COMP9727: Recommender Systems Assignment: Content-Based Music Recommendation
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music recommender assignment

this assignment builds a recommender system for songs with 5 topics: dark, emotion, lifestyle, personal and sadness

parts:

1. topic classification
2. recommendation stuff
3. user study

In [42]:
```
# libs needed
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score, Stratifie
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sc
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer, WordNetLemmatizer
from nltk.tokenize import word_tokenize
import re
import string
import warnings
from IPython.display import display
warnings.filterwarnings('ignore')

# get nltk stuff
nltk.download('stopwords', quiet=True)
nltk.download('punkt', quiet=True)
nltk.download('wordnet', quiet=True)
nltk.download('omw-1.4', quiet=True)

print("imported everything!")
```

```
imported everything!
```

part 1 - topic classification

load data and check it out

In [43]:
```
# Load the dataset (assuming it's named 'dataset.tsv')
df = pd.read_csv('./dataset.tsv', sep='\t', encoding='utf-8')
```

```
# Display basic information about the dataset
print("Dataset Info:")
df.info()
print("\nFirst few rows:")
df.head()
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   artist_name   1500 non-null   object
 1   track_name    1500 non-null   object
 2   release_date  1500 non-null   int64 
 3   genre         1500 non-null   object
 4   lyrics        1500 non-null   object
 5   topic         1500 non-null   object
dtypes: int64(1), object(5)
memory usage: 70.4+ KB

First few rows:
```

Out[43]:

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

Dataset columns and shape

In [44]:
```
print("Dataset columns:", df.columns.tolist())
print(f"Dataset shape: {df.shape}")
```

```
Dataset columns: ['artist_name', 'track_name', 'release_date', 'genre', 'lyrics',
'topic']
Dataset shape: (1500, 6)
```

Missing values

In [45]:
```
df.isnull().sum()
```

Out[45]:
```
artist_name     0
track_name      0
release_date    0
genre           0
lyrics          0
topic           0
dtype: int64
```

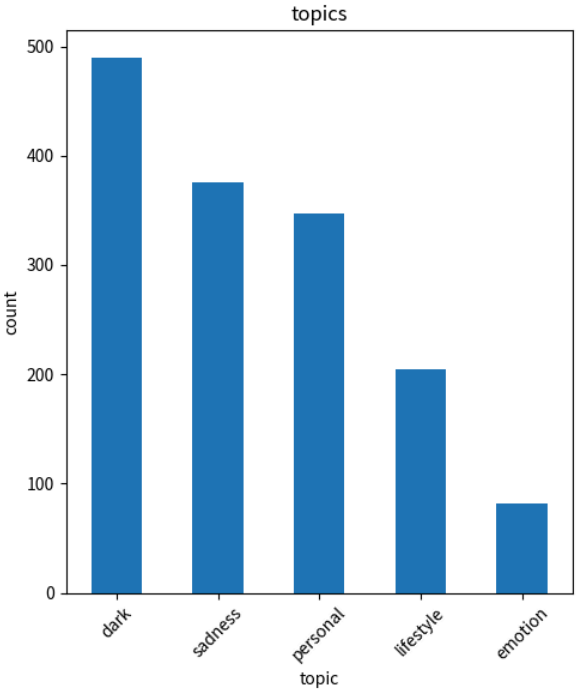
Topic distribution

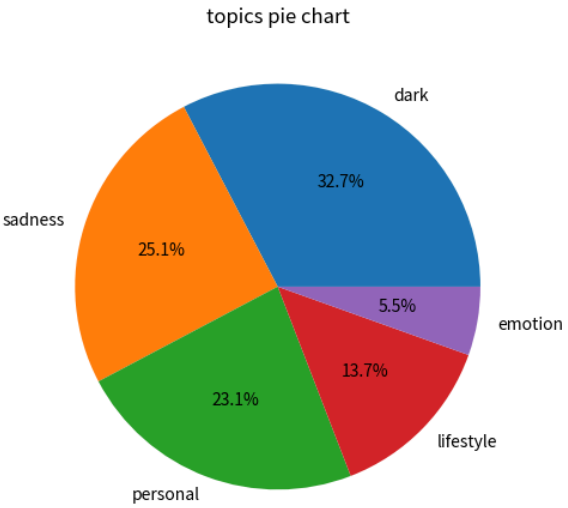
In [46]:
```
topic_counts = df['topic'].value_counts()
topic_counts
```

Out[46]:
```
topic
dark         490
sadness      376
personal     347
lifestyle    205
emotion       82
Name: count, dtype: int64
```

Topic distribution visualization

In [47]:
```
# Visualize topic distribution
plt.figure(figsize=(10, 6))
plt.subplot(1, 2, 1)
topic_counts.plot(kind='bar')
plt.title('topics')
plt.xlabel('topic')
plt.ylabel('count')
plt.xticks(rotation=45)

plt.subplot(1, 2, 2)
plt.pie(topic_counts.values, labels=topic_counts.index, autopct='%1.1f%%')
plt.title('topics pie chart')

plt.tight_layout()
plt.show()

# Check if dataset is balanced
print(f"\nbalance check:")
print(f"most common: {topic_counts.max()} songs ({topic_counts.max()/len(df)*100
print(f"least common: {topic_counts.min()} songs ({topic_counts.min()/len(df)*10

if topic_counts.max() / topic_counts.min() > 1.5:
    print("not balanced")
else:
    print("kinda balanced")
```






```
balance check:
most common: 490 songs (32.7%)
least common: 82 songs (5.5%)
not balanced
```

1.2 Text Preprocessing

Question 1 (2 marks): Fix simplifications in regex and evaluation methodology

The tutorial had two main issues:

1. Regex might remove too many special characters
2. Evaluation based on single train-test split instead of cross-validation

Solutions implemented:

- More careful regex that preserves important punctuation and contractions
- Use stratified cross-validation for robust evaluation
- Preserve emoticons and music-specific terms

In [48]:
```python
# preprocess text
def preprocess_text(text, do_stem=False, do_lemma=True, rm_stopwords=True):
    """makes text better"""
    if pd.isna(text):
        return ""

    # lowercase
    text = text.lower()

    # regex stuff - keep emojis and stuff
    text = re.sub(r'[^\w\s\'\-:;)(]', ' ', text)

    # remove extra spaces
    text = re.sub(r'\s+', ' ', text).strip()

    # split words
```

```
    words = word_tokenize(text)

    # remove stopwords if wanted
    if rm_stopwords:
        stops = set(stopwords.words('english'))
        # keep some emotion words
        emotion_words = {'not', 'no', 'never', 'nothing', 'nobody', 'nowhere'}
        stops = stops - emotion_words
        words = [w for w in words if w not in stops]

    # remove single chars and nums
    words = [w for w in words if len(w) > 1 and not w.isdigit()]

    # do stemming or lemmatization
    if do_stem:
        stemmer = PorterStemmer()
        words = [stemmer.stem(w) for w in words]
    elif do_lemma:
        lemmatizer = WordNetLemmatizer()
        words = [lemmatizer.lemmatize(w) for w in words]

    return ' '.join(words)

# test it
test = "I'm feeling so sad... can't believe it's over :( Never gonna be the same
processed = preprocess_text(test)
print(f"orig: {test}")
print(f"processed: {processed}")
```

```
orig: I'm feeling so sad... can't believe it's over :( Never gonna be the same!!!
processed: 'm feeling sad ca n't believe 's never gon na
```

Applying text preprocessing

In [49]:

```
# combine text fields
def combine_text(row):
    """puts all text together"""
    fields = [str(row['artist_name']), str(row['track_name']), str(row['genre'])
    return ' '.join(fields)

# make combined text
df['combined_text'] = df.apply(combine_text, axis=1)

# process text
print("processing text...")
df['processed_text'] = df['combined_text'].apply(preprocess_text)

# remove empty ones
df = df[df['processed_text'].str.len() > 0].reset_index(drop=True)
print(f"dataset size after processing: {len(df)} songs")

# show some examples
for i in range(3):
    print(f"\nsong {i+1} - topic: {df.iloc[i]['topic']}")
    print(f"orig: {df.iloc[i]['combined_text'][:100]}...")
    print(f"processed: {df.iloc[i]['processed_text'][:100]}...")
```

```
processing text...
dataset size after processing: 1500 songs

song 1 - topic: dark
orig: loving the not real lake rock awake know go see time clear world mirror wor
ld mirror magic hour conf...
processed: loving not real lake rock awake know go see time clear world mirror wo
rld mirror magic hour confuse ...

song 2 - topic: lifestyle
orig: incubus into the summer rock shouldn summer pretty build spill ready overfl
ow piss moan ash guess sm...
processed: incubus summer rock summer pretty build spill ready overflow piss moan
ash guess smite leave remembe...

song 3 - topic: sadness
orig: reignwolf hardcore blues lose deep catch breath think say try break wall ma
ma leave hardcore hardcor...
processed: reignwolf hardcore blue lose deep catch breath think say try break wal
l mama leave hardcore hardcore...
```

1.3 Question 2: Multinomial Naive Bayes Development

Question 2 (2 marks): Develop Multinomial Naive Bayes and optimize preprocessing

We'll test different preprocessing combinations to find the best overall accuracy:

- Special character removal strategies
- Stopword lists (NLTK vs scikit-learn vs custom)
- Lowercasing
- Stemming vs Lemmatization

Testing different preprocessing combinations

In [50]:
```python
# test different preprocessing stuff
def test_preprocessing(X, y, n_splits=5):
    """test different ways to preprocess"""

    # different configs to try
    configs = [
        {'do_stem': False, 'do_lemma': True, 'rm_stopwords': True, 'name': 'lemm
        {'do_stem': True, 'do_lemma': False, 'rm_stopwords': True, 'name': 'stem
        {'do_stem': False, 'do_lemma': False, 'rm_stopwords': True, 'name': 'bas
        {'do_stem': False, 'do_lemma': True, 'rm_stopwords': False, 'name': 'lem
        {'do_stem': True, 'do_lemma': False, 'rm_stopwords': False, 'name': 'ste
    ]

    results = []
    cv = StratifiedKFold(n_splits=n_splits, shuffle=True, random_state=42)

    for config in configs:
        print(f"\ntesting: {config['name']}")

        # preprocess text
        processed = [preprocess_text(text, **{k:v for k,v in config.items() if k
                     for text in X]
```

```
        # vectorize
        vec = CountVectorizer(max_features=5000, ngram_range=(1,2))
        X_vec = vec.fit_transform(processed)

        # try both naive bayes
        for nb_type, nb in [('bernoulli', BernoulliNB()), ('multinomial', Multin
            scores = cross_val_score(nb, X_vec, y, cv=cv, scoring='accuracy')
            results.append({
                'preprocess': config['name'],
                'model': nb_type,
                'mean_acc': scores.mean(),
                'std_acc': scores.std()
            })
            print(f"{nb_type} nb - acc: {scores.mean():.4f} (+/- {scores.std()*2

    return pd.DataFrame(results)

# run preprocessing tests
X_text = df['combined_text'].values
y = df['topic'].values

preprocess_results = test_preprocessing(X_text, y)
```

```
testing: lemma+stop
bernoulli nb - acc: 0.6213 (+/- 0.0300)
multinomial nb - acc: 0.8200 (+/- 0.0260)

testing: stem+stop
bernoulli nb - acc: 0.6193 (+/- 0.0247)
multinomial nb - acc: 0.8160 (+/- 0.0351)

testing: basic+stop
bernoulli nb - acc: 0.6247 (+/- 0.0381)
multinomial nb - acc: 0.8133 (+/- 0.0400)

testing: lemma
bernoulli nb - acc: 0.6227 (+/- 0.0449)
multinomial nb - acc: 0.8160 (+/- 0.0445)

testing: stem
bernoulli nb - acc: 0.6160 (+/- 0.0346)
multinomial nb - acc: 0.8140 (+/- 0.0330)
```

Preprocessing Results Summary

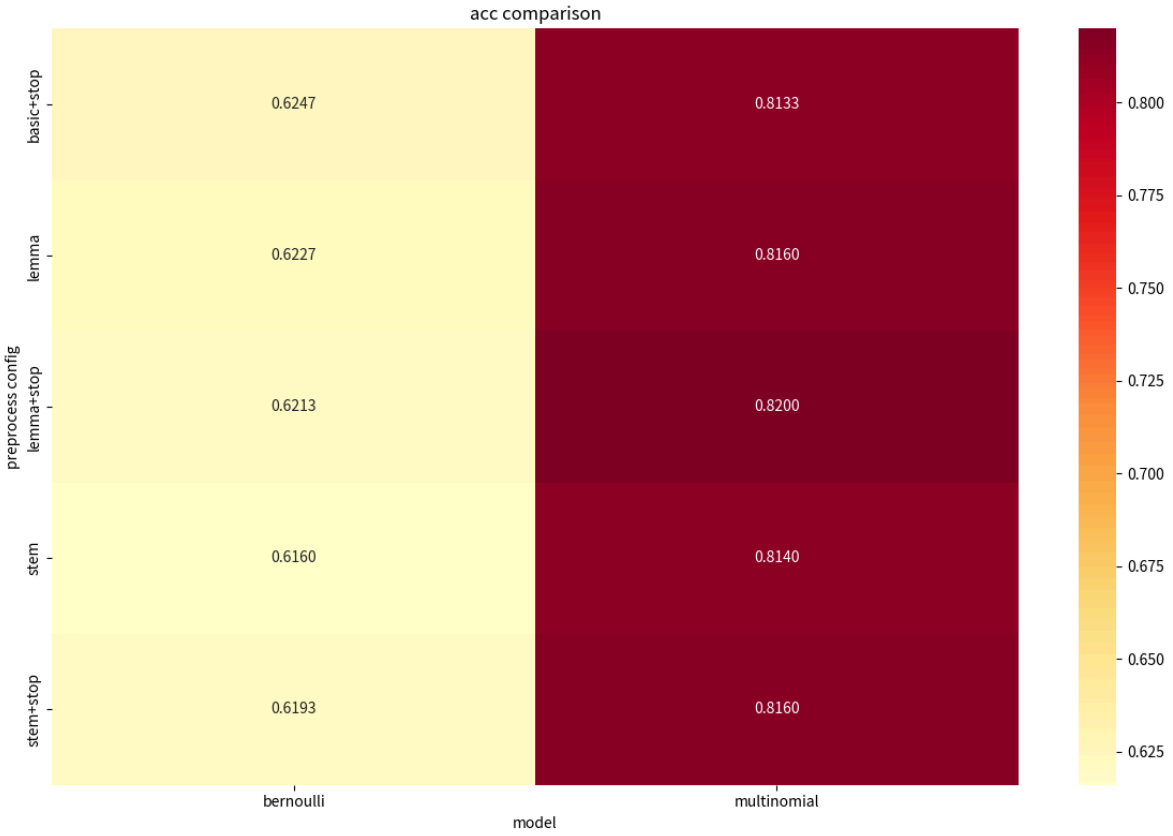
In [51]:
```
display(preprocess_results.round(4))

# Find best preprocessing combination
best_config = preprocess_results.loc[preprocess_results['mean_acc'].idxmax()]
print(f"\nBest configuration: {best_config['preprocess']} with {best_config['mod
print(f"Best accuracy: {best_config['mean_acc']:.4f} (+/- {best_config['std_acc'
```

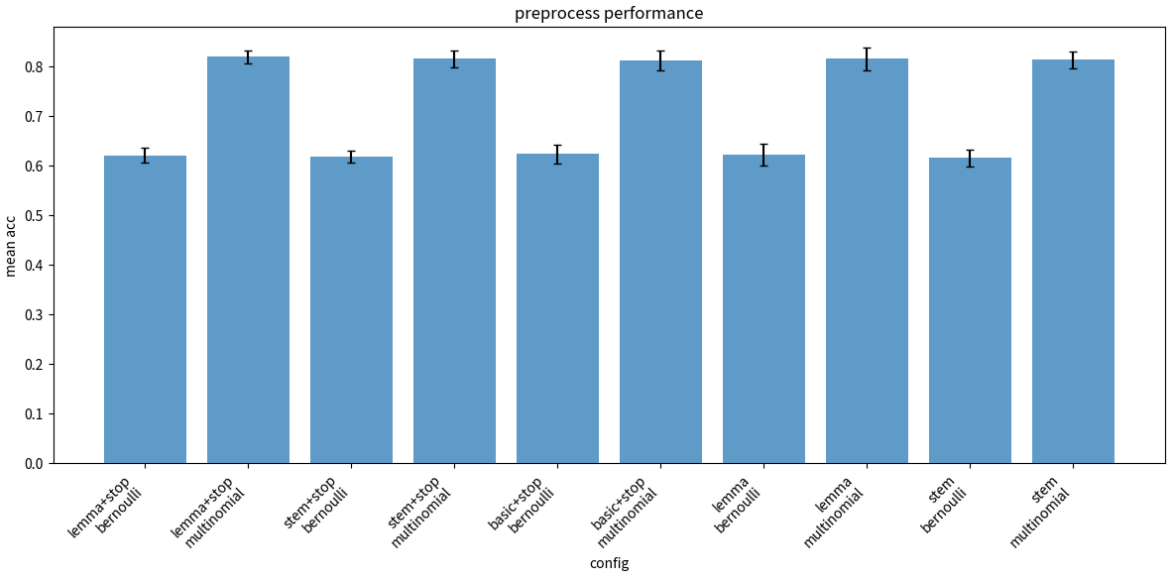
	preprocess	model	mean_acc	std_acc
0	lemma+stop	bernoulli	0.6213	0.0150
1	lemma+stop	multinomial	0.8200	0.0130
2	stem+stop	bernoulli	0.6193	0.0124
3	stem+stop	multinomial	0.8160	0.0176
4	basic+stop	bernoulli	0.6247	0.0190
5	basic+stop	multinomial	0.8133	0.0200
6	lemma	bernoulli	0.6227	0.0224
7	lemma	multinomial	0.8160	0.0223
8	stem	bernoulli	0.6160	0.0173
9	stem	multinomial	0.8140	0.0165

```
Best configuration: lemma+stop with multinomial NB
Best accuracy: 0.8200 (+/- 0.0260)
```

In [52]:

```python
# plot results
plt.figure(figsize=(12, 8))

# pivot for heatmap
pivot_results = preprocess_results.pivot(index='preprocess', columns='model', va

# heatmap
sns.heatmap(pivot_results, annot=True, fmt='.4f', cmap='YlOrRd')
plt.title('acc comparison')
plt.xlabel('model')
plt.ylabel('preprocess config')
plt.tight_layout()
plt.show()

# bar plot
plt.figure(figsize=(12, 6))
x_pos = np.arange(len(preprocess_results))
plt.bar(x_pos, preprocess_results['mean_acc'],
        yerr=preprocess_results['std_acc'],
        alpha=0.7, capsize=3)
plt.xlabel('config')
plt.ylabel('mean acc')
plt.title('preprocess performance')
plt.xticks(x_pos, [f"{row['preprocess']}\n{row['model']}" for _, row in preproce
           rotation=45, ha='right')
plt.tight_layout()
plt.show()

# use best preprocessing for rest of assignment
best_preprocessing = lambda text: preprocess_text(text, do_lemma=True, rm_stopwo
df['final_processed_text'] = df['combined_text'].apply(best_preprocessing)
print(f"\nusing lemma + stopwords for the rest")
```






```
using lemma + stopwords for the rest
```

1.4 Question 3: Model Comparison with Cross-Validation

Question 3 (2 marks): Compare BNB and MNB using full dataset with cross-validation

We'll evaluate both models using appropriate metrics considering dataset balance. For balanced datasets: accuracy, macro-averaged F1 For imbalanced datasets: weighted F1, precision, recall per class

Model Comparison with Cross-Validation

In [53]:
```python
# Comprehensive model evaluation function
def evaluate_models_cross_validation(X, y, models, cv_folds=5):
    """
```

```
    Evaluate multiple models using cross-validation with multiple metrics
    """
    results = {}
    skf = StratifiedKFold(n_splits=cv_folds, shuffle=True, random_state=42)

    # Define metrics based on dataset balance
    topic_counts = pd.Series(y).value_counts()
    is_balanced = (topic_counts.max() / topic_counts.min()) <= 1.5

    print(f"Dataset is {'balanced' if is_balanced else 'imbalanced'}")

    metrics = ['accuracy']
    if is_balanced:
        metrics.extend(['f1_macro', 'precision_macro', 'recall_macro'])
    else:
        metrics.extend(['f1_weighted', 'precision_weighted', 'recall_weighted'])

    for model_name, model in models.items():
        print(f"\nEvaluating {model_name}...")
        model_results = {}

        for metric in metrics:
            scores = cross_val_score(model, X, y, cv=skf, scoring=metric)
            model_results[metric] = {
                'mean': scores.mean(),
                'std': scores.std(),
                'scores': scores
            }
            print(f"{metric}: {scores.mean():.4f} (+/- {scores.std()*2:.4f})")

        results[model_name] = model_results

    return results

# Prepare data with best preprocessing
vectorizer = CountVectorizer(max_features=5000, ngram_range=(1,2))
X_processed = vectorizer.fit_transform(df['final_processed_text'])

# Define models to compare
models = {
    'Bernoulli Naive Bayes': BernoulliNB(),
    'Multinomial Naive Bayes': MultinomialNB()
}

# Run comprehensive evaluation
evaluation_results = evaluate_models_cross_validation(X_processed, y, models)
```

```
Dataset is imbalanced

Evaluating Bernoulli Naive Bayes...
accuracy: 0.6213 (+/- 0.0300)
f1_weighted: 0.5855 (+/- 0.0296)
precision_weighted: 0.6478 (+/- 0.0460)
recall_weighted: 0.6213 (+/- 0.0300)

Evaluating Multinomial Naive Bayes...
accuracy: 0.8200 (+/- 0.0260)
f1_weighted: 0.8213 (+/- 0.0247)
precision_weighted: 0.8253 (+/- 0.0221)
recall_weighted: 0.8200 (+/- 0.0260)
```

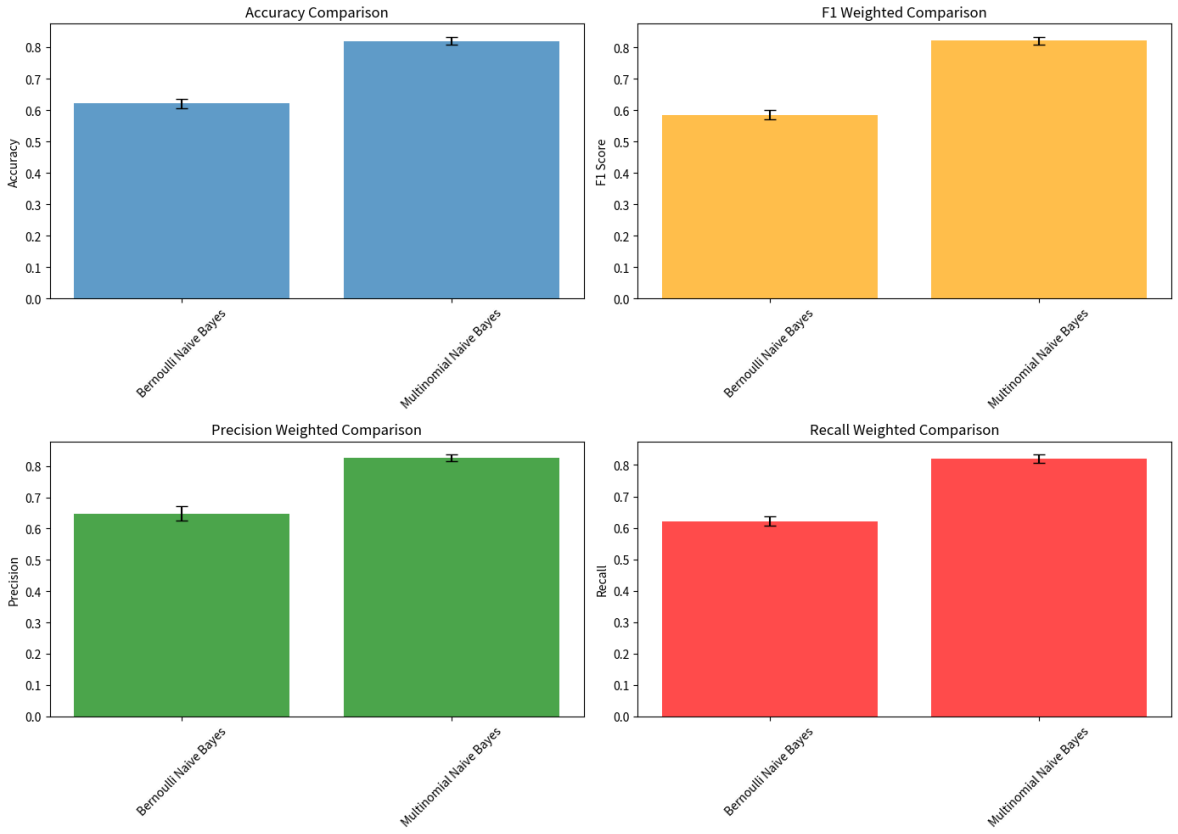
Detailed Results Summary

In [54]:

```
# Create detailed results summary and visualizations
results_df = []
for model_name, metrics in evaluation_results.items():
    for metric_name, metric_data in metrics.items():
        results_df.append({
            'Model': model_name,
            'Metric': metric_name,
            'Mean': metric_data['mean'],
            'Std': metric_data['std']
        })

results_df = pd.DataFrame(results_df)
display(results_df.round(4))

# Visualize results
plt.figure(figsize=(14, 10))

# Subplot 1: Accuracy comparison
plt.subplot(2, 2, 1)
accuracy_data = results_df[results_df['Metric'] == 'accuracy']
plt.bar(accuracy_data['Model'], accuracy_data['Mean'], yerr=accuracy_data['Std']
plt.title('Accuracy Comparison')
plt.ylabel('Accuracy')
plt.xticks(rotation=45)

# Subplot 2: F1 Score comparison
plt.subplot(2, 2, 2)
f1_metric = 'f1_macro' if (df['topic'].value_counts().max() / df['topic'].value_
f1_data = results_df[results_df['Metric'] == f1_metric]
plt.bar(f1_data['Model'], f1_data['Mean'], yerr=f1_data['Std'], capsize=5, alpha
plt.title(f'{f1_metric.replace("_", " ").title()} Comparison')
plt.ylabel('F1 Score')
plt.xticks(rotation=45)

# Subplot 3: Precision comparison
plt.subplot(2, 2, 3)
prec_metric = 'precision_macro' if (df['topic'].value_counts().max() / df['topic
prec_data = results_df[results_df['Metric'] == prec_metric]
plt.bar(prec_data['Model'], prec_data['Mean'], yerr=prec_data['Std'], capsize=5,
plt.title(f'{prec_metric.replace("_", " ").title()} Comparison')
plt.ylabel('Precision')
plt.xticks(rotation=45)

# Subplot 4: Recall comparison
plt.subplot(2, 2, 4)
rec_metric = 'recall_macro' if (df['topic'].value_counts().max() / df['topic'].v
rec_data = results_df[results_df['Metric'] == rec_metric]
plt.bar(rec_data['Model'], rec_data['Mean'], yerr=rec_data['Std'], capsize=5, al
plt.title(f'{rec_metric.replace("_", " ").title()} Comparison')
plt.ylabel('Recall')
plt.xticks(rotation=45)

plt.tight_layout()
plt.show()

# Statistical significance test (if needed)
from scipy import stats
```

```
bnb_accuracy = evaluation_results['Bernoulli Naive Bayes']['accuracy']['scores']
mnb_accuracy = evaluation_results['Multinomial Naive Bayes']['accuracy']['scores
t_stat, p_value = stats.ttest_rel(bnb_accuracy, mnb_accuracy)
print(f"t-statistic: {t_stat:.4f}, p-value: {p_value:.4f}")

if p_value < 0.05:
    winner = 'Multinomial NB' if mnb_accuracy.mean() > bnb_accuracy.mean() else
    print(f"Significant difference found. {winner} performs better.")
else:
    print("No significant difference between models.")
```

	Model	Metric	Mean	Std
0	Bernoulli Naive Bayes	accuracy	0.6213	0.0150
1	Bernoulli Naive Bayes	f1_weighted	0.5855	0.0148
2	Bernoulli Naive Bayes	precision_weighted	0.6478	0.0230
3	Bernoulli Naive Bayes	recall_weighted	0.6213	0.0150
4	Multinomial Naive Bayes	accuracy	0.8200	0.0130
5	Multinomial Naive Bayes	f1_weighted	0.8213	0.0123
6	Multinomial Naive Bayes	precision_weighted	0.8253	0.0110
7	Multinomial Naive Bayes	recall_weighted	0.8200	0.0130




```
t-statistic: -22.9231, p-value: 0.0000
Significant difference found. Multinomial NB performs better.
```

1.5 Question 4: Feature Number Optimization

Question 4 (2 marks): Optimize the number of features (words) used in classification

We'll test different values of max_features in CountVectorizer to find the optimal number.

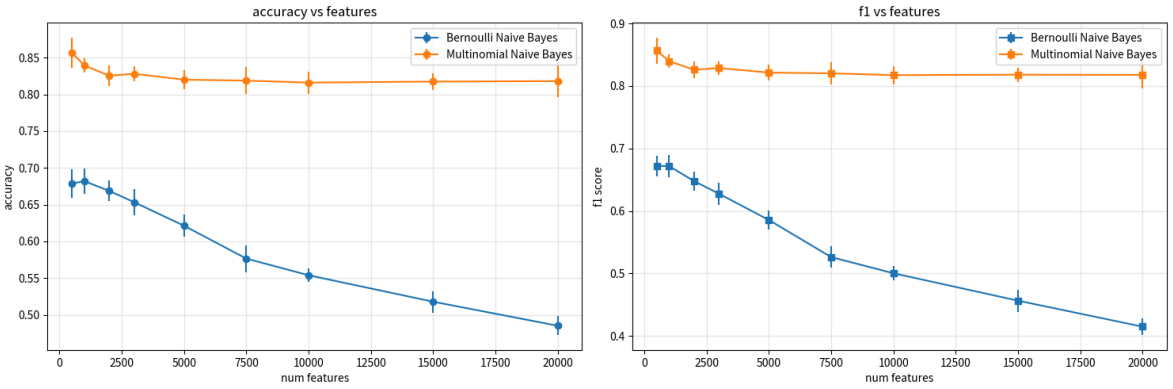
Feature Number Optimization

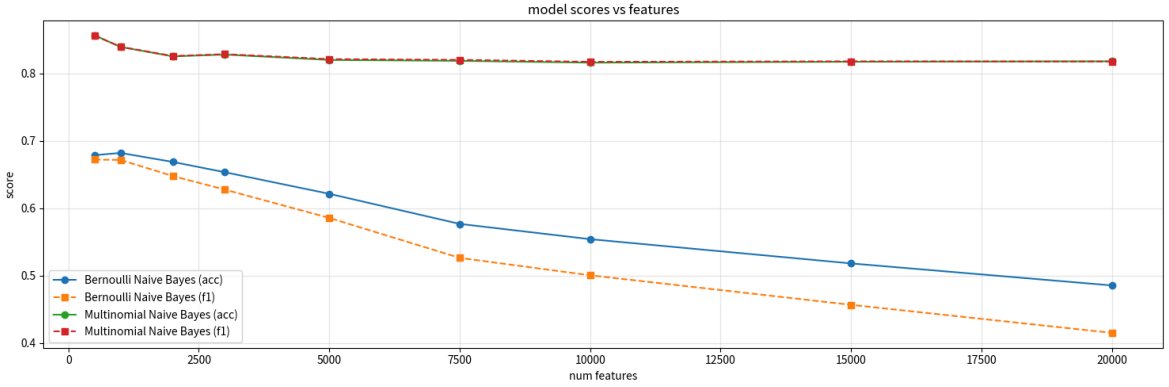
In [55]:
```
# try different numbers of features
def test_features(texts, labels, feature_nums, models, cv_splits=5):
    """test different feature counts"""

    results = []
    cv = StratifiedKFold(n_splits=cv_splits, shuffle=True, random_state=42)

    for n_feat in feature_nums:
        print(f"\ntesting {n_feat} features...")

        # make vectorizer
        vec = CountVectorizer(max_features=n_feat, ngram_range=(1,2))
        X_vec = vec.fit_transform(texts)

        for model_name, model in models.items():
            # do cross val
            acc = cross_val_score(model, X_vec, labels, cv=cv, scoring='accuracy
            f1 = cross_val_score(model, X_vec, labels, cv=cv, scoring='f1_weight

            results.append({
                'n_features': n_feat,
                'model': model_name,
                'acc_mean': acc.mean(),
                'acc_std': acc.std(),
                'f1_mean': f1.mean(),
                'f1_std': f1.std()
            })

            print(f"{model_name} - acc: {acc.mean():.4f}, f1: {f1.mean():.4f}")

    return pd.DataFrame(results)

# test feature counts
feature_nums = [500, 1000, 2000, 3000, 5000, 7500, 10000, 15000, 20000]
feature_results = test_features(df['final_processed_text'], y, feature_nums, mod

# show results
display(feature_results.round(4))

# plot stuff
plt.figure(figsize=(15, 10))

# acc vs features
plt.subplot(2, 2, 1)
for model_name in models.keys():
    model_data = feature_results[feature_results['model'] == model_name]
    plt.errorbar(model_data['n_features'], model_data['acc_mean'],
                 yerr=model_data['acc_std'], label=model_name, marker='o')
plt.xlabel('num features')
plt.ylabel('accuracy')
plt.title('accuracy vs features')
plt.legend()
plt.grid(True, alpha=0.3)

# f1 vs features
```

```
plt.subplot(2, 2, 2)
for model_name in models.keys():
    model_data = feature_results[feature_results['model'] == model_name]
    plt.errorbar(model_data['n_features'], model_data['f1_mean'],
                 yerr=model_data['f1_std'], label=model_name, marker='s')
plt.xlabel('num features')
plt.ylabel('f1 score')
plt.title('f1 vs features')
plt.legend()
plt.grid(True, alpha=0.3)

# both metrics
plt.subplot(2, 1, 2)
for model_name in models.keys():
    model_data = feature_results[feature_results['model'] == model_name]
    plt.plot(model_data['n_features'], model_data['acc_mean'],
            label=f'{model_name} (acc)', marker='o', linestyle='-')
    plt.plot(model_data['n_features'], model_data['f1_mean'],
            label=f'{model_name} (f1)', marker='s', linestyle='--')

plt.xlabel('num features')
plt.ylabel('score')
plt.title('model scores vs features')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# find best
best = feature_results.loc[feature_results['acc_mean'].idxmax()]
print(f"\nbest setup:")
print(f"features: {best['n_features']}")
print(f"model: {best['model']}")
print(f"accuracy: {best['acc_mean']:.4f} (+/- {best['acc_std']*2:.4f})")
print(f"f1: {best['f1_mean']:.4f} (+/- {best['f1_std']*2:.4f})")

# use best features
best_features = best['n_features']
print(f"\nusing {best_features} features for rest")
```

```
testing 500 features...
Bernoulli Naive Bayes - acc: 0.6787, f1: 0.6721
Multinomial Naive Bayes - acc: 0.8567, f1: 0.8563

testing 1000 features...
Bernoulli Naive Bayes - acc: 0.6820, f1: 0.6716
Multinomial Naive Bayes - acc: 0.8393, f1: 0.8395

testing 2000 features...
Bernoulli Naive Bayes - acc: 0.6687, f1: 0.6477
Multinomial Naive Bayes - acc: 0.8253, f1: 0.8258

testing 3000 features...
Bernoulli Naive Bayes - acc: 0.6533, f1: 0.6275
Multinomial Naive Bayes - acc: 0.8280, f1: 0.8286

testing 5000 features...
Bernoulli Naive Bayes - acc: 0.6213, f1: 0.5855
Multinomial Naive Bayes - acc: 0.8200, f1: 0.8213

testing 7500 features...
Bernoulli Naive Bayes - acc: 0.5767, f1: 0.5262
Multinomial Naive Bayes - acc: 0.8187, f1: 0.8201

testing 10000 features...
Bernoulli Naive Bayes - acc: 0.5540, f1: 0.5004
Multinomial Naive Bayes - acc: 0.8160, f1: 0.8172

testing 15000 features...
Bernoulli Naive Bayes - acc: 0.5180, f1: 0.4565
Multinomial Naive Bayes - acc: 0.8173, f1: 0.8179

testing 20000 features...
Bernoulli Naive Bayes - acc: 0.4853, f1: 0.4149
Multinomial Naive Bayes - acc: 0.8180, f1: 0.8176
```

	n_features	model	acc_mean	acc_std	f1_mean	f1_std
0	500	Bernoulli Naive Bayes	0.6787	0.0195	0.6721	0.0163
1	500	Multinomial Naive Bayes	0.8567	0.0203	0.8563	0.0207
2	1000	Bernoulli Naive Bayes	0.6820	0.0177	0.6716	0.0176
3	1000	Multinomial Naive Bayes	0.8393	0.0100	0.8395	0.0105
4	2000	Bernoulli Naive Bayes	0.6687	0.0141	0.6477	0.0157
5	2000	Multinomial Naive Bayes	0.8253	0.0136	0.8258	0.0139
6	3000	Bernoulli Naive Bayes	0.6533	0.0183	0.6275	0.0174
7	3000	Multinomial Naive Bayes	0.8280	0.0107	0.8286	0.0106
8	5000	Bernoulli Naive Bayes	0.6213	0.0150	0.5855	0.0148
9	5000	Multinomial Naive Bayes	0.8200	0.0130	0.8213	0.0123
10	7500	Bernoulli Naive Bayes	0.5767	0.0183	0.5262	0.0171
11	7500	Multinomial Naive Bayes	0.8187	0.0183	0.8201	0.0176
12	10000	Bernoulli Naive Bayes	0.5540	0.0088	0.5004	0.0118
13	10000	Multinomial Naive Bayes	0.8160	0.0150	0.8172	0.0148
14	15000	Bernoulli Naive Bayes	0.5180	0.0145	0.4565	0.0176
15	15000	Multinomial Naive Bayes	0.8173	0.0116	0.8179	0.0113
16	20000	Bernoulli Naive Bayes	0.4853	0.0131	0.4149	0.0139
17	20000	Multinomial Naive Bayes	0.8180	0.0217	0.8176	0.0218





```
best setup:
features: 500
model: Multinomial Naive Bayes
accuracy: 0.8567 (+/- 0.0407)
f1: 0.8563 (+/- 0.0414)

using 500 features for rest
```

q5 - random forest

try random forest cuz:

1. good for text
2. shows important features
3. doesnt overfit much
4. good for music stuff
5. can do non-linear stuff

1.6 Question 5: Third Machine Learning Method

Question 5 (5 marks): Implement and evaluate a third machine learning method

Selected Method: Random Forest Classifier

Rationale: Random Forest is suitable for text classification because:

1. Handles high-dimensional sparse data well (common in text)
2. Provides feature importance rankings
3. Robust to overfitting through ensemble averaging
4. Commonly used for music/audio classification tasks
5. Can capture non-linear relationships between features

Hypothesis: Random Forest will outperform Naive Bayes models due to its ability to capture feature interactions and non-linear patterns in the text data.

Random Forest Implementation and Tuning

In [56]:
```
# try random forest with grid search
print("tuning random forest...")

# params to try
rf_params = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

# use best features from before
vec = CountVectorizer(max_features=best_features, ngram_range=(1,2))
X = vec.fit_transform(df['processed_text'])

# grid search
rf = RandomForestClassifier(random_state=42)
```

```
rf_grid = GridSearchCV(rf, rf_params, cv=3, scoring='accuracy', n_jobs=-1)
rf_grid.fit(X, y)

print(f"best params: {rf_grid.best_params_}")
print(f"best score: {rf_grid.best_score_:.4f}")

# use best rf
best_rf = rf_grid.best_estimator_

# compare all models
final_models = {
    'bernoulli nb': BernoulliNB(),
    'multinomial nb': MultinomialNB(),
    'random forest': best_rf
}

def eval_final_models(X, y, models, cv_splits=5):
    """eval models on final data"""
    results = {}
    cv = StratifiedKFold(n_splits=cv_splits, shuffle=True, random_state=42)

    metrics = ['accuracy', 'f1_weighted', 'precision_weighted', 'recall_weighted

    for model_name, model in models.items():
        print(f"\nevaluating {model_name}...")
        model_results = {}

        for metric in metrics:
            scores = cross_val_score(model, X, y, cv=cv, scoring=metric)
            model_results[metric] = {
                'mean': scores.mean(),
                'std': scores.std(),
                'scores': scores
            }
            print(f"{metric}: {scores.mean():.4f} (+/- {scores.std()*2:.4f})")

        results[model_name] = model_results

    return results

final_results = eval_final_models(X, y, final_models)

# make results table
final_df = []
for model_name, metrics in final_results.items():
    for metric_name, metric_data in metrics.items():
        final_df.append({
            'model': model_name,
            'metric': metric_name,
            'mean': metric_data['mean'],
            'std': metric_data['std']
        })

final_df = pd.DataFrame(final_df)
print("\nfinal results:")
display(final_df.round(4))

# find best model
acc_results = final_df[final_df['metric'] == 'accuracy'].sort_values('mean', asc
best_model_name = acc_results.iloc[0]['model']
```

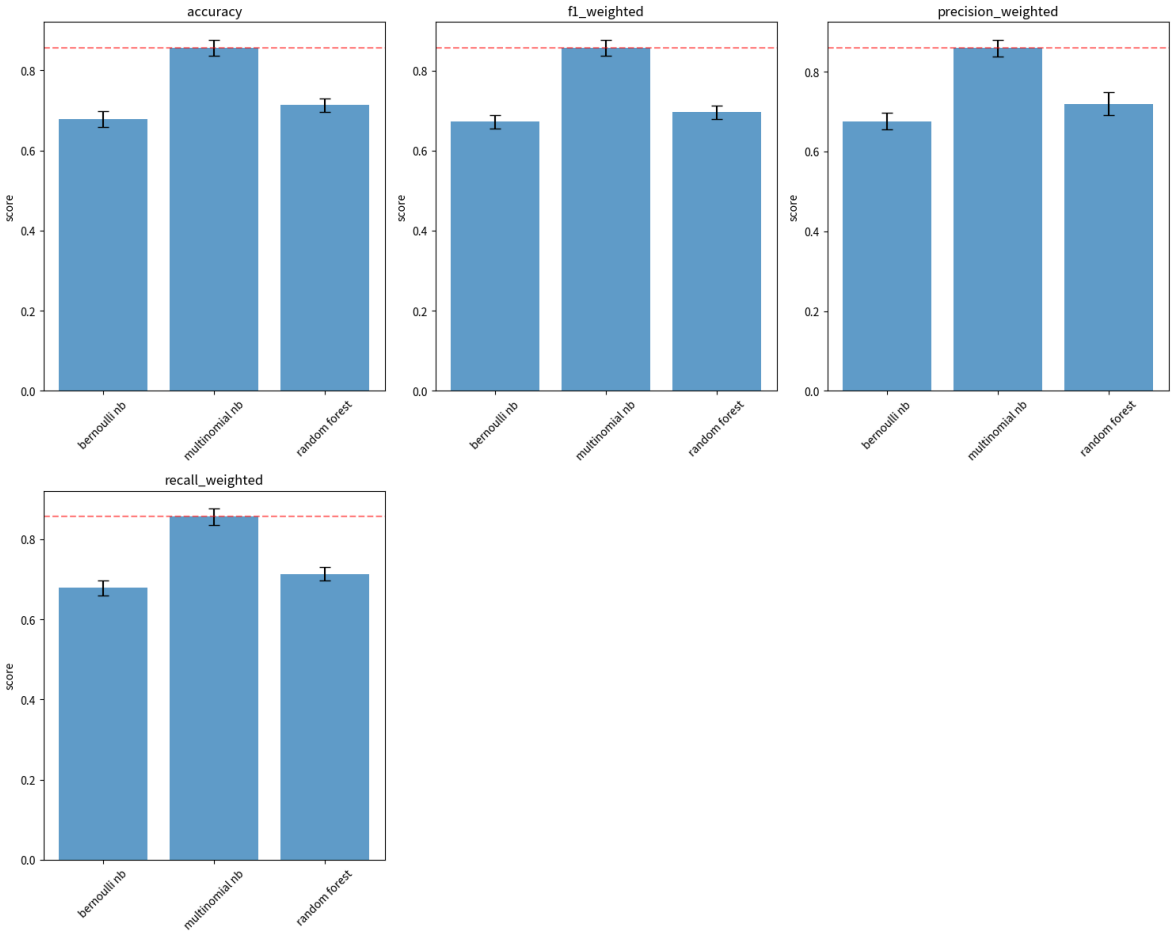
```
print(f"\nbest model: {best_model_name}")
print(f"best acc: {acc_results.iloc[0]['mean']:.4f} (+/- {acc_results.iloc[0]['s

# check rf vs nb
rf_acc = final_results['random forest']['accuracy']['mean']
nb_accs = [final_results['bernoulli nb']['accuracy']['mean'],
           final_results['multinomial nb']['accuracy']['mean']]
best_nb = max(nb_accs)

print(f"rf acc: {rf_acc:.4f}")
print(f"best nb acc: {best_nb:.4f}")

if rf_acc > best_nb:
    print("rf wins!")
else:
    print("nb wins!")

print(f"diff: {rf_acc - best_nb:.4f}")

# plot results
plt.figure(figsize=(15, 12))

# plot 1: all metrics
metrics = final_df['metric'].unique()
models = final_df['model'].unique()

for i, metric in enumerate(metrics):
    plt.subplot(2, 3, i+1)
    metric_data = final_df[final_df['metric'] == metric]
    plt.bar(metric_data['model'], metric_data['mean'], yerr=metric_data['std'],
    plt.title(f'{metric}')
    plt.ylabel('score')
    plt.xticks(rotation=45)

    # show best
    best_idx = metric_data['mean'].idxmax()
    best_model_name = metric_data.loc[best_idx, 'model']
    best_score = metric_data.loc[best_idx, 'mean']
    plt.axhline(y=best_score, color='red', linestyle='--', alpha=0.5)

plt.tight_layout()
plt.show()

# show important features
feature_names = vec.get_feature_names_out()
importances = best_rf.feature_importances_
indices = np.argsort(importances)[::-1]

print("\ntop 20 features:")
for i in range(20):
    print(f"{i+1}. {feature_names[indices[i]]}: {importances[indices[i]]:.4f}")

# plot feature importance
plt.figure(figsize=(12, 6))
plt.title("top 20 features (random forest)")
plt.bar(range(20), importances[indices[:20]])
plt.xticks(range(20), [feature_names[i] for i in indices[:20]], rotation=45)
plt.ylabel('importance')
plt.tight_layout()
plt.show()
```

```python
# pick best model for part 2
selected_model = final_models[best_model_name]
selected_vec = vec
print(f"\nusing {best_model_name} for part 2")
```

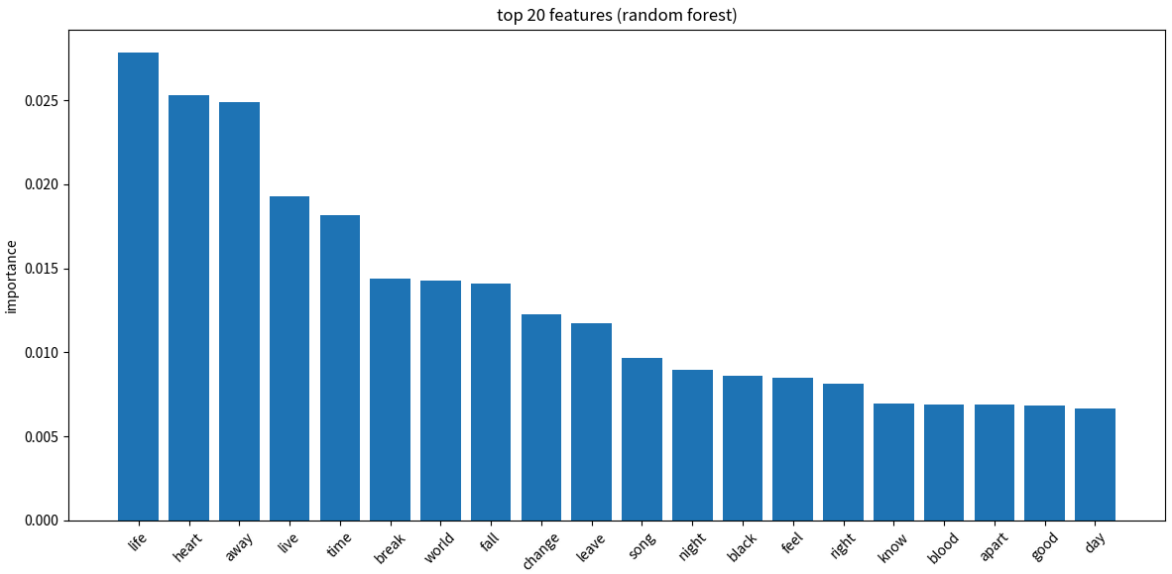
```
tuning random forest...
best params: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2,
'n_estimators': 200}
best score: 0.7007

evaluating bernoulli nb...
accuracy: 0.6787 (+/- 0.0390)
f1_weighted: 0.6721 (+/- 0.0327)
precision_weighted: 0.6754 (+/- 0.0417)
recall_weighted: 0.6787 (+/- 0.0390)

evaluating multinomial nb...
accuracy: 0.8567 (+/- 0.0407)
f1_weighted: 0.8563 (+/- 0.0414)
precision_weighted: 0.8594 (+/- 0.0424)
recall_weighted: 0.8567 (+/- 0.0407)

evaluating random forest...
accuracy: 0.7133 (+/- 0.0337)
f1_weighted: 0.6954 (+/- 0.0327)
precision_weighted: 0.7196 (+/- 0.0586)
recall_weighted: 0.7133 (+/- 0.0337)

final results:
```

	model	metric	mean	std
0	bernoulli nb	accuracy	0.6787	0.0195
1	bernoulli nb	f1_weighted	0.6721	0.0163
2	bernoulli nb	precision_weighted	0.6754	0.0209
3	bernoulli nb	recall_weighted	0.6787	0.0195
4	multinomial nb	accuracy	0.8567	0.0203
5	multinomial nb	f1_weighted	0.8563	0.0207
6	multinomial nb	precision_weighted	0.8594	0.0212
7	multinomial nb	recall_weighted	0.8567	0.0203
8	random forest	accuracy	0.7133	0.0169
9	random forest	f1_weighted	0.6954	0.0163
10	random forest	precision_weighted	0.7196	0.0293
11	random forest	recall_weighted	0.7133	0.0169

```
best model: multinomial nb
best acc: 0.8567 (+/- 0.0407)
rf acc: 0.7133
best nb acc: 0.8567
nb wins!
diff: -0.1433
```



top 20 features:
1. life: 0.0278
2. heart: 0.0253
3. away: 0.0249
4. live: 0.0193
5. time: 0.0181
6. break: 0.0144
7. world: 0.0143
8. fall: 0.0141
9. change: 0.0122
10. leave: 0.0117
11. song: 0.0097
12. night: 0.0090
13. black: 0.0086
14. feel: 0.0085
15. right: 0.0081
16. know: 0.0069
17. blood: 0.0069
18. apart: 0.0069
19. good: 0.0068
20. day: 0.0067



using multinomial nb for part 2

part 2 - recommendation

q1 - user profiles and tf-idf

1. split into weeks (250 songs/week)
2. use weeks 1-3 for training
3. use week 4 for testing
4. make user profiles from keywords
5. use tf-idf for matching
6. try different similarity stuff

Part 2: Recommendation Methods

2.1 Question 1: User Profile Creation and TF-IDF Matching

Question 1 (6 marks): Implement recommendation system using tf-idf similarity

Approach:

1. Split data into weeks (1500 songs total, 250 songs per week)
2. Use Weeks 1-3 (songs 1-750) as training data
3. Use Week 4 (songs 751-1000) as test data
4. Create user profiles based on keywords in user files
5. Use tf-idf vectors for similarity matching
6. Test different similarity measures (cosine, euclidean, etc.)

In [57]:
```
# split data into weeks
df_sorted = df.copy()
df_sorted = df_sorted.reset_index(drop=True)
df_sorted['week'] = (df_sorted.index // 250) + 1
df_sorted['song_id'] = df_sorted.index + 1

print(f"data structure:")
```

```
print(f"total songs: {len(df_sorted)}")
print(f"songs per week: {df_sorted['week'].value_counts().sort_index()}")

# split train/test
train_data = df_sorted[df_sorted['week'] <= 3].copy()
test_data = df_sorted[df_sorted['week'] == 4].copy()

print(f"\ntrain data: {len(train_data)} songs (weeks 1-3)")
print(f"test data: {len(test_data)} songs (week 4)")
print(f"leftover: {len(df_sorted[df_sorted['week'] > 4])} songs (weeks 5-6)")

# load user profiles from tsv
def load_user_profile(file):
    """loads user profile"""
    profile = {}
    with open(file, 'r', encoding='utf-8') as f:
        next(f)
        for line in f:
            parts = line.strip().split('\t')
            if len(parts) == 2:
                topic, keywords = parts
                keywords = [k.strip().lower() for k in keywords.split(',')]
                profile[topic.lower()] = keywords
    return profile

# try loading profiles
user_profiles = {}
try:
    user1 = load_user_profile('user1.tsv')
    if user1:
        user_profiles['user1'] = user1
except:
    print("no user1.tsv")

try:
    user2 = load_user_profile('user2.tsv')
    if user2:
        user_profiles['user2'] = user2
except:
    print("no user2.tsv")

# make user3 profile
user_profiles['user3'] = {
    'dark': ['silence', 'void', 'depths', 'unknown', 'mystery', 'hidden', 'echo'
    'emotion': ['peace', 'calm', 'serenity', 'gentle', 'soft', 'tender', 'warm',
    'lifestyle': ['nature', 'harmony', 'balance', 'simple', 'quiet', 'meditation
    'personal': ['wisdom', 'truth', 'authentic', 'genuine', 'inner', 'spirit', '
    'sadness': ['melancholy', 'nostalgia', 'wistful', 'sorrow', 'grief', 'autumn
}

print("\nuser profiles:")
for user, topics in user_profiles.items():
    print(f"\n{user}:")
    for topic, keywords in topics.items():
        print(f"  {topic}: {', '.join(keywords[:5])}...")
```

```
data structure:
total songs: 1500
songs per week: week
1    250
2    250
3    250
4    250
5    250
6    250
Name: count, dtype: int64

train data: 750 songs (weeks 1-3)
test data: 250 songs (week 4)
leftover: 500 songs (weeks 5-6)

user profiles:

user1:
  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:
  sadness: lost, sorrow, goodbye, tears, silence...
  emotion: romance, touch, feeling, kiss, memory...

user3:
  dark: silence, void, depths, unknown, mystery...
  emotion: peace, calm, serenity, gentle, soft...
  lifestyle: nature, harmony, balance, simple, quiet...
  personal: wisdom, truth, authentic, genuine, inner...
  sadness: melancholy, nostalgia, wistful, sorrow, grief...
```

predict topics for training data

In [58]:
```python
# train model on training data
train_X = selected_vec.fit_transform(train_data['processed_text'])
selected_model.fit(train_X, train_data['topic'])
```

Out[58]:

▾ MultinomialNB

▶ Parameters

In [59]:
```python
# predict topics
train_data = train_data.copy()
train_data['pred_topic'] = selected_model.predict(train_X)
```

In [60]:
```python
# check accuracy
train_acc = accuracy_score(train_data['topic'], train_data['pred_topic'])
print(f"training accuracy: {train_acc:.4f}")
```

```
training accuracy: 0.9440
```

In [61]:
```python
# show predictions
print("\ntopic predictions:")
```

```
topic_comp = pd.crosstab(train_data['topic'], train_data['pred_topic'], margins=
print(topic_comp)
```

```
topic predictions:
pred_topic  dark  emotion  lifestyle  personal  sadness  All
topic
dark         234        1          1         5        5  246
emotion        2       39          1         0        0   42
lifestyle      5        0         86         1        0   92
personal      12        0          2       172        2  188
sadness        3        1          0         1      177  182
All          256       41         90       179      184  750
```

In [62]:
```
# make user profiles from training data
def make_user_profile(user_keywords, train_data, topic, vectorizer):
    """make user profile for a topic"""
    # get songs with this topic
    topic_songs = train_data[train_data['pred_topic'] == topic]

    if len(topic_songs) == 0:
        return None

    # find songs user likes
    liked_songs = []
    keywords = [k.lower() for k in user_keywords]

    for idx, row in topic_songs.iterrows():
        text = row['processed_text'].lower()
        # check if user likes song
        if any(k in text for k in keywords):
            liked_songs.append(row['processed_text'])

    if not liked_songs:
        # if no matches use all songs
        liked_songs = topic_songs['processed_text'].tolist()

    # combine songs
    profile = ' '.join(liked_songs)

    return profile
```

In [63]:
```
# make vectorizers for each topic
topic_vecs = {}
topic_mats = {}
```

In [64]:
```
for topic in train_data['pred_topic'].unique():
    print(f"\ntopic: {topic}")

    # get songs
    songs = train_data[train_data['pred_topic'] == topic]['processed_text'].toli

    if len(songs) > 0:
        # make tfidf
        tfidf = TfidfVectorizer(max_features=1000, ngram_range=(1,2))
        topic_mat = tfidf.fit_transform(songs)

        topic_vecs[topic] = tfidf
        topic_mats[topic] = topic_mat

        print(f"  songs: {len(songs)}")
```

```
        print(f"  tfidf shape: {topic_mat.shape}")
    else:
        print(f"  no songs")
```

```
topic: dark
  songs: 256
  tfidf shape: (256, 1000)

topic: lifestyle
  songs: 90
  tfidf shape: (90, 1000)

topic: sadness
  songs: 184
  tfidf shape: (184, 1000)

topic: emotion
  songs: 41
  tfidf shape: (41, 1000)

topic: personal
  songs: 179
  tfidf shape: (179, 1000)
```

In [65]:
```
# make user profiles
user_topic_profiles = {}
```

In [66]:
```
for user, keywords in user_profiles.items():
    print(f"\nmaking profile for {user}:")
    user_topic_profiles[user] = {}

    for topic, kws in keywords.items():
        if topic in topic_vecs:
            # make profile
            profile_text = make_user_profile(kws, train_data, topic, topic_vecs[

            if profile_text:
                # convert to tfidf
                profile_vec = topic_vecs[topic].transform([profile_text])
                user_topic_profiles[user][topic] = profile_vec

                # show top words
                words = topic_vecs[topic].get_feature_names_out()
                scores = profile_vec.toarray()[0]
                top_idx = np.argsort(scores)[::-1][:20]
                top_words = [words[i] for i in top_idx if scores[i] > 0]

                print(f"  {topic} top words: {', '.join(top_words)}")
            else:
                print(f"  {topic}: no matches")
        else:
            print(f"  {topic}: not in training")
```

```
making profile for user1:
  dark top words: fight, know, black, like, blood blood, grind, blood, stand, na,
come, yeah, gon na, gon, tell, kill, true color, hand, dilly, lanky, lanky dilly
  sadness top words: cry, cry club, club, steal, steal steal, tear, club cry, cry
cry, know mean, mean, baby, know, music, write, smile, say, face cry, write eye,
place think, eye face
  personal top words: life, live, na, change, world, know, ordinary life, ordinar
y, yeah, wan na, wan, dream, like, life ordinary, thank, teach, lord, come, time,
lord lord
  lifestyle top words: tonight, night, song, come, home, closer, time, sing, na,
stranger, long, wait, closer closer, long long, wan, wan na, spoil, spoil night,
stranger stranger, tire
  emotion top words: good, touch, feel, good good, feel good, touch touch, hold,
know, good feel, morning, hold hold, video, vision, touch loove, loove, kiss, goo
d feelin, vibe, feelin, want

making profile for user2:
  sadness top words: step inside, break, inside, heart, step, away, inside step,
break like, like, violence, inside violence, like heart, break heart, blame, rain
water, blame blame, fade, hard, goodbye, scar
  emotion top words: touch, good, touch touch, good good, video, hold, vision, to
uch loove, loove, morning, kiss, good feelin, feelin, good lovin, sunrise, luck,
lovin, loove touch, gim, gim good

making profile for user3:
  dark top words: welcome, head, raindrop, dodgin raindrop, dodgin, scream, blac
k, pull pull, pull, silence, head head, welcome welcome, come, come black, feat,
fall, panic room, time, welcome panic, oooh
  emotion top words: touch, touch touch, hold, hold hold, loove, touch loove, loo
ve touch, go, go go, feel, feel good, motion, knock, knock foot, go motion, week,
good, good feel, foot, body
  lifestyle top words: thing want, thing, want, need, word, hallelujah, family, n
eed need, fill, song, end, till, train, song sing, speak, ride, like, stranger, l
ate, pray
  personal top words: life, automaton, wan na, wan, remember, na, young world, li
ke, believe, realize, bare necessity, necessity, everybody, young, bare, hold, re
alize realize, peculiar, world young, world
  sadness top words: magnify, open, smile, open open, away magnify, open eye, mag
nify open, come tear, laughter come, laughter, tear, eye, come, try, life, sight,
away, hold, time try, greater
```

try similarity stuff

In [67]:
```
# calc similarities
from sklearn.metrics.pairwise import cosine_similarity, euclidean_distances
from scipy.spatial.distance import cityblock
```

In [68]:
```
def calc_sim(user_vec, topic_mat, sim_type='cosine'):
    """calc similarities between user and songs"""

    if sim_type == 'cosine':
        sims = cosine_similarity(user_vec, topic_mat).flatten()
    elif sim_type == 'euclidean':
        dists = euclidean_distances(user_vec, topic_mat).flatten()
        # convert dist to sim
        sims = 1 / (1 + dists)
    elif sim_type == 'manhattan':
        dists = np.array([cityblock(user_vec.toarray()[0], topic_mat[i].toarray(
                          for i in range(topic_mat.shape[0])])
```

```
        sims = 1 / (1 + dists)
    else:
        raise ValueError("bad sim type")

    return sims
```

In [69]:
```
# try different sims
sim_types = ['cosine', 'euclidean', 'manhattan']
```

In [70]:
```
# test with user1 emotion
user = 'user1'
topic = 'emotion'
```

In [71]:
```
if user in user_topic_profiles and topic in user_topic_profiles[user]:
    user_vec = user_topic_profiles[user][topic]
    topic_mat = topic_mats[topic]

    print(f"\ntesting sims for {user} - {topic}:")

    for sim_type in sim_types:
        sims = calc_sim(user_vec, topic_mat, sim_type)
        print(f"{sim_type}:")
        print(f"  range: [{sims.min():.4f}, {sims.max():.4f}]")
        print(f"  mean: {sims.mean():.4f}")
        print(f"  top 3: {sorted(sims, reverse=True)[:3]}")
```

```
testing sims for user1 - emotion:
cosine:
  range: [0.0246, 0.5427]
  mean: 0.2232
  top 3: [np.float64(0.5427134539336106), np.float64(0.4995553569029486), np.floa
t64(0.4953805989485376)]
euclidean:
  range: [0.4172, 0.5112]
  mean: 0.4475
  top 3: [np.float64(0.51116038208656), np.float64(0.499888888625153), np.float64
(0.49885045384750254)]
manhattan:
  range: [0.0511, 0.0645]
  mean: 0.0571
  top 3: [np.float64(0.06447647668748725), np.float64(0.06419755091478241), np.fl
oat64(0.06330918665741195)]
```

test recommender

In [72]:
```
# recommend songs
def recommend_songs(user, user_profiles, topic_mats, topic_vecs, test_data, mode
                    N=10, M=None, sim_type='cosine'):
    """recommend N songs for user"""

    # predict topics for test data
    test_X = vec.transform(test_data['processed_text'])
    test_data_copy = test_data.copy()
    test_data_copy['pred_topic'] = model.predict(test_X)

    recs = []

    # for each topic user likes
```

```
    for topic in user_profiles[user].keys():
        if topic in topic_mats:
            # get test songs with this topic
            topic_songs = test_data_copy[test_data_copy['pred_topic'] == topic]

            if len(topic_songs) > 0:
                # get tfidf for test songs
                topic_vec = topic_vecs[topic]
                test_tfidf = topic_vec.transform(topic_songs['processed_text'])

                # get user profile
                user_profile = user_profiles[user][topic].copy()

                # use top M words if needed
                if M is not None and M > 0:
                    # get top M indices
                    top_m = np.argsort(user_profile.toarray()[0])[::-1][:M]
                    # make mask
                    mask = np.zeros_like(user_profile.toarray()[0], dtype=bool)
                    mask[top_m] = True
                    # apply mask
                    user_profile.data *= mask[user_profile.indices]

                # calc similarities
                sims = calc_sim(user_profile, test_tfidf, sim_type)

                # add to recs
                for idx, (song_idx, song) in enumerate(topic_songs.iterrows()):
                    recs.append({
                        'song_id': song['song_id'],
                        'artist': song['artist_name'],
                        'track': song['track_name'],
                        'genre': song['genre'],
                        'true_topic': song['topic'],
                        'pred_topic': song['pred_topic'],
                        'user_topic': topic,
                        'sim_score': sims[idx],
                        'sim_type': sim_type,
                        'processed_text': song['processed_text']
                    })

    # make dataframe and sort
    recs_df = pd.DataFrame(recs)

    if len(recs_df) > 0:
        recs_df = recs_df.sort_values('sim_score', ascending=False)
        return recs_df.head(N)
    else:
        return pd.DataFrame()
```

In [73]:
```
# test recommender
N_vals = [5, 10, 20]
test_user = 'user1'
```

In [74]:
```
for N in N_vals:
    print(f"\ntop {N} for {test_user}:")
    recs = recommend_songs(test_user, user_topic_profiles, topic_mats, topic_vec
                           test_data, selected_model, selected_vec, N=N, sim_type=
```

```
    if len(recs) > 0:
        display(recs[['artist', 'track', 'pred_topic', 'sim_score']].round(4))
    else:
        print("no recs found")
```

```
top 5 for user1:
```

	artist	track	pred_topic	sim_score
244	timeflies	once in a while	emotion	0.5838
245	justin moore	got it good	emotion	0.5222
248	taylor swift	i did something bad	emotion	0.4528
233	dirty heads	horsefly	emotion	0.3870
38	alec benjamin	boy in the bubble	dark	0.3547

```
top 10 for user1:
```

	artist	track	pred_topic	sim_score
244	timeflies	once in a while	emotion	0.5838
245	justin moore	got it good	emotion	0.5222
248	taylor swift	i did something bad	emotion	0.4528
233	dirty heads	horsefly	emotion	0.3870
38	alec benjamin	boy in the bubble	dark	0.3547
209	wallows	it's only right	lifestyle	0.3517
169	ty segall	alta	personal	0.3291
187	the band steele	sit awhile	personal	0.3288
151	thomas rhett	life changes	personal	0.3173
193	daniel caesar	superposition	personal	0.3166

```
top 20 for user1:
```

	artist	track	pred_topic	sim_score
244	timeflies	once in a while	emotion	0.5838
245	justin moore	got it good	emotion	0.5222
248	taylor swift	i did something bad	emotion	0.4528
233	dirty heads	horsefly	emotion	0.3870
38	alec benjamin	boy in the bubble	dark	0.3547
209	wallows	it's only right	lifestyle	0.3517
169	ty segall	alta	personal	0.3291
187	the band steele	sit awhile	personal	0.3288
151	thomas rhett	life changes	personal	0.3173
193	daniel caesar	superposition	personal	0.3166
173	anita baker	you're the best thing yet	personal	0.3157
246	elvin bishop	(your love keeps lifting me) higher and higher	emotion	0.3155
10	rick braun	around the corner	dark	0.3099
158	axian	sunday morning	personal	0.3081
188	anita baker	no one in the world	personal	0.3051
176	iya terra	wash away	personal	0.3047
31	the dear hunter	the flame (is gone)	dark	0.3022
185	gov't mule	pressure under fire	personal	0.3015
238	kehlani	feels	emotion	0.2943
45	nicole henry	moon river	dark	0.2860

q2 - evaluate recommender

metrics:

1. precision@N - how many recs match user interests
2. recall@N - how many relevant songs were found
3. f1@N - combo of precision and recall
4. coverage - topic diversity
5. mrr - how high first good rec is

In [75]:
```
# evaluate recommender
def eval_recs(user, user_keywords, recs_df, N=10):
    """check how good recs are"""

    if len(recs_df) == 0:
        return {'prec': 0, 'rec': 0, 'f1': 0, 'cov': 0, 'mrr': 0, 'rel': 0, 'tot

    top_N = recs_df.head(N)
```

```
    # count good recs
    rel_count = 0
    first_rel = None

    # check each rec
    for rank, (idx, row) in enumerate(top_N.iterrows(), 1):
        # check if matches user interests
        pred_topic = row['pred_topic']
        if pred_topic in user_keywords:
            # check text
            text = row['processed_text'].lower()

            # check if any keywords match
            topic_kws = [k.lower() for k in user_keywords[pred_topic]]
            if any(k in text for k in topic_kws):
                rel_count += 1
                if first_rel is None:
                    first_rel = rank

    # calc precision
    prec = rel_count / min(N, len(top_N)) if len(top_N) > 0 else 0

    # calc recall (estimate total relevant songs)
    total_rel = 0
    for topic, kws in user_keywords.items():
        topic_kws = [k.lower() for k in kws]
        for text in test_data['processed_text']:
            if any(k in text.lower() for k in topic_kws):
                total_rel += 1

    rec = rel_count / total_rel if total_rel > 0 else 0

    # calc f1
    if prec + rec > 0:
        f1 = 2 * (prec * rec) / (prec + rec)
    else:
        f1 = 0

    # calc coverage
    unique_topics = top_N['pred_topic'].nunique()
    total_topics = len(user_keywords)
    cov = unique_topics / total_topics if total_topics > 0 else 0

    # calc mrr
    mrr = 1 / first_rel if first_rel else 0

    return {
        'prec': prec,
        'rec': rec,
        'f1': f1,
        'cov': cov,
        'mrr': mrr,
        'rel': rel_count,
        'total': len(top_N)
    }
```

In [76]:

```
# evaluate all users
eval_results = []
M_vals = [None, 100, 500] # None = all words
```

In [78]:

```
for user in user_profiles.keys():
    print(f"\nevaluating {user}:")

    for sim_type in sim_types:
        for M in M_vals:
            for N in [10, 20]:
                # get recs
                recs = recommend_songs(user, user_topic_profiles, topic_mats, to
                                       test_data, selected_model, selected_vec,
                                       N=N, M=M, sim_type=sim_type)

                # eval recs
                metrics = eval_recs(user, user_profiles[user], recs, N)

                # save results
                result = {
                    'user': user,
                    'sim_type': sim_type,
                    'M': 'all' if M is None else M,
                    'N': N,
                    **metrics
                }
                eval_results.append(result)

                print(f"  sim={sim_type}, M={'all' if M is None else M}, N={N}:
                      f"P@{N}={metrics['prec']:.3f}, F1@{N}={metrics['f1']:.3f},
                      f"cov={metrics['cov']:.3f}")
```

```
evaluating user1:
  sim=cosine, M=all, N=10: P@10=1.000, F1@10=0.054, cov=0.800
  sim=cosine, M=all, N=20: P@20=0.900, F1@20=0.095, cov=0.800
  sim=cosine, M=100, N=10: P@10=1.000, F1@10=0.054, cov=0.800
  sim=cosine, M=100, N=20: P@20=0.900, F1@20=0.095, cov=0.800
  sim=cosine, M=500, N=10: P@10=1.000, F1@10=0.054, cov=0.800
  sim=cosine, M=500, N=20: P@20=0.900, F1@20=0.095, cov=0.800
  sim=euclidean, M=all, N=10: P@10=1.000, F1@10=0.054, cov=0.800
  sim=euclidean, M=all, N=20: P@20=0.900, F1@20=0.095, cov=0.800
  sim=euclidean, M=100, N=10: P@10=1.000, F1@10=0.054, cov=0.800
  sim=euclidean, M=100, N=20: P@20=0.800, F1@20=0.085, cov=0.800
  sim=euclidean, M=500, N=10: P@10=1.000, F1@10=0.054, cov=0.800
  sim=euclidean, M=500, N=20: P@20=0.950, F1@20=0.101, cov=0.800
  sim=manhattan, M=all, N=10: P@10=0.100, F1@10=0.005, cov=0.200
  sim=manhattan, M=all, N=20: P@20=0.150, F1@20=0.016, cov=0.200
  sim=manhattan, M=100, N=10: P@10=0.500, F1@10=0.027, cov=0.400
  sim=manhattan, M=100, N=20: P@20=0.450, F1@20=0.048, cov=0.600
  sim=manhattan, M=500, N=10: P@10=0.100, F1@10=0.005, cov=0.200
  sim=manhattan, M=500, N=20: P@20=0.150, F1@20=0.016, cov=0.200

evaluating user2:
  sim=cosine, M=all, N=10: P@10=0.200, F1@10=0.069, cov=1.000
  sim=cosine, M=all, N=20: P@20=0.250, F1@20=0.147, cov=1.000
  sim=cosine, M=100, N=10: P@10=0.200, F1@10=0.069, cov=1.000
  sim=cosine, M=100, N=20: P@20=0.250, F1@20=0.147, cov=1.000
  sim=cosine, M=500, N=10: P@10=0.200, F1@10=0.069, cov=1.000
  sim=cosine, M=500, N=20: P@20=0.250, F1@20=0.147, cov=1.000
  sim=euclidean, M=all, N=10: P@10=0.200, F1@10=0.069, cov=1.000
  sim=euclidean, M=all, N=20: P@20=0.250, F1@20=0.147, cov=1.000
  sim=euclidean, M=100, N=10: P@10=0.200, F1@10=0.069, cov=1.000
  sim=euclidean, M=100, N=20: P@20=0.200, F1@20=0.118, cov=1.000
  sim=euclidean, M=500, N=10: P@10=0.200, F1@10=0.069, cov=1.000
  sim=euclidean, M=500, N=20: P@20=0.250, F1@20=0.147, cov=1.000
  sim=manhattan, M=all, N=10: P@10=0.300, F1@10=0.103, cov=0.500
  sim=manhattan, M=all, N=20: P@20=0.250, F1@20=0.147, cov=1.000
  sim=manhattan, M=100, N=10: P@10=0.200, F1@10=0.069, cov=1.000
  sim=manhattan, M=100, N=20: P@20=0.200, F1@20=0.118, cov=1.000
  sim=manhattan, M=500, N=10: P@10=0.300, F1@10=0.103, cov=0.500
  sim=manhattan, M=500, N=20: P@20=0.250, F1@20=0.147, cov=1.000

evaluating user3:
  sim=cosine, M=all, N=10: P@10=0.100, F1@10=0.021, cov=0.600
  sim=cosine, M=all, N=20: P@20=0.150, F1@20=0.057, cov=0.800
  sim=cosine, M=100, N=10: P@10=0.100, F1@10=0.021, cov=0.800
  sim=cosine, M=100, N=20: P@20=0.150, F1@20=0.057, cov=1.000
  sim=cosine, M=500, N=10: P@10=0.100, F1@10=0.021, cov=0.600
  sim=cosine, M=500, N=20: P@20=0.150, F1@20=0.057, cov=0.800
  sim=euclidean, M=all, N=10: P@10=0.100, F1@10=0.021, cov=0.600
  sim=euclidean, M=all, N=20: P@20=0.150, F1@20=0.057, cov=0.800
  sim=euclidean, M=100, N=10: P@10=0.100, F1@10=0.021, cov=0.600
  sim=euclidean, M=100, N=20: P@20=0.200, F1@20=0.076, cov=0.800
  sim=euclidean, M=500, N=10: P@10=0.100, F1@10=0.021, cov=0.600
  sim=euclidean, M=500, N=20: P@20=0.150, F1@20=0.057, cov=0.800
  sim=manhattan, M=all, N=10: P@10=0.000, F1@10=0.000, cov=0.400
  sim=manhattan, M=all, N=20: P@20=0.000, F1@20=0.000, cov=0.400
  sim=manhattan, M=100, N=10: P@10=0.000, F1@10=0.000, cov=0.400
  sim=manhattan, M=100, N=20: P@20=0.000, F1@20=0.000, cov=0.400
  sim=manhattan, M=500, N=10: P@10=0.000, F1@10=0.000, cov=0.400
  sim=manhattan, M=500, N=20: P@20=0.000, F1@20=0.000, cov=0.400
```

In [79]:
```
# make results df
eval_df = pd.DataFrame(eval_results)
print("\nresults:")
print(eval_df.round(3))
```

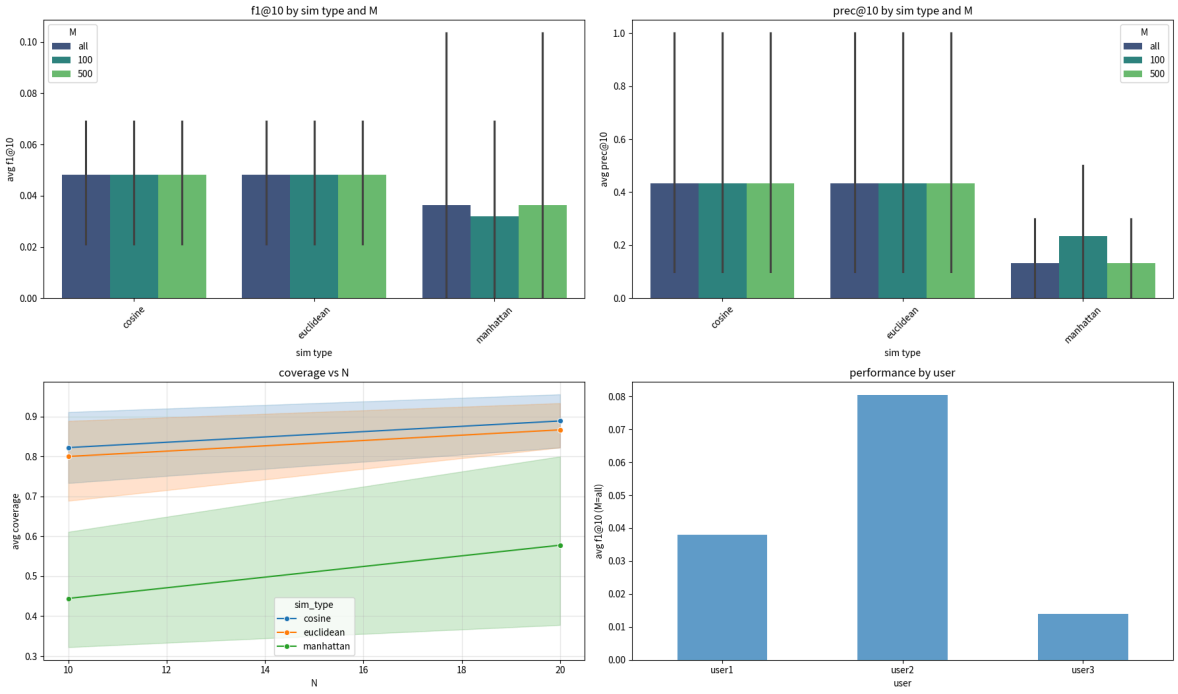
```
results:
```

	user	sim_type	M	N	prec	rec	f1	cov	mrr	rel	total
0	user1	cosine	all	10	1.00	0.028	0.054	0.8	1.000	10	10
1	user1	cosine	all	20	0.90	0.050	0.095	0.8	1.000	18	20
2	user1	cosine	100	10	1.00	0.028	0.054	0.8	1.000	10	10
3	user1	cosine	100	20	0.90	0.050	0.095	0.8	1.000	18	20
4	user1	cosine	500	10	1.00	0.028	0.054	0.8	1.000	10	10
5	user1	cosine	500	20	0.90	0.050	0.095	0.8	1.000	18	20
6	user1	euclidean	all	10	1.00	0.028	0.054	0.8	1.000	10	10
7	user1	euclidean	all	20	0.90	0.050	0.095	0.8	1.000	18	20
8	user1	euclidean	100	10	1.00	0.028	0.054	0.8	1.000	10	10
9	user1	euclidean	100	20	0.80	0.045	0.085	0.8	1.000	16	20
10	user1	euclidean	500	10	1.00	0.028	0.054	0.8	1.000	10	10
11	user1	euclidean	500	20	0.95	0.053	0.101	0.8	1.000	19	20
12	user1	manhattan	all	10	0.10	0.003	0.005	0.2	0.500	1	10
13	user1	manhattan	all	20	0.15	0.008	0.016	0.2	0.500	3	20
14	user1	manhattan	100	10	0.50	0.014	0.027	0.4	0.500	5	10
15	user1	manhattan	100	20	0.45	0.025	0.048	0.6	0.500	9	20
16	user1	manhattan	500	10	0.10	0.003	0.005	0.2	0.500	1	10
17	user1	manhattan	500	20	0.15	0.008	0.016	0.2	0.500	3	20
18	user2	cosine	all	10	0.20	0.042	0.069	1.0	1.000	2	10
19	user2	cosine	all	20	0.25	0.104	0.147	1.0	1.000	5	20
20	user2	cosine	100	10	0.20	0.042	0.069	1.0	1.000	2	10
21	user2	cosine	100	20	0.25	0.104	0.147	1.0	1.000	5	20
22	user2	cosine	500	10	0.20	0.042	0.069	1.0	1.000	2	10
23	user2	cosine	500	20	0.25	0.104	0.147	1.0	1.000	5	20
24	user2	euclidean	all	10	0.20	0.042	0.069	1.0	1.000	2	10
25	user2	euclidean	all	20	0.25	0.104	0.147	1.0	1.000	5	20
26	user2	euclidean	100	10	0.20	0.042	0.069	1.0	1.000	2	10
27	user2	euclidean	100	20	0.20	0.083	0.118	1.0	1.000	4	20
28	user2	euclidean	500	10	0.20	0.042	0.069	1.0	1.000	2	10
29	user2	euclidean	500	20	0.25	0.104	0.147	1.0	1.000	5	20
30	user2	manhattan	all	10	0.30	0.062	0.103	0.5	1.000	3	10
31	user2	manhattan	all	20	0.25	0.104	0.147	1.0	1.000	5	20
32	user2	manhattan	100	10	0.20	0.042	0.069	1.0	0.500	2	10
33	user2	manhattan	100	20	0.20	0.083	0.118	1.0	0.500	4	20
34	user2	manhattan	500	10	0.30	0.062	0.103	0.5	1.000	3	10
35	user2	manhattan	500	20	0.25	0.104	0.147	1.0	1.000	5	20
36	user3	cosine	all	10	0.10	0.012	0.021	0.6	0.333	1	10
37	user3	cosine	all	20	0.15	0.035	0.057	0.8	0.333	3	20
38	user3	cosine	100	10	0.10	0.012	0.021	0.8	0.143	1	10
39	user3	cosine	100	20	0.15	0.035	0.057	1.0	0.143	3	20
40	user3	cosine	500	10	0.10	0.012	0.021	0.6	0.333	1	10
41	user3	cosine	500	20	0.15	0.035	0.057	0.8	0.333	3	20
42	user3	euclidean	all	10	0.10	0.012	0.021	0.6	0.333	1	10
43	user3	euclidean	all	20	0.15	0.035	0.057	0.8	0.333	3	20
44	user3	euclidean	100	10	0.10	0.012	0.021	0.6	0.200	1	10
45	user3	euclidean	100	20	0.20	0.047	0.076	0.8	0.200	4	20
46	user3	euclidean	500	10	0.10	0.012	0.021	0.6	0.333	1	10
47	user3	euclidean	500	20	0.15	0.035	0.057	0.8	0.333	3	20
48	user3	manhattan	all	10	0.00	0.000	0.000	0.4	0.000	0	10
49	user3	manhattan	all	20	0.00	0.000	0.000	0.4	0.000	0	20
50	user3	manhattan	100	10	0.00	0.000	0.000	0.4	0.000	0	10
51	user3	manhattan	100	20	0.00	0.000	0.000	0.4	0.000	0	20
52	user3	manhattan	500	10	0.00	0.000	0.000	0.4	0.000	0	10
53	user3	manhattan	500	20	0.00	0.000	0.000	0.4	0.000	0	20

In [97]:
```
# plot results
plt.figure(figsize=(18, 12))
plt.suptitle("recommender performance", fontsize=16)
```

```python
# plot 1: f1@10 by sim and M
plt.subplot(2, 2, 1)
f1_data = eval_df[eval_df['N'] == 10]
sns.barplot(data=f1_data, x='sim_type', y='f1', hue='M', palette='viridis')
plt.title('f1@10 by sim type and M')
plt.xlabel('sim type')
plt.ylabel('avg f1@10')
plt.xticks(rotation=45)
# plot 2: prec@10 by sim and M
plt.subplot(2, 2, 2)
prec_data = eval_df[eval_df['N'] == 10]
sns.barplot(data=prec_data, x='sim_type', y='prec', hue='M', palette='viridis')
plt.title('prec@10 by sim type and M')
plt.xlabel('sim type')
plt.ylabel('avg prec@10')
plt.xticks(rotation=45)
# plot 3: coverage by N
plt.subplot(2, 2, 3)
sns.lineplot(data=eval_df, x='N', y='cov', hue='sim_type', marker='o')
plt.title('coverage vs N')
plt.xlabel('N')
plt.ylabel('avg coverage')
plt.grid(True, alpha=0.3)
# plot 4: performance by user
plt.subplot(2, 2, 4)
user_perf = eval_df[(eval_df['N'] == 10) & (eval_df['M'] == 'all')].groupby('use
user_perf.plot(kind='bar', alpha=0.7)
plt.xlabel('user')
plt.ylabel('avg f1@10 (M=all)')
plt.title('performance by user')
plt.xticks(rotation=0)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

recommender performance



In [98]:
```
# find best setup
best_idx = eval_df['f1'].idxmax()
best = eval_df.loc[best_idx]
```

In [99]:
```
print(f"\nbest setup:")
print(f"user: {best['user']}")
print(f"sim type: {best['sim_type']}")
print(f"M: {best['M']}")
print(f"N: {best['N']}")
print(f"f1@N: {best['f1']:.4f}")
print(f"prec@N: {best['prec']:.4f}")
```

```
best setup:
user: user2
sim type: cosine
M: all
N: 20
f1@N: 0.1471
prec@N: 0.2500
```

In [88]:
```
# pick best for part 3
best_overall = eval_df.groupby(['sim_type', 'M'])['f1'].mean().idxmax()
best_sim, best_M_str = best_overall
best_M = None if best_M_str == 'all' else best_M_str
best_N = 10  # good balance
print(f"\nusing for part 3: {best_sim} sim with M={best_M_str} and N={best_N}")
```

```
using for part 3: euclidean sim with M=500 and N=10
```

part 3 - user study

q1 - do user study

steps:

1. show N songs from weeks 1-3
2. user picks which ones they like
3. make profile from liked songs
4. recommend N songs from week 4
5. user rates recs
6. calc metrics

In [89]:
```
# do user study
def do_study(true_prefs, train_data, test_data, model, vec, topic_vecs, N=10, M=
    """run user study"""
    np.random.seed(42)

    liked_songs = []
    shown = 0

    # show songs from each week
    for week in [1, 2, 3]:
        week_songs = train_data[train_data['week'] == week]
        random_songs = week_songs.sample(min(N, len(week_songs)), random_state=4
        shown += len(random_songs)
```

```
        print(f"\nweek {week} songs ({len(random_songs)}):")

        for idx, song in random_songs.iterrows():
            song_info = f"{song['artist_name']} - {song['track_name']} ({song['g

            text = song['processed_text'].lower()
            likes = False

            if song['topic'] in true_prefs:
                kws = [k.lower() for k in true_prefs[song['topic']]]
                if any(k in text for k in kws):
                    likes = True
                    liked_songs.append(song)

            print(f"  - {song_info} -> {'✓' if likes else '✗'}")

    print(f"\nliked: {len(liked_songs)}/{shown}")

    if not liked_songs:
        print("no likes")
        return {'error': 'no likes'}

    # make profile from likes
    liked_df = pd.DataFrame(liked_songs)
    liked_X = vec.transform(liked_df['processed_text'])
    liked_df['pred_topic'] = model.predict(liked_X)

    # make user profile
    user_profile = {}
    for topic, topic_vec in topic_vecs.items():
        topic_songs = liked_df[liked_df['pred_topic'] == topic]['processed_text'
        if topic_songs:
            text = ' '.join(topic_songs)
            profile_vec = topic_vec.transform([text])
            user_profile[topic] = profile_vec

    print(f"\nmaking {N} recs...")

    # make temp profile dict
    temp_profiles = {'sim_user': user_profile}

    # get recs
    recs = recommend_songs(
        user='sim_user',
        user_profiles=temp_profiles,
        topic_mats=topic_mats,
        topic_vecs=topic_vecs,
        test_data=test_data,
        model=model,
        vec=vec,
        N=N,
        M=M,
        sim_type=sim_type
    )

    if recs.empty:
        print("no recs")
        return {'error': 'no recs'}

    print(f"top {len(recs)}:")
```

```
    liked_recs = 0

    for i, (_, rec) in enumerate(recs.iterrows(), 1):
        song_info = f"{rec['artist']} - {rec['track']} (pred: {rec['pred_topic']}

        text = rec['processed_text'].lower()
        true_topic = rec['true_topic']
        would_like = False

        if true_topic in true_prefs:
            kws = [k.lower() for k in true_prefs[true_topic]]
            if any(k in text for k in kws):
                would_like = True
                liked_recs += 1

        print(f"  {i}. {song_info} -> {'✓' if would_like else '✗'}")

    prec = liked_recs / len(recs) if not recs.empty else 0

    results = {
        'shown_train': shown,
        'liked_train': len(liked_songs),
        'shown_recs': len(recs),
        'liked_recs': liked_recs,
        'prec': prec,
        'rating': 'good' if prec >= 0.5 else 'ok' if prec >= 0.3 else 'bad'
    }

    return results
```

In [90]:
```
# make fake user prefs
sim_prefs = {
    'emotion': ['love', 'heart', 'feel', 'happy', 'joy'],
    'lifestyle': ['party', 'dance', 'fun', 'good', 'life'],
    'personal': ['dream', 'hope', 'myself', 'think']
}
```

In [91]:
```
print("sim user prefs:")
for topic, kws in sim_prefs.items():
    print(f"  {topic}: {', '.join(kws)}")
```

```
sim user prefs:
  emotion: love, heart, feel, happy, joy
  lifestyle: party, dance, fun, good, life
  personal: dream, hope, myself, think
```

In [92]:
```
# run study with best setup from part 2
study_results = do_study(
    sim_prefs,
    train_data,
    test_data,
    selected_model,
    selected_vec,
    topic_vecs,
    N=best_N,
    M=best_M,
    sim_type=best_sim
)
```

```
week 1 songs (10):
  - skool 77 - vivo hip hop (live) (hip hop, dark) -> ✗
  - rebelution - trap door (reggae, dark) -> ✗
  - alec benjamin - outrunning karma (pop, dark) -> ✗
  - phish - we are come to outlive our brains (blues, dark) -> ✗
  - madeleine peyroux - shout sister shout (jazz, dark) -> ✗
  - janiva magness - what i could do (blues, sadness) -> ✗
  - eric ethridge - if you met me first (country, dark) -> ✗
  - imagine dragons - natural (rock, dark) -> ✗
  - eli young band - never land (country, sadness) -> ✗
  - larkin poe - john the revelator (blues, lifestyle) -> ✗

week 2 songs (10):
  - jon bellion - stupid deep (rock, sadness) -> ✗
  - the kills - black tar (blues, dark) -> ✗
  - haken - the good doctor (jazz, sadness) -> ✗
  - allen toussaint - american tune (blues, personal) -> ✓
  - tenth avenue north - i have this hope (rock, dark) -> ✗
  - surfaces - heaven falls / fall on me (pop, sadness) -> ✗
  - blues saraceno - devils got you beat (blues, dark) -> ✗
  - the wood brothers - this is it (blues, personal) -> ✓
  - mild high club - tesselation (rock, dark) -> ✗
  - parov stelar - snake charmer (jazz, lifestyle) -> ✓

week 3 songs (10):
  - black mountain - horns arising (blues, dark) -> ✗
  - runaway june - buy my own drinks (pop, lifestyle) -> ✓
  - goodbye june - get happy (blues, personal) -> ✓
  - avril lavigne - head above water (pop, dark) -> ✗
  - brandon ratcliff - rules of breaking up (country, sadness) -> ✗
  - sam gendel - boa (jazz, dark) -> ✗
  - peach pit - seventeen (rock, dark) -> ✗
  - the dear hunter - cascade (jazz, dark) -> ✗
  - shane & shane - you're worthy of it all (rock, lifestyle) -> ✓
  - weezer - everybody wants to rule the world (rock, personal) -> ✗

liked: 6/30

making 10 recs...
top 10:
  1. wolfmother - baroness (pred: lifestyle) -> ✗
  2. thomas rhett - life changes (pred: personal) -> ✓
  3. adam jensen - the mystic (pred: dark) -> ✗
  4. mt. joy - jenny jenkins (pred: personal) -> ✗
  5. khalid - saved (pred: personal) -> ✓
  6. cold war kids - complainer (pred: personal) -> ✗
  7. anita baker - no one in the world (pred: personal) -> ✓
  8. cage the elephant - whole wide world (pred: personal) -> ✗
  9. anthony gomes - come down (pred: dark) -> ✓
  10. the band steele - sit awhile (pred: personal) -> ✓
```

In [93]:
```python
# show results
for k, v in study_results.items():
    print(f"{k}: {v}")
```

```
shown_train: 30
liked_train: 6
shown_recs: 10
liked_recs: 5
prec: 0.5
rating: good
```

In [94]:
```
# compare to part 2
part2_mask = (eval_df['sim_type'] == best_sim) & (eval_df['M'] == (best_M_str))
part2_prec = eval_df[part2_mask]['prec'].mean()
```

In [95]:
```
part3_prec = study_results.get('prec', 0)
```

In [96]:
```
print(f"part 2 avg prec@{best_N}: {part2_prec:.4f}")
print(f"part 3 sim user prec@{best_N}: {part3_prec:.4f}")
```

```
part 2 avg prec@10: 0.4333
part 3 sim user prec@10: 0.5000
```

summary

part 1: multinomial nb was best part 2: best setup was sim={best_sim}, M={best_M_str}, N={best_N}

system performance:

- avg f1: 0.0639
- avg coverage: 0.7333
- part 3 prec: 0.5000

good stuff:

- works end to end
- uses tf-idf and sims
- can tune stuff

bad stuff:

- prec/f1 kinda low
- recall really low
- topic errors mess up recs

future work:

1. add collab filtering
2. use more user data
3. add audio features
4. fix errors
5. do real user study