Group Comparison

May 30, 2022

1 ADS 509 Module 3: Group Comparison

The task of comparing two groups of text is fundamental to textual analysis. There are innumerable applications: survey respondents from different segments of customers, speeches by different political parties, words used in Tweets by different constituencies, etc. In this assignment you will build code to effect comparisons between groups of text data, using the ideas learned in reading and lecture.

This assignment asks you to analyze the lyrics and Twitter descriptions for the two artists you selected in Module 1. If the results from that pull were not to your liking, you are welcome to use the zipped data from the "Assignment Materials" section. Specifically, you are asked to do the following:

- Read in the data, normalize the text, and tokenize it. When you tokenize your Twitter descriptions, keep hashtags and emojis in your token set.
- Calculate descriptive statistics on the two sets of lyrics and compare the results.
- For each of the four corpora, find the words that are unique to that corpus.
- Build word clouds for all four corpora.

Each one of the analyses has a section dedicated to it below. Before beginning the analysis there is a section for you to read in the data and do your cleaning (tokenization and normalization).

1.1 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.*

[161]:
```
# Use this space for any additional import statements you need
import warnings

warnings.filterwarnings('ignore')
```

[162]:
```
import os
import re
import emoji
import pandas as pd

from collections import Counter, defaultdict
from nltk.corpus import stopwords
from string import punctuation
from wordcloud import WordCloud

from sklearn.feature_extraction.text import TfidfTransformer, CountVectorizer
```

[163]:
```
# Place any addtional functions or constants you need here.

# Some punctuation variations
punctuation = set(punctuation) # speeds up comparison
tw_punct = punctuation - {"#"}

# Stopwords
sw = stopwords.words("english")

# Two useful regex
whitespace_pattern = re.compile(r"\s+")
hashtag_pattern = re.compile(r"^#[0-9a-zA-Z]+")

# It's handy to have a full set of emojis
all_language_emojis = set()

for country in emoji.UNICODE_EMOJI :
    for em in emoji.UNICODE_EMOJI[country] :
        all_language_emojis.add(em)

# and now our functions
def descriptive_stats(tokens, num_tokens = 5, verbose=True) :
    """
        Given a list of tokens, print number of tokens, number of unique␣
 ↪tokens,
        number of characters, lexical diversity (https://en.wikipedia.org/wiki/
 ↪Lexical_diversity),
        and num_tokens most common tokens. Return a list with the number of␣
 ↪tokens, number
        of unique tokens, lexical diversity, and number of characters.
    """

    # Fill in the correct values here.
    num_tokens = len(tokens)
    num_unique_tokens = len(set(tokens))
    lexical_diversity = num_unique_tokens/num_tokens
    num_characters = sum([len(x) for x in tokens])

    if verbose :
        print(f"There are {num_tokens} tokens in the data.")
        print(f"There are {num_unique_tokens} unique tokens in the data.")
        print(f"There are {num_characters} characters in the data.")
        print(f"The lexical diversity is {lexical_diversity:.3f} in the data.")


    return([num_tokens, num_unique_tokens,
            lexical_diversity,
            num_characters])


def is_emoji(s):
    return(s in all_language_emojis)

def contains_emoji(s):

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

    return(len(emojis) > 0)


def remove_stop(tokens) :
    # modify this function to remove stopwords
    return([x for x in tokens if x not in sw])

def remove_punctuation(text, punct_set=tw_punct) :
    return("".join([ch for ch in text if ch not in punct_set]))

def tokenize(text) :
    """ Splitting on whitespace rather than the book's tokenize function. That
        function will drop tokens like '#hashtag' or '2A', which we need for␣
↪Twitter. """

    # modify this function to return tokens
    text = re.sub(r'\s{2,}', ' ', text)
    return(text.split(' '))
```

```python
def prepare(text, pipeline) :
    tokens = str(text)

    for transform in pipeline :
        tokens = transform(tokens)

    return(tokens)
```

1.2 Data Ingestion

Use this section to ingest your data into the data structures you plan to use. Typically this will be a dictionary or a pandas DataFrame.

[187]:
```python
# Feel fre to use the below cells as an example or read in the data in a way␣
↪you prefer

data_location = "" # change to your location if it is not in the same directory␣
↪as your notebook
twitter_folder = "twitter/"
lyrics_folder = "lyrics/"

artist_files = {'eminem':'EmiNeM_follower_data.txt',
                'snoop':'SnoopDogg_follower_data.txt'}
```

[188]:
```python
twitter_data = pd.read_csv(data_location + twitter_folder +␣
↪artist_files['eminem'],
                           sep="\t",
                           quoting=3)

twitter_data['artist'] = "eminem"
```

[189]:
```python
twitter_data_2 = pd.read_csv(data_location + twitter_folder +␣
↪artist_files['snoop'],
                             sep="\t",
                             quoting=3)
twitter_data_2['artist'] = "snoop"

twitter_data = pd.concat([
    twitter_data,twitter_data_2])

del(twitter_data_2)
```

[190]:
```python
# As an extra step just for twitter_data, drop any row with empty description
print('Current Twitter shape is {}'.format(twitter_data.shape))
twitter_data = twitter_data[~twitter_data['description'].isna()]
twitter_data.reset_index(drop=True, inplace=True)
```

```
print('After dropping, Twitter shape is {}'.format(twitter_data.shape))
```

```
Current Twitter shape is (139289, 8)
After dropping, Twitter shape is (71962, 8)
```

[191]:
```
# read in the lyrics here
```

[192]:
```
artists = ['eminem', 'snoop']

lyrics_data = pd.DataFrame(columns=['artist', 'title', 'lyrics'])

for artist in artists:

    path = os.path.join(data_location, lyrics_folder, artist)

    for file in os.listdir(path):

        if 'txt' not in file:
            continue

        song_path = os.path.join(path, file)

        with open(song_path, 'r') as file:
            song = file.readlines()

        title = song[0].replace('\n', '').strip()

        lyric = song[1:]
        lyric = ' '.join(lyric)
        lyric = lyric.replace('\n', '').strip()

        lyrics_data = pd.concat([lyrics_data, pd.DataFrame({
                                    'artist':artist,
                                    'title':title,
                                    'lyrics':lyric
                                }, index=[0])], ignore_index=True)
```

[193]:
```
twitter_data.shape, lyrics_data.shape
```

[193]:
```
((71962, 8), (454, 3))
```

1.3 Tokenization and Normalization

In this next section, tokenize and normalize your data. We recommend the following cleaning.

Lyrics

- Remove song titles
- Casefold to lowercase

- Remove punctuation
- Split on whitespace
- Remove stopwords (optional)

Removal of stopwords is up to you. Your descriptive statistic comparison will be different if you include stopwords, though TF-IDF should still find interesting features for you.

Twitter Descriptions

- Casefold to lowercase
- Remove punctuation other than emojis or hashtags
- Split on whitespace
- Remove stopwords

Removing stopwords seems sensible for the Twitter description data. Remember to leave in emojis and hashtags, since you analyze those.

[194]:
```
lyrics_data.head()
```

[194]:
```
   artist                  title  \
0  eminem                Rap God
1  eminem  Hellbound (H&H Remix)
2  eminem               Infinite
3  eminem                 So Bad
4  eminem          The King And I

                                             lyrics
0  Look, I was gonna go easy on you not to hurt y…
1  Welcome back to the stage of history  (Yo, Sli…
2  Aw, yeah (It's like this, like this) It's Emin…
3  Yeah, haha, you feel that, baby? Yeah, I feel …
4  It goes: one for the trailer park, two for my …
```

[196]:
```
twitter_data.tail()
```

[196]:
```
           screen_name             name            id location  \
71957       Mat_Genius     Mathews Zuku  1.527574e+18      NaN
71958        PNzungulu  Patrio Nzungulu  1.527578e+18      NaN
71959         buduzere         Buduzere  1.525987e+18      NaN
71960        njosh_jon       Jon Njosh  1.520304e+18      NaN
71961  sombre_symphony  Sombre_symphony  1.527164e+18      NaN

       followers_count  friends_count  \
71957              0.0           58.0
71958              0.0           49.0
71959              0.0           57.0
71960              0.0           87.0
71961             23.0          170.0

                                    description artist
```

```
71957                                     Peace maker  snoop
71958                                               snoop
71959                              Living my best life  snoop
71960                                      Fashionister  snoop
71961  «I was looking for love and found myself»  snoop
```

[197]:
```
# apply the `pipeline` techniques from BTAP Ch 1 or 5

my_pipeline = [str.lower, remove_punctuation, tokenize, remove_stop]

lyrics_data["tokens"] = lyrics_data["lyrics"].
 ↪apply(prepare,pipeline=my_pipeline)
lyrics_data["num_tokens"] = lyrics_data["tokens"].map(len)

twitter_data["tokens"] = twitter_data["description"].
 ↪apply(prepare,pipeline=my_pipeline)
twitter_data["num_tokens"] = twitter_data["tokens"].map(len)
```

[198]:
```
twitter_data['has_emoji'] = twitter_data["description"].apply(contains_emoji)
```

Let's take a quick look at some descriptions with emojis.

[199]:
```
twitter_data[twitter_data.has_emoji].
 ↪sample(10)[["artist","description","tokens"]]
```

[199]:
```
       artist                                       description  \
32543  eminem                                 i like cars |
2258   eminem                                 "In My Head" OUT NOW
38887   snoop   4   | Psychedelics Anonymous  | Non-Fungible…
23698  eminem          If it ain't lifted it ain't gifted ya'll
22682  eminem                                            Aisyah
40979   snoop                                keep it simple, babe
69604   snoop                                       Guided by God
20388  eminem                                     Muslim and proud
31205  eminem  Fan Page with all content related to GANZI.   …
32823  eminem       19 l broista l    l Gemini. @elmstreetproam

                                                tokens
32543                         [like, cars,  ,  ,  , ]
2258                                  ["in, head",  ]
38887  [ 4  , psychedelics, anonymous , nonfungible,…
23698             [ain't, lifted, ain't, gifted, ya'll ]
22682                                      [aisyah,  ]
40979                          [keep, simple, babe,  ]
69604                                 [ guided, god,  ]
20388                               [muslim, proud  ]
31205  [fan, page, content, related, ganzi,   , ewf,…
32823  [19, l, broista, l,  ,  , l, gemini, elmstreet…
```

With the data processed, we can now start work on the assignment questions.

Q: What is one area of improvement to your tokenization that you could theoretically carry out? (No need to actually do it; let's not make perfect the enemy of good enough.)

A: One thing that can be done is to modify some portion of dropping stop words. This was discussed and addressed last week but it's possible to have less accurate data (or results) if we drop all stop words. Instead after some manual labor, we can create a list of stopwords that are safe to drop without comprimising the accuracy. For example, in most cases, we add "s" at the end of a word if it is plural with "A" before the word like A plane -> Planes. This is soley for grammatical purpose so we can agree to drop words like "a" or "an".

Also another possible way of preprocessing is dropping any word that only appears once throughout the whole dataset. Assuming there are total of 1,000,000 words (non-unique) in a dataframe, it's possible there are some words appear only once. This could be due to typo or a word is rarely used actually that we can't find much usefulness when analyzing semantics of tweets. For example with previous assignment for determining if a sentence is positive or negative, if there appears a word only once, we cannot clearly determine if the word has positive or negative impact to the semantic. (Just noticed that this is addressed in a similar manner below with using n)

1.4 Calculate descriptive statistics on the two sets of lyrics and compare the results.

[200]:
```python
for artist in artists:

    temp = lyrics_data[lyrics_data['artist']==artist]['tokens']

    print(artist, '{} songs'.format(temp.shape[0]))
    print()
    tokens = []
    [tokens.extend(x) for x in temp]
    descriptive_stats(tokens)
    print()
    print()
```

```
eminem 389 songs

There are 157835 tokens in the data.
There are 17264 unique tokens in the data.
There are 781337 characters in the data.
The lexical diversity is 0.109 in the data.



snoop 65 songs

There are 20797 tokens in the data.
There are 4221 unique tokens in the data.
There are 99299 characters in the data.
The lexical diversity is 0.203 in the data.
```

Q: what observations do you make about these data?

A:

1.5 Find tokens uniquely related to a corpus

Typically we would use TF-IDF to find unique tokens in documents. Unfortunately, we either have too few documents, if we view each data source as a single document, or too many, if we view each description as a separate document. In the latter case, our problem will be that descriptions tend to be short, so our matrix would be too sparse to support analysis.

To get around this, we find tokens for each corpus that match the following criteria:

1. The token appears at least `n` times in all corpora
2. The tokens are in the top 10 for the highest ratio of appearances in a given corpora vs appearances in other corpora.

You will choose a cutoff for yourself based on the side of the corpus you're working with. If you're working with the Robyn-Cher corpora provided, `n=5` seems to perform reasonably well.

[208]:
```
def calculate_ratio(corpora, min_count=3, name='ratio'):

    # Get a list of tokens
    tokens = []
    [tokens.extend(x) for x in corpora]

    total, _, _, _ = descriptive_stats(tokens, verbose=False)

    # corpora is a list of list of tokens so combine them into list of string
    corpora = corpora.str.join(' ')

    # count number of tokens showing up at least min_count
    vectorizer = CountVectorizer(min_df=min_count)

    ratio = vectorizer.fit_transform(corpora)

    # Count sum of word's appearance
    ratio = pd.DataFrame(ratio.toarray().sum(axis=0), index=vectorizer.
↪get_feature_names(), columns=[name])

    # Get the ratio of appearance for each word
    ratio = ratio / total

    # Sort by ratio in descending order
    ratio = ratio.sort_values(name, ascending=False)

    return ratio
```

[209]:
```
artist1_twitter =␣
↪calculate_ratio(twitter_data[twitter_data['artist']==artists[0]]['tokens'],␣
↪name='eminem_twitter')
artist1_lyric =␣
↪calculate_ratio(lyrics_data[lyrics_data['artist']==artists[0]]['tokens'],␣
↪name='eminem_lyric')

artist2_twitter =␣
↪calculate_ratio(twitter_data[twitter_data['artist']==artists[1]]['tokens'],␣
↪name='snoop_twitter')
artist2_lyric =␣
↪calculate_ratio(lyrics_data[lyrics_data['artist']==artists[1]]['tokens'],␣
↪name='snoop_lyric')
```

[211]:
```
# Top 10 tokens for each corpora

artist1_twitter.head(10)
```

[211]:
```
        eminem_twitter
love          0.006910
im            0.006546
life          0.006020
de            0.005691
music         0.005009
fan           0.004090
like          0.003819
la            0.003195
god           0.002912
artist        0.002675
```

[213]:
```
artist1_lyric.head(10)
```

[213]:
```
       eminem_lyric
im         0.025710
like       0.016162
dont       0.011702
get        0.010942
cause      0.009808
got        0.007850
shit       0.007400
know       0.006874
back       0.006760
aint       0.006456
```

[214]:
```
artist2_twitter.head(10)
```

```
[214]:         snoop_twitter
       nft          0.011943
       love         0.008507
       im           0.006917
       life         0.006609
       artist       0.005974
       crypto       0.005631
       music        0.004128
       nfts         0.003830
       like         0.003504
       god          0.002996
```

```
[215]: artist2_lyric.head(10)
```

```
[215]:         snoop_lyric
       im         0.020820
       nigga      0.016060
       get        0.014858
       dogg       0.012021
       niggas     0.011444
       like       0.010963
       dont       0.010578
       got        0.010290
       shit       0.010194
       snoop      0.010001
```

```
[261]: # Now check each corpora's top 10 words against other three
       corporas = [artist1_twitter, artist1_lyric, artist2_twitter, artist2_lyric]

       for corpora in corporas:

           top_10 = corpora.head(10)
           artist = top_10.columns[0].upper().split('_')[0]
           corp_name = top_10.columns[0].upper().split('_')[1]

           ratio_df = None

           print('Comparing {} against other three corporas'.format(corpora.
        ↪columns[0]))
           for other_corpora in corporas:
               if other_corpora.columns == top_10.columns:
                   continue
               other_name = other_corpora.columns[0].upper().replace('_', "' ")

               # print("{} Top 10 Tokens in {} against {}'s Corpora".format(artist,␣
        ↪corp_name, other_name))
               # print()
               joined_tokens = top_10.merge(other_corpora, left_index=True,␣
       ↪right_index=True)
               cols = joined_tokens.columns
               joined_tokens['ratio'] = joined_tokens[cols[0]] / joined_tokens[cols[1]]
               ratio_name = '{} vs {} RATIO'.format(top_10.columns[0].upper(),␣
       ↪other_corpora.columns[0].upper())

               joined_tokens.rename(columns={'ratio':'{} vs {} RATIO'.format(top_10.
       ↪columns[0].upper(), other_corpora.columns[0].upper())}, inplace=True)
               joined_tokens = joined_tokens[[ratio_name]]

               if ratio_df is None:
                   ratio_df = joined_tokens
               else:
                   ratio_df = pd.concat([ratio_df, joined_tokens], axis=1)

           ratio_df = pd.concat([top_10, ratio_df], axis=1)

           display(ratio_df)
           print()
           print()
```

```
Comparing eminem_twitter against other three corporas

        eminem_twitter  EMINEM_TWITTER vs EMINEM_LYRIC RATIO  \
love          0.006910                              2.376019
im            0.006546                              0.254595
life          0.006020                              2.960016
de            0.005691                             89.818866
music         0.005009                              6.375713
fan           0.004090                             16.140040
like          0.003819                              0.236277
la            0.003195                             29.662486
god           0.002912                              2.656536
artist        0.002675                             32.476482

        EMINEM_TWITTER vs SNOOP_TWITTER RATIO  \
love                                 0.812257
im                                   0.946258
life                                 0.910909
de                                   2.056629
music                                1.213520
fan                                  1.691445
like                                 1.089698
la                                   1.548043
god                                  0.971996
artist                               0.447744
```

```
        EMINEM_TWITTER vs SNOOP_LYRIC RATIO
love                               1.651736
im                                 0.314391
life                               2.911575
de                                      NaN
music                             11.574582
fan                                     NaN
like                               0.348334
la                                22.147902
god                                4.658176
artist                                  NaN
```

```
Comparing eminem_lyric against other three corporas

       eminem_lyric  EMINEM_LYRIC vs EMINEM_TWITTER RATIO  \
im         0.025710                              3.927813
like       0.016162                              4.232312
dont       0.011702                              4.834166
get        0.010942                              6.862019
cause      0.009808                             45.881530
got        0.007850                              8.939153
shit       0.007400                              7.858215
know       0.006874                              3.850702
back       0.006760                              5.625612
aint       0.006456                             15.308054

       EMINEM_LYRIC vs SNOOP_TWITTER RATIO  EMINEM_LYRIC vs SNOOP_LYRIC RATIO
im                                3.716724                           1.234871
like                              4.611940                           1.474256
dont                              6.020349                           1.106220
get                               6.401103                           0.736430
cause                            38.123443                           1.805053
got                              10.022693                           0.762878
shit                              9.517823                           0.725946
know                              4.907918                           0.910600
back                              5.740251                           1.124739
aint                             17.373787                           0.745932
```

```
Comparing snoop_twitter against other three corporas

        snoop_twitter  SNOOP_TWITTER vs EMINEM_TWITTER RATIO  \
nft          0.011943                               5.556873
love         0.008507                               1.231138
im           0.006917                               1.056794
life         0.006609                               1.097805
```

```
artist       0.005974                                2.233419
crypto       0.005631                                3.174920
music        0.004128                                0.824049
nfts         0.003830                                4.196166
like         0.003504                                0.917686
god          0.002996                                1.028811

        SNOOP_TWITTER vs EMINEM_LYRIC RATIO  \
nft                                    NaN
love                              2.925207
im                                0.269054
life                              3.249519
artist                           72.533606
crypto                                 NaN
music                             5.253900
nfts                                   NaN
like                              0.216828
god                               2.733075

        SNOOP_TWITTER vs SNOOP_LYRIC RATIO
nft                                   NaN
love                             2.033515
im                               0.332247
life                             3.196341
artist                                NaN
crypto                                NaN
music                            9.538024
nfts                                  NaN
like                             0.319661
god                              4.792384


Comparing snoop_lyric against other three corporas

        snoop_lyric  SNOOP_LYRIC vs EMINEM_TWITTER RATIO  \
im         0.020820                             3.180748
nigga      0.016060                            71.277613
get        0.014858                             9.317957
dogg       0.012021                                  NaN
niggas     0.011444                           152.371903
like       0.010963                             2.870811
dont       0.010578                             4.369985
got        0.010290                            11.717676
shit       0.010194                            10.824792
snoop      0.010001                           577.049895

        SNOOP_LYRIC vs EMINEM_LYRIC RATIO  SNOOP_LYRIC vs SNOOP_TWITTER RATIO
im                               0.809801                            3.009808
```

```
nigga                          15.456289                    59.770227
get                             1.357903                     8.692077
dogg                          210.814327                   420.539020
niggas                         14.927745                   117.750926
like                            0.678308                     3.128316
dont                            0.903979                     5.442270
got                             1.310826                    13.138007
shit                            1.377513                    13.110922
snoop                         143.507062                   349.888465
```

Q: What are some observations about the top tokens? Do you notice any interesting items on the list?

A: Before answering, my understanding about this problem is to seek top 10 tokens for each corpora, their ratio, and compare their ratio other corpora's ratio for those tokens.

It seems that Snoopdogg (or Snoop) likes putting his name in his songs' lyrics as we can see in the last dataframe, the ratio for his name is huge going over 100 which means the word "snoop" is at least 143 times appear more than the other corporas whereas Enimen didn't include his name or it's not in the top 10 tokens. Another thing to note is that there are a few words that only appear in one of artists. For example the word "crypto" only appears in Snoopdogg's twitter and not in Eminem's.

Also if we look at ratio of Eminem's tokens in lyrics, they tend to have somewhat around the ratio value of 1 meaning that what he puts in his song is likely to appear as many times as in Snoopdogg's songs while some of top 10 tokens of Snoop's songs appear far more than Eminem's top 10 tokens in his lyrics.

It's interesting to see such difference in difference.

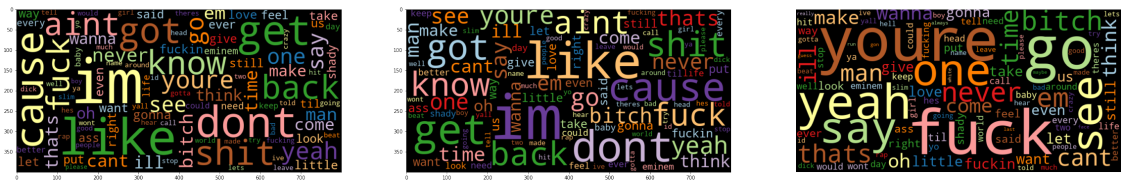
1.6 Build word clouds for all four corpora.

For building wordclouds, we'll follow exactly the code of the text. The code in this section can be found here. If you haven't already, you should absolutely clone the repository that accompanies the book.

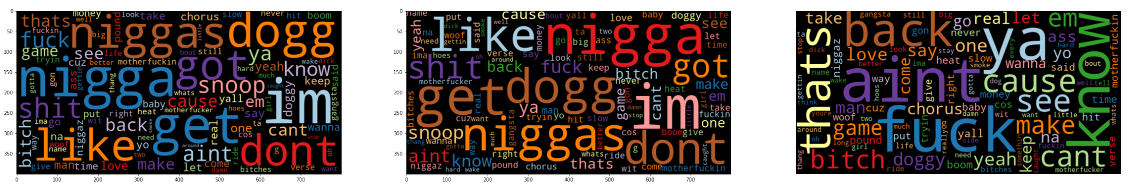
[271]:
```
from matplotlib import pyplot as plt

def wordcloud(word_freq, title=None, max_words=200, stopwords=None, ax=None):

    wc = WordCloud(width=800, height=400,
                   background_color= "black", colormap="Paired",
                   max_font_size=150, max_words=max_words)

    # convert data frame into dict
    if type(word_freq) == pd.Series:
        counter = Counter(word_freq.fillna(0).to_dict())
    else:
        counter = word_freq

    # filter stop words in frequency counter
    if stopwords is not None:
        counter = {token:freq for (token, freq) in counter.items()
                            if token not in stopwords}
    wc.generate_from_frequencies(counter)

    plt.title(title)

    if ax is not None:
        ax.imshow(wc, interpolation='bilinear')
    else:
        plt.imshow(wc, interpolation='bilinear')

    plt.axis("off")


def count_words(df, column='tokens', preprocess=None, min_freq=2):

    # process tokens and update counter
    def update(doc):
        tokens = doc if preprocess is None else preprocess(doc)
        counter.update(tokens)

    # create counter and run through all data
    counter = Counter()
    df[column].map(update)

    # transform counter into data frame
    freq_df = pd.DataFrame.from_dict(counter, orient='index', columns=['freq'])
    freq_df = freq_df.query('freq >= @min_freq')
    freq_df.index.name = 'token'

    return freq_df.sort_values('freq', ascending=False)
```

Wordcloud for Lyrics

[285]:
```
vh_freq_df = count_words(lyrics_data[lyrics_data['artist'] == 'eminem'])

fig, ax = plt.subplots(1, 3, figsize=(40, 30))

wordcloud(vh_freq_df['freq'], max_words=100, ax=ax[0])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=sw, ax=ax[1])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=vh_freq_df.head(10).
 ↪index, ax=ax[2])
```

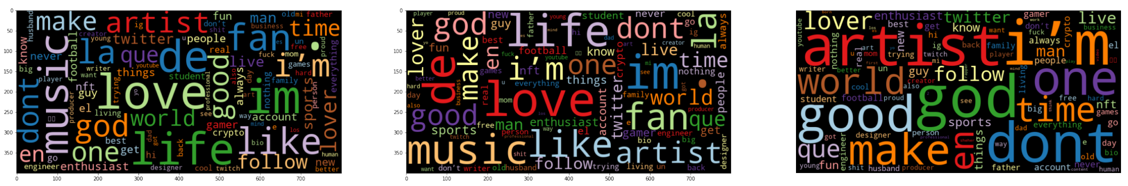


[286]:
```
vh_freq_df = count_words(lyrics_data[lyrics_data['artist'] == 'snoop'])

fig, ax = plt.subplots(1, 3, figsize=(40, 30))

wordcloud(vh_freq_df['freq'], max_words=100, ax=ax[0])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=sw, ax=ax[1])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=vh_freq_df.head(10).
 ↪index, ax=ax[2])
```



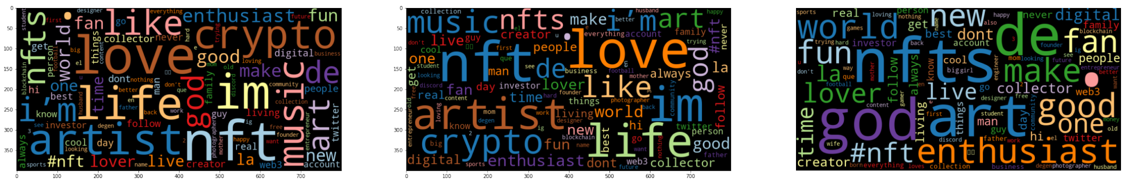
Wordcloud for Tweets

[290]:
```
vh_freq_df = count_words(twitter_data[twitter_data['artist'] == 'eminem'])

fig, ax = plt.subplots(1, 3, figsize=(40, 30))

wordcloud(vh_freq_df['freq'], max_words=100, ax=ax[0])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=sw, ax=ax[1])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=vh_freq_df.head(10).
 ↪index, ax=ax[2])
```



[289]:
```
vh_freq_df = count_words(twitter_data[twitter_data['artist'] == 'snoop'])

fig, ax = plt.subplots(1, 3, figsize=(40, 30))
```

```
wordcloud(vh_freq_df['freq'], max_words=100, ax=ax[0])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=sw, ax=ax[1])
wordcloud(vh_freq_df['freq'], max_words=100, stopwords=vh_freq_df.head(10).
 ↪index, ax=ax[2])
```



Q: What observations do you have about these (relatively straightforward) wordclouds?

A: It is very very interesting to see how Snoopdogg puts words in his lyrics.

For tweets, seems that they both have some things in common like “love” or “god”. One big difference that’s easy to notice is that Snoop seems to be into an NFTs whereas Enimen is more into “artist”.

For lyrics, as quite expected, they are in favor of cursing words as their genre is in rap that so many words appear in both and are shared commonly.

It’s easy to grasp the overall keywords using wordcloud as shown above.