Jupyter Notebook

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1 Computer Vision Analysis

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[1]:
```
#Import Statements
import numpy as np
import pandas as pd
import scipy.stats as stats

import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns

import sqlite3
from zipfile import ZipFile

import string
import regex as re

import warnings
#use to ignore warnings
warnings.filterwarnings('ignore')

%matplotlib inline
```

[2]:
```
color_palette = ['#86BC25'] #Set Color of PLots to Deloitte Green
sns.set_palette(palette=color_palette)
```

2 Import Data

The two datasets that we utilized are imported below. The numbers is a tabular dataset that contains information regarding budgets and gross for movies while the IMDB database is a relational database that contains information about movie genres and the production personnel behind it.

[3]:
```
#Import and preview the dataset from The numbers
the_numbers = pd.read_csv('zippedData/tn.movie_budgets.csv.gz')
the_numbers.head()
```

[3]:
```
   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
0      $425,000,000   $760,507,625  $2,776,345,279
1      $410,600,000   $241,063,875  $1,045,663,875
2      $350,000,000    $42,762,350    $149,762,350
3      $330,600,000   $459,005,868  $1,403,013,963
4      $317,000,000   $620,181,382  $1,316,721,747
```

[4]:
```
#Run only first time to unzip the file

#Confirm with Instructors if we need to have this run
#file_name = './zippedData/im.db.zip'
#opening the zip file in READ mode
#with ZipFile(file_name, 'r') as zip:
#    # printing all the contents of the zip file
#    #zip.printdir()
#    zip.extractall()
```

[5]:
```
#Sets the connected for idmb
conn = sqlite3.connect('./im.db')
```

3 Data Cleaning and EDA

[6]:
```
#preview the numbers db
the_numbers.info()
```

```
<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
```

We can see that all of the data is stored as a string (not good for us). We decided to make any numerical value into integers so that we can perform statistical calculations appropriately.

[7]:
```python
#Function that turns strings into integers
def make_int(string):
    return int(string.replace('$','').replace(',',''))
```

We also created updated the format of the 'release_date' column to be in datetime format for easier calculations, and separated the values to month, day, and year respectively. We also added a 'title' to standardize names between the datasets.

[8]:
```python
#Turns all the strings into numbers for processing
the_numbers['production_budget'] = (
    the_numbers['production_budget'].apply(lambda x: make_int(x)))
the_numbers['domestic_gross'] = (
    the_numbers['domestic_gross'].apply(lambda x: make_int(x)))
the_numbers['worldwide_gross'] = (
    the_numbers['worldwide_gross'].apply(lambda x: make_int(x)))

#Creates a date time from release date
the_numbers['release_date']=(
    pd.to_datetime(the_numbers['release_date'], format='%b %d, %Y'))

#Creates a new title column
the_numbers['title']= (
    the_numbers['movie'].map(
        lambda x :''.join(filter(str.isalnum, x)).lower()))

#Gets the days months and eyars from the date time column
the_numbers['days'] = the_numbers['release_date'].dt.day_name()
the_numbers['months'] = the_numbers['release_date'].dt.month_name()
the_numbers['year'] = the_numbers['release_date'].dt.year
```

We can now see the changes that we made to the table.

[9]:
```python
#preview the DB
the_numbers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   int64
 4   domestic_gross     5782 non-null   int64
 5   worldwide_gross    5782 non-null   int64
 6   title              5782 non-null   object
 7   days               5782 non-null   object
 8   months             5782 non-null   object
```

```
 9   year               5782 non-null   int64
dtypes: datetime64[ns](1), int64(5), object(4)
memory usage: 451.8+ KB
```

4 Production Budget

Let's see if there is any correlation between the columns within The Numbers dataset.

[10]:
```
#checking for correlation
the_numbers.corr()
```

[10]:
```
                         id  production_budget  domestic_gross  \
id                 1.000000          -0.035278        0.008255
production_budget -0.035278           1.000000        0.685682
domestic_gross     0.008255           0.685682        1.000000
worldwide_gross   -0.009422           0.748306        0.938853
year              -0.011652           0.176091        0.036690

                   worldwide_gross      year
id                       -0.009422 -0.011652
production_budget         0.748306  0.176091
domestic_gross            0.938853  0.036690
worldwide_gross           1.000000  0.100588
year                      0.100588  1.000000
```

We can see a fairly strong positive correlation between the production budget and worldwide gross. Let's plot the two values and see if we can notice anything.

[11]:
```
#Scatterplot of Production Budget vs. Worldwide Gross
sns.set_theme()
sns.set(font_scale=2)

color_palette = ['#86BC25', '#007CB0'] #Set Color of PLots to Deloitte Green
sns.set_palette(palette=color_palette)

fig, ax = plt.subplots()

#Let's Focus only budgets less than 100M since we do not want to make a budget
#so large that it is unreasonable. Sample for 1500 to keep the graph clean
sampled = the_numbers[the_numbers['production_budget'] < 100000000]
sampled = sampled.sample(1500)

#Create the plot with appropriate features
ax = sns.regplot(data=sampled, x='production_budget', y='worldwide_gross',
            scatter_kws={'alpha':0.5}, line_kws={'color': '#007CB0'})
fig.set_size_inches(18.5, 10.5)

#Sets the tick information
```

```python
ax.set_xticklabels(['0','20','40','60','80','100'])
ax.set_yticklabels(['0','200','400','600','800','1B','1.2B','1.4B','1.6B'])

#Sets the labels
ax.set_title('Production Budget vs. Worldwide Gross')
ax.set_xlabel('Production Budget (in Millions)'')
ax.set_ylabel('Worldwide Gross (in Millions)'')
```

[11]: Text(0, 0.5, 'Worldwide Gross (in Millions)')

We can see the positive correlation in the graph above. Next, we want to see if there are any notable frequencies for famous actors/personnel within the highest grossing movies. To do this, we want to look for the most extreme values. With our data being so large, we can assume it's normal (Central Limit Theorem), and can take the z score to see how far something is off the mean.

[12]:
```python
#Function for calculating the z-score
def z_score(value, mean, std):
    return (value - mean) / std
```

[13]:
```python
#Calculate stats for the worldwide gross
the_numbers_mean = the_numbers['worldwide_gross'].mean()
the_numbers_med = the_numbers['worldwide_gross'].median()
the_numbers_std = the_numbers['worldwide_gross'].std()

print(the_numbers_mean)
print(the_numbers_med)
```

```python
#Gets the zscore
the_numbers['z_score'] = the_numbers['worldwide_gross'].apply(
    lambda x: z_score(x, the_numbers_mean, the_numbers_std))
```

```
91487460.90643376
27984448.5
```

Let's take a look at the movies that are over 3 times greater than the mean (aka Z-score greater than 3)

[14]:
```python
#Gets the outiers in the dataset based off gross
gross_outliers = the_numbers[the_numbers['z_score'] > 3]
outliers_movies_lst = list(gross_outliers['movie'].values)
outliers_movies_lst[:5]
```

[14]:
```
['Avatar',
 'Pirates of the Caribbean: On Stranger Tides',
 'Avengers: Age of Ultron',
 'Star Wars Ep. VIII: The Last Jedi',
 'Star Wars Ep. VII: The Force Awakens']
```

Now combine that with our IMDB Database

[15]:
```python
#SQL querey to combine some datasets with needed categories
imdb_people = pd.read_sql(f'''
SELECT pr.person_id, primary_name, death_year, category, primary_title,
       original_title
FROM persons p
LEFT JOIN principals pr ON pr.person_id = p.person_id
LEFT JOIN movie_basics mb ON pr.movie_id = mb.movie_id
''', conn)
```

We want to make sure that the personnel are alive, in the outlier movies list, and then group the frequency we see them.

[16]:
```python
#Make Sure Personnel is Alive
imdb_alive = imdb_people[imdb_people['death_year'].isnull() == True]

#Check if Person is in List of Outliers
imdb_outliers = imdb_alive[imdb_alive['primary_title'].isin(
    outliers_movies_lst)]
display(imdb_outliers)

#Group Outliers Together to Get Counts
grouped = imdb_outliers.groupby(['category','primary_name']
                               ).size().reset_index(name='counts')
grouped.head()
```

```
         person_id          primary_name  death_year  category  \
```

```
480       nm0125336       Jez Butterworth         NaN    writer
2286      nm0671567          Michael Peña         NaN     actor
2797      nm0834902      Robert Stromberg         NaN  director
2799      nm0837112        Richard Suckle         NaN  producer
3273      nm1014201           Rhett Reese         NaN    writer
…             …                    …          …       …
1005549   nm9989238         Suneet Gautam         NaN  composer
1009487   nm9989231       Mahesh Vashisht         NaN  composer
1013926   nm9039216          Neil Boultby         NaN     actor
1029087   nm9061881  Natalia Kaverznikova         NaN   actress
1029088   nm9061886       Isabelle Stokes         NaN   actress

                  primary_title        original_title
480                     Spectre               Spectre
2286       Ant-Man and the Wasp  Ant-Man and the Wasp
2797                 Maleficent            Maleficent
2799              Suicide Squad         Suicide Squad
3273                   Deadpool              Deadpool
…                           …                    …
1005549                 Titanic               Titanic
1009487                 Titanic               Titanic
1013926                    Coco                  Coco
1029087                    Coco                  Coco
1029088                    Coco                  Coco

[956 rows x 6 columns]
```

[16]:

	category	primary_name	counts
0	actor	Aarif Rahman	1
1	actor	Adil Hussain	1
2	actor	Alan Mathis	1
3	actor	Alan Tudyk	1
4	actor	Albert Brooks	1

Taking the same concept as before, let's take the creme de la creme, and get the most occurred actors.

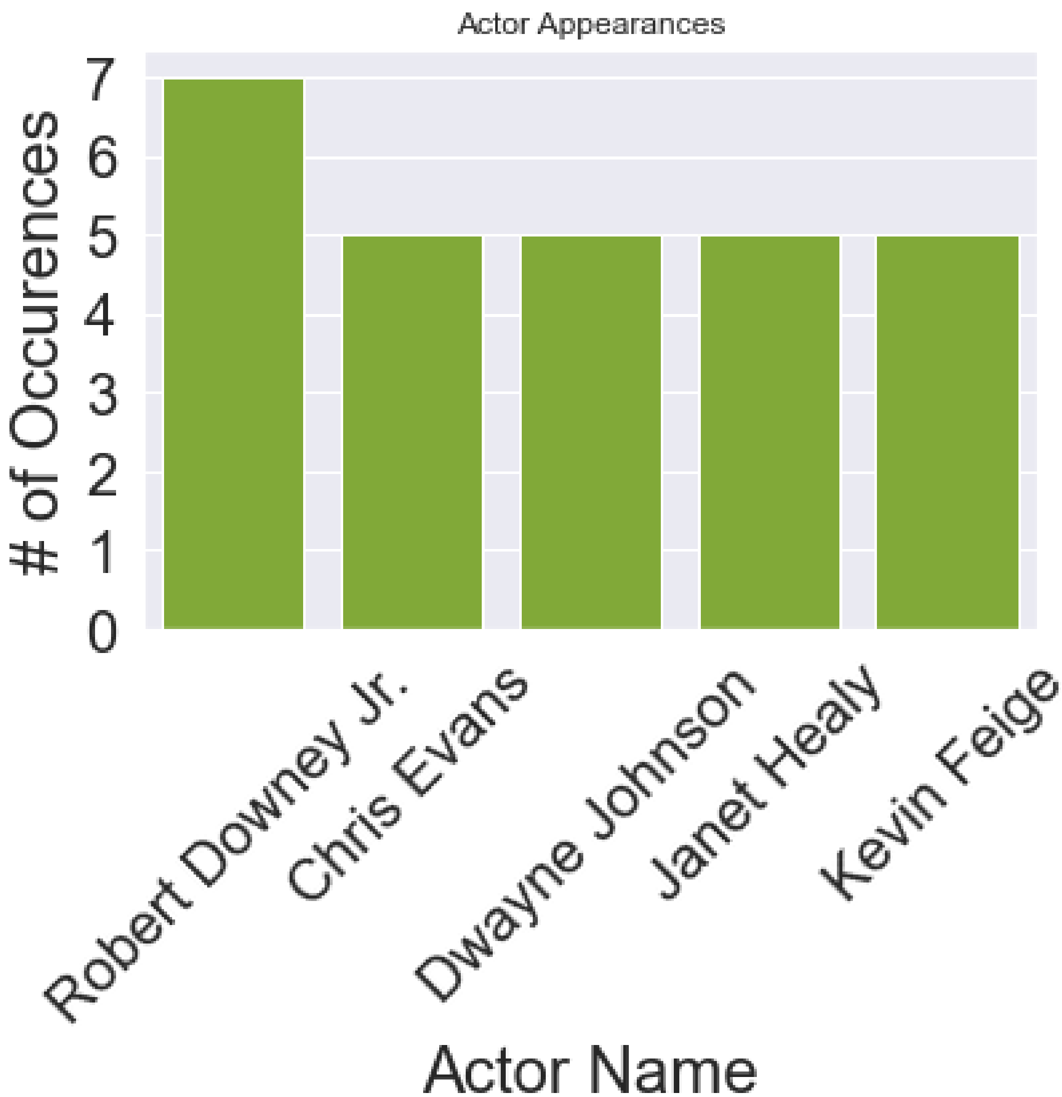
[17]:
```
#Lets find the actors that are in the most movies
grouped['counts'].mean() + (3 * grouped['counts'].std())
```

[17]: 3.5381775991830686

[18]:
```
#conitnuation of above
grouped3 = grouped[grouped['counts'] > 4]
```

[19]:
```
#Create the plot for the number of actor appearences
ax = sns.barplot(x='primary_name',
                 y='counts',
```

```
                 data=grouped3,
                 color='#86BC25',
                 order=grouped3.sort_values(
                     'counts', ascending=False).primary_name)

#Set graph properties
sns.set(rc={'figure.figsize':(15,10)})
#Title and labels
ax.set_title('Actor Appearances')
ax.set_xlabel('Actor Name')
ax.set_ylabel('# of Occurences')
ax.set_xticklabels(ax.get_xticklabels(),rotation = 45)

plt.show()
```



I guess Ironman or Captain America could make any film better!

5 Genre

We want to see if there was any difference in worldwide gross between genres to see what kind of genre would be best to produce.

[20]:
```
#Create query
q = '''
SELECT *
FROM movie_basics
'''
#create a DF from the IMBD sql table
imdb_movie_ratings = pd.read_sql(q, conn)
#remove na's from the original title due to low numbers
imdb_movie_ratings.dropna(subset=['original_title'], inplace = True)
imdb_movie_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 146123 entries, 0 to 146143
Data columns (total 6 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   movie_id         146123 non-null  object
 1   primary_title    146123 non-null  object
 2   original_title   146123 non-null  object
 3   start_year       146123 non-null  int64
 4   runtime_minutes  114401 non-null  float64
 5   genres           140734 non-null  object
dtypes: float64(1), int64(1), object(4)
memory usage: 7.8+ MB
```

After we have the data from the query, we want to make sure that we can map the titles with The Numbers dataset.

[21]:
```
#Making a copy just to make sure that we don't manipulate anything from before
tn_movie_budgets = the_numbers.copy()

#create a column for movie names to merge with other DFs   tn_movie_budgets
imdb_movie_ratings['title'] = (
    imdb_movie_ratings['original_title'].map(
        lambda x :''.join(filter(str.isalnum, x)).lower()))

#sets the index on the title field for the merge
tn_movie_budgets.set_index('title', inplace=True)
imdb_movie_ratings.set_index('title', inplace=True)
```

```python
imdb_movie_ratings.head()
```

[21]:
```
                         movie_id                     primary_title  \
title
sunghursh               tt0063540                         Sunghursh
ashadkaekdin            tt0066787  One Day Before the Rainy Season
theothersideofthewind   tt0069049        The Other Side of the Wind
sabsebadasukh           tt0069204                   Sabse Bada Sukh
latelenovelaerrante     tt0100275          The Wandering Soap Opera

                                    original_title  start_year  \
title
sunghursh                                Sunghursh        2013
ashadkaekdin                          Ashad Ka Ek Din        2019
theothersideofthewind  The Other Side of the Wind        2018
sabsebadasukh                       Sabse Bada Sukh        2018
latelenovelaerrante            La Telenovela Errante        2017

                       runtime_minutes                genres
title
sunghursh                        175.0    Action,Crime,Drama
ashadkaekdin                     114.0       Biography,Drama
theothersideofthewind            122.0                 Drama
sabsebadasukh                      NaN          Comedy,Drama
latelenovelaerrante               80.0  Comedy,Drama,Fantasy
```

Now, let's join the two datasets together.

[22]:
```python
#combine imdb and the numbers tables
rating_and_budgets = tn_movie_budgets.join(imdb_movie_ratings, how = 'inner')
rating_and_budgets.reset_index(inplace=True)
rating_and_budgets = (
    rating_and_budgets.drop_duplicates(subset='title', keep='first'))
rating_and_budgets.head()
```

[22]:
```
                title  id release_date                  movie  \
0  10cloverfieldlane  54   2016-03-11    10 Cloverfield Lane
1  10daysinamadhouse  48   2015-11-11  10 Days in a Madhouse
2           127hours   6   2010-11-05              127 Hours
3           12rounds  37   2009-03-27              12 Rounds
4           12strong  64   2018-01-19              12 Strong

   production_budget  domestic_gross  worldwide_gross       days    months  \
0            5000000        72082999        108286422     Friday     March
1           12000000           14616            14616  Wednesday  November
2           18000000        18335230         60217171     Friday  November
3           20000000        12234694         17306648     Friday     March
4           35000000        45819713         71118378     Friday   January
```

```
   year   z_score   movie_id         primary_title        original_title  \
0  2016  0.096148  tt1179933   10 Cloverfield Lane   10 Cloverfield Lane
1  2015 -0.523540  tt3453052 10 Days in a Madhouse 10 Days in a Madhouse
2  2010 -0.178974  tt1542344             127 Hours             127 Hours
3  2009 -0.424570  tt3517850             12 Rounds             12 Rounds
4  2018 -0.116581  tt1413492             12 Strong             12 Strong

   start_year  runtime_minutes                    genres
0        2016            103.0       Drama,Horror,Mystery
1        2015            111.0                     Drama
2        2010             94.0  Adventure,Biography,Drama
3        2017              NaN       Action,Drama,Romance
4        2018            130.0       Action,Drama,History
```

We now want to split the genres into a list, not just have it be a string (as it we would need to catagorize the genres later).

[23]:
```
rating_and_budgets['genres'] =  rating_and_budgets['genres'].str.split(',')
rating_and_budgets.head()
```

[23]:
```
               title  id release_date                  movie  \
0  10cloverfieldlane  54   2016-03-11    10 Cloverfield Lane
1  10daysinamadhouse  48   2015-11-11  10 Days in a Madhouse
2           127hours   6   2010-11-05              127 Hours
3           12rounds  37   2009-03-27              12 Rounds
4           12strong  64   2018-01-19              12 Strong

   production_budget  domestic_gross  worldwide_gross       days    months  \
0            5000000        72082999        108286422     Friday     March
1           12000000           14616            14616  Wednesday  November
2           18000000        18335230         60217171     Friday  November
3           20000000        12234694         17306648     Friday     March
4           35000000        45819713         71118378     Friday   January

   year   z_score   movie_id         primary_title        original_title  \
0  2016  0.096148  tt1179933   10 Cloverfield Lane   10 Cloverfield Lane
1  2015 -0.523540  tt3453052 10 Days in a Madhouse 10 Days in a Madhouse
2  2010 -0.178974  tt1542344             127 Hours             127 Hours
3  2009 -0.424570  tt3517850             12 Rounds             12 Rounds
4  2018 -0.116581  tt1413492             12 Strong             12 Strong

   start_year  runtime_minutes                          genres
0        2016            103.0       [Drama, Horror, Mystery]
1        2015            111.0                         [Drama]
2        2010             94.0  [Adventure, Biography, Drama]
3        2017              NaN       [Action, Drama, Romance]
4        2018            130.0       [Action, Drama, History]
```

We want to process the genres now into something more readable. The easiest way to do this would be to One-Hot Encode it so that we can retain all of the information we still have, but compare it to each other more easily.

[24]:
```
#create dummy collumns to get counts and easy splits
rating_and_budgets= (
    rating_and_budgets.drop('genres',1).join(
        rating_and_budgets.genres.str.join('|').str.get_dummies()))
```

Now, let's get a count of all the genres.

[25]:
```
#Gets the counts or all of the genre categories
counts = rating_and_budgets.iloc[:,16:42].sum()
#Highest counts - Drama, comedy
print(counts)
```

```
Action          558
Adventure       428
Animation       131
Biography       189
Comedy          680
Crime           310
Documentary     196
Drama          1144
Family          139
Fantasy         156
History          69
Horror          285
Music            70
Musical          20
Mystery         169
News              1
Romance         276
Sci-Fi          176
Sport            48
Thriller        392
War              37
Western          20
dtype: int64
```

Let's run some basic stastics on the genres.

[26]:
```
#Lists for each individual statistics
#for genre in counts.index:
#    worldwide_gross_median.append(
#        rating_and_budgets[rating_and_budgets[genre] == 1]\
#            ['worldwide_gross'].median())

# Goes through each category and gets the statistic from it.
```

```python
# Then puts it in a dict with the counts

#Creates a new DF for processing
randb = rating_and_budgets.copy()
#median

worldwide_gross_median= [randb[randb[i] == 1]['worldwide_gross'].median()
                         for i in counts.index]
median_worldwide_gross = dict(zip(counts.index, worldwide_gross_median))

#mode
worldwide_gross_means = [randb[randb[i] == 1]['worldwide_gross'].mean()
                         for i in counts.index]
mean_worldwide_gross = dict(zip(counts.index, worldwide_gross_means))

#count
worldwide_gross_counts = [randb[randb[i] == 1]['worldwide_gross'].count()
                          for i in counts.index]
worldwide_gross_counts = dict(zip(counts.index, worldwide_gross_counts))

#max
worldwide_gross_max = [randb[randb[i] == 1]['worldwide_gross'].max()
                       for i in counts.index]
worldwide_gross_max = dict(zip(counts.index, worldwide_gross_max))

#min
worldwide_gross_min = [randb[randb[i] == 1]['worldwide_gross'].min()
                       for i in counts.index]
worldwide_gross_min = dict(zip(counts.index, worldwide_gross_min))
```

[27]:

```python
#sorts the values for data exploration
rating_and_budgets[rating_and_budgets['Music']==1].sort_values(
                                                  'worldwide_gross',ascending=False)
```

[27]:

```
                  title  id release_date                 movie  \
403    bohemianrhapsody  84   2018-11-02     Bohemian Rhapsody
248         astarisborn   5   2018-10-05       A Star is Born
1583           lalaland  92   2016-12-09           La La Land
2101      pitchperfect2  14   2015-05-15       Pitch Perfect 2
2102      pitchperfect3  58   2017-12-22       Pitch Perfect 3
…                   …   ..          …                   …
147    alongtheroadside  91   2015-03-24   Along the Roadside
162        americanhero   3   2015-12-11        American Hero
3220  theresaisamother  40   2015-09-29  Theresa Is a Mother
2548        steelspirit  58   2003-12-01          Steel Spirit
3107       themagicflute  18   2006-12-31       The Magic Flute
```

```
      production_budget  domestic_gross  worldwide_gross     days     months  \
403            55000000       216303339        894985342   Friday   November
248            36000000       215288866        433449571   Friday    October
1583           20000000       151101803        426351163   Friday   December
2101           29000000       184296230        287625468   Friday        May
2102           45000000       104897530        185736412   Friday   December
…                   …             …                …      …        …
147              250000               0             3234  Tuesday      March
162             1000000               0               26   Friday   December
3220             200000               0                0  Tuesday  September
2548              20000               0                0   Monday   December
3107           27000000               0                0   Sunday   December

      year  …  Music Musical Mystery News  Romance  Sci-Fi  Sport  Thriller  \
403   2018  …      1       0       0    0        0       0      0         0
248   2018  …      1       0       0    0        1       0      0         0
1583  2016  …      1       0       0    0        0       0      0         0
2101  2015  …      1       0       0    0        0       0      0         0
2102  2017  …      1       0       0    0        0       0      0         0
…     …  …    …     …      …  …       …     …    …       …
147   2015  …      1       0       0    0        1       0      0         0
162   2015  …      1       0       0    0        0       0      0         0
3220  2015  …      1       0       0    0        0       0      0         0
2548  2003  …      1       0       0    0        0       0      0         0
3107  2006  …      1       0       0    0        0       0      0         0

      War  Western
403     0        0
248     0        0
1583    0        0
2101    0        0
2102    0        0
…    …      …
147     0        0
162     0        0
3220    0        0
2548    0        0
3107    0        0

[70 rows x 38 columns]
```

For easier access, let's create a dataframe of all the statistics.

[28]:
```
#creates dataframe to highlight the stats
movie_stats = pd.DataFrame(
    zip(median_worldwide_gross.values(),
        mean_worldwide_gross.values(),
```

```
        worldwide_gross_counts.values(),
        worldwide_gross_max.values(),
        worldwide_gross_min.values()),
    median_worldwide_gross.keys(),
        ['Medians','Means','Counts','Max','Min'])
```

[29]:
```
#sorts the DF by median
movie_stats.sort_values('Medians', ascending=False)
```

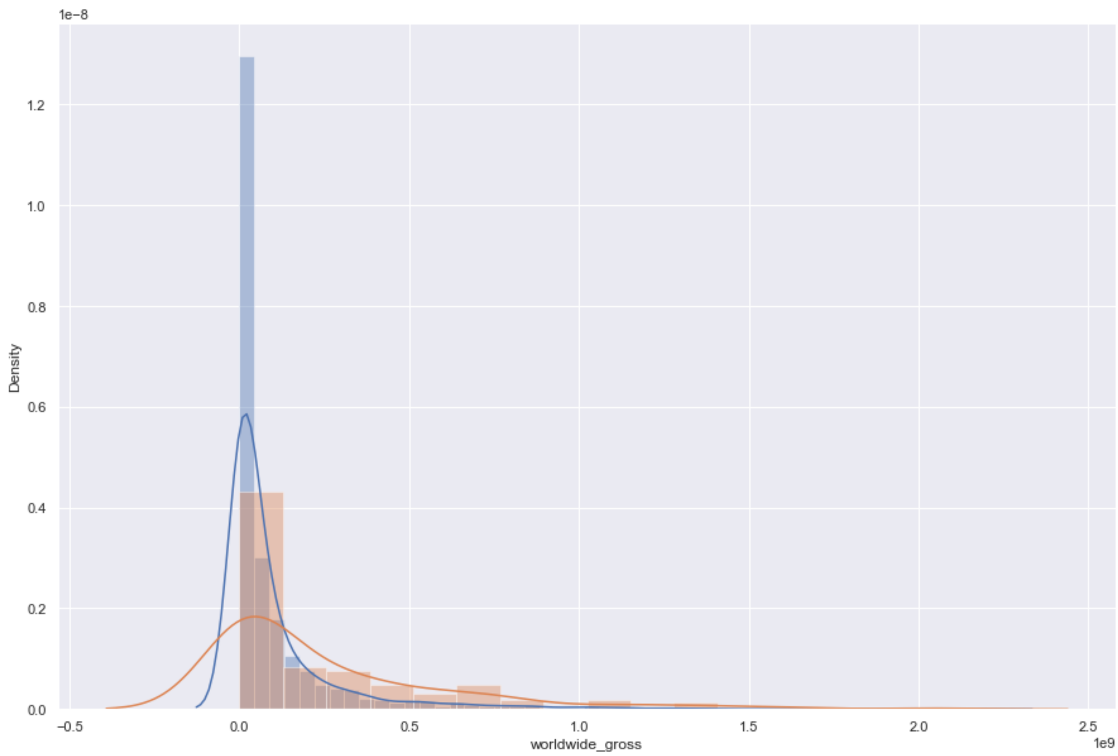
[29]:

	Medians	Means	Counts	Max	Min
Animation	197578586.0	3.006570e+08	131	1242520711	0
Adventure	182667975.0	3.034551e+08	428	2208208395	0
Action	87359119.5	1.993443e+08	558	2048134200	0
Fantasy	84720721.5	2.078764e+08	156	1259199706	0
Sci-Fi	79476525.5	2.553969e+08	176	2048134200	0
News	57293371.0	5.729337e+07	1	57293371	57293371
Comedy	46055025.0	1.122968e+08	680	1160336173	0
Family	42174545.0	1.401701e+08	139	1259199706	0
Mystery	34246770.0	7.642743e+07	169	586464305	0
Musical	30128794.5	1.309215e+08	20	1259199706	0
Crime	27552360.5	6.265413e+07	310	1234846267	0
Thriller	25696249.5	8.100579e+07	392	1234846267	0
Biography	25187026.0	6.652760e+07	189	894985342	0
Romance	22074698.5	5.774931e+07	276	570998101	0
Sport	19201039.5	6.734483e+07	48	1272469910	0
Drama	18749625.5	6.184505e+07	1144	1272469910	0
Horror	18344729.0	5.423266e+07	285	697457969	0
Music	17092887.5	6.308906e+07	70	894985342	0
History	16891011.0	5.418766e+07	69	499837368	0
War	16038343.0	5.559716e+07	37	330780051	0
Documentary	8990022.5	4.729548e+07	196	457683805	0
Western	8332261.5	6.696936e+07	20	449948323	0

Let's explore the distribution of the genres.

[30]:
```
#plot the distribution of overall and the category
sns.distplot(rating_and_budgets['worldwide_gross'])
sns.distplot(
    rating_and_budgets[rating_and_budgets['Sci-Fi']==1]['worldwide_gross'])
```

[30]: <AxesSubplot:xlabel='worldwide_gross', ylabel='Density'>



We can see a right skew of the data from the graph above.

6 Statistical Test for Animation

We are using a hypothesis test to determine if there was a significant difference between the worldwide gross of animated movies compared to the rest of the sample of movies. We used a 1 sample t-test instead of a graph so that we could see if the difference was statistically significant.

Null Hypothesis: Animation Movies produce the same Worldwide Gross as other genres of movies.

Alternative Hypothesis: Animation Movies produce a higher Worldwide Gross than other genres of movies.

Alpha: 0.05

[31]:
```
#Creates two DFs, one with Sci-Fi and one without
animated_movies = rating_and_budgets[rating_and_budgets['Animation'] == 1]
not_animated_movies = rating_and_budgets[rating_and_budgets['Animation'] == 0]
```

[32]:
```
#Runs a ttest
stats.ttest_ind(animated_movies['worldwide_gross'],
                not_animated_movies['worldwide_gross'])
```

[32]:
```
Ttest_indResult(statistic=11.819691277138588, pvalue=2.2692702400680073e-31)
```

With a p-value that is approaching 0, we can reject the null hypothesis and say that there is a significant difference between Animated movies gross compared to other genres' worldwide gross.

We do want to address the limitations of this test. The largest issue that comes here is due to the skewness of the data. This is likely due to the data collection hear, as the database with the production value and worldwide gross only has around 4k movies, compared to the 150k+ movies on the IMDB database. These movies also appear to be larger movies that have a much higher production value.

Just out of curiousity, we ran this test on the other genres as well.

[33]:
```
#Does the above tests for every genre
ttest_res = []
for genre in counts.index:
    genre_movie = rating_and_budgets[rating_and_budgets[genre] == 1]
    not_genre_movies = rating_and_budgets[rating_and_budgets[genre] == 0]
    ttest_res.append(stats.ttest_ind(genre_movie['worldwide_gross'],
                                     not_genre_movies['worldwide_gross']))
#Warning happens due to th T-test being ran on news, which has 2 samples
```

[34]:
```
#Creates a DF for all the t-statistics and pvals
tscores = pd.DataFrame(dict(zip(counts.index, ttest_res)),
                       ['Statistic', 'Pvalue']).T
```

[35]:
```
#sorts the df by statistic
tscores.sort_values('Statistic')
```

[35]:

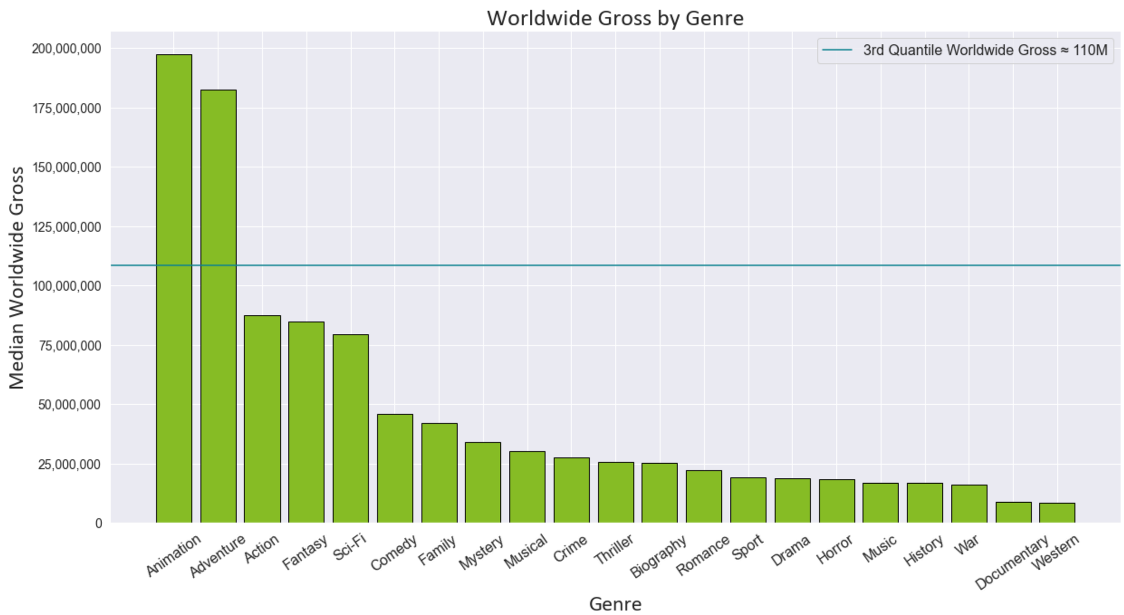
	Statistic	Pvalue
Drama	-10.456188	4.725722e-25
Horror	-4.632482	3.807083e-06
Documentary	-4.269255	2.037877e-05
Romance	-4.233917	2.383419e-05
Crime	-4.057785	5.113105e-05
Biography	-2.796640	5.205042e-03
Thriller	-2.656510	7.947929e-03
History	-2.165104	3.047846e-02
Mystery	-1.962300	4.984347e-02
Music	-1.802306	7.162329e-02
War	-1.530645	1.259896e-01
Sport	-1.335975	1.816847e-01
Western	-0.865509	3.868466e-01
Musical	0.570856	5.681511e-01
Comedy	1.047406	2.950184e-01
Family	2.107876	3.514564e-02
Fantasy	6.674639	3.070756e-11
Sci-Fi	10.570234	1.487174e-25
Animation	11.819691	2.269270e-31
Action	13.107347	5.900928e-38
Adventure	25.489776	5.633579e-127

```
News                  NaN             NaN
```

Let's now plot to see how the worldwide gross compares for each genre.

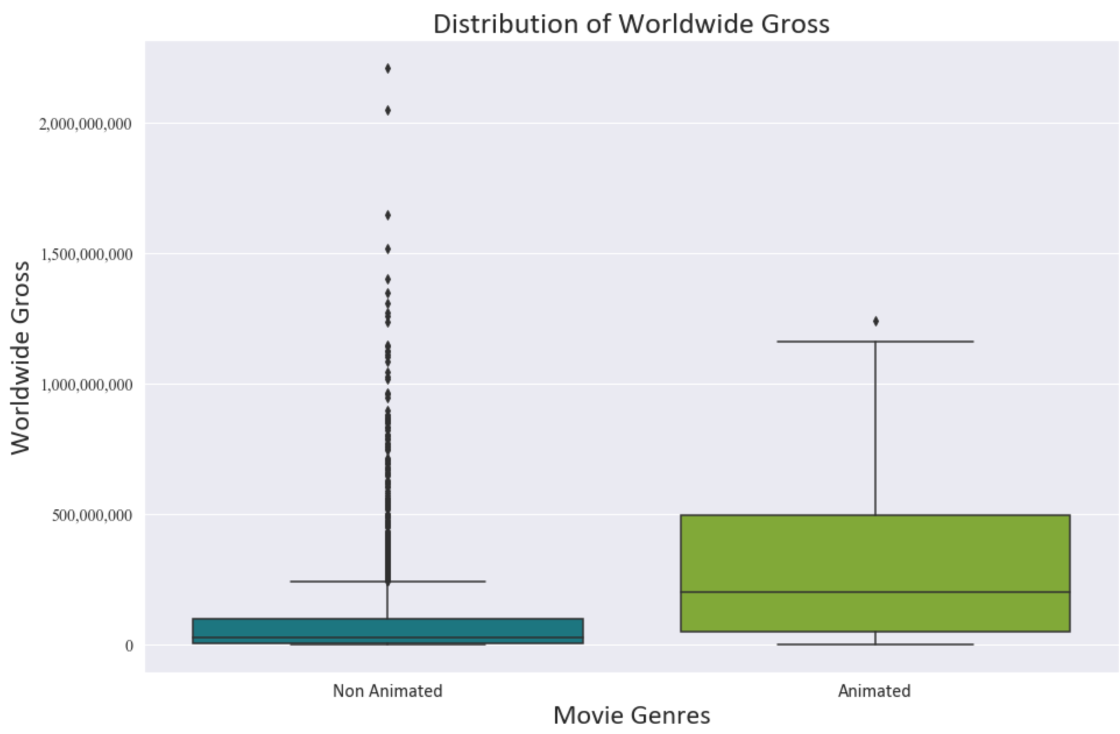
[36]:
```
#Sets the theme to seaborn
sns.set_theme()

#Set a default font
font = {'fontname':'Calibri'}

#Remove News as there is only 1 sample
cleaned_stats = movie_stats.drop(
    index='News').sort_values('Medians', ascending=False)

#Create figure
fig, ax = plt.subplots(figsize=(20,10))

#Create a bar plot for all of the medians for each genre
ax.bar(range(0,len(cleaned_stats['Medians'])),
       list(cleaned_stats['Medians']),
       color = '#86BC25',
       edgecolor = 'black')

#Creates the xticks
ax.set_xticks(range(0,len(cleaned_stats['Medians'])))
ax.set_xticklabels(list(cleaned_stats.index.values),
                   rotation = 35,
                   fontsize = 16)

#Sets the tables and the titles
ax.set_xlabel('Genre', fontsize = 24,**font)
ax.set_ylabel('Median Worldwide Gross', fontsize=24,**font)
ax.set_title('Worldwide Gross by Genre', fontsize=26,**font)

#Cleans up the formatting of ticks
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
plt.yticks(fontsize=14)

#plot 3rd Quantile gross line line
plt.axhline(y = rating_and_budgets['worldwide_gross'].quantile(.75),
            color = '#0D8390', linestyle = '-',
            label = '3rd Quantile Worldwide Gross   110M')

#Shows the legend
ax.legend(prop={'size': 16})
#Set the legend font
```

```
matplotlib.rc('font',family='Times New Roman')

plt.show()
```



And see the difference in Animated Movies compared to non-animated movies.

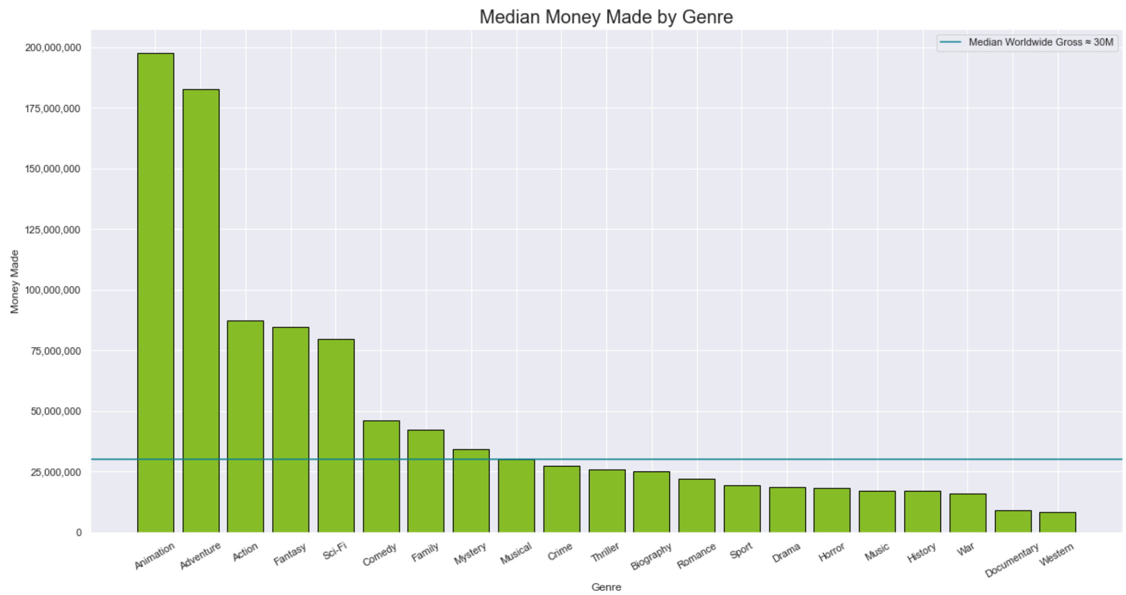
[37]:
```
#Create a boxplot of
medianbox = sns.boxplot(data=rating_and_budgets,
                        x = 'Animation',
                        y = 'worldwide_gross',
                        palette = ['#0D8390','#86BC25'])
#Set the title and fonts
medianbox.set_title('Distribution of Worldwide Gross', fontsize=26,**font)
#Sets the labels and fonts
medianbox.set_xlabel('Movie Genres', fontsize=24,**font)
medianbox.set_ylabel('Worldwide Gross', fontsize=24,**font)

#Adjusts the labels for the boxes
medianbox.set_xticklabels(['Non Animated','Animated'], fontsize=16,**font)

#Formatts the y ticks
medianbox.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
plt.yticks(fontsize=14)

plt.show()
```



Let's take this a step further and see the spread of the data per genre.

[38]:
```
#Sets the theme to seaborn
sns.set_theme()

#Remove News as there is only 1 sample
cleaned_stats = movie_stats.drop(
    index='News').sort_values('Medians', ascending=False)

#Create figure
fig, ax = plt.subplots(figsize=(20,10))

#Create a bar plot for all of the medians for each genre
ax.bar(range(0,len(cleaned_stats['Medians'])),
       list(cleaned_stats['Medians']), color = '#86BC25',edgecolor = 'black')

#Creates the xticks
ax.set_xticks(range(0,len(cleaned_stats['Medians'])))
ax.set_xticklabels(list(cleaned_stats.index.values), rotation = 30)

#Sets the tables and the titles
ax.set_xlabel('Genre')
ax.set_ylabel('Money Made')
ax.set_title('Median Money Made by Genre', fontsize=20)
```

```
#Cleans up the formatting of
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))

#plot median income line
plt.axhline(y = rating_and_budgets['worldwide_gross'].median(),
            color = '#0D8390', linestyle = '-',
            label = 'Median Worldwide Gross   30M')
#Shows the legend
ax.legend()

plt.show()
```



7 Release Date

Let's explore how the movies performed in each month.

After extracting and creating a new column called "months" during our data cleaning process, we wanted to create a numeric column for months to sort the data and display the months in ascending order.

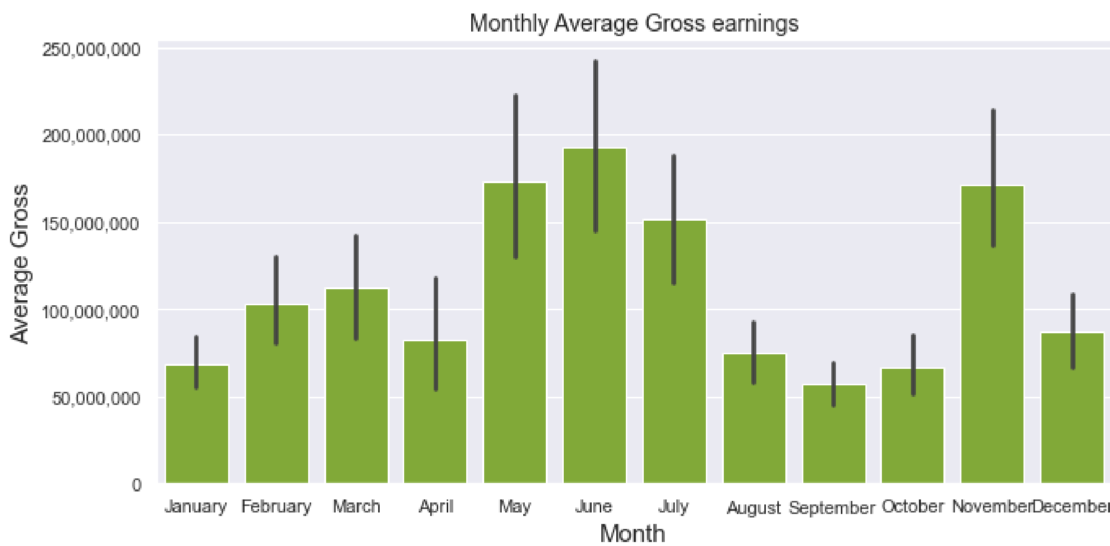
To take a closer look at the recent trends, we filtered our dataset with movies released after 2000.

[39]:
```
#Create a dictionary
months_dict = { 'January': 1, 'February': 2, 'March': 3, 'April': 4, 'May': 5,
               'June': 6, 'July': 7, 'August': 8, 'September': 9,
               'October': 10, 'November': 11, 'December': 12}
```

```
#Map the dictionary to the 'month' column
rating_and_budgets['months_numeric'] = rating_and_budgets['months'].apply(
    lambda x: months_dict.get(x))

#Sort the numeric months column in the ascending order
rating_and_budgets = rating_and_budgets.sort_values('months_numeric')

#Filtering the dataset with movies released from the year 2000
rating_and_budgets = rating_and_budgets[rating_and_budgets['year'] >= 2000]
```

Let's see the average gross earnings made from all the movies post 2000 by month.

[40]:
```
#Create the plot
fig, ax = plt.subplots()
ax = sns.barplot(data = rating_and_budgets, x='months', y='worldwide_gross',
                 color ='#86BC25')
#Set plot size
fig.set_size_inches(10.5, 5)
#Set title and labels
ax.set_title('Monthly Average Gross earnings', fontsize=14)
ax.set_xlabel('Month', fontsize=15)
ax.set_ylabel('Average Gross', fontsize=15)
#Format the ticks
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
```



From the graph above, we can see that the average gross earnings is significantly higher during the holiday seasons.

[41]:
```
#Creating a seperate dataframe called df_plot for visualisations.

df_plot = tn_movie_budgets.join(imdb_movie_ratings, how = 'inner')
df_plot.reset_index(inplace=True)
df_plot = (df_plot.drop_duplicates(subset='title', keep='first'))
# Convert values into string and split them
df_plot['genres'] = df_plot['genres'].str.split(',')
# Convert values into list of strings
df_plot['genres'] = df_plot['genres'].tolist()
# Explode list into individual values
df_plot = df_plot.explode('genres')


months_dict = {'January': 1, 'February': 2, 'March': 3, 'April': 4, 'May': 5,
               'June': 6, 'July': 7, 'August': 8, 'September': 9,
               'October': 10, 'November': 11, 'December': 12}
df_plot['months_numeric'] = df_plot['months'].apply(
    lambda x: months_dict.get(x))
df_plot = df_plot.sort_values('months_numeric')
df_plot = df_plot[df_plot['year'] >= 2000]
```

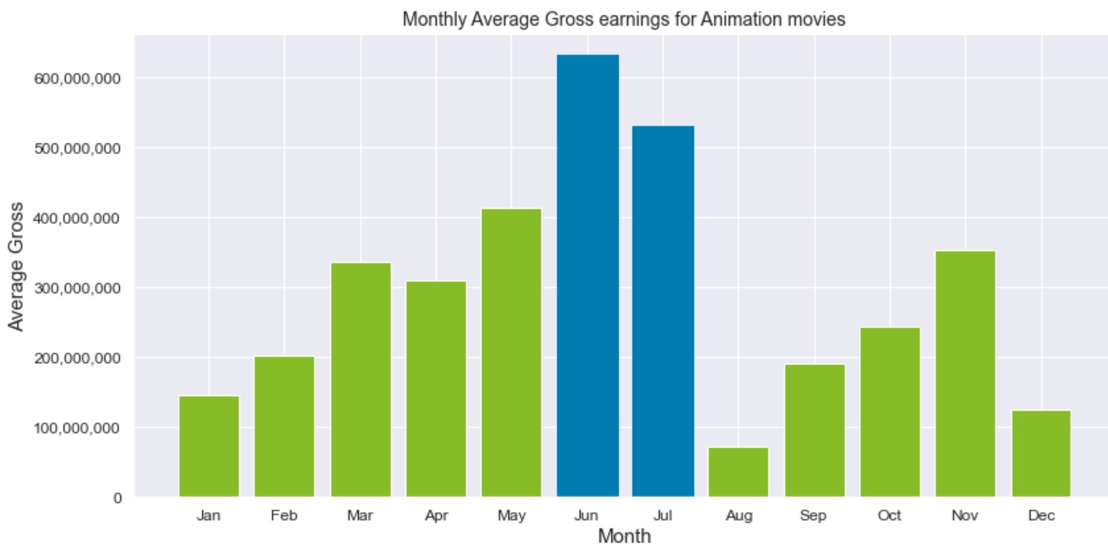
As we progressed with our analysis, we thought it would be interesting to see how “Animation” and “Adventure” performed and when would be the best release time for these 2 genres.

[42]:
```
# Plotting world gross by month for top 2 genres : Animation and Adventure
def plots(df, genre, colors,n1,n2):
    animated_df=df[df['genres']==genre]
    animated_df = animated_df.drop_duplicates('title')
    animated_df = animated_df.groupby(['months_numeric']
                                     ).worldwide_gross.mean()
    # Create a figure and axis
    fig, ax = plt.subplots(figsize=(12,6))
    # Get x and y data
    x1 = animated_df.index
    y1 = animated_df.values
    graph = ax.bar(x1, y1, color ='#86BC25')
    graph[n1].set_color(colors)
    graph[n2].set_color(colors)
    months =['Jan','Feb', 'Mar', 'Apr', 'May', 'Jun',
             'Jul','Aug', 'Sep', 'Oct', 'Nov', 'Dec']
    months_num = range(1,13)
    ax.set_xticks(months_num)
    ax.set_xticklabels(months)
    plt.xticks(fontsize=12)
    plt.yticks(fontsize=12)
    ax.set_title('Monthly Average Gross earnings for '
                 + genre + ' movies', fontsize=14)
    ax.set_xlabel('Month', fontsize=15)
```

```python
    ax.set_ylabel('Average Gross', fontsize=15)
    ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
    plt.tight_layout()
    plt.savefig('plot3.jpg')
```

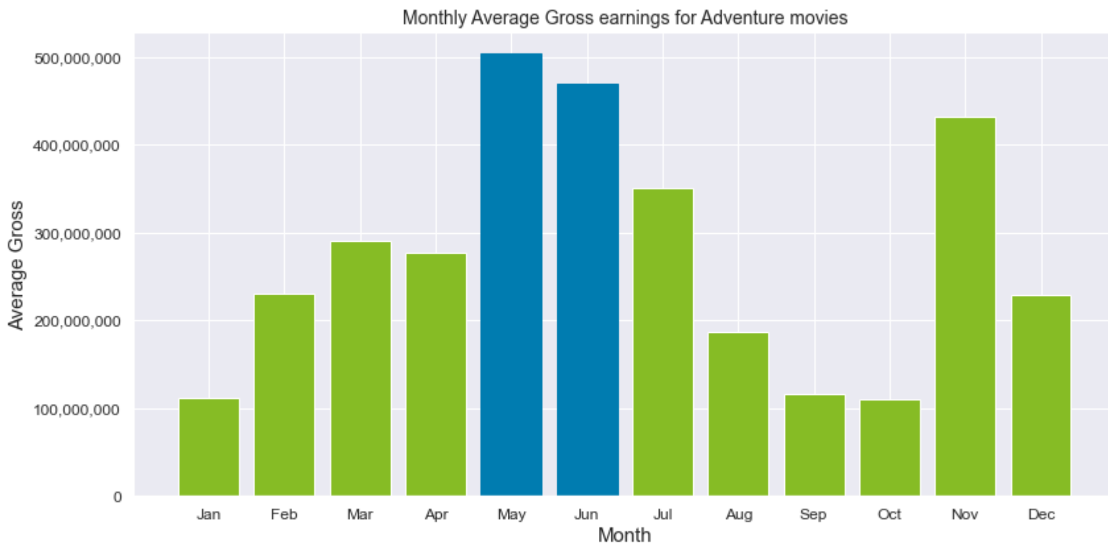
Plot's for Animation and Adventure

[43]:
```python
# Visualisation of average gross earnings for Animated movies
plots(df_plot, 'Animation','#007CB0',5,6)
```



Animated movies released in the month of June yielded highest average gross earnings. We noticed that movies release in the early summer returned higher gross compared to other months (this could be because of the schools and colleges being off and people tending to have more leisure time).

[44]:
```python
# Visualisation of average gross earnings for Adventure movies
plots(df_plot, 'Adventure', '#007CB0',4,5)
```



We can see that May has returned highest average gross earnings for Adventure movies, but having a very similar pattern to the Animated movies release time.