Skoroszyt do rekomendacji filmu na podstawie algorytmu Machine Learning podobienstwa kosinusowego - Analiza objaśniająca i storytelling

SIWB, Adam Heczko, 2020/21Z

Główne cechy skoroszytu rekomenduj-film

Skoroszyt składa się z następujących sekcji:

- Wczytanie danych
- Analiza eksploracyjna i pre-processing
- Analiza objaśniająca i prezentacja głównych danych statystycznych, storytelling
- Zawiera więcej niż 4 wykresy
- Działa w środowisku Binder, aczkolwiek ze względów wydajnościowych wskazane jest uruchomienie na wydajnej maszynie lokalnej
- Bazuje na zbiorze danych IMDb z platformy Kaggle, https://www.kaggle.com/stefanoleone992/imdb-extensive-dataset (https://www.kaggle.com/stefanoleone992/imdb-extensive-dataset)
- W celu predykcji podobnego filmu, wykorzystuje algorytm uczenia maszynowego (ML) "cosine similarity" zaimplementowany na podstawie biblioteki SciKit.

Skoroszyt wymaga instalacji pakietów:

- pip3 install --user numpy
- pip3 install --user pandas
- pip3 install --user matplotlib
- pip3 install --user currencyconverter
- pip3 install --user wordcloud
- pip3 install --user seaborn
- pip3 install --user nltk
- pip3 install --user sklearn # Podobienstwo kosinusowe

Skoroszyt działa w środowisku MyBinder, jednak ze względu na duży rozmiar zbioru IMDb, rekomendowane jest uruchomienie lokalne ponieważ przetwarzanie tak dużej ilości danych jest czasochłonne.

Repozytorium skoroszytu: https://github.com/miradam/siwb-rekomenduj-film (https://github.com/miradam/siwb-rekomenduj-film)

In [1]:

```
# Import bibliotek
# Pobranie NLTK Stopwords - potrzebne do obrobki tekstu IMDb

import numpy as np
import pandas as pd
pd.options.mode.chained_assignment = None
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='whitegrid')
from currency_converter import CurrencyConverter
import datetime
from wordcloud import WordCloud, STOPWORDS
import textwrap
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.feature_extraction.text import CountVectorizer
import nltk
nltk.download('stopwords')
```

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

Out[1]:

```
True
```

Ładowanie danych

Proszę wybrać sposób ładowania danych wejściowych. Możne je załadować z dysku lokalnego (szybkie) bądź też z Github (wolniejsze).

Wariant 1 - skoroszyt uruchomiony na maszynie lokalnej, ładujemy z dysku (szybkie)

In [2]:

```
# Ladowanie danych do Pandas Data Frame - lokalnie

data_imdb_movies = pd.read_csv('IMDb-movies.csv', low_memory=False)
data_imdb_names = pd.read_csv('IMDb-names.csv', low_memory=False)
data_imdb_title_principals = pd.read_csv('IMDb-title_principals.csv', low_memory=Fa
```

Wariant 2 - skoroszyt uruchomiony w MyBinder, ładujemy z Github (powolne)

In [63]:

```
# Ladowanie danych do Pandas Data Frame - z Github, ze względu na wielki rozmiar da
# używany jest format git-lfs
# LFS - Large File Storage , media.githubusercontent.com


data_imdb_movies = pd.read_csv('https://media.githubusercontent.com/media/miradam/s
data_imdb_names = pd.read_csv('https://media.githubusercontent.com/media/miradam/si
data_imdb_title_principals = pd.read_csv('https://media.githubusercontent.com/media
```

In [3]:

```
# Sprawdzenie kolumn zbioru IMDb-movies.csv
imdb_movies = data_imdb_movies.copy()
imdb_movies.head()
```

Out[3]:

	imdb_title_id	title	original_title	year	date_published	genre	duration	country
0	tt0000009	Miss Jerry	Miss Jerry	1894	1894-10-09	Romance	45	USA
1	tt0000574	The Story of the Kelly Gang	The Story of the Kelly Gang	1906	1906-12-26	Biography, Crime, Drama	70	Australia
2	tt0001892	Den sorte drøm	Den sorte drøm	1911	1911-08-19	Drama	53	Germany, Denmark
3	tt0002101	Cleopatra	Cleopatra	1912	1912-11-13	Drama, History	100	USA
4	tt0002130	L'Inferno	L'Inferno	1911	1911-03-06	Adventure, Drama, Fantasy	68	Italy

5 rows × 22 columns

In [4]:

```
# Sprawdzenie kolumn zbioru IMDb-names.csv
# Kopiuje DataFrame zeby oryginalny obiekt nie ulegl zmianie
imdb_names = data_imdb_names.copy()
imdb_names.head()
```

Out[4]:

	imdb_name_id	name	birth_name	height	bio	birth_details	date_of_birth	place_
0	nm0000001	Fred Astaire	Frederic Austerlitz Jr.	177.0	Fred Astaire was born in Omaha, Nebraska, to J...	May 10, 1899 in Omaha, Nebraska, USA	1899-05-10	Nebras
1	nm0000002	Lauren Bacall	Betty Joan Perske	174.0	Lauren Bacall was born Betty Joan Perske on Se...	September 16, 1924 in The Bronx, New York City...	1924-09-16	Tl New ` New Y
2	nm0000003	Brigitte Bardot	Brigitte Bardot	166.0	Brigitte Bardot was born on September 28, 1934...	September 28, 1934 in Paris, France	1934-09-28	Paris
3	nm0000004	John Belushi	John Adam Belushi	170.0	John Belushi was born in Chicago, Illinois, US...	January 24, 1949 in Chicago, Illinois, USA	1949-01-24	Illin
4	nm0000005	Ingmar Bergman	Ernst Ingmar Bergman	179.0	Ernst Ingmar Bergman was born July 14, 1918, t...	July 14, 1918 in Uppsala, Uppsala län, Sweden	1918-07-14	Upp

In [5]:

```
# Sprawdzenie kolumn zbioru  IMDb-title_principals.csv
imdb_title_principals = data_imdb_title_principals.copy()
imdb_title_principals.head()
```

Out[5]:

	imdb_title_id	ordering	imdb_name_id	category	job	characters
0	tt0000009	1	nm0063086	actress	NaN	["Miss Geraldine Holbrook (Miss Jerry)"]
1	tt0000009	2	nm0183823	actor	NaN	["Mr. Hamilton"]
2	tt0000009	3	nm1309758	actor	NaN	["Chauncey Depew - the Director of the New Yor...
3	tt0000009	4	nm0085156	director	NaN	NaN
4	tt0000574	1	nm0846887	actress	NaN	["Kate Kelly"]

In [29]:

```
# Informacja o typach danych

print(imdb_movies.info())
print('\n')
print(imdb_names.info())
print('\n')
print(imdb_title_principals.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 34325 entries, 0 to 85839
Data columns (total 22 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   imdb_title_id          34325 non-null  object 
 1   title                  34325 non-null  object 
 2   original_title         34325 non-null  object 
 3   year                   34325 non-null  object 
 4   date_published         34325 non-null  object 
 5   genre                  34325 non-null  object 
 6   duration               34325 non-null  int64  
 7   country                34325 non-null  object 
 8   language               33961 non-null  object 
 9   director               34289 non-null  object 
 10  writer                 34106 non-null  object 
 11  production_company     33085 non-null  object 
 12  actors                 34297 non-null  object 
 13  description            34228 non-null  object 
 14  avg_vote               34325 non-null  float64
 15  votes                  34325 non-null  int64  
 16  budget                 13626 non-null  object 
 17  usa_gross_income       10587 non-null  object 
 18  worlwide_gross_income  11341 non-null  object 
 19  metascore              9508 non-null   float64
 20  reviews_from_users     33931 non-null  float64
 21  reviews_from_critics   32250 non-null  float64
dtypes: float64(4), int64(2), object(16)
memory usage: 6.0+ MB
None


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 297705 entries, 0 to 297704
Data columns (total 17 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   imdb_name_id           297705 non-null  object 
 1   name                   297705 non-null  object 
 2   birth_name             297705 non-null  object 
 3   height                 44681 non-null   float64
 4   bio                    204698 non-null  object 
 5   birth_details          110612 non-null  object 
 6   date_of_birth          110612 non-null  object 
 7   place_of_birth         103992 non-null  object 
 8   death_details          39933 non-null   object 
 9   date_of_death          39933 non-null   object 
 10  place_of_death         37038 non-null   object 
 11  reason_of_death        22694 non-null   object 
 12  spouses_string         45352 non-null   object 
 13  spouses                297705 non-null  int64  
```

```
 14  divorces              297705 non-null  int64
 15  spouses_with_children 297705 non-null  int64
 16  children              297705 non-null  int64
dtypes: float64(1), int64(4), object(12)
memory usage: 38.6+ MB
None


<class 'pandas.core.frame.DataFrame'>
Int64Index: 835512 entries, 0 to 835511
Data columns (total 8 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   imdb_title_id  835512 non-null  object
 1   ordering       835512 non-null  int64
 2   imdb_name_id   835512 non-null  object
 3   name_x         835512 non-null  object
 4   category       835512 non-null  object
 5   job            212731 non-null  object
 6   characters     340835 non-null  object
 7   name_y         835512 non-null  object
dtypes: int64(1), object(7)
memory usage: 57.4+ MB
None
```

Czyszczenie i normalizacja danych

In [30]:

```
# Łączenie danych ze zbiorow principals, names
imdb_title_principals = pd.merge(imdb_title_principals, imdb_names[['imdb_name_id',

# Sortowanie danych i wyświetlenie
imdb_title_principals = imdb_title_principals[['imdb_title_id', 'ordering', 'imdb_n
imdb_title_principals.head()
```

Out[30]:

	imdb_title_id	ordering	imdb_name_id	name	category	job	characters
0	tt0000009	1	nm0063086	Blanche Bayliss	actress	NaN	["Miss Geraldine Holbrook (Miss Jerry)"]
1	tt0000009	2	nm0183823	William Courtenay	actor	NaN	["Mr. Hamilton"]
2	tt0020403	2	nm0183823	William Courtenay	actor	NaN	["The Minister - Guillotine Sequence"]
3	tt0000009	3	nm1309758	Chauncey Depew	actor	NaN	["Chauncey Depew - the Director of the New Yor...
4	tt0000009	4	nm0085156	Alexander Black	director	NaN	NaN

In [31]:

```
# Tworzenie kolumny "cinematographer" w zbiorze Movies
cinematographer_name = imdb_title_principals[imdb_title_principals['category']=='ci
cinematographer_name.rename(columns={'name' : 'cinematographer'}, inplace = True)
imdb_movies = pd.merge(imdb_movies, cinematographer_name[['imdb_title_id', 'cinemat

cinematographer_name.head()
# imdb_title_principals.head()
# imdb_movies.head()
```

Out[31]:

	index	imdb_title_id	ordering	imdb_name_id	cinematographer	category	job	chai
0	14	tt0000574	10	nm0675239	Orrie Perry	cinematographer	NaN	
1	23	tt0001892	7	nm0423762	Adam Johansen	cinematographer	NaN	
2	24	tt0001892	8	nm0005869	Guido Seeber	cinematographer	NaN	
3	25	tt0003419	9	nm0005869	Guido Seeber	cinematographer	NaN	
4	26	tt0004026	6	nm0005869	Guido Seeber	cinematographer	NaN	

In [32]:

```
# Łączenie danych do kolumny "cinematographer" i normalizacja
duplicated_data = imdb_movies[imdb_movies['imdb_title_id'].duplicated(keep = False)
multiple_names_cinematographer = duplicated_data.groupby('imdb_title_id')['cinemato
duplicated_data.drop(['cinematographer'], axis = 1, inplace = True)
duplicated_data.drop_duplicates(subset=['imdb_title_id'], inplace = True)
data_multiple_names = pd.merge(duplicated_data, multiple_names_cinematographer[['im
data_multiple_names[['imdb_title_id', 'cinematographer']].head()
```

Out[32]:

	imdb_title_id	cinematographer
0	tt0004134	Dal Clawson, George W. Hill
1	tt0005149	Robert Newhard, Joseph H. August
2	tt0007340	King D. Gray, Stephen S. Norton
3	tt0007755	John W. Brown, Ben F. Reynolds
4	tt0008196	Walter Stradling, Charles Rosher

In [33]:

```
# Usuwanie zduplikowanych danych z kolumny 'cinematographer'
imdb_movies.drop_duplicates(subset=['imdb_title_id'], keep = False, inplace = True)
imdb_movies = pd.concat((imdb_movies, data_multiple_names), sort = False).sort_valu

# Zmiana położenia kolumny 'cinematographer'
cols = imdb_movies.columns.tolist()
cols = cols[0:13] + cols[-1:] + cols [13:-1]
imdb_movies = imdb_movies[cols]
imdb_movies.head()
```

Out[33]:

	imdb_title_id	title	original_title	year	date_published	genre	duration	country
0	tt0000009	Miss Jerry	Miss Jerry	1894	1894-10-09	Romance	45	USA
1	tt0002101	Cleopatra	Cleopatra	1912	1912-11-13	Drama, History	100	USA
2	tt0002199	From the Manger to the Cross; or, Jesus of Naz...	From the Manger to the Cross; or, Jesus of Naz...	1912	1913	Biography, Drama	60	USA
3	tt0002461	Richard III	Richard III	1912	1912-10-15	Drama	55	France, USA
4	tt0003167	Amore di madre	Home, Sweet Home	1914	1914-05-17	Drama	55	USA

5 rows × 23 columns

In [34]:

```
# Filtrowanie danych. Pozostawienie rekordów dotyczących wyłącznie filmów wyproduko
# Można również łatwo pozostawić filmy NIE wyprodukowane w USA poprzez zmianę warun
imdb_movies['country'].fillna('', inplace = True)
imdb_movies = imdb_movies[imdb_movies['country'].str.contains('USA')]
```

In [35]:

```
# Czyszczenie i normalizacja danych w zakresie waluty i konwersja na USD
imdb_movies['budget_currency'] = imdb_movies['budget'].str.split(' ', expand = True
imdb_movies['budget_currency'] = imdb_movies['budget_currency'].str.replace('$', 'U
imdb_movies['budget'] = imdb_movies['budget'].str.split(' ', expand = True)[1]
imdb_movies['budget'] = pd.to_numeric(imdb_movies['budget'], errors='coerce')

# Czyszczenie i normalizacja danych związanych z przychodami filmu - przeliczenie w
# na USD
imdb_movies['worlwide_gross_income_currency'] = imdb_movies['worlwide_gross_income'
imdb_movies['worlwide_gross_income_currency'] = imdb_movies['worlwide_gross_income_
imdb_movies['worlwide_gross_income'] = imdb_movies['worlwide_gross_income'].str.spl
imdb_movies['worlwide_gross_income'] = pd.to_numeric(imdb_movies['worlwide_gross_in

# Przygotowanie kolumny Konwersja usa_gross_income_currency do konwersji na typ num
imdb_movies['usa_gross_income_currency'] = imdb_movies['usa_gross_income'].str.spli
imdb_movies['usa_gross_income_currency'] = imdb_movies['usa_gross_income_currency']
imdb_movies['usa_gross_income'] = imdb_movies['usa_gross_income'].str.split(' ', ex
imdb_movies['usa_gross_income'] = pd.to_numeric(imdb_movies['usa_gross_income'], er
```

```
<ipython-input-35-4ce2eb479ade>:3: FutureWarning: The default value o
f regex will change from True to False in a future version. In additi
on, single character regular expressions will*not* be treated as lite
ral strings when regex=True.
  imdb_movies['budget_currency'] = imdb_movies['budget_currency'].st
r.replace('$', 'USD')
<ipython-input-35-4ce2eb479ade>:10: FutureWarning: The default value
of regex will change from True to False in a future version. In addit
ion, single character regular expressions will*not* be treated as lit
eral strings when regex=True.
  imdb_movies['worlwide_gross_income_currency'] = imdb_movies['worlwi
de_gross_income_currency'].str.replace('$', 'USD')
<ipython-input-35-4ce2eb479ade>:18: FutureWarning: The default value
of regex will change from True to False in a future version. In addit
ion, single character regular expressions will*not* be treated as lit
eral strings when regex=True.
  imdb_movies['usa_gross_income_currency'] = imdb_movies['usa_gross_i
ncome_currency'].str.replace('$', 'USD')
```

Uwaga! poniższe operacje są długotrwałe ze względu na rozmiar danych i fakt że operujemy na polach tekstowych.

In [36]:

```
# Konwersja danych tekstowych na typ liczbowy - ujednolicenie do USD

c = CurrencyConverter()
for i in range(imdb_movies.shape[0]):
    # budget column
    if (imdb_movies['budget_currency'].iloc[i] in c.currencies):
        imdb_movies['budget'].iloc[i] = c.convert(imdb_movies['budget'].iloc[i], im
    else :
        imdb_movies['budget'].iloc[i] = np.nan

    # worlwide_gross_income column
    if (imdb_movies['worlwide_gross_income_currency'].iloc[i] in c.currencies):
        imdb_movies['worlwide_gross_income'].iloc[i] = c.convert(imdb_movies['worlw
                                                          imdb_movies['worlwide_g
    else :
        imdb_movies['worlwide_gross_income'].iloc[i] = np.nan

    # usa_gross_income column
    if (imdb_movies['usa_gross_income_currency'].iloc[i] in c.currencies):
        imdb_movies['usa_gross_income'].iloc[i] = c.convert(imdb_movies['usa_gross_
                                                     imdb_movies['usa_gross_incom
                                                     )
    else :
        imdb_movies['usa_gross_income'].iloc[i] = np.nan
```

Analiza eksploracyjna

Analiza danych liczbowych

In [37]:

```
num_data = ['duration', 'avg_vote', 'votes', 'budget', 'usa_gross_income', 'worlwid
            'metascore', 'reviews_from_users', 'reviews_from_critics']
imdb_movies[num_data].describe()
```

Out[37]:

	duration	avg_vote	votes	budget	usa_gross_income	worlwide_
count	34325.000000	34325.000000	3.432500e+04	1.361000e+04	1.058700e+04	
mean	94.605273	5.609413	1.999168e+04	1.616476e+07	2.745402e+07	
std	18.796947	1.273202	8.161522e+04	3.125879e+07	5.607265e+07	
min	42.000000	1.100000	9.900000e+01	0.000000e+00	3.000000e+01	
25%	85.000000	4.800000	2.520000e+02	6.700000e+05	2.813985e+05	
50%	92.000000	5.800000	7.380000e+02	3.341750e+06	6.014341e+06	
75%	102.000000	6.500000	4.561000e+03	1.800000e+07	3.072612e+07	
max	398.000000	9.700000	2.278845e+06	3.560000e+08	9.366622e+08	

Analiza danych wg kategorii

Which Decade Has Release Most Movies and Highest Average Vote (Rating)

In [38]:

```
# Zmiana w kolumnie 'year'
imdb_movies['year'].replace('TV Movie 2019', 2019, inplace = True)
imdb_movies['year'] = imdb_movies['year'].astype(int)

# Grupowanie po kolumnie 'decades'
movies_by_decades = imdb_movies[['imdb_title_id', 'original_title', 'year','avg_vot
decades = movies_by_decades['year']//10*10
decades = decades.astype(str)+' - '+ (decades+9).astype(str)
decades_column = pd.DataFrame(decades)
movies_by_decades.insert(3, 'decades', decades_column)
movies_by_decades.head()
```

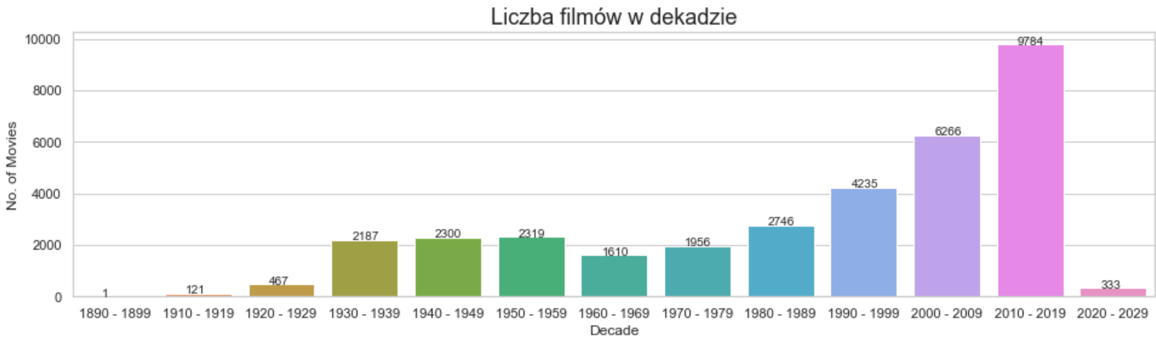
Out[38]:

	imdb_title_id	original_title	year	decades	avg_vote	votes
0	tt0000009	Miss Jerry	1894	1890 - 1899	5.9	154
1	tt0002101	Cleopatra	1912	1910 - 1919	5.2	446
2	tt0002199	From the Manger to the Cross; or, Jesus of Naz...	1912	1910 - 1919	5.7	484
3	tt0002461	Richard III	1912	1910 - 1919	5.5	225
4	tt0003167	Home, Sweet Home	1914	1910 - 1919	5.8	187

Analiza objaśniająca i storytelling

In [39]:

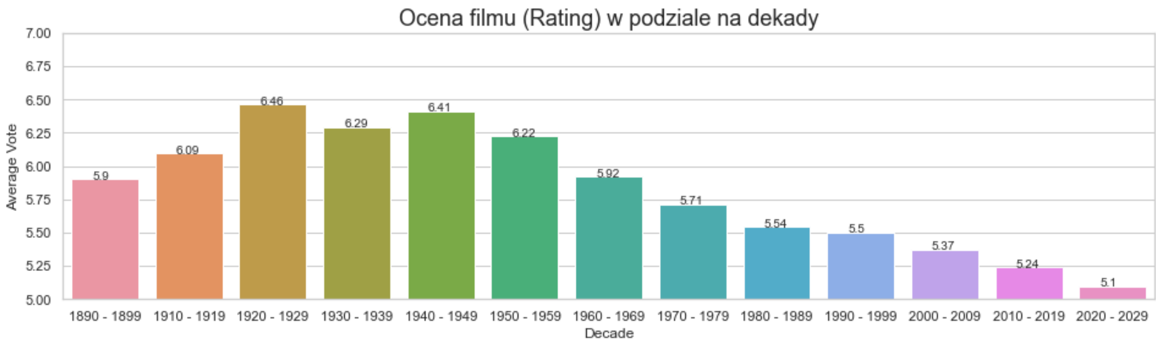
```
# Wizualizacja - wykres typu barchart

max_width = 15
fig, ax = plt.subplots(figsize = (16,4))
decades = movies_by_decades.groupby('decades')['imdb_title_id'].count().index
count = movies_by_decades.groupby('decades')['imdb_title_id'].count()
sns.barplot(ax = ax, x = decades, y = count)
ax.set_title('Liczba filmów w dekadzie', fontsize = 18)
ax.set_xlabel('Decade')
for index,count in enumerate(count.astype(int)):
       ax.text(x=index-0.15 , y =count+1 , s=f"{count}" , fontdict=dict(fontsize=10
ax.set_ylabel('No. of Movies')
plt.show()
```



Widać wyraźny, znaczący przyrost liczby wyprodukowanych filmów.

In [40]:

```
# Wizualizacja oceny filmu, w rozbiciu na dekady

max_width = 15
fig, ax = plt.subplots(figsize = (16,4))
decades = movies_by_decades.groupby('decades')['avg_vote'].mean().index
avg_vote = movies_by_decades.groupby('decades')['avg_vote'].mean()
sns.barplot(ax = ax, x = decades, y = avg_vote)
ax.set_title('Ocena filmu (Rating) w podziale na dekady', fontsize = 18)
ax.set_xlabel('Decade')
for index,avg_vote in enumerate(np.round(avg_vote, 2)):
       ax.text(x=index-0.15 , y =avg_vote+0 , s=f"{avg_vote}" , fontdict=dict(fonts
ax.set_ylabel('Average Vote')
ax.set_ylim((5, 7))

plt.show()
```



Widać korelację pomiędzy średnią jakością filmów a ilością wyprodukowanych.

Analiza w podziale na miesiące

In [41]:

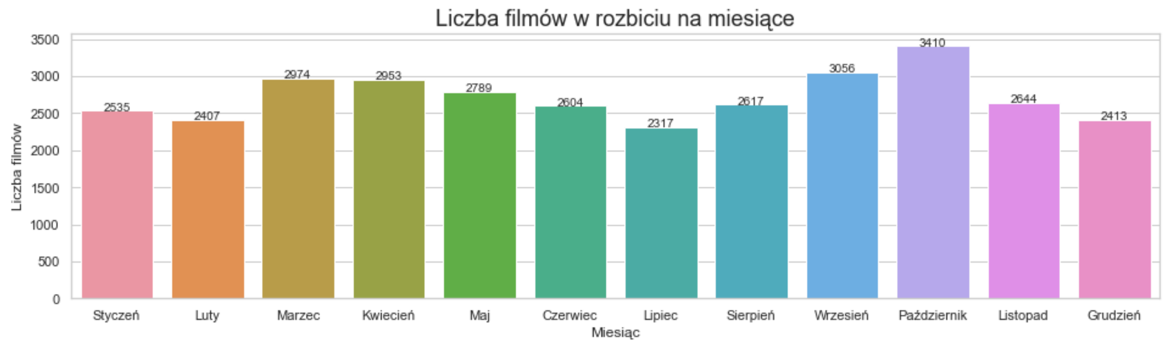
```
# Preprocessing

imdb_movies['date_published'].replace('TV Movie 2019', 2019, inplace = True)
movies_published = imdb_movies[['imdb_title_id', 'original_title', 'genre', 'date_p
movies_published['month_published'] = [month[5:7] for month in movies_published['da

# Zamiana pustych wartości na NaN
movies_published['month_published'][movies_published['month_published']==''] = np.n
movies_published.head()
```

Out[41]:

	imdb_title_id	original_title	genre	date_published	month_published
0	tt0000009	Miss Jerry	Romance	1894-10-09	10
1	tt0002101	Cleopatra	Drama, History	1912-11-13	11
2	tt0002199	From the Manger to the Cross; or, Jesus of Naz...	Biography, Drama	1913	NaN
3	tt0002461	Richard III	Drama	1912-10-15	10
4	tt0003167	Home, Sweet Home	Drama	1914-05-17	05

In [42]:

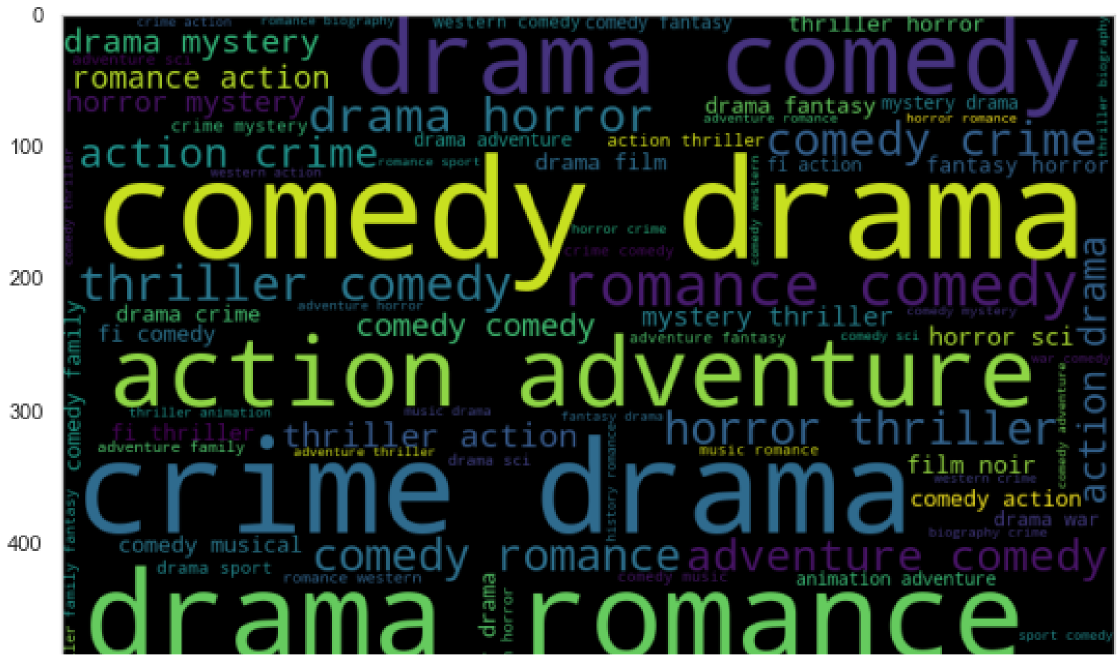
```
# Wizualizacja w rozbiciu na miesiące

max_width = 15
fig, ax = plt.subplots(figsize = (16,4))
months_published = movies_published.groupby('month_published')['imdb_title_id'].cou
count_movies = movies_published.groupby('month_published')['imdb_title_id'].count()
sns.barplot(ax = ax, x = months_published, y = count_movies)
ax.set_title('Liczba filmów w rozbiciu na miesiące', fontsize = 18)
ax.set_xlabel('Miesiąc')
ax.set_ylabel('Liczba filmów')
for index,count_movies in enumerate(count_movies):
       ax.text(x=index-0.15 , y =count_movies+0 , s=f"{count_movies}" , fontdict=di
ax.set_xticklabels(['Styczeń', 'Luty', 'Marzec', 'Kwiecień', 'Maj', 'Czerwiec'
                    , 'Lipiec', 'Sierpień', 'Wrzesień', 'Październik', 'Listopad',

plt.show()
```



Analiza gatunków filmów

In [43]:

```
# Preprocessing

comment_words = ''
stop_words = set(STOPWORDS)

for val in imdb_movies['genre']:
    val = str(val)
    tokens = val.split()

    for i in range(len(tokens)):
        tokens[i] = tokens[i].lower()

    comment_words += " ".join(tokens)+" "

wordcloud = WordCloud(width = 800, height = 600, background_color = 'black'
                      , stopwords = stop_words, min_font_size = 10).generate(commen

fig, ax = plt.subplots(figsize = (8, 6))
ax.grid(False)
ax.imshow((wordcloud))
fig.tight_layout(pad=0)
plt.show()
```



Widać wyraźną przewagę filmów gatunku Komedia, dramat, romans, również kryminalne są popularne.

Podział Gatunek względem Ocena

In [44]:

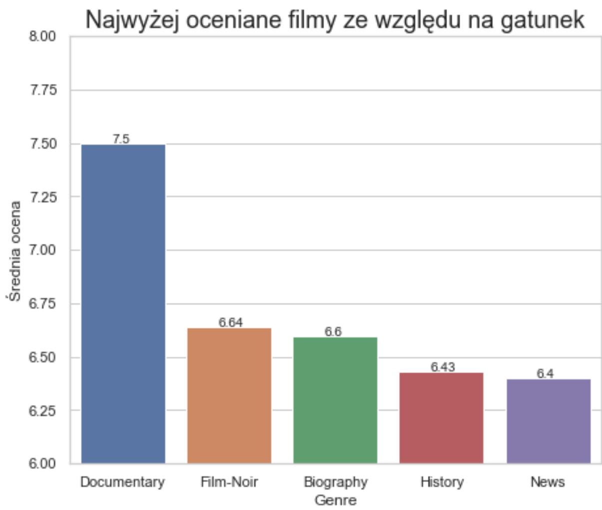
```
# Preprocessing i podział kolumn gatunek, bo film może należeć do kilku gatunków je

movies_genre = imdb_movies[['imdb_title_id', 'original_title', 'genre', 'avg_vote']
movies_genre['genre'] = movies_genre['genre'].astype('str')

genre_split = pd.DataFrame(movies_genre['genre'].str.split(',').tolist(), index=mov
genre_split = genre_split.reset_index(['imdb_title_id'])
genre_split.columns = ['imdb_title_id', 'genre_split']
movies_genre_split = pd.merge(genre_split, movies_genre[['imdb_title_id', 'original
                              left_on = 'imdb_title_id', right_on = 'imdb_title_id'
movies_genre_split['genre_split'] = movies_genre_split['genre_split'].str.lstrip('
movies_genre_split.head()
```

Out[44]:

	imdb_title_id	genre_split	original_title	avg_vote
0	tt0000009	Romance	Miss Jerry	5.9
1	tt0002101	Drama	Cleopatra	5.2
2	tt0002101	History	Cleopatra	5.2
3	tt0002199	Biography	From the Manger to the Cross; or, Jesus of Naz...	5.7
4	tt0002199	Drama	From the Manger to the Cross; or, Jesus of Naz...	5.7

In [52]:

```
# Wykres dla 5 Najliczniejszych gatunków

fig, ax = plt.subplots(1, 2, figsize = (16,6))

genres = movies_genre_split.groupby('genre_split')['imdb_title_id'].count().sort_va
count_movies = movies_genre_split.groupby('genre_split')['imdb_title_id'].count().s
ax[0].pie(x=count_movies, autopct="%.2f%%", labels=genres, pctdistance=0.5)
ax[0].set_title('5 Najliczniejszych gatunków', fontsize = 18)

genres = movies_genre_split.groupby('genre_split')['avg_vote'].mean().sort_values(a
avg_votes = movies_genre_split.groupby('genre_split')['avg_vote'].mean().sort_value
sns.barplot(ax = ax[1], x = genres, y = avg_votes)
ax[1].set_title('Najwyżej oceniane filmy ze względu na gatunek', fontsize = 18)
ax[1].set_xlabel('Genre')
for index,avg_votes in enumerate(round(avg_votes, 2)):
    ax[1].text(x=index-0.1 , y =avg_votes+0 , s=f"{avg_votes}" , fontdict=dict(font
ax[1].set_ylabel('Średnia ocena')
ax[1].set_ylim(6, 8)

plt.show()
```



Widać że najwyższe oceny otrzymały filmy dokumentalne.

Który scenarzysta napisał najwięcej scenariuszy o najwyższej ocenie

In [55]:

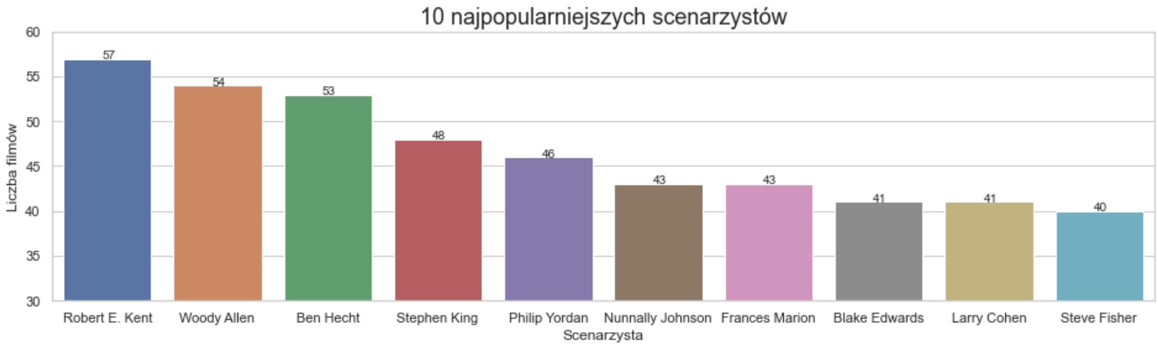
```
# Preprocessing

movies_writer = imdb_movies[['imdb_title_id', 'original_title', 'writer', 'avg_vote
movies_writer['writer'] = movies_writer['writer'].astype('str')

writer_split = pd.DataFrame(movies_writer['writer'].str.split(',').tolist(), index=
writer_split = writer_split.reset_index(['imdb_title_id'])
writer_split.columns = ['imdb_title_id', 'writer_split']
movies_writer_split = pd.merge(writer_split, movies_writer[['imdb_title_id', 'origi
                              left_on = 'imdb_title_id', right_on = 'imdb_title_id'
movies_writer_split['writer_split'] = movies_writer_split['writer_split'].str.lstri
gb_writer = movies_writer_split.groupby('writer_split').agg({ 'imdb_title_id' : ['c
gb_writer.drop(gb_writer[gb_writer.index == 'nan'].index, inplace = True)
gb_writer.head()
```

Out[55]:

	imdb_title_id	avg_vote
	count	mean
writer_split		
'A.J.' Marriot	1	7.2
'Evil' Ted Smith	1	4.0
'Weird Al' Yankovic	1	7.0
50 Cent	2	4.6
A. Channing Edington	1	5.7

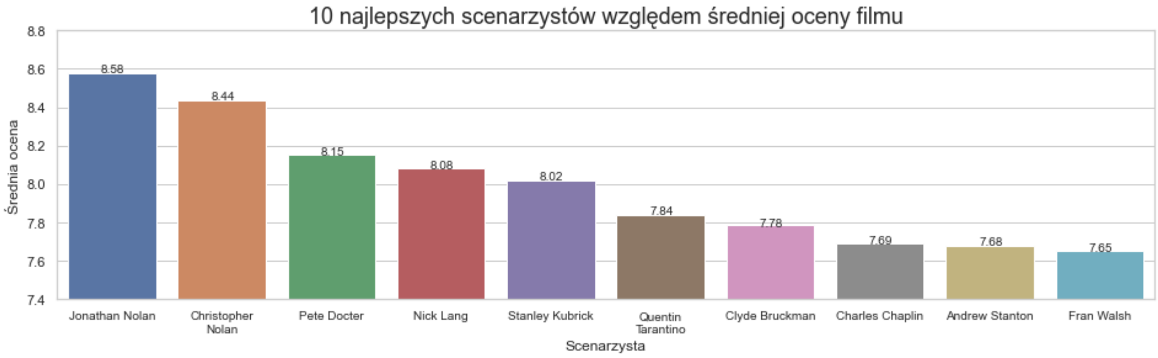
In [57]:

```
# Wykres 10 najpopularniejszych scenarzystów

max_width = 15
fig, ax = plt.subplots(figsize = (16,4))

writers = gb_writer[('imdb_title_id', 'count')].sort_values(ascending = False)[0:10
count_movies = gb_writer[('imdb_title_id', 'count')].sort_values(ascending = False)

sns.barplot(ax = ax, x = writers, y = count_movies)
ax.set_title('10 najpopularniejszych scenarzystów', fontsize = 18)
ax.set_xlabel('Scenarzysta')
for index,count_movies in enumerate(count_movies):
    ax.text(x=index-0.05 , y =count_movies+0 , s=f"{count_movies}" , fontdict=dict(
ax.set_ylabel('Liczba filmów')
ax.set_ylim(30, 60)
plt.show()
```



In [58]:

```
# 10 scenarzystów w rozbiciu na ocenę filmu

max_width = 15
fig, ax = plt.subplots(figsize = (16,4))

# Specification : at least have write 5 movies
mask = movies_writer_split.groupby('writer_split')['imdb_title_id'].count() >= 5
writers = gb_writer.loc[mask][('avg_vote',  'mean')].sort_values(ascending = False)
avg_vote = gb_writer.loc[mask][('avg_vote',  'mean')].sort_values(ascending = False

sns.barplot(ax = ax, x = writers, y = avg_vote)
ax.set_title('10 najlepszych scenarzystów względem średniej oceny filmu', fontsize
ax.set_xlabel('Scenarzysta')
ax.set_xticklabels((textwrap.fill(x.get_text(), max_width) for x in ax.get_xticklab
for index,avg_vote in enumerate(round(avg_vote, 2)):
    ax.text(x=index-0.1 , y =avg_vote+0 , s=f"{avg_vote}" , fontdict=dict(fontsize=
ax.set_ylabel('Średnia ocena')
ax.set_ylim(7.4, 8.8)
plt.show()
```



Analizy w rozbiciu na aktorów

In [59]:

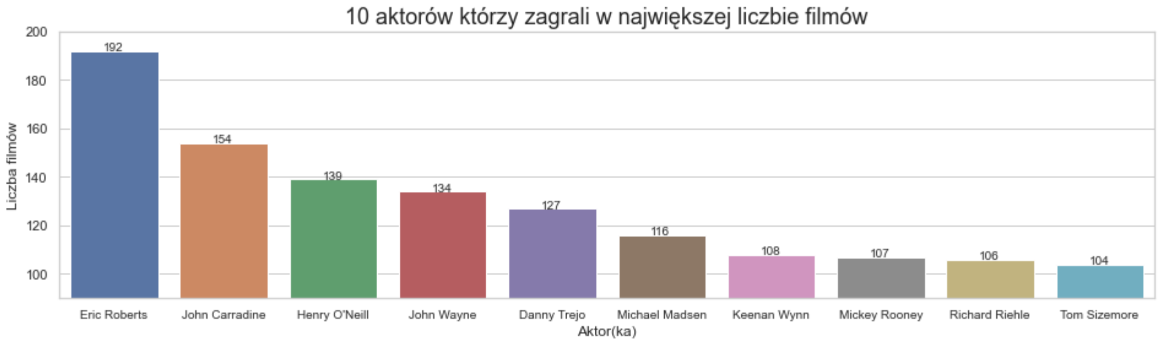
```
# Preprocessing

movies_actor = imdb_movies[['imdb_title_id', 'original_title', 'actors', 'avg_vote'
movies_actor['actors'] = movies_actor['actors'].astype('str')

actor_split = pd.DataFrame(movies_actor['actors'].str.split(',').tolist(), index=mo
actor_split = actor_split.reset_index(['imdb_title_id'])
actor_split.columns = ['imdb_title_id', 'actor_split']
movies_actor_split = pd.merge(actor_split, movies_actor[['imdb_title_id', 'original
                              left_on = 'imdb_title_id', right_on = 'imdb_title_id'
movies_actor_split['actor_split'] = movies_actor_split['actor_split'].str.lstrip('
gb_actor = movies_actor_split.groupby('actor_split').agg({ 'imdb_title_id' : ['coun
gb_actor.drop((gb_actor[gb_actor.index == 'nan'].index), inplace = True)
gb_actor.head()
```

Out[59]:

	imdb_title_id	avg_vote
	count	mean
actor_split		
'Baby' Carmen De Rue	3	5.166667
'Big Al' Solomon	1	3.400000
'Big Jack' Provan	1	6.000000
'Big Walter' Price	1	5.800000
'Big' Jack Little	1	4.300000

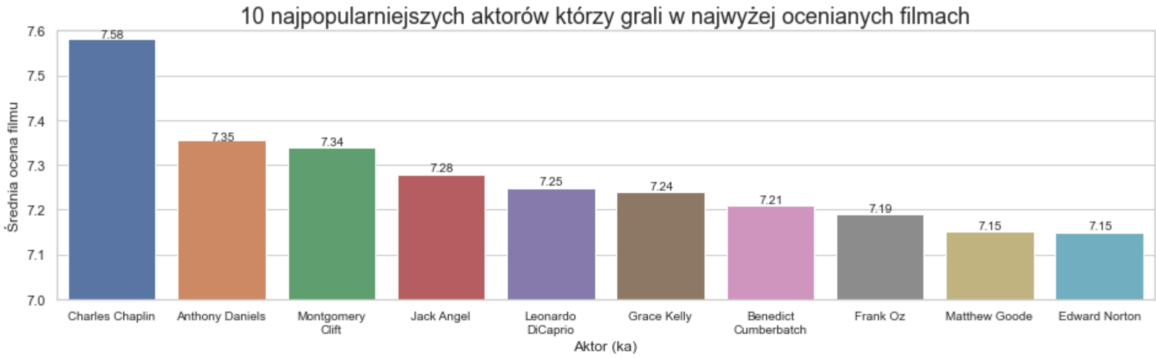
In [62]:

```
# 10 aktorów którzy zagrali w największej liczbie filmów

max_width = 15
fig, ax = plt.subplots(figsize = (16,4))

actor = gb_actor[('imdb_title_id', 'count')].sort_values(ascending = False)[0:10].i
count_movies = gb_actor[('imdb_title_id', 'count')].sort_values(ascending = False)[

sns.barplot(ax = ax, x = actor, y = count_movies)
ax.set_title('10 aktorów którzy zagrali w największej liczbie filmów', fontsize = 1
ax.set_xlabel('Aktor(ka)')
ax.set_xticklabels((textwrap.fill(x.get_text(), max_width) for x in ax.get_xticklab
for index,count_movies in enumerate(count_movies):
    ax.text(x=index-0.1 , y =count_movies+0 , s=f"{count_movies}" , fontdict=dict(f
ax.set_ylabel('Liczba filmów')
ax.set_ylim(90, 200)
plt.show()
```



In [63]:

```
# 10 najpopularniejszych aktorów którzy grali w najwyżej ocenianych filmach

max_width = 15
fig, ax = plt.subplots(figsize = (16,4))

# Filtr dla tych którzy zagrali w co najmniej 10 filmach
mask = movies_actor_split.groupby('actor_split')['imdb_title_id'].count() >= 10
actor = gb_actor.loc[mask][('avg_vote',  'mean')].sort_values(ascending = False)[0:
avg_vote = gb_actor.loc[mask][('avg_vote',  'mean')].sort_values(ascending = False)

sns.barplot(ax = ax, x = actor, y = avg_vote)
ax.set_title('10 najpopularniejszych aktorów którzy grali w najwyżej ocenianych fil
ax.set_xlabel('Aktor (ka)')
ax.set_xticklabels((textwrap.fill(x.get_text(), max_width) for x in ax.get_xticklab
for index,avg_vote in enumerate(round(avg_vote, 2)):
    ax.text(x=index-0.1 , y =avg_vote+0.005 , s=f"{avg_vote}" , fontdict=dict(fonts
ax.set_ylabel('Średnia ocena filmu')
ax.set_ylim(7, 7.6)
plt.show()
```



Element Machine Learning - Rekomendacja tytułu filmu do obejrzenia na podstawie podanego tytułu

Algorytm rekomendacji filmu bazuje na następujących danych:

- original_title - podana nazwa filmu względem którego liczona jest rekomendacja kolejnego filmu do obejrzenia
- genre - gatunek
- director - reżyser
- actors - obsada
- description - opis filmu

Skororszyt stara się dobrać na podstawie powyższych danych, przy pomocy algorytmu podobieństwa kosinusowego, film podobny do podanego tzn. 'original title'

In [64]:

```
data_recsys=imdb_movies[['original_title', 'genre', 'director', 'actors', 'descript
data_recsys.head()
```

Out[64]:

	original_title	genre	director	actors	description
0	Miss Jerry	Romance	Alexander Black	Blanche Bayliss, William Courtenay, Chauncey D...	The adventures of a female reporter in the 1890s.
1	Cleopatra	Drama, History	Charles L. Gaskill	Helen Gardner, Pearl Sindelar, Miss Fielding, ...	The fabled queen of Egypt's affair with Roman ...
2	From the Manger to the Cross; or, Jesus of Naz...	Biography, Drama	Sidney Olcott	R. Henderson Bland, Percy Dyer, Gene Gauntier,...	An account of the life of Jesus Christ, based ...
3	Richard III	Drama	André Calmettes, James Keane	Robert Gemp, Frederick Warde, Albert Gardner, ...	Richard of Gloucester uses manipulation and mu...
4	Home, Sweet Home	Drama	D.W. Griffith	Henry B. Walthall, Josephine Crowell, Lillian ...	John Howard Payne at his most miserable point ...

In [65]:

```
# Preprocessing

data_recsys.set_index('original_title', inplace = True)

data_recsys['genre'] = data_recsys['genre'].fillna('').astype('str').str.lower()
data_recsys['genre'] = data_recsys['genre'].str.split(',')

data_recsys['director'] = data_recsys['director'].fillna('').astype('str').str.lowe
data_recsys['director'] = data_recsys['director'].str.split(',')

data_recsys['actors'] = data_recsys['actors'].fillna('').astype('str').str.lower()
data_recsys['actors'] = data_recsys['actors'].str.split(',')
```

Uwaga! Poniższe operacje są czasochłonne ze względu na operacje tekstowe na dużym zbiorze danych.

In [66]:

```
# Preprocessing

data_recsys['description'] = data_recsys['description'].fillna('').astype('str').st
data_recsys['description'] = data_recsys['description'].str.translate(str.maketrans

#from nltk.corpus import stopwords
listStopwords = set(stopwords.words('english'))
filtered = []
ps = PorterStemmer()
for i, text in enumerate(data_recsys['description'].str.split()):
    for word in text:
        # Filtering/Removing stopwords in the text
        if word not in listStopwords:
            # Stemming words
            word_stemmed = ps.stem(word)
            filtered.append(word_stemmed)
    data_recsys['description'][i] = filtered
    filtered = []
```

In [67]:

```
# Tworzenie nowej kolumny 'bunch_of_words' która zawiera słowa kluczowe z pozostały

data_recsys['bunch_of_words'] = ''
for i, text in data_recsys.iterrows():
    words = ''
    for col in data_recsys.columns:
        words = words + ' '.join(text[col]) + ' '
    data_recsys['bunch_of_words'][i] = words
```

In [68]:

```
data_recsys.head()
```

Out[68]:

	genre	director	actors	description	bunch_of_words
original_title					
Miss Jerry	[romance]	[alexander black]	[blanche bayliss, william courtenay, chaunce...	[adventur, femal, report, 1890]	romance alexander black blanche bayliss willi...
Cleopatra	[drama, history]	[charles l. gaskill]	[helen gardner, pearl sindelar, miss fieldin...	[fabl, queen, egypt, affair, roman, gener, mar...	biography drama history joseph l. mankiewicz...
From the Manger to the Cross; or, Jesus of Nazareth	[biography, drama]	[sidney olcott]	[r. henderson bland, percy dyer, gene gaunti...	[account, life, jesu, christ, base, book, new,...	biography drama sidney olcott r. henderson bl...
Richard III	[drama]	[andré calmettes, james keane]	[robert gemp, frederick warde, albert gardne...	[richard, gloucest, use, manipul, murder, gain...	drama andré calmettes james keane robert gemp...
Home, Sweet Home	[drama]	[d.w. griffith]	[henry b. walthall, josephine crowell, lilli...	[john, howard, payn, miser, point, life, write...	drama d.w. griffith henry b. walthall josephi...

In [69]:

```
# Konwersja 'bunch of words' do wektora słowo/wartość (CountVectorizer)

count = CountVectorizer()
count_matrix = count.fit_transform(data_recsys['bunch_of_words']).astype(np.uint8)
```

In [70]:

```
# Kasujemy niepotrzebne już dane, pozwala zaoszczędzić pamięć
del data_imdb_names
del data_imdb_title_principals
```

Obliczenie podobieństwa kosinusowego

Podobieństwo kosinusowe jest miarą używaną do mierzenia stopnia podobieństwa dokumentów niezależnie od ich wielkości.

Uwaga! Poniższa operacja jest czasochłonna.

In [72]:

```
# Obliczenie podobieństwa kosinusowego - Cosine Similarity
# W małych porcjach chunk_size

chunk_size = 500
matrix_len = count_matrix.shape[0]

# Obliczenie w porcji
def similarity_cosine_by_chunk(start, end):
    if end > matrix_len:
        end = matrix_len
    return cosine_similarity(X=count_matrix[start:end], Y=count_matrix)
cosine_similarity_all = []
i=0
for chunk_start in range(0, matrix_len, chunk_size):

    # Inicjalizacja pierwszej porcji
    if i == 0:
        cosine_sim = similarity_cosine_by_chunk(chunk_start, chunk_start+chunk_size

    # Inicjalizacja kolejnej porcji, następnie łączenie porcji tak aż wszystki porc
    else :
        cosine_similarity_chunk= similarity_cosine_by_chunk(chunk_start, chunk_star
        # Użycie typu float32
        cosine_sim = np.concatenate((cosine_sim.astype(np.float32), cosine_similari

    # Zmiana wartości i != 0 do wykonania polecenia else:
    # (nie potrzebujemy więcej wykonywać polecenia if: jeśli pierwsza porcja został
    i= 1
```

In [74]:

```
# Funkcja zwracająca 10 rekomendacji bazując na podanym tytule

# Utworzenie Pandas Index
index_movies = pd.Series(data_recsys.index)

# Funkcja poszukiwania rekomendacji
def recommendation_movies(title, cosine_sim = cosine_sim):
    recommended_movies = []
    index_movie_input = index_movies[index_movies == title].index[0]
    score_movies = pd.Series(cosine_sim[index_movie_input]).sort_values(ascending =
    top_10_index_movies = list(score_movies.iloc[1:11].index)
    # Get movies title and year by index (top 10 movies)
    for i in top_10_index_movies:
        recommended_movies.append(imdb_movies['original_title'].iloc[i] + ' (' + st
    return recommended_movies
```

Obliczenie rekomendacji

W celu obliczenia rekomendacji należy podać tytuł istniejącego w bazie IMDb filmu, na podstawie którego za pomocą algorytmu ML zostanie podana rekomendacja kolejnego tytułu do obejrzenia.

In [75]:

```
# recommendation_movies('The Dark Knight')
recommendation_movies('Hamburger Hill')
```

Out[75]:

```
['Journey to Shiloh (1968)',
 'Haywire (2011)',
 'Shake Hands with the Devil (1959)',
 'Kid (1990)',
 'Merchant of Death (1997)',
 'Frisk (1995)',
 'Ablaze (2001)',
 'Robot Ninja (1989)',
 'A Boy and His Dog (1975)',
 'Miles Ahead (2015)']
```

Bibliografia

- https://towardsdatascience.com/understanding-cosine-similarity-and-its-application-fd42f585296a (https://towardsdatascience.com/understanding-cosine-similarity-and-its-application-fd42f585296a)
- https://scikit-learn.org/stable/modules/metrics.html#cosine-similarity (https://scikit-learn.org/stable/modules/metrics.html#cosine-similarity)
- https://en.wikipedia.org/wiki/Cosine_similarity (https://en.wikipedia.org/wiki/Cosine_similarity)