TMDB MOVIE DATA ANALYSIS AND PREDICITNG THE MODEL

Introduction

In a world... where movies made an estimated $41.7 billion in 2018, the film industry is more popular than ever. But what movies make the most money at the box office? How much does a director matter? Or the budget? For some movies, it's "You had me at 'Hello.'" For others, the trailer falls short of expectations and you think "What we have here is a failure to communicate."

From business point of view, one of the main interests of the film studios and its related stakeholders is a prediction of revenue that a new movie can generate based on a few given input attributes before its released date.

Data Set

This dataset taken from Kaggle, are provided with 3000 movies and a variety of metadata obtained from The Movie Database (TMDB). Movies are labeled with id. Data points include cast, crew, plot keywords, budget, posters, release dates, languages, production companies, and countries. [Source (https://www.kaggle.com/zero92/tmdb-prediction/data)](https://www.kaggle.com/zero92/tmdb-prediction/data) file name train.csv

Project Objective

The primary goal is to build a machine-learning model to predict the revenue of a new movie given such features as budget, release dates, genres. The modeling performance is evaluating based on the Rsquare.

The secondary goal is to practice skills data wrangling, data visualization, Random forest, Linear Regression,LGB boost, GB regressor

Project Methodlogy

This project has 4 high-level steps:

- Step 1: Data acquisition which we have extracted for TMDB data set.
- Step 2: data exploratory analysis and features engineering explore and visualize the data to have an overview with-in and between the variables, what's insights gained and what's new features added in.
- Step 3: modeling experiments design and conduct a set of experiments to evaluate performance and select machine learning method, compare and select features selection approach.
- Step 4: final evaluate the model on the validation set using R Square.

Software Needed

Software: Python and Jupyter Notebook

The following packages (libraries) need to be installed:

1. pandas
2. NumPy
3. scikit Learn
4. wordcount
5. eli5
6. TFID
7. LGB boost
8. GB regressor

Loading the Data and Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import sklearn
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
from sklearn import model_selection
from sklearn.metrics import accuracy_score
from sklearn import model_selection # for splitting into train and test
import json
import ast
from urllib.request import urlopen
from PIL import Image
from sklearn.preprocessing import LabelEncoder
import time
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn import linear_model
import eli5
import xgboost as xgb
import lightgbm as lgb
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from matplotlib import pyplot
print('Libraries imported..')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\python\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:144: FutureWarning:

The sklearn.metrics.scorer module is  deprecated in version 0.22 and will be removed in version 0.24. The corresponding
classes / functions should instead be imported from sklearn.metrics. Anything that cannot be imported from sklearn.metr
ics is now part of the private API.

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:144: FutureWarning:

The sklearn.feature_selection.base module is  deprecated in version 0.22 and will be removed in version 0.24. The corre
sponding classes / functions should instead be imported from sklearn.feature_selection. Anything that cannot be importe
d from sklearn.feature_selection is now part of the private API.


Libraries imported..
```

Gathering Data

In [2]:
```python
#loading the data set
df = pd.read_csv("data/train.csv")
#displaying top 5 data set
df.head()
```

Out[2]:

	id	belongs_to_collection	budget	genres	homepage	imdb_id	original_language	original_title	overview	popularity	
0	1	[{'id': 313576, 'name': 'Hot Tub Time Machine ...	14000000	[{'id': 35, 'name': 'Comedy'}]	NaN	tt2637294	en	Hot Tub Time Machine 2	When Lou, who has become the "father of the In...	6.575393	/
1	2	[{'id': 107674, 'name': 'The Princess Diaries ...	40000000	[{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam...	NaN	tt0368933	en	The Princess Diaries 2: Royal Engagement	Mia Thermopolis is now a college graduate and ...	8.248895	/w
2	3	NaN	3300000	[{'id': 18, 'name': 'Drama'}]	http://sonyclassics.com/whiplash/	tt2582802	en	Whiplash	Under the direction of a ruthless instructor, ...	64.299990	
3	4	NaN	1200000	[{'id': 53, 'name': 'Thriller'}, {'id': 18, 'n...	http://kahaanithefilm.com/	tt1821480	hi	Kahaani	Vidya Bagchi (Vidya Balan) arrives in Kolkata ...	3.174936	/a
4	5	NaN	0	[{'id': 28, 'name': 'Action'}, {'id': 53, 'nam...	NaN	tt1380152	ko	마린보이	Marine Boy is the story of a former national s...	1.148070	/

In [ ]:
```
#printing out column
#for col in df.columns:
    #print(col)
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 23 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     3000 non-null   int64  
 1   belongs_to_collection  604 non-null    object 
 2   budget                 3000 non-null   int64  
 3   genres                 2993 non-null   object 
 4   homepage               946 non-null    object 
 5   imdb_id                3000 non-null   object 
 6   original_language      3000 non-null   object 
 7   original_title         3000 non-null   object 
 8   overview               2992 non-null   object 
 9   popularity             3000 non-null   float64
 10  poster_path            2999 non-null   object 
 11  production_companies   2844 non-null   object 
 12  production_countries   2945 non-null   object 
 13  release_date           3000 non-null   object 
 14  runtime                2998 non-null   float64
 15  spoken_languages       2980 non-null   object 
 16  status                 3000 non-null   object 
 17  tagline                2403 non-null   object 
 18  title                  3000 non-null   object 
 19  Keywords               2724 non-null   object 
 20  cast                   2987 non-null   object 
 21  crew                   2984 non-null   object 
 22  revenue                3000 non-null   int64  
dtypes: float64(2), int64(3), object(18)
memory usage: 539.2+ KB
```

In [5]:
```
# get number of rows and columns
df.shape
```

Out[5]:
```
(3000, 23)
```

In [6]:
```
#finding null value
df.isnull().sum()
```

Out[6]:
```
id                          0
belongs_to_collection    2396
budget                      0
genres                      7
homepage                 2054
imdb_id                     0
original_language           0
original_title              0
overview                    8
popularity                  0
poster_path                 1
production_companies      156
production_countries       55
release_date                0
runtime                     2
spoken_languages           20
status                      0
tagline                   597
title                       0
Keywords                  276
cast                       13
crew                       16
revenue                     0
dtype: int64
```

In [7]:
```
#Let's find duplicate data set
df.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
df.isna().sum().sum()
```
Out[8]:
```
5601
```
In [9]:
```
#df['release_date'] = pd.to_datetime(df['release_date'])
df['release_date'].head()
```
Out[9]:
```
0     2/20/15
1      8/6/04
2    10/10/14
3      3/9/12
4      2/5/09
Name: release_date, dtype: object
```
In [10]:
```
 # statistical description, only for numeric values
df.describe()
```
Out[10]:

	id	budget	popularity	runtime	revenue
count	3000.000000	3.000000e+03	3000.000000	2998.000000	3.000000e+03
mean	1500.500000	2.253133e+07	8.463274	107.856571	6.672585e+07
std	866.169729	3.702609e+07	12.104000	22.086434	1.375323e+08
min	1.000000	0.000000e+00	0.000001	0.000000	1.000000e+00
25%	750.750000	0.000000e+00	4.018053	94.000000	2.379808e+06
50%	1500.500000	8.000000e+06	7.374861	104.000000	1.680707e+07
75%	2250.250000	2.900000e+07	10.890983	118.000000	6.891920e+07
max	3000.000000	3.800000e+08	294.337037	338.000000	1.519558e+09

In [11]:
```
df.corr()
```

Out[11]:

	id	budget	popularity	runtime	revenue
id	1.000000	0.019732	-0.007470	0.010750	0.000610
budget	0.019732	1.000000	0.342356	0.238373	0.752965
popularity	-0.007470	0.342356	1.000000	0.133690	0.461460
runtime	0.010750	0.238373	0.133690	1.000000	0.216380
revenue	0.000610	0.752965	0.461460	0.216380	1.000000

In [12]:
```
# Checking for an zero values in the budget and revenue columns
print("Rows With Zero Values In The Budget Column:",df[(df['budget']==0)].shape[0])
print("Rows With Zero Values In The Revenue Column:",df[(df['revenue']==0)].shape[0])
```

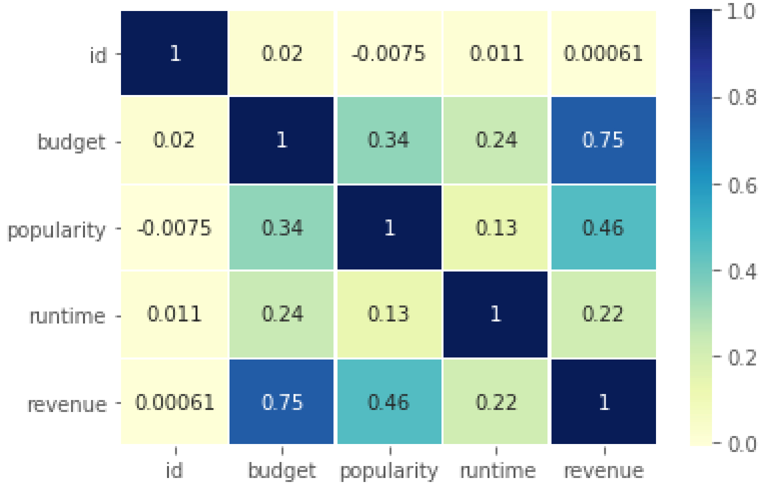
```
Rows With Zero Values In The Budget Column: 812
Rows With Zero Values In The Revenue Column: 0
```

The budget column those has zero value will be replaced with suitable value later duing our analysis purpose.

Exploratory Data Analysis

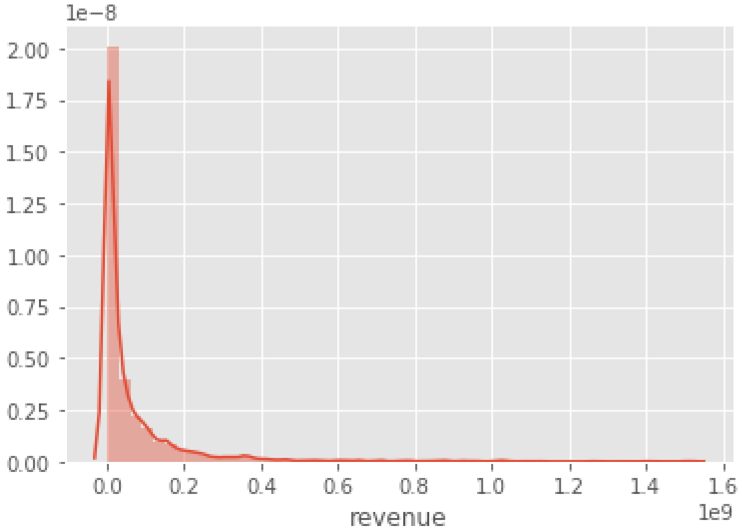
We know that reveune is continous data there we will be using regression method. Regression method is used in column to predict particular to look distribution of target variable.

In [13]:
```
sns.heatmap(df.corr(), cmap='YlGnBu', annot=True, linewidths = 0.2);
```



From this corr chart we can see that revenue is strongly correlated with budget where as least correlated runtime.

In [15]:
```
sns.distplot(df.revenue);
```



We can see that this data is very skewed and therefore it is difficult to draw conclusion from this graph.we knew to normalise this data.

Introducing log

Why skewed data is not good fit for modeling in Linear Regression ?

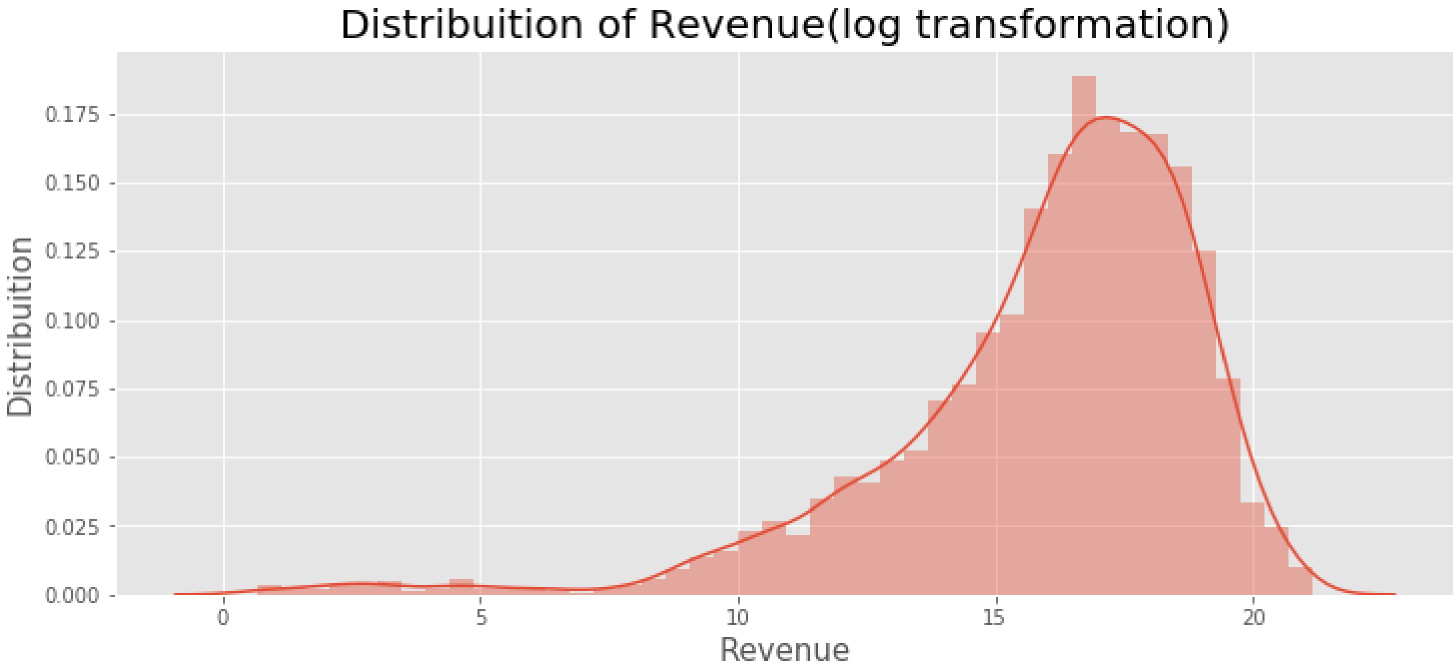
- Because they may act as an outlier ,and we know that outlier is not good for our model performance.
- They have un even mean,median , mode and by law of large number, normal distribution allows the researcher to make more accurate predictions.
- To linearize the fit as much as possible. Statistical test are usually based on the assumption of normality(normal distribution).

The log transformation, a widely used method to address skewed data, is one of the most popular transformations used in research.There fore we will be using log transformation in reveune.

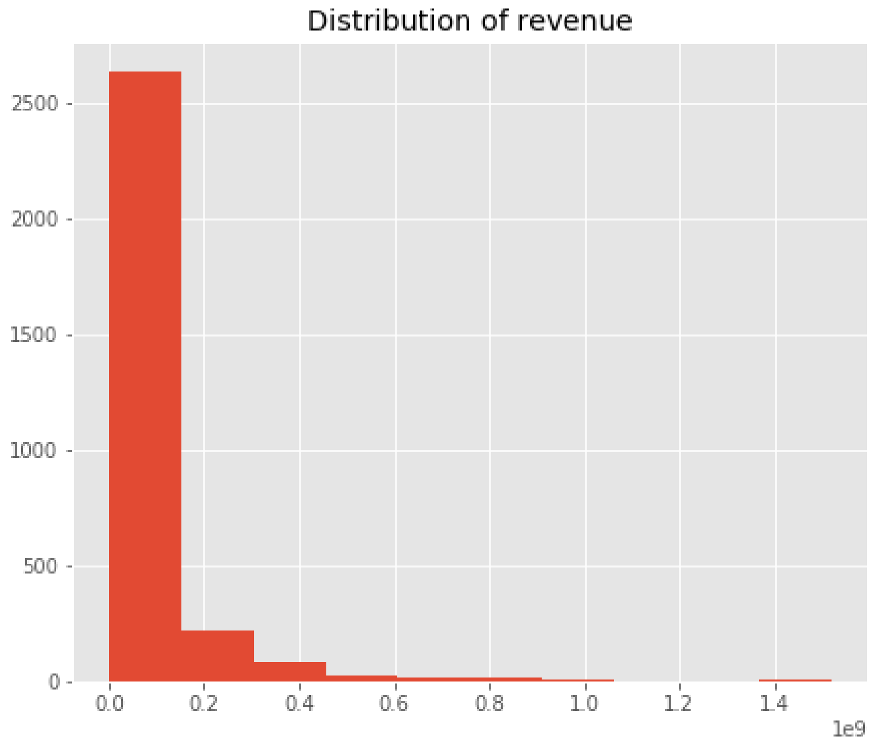
In [16]:
```
#creating log transformation for reveune
df['log_revenue'] = np.log1p(df['revenue']) #we are not using log0 to avoid & and null value as there might be 0 value
```

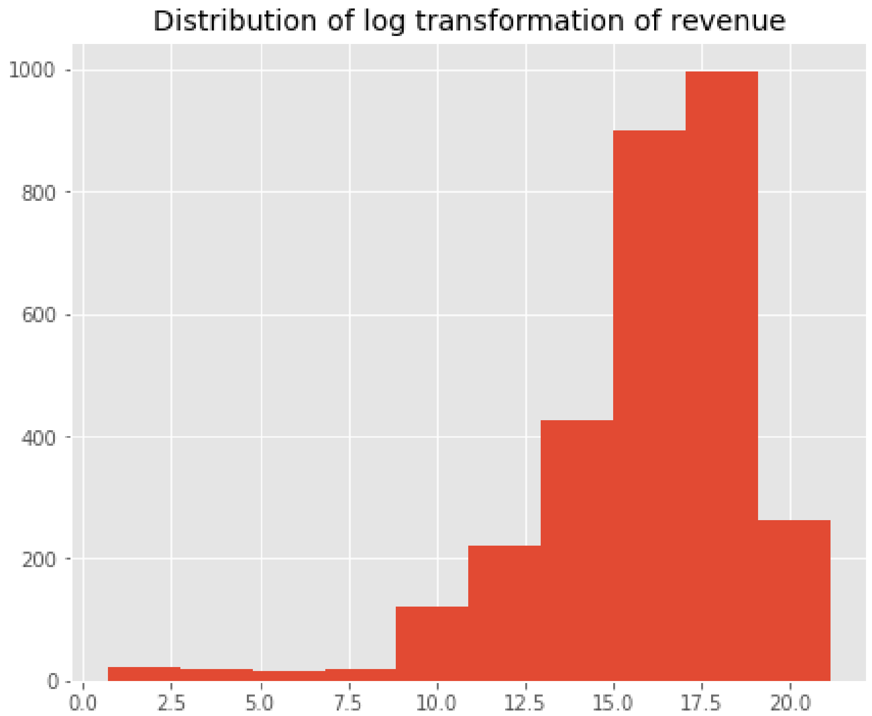
In [17]:
```
plt.figure(figsize=(12,5))

# Subplot allow us to plot more than one
# in this case, will be create a subplot grid of 2 x 1

# seting the distribuition of our data and normalizing using np.log on values highest than 0 and +
# also, we will set the number of bins and if we want or not kde on our histogram
ax = sns.distplot(df['log_revenue'])
ax.set_xlabel('Revenue', fontsize=15) #seting the xlabel and size of font
ax.set_ylabel('Distribuition', fontsize=15) #seting the ylabel and size of font
ax.set_title("Distribuition of Revenue(log transformation)", fontsize=20) #seting the title and size of font
```

Out[17]:
```
Text(0.5, 1.0, 'Distribuition of Revenue(log transformation)')
```



In [18]:
```
#comapring distribution of reveune and log revune side by side with histogram
fig, ax = plt.subplots(figsize = (16, 6))
plt.subplot(1, 2, 1) #1 means 1 plot, 2 means column and 1 mean 1 sub plot
plt.hist(df['revenue']);
plt.title('Distribution of revenue');
plt.subplot(1, 2, 2)#1 means 1 plot, 2 means column and 2 mean second sub plot
plt.hist(df['log_revenue']);
plt.title('Distribution of log transformation of revenue');
```





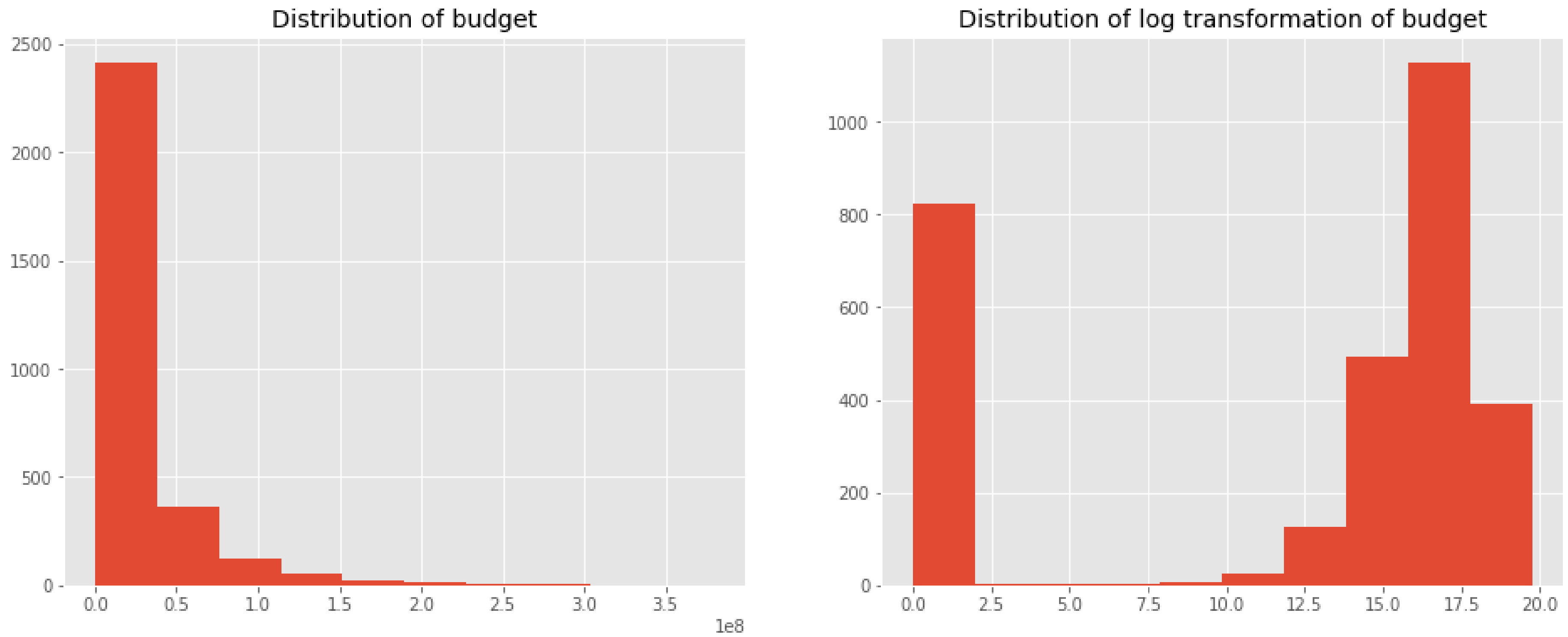
We can see that orginal distribution i.e (one without log) is extremely skewed. We used log transformation method and made data normally distribution which has less skeweness and kurtosis.

Relationship between Film Revenue and Budget

Let's find correlation between revenue and budget. Let's also find the degree of co-relation.

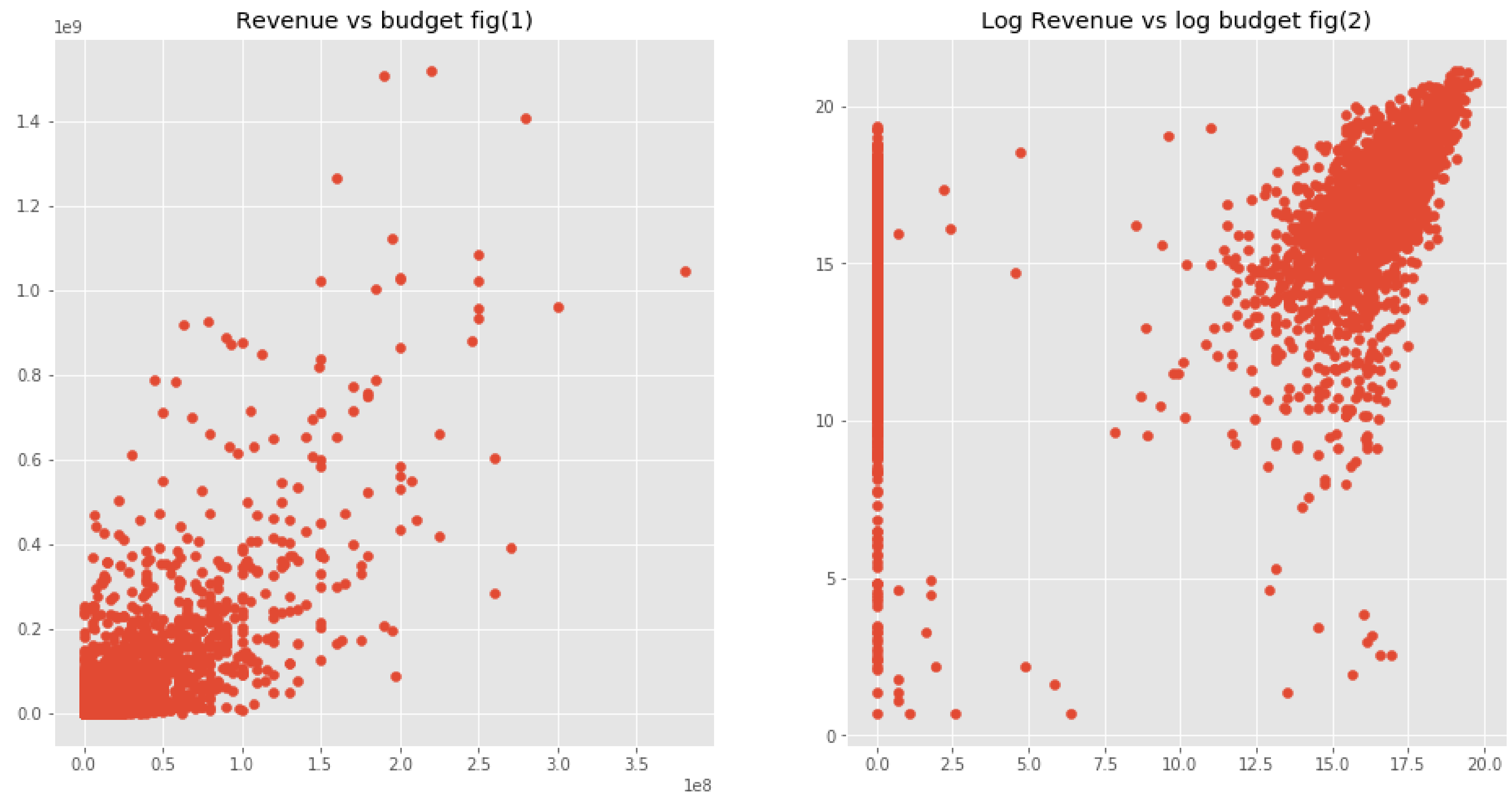
In [19]:
```
#log transformation of budget
df['log_budget'] = np.log1p(df['budget'])
```

In [21]:
```
fig, ax = plt.subplots(figsize = (16, 6))
plt.subplot(1, 2, 1)
plt.hist(df['budget']);
plt.title('Distribution of budget');
plt.subplot(1, 2, 2)
plt.hist(df['log_budget']);
plt.title('Distribution of log transformation of budget');
```



In [22]:

```
#let's create scatter plot
plt.figure(figsize=(16, 8))
plt.subplot(1, 2, 1)
plt.scatter(df['budget'], df['revenue'])
plt.title('Revenue vs budget fig(1)');
plt.subplot(1, 2, 2)
plt.scatter(df['log_budget'], df['log_revenue'])
plt.title('Log Revenue vs log budget fig(2)');
```



Fig(1) : we can see that they are some what correlation beween budget and revenue, but we are not clear.

Fig(2) how ever indicates that there is correlation between both variable that is log transformation of reveune and log transformation of budget.

We can also see many movies on zero budget as we identified there were 815 movie that has zero budget which we will clear later.

Is there any relationship with Homepage and Revenue?

Let's find out the correlation between two variable. We are more interested on answering if having official homepage for movie affects Reveune or not.

We all know that home page will be unique for each movie. Means differnet movie has different home page except the movie that has sequel/prequel.

In [23]:
```
#lets check if movies website has count less than 1( means unique) or more than 1( means repeatetive) or not.
df['homepage'].value_counts().head(10)
```

Out[23]:
```
http://www.transformersmovie.com/ (http://www.transformersmovie.com/)                                   4
http://www.lordoftherings.net/ (http://www.lordoftherings.net/)                                      2
http://www.thehobbit.com/ (http://www.thehobbit.com/)                                            2
http://marvel.com/avengers_movie/ (http://marvel.com/avengers_movie/)                                   1
http://www.ballsoffury.com/ (http://www.ballsoffury.com/)                                          1
http://www.blankcityfilm.com/ (http://www.blankcityfilm.com/)                                        1
http://www.dorothyofozthemovie.com/ (http://www.dorothyofozthemovie.com/)                                   1
https://www.bankside-films.com/screeners/ashby.html# (https://www.bankside-films.com/screeners/ashby.html#)
1
http://www.antitrustthemovie.com/ (http://www.antitrustthemovie.com/)                                   1
http://bcdfpictures.com/index.php?projects/peace-love-and-misunderstanding (http://bcdfpictures.com/index.php?projects/
peace-love-and-misunderstanding)    1
Name: homepage, dtype: int64
```

we can see that transformers movies web page is listed 4 times which is obivous because we are all aware that this movie has seque. Same goes with lord of the rings and hobits.

Let's find if having home page affects revenue or not. And for that lets first find out movies has home page or not.

In [24]:
```
#let's creat column called has_homepage and pass two value 1,0 (1, indicates has home page, 0 indicates no page)
df['has_homepage'] = 0
df.loc[df['homepage'].isnull() == False, 'has_homepage'] = 1 #1 here means it has home page
```

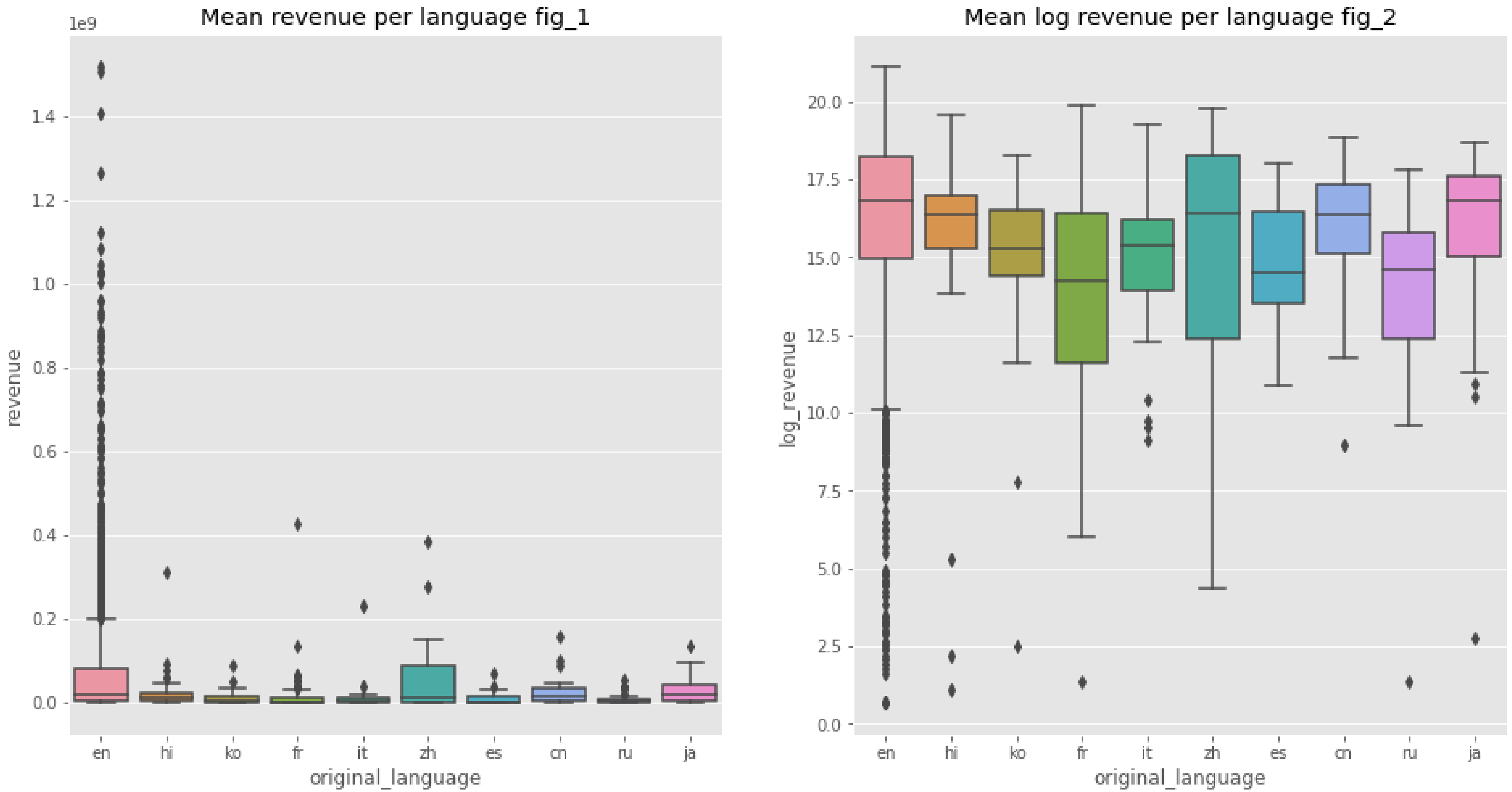
In [25]:
```
#since has_homepage is categorical value we will be using seaborn catplot.
sns.catplot(x='has_homepage', y='revenue', data=df);
plt.title('Revenue for movie with and w/o homepage');
```

From the above fig we can see that movie that has home page (indicated by blue) has more revenue compared to the movie that has no home page. From this scatterplot we can say that they may be correlated.

Langauge distribution vs mean reveune

Let's find out the relationship between language and revenue .We will be calcualting top 10 langauge from the data frame and will be selecting langauage which is in df orginale_langauge. Here we will be using box plot as box plot is very useful for identifying outlier.

In [26]:
```
#we will be using blox pot
plt.figure(figsize=(16, 8))
plt.subplot(1, 2, 1)
sns.boxplot(x='original_language', y='revenue', data=df.loc[df['original_language'].isin(df['original_language'].value_c
plt.title('Mean revenue per language fig_1');
plt.subplot(1, 2, 2)
sns.boxplot(x='original_language', y='log_revenue', data=df.loc[df['original_language'].isin(df['original_language'].valu
plt.title('Mean log revenue per language fig_2');
```



> From the fig_1 we can see that x-axis indicated langaue plotted. We can see that english language has higher revenue by far margin compared to toher lagnguage. This graph also says us that english language over shadowed all other language in terms of revenue. This information may be quite incorrect and mis leading. Lets see fig_2 for more details

> From the fig_2 : We can see that orginal langauge vs log transformation of revenue and we can see that other language are also creating revenue near english language . How ever it's english language movie that is leading.

What are the frequent Words in Film Titles and Discriptions ?

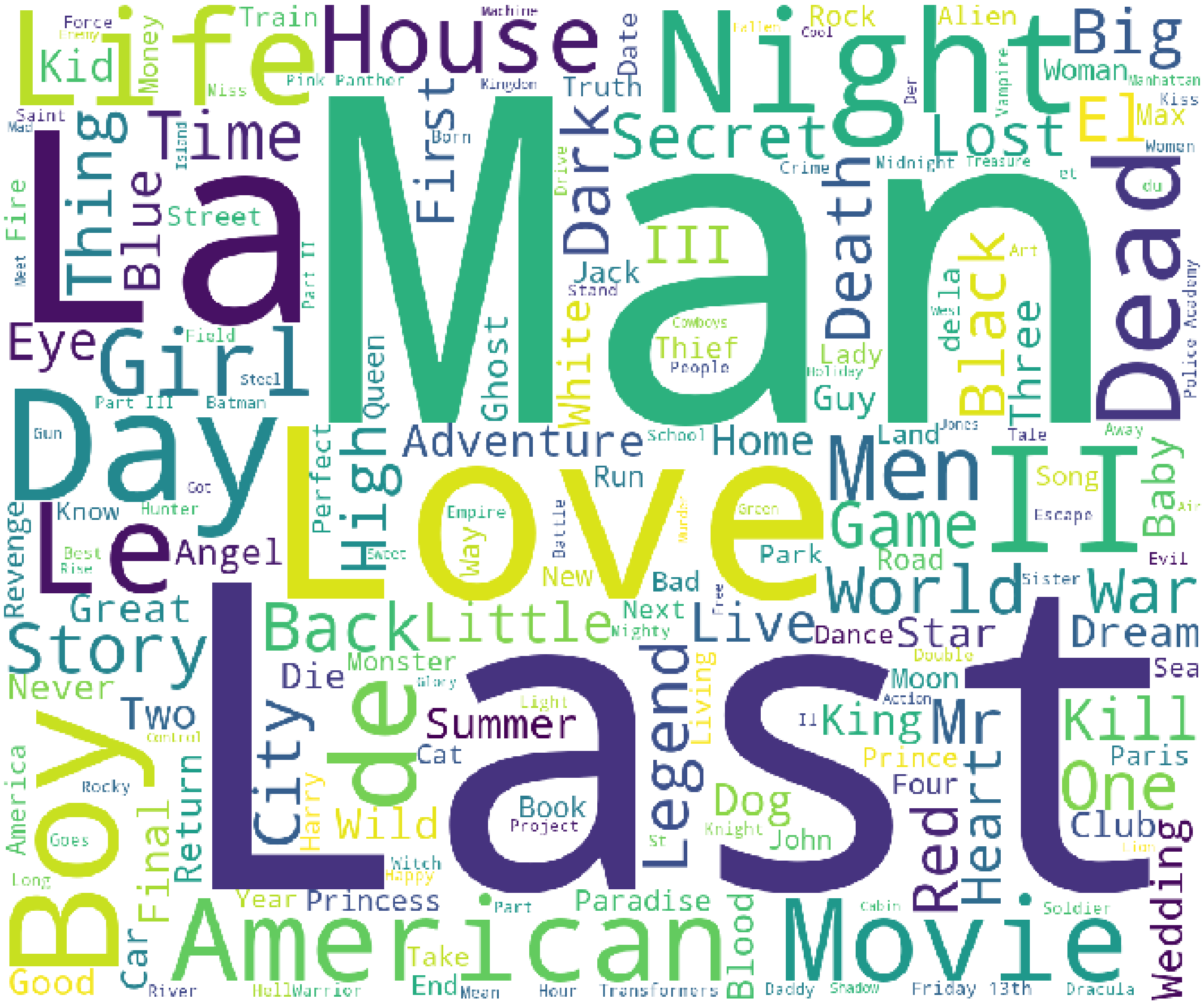
This is one of my favourite part of this analysis. I am very curious to know the popular film titles also wanted to know if description/synopsis affects revenue or not.

We will be using wordcount library. Word cloud is data visualization technique used for representaion of text data in which size of each word indicates it frequency or importance.

In [27]:

```
#let's find top words from movie Titles
start = time.time()
plt.figure(figsize = (12, 12))
token_title = ' '.join(df['original_title'].values) #create split to title by sprace to extract the text.
#bg color set to white for good contrast, by default bg color is darker
wordcloud = WordCloud(max_font_size=None, background_color='white', width=1200, height=1000).generate(token_title)
plt.imshow(wordcloud)
plt.title('Top words from movie titles ')
plt.axis("off") # we dont need axes for this
plt.show()
print(" Time taken to complete this operation is", time.time() - start, 'seconds')
```

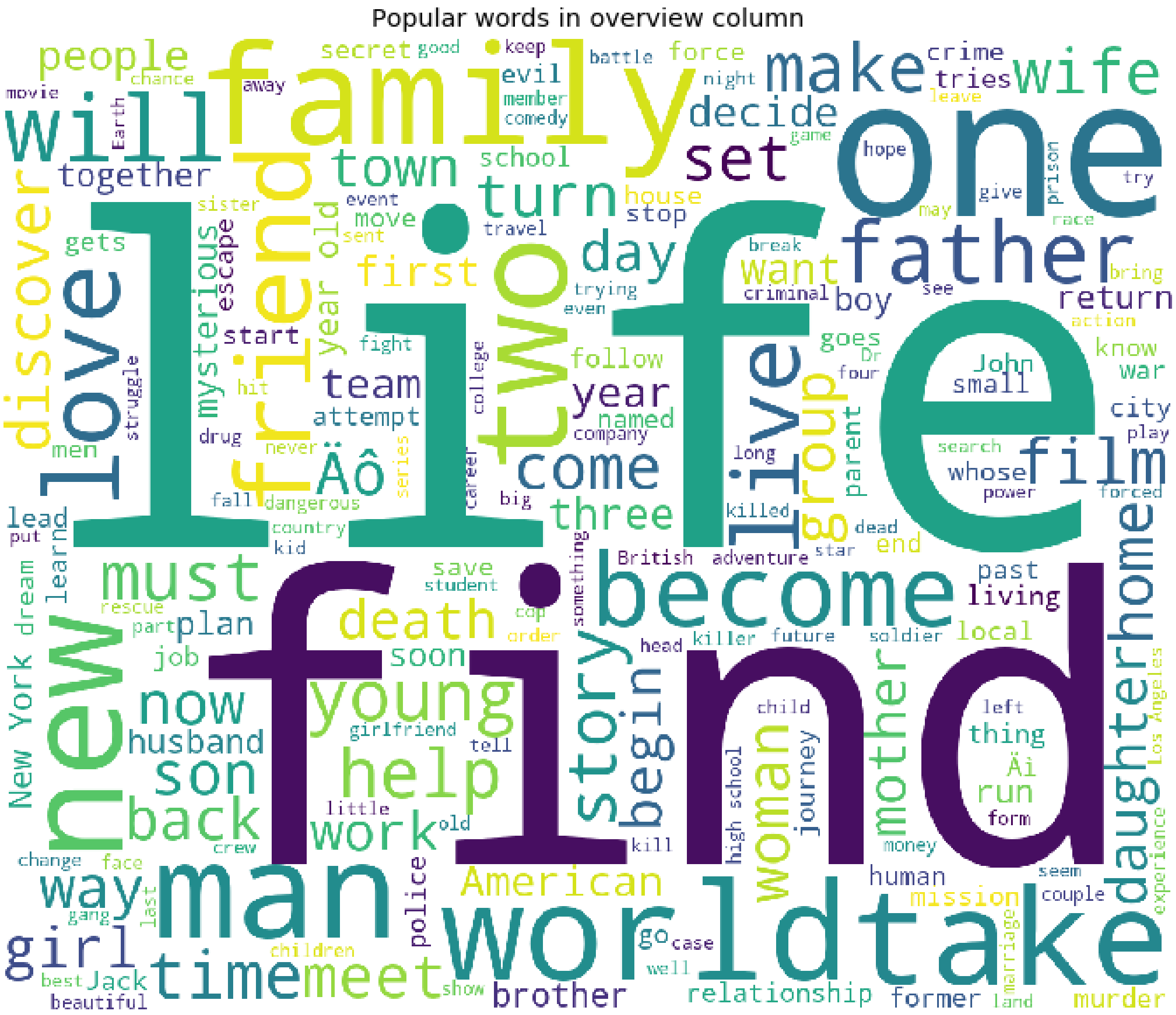
Top words from movie titles




```
Time taken to complete this operation is 5.02456259727478 seconds
```

We can see that the most popular word are Man,Last, La and so on. The most popular or frequent words are in bigger in size.

In [28]:
```
#let's find the popular words from overview coulumn
start = time.time()
plt.figure(figsize = (12, 12))
text = ' '.join(df['overview'].fillna('').values) #fill the values with empty string if there is no value in it.
wordcloud = WordCloud(max_font_size=None, background_color='white', width=1200, height=1000).generate(text)
plt.imshow(wordcloud)
plt.title('Popular words in overview column')
plt.axis("off")
plt.show()
print(" Time taken to complete this operation is", time.time() - start, 'seconds')
```




```
Time taken to complete this operation is 5.240977764129639 seconds
```

Larger words means frequent occuring words. We can see that life, find,one and so on are most popular words in movie description.

Does the film description affects revenue

Let's find out if there is any link between words and revenue. Does the word in description affects revenue?

For this approach we will be using linear regression method . Yes linear regression for string data and we can achieve this by using TFID vector.

- TFID helps tp transforms text to feature vectors that can be used as input to estimator.
- TFID is numerical represenation of frequency of words around data description.

We will fit a linear regression model to this data to predict revenue generate. For this we will be using eli5 pacakge which helps to debug Machine learning classifier and also helps us to explain the prediction.So that it wil be easier to find which words affect revenue.

In [29]:
```python
vectorizer = TfidfVectorizer(
            sublinear_tf=True,
            analyzer='word',
            token_pattern=r'\w{1,}',
            ngram_range=(1, 2),
            min_df=5)

overview_text = vectorizer.fit_transform(df['overview'].fillna(''))
linreg = LinearRegression()
linreg.fit(overview_text, df['log_revenue'])
eli5.show_weights(linreg, vec=vectorizer, top=20, feature_filter=lambda x: x != '<BIAS>')
```

Out[29]: 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

We can see that words in description can have both positve and negative impacts on revenue. Words like to, bombing ,complication has positive impact and words like politicina,18, violence has negative impact on revenue.

In [30]:
```python
print('Target value:', df['log_revenue'][1000])
eli5.show_prediction(linreg, doc=df['overview'].values[1000], vec=vectorizer)
```

```
Target value: 16.44583954907521
```

Out[30]: y (score **16.446**) top features

Contribution?	Feature
+12.762	<BIAS>
+1.302	the chaos
+0.917	to
+0.874	fred
+0.760	chaos and
+0.633	s home
+0.555	return to
+0.504	home
+0.462	her job
+0.456	the
+0.390	creates
+0.355	escape from
+0.354	her
+0.321	childhood
+0.307	husband
+0.278	mother s
+0.221	from
+0.196	after
+0.196	her mother
+0.179	to win
+0.135	elizabeth
+0.129	s
+0.127	marriage
+0.108	up
+0.093	to her
+0.089	and her
+0.088	husband and
+0.074	between
+0.071	that
+0.068	of
+0.060	returns to
+0.057	and
+0.050	when
+0.047	win
+0.024	losing her
+0.003	breaks
-0.042	she
-0.057	between the
-0.062	in
-0.086	her husband
-0.100	job

Contribution?	Feature
-0.113	losing
-0.130	attempts
-0.145	after her
-0.232	friend
-0.255	returns
-0.261	escape
-0.284	attempts to
-0.290	mother
-0.327	to escape
-0.419	back
-0.478	job in
-0.481	from the
-0.504	return
-0.695	mayhem
-0.913	and return
-0.927	chaos

We can see that words in title can have both positve and negative impacts on revenue. Words like don,t age, the secret adn so on has positive impact and words like death, she, land, hell and so on from movie titles has negative impact.

Featured Engineering

Issue with release_date is its not in right format so we need to standarlize using pandas date time format.

In [3]:
```
df.loc[df['release_date'].isnull() == False, 'release_date'].head() #to see if release date has null value.
```

Out[3]:
```
0     2/20/15
1      8/6/04
2    10/10/14
3      3/9/12
4      2/5/09
Name: release_date, dtype: object
```

fixing date column

In [4]:
```python
def fix_date(x):
    '''
    if the value of date here is less than
    or equal to 19 we can prepend 20 infront of this
    to say that movie is from 2000s
    else we can prepend 19 to say that the movie is
    from 1900s
    '''
    year = x.split('/')[2]
    if int(year) <= 19:
        return x[:-2] + '20' + year
    else:
        return x[:-2] + '19' + year
```

In [5]:
```python
df['release_date'] = df['release_date'].apply(lambda x: fix_date(x)) #applying lambda function
```

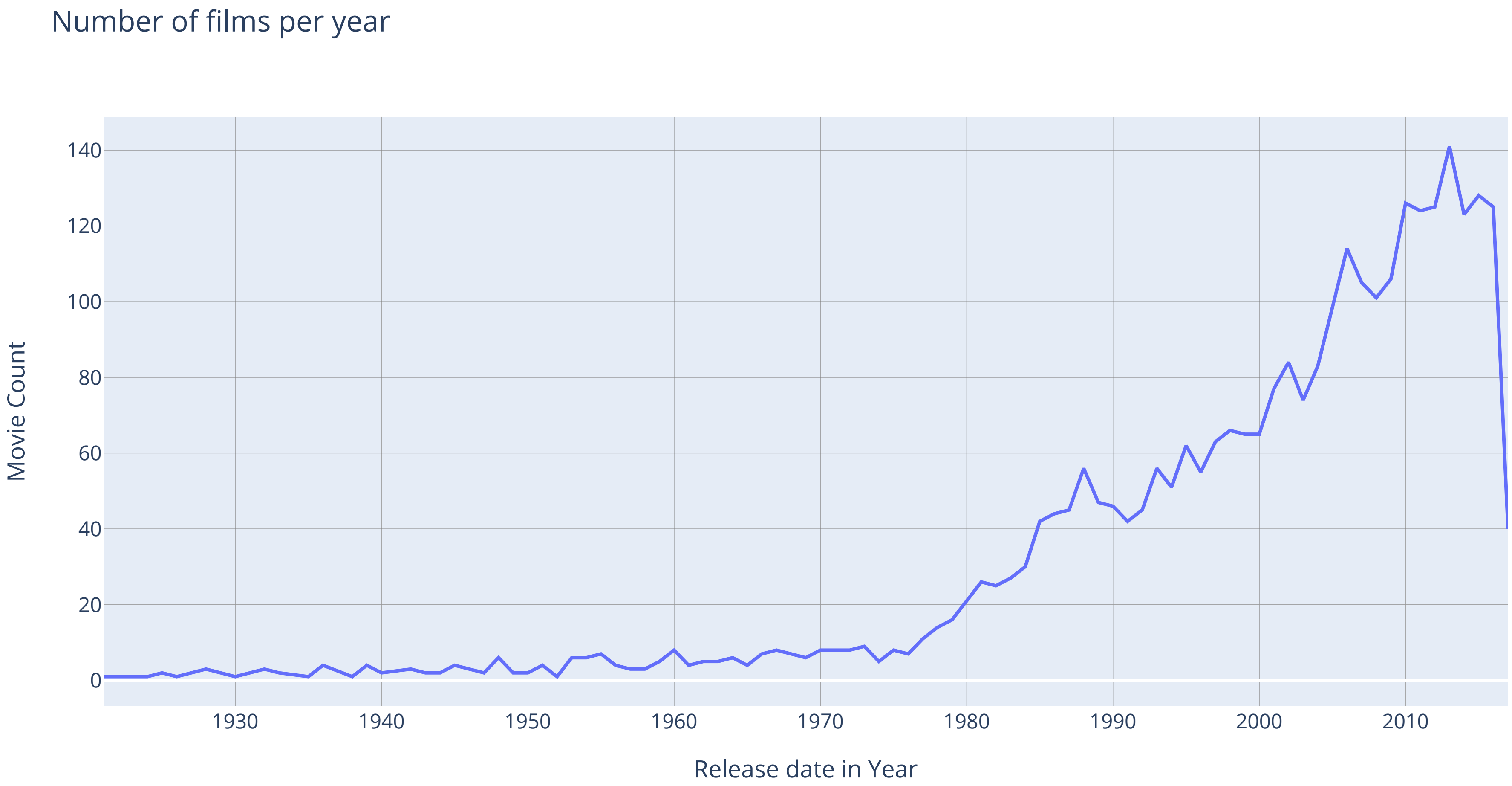
In [6]:
```python
#let's create additional column like Year, month, week, quarter
df['release_date'] = pd.to_datetime(df['release_date']) #converting into panda date time
df['release_date'].head()
```

Out[6]:
```
0   2015-02-20
1   2004-08-06
2   2014-10-10
3   2012-03-09
4   2009-02-05
Name: release_date, dtype: datetime64[ns]
```

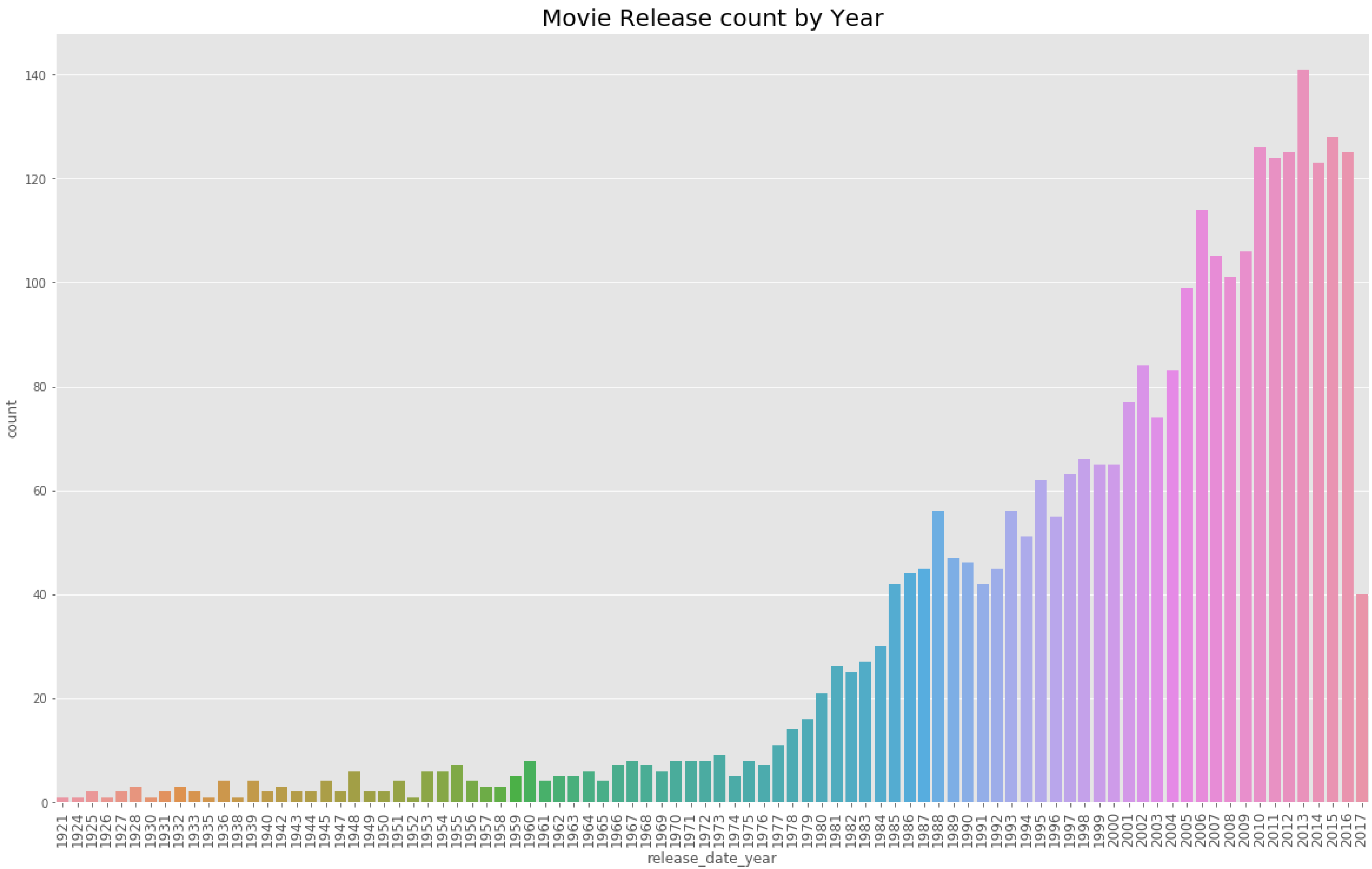
In [7]:
```python
def process_date(df_date):
    '''this function add column like
     year, weeekday, month and so on column
    and add prefix of release_date before
    all the above column eg realease_date_year'''
    date_parts = ["year", "weekday", "month", 'weekofyear', 'day', 'quarter']
    for part in date_parts:
        part_col = 'release_date' + "_" + part #add prefix as  "release_date" before the columne
        df[part_col] = getattr(df['release_date'].dt, part).astype(int)

    return df_date
```

In [8]:
```
df = process_date(df)
```

In [9]:
```
# Count no.of films released per year and sort the years in ascending order
# Do this for both Train and Test Sets
d1 = df['release_date_year'].value_counts().sort_index()


# x values are years, and y values are movie counts, name=legend
data = go.Scatter(x=d1.index, y=d1.values, name='movies data')

layout = go.Layout(title = "Number of films per year", xaxis_title = 'Release date in Year',yaxis_title = 'Movie Count')
py.iplot(dict(data=data, layout=layout))
```

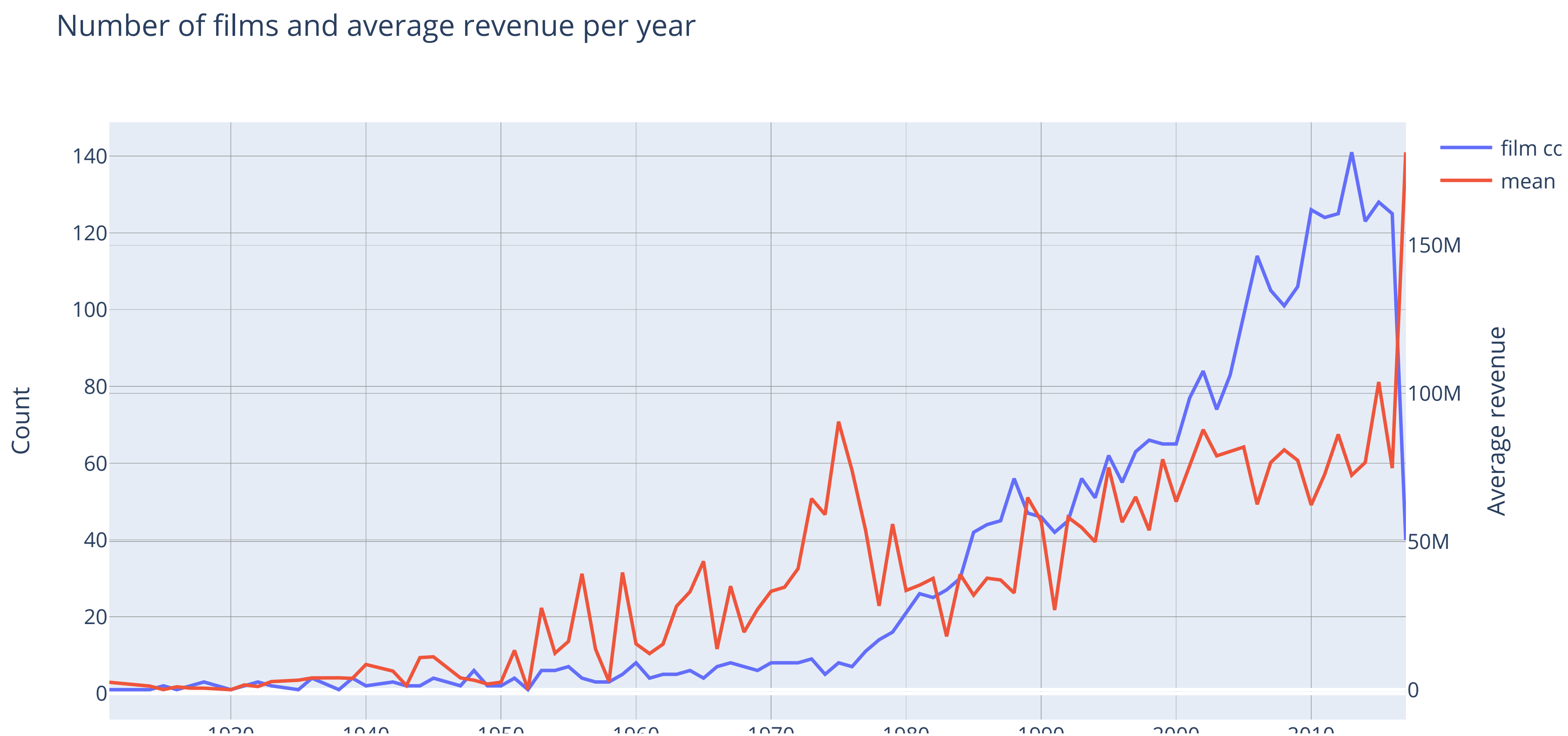


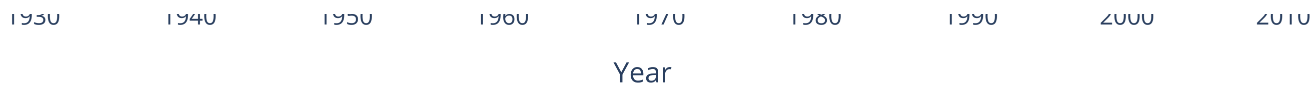
In [38]:
```
#countplot chart for movies release year
plt.figure(figsize=(20,12))
sns.countplot(df['release_date_year'].sort_values())
plt.title("Movie Release count by Year",fontsize=20)
loc, labels = plt.xticks()
plt.xticks(fontsize=12,rotation=90)
plt.show()
```



We can see that since 2000s there are more movies that has been released.We can see that year 2013 has highes number of movie released i.e 140+ movie in a year.

In [10]:
```
#plot for release date vs revenue
d1 = df['release_date_year'].value_counts().sort_index()
d2 = df.groupby(['release_date_year'])['revenue'].mean()

data = [go.Scatter(x=d1.index, y=d1.values, name='film count'),
        go.Scatter(x=d2.index, y=d2.values, name='mean revenue', yaxis='y2')]

layout = go.Layout(dict(title = "Number of films and average revenue per year",
                  xaxis = dict(title = 'Year'),
                  yaxis = dict(title = 'Count'),
                  yaxis2=dict(title='Average revenue', overlaying='y', side='right')
                  ),legend=dict(
                orientation="v"))
py.iplot(dict(data=data, layout=layout))
```





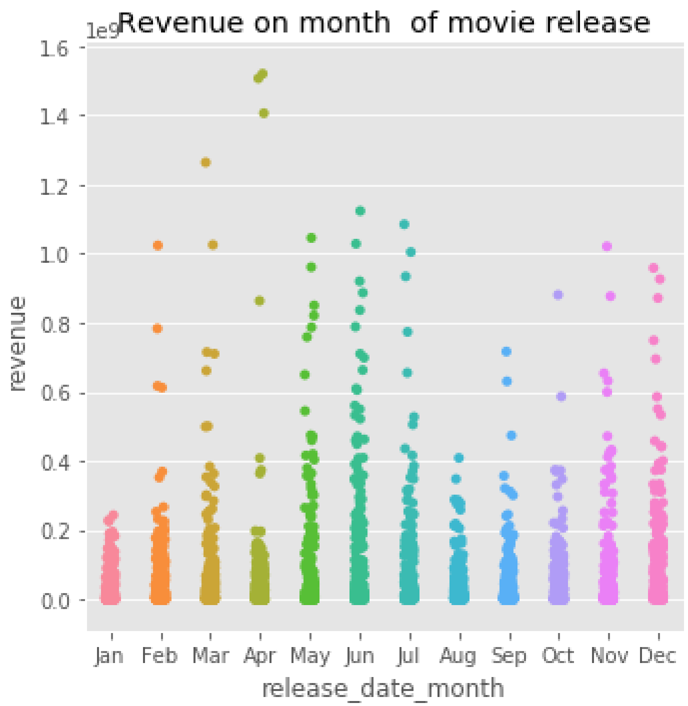
From this chart we can see that graph of total revenue vs movie release count from the year 1930 to 2017

Do release date affects revenue ?

we will be creating categorical plot as day of the week, month are not continuous data.

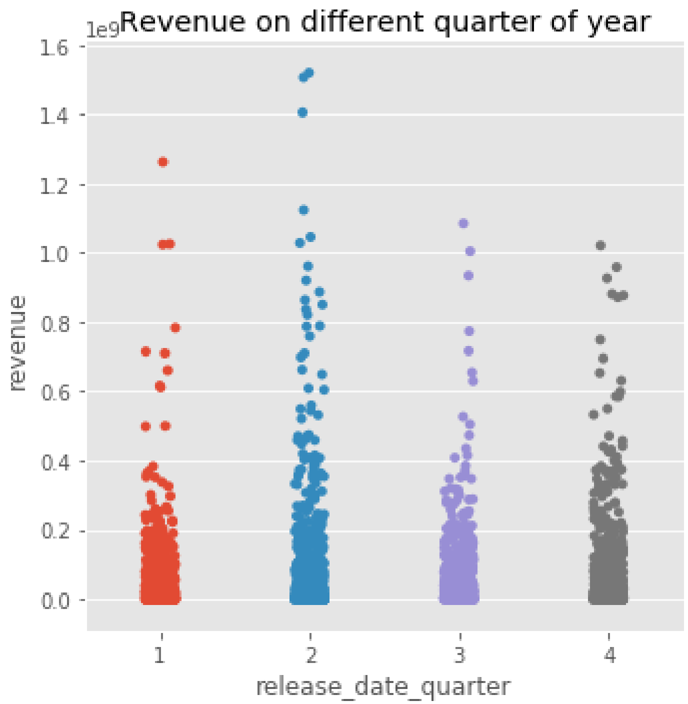
In [40]:
```
#since day, month are categorical variable
plt.figure(figsize=(20,5));
sns.catplot(x='release_date_month', y='revenue', data=df);
plt.title('Revenue on month  of movie release');
#lets replace number by actual month name
loc, labels = plt.xticks()
loc, labels = loc, ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
plt.xticks(loc, labels,fontsize=10)
plt.show()
```

```
<Figure size 1440x360 with 0 Axes>
```



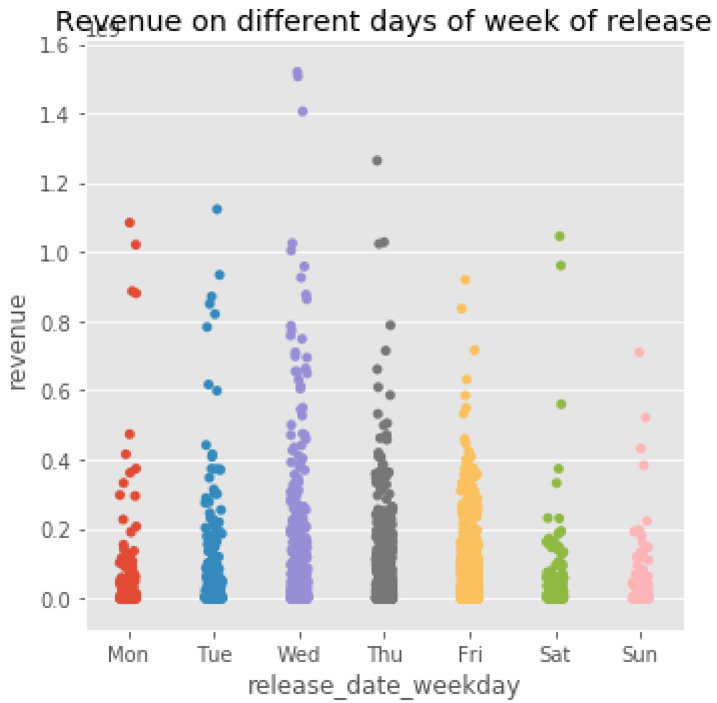
From the above chart we can see that movie released in April has maximum revenue where as movie released in jan has less revenue compared to other months.

In [41]:
```
sns.catplot(x='release_date_quarter', y='revenue', data=df);
plt.title('Revenue on different quarter of year');
```



From the above chart we can see that movie released in second quarter (April-June) has more revenue compared to movie released in last quarter

In [42]:
```
sns.catplot(x='release_date_weekday', y='revenue', data=df);
plt.title('Revenue on different days of week of release');
loc, labels = plt.xticks()
#putting label for days
loc, labels = loc, ["Mon","Tue","Wed","Thu","Fri","Sat","Sun"]
plt.xticks(loc, labels)
plt.show()
```



Surprisingly movie released on wednesday and thursday has more revenue.

Well there seems to have correlation but it may not have one to one causal effect.

In [93]:
```
#top 20 movie by revenue
movies_20 =  df.sort_values(by='revenue', ascending=False).head(20)[['title','revenue','release_date_year']]
```

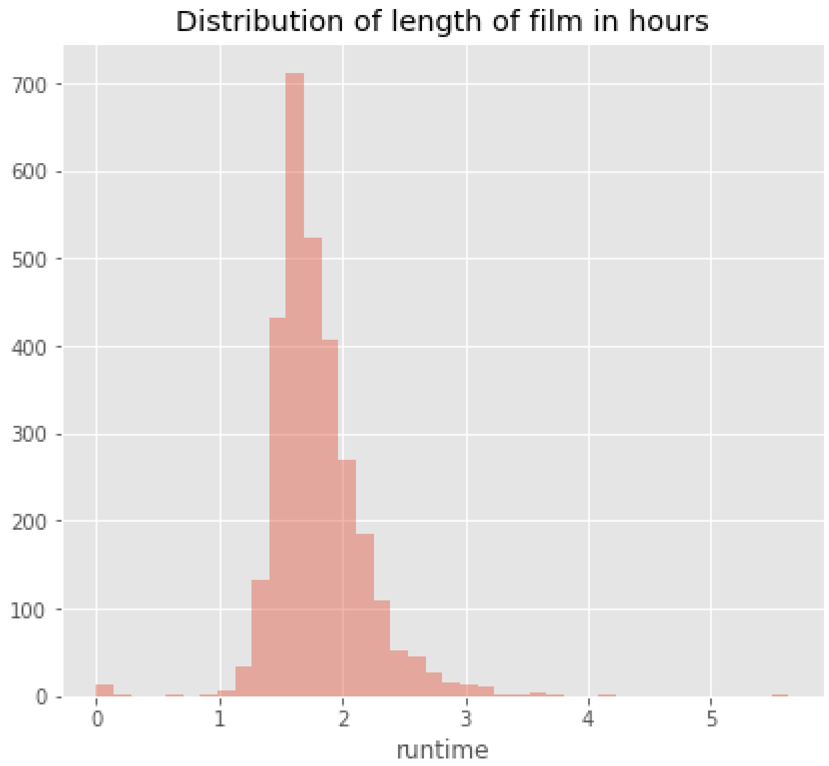
In [94]:
```
movies_20
```

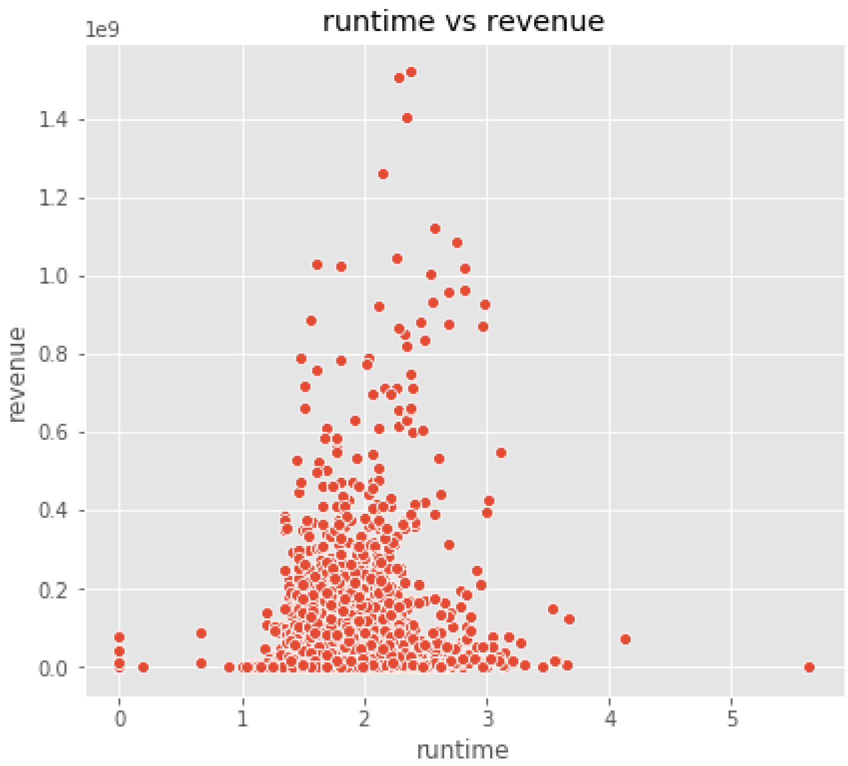
Out[94]:

	title	revenue	release_date_year
1126	The Avengers	1519557910	2012
1761	Furious 7	1506249360	2015
2770	Avengers: Age of Ultron	1405403694	2015
684	Beauty and the Beast	1262886337	2017
2322	Transformers: Dark of the Moon	1123746996	2011
906	The Dark Knight Rises	1084939099	2012
2135	Pirates of the Caribbean: On Stranger Tides	1045713802	2011
2562	Finding Dory	1028570889	2016
881	Alice in Wonderland	1025491110	2010
734	Zootopia	1023784195	2016
2532	The Hobbit: An Unexpected Journey	1021103568	2012
1673	The Dark Knight	1004558444	2008
2209	Pirates of the Caribbean: At World's End	961000000	2007
666	The Hobbit: The Desolation of Smaug	958400000	2013
961	Harry Potter and the Half-Blood Prince	933959197	2009
543	The Lord of the Rings: The Two Towers	926287400	2002
1735	Jurassic Park	920100000	1993
2387	Ice Age: Dawn of the Dinosaurs	886686817	2009
2737	Spectre	880674609	2015
2802	Harry Potter and the Chamber of Secrets	876688482	2002

Relation between runtime and revenue ?

In [96]:
```
plt.figure(figsize=(15, 6))
plt.subplot(1, 2, 1)
sns.distplot(df['runtime'].fillna(0) / 60, bins=40, kde=False); #filling runtime with 0 if there were any missing values
plt.title('Distribution of length of film in hours');
plt.subplot(1, 2, 2)
sns.scatterplot(df['runtime'].fillna(0)/60, df['revenue'])
plt.title('runtime vs revenue');
```





Here we have run time in hour on x-axis and freq of movie in on y axis and then we cas see that most of the movie are between 1-3 hr.And the movie that fall on this duration has highest revenue.

Find top genres from the movie list

In [45]:
```
# Apply the same preprocessing on the string values
df.genres = df.genres.apply(lambda x: list(map(lambda d: list(d.values())[1], ast.literal_eval(x)) if isinstance(x, str)
df.genres.head()
```

Out[45]:
```
0                              [Comedy]
1     [Comedy, Drama, Family, Romance]
2                               [Drama]
3                     [Thriller, Drama]
4                    [Action, Thriller]
Name: genres, dtype: object
```

In [46]:
```
unique_genres = df["genres"].apply(pd.Series).stack().unique()
print("Number of genres: {}".format(len(unique_genres)))
print("Genres: {}".format(unique_genres))
```

```
Number of genres: 20
Genres: ['Comedy' 'Drama' 'Family' 'Romance' 'Thriller' 'Action' 'Animation'
 'Adventure' 'Horror' 'Documentary' 'Music' 'Crime' 'Science Fiction'
 'Mystery' 'Foreign' 'Fantasy' 'War' 'Western' 'History' 'TV Movie']
```

In [47]:
```
genres_dummies = pd.get_dummies(df["genres"].apply(pd.Series).stack()).sum(level=0) #one hot encoding
genres_dummies.head()
```

Out[47]:

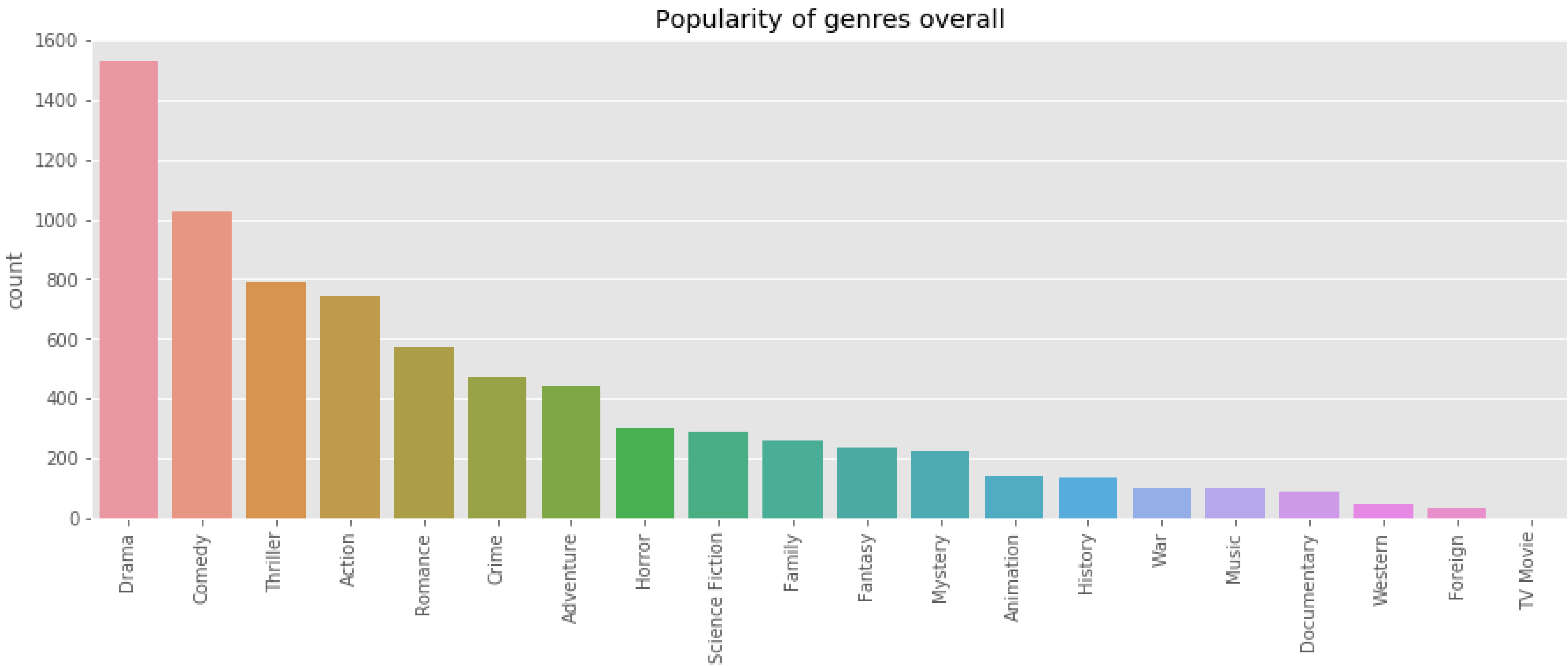
	Action	Adventure	Animation	Comedy	Crime	Documentary	Drama	Family	Fantasy	Foreign	History	Horror	Music	Mystery	Romance	Science Fiction
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	1	0	0	1	1	0	0	0	0	0	0	1	0
2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

In [48]:
```
train_genres = pd.concat([df, genres_dummies],axis=1, sort=False) #merging two data frame
train_genres.head(5)
```

Out[48]:

	id	belongs_to_collection	budget	genres	homepage	imdb_id	original_language	original_title	overview	popularity	
0	1	[{'id': 313576, 'name': 'Hot Tub Time Machine ...	14000000	[Comedy]	NaN	tt2637294	en	Hot Tub Time Machine 2	When Lou, who has become the "father of the In...	6.575393	/t
1	2	[{'id': 107674, 'name': 'The Princess Diaries ...	40000000	[Comedy, Drama, Family, Romance]	NaN	tt0368933	en	The Princess Diaries 2: Royal Engagement	Mia Thermopolis is now a college graduate and ...	8.248895	/w9
2	3	NaN	3300000	[Drama]	http://sonyclassics.com/whiplash/	tt2582802	en	Whiplash	Under the direction of a ruthless instructor, ...	64.299990	
3	4	NaN	1200000	[Thriller, Drama]	http://kahaanithefilm.com/	tt1821480	hi	Kahaani	Vidya Bagchi (Vidya Balan) arrives in Kolkata ...	3.174936	/a
4	5	NaN	0	[Action, Thriller]	NaN	tt1380152	ko	마린보이	Marine Boy is the story of a former national s...	1.148070	/r

In [49]:
```
genres_overall = train_genres[unique_genres].sum().sort_values(ascending=False)
plt.figure(figsize=(15,5))
ax = sns.barplot(x=genres_overall.index, y=genres_overall.values)
plt.xticks(rotation=90)
plt.title("Popularity of genres overall")
plt.ylabel("count")
plt.show()
```



We can see that , from above genre, Drama is more popular ad foreign movie are least popular.

Model Prediction

In [50]:
```
train_genres.columns
```

Out[50]:
```
Index(['id', 'belongs_to_collection', 'budget', 'genres', 'homepage',
       'imdb_id', 'original_language', 'original_title', 'overview',
       'popularity', 'poster_path', 'production_companies',
       'production_countries', 'release_date', 'runtime', 'spoken_languages',
       'status', 'tagline', 'title', 'Keywords', 'cast', 'crew', 'revenue',
       'log_revenue', 'log_budget', 'has_homepage', 'release_date_year',
       'release_date_weekday', 'release_date_month', 'release_date_weekofyear',
       'release_date_day', 'release_date_quarter', 'Action', 'Adventure',
       'Animation', 'Comedy', 'Crime', 'Documentary', 'Drama', 'Family',
       'Fantasy', 'Foreign', 'History', 'Horror', 'Music', 'Mystery',
       'Romance', 'Science Fiction', 'TV Movie', 'Thriller', 'War', 'Western'],
      dtype='object')
```

In [51]:
```
#selecting the numeric column
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64'] #so that easy for us to perform  train and test
df_train=train_genres.select_dtypes(include=numerics)
```

In [52]:
```
#dropping the id coulmn
df_train.drop(columns=['id'],inplace=True) #we will be dropping ID
df_train=df_train.fillna(df_train.median()) #let's film the empty value with median of the data set
```

```
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\frame.py:3997: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a
-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py)
```

In [53]:
```
#selecting dataframe that is float,int
df_train.columns
```

Out[53]:
```
Index(['budget', 'popularity', 'runtime', 'revenue', 'log_revenue',
       'log_budget', 'has_homepage', 'release_date_year',
       'release_date_weekday', 'release_date_month', 'release_date_weekofyear',
       'release_date_day', 'release_date_quarter', 'Action', 'Adventure',
       'Animation', 'Comedy', 'Crime', 'Documentary', 'Drama', 'Family',
       'Fantasy', 'Foreign', 'History', 'Horror', 'Music', 'Mystery',
       'Romance', 'Science Fiction', 'TV Movie', 'Thriller', 'War', 'Western'],
      dtype='object')
```

Loading data from Training

In [54]:
```
#training the model
X = df_train.drop(['revenue', 'log_revenue'], axis=1)
y= df_train['revenue'] #prediction
```

In [63]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 1)
```

In [64]:
```
#linear regression
lm = LinearRegression() #our 6th model
lm.fit(X_train, y_train)
lm_preds = lm.predict(X_test)
print("R Square: ", r2_score(y_test, lm_preds))
```

```
R Square:  0.6202258487857504
```

Our R square value is 62%

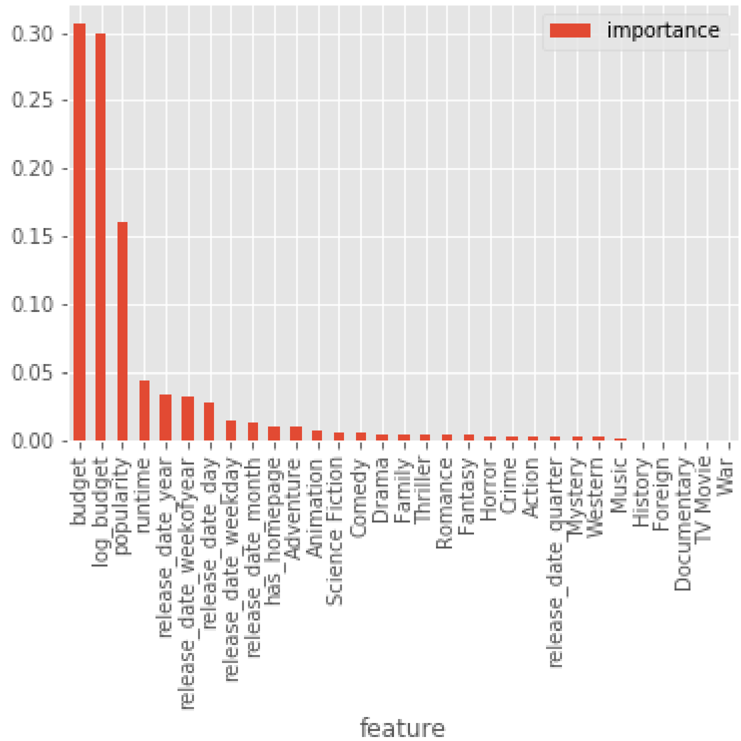
In [59]:
```
#random forrest
import sklearn.metrics as metrics
from sklearn.ensemble import RandomForestRegressor

RF_model = RandomForestRegressor(random_state =0, n_estimators=500, max_depth=10)
RF_model.fit(X_train, y_train)

y_hat = RF_model.predict(X_test)
print ("R-Squared is:", metrics.r2_score(y_hat, y_test))
```

```
R-Squared is: 0.5643712234342768
```

Our predicted from Random forest is 56% accurate.

In [60]:
```python
importances = pd.DataFrame({'feature':X_train.columns,'importance':np.round(RF_model.feature_importances_,3)})
importances = importances.sort_values('importance',ascending=False).set_index('feature');
print(importances)
importances.plot.bar();
```

```
                          importance
feature
budget                         0.306
log_budget                     0.299
popularity                     0.161
runtime                        0.043
release_date_year              0.033
release_date_weekofyear        0.032
release_date_day               0.027
release_date_weekday           0.014
release_date_month             0.012
has_homepage                   0.010
Adventure                      0.009
Animation                      0.007
Science Fiction                0.005
Comedy                         0.005
Drama                          0.004
Family                         0.004
Thriller                       0.004
Romance                        0.004
Fantasy                        0.004
Horror                         0.003
Crime                          0.003
Action                         0.003
release_date_quarter           0.003
Mystery                        0.002
Western                        0.002
Music                          0.001
History                        0.000
Foreign                        0.000
Documentary                    0.000
TV Movie                       0.000
War                            0.000
```



We can see that Budget, popularity, runtime and release date of year (as release date of year is associated with population)has more weight on our feature.

LGB MODEL

In [89]:
```
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2)
params = {'num_leaves': 30,
         'min_data_in_leaf': 20,
         'objective': 'regression',
         'max_depth': 5,
         'learning_rate': 0.01,
         "boosting": "gbdt",
         "feature_fraction": 0.9,
         "bagging_freq": 1,
         "bagging_fraction": 0.9,
         "bagging_seed": 11,
         "metric": 'rmse',
         "lambda_l1": 0.2,
         "verbosity": -1}
```

In [87]:
```
lgb_model = lgb.LGBMRegressor(**params, n_estimators = 10000, nthread = 4, n_jobs = -1)
```

In [90]:
```
lgb_model.fit(X_train, y_train,
        eval_set=[(X_train, y_train), (X_valid, y_valid)], eval_metric='rmse',
        verbose=1000, early_stopping_rounds=200)

eli5.show_weights(lgb_model, feature_filter=lambda x: x != '<BIAS>')
```

```
Training until validation scores don't improve for 200 rounds
Early stopping, best iteration is:
[767]	training's rmse: 5.49628e+07	valid_1's rmse: 8.52096e+07
```

Out[90]:

Weight	Feature
0.5822	budget
0.1697	popularity
0.0823	log_budget
0.0563	runtime
0.0159	release_date_year
0.0143	release_date_weekday
0.0125	has_homepage
0.0123	Adventure
0.0102	release_date_weekofyear
0.0100	release_date_day
0.0076	Animation
0.0046	release_date_month
0.0043	Romance
0.0036	Thriller
0.0026	Family
0.0026	Comedy
0.0019	Science_Fiction
0.0017	Drama
0.0014	Fantasy
0.0013	History
	… 11 more …

GB regressor

In [65]:
```
#Gradient Boosting Regressor
# Fit regression model
from sklearn import ensemble
params = {'n_estimators': 500, 'max_depth': 4, 'min_samples_split': 2,
          'learning_rate': .01, 'loss': 'ls'}
clf = ensemble.GradientBoostingRegressor(**params)
predictions2 = clf.fit(X_train,y_train)
training_score = clf.score(X_train, y_train)
print(f"Training Score: {training_score}")
```

```
Training Score: 0.865629813071184
```

In [66]:
```
predictions2 = np.expand_dims(clf.predict(X_test), axis = 1)
MSE = mean_squared_error(y_test, predictions2)
r2 = clf.score(X_test, y_test)
print(f"MSE: {MSE}, R2: {r2}")
```

```
MSE: 5471312048272168.0, R2: 0.6767814911469758
```

Our R square predicted from GB booster is quite better than other model with R square of 67%

In [69]:
```
#Predictions for the test data
revenue_predictions = clf.predict(X_test)
gbr_predictions = pd.DataFrame(revenue_predictions, columns = ['predicted_revenue'])
gbr_predictions.head()
```

Out[69]:

	predicted_revenue
0	1.131428e+08
1	2.193659e+07
2	6.906060e+08
3	2.781506e+07
4	1.095287e+08

In [71]:
```
test_result = pd.concat([train_genres, gbr_predictions], axis = 1, sort=True)
#look at top values only
test_result = test_result[[ 'budget', 'popularity', 'release_date_year','release_date_month', 'revenue','predicted_reven
test_result.head()
```

Out[71]:

	budget	popularity	release_date_year	release_date_month	revenue	predicted_revenue
0	14000000	6.575393	2015	2	12314651	1.131428e+08
1	40000000	8.248895	2004	8	95149435	2.193659e+07
2	3300000	64.299990	2014	10	13092000	6.906060e+08
3	1200000	3.174936	2012	3	16000000	2.781506e+07
4	0	1.148070	2009	2	3923970	1.095287e+08

Here we can see reveune predicted from our testing model

Conclusion

Key Finding:

- Drama is the most popular genre, followed by Comedy, Thriller, and Action.
- Foreign Movie has Less revenue among all the genres.
- 2013 had the most movie released in a single calendar year.
- Avenger, Furious 7, Beauty and the Beast were among the top 3 revenue generated by the movie.
- Movies released in the second quarter of the year generated the most revenue.
- There was a high correlation between movie budget and movie revenue.
- Movies with a high budget have shown the tendency of high revenues.

The key point from the above model training and the tunning process is that we may be able to predict the movie revenue using featured labels like the Movie release date of the year(as the year is associated with the population of that time, Budget of movie, Popularity, run time. And Movie industries and persons associated with Movies can use the Machine learning model to predict the revenue of the movie by inputting the above featured.

We had a data set of 3000 rows and 23 columns originally. We trained and test using the above data set. There fore, we have some limitations on our model as it could not provide accurate results and to improve model performance we have to add more data set and add a few featured variables.Therefore, a larger number of observations to capture more variability in the movie data in our testing data set is required to have a better measure of the model’s accuracy.

In [ ]:
```

```