Assignment 3.1: Group Comparison

Course: ADS 509, Applied Large Language Models for Data Science

Name: Anna Shekikyan

Date: 09/22/2025

GitHub: https://github.com/AnahitShekikyan/ADS-509-Assignment-3.1-Group-Comparison

ipynb: https://colab.research.google.com/drive/1EIudyZtoDizfVaCL1ruPOl-MwD3cgcnN?usp=sharing

In [86]:
```
import os
import re
# ! pip install emoji
import emoji
import pandas as pd, csv

from collections import Counter, defaultdict
from nltk.corpus import stopwords
from string import punctuation
# ! pip install WordCloud
from wordcloud import WordCloud

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

In [100…
```
# additional import
import nltk
import numpy as np
import random, numpy as np
random.seed(509); np.random.seed(509)

from matplotlib import pyplot as plt
from nltk.probability import FreqDist
```

In [88]:
```
# Place any addtional functions or constants you need here.

import nltk
nltk.download('stopwords')

# 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+")
```

```python
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.EMOJI_DATA :
    for em in emoji.EMOJI_DATA[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, and num_tokens most common
        tokens. Return a list of
    """

    num_tokens_total = len(tokens)
    num_unique_tokens = len(set(tokens))
    lexical_diversity = (num_unique_tokens / num_tokens_total) if num_tokens_total
    num_characters = sum(len(t) for t in tokens)

    if verbose:
        print(f"There are {num_tokens_total} 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.")
        # print the most common tokens
        top = Counter(tokens).most_common(num_tokens)
        print(f"Top {num_tokens} tokens: {top}")

    return(0)


def contains_emoji(s):

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

    return(len(emojis) > 0)


def remove_stop(tokens) :
    # modify this function to remove stopwords
    sw_set = set(sw)
    cleaned = []
    for tok in tokens:
        # keep hashtags and single-character emojis
        if tok.startswith("#"):
            cleaned.append(tok)
        elif len(tok) == 1 and tok in all_language_emojis:
            cleaned.append(tok)
        elif tok not in sw_set:
            cleaned.append(tok)
    return cleaned
```

```
    return(tokens)

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 Twitte

    # modify the function to return tokens
    s = str(text).lower()
    # drop URLs and @mentions
    s = re.sub(r"https?://\S+", " ", s)
    s = re.sub(r"@\w+", " ", s)
    # put spaces around emoji so they survive split
    s = "".join((f" {ch} " if ch in all_language_emojis else ch) for ch in s)
    # remove punctuation except '#'
    s = remove_punctuation(s, punct_set=tw_punct)
    # collapse whitespace and split to tokens
    tokens = whitespace_pattern.sub(" ", s).strip().split()

    text = tokens
    return(text)

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

    for transform in pipeline :
        tokens = transform(tokens)

    return(tokens)
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\annas\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

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.

In [101…

```
data_location = r"C:\Users\annas\Downloads\M1 Assignment Data\M1 Results"

twitter_folder = "twitter/"
lyrics_folder = "lyrics/"

artist_files = {
    "cher":  "cher_followers_data.txt",
    "robyn": "robynkonichiwa_followers_data.txt",
}
```

In [103…

```
twitter_data = pd.read_csv(
    data_location + "/" + twitter_folder + artist_files['cher'],
```

```
    sep="\t",
    quoting=csv.QUOTE_NONE,
    engine="python"
)
twitter_data['artist'] = "cher"
```

In [104…

```
twitter_data.head(2)
```

Out[104…

	screen_name	name	id	location	followers_count	friends_count	de
0	hsmcnp	Country Girl	35152213	NaN	1302	1014	
1	horrormomy	Jeny	742153090850164742	Earth	81	514	su ‹ l

In [105…

```
twitter_data_2 = pd.read_csv(
    data_location + "/" + twitter_folder + artist_files['robyn'],
    sep="\t",
    quoting=csv.QUOTE_NONE,
    engine="python"
)
twitter_data_2['artist'] = "robyn"

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

In [106…

```
# read in the lyrics here
# data_location and lyrics_folder are already set above
base_lyrics_dir = os.path.join(data_location, lyrics_folder)

def load_txt_folder(artist: str) -> pd.DataFrame:
    folder = os.path.join(base_lyrics_dir, artist)
    rows = []
    for fname in os.listdir(folder):
        if fname.lower().endswith(".txt"):
            path = os.path.join(folder, fname)
            with open(path, "r", encoding="utf-8", errors="replace") as f:
                text = f.read()
            # simple title from filename
            title = fname[:-4]  # drop .txt
            if title.lower().startswith(artist.lower() + "_"):
                title = title[len(artist) + 1:]
            rows.append({
                "lyrics": text,
                "title": title,
                "artist": artist,
                "source_file": fname
            })
    return pd.DataFrame(rows)

lyrics_cher  = load_txt_folder("cher")
```

```python
lyrics_robyn = load_txt_folder("robyn")

lyrics_data = pd.concat([lyrics_cher, lyrics_robyn], ignore_index=True)

# column for pipeline uses
LYR_COL = "lyrics"

print("Loaded lyrics_data:", lyrics_data.shape)
lyrics_data.head(3)
```

```
Loaded lyrics_data: (420, 4)
```

Out[106…

	lyrics	title	artist	source_file
0	"88 Degrees"\n\n\n\nStuck in L.A., ain't got n...	88degrees	cher	cher_88degrees.txt
1	"A Different Kind Of Love Song"\n\n\n\nWhat if...	adifferentkindoflovesong	cher	cher_adifferentkindoflovesong.txt
2	"After All"\n\n\n\nWell, here we are again\nI ...	afterall	cher	cher_afterall.txt

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 stopwords (optional)
- Remove punctuation
- Split on whitespace

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. Note that we remove stopwords before removing punctuation because the stopword set includes punctuation.

Twitter Descriptions

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

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

In [107…

```
# tokenize + normalize lyrics
lyrics_pipeline = [str.lower, remove_punctuation, tokenize, remove_stop]  # remove_

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

print(lyrics_data.groupby("artist")["title"].count())
lyrics_data.head(3)[["artist","title","num_tokens"]]
```

```
artist
cher     316
robyn    104
Name: title, dtype: int64
```

Out[107…

	artist	title	num_tokens
0	cher	88degrees	182
1	cher	adifferentkindoflovesong	137
2	cher	afterall	120

In [108…

```
# drop missing bios first
twitter_data = twitter_data.dropna(subset=["description"]).reset_index(drop=True)

# tokenize + normalize twitter (keeps hashtags/emojis by design of tokenize)
twitter_pipeline = [str.lower, tokenize, remove_stop]

twitter_data = twitter_data.copy()
twitter_data["tokens"] = twitter_data["description"].apply(prepare, pipeline=twitte
twitter_data["num_tokens"] = twitter_data["tokens"].map(len)

print(twitter_data.groupby("artist")["screen_name"].count())
twitter_data.head(3)[["artist","description","tokens"]]
```

```
artist
cher     2000921
robyn     190023
Name: screen_name, dtype: int64
```

Out[108…

	artist	description	tokens
0	cher	Proud supporter of messy buns & leggings	[Proud, supporter, of, messy, buns, leggings]
1	cher	163㎝ / 愛かっぷ💜26歳🍒 工〇好きな女の子💓 フォローしてくれたらDMします🧡	[163㎝ / 愛かっぷ💜26歳🍒, 工〇好きな女の子💓, フォローしてくれたらdmします🧡]
2	cher	csu	[csu]

In [109…
```
twitter_data['has_emoji'] = twitter_data["description"].apply(contains_emoji)
```

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

In [110…
```
twitter_data[twitter_data.has_emoji].sample(10)[["artist","description","tokens"]]
```

Out[110…

	artist	description	tokens
1455509	cher	I meditate & are motivated to get mine!#NewBeg...	[meditate, motivated, get, mine#newbeginnings,...
392125	cher	19 | she/her 🏳️‍🌈	[19, sheher, 🏳️‍🌈]
1847983	cher	Producer of the @NomadFamProject , creator/pro...	[producer, creatorproducerhost, ❤️s, #dogs, sw...
412759	cher	21 Gay🌈 💯 4:20 Friendly🍀	[21, gay🌈 💯, 420, friendly🍀]
720814	cher	Odalys 🧡 💫 222 🌌	[odalys, 🧡 💫, 222, 🌌]
573942	cher	ᴋʀKPOPERᴋʀ ❤️BTS❤️ ❤️ A.R.M.Y❤️ JUNG KOOK❤️V❤️ ...	[ᴋʀkpoperᴋʀ, ❤️bts❤️ ❤️, army❤️, jung, kook❤️v♥...
317669	cher	SF | Immunology/Virology | he/him 🏳️‍🌈|6′5″	[sf, immunologyvirology, hehim, 🏳️‍🌈 6′5″]
1229496	cher	Lifelong runner-18 Bostons,13 NYCs,2 Phila,1 M...	[lifelong, runner18, bostons13, nycs2, phila1,...
1798858	cher	Sou casada gosto de rock e heavy metal adoro i...	[sou, casada, gosto, de, rock, e, heavy, metal...
599717	cher	Mom of 3 beautiful children DJ Nicholas and Ha...	[mom, 3, beautiful, children, dj, nicholas, ha...

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:` **Areas for improvement:** handling mixed tokens (split #artist🎤 → #artist, 🎤), standardizing hyphenation (“hype-girl” → hype, girl or keep as one), and optionally segmenting camelCase hashtags (#WeAllSleepAlone → we, all, sleep, alone).

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

In [111…
```
# pipeline for lyrics
lyrics_pipeline = [str.lower, remove_punctuation, tokenize, remove_stop]

# split by artist
cher_lyrics  = lyrics_data.loc[lyrics_data["artist"]=="cher",  LYR_COL].dropna()
```

```python
robyn_lyrics = lyrics_data.loc[lyrics_data["artist"]=="robyn", LYR_COL].dropna()

# tokenize per song (doc)
cher_docs  = [prepare(t, lyrics_pipeline) for t in cher_lyrics]
robyn_docs = [prepare(t, lyrics_pipeline) for t in robyn_lyrics]

# flatten to corpus level
cher_all  = [tok for doc in cher_docs  for tok in doc]
robyn_all = [tok for doc in robyn_docs for tok in doc]

print("cher — lyrics")
descriptive_stats(cher_all, num_tokens=15, verbose=True)

print("\nrobyn — lyrics")
descriptive_stats(robyn_all, num_tokens=15, verbose=True)

# compact comparison table
import numpy as np, pandas as pd
def summarize(docs):
    toks = [tok for d in docs for tok in d]
    types = set(toks)
    lens = [len(d) for d in docs]
    return pd.Series({
        "songs": len(docs),
        "total_tokens": len(toks),
        "unique_types": len(types),
        "TTR": (len(types) / (len(toks) or 1)),
        "tokens_per_song_mean": float(np.mean(lens) if lens else 0.0),
        "tokens_per_song_median": float(np.median(lens) if lens else 0.0),
    })

comparison = pd.concat(
    {"cher": summarize(cher_docs), "robyn": summarize(robyn_docs)},
    axis=1
)
comparison
```

```
cher — lyrics
There are 35916 tokens in the data.
There are 3703 unique tokens in the data.
There are 172634 characters in the data.
The lexical diversity is 0.103 in the data.
Top 15 tokens: [('love', 1004), ('im', 513), ('know', 486), ('dont', 440), ('youre', 333), ('time', 319), ('baby', 319), ('see', 308), ('oh', 306), ('one', 282), ('go', 274), ('like', 271), ('come', 270), ('take', 263), ('heart', 260)]

robyn — lyrics
There are 15227 tokens in the data.
There are 2156 unique tokens in the data.
There are 73787 characters in the data.
The lexical diversity is 0.142 in the data.
Top 15 tokens: [('know', 308), ('dont', 301), ('im', 299), ('love', 275), ('got', 251), ('like', 232), ('baby', 222), ('youre', 169), ('never', 155), ('dance', 150), ('beat', 146), ('get', 143), ('killing', 136), ('gonna', 126), ('right', 125)]
```

Out[111…

	cher	robyn
songs	316.000000	104.000000
total_tokens	35916.000000	15227.000000
unique_types	3703.000000	2156.000000
TTR	0.103102	0.141591
tokens_per_song_mean	113.658228	146.413462
tokens_per_song_median	110.000000	137.000000

`Q:` What observations do you make about these data?

`A:` Cher’s corpus is larger (316 songs, 35.9k tokens) but shows lower lexical diversity (TTR≈0.103), likely due to repetition across many tracks. Robyn’s smaller set (104 songs, 15.2k tokens) has higher diversity (TTR≈0.142) and longer songs on average (≈146 vs. ≈114 tokens). Top words suggest Cher leans toward romance/ballad vocabulary (“love,” “heart”), while Robyn mixes pop romance with dance/club language (“dance,” “beat”).

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 avoid these problems, we will create a custom statistic to identify words that are uniquely related to each corpus. The idea is to find words that occur often in one corpus and infrequently in the other(s). Since corpora can be of different lengths, we will focus on the *concentration* of tokens within a corpus. "Concentration" is simply the count of the token divided by the total corpus length. For instance, if a corpus had length 100,000 and a word appeared 1,000 times, then the concentration would be $\frac{1000}{100000} = 0.01$. If the same token had a concentration of 0.005 in another corpus, then the concentration ratio would be $\frac{0.01}{0.005} = 2$. Very rare words can easily create infinite ratios, so you will also add a cutoff to your code so that a token must appear at least n times for you to return it.

An example of these calculations can be found in this spreadsheet. Please don't hesitate to ask questions if this is confusing.

In this section find 10 tokens for each of your four corpora that meet 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.

In [112…

```
# Find tokens uniquely related to a corpus via concentration ratios

# flatten twitter tokens
flat_cher_tw = [tok for tokens_list in twitter_data.loc[twitter_data["artist"]=="ch
flat_robyn_tw = [tok for tokens_list in twitter_data.loc[twitter_data["artist"]=="r


# build corpora
corpora = {
    "cher_lyrics":  cher_all,
    "robyn_lyrics": robyn_all,
    "cher_twitter": flat_cher_tw,
    "robyn_twitter": flat_robyn_tw,
}

# counters and totals
counters = {k: Counter(v) for k, v in corpora.items()}
totals   = {k: sum(cnt.values()) for k, cnt in counters.items()}

# global cutoff n (appears at least n times in ALL corpora)
n = 5  # adjust if needed
common_vocab = set.intersection(*[
    {tok for tok, c in cnt.items() if c >= n}
    for cnt in counters.values()
])

# helper to compute top-k distinctive tokens for one corpus
def top_distinctive_for(target_name, topk=10):
    target_cnt = counters[target_name]
    target_tot = totals[target_name]

    # aggregate "other corpora"
    other_names = [k for k in counters if k != target_name]
    other_cnt_sum = Counter()
    other_tot_sum = 0
    for name in other_names:
        other_cnt_sum.update(counters[name])
        other_tot_sum += totals[name]

    rows = []
    for tok in common_vocab:
        c_i = target_cnt.get(tok, 0)
        c_o = other_cnt_sum.get(tok, 0)
        conc_i = c_i / target_tot if target_tot else 0.0
        conc_o = c_o / other_tot_sum if other_tot_sum else 0.0
        if conc_o == 0:
            # skip if totally absent elsewhere after cutoff
            continue
        ratio = conc_i / conc_o
        rows.append((tok, c_i, conc_i, conc_o, ratio))
```

```python
    df = pd.DataFrame(rows, columns=["token", "count_in_corpus", "conc_in_corpus",
    df = df.sort_values("ratio", ascending=False).head(topk).reset_index(drop=True)
    return df

# top-10 for each corpus
print("cher — Lyrics"); display(top_cher_lyrics)
print("robyn — Lyrics"); display(top_robyn_lyrics)
print("cher — Twitter"); display(top_cher_twitter)
print("robyn — Twitter"); display(top_robyn_twitter)
```

cher — Lyrics

	token	count_in_corpus	conc_in_corpus	conc_in_others	ratio
0	ooh	60	0.001671	0.000008	206.462256
1	chorus	60	0.001671	0.000011	158.906343
2	knock	36	0.001002	0.000015	68.709301
3	tonight	61	0.001698	0.000029	59.537787
4	ohh	12	0.000334	0.000007	47.538368
5	ooo	6	0.000167	0.000004	45.621499
6	tears	57	0.001587	0.000036	43.621855
7	gonna	222	0.006181	0.000218	28.369671
8	deny	8	0.000223	0.000008	27.132210
9	gotta	108	0.003007	0.000111	27.081698

robyn — Lyrics

	token	count_in_corpus	conc_in_corpus	conc_in_others	ratio
0	chorus	57	0.003743	0.000011	350.598642
1	ooo	6	0.000394	0.000004	107.739141
2	ohh	11	0.000722	0.000007	102.052909
3	beat	146	0.009588	0.000107	89.852101
4	88	14	0.000919	0.000011	87.563272
5	ooh	13	0.000854	0.000011	78.657380
6	deny	9	0.000591	0.000008	72.606813
7	itll	13	0.000854	0.000013	66.695659
8	crash	9	0.000591	0.000010	57.255658
9	alright	30	0.001970	0.000038	51.383283

cher — Twitter

	token	count_in_corpus	conc_in_corpus	conc_in_others	ratio
0	god	23143	0.001497	0.000571	2.621423
1	proud	30972	0.002004	0.000810	2.474702
2	faith	3243	0.000210	0.000095	2.214296
3	friend	16328	0.001056	0.000486	2.174973
4	woman	12523	0.000810	0.000379	2.137653
5	truth	7228	0.000468	0.000230	2.033824
6	stand	4773	0.000309	0.000161	1.917829
7	boys	8677	0.000561	0.000315	1.779867
8	two	15062	0.000974	0.000557	1.750766
9	mama	5797	0.000375	0.000215	1.741585

```
robyn — Twitter
```

	token	count_in_corpus	conc_in_corpus	conc_in_others	ratio
0	till	1294	0.000887	0.000128	6.944026
1	til	370	0.000254	0.000060	4.245244
2	sound	560	0.000384	0.000142	2.697551
3	men	944	0.000647	0.000255	2.536746
4	spinning	48	0.000033	0.000014	2.299688
5	music	14860	0.010191	0.005598	1.820559
6	88	26	0.000018	0.000011	1.665889
7	head	872	0.000598	0.000360	1.660634
8	dance	1555	0.001066	0.000656	1.625781
9	crash	24	0.000016	0.000010	1.595409

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

`A:` Cher’s lyric-unique tokens skew toward interjections and section markers—“ooh,” “ohh,” ”ooo,” and especially “chorus”—plus emotive/action words like “tonight,” “tears,” “gonna,” and “gotta,” which fits a pop-ballad, verse/chorus style. Robyn’s lyric-unique list leans club/pop: “beat,” “crash,” “alright,” with “88” pointing to a specific track/era and normalized contractions like “itll.”

On Twitter, Cher’s followers emphasize identity/values (“god,” “proud,” “faith,” “friend,” ”woman,” “truth,” “mama”), while Robyn’s emphasize music/nightlife vocabulary (“music,” “dance,” “sound,” “spinning,” “head”) and timing variants (“till/til”). The frequent “chorus” token likely comes from transcription headers and could be filtered if cleaner semantic signals are desired.

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.

In [113…

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

    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)
```

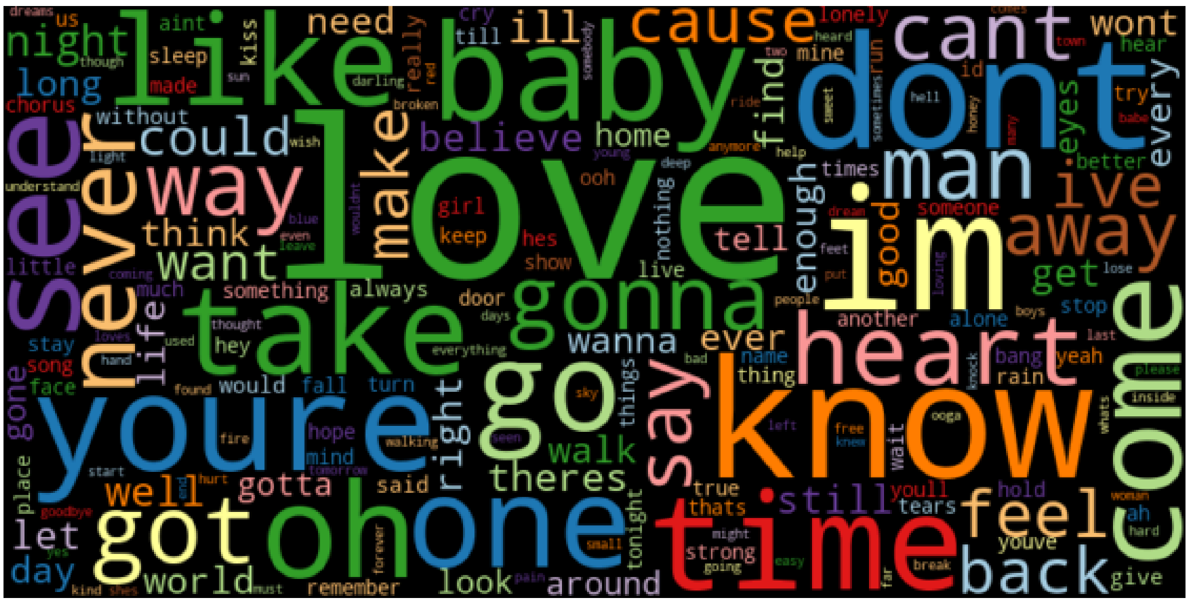
In [84]:

```python
# word clouds for all four corpora, frequencies
cher_lyrics_freq  = count_words(lyrics_data[lyrics_data["artist"]=="cher"],  column
robyn_lyrics_freq = count_words(lyrics_data[lyrics_data["artist"]=="robyn"], column

cher_tw_freq  = count_words(twitter_data[twitter_data["artist"]=="cher"],  column="
robyn_tw_freq = count_words(twitter_data[twitter_data["artist"]=="robyn"], column="

# word clouds
plt.figure(figsize=(8,6)); wordcloud(cher_lyrics_freq["freq"],  title="cher — lyric
plt.figure(figsize=(8,6)); wordcloud(robyn_lyrics_freq["freq"], title="robyn — lyri
plt.figure(figsize=(8,6)); wordcloud(cher_tw_freq["freq"],      title="cher — twitt
plt.figure(figsize=(8,6)); wordcloud(robyn_tw_freq["freq"],     title="robyn — twit
plt.show()
```

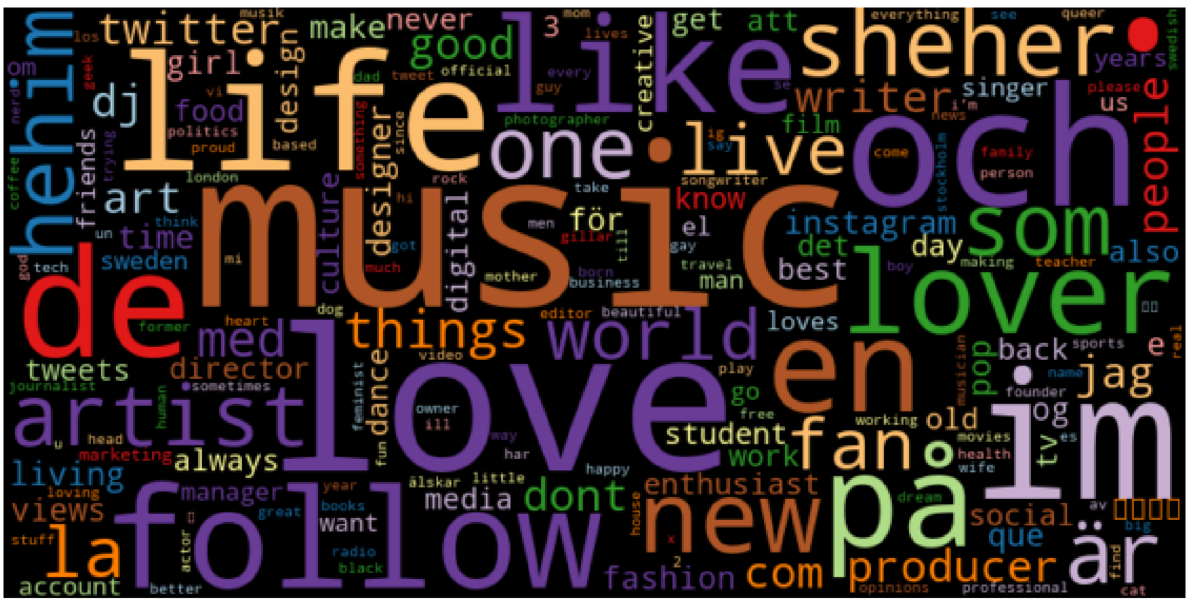
cher — Lyrics



robyn — Lyrics

cher — Twitter

robyn — Twitter



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

`A:` The lyric clouds are classic pop: Cher leans into romance/ballad words (“love,” “heart,” “time,” “baby”), while Robyn mixes that with clear dance-club terms (“dance,” “beat,” “boom,” “killing”). The Twitter clouds center on bio staples (“music,” “love,” “life,” “follow”) plus identity tags (“sheher,” “hehim”), with language hints—Spanish (“de,” “la”) around Cher and Swedish (“och,” “på,” “är,” “jag”) around Robyn. Normalization shows up as “im/dont/youre,” but overall the visuals match the earlier story: Cher = classic pop/romance; Robyn = pop with a club edge.