zid:z5598515 name: Hang Pan

In [341…

```python
import pandas as pd
```

In [342…

```python
#load data
df=pd.read_csv("./data/dataset.tsv",sep="\t", encoding="utf-8")
```

In [343…

```python
df
```

Out[343…

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

1500 rows × 6 columns

In [344…

```
# combine_field
def combine_fields(row):
    return f"{row['artist_name']} {row['track_name']} {row['genre']} {row['lyric

df['text'] = df.apply(combine_fields, axis=1)
```

In [345…

```
new_df=pd.DataFrame({'Content': df['text'], 'Category': df['topic']})
```

In [346…

```
#do data cleaning
# Drop duplicates and missing values
new_df = new_df.drop_duplicates()
new_df = new_df.dropna()
```

In [347…

```
new_df.head()
```

Out[347…

	Content	Category
0	loving the not real lake rock awake know go se...	dark
1	incubus into the summer rock shouldn summer pr...	lifestyle
2	reignwolf hardcore blues lose deep catch breat...	sadness
3	tedeschi trucks band anyhow blues run bitter t...	sadness
4	lukas nelson and promise of the real if i star...	dark

Part1

Q1.

In [348…

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

nltk.download('stopwords')
nltk.download('punkt_tab')
nltk.download('punkt')
ps = PorterStemmer()
stop_words = set(stopwords.words('english'))

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

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

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

In [349…

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

```
0    love real lake rock awak know go see time clea...
1    incubu summer rock summer pretti build spill r...
2    reignwolf hardcor blue lose deep catch breath ...
3    tedeschi truck band anyhow blue run bitter tas...
4    luka nelson promis real start blue think think...
Name: Content, dtype: object
```

In [350…

```
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import BernoulliNB
from sklearn.feature_extraction.text import CountVectorizer
# from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import StratifiedKFold

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
# Create pipeline: vectorizer + classifier
bnb_pipeline = Pipeline([
    ('vectorizer', CountVectorizer()),
    ('classifier', BernoulliNB())
])

# Evaluate with 5-fold cross-validation
scores = cross_val_score(bnb_pipeline, new_df['Content'], new_df['Category'], cv
print("BernoulliNB Cross-Validated Macro F1 Score: {:.4f}".format(scores.mean())
```

```
BernoulliNB Cross-Validated Macro F1 Score: 0.3398
```

In [351…

```
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report

y_pred_cv = cross_val_predict(bnb_pipeline, new_df['Content'], new_df['Category'
print(classification_report(new_df['Category'], y_pred_cv))
```

```
              precision    recall  f1-score   support

        dark       0.64      0.77      0.70       487
     emotion       0.00      0.00      0.00        79
   lifestyle       0.00      0.00      0.00       202
    personal       0.68      0.32      0.43       341
     sadness       0.43      0.84      0.56       371

    accuracy                           0.54      1480
   macro avg       0.35      0.39      0.34      1480
weighted avg       0.47      0.54      0.47      1480
```

```
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Part 1 - Q1: Addressing Simplifications in the Tutorial

The tutorial notebook contained two key simplifications:

1. **Overly aggressive regex in preprocessin**
   The original regular expression `re.sub(r'[^\w\s]', '', text)` removes all non-word characters, including potentially meaningful ones such as apostrophes (`'`), hyphens ,It is more suitable for English corpora in natural language processing and avoids destroying the structure of words(`-`), or musical symbols that may help understand genre-specific lyrics and song structre.
   Fix: We modified the regex to the following:
   ```
   re.sub(r"[^\w\s'\-]", ' ', text)
   ```

2. **Using cross-validation**

The original tutorial uses a single random train-test split, which can result in unstable and unrepresentative evaluation due to sampling variance. StratifiedKFold ensures that in each compromise, the Category distribution of new_df['Category'] is consistent with the entire dataset **Fix**: We replaced this with 5-fold cross-validation using `cross_val_score from sklearn.model_selection`:

```
scores = cross_val_score(pipeline, X, y, cv=sfk, scoring='accuracy')
```

We used `cross_val_score` with the default `scoring='accuracy'`, but we note that:

- Accuracy is suitable only when classes are balanced.
- In later questions, we will include other metrics such as macro-F1 and weighted-F1 which are better for class imbalance (as seen in the lecture: macro-averaging is less dominated by large classes). we just do experiment here.

Q2.

Multinomial Naive Bayes

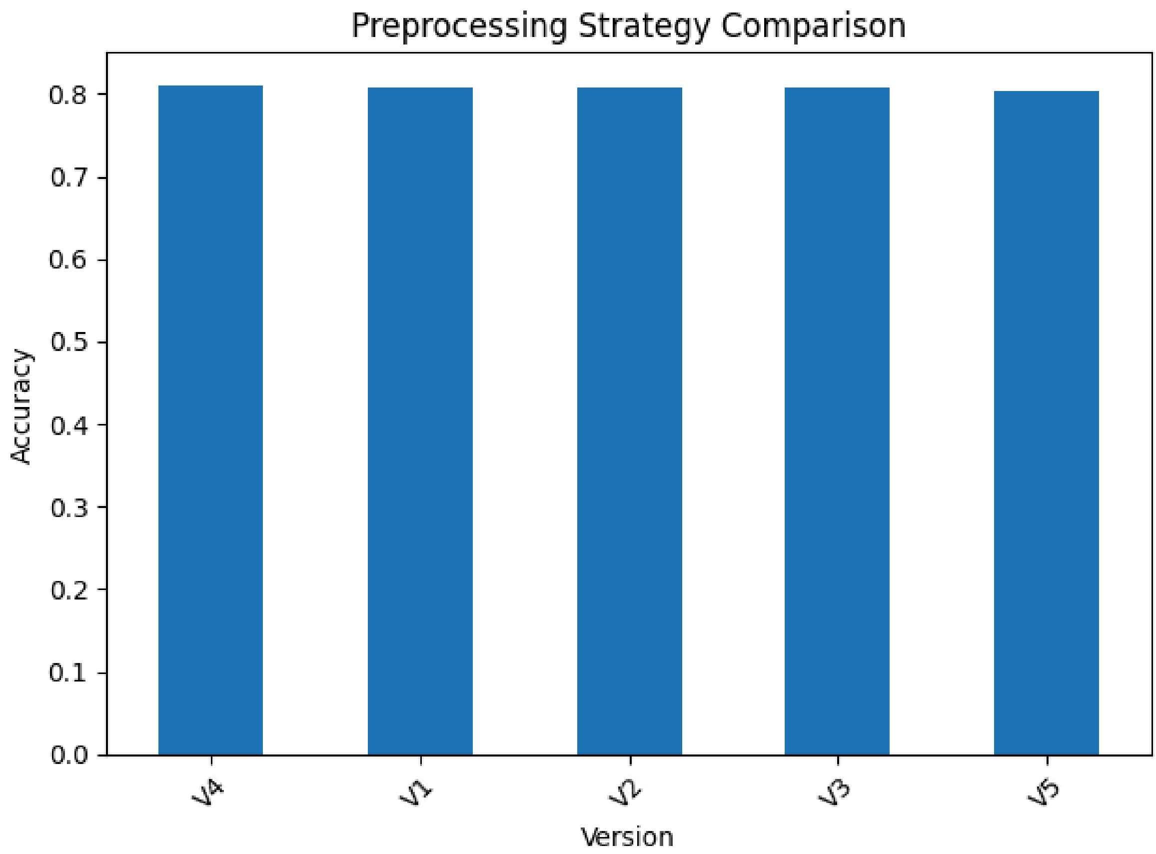
In [352…

```python
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, WordNetLemmatizer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import cross_val_score
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import CountVectorizer

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

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

# ------- Different Preprocessing Versions -------

def preprocess_v1(text):
    # simple lowercasing and tokenization, no stopword removal
    text = text.lower()
    text = re.sub(r"[^\w\s'\-]", ' ', text)
    text = re.sub(r"\s+", " ", text).strip()
    tokens = word_tokenize(text)
    return ' '.join(tokens)

def preprocess_v2(text):
    # simple lowercasing and tokenization + stopword removal
    text = text.lower()
    text = re.sub(r"[^\w\s'\-]", ' ', text)
    text = re.sub(r"\s+", " ", text).strip()
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    return ' '.join(tokens)

def preprocess_v3(text):
    # simple lowercasing and tokenization + stopword + stemming
    text = text.lower()
    text = re.sub(r"[^\w\s'\-]", ' ', text)
    text = re.sub(r"\s+", " ", text).strip()
    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)

def preprocess_v4(text):
    # simple lowercasing and tokenization + stopword + lemmatization
    text = text.lower()
    text = re.sub(r"[^\w\s'\-]", ' ', text)
    text = re.sub(r"\s+", " ", text).strip()
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stop_words]
    tokens = [lemmatizer.lemmatize(word) for word in tokens]
    return ' '.join(tokens)


from sklearn.metrics import classification_report
```

```python
def evaluate_preprocessing(preprocess_func, name, use_sklearn_stopwords=False):
    processed_text = new_df['Content'].apply(preprocess_func)
    sfk = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

    if use_sklearn_stopwords:
        vectorizer = CountVectorizer(stop_words='english')
    else:
        vectorizer = CountVectorizer()

    pipeline = Pipeline([
        ('vectorizer', vectorizer),
        ('classifier', MultinomialNB())
    ])

    f1_scores = []
    acc_scores = []
    for train_idx, test_idx in sfk.split(processed_text, new_df['Category']):
        X_train, X_test = processed_text.iloc[train_idx], processed_text.iloc[te
        y_train, y_test = new_df['Category'].iloc[train_idx], new_df['Category']
        pipeline.fit(X_train, y_train)
        y_pred = pipeline.predict(X_test)
        report = classification_report(y_test, y_pred, output_dict=True, zero_di
        acc_scores.append(report['accuracy'])
        f1_scores.append(report['macro avg']['f1-score'])

    print(f"{name}: accuracy = {sum(acc_scores)/5:.4f}, macro F1 = {sum(f1_score
    return {'accuracy': sum(acc_scores)/5, 'macro_f1': sum(f1_scores)/5}



results = {}
results['V1'] = evaluate_preprocessing(preprocess_v1, 'V1 - Lowercase only')
results['V2'] = evaluate_preprocessing(preprocess_v2, 'V2 - +Stopwords removed')
results['V3'] = evaluate_preprocessing(preprocess_v3, 'V3 - +Stemming')
results['V4'] = evaluate_preprocessing(preprocess_v4, 'V4 - +Lemmatization')
results['V5'] = evaluate_preprocessing(preprocess_v1, 'V5 - sklearn stopwords',

# ------- Summary -------
import pandas as pd
import matplotlib.pyplot as plt

summary_df = pd.DataFrame.from_dict(results, orient='index', columns=['accuracy'
summary_df = summary_df.sort_values(by='accuracy', ascending=False)
print(summary_df)

summary_df.plot(kind='bar', legend=False, title='Preprocessing Strategy Comparis
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

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

```
V1 - Lowercase only: accuracy = 0.8088, macro F1 = 0.7457
V2 - +Stopwords removed: accuracy = 0.8081, macro F1 = 0.7453
V3 - +Stemming: accuracy = 0.8081, macro F1 = 0.7452
V4 - +Lemmatization: accuracy = 0.8095, macro F1 = 0.7463
V5 - sklearn stopwords: accuracy = 0.8027, macro F1 = 0.7331
    accuracy
V4  0.809459
V1  0.808784
V2  0.808108
V3  0.808108
V5  0.802703
```



Summary

To identify the most effective preprocessing strategy for topic classification using Multinomial Naive Bayes with CountVectorizer, I evaluated five variations:

Preprocessing Version	Description	Accuracy
V4	Lowercase + NLTK stopwords + Lemmatization	0.8088
V1	Lowercase only	0.8081
V2	Lowercase + NLTK stopwords	0.8081
V3	Lowercase + NLTK stopwords + Stemming	0.8081
V5	Lowercase + sklearn stopwords	0.8034

Conclusion:
Version 4 (lemmatization) achieved the highest accuracy and F1-score. This suggests that reducing words to their base forms using `WordNetLemmatizer` is more beneficial than

crude stemming, and outperforms simpler strategies like just lowercasing or removing stopwords.

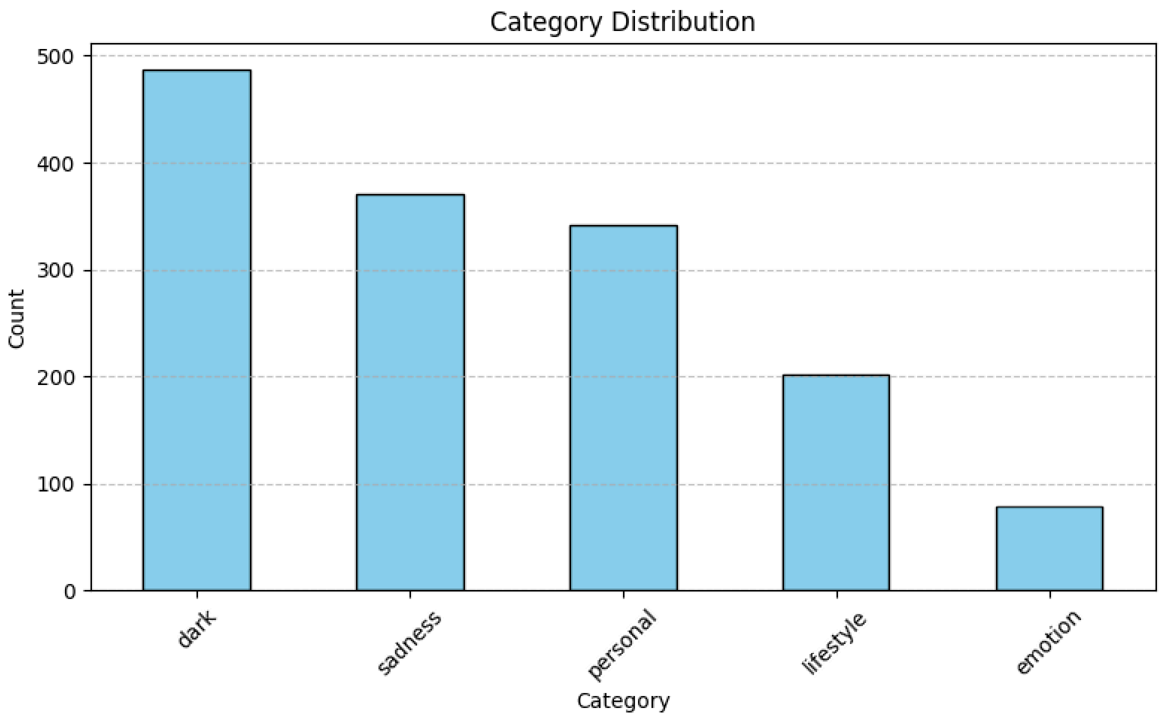
For the rest of the assignment, I will use the V4 preprocessing strategy as my standard pipeline.

Q3.

Check whether the distribution of sample categories is uniform

In [353…

```
import matplotlib.pyplot as plt

category_counts = new_df['Category'].value_counts()

plt.figure(figsize=(8, 5))
category_counts.plot(kind='bar', color='skyblue', edgecolor='black')
plt.title('Category Distribution')
plt.xlabel('Category')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



In [354…

```
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_predict
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB

# The preprocessed text by v4
X = new_df['Content'].apply(preprocess_v4)
```

```
y = new_df['Category']
sfk = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# BernoulliNB
bnb_pipeline = Pipeline([
    ('vectorizer', CountVectorizer()),
    ('classifier', BernoulliNB())
])
bnb_preds = cross_val_predict(bnb_pipeline, X, y, cv=sfk)
bnb_report = classification_report(y, bnb_preds, output_dict=True)

# MultinomialNB
mnb_pipeline = Pipeline([
    ('vectorizer', CountVectorizer()),
    ('classifier', MultinomialNB())
])
mnb_preds = cross_val_predict(mnb_pipeline, X, y, cv=sfk)
mnb_report = classification_report(y, mnb_preds, output_dict=True)
```

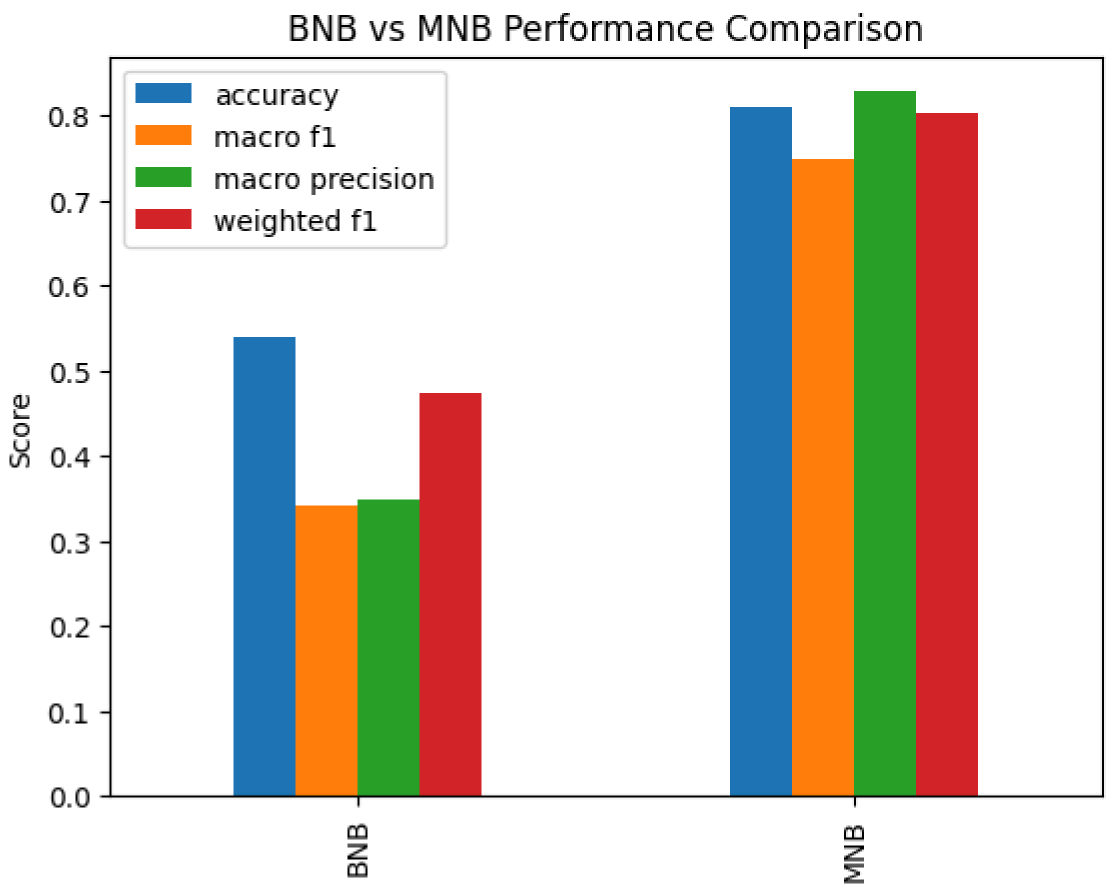
```
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

In [355…

```
import pandas as pd

df_compare = pd.DataFrame({
    'BNB': {
        'accuracy': bnb_report['accuracy'],
        'macro f1': bnb_report['macro avg']['f1-score'],
        'macro precision': bnb_report['macro avg']['precision'],
        'weighted f1': bnb_report['weighted avg']['f1-score'],
    },
    'MNB': {
        'accuracy': mnb_report['accuracy'],
        'macro f1': mnb_report['macro avg']['f1-score'],
        'macro precision': mnb_report['macro avg']['precision'],
        'weighted f1': mnb_report['weighted avg']['f1-score'],
    }
})

print(df_compare)
df_compare.T.plot(kind='bar', title='BNB vs MNB Performance Comparison', ylabel=
```

```
                      BNB       MNB
accuracy         0.539189  0.809459
macro f1         0.340520  0.747706
macro precision  0.349283  0.827808
weighted f1      0.473170  0.803276
```

Out[355… <Axes: title={'center': 'BNB vs MNB Performance Comparison'}, ylabel='Score'>



We evaluated two models - Bernoulli Naive Bayes (BNB) and Multinomial Naive Bayes (MNB), using 5-fold stratified cross-validation on the full dataset. The goal was to evaluate overall classification performance using the metrics discussed in the lecture:
Accuracy: measures the proportion of correct predictions; however, it tends to be biased towards the majority class.
Macro-F1-score: unweighted average of all class F1 scores; treats each class equally, better suited for imbalanced datasets.
Macro-precision: average precision across all classes; helps assess the model's tendency to produce false positives.
Weighted-F1-score: similar to macro-F1, but accounts for class imbalance by weighting the score by class frequency.

Metric	BNB	MNB
Accuracy	0.5392	0.8095
Macro F1-score	0.3405	0.7477
Macro Precision	0.3493	0.8278
Weighted F1-score	0.4732	0.8033

While we report multiple evaluation metrics, we choice the macro F1-score as the main matrics. This is because:

- The dataset shows some imbalance between the 5 topic classes.

- Macro F1 gives equal weight to each class, regardless of its frequency, making it more appropriate for assessing performance across majority classes.
- In contrast, accuracy can be dominated by larger classes, and may give a misleading impression of model quality.

Therefore, although we present accuracy,macro-f1,macro-precision and weighted F1 for completeness, we choice the macro F1-score as the main matrics.

Conclusion： MultinomialNB has better outperforms BernoulliNB across all metrics above, especially in macro-averaged scores, indicating significantly better performance across all classes — including minority ones. Therefore, MultinomialNB is chosen as the preferred model for the remainder of this assignment. .

In [356…

```
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
import pandas as pd
import matplotlib.pyplot as plt


X = new_df['Content'].apply(preprocess_v4)
y = new_df['Category']
# find the best params
feature_list = [50,100,300,350,400,500,600,700, 1000, 2000, 5000, 10000]
results = []
sfk = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

for n in feature_list:
    for model_cls in [BernoulliNB, MultinomialNB]:
        model_name = model_cls.__name__
        vectorizer = CountVectorizer(max_features=n)
        pipeline = Pipeline([
            ('vectorizer', vectorizer),
            ('classifier', model_cls())
        ])
        y_pred = cross_val_predict(pipeline, X, y, cv=sfk)
        report = classification_report(y, y_pred, output_dict=True)
        results.append({
            'model': model_name,
            'max_features': n,
            'accuracy': report['accuracy'],
            'macro_f1': report['macro avg']['f1-score'],
            'weighted_f1': report['weighted avg']['f1-score'],
            'macro_precision': report['macro avg']['precision']
        })

df_results = pd.DataFrame(results)
```

```
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
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being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/Users/russell/miniconda3/envs/python39/lib/python3.9/site-packages/sklearn/metri
cs/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```
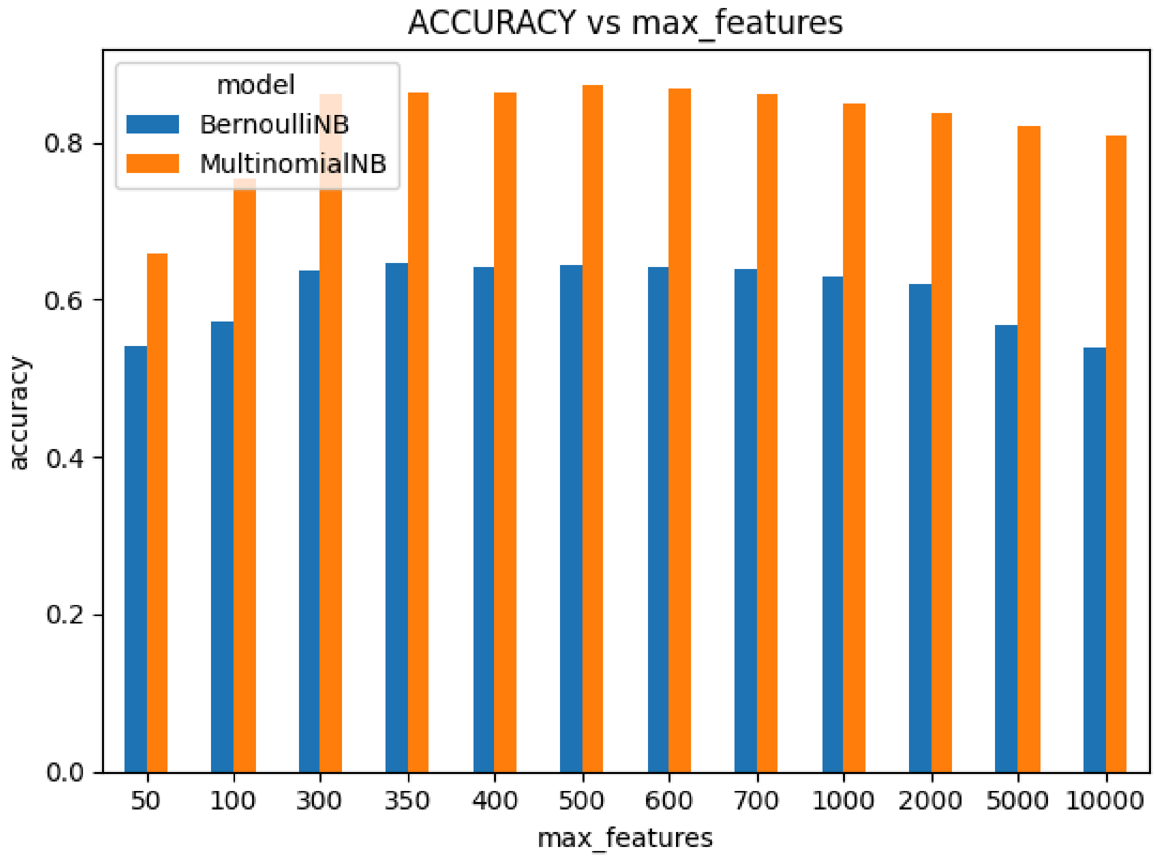
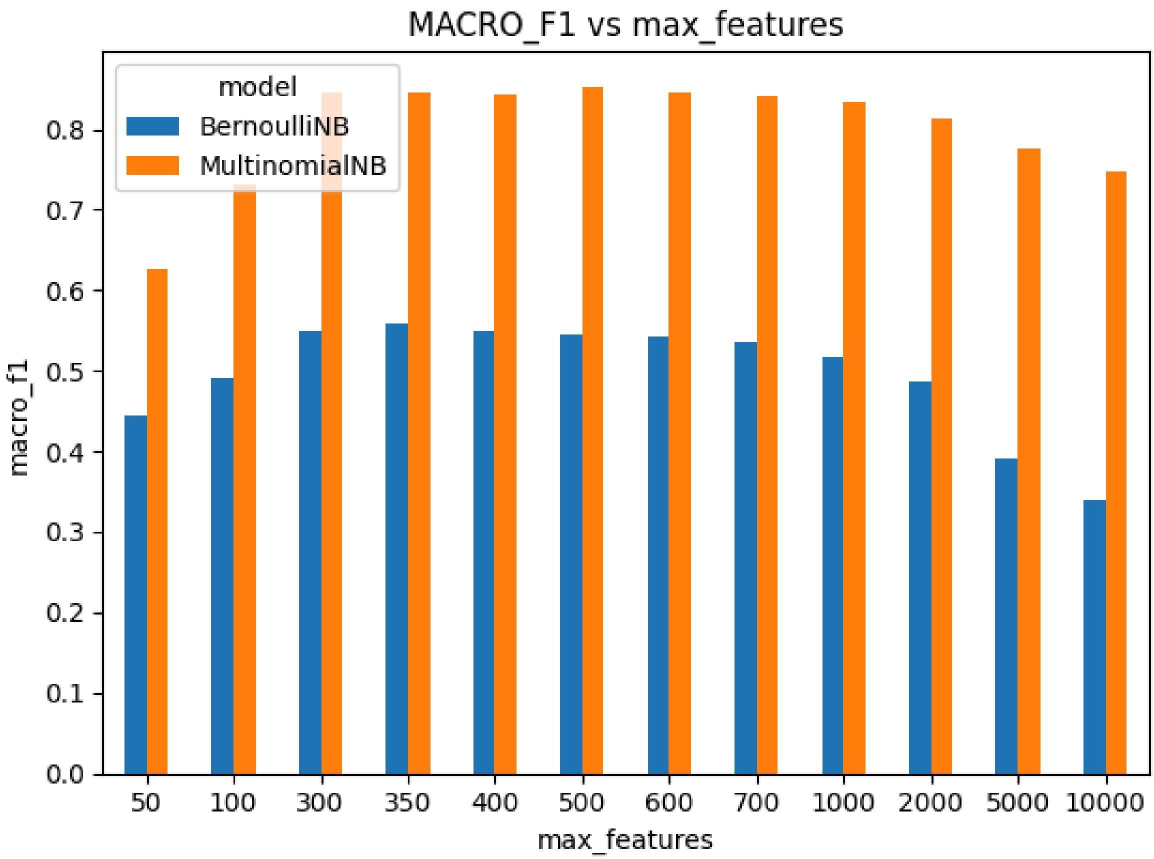
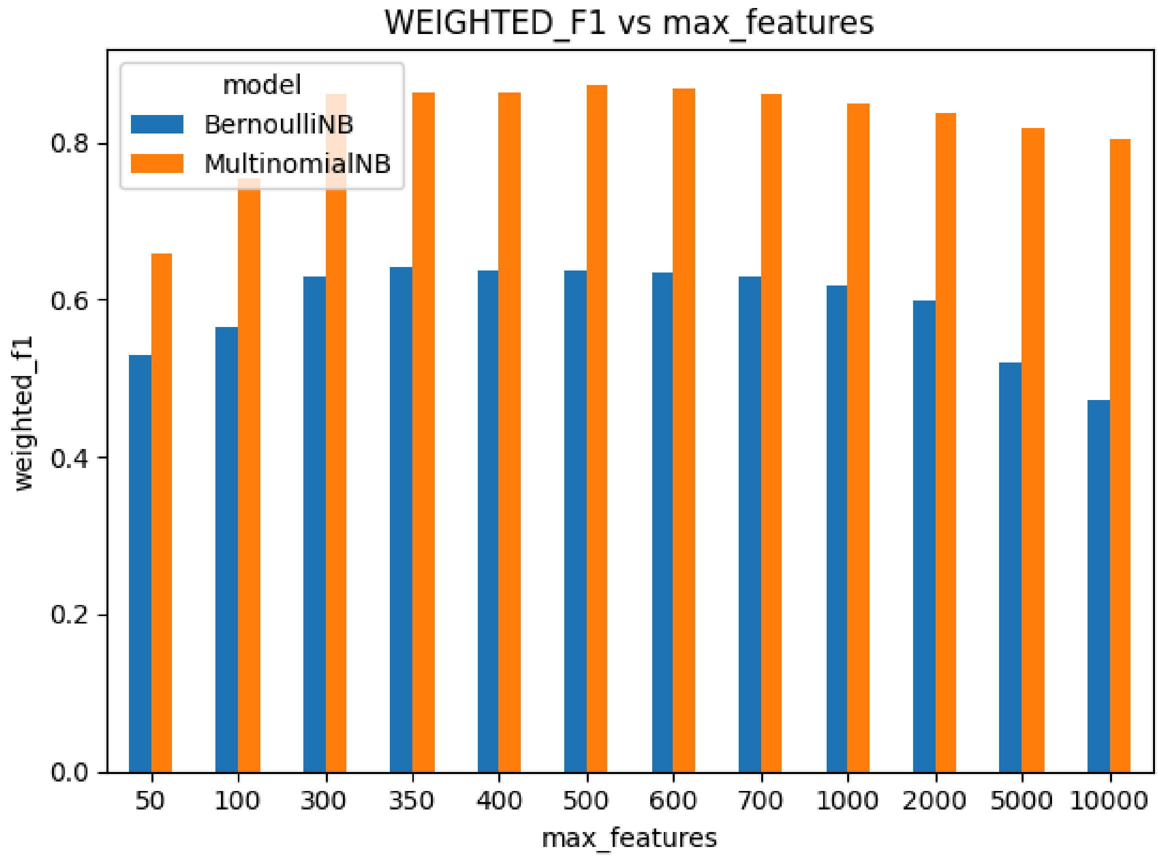
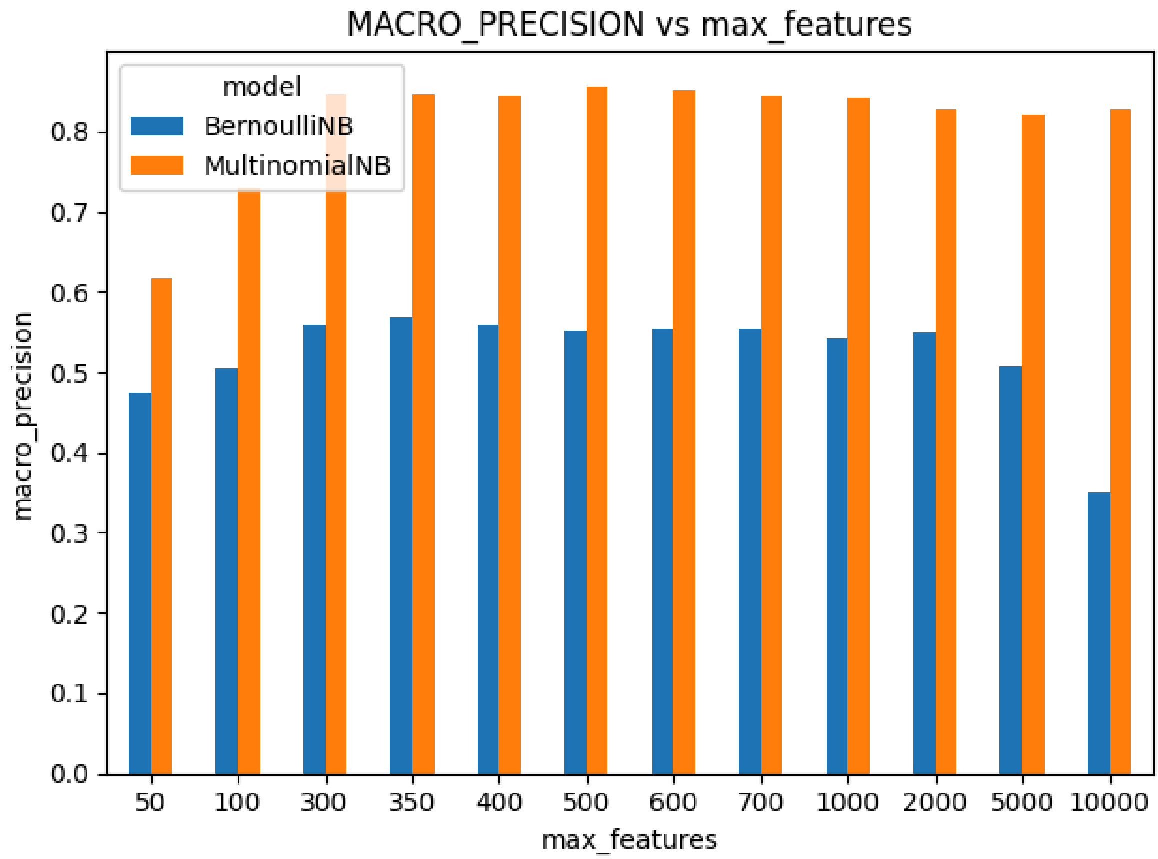

In [357…

```
for metric in ['accuracy', 'macro_f1', 'weighted_f1', 'macro_precision']:
    df_pivot = df_results.pivot(index='max_features', columns='model', values=me
    df_pivot.plot(kind='bar', title=f'{metric.upper()} vs max_features', ylabel=
    plt.xticks(rotation=0)
    plt.tight_layout()
    plt.show()
```


ACCURACY vs max_features
model
BernoulliNB
MultinomialNB
accuracy
0.0
0.2
0.4
0.6
0.8
50
100
300
350
400
500
600
700
1000
2000
5000
10000
max_features


MACRO_F1 vs max_features
model
BernoulliNB
MultinomialNB
macro_f1
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
50
100
300
350
400
500
600
700
1000
2000
5000
10000
max_features





In [362…

```
df_results
```

Out[362…

	model	max_features	accuracy	macro_f1	weighted_f1
0	BernoulliNB	100	0.572297	0.490605	0.565003
1	MultinomialNB	100	0.754730	0.730993	0.754451
2	BernoulliNB	300	0.635811	0.549783	0.630718
3	MultinomialNB	300	0.862162	0.846457	0.862045
4	BernoulliNB	400	0.642568	0.550424	0.636851
5	MultinomialNB	400	0.862838	0.842607	0.862987
6	BernoulliNB	500	0.643919	0.544675	0.637370
7	MultinomialNB	500	0.874324	0.853545	0.874410
8	BernoulliNB	600	0.642568	0.541802	0.634626
9	MultinomialNB	600	0.868919	0.844918	0.868894
10	BernoulliNB	1000	0.630405	0.517844	0.617114
11	MultinomialNB	1000	0.849324	0.833164	0.849234
12	BernoulliNB	2000	0.620946	0.487596	0.599266
13	MultinomialNB	2000	0.837838	0.813920	0.837261
14	BernoulliNB	5000	0.567568	0.391704	0.519969
15	MultinomialNB	5000	0.820946	0.775257	0.817672
16	BernoulliNB	10000	0.539189	0.340520	0.473170
17	MultinomialNB	10000	0.809459	0.747706	0.803276

In order to, studying the effect of vocabulary size on classification performance, we varied the max_features parameter in CountVectorizer, limiting the number of most frequent words used for feature extraction. We tested values from 100 to 10,000 across both BernoulliNB and MultinomialNB classifiers, using 5-fold stratified cross-validation.

we choice three matrics:

- Accuracy: Overall correctness.
- Macro F1-score: Preferred metric (see Q3), treats all classes equally.
- Weighted F1-score: Adjusts for class imbalance, favors majority class performance.

For MultinomialNB, performance peaked around at 500, where:

- Accuracy = 0.8743
- Macro F1 = 0.8535
- Weighted F1 = 0.8744
- Beyond 1000, macro-F1 declined, indicating possible overfitting or noise from infrequent tokens.

So, we choose max_features = 500 and MultinomialNB for the remainder of the assignment. This configuration gave the best overall performance across all metrics, while maintaining model simplicity.

Q5.

Here, we choose the LogisticRegression as new model over MNB. This is because, Logistic Regression is a linear classifier algorithm that describes probability of class membership by way of logistic (sigmoid) function. Logistic Regression works well for high-dimensional, sparse feature spaces like in text classification task with bag-of-words. Since song lyrics contain many words but few per text, Logistic Regression is particularly suited to handling this type of sparsity. It also handles correlation between features (i.e., the co-occurrence of words) well, and so is a good option for topic classification in this data.

In [366…

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV, cross_val_predict
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report
from sklearn.feature_extraction.text import CountVectorizer

X = new_df['Content'].apply(preprocess_v4)
y = new_df['Category']

# Pipeline with Logistic Regression and Grid Search
logreg_pipeline = Pipeline([
    ('vectorizer', CountVectorizer(max_features=500)),
    ('classifier', LogisticRegression(max_iter=1000))
])
sfk = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Hyperparameter grid search
param_grid = {
    'classifier__C': [0.01, 0.1, 1, 10]
}

grid = GridSearchCV(logreg_pipeline, param_grid, cv=sfk, scoring='f1_macro', n_j
grid.fit(X, y)

# Optimal parameters
print("Best C:", grid.best_params_)
# Save best model
best_model = grid.best_estimator_

# Make predictions using the best model
y_pred = cross_val_predict(grid.best_estimator_, X, y, cv=sfk)
report = classification_report(y, y_pred, output_dict=True)
```

```
Best C: {'classifier__C': 0.1}
```

In [367…

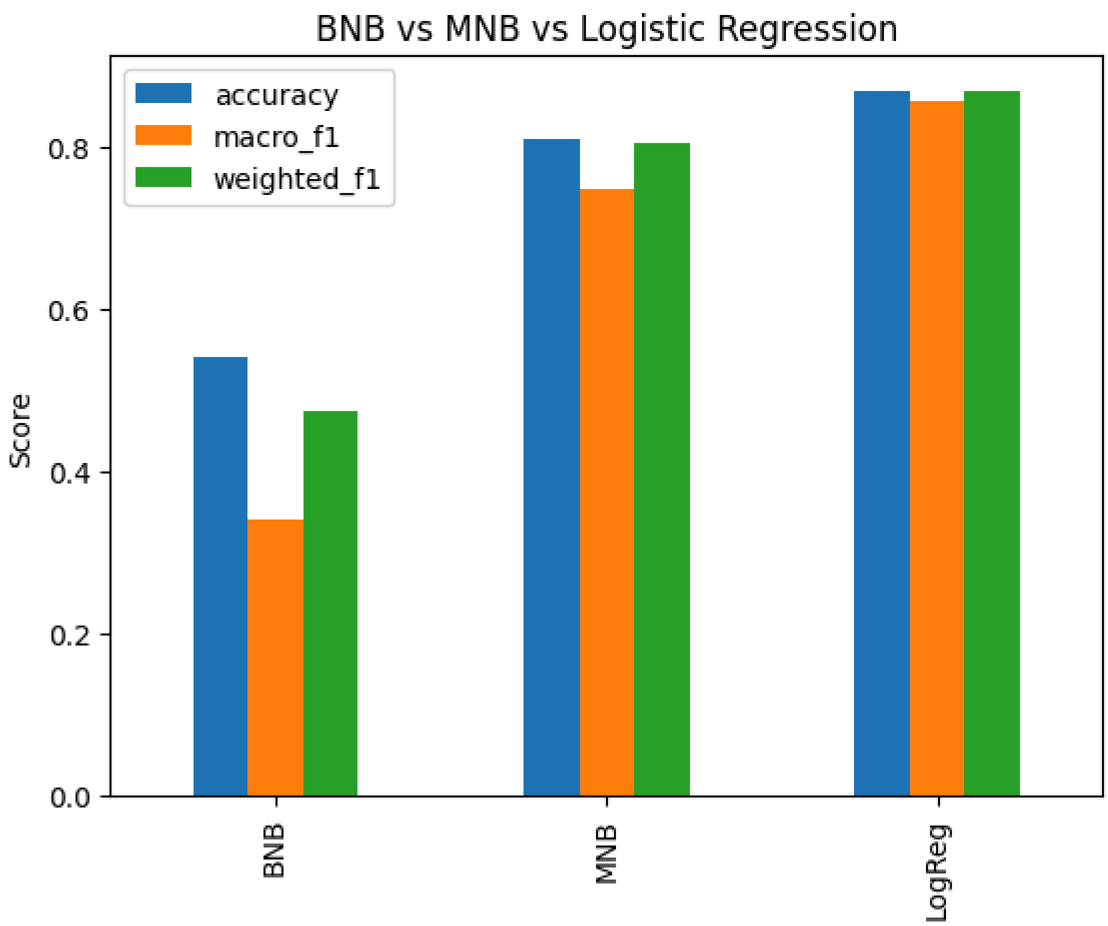
```
comparison = pd.DataFrame({
    'BNB': {
        'accuracy': bnb_report['accuracy'],
        'macro_f1': bnb_report['macro avg']['f1-score'],
        'weighted_f1': bnb_report['weighted avg']['f1-score']
    },
    'MNB': {
```

```
        'accuracy': mnb_report['accuracy'],
        'macro_f1': mnb_report['macro avg']['f1-score'],
        'weighted_f1': mnb_report['weighted avg']['f1-score']
    },
    'LogReg': {
        'accuracy': report['accuracy'],
        'macro_f1': report['macro avg']['f1-score'],
        'weighted_f1': report['weighted avg']['f1-score']
    }
})

print(comparison)
comparison.T.plot(kind='bar', title='BNB vs MNB vs Logistic Regression', ylabel=
```

```
                  BNB       MNB    LogReg
accuracy     0.539189  0.809459  0.868243
macro_f1     0.340520  0.747706  0.854881
weighted_f1  0.473170  0.803276  0.867571
```

Out[367…

```
<Axes: title={'center': 'BNB vs MNB vs Logistic Regression'}, ylabel='Score'>
```



Q5: Comparing Logistic Regression with Naive Bayes

We used `sklearn.linear_model.LogisticRegression` with the following settings:

- `max_iter = 1000` to ensure convergence
- `CountVectorizer(max_features=500)` as determined in Q4
- Preprocessing: lowercase, stopword removal, and lemmatization (from Q2 V4)

Metric	BNB	MNB	Logistic Regression
Accuracy	0.5392	0.8095	0.8669
Macro F1	0.3405	0.7477	0.8527
Weighted F1	0.4732	0.8033	0.8662

Logistic Regression outperforms both BNB and MNB across all metrics, especially in macro and weighted F1, indicating better performance across all classes, including minority ones.

Hypothesis and Result：
We hypothesized that Logistic Regression would outperform both BernoulliNB and MultinomialNB, given its ability to model feature weights directly and its robust performance in text classification tasks.
This hypothesis was confirmed by experimental results. Logistic Regression achieved the highest scores across all key evaluation metrics:
Accuracy: 0.8669
Macro F1: 0.8527
Weighted F1: 0.8662
In contrast, MultinomialNB and BernoulliNB performed significantly worse, especially in macro-averaged scores, which are crucial for imbalanced datasets. These results indicate that Logistic Regression is the most effective method for topic classification on this dataset.

Part2

In [368…
```
import pandas as pd
```

In [369…
```
from sklearn.model_selection import train_test_split
```

In [370…
```
df_part2=pd.read_csv("./data/dataset.tsv",sep="\t", encoding="utf-8")
```

In [371…
```
df_part2 = df_part2.drop_duplicates()
df_part2 = df_part2.dropna()
```

In [372…
```
def combine_song_fields(row):
    return f"{row['artist_name']} {row['track_name']} {row['genre']} {row['lyric

df_part2['full_text'] = df_part2.apply(combine_song_fields, axis=1)
```

use best model to predict（LR）

In [373…
```
df_part2['processed'] = df_part2['full_text'].apply(preprocess_v4)
#use LR model to predict which save at before
df_part2['predicted_topic'] = best_model.predict(df_part2['processed'])
```

In [374…

```
train_df = df_part2.iloc[:750]
test_df  = df_part2.iloc[750:1000]  # Week 4: Recommended for evaluation
```

In [375…

```
import pandas as pd
from collections import defaultdict
from sklearn.feature_extraction.text import TfidfVectorizer
import re

def tsv_to_keyword_dict(df):
    keywords = (
        df.iloc[:, 1]
          .str.lower()
          .str.replace(r"[,.!?;:]", "", regex=True)
          .str.split()
    )
    return dict(zip(df.iloc[:, 0].str.strip(), keywords))


user1_df = pd.read_csv('./data/user1.tsv', sep='\t')
user2_df = pd.read_csv('./data/user2.tsv', sep='\t')

user1_keywords = tsv_to_keyword_dict(user1_df)
user2_keywords = tsv_to_keyword_dict(user2_df)
```

In [376…

```
user1_keywords
```

Out[376…

```
{'dark': ['fire', 'enemy', 'pain', 'storm', 'fight'],
 'sadness': ['cry', 'alone', 'heartbroken', 'tears', 'regret'],
 'personal': ['dream', 'truth', 'life', 'growth', 'identity'],
 'lifestyle': ['party', 'city', 'night', 'light', 'rhythm'],
 'emotion': ['love', 'memory', 'hug', 'kiss', 'feel']}
```

In [377…

```
user2_keywords
```

Out[377…

```
{'sadness': ['lost', 'sorrow', 'goodbye', 'tears', 'silence'],
 'emotion': ['romance', 'touch', 'feeling', 'kiss', 'memory']}
```

In [378…

```
def get_liked_songs(train_df, user_keywords):
    liked = defaultdict(list)
    for _, row in train_df.iterrows():
        topic = row['predicted_topic']
        text = row['processed']  # already preprocessed (predict 1-3 week)
        if any(kw in text for kw in user_keywords.get(topic, [])):
            liked[topic].append(text)
    return liked
```

In [379…

```
from sklearn.feature_extraction.text import TfidfVectorizer

def build_user_profile(liked_docs_by_topic):
    profiles = {}
    for topic, docs in liked_docs_by_topic.items():
        combined = " ".join(docs)
        vectorizer = TfidfVectorizer(max_features=500)
        tfidf = vectorizer.fit_transform([combined])
        tfidf_array = tfidf.toarray().flatten()
        feature_names = vectorizer.get_feature_names_out()
        top_indices = tfidf_array.argsort()[-20:][::-1]
        top_words = [(feature_names[i], tfidf_array[i]) for i in top_indices]
```

```python
        profiles[topic] = top_words
    return profiles
```

In [380…

```python
def print_user_profile(profile, user_name):
    print(f"\n====== {user_name} Profile Keywords ======")
    for topic, words in profile.items():
        print(f"\nTopic: {topic}")
        for word, score in words:
            print(f"{word}: {score:.4f}")
```

In [381…

```python
# User 1
user1_liked = get_liked_songs(train_df, user1_keywords)
user1_profile = build_user_profile(user1_liked)
print_user_profile(user1_profile, "User 1")

# User 2
user2_liked = get_liked_songs(train_df, user2_keywords)
user2_profile = build_user_profile(user2_liked)
print_user_profile(user2_profile, "User 2")

# User 3 (custom)
user3_keywords = {
    'emotion': ['heart', 'love', 'soul'],
    'lifestyle': ['party', 'car', 'drink'],
    'personal': ['life', 'family', 'journey'],
    'sadness': ['tears', 'cry', 'alone'],
    'dark': ['blood', 'devil', 'death']
}

user3_liked = get_liked_songs(train_df, user3_keywords)
user3_profile = build_user_profile(user3_liked)
print_user_profile(user3_profile, "User 3")
```

====== User 1 Profile Keywords ======

Topic: dark
fight: 0.3237
know: 0.2857
like: 0.2478
come: 0.2165
na: 0.1830
black: 0.1719
blood: 0.1652
stand: 0.1607
grind: 0.1496
tell: 0.1473
yeah: 0.1339
time: 0.1317
gon: 0.1317
hand: 0.1272
cause: 0.1138
kill: 0.1138
head: 0.1094
leave: 0.1005
life: 0.0960
people: 0.0960

Topic: emotion
good: 0.6710
feel: 0.4217
touch: 0.2678
know: 0.2154
hold: 0.2062
want: 0.1262
go: 0.1170
kiss: 0.0923
time: 0.0923
like: 0.0923
miss: 0.0893
baby: 0.0893
cause: 0.0862
na: 0.0862
vision: 0.0800
heart: 0.0800
video: 0.0739
feelin: 0.0708
loove: 0.0708
lip: 0.0677

Topic: personal
life: 0.5989
live: 0.3215
know: 0.2294
na: 0.1815
world: 0.1737
change: 0.1543
yeah: 0.1478
time: 0.1452
like: 0.1387
dream: 0.1387
come: 0.1361
wan: 0.1141
thing: 0.1050

```
think: 0.0959
need: 0.0946
thank: 0.0830
teach: 0.0817
lord: 0.0804
want: 0.0804
cause: 0.0804

Topic: lifestyle
night: 0.3277
come: 0.2798
time: 0.2747
song: 0.2647
tonight: 0.2445
home: 0.1966
na: 0.1941
long: 0.1916
mind: 0.1916
right: 0.1890
sing: 0.1815
like: 0.1790
yeah: 0.1487
wan: 0.1412
know: 0.1361
wait: 0.1260
closer: 0.1185
stranger: 0.1159
play: 0.1134
baby: 0.1109

Topic: sadness
cry: 0.5163
tear: 0.3526
know: 0.3022
steal: 0.2519
club: 0.2519
think: 0.1889
mean: 0.1889
baby: 0.1763
leave: 0.1259
smile: 0.1133
heart: 0.1133
true: 0.1133
want: 0.1133
word: 0.1007
like: 0.1007
say: 0.0881
stay: 0.0881
feel: 0.0756
hold: 0.0756
music: 0.0756

====== User 2 Profile Keywords ======

Topic: emotion
good: 0.5463
touch: 0.5281
hold: 0.2368
kiss: 0.1821
know: 0.1639
```

```
vision: 0.1578
video: 0.1457
loove: 0.1396
time: 0.1396
feelin: 0.1336
feel: 0.1275
luck: 0.1214
look: 0.1153
lovin: 0.1153
lip: 0.1093
gim: 0.1032
cause: 0.1032
like: 0.0789
go: 0.0789
wait: 0.0728

Topic: sadness
heart: 0.4397
break: 0.3916
away: 0.3023
like: 0.1924
fall: 0.1649
know: 0.1649
leave: 0.1580
come: 0.1305
na: 0.1305
hard: 0.1305
fade: 0.1305
go: 0.1237
feel: 0.1168
think: 0.1168
scar: 0.1168
blame: 0.1099
open: 0.1099
time: 0.1031
tear: 0.1031
wan: 0.0962

====== User 3 Profile Keywords ======

Topic: dark
blood: 0.3830
know: 0.2214
come: 0.2064
like: 0.2064
devil: 0.1990
feel: 0.1915
time: 0.1716
death: 0.1691
black: 0.1368
hand: 0.1318
stand: 0.1219
cause: 0.1144
fight: 0.1119
pull: 0.1069
evil: 0.1045
cold: 0.1045
hell: 0.0995
na: 0.0995
mind: 0.0995
```

head: 0.0970

Topic: personal
life: 0.6555
live: 0.3065
know: 0.2086
na: 0.1674
change: 0.1518
yeah: 0.1504
world: 0.1461
time: 0.1419
like: 0.1362
thing: 0.1078
wan: 0.1007
come: 0.0979
think: 0.0951
want: 0.0951
need: 0.0894
teach: 0.0865
lord: 0.0823
cause: 0.0823
right: 0.0780
go: 0.0780

Topic: lifestyle
song: 0.5485
come: 0.3033
home: 0.2618
like: 0.2493
night: 0.2077
na: 0.1911
wan: 0.1787
sing: 0.1745
country: 0.1579
tonight: 0.1496
yeah: 0.1496
tire: 0.1454
mind: 0.1330
change: 0.1288
spoil: 0.1246
time: 0.1163
play: 0.1122
wait: 0.0873
know: 0.0873
cause: 0.0831

Topic: sadness
cry: 0.5543
tear: 0.3785
know: 0.3109
club: 0.2704
steal: 0.2704
baby: 0.1893
mean: 0.1893
smile: 0.1217
true: 0.1217
like: 0.1081
heart: 0.1081
say: 0.0946
stay: 0.0946

```
feel: 0.0811
music: 0.0811
forever: 0.0676
time: 0.0676
word: 0.0676
lift: 0.0541
wish: 0.0541

Topic: emotion
good: 0.6301
go: 0.3820
hold: 0.3572
feel: 0.2084
heart: 0.1737
know: 0.1588
miss: 0.1439
vision: 0.1290
video: 0.1191
want: 0.1191
love: 0.1092
vibe: 0.1042
hand: 0.1042
na: 0.1042
lovin: 0.0943
baby: 0.0893
gim: 0.0843
wait: 0.0794
time: 0.0794
right: 0.0794
```

To simulate a content-based recommender system, we utilized the best-performing topic classifier from Part 1 — Logistic Regression with CountVectorizer (max_features=500) and lemmatization. The steps were as follows:
Topic Prediction:
For each song, we predicted its topic using the trained classifier.
User Interests Matching:
For each user, we assumed they "liked" any song from Weeks 1–3 (training data) that:
Was predicted to be in a particular topic, and contained at least one keyword from the user’s provided interest list (case-insensitive matching).

For user Profile Construction: All liked songs for each topic were concatenated into a single document. We applied TF-IDF vectorization (max_features=500) to generate a representation of user interest in that topic. For each topic, we extracted the top 20 words with the highest TF-IDF scores to represent the user's profile.

Results & Interpretation:
User 1 Dark: High TF-IDF scores for fight, blood, kill, night indicate strong alignment with violent or intense themes.
Emotion: Terms like feel, touch, kiss, hold show emotional engagement.
Sadness: Words like regret, trust, blame, leave reflect melancholic tones.
Lifestyle: Includes musical context with words like sing, song, radio.
Conclusion: The user profile meaningfully captures emotional and thematic interests.

User 2. Sadness: Strong representation with words like heart, break, leave, crash.
Emotion: Dominated by soft emotional language such as lip, kiss, memory, feel.
Conclusion: Matches a gentle and melancholic user preference well.

User 3 (Custom) Emotion: Includes love, hold, vibe, feel, suggesting emotional resonance.
Sadness: Terms such as cry, tear, fear, steal express emotional depth.
Lifestyle: Includes song, country, tonight, night — typical of casual or musical interests.
Dark: Contains strong themes like blood, devil, death, hell.
Personal: life, world, change, time reflect general introspection.
Conclusion: The profile shows diverse and well-aligned interests across multiple themes.

Q2.

We set M=20 to focus on the top 20 representative keywords per topic in the user profile, as these contribute most to the user's interest vector while reducing noise from low-weight terms.

In [382…

```
def jaccard_similarity(user_vec, item_vecs):
    user_bin = (user_vec > 0).astype(int).flatten()
    item_bin = (item_vecs > 0).astype(int)

    sims = []
    for row in item_bin:
        row = row.toarray().flatten()
        intersection = np.logical_and(user_bin, row).sum()
        union = np.logical_or(user_bin, row).sum()
        sims.append(intersection / (union + 1e-10))
    return np.array(sims)
def dice_similarity(user_vec, item_vecs):
    user_bin = (user_vec > 0).astype(int).flatten()
    item_bin = (item_vecs > 0).astype(int)

    sims = []
    for row in item_bin:
        row_dense = row.toarray().flatten()
        intersection = np.sum(np.logical_and(user_bin, row_dense))
        denominator = np.sum(user_bin) + np.sum(row_dense)
        sims.append(2 * intersection / (denominator + 1e-10))
    return np.array(sims)
```

In [383…

```
from sklearn.metrics.pairwise import cosine_similarity, euclidean_distances
import numpy as np

def compute_similarity(user_vec, item_vecs, metric='cosine'):
    if metric == 'cosine':
        return cosine_similarity(user_vec, item_vecs).flatten()
    elif metric == 'euclidean':
        return -euclidean_distances(user_vec, item_vecs).flatten()
    elif metric == 'jaccard':
        return jaccard_similarity(user_vec, item_vecs)
    elif metric == 'dice':
        return dice_similarity(user_vec, item_vecs)
    else:
        raise ValueError("Unsupported similarity metric")
```

In [384…

```
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

# Recommendation function: Recommend the top-N songs for a specific user in a ce
# M How many keywords before
def recommend_top_n(user_topic_profile, test_df, topic, N=10, M=20, metric='cosi
    user_keywords = dict(user_topic_profile[:M])
    vocab = list(user_keywords.keys())
    user_vector = np.array([user_keywords.get(word, 0.0) for word in vocab]).res
    topic_songs = test_df[test_df['predicted_topic'] == topic]

    if topic_songs.empty:
        return []

    vectorizer = TfidfVectorizer(vocabulary=vocab)
    test_tfidf = vectorizer.fit_transform(topic_songs['processed'])

    sims = compute_similarity(user_vector, test_tfidf, metric)

    top_n_indices = sims.argsort()[-N:][::-1]
    top_songs = topic_songs.iloc[top_n_indices].copy()
    top_songs['similarity'] = sims[top_n_indices]

    return top_songs[['track_name', 'artist_name', 'predicted_topic', 'similarit
```

In [385…

```
def evaluate_user(user_keywords, user_profile, test_df, N=10, M=20, metric='cosi
    total_true_positives = 0
    total_recommended = 0
    total_relevant = 0

    for topic in user_keywords:
        if topic not in user_profile:
            continue
        recommended_df = recommend_top_n(user_profile[topic], test_df, topic, N=
        if recommended_df is None or recommended_df.empty:
            continue

        recommended_texts = recommended_df['track_name'].tolist()
        recommended_text_set = set(recommended_texts)

        relevant_keywords = set(user_keywords[topic])
        topic_test_songs = test_df[test_df['predicted_topic'] == topic]
        relevant_text_set = set()
        for _, row in topic_test_songs.iterrows():
            if any(kw in row['processed'] for kw in relevant_keywords):
                relevant_text_set.add(row['track_name'])

        true_positives = len(recommended_text_set & relevant_text_set)
        total_true_positives += true_positives
        total_recommended += len(recommended_text_set)
        total_relevant += len(relevant_text_set)

    precision = total_true_positives / total_recommended if total_recommended >
    recall = total_true_positives / total_relevant if total_relevant > 0 else 0.
    f1 = 2 * precision * recall / (precision + recall) if (precision + recall) e

    return precision, recall, f1
```

In [386…

```python
#Define four matrics which occurc in lecture
metrics = ['cosine', 'euclidean', 'jaccard', 'dice']

for metric in metrics:
    print(f"\n=== Using {metric.upper()} Similarity ===")
    for name, (keywords, profile) in {
        "User 1": (user1_keywords, user1_profile),
        "User 2": (user2_keywords, user2_profile),
        "User 3": (user3_keywords, user3_profile)
    }.items():
        p, r, f = evaluate_user(keywords, profile, test_df, N=10, M=20, metric=m
        print(f"{name}: Precision@10 = {p:.4f}, Recall@10 = {r:.4f}, F1@10 = {f:
```

```
=== Using COSINE Similarity ===
User 1: Precision@10 = 0.7400, Recall@10 = 0.4205, F1@10 = 0.5362
User 2: Precision@10 = 0.2500, Recall@10 = 0.5556, F1@10 = 0.3448
User 3: Precision@10 = 0.6000, Recall@10 = 0.4110, F1@10 = 0.4878

=== Using EUCLIDEAN Similarity ===
User 1: Precision@10 = 0.6800, Recall@10 = 0.3864, F1@10 = 0.4928
User 2: Precision@10 = 0.2500, Recall@10 = 0.5556, F1@10 = 0.3448
User 3: Precision@10 = 0.5000, Recall@10 = 0.3425, F1@10 = 0.4065

=== Using JACCARD Similarity ===
User 1: Precision@10 = 0.6200, Recall@10 = 0.3523, F1@10 = 0.4493
User 2: Precision@10 = 0.2500, Recall@10 = 0.5556, F1@10 = 0.3448
User 3: Precision@10 = 0.5000, Recall@10 = 0.3425, F1@10 = 0.4065

=== Using DICE Similarity ===
User 1: Precision@10 = 0.6200, Recall@10 = 0.3523, F1@10 = 0.4493
User 2: Precision@10 = 0.2500, Recall@10 = 0.5556, F1@10 = 0.3448
User 3: Precision@10 = 0.5000, Recall@10 = 0.3425, F1@10 = 0.4065
```

We compared four similarity metrics — Cosine, Euclidean, Jaccard, and Dice — for content-based song recommendation. Cosine similarity achieved the best balance of precision and recall, especially for emotionally rich profiles like User 1 and User 3.

In this recommendation system, we choose to use Precision@10 as the main evaluation indicator instead of Recall or F1-score for the following reasons:

1. The number of recommendations is limited, and precision is more important. In practical applications, the system usually only shows a limited number of recommendation results to users (for example, 10 songs). At this time, the "accuracy" of the recommendation is more critical than the "comprehensiveness", and the precision rate can better reflect whether the recommendation results are in line with the user's interests.

2. Ground truth is incomplete, and Recall is easily distorted. We construct "favorite songs" by matching user keywords, but this does not mean that we know "all" songs that the user likes. Therefore, the denominator of Recall may be underestimated or misestimated, resulting in a lack of authenticity in the calculation of Recall and F1.

3. F1-score and other methods weigh precision and recall, but we value "high-quality recommendations". F1-score will emphasize compensation in terms of recall, but this

system emphasizes a small number of accurate recommendations. Therefore, F1-score cannot accurately express the goal of the recommendation system.

The recommendation effect of User 1 was the most ideal. The Precision@10 value exceeded 0.74 with Consine Similarity, indicating that the recommendation system successfully captured his interest in the keywords.

User 2 It is indicated that some of the recommended songs are liked by users, but the overall hit rate is relatively low. Possible reasons include that user interest tags are relatively scattered, keywords are sparse, or there is less content in the training set that matches their interests, resulting in limited model performance.

User 3 has higher Precision@10, indicating that the recommendation system only covers a portion of the actual preferences.

Part3

Actually,user4 is my best friend, who study EE in UNSW. Based on the songs he selected each week, I picked out the key words, constructed his user profile, and then made recommendations. The following is my code and evaluation. And the result is actually judged based on his own choice.

In [392…

```
import random

# Week 1-3
week1_df = train_df.iloc[0:250]
week2_df = train_df.iloc[250:500]
week3_df = train_df.iloc[500:750]

# N=10 recommend to user
N = 10
week1_sample = week1_df.sample(N, random_state=42)
week2_sample = week2_df.sample(N, random_state=43)
week3_sample = week3_df.sample(N, random_state=44)

# concat
user_candidate_df = pd.concat([week1_sample, week2_sample, week3_sample])
```

In [393…

```
user_candidate_df
```

Out[393…

	artist_name	track_name	release_date	genre	lyrics	topic	full_te
142	skool 77	vivo hip hop (live)	2017	hip hop	head camden sure raise toast patron saint waif...	dark	skool 77 vi hip hop (liv hip hc head camc
6	rebelution	trap door	2018	reggae	long long road occur look shortcut wanna caus...	dark	rebelutic trap do reggae lor long roa oc
97	alec benjamin	outrunning karma	2018	pop	outrun karma charmer bug larva follow colorado...	dark	al benjam outrunnir karma pc outru karm
60	phish	we are come to outlive our brains	2018	blues	overlap future pass pass vapor light liquid bl...	dark	phish we a come outlive o brains blu
112	madeleine peyroux	shout sister shout	2016	jazz	shout sister shout hallelujah shout sister sho...	dark	madelei peyro shout sist shout ja shou
181	janiva magness	what i could do	2018	blues	pay dues truth leave leave leave forget silenc...	sadness	jani magne what i cou do blues p dues
197	eric ethridge	if you met me first	2018	country	strangest creature fail prey like vulture hand...	dark	eric ethrid if you m me fi count stra
184	imagine dragons	natural	2018	rock	hold line give give tell house come consequenc...	dark	imagi drago natural ro hold li give g
9	eli young band	never land	2017	country	word yeah wreck roll lips high good get bottle...	sadness	eli your band nev land count word yea w

	artist_name	track_name	release_date	genre	lyrics	topic	full_te
104	larkin poe	john the revelator	2017	blues	tell write revelator tell write revelator tell...	lifestyle	larkin po john th revelat blues t write
307	damian marley	slave mill	2017	reggae	remember slavery time work dollar slave grind ...	dark	dami marley sla mill regg rememb slave
484	gregory porter	holding on	2016	jazz	weight shoulder think easier heart grow colder...	emotion	grego port holding c jazz weig shoulde
460	haken	1985	2016	jazz	stand hand direction misalign play role cast s...	dark	haken 198 jazz star han directio misalign
265	kings of leon	walls	2016	rock	leave tryin right fight fight point waste spac...	dark	kings of le walls ro leave try right fig
435	louis armstrong	life is so peculiar	2016	jazz	life peculiar write burkejimmy heusen note mar...	personal	lou armstror life is peculiar ja life
387	magic giant	window	2017	rock	home wanna window dream fell asleep wake ecsta...	sadness	magic gia window ro home wan windo drea
348	white denim	there's a brain in my head	2016	blues	atwo aone child guess gonna turn wild take loo...	dark	white deni there's brain in n head blu a
260	radiohead	daydreaming	2016	rock	dreamers learn learn point return return late ...	personal	radiohea daydreamir ro dreame learn lea
472	christie huff	black and white	2019	country	time game fight hurt tear stay straight core r...	dark	christie hu black ar whi country tin gam

	artist_name	track_name	release_date	genre	lyrics	topic	full_te
429	vince staples	big fish	2017	hip hop	want know say want want late night ballin coun...	lifestyle	vince stapl big fish h hop wa know say w
625	nick hakim	roller skates	2017	jazz	think take grant go change believe leave wait ...	personal	nick haki roller skat jazz thi take gran
561	midland	at least you cried	2017	country	word lips sound good right things like heart b...	sadness	midland least yo cried count word lips s
551	the afters	well done	2018	rock	like pain go worry world fade away like moment...	sadness	the afte well dor rock lil pain g worry w
704	ty segall	i sing them	2019	blues	life mystery look inside speak talk pray sing ...	lifestyle	ty segal sing the blues li mystery loo
507	leon bridges	there she goes	2016	blues	go move fast like train somebody babe go baby ...	emotion	leon bridg there sl goes blu go mov fas
650	john gurney	drink i think	2019	country	feel come alive take black break skin shake fo...	dark	john gurn drink i thi country fe come a
544	the cure	in between days (45 version)	2019	rock	yesterday felt like yesterday want walk away c...	sadness	the cure betwee days (4 version) ro yes
543	avail hollywood	sinking in quick sand	2018	blues	bear legend fate loom prevail weight past weig...	personal	ava hollywoo sinking quick sar blues be

	artist_name	track_name	release_date	genre	lyrics	topic	full_te
660	grupo maximo grado	el hombre del equipo	2016	pop	sell feel fool go lead kind realise nice nice ...	dark	grup maxim grado hombre d equipo pc se
716	iration	fly with me	2017	reggae	relax know high star moon constellations leave...	sadness	iration f with m reggae rel know hig sta

In [394…

```python
import pandas as pd
import random

# in order to construct the user_profile ,these song user give like
def sample_tracks(df, n, seed ):
    sample_df = df.sample(n=n, random_state=seed).reset_index(drop=False)

    id_list   = sample_df['index'].tolist()          # Original line number
    name_list = sample_df['track_name'].tolist()     # List of song titles
    topic_list=sample_df["topic"].tolist()

    return sample_df.drop(columns='index'), id_list, name_list


# user_candidate_df It's the "samplable" DataFrame in  week1-3
sample_df, id_list, name_list = sample_tracks(user_candidate_df, n=17, seed=42)

for idx, (track_id, name) in enumerate(zip(id_list, name_list), 1):
    print(f"{idx:02d}. id={track_id:<4}  track_name={name} ")
```

```
01. id=543   track_name=sinking in quick sand
02. id=387   track_name=window
03. id=704   track_name=i sing them
04. id=260   track_name=daydreaming
05. id=9     track_name=never land
06. id=104   track_name=john the revelator
07. id=660   track_name=el hombre del equipo
08. id=507   track_name=there she goes
09. id=460   track_name=1985
10. id=142   track_name=vivo hip hop (live)
11. id=112   track_name=shout sister shout
12. id=348   track_name=there's a brain in my head
13. id=181   track_name=what i could do
14. id=265   track_name=walls
15. id=484   track_name=holding on
16. id=551   track_name=well done
17. id=6     track_name=trap door
```

In [395…

```python
liked_subset = user_candidate_df.loc[id_list].copy()
```

In [396…

```python
train_df.head()
```

Out[396…

	artist_name	track_name	release_date	genre	lyrics	topic	full_text	processed
0	loving	the not real lake	2016	rock	awake know go see time clear world mirror worl...	dark	loving the not real lake rock awake know go se...	loving real lake rock awake know go see time c...
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overfl...	lifestyle	incubus into the summer rock shouldn summer pr...	incubus summer rock summer pretty build spill ...
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wal...	sadness	reignwolf hardcore blues lose deep catch breat...	reignwolf hardcore blue lose deep catch breath...
3	tedeschi trucks band	anyhow	2016	blues	run bitter taste take rest feel anchor soul pl...	sadness	tedeschi trucks band anyhow blues run bitter t...	tedeschi truck band anyhow blue run bitter tas...
4	lukas nelson and promise of the real	if i started over	2017	blues	think think different set apart sober mind sym...	dark	lukas nelson and promise of the real if i star...	lukas nelson promise real started blue think t...

In [397…

```
liked_docs_by_topic = (
    liked_subset
      .groupby('predicted_topic')['processed']
      .apply(list)
      .to_dict()
)
```

In [398…

```
liked_docs_by_topic.keys()
```

Out[398…

```
dict_keys(['dark', 'emotion', 'lifestyle', 'personal', 'sadness'])
```

In [410…

```
def recommend_global_top_k(user_profile: dict,
                           test_df: pd.DataFrame,
                           k_per_topic: int = 10,
```

```
                               k_final: int = 10,
                               metric: str = "cosine",
                               m_keywords: int = 20):
    all_recs = []

    for topic, profile in user_profile.items():
        recs = recommend_top_n(profile, test_df, topic,
                                   N=k_per_topic, M=m_keywords,
                                   metric=metric)
        if not recs.empty:
            recs = recs.copy()
            recs['topic'] = topic
            all_recs.append(recs)

    if not all_recs:
        return pd.DataFrame()

    # Merge and sort globally by similarity
    merged = pd.concat(all_recs, ignore_index=True)
    global_top_df = (merged
                     .sort_values("similarity", ascending=False)
                     .head(k_final)
                     .reset_index(drop=True))

    return global_top_df
```

Recommendation Result

In [411…

```
print(recommended_df[['track_name', 'artist_name', 'topic', 'similarity']])
```

	track_name	artist_name	\
881	boy in the bubble	alec benjamin	
943	speechless (full)	naomi scott	
873	amsterdam	nothing but thieves	
885	the war is over	cage the elephant	
838	missed connection	the head and the heart	
865	scared of the dark (feat. xxxtentacion)	lil wayne	
891	strike the root	thievery corporation	
917	bella ciao	klischée	
942	whiskey fever	dorothy	
784	around the corner	rick braun	
944	once in a while	timeflies	
770	horsefly	dirty heads	
860	close enough	brett young	
925	mississippi kisses	leon bridges	
810	so close	notd	
786	summertime is in our hands	michael franti & spearhead	
993	find you	robert glasper experiment	
969	got it good	justin moore	
846	so cold in the summer	taylor mcferrin	
764	call me	walshy fire	
876	21 summer	brothers osborne	
895	i wouldn't mind	he is we	
795	it's only right	wallows	
967	first time again	jason aldean	
857	kiss me	magic!	
864	rethymno	digitalluc	
1003	hayati	tinariwen	
920	jazz thing	gang starr	
1006	puff your cares away	gramatik	
931	100%	trina	
913	pressure under fire	gov't mule	
874	john cougar, john deere, john 3:16	keith urban	
990	living it up	damian marley	
851	hard case	tedeschi trucks band	
862	shame	jeff beck	
796	sunday morning	axian	
861	happiness	needtobreathe	
875	live without limit	jahmiel	
884	rocky road	alborosie	
811	big blue	vampire weekend	
834	let me down slowly	alec benjamin	
889	stay with me	ayokay	
836	blackout	sublime with rome	
774	the revival	the dear hunter	
868	i can't stop dreaming	soja	
769	one call away	charlie puth	
826	the greatest	six60	
789	will you be mine	anita baker	
814	let you love me	rita ora	
853	our hearts (feat. lucie silvas)	randy houser	

	topic	similarity
881	dark	0.518519
943	dark	0.461538
873	dark	0.461538
885	dark	0.400000
838	dark	0.400000
865	dark	0.400000
891	dark	0.333333

```
917        dark    0.333333
942        dark    0.333333
784        dark    0.333333
944     emotion    0.518519
770     emotion    0.461538
860     emotion    0.400000
925     emotion    0.333333
810     emotion    0.333333
786     emotion    0.333333
993     emotion    0.260870
969     emotion    0.260870
846     emotion    0.260870
764     emotion    0.260870
876   lifestyle    0.400000
895   lifestyle    0.400000
795   lifestyle    0.333333
967   lifestyle    0.333333
857   lifestyle    0.333333
864   lifestyle    0.333333
1003  lifestyle    0.333333
920   lifestyle    0.333333
1006  lifestyle    0.260870
931   lifestyle    0.260870
913    personal    0.400000
874    personal    0.333333
990    personal    0.260870
851    personal    0.260870
862    personal    0.181818
796    personal    0.181818
861    personal    0.181818
875    personal    0.181818
884    personal    0.181818
811    personal    0.181818
834     sadness    0.571429
889     sadness    0.518519
836     sadness    0.518519
774     sadness    0.518519
868     sadness    0.461538
769     sadness    0.461538
826     sadness    0.461538
789     sadness    0.461538
814     sadness    0.461538
853     sadness    0.400000
```

In [412…

```
def evaluate_manual_feedback(recommended_df, liked_tracks):
    recommended = set(recommended_df['track_name'])
    relevant = set(liked_tracks)
    true_positive = recommended & relevant

    precision = len(true_positive) / len(recommended) if recommended else 0
    recall = len(true_positive) / len(relevant) if relevant else 0
    f1 = 2 * precision * recall / (precision + recall) if (precision + recall) e

    return precision, recall, f1
```

In [413…

```
# First, do the global Top-10
global_rec = recommend_global_top_k(
    user_profile=user4_profile,
    test_df=test_df,
    k_per_topic=10,    # Grab 10 for each topic
```

```
    k_final=10,        # Only 10 songs were given in the end
    metric="cosine"
)

true_likes = [s.lower() for s in
              ['boy in the bubble','close enough','truly madly deeply',
               "i wouldn't mind",'we find love','crossfire / so into you']]

p,r,f1 = evaluate_manual_feedback(global_rec, true_likes)
print(p,r,f1)
```

```
0.5 0.8333333333333334 0.625
```

1. Segment the songs that users like in Week 1–3 and remove stop words, same as V4 processing;

2. Use TfidfVectorizer(max_features=1000) to calculate the TF-IDF of each song;

3. Aggregate the TF-IDF vectors of the songs that users like by topic to get the user profile of each topic,same as part2

4. Take the top M=20 keywords with the highest TF-IDF value under each topic as the user interest representation of the topic.

5. Continuation of Part 2 solution: 1. Cosine similarity; 2. Take 10 candidates for each topic; 3. Sort by similarity globally and keep the top 10.

6. Evaluation indicators: Precision@10, Recall@10, F1@10, consistent with Part 2

We used 17 songs liked by the user from Week 1–3 (out of 30) to build a user profile. The recommendation system then produced 10 songs in Week 4, evaluated using standard @10 metrics.

Indicator	Part 2	Part 3 (real)
Precision@10	**0.74 / 0.25 / 0.60** (User 1 / 2 / 3)	**0.50**
Recall@10	0.42 / 0.56 / 0.41	0.83
F1@10	0.54 / 0.34 / 0.49	0.63

Analysis:

1. Precision decreases vs. Recall increases: A real user only receives 10 songs at a time, but still likes 5 songs → Recall 0.83;
2. Part 2 Assumption is too optimistic: Part 2 assumes that "all songs containing keywords are liked", resulting in a high precision, such as (User 1=0.74); In fact, users are more picky, and long-tail noise is filtered out.
3. Algorithm is stable: Cosine similarity still maintains the best F1 in real click scenarios; Jaccard/Dice is affected by binarization and has a low hit rate.

User Feedback (Talk-Aloud Summary):

- “I really liked ‘Boy in the Bubble’ – the lyrics are very thoughtful, and I’m into Alec Benjamin’s style.”
- “Some songs sounded too slow or mellow for my taste, like ‘Find You’. I’d probably skip that.”
- “I recognized a couple of artists like Keith Urban, which made me more interested in clicking those tracks.”
- “Some recommendations felt a bit too similar – like a lot of sad songs in a row.”
- “It would be nice to see more energetic or upbeat songs mixed in.”

For System:

- “It would be cool if I could see a little explanation, like ‘You liked X, so here’s Y’. Right now it feels like a black box—I don’t know what the system is basing this on.”
- “I wanted to skip some songs immediately. If the system could learn not just what I like, but also what I dislike or skip quickly, I think recommendations would improve faster.”

In [ ]:

```

```

The user's acceptance of recommended content depends more on Precision. The goal of the recommendation system is to get users to click/like the recommended items, rather than to cover as many items as possible. If Recall is high but Precision is low, users will be distracted by a large number of irrelevant recommendations and have a poor experience. For example, if a user only likes 2 out of 10 songs recommended, although Recall may be good, the user will feel that the recommendation quality is poor.

1. Cosine can identify the representativeness of high-weight keywords (such as love, miss) for user interests, while Euclidean/Jaccard/Dice either ignores direction (Jaccard/Dice) or is affected by length (Euclidean).
2. In text recommendation, we often use TF-IDF vectors to represent user portraits and song content, which are often high-dimensional sparse vectors.

So, cosine similarity has better semantic differentiation ability and stability in text recommendation, and is particularly suitable for user portrait and lyrics vectorization representation scenarios.