Part1: 1.Optimizing the clean method & Using 5 fold cross validation rather than train_test_split to make the output more stable and reliable

In [269…

```
import pandas as pd
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.linear_model import LogisticRegression

#initializing a sample df
df = pd.read_csv("/Users/yangshuming/Downloads/dataset.tsv", sep="\t")
print(df.shape)
print(df["topic"].value_counts())
print(df.head())

#create a new colunm which gathers 'artist_name, track_name, genre and lyrics' a
df["doc"] = (
    df["artist_name"].fillna("") + " "
    + df["track_name"].fillna("") + " "
    + df["genre"].fillna("") + " "
    + df["lyrics"].fillna("")
)

import re, nltk, string
from nltk.stem import PorterStemmer
from nltk.corpus import stopwords
nltk.download("stopwords", quiet=True)
stemmer = PorterStemmer()
stop    = set(nltk.corpus.stopwords.words("english"))

#cleaning the dataset
def clean(text):
    # Keep apostrophes inside words (e.g. **rock'n'roll**)
    text = re.sub(r"[^\w\s'’\-]", " ", text)      # remove every symbol except l
    text = text.lower()
    tokens = [stemmer.stem(t) for t in text.split() if t not in stop]
    return " ".join(tokens)


X_clean = df["doc"].apply(clean).values
y = df["topic"].values

# Imports you still need
from sklearn.pipeline import make_pipeline              # <- this line is missin
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import cross_validate, StratifiedKFold

# Vectorisers (tweak max_features to your chosen N)
vectoriser_binary  = CountVectorizer(binary=True,  max_features=10000)
vectoriser_counts  = CountVectorizer(binary=False, max_features=10000)
vectoriser_tfidf   = TfidfVectorizer(sublinear_tf=True, max_features=10000)

# using Stratified 5-fold object rather than train_test_split
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
scoring = ["accuracy", "precision_macro", "recall_macro", "f1_macro"]

# The pipelines dictionary
pipelines = {
    "BNB":    make_pipeline(vectoriser_binary, BernoulliNB()),
    "MNB":    make_pipeline(vectoriser_counts, MultinomialNB(alpha=1.0)),
```

```python
    "LogReg": make_pipeline(vectoriser_tfidf, LogisticRegression(max_iter=500))
}
# Evaluate
import numpy as np
for name, pipe in pipelines.items():
    scores = cross_validate(pipe, X_clean, y, cv=cv, scoring=scoring)
    print(f"{name:6s}  F1-macro = {scores['test_f1_macro'].mean():.3f}")
```

```
(1500, 6)
topic
dark         490
sadness      376
personal     347
lifestyle    205
emotion       82
Name: count, dtype: int64
                            artist_name         track_name  release_date  \
0                                loving  the not real lake          2016
1                               incubus    into the summer          2019
2                             reignwolf           hardcore          2016
3                   tedeschi trucks band             anyhow          2016
4  lukas nelson and promise of the real  if i started over          2017

  genre                                             lyrics      topic
0  rock  awake know go see time clear world mirror worl...       dark
1  rock  shouldn summer pretty build spill ready overfl...  lifestyle
2  blues  lose deep catch breath think say try break wal...    sadness
3  blues  run bitter taste take rest feel anchor soul pl...    sadness
4  blues  think think different set apart sober mind sym...       dark
/opt/anaconda3/envs/rs9727/lib/python3.12/site-packages/sklearn/metrics/_classifi
cation.py:1706: 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", result.shape[0])
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this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
BNB     F1-macro = 0.354
MNB     F1-macro = 0.737
```

```
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0.0 in labels with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
LogReg  F1-macro = 0.625
```

2.Temprarily producing the corresponding clean function to get X_cleaner for all the set of preprocessing. Then using the same StratifiedKFold to get the score of each set. Recording all the output to df_res. Picking up the best set which gets the heighest score. Writhing the arguments of the set into BEST_PREPROC for the following step.

In [270…

```python
import itertools, re, nltk, pandas as pd
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.pipeline import make_pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from nltk.stem import PorterStemmer, WordNetLemmatizer
from nltk.corpus import stopwords
import nltk
nltk.download("wordnet")
nltk.download("omw-1.4")


# options of preprocessing
stem_opts   = {"none": None, "porter": PorterStemmer(), "lemma": WordNetLemmatiz
lower_opts  = [True, False]
stop_lists  = {"none": None,
               "nltk":  set(stopwords.words("english")),
               "sklearn": "english"}
keep_apos   = [True, False]
keep_hyphen = [True, False]

# clean function
def make_cleaner(lower, stop_set, stemmer, keep_ap, keep_hy):
    regex = r"[^\w\s" + ("'’" if keep_ap else "") + (r"\-" if keep_hy else "") +
    stop  = stop_set if isinstance(stop_set, set) else set()
    def _clean(text):
        txt = re.sub(regex, " ", text)
        if lower: txt = txt.lower()
        toks = txt.split()
        if stop: toks = [t for t in toks if t not in stop]
        if stemmer: toks = [stemmer.stem(t) if hasattr(stemmer, "stem")
                            else stemmer.lemmatize(t) for t in toks]
        return " ".join(toks)
    return _clean

# setting cross validation
```

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

results = []
grid_iter = itertools.product(lower_opts, stop_lists.items(),
                              stem_opts.items(), keep_apos, keep_hyphen)

for lower, (stop_name, stop_set), (stem_name, stemmer), ap, hy in grid_iter:
    cleaner   = make_cleaner(lower, stop_set, stemmer, ap, hy)
    X_cleaner = df["doc"].apply(cleaner).values

    for model_name, model in [("BNB", BernoulliNB()), ("MNB", MultinomialNB())]:
        vec = CountVectorizer(binary=(model_name=="BNB"),
                              max_features=10000,
                              stop_words=(stop_set if isinstance(stop_set,str) e
        pipe = make_pipeline(vec, model)
        f1 = cross_val_score(pipe, X_cleaner, y,
                             cv=cv, scoring="f1_macro").mean()
        results.append({
            "model": model_name, "lower": lower, "stop": stop_name,
            "stem": stem_name, "keep_'": ap, "keep-": hy, "macro_F1": round(f1,3
        })

# evaluation
df_res = pd.DataFrame(results).sort_values("macro_F1", ascending=False)
display(df_res.head(5))
# displaying the top3 of each model
top_each = df_res.groupby("model").head(3)
display(top_each)


# choose the set that gets the highest score, then using this set following
best = df_res.iloc[0]
BEST_PREPROC = best.to_dict()
print("Chosen BEST_PREPROC →", BEST_PREPROC)

# define clean_best function based on BEST_PREPROC
def build_cleaner_from_cfg(cfg):
    lower     = cfg["lower"]
    stop_set  = stop_lists[cfg["stop"]]
    stemmer   = stem_opts[cfg["stem"]]
    keep_ap   = cfg["keep_'"]
    keep_hy   = cfg["keep-"]
    return make_cleaner(lower, stop_set, stemmer, keep_ap, keep_hy)

clean_best = build_cleaner_from_cfg(BEST_PREPROC)
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     /Users/yangshuming/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     /Users/yangshuming/nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
```

	model	lower	stop	stem	keep_'	keep-	macro_F1
115	MNB	False	nltk	lemma	True	False	0.737
35	MNB	True	nltk	porter	True	False	0.737
107	MNB	False	nltk	porter	True	False	0.737
33	MNB	True	nltk	porter	True	True	0.737
105	MNB	False	nltk	porter	True	True	0.737

	model	lower	stop	stem	keep_'	keep-	macro_F1
115	MNB	False	nltk	lemma	True	False	0.737
35	MNB	True	nltk	porter	True	False	0.737
107	MNB	False	nltk	porter	True	False	0.737

12	BNB	True	none	porter	False	True	0.356
14	BNB	True	none	porter	False	False	0.356
84	BNB	False	none	porter	False	True	0.356

```
Chosen BEST_PREPROC → {'model': 'MNB', 'lower': False, 'stop': 'nltk', 'stem': 'l
emma', "keep_'": True, 'keep-': False, 'macro_F1': 0.737}
```

3.Transforming text into matrix, then evaluate each metrics for model BNB & MNB. The dataset, which rate of each type is 490 : 376 : 347 : 205 : 82, is imbalanced. So choosing Macro-F1 as the primary metric and accuracy as the secondary metric to evaluate the models. As the result, MNB is the better model for classification. MNB plus the best preprocessing will be used as the default classifier.

In [271…

```python
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import StratifiedKFold, cross_validate
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
import pandas as pd, matplotlib.pyplot as plt

X = df["doc"].apply(clean_best).values
y = df["topic"].values

# ② vectorizer + model
vec_B   = CountVectorizer(binary=True,  max_features=10000)
vec_M   = CountVectorizer(binary=False, max_features=10000)

pipe_BNB = make_pipeline(vec_B, BernoulliNB())
pipe_MNB = make_pipeline(vec_M, MultinomialNB())

# ③ 5-fold CV
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
scoring = {"acc":"accuracy",
           "bal_acc":"balanced_accuracy",
           "macroF1":"f1_macro",
           "wF1":"f1_weighted",
           "macroRec"   : "recall_macro",
           "macroPrec"  : "precision_macro",}
```

```
res = {}
for name, pipe in {"BNB":pipe_BNB, "MNB":pipe_MNB}.items():
    scores = cross_validate(pipe, X, y, cv=cv, scoring=scoring, n_jobs=-1)
    res[name] = {m: scores[f"test_{m}"].mean() for m in scoring}

df_cmp = pd.DataFrame(res).T.round(3)
display(df_cmp)
```

```
/opt/anaconda3/envs/rs9727/lib/python3.12/site-packages/sklearn/metrics/_classifi
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0.0 in labels with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
```

	acc	bal_acc	macroF1	wF1	macroRec	macroPrec
BNB	0.542	0.392	0.350	0.478	0.392	0.475
MNB	0.802	0.711	0.737	0.795	0.711	0.824

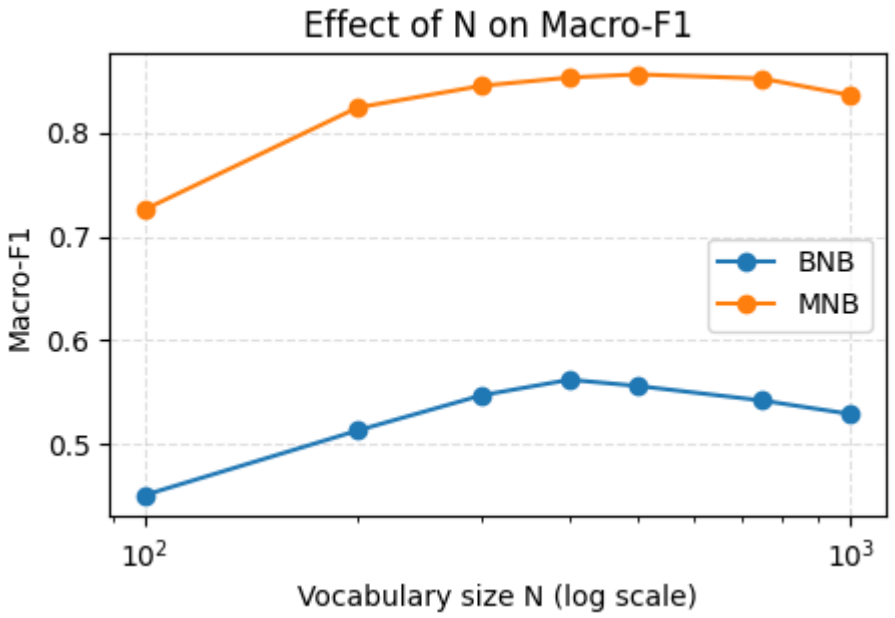
4.setting several N, 100 200 300 400 500 750 and 1000, to measure which is the best N. As we can see the result, the Macro-F1 rises first then drop. So comparing all the N's, 400 is the best N for the most frequent words in the Vectorizer

In [272...

```
import numpy as np, pandas as pd, matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.pipeline import make_pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB

# cleaning data
X_best = df["doc"].apply(clean_best).values
y      = df["topic"].values

# setting N's
N_list = [100, 200, 300, 400, 500, 750, 1000]

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

```
rows = []
for N in N_list:
    # BNB: binary feature
    vec_B = CountVectorizer(binary=True,  max_features=N)
    f1_B  = cross_val_score(make_pipeline(vec_B, BernoulliNB()),
                            X_best, y, cv=cv, scoring="f1_macro").mean()
    # MNB: frequency feature
    vec_M = CountVectorizer(binary=False, max_features=N)
    f1_M  = cross_val_score(make_pipeline(vec_M, MultinomialNB()),
                            X_best, y, cv=cv, scoring="f1_macro").mean()
    rows.append((N, round(f1_B,3), round(f1_M,3)))

df_N = pd.DataFrame(rows, columns=["N", "BNB_macroF1", "MNB_macroF1"])
display(df_N)

plt.figure(figsize=(5,3))
plt.plot(df_N["N"], df_N["BNB_macroF1"], marker="o", label="BNB")
plt.plot(df_N["N"], df_N["MNB_macroF1"], marker="o", label="MNB")
plt.xscale("log"); plt.xlabel("Vocabulary size N (log scale)")
plt.ylabel("Macro-F1"); plt.title("Effect of N on Macro-F1")
plt.legend(); plt.grid(True, ls="--", alpha=.4)
plt.show()
```

	N	BNB_macroF1	MNB_macroF1
0	100	0.451	0.726
1	200	0.513	0.824
2	300	0.547	0.845
3	400	0.562	0.853
4	500	0.556	0.856
5	750	0.542	0.852
6	1000	0.529	0.836



5.Another machine learning method that i use is linear SVM, which is a discriminative classifier. Different from the MNB and BNB, it maximizes the gap between classes, perfoming dominatively on Countvectorizer and tf-idf vector. For linear SVM i use here, preprocessing is same used for BNB and MNB, and N, which is 400, the best for MNB and BNB, is used for linear SVM as well. In additioin, i tune another hyperparameter C. i choose three value of C, for example 0.01, 0,1 and 1. Using GridSearch to select the best result of each C, then return the C.

In [273…

```
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn.svm import LinearSVC
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import StratifiedKFold, cross_validate, GridSearchC

# text → tf-idf features
vec   = CountVectorizer(max_features=400,
                        stop_words=None, binary=False)
tfidf = TfidfTransformer(sublinear_tf=True)

# Linear SVM classifier
svm   = LinearSVC(class_weight="balanced", dual=False)

pipe_svm = make_pipeline(vec, tfidf, svm)

# testing the best C
param_grid = {"linearsvc__C": [0.01, 0.1, 1]}

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

grid = GridSearchCV(pipe_svm, param_grid,
                    scoring="f1_macro", cv=cv, n_jobs=-1)
grid.fit(df["doc"].apply(clean_best).values, y)

print("the best C =", grid.best_params_["linearsvc__C"])
print("5-fold Macro-F1 =", round(grid.best_score_, 3))

svm_best = grid.best_estimator_
scoring = {"acc":"accuracy",
           "bal_acc":"balanced_accuracy",
           "macroF1":"f1_macro",
           "wF1":"f1_weighted",
           "macroRec"   : "recall_macro",
           "macroPrec"  : "precision_macro",}

models = {
    "BNB" : pipe_BNB,
    "MNB" : pipe_MNB,
    "SVM" : svm_best, # uing the best C of SVM
}

records = []
for name, est in models.items():
    scores = cross_validate(est, X_best, y, cv=cv,
                            scoring=scoring, n_jobs=-1)
    records.append({
        k: scores[f"test_{k}"].mean() for k in scoring
    } | {"Model": name})
```

```
df_cmp = (pd.DataFrame(records)
            .set_index("Model")
            .round(3)
            .sort_values("macroF1", ascending=False))
display(df_cmp)
```

```
the best C = 0.1
5-fold Macro-F1 = 0.791
```

```
/opt/anaconda3/envs/rs9727/lib/python3.12/site-packages/sklearn/metrics/_classification.py:1706: 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.
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
```

	acc	bal_acc	macroF1	wF1	macroRec	macroPrec
Model						
SVM	0.829	0.791	0.791	0.829	0.791	0.795
MNB	0.802	0.711	0.737	0.795	0.711	0.824
BNB	0.542	0.392	0.350	0.478	0.392	0.475

Part2: 1.Deviding the first 1000 data into training data and test data, first 750 of 1000 are training data and last 250 of 1000 are test data. predicting the topic for all the 1500 songs, training data and test data.

In [274…

```
# split the dataset. The first 750 rows are splited to train data and data from
train_df = df.iloc[:750].reset_index(drop=True)
test_df  = df.iloc[750:1000].reset_index(drop=True)

X_clean_train = train_df["doc"].apply(clean_best).values
y_train       = train_df["topic"].values

# training the model
best_clf = svm_best
best_clf.fit(X_clean_train, y_train)
```

```
# getting the label of each songs
df["pred_topic"] = best_clf.predict(df["doc"].apply(clean_best))

train_df["pred_topic"] = df.loc[:749,  "pred_topic"].values
test_df ["pred_topic"] = df.loc[750:999, "pred_topic"].values

print("the predicted label of all songs:\n",df["pred_topic"], sep="")
print("the predicted label of training data:\n", train_df["pred_topic"], sep="")
print("the predicted label of test data:\n", test_df["pred_topic"], sep="")
```

```
the predicted label of all songs:
0            dark
1       lifestyle
2         sadness
3         sadness
4            dark
          ...
1495      emotion
1496         dark
1497         dark
1498     personal
1499      sadness
Name: pred_topic, Length: 1500, dtype: object
the predicted label of training data:
0            dark
1       lifestyle
2         sadness
3         sadness
4            dark
          ...
745      personal
746     lifestyle
747     lifestyle
748       sadness
749          dark
Name: pred_topic, Length: 750, dtype: object
the predicted label of test data:
0        sadness
1       personal
2           dark
3           dark
4           dark
          ...
245      sadness
246     personal
247      sadness
248         dark
249         dark
Name: pred_topic, Length: 250, dtype: object
```

Collecting text for each topics, and fitting vectorizer

In [275…

```
# gurantee that every data has its correct topic
topics = ["dark", "emotion", "lifestyle", "personal", "sadness"]

# producing fitVector for every topics. Each topic has its own vector
from sklearn.feature_extraction.text import TfidfVectorizer

N = 400
topic_vecs  = {}            # {'dark': vectorizer, ...}
```

```
song_tfidf  = {}            # {'dark': matrix (n_doc × N), ...}

for t in topics:
    # extracting all the lyrics from training data of the topic
    docs_t = train_df.loc[train_df["pred_topic"] == t, "doc"].apply(clean_best).
    if not docs_t:
        continue

    # vectorizer
    vec = TfidfVectorizer(max_features=N, sublinear_tf=True)
    X_t = vec.fit_transform(docs_t)

    topic_vecs[t] = vec
    song_tfidf[t] = X_t

    print(f"{t:<9s}  songs={X_t.shape[0]:3d}  vocab={len(vec.vocabulary_):4d}")
```

```
dark       songs=243  vocab= 400
emotion    songs= 45  vocab= 400
lifestyle  songs= 96  vocab= 400
personal   songs=185  vocab= 400
sadness    songs=181  vocab= 400
```

Users liking the songs, matching the keywords of each users with the lyrics of songs to demonstrate the user like which topic songs. Reading to users profiles, user1 and user2, and creating a new user3 given topics and keywords. Searching the training dataset and fufilling the likes list.

In [276…

```
import pandas as pd, re

# reading the keywords of user1 and user2.
def load_user_keywords(tsv_path):

    d = {}
    for line in open(tsv_path, encoding="utf-8"):
        topic, kw_str = line.strip().split("\t")
        kws = [k.strip().lower() for k in kw_str.split(",") if k.strip()]
        d[topic] = kws
    return d

user_kw = {
    "user1": load_user_keywords("/Users/yangshuming/Downloads/user1.tsv"),
    "user2": load_user_keywords("/Users/yangshuming/Downloads/user2.tsv"),
}

# defining a user3 with topics and keywords
user_kw["user3"] = {
    "dark"     : ["night", "shadow", "death"],
    "lifestyle": ["party", "dance", "money"],
    "personal" : ["family", "home"]

}

# users liking songs

train_df = df.iloc[:750]

# initializing: {user: {topic: [doc, doc, ...]}}
user_likes = {u:{t:[] for t in topics} for u in user_kw.keys()}
```

```
pattern = re.compile(r"[a-z']+")

def liked(lyric, kw_list):
    if not kw_list:
        return False
    words = set(pattern.findall(lyric.lower()))
    return any(k in words for k in kw_list)


for _, row in train_df.iterrows():
    topic_pred  = row["pred_topic"].lower()
    lyric_lower = row["lyrics"].lower()

    for usr, kw_dict in user_kw.items():
        if liked(lyric_lower, kw_dict.get(topic_pred, [])):
            user_likes[usr][topic_pred].append(lyric_lower)

# print the liked songs for each users
for usr in user_likes:
    print(f"\n{usr} liked songs per topic:")
    for t in topics:
        print(f"  {t:<9s}: {len(user_likes[usr][t])}")
```

```
user1 liked songs per topic:
  dark     : 64
  emotion  : 26
  lifestyle: 35
  personal : 118
  sadness  : 10

user2 liked songs per topic:
  dark     : 0
  emotion  : 13
  lifestyle: 0
  personal : 0
  sadness  : 17

user3 liked songs per topic:
  dark     : 52
  emotion  : 0
  lifestyle: 18
  personal : 33
  sadness  : 0
```

Integrating user_likes and topic_vecs to generate tf-idf vector of each users in every topics. TfidfVectorizer (vec) transforming text into tf-idf vector to get user profile user_profiles[user][t]. Getting top-20 words by using arr.argsort().

Comment: Some words seem not reasonable. for example, the top-20 existing words of user1 for the dark topic have 'oouuu, platform, whoaohoh...', which don't represent dark.

In [277…

```
from collections import defaultdict
import numpy as np

user_profiles = defaultdict(dict)

for user, likes_by_topic in user_likes.items():
    print(f"\n=====  {user.upper()}  =====")
```

```
    for t in topics:
        docs = likes_by_topic[t]
        if not docs:
            print(f"{t:<9s}: <no liked songs>")
            continue

        # merging all the lyrics of liked songs into one text
        big_doc = " ".join(docs)

        # reflecting to the tf-idf vector space of the topic
        vec = topic_vecs[t]
        tfidf_vec = vec.transform([clean_best(big_doc)])
        user_profiles[user][t] = tfidf_vec

        # getting top-20 words
        arr = tfidf_vec.toarray().ravel()
        top_idx = arr.argsort()[-20:][::-1]
        terms   = vec.get_feature_names_out()[top_idx]
        weights = arr[top_idx]


        term_list = ", ".join(f"{w}({s:.2f})" for w, s in zip(terms, weights))
        print(f"{t:<9s}: {term_list}")
```

```
=====  USER1  =====
dark     : dilly(0.11), lanky(0.11), oouuu(0.10), gladiator(0.10), platform(0.0
9), slave(0.09), whoaohoh(0.09), statue(0.09), harder(0.08), slow(0.08), papa(0.0
8), silent(0.08), murder(0.08), riot(0.08), brother(0.08), sword(0.08), story(0.0
8), cry(0.07), battle(0.07), follow(0.07)
emotion  : video(0.12), loove(0.12), vibe(0.12), touch(0.11), sunrise(0.11), gimm
e(0.11), vision(0.11), feelin(0.11), luck(0.10), lovin(0.10), human(0.10), mornin
g(0.10), traffic(0.10), miss(0.09), doin(0.09), addiction(0.09), week(0.09), soft
(0.09), body(0.09), coast(0.09)
lifestyle: spoil(0.12), closer(0.12), lalala(0.11), telephone(0.11), ring(0.11),
oohoohooh(0.11), depression(0.11), snake(0.10), tire(0.10), bada(0.10), charmer
(0.10), backroad(0.09), ready(0.09), woah(0.09), unconditional(0.09), dear(0.09),
thought(0.09), mooooooove(0.09), celebrate(0.09), boom(0.09)
personal : ordinary(0.10), shout(0.09), oohoohoohooh(0.09), automaton(0.09), cray
on(0.08), habit(0.08), vibe(0.07), necessity(0.07), wicked(0.07), tooth(0.07), ch
emical(0.07), heartbreak(0.07), peculiar(0.07), realize(0.07), bare(0.07), wonder
ful(0.07), sister(0.07), thank(0.07), teach(0.07), american(0.07)
sadness  : club(0.23), cry(0.23), steal(0.19), music(0.16), greater(0.15), smile
(0.14), true(0.14), tear(0.14), mean(0.13), lift(0.13), darling(0.13), forever(0.
13), blame(0.13), fire(0.12), fear(0.12), ring(0.12), baby(0.12), thousand(0.12),
word(0.11), say(0.10)

=====  USER2  =====
dark     : <no liked songs>
emotion  : video(0.16), loove(0.16), touch(0.15), sunrise(0.15), gimme(0.15), vis
ion(0.15), luck(0.14), lovin(0.14), morning(0.13), addiction(0.13), week(0.13), b
ody(0.12), soft(0.12), knock(0.12), laughter(0.11), fly(0.11), strong(0.11), wait
(0.11), kiss(0.10), spit(0.10)
lifestyle: <no liked songs>
personal : <no liked songs>
sadness  : violence(0.16), rainwater(0.16), magnify(0.14), step(0.14), icecold(0.
13), ahead(0.12), crash(0.12), silence(0.11), goodbye(0.11), sing(0.11), spin(0.1
1), beer(0.11), blame(0.11), inside(0.11), body(0.11), wave(0.11), open(0.11), dr
ift(0.11), smile(0.11), laughter(0.11)

=====  USER3  =====
dark     : lanky(0.12), dilly(0.12), melodiesinfonie(0.11), gladiator(0.11), unti
tled(0.11), wing(0.10), oooh(0.10), marijuana(0.09), needle(0.09), whisper(0.09),
frame(0.09), slide(0.09), feat(0.09), travel(0.08), desperate(0.08), remix(0.08),
death(0.08), follow(0.08), evil(0.08), murder(0.08)
emotion  : <no liked songs>
lifestyle: spoil(0.17), snake(0.14), charmer(0.13), tire(0.13), drinkin(0.13), he
artache(0.13), medication(0.13), punch(0.13), unconditional(0.12), ready(0.12), m
ooooooove(0.12), crawl(0.11), belief(0.11), flute(0.11), gonna(0.11), journey(0.1
1), tonight(0.10), whoa(0.10), jukebox(0.10), drink(0.10)
personal : necessity(0.12), israelite(0.12), peculiar(0.12), bare(0.12), ironside
(0.12), bore(0.11), lord(0.11), thank(0.11), softly(0.11), whoaohohoh(0.11), beat
(0.11), teach(0.10), isolation(0.10), inch(0.10), return(0.09), learn(0.09), plac
e(0.09), gotta(0.09), home(0.08), alright(0.08)
sadness  : <no liked songs>
```

2.Selecting N=25 for the recommendation list, then generating the recommondation list according to the cosine similarity, higher score representing user likes the song more possibly.

In [278…

```
import numpy as np
from sklearn.metrics.pairwise import cosine_similarity
import pandas as pd
```

```python
N_RECOMMEND = 25
users       = ["user1", "user2", "user3"]
topics      = ["dark", "emotion", "lifestyle", "personal", "sadness"]


test_df = df.iloc[750:1000].copy().reset_index()
test_df.rename(columns={"index": "row_id"}, inplace=True)

# generating tf-idf vector of Week-4 songs for each topics
song_tfidf_test = {}
song_meta_test  = {}

for t in topics:
    mask = test_df["pred_topic"] == t
    docs = test_df.loc[mask, "doc"].apply(clean_best).tolist()
    if not docs:
        continue
    vec = topic_vecs[t]
    X   = vec.transform(docs)
    song_tfidf_test[t] = X
    song_meta_test[t] = test_df.loc[mask, ["row_id", "artist_name", "track_name"
                                           .reset_index(drop=True)

print({k: m.shape for k, m in song_tfidf_test.items()})



# calculating the score of all the songs of week-4 for every users
recomm_all = {}

for u in users:
    rows = []

    for t in topics:

        user_vec = user_profiles[u].get(t)
        if user_vec is None or user_vec.nnz == 0:
            continue

        song_mat = song_tfidf_test.get(t)
        if song_mat is None or song_mat.shape[0] == 0:
            continue

        # calculating the cosine similarity
        sims = cosine_similarity(song_mat, user_vec).ravel()

        meta_df = song_meta_test[t].copy()
        meta_df["topic"] = t
        meta_df["score"] = sims
        rows.append(meta_df)


    if rows:
        full_df = pd.concat(rows, ignore_index=True)
        recomm_all[u] = full_df.sort_values("score", ascending=False)\
                               .head(N_RECOMMEND)\
                               .reset_index(drop=True)
    else:
        recomm_all[u] = pd.DataFrame()
```

```
for u, rec in recomm_all.items():
    print(f"\n=====  Top-{N_RECOMMEND} for {u}  =====")
    if rec.empty:
        print(" <no recommendation>")
    else:
        display(rec[["row_id", "topic", "artist_name", "track_name", "score"]].h
```

```
{'dark': (70, 400), 'emotion': (19, 400), 'lifestyle': (29, 400), 'personal': (5
8, 400), 'sadness': (74, 400)}
```

```
=====  Top-25 for user1  =====
```

	row_id	topic	artist_name	track_name	score
0	881	dark	alec benjamin	boy in the bubble	0.340272
1	792	dark	deca	donner bell	0.338837
2	789	sadness	anita baker	will you be mine	0.332036
3	992	emotion	taylor swift	i did something bad	0.316069
4	884	personal	alborosie	rocky road	0.311450
5	901	dark	hunter hayes	still	0.303940
6	855	dark	the dear hunter	the flame (is gone)	0.300484
7	795	lifestyle	wallows	it's only right	0.299917
8	926	personal	the band steele	sit awhile	0.294589
9	897	personal	playboi carti	love hurts (feat. travis scott)	0.293744

```
=====  Top-25 for user2  =====
```

	row_id	topic	artist_name	track_name	score
0	802	sadness	skip marley	cry to me	0.311086
1	943	sadness	naomi scott	speechless (full)	0.293870
2	865	sadness	lil wayne	scared of the dark (feat. xxxtentacion)	0.271859
3	766	sadness	kygo	remind me to forget	0.270693
4	818	sadness	311	hey yo	0.262529
5	899	emotion	parker millsap	hands up	0.260328
6	868	sadness	soja	i can't stop dreaming	0.259380
7	789	sadness	anita baker	will you be mine	0.256330
8	791	sadness	hellyeah	love falls	0.246589
9	952	sadness	jonas brothers	don't throw it away	0.246517

```
=====  Top-25 for user3  =====
```

	row_id	topic	artist_name	track_name	score
0	884	personal	alborosie	rocky road	0.339611
1	926	personal	the band steele	sit awhile	0.328652
2	792	dark	deca	donner bell	0.322562
3	901	dark	hunter hayes	still	0.321354
4	944	personal	timeflies	once in a while	0.312705
5	797	personal	billie eilish	bored	0.312659
6	984	dark	busta rhymes	why we die (feat. dmx and jay z)	0.305355
7	881	dark	alec benjamin	boy in the bubble	0.305321
8	765	personal	iya terra	follow your heart (feat. zion thompson from th...	0.297358
9	923	personal	soja	everything to me	0.290564

producing the truth label, using the pattern of keywords + predicted topics to discriminate the song is liked, while the keywords matching the lyrics of the song, or disliked, and put the result in truth_df, which is a table including all the songs from week-4 liked or disliked by each users. Then defining an estimation function merging the recommadation result and truth_df to calculate Precision/Recall/F1@N.

In [279…

```
records = []

for user in users:
    for _, row in test_df.iterrows():
        pred_t   = row["pred_topic"]
        kw_list  = user_kw[user].get(pred_t, [])
        liked    = int(is_liked(row["lyrics"], kw_list))

        records.append({
            "row_id": row["row_id"],
            "user"  : user,
            "liked" : liked
        })

truth_df = pd.DataFrame(records)
tdf = truth_df.groupby("user")["liked"].sum()
print(tdf)

def metrics_at_N(recommend_df, truth_subset, N=25):

    merged = (recommend_df[["row_id"]]
                .merge(truth_subset, on="row_id", how="left")
                .fillna({"liked":0}))
    hit      = int(merged["liked"].sum())
    precision= hit / N
    total_like = int(truth_subset["liked"].sum())
    recall   = hit / total_like if total_like else 0
    f1       = 0 if precision+recall==0 else 2*precision*recall/(precision+recal
    return precision, recall, f1
```

```
rows = []
for u in users:
    p,r,f1 = metrics_at_N(recomm_all[u], truth_df[truth_df["user"]==u])
    rows.append({"user":u, "P@25":round(p,3),
                           "R@25":round(r,3),
                           "F1@25":round(f1,3)})
print(pd.DataFrame(rows))
```

```
user
user1    83
user2    11
user3    31
Name: liked, dtype: int64
    user  P@25   R@25  F1@25
0  user1  0.64  0.193  0.296
1  user2  0.24  0.545  0.333
2  user3  0.44  0.355  0.393
```

Comparing hyperparameters. We have argument M, the number of words in the user profile for each topic, matching algorithm, cosine similarity and dot, and fixed N. As the result shows below, M = 50, which means each topic remains top 50 words, with cosine similarity gets the highest average F1@25 which equals to 0.371 . In addition, the combination of M=50 with cosine similarity keeps other metrics in an appropriate scale, so choosing it as the default matching strategy.

In [280…

```
import numpy as np, pandas as pd
from sklearn.metrics.pairwise import cosine_similarity
from scipy.sparse import csr_matrix
import re



def truncate_vec(vec, topM: int | None):
    if topM is None:
        return vec
    if vec.nnz == 0:
        return vec

    arr = vec.toarray().ravel()
    if vec.nnz <= topM:
        return vec
    # getting index of topM which have the higher weight
    top_idx = arr.argsort()[-topM:]
    mask = np.zeros_like(arr); mask[top_idx] = 1
    arr = arr * mask
    return csr_matrix(arr)

# dot score
def dot_score(song_mat, user_vec):
    return (song_mat @ user_vec.T).toarray().ravel()


def metrics_at_N(recommend_df, truth_subset, N):
    merged = (recommend_df[["row_id"]]
                .merge(truth_subset, on="row_id", how="left")
                .fillna({"liked":0}))
    hit = merged["liked"].sum()
```

```
    precision = hit / N
    total_like = truth_subset["liked"].sum()
    recall = hit / total_like if total_like else 0
    f1 = 0 if precision+recall==0 else 2*precision*recall/(precision+recall)
    return precision, recall, f1


# parameter grid
max_nnz = max(vec.nnz for u in user_profiles.values() for vec in u.values())
# testing different M to illustrate which value of M has the best output
M_options = {f"{m:03d}": m for m in range(10, max_nnz + 1, 10)}
M_options["All"] = None
matchers    = {"cosine": cosine_similarity, "dot": dot_score}
N_RECOMMEND = 25

rows = []

for M_name, topM in M_options.items():

    user_prof_M = {}
    for u in users:
        d = {}
        for t, vec in user_profiles[u].items():
            d[t] = truncate_vec(vec, topM)
        user_prof_M[u] = d

    for matcher_name, scorer in matchers.items():
        # generating recommendation list
        recomm_all_tmp = {}
        for u in users:
            basket = []
            for t in topics:
                u_vec = user_prof_M[u].get(t)
                S_mat = song_tfidf_test.get(t)
                if u_vec is None or u_vec.nnz == 0 or S_mat is None:
                    continue
                sims = (scorer(S_mat, u_vec).ravel()
                        if matcher_name=="cosine"
                        else dot_score(S_mat, u_vec))
                tmp = song_meta_test[t].copy()
                tmp["score"] = sims; tmp["topic"]=t
                basket.append(tmp)
            if basket:
                df_top = (pd.concat(basket, ignore_index=True)
                            .sort_values("score", ascending=False)
                            .head(N_RECOMMEND))
                recomm_all_tmp[u] = df_top
            else:
                recomm_all_tmp[u] = pd.DataFrame()

        # evaluating
        for u in users:
            P,R,F1 = metrics_at_N(recomm_all_tmp[u],
                                  truth_df[truth_df["user"]==u],
                                  N_RECOMMEND)
            rows.append({"user":u, "M":M_name, "matcher":matcher_name,
                         "P@25":round(P,3), "R@25":round(R,3), "F1@25":round(F1,

df_cmp = (pd.DataFrame(rows)
            .set_index(["M","matcher","user"])
```

```
            .unstack("user")
            .round(3))

display(df_cmp)

f1_cols = df_cmp['F1@25']
# calculating the average of F1
df_cmp = df_cmp.copy()
df_cmp['macroF1'] = f1_cols.mean(axis=1)
# macroF1 descend
print(df_cmp['macroF1'].sort_values(ascending=False))
```

		P@25			R@25			F1@25	
	user	user1	user2	user3	user1	user2	user3	user1	user2	user3
M	matcher									
010	cosine	0.40	0.32	0.28	0.120	0.727	0.226	0.185	0.444	0.250
	dot	0.32	0.32	0.28	0.096	0.727	0.226	0.148	0.444	0.250
020	cosine	0.32	0.20	0.44	0.096	0.455	0.355	0.148	0.278	0.393
	dot	0.28	0.20	0.40	0.084	0.455	0.323	0.130	0.278	0.357
030	cosine	0.32	0.24	0.36	0.096	0.545	0.290	0.148	0.333	0.321
...	...	...	...	...	...	...	...	...	...	...
370	dot	0.64	0.24	0.44	0.193	0.545	0.355	0.296	0.333	0.393
380	cosine	0.64	0.24	0.44	0.193	0.545	0.355	0.296	0.333	0.393
	dot	0.64	0.24	0.44	0.193	0.545	0.355	0.296	0.333	0.393
All	cosine	0.64	0.24	0.44	0.193	0.545	0.355	0.296	0.333	0.393
	dot	0.64	0.24	0.44	0.193	0.545	0.355	0.296	0.333	0.393

78 rows × 9 columns

```
M    matcher
050  cosine     0.370667
310  dot        0.352667
300  dot        0.346667
All  dot        0.340667
360  dot        0.340667
                  ...
100  dot        0.254667
170  dot        0.254667
140  dot        0.254333
110  dot        0.248333
160  dot        0.236667
Name: macroF1, Length: 78, dtype: float64
```

Part3: for week1, 2 and 3, randomly selecting 25 songs of each week to the user, then let they mark "y" representing like the song.

In [281…

```
import random
from pathlib import Path
```

```
N = 25
random.seed(42)

df = df.copy()
df["row_id"] = df.index

# Week1-3
week_ranges = {"Week1": (0, 250), "Week2": (250, 500), "Week3": (500, 750)}

out_dir = Path("user_study_batches"); out_dir.mkdir(exist_ok=True)

batch_info = {}
def export_batch_with_like(df_batch: pd.DataFrame, path: str):
    out = df_batch.copy()
    out["Like"] = ""
    out.to_csv(path, index=False, encoding="utf-8-sig")
    print(f"file saved: {path}")

for wk, (start, end) in week_ranges.items():
    batch_df = (df.iloc[start:end]
                  .sample(N, random_state=start)
                  [["row_id","artist_name","track_name"]])
    export_batch_with_like(batch_df, out_dir / f"{wk}.csv")
```

```
file saved: user_study_batches/Week1.csv
file saved: user_study_batches/Week2.csv
file saved: user_study_batches/Week3.csv
```

reading the three files of three weeks songs marked like. priting the total count of liked songs.

In [285…

```
def read_likes(csv_path):
    tbl = pd.read_csv(csv_path)
    liked_idx = tbl.loc[tbl["Like"].astype(str).str.upper().str.startswith("Y"),
    return liked_idx.tolist()

likes_idx = []
for wk in week_ranges:
    likes_idx.extend(read_likes(out_dir / f"/Users/yangshuming/user_study_batche

print(f"the user likes {len(likes_idx)} songs")


global_tfidf = TfidfVectorizer(sublinear_tf=True, max_features=400)
global_tfidf.fit(df["doc"].apply(clean_best))
def build_profile_from_idx(idx_list):
    lyrics_concat = " ".join(df.loc[idx_list, "lyrics"].apply(clean_best))
    vec   = global_tfidf
    tfidf = vec.transform([lyrics_concat])
    return truncate_vec(tfidf, 50)

user_profile_real = build_profile_from_idx(likes_idx)
```

```
the user likes 27 songs
```

recommanding songs from week4 to user, based on the songs that user likes from training data week1-3. and let user mark the songs that they like.

In [286…

```
week4_df = df.iloc[750:1000].copy().reset_index()
X_week4   = global_tfidf.transform(week4_df["doc"].apply(clean_best))
week4_meta = week4_df[["row_id","artist_name","track_name"]]

def recommend_week4(profile_vec, topN=25):
    sim = cosine_similarity(X_week4, profile_vec).ravel()
    return (week4_meta.assign(score=sim)
                      .sort_values("score", ascending=False)
                      .head(topN)
                      .reset_index(drop=True))

N = 25
recs = recommend_week4(user_profile_real, N)
recs["Like"] = ""
cols = ["row_id","artist_name","track_name","score","Like"]
recs.to_csv(out_dir / "Week4recommend.csv",
            columns=cols, index=False, encoding="utf-8-sig")

print(" Week-4 recommendation list saved as Week4recommend.csv")
```

```
Week-4 recommendation list saved as Week4recommend.csv
```

read the file of Week4recommend, counting the songs are liked.

In [288…

```
import pandas as pd

fb4 = pd.read_csv("/Users/yangshuming/user_study_batches/Week4recommend.csv")

liked_mask = (
    fb4["Like"]
      .astype(str)
      .str.strip()
      .str.lower()
      .str.startswith("y")
)

liked_count = liked_mask.sum()
print(f"user likes {liked_count} songs in 25 that are recommended。 ")
```

```
user likes 13 songs in 25 that are recommended。
```