imports

In [2]:
```
import pandas as pd
import numpy as np
import sklearn
import matplotlib.pyplot as plt
import nltk, re, string
import sys, os
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from sklearn.metrics import accuracy_score, classification_report, precision_sco
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import cross_val_score, cross_validate, StratifiedK
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.svm import SVC
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
from nltk.stem import WordNetLemmatizer
```

Part 1

Part 1 Question 1

i)

Currently the regex might remove to many special characters.

The regex used was: text = re.sub(r'[^\w\s]', '', text)

which effectively removes anything that is not a word or a white space. The removal of punctuation by the above regex may be too much.

For example, in the dataset the line "john deere, john 3:16 2016" exists. With the regex applied, it would instead read "john deere, john 316 2016". With the colon removed, the clear religious context of "john 3:16" is now "john 316" which has ambiguous meaning.

To fix this mistake, the regex can be modified to include punctuation, as demonstrated in the cell below.

In [ ]:
```
# include punctuation in regex pattern
text = "hello你好 !!123🗿 🤫 🧏‍♂️ John 3:16"

import string
pattern = rf"[^\w\s{re.escape(string.punctuation)}]"  # modified regex pattern t
text = re.sub(pattern, '', text)
print(text)
```

```
hello你好 !!123   John 3:16
```

ii)

K-Fold cross validation can be used instead of only one training-test split.

K-Fold CV divides the subset into *k subsets. Then,* k-1 subsets are used for training and the remaining subset is used for validation. In this method, the training is iterated *k times, with a different subset used for validation each time.

Stratified K-Fold is an additional type of K-Fold CV that ensures each "fold" of the dataset has the same proportion of observations with a given label. This helps in creating better class distribution accross folds.

Below is a code snippet that demonstrates the use of Stratified K-Fold CV in this assignment.

In [429…

```
### non-working code. for demonstration only!! ###
print("####################################################")
print("THIS CODE BLOCK IS FOR DEMONSTRATION ONLY!!")
print("####################################################")

# assert(True == False)
# pipeline = make_pipeline(
#     TfidfVectorizer(),
#     BernoulliNB()
# )

# cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# bnb_scores = cross_val_score(
#     pipeline,
#     df['content'],       # input features
#     df['topic'],         # labels
#     cv=cv,
#     scoring='accuracy'
# )
```

```
####################################################
THIS CODE BLOCK IS FOR DEMONSTRATION ONLY!!
####################################################
```

Part 2 Question 2

Data import and Pre-processing steps.

Best pre-processing steps:

- Lowercasing
- removal of special characters except punctuation
- removal of numbers
- tokenizing words
- filtering stop words
- lemmatizing words instead of stemming

In [3]:
```
#all common setup code.

df = pd.read_csv('dataset.tsv', sep='\t')
df = df.drop_duplicates()
df = df.dropna()

# concantenante

df['content'] = df['artist_name'].astype(str) + " " + df['track_name'].astype(st

# pre-processing

nltk.download('stopwords')
nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('wordnet')

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


df['original'] = df['content']  # keep original content for reference
def preprocess_text(text):
    text = text.lower()            # no impact
    pattern = rf"[^\w\s{re.escape(string.punctuation)}]"  # modified regex patte
    text = re.sub(pattern, '', text)
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    tokens = [WordNetLemmatizer().lemmatize(tok, pos='v') for tok in tokens]
    return ' '.join(tokens)

df['content'] = df['content'].apply(preprocess_text)
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/raymond/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /home/raymond/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to
[nltk_data]     /home/raymond/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package wordnet to /home/raymond/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Multinomial Naive Bayes method

In [4]:
```
mnb_pipeline = make_pipeline(
    TfidfVectorizer(),
    MultinomialNB()
)

#define cross-validation strategy and scoring metrics
mnb_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
mnb_scoring = {
    'accuracy'        : 'balanced_accuracy',  # you can still use the built-in s
    'precision_macro' : make_scorer(
        precision_score,
```

```
        average='macro',
        zero_division=0      # or 1, or 'warn'—your choice
    ),
    'f1_macro'        : make_scorer(
        f1_score,
        average='macro',
        zero_division=0      # ensures F1 handles any 0/0 in its internal precis
    )
}

# Perform cross-validation
mnb_results = cross_validate(
    mnb_pipeline,
    df['content'],       # input features
    df['topic'],         # labels
    cv=mnb_cv,
    scoring=mnb_scoring,
    return_train_score=False
)

# Print the results for each metric
for metric in mnb_scoring:
    key = f"test_{metric}"
    mnb_scores = mnb_results[key]
    # print(f"Per-fold {key}:", mnb_scores)
    print(f"Mean {key}      :", np.mean(mnb_scores))
```

```
Mean test_accuracy      : 0.46983372182264793
Mean test_precision_macro      : 0.5256795592929449
Mean test_f1_macro      : 0.43918790848991895
```

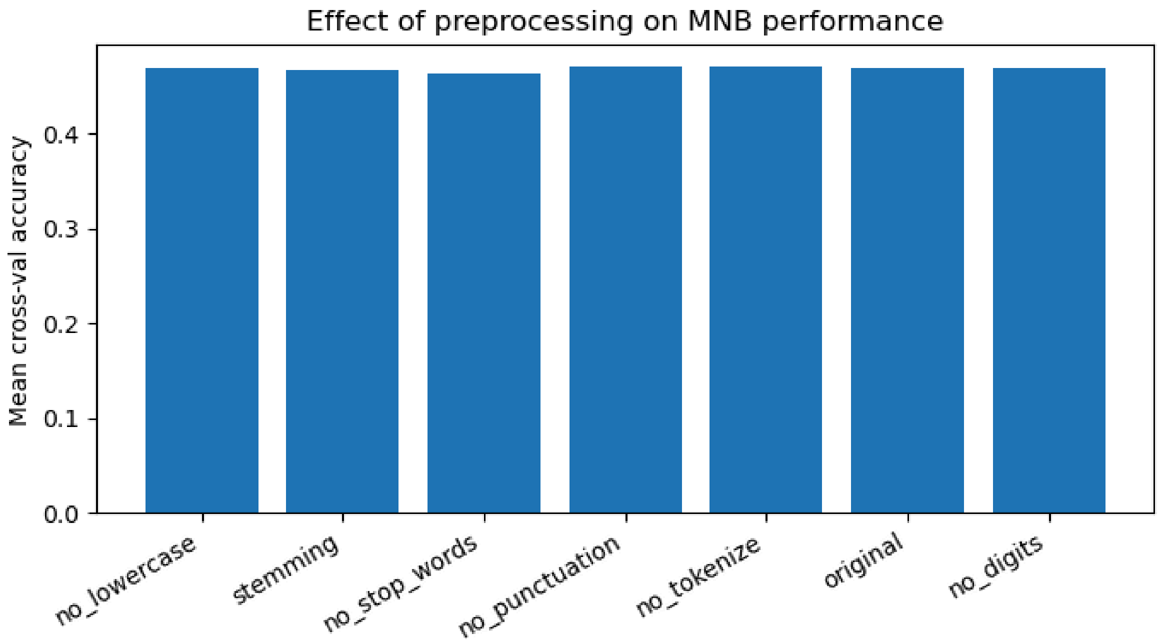
In [5]:

```
#try different preprocessing methods with default mnb.
def preprocess_text_no_text_lower(text):
    # text = text.lower()          # no impact
    pattern = rf"[^\w\s{re.escape(string.punctuation)}]"  # modified regex patte
    text = re.sub(pattern, '', text)
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    tokens = [WordNetLemmatizer().lemmatize(tok, pos='v') for tok in tokens]
    return ' '.join(tokens)

# stem words instead of lemmatizing
def preprocess_text_stem_words(text):
    text = text.lower()          # no impact
    pattern = rf"[^\w\s{re.escape(string.punctuation)}]"  # modified regex patte
    text = re.sub(pattern, '', 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)

# no stop words
def preprocess_text_no_stop_words(text):
    text = text.lower()          # no impact
    pattern = rf"[^\w\s{re.escape(string.punctuation)}]"  # modified regex patte
    text = re.sub(pattern, '', text)
    tokens = word_tokenize(text)
    tokens = [WordNetLemmatizer().lemmatize(tok, pos='v') for tok in tokens]
    return ' '.join(tokens)
```

```python
# removes punctuation
def preprocess_text_no_punctuation(text):
    text = text.lower()          # no impact
    pattern = rf"[^\w\s]"  # modified regex pattern to remove punctuation
    text = re.sub(pattern, '', text)
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    tokens = [WordNetLemmatizer().lemmatize(tok, pos='v') for tok in tokens]
    return ' '.join(tokens)

# do not tokenize words
def preprocess_text_no_tokenize(text):
    text = text.lower()          # no impact
    pattern = rf"[^\w\s{re.escape(string.punctuation)}]"  # modified regex patte
    text = re.sub(pattern, '', text)
    tokens = [word for word in text.split() if word not in stop_words]
    tokens = [WordNetLemmatizer().lemmatize(tok, pos='v') for tok in tokens]
    return ' '.join(tokens)

#strip digits
def preprocess_text_no_digits(text):
    """
    Same pipeline as preprocess_text, but also strips out any digits (0-9).
    """
    text = text.lower()

    # First remove digits explicitly
    text = re.sub(r"\d+", "", text)          # drop all numeric characters

    # Then remove any other unwanted symbols (keeps words, whitespace, punctuati
    pattern = rf"[^\w\s{re.escape(string.punctuation)}]"
    text = re.sub(pattern, "", text)

    # Tokenise and clean
    tokens = word_tokenize(text)
    tokens = [tok for tok in tokens if tok not in stop_words]
    tokens = [WordNetLemmatizer().lemmatize(tok, pos="v") for tok in tokens]

    return " ".join(tokens)


preprocess_variants = {
    "no_lowercase"  : preprocess_text_no_text_lower,
    "stemming"      : preprocess_text_stem_words,
    "no_stop_words" : preprocess_text_no_stop_words,
    "no_punctuation": preprocess_text_no_punctuation,
    "no_tokenize"   : preprocess_text_no_tokenize,
    "original"      : preprocess_text,
    "no_digits"     : preprocess_text_no_digits
}

# 2) Evaluate each preprocessing method using mnb and CV.
mean_acc = {}
for name, func in preprocess_variants.items():
    X = df['original'].apply(func)
    cv_res = cross_validate(
        mnb_pipeline,
        X,
        df['topic'],
        cv=mnb_cv,
```

```
        scoring=mnb_scoring,        # must include "accuracy"
        return_train_score=False
    )
    mean_acc[name] = np.mean(cv_res["test_accuracy"])
    print(f"{name:15s}  Mean accuracy: {mean_acc[name]:.3f}")

# 3) Bar plot of mean accuracies
plt.figure(figsize=(7,4))
plt.bar(range(len(mean_acc)), list(mean_acc.values()), tick_label=list(mean_acc.
plt.ylabel("Mean cross-val accuracy")
plt.title("Effect of preprocessing on MNB performance")
plt.xticks(rotation=30, ha='right')
plt.tight_layout()
plt.show()
```

```
no_lowercase     Mean accuracy: 0.470
stemming         Mean accuracy: 0.468
no_stop_words    Mean accuracy: 0.465
no_punctuation   Mean accuracy: 0.470
no_tokenize      Mean accuracy: 0.470
original         Mean accuracy: 0.470
no_digits        Mean accuracy: 0.470
```



In the above cell modifications were made to assess the impact of changes, such as skipping the tokenize stage or using stemming instead of lemmatizing. It was found that factors such as keeping/removing the punctuation, keeping/removing digits, lowercasing or tokenizing had negligible impact on the performance. There was an observable performance difference when stemming was used instead of lemmatization, and when stop words were not removed.

It was validated that the method described at the start of this question was equal or better to other assessed options.

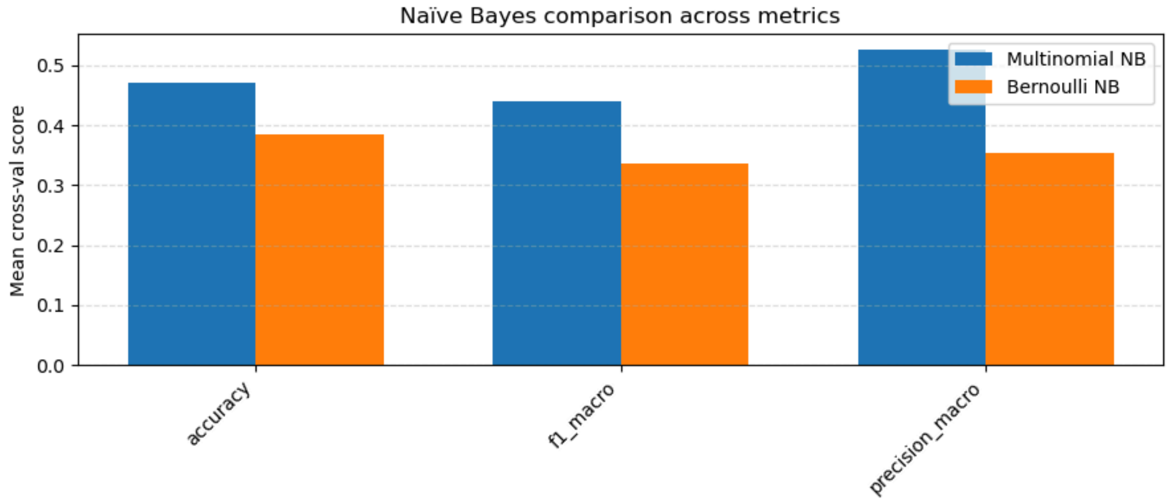
Question 3)

Bernoulli Naive Bayes method

In [6]:
```python
bnb_pipeline = make_pipeline(
    TfidfVectorizer(),
    BernoulliNB()
)

# define cross-validation strategy and scoring metrics
bnb_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
bnb_scoring = {
    'accuracy'        : 'balanced_accuracy',  # you can still use the built-in s
    'precision_macro' : make_scorer(
        precision_score,
        average='macro',
        zero_division=0      # or 1, or 'warn'—your choice
    ),
    'f1_macro'        : make_scorer(
        f1_score,
        average='macro',
        zero_division=0      # ensures F1 handles any 0/0 in its internal precis
    )
}

# Perform cross-validation for BernoulliNB
bnb_results = cross_validate(
    bnb_pipeline,
    df['content'],       # input features
    df['topic'],         # labels
    cv=bnb_cv,
    scoring=bnb_scoring,
    return_train_score=False
)

# Print the results for each metric for BernoulliNB
for metric in bnb_scoring:
    key = f"test_{metric}"
    bnb_scores = bnb_results[key]
    # print(f"Per-fold {key}:", bnb_scores)
    print(f"Mean {key}      :", np.mean(bnb_scores))
```

```
Mean test_accuracy      : 0.38483308268247757
Mean test_precision_macro      : 0.35398432722673523
Mean test_f1_macro      : 0.33619197014798285
```

In [ ]:
```python
#plot out the results for both MultinomialNB and BernoulliNB
metrics = sorted(set(mnb_scoring) | set(bnb_scoring))
mnb_means = [np.mean(mnb_results[f"test_{m}"]) for m in metrics]
bnb_means = [np.mean(bnb_results[f"test_{m}"]) for m in metrics]
x      = np.arange(len(metrics))
width = 0.35
fig, ax = plt.subplots(figsize=(9, 4))
ax.bar(x - width/2, mnb_means, width, label='Multinomial NB')
ax.bar(x + width/2, bnb_means, width, label='Bernoulli NB')
ax.set_ylabel('Mean cross-val score')
ax.set_title('Naïve Bayes comparison across metrics')
ax.set_xticks(x, metrics, rotation=45, ha='right')
ax.legend()
ax.grid(axis='y', linestyle='--', alpha=0.4)

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



In [8]:
```python
#assessing the balance of the dataset.
counts = df['topic'].value_counts()
print(counts)
```

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

Metrics were picked based on this being a multiple class classification problem.

- The balance of the class is assessed.

As the balance is off (dark has 487 whilst emotion has 79), a possible solutions is to instead use a macro-average of the metrics to account for multiple-classes. This approach gives higher than normal influence to dominated (smaller) classes. Smaller classes are still important as a lower number of songs does not neccessarily mean that topic has a lower number of users.

- Appropriate metrics: Precision, Recall, F1, Accuracy

1. Macro Precision:

Macro-precision is useful when false positives are costly.

```
2. Macro Recall / balanced accuracy  (they are the same thing):
```

Used when the coverage of each class is important. Helps to neutralise class imbalance even more as it rewards minority classes.

```
3. Macro F1: Harmonic mean of Precision and Recall.
Useful when using one metric, but both coverage and having
minimal false positives are important.
```

-Tradeoffs: There is a tradeoff between precision and recall. Prioritising recall is likely to reduce precision, whilst prioritising precision is likely to reduce recall.

- Therefore, balanced_accuracy(macro recall), and macro-f1, macro-precision was used as the main metrics. Accuracy for parts 1 and 2 will refer to macro recall.

An overall comparison of BNB and MNB found that MNB was superior. It had both better accuracy/recall and precision.

Question 4)

Gridsearch through top N words.

In [9]:
```
#gridsearch through bnb.
feature_limits = [1, 5, 10, 100, 325, 350, 375, 500, 1000, 10000]
bnb_results_df = pd.DataFrame({
    'Feature Limit': feature_limits,
    'accuracy': [0.0 for _ in feature_limits],
    'precision_macro': [0.0 for _ in feature_limits],
    'f1_macro': [0.0 for _ in feature_limits],
})

#execute grid search on bnb
for limit in feature_limits:
    bnb_pipeline = make_pipeline(
        TfidfVectorizer(max_features=limit),
        BernoulliNB()
    )
    bnb_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
    bnb_results = cross_validate(
        bnb_pipeline,
        df['content'],       # input features
        df['topic'],         # labels
        cv=bnb_cv,
        scoring=bnb_scoring,
        return_train_score=False
    )
    # print(f"Max features: {limit}")
    for metric in bnb_scoring:
        key = f"test_{metric}"
        bnb_scores = bnb_results[key]
        bnb_results_df.loc[bnb_results_df['Feature Limit'] == limit, metric] = n
        # print(f"Mean {key}      :", np.mean(bnb_scores))
```

In [10]:
```
#gridsearch through mnb
feature_limits = [1, 5, 10, 100, 325, 350, 375, 500, 1000, 10000]
mnb_results_df = pd.DataFrame({
    'Feature Limit': feature_limits,
    'accuracy': [0.0 for _ in feature_limits],
    'precision_macro': [0.0 for _ in feature_limits],
    'f1_macro': [0.0 for _ in feature_limits],
})

#execute gridsearch on mnb
for limit in feature_limits:
    mnb_pipeline = make_pipeline(
        TfidfVectorizer(max_features=limit),
```

```
        MultinomialNB()
    )
    mnb_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
    mnb_results = cross_validate(
        mnb_pipeline,
        df['content'],       # input features
        df['topic'],         # labels
        cv=mnb_cv,
        scoring=mnb_scoring,
        return_train_score=False
    )
    # print(f"Max features: {limit}")
    for metric in mnb_scoring:
        key = f"test_{metric}"
        mnb_scores = mnb_results[key]
        mnb_results_df.loc[mnb_results_df['Feature Limit'] == limit, metric] = n
        # print(f"Mean {key}      :", np.mean(mnb_scores))
```

In [11]:

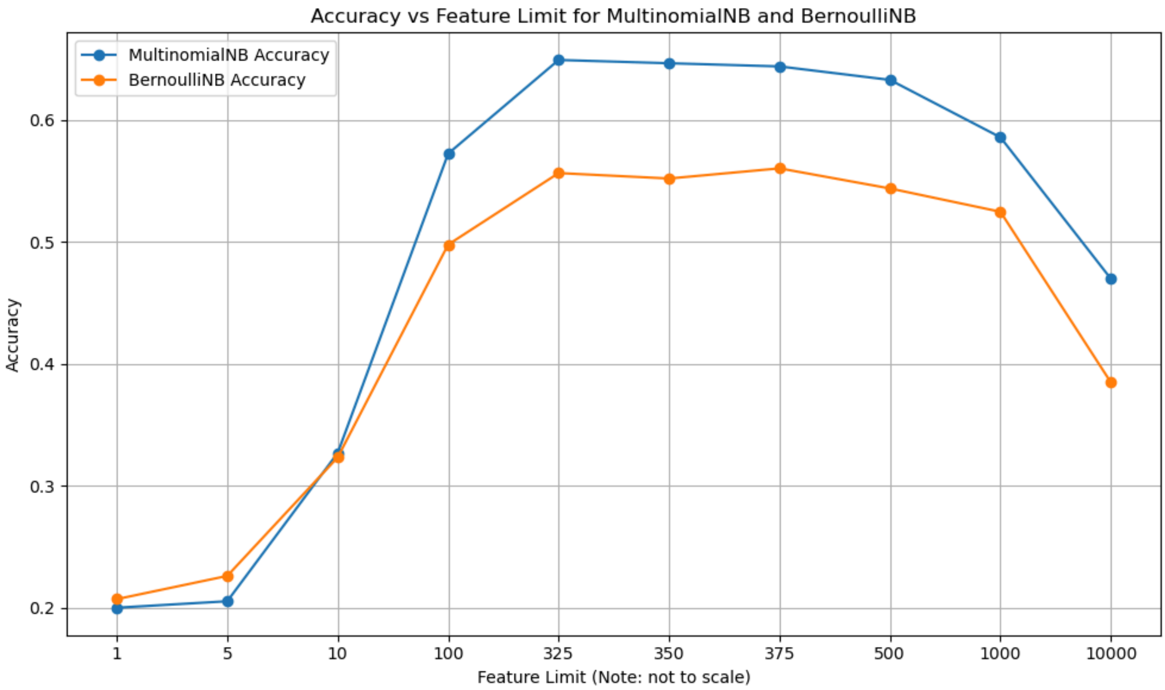
```
#plot out mnb vs bnb gridsearch results
print("MultinomialNB Gridsearch Raw Results:")
print(mnb_results_df)
print("\n")
print("BernoulliNB Gridsearch Raw Results:")
print(bnb_results_df)
# plotting feature limits against accuracy
plt.figure(figsize=(10, 6))
plt.plot(mnb_results_df['Feature Limit'].astype(str), mnb_results_df['accuracy']
plt.plot(bnb_results_df['Feature Limit'].astype(str), bnb_results_df['accuracy']
plt.xlabel('Feature Limit (Note: not to scale)')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Feature Limit for MultinomialNB and BernoulliNB')
plt.legend()
plt.grid()
plt.tight_layout()
```

MultinomialNB Gridsearch Raw Results:

	Feature Limit	accuracy	precision_macro	f1_macro
0	1	0.200000	0.065811	0.099034
1	5	0.205301	0.119884	0.124552
2	10	0.326951	0.339862	0.305387
3	100	0.572495	0.732112	0.589119
4	325	0.649340	0.749404	0.654376
5	350	0.646663	0.709775	0.647626
6	375	0.644061	0.709187	0.644757
7	500	0.633002	0.670559	0.631508
8	1000	0.585905	0.653998	0.579244
9	10000	0.469834	0.525680	0.439188

BernoulliNB Gridsearch Raw Results:

	Feature Limit	accuracy	precision_macro	f1_macro
0	1	0.207040	0.090140	0.123347
1	5	0.226080	0.185065	0.182712
2	10	0.323355	0.278663	0.295077
3	100	0.497854	0.529942	0.506722
4	325	0.556561	0.566924	0.558029
5	350	0.552103	0.561230	0.553411
6	375	0.560431	0.567153	0.560939
7	500	0.543933	0.551431	0.542369
8	1000	0.524817	0.535834	0.520360
9	10000	0.384833	0.353984	0.336192



Through a gridsearch, it was found that each model performed best at about N=~350. The performance was vastly superior to N=inf (which is the default setting.)

N=350 is used as the feature number.

Question 5)

Other machine learning method (Support Vector machine SVM selected)

SVMs separate classes by forming a decision boundary (hyperplane) in the feature space that seeks to maximise the margin between two classifications.

A margin is the distance between the decision boundary and the closest data-points in each class. The data-points closest to the decision boundary are also known as the "support vectors". These closest-datapoints then define the boundary between two classes.

SVMs are suitable for classification over vectorized words. Vectorized words are typically sparse and high-dimensional. SVMs are good for this task because they only focus on a few key points which is much more computationally efficient that other methods that account for all datapoints, such as K-NNs. Flexible kernels that support sparse feature spaces additionally help to ensure good performance. Additionally, optimizations in embedding methods such as TF-IDF means that semantically similar words end up closer to each other compared to dissimilar words. This feature common to many word-vectorization method naturally forms clusters between similar words and spatial relationships (e.g. king - queen ~= man - woman) which lends themselves to natural and effective decision boundaries that can be identified by a SVM.

A SVM is primarily tunable through three parameters. The type of decision boundary / kernel (linear, polynomial etc), C: the penalty term for misclassifying points, and γ: which influences the flexibility of the decision boundary. A basic gridsearch will be performed over these parameters to find the best ones.

Due to the reasons presented above, it is hypothesised that the SVM would be much better than the MNB and BNB. This is because the SVM utilises and real-valued feature weights extracted by vectorization, as well as optimizations involved in TF-IDF vectorization. Conversely, the MNB and BNB instead relies on probabilistic calculations related to binary presence/absence or raw word counts. This approach by the MNB and BNB means that it is simply using much less information to make it's decisions, failing to leverage the rich features extracted by optimised vectorization methods such as TF-IDF.

In [12]:

```
# performing gridsearch on SVM to find optimal parameters

svm_pipeline = make_pipeline(
    TfidfVectorizer(max_features=350),
    SVC()
)

svm_param_grid = [
    # For linear kernel we only need C
    {
        'svc__kernel': ['linear'],
        'svc__C':      [0.1, 1, 10, 100]
    },
    # For RBF, poly, sigmoid we also tune gamma
    {
        'svc__kernel': ['rbf', 'poly', 'sigmoid'],
        'svc__C':      [0.1, 1, 10, 100],
        'svc__gamma':  ['scale', 'auto', 0.001, 0.01, 0.1, 1]
    }
]

svm_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

```python
svm_grid = GridSearchCV(
    estimator=svm_pipeline,
    param_grid=svm_param_grid,
    cv=svm_cv,
    scoring='accuracy',
    n_jobs=-1,            # parallelize across cores if you like
    verbose=1
)

svm_grid.fit(df['content'], df['topic'])

print("Best params :", svm_grid.best_params_)
print("Best score  :", svm_grid.best_score_)
```

```
Fitting 5 folds for each of 76 candidates, totalling 380 fits
Best params : {'svc__C': 10, 'svc__gamma': 1, 'svc__kernel': 'rbf'}
Best score  : 0.8783783783783784
```

In [ ]:

```python
# fitting SVM model based on the best parameters found in grid search
svm_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

pipeline = make_pipeline(
    TfidfVectorizer(max_features=350),
    SVC(kernel='rbf', C=10, gamma='scale')  # using best params from grid search
)
pipeline.fit(df['content'], df['topic'])
svm_scoring = mnb_scoring  # reusing the same scoring metrics
svm_results = cross_validate(
    pipeline,
    df['content'],       # input features
    df['topic'],         # labels
    cv=svm_cv,
    scoring=svm_scoring,
    return_train_score=False
)
for metric in svm_scoring:
    key = f"test_{metric}"
    svm_scores = svm_results[key]
    print(f"Mean {key}      :", np.mean(svm_scores))

svm_model = pipeline
```

```
Mean test_accuracy      : 0.8577657013503703
Mean test_precision_macro      : 0.878426542835359
Mean test_f1_macro      : 0.8662559245095492
```

My hypothesis regarding SVMs was correct, in that it was very effective in classifying words. MNB and BNB accuracy peaked at around 0.649 and 0.560 respectively, whilst SVM was able to achieve a significantly higher accuracy of 0.8577. Other metrics yielded similar results.

Therefore, the "best" method was the SVM, with settings " kernel='rbf', C=10, gamma='scale' "

Part 2

Question 1

In [ ]:
```
#load dataset for question 2
import sklearn.model_selection


df2 = pd.read_csv('dataset.tsv', sep='\t')
df2['content'] = df2['artist_name'].astype(str) + " " + df2['track_name'].astype
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('wordnet')

ps = PorterStemmer()
stop_words = set(stopwords.words('english'))
stop_words2 = set(stopwords.words('english'))
custom = {'come', 'like', 'yeah'}          # put any others here
stop_words2.update(custom)                  # now they're treated as stop-words

df2['content'] = df2['content'].apply(preprocess_text)

print(df2['content'].head())

# make train test split, and fit vectorizer on training data to generate vocabul
q2train, q2test = sklearn.model_selection.train_test_split(df2['content'], train
q2vectorizer = TfidfVectorizer(max_features=350)

q2vectorizer.fit(q2train)   #set vocabulary
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/raymond/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /home/raymond/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to
[nltk_data]     /home/raymond/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package wordnet to /home/raymond/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
0    love real lake rock awake know go see time cle...
1    incubus summer rock summer pretty build spill ...
2    reignwolf hardcore blue lose deep catch breath...
3    tedeschi truck band anyhow blue run bitter tas...
4    lukas nelson promise real start blue think thi...
Name: content, dtype: object
```

Out[ ]:
```
▾ TfidfVectorizer

TfidfVectorizer(max_features=350)
```

create 5 vectors and matrices, one for each topic where each song "document" has a vector.

In [ ]:
```
# sort the training data by topic
topic_predict = svm_model.predict(q2train)
df3 = pd.DataFrame()
df3['predictions'] = topic_predict
counts = df3['predictions'].value_counts()
```

```
print(counts)
dark_raw = [document for idx, document in enumerate(q2train) if topic_predict[id
sadness_raw = [document for idx, document in enumerate(q2train) if topic_predict
personal_raw = [document for idx, document in enumerate(q2train) if topic_predic
lifestyle_raw = [document for idx, document in enumerate(q2train) if topic_predi
emotion_raw = [document for idx, document in enumerate(q2train) if topic_predict

# transform the raw data into vectors using the fitted vectorizer
dark = q2vectorizer.transform(dark_raw)
sadness = q2vectorizer.transform(sadness_raw)
personal = q2vectorizer.transform(personal_raw)
lifestyle = q2vectorizer.transform(lifestyle_raw)
emotion = q2vectorizer.transform(emotion_raw)

print("Dark shape      :", dark.shape)
print("Sadness shape   :", sadness.shape)
print("Personal shape  :", personal.shape)
print("Lifestyle shape :", lifestyle.shape)
print("Emotion shape   :", emotion.shape)
```

```
predictions
dark         246
personal     188
sadness      182
lifestyle     92
emotion       42
Name: count, dtype: int64
Dark shape      : (246, 350)
Sadness shape   : (182, 350)
Personal shape  : (188, 350)
Lifestyle shape : (92, 350)
Emotion shape   : (42, 350)
```

User 1 profile:

In [19]:

```
############
# for each topic, vectorize the songs that match the user's keywords.
# this represents the user's profile for that topic.
############
df_user1 = pd.read_csv('user1.tsv', sep='\t')
user1_dark_kw_str = df_user1['keywords'][0].split(',')  # assuming keywords are
for idx, kw in enumerate(user1_dark_kw_str):
    user1_dark_kw_str[idx] = preprocess_text(kw)
dark_user1 = [document for document in dark_raw if any(kw in document for kw in
dark_user1_str = " ".join(dark_user1).splitlines()  # join the list into a singl
user1_dark_profile = q2vectorizer.transform(dark_user1_str)

user1_sadness_kw_str = df_user1['keywords'][1].split(',')  # assuming keywords a
for idx, kw in enumerate(user1_sadness_kw_str):
    user1_sadness_kw_str[idx] = preprocess_text(kw)
sadness_user1 = [document for document in sadness_raw if any(kw in document for
sadness_user1_str = " ".join(sadness_user1).splitlines()  # join the list into a
user1_sadness_profile = q2vectorizer.transform(sadness_user1_str)

user1_personal_kw_str = df_user1['keywords'][2].split(',')  # assuming keywords
for idx, kw in enumerate(user1_personal_kw_str):
    user1_personal_kw_str[idx] = preprocess_text(kw)
personal_user1 = [document for document in personal_raw if any(kw in document fo
personal_user1_str = " ".join(personal_user1).splitlines()  # join the list into
user1_personal_profile = q2vectorizer.transform(personal_user1_str)
```

```
user1_lifestyle_kw_str = df_user1['keywords'][3].split(',')  # assuming keywords
for idx, kw in enumerate(user1_lifestyle_kw_str):
    user1_lifestyle_kw_str[idx] = preprocess_text(kw)
lifestyle_user1 = [document for document in lifestyle_raw if any(kw in document
lifestyle_user1_str = " ".join(lifestyle_user1).splitlines()  # join the list in
user1_lifestyle_profile = q2vectorizer.transform(lifestyle_user1_str)

user1_emotion_kw_str = df_user1['keywords'][4].split(',')  # assuming keywords a
for idx, kw in enumerate(user1_emotion_kw_str):
    user1_emotion_kw_str[idx] = preprocess_text(kw)
emotion_user1 = [document for document in emotion_raw if any(kw in document for
emotion_user1_str = " ".join(emotion_user1).splitlines()  # join the list into a
user1_emotion_profile = q2vectorizer.transform(emotion_user1_str)

############
# get top 20 terms for each topic based on the user's profile.
############

user1_dark_profile = user1_dark_profile.mean(axis=0).A1            # mean over o
darktop20_idx   = user1_dark_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
darktop20_terms    = feature_names[darktop20_idx]
darktop20_scores   = user1_dark_profile[darktop20_idx]
print("=== Dark Top 20 Terms ===")
for term, score in zip(darktop20_terms, darktop20_scores):
    print(f"{term:<15s} {score:.4f}")

user1_sadness_profile = user1_sadness_profile.mean(axis=0).A1            # mean
sadnesstop20_idx   = user1_sadness_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
sadnesstop20_terms    = feature_names[sadnesstop20_idx]
sadnesstop20_scores   = user1_sadness_profile[sadnesstop20_idx]
print("=== Sadness Top 20 Terms ===")
for term, score in zip(sadnesstop20_terms, sadnesstop20_scores):
    print(f"{term:<15s} {score:.4f}")

user1_personal_profile = user1_personal_profile.mean(axis=0).A1            # mea
personaltop20_idx   = user1_personal_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
personaltop20_terms    = feature_names[personaltop20_idx]
personaltop20_scores   = user1_personal_profile[personaltop20_idx]
print("=== Personal Top 20 Terms ===")
for term, score in zip(personaltop20_terms, personaltop20_scores):
    print(f"{term:<15s} {score:.4f}")

user1_lifestyle_profile = user1_lifestyle_profile.mean(axis=0).A1            # m
lifestyletop20_idx   = user1_lifestyle_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
lifestyletop20_terms    = feature_names[lifestyletop20_idx]
lifestyletop20_scores   = user1_lifestyle_profile[lifestyletop20_idx]
print("=== Lifestyle Top 20 Terms ===")
for term, score in zip(lifestyletop20_terms, lifestyletop20_scores):
    print(f"{term:<15s} {score:.4f}")

user1_emotion_profile = user1_emotion_profile.mean(axis=0).A1            # mean
emotiontop20_idx   = user1_emotion_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
emotiontop20_terms    = feature_names[emotiontop20_idx]
emotiontop20_scores   = user1_emotion_profile[emotiontop20_idx]
```

```
print("=== Emotion Top 20 Terms ===")
for term, score in zip(emotiontop20_terms, emotiontop20_scores):
    print(f"{term:<15s} {score:.4f}")
```

```
=== Dark Top 20 Terms ===
fight           0.3571
black           0.2188
blood           0.2122
grind           0.2011
stand           0.1729
know            0.1651
come            0.1621
like            0.1560
kill            0.1432
na              0.1407
gon             0.1349
tell            0.1333
hand            0.1214
head            0.1155
yeah            0.1127
follow          0.1104
build           0.1074
death           0.1016
bone            0.0996
paint           0.0993
=== Sadness Top 20 Terms ===
tear            0.3734
cry             0.3482
away            0.1975
na              0.1931
woah            0.1885
baby            0.1867
break           0.1811
know            0.1662
heart           0.1657
hurt            0.1535
steal           0.1453
fall            0.1392
gon             0.1332
fade            0.1302
place           0.1296
apart           0.1262
want            0.1261
feel            0.1247
think           0.1205
wish            0.1191
=== Personal Top 20 Terms ===
life            0.5314
live            0.3073
change          0.1852
world           0.1642
ordinary        0.1586
na              0.1500
dream           0.1454
know            0.1424
yeah            0.1357
teach           0.1331
thank           0.1293
lord            0.1188
wan             0.1111
time            0.1065
like            0.1048
learn           0.1000
beat            0.0964
```

```
think           0.0954
come            0.0885
things          0.0884
=== Lifestyle Top 20 Terms ===
tonight         0.3270
night           0.3063
song            0.2322
strangers       0.2235
sing            0.2223
home            0.2146
closer          0.2049
come            0.2028
long            0.1993
time            0.1824
spoil           0.1637
tire            0.1626
wait            0.1621
right           0.1612
na              0.1590
wan             0.1410
struggle        0.1350
play            0.1288
yeah            0.1228
mind            0.1134
=== Emotion Top 20 Terms ===
good            0.6685
touch           0.4003
feel            0.3207
hold            0.1954
morning         0.1382
vibe            0.1287
feelin          0.1286
know            0.1257
kiss            0.1254
miss            0.1145
luck            0.1099
go              0.1041
want            0.0993
love            0.0969
lips            0.0947
baby            0.0877
real            0.0776
na              0.0695
yeah            0.0621
like            0.0621
```

User 2.

In [20]:

```
############
# for each topic, vectorize the songs that match the user's keywords.
# this represents the user's profile for that topic.
############

df_user2 = pd.read_csv('user2.tsv', sep='\t')


user2_sadness_kw_str = df_user2['keywords'][0].split(',')  # assuming keywords a
for idx, kw in enumerate(user2_sadness_kw_str):
    user2_sadness_kw_str[idx] = preprocess_text(kw)
sadness_user2 = [document for document in sadness_raw if any(kw in document for
```

```
sadness_user2_str = " ".join(sadness_user2).splitlines()  # join the list into a
user2_sadness_profile = q2vectorizer.transform(sadness_user2_str)

user2_emotion_kw_str = df_user2['keywords'][1].split(',')  # assuming keywords a
for idx, kw in enumerate(user2_emotion_kw_str):
    user2_emotion_kw_str[idx] = preprocess_text(kw)
emotion_user2 = [document for document in emotion_raw if any(kw in document for 
emotion_user2_str = " ".join(emotion_user2).splitlines()  # join the list into a
user2_emotion_profile = q2vectorizer.transform(emotion_user2_str)

############
# get top 20 terms for each topic based on the user's profile.
############

user2_sadness_profile = user2_sadness_profile.mean(axis=0).A1            # mean 
sadnesstop20_idx    = user2_sadness_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
sadnesstop20_terms    = feature_names[sadnesstop20_idx]
sadnesstop20_scores   = user2_sadness_profile[sadnesstop20_idx]
print("=== Sadness Top 20 Terms ===")
for term, score in zip(sadnesstop20_terms, sadnesstop20_scores):
    print(f"{term:<15s} {score:.4f}")

user2_emotion_profile = user2_emotion_profile.mean(axis=0).A1          # mean ov
emotiontop20_idx    = user2_emotion_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
emotiontop20_terms    = feature_names[emotiontop20_idx]
emotiontop20_scores   = user2_emotion_profile[emotiontop20_idx]
print("=== Emotion Top 20 Terms ===")
for term, score in zip(emotiontop20_terms, emotiontop20_scores):
    print(f"{term:<15s} {score:.4f}")
```

```
=== Sadness Top 20 Terms ===
heart           0.2938
away            0.2630
break           0.2574
fall            0.2037
hurt            0.1971
na              0.1918
tear            0.1839
know            0.1637
think           0.1526
baby            0.1520
wan             0.1460
leave           0.1448
inside          0.1431
apart           0.1272
feel            0.1198
yeah            0.1147
fade            0.1143
step            0.1127
cry             0.1124
cause           0.1111
=== Emotion Top 20 Terms ===
good            0.6757
touch           0.4046
feel            0.3241
hold            0.1975
vibe            0.1301
feelin          0.1300
kiss            0.1268
know            0.1252
morning         0.1228
miss            0.1157
luck            0.1110
go              0.1052
want            0.0977
lips            0.0914
baby            0.0795
real            0.0784
na              0.0702
light           0.0625
like            0.0607
cause           0.0607
```

User 3

In [21]:

```
############
# for each topic, vectorize the songs that match the user's keywords.
# this represents the user's profile for that topic.
############

df_user3 = pd.DataFrame(
    {
        "topic": ["dark", "personal", "emotion"],
        "keywords": [
            "blood",
            "live, life, discover, fate",
            "feel, good, babe",
        ],
    }
)
```

```
user3_dark_kw_str = df_user3['keywords'][0].split(',')  # assuming keywords are
for idx, kw in enumerate(user3_dark_kw_str):
    user3_dark_kw_str[idx] = preprocess_text(kw)
dark_user3 = [document for document in dark_raw if any(kw in document for kw in
dark_user3_str = " ".join(dark_user3).splitlines()  # join the list into a singl
user3_dark_profile = q2vectorizer.transform(dark_user3_str)

user3_personal_kw_str = df_user3['keywords'][0].split(',')  # assuming keywords
for idx, kw in enumerate(user3_personal_kw_str):
    user3_personal_kw_str[idx] = preprocess_text(kw)
personal_user3 = [document for document in personal_raw if any(kw in document fo
personal_user3_str = " ".join(personal_user3).splitlines()  # join the list into
user3_personal_profile = q2vectorizer.transform(personal_user3_str)

user3_emotion_kw_str = df_user3['keywords'][1].split(',')  # assuming keywords a
for idx, kw in enumerate(user3_emotion_kw_str):
    user3_emotion_kw_str[idx] = preprocess_text(kw)
emotion_user3 = [document for document in emotion_raw if any(kw in document for
emotion_user3_str = " ".join(emotion_user3).splitlines()  # join the list into a
user3_emotion_profile = q2vectorizer.transform(emotion_user3_str)

############
# get top 20 terms for each topic based on the user's profile.
############

user3_dark_profile = user3_dark_profile.mean(axis=0).A1            # mean over o
darktop20_idx    = user3_dark_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
darktop20_terms    = feature_names[darktop20_idx]
darktop20_scores   = user3_dark_profile[darktop20_idx]
print("=== Dark Top 20 Terms ===")
for term, score in zip(darktop20_terms, darktop20_scores):
    print(f"{term:<15s} {score:.4f}")

user3_personal_profile = user3_personal_profile.mean(axis=0).A1          # mean
personaltop20_idx    = user3_personal_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
personaltop20_terms    = feature_names[personaltop20_idx]
personaltop20_scores   = user3_personal_profile[personaltop20_idx]
print("=== Personal Top 20 Terms ===")
for term, score in zip(personaltop20_terms, personaltop20_scores):
    print(f"{term:<15s} {score:.4f}")

user3_emotion_profile = user3_emotion_profile.mean(axis=0).A1          # mean
emotiontop20_idx    = user3_emotion_profile.argsort()[::-1][:20]
feature_names = np.array(q2vectorizer.get_feature_names_out())
emotiontop20_terms    = feature_names[emotiontop20_idx]
emotiontop20_scores   = user3_emotion_profile[emotiontop20_idx]
print("=== Emotion Top 20 Terms ===")
for term, score in zip(emotiontop20_terms, emotiontop20_scores):
    print(f"{term:<15s} {score:.4f}")
```

```
=== Dark Top 20 Terms ===
blood           0.6347
cold            0.1599
feel            0.1410
hole            0.1392
list            0.1383
pull            0.1366
skin            0.1323
south           0.1320
dirty           0.1277
devil           0.1237
come            0.1234
black           0.1233
like            0.1210
scream          0.1188
soul            0.1151
bone            0.1115
river           0.1017
raise           0.1009
grind           0.0970
hell            0.0954
=== Personal Top 20 Terms ===
teach           0.5941
beat            0.5404
live            0.2926
dream           0.2582
come            0.1659
believe         0.1338
blood           0.1328
save            0.0988
life            0.0774
years           0.0730
cause           0.0691
feel            0.0669
reach           0.0615
go              0.0591
true            0.0584
step            0.0584
half            0.0537
sing            0.0534
know            0.0532
rock            0.0483
=== Emotion Top 20 Terms ===
good            0.7310
go              0.4039
hand            0.2267
vibe            0.2234
feelin          0.2232
morning         0.1672
feel            0.0968
come            0.0914
want            0.0885
somebody        0.0884
look            0.0878
wait            0.0862
live            0.0800
life            0.0788
yeah            0.0764
luck            0.0762
cause           0.0583
```

```
know            0.0577
like            0.0575
love            0.0517
```

The words seem reasonable for their genres for all users. In many cases, it included the keywords that we were searching for, which provided a sort of qualitative verification.

Part 2, Question 2

Appropriate Metrics:

- Precision@N

These are appropriate metrics as there is exactly one positive class (likes), and top-N reccomendations are being assessed. Recall@N is also another possible metric but was not chosen because we are not interested in reccomending *all* relevant songs, just presenting relevant songs in the top-N.

- Cumulative Gain

This is an appropriate metrics for ranked data, each with a relevance rel(i). In our case, this is very simple as the relevane is a 1 or 0 case, and the data is simply ranked in accordinace to whether it is a 1 or a 0. Discounted Cumulative gain was another option, but was not selected as the position that the reccomendation does not matter in my reccomendation system, as long as it was within the top-N.

However, we note that Cumulative Gain and precision in this case are almost identical, as since rel(i) takes the form of 1 or 0, it simply becomes a count of TP in topN. Precision@N is TP in topN/N, and since N is fixed in this assignment, they are effectively the same, but at a different scale.
In terms of similarity score, the following metrics will be used.

- Jaccard
- Cosine
- Sorensen-Dice
- Euclidean.

These are suitable for similarity between two vectors, such as tf-idf vectors.

For this part, I have chosen N = 10, and 10 songs in **total** will be shown.

In [22]:
```
#assemble user profiles

user1_profiles = np.array([user1_dark_profile, user1_sadness_profile, user1_pers
user2_profiles = np.array([user2_sadness_profile, user2_emotion_profile])
user3_profiles = np.array([user3_dark_profile, user3_personal_profile, user3_emo

# create test datat from songs 750-1.5k, sorted by topic.
topic_predict_test = svm_model.predict(q2test)
df4 = pd.DataFrame()
```

```
df4['predictions'] = topic_predict_test
counts = df4['predictions'].value_counts()
print(counts)
dark_songs_test = np.array([document for idx, document in enumerate(q2test) if t
sadness_songs_test = np.array([document for idx, document in enumerate(q2test) i
personal_songs_test = np.array([document for idx, document in enumerate(q2test)
lifestyle_songs_test = np.array([document for idx, document in enumerate(q2test)
emotion_songs_test = np.array([document for idx, document in enumerate(q2test) i
q3test = np.array([document for document in q2test])

#define similarity functions
def jaccard_similarity(song, profile2):
    profile_bin = profile2 > 0
    songs_bin   = song > 0

    # compute intersection & union counts for each song
    intersection = np.logical_and(songs_bin, profile_bin).sum(axis=1)
    union = np.logical_or (songs_bin, profile_bin).sum(axis=1)
    if union == 0:
        return 0
    jaccard_sim = intersection / union  # shape (n_songs,)
    return jaccard_sim

def sorensen_dice_similarity(song, profile2):
    songs_bin   = song    > 0
    profile_bin = profile2 > 0
    intersection = np.logical_and(songs_bin, profile_bin).sum(axis=1)
    sizes_sum    = songs_bin.sum(axis=1) + profile_bin.sum()
    dice = np.zeros_like(intersection, dtype=float)
    nonzero = sizes_sum > 0
    dice[nonzero] = 2 * intersection[nonzero] / sizes_sum[nonzero]
    return dice

def cosine_similarity(song, profile2):
    # compute dot product
    dot_product = np.dot(song, profile2.T)  # shape (n_songs, n_songs)
    # compute norms
    norm1 = np.linalg.norm(song, axis=1)  # shape (n_songs,)
    norm2 = np.linalg.norm(profile2)  # shape (n_songs,)
    denom = norm1 * norm2

    cos_sim = np.zeros_like(dot_product, dtype=float)
    nonzero = denom > 0
    cos_sim[nonzero] = dot_product[nonzero] / denom[nonzero]
    return cos_sim

def euclidean_distance(song, profile2):
    return np.linalg.norm(song - profile2, axis=1)

# compute similarity scores for each song against the user's profile.
# returns a dictionary with keys for each similarity measure and values as array
def compute_similarity_dict(songs, relevant_profile):
    n_songs = songs.shape[0]
    jaccard_similarities = np.zeros((n_songs, 1), dtype=float)
    sorensen_dice_similarities = np.zeros((n_songs, 1), dtype=float)
    cosine_similarities = np.zeros((n_songs, 1), dtype=float)
    euclidean_distances = np.zeros((n_songs, 1), dtype=float)
    for i in range(n_songs):
        song_tfidf = q2vectorizer.transform([songs[i]]).toarray().astype(float)
        jaccard_similarities[i] = cosine_similarity(song_tfidf, relevant_profile
```

```python
        sorensen_dice_similarities[i] = sorensen_dice_similarity(song_tfidf, rel
        cosine_similarities[i] = cosine_similarity(song_tfidf, relevant_profile)
        euclidean_distances[i] = euclidean_distance(song_tfidf, relevant_profile

    return {
        "jaccard": jaccard_similarities,
        "sorensen_dice": sorensen_dice_similarities,
        "cosine": cosine_similarities,
        "euclidean": euclidean_distances
    }

# ranks songs based on the similarity scores for a given topic.
def rank_songs(songs_list, similarity_scores):
    top_n_indices = np.argsort(similarity_scores, axis=0).flatten()[::-1]
    top_n_songs = [songs_list[i] for i in top_n_indices]
    return top_n_songs, similarity_scores[top_n_indices].flatten()

# based on the similarity scores, get the top N songs and their corresponding ke
def get_top_n_songs(songs_list, similarity_scores, kw_list, topn=10):
    top_n_indices = np.argsort(similarity_scores, axis=0)[-topn:].flatten()[::-1
    top_n_songs = [songs_list[i] for i in top_n_indices]
    corresponding_kw = [kw_list[i] for i in top_n_indices]
    return top_n_songs, similarity_scores[top_n_indices].flatten(), correspondin

# check for an interest "match"
def assess_relevance(song, keywords):
    keywords_copy = keywords.copy()
    for idx, kw in enumerate(keywords_copy):
        keywords_copy[idx] = preprocess_text(kw)
    return any(kw in song for kw in keywords_copy)

#calculate top N precision
def get_top_N_precision(songs, keywords):
    counter = 0
    for idx, song in enumerate(songs):
        if assess_relevance(song, keywords[idx]):
            counter += 1
    return counter / len(songs) if songs else 0

# calculate cumulative gain for the top N songs
def get_cum_gain(songs, keywords):
    counter = 0
    for idx, song in enumerate(songs):
        if assess_relevance(song, keywords[idx]):
            counter += 1
    return counter
```

```
predictions
dark         244
sadness      194
personal     159
lifestyle    113
emotion       40
Name: count, dtype: int64
```

In [ ]:

```python
# Define each user’s categories, test-songs and profiles
user_configs = {
    "user1": [
        (q3test,     user1_dark_profile, user1_dark_kw_str),
```

```python
        (q3test,  user1_sadness_profile, user1_sadness_kw_str),
        (q3test, user1_personal_profile, user1_personal_kw_str),
        (q3test, user1_lifestyle_profile, user1_lifestyle_kw_str),
        (q3test,  user1_emotion_profile, user1_emotion_kw_str),
    ],
    "user2": [
        (q3test, user2_sadness_profile, user2_sadness_kw_str),
        (q3test, user2_emotion_profile, user2_emotion_kw_str),
    ],
    "user3": [
        (q3test,     user3_dark_profile, user3_dark_kw_str),
        (q3test, user3_personal_profile, user3_personal_kw_str),
        (q3test,  user3_emotion_profile, user3_emotion_kw_str),
    ],
}

# Compute & rank for each user
top_n = 10
all_user_recs = {}
scores = {}
kws = {}


similarity_methods = ["cosine", "jaccard", "sorensen_dice", "euclidean"]
top_n              = 20

rows = []   # collect (user, metric, precision, gain)

for user, cfg in user_configs.items():
    for metric in similarity_methods:
        merged_songs, merged_scores, merged_kws = [], np.empty(0), []

        for songs, profile, kw in cfg:
            sims = compute_similarity_dict(songs, profile)[metric]   # <-- pick
            ranked_songs, ranked_scores = rank_songs(songs, sims)

            merged_songs.extend(ranked_songs)
            merged_scores = np.concatenate([merged_scores, ranked_scores])
            merged_kws.extend([kw] * len(ranked_songs))

        top_songs, _, top_kws = get_top_n_songs(merged_songs,
                                                merged_scores,
                                                merged_kws,
                                                topn=top_n)

        precision = get_top_N_precision(top_songs, top_kws)
        gain      = get_cum_gain(top_songs, top_kws)
        rows.append((user, metric, precision, gain))

# print out in tabular form.
df = pd.DataFrame(rows,
                  columns=["User", "Similarity", "Precision@20", "Cumulative Gai

precision_tbl = df.pivot(index="User",
                         columns="Similarity",
                         values="Precision@20").round(3)
gain_tbl      = df.pivot(index="User",
                         columns="Similarity",
                         values="Cumulative Gain").astype(int)
```

```
print("=== Precision@20 ===")
print(precision_tbl.to_string())
print("\n=== Cumulative Gain ===")
print(gain_tbl.to_string())
```

```
=== Precision@20 ===
Similarity  cosine  euclidean  jaccard  sorensen_dice
User
user1         0.90       0.05     0.90           0.75
user2         0.65       0.00     0.65           0.85
user3         0.65       0.05     0.65           0.55

=== Cumulative Gain ===
Similarity  cosine  euclidean  jaccard  sorensen_dice
User
user1           18          1       18             15
user2           13          0       13             17
user3           13          1       13             11
```

See metrics for each user.

Analysis of M. For M, users 1 and 2 were evaluated with only a portion of their 5 words per topic and the relevant metrics were used to evaluate the performance.

For this section, as only the *relative* values are significant, the sample size N was increased to 20 to have better resolution over the impact of changing M. Through experimentation, it was found that 20 will not be a limiting factor in terms of there not being enough correct songs to fill up the top-N reccomendations.

We use cosine (the best performing method according to the above.)

The results show that adding more keywords improves recommendation quality.

Adding more keywords not only widens the net of songs that can be matched but also strengthens the underlying TF-IDF profile: with each additional term, the seed set of songs grows, so the averaged TF-IDF vector becomes denser and less sparse, giving cosine, Dice, and Jaccard scores a more stable and discriminative basis.

Having a larger sample size within a theme also tends to increase the weighting of key terms found commonly in the theme, whilst common terms retain their original weighting. This means that relatively the TF-IDF vector becomes more biased towards the distinctive terms, making the definition better.

Additionally, because of the way a "match" is defined, i.e. if the interest "word" exists in the song, just having more "words" by default means that more songs qualify to be a "match". Thus, the portion of "correct" songs increases which makes it easier to even "accidently" guess songs that match the interest.

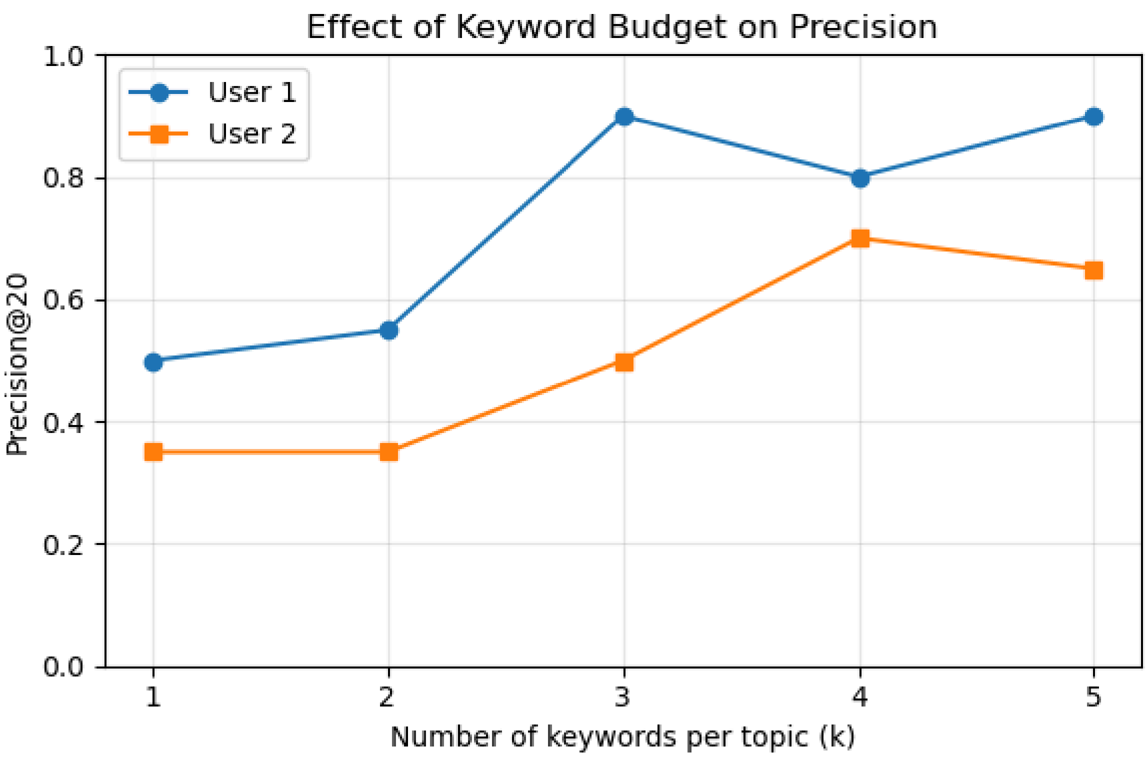
There seemed to be no difference between Jaccard and Cosine similarity. These seemed to far outperform euclidean, and perform better in 2 of the 3 cases compared to Sorensen-Dice. Therefore, we take Jaccard similarity as our similarity metric.

In [25]:
```
# utility dictionaries to store data for accessing.
top_n = 20
```

```python
topic_raw = {
    "dark":       dark_raw,
    "sadness":    sadness_raw,
    "personal":   personal_raw,
    "lifestyle":  lifestyle_raw,
    "emotion":    emotion_raw,
}
songs_test = {
    "dark":       q3test,
    "sadness":    q3test,
    "personal":   q3test,
    "lifestyle":  q3test,
    "emotion":    q3test,
}

user_kw_full = {
    "user1": {
        "dark":       user1_dark_kw_str,
        "sadness":    user1_sadness_kw_str,
        "personal":   user1_personal_kw_str,
        "lifestyle":  user1_lifestyle_kw_str,
        "emotion":    user1_emotion_kw_str,
    },
    "user2": {
        "sadness":    user2_sadness_kw_str,
        "emotion":    user2_emotion_kw_str,
    },
}

# Build a mean TF-IDF profile from the first k keywords
def build_profile(raw_docs, kw_list, k):
    sel = [preprocess_text(w) for w in kw_list[:k]]
    matched = [doc for doc in raw_docs if any(kw in doc for kw in sel)]
    if not matched:
        return np.zeros((len(q2vectorizer.vocabulary_),))
    vec = q2vectorizer.transform(" ".join(matched).splitlines()).mean(axis=0)
    return np.asarray(vec).ravel()

# Run keyword-budget experiment for each user
precisions = {"user1": [], "user2": []}
for uname, kw_dict in user_kw_full.items():
    print(f"\n====== {uname.upper()} ======")
    for k in range(1, 6):                        # 1 … 5 keywords/topic
        # Build per-topic TF-IDF profiles (only topics user has)
        profiles = {
            t: build_profile(topic_raw[t], kw_dict[t], k)
            for t in kw_dict
        }

        # Assemble candidate list across topics
        merged_songs, merged_scores, merged_kws = [], np.empty(0), []
        for t in kw_dict:
            sims = compute_similarity_dict(songs_test[t], profiles[t])["jaccard"
            ranked_songs, ranked_scores = rank_songs(songs_test[t], sims)
            merged_songs.extend(ranked_songs)
            merged_scores = np.concatenate([merged_scores, ranked_scores])
            merged_kws.extend([kw_dict[t][:k]] * len(ranked_songs))

        # Select overall top-N
        top_songs, _, top_kw = get_top_n_songs(merged_songs,
```

```python
                                                merged_scores,
                                                merged_kws,
                                                topn=top_n)

        # Metrics
        prec  = get_top_N_precision(top_songs, top_kw)
        precisions[uname].append(prec)
        cgain = get_cum_gain(top_songs, top_kw)
        print(f"[k={k}]  Precision@{top_n}: {prec:.3f}   |   Cum.Gain: {cgain}")

import matplotlib.pyplot as plt

ks = range(1, 6)
plt.figure(figsize=(6, 4))
plt.plot(ks, precisions["user1"], marker='o', label='User 1')
plt.plot(ks, precisions["user2"], marker='s', label='User 2')
plt.xlabel('Number of keywords per topic (k)')
plt.ylabel(f'Precision@{top_n}')
plt.title('Effect of Keyword Budget on Precision')
plt.xticks(ks)
plt.ylim(0, 1)            # optional: fix y-axis to [0, 1]
plt.grid(alpha=0.3)
plt.legend()
plt.tight_layout()
plt.show()
```

```
====== USER1 ======
[k=1]  Precision@20: 0.500   |   Cum.Gain: 10
[k=2]  Precision@20: 0.550   |   Cum.Gain: 11
[k=3]  Precision@20: 0.900   |   Cum.Gain: 18
[k=4]  Precision@20: 0.800   |   Cum.Gain: 16
[k=5]  Precision@20: 0.900   |   Cum.Gain: 18

====== USER2 ======
[k=1]  Precision@20: 0.350   |   Cum.Gain: 7
[k=2]  Precision@20: 0.350   |   Cum.Gain: 7
[k=3]  Precision@20: 0.500   |   Cum.Gain: 10
[k=4]  Precision@20: 0.700   |   Cum.Gain: 14
[k=5]  Precision@20: 0.650   |   Cum.Gain: 13
```



Explaining the differences between users:

We found that User 1 >> User 2 =(roughly) User 3.

User 1 supplies five distinct topics, each described by five carefully chosen keywords, whereas User 2 provides only two such topic-keyword sets. Because the recommender draws the same overall **Top-N** list for every user, it must allocate those N slots across the topics available. With five topics, User 1 needs, on average, only the two best-scoring songs per topic to fill the list (N ÷ 5 ≈ 2), while User 2 must take roughly the five best songs from each of just two topics (N ÷ 2 = 5). A stricter cut-off within each topic means the songs that survive for User 1 come from deeper competition and therefore tend to have higher similarity scores. Put differently, expanding the number of topics widens the candidate pool without increasing the quota of final recommendations, so the average similarity threshold for inclusion rises.

User 2 being about even in performance over user 3 can be explained by the above discussion, where having more words was found to have a significant impact. User 2 has 10 words in total, 5 each, whilst user 3 has 8 words across 3 classes, averaging 2.6 words/class. However, the addition for an additional class does bring the benefits of a wider pool of candidates to choose from as discussed above, and the difference in keywords is not massive. This explains why User 2 and 3 have statistically insignificant differences.

Part 3

In [26]:
```
import pandas as pd

#load dataset for question 3
```

```python
df3 = pd.read_csv('dataset.tsv', sep='\t')
df3['content'] = (
    df3['artist_name'].astype(str) + " "
    + df3['track_name'].astype(str) + " "
    + df3['genre'] + " "
    + df3['lyrics']
)
# generate N songs per batch
weeks = [df3['content'][i:i+250] for i in range(0, 1000, 250)]
samples = [wk.sample(n=10, random_state=42) for wk in weeks]
def print_week(sample_series, label):
    print(f"\n{label}:")
    for pos, (orig_idx, song) in enumerate(sample_series.items(), start=1):
        print(f"{pos:>2}. [idx {orig_idx}] {song}")

print_week(samples[0], "Week 1 Sample")
print_week(samples[1], "Week 2 Sample")
print_week(samples[2], "Week 3 Sample")
```

Week 1 Sample:

```
 1. [idx 142] skool 77 vivo hip hop (live) hip hop head camden sure raise toast p
atron saint waifs stray bingham ghost freshfaced lass kentish come people pedlars
bingham husband camden coach house till hang neck tyburn tree steal sheep break h
eart lose child name take hand meek mild drinker thinker daily bring wife tear ca
mden winter morning simply disappear head camden sure raise toast patron saint wa
ifs stray bingham ghost earn reputation bitter camden streets tarry bingham girl
hold manhood cheap miser pitcher lips till night check oven burn crisp try murder
think finally cook die slip noose fugitive justice take beat poison head camden s
ure raise toast patron saint waifs stray bingham ghost locals like false word fol
low call wicked woman sorceress renown swear gravestones husband grow ribald righ
teous know witch reason hat simple kindness careless take need guilty gamblers ha
rlots  know offer sanctuary judgement judge fall die swear devil break door chair
body pry tavern stand call underworld offer sanctuary break boys girls head camde
n folks raise toast patron saint waifs stray bingham ghost
 2. [idx 6] rebelution trap door reggae  long long road occur look shortcut wanna
cause scene wanna close okay outspoken look trap door sneak grind floor careful w
ish need answer head time solve problems scream perfect expect human look trap do
or sneak grind floor careful wish
 3. [idx 97] alec benjamin outrunning karma pop outrun karma charmer bug larva fo
llow colorado dozen hearts body lie drag colorado modern desperado race night run
know hide gonna poor people forsake karma gonna lie game wait church steeple sata
n karma escape die outrun karma farther days sparta follow meet brace battle nigh
t fight know hide gonna poor people forsake karma gonna lie game wait church stee
ple satan karma escape die lalalalala lalalalala lalalalala lala lalalalala lalal
alala lalalalala lala gonna poor people forsake karma gonna lie game wait church
steeple satan karma escape die lalalalala lalalalala lalalalala lala
 4. [idx 60] phish we are come to outlive our brains blues overlap future pass pa
ss vapor light liquid blue look exactly suppose look shape hang look shape hang l
ook stop try rush nature slow come outlive brain distance frown come outlive brai
n distance frown come outlive brain distance frown come outlive brain distance fr
own cub cub cub cub cub cub cub cub cub cub cub cub glue magnet glue magnet glue
magnet glue magnet glue magnet glue magnet glue magnet glue magnet glue magnet gl
ue magnet glue magnet glue glue magnet glue magnet glue magnet glue magnet glue m
agnet come outlive brain come outlive brain come outlive brain come outlive brain
come outlive brain
 5. [idx 112] madeleine peyroux shout sister shout jazz shout sister shout hallel
ujah shout sister shout shout sister shout tell world reason live reason die darn
good reason woman start cry reason mole reason dimple reason simple shout sister
shout hallelujah shout sister shout hallelujah shout sister shout mmhmm yeah shou
t sister shout tell world brilliant fool heaven observe golden rule sweetheart wi
fe quit baby lose life shout sister shout hallelujah shout sister shout halleluja
h shout sister shout yeah tell world reason mountain reason reason doctor give pa
tient pill reason dance reason sing reason band swing understand bird understand
be understand eat cheese understand understand cat rhythm understand shout sister
shout hallelujah shout sister shout hallelujah shout sister shout mmhmm halleluja
h tell world know gonna shout shout sister go shout shout sister go shout tell wo
rld
 6. [idx 181] janiva magness what i could do blues pay dues truth leave leave lea
ve forget silence rule blind fool learn learn learn break away rise days fireligh
t fade night estrange draw flame like rain strange go away go away pay dues truce
leave leave leave forget rule truth learn learn learn break away rise days fireli
ght fade night estrange draw flame like rain strange strange days firelight fade
night estrange draw flame like rain strange go away away
 7. [idx 197] eric ethridge if you met me first country strangest creature fail p
rey like vulture hand follow follow follow life steal light sweet taste talk wann
a face crowd friend failure trust gods couldn felt lose steal light sweet taste t
alk wanna face crowd steal light sweet taste talk wanna face crowd
 8. [idx 184] imagine dragons natural rock hold line give give tell house come co
nsequence cost tell star align heaven step save cause house stand strong leave he
```

art cast away product today prey stand edge face cause natural beat heart stone gotta cold world yeah natural live life cutthroat gotta cold yeah natural lyric commercial

9. [idx 9] eli young band never land country word yeah wreck roll lips high good get bottle right right wanna feet cold hard floor kiss steal wanna steal right palm hand fall fall like land head heartbeat hit feel like gravity exist wanna stop know fall fall like land hang like dance stretch song long float like make memories night night wanna feet cold hard floor kiss steal wanna steal right palm hand fall fall like land head heartbeat hit feel like gravity exist wanna stop know fall fall like land fall like land stay get fly wanna feet cold hard floor kiss steal wanna steal right palm hand fall fall like land head heartbeat hit feel like gravity exist wanna stop know fall fall like land fall like land fall like land fall fall fall like land fall fall fall like land fall fall fall like land
10. [idx 104] larkin poe john the revelator blues tell write revelator tell write revelator tell write revelator write book seven seal tell write revelator tell write revelator tell write revelator write book seven seal walk cool call refuse answer cause naked ashamed tell write revelator tell write revelator tell write revelator write book seven seal apostles away say watch hour till yonder pray tell write revelator tell write revelator tell write revelator write book seven seal tell write revelator tell write revelator tell write revelator write book seven seal yeah tell write revelator tell write revelator tell write revelator write book seven seal write book seven seal write book seven seal

Week 2 Sample:

1. [idx 392] jon bellion stupid deep rock hop fight feel free things yeah attempt earn yeah cause hole inside heart stupid deep stupid deep try path try clear life plan yeah money hand need stupid cheap stupid cheap hop fight feel free things attempt earn yeah cause hole inside heart stupid deep stupid deep hop fight feel free things things attempt earn hole inside heart stupid deep stupid deep deep
2. [idx 256] the kills black tar blues invention handsome fairytales fair game world look sharpen blade london blood thirsty paris vein open vein pulse mean bruise wing sparrow gonna catch hair night arrow prick quick pick fight world trip bid blood catatonia york black run run bruise wing sparrow cook light tuck prim prim divine cool thing crazy look white screen field daisies pull stay stand stay stand
3. [idx 347] haken the good doctor jazz call cell block nurse inmates scream bed silent unusual delude psychotic catatonic good doctor look smile time game electricity prescription need bring society electricity cure need bring empire knees inside mind spark vague memories cave break life inside mind spark vague memories cave break life electricity prescription need bring society electricity cure need bring empire knees sure arm bind pills secrets drown render mind unsound inside mind spark vague memories cave break life inside mind inside mind spark spark vague memories cave break life electricity prescription need bring society electricity cure need bring empire knees
4. [idx 310] allen toussaint american tune blues time mistake time confuse fall forsake certainly misuse alright alright weary bone expect bright bear divine away home away home know soul better friend feel ease know dream shatter drive knees alright alright live long think road travel wonder go wrong help wonder go wrong dream die dream soul unexpectedly look smile assuredly dream fly high eye clearly statue liberty sail away dream fly come ship mayflower come ship sail moon come hat uncertain hours sing american tune alright alright alright forever bless tomorrow gonna work try rest try rest alright alright alright forever bless tomorrows gonna work try rest try rest
5. [idx 362] tenth avenue north i have this hope rock walk great unknown question come question purpose pain tear vain want live fear want trust near trust see triumph tragedy depth soul flood feel like night catch tear leave depth soul flood depth soul flood happen afraid cause closer breath calm hear believe face depth soul flood depth soul flood flood flood
6. [idx 431] surfaces heaven falls / fall on me pop wake early mornin feel light open window shadow banana pancakes problems jam johnson swear hear call outside h

eaven fall heaven fall heaven faaaalls heaven fall heaven fall heaven faaall noth
in like color couldn paint better good time horizon couple bird come fee swear he
ar call outside heaven fall heaven fall heaven faaaalls heaven fall heaven fall h
eaven faaall heaven fall heaven fall heaven faaaalls heaven fall heaven fall heav
en faaall fall fall fall fall fall fall fall fall
 7. [idx 447] blues saraceno devils got you beat blues evil mind trouble feet liv
e devil beat evil mind trouble feet live devil devil beat walk course shoot hand
take flix want tall want evil mind trouble feet live devil beat evil mind trouble
feet live devil devil beat cross line taste devil pill shoot shoot pill wrong tal
l wrong evil mind trouble feet live devil beat evil mind trouble feet live devil
devil beat evil mind trouble feet live devil beat evil mind trouble feet live evi
l mind trouble feet live devil beat evil mind trouble feet live devil beat devil
devil beat
 8. [idx 434] the wood brothers this is it blues things think miss miss shouldn m
iss dream free miss change world change world need things think know things know
know change world change world need wanna know eitheror yeah things think miss th
ings think miss change world change world change world change world need need nee
d
 9. [idx 259] mild high club tesselation rock daddy know hand pool head fool push
weight hollywood gestalt hang edge fault learn trick uncle education sloganeer na
scent vagabond motion picture babylon twist gestalt hang edge fault learn trick u
ncle revelation think paradigm rare design block tesselation
10. [idx 354] parov stelar snake charmer jazz hear music away party night walk ci
ty streets bump blow whistle everyday hear time change look eye think hypnotize f
eel dance time play put trance black mamba lady slowly come hide basket music sto
p mister snake charmer play flute crawl play tune snake charmer play flute crawl
play tune snake charmer play flute crawl play tune snake charmer snake tattoo tel
l want want think hypnotize feel dance time play put trance black mamba lady slow
ly come hide basket music stop dance kill venom think escape tongue swallow piece
completely numb look charmer play song mister snake charmer play flute crawl play
tune snake charmer play flute crawl play tune snake charmer play flute crawl play
tune snake charmer snake tattoo tell want want want mister snake charmer play flu
te crawl play tune snake charmer snake tattoo tell want want

Week 3 Sample:
 1. [idx 642] black mountain horns arising blues tiny island lock ocean draw dark
ness light silence drown silence drop bomb thousand horse form fly desert bear se
quence fair weather warfare forever voice bear ask horn rise forever swarm fly e
mbers corridors hear faint choir violent shore break violent score horn arise hor
n rise lake horn arise horn rise lake forever swarm fly embers corridors hear fai
nt choir
 2. [idx 506] runaway june buy my own drinks pop yeah try unfall apart think neon
light real good start call couple friends stay guess go heart break mean gotta st
ay home yeah drink night light drop change jukebox dance stop thinkin bout drinki
n bout need yeah drink tonight tonight tonight yeah drink tonight tonight tonight
dive type walk see drink hand yeah say sweet glass gonna pass time yeah fine drin
k night light drop change jukebox dance stop thinkin bout drinkin bout need yeah
drink tonight tonight tonight yeah drink tonight tonight tonight walk self door s
elf medicate headache yeah boyfriend drink night light drop change jukebox dance
time stop stop thinkin bout drinkin bout need yeah drink tonight tonight tonight
yeah drink tonight tonight tonight drop change jukebox tonight tonight tonight th
inkin bout drinkin bout dance tonight tonight tonight
 3. [idx 597] goodbye june get happy blues begin yellow skin black night drink ti
ll light cocaine closest distance line mind try erase past ways kill pain maybe p
ills alcohol weed shake memories try therapy gonna bring check doubt maybe pills
alcohol weed shake memories think need sleep live dream high like anxiety change
baby believe shake shake shake memories try forgive lose pain okay try forgive tr
y bottle shelf know help till
 4. [idx 560] avril lavigne head above water pop gotta calm want want windows doo
rs safe warm yeah life fight reach shore voice drive force pull overboard head wa

```
ter drown get harder meet altar fall knees drown drown drown drown pull cause und
erneath undertow come hold close need need head water drown get harder meet altar
fall knees drown drown drown drown drown drown drown head water water drown weath
er swim ocean like forever breathe head water lose breath come rescue wait young
fall asleep head water drown get harder meet altar fall knees drown drown drown d
rown head water water drown
 5. [idx 612] brandon ratcliff rules of breaking up country see cause gotta space
friends work tell think place time drink hop come write rule break kiss lips touc
h skin hold world fingertips clue heaven lose kind smile felt know go write rule
break break break guess suppose right meet somebody go confident intelligent cool
hell know say probably best gotta chest write rule break kiss lips touch skin hol
d world fingertips clue heaven lose kind smile felt know go write rule break brea
k break need time apart stop hop hop rule like hearts break write rule break kiss
lips touch skin hold world fingertips clue heaven lose kind smile felt know go go
write rule break break break break break break break break break break write rule
break
 6. [idx 681] sam gendel boa jazz rebel rebel yell cause people dwell hell lock c
ell structure cell story tell long seein stake action reaction mind somewhat comp
lacent state check stick freedom life lord wish peaceful sequel freedom fundament
al johannesburg south central cause tell kick township rebellion yeah sucka yeah
think hardlines mind thoughts battle fight lessons teach display fitness flip lik
e gymnast raise fist resist asleep stand midst gotta gotta keepin warm cause offe
r think nothin coffin gotta wreck neck swing rope cape freedom fundamental johann
esburg south central cause tell kick township rebellion stand silent platform fig
ht  stand silent platform fight  stand silent platform fight  stand silent platfo
rm fight  stand silent platform fight  stand silent platform fight  stand silent
platform fight  stand silent platform fight  gonna shackle mind bend cross ignora
nce reign life lose shackle mind leave cross ignorance reign life lose shackle mi
nd bend cross ignorance reign life lose shackle mind leave cross ignorance reign
life lose lose lose shackle mind leave cross ignorance reign life lose shackle mi
nd bend cross ignorance reign life lose lose stand silent platform fight  stand s
ilent platform fight  stand silent platform fight  stand silent platform fight
 7. [idx 697] peach pit seventeen rock stand look tough stand dark beerstained mi
nd say dark hang head seventeen hold breath lyric commercial
 8. [idx 684] the dear hunter cascade jazz hear sleep bring body altar good say r
aise dead see forget form different halfhearted truths hang holy ghost sing hymn
devil confessional run night try wild things wouldn keep hate sinner hate wake st
rangest state draw line body recall place feel heat thousand breaths neck gaze th
ousand eye burn hole stick alive run night try wild things wouldn keep hate sinne
r hate search remedy hand guide shadow know look quicker afraid find know need qu
icker hate sinner look quicker wouldn know hate sinner run night try wild things
wouldn keep hate sinner hate search remedy hand guide shadow know
 9. [idx 509] shane & shane you’re worthy of it all rock sing song lift voice dar
k sing sing lift eye stand sing hop fear want years life resolve sing song lift v
oice dark lyric commercial
10. [idx 604] weezer everybody wants to rule the world rock welcome life turn sle
ep act best behavior turn mother nature everybody want rule world design remorse
help decide help freedom pleasure last forever everybody want rule world room lig
ht hold hand wall come tumble right fade everybody want rule world stand indecisi
on marry lack vision everybody want rule world need headline believe everybody wa
nt rule world freedom pleasure last forever everybody want rule world
```

In [27]:

```python
# manual selection of songs from weeks 1 - 3 by index made by user.
selected_index = [60, 112, 197, 104, 256, 431, 354, 642, 506]

# preprocess the selected songs, and sort them by topic.
selected_songs = df3['content'].iloc[selected_index].tolist()
selected_songs_preprocessed = [preprocess_text(song) for song in selected_songs]
predictions = svm_model.predict(selected_songs_preprocessed)
```

```python
# collect data structures
all_topics = ["dark", "sadness", "personal", "lifestyle", "emotion"]
topic_samples = {t: [] for t in all_topics}

for song, pred in zip(selected_songs, predictions):
    topic_samples[pred].append(song)          # assign to its topic

# mark empty topics explicitly as None
for t in all_topics:
    if not topic_samples[t]:
        topic_samples[t] = None

# create a vector for each topic
topic_profiles = {}
for t, lst in topic_samples.items():
    if lst is None:
        topic_profiles[t] = None
    else:
        vec = q2vectorizer.transform([preprocess_text(s) for s in lst]).mean(axi
        topic_profiles[t] = np.asarray(vec).ravel()

week4_raw   = df3['content'][750:1000].tolist()          # 250 songs
week4_array = np.array(week4_raw)

merged_songs  = []
merged_scores = np.empty(0)

# for each topic, compute similarity scores and rank songs
for t, profile in topic_profiles.items():
    if profile is None:
        continue

    sims = compute_similarity_dict(week4_array, profile)["jaccard"]  # (250,1)
    ranked_songs, ranked_scores = rank_songs(week4_raw, sims)
    merged_songs.extend(ranked_songs)
    merged_scores = np.concatenate([merged_scores, ranked_scores.flatten()])

# keep best rank for each song.
best = {}
for song, score in zip(merged_songs, merged_scores):
    if song not in best or score > best[song]:
        best[song] = score

#sort by top10.
top10 = sorted(best.items(), key=lambda x: x[1], reverse=True)[:10]

#print.
print("\n=== Topic assignment of the 10 sampled songs ===")
for t in all_topics:
    print(f"{t:<10s}: {len(topic_samples[t]) if topic_samples[t] else 0}")

print("\n=== Top-10 Week-4 recommendations (Jaccard) ===")
for i, (song, score) in enumerate(top10, 1):
    print(f"{i:>2}.  {score:.4f}  {song[:120]}…")   # truncate long lyrics
```

```
=== Topic assignment of the 10 sampled songs ===
dark      : 5
sadness   : 1
personal  : 0
lifestyle : 3
emotion   : 0

=== Top-10 Week-4 recommendations (Jaccard) ===
 1.  0.5195  yoke lore truly madly deeply pop dream wish fantasy need breath trul
y madly deeply strong faithful cause count begin rea…
 2.  0.5108  daniel caesar we find love pop anymore like song walk door wonder ta
ke long know girl dream anymore like song fall fall …
 3.  0.4826  hellyeah love falls rock cry sleep felt incomplete deep bleed feel w
ant feel need feel like hang thread rope noose neck …
 4.  0.4330  wolfmother baroness blues live peasantry live higher class sleep man
sion sleep grass come darkness baroness tonight toni…
 5.  0.4218  nai palm crossfire / so into you jazz crossfire fall fall fall fall
defend good define give time crossroad better crossf…
 6.  0.3937  nicole henry moon river jazz put word mouth know troublin gonna know
hear loud stop deserve tell deserve hear word come …
 7.  0.3615  keith urban the fighter country know hurt scar scar deserve cause pr
ecious heart precious heart know thank gonna little …
 8.  0.3239  the detroit cobras shout bamalama blues alabama shout bamalama louis
iana go lord soul chickens steal night night go unin…
 9.  0.3070  queens of the stone age fortress blues heart like fortress feel lock
away easier feel safe wander darkness wilderness ey…
10.  0.2997  diana krall but not for me jazz write songs lead cloud grey russian
play guarantee fool fall heighho alas lackaday plot …
```

In [28]:

```python
# manual input of user likes.
likes = [1, 4, 6]
likes_size    = len(likes)
precision10   = likes_size / 10          # Precision@10
cum_gain      = likes_size               # Cumulative gain

# Print in table format
metrics_df = pd.DataFrame({
    "Metric": ["Precision@10", "Cumulative Gain"],
    "Value":  [precision10,     cum_gain]
})

print(metrics_df.to_string(index=False))
```

```
         Metric  Value
   Precision@10    0.3
Cumulative Gain    3.0
```

In reality, talking to the user, it was clear that the recommendation system was very disconnected from reality. This reflects in the precision rate (30%) - which was low compared to “theoretical" experiments.

The user mostly evaluated the songs by these criteria: the lyrics making sense / intuitively resonating within the first ~20 words, the user did not like songs that were obviously too dark (e.g. "blood blood death ..."), and the user liked the songs that sounded like potential rave music.

One discrepancy between the recommender and the real-world use is that songs are rarely evaluated by their lyrics on the first-listen. Through a text-only model, key parts of what makes a song appealing (rhythm, tune) are missing. This makes it very difficult for a user to evaluate whether they "like" a song.

Additionally, the recommender finds the "similarity" of a song by vectorizing it's entire contents. However, when evaluating song on a purely textual-based method, users do not want to read through the entire song and instead choosing to just look at the first few words. This is not helped by how most songs are designed to work best with their musical elements, and not as standalone literature pieces to read.

Overall, the recommendations were considered "poor" by the user, but the user attributes this rating mostly to it being difficult to differentiate song features purely based on the first few words, which are often written in "poor" english grammar.

Perhaps the main criticism is that this recommender system attempts to find patterns for human behaviour which are simply not relevant in the real world.