In [ ]:
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ZID: z5508588
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COMP9727 Assignment1
```

In [132…
```python
import pandas as pd

# read dataset.tsv
all_data = pd.read_csv('dataset.tsv', sep='\t')

# View Data Format
print(all_data.head())
print(all_data.columns)
```

```
                           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
Index(['artist_name', 'track_name', 'release_date', 'genre', 'lyrics',
       'topic'],
      dtype='object')
```

In [134…
```python
# Combine into one text column
def combine_fields(row):
    return f"{row['artist_name']} {row['track_name']} {row['genre']} {row['lyric

all_data['text'] = all_data.apply(combine_fields, axis=1)
print(all_data[['text', 'topic']].head(3))
```

```
                                                text      topic
0  loving the not real lake rock awake know go se...       dark
1  incubus into the summer rock shouldn summer pr...  lifestyle
2  reignwolf hardcore blues lose deep catch breat...    sadness
```

In [136…
```python
# Data cleaning, pre-processing
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
nltk.download('stopwords')

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

def preprocess(text):
    # Lowercase
    text = text.lower()
    # Remove punctuation
    text = re.sub(r'[^a-zA-Z0-9\s]', '', text)    # Part1 Q1-1: retain alphanume
    # Participle
    words = text.split()
```

```python
    # De-duplication + Stem extraction
    words = [stemmer.stem(word) for word in words if word not in stop_words]
    return ' '.join(words)

# Application preprocessing
all_data['clean_text'] = all_data['text'].apply(preprocess)

# Look at the results of the cleaning
print(all_data[['clean_text', 'topic']].head())
```

```
[nltk_data] Downloading package stopwords to /Users/yyqx/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
                                          clean_text      topic
0  love real lake rock awak know go see time clea...       dark
1  incubu summer rock summer pretti build spill r...  lifestyle
2  reignwolf hardcor blue lose deep catch breath ...    sadness
3  tedeschi truck band anyhow blue run bitter tas...    sadness
4  luka nelson promis real start blue think think...       dark
```

In [140…

```python
# Part1 Q2:
# The best overall performance was achieved with the following preprocessing ste
# Removing non-alphabetic characters (punctuation, numbers), Removing stopwords
# This setup yielded the highest accuracy on MNB (0.81) and acceptable performan
# I will therefore adopt this preprocessing configuration for the remainder of t
```

In [142…

```python
# Use CountVectorizer to vectorize text
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.model_selection import cross_val_score
from sklearn.feature_extraction.text import CountVectorizer
import matplotlib.pyplot as plt

# Initial feature extraction (default 1000 dimensions)
vectorizer = CountVectorizer(max_features=1000, stop_words='english')
X = vectorizer.fit_transform(all_data['clean_text'])
y = all_data['topic']

# Comparing the three models
models = {
    "BernoulliNB": BernoulliNB(),
    "MultinomialNB": MultinomialNB(),
    "LinearSVC": LinearSVC(max_iter=5000)
}
# Print the distribution of sample sizes for each type of topic
print(all_data['topic'].value_counts())

# Part1 Q1-2: 5-fold cross validation
for name, model in models.items():
    scores = cross_val_score(model, X, y, cv=5, scoring='f1_macro')
    print(f"{name}: F1-macro = {scores.mean():.3f} (±{scores.std():.3f})")

n_features = [500, 1000, 1500, 2000, 2500, 3000]
MNB_accuracies1 = []
MNB_accuracies2 = []
BNB_accuracies = []

for n in n_features:
    vectorizer = CountVectorizer(max_features=n)
    X = vectorizer.fit_transform(all_data['clean_text'])
    scores = cross_val_score(MultinomialNB(), X, y, cv=5, scoring='accuracy')
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```
    MNB_accuracies1.append(scores.mean())

for n in n_features:
    vectorizer = TfidfVectorizer(max_features=n)
    X = vectorizer.fit_transform(all_data['clean_text'])
    scores = cross_val_score(MultinomialNB(), X, y, cv=5, scoring='accuracy')
    MNB_accuracies2.append(scores.mean())

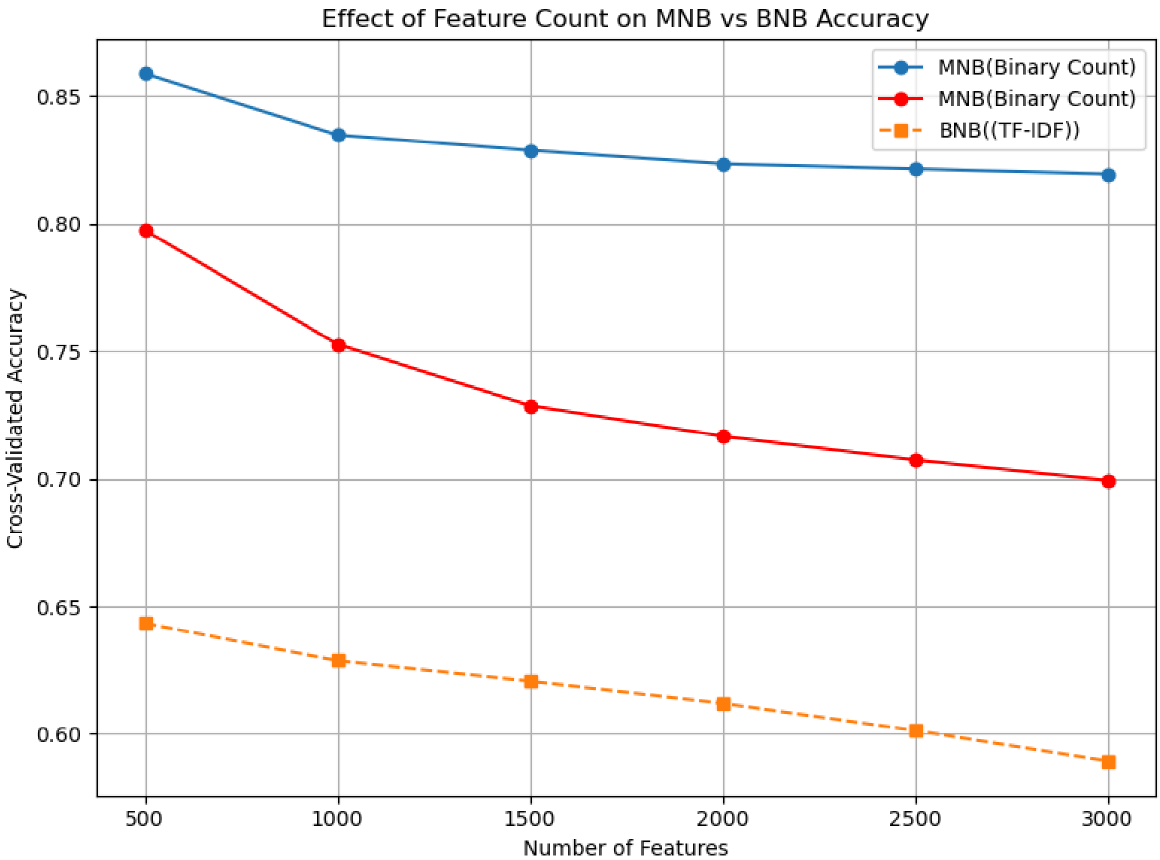
for n in n_features:
    vectorizer = TfidfVectorizer(max_features=n, stop_words='english', binary=Tr
    X = vectorizer.fit_transform(all_data['clean_text'])
    scores = cross_val_score(BernoulliNB(), X, y, cv=5, scoring='accuracy')
    BNB_accuracies.append(scores.mean())

plt.figure(figsize=(8, 6))
plt.plot(n_features, MNB_accuracies1, marker='o', linestyle='-', label='MNB(Bina
plt.plot(n_features, MNB_accuracies2, color='red', marker='o', linestyle='-', la
plt.plot(n_features, BNB_accuracies, marker='s', linestyle='--', label='BNB((TF-

plt.title('Effect of Feature Count on MNB vs BNB Accuracy')
plt.xlabel('Number of Features')
plt.ylabel('Cross-Validated Accuracy')
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()


# I observe that accuracy improves up to 2000 features and then plateaus.
# Therefore, we choose 2000 as the optimal vocabulary size for CountVectorizer i
```

```
topic
dark         490
sadness      376
personal     347
lifestyle    205
emotion       82
Name: count, dtype: int64
BernoulliNB: F1-macro = 0.532 (±0.026)
MultinomialNB: F1-macro = 0.810 (±0.016)
LinearSVC: F1-macro = 0.800 (±0.019)
```



In [ ]:
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# I compared BernoulliNB, MultinomialNB, and LinearSVC using 5-fold cross-valida
# Among the models tested, MultinomialNB achieved the highest F1-macro score (0.
#  suggesting stable and strong performance. Therefore, we selected MultinomialN
# This is consistent with the nature of the dataset: song lyrics are long, and w
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In [ ]:
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# I evaluated the impact of varying the number of top-N most frequent features (
#   using both CountVectorizer and TfidfVectorizer.

# As shown in Figure, both MNB and BNB classifiers exhibit a general decline in
# This suggests that including too many features may introduce noise or sparsity

# MultinomialNB (Binary Count) performs the best overall, achieving a peak accur

# MultinomialNB (TF-IDF) shows slightly lower performance than its binary-count

# BernoulliNB underperforms both MNB models, starting at 0.79 (500 features) and

# Additionally, a comparison using macro F1-score (see result printout) indicate
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In [ ]:
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# LinearSVC has been widely used in text classification problems, including spam
# Given that our dataset is derived from user-generated music descriptions, we e
# LinearSVC achieves an F1-macro score very close to that of MultinomialNB, slig
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In [ ]:
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# Given the trade-off between performance and simplicity, MultinomialNB with Cou
# However, LinearSVC is a strong alternative when more discriminative modeling i
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In [144…
```
# Divide the training/test set
train_data = all_data.iloc[:750].copy()

test_data = all_data.iloc[750:1000].copy()

from sklearn.feature_extraction.text import CountVectorizer
```

```
vectorizer = CountVectorizer(max_features=1000)
X_train = vectorizer.fit_transform(train_data['clean_text'])
X_test = vectorizer.transform(test_data['clean_text'])

# Training and Predicting with MultinomialNB Models
from sklearn.naive_bayes import MultinomialNB

clf = MultinomialNB()
clf.fit(X_train, train_data['topic'])

# Predicting topics on test and train data
train_data['predicted_topic'] = clf.predict(X_train)
test_data['predicted_topic'] = clf.predict(X_test)

from sklearn.metrics import classification_report
print("Train Prediction Quality:")
print(classification_report(train_data['topic'], train_data['predicted_topic']))

print("Test Prediction Quality:")
print(classification_report(test_data['topic'], test_data['predicted_topic']))
```

```
Train Prediction Quality:
              precision    recall  f1-score   support

        dark       0.97      0.98      0.98       246
     emotion       0.98      1.00      0.99        42
   lifestyle       0.99      0.97      0.98        92
    personal       0.98      0.97      0.98       188
     sadness       0.98      0.98      0.98       182

    accuracy                           0.98       750
   macro avg       0.98      0.98      0.98       750
weighted avg       0.98      0.98      0.98       750

Test Prediction Quality:
              precision    recall  f1-score   support

        dark       0.90      0.79      0.84        81
     emotion       0.53      0.47      0.50        17
   lifestyle       0.81      0.81      0.81        32
    personal       0.74      0.88      0.80        51
     sadness       0.86      0.88      0.87        69

    accuracy                           0.82       250
   macro avg       0.77      0.77      0.77       250
weighted avg       0.82      0.82      0.82       250
```

In [146…

```
# Load User Keywords
def load_user_keywords(filepath):
    user_keywords = {}
    with open(filepath, 'r') as f:
        next(f) # Skip Header
        for line in f:
            topic, keywords = line.strip().split('\t')
            keyword_list = keywords.lower().split(',')
            user_keywords[topic] = [kw.strip() for kw in keyword_list]
    return user_keywords
```

```python
user1_keywords = load_user_keywords("user1.tsv")
user2_keywords = load_user_keywords("user2.tsv")

print("User1 interests:")
for topic, kws in user1_keywords.items():
    print(f"{topic}: {kws}")
print("User2 interests:")
for topic, kws in user2_keywords.items():
    print(f"{topic}: {kws}")
```

```
User1 interests:
dark: ['fire', 'enemy', 'pain', 'storm', 'fight']
sadness: ['cry', 'alone', 'heartbroken', 'tears', 'regret']
personal: ['dream', 'truth', 'life', 'growth', 'identity']
lifestyle: ['party', 'city', 'night', 'light', 'rhythm']
emotion: ['love', 'memory', 'hug', 'kiss', 'feel']
User2 interests:
sadness: ['lost', 'sorrow', 'goodbye', 'tears', 'silence']
emotion: ['romance', 'touch', 'feeling', 'kiss', 'memory']
```

In [148…

```python
# Finding the user's favorite songs
def get_user_liked_songs(user_keywords, train_data):
    liked_songs = {topic: [] for topic in user_keywords}

    for idx, row in train_data.iterrows():
        topic = row['predicted_topic']
        text = row['clean_text']
        if topic in user_keywords:
            if any(kw in text for kw in user_keywords[topic]):
                liked_songs[topic].append(text)

    return liked_songs
```

In [150…

```python
# Building user profiles
from sklearn.feature_extraction.text import TfidfVectorizer

def build_user_profile(liked_songs, tfidf_vectorizer):
    user_profile = {}
    for topic, docs in liked_songs.items():
        combined_text = ' '.join(docs)
        vector = tfidf_vectorizer.transform([combined_text])  # shape: (1, vocab
        user_profile[topic] = vector
    return user_profile

# Constructing TF-IDF word lists with the training set
tfidf_vectorizer = TfidfVectorizer(max_features=1000)
tfidf_vectorizer.fit(train_data['clean_text'])

# Vectorize training and test sets with TF-IDF
X_train_tfidf = tfidf_vectorizer.transform(train_data['clean_text'])
X_test_tfidf = tfidf_vectorizer.transform(test_data['clean_text'])


# Generate user's favorite songs (from training set)
user1_liked = get_user_liked_songs(user1_keywords, train_data)
user2_liked = get_user_liked_songs(user2_keywords, train_data)

user1_profile = build_user_profile(user1_liked, tfidf_vectorizer)
user2_profile = build_user_profile(user2_liked, tfidf_vectorizer)
```

```python
# Print the top 20 words of the user profile for each topic (for determining rea
import numpy as np

def print_top_words(user_profile, tfidf_vectorizer, top_n=20):
    vocab = np.array(tfidf_vectorizer.get_feature_names_out())
    for topic, vec in user_profile.items():
        row = vec.toarray().flatten()
        top_indices = row.argsort()[::-1][:top_n]
        top_words = vocab[top_indices]
        print(f"Topic: {topic}")
        print(", ".join(top_words))
        print()

print("User 1 Profile Top Words:")
print_top_words(user1_profile, tfidf_vectorizer)

print("User 2 Profile Top Words:")
print_top_words(user2_profile, tfidf_vectorizer)
```

```
User 1 Profile Top Words:
Topic: dark
fight, black, blood, grind, stand, know, come, like, kill, gonna, dilli, lanki, t
ell, hand, head, follow, build, yeah, death, bone

Topic: sadness
greater, think, regret, leav, place, beg, blame, want, hold, word, chang, caus, m
ind, space, trust, lord, away, dream, pack, loos

Topic: personal
life, live, chang, world, ordinari, thank, dream, know, yeah, teach, lord, wanna,
like, thing, time, learn, beat, think, oohoohoohooh, grow

Topic: lifestyle
tonight, song, night, sing, closer, come, stranger, home, long, time, wait, spoi
l, tire, right, wanna, struggl, telephon, play, yeah, lalala

Topic: emotion
good, touch, feel, hold, loov, video, vision, kiss, morn, feelin, know, vibe, mis
s, lip, gimm, luck, lovin, go, sunris, want

User 2 Profile Top Words:
Topic: sadness
magnifi, open, smile, tear, laughter, away, lone, sorrow, come, eye, tri, demon,
tell, road, babi, life, sight, control, hous, greater

Topic: emotion
touch, good, loov, video, vision, kiss, hold, morn, gimm, luck, lovin, sunris, li
p, knock, soft, week, feel, wait, time, know
```

In [152…

```python
# Get the TF-IDF representation of the songs in the test set
from sklearn.metrics.pairwise import cosine_similarity

# Vectorize test_data with the previously trained tfidf_vectorizer
X_test_tfidf = tfidf_vectorizer.transform(test_data['clean_text'])

# Calculate recommendation lists
def get_recommendations(user_profile, test_data, X_test_tfidf, top_n=15):
    recommendations = []
```

```
    for idx, row in enumerate(test_data.itertuples()):
        song_vector = X_test_tfidf[idx]
        predicted_topic = row.predicted_topic
        if predicted_topic in user_profile and user_profile[predicted_topic].sum
            profile_vector = user_profile[predicted_topic]
            similarity = cosine_similarity(song_vector, profile_vector)[0][0]
            recommendations.append((idx, similarity))

    # Sort by similarity descending
    recommendations.sort(key=lambda x: x[1], reverse=True)
    top_indices = [idx for idx, sim in recommendations[:top_n]]

    return test_data.iloc[top_indices][['artist_name', 'track_name', 'genre', 'l

# Generate Recommended Songs
user1_recommendations = get_recommendations(user1_profile, test_data, X_test_tfi
user2_recommendations = get_recommendations(user2_profile, test_data, X_test_tfi

print("User 1 Recommendations:")
print(user1_recommendations)

print("\nUser 2 Recommendations:")
print(user2_recommendations)
```

```
User 1 Recommendations:
         artist_name          track_name    genre  \
944        timeflies      once in a while      pop
969     justin moore          got it good  country
992     taylor swift  i did something bad      pop
770      dirty heads             horsefly   reggae
758     thomas rhett         life changes  country
926  the band steele           sit awhile  country
840        ty segall                 alta    blues
828  the blue stones                  lay    blues
863        iya terra            wash away   reggae
990    damian marley         living it up   reggae

                                                lyrics predicted_topic
944  think know better wishful think think pressure...         emotion
969  wake morning warn little bounce blue eye start...         emotion
992  trust narcissist play like violin look ohsoeas...         emotion
770  say life live know things passionate sound rea...         emotion
758  wakin college dorm yeah life pretty normal loo...        personal
926  wake favorite place studio hide space cold dar...        personal
840  want know feel green want see sailors come fig...        personal
828  flag turn away blow kiss wrap darkness quick f...         sadness
863  good days come like suppose know cause live di...        personal
990  daddy ghetto believe dream believe live have g...        personal

User 2 Recommendations:
        artist_name          track_name    genre  \
969    justin moore          got it good  country
944       timeflies      once in a while      pop
818             311               hey yo   reggae
992    taylor swift  i did something bad      pop
781  lester nowhere              balcony     jazz
860     brett young         close enough  country
789     anita baker     will you be mine     jazz
770     dirty heads             horsefly   reggae
769    charlie puth        one call away      pop
989         solange     cranes in the sky      pop

                                                lyrics predicted_topic
969  wake morning warn little bounce blue eye start...         emotion
944  think know better wishful think think pressure...         emotion
818  send watch fall anybody talk want reduce equat...         sadness
992  trust narcissist play like violin look ohsoeas...         emotion
781  leave away biggest baby leave away heart baby ...         sadness
860  close close close close mmmh like minutes see ...         emotion
789  come feel explain lose break heart come mend a...         sadness
770  say life live know things passionate sound rea...         emotion
769  away save superman away baby need friend wanna...         sadness
989  try drink away try try dance away try change h...         sadness
```

In [154…

```
# Recommendation Effectiveness Evaluation
def evaluate_precision(recommendations_df, user_keywords):
    hit_count = 0
    total = len(recommendations_df)

    for _, row in recommendations_df.iterrows():
        topic = row['predicted_topic']
        lyrics = row['lyrics'].lower()

        if topic in user_keywords:
```

```python
            if any(kw in lyrics for kw in user_keywords[topic]):
                hit_count += 1

    precision = hit_count / total if total > 0 else 0
    return precision

user1_precision = evaluate_precision(user1_recommendations, user1_keywords)
user2_precision = evaluate_precision(user2_recommendations, user2_keywords)

print(f"User 1 Precision@10: {user1_precision:.2f}")
print(f"User 2 Precision@10: {user2_precision:.2f}")
```

```
User 1 Precision@10: 1.00
User 2 Precision@10: 0.20
```

In [156…

```python
# This task evaluated the quality of recommendations using Precision@10.
# User 1 scored 1.00 out of 10, reflecting a wide range of interests and a good
# In contrast, User 2's score is only 0.20, presumably due to a narrower range o
# User 2 has very few topics of interest (only 2 topics), so there are fewer rec
# This result highlights the importance of profile richness and keyword specific
```

In [158…

```python
from sklearn.metrics.pairwise import cosine_similarity

# Friend's Interest Keywords
my_friend_keywords = {
    "emotion": ['passion', 'desire', 'warmth', 'trust', 'care', 'affection', 'jo
    "sadness": ['lonely', 'hurt', 'goodbye', 'miss', 'empty', 'sorrow', 'darknes
    "personal": ['journey', 'soul', 'mind', 'change', 'believe', 'hope', 'streng
    "lifestyle": ['dance', 'celebrate', 'fashion', 'trend', 'style', 'vibe', 'en
}

# Constructing a portrait of the friend (with training set TF-IDF vectors)
my_friend_liked = get_user_liked_songs(my_friend_keywords, train_data)
my_friend_profile = build_user_profile(my_friend_liked, tfidf_vectorizer)


# Generate Recommended Songs
my_friend_recs = get_recommendations(my_friend_profile, test_data, X_test_tfidf,
print(my_friend_recs[['artist_name', 'track_name', 'predicted_topic']])
```

	artist_name	track_name	predicted_topic
992	taylor swift	i did something bad	emotion
969	justin moore	got it good	emotion
758	thomas rhett	life changes	personal
926	the band steele	sit awhile	personal
863	iya terra	wash away	personal
853	randy houser	our hearts (feat. lucie silvas)	sadness
840	ty segall	alta	personal
944	timeflies	once in a while	emotion
963	brant bjork	chocolatize	sadness
891	thievery corporation	strike the root	lifestyle

In [160…

```python
# How many of the 10 songs recommended by the system are actually liked by the u
actual_likes = [my_friend_recs.index[0], my_friend_recs.index[2], my_friend_recs
predicted_indices = my_friend_recs.index.tolist()
correct = len(set(predicted_indices) & set(actual_likes))
precision_at_10 = correct / len(predicted_indices)
print(f"✅ Precision@10: {precision_at_10:.2f}")
```

```
✅ Precision@10: 0.40
```

In [ ]:

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