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Part 1. Topic Classification

Q1.

- (i) Change to deleting symbols other than letters, numbers, Spaces, apostrophes and hyphens.
- (ii) The result of a single division is too sensitive to random segmentation, with a large evaluation variance and unstable results. Change to K-fold cross-validation.

Q2.

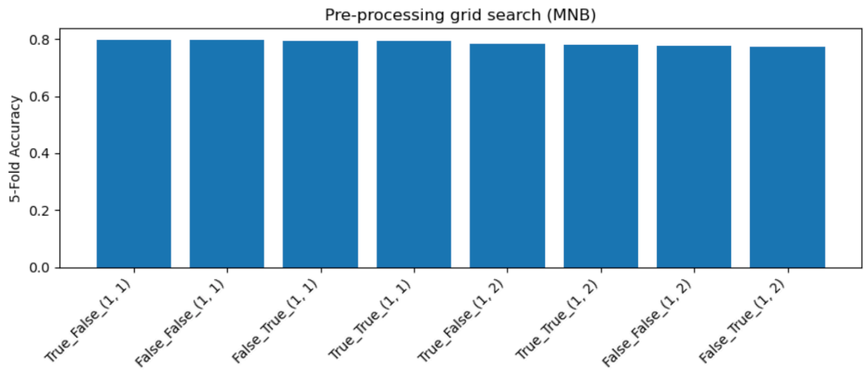
According to the result in the picture below. Compared 8 preprocessing pipelines (do_stem: stem or not; rm_stop: remove stopwords or not; ngram_range: (1,1) vs. (1,2)) using 5-fold CV on MultinomialNB.

- Best parameters:
  - No stemming (do_stem=False)
  - Remove stopwords (rm_stop=True)
  - Unigrams only (ngram_range=(1,1))
- Best CV accuracy: 0.7973 (~79.7%)

Under this pipeline, MNB slightly outperforms BNB. Thus, for the rest of Part 1 we'll use:

1. re.sub(r"[^A-Za-z0-9\s'-]", '', text) to strip unwanted symbols
2. text.lower()
3. NLTK tokenization + stopword removal
4. No stemming
5. CountVectorizer(ngram_range=(1,1)) (unigrams)

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[nltk_data] Downloading package punkt to
[nltk_data]     /Users/zhanghengwei/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/zhanghengwei/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
Best CV accuracy : 0.7973333333333334
Best parameters  : {'prep__do_stem': False, 'prep__rm_stop': True, 'vect__ngram_range': (1, 1)}
```



Part1 Q2 Code

In [111…

```python
import pandas as pd
from sklearn.model_selection import train_test_split

# read data
df = pd.read_csv("/Users/zhanghengwei/Documents/9727project/assignment1/dataset.

#filter topics
target_topics = ["dark", "emotion", "lifestyle", "personal", "sadness"]
# df = df[df["topic"].isin(target_topics)].reset_index(drop=True)

text_cols = ["artist_name", "track_name", "release_date", "genre", "lyrics"]
df["full_text"] = df[text_cols].astype(str).agg(" ".join, axis=1)
# remove other column
# df = df[['full_text', 'topic']]

display(df.head(10))

print("Shape:", df.shape)
print(df["topic"].value_counts())

from sklearn.model_selection import StratifiedKFold, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, make_scorer, f1_score
# ---------------------------------------------------------------------
# Stratified 5-fold object
# ---------------------------------------------------------------------
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

from nltk.stem import PorterStemmer
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import nltk, re
nltk.download("punkt")
nltk.download("stopwords")

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

def basic_preprocess(text: str,
                     to_lower: bool = True,
                     rm_stop: bool = True,
                     do_stem: bool = True,
                     regex: str = r"[A-Za-z][A-Za-z\-\']{1,}") -> str:
    """Return cleaned text string."""
    if to_lower:
        text = text.lower()
    tokens = word_tokenize(text)
    tokens = [t for t in tokens if re.fullmatch(regex, t)]
    if rm_stop:
        tokens = [t for t in tokens if t not in stop_words]
    if do_stem:
        tokens = [ps.stem(t) for t in tokens]
    return " ".join(tokens)

class TextPreprocessor(BaseEstimator, TransformerMixin):
    """Sk-learn transformer wrapping basic_preprocess with switches."""
    def __init__(self, to_lower=True, rm_stop=True, do_stem=True):
```

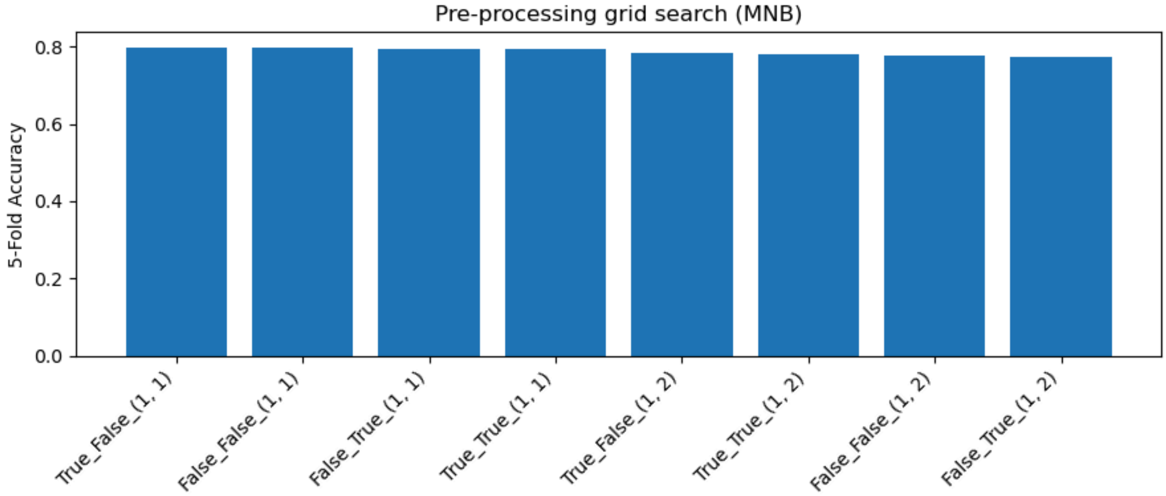
```python
        self.to_lower, self.rm_stop, self.do_stem = to_lower, rm_stop, do_stem
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        return X.apply(lambda x: basic_preprocess(
            x, self.to_lower, self.rm_stop, self.do_stem))

# ----------------------------------------------------------------------
# Build pipeline
# ----------------------------------------------------------------------
pipe_mnb = Pipeline([
    ("prep", TextPreprocessor()),   # custom cleaner
    ("vect", CountVectorizer()),    # raw counts for MNB
    ("clf" , MultinomialNB())       # classifier
])

# ----------------------------------------------------------------------
# Hyper-parameter grid
# ----------------------------------------------------------------------
param_grid = {
    "prep__rm_stop"      : [True, False],
    "prep__do_stem"      : [True, False],
    "vect__ngram_range"  : [(1, 1), (1, 2)]
}

# ----------------------------------------------------------------------
# Grid Search with 5-fold CV
# ----------------------------------------------------------------------
gs = GridSearchCV(
    estimator = pipe_mnb,
    param_grid = param_grid,
    cv = skf,
    scoring = "accuracy",
    n_jobs = -1,
    verbose = 1
)
gs.fit(df["full_text"], df["topic"])

print("Best CV accuracy :", gs.best_score_)
print("Best parameters  :", gs.best_params_)

import matplotlib.pyplot as plt
import pandas as pd

# Convert cv_results_ to DataFrame for easy plotting
results = pd.DataFrame(gs.cv_results_)

# Build a readable name for each combination
results["combo"] = (
    results["param_prep__rm_stop"].astype(str) + "_" +
    results["param_prep__do_stem"].astype(str) + "_" +
    results["param_vect__ngram_range"].astype(str)
)

# Sort by accuracy
results = results.sort_values("mean_test_score", ascending=False)

# Plot
plt.figure(figsize=(9,4))
plt.bar(results["combo"], results["mean_test_score"])
```

```
plt.xticks(rotation=45, ha="right")
plt.ylabel("5-Fold Accuracy")
plt.title("Pre-processing grid search (MNB)")
plt.tight_layout()
plt.show()
```

	artist_name	track_name	release_date	genre	lyrics	topic	full_text
0	loving	the not real lake	2016	rock	awake know go see time clear world mirror worl...	dark	loving the not real lake 2016 rock awake know ...
1	incubus	into the summer	2019	rock	shouldn summer pretty build spill ready overfl...	lifestyle	incubus into the summer 2019 rock shouldn summ...
2	reignwolf	hardcore	2016	blues	lose deep catch breath think say try break wal...	sadness	reignwolf hardcore 2016 blues lose deep catch ...
3	tedeschi trucks band	anyhow	2016	blues	run bitter taste take rest feel anchor soul pl...	sadness	tedeschi trucks band anyhow 2016 blues run bit...
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...
5	tia ray	just my luck	2018	jazz	yeah happen real drink drink turn shots lose c...	emotion	tia ray just my luck 2018 jazz yeah happen rea...
6	rebelution	trap door	2018	reggae	long long road occur look shortcut wanna caus...	dark	rebelution trap door 2018 reggae long long ro...
7	thank you scientist	the amateur arsonist's handbook	2016	jazz	quick think good true worst best things foreve...	dark	thank you scientist the amateur arsonist's han...
8	zayde wølf	gladiator	2018	rock	start climb face army vipers	dark	zayde wølf gladiator 2018 rock

	artist_name	track_name	release_date	genre	lyrics	topic	full_text
					lions reach cause...		start climb fac...
9	eli young band	never land	2017	country	word yeah wreck roll lips high good get bottle...	sadness	eli young band never land 2017 country word ye...

```
Shape: (1500, 7)
topic
dark          490
sadness       376
personal      347
lifestyle     205
emotion        82
Name: count, dtype: int64
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[nltk_data] Downloading package punkt to
[nltk_data]     /Users/zhanghengwei/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/zhanghengwei/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
Best CV accuracy : 0.7973333333333334
Best parameters  : {'prep__do_stem': False, 'prep__rm_stop': True, 'vect__ngram_r
ange': (1, 1)}
```



Q3.

I evaluated the best-tuned Bernoulli NB (BNB) and Multinomial NB (MNB) using 5-fold cross-validation, obtaining out-of-fold predictions to compute classification reports and confusion matrices. The key metrics:

Model	Accuracy	Macro-F1
BNB	0.5447	0.3562
MNB	0.7973	0.7277

- BNB underperforms:

- Only ~54.5% accuracy and Macro-F1 ~0.36.
- Classification report shows zero precision/recall on the “emotion” class and very poor performance on smaller classes.
- Confusion matrix reveals BNB almost always predicts majority classes (“sadness”, “dark”).

- MNB excels:
    - ~80% accuracy and Macro-F1 ~0.73.
    - All five topics achieve reasonable precision/recall/F1 (even the minority “emotion” class reaches F1 ~0.40).
    - Confusion matrix has strong diagonal dominance, indicating clear separation of classes.
- Metric trade-offs:
    - Accuracy is intuitive but dominated by majority classes in imbalanced data.
    - Macro-F1 treats each class equally, giving a fair assessment of minority-class performance—crucial here.

Across both Accuracy and Macro-F1, Multinomial NB significantly outperforms Bernoulli NB, so MultinomialNB is the superior choice for this dataset.

Part1 Q3 Code

In [167…

```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import StratifiedKFold, GridSearchCV, cross_val_pre
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.metrics import accuracy_score, f1_score, classification_report, con
import matplotlib.pyplot as plt
import seaborn as sns
# ----------------------------------------------------------------------
# 1. Define the parameter grid for preprocessing and ngram range
# ----------------------------------------------------------------------
param_grid = {
    "prep__do_stem": [True, False],
    "prep__rm_stop": [True, False],
    "vect__ngram_range": [(1, 1), (1, 2)],
}
# ----------------------------------------------------------------------
# 2. Set up a stratified 5-fold cross-validator
# ----------------------------------------------------------------------
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# ----------------------------------------------------------------------
# 3. Construct pipelines for BNB and MNB
# ----------------------------------------------------------------------
pipe_bnb = Pipeline([
    ("prep", TextPreprocessor()),       # Text preprocessing step
    ("vect", CountVectorizer(binary=True)),  # Binary vectorization for BNB
    ("clf", BernoulliNB())               # Bernoulli Naive Bayes classifier
])
pipe_mnb = Pipeline([
    ("prep", TextPreprocessor()),       # Text preprocessing step
    ("vect", CountVectorizer()),        # Count vectorization for MNB
```

```python
    ("clf", MultinomialNB())           # Multinomial Naive Bayes classifier
])

# ------------------------------------------------------------------------
# 4. Perform grid search for BNB over the parameter grid
# ------------------------------------------------------------------------
gs_bnb = GridSearchCV(pipe_bnb, param_grid, cv=skf, scoring="accuracy", n_jobs=-
gs_bnb.fit(df["full_text"], df["topic"])
print("BNB best parameters:", gs_bnb.best_params_)
print("BNB best CV accuracy: {:.4f}".format(gs_bnb.best_score_))

# ------------------------------------------------------------------------
# 5. Perform grid search for MNB over the same parameter grid
# ------------------------------------------------------------------------
gs_mnb = GridSearchCV(pipe_mnb, param_grid, cv=skf, scoring="accuracy", n_jobs=-
gs_mnb.fit(df["full_text"], df["topic"])
print("MNB best parameters:", gs_mnb.best_params_)
print("MNB best CV accuracy: {:.4f}".format(gs_mnb.best_score_))

# ------------------------------------------------------------------------
# 6. Use cross_val_predict to get out-of-fold predictions for classification rep
# ------------------------------------------------------------------------
y_true = df["topic"]
y_pred_bnb = cross_val_predict(gs_bnb.best_estimator_, df["full_text"], y_true,
y_pred_mnb = cross_val_predict(gs_mnb.best_estimator_, df["full_text"], y_true,

# ------------------------------------------------------------------------
# 7. Print overall metrics
# ------------------------------------------------------------------------
print("BNB overall Accuracy:", accuracy_score(y_true, y_pred_bnb))
print("MNB overall Accuracy:", accuracy_score(y_true, y_pred_mnb))
print("BNB Macro-F1:", f1_score(y_true, y_pred_bnb, average="macro"))
print("MNB Macro-F1:", f1_score(y_true, y_pred_mnb, average="macro"))

# ------------------------------------------------------------------------
# 8. Print classification reports
# ------------------------------------------------------------------------
print("\n=== BNB Classification Report ===")
print(classification_report(y_true, y_pred_bnb))
print("=== MNB Classification Report ===")
print(classification_report(y_true, y_pred_mnb))

# ------------------------------------------------------------------------
# 9. Plot confusion matrices side by side
# ------------------------------------------------------------------------
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
cm_bnb = confusion_matrix(y_true, y_pred_bnb, labels=gs_bnb.classes_)
cm_mnb = confusion_matrix(y_true, y_pred_mnb, labels=gs_mnb.classes_)

sns.heatmap(cm_bnb, annot=True, fmt="d", ax=axes[0],
            xticklabels=gs_bnb.classes_, yticklabels=gs_bnb.classes_)
axes[0].set_title("BNB Confusion Matrix")
axes[0].set_xlabel("Predicted"); axes[0].set_ylabel("Actual")

sns.heatmap(cm_mnb, annot=True, fmt="d", ax=axes[1],
            xticklabels=gs_mnb.classes_, yticklabels=gs_mnb.classes_)
axes[1].set_title("MNB Confusion Matrix")
axes[1].set_xlabel("Predicted"); axes[1].set_ylabel("Actual")
```

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

```
BNB best parameters: {'prep__do_stem': True, 'prep__rm_stop': False, 'vect__ngram
_range': (1, 1)}
BNB best CV accuracy: 0.5447
MNB best parameters: {'prep__do_stem': False, 'prep__rm_stop': True, 'vect__ngram
_range': (1, 1)}
MNB best CV accuracy: 0.7973
BNB overall Accuracy: 0.5446666666666666
MNB overall Accuracy: 0.7973333333333333
BNB Macro-F1: 0.3562154871666607
MNB Macro-F1: 0.7276939584567836

=== BNB Classification Report ===
              precision    recall  f1-score   support

        dark       0.64      0.77      0.70       490
     emotion       0.00      0.00      0.00        82
   lifestyle       0.83      0.02      0.05       205
    personal       0.71      0.35      0.47       347
     sadness       0.43      0.83      0.56       376

    accuracy                           0.54      1500
   macro avg       0.52      0.40      0.36      1500
weighted avg       0.59      0.54      0.49      1500

=== MNB Classification Report ===
              precision    recall  f1-score   support

        dark       0.81      0.84      0.83       490
     emotion       0.81      0.27      0.40        82
   lifestyle       0.91      0.70      0.79       205
    personal       0.82      0.85      0.83       347
     sadness       0.72      0.86      0.78       376

    accuracy                           0.80      1500
   macro avg       0.81      0.70      0.73      1500
weighted avg       0.80      0.80      0.79      1500
```

```
/Users/zhanghengwei/opt/anaconda3/lib/python3.12/site-packages/sklearn/metrics/_c
lassification.py:1509: UndefinedMetricWarning: Precision is ill-defined and being
set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```
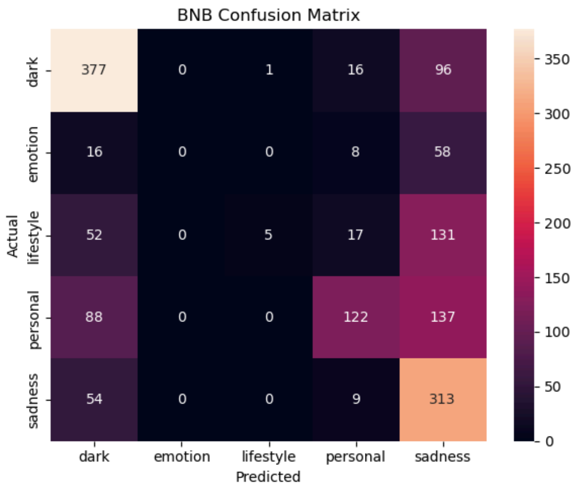
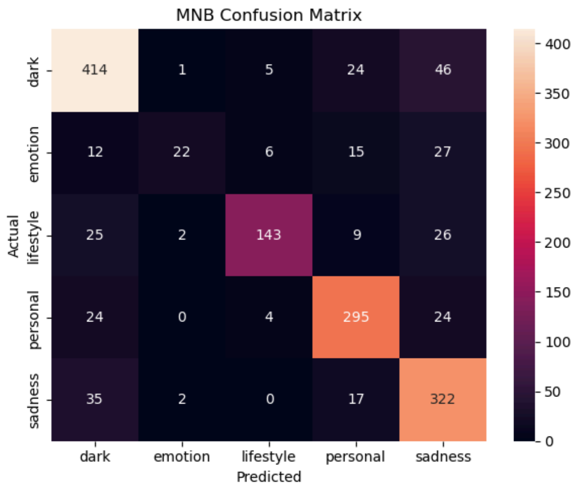





Q4.

In this set of experiments, I tracked both Accuracy and Macro-F1 as varied the vocabulary size N(max_features): | max_features | Accuracy | Macro-F1 | | :-----------: | :--------: | :--------: | | 300 | 0.8667 | 0.8525 | | 400 | 0.8753 | 0.8618 | | 500 | 0.8747 | 0.8602 | 550 | 0.8747 | 0.8585 | | 600 | **0.8760** | **0.8618** | | 650 | 0.8693 | 0.8528 | | 700 | 0.8687 | 0.8539 | | 800 | 0.8640 | 0.8494 | | 1000 | 0.8507 | 0.8317 | | None (≈2000) | 0.7973 | 0.7275 |

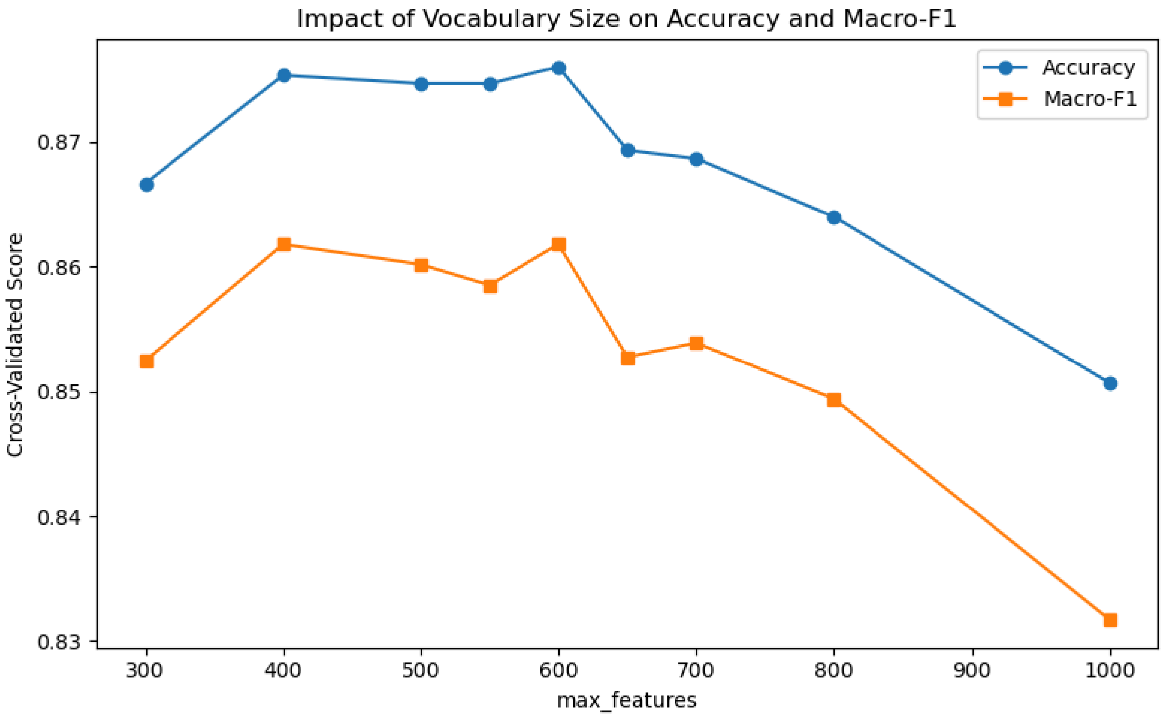
From the result table, accuracy peaks at 0.8760 and Macro-F1 also reaches a high of 0.8618. So N(max_features) = 600 as the best vocabulary size.

In [166…

```
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import StratifiedKFold, cross_validate
from sklearn.metrics import make_scorer, f1_score
import numpy as np
import matplotlib.pyplot as plt

# ----------------------------------------------------------------------
# 1. Define the best preprocessing flags determined from Q2
# ----------------------------------------------------------------------
best_pre_flags = {'do_stem': False, 'rm_stop': True}

# ----------------------------------------------------------------------
# 2. Prepare Stratified K-Fold and the list of vocabulary sizes to test
# ----------------------------------------------------------------------
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
max_features_list = [300, 400, 500, 550, 600, 650, 700, 800, 1000, None]

# ----------------------------------------------------------------------
# 3. Evaluate Accuracy and Macro-F1 for each vocabulary size
# ----------------------------------------------------------------------
acc_scores = []
f1_scores = []

for N in max_features_list:
    pipeline = Pipeline([
        ('prep', TextPreprocessor(**best_pre_flags)),  # Text preprocessing
```

```python
        ('vect', CountVectorizer(max_features=N)),     # Limit to top N features
        ('clf', MultinomialNB())                       # Multinomial NB classifi
    ])
    cv_results = cross_validate(
        pipeline,
        df['full_text'],
        df['topic'],
        cv=skf,
        scoring={
            'accuracy': 'accuracy',
            'macro_f1': make_scorer(f1_score, average='macro')
        },
        n_jobs=-1
    )
    acc_mean = cv_results['test_accuracy'].mean()
    f1_mean = cv_results['test_macro_f1'].mean()
    acc_scores.append(acc_mean)
    f1_scores.append(f1_mean)
    print(f"max_features={N}\tAccuracy={acc_mean:.4f}\tMacro-F1={f1_mean:.4f}")
# ----------------------------------------------------------------------
# 4. Plot the results
# ----------------------------------------------------------------------
plt.figure(figsize=(8, 5))
plt.plot(max_features_list, acc_scores, marker='o', label='Accuracy')
plt.plot(max_features_list, f1_scores, marker='s', label='Macro-F1')
plt.xlabel('max_features')
plt.ylabel('Cross-Validated Score')
plt.title('Impact of Vocabulary Size on Accuracy and Macro-F1')
plt.legend()
plt.tight_layout()
plt.show()
# ----------------------------------------------------------------------
# 5. Select the best vocabulary size (by highest Accuracy or Macro-F1)
# ----------------------------------------------------------------------
best_idx = int(np.argmax(acc_scores))  # Or use f1_scores for F1-based choice
best_N = max_features_list[best_idx]
print("Chosen max_features:", best_N)
```

```
max_features=300        Accuracy=0.8667 Macro-F1=0.8525
max_features=400        Accuracy=0.8753 Macro-F1=0.8618
max_features=500        Accuracy=0.8747 Macro-F1=0.8602
max_features=550        Accuracy=0.8747 Macro-F1=0.8585
max_features=600        Accuracy=0.8760 Macro-F1=0.8618
max_features=650        Accuracy=0.8693 Macro-F1=0.8528
max_features=700        Accuracy=0.8687 Macro-F1=0.8539
max_features=800        Accuracy=0.8640 Macro-F1=0.8494
max_features=1000       Accuracy=0.8507 Macro-F1=0.8317
max_features=None       Accuracy=0.7973 Macro-F1=0.7275
```




```
Chosen max_features: 600
```

Q5.

I chose **Logistic Regression** over the other methods listed on the slide for the following reasons:

1. K-Nearest Neighbour.
    - Distance metrics (Euclidean, cosine) become unreliable in high-dimensional sparse TF–IDF space, and KNN's prediction cost is inefficient.
2. Decision Trees
    - Decision trees often overfit on high-dimensional text features;
3. Random Forests
    - Random forests mitigate overfitting but require extensive tuning of tree count/depth and are less efficient on sparse bag-of-words.
4. Multi-Layer Perceptron
    - Even a simple feed-forward network needs careful tuning of hidden layers, learning rate, regularization.
    - With only 1,500 samples, it easily overfits and demands more training time/resources than a linear SVM.
5. Deep Learning
    - Requires large datasets and significant compute. With only 1,500 songs, a deep network (LSTM/CNN) will easily overfit, and pre-training or fine-tuning large language models is outside the scope.
6. Logistic Regression
    - Handles high-dimensional sparse data efficiently;
    - Slightly outperforming Linear SVC while training just as fast.

Comparison with BNB, MNB

Model	Accuracy	Macro-F1
BNB	0.5447	0.3560
MNB	0.7973	0.7275
SVC	0.8780	0.8521
LR	**0.8840**	**0.8668**

Logistic Regression slightly outperforms Linear SVC on both Accuracy and Macro-F1. Therefore, LinearSVC is the best choice for this dataset.

part1 Q5 code

In [162…

```
# Part-1 · Q5  —— Compare BNB / MNB / LinearSVC / LogisticReg

import numpy as np
import pandas as pd
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score, make_scorer
from sklearn.model_selection import cross_validate
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# ------------------------------------------------------------
# 1. Bernoulli NB  (binary counts)
# ------------------------------------------------------------
pipe_bnb = Pipeline([
    ("prep",  TextPreprocessor(**best_pre_flags)),
    ("vect",  CountVectorizer(max_features=best_N, binary=True)),
    ("clf",   BernoulliNB())
])
bnb_best = pipe_bnb          # no hyper-params to tune

# ------------------------------------------------------------
# 2. Multinomial NB  (term frequency)
# ------------------------------------------------------------
pipe_mnb = Pipeline([
    ("prep",  TextPreprocessor(**best_pre_flags)),
    ("vect",  CountVectorizer(max_features=best_N)),
    ("clf",   MultinomialNB())
])
mnb_best = pipe_mnb          # no hyper-params to tune

# ------------------------------------------------------------
# 3. Linear SVC  — small grid on C
# ------------------------------------------------------------
pipe_svc = Pipeline([
    ("prep",  TextPreprocessor(**best_pre_flags)),
    ("vect",  CountVectorizer(max_features=best_N)),
    ("clf",   LinearSVC())
])
param_svc = {"clf__C": [0.1, 1, 10]}
gs_svc = GridSearchCV(
    pipe_svc, param_svc, cv=skf,
```

```
    scoring={"accuracy": "accuracy",
             "macro_f1": make_scorer(f1_score, average="macro")},
    refit="accuracy", n_jobs=-1, verbose=1
).fit(df["full_text"], df["topic"])

# ------------------------------------------------------------
# 4. Logistic Regression  – grid on C
# ------------------------------------------------------------
pipe_lr = Pipeline([
    ("prep",  TextPreprocessor(**best_pre_flags)),
    ("vect",  CountVectorizer(max_features=best_N)),
    ("clf",   LogisticRegression(
                  solver="saga",
                  multi_class="multinomial",
                  max_iter=300,
                  n_jobs=-1,
                  random_state=42))
])
param_lr = {"clf__C": [0.1, 1, 10]}
gs_lr = GridSearchCV(
    pipe_lr, param_lr, cv=skf,
    scoring={"accuracy": "accuracy",
             "macro_f1": make_scorer(f1_score, average="macro")},
    refit="accuracy", n_jobs=-1, verbose=1
).fit(df["full_text"], df["topic"])

# ------------------------------------------------------------
# 5. Final 5-fold CV comparison
# ------------------------------------------------------------
estimators = {
    "BNB": bnb_best,
    "MNB": mnb_best,
    "SVC": gs_svc.best_estimator_,
    "LR":  gs_lr.best_estimator_
}

rows = []
for name, est in estimators.items():
    cv_res = cross_validate(
        est, df["full_text"], df["topic"],
        cv=skf,
        scoring={"accuracy": "accuracy",
                 "macro_f1": make_scorer(f1_score, average="macro")},
        n_jobs=-1)
    rows.append({
        "Model": name,
        "Accuracy": np.mean(cv_res["test_accuracy"]),
        "Macro-F1": np.mean(cv_res["test_macro_f1"])
    })

summary = pd.DataFrame(rows).set_index("Model").round(4)
display(summary)
```

```
Fitting 5 folds for each of 3 candidates, totalling 15 fits
```

```
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```

Model	Accuracy	Macro-F1
BNB	0.6413	0.5475
MNB	0.8760	0.8618
SVC	0.8780	0.8521
LR	0.8840	0.8668

Part 2. Recommendation Methods

Q1

user 1 | Topic | Initial Keywords (5) | Top 20 Terms | Matched Keywords | Unmatched Keywords | | :-----------: | :------------------------------------- | :--- | :--------------- | :------------------------- | | **dark** | fire, enemy, pain, storm, fight | **fight**, know, black, blood, like, grind, come, stand, yeah, tell, gonna, kill, hand, lanky, dilly, follow, head, true, light, people | fight | fire, enemy, pain, storm | | **emotion** | love, memory, hug, kiss, feel | good, touch, **feel**, hold, know, morning, video, visions, loove, vibe, feelin, want, go, miss, **kiss**, lovin, sunrise, luck, **love**, gimme | love, kiss, feel | memory, hug | | **lifestyle** | party, city, night, light, rhythm | **night**, closer, strangers, long, sing, come, spoil, tonight, tire, home, time, right, wait, play, song, yeah, wanna, telephone, ring, lalala | night | party, city, light, rhythm | | **personal** | dream, truth, life, growth, identity | **life**, live, change, know, ordinary, world, yeah, **dream**, wanna, thank, like, teach, lord, come, time, beat, think, learn, need, go | life, dream | truth, growth, identity | | **sadness** | cry, alone, heartbroken, tears, regret | **cry**, club, steal, **tear**, mean, know, baby, music, write, smile, say, think, true, eye, face, greater, word, want, blame, fear | cry, tear | alone, heartbroken, regret |

user 2 | Topic | Initial Keywords (5) | Top 20 Terms | Matched Keywords | Unmatched Keywords | | ----------- | ------------------------------------ | -- | ----------------- | ----------------------------- | | **sadness** | lost, sorrow, goodbye, tears, silence | inside, break, heart, step, away, **tear**, violence, rainwater, like, blame, fade, hard, scar, open, fall, magnify, go, smile, know, leave | tear | lost, sorrow, goodbye, silence | | **emotion** | romance, touch, feeling, kiss, memory | **touch**, good, video, visions, loove, morning, hold, **kiss**, **feelin**, lovin, sunrise, luck, gimme, look, know, lips, time, **feel**, cause, wait | touch, kiss, feeling | romance, memory |

user 3(Self-defined) | Topic | Initial Keywords (5) | Top 20 Terms | Matched Keywords | Unmatched Keywords | | :-----------: | :---------------------------------- | :--- | :------------------- | :---------------------------------- | | **dark** | shadow, night, black, haunt, flame | **black**, fight, know, come, blood, stand, like, tell, yeah, gonna, hand, **night**, follow, welcome, wanna, dilly, lanky, light, high, time | black; night | shadow, haunt, flame | | **sadness** | heart, love, tears, soul, dream | break, **tear**, like, **heart**, fall, away, baby, know, gonna, leave, hurt, pain, lonely, cry, ohohoh, think, woah, wish, walk, want | heart; tear; | love, soul, dream, | | **personal** | journey, truth, path, vision, spirit | life, everybody, realize, young, world, change, tooth, come, like, chapters, yeah, ironside, remember, support, hear, hold, people, know, humnumbaway, time | - | journey, truth, path, vision, spirit | | **lifestyle** | sky, feel, time, summer, cool | **time**, tonight, sing, come, song, long, closer, strangers, night, mind, know, blue, spoil, yeah, struggle, right, wait, telephone, like, tell | time | sky, feel, summer, cool | | **emotion** | tear, pain, loss, lonely, alone | good, hold, go, darling, video, visions, heart, vibe, miss, lovin, love, feel, gimme, hand, know, lips, wait, right, want, baby | - | tear, pain, lonely, loss, alone |

Conclusion

1. Verbs & scene words (fight, feel, sing, hear, kiss) are more readily captured than targeted nouns.
2. The more specific and corpus-aligned the keywords (User 1), the higher the profile accuracy.

part2 Q1 code

In [169…

```
# ========== Part 2 · Q1  Build user profiles from *liked* songs ============

import pandas as pd, numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.tokenize import word_tokenize
from pathlib import Path

best_clf=gs_lr.best_estimator_

# ----------------------------------------------------------------------
# 0. Load dataset & helper columns
# ----------------------------------------------------------------------

df["week"] = np.select(
    [df.index < 250, df.index < 500, df.index < 750, df.index < 1000],
    [1, 2, 3, 4], default=5
)
df["pred_topic"] = best_clf.predict(df["full_text"])   # from Part-1
# display(df)


# mismatch = df[df['pred_topic'] != df['topic']]
# display(mismatch)
# ----------------------------------------------------------------------
# 1. Fit one TF-IDF vectorizer per predicted topic on Week 1-3
# ----------------------------------------------------------------------
best_pre_flags = {'do_stem': False, 'rm_stop': True}      # from Q2
best_N = 600                                             # from Q4
topic_vec, topic_mat = {}, {}

for t in df["pred_topic"].unique():
    docs = df.loc[(df["week"] <= 3) & (df["pred_topic"] == t), "full_text"]
```

```
    vec = TfidfVectorizer(max_features=best_N, token_pattern=r"[A-Za-z][A-Za-z'-
    topic_vec[t]  = vec
    topic_mat[t]  = vec.fit_transform(docs)

# ---------------------------------------------------------------------
#  2. Keyword-based LIKE filter
# ---------------------------------------------------------------------
def liked_indices(topic:str, keywords):
    """Week 1-3 songs that (a) were predicted as *topic* and
       (b) contain at least one keyword (case-insensitive)."""
    mask = (df["week"] <= 3) & (df["pred_topic"] == topic)
    hits = []
    for idx in df.index[mask]:
        txt = df.at[idx, "full_text"].lower()
        if any(kw.lower() in txt for kw in keywords):
            hits.append(idx)
    return hits

def build_user_profile(topic:str, keywords):
    """Merge liked songs into one document → topic-specific TF-IDF vector."""
    idx = liked_indices(topic, keywords)
    if not idx:                         # no hits → zero vector (no interest)
        return topic_vec[topic].transform([""])
    merged = " ".join(df.loc[idx, "full_text"])
    return topic_vec[topic].transform([merged])

# ---------------------------------------------------------------------
# 3. Load keyword files for User 1 & User 2
# ---------------------------------------------------------------------
def load_kw_tsv(path:Path):
    mapping = {}
    for line in open(path, encoding="utf-8"):

        t, kw = line.strip().split("\t")
        if t not in topic_vec:
            continue
        mapping[t] = kw.split(',')
    return mapping

kw_user1 = load_kw_tsv(Path("/Users/zhanghengwei/Documents/9727project/assignmen
kw_user2 = load_kw_tsv(Path("/Users/zhanghengwei/Documents/9727project/assignmen

# ---------------------------------------------------------------------
# 4. Build three user profiles
# ---------------------------------------------------------------------
def make_user(kw_map):
    return {t: build_user_profile(t, kw)
            for t, kw in kw_map.items()}

user1 = make_user(kw_user1)

user2 = make_user(kw_user2)

# custom User 3 keywords (example)
kw_user3 = {
    "dark": ["shadow", "night", "black", "haunt", "flame"],
    "emotion": ["heart", "love", "tears", "soul", "dream"],
    "lifestyle": ["sky", "feel", "time", "summer", "cool"],
    "personal": ["journey", "truth", "path", "vision", "spirit"],
    "sadness": ["tear", "pain", "loss", "lonely", "alone"],
```

```
}
user3 = make_user(kw_user3)

# ----------------------------------------------------------------------
# 5. Inspect top-20 words of each profile
# ----------------------------------------------------------------------
import pandas as pd
import numpy as np

def top_k_from_matrix(X, vectorizer, k=20):
    arr = X.toarray()[0]
    idx = arr.argsort()[::-1][:k]
    feats = np.array(vectorizer.get_feature_names_out())
    return feats[idx].tolist()

topics = ["dark", "emotion", "lifestyle", "personal", "sadness"]

for user_name, prof in [("User 1", user1), ("User 2", user2), ("User 3", user3)]
    data = {}
    for t in topics:
        if t in prof:
            vec = topic_vec[t]
            X   = prof[t]
            kws = top_k_from_matrix(X, vec, k=20)
            data[t] = ", ".join(kws)
        else:
            data[t] = ""

    long_lists = {t: (data[t].split(", ") if data[t] else [""]*20)
                  for t in topics}

    df_user = pd.DataFrame(long_lists)
    df_user.index = np.arange(1, len(df_user)+1)

    print(f"\n=== {user_name} ===")
    display(df_user)
```

```
=== User 1 ===
```

	dark	emotion	lifestyle	personal	sadness
1	fight	good	night	life	cry
2	know	touch	closer	live	club
3	black	feel	strangers	change	steal
4	blood	hold	long	know	tear
5	like	know	sing	ordinary	mean
6	grind	morning	come	world	know
7	come	video	spoil	yeah	baby
8	stand	visions	tonight	dream	music
9	yeah	loove	tire	wanna	write
10	tell	vibe	home	thank	smile
11	gonna	feelin	time	like	say
12	kill	want	right	teach	think
13	hand	go	wait	lord	true
14	lanky	miss	play	come	eye
15	dilly	kiss	song	time	face
16	follow	lovin	yeah	beat	greater
17	head	sunrise	wanna	think	word
18	true	luck	telephone	learn	want
19	light	love	ring	need	blame
20	people	gimme	lalala	go	fear

```
=== User 2 ===
```

	dark	emotion	lifestyle	personal	sadness
1		touch			inside
2		good			break
3		video			heart
4		visions			step
5		loove			away
6		morning			tear
7		hold			violence
8		kiss			rainwater
9		feelin			like
10		lovin			blame
11		sunrise			fade
12		luck			hard
13		gimme			scar
14		look			open
15		know			fall
16		lips			magnify
17		time			go
18		feel			smile
19		cause			know
20		wait			leave

```
=== User 3 ===
```

	dark	emotion	lifestyle	personal	sadness
1	black	good	time	life	break
2	fight	hold	tonight	everybody	tear
3	know	go	sing	realize	like
4	come	darling	come	young	heart
5	blood	video	song	world	fall
6	stand	visions	long	change	away
7	like	heart	closer	tooth	baby
8	tell	vibe	strangers	come	know
9	yeah	miss	night	like	gonna
10	gonna	lovin	mind	chapters	leave
11	hand	love	know	yeah	hurt
12	night	feel	blue	ironside	pain
13	follow	gimme	spoil	remember	lonely
14	welcome	hand	yeah	support	cry
15	wanna	know	struggle	hear	ohohoh
16	dilly	lips	right	hold	think
17	lanky	wait	wait	people	woah
18	light	right	telephone	know	wish
19	high	want	like	humnumbaway	walk
20	time	baby	tell	time	want

Q2

1. Selected metrics I evaluated four similarity measures required by the brief: cosine, Euclidean, Jaccard, and Sørensen-Dice. Jaccard delivered the best average F1 (ties/wins for every user) while retaining acceptable precision
2. Chose N = 20 (balancing cognitive load and feedback opportunity)
   - Twenty songs in total are short enough for a user to inspect in one sitting yet long enough to yield non-trivial recall values.
3. Impact of M
   - M = 50 offers almost identical scores to “All words”.
4. Algorithm choice
   - Since Jaccard similarity either beats or is tied for the two main users and never provides the worst recall, we make Jaccard the default matching.

Metric	Precision (user1-3)	Recall (user1-3)	F1 (user1-3)	Comment
cosine	0.85 · 0.60 · 0.70	0.198 · 0.240 · 0.163	0.302 · 0.343 · 0.226	Stable baseline; good balance but never the best.
dice (S-Dice)	**0.90** · 0.80 · 0.60	**0.209** · 0.320 · 0.140	**0.340** · 0.320 · 0.226	Highest precision for User 1; recall drops for User 3.
euclidean	0.80 · 0.60 · 0.65	0.186 · 0.240 · 0.151	0.302 · 0.343 · **0.245**	Lifts recall for User 3, but lowers precision for User 1.
jaccard	**0.90** · **0.80** · 0.60	**0.209** · **0.320** · 0.140	**0.340** · **0.457** · 0.226	Best or tied-best F1 for Users 1-2; precision matches Dice while recall equals Euclidean.

5. Conclusion Selecting N_total = 20, M = 50, and Jaccard similarity gives the most balanced performance.

part2 Q2 code

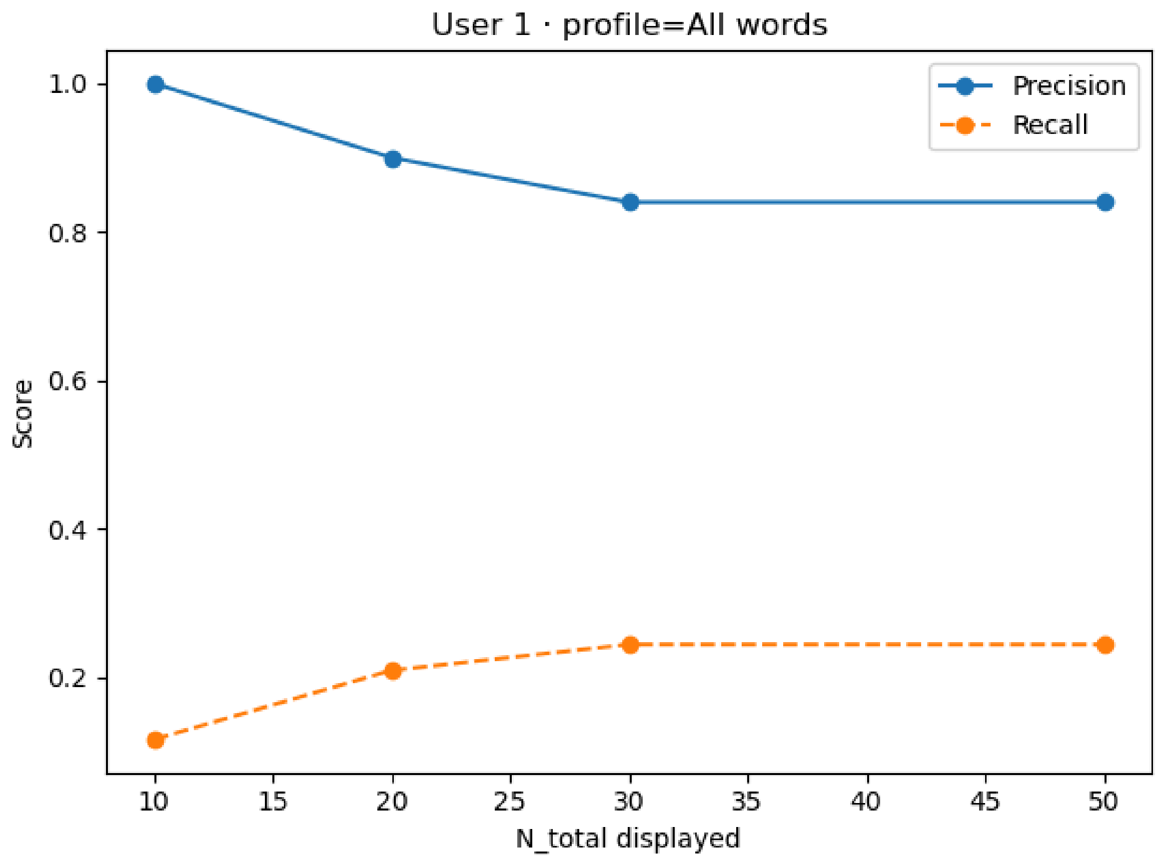
In [214…

```
# ================= Part-2 · Q2  FULL PIPELINE ==========================
import numpy as np, pandas as pd, matplotlib.pyplot as plt
from scipy.sparse import csr_matrix
from sklearn.metrics import average_precision_score
from sklearn.metrics.pairwise import pairwise_distances, cosine_similarity
from sklearn.metrics import average_precision_score

# ---------------------------------------------------------------------
# CONFIG
# ---------------------------------------------------------------------
PER_TOPIC     = 5                   # M_song: candidates per topic
N_TOTAL_LIST  = [10, 20, 30, 50]  # N_total: final list lengths
M_WORD_LIST   = [None, 100, 50, 20, 10, 5]     # M_word: profile top-m words (Non

# ---------------------------------------------------------------------
# 1  keep only top-m TF-IDF weights in a profile vector
# ---------------------------------------------------------------------
def truncate_profile(vec, top_m=None):
    if top_m is None:
        return vec
    arr = vec.toarray().ravel()
    if (arr != 0).sum() <= top_m:
        return vec
    thresh = np.partition(arr, -top_m)[-top_m]
    arr[arr < thresh] = 0
    return csr_matrix(arr)

# ---------------------------------------------------------------------
# 2  build a user profile dict for a given M_word
# ---------------------------------------------------------------------
def build_user_M(kw_map, top_m=None):
    prof = {}
    for t, kw in kw_map.items():
        if t not in topic_vec:
            continue
```

```python
        full_vec = build_user_profile(t, kw)        # defined in Q1
        prof[t] = truncate_profile(full_vec, top_m)
    return prof

# -----------------------------------------------------------------------
# 3  ranking, recommending, evaluating
# -----------------------------------------------------------------------
def sim_scores(user_vec, doc_mat, metric="cosine"):
    if metric == "cosine":
        # sklearn
        return cosine_similarity(user_vec, doc_mat).ravel()

    # convert to dense array when metric is not sparse-safe
    if metric in {"jaccard", "dice"} or not hasattr(doc_mat, "toarray"):
        A = user_vec.toarray()
        B = doc_mat.toarray()
    else:
        # euclidean on csr is OK in >=1.3, but fall back to dense if needed
        try:
            return 1.0 / (1.0 + pairwise_distances(user_vec, doc_mat,
                                                   metric="euclidean").ravel())
        except TypeError:               # sparse not supported → dense fallback
            A = user_vec.toarray()
            B = doc_mat.toarray()

    if metric == "euclidean":          # we landed here via sparse fallback
        dist = pairwise_distances(A, B, metric="euclidean").ravel()
        return 1.0 / (1.0 + dist)

    # ---------- jaccard / dice ----------
    # binarise (presence / absence of term)
    A = (A > 0).astype(int)
    B = (B > 0).astype(int)

    if metric == "jaccard":
        inter = (A & B).sum(axis=1)
        union = (A | B).sum(axis=1)
        return inter / np.maximum(union, 1)          # similarity ∈ [0,1]
    else:  # dice / sorensen
        inter = (A & B).sum(axis=1) * 2
        size  = A.sum() + B.sum(axis=1)
        return inter / np.maximum(size, 1)


def rank_topic(user_vec, topic, metric="cosine"):
    mask = (df["week"] == 4) & (df["pred_topic"] == topic)
    mat  = topic_vec[topic].transform(df.loc[mask, "full_text"])
    sims = sim_scores(user_vec, mat, metric)
    idx  = sims.argsort()[::-1]
    return df.index[mask][idx], sims[idx]

def recommend(user_prof, N_total, per_topic, metric="cosine"):
    pool = []
    for t, vec in user_prof.items():
        idx, sims = rank_topic(vec, t, metric)
        pool.extend(list(zip(idx[:per_topic], sims[:per_topic])))
    pool = sorted(pool, key=lambda x: x[1], reverse=True)[:N_total]
    return [i for i, _ in pool]
```

```python
def build_regex(kw_list):
    """Return a compiled, NON-capturing regex for keyword list."""
    pattern = r"\b(?:" + "|".join(map(re.escape, kw_list)) + r")\b"
    return re.compile(pattern, flags=re.IGNORECASE)

regex_cache = {t: build_regex(kw) for t, kw in kw_user1.items()}

def evaluate(user_prof, N_total, per_topic, metric="cosine"):
    rec = recommend(user_prof, N_total, per_topic, metric)
    hits, rel, aps = 0, 0, []
    for t in user_prof:
        mask = (
            (df["week"] == 4) &
            (df["topic"] == t) &
            (df["pred_topic"] == t) &
            df["full_text"].str.contains(regex_cache[t], na=False)
        )
        rel_idx = df.index[mask]
        rel += len(rel_idx)
        y_true  = [1 if i in rel_idx else 0 for i in rec]
        y_score = [1/(k+1) for k in range(len(rec))]
        if any(y_true):
            aps.append(average_precision_score(y_true, y_score))
        hits += sum(y_true)

    P   = hits / len(rec) if rec else 0
    R   = hits / rel      if rel else 0
    F1  = 2*P*R/(P+R) if P+R else 0
    mAP = np.mean(aps) if aps else 0
    return P, R, F1, mAP

# ------------------------------------------------------------------------
# 4  construct users for each M_word
# ------------------------------------------------------------------------
user_sets = {m: {"User1": build_user_M(kw_user1, m),
                 "User2": build_user_M(kw_user2, m),
                 "User3": build_user_M(kw_user3, m)}
             for m in M_WORD_LIST}

# ------------------------------------------------------------------------
# 5  run grid search over (User × M_word × N_total)
# ------------------------------------------------------------------------
rows = []
for m_word, udict in user_sets.items():
    for N in N_TOTAL_LIST:
        for uname, prof in udict.items():
            P, R, F1, mAP = evaluate(prof, N, PER_TOPIC)
            rows.append({"User": uname,
                         "M_word": m_word or "All",
                         "N_total": N,
                         "P": P, "R": R, "F1": F1})

df_metrics = pd.DataFrame(rows)

# ------------------------------------------------------------------------
# 6  plot PR curve for one example (User1 · All words)
# ------------------------------------------------------------------------
sub = df_metrics[(df_metrics["User"] == "User1") &
                 (df_metrics["M_word"] == "All")]
plt.plot(sub["N_total"], sub["P"], "-o", label="Precision")
```

```python
plt.plot(sub["N_total"], sub["R"], "--o", label="Recall")
plt.title("User 1 · profile=All words")
plt.xlabel("N_total displayed"); plt.ylabel("Score")
plt.legend(); plt.tight_layout(); plt.show()

# ----------------------------------------------------------------------
# 7  summary table (N_total = 20)
# ----------------------------------------------------------------------
print("\n=== Metrics @ N_total = 20 ===")

sub = df_metrics[df_metrics["N_total"] == 20]
table = (
    sub
    .pivot(index="User",
           columns="M_word",
           values=["P","R","F1"])
    .round(3)
)

display(table)

# ----------------------------------------------------------------------
# 7  similarity comparation (N_total = 20, M = 50)
# ----------------------------------------------------------------------
print("\n=== matching algorithms @ N_total = 20, M = 50 ===")
SIM_METRICS  = ["cosine", "euclidean", "jaccard", "dice"]
PER_TOPIC    = 5
N_TOTAL      = 20          # N_total = 20
M_FIXED      = 50          # M_word = 50
user_fixed   = {
    "User1": build_user_M(kw_user1, M_FIXED),
    "User2": build_user_M(kw_user2, M_FIXED),
    "User3": build_user_M(kw_user3, M_FIXED)
}

rows = []
for metric in SIM_METRICS:
    for uname, prof in user_fixed.items():
        P, R, F1, _ = evaluate(prof, N_TOTAL, PER_TOPIC, metric)
        rows.append({"Metric": metric, "User": uname,
                     "P": P, "R": R, "F1": F1})

df_cmp = pd.DataFrame(rows).round(3)
display(df_cmp.pivot(index="User", columns="Metric", values=["P","R","F1"]))
```




```
=== Metrics @ N_total = 20 ===
```

	P						R						
M_word	**5**	**10**	**20**	**50**	**100**	**All**	**5**	**10**	**20**	**50**	**100**	**All**	**5**
User													
User1	0.85	0.85	0.90	0.85	0.85	0.9	0.198	0.198	0.209	0.198	0.198	0.209	0.321
User2	0.50	0.50	0.50	0.60	0.60	0.6	0.200	0.200	0.200	0.240	0.240	0.240	0.286
User3	0.50	0.45	0.65	0.70	0.70	0.7	0.116	0.105	0.151	0.163	0.163	0.163	0.189

```
=== matching algorithms @ N_total = 20, M = 50 ===
```

	P				R					
Metric	**cosine**	**dice**	**euclidean**	**jaccard**	**cosine**	**dice**	**euclidean**	**jaccard**	**cosine**	**dice**
User										
User1	0.85	0.9	0.80	0.9	0.198	0.209	0.186	0.209	0.321	0.340
User2	0.60	0.8	0.60	0.8	0.240	0.320	0.240	0.320	0.343	0.457
User3	0.70	0.6	0.65	0.6	0.163	0.140	0.151	0.140	0.264	0.226

Part 3. User Evaluation

Q1

Part 3 · User Study

- **Participant** A 32 years old male Youtube、NeteaseMusic user who mainly listens to pop & ballads.
- **Procedure**
  1. Show 20 random songs for each of Weeks 1-3; the participant marked Like/Skip, yielding **18 likes** in total.
  2. Merge those likes to build one TF-IDF profile; run the "LR + jaccard" recommender chosen in Part 2.
  3. Present 20 ranked recommendations for Week 4; collect Likes.

Metric	Value
Precision jaccard	**0.55**

- **Differences from the metrics in Part 2**
  - precision drop from ≈ 0.85 to 0.55

  | Cause | Offline (Part 2) | Live test (Part 3) |

| -------------------------- | ---------------------------- | --- | | **Ideal keyword rule** | every keyword hit deemed liked | user keeps only half the keyword-hits | | **Lyrics-only features** | adequate for simulations | user rejects songs with right words but wrong genre / mood | | **Profile freshness** | fixed after week 3 | new favourite words appear week 4 |

- **Interpretation** 55 percent of the list matches the user's taste and below the idealised 0.85. Because I didn't know the total number of songs that users liked among all the songs in week4, I didn't count the recall and f1 score.
- **Qualitative feedback**
  Positive "The first few songs felt spot-on."
  Negative "Some songs are quite similar to my style, but I don't like them very much. For some genres, I have favorite artists, and some of the songs I like only appear in Week 4."

Overall, the recommender achieves 55 % precision in a real-user setting. Adding acoustic / artist features and updating the profile after each session should close much of the gap while keeping list length acceptable.

part3 Q1 code

In [188…

```
import pandas as pd, numpy as np, random
from pathlib import Path
from sklearn.metrics import average_precision_score
from IPython.display import display

likes_dict = {}

# -------- Week 1 random --------
week_no = 1
random.seed(42)
candidates = random.sample(df.index[df["week"] == week_no].tolist(), 20)

print("Week 1 – Sampled 20 songs:")
```

```python
for i, idx in enumerate(candidates, 1):
    title = df.at[idx, "track_name"]
    artist = df.at[idx, "artist_name"]
    print(f"{i:2d}. [{idx}]  {artist} - {title}")
```

```
Week 1 - Sampled 20 songs:
 1. [163]  skillet - anchor
 2. [28]  imagine dragons - walking the wire
 3. [6]  rebelution - trap door
 4. [189]  andy grammer - wish you pain
 5. [70]  scotty mccreery - this is it
 6. [62]  jd mcpherson - desperate love
 7. [57]  gregg allman - going going gone
 8. [35]  george strait - take me away
 9. [188]  the movement - cool me down
10. [26]  nappy roots - these walls (dirty mc edit)
11. [173]  santana - blue skies
12. [228]  sleeping wolf - new kings
13. [139]  chris young - blacked out
14. [22]  peter bradley adams - my arms were always around you
15. [151]  vhs collection - so i met someone
16. [108]  james arthur - train wreck
17. [8]  zayde wølf - gladiator
18. [7]  thank you scientist - the amateur arsonist's handbook
19. [23]  imagine dragons - mouth of the river
20. [55]  keb' mo' - this is my home
```

In [211…

```python
# -------- Week1 like list --------
likes = [163, 28, 70, 22, 151 ]

# record
likes_dict[week_no] = likes
print("Week 1 likes saved ✓")
```

```
Week 1 likes saved ✓
```

In [190…

```python
# -------- Week 2 random --------
week_no = 2
random.seed(99)
candidates = random.sample(df.index[df["week"] == week_no].tolist(), 20)
print("Week 2 - Sampled songs:")
for i, idx in enumerate(candidates, 1):
    print(f"{i:2d}. [{idx}]  {df.at[idx,'artist_name']} - {df.at[idx,'track_name
```

```
Week 2 - Sampled songs:
 1. [353]  jah cure - life is real (feat. popcaan & padrino)
 2. [347]  haken - the good doctor
 3. [301]  dorothy - black tar & nicotine
 4. [403]  temporex - nice boys
 5. [295]  pepper - bones
 6. [308]  thee oh sees - the daily heavy
 7. [313]  curtis salgado - i want my dog to live longer (the greatest wish)
 8. [284]  drake white - it feels good
 9. [444]  lanco - greatest love story
10. [272]  brett young - chapters
11. [314]  the last shadow puppets - miracle aligner
12. [436]  devin townsend - spirits will collide
13. [348]  white denim - there's a brain in my head
14. [385]  adam doleac - puzzle of us
15. [425]  tribal seeds - empress
16. [429]  vince staples - big fish
17. [387]  magic giant - window
18. [490]  luke combs - refrigerator door
19. [409]  peach pit - alrighty aphrodite
20. [375]  sudan archives - come meh way
```

In [210…

```
# -------- Week2 Like List --------
likes = [295, 444, 385, 425, 429, 387, 490]
likes_dict[week_no] = likes
print("Week 2 likes saved ✓")
```

```
Week 2 likes saved ✓
```

In [192…

```
# -------- Week 3 random --------
week_no = 3
random.seed(66)
candidates = random.sample(df.index[df["week"] == week_no].tolist(), 20)
print("Week 3 - Sampled songs:")
for i, idx in enumerate(candidates, 1):
    print(f"{i:2d}. [{idx}]  {df.at[idx,'artist_name']} - {df.at[idx,'track_name
```

```
Week 3 - Sampled songs:
 1. [518]  kari jobe - cover the earth
 2. [579]  shag rock - lip addiction
 3. [611]  the black angels - life song
 4. [736]  dierks bentley - living
 5. [563]  ariana grande - thank u, next
 6. [701]  yazmin lacey - something my heart trusts
 7. [614]  ivan ave - squint
 8. [575]  dirty heads - realize it
 9. [565]  twenty one pilots - chlorine
10. [720]  anderson east - surrender
11. [700]  dean lewis - waves
12. [643]  the score - the fear
13. [524]  michael lington - break the ice
14. [690]  yungblud - medication
15. [721]  young the giant - titus was born
16. [737]  death from above 1979 - all i c is u & me
17. [715]  lady gaga - million reasons
18. [626]  nahko and medicine for the people - runner
19. [547]  robert plant - carry fire
20. [619]  brian culbertson - colors of love
```

In [209…

```
# -------- Week3 Like List --------
likes = [563, 565, 715, 626, 619, 575]
```

```python
likes_dict[week_no] = likes
print("Week 3 likes saved ✓")
```

```
Week 3 likes saved ✓
```

In [212…

```python
from scipy.sparse import csr_matrix
from sklearn.metrics import precision_score, recall_score
from sklearn.feature_extraction.text import TfidfVectorizer

# -------- build profile from Likes Weeks 1-3 ----------
profile = {}
for topic in df["pred_topic"].unique():
    idxs = [idx for wk in [1,2,3] for idx in likes_dict.get(wk, [])
            if df.at[idx,"pred_topic"] == topic]
    doc = " ".join(df.loc[idxs, "full_text"]) if idxs else ""
    profile[topic] = topic_vec[topic].transform([doc])


# -------- Week 4 recommendation ----------
# rec20 = recommend(profile, N_total=20, per_topic=5)

# print("\n=== Week 4 Recommendation List ===")
# for r, idx in enumerate(rec20, 1):
#     print(f"{r:2d}. [{idx}] {df.at[idx,'artist_name']} – {df.at[idx,'track_nam

N_TOTAL      = 20
PER_TOPIC    = 5

rec20 = recommend(profile, N_total=N_TOTAL,
                  per_topic=PER_TOPIC, metric="jaccard")

print(f"\n=== Week-4 recommendation · jaccard ===")
for rank, idx in enumerate(rec20, 1):
    art = df.at[idx, "artist_name"]
    title = df.at[idx, "track_name"]
    print(f"{rank:2d}. [{idx}] {art} – {title}")
```

```
=== Week-4 recommendation · jaccard ===
 1. [826] six60 – the greatest
 2. [873] nothing but thieves – amsterdam
 3. [885] cage the elephant – the war is over
 4. [868] soja – i can't stop dreaming
 5. [789] anita baker – will you be mine
 6. [931] trina – 100%
 7. [926] the band steele – sit awhile
 8. [928] anita baker – no one in the world
 9. [774] the dear hunter – the revival
10. [881] alec benjamin – boy in the bubble
11. [901] hunter hayes – still
12. [991] grouplove – good morning
13. [943] naomi scott – speechless (full)
14. [980] lukas graham – 7 years
15. [920] gang starr – jazz thing
16. [765] iya terra – follow your heart (feat. zion thompson from the green)
17. [863] iya terra – wash away
18. [795] wallows – it's only right
19. [941] adam hambrick – all you, all night, all summer
20. [845] jada kingdom – wasteman
```

In [213…

```python
# ---- Week4 Like, after listening ----
like_week4_jaccard = [826, 868, 873, 931, 943, 884, 765, 980, 795, 941, 845]
```

```python
# -------- metrics ----------
y_true_jaccard  = [1 if idx in like_week4_jaccard else 0 for idx in rec20]
precision_jaccard = sum(y_true_jaccard)/20
print(f"\nPrecision jaccard = {precision_jaccard:.3f}")
```

```
Precision jaccard = 0.500
```