ADS 509 Sentiment Assignment

This notebook holds the Sentiment Assignment for Module 6 in ADS 509, Applied Text Mining. Work through this notebook, writing code and answering questions where required.

In a previous assignment you put together Twitter data and lyrics data on two artists. In this assignment we apply sentiment analysis to those data sets. If, for some reason, you did not complete that previous assignment, data to use for this assignment can be found in the assignment materials section of Blackboard.

General Assignment Instructions

These instructions are included in every assignment, to remind you of the coding standards for the class. Feel free to delete this cell after reading it.

One sign of mature code is conforming to a style guide. We recommend the [Google Python Style Guide]. If you use a different style guide, please include a cell with a link.

Your code should be relatively easy-to-read, sensibly commented, and clean. Writing code is a messy process, so please be sure to edit your final submission. Remove any cells that are not needed or parts of cells that contain unnecessary code. Remove inessential `import` statements and make sure that all such statements are moved into the designated cell.

Make use of non-code cells for written commentary. These cells should be grammatical and clearly written. In some of these cells you will have questions to answer. The questions will be marked by a "Q:" and will have a corresponding "A:" spot for you. *Make sure to answer every question marked with a `Q:` for full credit.*

In [1]:
```
import os
import re
import emoji
import pandas as pd
import numpy as np
import nltk

from collections import Counter, defaultdict
from string import punctuation

from nltk.corpus import stopwords

sw = stopwords.words("english")
```

In [2]:
```
# Add any additional import statements you need here
punctuation = set(punctuation)
whitespace_pattern = re.compile(r"\s+")
import emoji
```

In [3]:

```
# change `data_location` to the location of the folder on your machine.
data_location = "C:/Users/19545/ADS509 Text Mining/ADS-509-Module-6/"

# These subfolders should still work if you correctly stored the
# data from the Module 1 assignment
twitter_folder = "twitter/"
lyrics_folder = "lyrics/"

positive_words_file = "positive-words.txt"
negative_words_file = "negative-words.txt"
tidy_text_file = "tidytext_sentiments.txt"
```

Data Input

Now read in each of the corpora. For the lyrics data, it may be convenient to store the entire contents of the file to make it easier to inspect the titles individually, as you'll do in the last part of the assignment. In the solution, I stored the lyrics data in a dictionary with two dimensions of keys: artist and song. The value was the file contents. A Pandas data frame would work equally well.

For the Twitter data, we only need the description field for this assignment. Feel free all the descriptions read it into a data structure. In the solution, I stored the descriptions as a dictionary of lists, with the key being the artist.

In [4]:

```
# Read in the lyrics data
lyrics_list = []
for artist in os.listdir("lyrics"):
    artist_path = os.path.join('lyrics',artist)
    for file in os.listdir(artist_path):
        lyrics = os.path.join('lyrics',artist,file)
        with open(lyrics, 'r') as f:
            song = file.replace('.txt','').split('_')[-1]
            lyrics_file = f.read()
            lyrics_list.append({
                "artist_name": artist,
                "song_title": song,
                "lyrics": lyrics_file
            })

# create pandas dataframe
lyrics_data = pd.DataFrame(lyrics_list)
lyrics_data.tail()
```

Out[4]:

	artist_name	song_title	lyrics
415	robyn	wedancetothebeat114528	"We Dance To The Beat"\n\n\n\nWe dance to the ...
416	robyn	wheredidourlovego	"Where Did Our Love Go"\n\n\n\nThoughts about ...
417	robyn	whosthatgirl	"Who's That Girl"\n\n\n\nGood girls are pretty...
418	robyn	witheveryheartbeat	"With Every Heartbeat"\n\n\n\nMaybe we could m...
419	robyn	youvegotthatsomething	"You've Got That Something"\n\n\n\nLook at me ...

In [5]:
```python
# Read in the twitter data
cher_path = 'C:/Users/19545/ADS509 Text Mining/ADS-509-Module-6/twitter/cher_followers
robynkonichiwa_path = 'C:/Users/19545/ADS509 Text Mining/ADS-509-Module-6/twitter/roby

#reading in cher data
cher_data = pd.read_csv(cher_path, sep = '\t', error_bad_lines = False)
cher_data['Artist_name'] = 'cher'
first_column = cher_data.pop('Artist_name')
cher_data.insert(0, 'Artist_name', first_column)

#Reading Robynkonichiwa data
robynkonichiwa_data = pd.read_csv(robynkonichiwa_path, sep = '\t', encoding = 'utf-8')
robynkonichiwa_data['Artist_name'] = 'robynkonichiwa'
first_column = robynkonichiwa_data.pop('Artist_name')
robynkonichiwa_data.insert(0, 'Artist_name', first_column)
robynkonichiwa_data.head()
```

```
C:\Users\19545\AppData\Local\Temp\ipykernel_27260\4049948151.py:6: FutureWarning: The
error_bad_lines argument has been deprecated and will be removed in a future version.
Use on_bad_lines in the future.


  cher_data = pd.read_csv(cher_path, sep = '\t', error_bad_lines = False)
b'Skipping line 624: expected 7 fields, saw 12\nSkipping line 17506: expected 7 field
s, saw 12\nSkipping line 104621: expected 7 fields, saw 12\n'
b'Skipping line 188924: expected 7 fields, saw 12\n'
b'Skipping line 301600: expected 7 fields, saw 12\n'
b'Skipping line 429936: expected 7 fields, saw 12\nSkipping line 444405: expected 7 f
ields, saw 12\n'
b'Skipping line 677792: expected 7 fields, saw 12\nSkipping line 773482: expected 7 f
ields, saw 12\n'
b'Skipping line 818258: expected 7 fields, saw 12\nSkipping line 895225: expected 7 f
ields, saw 12\n'
b'Skipping line 955213: expected 7 fields, saw 10\nSkipping line 994827: expected 7 f
ields, saw 12\n'
b'Skipping line 1246039: expected 7 fields, saw 12\n'
b'Skipping line 1569117: expected 7 fields, saw 12\n'
b'Skipping line 2127250: expected 7 fields, saw 12\n'
b'Skipping line 2335031: expected 7 fields, saw 12\n'
b'Skipping line 2681065: expected 7 fields, saw 10\n'
b'Skipping line 3147696: expected 7 fields, saw 12\n'
```

Out[5]:

	Artist_name	screen_name	name	id	location	followers_count	friends_cc
0	robynkonichiwa	AngelxoArts	Angelxo	1424055675030806529	Zacatlan, Puebla, Mexico	29	
1	robynkonichiwa	songsfornikola	johnny	1502717352575651840	NaN	6	
2	robynkonichiwa	thibaud_lola	Thibaud Lola	1502407708246478852	NaN	3	
3	robynkonichiwa	KyleSew2112	Kyle S 🌹 GBUA	3423966821	South East London	1258	
4	robynkonichiwa	MusiFlo	MusiFlo	3324069364	Canada	470	

In [6]:

```
df_twitter = pd.concat([cher_data, robynkonichiwa_data])
df_twitter.head()
```

Out[6]:

	Artist_name	screen_name	name	id	location	followers_count	friends_count
0	cher	hsmcnp	Country Girl	3.515221e+07	NaN	1302.0	1014.0
1	cher	horrormomy	Jeny	7.421531e+17	Earth	81.0	514.0
2	cher	anju79990584	anju	1.496463e+18	NaN	13.0	140.0
3	cher	gallionjenna	J	3.366480e+09	NaN	752.0	556.0
4	cher	bcscomm	bcscomm	8.391504e+07	Washington, DC	888.0	2891.0

In [7]:
```
# Read in the positive and negative words and the
# tidytext sentiment. Store these so that the positive
# words are associated with a score of +1 and negative words
# are associated with a score of -1. You can use a dataframe or a
# dictionary for this.

pos_words = pd.read_csv(positive_words_file, skiprows=35,
                        header=None).assign(score=1).rename(columns={0:'word'})
neg_words = pd.read_csv(negative_words_file, encoding = 'ISO-8859-1', skiprows=35,
                        header=None).assign(score=-1).rename(columns={0:'word'})

tidy_text = pd.read_csv(tidy_text_file, sep='\t')
```

In [8]:
```
tidy_text['score'] = np.where(tidy_text['sentiment'] == 'negative', -1, 1)
pos_neg_words = pd.concat((pos_words,neg_words, tidy_text[['word', 'score']]), ignore_
tidy_text.head()
```

Out[8]:

	word	sentiment	lexicon	score
0	abandon	negative	nrc	-1
1	abandoned	negative	nrc	-1
2	abandonment	negative	nrc	-1
3	abba	positive	nrc	1
4	abduction	negative	nrc	-1

In [9]:
```
pos_neg_words.head()
```

Out[9]:

	word	score
0	a+	1
1	abound	1
2	abounds	1
3	abundance	1
4	abundant	1

In [10]:
```
#convertting pos neg words to dictionary
word = pos_neg_words['word'].to_list()
score = pos_neg_words['score'].to_list()
pos_neg_dict = dict(zip(word, score))
```

Sentiment Analysis on Songs

In this section, score the sentiment for all the songs for both artists in your data set. Score the sentiment by manually calculating the sentiment using the combined lexicons provided in this repository.

After you have calculated these sentiments, answer the questions at the end of this section.

In [11]:
```
### sentiment score function
def sentiment_score(words):
    score = 0
    for word in words:
        if word in pos_neg_dict:
            score += pos_neg_dict[word]
    return score/(len(words) or not len(words))
```

In [12]:
```
#functions to clean text
def remove_punctuation(text, punct_set=punctuation) :
    return("".join([ch for ch in text if ch not in punct_set]))

sw = set([remove_punctuation(w) for w in sw])
def remove_stop(tokens) :
    return([t for t in tokens if t.lower() not in sw])

def tokenize(text) :
    return([t for t in whitespace_pattern.split(text) if t])

def prepare(text, pipeline) :
    tokens = str(text)
    for transform in pipeline :
        tokens = transform(tokens)
    return(tokens)

clean_pipeline = [str.lower, remove_punctuation, tokenize, remove_stop]
```

In [13]:
```
# cleaning lyrics data
lyrics_data['cleaned lyrics'] = lyrics_data['lyrics'].apply(prepare, pipeline = clean_
```

In [14]:
```
#calculating the number of results words for each text
lyrics_data['total_len'] = lyrics_data['cleaned lyrics'].map(lambda x: len(x))
```

In [15]:
```
#calculating the sentiment score
lyrics_data['sentiment_score'] = lyrics_data['cleaned lyrics'].apply(sentiment_score)
```

In [16]:
```
lyrics_data.head()
```

Out[16]:

	artist_name	song_title	lyrics	cleaned lyrics	total_len	sentiment_score
0	cher	88degrees	"88 Degrees"\n\n\n\nStuck in L.A., ain't got n...	[88, degrees, stuck, la, aint, got, friends, h...	182	0.054945
1	cher	adifferentkindoflovesong	"A Different Kind Of Love Song"\n\n\n\nWhat if...	[different, kind, love, song, world, crazy, sa...	137	0.284672
2	cher	afterall	"After All"\n\n\n\nWell, here we are again\nI ...	[well, guess, must, fate, weve, tried, deep, i...	120	-0.041667
3	cher	again	"Again"\n\n\n\nAgain evening finds me at your ...	[evening, finds, door, ask, could, try, know, ...	30	-0.066667
4	cher	alfie	"Alfie"\n\n\n\nWhat's it all about, Alfie?\nIs...	[alfie, whats, alfie, moment, live, whats, sor...	63	0.174603

In [17]:

```
#Calculating the artist with the highest sentiment score average.
lyrics_data.groupby(['artist_name'])['sentiment_score'].mean()
```

Out[17]:

```
artist_name
cher     0.059475
robyn    0.066259
Name: sentiment_score, dtype: float64
```

In [18]:

```
#Calculating cher highest and lowest sentiment score for her songs
cher = lyrics_data[lyrics_data['artist_name'] == 'cher']

#highest sentiment for cher
cher[cher['sentiment_score'] == cher['sentiment_score'].max()][['song_title', 'sentime
```

Out[18]:

	song_title	sentiment_score
181	mylove	0.54321

In [19]:

```
#lowest sentiment for cher
```

```
cher[cher['sentiment_score'] == cher['sentiment_score'].min()][['song_title', 'sentime
```

Out[19]:

	song_title	sentiment_score
16	bangbang	-0.417647

In [20]:

```
#Calculating cher highest and lowest sentiment score for her songs
robyn = lyrics_data[lyrics_data['artist_name'] == 'robyn']

#highest sentiment for cher
robyn[robyn['sentiment_score'] == robyn['sentiment_score'].max()][['song_title', 'sent
```

Out[20]:

	song_title	sentiment_score
319	babyforgiveme	0.554054

In [21]:

```
#highest sentiment for cher
robyn[robyn['sentiment_score'] == robyn['sentiment_score'].min()][['song_title', 'sent
```

Out[21]:

	song_title	sentiment_score
342	dontfuckingtellmewhattodo	-0.572327
343	dontfuckingtellmewhattodo114520	-0.572327

Questions

Q: Overall, which artist has the higher average sentiment per song?

A: Robyn has the highest sentiment score per song. She averaged 0.066259

Q: For your first artist, what songs have the highest and lowest sentiments? Print those songs to the screen.

A: Cher highest sentiment score is 0.54321 for the song My love and lowest sentiment score is -0.417647 for the song Bang Bang

---

Q: For your second artist, what songs have the highest and lowest sentiments? Print those songs to the screen.

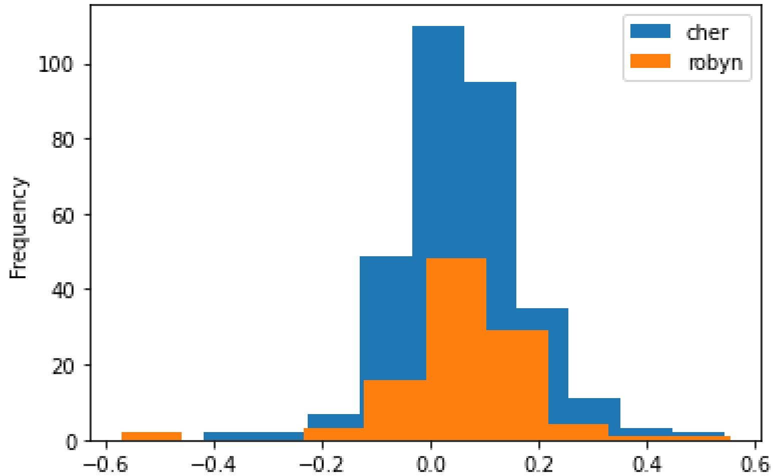
A: Robyn highest sentiment score is 0.554054 for the song Baby Forgive Me and lowest sentiment score is -0.572327 for the song Don't Fucking Tell Me What To Do.

Q: Plot the distributions of the sentiment scores for both artists. You can use `seaborn` to plot densities or plot histograms in matplotlib.

In [22]:

```
lyrics_data.groupby('artist_name')['sentiment_score'].plot(kind = 'hist', legend = Tru
```

Out[22]:
```
artist_name
cher      AxesSubplot(0.125,0.125;0.775x0.755)
robyn     AxesSubplot(0.125,0.125;0.775x0.755)
Name: sentiment_score, dtype: object
```



Sentiment Analysis on Twitter Descriptions

In this section, define two sets of emojis you designate as positive and negative. Make sure to have at least 10 emojis per set. You can learn about the most popular emojis on Twitter at the emojitracker.

Associate your positive emojis with a score of +1, negative with -1. Score the average sentiment of your two artists based on the Twitter descriptions of their followers. The average sentiment can just be the total score divided by number of followers.

In [23]:
```
#reading in emoji file
emoji_data = pd.read_csv('C:/Users/19545/ADS509 Text Mining/ADS-509-Module-6/Emoji_Ser
```

In [24]:
```
emoji_data.head()
```

Out[24]:

	Emoji	Negative	Positive
0	😂	3614	6845
1	❤️	355	6361
2	♥	252	4950
3	😍	329	4640
4	😭	2412	1896

In [25]:
```
emoji_data['sentiment_score'] = emoji_data[['Negative','Positive']].idxmax(axis = 1)
emoji_data.head()
```

Out[25]:

	Emoji	Negative	Positive	sentiment_score
0	😂	3614	6845	Positive
1	❤️	355	6361	Positive
2	♥	252	4950	Positive
3	😍	329	4640	Positive
4	😭	2412	1896	Negative

In [26]:
```
emoji_data['sentiment_score'] = np.where(emoji_data['sentiment_score'] == 'Negative',
emoji_score = emoji_data[['Emoji', 'sentiment_score']]
emoji_score.head()
```

Out[26]:

	Emoji	sentiment_score
0	😂	1
1	❤️	1
2	♥	1
3	😍	1
4	😭	-1

In [27]:
```
def contains_emoji(s):

    s = str(s)
    emojis = [ch for ch in s if emoji.is_emoji(ch)]

    return(len(emojis) > 0)

def emoji_extraction(s):
    return emoji.distinct_emoji_list(s)
```

In [28]:
```
word_emoji_score = pd.concat([emoji_score, pos_neg_words], axis = 0)
```

In [29]:
```
# convert to dictionary
emoji_word = word_emoji_score['word'].to_list()
score = word_emoji_score['score'].to_list()
emoji_word_dict = dict(zip(emoji_word, score))
```

In [30]:
```
# your code here
# cleaning lyrics data
df_twitter['cleaned description'] = df_twitter['description'].apply(prepare, pipeline
```

In [32]:
```
#calculating the number of results words for each text
df_twitter['total_len'] = df_twitter['cleaned description'].map(lambda x: len(x))
```

In [33]:
```
df_twitter.head()
```

Out[33]:

	Artist_name	screen_name	name	id	location	followers_count	friends_count
0	cher	hsmcnp	Country Girl	3.515221e+07	NaN	1302.0	1014.0
1	cher	horrormomy	Jeny	7.421531e+17	Earth	81.0	514.0
2	cher	anju79990584	anju	1.496463e+18	NaN	13.0	140.0
3	cher	gallionjenna	J	3.366480e+09	NaN	752.0	556.0
4	cher	bcscomm	bcscomm	8.391504e+07	Washington, DC	888.0	2891.0

In [35]:

```
df_twitter['sentiment_score'] = df_twitter['cleaned description'].apply(sentiment_scor
df = df_twitter[['Artist_name', 'emoji tokens', 'sentiment_score']]
```

In [37]:

```
df
```

Out[37]:

	Artist_name	emoji tokens	sentiment_score
0	cher	False	0.000000
1	cher	False	0.000000
2	cher	False	0.000000
3	cher	False	0.000000
4	cher	False	0.176471
...	...	...	...
351834	robynkonichiwa	False	-0.111111
351835	robynkonichiwa	False	0.000000
351836	robynkonichiwa	False	0.000000
351837	robynkonichiwa	False	0.000000
351838	robynkonichiwa	False	0.200000

4268141 rows × 3 columns

In [38]:

```
#Calculating the artist with the highest sentiment score average.
```

```
df.groupby(['Artist_name'])['sentiment_score'].mean()
```

Out[38]:

```
Artist_name
cher                0.050025
robynkonichiwa      0.043586
Name: sentiment_score, dtype: float64
```

Q: What is the average sentiment of your two artists?

A: The average sentiment for cher is 0.050025 and the average sentiment for robyn is 0.043586

Q: Which positive emoji is the most popular for each artist? Which negative emoji?

A:

In [ ]:

```

```