# **Worldwide Box Office Data Analysis**



Libraries

#### In [1]:

```
import numpy as np
import pandas as pd
pd.set option('max columns', None)
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
plt.style.use('ggplot')
import datetime
from scipy import stats
from scipy.sparse import hstack, csr matrix
from sklearn.model_selection import train_test_split, KFold
from wordcloud import WordCloud
from collections import Counter
from nltk.corpus import stopwords
from nltk.util import ngrams
from sklearn.feature extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.preprocessing import StandardScaler
import nltk
nltk.download('stopwords')
stop = set(stopwords.words('english'))
import os
import plotly.offline as py
py.init notebook mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls
import json
import ast
from urllib.request import urlopen
from PIL import Image
print("Packages imported successfully")
```

Packages imported successfully

### Task: Data Loading and Exploration

```
In [2]:
```

```
train = pd.read_csv("data/train.csv")
test = pd.read_csv("data/test.csv")
```

# In [3]:

train.head()

# Out[3]:

|   | id | budget   | homepage                          | imdb_id   | original_language | origina                |
|---|----|----------|-----------------------------------|-----------|-------------------|------------------------|
| 0 | 1  | 14000000 | NaN                               | tt2637294 | en                | Hot Tu<br>Mac          |
| 1 | 2  | 40000000 | NaN                               | tt0368933 | en                | The Pr<br>Dia<br>Engag |
| 2 | 3  | 3300000  | http://sonyclassics.com/whiplash/ | tt2582802 | en                | Wł                     |
| 3 | 4  | 1200000  | http://kahaanithefilm.com/        | tt1821480 | hi                | К                      |
| 4 | 5  | 0        | NaN                               | tt1380152 | ko                | 마                      |
| 4 |    |          |                                   |           |                   | •                      |

# In [4]:

train.shape

# Out[4]:

(3000, 203)

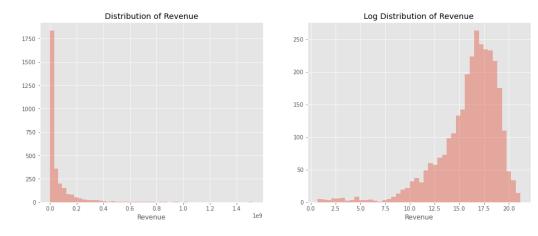
# **Task: Visualizing the Target Distribution**

#### In [5]:

```
fig, ax = plt.subplots(figsize = (16, 6))
plt.subplot(1, 2, 1)
sns.distplot(train['revenue'], kde = False)
plt.title("Distribution of Revenue")
plt.xlabel("Revenue")
plt.subplot(1, 2, 2)
sns.distplot(np.log1p(train['revenue']), kde = False)
plt.title("Log Distribution of Revenue")
plt.xlabel("Revenue")
```

#### Out[5]:

#### Text(0.5, 0, 'Revenue')



#### In [6]:

```
train['log_revenue'] = np.log1p(train['revenue'])
```

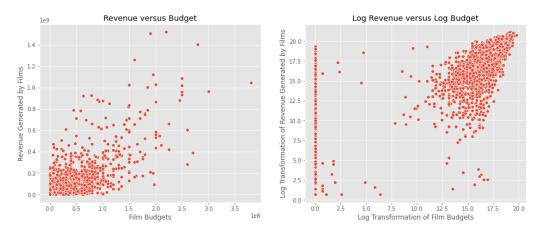
# Task: Relationship between Film Revenue and Budget

#### In [7]:

```
fig, ax = plt.subplots(figsize = (16, 6))
plt.subplot(1, 2, 1)
sns.scatterplot(train['budget'], train['revenue'])
plt.title("Revenue versus Budget")
plt.xlabel("Film Budgets")
plt.ylabel("Revenue Generated by Films")
plt.subplot(1, 2, 2)
sns.scatterplot(np.log1p(train['budget']), np.log1p(train['revenue']))
plt.title("Log Revenue versus Log Budget")
plt.xlabel("Log Transformation of Film Budgets")
plt.ylabel("Log Transformation of Revenue Generated by Films")
```

#### Out[7]:

Text(0, 0.5, 'Log Transformation of Revenue Generated by Films')



#### In [8]:

```
train['log_budget'] = np.log1p(train['budget'])
test['log_budget'] = np.log1p(test['budget'])
```

# Task: Does having an Official Homepage Affect Revenue?

#### In [9]:

```
train['homepage'].value_counts().head(10)
```

#### Out[9]:

```
http://www.transformersmovie.com/
                                                                4
http://www.lordoftherings.net/
                                                                2
http://www.thehobbit.com/
                                                                2
http://phoenixforgotten.com/
                                                                1
http://www.the-scorpion-king.com/
                                                                1
http://disneydvd.disney.go.com/tarzanr-special-edition.html
                                                                1
http://constantinemovie.warnerbros.com/
                                                                1
http://www.paranormalactivity-movie.com/
                                                                1
http://www.moanmovie.com/
                                                                1
http://www.imdb.com/title/tt0095169/
                                                                1
Name: homepage, dtype: int64
```

#### In [10]:

```
train['has_homepage'] = 0
train.loc[train['homepage'].isnull() == False, 'has_homepage'] = 1
test['has_homepage'] = 0
test.loc[test['homepage'].isnull() == False, 'has_homepage'] = 1
```

#### In [11]:

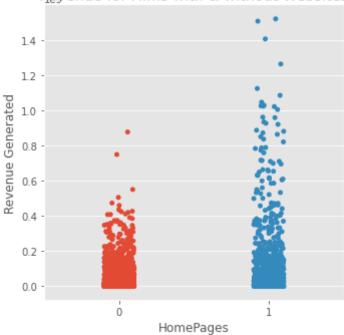
```
fig = plt.figure(figsize = (10, 8))
sns.catplot(x = "has_homepage", y = "revenue", data = train)
plt.title("Revenue for Films with & without Websites")
plt.xlabel("HomePages")
plt.ylabel("Revenue Generated")
```

#### Out[11]:

Text(6.7999999999997, 0.5, 'Revenue Generated')

<Figure size 720x576 with 0 Axes>

### Revenue for Films with & without Websites



# Task: Distribution of Languages in Film

#### In [12]:

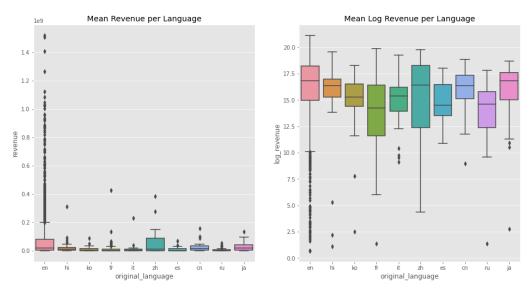
```
language_data = train.loc[train['original_language'].isin(train['original_language'].value_counts().head(10).index)]
```

#### In [13]:

```
plt.figure(figsize = (16, 8))
plt.subplot(1, 2, 1)
sns.boxplot(x = "original_language", y = "revenue", data = language_data)
plt.title("Mean Revenue per Language")
plt.subplot(1, 2, 2)
sns.boxplot(x = "original_language", y = "log_revenue", data = language_data)
plt.title("Mean Log Revenue per Language")
```

#### Out[13]:

Text(0.5, 1.0, 'Mean Log Revenue per Language')

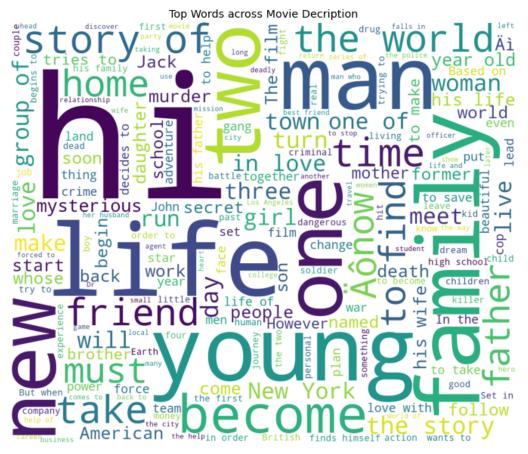


# Task: Frequent Words in Film Titles and Descriptions

#### In [14]:



#### In [15]:



# Task: Do Film Descriptions Impact Revenue?

#### In [16]:

```
import eli5
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LinearRegression
```

C:\Users\vedan\anaconda3\lib\site-packages\sklearn\utils\deprecati
on.py:143: FutureWarning:

The sklearn.metrics.scorer module is deprecated in version 0.22 a nd will be removed in version 0.24. The corresponding classes / fu nctions should instead be imported from sklearn.metrics. Anything that cannot be imported from sklearn.metrics is now part of the private API.

C:\Users\vedan\anaconda3\lib\site-packages\sklearn\utils\deprecati
on.py:143: FutureWarning:

The sklearn.feature\_selection.base module is deprecated in versio n 0.22 and will be removed in version 0.24. The corresponding clas ses / functions should instead be imported from sklearn.feature\_se lection. Anything that cannot be imported from sklearn.feature\_sel ection is now part of the private API.

#### In [17]:

```
vectorizer = TfidfVectorizer(
    sublinear_tf=True,
    analyzer='word',
    token_pattern=r'\w{1,}',
    ngram_range=(1, 2),
    min_df=5
)
```

#### In [18]:

```
overview_text = vectorizer.fit_transform(train['overview'].fillna(''))
linreg = LinearRegression()
linreg.fit(overview_text, train['log_revenue'])
```

#### Out[18]:

LinearRegression()

#### In [19]:

### Out[19]:

#### y top features

| Weight?            | Feature       |  |  |  |
|--------------------|---------------|--|--|--|
| +13.074            | to            |  |  |  |
| +10.131            | bombing       |  |  |  |
| +9.981             | the           |  |  |  |
| +9.777             | complications |  |  |  |
| 3858 more positive |               |  |  |  |
| 3315 more negative |               |  |  |  |
| -9.281             | politicians   |  |  |  |
| -9.391             | 18            |  |  |  |
| -9.481             | violence      |  |  |  |
| -9.628             | escape and    |  |  |  |
| -9.716             | life they     |  |  |  |
| -10.021            | ones          |  |  |  |
| -10.111            | sally         |  |  |  |
| -10.291            | attracted to  |  |  |  |
| -10.321            | who also      |  |  |  |
| -10.421            | casino        |  |  |  |
| -10.614            | receiving     |  |  |  |
| -10.759            | kept          |  |  |  |
| -12.139            | and be        |  |  |  |
| -12.939            | campaign      |  |  |  |
| -13.858            | mike          |  |  |  |
| -15.273            | woman from    |  |  |  |

# **Task: Analyzing Movie Release Dates**

```
In [20]:
```

```
test.loc[test['release_date'].isnull() == False, 'release_date'].head()
```

### Out[20]:

```
0 7/14/07
1 5/19/58
2 5/23/97
3 9/4/10
4 2/11/05
Name: release_date, dtype: object
```

# **Task: Preprocessing Features**

```
In [21]:
def fix_date(x) :
     year = x.split('/')[2]
     if int(year) <= 19 :
         return x[:-2] + '20' + year
         return x[:-2] + '19' + year
In [22]:
test.loc[test['release_date'].isnull() == True].head()
Out[22]:
        id budget homepage
                             imdb_id original_language original_title overview
                                                                   Jails,
                                                                Hospitals
                                                          Jails,
                                                                  &
 828 3829
               0
                       NaN tt0210130
                                                 en
                                                      Hospitals &
                                                                 Hip-Hop
                                                        Hip-Hop
                                                                    is a
                                                                cinematic
4
In [23]:
test.loc[test['release date'].isnull() == True, 'release date'] = '05/01/00'
In [24]:
train['release date'] = train['release date'].apply(lambda x: fix date(x))
test['release_date'] = test['release_date'].apply(lambda x: fix_date(x))
Task: Creating Features Based on Release Date
In [25]:
train['release_date'] = pd.to_datetime(train['release_date'])
test['release_date'] = pd.to_datetime(test['release_date'])
```

#### In [26]:

```
def process_date(df) :
    date_parts = ['year', 'weekday', 'month', 'weekofyear', 'day', 'quarter']
    for part in date_parts :
        part_col = 'release_date' + '_' + part
        df[part_col] = getattr(df['release_date'].dt, part).astype(int)
    return df

train = process_date(train)
test = process_date(test)
```

# Task: Using Plotly to Visualize the Number of Films Per Year

#### In [30]:

```
d1 = train['release_date_year'].value_counts().sort_index()
d2 = test['release_date_year'].value_counts().sort_index()
```

### In [32]:

### Distribution of Films Per Year



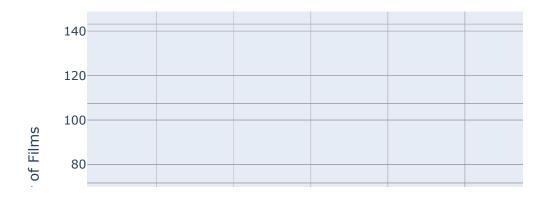
### Task: Number of Films and Revenue Per Year

#### In [ ]:

```
d1 = train['release_date_year'].value_counts().sort_index()
d2 = train.groupby(['release_date_year'])['revenue'].sum()
```

#### In [33]:

#### Distribution of Films and Total Revenue Per Year

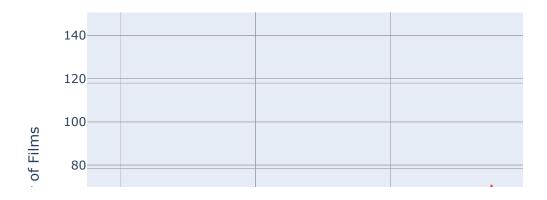


#### In [35]:

```
d1 = train['release_date_year'].value_counts().sort_index()
d2 = train.groupby(['release_date_year'])['revenue'].mean()
```

#### In [41]:

# Distribution of Films and Average Revenue Per Year



# Task: Do Release Days Impact Revenue

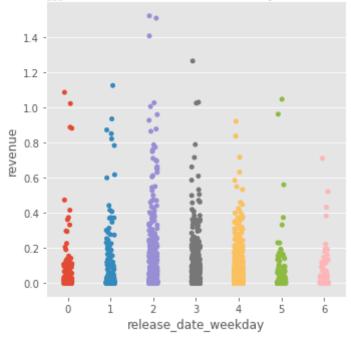
#### In [37]:

```
sns.catplot(x = "release_date_weekday", y = "revenue", data = train)
plt.title("Revenue w.r.t. Film Releases on Days of the Week")
```

### Out[37]:

Text(0.5, 1.0, 'Revenue w.r.t. Film Releases on Days of the Week')

### Revenue w.r.t. Film Releases on Days of the Week



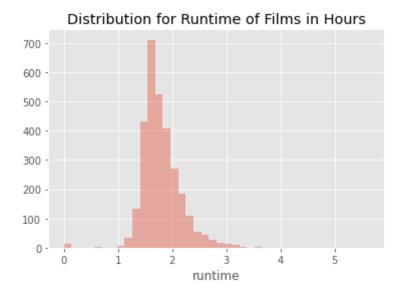
Task: Relationship between Runtime and Revenue

# In [39]:

```
sns.distplot(train['runtime'].fillna(0) / 60, bins = 40, kde = False)
plt.title('Distribution for Runtime of Films in Hours')
```

### Out[39]:

Text(0.5, 1.0, 'Distribution for Runtime of Films in Hours')

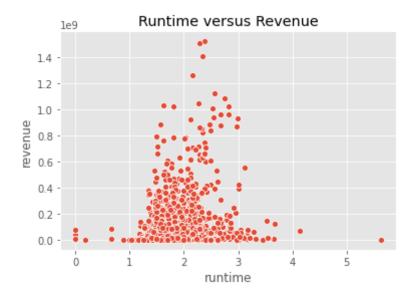


### In [40]:

```
sns.scatterplot(x = train['runtime'].fillna(0) / 60, y = train['revenue'])
plt.title("Runtime versus Revenue")
```

### Out[40]:

### Text(0.5, 1.0, 'Runtime versus Revenue')



# In [ ]: