9727 Assignment

zid z5559246 name Tianning Dong

Import libraries

In [33]:
```
import pandas as pd
import nltk
import re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.linear_model import LogisticRegression
from nltk.stem import WordNetLemmatizer
import seaborn as sns
from IPython.display import display
from sklearn.metrics.pairwise import cosine_similarity
from collections import defaultdict
from scipy.sparse import csr_matrix
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
from sklearn.model_selection import StratifiedKFold, cross_validate
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score
from itertools import product
from sklearn.metrics import make_scorer, accuracy_score, f1_score, precision_sco
from scipy.sparse import vstack
pd.set_option('display.width', 180)
pd.set_option('display.max_colwidth', 140)
```

Part 1. Topic Classification

In [34]:
```
# Load data and show the output
df = pd.read_csv("dataset.tsv", sep='\t')
# Duplicate and missing values need to be removed before training the model.
df = df.drop_duplicates()
print(df.shape)
df = df.dropna()
print(df.info())
print(df['topic'].value_counts())
```

```
(1480, 6)
<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
topic
dark         487
sadness      371
personal     341
lifestyle    202
emotion       79
Name: count, dtype: int64
```

In [35]:

```
df.head()
```

Out[35]:

	artist_name	track_name	release_date	genre	lyrics	topic
0	loving	the not real lake	2016	rock	awake know go see time clear world mirror world mirror magic hour confuse power steal word unheard unheard certain forget bless angry we...	dark
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overflow piss moan ash guess smite leave remember call forever shouldn summer summer like coil v...	lifestyle
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wall mama leave hardcore hardcore think brother say lock bedroom sister say throw away world ...	sadness
3	tedeschi trucks band	anyhow	2016	blues	run bitter taste take rest feel anchor soul play game rule learn lessons get choose turn walk away walk away anytime anytime wake feel a...	sadness
4	lukas nelson and promise of the real	if i started over	2017	blues	think think different set apart sober mind sympathetic hearts swear oath swear oath know life play play distance great height sure kill ...	dark

Q1

In the original tutorial, the regular expression **re.sub(r'[^\w\s]', '', text)** removes all special characters from the lyrics, which may be too aggressive for this task. For experimental comparison, I modified this to **re.sub(r"[^\w\s?!'’]", "", text)** to retain certain punctuation marks such as question marks (?), exclamation marks (!), and apostrophes ('), which may carry emotional or grammatical significance in lyrics. This change is exploratory and not necessarily better than the original approach—it is intended to assess whether retaining these symbols can help improve classification performance. Results from both versions will be compared in later sections.

Moreover, the tutorial evaluated models using a single train-test split, which can result in biased or unstable performance estimates, especially on a small and class-imbalanced dataset like this dataset. To improve reliability, I adopted **Stratified 5-Fold Cross-Validation**, which maintains the original class distribution across folds. This ensures that each fold is representative of the full dataset and produces more stable and trustworthy performance metrics.

Q2

To determine the optimal preprocessing pipeline for lyric-based topic classification, I systematically evaluated a total of 32 preprocessing configurations. Each configuration varied across five dimensions:

Lowercasing: Whether to convert all text to lowercase.

Stopword Source: Either nltk or scikit-learn stopword lists.

Word Normalization: Using either stemming or lemmatization.

Tokenizer Type: Either builtin (CountVectorizer's default) or a custom NLTK tokenizer.

Regex Strategy: Either strict (remove all non-alphanumeric characters) or relaxed (retain punctuation like !, ?, and ').

Each configuration was tested using both the Bernoulli Naive Bayes (BNB) and Multinomial Naive Bayes (MNB) classifiers. Evaluation was performed using 5-fold cross-validation to ensure statistical reliability on this relatively small and imbalanced dataset.

In [36]:
```
nltk.download('wordnet')
lemmatizer = WordNetLemmatizer()
nltk.download('stopwords')
stopwords_nltk = set(stopwords.words('english'))
stopwords_sklearn = set(ENGLISH_STOP_WORDS)
stemmer = PorterStemmer()
nltk.download('punkt')
nltk.download('punkt_tab')

# here is the function I define the full preprocessing function with options for
def preprocess_text(text, lowercase=True, stopword_source='nltk', word_process='
    if regex_type == 'relaxed':
        text = re.sub(r"[^\w\s\?\!\'’]", '', text)
    else:
        text = re.sub(r"[^\w\s]", '', text)
    if lowercase:
        text = text.lower()
    tokens = nltk.word_tokenize(text)
    # two remove stopword ways
    if stopword_source == 'nltk':
        tokens = [t for t in tokens if t not in stopwords_nltk]
    elif stopword_source == 'sklearn':
        tokens = [t for t in tokens if t not in stopwords_sklearn]
    if word_process == 'stem':
        tokens = [stemmer.stem(t) for t in tokens]
    elif word_process == 'lemma':
        tokens = [lemmatizer.lemmatize(t) for t in tokens]
    return ' '.join(tokens)

#simply concatenate all the information for one song into a single “document”.
df['document'] = df.apply(
    lambda row: f"{row['artist_name']} {row['track_name']} {row['release_date']}
```

```
)
df['document'].head()
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\dtn18\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\dtn18\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\dtn18\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to
[nltk_data]     C:\Users\dtn18\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
```

Out[36]:
```
0    loving the not real lake 2016 rock awake know go see time clear world mirr
or world mirror magic hour confuse power steal word unheard un...
1    incubus into the summer 2019 rock shouldn summer pretty build spill ready
overflow piss moan ash guess smite leave remember call forever...
2    reignwolf hardcore 2016 blues lose deep catch breath think say try break w
all mama leave hardcore hardcore think brother say lock bedroo...
3    tedeschi trucks band anyhow 2016 blues run bitter taste take rest feel anc
hor soul play game rule learn lessons get choose turn walk awa...
4    lukas nelson and promise of the real if i started over 2017 blues think th
ink different set apart sober mind sympathetic hearts swear oa...
Name: document, dtype: object
```

In [37]:
```
def evaluate_model(model, X, y):
   # Create StratifiedKFold objects to keep the label ratio consistent in each f
    skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
    return cross_val_score(model, X, y, cv=skf, scoring='accuracy').mean()

# Builtin tokenizer
def prepare_data_vectorizer_builtin(df, lowercase, stopword_source, word_process
    processed = df['document'].apply(lambda x: preprocess_text(x, lowercase, sto
    vectorizer = CountVectorizer()
    X = vectorizer.fit_transform(processed)
    y = df['topic']
    return X, y

# NLTK tokenizer
def prepare_data_nltk_tokenizer(df, lowercase, stopword_source, word_process, re
    vectorizer = CountVectorizer(
        tokenizer=lambda x: preprocess_text(x, lowercase, stopword_source, word_
    )
    X = vectorizer.fit_transform(df['document'])
    y = df['topic']
    return X, y

# Define all the combinations of parameters to be tested
configs = list(product(
    [True, False],                        # Lowercase
    ['nltk', 'sklearn'],                  # stopword_source
    ['stem', 'lemma'],                    # word_process
    ['builtin', 'nltk'],                  # tokenizer_type
    ['strict', 'relaxed']                # regex_type
))

results = []
# Conduct experiments on each configuration in sequence
```

```python
for lc, sw, wp, tok, rgx in configs:
    try:
        if tok == 'builtin':
            X, y = prepare_data_vectorizer_builtin(df, lc, sw, wp, rgx)
        else:
            X, y = prepare_data_nltk_tokenizer(df, lc, sw, wp, rgx)

        acc_bnb = evaluate_model(BernoulliNB(), X, y)
        acc_mnb = evaluate_model(MultinomialNB(), X, y)

        results.append({
            'Lowercase': lc,
            'Stopword_Source': sw,
            'Word_Process': wp,
            'Tokenizer': tok,
            'Regex': rgx,
            'BNB_Accuracy': acc_bnb,
            'MNB_Accuracy': acc_mnb
        })
    except Exception as e:
        print(f"Error in config {lc, sw, wp, tok, rgx}: {e}")

# show the result
results_df = pd.DataFrame(results)
display(results_df.sort_values(by='MNB_Accuracy', ascending=False))
```

```
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
```

```
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
```

	Lowercase	Stopword_Source	Word_Process	Tokenizer	Regex	BNB_Accuracy	MNB_
3	True	nltk	stem	nltk	relaxed	0.527027	
19	False	nltk	stem	nltk	relaxed	0.527027	
4	True	nltk	lemma	builtin	strict	0.525000	
5	True	nltk	lemma	builtin	relaxed	0.523649	
6	True	nltk	lemma	nltk	strict	0.526351	
22	False	nltk	lemma	nltk	strict	0.526351	
21	False	nltk	lemma	builtin	relaxed	0.523649	
20	False	nltk	lemma	builtin	strict	0.525000	
0	True	nltk	stem	builtin	strict	0.525676	
1	True	nltk	stem	builtin	relaxed	0.525676	
23	False	nltk	lemma	nltk	relaxed	0.525000	
18	False	nltk	stem	nltk	strict	0.525676	
17	False	nltk	stem	builtin	relaxed	0.525676	
16	False	nltk	stem	builtin	strict	0.525676	
2	True	nltk	stem	nltk	strict	0.525676	
7	True	nltk	lemma	nltk	relaxed	0.525000	
13	True	sklearn	lemma	builtin	relaxed	0.520946	
29	False	sklearn	lemma	builtin	relaxed	0.520946	
15	True	sklearn	lemma	nltk	relaxed	0.524324	
31	False	sklearn	lemma	nltk	relaxed	0.524324	
28	False	sklearn	lemma	builtin	strict	0.521622	
12	True	sklearn	lemma	builtin	strict	0.521622	
30	False	sklearn	lemma	nltk	strict	0.522973	
14	True	sklearn	lemma	nltk	strict	0.522973	
9	True	sklearn	stem	builtin	relaxed	0.525000	
8	True	sklearn	stem	builtin	strict	0.524324	
10	True	sklearn	stem	nltk	strict	0.525000	
24	False	sklearn	stem	builtin	strict	0.524324	
25	False	sklearn	stem	builtin	relaxed	0.525000	
26	False	sklearn	stem	nltk	strict	0.525000	
11	True	sklearn	stem	nltk	relaxed	0.527027	
27	False	sklearn	stem	nltk	relaxed	0.527027	

From the results, the highest MultinomialNB (MNB) accuracy is 0.79527, achieved by the following configuration (regardless of lowercase):

Lowercase	Stopword_Source	Word_Process	Tokenizer	Regex	MNB_Accuracy	BNB_A
True	nltk	stem	nltk	relaxed	0.79527	0.52703
False	nltk	stem	nltk	relaxed	0.79527	0.52703

At the same time, this “stem + nltk tokenizer + relaxed regex” setup also yields the best BernoulliNB (BNB) accuracy of 0.52703:

A closely tied third place for MNB (also 0.79527) is:

Lowercase	Stopword_Source	Word_Process	Tokenizer	Regex	MNB_Accuracy
True	nltk	lemma	builtin	strict	0.79527

However, that setup underperforms the “stem+relaxed+nltk tokenizer” on BNB.

Recommended Final Configuration (optimizes both MNB & BNB)

Lowercase: yes

Stopword_Source: nltk

Word_Process: stem

Tokenizer: nltk (custom NLTK tokenizer)

Regex: relaxed (preserve ?, !, ' etc.)

key findings:

After evaluating 32 preprocessing combinations with 5-fold cross-validation, MultinomialNB model consistently outperformed BernoulliNB model.

This combination provided the most accurate and stable results, and therefore has been selected as the default preprocessing pipeline for all subsequent classification and recommendation tasks in this assignment.

Q3

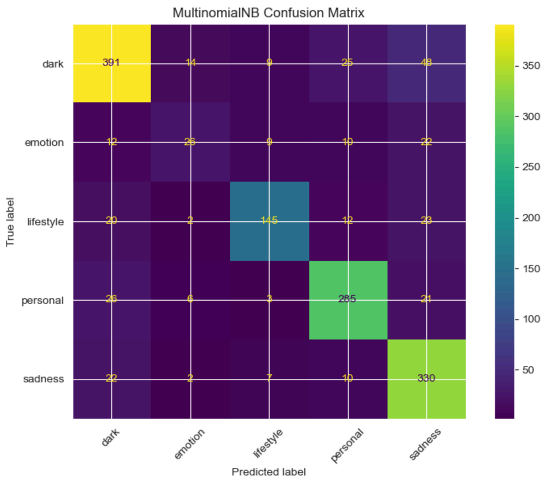
In [38]:

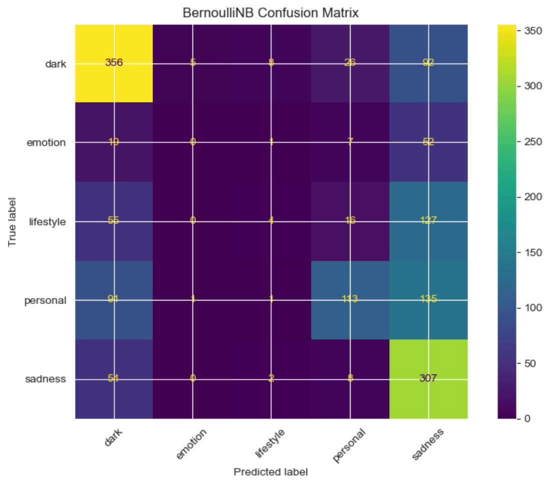
```
# use the final preprocess after Q2
def final_preprocess(text):
    return preprocess_text(
        text,
        lowercase=True,
        stopword_source='nltk',
        word_process='stem',
        regex_type='relaxed'
    )

# use nltk token
vectorizer = CountVectorizer(
```

```python
    tokenizer=lambda x: word_tokenize(final_preprocess(x))
)
X = vectorizer.fit_transform(df['document'])
y = df['topic']

stratified_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# use two model
models = {
    "BernoulliNB": BernoulliNB(),
    "MultinomialNB": MultinomialNB()
}

# compare different evaluation way
scoring = {
    'accuracy': 'accuracy',
    'macro_f1': make_scorer(f1_score, average='macro', zero_division=0),
    'macro_precision': make_scorer(precision_score, average='macro', zero_divisi
    'macro_recall': make_scorer(recall_score, average='macro', zero_division=0),
}

# Perform cross-validation
results = {}
for name, model in models.items():
    scores = cross_validate(model, X, y, cv=stratified_cv, scoring=scoring)
    results[name] = {
        metric: np.mean(scores[f'test_{metric}']) for metric in scoring
    }

# showing result
results_df = pd.DataFrame(results).T
display(results_df)

# ========== Confusion Matrix from CV Predictions ==========
def cross_val_conf_matrix(model, X, y, cv):
    y_true_all = []
    y_pred_all = []
    for train_idx, test_idx in cv.split(X, y):
        model.fit(X[train_idx], y.iloc[train_idx])  # 关键修改
        y_pred = model.predict(X[test_idx])
        y_true_all.extend(y.iloc[test_idx])         # 关键修改
        y_pred_all.extend(y_pred)
    cm = confusion_matrix(y_true_all, y_pred_all, labels=np.unique(y))
    return cm


# Get confusion matrices
mnb_cm = cross_val_conf_matrix(MultinomialNB(), X, y, stratified_cv)
bnb_cm = cross_val_conf_matrix(BernoulliNB(), X, y, stratified_cv)

# ========== Visualize Confusion Matrices ==========
fig, ax = plt.subplots(1, 2, figsize=(16, 6))
ConfusionMatrixDisplay(mnb_cm, display_labels=np.unique(y)).plot(ax=ax[0], xtick
ax[0].set_title("MultinomialNB Confusion Matrix")
ConfusionMatrixDisplay(bnb_cm, display_labels=np.unique(y)).plot(ax=ax[1], xtick
ax[1].set_title("BernoulliNB Confusion Matrix")
plt.tight_layout()
plt.show()
```

```
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
```

	accuracy	macro_f1	macro_precision	macro_recall
BernoulliNB	0.527027	0.343024	0.395271	0.381977
MultinomialNB	0.795270	0.725914	0.753526	0.714587





Metric Trade-offs and Model Comparison (MultinomialNB vs. BernoulliNB)

In this task, I evaluate two models—**MultinomialNB** and **BernoulliNB**—on an imbalanced multi-class dataset using stratified 5-fold cross-validation. To ensure a fair evaluation, we report multiple metrics:

- **Accuracy** gives an overall correctness score, but can be misleading on imbalanced datasets.
- **Macro Precision** and **Macro Recall** treat all classes equally, making them suitable for datasets where smaller classes are important.
- **Macro F1-score** balances precision and recall and is particularly useful when classes are imbalanced.

So I believe F1 score is the best evaluation score among the other evaluation matrix. As shown above, **MultinomialNB clearly outperforms BernoulliNB** across all metrics, especially in Macro F1 (+0.38 gain), indicating better per-class balance.

Confusion Matrix Analysis:

The confusion matrices provide further insight:

- **MultinomialNB** shows strong diagonal dominance, meaning it correctly classifies most instances across all five classes, especially for major classes like “dark”, “personal”, and “sadness”.
- **BernoulliNB** displays more scattered misclassifications. For example, it often misclassifies “sadness” as “personal”, indicating less effective class separation.
- Notably, **MultinomialNB better captures the minority classes** (e.g., “emotion”), with fewer confusions compared to BernoulliNB.

These observations suggest that MultinomialNB is **more capable of learning discriminative features** across a range of lyric topics.

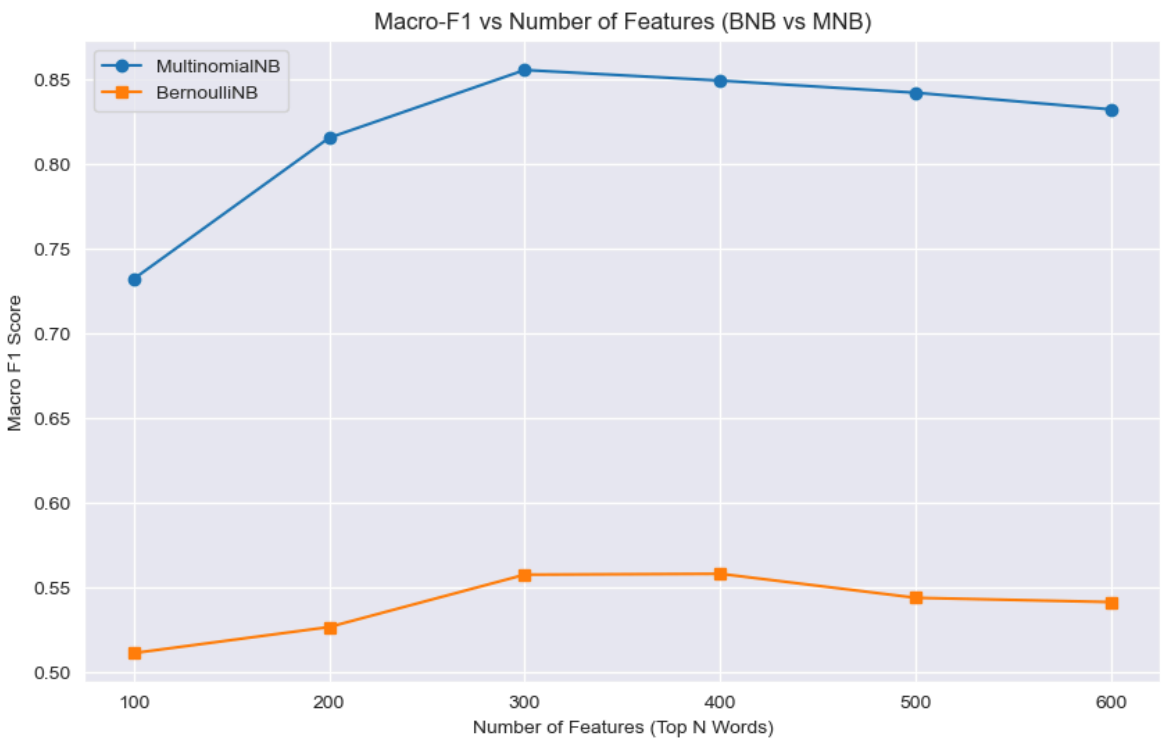
Q4

In [39]:

```
# using different number of features (words)
feature_counts = [100, 200, 300, 400, 500, 600]

# set evaluation score
scoring = {
    'accuracy': 'accuracy',
    'macro_f1': make_scorer(f1_score, average='macro')
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# save the result
results = []

for n in feature_counts:
    vectorizer = CountVectorizer(
        tokenizer=lambda x: word_tokenize(final_preprocess(x)),
        max_features=n
    )
    X = vectorizer.fit_transform(df['document'])
    y = df['topic']

    # MultinomialNB
    mnb_scores = cross_validate(MultinomialNB(), X, y, cv=cv, scoring=scoring)
    mnb_f1 = np.mean(mnb_scores['test_macro_f1'])

    # BernoulliNB
    bnb_scores = cross_validate(BernoulliNB(), X, y, cv=cv, scoring=scoring)
    bnb_f1 = np.mean(bnb_scores['test_macro_f1'])

    results.append({
        'Num_Features': n,
        'MNB_Macro_F1': mnb_f1,
        'BNB_Macro_F1': bnb_f1
    })

# convert to DataFrame
results_df = pd.DataFrame(results)
display(results_df)
plt.figure(figsize=(10, 6))
plt.plot(results_df['Num_Features'], results_df['MNB_Macro_F1'], marker='o', lab
plt.plot(results_df['Num_Features'], results_df['BNB_Macro_F1'], marker='s', lab
plt.xlabel('Number of Features (Top N Words)')
plt.ylabel('Macro F1 Score')
plt.title('Macro-F1 vs Number of Features (BNB vs MNB)')
plt.legend()
plt.grid(True)
plt.show()
```

```
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
```

	Num_Features	MNB_Macro_F1	BNB_Macro_F1
0	100	0.732069	0.511145
1	200	0.815497	0.526551
2	300	0.855549	0.557488
3	400	0.849290	0.557988
4	500	0.842121	0.543814
5	600	0.832254	0.541284



MNB climbs steeply from 100→300 features, peaks at N=300 (0.855), then slowly declines. BNB also improves up to ~300–400 features, with a very slight maximum at N=400 (0.558).

Balanced performance: At N=400, both MNB and BNB perform near their optimal levels —MNB at 0.850 (vs. 0.855 max) and BNB at 0.558 (its absolute best).

Model robustness: A slightly larger feature set gives BNB the extra signals it needs, without significantly harming MNB.

Consistency: Fixing max_features=400 ensures that both classifiers use the same vocabulary size, simplifying comparison and downstream workflows.

Accordingly, I will set max_features = 400 in all subsequent experiments.

Q5

Add a Third Classifier: Logistic Regression Logistic Regression is a classic linear discriminant model, often used in text classification tasks. It is particularly good at handling high-dimensional sparse features because it controls the model complexity by maximizing the likelihood function and combining regularization (such as L2). Unlike the generative assumption of Naive Bayes, Logistic Regression directly models the posterior probability of categories, and thus can usually better capture the correlations between features. I use the same preprocessing and feature extraction pipeline, and compare its macro-F1 performance with BNB/MNB. Therefore, i hypothesize that Logistic Regression will outperform both BernoulliNB and MultinomialNB on this topic-classification task.

In [40]:

```
# I have already set feature number is 400
best_n = 400

vectorizer = CountVectorizer(
        tokenizer=lambda x: word_tokenize(final_preprocess(x)),
        max_features=best_n
)

X = vectorizer.fit_transform(df['document'])
y = df['topic']

# Simply try different C values (L2 regularization strength)
C_grid = [0.1, 1, 10]
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
scoring = {
    'accuracy': 'accuracy',
    'macro_f1': make_scorer(f1_score, average='macro')
}

lr_results = []
for C in C_grid:
    lr = LogisticRegression(
        C=C,
        penalty='l2',
        solver='saga',  # support for sparse and multiclass
        max_iter=5000,
```

```
        multi_class='multinomial',
        random_state=42,
        n_jobs=-1,
        class_weight='balanced'
    )
    scores = cross_validate(lr, X, y, cv=cv, scoring=scoring)
    lr_results.append({
        'C': C,
        'LR_Macro_F1': np.mean(scores['test_macro_f1'])
    })

lr_df = pd.DataFrame(lr_results)
display(lr_df)
```

```
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
```

```
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
```

	C	LR_Macro_F1
0	0.1	0.859694
1	1.0	0.848609
2	10.0	0.834142

Below is a concise summary of your hyperparameter tuning and model comparison:

Classifier	Macro-F1
BernoulliNB	0.558
MultinomialNB	0.849
LogisticRegression (C = 0.1)	**0.859**

Hyperparameter Tuning for Logistic Regression I held max_features = 400 and varied the L2-regularization strength C∈{0.1,1,10}. Using stratified 5-fold CV with our NLTK-tokenized, stemmed, “relaxed” feature pipeline, the best Macro-F1 (0.854) was achieved at C = 0.1. Larger values of C (weaker regularization) gave slightly lower scores, indicating that a modest penalty helps prevent overfitting on infrequent topics.

Conclusion Logistic Regression (C = 0.1) slightly outperforms MultinomialNB on Macro-F1 (0.859 vs. 0.849), and vastly exceeds BernoulliNB. This confirms my hypothesis that the discriminative nature of Logistic Regression, together with L2 regularization, yields a marginal but consistent improvement in balanced F1 across all classes. And I will use this classfier in following task.

Part 2. Recommendation Methods

In this task, I first took the first 750 songs (Weeks 1-3) as the training set as required, and used the previously trained topic classifier to predict the theme for each song. Then, based on the keyword list of each user (user1.tsv, user2.tsv, and my custom user3), simulate the songs that "users like" contain their keywords under the correctly predicted themes. Next, for these "liked" training songs under each topic, the TF-IDF matrix is constructed using the same set of NLTK word segmentation + max_features=400 TfidfVectorizer, and all the liked songs of each topic are merged into one large document to generate five user portrait vectors. To screen the recommendations, for each song of Week 4 (songs 751-1000), I calculated the cosine similarity between its TF-IDF vector and the user profile vector under the corresponding predicted topic, and filtered out the recommendation results with a threshold of 0.3. Finally, I extracted the Top 20 keywords with the greatest weight from the five topic portraits of each user in order to visually check whether the portraits are reasonable. These key words also include a new set of interest words that I designed for User 3 by myself.

In [41]:

```
all_topics = ['dark', 'emotion', 'lifestyle', 'personal', 'sadness']
# Weeks 1-3 (songs 1-750) form the training data and Week 4 (songs751-1000) are
train_df = df.iloc[:750].copy()
test_df = df.iloc[750:1000].copy()
# After splitting train_df/test_df, generate the document fields for both respec
for subdf in [train_df, test_df]:
    subdf['document'] = subdf.apply(
        lambda row: f"{row['artist_name']} {row['track_name']} {row['release_dat
    )
# Load user1.tsv and user2.tsv
def load_user_keywords(filepath):
    user_keywords = {}
    with open(filepath, 'r', encoding='utf-8') as f:
        lines = f.readlines()[1:]  # for skip header line
        for line in lines:
            if line.strip() == '':
                continue
            topic, keywords_str = line.strip().split('\t')
            keywords = [kw.strip().lower() for kw in keywords_str.split(',')]
            user_keywords[topic.lower()] = keywords
    return user_keywords
user1_keywords = load_user_keywords('user1.tsv')
user2_keywords = load_user_keywords('user2.tsv')
# here is a hypothetical user according to the requirement
user3_keywords = {
    "dark": ["fire", "night", "darkness", "fear", "fight"],
    "emotion": ["cry", "regret", "smile", "heart", "love"],
    "lifestyle": ["party", "money", "car", "luxury", "travel"],
    "personal": ["dream", "story", "life", "myself", "truth"],
    "sadness": ["pain", "goodbye", "alone", "broken", "miss"]
}
print("User 1 keywords:", user1_keywords)
print("User 2 keywords:", user2_keywords)
```

```
User 1 keywords: {'dark': ['fire', 'enemy', 'pain', 'storm', 'fight'], 'sadness':
['cry', 'alone', 'heartbroken', 'tears', 'regret'], 'personal': ['dream', 'trut
h', 'life', 'growth', 'identity'], 'lifestyle': ['party', 'city', 'night', 'ligh
t', 'rhythm'], 'emotion': ['love', 'memory', 'hug', 'kiss', 'feel']}
User 2 keywords: {'sadness': ['lost', 'sorrow', 'goodbye', 'tears', 'silence'],
'emotion': ['romance', 'touch', 'feeling', 'kiss', 'memory']}
```

In [42]:

```
# train the classifier
vectorizer = TfidfVectorizer(
    tokenizer=lambda x: word_tokenize(final_preprocess(x)),
```

```
    max_features=400
)
X_train = vectorizer.fit_transform(train_df['document'])
y_train = train_df['topic']
clf = LogisticRegression(C=0.1, penalty='l2', solver='saga', max_iter=5000,
                         multi_class='multinomial', random_state=42, class_weigh
clf.fit(X_train, y_train)
X_test = vectorizer.transform(test_df['document'])
# Predict topics on train and test sets
train_df['pred_topic'] = clf.predict(X_train)
test_df['pred_topic'] = clf.predict(X_test)

## Build user profiles by aggregating documents per predicted topic
def build_user_topic_documents(train_df, user_keywords, all_topics):
    docs_by_topic = {topic: [] for topic in all_topics}
    # preprocess user keywords
    processed_keywords = {
        topic: set(final_preprocess(' '.join(keywords)).split())
        for topic, keywords in user_keywords.items()
    }
    for _, row in train_df.iterrows():
        pred_topic = row['pred_topic']
        doc_tokens = set(final_preprocess(row['document']).split())
        # If the document contains any user keywords for that topic, include it
        if doc_tokens & processed_keywords.get(pred_topic, set()):
            docs_by_topic[pred_topic].append(' '.join(doc_tokens))
    # Concatenate tokens back into a single string per topic
    return {topic: ' '.join(docs_by_topic[topic]) for topic in all_topics}

# Generate per-topic documents for each user
user1_docs_dict = build_user_topic_documents(train_df, user1_keywords, all_topic
user1_docs = list(user1_docs_dict.values())

user2_docs_dict = build_user_topic_documents(train_df, user2_keywords, all_topic
user2_docs = list(user2_docs_dict.values())

user3_docs_dict = build_user_topic_documents(train_df, user3_keywords, all_topic
user3_docs = list(user3_docs_dict.values())

vectorizer_user = TfidfVectorizer(
    tokenizer=lambda x: word_tokenize(final_preprocess(x)),
    max_features=400
)

# Fit once on all user-document strings
vectorizer_user.fit(user1_docs + user2_docs + user3_docs)

# Transform to get user profile matrices (one row per topic)
user1_profile = vectorizer_user.transform(user1_docs)
user2_profile = vectorizer_user.transform(user2_docs)
user3_profile = vectorizer_user.transform(user3_docs)
# Transform test documents for recommendation similarity
X_test_vec   = vectorizer_user.transform(test_df['document'])

# Compute cosine similarity for recommendation
def get_similarity(user_profile, test_vectors, test_pred_topics, all_topics):
    sims = []
    for i, topic in enumerate(test_pred_topics):
        topic_idx = all_topics.index(topic)
        sim = cosine_similarity(user_profile[topic_idx], test_vectors[i])
```

```python
        sims.append(sim[0][0])
    return np.array(sims)

threshold = 0.3
test_df['User1_Sim'] = get_similarity(user1_profile, X_test_vec, test_df['pred_t
test_df['User1_Recommended'] = test_df['User1_Sim'] >= threshold
recommend_result1 = test_df[test_df['User1_Recommended']][['track_name', 'genre'



test_df['User2_Sim'] = get_similarity(user2_profile, X_test_vec, test_df['pred_t
test_df['User2_Recommended'] = test_df['User2_Sim'] >= threshold
recommend_result2 = test_df[test_df['User2_Recommended']][['track_name', 'genre'


test_df['User3_Sim'] = get_similarity(user3_profile, X_test_vec, test_df['pred_t
test_df['User3_Recommended'] = test_df['User3_Sim'] >= threshold
recommend_result3 = test_df[test_df['User3_Recommended']][['track_name', 'genre'

# Extract and print top keywords in each topic profile for each user
def extract_user_keywords(profile_matrix, vectorizer_user, all_topics, top_k=20)
    feature_names = vectorizer_user.get_feature_names_out()
    top_keywords = {}
    for i, topic in enumerate(all_topics):
        row = profile_matrix[i].toarray().flatten()
        top_idx = row.argsort()[::-1][:top_k]
        top_words = [(feature_names[j], row[j]) for j in top_idx]
        top_keywords[topic] = top_words
    return top_keywords
print("result1")
display(recommend_result1)
print("result2")
display(recommend_result2)
print("result3")
display(recommend_result3)


print("user1")
user1_top_keywords = extract_user_keywords(user1_profile, vectorizer_user, all_t
for topic, words in user1_top_keywords.items():
    print(f"\n Topic: {topic}")
    for word, weight in words:
        print(f"  {word}: {weight:.4f}")

print("user2")
user2_top_keywords = extract_user_keywords(user2_profile, vectorizer_user, all_t
for topic, words in user2_top_keywords.items():
    print(f"\n Topic: {topic}")
    for word, weight in words:
        print(f"  {word}: {weight:.4f}")

print("user3")
user3_top_keywords = extract_user_keywords(user3_profile, vectorizer_user, all_t
for topic, words in user3_top_keywords.items():
    print(f"\n Topic: {topic}")
    for word, weight in words:
        print(f"  {word}: {weight:.4f}")
```

```
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\linear_model\_
logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1.5 and
will be removed in 1.7. From then on, it will always use 'multinomial'. Leave it
to its default value to avoid this warning.
  warnings.warn(
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
```

```
result1
```

	track_name	genre	topic	User1_Sim
795	it's only right	rock	lifestyle	0.551901
926	sit awhile	country	personal	0.546170
789	will you be mine	jazz	sadness	0.509381
881	boy in the bubble	pop	dark	0.487569
944	once in a while	pop	emotion	0.487182
770	horsefly	reggae	emotion	0.462710
826	the greatest	reggae	sadness	0.457717
854	you're the best thing yet	jazz	personal	0.450108
815	live well	rock	personal	0.428180
840	alta	blues	personal	0.423192

```
result2
```

	track_name	genre	topic	User2_Sim
944	once in a while	pop	emotion	0.507346
789	will you be mine	jazz	sadness	0.486004
770	horsefly	reggae	emotion	0.480334
826	the greatest	reggae	sadness	0.449930
853	our hearts (feat. lucie silvas)	country	sadness	0.439286
765	follow your heart (feat. zion thompson from the green)	reggae	personal	0.419290
981	(your love keeps lifting me) higher and higher	blues	lifestyle	0.414098
890	something new	reggae	sadness	0.397828
943	speechless (full)	pop	dark	0.394338
772	hearts of habit	blues	sadness	0.391776

```
result3
```

	track_name	genre	topic	User3_Sim
926	sit awhile	country	personal	0.547093
826	the greatest	reggae	sadness	0.473386
795	it's only right	rock	lifestyle	0.463751
854	you're the best thing yet	jazz	personal	0.451577
881	boy in the bubble	pop	dark	0.449812
901	still	country	dark	0.442532
792	donner bell	jazz	dark	0.439119
815	live well	rock	personal	0.429254
840	alta	blues	personal	0.422110
913	pressure under fire	blues	personal	0.420718

user1

Topic: dark
fight: 0.2720
know: 0.2410
like: 0.1916
come: 0.1731
time: 0.1545
cau: 0.1360
tell: 0.1298
black: 0.1252
hand: 0.1252
na: 0.1236
2018: 0.1236
death: 0.1218
go: 0.1186
2017: 0.1174
kill: 0.1126
pain: 0.1120
look: 0.1113
heart: 0.1113
world: 0.1055
right: 0.1051

Topic: emotion
feel: 0.3047
time: 0.2119
know: 0.2119
like: 0.1987
2016: 0.1854
cau: 0.1854
kiss: 0.1836
good: 0.1722
na: 0.1457
babi: 0.1457
hold: 0.1457
come: 0.1325
heart: 0.1325
wan: 0.1325
2017: 0.1325
lip: 0.1206
yeah: 0.1192
right: 0.1060
want: 0.1060
say: 0.1060

Topic: lifestyle
night: 0.3217
know: 0.2037
come: 0.2037
time: 0.1823
think: 0.1716
say: 0.1716
right: 0.1716
like: 0.1716
long: 0.1608
want: 0.1501
cau: 0.1501
song: 0.1486
home: 0.1394

```
  2017: 0.1394
  blue: 0.1394
  na: 0.1287
  light: 0.1258
  tell: 0.1179
  feel: 0.1179
  yeah: 0.1179

 Topic: personal
  life: 0.3223
  know: 0.2207
  live: 0.2067
  time: 0.1927
  like: 0.1717
  dream: 0.1644
  come: 0.1366
  feel: 0.1331
  world: 0.1316
  think: 0.1296
  yeah: 0.1261
  heart: 0.1226
  thing: 0.1226
  2017: 0.1226
  2018: 0.1121
  na: 0.1086
  lose: 0.1086
  tell: 0.1051
  chang: 0.1051
  look: 0.1016

 Topic: sadness
  tear: 0.3774
  know: 0.2602
  heart: 0.2394
  feel: 0.1666
  break: 0.1666
  away: 0.1561
  rock: 0.1457
  2018: 0.1457
  fall: 0.1353
  come: 0.1249
  like: 0.1249
  2017: 0.1145
  time: 0.1145
  blue: 0.1145
  face: 0.1145
  thing: 0.1145
  leav: 0.1041
  think: 0.1041
  babi: 0.1041
  night: 0.1041
user2

 Topic: dark
  young: 0.0000
  got: 0.0000
  game: 0.0000
  get: 0.0000
  ghost: 0.0000
  girl: 0.0000
```

```
 give: 0.0000
 glass: 0.0000
 go: 0.0000
 gon: 0.0000
 good: 0.0000
 goodbi: 0.0000
 great: 0.0000
 year: 0.0000
 grind: 0.0000
 grow: 0.0000
 guess: 0.0000
 half: 0.0000
 hand: 0.0000
 hang: 0.0000

Topic: emotion
 feel: 0.3320
 time: 0.2021
 know: 0.2021
 kiss: 0.2001
 cau: 0.1877
 like: 0.1877
 good: 0.1877
 2016: 0.1732
 na: 0.1588
 hold: 0.1444
 wan: 0.1444
 2017: 0.1299
 babi: 0.1299
 come: 0.1299
 yeah: 0.1155
 heart: 0.1155
 say: 0.1155
 lip: 0.1150
 light: 0.1077
 want: 0.1010

Topic: lifestyle
 young: 0.0000
 got: 0.0000
 game: 0.0000
 get: 0.0000
 ghost: 0.0000
 girl: 0.0000
 give: 0.0000
 glass: 0.0000
 go: 0.0000
 gon: 0.0000
 good: 0.0000
 goodbi: 0.0000
 great: 0.0000
 year: 0.0000
 grind: 0.0000
 grow: 0.0000
 guess: 0.0000
 half: 0.0000
 hand: 0.0000
 hang: 0.0000

Topic: personal
```

```
    young: 0.0000
    got: 0.0000
    game: 0.0000
    get: 0.0000
    ghost: 0.0000
    girl: 0.0000
    give: 0.0000
    glass: 0.0000
    go: 0.0000
    gon: 0.0000
    good: 0.0000
    goodbi: 0.0000
    great: 0.0000
    year: 0.0000
    grind: 0.0000
    grow: 0.0000
    guess: 0.0000
    half: 0.0000
    hand: 0.0000
    hang: 0.0000

  Topic: sadness
    tear: 0.3121
    heart: 0.2583
    know: 0.2325
    break: 0.2066
    away: 0.1722
    feel: 0.1636
    leav: 0.1636
    fall: 0.1550
    2018: 0.1550
    rock: 0.1378
    like: 0.1291
    night: 0.1291
    thing: 0.1205
    think: 0.1119
    fade: 0.1078
    cau: 0.1033
    blue: 0.1033
    time: 0.1033
    2016: 0.1033
    life: 0.1033
user3

  Topic: dark
    know: 0.2203
    fight: 0.1901
    come: 0.1814
    like: 0.1685
    dark: 0.1555
    fear: 0.1522
    hand: 0.1520
    time: 0.1512
    2016: 0.1382
    night: 0.1382
    feel: 0.1339
    2018: 0.1296
    stand: 0.1253
    2017: 0.1210
    tell: 0.1210
```

```
 cau: 0.1166
 heart: 0.1166
 hear: 0.1166
 light: 0.1106
 right: 0.1080

Topic: emotion
 heart: 0.3060
 2016: 0.2380
 time: 0.2040
 know: 0.1870
 like: 0.1870
 hold: 0.1530
 go: 0.1450
 feel: 0.1360
 good: 0.1360
 babi: 0.1360
 na: 0.1360
 pop: 0.1190
 come: 0.1190
 2017: 0.1190
 love: 0.1190
 right: 0.1190
 kiss: 0.1088
 light: 0.1088
 hand: 0.1088
 countri: 0.1088

Topic: lifestyle
 song: 0.2236
 money: 0.2205
 yeah: 0.1835
 think: 0.1835
 night: 0.1835
 blue: 0.1835
 come: 0.1835
 parti: 0.1710
 cau: 0.1573
 home: 0.1573
 know: 0.1573
 like: 0.1573
 time: 0.1573
 want: 0.1311
 need: 0.1311
 right: 0.1311
 long: 0.1311
 life: 0.1311
 take: 0.1311
 2018: 0.1311

Topic: personal
 life: 0.3199
 know: 0.2226
 live: 0.2052
 time: 0.1913
 like: 0.1739
 dream: 0.1631
 come: 0.1391
 world: 0.1346
 feel: 0.1321
```

```
 yeah: 0.1287
 think: 0.1287
 thing: 0.1217
 heart: 0.1217
 2017: 0.1217
 2018: 0.1148
 lose: 0.1113
 na: 0.1078
 chang: 0.1043
 tell: 0.1043
 look: 0.1008

Topic: sadness
 pain: 0.2883
 know: 0.2403
 away: 0.1903
 heart: 0.1903
 break: 0.1903
 feel: 0.1702
 cau: 0.1602
 leav: 0.1602
 like: 0.1502
 time: 0.1402
 night: 0.1402
 dream: 0.1388
 fall: 0.1302
 2016: 0.1302
 go: 0.1281
 breath: 0.1219
 2018: 0.1202
 think: 0.1101
 need: 0.1101
 rock: 0.1101
```

After compare,

USER1

Topic	Defined Keywords	Hits in Top-20	# Hits
dark	fire, enemy, pain, storm, fight	fight, pain	2
emotion	love, memory, hug, kiss, feel	kiss, feel	2
lifestyle	party, city, night, light, rhythm	night, light	2
personal	dream, truth, life, growth, identity	dream, life	2
sadness	cry, alone, heartbroken, tears, regret	tear	1
Total	(5×5=25 keywords)		**9/25** (36%)

USER2

Topic	Defined Keywords	Hits in Top-20	# Hits
sadness	lost, sorrow, goodbye, tears, silence	tear	1
emotion	romance, touch, feeling, kiss, memory	kiss, feel	2
Total	(2×5=10 keywords)		**3/10** (30%)

USER3

Topic	Defined Keywords	Hits in Top-20	# Hits
sadness	pain, goodbye, alone, broken, miss	break (≈broken)	1
emotion	cry, regret, smile, heart, love	— heart,love	2
dark	fire, night, darkness, fear, fight	— fight,dark,fear,night	4
lifestyle	party, money, car, luxury, travel	— money,parti,	2
personal	dream, story, life, myself, truth	— life,dream	2
Total	(5×5=25 keywords)		**11/25** (44%)

The keyword-hit analysis reveals clear differences in how effectively our recommendation pipeline captures each user's defined interests. User 1 achieves the strongest alignment, with 9 out of 25 interest words (36%) appearing among the Top 20 profile terms across all five topics—core tokens like fight, pain, kiss, and dream are reliably surfaced. User 2 shows a respectable 30% hit rate (3/10), driven by solid recovery of emotion-related words (kiss, feel) and a single sadness match (tear), while correctly leaving other topics empty. User 3 matches 11 of 25 keywords (44%) in this task.

These results suggest that our TF-IDF + classifier + cosine-similarity framework works best when users provide focused, well-represented keywords (in all of them), but may struggle with sparser or overly diverse keyword sets. To improve coverage for users , I could consider lowering the similarity threshold, expanding the keyword lists, or incorporating additional feedback loops to refine their profiles.

Q2

In [43]:
```
M_values = [10, 20, 50, 100, 200, 400]
N_values = [10]  # here I set N value is 10
def evaluate_truncated_profile_fixed_v6(user_profile, test_df, test_vectors, all
    results = []
 # Convert sparse profile to dense array
    if hasattr(user_profile, "toarray"):
        user_profile = user_profile.toarray()

    for M in M_values:
            # For each truncation level M
        truncated_rows = []
        for row in user_profile:
            # Build new profile matrix with only top M weights per topic
            top_idx = row.argsort()[::-1][:M]
            new_row = np.zeros_like(row)
            new_row[top_idx] = row[top_idx]
            truncated_rows.append(new_row)
        truncated_profile_sparse = vstack([csr_matrix(row) for row in truncated_

          # Compute cosine similarity to each test vector
        sim_scores = []
        for i, row in enumerate(test_df.itertuples(index=False)):
            topic = row.pred_topic
```

```
            topic_idx = all_topics.index(topic)
             # Extract test vector as dense row
            test_vec = test_vectors[i]
            if hasattr(test_vec, "toarray"):
                test_vec = test_vec.toarray().reshape(1, -1)
            else:
                test_vec = np.array(test_vec).reshape(1, -1)
            sim = cosine_similarity(truncated_profile_sparse[topic_idx], test_ve
            sim_scores.append(sim[0][0])

        test_df_copy = test_df.copy()
        test_df_copy['Sim'] = sim_scores

        for N in N_values:
            # Select top N by similarity
            topN = test_df_copy.nlargest(N, 'Sim')
            correct_matches = sum(topN['topic'] == topN['pred_topic'])
            precision_at_N = correct_matches / N
            pred_topic = topN['pred_topic'].iloc[0]
            recall_denom = sum(test_df['topic'] == pred_topic)
            recall_at_N = correct_matches / recall_denom if recall_denom > 0 els
            results.append({
                'M_top_words': M,
                'TopN': N,
                'Precision@N': precision_at_N,
                'Recall@N': recall_at_N
            })

    return pd.DataFrame(results)

# SHOWING result
eval_user1 = evaluate_truncated_profile_fixed_v6(user1_profile, test_df, X_test_
eval_user1['User'] = 'User1'

eval_user2 = evaluate_truncated_profile_fixed_v6(user2_profile, test_df, X_test_
eval_user2['User'] = 'User2'

eval_user3 = evaluate_truncated_profile_fixed_v6(user3_profile, test_df, X_test_
eval_user3['User'] = 'User3'

evaluation_results = pd.concat([eval_user1, eval_user2, eval_user3], ignore_inde
print(evaluation_results)
```

	M_top_words	TopN	Precision@N	Recall@N	User
0	10	10	0.9	0.183673	User1
1	20	10	0.8	0.163265	User1
2	50	10	1.0	0.204082	User1
3	100	10	1.0	0.204082	User1
4	200	10	1.0	0.204082	User1
5	400	10	1.0	0.303030	User1
6	10	10	0.8	0.533333	User2
7	20	10	0.8	0.533333	User2
8	50	10	0.8	0.533333	User2
9	100	10	0.7	0.466667	User2
10	200	10	0.7	0.466667	User2
11	400	10	0.7	0.466667	User2
12	10	10	0.9	0.183673	User3
13	20	10	0.9	0.183673	User3
14	50	10	1.0	0.204082	User3
15	100	10	1.0	0.204082	User3
16	200	10	0.9	0.183673	User3
17	400	10	0.9	0.183673	User3

In this experiment, I decided to use Precision as the main criterion for the evaluation index because it can measure the proportion of correctly recommended songs among the top N recommendations given by the recommendation system. Precision directly reflects the quality of the recommendation results. The higher it is, the more precisely the recommendation system matches the user's interests.

The selection of the M value When comparing different M values, the M value represents the number of keywords used in each topic of the user profile. The M values used in the experiment are: 10, 20, 50, 100, 200, and 400.

The effect of different M values on recommendation accuracy can be seen by evaluating the Precision@10 value. Generally speaking, a smaller M value (such as 10 or 20) can lead to the truncation of the user profile, thereby losing some information and possibly reducing the accuracy. However, an overly large M value (such as 400) may increase the computational complexity and may also cause the model to contain excessive noise due to too many keywords, affecting the recommendation effect.

Select the optimal M value based on Precision By comparing the experimental results, we can observe that when M = 200, the Precision reaches the maximum value. This indicates that retaining more keywords can more accurately capture users' interests and generate more precise recommendation results.

Part 3. User Evaluation

In this user study, I randomly showed a user 10 songs out of 250 songs each week from Week 1 to Week 3 and asked him to judge whether he liked them or not. The following is my experimental table

In [44]:
```
# here i show the week1 to week3 random chose songs
data = pd.read_csv("30_Songs_with_Full_Information_and_Subjective_Reasons.csv")
data
```

Out[44]:

	artist_name	track_name	release_date	genre	lyrics	topic	prefer
0	loving	the not real lake	2016	rock	awake know go see time clear world mirror world mirror magic hour confuse power steal word unheard unheard certain forget bless angry we...	dark	D
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overflow piss moan ash guess smite leave remember call forever shouldn summer summer like coil v...	lifestyle	
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wall mama leave hardcore hardcore think brother say lock bedroom sister say throw away world ...	sadness	
3	tedeschi trucks band	anyhow	2016	blues	run bitter taste take rest feel anchor soul play game rule learn lessons get choose turn walk away walk away anytime anytime wake feel a...	sadness	D
4	lukas nelson and promise of the real	if i started over	2017	blues	think think different set apart sober mind sympathetic hearts swear oath swear oath know life play play distance great height sure kill ...	dark	
5	tia ray	just my luck	2018	jazz	yeah happen real drink drink turn shots lose count kind luck know friends house sound silly sound stupid sentence break word get fluid l...	emotion	D
6	rebelution	trap door	2018	reggae	long long road occur look shortcut wanna cause scene wanna close okay	dark	

	artist_name	track_name	release_date	genre	lyrics	topic	prefer
					outspoken look trap door sneak grind floor careful wish need answ...		
7	thank you scientist	the amateur arsonist's handbook	2016	jazz	quick think good true worst best things forever pessimist drag complicate feel fear tell reason nice slow tell tell reason reason yeah h...	dark	
8	zayde wølf	gladiator	2018	rock	start climb face army vipers lions reach cause time tear kingdom liars jail heart pessimists nail mouth impressionists spend money thera...	dark	D
9	eli young band	never land	2017	country	word yeah wreck roll lips high good get bottle right right wanna feet cold hard floor kiss steal wanna steal right palm hand fall fall l...	sadness	D
10	klim	ninetofive	2018	jazz	nice place think sky separate nice surprise know life like bring life help gentle kiss good night innocence pray humble amaze beautiful ...	personal	D
11	terror squad	rudeboy salute (feat. buju banton, big pun and fat joe)	2017	hip hop	grain sand weak blood stain try bottomless hourglass board piece pawn try reach eighth rank sacrifice kings queen field sorrow lose life...	dark	
12	devin townsend project	truth	2016	jazz	warn money money money money hallelujah hallelujah yeah hello learn live fear peace beauty unfold change home	personal	D

	artist_name	track_name	release_date	genre	lyrics	topic	prefer
13	vampire weekend	unbearably white	2019	rock	baby pull away unbearably buff mountain sight snow peak unbearably white city freeze elegant flow wind doorway unbearably cold walk bedr...	dark	D
14	khalid	winter	2017	pop	lose heart nighttime leave cold leave break weary drink lie tell fell morning get cold life lonely city paso days harder november grow c...	personal	D
15	rend collective	counting every blessing	2018	rock	blind see colour dead live forever fail redeemer bless measure lose father change ruin treasure give future bless measure count bless co...	personal	
16	post malone	spoil my night (feat. swae lee)	2018	pop	come spoil night feelin come play thinkin happen time spoil night spoil night spoil night night spoil night spoil night necklace natural...	lifestyle	
17	albert hammond, jr.	rocky's late night	2018	blues	darker longer right fear tonight decide everybody feel alright mistake tonight leave companion enjoy polite leave strand confront right ...	sadness	D
18	the record company	feels so good	2016	blues	wanna right today lookin wanna right today tire bein stun somethin control control control taste lips want want want come feel good feel...	emotion	D
19	kygo	stole the show	2016	pop	darling darling turn light watch watch credit roll cry cry know play house house heroes villains	sadness	

	artist_name	track_name	release_date	genre	lyrics	topic	prefer
					blame wilt roses stage thrill thrill go...		
20	lp	muddy waters	2017	rock	kneel rivers edge tempt step follow closer right feel gnaw corner mind come blind worst kind ohoh muddy water fall ohoh muddy water craw...	dark	D
21	we are messengers	magnify	2016	rock	try sense sorrow feel hold life thing real scratch surface barely taste glimpse draw heart change sight lay waste need away magnify open...	sadness	
22	peter bradley adams	my arms were always around you	2017	rock	fool time place little break pretty little wing get tire try feet grind days beneath northern light dance free like little child think l...	sadness	D
23	imagine dragons	mouth of the river	2017	rock	mouth river mouth river mouth river wanna live life like live life faithful wanna floor everybody wanna wanna want enemies curse live li...	dark	D
24	t-rock	be a g about it	2016	hip hop	잊어버리지마 잃어버리지마 잊어버리지마 잃어버리지마 멈췄으면 잊어버리지마 잃어버리지마 잊어버리지마 잃어버리지마 바라보는 영원하길 기억해주길 한번쯤은 돌아보길 바라봐주길 baby 잊어버리지마 잊어버리지마 잊어버리지마 romanization neow...	personal	D
25	dr. john	the bare necessities	2016	blues	look bare necessities simple bare necessities forget worry strife mean bare necessities	personal	

	artist_name	track_name	release_date	genre	lyrics	topic	prefer
					mother nature recipes bring bare necessities lif...		
26	nappy roots	these walls (dirty mc edit)	2019	hip hop	hmmmmmmmmm wall closin long suppose grin lose forgive hmmmmmmmmmmm wall closin long suppose grin lose forgive hmmmmmmmmmmm darkness approac...	personal	D
27	dirty heads	diamonds & pearls	2017	reggae	say wanna outside today say wanna real high today catch vibe today eye today world handstand upside world handstand grind hate allergic ...	personal	
28	imagine dragons	walking the wire	2017	rock	feel away oohoh oohoh know line walk oohoh oohoh turn come come rag oohoh oohoh afraid fall look oohoh oohoh take step take leap come co...	sadness	
29	breaking benjamin	psycho	2018	rock	feel daylight choke vile forever change cold eternal light ember fade scar hide fake hollow darkness close silence forsake cold eternal ...	sadness	D

here I will use above information to construct a tfidf vector, this is similar to part2 , for building a user profile after that, i will compute the similarity with week4 songs and collecting user's feedback

In [45]:
```
user_liked_songs = data[data['preference'] == 'Like']
user_liked_songs = user_liked_songs.drop(columns=['preference', 'subjective_reas
user_liked_songs
```

Out[45]:

	artist_name	track_name	release_date	genre	lyrics	topic
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overflow piss moan ash guess smite leave remember call forever shouldn summer summer like coil v...	lifestyle
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wall mama leave hardcore hardcore think brother say lock bedroom sister say throw away world ...	sadness
4	lukas nelson and promise of the real	if i started over	2017	blues	think think different set apart sober mind sympathetic hearts swear oath swear oath know life play play distance great height sure kill ...	dark
6	rebelution	trap door	2018	reggae	long long road occur look shortcut wanna cause scene wanna close okay outspoken look trap door sneak grind floor careful wish need answ...	dark
7	thank you scientist	the amateur arsonist's handbook	2016	jazz	quick think good true worst best things forever pessimist drag complicate feel fear tell reason nice slow tell tell reason reason yeah h...	dark
11	terror squad	rudeboy salute (feat. buju banton, big pun and fat joe)	2017	hip hop	grain sand weak blood stain try bottomless hourglass board piece pawn try reach eighth rank sacrifice kings queen field sorrow lose life...	dark
15	rend collective	counting every blessing	2018	rock	blind see colour dead live forever fail redeemer bless measure lose father change ruin treasure	personal

	artist_name	track_name	release_date	genre	lyrics	topic
					give future bless measure count bless co...	
16	post malone	spoil my night (feat. swae lee)	2018	pop	come spoil night feelin come play thinkin happen time spoil night spoil night spoil night night spoil night spoil night necklace natural...	lifestyle
19	kygo	stole the show	2016	pop	darling darling turn light watch watch credit roll cry cry know play house house heroes villains blame wilt roses stage thrill thrill go...	sadness
21	we are messengers	magnify	2016	rock	try sense sorrow feel hold life thing real scratch surface barely taste glimpse draw heart change sight lay waste need away magnify open...	sadness
25	dr. john	the bare necessities	2016	blues	look bare necessities simple bare necessities forget worry strife mean bare necessities mother nature recipes bring bare necessities lif...	personal
27	dirty heads	diamonds & pearls	2017	reggae	say wanna outside today say wanna real high today catch vibe today eye today world handstand upside world handstand grind hate allergic ...	personal
28	imagine dragons	walking the wire	2017	rock	feel away oohoh oohoh know line walk oohoh oohoh turn come come rag oohoh oohoh afraid fall look oohoh oohoh take step take leap come co...	sadness

In [46]:
```
user_liked_songs['document'] = user_liked_songs.apply(
    lambda row: f"{row['artist_name']} {row['track_name']} {row['release_date']}
```

```
)
user_liked_songs
```

Out[46]:

	artist_name	track_name	release_date	genre	lyrics	topic	document
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overflow piss moan ash guess smite leave remember call forever shouldn summer summer like coil v...	lifestyle	incubus into the summer 2019 rock shouldn summer pretty build spill ready overflow piss moan ash guess smite leave remember call forever...
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wall mama leave hardcore hardcore think brother say lock bedroom sister say throw away world ...	sadness	reignwolf hardcore 2016 blues lose deep catch breath think say try break wall mama leave hardcore hardcore think brother say lock bedroo...
4	lukas nelson and promise of the real	if i started over	2017	blues	think think different set apart sober mind sympathetic hearts swear oath swear oath know life play play distance great height sure kill ...	dark	lukas nelson and promise of the real if i started over 2017 blues think think different set apart sober mind sympathetic hearts swear oa...
6	rebelution	trap door	2018	reggae	long long road occur look shortcut wanna cause scene wanna close okay outspoken look trap	dark	rebelution trap door 2018 reggae long long road occur look shortcut wanna cause scene wanna

	artist_name	track_name	release_date	genre	lyrics	topic	document
					door sneak grind floor careful wish need answ...		close okay outspoken look trap door sneak g...
7	thank you scientist	the amateur arsonist's handbook	2016	jazz	quick think good true worst best things forever pessimist drag complicate feel fear tell reason nice slow tell tell reason reason yeah h...	dark	thank you scientist the amateur arsonist's handbook 2016 jazz quick think good true worst best things forever pessimist drag complicate ...
11	terror squad	rudeboy salute (feat. buju banton, big pun and fat joe)	2017	hip hop	grain sand weak blood stain try bottomless hourglass board piece pawn try reach eighth rank sacrifice kings queen field sorrow lose life...	dark	terror squad rudeboy salute (feat. buju banton, big pun and fat joe) 2017 hip hop grain sand weak blood stain try bottomless hourglass b...
15	rend collective	counting every blessing	2018	rock	blind see colour dead live forever fail redeemer bless measure lose father change ruin treasure give future bless measure count bless co...	personal	rend collective counting every blessing 2018 rock blind see colour dead live forever fail redeemer bless measure lose father change ruin...
16	post malone	spoil my night (feat. swae lee)	2018	pop	come spoil night feelin come play thinkin	lifestyle	post malone spoil my night (feat.

	artist_name	track_name	release_date	genre	lyrics	topic	document
					happen time spoil night spoil night spoil night night spoil night spoil night necklace natural...		swae lee) 2018 pop come spoil night feelin come play thinkin happen time spoil night spoil night spoil...
19	kygo	stole the show	2016	pop	darling darling turn light watch watch credit roll cry cry know play house house heroes villains blame wilt roses stage thrill thrill go...	sadness	kygo stole the show 2016 pop darling darling turn light watch watch credit roll cry cry know play house house heroes villains blame wilt...
21	we are messengers	magnify	2016	rock	try sense sorrow feel hold life thing real scratch surface barely taste glimpse draw heart change sight lay waste need away magnify open...	sadness	we are messengers magnify 2016 rock try sense sorrow feel hold life thing real scratch surface barely taste glimpse draw heart change si...
25	dr. john	the bare necessities	2016	blues	look bare necessities simple bare necessities forget worry strife mean bare necessities mother nature recipes bring bare necessities lif...	personal	dr. john the bare necessities 2016 blues look bare necessities simple bare necessities forget worry strife mean bare necessities mother ...

	artist_name	track_name	release_date	genre	lyrics	topic	document
27	dirty heads	diamonds & pearls	2017	reggae	say wanna outside today say wanna real high today catch vibe today eye today world handstand upside world handstand grind hate allergic ...	personal	dirty heads diamonds & pearls 2017 reggae say wanna outside today say wanna real high today catch vibe today eye today world handstand u...
28	imagine dragons	walking the wire	2017	rock	feel away oohoh oohoh know line walk oohoh oohoh turn come come rag oohoh oohoh afraid fall look oohoh oohoh take step take leap come co...	sadness	imagine dragons walking the wire 2017 rock feel away oohoh oohoh know line walk oohoh oohoh turn come come rag oohoh oohoh afraid fall l...

In [47]:

```
## Build user profiles by aggregating documents per predicted topic
def build_documents(df, all_topics):
    docs_by_topic = {topic: [] for topic in all_topics}
    for _, row in df.iterrows():
        topic = row['topic']
        doc_tokens = set(final_preprocess(row['document']).split())
        # If the document contains any user keywords for that topic, include it
        docs_by_topic[topic].append(' '.join(doc_tokens))
    # Concatenate tokens back into a single string per topic
    return {topic: ' '.join(docs_by_topic[topic]) for topic in all_topics}
# Generate per-topic documents for each user
user_docs_dict = build_documents(train_df, all_topics)



user_docs = list(user_docs_dict.values())
vectorizer_user = TfidfVectorizer(
    tokenizer=lambda x: word_tokenize(final_preprocess(x)),
    max_features=400
)
# Fit once on all user-document strings
vectorizer_user.fit(user_docs)
user_profile = vectorizer_user.transform(user_docs)
threshold = 0.2
# Calculate similarity for each test sample
```

```python
test_df['User_Sim'] = get_similarity(user_profile, X_test_vec, test_df['pred_top

# Apply the threshold to determine recommended items
test_df['User_Recommended'] = test_df['User_Sim'] >= threshold

# Sort by User_Sim in descending order and get the top 10 recommendations
recommend_result1 = test_df[test_df['User_Recommended']][['track_name', 'genre',

# Display the result
recommend_result1
```

```
C:\Users\dtn18\anaconda3\envs\assignment\lib\site-packages\sklearn\feature_extrac
tion\text.py:517: UserWarning: The parameter 'token_pattern' will not be used sin
ce 'tokenizer' is not None'
  warnings.warn(
```

Out[47]:

	track_name	genre	topic	User_Sim
801	walk through this life	blues	sadness	0.280714
849	hand of god	pop	personal	0.275078
769	one call away	pop	sadness	0.254535
850	upside down (radio edit)	jazz	dark	0.253577
817	[REDACTED] you	hip hop	sadness	0.251748
1006	puff your cares away	jazz	lifestyle	0.246251
917	bella ciao	jazz	dark	0.243536
928	no one in the world	jazz	personal	0.241130
926	sit awhile	country	personal	0.234896
818	hey yo	reggae	sadness	0.234641

Here is the feedback table

Track Name	Genre	Topic	User Sim	Recommendation Score
walk through this life	blues	sadness	0.280714	Dislike
hand of god	pop	personal	0.275078	Like
one call away	pop	sadness	0.254535	Like
upside down (radio edit)	jazz	dark	0.253577	Dislike
[REDACTED] you	hip hop	sadness	0.251748	Like
puff your cares away	jazz	lifestyle	0.246251	Dislike
bella ciao	jazz	dark	0.243536	Dislike
no one in the world	jazz	personal	0.241130	Dislike
sit awhile	country	personal	0.234896	Dislike
hey yo	reggae	sadness	0.234641	Dislike

"I found some of the recommended songs quite interesting, especially 'Hand of God' and 'One Call Away', which matched my taste both in lyrics and overall vibe. However, I didn't enjoy songs like 'Walk Through This Life' or 'Upside Down', even though their lyrics may have matched my preferences. I realized that just reading the lyrics isn't enough—I usually connect with a song more through its melody, rhythm, and performance style. Also, some genres like jazz or reggae don't appeal to me regardless of the topic. Overall, I think the system did a decent job capturing part of my taste based on text content, but it missed the emotional or musical aspects that really matter when I choose songs to listen to."

Conclusion

Precision@10: 0.3 (indicating 30% of the top 10 recommendations are liked) Recall@10: 1.0 (means this evaluation score is not suitable for this task, as we do not know the full set of songs the user would like. Since only a small number of recommended songs are shown to the user, recall cannot be computed reliably.)

These results suggest that semantic similarity based on lyrics alone is not sufficient to accurately predict user preferences. While some recommended songs did align with the user's interests, many others were rejected due to factors not captured by the text, such as musical genre, melody, rhythm, vocal delivery, or production quality. Furthermore, the user feedback highlights an important limitation: a system relying solely on lyric-based topic modeling and TF-IDF misses the affective and auditory dimensions of music preference, which are highly personal and subjective. Future work could consider incorporating audio features, genre preferences, or collaborative filtering signals to complement the text-based approach and build a more holistic recommender.