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October 17, 2022

ADS-509-Fall

Github Link: https://github.com/CFRichardson/ADS_509_HW6

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.

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

from collections import Counter, defaultdict
from string import punctuation

from nltk.corpus import stopwords

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

In [2]:
```
from nltk.tokenize import word_tokenize
def dict_2_df_lexicon_builder(dict_):

    df = pd.DataFrame.from_dict(dict_, orient='index').reset_index()
    df.rename(columns={'index':'words',
                       0:'values'},
              inplace=True)
    print('Shape', df.shape)
    return df
```

In [3]:
```
# change `data_location` to the location of the folder on your machine.
data_location = "/Volumes/GoogleDrive/My Drive/_509/my_M1_data"

# 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
path_ = data_location + '/lyrics/FFDP/FFDP_song_lyrics_df.csv'
ffdp_lyrics = pd.read_csv(path_)

# Read in the lyrics data
path_ = data_location + '/lyrics/OfficialRezz/OfficialRezz_song_lyrics_df.csv'
rezz_lyrics = pd.read_csv(path_)
```

In [5]:
```
# Read in the twitter data
path_ = data_location + '/twitter/FFDP_followers_data.txt'
ffdp_twitter = pd.read_csv(path_,
                           sep="\t",
                           engine='python')

path_ = data_location + '/twitter/OfficialRezz_followers_data.txt'
rezz_twitter = pd.read_csv(path_,
                           sep="\t",
                           engine='python')
```

Bing Liu Lexicon build

In [6]:
```
bing_liu_df = {}
word_files = [negative_words_file, positive_words_file]

for file_num, file_ in enumerate(word_files):
    with open(file_, 'r', encoding="ISO-8859-1") as f:

        for idx, line in enumerate(f.readlines()):

            if line[:1] != ';' and line != '\n':

                if file_num == 0: # negative_words_file
                    bing_liu_df[line[:-1]] = -1
                else:
                    bing_liu_df[line[:-1]] = +1

bing_liu_df = dict_2_df_lexicon_builder(bing_liu_df)
bing_liu_df.sample(5)
```

Shape (6786, 2)

Out[6]:

	words	values
3812	shrug	-1
3079	obstinate	-1
564	checkered	-1
3459	rascal	-1
932	demeaning	-1

TidyText Lexicon

In [7]:
```
tidytext_df = pd.read_csv(tidy_text_file, sep='\t')
print('Shape', tidytext_df.shape)
tidytext_df.sample(10)
```

Shape (15133, 3)

Out[7]:

	word	sentiment	lexicon
6436	caustically	negative	bing
8993	inexorably	negative	bing
8115	forebodingly	negative	bing
11690	thriving	positive	bing
9077	insecure	negative	bing
11126	slothful	negative	bing
13177	displace	negative	loughran
5663	abundant	positive	bing
786	charade	negative	nrc
5634	zest	positive	nrc

The Great Lexicon Merge

Interestingly TidyText already has Bing Liu lexicon, but I assume the included Bing Lui lexicon is different from the Tidy Text combined lexicon.

In [8]:
```
bing_liu_words = set(bing_liu_df['words'])

combined_df = {}
for idx, row in tidytext_df.iterrows():

    sentiment_val = row['sentiment']
    word = row['word']

    if word not in bing_liu_words:
        if sentiment_val == 'positive':
            combined_df[word] = 1
        else:
            combined_df[word] = -1

combined_df = dict_2_df_lexicon_builder(combined_df)
combined_df.sample(10)
```

Shape (4622, 2)

Out[8]:

	words	values
709	cove	1
2420	represented	1
1275	ghostly	-1
4431	unscheduled	-1
1975	obvious	1
2542	scientific	1
4381	underreporting	-1
2799	sun	1
3139	wildcat	-1
133	annul	-1

In [9]:
```
combined_df = pd.concat([bing_liu_df, combined_df])
combined_df.shape
```

Out[9]: (11408, 2)

Well that is interesting, the original TidyText doc has roughly 5k more records. Let's see what is going on.

In [10]:
```
tidytext_df['word'].value_counts()[:5]
```

Out[10]:
```
abundance     4
confess       4
unexpected    4
malice        3
renounce      3
Name: word, dtype: int64
```

In [11]:
```
tidytext_df[tidytext_df['word'] == 'abundance']
```

Out[11]:

	word	sentiment	lexicon
32	abundance	negative	nrc
33	abundance	positive	nrc
5662	abundance	positive	bing
14780	abundance	positive	loughran

Well that is interesting, NRC has abundance as both negative and positive.

We also now see why, TidyText has more records. Some words are in multiple, if not all lexicons and some lexicons even have a word twice!

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 [12]:
```
combined_word_set = set(combined_df['words'])
combined_word_dict = dict(zip(combined_df['words'], combined_df['values']))

# code below is a modified version of the "bing_liu_score" function from BTAP pg. 301
def sentiment_scorer(text):
    sentiment_score = 0
    # tokenize string
    bow = word_tokenize(text.lower())
    # remove stop words
    bow = [word for word in bow if word not in sw]

    for word in bow:
        if word in combined_word_set:
            sentiment_score += combined_word_dict[word]

    return round(sentiment_score / len(bow),4)
```

FFDP Sentiment

In [13]:
```
ffdp_lyrics['sentiment_score'] = ffdp_lyrics['Lyrics'].apply(sentiment_scorer)
ffdp_lyrics.sample(5)
```

Out[13]:

	Artist	Title	Lyrics	sentiment_score
19	FFDP	Burn_It_Down	You think you know me? You don't know shit ...	-0.2935
14	FFDP	Dying_Breed	Round one! I swear to God I'd do it for fun...	-0.0055
8	FFDP	Death_Before_Dishonor	To the haters, the takers, the liars, all t...	-0.0451
2	FFDP	Salvation	Disgusted by your weakness You have no righ...	0.0250
6	FFDP	White_Knuckles	Oh, fuck it all! Sick of being sick and ti...	-0.1130

Rezz Sentiment

In [14]:
```
rezz_lyrics['sentiment_score'] = rezz_lyrics['Lyrics'].apply(sentiment_scorer)
rezz_lyrics.sample(5)
```

Out[14]:

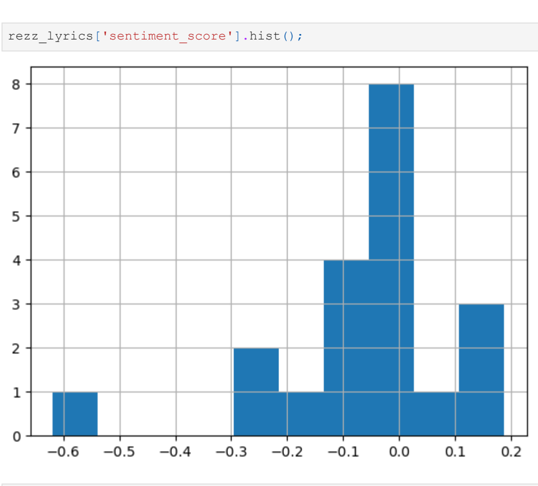
	Artist	Title	Lyrics	sentiment_score
7	OfficialRezz	Stress	I know how to undo all the straps that Keep...	-0.2258
9	OfficialRezz	Lonely	Little pieces come my way You say it's just...	-0.0600
6	OfficialRezz	Kiss_Of_Death	Kiss of Death Kiss of Death Kiss of Death K...	0.1429
4	OfficialRezz	Toxin	You're lovely, but looks can kill You're a ...	-0.0581
12	OfficialRezz	Paper_Walls	And here's my stop, just drop me off And I'...	0.0628

Questions

Q1

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

In [15]:
```
ffdp_lyrics['sentiment_score'].hist();
```



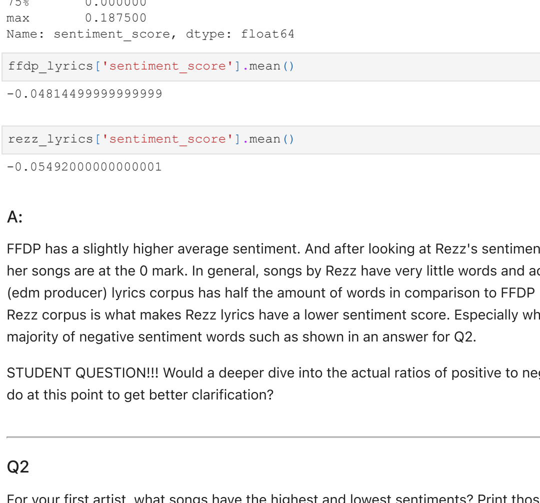
In [16]:
```
ffdp_lyrics['sentiment_score'].describe()
```

Out[16]:
```
count    20.000000
mean     -0.048145
std       0.089823
min      -0.293500
25%      -0.100100
50%      -0.010450
75%       0.004350
max       0.059700
Name: sentiment_score, dtype: float64
```

In [17]:
```
ffdp_lyrics['sentiment_score'].sum()
```

Out[17]: -0.9629

In [18]:
```
rezz_lyrics['sentiment_score'].hist();
```



In [19]:
```
rezz_lyrics['sentiment_score'].sum()
```

Out[19]: -1.0983999999999998

In [20]:
```
rezz_lyrics['sentiment_score'].describe()
```

Out[20]:
```
count    20.000000
mean     -0.054920
std       0.173237
min      -0.619000
25%      -0.074925
50%       0.000000
75%       0.000000
max       0.187500
Name: sentiment_score, dtype: float64
```

In [21]:
```
ffdp_lyrics['sentiment_score'].mean()
```

Out[21]: -0.04814499999999999

In [22]:
```
rezz_lyrics['sentiment_score'].mean()
```

Out[22]: -0.05492000000000001

A:

FFDP has a slightly higher average sentiment. And after looking at Rezz's sentiment histogram, we clearly see a good proportion of her songs are at the 0 mark. In general, songs by Rezz have very little words and according to my previous homework, the Rezz (edm producer) lyrics corpus has half the amount of words in comparison to FFDP (metal band). This lack of word variety within the Rezz corpus is what makes Rezz lyrics have a lower sentiment score. Especially when a good amount of her songs containing a majority of negative sentiment words such as shown in an answer for Q2.

STUDENT QUESTION!!! Would a deeper dive into the actual ratios of positive to negative counts be useful? If not, what would you do at this point to get better clarification?

Q2

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

In [23]:
```
ffdp_lyrics.loc[ffdp_lyrics['sentiment_score'].idxmax(),:]
```

Out[23]:
```
Artist                                                          FFDP
Title                                                   Never_Enough
Lyrics             I'm so fed up with everyone around me No on...
sentiment_score                                               0.0597
Name: 12, dtype: object
```

In [24]:
```
ffdp_lyrics.loc[ffdp_lyrics['sentiment_score'].idxmin(),:]
```

Out[24]:
```
Artist                                                          FFDP
Title                                                   Burn_It_Down
Lyrics             You think you know me? You don't know shit ...
sentiment_score                                              -0.2935
Name: 19, dtype: object
```

Q3

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

In [25]:
```
rezz_lyrics.loc[rezz_lyrics['sentiment_score'].idxmax(),:]
```

Out[25]:
```
Artist                                                  OfficialRezz
Title                                                          Relax
Lyrics             Just take a nice breath in. Exhale the brea...
sentiment_score                                               0.1875
Name: 2, dtype: object
```

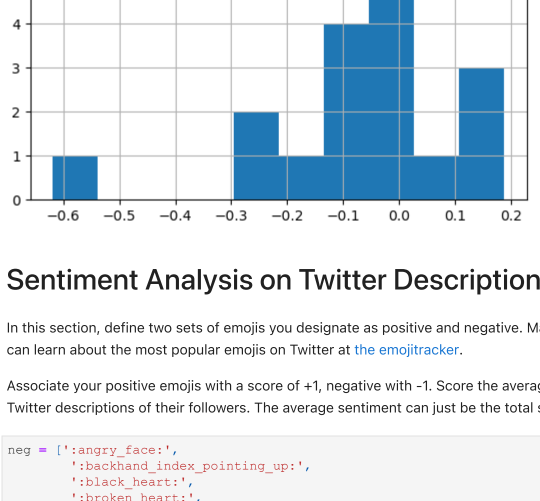
In [26]:
```
rezz_lyrics.loc[rezz_lyrics['sentiment_score'].idxmin(),:]
```

Out[26]:
```
Artist                                                  OfficialRezz
Title                                                   Life_&_Death
Lyrics             Life and Death Death Death  Life Death Life...
sentiment_score                                               -0.619
Name: 3, dtype: object
```

Q4

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

In [27]:
```
ffdp_lyrics['sentiment_score'].hist();
```



In [28]:
```
rezz_lyrics['sentiment_score'].hist();
```

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 [29]:
```
neg = [':angry_face:',
       ':backhand_index_pointing_up:',
       ':black_heart:',
       ':broken_heart:',
       ':dissapointed_relieved:',
       ':exploding_head:',
       ':expressionless_face:',
       ':face_exhaling:',
       ':grimacing_face:',
       ':middle_finger:',
       ':pensive_face:',
       ':sob:',
       ':worried_face:']

pos = [':beating_heart:',
       ':beaming_face_with_smiling_eyes:',
       ':blue_heart:',
       ':clapping_hands:',
       ':face_blowing_a_kiss:',
       ':face_with_tears_of_joy:',
       ':fire:',
       ':fireworks:',
       ':folded_hands:',
       ':green_heart:',
       ':growing_heart:',
       ':heart_hands:',
       ':heart_suit:',
       ':kissing_face:',
       ':light_bulb:',
       ':love-you_gesture:',
       ':no_entry:',
       ':purple_heart:',
       ':red_heart:',
       ':revolving_hearts:',
       ':smiling_face_with_sunglasses:',
       ':sparkling_heart:',
       ':sun:',
       ':two_hearts:',
       ':white_heart:',
       ':winking_face:',
       ':yellow_heart:']

sentiments = [neg, pos]

emoji_sentiment_dict = {}
for num, sentiment_type in enumerate(sentiments):
    for emoji_short_hand in sentiment_type:

        if num == 0:
            emoji_sentiment_dict[emoji_short_hand] = -1
        else:
            emoji_sentiment_dict[emoji_short_hand] = 1
```

Q1

What is the average sentiment of your two artists?

In [30]:
```
def emoji_sentiment_scorer(text):
    '''Returns 0 if there is no Emojis in text'''
    sentiment_score = 0
    emoji_count = emoji.emoji_count(text)

    if emoji_count > 0:
        emoji_series = pd.DataFrame(emoji.emoji_list(text))['emoji']

        emoji_text_list = []
        for emoji_graphic in emoji_series:
            emoji_short_hand = emoji.demojize(emoji_graphic)
            emoji_text_list.append(emoji_short_hand)

        for emoji_short_hand in emoji_text_list:
            try:
                sentiment_score += emoji_sentiment_dict[emoji_short_hand]
            except:
                '''Some emojis are able to be both + or - dependent on context
                 & thus are given a 0. I.e. "pleading face".'''
                pass

        sentiment_score = sentiment_score / len(emoji_text_list)
        sentiment_score = round(sentiment_score, 4)
    return sentiment_score
```

In [31]:
```
# remove any row with NaN values
ffdp_twitter = ffdp_twitter.dropna().reset_index(drop=True)

rezz_twitter = rezz_twitter.dropna().reset_index(drop=True)
```

In [32]:
```
ffdp_twitter['Sentiment'] = ffdp_twitter['Description'].apply(emoji_sentiment_scorer)
ffdp_sentiment = round(ffdp_twitter['Sentiment'].mean(),5)
print(f"FFDP's average sentiment is {ffdp_sentiment}")
```

FFDP's average sentiment is 0.03897

In [33]:
```
rezz_twitter['Sentiment'] = rezz_twitter['Description'].apply(emoji_sentiment_scorer)
rezz_sentiment = round(rezz_twitter['Sentiment'].mean(),5)
print(f"FFDP's average sentiment is {rezz_sentiment}")
```

FFDP's average sentiment is 0.0407

Q2

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

In [36]:
```
def top_emojis(artist_twitter_df):
  '''
   Returns top 10 positive emojis.
   If positive=False, return top 10 negative emojis.
  '''
  emojis_list = []

  for idx, row in artist_twitter_df.iterrows():
      text = row['Description']
      emoji_count = emoji.emoji_count(text)

      if emoji_count > 0:
          emo_series = pd.DataFrame(emoji.emoji_list(text))
          emojis_list.extend(emo_series['emoji'])

  df = pd.DataFrame.from_dict(Counter(emojis_list), orient='index')
  df.reset_index(inplace=True)
  df.rename(columns={'index':'emoji',0:'count'},
            inplace=True)

  df['shorthand'] = df['emoji'].apply(emoji.demojize)

  def shorthand_sentiment_value(shorthand_text):
      try:
        row_emoji = emoji.demojize(shorthand_text)
        sentiment_val = emoji_sentiment_dict[row_emoji]
      except:
        sentiment_val = np.nan

      return sentiment_val

  df['sentiment_val'] = df['shorthand'].apply(shorthand_sentiment_value)
  df = df.dropna()
  df = df.sort_values('count',ascending=False)
  df.reset_index(drop=True, inplace=True)

  return df

def top(top_emoji_df, positive=True, num=10):
  if positive:
    top_emoji_df = top_emoji_df[top_emoji_df['sentiment_val'] == 1].sort_values('count', ascending=False)
    top_emoji_df = top_emoji_df.reset_index(drop=True)
  else:
    top_emoji_df = top_emoji_df[top_emoji_df['sentiment_val'] == -1].sort_values('count', ascending=False)
    top_emoji_df = top_emoji_df.reset_index(drop=True)

  return top_emoji_df.head(num)
```

Rezz Top Emojis

In [37]:
```
rezz_top_emojis = top_emojis(rezz_twitter)
rezz_top_emojis.head(10)
```

Out[37]:

	emoji	count	shorthand	sentiment_val
0	🖤	920	:black_heart:	-1.0
1	❤️	826	:red_heart:	1.0
2	💜	661	:purple_heart:	1.0
3	🔥	540	:fire:	1.0
4	💙	529	:blue_heart:	1.0
5	💕	409	:two_hearts:	1.0
6	🤍	381	:white_heart:	1.0
7	💚	335	:green_heart:	1.0
8	☀️	318	:sun:	1.0
9	💖	299	:sparkling_heart:	1.0

Rezz Top 10 Positive Emojis

In [38]:
```
rezz_top_pos = top(rezz_top_emojis, positive=True)
rezz_top_pos_emojis = rezz_top_pos['emoji']
rezz_top_pos
```

Out[38]:

	emoji	count	shorthand	sentiment_val
0	❤️	826	:red_heart:	1.0
1	💜	661	:purple_heart:	1.0
2	🔥	540	:fire:	1.0
3	💙	529	:blue_heart:	1.0
4	💕	409	:two_hearts:	1.0
5	🤍	381	:white_heart:	1.0
6	💚	335	:green_heart:	1.0
7	☀️	318	:sun:	1.0
8	💖	299	:sparkling_heart:	1.0
9	💛	289	:yellow_heart:	1.0

Rezz Top 10 Negative Emojis

In [39]:
```
rezz_top_neg = top(rezz_top_emojis, positive=False)
rezz_top_neg_emojis = rezz_top_neg['emoji']
rezz_top_neg
```

Out[39]:

	emoji	count	shorthand	sentiment_val
0	🖤	920	:black_heart:	-1.0
1	💔	75	:broken_heart:	-1.0
2	🤯	34	:exploding_head:	-1.0
3	🖕	20	:middle_finger:	-1.0
4	😔	19	:pensive_face:	-1.0
5	😬	12	:grimacing_face:	-1.0
6	😮‍💨	9	:face_exhaling:	-1.0
7	👆	9	:backhand_index_pointing_up:	-1.0
8	😑	4	:expressionless_face:	-1.0

FFDP Top Emojis

In [40]:
```
ffdp_top_emojis = top_emojis(ffdp_twitter)
ffdp_top_emojis.head(10)
```

Out[40]:

	emoji	count	shorthand	sentiment_val
0	🖤	897	:black_heart:	-1.0
1	❤️	718	:red_heart:	1.0
2	💙	476	:blue_heart:	1.0
3	❤️	413	:red_heart:	1.0
4	💜	407	:purple_heart:	1.0
5	🔥	292	:fire:	1.0
6	🤍	251	:white_heart:	1.0
7	💚	233	:green_heart:	1.0
8	💕	212	:two_hearts:	1.0
9	😎	195	:smiling_face_with_sunglasses:	1.0

FFDP Top 10 Positive

In [41]:
```
ffdp_top_pos = top(ffdp_top_emojis, positive=True)
ffdp_top_pos_emojis = ffdp_top_pos['emoji']
ffdp_top_pos
```

Out[41]:

	emoji	count	shorthand	sentiment_val
0	❤️	718	:red_heart:	1.0
1	💙	476	:blue_heart:	1.0
2	❤️	413	:red_heart:	1.0
3	💜	407	:purple_heart:	1.0
4	🔥	292	:fire:	1.0
5	🤍	251	:white_heart:	1.0
6	💚	233	:green_heart:	1.0
7	💕	212	:two_hearts:	1.0
8	😎	195	:smiling_face_with_sunglasses:	1.0
9	💛	170	:yellow_heart:	1.0

FFDP Top 10 Negative

In [42]:
```
ffdp_top_neg = top(ffdp_top_emojis, positive=False)
ffdp_top_neg_emojis = ffdp_top_neg['emoji']
ffdp_top_neg
```

Out[42]:

	emoji	count	shorthand	sentiment_val
0	🖤	897	:black_heart:	-1.0
1	💔	53	:broken_heart:	-1.0
2	🖕	51	:middle_finger:	-1.0
3	😬	13	:grimacing_face:	-1.0
4	😔	9	:pensive_face:	-1.0
5	🤯	7	:exploding_head:	-1.0
6	😑	5	:expressionless_face:	-1.0
7	👆	3	:backhand_index_pointing_up:	-1.0
8	😮‍💨	3	:face_exhaling:	-1.0
9	😠	1	:angry_face:	-1.0

Top Positive Emojis for both Artist

In [43]:
```
ffdp_top_pos_emojis.to_frame().merge(rezz_top_pos_emojis,
                                     left_index=True,
                                     right_index=True,
                                     suffixes=('_ffdp','_rezz'))
```

Out[43]:

	emoji_ffdp	emoji_rezz
0	❤️	❤️
1	💙	💜
2	❤️	🔥
3	💜	💙
4	🔥	💕
5	🤍	🤍
6	💚	💚
7	💕	☀️
8	😎	💖
9	💛	💛

Looking at index 8, we can see FFDP fans think they are pretty cool while Rezz fans love the sun. Other than those two differences, it appears both fan bases love their various hearts.

Top Negative Emojis for both Artist

In [44]:
```
ffdp_top_neg_emojis.to_frame().merge(rezz_top_neg_emojis,
                                     left_index=True,
                                     right_index=True,
                                     suffixes=('_ffdp','_rezz'))
```

Out[44]:

	emoji_ffdp	emoji_rezz
0	🖤	🖤
1	💔	💔
2	🖕	🤯
3	😬	🖕
4	😔	😔
5	🤯	😬
6	😑	😥
7	👆	👆
8	😥	😑

Interesting to see the top emojis for both artist are the same in both the positive and negative light. Then again the amount of negative emojis in my lexicon is only 13 with 26 positive emojis.

References

Minqing Hu and Bing Liu. "Mining and Summarizing Customer Reviews."
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