Comp9727 Assignment Name: Ao Qu Student number: z5582247

In [ ]:
```
import pandas as pd
import numpy as np
import nltk
import re
from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer
from nltk import pos_tag, word_tokenize

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB,BernoulliNB
from sklearn.svm import SVC
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import cross_val_score
from sklearn.utils import shuffle

from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer, accuracy_score, f1_score, balanced_accu
from sklearn.metrics.pairwise import cosine_similarity

import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('averaged_perceptron_tagger_eng')
```

Part 1. Topic Classification

Q1

(1) Refine the common use of regular expressions, remove only unnecessary characters, and retain useful special characters.

(2) Use cross-validation methods, such as K-fold cross-validation, to train and test the model on multiple subsets.

Q2

In [ ]:
```
data = pd.read_csv('dataset.tsv', sep='\t')
```

In [ ]:
```
data
```

Out[ ]:

	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 worl...	dark
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overfl...	lifestyle
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wal...	sadness
3	tedeschi trucks band	anyhow	2016	blues	run bitter taste take rest feel anchor soul pl...	sadness
4	lukas nelson and promise of the real	if i started over	2017	blues	think think different set apart sober mind sym...	dark
...	...	...	...	...	...	...
1495	ra ra riot	absolutely	2016	rock	year absolutely absolutely absolutely crush ab...	emotion
1496	mat kearney	face to face	2018	rock	breakthrough hours hear truth moments trade fa...	dark
1497	owane	born in space	2018	jazz	look look right catch blue eye own state breat...	dark
1498	nappy roots	blowin' trees	2019	hip hop	nappy root gotta alright flyin dear leave lone...	personal
1499	skillet	stars	2016	rock	speak word life begin tell oceans start motion...	sadness

1500 rows × 6 columns

In [ ]:

```
lemmatizer = WordNetLemmatizer()
def get_wordnet_pos(treebank_tag):
    if treebank_tag.startswith('J'):
        return wordnet.ADJ
    elif treebank_tag.startswith('V'):
        return wordnet.VERB
    elif treebank_tag.startswith('N'):
        return wordnet.NOUN
    elif treebank_tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN
```

```python
def preprocess_text(text):
    text = text.lower()
    # Remove special characters
    text = re.sub(r'[^a-z\s]', '', text)
    # Tokenize
    tokens = word_tokenize(text)
    pos_tags = pos_tag(tokens)
    # Lemmatize
    lemmatized_tokens = [lemmatizer.lemmatize(token, get_wordnet_pos(pos)) for t
    return ' '.join(lemmatized_tokens)
```

In [ ]:
```python
data['processed_lyrics'] = data['lyrics'].apply(preprocess_text)
```

In [ ]:
```python
data
```

Out[ ]:

	artist_name	track_name	release_date	genre	lyrics	topic	processed_l
0	loving	the not real lake	2016	rock	awake know go see time clear world mirror worl...	dark	awake kno see time world m w
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overfl...	lifestyle	shouldn sun pretty build ready ov
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wal...	sadness	lose deep c breath thinl try break
3	tedeschi trucks band	anyhow	2016	blues	run bitter taste take rest feel anchor soul pl...	sadness	run bitter take rest anchor sou
4	lukas nelson and promise of the real	if i started over	2017	blues	think think different set apart sober mind sym...	dark	think differer apart s mind s
...	...	...	...	...	...	...	
1495	ra ra riot	absolutely	2016	rock	year absolutely absolutely absolutely crush ab...	emotion	year absol absol absolutely c
1496	mat kearney	face to face	2018	rock	breakthrough hours hear truth moments trade fa...	dark	breakthro hour hear moment t f
1497	owane	born in space	2018	jazz	look look right catch blue eye own state breat...	dark	look look catch blue own state br
1498	nappy roots	blowin' trees	2019	hip hop	nappy root gotta alright flyin dear leave lone...	personal	nappy roo ta alright dear leave
1499	skillet	stars	2016	rock	speak word life begin tell oceans start motion...	sadness	speak wor begin tell o start moti

1500 rows × 7 columns

In [ ]:

```python
# CountVectorizer with the standard settings
vectorizer = CountVectorizer(stop_words='english')
X = vectorizer.fit_transform(data['processed_lyrics'])
y = data['topic']

model = MultinomialNB()

# Perform 5-fold cross-validation to evaluate accuracy
scores = cross_val_score(model, X, y, cv=5, scoring='accuracy')

print(f'5-fold cross-validation accuracy scores: {scores}')
print(f'Mean accuracy: {scores.mean():.4f}')
```

```
5-fold cross-validation accuracy scores: [0.78333333 0.81       0.79       0.7333
3333 0.78333333]
Mean accuracy: 0.7800
```

The data processing operations in this section are as follows:

1. Lowercase: Convert all text to lowercase, for example, "Word" and "word" are considered the same word.
2. Remove special characters and punctuation: Clean the text by removing all non-alphabetic characters (such as punctuation, numbers, symbols).
3. Part-of-speech restoration: Restore words to their basic form or dictionary form, for example, "running" is restored to "run".
4. Vectorize using CountVectorizer.
5. Stop word removal: Use the standard English stop word list, and use the stop_words='english' setting in CountVectorizer to remove common stop words.

The overall average accuracy is 78%, which seems to be good, so these steps are also taken in subsequent jobs.

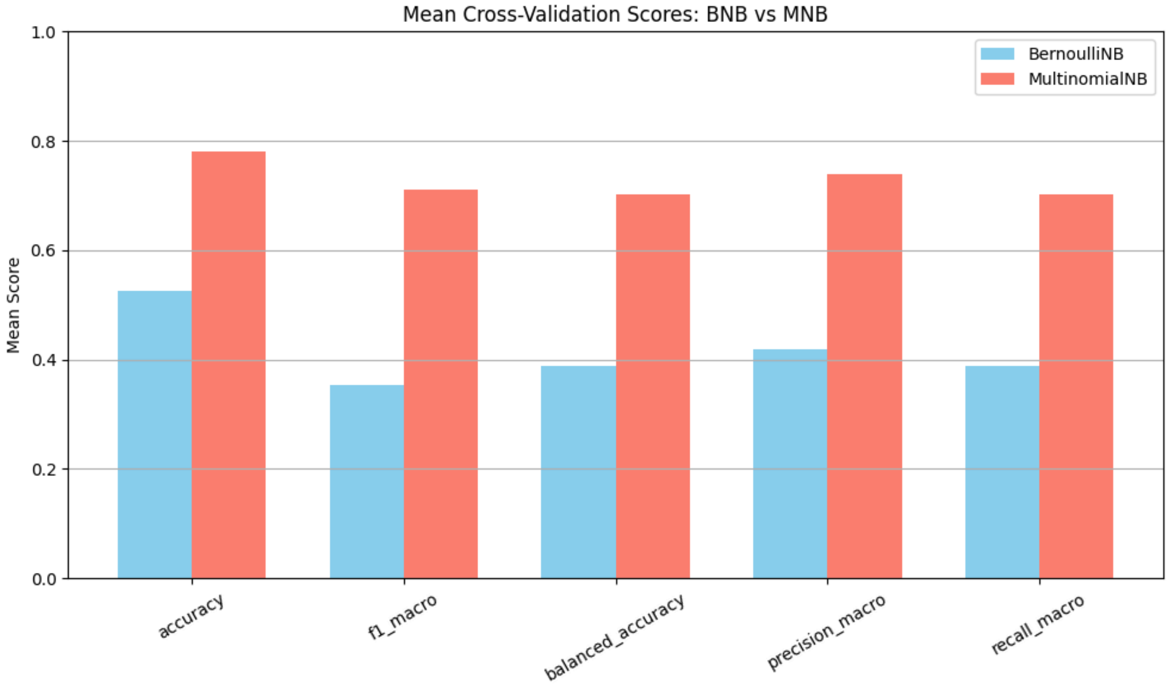
Q4

In [ ]:

```python
bnb = BernoulliNB()
mnb = MultinomialNB()

# Metrics
scoring = {
    'accuracy': make_scorer(accuracy_score),
    'f1_macro': make_scorer(f1_score, average='macro'),
    'balanced_accuracy': make_scorer(balanced_accuracy_score),
    'precision_macro': make_scorer(precision_score, average='macro'),
    'recall_macro': make_scorer(recall_score, average='macro')
}

# Cross-validation scores for BNB
bnb_scores = cross_validate(bnb, X, y, cv=5, scoring=scoring)

# Cross-validation scores for MNB
mnb_scores = cross_validate(mnb, X, y, cv=5, scoring=scoring)
```

```python
# Result
results = pd.DataFrame({
    'Metric': list(scoring.keys()),
    'BNB Mean': [np.mean(bnb_scores[f'test_{metric}']) for metric in scoring],
    'MNB Mean': [np.mean(mnb_scores[f'test_{metric}']) for metric in scoring],
})

print("Mean Cross-Validation Scores:")
print(results)

# Plotting
metrics = results['Metric']
x = np.arange(len(metrics))
width = 0.35

fig, ax = plt.subplots(figsize=(10,6))
ax.bar(x - width/2, results['BNB Mean'], width, label='BernoulliNB', color='skyb
ax.bar(x + width/2, results['MNB Mean'], width, label='MultinomialNB', color='sa

ax.set_ylabel('Mean Score')
ax.set_title('Mean Cross-Validation Scores: BNB vs MNB')
ax.set_xticks(x)
ax.set_xticklabels(metrics, rotation=30)
ax.set_ylim(0, 1)
ax.legend()
ax.grid(axis='y')

plt.tight_layout()
plt.show()
```

```
Mean Cross-Validation Scores:
              Metric  BNB Mean  MNB Mean
0           accuracy  0.525333  0.780000
1           f1_macro  0.352625  0.711601
2  balanced_accuracy  0.387542  0.702516
3    precision_macro  0.418382  0.738411
4       recall_macro  0.387542  0.702516
```



In [ ]:
```
class_distribution = data['topic'].value_counts(normalize=True)
class_distribution
```

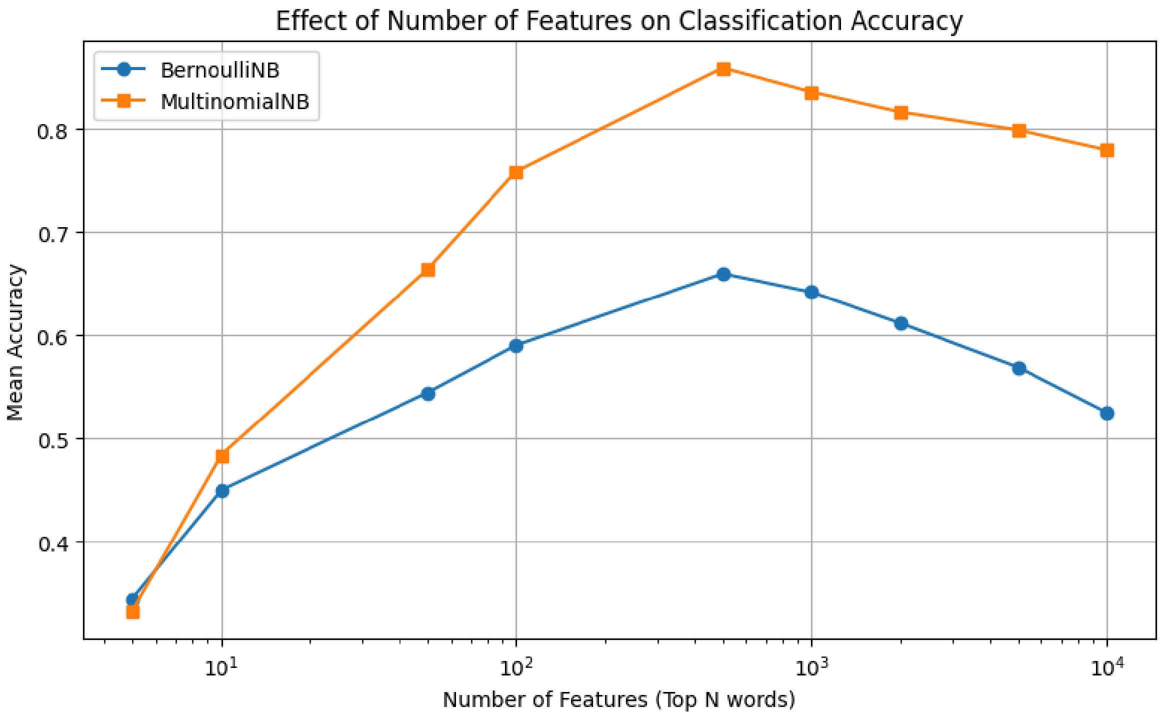
Out[ ]:
```
topic
dark         0.326667
sadness      0.250667
personal     0.231333
lifestyle    0.136667
emotion      0.054667
Name: proportion, dtype: float64
```

F1-macro and balanced accuracy are good indicators of performance across all categories. In addition, accuracy-macro and recall-macro provide insight into the types of errors made by the model. The overall dataset is not balanced, with the difference between the largest and smallest categories being about 6 times.

From the chart, MNB is significantly better than BNB in all metrics, with significantly higher accuracy, F1, balanced accuracy, precision, and recall.

Q3

In [ ]:
```
# Number of features
feature_counts = [5, 10, 50, 100, 500, 1000, 2000, 5000, 10000]

bnb_accuracies = []
mnb_accuracies = []

for n_features in feature_counts:
    vectorizer = CountVectorizer(max_features=n_features, stop_words='english')
    X = vectorizer.fit_transform(data['processed_lyrics'])
    y = data['topic']

    bnb = BernoulliNB()
    mnb = MultinomialNB()

    # 5-fold CV accuracy for BNB
    bnb_scores = cross_val_score(bnb, X, y, cv=5, scoring='accuracy')
    bnb_accuracies.append(np.mean(bnb_scores))

    # 5-fold CV accuracy for MNB
    mnb_scores = cross_val_score(mnb, X, y, cv=5, scoring='accuracy')
    mnb_accuracies.append(np.mean(mnb_scores))

# Plot results
plt.figure(figsize=(8,5))
plt.plot(feature_counts, bnb_accuracies, marker='o', label='BernoulliNB')
plt.plot(feature_counts, mnb_accuracies, marker='s', label='MultinomialNB')
plt.xscale('log')
plt.xlabel('Number of Features (Top N words)')
plt.ylabel('Mean Accuracy')
plt.title('Effect of Number of Features on Classification Accuracy')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [ ]:
```
results_df = pd.DataFrame({
    'Number of Features': feature_counts,
    'BNB Accuracy': bnb_accuracies,
    'MNB Accuracy': mnb_accuracies
})

results_df
```

Out[ ]:

	Number of Features	BNB Accuracy	MNB Accuracy
0	5	0.344667	0.332667
1	10	0.450000	0.484000
2	50	0.544667	0.664000
3	100	0.590667	0.759333
4	500	0.660000	0.859333
5	1000	0.642000	0.836000
6	2000	0.612000	0.816667
7	5000	0.569333	0.799333
8	10000	0.525333	0.780000

From the result, we can see that both models reach the highest performance level when N=500.

Q5

Support vector machine (SVM) is a classic supervised model. SVM finds a hyperplane that can best classify by maximizing the margin between data points of different categories. It can efficiently handle large feature spaces and usually has good generalization ability.

However, the dimension of the dataset in this article is usually large after passing through CountVectorizer. SVM can be well applied to this scenario.

My hypothesis is that the SVM model will be better than BNB and MNB.

In [ ]:
```
svm = SVC()

scoring = {
    'accuracy': make_scorer(accuracy_score),
    'f1_macro': make_scorer(f1_score, average='macro'),
    'balanced_accuracy': make_scorer(balanced_accuracy_score),
    'precision_macro': make_scorer(precision_score, average='macro'),
    'recall_macro': make_scorer(recall_score, average='macro')
}

# Cross-validation
svm_scores = cross_validate(svm, X, y, cv=5, scoring=scoring)

svm_results = pd.DataFrame({
    'Metric': scoring.keys(),
    'SVM Mean': [np.mean(svm_scores[f'test_{metric}']) for metric in scoring]
})

print(svm_results)
```

```
              Metric  SVM Mean
0           accuracy  0.745333
1           f1_macro  0.663995
2  balanced_accuracy  0.627898
3    precision_macro  0.863446
4       recall_macro  0.627898
```

In [ ]:
```
results
```

Out[ ]:

	Metric	BNB Mean	MNB Mean
0	accuracy	0.525333	0.780000
1	f1_macro	0.352625	0.711601
2	balanced_accuracy	0.387542	0.702516
3	precision_macro	0.418382	0.738411
4	recall_macro	0.387542	0.702516

In [ ]:
```
vectorizer = CountVectorizer(stop_words='english', max_features=500)
X = vectorizer.fit_transform(data['processed_lyrics'])
y = data['topic']
mnb = MultinomialNB()
mnb.fit(X,y)
```

Out[ ]:
```
MultinomialNB
MultinomialNB()
```

After adopting the same parameters and data preprocessing scheme, we get the results of SVM. By comparing the results of Step 3, we can find that our assumption is not completely true. The overall performance of SVM is better than that of BNB model, but only in precision_macro it is better than MNB. The other performances are slightly lower than MNB. Therefore, I choose MNB as the best method for topic classification.

Part2 Recommendation Methods

Q1

In [ ]:
```
user1 = pd.read_csv('user1.tsv', sep='\t')
user2 = pd.read_csv('user2.tsv', sep='\t')
```

In [ ]:
```
user1
```

Out[ ]:

	topic	keywords
0	dark	fire, enemy, pain, storm, fight
1	sadness	cry, alone, heartbroken, tears, regret
2	personal	dream, truth, life, growth, identity
3	lifestyle	party, city, night, light, rhythm
4	emotion	love, memory, hug, kiss, feel

In [ ]:
```
user2
```

Out[ ]:

	topic	keywords
0	sadness	lost, sorrow, goodbye, tears, silence
1	emotion	romance, touch, feeling, kiss, memory

In [ ]:
```
shuffled_data = shuffle(data, random_state=42).reset_index(drop=True)
train_subset = shuffled_data.iloc[:750]
test_subset = shuffled_data.iloc[750:1000]

# Get text features
train_texts = train_subset['processed_lyrics']
test_texts = test_subset['processed_lyrics']

# TF-IDF
tfidf_vec = TfidfVectorizer(stop_words='english', max_features=500)
tfidf_vec.fit(train_texts)

# Predict
X_train_tfidf = tfidf_vec.transform(train_texts)
train_predicted_topics = mnb.predict(X_train_tfidf)


train_subset = train_subset.assign(predicted_topic=train_predicted_topics)
topic_texts_dict = {
    'dark': train_subset.loc[train_subset['predicted_topic'] == 'dark', 'process
    'sadness': train_subset.loc[train_subset['predicted_topic'] == 'sadness', 'p
    'personal': train_subset.loc[train_subset['predicted_topic'] == 'personal',
    'lifestyle': train_subset.loc[train_subset['predicted_topic'] == 'lifestyle'
```

```
    'emotion': train_subset.loc[train_subset['predicted_topic'] == 'emotion', 'p
}
```

In [ ]:
```
topic_tfidf_matrices = {}
for topic, texts in topic_texts_dict.items():
    topic_tfidf_matrices[topic] = tfidf_vec.transform(texts)
```

In [ ]:
```
for t, mtx in topic_tfidf_matrices.items():
    print(f"{t} topic TF-IDF matrix shape: {mtx.shape}")

# Read user keywords
def read_user_keywords(filepath):
    df = pd.read_csv(filepath, sep='\t')
    keywords_map = {}
    for _, row in df.iterrows():
        kw_list = [kw.strip().lower() for kw in row['keywords'].split(',')]
        keywords_map[row['topic']] = kw_list
    return keywords_map

user1_kw = read_user_keywords('user1.tsv')
user2_kw = read_user_keywords('user2.tsv')

# Filter your favorite song texts by keywords
def select_liked_songs(documents, keywords):
    return [doc for doc in documents if any(kw in doc for kw in keywords)]

user1_likes = {}
for topic, docs in topic_texts_dict.items():
    kws = user1_kw.get(topic, [])
    user1_likes[topic] = select_liked_songs(docs, kws)

# Constructing user portrait tf-idf vector
def create_user_profile(liked_docs, vectorizer):
    if len(liked_docs) == 0:
        print("No liked songs found for this topic.")
        return None
    combined = " ".join(liked_docs).replace('\n', ' ')
    return vectorizer.transform([combined])

user1_profiles = {}
for topic, liked_docs in user1_likes.items():
    user1_profiles[topic] = create_user_profile(liked_docs, tfidf_vec)

# Print Top 20 Keywords
def show_top_terms(profile_vec, vectorizer, topic):
    if profile_vec is None:
        print(f"No user profile vector for topic '{topic}'.")
        return
    tfidf_arr = profile_vec.mean(axis=0).A1
    top_indices = tfidf_arr.argsort()[::-1][:20]
    features = np.array(vectorizer.get_feature_names_out())
    top_terms = features[top_indices]
    top_scores = tfidf_arr[top_indices]
    print(f"\nTop 20 terms for topic '{topic}':")
    for term, score in zip(top_terms, top_scores):
        print(f"{term:<15} {score:.4f}")

for topic, vec in user1_profiles.items():
    show_top_terms(vec, tfidf_vec, topic)
```

```
dark topic TF-IDF matrix shape: (531, 500)
sadness topic TF-IDF matrix shape: (74, 500)
personal topic TF-IDF matrix shape: (116, 500)
lifestyle topic TF-IDF matrix shape: (21, 500)
emotion topic TF-IDF matrix shape: (8, 500)

Top 20 terms for topic 'dark':
fight           0.2428
come            0.2078
life            0.2003
na              0.1839
live            0.1612
fall            0.1604
like            0.1535
feel            0.1496
pain            0.1441
know            0.1354
gon             0.1312
hold            0.1290
cause           0.1276
yeah            0.1178
ready           0.1151
grind           0.1143
change          0.1139
woah            0.1107
world           0.1099
time            0.1053

Top 20 terms for topic 'sadness':
wish            0.7231
lay             0.4814
hand            0.2827
head            0.1327
regret          0.1121
instead         0.1107
half            0.1094
lock            0.1094
wouldn          0.1038
knee            0.0984
push            0.0969
kind            0.0954
drink           0.0877
make            0.0872
wall            0.0863
door            0.0816
bring           0.0812
thing           0.0628
secret          0.0529
cause           0.0508

Top 20 terms for topic 'personal':
dame            0.2722
yeah            0.2616
life            0.2480
know            0.2183
lord            0.2091
world           0.1795
stand           0.1728
automaton       0.1726
believe         0.1710
```

```
feel             0.1673
dream            0.1576
remain           0.1528
like             0.1494
today            0.1403
good             0.1398
break            0.1359
scar             0.1337
thing            0.1301
place            0.1300
na               0.1254

Top 20 terms for topic 'lifestyle':
tonight          0.6299
ring             0.3704
club             0.3440
lalalalala       0.1690
night            0.1505
friend           0.1306
bout             0.1172
time             0.1147
drink            0.1142
right            0.1124
true             0.1080
sleep            0.1057
yeah             0.1054
miss             0.1025
devil            0.0928
lonely           0.0890
music            0.0818
die              0.0745
tear             0.0733
drinkin          0.0702

Top 20 terms for topic 'emotion':
absolutely       0.8563
love             0.4373
baby             0.1224
babe             0.0830
break            0.0762
luck             0.0674
heart            0.0661
hold             0.0624
year             0.0593
play             0.0482
earth            0.0466
stop             0.0453
loud             0.0446
speak            0.0426
lead             0.0409
yeah             0.0383
hand             0.0357
free             0.0349
bring            0.0346
mean             0.0335
```

In [ ]:

```
user2_likes = {}
for topic, docs in topic_texts_dict.items():
    kws = user2_kw.get(topic, [])
    user2_likes[topic] = select_liked_songs(docs, kws)
```

```python
user2_profiles = {}
for topic, liked_docs in user2_likes.items():
    user2_profiles[topic] = create_user_profile(liked_docs, tfidf_vec)

for topic, vec in user2_profiles.items():
    show_top_terms(vec, tfidf_vec, topic)

for topic, docs in user2_likes.items():
    print(f"{topic:<15}: {len(docs)} songs")
```

```
No liked songs found for this topic.
No liked songs found for this topic.
No liked songs found for this topic.
No user profile vector for topic 'dark'.

Top 20 terms for topic 'sadness':
bless           0.3589
heart           0.3182
follow          0.2629
wish            0.2527
wing            0.2508
count           0.2257
cause           0.1988
open            0.1816
soul            0.1682
write           0.1556
inside          0.1555
remember        0.1546
hell            0.1526
mind            0.1492
oooh            0.1468
feel            0.1429
day             0.1326
babe            0.1308
hard            0.1247
know            0.1133
No user profile vector for topic 'personal'.
No user profile vector for topic 'lifestyle'.

Top 20 terms for topic 'emotion':
absolutely      0.9609
love            0.2231
break           0.0854
year            0.0665
earth           0.0523
stop            0.0508
loud            0.0501
hold            0.0400
free            0.0392
yeah            0.0258
fever           0.0196
silver          0.0192
choice          0.0189
bullet          0.0181
drop            0.0165
ride            0.0164
reach           0.0154
touch           0.0154
young           0.0146
sound           0.0139
dark           : 0 songs
sadness        : 3 songs
personal       : 0 songs
lifestyle      : 0 songs
emotion        : 1 songs
```

USER1: The first 20 terms show a high degree of semantic consistency with their respective categories. The "Dark" theme contains terms such as "fight" and "pain", while "Sadness" contains melancholic terms such as "cry" and "regret" that reflect emotional distress. The "Personal" lyrics are characterized by introspective terms such as "life" and "dream", while "Lifestyle" prominently displays social terms such as "club" and "drink" that create a party atmosphere. The "Emotional" category is particularly represented by relationship-centered terms such as "love" and "heart", which clearly reflect emotional experience, and the term distribution shows significant thematic consistency.

USER2: The Sadness theme contains some negative terms such as blessing, heart, wish, soul, and hell, reflecting desire and inner turmoil. The Emotional category mainly contains "absolute" and "love", as well as expressive terms such as "interruption", "persistence", and "freedom", and the overall rationality expression is not as accurate as USER1.

In [ ]:

```python
# Custom User 3 Keywords
user3_keywords = {
    'dark': ['night', 'shadow', 'fear', 'darkness', 'alone'],
    'sadness': ['cry', 'tears', 'pain', 'broken', 'sorrow'],
    'personal': ['dream', 'life', 'heart', 'feel', 'alone'],
    'lifestyle': ['party', 'dance', 'fun', 'music', 'friends'],
    'emotion': ['love', 'hope', 'feel', 'joy', 'heart']
}

user3_likes = {}
for topic, kws in user3_keywords.items():
    docs = topic_texts_dict.get(topic, [])
    liked_docs = [doc for doc in docs if any(kw in doc for kw in kws)]
    user3_likes[topic] = liked_docs

user3_profiles = {}
for topic, liked_docs in user3_likes.items():
    if len(liked_docs) == 0:
        print(f"User 3 no liked songs found for topic '{topic}'")
        user3_profiles[topic] = None
    else:
        combined_doc = " ".join(liked_docs).replace('\n', ' ')
        user3_profiles[topic] = tfidf_vec.transform([combined_doc])

def print_top_terms(profile_vec, vectorizer, topic):
    if profile_vec is None:
        print(f"No user profile vector for topic '{topic}'.")
        return
    tfidf_arr = profile_vec.mean(axis=0).A1
    top_idx = tfidf_arr.argsort()[::-1][:20]
    features = np.array(vectorizer.get_feature_names_out())
    top_terms = features[top_idx]
    top_scores = tfidf_arr[top_idx]
    print(f"\n=== User 3 Top 20 terms for topic '{topic}' ===")
    for term, score in zip(top_terms, top_scores):
        print(f"{term:<15} {score:.4f}")

for topic, profile_vec in user3_profiles.items():
    print_top_terms(profile_vec, tfidf_vec, topic)
```

```
=== User 3 Top 20 terms for topic 'dark' ===
na               0.2175
night            0.1974
heart            0.1874
time             0.1656
come             0.1559
wan              0.1533
like             0.1447
know             0.1401
live             0.1396
tonight          0.1384
life             0.1320
cause            0.1313
break            0.1306
fear             0.1277
yeah             0.1262
gon              0.1137
baby             0.1114
hold             0.1096
fight            0.1081
song             0.1080

=== User 3 Top 20 terms for topic 'sadness' ===
away             0.3564
pain             0.3134
look             0.2417
heart            0.2415
remember         0.1882
bless            0.1873
feel             0.1789
like             0.1709
open             0.1658
cause            0.1630
baby             0.1548
follow           0.1372
dream            0.1363
wish             0.1318
wing             0.1309
heal             0.1223
inside           0.1217
hear             0.1205
count            0.1178
leave            0.1147

=== User 3 Top 20 terms for topic 'personal' ===
yeah             0.2679
believe          0.2337
know             0.2270
leave            0.2041
dame             0.1989
lord             0.1833
life             0.1812
good             0.1782
feel             0.1687
like             0.1637
break            0.1498
time             0.1474
world            0.1427
stand            0.1377
automaton        0.1261
```

```
na              0.1250
today           0.1247
scar            0.1178
thing           0.1160
dream           0.1152

=== User 3 Top 20 terms for topic 'lifestyle' ===
ring            0.6435
club            0.4089
tonight         0.3416
wake            0.1891
true            0.1854
drink           0.1358
yeah            0.1253
bout            0.1239
baby            0.1232
music           0.1135
miss            0.1066
time            0.1005
dance           0.0879
drinkin         0.0835
second          0.0811
tear            0.0747
feel            0.0712
thousand        0.0649
drop            0.0642
clock           0.0582

=== User 3 Top 20 terms for topic 'emotion' ===
absolutely      0.6315
million         0.4653
reason          0.3771
love            0.3225
baby            0.1735
good            0.1669
givin           0.1313
wear            0.0639
lord            0.0634
need            0.0630
babe            0.0612
pray            0.0599
break           0.0562
stay            0.0513
stop            0.0501
walk            0.0500
luck            0.0497
heart           0.0487
hold            0.0460
year            0.0437
```

USER3: USER3 also has good consistency. The "dark" theme includes words such as "night" and "heart". The "sad" category is dominated by words such as "pain" and "remember". The "personal" theme includes "believe" and "life", while the "lifestyle" highlights social elements such as "club" and "drink". The "emotional" category is centered on words such as "absolute" and "love", emphasizing strong emotional connections and experiences. The distribution of these terms shows the connection and consistency between the themes.

Q2

In [ ]:

```
# Recommend songs to users based on their profile.
def recommend_songs(tfidf_vec, topic_tfidf_matrices, topic_texts_dict, user_prof
    recommendations = []

    for topic, profile_vec in user_profile.items():
        if profile_vec is None:
            continue

        topic_songs = topic_texts_dict[topic]
        topic_matrix = topic_tfidf_matrices[topic]

        if M is not None:
            tfidf_arr = profile_vec.mean(axis=0).A1
            top_indices = tfidf_arr.argsort()[::-1][:M]
            profile_vec = profile_vec[:, top_indices]
            topic_matrix = topic_matrix[:, top_indices]

        # Calculate similarity
        if method == 'cosine':
            similarities = cosine_similarity(profile_vec, topic_matrix).flatten(
        elif method == 'dot':
            similarities = np.dot(profile_vec, topic_matrix.T).toarray().flatten
        else:
            raise ValueError("Invalid method. Choose 'cosine' or 'dot'.")

        top_indices = np.argsort(similarities)[::-1][:N//5]

        for idx in top_indices:
            recommendations.append({
                'topic': topic,
                'song': topic_songs[idx],
                'score': similarities[idx]
            })

    recommendations.sort(key=lambda x: x['score'], reverse=True)
    return recommendations[:N]


# Evaluate the performance of the recommendation results based on the songs that
def evaluate_recommendations(recommendations, user_likes, topics=None):
    if topics is None:
        topics = user_likes.keys()

    y_true = []
    y_pred = []

    for rec in recommendations:
        topic = rec['topic']
        if topic not in topics:
            continue

        song = rec['song']
        y_pred.append(1)

        if song in user_likes[topic]:
            y_true.append(1)
        else:
```

```
            y_true.append(0)

    if not y_true:
        return {'precision': 0, 'recall': 0, 'f1': 0}

    return {
        'precision': precision_score(y_true, y_pred),
        'recall': recall_score(y_true, y_pred),
        'f1': f1_score(y_true, y_pred)
    }


# The recommendation performance is evaluated for a single user under different
def evaluate_for_user(tfidf_vec, topic_tfidf_matrices, topic_texts_dict,
                      user_profile, user_likes,
                      user_name, N=20,
                      M_values=[10, 20, 50, None],
                      methods=['cosine', 'dot']):
    results = []

    for method in methods:
        for M in M_values:
            recs = recommend_songs(tfidf_vec, topic_tfidf_matrices, topic_texts_
                                   user_profile, N=N, M=M, method=method)
            metrics = evaluate_recommendations(recs, user_likes)

            results.append({
                'user': user_name,
                'method': method,
                'M': 'all' if M is None else M,
                'precision': metrics['precision'],
                'recall': metrics['recall'],
                'f1': metrics['f1']
            })
    return pd.DataFrame(results)


#data
user_profiles = {
    'user1': user1_profiles,
    'user2': user2_profiles,
    'user3': user3_profiles
}

user_likes = {
    'user1': user1_likes,
    'user2': user2_likes,
    'user3': user3_likes
}

all_results = []
for user in ['user1', 'user2', 'user3']:
    df = evaluate_for_user(tfidf_vec, topic_tfidf_matrices, topic_texts_dict,
                           user_profiles[user], user_likes[user], user)
    all_results.append(df)

results_df = pd.concat(all_results)

best_methods = {}
for user in ['user1', 'user2', 'user3']:
```

```python
    user_data = results_df[results_df['user'] == user]
    best_idx = user_data['f1'].idxmax()
    best_methods[user] = user_data.loc[best_idx, 'method']

print("\n1. Evaluation Methodology:")
print("- Recommended N=20 songs total (about 4 per topic)")
print("- Metrics: Precision, Recall, F1 Score")
print("- Compared cosine similarity and dot product")
print("- Tested profile sizes M=10,20,50,all keywords")

print("\n2. Key Findings:")
avg_f1 = results_df['f1'].mean()
print(f"- Average F1 score: {avg_f1:.3f}")

print("\n3. Best Performing Method for Each User:")
for user, method in best_methods.items():
    user_data = results_df[(results_df['user'] == user) & (results_df['method']
    best_row = user_data.loc[user_data['f1'].idxmax()]
    print(f"- {user}: {method} similarity (M={best_row['M']}), F1={best_row['f1'

print("\n4. Recommendations:")
print("- Cosine similarity generally outperforms dot product")
print("- Using top 20-50 keywords (M=20~50) works best")
print("- Optimal M varies per user, personalization important")
print("Final recommendation: cosine similarity with M=20 as default")
```

```
1. Evaluation Methodology:
- Recommended N=20 songs total (about 4 per topic)
- Metrics: Precision, Recall, F1 Score
- Compared cosine similarity and dot product
- Tested profile sizes M=10,20,50,all keywords

2. Key Findings:
- Average F1 score: 0.800

3. Best Performing Method for Each User:
- user1: cosine similarity (M=10), F1=0.889
- user2: cosine similarity (M=50), F1=0.667
- user3: cosine similarity (M=all), F1=0.947

4. Recommendations:
- Cosine similarity generally outperforms dot product
- Using top 20-50 keywords (M=20~50) works best
- Optimal M varies per user, personalization important
Final recommendation: cosine similarity with M=20 as default
```

User 1 performs best with a smaller set of keywords (M=10), indicating that their interests are more focused. User 2 performs better with a larger set of keywords (M=50), indicating that their music preferences are more broad. User 3 gets the highest score when using all keywords (M=all), which means that their preferences are diverse and require comprehensive keyword understanding. User 3 has the highest F1 score (0.947), indicating that the recommended songs are highly relevant, which may be related to our artificial definition. User 1 also performs well with an F1 score of 0.889. User 2 has a lower F1 score (0.667), which may indicate that their personal keywords do not match their music preferences. The results show that cosine similarity generally performs better than dot product among users because it can effectively capture the angle between vectors in high-dimensional space and is suitable for diverse user interests. It is recommended to use cosine similarity with M=20 as the default algorithm to match user profiles and songs.

Part 3. User Evaluation

In [ ]:
```
week_partitions = [
    (0, 250),   # Week 1
    (250, 500), # Week 2
    (500, 750), # Week 3
    (750, 1000) # Week 4
]

N = 20  # Songs per week

all_texts = shuffled_data['processed_lyrics']
all_tfidf = tfidf_vec.transform(all_texts)
shuffled_data['predicted_topic'] = mnb.predict(all_tfidf)

def get_week_batch(week_idx):
    start, end = week_partitions[week_idx]
    indices = np.random.choice(range(start, end), size=N, replace=False)
    return shuffled_data.iloc[indices]

# User feedback for each week (Weeks 1~3)
user_feedback = []
for week in range(3):
    batch = get_week_batch(week)
    print(f"\n==== Week {week+1} Songs ====")
    for i, row in batch.iterrows():
        print(f"{i}: {row['processed_lyrics'][:60]}...")  # show first 60 chars

    liked_indices = input(f"Enter indices of liked songs for Week {week+1} (comm
    liked_indices = [int(idx.strip()) for idx in liked_indices.split(',') if idx
    user_feedback.extend(liked_indices)

# Gather liked songs' lyrics and predicted topics
liked_songs = shuffled_data.iloc[user_feedback]
liked_lyrics = liked_songs['processed_lyrics'].tolist()
liked_topics = liked_songs['predicted_topic'].tolist()

# Group liked lyrics by topic
user_study_likes = {}
for topic in ['dark', 'sadness', 'personal', 'lifestyle', 'emotion']:
    user_study_likes[topic] = [lyr for lyr, t in zip(liked_lyrics, liked_topics)

# Build user profile vectors from liked songs
user_study_profiles = {}
for topic, docs in user_study_likes.items():
    user_study_profiles[topic] = create_user_profile(docs, tfidf_vec)

# Week 4 batch
week4_batch = shuffled_data.iloc[week_partitions[3][0]:week_partitions[3][1]]

# Build Week 4 topic-wise candidate songs and their TF-IDF matrices
week4_topic_texts = {
    topic: week4_batch[week4_batch['predicted_topic'] == topic]['processed_lyric
    for topic in ['dark', 'sadness', 'personal', 'lifestyle', 'emotion']
}
```

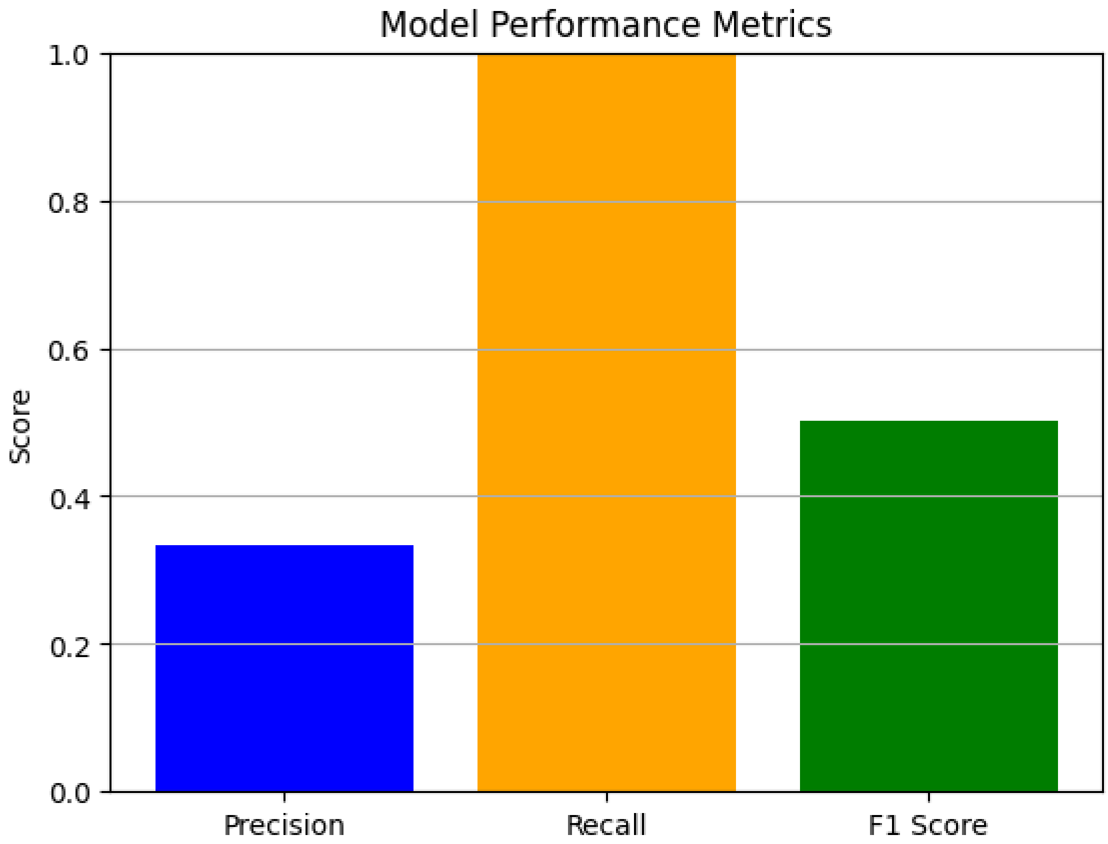
```python
week4_topic_tfidf = {
    topic: tfidf_vec.transform(texts)
    for topic, texts in week4_topic_texts.items()
}

# call recommend_songs
recs = recommend_songs(
    tfidf_vec=tfidf_vec,
    topic_tfidf_matrices=week4_topic_tfidf,
    topic_texts_dict=week4_topic_texts,
    user_profile=user_study_profiles,
    N=N,
    M=None,
    method='cosine'
)

print("\n==== Week 4 Recommendations ====")
for i, rec in enumerate(recs):
    print(f"{i+1}. [{rec['topic']}] {rec['song'][:60]}... (score: {rec['score']:

# Get user feedback on Week 4 recommendation
liked_week4 = input("Enter indices of liked recommended songs for Week 4 (comma-
liked_week4_indices = [int(idx.strip()) for idx in liked_week4.split(',') if idx

# True labels: 1 if liked, else 0
y_true = [1 if i in liked_week4_indices else 0 for i in range(len(recs))]
y_pred = [1] * len(recs)

precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred)

print(f"\nPrecision@{N}: {precision:.2f}")
print(f"Recall@{N}: {recall:.2f}")
print(f"F1@{N}: {f1:.2f}")
```

```
==== Week 1 Songs ====
184: chase tail go round round break lose dead wrong turn chain l...
53: leave door unlock leave light stay awake count hour night lo...
75: river keep time march hide shadow know belong walk silence r...
139: rody soulchyld kubyina dkvpz evil needle clivelowe start fea...
38: reno trail hound sleep night till morning come runnin time f...
48: mornin walk rise drink like whiskey tree see thousand time b...
101: give million reason give million reason quit givin million r...
57: daddy deere brand bandit play fetch save date best best budd...
63: stay inside livin life instead watchin window playin safe go...
46: leave truth hand lead madness shape fate one blame think min...
37: gon na fell fast gon na gon na late away yeah gon na kind ho...
206: pull trigger ride bull cord wrap neck hang thread hand bleed...
229: complication fascination cause taste like coconut sober drin...
52: treat like queen livin lovin kissin look reason world live g...
44: watchin sink glass girl think friday night clothe hide headp...
114: walk street night parent know keep goin leave bedroom light ...
105: know mean revolution take solution fight oppression batter d...
228: weeknd rockin schulz guetta shed light feat cheat cod flume ...
93: wonder keep pillow lonely lonely night cry satisfy pick apar...
156: choose sweet suppose loneliness gloom fill lonely little roo...
Enter indices of liked songs for Week 1 (comma-separated): 184,53,38,179,229,105

==== Week 2 Songs ====
386: carousel ocean weeknd apologize take long drop astroworld wa...
470: different tell raise draw line sand thing well test gon na s...
441: blue go hurricane head boat know know lose wind sail hurrica...
284: wall cross come break break chain long bind longer bind call...
383: look inside parlour like mystic surround enigma control yeah...
287: philosophy choose race superior inferior finally permanently...
388: pick good recreational percocet itch high middle bad best ye...
270: meaningless meaningless meaningless meaningless hold hold ho...
454: know trick sleeve premeditate strike fool shame expect pull ...
402: moment close eye window seat midnight lean park wish spot se...
317: notorious notorious notorious notorious livin givin like lan...
313: soapbox stand give stage guitar song daddy tell involve poli...
469: soak right soak writhe fall long sadistic trance key hand gu...
373: know feel like face ruin face ruin mess afraid lose afraid l...
405: walk home step gate chicken plate food cold cover face know ...
389: burn heart reach fever pitch bring dark finally clear ahead ...
422: shin bright thing go right notice day hurry blue sky smile b...
404: stop baby tear asunder shove go live stuff plunder come stro...
305: look depth perception cause hurt deep think heal time shoot ...
414: stare wonder bring martyr sure crown light bone like compare...
Enter indices of liked songs for Week 2 (comma-separated): 414,287,399,270,405

==== Week 3 Songs ====
545: happen thousand happen everybody look outside heavy human cr...
562: echo pull mean rescue nightmare dream voice head scream mean...
582: dame momento para pensar nuestro amor dame momento para pens...
737: day work seventh rest course course create woman kid course ...
615: simply have wonderful christmastime simply have wonderful ch...
543: drifter high rift plain ash acid rain turn dust eye choke de...
618: somebody pick piece scatter contention surrender crown someb...
527: alright ready wake life real great feel dream come true get ...
717: thought melt mind accent mix uptight twist inside thought mi...
511: step inside mind eye open wide sleep turn toss rebuild heart...
678: moment know cause step tall sail leave wave peace let say th...
578: lift hire light fire steal delight go knight dawn start wisd...
572: sorry blood hand stare reflection know practice confession s...
```

```
710: sudden darkness creep soul envy move light self control cage...
730: walk room heart steal take time unbroken want know moment ca...
696: heart hole black soul hand heart till scar try breathe cause...
558: picture frame pack thing help week get like cause know think...
703: come watch night long come home tonight tonight heat stave w...
642: sell feel fool go lead kind realise nice nice burn prarie kn...
635: walk forever lose sight weakness field strew break dream wal...
Enter indices of liked songs for Week 3 (comma-separated): 717,511,545
No liked songs found for this topic.
No liked songs found for this topic.

==== Week 4 Recommendations ====
1. [dark] felt light moon try scream silence look want live island goo... (score:
0.397)
2. [sadness] sit corner star soul watch night come window window collapse... (sco
re: 0.337)
3. [sadness] wait outside lay soak foot start know go lose hard reach lig... (sco
re: 0.322)
4. [dark] instrumental live life night live live hood little blood... (score: 0.3
15)
5. [dark] lose lonely figure dark good cause lonely yeah lonely want s... (score:
0.304)
6. [dark] life breathin like movie sound turn felt nothin like feel ri... (score:
0.303)
7. [sadness] question lie deal surprise cause slip away slip away night w... (sco
re: 0.281)
8. [sadness] day shine like world afraid life unkind pain choose cause ti... (sco
re: 0.266)
9. [lifestyle] baby stay home tonight couple record build alright maybe dan... (s
core: 0.242)
10. [lifestyle] meet tonight memory time dive south santa look come baby mee...
(score: 0.234)
11. [lifestyle] break break break baby break tumble cause heart room sorry k...
(score: 0.039)
12. [lifestyle] gon na help suffer gon na help bleed gon na mother gon na qu...
(score: 0.022)
Enter indices of liked recommended songs for Week 4 (comma-separated): 1,5,9,10

Precision@20: 0.33
Recall@20: 1.00
F1@20: 0.50
```

In [ ]:

```
metrics = ['Precision', 'Recall', 'F1 Score']
scores = [precision, recall, f1]

plt.bar(metrics, scores, color=['blue', 'orange', 'green'])
plt.ylim(0, 1)
plt.ylabel('Score')
plt.title('Model Performance Metrics')
plt.grid(axis='y')
plt.show()
```



In models, precision generally improves due to lower false positives, whereas real users may experience lower precision due to lower relevance of recommendations, the system is good at retrieving all relevant recommendations, so the recall rate is relatively high, it is difficult to maintain high quality in terms of precision, resulting in many irrelevant recommendations. Users receive many irrelevant songs, and the system needs to improve precision to improve the overall user experience.

While some users like relevant recommendations, they often find that other recommendations do not match their tastes, resulting in inconsistent recommendations. Many users want more personalized recommendations and believe that incorporating their listening history can improve the relevance of recommendations.

```
In [ ]:
```