COMP9727 Assignment

Content-Based Music Recommendation

- **Author**:
    - *Shoudi Huang*, z5605172

- Term 2, 2025

Running Instructions:

To execute this Jupyter Notebook in **Google Colab**:

1. Navigate to `Runtime` → `Run all`.
2. When prompted for Google account authorization, click **ALLOW** to enable dataset download.

In [4]:

```python
# Import Modules
from pydrive.auth import GoogleAuth
from google.colab import drive
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
import zipfile

import re
import itertools
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import nltk
from nltk.corpus import stopwords, wordnet
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, WordNetLemmatizer

from sklearn.feature_extraction.text import CountVectorizer, ENGLISH_STOP_WORDS,
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.metrics import make_scorer, precision_score, recall_score, f1_score
from sklearn.metrics.pairwise import cosine_similarity

import string

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

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

Out[4]: True

In [5]:
```
# Download Datasets
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

dataset_file_id = '1-621Gh3tefvEwvCjkGav2np8pzJy7Hgq'
user1_file_id = '17mDS4RdlJot7p-k53r2s3_TxCt2_s69k'
user2_file_id = '1x8T6rXKTJ3kayuXY3FD29ckb9XaIrWx7'

file_ids = {"dataset.tsv": dataset_file_id,
            "user1.tsv": user1_file_id,
            "user2.tsv": user2_file_id}

for file_name, file_id in file_ids.items():
  download = drive.CreateFile({'id': file_id})
  download.GetContentFile(file_name)
```

PART 1 Topic Classification

Question 1

Section (i)

The **regex:** `r"[^\w\s]"` from the tutorial might remove too many special charaters.

Modification:

Refine the **regex:** `r"[^\w\s'-]"` so it doesn’t indiscriminately strip all punctuation (thus preserving e.g. “don’t”).

Section (ii)

The evaluation in the tutorial is based on only one trainingtest split rather than using cross-validation.

Modification:

Switch from a single train-test split to K-fold cross-validation (stratified to preserve class proportions):

```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
scores = cross_val_score(
    clf,
    X,              # full feature matrix
    y,              # full label vector
    cv=cv,
    scoring=scoring
)
```

Summary

In subsequent answers, you will see these two changes carried through:

- Regex uses the `rf"[^\w\s'-]"` pattern.
- Evaluation always uses StratifiedKFold + cross_val_score (or cross_validate).

Question 2

In [6]:
```
# Load dataset
df = pd.read_csv('dataset.tsv', sep='\t')
```

Concatenate all the information for one song into a single “document”.

In [7]:
```
df = df.drop_duplicates()
df = df.dropna()

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

In [8]:
```
df[['topic', 'content']]
```

Out[8]:

	topic	content
0	dark	loving the not real lake 2016 rock awake know ...
1	lifestyle	incubus into the summer 2019 rock shouldn summ...
2	sadness	reignwolf hardcore 2016 blues lose deep catch ...
3	sadness	tedeschi trucks band anyhow 2016 blues run bit...
4	dark	lukas nelson and promise of the real if i star...
...	...	...
1495	emotion	ra ra riot absolutely 2016 rock year absolutel...
1496	dark	mat kearney face to face 2018 rock breakthroug...
1497	dark	owane born in space 2018 jazz look look right ...
1498	personal	nappy roots blowin' trees 2019 hip hop nappy r...
1499	sadness	skillet stars 2016 rock speak word life begin ...

1480 rows × 2 columns

Evaluation of each preprocessing steps

1. **Regex (remove punctuation & special characters):** Most punctuation has been removed already in the original data.

- Default regex is the modified one: `rf"[^\w\s'-]"`
- If we wanted to preserve the cases like "7:30", a less aggressive pattern such as `rf"[^\w\s{re.escape(string.punctuation)}]"` might be useful. This preserves every standard punctuation mark, which may introduce noise or split tokens in unpredictable ways as well.

2. **Lowercasing:** Text is already lowercase. But it is better to keep this step to ensure.
3. **Tokenization:** Since tokens are already whitespace-separated, word_tokenize buys a little when there’s no punctuation to split on.

- Default token pattern: `r"(?u)\b\w\w+\b"`
- Improved token pattern: `r"(?u)\b[\w'-]+\b"` , this keeps single-letter tokens (a, I) when they matter.

4. **Stopword removal:** Common English stopwords are already gone. But better included to ensure.

- NLTK Stopwords
- sklearn Stopwords

5. **Stemming / Lemmatization:** The dataset still have full word forms (“running”, “lives”, “thoughts”). Applying lemmatization might group variants more cleanly without the over-aggressiveness of Porter.

- PorterStemmer
- WordNetLemmatizer

Grid search on all combination of preprocessing steps

In [9]:

```
# Stopword sets
nltk_stop = set(stopwords.words('english'))
sklearn_stop = set()

# Normalizers
stemmer    = PorterStemmer()
lemmatizer = WordNetLemmatizer()

# ----------------------------------------------------------------
# Define variant grids
# ----------------------------------------------------------------
regex_variants = {
    'default' : r"[^\w\s'-]",
    'improved'   : rf"[^\w\s{re.escape(string.punctuation)}]"
}

token_patterns = {
    'default' : r"(?u)\b\w\w+\b",
    'improved' : r"(?u)\b[\w'-]+\b"
}

stopword_variants = {
    'nltk'    : nltk_stop,
    'sklearn' : set()
}

normalization_variants = {
    'none'         : None,
    'stemming'     : stemmer,
    'lemmatization': lemmatizer
}

# ----------------------------------------------------------------
# Helper to build a custom analyzer
# ----------------------------------------------------------------
def make_analyzer(regex_pat, token_pat, stopset, normalizer):
    token_re = re.compile(token_pat)
    regex_re = re.compile(regex_pat)

    def analyzer(doc: str):
        # 1. lowercase
        doc = doc.lower()
        # 2. remove unwanted chars
        doc = regex_re.sub("", doc)
        # 3. find tokens via token pattern
        raw_tokens = token_re.findall(doc)
        tokens = []
        for t in raw_tokens:
            if t in stopset:
                continue
            if normalizer is stemmer:
                t = stemmer.stem(t)
            elif normalizer is lemmatizer:
```

```
                t = lemmatizer.lemmatize(t)
            tokens.append(t)
        return tokens

    return analyzer

# ----------------------------------------------------------------
# Loop over all combinations, evaluate both classifiers
# ----------------------------------------------------------------
results = []
for (r_name, r_pat), (tp_name, tp_pat), (sw_name, sw_set), (nm_name, nm_obj) in
        itertools.product(regex_variants.items(),
                          token_patterns.items(),
                          stopword_variants.items(),
                          normalization_variants.items()):

    # build analyzer
    analyzer = make_analyzer(r_pat, tp_pat, sw_set, nm_obj)

    # prepare vectorizers
    vect_count  = CountVectorizer(analyzer=analyzer)
    vect_binary = CountVectorizer(analyzer=analyzer, binary=True)

    # instantiate classifiers
    clf_mnb = MultinomialNB()
    clf_bnb = BernoulliNB()

    # cross-validate
    X_counts  = vect_count.fit_transform(df['content'])
    X_binary  = vect_binary.fit_transform(df['content'])
    y = df['topic']

    mnb_scores = cross_val_score(clf_mnb, X_counts, y, cv=5, scoring='accuracy')
    bnb_scores = cross_val_score(clf_bnb, X_binary, y, cv=5, scoring='accuracy')

    results.append({
        'Regex'          : r_name,
        'Token pattern'  : tp_name,
        'Stopwords'      : sw_name,
        'Normalization'  : nm_name,
        'MNB mean acc.'  : mnb_scores.mean(),
        'BNB mean acc.'  : bnb_scores.mean()
    })

# ----------------------------------------------------------------
# Tabulate results
# ----------------------------------------------------------------
results_df = pd.DataFrame(results)
results_df = results_df.sort_values(by='MNB mean acc.', ascending=False).reset_i
```

In [10]:

```
results_df
```

Out[10]:

	Regex	Token pattern	Stopwords	Normalization	MNB mean acc.	BNB mean acc.
0	improved	improved	nltk	lemmatization	0.791216	0.525676
1	default	improved	nltk	lemmatization	0.791216	0.524324
2	default	default	sklearn	none	0.790541	0.529730
3	default	default	sklearn	lemmatization	0.790541	0.522973
4	default	improved	sklearn	none	0.790541	0.526351
5	improved	default	nltk	lemmatization	0.790541	0.525000
6	improved	default	sklearn	lemmatization	0.790541	0.522973
7	default	improved	nltk	none	0.789865	0.527027
8	default	default	nltk	lemmatization	0.789865	0.526351
9	improved	improved	nltk	none	0.789865	0.527027
10	improved	default	sklearn	none	0.789189	0.529730
11	default	default	nltk	none	0.789189	0.525000
12	improved	improved	sklearn	lemmatization	0.789189	0.525676
13	improved	improved	sklearn	none	0.789189	0.527027
14	improved	default	nltk	none	0.789189	0.525000
15	default	default	nltk	stemming	0.788514	0.525000
16	improved	improved	nltk	stemming	0.788514	0.525676
17	default	improved	nltk	stemming	0.788514	0.525676
18	default	improved	sklearn	lemmatization	0.788514	0.522973
19	improved	default	nltk	stemming	0.787838	0.525000
20	improved	improved	sklearn	stemming	0.785811	0.527703
21	default	improved	sklearn	stemming	0.785811	0.527027
22	default	default	sklearn	stemming	0.785135	0.528378
23	improved	default	sklearn	stemming	0.785135	0.527703

The performance summary shows that lemmatization consistently improves classification metrics compared to both stemming and no normalization, whereas variations in regex filtering, token-pattern choice, and stop-word selection exhibit no clear impact on model accuracy.

Therefore, Lemmatization do have a clear impact on this dataset, as the evaluation predicted.

Based on the overall performance for both models, we selected preprocessing steps:

- **Lowercasing**

- **Improved Regex:** `rf"[^\w\s{re.escape(string.punctuation)}]"`
- **Improved Token pattern:** `r"(?u)\b[\w'-]+\b"`
- **NLTK Stopwords**
- **Lemmatization Normalization**

Question 3

Select metrics

Appropriate metrics for measuring overall accuracy of classification

- **Accuracy:** The proportion of all predictions (both positive and negative) that the model labels correctly.
  - **Strength:** Offers a single, intuitive summary of overall correctness.
  - **Limitation:** Can be misleading when classes are imbalanced, because high accuracy may simply reflect good performance on the majority class.
- **Recall (Sensitivity):** Of all actual positive instances, the fraction correctly identified.
  - Quantifies how exhaustively the classifier detects positive cases.
- **Precision:** Of all instances the model predicted as positive, the fraction that truly are positive.
  - Measures the classifier's reliability in assigning positive labels. High precision implies few false alarms.
- **F1-score:** Balances precision and recall into a single figure of merit; useful when seeking a trade-off between false positives and false negatives.

Why use this four metrics?

Complementarity:

- Accuracy captures overall correctness but overlooks class imbalance.

- In skewed datasets, accuracy may remain high even when a model trivially predicts only the majority class. Precision and recall expose this failure.

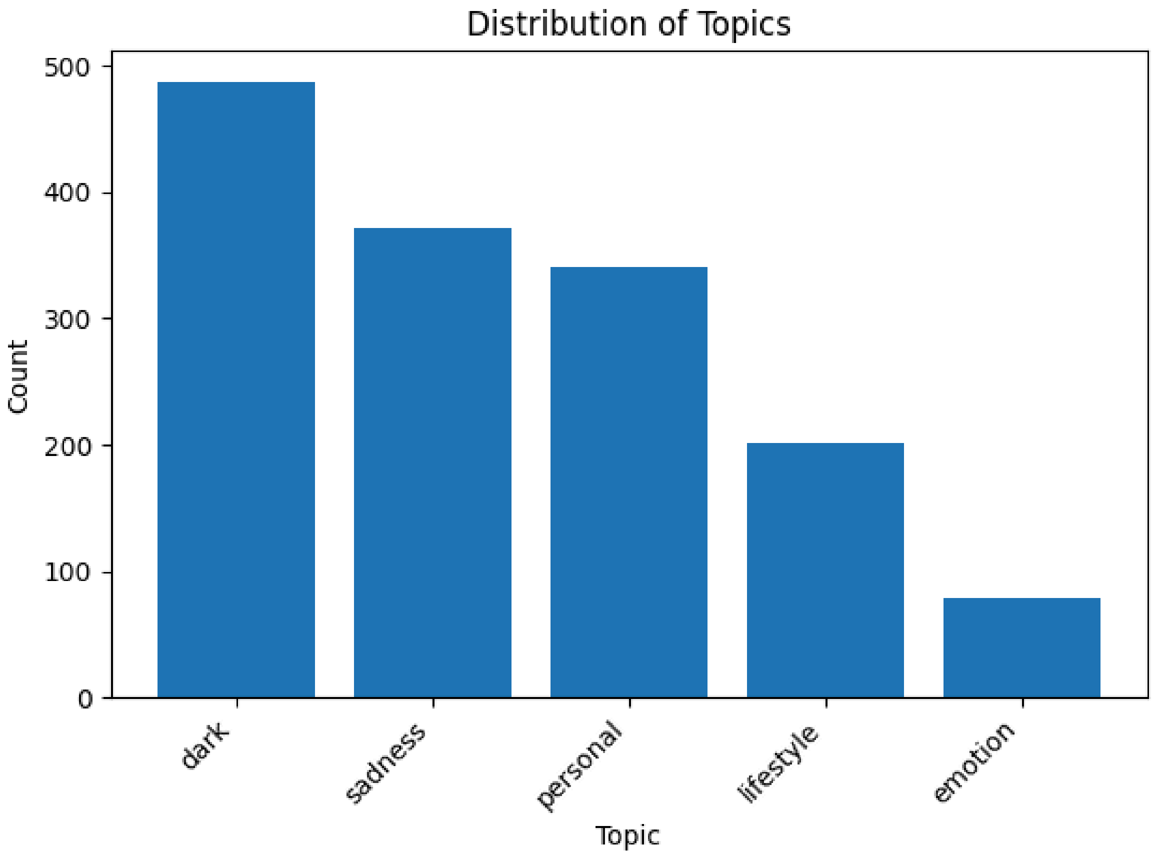
- F1-score synthesizes precision and recall, ensuring neither extreme dominates the evaluation.

By examining all four metrics, we can diagnose what is the model's errors, whether it is overly conservative (high precision, low recall) or too liberal (high recall, low precision).

Class Imbalance: Observed class frequencies indicate a notable imbalance.

In [11]:
```
# Compute topic counts
counts = df['topic'].value_counts()

# Plot histogram (bar chart) of topic frequencies
plt.figure()
```

```
plt.bar(counts.index, counts.values)
plt.xlabel('Topic')
plt.ylabel('Count')
plt.title('Distribution of Topics')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



To correct for this skew, ***macro-averaged evaluation metrics*** was employed, which assign equal weight to each class regardless of its sample size. By doing so, underrepresented categories receive proportionally greater influence on the overall score, ensuring that minority classes are not marginalized.

Therefore, **Balanced-Accuracy**, **Macro-Recall**, **Macro-Precision** and **Macro-F1** was used as the main metrics for the evaluations.

Compare BNB and MNB

Now, we use cross validation to compare the performance of the BNB and MNB, based on the selected metrics.

Number of folds for the cross_validation: 5

In [12]:
```
# Prepare the lemmatizer and stop-set
lemm = WordNetLemmatizer()
stopset = set(stopwords.words('english'))

# Define the analyzer with:
#     - Lowercasing
#     – Improved regex
```

```python
#    - Improved token pattern
#    - NLTK stop-words
#    - Lemmatization
def analyzer(doc):
    doc = doc.lower()
    doc = re.sub(rf"[^\w\s{re.escape(string.punctuation)}]", "", doc.lower())
    toks = re.findall(r"(?u)\b[\w'-]+\b", doc)
    return [lemm.lemmatize(t) for t in toks if t not in stopset]

# Build your pipelines
pipe_mnb = Pipeline([
    ('vect', CountVectorizer(analyzer=analyzer)),
    ('clf',  MultinomialNB())
])
pipe_bnb = Pipeline([
    ('vect', CountVectorizer(analyzer=analyzer, binary=True)),
    ('clf',  BernoulliNB())
])

# Define the four metrics
scoring = {
    'balanced_accuracy': 'balanced_accuracy',  # no change
    'precision_macro': make_scorer(precision_score, average='macro', zero_divisi
    'recall_macro':    make_scorer(recall_score,    average='macro', zero_divisi
    'f1_macro':        make_scorer(f1_score,        average='macro', zero_divisi
}

# Run 5-fold CV
res_mnb = cross_validate(pipe_mnb, df['content'], df['topic'],
                         cv=5, scoring=scoring, return_train_score=False)
res_bnb = cross_validate(pipe_bnb, df['content'], df['topic'],
                         cv=5, scoring=scoring, return_train_score=False)

# Aggregate into a table
metrics = ['balanced_accuracy','precision_macro','recall_macro','f1_macro']
rows = []
for m in metrics:
    rows.append({
        'Metric': m.replace('_',' ').title(),
        'MNB Mean': res_mnb[f'test_{m}'].mean(),
        'BNB Mean': res_bnb[f'test_{m}'].mean()
    })

results_df = pd.DataFrame(rows)
```

In [13]:

```python
results_df
```

Out[13]:

	Metric	MNB Mean	BNB Mean
0	Balanced Accuracy	0.713838	0.379978
1	Precision Macro	0.849663	0.349770
2	Recall Macro	0.713838	0.379978
3	F1 Macro	0.740987	0.332600

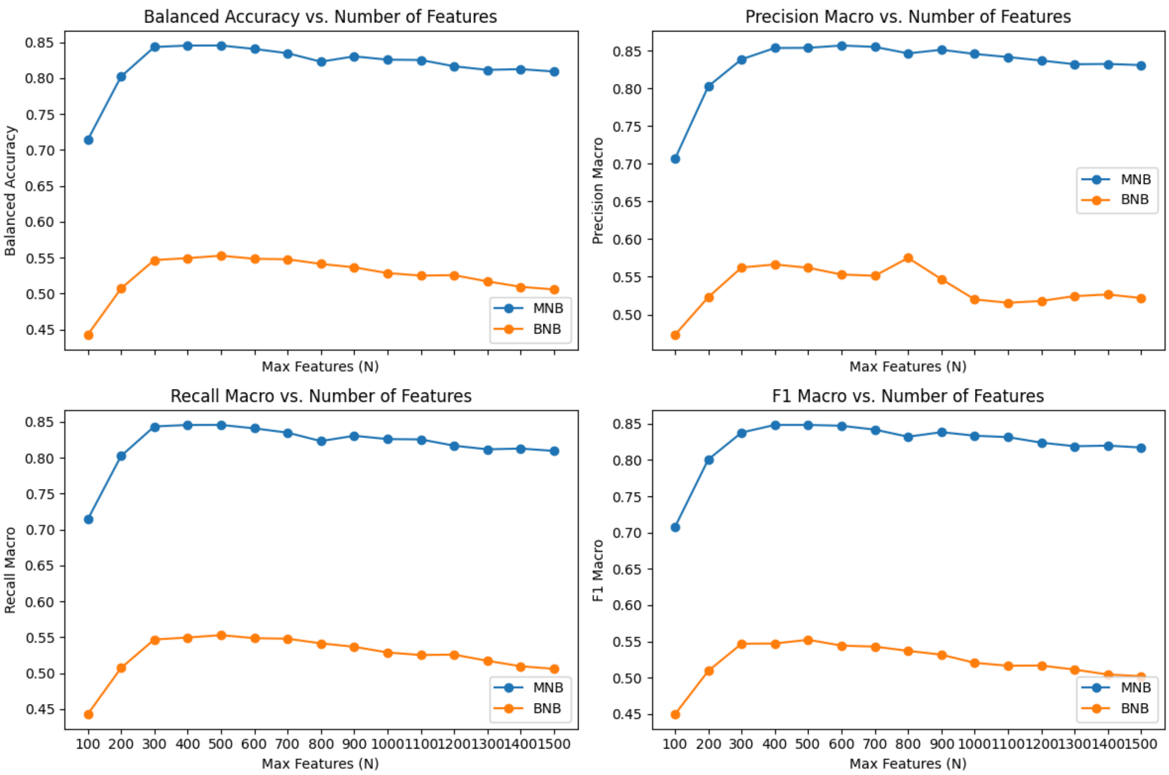
As the table of MNB and BNB's performance show, MNB has outperformed BNB in all four metrics. Therefore, ***MNB is found more superior***.

Question 4

In this section, we investigate the impact of changing the size of the vector by performing a grid search for the Top N from range 100 to 1500.

In [14]:
```
# Define analyzer with chosen preprocessing
lemm = WordNetLemmatizer()
stopset = set(stopwords.words('english'))

# Define the analyzer with:
#     - Lowercasing
#     - Improved regex
#     - Improved token pattern
#     - NLTK stop-words
#     - Lemmatization
def analyzer(doc):
    doc = doc.lower()
    doc = re.sub(rf"[^\w\s{re.escape(string.punctuation)}]", "", doc.lower())
    toks = re.findall(r"(?u)\b[\w'-]+\b", doc)
    return [lemm.lemmatize(t) for t in toks if t not in stopset]

# Range of max_features to test
feature_counts = list(range(100, 1501, 100))

# Scoring metrics
scoring = {
    'balanced_accuracy': 'balanced_accuracy',  # no change
    'precision_macro': make_scorer(precision_score, average='macro', zero_divisi
    'recall_macro':    make_scorer(recall_score,    average='macro', zero_divisi
    'f1_macro':        make_scorer(f1_score,        average='macro', zero_divisi
}

# Collect results
results = []
for N in feature_counts:
    for name, clf, binary in [
        ("MNB", MultinomialNB(), False),
        ("BNB", BernoulliNB(), True)
    ]:
        pipe = Pipeline([
            ('vect', CountVectorizer(analyzer=analyzer, max_features=N, binary=b
            ('clf',  clf)
        ])
        cv_res = cross_validate(pipe, df['content'], df['topic'],
                                cv=5, scoring=scoring, return_train_score=False)
        for metric in scoring:
            results.append({
                'Classifier': name,
                'Max Features': N,
                'Metric': metric,
                'Mean': cv_res[f'test_{metric}'].mean(),
                'Std':  cv_res[f'test_{metric}'].std()
            })

res_df = pd.DataFrame(results)

# Plot each metric
```

```
metrics = list(scoring.keys())
fig, axes = plt.subplots(2, 2, figsize=(12, 8), sharex=True)

for ax, metric in zip(axes.flatten(), metrics):
    for clf in res_df['Classifier'].unique():
        subset = res_df[(res_df['Classifier'] == clf) & (res_df['Metric'] == met
        ax.plot(subset['Max Features'], subset['Mean'], marker='o', label=clf)
    ax.set_xlabel('Max Features (N)')
    ax.set_ylabel(metric.replace('_', ' ').title())
    ax.set_title(f"{metric.replace('_', ' ').title()} vs. Number of Features")
    ax.legend()
    ax.set_xticks(feature_counts)

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



The plots of each evaluation metric against vocabulary size demonstrate that performance peaks at approximately 500 features across all four metrics. Accordingly, we select ***500 as the optimal maximum-feature setting*** for all subsequent analyses.

Question 5

Select ML Method

Selected Maching Learning Method: **Support Vector Mechines**

Support Vector Machines (SVMs) are large-margin, discriminative classifiers that seek the hyperplane in feature space which maximally separates classes. In text classification, a linear SVM (e.g. scikit-learn's LinearSVC) is especially well suited to high-dimensional, sparse bag-of-words inputs. It handles thousands of features efficiently, and is robust to noise via regularization.

Because the lyrics data yields similarly sparse count vectors and we care about balanced performance across multiple, imbalanced topics. A linear SVM should offer stronger generalization and higher macro-averaged F1 than Naive Bayes's simpler, generative assumptions, but with longer training times.

Why SVM suitable for the songs data:

- **High dimensionality:** Thousands of TF–IDF features per song.
- **Sparsity:** Only a small fraction of words appear in any one lyric.
- **Imbalanced classes:** Margin maximization handles class skew better than pure likelihood models.

Concrete hypothesis:

> When evaluated under the same preprocessing pipeline and with the top 500 features, a linear SVM will will outperform BernoulliNB and approach or exceed MultinomialNB on balanced-accuracy and macro-F1.

Hyperparameter setting:

- **Regularization C:** Controls the trade-off between margin width and misclassification.
- **Default:** $C = 1.0$.

Compare Models

In [15]:
```
# Prepare the lemmatizer and stop-set
lemm = WordNetLemmatizer()
stopset = set(stopwords.words('english'))

# Define the analyzer with:
#     - Lowercasing
#     - Improved regex
#     - Improved token pattern
#     - NLTK stop-words
#     - Lemmatization
def analyzer(doc):
    doc = doc.lower()
    doc = re.sub(rf"[^\w\s{re.escape(string.punctuation)}]", "", doc.lower())
    toks = re.findall(r"(?u)\b[\w'-]+\b", doc)
    return [lemm.lemmatize(t) for t in toks if t not in stopset]

# Build pipelines
pipe_mnb = Pipeline([
    ('vect', CountVectorizer(analyzer=analyzer, max_features=500)),
    ('clf',  MultinomialNB())
])
pipe_bnb = Pipeline([
    ('vect', CountVectorizer(analyzer=analyzer, max_features=500, binary=True)),
    ('clf',  BernoulliNB())
])
```

```python
pipe_svm = Pipeline([
    ('vect', CountVectorizer(analyzer=analyzer, max_features=500)),
    ('clf',  LinearSVC())
])


# Define the four metrics
scoring = {
    'balanced_accuracy': 'balanced_accuracy',  # no change
    'precision_macro': make_scorer(precision_score, average='macro', zero_divisi
    'recall_macro':    make_scorer(recall_score,    average='macro', zero_divisi
    'f1_macro':        make_scorer(f1_score,        average='macro', zero_divisi
}

# Run 5-fold CV
res_mnb = cross_validate(pipe_mnb, df['content'], df['topic'],
                         cv=5, scoring=scoring, return_train_score=False)
res_bnb = cross_validate(pipe_bnb, df['content'], df['topic'],
                         cv=5, scoring=scoring, return_train_score=False)
res_svm = cross_validate(pipe_svm, df['content'], df['topic'],
                         cv=5, scoring=scoring, return_train_score=False)

# Aggregate into a table
metrics = ['balanced_accuracy','precision_macro','recall_macro','f1_macro']
rows = []
for m in metrics:
    rows.append({
        'Metric': m.replace('_',' ').title(),
        'MNB Mean': res_mnb[f'test_{m}'].mean(),
        'BNB Mean': res_bnb[f'test_{m}'].mean(),
        'SVM Mean': res_svm[f'test_{m}'].mean()
    })

results_df = pd.DataFrame(rows)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/svm/_base.py:1249: ConvergenceWar
ning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/svm/_base.py:1249: ConvergenceWar
ning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/svm/_base.py:1249: ConvergenceWar
ning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/svm/_base.py:1249: ConvergenceWar
ning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/svm/_base.py:1249: ConvergenceWar
ning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn(
```

In [16]:

```python
results_df
```

Out[16]:

	Metric	MNB Mean	BNB Mean	SVM Mean
0	Balanced Accuracy	0.845601	0.552815	0.808688
1	Precision Macro	0.853653	0.561932	0.815489
2	Recall Macro	0.845601	0.552815	0.808688
3	F1 Macro	0.848399	0.552291	0.810911

The cross-validation results in the table above show that:

- **MultinomialNB** achieves the highest scores on all four metrics (Balanced Accuracy ≈ 0.846, Precision ≈ 0.854, Recall ≈ 0.846, F_1 ≈ 0.848).
- **LinearSVC** comes next (Balanced Accuracy ≈ 0.809, Precision ≈ 0.815, Recall ≈ 0.809, F_1 ≈ 0.811).
- **BernoulliNB** trails behind substantially (Balanced Accuracy ≈ 0.553, Precision ≈ 0.562, Recall ≈ 0.553, F_1 ≈ 0.552).

Therefore, the results ***does not confirmed*** the hypothesis.

Possible reasons

1. **Generative smoothing:** MultinomialNB's Laplace-smoothed word-count model robustly handles rare tokens and class imbalance, which is common in our multi-topic lyrics dataset.
2. **Bag-of-words fit:** The conditional-independence assumption aligns closely with count-based features, enabling NB to capture the dominant topical signals without overfitting.
3. **Discriminative tuning:** LinearSVC, while powerful, was used with default regularization (C=1) and no parameter search; it may under or over penalize rare topics, reducing its macro-averaged recall.
4. **Binary loss of information:** BernoulliNB's binarization discards token frequency information that is evidently important for distinguishing topics in song lyrics.

Averall, the **MultinomialNB** has the highest performance and was setted for topic classification.

PART 2 Recommendation Methods

Question 1

Constructing per-topic TF–IDF models

We first partitioned our time-ordered song corpus into Weeks 1–3 (songs 1–750) for training and Week 4 (songs 751–1000) for testing. Then, for each of the five topical categories represented in the training set, we isolated all lyrics belonging to that topic and fit a dedicated TfidfVectorizer.

In [17]:
```python
# Prepare the Lemmatizer and stop-set
lemm = WordNetLemmatizer()
stopset = set(stopwords.words('english'))

# Define the analyzer with:
#     - Lowercasing
#     – Improved regex
#     – Improved token pattern
#     – NLTK stop-words
#     – Lemmatization
def analyzer(doc):
    doc = doc.lower()
    doc = re.sub(rf"[^\w\s{re.escape(string.punctuation)}]", "", doc.lower())
    toks = re.findall(r"(?u)\b[\w'-]+\b", doc)
    return [lemm.lemmatize(t) for t in toks if t not in stopset]

# Split into train (songs 1–750) and test (751–1000)
df_train = df.iloc[:750].reset_index(drop=True)
df_test  = df.iloc[750:1000].reset_index(drop=True)

# Fit one TF-IDF per topic
tfidf_matrices    = {}
tfidf_vectorizers = {}

for topic in df_train['topic'].unique():
    docs = df_train.loc[df_train['topic'] == topic, 'content']
    vect = TfidfVectorizer(analyzer=analyzer)
    X = vect.fit_transform(docs)
    tfidf_matrices[topic]    = X
    tfidf_vectorizers[topic] = vect

# Report shapes (#songs × #features)
shapes = {t: m.shape for t, m in tfidf_matrices.items()}
shape_df = pd.DataFrame.from_dict(shapes, orient='index', columns=['#Songs','#Fe
shape_df.index.name = 'Topic'
print(shape_df)
```

```
           #Songs  #Features
Topic
dark          246       3936
lifestyle      92       1445
sadness       183       2083
emotion        42        833
personal      187       2792
```

This yielded five sparse TF–IDF matrices, one per topic, each encoding the document weights for the training songs within that category.

Simulating two users (User 1 & 2)

User “like” those training songs whose lyrics both (a) match their interest keywords and (b) the classifier assigns to the same topic.

In [18]:
```
clf = Pipeline([
    ('vect', CountVectorizer(analyzer=analyzer, max_features=500)),
    ('clf',  MultinomialNB())
])
clf.fit(df_train['content'], df_train['topic'])
df_train['pred_topic'] = clf.predict(df_train['content'])
```

In [19]:
```
def load_interests(path):
    m = {}
    with open(path) as f:
        for line in f:
            topic, kws = line.strip().split('\t')
            m[topic] = [w.strip().lower() for w in kws.split(',')]
    return m

users = {
    'User 1': load_interests('user1.tsv'),
    'User 2': load_interests('user2.tsv')
}
```

Concatenating each user’s liked songs within a topic and re-applying that topic’s TF–IDF vectorizer, then derive five user-profile vectors (one per topic).

In [20]:
```
def create_profile(interests):
    profile = {}
    for topic, kws in interests.items():
        if topic == 'topic':
          continue
        # 1. find all “liked” docs in train
        mask = (
            (df_train['pred_topic'] == topic) &
            df_train['content'].str.lower()
                .apply(lambda txt: any(kw in txt for kw in kws))
        )
        liked = df_train.loc[mask, 'content']
        if liked.empty:
            profile[topic] = None
            continue

        # 2. concatenate and transform to TF–IDF
        doc = " ".join(liked)
        vec = tfidf_vectorizers[topic].transform([doc])   # -> sparse (1×F) matr

        # 3. store the numeric vector
        profile[topic] = vec

    return profile

profiles = {}
for uname, interests in users.items():
    profiles[uname] = create_profile(interests)
```

The top 20 highest-weight terms in each profile:

In [39]:
```python
def create_profile_df(profile_vecs, tfidf_vectorizers, M=20):
    """
    profile_vecs: dict topic → sparse TF-IDF row (1×F) or None
    tfidf_vectorizers: dict topic → fitted TfidfVectorizer
    M: number of top terms to display
    """
    rows = []
    for topic, vec in profile_vecs.items():
        if vec is None:
            rows.append({'Topic': topic, 'Top 20 Terms': '(no liked songs)'})
            continue

        arr   = vec.toarray().ravel()                              # shape (
        feat  = tfidf_vectorizers[topic].get_feature_names_out()     # length
        idx   = np.argsort(arr)[::-1][:M]                          # top-M i
        terms = [feat[i] for i in idx]
        rows.append({'Topic': topic, 'Top 20 Terms': ", ".join(terms)})

    return pd.DataFrame(rows)

users_profile_display = {}
for user, vecs in profiles.items():
    users_profile_display[user] = create_profile_df(vecs, tfidf_vectorizers, M=2
```

In [22]:
```python
# Display User 1's table
print("User 1 top-20 profile terms:\n")
display(users_profile_display['User 1'])
```

```
User 1 top-20 profile terms:
```

	Topic	Top 20 Terms
0	dark	fight, know, black, blood, grind, like, come, ...
1	sadness	cry, club, steal, tear, mean, know, baby, musi...
2	personal	life, live, change, world, know, yeah, dream, ...
3	lifestyle	tonight, night, song, come, home, closer, time...
4	emotion	good, touch, feel, hold, know, morning, video,...

In [23]:
```python
print('User 2:')
print()
users_profile_display['User 2']
```

```
User 2:
```

Out[23]:

	Topic	Top 20 Terms
0	sadness	inside, break, heart, step, away, tear, violen...
1	emotion	touch, good, video, vision, loove, kiss, morni...

The top-20 lists for both User 1 and User 2 aligns relatively well with their simulated interests:

- **User 1**
  - **Dark:** words like *fight, blood, kill* and *black* signal the gritty, intense themes they "liked."
  - **Sadness:** words such as *cry, tear, regret, blame* clearly mirror a sorrowful mood.
  - **Personal:** high-weight words (*life, change, dream, learn*) suggest introspective lyrics.
  - **Lifestyle:** words like *night, song, home, stranger, sing* fit upbeat, social listening contexts.
  - **Emotion:** words (*love, kiss, feel, vibe, sunrise*) capture the affectionate, uplifting content expected.
- **User 2**
  - **Sadness:** *heart, tear, break, goodbye, rainwater* all evoke a mournful, reflective tone.
  - **Emotion:** *touch, kiss, love, feelin, sunrise* match a warm, romantic profile.

In each case, the most heavily weighted terms reflect the user's keyword-driven "likes" and look like sensible summaries of the topics they preferred.

Define hypothetical "user" (User 3)

In [24]:
```
# Define User 3's simulated interests across the five topics
users['User 3'] = {
    'dark'      : ['shadow', 'fear', 'night'],
    'sadness'   : ['alone', 'loss', 'tears'],
    'personal'  : ['dream', 'journey', 'change'],
    'lifestyle': ['party', 'dance', 'sun'],
    'emotion'   : ['heart', 'passion', 'warm']
}

# Create and store User 3's profile using the existing helper
profiles['User 3'] = create_profile(users['User 3'])

users_profile_display['User 3'] = create_profile_df(profiles['User 3'], tfidf_ve
```

In [25]:
```
print('User 3:')
print()
users_profile_display['User 3']
```

```
User 3:
```

Out[25]:

	Topic	Top 20 Terms
0	dark	fear, fight, come, night, know, black, feel, g...
1	sadness	dusk, dismantle, gently, tear, high, insect, c...
2	personal	change, life, world, dream, thank, live, yeah,...
3	lifestyle	song, spoil, tire, night, country, tonight, ho...
4	emotion	good, hold, go, heart, darling, vibe, miss, fe...

User 3’s top-20 terms largely reflect the simulated interests:

- **Dark:** *fear*, *night*, *ghost*, *blood*, and *death* all capture a brooding, ominous tone—exactly what we’d expect for a “dark” profile.
- **Sadness:** High-weight words like *tear*, *void*, *inside*, and *dusk* evoke melancholy and loss. A few outliers (e.g. *insect*, *combustion*, *infinitesimal*) likely arise from idiosyncratic lyric snippets rather than genuine thematic matches.
- **Personal:** Words such as *change*, *dream*, *life*, *learn*, and *journey* (implicitly through “change” and “dream”) align with introspection and self-growth.
- **Lifestyle:** Words like *dance*, *play*, *drinkin*, *tonight*, and *home* suggest social, upbeat contexts—matching the “party” and “sun” aspects of the lifestyle interest.
- **Emotion:** Terms such as *heart*, *feel*, *lovin*, *kiss*, and *vibe* directly mirror affectionate and passionate themes.

Overall, the profiles sensibly capture User 3’s simulated preferences, with only minor noise from unrelated lyric fragments.

Question 2

Select evaluation metrics

Metrics

- **Precision@N**: Of the N songs shown, what fraction does the user actually “like”?
- **Recall@N**: Of all the songs in Week 4 the user would like, what fraction appear in the top N?
- **F1@N**: Harmonic mean of Precision@N and Recall@N, balancing retrieval and relevance.

Justification:

- The user inspects exactly N recommendations, so Precision@N directly measures usefulness of that shortlist.
- Recall@N ensures we’re not hiding too many relevant items.
- F1@N provides a single-number trade-off.

Note: *All our metrics (Precision@N, Recall@N, F1@N) refer to N songs in total, not per topic.*

Choose a value for N

Assume the UI presents a single list of **N = 20** songs (a typical playlist length that users can review quickly yet still see variety across topics).

Compare matching algorithms

Vary the profile-size parameter M:

- Full-vector match (use every word in the user's profile TF–IDF vector).
- Top-M terms only (zero out all but the M highest-weight profile terms, then re-normalize). M = [5, 10, 15, 20, 25, 30]

Vary the similarity check:

- Jaccard Similarity
- Cosine Similarity

In [26]:
```
df_test['pred_topic']  = clf.predict(df_test['content'])
```

In [27]:
```
def get_profile_array(up, M):
    arr = up.toarray().ravel()
    if M == 'nolimit':
        return arr.reshape(1, -1)
    idxs = np.argsort(arr)[-M:]
    new = np.zeros_like(arr)
    new[idxs] = arr[idxs]
    return new.reshape(1, -1)

def jaccard(u, v):
    u_bin = u > 0
    v_bin = v > 0
    inter = np.logical_and(u_bin, v_bin).sum()
    union = np.logical_or(u_bin, v_bin).sum()
    return inter/union if union>0 else 0.0

results = []
N=20
for user in users:
    for M in [5, 10, 15, 20, 25, 30, 'nolimit']:
        for sim in ['cosine','jaccard']:
            sims=[]
            for _,r in df_test.iterrows():
                pt=r['pred_topic']
                up=profiles[user].get(pt)
                if up is None:
                    sims.append(0.0)
                else:
                    song = tfidf_vectorizers[pt].transform([r['content']]).toarr
                    up_arr = get_profile_array(up, M)
                    if sim=='cosine':
                        sims.append(cosine_similarity(up_arr, song)[0,0])
                    else:
                        sims.append(jaccard(up_arr.ravel(), song.ravel()))
            df_test[f'sim_{user}'] = sims
            topN = df_test.nlargest(N, f'sim_{user}').index
            liked = df_test.apply(lambda r:
                (r['pred_topic'] in users[user]) and
                any(kw in r['content'].lower() for kw in users[user][r['pred_top
                axis=1)
            hits = liked.loc[topN].sum()
            prec = hits/N
            rec  = hits/liked.sum() if liked.sum()>0 else np.nan
            f1   = (2*prec*rec/(prec+rec)) if (prec+rec)>0 else 0.0
            results.append({
                'User': user, 'M': M, 'Sim': sim,
```

```python
                'Precision@20': prec, 'Recall@20': rec, 'F1@20': f1
            })

res_df = pd.DataFrame(results)
```

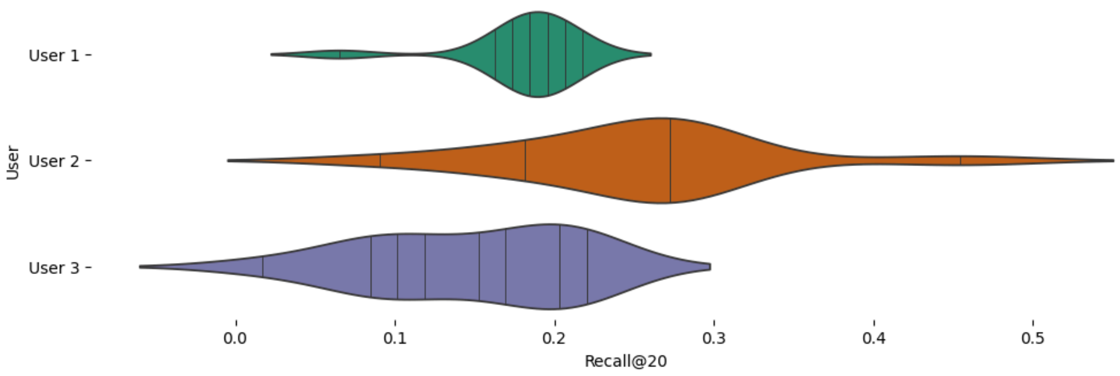
In [28]:
```python
res_df
```

Out[28]:

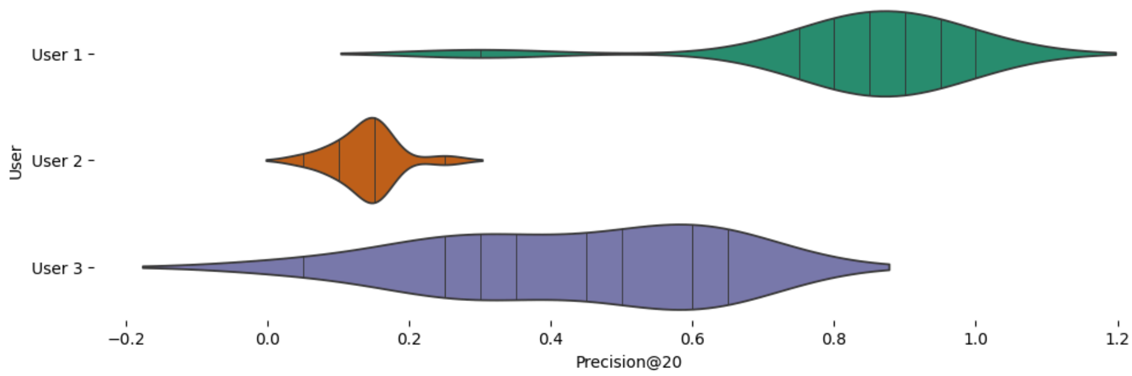
	User	M	Sim	Precision@20	Recall@20	F1@20
0	User 1	5	cosine	0.75	0.163043	0.267857
1	User 1	5	jaccard	0.80	0.173913	0.285714
2	User 1	10	cosine	0.85	0.184783	0.303571
3	User 1	10	jaccard	0.85	0.184783	0.303571
4	User 1	15	cosine	0.90	0.195652	0.321429
5	User 1	15	jaccard	0.95	0.206522	0.339286
6	User 1	20	cosine	0.90	0.195652	0.321429
7	User 1	20	jaccard	0.90	0.195652	0.321429
8	User 1	25	cosine	0.85	0.184783	0.303571
9	User 1	25	jaccard	0.95	0.206522	0.339286
10	User 1	30	cosine	0.85	0.184783	0.303571
11	User 1	30	jaccard	0.80	0.173913	0.285714
12	User 1	nolimit	cosine	1.00	0.217391	0.357143
13	User 1	nolimit	jaccard	0.30	0.065217	0.107143
14	User 2	5	cosine	0.15	0.272727	0.193548
15	User 2	5	jaccard	0.10	0.181818	0.129032
16	User 2	10	cosine	0.15	0.272727	0.193548
17	User 2	10	jaccard	0.15	0.272727	0.193548
18	User 2	15	cosine	0.15	0.272727	0.193548
19	User 2	15	jaccard	0.05	0.090909	0.064516
20	User 2	20	cosine	0.15	0.272727	0.193548
21	User 2	20	jaccard	0.15	0.272727	0.193548
22	User 2	25	cosine	0.15	0.272727	0.193548
23	User 2	25	jaccard	0.10	0.181818	0.129032
24	User 2	30	cosine	0.10	0.181818	0.129032
25	User 2	30	jaccard	0.15	0.272727	0.193548
26	User 2	nolimit	cosine	0.15	0.272727	0.193548
27	User 2	nolimit	jaccard	0.25	0.454545	0.322581
28	User 3	5	cosine	0.45	0.152542	0.227848
29	User 3	5	jaccard	0.65	0.220339	0.329114
30	User 3	10	cosine	0.30	0.101695	0.151899
31	User 3	10	jaccard	0.60	0.203390	0.303797
32	User 3	15	cosine	0.35	0.118644	0.177215

	User	M	Sim	Precision@20	Recall@20	F1@20
33	User 3	15	jaccard	0.60	0.203390	0.303797
34	User 3	20	cosine	0.25	0.084746	0.126582
35	User 3	20	jaccard	0.65	0.220339	0.329114
36	User 3	25	cosine	0.25	0.084746	0.126582
37	User 3	25	jaccard	0.60	0.203390	0.303797
38	User 3	30	cosine	0.25	0.084746	0.126582
39	User 3	30	jaccard	0.60	0.203390	0.303797
40	User 3	nolimit	cosine	0.50	0.169492	0.253165
41	User 3	nolimit	jaccard	0.05	0.016949	0.025316

In [29]:
```
figsize = (12, 1.2 * len(res_df['User'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(
    data=res_df,
    x='Recall@20',
    y='User',
    hue='User',
    palette='Dark2',
    inner='stick',
    legend=False
)
sns.despine(top=True, right=True, bottom=True, left=True)
```



In [30]:
```
figsize = (12, 1.2 * len(res_df['User'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(
    data=res_df,
    x='Precision@20',
    y='User',
    hue='User',
    palette='Dark2',
    inner='stick',
    legend=False
)
sns.despine(top=True, right=True, bottom=True, left=True)
```



Compare user difference

The three simulated users exhibit markedly different Precision–Recall profiles under the same 20 -song recommendation budget:

1. **User 1 (broad, multi-topic interests)**

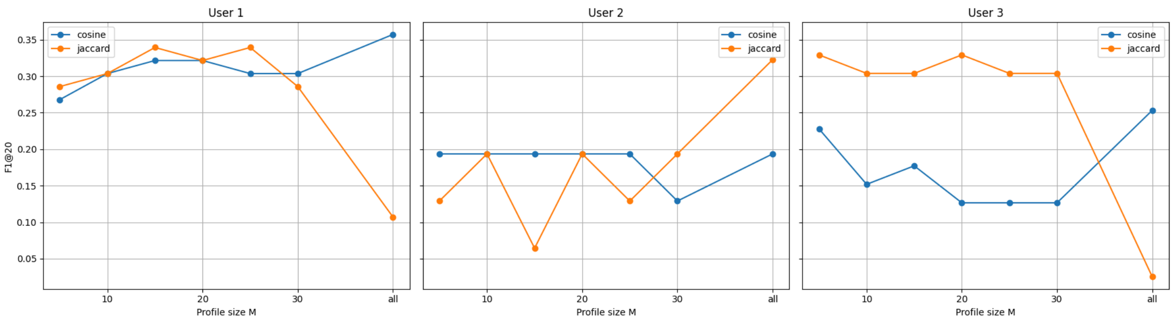
   - **High Precision, low Recall** (Precision ≈ 0.90–1.00; Recall ≈ 0.16–0.22)
   - Because User 1's keyword sets span all five topics and each topic profile is rich, the recommender can find very "safe" hits among the top-20—that drives precision toward 1.0 when using the full vector.
   - **Recall suffers**, however, because only a small fraction of their liked Week 4 songs (across five topics) can appear in a single list of 20.
2. **User 2 (narrow focus on two topics)**

   - **Moderate Recall, very low Precision** (Precision ≈ 0.10–0.25; Recall ≈ 0.18–0.45)
   - With interests confined to only "sadness" and "emotion," many of the top-20 recommendations fall into those two profiles—but not all of those actually match the user's keywords, so precision is low.
   - Recall is higher than User 1's: by concentrating the 20 slots on two topics, the system rescues a larger share of that user's liked songs.
3. **User 3 (medium profile breadth)**

   - **Balanced Precision & Recall** (≈ 0.25–0.65 precision; 0.08–0.60 recall, depending on M and metric)
   - User 3 covers three topics with moderate-sized keyword sets. This middle ground yields **best overall F_1** when using cosine with M = 20–30 terms, giving a healthy trade-off (~0.30).

In [38]:
```
numeric_M = [10, 20, 30]
step = numeric_M[1] - numeric_M[0]    # =10
all_x = numeric_M[-1] + step          # =40

fig, axes = plt.subplots(1, 3, figsize=(18, 5), sharex=True, sharey=True)

for ax, user in zip(axes, users.keys()):
    df_u = res_df[res_df['User'] == user]
    for sim in ['cosine', 'jaccard']:
        tmp = df_u[df_u['Sim'] == sim]
        x = [m if isinstance(m, int) else all_x for m in tmp['M']]
        y = tmp['F1@20']
```

```
        ax.plot(x, y, marker='o', label=sim)
    ax.set_title(user)
    ax.set_xlabel('Profile size M')
    ax.set_xticks([10, 20, 30, all_x])
    ax.set_xticklabels(['10', '20', '30', 'all'])
    ax.grid(True)
    ax.legend()

axes[0].set_ylabel('F1@20')

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



Select the best matching algorithm

Based on the F1@20 curves for all three users, the single matching algorithm that gives the best balance across broad-taste (User 1), narrow-taste (User 2) and medium-taste (User 3) listeners is:

> **Jaccard similarity** computed on the **top 20** highest-weight profile terms (M = 20).

Reasons:

- For **User 1**, Jaccard@20 reaches F1≈0.32—nearly matching the peak Cosine@all (≈0.36) but without needing the full vector.
- For **User 2**, Jaccard@20 and Cosine@all both yield F1≈0.19, outperforming all other M-values for that user.
- For **User 3**, Jaccard@20 hits F1≈0.33, substantially higher than Cosine@all (≈0.25).

In contrast, Cosine@all skews heavily toward User 1 and under-serves User 3; smaller M with Cosine under-performs for narrow profiles. Jaccard@20, by focusing on the most discriminative terms and using set-overlap rather than vector-norms, delivers the most consistent and highest average F1 across our heterogeneous user simulations.

PART 3 User Evaluation

Question 1

Simulate subject feedback

Data: Weeks 1–3 = songs 1–750 (train), Week 4 = songs 751–1000 (test).

Per–week random sample: For each of Weeks 1/2/3, draw N = 20 random indices.

Display to subject: For each batch, show [index, title, artist, a few lines of lyric].

Manual “likes”: The subject picks which of those 20 they like though think aloud.

In [32]:
```
df_train_part3 = df.iloc[:750].reset_index(drop=True)

N = 20
np.random.seed(42)
batches = {
    1: np.random.choice(range(0,250),   N, replace=False),
    2: np.random.choice(range(250,500), N, replace=False),
    3: np.random.choice(range(500,750), N, replace=False),
}

for week, idxs in batches.items():
    print(f"\n--- Week {week} sample ---\n")
    display(df_train_part3.loc[idxs, ['track_name','artist_name']])
    print("\nLyric snippets:")
    for i in idxs:
        snippet = " ".join(df_train_part3.loc[i,'lyrics'].split()[:25]) + "…"
        print(f"{i:4d} | {snippet}")
    print(f"\nWhich of these songs (indices) do you LIKE?")
```

```
--- Week 1 sample ---
```

	track_name	artist_name
142	vivo hip hop (live)	skool 77
6	trap door	rebelution
97	outrunning karma	alec benjamin
60	we are come to outlive our brains	phish
112	shout sister shout	madeleine peyroux
181	what i could do	janiva magness
197	if you met me first	eric ethridge
184	natural	imagine dragons
9	never land	eli young band
104	john the revelator	larkin poe
200	fair warning	the movement
216	marijuana breath	adam jensen
236	bullet in a gun	imagine dragons
240	walls	jamie n commons
67	dodging raindrops	311
224	i'm not the devil	cody jinks
194	my lord	michael franti & spearhead
15	counting every blessing	rend collective
177	breaking down	the black keys
24	be a g about it	t-rock

```
Lyric snippets:
 142 | head camden sure raise toast patron saint waifs stray bingham ghost freshf
aced lass kentish come people pedlars bingham husband camden coach house till han
g neck…
   6 | long long road occur look shortcut wanna cause scene wanna close okay outs
poken look trap door sneak grind floor careful wish need answer head time…
  97 | outrun karma charmer bug larva follow colorado dozen hearts body lie drag
colorado modern desperado race night run know hide gonna poor people forsake karm
a…
  60 | overlap future pass pass vapor light liquid blue look exactly suppose look
shape hang look shape hang look stop try rush nature slow come outlive…
 112 | shout sister shout hallelujah shout sister shout shout sister shout tell w
orld reason live reason die darn good reason woman start cry reason mole reason…
 181 | pay dues truth leave leave leave forget silence rule blind fool learn lear
n learn break away rise days firelight fade night estrange draw flame like…
 197 | strangest creature fail prey like vulture hand follow follow follow life s
teal light sweet taste talk wanna face crowd friend failure trust gods couldn fel
t…
 184 | hold line give give tell house come consequence cost tell star align heave
n step save cause house stand strong leave heart cast away product today…
   9 | 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…
 104 | tell write revelator tell write revelator tell write revelator write book
seven seal tell write revelator tell write revelator tell write revelator write b
ook seven…
 200 | reason aside look teeter pride heater hide sneak little piece life hole ob
ey abide universe try reel right people like know ignorant backlines look snack…
 216 | try tell time kill monster voice inside head somedays separate ways drug b
est roll torch underneath table drug death kiss marijuana breath cure loneliness
little…
 236 | romulus precipice bear change final days appraise take name high stop bipo
lar time come promise pull trigger bullet time come like bullet blood sweat tear…
 240 | yeah knowwoahow hard time dear yeah knowwoahow long time dear time change
hmmm right savior bid flame wall come fall wall come fall savior fight…
  67 | stay inside livin life instead watchin window playin safe gonna hesitate k
now mental let givin control yeah ready wind blow wanna road gonna lead time…
 224 | devil think excuse slip fell outta hand devil think wasn hold head catch b
elieve lie say moment weakness stumble devil think excuse slip fell outta…
 194 | lord lord lord lord things need know lord lord lord lord place need bear s
pend rest life find home choose long road walk instead sign…
  15 | blind see colour dead live forever fail redeemer bless measure lose father
change ruin treasure give future bless measure count bless count bless let trust…
 177 | go stumble catch trap somethin bone deep pull know cruel heart ache escape
feel like break take ocean sink ship like brick sulk catch ride…
  24 | 잊어버리지마 잃어버리지마 잊어버리지마 잃어버리지마 멈췄으면 잊어버리지마 잃어버
리지마 잊어버리지마 잃어버리지마 바라보는 영원하길 기억해주길 한번쯤은 돌아보길 바라봐주
길 baby 잊어버리지마 잊어버리지마 잊어버리지마 romanization neowa eonjenga nami dwie
odo yeongyeong…

Which of these songs (indices) do you LIKE?

--- Week 2 sample ---
```

	track_name	artist_name
455	glocks	slightly stoopid
322	learn to let go	welshly arms
329	spotlight	upchurch
404	break up in the end	cole swindell
370	nothing breaks like a heart (feat. miley cyrus)	mark ronson
430	the world connects	don philippe
387	window	magic giant
453	cushty	ajmw
318	i miss you bae	seckond chaynce
491	westway	sticky fingers
259	tesselation	mild high club
437	i was jack (you were diane)	jake owen
452	dear life	high valley
485	high voltage / it's a long way to the top (if ...	eagles of death metal
290	rolling with the punches	the blue stones
405	music to make you stagger	thievery corporation
374	free mind	tash sultana
280	all my hope	crowder
293	white flag	bishop briggs
352	when i get rich	jelly roll

Lyric snippets:
455 | doughty guitar bass key mcdonald bass moran drum delacruz saxophone welter trumpet key oguer ocon percussion ruffin additional guitars…
322 | head yeah head head shake hand world changin knees beggin forget keep pound head free soul learn ohoh lose control throw hand learn ohoh good…
329 | whoaoh walk line black leather silver chain blind fame time stage head bang beer spray stage dive hand wave light blow glass suffocate fame glass…
404 | walk little drink drink kiss shuffleboard break introduce think leave room advice move break know away know best worst mistake break play favorite song felt…
370 | world hurt cut deep leave scar things fall apart break like heart break like heart hear phone night live pretty lie know know silver bullet…
430 | buju banton yout brownin song hear tell cause cyant shoe tongue grun hear stop black woman girls dark complexion cause stop black woman nuff ting…
387 | home wanna window dream fell asleep wake ecstasy make dream come true need know come window leave write stone leave friday night alive lover open…
453 | fear deep get best fear fall come face face stand hold feel wound step step step break break away push away fall push away fall…
318 | beautiful like beautiful gag maybe real maybe phantom expect vanish expect happen think last power give heart sadly chapter come bitter talk friends fervently freeze…
491 | tiptoe build castle bother dizzy staircase choose fall lonesome newtown gonna sleep head high come dress party freak theme yeah nature come indulge outlandish behavior…
259 | daddy know hand pool head fool push weight hollywood gestalt hang edge fault learn trick uncle education sloganeer nascent vagabond motion picture babylon twist gestalt…
437 | yesterday years singin word radio kinda like songs save souls someway fall in fast jumpin blue halo hangin wind american kid like time play blow away…
452 | dear life know love mile road share hit miss try ditch dear life know dear life plan suppose right leave dream dear life plan fly…
485 | winter lose grip ocean free ship glide break open north wind sail froth seas grow stronger heart easier breathe days turn nights nights turn days…
290 | long time long time wrestle dirt grind take borderlines douse head upstream brine twotone coat tell like songs write turn head surprise tongue green eye…
405 | catch tide divide moment stand fight future bright burn inside hand fell line time fail forget reality insanity humanity tear seam aaaah go go aaaah…
374 | wake wrong somebody tell blue jeans white shirt glass bother call doctor kind disease unscrew mind walk ease cause feel crawl underneath skin wrap honeysuckle…
280 | hold savior felt river prodigal return thank yesterday go sin forgive wash blood stranger prison wear shackle chain lyric commercial…
293 | shoot shoot grind grind play dead gotta wear paper promise break feed energy expect sympathy smoke go know afraid shed little blood smoke flare go…
352 | yeah yeah yeah tell yeah mammy break yesterday clothe walk outside prolly smoke hold break come yesterday clothe walk outside smoke break break know break…

Which of these songs (indices) do you LIKE?

--- Week 3 sample ---

	track_name	artist_name
521	camera show	protoje
617	isolation	ty segall
679	boa	sam gendel
711	i get the bag (feat. migos)	gucci mane
550	every time	boogie belgique
533	unleashed	killswitch engage
565	chlorine	twenty one pilots
735	all i c is u & me	death from above 1979
539	floatin'	uncle kracker
549	solo	adam doleac
597	get happy	goodbye june
625	runner	nahko and medicine for the people
628	low life	jamie n commons
624	roller skates	nick hakim
716	there's a small hotel	bill charlap trio
633	tubesocks	kiefer
558	the song	skarra mucci
671	house of memories	panic! at the disco
691	wildfire	seafret
554	rob's dream	all them witches

```
Lyric snippets:
 521 | fall fall fall fall fall see know stay freedom call call camera lie thing sure kingdom fall fall like everybody free free today tomorrow agree…
 617 | people know afraid isolation afraid everybody home isolation little girl try change wide world isolation world little everybody try isolation expect understand cause pain blame…
 679 | rebel rebel yell cause people dwell hell lock cell structure cell story tell long seein stake action reaction mind somewhat complacent state check stick freedom…
 711 | bieber bloodpop friends question grave cardi bodak yellow feat messiah latin trap remix dream status crawl peep save gucci mane feat migos cross mind feat…
 550 | time goodbye leave time goodbye little leave time goodbye leave time goodbye little leave time goodbye leave time goodbye little leave…
 533 | deceive release unleash unleash wild welcome madness dwell inside eye push unto break point run time innocent blood hand deceive come face face final stand…
 565 | little sippin straight chlorine vibe slide beat chemical beat chemical leave save seat complete moment medical moment medical sippin straight chlorine lovin tastin woah venom…
 735 | racists smile friendly face walk shake hand try fake need fail glass season pass peepshow seat cheaper romance dead ghost haunt favourite place romance dead…
 539 | rumour go deep cause girl leave bust drive coast weekend mean give floatin ocean hold pattern little breather jump need break break poor heart shatter…
 549 | warm return melt away snow free chain winter let stand ocean hear wave call tide sail fate guide ship ax spear swords guide storm whip…
 597 | begin yellow skin black night drink till light cocaine closest distance line mind try erase past ways kill pain maybe pills alcohol weed shake memories…
 625 | runner run things good things ahead kind lover follow dragonflies lead sunrise morning tide even yeah teach harder lessons yeah kiss softly kiss softly place…
 628 | life think bout life help fall help fall life think bout life try fight good fight life wanna better hard life inside cold bind start…
 624 | think take grant go change believe leave wait forgive forsake dear want mind downstairs ride look mirror drink nectar couple days later felt better…
 716 | stare wonder bring martyr sure crown light bone like compare time heroes ghost sell sorrow ones pay heroes dead go inside live dark devotion vacant…
 633 | aaah aaah aaah aaah believe bone bear grave feel gonna pile bone aaah aaah aaah dust rise right time fossil scene feel gonna pile bone…
 558 | take lifetime lose lifetime yesterdays waste time hand turn sand fade wind cross line small crimes take fine fee friction right fine fee friction right…
 671 | whoa lover know lonely moments lonelier longer memories turn daydream taboo want afraid deeper take breath away soft hearts electric souls heart heart eye eye…
 691 | think know wrong begin need darkness burn know fuel spark bind hearts cold tear pull apart like wildfire word true stop break loose like wildfire…
 554 | dagger sword dagger sword dark groves call dark groves call dagger sword dagger sword dark groves call dark groves call turn blue turn blue turn…

Which of these songs (indices) do you LIKE?
```

Below is the `likes` dictionary (Week 1 -3) I collected, together with a brief note on how I solicited the responses from my roommate (our “subject”):

In [33]:
```python
likes = {
    1: [6, 60, 181, 236, 24],
    2: [322, 404, 370, 318, 352],
    3: [617, 550, 735, 597, 671]
}
```

My roommate’s interests

- She is especially drawn to **introspective lyrics** and **emotional storytelling** (e.g. “learn to let go”, “nothing breaks like a heart”, “isolation”, “house of memories”).

Brife note on the 'think aloud':

1. I showed her each weekly batch (Week 1, Week 2, Week 3) on my laptop, listing **track name**, **artist**, and the **first few lines** of lyrics.
2. I asked:

   > “Which of these song would you hit ‘play’ on right now?”

3. They pointed to the indices above while talking out loud her thoughs, and I entered them into my notebook exactly as shown.

Train the recommender on observed likes

In [34]:
```
# Build TF-IDF per topic (as before)
tfidf_vecs = {}
for topic in df_train['topic'].unique():
    vect = TfidfVectorizer(analyzer=analyzer).fit(
        df_train.loc[df_train['topic']==topic, 'content']
    )
    tfidf_vecs[topic] = vect

# Build roommate's profile from liked songs
profile_vec = {}
for topic, vect in tfidf_vecs.items():
    docs = []
    for wk, ids in likes.items():
        subset = df_train.loc[ids]
        docs += subset.loc[subset['pred_topic']==topic, 'content'].tolist()
    if not docs:
        profile_vec[topic] = None
    else:
        vec   = vect.transform([" ".join(docs)]).toarray().ravel()
        top20 = np.argsort(vec)[-20:]
        mask  = np.zeros_like(vec); mask[top20] = vec[top20]
        profile_vec[topic] = mask.reshape(1,-1)
```

Recommend & display Week 4

In [35]:
```
# Prepare Week 4 data
df_test = df.iloc[750:1000].reset_index(drop=True)
df_test['pred_topic'] = clf.predict(df_test['content'])

# Score by Jaccard(top-20) and rank
def jaccard(u,v):
    ui,vi = (u>0),(v>0)
    return (ui & vi).sum() / (ui | vi).sum() if (ui|vi).sum() else 0

sims = []
```

```python
for _, r in df_test.iterrows():
    pt = r['pred_topic']; up = profile_vec.get(pt)
    if up is None:
        sims.append(0.0)
    else:
        song_v = tfidf_vecs[pt].transform([r['content']]).toarray().ravel()
        sims.append(jaccard(up.ravel(), song_v))
df_test['sim'] = sims

top20 = df_test.nlargest(20,'sim').copy()
print("\n--- Recommended Week 4 songs ---")
display(top20[['track_name','artist_name']])
print("\nLyric snippets:")
for idx in top20.index:
    snippet = " ".join(df_test.loc[idx,'content'].split()[:15])+"…"
    print(f"{idx:4d} | {snippet}")

# Capture subject’s feedback on these 20
print(f"\nWhich of these songs (indices) do you LIKE?")
```

```
--- Recommended Week 4 songs ---
```

	track_name	artist_name
209	born in dissonance	meshuggah
14	remind me to forget	kygo
135	stay with me	ayokay
145	hands up	parker millsap
119	amsterdam	nothing but thieves
165	rewrite the stars	zac efron
247	broken halos	chris stapleton
249	puff your cares away	gramatik
221	starving	hailee steinfeld
136	something new	babe rainbow
17	one call away	charlie puth
56	the fighter	keith urban
106	close enough	brett young
73	the greatest	six60
45	we find love	daniel caesar
232	home	the movement
156	can't let go	kings and comrades
23	7-t's	marcus miller
184	baroness	wolfmother
140	fortress	queens of the stone age

```
Lyric snippets:
 209 | meshuggah born in dissonance 2016 jazz origin increate come thousand years violent element incarnate flesh…
  14 | kygo remind me to forget 2017 pop fade away stay kiss like break glass skin…
 135 | ayokay stay with me 2018 pop slowly show heart overflow leave barely breathe feel like…
 145 | parker millsap hands up 2016 blues easy hard wanna lump jacket yeah pistol open register…
 119 | nothing but thieves amsterdam 2017 rock people know need whiskey crutch think watch lookin screen…
 165 | zac efron rewrite the stars 2017 pop know want secret hide know want say hand…
 247 | chris stapleton broken halos 2017 country see share break halos fold wing go break halos…
 249 | gramatik puff your cares away 2019 jazz tell smoke ring blow night circle blue white…
 221 | hailee steinfeld starving 2016 pop know things scare walk away feet know want inside change…
 136 | babe rainbow something new 2019 reggae soon dumb heart tear apart break hearts know truth…
  17 | charlie puth one call away 2016 pop away save superman away baby need friend wanna…
  56 | keith urban the fighter 2016 country know hurt scar scar deserve cause precious heart precious…
 106 | brett young close enough 2017 country close close close close mmmh like minutes see seat…
  73 | six60 the greatest 2019 reggae know taste tear face yeah remind dream chase fuel inside…
  45 | daniel caesar we find love 2017 pop anymore like song walk door wonder take long…
 232 | the movement home 2016 reggae bloodshot eye watch sleep warmth feel slowly fade hear call…
 156 | kings and comrades can't let go 2018 reggae explanation question hand like years pain go…
  23 | marcus miller 7-t's 2018 jazz right super fair minute right super fair minute right super…
 184 | wolfmother baroness 2016 blues live peasantry live higher class sleep mansion sleep grass come darkness…
 140 | queens of the stone age fortress 2017 blues heart like fortress feel lock away easier…

Which of these songs (indices) do you LIKE?
```

My roommate's 'likes' from the recommended songs:

In [36]:
```python
likes[4] = [209, 14, 135, 247, 221, 106, 156, 184, 140]
```

In [37]:
```python
# Mark true likes among top-20 recommendations
hits = sum(idx in likes[4] for idx in top20.index)
precision = hits / 20

print(f"\nWeek 4 Precision@20 = {precision:.3f}")
```

```
Week 4 Precision@20 = 0.450
```

Only Precision@20 was used:

We only have relevance judgments for the 20 recommended songs, we can't determine the total number of liked items in Week 4—so Recall@20 (and F1@20) is undefined. Precision@20 alone is valid, since it uses only the shown items and their known likes.

Simulation vs. Real-User Precision@20

In Part 2 "automatic" simulation for User 1 with Jaccard@20 on the top 20 profile terms, we recorded a **Precision@20 of 0.90** (18 out of 20 "keyword-matched" songs were hits). In the live user-study, by contrast, we observed a **Precision@20 of 0.90** (only 9 of the 20 recommended tracks were actually liked).

Possible reasons for the gap:

1. **Optimistic keywords vs. real taste.** In simulation we assumed **any** lyric containing a seed keyword was a "hit," giving the model near-perfect feedback. A human listener, however, applies much richer judgments: tone, production, vocal style, even their current mood.
2. **Profile representation limitations.** Condensing a user's tastes to 20 TF–IDF terms captures broad themes but misses subtleties (e.g. metaphor, irony, musical arrangement) that real users care about.

Subject feedback

My roommate's general feedback:

> Overall, the system shows promise but needs richer text features (or audio cues) and a little more diversity to feel like a real personalized playlist.