Topic Models

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1 Final Project - Movie Reviews Analysis

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2 Packages

[1]:
```
import numpy as np
import pandas as pd
from tqdm.auto import tqdm
import pyLDAvis
import pyLDAvis.sklearn
import pyLDAvis.gensim_models
import spacy
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import NMF, TruncatedSVD, LatentDirichletAllocation
from spacy.lang.en.stop_words import STOP_WORDS as stopwords
from collections import Counter, defaultdict
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation
from wordcloud import WordCloud
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)


# Define function to display topics for the topic models (directly from BTAP␣
↪repo)
def display_topics(model, features, no_top_words=5):
    for topic, words in enumerate(model.components_):
        total = words.sum()
        largest = words.argsort()[::-1] # invert sort order
        print("\nTopic %02d" % topic)
        for i in range(0, no_top_words):
            print("  %s (%2.2f)" % (features[largest[i]],␣
↪abs(words[largest[i]]*100.0/total)))
```

```
/home/jimmynguyen/anaconda3/envs/ads509/lib/python3.9/site-
packages/tqdm/auto.py:22: TqdmWarning: IProgress not found. Please update
jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

3 Prepare Data

[2]:
```
# Read in the cleaned plot data
plot_data = pd.read_csv('Cleaned Plot Data.csv')
# View dataframe
plot_data.sample(5)
```

[2]:
```
                                title  first_genre  \
394                   The Perfect One        drama
115          Father There Is Only One       comedy
1656  One Wish for Iran, Love Israel  documentary
1817                One Hundred Steps  documentary
913                     The Lucky One       comedy

                                           cleaned_plot  imdb_rating
394   ['new', 'mother', 'dealing', 'postpartum', 'de…          5.6
115   ['family', 'father', 'discovers', 'hard', 'car…          6.0
1656  ['one', 'wish', 'iran', 'love', 'israel', 'hig…          NaN
1817  ['forty', 'years', 'frank', 'garfunkel', 'taug…          NaN
913   ['countryman', 'arrives', 'athens', 'make', 'b…          5.0
```

[3]:
```
# Untokenize plot descriptions
plot_data['cleaned_plot'] = plot_data['cleaned_plot'].str.replace(r'[^\w\s]',␣
↪'', regex= True).str.strip()
plot_data['cleaned_plot'].sample(5)
```

[3]:
```
1806    sensitive portrait psychotic glamorous drugadd…
496     gold lion shiki offered alliance gol roger lat…
1734    modern day parable setting mail package proces…
903     early 1980s beginning would become 12yearlong …
1620    wal junior meg get selected go france study la…
Name: cleaned_plot, dtype: object
```

[4]:
```
# TF-IDF text vectorization
tfidf_text_vectorizer = TfidfVectorizer(stop_words=stopwords, min_df=3)
plot_data_tfidf = tfidf_text_vectorizer.fit_transform(plot_data["cleaned_plot"])
plot_data_tfidf.shape
```

[4]:
```
(1828, 2414)
```

4 Topic Modeling

4.0.1 Non-Negative Matrix Factorization

[5]:
```python
# Non-Negative Matrix Factorization Model
plot_nmf_model = NMF(n_components=5, random_state=42)
W_text_matrix = plot_nmf_model.fit_transform(plot_data_tfidf)
H_text_matrix = plot_nmf_model.components_

# Show results of the topic model
display_topics(plot_nmf_model, tfidf_text_vectorizer.get_feature_names())
```

```
Topic 00
  young (2.01)
  man (1.94)
  woman (1.49)
  love (1.49)
  girl (0.91)

Topic 01
  documentary (3.88)
  film (3.86)
  short (1.53)
  new (1.04)
  making (0.77)

Topic 02
  story (7.19)
  tells (1.62)
  based (1.29)
  journey (1.11)
  true (0.98)

Topic 03
  life (7.42)
  years (1.29)
  art (0.85)
  musician (0.70)
  jokes (0.70)

Topic 04
  day (8.09)
  lives (1.51)
  night (1.07)
  peace (0.96)
  city (0.86)
```

```
[6]: # Create document-topic dataframe and add genre column
def genre_by_topic(df):
    document_topic = pd.DataFrame(df)
    topic_genre = pd.concat([document_topic.idxmax(axis=1),␣
 ↪plot_data['first_genre']], axis=1)
    topic_genre.columns = ['topic', 'genre']
    return topic_genre.groupby(['topic', 'genre']).size()
genre_by_topic(W_text_matrix)
```

```
[6]: topic  genre
     0      action          68
            animation       52
            comedy         210
            documentary     92
            drama          210
     1      action          20
            animation       28
            comedy          59
            documentary    313
            drama           31
     2      action          28
            animation       31
            comedy          34
            documentary    124
            drama           68
     3      action          11
            animation       16
            comedy          45
            documentary    120
            drama           71
     4      action           5
            animation       18
            comedy          32
            documentary     94
            drama           48
     dtype: int64
```

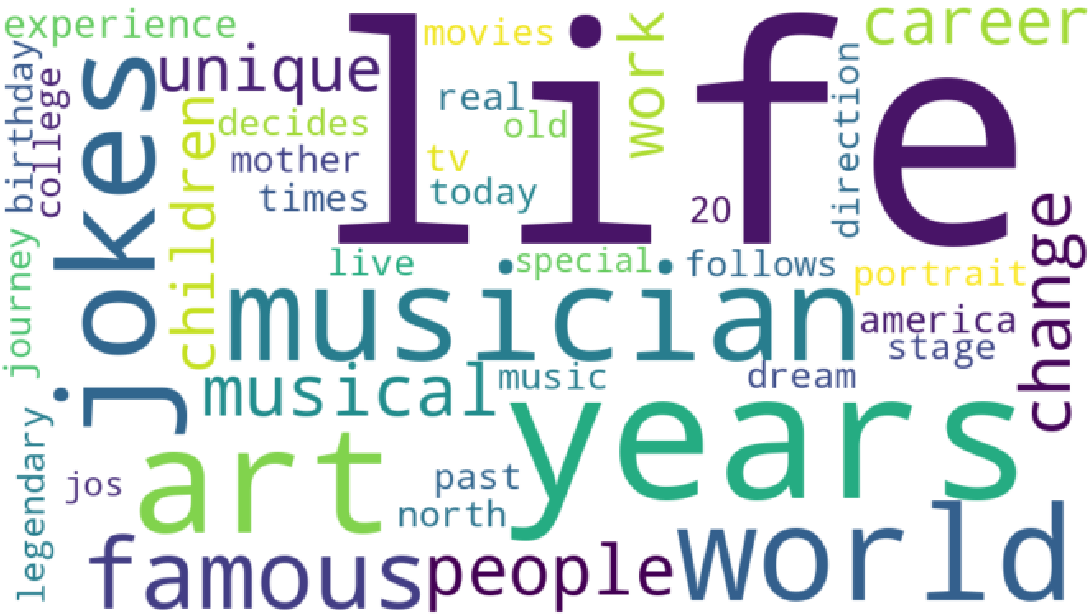
The NMF topic model appears to spread each genre around within each topic. Topic 0 has a higher concentration of drama and comedy. Topic 1 does appear to group documentary primarily, but the last 3 topics appear to just spread the top 3 genres around. It is difficult to determine which topic would match with which genre.

```
[7]: # display word cloud function
def wordcloud_topics(model, features, no_top_words=40):
    for topic, words in enumerate(model.components_):
        size = {}
        largest = words.argsort()[::-1] # invert sort order
```

```
        for i in range(0, no_top_words):
            size[features[largest[i]]] = abs(words[largest[i]])
        wc = WordCloud(background_color="white", max_words=100,
            width=960, height=540)
        wc.generate_from_frequencies(size)
        plt.figure(figsize=(12,12))
        plt.imshow(wc, interpolation='bilinear')
        plt.axis("off")


#NMF Word Cloud for Review


wordcloud_topics(plot_nmf_model, tfidf_text_vectorizer.get_feature_names())
```


life
years
musician
jokes
art
world
famous
people
musical
children
unique
work
career
change
experience
movies
real
old
decides
mother
tv
times
today
20
direction
birthday
college
journey
live
special
follows
portrait
america
stage
music
dream
legendary
jos
past
north


day
lives
night
city
peace
launched
jeremy
inspired
documented
states
project
gilley
unanimous
filmmaker
de
1999
old
years
race
la
modern
ordinary
place
school
sweet
adoption
mother
stories
people
community
wake
single
new
created
british
un
date
year
member
international

4.0.2 Latent Dirichlet Allocation

[8]:
```
# Create Topics For LDA
count_para_vectorizer = CountVectorizer(stop_words=stopwords, min_df=3)
count_para_vectors = count_para_vectorizer.
↪fit_transform(plot_data['cleaned_plot'])
lda_para_model = LatentDirichletAllocation(n_components=5, random_state=42)
W_lda_para_matrix = lda_para_model.fit_transform(count_para_vectors)
H_lda_para_matrix = lda_para_model.components_

display_topics(lda_para_model, count_para_vectorizer.get_feature_names())
```

```
Topic 00
  film (1.26)
  world (1.23)
  documentary (1.02)
  love (0.92)
  girl (0.66)

Topic 01
  life (2.30)
  film (1.18)
  new (1.14)
  world (0.98)
  story (0.88)

Topic 02
  young (1.25)
  man (1.21)
  night (0.94)
  story (0.68)
  lives (0.63)

Topic 03
  story (1.48)
  man (0.92)
  film (0.92)
  life (0.85)
  years (0.84)

Topic 04
  young (1.19)
  woman (1.03)
  man (0.93)
  love (0.78)
  life (0.74)
```

[9]:
```
# Compare LDA topic modeling to original genres
genre_by_topic(W_lda_para_matrix)
```

[9]:
```
topic  genre
0      action          18
       animation       33
       comedy          53
       documentary    179
       drama           56
1      action          31
       animation       21
       comedy          61
       documentary    221
       drama           83
2      action          28
       animation       49
       comedy         100
       documentary     85
       drama          104
3      action          19
       animation       16
       comedy          78
       documentary    171
       drama           91
4      action          36
       animation       26
       comedy          88
       documentary     87
       drama           94
dtype: int64
```

Once again, it appears the genres are spread across topics. Each genre has one topic where there is a slightly higher concentration, but overall there is a fairly even distribution across groups.

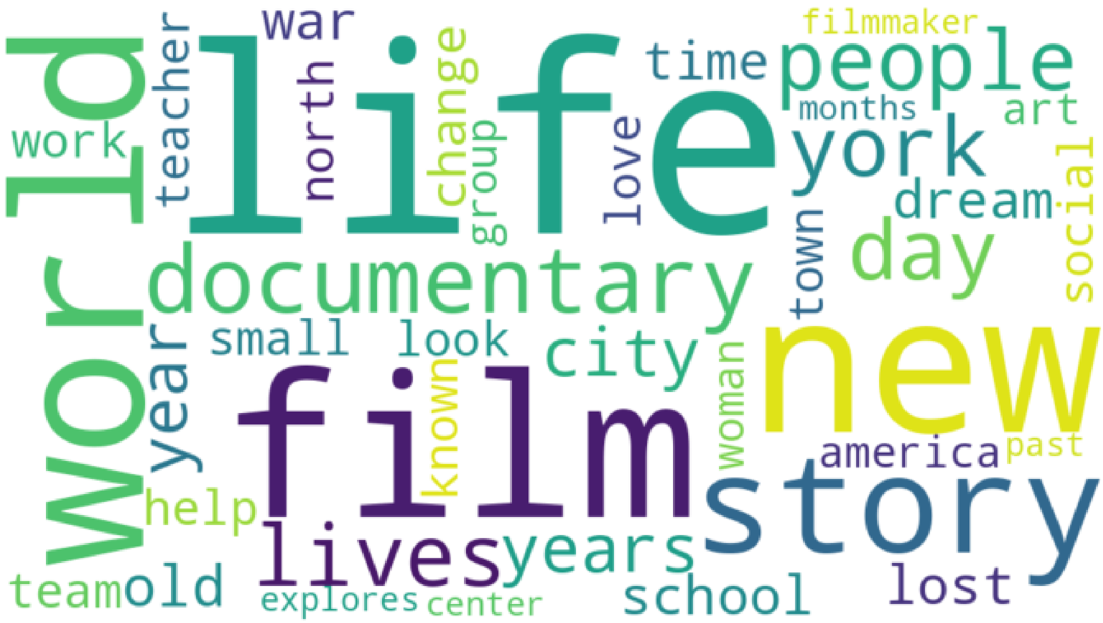
[10]:
```
lda_display = pyLDAvis.sklearn.prepare(lda_para_model, count_para_vectors,
 count_para_vectorizer, sort_topics=False)
pyLDAvis.display(lda_display)
```

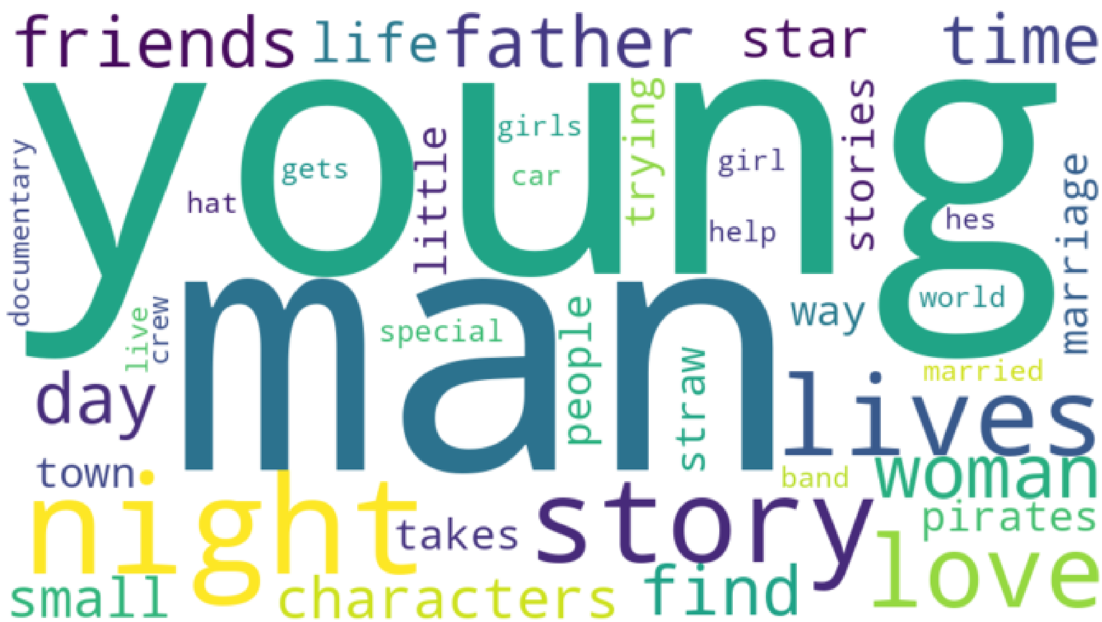
```
/home/jimmynguyen/anaconda3/envs/ads509/lib/python3.9/site-
packages/past/builtins/misc.py:45: DeprecationWarning: the imp module is
deprecated in favour of importlib; see the module's documentation for
alternative uses
  from imp import reload
/home/jimmynguyen/anaconda3/envs/ads509/lib/python3.9/site-
packages/past/builtins/misc.py:45: DeprecationWarning: the imp module is
deprecated in favour of importlib; see the module's documentation for
alternative uses
  from imp import reload
```

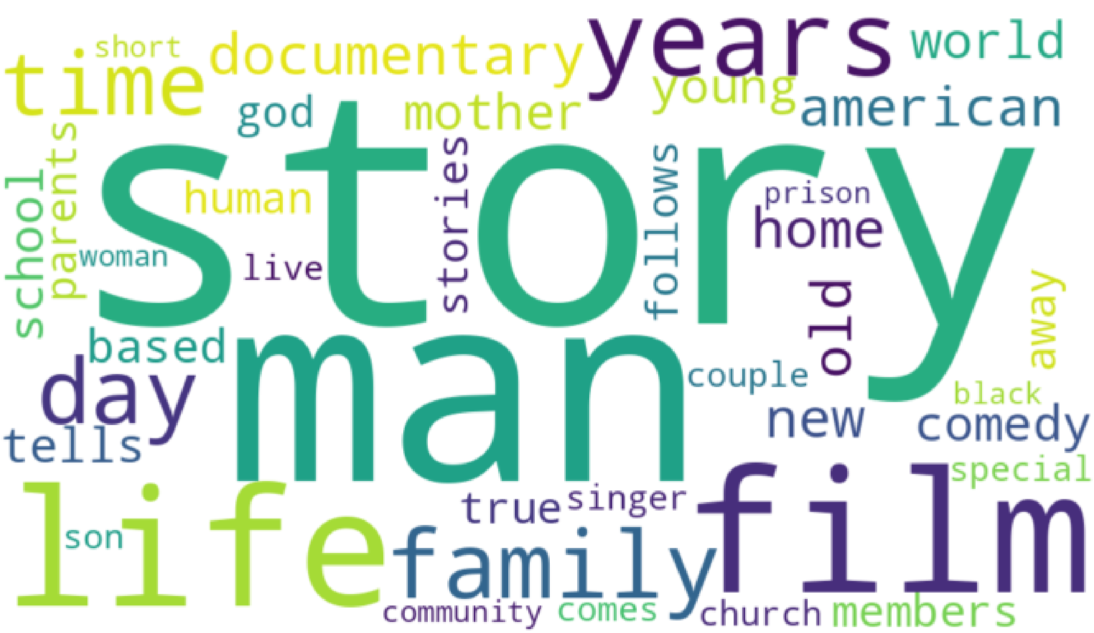
```
/home/jimmynguyen/anaconda3/envs/ads509/lib/python3.9/site-
packages/past/builtins/misc.py:45: DeprecationWarning: the imp module is
deprecated in favour of importlib; see the module's documentation for
alternative uses
  from imp import reload
/home/jimmynguyen/anaconda3/envs/ads509/lib/python3.9/site-
packages/past/builtins/misc.py:45: DeprecationWarning: the imp module is
deprecated in favour of importlib; see the module's documentation for
alternative uses
  from imp import reload
```

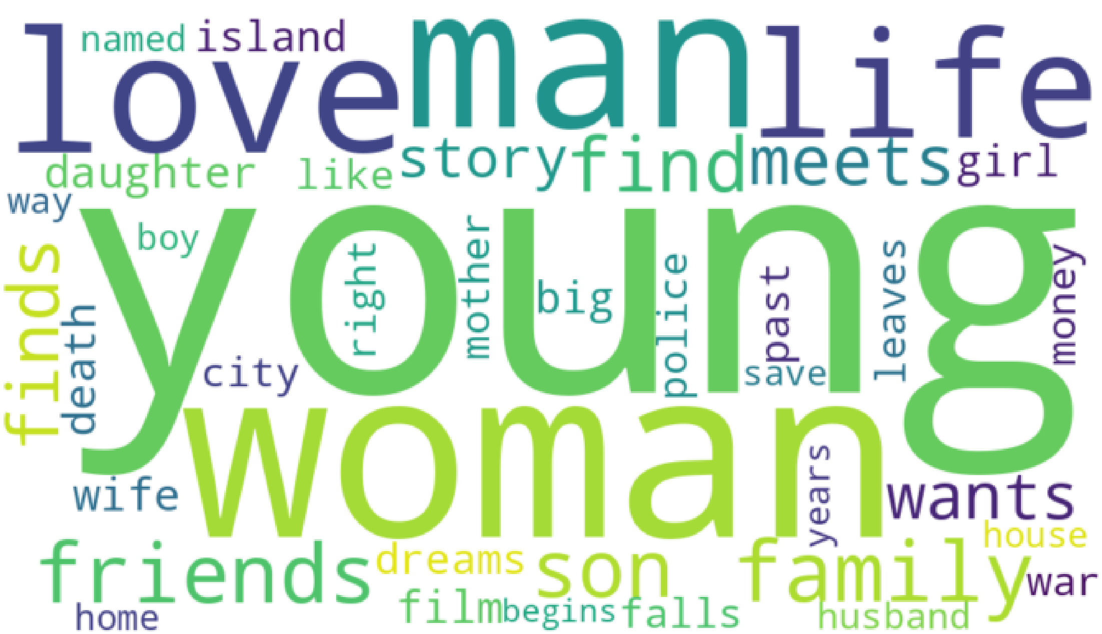
[10]: <IPython.core.display.HTML object>

[11]:
```
#LDA Word Cloud for Review
wordcloud_topics(lda_para_model, count_para_vectorizer.get_feature_names())
```


world
life
war
teacher
north
change
group
love
time
filmmaker
people
months
art
york
work
dream
social
day
documentary
town
year
small
look
city
new
film
known
woman
america
past
story
help
lives
years
team
old
explores
center
school
lost


friends
life
father
star
time
young
documentary
girls
gets
little
trying
car
girl
stories
hat
marriage
help
hes
live
crew
world
special
people
way
man
married
day
straw
lives
town
band
woman
night
takes
story
pirates
love
small
characters
find





5 Recommendations

1. Add more genres in the future (Where it can pull multiple genres if the plot fits in more than one)
2. More in depth design with the application to make it more attractive for the user

3. Train the models on shorter descriptions (Currently accuracy with less words is down)
4. Create a model that can work for longer plot descriptions that way if a movie writer was unsure of the genre of their future film they can put the entire plot into the application and then it will give them an accurate genre

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