COMP9727 Recommender Systems 25T2 Assignment:

Content-Based Music Recommendation

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In [39]:
```
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 nltk.stem import WordNetLemmatizer
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.model_selection import cross_validate, StratifiedKFold
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
import numpy as np
import random
```

In [2]:
```
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     D:\anaconda3\envs\envpytorch\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     D:\anaconda3\envs\envpytorch\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     D:\anaconda3\envs\envpytorch\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[2]:
```
True
```

Part 1. Topic Classification

Data Loading and Preprocessing

In [3]:

```
# Loading the dataset
df = pd.read_csv('dataset.tsv', sep='\t')

# Combine all columns into one column 'content'
df['content'] = (df['artist_name'] + ' ' + df['track_name'] + ' ' + df['genre']

# Drop duplicates and missing values
df = df.drop_duplicates()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1480 entries, 0 to 1499
Data columns (total 7 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
 6   content       1480 non-null   object
dtypes: int64(1), object(6)
memory usage: 92.5+ KB
```

In the initial Data Clean, there were 20 duplicates that were removed.

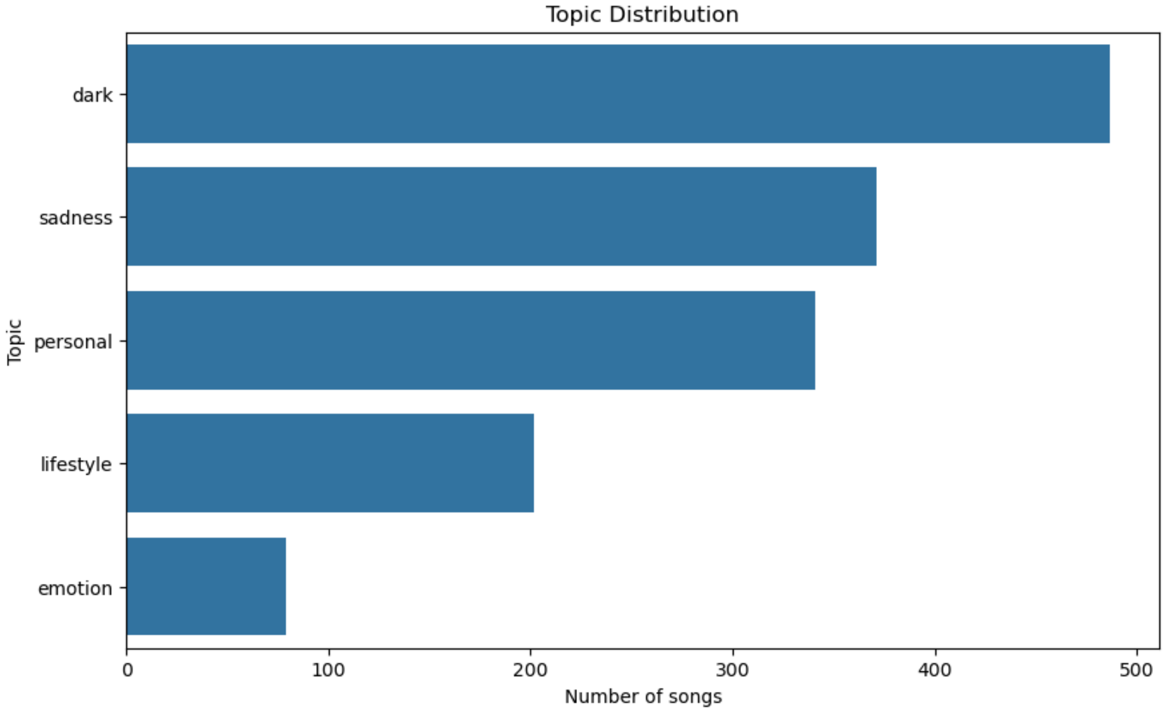
In [4]:

```
# Text Preprocessing
ps = PorterStemmer()
lemmatizer = WordNetLemmatizer()
nltk_stop_words = set(stopwords.words('english'))
sklearn_stop_words = set(ENGLISH_STOP_WORDS)

def preprocess_text(text, flag=False, stop_words=nltk_stop_words, method='lemma'
    text = text.lower()

    if flag:
        # Remove characters other than letters and numbers
        text = re.sub(r'[^\w\s]', '', text)
        tokens = word_tokenize(text)
    else:
        # Remove characters other than letters, numbers, \-!?+=/\.: symbols
        text = re.sub(r"[^\w\s'\-!?+=/\.:]", "", text)
        tokens = word_tokenize(text)
        # Delete single .
        tokens = [token for token in tokens if token != "."]

    tokens = [word for word in tokens if word not in stop_words]

    if method == 'stem':
        tokens = [ps.stem(word) for word in tokens]
    elif method == 'lemma':
        tokens = [lemmatizer.lemmatize(word) for word in tokens]

    return ' '.join(tokens)
```

In [5]:

```
plt.figure(figsize=(10, 6))
sns.countplot(y=df['topic'], order=df['topic'].value_counts().index)
plt.title('Topic Distribution')
```

```
plt.xlabel('Number of songs')
plt.ylabel('Topic')
plt.show()

print("\nTopic Distribution:")
print(df['topic'].value_counts())
```




```
Topic Distribution:
topic
dark          487
sadness       371
personal      341
lifestyle     202
emotion        79
Name: count, dtype: int64
```

Given the imbalanced nature of the dataset (e.g., the smallest class emotion has only 5.3% (79 samples) of the total samples), relying solely on overall **accuracy** would not give a realistic picture of the model's true performance. Therefore, we selected macro-averaged metrics: **F1-macro**, **precision-macro**, and **recall-macro**, as they treat all classes equally regardless of their frequency.

Among these, F1-macro is chosen as our main evaluation metric because it balances precision and recall across all classes. This is particularly important in imbalanced multi-class classification tasks, where a good model should not only be accurate on majority classes but also avoid neglecting the minority ones.

Precision-macro and recall-macro are also used to provide deeper insight into the model’s trade-off between correctly predicting a class (precision) and covering all true instances of a class (recall).

Analysis of optimal pre-processing steps

In [6]:
```
# Define evaluation metrics for cross-validation
scoring_metrics = ['accuracy', 'f1_macro', 'precision_macro', 'recall_macro']

# Create Bernoulli Naive Bayes (BNB) Pipeline
bnb = Pipeline([('vectorizer', CountVectorizer(binary=True)), ('classifier', Ber

# Create Multinomial Naive Bayes (MNB) Pipeline
mnb = Pipeline([('vectorizer', CountVectorizer()), ('classifier', MultinomialNB(

# Use cross-validation to evaluate the performance of the models
cv= StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

Comparison of Special Character Preprocessing Solutions

Based on the preliminary analysis of the dataset content, I will compare two strategies for handling special characters:

1. **Remove special characters before tokenization**, keeping only letters and numbers.

2. **Perform a lighter cleaning before tokenization**, keeping letters, numbers, and certain special characters (such as **-!?.,+=/**), and then **apply a second cleaning after tokenization** to remove only the single-character token **.** (while keeping ... intact).

In [7]:
```
y = df['topic']
# First strategy: Remove special characters before tokenization
X = df['content'].apply(lambda x: preprocess_text(x, flag=True))
bnb_scores_1 = cross_validate(bnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=
mnb_scores_1 = cross_validate(mnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=


# Second strategy: Perform a lighter cleaning before tokenization and remove . a
X = df['content'].apply(lambda x: preprocess_text(x, flag=False))
bnb_scores_2 = cross_validate(bnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=
mnb_scores_2 = cross_validate(mnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=
```

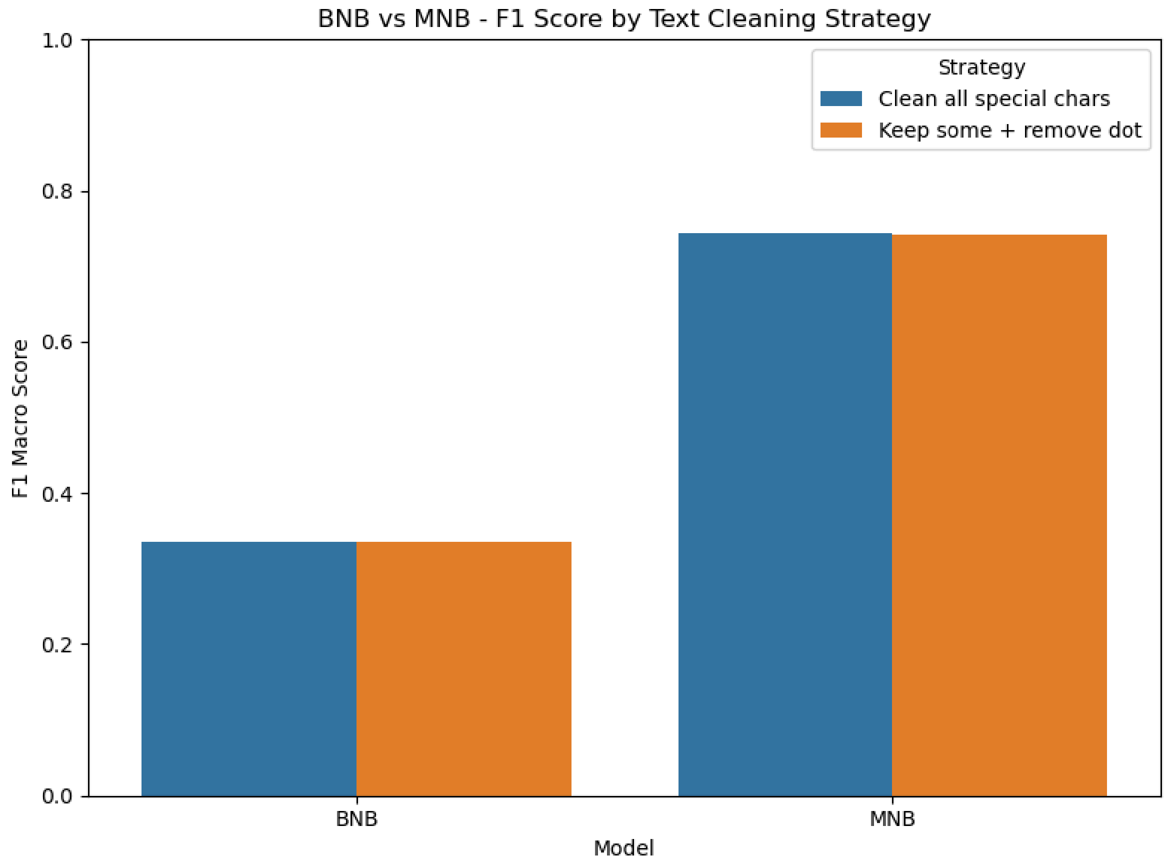
In [8]:
```
def evaluate_and_plot_results(
    bnb_scores_1, mnb_scores_1, bnb_scores_2, mnb_scores_2,
    strategy_labels=('Strategy 1', 'Strategy 2'),
    table_title="BNB vs MNB - Performance Comparison Under Two Preprocessing Str
    plot_title="BNB vs MNB - F1 Score by Preprocessing Strategy"
):
    """
    Integrate cross-validation results and plot comparative histograms.
    """
    results_df = pd.DataFrame([
        {
            'Strategy': strategy_labels[0],
            'Model': 'BNB',
            'Accuracy': np.mean(bnb_scores_1['test_accuracy']),
            'F1 (Macro)': np.mean(bnb_scores_1['test_f1_macro']),
            'Precision (Macro)': np.mean(bnb_scores_1['test_precision_macro']),
            'Recall (Macro)': np.mean(bnb_scores_1['test_recall_macro']),
        },
        {
            'Strategy': strategy_labels[0],
            'Model': 'MNB',
```

```python
            'Accuracy': np.mean(mnb_scores_1['test_accuracy']),
            'F1 (Macro)': np.mean(mnb_scores_1['test_f1_macro']),
            'Precision (Macro)': np.mean(mnb_scores_1['test_precision_macro']),
            'Recall (Macro)': np.mean(mnb_scores_1['test_recall_macro']),
        },
        {
            'Strategy': strategy_labels[1],
            'Model': 'BNB',
            'Accuracy': np.mean(bnb_scores_2['test_accuracy']),
            'F1 (Macro)': np.mean(bnb_scores_2['test_f1_macro']),
            'Precision (Macro)': np.mean(bnb_scores_2['test_precision_macro']),
            'Recall (Macro)': np.mean(bnb_scores_2['test_recall_macro']),
        },
        {
            'Strategy': strategy_labels[1],
            'Model': 'MNB',
            'Accuracy': np.mean(mnb_scores_2['test_accuracy']),
            'F1 (Macro)': np.mean(mnb_scores_2['test_f1_macro']),
            'Precision (Macro)': np.mean(mnb_scores_2['test_precision_macro']),
            'Recall (Macro)': np.mean(mnb_scores_2['test_recall_macro']),
        }
    ])

    print("\n" + table_title)
    print(results_df.round(4))

    plt.figure(figsize=(8, 6))
    sns.barplot(data=results_df, x='Model', y='F1 (Macro)', hue='Strategy')
    plt.title(plot_title)
    plt.ylabel("F1 Macro Score")
    plt.ylim(0, 1)
    plt.tight_layout()
    plt.show()
```

In [9]:

```python
evaluate_and_plot_results(
    bnb_scores_1, mnb_scores_1, bnb_scores_2, mnb_scores_2,
    strategy_labels=('Clean all special chars', 'Keep some + remove dot'),
    table_title="BNB vs MNB - Preprocessing Strategy Comparison",
    plot_title="BNB vs MNB - F1 Score by Text Cleaning Strategy"
)
```

```
BNB vs MNB - Preprocessing Strategy Comparison
                  Strategy Model  Accuracy  F1 (Macro)  Precision (Macro)  \
0  Clean all special chars   BNB    0.5358      0.3350             0.3510
1  Clean all special chars   MNB    0.8135      0.7433             0.8291
2   Keep some + remove dot   BNB    0.5345      0.3343             0.3505
3   Keep some + remove dot   MNB    0.8128      0.7426             0.8278

   Recall (Macro)
0          0.3829
1          0.7199
2          0.3819
3          0.7194
```



Conclusion

We can see from the results: For the **BNB** model, the effect of adopting the second strategy is not significantly improved; For the **MNB** model, there is a slight improvement in adopting the second strategy. For this dataset, the handling of special characters may not have much of an impact. In the following analysis, I will default to the second strategy.

Evaluation of Different Stop Words

In the following experiment, I will compare the impact of **NLTK** and **Scikit-learn** on the model in terms of handling stop words.

In [10]:

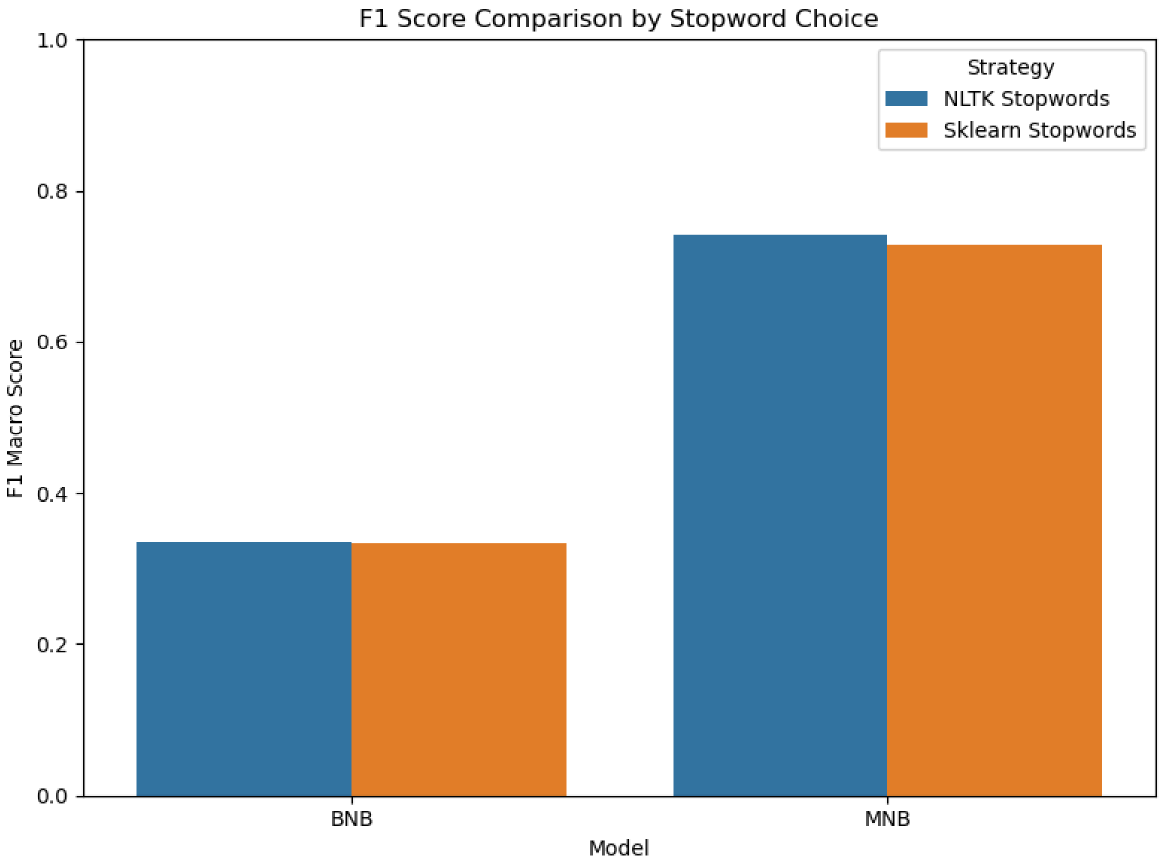
```
y = df['topic']
# Using nltk stop words
X = df['content'].apply(lambda x: preprocess_text(x, stop_words=nltk_stop_words))
bnb_nltk = cross_validate(bnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=-1)
mnb_nltk = cross_validate(mnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=-1)


# Using sklearn stop words
X = df['content'].apply(lambda x: preprocess_text(x, stop_words=sklearn_stop_wor
bnb_sklearn = cross_validate(bnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=-
mnb_sklearn = cross_validate(mnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=-
```

In [11]:

```
evaluate_and_plot_results(
    bnb_nltk, mnb_nltk, bnb_sklearn, mnb_sklearn,
    strategy_labels=('NLTK Stopwords', 'Sklearn Stopwords'),
    table_title="BNB vs MNB - NLTK vs Sklearn Stopwords",
```

```
    plot_title="F1 Score Comparison by Stopword Choice"
)
```

```
BNB vs MNB - NLTK vs Sklearn Stopwords
            Strategy Model  Accuracy  F1 (Macro)  Precision (Macro)  \
0     NLTK Stopwords   BNB    0.5345      0.3343             0.3505
1     NLTK Stopwords   MNB    0.8128      0.7426             0.8278
2  Sklearn Stopwords   BNB    0.5331      0.3335             0.3489
3  Sklearn Stopwords   MNB    0.8020      0.7275             0.8077

   Recall (Macro)
0          0.3819
1          0.7194
2          0.3813
3          0.7058
```



Conclusion

The results show that the choice of stopword list has little to no effect on the **BNB** model, with F1 scores remaining nearly identical under both settings. However, for the **MNB** model, using the NLTK stopword list led to slightly better performance, achieving a higher F1 macro score and recall compared to the Scikit-learn version.

This difference may be attributed to the richer and more linguistically diverse vocabulary of the **NLTK** stopword list, which is more suitable for informal and expressive texts. In contrast, the **Scikit-learn** list is more concise and optimized for formal written content.

Therefore, I will use the **NLTK** stop words list in the following analysis.

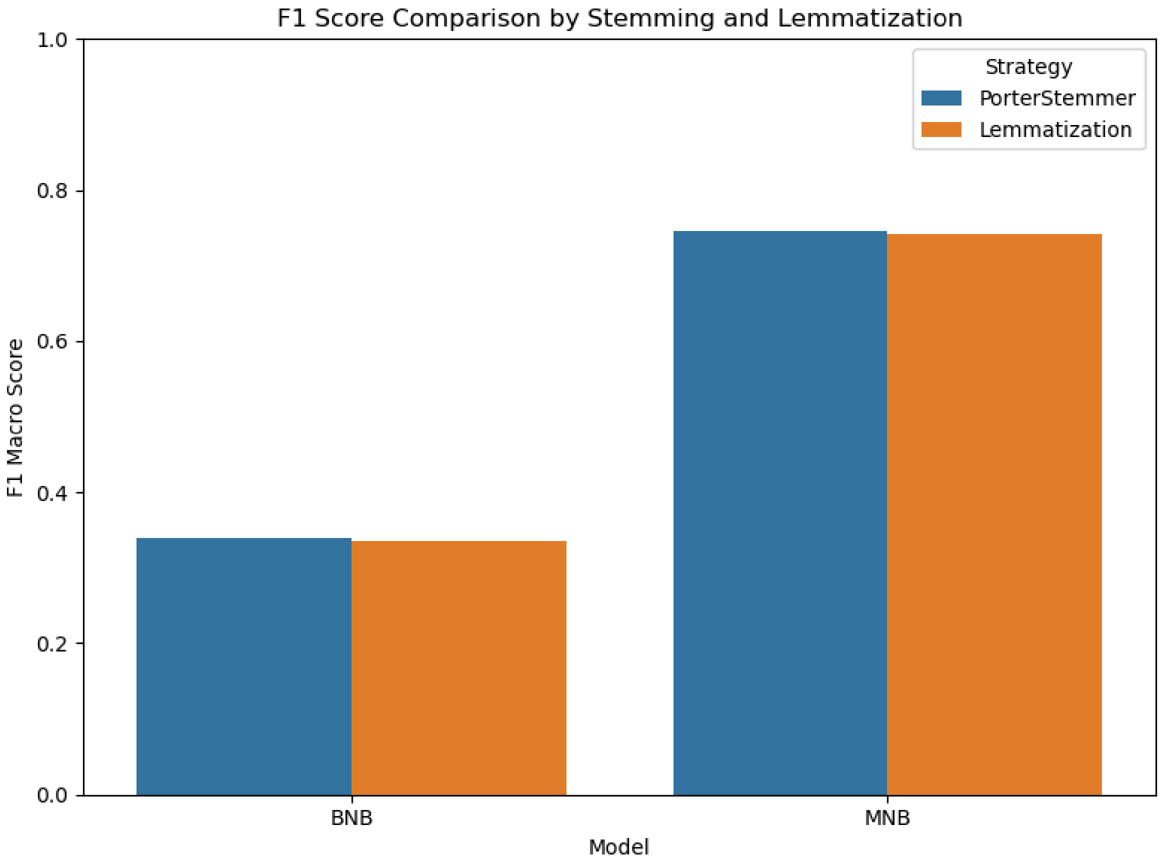
Comparison of Stemming and Lemmatization

In the following experiment, I will compare the impact of **PorterStemmer** and **Lemmatization** on the model.

In [12]:
```
y = df['topic']
# Stemming
X = df['content'].apply(lambda x: preprocess_text(x, method='stem'))
bnb_stemmed = cross_validate(bnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=-
mnb_stemmed = cross_validate(mnb, X, y, cv=cv, scoring=scoring_metrics, n_jobs=-

# Lemmatization
X = df['content'].apply(lambda x: preprocess_text(x, method='lemma'))
bnb_lemmatized = cross_validate(bnb, X, y, cv=cv, scoring=scoring_metrics, n_job
mnb_lemmatized = cross_validate(mnb, X, y, cv=cv, scoring=scoring_metrics, n_job
```

In [13]:
```
evaluate_and_plot_results(
    bnb_stemmed, mnb_stemmed, bnb_lemmatized, mnb_lemmatized,
    strategy_labels=('PorterStemmer', 'Lemmatization'),
    table_title="BNB vs MNB - Stemming vs Lemmatization",
    plot_title="F1 Score Comparison by Stemming and Lemmatization"
)
```

```
BNB vs MNB - Stemming vs Lemmatization
        Strategy Model  Accuracy  F1 (Macro)  Precision (Macro)  \
0  PorterStemmer   BNB    0.5378      0.3389             0.3496
1  PorterStemmer   MNB    0.8095      0.7462             0.8283
2  Lemmatization   BNB    0.5345      0.3343             0.3505
3  Lemmatization   MNB    0.8128      0.7426             0.8278

   Recall (Macro)
0          0.3858
1          0.7213
2          0.3819
3          0.7194
```



Conclusion

I compared **Porter Stemming** and **Lemmatization** in text preprocessing. The results show that both methods perform similarly for BNB, with low F1 scores around 0.34. However, for MNB, lemmatization gives slightly better results across accuracy, F1, precision, and recall.

Therefore, I will use the **Lemmatization** in the following analysis.

Evaluation of Top-N Words in the Vectorizer

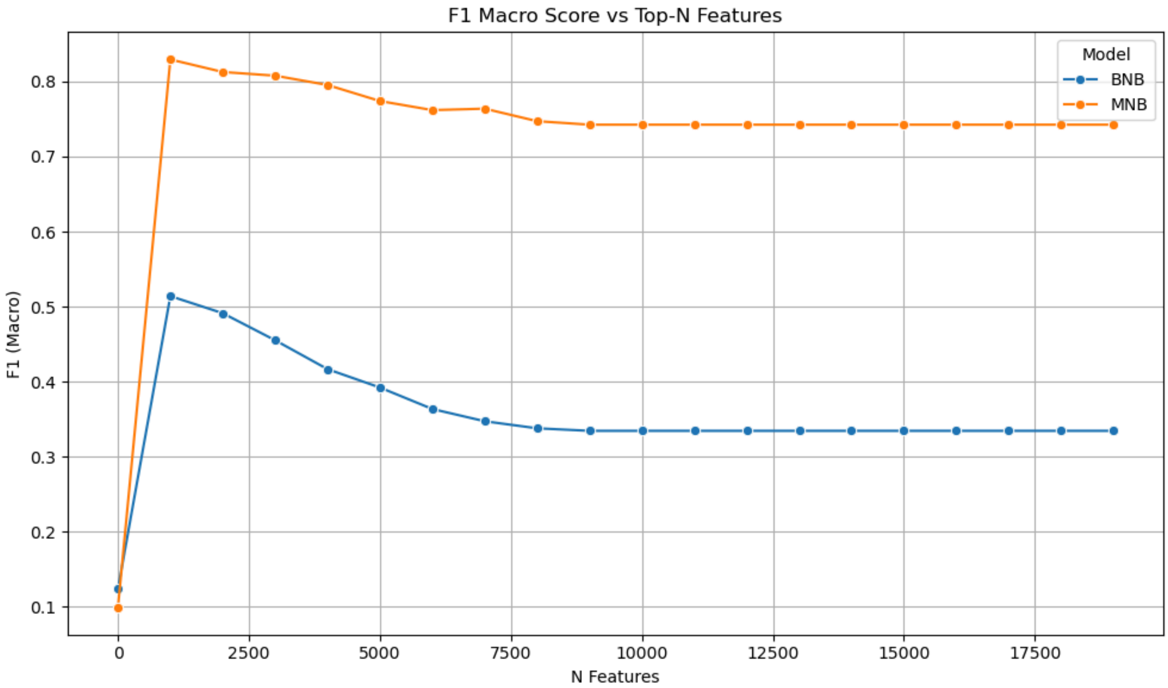
In this analysis, I will evaluate the impact of the number of top words on the performance of **BNB** and **MNB** models. I choose the macro **F1 score** as the key score to evaluate, ensuring a robust evaluation across all classes in the context of **Top-N** feature selection.

I will vary the number of top-level words from 1 to $20,000$ in increments of 1000, and calculate the average macro F1 score for each model at different Top-N values to determine the optimal number of features for the model.

In [14]:
```
X = df['content'].apply(preprocess_text)
y = df['topic']
bnb_results = []
mnb_results = []
n_range = range(1, 20000, 1000)

for n in n_range:
    # BNB
    bnb_pipeline = Pipeline([
        ('vectorizer', CountVectorizer(binary=True, max_features=n)),
        ('classifier', BernoulliNB())
    ])
    bnb_scores = cross_validate(bnb_pipeline, X, y, cv=cv, scoring='f1_macro', n
    bnb_results.append({
        'Model': 'BNB',
        'N Features': n,
        'F1 (Macro)': np.mean(bnb_scores['test_score']),
    })

    # MNB
    mnb_pipeline = Pipeline([
        ('vectorizer', CountVectorizer(max_features=n)),
        ('classifier', MultinomialNB())
    ])
    mnb_scores = cross_validate(mnb_pipeline, X, y, cv=cv, scoring='f1_macro', n
    mnb_results.append({
        'Model': 'MNB',
        'N Features': n,
        'F1 (Macro)': np.mean(mnb_scores['test_score']),
    })

df_all = pd.DataFrame(bnb_results + mnb_results)
```

In [15]:
```
plt.figure(figsize=(10, 6))
sns.lineplot(data=df_all, x='N Features', y='F1 (Macro)', hue='Model', marker='o
plt.title("F1 Macro Score vs Top-N Features")
```

```
plt.grid(True)
plt.tight_layout()
plt.show()
```

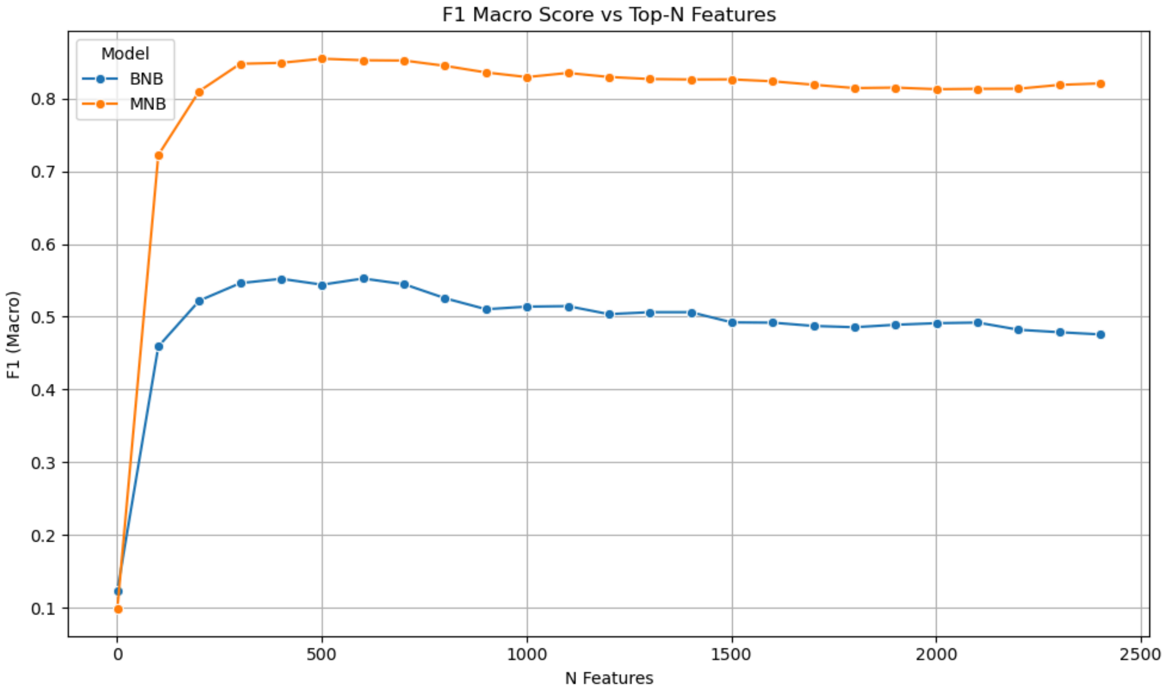


According to this plot, it seems that a higher score is obtained when the maximum feature is between 1 and 2500. In order to get a more precise indicator within this range, I will perform an additional test in increments of 100.

In [16]:
```
bnb_results = []
mnb_results = []
n_range = range(1, 2500, 100)

for n in n_range:
    # BNB
    bnb_pipeline = Pipeline([
        ('vectorizer', CountVectorizer(binary=True, max_features=n)),
        ('classifier', BernoulliNB())
    ])
    bnb_scores = cross_validate(bnb_pipeline, X, y, cv=cv, scoring='f1_macro', n
    bnb_results.append({
        'Model': 'BNB',
        'N Features': n,
        'F1 (Macro)': np.mean(bnb_scores['test_score']),
    })

    # MNB
    mnb_pipeline = Pipeline([
        ('vectorizer', CountVectorizer(max_features=n)),
        ('classifier', MultinomialNB())
    ])
    mnb_scores = cross_validate(mnb_pipeline, X, y, cv=cv, scoring='f1_macro', n
    mnb_results.append({
        'Model': 'MNB',
        'N Features': n,
        'F1 (Macro)': np.mean(mnb_scores['test_score']),
    })
```

```python
df_all = pd.DataFrame(bnb_results + mnb_results)
```

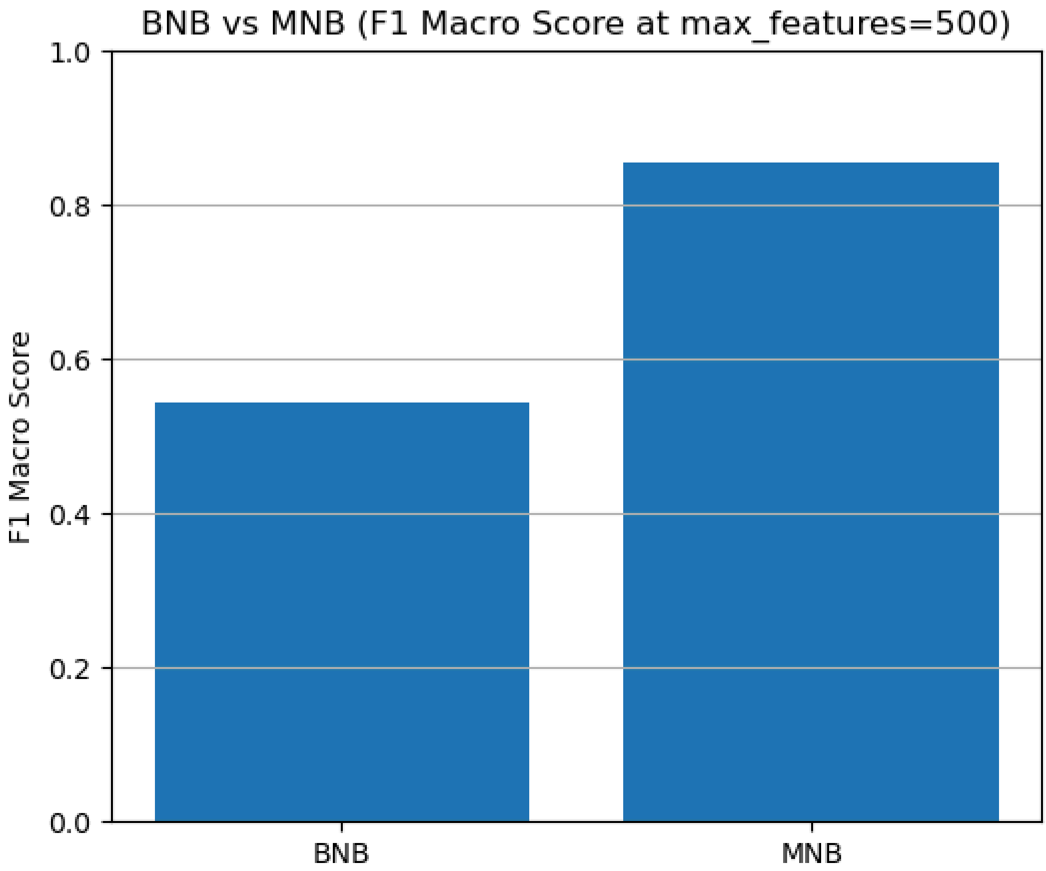
In [17]:
```python
plt.figure(figsize=(10, 6))
sns.lineplot(data=df_all, x='N Features', y='F1 (Macro)', hue='Model', marker='o
plt.title("F1 Macro Score vs Top-N Features")
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [18]:
```python
bnb_pipeline = Pipeline([
    ('vectorizer', CountVectorizer(max_features=500, binary=True)),
    ('classifier', BernoulliNB())
])
bnb_scores = cross_validate(bnb_pipeline, X, y, cv=cv, scoring='f1_macro', n_job
bnb_f1 = np.mean(bnb_scores['test_score'])

mnb_pipeline = Pipeline([
    ('vectorizer', CountVectorizer(max_features=500)),
    ('classifier', MultinomialNB())
])
mnb_scores = cross_validate(mnb_pipeline, X, y, cv=cv, scoring='f1_macro', n_job
mnb_f1 = np.mean(mnb_scores['test_score'])

results_df = pd.DataFrame([
    {'Model': 'BNB', 'F1 (Macro)': bnb_f1},
    {'Model': 'MNB', 'F1 (Macro)': mnb_f1}
])

print("\nBNB vs MNB at max_features = 500:")
print(results_df.round(4))

plt.figure(figsize=(6, 5))
plt.bar(results_df['Model'], results_df['F1 (Macro)'])
plt.title("BNB vs MNB (F1 Macro Score at max_features=500)")
plt.ylabel("F1 Macro Score")
plt.ylim(0, 1)
```

```python
plt.grid(axis='y')
plt.show()
```

```
BNB vs MNB at max_features = 500:
  Model  F1 (Macro)
0   BNB      0.5444
1   MNB      0.8548
```



Conclusion

To determine the optimal number of features (i.e., vocabulary size) for text classification, we conducted a range test using different values of `max_features` in the CountVectorizer, varying from 1 to $20,000$ in steps of $1,000$ and 1 to 2500 in steps of 100. We evaluated model performance using the **macro F1 score**, which is appropriate for our imbalanced multi-class dataset as it gives equal weight to each class.

The results showed a clear trend: both **BNB** and **MNB** achieved their highest macro F1 scores when the number of features was around 500. After this point, performance plateaued or slightly declined, likely due to the inclusion of sparse or less informative features.

Based on this finding, we selected **500** features as the optimal setting for max_features and used this value consistently in the remaining experiments to balance model performance and complexity.

Logistic Regression

Logistic Regression (LR) is a linear classification model that estimates the probability of a sample belonging to a particular class using the logistic (sigmoid) function. In the multiclass setting, it is commonly implemented with a one-vs-rest strategy. **LR** is especially well-suited for high-dimensional and sparse data, such as bag-of-words (BoW) or TF-IDF representations of text. Since our music dataset consists of short text descriptions (song lyrics, genre tags, etc.), LR is a logical choice as it can capture linear decision boundaries between topics effectively.

In the next analysis, I will use Grid search to adjust the parameters of the LR. Based on the previous conclusions, the `max_features` parameter for the vectorizer will be set to **500**.

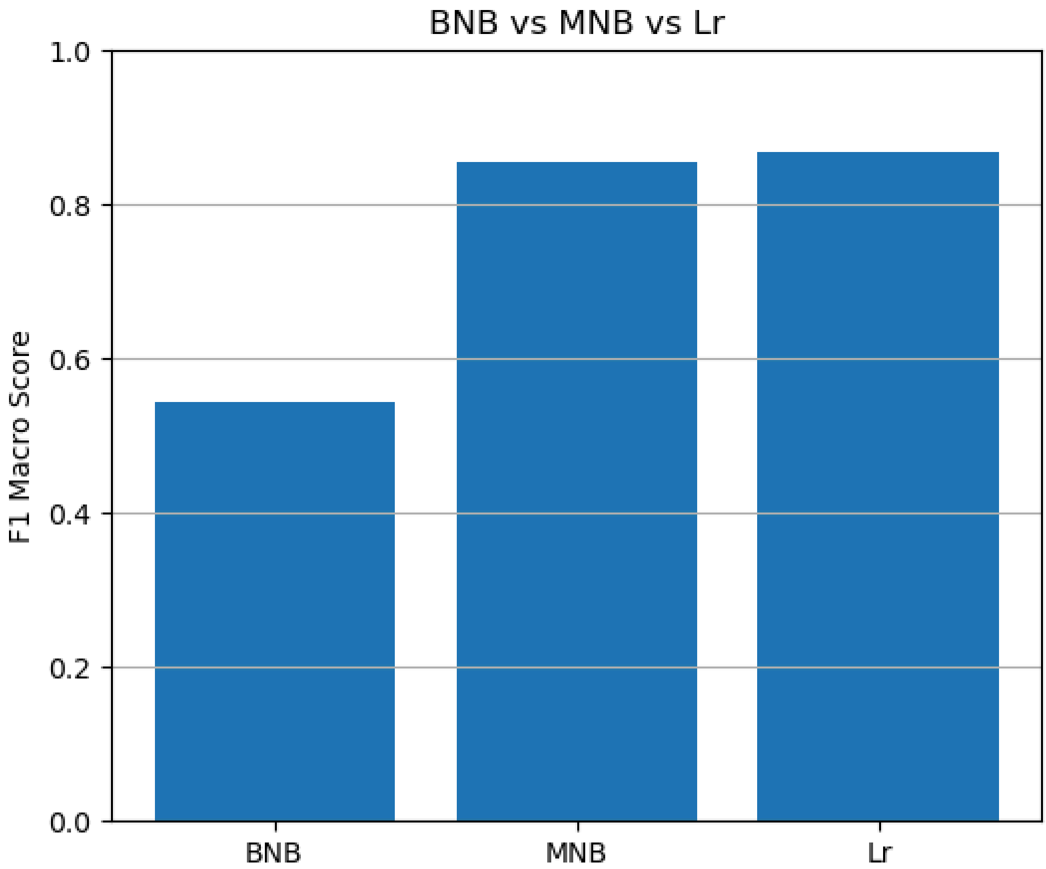
In [19]:
```
X = df['content'].apply(preprocess_text)
y = df['topic']

lr_pipeline = Pipeline([
    ('vectorizer', CountVectorizer(max_features=500)),
    ('classifier', LogisticRegression(solver='liblinear', random_state=42))
])

# Parameters grid
param_grid = {
    'classifier__C': [0.01, 0.05, 0.1, 0.15, 0.2, 0.3, 1],
    'classifier__penalty': ['l1', 'l2'],
    'classifier__class_weight': [None, 'balanced'],
    'classifier__max_iter': [1000,1500,2000]
}

# Cross Validation Grid Search
grid_search = GridSearchCV(lr_pipeline, param_grid=param_grid, cv=cv, scoring='f
grid_search.fit(X, y)

# Output optimal parameters and scores
print("Best Parameters:", grid_search.best_params_)
print("Best F1 Macro Score:", round(grid_search.best_score_, 4))
```

```
Best Parameters: {'classifier__C': 0.15, 'classifier__class_weight': None, 'class
ifier__max_iter': 1000, 'classifier__penalty': 'l2'}
Best F1 Macro Score: 0.8674
```

In [20]:
```
lr_pipeline = Pipeline([
    ('vectorizer', CountVectorizer(max_features=500)),
    ('classifier', LogisticRegression(C=0.15, max_iter=1000, penalty='l2', solve
])
lr_scores = cross_validate(lr_pipeline, X, y, cv=cv, scoring='f1_macro', n_jobs=
lr_f1 = np.mean(lr_scores['test_score'])

results_df = pd.DataFrame([
    {'Model': 'BNB', 'F1 (Macro)': bnb_f1},
    {'Model': 'MNB', 'F1 (Macro)': mnb_f1},
    {'Model': 'Lr', 'F1 (Macro)': lr_f1}
])

print("\nBNB vs MNB vs Lr")
print(results_df.round(4))

plt.figure(figsize=(6, 5))
plt.bar(results_df['Model'], results_df['F1 (Macro)'])
```

```python
plt.title("BNB vs MNB vs Lr")
plt.ylabel("F1 Macro Score")
plt.ylim(0, 1)
plt.grid(axis='y')
plt.show()
```

```
BNB vs MNB vs Lr
  Model  F1 (Macro)
0   BNB      0.5444
1   MNB      0.8548
2    Lr      0.8674
```



Conclusion

The results show that **BNB** performs the worst, likely because it only captures binary presence/absence of words, which loses important frequency information. **MNB** significantly improves performance by considering term frequencies, making it more suitable for text classification tasks. **Logistic Regression (LR)** achieves the best performance overall, slightly outperforming MNB.

This confirms our hypothesis that LR, with its ability to learn weighted feature contributions and handle correlated features, is better suited for high-dimensional sparse text data.

Part 2. Recommendation Methods

Data Loading and Preprocessing

In [21]:

```python
# Data split
train_data = df.iloc[:750].copy()
test_data = df.iloc[750:1000].copy()

# Preprocessing
X_train = train_data['content'].apply(preprocess_text)
y_train = train_data['topic']

### TfidfVectorizer is not as effective as CountVectorizer.
# best_classifier = Pipeline([
#     ('vectorizer', TfidfVectorizer(max_features=400, stop_words='english')),
#     ('classifier', LogisticRegression(C=0.15, max_iter=1000, penalty='l2',
#                                       solver='liblinear', random_state=42))
# ])

best_classifier = Pipeline([
    ('vectorizer', CountVectorizer(max_features=500)),
    ('classifier', LogisticRegression(C=0.15, max_iter=1000, penalty='l2',
                                      solver='liblinear', random_state=42))
])

# Classifier training
best_classifier.fit(X_train, y_train)

# Extract fitted vectorizers from Pipeline
vectorizer = best_classifier.named_steps['vectorizer']
```

With comparative tests, I found that using TfidfVectorizer with the best model parameters is not as effective as CountVectorizer, so in part2 I will continue to follow the parameter settings of part1.

In [22]:

```python
# Read user data
user1_data = pd.read_csv('user1.tsv', sep='\t')
user2_data = pd.read_csv('user2.tsv', sep='\t')

# Convert user data to dictionary format
user1_keywords = {}
for _, row in user1_data.iterrows():
    keywords = [kw.strip() for kw in row['keywords'].split(',')]
    user1_keywords[row['topic']] = keywords

user2_keywords = {}
for _, row in user2_data.iterrows():
    keywords = [kw.strip() for kw in row['keywords'].split(',')]
    user2_keywords[row['topic']] = keywords

print("User 1 keywords:")
for topic, keywords in user1_keywords.items():
    print(f"  {topic}: {keywords}")

print("\nUser 2 keywords:")
for topic, keywords in user2_keywords.items():
    print(f"  {topic}: {keywords}")
```

```
User 1 keywords:
  dark: ['fire', 'enemy', 'pain', 'storm', 'fight']
  sadness: ['cry', 'alone', 'heartbroken', 'tears', 'regret']
  personal: ['dream', 'truth', 'life', 'growth', 'identity']
  lifestyle: ['party', 'city', 'night', 'light', 'rhythm']
  emotion: ['love', 'memory', 'hug', 'kiss', 'feel']

User 2 keywords:
  sadness: ['lost', 'sorrow', 'goodbye', 'tears', 'silence']
  emotion: ['romance', 'touch', 'feeling', 'kiss', 'memory']
```

Create user profile

In [23]:

```python
# Topic prediction on training set data
train_data['predicted_topic'] = best_classifier.predict(X_train)

def create_user_profile(user_keywords, train_df, vectorizer):
    """
    Create user profiles based on user keywords and topic vectors
    """
    user_topic_profiles = {}

    # Iterate through each topic of interest to the user
    for topic, keywords in user_keywords.items():

        # a helper function to check for keywords
        def contains_keyword(text, kws):
            return any(kw in text for kw in kws)

        # Apply the filter
        liked_songs_df = train_df[
            (train_df['predicted_topic'] == topic) &
            (train_df['content'].apply(lambda x: contains_keyword(preprocess_tex
        ]

        # Merge song text
        if not liked_songs_df.empty:
            combined_document = ' '.join(liked_songs_df['content'].apply(preproc
            profile_vector = vectorizer.transform([combined_document])
            user_topic_profiles[topic] = profile_vector
        else:
            # If no matching song is found, the image vector is empty.
            user_topic_profiles[topic] = None

    return user_topic_profiles

# Get and print Top 20 keywords
def get_top_words(profile_vector, vectorizer, top_n=20):
    """
    Extract the top-ranked 20 words from a TF-IDF vector
    """
    if profile_vector is None:
        return ["No songs found for this topic."]

    # Convert sparse matrix to numpy array
    vec_array = profile_vector.toarray().flatten()

    # Gets the index of the sorted word (from high to low)
    top_indices = vec_array.argsort()[::-1][:top_n]
```

```python

    # Get all the feature words
    feature_names = vectorizer.get_feature_names_out()

    # Extract Top N keywords
    top_words = [feature_names[i] for i in top_indices if vec_array[i] > 0]

    return top_words

# Creating user profiles
user1_profiles = create_user_profile(user1_keywords, train_data, vectorizer)
user2_profiles = create_user_profile(user2_keywords, train_data, vectorizer)
```

In [24]:
```python
# Define keywords for user3
user3_keywords = {
    'personal': ['time', 'life', 'remember', 'story', 'soul'],
    'sadness': ['rain', 'tear', 'goodbye', 'alone', 'broken'],
    'emotion': ['demon', 'blood', 'hell', 'cursed', 'grave']
}
user3_profiles = create_user_profile(user3_keywords, train_data, vectorizer)

users_data = {
    "User 1": (user1_profiles, user1_keywords),
    "User 2": (user2_profiles, user2_keywords),
    "User 3": (user3_profiles, user3_keywords)
}

all_dataset_topics = sorted(df['topic'].unique())
for user_name, (profiles, initial_keywords) in users_data.items():
    print(f"\n{'='*15} {user_name} Profile Keywords {'='*15}")
    print(f"Initial keywords provided: {initial_keywords}")

    if not profiles:
        print("\n  No topics of interest specified for this user.")
        continue

    for topic in all_dataset_topics:
        print(f"\n  Top 20 words for topic '{topic}':")
        profile_vec = profiles.get(topic)
        top_words = get_top_words(profile_vec, vectorizer)
        print(f"    {top_words}")
```

```
=============== User 1 Profile Keywords ===============
Initial keywords provided: {'dark': ['fire', 'enemy', 'pain', 'storm', 'fight'],
'sadness': ['cry', 'alone', 'heartbroken', 'tears', 'regret'], 'personal': ['drea
m', 'truth', 'life', 'growth', 'identity'], 'lifestyle': ['party', 'city', 'nigh
t', 'light', 'rhythm'], 'emotion': ['love', 'memory', 'hug', 'kiss', 'feel']}

  Top 20 words for topic 'dark':
    ['fight', 'know', 'like', 'come', 'na', 'black', 'blood', 'stand', 'grind',
'tell', 'hand', 'yeah', 'gon', 'time', 'cause', 'kill', 'head', 'right', 'light',
'leave']

  Top 20 words for topic 'emotion':
    ['good', 'feel', 'touch', 'know', 'hold', 'go', 'want', 'morning', 'kiss', 'l
ike', 'baby', 'time', 'vision', 'na', 'cause', 'miss', 'heart', 'yeah', 'video',
'loove']

  Top 20 words for topic 'lifestyle':
    ['night', 'come', 'time', 'song', 'tonight', 'home', 'long', 'na', 'right',
'sing', 'yeah', 'like', 'wan', 'know', 'wait', 'closer', 'stranger', 'mind', 'pla
y', 'tire']

  Top 20 words for topic 'personal':
    ['life', 'live', 'know', 'na', 'world', 'change', 'time', 'yeah', 'like', 'dr
eam', 'come', 'wan', 'thing', 'think', 'need', 'feel', 'go', 'cause', 'thank', 't
each']

  Top 20 words for topic 'sadness':
    ['cry', 'tear', 'know', 'club', 'steal', 'think', 'mean', 'baby', 'say', 'lea
ve', 'eye', 'face', 'true', 'heart', 'want', 'feel', 'time', 'write', 'smile', 'm
usic']

=============== User 2 Profile Keywords ===============
Initial keywords provided: {'sadness': ['lost', 'sorrow', 'goodbye', 'tears', 'si
lence'], 'emotion': ['romance', 'touch', 'feeling', 'kiss', 'memory']}

  Top 20 words for topic 'dark':
    ['No songs found for this topic.']

  Top 20 words for topic 'emotion':
    ['good', 'touch', 'hold', 'kiss', 'morning', 'know', 'vision', 'video', 'tim
e', 'loove', 'feel', 'feelin', 'luck', 'look', 'lovin', 'lip', 'sunrise', 'caus
e', 'like', 'go']

  Top 20 words for topic 'lifestyle':
    ['No songs found for this topic.']

  Top 20 words for topic 'personal':
    ['No songs found for this topic.']

  Top 20 words for topic 'sadness':
    ['heart', 'break', 'away', 'inside', 'like', 'step', 'know', 'fall', 'leave',
'come', 'go', 'fade', 'hard', 'na', 'think', 'feel', 'scar', 'tear', 'open', 'bla
me']

=============== User 3 Profile Keywords ===============
Initial keywords provided: {'personal': ['time', 'life', 'remember', 'story', 'so
ul'], 'sadness': ['rain', 'tear', 'goodbye', 'alone', 'broken'], 'emotion': ['dem
on', 'blood', 'hell', 'cursed', 'grave']}

  Top 20 words for topic 'dark':
```

```
    ['No songs found for this topic.']

  Top 20 words for topic 'emotion':
    ['morning', 'sunrise', 'good', 'kiss', 'know', 'goodbye', 'na', 'feel', 'yea
h', 'gon', 'hold', 'like', 'time', 'heart', 'okay', 'hand', 'reach', 'year', 'tig
ht', 'baby']

  Top 20 words for topic 'lifestyle':
    ['No songs found for this topic.']

  Top 20 words for topic 'personal':
    ['life', 'live', 'know', 'time', 'world', 'like', 'yeah', 'change', 'na', 'da
y', 'thank', 'want', 'come', 'thing', 'go', 'need', 'think', 'wan', 'feel', 'caus
e']

  Top 20 words for topic 'sadness':
    ['heart', 'break', 'know', 'away', 'tear', 'na', 'feel', 'like', 'baby', 'fal
l', 'leave', 'inside', 'yeah', 'walk', 'think', 'wan', 'time', 'right', 'hurt',
'cry']
```

Conclusion

User 1 & User 2

The user profiles for User 1 and User 2 are **overall reasonable**, confirming the effectiveness of the profile construction.

- Strong Performance on Emotional Topics: For topics like sadness, personal, and emotion, the model correctly identified core keywords and extended them with semantically related terms. In User 2's sadness profile, words like break, fade, and scar created a deep emotional theme.
- Generalization in Broad Topics: Themes such as dark and lifestyle showed less focus, suggesting that generic terms in lyrics can dilute the specificity of the resulting profile.

User 3

User 3 included typical preferences (personal, sadness) and a deliberately contradictory case—using dark words to define the emotion topic.

- Stable on Regular Topics: Profiles for sadness and personal were consistent with other users, demonstrating robustness.
- Contradictory Topic: Although emotion was defined using words like demon and hell, the resulting profile was dominated by positive words like sunrise, kiss, and heart. This highlights how rare trigger words may influence topic classification, but high-frequency content determines the final profile.

Evaluate the performance of the recommendation method

In [25]:
```
# Test data preprocessing
X_test = test_data['content'].apply(preprocess_text)
```

```python
test_data['predicted_topic'] = best_classifier.predict(X_test)
X_test_vectors = vectorizer.transform(X_test)
```

In [36]:
```python
def create_truncated_profile(profile_vector, vectorizer, m_val):
    """
    Create a truncated vector of user profiles based on the given M value.
    """
    if profile_vector is None:
        return None

    vec_array = profile_vector.toarray().flatten()

    # Get an index of the M highest scoring words
    top_indices = vec_array.argsort()[::-1][:m_val]

    truncated_vec_array = np.zeros_like(vec_array)

    for i in top_indices:
        truncated_vec_array[i] = vec_array[i]

    return csr_matrix(truncated_vec_array)

def is_relevant(song_text, keywords):
    """
    Check if the song text contains any of the user keywords.
    """
    return any(kw in song_text for kw in keywords)
```

In [38]:
```python
# Setting evaluation parameters
N = 10
M_values = [5, 10, 20]

for m_val in M_values:
    print(f"\n{'='*25}")
    print(f" EVALUATION FOR PROFILE SIZE M = {m_val}")
    print(f"{'='*25}")

    for user_name, (profiles, keywords_map) in users_data.items():
        print(f"\n----- User: {user_name} -----")

        overall_metrics = {'precision': [], 'recall': [], 'f1': []}

        # Iterate over every topic of interest to the user
        for topic, full_profile_vec in profiles.items():
            if full_profile_vec is None:
                print(f"\n  Topic: {topic}\n    No profile generated (no liked s
                continue

            # Create a user profile with the current M value
            active_profile_vec = create_truncated_profile(full_profile_vec, vect

            # Filter the songs in the test set that are predicted to be on the c
            topic_test_df = test_data[test_data['predicted_topic'] == topic]

            if topic_test_df.empty:
                print(f"\n  Topic: {topic}\n    No test songs found for this top
                continue

            X_topic_test_vectors = vectorizer.transform(topic_test_df['content']
```

```
        # Calculate Similarity and Get Top-N Recommendations
        similarities = cosine_similarity(active_profile_vec, X_topic_test_ve

        # Make sure the number of recommendations does not exceed the total
        num_recommendations = min(N, len(similarities))

        # Get an index of the highest scoring songs
        top_n_indices = similarities.argsort()[::-1][:num_recommendations]
        recommended_songs_df = topic_test_df.iloc[top_n_indices]

        # Count how many of the recommended lists are relevant (Hits)
        hits = sum(1 for _, row in recommended_songs_df.iterrows() if is_rel

        # The total number of related songs in the topic in the statistic te
        total_relevant_in_topic = sum(1 for _, row in topic_test_df.iterrows

        # Calculate the evaluation metrics
        precision = hits / num_recommendations if num_recommendations > 0 el
        recall = hits / total_relevant_in_topic if total_relevant_in_topic >
        if precision + recall == 0:
            f1_score = 0.0
        else:
            f1_score = 2 * (precision * recall) / (precision + recall)

        # Stored results are used to calculate an overall average
        # Evaluation of the topic is only meaningful if there are related so
        if total_relevant_in_topic > 0:
            overall_metrics['precision'].append(precision)
            overall_metrics['recall'].append(recall)
            overall_metrics['f1'].append(f1_score)

        print(f"\n  Topic: {topic}")
        print(f"    - Precision@{N}: {precision:.2f}")
        print(f"    - Recall@{N}:    {recall:.2f}")
        print(f"    - F1-Score@{N}:  {f1_score:.2f}")
        print(f"    (Found {hits} relevant songs in top {num_recommendations

    # Calculate and print the overall average metrics for this user
    avg_precision = np.mean(overall_metrics['precision']) if overall_metrics
    avg_recall = np.mean(overall_metrics['recall']) if overall_metrics['reca
    avg_f1 = np.mean(overall_metrics['f1']) if overall_metrics['f1'] else 0.

    print("\n  -----------------------------")
    print(f"  Overall for {user_name}:")
    print(f"    - Avg. Precision@{N}: {avg_precision:.2f}")
    print(f"    - Avg. Recall@{N}:    {avg_recall:.2f}")
    print(f"    - Avg. F1-Score@{N}:  {avg_f1:.2f}")
    print("  -----------------------------")
```

```
========================
 EVALUATION FOR PROFILE SIZE M = 5
========================

----- User: User 1 -----

  Topic: dark
    - Precision@10: 0.40
    - Recall@10:    0.22
    - F1-Score@10:  0.29
    (Found 4 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 18)

  Topic: sadness
    - Precision@10: 0.30
    - Recall@10:    0.25
    - F1-Score@10:  0.27
    (Found 3 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 12)

  Topic: personal
    - Precision@10: 1.00
    - Recall@10:    0.25
    - F1-Score@10:  0.40
    (Found 10 relevant songs in top 10 recommendations. Total relevant songs in t
est set for this topic: 40)

  Topic: lifestyle
    - Precision@10: 0.70
    - Recall@10:    0.50
    - F1-Score@10:  0.58
    (Found 7 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 14)

  Topic: emotion
    - Precision@10: 0.78
    - Recall@10:    1.00
    - F1-Score@10:  0.88
    (Found 7 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 7)

  ----------------------------
  Overall for User 1:
    - Avg. Precision@10: 0.64
    - Avg. Recall@10:    0.44
    - Avg. F1-Score@10:  0.48
  ----------------------------

----- User: User 2 -----

  Topic: sadness
    - Precision@10: 0.20
    - Recall@10:    0.29
    - F1-Score@10:  0.24
    (Found 2 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 7)

  Topic: emotion
    - Precision@10: 0.22
    - Recall@10:    1.00
```

```
    - F1-Score@10:  0.36
    (Found 2 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 2)

  ----------------------------
  Overall for User 2:
    - Avg. Precision@10: 0.21
    - Avg. Recall@10:    0.64
    - Avg. F1-Score@10:  0.30
  ----------------------------

----- User: User 3 -----

  Topic: personal
    - Precision@10: 1.00
    - Recall@10:    0.22
    - F1-Score@10:  0.36
    (Found 10 relevant songs in top 10 recommendations. Total relevant songs in t
est set for this topic: 45)

  Topic: sadness
    - Precision@10: 0.40
    - Recall@10:    0.17
    - F1-Score@10:  0.24
    (Found 4 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 24)

  Topic: emotion
    - Precision@10: 0.22
    - Recall@10:    1.00
    - F1-Score@10:  0.36
    (Found 2 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 2)

  ----------------------------
  Overall for User 3:
    - Avg. Precision@10: 0.54
    - Avg. Recall@10:    0.46
    - Avg. F1-Score@10:  0.32
  ----------------------------

=========================
 EVALUATION FOR PROFILE SIZE M = 10
=========================

----- User: User 1 -----

  Topic: dark
    - Precision@10: 0.40
    - Recall@10:    0.22
    - F1-Score@10:  0.29
    (Found 4 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 18)

  Topic: sadness
    - Precision@10: 0.30
    - Recall@10:    0.25
    - F1-Score@10:  0.27
    (Found 3 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 12)
```

```
  Topic: personal
    - Precision@10: 1.00
    - Recall@10:    0.25
    - F1-Score@10:  0.40
    (Found 10 relevant songs in top 10 recommendations. Total relevant songs in t
est set for this topic: 40)

  Topic: lifestyle
    - Precision@10: 0.70
    - Recall@10:    0.50
    - F1-Score@10:  0.58
    (Found 7 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 14)

  Topic: emotion
    - Precision@10: 0.78
    - Recall@10:    1.00
    - F1-Score@10:  0.88
    (Found 7 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 7)

  ----------------------------
  Overall for User 1:
    - Avg. Precision@10: 0.64
    - Avg. Recall@10:    0.44
    - Avg. F1-Score@10:  0.48
  ----------------------------

----- User: User 2 -----

  Topic: sadness
    - Precision@10: 0.10
    - Recall@10:    0.14
    - F1-Score@10:  0.12
    (Found 1 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 7)

  Topic: emotion
    - Precision@10: 0.22
    - Recall@10:    1.00
    - F1-Score@10:  0.36
    (Found 2 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 2)

  ----------------------------
  Overall for User 2:
    - Avg. Precision@10: 0.16
    - Avg. Recall@10:    0.57
    - Avg. F1-Score@10:  0.24
  ----------------------------

----- User: User 3 -----

  Topic: personal
    - Precision@10: 1.00
    - Recall@10:    0.22
    - F1-Score@10:  0.36
    (Found 10 relevant songs in top 10 recommendations. Total relevant songs in t
est set for this topic: 45)
```

```
  Topic: sadness
    - Precision@10: 0.30
    - Recall@10:    0.12
    - F1-Score@10:  0.18
    (Found 3 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 24)

  Topic: emotion
    - Precision@10: 0.22
    - Recall@10:    1.00
    - F1-Score@10:  0.36
    (Found 2 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 2)

  -----------------------------
  Overall for User 3:
    - Avg. Precision@10: 0.51
    - Avg. Recall@10:    0.45
    - Avg. F1-Score@10:  0.30
  -----------------------------

=========================
 EVALUATION FOR PROFILE SIZE M = 20
=========================

----- User: User 1 -----

  Topic: dark
    - Precision@10: 0.30
    - Recall@10:    0.17
    - F1-Score@10:  0.21
    (Found 3 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 18)

  Topic: sadness
    - Precision@10: 0.30
    - Recall@10:    0.25
    - F1-Score@10:  0.27
    (Found 3 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 12)

  Topic: personal
    - Precision@10: 1.00
    - Recall@10:    0.25
    - F1-Score@10:  0.40
    (Found 10 relevant songs in top 10 recommendations. Total relevant songs in t
est set for this topic: 40)

  Topic: lifestyle
    - Precision@10: 0.70
    - Recall@10:    0.50
    - F1-Score@10:  0.58
    (Found 7 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 14)

  Topic: emotion
    - Precision@10: 0.78
    - Recall@10:    1.00
    - F1-Score@10:  0.88
```

```
    (Found 7 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 7)

  ----------------------------
  Overall for User 1:
    - Avg. Precision@10: 0.62
    - Avg. Recall@10:    0.43
    - Avg. F1-Score@10:  0.47
  ----------------------------

----- User: User 2 -----

  Topic: sadness
    - Precision@10: 0.10
    - Recall@10:    0.14
    - F1-Score@10:  0.12
    (Found 1 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 7)

  Topic: emotion
    - Precision@10: 0.22
    - Recall@10:    1.00
    - F1-Score@10:  0.36
    (Found 2 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 2)

  ----------------------------
  Overall for User 2:
    - Avg. Precision@10: 0.16
    - Avg. Recall@10:    0.57
    - Avg. F1-Score@10:  0.24
  ----------------------------

----- User: User 3 -----

  Topic: personal
    - Precision@10: 1.00
    - Recall@10:    0.22
    - F1-Score@10:  0.36
    (Found 10 relevant songs in top 10 recommendations. Total relevant songs in t
est set for this topic: 45)

  Topic: sadness
    - Precision@10: 0.30
    - Recall@10:    0.12
    - F1-Score@10:  0.18
    (Found 3 relevant songs in top 10 recommendations. Total relevant songs in te
st set for this topic: 24)

  Topic: emotion
    - Precision@10: 0.22
    - Recall@10:    1.00
    - F1-Score@10:  0.36
    (Found 2 relevant songs in top 9 recommendations. Total relevant songs in tes
t set for this topic: 2)

  ----------------------------
  Overall for User 3:
    - Avg. Precision@10: 0.51
    - Avg. Recall@10:    0.45
```

```
  - Avg. F1-Score@10:  0.30
-----------------------------
```

Analysis of Recommendation Performance

To evaluate the effectiveness of our content-based music recommender system, we tested three users with different topic interests using **profile sizes M = 5, 10, 20**, **CountVectorizer** for text representation, and **cosine similarity** for matching.

Each user profile was constructed from the top M most frequent words in the songs they liked from Weeks 1–3. We then recommended songs from Week 4 and evaluated using the following metrics:

- **Precision@10**: Proportion of recommended songs that were relevant.
- **Recall@10**: Proportion of relevant songs that appeared in the top 10 recommendations.
- **F1-Score@10**: Balance between precision and recall.

Evaluation Insights

User 1

- Achieved consistently strong results across all M values.
- Precision remained at **0.64** and F1-Score around **0.48**, indicating high relevance in the top 10 recommendations.
- Particularly in the "emotion" topic, the system achieved **perfect recall (1.00)** and **high precision (0.78)**, showing excellent topic alignment.
- Increasing M beyond 5 offered **no measurable gain**, suggesting a focused and well-captured preference profile.

User 2

- Exhibited a **clear trade-off** between precision and recall.
- For M = 5, precision was **0.21** but recall was **0.64**, leading to an F1-Score of **0.30**.
- As M increased to 10 and 20, precision dropped further (down to **0.16**), with recall remaining constant.
- This indicates that expanding the profile introduced noise without improving recommendation coverage.

User 3

- Maintained **stable and reliable performance** across all M values.
- Precision stayed above **0.50**, with F1-Scores around **0.30–0.32**.
- Notably, the "personal" topic achieved **precision of 1.00** and reasonable recall.
- The stability suggests that even a small profile (M = 5) is sufficient to model this user's preferences effectively.

Final Decision

Based on these results, we conclude the following:

- **M = 5** provides the best balance of precision and recall across all users, with minimal risk of introducing irrelevant words.
- **Larger profile sizes** (M = 10, 20) do not improve performance and may reduce precision due to added noise.
- The use of **CountVectorizer** for user profiles, combined with **cosine similarity** for recommendation matching, proves to be both simple and effective.

Part 3. User Evaluation

To simulate a realistic user evaluation, we selected a user to act as the test subject. The user was shown N = 10 songs per week for Weeks 1–3 (i.e., 30 training songs total), randomly selected from each week's pool.

The user was asked to indicate which songs they "liked". This feedback was used to build the user's profile following the same method from Part 2.

In Week 4, the system recommended 10 songs using the selected matching algorithm (e.g., cosine similarity) and topic-based filtering.

The user was asked to review these 10 songs and indicate whether they matched their preferences.

In [44]:
```
N = 10

# Week ranges (250 songs per week)
week_ranges = {
    'Week 1': (0, 250),
    'Week 2': (250, 500),
    'Week 3': (500, 750)
}

def display_song_info(song_row):
    print(f"{song_row['track_name']}    By    {song_row['artist_name']}")

    if 'release_date' in song_row:
        print(f"Released: {song_row['release_date']}")
    if 'genre' in song_row:
        print(f"Genre: {song_row['genre']}")

    lyrics = song_row['content']
    lines = lyrics.split('\n')
    short_lyrics = '\n   '.join(lines[:2])  # Show first 2 lines of lyrics
    print(f"Lyrics:\n   {short_lyrics}")
    print("-" * 50)

# Dictionary to store songs shown to user for each week
user_interactions = {}

for week, (start_idx, end_idx) in week_ranges.items():
    # Sample N unique random indices from the week
    sampled_indices = random.sample(range(start_idx, end_idx), N)

    # Get the corresponding song rows
```

```python
    sampled_songs = train_data.iloc[sampled_indices]

    # Save for future analysis
    user_interactions[week] = sampled_songs

    # Display for user interaction
    print(f"\n {week} \n")
    for idx, row in sampled_songs.iterrows():
        display_song_info(row)
```

Week 1

crystal night   By   black lips
Released: 2017
Genre: blues
Lyrics:
black lips crystal night blues remember snow fall hold arm kiss think november time say goodbye night go wish hop pray long time say goodbye night wanna know alive mind night night night night remember time look eye think sugar life say goodbye send night live planet meet heaven goodbye night wanna know like tell end things right night night night night
----
your love awakens me   By   phil wickham
Released: 2016
Genre: rock
Lyrics:
phil wickham your love awakens me rock wall cross come break break chain longer bind longer bind call grave call light call heart come alive greater stronger awaken awaken awaken greater stronger awaken awaken awaken feel darkness shake dead come life life hear song awaken creation sing alive cause alive death hold shout alive cause alive
----
the wild   By   mumford & sons
Released: 2018
Genre: rock
Lyrics:
mumford & sons the wild rock burn death make kind come sparkle mind earth tie knot lyric commercial
----
walls   By   jamie n commons
Released: 2018
Genre: blues
Lyrics:
jamie n commons walls blues yeah knowwoahow hard time dear yeah knowwoahow long time dear time change hmmm right savior bid flame wall come fall wall come fall savior fight flame wall come fall wall come fall wall come fall wall come fall wall come fall wall come fall wall come fall hand understand savior bid flame wall come fall wall come fall savior fight flame wall come fall wall come fall wall come fall wall come fall wall come fall wall come fall wall come fall savior bid flame wall come fall wall come fall savior fight flame wall come fall wall come fall wall come fall wall come fall wall come fall wall come fall wall come fall
----
mystery of love   By   sufjan stevens
Released: 2017
Genre: rock
Lyrics:
sufjan stevens mystery of love rock eye time kiss boundless time cry build wall white noise awful sound fumble rogue river feel feet grind hand deliver woeohwoah time touch wonder cease bless mystery lyric commercial
----
your love defends me   By   matt maher
Released: 2017
Genre: rock
Lyrics:
matt maher your love defends me rock song draw refuge life long surely strength soul defend defend feel like defend defend night night remember fight battle rag know surely strength soul lyric commercial
----
natural   By   imagine dragons
Released: 2018

Genre: rock
Lyrics:
  imagine dragons natural rock hold line give give tell house come consequence co
st tell star align heaven step save cause house stand strong leave heart cast awa
y product today prey stand edge face cause natural beat heart stone gotta cold wo
rld yeah natural live life cutthroat gotta cold yeah natural lyric commercial
----
within you, without you   By   tedeschi trucks band
Released: 2017
Genre: blues
Lyrics:
  tedeschi trucks band within you, without you blues talk space people hide wall
illusion glimpse truth late pass away talk share best hold save world know realis
e change small life flow talk go cold people gain world lose soul know see peace
mind wait time come life flow
----
hurt you   By   the weeknd
Released: 2018
Genre: pop
Lyrics:
  the weeknd hurt you pop know relationship enemy stay away warn void meet cause
upset warn cause nights sleep dryin eye nights think takin life cause want waste
time sight wanna hurt wanna hurt wanna hurt wanna hurt close eye think weak girl
come legs heart nights sleep dryin eye cause baby nights think takin life cause b
aby want waste time waste sight wanna hurt wanna hurt wanna hurt wanna hurt wann
a hurt wanna hurt wanna hurt wanna hurt want want want want wanna baby wanna baby
----
the movie song   By   the record company
Released: 2018
Genre: blues
Lyrics:
  the record company the movie song blues come point life search search days drea
m rid father country roads pretend drive windows roll think brothers things come
point life remember remember days things weren complicate run trail call head tai
l work school try tell truth fast free free think summer young know think alout m
other fill everybody wanna movie everybody act like time change everybody wanna m
ovie everybody act like time change yeah yeah yeah yeah come point life remember
remember afraid like younger days life thousands smile goodbyes crossroads straig
htways think grandfather teach teach work harder folks depend everybody wanna mov
ie everybody act like time change everybody wanna movie everybody act like time c
hange everybody wanna movie everybody act like time change yeah yeah yeah yeah ch
ange yeah yeah yeah change wanna tell baby change wanna tell baby change wanna te
ll baby change wanna tell change everybody wanna movie everybody act like time ch
ange yeah yeah change yeah yeah change

 Week 2

black and white   By   christie huff
Released: 2019
Genre: country
Lyrics:
  christie huff black and white country time game fight hurt tear stay straight c
ore room second place home rise rise versus beast rise strong survive rise time w
eak time rise break dust come reach deep break grind beat brush come come time se
ttle score blood fight break talk trash step plate rise refuse rise ash dust rise
remember rise trust
----
everything now   By   arcade fire
Released: 2017

Genre: rock
Lyrics:
  arcade fire everything now rock inch inch skin scar guess inch space head fill things read guess film see fill space dream remind inch road sign use line pledge allegiance song hear play time absurd remind turn speakers break cause time smile fake stop pretend need want live live inch road daddy come miss like mama leave food stave leave middle road family turn speakers break cause time smile fake stop pretend need want live live room house fill couldn live need live lalala lalala lala lalala lalala lala stop pretend need want live live live room house fill couldn live need live live inch space heart fill start ash black
----
american dream   By   samantha fish
Released: 2017
Genre: blues
Lyrics:
  samantha fish american dream blues blood street lose count die liberate free free disenfranchise bless country live american dream live american dream live american dream live american dream hand bible foot neck live halfpast halfmast semiautomatic help come start pray cause live american dream live american dream live american dream live american dream babe live american dream live american dream live american dream live american dream woah live american dream baby live american dream live american dream live american dream
----
graveyard   By   kelsea ballerini
Released: 2018
Genre: country
Lyrics:
  kelsea ballerini graveyard country wanna skeleton closet throw cause know okay stone road forget cause fall fast dash date wanna heart graveyard cold hard dirt throw wanna watch drive away black hopeless break girl little black dress break heart rest peace right maybe naive believe hurt know hide darkest suit shade know hand shoe dirty guess need shovel grave wanna heart graveyard cold hard dirt throw wanna watch drive away black hopeless break girl little black dress break heart rest peace right yeah gonna night cause ghost break heart stay feet yeah gonna night cause ghost break heart stay feet wanna heart graveyard cold hard dirt throw wanna watch drive away black hopeless break girl little black dress break heart rest peace right hopeless break girl break heart rest peace right wanna heart wanna heart graveyard babe graveyard
----
let me live / let me die   By   des rocs
Released: 2018
Genre: blues
Lyrics:
  des rocs let me live / let me die blues know pain know dread wicked vein turn lead tear stop kill time dead eye leave kiss cobra kill time live live live live live live live live right like moment kill time fear dark thoughts yeah stop meet friend lonesome kill time live live live live live live live live whoa whoa live live live live live live live live
----
anthem   By   greta van fleet
Released: 2018
Genre: blues
Lyrics:
  greta van fleet anthem blues news people think different ways music tune free soul simple lyric unite know opinion know thing want choose save time stay open mind glow twilight know world world agree disagree world world noise face color world turn grey void place come step want lord opinion know thing want choose save time stay open mind glow twilight know world world agree disagree world world glow twilight know world world agree disagree world world glow twilight know world world agree disagree world world glow twilight know world world agree disagree world

world
----
hobo   By   charlie parr
Released: 2016
Genre: blues
Lyrics:
  charlie parr hobo blues want dead book start read bear follow step tread know f
lee somebody tell somebody tell go somebody spend minute pray hobo go wrong song
sing contain refrain change remember face maybe somebody tell somebody tell go so
mebody spend minute pray hobo go wrong life long hours long breathe close eye rol
l miss somebody tell somebody tell go somebody spend minute pray hobo go wrong wo
ods end live lake know come somebody tell somebody tell go somebody spend minute
pray hobo go wrong
----
the world connects   By   don philippe
Released: 2016
Genre: jazz
Lyrics:
  don philippe the world connects jazz buju banton yout brownin song hear tell ca
use cyant shoe tongue grun hear stop black woman girls dark complexion cause stop
black woman nuff ting gwan complexion black beauty colla million birth natural sm
ooth lika grape true lotion teki teki care complexion whola plan wrong bcaw black
woman stop black woman girls dark complexion cause stop black woman nuff ting gwa
n complexion true lite skin want woman baddah worry intension wedah black buju ri
ght spead nation backitive buju banton stop black woman girls dark complexion cau
se stop black woman nuff ting gwan complexion black proud folla buju banton shout
loud black stand crowd like line behin dark cloud stop black woman girls dark com
plexion cause stop black woman nuff ting gwan complexion
----
my queen is ada eastman   By   sons of kemet
Released: 2018
Genre: jazz
Lyrics:
  sons of kemet my queen is ada eastman jazz grind hustle strive dark time dark m
ind chime wanna smile wanna grimey politics lively sirens thunder clap violence d
ust scribe visit highness dear despite prophecies seers smash piece like ikea bra
ss garment wash starch london wind bite harsh shiver moustache crude crass will a
ble task high fact high like cool like queen castle school like tomatoes stand sh
oulder greats hand enemies cake river lake will rebel revel calm inside kettle ca
lm time unsettle settle want beef serve feline vermin black proud determine jump
leave ditch priest drive witch heartbreak flag pitch cut hunger fine things learn
lesson time bring acquire taste london pride spread wing noxious sky streets stre
ets fox hide wise strife stride admit tough time like dive end pressure pile unru
ly sound fury frown fury fury peer jury burn ukip tories fascists story   truly
roach cause resilient bear strong immigrant struggle element cities sediment bord
er fence leave bank stop sell debt leaders stop sell death lose relevance corner
paper scribe testament know
----
pearl cadillac   By   gary clark jr.
Released: 2019
Genre: blues
Lyrics:
  gary clark jr. pearl cadillac blues nothin world somethin nothin thank beautifu
l girl bring world yeah remember leave home cadillac search kinda proud money und
erstand sacrifice late nights fuss fight home sorry things wrong remember leave h
ome cadillac search kinda proud wanna wanna proud nothin world somethin nothin th
ank beautiful girl world yeah
----

backroad song   By   granger smith
Released: 2016
Genre: pop
Lyrics:
  granger smith backroad song pop barb wire fence carve hillside cut hole midday like postcard frame windshield cover dust rhythm grey blacktop whistle steer whee l hand hug line windows sing oohoohooh freedom roll oohoohooh cruise backroad son g feel wheel like like radio dial strong come come sing sing backroad song oohooh ooh oohoohooh brake holland hammer pass breeze smell like summertime field window s sing oohoohooh freedom roll oohoohooh cruise backroad song feel wheel like like radio dial strong sing sing backroad song oohoohooh oohoohooh today better girl t hink pick slide truck hear sing oohoohooh hear sing oohoohooh oohoohooh freedom r oll oohoohooh cruise backroad song feel wheel like like radio dial strong sing si ng backroad song sing sing backroad song backroad song oohoohooh feel rhythm feel rhythm backroad song oohoohooh feel rhythm feel rhythm come come sing oohoohooh f eel rhythm feel rhythm backroad song oohoohooh feel rhythm feel rhythm
----
distraction (feat. garrett douglas)   By   unified highway
Released: 2016
Genre: reggae
Lyrics:
  unified highway distraction (feat. garrett douglas) reggae know talk focus matt er hear scream shout zero chatter distraction reaction gonna stay grind eskimo cu tter surround frown matter distraction reaction
----
chlorine   By   twenty one pilots
Released: 2018
Genre: pop
Lyrics:
  twenty one pilots chlorine pop little sippin straight chlorine vibe slide beat chemical beat chemical leave save seat complete moment medical moment medical sip pin straight chlorine lovin tastin woah venom tongue dependent time poisonous vib rations woah help body runnin life runnin life sippin straight chlorine vibe slid e beat chemical beat chemical leave save seat complete moment medical moment medi cal sippin straight chlorine fall formation woah plan escape wall confine rebel c arnation woaaoh grow decay runnin life runnin life yeah runnin life runnin life h ide coat pocket keep rebel felt invincible wrap head different live lead body liv e lead line read incorrect say lead terrible flavor double paper maker despise ha te fight life like sippin straight chlorine vibe slide beat chemical beat chemica l leave save seat complete moment medical moment medical sippin straight chlorine vibe vibe vibe vibe beat chemical yeah vibe vibe vibe vibe moment medical yeah si ppin straight chlorine vibe vibe vibe vibe beat chemical yeah vibe vibe vibe vibe moment medical yeah sorry forget catch speed test like end weather flag build hou se piece chemical build house piece chemical build house piece chemical build hou se piece chemical
----
there's a small hotel   By   bill charlap trio
Released: 2017
Genre: jazz
Lyrics:
  bill charlap trio there's a small hotel jazz stare wonder bring martyr sure cro wn light bone like compare time heroes ghost sell sorrow ones pay heroes dead go inside live dark devotion vacant paradise show emotion will sacrifice trial guilt y cage animal away rage like compare time heroes ghost sell sorrow ones pay heroe s dead go inside live heroes ghost sell sorrow ones pay heroes dead go inside liv e dead go
----
champ   By   govana
Released: 2018

Genre: reggae
Lyrics:
govana champ reggae ghetto youths things dream dream yeah matter hard dream matter hard feel like champ right smile bank right yeah mansion plan right start bimmer drive yeah haffi thank worst pass time touch plane class nuff reach noweh easily take girl draw ghetto youth idol survival final thirtytwo clip know hate sister wife gyal build spliff vital suck mother grabba burn sliff ital dream matter hard yeah believe self dweet hard world take ghetto youth make right go dough bigzim smell bread bake create money money save rain come future bright like match play stadium gainst lose money homestead scar fear know badmind look somebody meds tear right bimmer gear dream know older experience wiser govana gain matter hard dream truly deablo youth matter hard youthes mean cause people real enuh know gwaan

----

most people are good By luke bryan
Released: 2017
Genre: country
Lyrics:
luke bryan most people are good country believe kid oughta stay kid long turn screen climb tree dirt hand believe gotta forgive amend cause get second friends believe work hard hell believe people good mamas oughta qualify sainthood believe friday nights look better neon stadium light believe ashamed believe world half look believe people good believe streets gold work wanna pave dirt believe youth spend young cause wisdom teens believe nightly news mankind thing lose believe people good mamas oughta qualify sainthood believe friday nights look better neon stadium light believe ashamed believe world half look believe people good believe days slow years fast breath gift believe people good mamas oughta qualify sainthood believe friday nights look better neon stadium light believe ashamed believe world half look believe people good believe people good believe people good

----

boa By sam gendel
Released: 2018
Genre: jazz
Lyrics:
sam gendel boa jazz rebel rebel yell cause people dwell hell lock cell structure cell story tell long seein stake action reaction mind somewhat complacent state check stick freedom life lord wish peaceful sequel freedom fundamental johannesburg south central cause tell kick township rebellion yeah sucka yeah think hardlines mind thoughts battle fight lessons teach display fitness flip like gymnast raise fist resist asleep stand midst gotta gotta keepin warm cause offer think nothin coffin gotta wreck neck swing rope cape freedom fundamental johannesburg south central cause tell kick township rebellion stand silent platform fight stand silent platform fight stand silent platform fight stand silent platform fight stand silent platform fight stand silent platform fight stand silent platform fight stand silent platform fight gonna shackle mind bend cross ignorance reign life lose shackle mind leave cross ignorance reign life lose shackle mind bend cross ignorance reign life lose shackle mind leave cross ignorance reign life lose lose lose shackle mind leave cross ignorance reign life lose shackle mind bend cross ignorance reign life lose lose stand silent platform fight stand silent platform fight stand silent platform fight stand silent platform fight

----

soul eyes By walt weiskopf
Released: 2018
Genre: jazz
Lyrics:
walt weiskopf soul eyes jazz bear dark cloud hover city stay recollect clear days haze city stay grey great consistently hat want change wasn afraid think live days year eternity yeah think keep hush keep hush keep hush yeah keep quiet open philosophy corrupt decision make music pass time store mind push realise lot criticise days days think days days days days reminisce days days days days think day

```
s days days days reminisce days days celebrate time add number start routine morn
ing thing week speak open mouth pretend listen space start doubt instead devout s
ay loud think allow keep hush keep hush keep hush yeah keep quiet open philosophy
corrupt decision make music pass time store mind push realise lot criticise days
days think days days days days reminisce days days days days think days days days
days reminisce days days days days think days days days days reminisce days days
days days think days days days days reminisce days days
--------------------------------------------------
self-inflicted wounds    By    joe bonamassa
Released: 2018
Genre: blues
Lyrics:
  joe bonamassa self-inflicted wounds blues nerve blame mistake nerve open head w
eight yeah late night yeah pretend know selfinflicted wound yeah draw knife throw
stone trust abuse selfinflicted wound away try tell lie away hold tear darling ho
ld explain darling hold tryin pain selfinflicted wound draw knife throw stone tru
st abuse selfinflicted wound yeah look redemption hallow grind yeah pray forgiven
ess search selfinflicted wound draw knife throw stone trust abuse self inflict wo
und selfinflicted wound
--------------------------------------------------
moth into flame    By    metallica
Released: 2016
Genre: rock
Lyrics:
  metallica moth into flame rock black queen amphetamine scream crash silence tap
douse gasoline high time go timeless decadence death innocence pathway start spir
al infamy publicity destruction go viral light light erase pain bulletproof kill
truth fall think fly high high sell soul build higher wall yesterday throw away r
ise fall care seduce fame moth flame twist backstabbing wicked delusion absolutio
n perjurer fame murderer seduce ruin light light erase pain bulletproof tell trut
h fall think fly high high sell soul build higher wall yesterday throw away rise
fall care seduce fame moth flame burn guarantee kill vultures feast overdose sham
e insecurity fistful death scene black hearse limousine grave fill seduction vacc
ine fame murder build destruction light light erase pain bulletproof excuse fall
think fly high high sell soul build higher wall yesterday throw away rise fall ca
re seduce fame moth flame addict fame
--------------------------------------------------
```

My friend's choice

In [53]:
```python
# Stores an index of the user's favorite song list
user_likes = {
    'Week 1': [154],
    'Week 2': [450, 430],
    'Week 3': [565]
}

liked_indices = [idx for week_likes in user_likes.values() for idx in week_likes
liked_songs_df = df.iloc[liked_indices]
combined_liked_lyrics = ' '.join(liked_songs_df['content'].apply(preprocess_text
user_profile_vector = vectorizer.transform([combined_liked_lyrics])
```

In [54]:
```python
week_4_data = df.iloc[750:1000]
week_4_vectors = vectorizer.transform(week_4_data['content'].apply(preprocess_te
similarities = cosine_similarity(user_profile_vector, week_4_vectors).flatten()

# Get the index of the N songs with the highest similarity
top_n_relative_indices = similarities.argsort()[::-1][:N]
```

```python
top_n_absolute_indices = week_4_data.index[top_n_relative_indices]

# Get recommended songs
recommended_songs_df = df.loc[top_n_absolute_indices]

print("\n==================== RECOMMENDED FOR YOU IN WEEK 4 ====================
print("Based on your likes from the past 3 weeks, here are 10 songs for you:\n")
for _, row in recommended_songs_df.iterrows():
    display_song_info(row)
```

==================== RECOMMENDED FOR YOU IN WEEK 4 ====================
Based on your likes from the past 3 weeks, here are 10 songs for you:

living it up   By   damian marley
Released: 2017
Genre: reggae
Lyrics:
  damian marley living it up reggae daddy ghetto believe dream believe live have good time baby bear uptown ghetto dream life crazy daddy ghetto believe dream believe live have good time baby bear uptown ghetto dream lazy trenchtown grandson growin somebody gong zilly flow phenomenally kind thing happen normally zillion dawg want good life finally change night time hobby come crime lobby benefit wisdom gwaan live life better great voice dozen dubplate hustle sidung tough unnu muscle late gwaan celebrate people place likkle rastaman trenchtown gate food plate drink crate sing till neighbour daddy ghetto believe dream believe live have good time baby bear uptown ghetto dream life crazy daddy ghetto believe dream believe live have good time baby bear uptown ghetto dream lazy uptown jamaica bear raise playground spend days burnin babylon dirty ways watchin kid goin astray uptown jamaica bear raise playground spend days city life mobay think sell tell live trenchtown rema riverton southside jungle garden spanglers payneland mile backto portmore seaview spanish mile brownstown flankers falmouth westside orange daddy ghetto believe dream believe live have good time baby bear uptown ghetto dream life crazy daddy ghetto believe dream believe live have good time baby bear uptown ghetto dream lazy
----
sit awhile   By   the band steele
Released: 2017
Genre: country
Lyrics:
  the band steele sit awhile country wake favorite place studio hide space cold dark room need feet walk streets headphones beat know go want yeah yeah shall time lose open road lose lesson learn road choose concern time live time time laugh time time time hate world heavy feel weight know yeah know know yeah know things finally look shoot truth hurt turn world upside catch middle go come dream dream high tell live life know certain think agree real life dream yeah yeah dream dream dream dream
----
live well   By   palace
Released: 2016
Genre: rock
Lyrics:
  palace live well rock sundown slow remind free freeer feel wonderfully breathe bless rainfall cleanse like downpour know fine time safe true think live reap future bright flow save goodness give moonrise headlights right trail take life tie upside live sweet sound laugh like warm cut like know fine time safe true think live reap future bright flow save goodness give mystery come come know dream depart end start pray come thank live reap future bright flow save goodness give live reap future bright flow save goodness give
----
paranormal   By   alice cooper
Released: 2017
Genre: blues
Lyrics:
  alice cooper paranormal blues condemn long endless night live absense light life watch sleep night cool skin bone wrap sheet ring dead telephone scar home like spider kiss face familiar smell scent leave lace condemn long endless night live absense light
----
this love   By   kadhja bonet
Released: 2016

Genre: jazz
Lyrics:
  kadhja bonet this love jazz better match know catch give pair cavalier friend want care confidant bravery embolden renew think love show years live dream days apart wear heart draw path memories begin walk turtle remain share window pane path dream think love show years live dream promise need think love show years live dream

----

pressure under fire   By   gov't mule
Released: 2017
Genre: blues
Lyrics:
  gov't mule pressure under fire blues song thing write think know better maybe lonely voice gonna sing fight thing travel life road people share yeah share time hear pressure live fear understand clear pressure live land know end time place think learn time blow face time burn move wrong direction head track time turn back people turn back time hear pressure live fear understand clear pressure live land wise say human race race dispel darkness darkness say time learn work gonna mess song thing sing think know better time hear pressure live fear understand clear pressure live land pressure live fear understand clear pressure live land live live land

----

black   By   dierks bentley
Released: 2016
Genre: country
Lyrics:
  dierks bentley black country moon outside bright blind yeah close know hand know finger tip lips flip switch world black like heart attack knock flat yeah thing brush hair swear know long world black black world black black like dress floor yeah need anymore black like star fall arm world black like heart attack knock flat yeah thing brush hair swear know long world black black world black black wanna thing baby wanna feel touch feel rush wanna thing wanna feel world black like heart attack knock flat yeah thing brush hair swear know long world black black world black black world black black wanna thing black black wanna feel touch feel rush black black black black

----

live without limit   By   jahmiel
Released: 2018
Genre: reggae
Lyrics:
  jahmiel live without limit reggae yeah yeah yeah yellow moon clock tick eye drip give time hear life live hard yeah yeah tomorrow promise live limit live limit yeah yeah yeah sure bout tomorrow hard nuff know stop yeah afraid live fear greater reason life live hard yeah yeah tomorrow promise live limit live limit yeah yeah yeah señorita feature yeah like whoa life like speaker thing turn load things easier cyaan ease people time hand sit watch people grow time things whoa life live hard yeah yeah tomorrow promise live limit live limit yeah yeah yeah clock tick eye drip give yeah yeah yeah yeah clock tick eye drip give yellow moon yeah life live hard yeah yeah tomorrow promise live limit live limit yeah yeah yeah

----

brace for impact (live a little)   By   sturgill simpson
Released: 2016
Genre: country
Lyrics:
  sturgill simpson brace for impact (live a little) country life party break burden shoulder die live live matter believe ones leave live little bone turn brittle skin wither eye sure little great unknown forgiveness scream like baby cry world goodbye welcome live little bone turn brittle skin wither eye sure little great unknown

----

```
under your scars    By    godsmack
Released: 2018
Genre: rock
Lyrics:
  godsmack under your scars rock sense think spite black white wrong long feel ri
ght think star align scar pray like shoot rain feel like home yeah scar live insi
de time time live inside live inside lyric commercial
--------------------------------------------------
```

In [59]:

```python
liked_song_indices = {815, 985, 839, 875}

print("\nUser's Feedback on the Recommendation List:")
print("-" * 45)

for idx, row in recommended_songs_df.iterrows():
    if idx in liked_song_indices:
        feedback = "Yes"
    else:
        feedback = "No"

    print(f"Song:   {row['track_name']}    By    {row['artist_name']}")
    print(f"  Liked by user: {feedback}\n")

print("-" * 45)
```

```
User's Feedback on the Recommendation List:
---------------------------------------------
Song:   living it up    By    damian marley
  Liked by user: No

Song:   sit awhile    By    the band steele
  Liked by user: No

Song:   live well    By    palace
  Liked by user: Yes

Song:   paranormal    By    alice cooper
  Liked by user: Yes

Song:   this love    By    kadhja bonet
  Liked by user: Yes

Song:   pressure under fire    By    gov't mule
  Liked by user: No

Song:   black    By    dierks bentley
  Liked by user: No

Song:   live without limit    By    jahmiel
  Liked by user: Yes

Song:   brace for impact (live a little)    By    sturgill simpson
  Liked by user: No

Song:   under your scars    By    godsmack
  Liked by user: No

---------------------------------------------
```

User feedback

During the session, my friend expressed that:

- He appreciated that the system found "some songs that matched his taste".
- A few songs felt out of place due to lyrics or genre mismatch, even though the topic was technically correct.

This suggests that while topic classification and keyword matching are helpful, incorporating additional features like genre or sentiment might improve satisfaction.

In [60]:
```
# Performance evaluation
hits = len(liked_recs_df)
precision_at_10 = hits / N

recall_at_10 = hits / hits if hits > 0 else 0.0 # This will be 1.0, not very inf
if precision_at_10 + recall_at_10 == 0:
    f1_score_at_10 = 0.0
else:
    f1_score_at_10 = 2 * (precision_at_10 * recall_at_10) / (precision_at_10 + r

metrics_data = {
    'Metric': ['Precision@10', 'Recall@10', 'F1-Score@10'],
    'Score': [f"{precision_at_10:.2f}", f"{recall_at_10:.2f}", f"{f1_score_at_10
}
metrics_df = pd.DataFrame(metrics_data)

print("\n==================== PERFORMANCE METRICS (WEEK 4) ===================="
print(metrics_df.to_string(index=False))
print("=======================================================================")
```

```
==================== PERFORMANCE METRICS (WEEK 4) ====================
      Metric Score
Precision@10  0.40
   Recall@10  1.00
 F1-Score@10  0.57
=======================================================================
```

Conclusion

- **Precision@10 = 0.40** is the most informative metric in this user evaluation. It indicates that under *cold-start* conditions — with only four songs used to build the user profile — the system achieved a 40% hit rate in its recommendations. This is a promising result that demonstrates the baseline effectiveness of the content-based recommendation engine.

- **Recall@10 = 1.00**, however, is less meaningful in this context. Since we cannot know all the songs that the user might actually like in the full test set, the recall metric is artificially inflated by the evaluation setup and does not offer reliable insight into the system's true coverage performance.

- Consequently, **F1-Score@10 = 0.57** is also affected by this inflated recall, and its interpretability is limited. Therefore, analysis in this study should primarily focus on **precision**, which more directly reflects the usefulness of the recommendations shown to the user.

- **Data sparsity** is a significant challenge. The real user profile was constructed from only four liked songs, in contrast to simulated users whose profiles were derived from a much larger number of known preferences. This makes the real-user recommendation task substantially harder and more representative of practical system performance.

- **Improving precision is a priority for future work**. Potential directions include:

    - Employing more sophisticated topic classifiers, such as tree-based models.
    - Incorporating additional song metadata (e.g., genre, release year).
    - Learning personalized weights for different topics based on user preferences.
- Overall, the user study supports the feasibility of our **content-based recommendation approach**. While current results are encouraging, further enhancements are necessary to achieve the robustness and accuracy required for real-world deployment.

In [ ]: