Homework 3 - TMDB Box Office Prediction

For all parts below, answer all parts as shown in the Google document for Homework 3. Be sure to include both code that justifies your answer as well as text to answer the questions. Show runtime results for each cell. We also ask that code be commented to make it easier to follow.

In [1]:

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, ca
ll drive.mount("/content/gdrive", force_remount=True).
```

In [2]:

```
cd '/content/gdrive/My Drive/519/HW3'
```

```
/content/gdrive/My Drive/519/HW3
```

In [ ]:

```
!pip install catboost
!pip install ipywidgets
!jupyter nbextension enable --py widgetsnbextension
```

In [4]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import ast
import copy
from collections import Counter
import datetime
from wordcloud import WordCloud
import xgboost as xgb
import lightgbm as lgb
import catboost as cat
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn import preprocessing
from sklearn.model_selection import KFold
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import permutation_test_score
```

Part 1 - Data Cleaning and Reformatting

In [5]:

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

In [6]:

```
train.head()
```

Out[6]:

	id	belongs_to_collection	budget	genres	homepage	imdb_id	orig
0	1	[{'id': 313576, 'name': 'Hot Tub Time Machine ...	14000000	[{'id': 35, 'name': 'Comedy'}]	NaN	tt2637294	
1	2	[{'id': 107674, 'name': 'The Princess Diaries ...	40000000	[{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam...	NaN	tt0368933	
2	3	NaN	3300000	[{'id': 18, 'name': 'Drama'}]	http://sonyclassics.com/whiplash/	tt2582802	
3	4	NaN	1200000	[{'id': 53, 'name': 'Thriller'}, {'id': 18, 'n...	http://kahaanithefilm.com/	tt1821480	
4	5	NaN	0	[{'id': 28, 'name': 'Action'}, {'id': 53, 'nam...	NaN	tt1380152	

1. Reformating

Dict Columns:

In [7]:

```
reformat_columns = ['belongs_to_collection', 'genres', 'production_companies','product
```

In [8]:

```
# transfer from string to list of dicts
def str_to_dict(x):
  if pd.isna(x):
    x = {0}
  else:
    x = ast.literal_eval(x)
  return x
```

In [9]:

```
for col in reformat_columns:
  train[col] = train[col].apply(str_to_dict)
  test[col] = test[col].apply(str_to_dict)
train[reformat_columns].head()
```

Out[9]:

	belongs_to_collection	genres	production_companies	production_countries	spoken_langua
0	[{'id': 313576, 'name': 'Hot Tub Time Machine ...	[{'id': 35, 'name': 'Comedy'}]	[{'name': 'Paramount Pictures', 'id': 4}, {'na...	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'iso_639_1': 'name': 'Engl
1	[{'id': 107674, 'name': 'The Princess Diaries ...	[{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam...	[{'name': 'Walt Disney Pictures', 'id': 2}]	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'iso_639_1': 'name': 'Engl
2	{0}	[{'id': 18, 'name': 'Drama'}]	[{'name': 'Bold Films', 'id': 2266}, {'name': ...	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'iso_639_1': 'name': 'Engl
3	{0}	[{'id': 53, 'name': 'Thriller'}, {'id': 18, 'n...	{0}	[{'iso_3166_1': 'IN', 'name': 'India'}]	[{'iso_639_1': 'name': 'Engl {'
4	{0}	[{'id': 28, 'name': 'Action'}, {'id': 53, 'nam...	{0}	[{'iso_3166_1': 'KR', 'name': 'South Korea'}]	[{'iso_639_1': 'name': '한국어/

In [10]:

```
# keep useful part from dict
string_space = 'name'

def extract_name(x):
  y=[]
  if x != {0}:
    for i in x:
      #print(i['name'])
      y.append(i[string_space])
    x=y
    #print(y)
  else:
    x = []
  return x

train['belongs_to_collection'] = train['belongs_to_collection'].apply(extract_name)
test['belongs_to_collection'] = test['belongs_to_collection'].apply(extract_name)

list_of_genres = train['genres'].apply(extract_name)
train['genres'] = train['genres'].apply(extract_name)
test['genres'] = test['genres'].apply(extract_name)

list_companies = train['production_companies'].apply(extract_name)
train['production_companies'] = train['production_companies'].apply(extract_name)
test['production_companies'] = test['production_companies'].apply(extract_name)

string_space = 'iso_3166_1'
list_of_countries = train['production_countries'].apply(extract_name)
train['production_countries'] = train['production_countries'].apply(extract_name)
test['production_countries'] = test['production_countries'].apply(extract_name)

string_space = 'iso_639_1'
list_of_spoken_lang = train['spoken_languages'].apply(extract_name)
train['spoken_languages'] = train['spoken_languages'].apply(extract_name)
test['spoken_languages'] = test['spoken_languages'].apply(extract_name)

string_space = 'name'
#train['cast_name'] = train['cast'].apply(extract_name)

list_keyword = train['Keywords'].apply(extract_name)
train['Keywords'] = train['Keywords'].apply(extract_name)
test['Keywords'] = test['Keywords'].apply(extract_name)

```

In [11]:

```
1 train[reformat_columns].head()
```

Out[11]:

	belongs_to_collection	genres	production_companies	production_countries	spoken_langua
0	[Hot Tub Time Machine Collection]	[Comedy]	[Paramount Pictures, United Artists, Metro-Gol...	[US]	
1	[The Princess Diaries Collection]	[Comedy, Drama, Family, Romance]	[Walt Disney Pictures]	[US]	
2	[]	[Drama]	[Bold Films, Blumhouse Productions, Right of W...	[US]	
3	[]	[Thriller, Drama]	[]	[IN]	[er
4	[]	[Action, Thriller]	[]	[KR]	

Realease Date:

In [12]:

```
train['release_date'] = pd.to_datetime(train['release_date'])

def fix_date(x):
    if x.year > 2017:
        year = x.year - 100
    else:
        year = x.year
    return datetime.date(year,x.month,x.day)

train['release_date'] = train['release_date'].apply(fix_date)

# insert year, month, weekday columns
train.insert(14,"year",pd.to_datetime(train["release_date"]).dt.strftime('%Y').astype(
train.insert(15,"month",pd.to_datetime(train["release_date"]).dt.strftime('%m').astype
train.insert(16,"weekday",pd.to_datetime(train["release_date"]).dt.strftime('%A'))
train.insert(17,"day_of_week",pd.to_datetime(train["release_date"]).dt.strftime('%w').

test.loc[test['release_date'].isna(),'release_date'] = '1/5/20'
test['release_date'] = pd.to_datetime(test['release_date'])
test['release_date'] = test['release_date'].apply(fix_date)

test.insert(14,"year",pd.to_datetime(test["release_date"]).dt.strftime('%Y').astype(in
test.insert(15,"month",pd.to_datetime(test["release_date"]).dt.strftime('%m').astype(i
test.insert(16,"weekday",pd.to_datetime(test["release_date"]).dt.strftime('%A'))
test.insert(17,"day_of_week",pd.to_datetime(test["release_date"]).dt.strftime('%w').as

train[['release_date']].head()
```

Out[12]:

	release_date
0	2015-02-20
1	2004-08-06
2	2014-10-10
3	2012-03-09
4	2009-02-05

##2. Data Cleaning

Runtime:

In [13]:

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

Out[13]:

```
count    2998.000000
mean      107.856571
std        22.086434
min         0.000000
25%        94.000000
50%       104.000000
75%       118.000000
max       338.000000
Name: runtime, dtype: float64
```

In [14]:

```
#train runtime
runtime_na = train[train['runtime'].isna()][['id','title','runtime','release_date','im
runtime_zero = train.loc[train['runtime']==0,['id','title','runtime','release_date','i
runtime_anom = pd.concat([runtime_zero,runtime_na])
runtime_anom
```

Out[14]:

	id	title	runtime	release_date	imdb_id
390	391	The Worst Christmas of My Life	0.0	2012-12-22	tt2550838
591	592	А поутру они проснулись	0.0	2003-12-04	tt0768690
924	925	¿Quién mató a Bambi?	0.0	2013-11-15	tt2604346
977	978	La peggior settimana della mia vita	0.0	2011-10-27	tt2076251
1255	1256	Cry, Onion!	0.0	1975-08-25	tt0072785
1541	1542	All at Once	0.0	2014-06-05	tt3805180
1874	1875	Missing	0.0	2007-01-01	tt1133617
2150	2151	Mechenosets	0.0	2006-10-12	tt0477337
2498	2499	Hooked on the Game 2. The Next Level	0.0	2010-04-15	tt1620549
2645	2646	My Old Classmate	0.0	2014-04-25	tt3956312
2785	2786	Revelation	0.0	2001-04-12	tt0278675
2865	2866	Tutto tutto niente niente	0.0	2012-11-30	tt2456720
1335	1336	Королёв	NaN	2007-10-29	tt1107828
2302	2303	Happy Weekend	NaN	1996-03-14	tt0116485

In [15]:

```
# fill with accurate data

train.loc[train['id']==391,'runtime']= 86
train.loc[train['id']==592,'runtime']= 90
train.loc[train['id']==925,'runtime']= 86
train.loc[train['id']==978,'runtime']= 93
train.loc[train['id']==1256,'runtime']= 92
train.loc[train['id']==1542,'runtime']= 93
train.loc[train['id']==1875,'runtime']= 86
train.loc[train['id']==2151,'runtime']= 108
train.loc[train['id']==2499,'runtime']= 86
train.loc[train['id']==2646,'runtime']= 98
train.loc[train['id']==2786,'runtime']= 101
train.loc[train['id']==2866,'runtime']= 96
train.loc[train['id']==1336,'runtime']= 130
train.loc[train['id']==2303,'runtime']= 108

test.loc[test['id'] == 3244,'runtime'] = 93
test.loc[test['id'] == 4490,'runtime'] = 90
test.loc[test['id'] == 4633,'runtime'] = 108
test.loc[test['id'] == 6818,'runtime'] = 90
test.loc[test['id'] == 4074,'runtime'] = 103
test.loc[test['id'] == 4222,'runtime'] = 91
test.loc[test['id'] == 4431,'runtime'] = 96
test.loc[test['id'] == 5520,'runtime'] = 86
test.loc[test['id'] == 5845,'runtime'] = 83
test.loc[test['id'] == 5849,'runtime'] = 140
test.loc[test['id'] == 6210,'runtime'] = 104
test.loc[test['id'] == 6804,'runtime'] = 140
test.loc[test['id'] == 7321,'runtime'] = 87
```

In [16]:

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

Out[16]:

```
count    3000.000000
mean      108.235667
std        21.024433
min        11.000000
25%        94.000000
50%       104.000000
75%       118.000000
max       338.000000
Name: runtime, dtype: float64
```

Budget:

In [17]:

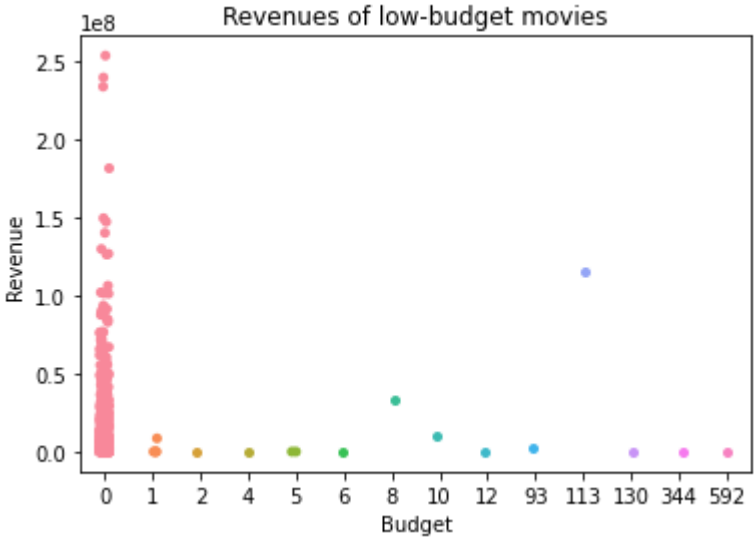
```
train['budget'].describe()
```

Out[17]:

```
count    3.000000e+03
mean     2.253133e+07
std      3.702609e+07
min      0.000000e+00
25%      0.000000e+00
50%      8.000000e+06
75%      2.900000e+07
max      3.800000e+08
Name: budget, dtype: float64
```

In [18]:

```
low_budget = train[train["budget"] <= 1000]

sns.stripplot(x='budget', y='revenue', data = low_budget, jitter=True)
plt.xlabel('Budget')
plt.ylabel('Revenue')
plt.title('Revenues of low-budget movies')
plt.show()
```



In [19]:

```
1 low_budget[low_budget["revenue"] >= 100000000][['id','budget','original_title','year',
```

Out[19]:

	id	budget	original_title	year	imdb_id	revenue
89	90	0	Sommersby	1993	tt0108185	140081992
104	105	0	Recep İvedik 4	2014	tt3477064	149521495
117	118	0	Wild Hogs	2007	tt0486946	253625427
148	149	0	Beethoven	1992	tt0103786	147214049
463	464	0	Parenthood	1989	tt0098067	126297830
469	470	113	The Karate Kid, Part II	1986	tt0091326	115103979
818	819	0	Alvin and the Chipmunks: The Road Chip	2015	tt2974918	233755553
1111	1112	0	An Officer and a Gentleman	1982	tt0084434	129795554
1130	1131	0	Smokey and the Bandit	1977	tt0076729	126737428
1358	1359	0	Stir Crazy	1980	tt0081562	101300000
1569	1570	0	Crocodile Dundee II	1988	tt0092493	239606210
1713	1714	0	The Recruit	2003	tt0292506	101191884
1864	1865	0	Scooby-Doo 2: Monsters Unleashed	2004	tt0331632	181466833
2601	2602	0	Mr. Holland's Opus	1995	tt0113862	106269971
2940	2941	0	The Goodbye Girl	1977	tt0076095	102000000

In [20]:

```
# fill those have the most difference (budget <= 1000 & revenue>100000000)

train.loc[train.id == 90,'budget'] = 30000000
train.loc[train.id == 118,'budget'] = 60000000
train.loc[train.id == 149,'budget'] = 18000000
train.loc[train.id == 464,'budget'] = 20000000
train.loc[train.id==470,'budget'] = 13000000
train.loc[train.id == 819,'budget'] = 90000000
train.loc[train.id == 1112,'budget'] = 6000000
train.loc[train.id == 1131,'budget'] = 4300000
train.loc[train.id == 1359,'budget'] = 10000000
train.loc[train.id == 1570,'budget'] = 15800000
train.loc[train.id == 1714,'budget'] = 46000000
train.loc[train.id == 1865,'budget'] = 80000000
train.loc[train.id == 2602,'budget'] = 31000000

train.loc[train.id == 850,'budget'] = 1500000  # Modern Times
train.loc[train.id == 2256,'budget'] = 1500000  # Lost & Found
train.loc[train.id == 335,'budget'] = 1848922 #Saamy

# na values
train.loc[train['id']==334,'budget'] = 1820717
train.loc[train['id']==645,'budget'] = 1810798
train.loc[train['id']==1668,'budget'] = 1820717
train.loc[train['id']==2324,'budget'] = 403251

```

In [21]:

```
# for test budget, fix the wrong scale
low_budget_test = test[test["budget"] <= 1000]
for index, row in low_budget_test.iterrows():
  if row['budget'] < 100:
    test.loc[test.index==index,'budget'] = test.loc[test.index==index,'budget'] * 1000
  elif row['budget'] < 1000:
    test.loc[test.index==index,'budget'] = row['budget'] * 1000

## for 0 values, fill zero value with mean budget per year
year_list = train['year'].unique()

#train budget
for year in year_list:
    year_mean = train[(train['year']==year) & (train['budget']!=0)]['budget'].mean()
    if year_mean != np.nan:
      train[train["year"]==year] = train[train["year"]==year].replace({"budget": 0}, y
#test budget
for year in year_list:
    year_mean = test[(test['year']==year) & (test['budget']!=0)]['budget'].mean()
    if year_mean != np.nan:
      test[test["year"]==year] = test[test["year"]==year].replace({"budget": 0}, year_
```

In [22]:

```
# for the rest small budgets
low_budget = train[(train["budget"] <= 100) & (train["revenue"] > 100)][['id','budget'
low_budget
```

Out[22]:

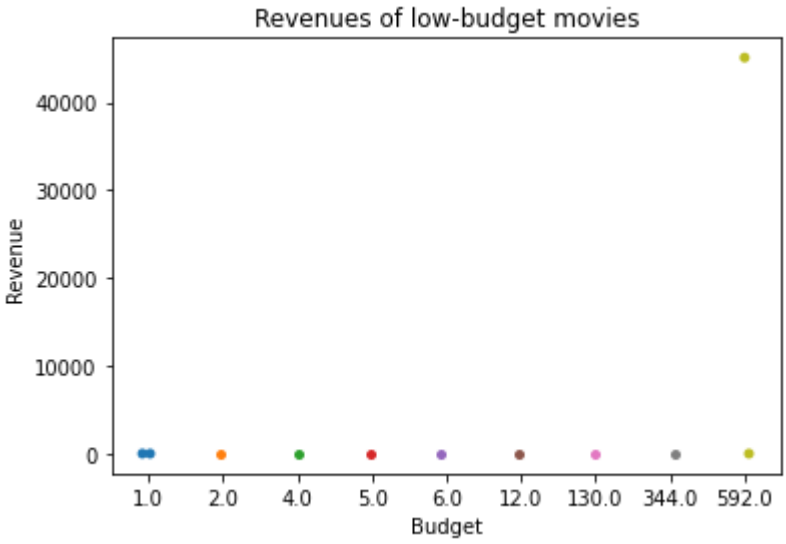
	id	budget	original_title	year	imdb_id	revenue
512	513	93.0	From Prada to Nada	2011	tt0893412	2500000
796	797	8.0	웰컴 투 동막골	2005	tt0475783	33579813
1800	1801	5.0	The Cherry Orchard	1999	tt0144134	135
2695	2696	10.0	Nurse 3-D	2013	tt1913166	10000000

In [23]:

```
train.loc[train['id']==513,'budget'] = 1100000 # From Prada to Nada
train.loc[train['id']==797,'budget'] = 8000000 # 웰컴 투 동막골
train.loc[train['id']==2696,'budget'] = 10000000 # Nurse 3-D
train.loc[train.index==1800,'budget'] = 5000000 # The Cherry Orchard
```

In [24]:

```
low_budget = train[train["budget"] <= 1000]
sns.stripplot(x='budget', y='revenue', data = low_budget, jitter=True)
plt.xlabel('Budget')
plt.ylabel('Revenue')
plt.title('Revenues of low-budget movies')
plt.show()
```



Most budget with anomalies are fixed.

In [25]:

```
train[train["budget"] <= 100][['id','budget','original_title','year','imdb_id','revenu
```

Out[25]:

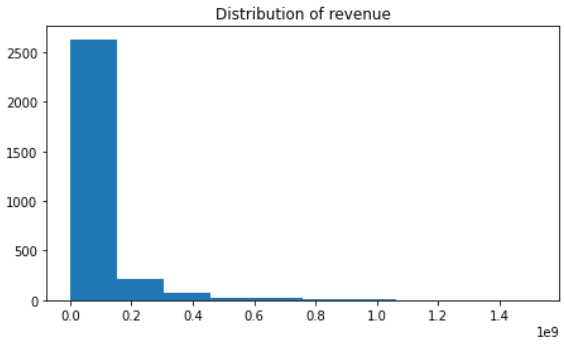
	id	budget	original_title	year	imdb_id	revenue
347	348	12.0	The Wind in the Willows	1996	tt0118172	1
639	640	6.0	Pollock	2000	tt0183659	8
695	696	1.0	Tere Naam	2003	tt0374271	2
1198	1199	5.0	Every Which Way But Loose	1978	tt0077523	85
1346	1347	1.0	East of Eden	1955	tt0048028	5
1754	1755	2.0	Mute Witness	1995	tt0110604	1
2032	2033	4.0	A Farewell to Arms	1932	tt0022879	25

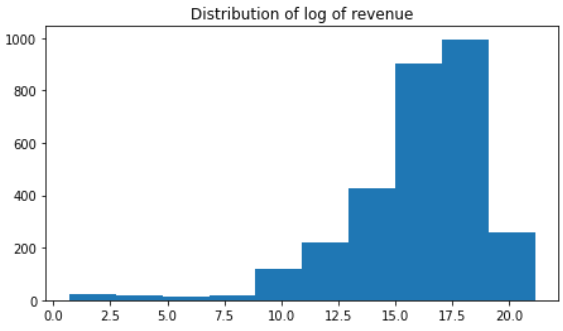
These low-budget data might have some scaling problems, so they could be dealt with revenue together.

Revenue:

In [26]:

```
fig, ax = plt.subplots(figsize = (16, 4))
plt.subplot(1, 2, 1)
plt.hist(train['revenue']);
plt.title('Distribution of revenue');
plt.subplot(1, 2, 2)
plt.hist(np.log1p(train['revenue']));
plt.title('Distribution of log of revenue');
```





In [27]:

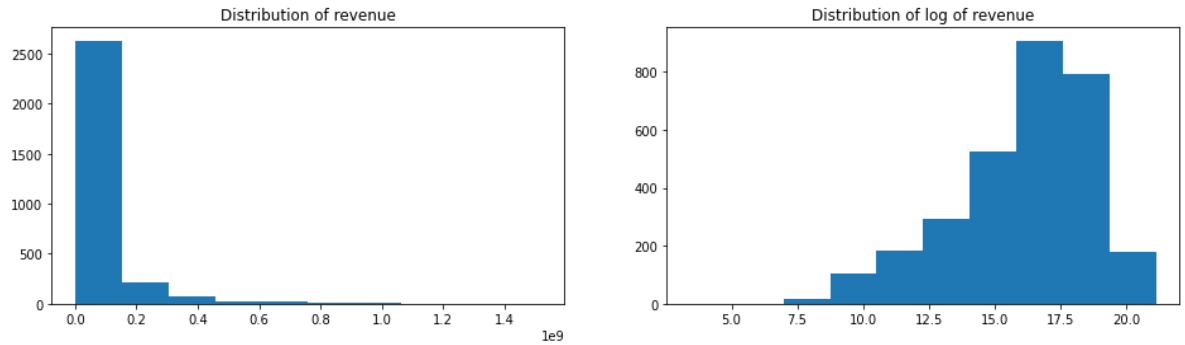
```
# fix the revenue with wrong scale
low_revenue = train.loc[train['revenue']<100,['budget','original_title','imdb_id','yea

fix_idx = [150,280,450,1138,1198,1281,1884,2399,2433,2474]
for index, row in low_revenue.iterrows():
  if index in fix_idx:
    train.loc[train.index==index,'revenue'] = train.loc[train.index==index,'revenue']
    if row['budget'] < 10:
      train.loc[train.index==index,'budget'] = row['budget'] * 1000
  elif row['revenue'] < 10:
    train.loc[train.index==index,'revenue'] = row['revenue'] * 1000000
    if row['budget'] < 20:
      train.loc[train.index==index,'budget'] = row['budget'] * 1000000
  else:
    train.loc[train.index==index,'revenue'] = row['revenue'] * 1000
    if row['budget'] < 1000:
      train.loc[train.index==index,'budget'] = row['budget'] * 1000

# revenue that not following the rules
train.loc[train.index==579,'revenue'] = 2400000 #Blood on the moon
train.loc[train.index==1006,'revenue'] = 30 # Zyzzyx Road
train.loc[train.index==1346,'revenue'] = 24079 # East of Eden
train.loc[train.index==2117,'revenue'] = 344992 # American Adobo
train.loc[train.index==2759,'revenue'] = 1694899 # Dou Sing2
```

In [28]:

```
# revenue with 3 digits
medium_revenue = train.loc[((train['revenue']>=100) & (train['revenue']<=1000)),['budg

for index, row in medium_revenue.iterrows():
  train.loc[train.index==index,'revenue'] = row['revenue'] * 1000
```

In [29]:

```
fig, ax = plt.subplots(figsize = (16, 4))
plt.subplot(1, 2, 1)
plt.hist(train['revenue']);
plt.title('Distribution of revenue');
plt.subplot(1, 2, 2)
plt.hist(np.log1p(train['revenue']));
plt.title('Distribution of log of revenue');
```



The distribution of log_revenue is no longer as skewed as before.

Part 2 - Word Cloud

In [30]:

```
list_all_genres = []
for x in list_of_genres:
  for i in range(len(x)):
    list_all_genres.append(x[i])
list_all_genres[:5]
```

Out[30]:

```
['Comedy', 'Comedy', 'Drama', 'Family', 'Romance']
```

In [31]:

```
genres_values, genres_counts = np.unique(list_all_genres, return_counts=True)
wordcloud_genres = Counter(list_all_genres)
wordcloud_genres.most_common(4)
```

Out[31]:

```
[('Drama', 1531), ('Comedy', 1028), ('Thriller', 789), ('Action', 741)]
```

In [32]:

```
plt.figure(figsize=(18,6))
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False
plt.imshow(wordcloud)
plt.title('genres',size=24)
plt.axis("off")
plt.show()
```

In [33]:

```
list_all_keyword = []
for x in list_keyword:
  for i in range(len(x)):
    list_all_keyword.append(x[i])
list_all_keyword[:5]
```

Out[33]:

```
['time travel', 'sequel', 'hot tub', 'duringcreditsstinger', 'coronation']
```

In [34]:

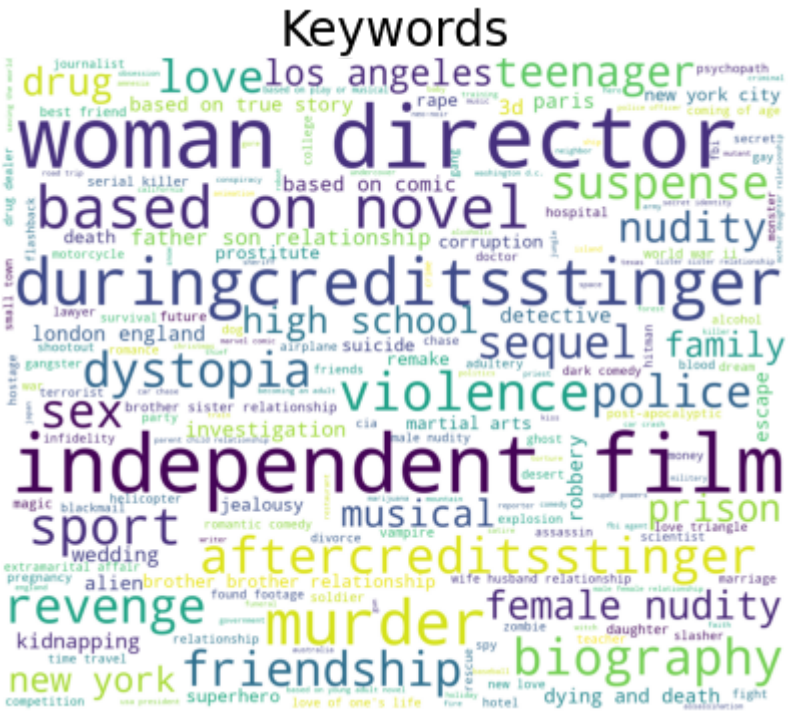
```
wordcloud_keywords = Counter(list_all_keyword)
wordcloud_keywords.most_common(4)
```

Out[34]:

```
[('woman director', 175),
 ('independent film', 155),
 ('duringcreditsstinger', 134),
 ('murder', 123)]
```

In [35]:

```
plt.figure(figsize=(18,6))
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False
plt.imshow(wordcloud)
plt.title('Keywords',size=24)
plt.axis("off")
plt.show()
```



In [36]:

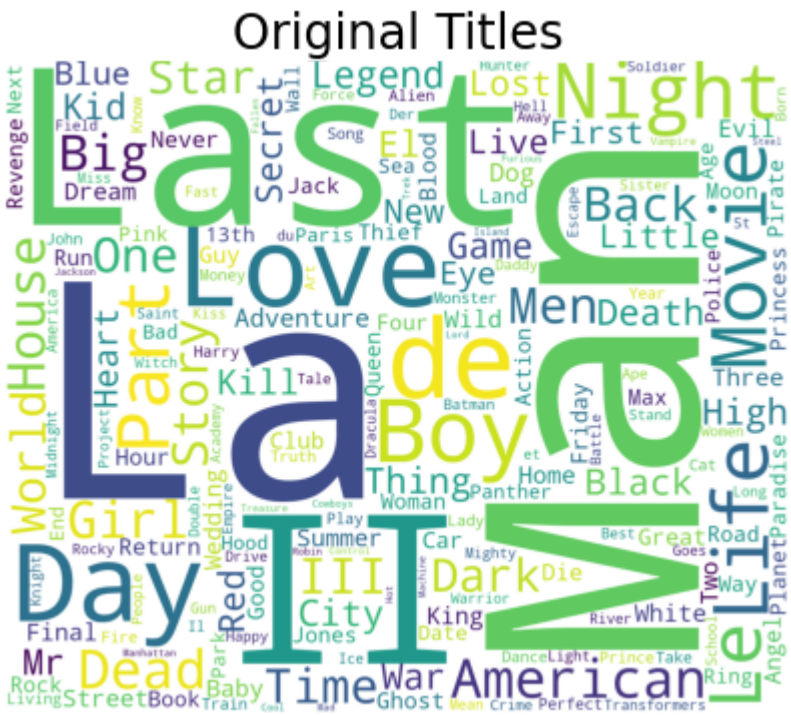
```
list_all_original_titles = []
for x in train['original_title']:
  list_all_original_titles.append(x)
list_all_original_titles[:3]
```

Out[36]:

```
['Hot Tub Time Machine 2',
 'The Princess Diaries 2: Royal Engagement',
 'Whiplash']
```

In [37]:

```
wordcloud_orig_title = ' '.join(list_all_original_titles)

plt.figure(figsize=(18,6))
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False
plt.imshow(wordcloud)
plt.title('Original Titles',size=24)
plt.axis("off")
plt.show()
```



In [38]:

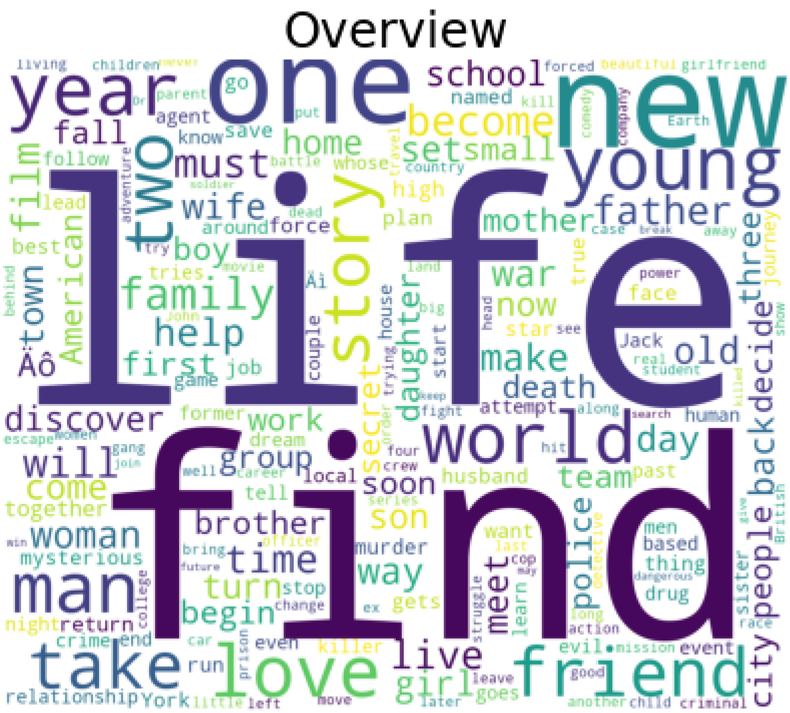
```python
list_all_overview = []
for x in train['overview']:
  if (type(x)==str):
    list_all_overview.append(x)
list_all_overview[:3]
```

Out[38]:

```
['When Lou, who has become the "father of the Internet," is shot by an unkno
wn assailant, Jacob and Nick fire up the time machine again to save their fr
iend.',
 "Mia Thermopolis is now a college graduate and on her way to Genovia to tak
e up her duties as princess. Her best friend Lilly also joins her for the su
mmer. Mia continues her 'princess lessons'- riding horses side-saddle, arche
ry, and other royal. But her complicated life is turned upside down once aga
in when she not only learns that she is to take the crown as queen earlier t
han expected...",
 'Under the direction of a ruthless instructor, a talented young drummer beg
ins to pursue perfection at any cost, even his humanity.']
```

In [39]:

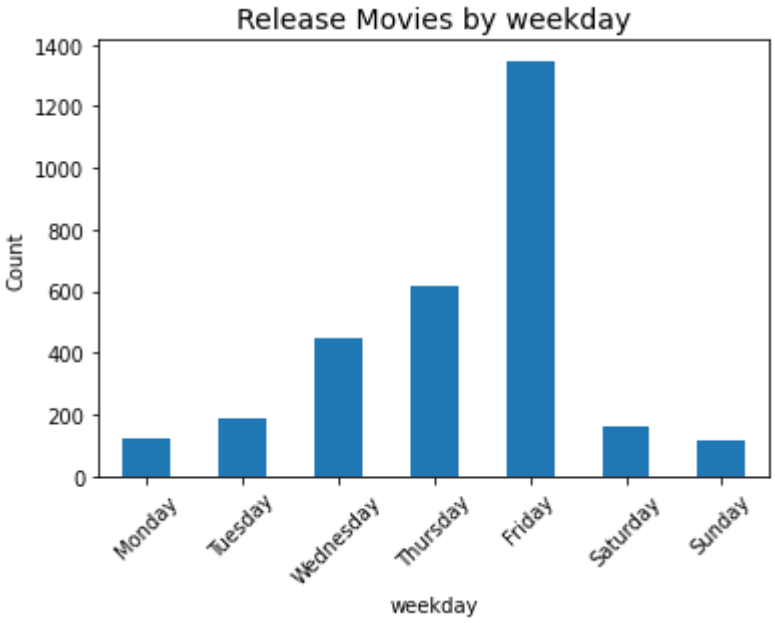
```python
wordcloud_overview = ' '.join(list_all_overview)

plt.figure(figsize=(18,6))
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False
plt.imshow(wordcloud)
plt.title('Overview',size=24)
plt.axis("off")
plt.show()
```



Part 3 - Time Series Analysis

In [40]:

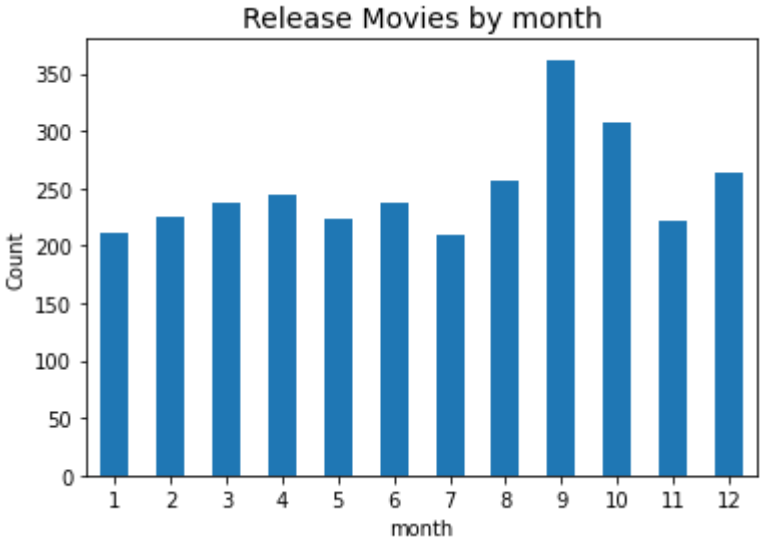
```
days = [ 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
mons = [ '01', '02', '03', '04', '05', '06', '07', '08', '09', '10', '11', '12']

train.groupby('weekday')['imdb_id'].count().reindex(days).plot(kind='bar')

plt.title("Release Movies by weekday", size=14)
plt.xticks(rotation=45)
plt.ylabel('Count')
plt.show()
```



Most of the movies released on Friday, so that people can go to see the movies on weekends.

In [41]:

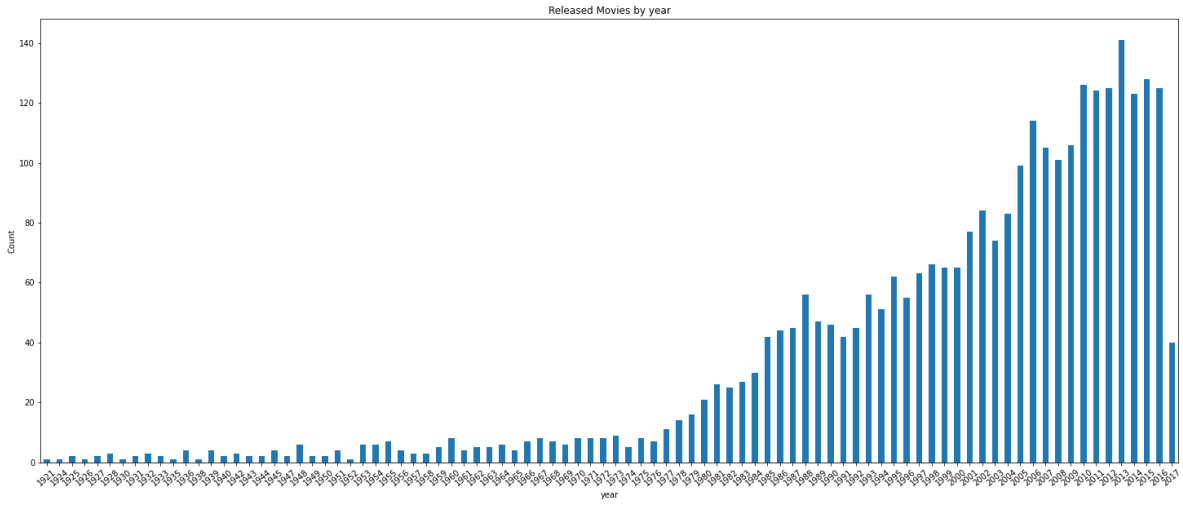
```
train.groupby('month')['imdb_id'].count().plot(kind='bar')
plt.title("Release Movies by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Count')
plt.show()
```



September and October has the most released movie number. In other months there isn't an obvious trending.

In [42]:

```
year_list.tolist()
year_list.sort()

plt.figure(figsize=(25,10))
train.groupby('year')['imdb_id'].count().reindex(year_list).plot(kind='bar')
plt.title("Released Movies by year", size=12)
plt.xticks(rotation = 40)
plt.ylabel('Count')
plt.show()
```



Starting from the late 70's, the number of released films has a tremendous growth, indicating there is a big market in this area.
In 2017 there are not many records, leading a huge decreasing.

Part 4 - Cast Power

In [43]:

```
# extract the cast name
train['cast_name'] = train['cast'].apply(extract_name)
test['cast_name'] = test['cast'].apply(extract_name)
train[['cast_name']].head()
```

Out[43]:

	cast_name
0	[Rob Corddry, Craig Robinson, Clark Duke, Adam...
1	[Anne Hathaway, Julie Andrews, H√©ctor Elizond...
2	[Miles Teller, J.K. Simmons, Melissa Benoist, ...
3	[Vidya Balan, Nawazuddin Siddiqui, Parambrata ...
4	[Kim Kang-woo, Jo Jae-hyeon, Park Si-yeon, Kim...

1) Actor Power Score (APS)
Compute each actor's 'Actor Power Score (APS)' by counting the number of times this actor appears in the dataset.

In [44]:

```
# split the cast list
list_all_cast = []
for x in train['cast_name']:
  for i  in x:
    list_all_cast.append(i)
list_all_cast[:5]

# count the occurence
cast_values, cast_counts = np.unique(list_all_cast, return_counts=True)
cast_count_pair = list(zip(cast_values,cast_counts))
cast_count_pair.sort(key = lambda x: x[1],reverse=True)
cast_count_pair[:10]
```

Out[44]:

```
[('Robert De Niro', 30),
 ('Samuel L. Jackson', 30),
 ('Morgan Freeman', 27),
 ('Bruce Willis', 25),
 ('J.K. Simmons', 25),
 ('Liam Neeson', 25),
 ('Susan Sarandon', 25),
 ('Bruce McGill', 24),
 ('John Turturro', 24),
 ('Forest Whitaker', 23)]
```

2) Average Actor Star-power (AvAS) = Total Actor Star-power (TAS) / Number of Actors(NAct)
For each movie the dataset, add the power scores of all the actors in the movie to compute the 'Total Actor Star-power (TAS)' of it.

Then divide this by the number of actors (NAct) in the movie to calculate the 'Average Actor Star-power (AvAS)'.

In [45]:

```
# Total Actor Star-power (TAS)
cast_pair_dict = dict(cast_count_pair)

def actor_power_count(x):
  score = 0
  for i in x:
    if i in cast_pair_dict.keys():
      score += cast_pair_dict[i]
  return score
```

In [46]:

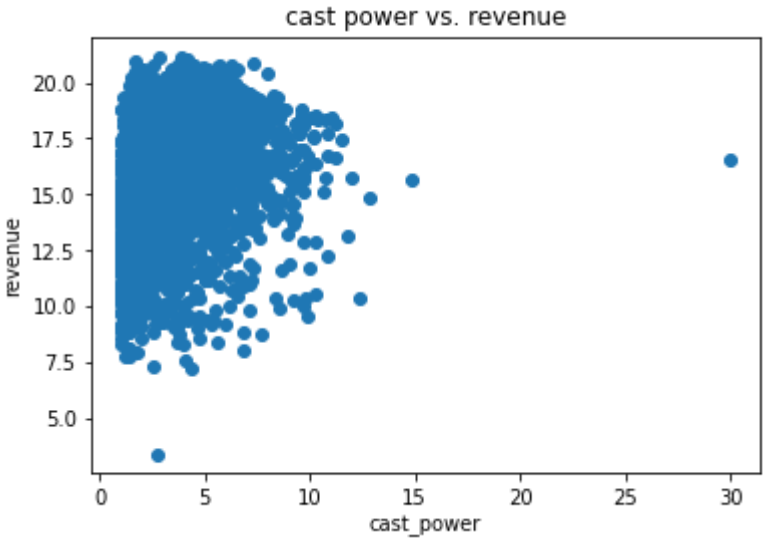
```
def cast_power(df):
  # total cast power
  df['total_cast_power'] = df['cast_name'].apply(actor_power_count)

  #cast count
  df['cast_count'] = df['cast_name'].apply(lambda x: len(x) if x != {0} else 0)

  # cast power = total_cast_power / cast_count
  df['cast_power'] = df['total_cast_power'] / df['cast_count']
  df['cast_power'] = df['cast_power'].fillna(df['cast_power'].mean())

  #normalization
  df['norm_cast_power'] = df['cast_power'].apply(lambda x: (x - df['cast_power'].min()

  df['log_cast_power'] = np.log1p(df['cast_power'])
  df['log_budget'] = np.log1p(df['budget'])
  if 'revenue' in df.columns.values:
    df['log_revenue'] = np.log1p(df['revenue'])

  return df

train = cast_power(train)
test = cast_power(test)
train[['total_cast_power','cast_count','cast_power','norm_cast_power']].head()
```

Out[46]:

	total_cast_power	cast_count	cast_power	norm_cast_power
0	101	24	4.208333	0.110632
1	95	20	4.750000	0.129310
2	108	51	2.117647	0.038540
3	11	7	1.571429	0.019704
4	5	4	1.250000	0.008621

In [47]:

```
plt.scatter(train['cast_power'],train['log_revenue'])
plt.title('cast power vs. revenue');
plt.xlabel('cast_power')
plt.ylabel('revenue')
plt.show()
```



In [52]:

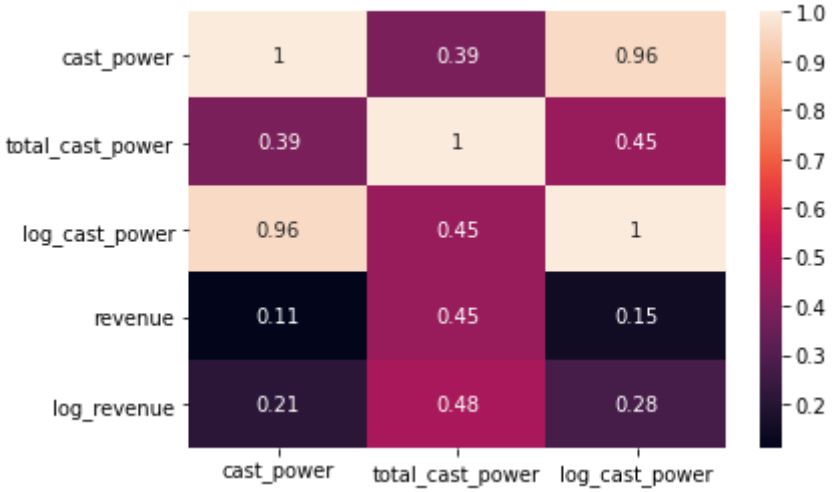
```
diff = train[['cast_power','total_cast_power','log_cast_power','revenue','log_revenue'
corr = diff.corr(method="pearson")
corr[['cast_power','total_cast_power','log_cast_power']]
```

Out[52]:

	cast_power	total_cast_power	log_cast_power
cast_power	1.000000	0.388451	0.960536
total_cast_power	0.388451	1.000000	0.448426
log_cast_power	0.960536	0.448426	1.000000
revenue	0.110561	0.449507	0.149522
log_revenue	0.214146	0.481159	0.277080

In [56]:

```
sns.heatmap(corr[['cast_power','total_cast_power','log_cast_power']], annot=True)
plt.show()
```



Cast power does show some relation with revenue, and ***Total Cast Power*** shows a higher value, but not as high as other features like budgets.

Part 5 - External Dataset

In [57]:

```
print("train shape before: ",train.shape)

train_add = pd.read_csv('TrainAdditionalFeatures.csv')
test_add = pd.read_csv('TestAdditionalFeatures.csv')

train = pd.merge(train, train_add, how='left', on=['imdb_id'])
test = pd.merge(test, test_add, how='left', on=['imdb_id'])

print("train shape after: ",train.shape)
```

```
train shape before:  (3000, 35)
train shape after:  (3000, 38)
```

In [58]:

```
train.columns.shape,test.columns.shape
```

Out[58]:

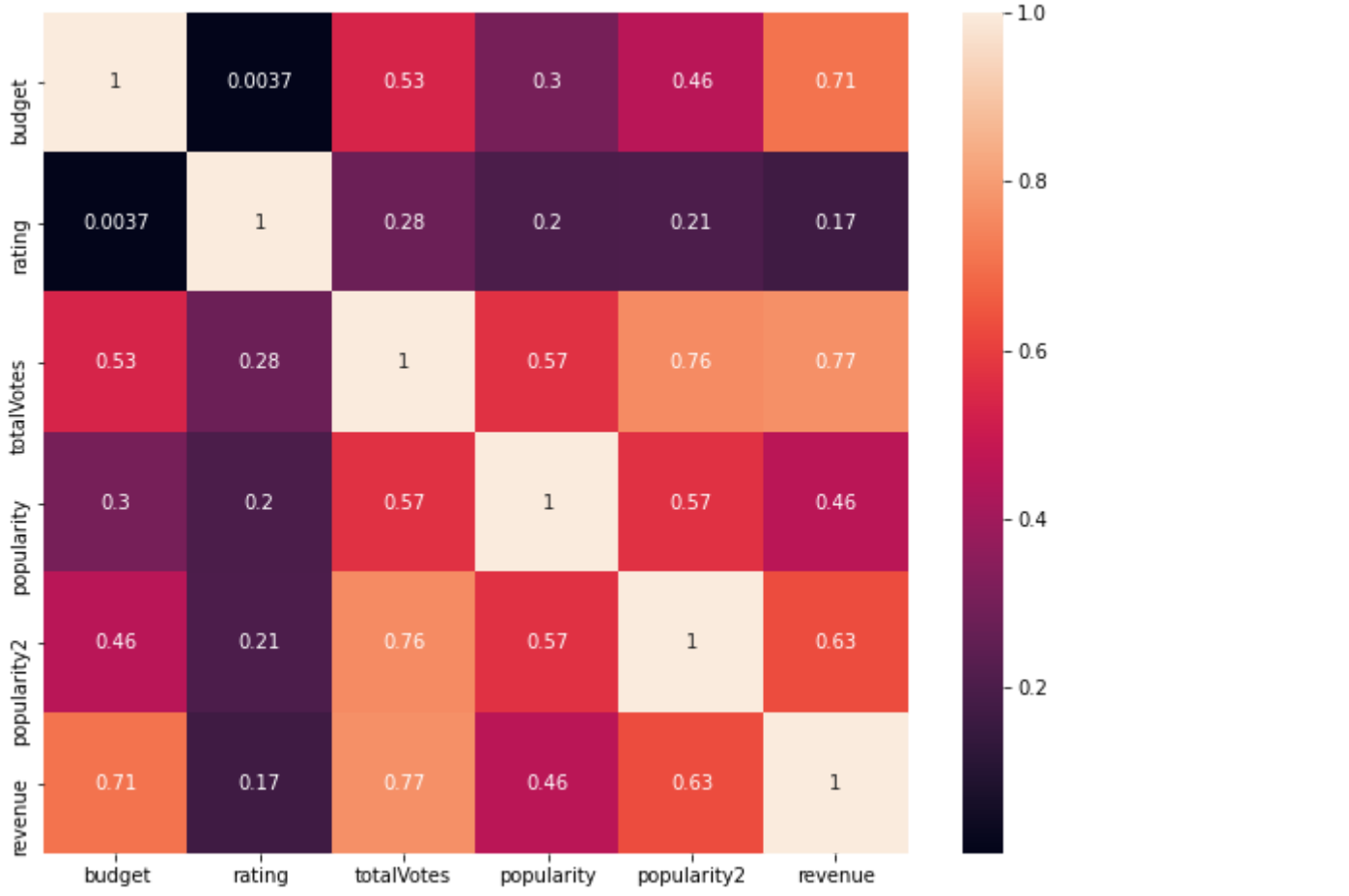
```
((38,), (36,))
```

In [59]:

```
train['rating'] = train['rating'].fillna(1.5)
train['totalVotes'] = train['totalVotes'].fillna(6)

test['rating'] = test['rating'].fillna(1.5)
test['totalVotes'] = test['totalVotes'].fillna(6)

train['popularity2'] = train['popularity2'].fillna(train.groupby(['original_language',
test['popularity2'] = test['popularity2'].fillna(test.groupby(['original_language','ye
```

In [60]:

```
corr_matrix = train[['budget','rating','totalVotes','popularity','popularity2','revenu
f,ax = plt.subplots(figsize=(10, 8))
sns.heatmap(corr_matrix.corr(), annot=True)
plt.show()
```



###Analysis: Data set source: https://www.kaggle.com/kamalchhirang/tmdb-competition-additional-features (https://www.kaggle.com/kamalchhirang/tmdb-competition-additional-features)
What information it contains: This data set contains the rating, total votes and popularity.

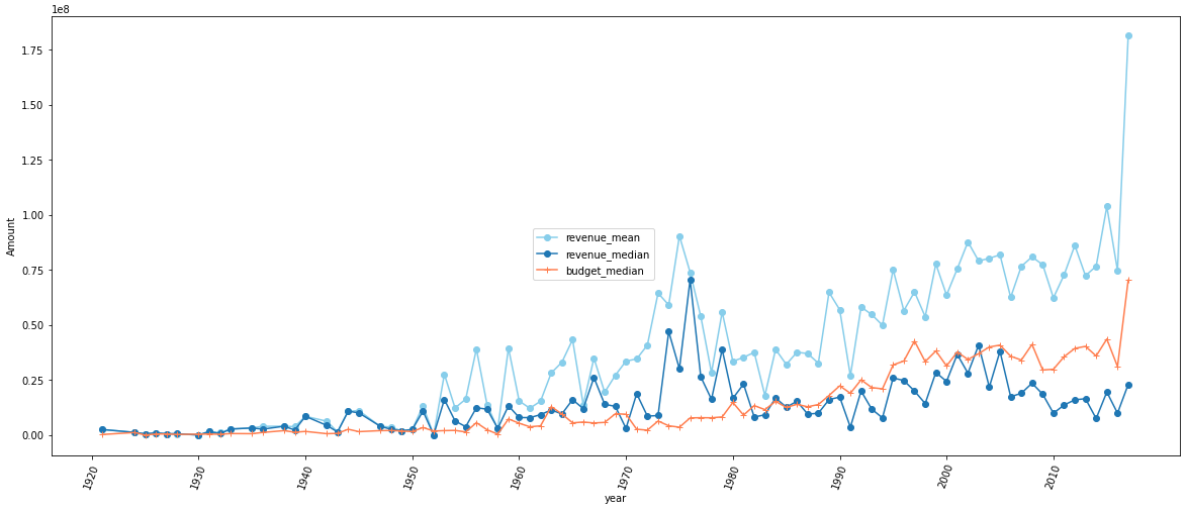
From the corrlation heatmap, ***total votes*** and ***popularity2*** have a high correlation with revenue, so it would be helpful to use it in later analysis.

Part 6 - Informative Plots

Plot 1: Revenue by year

In [61]:

```
#fig,ax=plt.subplots()
plt.figure(figsize=(20,8))
ax = train.groupby('year')['revenue'].mean().reindex(year_list.sort()).plot( color='sky
ax.set_ylabel("Amount")
ax = train.groupby('year')['revenue'].median().reindex(year_list.sort()).plot(marker =
ax = train.groupby('year')['budget'].mean().reindex(year_list.sort()).plot(color='cora
ax.figure.legend(loc='center')
plt.xticks(np.arange(1920,2018,10), rotation=70,size=10)
plt.show()
```



1. Revenue Info:
   The mean revenue has increasing a lot during these years. However, the median revenue does not increase much all the time. The mean value could be effected by the extrem high revenue, thus median may be a better indicator of the revenue change.
   Both the mean and median revenue have an obious peak in the 70s, indicating that there is indeed a popularity at that time.
2. Budget and Revenue:
   From the median budget and revenue we can see that, the budget over the years is increasing, but the revenue does not increase accordingly. Thus although the numbers of released movies grows a lot, the film industry may not make much profit these years.

Plot2: How the genres effect revenue

In [62]:

```
# create a genres dict to store number of movies in each genre.
genres_dict = dict()

for genre in train["genres"]:
    for elem in genre:
        if elem not in genres_dict:
            genres_dict[elem] = 1
            #print('1',elem)
        else:
            genres_dict[elem] += 1
            #print('2',elem)
```

In [63]:

```
genres_df = pd.DataFrame.from_dict(genres_dict, orient='index')
genres_df.columns = ["count_of_genres"]
genres_df = genres_df.sort_values(by="count_of_genres", ascending=False)
genres_df.head()
```

Out[63]:

	count_of_genres
Drama	1531
Comedy	1028
Thriller	789
Action	741
Romance	571

In [64]:

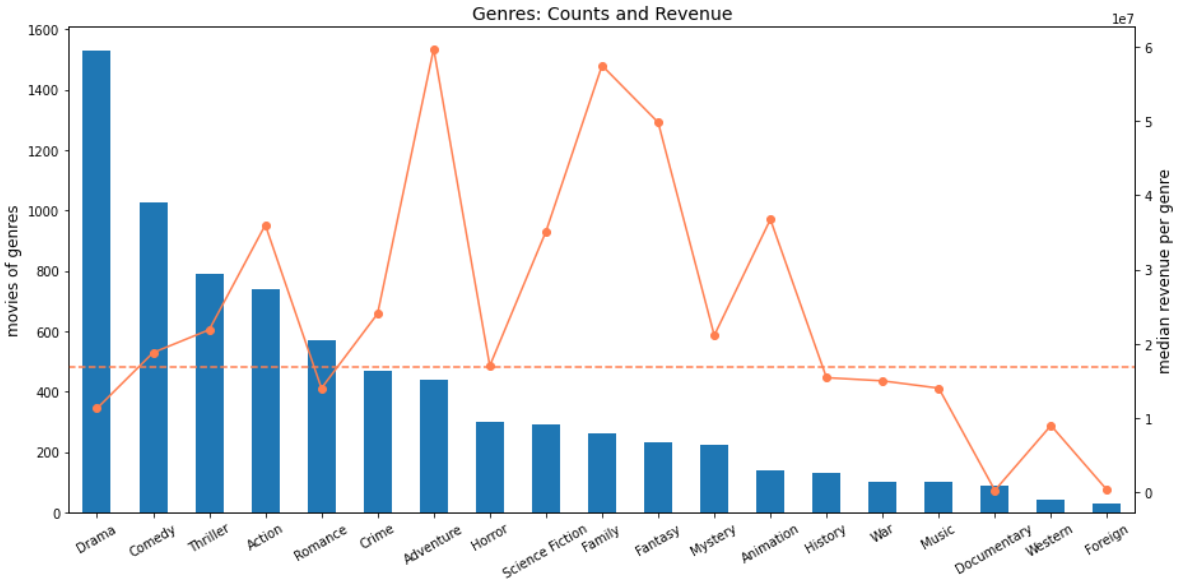
```
genres_split = pd.DataFrame()
genres_values, genres_counts = np.unique(list_all_genres, return_counts=True)

for g in genres_values:
    genres_split['genres_' + g] = train['genres'].apply(lambda x: 1 if g in x else 0)

for index, genres in enumerate(genres_df.index.values):
    genres_df.loc[genres, "median_revenue"] = train[genres_split['genres_' + genres]==1

genres_df.sort_values(by=["count_of_genres", "median_revenue"], ascending=False)
genres_df.drop('TV Movie',inplace=True)
genres_df.head()
```

Out[64]:

	count_of_genres	median_revenue
Drama	1531	11293663.0
Comedy	1028	18809184.0
Thriller	789	21890845.0
Action	741	36000000.0
Romance	571	14016568.0

In [65]:

```
plt.figure(figsize=(15,7))
ax1 = genres_df['count_of_genres'].plot(kind='bar')
ax2 = genres_df['median_revenue'].plot(secondary_y=True, marker = 'o',color='coral')

ax2.set_title("Genres: Counts and Revenue", size=14)
ax1.set_ylabel("movies of genres",size=12)
ax2.set_ylabel('median revenue per genre',size=12)
for label in ax1.get_xticklabels():
    label.set_ha("center")
    label.set_rotation(30)

ax2.axhline(train['revenue'].median(),color='coral',linestyle='--')
plt.show()
```



From the plot, ***Drama, Comdedy, Thriller*** are the top 3 genres that have the most numbers.
However, they are not the ones that make the most revenue. Instead, the revenue shows an opposite trend.
Thus, just making movies of the top genres may not guarantee profits.

Plot 3: Production Companies with Revenue

In [66]:

```
# create a genres dict to store number of movies in each genre.
company_dict = dict()

for comp in train["production_companies"]:
    for elem in comp:
        if elem not in company_dict:
            company_dict[elem] = 1
            #print('1',elem)
        else:
            company_dict[elem] += 1
            #print('2',elem)
comp_df = pd.DataFrame.from_dict(company_dict, orient='index')
comp_df.columns = ["count_of_movies"]
comp_df = comp_df.sort_values(by="count_of_movies", ascending=False)
```

In [67]:

```
list_all_companies = []
for x in list_companies:
  for i in range(len(x)):
    list_all_companies.append(x[i])

company_values, company_counts = np.unique(list_all_companies, return_counts=True)
company_count_pair = list(zip(company_values,company_counts))
company_count_pair.sort(key = lambda x: x[1],reverse=True)

top10_companies = []
for p in company_count_pair[:10]:
  top10_companies.append(p[0])
```

In [68]:

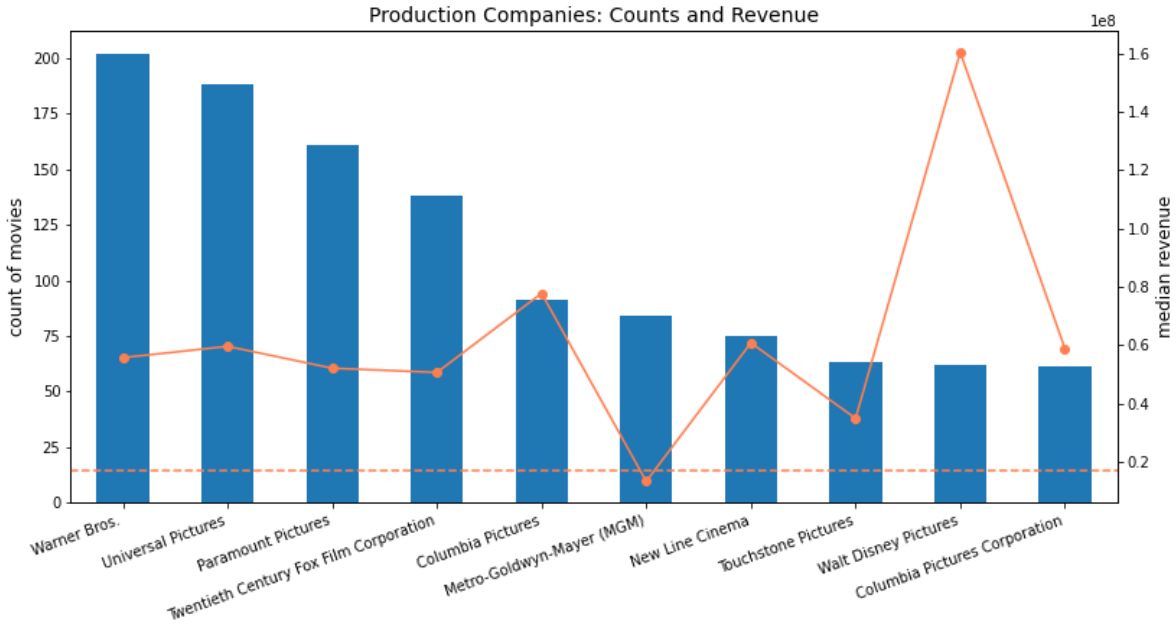
```
comp_split = pd.DataFrame()
comp_values, comp_counts = np.unique(list_all_companies, return_counts=True)

for g in top10_companies:
    comp_split['comp_' + g] = train['production_companies'].apply(lambda x: 1 if g in x


for index, company in enumerate(comp_df.head(10).index.values):
   comp_df.loc[company, "median_revenue"] = train[comp_split['comp_' + company]==1].rev
   #comp_df.loc[company, "mean_budget"] = train[comp_split['comp_' + company]==1].budge
   #comp_df.loc[company, "mean_popularity"] = train[comp_split['comp_' + company]==1].p

comp_df.sort_values(by=["count_of_movies"], ascending=False)
comp_df = comp_df.head(10)
comp_df
```

Out[68]:

	count_of_movies	median_revenue
Warner Bros.	202	55653705.5
Universal Pictures	188	59540581.5
Paramount Pictures	161	52034889.0
Twentieth Century Fox Film Corporation	138	50589532.0
Columbia Pictures	91	77737889.0
Metro-Goldwyn-Mayer (MGM)	84	13220811.0
New Line Cinema	75	60740827.0
Touchstone Pictures	63	34808403.0
Walt Disney Pictures	62	160440216.0
Columbia Pictures Corporation	61	58853106.0

In [69]:

```
plt.figure(figsize=(13,6))
ax1 = comp_df['count_of_movies'].plot(kind='bar')
ax2 = comp_df['median_revenue'].plot(secondary_y=True, marker = 'o',color='coral')
#ax3 = comp_df['mean_budget'].plot(secondary_y=True, marker = 'o',color='r')

ax2.set_title("Production Companies: Counts and Revenue", size=14)
ax1.set_ylabel("count of movies",size=12)
ax2.set_ylabel('median revenue',size=12)
for label in ax1.get_xticklabels():
    label.set_ha("right")
    label.set_rotation(20)
ax2.axhline(train['revenue'].median(),color = 'coral',linestyle='--')
plt.show()
```

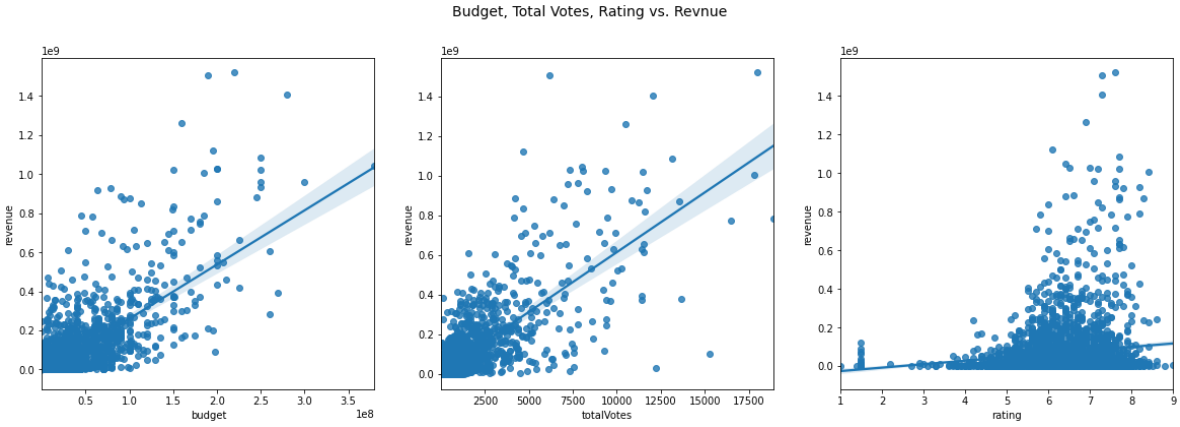


Warner Bros, Universal Pictures, Paramount Pictures are the top 3 companies that make the most movies. Almost all top10 companies make revenue far more than the average, except ***Metro-Goldwyn-Mayer***.
Walt Disney Pictures makes the highest revenue among all top10 companies, which is around 8 times more than the average revenue.

Plot4: Other features and their relations with revenue

In [70]:

```
fig, axs = plt.subplots(1,3,figsize=(20,6))

sns.regplot(x=train["budget"],y=train["revenue"],ax=axs[0])

sns.regplot(x=train["totalVotes"],y=train["revenue"],ax=axs[1])

sns.regplot(x=train["rating"],y=train["revenue"],ax=axs[2])

fig.suptitle('Budget, Total Votes, Rating vs. Revnue', position=(.5,1), fontsize=14)
plt.show()
```



From the plots we can see that, ***budget*** and ***total votes*** show a higher relation with revenue, while ***rating*** shows a much weaker relation.
Thus a good movie may not represent a high revenue.

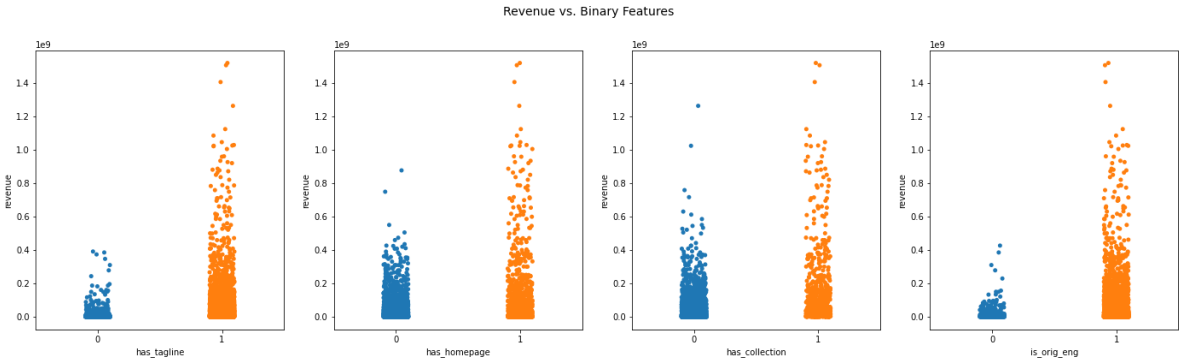
Plot 5: Binary features and revenue

In [72]:

```
#binary features
train['has_collection'] = train['belongs_to_collection'].apply(lambda x: len(x) if x !=
train['has_homepage'] = 0
train.loc[train['homepage'].isnull() == False, 'has_homepage'] = 1
train['has_tagline'] = 0
train.loc[train['tagline'].isnull() == False, 'has_tagline'] = 1

test['has_collection'] = test['belongs_to_collection'].apply(lambda x: len(x) if x != 
test['has_homepage'] = 0
test.loc[test['homepage'].isnull() == False, 'has_homepage'] = 1
test['has_tagline'] = 0
test.loc[test['tagline'].isnull() == False, 'has_tagline'] = 1

train["is_orig_eng"] = train['original_language'].apply(lambda x: 1 if x == "en" else 
test["is_orig_eng"] = test['original_language'].apply(lambda x: 1 if x == "en" else 0)
```

In [73]:

```
fig, axs = plt.subplots(1,4,figsize=(24,6))

sns.stripplot(x="has_tagline", y="revenue", data=train,ax=axs[0])
sns.stripplot(x="has_homepage", y="revenue", data=train,ax=axs[1])
sns.stripplot(x="has_collection", y="revenue", data=train,ax=axs[2])
sns.stripplot(x="is_orig_eng", y="revenue", data=train,ax=axs[3])

fig.suptitle('Revenue vs. Binary Features', position=(.5,1), fontsize=14)
plt.show()
```



From the binary features plot we can see that, English movies or those have the tagline and homepage will make a lot more revenue.
As for the collection, if a movie has a collection, it will also make more revenue, but not as much as the other flag features.
In brief, the prferrable properties of a movie are:
1) having a tagline or a homepage,
2) English as the original language,
3) being in a collection.

Part 7 - Pairwise Pearson Correlation

In [74]:

```
def gender_count(x,code):
  gender_sum=0
  #print(type(i['gender']))
  for i in x:
    try:
      if(i['gender'] == code):
        gender_sum +=1
    except:
      gender_sum+=0
  return gender_sum

for i in range(3):
  train['num_gender'+str(i)+"_cast"] = train['cast'].apply(lambda x: gender_count(x,i)
  train['num_gender'+str(i)+"_crew"] = train['crew'].apply(lambda x: gender_count(x,i)
  test['num_gender'+str(i)+"_cast"] = test['cast'].apply(lambda x: gender_count(x,i))
  test['num_gender'+str(i)+"_crew"] = test['crew'].apply(lambda x: gender_count(x,i))

```

In [75]:

```
## new features

train['crew_name'] = train['crew'].apply(extract_name)
test['crew_name'] = test['crew'].apply(extract_name)

num_columns = ['genres','production_companies','production_countries','spoken_language
for col in num_columns:
  train['num_'+ col] = train[col].apply(lambda x: len(x) if x != {0} else 0)
  test['num_'+ col] = test[col].apply(lambda x: len(x) if x != {0} else 0)

len_columns = ['tagline','overview','title']
for col in len_columns:
  train['len_'+ col] = train[col].map(lambda x: len(str(x).split()))
  test['len_'+ col] = test[col].map(lambda x: len(str(x).split()))

```

In [76]:

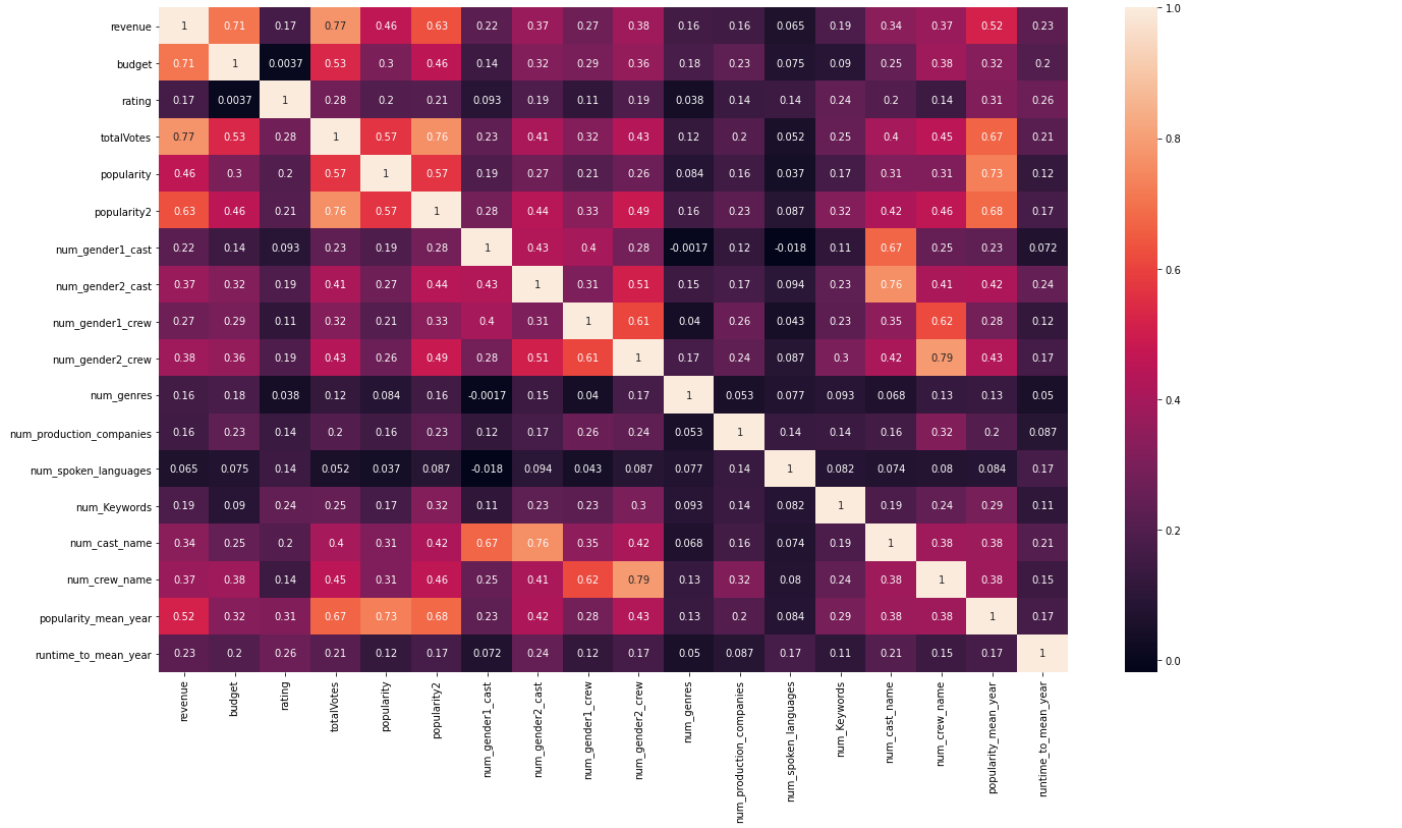
```
def new_feature_df(df):
  df['popularity_mean_year']=df['popularity']/df.groupby("year")["popularity"].transfo
  df['runtime_to_mean_year'] = df['runtime'] / df.groupby("year")["runtime"].transform
  df['budget_to_mean_year'] = df['budget'] / df.groupby("year")["budget"].transform('m
  return df
```

In [78]:

```
train = new_feature_df(train)
test =new_feature_df(test)
```

In [79]:

```
corr_matrix = train[['revenue','budget','rating','totalVotes','popularity','popularity
                     'crew_name',  'num_gender1_crew','num_gender2_crew','num_genres',
                     'num_cast_name', 'num_crew_name','popularity_mean_year','runtime_
f,ax = plt.subplots(figsize=(20, 12))
sns.heatmap(corr_matrix.corr(), annot=True)
plt.show()
```



Most positive correlation: total votes & revenue, buget-to-mean-year & revenue
Most negative correlation: num_spoken_languages & num_gender1_cast
It is also interesting to see that *the number of female crew* has a relative high relation with *revenue, total votes* and *popularity*.

Part 8 - Regression and Permutation Test

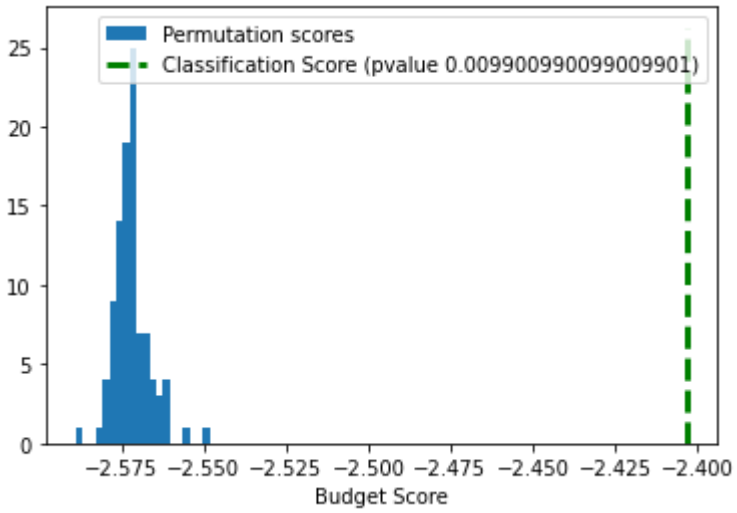
Budget

In [80]:

```
X_train, X_test, y_train, y_test = train_test_split(np.log1p(train['budget']).values,t
X_train = X_train.reshape(-1,1)
X_test = X_test.reshape(-1,1)
reg = LinearRegression().fit(X_train, y_train)
```

In [81]:

```
score, permutation_scores, pvalue = permutation_test_score(reg, X_test, y_test, scorin
plt.hist(permutation_scores, 20, label='Permutation scores')
ylim = plt.ylim()
plt.vlines(score, ylim[0], ylim[1], linestyle='--',color='g', linewidth=3, label='Clas
plt.legend()
plt.xlabel('Budget Score')
plt.show()
```



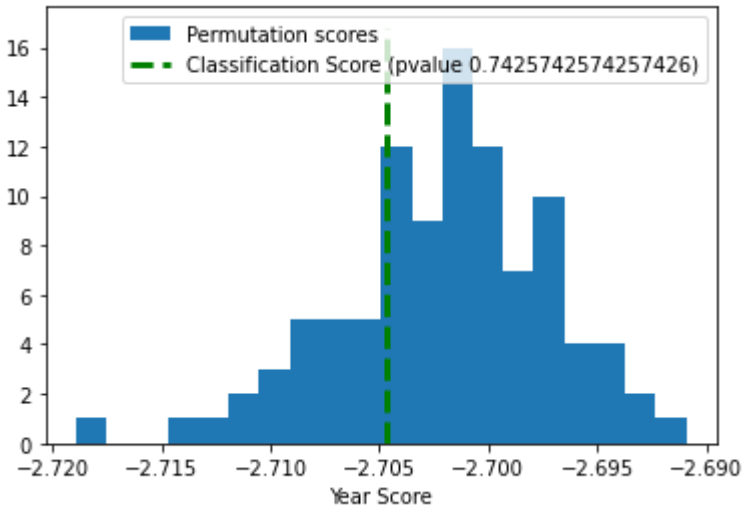
Year

In [82]:

```
X_train, X_test, y_train, y_test = train_test_split(train['year'].values,train['log_re
X_train = X_train.reshape(-1,1)
X_test = X_test.reshape(-1,1)
reg = LinearRegression().fit(X_train, y_train)
```

In [83]:

```
score, permutation_scores, pvalue = permutation_test_score(reg, X_test, y_test, scorin
plt.hist(permutation_scores, 20, label='Permutation scores')
ylim = plt.ylim()
plt.vlines(score, ylim[0], ylim[1], linestyle='--',color='g', linewidth=3, label='Clas
plt.legend()
plt.xlabel('Year Score')
plt.show()
```



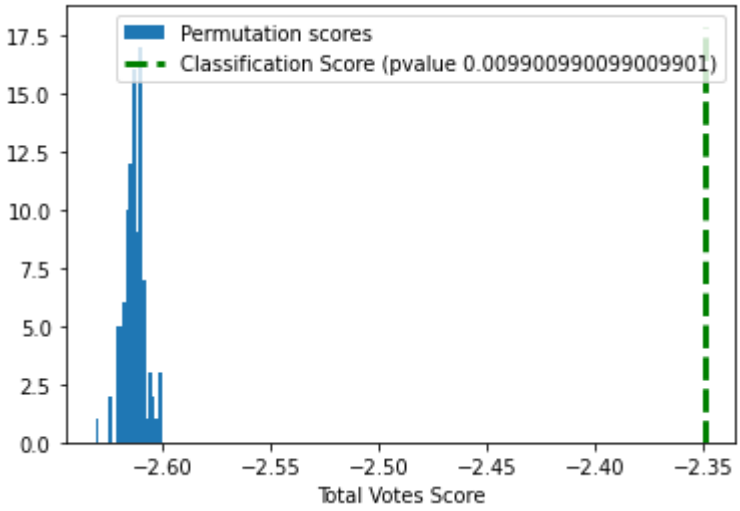
Total Votes

In [116]:

```
X_train, X_test, y_train, y_test = train_test_split(train['totalVotes'].values,train['
X_train = X_train.reshape(-1,1)
X_test = X_test.reshape(-1,1)
reg = LinearRegression().fit(X_train, y_train)
```

In [117]:

```
score, permutation_scores, pvalue = permutation_test_score(reg,X_test, y_test, scoring=
plt.hist(permutation_scores, 20, label='Permutation scores')
ylim = plt.ylim()
plt.vlines(2 *[score], ylim[0], ylim[1], linestyle='--',color='g', linewidth=3, label=
plt.legend()
plt.xlabel('Total Votes Score')
plt.show()
```



Budget and ***Total Votes*** should have a relatively high relation with revenue, while ***year*** should not.
The permutation test plot proved this pattern.

Part 9 - Predicton

In [91]:

```
## top 30 companies
list_all_companies = []
for x in list_companies:
  for i in range(len(x)):
    list_all_companies.append(x[i])
company_values, company_counts = np.unique(list_all_companies, return_counts=True)
company_count_pair = list(zip(company_values,company_counts))
company_count_pair.sort(key = lambda x: x[1],reverse=True)

top_30_companies = []
for p in company_count_pair[:30]:
  top_30_companies.append(p[0])


## top 15 countries
list_all_countries = []
for x in list_of_countries:
  for i in range(len(x)):
    list_all_countries.append(x[i])
country_values, country_counts = np.unique(list_all_countries, return_counts=True)
country_count_pair = list(zip(country_values,country_counts))
country_count_pair.sort(key = lambda x: x[1],reverse=True)

top_15_contries = []
for p in country_count_pair[:15]:
  top_15_contries.append(p[0])

#top 20 crew job
string_space = 'job'
train['crew_job'] = train['crew'].apply(extract_name)
test['crew_job'] = test['crew'].apply(extract_name)

list_all_crew_job = []
for x in train['crew_job']:
  for i in range(len(x)):
    list_all_crew_job.append(x[i])

crew_job_values, crew_job_counts = np.unique(list_all_crew_job, return_counts=True)
crew_job_count_pair = list(zip(crew_job_values,crew_job_counts))
crew_job_count_pair.sort(key = lambda x: x[1],reverse=True)

top_20_jobs = []
for p in crew_job_count_pair[:20]:
  top_20_jobs.append(p[0])

# top crew department
string_space = 'department'
train['crew_department'] = train['crew'].apply(extract_name)
test['crew_department'] = test['crew'].apply(extract_name)

list_all_crew_depart = []
for x in train['crew_department']:
  for i in range(len(x)):
    list_all_crew_depart.append(x[i])

crew_depart_values, crew_depart_counts = np.unique(list_all_crew_depart, return_counts

#top original language
n_language = train.loc[:train.index[-1], "original_language"].value_counts()
```

```
large_language = n_language[n_language>=16].index
train.loc[~train["original_language"].isin(large_language), "original_language"] = "sm
top_orig_lang = list(large_language)
top_orig_lang.append('small')
```

In [92]:

```
# encoding
for c in top_30_companies:
    train['prod_company_' + c] = train['production_companies'].apply(lambda x: 1 if c 
    test['prod_company_' + c] = test['production_companies'].apply(lambda x: 1 if c in 

for c in top_15_contries:
    train['prod_country_' + c] = train['production_countries'].apply(lambda x: 1 if c 
    test['prod_country_' + c] = test['production_countries'].apply(lambda x: 1 if c in 

for g in genres_values:
    train['genre_'+g] = train['genres'].apply(lambda x: 1 if g in x else 0)
    test['genre_'+g] = test['genres'].apply(lambda x: 1 if g in x else 0)

for j in top_20_jobs:
    train['job_'+j] = train['crew_job'].apply(lambda x: 1 if j in x else 0)
    test['job_'+j] = test['crew_job'].apply(lambda x: 1 if j in x else 0)

for l in top_orig_lang:
    train['orig_lang_'+l] = train['original_language'].apply(lambda x: 1 if l in x else
    test['orig_lang_'+l] = test['original_language'].apply(lambda x: 1 if l in x else 

for d in crew_depart_values:
    train['depart_'+d] = train['crew_department'].apply(lambda x: 1 if d in x else 0)
    test['depart_'+d] = test['crew_department'].apply(lambda x: 1 if d in x else 0)

```

In [93]:

```
def prepare_df(df):
  df['budget_runtime_ratio']=df['budget']/df['runtime']
  df['budget_popularity_ratio']=df['budget']/df['popularity']
  df['budget_popularity2_ratio'] = df['budget']/df['popularity2']
  df['budget_year_ratio']=df['budget']/(df['year']*df['year'])
  df['popularity_totalVotes_ratio']=df['totalVotes']/df['popularity']
  df['rating_totalVotes_ratio']=df['totalVotes']/df['rating']
  df['totalVotes_releaseYear_ratio']=df['totalVotes']/df['year']
  df['budget_rating_ratio']=df['budget']/df['rating']
  df['budget_totalVotes_ratio']=df['budget']/df['totalVotes']
  return df
```

In [94]:

```
train = prepare_df(train)
test = prepare_df(test)
train.shape,test.shape
```

Out[94]:

```
((3000, 183), (4398, 181))
```

In [102]:

```
train_use = train.drop(['id','belongs_to_collection','genres','homepage','imdb_id','or
                        'production_companies','production_countries','release_date','wee
                        'tagline','title','Keywords','cast','cast_name','crew','crew_name
                        'cast_power','log_cast_power','revenue','log_revenue'],axis=1)

test_use = test.drop(['id','belongs_to_collection','genres','homepage','imdb_id','orig
                        'production_companies','production_countries','release_date','wee
                        'tagline','title','Keywords','cast','cast_name','crew','crew_name
                        'cast_power','log_cast_power'],axis=1)
```

In [103]:

```
train_use.shape,test_use.shape
```

Out[103]:

```
((3000, 151), (4398, 151))
```

Split the train data

In [104]:

```
trainy = train["log_revenue"]
X_train, X_test, y_train, y_test = train_test_split(train_use,trainy,test_size=0.3,ran
```

XGboost Model

In [105]:

```
xgbmodel = xgb.XGBRegressor(max_depth=8,
                            min_child_weight=3,
                            alpha = 0.5,
                            learning_rate=0.05,
                            n_estimators=150,
                            objective='reg:linear',
                            gamma=0.01,
                            silent=1,
                            subsample=0.8,
                            colsample_bytree=0.8)
```

In [106]:

```
xgbmodel.fit(X_train, y_train)
```

Out[106]:

```
XGBRegressor(alpha=0.5, base_score=0.5, booster='gbtree', colsample_bylevel=
1,
             colsample_bynode=1, colsample_bytree=0.8, gamma=0.01,
             importance_type='gain', learning_rate=0.05, max_delta_step=0,
             max_depth=8, min_child_weight=3, missing=None, n_estimators=15
0,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None, silen
t=1,
             subsample=0.8, verbosity=1)
```

In [107]:

```
pred_train1 = xgbmodel.predict(X_train)
pred_test1 = xgbmodel.predict(X_test)

print(np.sqrt(mean_squared_error(y_train, pred_train1)))
print(np.sqrt(mean_squared_error(y_test, pred_test1)))
```

```
0.43939800007561897
1.5744937685248956
```

In [108]:

```
pred_xgb = xgbmodel.predict(test_use)
pred_xgb = pd.DataFrame(np.exp(pred_xgb)-1,columns=["revenue"])
pred_xgb.head()
```

Out[108]:

	revenue
0	8.970780e+06
1	1.245184e+06
2	1.191645e+07
3	4.501956e+06
4	8.686692e+05

In [109]:

```
sub=pd.concat([test["id"], pred_xgb],axis=1)
sub.to_csv('xgb.csv',index=False)
```

CATboost Model

In [110]:

```
catmodel = cat.CatBoostRegressor(iterations=2000,
                                 learning_rate=0.01,
                                 depth=8,
                                 eval_metric='RMSE',
                                 colsample_bylevel=0.8,
                                 bagging_temperature = 0.2,
                                 metric_period = None,
                                 early_stopping_rounds=200)
```

In [ ]:

```
catmodel.fit(X_train, y_train)
```

In [112]:

```
pred_train3 = catmodel.predict(X_train)
pred_test3 = catmodel.predict(X_test)

print(np.sqrt(mean_squared_error(y_train, pred_train3)))
print(np.sqrt(mean_squared_error(y_test, pred_test3)))
```

```
0.6886609858234608
1.5410113246700483
```

In [113]:

```
pred_cat = catmodel.predict(test_use)
pred_cat = pd.DataFrame(np.exp(pred_cat)-1,columns=["revenue"])
pred_cat.head()
```

Out[113]:

	revenue
0	7.025692e+06
1	1.876075e+06
2	1.226077e+07
3	5.374579e+06
4	8.207703e+05

In [114]:

```
sub2=pd.concat([test['id'], pred_cat],axis=1)
sub2.to_csv('cat.csv',index=False)
```

I first extract some more features that may help to predict. Then I split the test and train data, and use XGBboost and Catboost model to predict. Since XGBoost doesn't have an inbuilt method for categorical features, so I did one-hot encoding manually before fitting the model.
As a result, the XGB model perform a little better than the Catboost model with a Kaggle score of 2.11139.

Part 10 - Final Result

Report your highest score. Include a snapshot of your best score after submission as confirmation. Be sure to provide a link to your Kaggle profile. Make sure your profile includes your face and affiliation with SBU.

Kaggle Link: https://www.kaggle.com/haruka03 (https://www.kaggle.com/haruka03)

Highest Score: 2.11139

Number of entries: 10