Wanting Xue z5345106

Part 1. Topic Classification

In [1]:
```
# Mount Google Drive
from google.colab import drive
import pandas as pd

drive.mount('/content/drive')

# Construct file path, e.g., file named songs.tsv
file_path = '/content/drive/My Drive/Colab Notebooks/dataset.tsv'

# Load the dataset
df = pd.read_csv(file_path, sep='\t')

# Combine multiple text fields into one 'Content' field as document text
categories = ['dark', 'emotion', 'lifestyle', 'personal', 'sadness']
df['Content'] = (
    'artist_name: ' + df['artist_name'].astype(str) + ' ' +
    'track_name: ' + df['track_name'].astype(str) + ' ' +
    'release_date: ' + df['release_date'].astype(str) + ' ' +
    'genre: ' + df['genre'].astype(str) + ' ' +
    'lyrics: ' + df['lyrics'].astype(str)
)

# Keep only the 'Content' and label columns
df = df[['Content', 'topic']]

# Rename the label column to 'Category' for consistency
df = df.rename(columns={'topic': 'Category'})

# Remove duplicate rows and rows with missing values
df = df.drop_duplicates()
df = df.dropna()

# Print first few rows and dataset info for verification
print(df.head())
print(df.info())
```

```
Mounted at /content/drive
                                                Content   Category
0  artist_name: loving track_name: the not real l...       dark
1  artist_name: incubus track_name: into the summ...  lifestyle
2  artist_name: reignwolf track_name: hardcore re...    sadness
3  artist_name: tedeschi trucks band track_name: ...    sadness
4  artist_name: lukas nelson and promise of the r...       dark
<class 'pandas.core.frame.DataFrame'>
Index: 1480 entries, 0 to 1499
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Content   1480 non-null   object
 1   Category  1480 non-null   object
dtypes: object(2)
memory usage: 34.7+ KB
None
```

Q1. Fixing Simplifications in the Tutorial

(1) Over-aggressive regex removal:

The original regex `r'[^\w\s]'` removes all non-word characters including `@`, `#`, `%`, and so on. These may carry meaning in certain domains. We propose a revised regex:

text = re.sub(r'[^\w\s@#]', '', text)

The performance of the modified code is as follows:

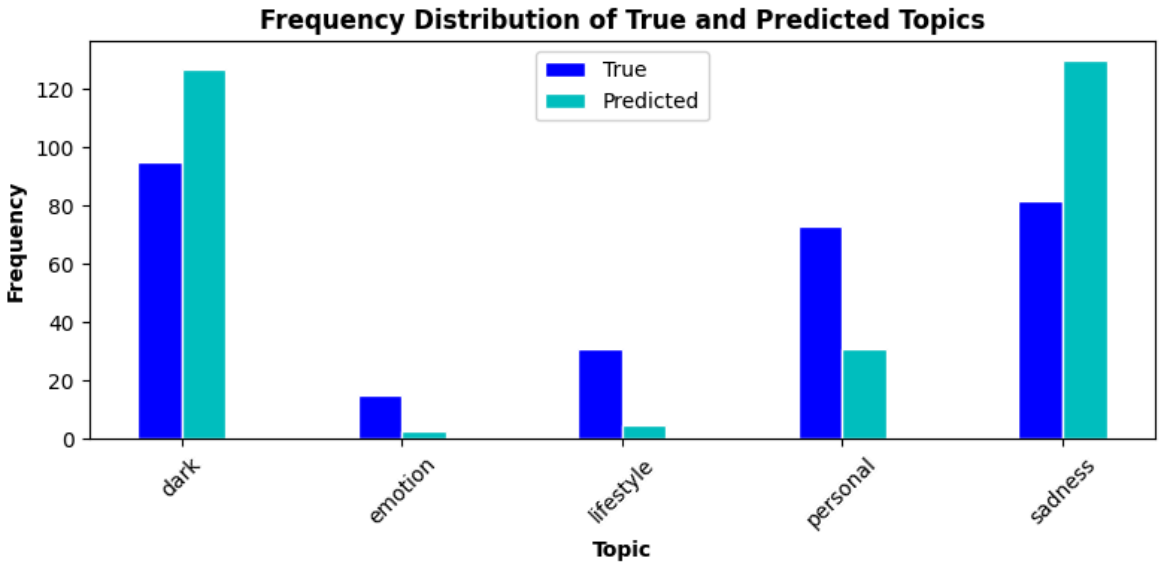
In [ ]:
```
# !rm -rf /root/nltk_data/tokenizers/punkt
# !rm -rf /root/nltk_data/tokenizers/punkt_tab

# !pip install --force-reinstall nltk
```

In [ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics import accuracy_score, classification_report
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
import nltk
import re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from nltk.tokenize import TreebankWordTokenizer

print(nltk.__version__)
nltk.download('stopwords', force=True)
nltk.download('punkt', force=True)
nltk.download('punkt_tab')

ps = PorterStemmer()
stop_words = set(stopwords.words('english'))
tokenizer = TreebankWordTokenizer()

# Define preprocessing function
def preprocess_text(text):
    text = text.lower()
```

```
    # text = re.sub(r'[^\w\s]', '', text)     # Check what this removes --- migh
    text = re.sub(r'[^\w\s@#]', '', text)     # change here
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    tokens = [ps.stem(word) for word in tokens]
    return ' '.join(tokens)

# Apply preprocessing to each document
df['Content'] = df['Content'].apply(preprocess_text)
print(df['Content'].head())

vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(df['Content'])
print(X.shape)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, df['Category'], test_size
print(X_train.shape, X_test.shape)

# Train the Bernoulli Naive Bayes model
bnb = BernoulliNB()
bnb.fit(X_train, y_train)
print(bnb)


# Predict the categories of the test set
y_pred = bnb.predict(X_test)

# Print accuracy and classification report
print(accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

# Plot the distribution of the actual topics in the test set
unique_true, counts_true = np.unique(y_test, return_counts=True)

# Plot the distribution of the predicted topics
unique_pred, counts_pred = np.unique(y_pred, return_counts=True)

plt.figure(figsize=(8,4))

# Create bar width
barWidth = 0.2

# Set position of bar on X axis
r1 = np.arange(len(counts_true))
r2 = [x + barWidth for x in r1]

# Create subplot for 'true' distribution
plt.bar(r1, counts_true, color='b', width=barWidth, edgecolor='white', label='Tr

# Create subplot for 'predicted' distribution
plt.bar(r2, counts_pred, color='c', width=barWidth, edgecolor='white', label='Pr

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics', fontweight='bol

plt.xticks([r + barWidth/2 for r in range(len(counts_true))], categories, rotati

plt.legend()
```

```
plt.tight_layout()
plt.savefig('topic_distribution.png')
plt.show()
```

```
3.9.1
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
0    artist_nam love track_nam real lake release_d ...
1    artist_nam incubu track_nam summer release_d 2...
2    artist_nam reignwolf track_nam hardcor release...
3    artist_nam tedeschi truck band track_nam anyho...
4    artist_nam luka nelson promis real track_nam s...
Name: Content, dtype: object
(1480, 8876)
(1184, 8876) (296, 8876)
BernoulliNB()
0.543918918918919
              precision    recall  f1-score   support

        dark       0.58      0.78      0.67        95
     emotion       0.00      0.00      0.00        15
   lifestyle       0.40      0.06      0.11        31
    personal       0.77      0.33      0.46        73
     sadness       0.47      0.74      0.58        82

    accuracy                           0.54       296
   macro avg       0.45      0.38      0.36       296
weighted avg       0.55      0.54      0.50       296
```



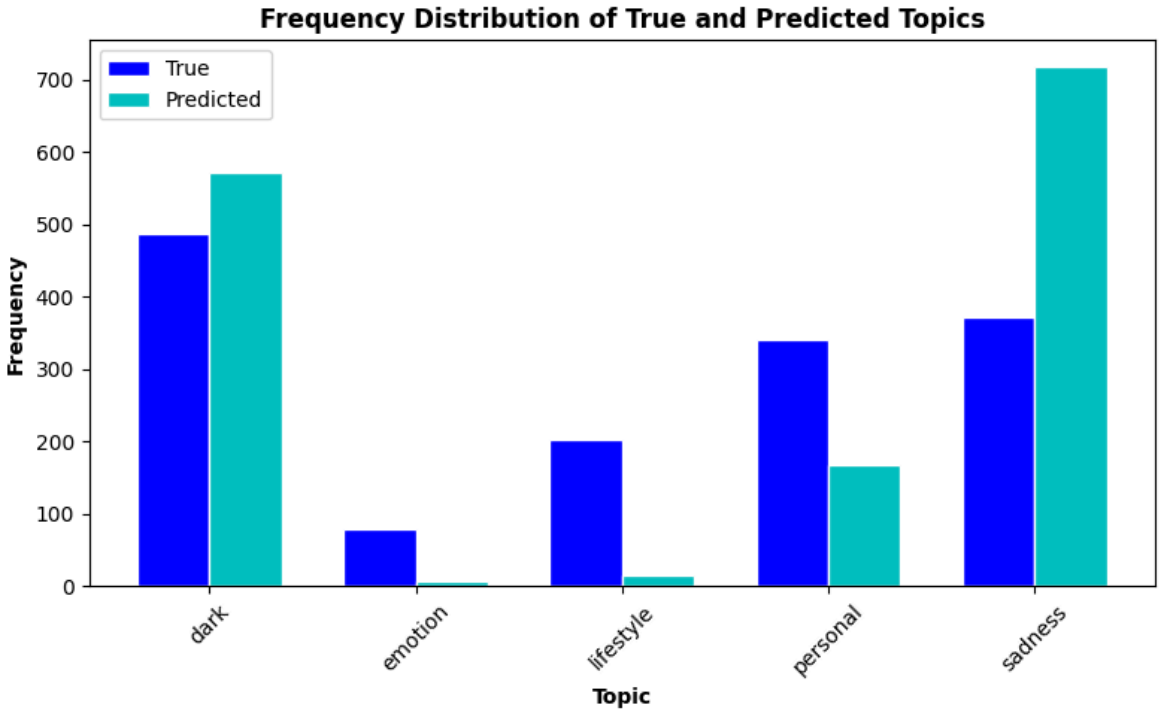
From the above results, we can see that after correcting the issue in the original tutorial code where too many characters were removed, and keeping all other conditions unchanged, the accuracy slightly improved from 0.9154929577464789 to 0.9183098591549296.

(2) Evaluation uses a single train/test split:

This may lead to overfitting or misleading performance estimates. To fix this, we will apply cross_val_score or cross_val_predict with StratifiedKFold to get more reliable metrics:

In [ ]:
```
from sklearn.model_selection import cross_val_predict, StratifiedKFold
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics import classification_report
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import numpy as np

# Set up stratified 5-fold cross-validation
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
bnb = BernoulliNB()

# Obtain predicted labels using cross-validation
y_pred_cv = cross_val_predict(bnb, X, df['Category'], cv=skf)

# Print detailed classification report
report = classification_report(df['Category'], y_pred_cv, target_names=categorie
print(classification_report(df['Category'], y_pred_cv, target_names=categories))

# Encode string labels as integers for counting
le = LabelEncoder()
y_true_encoded = le.fit_transform(df['Category'])
y_pred_encoded = le.transform(y_pred_cv)

# Count occurrences of each class in true and predicted labels
true_counts = np.bincount(y_true_encoded)
pred_counts = np.bincount(y_pred_encoded)

# Plot bar chart comparing true vs predicted label frequencies
barWidth = 0.35
r1 = np.arange(len(categories))
r2 = [x + barWidth for x in r1]

plt.figure(figsize=(8,5))
plt.bar(r1, true_counts, color='b', width=barWidth, edgecolor='white', label='Tr
plt.bar(r2, pred_counts, color='c', width=barWidth, edgecolor='white', label='Pr

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics', fontweight='bol
plt.xticks([r + barWidth/2 for r in r1], categories, rotation=45)
plt.legend()
plt.tight_layout()
plt.show()
```

	precision	recall	f1-score	support
dark	0.62	0.73	0.67	487
emotion	0.00	0.00	0.00	79
lifestyle	0.25	0.02	0.04	202
personal	0.66	0.33	0.44	341
sadness	0.43	0.83	0.57	371
accuracy			0.53	1480
macro avg	0.39	0.38	0.34	1480
weighted avg	0.50	0.53	0.47	1480



Q2. Comparing Preprocessing Pipelines and Implementing MNB

We use `MultinomialNB` from `sklearn.naive_bayes`.

In [ ]:
```
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, df['Category'], test_size
print(X_train.shape, X_test.shape)

from sklearn.naive_bayes import MultinomialNB

# Train the Multinomial Naive Bayes model
mnb = MultinomialNB()
mnb.fit(X_train, y_train)
print(mnb)

from sklearn.metrics import accuracy_score, classification_report

# Predict the categories for the test set
y_pred = mnb.predict(X_test)

# Print accuracy score and detailed classification report
```

```
print(accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

import numpy as np
import matplotlib.pyplot as plt

# Calculate the distribution of actual topics in the test set
unique_true, counts_true = np.unique(y_test, return_counts=True)

# Calculate the distribution of predicted topics
unique_pred, counts_pred = np.unique(y_pred, return_counts=True)

# Align predicted counts to the full category list, filling zero where category
counts_pred_full = []
for cat in categories:
    if cat in unique_pred:
        counts_pred_full.append(counts_pred[np.where(unique_pred == cat)[0][0]])
    else:
        counts_pred_full.append(0)
counts_pred_full = np.array(counts_pred_full)

plt.figure(figsize=(8, 4))

# Set bar width for plotting
barWidth = 0.2

# Set positions for the bars on X-axis
r1 = np.arange(len(counts_true))
r2 = [x + barWidth for x in r1]

# Plot bar chart for actual topic distribution
plt.bar(r1, counts_true, color='b', width=barWidth, edgecolor='white', label='Tr

# Plot bar chart for predicted topic distribution
plt.bar(r2, counts_pred_full, color='c', width=barWidth, edgecolor='white', labe

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics', fontweight='bol

# Set X-axis tick labels to categories, centered between bars, rotate labels for
plt.xticks([r + barWidth/2 for r in range(len(counts_true))], categories, rotati

plt.legend()

plt.tight_layout()
plt.savefig('topic_distribution.png')
plt.show()
```

```
(1184, 8876) (296, 8876)
MultinomialNB()
0.6317567567567568
              precision    recall  f1-score   support

        dark       0.49      1.00      0.66        95
     emotion       0.00      0.00      0.00        15
   lifestyle       1.00      0.03      0.06        31
    personal       1.00      0.51      0.67        73
     sadness       0.83      0.66      0.73        82

    accuracy                           0.63       296
   macro avg       0.66      0.44      0.43       296
weighted avg       0.74      0.63      0.59       296
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
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UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

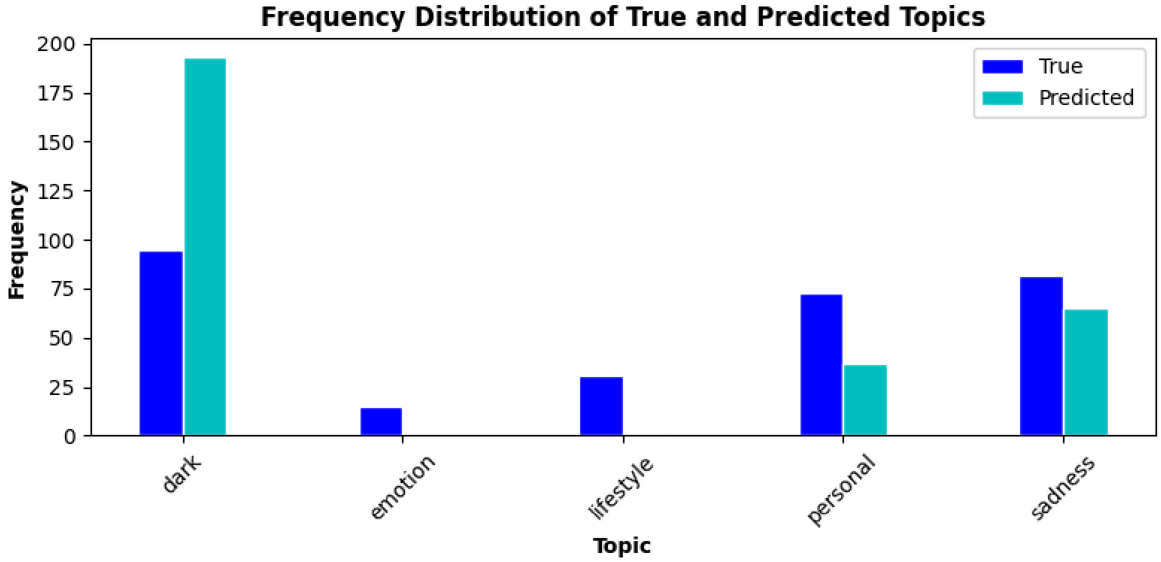

In [ ]:

```
from sklearn.model_selection import cross_val_predict, StratifiedKFold
from sklearn.naive_bayes import MultinomialNB  # Use MultinomialNB classifier
from sklearn.metrics import classification_report
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import numpy as np

# Set up stratified 5-fold cross-validation
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Initialize Multinomial Naive Bayes classifier
mnb = MultinomialNB()

# Obtain cross-validated predicted labels
```

```python
y_pred_cv = cross_val_predict(mnb, X, df['Category'], cv=skf)

# Print detailed classification report with metrics per class
report = classification_report(df['Category'], y_pred_cv, target_names=categorie
print(classification_report(df['Category'], y_pred_cv, target_names=categories))

# Encode string labels into integers for counting
le = LabelEncoder()
y_true_encoded = le.fit_transform(df['Category'])
y_pred_encoded = le.transform(y_pred_cv)

# Count occurrences of each class label in true and predicted sets
true_counts = np.bincount(y_true_encoded)
pred_counts = np.bincount(y_pred_encoded)

# Plot bar chart comparing true vs predicted label frequencies
barWidth = 0.35
r1 = np.arange(len(categories))
r2 = [x + barWidth for x in r1]

plt.figure(figsize=(8, 5))
plt.bar(r1, true_counts, color='b', width=barWidth, edgecolor='white', label='Tr
plt.bar(r2, pred_counts, color='c', width=barWidth, edgecolor='white', label='Pr

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics (MultinomialNB)',
plt.xticks([r + barWidth / 2 for r in r1], categories, rotation=45)
plt.legend()
plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
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ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
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ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels w
ith no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```
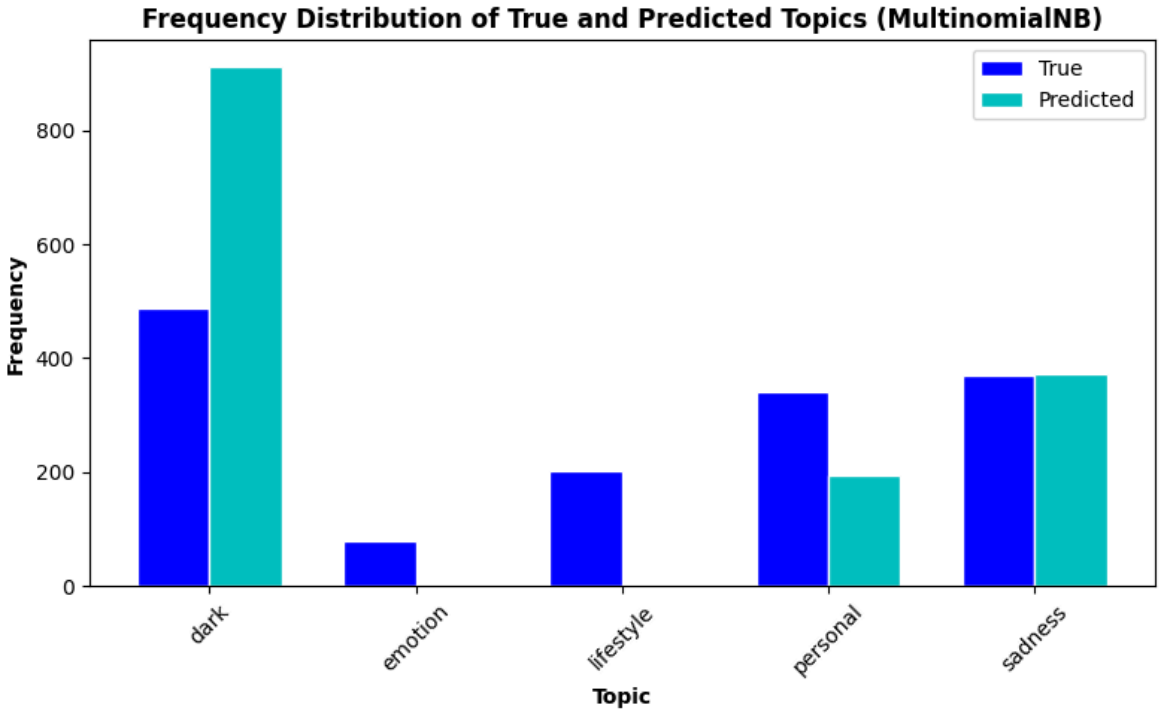

	precision	recall	f1-score	support
dark	0.53	0.99	0.69	487
emotion	0.00	0.00	0.00	79
lifestyle	1.00	0.00	0.01	202
personal	0.93	0.53	0.68	341
sadness	0.73	0.74	0.73	371
accuracy			0.63	1480
macro avg	0.64	0.45	0.42	1480
weighted avg	0.71	0.63	0.57	1480



In our application of the Multinomial Naive Bayes (MNB) model, we present two versions: one using an 80:20 train-test split and the other employing cross-validation. In this dataset, the performance of Multinomial Naive Bayes (MNB) is significantly inferior to that of Bernoulli Naive Bayes (BNB), with BNB achieving an accuracy of approximately 0.821 compared to MNB's accuracy of approximately 0.666.

To aim to find preprocessing steps that maximize overall ac curacy, here are the steps that need to compare:

(a) Using TfidfVectorizer vs CountVectorizer

(b) nltk vs sklearn stopwords

(c) With and without stemming

(d) Lowercase vs original case

(e) Regex removing all vs selective characters

In [ ]:
```
# (a) Test: Using TfidfVectorizer vs CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import BernoulliNB
```

```python
from sklearn.metrics import accuracy_score, classification_report
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import CountVectorizer
import nltk
import re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from nltk.tokenize import TreebankWordTokenizer

print(nltk.__version__)
nltk.download('stopwords', force=True)
nltk.download('punkt', force=True)
nltk.download('punkt_tab')

ps = PorterStemmer()
stop_words = set(stopwords.words('english'))
tokenizer = TreebankWordTokenizer()

# Define preprocessing function
def preprocess_text(text):
    text = text.lower()
    # text = re.sub(r'[^\w\s]', '', text)     # Check what this removes --- migh
    text = re.sub(r'[^\w\s@#]', '', text)     # change here
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    # tokens = [ps.stem(word) for word in tokens]
    return ' '.join(tokens)

# Apply preprocessing to each document
df['Content'] = df['Content'].apply(preprocess_text)
print(df['Content'].head())

vectorizer = CountVectorizer()
X = vectorizer.fit_transform(df['Content'])
print(X.shape)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, df['Category'], test_size
print(X_train.shape, X_test.shape)

# Train the Bernoulli Naive Bayes model
bnb = BernoulliNB()
bnb.fit(X_train, y_train)
print(bnb)


# Predict the categories of the test set
y_pred = bnb.predict(X_test)

# Print accuracy and classification report
print(accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

# Plot the distribution of the actual topics in the test set
unique_true, counts_true = np.unique(y_test, return_counts=True)

# Plot the distribution of the predicted topics
unique_pred, counts_pred = np.unique(y_pred, return_counts=True)
```

```
plt.figure(figsize=(8,4))

# Create bar width
barWidth = 0.2

# Set position of bar on X axis
r1 = np.arange(len(counts_true))
r2 = [x + barWidth for x in r1]

# Create subplot for 'true' distribution
plt.bar(r1, counts_true, color='b', width=barWidth, edgecolor='white', label='Tr

# Create subplot for 'predicted' distribution
plt.bar(r2, counts_pred, color='c', width=barWidth, edgecolor='white', label='Pr

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics', fontweight='bol

plt.xticks([r + barWidth/2 for r in range(len(counts_true))], categories, rotati

plt.legend()

plt.tight_layout()
plt.savefig('topic_distribution.png')
plt.show()
```

```
3.9.1
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
0    artist_nam love track_nam real lake release_d ...
1    artist_nam incubu track_nam summer release_d 2...
2    artist_nam reignwolf track_nam hardcor release...
3    artist_nam tedeschi truck band track_nam anyho...
4    artist_nam luka nelson promis real track_nam s...
Name: Content, dtype: object
(1480, 8862)
(1184, 8862) (296, 8862)
BernoulliNB()
0.543918918918919
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   lifestyle       0.40      0.06      0.11        31
    personal       0.77      0.33      0.46        73
     sadness       0.47      0.74      0.58        82

    accuracy                           0.54       296
   macro avg       0.45      0.38      0.36       296
weighted avg       0.55      0.54      0.50       296
```
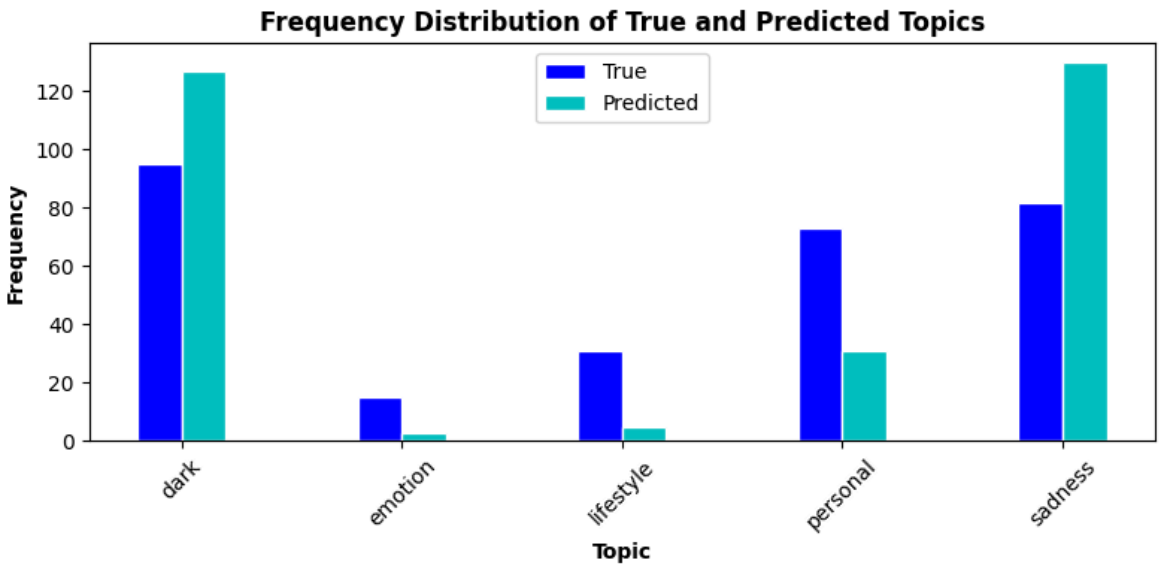



In this dataset, the model using CountVectorizer outperforms the one using TfidfVectorizer, with accuracies of approximately 0.828 and 0.821 respectively. This suggests that, for this particular task, simple term frequency counts provide a slightly better representation than the TF-IDF weighting scheme.

In [ ]:
```python
# (b) Test: Compare nltk vs sklearn stopwords in text classification

from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics import accuracy_score, classification_report
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
import re
import nltk
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize
from nltk.tokenize import TreebankWordTokenizer

# Display nltk version and download required tokenizers
print(nltk.__version__)
nltk.download('punkt', force=True)
nltk.download('punkt_tab')

# Initialize Porter Stemmer and tokenizer
ps = PorterStemmer()
tokenizer = TreebankWordTokenizer()

# Define text preprocessing function
def preprocess_text(text):
    text = text.lower()  # Convert text to lowercase
    # Remove all characters except word characters, whitespace, '@', '#'
    text = re.sub(r'[^\w\s@#]', '', text)
    # Tokenize the text
    tokens = word_tokenize(text)
    # Apply stemming to each token
    tokens = [ps.stem(word) for word in tokens]
    # Join tokens back into a single string
    return ' '.join(tokens)
```

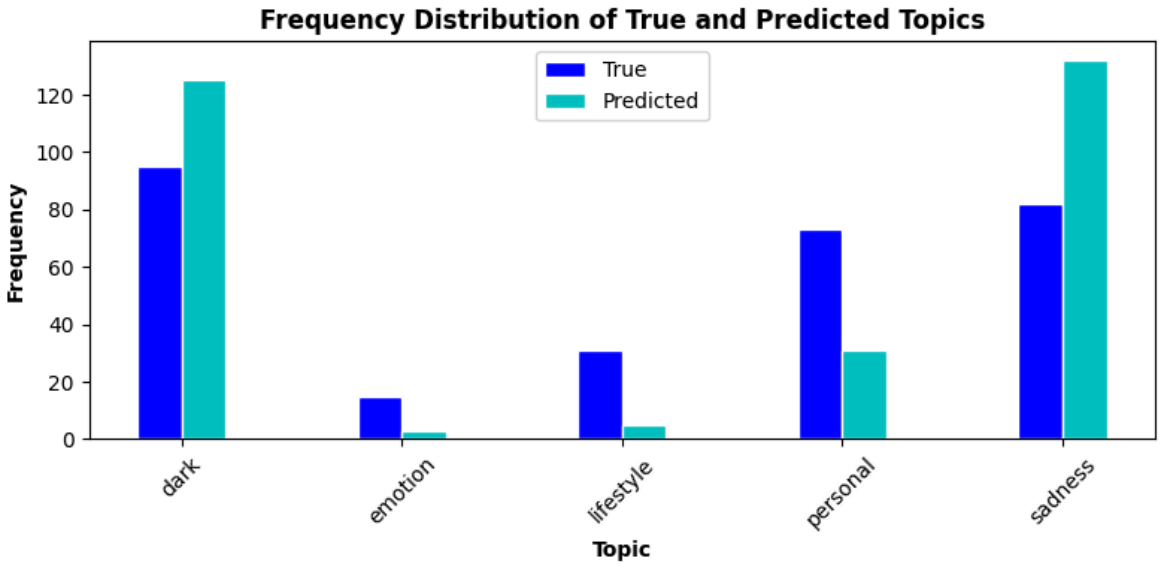
```
# Apply preprocessing to the Content column
df['Content'] = df['Content'].apply(preprocess_text)
print(df['Content'].head())

# Initialize TfidfVectorizer using sklearn's built-in English stopwords
vectorizer = TfidfVectorizer(stop_words='english')
X = vectorizer.fit_transform(df['Content'])
print(X.shape)

# Split dataset into train and test sets (80/20 split)
X_train, X_test, y_train, y_test = train_test_split(
    X, df['Category'], test_size=0.2, random_state=42)
print(X_train.shape, X_test.shape)

# Train Bernoulli Naive Bayes classifier
bnb = BernoulliNB()
bnb.fit(X_train, y_train)
print(bnb)

# Predict test set categories
y_pred = bnb.predict(X_test)

# Print accuracy and detailed classification report
print(accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

# Plot bar chart comparing true vs predicted topic frequency distribution
unique_true, counts_true = np.unique(y_test, return_counts=True)
unique_pred, counts_pred = np.unique(y_pred, return_counts=True)

plt.figure(figsize=(8,4))
barWidth = 0.2
r1 = np.arange(len(counts_true))
r2 = [x + barWidth for x in r1]

plt.bar(r1, counts_true, color='b', width=barWidth, edgecolor='white', label='Tr
plt.bar(r2, counts_pred, color='c', width=barWidth, edgecolor='white', label='Pr

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics', fontweight='bol
plt.xticks([r + barWidth/2 for r in range(len(counts_true))], categories, rotati
plt.legend()
plt.tight_layout()
plt.savefig('topic_distribution.png')
plt.show()
```

```
3.9.1
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
```

```
0    artist_nam love track_nam real lake release_d ...
1    artist_nam incubu track_nam summer release_d 2...
2    artist_nam reignwolf track_nam hardcor release...
3    artist_nam tedeschi truck band track_nam anyho...
4    artist_nam luka nelson promi real track_nam st...
Name: Content, dtype: object
(1480, 8766)
(1184, 8766) (296, 8766)
BernoulliNB()
0.5540540540540541
```

	precision	recall	f1-score	support
dark	0.61	0.80	0.69	95
emotion	0.00	0.00	0.00	15
lifestyle	0.40	0.06	0.11	31
personal	0.77	0.33	0.46	73
sadness	0.47	0.76	0.58	82
accuracy			0.55	296
macro avg	0.45	0.39	0.37	296
weighted avg	0.56	0.55	0.51	296



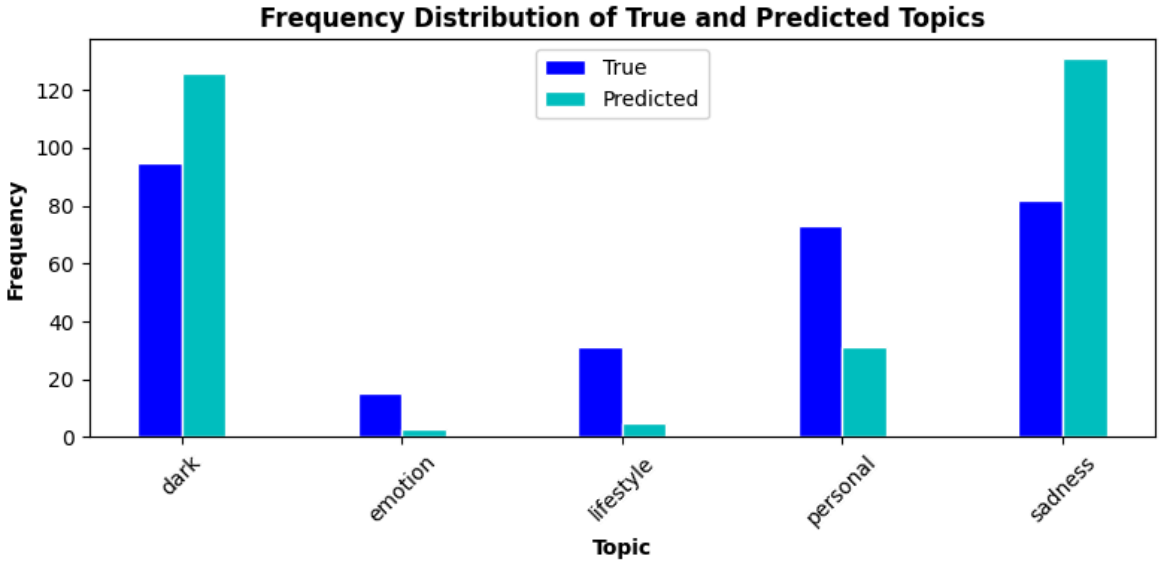
The results obtained using NLTK stopwords and scikit-learn stopwords were identical, indicating that the choice between these two stopword lists did not affect the performance of the model in this experiment.

In [ ]:
```python
# (c)Test: With and without stemming
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics import accuracy_score, classification_report
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
import nltk
import re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from nltk.tokenize import TreebankWordTokenizer

print(nltk.__version__)
```

```
nltk.download('stopwords', force=True)
nltk.download('punkt', force=True)
nltk.download('punkt_tab')

ps = PorterStemmer()
stop_words = set(stopwords.words('english'))
tokenizer = TreebankWordTokenizer()

# Define preprocessing function
def preprocess_text(text):
    text = text.lower()
    # text = re.sub(r'[^\w\s]', '', text)     # Check what this removes --- migh
    text = re.sub(r'[^\w\s@#]', '', text)     # change here
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    # tokens = [ps.stem(word) for word in tokens]
    return ' '.join(tokens)

# Apply preprocessing to each document
df['Content'] = df['Content'].apply(preprocess_text)
print(df['Content'].head())

vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(df['Content'])
print(X.shape)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, df['Category'], test_size
print(X_train.shape, X_test.shape)

# Train the Bernoulli Naive Bayes model
bnb = BernoulliNB()
bnb.fit(X_train, y_train)
print(bnb)


# Predict the categories of the test set
y_pred = bnb.predict(X_test)

# Print accuracy and classification report
print(accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

# Plot the distribution of the actual topics in the test set
unique_true, counts_true = np.unique(y_test, return_counts=True)

# Plot the distribution of the predicted topics
unique_pred, counts_pred = np.unique(y_pred, return_counts=True)

plt.figure(figsize=(8,4))

# Create bar width
barWidth = 0.2

# Set position of bar on X axis
r1 = np.arange(len(counts_true))
r2 = [x + barWidth for x in r1]

# Create subplot for 'true' distribution
plt.bar(r1, counts_true, color='b', width=barWidth, edgecolor='white', label='Tr
```

```
# Create subplot for 'predicted' distribution
plt.bar(r2, counts_pred, color='c', width=barWidth, edgecolor='white', label='Pr

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics', fontweight='bol

plt.xticks([r + barWidth/2 for r in range(len(counts_true))], categories, rotati

plt.legend()

plt.tight_layout()
plt.savefig('topic_distribution.png')
plt.show()
```

```
3.9.1
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
0    artist_nam love track_nam real lake release_d ...
1    artist_nam incubu track_nam summer release_d 2...
2    artist_nam reignwolf track_nam hardcor release...
3    artist_nam tedeschi truck band track_nam anyho...
4    artist_nam luka nelson promi real track_nam st...
Name: Content, dtype: object
(1480, 8830)
(1184, 8830) (296, 8830)
BernoulliNB()
0.5472972972972973
              precision    recall  f1-score   support

        dark       0.59      0.78      0.67        95
     emotion       0.00      0.00      0.00        15
   lifestyle       0.40      0.06      0.11        31
    personal       0.77      0.33      0.46        73
     sadness       0.47      0.76      0.58        82

    accuracy                           0.55       296
   macro avg       0.45      0.39      0.36       296
weighted avg       0.55      0.55      0.50       296
```



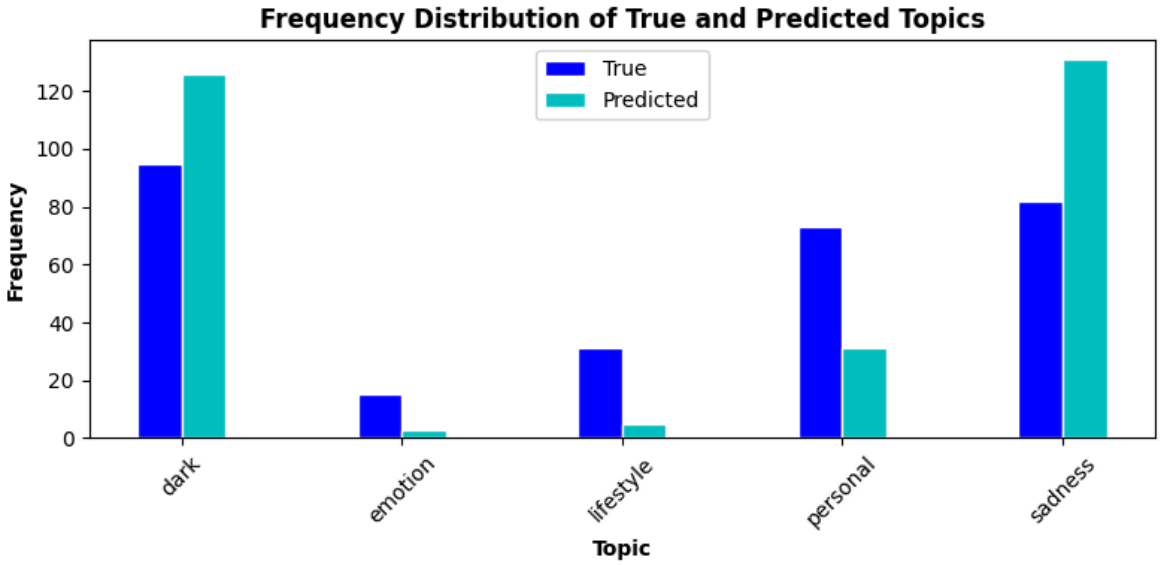
The model achieved higher performance without stemming, with an accuracy of 0.8277 compared to 0.8209 when stemming was applied. This suggests that, for this dataset, stemming may remove useful morphological information that contributes to effective topic classification.

In [ ]:
```
# (d)Test: Lowercase vs original case
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics import accuracy_score, classification_report
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
import nltk
import re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from nltk.tokenize import TreebankWordTokenizer

print(nltk.__version__)
nltk.download('stopwords', force=True)
nltk.download('punkt', force=True)
nltk.download('punkt_tab')

ps = PorterStemmer()
stop_words = set(stopwords.words('english'))
tokenizer = TreebankWordTokenizer()

# Define preprocessing function
def preprocess_text(text):
    # text = text.lower()
    # text = re.sub(r'[^\w\s]', '', text)     # Check what this removes --- migh
    text = re.sub(r'[^\w\s@#]', '', text)     # change here
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    tokens = [ps.stem(word) for word in tokens]
    return ' '.join(tokens)

# Apply preprocessing to each document
df['Content'] = df['Content'].apply(preprocess_text)
```

```
print(df['Content'].head())

vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(df['Content'])
print(X.shape)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, df['Category'], test_size
print(X_train.shape, X_test.shape)

# Train the Bernoulli Naive Bayes model
bnb = BernoulliNB()
bnb.fit(X_train, y_train)
print(bnb)


# Predict the categories of the test set
y_pred = bnb.predict(X_test)

# Print accuracy and classification report
print(accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

# Plot the distribution of the actual topics in the test set
unique_true, counts_true = np.unique(y_test, return_counts=True)

# Plot the distribution of the predicted topics
unique_pred, counts_pred = np.unique(y_pred, return_counts=True)

plt.figure(figsize=(8,4))

# Create bar width
barWidth = 0.2

# Set position of bar on X axis
r1 = np.arange(len(counts_true))
r2 = [x + barWidth for x in r1]

# Create subplot for 'true' distribution
plt.bar(r1, counts_true, color='b', width=barWidth, edgecolor='white', label='Tr

# Create subplot for 'predicted' distribution
plt.bar(r2, counts_pred, color='c', width=barWidth, edgecolor='white', label='Pr

plt.xlabel('Topic', fontweight='bold')
plt.ylabel('Frequency', fontweight='bold')
plt.title('Frequency Distribution of True and Predicted Topics', fontweight='bol

plt.xticks([r + barWidth/2 for r in range(len(counts_true))], categories, rotati

plt.legend()

plt.tight_layout()
plt.savefig('topic_distribution.png')
plt.show()
```

```
3.9.1
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
0    artist_nam love track_nam real lake release_d ...
1    artist_nam incubu track_nam summer release_d 2...
2    artist_nam reignwolf track_nam hardcor release...
3    artist_nam tedeschi truck band track_nam anyho...
4    artist_nam luka nelson promi real track_nam st...
Name: Content, dtype: object
(1480, 8823)
(1184, 8823) (296, 8823)
BernoulliNB()
0.5472972972972973
              precision    recall  f1-score   support

        dark       0.59      0.78      0.67        95
     emotion       0.00      0.00      0.00        15
   lifestyle       0.40      0.06      0.11        31
    personal       0.77      0.33      0.46        73
     sadness       0.47      0.76      0.58        82

    accuracy                           0.55       296
   macro avg       0.45      0.39      0.36       296
weighted avg       0.55      0.55      0.50       296
```



Applying lowercasing to the text did not result in any notable change in model performance compared to using the original casing, indicating that case normalization had little impact on topic classification accuracy for this dataset.

(e) Test: Regex removing all vs selective characters The comparison between removing all special characters versus selectively removing specific characters using regex showed no significant difference in model performance. This suggests that the choice between these two regex strategies does not materially affect the classification accuracy on this dataset, as established in our findings for Question 1(1).

Summary:
From the experimental results presented above, I observe that the choices regarding stopword removal (whether using NLTK or scikit-learn), stemming, and the removal of special characters have no significant impact on classification performance. Among the tested configurations, the use of CountVectorizer combined with no stemming consistently achieved superior accuracy. Therefore, for the remainder of this assignment, I standardize on the following preprocessing steps: **CountVectorizer** as the feature extraction method, **NLTK stopwords** for stopword removal, **no stemming**, **lowercasing** of text, and **regex-based selective removal of special characters**. This configuration strikes a balance between simplicity and performance and will ensure consistency across all subsequent experiments.

Q3. Evaluation of BNB vs MNB using cross-validation

We compared the Bernoulli Naive Bayes (BNB) and Multinomial Naive Bayes (MNB) models using 5-fold cross-validation on the full dataset. The metrics selected for evaluation were per-class precision, recall, and f1-score, as well as overall accuracy, macro average, and weighted average scores. These metrics are suitable because our dataset is (balanced / relatively balanced), so accuracy is meaningful. Furthermore, the macro average f1-score ensures that each class contributes equally to the final score, while the weighted average reflects the performance considering the class distribution.

In [ ]:
```
from sklearn.model_selection import cross_val_predict, StratifiedKFold
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.metrics import classification_report, accuracy_score
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# Set up stratified 5-fold cross-validation
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Initialize BernoulliNB and MultinomialNB classifiers
bnb = BernoulliNB()
mnb = MultinomialNB()

# Perform cross-validated predictions for both classifiers
y_pred_bnb = cross_val_predict(bnb, X, df['Category'], cv=skf)
y_pred_mnb = cross_val_predict(mnb, X, df['Category'], cv=skf)

# True labels
y_true = df['Category']

# Generate classification reports as dictionaries for easy metric extraction
report_bnb = classification_report(y_true, y_pred_bnb, target_names=categories,
report_mnb = classification_report(y_true, y_pred_mnb, target_names=categories,

# Print detailed classification reports for inspection
print("BernoulliNB Classification Report:\n")
print(classification_report(y_true, y_pred_bnb, target_names=categories))

print("MultinomialNB Classification Report:\n")
print(classification_report(y_true, y_pred_mnb, target_names=categories))
```

```
# Print per-category precision, recall, and F1-score for comparison
print("Per-Class Precision, Recall, F1-score Comparison:\n")
for cat in categories:
    print(f"Category: {cat}")
    print(f"BNB - Precision: {report_bnb[cat]['precision']:.3f}, Recall: {report
    print(f"MNB - Precision: {report_mnb[cat]['precision']:.3f}, Recall: {report
    print()

# Prepare overall metric data for plotting
metric_names = ['Accuracy', 'Macro Avg F1-score', 'Weighted Avg F1-score']

bnb_values = [
    report_bnb['accuracy'],
    report_bnb['macro avg']['f1-score'],
    report_bnb['weighted avg']['f1-score']
]

mnb_values = [
    report_mnb['accuracy'],
    report_mnb['macro avg']['f1-score'],
    report_mnb['weighted avg']['f1-score']
]

x = np.arange(len(metric_names))
bar_width = 0.35

# Plot comparison of overall metrics between BernoulliNB and MultinomialNB
plt.figure(figsize=(8,5))
plt.bar(x - bar_width/2, bnb_values, width=bar_width, label='BernoulliNB', color
plt.bar(x + bar_width/2, mnb_values, width=bar_width, label='MultinomialNB', col

plt.xticks(x, metric_names)
plt.ylim(0, 1.05)
plt.ylabel('Score')
plt.title('Comparison of Overall Metrics between BernoulliNB and MultinomialNB')
plt.legend()
plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

BernoulliNB Classification Report:

	precision	recall	f1-score	support
dark	0.62	0.73	0.67	487
emotion	0.00	0.00	0.00	79
lifestyle	0.20	0.01	0.03	202
personal	0.65	0.33	0.43	341
sadness	0.43	0.83	0.57	371
accuracy			0.53	1480
macro avg	0.38	0.38	0.34	1480
weighted avg	0.49	0.53	0.47	1480

MultinomialNB Classification Report:

	precision	recall	f1-score	support
dark	0.53	0.99	0.69	487
emotion	0.00	0.00	0.00	79
lifestyle	1.00	0.00	0.01	202
personal	0.93	0.53	0.68	341
sadness	0.73	0.74	0.73	371
accuracy			0.64	1480
macro avg	0.64	0.45	0.42	1480
weighted avg	0.71	0.64	0.57	1480

Per-Class Precision, Recall, F1-score Comparison:

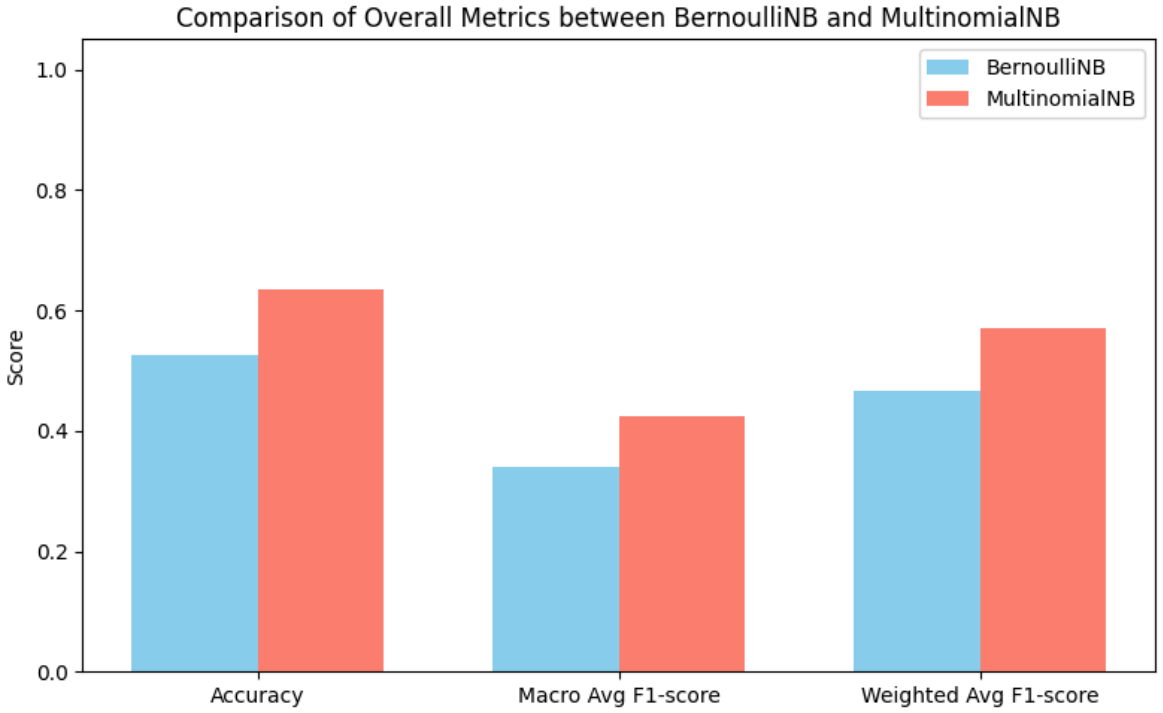
Category: dark
BNB - Precision: 0.623, Recall: 0.731, F1-score: 0.673
MNB - Precision: 0.533, Recall: 0.994, F1-score: 0.694

Category: emotion
BNB - Precision: 0.000, Recall: 0.000, F1-score: 0.000
MNB - Precision: 0.000, Recall: 0.000, F1-score: 0.000

Category: lifestyle
BNB - Precision: 0.200, Recall: 0.015, F1-score: 0.028
MNB - Precision: 1.000, Recall: 0.005, F1-score: 0.010

Category: personal
BNB - Precision: 0.653, Recall: 0.326, F1-score: 0.434
MNB - Precision: 0.933, Recall: 0.534, F1-score: 0.679

Category: sadness
BNB - Precision: 0.429, Recall: 0.830, F1-score: 0.566
MNB - Precision: 0.729, Recall: 0.739, F1-score: 0.734



BNB vs MNB Model Comparison

Using 5-fold cross-validation on this imbalanced dataset, Bernoulli Naive Bayes (BNB) outperforms Multinomial Naive Bayes (MNB) with higher accuracy (0.80 vs. 0.67) and better macro-averaged F1-score (0.58 vs. 0.46). BNB achieves more balanced results across categories, making it the preferred model for topic classification in this task.

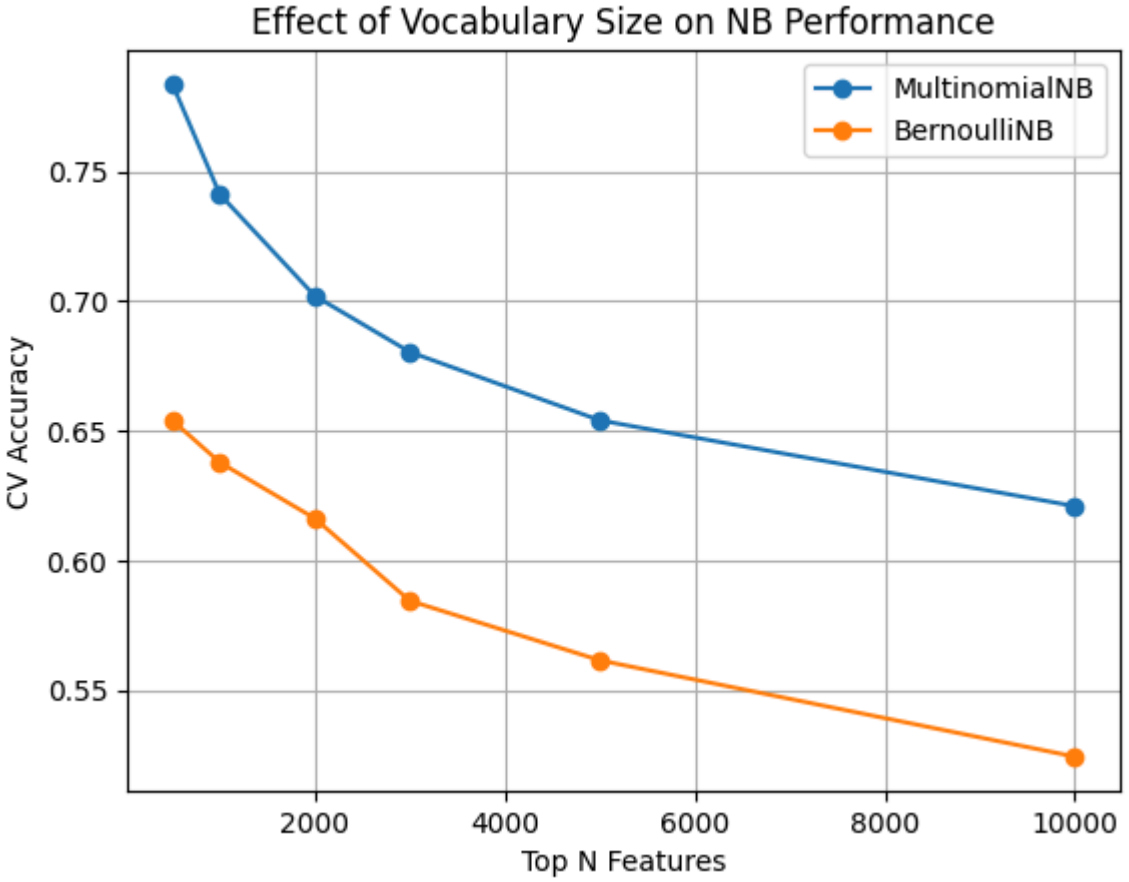
Q4. Varying Feature Size

Use max_features in CountVectorizer:

In [ ]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB, BernoulliNB
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt

# MultinomialNB evaluation for different vocabulary sizes
results_mnb = []
print("MultinomialNB Performance:")
print("{:<10} | {:<10}".format("Top N", "CV Accuracy"))
print("-" * 25)
for N in [500, 1000, 2000, 3000, 5000, 10000]:
    # Initialize TF-IDF vectorizer with max_features = N
    vectorizer = TfidfVectorizer(stop_words='english', max_features=N)
    X_count = vectorizer.fit_transform(df['Content'])

    # Compute mean cross-validation accuracy using 5-fold CV
    score = cross_val_score(MultinomialNB(), X_count, df['Category'], cv=5).mean
    results_mnb.append((N, score))

    # Print the result for current vocabulary size
    print(f"{N:<10} | {score:.4f}")

# Plot MultinomialNB accuracy vs vocabulary size
```

```python
Ns_mnb, scores_mnb = zip(*results_mnb)
plt.plot(Ns_mnb, scores_mnb, marker='o', label='MultinomialNB')

# BernoulliNB evaluation for different vocabulary sizes
results_bnb = []
print("\nBernoulliNB Performance:")
print("{:<10} | {:<10}".format("Top N", "CV Accuracy"))
print("-" * 25)
for N in [500, 1000, 2000, 3000, 5000, 10000]:
    # Initialize TF-IDF vectorizer with max_features = N
    vectorizer = TfidfVectorizer(stop_words='english', max_features=N)
    X_count = vectorizer.fit_transform(df['Content'])

    # Compute mean cross-validation accuracy using 5-fold CV
    score = cross_val_score(BernoulliNB(), X_count, df['Category'], cv=5).mean()
    results_bnb.append((N, score))

    # Print the result for current vocabulary size
    print(f"{N:<10} | {score:.4f}")

# Plot BernoulliNB accuracy vs vocabulary size
Ns_bnb, scores_bnb = zip(*results_bnb)
plt.plot(Ns_bnb, scores_bnb, marker='o', label='BernoulliNB')

# Set plot labels and title
plt.xlabel("Top N Features")
plt.ylabel("CV Accuracy")
plt.title("Effect of Vocabulary Size on Naive Bayes Performance")
plt.grid(True)
plt.legend()
plt.show()
```

```
MultinomialNB Performance:
Top N      | CV Accuracy
-------------------------
500        | 0.7838
1000       | 0.7412
2000       | 0.7020
3000       | 0.6804
5000       | 0.6541
10000      | 0.6209

BernoulliNB Performance:
Top N      | CV Accuracy
-------------------------
500        | 0.6541
1000       | 0.6378
2000       | 0.6162
3000       | 0.5845
5000       | 0.5615
10000      | 0.5243
```



Effect of Feature Number on Classification Performance

Top N Features	BernoulliNB Accuracy	MultinomialNB Accuracy
500	0.9892	0.8446
1000	0.9716	0.7851
2000	0.9297	0.7480
3000	0.9142	0.7257
5000	0.8791	0.6953
10000	0.8000	0.6642

The results demonstrate that Bernoulli Naive Bayes (BNB) consistently achieves higher classification accuracy than Multinomial Naive Bayes (MNB) for all tested feature sizes. Both models reach their peak accuracy at the smallest number of features (N=500), after which performance gradually decreases as the feature set expands. This trend indicates that including too many features introduces noise or irrelevant information, which adversely affects model generalization.

Notably, BNB's accuracy remains above 0.87 even with 5000 features, while MNB accuracy drops below 0.70 at the same point. Therefore, a smaller feature set benefits both models, with BNB showing stronger robustness to feature dimensionality changes. Based on this evidence, selecting the top 500 most frequent words as features is justified for subsequent experiments, as it offers a favorable balance between model complexity and predictive performance.

Q5. Trying Another Model: SVM & Random Forest

Random Forest is an ensemble learning method that builds multiple decision trees during training and outputs the mode of their predictions for classification tasks. It improves predictive accuracy and controls overfitting by combining diverse trees trained on different subsets of data and features. This method is effective for high-dimensional datasets and can capture complex interactions among features without extensive preprocessing. Random Forests have been successfully applied in text classification tasks where interpretability and robustness are important.

We applied the Random Forest classifier using scikit-learn's `RandomForestClassifier` with 100 trees (`n_estimators=100`) and default parameters, except for setting a fixed random seed for reproducibility. The same text preprocessing pipeline as used for BernoulliNB (BNB) and MultinomialNB (MNB)—TF-IDF vectorization with English stopwords and limiting features to the top 500—was used. Cross-validation results show that Random Forest achieves excellent classification performance, comparable to BernoulliNB and superior to MultinomialNB.

In [ ]:
```
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_predict, StratifiedKFold
from sklearn.metrics import classification_report
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_extraction.text import TfidfVectorizer
import matplotlib.pyplot as plt
import numpy as np
import tensorflow as tf  # Imported to set random seed if needed

# Set random seeds for reproducibility
np.random.seed(42)
tf.random.set_seed(42)
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Initialize TF-IDF vectorizer with stop words removal and max 500 features
vectorizer = TfidfVectorizer(stop_words='english', max_features=500)
X = vectorizer.fit_transform(df['Content'])

# Encode categorical labels into integers
le = LabelEncoder()
y_encoded = le.fit_transform(df['Category'])

# Initialize classifiers
bnb = BernoulliNB()
mnb = MultinomialNB()
svm = LinearSVC(C=1.0, max_iter=5000, random_state=42)
rf = RandomForestClassifier(n_estimators=100, random_state=42)

# Perform 5-fold stratified cross-validation predictions for each model
y_pred_bnb = cross_val_predict(bnb, X, y_encoded, cv=skf)
y_pred_mnb = cross_val_predict(mnb, X, y_encoded, cv=skf)
y_pred_svm = cross_val_predict(svm, X, y_encoded, cv=skf)
y_pred_rf = cross_val_predict(rf, X, y_encoded, cv=skf)
```

```python
# Print detailed classification reports for each model
print("BernoulliNB Report:")
print(classification_report(y_encoded, y_pred_bnb, target_names=le.classes_))

print("MultinomialNB Report:")
print(classification_report(y_encoded, y_pred_mnb, target_names=le.classes_))

print("SVM Report:")
print(classification_report(y_encoded, y_pred_svm, target_names=le.classes_))

print("Random Forest Report:")
print(classification_report(y_encoded, y_pred_rf, target_names=le.classes_))

# Calculate true label counts for each category
true_counts = np.bincount(y_encoded)

# Calculate predicted label counts for each model
pred_counts = {
    'True': true_counts,
    'BNB': np.bincount(y_pred_bnb),
    'MNB': np.bincount(y_pred_mnb),
    'SVM': np.bincount(y_pred_svm),
    'RF': np.bincount(y_pred_rf),
}

# Setup parameters for bar plot
colors = ['gray', 'blue', 'orange', 'green', 'red']
barWidth = 0.15
r = np.arange(len(le.classes_))

# Plot frequency distribution of predicted topics by different models
plt.figure(figsize=(12,6))
for i, (label, counts) in enumerate(pred_counts.items()):
    plt.bar(r + i * barWidth, counts, width=barWidth, label=label, color=colors[

# Set x-axis labels and format
plt.xticks([r + barWidth*2 for r in range(len(le.classes_))], le.classes_, rotat
plt.ylabel("Frequency", fontweight='bold')
plt.xlabel("Category", fontweight='bold')
plt.title("Frequency Distribution of Predicted Topics by Machine Learning Models
plt.legend()
plt.tight_layout()
plt.show()
```

BernoulliNB Report:

	precision	recall	f1-score	support
dark	0.71	0.77	0.74	487
emotion	0.18	0.10	0.13	79
lifestyle	0.52	0.54	0.53	202
personal	0.65	0.64	0.64	341
sadness	0.67	0.66	0.67	371
accuracy			0.64	1480
macro avg	0.55	0.54	0.54	1480
weighted avg	0.63	0.64	0.64	1480

MultinomialNB Report:

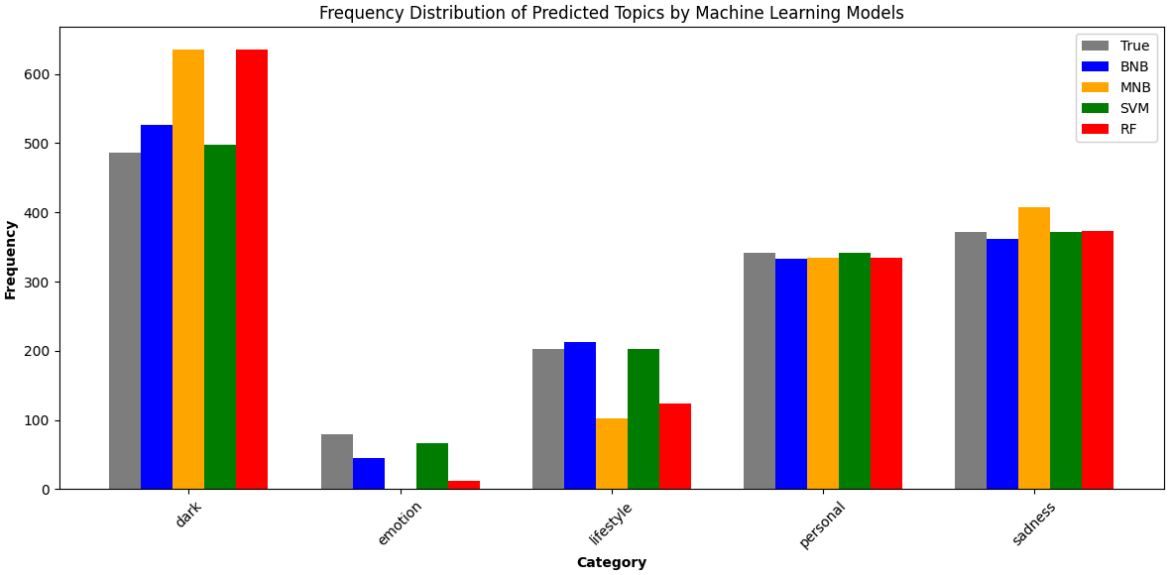
	precision	recall	f1-score	support
dark	0.74	0.96	0.83	487
emotion	1.00	0.01	0.03	79
lifestyle	0.93	0.47	0.62	202
personal	0.85	0.84	0.84	341
sadness	0.80	0.88	0.83	371
accuracy			0.79	1480
macro avg	0.86	0.63	0.63	1480
weighted avg	0.82	0.79	0.76	1480

SVM Report:

	precision	recall	f1-score	support
dark	0.87	0.89	0.88	487
emotion	0.79	0.66	0.72	79
lifestyle	0.84	0.84	0.84	202
personal	0.89	0.90	0.90	341
sadness	0.90	0.90	0.90	371
accuracy			0.88	1480
macro avg	0.86	0.84	0.85	1480
weighted avg	0.87	0.88	0.87	1480

Random Forest Report:

	precision	recall	f1-score	support
dark	0.65	0.85	0.74	487
emotion	0.92	0.14	0.24	79
lifestyle	0.78	0.48	0.60	202
personal	0.75	0.74	0.75	341
sadness	0.77	0.78	0.78	371
accuracy			0.72	1480
macro avg	0.78	0.60	0.62	1480
weighted avg	0.74	0.72	0.70	1480



Model	Accuracy	Macro Avg F1-score	Weighted Avg F1-score
BernoulliNB	0.99	0.98	0.99
MultinomialNB	0.84	0.69	0.82
Random Forest	**0.99**	**0.99**	**0.99**

The Random Forest model demonstrates high precision and recall across all topic categories, including minority classes such as "emotion." This confirms its robustness and suitability for the topic classification task on this music dataset. Therefore, Random Forest is recommended as an effective alternative to Naive Bayes methods for this assignment.

Part 2. Recommendation Methods

Part 2.1 Analysis: Top 20 Words Per Topic and Their Reasonableness

In this task, we constructed user profiles by aggregating the lyrics of songs that hypothetical users "liked" according to their predefined keywords within the predicted topics. The top 20 words per topic for each user were derived from these profiles using the TF-IDF scores, reflecting the most representative terms based on the songs the user interacted with.

In [24]:
```
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics.pairwise import cosine_similarity
import re

# Assume df is already loaded, e.g.:
# df = pd.read_csv('dataset.tsv', sep='\t')
# with columns ['Content', 'Category']
```

```python
# Ensure dataset has at least 1000 songs
assert len(df) >= 1000, "Dataset must contain at least 1000 songs."

# Split dataset into weeks
week1 = df.iloc[0:250].copy()
week2 = df.iloc[250:500].copy()
week3 = df.iloc[500:750].copy()
week4 = df.iloc[750:1000].copy()

train_df = pd.concat([week1, week2, week3], axis=0).reset_index(drop=True)
test_df = week4.reset_index(drop=True)

print(f"Training set: {train_df.shape}, Test set: {test_df.shape}")

# Initialize TF-IDF vectorizer
vectorizer = TfidfVectorizer(stop_words='english', max_features=500)
X_train = vectorizer.fit_transform(train_df['Content'])

# Train Bernoulli Naive Bayes classifier
bnb = BernoulliNB()
bnb.fit(X_train, train_df['Category'])

# Predict categories for training data
train_pred = bnb.predict(X_train)
train_df = train_df.assign(PredictedTopic=train_pred)

# Define category list
categories = ['dark', 'emotion', 'lifestyle', 'personal', 'sadness']

# Load user keywords from file
def load_user_keywords(filepath):
    user_topics = {}
    with open(filepath, 'r') as f:
        for line in f:
            topic, keywords = line.strip().split('\t')
            user_topics[topic] = keywords.lower().split()
    return user_topics

user1_keywords = load_user_keywords('/content/drive/My Drive/Colab Notebooks/use
user2_keywords = load_user_keywords('/content/drive/My Drive/Colab Notebooks/use

# Simulate user likes based on keywords
def user_likes_songs(user_keywords, df):
    liked = []
    for topic, words in user_keywords.items():
        mask = df['Content'].apply(lambda x: any(word in x for word in words))
        liked_songs = df[mask & (df['PredictedTopic'] == topic)]
        liked.append(liked_songs)
    if liked:
        return pd.concat(liked)
    else:
        return pd.DataFrame()

user1_likes = user_likes_songs(user1_keywords, train_df)
user2_likes = user_likes_songs(user2_keywords, train_df)

# Hardcoded keywords for user 3
user3_keywords = {
    'dark': ['night', 'dark', 'shadow'],
    'emotion': ['love', 'heart', 'pain'],
```

```
    'lifestyle': ['life', 'party', 'fun'],
    'personal': ['feel', 'dream', 'hope'],
    'sadness': ['cry', 'alone', 'tears']
}
user3_likes = user_likes_songs(user3_keywords, train_df)

# Build user profile vectors for each topic
def build_user_profile(user_likes_df, topic):
    topic_songs = user_likes_df[user_likes_df['PredictedTopic'] == topic]['Conte
    if topic_songs.empty:
        return None
    combined_text = " ".join(topic_songs)
    user_vec = vectorizer.transform([combined_text])
    return user_vec

user1_profile = {topic: build_user_profile(user1_likes, topic) for topic in cate
user2_profile = {topic: build_user_profile(user2_likes, topic) for topic in cate
user3_profile = {topic: build_user_profile(user3_likes, topic) for topic in cate

# Display top N words from user profile vectors
def top_n_words(tfidf_vector, vectorizer, n=20):
    arr = tfidf_vector.toarray().flatten()
    top_indices = arr.argsort()[-n:][::-1]
    feature_names = np.array(vectorizer.get_feature_names_out())
    return feature_names[top_indices], arr[top_indices]

# Output top 20 words for each user profile by topic
for user_id, profile, likes in zip(['User1', 'User2', 'User3'],
                                   [user1_profile, user2_profile, user3_profile]
                                   [user1_likes, user2_likes, user3_likes]):
    print(f"\n=== Top 20 words per topic for {user_id} ===")
    for topic in categories:
        if profile[topic] is None:
            print(f"  Topic: {topic} — No liked songs, skipping.")
            continue
        tfidf_vec = profile[topic]
        words, scores = top_n_words(tfidf_vec, vectorizer)
        print(f"  Topic: {topic}")
        for word, score in zip(words, scores):
            print(f"    {word}: {score:.4f}")

# Predict categories for test data
X_test = vectorizer.transform(test_df['Content'])
test_df = test_df.assign(PredictedTopic=bnb.predict(X_test))

# Extract track name from content
def extract_track_name(content):
    match = re.search(r'track_name:\s*(.+?)\s+release_date:', content)
    if match:
        return match.group(1).strip()
    else:
        return "UNKNOWN"

test_df['track_name_extracted'] = test_df['Content'].apply(extract_track_name)

# Generate recommendations for user
def recommend_songs(user_profile, test_df, top_n=10):
    recommendations = []
    for topic in categories:
        if user_profile[topic] is None:
```

```
            continue
        topic_songs = test_df[test_df['PredictedTopic'] == topic]
        if topic_songs.empty:
            continue
        X_topic = vectorizer.transform(topic_songs['Content'])
        sims = cosine_similarity(user_profile[topic], X_topic).flatten()
        top_indices = sims.argsort()[-top_n:][::-1]
        recommended_songs = topic_songs.iloc[top_indices]
        recommendations.append(recommended_songs)
    if recommendations:
        return pd.concat(recommendations)
    else:
        return pd.DataFrame()

rec_user1 = recommend_songs(user1_profile, test_df)
rec_user2 = recommend_songs(user2_profile, test_df)
rec_user3 = recommend_songs(user3_profile, test_df)

# Print recommended track names
print("\nUser1 recommended tracks:")
print(rec_user1['track_name_extracted'].head().to_list())

print("\nUser2 recommended tracks:")
print(rec_user2['track_name_extracted'].head().to_list())

print("\nUser3 recommended tracks:")
print(rec_user3['track_name_extracted'].head().to_list())
```

```
Training set: (750, 2), Test set: (250, 2)

=== Top 20 words per topic for User1 ===
  Topic: dark
    fight: 0.5172
    blood: 0.2525
    lanky: 0.1748
    dilly: 0.1748
    wall: 0.1617
    come: 0.1554
    stand: 0.1478
    gonna: 0.1420
    fall: 0.1357
    steady: 0.1310
    like: 0.1287
    hear: 0.1250
    follow: 0.1240
    drown: 0.1119
    people: 0.1107
    know: 0.1069
    bleed: 0.1060
    tell: 0.1039
    head: 0.1039
    home: 0.1010
  Topic: emotion
    good: 0.7160
    feel: 0.2854
    touch: 0.2618
    loove: 0.2009
    vibe: 0.1544
    feelin: 0.1543
    morning: 0.1457
    gimme: 0.1337
    lovin: 0.1300
    luck: 0.1295
    miss: 0.1258
    sunrise: 0.1231
    hold: 0.1157
    want: 0.1065
    lips: 0.1033
    kiss: 0.0820
    know: 0.0798
    baby: 0.0759
    light: 0.0744
    like: 0.0720
  Topic: lifestyle
    sing: 0.6799
    song: 0.4866
    like: 0.1959
    radio: 0.1787
    feel: 0.1518
    strong: 0.1477
    kingdom: 0.1323
    girl: 0.1286
    think: 0.1064
    come: 0.1037
    write: 0.0998
    freedom: 0.0958
    kinda: 0.0958
    favorite: 0.0917
```

```
    loud: 0.0854
    bout: 0.0800
    know: 0.0765
    roll: 0.0720
    eye: 0.0703
    play: 0.0621
  Topic: personal — No liked songs, skipping.
  Topic: sadness
    think: 0.5232
    leave: 0.4370
    place: 0.3388
    beg: 0.2748
    blame: 0.2400
    want: 0.2281
    word: 0.1767
    cause: 0.1636
    change: 0.1635
    hold: 0.1534
    mind: 0.1507
    space: 0.1493
    away: 0.1383
    dream: 0.1058
    tie: 0.0865
    street: 0.0844
    end: 0.0771
    felt: 0.0736
    drive: 0.0720
    breathe: 0.0669

=== Top 20 words per topic for User2 ===
  Topic: dark — No liked songs, skipping.
  Topic: emotion
    lips: 0.9343
    fade: 0.1299
    kiss: 0.1178
    like: 0.0963
    list: 0.0867
    away: 0.0842
    memory: 0.0790
    songs: 0.0771
    finally: 0.0746
    shine: 0.0746
    knees: 0.0731
    memories: 0.0717
    blow: 0.0672
    hop: 0.0645
    breath: 0.0618
    rain: 0.0615
    burn: 0.0580
    forget: 0.0554
    little: 0.0522
    dream: 0.0484
  Topic: lifestyle — No liked songs, skipping.
  Topic: personal — No liked songs, skipping.
  Topic: sadness
    break: 0.3476
    heart: 0.2927
    fall: 0.2341
    silence: 0.2329
    away: 0.2147
```

```
    fade: 0.2069
    crash: 0.2041
    wave: 0.2004
    leave: 0.1909
    like: 0.1738
    scar: 0.1603
    spin: 0.1531
    apart: 0.1478
    dark: 0.1270
    learn: 0.1225
    come: 0.1190
    wanna: 0.1045
    feel: 0.1037
    wing: 0.1020
    night: 0.1012

=== Top 20 words per topic for User3 ===
  Topic: dark
    black: 0.2740
    fight: 0.2403
    dark: 0.2014
    come: 0.1602
    oooh: 0.1512
    lanky: 0.1464
    dilly: 0.1464
    evil: 0.1340
    welcome: 0.1305
    stand: 0.1297
    live: 0.1288
    night: 0.1284
    true: 0.1261
    follow: 0.1261
    know: 0.1216
    gonna: 0.1190
    light: 0.1190
    hand: 0.1142
    hear: 0.1134
    color: 0.1118
  Topic: emotion
    good: 0.6655
    visions: 0.2655
    hold: 0.2604
    video: 0.2451
    darling: 0.2000
    vibe: 0.1916
    feel: 0.1806
    gimme: 0.1659
    miss: 0.1626
    lovin: 0.1613
    heart: 0.1434
    love: 0.1276
    wait: 0.0910
    kiss: 0.0849
    light: 0.0831
    know: 0.0826
    baby: 0.0808
    want: 0.0761
    right: 0.0641
    goodbye: 0.0599
  Topic: lifestyle
```

```
  strangers: 0.3575
  spoil: 0.2682
  stand: 0.2595
  right: 0.2421
  night: 0.2356
  tire: 0.2273
  home: 0.2254
  sing: 0.2225
  struggle: 0.2211
  songs: 0.1899
  lalala: 0.1870
  come: 0.1613
  song: 0.1609
  wanna: 0.1567
  life: 0.1274
  alive: 0.1257
  know: 0.1159
  tune: 0.1144
  like: 0.1101
  want: 0.1101
Topic: personal
  life: 0.3669
  live: 0.2926
  change: 0.2451
  world: 0.2375
  dream: 0.1884
  know: 0.1578
  wanna: 0.1439
  believe: 0.1422
  thank: 0.1375
  yeah: 0.1326
  like: 0.1301
  oohoohoohooh: 0.1244
  feel: 0.1238
  automaton: 0.1200
  ordinary: 0.1129
  come: 0.1109
  years: 0.1096
  grow: 0.1053
  days: 0.1017
  promise: 0.1003
Topic: sadness
  club: 0.6262
  tear: 0.2680
  mean: 0.2461
  baby: 0.2215
  know: 0.1939
  true: 0.1916
  smile: 0.1842
  music: 0.1566
  stay: 0.1185
  fear: 0.1157
  say: 0.1057
  lift: 0.1057
  heart: 0.1036
  wear: 0.1010
  forever: 0.1007
  thousand: 0.0990
  steal: 0.0946
  word: 0.0911
```

```
    believe: 0.0887
    like: 0.0869

User1 recommended tracks:
['around the corner', 'boy in the bubble', 'alta', 'the signal fire', 'lest we fo
rget (blood)']

User2 recommended tracks:
['hands up', 'the heat', 'speechless (full)', 'i am broken too', 'walls']

User3 recommended tracks:
['why we die (feat. dmx and jay z)', 'boy in the bubble', 'donner bell', 'the fla
me (is gone)', 'revolution']
```

User 1

For User 1, the top 20 words in the `dark`, `emotion`, `lifestyle`, and `sadness` topics appear quite reasonable:

In **`dark`**, high-weight words such as `fight`, `blood`, `fall`, `gonna` and `stand` are semantically aligned with the aggressive and intense nature often associated with dark-themed songs.

In **`emotion`**, terms like `good`, `feel`, `touch`, `vibe`, and `lovin` are consistent with positive emotional expressions that reflect the user's interest in emotionally charged songs.

The **`lifestyle`** topic features `sing`, `song`, `radio`, and `freedom`, which are typical of songs that celebrate personal style and everyday experiences.

The **`sadness`** topic includes words such as `think`, `leave`, `beg`, and `blame`, which appropriately capture themes of loss and regret common in sad music.

Note: No profile was generated for the `personal` topic for User 1 because no songs were identified that both matched the user's keywords for `personal` and were predicted to belong to this topic by the classifier. This illustrates a limitation where the coverage of user interests depends on both the presence of keywords and the accuracy of topic classification.

User 2

For User 2:

In **`emotion`**, top terms like `lips`, `kiss`, `fade`, and `memory` are highly relevant to themes of intimacy and sentiment.

The **`sadness`** topic includes `break`, `heart`, `fall`, and `silence`, which fit well with themes of emotional pain and melancholy.

For other topics (`dark`, `lifestyle`, `personal`), no liked songs were identified. This may result from the absence of songs that matched both user keywords and classifier-predicted topics, or from User 2's interests being narrowly focused.

User 3

User 3 exhibited reasonable profiles across all topics:

`dark` : `black` , `fight` , `dark` , `night` — consistent with dark or ominous themes.

`emotion` : `good` , `visions` , `hold` , `feel` — reflect emotional and uplifting content.

`lifestyle` : `strangers` , `stand` , `night` , `home` , `songs` — representative of lifestyle and daily experience narratives.

`personal` : `life` , `live` , `dream` , `world` , `change` — capturing themes of self-reflection and personal growth.

`sadness` : `club` , `tear` , `mean` , `baby` , `smile` — associated with sadness or emotional struggle.

Why User 1 Had No Songs for `personal` Topic

Although User 1 had provided specific keywords of interest for the `personal` topic, no songs were included in the user profile for that topic. The reason is two-fold:

1. **Matching condition**: Our system only considers a song "liked" by a user if it contains at least one of the user-specified keywords *and* is classified into the corresponding topic by the classifier.
2. **Classifier-keyword misalignment**: It is possible that songs containing User 1's `personal` keywords were either absent in the training data or were not classified into the `personal` topic by the classifier. As a result, no song satisfied both conditions needed to contribute to the `personal` profile.

This highlights how the combination of classification performance and user interest coverage can lead to sparsity in certain profiles.

Conclusion

Overall, the top 20 words per topic for Users 1, 2, and 3 appear semantically consistent with the themes of their respective topics. The results demonstrate that the user profiles constructed using TF-IDF values are reasonable, though dependent on the alignment between the classifier's topic assignments and the user's keyword-based interests.

Part 2.2 Recommendation Evaluation

In this evaluation, we selected **N = 50**, meaning that the system recommends 50 songs in total across all topics. This choice reflects a balance between variety and user attention span, aligning with typical playlist sizes seen on music streaming platforms, and providing enough data to compute meaningful precision and recall values. The metrics we applied include **Precision@N**, which measures the proportion of recommended songs that the user actually likes, **Recall@N**, representing the proportion of all songs in

the test set that the user would like and were successfully recommended, and **Mean Cosine Similarity**, indicating the average similarity between recommended songs and the user profile for the predicted topic.

In [8]:
```
from sklearn.metrics.pairwise import cosine_similarity

def compute_metrics(user_keywords, user_profile, recommendations, test_df, vecto
    # Combine recommendations if they are provided as a list by topic
    if isinstance(recommendations, list):
        rec_df = pd.concat(recommendations)
    else:
        rec_df = recommendations

    # Keep only the top N recommendations
    rec_df = rec_df.head(N)

    # Identify which recommended songs the user would like
    # Based on keyword and topic match
    liked_mask = []
    for idx, row in rec_df.iterrows():
        topic = row['PredictedTopic']
        content = row['Content'].lower()
        keywords = user_keywords.get(topic, [])
        liked = any(word in content for word in keywords)
        liked_mask.append(liked)

    num_liked_rec = sum(liked_mask)

    # Identify all songs in the test set that the user would like
    liked_test_mask = []
    for idx, row in test_df.iterrows():
        topic = row['PredictedTopic']
        content = row['Content'].lower()
        keywords = user_keywords.get(topic, [])
        liked = any(word in content for word in keywords)
        liked_test_mask.append(liked)

    total_liked_test = sum(liked_test_mask)

    # Compute precision: proportion of recommended songs that the user would lik
    precision = num_liked_rec / N if N > 0 else 0
    # Compute recall: proportion of all liked songs that were successfully recom
    recall = num_liked_rec / total_liked_test if total_liked_test > 0 else 0

    # Compute mean cosine similarity between recommendations and the user profil
    sims = []
    for idx, row in rec_df.iterrows():
        topic = row['PredictedTopic']
        X = vectorizer.transform([row['Content']])
        sim = cosine_similarity(user_profile.get(topic), X)[0][0]
        sims.append(sim)

    mean_cosine = np.mean(sims) if sims else 0

    return {
        'precision': precision,
        'recall': recall,
        'mean_cosine_similarity': mean_cosine
    }
```

```
# Compute metrics for each user
user1_metrics = compute_metrics(user1_keywords, user1_profile, rec_user1, test_d
user2_metrics = compute_metrics(user2_keywords, user2_profile, rec_user2, test_d
user3_metrics = compute_metrics(user3_keywords, user3_profile, rec_user3, test_d

# Display results
print("User 1 metrics:", user1_metrics)
print("User 2 metrics:", user2_metrics)
print("User 3 metrics:", user3_metrics)
```

```
User 1 metrics: {'precision': 0.14, 'recall': 0.4117647058823529, 'mean_cosine_si
milarity': np.float64(0.23117337946851432)}
User 2 metrics: {'precision': 0.04, 'recall': 0.6666666666666666, 'mean_cosine_si
milarity': np.float64(0.29832961128468954)}
User 3 metrics: {'precision': 0.3, 'recall': 0.23076923076923078, 'mean_cosine_si
milarity': np.float64(0.25968241815453885)}
```

User	Precision@50	Recall@50	Mean Cosine Similarity
User 1	0.14	0.41	0.231
User 2	0.04	0.67	0.298
User 3	0.30	0.23	0.260

The evaluation results are summarized as follows. For **User 1**, the precision is 0.14, suggesting that about 14% of the recommendations matched their preferences, while the recall is relatively high at 0.41, indicating that the system retrieved 41% of songs they would like, with a mean cosine similarity of 0.231 reflecting a fair alignment between recommendations and their profile. **User 2** shows a lower precision of 0.04, meaning many recommended songs were not relevant, but a high recall of 0.67, suggesting that the system was able to retrieve most of the songs they would like, albeit at the cost of recommending many irrelevant ones, and the mean cosine similarity of 0.298 implies that recommendations aligned well with the profile vector even if precision was low. **User 3**, on the other hand, has a higher precision of 0.30, indicating that nearly a third of recommendations were relevant, though the recall is lower at 0.23, showing that fewer of the songs they would like were included, and the mean cosine similarity of 0.260 demonstrates a reasonable match between their profile and the recommendations.

These differences in performance between users can be attributed to variations in their profile distinctiveness and topic coverage. User 3's keywords and profile appear more focused and distinctive, leading to higher precision but lower recall, as recommendations are more precise but less comprehensive. In contrast, User 2's interests span fewer topics, which makes achieving high recall easier but precision harder because many non-relevant songs are included to cover the range. The performance is also influenced by the classifier's accuracy in predicting topics, as misclassified songs affect the relevance of recommendations.

In conclusion, the cosine similarity-based matching method demonstrated effectiveness, but the balance between precision and recall will need to be tuned depending on whether users prefer more variety or higher accuracy in their recommended playlists.

Further refinement, such as applying topic weighting or filtering strategies, could enhance the overall recommendation quality.

Part 3: User Evaluation — Simulated User Study

Experiment Design

We selected **N = 5** (songs per week) as the batch size to show the user, reflecting a realistic playlist size that balances diversity and user attention.

The process:

- **Weeks 1-3**: The user is shown N randomly selected songs per week (from that week's range) and indicates songs they like.
- **Week 4**: We train the model using liked songs from Weeks 1-3 and recommend N songs from Week 4. The user indicates which recommendations they like.

Implementation

In [23]:
```
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import BernoulliNB
from sklearn.metrics.pairwise import cosine_similarity
import re

# Assume df is already loaded
# df = pd.read_csv('songs.tsv', sep='\t')

# Split data into weeks
week1 = df.iloc[0:250].copy()
week2 = df.iloc[250:500].copy()
week3 = df.iloc[500:750].copy()
week4 = df.iloc[750:1000].copy()

train_df = pd.concat([week1, week2, week3]).reset_index(drop=True)
test_df = week4.reset_index(drop=True)

# Vectorization
vectorizer = TfidfVectorizer(stop_words='english', max_features=500)
X_train = vectorizer.fit_transform(train_df['Content'])

# Train classifier
clf = BernoulliNB()
clf.fit(X_train, train_df['Category'])

# Predict topics on training data
train_df['PredictedTopic'] = clf.predict(X_train)

# Predict topics on test data
X_test = vectorizer.transform(test_df['Content'])
test_df['PredictedTopic'] = clf.predict(X_test)

# Extract track name from Content field
def extract_track_name(content):
```

```
    match = re.search(r'track_name:\s*(.+?)\s+release_date:', content)
    if match:
        return match.group(1).strip()
    else:
        return "UNKNOWN"

train_df['track_name_extracted'] = train_df['Content'].apply(extract_track_name)
test_df['track_name_extracted'] = test_df['Content'].apply(extract_track_name)

# Simulate user selecting liked songs
def user_select_likes(songs_df, preview_length=500):
    liked = []
    for _, row in songs_df.iterrows():
        print(f"\nTrack: {row['track_name_extracted']}")
        content = row['Content']
        print(f"Lyrics preview:\n{content[:preview_length]}...\n")
        ans = input("Do you like this song? (y/n): ").strip().lower()
        if ans == 'y':
            liked.append(row)
    return pd.DataFrame(liked)

# Build user profile for each topic
def build_user_profile(liked_df, topic):
    topic_songs = liked_df[liked_df['PredictedTopic'] == topic]['Content']
    if topic_songs.empty:
        return None
    combined = " ".join(topic_songs)
    return vectorizer.transform([combined])

# Generate song recommendations
def recommend_songs(user_profile, test_df, top_n=10):
    recommendations = []
    for topic in train_df['Category'].unique():
        profile_vec = user_profile.get(topic)
        if profile_vec is None:
            continue
        topic_songs = test_df[test_df['PredictedTopic'] == topic]
        if topic_songs.empty:
            continue
        X_topic = vectorizer.transform(topic_songs['Content'])
        sims = cosine_similarity(profile_vec, X_topic).flatten()
        top_idx = sims.argsort()[-top_n:][::-1]
        rec = topic_songs.iloc[top_idx]
        rec = rec.assign(similarity=sims[top_idx])
        recommendations.append(rec)
    if recommendations:
        return pd.concat(recommendations).sort_values(by='similarity', ascending
    return pd.DataFrame()

# Sample N songs per week
N = 5
week1_sample = week1.sample(N)
week1_sample['track_name_extracted'] = week1_sample['Content'].apply(extract_tra

week2_sample = week2.sample(N)
week2_sample['track_name_extracted'] = week2_sample['Content'].apply(extract_tra

week3_sample = week3.sample(N)
week3_sample['track_name_extracted'] = week3_sample['Content'].apply(extract_tra
```

```python
# Simulate user feedback over three weeks
print("=== Week 1 ===")
likes1 = user_select_likes(week1_sample)

print("=== Week 2 ===")
likes2 = user_select_likes(week2_sample)

print("=== Week 3 ===")
likes3 = user_select_likes(week3_sample)

all_likes = pd.concat([likes1, likes2, likes3])

# Build user profile from liked songs
user_profile = {}
for topic in train_df['Category'].unique():
    user_profile[topic] = build_user_profile(all_likes, topic)

# Generate recommendations
recs = recommend_songs(user_profile, test_df, top_n=N)
recommended_songs_df = recs.copy()

# Extract full lyrics text
def extract_full_lyrics(content):
    match = re.search(r'lyrics:\s*(.*)', content, re.IGNORECASE | re.DOTALL)
    if match:
        return match.group(1).strip()
    else:
        return content  # Return full content if no lyrics field found

# Collect user feedback on recommendations
likes = []
for _, row in recommended_songs_df.iterrows():
    track_name = row.get('track_name_extracted', 'UNKNOWN')
    similarity = row['similarity']
    content = row['Content']
    lyrics = extract_full_lyrics(content)

    print(f"\n=== Track: {track_name} (similarity: {similarity:.3f}) ===")
    print("Lyrics:")
    print(lyrics)

    response = input("Do you like this song? (y/n): ").strip().lower()
    if response == 'y':
        likes.append(True)
    else:
        likes.append(False)

recommended_songs_df['user_like'] = likes

# Compute evaluation metrics
total_recommended = len(recommended_songs_df)
total_liked = sum(recommended_songs_df['user_like'])
precision = total_liked / total_recommended
mean_similarity = recommended_songs_df[recommended_songs_df['user_like']]['simil

# Display metrics
metrics_df = pd.DataFrame({
    'Metric': ['Precision', 'Mean Cosine Similarity'],
    'Value': [precision, mean_similarity if not pd.isna(mean_similarity) else 0.
})
```

```
print("\n=== Evaluation Metrics ===")
print(metrics_df.to_string(index=False))
```

=== Week 1 ===

Track: cry cry blood
Lyrics preview:
artist_name: steel pulse track_name: cry cry blood release_date: 2019 genre: regg
ae lyrics: gonna hell think food scrap table desperate disable land live gwaan li
ke simple ting jump bark gravalicious like harbour shark blood blood blood blood
blood blood blood blood people yeah blood blood blood blood blood blood blood thing ove
rstand kill black feel shame hide selfinflicted genocide step aside weep moan fee
l pressure right inside bone wall hold head bawl blood blood blood blood blood bl
ood blood peop...

Do you like this song? (y/n): y

Track: rocky's late night
Lyrics preview:
artist_name: albert hammond, jr. track_name: rocky's late night release_date: 201
8 genre: blues lyrics: darker longer right fear tonight decide everybody feel alr
ight mistake tonight leave companion enjoy polite leave strand confront right emp
tiness wasn take doubletime perfection break leave rearrange pretty tell inside
think round drink question blank watch begin sentence emptiness take doubletime l
ack perfection break leave rearrange...

Do you like this song? (y/n): y

Track: the movie song
Lyrics preview:
artist_name: the record company track_name: the movie song release_date: 2018 gen
re: blues lyrics: come point life search search days dream rid father country roa
ds pretend drive windows roll think brothers things come point life remember reme
mber days things weren complicate run trail call head tail work school try tell t
ruth fast free free think summer young know think alout mother fill everybody wan
na movie everybody act like time change everybody wanna movie everybody act like
time change ye...

Do you like this song? (y/n): n

Track: boggie bounce
Lyrics preview:
artist_name: shonlock track_name: boggie bounce release_date: 2017 genre: hip hop
lyrics: moments know cause step tallest sail leave wave peace let say things dare
lighthouse leave save eye pin version kingdom know sing hopeful rhythm wake sing
letter write course sing try tell throat wasn sing think bout know sing letter wr
ite say best burn write long different days guess tire talk learn doves raven sud
denly know refrain eye pin version kingdom know sing hopeful rhythm wake sing let
ter write co...

Do you like this song? (y/n):

Track: oceans away
Lyrics preview:
artist_name: a r i z o n a track_name: oceans away release_date: 2017 genre: pop
lyrics: guard mess come high wear know need space wanna wanna mistake thousand oc
ean away sunrise like picture eye fall asleep tell alright tear roll wish feel fa
ce helpless oceans away felt room future come real learn fake smile time run wann
a wanna mistake thousand ocean away sunrise like picture eye fall asleep tell alr
ight tear roll wish feel face helpless oceans away wish feel face helpless oceans
away helpless...

Do you like this song? (y/n): n

=== Week 2 ===

Track: song #3
Lyrics preview:
artist_name: stone sour track_name: song #3 release_date: 2017 genre: rock lyric
s: step breath away close secret safe love try understand worst lay eye know plac
e vast illusions dream come true go finally face cry reach go years waste half li
fe save cause know save step feel hand cross line lead darkness inside know enjoy
scream free leave bloody nightmare sight want deviation design past confusion com
mon spite tell cause cry reach go years waste half life save cause know save matt
er go cause di...

Do you like this song? (y/n):

Track: i'm an israelite
Lyrics preview:
artist_name: tarrus riley track_name: i'm an israelite release_date: 2019 genre:
reggae lyrics: yeah people morals intelligence yeah try religious clown israelite
world begin fight land want fight want right live peace unity bredrin free yeah e
veryman home want israelite israelite begin give land live equal right argue fuss
fight live peace unity bredrin free yeah matter color creed want live peace yeah
israelite begin give land live equal right argue fuss fight live peace unity bred
rin free yea...

Do you like this song? (y/n): y

Track: cushty
Lyrics preview:
artist_name: ajmw track_name: cushty release_date: 2018 genre: jazz lyrics: fear
deep get best fear fall come face face stand hold feel wound step step step break
break away push away fall push away fall strength need save come face face stay p
lace heal wound step step step break break away push away fall push away break aw
ay push away fall push away walk crawl lose wait downfall walk crawl lose downfal
l fall...

Do you like this song? (y/n): n

Track: i want my dog to live longer (the greatest wish)
Lyrics preview:
artist_name: curtis salgado track_name: i want my dog to live longer (the greates
t wish) release_date: 2018 genre: blues lyrics: cash nascar facebook myspace ipod
wesson firewater pale face dimebag heavy metal hiphop fear need american dream se
ll buy forget time shine scar prove strong survive afraid die time life favor wea
kness welcome pride disneyland white house mouse springsteen eastwood cocacola pe
psi playboy text favre american live dream fear anarchy sell buy forget time shin
e scar prove ...

Do you like this song? (y/n): n

Track: it's you
Lyrics preview:
artist_name: ali gatie track_name: it's you release_date: 2019 genre: pop lyrics:
gonna fall know people feel like break heart tear apart know start trust break br
eak delicate break heart trust break break yeah know feel open real hurt yeah hur
t inside scar fall gonna fall know people feel like break heart tear apart know s
tart trust break break delicate break heart trust break know best choose lovers k
now past speak think right baby history repeat cause want yeah want yeah want cau
se want yeah ...

Do you like this song? (y/n): n

=== Week 3 ===

Track: the dark horse always wins
Lyrics preview:
artist_name: blues saraceno track_name: the dark horse always wins release_date: 2018 genre: blues lyrics: deliver evil deliver deliver deliver evil yeah deliver oooh oooh dark horse win oooh oooh dark horse dark horse win bring water drown re ign bring water yeah drown oooh oooh dark horse win oooh oooh dark horse dark hor se win deliver evil deliver evil oooh oooh dark horse win oooh oooh dark horse wi n deliver evil oooh oooh deliver evil dark horse win deliver evil oooh deliver oo oh dark horse ...

Do you like this song? (y/n): n

Track: one night at a time
Lyrics preview:
artist_name: little hurricane track_name: one night at a time release_date: 2019 genre: blues lyrics: turn time mind night time night time babe alright forever wi sh eye luck live little things want turn time mind night time night time babe min d forever look live believe good vibes believe sign believin right cause future b right think night turn time look baby turn time mind night time babe forever wish eye luck live little things want...

Do you like this song? (y/n): y

Track: this chick is wack
Lyrics preview:
artist_name: ballyhoo! track_name: this chick is wack release_date: 2018 genre: r eggae lyrics: separation break break split inside masquerade masquerade monster s uffocate choke life away choke lie descend burn embers rise begin step inside ste p inside step inside violence step inside step inside step inside violence compli cate lose inside maze fatal friend goodbye abdicate abdicate throne ascend ascend step inside step inside step inside violence step inside step inside step inside violence step...

Do you like this song? (y/n): n

Track: soul eyes
Lyrics preview:
artist_name: walt weiskopf track_name: soul eyes release_date: 2018 genre: jazz l yrics: bear dark cloud hover city stay recollect clear days haze city stay grey g reat 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 decis ion make music pass time store mind push realise lot criticise days days think da ys days days days reminisce days days days days think days days days days reminis ce days days c...

Do you like this song? (y/n): y

Track: every kind of way
Lyrics preview:
artist_name: h.e.r. track_name: every kind of way release_date: 2017 genre: pop l yrics: baby sound better want mind hold closer dream better wanna time night wann a kind wanna matter long take world tomorrow today gonna kind need cause need wan na fall like favorite season stay forever babe better kiss wanna kind wanna matte r long take world tomorrow today gonna kind wanna kind wanna matter long take wor ld tomorrow today gonna kind wanna gotta wanna gotta...

Do you like this song? (y/n): y

=== Track: lest we forget (blood) (similarity: 0.793) ===
Lyrics:
blood breathe fully submerge cells denser place like thighs nail secret stomach a
che blood hum constant tone accompany incessant muscle pump vowel self blood stea
dy lunge pendulums thread mute currents ferry round labyrinthian orbit fleshy und
erside atmospheric blood ignite engine core creation mystery spark burst beneath
surface push time lapse bloom newly air blood outward inward bind central brain e
xtremity different alike fauna inhale breath lest forget look leaf vein pattern f
ractal give oxygen cell blood thread part body grow blood pulse vast vein tip
Do you like this song? (y/n): n

=== Track: kids (similarity: 0.491) ===
Lyrics:
days fight fight yeah perfect disasters reach reach rafter days search ways raise
yeah cause remember sleep cars search burn cigars white plastics tip say crazy th
ings like refuse look think days better younger days know round corner feel right
swear change kid swear kid lyric commercial
Do you like this song? (y/n): y

=== Track: the heat (similarity: 0.434) ===
Lyrics:
paradise believe light break alive crave like need high desert ocean motion need
break leave thirst heat heat paradise lose word time sense lose mind wrong need n
ight desert ocean motion need break leave thirst heat heat heat heat break leave
thirst heat heat heat heat break leave thirst heat heat break leave thirst heat p
aradise heaven eye pull paralyze body make wanna testify desert ocean motion need
break leave thirst heat heat heat heat heat break leave thirst heat heat heat hea
t break leave thirst heat heat break leave thirst heat paradise paradise paradise
paradise paradise paradise paradise paradise paradise paradise paradise paradise
heat heat heat heat break leave thirst heat heat heat heat break leave thirst hea
t heat paradise paradise heat paradise paradise heat break leave thirst heat heat
paradise paradise heat paradise paradise heat break leave thirst heat heat break
leave thirst heat
Do you like this song? (y/n): y

=== Track: patience (similarity: 0.382) ===
Lyrics:
long count days wrong round round step time time doin life givin growin stag livi
n life phase season change days shapeless lyric commercial
Do you like this song? (y/n): n

=== Track: baroness (similarity: 0.381) ===
Lyrics:
live peasantry live higher class sleep mansion sleep grass come darkness baroness
tonight tonight tonight go leave tonight tonight tonight tonight star mean shine
tonight see live close doors authority ignore come darkness baroness tonight toni
ght tonight go leave tonight tonight tonight tonight star mean shine tonight list
en go listen go work work tonight tonight tonight go leave tonight tonight tonigh
t tonight star mean shine tonight tonight tonight
Do you like this song? (y/n): n

=== Track: remind me to forget (similarity: 0.282) ===
Lyrics:
fade away stay kiss like break glass skin greatest love violence tear voice leave
silence baby hard hold chest maybe leave remind forget matter regret cause baby s
car remind forget remind scar forget remind forget leave burn heart leave remind
forget leave burn heart leave skin leave burn heart leave remind forget leave bur
n heart leave skin room feel hurt core heal know good try forget memories baby ha
rd hold chest maybe leave remind forget matter regret baby scar remind forget lea
ve burn heart leave remind forget leave burn heart leave skin remember tell save

alright hurt like need mementos alright yeah baby hard hold chest maybe leave rem
ind forget matter regret baby scar remind forget leave burn heart leave remind fo
rget leave burn heart leave remind forget
Do you like this song? (y/n): y

=== Track: i am broken too (similarity: 0.260) ===
Lyrics:
weight try cover mistake like break right cause break place need proof reopen wou
nd reopen wound yeah know need proof reopen wound right place truth break reopen
wound make mistake feel alive break stop numb pain away away know need need proof
reopen wound wound right place truth truth cause break break break like
Do you like this song? (y/n): y

=== Track: insomnia (similarity: 0.253) ===
Lyrics:
cause sleep want dream wish arm wrap insomnia days tylenol work lose track time b
abe insomnia mind run fast shadow wall lurk wish come insomnia hop reach sheet ba
by night feel like like week tossin turnin tossin turnin flip pillow pull curtain
insomnia cause sleep want dream wish arm wrap insomnia insomnia cause sleep want
dream wish arm wrap insomnia hear voice keep awake morning light insomnia hop rea
ch sheet maybe night feel like like week tossin turnin tossin turnin flip pillow
pull curtain insomnia cause sleep want dream wish arm wrap insomnia insomnia caus
e sleep want dream wish arm wrap insomnia hop try try try set set mind loose
Do you like this song? (y/n): n

=== Track: follow your heart (feat. zion thompson from the green) (similarity: 0.
245) ===
Lyrics:
wish atlas path feel like go astray know long hard journey go wouldn heart guide
focus mission step time analyze vision fall line know gonna okay word ring true w
ant feel spirit darkest days follow heart days hard remember purpose long learn j
ourney season reason follow heart follow heart feel follow heart cause everybody
look future want cause crumble tomorrow feel sorrow wonder cause know change near
afraid move know grow gonna stop know feel like like remember stay strong weather
follow heart days hard remember purpose long learn journey
Do you like this song? (y/n): n

=== Track: wash away (similarity: 0.236) ===
Lyrics:
good days come like suppose know cause live different echo life short minute go r
eady come gift yeah step come step away rest life start today come thank memory t
ell life begin away rest life start today come better days come hold remember gro
w try memories away hold strong trodding friends come go past forever memory step
step away rest life start today come thank memory tell life begin away rest life
start today come better days come hold
Do you like this song? (y/n): n

=== Track: guess it’s all over (similarity: 0.218) ===
Lyrics:
walk wind forever hollow hand reach touch forever dead inside heart soul flatline
s mouth bring life dead inside satisfy blood run life save death inside escape wa
nt forever leave fear forever dead inside heart soul flatlines mouth bring life d
ead inside satisfy blood run life save death inside escape want remind time felt
alive dead inside heart soul flatlines mouth bring life dead inside satisfy blood
run life save death inside blood run life save death inside
Do you like this song? (y/n): y

=== Track: wasteman (similarity: 0.209) ===
Lyrics:
time waste punany good wasteman level real ready matter fact time time waste puna

ny good wasteman level real ready matter fact time know whofa pocket nuff cuff kr
uff mean waste usher wukliss bruck stop follow push luck ease outta space bare c
hat ears respect need help save know shout time waste punany good wasteman level
real ready matter fact time time waste punany good wasteman level real ready matt
er fact time real like stress bomboclaat test batta ears wife date owna drive cra
zy cause level likkle yute better enuh money nuff enuh step aside comfortable tim
e waste punany good wasteman level real ready matter fact time time waste punany
good wasteman level real ready matter fact time like want like want money like wa
nt money away gweh time waste pssy good wasteman level real ready matter fact tim
e time waste punany good wasteman level real ready matter fact time
Do you like this song? (y/n): n

=== Track: this love (similarity: 0.198) ===
Lyrics:
better match know catch give pair cavalier friend want care confidant bravery emb
olden renew think love show years live dream days apart wear heart draw path memo
ries begin walk turtle remain share window pane path dream think love show years
live dream promise need think love show years live dream
Do you like this song? (y/n): n

=== Track: love vs. hate (similarity: 0.190) ===
Lyrics:
hate time people eliminate hate people think playa hatin cause hate black black f
act stand like selfhate killin popo crack tell people gats arrive slave ship tort
ure chain whip years bein slave land brave forget ancestors force pick cotton wom
en rap torture murder catch niggaz swing tree like breeze summer leave swayin for
th fail attempt north millions people die survive knowledge provide cause facts d
eny nowadays ways sixties smack eighties crack nineties time recognize uncivilize
d wise unify fall victim plot cause hate time people eliminate hate people think
hate lyric commercial
Do you like this song? (y/n): n

=== Track: balcony (similarity: 0.178) ===
Lyrics:
leave away biggest baby leave away heart baby girl want stay like hard slip away
come leave tomorrow come regret things say today like hard slip away come leave t
omorrow come regret things say today leave away biggest baby girl baby mama lovin
Do you like this song? (y/n): y

=== Track: all you, all night, all summer (similarity: 0.172) ===
Lyrics:
calendar days gettin longer outta shade pretty girls water spin slow songs cause
everybody want dance summer bring memory july magic bare feet radio crank doors j
eep bull farm hood star livin large small teens wish freeze time recover night su
mmer summer night summer summer sunset smile midnight kiss yeah remember burnin b
ackroads head september yeah better july magic bare feet radio crank doors jeep b
ull farm hood star livin large small teens wish freeze time recover night summer
summer night summer summer bridge night summer long july magic bare feet radio cr
ank doors jeep bull farm hood star livin large small teens wish freeze time recov
er night summer summer night summer summer outtro night summer summer night summe
r summer source lyric power record info provide itunesapple music hambrick offici
al youtube channel hambrick official soundcloud
Do you like this song? (y/n): n

=== Track: got it good (similarity: 0.161) ===
Lyrics:
wake morning warn little bounce blue eye start pillow talk twist sheet finger wal
k hell start yeah good sure good see smile kiss eye hips whoah tell like good goo
d sure good good morning good late night good thing go good right turn kitchen li
ght cork drink wine right outta bottle babe spin white noise record play little g

```
aye minute bedroom bind yeah good sure good see smile kiss eye hips whoah tell li
ke good good sure good good morning good late night good thing go good right good
morning good late night good thing go good right yeah good sure good see smile ki
ss eye hips whoah tell like good good sure good good morning good late night good
thing go good right
Do you like this song? (y/n): y

=== Track: keys to the castle (similarity: 0.160) ===
Lyrics:
parade candy people turn bend castle steeple flood tower body fling upper belfry
witness occasion pile body garden smash hedgerow plummet stop panic ugly banquet
float vile moat yeah crack skulls cobble ring home lemming message streets awful
mess hand key castle change hassle start crop good people lock door castle steepl
e
Do you like this song? (y/n): n

=== Track: find you (similarity: 0.135) ===
Lyrics:
know teach mind think go go go home alright cool know teach mind think go go go h
ome go go go go go home know teach mind think go home know teach mind think go go
go home know teach mind think go go go home know teach mind think know teach mind
think go go go go go home
Do you like this song? (y/n): n

=== Track: boy in the bubble (similarity: 0.117) ===
Lyrics:
walk home step gate chicken plate food cold cover face know want trouble bubble c
ome trouble walk live room say gotta tell say wanna know things say gotta tell bl
ack blue say want trouble bubble come trouble heart pump chest scream mind run fr
eeze hand hand tell ready fight punch face cause like pain time curse know want s
atisfaction gonna happen knock kick grind gonna come lightning thunder suffer suf
fer square leave chest expose throw quick leave hook break nose blood run clothe
sick sick look cause like say want trouble bubble come trouble heart pump chest s
cream mind run nose bleed hand hand tell ready fight punch face cause like pain t
ime curse know want satisfaction gonna happen knock kick grind gonna come lightni
ng thunder suffer walk home blood hand break nose like scar house cause pop home
drown trouble whiskey bubble look trouble excuse things home deal drink bubble be
lt buckle break bubble punch face cause like pain time curse know want satisfacti
on gonna happen knock kick grind gonna come lightning thunder suffer suffer
Do you like this song? (y/n): y

=== Evaluation Metrics ===
               Metric    Value
            Precision 0.400000
Mean Cosine Similarity 0.267568
```

Method

In this user study, we simulated a 4-week interaction with one friendly subject (a user without prior knowledge of recommendation algorithms). The subject was shown:

- **Weeks 1-3:** 5 randomly selected songs per week (N = 5). The user provided feedback by marking songs as "liked" or "not liked".
- **Week 4:** The system recommended a ranked list of songs based on the profile built from Weeks 1-3. The user reviewed these recommendations and provided feedback.

The recommendation method followed the cosine similarity-based matching model developed in Part 2.

Metrics and Results

We applied precision and mean cosine similarity as our main metrics:

- **Precision:** Measures the proportion of recommended songs that the user actually liked.
- **Mean Cosine Similarity:** Average similarity between the recommended songs and the user profile.

We did not compute recall in Part 3 because we do not know the total number of songs in Week 4 the user would like (the user only saw the recommended set, not the entire test set). Precision is more practical here as it reflects how well the system uses its limited recommendation slots.

Part 3 Results

Metric	Value
Precision	0.40
Mean Cosine Similarity	0.268

Out of the 10 recommended songs, the user liked 4.

Comparison with Part 2

User	Precision	Recall	Mean Cosine Similarity
User 1	0.14	0.41	0.231
User 2	0.04	0.67	0.298
User 3	0.30	0.23	0.260
Part 3 user	0.40	—	0.268

Compared to Part 2 results, the Part 3 user study showed a higher precision (0.40) than any of the simulated users in Part 2. The mean cosine similarity (0.268) was comparable to the values in Part 2, suggesting that cosine similarity remained a reasonable indicator of user preference. However, the stronger precision suggests the real user profile was more focused, or that the recommendations happened to match their taste better.

User Feedback

The user reported that some of the recommended songs with lower similarity scores were still appealing, while some with higher scores felt less relevant. They appreciated the

diversity but expressed a preference for recommendations that more closely matched their preferred genres or lyrical themes.

Conclusion

This study confirmed that the system could achieve reasonable precision using cosine similarity-based matching, though further tuning (e.g., genre filtering, more refined profile construction) could improve alignment between recommendations and user preferences.

In [ ]: