dsc_phase1_project_EVK_final

March 22, 2021

1 How a company squeezes into "making movie business" and gets successful

Phase 1 Final Project Authors: Elena Kazakova **Cohort:** DS02222021 **Instructor:** James Irving ***

2 Overview

This project analyzes the three publically avalable online databases, IMDb, TN and BOM. IMDb (an acronym for Internet Movie Database) is an online database of information related to films, television programs, home videos, video games, and streaming content online. The Numbers (TN) is a film industry data website that tracks box office revenue in a systematic, algorithmic way.Box Office Mojo (BOM) is an American website that tracks box-office revenue in a systematic, algorithmic way. Descriptive analysis suggests that a company looking into joining lucrative movie business needs to partner with the studios producing the highest ROIs, look into investing into making movies in Horror, Mystery and Thriller genres and carefully plan the release date of their products.

3 Business Problem

Microsoft sees all the big companies creating original video content and they want to get in on the fun. They have decided to create a new movie studio, but they don't know anything about creating movies. They need recommendations how to minimize the risk to their investment and to maximize the profitability of their future products. Though the scope of this project is limited and further in depth analysis should be considered the results of the analysis reveals several valuable recommendations.

---

4 Data Understanding

As it has been pointed in the overview section the project uses the data from three databases already available as zipped csv files imported from IMDb, TN and BOM databases. Additional data from Rotten Tomatoes (RT) and The Movie Database (TMdb) were explored and initially considered and it has been decided not to use this information in the analysis performed. This data might be considered for future exploration. To make this decision an analysis of the content in all the sources available was performed, data diagram of all the tables was created and only tables with movie financial and most easily joined tables have been chosen for the further analysis. The rest of the tables should be considered for performing analysis of ratings and professional staff performance. Another consideration for the choice of the data sources was the number of movie records available in each of the tables. Please see below the description and the results of data sources analysis. ***

4.1 Importing packages and defining functions

[1]:
```
# Import standard packages to be used in the process, it essential to run␣
↪methods associated with all the packages
import pandas as pd
from pandasql import sqldf
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import gzip
import shutil
import os
import sqlite3
from sqlite3 import Error
import csv
import io


%matplotlib inline
```

[2]:
```
# This function might not be needed but is left here just in case I need and␣
↪might be removed later
```

```
def insert_nulls(table_name):
    q1 = 'SELECT * FROM '+ table_name+''
    df = pd.DataFrame(cur.execute(q1))
    df.columns = [x[0] for x in cur.description]
    column_names=list(df.columns)

# dictReader reads empty values as '', they need to be replaced with Nulls in␣
↪all fields similar to the statement below
    for i in column_names:
        q2='UPDATE '+table_name+' SET '+i+' =NULL WHERE '+i+'=""'
        cur.execute(q2)
    return
```

[3]:
```
# This function is needed to easily display the dataframe from a table with all␣
↪the columns names

def display_tableDF(table_name):
    q1 = 'SELECT * FROM '+ table_name+''
    df = pd.DataFrame(cur.execute(q1))
    df.columns = [x[0] for x in cur.description]
    return df
```

[4]:
```
# This function is needed to easily display the dataframe from a csv file with␣
↪all the columns names

def display_csvfileDF(file_name):
    df = pd.read_csv('data/unzippedData/'+file_name, header=0, encoding='UTF-8')
    return df
```

[5]:
```
# This function is needed to easily display the dataframe from a tsv file with␣
↪all the columns names
def display_tsvfileDF(file_name):
    df = pd.read_csv('data/unzippedData/'+file_name, sep = '\t', header=0,␣
↪encoding='latin1')
    return df
```

[6]:
```
def table_query(q):
    df = pd.DataFrame(cur.execute(q))
    df.columns = [x[0] for x in cur.description]
    return df
```

4.2 Unzipping the source csv and tsv files and converting them into movies.db tables

4.2.1 Unzipping the files

[7]:
```
# Testing unzipping the gz file

# The first step to unzip the files provided is to create a separate directory␣
↪for unzipped csv files through bash terminal
# the address is  ~/Documents/Flatiron/Phase1/Project/dsc-project-template/data/
↪unzippedData

with gzip.open('data/zippedData/bom.movie_gross.csv.gz') as f:
            bom_movie_gross = pd.read_csv(f)
bom_movie_gross.head()
```

[7]:
```
                                         title studio  domestic_gross  \
0                                  Toy Story 3     BV     415000000.0
1                   Alice in Wonderland (2010)     BV     334200000.0
2  Harry Potter and the Deathly Hallows Part 1     WB     296000000.0
3                                    Inception     WB     292600000.0
4                          Shrek Forever After   P/DW     238700000.0

  foreign_gross  year
0     652000000  2010
1     691300000  2010
2     664300000  2010
3     535700000  2010
4     513900000  2010
```

[8]:
```
#Testing Saving the file above as an csv file to a directory where unzipped␣
↪files will live, testing

with gzip.open('data/zippedData/bom.movie_gross.csv.gz', 'rb') as f_out:
    with open('data/unzippedData/bom.movie_gross.csv', 'wb') as f_in:
        shutil.copyfileobj(f_out, f_in)
```

[9]:
```
# Creating a list of file names to loop throught unzipping;

# Unzipping the files in the list of gz files

file_list_to_unzip_raw = ['bom.movie_gross.csv.gz', 'imdb.name.basics.csv.gz',␣
↪'imdb.title.akas.csv.gz',
                          'imdb.title.basics.csv.gz', 'imdb.title.crew.csv.gz',␣
↪'imdb.title.principals.csv.gz',
                          'imdb.title.ratings.csv.gz', 'rt.movie_info.tsv.gz',␣
↪'rt.reviews.tsv.gz',
                          'tmdb.movies.csv.gz', 'tn.movie_budgets.csv.gz']
addition_path_from = 'data/zippedData/'
addition_path_to = 'data/unzippedData/'
```

```
for file in file_list_to_unzip_raw:
    with gzip.open(addition_path_from + file, 'rb') as f_out:
        with open(addition_path_to + file[0:-3], 'wb') as f_in:
            shutil.copyfileobj(f_out, f_in)
```

[10]:
```
# Checking the content of the data/zippedData directory

!ls -l data/zippedData/
```

```
total 45716
-rw-r--r-- 1 elena 197121    53544 Mar 13 22:49 bom.movie_gross.csv.gz
-rw-r--r-- 1 elena 197121 18070960 Mar 13 22:49 imdb.name.basics.csv.gz
-rw-r--r-- 1 elena 197121  5599979 Mar 13 22:49 imdb.title.akas.csv.gz
-rw-r--r-- 1 elena 197121  3459897 Mar 13 22:49 imdb.title.basics.csv.gz
-rw-r--r-- 1 elena 197121  1898523 Mar 13 22:49 imdb.title.crew.csv.gz
-rw-r--r-- 1 elena 197121 12287583 Mar 13 22:49 imdb.title.principals.csv.gz
-rw-r--r-- 1 elena 197121   539530 Mar 13 22:49 imdb.title.ratings.csv.gz
-rw-r--r-- 1 elena 197121   498202 Mar 13 22:49 rt.movie_info.tsv.gz
-rw-r--r-- 1 elena 197121  3402194 Mar 13 22:49 rt.reviews.tsv.gz
-rw-r--r-- 1 elena 197121   827840 Mar 13 22:49 tmdb.movies.csv.gz
-rw-r--r-- 1 elena 197121   153218 Mar 13 22:49 tn.movie_budgets.csv.gz
```

[11]:
```
# Checking if all the files have been unzipped

!ls -l data/unzippedData/
```

```
total 147828
-rw-r--r-- 1 elena 197121   142555 Mar 22 01:58 bom.movie_gross.csv
-rw-r--r-- 1 elena 197121 48926352 Mar 22 01:58 imdb.name.basics.csv
-rw-r--r-- 1 elena 197121 18945529 Mar 22 01:58 imdb.title.akas.csv
-rw-r--r-- 1 elena 197121 11852240 Mar 22 01:58 imdb.title.basics.csv
-rw-r--r-- 1 elena 197121  5728745 Mar 22 01:58 imdb.title.crew.csv
-rw-r--r-- 1 elena 197121 50505795 Mar 22 01:58 imdb.title.principals.csv
-rw-r--r-- 1 elena 197121  1950137 Mar 22 01:58 imdb.title.ratings.csv
-rw-r--r-- 1 elena 197121  1184685 Mar 22 01:58 rt.movie_info.tsv
-rw-r--r-- 1 elena 197121  9395716 Mar 22 01:58 rt.reviews.tsv
-rw-r--r-- 1 elena 197121  2301228 Mar 22 01:58 tmdb.movies.csv
-rw-r--r-- 1 elena 197121   422521 Mar 22 01:58 tn.movie_budgets.csv
```

Result: All the files unzipped correctly

4.2.2 Tesing converting the unzipped files to DataFrames

[12]:
```
#Testing conversion of an unzipped tsv file into a DataFrame and printing info␣
↪along with a head of a DF

rt_movie_info = pd.read_csv('data/unzippedData/rt.reviews.tsv', sep = '\t',␣
↪header=0, encoding='latin1')
```

```python
print(rt_movie_info.info())
rt_movie_info.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   id          54432 non-null  int64
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
None
```

[12]:

```
   id                                             review rating   fresh  \
0   3  A distinctly gallows take on contemporary fina…    3/5   fresh
1   3  It's an allegory in search of a meaning that n…    NaN  rotten
2   3  … life lived in a bubble in financial dealin…    NaN   fresh
3   3  Continuing along a line introduced in last yea…    NaN   fresh
4   3             … a perverse twist on neorealism…     NaN   fresh

           critic  top_critic         publisher               date
0      PJ Nabarro           0   Patrick Nabarro  November 10, 2018
1  Annalee Newitz           0           io9.com       May 23, 2018
2    Sean Axmaker           0  Stream on Demand    January 4, 2018
3   Daniel Kasman           0              MUBI  November 16, 2017
4             NaN           0      Cinema Scope    October 12, 2017
```

[13]:

```python
#Testing conversion of an unzipped csv file into a DataFrame and printing info␣
↪along with a head of a DF

imdb_name_basics = pd.read_csv('data/unzippedData/imdb.name.basics.csv',␣
↪header=0, encoding='UTF-8')
print(imdb_name_basics.info())
imdb_name_basics.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 606648 entries, 0 to 606647
Data columns (total 6 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   nconst              606648 non-null  object
```

```
 1   primary_name        606648 non-null  object
 2   birth_year          82736 non-null   float64
 3   death_year          6783 non-null    float64
 4   primary_profession  555308 non-null  object
 5   known_for_titles    576444 non-null  object
dtypes: float64(2), object(4)
memory usage: 27.8+ MB
None
```

[13]:
```
      nconst       primary_name  birth_year  death_year  \
0  nm0061671  Mary Ellen Bauder         NaN         NaN
1  nm0061865       Joseph Bauer         NaN         NaN
2  nm0062070         Bruce Baum         NaN         NaN
3  nm0062195       Axel Baumann         NaN         NaN
4  nm0062798        Pete Baxter         NaN         NaN

                                 primary_profession  \
0         miscellaneous,production_manager,producer
1        composer,music_department,sound_department
2                        miscellaneous,actor,writer
3  camera_department,cinematographer,art_department
4  production_designer,art_department,set_decorator

                              known_for_titles
0  tt0837562,tt2398241,tt0844471,tt0118553
1  tt0896534,tt6791238,tt0287072,tt1682940
2  tt1470654,tt0363631,tt0104030,tt0102898
3  tt0114371,tt2004304,tt1618448,tt1224387
4  tt0452644,tt0452692,tt3458030,tt2178256
```

4.2.3 Creating DataFrames out of all unzipped files and displaying all DF info for each

[14]:
```
#Leaving this code for now, most probably needs to be removed

#listing the files in the unzipped directory to make a list with path defined␣
 ↪out of these files
list_unzipped_files = os.listdir('data/unzippedData')
list_unzipped_files
```

[14]:
```
['bom.movie_gross.csv',
 'imdb.name.basics.csv',
 'imdb.title.akas.csv',
 'imdb.title.basics.csv',
 'imdb.title.crew.csv',
 'imdb.title.principals.csv',
 'imdb.title.ratings.csv',
 'rt.movie_info.tsv',
```

```
 'rt.reviews.tsv',
 'tmdb.movies.csv',
 'tn.movie_budgets.csv']
```

[15]:
```python
list_csv_files=[]
list_tsv_files=[]

for i in list_unzipped_files:
    if i[-3:]=='csv':
        list_csv_files.append(i)
    else:
        list_tsv_files.append(i)
print(list_csv_files)
print(list_tsv_files)
```

```
['bom.movie_gross.csv', 'imdb.name.basics.csv', 'imdb.title.akas.csv',
'imdb.title.basics.csv', 'imdb.title.crew.csv', 'imdb.title.principals.csv',
'imdb.title.ratings.csv', 'tmdb.movies.csv', 'tn.movie_budgets.csv']
['rt.movie_info.tsv', 'rt.reviews.tsv']
```

[16]:
```python
#Creating an empty sqlite3 movies database. The directory sqlite within data␣
↪directory.
#sqlite directory was created in bash terminal by mkdir data/sqlite/db

conn = sqlite3.connect('data/sqlite/db/movies.db')
cur = conn.cursor()
```

[17]:
```python
# Checking if the database has no tables

cur.execute("""SELECT name FROM sqlite_master WHERE type='table'""").fetchall()
```

[17]: `[]`

4.2.4 Displaying files info in order to create a data diagram

[18]:
```python
for i in list_tsv_files:
    print(i)
    display_tsvfileDF(i).info()
    print('***********************************************************')
```

```
rt.movie_info.tsv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            1560 non-null   int64
 1   synopsis      1498 non-null   object
```

```
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
**********************************************************
rt.reviews.tsv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   id          54432 non-null  int64
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
**********************************************************
```

[19]:

```
for i in list_csv_files:
    print(i)
    display_csvfileDF(i).info()
    print('**********************************************************')
```

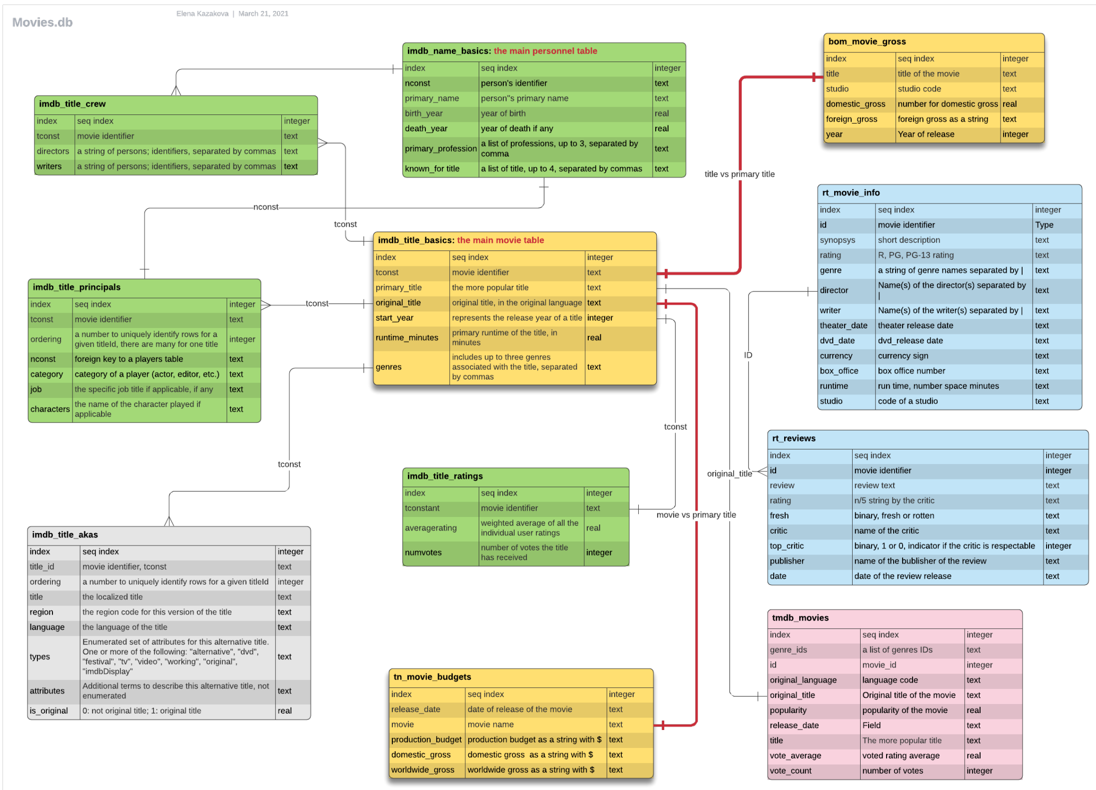
```
bom.movie_gross.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           3387 non-null   object
 1   studio          3382 non-null   object
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object
 4   year            3387 non-null   int64
dtypes: float64(1), int64(1), object(3)
```

```
memory usage: 132.4+ KB
**********************************************************
imdb.name.basics.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 606648 entries, 0 to 606647
Data columns (total 6 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   nconst              606648 non-null  object
 1   primary_name        606648 non-null  object
 2   birth_year          82736 non-null   float64
 3   death_year          6783 non-null    float64
 4   primary_profession  555308 non-null  object
 5   known_for_titles    576444 non-null  object
dtypes: float64(2), object(4)
memory usage: 27.8+ MB
**********************************************************
imdb.title.akas.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 331703 entries, 0 to 331702
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   title_id           331703 non-null  object
 1   ordering           331703 non-null  int64
 2   title              331703 non-null  object
 3   region             278410 non-null  object
 4   language           41715 non-null   object
 5   types              168447 non-null  object
 6   attributes         14925 non-null   object
 7   is_original_title  331678 non-null  float64
dtypes: float64(1), int64(1), object(6)
memory usage: 20.2+ MB
**********************************************************
imdb.title.basics.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   tconst           146144 non-null  object
 1   primary_title    146144 non-null  object
 2   original_title   146123 non-null  object
 3   start_year       146144 non-null  int64
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
```

```
**********************************************************
imdb.title.crew.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 3 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   tconst     146144 non-null  object
 1   directors  140417 non-null  object
 2   writers    110261 non-null  object
dtypes: object(3)
memory usage: 3.3+ MB
**********************************************************
imdb.title.principals.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1028186 entries, 0 to 1028185
Data columns (total 6 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   tconst      1028186 non-null  object
 1   ordering    1028186 non-null  int64
 2   nconst      1028186 non-null  object
 3   category    1028186 non-null  object
 4   job         177684 non-null   object
 5   characters  393360 non-null   object
dtypes: int64(1), object(5)
memory usage: 47.1+ MB
**********************************************************
imdb.title.ratings.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   tconst         73856 non-null  object
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
**********************************************************
tmdb.movies.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         26517 non-null  int64
 1   genre_ids          26517 non-null  object
```

```
 2   id                 26517 non-null  int64
 3   original_language  26517 non-null  object
 4   original_title     26517 non-null  object
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object
 7   title              26517 non-null  object
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
**********************************************************
tn.movie_budgets.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
**********************************************************
```

4.2.5 The following future database tables diagram was created in LucidChart:



4.3 Analysis of the diagram

- Based on the diagram above the tables highlighted in yellow provide basic movie information and financial information and information that can be used easily by joining them using the title fields in each table.
- The tables imdb_title_basics contains additional information on runtime of a movie and its' genres
- The table tn_movie_budgets table has production budget information along with domestic and worldwide gross income
- The table bom_movie_gross table has domestic and worldwide gross income information along with data on the production studios ***

4.4 Importing file data into the database

[20]:
```
# Testing generation of a list of table names out of a list of filenames to
↪import into a database
# by replacing '.' with '_'# creating a function
list_table_names=[]
for i in list_unzipped_files:
    if i[-3:]=='csv':
```

```
        list_table_names.append(i.replace('.','_').replace('_csv',''))
    else:
        list_table_names.append(i.replace('.','_').replace('_tsv',''))
list_table_names
```

[20]:
```
['bom_movie_gross',
 'imdb_name_basics',
 'imdb_title_akas',
 'imdb_title_basics',
 'imdb_title_crew',
 'imdb_title_principals',
 'imdb_title_ratings',
 'rt_movie_info',
 'rt_reviews',
 'tmdb_movies',
 'tn_movie_budgets']
```

[21]:
```
list_unzipped_files
```

[21]:
```
['bom.movie_gross.csv',
 'imdb.name.basics.csv',
 'imdb.title.akas.csv',
 'imdb.title.basics.csv',
 'imdb.title.crew.csv',
 'imdb.title.principals.csv',
 'imdb.title.ratings.csv',
 'rt.movie_info.tsv',
 'rt.reviews.tsv',
 'tmdb.movies.csv',
 'tn.movie_budgets.csv']
```

[22]:
```
cur.execute("""SELECT name FROM sqlite_master WHERE type='table'""").fetchall()
```

[22]:
```
[]
```

[23]:
```
display_csvfileDF('bom.movie_gross.csv').to_sql('bom_movie_gross', conn,␣
 ↪if_exists='replace', index = False)
display_csvfileDF('imdb.name.basics.csv').to_sql('imdb_name_basics', conn,␣
 ↪if_exists='replace', index = False)
display_csvfileDF('imdb.title.akas.csv').to_sql('imdb_title_akas', conn,␣
 ↪if_exists='replace', index = False)
display_csvfileDF('imdb.title.basics.csv').to_sql('imdb_title_basics', conn,␣
 ↪if_exists='replace', index = False)
display_csvfileDF('imdb.title.crew.csv').to_sql('imdb_title_crew', conn,␣
 ↪if_exists='replace', index = False)
display_csvfileDF('imdb.title.principals.csv').to_sql('imdb_title_principals',␣
 ↪conn, if_exists='replace', index = False)
```

```
display_csvfileDF('imdb.title.ratings.csv').to_sql('imdb_title_ratings', conn,␣
↪if_exists='replace', index = False)
display_tsvfileDF('rt.movie_info.tsv').to_sql('rt_movie_info', conn,␣
↪if_exists='replace', index = False)
display_tsvfileDF('rt.reviews.tsv').to_sql('rt_reviews', conn,␣
↪if_exists='replace', index = False)
display_csvfileDF('tmdb.movies.csv').to_sql('tmdb_movies', conn,␣
↪if_exists='replace', index = False)
display_csvfileDF('tn.movie_budgets.csv').to_sql('tn_movie_budgets', conn,␣
↪if_exists='replace', index = False)
```

```
C:\Users\elena\anaconda3\envs\learn-env\lib\site-
packages\pandas\core\generic.py:2605: UserWarning: The spaces in these column
names will not be changed. In pandas versions < 0.14, spaces were converted to
underscores.
  sql.to_sql(
```

[24]:
```
cur.execute("""SELECT name FROM sqlite_master WHERE type='table'""").fetchall()
```

[24]:
```
[('bom_movie_gross',),
 ('imdb_name_basics',),
 ('imdb_title_akas',),
 ('imdb_title_basics',),
 ('imdb_title_crew',),
 ('imdb_title_principals',),
 ('imdb_title_ratings',),
 ('rt_movie_info',),
 ('rt_reviews',),
 ('tmdb_movies',),
 ('tn_movie_budgets',)]
```

[25]:
```
conn.commit()
```

[26]:
```
for i in list_table_names:
    print(i)
    display_tableDF(i).info()
    print('**********************************************************')
```

```
bom_movie_gross
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           3387 non-null   object
 1   studio          3382 non-null   object
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object
```

```
 4   year            3387 non-null   int64
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
**********************************************************
imdb_name_basics
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 606648 entries, 0 to 606647
Data columns (total 6 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   nconst              606648 non-null  object
 1   primary_name        606648 non-null  object
 2   birth_year          82736 non-null   float64
 3   death_year          6783 non-null    float64
 4   primary_profession  555308 non-null  object
 5   known_for_titles    576444 non-null  object
dtypes: float64(2), object(4)
memory usage: 27.8+ MB
**********************************************************
imdb_title_akas
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 331703 entries, 0 to 331702
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   title_id           331703 non-null  object
 1   ordering           331703 non-null  int64
 2   title              331703 non-null  object
 3   region             278410 non-null  object
 4   language           41715 non-null   object
 5   types              168447 non-null  object
 6   attributes         14925 non-null   object
 7   is_original_title  331678 non-null  float64
dtypes: float64(1), int64(1), object(6)
memory usage: 20.2+ MB
**********************************************************
imdb_title_basics
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   tconst           146144 non-null  object
 1   primary_title    146144 non-null  object
 2   original_title   146123 non-null  object
 3   start_year       146144 non-null  int64
 4   runtime_minutes  114405 non-null  float64
 5   genres           140736 non-null  object
```

```
dtypes: float64(1), int64(1), object(4)
memory usage: 6.7+ MB
**********************************************************
imdb_title_crew
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146144 entries, 0 to 146143
Data columns (total 3 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   tconst     146144 non-null  object
 1   directors  140417 non-null  object
 2   writers    110261 non-null  object
dtypes: object(3)
memory usage: 3.3+ MB
**********************************************************
imdb_title_principals
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1028186 entries, 0 to 1028185
Data columns (total 6 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   tconst      1028186 non-null  object
 1   ordering    1028186 non-null  int64
 2   nconst      1028186 non-null  object
 3   category    1028186 non-null  object
 4   job         177684 non-null   object
 5   characters  393360 non-null   object
dtypes: int64(1), object(5)
memory usage: 47.1+ MB
**********************************************************
imdb_title_ratings
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73856 entries, 0 to 73855
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   tconst         73856 non-null  object
 1   averagerating  73856 non-null  float64
 2   numvotes       73856 non-null  int64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.7+ MB
**********************************************************
rt_movie_info
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1560 entries, 0 to 1559
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
```

```
 0   id            1560 non-null   int64
 1   synopsis      1498 non-null   object
 2   rating        1557 non-null   object
 3   genre         1552 non-null   object
 4   director      1361 non-null   object
 5   writer        1111 non-null   object
 6   theater_date  1201 non-null   object
 7   dvd_date      1201 non-null   object
 8   currency      340 non-null    object
 9   box_office    340 non-null    object
 10  runtime       1530 non-null   object
 11  studio        494 non-null    object
dtypes: int64(1), object(11)
memory usage: 146.4+ KB
**********************************************************
rt_reviews
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54432 entries, 0 to 54431
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   id          54432 non-null  int64
 1   review      48869 non-null  object
 2   rating      40915 non-null  object
 3   fresh       54432 non-null  object
 4   critic      51710 non-null  object
 5   top_critic  54432 non-null  int64
 6   publisher   54123 non-null  object
 7   date        54432 non-null  object
dtypes: int64(2), object(6)
memory usage: 3.3+ MB
**********************************************************
tmdb_movies
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         26517 non-null  int64
 1   genre_ids          26517 non-null  object
 2   id                 26517 non-null  int64
 3   original_language  26517 non-null  object
 4   original_title     26517 non-null  object
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object
 7   title              26517 non-null  object
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64
```

```
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
**********************************************************
tn_movie_budgets
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
**********************************************************
```

5 Data Preparation

In the process of cleaning the data I did not drop any columns, leaving the tables in their original form. The reason was that I could manipulate DataFrames out of the tables and not recreate the tables every time I made a mistake. However I did check for duplicates and null values in the tables and handle them according to the goals of the project

---

Steps taken: * Checking for null values in the columns of the tables * Checking for duplicates in the tables to be used in the analysis * Cleaning the data by updating some values and removing rows with NULL values in the essential columns ***

5.1 Checking for null values in the columns of the tables

[27]:
```
#In imdb__title_basics null values
display_tableDF('imdb_title_basics').isna().sum()
```

[27]:
```
tconst                 0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres              5408
dtype: int64
```

[28]:
```
#In imdb__title_basics null values
display_tableDF('tn_movie_budgets').isna().sum()
```

[28]:
```
id                    0
release_date          0
movie                 0
production_budget     0
domestic_gross        0
worldwide_gross       0
dtype: int64
```

[29]:
```python
#In imdb__title_basics null values
display_tableDF('bom_movie_gross').isna().sum()
```

[29]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

5.2 Checking for duplicates in the tables to be used in the analysis

[30]:
```python
df1 = display_tableDF('imdb_title_basics')
df2 = df1.duplicated()
df2[df2==True]
```

[30]:
```
Series([], dtype: bool)
```

[31]:
```python
df1 = display_tableDF('tn_movie_budgets')
df2 = df1.duplicated()
df2[df2==True]
```

[31]:
```
Series([], dtype: bool)
```

[32]:
```python
df1 = display_tableDF('bom_movie_gross')
df2 = df1.duplicated()
df2[df2==True]
```

[32]:
```
Series([], dtype: bool)
```

5.3 Description of the data in the tables under consideration

tn_movie_budgets table:
>**Original number** of records **5782**
>No **Null** values in tn_movie_budgets therefore nothing to clean in this department
>**No Duplicates**
>After removing movies older than 2010 and newer than 2019
>the number of records is **2191**

imdb_title_basics table: >**Original number** of records **146144**
>**21 Null cells** in **original_title**: replaced with "Missing original title"

>**5408 Null cells** in **genres**: replaced with "Unknown" and split by **.explode**
>**31739 Null cells** in **runtime_minutes**: left as is
>**No Duplicates**
>After splitting genres and removing movies older than 2010 and newer than 2019
>the number of records is **233337**

bom_movie_gross table: >**Original Number** of records **3387**
>**5 Null cells** in **studio**: replaced with **Unknown**
>**28 Null cells** in **domestic_gross**
>**1350 Null cells** in **foreign_gross**
>**No Duplicates**

5.4 Cleaning the data

[33]:
```
#Replacing NULL values in genres column in imdb_title_basics table with␣
↪"Unknown"
cur.execute("""UPDATE imdb_title_basics SET genres='Unknown' WHERE genres is␣
↪NULL""")
```

[33]:
```
<sqlite3.Cursor at 0x201e9289260>
```

[34]:
```
display_tableDF('imdb_title_basics').isna().sum()
```

[34]:
```
tconst                 0
primary_title          0
original_title        21
start_year             0
runtime_minutes    31739
genres                 0
dtype: int64
```

[35]:
```
#Replacing NULL values in original_title column in imdb_title_basics table with␣
↪"Missing original title"
cur.execute("""UPDATE imdb_title_basics SET original_title='Missing original␣
↪title' WHERE original_title is NULL""")
```

[35]:
```
<sqlite3.Cursor at 0x201e9289260>
```

5.5 Manipulating the data

Steps: for all the table under consideration where applicable

---

Steps taken: * Splitting genres field list of genres into separate genres multiple rows in imdb_title_basics * Splitting release_date to fill in year, quarter, month in tn_movie_budgets * Deleting records from the years prior to 2010 and after 2019 in all three tables * Replacing studio NULL values in bom_movie_gross with "Unknown" ***

[36]:
```python
df_test = display_tableDF('imdb_title_basics')
df_test_exploded = df_test.assign(genres=df_test.genres.str.split(",")).
    ↪explode('genres')
```

[37]:
```python
df_test_exploded
```

[37]:
```
           tconst                    primary_title  \
0       tt0063540                        Sunghursh
0       tt0063540                        Sunghursh
0       tt0063540                        Sunghursh
1       tt0066787  One Day Before the Rainy Season
1       tt0066787  One Day Before the Rainy Season
…             …                              …
146139  tt9916538              Kuambil Lagi Hatiku
146140  tt9916622  Rodolpho Teóphilo - O Legado de um Pioneiro
146141  tt9916706                  Dankyavar Danka
146142  tt9916730                           6 Gunn
146143  tt9916754   Chico Albuquerque - Revelações

                                     original_title  start_year  \
0                                         Sunghursh        2013
0                                         Sunghursh        2013
0                                         Sunghursh        2013
1                                  Ashad Ka Ek Din        2019
1                                  Ashad Ka Ek Din        2019
…                                               …         …
146139                          Kuambil Lagi Hatiku        2019
146140  Rodolpho Teóphilo - O Legado de um Pioneiro        2015
146141                              Dankyavar Danka        2013
146142                                       6 Gunn        2017
146143               Chico Albuquerque - Revelações        2013

        runtime_minutes       genres
0                 175.0       Action
0                 175.0        Crime
0                 175.0        Drama
1                 114.0    Biography
1                 114.0        Drama
…                   …           …
146139            123.0        Drama
146140              NaN  Documentary
146141              NaN       Comedy
146142            116.0      Unknown
146143              NaN  Documentary

[234958 rows x 6 columns]
```

5.6 Importing the cleaned data back into the tables

[38]:
```
df_test_exploded.to_sql('imdb_title_basics', conn, if_exists='replace', index =␣
↪False)
```

[39]:
```
display_tableDF('imdb_title_basics').head()
```

[39]:
```
      tconst                    primary_title   original_title  start_year  \
0  tt0063540                        Sunghursh        Sunghursh        2013
1  tt0063540                        Sunghursh        Sunghursh        2013
2  tt0063540                        Sunghursh        Sunghursh        2013
3  tt0066787  One Day Before the Rainy Season  Ashad Ka Ek Din        2019
4  tt0066787  One Day Before the Rainy Season  Ashad Ka Ek Din        2019

   runtime_minutes     genres
0            175.0     Action
1            175.0      Crime
2            175.0      Drama
3            114.0  Biography
4            114.0      Drama
```

[40]:
```
display_tableDF('imdb_title_basics').info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 234958 entries, 0 to 234957
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   tconst           234958 non-null  object
 1   primary_title    234958 non-null  object
 2   original_title   234958 non-null  object
 3   start_year       234958 non-null  int64
 4   runtime_minutes  195904 non-null  float64
 5   genres           234958 non-null  object
dtypes: float64(1), int64(1), object(4)
memory usage: 10.8+ MB
```

[41]:
```
conn.commit()
```

[42]:
```
cur.execute("""ALTER TABLE tn_movie_budgets ADD COLUMN year""")
```

[42]:
```
<sqlite3.Cursor at 0x201e9289260>
```

[43]:
```
cur.execute("""ALTER TABLE tn_movie_budgets ADD COLUMN quarter""")
```

[43]:
```
<sqlite3.Cursor at 0x201e9289260>
```

[44]:
```
cur.execute("""ALTER TABLE tn_movie_budgets ADD COLUMN month""")
```

[44]: <sqlite3.Cursor at 0x201e9289260>

[45]:
```
#Adding 3 new columns as integers
df_ = display_tableDF('tn_movie_budgets')
df_['year'] = pd.to_datetime(df_['release_date']).dt.year
df_['quarter'] = pd.to_datetime(df_['release_date']).dt.quarter
df_['month'] = pd.to_datetime(df_['release_date']).dt.month
df_.to_sql('tn_movie_budgets', conn, if_exists='replace', index = False)
```

[46]:
```
#updated the new column from the dataframe df_ with datatime operation
df_.to_sql('tn_movie_budgets', conn, if_exists='replace', index = False)
```

[47]:
```
display_tableDF('tn_movie_budgets').info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
 6   year               5782 non-null   int64
 7   quarter            5782 non-null   int64
 8   month              5782 non-null   int64
dtypes: int64(4), object(5)
memory usage: 406.7+ KB
```

[48]:
```
conn.commit()
```

[49]:
```
display_tableDF('tn_movie_budgets').head()
```

[49]:
```
   id  release_date                                        movie  \
0   1  Dec 18, 2009                                       Avatar
1   2  May 20, 2011  Pirates of the Caribbean: On Stranger Tides
2   3   Jun 7, 2019                                 Dark Phoenix
3   4   May 1, 2015                      Avengers: Age of Ultron
4   5  Dec 15, 2017            Star Wars Ep. VIII: The Last Jedi

  production_budget domestic_gross worldwide_gross  year  quarter  month
0      $425,000,000   $760,507,625  $2,776,345,279  2009        4     12
1      $410,600,000   $241,063,875  $1,045,663,875  2011        2      5
2      $350,000,000    $42,762,350    $149,762,350  2019        2      6
3      $330,600,000   $459,005,868  $1,403,013,963  2015        2      5
4      $317,000,000   $620,181,382  $1,316,721,747  2017        4     12
```

[50]:
```
# Replacing studio NULL values
cur.execute("""UPDATE bom_movie_gross SET studio='Unknown' WHERE studio is␣
↪NULL""")
```

[50]:
```
<sqlite3.Cursor at 0x201e9289260>
```

[51]:
```
q="Select * from bom_movie_gross WHERE foreign_gross is NULL"
df=table_query(q)
df
```

[51]:
```
                                    title      studio  domestic_gross  \
0                                 Flipped          WB       1800000.0
1      The Polar Express (IMAX re-issue 2010)      WB        673000.0
2                          Tiny Furniture         IFC        392000.0
3              Grease (Sing-a-Long re-issue)     Par.        366000.0
4                         Last Train Home       Zeit.        288000.0
…                                       …          …               …
1345                            The Quake       Magn.          6200.0
1346             Edward II (2018 re-release)       FM          4800.0
1347                             El Pacto        Sony          2500.0
1348                             The Swan  Synergetic          2400.0
1349                     An Actor Prepares       Grav.          1700.0

     foreign_gross  year
0             None  2010
1             None  2010
2             None  2010
3             None  2010
4             None  2010
…                …     …
1345          None  2018
1346          None  2018
1347          None  2018
1348          None  2018
1349          None  2018

[1350 rows x 5 columns]
```

[52]:
```
q="Select * from bom_movie_gross WHERE domestic_gross is NULL"
df=table_query(q)
df
```

[52]:
```
                                 title   studio domestic_gross  \
0            It's a Wonderful Afterlife      UTV           None
1    Celine: Through the Eyes of the World   Sony           None
2                            White Lion    Scre.           None
3                      Badmaash Company     Yash           None
```

4	Aashayein (Wishes)	Relbig.	None
5	Force	FoxS	None
6	Empire of Silver	NeoC	None
7	Solomon Kane	RTWC	None
8	The Tall Man	Imag.	None
9	Keith Lemon: The Film	Unknown	None
10	Lula, Son of Brazil	NYer	None
11	The Cup (2012)	Myr.	None
12	Dark Tide	WHE	None
13	The Green Wave	RF	None
14	22 Bullets	Cdgm.	None
15	Matru Ki Bijlee Ka Mandola	FIP	None
16	The Snitch Cartel	PI	None
17	All the Boys Love Mandy Lane	RTWC	None
18	6 Souls	RTWC	None
19	Jessabelle	LGF	None
20	14 Blades	RTWC	None
21	Jack and the Cuckoo-Clock Heart	Shout!	None
22	Lila Lila	Crnth	None
23	Surprise - Journey To The West	AR	None
24	Finding Mr. Right 2	CL	None
25	Solace	LGP	None
26	Viral	W/Dim.	None
27	Secret Superstar	Unknown	None

	foreign_gross	year
0	1300000	2010
1	119000	2010
2	99600	2010
3	64400	2010
4	3800	2010
5	4800000	2011
6	19000	2011
7	19600000	2012
8	5200000	2012
9	4000000	2012
10	3800000	2012
11	1800000	2012
12	432000	2012
13	70100	2012
14	21300000	2013
15	6000000	2013
16	2100000	2013
17	1900000	2013
18	852000	2013
19	7000000	2014
20	3800000	2014

```
21      3400000  2014
22      1100000  2014
23     49600000  2015
24    114700000  2016
25     22400000  2016
26       552000  2016
27    122000000  2017
```

[53]:
```python
cur.execute("""DELETE FROM imdb_title_basics WHERE start_year not IN
(2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019)""")
```

[53]:
```
<sqlite3.Cursor at 0x201e9289260>
```

[54]:
```python
cur.execute("""DELETE FROM tn_movie_budgets WHERE year not IN
(2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019)""")
```

[54]:
```
<sqlite3.Cursor at 0x201e9289260>
```

[55]:
```python
#Listing the number of movies made each year and their percentage from all the␣
↪movies made over these years (2009-2018)
# bom_movie_gross table
#Note that 2019 is not represented in this table

q="SELECT year, COUNT(*) as num_movies FROM bom_movie_gross group by year order␣
↪by year ASC"
df_bom_year = table_query(q)
df_bom_year['percentage_of_all'] = round(df_bom_year['num_movies']/
↪df_bom_year['num_movies'].sum()*100, 2)
df_bom_year
```

[55]:

	year	num_movies	percentage_of_all
0	2010	328	9.68
1	2011	399	11.78
2	2012	400	11.81
3	2013	350	10.33
4	2014	395	11.66
5	2015	450	13.29
6	2016	436	12.87
7	2017	321	9.48
8	2018	308	9.09

[56]:
```python
#Listing the number of movies made each year and their percentage from all the␣
↪movies made over these years (2009-2019)
# imdb_title_basics table

q="SELECT start_year, COUNT(DISTINCT tconst) as num_movies FROM␣
↪imdb_title_basics group by start_year order by start_year ASC"
```

```
df_imdb_year = table_query(q)
df_imdb_year['percentage_of_all'] = round(df_imdb_year['num_movies']/
 ↪df_imdb_year['num_movies'].sum()*100, 2)
df_imdb_year
```

[56]:

	start_year	num_movies	percentage_of_all
0	2010	11849	8.17
1	2011	12900	8.89
2	2012	13787	9.50
3	2013	14709	10.14
4	2014	15589	10.75
5	2015	16243	11.20
6	2016	17272	11.91
7	2017	17504	12.06
8	2018	16849	11.61
9	2019	8379	5.78

[57]:

```
#Listing the number of movies made each year and their percentage from all the␣
 ↪movies made over these years (2009-2019)
# tn_movie_budgets table

q="SELECT year, count(*) as num_movies FROM tn_movie_budgets group by year␣
 ↪order by year ASC"
df_tn_year = table_query(q)
df_tn_year['percentage_of_all'] = round(df_tn_year['num_movies']/
 ↪df_tn_year['num_movies'].sum()*100, 2)
df_tn_year
```

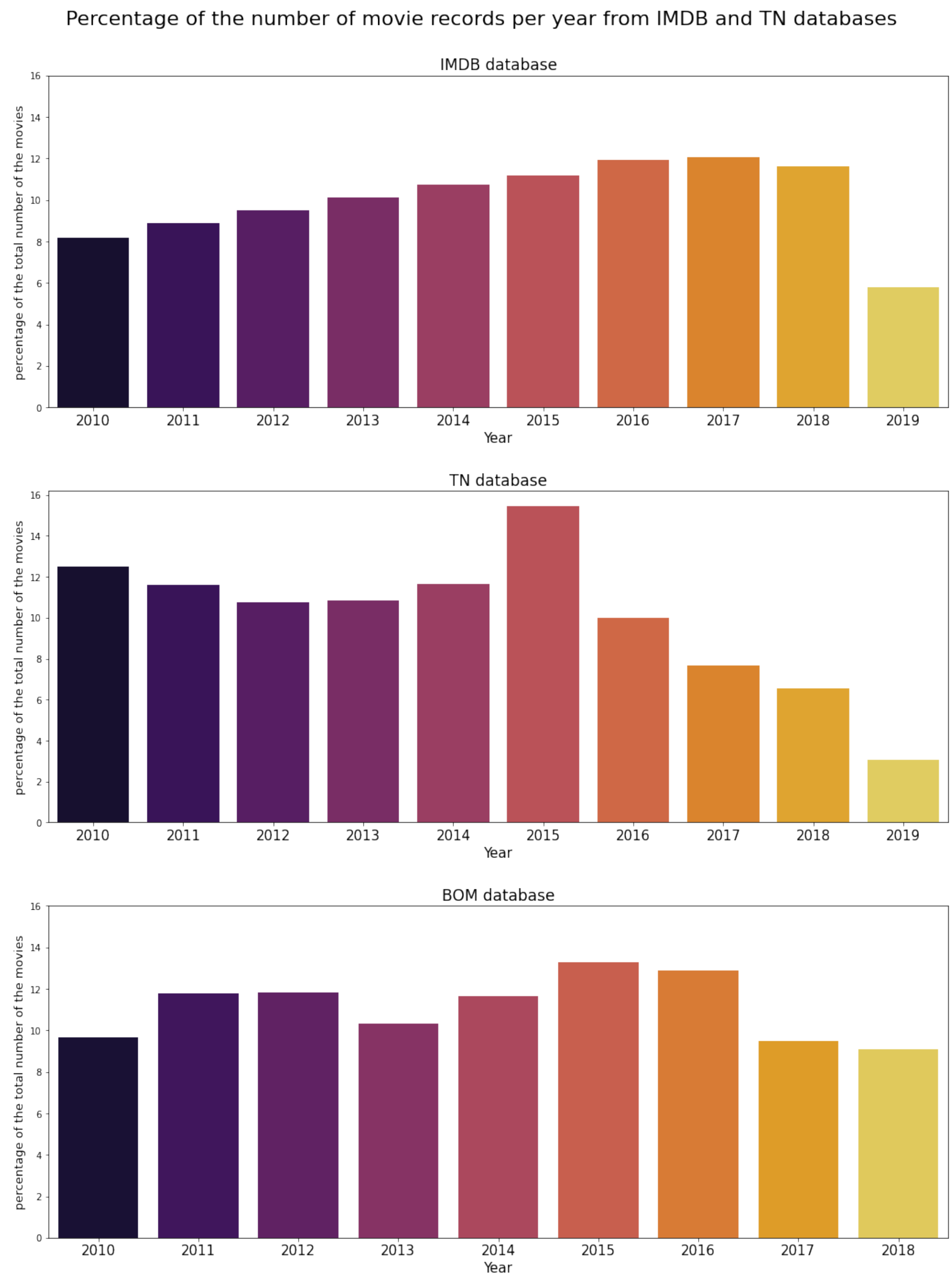
[57]:

	year	num_movies	percentage_of_all
0	2010	274	12.51
1	2011	254	11.59
2	2012	235	10.73
3	2013	238	10.86
4	2014	255	11.64
5	2015	338	15.43
6	2016	219	10.00
7	2017	168	7.67
8	2018	143	6.53
9	2019	67	3.06

[58]:

```
# Visualizing how well movies are reresented in each of the tables for yeach␣
 ↪year
#

fig, axes = plt.subplots(figsize=(15,20), nrows=3)
fig.suptitle('Percentage of the number of movie records per year from IMDB and␣
 ↪TN databases', fontsize=22)
```

```
sns.barplot(data=df_imdb_year, x='start_year', y='percentage_of_all',␣
 ↪ax=axes[0], palette ='inferno')
axes[0].set_title('IMDB database', fontsize=17)
axes[0].set_ylabel('percentage of the total number of the movies', fontsize=13)
axes[0].set_xlabel('Year', fontsize=15)
axes[0].set_xticklabels(df_imdb_year['start_year'], fontsize=15)
axes[0].set_ylim(0, 16)

sns.barplot(data=df_tn_year, x='year',  y='percentage_of_all', ax=axes[1],␣
 ↪palette ='inferno')
axes[1].set_title('TN database', fontsize=17)
axes[1].set_ylabel('percentage of the total number of the movies', fontsize=13)
axes[1].set_xlabel('Year', fontsize=15)
axes[1].set_xticklabels(df_tn_year['year'], fontsize=15)

sns.barplot(data=df_bom_year, x='year',  y='percentage_of_all', ax=axes[2],␣
 ↪palette ='inferno')
axes[2].set_title('BOM database', fontsize=17)
axes[2].set_ylabel('percentage of the total number of the movies', fontsize=13)
axes[2].set_xlabel('Year', fontsize=15)
axes[2].set_xticklabels(df_bom_year['year'], fontsize=15)
axes[2].set_ylim(0, 16)
plt.tight_layout(pad=3)
```



Visualization above establishes the fact that the TN and BOM databases do not represent the movies released between 2010 and 2019 as well as IMDB database. The other conclusion is that

2019 is not well represented in any of these database and therefore the data from this year is not very reliable. However, I decided to leave the records from this year in for now. These factors should be taken into consideration when evaluating the reliability of the conclusion of this study

5.7 Joining the tables by movie titles

5.7.1 bom_movie_gross with tn_movie_budget into df_tn_bom DataFrame and a new table ROI_tn_bom

---

- These tables need to be joined on two column, title and year, because there are movies with the same title but different years on release
- I dropped the rows that have ROI < -99% due to unreliability of the data
- Data from this process is going to be used to identify the **most successful studios** (the highest median ROI is the measurement of success), overall distribution of ROI (domestic and worldwide) as box plots per year, and the most successful months of the year (highest median ROI per month of the year)
- The DataFrame with all financial measure is going to be saved for future use and visuals, there are **1208** record matched ***

[59]:
```
#Joining tn_movie_budgets and bom_movie_gross table with titles and year of␣
↪release.
#The year is necessary because there are movies with the same titles but␣
↪different years of release

q="""SELECT title, bom.year, month, studio, production_budget, tn.
↪domestic_gross 'domestic_gross',
     worldwide_gross from tn_movie_budgets tn
     JOIN bom_movie_gross bom ON
     (tn.movie=bom.title) AND (tn.year=bom.year)"""

df_tn_bom = table_query(q)

for i in range(len(df_tn_bom['domestic_gross'])):
    row = df_tn_bom['domestic_gross'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_bom['domestic_gross'][i]=row_num

for i in range(len(df_tn_bom['production_budget'])):
    row = df_tn_bom['production_budget'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_bom['production_budget'][i]=row_num

for i in range(len(df_tn_bom['worldwide_gross'])):
    row = df_tn_bom['worldwide_gross'][i]
    row = row.replace(',', '').replace('$','')
```

```
    row_num = float(row)
    df_tn_bom['worldwide_gross'][i]=row_num

#df_tn_bom['diff'] =␣
 ↪df_tn_bom['bom_domestic_gross']-df_tn_bom['tn_domestic_gross']
#df_tn_bom.loc[df_tn_bom['diff']==max(df_tn_bom['diff'])]
#df_tn_bom.sort_values('diff').tail(30)
df_tn_bom['domestic_revenue'] = df_tn_bom['domestic_gross'] -␣
 ↪df_tn_bom['production_budget']
df_tn_bom['worldwide_revenue'] = df_tn_bom['worldwide_gross'] -␣
 ↪df_tn_bom['production_budget']
df_tn_bom['ROI_domestic'] = df_tn_bom['domestic_revenue']/
 ↪df_tn_bom['production_budget']*100
df_tn_bom['ROI_worldwide'] = df_tn_bom['worldwide_revenue']/
 ↪df_tn_bom['production_budget']*100
df_tn_bom.drop(df_tn_bom.loc[df_tn_bom['ROI_worldwide']<=(-99.0)].index,␣
 ↪inplace=True)
df_tn_bom.sort_values('ROI_worldwide')
```

```
<ipython-input-59-da7ef484df03>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_bom['domestic_gross'][i]=row_num
<ipython-input-59-da7ef484df03>:21: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_bom['production_budget'][i]=row_num
<ipython-input-59-da7ef484df03>:27: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_bom['worldwide_gross'][i]=row_num
```

[59]:

```
                                 title  year  month   studio production_budget  \
1102                           13 Sins  2014      4     RTWC             4e+06
834                 The Last Godfather  2011      4    RAtt.          1.34e+07
1202  They Will Have to Kill Us First  2016      3      BBC            600000
729                        The Tempest  2010     12    Mira.             2e+07
953                       Strangerland  2015      7      Alc             1e+07
…                                    …   …     …       …                 …
1115              Paranormal Activity 2  2010     10     Par.             3e+06
1177                         Unfriended  2015      4     Uni.             1e+06
```

```
1171                          Insidious  2011      4       FD            1.5e+06
1176                   The Devil Inside  2012      1     Par.              1e+06
1212                        The Gallows  2015      7  WB (NL)             100000

     domestic_gross worldwide_gross domestic_revenue worldwide_revenue  \
1102           9134           47552      -3.99087e+06      -3.95245e+06
834          164247          164247      -1.32358e+07      -1.32358e+07
1202              0            7943           -600000           -592057
729          277943          277943      -1.97221e+07      -1.97221e+07
953           17472          161097      -9.98253e+06       -9.8389e+06
…               …               …                …                 …
1115    8.47529e+07     1.77512e+08       8.17529e+07       1.74512e+08
1177    3.27896e+07     6.43642e+07       3.17896e+07       6.33642e+07
1171    5.40092e+07     9.98709e+07       5.25092e+07       9.83709e+07
1176    5.32629e+07     1.01759e+08       5.22629e+07       1.00759e+08
1212    2.27644e+07     4.16565e+07       2.26644e+07       4.15565e+07

     ROI_domestic ROI_worldwide
1102     -99.7716      -98.8112
834      -98.7743      -98.7743
1202         -100      -98.6762
729      -98.6103      -98.6103
953      -99.8253       -98.389
…             …             …
1115       2725.1       5817.07
1177      3178.96       6336.42
1171      3500.61       6558.06
1176      5226.29       10075.9
1212      22664.4       41556.5

[1208 rows x 11 columns]
```

[60]:

```
#Creating additional table out of this join
df_tn_bom.to_sql('ROI_tn_bom', conn, if_exists='replace', index = False)
```

[61]:

```
display_tableDF('ROI_tn_bom').info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1208 entries, 0 to 1207
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   title              1208 non-null   object
 1   year               1208 non-null   int64
 2   month              1208 non-null   int64
 3   studio             1208 non-null   object
 4   production_budget  1208 non-null   float64
 5   domestic_gross     1208 non-null   float64
```

```
 6   worldwide_gross    1208 non-null   float64
 7   domestic_revenue   1208 non-null   float64
 8   worldwide_revenue  1208 non-null   float64
 9   ROI_domestic       1208 non-null   float64
 10  ROI_worldwide      1208 non-null   float64
dtypes: float64(7), int64(2), object(2)
memory usage: 103.9+ KB
```

[62]:
```
conn.commit()
```

5.7.2 imdb_title_basics with tn_movie_budget into df_tn_imdb DataFrame and a new table ROI_tn_imdb

---

- These tables need to be joined on two column, title and year, because there are movies with the same title but different years on release
- I dropped the rows that have ROI < -99% due to unreliability of the data
- Data from this process is going to be used to identify the **most successful genres** (the highest median ROI is the measurement of success) and overall distribution of ROI (domestic and world wide) as box plots per year and and the most successful months of the year (highest median ROI per month of the year)
- Additional visual will include runtime (buckets) with their average ROI per year (the idea is that over time shorter runtime translates into more profitability
- The DataFrame with all financial measure is going to be saved for future use and visuals, there are **1388** record matched ***

[63]:
```
q="""SELECT DISTINCT tconst, primary_title 'title', start_year 'year', month,␣
↪runtime_minutes, production_budget, tn.domestic_gross 'domestic_gross',
     worldwide_gross FROM imdb_title_basics imdb
     JOIN tn_movie_budgets tn
     ON (imdb.primary_title=tn.movie) AND (imdb.start_year=tn.year)"""

df_tn_imdb = table_query(q)

for i in range(len(df_tn_imdb['domestic_gross'])):
    row = df_tn_imdb['domestic_gross'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_imdb['domestic_gross'][i]=row_num

for i in range(len(df_tn_imdb['production_budget'])):
    row = df_tn_imdb['production_budget'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_imdb['production_budget'][i]=row_num

for i in range(len(df_tn_imdb['worldwide_gross'])):
```

```
    row = df_tn_imdb['worldwide_gross'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_imdb['worldwide_gross'][i]=row_num

df_tn_imdb['domestic_revenue'] = df_tn_imdb['domestic_gross'] -␣
 ↪df_tn_imdb['production_budget']
df_tn_imdb['worldwide_revenue'] = df_tn_imdb['worldwide_gross'] -␣
 ↪df_tn_imdb['production_budget']
df_tn_imdb['ROI_domestic'] = df_tn_imdb['domestic_revenue']/
 ↪df_tn_imdb['production_budget']*100
df_tn_imdb['ROI_worldwide'] = df_tn_imdb['worldwide_revenue']/
 ↪df_tn_imdb['production_budget']*100
df_tn_imdb.drop(df_tn_imdb.loc[df_tn_imdb['ROI_worldwide']<=(-99.0)].index,␣
 ↪inplace=True)
#df_tn_imdb.sort_values('ROI_worldwide')
df_tn_imdb
```

```
<ipython-input-63-a2603e62e1d1>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_imdb['domestic_gross'][i]=row_num
<ipython-input-63-a2603e62e1d1>:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_imdb['production_budget'][i]=row_num
<ipython-input-63-a2603e62e1d1>:24: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_imdb['worldwide_gross'][i]=row_num
```

[63]:

```
         tconst                           title  year  month  \
1     tt0359950  The Secret Life of Walter Mitty  2013     12
2     tt0365907      A Walk Among the Tombstones  2014      9
3     tt0369610                   Jurassic World  2015      6
4     tt0376136                    The Rum Diary  2011     10
5     tt0383010                 The Three Stooges  2012      4
…           …                           …     …     …
1537  tt8155288               Happy Death Day 2U  2019      2
1541  tt8632862                 Fahrenheit 11/9  2018      9
1543  tt9024106                        Unplanned  2019      3
```

```
1544  tt9347476                         Believe  2016     12
1545  tt9889072                     The Promise  2017      4

      runtime_minutes production_budget domestic_gross worldwide_gross  \
1               114.0            9.1e+07    5.82368e+07     1.87861e+08
2               114.0            2.8e+07    2.60177e+07     6.21086e+07
3               124.0           2.15e+08    6.52271e+08     1.64885e+09
4               119.0            4.5e+07    1.31098e+07     2.15447e+07
5                92.0              3e+07    4.43382e+07     5.40522e+07
…                 …                 …              …               …
1537            100.0              9e+06     2.8051e+07     6.41795e+07
1541            128.0              5e+06    6.35231e+06     6.65372e+06
1543            106.0              6e+06    1.81076e+07     1.81076e+07
1544              NaN            3.5e+06         890303          890303
1545              NaN              9e+07    8.22429e+06     1.05514e+07

     domestic_revenue worldwide_revenue ROI_domestic ROI_worldwide
1         -3.27632e+07       9.68612e+07     -36.0035       106.441
2         -1.98232e+06       3.41086e+07      -7.0797       121.816
3          4.37271e+08       1.43385e+09      203.382       666.909
4         -3.18902e+07      -2.34553e+07     -70.8671      -52.1228
5          1.43382e+07       2.40522e+07      47.7941       80.1742
…                 …                 …           …            …
1537        1.9051e+07       5.51795e+07      211.678       613.106
1541       1.35231e+06       1.65372e+06      27.0461       33.0743
1543       1.21076e+07       1.21076e+07      201.794       201.794
1544       -2.6097e+06       -2.6097e+06     -74.5628      -74.5628
1545      -8.17757e+07      -7.94486e+07     -90.8619      -88.2762

[1388 rows x 12 columns]
```

[64]:
```python
#Creating a new table
df_tn_imdb.to_sql('ROI_tn_imdb', conn, if_exists='replace', index = False)
```

[65]:
```python
conn.commit()
```

6 Data Modeling

The analysis below is intended to answer four main questions:

- What studios are most successful in movie production business?
- Does runtime of a movie affect the movie's profitability?
- How does the timing of a movie release affect its' profitability?
- What movie genres are most profitable considering Return of Investment measurement? ***

6.1 Descriptive analysis of studio profitability data and Visualization of the results

6.1.1 Descriptive analysis of Domestic ROI of movies produced by different studios

[66]:
```
# How many unique studios are in TheNumbers database
len(df_tn_bom['studio'].unique())
```

[66]: 95

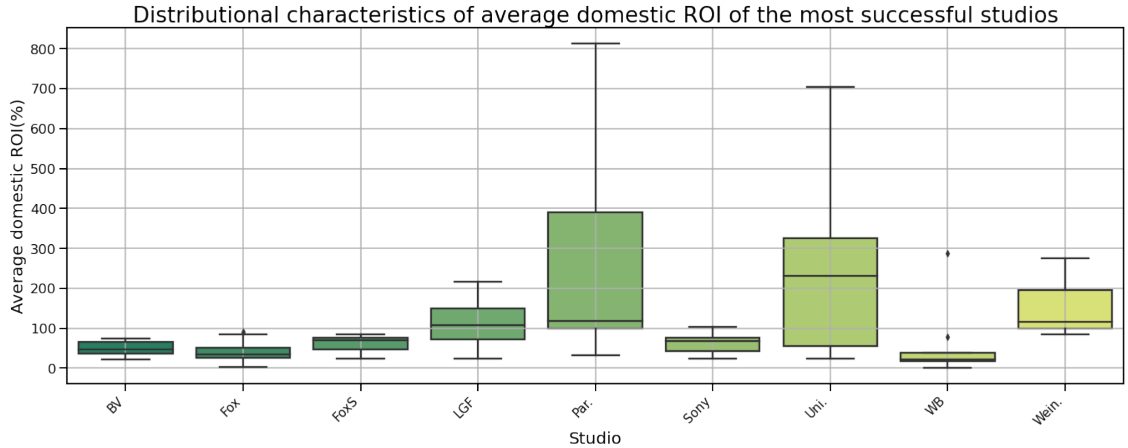
[67]:
```
q="""SELECT count(*) num_movies, avg(ROI_domestic) ROI, year,
     studio FROM ROI_tn_bom GROUP BY studio, year"""
df_studios_d=table_query(q)
```

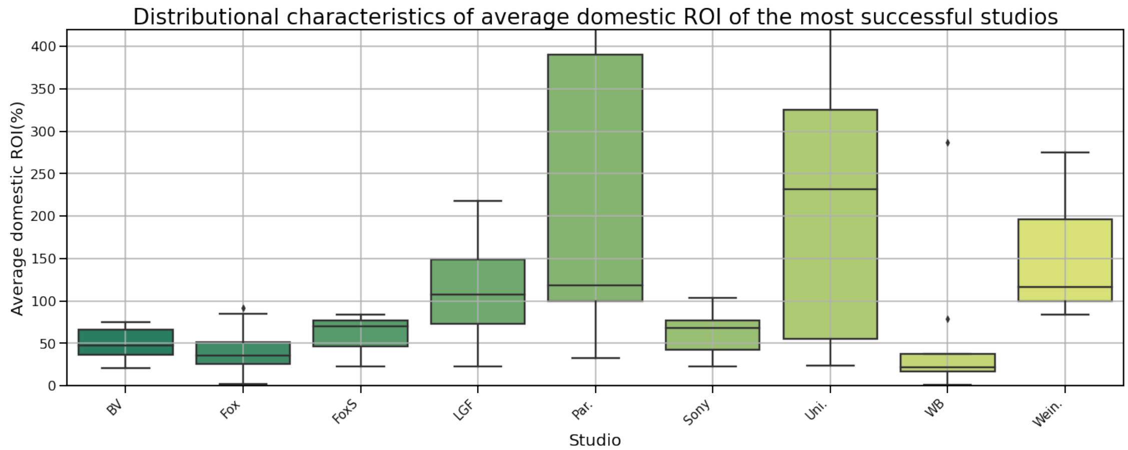
[68]:
```
#Only studios with a number of movies per each year of the period 2009-2018 are␣
 ↪being considered in this segment
#From this pool studios with very low profitability are removed to make␣
 ↪visualization more prominent
#I am also dropping the records from several studios that exibit either very␣
 ↪low ROI values or
#made movies over too few years in the studies period. The decision is made to␣
 ↪clean up the visualization

df_studios_d.drop(df_studios_d.loc[df_studios_d['num_movies']<=6].index,␣
 ↪inplace=True)
df_studios_d.drop(df_studios_d.loc[df_studios_d['studio']=='IFC'].index,␣
 ↪inplace=True)
df_studios_d.drop(df_studios_d.loc[df_studios_d['studio']=='LG/S'].index,␣
 ↪inplace=True)
df_studios_d.drop(df_studios_d.loc[df_studios_d['studio']=='Magn.'].index,␣
 ↪inplace=True)
df_studios_d.drop(df_studios_d.loc[df_studios_d['studio']=='RAtt.'].index,␣
 ↪inplace=True)
df_studios_d.drop(df_studios_d.loc[df_studios_d['studio']=='Rela.'].index,␣
 ↪inplace=True)
df_studios_d.drop(df_studios_d.loc[df_studios_d['studio']=='SPC'].index,␣
 ↪inplace=True)
```

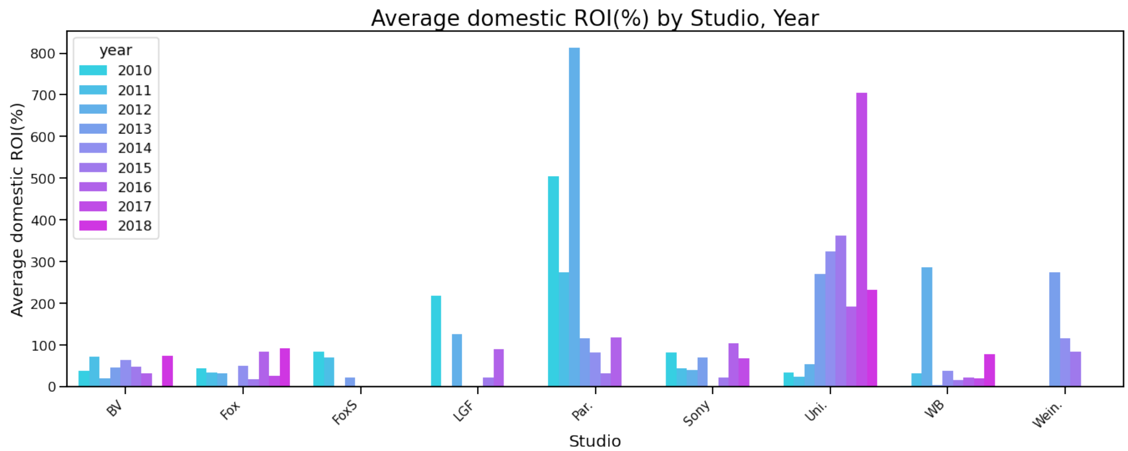
[69]:
```
sns.set_context("talk");
```

[70]:
```
fig, axes = plt.subplots(figsize=(20,25), nrows=3)
sns.boxplot(data=df_studios_d, x="studio", y= "ROI", palette='summer',␣
 ↪ax=axes[0])
sns.boxplot(data=df_studios_d, x="studio", y= "ROI", palette='summer',␣
 ↪ax=axes[1])
sns.barplot(data=df_studios_d, x="studio", y="ROI", hue="year", palette='cool',␣
 ↪ax=axes[2]);
```

```
axes[0].set_title("Distributional characteristics of average domestic ROI of␣
↪the most successful studios", fontsize=26);
axes[0].grid();
axes[0].set_ylabel('Average domestic ROI(%)', fontsize=20);
axes[0].set_xlabel('Studio', fontsize=20);
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=45, ha='right',␣
↪fontsize=15)
#axes[0].set_yticklabels(axes[0].get_yticklabels(), fontsize=15)

axes[1].set_title("Distributional characteristics of average domestic ROI of␣
↪the most successful studios", fontsize=26);
axes[1].set_ylim(0, 420);
axes[1].set_ylabel('Average domestic ROI(%)', fontsize=20);
axes[1].set_xlabel('Studio', fontsize=20);
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, ha='right',␣
↪fontsize=15)
axes[1].grid();

axes[2].set_title("Average domestic ROI(%) by Studio, Year", fontsize=26);
axes[2].set_ylabel('Average domestic ROI(%)', fontsize=20)
axes[2].set_xlabel('Studio', fontsize=20);
axes[2].set_xticklabels(axes[2].get_xticklabels(), rotation=45, ha='right',␣
↪fontsize=15)


plt.tight_layout(pad=3)
sns.set_context("talk");
```







The next step is to investigate worldwide profitability of the movies in the database by using the same approach as above.

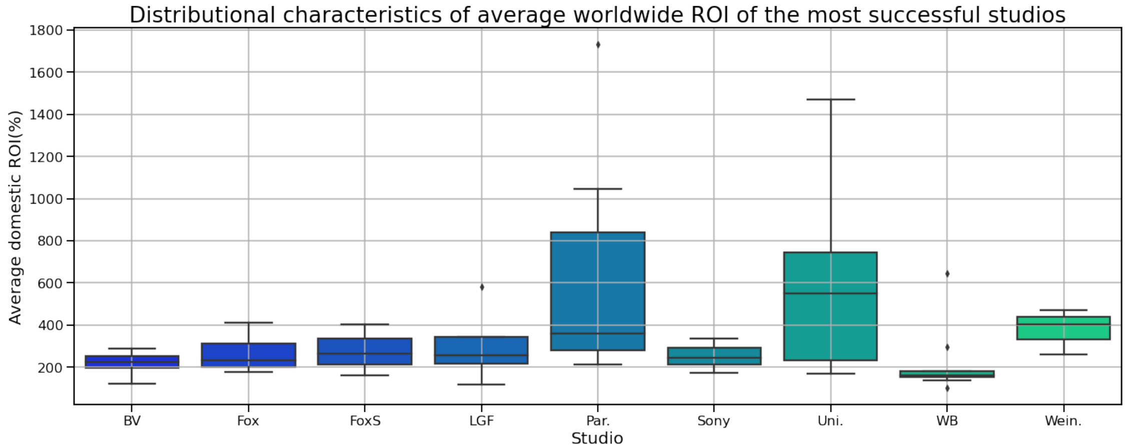
6.1.2 Descriptive analysis of Worldwide ROI of movies produced by different studios

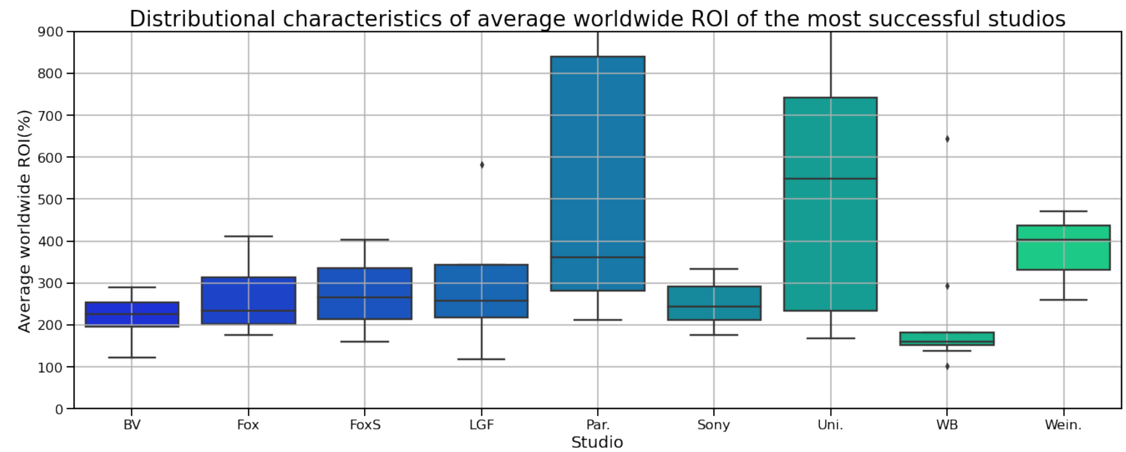
[71]:
```
q="""SELECT count(*) num_movies, avg(ROI_worldwide) ROI, year,
     studio FROM ROI_tn_bom GROUP BY studio, year"""
df_studios_w=table_query(q)
```

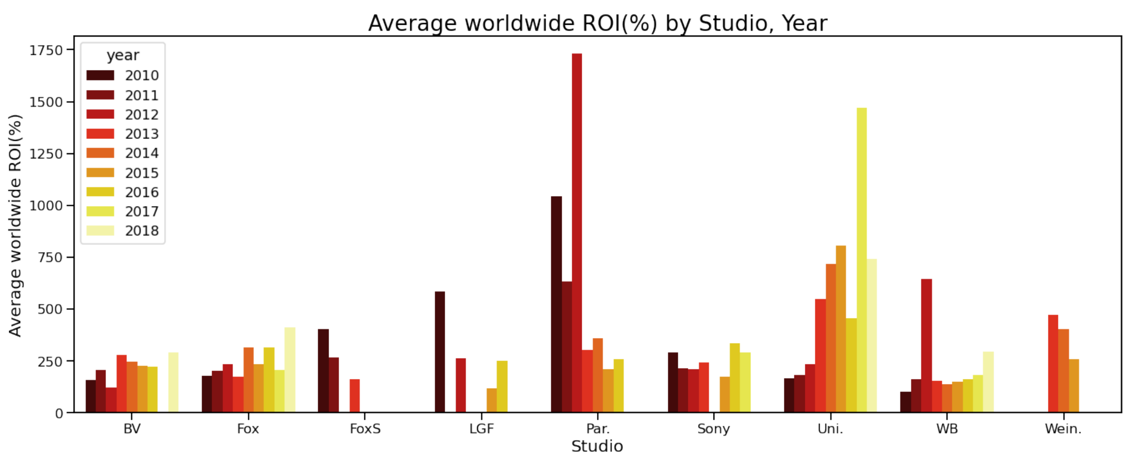
[72]:
```
#Only studios with a number of movies per each year of the period 2009-2018 are␣
↪being considered in this segment
#From this pool studios with very low profitability are removed to make␣
↪visualization more prominent
df_studios_w.drop(df_studios_w.loc[df_studios_w['num_movies']<=6].index,␣
↪inplace=True)
df_studios_w.drop(df_studios_w.loc[df_studios_w['studio']=='IFC'].index,␣
↪inplace=True)
df_studios_w.drop(df_studios_w.loc[df_studios_w['studio']=='LG/S'].index,␣
↪inplace=True)
df_studios_w.drop(df_studios_w.loc[df_studios_w['studio']=='Magn.'].index,␣
↪inplace=True)
df_studios_w.drop(df_studios_w.loc[df_studios_w['studio']=='RAtt.'].index,␣
↪inplace=True)
df_studios_w.drop(df_studios_w.loc[df_studios_w['studio']=='Rela.'].index,␣
↪inplace=True)
df_studios_w.drop(df_studios_w.loc[df_studios_w['studio']=='SPC'].index,␣
↪inplace=True)
```

[73]:
```
fig, axes = plt.subplots(figsize=(20,25), nrows=3)
sns.boxplot(data=df_studios_w, x="studio", y= "ROI", palette='winter',␣
↪ax=axes[0])
sns.boxplot(data=df_studios_w, x="studio", y= "ROI", palette='winter',␣
↪ax=axes[1])
sns.barplot(data=df_studios_w, x="studio", y="ROI", hue="year", palette='hot',␣
↪ax=axes[2]);

axes[0].set_title("Distributional characteristics of average worldwide ROI of␣
↪the most successful studios", fontsize=26);
axes[0].grid();
axes[0].set_ylabel('Average domestic ROI(%)', fontsize=20);
axes[0].set_xlabel('Studio', fontsize=20);


axes[1].set_title("Distributional characteristics of average worldwide ROI of␣
↪the most successful studios", fontsize=26);
axes[1].set_ylim(0, 900);
axes[1].set_ylabel('Average worldwide ROI(%)', fontsize=20);
axes[1].set_xlabel('Studio', fontsize=20);
axes[1].grid();
```

```
axes[2].set_title("Average worldwide ROI(%) by Studio, Year", fontsize=26);
axes[2].set_ylabel('Average worldwide ROI(%)', fontsize=20)
axes[2].set_xlabel('Studio', fontsize=20);


plt.tight_layout(pad=3)
sns.set_context("talk");
```







Conclusion of the analysis of the data above, based on Box-Office Mojo and TheNumbers financial data: Universal Studios, Paramount Pictures, The Weinstein Company and Lions Gate Films Corporation studios (in that order) have been the most successful studios over the course of the last 9 years. The median of the average domestic ROI for these studios is above 100 % and lower and upper quartiles are between 50% and 400% with wiskers of all four never going below the red line. The same tendencies can be observed in the analysis of worldwide profitability of movies by major players in the industry. Universal Studios, Paramount Picture, The Weinstein Company and Lions Gate Films Corporation studios remain the most successful American studios on the world scene. However, all of the studios under consideration maintained average ROI above 100%.

6.2 Descriptive analysis of runtime changes over the last 10 years and its' possible correlation with profitability

[74]:
```
q="""SELECT  year, AVG(runtime_minutes) average_runtime FROM ROI_tn_imdb GROUP␣
↪BY year"""
df_runtime=table_query(q)
df_runtime
```

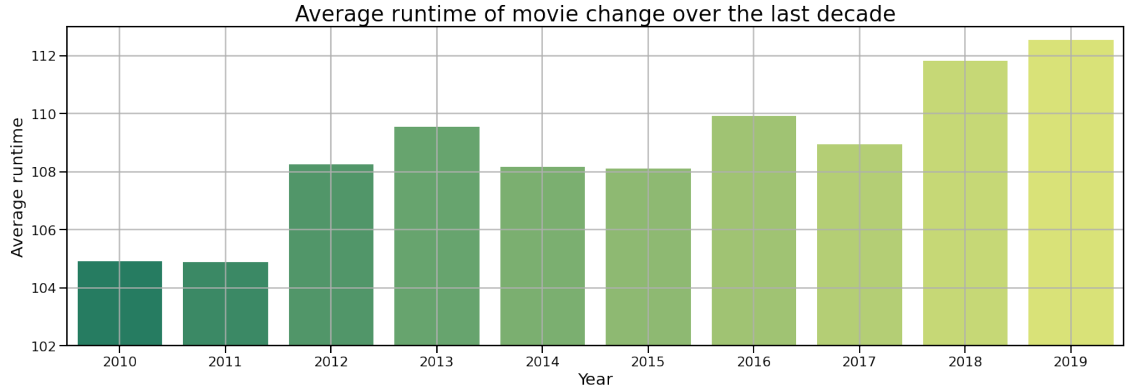
[74]:

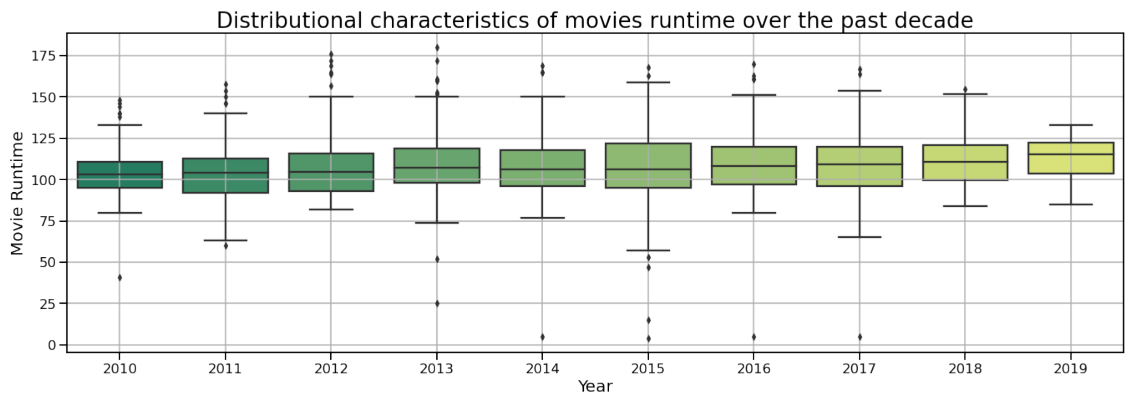
	year	average_runtime
0	2010	104.907407
1	2011	104.884393
2	2012	108.260563
3	2013	109.537037
4	2014	108.159236
5	2015	108.112500
6	2016	109.915033
7	2017	108.932203
8	2018	111.818966
9	2019	112.531250

[75]:
```
df_ROI_runtime= display_tableDF('ROI_tn_imdb')
```

[76]:
```
fig, axes = plt.subplots(figsize=(20,15), nrows=2)
sns.barplot(data=df_runtime, x="year", y="average_runtime",␣
↪palette='summer',ax=axes[0]);

axes[0].set_ylim(102, 113);
axes[0].set_title("Average runtime of movie change over the last decade",␣
↪fontsize=26);
axes[0].set_ylabel('Average runtime', fontsize=20);
axes[0].set_xlabel('Year', fontsize=20);
axes[0].grid();

sns.boxplot(data=df_ROI_runtime, x="year", y="runtime_minutes",␣
↪palette='summer',ax=axes[1]);

axes[1].set_title("Distributional characteristics of movies runtime over the␣
↪past decade", fontsize=26);
axes[1].set_ylabel('Movie Runtime', fontsize=20);
axes[1].set_xlabel('Year', fontsize=20);
```

```
axes[1].grid();

plt.tight_layout(pad=3)
```





Conclusion of the analysis of the data above: Though the average runtime of a movie within the industry grew between years 2010 and 2019, the tendency is very weakly pronounced and is within the margin of error

6.3 ROI statistics evaluation

[77]:
```
#Describing statistical measures of ROI (domestically and worldwide) based on␣
↪the data in TN and IMBD joined data
q="""SELECT  year, ROI_domestic, ROI_worldwide FROM ROI_tn_imdb"""
df_ROI_stat=table_query(q)
df_ROI_stat.describe()
```

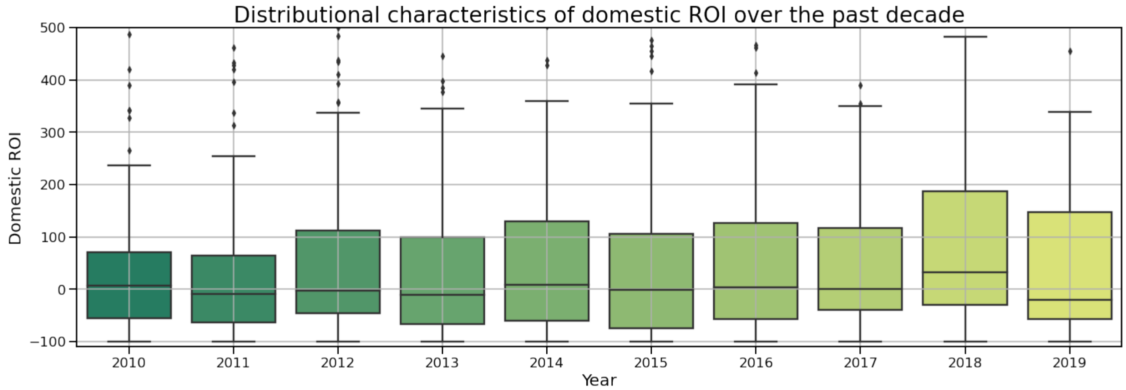
[77]:

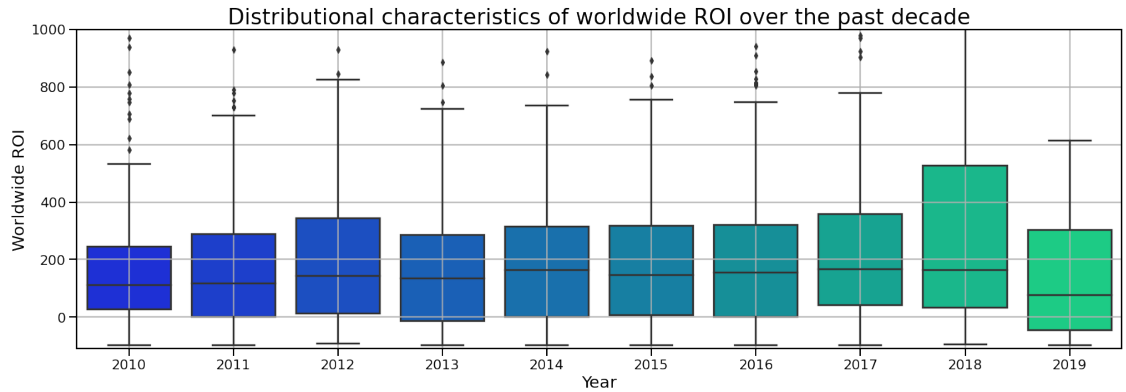
	year	ROI_domestic	ROI_worldwide
count	1388.000000	1388.000000	1388.000000
mean	2013.888329	100.937681	304.048304
std	2.612389	681.511253	1248.468460
min	2010.000000	-100.000000	-98.906170

```
25%    2012.000000    -55.890353       8.420845
50%    2014.000000      2.602221     135.418452
75%    2016.000000    110.078026     320.349247
max    2019.000000  22664.410000   41556.474000
```

[78]:

```
fig, axes = plt.subplots(figsize=(20,15), nrows=2)
sns.boxplot(data=df_ROI_stat, x="year", y="ROI_domestic",␣
↪palette='summer',ax=axes[0]);

axes[0].set_ylim(-110, 500);
axes[0].set_title("Distributional characteristics of domestic ROI over the past␣
↪decade", fontsize=26);
axes[0].set_ylabel('Domestic ROI', fontsize=20);
axes[0].set_xlabel('Year', fontsize=20);
axes[0].grid();

sns.boxplot(data=df_ROI_stat, x="year", y="ROI_worldwide",␣
↪palette='winter',ax=axes[1]);

axes[1].set_ylim(-110, 1000);
axes[1].set_title("Distributional characteristics of worldwide ROI over the␣
↪past decade", fontsize=26);
axes[1].set_ylabel('Worldwide ROI', fontsize=20);
axes[1].set_xlabel('Year', fontsize=20);
axes[1].grid();

plt.tight_layout(pad=3)
```





Conclusion of the analysis of the data above: Though the distribution of domestic ROI shows that the median of it over the years is remaining close to 0%, the overall tendency is shifted toward the upper quartile and the mean is close to 100% The distribution of worldwide ROI assures a more promising outcome for newcoming studios, with lower and upper quartiles above 0% and the mean of the distribution slightly above 300%. A customer should be advised to expand into foreign markets to increase their overall profit. Additional analysis is suggested for the most promising foreign markets (needs more data)

6.4 Descriptive analysis of month of release/ROI correlation

6.4.1 Analysis based on joined ROI_tn_imdb table

[79]:
```
#creating a DataFrame out of TN IMDB data

q="""SELECT  month, ROI_domestic, ROI_worldwide FROM ROI_tn_imdb"""
df_ROI_stat_month=table_query(q)
df_ROI_stat_month
```

[79]:

	month	ROI_domestic	ROI_worldwide
0	12	-36.003475	106.440860
1	9	-7.079696	121.816382

```
2        6    203.381686    666.909239
3       10    -70.867078    -52.122818
4        4     47.794080     80.174163
…      …          …             …
1383     2    211.678278    613.105500
1384     9     27.046120     33.074300
1385     3    201.793683    201.793683
1386    12    -74.562771    -74.562771
1387     4    -90.861902    -88.276203

[1388 rows x 3 columns]
```

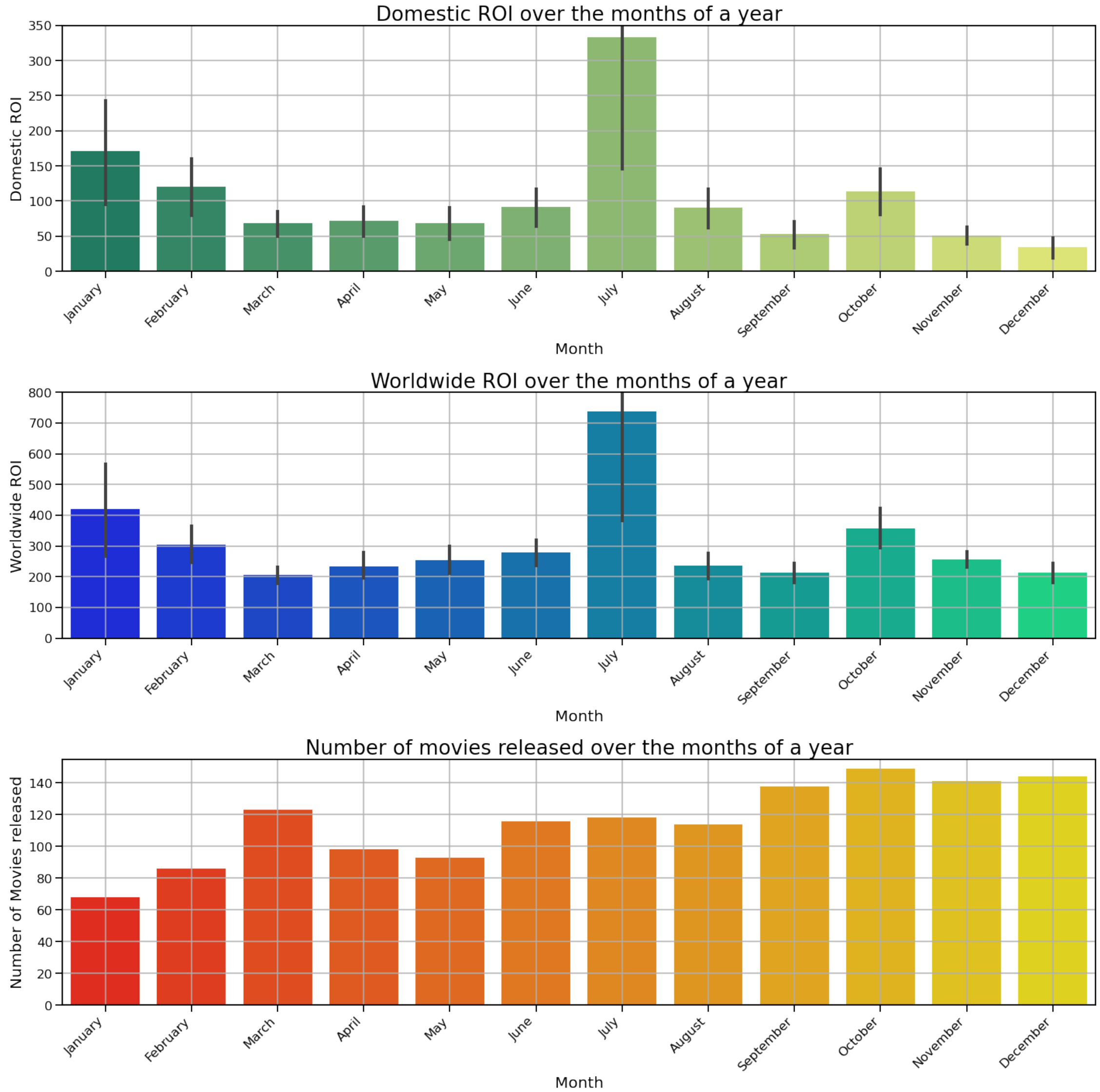
[80]:
```
#Replacing month numbers by their names for better visualization

q="""SELECT  month, count(*) num_movies FROM ROI_tn_imdb GROUP by month"""
df_num_month=table_query(q)
df_num_month

months={1:'January', 2: 'February', 3:'March', 4:'April', 5: 'May', 6: 'June',␣
↪7: 'July', 8: 'August',
         9: 'September', 10: 'October', 11: 'November', 12: 'December'}
df_num_month['month']=df_num_month['month'].map(months)
df_num_month
```

[80]:

	month	num_movies
0	January	68
1	February	86
2	March	123
3	April	98
4	May	93
5	June	116
6	July	118
7	August	114
8	September	138
9	October	149
10	November	141
11	December	144

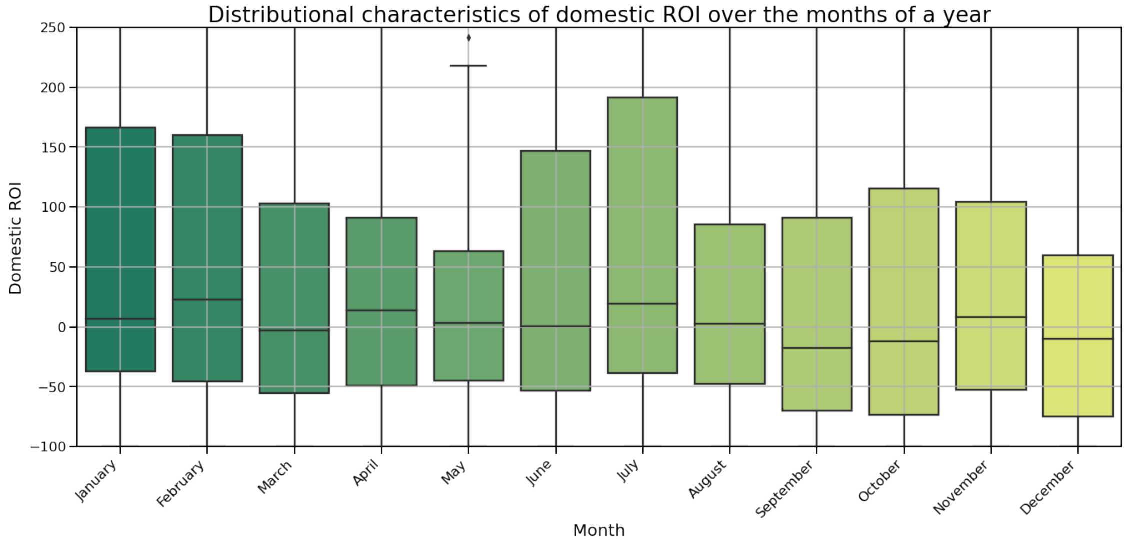
[81]:
```
fig, axes = plt.subplots(figsize=(20,20), nrows=3)
sns.barplot(data=df_ROI_stat_month, x="month", y="ROI_domestic",␣
↪palette='summer',ax=axes[0], ci=65);

axes[0].set_ylim(0, 350);
axes[0].set_title("Domestic ROI over the months of a year", fontsize=26);
axes[0].set_ylabel('Domestic ROI', fontsize=20);
axes[0].set_xlabel('Month', fontsize=20);
```

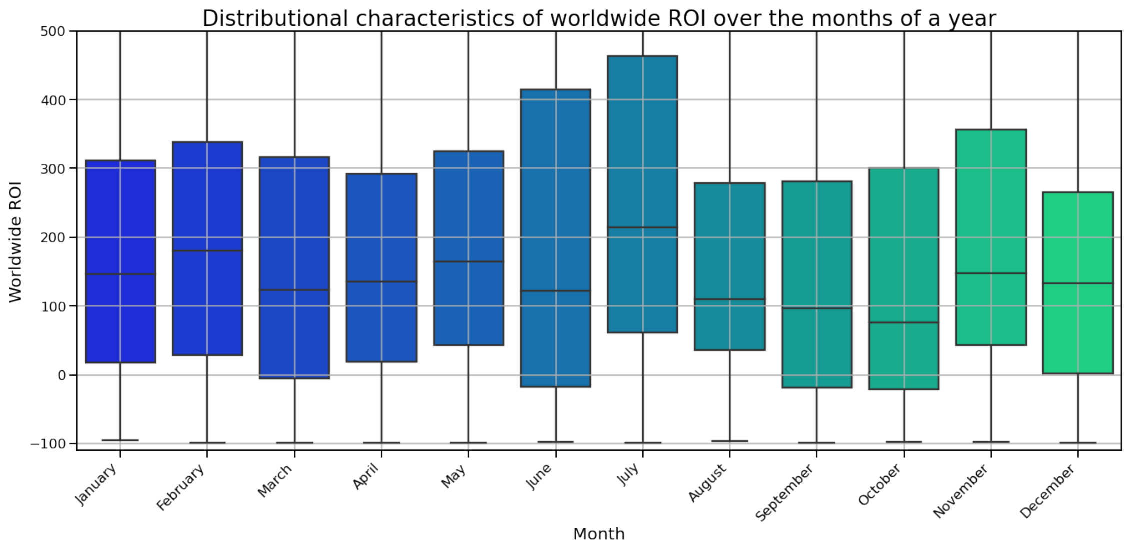
```
axes[0].set_xticklabels(['January', 'February','March', 'April', 'May', 'June',␣
↪'July', 'August',
         'September', 'October', 'November', 'December'], rotation=45,␣
↪ha='right')
axes[0].grid();

sns.barplot(data=df_ROI_stat_month, x="month", y="ROI_worldwide",␣
↪palette='winter',ax=axes[1], ci=65);

axes[1].set_ylim(0, 800);
axes[1].set_title('Worldwide ROI over the months of a year', fontsize=26);
axes[1].set_ylabel('Worldwide ROI', fontsize=20);
axes[1].set_xlabel('Month', fontsize=20);
axes[1].set_xticklabels(['January', 'February','March', 'April', 'May', 'June',␣
↪'July', 'August',
         'September', 'October', 'November', 'December'], rotation=45,␣
↪ha='right')
axes[1].grid();

sns.barplot(data=df_num_month, x="month", y="num_movies",␣
↪palette='autumn',ax=axes[2], ci=65);

axes[2].set_ylim(0, 155);
axes[2].set_title("Number of movies released over the months of a year",␣
↪fontsize=26);
axes[2].set_ylabel('Number of Movies released', fontsize=20);
axes[2].set_xlabel('Month', fontsize=20);
axes[2].set_xticklabels(axes[2].get_xticklabels(), rotation=45, ha='right')
axes[2].grid();

plt.tight_layout()
```



[82]:
```
# This visualization is for my own evaluation of the statistics of ROI values and to confirm the results above

fig, axes = plt.subplots(figsize=(20,20), nrows=2)
sns.boxplot(data=df_ROI_stat_month, x="month", y="ROI_domestic", palette='summer',ax=axes[0]);

axes[0].set_ylim(-100, 250);
axes[0].set_title("Distributional characteristics of domestic ROI over the months of a year", fontsize=26);
axes[0].set_ylabel('Domestic ROI', fontsize=20);
axes[0].set_xlabel('Month', fontsize=20);
```

```
axes[0].set_xticklabels(['January', 'February','March', 'April', 'May', 'June',␣
↪'July', 'August',
         'September', 'October', 'November', 'December'], rotation=45,␣
↪ha='right')
axes[0].grid();

sns.boxplot(data=df_ROI_stat_month, x="month", y="ROI_worldwide",␣
↪palette='winter',ax=axes[1]);

axes[1].set_ylim(-110, 500);
axes[1].set_title("Distributional characteristics of worldwide ROI over the␣
↪months of a year", fontsize=26);
axes[1].set_ylabel('Worldwide ROI', fontsize=20);
axes[1].set_xlabel('Month', fontsize=20);
axes[1].set_xticklabels(['January', 'February','March', 'April', 'May', 'June',␣
↪'July', 'August',
         'September', 'October', 'November', 'December'], rotation=45,␣
↪ha='right')
axes[1].grid();

plt.tight_layout(pad=3)
```





The data above suggests that there might be a negative correlation between the number of the movies released and the ROI (domestic and worldwide) which might be related to the choice of released movies customers have in a particular month as well as holidays and weather in each month

6.4.2 Exploring correlations between average ROIs (domestic and worldwide)

[83]:
```
# Bringing up a correlation matrix to confirm or otherwise the conclusion drawn␣
↪above
q="""SELECT  month, AVG(ROI_domestic) AVG_dom_ROI, AVG(ROI_worldwide)␣
↪AVG_ww_ROI, count(*) num_movies FROM ROI_tn_imdb GROUP by month"""
df_ROI_month_num=table_query(q)
df_ROI_month_num
df_ROI_month_num.corr(method='pearson')
```

[83]:

	month	AVG_dom_ROI	AVG_ww_ROI	num_movies
month	1.000000	-0.251537	-0.114142	0.882608
AVG_dom_ROI	-0.251537	1.000000	0.980399	-0.274592
AVG_ww_ROI	-0.114142	0.980399	1.000000	-0.162320
num_movies	0.882608	-0.274592	-0.162320	1.000000

There are negative correlations indeed. They are not very strong ones and the correlation with the average ROI is less pronounced abroad. The fact of the difference might be related to the fact that all three factors, number of released movies, holidays and weather, domestically and abroad are different and the picture is less pronounced

Visual exploration of the correlations between average ROIs (domestic and worldwide) Due to the fact that visual information is consumed by general public easier, the correlation is presented in a visual form.

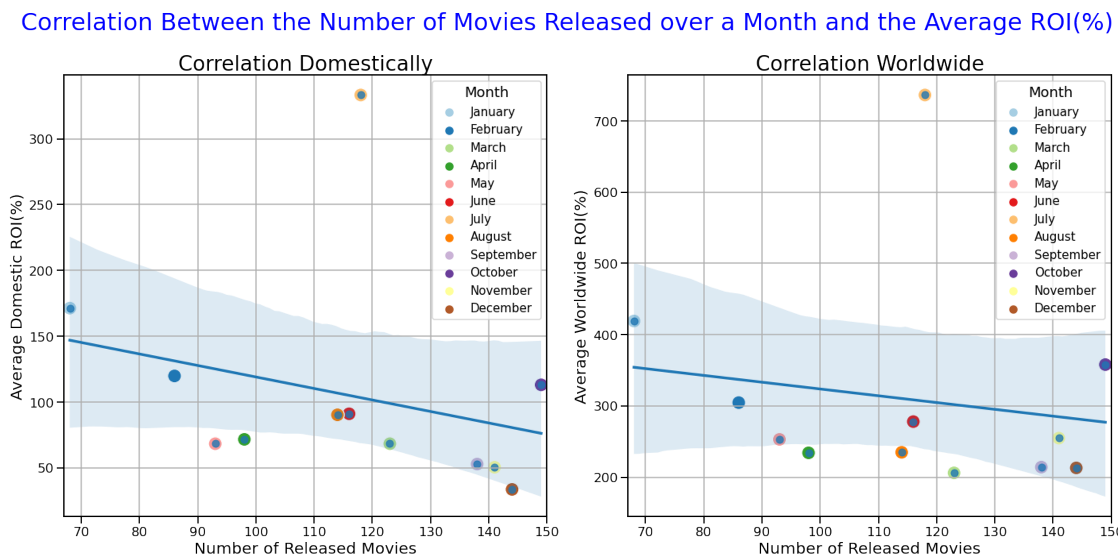
[84]:
```
months={1:'January', 2: 'February', 3:'March', 4:'April', 5: 'May', 6: 'June',␣
↪7: 'July', 8: 'August',
                    9: 'September', 10: 'October', 11: 'November', 12: 'December'}
df_ROI_month_num['month']=df_ROI_month_num['month'].map(months)
df_ROI_month_num
```

[84]:

	month	AVG_dom_ROI	AVG_ww_ROI	num_movies
0	January	171.390237	419.234690	68
1	February	119.888883	304.706920	86
2	March	68.399687	206.108429	123
3	April	71.700163	234.234485	98
4	May	68.384754	253.086232	93
5	June	91.143942	278.057627	116
6	July	333.312316	736.334952	118
7	August	90.342197	234.981215	114
8	September	52.931118	214.220586	138
9	October	113.122930	358.019641	149
10	November	50.515662	254.869722	141
11	December	33.693626	213.117295	144

[85]:
```
fig, axes = plt.subplots(figsize=(20,10), ncols=2)
sns.scatterplot(data=df_ROI_month_num, x="num_movies", y="AVG_dom_ROI", hue␣
↪='month', palette='Paired', s=300,
                      ax=axes[0])
sns.scatterplot(data=df_ROI_month_num, x="num_movies", y="AVG_ww_ROI",␣
↪hue='month', palette='Paired', s=300,
                   ax=axes[1])

sns.regplot(data=df_ROI_month_num, x="num_movies", y="AVG_dom_ROI", ax=axes[0])
sns.regplot(data=df_ROI_month_num, x="num_movies", y="AVG_ww_ROI", ax=axes[1])

axes[0].set_title("Correlation Domestically", fontsize=26);
```

```
axes[0].set_xlabel('Number of Released Movies', fontsize=20)
axes[0].set_ylabel('Average Domestic ROI(%)', fontsize=20)
axes[0].grid()
axes[0].set_xlim(67, 150);
axes[0].legend(title='Month', loc='upper right', fontsize=15)

axes[1].set_title("Correlation Worldwide", fontsize=26);
axes[1].set_ylabel('Average Worldwide ROI(%)', fontsize=20);
axes[1].set_xlabel('Number of Released Movies', fontsize=20);
axes[1].grid();
axes[1].set_xlim(67, 150);
axes[1].legend(title='Month', loc='upper right', fontsize=15)

plt.suptitle("Correlation Between the Number of Movies Released over a Month␣
↪and the Average ROI(%)", size=30, c="Blue")
plt.tight_layout()
```



Conclusion of the analysis of the data above: The negative correlation between the number of movies released over a time period suggests that the customer should consider this factor when planning a release of their movie. The only exception is a month of July, an outlier among other months of a year. It seems that no matter how many movies are in the theaters, it is going to be more profitable than in other months of a year.

6.5 Descriptive analysis of genre effect on movies profitability and Visualization of the results

6.5.1 Exploration of Single Genre effect on ROI of a movie (domestic and worldwide)

In this section we are going to explore how profitable movies of a particular genre are based on the data in IMDB and TN databases.

[86]:
```
#Joining IMDB and TN databases with genres as a column

q="""SELECT DISTINCT tconst, primary_title title, genres, start_year year,␣
↪month, runtime_minutes,
     production_budget, tn.domestic_gross domestic_gross,
     worldwide_gross FROM imdb_title_basics imdb
     JOIN tn_movie_budgets tn
     ON (imdb.primary_title=tn.movie) AND (imdb.start_year=tn.year)"""

df_tn_imdb_genres = table_query(q)


for i in range(len(df_tn_imdb_genres['domestic_gross'])):
    row = df_tn_imdb_genres['domestic_gross'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_imdb_genres['domestic_gross'][i]=row_num

for i in range(len(df_tn_imdb_genres['production_budget'])):
    row = df_tn_imdb_genres['production_budget'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_imdb_genres['production_budget'][i]=row_num

for i in range(len(df_tn_imdb_genres['worldwide_gross'])):
    row = df_tn_imdb_genres['worldwide_gross'][i]
    row = row.replace(',', '').replace('$','')
    row_num = float(row)
    df_tn_imdb_genres['worldwide_gross'][i]=row_num

df_tn_imdb_genres['domestic_revenue'] = df_tn_imdb_genres['domestic_gross'] -␣
↪df_tn_imdb_genres['production_budget']
df_tn_imdb_genres['worldwide_revenue'] = df_tn_imdb_genres['worldwide_gross'] -␣
↪df_tn_imdb_genres['production_budget']
df_tn_imdb_genres['ROI_domestic'] = df_tn_imdb_genres['domestic_revenue']/
↪df_tn_imdb_genres['production_budget']*100
df_tn_imdb_genres['ROI_worldwide'] = df_tn_imdb_genres['worldwide_revenue']/
↪df_tn_imdb_genres['production_budget']*100
df_tn_imdb_genres.drop(df_tn_imdb_genres.
↪loc[df_tn_imdb_genres['ROI_worldwide']<=(-99.0)].index, inplace=True)
#df_tn_imdb.sort_values('ROI_worldwide')
df_tn_imdb_genres
```

```
<ipython-input-86-32ed9c593cb4>:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_imdb_genres['domestic_gross'][i]=row_num
<ipython-input-86-32ed9c593cb4>:22: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_imdb_genres['production_budget'][i]=row_num
<ipython-input-86-32ed9c593cb4>:28: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_tn_imdb_genres['worldwide_gross'][i]=row_num
```

[86]:

```
        tconst                           title        genres  year  month  \
3     tt0359950  The Secret Life of Walter Mitty    Adventure  2013     12
4     tt0359950  The Secret Life of Walter Mitty       Comedy  2013     12
5     tt0359950  The Secret Life of Walter Mitty        Drama  2013     12
6     tt0365907       A Walk Among the Tombstones      Action  2014      9
7     tt0365907       A Walk Among the Tombstones       Crime  2014      9
…           …                               …          …     …      …
3878  tt8632862                  Fahrenheit 11/9  Documentary  2018      9
3880  tt9024106                        Unplanned    Biography  2019      3
3881  tt9024106                        Unplanned        Drama  2019      3
3882  tt9347476                          Believe      Unknown  2016     12
3883  tt9889072                      The Promise        Drama  2017      4

      runtime_minutes production_budget domestic_gross worldwide_gross  \
3               114.0            9.1e+07    5.82368e+07     1.87861e+08
4               114.0            9.1e+07    5.82368e+07     1.87861e+08
5               114.0            9.1e+07    5.82368e+07     1.87861e+08
6               114.0            2.8e+07    2.60177e+07     6.21086e+07
7               114.0            2.8e+07    2.60177e+07     6.21086e+07
…                 …                  …             …               …
3878            128.0              5e+06    6.35231e+06     6.65372e+06
3880            106.0              6e+06    1.81076e+07     1.81076e+07
3881            106.0              6e+06    1.81076e+07     1.81076e+07
3882              NaN            3.5e+06         890303          890303
3883              NaN              9e+07    8.22429e+06     1.05514e+07

     domestic_revenue worldwide_revenue ROI_domestic ROI_worldwide
3        -3.27632e+07       9.68612e+07     -36.0035       106.441
```

```
4       -3.27632e+07      9.68612e+07    -36.0035       106.441
5       -3.27632e+07      9.68612e+07    -36.0035       106.441
6       -1.98232e+06      3.41086e+07     -7.0797       121.816
7       -1.98232e+06      3.41086e+07     -7.0797       121.816
…                …                …           …            …
3878      1.35231e+06     1.65372e+06     27.0461        33.0743
3880      1.21076e+07     1.21076e+07    201.794        201.794
3881      1.21076e+07     1.21076e+07    201.794        201.794
3882      -2.6097e+06     -2.6097e+06    -74.5628       -74.5628
3883     -8.17757e+07    -7.94486e+07    -90.8619       -88.2762

[3548 rows x 13 columns]
```

[87]:
```
#Creating a new table
df_tn_imdb_genres.to_sql('ROI_tn_imdb_genres', conn, if_exists='replace', index␣
↪= False)
```

[88]:
```
conn.commit()
```

[89]:
```
#How many unique genres are there?
len(df_tn_imdb_genres['genres'].unique())
```

[89]: 22

[90]:
```
q="""SELECT count(*) num_movies, avg(ROI_domestic) ROI_d, avg(ROI_worldwide)␣
↪ROI_w, genres
     FROM ROI_tn_imdb_genres GROUP BY genres"""
df_ROI_genres=table_query(q)
df_ROI_genres
```

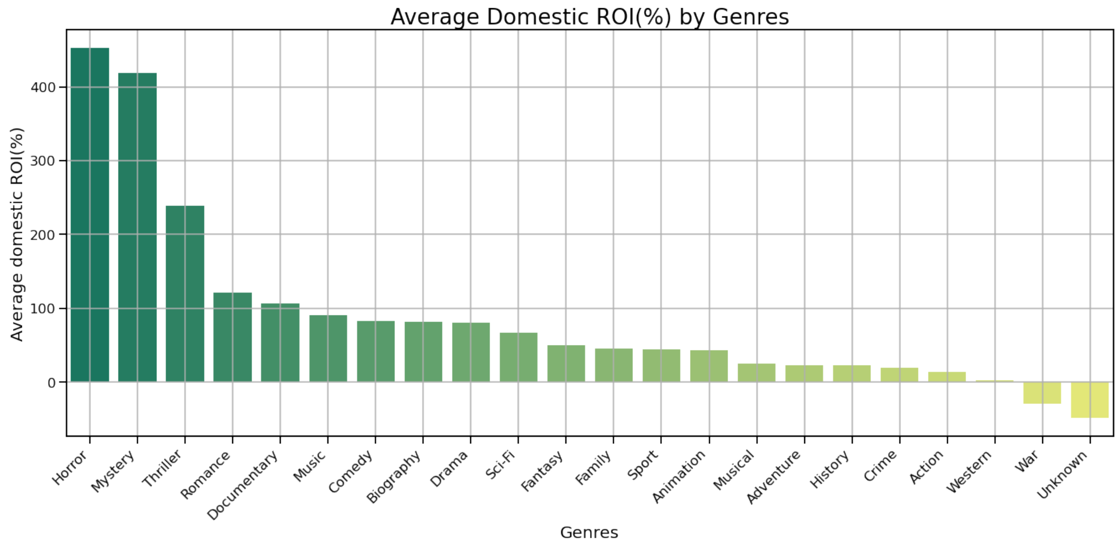
[90]:

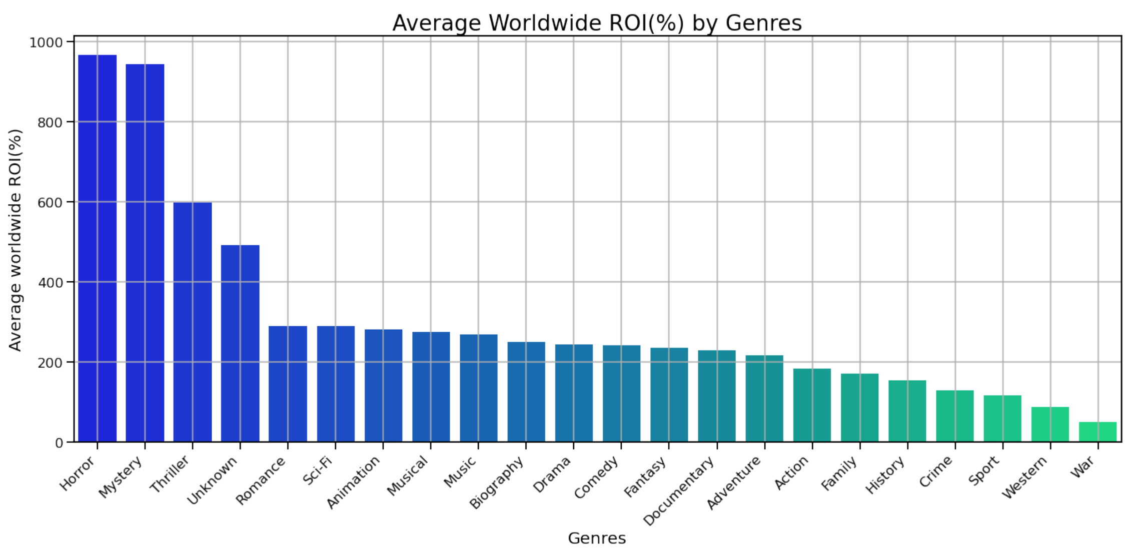
	num_movies	ROI_d	ROI_w	genres
0	410	14.016189	184.090202	Action
1	340	22.883264	217.499552	Adventure
2	97	43.555617	282.592459	Animation
3	130	81.652163	251.161007	Biography
4	474	82.976304	242.476102	Comedy
5	218	19.295245	130.768016	Crime
6	45	106.361963	230.621110	Documentary
7	672	79.986621	244.995889	Drama
8	87	45.364585	172.140462	Family
9	116	50.135361	235.957915	Fantasy
10	39	22.747490	154.924390	History
11	152	452.788298	967.473325	Horror
12	48	90.751560	269.447152	Music
13	7	24.571384	276.252407	Musical
14	117	418.803413	944.531168	Mystery
15	176	121.683535	290.467763	Romance

```
16          124   66.709295  289.939903       Sci-Fi
17           33   44.773880  116.350760        Sport
18          234  238.701633  599.538310     Thriller
19            4  -48.600458  493.001530      Unknown
20           16  -28.882477   49.884569          War
21            9    2.509016   87.547842      Western
```

[91]:

```
#Answering the question what genres are most profitable in average ROI terms,␣
↪no gross income

fig, axes = plt.subplots(figsize=(20,20), nrows=2)
sns.barplot(data=df_ROI_genres, x="genres", y="ROI_d", palette='summer',
            order=df_ROI_genres.sort_values('ROI_d', ascending = False).genres,␣
↪ax=axes[0]);
sns.barplot(data=df_ROI_genres, x="genres", y="ROI_w", palette='winter',
            order=df_ROI_genres.sort_values('ROI_w', ascending = False).genres,␣
↪ax=axes[1]);



axes[0].set_title("Average Domestic ROI(%) by Genres", fontsize=26);
axes[0].set_ylabel('Average domestic ROI(%)', fontsize=20)
axes[0].set_xlabel('Genres', fontsize=20);
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=45, ha='right')
axes[0].grid();

axes[1].set_title("Average Worldwide ROI(%) by Genres", fontsize=26);
axes[1].set_ylabel('Average worldwide ROI(%)', fontsize=20)
axes[1].set_xlabel('Genres', fontsize=20);
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, ha='right')
axes[1].grid();

plt.tight_layout(pad=3)
sns.set_context("talk");
```





Conclusion of the analysis of the data in this subsection: Conclusions of the analysis in this subsection suggests that three most profitable genres are Horror, Mystery and Thriller (in that order), both domestically and abroad. There is a strong presence on the second plot of the "Unknown" category of movies released internationally. That might be might be in part due to a practice of categorizing them abroad differently. It is just a guess but given the significance of the difference, the issue should not be brushed aside but further investigated.

6.5.2 Exploration of an effect of production budget on gross income of a movie

In this section we are going to explore how profitable movies based on their production budgets. DAta used are from IMDB and TN tables.

[92]:
```
# DataFrame with budget, gross income and genres
q="""SELECT production_budget budget, domestic_gross, worldwide_gross, genres
     FROM ROI_tn_imdb_genres"""
df_budget_gross_income=table_query(q)
df_budget_gross_income
```

[92]:
```
           budget  domestic_gross  worldwide_gross       genres
0      91000000.0      58236838.0      187861183.0    Adventure
1      91000000.0      58236838.0      187861183.0       Comedy
2      91000000.0      58236838.0      187861183.0        Drama
3      28000000.0      26017685.0       62108587.0       Action
4      28000000.0      26017685.0       62108587.0        Crime
…             …             …              …            …
3543    5000000.0       6352306.0        6653715.0  Documentary
3544    6000000.0      18107621.0       18107621.0    Biography
3545    6000000.0      18107621.0       18107621.0        Drama
3546    3500000.0        890303.0         890303.0      Unknown
3547   90000000.0       8224288.0       10551417.0        Drama

[3548 rows x 4 columns]
```

[93]:
```
# Pearson correlation for the daraFrame above
df_budget_gross_income.corr(method='pearson')
```

[93]:
```
                   budget  domestic_gross  worldwide_gross
budget           1.000000        0.697090         0.774382
domestic_gross   0.697090        1.000000         0.943957
worldwide_gross  0.774382        0.943957         1.000000
```

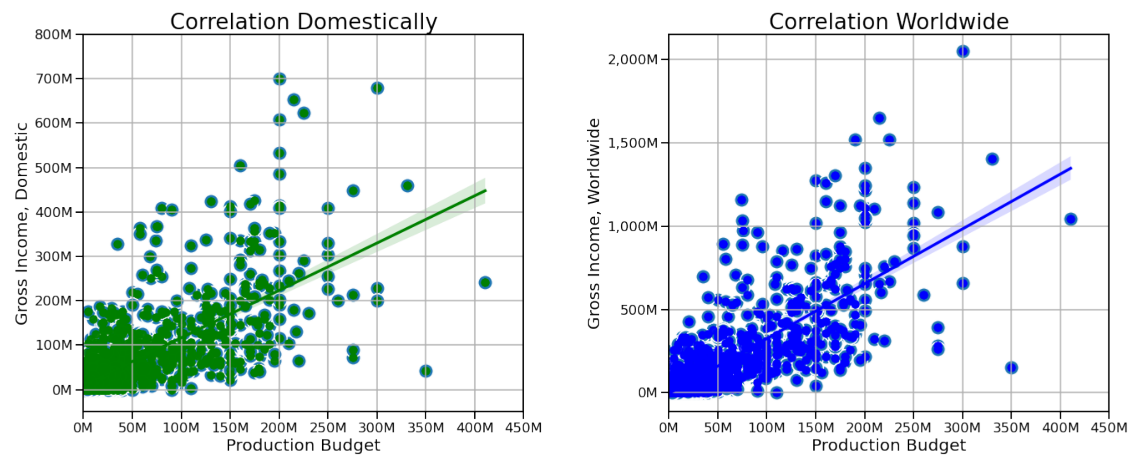
Based on the Pearson correlation coefficients averaged over the past decade, the correlation between the gross income and the budget of the movie is strong both domestically and worldwide. Now let's represent is visually.

[94]:
```
#Visualizing the correlation for movies of all genres
fig, axes = plt.subplots(figsize=(20,10), ncols=2)
sns.scatterplot(data=df_budget_gross_income, x="budget", y="domestic_gross",␣
 ↪s=300,
               ax=axes[0])
sns.scatterplot(data=df_budget_gross_income, x="budget", y="worldwide_gross",␣
 ↪s=300,
               ax=axes[1])
g1=sns.regplot(data=df_budget_gross_income, x="budget", y="domestic_gross",␣
 ↪color="Green", ax=axes[0])
g2=sns.regplot(data=df_budget_gross_income, x="budget", y="worldwide_gross",␣
 ↪color="Blue", ax=axes[1])

axes[0].set_title("Correlation Domestically", fontsize=26);
axes[0].set_ylabel('Gross Income, Domestic', fontsize=20)
```

```python
axes[0].set_xlabel('Production Budget', fontsize=20)
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g1.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g1.get_yticks()/1000000]
axes[0].set_xticklabels(xlabels)
axes[0].set_yticklabels(ylabels)
axes[0].set_ylim(-50000000, 800000000)
axes[0].set_xlim(0, 450000000)
axes[0].grid()

axes[1].set_title("Correlation Worldwide", fontsize=26);
axes[1].set_ylabel('Gross Income, Worldwide', fontsize=20)
axes[1].set_xlabel('Production Budget', fontsize=20)
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g2.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g2.get_yticks()/1000000]
axes[1].set_xticklabels(xlabels)
axes[1].set_yticklabels(ylabels)
axes[1].set_xlim(0, 450000000)
#axes[1].set_ylim(-50000000, 2000000000)
axes[1].grid();

plt.suptitle("Correlation Between Production Budget and Gross Income", size=30,␣
 ↪c="Blue")
plt.tight_layout(pad=3)
```

```
<ipython-input-94-ac2ba7c2ce5c>:15: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0].set_xticklabels(xlabels)
<ipython-input-94-ac2ba7c2ce5c>:16: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0].set_yticklabels(ylabels)
<ipython-input-94-ac2ba7c2ce5c>:26: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1].set_xticklabels(xlabels)
<ipython-input-94-ac2ba7c2ce5c>:27: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1].set_yticklabels(ylabels)
```

Correlation Between Production Budget and Gross Income



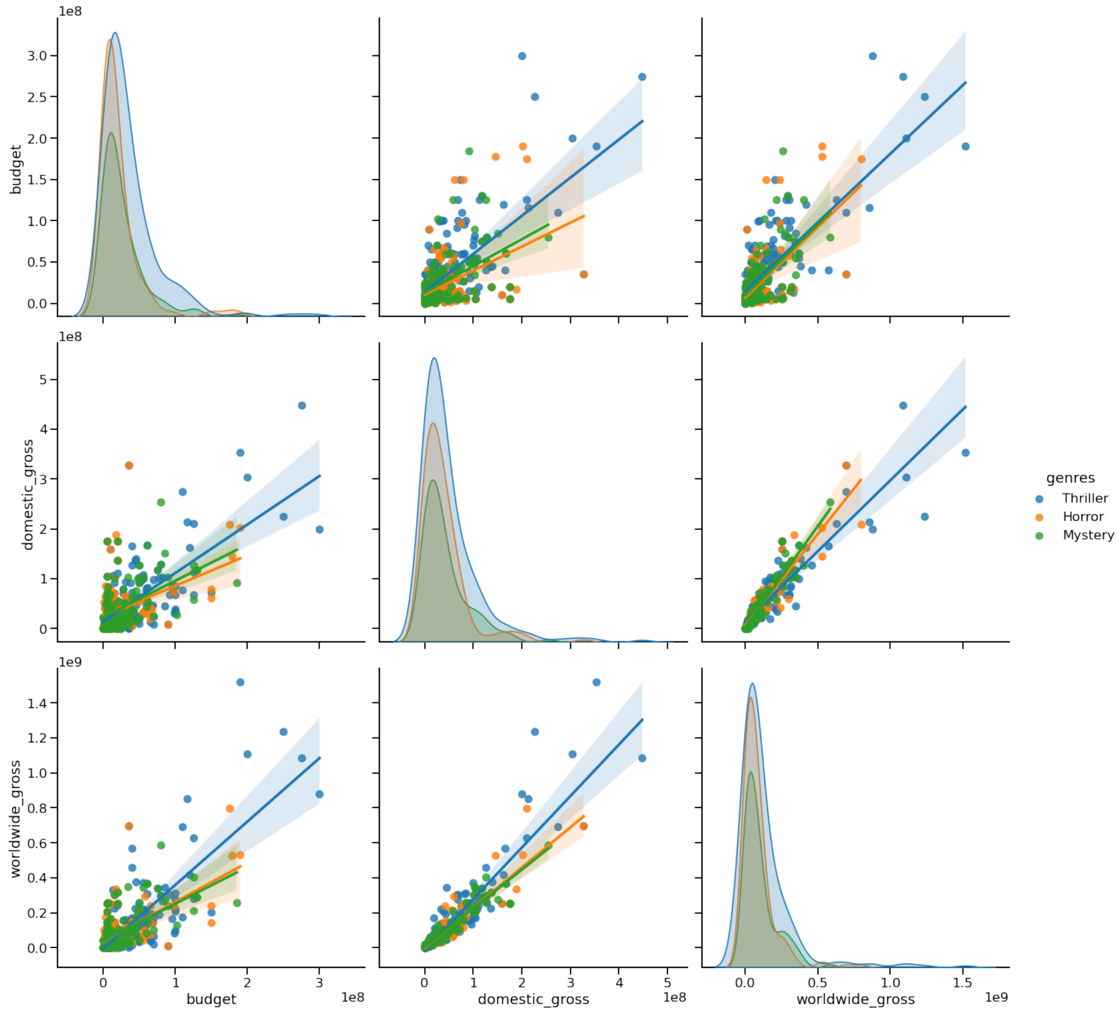

```
The correlation between Gross Income and budget can be seen on the plots above. However, it mi
It would be a good exercise to put side by side the correlations within all three genres that 
</div>
```

[95]:
```
#Generating a Dataframe with financial data for three genres
q="""SELECT production_budget budget, domestic_gross, worldwide_gross, genres
     FROM ROI_tn_imdb_genres where genres in ('Horror', 'Mystery','Thriller')"""
df_budget_gross_income_three_genres=table_query(q)
```

[96]:
```
#Generating three separate DataFrames per genre
q="""SELECT production_budget budget, domestic_gross, worldwide_gross, genres
     FROM ROI_tn_imdb_genres where genres='Horror'"""
df_budget_gross_income_horror=table_query(q)

q="""SELECT production_budget budget, domestic_gross, worldwide_gross, genres
     FROM ROI_tn_imdb_genres where genres='Mystery'"""
df_budget_gross_income_mystery=table_query(q)

q="""SELECT production_budget budget, domestic_gross, worldwide_gross, genres
     FROM ROI_tn_imdb_genres where genres='Thriller'"""
df_budget_gross_income_thriller=table_query(q)
```

[97]:
```
#To visualize the correlation between domestic/worldwide pairplot is being used
sns.pairplot(data=df_budget_gross_income_three_genres, kind='reg',␣
 ↪hue='genres', height=6)
```

[97]:
```
<seaborn.axisgrid.PairGrid at 0x20186054f70>
```



Visual investigation of the plots above clearly leads to the conclusion that there are three separate correlations between gross income and production budget for movies in Horror, Mystery and Thriller genres

Based on the analysis above it would be logical to visualize the correlation of all three genres to present them to the customer

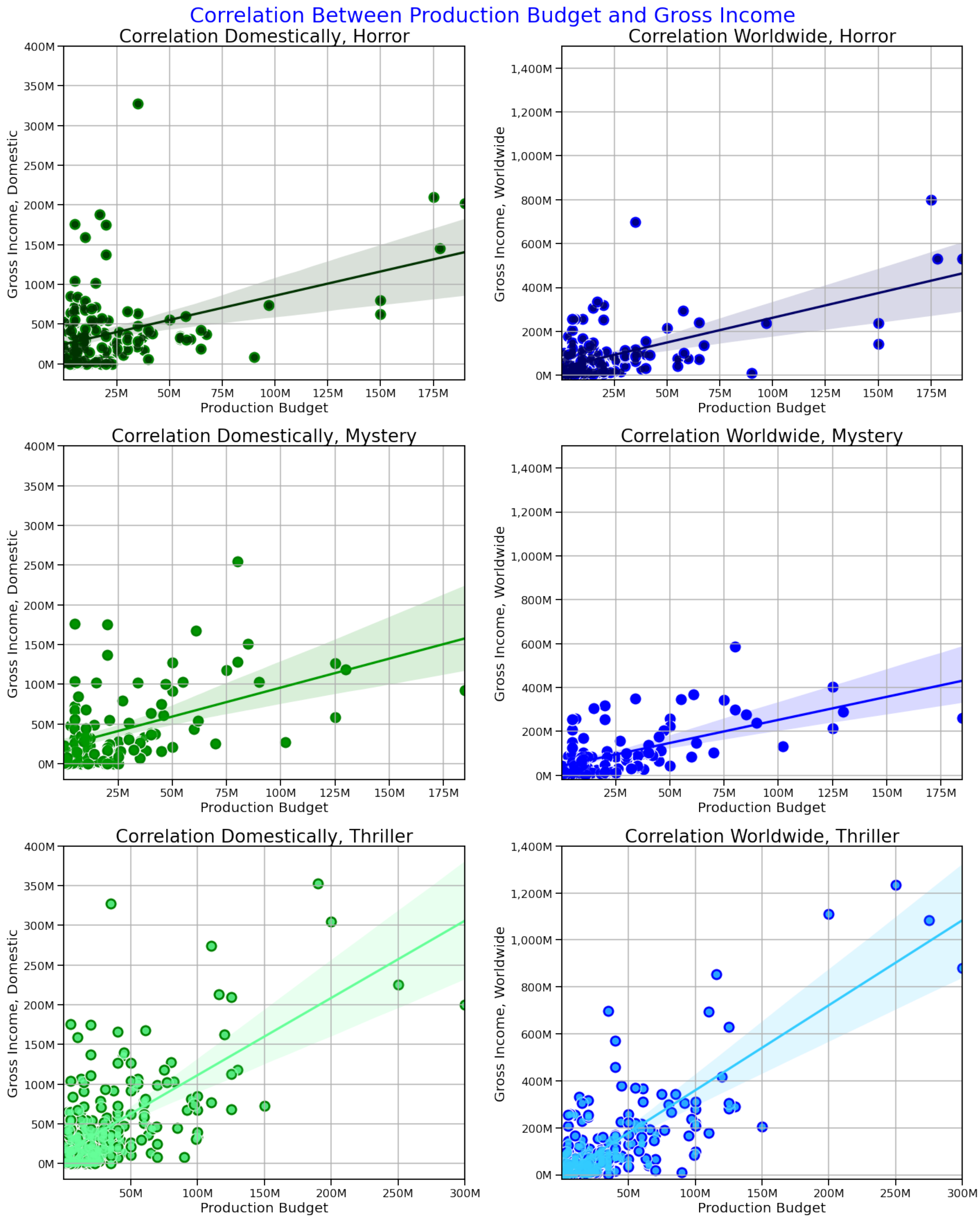
[98]:
```
fig, axes = plt.subplots(figsize=(20,25), ncols=2, nrows=3)
#sns.set_style('whitegrid')
sns.scatterplot(data=df_budget_gross_income_horror, x="budget", y="domestic_gross", s=300, color='Green', ax=axes[0,0])
sns.scatterplot(data=df_budget_gross_income_horror, x="budget", y="worldwide_gross", s=300, color= 'Blue', ax=axes[0,1])
sns.scatterplot(data=df_budget_gross_income_mystery, x="budget", y="domestic_gross", s=300, color='Green', ax=axes[1,0])
```

```
sns.scatterplot(data=df_budget_gross_income_mystery, x="budget",␣
↪y="worldwide_gross", s=300, color= 'Blue', ax=axes[1,1])
sns.scatterplot(data=df_budget_gross_income_thriller, x="budget",␣
↪y="domestic_gross", s=300, color='Green', ax=axes[2,0])
sns.scatterplot(data=df_budget_gross_income_thriller, x="budget",␣
↪y="worldwide_gross", s=300, color= 'Blue', ax=axes[2,1])

g1=sns.regplot(data=df_budget_gross_income_horror, x="budget",␣
↪y="domestic_gross", color="#003300", ax=axes[0,0]);
g2=sns.regplot(data=df_budget_gross_income_horror, x="budget",␣
↪y="worldwide_gross", color="#000066", ax=axes[0,1]);
g3=sns.regplot(data=df_budget_gross_income_mystery, x="budget",␣
↪y="domestic_gross", color="#009900", ax=axes[1,0]);
g4=sns.regplot(data=df_budget_gross_income_mystery, x="budget",␣
↪y="worldwide_gross", color="#0000ff", ax=axes[1,1]);
g5=sns.regplot(data=df_budget_gross_income_thriller, x="budget",␣
↪y="domestic_gross", color="#66ff99", ax=axes[2,0]);
g6=sns.regplot(data=df_budget_gross_income_thriller, x="budget",␣
↪y="worldwide_gross", color="#33ccff", ax=axes[2,1]);

axes[0,0].set_title("Correlation Domestically, Horror", fontsize=26);
axes[0,0].set_ylabel('Gross Income, Domestic', fontsize=20)
axes[0,0].set_xlabel('Production Budget', fontsize=20)
axes[0,0].set_ylim((-20000000.0), (400000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g1.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g1.get_yticks()/1000000]
axes[0,0].set_xticklabels(xlabels)
axes[0,0].set_yticklabels(ylabels)
axes[0,0].grid()

axes[0,1].set_title("Correlation Worldwide, Horror", fontsize=26);
axes[0,1].set_ylabel('Gross Income, Worldwide', fontsize=20)
axes[0,1].set_xlabel('Production Budget', fontsize=20)
axes[0,1].set_ylim((-20000000.0), (1500000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g2.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g2.get_yticks()/1000000]
axes[0,1].set_xticklabels(xlabels)
axes[0,1].set_yticklabels(ylabels)
axes[0,1].grid()

axes[1,0].set_title("Correlation Domestically, Mystery", fontsize=26);
axes[1,0].set_ylabel('Gross Income, Domestic', fontsize=20)
axes[1,0].set_xlabel('Production Budget', fontsize=20)
axes[1,0].set_ylim((-20000000.0), (400000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g3.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g3.get_yticks()/1000000]
```

```
axes[1,0].set_xticklabels(xlabels)
axes[1,0].set_yticklabels(ylabels)
axes[1,0].grid()

axes[1,1].set_title("Correlation Worldwide, Mystery", fontsize=26);
axes[1,1].set_ylabel('Gross Income, Worldwide', fontsize=20)
axes[1,1].set_xlabel('Production Budget', fontsize=20)
axes[1,1].set_ylim((-20000000.0), (1500000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g4.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g4.get_yticks()/1000000]
axes[1,1].set_xticklabels(xlabels)
axes[1,1].set_yticklabels(ylabels)
axes[1,1].grid()

axes[2,0].set_title("Correlation Domestically, Thriller", fontsize=26);
axes[2,0].set_ylabel('Gross Income, Domestic', fontsize=20)
axes[2,0].set_xlabel('Production Budget', fontsize=20)
axes[2,0].set_ylim((-20000000.0), (400000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g5.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g5.get_yticks()/1000000]
axes[2,0].set_xticklabels(xlabels)
axes[2,0].set_yticklabels(ylabels)
axes[2,0].grid()

axes[2,1].set_title("Correlation Worldwide, Thriller", fontsize=26);
axes[2,1].set_ylabel('Gross Income, Worldwide', fontsize=20)
axes[2,1].set_xlabel('Production Budget', fontsize=20)
axes[2,1].set_ylim((-20000000.0), (1400000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g6.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g6.get_yticks()/1000000]
axes[2,1].set_xticklabels(xlabels)
axes[2,1].set_yticklabels(ylabels)
axes[2,1].grid()

plt.suptitle("Correlation Between Production Budget and Gross Income", size=30,␣
 ↪c="Blue")
plt.tight_layout()
```

```
<ipython-input-98-47ae24401000>:23: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0,0].set_xticklabels(xlabels)
<ipython-input-98-47ae24401000>:24: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0,0].set_yticklabels(ylabels)
<ipython-input-98-47ae24401000>:33: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0,1].set_xticklabels(xlabels)
<ipython-input-98-47ae24401000>:34: UserWarning: FixedFormatter should only be
```

```
used together with FixedLocator
  axes[0,1].set_yticklabels(ylabels)
<ipython-input-98-47ae24401000>:43: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,0].set_xticklabels(xlabels)
<ipython-input-98-47ae24401000>:44: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,0].set_yticklabels(ylabels)
<ipython-input-98-47ae24401000>:53: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,1].set_xticklabels(xlabels)
<ipython-input-98-47ae24401000>:54: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,1].set_yticklabels(ylabels)
<ipython-input-98-47ae24401000>:63: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[2,0].set_xticklabels(xlabels)
<ipython-input-98-47ae24401000>:64: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[2,0].set_yticklabels(ylabels)
<ipython-input-98-47ae24401000>:73: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[2,1].set_xticklabels(xlabels)
<ipython-input-98-47ae24401000>:74: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[2,1].set_yticklabels(ylabels)
```



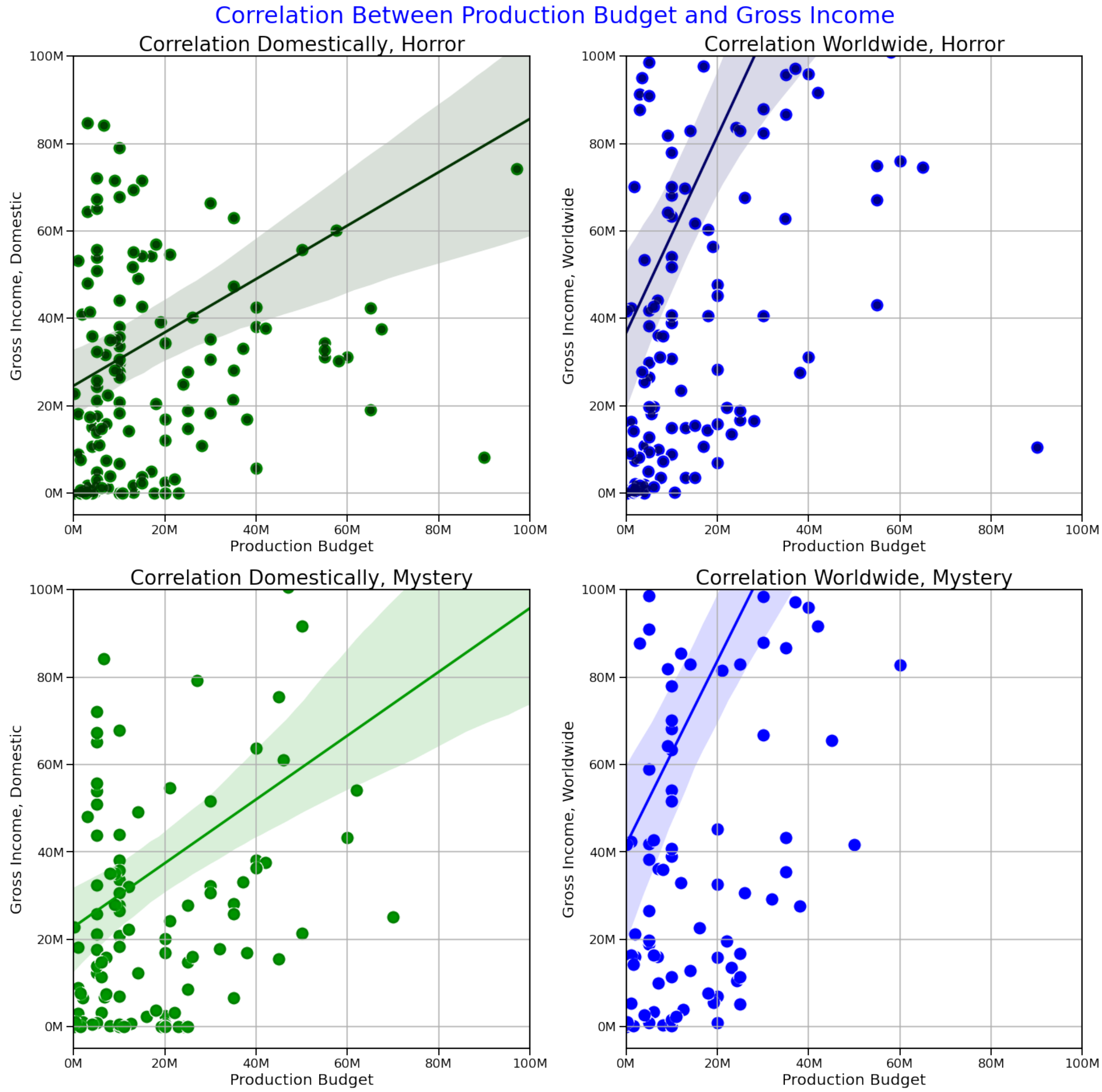
Visual investigation of the plots above suggests closer inverstigation of the lower quadrant data

[99]:
```
#Ploting Horror and Mystery movies data in the low quadrant plots above,␣
↪zooming into the previous plots and ploting withing comarable x, y areas
fig, axes = plt.subplots(figsize=(20,20), ncols=2, nrows=2)
```

```
#sns.set_style('whitegrid')
sns.scatterplot(data=df_budget_gross_income_horror, x="budget", y="domestic_gross", s=300, color='Green', ax=axes[0,0])
sns.scatterplot(data=df_budget_gross_income_horror, x="budget", y="worldwide_gross", s=300, color= 'Blue', ax=axes[0,1])
sns.scatterplot(data=df_budget_gross_income_mystery, x="budget", y="domestic_gross", s=300, color='Green', ax=axes[1,0])
sns.scatterplot(data=df_budget_gross_income_mystery, x="budget", y="worldwide_gross", s=300, color= 'Blue', ax=axes[1,1])

g1=sns.regplot(data=df_budget_gross_income_horror, x="budget", y="domestic_gross", color="#003300", ax=axes[0,0]);
g2=sns.regplot(data=df_budget_gross_income_horror, x="budget", y="worldwide_gross", color="#000066", ax=axes[0,1]);
g3=sns.regplot(data=df_budget_gross_income_mystery, x="budget", y="domestic_gross", color="#009900", ax=axes[1,0]);
g4=sns.regplot(data=df_budget_gross_income_mystery, x="budget", y="worldwide_gross", color="#0000ff", ax=axes[1,1]);

axes[0,0].set_title("Correlation Domestically, Horror", fontsize=26);
axes[0,0].set_ylabel('Gross Income, Domestic', fontsize=20)
axes[0,0].set_xlabel('Production Budget', fontsize=20)
axes[0,0].set_ylim((-5000000.0), (100000000.0))
axes[0,0].set_xlim((0), (100000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g1.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g1.get_yticks()/1000000]
axes[0,0].set_xticklabels(xlabels)
axes[0,0].set_yticklabels(ylabels)
axes[0,0].grid()

axes[0,1].set_title("Correlation Worldwide, Horror", fontsize=26);
axes[0,1].set_ylabel('Gross Income, Worldwide', fontsize=20)
axes[0,1].set_xlabel('Production Budget', fontsize=20)
axes[0,1].set_ylim((-5000000.0), (100000000.0))
axes[0,1].set_xlim((0), (100000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g2.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g2.get_yticks()/1000000]
axes[0,1].set_xticklabels(xlabels)
axes[0,1].set_yticklabels(ylabels)
axes[0,1].grid()

axes[1,0].set_title("Correlation Domestically, Mystery", fontsize=26);
axes[1,0].set_ylabel('Gross Income, Domestic', fontsize=20)
axes[1,0].set_xlabel('Production Budget', fontsize=20)
axes[1,0].set_ylim((-5000000.0), (100000000.0))
axes[1,0].set_xlim((0), (100000000.0))
```

```
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g3.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g3.get_yticks()/1000000]
axes[1,0].set_xticklabels(xlabels)
axes[1,0].set_yticklabels(ylabels)
axes[1,0].grid()

axes[1,1].set_title("Correlation Worldwide, Mystery", fontsize=26);
axes[1,1].set_ylabel('Gross Income, Worldwide', fontsize=20)
axes[1,1].set_xlabel('Production Budget', fontsize=20)
axes[1,1].set_ylim((-5000000.0), (100000000.0))
axes[1,1].set_xlim((0), (100000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g4.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g4.get_yticks()/1000000]
axes[1,1].set_xticklabels(xlabels)
axes[1,1].set_yticklabels(ylabels)
axes[1,1].grid()


plt.suptitle("Correlation Between Production Budget and Gross Income", size=30,␣
 ↪c="Blue")
plt.tight_layout()
```

```
<ipython-input-99-46ccc466aada>:21: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0,0].set_xticklabels(xlabels)
<ipython-input-99-46ccc466aada>:22: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0,0].set_yticklabels(ylabels)
<ipython-input-99-46ccc466aada>:32: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0,1].set_xticklabels(xlabels)
<ipython-input-99-46ccc466aada>:33: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0,1].set_yticklabels(ylabels)
<ipython-input-99-46ccc466aada>:43: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,0].set_xticklabels(xlabels)
<ipython-input-99-46ccc466aada>:44: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,0].set_yticklabels(ylabels)
<ipython-input-99-46ccc466aada>:54: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,1].set_xticklabels(xlabels)
<ipython-input-99-46ccc466aada>:55: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1,1].set_yticklabels(ylabels)
```

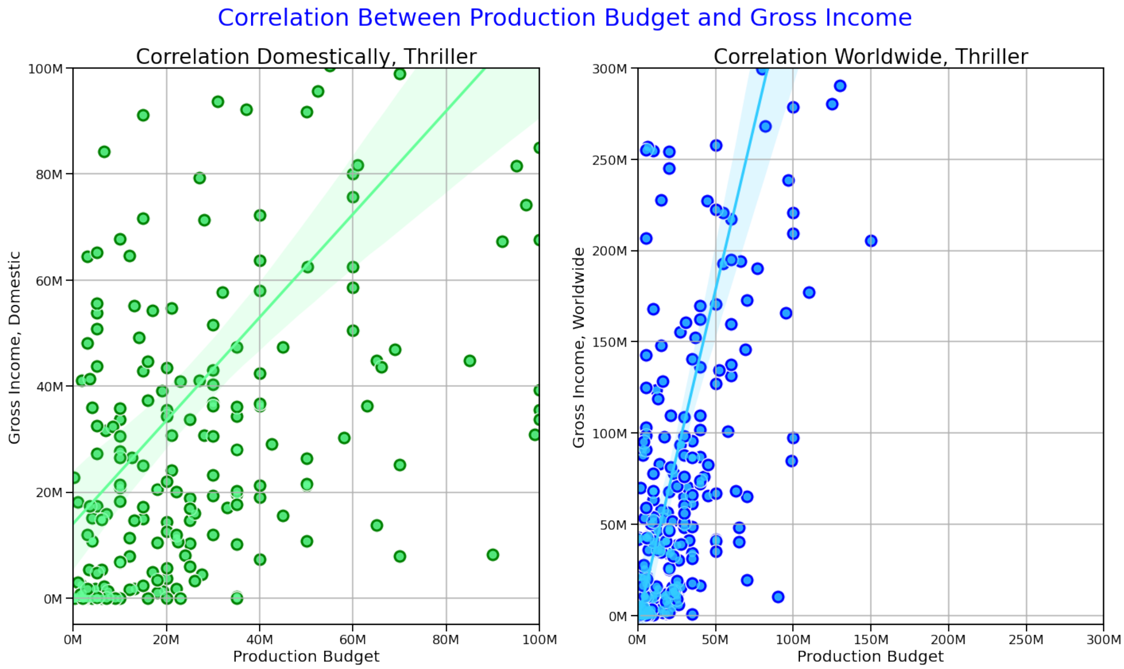


Visual investigation of the plots above suggests that in Domestic market one can expect a ratio between gross income and production close to 2.0 for movies with budgets of 20 millions and lower in Horror and Mystery categories However, as a budget grows the return drops

[100]:
```
fig, axes = plt.subplots(figsize=(20,12), ncols=2)
#sns.set_style('whitegrid')

sns.scatterplot(data=df_budget_gross_income_thriller, x="budget",␣
↪y="domestic_gross", s=300, color='Green', ax=axes[0])
sns.scatterplot(data=df_budget_gross_income_thriller, x="budget",␣
↪y="worldwide_gross", s=300, color= 'Blue', ax=axes[1])
```

```
g5=sns.regplot(data=df_budget_gross_income_thriller, x="budget",␣
 ↪y="domestic_gross", color="#66ff99", ax=axes[0]);
g6=sns.regplot(data=df_budget_gross_income_thriller, x="budget",␣
 ↪y="worldwide_gross", color="#33ccff", ax=axes[1]);


axes[0].set_title("Correlation Domestically, Thriller", fontsize=26);
axes[0].set_ylabel('Gross Income, Domestic', fontsize=20)
axes[0].set_xlabel('Production Budget', fontsize=20)
axes[0].set_ylim((-5000000.0), (100000000.0))
axes[0].set_xlim((0), (100000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g5.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g5.get_yticks()/1000000]
axes[0].set_xticklabels(xlabels)
axes[0].set_yticklabels(ylabels)
axes[0].grid()

axes[1].set_title("Correlation Worldwide, Thriller", fontsize=26);
axes[1].set_ylabel('Gross Income, Worldwide', fontsize=20)
axes[1].set_xlabel('Production Budget', fontsize=20)
axes[1].set_ylim((-5000000.0), (300000000.0))
axes[1].set_xlim((0), (300000000.0))
xlabels = ['{:,.0f}'.format(x) + 'M' for x in g6.get_xticks()/1000000]
ylabels = ['{:,.0f}'.format(x) + 'M' for x in g6.get_yticks()/1000000]
axes[1].set_xticklabels(xlabels)
axes[1].set_yticklabels(ylabels)
axes[1].grid()

plt.suptitle("Correlation Between Production Budget and Gross Income", size=30,␣
 ↪c="Blue")
plt.tight_layout()
```

```
<ipython-input-100-cec999eb1eb4>:19: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0].set_xticklabels(xlabels)
<ipython-input-100-cec999eb1eb4>:20: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[0].set_yticklabels(ylabels)
<ipython-input-100-cec999eb1eb4>:30: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1].set_xticklabels(xlabels)
<ipython-input-100-cec999eb1eb4>:31: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axes[1].set_yticklabels(ylabels)
```



- Visual investigation of the plots above suggests that while Thriller movies do not perform quite as well as horror and mystery movies domestically,i.e. the regression model suggests that 20 millions investment would generate slightly above 30 millions in gross income. Internationally the thriller movies tend to do much better and an estimate of an average ratio of gross income to production budget ratio is about 3.5. The recommendation to the customer is to release a movie both domestically and internationally to maximize the return on investment.
- The conclusion is that the budgets of Thriller movies should be higher than those of Horror and Mystery movies to generate higher Gross Income. In other words production of **several** Horror/Mystery movies might cost the same as production of one Thriller movie to generate the same amount of gross profit. However, production of several movies versus just one might be a smart move because it increases the probability of success overall, "not putting all your eggs in one backet" approach.

[101]:
```
conn.commit()
```

[102]:
```
cur.close()
```

7 Evaluation

The business problem solution should maximize the return over investment value along with minimizing the risks.

The provided analysis investigates: * How well various studios perform in terms of their ROI both domestically and worldwide * How timing of a release of a movie influences its' profitability * How a genre of a movie influences its' profitability * If a budget of a movie plays a significant role in the amount of its' gross income and if movies of different genres have different correlations between their budgets and gross income generated ***

8 Conclusions

The customer is advised: * To either partner with Universal Studios, Paramount Pictures, The Weinstein Company and Lions Gate Films Corporation studios (in that order) or invest into investigating their business practices and replicating them in their business. * To carefully plan the timing of releasing their movies due to the fact that ROI tends to be higher in the time periods when fewer movies are available to the viewers. The only exception is a month of July, an outlier among other months of a year. It seems that no matter how many movies are in the theaters, it is going to be more profitable than in other months of a year. * To invest in three most profitable genres in terms of a return on investment, Horror, Mystery and Thriller (in that order), both domestically and abroad. Their production budgets tend to be lower than movies other genres but the ratio between their gross incomes to the production costs is higher. In other words it is more profitable to make many movies in these genres than just one movie in a genre with higher production costs and higher one-movie gross income. This tactics has an additional benefit of minimizing the risk of investment. ***

Additional analysis suggested: * Update data available for analysis by either creating APIs with the sources or webscraping their sites * Investigate the effect of a choice of directors/writers on a profitability of a movie using additional tables in the database * Use Rotten Tomatoes tables to analyze the correlations between the profitability of a movie and its' critics rating and viewers' rating * Replicate the analysis of this project using Rotten Tomatoes tables to confirm the findings

[ ]:
```

```