box_office_revenue

May 15, 2021

1 Exploratory Data Analysis

In this task, we were given the Box Office Revenue Dataset and were asked to predict the revenue of movies not in the train dataset. The dataset contains the following attributes (features) for each movie:

id: Integer unique id of each movie

belongs_to_collection: Contains the TMDB Id, Name, Movie Poster and Backdrop URL of a movie in JSON format.

budget: Budget of a movie in dollars. Some row contains 0 values which represent unknown.

genres: Contains all the Genres Name & TMDB Id in JSON Format.

homepage: Contains the official URL of a movie.

imdb_id: IMDB id of a movie (string).

original_language: Two digit code of the original language, in which the movie was made.

original_title: The original title of a movie in original_language.

overview: Brief description of the movie.

popularity: Popularity of the movie.

poster_path: Poster path of a movie. You can see full poster image by adding url after this link –> https://image.tmdb.org/t/p/original/

production_companies: All production company names and TMDB ids in JSON format.

production_countries: Two digit codes and full names of the production company in JSON format.

release_date: Release date of a movie in mm/dd/yy format.

runtime: Total runtime of a movie in minutes (Integer).

spoken_languages: Two digit code and full name of the spoken language.

status: Is the movie released or rumored?

tagline: Tagline of a movie

title: English title of a movie

Keywords: TMDB Id and name of all the keywords in JSON format.

cast: All cast TMDB id, name, character name, gender (1 = Female, 2 = Male) in JSON format

crew: Name, TMDB id, profile path of various kind of crew members job like Director, Writer, Art, Sound etc.

revenue: Total revenue earned by a movie in dollars.

[1]:
```
import json
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
train = pd.read_csv('../data/train.tsv', sep='\t', parse_dates=['release_date'])

def name_dummies(column):  # Get dummies from list of items with name attribute␣
 ↪[{'name': _}, {'name': _}, ...]
    def parse_names(items):
        names = set()
        for item in eval(items):
            names.add(item['name'])
        return pd.Series([True] * len(names), index=names, dtype=bool)
    return column.apply(parse_names).fillna(False)
```

[3]:
```
train.describe()
```

[3]:
```
             budget             id   popularity       revenue      runtime  \
count  5.215000e+03    5215.000000  5215.000000  5.215000e+03  5211.000000
mean   2.147967e+07   98768.673442    10.016559  6.538743e+07   108.027442
std    3.631509e+07  143992.708567     7.075799  1.432381e+08    22.740973
min    0.000000e+00       5.000000     1.519000  1.000000e+00     0.000000
25%    0.000000e+00   10136.000000     6.264000  2.360718e+06    94.000000
50%    6.500000e+06   24662.000000     9.009000  1.515620e+07   104.000000
75%    2.600000e+07  121704.000000    11.801000  6.214247e+07   118.000000
max    3.800000e+08  679106.000000   151.237000  2.046240e+09   465.000000

       vote_average    vote_count
count   5215.000000   5215.000000
mean       6.399099   1062.859636
std        0.943931   2097.172266
min        0.000000      0.000000
25%        5.900000     74.000000
50%        6.400000    290.000000
75%        7.100000   1028.000000
max       10.000000  24834.000000
```

1.1 Genres

Genres Distribution

It is important to notice that a movie can be of more than one genre.

[4]:
```
genres = name_dummies(train['genres'])
genres.sum()
```

[4]:
```
Adventure           752
Action             1207
Fantasy             444
Comedy             1882
Horror              551
Documentary         155
Mystery             426
Thriller           1263
Science Fiction     515
Drama              2517
Romance            1008
Crime               751
War                 159
Music               177
History             217
Family              479
Animation           286
Western              80
TV Movie              5
dtype: int64
```

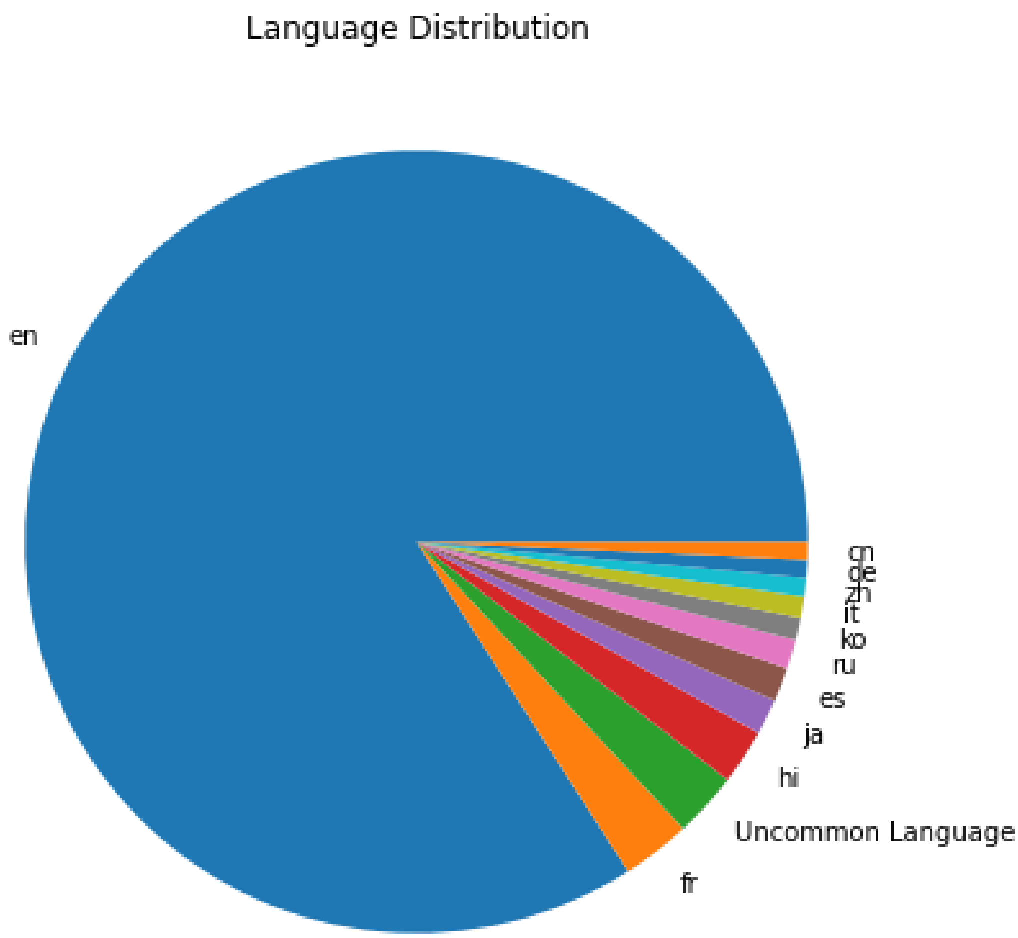
1.2 Original Language

We decided to handle the categorical variable using dummy variables. In order to lower the number of categories, which in our case are translated to additional columns (features), we dropped the dummy variables corresponding to languages that appeared in less than 15 movies. This leaves us with 12 languages without significant information loss, evident by the low percentage of deleted languages.

[5]:
```
languages = pd.get_dummies(train['original_language'])
print(f'Number of languages pre-filtering is {languages.shape[1]}')
uncommon_languages = languages.columns[languages.sum() <= 15]
print(f'percentage of movies with a deleted language is␣
↪{languages[uncommon_languages].sum().sum() / languages.sum().sum() * 100:.
↪2f}%')
languages['Uncommon Language'] = train['original_language'].apply(lambda l: l␣
↪in uncommon_languages)
languages = languages.drop(uncommon_languages, axis=1).astype(bool)
print(f'Number of languages post-filtering is {languages.shape[1]}')
```

```
Number of languages pre-filtering is 43
percentage of movies with a deleted language is 2.68%
Number of languages post-filtering is 12
```

[6]:
```python
languages.sum().sort_values(ascending=False).plot(kind='pie', figsize=(7, 7), ylabel='', title='Language Distribution')
plt.show()
```



1.3 Production Company

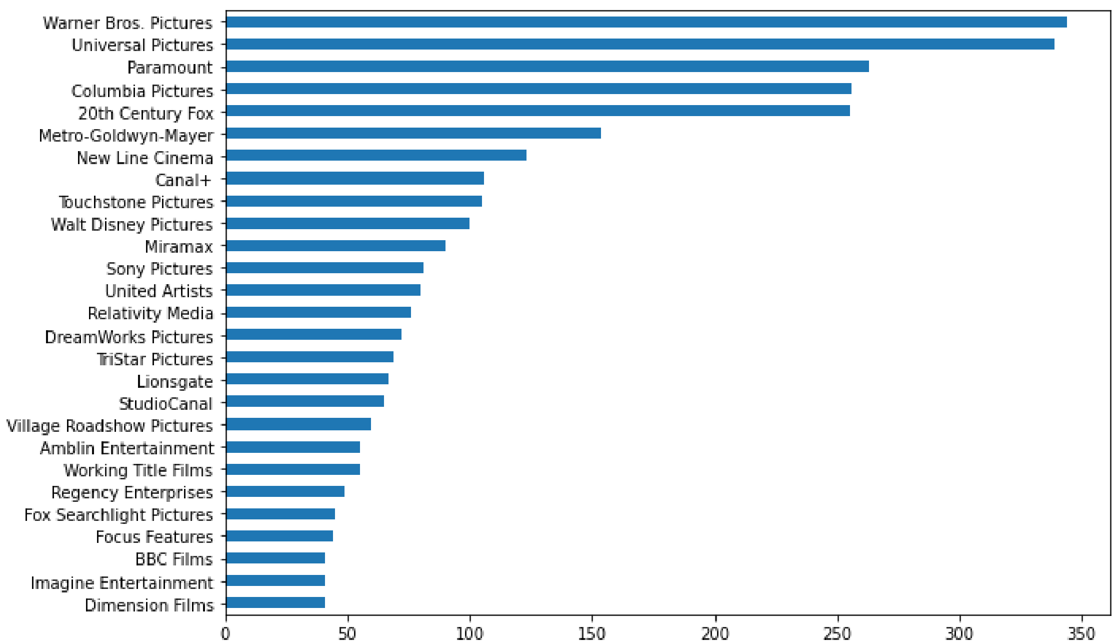
Similar to the handling of the languages above, we created dummy variables and filtered production companies that produced more than 20 movies.

[7]:
```python
production_companies = name_dummies(train['production_companies'])
production_companies_counts = production_companies.sum()
```

```
production_companies_counts[production_companies_counts > 20].
↪sort_values(ascending=False)
```

[7]:
```
Warner Bros. Pictures    344
Universal Pictures       339
Paramount                263
Columbia Pictures        256
20th Century Fox         255
                        …
Wild Bunch                23
CJ Entertainment          22
Film i Väst               21
Original Film             21
Revolution Studios        21
Length: 67, dtype: int64
```

[8]:
```
production_companies_counts[production_companies_counts > 40].sort_values().
↪plot(kind='barh', figsize=(10, 7))  # The filter is used for visualization␣
↪purposes
plt.show()
```



Including different amounts of production companies yielded non-significant improvements in performance while including more than the top 10 companies. Therefore, we excluded all companies other than the top 10 companies and grouped them to one category of "uncommon companies".

[9]:
```
production_companies = production_companies[production_companies_counts.
 ↪sort_values(ascending=False)[:10].index]

def has_uncommon_company(companies):
    names = set()
    for company in eval(companies):
        names.add(company['name'])
    return len(names.difference(production_companies.columns)) > 0

production_companies['Uncommon Production Company'] =␣
 ↪train['production_companies'].apply(has_uncommon_company)
```

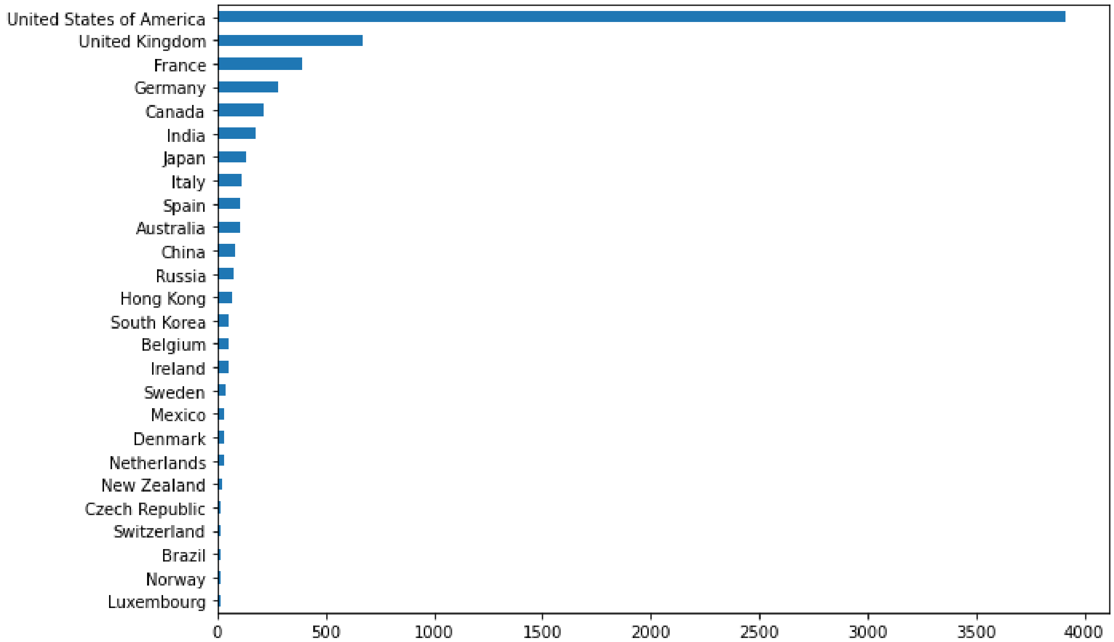
1.4 Production Country

A similar handling to that of the production companies. We observed no significant improvement for more than the top 5 countries, so all other countries were grouped.

[10]:
```
production_countries = name_dummies(train['production_countries'])
production_countries_counts = production_countries.sum()
production_countries_counts.sort_values(ascending=False)
```

[10]:
```
United States of America    3917
United Kingdom               671
France                       390
Germany                      283
Canada                       217
                            …
Pakistan                       1
Ghana                          1
Vietnam                        1
Czechoslovakia                 1
Liechtenstein                  1
Length: 86, dtype: int64
```

[11]:
```
production_countries_counts[production_countries_counts > 15].sort_values().
 ↪plot(kind='barh', figsize=(10, 7))
plt.show()
```



[12]:
```
production_countries = production_countries[production_countries_counts.
 ↪sort_values(ascending=False)[:5].index]

def has_uncommon_country(countries):
    names = set()
    for country in eval(countries):
        names.add(country['name'])
    return len(names.difference(production_countries.columns)) > 0

production_countries['Uncommon Production Country'] =␣
 ↪train['production_countries'].apply(has_uncommon_country)
```

1.5 Missing Data

We handled the missing data under the Feature Engineering section.

[13]:
```
missing = train.isnull().sum()
missing[missing > 0]
```

[13]:
```
backdrop_path             577
belongs_to_collection    4150
homepage                 3449
imdb_id                    15
overview                    6
poster_path               167
runtime                     4
```

```
tagline                      1025
dtype: int64
```

1.6 Feature Engineering

The following is a list of featuers added to the dataset:

Whether the movie belongs to a collection - Boolean

Genre dummy columns

Language dummy columns

Production company dummy columns

Production country dummy columns

The year the movie was released in

The month the mvie was released in

Season dummy columns

Number of spoken Languages in the movie

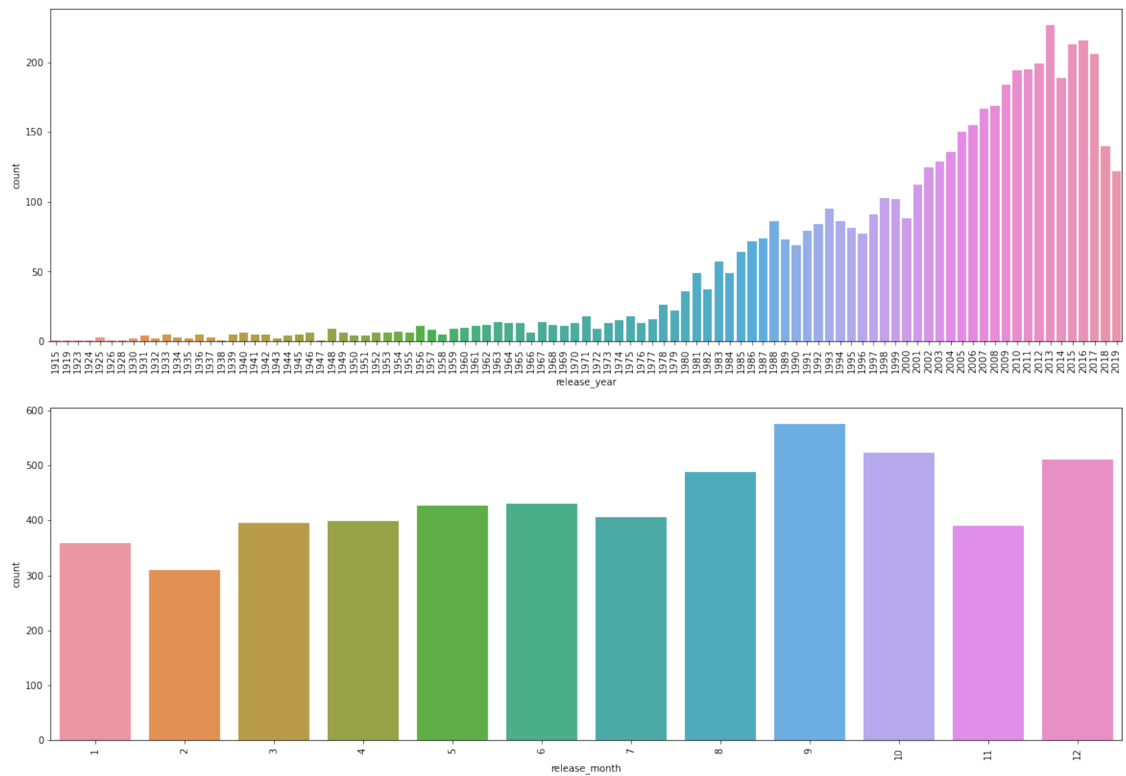
Log budget - a feature that was recommended for revealing a gaussian mixture as observed below.

[14]:
```
def season(date):
    if date.month in [12, 1, 2]:
        return 'Winter'
    elif date.month in [3, 4, 5]:
        return 'Spring'
    elif date.month in [6, 7, 8]:
        return 'Summer'
    else:
        return 'Autumn'

def count_spoken_languages(spoken_languages):
    if pd.isnull(spoken_languages):
        return 0
    languages = set()
    for language in eval(spoken_languages):
        languages.add(language['name'])
    return len(languages)
```

[15]:
```
train['has_collection'] = ~train['belongs_to_collection'].isnull()
train = pd.concat([train, genres], axis=1)
train['has_homepage'] = ~train['homepage'].isnull()
train = pd.concat([train, languages], axis=1)
train = pd.concat([train, production_companies], axis=1)
train = pd.concat([train, production_countries], axis=1)
train['release_year'] = train['release_date'].dt.year
```

```
train['release_month'] = train['release_date'].dt.month
train = pd.concat([train, pd.get_dummies(train['release_date'].apply(season))],␣
↪axis=1)
train['runtime'].fillna(train['runtime'].mean(), inplace=True)  # Mean␣
↪Imputation
train['spoken_languages_count'] = train['spoken_languages'].
↪apply(count_spoken_languages)
train['log1p_revenue'] = np.log1p(train['revenue'])
train['log1p_budget'] = np.log1p(train['budget'])

train = train.drop(['backdrop_path', 'belongs_to_collection', 'genres',␣
↪'homepage', 'imdb_id', 'original_language', 'original_title', 'overview',␣
↪'poster_path', 'production_companies', 'production_countries',␣
↪'release_date', 'spoken_languages', 'status', 'tagline', 'title', 'video',␣
↪'Keywords', 'cast', 'crew'], axis=1)
```

[16]:
```
plt.figure(figsize=(20, 14))
plt.subplot(2, 1, 1)
sns.countplot(train['release_year'])
plt.xticks(rotation=90)
plt.subplot(2, 1, 2)
sns.countplot(train['release_month'])
plt.xticks(rotation=90)
plt.show()
```



[17]:
```python
model_features = train.columns.to_list()
model_features.remove('id')
model_features.remove('revenue')
model_features.remove('log1p_revenue')
with open('features.json', 'w') as features:
    json.dump(
        [
            genres.columns.to_list(),
            languages.columns.to_list(),
            production_companies.columns.to_list(),
            production_countries.columns.to_list(),
            model_features
        ], features, indent=4)
```

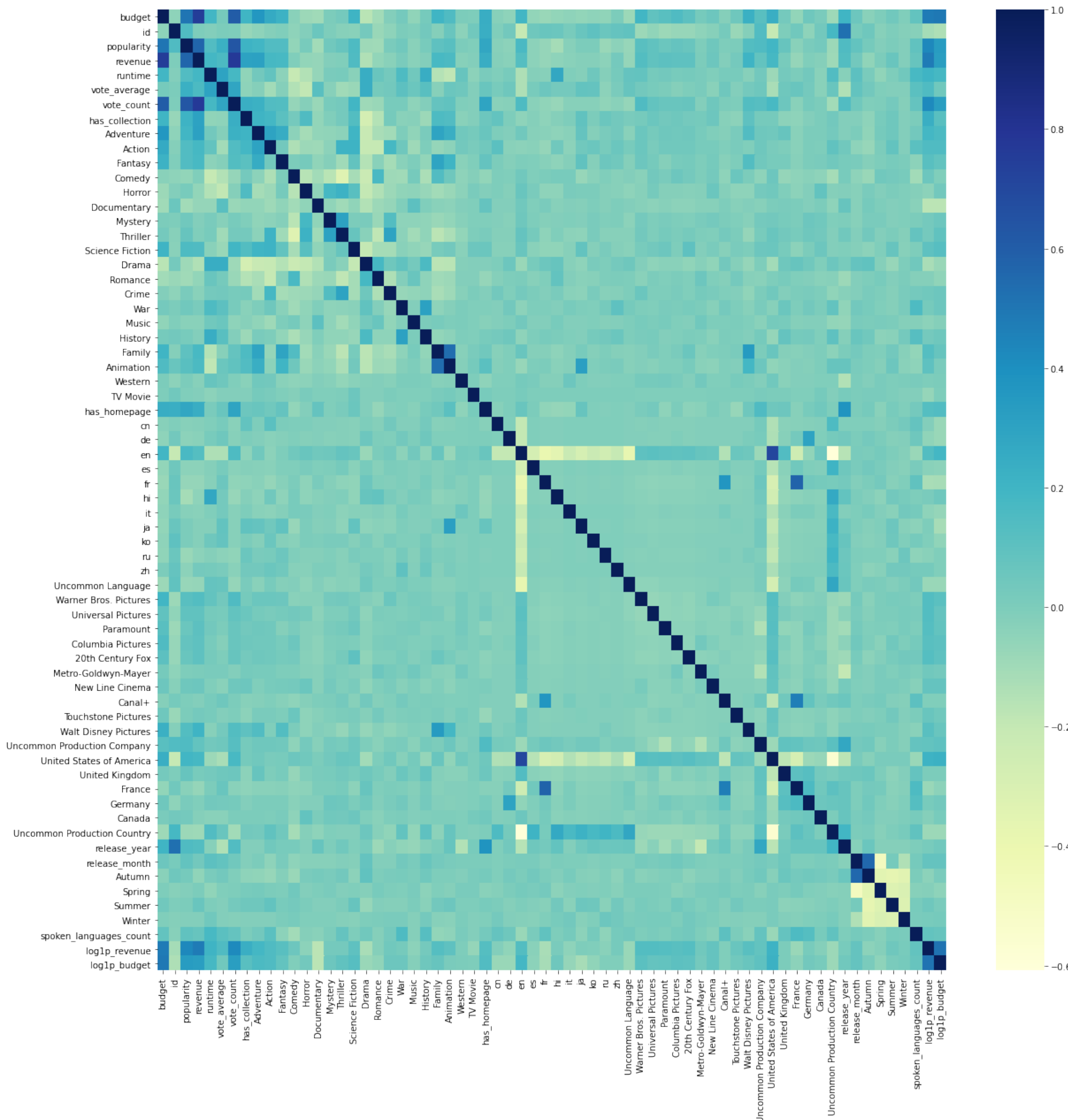
[18]:
```python
train.describe()
```

[18]:
```
             budget             id   popularity       revenue      runtime  \
count  5.215000e+03    5215.000000  5215.000000  5.215000e+03  5215.000000
mean   2.147967e+07   98768.673442    10.016559  6.538743e+07   108.027442
std    3.631509e+07  143992.708567     7.075799  1.432381e+08    22.732248
min    0.000000e+00       5.000000     1.519000  1.000000e+00     0.000000
25%    0.000000e+00   10136.000000     6.264000  2.360718e+06    94.000000
50%    6.500000e+06   24662.000000     9.009000  1.515620e+07   104.000000
75%    2.600000e+07  121704.000000    11.801000  6.214247e+07   118.000000
max    3.800000e+08  679106.000000   151.237000  2.046240e+09   465.000000

       vote_average    vote_count  release_year  release_month       Autumn  \
count   5215.000000   5215.000000   5215.000000    5215.000000  5215.000000
mean       6.399099   1062.859636   2000.802876       6.915820     0.285714
std        0.943931   2097.172266     15.990835       3.370261     0.451797
min        0.000000      0.000000   1915.000000       1.000000     0.000000
25%        5.900000     74.000000   1993.000000       4.000000     0.000000
50%        6.400000    290.000000   2005.000000       7.000000     0.000000
75%        7.100000   1028.000000   2013.000000      10.000000     1.000000
max       10.000000  24834.000000   2019.000000      12.000000     1.000000

            Spring       Summer       Winter  spoken_languages_count  \
count  5215.000000  5215.000000  5215.000000             5215.000000
mean      0.234132     0.253883     0.226270                1.444871
std       0.423496     0.435273     0.418456                0.883717
min       0.000000     0.000000     0.000000                0.000000
25%       0.000000     0.000000     0.000000                1.000000
50%       0.000000     0.000000     0.000000                1.000000
75%       0.000000     1.000000     0.000000                2.000000
```

```
max       1.000000     1.000000     1.000000                 10.000000

       log1p_revenue  log1p_budget
count    5215.000000   5215.000000
mean       15.897057     11.590391
std         3.076433      7.532126
min         0.693147      0.000000
25%        14.674476      0.000000
50%        16.533920     15.687313
75%        17.944940     17.073607
max        21.439270     19.755682
```

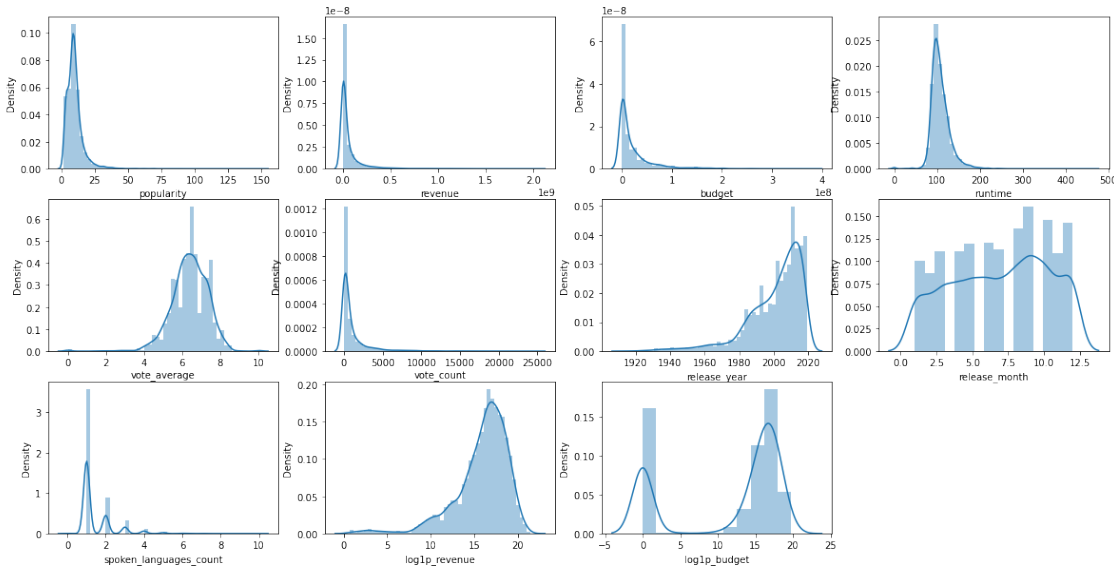
[19]:

```
plt.figure(figsize=(20, 20))
sns.heatmap(train.corr(), cmap='YlGnBu')
plt.xticks(rotation=90)
plt.show()
```

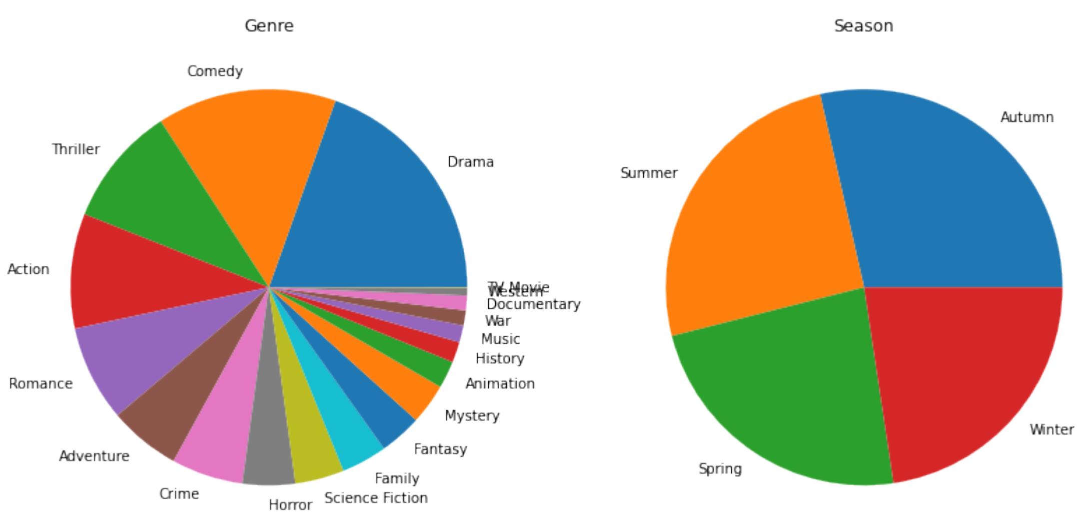


[20]:

```python
numeric_columns = ['popularity', 'revenue', 'budget', 'runtime', 'vote_average', 'vote_count', 'release_year', 'release_month', 'spoken_languages_count', 'log1p_revenue', 'log1p_budget']

plt.figure(figsize=(20, 10))
for i, column in enumerate(numeric_columns):
    plt.subplot(3, 4, i + 1)
    sns.distplot(train[column])
plt.subplots_adjust()
plt.show()
```



[21]:
```python
genre_categories = ['Action', 'Fantasy', 'Adventure', 'Comedy', 'Horror', 'Documentary', 'Thriller', 'Mystery', 'Science Fiction', 'Drama', 'Romance', 'Crime', 'War', 'History', 'Music', 'Family', 'Animation', 'Western', 'TV Movie']
season_categories = ['Autumn', 'Spring', 'Summer', 'Winter']
plt.subplot(1, 2, 1)
train[genre_categories].sum().sort_values(ascending=False).plot(kind='pie', figsize=(14, 14), ylabel='', title='Genre')
plt.subplot(1, 2, 2)
train[season_categories].sum().sort_values(ascending=False).plot(kind='pie', figsize=(14, 14), ylabel='', title='Season')
plt.show()
```



2 Models For Revenue Prediction

2.1 Transformations

These are neccesary transformations for the test set in order for it to contain the engineered features.

[22]:
```
test = pd.read_csv('../data/test.tsv', sep='\t', parse_dates=['release_date'])
with open('features.json', 'r') as features:
    (genres_index, languages_index, companies_index, countries_index,␣
 ↪model_features) = json.load(features)

def has_uncommon_production(index):
    def has_uncommon_production_(production):
        names = set()
        for item in eval(production):
            names.add(item['name'])
        return len(names.difference(index)) > 0
    return has_uncommon_production_

def transform_column(column, names, uncommon_production_column_name=None):
    def transform_list(data):
        values = []
        existing = set()
        for item in eval(data):
            existing.add(item['name'])
        for item in names:
            values.append(item in existing)
        return pd.Series(values, index=names, dtype=bool)

    transformed = column.apply(transform_list)
    if uncommon_production_column_name:
        transformed[uncommon_production_column_name] = column.
 ↪apply(has_uncommon_production(names))
    return transformed

test['has_collection'] = ~test['belongs_to_collection'].isnull()
test = pd.concat([test, transform_column(test['genres'], genres_index)], axis=1)
test['has_homepage'] = ~test['homepage'].isnull()
for language in languages_index:
    test[language] = test['original_language'] == language
test['Uncommon Language'] = test['original_language'].apply(lambda l: l not in␣
 ↪languages_index)
test = pd.concat([test, transform_column(test['production_companies'],␣
 ↪companies_index, 'Uncommon Production Company')], axis=1)
```

```
test = pd.concat([test, transform_column(test['production_countries'],␣
↪countries_index, 'Uncommon Production Country')], axis=1)
test['release_year'] = test['release_date'].dt.year
test['release_month'] = test['release_date'].dt.month
for s in ['Winter', 'Spring', 'Summer', 'Autumn']:
    test[s] = False
test[['Winter', 'Spring', 'Summer', 'Autumn']] = pd.
↪get_dummies(test['release_date'].apply(season)).astype(bool)
test['runtime'].fillna(test['runtime'].mean(), inplace=True)  # Mean Imputation
test['spoken_languages_count'] = test['spoken_languages'].
↪apply(count_spoken_languages)
test['log1p_budget'] = np.log1p(test['budget'])
test['log1p_revenue'] = np.log1p(test['revenue'])

test = test.drop(['backdrop_path', 'belongs_to_collection', 'genres',␣
↪'homepage', 'imdb_id', 'original_language', 'original_title', 'overview',␣
↪'poster_path', 'production_companies', 'production_countries',␣
↪'release_date', 'spoken_languages', 'status', 'tagline', 'title', 'video',␣
↪'Keywords', 'cast', 'crew'], axis=1)
```

2.2 Evaluation

[23]:
```
def rmse(values, predictions):
    return np.sqrt(np.mean(np.square(values - predictions)))

def rmsle(values, predictions):
    return rmse(np.log1p(values), np.log1p(predictions))
```

[24]:
```
X_col = model_features
y_col = 'log1p_revenue'
X_train, y_train = train[X_col], train[y_col]
X_test, y_test = test[X_col], test[y_col]
```

2.3 Linear Regression

Linear regression is a basic learning algorithm we use as a baseline in our experiments.

[25]:
```
from sklearn.linear_model import LinearRegression

regressor = LinearRegression()
regressor.fit(X_train, y_train)
print(f'Revenue RMSLE: {rmse(regressor.predict(X_test), y_test)}')
```

```
Revenue RMSLE: 2.199010241790404
```

2.4 Gradient Boosted Decision Trees

Research regarding the dataset and similar problems, combined with some experiments indicated that decision trees are the best model class for this problem. Decision trees and random forests suffer from some problems that can be mitigated by using gradient boosting. We experimented with 2 different classes of gradient boosted decision trees and got the following results.

2.5 LGB

[26]:
```
import lightgbm as lgb

model = lgb.LGBMRegressor(objective='regression')
model.fit(X_train, y_train, eval_metric='rmse', early_stopping_rounds=50,␣
 ↪eval_set=[(X_test, y_test)], eval_names=['test'], verbose=False)
test_rmse = model.best_score_['test']['rmse']
print(f'Revenue RMSLE {test_rmse}')
```

```
Revenue RMSLE 1.7983621922009152
```

2.6 CatBoost

[27]:
```
from catboost import CatBoostRegressor

model = CatBoostRegressor(iterations=10000, eval_metric='RMSE',␣
 ↪early_stopping_rounds=200)
model.fit(X_train, y_train, eval_set=(X_test, y_test), verbose=False)
model.save_model('catboost.model')
rmse = model.get_best_score()['validation']['RMSE']
print(f'Revenue RMSLE: {rmse}')
```

```
Revenue RMSLE: 1.7485321690780287
```

Overall, the algorithm that achieved the best results on a 5-fold cross-validation was the CatBoost algorithm and it is our chosen model.