Milestone_1_group_2

March 26, 2023

1 Problem Definition

The problem is supervised text classification, and our goal is to investigate which supervised machine learning methods are best suited to solve it.

Given a new movie information (overview, company, director, budget, …), we want to assign it to one of top genres. The classifier makes the assumption that each new movie is assigned to at least one dominant genres. This is multi-label classification problem.

Input: Overview description + other supporting features (TBD)

Output: Genre

TMDb Movies Dataset: https://www.kaggle.com/datasets/juzershakir/tmdb-movies-dataset

[18]:
```
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
from collections import Counter
import seaborn as sns
```

2 Read Data and divide genres into different columns

[7]:
```
df = pd.read_csv('tmdb_movies_data.csv')

train_df = df.sample(frac=0.8, random_state=123)
test_df = df.drop(train_df.index)
```

[8]:
```
train_df
```

[8]:
```
          id    imdb_id  popularity    budget    revenue  \
3420   71676  tt1071875    1.481016  57000000  149217355
1672   41360  tt1270291    0.356006    425000          0
293   277713  tt2262161    0.421790         0          0
8306   11066  tt0103859    0.410039  40000000   70100000
1748    2325  tt0432314    0.258982         0          0
```

```
…       …        …          …          …          …
9939     839  tt0067023    0.462681    450000          0
562   339060  tt3877296    0.096299         0          0
8890    1091  tt0084787    2.355353  10000000   13782838
1496   19840  tt1032815    0.767264  18000000          0
1378   42218  tt0075989    0.108321         0          0

                         original_title  \
3420  Ghost Rider: Spirit of Vengeance
1672                       Hunter Prey
293                        Sunset Song
8306                         Boomerang
1748                         Leningrad
…                                   …
9939                              Duel
562              The Cokeville Miracle
8890                         The Thing
1496           I Love You, Beth Cooper
1378                Empire of the Ants

                                                    cast  \
3420  Nicolas Cage|CiarÃ¡n Hinds|Violante Placido|Fe…
1672  Isaac C. Singleton Jr.|Clark Bartram|Damion Po…
293   Peter Mullan|Agyness Deyn|Kevin Guthrie|Hugh R…
8306  Eddie Murphy|Robin Givens|Halle Berry|David Al…
1748  Gabriel Byrne|Mira Sorvino|Armin Mueller-Stahl…
…                                                 …
9939  Dennis Weaver|Jacqueline Scott|Eddie Firestone…
562   Nathan Stevens|Jasen Wade|Caitlin E.J. Meyer|M…
8890  Kurt Russell|Keith David|Wilford Brimley|Donal…
1496  Hayden Panettiere|Paul Rust|Lauren London|Laur…
1378  Joan Collins|Robert Lansing|John David Carson|…

                                                homepage  \
3420               http://www.thespiritofvengeance.com/
1672                 http://www.hunterpreythemovie.com/
293                                                 NaN
8306                                                NaN
1748                      http://www.leningradfilm.com/
…                                                 …
9939                                                NaN
562                                                 NaN
8890  http://www.theofficialjohncarpenter.com/the-th…
1496            http://www.iloveyoubethcoopermovie.com/
1378                                                NaN

                          director                                     tagline  \
```

```
3420  Mark Neveldine|Brian Taylor                            He Rides Again.
1672               Sandy Collora            One man. One alien. One choice.
293               Terence Davies                                        NaN
8306             Reginald Hudlin        A Player Who's About to be Played.
1748          Aleksandr Buravsky    Some fight. Others fall. All are heroes.
…                            …                                         …
9939           Steven Spielberg                 Fear is the driving force.
562            T.C. Christensen                    Based on actual events.
8890              John Carpenter          Man is The Warmest Place to Hide.
1496              Chris Columbus  Popularity is nice. Popular girls are not.
1378               Bert I. Gordon                           It's no picnic!

      …                                            overview runtime  \
3420  …  When the devil resurfaces with aims to take ov…      95
1672  …  The Prometheus has dropped out of orbit. Commu…      90
293   …  The daughter of a Scottish farmer comes of age…     135
8306  …  Marcus is a successful advertising executive w…     117
1748  …  When in 1941 Nazi Germany invaded the Soviet U…     120
…   …                                               …       …
9939  …  Travelling businessman, David Mann, angers the…      90
562   …  On May 9, 1986, a small ranching community in …      94
8890  …  Scientists in the Antarctic are confronted by …     109
1496  …  Nerdy teenager Denis Cooverman (Paul Rust) har…     102
1378  …  Sleazy scam artist Joan Collins tries to sell …      89

                                     genres  \
3420              Action|Fantasy|Thriller
1672             Science Fiction|Thriller
293                                 Drama
8306                 Drama|Comedy|Romance
1748                            War|Drama
…                                      …
9939         Horror|Action|Mystery|Thriller
562    Mystery|Drama|History|Family|Thriller
8890  Horror|Science Fiction|Mystery|Thriller
1496                        Comedy|Romance
1378               Horror|Science Fiction

                                   production_companies release_date  \
3420  Columbia Pictures|Imagenation Abu Dhabi FZ|Mar…   12/10/2011
1672                          NBV Productions|Montauk Films     1/1/2009
293    Iris productions|Hurricane Films|SellOutPictures    12/4/2015
8306                                  Paramount Pictures    6/30/1992
1748  Channel One Russia|KoBura Film|Ministerstvo ku…     1/1/2009
…                                                    …          …
9939                                        Universal TV   11/10/1971
562                                                  NaN     6/5/2015
```

```
8890          Universal Pictures|Turman-Foster Company    6/25/1982
1496  Ingenious Film Partners|1492 Pictures|Fox Atom…    7/10/2009
1378                                        Cinema 77    6/29/1977

     vote_count  vote_average  release_year   budget_adj   revenue_adj
3420        752           4.7          2011  5.525569e+07  1.446510e+08
1672         22           5.5          2009  4.319702e+05  0.000000e+00
293          19           7.1          2015  0.000000e+00  0.000000e+00
8306         69           5.5          1992  6.216097e+07  1.089371e+08
1748         17           5.7          2009  0.000000e+00  0.000000e+00
…          …           …           …           …           …
9939        166           7.0          1971  2.423338e+06  0.000000e+00
562          13           5.1          2015  0.000000e+00  0.000000e+00
8890        797           7.5          1982  2.259642e+07  3.114429e+07
1496        106           4.9          2009  1.829521e+07  0.000000e+00
1378         11           4.6          1977  0.000000e+00  0.000000e+00

[8693 rows x 21 columns]
```

[9]:
```
train_df[['genres_1', 'genres_2', 'genres_3','genres_4', 'genres_5']] = df.
 ↪genres.str.split("|", expand = True)
print(train_df)
```

```
          id    imdb_id  popularity    budget    revenue  \
3420   71676  tt1071875    1.481016  57000000  149217355
1672   41360  tt1270291    0.356006    425000          0
293   277713  tt2262161    0.421790         0          0
8306   11066  tt0103859    0.410039  40000000   70100000
1748    2325  tt0432314    0.258982         0          0
…      …         …          …         …          …
9939     839  tt0067023    0.462681    450000          0
562   339060  tt3877296    0.096299         0          0
8890    1091  tt0084787    2.355353  10000000   13782838
1496   19840  tt1032815    0.767264  18000000          0
1378   42218  tt0075989    0.108321         0          0

                       original_title  \
3420  Ghost Rider: Spirit of Vengeance
1672                       Hunter Prey
293                        Sunset Song
8306                         Boomerang
1748                         Leningrad
…                                 …
9939                              Duel
562              The Cokeville Miracle
8890                         The Thing
1496             I Love You, Beth Cooper
```

```
1378                Empire of the Ants

                                                   cast  \
3420  Nicolas Cage|CiarÃ¡n Hinds|Violante Placido|Fe…
1672  Isaac C. Singleton Jr.|Clark Bartram|Damion Po…
293   Peter Mullan|Agyness Deyn|Kevin Guthrie|Hugh R…
8306  Eddie Murphy|Robin Givens|Halle Berry|David Al…
1748  Gabriel Byrne|Mira Sorvino|Armin Mueller-Stahl…
…                                                   …
9939  Dennis Weaver|Jacqueline Scott|Eddie Firestone…
562   Nathan Stevens|Jasen Wade|Caitlin E.J. Meyer|M…
8890  Kurt Russell|Keith David|Wilford Brimley|Donal…
1496  Hayden Panettiere|Paul Rust|Lauren London|Laur…
1378  Joan Collins|Robert Lansing|John David Carson|…

                                               homepage  \
3420             http://www.thespiritofvengeance.com/
1672               http://www.hunterpreythemovie.com/
293                                                 NaN
8306                                                NaN
1748                    http://www.leningradfilm.com/
…                                                   …
9939                                                NaN
562                                                 NaN
8890  http://www.theofficialjohncarpenter.com/the-th…
1496          http://www.iloveyoubethcoopermovie.com/
1378                                                NaN

                        director                                        tagline  \
3420  Mark Neveldine|Brian Taylor                               He Rides Again.
1672                Sandy Collora               One man. One alien. One choice.
293                Terence Davies                                           NaN
8306              Reginald Hudlin          A Player Who's About to be Played.
1748           Aleksandr Buravsky    Some fight. Others fall. All are heroes.
…                              …                                            …
9939             Steven Spielberg                  Fear is the driving force.
562              T.C. Christensen                     Based on actual events.
8890               John Carpenter           Man is The Warmest Place to Hide.
1496               Chris Columbus  Popularity is nice. Popular girls are not.
1378                Bert I. Gordon                             It's no picnic!

      … vote_count vote_average  release_year   budget_adj   revenue_adj  \
3420  …        752          4.7          2011  5.525569e+07  1.446510e+08
1672  …         22          5.5          2009  4.319702e+05  0.000000e+00
293   …         19          7.1          2015  0.000000e+00  0.000000e+00
8306  …         69          5.5          1992  6.216097e+07  1.089371e+08
1748  …         17          5.7          2009  0.000000e+00  0.000000e+00
…     …          …            …             …             …             …
```

```
9939  …       166          7.0          1971  2.423338e+06  0.000000e+00
562   …        13          5.1          2015  0.000000e+00  0.000000e+00
8890  …       797          7.5          1982  2.259642e+07  3.114429e+07
1496  …       106          4.9          2009  1.829521e+07  0.000000e+00
1378  …        11          4.6          1977  0.000000e+00  0.000000e+00

             genres_1         genres_2  genres_3  genres_4  genres_5
3420           Action          Fantasy  Thriller      None      None
1672  Science Fiction         Thriller      None      None      None
293             Drama             None      None      None      None
8306            Drama           Comedy   Romance      None      None
1748              War            Drama      None      None      None
…                 …                …   …       …       …
9939           Horror           Action   Mystery  Thriller      None
562           Mystery            Drama   History    Family  Thriller
8890           Horror  Science Fiction   Mystery  Thriller      None
1496           Comedy          Romance      None      None      None
1378           Horror  Science Fiction      None      None      None

[8693 rows x 26 columns]
```

3 Data Exploration

[10]:
```python
train_df.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8693 entries, 3420 to 1378
Data columns (total 26 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    8693 non-null   int64
 1   imdb_id               8684 non-null   object
 2   popularity            8693 non-null   float64
 3   budget                8693 non-null   int64
 4   revenue               8693 non-null   int64
 5   original_title        8693 non-null   object
 6   cast                  8642 non-null   object
 7   homepage              2358 non-null   object
 8   director              8658 non-null   object
 9   tagline               6413 non-null   object
 10  keywords              7525 non-null   object
 11  overview              8689 non-null   object
 12  runtime               8693 non-null   int64
 13  genres                8675 non-null   object
 14  production_companies  7872 non-null   object
 15  release_date          8693 non-null   object
```

```
 16  vote_count            8693 non-null   int64
 17  vote_average          8693 non-null   float64
 18  release_year          8693 non-null   int64
 19  budget_adj            8693 non-null   float64
 20  revenue_adj           8693 non-null   float64
 21  genres_1              8675 non-null   object
 22  genres_2              6795 non-null   object
 23  genres_3              4044 non-null   object
 24  genres_4              1564 non-null   object
 25  genres_5              410 non-null    object
dtypes: float64(4), int64(6), object(16)
memory usage: 12.5 MB
```

Numerical Variables

[11]:
```python
train_df.describe().transpose()
```

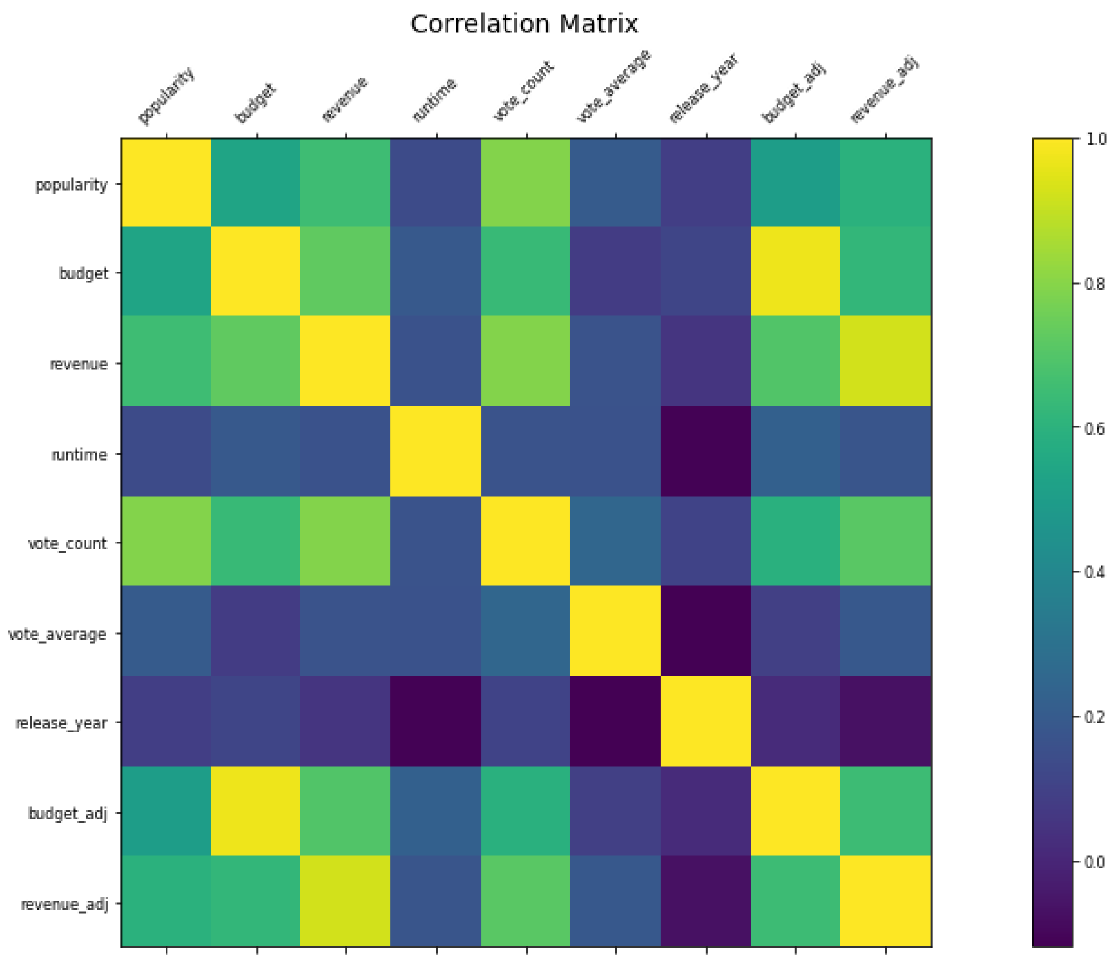
[11]:
```
               count          mean           std          min            25%  \
id            8693.0  6.680747e+04  9.248694e+04     5.000000   10641.000000
popularity    8693.0  6.409280e-01  1.018641e+00     0.000188       0.205701
budget        8693.0  1.433949e+07  3.045441e+07     0.000000       0.000000
revenue       8693.0  3.869294e+07  1.167752e+08     0.000000       0.000000
runtime       8693.0  1.017014e+02  3.118929e+01     0.000000      90.000000
vote_count    8693.0  2.121747e+02  5.661980e+02    10.000000      17.000000
vote_average  8693.0  5.968503e+00  9.407674e-01     1.500000       5.400000
release_year  8693.0  2.001315e+03  1.291234e+01  1960.000000    1995.000000
budget_adj    8693.0  1.719889e+07  3.375153e+07     0.000000       0.000000
revenue_adj   8693.0  5.005171e+07  1.424856e+08     0.000000       0.000000

                       50%           75%           max
id            20969.000000  7.717400e+04  4.178590e+05
popularity        0.381737  7.060230e-01  3.298576e+01
budget            0.000000  1.500000e+07  4.250000e+08
revenue           0.000000  2.343812e+07  2.781506e+09
runtime          99.000000  1.110000e+02  9.000000e+02
vote_count       38.000000  1.420000e+02  8.903000e+03
vote_average      6.000000  6.600000e+00  9.200000e+00
release_year   2006.000000  2.011000e+03  2.015000e+03
budget_adj        0.000000  2.026067e+07  4.250000e+08
revenue_adj       0.000000  3.300817e+07  2.827124e+09
```

[12]:
```python
num_vars = train_df.columns[train_df.dtypes != 'object']
print(num_vars)
```

```
Index(['id', 'popularity', 'budget', 'revenue', 'runtime', 'vote_count',
       'vote_average', 'release_year', 'budget_adj', 'revenue_adj'],
      dtype='object')
```

[13]:
```
train_df_num = pd.DataFrame(train_df, columns = ['popularity', 'budget',␣
↪'revenue', 'runtime', 'vote_count', 'vote_average', 'release_year',␣
↪'budget_adj', 'revenue_adj'])
```

[14]:
```
f = plt.figure(figsize=(20, 8))
plt.matshow(train_df_num.corr(), fignum=f.number)
plt.xticks(range(train_df_num.select_dtypes(['number']).shape[1]), train_df_num.
↪select_dtypes(['number']).columns, fontsize=8, rotation=45)
plt.yticks(range(train_df_num.select_dtypes(['number']).shape[1]), train_df_num.
↪select_dtypes(['number']).columns, fontsize=8)
cb = plt.colorbar()
cb.ax.tick_params(labelsize=8)
plt.title('Correlation Matrix', fontsize=14);
```



[15]:
```
train_df_num.corr()
```

[15]:

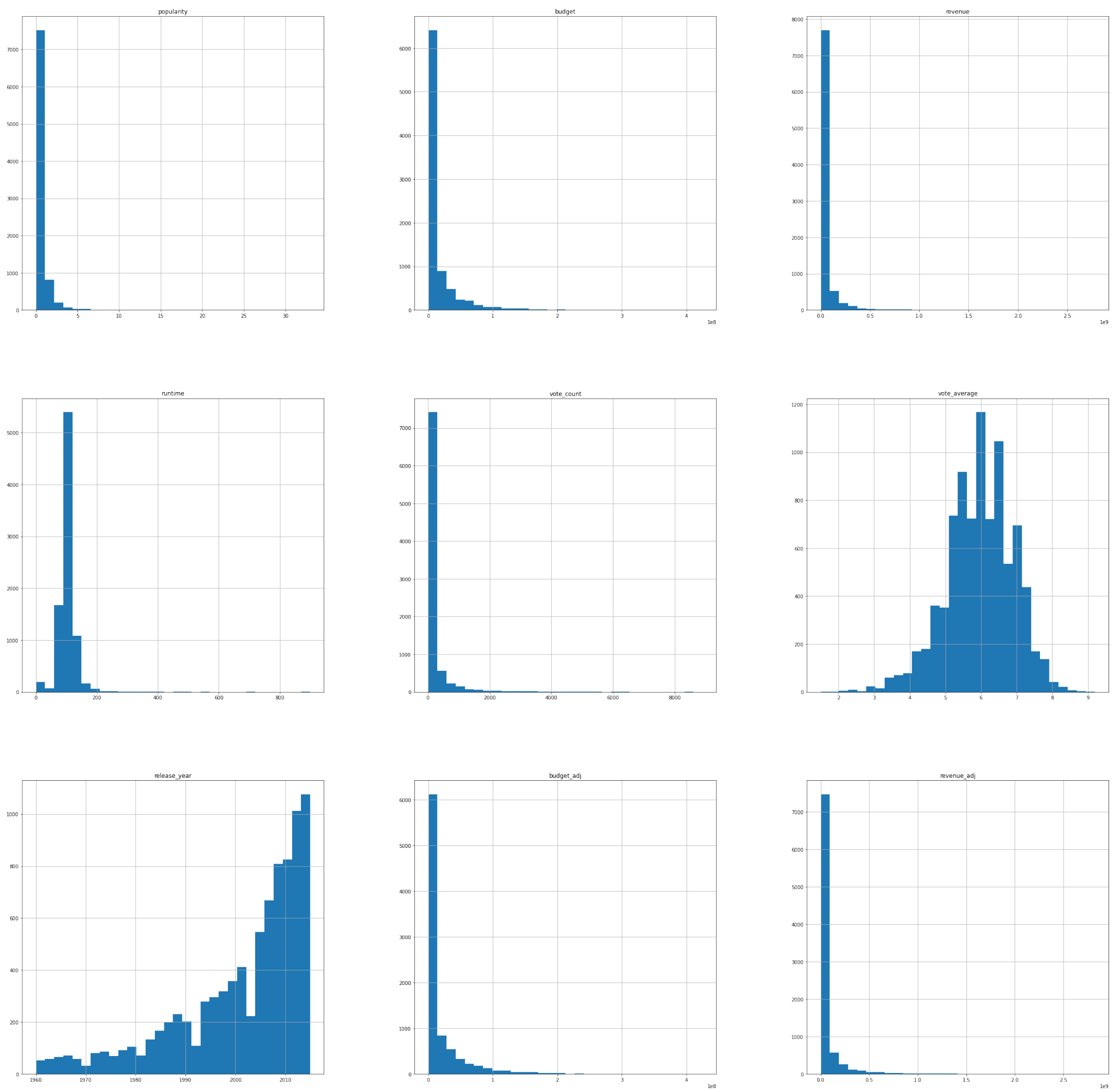
```
              popularity    budget   revenue   runtime  vote_count  \
popularity      1.000000  0.535266  0.653071  0.136958    0.792930
budget          0.535266  1.000000  0.725424  0.194861    0.636858
revenue         0.653071  0.725424  1.000000  0.161761    0.793027
runtime         0.136958  0.194861  0.161761  1.000000    0.165795
vote_count      0.792930  0.636858  0.793027  0.165795    1.000000
vote_average    0.201772  0.078076  0.168371  0.160907    0.250607
release_year    0.086455  0.115645  0.054817 -0.114907    0.104355
budget_adj      0.502846  0.969407  0.697545  0.221448    0.590762
revenue_adj     0.594029  0.621531  0.922385  0.176094    0.712120

              vote_average  release_year  budget_adj  revenue_adj
popularity        0.201772      0.086455    0.502846     0.594029
budget            0.078076      0.115645    0.969407     0.621531
revenue           0.168371      0.054817    0.697545     0.922385
runtime           0.160907     -0.114907    0.221448     0.176094
vote_count        0.250607      0.104355    0.590762     0.712120
vote_average      1.000000     -0.119782    0.090900     0.190427
release_year     -0.119782      1.000000    0.017840    -0.068409
budget_adj        0.090900      0.017840    1.000000     0.646710
revenue_adj       0.190427     -0.068409    0.646710     1.000000
```

[19]:

```
plt.rcParams["figure.figsize"] = (40, 40)
train_df_num.hist(bins=30)
```

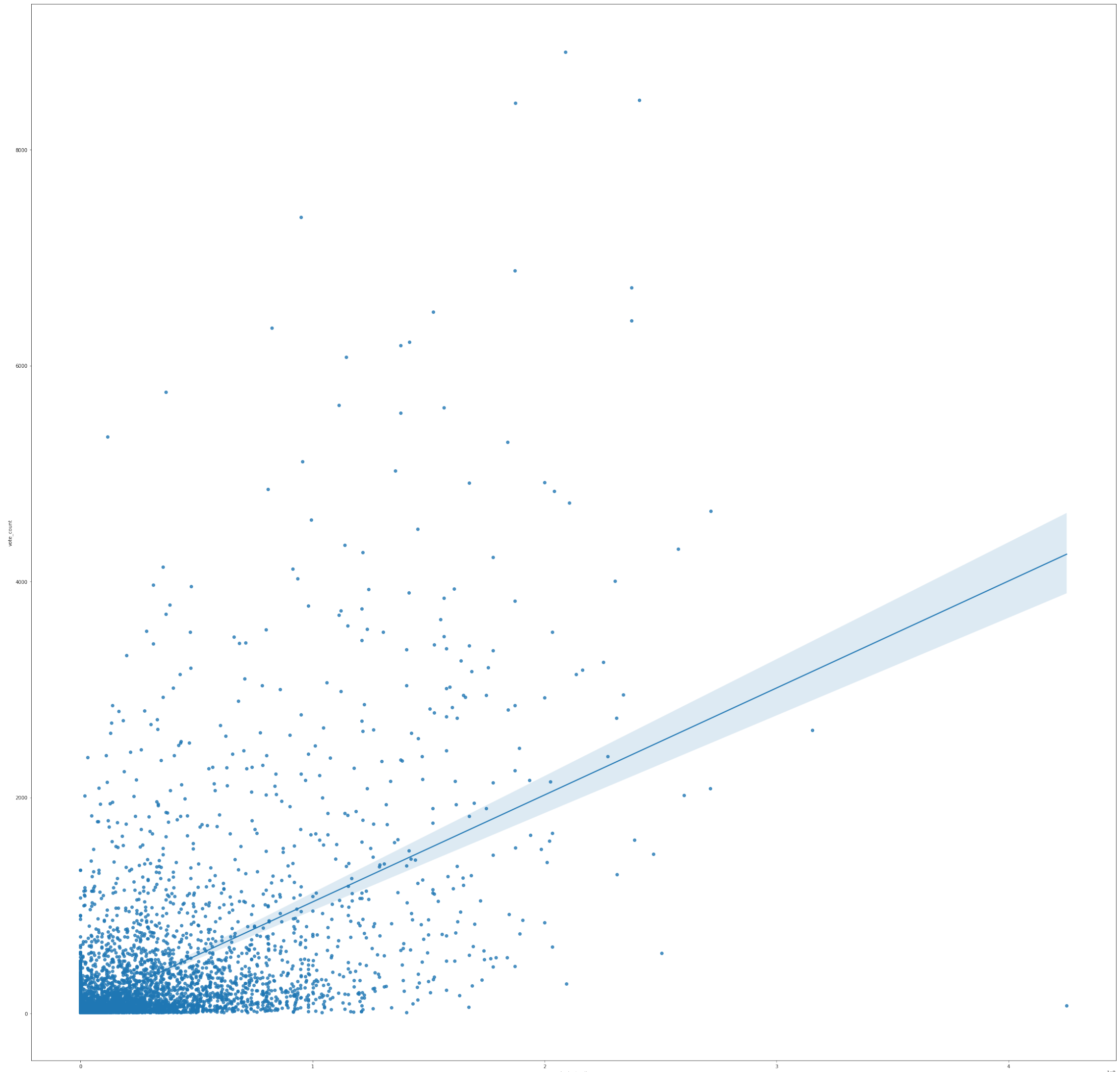
[19]:

```
array([[<Axes: title={'center': 'popularity'}>,
        <Axes: title={'center': 'budget'}>,
        <Axes: title={'center': 'revenue'}>],
       [<Axes: title={'center': 'runtime'}>,
        <Axes: title={'center': 'vote_count'}>,
        <Axes: title={'center': 'vote_average'}>],
       [<Axes: title={'center': 'release_year'}>,
        <Axes: title={'center': 'budget_adj'}>,
        <Axes: title={'center': 'revenue_adj'}>]], dtype=object)
```



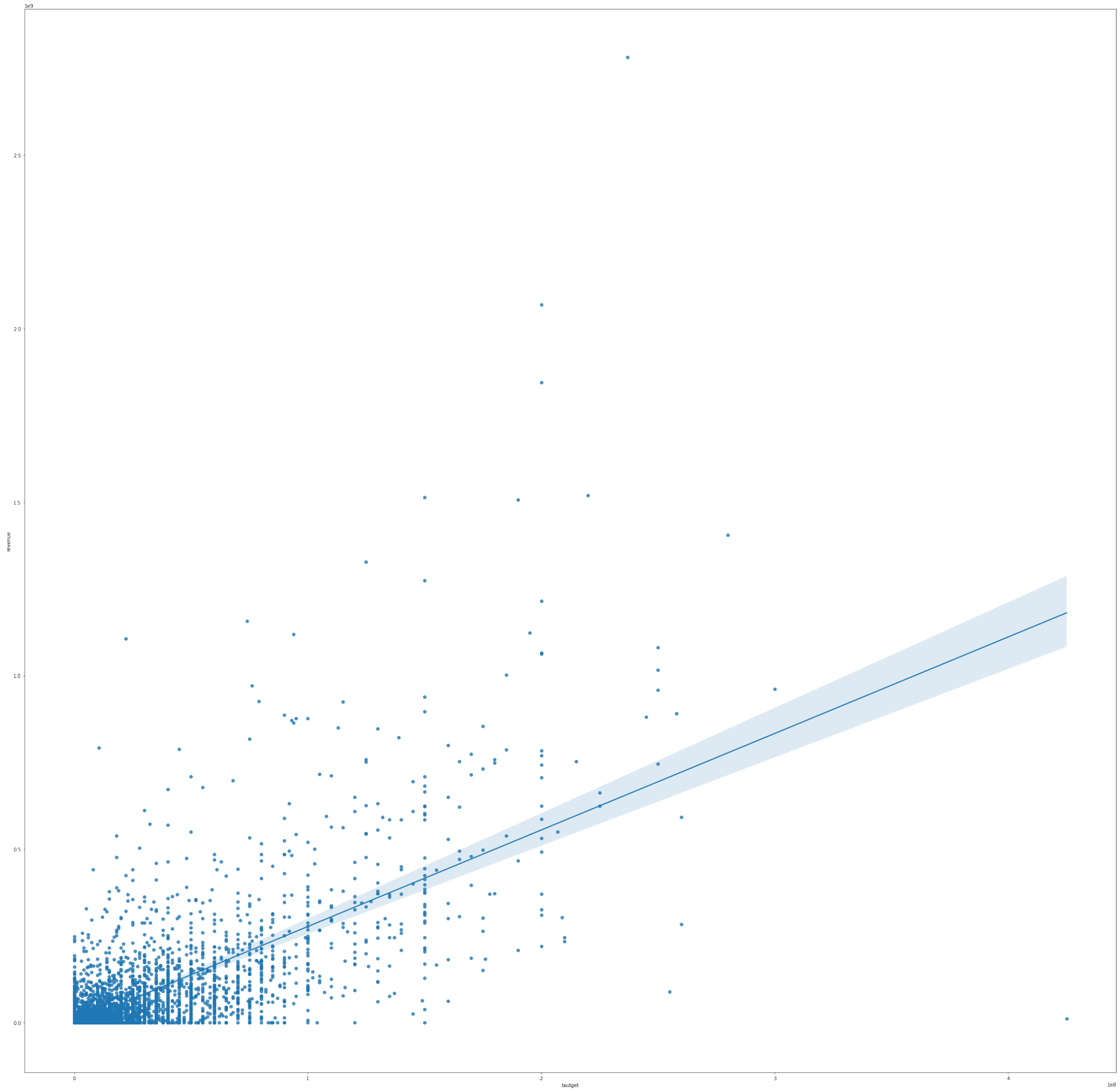
[20]:
```
sns.regplot(x='budget_adj',y='vote_count', data = train_df)
```

[20]: `<Axes: xlabel='budget_adj', ylabel='vote_count'>`



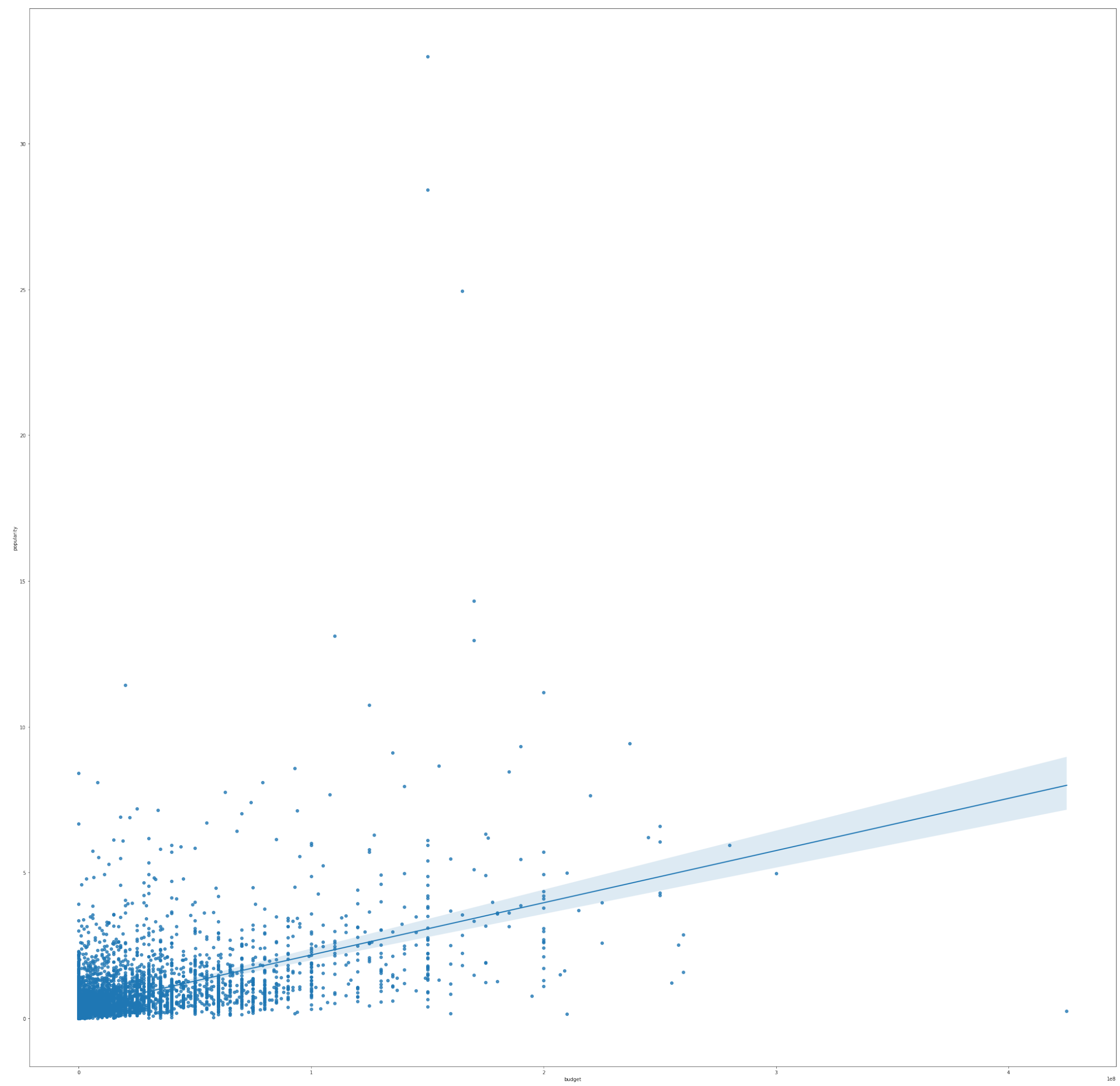

```
[21]: sns.regplot(x='budget',y='revenue', data = train_df)
```

```
[21]: <Axes: xlabel='budget', ylabel='revenue'>
```



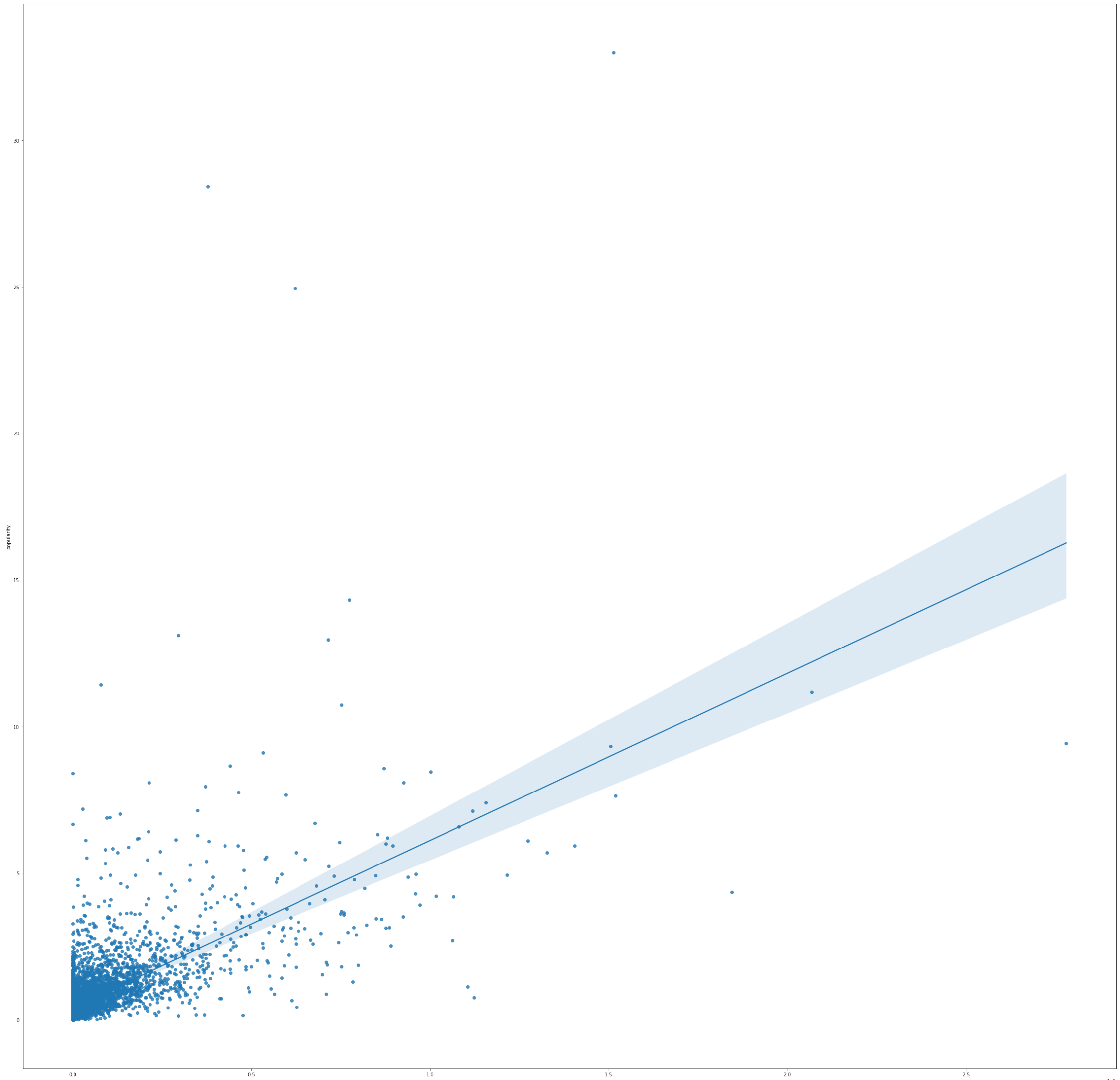
[22]:
```
sns.regplot(x='budget',y='popularity', data = train_df)
```

[22]: <Axes: xlabel='budget', ylabel='popularity'>



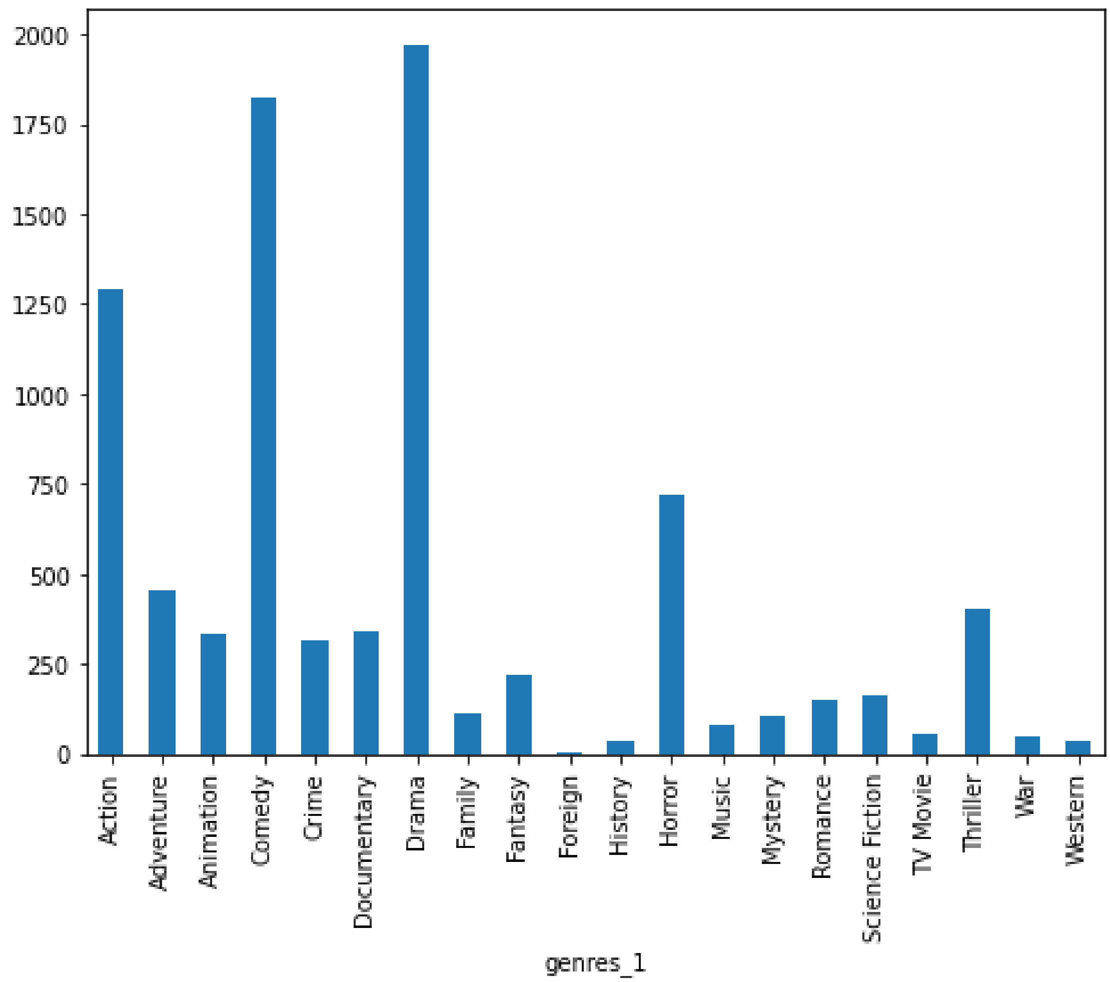
[23]:
```
sns.regplot(x='revenue',y='popularity', data = train_df)
```

[23]: <Axes: xlabel='revenue', ylabel='popularity'>

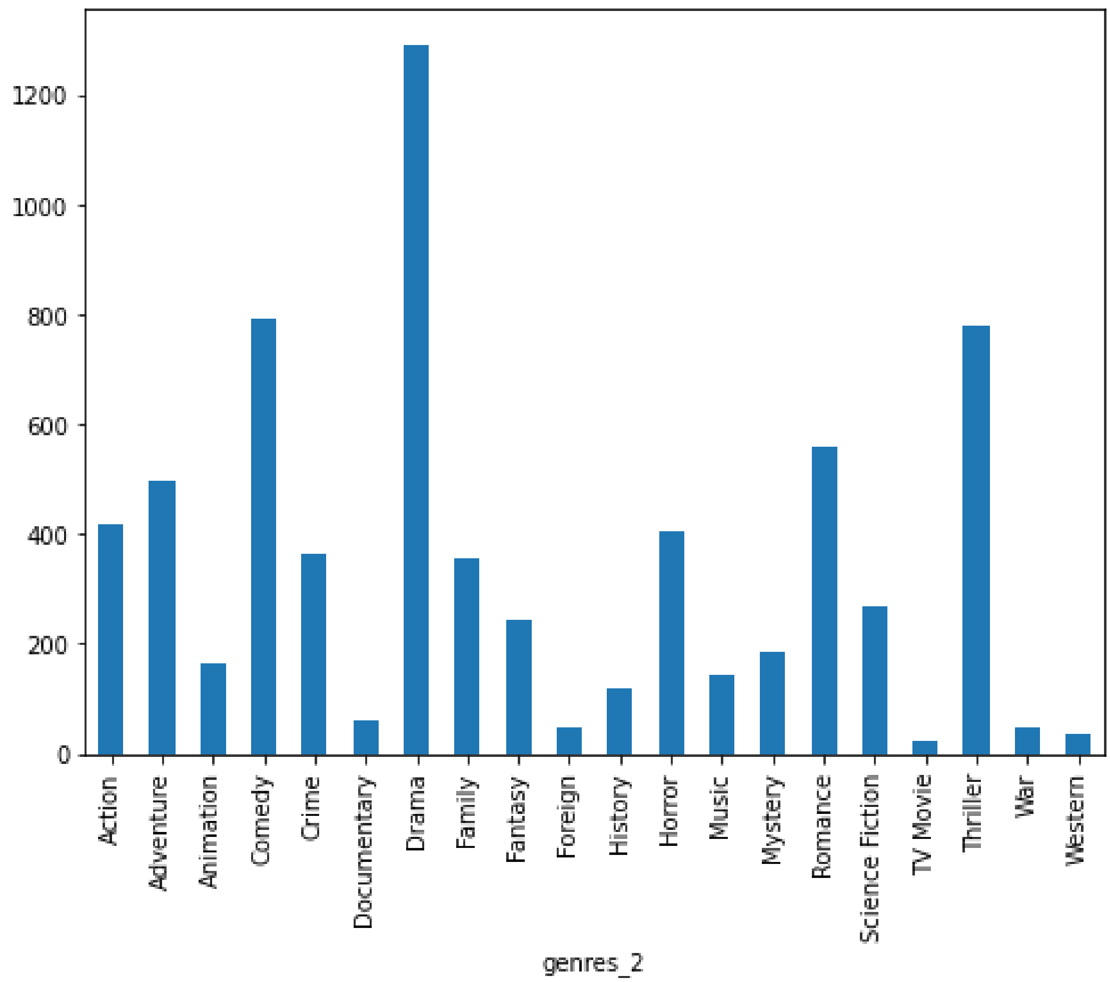


Categorical Variables

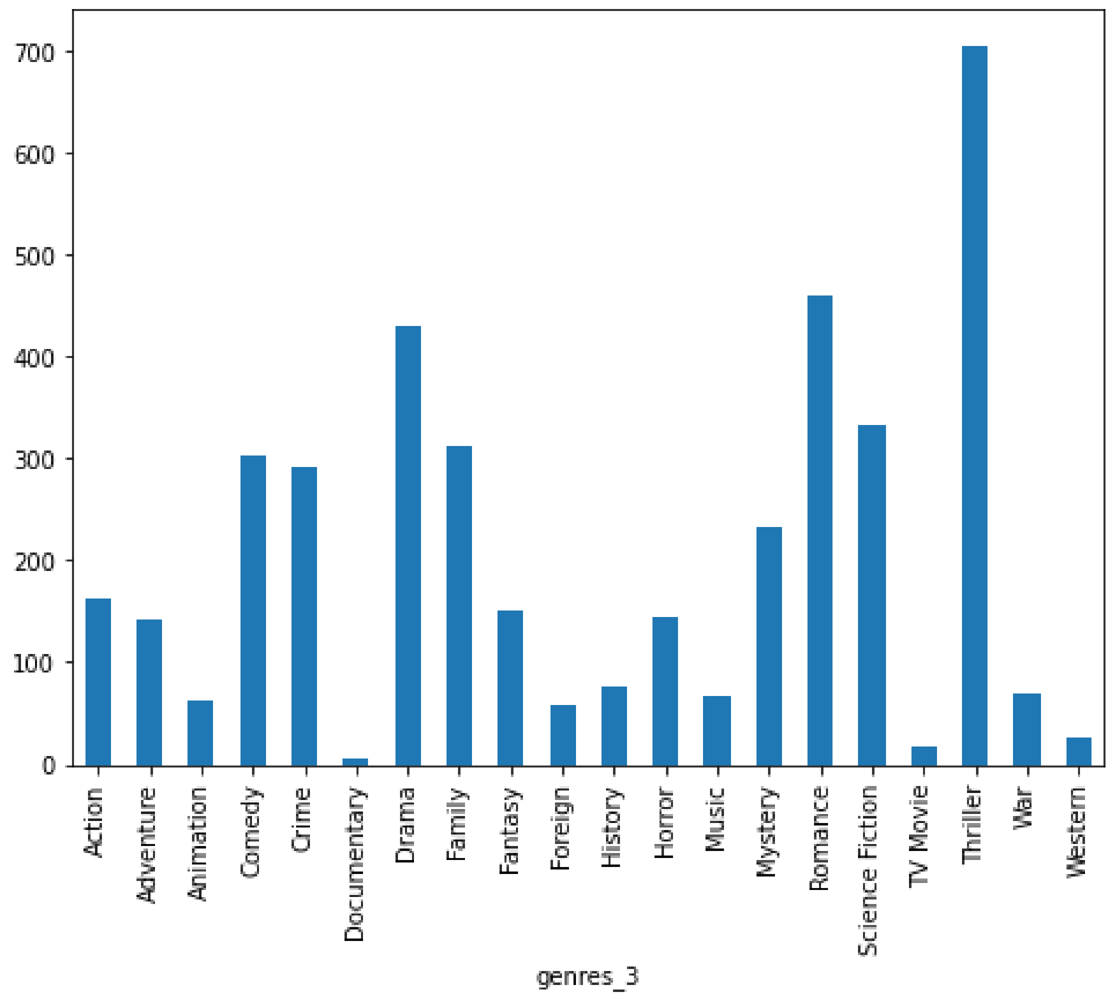
[24]:
```
fig = plt.figure(figsize=(8,6))
train_df.groupby('genres_1').overview.count().plot.bar(ylim=0)
plt.show()
```



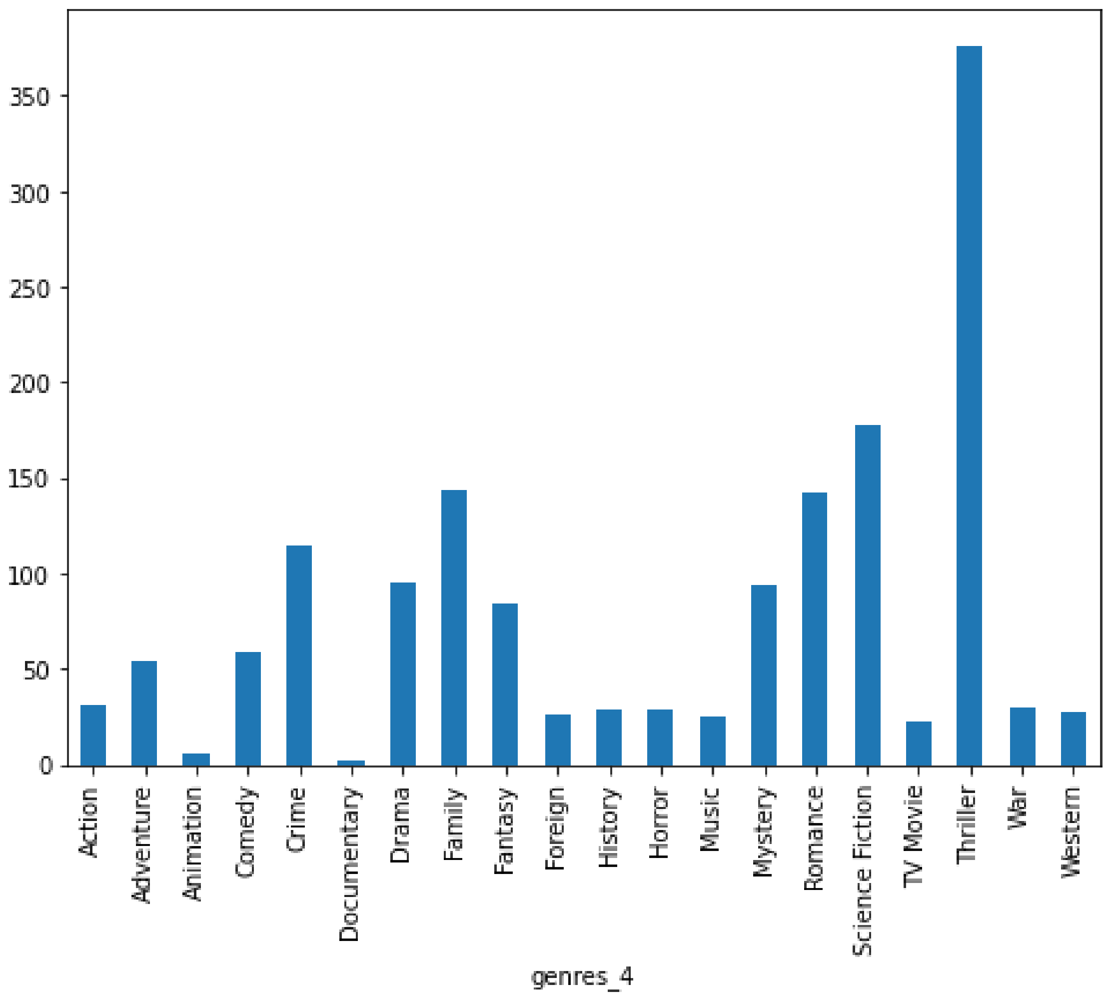
[25]:
```
fig = plt.figure(figsize=(8,6))
train_df.groupby('genres_2').overview.count().plot.bar(ylim=0)
plt.show()
```



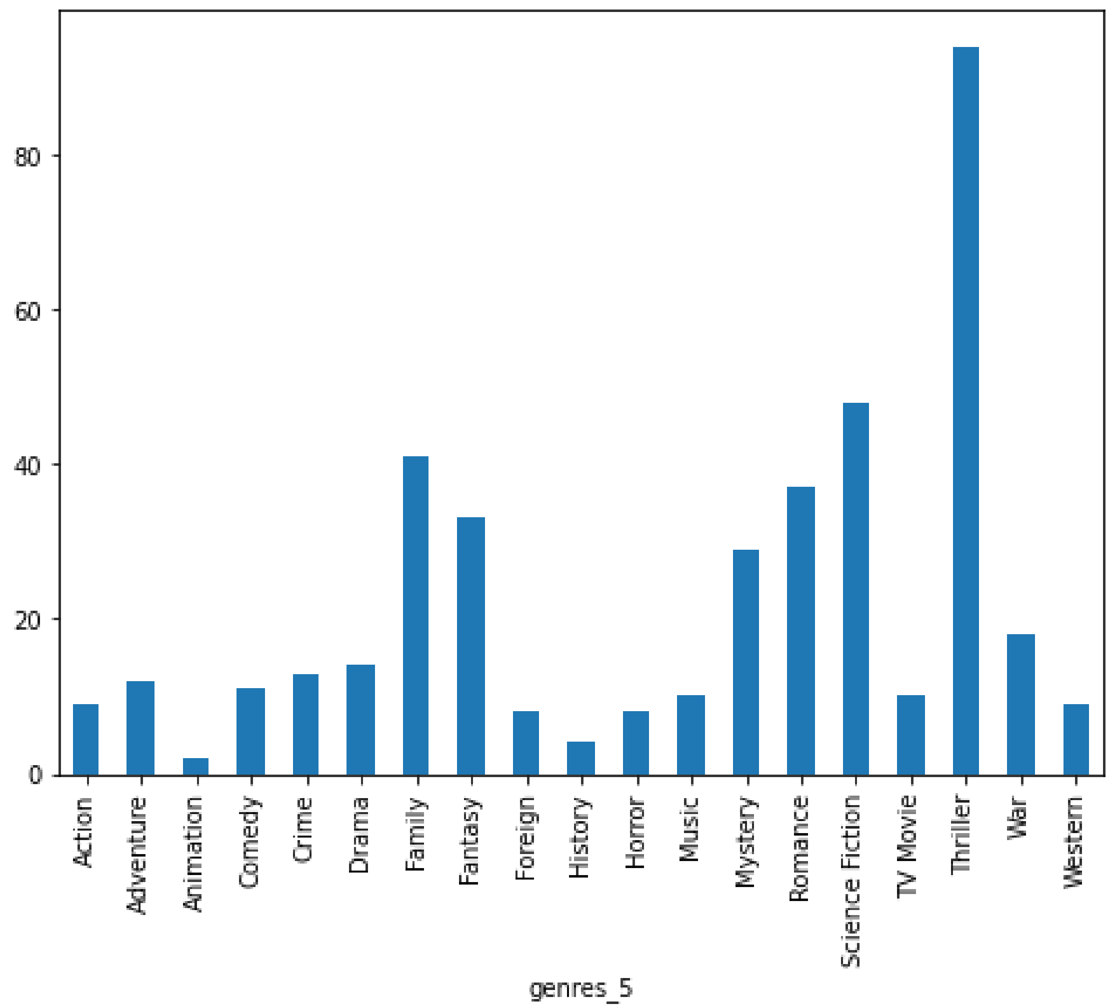
[26]:
```
fig = plt.figure(figsize=(8,6))
train_df.groupby('genres_3').overview.count().plot.bar(ylim=0)
plt.show()
```



[27]:
```
fig = plt.figure(figsize=(8,6))
train_df.groupby('genres_4').overview.count().plot.bar(ylim=0)
plt.show()
```



[28]:
```
fig = plt.figure(figsize=(8,6))
train_df.groupby('genres_5').overview.count().plot.bar(ylim=0)
plt.show()
```



[29]:
```
genre_columns = ['genres_1', 'genres_2', 'genres_3', 'genres_4', 'genres_5']
df_genres = train_df[genre_columns]
df_genres
```

[29]:

	genres_1	genres_2	genres_3	genres_4	genres_5
3420	Action	Fantasy	Thriller	None	None
1672	Science Fiction	Thriller	None	None	None
293	Drama	None	None	None	None
8306	Drama	Comedy	Romance	None	None
1748	War	Drama	None	None	None
…	…	…	…	…	…
9939	Horror	Action	Mystery	Thriller	None
562	Mystery	Drama	History	Family	Thriller
8890	Horror	Science Fiction	Mystery	Thriller	None
1496	Comedy	Romance	None	None	None
1378	Horror	Science Fiction	None	None	None

```
[8693 rows x 5 columns]
```

[30]:
```
print(df_genres.isnull().sum())
```

```
genres_1      18
genres_2    1898
genres_3    4649
genres_4    7129
genres_5    8283
dtype: int64
```

[31]:
```
import seaborn as sns
```

4 Explore important features related to Genres

- Budget
- Popularity
- Revenue and ajusted Revenue

From the ANOVA output table below: For the columns 'Genres_1', 'Genres_2', 'Genres_3', and 'Genres4', we can reject the null hypothesis that 'budget' has no statistical significance as the p values fall below our selected alpha of .05 for each of these columns. Therefore there is a significant relationship between 'genres_1' and 'budget'; 'genres_2' and 'budget'; 'genres_3' and 'budget', and 'genres_4' and 'budget'.

Using an alpha=.05, no significant relationship was found between 'genres_5' and 'budget'.

Re: see p values in the table below in the PR(>F) columnn which need to be less than our alpha of .05 in order to be significant

[32]:
```
import statsmodels.api as sm
from statsmodels.formula.api import ols

# Fit ANOVA model for each genre column
for genre_col in ['genres_1', 'genres_2', 'genres_3', 'genres_4', 'genres_5']:
    formula = f"budget ~ C({genre_col})"
    model = ols(formula, data=train_df).fit()
    anova_table = sm.stats.anova_lm(model, typ=2, alpha=.05)
    print(f"ANOVA results for {genre_col}:")
    print(anova_table)
```

```
ANOVA results for genres_1:
                     sum_sq      df          F         PR(>F)
C(genres_1)    6.914923e+17    19.0  42.760898  1.423597e-152
Residual       7.366378e+18  8655.0        NaN            NaN
ANOVA results for genres_2:
                     sum_sq      df          F        PR(>F)
```

```
C(genres_2)  4.754949e+17    19.0  24.454908  1.678480e-83
Residual     6.933229e+18  6775.0        NaN           NaN
ANOVA results for genres_3:
                   sum_sq      df          F        PR(>F)
C(genres_3)  3.085076e+17    19.0  11.667588  1.947609e-35
Residual     5.600014e+18  4024.0        NaN           NaN
ANOVA results for genres_4:
                   sum_sq      df         F        PR(>F)
C(genres_4)  1.503698e+17    19.0  4.77677  5.693018e-11
Residual     2.558114e+18  1544.0      NaN           NaN
ANOVA results for genres_5:
                   sum_sq     df          F    PR(>F)
C(genres_5)  4.075705e+16   18.0  1.129875  0.320091
Residual     7.835680e+17  391.0       NaN       NaN
```

Using an ANOVA table below, we can look at the significance of 'popularity'(numerical X) in relation to 'Genres_1' through 'Genres_5' columns (Categorical y).

Using an alpha=.05, all 5 genre columns each showed a significant relationship with the 'popularity' variable.

Re: see p values in the table below in the PR(>F) columnn which are all less than our alpha of .05.

[33]:
```
# Fit ANOVA model for each genre column
for genre_col in ['genres_1', 'genres_2', 'genres_3', 'genres_4', 'genres_5']:
    formula = f"popularity ~ C({genre_col})"
    model = ols(formula, data=train_df).fit()
    anova_table = sm.stats.anova_lm(model, typ=2, alpha=.05)
    print(f"ANOVA results for {genre_col}:")
    print(anova_table)
```

```
ANOVA results for genres_1:
                  sum_sq      df         F        PR(>F)
C(genres_1)   405.888959    19.0  21.47669  6.684103e-73
Residual     8609.012900  8655.0       NaN           NaN
ANOVA results for genres_2:
                  sum_sq      df          F        PR(>F)
C(genres_2)   239.451115    19.0  10.412953  2.981967e-31
Residual     8199.713423  6775.0        NaN           NaN
ANOVA results for genres_3:
                  sum_sq      df         F        PR(>F)
C(genres_3)   226.894664    19.0  7.226218  1.443606e-19
Residual     6649.937577  4024.0       NaN           NaN
ANOVA results for genres_4:
                  sum_sq      df         F    PR(>F)
C(genres_4)    99.488065    19.0  2.479652  0.000399
Residual     3260.423445  1544.0       NaN       NaN
ANOVA results for genres_5:
```

```
              sum_sq     df         F    PR(>F)
C(genres_5)   23.128089   18.0  1.988585  0.009611
Residual     252.638728  391.0       NaN       NaN
```

Using An ANOVA table below, we can look at the significance of 'revenue'(numerical X) in relation to 'Genre_1' through 'Genre_5' columns (Categorical y).

Using an alpha=.05, all 5 genre columns each showed a significant relationship with the 'revenue' variable.

Re: see p values in the table below in the PR(>F) columnn which are all less than our alpha of .05.

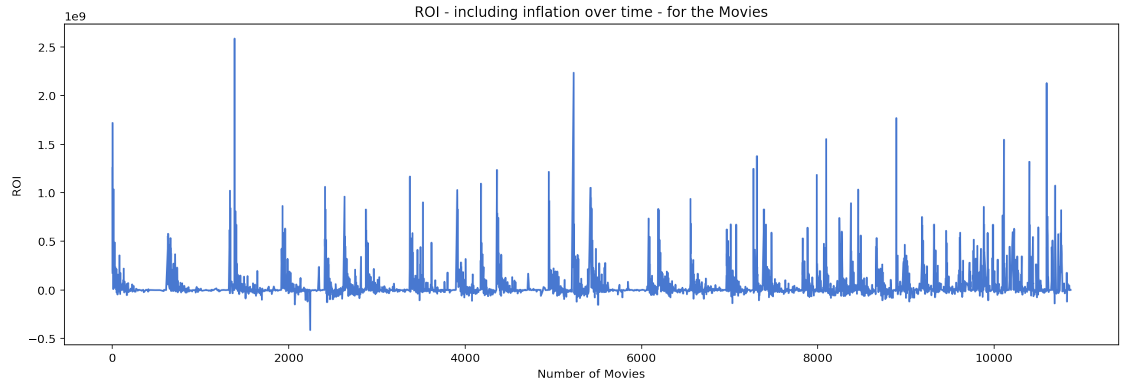
[34]:
```
for genre_col in ['genres_1', 'genres_2', 'genres_3', 'genres_4', 'genres_5']:
    formula = f"revenue ~ C({genre_col})"
    model = ols(formula, data=train_df).fit()
    anova_table = sm.stats.anova_lm(model, typ=2, alpha=.05)
    print(f"ANOVA results for {genre_col}:")
    print(anova_table)
```

```
ANOVA results for genres_1:
                   sum_sq      df          F        PR(>F)
C(genres_1)  6.152287e+18    19.0  24.944903  5.406090e-86
Residual     1.123487e+20  8655.0        NaN           NaN
ANOVA results for genres_2:
                   sum_sq      df          F        PR(>F)
C(genres_2)  4.403851e+18    19.0  14.500926  2.228284e-46
Residual     1.082911e+20  6775.0        NaN           NaN
ANOVA results for genres_3:
                   sum_sq      df         F        PR(>F)
C(genres_3)  3.341307e+18    19.0  7.760037  1.915735e-21
Residual     9.119206e+19  4024.0       NaN           NaN
ANOVA results for genres_4:
                   sum_sq      df         F        PR(>F)
C(genres_4)  1.984719e+18    19.0  4.068595  9.572616e-09
Residual     3.964133e+19  1544.0       NaN           NaN
ANOVA results for genres_5:
                   sum_sq     df         F    PR(>F)
C(genres_5)  8.039354e+17   18.0  2.284664  0.002159
Residual     7.643692e+18  391.0       NaN       NaN
```

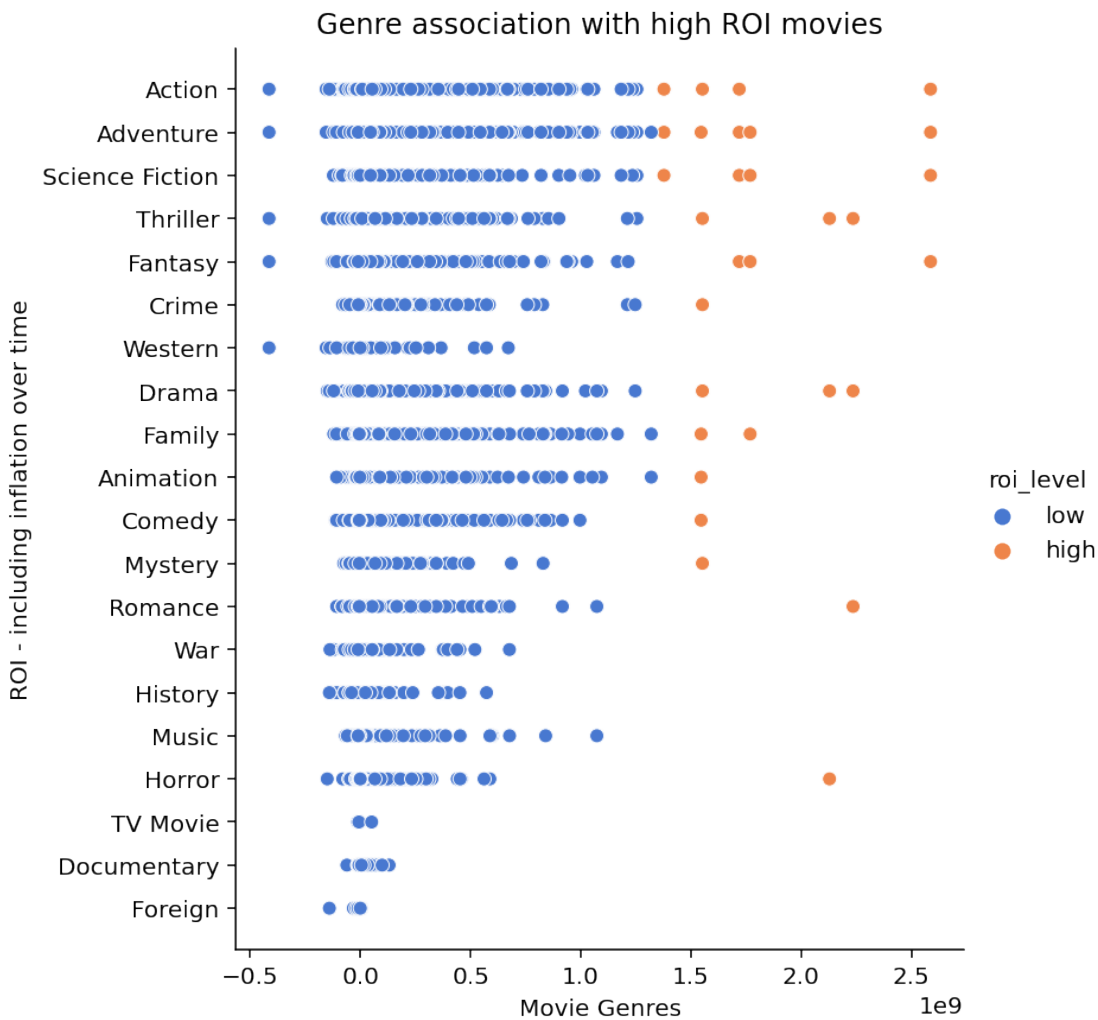
[89]:
```
df_genre = train_df_genre[train_df_genre['budget_adj']!=0]
df_genre['roi'] = df_genre['revenue_adj'] - df_genre['budget_adj']

# plot the revenues for all movies in the dataset
plt.subplots(figsize=(16, 5))
plt.plot(df_genre['roi'])
plt.title('ROI - including inflation over time - for the Movies')
plt.xlabel('Number of Movies')
```

```
plt.ylabel('ROI');
```

```
<ipython-input-89-1d101d96be5f>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_genre['roi'] = df_genre['revenue_adj'] - df_genre['budget_adj']
```



[90]:
```
# select high revenues
high_ROI = df_genre['roi'].nlargest(30)

# Get an entire dataframe for movies with high revenues
df_high_roi = df_genre.query('roi in @high_ROI')

# Add a new column "revenue_level" with "low" as default value
df_roi = df_genre.assign(roi_level='low')

# set "high" where for the movies with high revenues
for roi in high_ROI:
    df_roi.loc[df_roi['roi'] == roi, 'roi_level'] = 'high'

# plot of budget association with revenue
budgetplot = sns.relplot(x="roi", y="genre", hue="roi_level", data=df_roi,␣
 ↪height=6)
budgetplot.set(title='Genre association with high ROI movies',
               xlabel='Movie Genres',
               ylabel='ROI - including inflation over time');
```



#Text Cleaning

[35]:
```
import re

def clean_text(doc):
    # lower case and remove special characters\whitespaces
    if(type(doc) == str):
      doc = re.sub(r'[^a-zA-Z0-9\s]', '', doc, re.I)
      doc = doc.lower()
      doc = doc.strip()
    else:
      doc = ""

    return doc
```

[36]:

```
for i, row in train_df.iterrows():
  train_df.at[i, 'overview_clean'] = clean_text(row.overview)
```

5 part-of-speech (POS) tagging

[37]:

```
import locale
locale.setlocale(locale.LC_ALL, 'en_US.utf8')
locale.getpreferredencoding = lambda: "UTF-8"
```

[38]:

```
!pip install contractions
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting contractions
  Downloading contractions-0.1.73-py2.py3-none-any.whl (8.7 kB)
Collecting textsearch>=0.0.21
  Downloading textsearch-0.0.24-py2.py3-none-any.whl (7.6 kB)
Collecting pyahocorasick
  Downloading
pyahocorasick-2.0.0-cp39-cp39-manylinux_2_5_x86_64.manylinux1_x86_64.whl (103
kB)
                           103.2/103.2

KB 3.9 MB/s eta 0:00:00
Collecting anyascii
  Downloading anyascii-0.3.2-py3-none-any.whl (289 kB)
                          289.9/289.9 KB
14.4 MB/s eta 0:00:00
Installing collected packages: pyahocorasick, anyascii, textsearch,
contractions
Successfully installed anyascii-0.3.2 contractions-0.1.73 pyahocorasick-2.0.0
textsearch-0.0.24
```

[39]:

```
import spacy
nlp = spacy.load('en_core_web_sm')
import contractions
import unicodedata
```

[40]:

```
for i, row in train_df.iterrows():
    if i % 1000 == 0:
        print(i)
#     if(row["overview"] and len(str(row["overview"])) < 1000000):
    if row["overview_clean"]:
        # Remove special characters using regular expression
        clean_text = re.sub(r'[^\w\s]', '', str(row["overview_clean"]))
```

```
        # Remove accent characters using the unicodedata module
        no_accent_text = ''.join(char for char in unicodedata.normalize('NFD',␣
↪clean_text) if unicodedata.category(char) != 'Mn')
        # Expand contractions using contractions library
        expanded_text = contractions.fix(no_accent_text)
        doc = nlp(expanded_text)
        # Tokenization
        tokens = [token.text for token in doc]
#         print('tokens', tokens)
        # Stopword removal
        filtered_tokens = [token for token in doc if not token.is_stop]
#         print('filtered_tokens', filtered_tokens)
        # Lemmatization
        lemmas = [token.lemma_ for token in filtered_tokens if not token.is_stop]
#         print('lemmas', lemmas)
        adjectives = []
        nouns = []
        verbs = []
        # Add part-of-speech (POS) tagging
        for token in filtered_tokens:
            if token.pos_ == "ADJ":
                adjectives.append(token.lemma_)
            if token.pos_ == "NOUN" or token.pos_ == "PROPN":
                nouns.append(token.lemma_)
            if token.pos_ == "VERB":
                verbs.append(token.lemma_)
        train_df.at[i, "overview_lemma"] = " ".join(lemmas)
        train_df.at[i, "overview_nouns"] = " ".join(nouns)
        train_df.at[i, "overview_adjectives"] = " ".join(adjectives)
        train_df.at[i, "overview_verbs"] = " ".join(verbs)
        train_df.at[i, "overview_nav"] = " ".join(nouns+adjectives+verbs)
        train_df.at[i, "no_tokens"] = len(lemmas)
        person = []
        org = []
        gpe = [] # geopolitical entity
        date = []
        time = []
        money = []
        for ent in doc.ents:
#             print(ent.text, ent.label_)
            if ent.label_ == "PERSON":
                person.append(ent.text)
            if ent.label_ == "ORG":
                org.append(ent.text)
            if ent.label_ == "DATE":
                date.append(ent.text)
            if ent.label_ == "TIME":
```

```
                time.append(ent.text)
            if ent.label_ == "MONEY":
                money.append(ent.text)
            if ent.label_ == "GPE":
                gpe.append(ent.text)
        train_df.at[i, "overview_person"] = "|".join(person)
        train_df.at[i, "overview_org"] = "|".join(org)
        train_df.at[i, "overview_date"] = "|".join(date)
        train_df.at[i, "overview_time"] = "|".join(time)
        train_df.at[i, "overview_money"] = "|".join(money)
        train_df.at[i, "overview_gpe"] = "|".join(gpe)
```

```
9000
7000
1000
10000
4000
0
6000
8000
3000
```

[41]:
```
train_df.head(10)
```

[41]:
```
          id    imdb_id  popularity    budget    revenue  \
3420   71676  tt1071875    1.481016  57000000  149217355
1672   41360  tt1270291    0.356006    425000          0
293   277713  tt2262161    0.421790         0          0
8306   11066  tt0103859    0.410039  40000000   70100000
1748    2325  tt0432314    0.258982         0          0
3198   14248  tt0465502    0.259988  25000000   30000000
5327   17100  tt0120380    0.459782         0          0
5080    1807  tt0363589    0.426977   3000000   10012022
2859   21997  tt0263467    0.115051         0          0
2851   27834  tt0254199    0.133455         0          0

                       original_title  \
3420  Ghost Rider: Spirit of Vengeance
1672                       Hunter Prey
293                        Sunset Song
8306                         Boomerang
1748                         Leningrad
3198                              Igor
5327                            Trucks
5080                          Elephant
2859    In the Time of the Butterflies
2851                                CQ
```

```
                                                   cast  \
3420  Nicolas Cage|CiarÃ¡n Hinds|Violante Placido|Fe…
1672  Isaac C. Singleton Jr.|Clark Bartram|Damion Po…
293   Peter Mullan|Agyness Deyn|Kevin Guthrie|Hugh R…
8306  Eddie Murphy|Robin Givens|Halle Berry|David Al…
1748  Gabriel Byrne|Mira Sorvino|Armin Mueller-Stahl…
3198  John Cusack|Myleene Klass|Robin Walsh|Matt McK…
5327  Timothy Busfield|Brenda Bakke|Aidan Devine|Rom…
5080  Alex Frost|Eric Deulen|John Robinson|Elias McC…
2859  Salma Hayek|Edward James Olmos|MÃa Maestro|De…
2851  Jeremy Davies|Angela Lindvall|Ã‰lodie Bouchez|…

                                   homepage                     director  \
3420  http://www.thespiritofvengeance.com/  Mark Neveldine|Brian Taylor
1672    http://www.hunterpreythemovie.com/                Sandy Collora
293                                    NaN               Terence Davies
8306                                   NaN              Reginald Hudlin
1748         http://www.leningradfilm.com/           Aleksandr Buravsky
3198                                   NaN              Anthony Leondis
5327                                   NaN                Chris Thomson
5080                                   NaN                 Gus Van Sant
2859                                   NaN              Mariano Barroso
2851                                   NaN                Roman Coppola

                                                tagline  …  \
3420                                    He Rides Again.  …
1672                   One man. One alien. One choice.  …
293                                                 NaN  …
8306                  A Player Who's About to be Played.  …
1748            Some fight. Others fall. All are heroes.  …
3198                        All men aren't created Evil.  …
5327                                                NaN  …
5080  An ordinary high school day. Except that it's …  …
2859  Women had their place. Hers was in the revolut…  …
2851                        Every picture tells a story.  …

                                    overview_adjectives  \
3420               devil human supernatural unsavory
1672  critical unknown alien alive dangerous escaped…
293                                  scottish early
8306                                 successful new
1748                foreign kate dead young idealist
3198                                      evil evil
5327                                          short
5080                ordinary high daily malevolent
2859                      true mirabal underground
```

```
2851                         young personal newfound

                                      overview_verbs  \
3420               come transform flamespewe rescue
1672                      drop catch survive pursue
293                                             come
8306          woo bed find ravish treat traumatise go
1748  invade besiege evacuate presume miss help figh…
3198                       animate hunchbacke aspire
5327                           base tell come attack
5080                       prepare chronicle surround
2859                        inspire murder overthrow
2851                       direct direct cope crumble

                                        overview_nav no_tokens  \
3420  resurface aim world form johnny blaze hiding h…      23.0
1672  prometheus orbit communication life support sy…      33.0
293            daughter farmer age scottish early come       7.0
8306  marcus advertising executive woman company mer…      23.0
1748  nazi germany soviet union troop leningrad jour…      36.0
3198  fable clich scientist assistant scientist disp…      14.0
5327  story stephen king tale truck life owner short…      13.0
5080  school student routine film event school shoot…      14.0
2859  time butterfly story sister plot government tr…      13.0
2851  filmmaker 1960 paris juggle cheesy scifi debac…      22.0

     overview_person                 overview_org    overview_date  \
3420
1672
293                                                 the early 1900s
8306
1748                 nazi germany|nina tsvetnova             1941
3198
5327    stephen king
5080                                                        daily
2859                                                         1960
2851                                                        1960s

      overview_time  overview_money      overview_gpe
3420
1672
293
8306
1748                                  the soviet union
3198
5327
5080
```

```
2859
2851                                              paris

[10 rows x 39 columns]
```

6 Creating a List of Tokens from a List of Documents

[44]:
```python
def my_tokenizer(text):
    return text.split() if (text != None and isinstance(text, str)) else []
```

[45]:
```python
# transform list of documents into a single list of tokens
filtered_tokens = train_df.overview_lemma.map(my_tokenizer).sum()
```

[46]:
```python
print(filtered_tokens[:200])
```

```
['devil', 'resurface', 'aim', 'world', 'human', 'form', 'johnny', 'blaze',
'reluctantly', 'come', 'hiding', 'transform', 'flamespewe', 'supernatural',
'hero', 'ghost', 'rider', 'rescue', '10yearold', 'boy', 'unsavory', 'end',
'prometheus', 'drop', 'orbit', 'communication', 'life', 'support', 'system',
'situation', 'critical', 'status', 'crew', 'prisoner', 'unknown', 'order',
'catch', 'alien', 'prisoner', 'alive', 'survive', 'crew', 'spaceship',
'prometheus', 'pursue', 'dangerous', 'game', 'catandmouse', 'escaped',
'prisoner', 'deserted', 'barren', 'planet', 'hunter', 'prey', 'daughter',
'scottish', 'farmer', 'come', 'age', 'early', '1900s', 'marcus', 'successful',
'advertising', 'executive', 'woo', 'bed', 'woman', 'company', 'merger', 'find',
'new', 'boss', 'ravish', 'jacqueline', 'treat', 'exactly', 'way', 'completely',
'traumatise', 'work', 'go', 'badly', 'downhill', '1941', 'nazi', 'germany',
'invade', 'soviet', 'union', 'troop', 'quickly', 'besiege', 'leningrad',
'foreign', 'journalist', 'evacuate', 'kate', 'davy', 'presume', 'dead', 'miss',
'plane', 'city', 'help', 'nina', 'tsvetnova', 'young', 'idealist', 'police',
'officer', 'fight', 'survival', 'survival', 'people', 'besiege', 'leningrad',
'write', 'marcio', 'eduardo', 'animate', 'fable', 'clich', 'hunchbacke', 'evil',
'scientist', 'assistant', 'aspire', 'scientist', 'displeasure', 'rest', 'evil',
'science', 'community', 'base', 'short', 'story', 'stephen', 'king', 'tell',
'tale', 'truck', 'suddenly', 'come', 'life', 'attack', 'owner', 'ordinary',
'high', 'school', 'student', 'daily', 'routine', 'prepare', 'malevolent',
'film', 'chronicle', 'event', 'surround', 'school', 'shooting', 'time',
'butterfly', 'inspire', 'true', 'story', 'mirabal', 'sister', '1960', 'murder',
'underground', 'plot', 'overthrow', 'government', 'young', 'filmmaker', '1960',
'paris', 'juggle', 'direct', 'cheesy', 'scifi', 'debacle', 'direct', 'personal',
'art', 'film', 'cope', 'crumble', 'relationship', 'girlfriend', 'newfound',
'infatuation', 'scifi', 'film', 'starlet', 'captain', 'mack', 'lead']
```

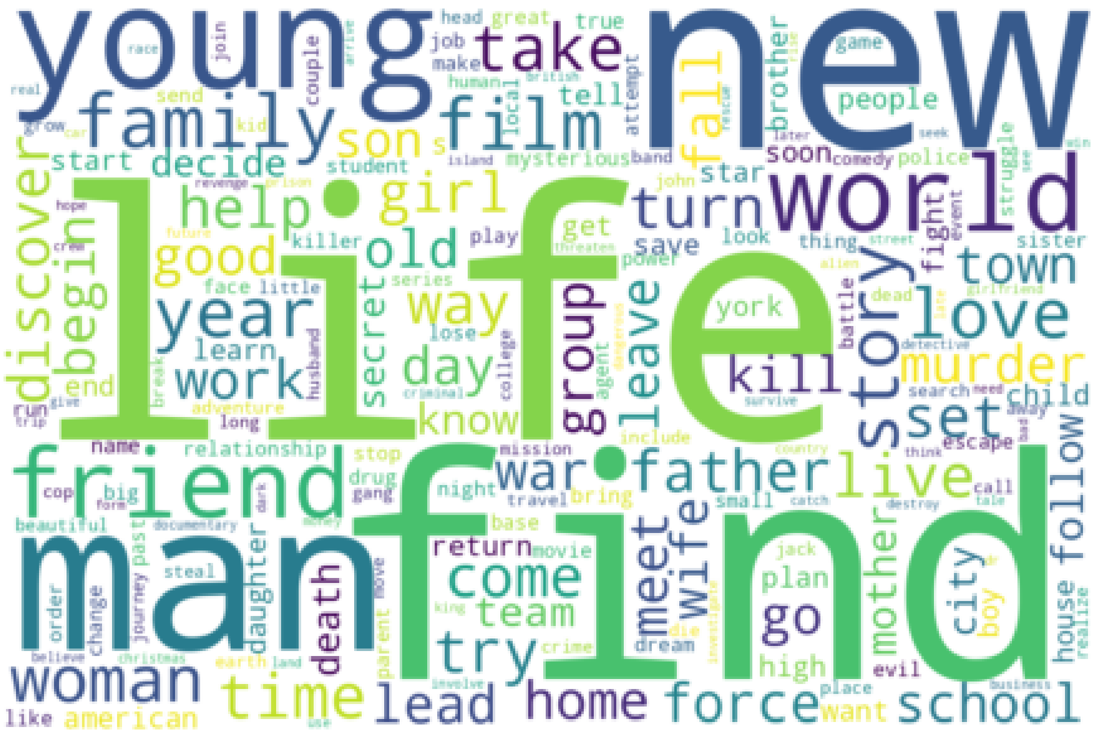
[47]:
```python
counter = Counter(filtered_tokens)
counter.most_common(20)
```

[47]: [('life', 1657),
 ('find', 1592),
 ('new', 1261),
 ('man', 1200),
 ('young', 1198),
 ('world', 1025),
 ('friend', 1022),
 ('family', 953),
 ('story', 891),
 ('film', 875),
 ('love', 856),
 ('year', 854),
 ('woman', 737),
 ('take', 736),
 ('time', 696),
 ('live', 641),
 ('try', 627),
 ('come', 608),
 ('father', 597),
 ('way', 593)]

7 Using Word Clouds

[48]:
```python
from wordcloud import WordCloud

def wordcloud(counter):
    """A small wordloud wrapper"""
    wc = WordCloud(width=1200, height=800,
                   background_color="white",
                   max_words=200)
    wc.generate_from_frequencies(counter)

    # Plot
    fig=plt.figure(figsize=(6, 4))
    plt.imshow(wc, interpolation='bilinear')
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.show()
```

[49]:
```python
# create wordcloud
wordcloud(counter)
```



8 Word frequency by genre

[60]:
```python
train_df['genres']
```

[60]:
```
3420                     Action|Fantasy|Thriller
1672                    Science Fiction|Thriller
293                                        Drama
8306                        Drama|Comedy|Romance
1748                                   War|Drama
                             ...
9939              Horror|Action|Mystery|Thriller
562          Mystery|Drama|History|Family|Thriller
8890     Horror|Science Fiction|Mystery|Thriller
1496                              Comedy|Romance
1378                      Horror|Science Fiction
Name: genres, Length: 8693, dtype: object
```

[51]:
```python
# Remove the "|" and split each cell content accordingly, in colums
train_df_genre = train_df.join(train_df.genres.str.strip('|').str.split('|',␣
↪expand=True).stack().reset_index(level=1, drop=True).rename('genre'))
```

```python
# Check visually the content of the new "genre" column
train_df_genre.genre.tail(4)
```

[51]:
```
10862      Drama
10863    Mystery
10863     Comedy
10865     Horror
Name: genre, dtype: object
```

[63]:
```python
genre_count = train_df_genre.groupby('genre').count()

genre_count = genre_count.reset_index()
genre_count
```

[63]:
```
              genre    id  imdb_id  popularity  budget  revenue  \
0            Action  1910     1906        1910    1910     1910
1         Adventure  1158     1157        1158    1158     1158
2         Animation   569      567         569     569      569
3            Comedy  2990     2989        2990    2990     2990
4             Crime  1095     1095        1095    1095     1095
5       Documentary   412      411         412     412      412
6             Drama  3798     3797        3798    3798     3798
7            Family   966      966         966     966      966
8           Fantasy   729      727         729     729      729
9           Foreign   142      142         142     142      142
10          History   263      263         263     263      263
11           Horror  1307     1307        1307    1307     1307
12            Music   327      326         327     327      327
13          Mystery   647      647         647     647      647
14          Romance  1345     1345        1345    1345     1345
15  Science Fiction   992      987         992     992      992
16         TV Movie   127      127         127     127      127
17         Thriller  2361     2361        2361    2361     2361
18              War   213      213         213     213      213
19          Western   137      137         137     137      137

    original_title  cast  homepage  director  …  overview_adjectives  \
0             1910  1909       515      1905  …                 1910
1             1158  1157       352      1155  …                 1158
2              569   549       209       564  …                  569
3             2990  2983       741      2982  …                 2989
4             1095  1095       260      1094  …                 1095
5              412   385       213       403  …                  411
6             3798  3791       970      3794  …                 3798
7              966   957       258       959  …                  966
8              729   726       215       726  …                  729
9              142   141        33       140  …                  142
```

10	263	261	70	263	…	263
11	1307	1307	308	1306	…	1307
12	327	326	101	323	…	326
13	647	647	157	646	…	647
14	1345	1345	329	1343	…	1344
15	992	991	309	986	…	991
16	127	127	31	123	…	127
17	2361	2359	606	2358	…	2361
18	213	212	52	213	…	213
19	137	137	19	137	…	137

	overview_verbs	overview_nav	no_tokens	overview_person	overview_org \
0	1910	1910	1910	1910	1910
1	1158	1158	1158	1158	1158
2	569	569	569	569	569
3	2989	2989	2989	2989	2989
4	1095	1095	1095	1095	1095
5	411	411	411	411	411
6	3798	3798	3798	3798	3798
7	966	966	966	966	966
8	729	729	729	729	729
9	142	142	142	142	142
10	263	263	263	263	263
11	1307	1307	1307	1307	1307
12	326	326	326	326	326
13	647	647	647	647	647
14	1344	1344	1344	1344	1344
15	991	991	991	991	991
16	127	127	127	127	127
17	2361	2361	2361	2361	2361
18	213	213	213	213	213
19	137	137	137	137	137

	overview_date	overview_time	overview_money	overview_gpe
0	1910	1910	1910	1910
1	1158	1158	1158	1158
2	569	569	569	569
3	2989	2989	2989	2989
4	1095	1095	1095	1095
5	411	411	411	411
6	3798	3798	3798	3798
7	966	966	966	966
8	729	729	729	729
9	142	142	142	142
10	263	263	263	263
11	1307	1307	1307	1307
12	326	326	326	326

```
13             647           647           647           647
14            1344          1344          1344          1344
15             991           991           991           991
16             127           127           127           127
17            2361          2361          2361          2361
18             213           213           213           213
19             137           137           137           137

[20 rows x 40 columns]
```

[64]:

```
top_10_genre = genre_count.nlargest(10, 'id')['genre']
# get top_10_lemma

def my_tokenizer(text):
    return text.split() if(text != None and isinstance(text, str)) else []

# transform list of documents into a single list of tokens
tokens = train_df_genre.overview_lemma.map(my_tokenizer).sum()

counter = Counter(tokens)
top_20_word = counter.most_common(20)

print([t[0] for t in top_20_word])
```

```
['find', 'life', 'new', 'man', 'young', 'world', 'friend', 'family', 'love',
'story', 'year', 'film', 'take', 'woman', 'time', 'help', 'try', 'set', 'come',
'discover']
```

[65]:

```
def get_counter_by_genre(genre):
    print(genre)
    df_filtered = train_df_genre[train_df_genre['genre'] == genre]
    tokens = df_filtered.overview_lemma.map(my_tokenizer).sum()
    return Counter(tokens)

counter_list = {}
for i in top_10_genre:
    counter_list[i] = get_counter_by_genre(i)

data = {'Genre': [genre for genre in top_10_genre]}

for word_info in top_20_word:
    word = word_info[0]
    word_count = []
    for genre in top_10_genre:
        word_count.append(counter_list[genre][word])
    data[word] = word_count
```

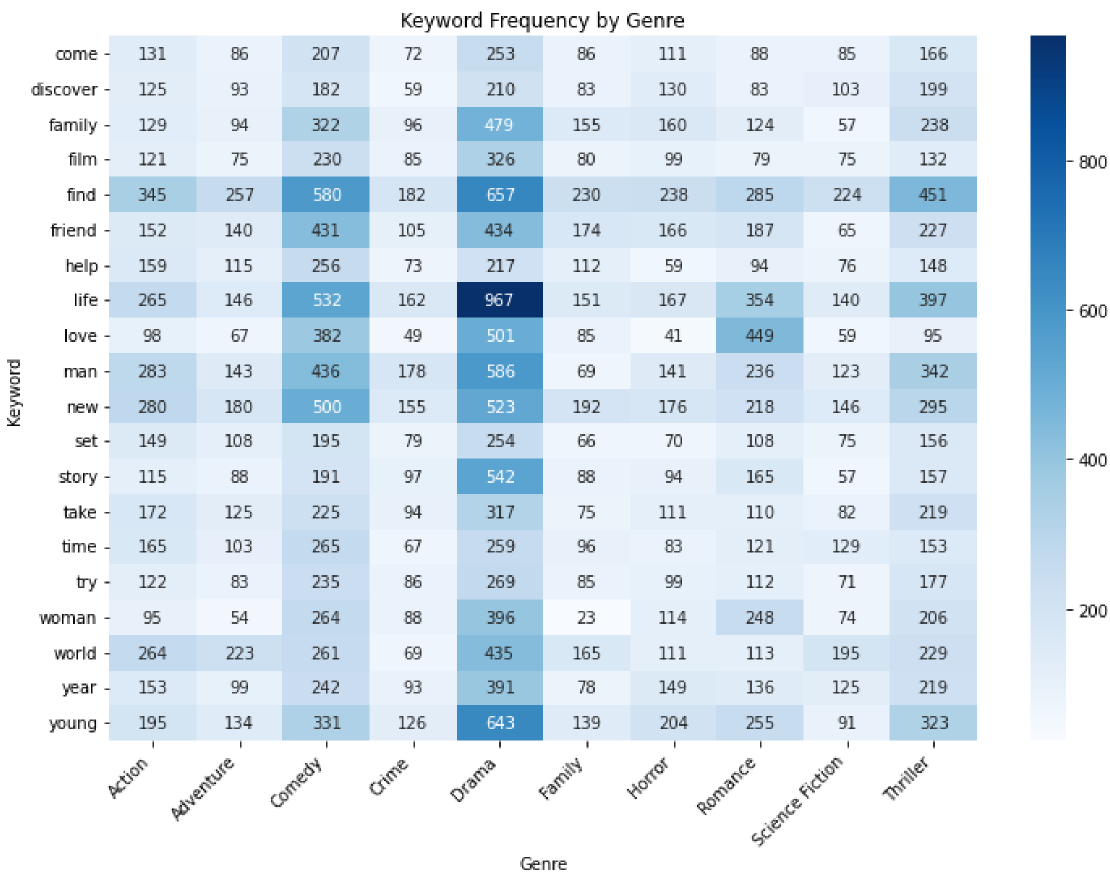
```
Drama
```

```
Comedy
Thriller
Action
Romance
Horror
Adventure
Crime
Science Fiction
Family
```

[66]:
```
top_10_genre
```

[66]:
```
6                Drama
3               Comedy
17            Thriller
0               Action
14             Romance
11              Horror
1            Adventure
4                Crime
15     Science Fiction
7               Family
Name: genre, dtype: object
```

[67]:
```
# Create a sample dataframe
df = pd.DataFrame(data)

# Convert dataframe to long format
df_long = pd.melt(df, id_vars=['Genre'], var_name='Keyword',␣
 ↪value_name='Frequency')


# Set the figure size
plt.figure(figsize=(12, 8))

# Create a heatmap
ax = sns.heatmap(df_long.pivot('Keyword', 'Genre', 'Frequency'), cmap='Blues',␣
 ↪annot=True, fmt='g')

# Set plot title and axis labels
plt.title('Keyword Frequency by Genre')
plt.xlabel('Genre')
plt.ylabel('Keyword')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

# Display the plot
plt.show()
```



9 Genre Breakdown of Named Entity Counts

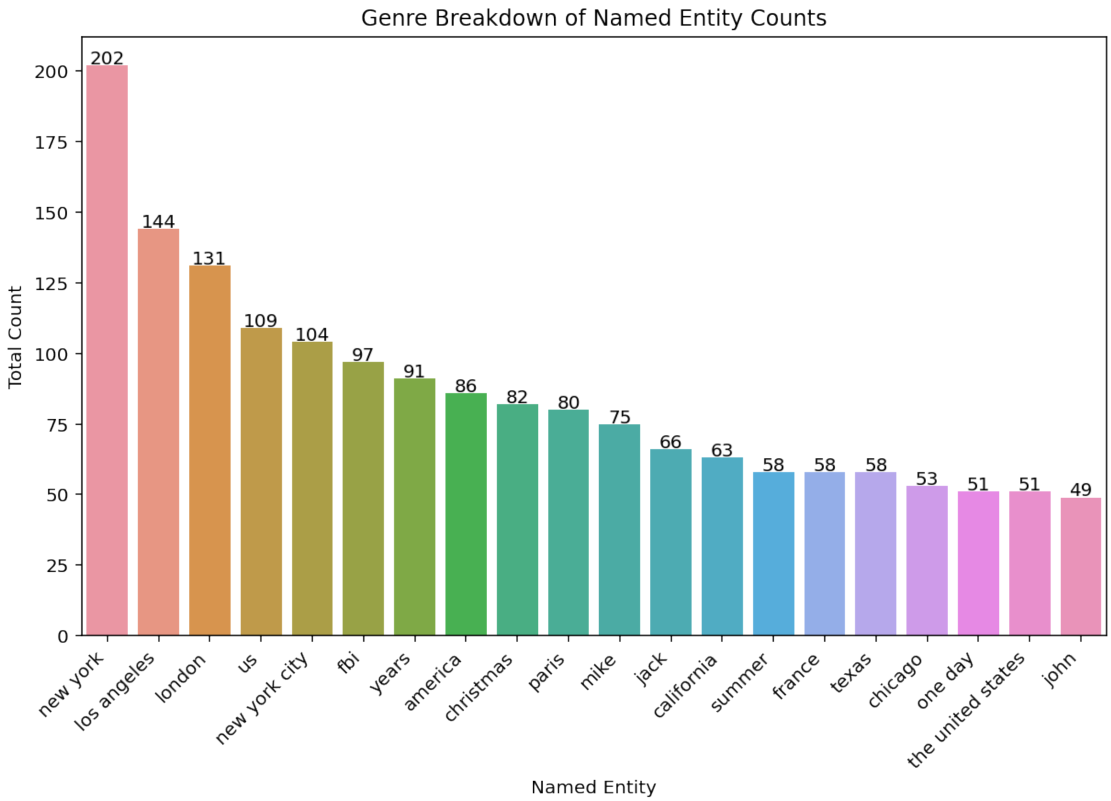
[86]:
```
# get top_entities

def my_tokenizer(text):
    return text.split('|') if(text != None and isinstance(text, str)) else []

# transform list of documents into a single list of tokens
names = train_df.overview_person.map(my_tokenizer).sum()
org = train_df.overview_org.map(my_tokenizer).sum()
date = train_df.overview_date.map(my_tokenizer).sum()
time = train_df.overview_time.map(my_tokenizer).sum()
money = train_df.overview_money.map(my_tokenizer).sum()
gpe = train_df.overview_gpe.map(my_tokenizer).sum()
```

[87]:
```
named_entities = names + org + date + time + money + gpe
named_entities = [x for x in named_entities if x != '']
```

```python
named_entitiy_counter = Counter(named_entities)
top_20_entities = named_entitiy_counter.most_common(20)

print([t[0] for t in top_20_entities])
```

```
['new york', 'los angeles', 'london', 'us', 'new york city', 'fbi', 'years',
'america', 'christmas', 'paris', 'mike', 'jack', 'california', 'summer',
'france', 'texas', 'chicago', 'one day', 'the united states', 'john']
```

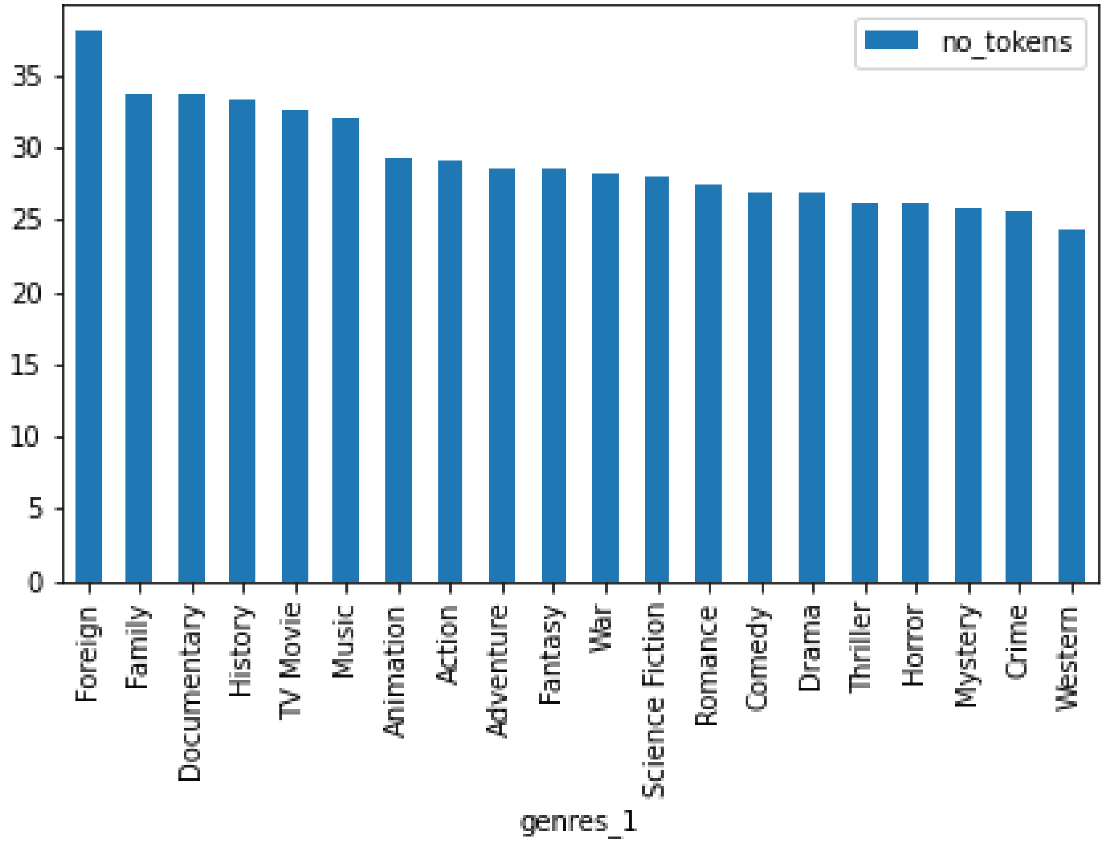
[88]:
```python
names = [t[0] for t in top_20_entities]
count = [t[1] for t in top_20_entities]

fig = plt.figure(figsize=(10,6))
sns.set_palette("muted")

named_entity_counts = pd.DataFrame({'names': names, 'count': count})
ax = sns.barplot(data=named_entity_counts, x='names', y='count',
                 order=named_entity_counts.sort_values('count',␣
 ↪ascending=False)['names'])

# Add numerical values to the bars
for p in ax.patches:
    ax.text(p.get_x() + p.get_width()/2, p.get_height()+0.5, int(p.get_height()),
            ha='center', fontsize=10)

ax.set(title='Genre Breakdown of Named Entity Counts', xlabel='Named Entity',␣
 ↪ylabel='Total Count')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

plt.show()
```



10 Exploring Text Complexity

[70]:
```
train_df['no_tokens'] = train_df.overview_lemma\
  .map(lambda l: 0 if (l==None or not isinstance(l, str)) else len(l.split()))
```

[71]:
```
# mean number of tokens by category
train_df.groupby(['genres_1']) \
  .agg({'no_tokens':'mean'}) \
  .sort_values(by='no_tokens', ascending=False) \
  .plot(kind='bar', figsize=(7,4));
```

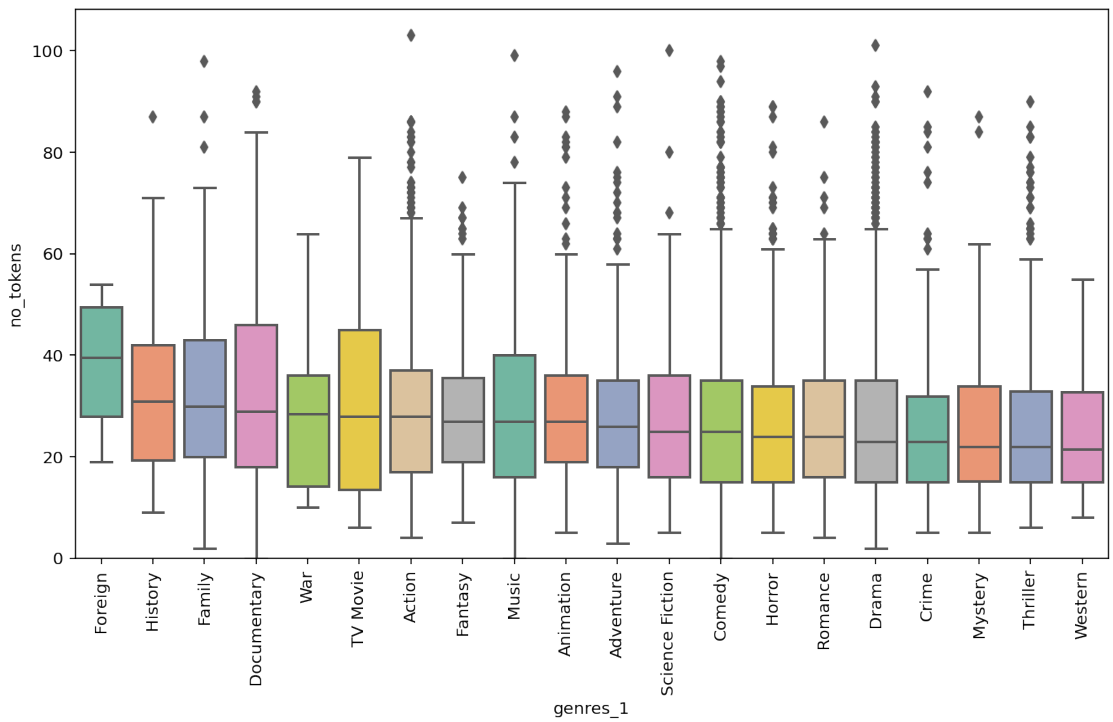


[72]:

```
# render plots as retina or png, because svg is very slow
%config InlineBackend.figure_format = 'retina'

import seaborn as sns

def multi_boxplot(data, x, y, ylim = None):
    '''Wrapper for sns boxplot with cut-off functionality'''
    # plt.figure(figsize=(30, 5))
    fig, ax = plt.subplots()
    plt.xticks(rotation=90)

    # order boxplots by median
    ordered_values = data.groupby(x)[[y]] \
                         .median() \
                         .sort_values(y, ascending=False) \
                         .index

    sns.boxplot(x=x, y=y, data=data, palette='Set2',
                order=ordered_values)
```

```python
    fig.set_size_inches(11, 6)

    # cut-off y-axis at value ylim
    ax.set_ylim(0, ylim)
```

[73]:
```python
multi_boxplot(train_df, 'genres_1', 'no_tokens');
```

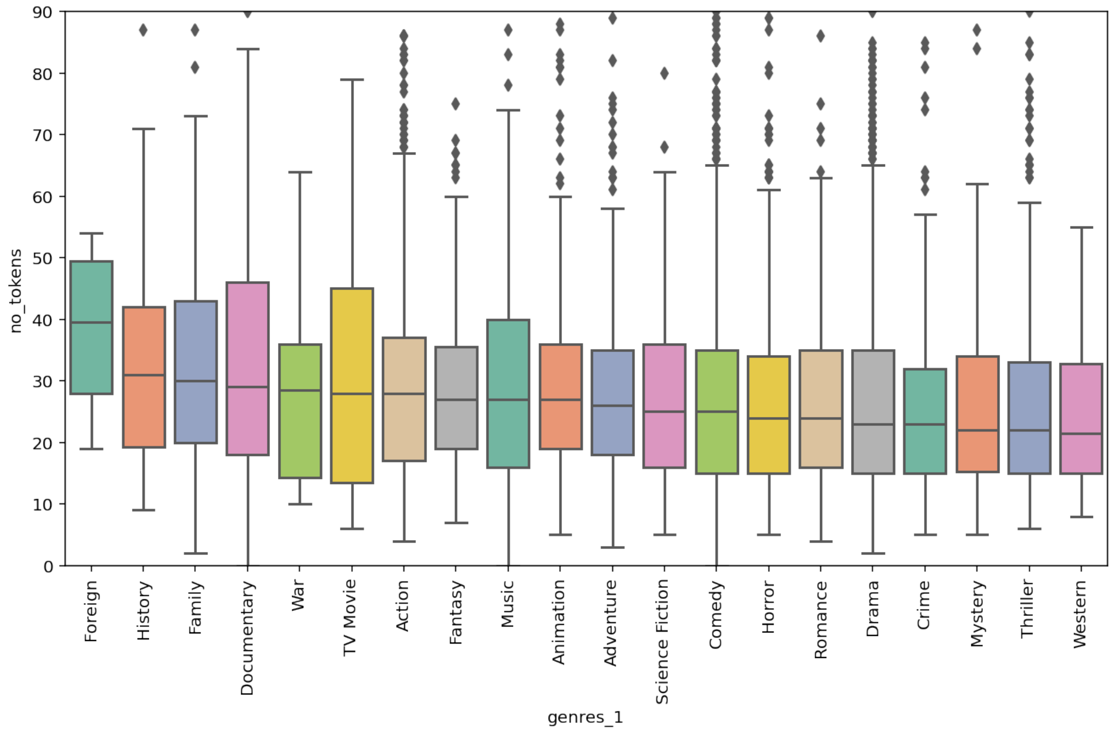


[78]:
```python
# print text of outliers
train_df['overview_lemma'][train_df.no_tokens > 90]
```

[78]:
```
2401    ongoing celebration 20th anniversary sweden op…
1317    hear insane rumour scandal attach illfate 1996…
3817    la vida ha llevado julin parez por caminos equ…
5691    wealthy american housewife mary morgan take bu…
5647    puppy stumble power ring inspiron alien artifa…
3192    gianni 50 ans et des poussire vit avec sa mama…
3763    year 2125 alec mason lead martian colony freed…
7756    la antena english aerial 2007 argentine drama …
3867    la vie nest pas rise tous les jours pour solwe…
3590    raise street turnofthe century london orphan p…
3551    dylan schoenfield pink princess upscale los an…
3894    story film odyssey write direct awardwinne fil…
3598    arabian peninsula 1930 war leader come face fa…
9899    kelly prostitute want transform life beat pimp…
```

```
435     christmas day away paige summerland los angele…
Name: overview_lemma, dtype: object
```

[79]:
```
# cut-off diagram at y=175
multi_boxplot(train_df, 'genres_1', 'no_tokens', ylim=90)
```



11 Finding Prominent Genres

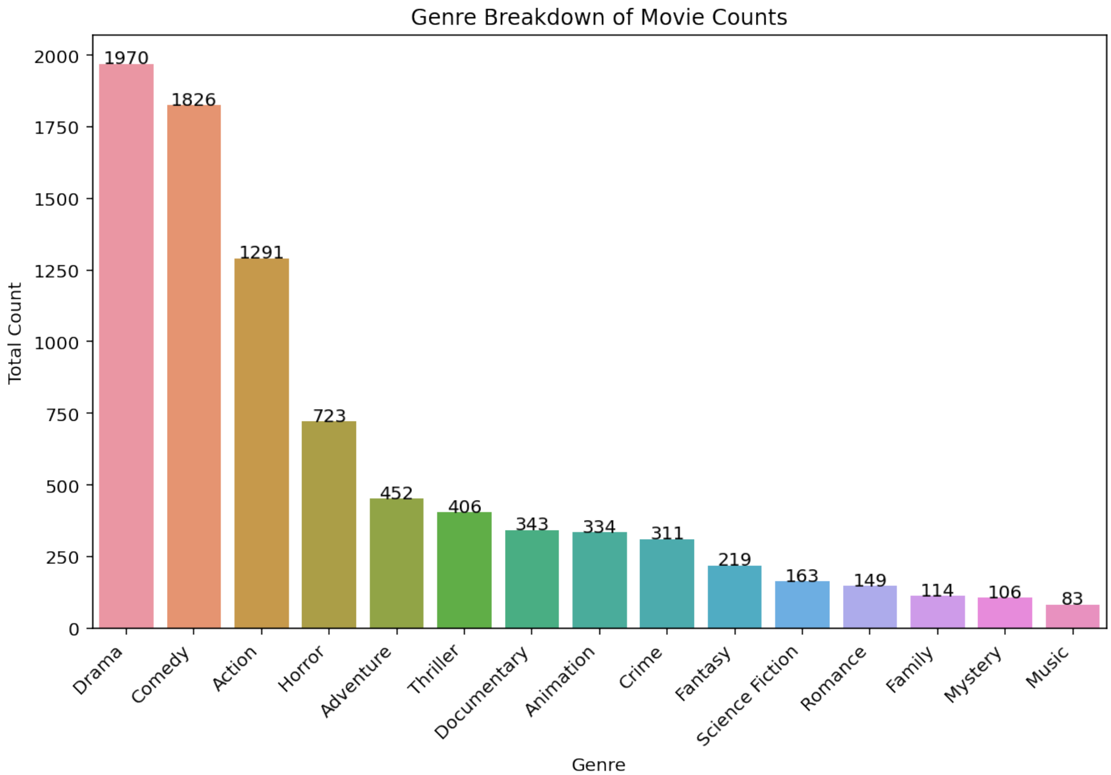
[76]:
```
genre_counter = Counter(train_df.genres_1)
genre_counter.most_common(15)
```

[76]:
```
[('Drama', 1970),
 ('Comedy', 1826),
 ('Action', 1291),
 ('Horror', 723),
 ('Adventure', 452),
 ('Thriller', 406),
 ('Documentary', 343),
 ('Animation', 334),
 ('Crime', 311),
 ('Fantasy', 219),
```

```
 ('Science Fiction', 163),
 ('Romance', 149),
 ('Family', 114),
 ('Mystery', 106),
 ('Music', 83)]
```

[83]:
```
genres = [t[0] for t in genre_counter.most_common(15)]
count = [t[1] for t in genre_counter.most_common(15)]
```

[85]:
```
fig = plt.figure(figsize=(10,6))
sns.set_palette("muted")

df = pd.DataFrame({'genres': genres, 'count': count})
ax = sns.barplot(data=df, x='genres', y='count',
                 order=df.sort_values('count', ascending=False)['genres'])

# Add numerical values to the bars
for p in ax.patches:
    ax.text(p.get_x() + p.get_width()/2, p.get_height()+0.5, int(p.get_height()),
            ha='center', fontsize=10)

ax.set(title='Genre Breakdown of Movie Counts', xlabel='Genre', ylabel='Total␣
 ↪Count')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

plt.show()
```


Genre Breakdown of Movie Counts
Total Count
Genre
0
250
500
750
1000
1250
1500
1750
2000
1970
1826
1291
723
452
406
343
334
311
219
163
149
114
106
83
Drama
Comedy
Action
Horror
Adventure
Thriller
Documentary
Animation
Crime
Fantasy
Science Fiction
Romance
Family
Mystery
Music