MOVIE GENRE CLASSIFICATION

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Description

- The objective of this notebook is to develop a ML algorithm for the classification of the multiple genres of a movie based on their plots.
- To do this classification, the kernal is divided into 4 parts which is;
  - Part 1: it describes the list libraries being used in this kernel.
  - Part 2: it is about data cleansing and identification of the genres to be used for the classification of the movies. The genres that are used to classify ~96% of movies will be used building the classification algorithms.

LIST OF LIBRARIES USED

- PANDAS
- NUMPY
- MATPLOTLIB
- SEABORN
- PICKLE
- nltk
- sklearn

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import re

import pickle
#import mglearn
import time
```

In [2]:

```
from nltk.tokenize import TweetTokenizer # doesn't split at apostrophes
import nltk
from nltk import Text
from nltk.tokenize import regexp_tokenize
from nltk.tokenize import word_tokenize
from nltk.tokenize import sent_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.stem import PorterStemmer
```

In [3]:

```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import make_pipeline
```

In [4]:

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.multiclass import OneVsRestClassifier
```

In [5]:

```
from sklearn.metrics import accuracy_score
from sklearn.svm import LinearSVC
```

In [6]:

```
movies = pd.read_csv('/Users/raghul/Downloads/wiki_movie_plot.csv', delimiter=',')
movies.dataframeName = 'wiki_movie_plots_deduped.csv'
nRow, nCol = movies.shape
print(f'There are {nRow} rows and {nCol} columns')
```

```
There are 34886 rows and 8 columns
```

In [7]:

```
movies.head()
```

Out[7]:

	Release Year	Title	Origin/Ethnicity	Director	Cast	Genre	Wiki Page	Plot
0	1901	Kansas Saloon Smashers	American	Unknown	NaN	unknown	https://en.wikipedia.org/wiki/Kansas_Saloon_Sm...	A bartender is working at a saloon, serving dr...
1	1901	Love by the Light of the Moon	American	Unknown	NaN	unknown	https://en.wikipedia.org/wiki/Love_by_the_Ligh...	The moon, painted with a smiling face hangs ov...
2	1901	The Martyred Presidents	American	Unknown	NaN	unknown	https://en.wikipedia.org/wiki/The_Martyred_Pre...	The film, just over a minute long, is composed...
3	1901	Terrible Teddy, the Grizzly King	American	Unknown	NaN	unknown	https://en.wikipedia.org/wiki/Terrible_Teddy,_...	Lasting just 61 seconds and consisting of two ...
4	1902	Jack and the Beanstalk	American	George S. Fleming, Edwin S. Porter	NaN	unknown	https://en.wikipedia.org/wiki/Jack_and_the_Bea...	The earliest known adaptation of the classic f...

In [8]:

```
# creation of the column count for aggregation
movies['Count']=1
movies[['Genre','Count']].groupby(['Genre'], as_index=False).count().shape[0]
```

Out[8]:

```
2265
```

There are 2265 different genres movies.

- It is not possible to build an ML algorithm having a good accuracy to estimate the genre of movies for the following reasons:
    - The number of classes is very high
    - Many classes have very few observation.

In [9]:

```
# harmonization
```

```
movies['GenreCorrected'] =movies['Genre']
movies['GenreCorrected']=movies['GenreCorrected'].str.strip()
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' - ', '|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' / ', '|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('/', '|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' & ', '|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(', ', '|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('; ', '|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('bio-pic', 'biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biopic', 'biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biographical', 'biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biodrama', 'biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('bio-drama', 'biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biographic', 'biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(film genre\)', '')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('animated','animation')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('anime','animation')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('children\'s','children')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('comedey','comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\[not in citation given\]','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' set 4,000 years ago in the canadian arctic','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('historical','history')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('romantic','romance')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('3-d','animation')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('3d','animation')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('viacom 18 motion pictures','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('sci-fi','science_fiction')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('ttriller','thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('.','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('based on radio serial','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' on the early years of hitler','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('sci fi','science_fiction')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('science fiction','science_fiction')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' (30min)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('16 mm film','short')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\[140\]','drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\[144\]','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' for ','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('adventures','adventure')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('kung fu','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('kung-fu','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('martial arts','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('world war ii','war')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('world war i','war')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biography about montreal canadiens star|maurice richard','biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('bholenath movies|cinekorn entertainment','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(volleyball\)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('spy film','spy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('anthology film','anthology')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biography fim','biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('avant-garde','avant_garde')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biker film','biker')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('buddy cop','buddy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('buddy film','buddy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('comedy 2-reeler','comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('films','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('film','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biography of pioneering american photographer eadweard muybridge','biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('british-german co-production','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('bruceploitation','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('comedy-drama adaptation of the mordecai richler novel','comedy-drama')
```

```
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('movies by the mob\|knkspl','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('movies','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('movie','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('coming of age','coming_of_age')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('coming-of-age','coming_of_age')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('drama about child soldiers','drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( based).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( co-produced).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( adapted).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( about).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('musical b','musical')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('animationchildren','animation|children')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' period','period')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('drama loosely','drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(aquatics|swimming\)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(aquatics|swimming\)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace("yogesh dattatraya gosavi's directorial debut \[9\]",'')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace("war-time","war")
movies['GenreCorrected']=movies['GenreCorrected'].str.replace("wartime","war")
movies['GenreCorrected']=movies['GenreCorrected'].str.replace("ww1","war")
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('unknown','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace("wwii","war")
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('psychological','psycho')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('rom-coms','romance')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('true crime','crime')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|007','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('slice of life','slice_of_life')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('computer animation','animation')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('gun fu','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('j-horror','horror')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(shogi|chess\)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('afghan war drama','war drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|6 separate stories','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(30min\)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' (road bicycle racing)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' v-cinema','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('tv miniseries','tv_miniseries')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|docudrama','\|documentary|drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' in animation','|animation')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((adaptation).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((adaptated).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((adapted).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( on ).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('american football','sports')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dev\|nusrat jahan','sports')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('television miniseries','tv_miniseries')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(artistic\)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \|direct-to-dvd','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('history dram','history drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('martial art','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('psycho thriller,','psycho thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|1 girl\|3 suitors','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(road bicycle racing\)','')
filterE = movies['GenreCorrected']=="ero"
movies.loc[filterE,'GenreCorrected']="adult"
filterE = movies['GenreCorrected']=="music"
movies.loc[filterE,'GenreCorrected']="musical"
filterE = movies['GenreCorrected']=="-"
movies.loc[filterE,'GenreCorrected']=''
filterE = movies['GenreCorrected']=="comedy–drama"
movies.loc[filterE,'GenreCorrected'] = "comedy|drama"
```

```
filterE = movies['GenreCorrected']=="comedy—horror"
movies.loc[filterE,'GenreCorrected'] = "comedy|horror"
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' ','|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace(',','|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('-','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actionadventure','action|adventure')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actioncomedy','action|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actiondrama','action|drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actionlove','action|love')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actionmasala','action|masala')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actionchildren','action|children')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('fantasychildren\|','fantasy|children')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('fantasycomedy','fantasy|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('fantasyperiod','fantasy|period')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('cbctv_miniseries','tv_miniseries')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dramacomedy','drama|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dramacomedysocial','drama|comedy|social')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dramathriller','drama|thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('comedydrama','comedy|drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dramathriller','drama|thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('comedyhorror','comedy|horror')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('sciencefiction','science_fiction')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('adventurecomedy','adventure|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('animationdrama','animation|drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|\|','|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('muslim','religious')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('thriler','thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('crimethriller','crime|thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('fantay','fantasy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actionthriller','action|thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('comedysocial','comedy|social')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('martialarts','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|\(children\|poker\|karuta\)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('epichistory','epic|history')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('erotica','adult')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('erotic','adult')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((\|produced\|).+)','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('chanbara','chambara')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('comedythriller','comedy|thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biblical','religious')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biblical','religious')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('colour\|yellow\|productions\|eros\|international','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|directtodvd','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('liveaction','live|action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('melodrama','drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('superheroes','superheroe')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('gangsterthriller','gangster|thriller')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('heistcomedy','comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('heist','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('historic','history')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('historydisaster','history|disaster')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('warcomedy','war|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('westerncomedy','western|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('ancientcostume','costume')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('computeranimation','animation')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dramatic','drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('familya','family')
```

```
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('familya','family')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dramedy','drama|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dramaa','drama')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('famil\|','family')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('superheroe','superhero')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biogtaphy','biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('devotionalbiography','devotional|biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('docufiction','documentary|fiction')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('familydrama','family|drama')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('espionage','spy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('supeheroes','superhero')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('romancefiction','romance|fiction')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('horrorthriller','horror|thriller')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('suspensethriller','suspense|thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('musicaliography','musical|biography')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('triller','thriller')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|\(fiction\)','|fiction')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('romanceaction','romance|action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('romancecomedy','romance|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('romancehorror','romance|horror')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('romcom','romance|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('rom\|com','romance|comedy')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('satirical','satire')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('science_fictionchildren','science_fiction|children')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('homosexual','adult')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('sexual','adult')

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('mockumentary','documentary')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('periodic','period')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('romanctic','romantic')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('politics','political')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('samurai','martial_arts')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('tv_miniseries','series')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('serial','series')

filterE = movies['GenreCorrected']=="musical–comedy"
movies.loc[filterE,'GenreCorrected'] = "musical|comedy"

filterE = movies['GenreCorrected']=="roman|porno"
movies.loc[filterE,'GenreCorrected'] = "adult"


filterE = movies['GenreCorrected']=="action–masala"
movies.loc[filterE,'GenreCorrected'] = "action|masala"


filterE = movies['GenreCorrected']=="horror–thriller"
movies.loc[filterE,'GenreCorrected'] = "horror|thriller"

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('family','children')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('martial_arts','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('horror','thriller')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('war','action')
```

```
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('adventure','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('science_fiction','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('western','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('western','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('noir','black')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('spy','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('superhero','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('social','')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('suspense','action')


filterE = movies['GenreCorrected']=="drama|romance|adult|children"
movies.loc[filterE,'GenreCorrected'] = "drama|romance|adult"

movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|-\|','|')
movies['GenreCorrected']=movies['GenreCorrected'].str.strip(to_strip='\|')
movies['GenreCorrected']=movies['GenreCorrected'].str.replace('actionner','action')
movies['GenreCorrected']=movies['GenreCorrected'].str.strip()
```

```
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:16: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(film genre\)', '')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:21: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\[not in citation given\]','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:30: FutureWarning: The default value of regex will change from True to False in a future ver
sion. In addition, single character regular expressions will*not* be treated as literal strings when regex=True.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('.','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:35: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' (30min)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:37: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\[140\]','drama')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:38: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\[144\]','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:46: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('biography about montreal canadiens star|maurice richard','biography')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:47: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('bholenath movies|cinekorn entertainment','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:48: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(volleyball\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:63: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('movies by the mob\|knkspl','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:69: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( based).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:70: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( co-produced).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:71: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( adapted).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:72: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( about).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:77: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
```

```
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(aquatics|swimming\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:78: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(aquatics|swimming\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:79: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace("yogesh dattatraya gosavi's directorial debut \[9\]",'')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:88: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|007','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:93: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(shogi|chess\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:95: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|6 separate stories','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:96: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(30min\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:97: FutureWarning: The default value of regex will change from True to False in a future ver
sion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' (road bicycle racing)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:100: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|docudrama','\|documentary|drama')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:102: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((adaptation).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:103: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((adaptated).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:104: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((adapted).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:105: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('(( on ).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:107: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('dev\|nusrat jahan','sports')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:109: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(artistic\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:110: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \|direct-to-dvd','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:114: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|1 girl\|3 suitors','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:115: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace(' \(road bicycle racing\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:136: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('fantasychildren\|','fantasy|children')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:149: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|\|','|')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:157: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|\(children\|poker\|karuta\)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:163: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('((\|produced\|).+)','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:168: FutureWarning: The default value of regex will change from True to False in a future ve
```

```
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('colour\|yellow\|productions\|eros\|international','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:169: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|directtodvd','')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:188: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('famil\|','family')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:206: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|\(fiction\)','|fiction')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:213: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('rom\|com','romance|comedy')
/var/folders/k4/ffhngpcx4z5545d3qcwq0_z40000gn/T/ipykernel_6981/2761400162.py:260: FutureWarning: The default value of regex will change from True to False in a future ve
rsion.
  movies['GenreCorrected']=movies['GenreCorrected'].str.replace('\|-\|','|')
```

In [10]:

```
moviesGenre = movies[['GenreCorrected','Count']].groupby(['GenreCorrected']).count()
moviesGenre.to_csv('GenreCorrected.csv',sep=',')
```

In [11]:

```
movies[['GenreCorrected','Count']].groupby(['GenreCorrected'], as_index=False).count().shape[0]
```

Out[11]:

```
1199
```

After harmonization, the number of movies genres decreased 1198 from 2265

Overview of the genre after cleansing

In [12]:

```
movies[['GenreCorrected','Count']].groupby(['GenreCorrected'],as_index=False).count().sort_values(['Count'], ascending=False).head(10)
```

Out[12]:

	GenreCorrected	Count
0		6206
516	drama	6107
359	comedy	4411
2	action	3790
1111	thriller	2163
964	romance	954
203	animation	601
973	romance|comedy	577
447	crime	573
387	comedy|drama	560

In [13]:

```
movies['GenreSplit']=movies['GenreCorrected'].str.split('|')
movies['GenreSplit']= movies['GenreSplit'].apply(np.sort).apply(np.unique)
```

In [14]:

```
movies['GenreSplit'][11]
```

Out[14]: array(['action', 'crime', 'short'], dtype='<U6')

Movies for each genre

In [15]:
```
genres_array = np.array([])

for i in range(0,movies.shape[0]-1):
    genres_array = np.concatenate((genres_array, movies['GenreSplit'][i] ))

genres_array
```

Out[15]: array(['', '', '', ..., 'comedy', 'comedy', 'romance'], dtype='<U32')

In [16]:
```
genres = pd.DataFrame({'Genre':genres_array})
```

In [17]:
```
genres = pd.DataFrame({'Genre':genres_array})
```

In [18]:
```
# Histogram for genre
genres['Count']=1
df = genres[['Genre','Count']].groupby(['Genre'], as_index=False).sum().sort_values(['Count'], ascending=False).head(10)
```

Identifying the genre to be selected

In [19]:
```
genres=genres[['Genre','Count']].groupby(['Genre'], as_index=False).sum().sort_values(['Count'], ascending=False)
```

In [20]:
```
genres = genres[genres['Genre']!='']
genres.head(25)
```

Out[20]:

	Genre	Count
116	drama	9487
85	comedy	7320
4	action	5952
426	thriller	3291
337	romance	2639
94	crime	1607
244	musical	951
16	animation	914
73	children	684
131	fantasy	542
245	mystery	481
46	biography	463
47	black	412
149	history	256
368	short	241
114	documentary	131
391	sports	121
357	series	86
6	adult	71
288	political	60
90	costume	49
429	tokusatsu	43
411	supernatural	41
223	masala	41
307	psycho	39

In [21]:

```
TotalCountGenres=sum(genres['Count'])
```

In [22]:

```
TotalCountGenres
```

Out[22]: 37321

In [23]:

```
genres['Frequency'] = genres['Count']/TotalCountGenres
genres['CumulativeFrequency'] = genres['Frequency'].cumsum()
genres.head(20)
```

Out[23]:

	Genre	Count	Frequency	CumulativeFrequency
116	drama	9487	0.254200	0.254200
85	comedy	7320	0.196136	0.450336
4	action	5952	0.159481	0.609818
426	thriller	3291	0.088181	0.697998
337	romance	2639	0.070711	0.768709
94	crime	1607	0.043059	0.811768
244	musical	951	0.025482	0.837250
16	animation	914	0.024490	0.861740
73	children	684	0.018327	0.880068
131	fantasy	542	0.014523	0.894590
245	mystery	481	0.012888	0.907478
46	biography	463	0.012406	0.919884
47	black	412	0.011039	0.930924
149	history	256	0.006859	0.937783
368	short	241	0.006457	0.944241
114	documentary	131	0.003510	0.947751
391	sports	121	0.003242	0.950993
357	series	86	0.002304	0.953297
6	adult	71	0.001902	0.955199
288	political	60	0.001608	0.956807

Selecting the genres having a cumulative frequency 95.7% (~96%) and below

In [24]:

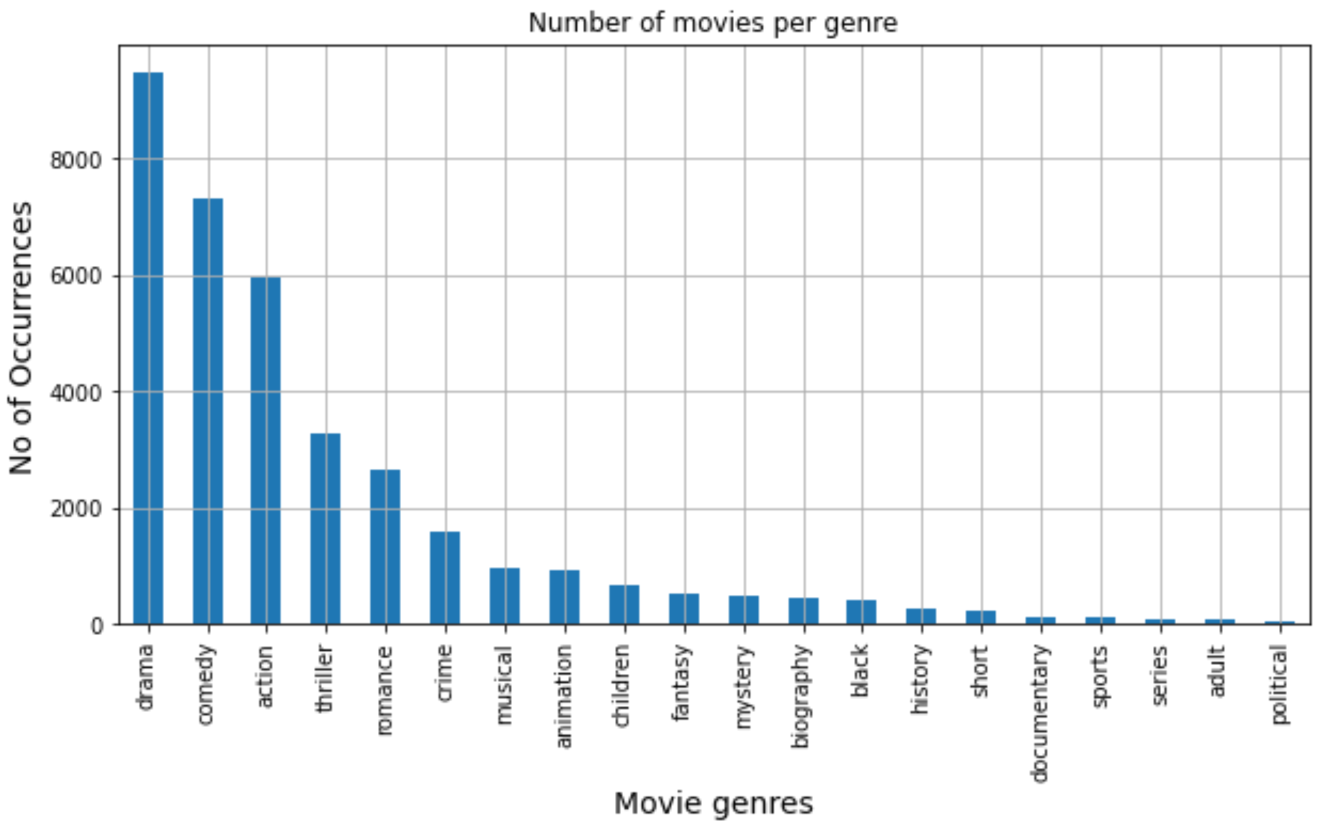
```
np.array(genres[genres['CumulativeFrequency']<=.957]['Genre'])
```

Out[24]:

```
array(['drama', 'comedy', 'action', 'thriller', 'romance', 'crime',
       'musical', 'animation', 'children', 'fantasy', 'mystery',
       'biography', 'black', 'history', 'short', 'documentary', 'sports',
       'series', 'adult', 'political'], dtype=object)
```

In [25]:

```
genres[genres['CumulativeFrequency']<=.957][['Genre','Count']].plot(x='Genre', y='Count', kind='bar', legend=False, grid=True, figsize=(10, 5))
plt.title("Number of movies per genre")
plt.ylabel('No of Occurrences', fontsize=14)
plt.xlabel('Movie genres', fontsize=14)
plt.show()
```



In [26]:
```
mainGenres=np.array(genres[genres['CumulativeFrequency']<=.957]['Genre'])
arr1=np.array(['adult', 'romance', 'drama','and'])

# Genres that are not in the "MainGenres" array will be deleted
arr1[np.in1d(arr1,mainGenres)]
```

Out[26]:
```
array(['adult', 'romance', 'drama'], dtype='<U7')
```

In [27]:
```
movies['GenreSplit'][10:12].apply(lambda x: x[np.in1d(x,mainGenres)])
```

Out[27]:
```
10                    [short]
11    [action, crime, short]
Name: GenreSplit, dtype: object
```

In [28]:
```
movies['GenreSplitMain'] = movies['GenreSplit'].apply(lambda x: x[np.in1d(x,mainGenres)])
```

In [29]:
```
movies[['GenreSplitMain','GenreSplit','Genre']][200:220]
```

Out[29]:

	GenreSplitMain	GenreSplit	Genre
200	[drama]	[drama]	drama
201	[drama]	[drama]	drama
202	[comedy]	[comedy]	comedy
203	[drama]	[drama]	drama
204	[comedy]	[comedy]	comedy
205	[comedy, drama]	[comedy, drama]	comedy drama
206	[mystery]	[mystery]	mystery
207	[drama]	[drama]	drama
208	[drama]	[drama]	drama
209	[comedy, drama]	[comedy, drama]	comedy drama
210	[comedy]	[comedy]	comedy
211	[fantasy]	[fantasy]	fantasy
212	[drama]	[drama]	drama
213	[action, drama]	[action, drama]	war drama
214	[action, drama]	[action, drama]	war drama
215	[action]	[action]	adventure
216	[comedy, romance]	[comedy, romance]	romantic comedy
217	[]	[propaganda]	propaganda
218	[action]	[action, propaganda]	ww1 propaganda
219	[action]	[action]	western

In [30]:

```
# Functions for cleaning the plots of the movies
def clean_text(text):
    text = text.lower()
    text = re.sub(r"what's", "what is ", text)
    text = re.sub(r"\'s", " ", text)
    text = re.sub(r"\'ve", " have ", text)
    text = re.sub(r"can't", "can not ", text)
    text = re.sub(r"n't", " not ", text)
    text = re.sub(r"i'm", "i am ", text)
    text = re.sub(r"\'re", " are ", text)
    text = re.sub(r"\'d", " would ", text)
    text = re.sub(r"\'ll", " will ", text)
    text = re.sub(r"\'scuse", " excuse ", text)
    #text = re.sub('\W', ' ', text)
    #text = re.sub('\s+', ' ', text)
    text = text.strip(' ')
    return text
```

In [31]:

```
list(movies['Plot'][10:12].apply(clean_text))
```

Out[31]: ['the rarebit fiend gorges on welsh rarebit at a restaurant. when he leaves, he begins to get dizzy as he starts to hallucinate. he desperately tries to hang onto a lamppost as the world spins all around him. a man helps him get home. he falls into bed and begins having more hallucinatory dreams. during a dream sequence, the furniture begins moving around the room. imps emerge from a floating welsh rarebit container and begin poking his head as he sleeps. his bed then begins dancing and spinning wildly around the room before flying out the window with the fiend in it. the bed floats across the city as the fiend floats up and off the bed. he hangs off the back and eventually gets caught on a weathervane atop a steeple. his bedclothes tear and he falls from the sky, crashing through his bedroom ceiling. the fiend awakens from the dream after falling out of his bed.',
 'the film features a train traveling through the rockies and a hold up created by two thugs placing logs on the line. they systematically rob the wealthy occupants at gunpoint and then make their getaway along the tracks and later by a hi-jacked horse and cart.']

In [32]:
```
list(movies['Plot'][10:12])
```

Out[32]: ['The Rarebit Fiend gorges on Welsh rarebit at a restaurant. When he leaves, he begins to get dizzy as he starts to hallucinate. He desperately tries to hang onto a lamppost as the world spins all around him. A man helps him get home. He falls into bed and begins having more hallucinatory dreams. During a dream sequence, the furniture begins moving around the room. Imps emerge from a floating Welsh rarebit container and begin poking his head as he sleeps. His bed then begins dancing and spinning wildly around the room before flying out the window with the Fiend in it. The bed floats across the city as the Fiend floats up and off the bed. He hangs off the back and eventually gets caught on a weathervane atop a steeple. His bedclothes tear and he falls from the sky, crashing through his bedroom ceiling. The Fiend awakens from the dream after falling out of his bed.',
 'The film features a train traveling through the Rockies and a hold up created by two thugs placing logs on the line. They systematically rob the wealthy occupants at gunpoint and then make their getaway along the tracks and later by a hi-jacked horse and cart.']

In [33]:
```
movies['PlotClean'] = movies['Plot'].apply(clean_text)
```

In [34]:
```
movies[['Plot','PlotClean','GenreSplitMain']][6:12]
```

Out[34]:

	Plot	PlotClean	GenreSplitMain
6	The film opens with two bandits breaking into ...	the film opens with two bandits breaking into ...	[action]
7	The film is about a family who move to the sub...	the film is about a family who move to the sub...	[comedy]
8	The opening scene shows the interior of the ro...	the opening scene shows the interior of the ro...	[]
9	Scenes are introduced using lines of the poem....	scenes are introduced using lines of the poem....	[]
10	The Rarebit Fiend gorges on Welsh rarebit at a...	the rarebit fiend gorges on welsh rarebit at a...	[short]
11	The film features a train traveling through th...	the film features a train traveling through th...	[action, crime, short]

In [35]:
```
len(movies['GenreSplitMain'][0])
```

Out[35]: 0

In [36]:
```
movies['GenreSplitMain'][0:5].apply(len)
```

Out[36]:
```
0    0
1    0
2    0
3    0
4    0
Name: GenreSplitMain, dtype: int64
```

In [37]:
```
movies['MainGenresCount'] = movies['GenreSplitMain'].apply(len)
```

In [38]:
```
max(movies['MainGenresCount'] )
```

Out[38]: 7

In [39]:

```python
movies[movies['MainGenresCount']==7]
```

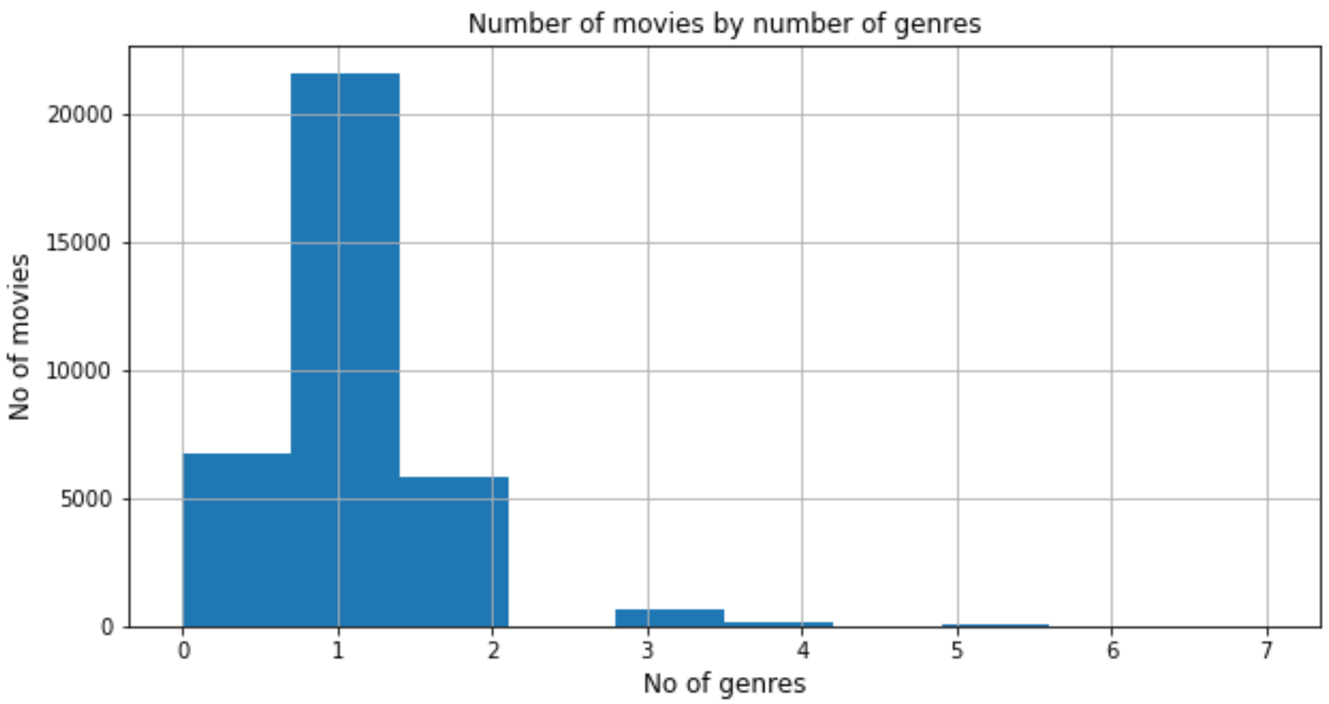
Out[39]:

	Release Year	Title	Origin/Ethnicity	Director	Cast	Genre	Wiki Page	Plot	Count	GenreCorrected	GenreSplit	GenreSplitMai
17314	2017	American Made	American	Doug Liman	Doug Liman (director); Gary Spinelli (screenpl...	biography, action, comedy, crime, drama, histo...	https://en.wikipedia.org/wiki/American_Made_(f...	In the late 1970s, Barry Seal, a pilot for com...	1	biography|action|comedy|crime|drama|history|th...	[action, biography, comedy, crime, drama, hist...	[actior biography comedy, crime drama, hist.

In [40]:

```python
movies['MainGenresCount'].hist(figsize = (10,5))

plt.title("Number of movies by number of genres")
plt.ylabel('No of movies', fontsize=12)
plt.xlabel('No of genres', fontsize=12)
plt.show()
```



Classifier Training

- Count Vectorizer
- TF-IDF Vectorizers

In [41]:

```python
txt = ["He is ::having a great Time, at the park time?",
       "She, unlike most women, is a big player on the park's grass.",
       "she can't be going"]
```

In [42]:
```
txt
```

Out[42]:
```
['He is ::having a great Time, at the park time?',
 "She, unlike most women, is a big player on the park's grass.",
 "she can't be going"]
```

In [43]:
```
# Initializing a CountVectorizer object
count_vec = CountVectorizer(stop_words="english", analyzer='word',
                            ngram_range=(1, 1), max_df=1.0, min_df=1, max_features=None)
```

In [44]:
```
# Transforming the data into a bag of words
count_train = count_vec.fit(txt)
bag_of_words = count_vec.transform(txt)

# Printing the first 10 features of the count_vec
print("Every feature:\n{}".format(count_vec.get_feature_names()))
print("\nEvery 3rd feature:\n{}".format(count_vec.get_feature_names()[::3]))
```

```
Every feature:
['big', 'going', 'grass', 'great', 'having', 'park', 'player', 'time', 'unlike', 'women']

Every 3rd feature:
['big', 'great', 'player', 'women']
```

```
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function get_feature_names is deprecated; get_feature_names is dep
recated in 1.0 and will be removed in 1.2. Please use get_feature_names_out instead.
  warnings.warn(msg, category=FutureWarning)
```

In [45]:
```
count_vec.fit_transform(txt).toarray()
```

Out[45]:
```
array([[0, 0, 0, 1, 1, 1, 0, 2, 0, 0],
       [1, 0, 1, 0, 0, 1, 1, 0, 1, 1],
       [0, 1, 0, 0, 0, 0, 0, 0, 0, 0]])
```

In [46]:
```
count_vec.get_feature_names()[:4]
```

Out[46]:
```
['big', 'going', 'grass', 'great']
```

In [47]:
```
z = movies.GenreSplitMain.str.split()
movies.GenreSplitMain[6:15].apply(lambda x: '-'.join(x)).str.split(pat='-',n=5,expand=True)
```

Out[47]:

	0	1	2
6	action	None	None
7	comedy	None	None
8		None	None
9		None	None
10	short	None	None
11	action	crime	short
12	short	None	None
13	biography	None	None
14	comedy	None	None

In [48]:

```
movies.GenreSplitMain[6:15].apply(lambda x: '-'.join(x)).str.get_dummies(sep='-')
```

Out[48]:

	action	biography	comedy	crime	short
6	1	0	0	0	0
7	0	0	1	0	0
8	0	0	0	0	0
9	0	0	0	0	0
10	0	0	0	0	1
11	1	0	0	1	1
12	0	0	0	0	1
13	0	1	0	0	0
14	0	0	1	0	0

In [49]:

```
movies.GenreSplitMain[6:15]
```

Out[49]:

```
6                    [action]
7                    [comedy]
8                          []
9                          []
10                    [short]
11    [action, crime, short]
12                    [short]
13                [biography]
14                   [comedy]
Name: GenreSplitMain, dtype: object
```

In [50]:

```
movies.columns
```

Out[50]:

```
Index(['Release Year', 'Title', 'Origin/Ethnicity', 'Director', 'Cast',
       'Genre', 'Wiki Page', 'Plot', 'Count', 'GenreCorrected', 'GenreSplit',
       'GenreSplitMain', 'PlotClean', 'MainGenresCount'],
      dtype='object')
```

In [51]:
```
movies.shape
```
Out[51]:
```
(34886, 14)
```
In [52]:
```
# Titles that are not unique
len(movies.Title.unique())
```
Out[52]:
```
32432
```
In [53]:
```
# Movies without genre
movies[movies.GenreCorrected==''].shape
```
Out[53]:
```
(6206, 14)
```

Classification Algorithm

- Creating classes: One dummy variable for each genre
- Split the data in train and test
- TfidfVectorizer

In [54]:
```
# Creating a dummy class
movies = pd.concat([movies, movies.GenreSplitMain.apply(lambda x: '-'.join(x)).str.get_dummies(sep='-')], axis=1)
```
In [55]:
```
# Creating a train_test_split
MoviesTrain, MoviesTest = train_test_split(movies[movies.GenreCorrected!=''], random_state=42, test_size=0.30, shuffle=True)
```

Feature Extraction

In [56]:
```
# definition the algorithm for feature extraction
tfidf = TfidfVectorizer(stop_words ='english', smooth_idf=False, sublinear_tf=False, norm=None, analyzer='word')
```
In [57]:
```
# Building the features ("Dimensionality mismatch")
x_train = tfidf.fit_transform(MoviesTrain.PlotClean)
x_test  = tfidf.transform(MoviesTest.PlotClean)
```
In [58]:
```
print('nrow of the MoviesTrain ={}'. format(MoviesTrain.shape[0]))
```
```
nrow of the MoviesTrain =20076
```
In [59]:
```
print('nrow of the MoviesTest ={}'. format(MoviesTest.shape[0]))
```
```
nrow of the MoviesTest =8604
```
In [60]:
```
type(x_train)
```
Out[60]:
```
scipy.sparse.csr.csr_matrix
```

In [61]:
```
x_train.toarray()
```

Out[61]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [62]:
```
tfidf.inverse_transform(x_train[0].toarray())
```

Out[62]:
```
[array(['1930s', '1937', 'abilities', 'able', 'accept', 'accepts',
        'acquaintance', 'actively', 'adversely', 'affects', 'aggressive',
        'agrees', 'aide', 'allow', 'amidst', 'apartment', 'arena', 'army',
        'arouses', 'arrives', 'artist', 'artists', 'arts', 'attempts',
        'away', 'bag', 'bandit', 'bandits', 'barely', 'barrage', 'battle',
        'beaten', 'beating', 'beats', 'blows', 'bruce', 'brutal',
        'challenge', 'challenges', 'chance', 'chaos', 'cheered', 'child',
        'chinese', 'ching', 'chow', 'chuen', 'chun', 'claimed', 'closed',
        'coal', 'colleagues', 'collect', 'colonel', 'come', 'compete',
        'competitions', 'consents', 'conserve', 'contain', 'cotton',
        'crowd', 'days', 'declines', 'decrepit', 'defeat', 'defeats',
        'defends', 'defense', 'demands', 'desperate', 'despite', 'direct',
        'disciples', 'discussing', 'displays', 'does', 'door', 'earlier',
        'earn', 'effective', 'embarrassing', 'energy', 'enhanced',
        'enraged', 'epilogue', 'equally', 'escaped', 'establishes',
        'eventually', 'exhibited', 'extort', 'family', 'feels', 'fellow',
        'fight', 'fighters', 'fighting', 'figures', 'finally', 'finds',
        'flee', 'food', 'forced', 'forshan', 'foshan', 'friend',
        'friendly', 'friends', 'gang', 'general', 'grows', 'gun', 'harass',
        'harassing', 'having', 'headquarters', 'held', 'help', 'highly',
        'hong', 'house', 'hub', 'humiliation', 'igniting', 'impatient',
        'impeccable', 'incapacitates', 'including', 'independent',
        'inflicting', 'insist', 'instead', 'instruct', 'invasion',
        'invisible', 'ip', 'japanese', 'jin', 'karate', 'karateka',
        'killed', 'kills', 'kong', 'later', 'learn', 'led', 'lee', 'lets',
        'li', 'life', 'lin', 'liu', 'local', 'lose', 'love', 'maintains',
        'man', 'martial', 'master', 'masters', 'match', 'matched',
        'matches', 'meeting', 'mercilessly', 'midway', 'military', 'miura',
        'money', 'moves', 'need', 'northern', 'occupied', 'offers',
        'officer', 'overwhelm', 'owns', 'participate', 'personally',
        'police', 'practiced', 'pride', 'professional', 'profile',
        'protection', 'public', 'rage', 'recruit', 'refuses', 'refusing',
        'regional', 'relentless', 'reputation', 'resentful', 'respected',
        'restraint', 'return', 'returning', 'reveals', 'rice', 'robbers',
        'room', 'rude', 'runs', 'sadistic', 'sato', 'school', 'schools',
        'scuffle', 'sees', 'self', 'sends', 'severe', 'shanzhao', 'shoots',
        'shoulder', 'showing', 'skill', 'skilled', 'soldiers', 'son',
        'southern', 'spared', 'spending', 'spends', 'square', 'students',
        'stylists', 'support', 'survived', 'taken', 'takes', 'taught',
        'teach', 'techniques', 'tells', 'time', 'trainees', 'training',
        'trains', 'translator', 'trying', 'unassuming', 'upholding',
        'used', 'using', 'various', 'visits', 'wants', 'warns', 'watch',
        'watches', 'wealth', 'wealthy', 'wife', 'win', 'wing', 'winning',
        'work', 'workers', 'working', 'zhao'], dtype='<U34')]
```

In [63]:
```
print('The corpus is huge. It contain {} words.'.format(len(x_train[0].toarray()[0])))
```

```
The corpus is huge. It contain 103411 words.
```

In [64]:
```
# Building the classes
y_train = MoviesTrain[MoviesTrain.columns[14:]]
y_test = MoviesTest[MoviesTest.columns[14:]]
```

In [65]:
```
len(y_train.columns)
```

Out[65]: 20

In [66]:
```
len(y_test.columns)
```

Out[66]: 20

Multinomial Naive Bayes Classification

In [67]:
```
multinomialNB=OneVsRestClassifier(MultinomialNB(fit_prior=True, class_prior=None))
```

In [68]:
```
# Model Fitting
multinomialNB.fit(x_train, y_train.action)
```

Out[68]:
```
OneVsRestClassifier(estimator=MultinomialNB())
```

In [69]:
```
# Testing accuracy
prediction = multinomialNB.predict(x_test)
```

In [70]:
```
print('Test accuracy is {}'.format(accuracy_score(y_test.action, prediction)))
```

```
Test accuracy is 0.8265922826592282
```

In [71]:
```
len(mainGenres)
```

Out[71]: 20

Multinomial Navie Bayes Classification for all the genre in the data

In [72]:
```
accuracy_multinomialNB=pd.DataFrame(columns=['Genre', 'accuracy_multinomialNB'])
accuracy_multinomialNB.head()
```

Out[72]:

Genre	accuracy_multinomialNB

In [73]:

```
i = 0
for genre in mainGenres:
    multinomialNB.fit(x_train, y_train[genre])
    prediction = multinomialNB.predict(x_test)
    accuracy_multinomialNB.loc[i,'Genre'] = genre
    accuracy_multinomialNB.loc[i,'accuracy_multinomialNB'] = accuracy_score(y_test[genre], prediction)
    i=i+1



accuracy_multinomialNB
```

Out[73]:

	Genre	accuracy_multinomialNB
0	drama	0.673756
1	comedy	0.733147
2	action	0.826592
3	thriller	0.884589
4	romance	0.843096
5	crime	0.911088
6	musical	0.937587
7	animation	0.973849
8	children	0.957578
9	fantasy	0.974314
10	mystery	0.974314
11	biography	0.967573
12	black	0.971292
13	history	0.98245
14	short	0.988726
15	documentary	0.992562
16	sports	0.991399
17	series	0.996048
18	adult	0.995932
19	political	0.995932

Linear Support Vector Classification for all the genres

In [74]:

```
linearSVC=OneVsRestClassifier(LinearSVC(), n_jobs=1)
```

In [75]:

```
accuracy_LinearSVC=pd.DataFrame(columns=['Genre', 'accuracy_LinearSVC'])
accuracy_LinearSVC.head()
```

Out[75]:

Genre	accuracy_LinearSVC

In [76]:

```
i = 0
for genre in mainGenres:
    linearSVC.fit(x_train, y_train[genre])
    prediction = linearSVC.predict(x_test)
    accuracy_LinearSVC.loc[i,'Genre'] = genre
    accuracy_LinearSVC.loc[i,'accuracy_LinearSVC'] = accuracy_score(y_test[genre], prediction)
    i=i+1
```

```
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/Users/raghul/opt/anaconda3/lib/python3.8/site-packages/sklearn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
```

In [77]:

```
accuracy_LinearSVC
```

Out[77]:

	Genre	accuracy_LinearSVC
0	drama	0.661669
1	comedy	0.746165
2	action	0.817178
3	thriller	0.884007
4	romance	0.882961
5	crime	0.924105
6	musical	0.956881
7	animation	0.977569
8	children	0.97013
9	fantasy	0.979777
10	mystery	0.980126
11	biography	0.982915
12	black	0.981172
13	history	0.989772
14	short	0.990934
15	documentary	0.995235
16	sports	0.994305
17	series	0.996629
18	adult	0.996862
19	political	0.997675

In [78]:

```
# Merging both Multinomial Navie Bayes and Linear Support Vector accuracy tables
accuracy_svc_mnb = pd.merge(accuracy_multinomialNB, accuracy_LinearSVC, on='Genre', how='inner')
```

In [79]:

```
accuracy_svc_mnb
```

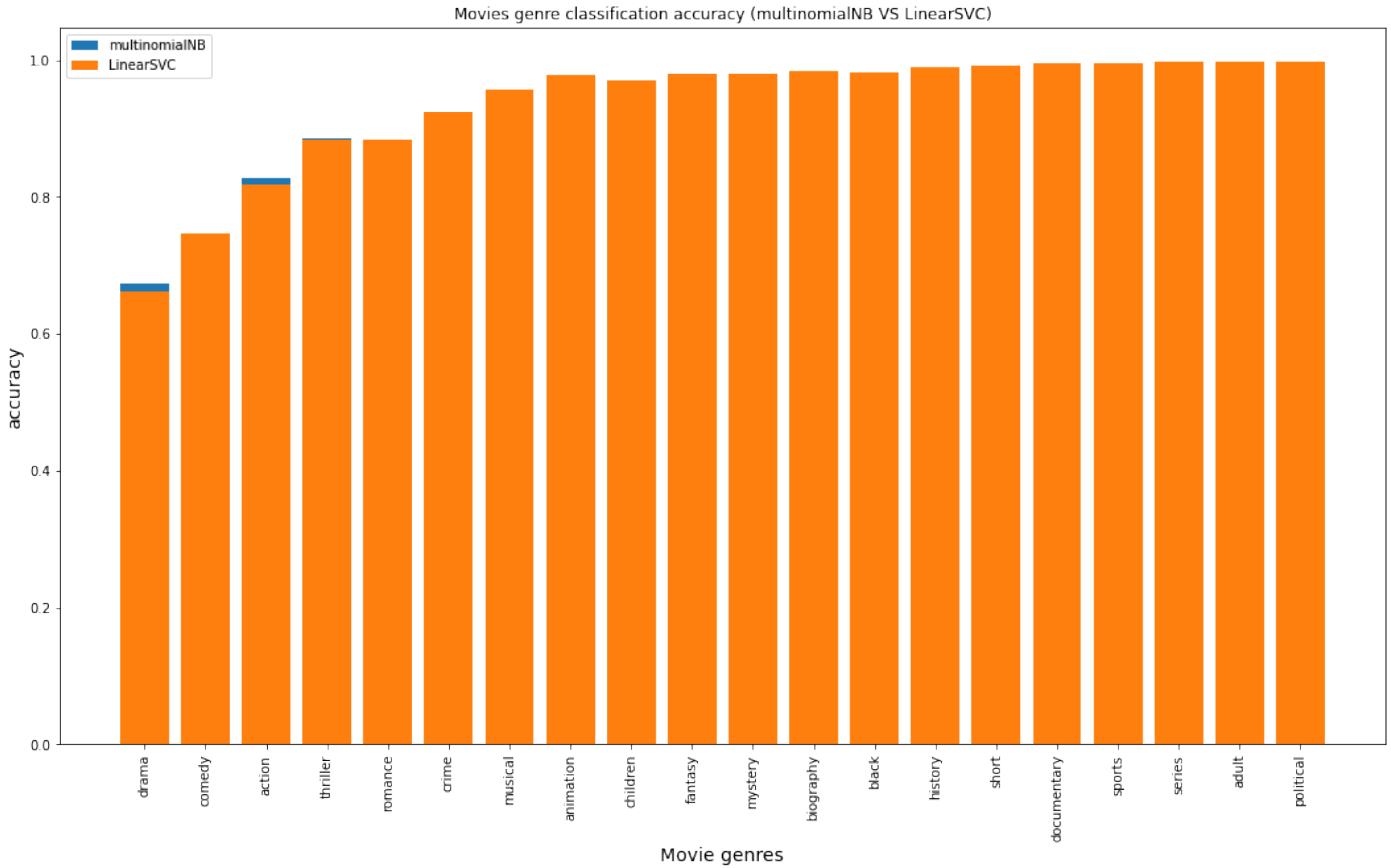
Out[79]:

	Genre	accuracy_multinomialNB	accuracy_LinearSVC
0	drama	0.673756	0.661669
1	comedy	0.733147	0.746165
2	action	0.826592	0.817178
3	thriller	0.884589	0.884007
4	romance	0.843096	0.882961
5	crime	0.911088	0.924105
6	musical	0.937587	0.956881
7	animation	0.973849	0.977569
8	children	0.957578	0.97013
9	fantasy	0.974314	0.979777
10	mystery	0.974314	0.980126
11	biography	0.967573	0.982915
12	black	0.971292	0.981172
13	history	0.98245	0.989772
14	short	0.988726	0.990934
15	documentary	0.992562	0.995235
16	sports	0.991399	0.994305
17	series	0.996048	0.996629
18	adult	0.995932	0.996862
19	political	0.995932	0.997675

- It is observed that both the classification gives almost similar accuracy score in the above constructed table.

In [80]:

```
plt.figure(figsize=(18,10))
p1 =plt.bar(accuracy_svc_mnb.Genre, height=accuracy_svc_mnb.accuracy_multinomialNB)
p2 =plt.bar(accuracy_svc_mnb.Genre, height=accuracy_svc_mnb.accuracy_LinearSVC)
plt.xticks( rotation=90)
plt.title("Movies genre classification accuracy (multinomialNB VS LinearSVC)")
plt.ylabel('accuracy', fontsize=14)
plt.xlabel('Movie genres', fontsize=14)
plt.legend((p1[0], p2[0]), ('multinomialNB', 'LinearSVC'))
plt.show()
```



- **Note:** This graph is not showing the comparision between the two classifiers, instead it shows just the depletion between certain values.

In [81]:

```
accuracy_multinomialNB1 = accuracy_multinomialNB
accuracy_multinomialNB1.columns = ['Genre', 'accuracy']
accuracy_multinomialNB1['classifier'] = 'multinomialNB'
```

In [82]:

```
accuracy_multinomialNB1
```

Out[82]:

	Genre	accuracy	classifier
0	drama	0.673756	multinomialNB
1	comedy	0.733147	multinomialNB
2	action	0.826592	multinomialNB
3	thriller	0.884589	multinomialNB
4	romance	0.843096	multinomialNB
5	crime	0.911088	multinomialNB
6	musical	0.937587	multinomialNB
7	animation	0.973849	multinomialNB
8	children	0.957578	multinomialNB
9	fantasy	0.974314	multinomialNB
10	mystery	0.974314	multinomialNB
11	biography	0.967573	multinomialNB
12	black	0.971292	multinomialNB
13	history	0.98245	multinomialNB
14	short	0.988726	multinomialNB
15	documentary	0.992562	multinomialNB
16	sports	0.991399	multinomialNB
17	series	0.996048	multinomialNB
18	adult	0.995932	multinomialNB
19	political	0.995932	multinomialNB

In [84]:

```
accuracy_LinearSVC1 = accuracy_LinearSVC
accuracy_LinearSVC1.columns = ['Genre', 'accuracy']
accuracy_LinearSVC1['classifier'] = 'linearSVC'
```

In [85]:

```
accuracy_LinearSVC1
```

Out[85]:

	Genre	accuracy	classifier
0	drama	0.661669	linearSVC
1	comedy	0.746165	linearSVC
2	action	0.817178	linearSVC
3	thriller	0.884007	linearSVC
4	romance	0.882961	linearSVC
5	crime	0.924105	linearSVC
6	musical	0.956881	linearSVC
7	animation	0.977569	linearSVC
8	children	0.97013	linearSVC
9	fantasy	0.979777	linearSVC
10	mystery	0.980126	linearSVC
11	biography	0.982915	linearSVC
12	black	0.981172	linearSVC
13	history	0.989772	linearSVC
14	short	0.990934	linearSVC
15	documentary	0.995235	linearSVC
16	sports	0.994305	linearSVC
17	series	0.996629	linearSVC
18	adult	0.996862	linearSVC
19	political	0.997675	linearSVC

In [86]:

```
accu_mnb_svc = accuracy_multinomialNB1.append(accuracy_LinearSVC1)
```

In [87]:

```
accu_mnb_svc
```

Out[87]:

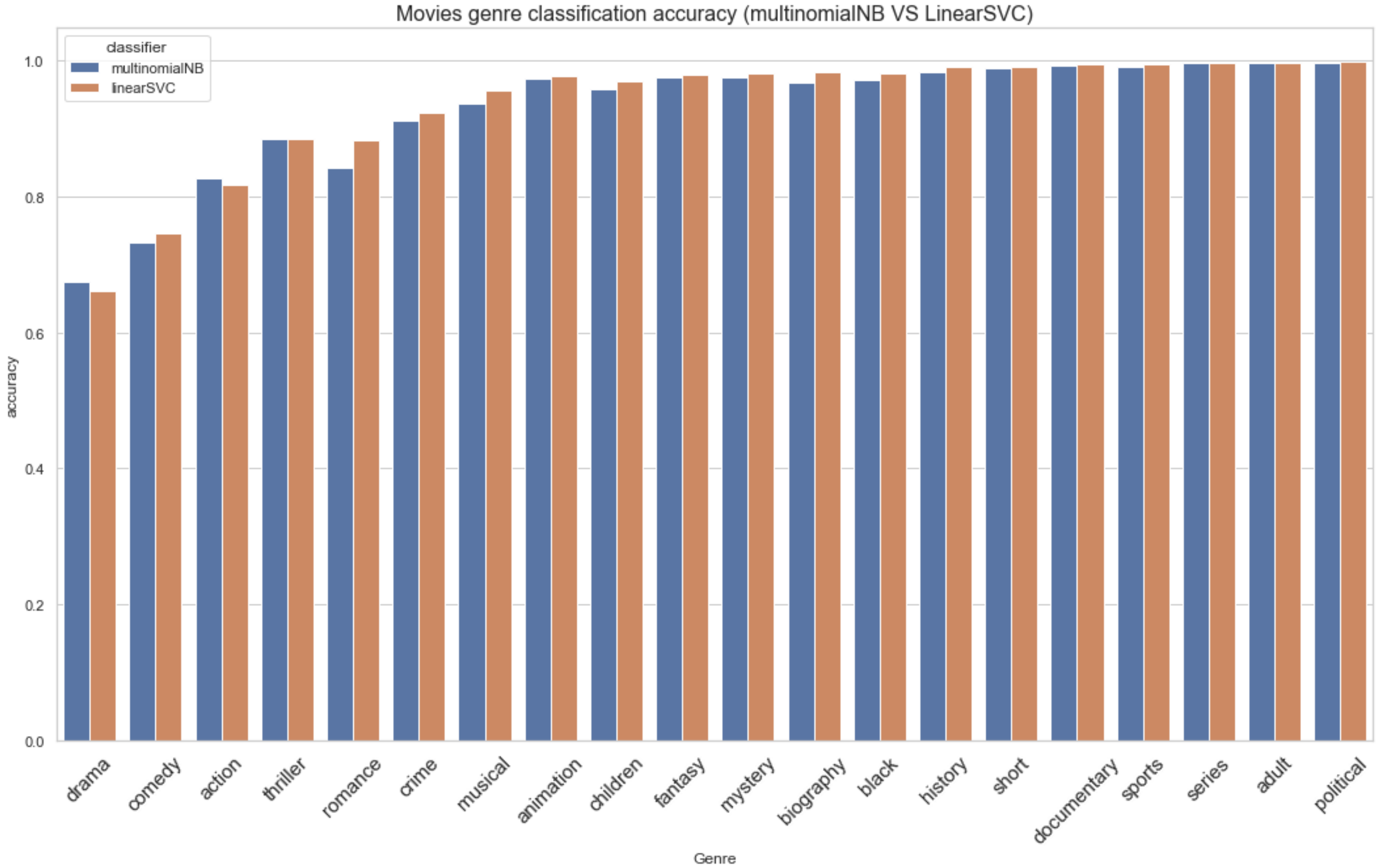
	Genre	accuracy	classifier
0	drama	0.673756	multinomialNB
1	comedy	0.733147	multinomialNB
2	action	0.826592	multinomialNB
3	thriller	0.884589	multinomialNB
4	romance	0.843096	multinomialNB
5	crime	0.911088	multinomialNB
6	musical	0.937587	multinomialNB
7	animation	0.973849	multinomialNB
8	children	0.957578	multinomialNB

9	fantasy	0.974314	multinomialNB
10	mystery	0.974314	multinomialNB
11	biography	0.967573	multinomialNB
12	black	0.971292	multinomialNB
13	history	0.98245	multinomialNB
14	short	0.988726	multinomialNB
15	documentary	0.992562	multinomialNB
16	sports	0.991399	multinomialNB
17	series	0.996048	multinomialNB
18	adult	0.995932	multinomialNB
19	political	0.995932	multinomialNB
0	drama	0.661669	linearSVC
1	comedy	0.746165	linearSVC
2	action	0.817178	linearSVC
3	thriller	0.884007	linearSVC
4	romance	0.882961	linearSVC
5	crime	0.924105	linearSVC
6	musical	0.956881	linearSVC
7	animation	0.977569	linearSVC
8	children	0.97013	linearSVC
9	fantasy	0.979777	linearSVC
10	mystery	0.980126	linearSVC
11	biography	0.982915	linearSVC
12	black	0.981172	linearSVC
13	history	0.989772	linearSVC
14	short	0.990934	linearSVC
15	documentary	0.995235	linearSVC
16	sports	0.994305	linearSVC
17	series	0.996629	linearSVC
18	adult	0.996862	linearSVC
19	political	0.997675	linearSVC

In [88]:

```
sns.set(rc={'figure.figsize':(18,10)})
sns.set(style="whitegrid")
s = sns.barplot(x="Genre", y="accuracy", hue="classifier", data=accu_mnb_svc)
s.set_title('Movies genre classification accuracy (multinomialNB VS LinearSVC)', size=16)
s.set_xticklabels(list(mainGenres) ,rotation=45, size=15)
```

```
Out[88]: [Text(0, 0, 'drama'),
 Text(1, 0, 'comedy'),
 Text(2, 0, 'action'),
 Text(3, 0, 'thriller'),
 Text(4, 0, 'romance'),
 Text(5, 0, 'crime'),
 Text(6, 0, 'musical'),
 Text(7, 0, 'animation'),
 Text(8, 0, 'children'),
 Text(9, 0, 'fantasy'),
 Text(10, 0, 'mystery'),
 Text(11, 0, 'biography'),
 Text(12, 0, 'black'),
 Text(13, 0, 'history'),
 Text(14, 0, 'short'),
 Text(15, 0, 'documentary'),
 Text(16, 0, 'sports'),
 Text(17, 0, 'series'),
 Text(18, 0, 'adult'),
 Text(19, 0, 'political')]
```



Conclusion

- Multinomial Navie Bayes Algorithm and Linear Support Vector Classification showed very good accuracy rate.
    - Lowest Accuracy: 66%
    - Highest Accuracy: 99%
- Also, Multinomial Navie Bayes Classification is faster that LinearSVC.
- Multinomial Navie Bayes Classification does not have any convergence issues compared to LinearSVC.

Limitations

- LinearSVC did not converge for some genres.
- The reliability of the accuracy rate needs further investigation.

In [ ]:

```

```