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**zID:** z5473453

In [3]:
```
import pandas as pd
```

In [4]:
```
# Load the dataset from TSV file into a DataFrame
df = pd.read_csv('dataset.tsv', sep = '\t')
print(df.columns)
print(df.head())
print(df.info())
```

```
Index(['artist_name', 'track_name', 'release_date', 'genre', 'lyrics',
       'topic'],
      dtype='object')
                          artist_name        track_name  release_date  \
0                              loving  the not real lake          2016
1                             incubus    into the summer          2019
2                           reignwolf           hardcore          2016
3                 tedeschi trucks band             anyhow          2016
4  lukas nelson and promise of the real  if i started over          2017

   genre                                             lyrics      topic
0   rock  awake know go see time clear world mirror worl...       dark
1   rock  shouldn summer pretty build spill ready overfl...  lifestyle
2  blues  lose deep catch breath think say try break wal...    sadness
3  blues  run bitter taste take rest feel anchor soul pl...    sadness
4  blues  think think different set apart sober mind sym...       dark
<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
None
```

# Part 1: Topic Classification

In [6]:
```
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
```

In [7]:
```
# Download necessary NLTK resources
nltk.download('punkt')
nltk.download('stopwords')
```

```
[nltk_data] Downloading package punkt to /Users/kimlee/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/kimlee/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[7]:
```
True
```

# Text Preprocessing

I performed preprocessing on the raw song lyrics to prepare them for modelling.
This included: Lowercasing text, Removing punctuation and special characters, Tokenising the lyrics into individual words, Removing common stopwords (like "the", "is", "and"), and Applying stemming to reduce words to their base form.
This part of the code refers to **Tutorial 2**.

In [9]:
```
# Remove duplicate rows and any rows with missing values
df = df.drop_duplicates()
df = df.dropna()
```

In [10]:
```
# Initialize stopword list and stemmer
stop_words = set(stopwords.words('english'))
ps = PorterStemmer()
```

In [11]:
```
# Define and apply preprocessing function:
# lowercase text, remove punctuation, tokenize, remove stopwords, and apply stem
def preprocess_lyrics(text):
    text = str(text).lower()
    text = re.sub(r'[^\w\s]', '', text)
    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)

df['clean_lyrics'] = df['lyrics'].apply(preprocess_lyrics)
```

# Feature Size Selection Analysis

To evaluate the effect of different vocabulary sizes on classification accuracy, I tested several values of top-N features using CountVectorizer, ranging from 250 to 3000. For each value of N, I trained a MultinomialNB classifier using 5-fold cross-validation and recorded the mean accuracy.

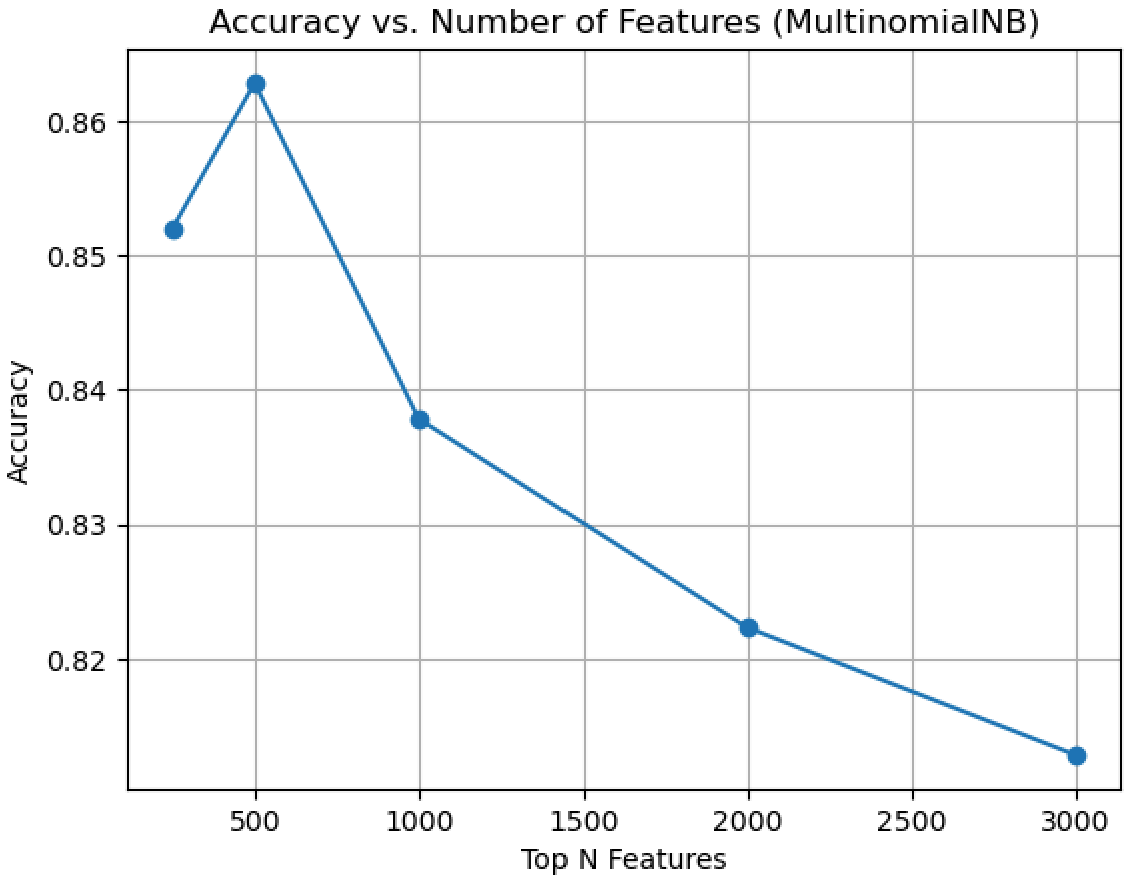
In [13]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import MultinomialNB
from sklearn.preprocessing import LabelEncoder
```

In [14]:
```
# Try different numbers of top-N features
n_values = [250, 500, 1000, 2000, 3000]
nb_results = []

le = LabelEncoder()
```

```
y = le.fit_transform(df['topic'])

# For each n, transform text to bag-of-words with n features, then evaluate usin
for n in n_values:
    vectorizer = CountVectorizer(max_features=n)
    X = vectorizer.fit_transform(df['clean_lyrics'])
    score = cross_val_score(MultinomialNB(), X, y, cv = 5, scoring = 'accuracy')
    nb_results.append(score)
```

In [15]:
```
import matplotlib.pyplot as plt
```

In [16]:
```
plt.plot(n_values, nb_results, marker = 'o')
plt.title('Accuracy vs. Number of Features (MultinomialNB)')
plt.xlabel('Top N Features')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()
```




As can be seen from the figure above, the classifier is most accurate at 0.865 with 500 features. Beyond 500 features, the performance decreases, which means including more features adds noise or redundancy but does not better distinguish topics.
This conclusion indicates a typical phenomenon for text classification: more features are not necessarily better. In this data set, a smaller, more concentrated vocabulary (top 500) was good enough to extract the most relevant words for each topic.

In [18]:
```
from sklearn.naive_bayes import BernoulliNB
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
```

To determine the most suitable classifier for our topic classification task, we compared three popular models:

- Bernoulli Naive Bayes
- Multinomial Naive Bayes
- Logistic Regression

Each model was evaluated using 5-fold cross-validation on the vectorized lyrics (with 500 features selected in the previous step).

**Logistic Regression** is a supervised learning algorithm commonly used for classification problems. It works by estimating the probability that a given input belongs to a particular class using the logistic (sigmoid) function.
This model is best suited for assigning topic classification of lyrics of a song, since it can more effectively model complex interactions of features of words without assuming independence. Logistic Regression has widely been used for text classification tasks, for example, spam detection, sentiment analysis, and topic modelling, with very good results.

In [21]:
```
# Define three models to compare
models = {
    'BernoulliNB': BernoulliNB(),
    'MultinomialNB': MultinomialNB(),
    'LogisticRegression': LogisticRegression(max_iter = 1000)
}
```

**Why max_iter = 1000?**
For classification of text with CountVectorizer, the high-dimensional sparse (high number of unique words, most of which have zero values for each document) space is a standard situation.
Specifying max_iter=1000 ensures that a solver at least gets a minimum number of iterations to converge and produce stable outputs.

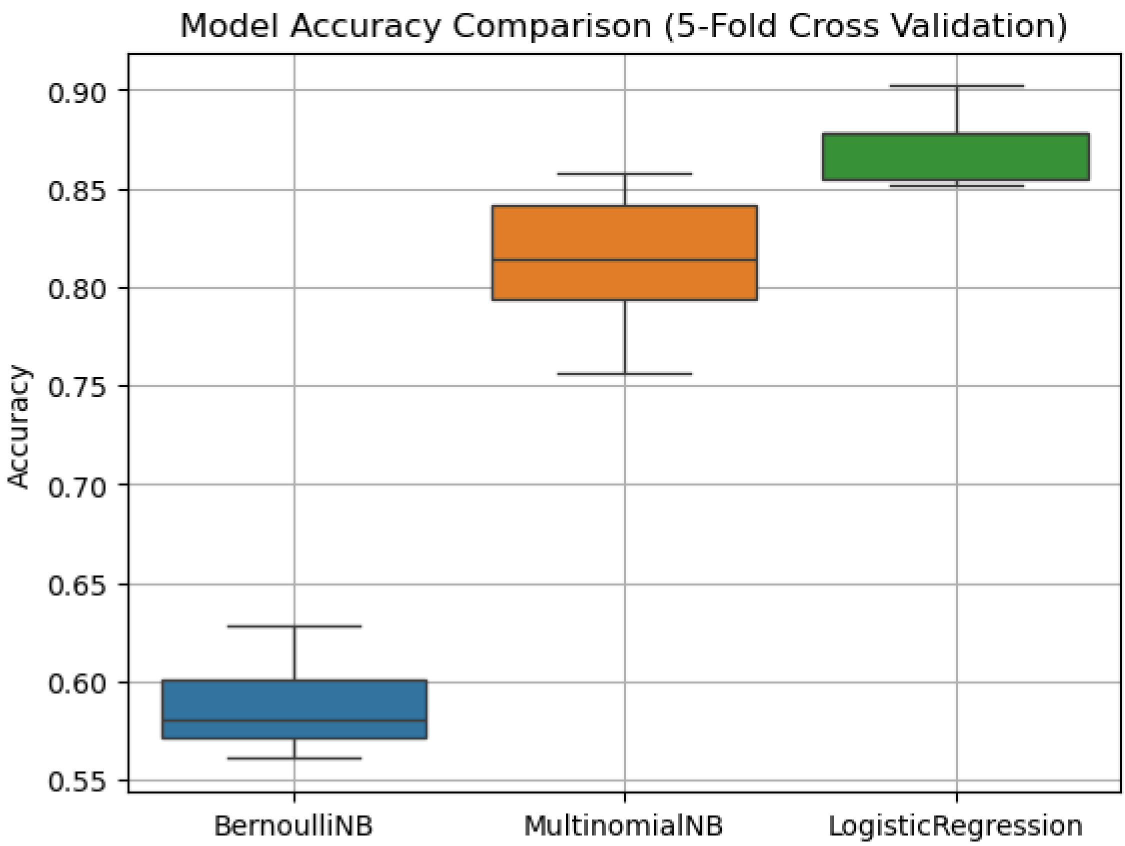
**Hypothesis**
I assume that Logistic Regression would outperform Multinomial Naive Bayes and Bernoulli Naive Bayes in terms of classification precision. This is because Logistic Regression does not rely on the assumption of strong independencies and can better utilize correlated word features of lyrics.

In [24]:
```
# Evaluate each model using 5-fold cross-validation
results = {}
for name, model in models.items():
    scores = cross_val_score(model, X, y, cv = 5, scoring='accuracy')
    results[name] = scores
    print(f'{name} Accuracy: {scores.mean():.4f} ± {scores.std():.4f}')
```

```
BernoulliNB Accuracy: 0.5885 ± 0.0240
MultinomialNB Accuracy: 0.8128 ± 0.0357
LogisticRegression Accuracy: 0.8730 ± 0.0185
```

In [25]:
```
import seaborn as sns
```

In [26]:
```
df_result = pd.DataFrame(results)
sns.boxplot(data=df_result)
plt.title('Model Accuracy Comparison (5-Fold Cross Validation)')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()
```




From the boxplot provided, we can see that:

- **Logistic Regression** always performs better than the other two models, having both the highest mean accuracy and lowest variance.
- **MultinomialNB** is a strong baseline, but less accurate and slightly less stable than Logistic Regression.
- **BernoulliNB** performs much worse, most likely because of binarization of the feature space and loss of informative frequency data.

I chose **Logistic Regression** as the final model for topic prediction.

# Part2: Recommendation Methods

This is a recommendation system based on an information retrieval (IR) approach. The main idea is to match user interests to songs by computing the cosine similarity between the TF-IDF vector of a test song and the user profile vector under the predicted topic. Each of the training set songs (Week 1 to Week 3) is labeled with one of five topics based on the Part 1 trained classifier. A user is supposed to “like” a training song if it both aligns with their keyword interests and falls under the appropriate topic. These liked songs are combined into one document per topic and transformed into a TF-IDF vector, here denoting the user profile for the topic.

In [29]:
```
train_df = df.iloc[:750].copy()
test_df = df.iloc[750:1000].copy()
```

In [30]:
```
vectorizer = CountVectorizer(max_features = 500)
X_train = vectorizer.fit_transform(train_df['clean_lyrics'])

clf = LogisticRegression(max_iter = 1000)
clf.fit(X_train, train_df['topic'])
train_df['predicted_topic'] = clf.predict(X_train)

X_test = vectorizer.transform(test_df['clean_lyrics'])
test_df['predicted_topic'] = clf.predict(X_test)
```

In [31]:
```
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.feature_extraction.text import TfidfVectorizer
```

1. **Collecting Liked Songs per Topic**
   Iterating over the training set (Weeks 1–3), and for each song:

   - Check its `predicted_topic` (from Part 1).
   - Tokenize its cleaned lyrics.
   - If the user's keyword list for that topic overlaps with the song's tokens, we mark the song as "liked" and append its lyrics to `liked_docs[topic]`.
2. **Constructing TF-IDF User Profiles**
   For each topic in `liked_docs`:

   - Merging all the liked lyrics into a single string (one "document" per topic).
   - Fitting a `TfidfVectorizer(max_features = 500)` on that document and obtaining a TF-IDF vector.

   This vector represents the user's interest profile for that topic.

3. **Scoring Test Songs**
   For each song in the test set (Week 4):

   - Predict its topic using the classifier from Part 1.
   - If the user has a profile for that topic, we transform the song's lyrics with the same TF-IDF vectorizer and compute the `cosine_similarity` to the user profile vector.
   - This similarity score quantifies how well the song matches the user's inferred interests.

In [33]:
```
def recommend_songs(user_keywords, train_df, test_df):
    # Collect all lyrics that the user 'liked' per topic
    liked_docs = {}
    for _, row in train_df.iterrows():
        topic = row['predicted_topic']
        tokens = row['clean_lyrics'].split()
        if topic in user_keywords:
            if any(k in tokens for k in user_keywords[topic]):
```

```
                liked_docs.setdefault(topic, []).append(row['clean_lyrics'])

    # Build a TF-IDF profile vector for each topic
    user_profiles = {}
    for topic, docs in liked_docs.items():
        joined_text = ' '.join(docs)
        tfidf = TfidfVectorizer(max_features = 500)
        tfidf_vec = tfidf.fit_transform([joined_text])
        user_profiles[topic] = (tfidf, tfidf_vec)

    # Score each test song by cosine similarity to the appropriate profile
    scores = []
    for _, row in test_df.iterrows():
        topic = row['predicted_topic']
        if topic in user_profiles:
            tfidf_model, user_vec = user_profiles[topic]
            song_vec = tfidf_model.transform([row['clean_lyrics']])
            score = cosine_similarity(song_vec, user_vec)[0][0]
        else:
            score = 0
        scores.append(score)

    return scores
```

# User 1 & 2 test

In [35]:

```
# User1
user1_keywords = {}
with open('user1.tsv', 'r') as f:
    for line in f.readlines():
        topic, keywords_str = line.strip().split('\t')
        keywords = [w.strip().lower() for w in keywords_str.split(',')]
        user1_keywords[topic] = keywords

# User2
user2_keywords = {}
with open('user2.tsv', 'r') as f:
    for line in f.readlines():
        topic, keywords_str = line.strip().split('\t')
        keywords = [w.strip().lower() for w in keywords_str.split(',')]
        user2_keywords[topic] = keywords
```

In [36]:

```
test_df_user1 = test_df.copy()

test_df_user1['score'] = recommend_songs(user1_keywords, train_df, test_df_user1
top_recommendations_user1 = test_df_user1.sort_values(by = 'score', ascending =
print("Top Recommendations for User1:")
print(top_recommendations_user1[['track_name', 'artist_name', 'score', 'predicte
```

```
Top Recommendations for User1:
           track_name   artist_name     score predicted_topic
944   once in a while     timeflies  0.777771         emotion
969       got it good  justin moore  0.679351         emotion
770          horsefly   dirty heads  0.645696         emotion
924     doors closing     moonchild  0.645204         sadness
810          so close          notd  0.634358         sadness
758      life changes  thomas rhett  0.571578        personal
840              alta     ty segall  0.564111        personal
796    sunday morning         axian  0.561273        personal
889      stay with me        ayokay  0.551690         sadness
802         cry to me   skip marley  0.540961         sadness
```

- **User1** defined keywords across all five topics (dark, emotion, personal, lifestyle, sadness), providing **rich and balanced coverage**. Their TF-IDF profiles were robust, yielding higher Precision@10.

In [38]:
```
test_df_user2 = test_df.copy()

test_df_user2['score'] = recommend_songs(user2_keywords, train_df, test_df_user2
top_recommendations_user2 = test_df_user2.sort_values(by = 'score', ascending =
print("Top Recommendations for User2:")
print(top_recommendations_user2[['track_name', 'artist_name', 'score', 'predicte
```

```
Top Recommendations for User2:
            track_name      artist_name     score predicted_topic
924      doors closing        moonchild  0.522838         sadness
969        got it good     justin moore  0.481999         emotion
789   will you be mine      anita baker  0.476945         sadness
988               home     the movement  0.463589         sadness
944    once in a while        timeflies  0.448300         emotion
844          snowflake    bumpin uglies  0.399083         sadness
782          open arms       prettymuch  0.391549         sadness
909              walls    the lumineers  0.389340         sadness
781            balcony   lester nowhere  0.365006         sadness
860       close enough      brett young  0.358365         sadness
```

- **User2**, by contrast, only supplied keywords for **sadness and emotion**—and only five words per topic. This sparse, skewed coverage led to:
  1. **Overly sparse TF-IDF profiles**, especially for "emotion," because few training songs contained those keywords.
  2. **Defaulting to the "sadness" profile** when "emotion" matches were weak, resulting in most recommendations falling into sadness.

In [40]:
```
def print_top_tfidf_words(user_keywords, train_df, top_n = 20):
    # Iterate over each song in the training data
    liked_docs = {}
    for _, row in train_df.iterrows():
        topic = row['predicted_topic']
        tokens = row['clean_lyrics'].split()
        if topic in user_keywords:
            if any(k in tokens for k in user_keywords[topic]):
                liked_docs.setdefault(topic, []).append(row['clean_lyrics'])

    # For each topic, build a TF-IDF vector from the liked documents
    for topic, docs in liked_docs.items():
```

```
    joined_text = ' '.join(docs)

    # Create a TF-IDF vectorizer limited to 500 features
    tfidf = TfidfVectorizer(max_features = 500)
    tfidf_matrix = tfidf.fit_transform([joined_text])

    # Calculate average TF-IDF score for each word
    avg_scores = tfidf_matrix.mean(axis = 0).A1
    feature_names = tfidf.get_feature_names_out()

    # Get indices of top-N words with the highest scores
    top_indices = avg_scores.argsort()[::-1][:top_n]
    top_words = [feature_names[i] for i in top_indices]
    print(f"\nTop words for topic '{topic}':")
    print(", ".join(top_words))
```

Each user is simulated to "like" songs whose predicted topic matches their interest, and whose lyrics contain at least one of the predefined keywords.

For each topic:

- Collect all liked songs.
- Concatenate the lyrics into one document.
- Use TF-IDF vectorization (limited to 500 features).
- Extract the top 20 words with the highest average TF-IDF scores.

In [42]:
```
print("Top TF-IDF words for user1:")
print_top_tfidf_words(user1_keywords, train_df)
```

```
Top TF-IDF words for user1:

Top words for topic 'dark':
fight, know, like, blood, stand, tell, na, come, grind, gon, black, head, kill, h
and, time, yeah, feel, right, caus, peopl

Top words for topic 'emotion':
good, feel, touch, know, hold, want, kiss, babi, time, morn, na, like, caus, visi
on, miss, heart, video, look, loov, yeah

Top words for topic 'personal':
life, live, know, na, chang, world, time, yeah, like, dream, come, wan, thing, th
ink, thank, need, go, feel, caus, teach

Top words for topic 'lifestyle':
night, come, song, long, time, sing, na, home, right, yeah, closer, know, play, l
ike, wan, tire, wait, tonight, spoil, mind

Top words for topic 'sadness':
think, leav, place, want, hold, regret, caus, greater, beg, blame, chang, word, m
ind, away, tell, space, wider, break, dream, lord
```

- **User 1: Profile Analysis**

The most frequently occurring words for themes like ‘dark’ are violent and forceful words like *fight*, *kill*, *grind*, *blood*, which suits the interests of ‘*dark*’ themes of the user quite well.

In the '*emotion*' category, the occurrence of *love*, *miss*, *heart*, and *vision* indicates a strong emphasis on sentiment and romance.

In [44]:
```
print("Top TF-IDF words for user2:")
print_top_tfidf_words(user2_keywords, train_df)
```

```
Top TF-IDF words for user2:

Top words for topic 'emotion':
touch, good, hold, kiss, morn, vision, know, video, loov, time, feel, luck, lovi
n, lip, gim, sunris, like, go, wait, heart

Top words for topic 'sadness':
open, tear, come, smile, magnifi, away, eye, babi, life, tri, laughter, hold, sor
row, heart, sight, near, real, face, forsak, frown
```

- **User 2: Profile Analysis**

User 2's keywords are more poetic or abstract (*vision*, *sunrise*, *sorrow*, *forsak*), leading to sparser matches.
Some topics like *emotion* and *sadness* include expected keywords, but other topics might suffer from low coverage due to limited matches in the training data.

# User 3 Setup

In [47]:
```
with open("user3.tsv", "w") as f:
    f.write('topic\tkeywords\n')
    f.write("emotion\tjoy, laugh, smile, sunshine, peace\n")
    f.write("personal\tfreedom, travel, myself, explore, journey\n")
    f.write("lifestyle\tparty, drink, dance, vibe, weekend\n")
    f.write("sadness\thank, growth, strength, survive, goodbye\n")
```

I intentionally left out the **dark** topic, assuming this user avoids violent or aggressive music content. The keywords were chosen to simulate a user with positive, reflective, and energetic preferences.

In [49]:
```
# User3
user3_keywords = {}
with open('user3.tsv', 'r') as f:
    for line in f.readlines():
        topic, keywords_str = line.strip().split('\t')
        keywords = [w.strip().lower() for w in keywords_str.split(',')]
        user3_keywords[topic] = keywords
```

In [50]:
```
test_df_user3 = test_df.copy()

test_df_user3['score'] = recommend_songs(user3_keywords, train_df, test_df_user3
top_recommendations_user3 = test_df_user3.sort_values(by = 'score', ascending =
print("Top Recommendations for User3:")
print(top_recommendations_user3[['track_name', 'artist_name', 'score', 'predicte
```

```
Top Recommendations for User3:
                      track_name      artist_name     score predicted_topic
846          so cold in the summer  taylor mcferrin  0.718606         emotion
932  every song’s a drinkin’ song          midland  0.595742       lifestyle
863                      wash away        iya terra  0.548283        personal
796                 sunday morning            axian  0.500817        personal
840                           alta        ty segall  0.484557        personal
923                everything to me             soja  0.468122        personal
816                   redneck life    chris janson  0.458095        personal
854      you're the best thing yet     anita baker  0.450064        personal
758                   life changes    thomas rhett  0.425608        personal
806                       moonglow      diana krall  0.418153       lifestyle
```

Most recommended songs fall under the **personal** and **lifestyle** categories, which aligns with User 3's interests.

In [52]:
```python
print("Top TF-IDF words for user3:")
print_top_tfidf_words(user3_keywords, train_df)
```

```
Top TF-IDF words for user3:

Top words for topic 'lifestyle':
song, tonight, countri, yeah, time, ring, like, drink, root, play, drinkin, mama,
caus, night, na, septemb, mind, medic, need, wan

Top words for topic 'emotion':
hold, love, oohooh, heart, danc, one, night, lose, babi, faceless, light, crowd,
low, matter, speak, high, fluentli, goodby, right, darl

Top words for topic 'personal':
life, come, automaton, rebel, thank, away, go, like, world, know, feel, live, tea
ch, tooth, dream, ironsid, alright, everyday, rule, digit

Top words for topic 'sadness':
ohohoh, lighthous, step, away, heart, place, fall, strength, lose, safe, walk, kn
ow, break, need, push, falter, stray, apart, till, time
```

- These results reflect relevant thematic vocabulary and show that the user profile is being meaningfully constructed.

In [54]:
```python
def is_song_liked(row, user_keywords):
    topic = row['predicted_topic']
    if topic in user_keywords:
        tokens = row['clean_lyrics'].split()
        for keyword in user_keywords[topic]:
            if keyword in tokens:
                return True
    return False
```

- **Precision@N** measures how many of the top-N recommended songs are actually relevant (i.e., liked by the user).
- It is simple, interpretable, and suitable for top-k recommendation tasks.

Choose **N = 10** because:

- It reflects a realistic recommendation batch (e.g., showing 10 songs at once on a music app).
- Since the database is relatively small, 10 songs is a good number. It is large enough to include diversity across topics, but small enough to expect meaningful user feedback.

In [56]:
```
def evaluate_precision(top_recommendations, user_keywords, N = 10):
    top_N = top_recommendations.head(N)
    liked_flags = top_N.apply(lambda row: is_song_liked(row, user_keywords), axi
    precision = liked_flags.sum() / N
    return precision
```

In [57]:
```
p1 = evaluate_precision(top_recommendations_user1, user1_keywords, N = 10)
p2 = evaluate_precision(top_recommendations_user2, user2_keywords, N = 10)
p3 = evaluate_precision(top_recommendations_user3, user3_keywords, N = 10)

print(f"Precision@10 for User1: {p1:.2f}")
print(f"Precision@10 for User2: {p2:.2f}")
print(f"Precision@10 for User3: {p3:.2f}")
```

```
Precision@10 for User1: 0.60
Precision@10 for User2: 0.10
Precision@10 for User3: 0.10
```

- **User 1** performs best, possibly due to having more matches between their keywords and training songs.
- **User 2** possesses a limited keyword-based profile, and hence may lower recommendation coverage.
- **User 3** performed bad. Although the keywords are very thematically related, the majority of the keywords are abstract and less likely to have precise matches with lyrics. Additionally, the user is not interested in the dark topic and does not have much overlap with sadness, so building strong matches within those terms becomes harder. This may explain the relatively lower precision.

**Result**
This works well when there are extensive and diverse keyword sets (as with User 1), so there are relevant training songs to retrieve and good topic-wise profiles to construct. However, with fewer keywords or less diversified interests (as with User 2 and User 3), there are poor profiles and poor matches.

# Effect of Profile Vocabulary Size (M) on Recommendation Precision

In [60]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
```

In [61]:
```
def build_topic_profile(docs, M = None):
    # Fit a temporary TF-IDF (no norm) to compute average term scores
    tmp = TfidfVectorizer(max_features = 500, norm = None)
    mat = tmp.fit_transform(docs)
```

```
    avg = mat.mean(axis=0).A1
    feat = tmp.get_feature_names_out()

    # Select top M terms
    if M is not None:
        top_idx = avg.argsort()[::-1][:M]
        vocab = [feat[i] for i in top_idx]
    else:
        vocab = list(feat)

    # Build the real L2-normalized TF-IDF on the selected vocabulary
    real_vec = TfidfVectorizer(vocabulary = vocab, norm = 'l2')
    user_vec = real_vec.fit_transform([" ".join(docs)])
    return real_vec, user_vec
```

In [62]:
```
def recommend_songs(user_keywords, train_df, test_df, M = None):
    # Collect all liked lyrics per topi
    liked = {}
    for _, row in train_df.iterrows():
        t = row['predicted_topic']
        if t in user_keywords and any(k in row['clean_lyrics'].split() for k in
            liked.setdefault(t, []).append(row['clean_lyrics'])

    # Build topic profiles with at most M terms each
    profiles = {}
    for t, docs in liked.items():
        vec, u_vec = build_topic_profile(docs, M)
        profiles[t] = (vec, u_vec)

    # Compute cosine similarity for each test song
    scores = []
    for _, row in test_df.iterrows():
        t = row['predicted_topic']
        if t in profiles:
            vec, u_vec = profiles[t]
            s_vec = vec.transform([row['clean_lyrics']])
            sc = cosine_similarity(s_vec, u_vec)[0,0]
        else:
            sc = 0
        scores.append(sc)
    return scores
```

In [63]:
```
for user_label, kws, df_user in [
    ('User1', user1_keywords, test_df_user1),
    ('User2', user2_keywords, test_df_user2),
    ('User3', user3_keywords, test_df_user3),
]:
    print(f"\n{user_label}")
    for M in [10, 20, 50, 100, None]:
        df_user['score'] = recommend_songs(kws, train_df, df_user, M)
        top10 = df_user.sort_values('score', ascending = False).head(10)
        prec = evaluate_precision(top10, kws, N=10)
        print(f"M = {M or 'all'}  P@10 = {prec:.2f}")
```

```
User1
M = 10  P@10 = 0.90
M = 20  P@10 = 0.90
M = 50  P@10 = 0.90
M = 100  P@10 = 0.80
M = all  P@10 = 0.60

User2
M = 10  P@10 = 0.00
M = 20  P@10 = 0.10
M = 50  P@10 = 0.10
M = 100  P@10 = 0.10
M = all  P@10 = 0.10

User3
M = 10  P@10 = 0.00
M = 20  P@10 = 0.20
M = 50  P@10 = 0.10
M = 100  P@10 = 0.10
M = all  P@10 = 0.10
```

**Discussion:**

- **User 1:** Retaining only the top 20 (or 50) keywords gives the highest precision (0.90). Including more keywords introduces noise and reduces precision.
- **User 2:** Precision remains low (0.10) regardless of M, indicating that a very sparse keyword profile cannot be improved by simply increasing M.
- **User 3:** Best precision at M = 20 (0.20); larger M values dilute the profile and lower precision.

# Algorithm Comparison (Inspired by Tutorials 3 & 4)

In [66]:

```
!pip install scikit-surprise
!pip install mlxtend
```

```
Requirement already satisfied: scikit-surprise in /opt/anaconda3/lib/python3.12/s
ite-packages (1.1.4)
Requirement already satisfied: joblib>=1.2.0 in /opt/anaconda3/lib/python3.12/sit
e-packages (from scikit-surprise) (1.4.2)
Requirement already satisfied: numpy>=1.19.5 in /opt/anaconda3/lib/python3.12/sit
e-packages (from scikit-surprise) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in /opt/anaconda3/lib/python3.12/site
-packages (from scikit-surprise) (1.13.1)
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ages (0.23.4)
Requirement already satisfied: scipy>=1.2.1 in /opt/anaconda3/lib/python3.12/site
-packages (from mlxtend) (1.13.1)
Requirement already satisfied: numpy>=1.16.2 in /opt/anaconda3/lib/python3.12/sit
e-packages (from mlxtend) (1.26.4)
Requirement already satisfied: pandas>=0.24.2 in /opt/anaconda3/lib/python3.12/si
te-packages (from mlxtend) (2.2.2)
Requirement already satisfied: scikit-learn>=1.3.1 in /opt/anaconda3/lib/python3.
12/site-packages (from mlxtend) (1.4.2)
Requirement already satisfied: matplotlib>=3.0.0 in /opt/anaconda3/lib/python3.1
2/site-packages (from mlxtend) (3.8.4)
Requirement already satisfied: joblib>=0.13.2 in /opt/anaconda3/lib/python3.12/si
te-packages (from mlxtend) (1.4.2)
Requirement already satisfied: contourpy>=1.0.1 in /opt/anaconda3/lib/python3.12/
site-packages (from matplotlib>=3.0.0->mlxtend) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /opt/anaconda3/lib/python3.12/site
-packages (from matplotlib>=3.0.0->mlxtend) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /opt/anaconda3/lib/python3.1
2/site-packages (from matplotlib>=3.0.0->mlxtend) (4.51.0)
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2/site-packages (from matplotlib>=3.0.0->mlxtend) (1.4.4)
Requirement already satisfied: packaging>=20.0 in /opt/anaconda3/lib/python3.12/s
ite-packages (from matplotlib>=3.0.0->mlxtend) (23.2)
Requirement already satisfied: pillow>=8 in /opt/anaconda3/lib/python3.12/site-pa
ckages (from matplotlib>=3.0.0->mlxtend) (10.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /opt/anaconda3/lib/python3.12/
site-packages (from matplotlib>=3.0.0->mlxtend) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in /opt/anaconda3/lib/python
3.12/site-packages (from matplotlib>=3.0.0->mlxtend) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /opt/anaconda3/lib/python3.12/site
-packages (from pandas>=0.24.2->mlxtend) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in /opt/anaconda3/lib/python3.12/si
te-packages (from pandas>=0.24.2->mlxtend) (2023.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in /opt/anaconda3/lib/python
3.12/site-packages (from scikit-learn>=1.3.1->mlxtend) (2.2.0)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/lib/python3.12/site-pac
kages (from python-dateutil>=2.7->matplotlib>=3.0.0->mlxtend) (1.16.0)
```

In [67]:

```
from surprise import Dataset, Reader, SVD
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules
```

In [68]:

```
# Content-based recommendation using TF-IDF + Cosine Similarity
def content_based_scores(train_df, test_df, user_kw, M = 20):
    # Filter training songs that match user interests
    docs = [row['clean_lyrics'] for _, row in train_df.iterrows() if is_song_lik
    vec, user_vec = build_topic_profile(docs, M) # Build the user profile vector

    scores = []
    for _, row in test_df.iterrows():
        song_vec = vec.transform([row['clean_lyrics']])
```

```python
        scores.append(cosine_similarity(song_vec, user_vec)[0,0])
    return np.array(scores)
```

In [69]:
```python
# Collaborative Filtering using SVD (single simulated user) - From Tutorial 3
def cf_svd_scores(train_df, test_df, user_kw):
    records = []
    for idx, row in train_df.iterrows(): # Assign a binary rating: 1 if liked, 0
        rating = 1 if is_song_liked(row, user_kw) else 0
        records.append(('user1', str(idx), rating))

    # Prepare dataset for Surprise library
    df_ratings = pd.DataFrame(records, columns=['user','item','rating'])
    reader = Reader(rating_scale=(0,1))
    data   = Dataset.load_from_df(df_ratings, reader)
    trainset = data.build_full_trainset()
    algo = SVD()
    algo.fit(trainset)

    scores = []
    for idx, row in test_df.iterrows():
        pred = algo.predict('user1', str(idx)).est
        scores.append(pred)
    return np.array(scores)
```

In [70]:
```python
# Association Rule-based scoring using Apriori - From Tutorial 4
def apriori_scores(train_df, test_df, user_kw, min_support=0.05, min_conf = 0.5)
    # Tokenize lyrics of songs user likes
    trans = [row['clean_lyrics'].split() for _, row in train_df.iterrows() if is
    te = TransactionEncoder() # Convert to transaction format
    te_ary = te.fit(trans).transform(trans)
    df_te = pd.DataFrame(te_ary, columns=te.columns_)

    # Mine frequent itemsets and generate rules
    fis = apriori(df_te, min_support = min_support, use_colnames = True)
    rules = association_rules(fis, metric = "confidence", min_threshold = min_co

    scores = []
    for _, row in test_df.iterrows():
        tokens = set(row['clean_lyrics'].split())
        sc = 0
        for _, rule in rules.iterrows():
            if set(rule['antecedents']).issubset(tokens):
                sc = max(sc, rule['confidence'])
        scores.append(sc)
    return np.array(scores)
```

In [71]:
```python
import numpy as np
```

In [72]:
```python
cb_scores  = content_based_scores(train_df, test_df, user1_keywords, M = 20)
svd_scores = cf_svd_scores(train_df, test_df, user1_keywords)
ap_scores  = apriori_scores(train_df, test_df, user1_keywords)

methods = {
    'TFIDF+Cosine': cb_scores,
    'SVD_CF': svd_scores,
    'Apriori': ap_scores
}

for name, sc in methods.items():
```

```
    df_tmp = test_df.copy()
    df_tmp['score'] = sc
    top10 = df_tmp.sort_values('score', ascending = False).head(10)
    prec = evaluate_precision(top10, user1_keywords, N = 10)
    print(f"{name} Precision@10 = {prec:.2f}")
```

```
TFIDF+Cosine Precision@10 = 0.70
SVD_CF Precision@10 = 0.30
Apriori Precision@10 = 0.50
```

- **TF–IDF + Cosine** achieves the highest precision (0.70) and demonstrates that content-based keyword weighting effectively captures User 1's interests within this one-user scenario.
- **SVD (Collaborative Filtering)** performs poorly (0.30), as we only have one artificially generated user and cannot learn robust latent factors from a multi-user ratings matrix—the method is borrowed from Tutorial 3.
- **Apriori Association Rules** obtains medium precision (0.50); by mining for frequent itemsets and confidence-based rules (according to Tutorial 4), some of the latent associations are uncovered but are constrained by rule support and coverage.

**Choose *TF-IDF + Cosine***

# Part3: User Evaluation

In [75]:
```
import random
```

In [76]:
```
# Display a batch of songs for a given week (used for simulated user review)
def display_week_songs(week_df, week_num):
    print(f"\nWeek {week_num} Songs ")
    for idx, row in week_df.iterrows():
        print(f"{idx}: {row['track_name']} - {row['artist_name']} | Topic: {row[
        print(f"Lyrics snippet: {row['lyrics'][:100]}...\n")
```

In [77]:
```
vectorizer_full = CountVectorizer(max_features = 500) # Prepare TF-IDF features
X_all = vectorizer_full.fit_transform(df['clean_lyrics'])

df['predicted_topic'] = clf.predict(X_all)
```

In [78]:
```
N = 10
week1_songs = df.iloc[0:250].sample(N, random_state = 25)
week2_songs = df.iloc[250:500].sample(N, random_state = 50)
week3_songs = df.iloc[500:750].sample(N, random_state = 75)
```

In [79]:
```
display_week_songs(week1_songs, 1)
```

```
Week 1 Songs
40: break my face - ajr | Topic: sadness
Lyrics snippet: okay mouth tongue fell right grind drown mouth kill make ugly lif
e give lemons give okay break face ...

19: stole the show - kygo | Topic: dark
Lyrics snippet: darling darling turn light watch watch credit roll cry cry know p
lay house house heroes villains bla...

73: that song that we used to make love to - carrie underwood | Topic: dark
Lyrics snippet: wanna hear stupid play repeat cause take place lay body drink lik
e wine wanna feel bass rattle bone ...

219: zombie (feat. madchild & insane clown posse) - jelly roll | Topic: dark
Lyrics snippet: hear allow good time tell smile frown shoot time fly point turn l
evel head oneway track tell road go...

149: oatmeal - sudan archives | Topic: dark
Lyrics snippet: bake oatmeal stay sorry stay bake oatmeal stay sorry stay want oa
tmeal want oatmeal try force true l...

126: dream small - josh wilson | Topic: dark
Lyrics snippet: mama sing songs lord daddy spend family time world say afford sim
ple moments change world pastor tin...

4: if i started over - lukas nelson and promise of the real | Topic: dark
Lyrics snippet: think think different set apart sober mind sympathetic hearts swe
ar oath swear oath know life play p...

105: can i be him - james arthur | Topic: dark
Lyrics snippet: walk room heart steal take time unbroken want know moment cause l
ight come hear song want sing swear...

96: learning - anderson east | Topic: dark
Lyrics snippet: remember grow rid shotgun daddy truck wheel learn learn drive pon
d rods reel little jones bait cast ...

164: boulevard of broken dreams - green day | Topic: dark
Lyrics snippet: walk lonely road know know go home walk walk street boulevard bre
ak dream city sleep walk walk walk ...
```

In [80]:

```
display_week_songs(week2_songs, 2)
```

```
Week 2 Songs
400: jameson & ginger - ballyhoo! | Topic: personal
Lyrics snippet: brain brain brain brain brain brain brain brain brain late rent c
oncern step firepit cause care burn...

266: rise up - ndidi o | Topic: dark
Lyrics snippet: mama say life hard grow days black girl scar come know know pain
hold head high ashamed know forth k...

357: dead end - chon | Topic: dark
Lyrics snippet: come quarter watch head state stick fabers deep empire mould cons
cience severe secret swear cuckoo r...

270: remember you young - thomas rhett | Topic: dark
Lyrics snippet: buddies grow straightlaced marry foolin wasn long roof light darl
in sippin wine classy kick couch sm...

338: don't bother me - the raconteurs | Topic: lifestyle
Lyrics snippet: bother bother bother bother hide agenda bother bother ruthless ru
le bender bother bother surface dup...

418: over & over - reignwolf | Topic: dark
Lyrics snippet: animals woods stick outside look analyze note criticize hear voic
e scream stick inside lose maze wat...

370: nothing breaks like a heart (feat. miley cyrus) - mark ronson | Topic: dark
Lyrics snippet: world hurt cut deep leave scar things fall apart break like heart
break like heart hear phone night ...

327: 4:20/reincarnated - t-rock | Topic: sadness
Lyrics snippet: feel feel felt spell feel like time fake finger button play maste
r anticipation touch knock feet wee...

289: hold you down - x ambassadors | Topic: dark
Lyrics snippet: ones dance light hold hold ones dance faceless crowd hold hold ho
ld talk speak loudly smile eye look...

288: to the moon - phora | Topic: dark
Lyrics snippet: moon wanna star send send orbit moon wanna star send send orbit y
eah say scar blame need somebody ho...
```

In [81]:
```
display_week_songs(week3_songs, 3)
```

```
Week 3 Songs
675: almost - thomas rhett | Topic: personal
Lyrics snippet: truck field quit team give guitar cause hurt play string everybod
y tell bout give dream break rid di...

660: el hombre del equipo - grupo maximo grado | Topic: lifestyle
Lyrics snippet: sell feel fool go lead kind realise nice nice burn prarie know co
me time unwind somebody suffer know...

502: one night at a time - little hurricane | Topic: sadness
Lyrics snippet: turn time mind night time night time babe alright forever wish ey
e luck live little things want turn...

712: i'm so tired... - lauv | Topic: dark
Lyrics snippet: tire songs tire songs tire songs tire wanna home wanna home wanna
home whoa tire songs tire songs ti...

620: psycho, pt. 2 - russ | Topic: dark
Lyrics snippet: go psycho go live tightrope go go psycho go live tightrope go kno
w like want tonight pick band feeli...

521: camera show - protoje | Topic: dark
Lyrics snippet: fall fall fall fall fall see know stay freedom call call camera l
ie thing sure kingdom fall fall lik...

542: try saying goodbye - john king | Topic: personal
Lyrics snippet: lord ghetto know sinner remember baby remember know anymore tell
free sense morning second memory he...

537: thank the rebels - steel pulse | Topic: personal
Lyrics snippet: consolidation build brand nation yeah political transformation re
conciliation hammer long crawl knee...

592: paranoia - a day to remember | Topic: dark
Lyrics snippet: expect worst meet count clock cause  sleep shoot pain like heart
attack friends doctor say head dest...

580: motions - magic! | Topic: lifestyle
Lyrics snippet: routine operate like machine live spontaneity happen wild ones se
nse hours happen freedom go go moti...
```

In [82]:
```python
# User "likes" the following songs (from weeks 1-3)
liked_indices = [219, 96, 400, 327, 19, 502, 620, 4, 537]
user_liked_df = df.loc[liked_indices]
```

In [83]:
```python
# Build user profile from liked songs, grouped by topic
def build_user_profile_from_likes(user_liked_df):
    user_profiles = {}
    for topic in user_liked_df['predicted_topic'].unique():
        topic_docs = user_liked_df[user_liked_df['predicted_topic'] == topic]['c
        joined_text = ' '.join(topic_docs.tolist())
        tfidf = TfidfVectorizer(max_features = 500)
        tfidf_vec = tfidf.fit_transform([joined_text])
        user_profiles[topic] = (tfidf, tfidf_vec)
    return user_profiles
```

In [84]:
```python
user4_profiles = build_user_profile_from_likes(user_liked_df)
```

In [85]:
```python
# Score all test songs (Week 4) by cosine similarity with the user profile
def recommend_by_profile(user_profiles, test_df):
    scores = []
    for _, row in test_df.iterrows():
        topic = row['predicted_topic']
        if topic in user_profiles:
            tfidf_model, user_vec = user_profiles[topic]
            song_vec = tfidf_model.transform([row['clean_lyrics']])
            score = cosine_similarity(song_vec, user_vec)[0][0]
        else:
            score = 0
        scores.append(score)
    return scores
```

In [86]:
```python
test_df_week4 = df.iloc[750:1000].copy()
test_df_week4['score'] = recommend_by_profile(user4_profiles, test_df_week4)
topN_week4 = test_df_week4.sort_values(by = 'score', ascending = False).head(N)
print(topN_week4[['track_name', 'artist_name', 'score', 'predicted_topic']])
```

```
                                              track_name        artist_name  \
759                                          woman, amen      dierks bentley
893                                        shout bamalama  the detroit cobras
823                                 the devil don't sleep    brantley gilbert
788                                           going down      joe bonamassa
897                          love hurts (feat. travis scott)      playboi carti
866                                          black betty         larkin poe
860                                         close enough        brett young
926                                           sit awhile     the band steele
765    follow your heart (feat. zion thompson from th...          iya terra
792                                           donner bell               deca

        score predicted_topic
759  0.532784        personal
893  0.471289            dark
823  0.439139        personal
788  0.438808            dark
897  0.415311            dark
866  0.408930            dark
860  0.366413            dark
926  0.355969            dark
765  0.355882            dark
792  0.338024            dark
```

In [87]:
```python
liked_week4_indices = [926, 759, 860, 866]
```

In [88]:
```python
# get the DataFrame indices of your top-10 recommendations
rec_indices = topN_week4.index.tolist()

# compute Precision@N
tp = len(set(rec_indices) & set(liked_week4_indices))
precision = tp / N

# compute Recall@N
recall = tp / len(liked_week4_indices)

# compute F1@N
f1 = 2 * precision * recall / (precision + recall) if (precision + recall) > 0 e

print(f"Precision@{N} = {precision:.2f}")
```

```python
print(f"Recall@{N} = {recall:.2f}")
print(f"F1@{N} = {f1:.2f}")
```

```
Precision@10 = 0.40
Recall@10 = 1.00
F1@10 = 0.57
```

- **Recall@10 = 1.00**: All of the user's liked songs in Week 4 were included in the top-10 recommendations—no positive item was missed.
- **Precision@10 = 0.40**: Only 40% of the recommendations were actually liked by the user, so 60% were irrelevant.
- **F1@10 = 0.57**: Balances high coverage with modest accuracy, indicating the trade-off between capturing all liked items and avoiding noise.

# User feedback

User zID: z5522806

There are a few songs I like in the recommended content, but the style is relatively simple and not diverse enough. I hope the content can be richer, but the overall feeling is good.

In [ ]:

```python

```