrisk_exploded[df_lowrisk_exploded['genres'] == 'Mystery']['production_budget'].mean()
print(f'Average cost of Mystery movies below ${threshold_budget_low/10**6:0.2f} million are ${mystery_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -2.769851906203676
$35 million = 0.009069978403655641
$50 million = 2.7879918630109874

Probability for profit f:
$20 million = 0.9966272916473534
$35 million = 0.49639116153943286
$50 million = 0.003203179748977769
Average cost of Mystery movies below $11.50 million are $4.97 millions
```

2.1.1 This means that Horror movies will cost about the same and will have a higher chance of getting more profit.

2.2 Low Risk - Director

Knowing which genre is more profitable, we need to choose directors who succed in making profitable horror movies. For this, we do not restrict the detaframe to early releases.

[24]:
```
df_merged = pd.merge(tn,imdb,how='inner',on='movie')
df_merged.drop_duplicates(subset=['release_date','movie'], inplace=True)
df_merged['genres'] = df_merged['genres'].str.split(',')
df_merged = df_merged.explode(column='genres')
df_horror = df_merged[df_merged['genres']=='Horror']
df_horror = df_horror[df_horror['production_budget']<=threshold_budget_low]
df_horror.sort_values(by='worldwide_net',ascending=False)
```

[24]:

	release_date	movie	production_budget	domestic_gross
2884	2017-02-24	Get Out	5000000	176040665
2879	2014-10-03	Annabelle	6500000	84273813
2845	2018-10-19	Halloween	10000000	159342015
2880	2011-10-21	Paranormal Activity 3	5000000	104028807
2891	2010-10-20	Paranormal Activity 2	3000000	84752907
…	…	…	…	…
294	2003-10-03	Wonderland	5500000	1060512
330	2009-05-08	Julia	6000000	65108
12	2009-08-14	Grace	5000000	8297
10	2015-05-15	Area 51	5000000	7556
104	2013-12-06	The Last Days on Mars	10600000	24084

	worldwide_gross	release_year	worldwide_net	ROI	start_year
2884	255367951	2017	250367951	50.073590	2017
2879	256862920	2014	250362920	38.517372	2014
2845	254900667	2018	244900667	24.490067	2018
2880	207039844	2011	202039844	40.407969	2011
2891	177512032	2010	174512032	58.170677	2010
…	…	…	…	…	…
294	1060512	2003	-4439488	-0.807180	2011
330	1365108	2009	-4634892	-0.772482	2014
12	8297	2009	-4991703	-0.998341	2011
10	7556	2015	-4992444	-0.998489	2015
104	261364	2013	-10338636	-0.975343	2013

	runtime_minutes	genres	director
2884	104.0	Horror	Jordan Peele
2879	99.0	Horror	John R. Leonetti
2845	106.0	Horror	David Gordon Green
2880	83.0	Horror	Henry Joost
2891	91.0	Horror	Tod Williams

```
…                 …      …                  …
294               80.0  Horror      Brandon Slagle
330               95.0  Horror    Matthew A. Brown
12                98.0  Horror      Rodger Edralin
10                91.0  Horror           Oren Peli
104               98.0  Horror     Ruairi Robinson

[119 rows x 12 columns]
```

[25]:

```
director_horror = df_horror.groupby('director')['worldwide_net'].mean().
 ↪sort_values(ascending=False).reset_index()
director_horror.head(10)
```

[25]:

```
             director  worldwide_net
0        Jordan Peele    250367951.0
1    John R. Leonetti    250362920.0
2        Tod Williams    174512032.0
3         Henry Joost    169928918.0
4        Adam Robitel    157885588.0
5  David Gordon Green    157287833.5
6           Gil Kenan    111006019.0
7    Dan Trachtenberg    103286422.0
8  William Brent Bell    100759490.0
9       James DeMonaco     99772063.0
```

[26]:

```
df_horror[df_horror['director'].isin(director_horror['director'].loc[:5])].
 ↪sort_values('director')
```

[26]:

```
     release_date                    movie  production_budget  domestic_gross  \
2814   2018-01-05  Insidious: The Last Key           10000000        67745330
2845   2018-10-19                Halloween           10000000       159342015
2923   1978-10-17                Halloween             325000        47000000
2856   2012-10-19     Paranormal Activity 4            5000000        53900335
2880   2011-10-21     Paranormal Activity 3            5000000       104028807
2879   2014-10-03                Annabelle            6500000        84273813
2884   2017-02-24                  Get Out            5000000       176040665
2891   2010-10-20     Paranormal Activity 2            3000000        84752907

      worldwide_gross  release_year  worldwide_net         ROI  start_year  \
2814        167885588          2018      157885588   15.788559        2018
2845        254900667          2018      244900667   24.490067        2018
2923         70000000          1978       69675000  214.384615        2018
2856        142817992          2012      137817992   27.563598        2012
2880        207039844          2011      202039844   40.407969        2011
2879        256862920          2014      250362920   38.517372        2014
2884        255367951          2017      250367951   50.073590        2017
2891        177512032          2010      174512032   58.170677        2010
```

```
      runtime_minutes  genres            director
2814            103.0  Horror        Adam Robitel
2845            106.0  Horror  David Gordon Green
2923            106.0  Horror  David Gordon Green
2856             88.0  Horror         Henry Joost
2880             83.0  Horror         Henry Joost
2879             99.0  Horror    John R. Leonetti
2884            104.0  Horror        Jordan Peele
2891             91.0  Horror        Tod Williams
```

2.2.1 For the animation movie, we recommend the directors:

- Jordan Peele;
- John R. Leonetti.

2.3 Low risk - Release Month

[27]:
```
df_horror['release_month'] = pd.to_datetime(df_horror['release_date'],␣
↪format='%m').dt.month
df_horror.drop('release_date',axis=1,inplace=True)
df_horror.head()
```

[27]:
```
                                movie  production_budget  domestic_gross  \
7   Eddie: The Sleepwalking Cannibal            1400000            1632
10                            Area 51            5000000            7556
12                              Grace            5000000            8297
35                             Circle            2000000           10024
51                        Blood Feast            1200000            8708

    worldwide_gross  release_year  worldwide_net       ROI  start_year  \
7              1632          2013       -1398368 -0.998834        2012
10             7556          2015       -4992444 -0.998489        2015
12             8297          2009       -4991703 -0.998341        2011
35            10024          2010       -1989976 -0.994988        2010
51             8708          2018       -1191292 -0.992743        2016

    runtime_minutes  genres            director  release_month
7              90.0  Horror     Boris Rodriguez              4
10             91.0  Horror           Oren Peli              5
12             98.0  Horror      Rodger Edralin              8
35             88.0  Horror  Michael W. Watkins              8
51             90.0  Horror         Marcel Walz              2
```

[28]:
```
horror_month_release = df_horror.groupby('release_month')['movie'].count().
↪reset_index()
```

```
fig,ax = plt.subplots(figsize=(10,5))

ax.bar(x='release_month',height='movie',data=horror_month_release);
ax.set_xticks(np.arange(1,13,1))
ax.set_yticks(np.arange(0,30,5))
ax.set_xlabel('Month')
ax.set_ylabel('Number of movies released');
# ax.vlines(x=2,ymin=0,ymax=18, color='r')
ax.vlines(x=4,ymin=0,ymax=25, color='r')
ax.vlines(x=10,ymin=0,ymax=25, color='r')
# ax.text(x=2.1,y=17, s='Spring Break')
ax.text(x=4.1,y=22.5, s='Easter')
ax.text(x=10.05,y=22.5, s='Halloween')
ax.set_title('Release Dates for Horror Movies');
```

Two options of release dates. - April - Easter: a lot of Horror movies have religious subtext; - November - Halloween.

We recommend releasing the movie during Halloween.

2.4 Low risk - Runtime

[29]:
```
n_horror = len(df_horror['runtime_minutes'].dropna())
mean_horror = df_horror['runtime_minutes'].dropna().mean()
std_horror = df_horror['runtime_minutes'].dropna().std()
Tcrit = stats.t.ppf(0.975,n_horror-1)
```

```
runtime_horror_low = mean_horror - Tcrit*std_horror/n_horror**0.5
runtime_horror_up = mean_horror + Tcrit*std_horror/n_horror**0.5

print(f'Runtime should be around {round(runtime_horror_low)} to␣
↪{ceil(runtime_horror_up)} minutes')
```

```
Runtime should be around 93 to 98 minutes
```

3 Medium Risk

We now repeat the same steps with medium risk budgets.

[30]:
```
df_mediumrisk_merged1 = pd.merge(tn_medium_risk,movie_db,how='inner',on='movie')
df_mediumrisk_merged1.drop_duplicates(subset=['release_date','genres','movie'],␣
↪inplace=True)
df_mediumrisk_merged1.drop('original_title', axis=1, inplace=True)
df_mediumrisk_merged1
```

[30]:
```
     release_date                   movie  production_budget  domestic_gross  \
0      2015-11-11  10 Days in a Madhouse           12000000           14616
1      2015-10-30        Freaks of Nature           33000000           70958
2      2015-10-30        Freaks of Nature           33000000           70958
3      2015-10-30        Freaks of Nature           33000000           70958
7      2013-09-06          Winnie Mandela           15000000           61847
…             …                       …                  …               …
1378   2016-12-09              La La Land           20000000       151101803
1382   2010-12-03              Black Swan           13000000       106954678
1383   2010-12-03              Black Swan           13000000       106954678
1384   2014-06-06  The Fault in Our Stars           12000000       124872350
1385   2014-06-06  The Fault in Our Stars           12000000       124872350

      worldwide_gross  release_year  worldwide_net        ROI           genres
0               14616          2015      -11985384  -0.998782            Drama
1               70958          2015      -32929042  -0.997850  Science Fiction
2               70958          2015      -32929042  -0.997850           Comedy
3               70958          2015      -32929042  -0.997850           Horror
7               61847          2013      -14938153  -0.995877            Drama
…                   …             …              …          …                …
1378        426351163          2016      406351163  20.317558          Romance
1382        331266710          2010      318266710  24.482055            Drama
1383        331266710          2010      318266710  24.482055         Thriller
1384        307166834          2014      295166834  24.597236          Romance
1385        307166834          2014      295166834  24.597236            Drama

[1250 rows x 9 columns]
```

[31]:
```
df_mediumrisk_merged2 = pd.merge(left=tn_medium_risk,␣
↪right=movie_db,how='inner',left_on='movie', right_on='original_title')
df_mediumrisk_merged2.
↪drop_duplicates(subset=['release_date','genres','movie_x'], inplace=True)
df_mediumrisk_merged2.rename(columns={'movie_x':'movie'},inplace=True)
df_mediumrisk_merged2.drop(['original_title', 'movie_y'],axis=1,inplace=True)
df_mediumrisk_merged2
```

[31]:
```
     release_date                    movie  production_budget  domestic_gross  \
0      2015-11-11   10 Days in a Madhouse           12000000           14616
1      2015-10-30         Freaks of Nature           33000000           70958
2      2015-10-30         Freaks of Nature           33000000           70958
3      2015-10-30         Freaks of Nature           33000000           70958
7      2013-09-06           Winnie Mandela           15000000           61847
…             …                       …                 …               …
1329   2016-12-09               La La Land           20000000       151101803
1333   2010-12-03              Black Swan           13000000       106954678
1334   2010-12-03              Black Swan           13000000       106954678
1335   2014-06-06  The Fault in Our Stars           12000000       124872350
1336   2014-06-06  The Fault in Our Stars           12000000       124872350

      worldwide_gross  release_year  worldwide_net        ROI           genres
0               14616          2015      -11985384  -0.998782            Drama
1               70958          2015      -32929042  -0.997850  Science Fiction
2               70958          2015      -32929042  -0.997850           Comedy
3               70958          2015      -32929042  -0.997850           Horror
7               61847          2013      -14938153  -0.995877            Drama
…                 …             …             …          …               …
1329        426351163          2016      406351163  20.317558          Romance
1333        331266710          2010      318266710  24.482055            Drama
1334        331266710          2010      318266710  24.482055         Thriller
1335        307166834          2014      295166834  24.597236          Romance
1336        307166834          2014      295166834  24.597236            Drama

[1219 rows x 9 columns]
```

[32]:
```
df_mediumrisk_merged3 = pd.merge(tn_medium_risk,imdb,how='inner',on='movie')
df_mediumrisk_merged3.drop_duplicates(subset=['release_date','movie'],␣
↪inplace=True)
df_mediumrisk_merged3.drop(['runtime_minutes', 'start_year','director'],␣
↪axis=1, inplace=True)
df_mediumrisk_merged3
```

[32]:
```
  release_date                    movie  production_budget  domestic_gross  \
0   2015-11-11   10 Days in a Madhouse           12000000           14616
1   2015-10-30         Freaks of Nature           33000000           70958
2   2013-09-06           Winnie Mandela           15000000           61847
```

```
3     2015-06-05         United Passions          30000000           918
4     2010-06-30              Love Ranch          25000000        137885
..           …                     …               …             …
862   2017-09-08                      It          35000000     327481748
863   2017-08-11      Annabelle: Creation         15000000     102092201
864   2016-12-09              La La Land          20000000     151101803
865   2010-12-03              Black Swan          13000000     106954678
866   2014-06-06  The Fault in Our Stars          12000000     124872350

     worldwide_gross  release_year  worldwide_net        ROI  \
0              14616          2015      -11985384  -0.998782
1              70958          2015      -32929042  -0.997850
2              61847          2013      -14938153  -0.995877
3             168832          2015      -29831168  -0.994372
4             146149          2010      -24853851  -0.994154
..               …           …            …          …
862        697457969          2017      662457969  18.927371
863        305384865          2017      290384865  19.358991
864        426351163          2016      406351163  20.317558
865        331266710          2010      318266710  24.482055
866        307166834          2014      295166834  24.597236

                       genres
0                       Drama
1        Comedy,Horror,Sci-Fi
2     Biography,Drama,History
3          Drama,History,Sport
4       Biography,Comedy,Drama
..                        …
862            Horror,Thriller
863   Horror,Mystery,Thriller
864        Comedy,Drama,Music
865            Drama,Thriller
866             Drama,Romance

[580 rows x 9 columns]
```

[33]:
```
df_mediumrisk_merged3['genres'] = df_mediumrisk_merged3['genres'].str.split(',')
df_mediumrisk_merged3 = df_mediumrisk_merged3.explode('genres')
df_mediumrisk_merged3['genres'].value_counts()
```

[33]:
```
genres
Drama          348
Comedy         191
Action         110
Crime          109
Thriller        96
```

```
Romance          94
Biography        69
Horror           55
Adventure        52
Mystery          37
Documentary      35
Sci-Fi           29
Family           27
Fantasy          26
Music            23
History          22
Sport            17
War              14
Animation        11
Western           3
Musical           1
Name: count, dtype: int64
```

[34]:
```python
df_mediumrisk_exploded = pd.concat([df_mediumrisk_merged1,
    df_mediumrisk_merged2, df_mediumrisk_merged3])
df_mediumrisk_exploded.
    drop_duplicates(subset=['release_date','movie','genres'], inplace=True)
df_mediumrisk_exploded['genres'].value_counts()
```

[34]:
```
genres
Drama              394
Comedy             213
Thriller           183
Crime              132
Action             132
Romance            113
Horror              74
Biography           69
Adventure           65
Mystery             59
History             45
Family              44
Documentary         42
Science Fiction     38
Fantasy             35
Sci-Fi              29
Music               28
War                 24
Sport               17
Animation           16
Western              5
TV Movie             1
```

```
Musical               1
Name: count, dtype: int64
```

[35]:
```
df_mediumrisk_exploded['genres'].replace(to_replace='Science Fiction',␣
↪value='Sci-Fi',inplace=True)
df_mediumrisk_exploded['genres'].value_counts()
```

```
/tmp/ipykernel_102626/381516847.py:1: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df_mediumrisk_exploded['genres'].replace(to_replace='Science Fiction',
value='Sci-Fi',inplace=True)
```

[35]:
```
genres
Drama          394
Comedy         213
Thriller       183
Crime          132
Action         132
Romance        113
Horror          74
Biography       69
Sci-Fi          67
Adventure       65
Mystery         59
History         45
Family          44
Documentary     42
Fantasy         35
Music           28
War             24
Sport           17
Animation       16
Western          5
TV Movie         1
Musical          1
Name: count, dtype: int64
```

3.1 Medium Risk - Genre

[36]:
```
df_mediumrisk_exploded.groupby('genres')['worldwide_net'].count().
  ↪sort_values(ascending=False).reset_index()
```

[36]:

	genres	worldwide_net
0	Drama	394
1	Comedy	213
2	Thriller	183
3	Action	132
4	Crime	132
5	Romance	113
6	Horror	74
7	Biography	69
8	Sci-Fi	67
9	Adventure	65
10	Mystery	59
11	History	45
12	Family	44
13	Documentary	42
14	Fantasy	35
15	Music	28
16	War	24
17	Sport	17
18	Animation	16
19	Western	5
20	Musical	1
21	TV Movie	1

[37]:
```
df_mediumrisk_exploded['genres'].replace(to_replace='Musical', value='Music')
df_mediumrisk_exploded =␣
  ↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']!='TV Movie']
```

[38]:
```
df_mediumrisk_exploded.groupby('genres')['worldwide_net'].median().
  ↪sort_values(ascending=False).reset_index().head(10)
```

[38]:

	genres	worldwide_net
0	Horror	32003693.5
1	Music	29954085.5
2	Comedy	28527161.0
3	Fantasy	27427346.0
4	Adventure	27427346.0
5	Family	27222287.0
6	Romance	26627836.0
7	Documentary	23277674.0
8	Biography	20044909.0
9	Thriller	18293628.0

[39]:
```
#Let us calculate the probability that an horror and horror movie will make␣
↪profits
mean_horror =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Horror']['worldwide_net'].
↪mean()/10**6
std_horror =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Horror']['worldwide_net'].
↪std()/10**6
n_horror =␣
↪len(df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Horror']['worldwide_net'])

t_horror_1 = (20-mean_horror)/(std_horror/n_horror**0.5)
t_horror_2 = (40-mean_horror)/(std_horror/n_horror**0.5)
t_horror_3 = (60-mean_horror)/(std_horror/n_horror**0.5)
t_horror_4 = (80-mean_horror)/(std_horror/n_horror**0.5)
print(f'T scores for profit of: \n$20 million = {t_horror_1}\n$40 million =␣
↪{t_horror_2}\n$60 million = {t_horror_3}\n$80 million = {t_horror_4}\n')

prob_horror_1 = 1-stats.t.cdf(t_horror_1,df=n_horror-1)
prob_horror_2 = 1-stats.t.cdf(t_horror_2,df=n_horror-1)
prob_horror_3 = 1-stats.t.cdf(t_horror_3,df=n_horror-1)
prob_horror_4 = 1-stats.t.cdf(t_horror_4,df=n_horror-1)
print(f'Probability for profit f: \n$20 million = {prob_horror_1}\n$40 million␣
↪= {prob_horror_2}\n$60 million = {prob_horror_3}\n$80 million =␣
↪{prob_horror_4}\n')

horror_avg_cost = df_mediumrisk_exploded[df_mediumrisk_exploded['genres'] ==␣
↪'Horror']['production_budget'].mean()
print(f'Average cost of horror movies above ${threshold_budget_low/10**6:0.02f}␣
↪millions but below ${threshold_budget_high/10**6} \
millions are ${horror_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -2.9818762248564195
$40 million = -1.2232467444970372
$60 million = 0.5353827358623451
$80 million = 2.2940122162217276

Probability for profit f:
$20 million = 0.9980541488043901
$40 million = 0.88741469485021
$60 million = 0.2970062721670568
$80 million = 0.012334480186491636

Average cost of horror movies above $11.50 millions but below $36.0 millions are
$22.15 millions
```

[40]:
```
#Let us calculate the probability that an music and music movie will make␣
↪profits
mean_music =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Music']['worldwide_net'].
↪mean()/10**6
std_music =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Music']['worldwide_net'].
↪std()/10**6
n_music =␣
↪len(df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Music']['worldwide_net'])

t_music_1 = (20-mean_music)/(std_music/n_music**0.5)
t_music_2 = (40-mean_music)/(std_music/n_music**0.5)
t_music_3 = (60-mean_music)/(std_music/n_music**0.5)
t_music_4 = (80-mean_music)/(std_music/n_music**0.5)
print(f'T scores for profit of: \n$20 million = {t_music_1}\n$40 million =␣
↪{t_music_2}\n$60 million = {t_music_3}\n$80 million = {t_music_4}\n')

prob_music_1 = 1-stats.t.cdf(t_music_1,df=n_music-1)
prob_music_2 = 1-stats.t.cdf(t_music_2,df=n_music-1)
prob_music_3 = 1-stats.t.cdf(t_music_3,df=n_music-1)
prob_music_4 = 1-stats.t.cdf(t_music_4,df=n_music-1)
print(f'Probability for profit f: \n$20 million = {prob_music_1}\n$40 million =␣
↪{prob_music_2}\n$60 million = {prob_music_3}\n$80 million =␣
↪{prob_music_4}\n')

music_avg_cost = df_mediumrisk_exploded[df_mediumrisk_exploded['genres'] ==␣
↪'Music']['production_budget'].mean()
print(f'Average cost of Music movies above ${threshold_budget_low/10**6:0.02f}␣
↪millions but below ${threshold_budget_high/10**6} \
millions are ${music_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -2.418205698375475
$40 million = -1.3112389607422235
$60 million = -0.20427222310897178
$80 million = 0.90269451452428

Probability for profit f:
$20 million = 0.9886917795972838
$40 million = 0.8995902806067388
$60 million = 0.5801636239084736
$80 million = 0.18733560352033518

Average cost of Music movies above $11.50 millions but below $36.0 millions are
$21.93 millions
```

[41]:

```
#Let us calculate the probability that an comedy and comedy movie will make␣
↪profits
mean_comedy =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Comedy']['worldwide_net'].
↪mean()/10**6
std_comedy =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Comedy']['worldwide_net'].
↪std()/10**6
n_comedy =␣
↪len(df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Comedy']['worldwide_net'])

t_comedy_1 = (20-mean_comedy)/(std_comedy/n_comedy**0.5)
t_comedy_2 = (40-mean_comedy)/(std_comedy/n_comedy**0.5)
t_comedy_3 = (60-mean_comedy)/(std_comedy/n_comedy**0.5)
t_comedy_4 = (80-mean_comedy)/(std_comedy/n_comedy**0.5)
print(f'T scores for profit of: \n$20 million = {t_comedy_1}\n$40 million =␣
↪{t_comedy_2}\n$60 million = {t_comedy_3}\n$80 million = {t_comedy_4}\n')

prob_comedy_1 = 1-stats.t.cdf(t_comedy_1,df=n_comedy-1)
prob_comedy_2 = 1-stats.t.cdf(t_comedy_2,df=n_comedy-1)
prob_comedy_3 = 1-stats.t.cdf(t_comedy_3,df=n_comedy-1)
prob_comedy_4 = 1-stats.t.cdf(t_comedy_4,df=n_comedy-1)
print(f'Probability for profit f: \n$20 million = {prob_comedy_1}\n$40 million␣
↪= {prob_comedy_2}\n$60 million = {prob_comedy_3}\n$80 million =␣
↪{prob_comedy_4}\n')

comedy_avg_cost = df_mediumrisk_exploded[df_mediumrisk_exploded['genres'] ==␣
↪'Comedy']['production_budget'].mean()
print(f'Average cost of Comedy movies above ${threshold_budget_low/10**6:0.02f}␣
↪millions but below ${threshold_budget_high/10**6} \
millions are ${comedy_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -5.975203447407423
$40 million = -1.3002000216391634
$60 million = 3.3748034041290964
$80 million = 8.049806829897356

Probability for profit f:
$20 million = 0.9999999951982208
$40 million = 0.9025279099464543
$60 million = 0.00043918078264115756
$80 million = 2.942091015256665e-14

Average cost of Comedy movies above $11.50 millions but below $36.0 millions are
$22.78 millions
```

[42]:
```
#Let us calculate the probability that an fantasy and fantasy movie will make␣
↪profits
mean_fantasy =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Fantasy']['worldwide_net'].
↪mean()/10**6
std_fantasy =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Fantasy']['worldwide_net'].
↪std()/10**6
n_fantasy =␣
↪len(df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Fantasy']['worldwide_net'])

t_fantasy_1 = (20-mean_fantasy)/(std_fantasy/n_fantasy**0.5)
t_fantasy_2 = (40-mean_fantasy)/(std_fantasy/n_fantasy**0.5)
t_fantasy_3 = (60-mean_fantasy)/(std_fantasy/n_fantasy**0.5)
t_fantasy_4 = (80-mean_fantasy)/(std_fantasy/n_fantasy**0.5)
print(f'T scores for profit of: \n$20 million = {t_fantasy_1}\n$40 million =␣
↪{t_fantasy_2}\n$60 million = {t_fantasy_3}\n$80 million = {t_fantasy_4}\n')

prob_fantasy_1 = 1-stats.t.cdf(t_fantasy_1,df=n_fantasy-1)
prob_fantasy_2 = 1-stats.t.cdf(t_fantasy_2,df=n_fantasy-1)
prob_fantasy_3 = 1-stats.t.cdf(t_fantasy_3,df=n_fantasy-1)
prob_fantasy_4 = 1-stats.t.cdf(t_fantasy_4,df=n_fantasy-1)
print(f'Probability for profit f: \n$20 million = {prob_fantasy_1}\n$40 million␣
↪= {prob_fantasy_2}\n$60 million = {prob_fantasy_3}\n$80 million =␣
↪{prob_fantasy_4}\n')

fantasy_avg_cost = df_mediumrisk_exploded[df_mediumrisk_exploded['genres'] ==␣
↪'Fantasy']['production_budget'].mean()
print(f'Average cost of Fantasy movies above ${threshold_budget_low/10**6:0.
↪02f} millions but below ${threshold_budget_high/10**6} \
millions are ${fantasy_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -2.645913242794863
$40 million = -0.21811964303040776
$60 million = 2.2096739567340475
$80 million = 4.637467556498502

Probability for profit f:
$20 million = 0.9938754234783517
$40 million = 0.5856801126099807
$60 million = 0.01698172621983829
$80 million = 2.5223421907805132e-05

Average cost of Fantasy movies above $11.50 millions but below $36.0 millions
are $22.54 millions
```

[43]:

```python
#Let us calculate the probability that an adventure and adventure movie will␣
↪make profits
mean_adventure =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Adventure']['worldwide_net'].
↪mean()/10**6
std_adventure =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Adventure']['worldwide_net'].
↪std()/10**6
n_adventure =␣
↪len(df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Adventure']['worldwide_net'])

t_adventure_1 = (20-mean_adventure)/(std_adventure/n_adventure**0.5)
t_adventure_2 = (40-mean_adventure)/(std_adventure/n_adventure**0.5)
t_adventure_3 = (60-mean_adventure)/(std_adventure/n_adventure**0.5)
t_adventure_4 = (80-mean_adventure)/(std_adventure/n_adventure**0.5)
print(f'T scores for profit of: \n$20 million = {t_adventure_1}\n$40 million =␣
↪{t_adventure_2}\n$60 million = {t_adventure_3}\n$80 million =␣
↪{t_adventure_4}\n')

prob_adventure_1 = 1-stats.t.cdf(t_adventure_1,df=n_adventure-1)
prob_adventure_2 = 1-stats.t.cdf(t_adventure_2,df=n_adventure-1)
prob_adventure_3 = 1-stats.t.cdf(t_adventure_3,df=n_adventure-1)
prob_adventure_4 = 1-stats.t.cdf(t_adventure_4,df=n_adventure-1)
print(f'Probability for profit f: \n$20 million = {prob_adventure_1}\n$40␣
↪million = {prob_adventure_2}\n$60 million = {prob_adventure_3}\n$80 million␣
↪= {prob_adventure_4}\n')

adventure_avg_cost = df_mediumrisk_exploded[df_mediumrisk_exploded['genres'] ==␣
↪'Adventure']['production_budget'].mean()
print(f'Average cost of Adventure movies above ${threshold_budget_low/10**6:0.
↪02f} millions but below ${threshold_budget_high/10**6} \
millions are ${adventure_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -2.439442048658327
$40 million = 0.9825688524966413
$60 million = 4.40457975365161
$80 million = 7.826590654806577

Probability for profit f:
$20 million = 0.991253876712623
$40 million = 0.16475981598027056
$60 million = 2.058929195369874e-05
$80 million = 3.258959768714931e-11

Average cost of Adventure movies above $11.50 millions but below $36.0 millions
are $25.94 millions
```

[44]:
```
#Let us calculate the probability that an family and family movie will make␣
↪profits
mean_family =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Family']['worldwide_net'].
↪mean()/10**6
std_family =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Family']['worldwide_net'].
↪std()/10**6
n_family =␣
↪len(df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Family']['worldwide_net'])

t_family_1 = (20-mean_family)/(std_family/n_family**0.5)
t_family_2 = (40-mean_family)/(std_family/n_family**0.5)
t_family_3 = (60-mean_family)/(std_family/n_family**0.5)
t_family_4 = (80-mean_family)/(std_family/n_family**0.5)
print(f'T scores for profit of: \n$20 million = {t_family_1}\n$40 million =␣
↪{t_family_2}\n$60 million = {t_family_3}\n$80 million = {t_family_4}\n')

prob_family_1 = 1-stats.t.cdf(t_family_1,df=n_family-1)
prob_family_2 = 1-stats.t.cdf(t_family_2,df=n_family-1)
prob_family_3 = 1-stats.t.cdf(t_family_3,df=n_family-1)
prob_family_4 = 1-stats.t.cdf(t_family_4,df=n_family-1)
print(f'Probability for profit f: \n$20 million = {prob_family_1}\n$40 million␣
↪= {prob_family_2}\n$60 million = {prob_family_3}\n$80 million =␣
↪{prob_family_4}\n')

family_avg_cost = df_mediumrisk_exploded[df_mediumrisk_exploded['genres'] ==␣
↪'Family']['production_budget'].mean()
print(f'Average cost of Family movies above ${threshold_budget_low/10**6:0.02f}␣
↪millions but below ${threshold_budget_high/10**6} \
millions are ${family_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$20 million = -2.561640089191682
$40 million = 0.019484380665674456
$60 million = 2.6006088505230314
$80 million = 5.181733320380388

Probability for profit f:
$20 million = 0.9929966155721592
$40 million = 0.492272414595484
$60 million = 0.0063533113993345935
$80 million = 2.785374063951629e-06

Average cost of Family movies above $11.50 millions but below $36.0 millions are
$22.77 millions
```

3.1.1 Genre for a medium risk production will be Music

3.2 Medium Risk - Director

[45]:
```
df_music_movies =␣
↪df_mediumrisk_exploded[df_mediumrisk_exploded['genres']=='Music']
df_music_directors = pd.merge(df_music_movies,imdb,how='inner',on='movie')
```

[46]:
```
df_music_directors.drop_duplicates(subset=['movie','director'],inplace=True)
df_music_directors.
↪drop(['release_date','production_budget','domestic_gross','worldwide_gross','release_year',
↪'runtime_minutes','genres_y'],axis=1,inplace=True)
df_music_directors.sort_values('director').
↪sort_values('worldwide_net',ascending=False).head()
```

[46]:

	movie	worldwide_net	director
30	La La Land	406351163	Damien Chazelle
20	Pitch Perfect 2	258625468	Elizabeth Banks
18	Straight Outta Compton	174182981	F. Gary Gray
28	Step Up 3D	135889117	Jon M. Chu
16	Step Up Revolution	132552290	Scott Speer

[47]:
```
director_count = df_music_directors.groupby('director')['worldwide_net'].
↪count().reset_index().sort_values('worldwide_net',ascending=False)#.iloc[:
↪15]#['director'].iloc[:7]
director_count = director_count.rename(columns={'worldwide_net':'count'})
# director_count = (director_count[director_count['count']>2])
director_count
```

[47]:

	director	count
15	Jon M. Chu	2
1	Andrijana Stojkovic	1
28	Todd Graff	1
27	Tate Taylor	1
26	Steven Soderbergh	1
25	Shana Feste	1
24	Scott Speer	1
23	Rachel Lambert	1
22	Princeton Holt	1
21	Nimród Antal	1
20	Kasi Lemmons	1
19	Julie Anne Robinson	1
18	Jorma Taccone	1
17	Jonathan Demme	1
16	Jonathan Baker	1
0	Andrew Adamson	1
14	Jennifer Oey	1
13	Jeffrey Vasseur	1

```
12          Jason Moore      1
11        Isaac Stewart      1
10       Gregory Jacobs      1
9          F. Gary Gray      1
8            Ethan Coen      1
7       Elizabeth Banks      1
6          Dan Cutforth      1
5       Damien Chazelle      1
4          Craig Brewer      1
3            Benson Lee      1
2        Barry Levinson      1
29          Woody Allen      1
```

Unfortunately, we just have one movie ffor each director, which does not allow us to extrapolate much.

[48]:
```python
df_music_directors.groupby('director').median('worldwide_net').
 ↪sort_values('worldwide_net', ascending=False)
```

[48]:
```
                      worldwide_net
director
Damien Chazelle         406351163.0
Elizabeth Banks         258625468.0
F. Gary Gray            174182981.0
Scott Speer             132552290.0
Jon M. Chu              110961621.0
Gregory Jacobs          109160597.0
Jason Moore              99044347.0
Julie Anne Robinson      72678948.0
Woody Allen              52826015.0
Ethan Coen               42160680.0
Craig Brewer             38989834.0
Steven Soderbergh        36742138.0
Jonathan Demme           23166033.0
Dan Cutforth             20700439.0
Isaac Stewart             9356760.0
Jeffrey Vasseur           9356760.0
Jennifer Oey              9356760.0
Andrijana Stojkovic       9356760.0
Shana Feste               5601987.0
Todd Graff                3657914.0
Tate Taylor               3339868.0
Andrew Adamson            3012862.0
Princeton Holt           -1168869.0
Benson Lee               -3276623.0
Nimród Antal             -8917094.0
Kasi Lemmons            -10214865.0
```

```
Jorma Taccone          -10462880.0
Barry Levinson         -11613847.0
Rachel Lambert         -19903179.0
Jonathan Baker         -19903179.0
```

For lack of data we recommend the director Damien Chazelle, as his Music movie sold 60% more than the second place.

3.3 Medium Risk - Release Date

[49]:
```
df_music_movies.head()
```

[49]:
```
    release_date                            movie  production_budget  \
101   2015-10-23                   Rock the Kasbah           15000000
180   2013-11-27                    Black Nativity           17500000
211   2016-06-03  Popstar: Never Stop Never Stopping           20000000
353   2013-09-20                 Battle of the Year           20000000
415   2014-08-01                         Get on Up           30000000

     domestic_gross  worldwide_gross  release_year  worldwide_net       ROI  \
101         3020665          3386153          2015      -11613847 -0.774256
180         7018188          7285135          2013      -10214865 -0.583707
211         9496130          9537120          2016      -10462880 -0.523144
353         8888355         16723377          2013       -3276623 -0.163831
415        30569935         33339868          2014        3339868  0.111329

    genres
101  Music
180  Music
211  Music
353  Music
415  Music
```

[50]:
```
df_music_movies['release_month'] = pd.
 ↪to_datetime(df_music_movies['release_date'], format='%m').dt.month
music_release_month = df_music_movies.groupby('release_month').count().
 ↪reset_index()[['release_month','movie']].rename(columns={'movie':'count'})
music_release_month
```

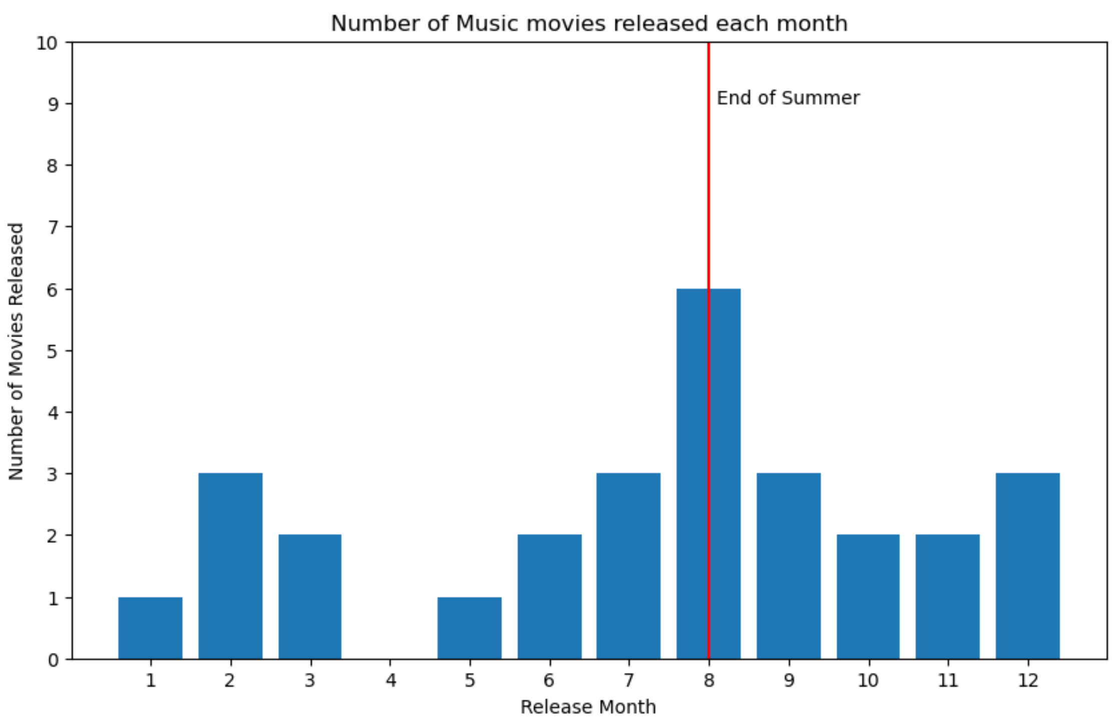
```
/tmp/ipykernel_102626/2876873447.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_music_movies['release_month'] =
pd.to_datetime(df_music_movies['release_date'], format='%m').dt.month
```

[50]:

	release_month	count
0	1	1
1	2	3
2	3	2
3	5	1
4	6	2
5	7	3
6	8	6
7	9	3
8	10	2
9	11	2
10	12	3

[51]:

```
fig,ax = plt.subplots(figsize=(10,6))

ax.bar(x='release_month',height='count', data=music_release_month)
ax.set_xticks(np.arange(1,13))
ax.set_yticks(np.arange(0,11))
ax.set_ylim(0,10)
ax.set_xlabel('Release Month')
ax.set_ylabel('Number of Movies Released')
ax.set_title('Number of Music movies released each month')
ax.vlines(x=8,ymin=0,ymax=40,color='r')
ax.text(x=8.1,y=9,s='End of Summer');
```



3.3.1 For some reason Music movies are more popular in August so we recommend this month for release.

3.4 Medium risk - Runtime

[52]:
```
df_music = pd.merge(df_music_movies,imdb,how='inner',on='movie')
df_music.drop_duplicates(subset=['movie'],inplace=True)

runtime_music_mean = df_music['runtime_minutes'].mean()
runtime_music_std = df_music['runtime_minutes'].std()
n_music = len(df_music['runtime_minutes'])
err_music = runtime_music_std/n_music**0.5

Tcrit = stats.t.ppf(0.975,n_music-1)

runtime_music_upper = runtime_music_mean + Tcrit*err_music
runtime_music_lower = runtime_music_mean - Tcrit*err_music

print(f'The duration of the Music movie should be in between␣
↪{floor(runtime_music_lower)} and {ceil(runtime_music_upper)} minutes.')
```

```
The duration of the Music movie should be in between 96 and 113 minutes.
```

4 High risk

We now do the same with the higher roisk budget.

[53]:
```
tn_high_risk
```

[53]:

	release_date	movie	production_budget	domestic_gross	\
1242	2013-11-01	Mr. Nobody	46500000	3622	
1536	2007-03-16	Nomad	40000000	79123	
1535	2004-09-24	The Last Shot	40000000	463730	
1582	2001-11-30	Texas Rangers	38000000	623374	
1531	2008-12-12	Delgo	40000000	915840	
…	…	…	…	…	
629	2017-06-30	Despicable Me 3	75000000	264624300	
955	2016-02-12	Deadpool	58000000	363070709	
1377	2015-02-13	Fifty Shades of Grey	40000000	166167230	
672	2015-07-10	Minions	74000000	336045770	
983	2018-11-02	Bohemian Rhapsody	55000000	216303339	

	worldwide_gross	release_year	worldwide_net	ROI
1242	22254	2013	-46477746	-0.999521
1536	79123	2007	-39920877	-0.998022
1535	463730	2004	-39536270	-0.988407
1582	623374	2001	-37376626	-0.983595
1531	915840	2008	-39084160	-0.977104

```
…            …           …         …        …
629     1034727750       2017   959727750  12.796370
955      801025593       2016   743025593  12.810786
1377     570998101       2015   530998101  13.274953
672     1160336173       2015  1086336173  14.680219
983      894985342       2018   839985342  15.272461

[1293 rows x 8 columns]
```

[54]:
```python
df_highrisk_merged1 = pd.merge(tn_high_risk,movie_db,how='inner',on='movie')
df_highrisk_merged1.drop_duplicates(subset=['release_date','genres','movie'],
 ↪inplace=True)
df_highrisk_merged1.drop('original_title', axis=1, inplace=True)
df_highrisk_merged1
```

[54]:
```
     release_date              movie  production_budget  domestic_gross  \
0      2013-11-01         Mr. Nobody           46500000            3622
1      2013-11-01         Mr. Nobody           46500000            3622
2      2013-11-01         Mr. Nobody           46500000            3622
3      2013-11-01         Mr. Nobody           46500000            3622
4      2011-05-06  There Be Dragons           36000000         1069334
…             …                  …                …              …
2001   2015-07-10            Minions           74000000       336045770
2002   2015-07-10            Minions           74000000       336045770
2003   2015-07-10            Minions           74000000       336045770
2004   2018-11-02  Bohemian Rhapsody           55000000       216303339
2005   2018-11-02  Bohemian Rhapsody           55000000       216303339

      worldwide_gross  release_year  worldwide_net        ROI           genres
0               22254          2013      -46477746  -0.999521  Science Fiction
1               22254          2013      -46477746  -0.999521            Drama
2               22254          2013      -46477746  -0.999521          Romance
3               22254          2013      -46477746  -0.999521          Fantasy
4             4020990          2011      -31979010  -0.888306            Drama
…                 …           …             …        …              …
2001       1160336173          2015     1086336173  14.680219        Animation
2002       1160336173          2015     1086336173  14.680219        Adventure
2003       1160336173          2015     1086336173  14.680219           Comedy
2004        894985342          2018      839985342  15.272461            Drama
2005        894985342          2018      839985342  15.272461            Music

[1788 rows x 9 columns]
```

[55]:
```python
df_highrisk_merged2 = pd.merge(left=tn_high_risk,
 ↪right=movie_db,how='inner',left_on='movie', right_on='original_title')
df_highrisk_merged2.drop_duplicates(subset=['release_date','genres','movie_x'],
 ↪inplace=True)
```

```python
df_highrisk_merged2.rename(columns={'movie_x':'movie'},inplace=True)
df_highrisk_merged2.drop(['original_title', 'movie_y'],axis=1,inplace=True)
df_highrisk_merged2
```

[55]:
```
     release_date              movie  production_budget  domestic_gross  \
0      2013-11-01         Mr. Nobody           46500000            3622
1      2013-11-01         Mr. Nobody           46500000            3622
2      2013-11-01         Mr. Nobody           46500000            3622
3      2013-11-01         Mr. Nobody           46500000            3622
4      2011-05-06  There Be Dragons           36000000         1069334
…             …                  …                  …               …
1972   2015-07-10            Minions           74000000       336045770
1973   2015-07-10            Minions           74000000       336045770
1974   2015-07-10            Minions           74000000       336045770
1975   2018-11-02  Bohemian Rhapsody           55000000       216303339
1976   2018-11-02  Bohemian Rhapsody           55000000       216303339

      worldwide_gross  release_year  worldwide_net        ROI           genres
0               22254          2013      -46477746  -0.999521  Science Fiction
1               22254          2013      -46477746  -0.999521            Drama
2               22254          2013      -46477746  -0.999521          Romance
3               22254          2013      -46477746  -0.999521          Fantasy
4             4020990          2011      -31979010  -0.888306            Drama
…                   …             …              …          …                …
1972       1160336173          2015     1086336173  14.680219        Animation
1973       1160336173          2015     1086336173  14.680219        Adventure
1974       1160336173          2015     1086336173  14.680219           Comedy
1975        894985342          2018      839985342  15.272461            Drama
1976        894985342          2018      839985342  15.272461            Music

[1771 rows x 9 columns]
```

[56]:
```python
df_highrisk_merged3 = pd.merge(tn_high_risk,imdb,how='inner',on='movie')
df_highrisk_merged3.drop_duplicates(subset=['release_date','movie'],␣
 ↪inplace=True)
df_highrisk_merged3.drop(['runtime_minutes', 'start_year','director'], axis=1,␣
 ↪inplace=True)
df_highrisk_merged3
```

[56]:
```
    release_date                         movie  production_budget  \
0     2007-03-16                         Nomad           40000000
3     2004-09-24                 The Last Shot           40000000
5     2019-06-14  Men in Black: International          110000000
6     2011-05-06              There Be Dragons           36000000
7     2017-04-21                   The Promise           90000000
..           …                             …                  …
819   2017-06-30                Despicable Me 3           75000000
```

```
820  2016-02-12                  Deadpool         58000000
821  2015-02-13        Fifty Shades of Grey         40000000
822  2015-07-10                   Minions         74000000
823  2018-11-02         Bohemian Rhapsody         55000000

     domestic_gross  worldwide_gross  release_year  worldwide_net        ROI  \
0             79123            79123          2007      -39920877  -0.998022
3            463730           463730          2004      -39536270  -0.988407
5           3100000          3100000          2019     -106900000  -0.971818
6           1069334          4020990          2011      -31979010  -0.888306
7           8224288         10551417          2017      -79448583  -0.882762
..              …                …            …              …          …
819       264624300       1034727750          2017      959727750  12.796370
820       363070709        801025593          2016      743025593  12.810786
821       166167230        570998101          2015      530998101  13.274953
822       336045770       1160336173          2015     1086336173  14.680219
823       216303339        894985342          2018      839985342  15.272461

                         genres
0                         Drama
3                        Action
5       Action,Adventure,Comedy
6           Biography,Drama,War
7                        Comedy
..                          …
819  Adventure,Animation,Comedy
820     Action,Adventure,Comedy
821       Drama,Romance,Thriller
822  Adventure,Animation,Comedy
823        Biography,Drama,Music

[625 rows x 9 columns]
```

[57]:
```
df_highrisk_merged3['genres'] = df_highrisk_merged3['genres'].str.split(',')
df_highrisk_merged3 = df_highrisk_merged3.explode('genres')
# df_highrisk_merged3['genres'].value_counts()
```

[58]:
```
df_highrisk_exploded = pd.concat([df_highrisk_merged1, df_highrisk_merged2,␣
↪df_highrisk_merged3])
df_highrisk_exploded.drop_duplicates(subset=['release_date','movie','genres'],␣
↪inplace=True)
df_highrisk_exploded['genres'].value_counts()
```

[58]:
```
genres
Action              328
Adventure           303
Drama               243
```

```
Comedy              229
Thriller            164
Fantasy             149
Family              141
Science Fiction     127
Animation           103
Crime               100
Sci-Fi               86
Romance              61
Mystery              56
Horror               47
Biography            35
History              26
Documentary          23
War                  22
Music                15
Western              10
Sport                 9
Musical               5
TV Movie              4
Name: count, dtype: int64
```

[59]:
```
df_highrisk_exploded['genres'].replace(to_replace='Science Fiction',␣
 ↪value='Sci-Fi',inplace=True)
df_highrisk_exploded['genres'].value_counts()
```

```
/tmp/ipykernel_102626/1961549059.py:1: FutureWarning: A value is trying to be
set on a copy of a DataFrame or Series through chained assignment using an
inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df_highrisk_exploded['genres'].replace(to_replace='Science Fiction',
value='Sci-Fi',inplace=True)
```

[59]:
```
genres
Action          328
Adventure       303
Drama           243
Comedy          229
Sci-Fi          213
```

```
Thriller       164
Fantasy        149
Family         141
Animation      103
Crime          100
Romance         61
Mystery         56
Horror          47
Biography       35
History         26
Documentary     23
War             22
Music           15
Western         10
Sport            9
Musical          5
TV Movie         4
Name: count, dtype: int64
```

4.1 High risk - Genre

[60]:
```python
df_highrisk_exploded.groupby('genres')['ROI'].median().
 ↪sort_values(ascending=False).reset_index().head()
```

[60]:
```
      genres       ROI
0  Animation  1.969215
1     Sci-Fi  1.778310
2  Adventure  1.714085
3     Family  1.671141
4  Biography  1.649823
```

[61]:
```python
df_highrisk_exploded.groupby('genres')['worldwide_net'].median().
 ↪sort_values(ascending=False).reset_index().head()
```

[61]:
```
      genres  worldwide_net
0  Animation    228648063.0
1     Sci-Fi    220098020.0
2  Adventure    179115534.0
3     Family    166562312.0
4    Fantasy    155270083.0
```

[62]:
```python
#Let us calculate the probability that an Animation, Sci-Fi and Adventure movie␣
 ↪will make profits
#Animation first
mean_animation =␣
 ↪df_highrisk_exploded[df_highrisk_exploded['genres']=='Animation']['worldwide_net'].
 ↪mean()/10**6
```

```
std_animation =␣
  ↪df_highrisk_exploded[df_highrisk_exploded['genres']=='Animation']['worldwide_net'].
  ↪std()/10**6
n_animation =␣
  ↪len(df_highrisk_exploded[df_highrisk_exploded['genres']=='Animation']['worldwide_net'])

t_animation_100 = (100-mean_animation)/(std_animation/n_animation**0.5)
t_animation_200 = (200-mean_animation)/(std_animation/n_animation**0.5)
t_animation_300 = (300-mean_animation)/(std_animation/n_animation**0.5)
t_animation_350 = (350-mean_animation)/(std_animation/n_animation**0.5)
print(f'T scores for profit of: \n$100 million = {t_animation_100}\n$200␣
  ↪million = {t_animation_200}\n$300 million = {t_animation_300}\n$350 million␣
  ↪= {t_animation_350}\n')

prob_animation_100 = 1-stats.t.cdf(t_animation_100,df=n_animation-1)
prob_animation_200 = 1-stats.t.cdf(t_animation_200,df=n_animation-1)
prob_animation_300 = 1-stats.t.cdf(t_animation_300,df=n_animation-1)
prob_animation_350 = 1-stats.t.cdf(t_animation_350,df=n_animation-1)
print(f'Probability for profit f: \n$100 million = {prob_animation_100}\n$200␣
  ↪million = {prob_animation_200}\n$300 million = {prob_animation_300}\n$350␣
  ↪million = {prob_animation_350}\n')

animation_avg_cost = df_highrisk_exploded[df_highrisk_exploded['genres'] ==␣
  ↪'Animation']['production_budget'].mean()
print(f'Average cost of animation movies above $20 million are␣
  ↪${animation_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$100 million = -6.942394636239825
$200 million = -3.5913826663853423
$300 million = -0.24037069653085955
$350 million = 1.4351352883963817

Probability for profit f:
$100 million = 0.9999999998168365
$200 million = 0.9997460681006808
$300 million = 0.5947373310370614
$350 million = 0.07715392088809236

Average cost of animation movies above $20 million are $109.87 millions
```

[63]:
```
#Let us calculate the probability that a scifi movie will make profits
mean_scifi =␣
  ↪df_highrisk_exploded[df_highrisk_exploded['genres']=='Sci-Fi']['worldwide_net'].
  ↪mean()/10**6
```

```
std_scifi =␣
 ↪df_highrisk_exploded[df_highrisk_exploded['genres']=='Sci-Fi']['worldwide_net'].
 ↪std()/10**6
n_scifi =␣
 ↪len(df_highrisk_exploded[df_highrisk_exploded['genres']=='Sci-Fi']['worldwide_net'])

t_scifi_100 = (100-mean_scifi)/(std_scifi/n_scifi**0.5)
t_scifi_200 = (200-mean_scifi)/(std_scifi/n_scifi**0.5)
t_scifi_300 = (300-mean_scifi)/(std_scifi/n_scifi**0.5)
t_scifi_350 = (350-mean_scifi)/(std_scifi/n_scifi**0.5)
print(f'T scores for profit of: \n$100 million = {t_scifi_100}\n$200 million =␣
 ↪{t_scifi_200}\n$300 million = {t_scifi_300}\n$350 million = {t_scifi_350}\n')

prob_scifi_100 = 1-stats.t.cdf(t_scifi_100,df=n_scifi-1)
prob_scifi_200 = 1-stats.t.cdf(t_scifi_200,df=n_scifi-1)
prob_scifi_300 = 1-stats.t.cdf(t_scifi_300,df=n_scifi-1)
prob_scifi_350 = 1-stats.t.cdf(t_scifi_350,df=n_scifi-1)
print(f'Probability for profit f: \n$100 million = {prob_scifi_100}\n$200␣
 ↪million = {prob_scifi_200}\n$300 million = {prob_scifi_300}\n$350 million =␣
 ↪{prob_scifi_350}\n')

scifi_avg_cost = df_highrisk_exploded[df_highrisk_exploded['genres'] ==␣
 ↪'Sci-Fi']['production_budget'].mean()
print(f'Average cost of Sci-Fi movies above $20 million are ${scifi_avg_cost/
 ↪10**6:.02f} millions')
```

```
T scores for profit of:
$100 million = -9.263001427062187
$200 million = -5.252235667837255
$300 million = -1.2414699086123224
$350 million = 0.7639129710001439

Probability for profit f:
$100 million = 1.0
$200 million = 0.9999998176509557
$300 million = 0.8920979817943603
$350 million = 0.22288422982561462

Average cost of Sci-Fi movies above $20 million are $133.26 millions
```

[64]:
```
#Let us calculate the probability that a adventure movie will make profits
mean_adventure =␣
 ↪df_highrisk_exploded[df_highrisk_exploded['genres']=='Adventure']['worldwide_net'].
 ↪mean()/10**6
std_adventure =␣
 ↪df_highrisk_exploded[df_highrisk_exploded['genres']=='Adventure']['worldwide_net'].
 ↪std()/10**6
```

```
n_adventure =␣
↪len(df_highrisk_exploded[df_highrisk_exploded['genres']=='Adventure']['worldwide_net'])

t_adventure_100 = (100-mean_adventure)/(std_adventure/n_adventure**0.5)
t_adventure_200 = (200-mean_adventure)/(std_adventure/n_adventure**0.5)
t_adventure_300 = (300-mean_adventure)/(std_adventure/n_adventure**0.5)
t_adventure_350 = (350-mean_adventure)/(std_adventure/n_adventure**0.5)
print(f'T scores for profit of: \n$100 million = {t_adventure_100}\n$200␣
↪million = {t_adventure_200}\n$300 million = {t_adventure_300}\n$350 million␣
↪= {t_adventure_350}\n')

prob_adventure_100 = 1-stats.t.cdf(t_adventure_100,df=n_adventure-1)
prob_adventure_200 = 1-stats.t.cdf(t_adventure_200,df=n_adventure-1)
prob_adventure_300 = 1-stats.t.cdf(t_adventure_300,df=n_adventure-1)
prob_adventure_350 = 1-stats.t.cdf(t_adventure_350,df=n_adventure-1)
print(f'Probability for profit f: \n$100 million = {prob_adventure_100}\n$200␣
↪million = {prob_adventure_200}\n$300 million = {prob_adventure_300}\n$350␣
↪million = {prob_adventure_350}\n')

adventure_avg_cost = df_highrisk_exploded[df_highrisk_exploded['genres'] ==␣
↪'Adventure']['production_budget'].mean()
print(f'Average cost of Adventure movies above $20 million are␣
↪${adventure_avg_cost/10**6:.02f} millions')
```

```
T scores for profit of:
$100 million = -10.136314209284892
$200 million = -4.824164279336895
$300 million = 0.4879856506111035
$350 million = 3.1440606155851025

Probability for profit f:
$100 million = 1.0
$200 million = 0.999998883029583
$300 million = 0.31295704864162976
$350 million = 0.0009159736985646649

Average cost of Adventure movies above $20 million are $127.28 millions
```

4.2 High Risk - Directors

FInally, for high risk budget.

[65]:
```
df_scifi_movies = df_highrisk_exploded[df_highrisk_exploded['genres']=='Sci-Fi']
df_scifi_directors = pd.merge(df_scifi_movies,imdb,how='inner',on='movie')
df_scifi_directors
```

[65]:

```
    release_date                           movie  production_budget  \
0     2017-01-13                  Monster Trucks          125000000
1     2011-04-08                    Your Highness           50000000
2     2013-03-15                     Upside Down           50000000
3     2013-03-15                     Upside Down           50000000
4     2013-03-15                     Upside Down           50000000
..           …                               …                  …
258   2017-01-27  Resident Evil: The Final Chapter           40000000
259   2012-03-23                 The Hunger Games           80000000
260   2014-07-25                            Lucy           40000000
261   2014-07-25                            Lucy           40000000
262   2014-07-25                            Lucy           40000000

     domestic_gross  worldwide_gross  release_year  worldwide_net        ROI  \
0          33370166         61642798          2017      -63357202  -0.506858
1          21596445         26121638          2011      -23878362  -0.477567
2            102118         26387039          2013      -23612961  -0.472259
3            102118         26387039          2013      -23612961  -0.472259
4            102118         26387039          2013      -23612961  -0.472259
..              …                …             …              …          …
258        26844692        314101190          2017      274101190   6.852530
259       408010692        677923379          2012      597923379   7.474042
260       126573960        457507776          2014      417507776  10.437694
261       126573960        457507776          2014      417507776  10.437694
262       126573960        457507776          2014      417507776  10.437694

    genres_x  start_year  runtime_minutes                    genres_y  \
0     Sci-Fi        2016            104.0    Action,Adventure,Comedy
1     Sci-Fi        2011            102.0   Adventure,Comedy,Fantasy
2     Sci-Fi        2012            109.0      Drama,Fantasy,Romance
3     Sci-Fi        2011              NaN                      Drama
4     Sci-Fi        2012             81.0                      Drama
..        …           …                …                          …
258   Sci-Fi        2016            107.0        Action,Horror,Sci-Fi
259   Sci-Fi        2012            142.0     Action,Adventure,Sci-Fi
260   Sci-Fi        2014             89.0      Action,Sci-Fi,Thriller
261   Sci-Fi        2016              9.0      Animation,Documentary
262   Sci-Fi        2016             40.0                Documentary

                director
0            Chris Wedge
1     David Gordon Green
2           Juan Solanas
3         John Shepphird
4             Ajay Singh
..                     …
258   Paul W.S. Anderson
```

```
259          Gary Ross
260         Luc Besson
261         Elisa Chee
262    Melinte Reitzema

[263 rows x 13 columns]
```

[66]:
```
df_scifi_directors.drop_duplicates(subset=['movie','director'],inplace=True)
df_scifi_directors.
 ↪drop(['release_date','production_budget','domestic_gross','worldwide_gross','release_year',
 ↪'runtime_minutes','genres_y'],axis=1,inplace=True)
df_scifi_directors.sort_values('director')
```

[66]:
```
                              movie  worldwide_net         director
22                             Vice       10883171       Adam McKay
4                       Upside Down      -23612961       Ajay Singh
26                        The Watch       12130045   Akiva Schaffer
51                  The Book of Eli       78750817    Albert Hughes
11                     Annihilation      -11929085     Alex Garland
..                              …              …                …
18                    Transcendence        3039258    Wally Pfister
139  Maze Runner: The Scorch Trials      249566162         Wes Ball
102                            Home      255997896      Yotam Rozin
83                     Man of Steel      442999518      Zack Snyder
56                  Justice League       355945209      Zack Snyder

[177 rows x 3 columns]
```

[67]:
```
director_count = df_scifi_directors.groupby('director')['worldwide_net'].
 ↪count().reset_index().sort_values('worldwide_net',ascending=False)#.iloc[:
 ↪15]#['director'].iloc[:7]
director_count = director_count.rename(columns={'worldwide_net':'count'})
director_count = (director_count[director_count['count']>2])
director_count
```

[67]:
```
              director  count
116  Paul W.S. Anderson      3
122        Ridley Scott      3
12       Anthony Russo      3
48    Francis Lawrence      3
103         Michael Bay      3
```

[68]:
```
director_list = list(director_count['director'])
director_list
```

[68]:
```
['Paul W.S. Anderson',
 'Ridley Scott',
```

```
 'Anthony Russo',
 'Francis Lawrence',
 'Michael Bay']
```

[69]:
```
scifi_topdirectors = df_scifi_directors[df_scifi_directors['director'].
 ↪isin(director_list)].groupby('director')['worldwide_net'].median().
 ↪reset_index().sort_values('worldwide_net',ascending=False)
scifi_topdirectors.rename(columns={'worldwide_net': 'Median Profit'})
#list_scifi_topdirectors
```

[69]:

	director	Median Profit
2	Michael Bay	894039076.0
0	Anthony Russo	890069413.0
1	Francis Lawrence	641575131.0
4	Ridley Scott	277448265.0
3	Paul W.S. Anderson	238374190.0

[70]:
```
df_scifi_directors[df_scifi_directors['director'].
 ↪isin(scifi_topdirectors['director'])].sort_values('director')#.
 ↪drop_duplicates(subset=['movie', 'director'])
```

[70]:

	movie	worldwide_net	director
126	Captain America: The Winter Soldier	544401889	Anthony Russo
132	Captain America: Civil War	890069413	Anthony Russo
253	Avengers: Infinity War	1748134200	Anthony Russo
123	The Hunger Games: Mockingjay - Part 2	488986787	Francis Lawrence
148	The Hunger Games: Mockingjay - Part 1	641575131	Francis Lawrence
151	The Hunger Games: Catching Fire	734868047	Francis Lawrence
80	Transformers: The Last Knight	385893340	Michael Bay
144	Transformers: Age of Extinction	894039076	Michael Bay
145	Transformers: Dark of the Moon	928790543	Michael Bay
115	Resident Evil: Retribution	175647629	Paul W.S. Anderson
140	Resident Evil: Afterlife	238374190	Paul W.S. Anderson
158	Resident Evil: The Final Chapter	274101190	Paul W.S. Anderson
67	Alien: Covenant	141521247	Ridley Scott
108	Prometheus	277448265	Ridley Scott
146	The Martian	547271443	Ridley Scott

Our recommendation for top directors are (in order of profit): - For movies about robots, Michael Bay; - For movies based on comics, Anthony Russo; - For movies based on books, Francis Lawrence;

4.3 High Risk - Release Month

[71]:
```
df_scifi_movies = df_highrisk_exploded[df_highrisk_exploded['genres']=='Sci-Fi']
df_scifi_movies
```

[71]:
```
     release_date                            movie  production_budget  \
0      2013-11-01                        Mr. Nobody           46500000
83     2017-01-13                    Monster Trucks          125000000
97     2011-04-08                     Your Highness           50000000
104    2013-03-15                       Upside Down           50000000
135    2011-10-14                         The Thing           38000000
..            …                                 …                  …
792    2015-06-12                    Jurassic World          215000000
793    2018-06-22     Jurassic World: Fallen Kingdom          170000000
794    2017-01-27  Resident Evil: The Final Chapter           40000000
803    2012-03-23                  The Hunger Games           80000000
813    2014-07-25                              Lucy           40000000

     domestic_gross  worldwide_gross  release_year  worldwide_net        ROI  \
0              3622            22254          2013      -46477746  -0.999521
83         33370166         61642798          2017      -63357202  -0.506858
97         21596445         26121638          2011      -23878362  -0.477567
104          102118         26387039          2013      -23612961  -0.472259
135        16999934         27573078          2011      -10426922  -0.274393
..              …                …             …              …          …
792       652270625       1648854864          2015     1433854864   6.669092
793       417719760       1305772799          2018     1135772799   6.681016
794        26844692        314101190          2017      274101190   6.852530
803       408010692        677923379          2012      597923379   7.474042
813       126573960        457507776          2014      417507776  10.437694

     genres
0    Sci-Fi
83   Sci-Fi
97   Sci-Fi
104  Sci-Fi
135  Sci-Fi
..      …
792  Sci-Fi
793  Sci-Fi
794  Sci-Fi
803  Sci-Fi
813  Sci-Fi

[213 rows x 9 columns]
```

[72]:
```python
df_scifi_movies['release_month'] = pd.
 ↪to_datetime(df_scifi_movies['release_date'], format='%m').dt.month
df_scifi_movies.head()
```

```
/tmp/ipykernel_102626/2176942267.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

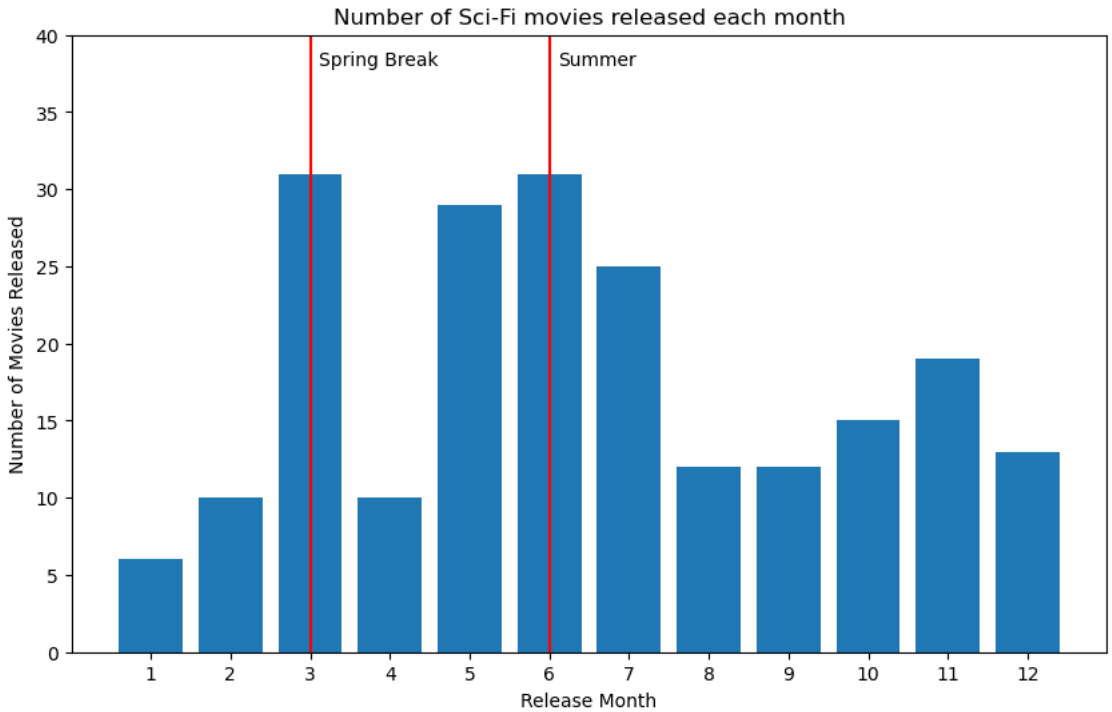
```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_scifi_movies['release_month'] =
pd.to_datetime(df_scifi_movies['release_date'], format='%m').dt.month
```

[72]:

```
    release_date           movie  production_budget  domestic_gross  \
0     2013-11-01      Mr. Nobody           46500000            3622
83    2017-01-13  Monster Trucks          125000000        33370166
97    2011-04-08    Your Highness           50000000        21596445
104   2013-03-15     Upside Down           50000000          102118
135   2011-10-14       The Thing           38000000        16999934

     worldwide_gross  release_year  worldwide_net       ROI  genres  \
0              22254          2013      -46477746 -0.999521  Sci-Fi
83          61642798          2017      -63357202 -0.506858  Sci-Fi
97          26121638          2011      -23878362 -0.477567  Sci-Fi
104         26387039          2013      -23612961 -0.472259  Sci-Fi
135         27573078          2011      -10426922 -0.274393  Sci-Fi

     release_month
0               11
83               1
97               4
104              3
135             10
```

[73]:

```
month_count = df_scifi_movies.groupby('release_month').count()['genres'].
 ↪reset_index().rename(columns={'genres':'count'})

fig,ax = plt.subplots(figsize=(10,6))

ax.bar(x='release_month',height='count', data=month_count)
ax.set_xticks(np.arange(1,13))
ax.set_yticks(np.arange(0,45,5))
ax.set_ylim(0,40)
ax.set_xlabel('Release Month')
ax.set_ylabel('Number of Movies Released')
ax.set_title('Number of Sci-Fi movies released each month')
ax.vlines(x=3,ymin=0,ymax=40,color='r')
ax.vlines(x=6,ymin=0,ymax=40,color='r')
ax.text(x=3.1,y=38,s='Spring Break')
ax.text(x=6.1,y=38,s='Summer');
```



Movie should be released either in March for Spring Break or in June for Summer.

4.4 High Risk - Runtime

[74]:
```
df_scifi = pd.merge(df_scifi_movies,imdb,how='inner',on='movie')
df_scifi.drop_duplicates(subset=['movie'],inplace=True)

runtime_scifi_mean = df_scifi['runtime_minutes'].mean()
runtime_scifi_std = df_scifi['runtime_minutes'].std()
n_scifi = len(df_scifi['runtime_minutes'])
err_scifi = runtime_scifi_std/n_scifi**0.5

Tcrit = stats.t.ppf(0.975,n_scifi-1)

runtime_scifi_upper = runtime_scifi_mean + Tcrit*err_scifi
runtime_scifi_lower = runtime_scifi_mean - Tcrit*err_scifi

print(f'The duration of the Sci-Fi movie should be in between␣
↪{floor(runtime_scifi_lower)} and {ceil(runtime_scifi_upper)} minutes.')
```

```
The duration of the Sci-Fi movie should be in between 115 and 123 minutes.
```

4.5 Recommendations

Low Risk: * Genre: Horror * Director: Jordan Peele or John R. Leonetti * Best release date: Halloween (October) or Easter (April) * Runtime: 96 to 100 minutes * Average cost: $7.53 millions

Medium Risk: * Genre: Music * Director: Damien Chazelle (La La Land) * Best release date: August * Runtime: 96 to 113 minutes * Average cost: $21.93 millions

High Risk: * Genre: Sci-Fi * Director: Michael Bay (Transformers), Anthony Russo (Marvel), Francis Lawrence (Hunger Games) * Best release date: March (Spring Break) or June (Summer) * Runtime: 112 to 120 minutes * Average cost: $155.73 millions

4.6 Next Steps

For further steps we recommend expanding analysis into several directions:

- Explore data on profits and movie perfomance on streaming services.
- Add budgets spent on marketing. "Many people get confused when they hear that a movie with a production budget of 100 million grosses 150 million worldwide and loses money. But the brutal fact is that movies get sunk by the massive costs of marketing and distribution all the time."

4.7 Contact

For contact with the authors of the project, please feel free to add us on LinkedIn and message us or check out our other projects.

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