Assignment

Yi Zhou

z5548349

Part 1

Data Preprocessing

step 1: Load the dataset

Use pandas to load the dataset.

In [262...

```
import pandas as pd

df = pd.read_csv('dataset.tsv', sep='\t')
pd.set_option('display.width', 180)
pd.set_option('display.max_colwidth', 30)
print(df.head(10))
```

```
                     artist_name                     track_name  release_date  
genre                         lyrics      topic
0                         loving              the not real lake          2016      
rock   awake know go see time cle...       dark
1                        incubus                into the summer          2019      
rock   shouldn summer pretty buil...  lifestyle
2                      reignwolf                       hardcore          2016     
blues   lose deep catch breath thi...    sadness
3             tedeschi trucks band                         anyhow          2016     
blues   run bitter taste take rest...    sadness
4   lukas nelson and promise o...              if i started over          2017     
blues   think think different set ...       dark
5                        tia ray                   just my luck          2018      
jazz   yeah happen real drink dri...    emotion
6                     rebelution                      trap door          2018    r
eggae   long long road occur look...       dark
7            thank you scientist  the amateur arsonist's han...          2016      
jazz   quick think good true wors...       dark
8                     zayde wølf                      gladiator          2018      
rock   start climb face army vipe...       dark
9                 eli young band                     never land          2017   co
untry   word yeah wreck roll lips ...    sadness
```

step 2: Initial Data Cleansing

Drop any duplicates and missing values.

In [263...

```
df = df.drop_duplicates()
df = df.dropna()
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1480 entries, 0 to 1499
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   artist_name   1480 non-null   object
 1   track_name    1480 non-null   object
 2   release_date  1480 non-null   int64 
 3   genre         1480 non-null   object
 4   lyrics        1480 non-null   object
 5   topic         1480 non-null   object
dtypes: int64(1), object(5)
memory usage: 80.9+ KB
None
```

step 3: Text Processing

PART 1 QUESTION 1

For this dataset, the regex will remove all kinds of symbols. It's reasonable to keep some symbols like '?' or '!'. So in the following code, I attempt to keep these symbols and try if it will show a different result. The following code will use 'cross_val_predict' from sklearn to train it with cross-validation.

PART 1 QUESTION 2

To find the best preprocessing methods, it's good idea to perform a grid search. The parameters will be:

```
lower_case: True, False.
methods to remove stop words: nltk, sklearn or none.
method to stem the word: porter, lancaster, snowball or
wordnetlemm
```

In [264…

```
import re
from itertools import product
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, LancasterStemmer, SnowballStemmer, WordNetL
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS

nltk.download('stopwords')
nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('wordnet')


stop_words = set(stopwords.words('english'))

all_matches = set()

# The function to perform the preprocessing
def preprocess_text(text, process_methods):
    if (process_methods['stem'] == 'porter'):
        ps = PorterStemmer()
    elif (process_methods['stem'] == 'lancaster'):
```

```
        ps = LancasterStemmer()
    elif (process_methods['stem'] == 'snowball'):
        ps = SnowballStemmer('english')
    else:
        ps = WordNetLemmatizer()

    if (process_methods['lower']):
        text = text.lower()
    # check the regex from the tutorial
    matches = re.findall(r'[^\w\s]', text)
    if len(matches):
        for m in matches:
            all_matches.add(m)
    # modified regex
    if (process_methods['remove_special']):
        text = re.sub(r'[^\w\s\'?!]', '', text)
    tokens = word_tokenize(text)
    if (process_methods['stop_words'] == 'nltk'):
        tokens = [word for word in tokens if word not in stop_words]
    elif (process_methods['stop_words'] == 'sklearn'):
        tokens = [word for word in tokens if word not in ENGLISH_STOP_WORDS]
    if (process_methods['stem'] == 'wordnetlemm'):
        tokens = [ps.lemmatize(word) for word in tokens]
    else:
        tokens = [ps.stem(word) for word in tokens]
    return ' '.join(tokens)

# set of the possible preprocessing methods
preprocessing_combination = {
    'lower': [False, True],
    'remove_special': [True,],
    'stop_words': ['nltk', 'sklearn', 'none'],
    'stem': ['porter', 'lancaster', 'snowball', 'wordnetlemm']
}
keys = list(preprocessing_combination.keys())
values = list(preprocessing_combination.values())
all_combination = [dict(zip(keys, combination)) for combination in product(*valu
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\carl7\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\carl7\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to
[nltk_data]     C:\Users\carl7\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\carl7\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Model Training

Combine all the columns except the 'topic' into one document and perform the preprocessing method to it. Get the result of MNB and calculate the accuracy. Store the best combination of preprocessing for future use.

In [265…

```
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.metrics import accuracy_score, classification_report, f1_score
from sklearn.model_selection import cross_val_predict
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.model_selection import train_test_split
import numpy as np
from tqdm import tqdm


max_accuracy = 0
best_comb = None
best_report = None

def getXy(comb, vectorizer):
    X = df['artist_name'] + ' ' + df['track_name'] + ' ' + df['lyrics'] + ' ' +
    X = X.apply(preprocess_text, args=(comb,))
    # pd.set_option('display.max_colwidth', 3000)

    # print(X.head())
    X = vectorizer.fit_transform(X)
    y = df['topic']
    return X, y

# Grid Search
for comb in tqdm(all_combination):
    vectorizer = CountVectorizer()
    X, y = getXy(comb, vectorizer)
    mnb = MultinomialNB()
    y_pred = cross_val_predict(mnb, X, y, cv=5)
    cur_accuracy = accuracy_score(y, y_pred)
    if (cur_accuracy > max_accuracy):
        max_accuracy = cur_accuracy
        best_comb = comb
        best_report = classification_report(y, y_pred)
```

```
100%|██████████| 24/24 [00:19<00:00,  1.26it/s]
```

Then we can get the best preprocess combination and the accuracy get from this. It's reasonable to find removing special characters will lead to a better result. But surprisingly, the best result is get by using lancaster stem and not removing any stop words.

In [266…

```
print(best_comb)
print(max_accuracy)
print(best_report)
```

```
{'lower': False, 'remove_special': True, 'stop_words': 'none', 'stem': 'lancaste
r'}
0.797972972972973
              precision    recall  f1-score   support

        dark       0.81      0.84      0.83       487
     emotion       0.53      0.32      0.40        79
   lifestyle       0.88      0.69      0.77       202
    personal       0.85      0.82      0.83       341
     sadness       0.75      0.88      0.81       371

    accuracy                           0.80      1480
   macro avg       0.76      0.71      0.73      1480
weighted avg       0.80      0.80      0.79      1480
```

PART 1 QUESTION 3

Accuracy measures the rate of correct predicted samples. However, in an unbalanced dataset, it's possible that it will ignore topics with little samples. Precision calculates how many predicted positive items are correct. Recall calculates how many true positive the model can find. F1 score balances precision and recall. Since this is an unbalanced dataset, if we want to treat the importance of the topics equally, it would be reasonable to choose macro F1-score. In this way, we can get a better result among all topics.

The following code uses the best-performing preprocessing methods get above and compare the metrics of BNB and MNB.

We can see MNB outperforms BNB since it also take the word frequency into consideration. Since some word may appear many times in a certain topic, this is especially helpful for classification.

In [267…

```
vectorizer = CountVectorizer()
X, y = getXy(best_comb, vectorizer)
mnb = MultinomialNB()
bnb = BernoulliNB()
y_b_pred = cross_val_predict(bnb, X, y, cv=5)
y_m_pred = cross_val_predict(mnb, X, y, cv=5)
print(classification_report(y, y_m_pred))
print('---------------------------------------')
print(classification_report(y, y_b_pred))
```

```
              precision    recall  f1-score   support

        dark       0.81      0.84      0.83       487
     emotion       0.53      0.32      0.40        79
   lifestyle       0.88      0.69      0.77       202
    personal       0.85      0.82      0.83       341
     sadness       0.75      0.88      0.81       371

    accuracy                           0.80      1480
   macro avg       0.76      0.71      0.73      1480
weighted avg       0.80      0.80      0.79      1480

--------------------------------------
              precision    recall  f1-score   support

        dark       0.64      0.74      0.69       487
     emotion       0.00      0.00      0.00        79
   lifestyle       0.24      0.02      0.04       202
    personal       0.68      0.35      0.46       341
     sadness       0.44      0.85      0.58       371

    accuracy                           0.54      1480
   macro avg       0.40      0.39      0.35      1480
weighted avg       0.51      0.54      0.48      1480
```

PART 1 QUESTION 4

The following code tries to find the which number of features perform best for BNB and MNB. As discussed above, the metric here to evaluate the performance will be the macro F1 score. The code limits the max_features for different values and try to find the optimal number.

In [268…

```
overall_F1_list = []
b_F1_list = []
m_F1_list = []
max_f1 = 0
best_N = -1
for i in tqdm(range(1, 4001, 20)):
    # limit the feature number
    vectorizer = CountVectorizer(max_features=i)
    X, y = getXy(best_comb, vectorizer)
    mnb = MultinomialNB()
    bnb = BernoulliNB()
    y_b_pred = cross_val_predict(bnb, X, y, cv=5)
    y_m_pred = cross_val_predict(mnb, X, y, cv=5)
    b_F1 = f1_score(y, y_b_pred, average='macro')
    m_F1 = f1_score(y, y_m_pred, average='macro')
    result = b_F1 + m_F1
    if (result > max_f1):
        max_f1 = result
        best_N = i
    overall_F1_list.append(result)
    b_F1_list.append(b_F1)
    m_F1_list.append(m_F1)
```

```
100%|██████████| 200/200 [02:55<00:00,  1.14it/s]
```

Here we can get a visualised result by ploting the F1 score with the x-axis being the number of max features.

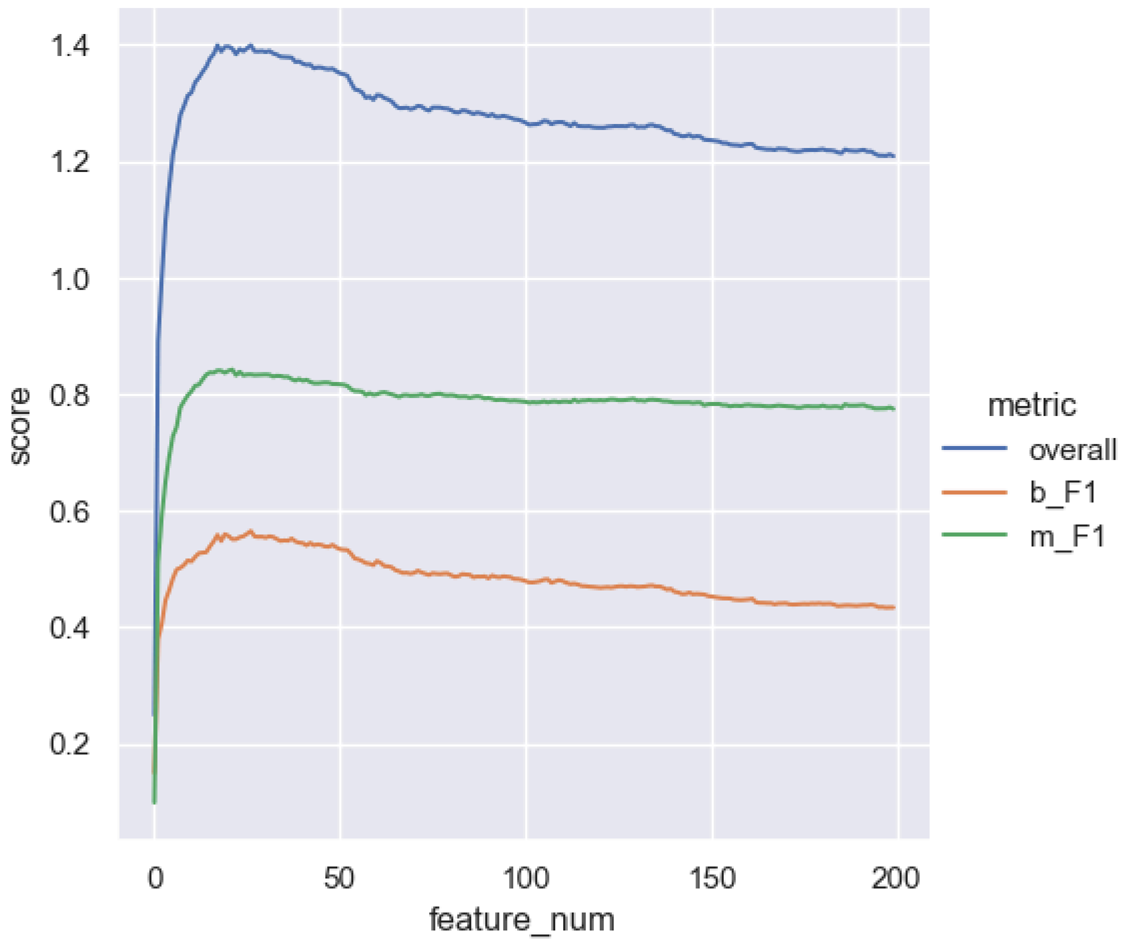
The result shows that increasing the number will significately improve the accuracy. Because the model has more features to evaluate. But after passing a certain number, adding more features tends to add more noise, so the performance starts to decrease. The trend is similar for BNB and MNB so we are able to get a value that work well for both of them.

In [269…

```
import seaborn as sns

sns.set_theme()
L = len(overall_F1_list)
f1_df = pd.DataFrame({'feature_num': list(range(L))*3, 'score': overall_F1_list
sns.relplot(data=f1_df, x='feature_num', y='score', hue='metric', kind='line')
print(best_N)
```

```
521
```



PART 1 QUESTION 5

For this part, the method chosen is LinearSVC. It aims to find the boundary between classes and it's suitable for sparse dataset classification. In our case, the songs are classified by it's lyrics and title and so on, making the method particularly suitable for this problem.

There are some hyperparameters for the function from sklearn.

The first one is 'C', which decides the regularization strength. Small C may cause underfitting and low accuracy, but may also help the model ignore more noise. A large C value applies less regularization but may make the model become overfitting.

The second parameter is 'max_iter', which decides how many number of iterations to train.

The third is 'class_weight', which may be useful when dealing with an unbalanced dataset.

To find the best hyperparameter settings, it's best to perform a Grid Search as the code below. And as mentioned above, the macro F1 score will be the metric to decide the model's performance.

In [270…

```
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
import warnings
from sklearn.exceptions import ConvergenceWarning
warnings.filterwarnings("ignore", category=ConvergenceWarning)

vectorizer = CountVectorizer(max_features=best_N)

param_combination = {
    'C': [0.0001, 0.001, 0.01, 0.1, 1, 10],
    'max_iter': [1000, 3000, 7000, 10000],
    'class_weight': ['balanced', None],
}

# get all combinations of the param settings
keys = list(param_combination.keys())
values = list(param_combination.values())
all_param_combination = [dict(zip(keys, combination)) for combination in product

best_score = -1
best_param_comb = None
best_param_report = None
for param_comb in tqdm(all_param_combination):
    svc = LinearSVC(**param_comb)
    X, y = getXy(best_comb, vectorizer)
    y_svc_pred = cross_val_predict(svc, X, y, cv=5)
    cur_score = f1_score(y, y_svc_pred, average='macro')
    if (cur_score > best_score):
        best_score = cur_score
        best_param_comb = param_comb
        best_param_report = classification_report(y, y_svc_pred)
```

```
100%|██████████| 48/48 [01:11<00:00,  1.49s/it]
```

Here we get the hyperparameter settings for best result. And the result shows an accuracy of 87% and macro F1 of 85%, which is better than BNB or MNB. It's worth noting that the best result comes from the one without balanced class weight. This could be because after applying a small 'C', the impact of the class_weight is smaller.

In [271…

```
print(best_param_comb)
print(best_param_report)
```

```
{'C': 0.001, 'max_iter': 1000, 'class_weight': None}
              precision    recall  f1-score   support

        dark       0.81      0.93      0.87       487
     emotion       0.93      0.67      0.78        79
   lifestyle       0.88      0.79      0.83       202
    personal       0.92      0.87      0.89       341
     sadness       0.91      0.88      0.90       371

    accuracy                           0.87      1480
   macro avg       0.89      0.83      0.85      1480
weighted avg       0.88      0.87      0.87      1480
```

PART 2

PART 2 QUESTION 1

Data Processing

First, the training and testing dataset are split from the dataset. Then a TF-IDF vector is built for each topic based on the content for this topic in the training dataset. The result is stored in a dictionary for future use.

In [272…

```
df['content'] = df['artist_name'] + ' ' + df['track_name'] + ' ' + df['lyrics']
train_dataset = df[:750]
test_dataset = df[750:1000]['content']
pd.set_option('display.max_colwidth', 30)
train_topic_content = {}
topic_list = ['dark', 'lifestyle', 'personal', 'sadness', 'emotion']
for topic in topic_list:
    train_topic_content[topic] = train_dataset[train_dataset['topic'] == topic][
train_tfidf_vec_list = {}
test_tfidf_vec_list = {}
# build a TF-IDF vector for each topic, this is not used for classification, but
for topic in topic_list:
    train_tfidf_vec_list[topic] = {}
    tem_vectorizer = TfidfVectorizer()
    train_tfidf_vec_list[topic]['matrix'] = tem_vectorizer.fit_transform(train_t
    train_tfidf_vec_list[topic]['vectorizer'] = tem_vectorizer
```

Train the classification model

Using the best method and settings from PART 1, we are able to train a model based on the training dataset.

In [273…

```
vectorizer = CountVectorizer(max_features=best_N)
X, y = getXy(best_comb, vectorizer)
train_X = X[:750]
train_y = list(y[:750])
train_topic_df = {}
for topic in topic_list:
    train_topic_df[topic] = []
for i in range(750):
    train_topic_df[train_y[i]].append(i)
for topic in topic_list:
    train_topic_df[topic] = train_X[train_topic_df[topic]]
svc = LinearSVC(**best_param_comb)
```

```
svc.fit(train_X, train_y)
pred_y = svc.predict(train_X)
print(classification_report(train_y, pred_y))
```

```
              precision    recall  f1-score   support

        dark       0.92      0.98      0.95       246
     emotion       1.00      0.88      0.94        42
   lifestyle       0.96      0.92      0.94        92
    personal       0.97      0.94      0.96       187
     sadness       0.98      0.97      0.98       183

    accuracy                           0.95       750
   macro avg       0.97      0.94      0.95       750
weighted avg       0.96      0.95      0.95       750
```

Since we don't have any actual user, we can only assume a user likes a song if the song contains any keywords the user likes.

In [274...

```
def is_interested(keywords, content):
    for keyword in keywords:
        if (keyword in content):
            return True
    return False
```

In [ ]:

```
# Load and build the user keywords dictionary
def load_user(filename):

    user = pd.read_csv(filename, sep='\t')
    user_topic_keywords = {}
    for row in user.values:
        user_topic_keywords[row[0]] = row[1].split(', ')
    return user_topic_keywords
```

We will test which songs in the training set the user likes. Then we are able to build a user profile, which is a document containing all the songs the user likes. By using the vectorizer build for the specific topic, we are able to get a metrix for the user.

In [276...

```
def get_user_profile(filename):
    user = load_user(filename)
    # print(user1)
    user_profile = {}
    for topic in topic_list:
        user_profile[topic] = []
    # add a song to the user's profile if its predicted topic matches the actual
    # and if the song contians keywords the user likes
    for topic, topic_df in train_topic_df.items():
        L = len(train_topic_content[topic])
        y_pred = svc.predict(topic_df)
        for i in range(L):
            cur_content = train_dataset.loc[i]['content']
            if (y_pred[i] == topic and user.get(topic) and is_interested(user[to
                user_profile[topic].append(cur_content)
    # store the number of songs the user like for each topic, we want to know ho
    # store the matrix get from the vectorizer build based on the whole topic do
    for topic in topic_list:
        liked_num = len(user_profile[topic])
```

```
        user_profile[topic] = {'doc': ' '.join(user_profile[topic]), 'len': like
        user_profile[topic]['vector'] = train_tfidf_vec_list[topic]['vectorizer'
    return user_profile
```

Get top 20 words

For each topic, we can then extract the feature from the user metrix and get the feature name. It's worth noting that the document for a certain topic can be empty. In this case, the user does not like any song from that topic and the value in the matrix will be 0. We won't get any words for these kinds of topic.

As the results shown below, we can definitely see the relavance between these words and the topic. For example, the 'dark' topic contains words like 'blood' and 'pain'.

For the same topic, we can also see the top words being different. Meaning we did manage to build and extract features for a certain user based on thier interests.

In [277…

```
def show_topM(user_profile, M=20):
    for topic, content in user_profile.items():
        # extract the feature from the TF-IDF matrix
        feature_names = train_tfidf_vec_list[topic]['vectorizer'].get_feature_na
        user_vector = content['vector']
        scores = user_vector.toarray()[0]
        score_index = np.argsort(scores)
        L = len(score_index) - 1
        res = []
        while (len(res) != 20):
            if (scores[score_index[L]] == 0):
                break
            res.append(feature_names[score_index[L]])
            L -= 1
        print(topic)
        print(res)

user1_profile = get_user_profile('user1.tsv')
print('top 20 words for user1:')
show_topM(user1_profile)
print()
print('top 20 words for user2:')
user2_profile = get_user_profile('user2.tsv')
show_topM(user2_profile)
```

```
top 20 words for user1:
dark
['fight', 'like', 'change', 'yeah', 'good', 'know', 'blood', 'hurt', 'fall', 'com
e', 'pain', 'heart', 'baby', 'woah', 'lanky', 'dilly', 'wall', 'life', 'gonna',
'mind']
lifestyle
['feel', 'promise', 'world', 'good', 'fall', 'telephone', 'south', 'know', 'wann
a', 'steal', 'gonna', 'like', 'away', 'stay', 'tonight', 'right', 'heart', 'wai
t', 'face', 'kiss']
personal
['strangers', 'life', 'wanna', 'night', 'away', 'like', 'heart', 'hurt', 'promis
e', 'look', 'know', 'come', 'head', 'break', 'walk', 'song', 'learn', 'live', 'fe
el', 'dream']
sadness
['blood', 'spoil', 'cry', 'night', 'sister', 'people', 'steal', 'yeah', 'woman',
'good', 'reason', 'come', 'control', 'like', 'regret', 'alive', 'go', 'hold', 'sa
y', 'time']
emotion
['promise', 'night', 'feel', 'good', 'fall', 'grow', 'luck', 'know', 'yeah', 'lif
e', 'anytime', 'understand', 'hand', 'lose', 'walk', 'like', 'doin', 'away', 'lea
ve', 'open']

top 20 words for user2:
dark
[]
lifestyle
[]
personal
[]
sadness
['like', 'pull', 'change', 'goodbye', 'sorrow', 'song', 'everybody', 'life', 'fie
ld', 'kiss', 'alive', 'come', 'magnify', 'lose', 'dead', 'yeah', 'tell', 'time',
'night', 'wanna']
emotion
['fall', 'luck', 'kiss', 'like', 'understand', 'life', 'know', 'wanna', 'yeah',
'beautiful', 'steal', 'goodbye', 'morning', 'remember', 'world', 'feel', 'hand',
'stop', 'gonna', 'hold']
```

Test a third user

Here we build a profile for another user. This user likes keywords that are more general in the database. So although we can still see how the top 20 words relavant to the topic, we also can see more general words appear in this list. This is also reasonalbe since the user could like a lot of the songs in the list.

In [ ]:
```
print('top 20 words for user3:')
# content for user3.tsv, please create this file if you want to run this block.
'''
topic	keywords
dark	scream, devil, black, burn, crawl
sadness	lonely, lose, heart, madness, worst
personal		reason, kiss, tomorrow, forever, grow
'''
user3_profile = get_user_profile('user3.tsv')
show_topM(user3_profile)
```

```
top 20 words for user3:
dark
['blood', 'gonna', 'black', 'know', 'lanky', 'dilly', 'burn', 'night', 'like', 's
outh', 'life', 'devil', 'yeah', 'people', 'right', 'wing', 'dirty', 'come', 'tim
e', 'stay']
lifestyle
[]
personal
['blood', 'gonna', 'wanna', 'kiss', 'fall', 'away', 'promise', 'steal', 'call',
'night', 'like', 'know', 'woah', 'live', 'hand', 'grow', 'luck', 'baby', 'fight',
'lose']
sadness
['wanna', 'know', 'blood', 'like', 'strangers', 'life', 'lose', 'live', 'right',
'heart', 'hand', 'night', 'feel', 'baby', 'good', 'break', 'gonna', 'promise', 's
poil', 'people']
emotion
[]
```

PART 2 QUESTION 2

Classify the test set

The first step is to classify the topic of the test set. The classifier is the one trained before. Then we can generate a TF-IDF vector for each song based on the predicted topic. This TF-IDF matrix will be used to calculate the similarity between the songs and the user profile.

In [279…

```
test_X = X[750:1000]
pred_topic = svc.predict(test_X)
test_topic_content = {}
test_tfidf_vec_list = {}
for topic in topic_list:
    test_topic_content[topic] = []
# separate the test set based on the predicted topic
for ind, topic in enumerate(pred_topic):
    test_topic_content[topic].append((ind))
# generate a TF-IDF vector for each song
for topic in topic_list:
    arr = test_topic_content[topic]
    test_topic_content[topic] = test_dataset.iloc[arr]
    test_tfidf_vec_list[topic] = train_tfidf_vec_list[topic]['vectorizer'].trans
print(test_topic_content)
```

```
{'dark': 752     soccer mommy your dog want...
753     the score revolution wolve...
754     l'indécis sunrise drive br...
757     adelitas way notorious not...
762     des rocs dead ringer hold ...
                    ...
998     godsmack under your scars ...
999     white denim just dropped i...
1000    meshuggah monstrocity skyl...
1001    thank you scientist blue a...
1005    bts not today 방탄소년단의 today...
Name: content, Length: 89, dtype: object, 'lifestyle': 755     gary hoey boxcar b
lues box...
775     marcus miller 7-t's right ...
785     gary clark jr. gotta get i...
795     wallows it's only right wa...
806     diana krall moonglow moong...
810     notd so close think lie dr...
845     jada kingdom wasteman time...
857     magic! kiss me kiss darlin...
858     glass animals mama's gun s...
864     digitalluc rethymno hearts...
869     fruit bats absolute loser ...
870     fumez the engineer pull up...
876     brothers osborne 21 summer...
883     jamie berry light up the n...
891     thievery corporation strik...
895     he is we i wouldn't mind f...
931     trina 100% wait wait wrong...
932     midland every song’s a dri...
938     wolfmother baroness live p...
941     adam hambrick all you, all...
953     ty segall radio body go aw...
956     crumb recently played rece...
961     prettymuch would you mind ...
967     jason aldean first time ag...
976     alessia cara ready think s...
981     elvin bishop (your love ke...
987     oscar jerome do you really...
1003    tinariwen hayati yeah yeah...
Name: content, dtype: object, 'personal': 756    cody jinks no words view w...
758    thomas rhett life changes ...
759    dierks bentley woman, amen...
761    passion build my life song...
763    jason isbell and the 400 u...
776    john mayer changing change...
777    jordan rakei mad world sta...
778    ocean alley bones feel fee...
779    ed sheeran save myself giv...
786    michael franti & spearhead...
796    axian sunday morning sunda...
801    tedeschi trucks band walk ...
808    sturgill simpson brace for...
811    vampire weekend big blue b...
815    palace live well sundown s...
816    chris janson redneck life ...
819    blink-182 bored to death e...
829    mt. joy jenny jenkins come...
831    the allman brothers band a...
839    kadhja bonet this love bet...
```

```
840    ty segall alta want know f...
849    jon bellion hand of god he...
851    tedeschi trucks band hard ...
852    onerepublic kids days figh...
854    anita baker you're the bes...
859    judah & the lion take it a...
861    needtobreathe happiness si...
863    iya terra wash away good d...
867    morgan delt some sunsick d...
871    sir charles jones i'm goin...
874    keith urban john cougar, j...
875    jahmiel live without limit...
884    alborosie rocky road road ...
897    playboi carti love hurts (...
904    cold war kids complainer c...
905    band of rascals holler hea...
906    phil wickham living hope g...
913    gov't mule pressure under ...
918    car bomb gratitude undo bl...
923    soja everything to me yeah...
926    the band steele sit awhile...
928    anita baker no one in the ...
930    kacey musgraves oh, what a...
936    killswitch engage us again...
937    anita baker same ole love ...
940    tame impala patience long ...
955    ron gallo please yourself ...
960    mike love forgiveness tell...
965    jamie n commons won't let ...
980    lukas graham 7 years seven...
983    matt maeson hallucinogenic...
985    alice cooper paranormal co...
990    damian marley living it up...
996    cage the elephant whole wi...
Name: content, dtype: object, 'sadness': 760     post malone blame it on me...
764     walshy fire call me zagada...
765     iya terra follow your hear...
766     kygo remind me to forget f...
768     diana krall but not for me...
                    ...
995     radio moscow 250 miles/bra...
997     tesseract smile calm sooth...
1002    breaking benjamin blood en...
1004    chris stapleton broken hal...
1006    gramatik puff your cares a...
Name: content, Length: 71, dtype: object, 'emotion': 770    dirty heads horsefly
say l...
846    taylor mcferrin so cold in...
899    parker millsap hands up ea...
900    the weeknd false alarm bat...
910    kings and comrades can't l...
944    timeflies once in a while ...
969    justin moore got it good w...
993    robert glasper experiment ...
Name: content, dtype: object}
```

Get recommendation

We decides to recommend a total number of 20 songs to a user. The interface would be a section called 'Guess you like' and showing 10 songs per page. This gives the user a certain amount of freedom to choose. However, considering the number of songs, we would want to place the song which the user might like at the front of the list.

We will test 4 different type of similarity algorithm and choose the best one from them. Some algorithms consider the actual position of the vector and compute the similarity, others simply calculate the similarity between two sets.

Based on the algorithm, we will rank the songs in each topic in Week 4 for evaluation.

In [280…

```
from sklearn.metrics.pairwise import cosine_similarity, euclidean_distances
from sklearn.metrics import ndcg_score, jaccard_score, pairwise_distances

N = 20

def get_rec_list(user_profile, sim_alg, M=0):
    for topic in topic_list:
        user_vector = user_profile[topic]['vector']
        # if using top M words from the user profile instead of all
        if (M != 0):
            # get the top M frequent words based on the vector
            top_M = np.argsort(user_profile[topic]['vector'].toarray().flatten()
            L = len(top_M)
            lil = user_vector.tolil()
            for i in range(L - M):
                lil[0,top_M[i]] = 0
            user_vector = lil.tocsr()
        if (sim_alg == 'cosine'):
            score = cosine_similarity(test_tfidf_vec_list[topic], user_vector)
            score = score.flatten()
        elif (sim_alg == 'euclidean'):
            dis = euclidean_distances(test_tfidf_vec_list[topic], user_vector)
            score = np.exp(-dis).flatten()
        elif (sim_alg == 'jaccard'):
            test_set = (test_tfidf_vec_list[topic] > 0)
            user_set = (user_vector > 0).toarray()[0]
            score = [jaccard_score(test_song.toarray()[0], user_set) for test_so
        elif (sim_alg == 'sorensen'):
            test_set = (test_tfidf_vec_list[topic] > 0).toarray()
            user_set = (user_vector > 0).toarray()
            sorensen_match = 1 - pairwise_distances(test_set, user_set, metric='
            score = sorensen_match.flatten()
        # print(score)
        top_songs = np.argsort(score)[::-1]
        user_profile[topic]['rec_list'] = top_songs
        user_profile[topic]['rec_scores'] = np.sort(score)[::-1]
```

Considering the user might enjoys a lot songs from one topic and only likes a few from other topics, we wouldn't want to recommend songs from every topic evenly. Instead, if the user likes a lot songs for one topic, the system will recommend more songs for this topic. So the 20 songs will be weighted-selected from 5 topics.

As for the evalutation, obviousely we care about the precision@N, which tells how accurate our recommendation is. Recall@N is not choosed because the number N here is 20, which is a small number comparing to the whole dataset, so the metric will always be small and lacks helpful information.

Another metric we choose is nDCG, which can also tell if the order of the list is correct.

As the result shows, we get an accurate recommendation for user 1 and user 3. The result for user 2 is pretty low. This could be because the user has a special taste and only likes a small group of songs.

As for the difference among the similarity algorithms, the nDCG metrics for these 4 algorithms are pretty close. As for the precision@N, we can see jaccard and sorensen performs a little bit better for user 1 and 2. If our system aims to provide accurate recommendation for all users, these two algorithms would be prefered. However, if we only care more about general user(e.g. user 3)'s interests and hope others can grow to like more songs, cosine similarity or euclidean similarity can be choosed.

In [281…

```
# calculate how many songs to return from each topic
# based on how many songs the user already likes in that topic
def get_weighted_recommend_list(user_profile, N):
    liked_num = []
    for topic in topic_list:
        liked_num.append(user_profile[topic]['len'])
    liked_num = liked_num / np.sum(liked_num) * N
    liked_num = np.round(liked_num)
    while (int(np.sum(liked_num)) != N):
        ind = np.argmax(liked_num)
        liked_num[ind] = liked_num[ind] + 1 if np.sum(liked_num) < N else liked_
    ans = []
    score_list = []
    for ind, topic in enumerate(topic_list):
        cur_topic_list = user_profile[topic]['rec_list']
        cur_topic_scores = user_profile[topic]['rec_scores']
        r = int(liked_num[ind])
        score_list.append(cur_topic_scores[:r])
        ans.append(cur_topic_list[:r])
    return ans, score_list

# after getting the list, check if the songs contains the keywords the user like
# returns precision@N and nDCG
def evaluate_rec(user_profile):
    rec_list, score_list = get_weighted_recommend_list(user_profile, N)

    pred_num = 0
    true_list = []
    for ind, topic in enumerate(topic_list):
        for song_ind in rec_list[ind]:
            cur_song = test_topic_content[topic].iloc[song_ind]
            if (is_interested(user_profile[topic]['key_words'], cur_song)):
                true_list.append(1)
            else:
                true_list.append(0)
    score_list = np.concatenate(score_list)
    p_N = np.sum(true_list) / N
    ndcg_s = ndcg_score([true_list], [score_list])
    return p_N, ndcg_s



for sim_alg in ['cosine', 'euclidean', 'jaccard', 'sorensen']:
    print('-----------------------------')
```

```
    print(sim_alg)
    get_rec_list(user1_profile, sim_alg)
    print(evaluate_rec(user1_profile))
    get_rec_list(user2_profile, sim_alg)
    print(evaluate_rec(user2_profile))
    get_rec_list(user3_profile, sim_alg)
    print(evaluate_rec(user3_profile))

# evaluate_rec(user2_profile)
# evaluate_rec(user3_profile)
```

```
-----------------------------
cosine
(0.85, 0.9526942787016631)
(0.1, 0.4140749156809286)
(0.75, 0.9545735931191556)
-----------------------------
euclidean
(0.85, 0.9526942787016631)
(0.1, 0.4140749156809286)
(0.75, 0.9545735931191556)
-----------------------------
jaccard
(0.85, 0.9999999999999999)
(0.25, 0.5898018459057794)
(0.5, 0.8665201629951848)
-----------------------------
sorensen
(0.85, 0.9999999999999999)
(0.25, 0.5898018459057794)
(0.5, 0.8665201629951848)
```

Then consider using top M words from the user profile instead of using the whole document. As the result shows below, it's won't provide a better result. This could be because TF-IDF already take consider of the frequency among the whole document. Common words will already have a small value so removing them won't help improve the accuracy.

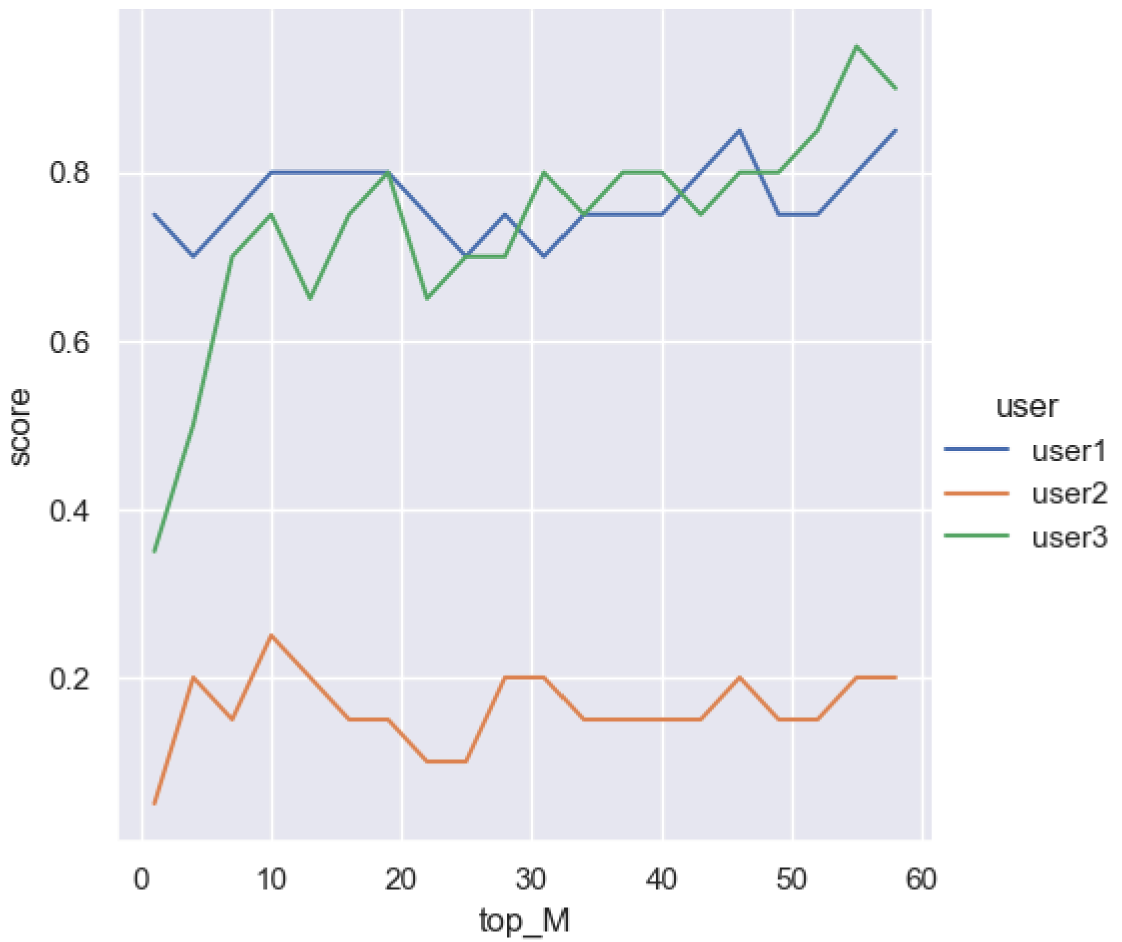
In [282…

```
user1_topM = []
user2_topM = []
user3_topM = []
for i in range(1, 60, 3):
    get_rec_list(user1_profile, 'jaccard', i)
    p, _ = evaluate_rec(user1_profile)
    user1_topM.append(p)
    get_rec_list(user2_profile, 'jaccard', i)
    p, _ = evaluate_rec(user2_profile)
    user2_topM.append(p)
    get_rec_list(user3_profile, 'jaccard', i)
    p, _ = evaluate_rec(user3_profile)
    user3_topM.append(p)
```

In [283…

```
L = len(user1_topM)
topM_df = pd.DataFrame({'top_M': list(range(1, 60, 3))*3, 'score': user1_topM +
sns.relplot(data=topM_df, x='top_M', y='score', hue='user', kind='line')
print(best_N)
```

```
521
```



PART 3

For the first three weeks, the system will just randomly choose 20 songs for the user to choose. Please note that random songs will be generated for each run. So the index may not match those which the user pick we asked for the users feedback a while ago.

In [284…

```
import random
pd.set_option('display.max_colwidth', 40)
def get_rand_songs(week):
    cur_week = df[(week-1)*250:week*250]
    rand_20 = random.sample(range(250), 20)
    # print(rand_20)
    print(cur_week.iloc[sorted(rand_20)])

get_rand_songs(1)
```

```
                              artist_name                    track_name  release
_date    genre                                  lyrics      topic  \
4    lukas nelson and promise of the real              if i started over
2017    blues  think think different set apart sobe...       dark
9                           eli young band                    never land
2017  country  word yeah wreck roll lips high good ...    sadness
10                                    klim                    ninetofive
2018     jazz  nice place think sky separate nice s...   personal
14                                  khalid                        winter
2017      pop  lose heart nighttime leave cold leav...   personal
30                                 popcaan                   traumatized
2019   reggae  screamin lorax gang deffame californ...       dark
43                           riley richard                        l.i.t.
2018     jazz  libertin class roster spring study t...  lifestyle
69                            taylor swift                    the archer
2019      pop  combat ready combat want cause cruel...  lifestyle
78                              larkin poe                     look away
2017    blues  lord rage mirror look chain dream ba...    sadness
85                                james tw          please keep loving me
2017      pop  know moments time hard impatient get...    emotion
89                                 ødyssee                summer delight
2019     jazz  face rise face rise streets crawl de...    sadness
94                            tarrus riley                       hurt me
2018   reggae  think think settle wrong wrong think...    sadness
134                         blues saraceno              wicked gonna come
2018    blues  wicked wicked gonna come wicked wick...       dark
137                             luke combs      beer never broke my heart
2019  country  largemouth bass bust line couple bea...    sadness
146                         gary clark jr.                  got to get up
2019    blues  yeah yeah know talk kill kill kill k...       dark
148                           george strait                   some nights
2019  country  take road lose hear wind fort heart ...   personal
151                         vhs collection              so i met someone
2017     rock  remind ways play tape rewind reason ...    sadness
155                                 buczer      hip hop prod. crackhouse
2017  hip hop  ghost porcelain waste innocence tran...       dark
157                          billie eilish  all the good girls go to hell
2019      pop  lucifer lonely stand kill time commi...       dark
173                                santana                    blue skies
2019    blues  lose feet grind color burn lonelines...  lifestyle
244                              buddy guy              you did the crime
2018    blues  lie cheat girl excuse criminal behav...   personal

                                         content
4    lukas nelson and promise of the real...
9    eli young band never land word yeah ...
10   klim ninetofive nice place think sky...
14   khalid winter lose heart nighttime l...
30   popcaan traumatized screamin lorax g...
43   riley richard l.i.t. libertin class ...
69   taylor swift the archer combat ready...
78   larkin poe look away lord rage mirro...
85   james tw please keep loving me know ...
89   ødyssee summer delight face rise fac...
94   tarrus riley hurt me think think set...
134  blues saraceno wicked gonna come wic...
137  luke combs beer never broke my heart...
146  gary clark jr. got to get up yeah ye...
148  george strait some nights take road ...
151  vhs collection so i met someone remi...
```

```
155    buczer hip hop prod. crackhouse ghos...
157    billie eilish all the good girls go ...
173    santana blue skies lose feet grind c...
244    buddy guy you did the crime lie chea...
```

In [285…

```
get_rand_songs(2)
```

```
                           artist_name                            track_name  r
elease_date    genre                                    lyrics      topic  \
263  nahko and medicine for the people                            directions
2016   reggae  north east south grandfather call ne...  lifestyle
264                        talib kweli                      ny weather report
2018  hip hop  come yeah like opportunity thank eve...       dark
276                          audio two                          make it funky
2017  hip hop  sameoldshawn kind music listen time ...  lifestyle
286                        high valley                              i be u be
2016  country  soldier line courage heart fight out...   personal
295                             pepper                                  bones
2016   reggae  say bonecrunching mayhem funk caroon...  lifestyle
319                       the movement                       life is a circle
2019   reggae  nation scira halla playas track call...   personal
321                          the score                       never going back
2017     rock  ohoh ohoh ohoh shrug shoulder tell w...       dark
350                              flume         never be like you (feat. kai)
2016      pop  untitled trainor vérité underdress k...       dark
351                   all them witches                    fishbelly 86 onions
2018    blues  fishbelly white night hang dark thin...       dark
353                           jah cure  life is real (feat. popcaan & padrino)
2018   reggae  meaningless meaningless meaningless ...       dark
373                     ky-mani marley                          rule my heart
2016   reggae  moment time like know kymani hide li...    sadness
385                        adam doleac                           puzzle of us
2019  country  leave corner shinin blue black bird ...       dark
403                           temporex                              nice boys
2017     rock  easy feel nice miss want feel lyric ...    emotion
405               thievery corporation              music to make you stagger
2018     jazz  catch tide divide moment stand fight...    sadness
426                           seedless                    it's always something
2016   reggae  know hard mind know tough leave ones...   personal
440                           bastille                                  blame
2016     rock  sleep fish room room wrap teeth pave...    sadness
447                     blues saraceno                    devils got you beat
2019    blues  evil mind trouble feet live devil be...       dark
455                    slightly stoopid                                glocks
2018   reggae  doughty guitar bass key mcdonald bas...  lifestyle
457                   jo mersa marley                          point of view
2018   reggae  flight time zone yeah look timeline ...  lifestyle
492                          badflower                                 animal
2018     rock  animal ungrateful cannibal soul impo...       dark

                                      content
263  nahko and medicine for the people di...
264  talib kweli ny weather report come y...
276  audio two make it funky sameoldshawn...
286  high valley i be u be soldier line c...
295  pepper bones say bonecrunching mayhe...
319  the movement life is a circle nation...
321  the score never going back ohoh ohoh...
350  flume never be like you (feat. kai) ...
351  all them witches fishbelly 86 onions...
353  jah cure life is real (feat. popcaan...
373  ky-mani marley rule my heart moment ...
385  adam doleac puzzle of us leave corne...
403  temporex nice boys easy feel nice mi...
405  thievery corporation music to make y...
426  seedless it's always something know ...
440  bastille blame sleep fish room room ...
```

```
447  blues saraceno devils got you beat e...
455  slightly stoopid glocks doughty guit...
457  jo mersa marley point of view flight...
492  badflower animal animal ungrateful c...
```

In [286…

```
get_rand_songs(3)
```

```
                              artist_name                       track_name  relea
se_date    genre                                   lyrics      topic  \
524                        michael lington                    break the ice
2018     jazz  haile selassie chapel power trinity ...   personal
541                                  kbong                       good lovin
2017   reggae  good good good lovin gimme good good...    emotion
548                          joe bonamassa  some other day, some other time
2016    blues  time wanna hold time wanna kiss baby...  lifestyle
584                          chris cornell            nothing compares 2 u
2018     rock  seven hours days take away night sle...    sadness
590                      fantastic negrito                     about a bird
2017    blues  window watch sell hop fall bush hand...       dark
591                            eric church                     hippie radio
2018  country  daddy pontiac beigeer yellow young l...  lifestyle
600                            the spaniels    goodnite sweetheart, goodnite
2018    blues  goodnight sweetheart time goodnight ...  lifestyle
608                             noah kahan                            cynic
2019     rock  change space rest face place head gl...   personal
624                                 bonobo                      break apart
2016     jazz  hard hate hard hate hate think caref...    sadness
627                              ballyhoo!             this chick is wack
2018   reggae  separation break break split inside ...    sadness
628                             ed sheeran                what do i know?
2017      pop  soapbox stand give stage guitar song...   personal
642                         black mountain                   horns arising
2019    blues  tiny island lock ocean draw darkness...       dark
654                          kenny chesney            song for the saints
2018  country  long boat anchor harbour long steel ...       dark
671                       sturgill simpson             the dead don't die
2019  country  dead ghost inside dream life walk pa...   personal
676                                 khalid                     cold blooded
2017      pop  cold blood cold blood treat get hand...       dark
705                        miranda lambert                     use my heart
2016  country  throw line reel throw dart stick thi...    sadness
709  lukas nelson and promise of the real                       high times
2017    blues  osoyoos prefix indigenous origin att...       dark
716                                iration                      fly with me
2017   reggae  relax know high star moon constellat...    sadness
727                                   korn                 rotting in vain
2016     rock  wouldn angry  tear arouse refresh su...    sadness
750                    two door cinema club                            once
2019     rock  away sugar dance tongue grow stay yo...    sadness

                                   content
524  michael lington break the ice haile ...
541  kbong good lovin good good good lovi...
548  joe bonamassa some other day, some o...
584  chris cornell nothing compares 2 u s...
590  fantastic negrito about a bird windo...
591  eric church hippie radio daddy ponti...
600  the spaniels goodnite sweetheart, go...
608  noah kahan cynic change space rest f...
624  bonobo break apart hard hate hard ha...
627  ballyhoo! this chick is wack separat...
628  ed sheeran what do i know? soapbox s...
642  black mountain horns arising tiny is...
654  kenny chesney song for the saints lo...
671  sturgill simpson the dead don't die ...
676  khalid cold blooded cold blood cold ...
705  miranda lambert use my heart throw l...
```

```
709  lukas nelson and promise of the real...
716  iration fly with me relax know high ...
727  korn rotting in vain wouldn angry  t...
750  two door cinema club once away sugar...
```

Below shows the songs picked by the user. Then we are able to use the same method from PART 2 to generate a recommendation list from week4.

In [ ]:

```
# song index picked by the user
selected_songs = [0, 19, 119, 151, 177, 196, 287, 296, 334, 368, 478, 538, 542,
pd.set_option('display.max_colwidth', 150)
# get the content of those songs and get the predicted topic
user_selected = real_user_df = df.loc[selected_songs]['content']
real_user_profile = {}
real_user_df = real_user_df.apply(preprocess_text, args=(best_comb,))
real_user_df = vectorizer.transform(real_user_df)
pred_topic = svc.predict(real_user_df)
# build a user profile based on the predicted topic
# use the same vectorizer build from week1 to 3.
for topic in topic_list:
    real_user_profile[topic] = []
for ind, topic in enumerate(pred_topic):
    real_user_profile[topic].append(user_selected.iloc[ind])
for topic in topic_list:
    liked_num = len(real_user_profile[topic])
    real_user_profile[topic] = {'doc': ' '.join(real_user_profile[topic]), 'len'
    real_user_profile[topic]['vector'] = train_tfidf_vec_list[topic]['vectorizer
# use the same method to get a recommend list and order it based on the score
get_rec_list(real_user_profile, 'jaccard')
rec_list, score_list = get_weighted_recommend_list(real_user_profile, N)
score_list = np.concatenate(score_list)
# the list is not ordered, so we need to get the correct order based on the scor
display_order = np.argsort(score_list)[::-1]
test_set = df[750:1000]
rec_song_list = []
for ind, topic in enumerate(topic_list):
    for song_ind in rec_list[ind]:
        cur_song = test_set[test_set['topic'] == topic].iloc[song_ind]
        rec_song_list.append(cur_song)
for order in display_order:
    print(order)
    print(rec_song_list[order])
```

```
9
artist_name
prettymuch
track_name
open arms
release_date
2017
genre
pop
lyrics          prettymuch try baby start face fact whoa cuff know catch slippin
need wanna touch turn away whoa girl tear apart help waitin open arm ready know
h...
topic
lifestyle
content         prettymuch open arms prettymuch try baby start face fact whoa cuf
f know catch slippin need wanna touch turn away whoa girl tear apart help waitin
...
Name: 782, dtype: object
11
artist_name
morgan delt
track_name
some sunsick day
release_date
2016
genre
rock
lyrics          blast level relax watch come maybe stay little cave finally need
ship leave forget live assign maybe time play run totally naked finally need sta
r...
topic
sadness
content         morgan delt some sunsick day blast level relax watch come maybe s
tay little cave finally need ship leave forget live assign maybe time play run t
o...
Name: 867, dtype: object
10
artist_name
jahmiel
track_name
live without limit
release_date
2018
genre
reggae
lyrics          yeah yeah yeah yellow moon clock tick eye drip give time hear lif
e live hard yeah yeah tomorrow promise live limit live limit yeah yeah yeah sure
...
topic
personal
content         jahmiel live without limit yeah yeah yeah yellow moon clock tick
eye drip give time hear life live hard yeah yeah tomorrow promise live limit liv
e...
Name: 875, dtype: object
0
artist_name
deca
track_name
donner bell
release_date
```

```
2019
genre
jazz
lyrics          donner ready table live watchin star fall like confetti slip worm
hole spiral descend pleasures fleshcovered meat light fare heavy peeve splittin
...
topic
dark
content         deca donner bell donner ready table live watchin star fall like c
onfetti slip worm hole spiral descend pleasures fleshcovered meat light fare hea
v...
Name: 792, dtype: object
1
artist_name
10 years
track_name
novacaine
release_date
2017
genre
rock
lyrics          dirt knees blood teeth want life lead believe come numb dive deep
er blissful kiss lips come yeah numb super novacaine dead dead feel thing sleepw
a...
topic
dark
content         10 years novacaine dirt knees blood teeth want life lead believe
come numb dive deeper blissful kiss lips come yeah numb super novacaine dead dea
d...
Name: 793, dtype: object
12
artist_name
the score
track_name
the heat
release_date
2017
genre
rock
lyrics          paradise believe light break alive crave like need high desert oc
ean motion need break leave thirst heat heat paradise lose word time sense lose
m...
topic
sadness
content         the score the heat paradise believe light break alive crave like
need high desert ocean motion need break leave thirst heat heat paradise lose wo
r...
Name: 827, dtype: object
2
artist_name
parker millsap
track_name
hands up
release_date
2016
genre
blues
lyrics          easy hard wanna lump jacket yeah pistol open register grab fistfu
l dollar bill hand baby home brother gotta fee know think kind trash stickin qui
k...
```

```
topic
dark
content         parker millsap hands up easy hard wanna lump jacket yeah pistol o
pen register grab fistful dollar bill hand baby home brother gotta fee know thin
k...
Name: 899, dtype: object
13
artist_name
charlie puth
track_name
one call away
release_date
2016
genre
pop
lyrics          away save superman away baby need friend wanna reach matter know
away save superman away come scar wanna free stay cause know wanna smile matter
k...
topic
sadness
content         charlie puth one call away away save superman away baby need frie
nd wanna reach matter know away save superman away come scar wanna free stay cau
s...
Name: 769, dtype: object
3
artist_name
death from above 1979
track_name
freeze me
release_date
2017
genre
blues
lyrics          tell think trouble feelin sorry struggle pickin piece siftin rubb
le ringin year listenin double outside safe space space pin spinnin rock freeze
c...
topic
dark
content         death from above 1979 freeze me tell think trouble feelin sorry s
truggle pickin piece siftin rubble ringin year listenin double outside safe spac
e...
Name: 896, dtype: object
14
artist_name
black pistol fire
track_name
hearts of habit
release_date
2017
genre
blues
lyrics          record little late wrong go know better baby know better break he
avy heart holy rollers hearted cryin door hidin cold shoulder hearts shatter bru
i...
topic
sadness
content         black pistol fire hearts of habit record little late wrong go kno
w better baby know better break heavy heart holy rollers hearted cryin door hidi
n...
Name: 772, dtype: object
```

```
15
artist_name
the dear hunter
track_name
the flame (is gone)
release_date
2016
genre
jazz
lyrics          tremble like earth fall feet like felt grind indication head know
settle score lie tell know stack problems like pile bricks gotta knock wall lik
e...
topic
sadness
content         the dear hunter the flame (is gone) tremble like earth fall feet
like felt grind indication head know settle score lie tell know stack problems l
i...
Name: 855, dtype: object
4
artist_name
dj grumble
track_name
hellohello
release_date
2018
genre
jazz
lyrics          mountain count days meet revenge friends build brain watch attack
know strike today like brain insane stop power pain stop power fight power crea
t...
topic
dark
content         dj grumble hellohello mountain count days meet revenge friends bu
ild brain watch attack know strike today like brain insane stop power pain stop
p...
Name: 922, dtype: object
16
artist_name
anita baker
track_name
will you be mine
release_date
2017
genre
jazz
lyrics          come feel explain lose break heart come mend apart best soul lose
dark night arrive come surprise remove darkness right eye plain need wanna know
...
topic
sadness
content         anita baker will you be mine come feel explain lose break heart c
ome mend apart best soul lose dark night arrive come surprise remove darkness ri
g...
Name: 789, dtype: object
17
artist_name
keith urban
track_name
the fighter
release_date
```

```
2016
genre
country
lyrics          know hurt scar scar deserve cause precious heart precious heart k
now thank gonna little time gonna bear fall fall scar hold tighter tryna baby fi
g...
topic
sadness
content         keith urban the fighter know hurt scar scar deserve cause preciou
s heart precious heart know thank gonna little time gonna bear fall fall scar ho
l...
Name: 809, dtype: object
18
artist_name
moonchild
track_name
doors closing
release_date
2017
genre
jazz
lyrics          doors close stand clear think open door come think open door comi
n round stealin beat think open door baby yeah takin away key think open door go
n...
topic
sadness
content         moonchild doors closing doors close stand clear think open door c
ome think open door comin round stealin beat think open door baby yeah takin awa
y...
Name: 924, dtype: object
19
artist_name
thank you scientist
track_name
swarm
release_date
2019
genre
jazz
lyrics          circle return time concentrate erase commotion come little urgenc
y best feel like feel like tear wall destroyer wonder take leave instead right b
l...
topic
sadness
content         thank you scientist swarm circle return time concentrate erase co
mmotion come little urgency best feel like feel like tear wall destroyer wonder
t...
Name: 975, dtype: object
5
artist_name
brand nubian
track_name
love vs. hate
release_date
2019
genre
hip hop
lyrics          hate time people eliminate hate people think playa hatin cause ha
te black black fact stand like selfhate killin popo crack tell people gats arriv
e...
```

```
topic
dark
content         brand nubian love vs. hate hate time people eliminate hate people
think playa hatin cause hate black black fact stand like selfhate killin popo c
r...
Name: 878, dtype: object
6
artist_name
passion
track_name
build my life
release_date
2017
genre
rock
lyrics          song sing praise bring breath breathe live save breath breathe li
ve holy like open eye wonder heart lead song sing praise bring breath breathe li
v...
topic
dark
content         passion build my life song sing praise bring breath breathe live
save breath breathe live holy like open eye wonder heart lead song sing praise b
r...
Name: 761, dtype: object
7
artist_name
klischée
track_name
bella ciao
release_date
2018
genre
jazz
lyrics          wooh oooh world wooh oooh peace enemy doubt fight inside poster c
hild denial hide punch hole wall build long sabotage see blame voice head wooh o
o...
topic
dark
content         klischée bella ciao wooh oooh world wooh oooh peace enemy doubt f
ight inside poster child denial hide punch hole wall build long sabotage see bla
m...
Name: 917, dtype: object
8
artist_name
the detroit cobras
track_name
shout bamalama
release_date
2016
genre
blues
lyrics          alabama shout bamalama louisiana go lord soul chickens steal nigh
t night go unintelligible chicken baby shout bamalama go feet feet go feild feet
...
topic
dark
content         the detroit cobras shout bamalama alabama shout bamalama louisian
a go lord soul chickens steal night night go unintelligible chicken baby shout b
a...
Name: 893, dtype: object
```

We asked if the user liked these songs and was able to get their feed back. Below shows the precision@N and nDCG value. We are able to get a 50% precision and the nDCG is acceptable.

Discussion

The precision@N is 50%. This is lower than the 0.8 from user1. This could be because since the actual user does not pick their interested songs base on a set of keywords, instead, they may put more weight on the title or the artist name. The algorithm treat all the information equally, so may lead to a lower accuracy.

User Comment

I would say the list is pretty accurate. I didn't see the label of the song, but I intended to pick songs that are somewhat sad and negative. So the result is pretty accurate. But to be honest, I kind of lost patient after the 10th song or so. So for the rest of the list, I decided that if I don't like the title or the first 10 words of the lyrics, I'll pass it. 20 songs are a lot if I have to check them one by one. But suppose they are listed in a section, I suppose it's fine for me to just check them randomly.

In [299…

```
real_liked_list = [0,1,1,0,0,1,0,1,0,0,1,1,1,0,0,1,1,1,0,0]
p_N = np.sum(real_liked_list) / N
ndcg_s = ndcg_score([real_liked_list], [score_list])
print(p_N)
print(ndcg_s)
```

```
0.5
0.7650531241737677
```