In [1]:

```
import pandas as pd
import re
import ast
from sklearn.preprocessing import MultiLabelBinarizer
import matplotlib.pyplot as plt
import numpy as np
import string
from nltk.stem.porter import PorterStemmer
from collections import Counter
import statistics
import nltk
from nltk.corpus import stopwords
import math
import random
```

In [2]:

```
df = pd.read_csv('train.tsv',sep='\t')
```

Feature Exploration and Feature Engineering

In [3]:

```
df.columns
```

Out[3]:

```
Index(['backdrop_path', 'belongs_to_collection', 'budget', 'genres',
       'homepage', 'id', 'imdb_id', 'original_language', 'original_title',
       'overview', 'popularity', 'poster_path', 'production_companies',
       'production_countries', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'status', 'tagline', 'title', 'video',
       'vote_average', 'vote_count', 'Keywords', 'cast', 'crew'],
      dtype='object')
```

In [4]:

```
df['ln_revenue'] = np.log(df['revenue']+1)
```

In [5]:

```
average_ln_revenue = df['ln_revenue'].mean()
average_revenue = df['revenue'].mean()
average_revenue = average_ln_revenue
train_set_size = len(df)
```

In [6]:

```
df.corr()
```

Out[6]:

	budget	id	popularity	revenue	runtime	video	vote_average	vote_count	ln_revenue
budget	1.000000	-0.045909	0.508048	0.753590	0.193121	-0.026635	0.020289	0.607103	0.483225
id	-0.045909	1.000000	0.146549	-0.001979	-0.017272	0.056707	0.004266	-0.002634	-0.110578
popularity	0.508048	0.146549	1.000000	0.567924	0.140087	-0.053811	0.232102	0.633513	0.432581
revenue	0.753590	-0.001979	0.567924	1.000000	0.183223	-0.025021	0.159344	0.769808	0.484683
runtime	0.193121	-0.017272	0.140087	0.183223	1.000000	0.135716	0.302452	0.179196	0.205085
video	-0.026635	0.056707	-0.053811	-0.025021	0.135716	1.000000	-0.057794	-0.029589	-0.041816
vote_average	0.020289	0.004266	0.232102	0.159344	0.302452	-0.057794	1.000000	0.284642	0.150904

	budget	id	popularity	revenue	runtime	video	vote_average	vote_count	ln_revenue
vote_count	0.607103	-0.002634	0.633513	0.769808	0.179196	-0.029589	0.284642	1.000000	0.427802
ln_revenue	0.483225	-0.110578	0.432581	0.484683	0.205085	-0.041816	0.150904	0.427802	1.000000

In [7]:

```
df.corr(method='spearman')
```

Out[7]:

	budget	id	popularity	revenue	runtime	video	vote_average	vote_count	ln_revenue
budget	1.000000	-0.213341	0.559653	0.686852	0.252063	-0.043986	-0.016472	0.620679	0.686852
id	-0.213341	1.000000	-0.189962	-0.264908	-0.083596	0.042096	-0.118153	-0.237973	-0.264908
popularity	0.559653	-0.189962	1.000000	0.636686	0.164733	-0.082624	0.222627	0.857544	0.636686
revenue	0.686852	-0.264908	0.636686	1.000000	0.274395	-0.051778	0.132838	0.702440	1.000000
runtime	0.252063	-0.083596	0.164733	0.274395	1.000000	0.054455	0.342145	0.191168	0.274395
video	-0.043986	0.042096	-0.082624	-0.051778	0.054455	1.000000	-0.016486	-0.095960	-0.051778
vote_average	-0.016472	-0.118153	0.222627	0.132838	0.342145	-0.016486	1.000000	0.278710	0.132838
vote_count	0.620679	-0.237973	0.857544	0.702440	0.191168	-0.095960	0.278710	1.000000	0.702440
ln_revenue	0.686852	-0.264908	0.636686	1.000000	0.274395	-0.051778	0.132838	0.702440	1.000000

In [8]:

```
df.describe()
```

Out[8]:

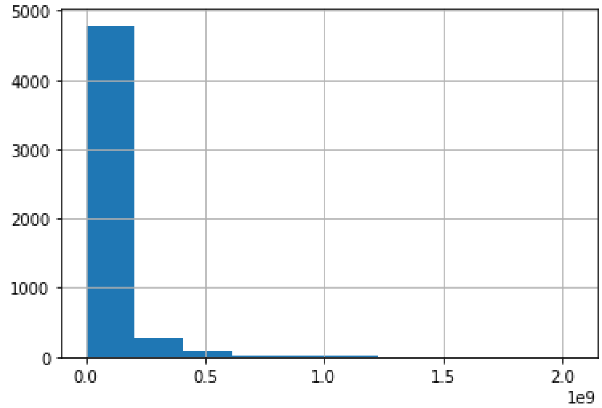
	budget	id	popularity	revenue	runtime	vote_average	vote_count	ln_revenue
count	5.215000e+03	5215.000000	5215.000000	5.215000e+03	5211.000000	5215.000000	5215.000000	5215.000000
mean	2.147967e+07	98768.673442	10.016559	6.538743e+07	108.027442	6.399099	1062.859636	15.897057
std	3.631509e+07	143992.708567	7.075799	1.432381e+08	22.740973	0.943931	2097.172266	3.076433
min	0.000000e+00	5.000000	1.519000	1.000000e+00	0.000000	0.000000	0.000000	0.693147
25%	0.000000e+00	10136.000000	6.264000	2.360718e+06	94.000000	5.900000	74.000000	14.674476
50%	6.500000e+06	24662.000000	9.009000	1.515620e+07	104.000000	6.400000	290.000000	16.533920
75%	2.600000e+07	121704.000000	11.801000	6.214247e+07	118.000000	7.100000	1028.000000	17.944940
max	3.800000e+08	679106.000000	151.237000	2.046240e+09	465.000000	10.000000	24834.000000	21.439270

In [9]:

```
df['revenue'].hist()
```

Out[9]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1679f8b8d0>
```

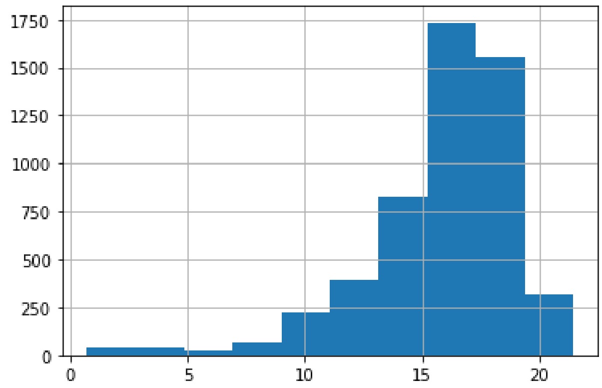


In [10]:

```python
df['ln_revenue'].hist()
```

Out[10]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x7f1679fee910&gt;
```



backdrop_path:

Links to some images - removed from the analysis

In [11]:

```python
df['backdrop_path']
```

Out[11]:

```
0        /7IBpOrw0ATwL1AOV97mtsceDpYs.jpg
1        /lYeE7k0OR3HXyoq7FeswyaxFJvL.jpg
2        /gVXLIfMR2hLmkn0nACctlMCJBfx.jpg
3        /rKjE17ncAGNzeImNWbdGTimzjtk.jpg
4        /zcJxJVhvxNHJJ2J7Q7NhgO9nPUV.jpg
                       ...
5210                                  NaN
5211     /sOw7TZzt3vRQXXCrwdspSHwCJDR.jpg
5212     /5txDq5g0JeCKpemRM2CpT7H2aP3.jpg
5213     /1dXTsaFxHoF9cas08UjAqE8NqOW.jpg
5214     /yZjbReSRgTGf5IZPmwpecPgm1Z1.jpg
Name: backdrop_path, Length: 5215, dtype: object
```

In [12]:

```python
df = df.drop(['backdrop_path'], axis=1)
```

release date:

we assume that the relevant parts of the relsease date are the year and the month (summer movies might be more profitable)

In [13]:

```python
def get_release_year(date):
    return int(date[:4])
```

In [14]:

```python
def get_release_month(date):
    return int(date[5:7])
```

In [15]:

```python
df['release_year'] = df['release_date'].apply(lambda x:get_release_year(x))
df['release_month'] = df['release_date'].apply(lambda x:get_release_month(x))
```

In [16]:

```
df = df.drop(['release_date'], axis=1)
```

Categorial variables:

We have some features which express belonging to some categories, where in some of them one movie can belong to several categories.

We convert this to a list of categories and analyse the number of categories and categories frequency.

We have some categorial features with a lot of categories, for some of them the movie can belong to more than one category (spoken languages,cast,text features words..). This will be hard for algorithms to handle.

To handle those we use 3 methods:

- One hot encoding of frequent categories.
- Target encoding with smoothing.
- Extracting a boolean variable if the movie belongs to a frequent category (top production comapnies, top production countries)

Target encoding with smoothing:

- For each of the categories we extract category frequency and the mean revenue of the movies belong to this category.
- For each movie, for each of the categories it belongs to we compute the average revenue of movies belong to this category, excluding the folds of movies which the movie belongs to, to prevent leakage from target to x.
- The average revenew of the category is smoothed with average revenew overall, with weightes depending on the category frequency.
- For features in which the movie can belong to several categories, we extract as features the min,max,mean and median

Target encoding equasion: \begin{equation*} \frac{n*category_mean+m*mean}{n+m} \end{equation*}

- n is the number of movies belonging to the category.
- category_mean is the mean revenue of movies belonging to the category (excluding current).
- mean is the revenue mean (full dataset)
- m is a hyperparameter which detrmains the weight of the overall mean. If m=n the category mean and mean are equally weighted.

In [17]:

```
m = 10
m_belongs_to_collection = m
m_spoken_languages = m
m_original_language = m
m_production_comapnies = m
m_director = m
m_producer = m
m_cast = m
m_keywords = m
m_title = m
m_overview = m
m_tagline = m
m_country_count = m
```

In [18]:

```
df.index
```

Out[18]:

```
RangeIndex(start=0, stop=5215, step=1)
```

In [19]:

```
def get_folds(df):
    fold_size = int(train_set_size/5)
    df['random_index'] = pd.Series(random.sample(list(df.index), train_set_size) )
    df['fold'] = df['random_index'].apply(lambda x:int(x/fold_size))
    return dict(df.groupby('fold')['ln_revenue'].sum()),dict(df.groupby('fold')['ln_revenue'].size(
```

```
))
```

In [20]:

```
folds_sum,fold_len = get_folds(df)
```

When one category is possible

In [21]:

```
def count_categories(series):
    return dict(series.value_counts())
```

In [22]:

```
def get_revenue_dict(df,column):
    fold_category_score = [{},{},{},{},{}]
    fold_category_count = [{},{},{},{},{}]
    for fold in [0,1,2,3,4]:
        fold_category_score[fold] = dict(df[df['fold']==fold].groupby(column)['ln_revenue'].sum())
        fold_category_count[fold] = dict(df[df['fold']==fold].groupby(column)['ln_revenue'].size())
    return dict(df.groupby(column)['ln_revenue'].mean()),fold_category_score,fold_category_count
```

In [23]:

```
def
get_category_score(category,fold,score_dict,count_dict,folds_score,folds_count,smoothing_factor):
    average_revenue_without = (average_revenue*train_set_size-folds_sum[fold])/(train_set_size-fold
_len[fold])
    if not isinstance(category, str):
        return average_revenue_without
    if count_dict[category]-folds_count[fold][category]>=5:
        score = (score_dict[category]*count_dict[category]-folds_score[fold][category])/(count_dict
[category]-folds_count[fold][category])
        score = (score*(count_dict[category]-folds_count[fold][category])+smoothing_factor*average_
revenue_without)/(smoothing_factor+count_dict[category]-folds_count[fold][category])
    else:
        score = average_revenue_without
    return score
```

When multiple categories are possible

In [24]:

```
def set_from_lists(lists):
    items_set = set()
    for nested_list in lists:
        for item in nested_list:
            items_set.add(item)
    return items_set
```

In [25]:

```
def get_frequency(categories_list_series):
    all_categories = []
    for categories in list(categories_list_series):
        all_categories = all_categories + categories
    category_count = dict(Counter(all_categories))
    return category_count
```

In [26]:

```
def compute_categories_mean_revenue_(series,revenues,folds,category_count):
    categories_score = {}
    categories_score_folds = [{},{},{},{},{}]
    categories_count_folds = [{},{},{},{},{}]
    for categories,revenue,fold in zip(list(series),list(revenues),list(folds)):
        for category in categories:
```

```
            if category not in categories_score:
                categories_score[category] = revenue
            else:
                categories_score[category] += revenue
            if category not in categories_score_folds[fold]:
                categories_score_folds[fold][category] = revenue
                categories_count_folds[fold][category] = 1
            else:
                categories_score_folds[fold][category] += revenue
                categories_count_folds[fold][category] += 1
    return categories_score,categories_score_folds,categories_count_folds
```

In [27]:

```
def
get_multiple_categories_score_(categories_list,fold,score_dict,count_dict,folds_score,folds_count,
smoothing_factor):
    scores = []
    average_revenue_without = (average_revenue*train_set_size-folds_sum[fold])/(train_set_size-fold
_len[fold])
    for category in categories_list:
        if count_dict[category]-folds_count[fold][category] >= 5:
            score = (score_dict[category]*count_dict[category]-folds_score[fold]
[category])/(count_dict[category]-folds_count[fold][category])
        else:
            score = average_revenue_without
        scores.append(score)
    smoothed_score = [(score*(count_dict[category]-folds_count[fold][category])+smoothing_factor*av
erage_revenue_without)/(smoothing_factor+count_dict[category]-folds_count[fold][category]) for cate
gory,score in zip(categories_list,scores)]
    return smoothed_score
```

In [28]:

```
def extract_target_encoding_features(df, column,category_count,m):
    category_score,folds_category_score,folds_category_count = compute_categories_mean_revenue_(df
[column],df['ln_revenue'],df['fold'],category_count)
    scores_series = df[[column,'fold']].apply(lambda x:get_multiple_categories_score_(x[0],x[1],cat
egory_score,category_count,folds_category_score,folds_category_count,m),axis=1)
    df['min_'+column+'_score'] = scores_series.apply(lambda x:min(x) if len(x)>0 else
average_revenue)
    df['max_'+column+'_score'] = scores_series.apply(lambda x:max(x) if len(x)>0 else
average_revenue)
    df['mean_'+column+'_score'] = scores_series.apply(lambda x:sum(x)/len(x) if len(x)>0 else averag
e_revenue)
    df['median_'+column+'_score'] = scores_series.apply(lambda x:statistics.median(x) if len(x)>0 e
lse average_revenue)
    return df, category_score
```

belongs_to_collection:

The collection which the movie belongs to (if any)

We convert this to a boolean variable (is the movie belongs to collection)

We encode james bond movis because this is a big collection.

We perform target encoding.

In [29]:

```
df['belongs_to_collection']
```

Out[29]:

```
0       {'id': 556, 'name': 'Spider-Man Collection', '...
1       {'id': 256296, 'name': 'Silent Night, Deadly N...
2                                                    NaN
3       {'id': 8917, 'name': 'Hellraiser Collection', ...
4       {'id': 108693, 'name': "National Lampoon's Vac...
                              ...
5210    {'id': 239968, 'name': 'La cage aux folles Col...
5211    {'id': 111751, 'name': 'Texas Chainsaw Massacr...
```

```
5212                                                  NaN
5213                                                  NaN
5214    {'id': 71458, 'name': '3 Ninjas Collection', '...
Name: belongs_to_collection, Length: 5215, dtype: object
```

In [30]:

```
df['no_collection'] = df['belongs_to_collection'].isna().astype(int)
```

In [31]:

```
df['belongs_to_collection'] = df['belongs_to_collection'].apply(lambda x:str(ast.literal_eval(x)['i
d']) if pd.notnull(x) else x)
```

In [32]:

```
df.groupby('belongs_to_collection')['ln_revenue'].var().dropna()
```

Out[32]:

```
belongs_to_collection
100286     0.005129
1006       1.167709
101471    13.182952
10194      0.195723
102322     0.100606
            ...
9735       0.644848
97445      0.333751
97771      2.308252
98580      0.189289
9887       1.579892
Name: ln_revenue, Length: 240, dtype: float64
```

In [33]:

```
df['ln_revenue'].var()
```

Out[33]:

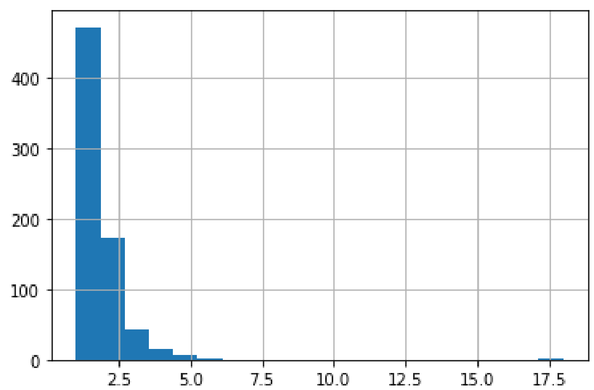
```
9.46444073082016
```

In [34]:

```
df['belongs_to_collection'].value_counts().hist(bins=20)
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f16797f9cd0>
```



In [35]:

```
collection_counts = count_categories(df['belongs_to_collection'])
```

In [36]:

```
list(df[df['belongs_to_collection']=='645']['title'])
```

Out[36]:

```
['Casino Royale',
 'Moonraker',
 'The Spy Who Loved Me',
 'From Russia with Love',
 'Thunderball',
 'A View to a Kill',
 'Diamonds Are Forever',
 'GoldenEye',
 'Dr. No',
 'Goldfinger',
 'Octopussy',
 'Skyfall',
 "On Her Majesty's Secret Service",
 'Tomorrow Never Dies',
 'The Living Daylights',
 'Die Another Day',
 'The World Is Not Enough',
 'You Only Live Twice']
```

In [37]:

```
df['is_james_bond'] = df['belongs_to_collection'].apply(lambda x:1 if x=='645' else 0)
```

In [38]:

```
collection_score,fold_collection_score, fold_collection_count =
get_revenue_dict(df,'belongs_to_collection')
```

In [39]:

```
df['collection_target_encoding'] = df[['belongs_to_collection','fold']].apply(lambda
x:get_category_score(x[0],x[1],collection_score,collection_counts,fold_collection_score,fold_collec
tion_count,m_belongs_to_collection),axis=1)
```

In [40]:

```
df = df.drop(['belongs_to_collection'], axis=1)
```

spoken_languages:

This feature includes the languages in which the movie is in. We transform it to a format of lists of the available languages and then to target encoding and produce one hot encoding for english and feature of number of spoken languages.

In [41]:

```
df['spoken_languages']
```

Out[41]:

```
0       [{'iso_639_1': 'en', 'name': 'English'}, {'iso...
1                [{'iso_639_1': 'en', 'name': 'English'}]
2                [{'iso_639_1': 'en', 'name': 'English'}]
3                [{'iso_639_1': 'en', 'name': 'English'}]
4                [{'iso_639_1': 'en', 'name': 'English'}]
                              ...
5210            [{'iso_639_1': 'fr', 'name': 'Français'}]
5211             [{'iso_639_1': 'en', 'name': 'English'}]
5212             [{'iso_639_1': 'en', 'name': 'English'}]
5213             [{'iso_639_1': 'en', 'name': 'English'}]
5214             [{'iso_639_1': 'en', 'name': 'English'}]
Name: spoken_languages, Length: 5215, dtype: object
```

In [42]:

In [42]:

```
def get_languages_list(item):
    item = ast.literal_eval(item)
    languages = [language_dict['iso_639_1'] for language_dict in item]
    return languages
```

In [43]:

```
df['spoken_languages'] = df['spoken_languages'].apply(lambda x:get_languages_list(x))
```

In [44]:

```
df['spoken_languages'][:5]
```

Out[44]:

```
0    [en, fr]
1        [en]
2        [en]
3        [en]
4        [en]
Name: spoken_languages, dtype: object
```

In [45]:

```
df[['spoken_languages','revenue']]
```

Out[45]:

	spoken_languages	revenue
0	[en, fr]	890871626
1	[en]	154323
2	[en]	176236
3	[en]	14564027
4	[en]	61399552
...	...	...
5210	[fr]	345280
5211	[en]	30859000
5212	[en]	6100000
5213	[en]	72258126
5214	[en]	29000301

5215 rows × 2 columns

In [46]:

```
df['spoken_languages_amount'] = df['spoken_languages'].apply(lambda x: len(x))
df['english_speaking'] = df['spoken_languages'].apply(lambda x: 1 if 'en' in x else 0)
```

In [47]:

```
spoken_languages_count = get_frequency(df['spoken_languages'])
```

In [48]:

```
df, spoken_languages_score =
extract_target_encoding_features(df,'spoken_languages',spoken_languages_count,m_spoken_languages)
```

In [49]:

```
df = df.drop(['spoken_languages'], axis=1)
```

genres:

In [50]:

```
def get_genres_list(item):
    item = ast.literal_eval(item)
    genres = [genre_dict['name'] for genre_dict in item]
    return genres
```

In [51]:

```
df['genres'] = df['genres'].apply(lambda x:get_genres_list(x))
```

In [52]:

```
genres_by_movie = list(df['genres'])
all_genres = set_from_lists(genres_by_movie)
```

In [53]:

```
for genre in all_genres:
    genre_binary = []
    for movie in genres_by_movie:
        if genre in movie:
            genre_binary.append(1)
        else:
            genre_binary.append(0)
    df[genre+'_movie'] = genre_binary
```

In [54]:

```
df = df.drop(['genres'], axis=1)
```

Original_language:

In [55]:

```
top_languages = ['en','cn','de','es','fr','hi','it','ja','ko','ru','zh']
```

In [56]:

```
for language in top_languages:
    df[language+'_original'] = df['original_language'].apply(lambda x: 1 if x == language else 0 )
```

In [57]:

```
language_counts = count_categories(df['original_language'])
language_score,language_fold_score,language_fold_count = get_revenue_dict(df,'original_language')
df['original_language_target_encoding'] = df[['original_language','fold']].apply(lambda
x:get_category_score(x[0],x[1], language_score,language_counts,language_fold_score,language_fold_co
unt,m_original_language),axis=1)
```

In [58]:

```
df = df.drop(['original_language'], axis=1)
```

production companies:

In [59]:

```
def apperance_count(movie_list):
    apperances = dict()
    for movie in movie_list:
        for participant in movie:
            if participant not in apperances:
```

```
                apperances[participant] = 0
        apperances[participant] += 1
    return apperances
```

In [60]:

```
def get_companies_list(item):
    item = ast.literal_eval(item)
    companies = [companies_dict['name'] for companies_dict in item]
    return companies
```

In [61]:

```
df['production_companies'] = df['production_companies'].apply(lambda x:get_companies_list(x))
```

In [62]:

```
df['production_companies_amount'] = df['production_companies'].apply(lambda x: len(x))
```

In [63]:

```
companies_by_movie = list(df['production_companies'])
all_companies = set_from_lists(companies_by_movie)
```

In [64]:

```
companies = apperance_count(companies_by_movie)
```

In [65]:

```
top_copanies = [company_name for company_name,apperences in companies.items() if apperences >= 10]
```

In [66]:

```
top_company_per_movie = []
for movie in companies_by_movie:
    flag = False
    for company in movie:
        if company in top_copanies:
            flag = True
    top_company_per_movie.append(int(flag))
```

In [67]:

```
df['top_production_company'] = top_company_per_movie
```

In [68]:

```
production_comapny_count = get_frequency(df['production_companies'])
```

In [69]:

```
df,production_comapny_score =
extract_target_encoding_features(df,'production_companies',production_comapny_count,m_production_cc
mapnies)
```

In [70]:

```
df = df.drop(['production_companies'], axis=1)
```

production countries:

In [71]:

```python
def get_countries_list(item):
    item = ast.literal_eval(item)
    countries = [countries_dict['name'] for countries_dict in item]
    return countries
```

In [72]:

```python
df['production_countries'] = df['production_countries'].apply(lambda x:get_countries_list(x))
```

In [73]:

```python
country_by_movie = list(df['production_countries'])
```

In [74]:

```python
countries_count = apperance_count(country_by_movie)
```

In [75]:

```python
top_countries = [country for country in countries_count if countries_count[country] >= 150]
```

In [76]:

```python
top_country_per_movie = []
american_production = []
for movie in country_by_movie:
    flag = False
    american = False
    for country in movie:
        if country in top_countries:
            flag = True
        if country == 'United States of America':
            american = True
    top_country_per_movie.append(int(flag))
    american_production.append(int(american))
```

In [77]:

```python
df['top_country'] = top_country_per_movie
df['american_production'] = american_production
```

In [78]:

```python
country_count = get_frequency(df['production_countries'])
df,countries_score = extract_target_encoding_features(df,'production_countries',country_count,m_co
untry_count)
```

In [79]:

```python
df = df.drop(['production_countries'], axis=1)
```

cast:

In [80]:

```python
def get_actors_list(item):
    item = ast.literal_eval(item)
    actors = [actor_dict['id'] for actor_dict in item]
    return actors
```

In [81]:

```python
df['cast_list'] = df['cast'].apply(lambda x: get_actors_list(x))
df['cast_size'] = df['cast'].apply(lambda x: len(x))
```

In [82]:

```
cast_count = get_frequency(df['cast_list'])
df,cast_score = extract_target_encoding_features(df,'cast_list',cast_count,m_cast)
```

In [83]:

```
df = df.drop(['cast_list','cast'],axis=1)
```

crew:

In [84]:

```
def get_crew_member(item, job):
    director = []
    item = ast.literal_eval(item)
    for crew_member in item:
        if crew_member['job'] == job:
            director.append(crew_member['id'])
    return director
```

In [85]:

```
df['director'] = df['crew'].apply(lambda x: get_crew_member(x, 'Director'))
df['producer'] = df['crew'].apply(lambda x: get_crew_member(x, 'Producer'))
df['crew_size'] = df['crew'].apply(lambda x: len(ast.literal_eval(x)))
```

In [86]:

```
director_count = get_frequency(df['director'])
df,director_score = extract_target_encoding_features(df,'director',director_count,m_director)
producer_count = get_frequency(df['producer'])
df,producer_score = extract_target_encoding_features(df,'producer',producer_count,m_producer)
```

In [87]:

```
df = df.drop(['crew','director','producer'], axis=1)
```

Text analysis:

There are 3 text features: title, overview, tagline.

The text is preprocessed:

- lowercase
- puctuation removal
- stemming

We split the text to words and explore word frequencies.

Now the words list are analysed as the multiple category variables.

In [88]:

```
stemmer = PorterStemmer()
def text_preprocessing(sentence):
    sentence = sentence.lower()
    sentence = sentence.translate(str.maketrans('', '', string.punctuation))
    words = [stemmer.stem(word) for word in sentence.split()]
    return words
```

title:

Title of movie

In [89]:

```
df['title']
```

Out[89]:

```
0                                    Spider-Man 3
1                  Silent Night, Deadly Night Part 2
2        Scotty and the Secret History of Hollywood
3                                      Hellraiser
4                        National Lampoon's Vacation
                             ...
5210               La Cage aux Folles 3: The Wedding
5211                    The Texas Chain Saw Massacre
5212                                  Almost Heroes
5213           Eternal Sunshine of the Spotless Mind
5214                                      3 Ninjas
Name: title, Length: 5215, dtype: object
```

In [90]:

```
df['title'] = df['title'].apply(lambda x:text_preprocessing(x))
```

In [91]:

```
original_title_count = get_frequency(df['title'])

nltk.download('stopwords')
stop_words = set(stopwords.words('english'))

original_title_count_stopwords = {word:count for word,count in original_title_count.items() if
word not in stop_words}
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/student/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [92]:

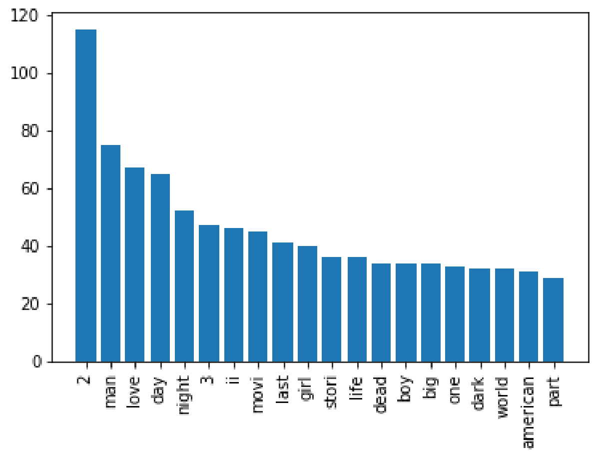
```
most_frequent = sorted(original_title_count_stopwords, key=original_title_count_stopwords.get,
reverse=True)[:20]
```

In [93]:

```
plt.bar(most_frequent, [original_title_count_stopwords[word] for word in most_frequent])
plt.xticks(rotation=90)
```

Out[93]:

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19],
 <a list of 20 Text major ticklabel objects>)
```



In [94]:

```
df_title_score = extract_target_encoding_features(df, 'title', original_title_count,m_title)
```

```
df,title_score = extract_target_encoding_features(df,'title','original_title_count',m_title)
df = df.drop(['title','original_title'],axis=1)
```

overview:

movie description

In [95]:

```
df['overview']
```

Out[95]:

```
0       The seemingly invincible Spider-Man goes up ag...
1       After being traumatized by his brother Billy's...
2       A deliciously scandalous portrait of unsung Ho...
3       An unfaithful wife encounters the zombie of he...
4       Clark Griswold is on a quest to take his famil...
                              ...                        
5210    Third and final version of the La Cage aux Fol...
5211    When Sally hears that her grandfather's grave ...
5212    Two hapless explorers lead an ill-fated 1804 e...
5213    Joel Barish, heartbroken that his girlfriend u...
5214    Each year, three brothers Samuel, Jeffrey and ...
Name: overview, Length: 5215, dtype: object
```

In [96]:

```
df['overview'].isna().sum()
```

Out[96]:

```
6
```

In [97]:

```
df['overview'] = df['overview'].replace(np.nan, '', regex=True)
```

In [98]:

```
df['overview'] = df['overview'].apply(lambda x:text_preprocessing(x))
```

In [99]:

```
overview_count = get_frequency(df['overview'])
stop_words = set(stopwords.words('english'))
overview_count_stopwords = {word:count for word,count in overview_count.items() if word not in stop
_words}
```

In [100]:

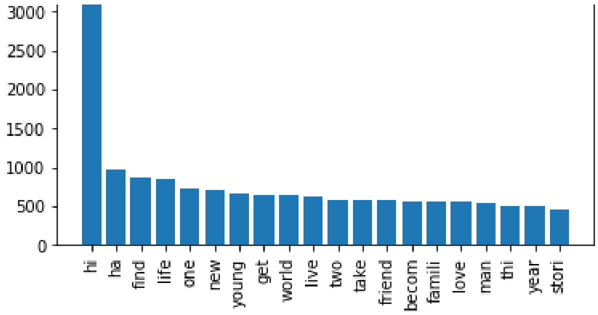
```
most_frequent = sorted(overview_count_stopwords, key=overview_count_stopwords.get, reverse=True)[:2
0]
```

In [101]:

```
plt.bar(most_frequent, [overview_count_stopwords[word] for word in most_frequent])
plt.xticks(rotation=90)
```

Out[101]:

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19],
 <a list of 20 Text major ticklabel objects>)
```



In [102]:

```
df,overview_score = extract_target_encoding_features(df,'overview',overview_count,m_overview)
df = df.drop(['overview'],axis=1)
```

tagline:

movie slogen

In [103]:

```
df['tagline']
```

Out[103]:

```
0                                   The battle within.
1              The nightmare is about to begin ... AGAIN!
2                                                  NaN
3                                  He'll tear your soul apart.
4       Every summer Chevy Chase takes his family on a...
                               ...
5210                                               NaN
5211      Who will survive and what will be left of them?
5212    Almost History... Almost Legends... Mostly Rid...
5213    You can erase someone from your mind. Getting ...
5214    Crosses Teenage Mutant Ninja Turtles and Home ...
Name: tagline, Length: 5215, dtype: object
```

In [104]:

```
df['tagline'].isna().sum()
```

Out[104]:

```
1025
```

In [105]:

```
df['no_tagline'] = df['tagline'].isna().astype(int) # Add feature for missing taglines
```

In [106]:

```
df['tagline'] = df['tagline'].replace(np.nan, '', regex=True)
df['tagline'] = df['tagline'].apply(lambda x:text_preprocessing(x))
tagline_count = get_frequency(df['tagline'])
stop_words = set(stopwords.words('english'))
tagline_count_stopwords = {word:count for word,count in tagline_count.items() if word not in stop_w
ords}
```

In [107]:

```
most_frequent = sorted(tagline_count_stopwords, key=tagline_count_stopwords.get, reverse=True)[:20]
```

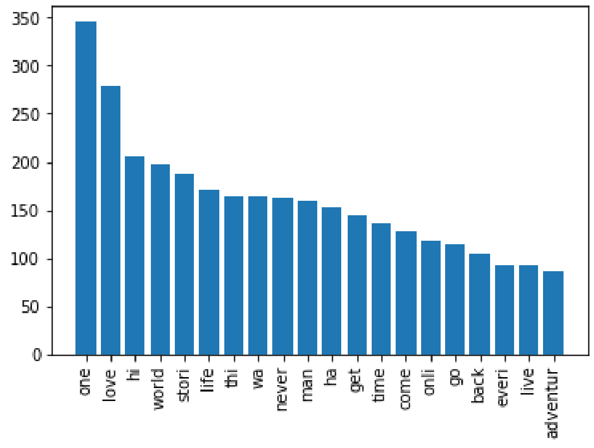
In [108]:

```
plt.bar(most_frequent, [tagline_count_stopwords[word] for word in most_frequent])
```

```
plt.xticks(rotation=90)
```

Out[108]:

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19],
 <a list of 20 Text major ticklabel objects>)
```



In [109]:

```
df,tagline_score = extract_target_encoding_features(df,'tagline',tagline_count,m_tagline)
df = df.drop(['tagline'],axis=1)
```

budget:

Movie budget

In [110]:

```
df['budget']
```

Out[110]:

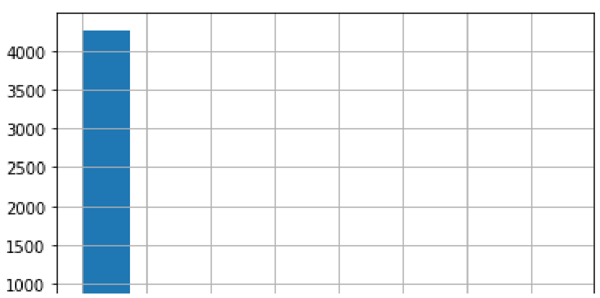
```
0       258000000
1          250000
2               0
3         1000000
4        15000000
          ...    
5210            0
5211        85000
5212     30000000
5213     20000000
5214      6500000
Name: budget, Length: 5215, dtype: int64
```

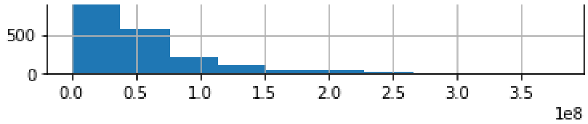
In [111]:

```
df['budget'].hist()
```

Out[111]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1674797810>
```





homepage:

Link to website, converted to boolean variable (is there a homepage)

In [112]:

```
df['homepage']
```

Out[112]:

```
0       https://www.sonypictures.com/movies/spiderman3
1                                                  NaN
2                             https://www.scottymovie.com/
3                                                  NaN
4                                                  NaN
                             ...
5210                                               NaN
5211                                               NaN
5212                                               NaN
5213                        http://www.eternalsunshine.com
5214                                               NaN
Name: homepage, Length: 5215, dtype: object
```

In [113]:

```
df['homepage'].isna().sum()
```

Out[113]:

```
3449
```

In [114]:

```
df['no_homepage'] = df['homepage'].isna().astype(int)
```

In [115]:

```
df = df.drop('homepage', axis=1)
```

popularity:

Popularity of movie

In [116]:

```
df['popularity']
```

Out[116]:

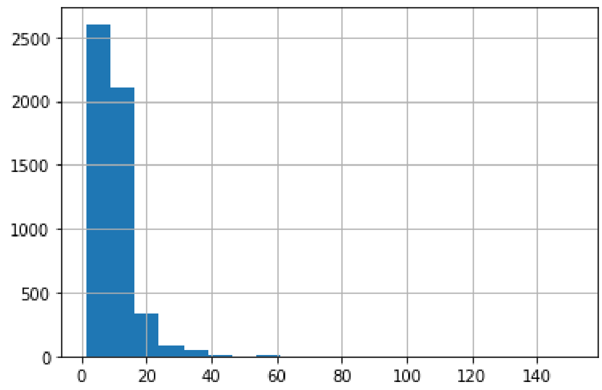
```
0       22.024
1        4.756
2        4.746
3       13.828
4       15.070
         ...
5210     3.050
5211    11.580
5212     7.946
5213    19.693
5214    10.913
Name: popularity, Length: 5215, dtype: float64
```

In [117]:

```python
df['popularity'].hist(bins=20)
```

Out[117]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f16746d9dd0>
```



runtime:

In [118]:

```python
df['runtime']
```

Out[118]:

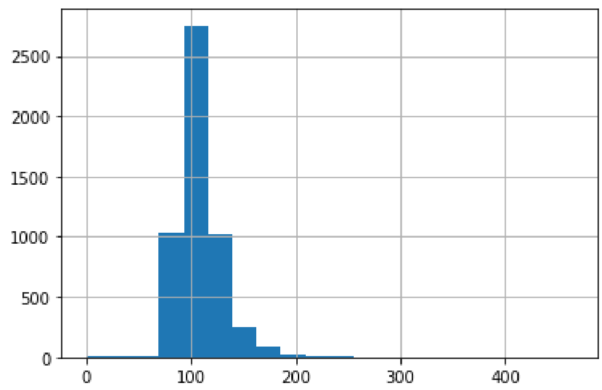
```
0       139.0
1        88.0
2        98.0
3        94.0
4        99.0
        ...
5210     87.0
5211     83.0
5212     90.0
5213    108.0
5214     84.0
Name: runtime, Length: 5215, dtype: float64
```

In [119]:

```python
df['runtime'].hist(bins=20)
```

Out[119]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1674636650>
```



In [120]:

```python
df['runtime'].isna().sum()
```

Out[120]:

```
4
```

In [121]:

```
df['runtime'] = df['runtime'].fillna(df['runtime'].mean())
```

status:

Only one category, removed from analysis

In [122]:

```
df['status']
```

Out[122]:

```
0       Released
1       Released
2       Released
3       Released
4       Released
          ...   
5210    Released
5211    Released
5212    Released
5213    Released
5214    Released
Name: status, Length: 5215, dtype: object
```

In [123]:

```
set(df['status'])
```

Out[123]:

```
{'Released'}
```

In [124]:

```
df = df.drop('status',axis=1)
```

video:

link to video

In [125]:

```
df['video']
```

Out[125]:

```
0       False
1       False
2       False
3       False
4       False
        ...  
5210    False
5211    False
5212    False
5213    False
5214    False
Name: video, Length: 5215, dtype: bool
```

In [126]:

```
df['video'].dtypes
```

```
df['video'].dtypes
```

Out[126]:

```
dtype('bool')
```

In [127]:

```
df['video'] = df['video'].astype(int)
```

In [128]:

```
len(df[df['video']==1])
```

Out[128]:

```
18
```

vote_average

In [129]:

```
df['vote_average']
```

Out[129]:

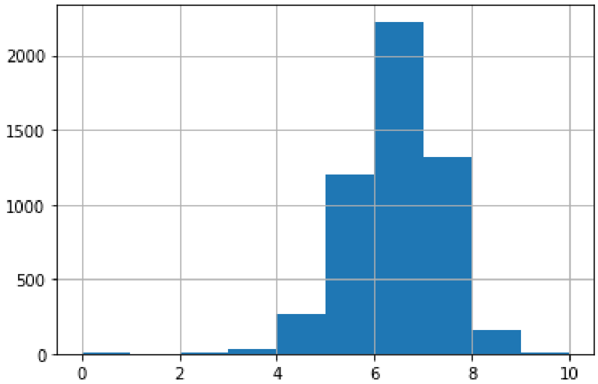
```
0       6.2
1       4.3
2       6.5
3       6.9
4       7.1
       ...
5210    4.7
5211    7.3
5212    5.6
5213    8.1
5214    5.7
Name: vote_average, Length: 5215, dtype: float64
```

In [130]:

```
df['vote_average'].hist()
```

Out[130]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1674564450>
```



vote_count

In [131]:

```
df['vote_count']
```

Out[131]:

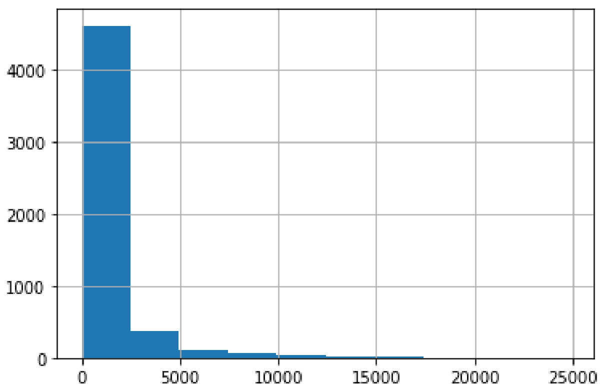
```
0        8180
1          68
2          15
3        1115
4         782
         ... 
5210       29
5211     1483
5212       91
5213     8753
5214      240
Name: vote_count, Length: 5215, dtype: int64
```

In [132]:

```
df['vote_count'].hist()
```

Out[132]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f16744d2310>
```



Keywords

In [133]:

```
df['Keywords']
```

Out[133]:

```
0       [{'id': 697, 'name': 'loss of loved one'}, {'i...
1       [{'id': 65, 'name': 'holiday'}, {'id': 1991, '...
2                        [{'id': 158718, 'name': 'lgbt'}]
3       [{'id': 1449, 'name': 'underworld'}, {'id': 31...
4       [{'id': 5493, 'name': 'relatives'}, {'id': 731...
                              ...                        
5210    [{'id': 237, 'name': 'gay'}, {'id': 824, 'name...
5211    [{'id': 1420, 'name': 'gas station'}, {'id': 1...
5212    [{'id': 1721, 'name': 'fight'}, {'id': 3930, '...
5213    [{'id': 563, 'name': 'deja vu'}, {'id': 802, '...
5214    [{'id': 380, 'name': 'sibling relationship'}, ...
Name: Keywords, Length: 5215, dtype: object
```

In [134]:

```
def get_Keywords_list(item):
    item = ast.literal_eval(item)
    Keywords = [Keyword_dict['name'] for Keyword_dict in item]
    return Keywords
```

In [135]:

```
df['Keywords'] = df['Keywords'].apply(lambda x: get_Keywords_list(x))
```

In [136]:

```
df['Keywords']
```

Out[136]:

```
0       [loss of loved one, dual identity, amnesia, sa...
1       [holiday, santa claus, sequel, murder, serial ...
2                                                  [lgbt]
3       [underworld, seduction, supernatural, revenge,...
4       [relatives, road trip, domestic life, family v...
                              ...
5210                      [gay, drag queen, gay marriage]
5211    [gas station, texas, van, midnight movie, leat...
5212    [fight, bravery, slapstick, native american, b...
5213    [deja vu, regret, jealousy, amnesia, dream, op...
5214    [sibling relationship, hero, rivalry, rescue, ...
Name: Keywords, Length: 5215, dtype: object
```

In [137]:

```
Keywords_count = get_frequency(df['Keywords'])
```

In [138]:

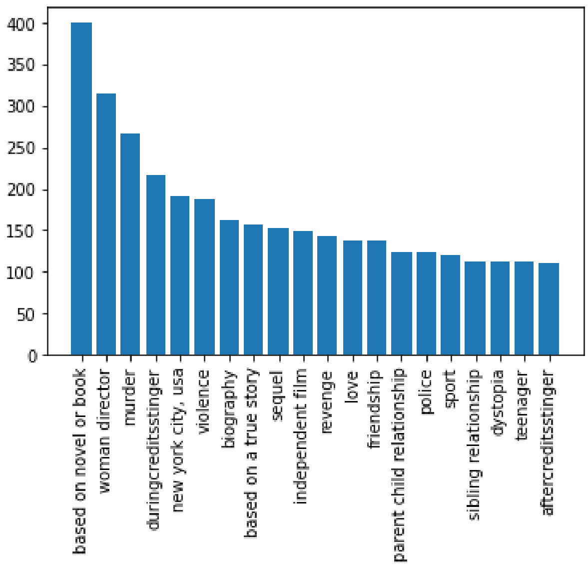
```
most_frequent = sorted(Keywords_count, key=Keywords_count.get, reverse=True)[:20]
```

In [139]:

```
plt.bar(most_frequent, [Keywords_count[word] for word in most_frequent])
plt.xticks(rotation=90)
```

Out[139]:

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19],
 <a list of 20 Text major ticklabel objects>)
```



In [140]:

```
df,Keywords_score = extract_target_encoding_features(df,'Keywords',Keywords_count,m_keywords)
```

In [141]:

```
df = df.drop(['Keywords'],axis=1)
```

In [142]:

```
df = df.drop(['id','imdb_id','poster_path','fold','random_index'],axis=1)
```

In [143]:

```
from sklearn.ensemble import RandomForestRegressor
```

In [144]:

```
X = df.drop(['revenue','ln_revenue'],axis=1)
Y = df['ln_revenue']
```

In [145]:

```
columns_list = ['budget','popularity','runtime','video','vote_average','vote_count','release_year'
,'release_month',
       'no_collection','is_james_bond','spoken_languages_amount', 'english_speaking',
       'Adventure_movie', 'TV Movie_movie', 'Mystery_movie', 'Fantasy_movie',
       'Science Fiction_movie', 'Family_movie', 'Western_movie', 'War_movie',
       'Animation_movie', 'Documentary_movie', 'Crime_movie', 'Thriller_movie',
       'Music_movie', 'Action_movie', 'Romance_movie', 'History_movie',
       'Horror_movie', 'Comedy_movie', 'Drama_movie', 'en_original',
       'cn_original', 'de_original', 'es_original', 'fr_original',
       'hi_original', 'it_original', 'ja_original', 'ko_original',
       'ru_original', 'zh_original','production_companies_amount','top_production_company','top_cou
ntry',
       'american_production','cast_size','crew_size','no_tagline','no_homepage']
```

In [146]:

```
from sklearn.model_selection import cross_val_score
X = X[columns_list]
regr = RandomForestRegressor(max_depth=20,random_state=1)
regr.fit(X, Y)
scores = list(cross_val_score(regr, X, Y, cv=5))
print(statistics.mean(scores))
print(statistics.stdev(scores))
print()
```

```
0.5419588580275361
0.03953503793263743
```

Feature selection

We have a lot of target encoding features. We check which target encoding features improve the model enough with low variance between folds. We include only some of those in the final model.

In [147]:

```
import statistics
from sklearn.model_selection import cross_val_score
feature_mean = {}
feature_var = {}
for feature in df.columns:
    if feature not in columns_list and feature not in ['revenue','ln_revenue']:
        X = df[columns_list+[feature]]
        regr = RandomForestRegressor(max_depth=20, random_state=1)
        regr.fit(X, Y)
        scores = list(cross_val_score(regr, X, Y, cv=5))
        print(feature)
        feature_var[feature] = statistics.variance(scores)
        feature_mean[feature] = statistics.mean(scores)
        print(statistics.mean(scores))
        print(statistics.stdev(scores))
        print()
```

```
collection_target_encoding
0.5426046914137981
0.03791868249964827
```

```
min_spoken_languages_score
0.5410271772026218
0.040513642120839195

max_spoken_languages_score
0.5392960224837051
0.043094499509156094

mean_spoken_languages_score
0.539874983049783
0.04222460729318608

median_spoken_languages_score
0.5395636722539932
0.04070144677599558

original_language_target_encoding
0.5419973741985914
0.0367518394115648

min_production_companies_score
0.5430732998260948
0.03493599989454237

max_production_companies_score
0.540399483039861
0.037488478097366676

mean_production_companies_score
0.5409360425120862
0.038068393761795466

median_production_companies_score
0.5441606419595014
0.04120476864596053

min_production_countries_score
0.5432769126573264
0.0390964408490078

max_production_countries_score
0.5392552649990915
0.038988816849922066

mean_production_countries_score
0.5412971751579752
0.038697449545020565

median_production_countries_score
0.5426724275822167
0.036037525394521035

min_cast_list_score
0.5403759088053156
0.040060322131926354

max_cast_list_score
0.5390071538260621
0.03766003286298115

mean_cast_list_score
0.5394441310597523
0.039486401268240504

median_cast_list_score
0.5401554576647043
0.03684260142426378

min_director_score
0.543394752238534
0.03708986329014043

max_director_score
0.543556652066146
0.037567281737019426

mean_director_score
```

```
mean_director_score
0.543840178794736
0.03757710323461927

median_director_score
0.5438866598535192
0.03762436561323503

min_producer_score
0.5419768307733113
0.03763919775924946

max_producer_score
0.5411137688474668
0.03717325448520422

mean_producer_score
0.5418557081392296
0.03823196642810249

median_producer_score
0.5424578259261289
0.03766106412911259

min_title_score
0.5427189664804477
0.03759888851727458

max_title_score
0.542158769342668
0.037620529445138516

mean_title_score
0.5411146894683292
0.04100398153725769

median_title_score
0.5397265410052353
0.04102051074611479

min_overview_score
0.5431157332067981
0.03696493721477341

max_overview_score
0.5417503773933022
0.03875665000688845

mean_overview_score
0.5389614928011197
0.03816804748219564

median_overview_score
0.5414067841482272
0.03704935126481367

min_tagline_score
0.5433429096246796
0.03875031979509366

max_tagline_score
0.5443853288177224
0.038674869918433136

mean_tagline_score
0.5446758990272642
0.03946525920044406

median_tagline_score
0.5410197597227958
0.03930817773588244

min_Keywords_score
0.5428290988380942
0.04119986439054024

max_Keywords_score
```

```
0.5439338255727839
0.04105369821899254

mean_Keywords_score
0.5430327561871543
0.039432987396239134

median_Keywords_score
0.5405526863033728
0.04129265080547261
```

In [148]:

```python
columns_list = ['budget','popularity','runtime','video','vote_average','vote_count','release_year'
,'release_month',
       'no_collection','is_james_bond','spoken_languages_amount', 'english_speaking',
       'Adventure_movie', 'TV Movie_movie', 'Mystery_movie', 'Fantasy_movie',
       'Science Fiction_movie', 'Family_movie', 'Western_movie', 'War_movie',
       'Animation_movie', 'Documentary_movie', 'Crime_movie', 'Thriller_movie',
       'Music_movie', 'Action_movie', 'Romance_movie', 'History_movie',
       'Horror_movie', 'Comedy_movie', 'Drama_movie', 'en_original',
       'cn_original', 'de_original', 'es_original', 'fr_original',
       'hi_original', 'it_original', 'ja_original', 'ko_original',
       'ru_original', 'zh_original','production_companies_amount','top_production_company','top_cou
ntry',

'american_production','cast_size','crew_size','no_tagline','no_homepage','max_Keywords_score','min_
spoken_languages_score',

'collection_target_encoding','min_production_companies_score','mean_title_score','min_tagline_score
']
```

In [149]:

```python
from sklearn.model_selection import cross_val_score
X = df[columns_list]
regr = RandomForestRegressor(max_depth=20, random_state=1)

scores = list(cross_val_score(regr, X, Y, cv=5))
print(statistics.mean(scores))
print(statistics.stdev(scores))
print()
```

```
0.5390265186995644
0.041450885975351376
```

In [150]:

```python
regr = RandomForestRegressor(max_depth=20, random_state=1)
regr.fit(X, Y)
```

Out[150]:

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=20, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=1, verbose=0, warm_start=False)
```

In [151]:

```python
sorted([(importance,feature) for feature,importance in
zip(list(X.columns),list(regr.feature_importances_))])
```

Out[151]:

```
[(9.706808894777038e-07, 'is_james_bond'),
 (0.00026063249822379025, 'hi_original'),
```

```
 (0.0003395769456564728, 'es_original'),
 (0.00037229727378342156, 'video'),
 (0.0004402583486793027, 'ru_original'),
 (0.0005119811684780308, 'cn_original'),
 (0.0007858737066528119, 'it_original'),
 (0.0008515408288257288, 'ko_original'),
 (0.0008624468979337933, 'ja_original'),
 (0.0012028075516322281, 'de_original'),
 (0.0012057048169752253, 'History_movie'),
 (0.0014349439968192894, 'Fantasy_movie'),
 (0.0015629707516471008, 'Animation_movie'),
 (0.0015901999639239862, 'TV Movie_movie'),
 (0.0016849112625441961, 'Documentary_movie'),
 (0.001723385433715559, 'zh_original'),
 (0.00190012820948522, 'War_movie'),
 (0.002000753787638834, 'Western_movie'),
 (0.0021052037458820032, 'Crime_movie'),
 (0.002126965191635307, 'Mystery_movie'),
 (0.0023003291766097336, 'english_speaking'),
 (0.002389304626121511, 'Romance_movie'),
 (0.002551040352606932, 'top_country'),
 (0.0026805153621339757, 'no_homepage'),
 (0.0032072067580645744, 'Thriller_movie'),
 (0.0034813013468831884, 'Adventure_movie'),
 (0.003483272166523131, 'no_tagline'),
 (0.003569994159962091, 'american_production'),
 (0.0036094781404200174, 'Music_movie'),
 (0.003701349343806705, 'Horror_movie'),
 (0.0037991340157966227, 'Action_movie'),
 (0.003843429269619746, 'Drama_movie'),
 (0.003974511686100547, 'Family_movie'),
 (0.004163260139024935, 'Comedy_movie'),
 (0.004461700024327749, 'Science Fiction_movie'),
 (0.004624019866062559, 'fr_original'),
 (0.004924628572588329, 'en_original'),
 (0.00588363279929541, 'collection_target_encoding'),
 (0.006934238218523005, 'spoken_languages_amount'),
 (0.009841292991799096, 'no_collection'),
 (0.013527228666651509, 'production_companies_amount'),
 (0.014830738391301534, 'top_production_company'),
 (0.01485879247444065, 'min_tagline_score'),
 (0.016297117322867895, 'release_month'),
 (0.016531626258574753, 'min_production_companies_score'),
 (0.023492075228253053, 'crew_size'),
 (0.023898199633830913, 'mean_title_score'),
 (0.027535495325990242, 'max_Keywords_score'),
 (0.028868766444124803, 'min_spoken_languages_score'),
 (0.035544758259256404, 'cast_size'),
 (0.03963112742895025, 'runtime'),
 (0.04140934447753187, 'vote_average'),
 (0.04773503692508785, 'popularity'),
 (0.057504890938023565, 'release_year'),
 (0.16890946337023954, 'vote_count'),
 (0.32303814677758363, 'budget')]
```

Random Forest Hyperparameter tunning

Since the loss is rmsle we train on the log(reveneu)

In [ ]:

```
n_estimators = [200]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 5)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
# Method of selecting samples for training each tree
bootstrap = [True, False]
```

```
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
print(random_grid)
```

In [ ]:

```
from sklearn.model_selection import RandomizedSearchCV
rf = RandomForestRegressor()
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter = 100, cv
= 5, verbose=2, random_state=42, n_jobs = -1)
rf_random.fit(X, Y)
```

In [ ]:

```
rf_random.best_params_
```

In [ ]:

```
from sklearn.model_selection import cross_val_score
regr = RandomForestRegressor(max_depth=110,min_samples_split=5, min_samples_leaf = 4 ,max_features=
'auto',bootstrap=True, random_state=1)
regr.fit(X,Y)
scores = list(cross_val_score(regr, X, Y, cv=5,scoring='neg_root_mean_squared_error'))
print(statistics.mean(scores))
print(statistics.stdev(scores))
print()
```

XGBoost Hyperparameter tunning

In [ ]:

```
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform, randint

xgb_model = xgb.XGBRegressor(objective="reg:squarederror", random_state=42)
```

In [ ]:

```
params = {
    "colsample_bytree": uniform(0.7, 0.3),
    "gamma": uniform(0, 0.5),
    "learning_rate": uniform(0.03, 0.3), # default 0.1
    "max_depth": randint(2, 6), # default 3
    "n_estimators": randint(100, 150), # default 100
    "subsample": uniform(0.6, 0.4)
}
```

In [ ]:

```
search = RandomizedSearchCV(xgb_model, param_distributions=params, random_state=42, n_iter=200, cv=
5, verbose=1, n_jobs=1, return_train_score=True)
search.fit(X,Y)
```

In [ ]:

```
final_params = search.best_params_
```

In [ ]:

```
final_params
```

In [ ]:

```python
from sklearn.model_selection import cross_val_score
xgboost_model =
xgb.XGBRegressor(objective="reg:squarederror",colsample_bytree=final_params['colsample_bytree'],
                       gamma=final_params['gamma'],learning_rate=final_params['learning_rate'],
                       max_depth=final_params['max_depth'],n_estimators=final_params['n_estimators'
],
                       subsample=final_params['subsample'], random_state=42)
xgboost_model.fit(X,Y)
scores = list(cross_val_score(xgboost_model, X, Y, cv=5,scoring='neg_root_mean_squared_error'))
print(statistics.mean(scores))
print(statistics.stdev(scores))
print()
```

In [ ]:

```python
model_dict = {'model':xgboost_model,
              'collection_score':collection_score,'collection_count':collection_counts,
              'spoken_languages_score':spoken_languages_score,'spoken_languages_counts':spoken_lang
uages_count,
              'genres_list':all_genres,
              'top_languages':top_languages,'languages_score':language_score,'languages_count':lang
uage_counts,
              'top_companies':top_copanies,'production_comapnies_count':production_comapny_count,'p
roduction_comapnies_score':production_comapny_score,
              'countries_count':country_count,'countries_score':countries_score,'top_countries':top
_countries,
              'cast_counts':cast_count,'cast_score':cast_score,
              'producer_count':producer_count,'producer_score':producer_score,'director_count':dire
ctor_count,'director_score':director_score,
              'title_count':original_title_count,'title_score':title_score,
              'overview_count':overview_count,'overview_score':overview_score,
              'tagline_count':tagline_count,'tagline_score':tagline_score,
              'key_words_count':Keywords_count,'Keywords_score':Keywords_score,
             'average_revenue':average_revenue}
```

In [ ]:

```python
import pickle
with open('model', 'wb') as f:
    pickle.dump(model_dict, f)
```