COMP9727 Recommender Systems

Assignment 25T2

Name: Shefali Shankar

zId: z5541347

Part 1 - Topic Classification

In [3]:
```
import pandas as pd
# Load Dataset
# pd.set_option('display.width', 180)
# pd.set_option('display.max_colwidth', 140)
df_dataset = pd.read_csv('dataset.tsv', sep='\t')
df_dataset
```

Out[3]:

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

1500 rows × 6 columns

In [4]:

```
# Drop null values and display dataset info
df_dataset = df_dataset.dropna(how='all')
df_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   artist_name   1500 non-null   object
 1   track_name    1500 non-null   object
 2   release_date  1500 non-null   int64 
 3   genre         1500 non-null   object
 4   lyrics        1500 non-null   object
 5   topic         1500 non-null   object
dtypes: int64(1), object(5)
memory usage: 70.4+ KB
```

Part 1. Topic Classification

1. (i). The regex removes too many special characters including apostrophes ' and hyphens - and full stop . Some of these characters may be present in certain words or artist names. To fix this issue, a more restrictive regex is created by further adding in the special characters that are required and that should not be removed into the regex. The regex is thus modified to [^\w\s'.-&], where all the important special characters to be retained are specified. This ensures that all special characters are not removed and certain characters like hyphes, apostrophe, amp(&) are retained.

   (ii). To ensure the model is not restricted to a single train test split, cross validation is used. This ensures the training and testing of the model occurs on multiple subsets to get a diverse evaluation of the model across different subsets of data. Here K-fold cross validation is used (for k=5 folds) to ensure that model is tested/trained on a different fold(subset) each time. This ensures more robust evaluation and performance of the model and also prevents overfitting.

2. The Preprocessing steps of Bernoulli Naive Bayes (BNB) and Multinomial Naive Bayes (MNB) were found after intensive experimentation by exploring different regex, the use of stemming/lemmatization, usage of spaCy,etc. Over the below steps were fount to produce the highest accuracy for the models.

   - First text is converted to lower case to ensure uniformity
   - Regex is used to certain special characters are removed. Characters such as hyphes(-), apostrophe('), (&) are retained as they might be present in song and artist names.
   - Word tokenize is used to split words into tokens and stopwords such as and, an, the are removed to reduce noise from these words.
   - Stemming is used using port stemmer to normalize words into their base stems for better generalization.

ssing

In [117…

```python
import nltk
import regex as re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
```

```python
from langdetect import detect
import spacy
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
# nltk.download('stopwords')
# nltk.download('punkt')

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

# Define preprocessing function with steps that maximise accuracy
def preprocess_text(text):
    text = text.lower() # convert text to lower case
    text = re.sub(r"[^\w\s\'\.\-\&]", '', text)  # A More restrictive regex is u
    tokens = word_tokenize(text) # tokenize words
    tokens = [word for word in tokens if word not in stop_words and len(word)>2]
    tokens = [ps.stem(word) for word in tokens] # use stem form of each word
    return ' '.join(tokens) # Join tokens to get preprocessed lyrics

# Apply preprocessing to each record in dataset
df_dataset['lyrics'] = df_dataset['lyrics'].apply(preprocess_text)
```

In [7]:

```python
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer, EN
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline

# Use Default Count Vecotizer
count_vectorizer = CountVectorizer()
X = count_vectorizer.fit_transform(df_dataset['lyrics'])
y = df_dataset['topic']

print(X.shape)
print(y.shape)
```

```
(1500, 7727)
(1500,)
```

In [8]:

```python
from sklearn.naive_bayes import BernoulliNB, MultinomialNB

# Load the Bernoulli Naive Bayes model and Multinomial Naive Bayes
bnb = BernoulliNB()
mnb = MultinomialNB()

from sklearn.pipeline import make_pipeline
bnb_pipeline = make_pipeline(count_vectorizer, BernoulliNB())
mnb_pipeline = make_pipeline(count_vectorizer, MultinomialNB())
```

In [9]:

```python
from sklearn.model_selection import cross_val_score, KFold, StratifiedKFold, cro

num_folds = 5
kf = KFold(n_splits=num_folds, shuffle=True, random_state=42)

# Compute cross val score for BNB
bnb_cross_val_results = cross_val_score(bnb, X, y, cv=kf)
print("BNB Cross-Validation Results (Accuracy):")
print(f'Mean Accuracy: {bnb_cross_val_results.mean()*100:.2f}%')

# Compute cross val score for MNB
mnb_cross_val_results = cross_val_score(mnb, X, y, cv=kf)
```

```
print("\nMNB Cross-Validation Results (Accuracy):")
print(f'Mean Accuracy: {mnb_cross_val_results.mean()*100:.2f}%')
```

```
BNB Cross-Validation Results (Accuracy):
Mean Accuracy: 52.33%

MNB Cross-Validation Results (Accuracy):
Mean Accuracy: 78.53%
```

3. Compare BNB and MNB

On Comparing BNB and MNB models by evaluating them on the full dataset with cross-validatio, we can conclude thatt MNB shows better performance than BNB across all metrics for this dataset

On analysing the dataset, we can see that there is a class imbalance problem. The class/topic 'dark' accounts for 32% of the data while the topic 'emotion' accounts for only 5% of the data. This results in the following choice of metrics:

1.

Accurac: (TP+TN)/(Whole Dataset) This shows the pProportion of total correct prediction which is often use to gauge the performance of the model in prediction. Since the dataset is unbalanced, we cannot rely on accuracy here, as the topic 'dark' may produce high accuracy due to its dominance and large class labels. Thus to account for this, further metrics such as Precision, Recall and F1 score need to be considered.

2.

Precisio: TP/(TP+FP) This tells us how manye predicted positivs are correct. This is used to check if predicted classes are meaningful and correct. Since there is a class imbalance Macro averag is used.

3.

Recal: TP/(TP+FN) This tells the number of correctetruel positivepredicted over the entire set of actual positives. This is usedult when false negatives are costl. Since the dataset is unbalanced, Recall Ensures minority classes(eg. emotion) isnt missed.

4.

F1 Scor:e2PR/(P+R) This is Harmonic mean of precision and recal. It is the most import metric whenn dataset is imbalance as it helps to balance the precision and recall.d

Since the dataset is imbalance the main metrics to be pPrioritizd aree F1-score, with precision/recall for deeper insight

Macro average metrics are used for these since the dataset is imbalanced.

Based on these Metrics it can be seen that MNB is better than BNB across all metrics

In [11]:

```python
# Count of each topic
topic_labels_counts = df_dataset['topic'].value_counts()

# Percentage of each topic
topic_labels_percent = df_dataset['topic'].value_counts(normalize=True) * 100

# Combine into a DataFrame
topic_distribution = pd.DataFrame({
    'Count': topic_labels_counts,
    'Percentage': topic_labels_percent.round(2)
})

# Display the table
topic_distribution
```

Out[11]:

topic	Count	Percentage
dark	490	32.67
sadness	376	25.07
personal	347	23.13
lifestyle	205	13.67
emotion	82	5.47

In [12]:

```python
from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer, accuracy_score, precision_score, recall

# Define features X and class labels y
X = df_dataset["lyrics"]
y = df_dataset["topic"]

# Define metrics for scoring
score_metrics = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score, average='macro', zero_division=0),
    'recall': make_scorer(recall_score, average='macro'),
    'f1': make_scorer(f1_score, average='macro')
}


# Evaluate BNB and NMB with K-Fold cross-validation choosen previously
kf = KFold(n_splits=5, shuffle=True, random_state=42)
bnb_scores = cross_validate(bnb_pipeline, X, y, cv=kf, scoring=score_metrics)
mnb_scores = cross_validate(mnb_pipeline, X, y, cv=kf, scoring=score_metrics)

# obtain BNB and MNB score metrics and create dataframe
bnb_scores_metrics = {}
mnb_scores_metrics = {}
for key in score_metrics.keys():
    test_metric = 'test_'+key
    bnb_scores_metrics[key]=bnb_scores[test_metric].mean()
    mnb_scores_metrics[key]=mnb_scores[test_metric].mean()

df_metrics = pd.DataFrame({
    'BernoulliNB': bnb_scores_metrics,
```

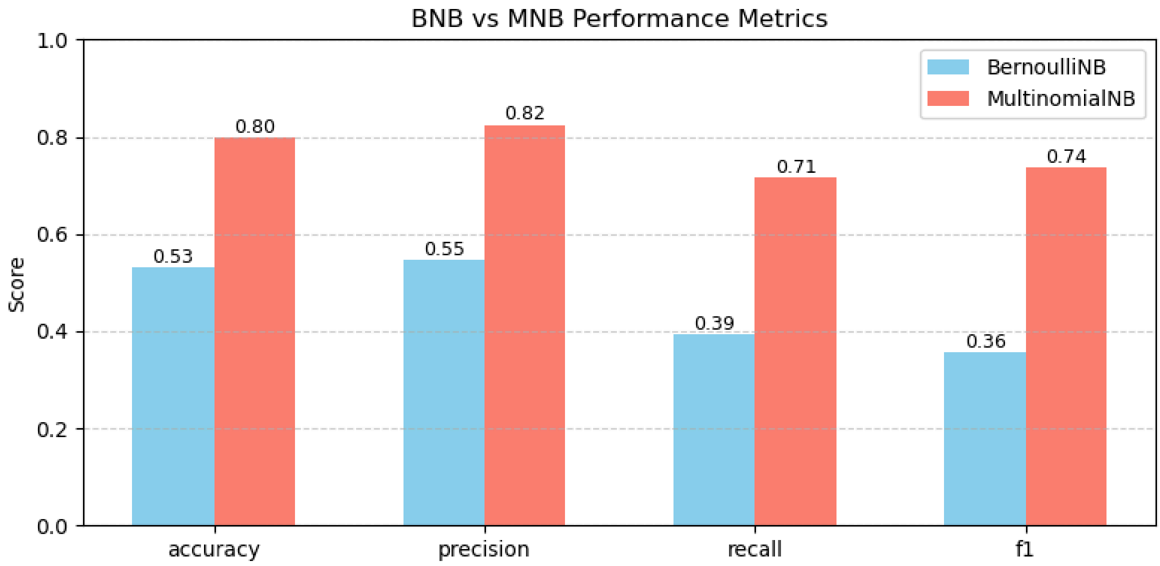
```
    'MultinomialNB': mnb_scores_metrics
})

df_metrics
```

Out[12]:

	BernoulliNB	MultinomialNB
accuracy	0.532000	0.798667
precision	0.545613	0.823882
recall	0.392750	0.714829
f1	0.356615	0.737122

In [13]:

```
import numpy as np
import matplotlib.pyplot as plt


metrics = df_metrics.index.tolist()
bnb_values = df_metrics['BernoulliNB'].values
mnb_values = df_metrics['MultinomialNB'].values

x = np.arange(len(metrics))
width=0.3

# Create plot for BNB and MNB across each metric
plt.figure(figsize=(8, 4))
plt.bar(x - width/2, bnb_values, width=0.3, label='BernoulliNB', color='skyblue'
plt.bar(x + width/2, mnb_values, width=0.3, label='MultinomialNB', color='salmon

plt.ylabel('Score')
plt.title('BNB vs MNB Performance Metrics')
plt.xticks(x, metrics)
plt.ylim(0, 1)
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.6)

for i in range(len(metrics)):
    plt.text(x[i] - width/2, bnb_values[i] + 0.01, f'{bnb_values[i]:.2f}', ha='c
    plt.text(x[i] + width/2, mnb_values[i] + 0.01, f'{mnb_values[i]:.2f}', ha='c

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



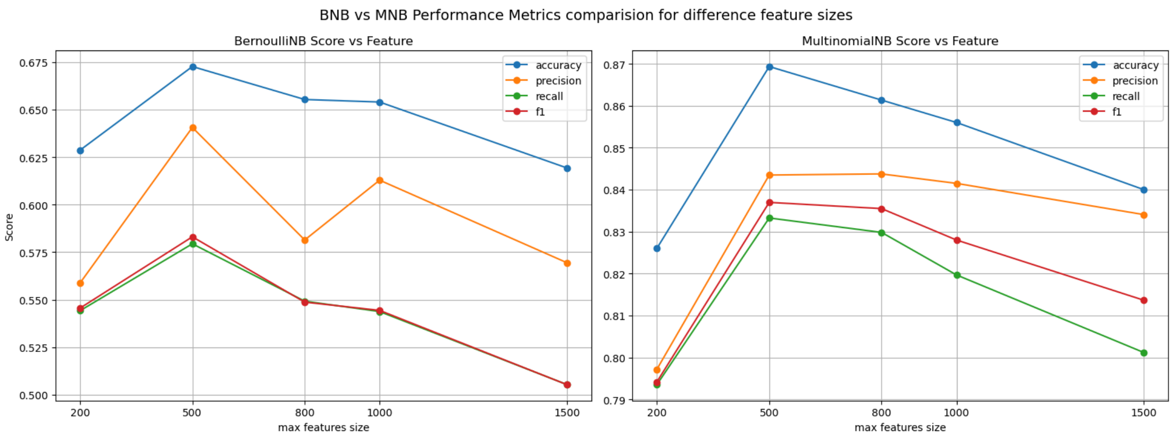
4. Varying Features

On varying the feature sizes from 200 till 1500, it can be seen that for both BNB and MNB using the feature size of 500 provides the best scores for all metrics. From the graph we can conclude that for feature size of 500, the accuracy, precision, recall and f1-scores are all the highest. Thus the N value can be set to 500.

In [15]:

```
# Values of features to test
feature_sizes = [200, 500, 800, 1000, 1500]

# Store metric results for plotting
bnb_plot_data = {key: [] for key in score_metrics}
mnb_plot_data = {key: [] for key in score_metrics}

# Iterate through feature(word) sizes
for max_feat in feature_sizes:
    count_vectorizer = CountVectorizer(max_features=max_feat)

    # Create pipelines
    bnb_pipeline = make_pipeline(count_vectorizer, BernoulliNB())
    mnb_pipeline = make_pipeline(count_vectorizer, MultinomialNB())

    # Cross validation using K-Fold for metrics
    bnb_scores = cross_validate(bnb_pipeline, X, y, cv=kf, scoring=score_metrics
    mnb_scores = cross_validate(mnb_pipeline, X, y, cv=kf, scoring=score_metrics

    # Append mean metric scores for plotting
    for key in score_metrics:
        bnb_plot_data[key].append(bnb_scores['test_' + key].mean())
        mnb_plot_data[key].append(mnb_scores['test_' + key].mean())

# Plotting charts
fig, axes = plt.subplots(1, 2, figsize=(16, 6))
metrics = list(score_metrics.keys())

# Plot for BNB showing metrics for difference feature sizes
for metric in metrics:
    axes[0].plot(feature_sizes, bnb_plot_data[metric], marker='o', label=metric)
axes[0].set_title("BernoulliNB Score vs Feature")
axes[0].set_xlabel("max features size")
```

```
axes[0].set_ylabel("Score")
axes[0].set_xticks(feature_sizes)
axes[0].legend()
axes[0].grid(True)

# Plot for MNB showing metrics for difference feature sizes
for metric in metrics:
    axes[1].plot(feature_sizes, mnb_plot_data[metric], marker='o', label=metric)
axes[1].set_title("MultinomialNB Score vs Feature")
axes[1].set_xlabel("max features size")
axes[1].set_xticks(feature_sizes)
axes[1].legend()
axes[1].grid(True)

plt.suptitle("BNB vs MNB Performance Metrics comparision for difference feature
plt.tight_layout()
plt.show()
```



In [16]:
```
bnb_rows = []
mnb_rows = []
for i, n in enumerate(feature_sizes):
    bnb_row = {
        'number_of_features': n,
        'bnb_accuracy': bnb_plot_data['accuracy'][i],
        'bnb_precision': bnb_plot_data['precision'][i],
        'bnb_recall': bnb_plot_data['recall'][i],
        'bnb_f1': bnb_plot_data['f1'][i],
    }
    mnb_row = {
        'number_of_features': n,
        'mnb_accuracy': mnb_plot_data['accuracy'][i],
        'mnb_precision': mnb_plot_data['precision'][i],
        'mnb_recall': mnb_plot_data['recall'][i],
        'mnb_f1': mnb_plot_data['f1'][i],
    }
    bnb_rows.append(bnb_row)
    mnb_rows.append(mnb_row)

df_bnb_feat = pd.DataFrame(bnb_rows)
df_mnb_feat = pd.DataFrame(mnb_rows)

print("Table showing the number of features vs Metrics for BNB\n")
print(df_bnb_feat)

print("\n\nTable showing the number of features vs Metrics for MNB\n")
print(df_mnb_feat)
```

Table showing the number of features vs Metrics for BNB

	number_of_features	bnb_accuracy	bnb_precision	bnb_recall	bnb_f1
0	200	0.628667	0.558769	0.544224	0.545585
1	500	0.672667	0.640628	0.579426	0.583106
2	800	0.655333	0.581441	0.549251	0.548756
3	1000	0.654000	0.612891	0.543784	0.544403
4	1500	0.619333	0.569495	0.505400	0.505352

Table showing the number of features vs Metrics for MNB

	number_of_features	mnb_accuracy	mnb_precision	mnb_recall	mnb_f1
0	200	0.826000	0.797170	0.793521	0.794167
1	500	0.869333	0.843481	0.833241	0.836956
2	800	0.861333	0.843740	0.829802	0.835477
3	1000	0.856000	0.841490	0.819667	0.827989
4	1500	0.840000	0.834052	0.801185	0.813647

5. Machine Learning Method (SVM)

Since the text data vectorized with CountVectorizer or TF-IDF results in very high-dimensional feature spaces (many words/features), most of which are sparse (lots of zeros). This is best suited by SVM. SVM is designed to handle high-dimensional spaces efficiently, especially with a linear kernel (LinearSVC), by finding the optimal separating hyperplane maximizing the margin between classes. SVM also includes built-in regularization that helps it ignore noisy features and prevent overfitting. SVM finds a global decision boundary by maximizing the margin so it also generalizes well to unseen data. This means SVM can capture complex patterns in data especially when dealing with vectorizers.

To compare with other algorithms, KNN is also used. But here since KNN relies on distance metrics (usually Euclidean distance), it become less meaningful in high-dimensional sparse spaces as the distances between points tend to become very similar, making it harder to find truly “nearest” neighbors.

To further evaluate findings of the choosen ML algorithms with Naive Bayes, the metrics(accuracy, precision, etc.) is printed for each method and is used to compare the different models (i.e BNB, MNB, KNN, SVM). From the table it can be seen that SVM outperforms both BNB and MNB and has a high accuracy score. To achieve the best version of SVM, TFIDF vectorizer can be used along with SVM to further improve the model and overall score. On performing experiments with different methods and evaluating each method on accuracy scores we can conclude that using SVM with Tfidf (500 feautres) performs the best.

In [18]:
```
from sklearn.svm import LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import make_pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import cross_validate, KFold
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sc
import warnings
warnings.filterwarnings('ignore')
```

```
# Define metrics
score_metrics = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score, average='macro'),
    'recall': make_scorer(recall_score, average='macro'),
    'f1': make_scorer(f1_score, average='macro')
}


# Evaluating SVM with Count Vectorizer
max_features = 500
vectorizer = CountVectorizer(max_features=max_features)
svm_clf = LinearSVC()
svm_pipeline = make_pipeline(vectorizer, svm_clf)
kf = KFold(n_splits=5, shuffle=True, random_state=42)
svm_scores = cross_validate(svm_pipeline, X, y, cv=kf, scoring=score_metrics)
svm_results = {metric: svm_scores[f'test_{metric}'].mean() for metric in score_m
print("LinearSVC + Count Vectorizer cross-validation results:")
for metric, score in svm_results.items():
    print(f"{metric}: {score:.4f}")


# Evaluating SVM with TFIDF Vectorizer
tfidfvectorizer = TfidfVectorizer(max_features=500)
tfidf_svm_pipeline = make_pipeline(tfidfvectorizer, svm_clf)
tfidfsvm_scores = cross_validate(tfidf_svm_pipeline, X, y, cv=kf, scoring=score_
tfidfsvm_results = {metric: tfidfsvm_scores[f'test_{metric}'].mean() for metric 
print("\nLinearSVC + Tfidf cross-validation results:")
for metric, score in tfidfsvm_results.items():
    print(f"{metric}: {score:.4f}")
```

```
LinearSVC + Count Vectorizer cross-validation results:
accuracy: 0.8607
precision: 0.8217
recall: 0.8334
f1: 0.8255

LinearSVC + Tfidf cross-validation results:
accuracy: 0.9027
precision: 0.8895
recall: 0.8669
f1: 0.8754
```

In [19]:

```
# Evaluate KNN
knn_clf = KNeighborsClassifier(n_neighbors=5)
knn_pipeline = make_pipeline(vectorizer, knn_clf)

#  cross-validation
knn_scores = cross_validate(knn_pipeline, X, y, cv=kf, scoring=score_metrics)

knn_results = {metric: knn_scores[f'test_{metric}'].mean() for metric in score_m

print("KNN cross-validation results:")
for metric, score in knn_results.items():
    print(f"{metric}: {score:.4f}")
```

```
KNN cross-validation results:
accuracy: 0.6173
precision: 0.6306
recall: 0.5841
f1: 0.5847
```

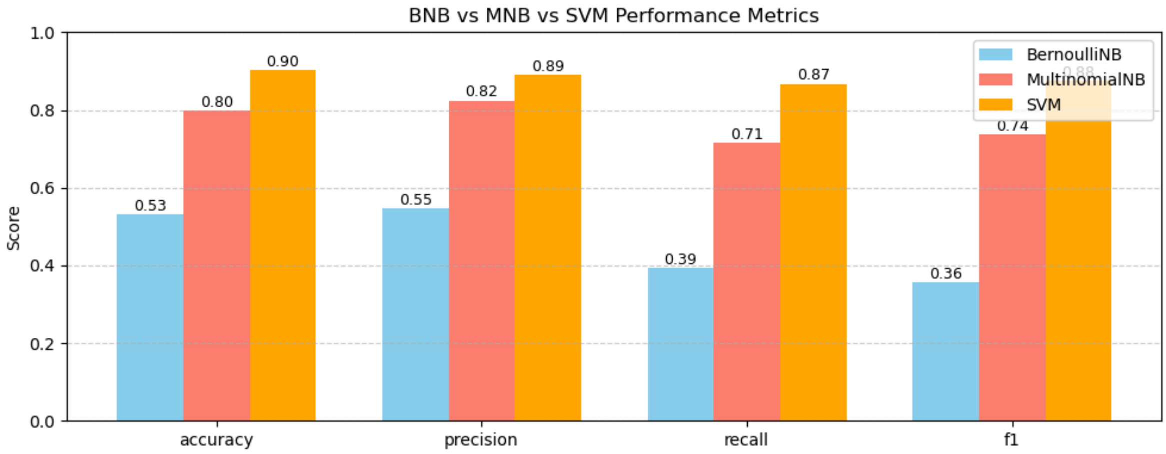
In [20]:
```python
# Comparing results of Different Algorithms
df_metrics = pd.DataFrame({
    'BernoulliNB': bnb_scores_metrics,
    'MultinomialNB': mnb_scores_metrics,
    'KNN': knn_results,
    'LinearSVC + CountVectorizer': svm_results,
    'LinearSVC + TfidfVectorizer': tfidfsvm_results,
}).round(4)

df_metrics
```

Out[20]:

	BernoulliNB	MultinomialNB	KNN	LinearSVC + CountVectorizer	LinearSVC + TfidfVectorizer
accuracy	0.5320	0.7987	0.6173	0.8607	0.9027
precision	0.5456	0.8239	0.6306	0.8217	0.8895
recall	0.3928	0.7148	0.5841	0.8334	0.8669
f1	0.3566	0.7371	0.5847	0.8255	0.8754

In [21]:
```python
import numpy as np
import matplotlib.pyplot as plt


metrics = df_metrics.index.tolist()
bnb_values = df_metrics['BernoulliNB'].values
mnb_values = df_metrics['MultinomialNB'].values
svm_values = df_metrics['LinearSVC + TfidfVectorizer'].values

x = np.arange(len(metrics))
width=0.25

# Create plot for BNB and MNB across each metric
plt.figure(figsize=(10, 4))
plt.bar(x - width, bnb_values, width=width, label='BernoulliNB', color='skyblue'
plt.bar(x, mnb_values, width=width, label='MultinomialNB', color='salmon')
plt.bar(x + width, svm_values, width=width, label='SVM', color='orange')

plt.ylabel('Score')
plt.title('BNB vs MNB vs SVM Performance Metrics')
plt.xticks(x, metrics)
plt.ylim(0, 1)
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.6)

for i in range(len(metrics)):
    plt.text(x[i] - width, bnb_values[i] + 0.01, f'{bnb_values[i]:.2f}', ha='cen
    plt.text(x[i], mnb_values[i] + 0.01, f'{mnb_values[i]:.2f}', ha='center', fo
    plt.text(x[i] + width, svm_values[i] + 0.01, f'{svm_values[i]:.2f}', ha='cen
```

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



As can be seen from the above graphs, SVM with TfidfVectorizer(max_features=500) performs the best.

Part 2. Recommendation Methods

In [23]:
```
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import LinearSVC
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from collections import defaultdict
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

# Split dataset into Training (weeks 1-3) and Test (week 4)
train_df = df_dataset.iloc[:751].copy()    # Weeks 1–3
df_test =df_dataset.iloc[751:1001].copy()  # Week 4

# splitting the training set into topics
topic_groups = train_df.groupby('topic')

# Create tfidf vector for documents(songs lyrics) in each topic
topic_vectorizers = {}
topic_tfidf_matrices = {}
for topic, group in topic_groups:
    vectorizer = TfidfVectorizer(max_features=500) # Tfidf using the same settin
    tfidf_matrix = vectorizer.fit_transform(group['lyrics'])
    topic_vectorizers[topic] = vectorizer
    topic_tfidf_matrices[topic] = tfidf_matrix
    print(f"Topic '{topic}': {tfidf_matrix.shape[0]} documents, {tfidf_matrix.sh


# Train a SVM classifier with settings as Part 1 on training set
vectorizer = TfidfVectorizer(max_features=500)
X_train = vectorizer.fit_transform(train_df['lyrics'])
y_train = train_df['topic']
svm_model = LinearSVC(random_state=42, max_iter=2000)
svm_model.fit(X_train, y_train)
```

```python
# Predict topics for the training set
train_df['predicted_topic'] = svm_model.predict(X_train)

X_test = vectorizer.transform(df_test['lyrics'])
df_test['predicted_topic'] = svm_model.predict(X_test)

train_df.head()
```

```
Topic 'dark': 246 documents, 500 features
Topic 'emotion': 42 documents, 500 features
Topic 'lifestyle': 92 documents, 500 features
Topic 'personal': 188 documents, 500 features
Topic 'sadness': 183 documents, 500 features
```

Out[23]:

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
0	loving	the not real lake	2016	rock	awak know see time clear world mirror world mi...	dark	dark
1	incubus	into the summer	2019	rock	summer pretti build spill readi overflow piss ...	lifestyle	lifestyle
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say tri break wal...	sadness	sadness
3	tedeschi trucks band	anyhow	2016	blues	run bitter tast take rest feel anchor soul pla...	sadness	sadness
4	lukas nelson and promise of the real	if i started over	2017	blues	think think differ set apart sober mind sympat...	dark	dark

In [24]:
```python
# Read User 1 file
df_user1 = pd.read_csv('user1.tsv', sep='\t')
```

```
df_user1
```

Out[24]:

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

In [25]:
```
# Read User 2 file
df_user2 = pd.read_csv('user2.tsv', sep='\t')
df_user2
```

Out[25]:

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

In [26]:
```
# Function to Build user profile from training data
def build_user_profile(train_df, df_user, topic_vectorizers):
    user_profiles = {}
    liked_topic_songs = {}
    keywords = []

    # Apply preprocess_text function defined in PArt 1
    df_user['keywords_preprocessed'] = df_user['keywords'].apply(preprocess_text

    # for topic in topic_vectorizers:
    for i, row in df_user.iterrows():
        topic = row['topic']
        keywords = []
        vectorizer = topic_vectorizers[topic]

        # Get preprocessed keywords for this topic row
        if not row.empty:
            keywords = row['keywords_preprocessed'].split()

        # Combine songs in the training set predicted to be in topic that user l
        df_topic = train_df[train_df['predicted_topic'] == topic]
        df_user_liked_songs = df_topic[df_topic['lyrics'].apply(lambda x: any(wo
        topic_document = " ".join(df_user_liked_songs['lyrics'])

        # Create vectorizer for user liked document(songs) in topic
        tfidf_vector = vectorizer.transform([topic_document])
        user_profiles[topic] = tfidf_vector
        liked_topic_songs[topic] = topic_document

    return user_profiles, liked_topic_songs


# Create profiles for user 1 and user 2
user1_profile, user_song_lyrics_liked = build_user_profile(train_df, df_user1, t
user2_profile, user_song_lyrics_liked = build_user_profile(train_df, df_user2, t
```

1.

The User profiles for User are build using the training data. Here to analyse the user liked songs, the keywords is used and based on the keywords the match the lyrics, the songs are selected as user liked songs. Further a vectorizer is created on these songs. This is done for each topic.

On analysing the dataset, the top 20 words printed for each User (1,2,3) are mostly within the topic(dark, lifestyle,etc) and appear to be Reasonable classified. The words for all the users mostly seem to be reasonable, and lie within the correct topic words. Overall the model is performing as expected. One thing to note is that since preprocessing is done on the words, the word stems(root words) are printed.

Another observation is that there are few words that are generally neutral but are also being classified into a partifular topic. Certain words are also being classified into multiple topic. Eg. the word 'yeah' appears in the Top 20 keywords in topics dark and lifestyle, even though it is a neutral word. This shows that the model is unable to grasp the sentiment of the word. Further the words in the topic 'sadness' are also similar for User 1 and 2.

It can also be seen that there are a lot of common words present in the different user profiles for each topic. Words printed across the user profiles for each topic are nearly the same. This may be due the limited dataset. Since the same document set is used having the same vocabulary, the words in the document may have the same vectorizer and score on each run.

In [28]:

```
# Function to print Top N Words for a User
def print_top_words(user_profiles, topic_vectorizers, top_n=20):
    for topic, profile_vector in user_profiles.items():
        vectorizer = topic_vectorizers[topic]
        feature_names = np.array(vectorizer.get_feature_names_out())

        # Retrieve top indices and words from vectorizer
        tfidf_array = profile_vector.toarray().flatten()
        top_indices = tfidf_array.argsort()[::-1][:top_n]
        top_words = feature_names[top_indices]

        print(f"Topic: {topic}")
        print(f"Top {top_n} words: {', '.join(top_words)}\n")

# Print top 20 words in each profile - These words appear to be reasonable and a
print("\nTop 20 words (words stem) in user 1 profile:\n")
print_top_words(user1_profile, topic_vectorizers, top_n=20)

print("\nTop 20 words (words stem) in user 2 profile:\n")
print_top_words(user2_profile, topic_vectorizers, top_n=20)
```

```
Top 20 words (words stem) in user 1 profile:

Topic: dark
Top 20 words: fight, like, grind, know, blood, stand, come, yeah, tell, gon, blac
k, kill, hand, lanki, dilli, caus, peopl, time, good, head

Topic: sadness
Top 20 words: cri, tear, babi, break, woah, fall, heart, know, club, away, want,
gon, feel, steal, think, wan, wish, hurt, place, right

Topic: personal
Top 20 words: life, live, chang, know, world, ordinari, yeah, dream, wan, thank,
like, teach, lord, come, time, beat, think, thing, learn, need

Topic: lifestyle
Top 20 words: tonight, night, song, come, home, closer, time, sing, stranger, lon
g, wait, wan, tire, spoil, right, struggl, yeah, mind, play, like

Topic: emotion
Top 20 words: good, touch, feel, hold, know, vision, video, loov, morn, vibe, fee
lin, want, miss, kiss, love, lovin, luck, gim, sunris, look


Top 20 words (words stem) in user 2 profile:

Topic: sadness
Top 20 words: tear, break, heart, away, cri, insid, babi, step, woah, fall, know,
fade, gon, like, club, hurt, open, wan, feel, wish

Topic: emotion
Top 20 words: good, touch, feel, hold, know, vision, video, loov, morn, vibe, fee
lin, want, miss, kiss, lovin, luck, gim, sunris, look, caus
```

In [29]:

```
# Define a user 3 by choosing keywords from a range of topics, based on personal
user3 = {'topic':['dark','sadness','personal','lifestyle','emotion'],
         'keywords':["steal, angry, kill, death, jail, liars",
                     "sorry, pain, funeral, sick, mistake",
                     "house, life, people, memory, dream",
                     "country, dance, money, travel, song",
                     "good, love, kiss, tense, worry"]}

df_user3 = pd.DataFrame(user3)
df_user3
```

Out[29]:

	topic	keywords
0	dark	steal, angry, kill, death, jail, liars
1	sadness	sorry, pain, funeral, sick, mistake
2	personal	house, life, people, memory, dream
3	lifestyle	country, dance, money, travel, song
4	emotion	good, love, kiss, tense, worry

In [30]:

```
# Build user profile for User 3 using the training dataset
user3_profile, user3_song_lyrics_liked = build_user_profile(train_df, df_user3,
```

```python
# Print top 20 words in User 3 profile
print("\nTop 20 words (word stem) in user 3 profile:\n")
print_top_words(user3_profile, topic_vectorizers, top_n=20)
```

```
Top 20 words (word stem) in user 3 profile:

Topic: dark
Top 20 words: kill, death, blood, grind, dilli, lanki, head, list, like, know, fe
at, fight, steadi, feel, come, peopl, gladiat, time, slow, face

Topic: sadness
Top 20 words: fall, break, pain, heart, yeah, ohohoh, away, caus, know, hurt, go
n, leav, babi, like, blame, sanctuari, time, think, feel, need

Topic: personal
Top 20 words: life, live, world, chang, thank, know, yeah, ordinari, wan, dream,
good, like, time, think, teach, lord, believ, year, come, thing

Topic: lifestyle
Top 20 words: song, sing, wan, spoil, home, struggl, tire, countri, play, night,
tonight, like, time, yeah, telephon, right, need, know, want, hallelujah

Topic: emotion
Top 20 words: good, feel, hand, hold, vision, darl, morn, luck, video, vibe, wan
t, heart, feelin, know, kiss, come, yeah, love, lovin, sunris
```

2. Evaluation

The recommender is created to sugges the top N recommendations based on the user profile. These recommendations show the top N songs in total. Since a Top-N recommender is built, top-N metrics are used to evaluate the performance. - Precision@N: This shows the proportion of top-N recommended songs that the user actually liked. This helps us analyse if our ssytem is showing useful songs - Recall@N: This shows us the liked songs when compared to all songs the user would have liked (in the test set) that are included in the top-N recommendations. Recall is chosen here to understand how well the system retrieves all relevant song information. The high recall shows us that most liked songs are not missed. - F1 Score@N: This is Harmonic mean of precision and recall. This is used as it helps to balance the trade-off between precision and recall, and also gives us a single score that reflects both accuracy and completeness of recommendations. - Hit Rate@N: This is used as it shows if at least one liked song appears in top-N recommendations based on user preferences. Hit rate is useful in determining how often users find something they like.

Choosing the Value of N: The value of N is choosen as 10 as this gives a good trade-off between metrics scores to the right amount of songs displayed to user. Choosing a very large N (>50) lowers the accuracy, precision of the model. It also provides too many recommendation options to the user and it would be difficult for the user to review the large number of songs and provide feedback. Choosing an N value <5 results in overfitting and also provides very few options to the user. thus N=15 is choosen. This N shows N songs in total so that it provides a distributed range of songs to the user, which account for the top songs aligning to user interest.

Evaluation of Recommender on Metrics - The matching algorithm is analysed on the precision, recall, and other metrics on different parameters such as N, M, similarity scores. This is done to determine the best algorithm

In [32]:
```
from sklearn.metrics.pairwise import cosine_similarity, euclidean_distances
import numpy as np
from scipy.sparse import issparse

# Function to calculate document similarity for information retrieval using diff
def similarity_scoring_func(user_vec, tfidf_matrix, similarity_algorithm):
    if similarity_algorithm == 'cosine': # Cosine Similarity
        return cosine_similarity(user_vec, tfidf_matrix).flatten()

    elif similarity_algorithm == 'jaccard': # Jaccard Similarity
        user_bin = (user_vec > 0).astype(int)
        doc_bin = (tfidf_matrix > 0).astype(int)

        if issparse(user_bin):
            user_bin = user_bin.toarray()
        if issparse(doc_bin):
            doc_bin = doc_bin.toarray()

        intersection = np.minimum(user_bin, doc_bin).sum(axis=1)
        union = np.maximum(user_bin, doc_bin).sum(axis=1)
        jaccard = intersection / (union)
        return jaccard

    elif similarity_algorithm == 'euclidean': # Euclidean Disatnce
        distances = euclidean_distances(user_vec, tfidf_matrix).flatten()
        similarity = 1 / (1 + distances)
        return similarity

# Recommend Top N songs based on user profile for N songs in Total
def recommend_top_n_songs(user_profile, df_test, topic_vectorizers, similarity_a
    all_recommendations = []

    for idx, row in df_test.iterrows():
        pred_topic = row['predicted_topic']
        lyrics = row['lyrics']

        # Skip topic if not present in user profile
        if pred_topic not in user_profile:
            continue

        user_vec = user_profile[pred_topic]
        vectorizer = topic_vectorizers[pred_topic]
        tfidf_vec = vectorizer.transform([lyrics])

        # Compute document similarity of topic vectorizer with user profile usin
        similarity_score = similarity_scoring_func(user_vec, tfidf_vec, similari

        row_copy = row.copy()
        row_copy['similarity_score'] = similarity_score
        all_recommendations.append(row_copy)

    # Create a DataFrame of all scored songs
    scored_df = pd.DataFrame(all_recommendations)

    # Select the top N songs having highest similarity score
```

```
    top_n_df = scored_df.sort_values(by='similarity_score', ascending=False).hea

    return top_n_df


# Function to restrict the words(features) in user profile to M
def user_profile_with_M(user_profile, topic_vectorizers, M):
    new_user_profile_m = {}

    for topic, user_vec in user_profile.items():
        vectorizer = topic_vectorizers[topic]
        arr = user_vec.toarray().flatten()

        # Get indices of M words
        top_indices = np.argsort(arr)[::-1][:M]

        # Create a new vector with only M words
        new_vec = np.zeros_like(arr)
        new_vec[top_indices] = arr[top_indices]

        # create reshaped 2D vector of user profile with M words
        new_user_profile_m[topic] = new_vec.reshape(1, -1)

    return new_user_profile_m
```

In [33]:
```
# View Top N songs recommeded to user 1 using Cosine similarity score
# When comparing with Jaccard and Euclidean distance (shown below) the Cosine si
recommend_top_n_songs(user1_profile, df_test, topic_vectorizers, similarity_algo
```

Out[33]:

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
0	timeflies	once in a while	2016	pop	think know better wish think think pressur wis...	emotion	emotion
1	justin moore	got it good	2016	country	wake morn warn littl bounc blue eye start pill...	emotion	emotion
2	taylor swift	i did something bad	2017	pop	trust narcissist play like violin look ohsoeas...	emotion	emotion
3	dirty heads	horsefly	2019	reggae	say life live know thing passion sound real ad...	emotion	emotion
4	the band steele	sit awhile	2017	country	wake favorit place studio hide space cold dark...	personal	personal
5	thomas rhett	life changes	2017	country	wakin colleg dorm yeah life pretti normal look...	personal	personal
6	anita baker	will you be mine	2017	jazz	come feel explain lose break heart come mend a...	sadness	sadness
7	anita baker	you're the best thing yet	2017	jazz	best thing come life understand hand world cal...	personal	personal
8	ty segall	alta	2018	blues	want know feel green want see sailor come figh...	personal	personal
9	kehlani	feels	2019	pop	real contempl bout feel	emotion	emotion

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
					hard think true want m...		

In [34]:
```
# View Top N songs recommeded to user 1 using Jaccard similarity score
# As seen from the similarity score column in table, Jaccard scores are very low
recommend_top_n_songs(user1_profile, df_test, topic_vectorizers, similarity_algo
```

Out[34]:

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
0	deca	donner bell	2019	jazz	donner readi tabl live watchin star fall like ...	dark	dark
1	soja	i can't stop dreaming	2017	reggae	wide awak move head question room leav littl c...	sadness	sadness
2	lil wayne	scared of the dark (feat. xxxtentacion)	2018	pop	scar dark run run afraid fall scar afraid ...	dark	sadness
3	alborosie	rocky road	2016	reggae	road road road road life cycl time wast life r...	personal	personal
4	mike love	forgiveness	2016	reggae	tell hide eye wonder embrac face know walk sho...	personal	personal
5	the dear hunter	the revival	2016	jazz	take littl longer hop know take villag rais sc...	sadness	sadness
6	alec benjamin	boy in the bubble	2018	pop	walk home step gate chicken plate food cold co...	dark	dark

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
7	hunter hayes	still	2019	country	soul worri okay stay time break count star yea...	dark	dark
8	timeflies	once in a while	2016	pop	think know better wish think think pressur wis...	emotion	emotion
9	post malone	blame it on me	2018	pop	free peopl wan takin piec away need hold drown...	sadness	sadness

In [35]:

```
# View Top N songs recommeded to user 1 using Euclidean similarity score
# Euclidean scores for each song is better than the Jaccard score
recommend_top_n_songs(user1_profile, df_test, topic_vectorizers, similarity_algo
```

Out[35]:

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
0	timeflies	once in a while	2016	pop	think know better wish think think pressur wis...	emotion	emotion
1	justin moore	got it good	2016	country	wake morn warn littl bounc blue eye start pill...	emotion	emotion
2	taylor swift	i did something bad	2017	pop	trust narcissist play like violin look ohsoeas...	emotion	emotion
3	dirty heads	horsefly	2019	reggae	say life live know thing passion sound real ad...	emotion	emotion
4	the band steele	sit awhile	2017	country	wake favorit place studio hide space cold dark...	personal	personal
5	thomas rhett	life changes	2017	country	wakin colleg dorm yeah life pretti normal look...	personal	personal
6	anita baker	will you be mine	2017	jazz	come feel explain lose break heart come mend a...	sadness	sadness
7	anita baker	you're the best thing yet	2017	jazz	best thing come life understand hand world cal...	personal	personal
8	ty segall	alta	2018	blues	want know feel green want see sailor come figh...	personal	personal
9	kehlani	feels	2019	pop	real contempl bout feel	emotion	emotion

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
					hard think true want m...		

In [36]:

```
# Function to evaluate recommendtations
def evaluate_recommendation(user_profile, df_user, df_test, topic_vectorizers, s
    # If M is set get user profile restricted to M words
    if M is not None:
        user_profile = user_profile_with_M(user_profile, topic_vectorizers, M)

    df_recommended_songs = recommend_top_n_songs(user_profile, df_test, topic_ve

    eval_scores = []
    total_relevant_songs = 0

    for idx, row in df_recommended_songs.iterrows():
        pred_topic = row['predicted_topic']
        lyrics = row['lyrics']

        # Check matching topic for keywords showing actual liked songs
        user_topic_row = df_user[df_user['topic'] == pred_topic]
        if user_topic_row.empty:
            actual_liked = 0
            continue

        # Match user interests to find actual liked songs which will be used to
        keywords = user_topic_row['keywords_preprocessed'].values[0].split()
        actual_liked = int(any(word in lyrics for word in keywords))
        if any(word in lyrics for word in keywords):
            total_relevant_songs += 1

        eval_scores.append(actual_liked)

    # Calculate metrics
    eval_scores = np.array(eval_scores)
    precision = np.sum(eval_scores) / len(eval_scores) if len(eval_scores) > 0 e
    recall = np.sum(eval_scores) / total_relevant_songs if total_relevant_songs
    f1 = 2 * (precision * recall) / (precision + recall + 1e-10)
    accuracy = np.mean(eval_scores)
    hit_rate = int(np.any(eval_scores))

    return {
        'accuracy': accuracy,
        'precision@N': precision,
        'recall@N': recall,
        'f1@N': f1,
        'hit_rate@N': hit_rate,
    }
```

In [37]:

```
# Evaluation of recommender when N words are recommended
# On analysing the performance of the recommender for different values of N, it
# This may be due to the fact that the recommender has to provide few songs that

N = [5, 10, 15, 20, 50]
metrics_result = {}

print("\nTable Evaluating Recommender on Top N Recommendations for User 1\n")
```

```python
for n in N:
    result = evaluate_recommendation(user1_profile, df_user1, df_test, topic_vec
    metrics_result[n] = result

df_N_analysis = pd.DataFrame(metrics_result).T
df_N_analysis.index.name = 'N'
print(df_N_analysis)


print("\n\nTable Evaluating Recommender on Top N Recommendations for User 2\n")
for n in N:
    result = evaluate_recommendation(user2_profile, df_user2, df_test, topic_vec
    metrics_result[n] = result

df_N_analysis2 = pd.DataFrame(metrics_result).T
df_N_analysis2.index.name = 'N'
print(df_N_analysis2)


print("\n\nTable Evaluating Recommender on Top N Recommendations for User 3\n")
for n in N:
    result = evaluate_recommendation(user3_profile, df_user3, df_test, topic_vec
    metrics_result[n] = result

df_N_analysis3 = pd.DataFrame(metrics_result).T
df_N_analysis3.index.name = 'N'
print(df_N_analysis3)
```

```
Table Evaluating Recommender on Top N Recommendations for User 1

    accuracy  precision@N  recall@N      f1@N  hit_rate@N
N
5       1.00         1.00       1.0  1.000000         1.0
10      1.00         1.00       1.0  1.000000         1.0
15      1.00         1.00       1.0  1.000000         1.0
20      0.95         0.95       1.0  0.974359         1.0
50      0.76         0.76       1.0  0.863636         1.0


Table Evaluating Recommender on Top N Recommendations for User 2

    accuracy  precision@N  recall@N      f1@N  hit_rate@N
N
5   1.000000     1.000000       1.0  1.000000         1.0
10  0.800000     0.800000       1.0  0.888889         1.0
15  0.666667     0.666667       1.0  0.800000         1.0
20  0.650000     0.650000       1.0  0.787879         1.0
50  0.400000     0.400000       1.0  0.571429         1.0


Table Evaluating Recommender on Top N Recommendations for User 3

    accuracy  precision@N  recall@N      f1@N  hit_rate@N
N
5   1.000000     1.000000       1.0  1.000000         1.0
10  0.900000     0.900000       1.0  0.947368         1.0
15  0.866667     0.866667       1.0  0.928571         1.0
20  0.850000     0.850000       1.0  0.918919         1.0
50  0.680000     0.680000       1.0  0.809524         1.0
```

In [109…

```
# Evaluation of recommender when different values of M (number of words in user
# On analysing the values of M for each User, we can see that it is consitent an
# For few Users it can be seen that as M values increases, the accuracy, precisi
# However this is not always the case. To ensure the model performs well in case

M = [10, 15, 20, 50, 100, 150]
metrics_result = {}

print("\nTable Evaluating Recommender on M words for User 1\n")
for m in M:
    result = evaluate_recommendation(user1_profile, df_user1, df_test, topic_vec
    metrics_result[m] = result

df_M_analysis = pd.DataFrame(metrics_result).T  # Transpose so M values are rows
df_M_analysis.index.name = 'M'
print(df_M_analysis)


print("\n\nTable Evaluating Recommender on M words for User 2\n")
for m in M:
    result = evaluate_recommendation(user2_profile, df_user2, df_test, topic_vec
    metrics_result[m] = result

df_M_analysis2 = pd.DataFrame(metrics_result).T  # Transpose so M values are row
df_M_analysis2.index.name = 'M'
print(df_M_analysis2)


print("\n\nTable Evaluating Recommender on M words for User 3\n")
for m in M:
    result = evaluate_recommendation(user3_profile, df_user3, df_test, topic_vec
    metrics_result[m] = result

df_M_analysis3 = pd.DataFrame(metrics_result).T  # Transpose so M values are row
df_M_analysis3.index.name = 'M'
print(df_M_analysis3)
```

```
Table Evaluating Recommender on M words for User 1

     accuracy  precision@N  recall@N  f1@N  hit_rate@N
M
10        1.0          1.0       1.0   1.0         1.0
15        1.0          1.0       1.0   1.0         1.0
20        1.0          1.0       1.0   1.0         1.0
50        1.0          1.0       1.0   1.0         1.0
100       1.0          1.0       1.0   1.0         1.0
150       1.0          1.0       1.0   1.0         1.0


Table Evaluating Recommender on M words for User 2

     accuracy  precision@N  recall@N      f1@N  hit_rate@N
M
10        0.7          0.7       1.0  0.823529         1.0
15        0.7          0.7       1.0  0.823529         1.0
20        0.7          0.7       1.0  0.823529         1.0
50        0.7          0.7       1.0  0.823529         1.0
100       0.7          0.7       1.0  0.823529         1.0
150       0.7          0.7       1.0  0.823529         1.0


Table Evaluating Recommender on M words for User 3

     accuracy  precision@N  recall@N      f1@N  hit_rate@N
M
10        0.8          0.8       1.0  0.888889         1.0
15        0.8          0.8       1.0  0.888889         1.0
20        0.9          0.9       1.0  0.947368         1.0
50        0.9          0.9       1.0  0.947368         1.0
100       0.9          0.9       1.0  0.947368         1.0
150       0.9          0.9       1.0  0.947368         1.0
```

In [39]:

```python
# Evaluate Recommender for each user for similarity scores (cosine, jaccard, euc
# Overall it can be seen that the model performs the best for Cosine similarity.
# cosine similarity provides a higher score for individual songs as compared to
# Thus cosine similarity provides the best results and can be used for the model

# Define similarity algorithms to test
similarity_algorithms = ['cosine', 'jaccard', 'euclidean']
metrics_result = {}

print("\nTable Evaluating Recommender on different Document Similarity Algorithm
for sim in similarity_algorithms:
    result = evaluate_recommendation(user1_profile, df_user1, df_test, topic_vec
    metrics_result[sim] = result
df_similarity = pd.DataFrame(metrics_result).T
print(df_similarity)

print("\n\nTable Evaluating Recommender on different Document Similarity Algorit
for sim in similarity_algorithms:
    result = evaluate_recommendation(user2_profile, df_user2, df_test, topic_vec
    metrics_result[sim] = result
df_similarity2 = pd.DataFrame(metrics_result).T
print(df_similarity2)


print("\n\nTable Evaluating Recommender on different Document Similarity Algorit
```

```
for sim in similarity_algorithms:
    result = evaluate_recommendation(user3_profile, df_user3, df_test, topic_vec
    metrics_result[sim] = result
df_similarity3 = pd.DataFrame(metrics_result).T
print(df_similarity3)
```

```
Table Evaluating Recommender on different Document Similarity Algorithms for User
1

           accuracy  precision@N  recall@N      f1@N  hit_rate@N
cosine          1.0          1.0       1.0  1.000000         1.0
jaccard         0.8          0.8       1.0  0.888889         1.0
euclidean       1.0          1.0       1.0  1.000000         1.0


Table Evaluating Recommender on different Document Similarity Algorithms for User
2

           accuracy  precision@N  recall@N  f1@N  hit_rate@N
cosine     0.666667     0.666667       1.0  0.80         1.0
jaccard    0.600000     0.600000       1.0  0.75         1.0
euclidean  0.666667     0.666667       1.0  0.80         1.0


Table Evaluating Recommender on different Document Similarity Algorithms for User
3

           accuracy  precision@N  recall@N      f1@N  hit_rate@N
cosine     0.866667     0.866667       1.0  0.928571         1.0
jaccard    0.466667     0.466667       1.0  0.636364         1.0
euclidean  0.866667     0.866667       1.0  0.928571         1.0
```

Based on the Above Analysis, we can determine that the algorithm performs the best when the value of N=10, M=100, similarity=Cosine.

Overall this is consistent for all users and these metrics may provide the best matching algorithm.

PART 3 - User Evaluation

In [42]:
```
import random
N=10 # Obtained from Part 2
seed=42
random.seed(seed)

# Create week-wise batches for the dataset
df_week1 = df_dataset.iloc[:251].copy()
df_week2 = df_dataset.iloc[251:501].copy()
df_week3 = df_dataset.iloc[501:751].copy()
# Note: df_test previously created in Part 1 has week 4 data
```

In [43]:
```
# N Random songs for Week 1
df1 = df_week1.sample(N, random_state=seed)
df1
```

Out[43]:

	artist_name	track_name	release_date	genre	lyrics	topic
155	buczer	hip hop prod. crackhouse	2017	hip hop	ghost porcelain wast innoc transluc eye shift ...	dark
6	rebelution	trap door	2018	reggae	long long road occur look shortcut wan caus sc...	dark
164	green day	boulevard of broken dreams	2017	pop	walk lone road know know home walk walk street...	sadness
60	phish	we are come to outlive our brains	2018	blues	overlap futur pass pass vapor light liquid blu...	dark
113	chase rice	whisper	2016	country	roll dial right minor chord steer night slide ...	dark
182	cody johnson	billy's brother	2016	country	bull fight lead gon fight gon fight brother fe...	dark
198	guts	peaceful life	2016	jazz	danger start futil think server law conceiv fa...	dark
248	the struts	kiss this	2016	rock	say stay home away say good make stori keep se...	emotion
9	eli young band	never land	2017	country	word yeah wreck roll lip high good get bottl r...	sadness
118	h.e.r.	hard place	2018	pop	mmhmm mmhmm wan believ hate day test yeah know...	sadness

In [44]:

```
# Based on my interaction with the user, the user has liked the following songs
df_userweek1 = df1.iloc[[2, 6, 7, 8, 9]].copy()
df_userweek1
```

Out[44]:

	artist_name	track_name	release_date	genre	lyrics	topic
164	green day	boulevard of broken dreams	2017	pop	walk lone road know know home walk walk street...	sadness
198	guts	peaceful life	2016	jazz	danger start futil think server law conceiv fa...	dark
248	the struts	kiss this	2016	rock	say stay home away say good make stori keep se...	emotion
9	eli young band	never land	2017	country	word yeah wreck roll lip high good get bottl r...	sadness
118	h.e.r.	hard place	2018	pop	mmhmm mmhmm wan believ hate day test yeah know...	sadness

In [45]:

```
# N Random songs for Week 2
df2 = df_week2.sample(N, random_state=seed)
df2
```

Out[45]:

	artist_name	track_name	release_date	genre	lyrics	topic
393	white denim	good news	2018	blues	good news long time stay long telephon telepho...	lifestyle
257	black rebel motorcycle club	haunt	2018	blues	apart flame wear face rap like scarecrow wing ...	sadness
348	white denim	there's a brain in my head	2016	blues	atwo aon child guess gon turn wild take look p...	dark
311	wrabel	poetry	2017	rock	summer learn number like rememb septemb drive ...	personal
363	mandisa	bleed the same	2017	rock	bleed beauti come bleed tell tell divid wake t...	dark
432	mitch rossell	ask me how i know	2019	country	stubborn come settl stick rule way got freedom...	sadness
448	sufjan stevens	visions of gideon	2017	rock	love time video video touch time video video l...	emotion
435	louis armstrong	life is so peculiar	2016	jazz	life peculiar write burkejimmi heusen note mar...	personal
260	radiohead	daydreaming	2016	rock	dreamer learn learn point return return late l...	personal
355	el michels affair	tearz	2017	jazz	laughter come tear laughter come tear laughter...	sadness

In [46]:

```
# Based on my interaction with the user, the user has liked the following songs
df_userweek2 = df2.iloc[[2, 3, 7, 8, 9]].copy()
df_userweek2
```

Out[46]:

	artist_name	track_name	release_date	genre	lyrics	topic
348	white denim	there's a brain in my head	2016	blues	atwo aon child guess gon turn wild take look p...	dark
311	wrabel	poetry	2017	rock	summer learn number like rememb septemb drive ...	personal
435	louis armstrong	life is so peculiar	2016	jazz	life peculiar write burkejimmi heusen note mar...	personal
260	radiohead	daydreaming	2016	rock	dreamer learn learn point return return late l...	personal
355	el michels affair	tearz	2017	jazz	laughter come tear laughter come tear laughter...	sadness

In [47]:

```
# N Random songs for Week 3
df3 = df_week3.sample(N, random_state=seed)
df3
```

Out[47]:

	artist_name	track_name	release_date	genre	lyrics	topic
643	the score	the fear	2019	rock	whoaohoh whoaohoh whoaohoh whoaohoh whoaohoh w...	dark
507	leon bridges	there she goes	2016	blues	move fast like train somebodi babe babi lie le...	emotion
598	chase rice	on tonight	2017	country	littl dress hang hanger wear feel danger slip ...	lifestyle
561	midland	at least you cried	2017	country	word lip sound good right thing like heart bre...	sadness
613	shenseea	tie me up	2018	reggae	shenseea oouuuu oouuuu oouuu oouuu strangl via...	dark
682	camila cabello	havana	2017	pop	havana half heart havana take east nanana hear...	sadness
698	nappy roots	headz up	2018	hip hop	head silli head shawti head head shawti head k...	dark
685	sabrina carpenter	thumbs	2016	pop	world father mother father mother mother daugh...	personal
510	the stooges	till the end of the night	2017	blues	wait station rememb think late stand quiet lik...	personal
605	blues saraceno	the dark horse always wins	2018	blues	deliv evil deliv deliv deliv evil yeah deliv o...	dark

In [48]:

```
# Based on my interaction with the user, the user has liked the following songs
df_userweek3 = df3.iloc[[1, 3, 4, 5,6]].copy()
df_userweek3
```

Out[48]:

	artist_name	track_name	release_date	genre	lyrics	topic
507	leon bridges	there she goes	2016	blues	move fast like train somebodi babe babi lie le...	emotion
561	midland	at least you cried	2017	country	word lip sound good right thing like heart bre...	sadness
613	shenseea	tie me up	2018	reggae	shenseea oouuuu oouuuu oouuu oouuu strangl via...	dark
682	camila cabello	havana	2017	pop	havana half heart havana take east nanana hear...	sadness
698	nappy roots	headz up	2018	hip hop	head silli head shawti head head shawti head k...	dark

In [49]:

```
# Create the training data for user profile from the songs the user liked (Week
df_user_train = pd.concat([df_userweek1, df_userweek2, df_userweek3], ignore_ind

# Apply same preprocessing used in part 1
df_user_train['lyrics'] = df_user_train['lyrics'].apply(preprocess_text)
df_user_train
```

Out[49]:

	artist_name	track_name	release_date	genre	lyrics	topic
0	green day	boulevard of broken dreams	2017	pop	walk lone road know know home walk walk street...	sadness
1	guts	peaceful life	2016	jazz	danger start futil think server law conceiv fa...	dark
2	the struts	kiss this	2016	rock	say stay home away say good make stori keep se...	emotion
3	eli young band	never land	2017	country	word yeah wreck roll lip high good get bottl r...	sadness
4	h.e.r.	hard place	2018	pop	mmhmm mmhmm wan believ hate day test yeah know...	sadness
5	white denim	there's a brain in my head	2016	blues	atwo aon child guess gon turn wild take look p...	dark
6	wrabel	poetry	2017	rock	summer learn number like rememb septemb drive ...	personal
7	louis armstrong	life is so peculiar	2016	jazz	life peculiar write burkejimmi heusen note mar...	personal
8	radiohead	daydreaming	2016	rock	dreamer learn learn point return return late l...	personal
9	el michels affair	tearz	2017	jazz	laughter come tear laughter come tear laughter...	sadness
10	leon bridges	there she goes	2016	blues	move fast like train somebodi babe babi lie le...	emotion
11	midland	at least you cried	2017	country	word lip sound good right thing like heart bre...	sadness
12	shenseea	tie me up	2018	reggae	shenseea oouuuu oouuuu oouuu oouuu strangl via...	dark
13	camila cabello	havana	2017	pop	havana half heart havana take east nanana hear...	sadness
14	nappy roots	headz up	2018	hip hop	head silli head shawti head head shawti head k...	dark

In [50]:
```python
# Create keywords indicating user liked songs for user profile.
# Group by predicted_topic and combine lyrics for each topic
df_user_train_profile = df_user_train.groupby('topic')['lyrics'].apply(lambda x:
df_user_train_profile.rename(columns={'lyrics': 'keywords'}, inplace=True)
df_user_train_profile
```

Out[50]:

	topic	keywords
0	dark	danger start futil think server law conceiv fa...
1	emotion	say stay home away say good make stori keep se...
2	personal	summer learn number like rememb septemb drive ...
3	sadness	walk lone road know know home walk walk street...

In [51]:
```python
# Using Same Approach as Part 2 to create the User Profile and Recommender
real_user_profile, real_user_song_lyrics_liked = build_user_profile(train_df, df
print("\nTop 20 words in user profile:\n")
print_top_words(real_user_profile, topic_vectorizers, top_n=20)
```

```
Top 20 words in user profile:

Topic: dark
Top 20 words: stand, come, like, know, head, blood, fight, black, gon, hand, fee
l, tell, kill, evil, yeah, time, grind, caus, wan, look

Topic: emotion
Top 20 words: good, hold, feel, hand, touch, know, lip, want, vision, darl, morn,
heart, luck, video, loov, yeah, come, vibe, feelin, miss

Topic: personal
Top 20 words: life, live, chang, world, thank, yeah, know, day, believ, good, tim
e, like, teach, want, need, wan, give, promis, reason, think

Topic: sadness
Top 20 words: fall, break, heart, away, leav, like, know, come, yeah, think, insi
d, feel, gon, wan, caus, time, babi, walk, hurt, want
```

In [52]:
```python
# Using Same approach as Part 2, train the recommender on the user profile and r
user_profile = user_profile_with_M(real_user_profile, topic_vectorizers, M=100)

# Top N songs recommended
df_recommended = recommend_top_n_songs(user_profile, df_test, topic_vectorizers,
df_recommended
```

Out[52]:

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
0	timeflies	once in a while	2016	pop	think know better wish think think pressur wis...	emotion	emotion
1	justin moore	got it good	2016	country	wake morn warn littl bounc blue eye start pill...	emotion	emotion
2	taylor swift	i did something bad	2017	pop	trust narcissist play like violin look ohsoeas...	emotion	emotion
3	dirty heads	horsefly	2019	reggae	say life live know thing passion sound real ad...	emotion	emotion
4	randy houser	our hearts (feat. lucie silvas)	2019	country	hand wrong folk think fall hard heart know nig...	sadness	sadness
5	thomas rhett	life changes	2017	country	wakin colleg dorm yeah life pretti normal look...	personal	personal
6	anita baker	no one in the world	2017	jazz	look good time share blind think better come s...	personal	personal
7	hellyeah	love falls	2016	rock	cri sleep felt incomplet deep	sadness	sadness

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
					bleed feel want ...		
8	keith urban	the fighter	2016	country	know hurt scar scar deserv caus preciou heart ...	sadness	sadness
9	the band steele	sit awhile	2017	country	wake favorit place studio hide space cold dark...	personal	personal

In [111…

```
# Evaluation Based on User Feedback
# Based on the user interaction, the user has liked 5 songs from week 4 songs as
df_liked = pd.concat([df_recommended.iloc[[2]].copy(), df_test.iloc[[12, 19, 24,
df_liked
```

Out[111…

	artist_name	track_name	release_date	genre	lyrics	topic	predicted_topic
0	taylor swift	i did something bad	2017	pop	trust narcissist play like violin look ohsoeas...	emotion	emotion
1	jason isbell and the 400 unit	white man's world	2017	country	white live white world roof babi girl think wo...	dark	dark
2	dirty heads	horsefly	2019	reggae	say life live know thing passion sound real ad...	emotion	emotion
3	marcus miller	7-t's	2018	jazz	right super fair minut right super fair minut ...	lifestyle	lifestyle
4	lester nowhere	balcony	2017	jazz	leav away biggest babi leav away heart babi gi...	sadness	sadness

In [54]:

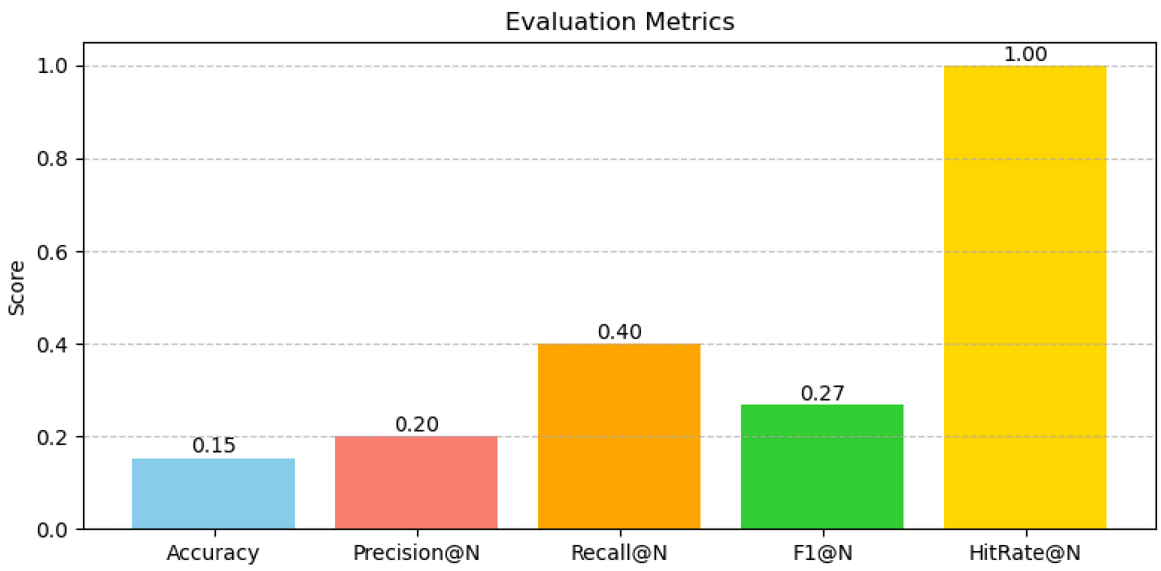
```
# Evaluting the Recommendations based on the user Liked songs and recommended so
def evaluate_recommendation_from_user_feedback(df_liked, df_recommended, top_n=N

    # Using 'track_name' column to match songs
    liked_set = set(df_liked['track_name'])
    recommended_set = set(df_recommended['track_name'])

    # True Positives
    true_positive = liked_set & recommended_set

    # Calculate Metrics
    accuracy = len(true_positive) / (len(df_liked) + len(df_recommended) - len(t
    precision = len(true_positive) / len(df_recommended)
    recall = len(true_positive) / len(df_liked)
    if precision + recall > 0:
        f1 = 2 * (precision * recall) / (precision + recall)
    else:
        f1 = 0

    hit_rate = 1 if len(true_positive) > 0 else 0

    return {
        'Accuracy': accuracy,
```

```
        'Precision@N': precision,
        'Recall@N': recall,
        'F1@N': f1,
        'HitRate@N': hit_rate
    }

user_feedback_metrics = evaluate_recommendation_from_user_feedback(df_liked, df_
df_metrics = pd.DataFrame([user_feedback_metrics], index=['User'])  # Use real u
print(df_metrics)
```

```
      Accuracy  Precision@N  Recall@N      F1@N  HitRate@N
User  0.153846          0.2       0.4  0.266667          1
```

In [55]:

```
# Create plot of metrics obtained from user study
labels = list(user_feedback_metrics.keys())
values = list(user_feedback_metrics.values())

plt.figure(figsize=(8, 4))
bars = plt.bar(labels, values, color=['skyblue', 'salmon', 'orange','limegreen',

# Add value labels on top of bars
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2.0, yval + 0.01, f'{yval:.2f}', ha='

plt.title('Evaluation Metrics')
plt.ylim(0, 1.05)
plt.ylabel('Score')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Metrics

```
- The same Top-N Metric as Part 2 are used in this task since
the same Top N Recommender system is used. Here Results are
available for all metrics (Accuracy, Precision, Recall, F1, and
even HitRate).
- When comparing this with the Part 2 metrics, the values of
metrics are lower for the real user. This is because the real
user is not restricted by keywords and may choose any song from
```

```
Week 4 that may not have a matching keyword as in the user
profile built. Due to this it is hard to find many matches. This
results in a low accuracy, precision, recall and F1 score.
- In Part 2 the Recall was often 1 which indicates it was able
to get matches, however here the recall is is very low.
Similarly the lower precision and F1 score as well indicate that
the model is unable to recommend songs which are liked by the
real user.
- Only the HitRate remains 1 in both cases, this is because the
recommender was able to find at least 1 match here. But in most
cases when we used the recommender for real user, the hit rate
was also often 0.
```

User Feedback:

```
- The quality of the recommender is not good. The recommender
system is not able to take the users likings into consideration.
It only gets 1 song correct.
- After trying the recommender multiple times and selecting
similar songs based on keywords/lyrics of previously liked songs
(Week1-3), the recommender was able to get hits on 1 songs.
- The recommender system performs well for hypothetical users
but fails to perform for real users. This is because a user may
like a song that does not have any relevant keywords in the
topic.
- The recommender system created overfits in Part 2 for the
hypothetical users, and it fails to perfrom well for Real user.
This suggests that keywords based matching is not ideal when
building content based recommender systems.
- The recommender is not able to grasp the users preferences as
it is restricted to the limited vocabulary, keywords and Top N
words.
```

In [ ]:

```

```