Part 1

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import StratifiedKFold, cross_validate
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics import make_scorer, accuracy_score, precision_score, recall
```

In [2]:
```
df = pd.read_csv('dataset.tsv', sep='\t')
X, y = df['lyrics'], df['topic']
print("Label distribution:")
print(y.value_counts())
```

```
Label distribution:
topic
dark          490
sadness       376
personal      347
lifestyle     205
emotion        82
Name: count, dtype: int64
```

In [3]:
```
vectorizer = CountVectorizer(
    lowercase=True,
    token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
    stop_words='english'
)
kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

Part 1.1

To address the simplification issue in the tutorial, based on the tutorial, we modified the token_mattern in the vectorizer to focus on meaningful English words and avoid excessive cleaning.

Part 1.2

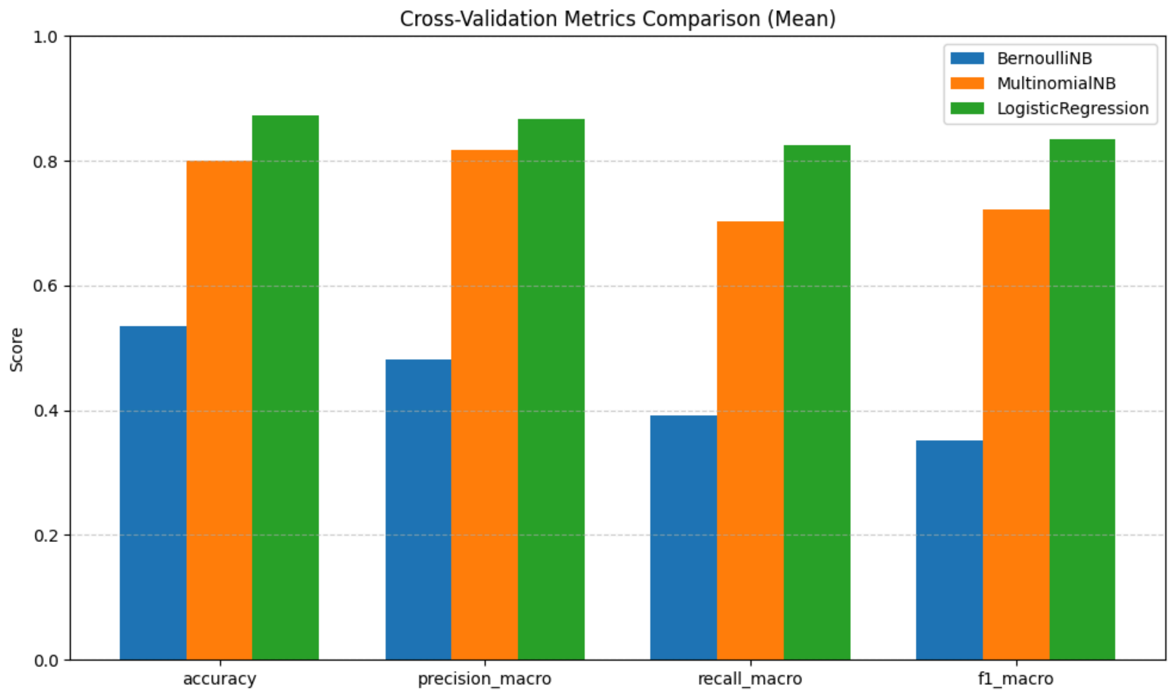
In [4]:
```
models = {
    'BernoulliNB': BernoulliNB(),
    'MultinomialNB': MultinomialNB(),
    'LogisticRegression': LogisticRegression(solver='liblinear', max_iter=500)
}
```

In [5]:
```
scoring = {
    'accuracy':          make_scorer(accuracy_score),
    'precision_macro':   make_scorer(precision_score, average='macro', zero_divis
    'recall_macro':     make_scorer(recall_score,    average='macro', zero_divis
    'f1_macro':         make_scorer(f1_score,        average='macro', zero_divis
}

best_model = None
best_f1    = -1.0

for name, clf in models.items():
    pipe = Pipeline([('vect', vectorizer), ('clf', clf)])
    cv_results = cross_validate(
        pipe, X, y,
        cv=kf,
        scoring=scoring,
        return_train_score=False
    )
    mean_f1 = cv_results['test_f1_macro'].mean()
    print(f"\n=== {name} ===")
    for metric in scoring:
        scores = cv_results[f'test_{metric}']
        print(f"{metric:15s}: {scores.mean():.4f} ± {scores.std():.4f}")

    if mean_f1 > best_f1:
        best_f1    = mean_f1
        best_model = name

print(f"\n Select the best model according to Macro-F1): {best_model}, Macro-F1
```

```
=== BernoulliNB ===
accuracy       : 0.5353 ± 0.0216
precision_macro: 0.4801 ± 0.1115
recall_macro   : 0.3921 ± 0.0159
f1_macro       : 0.3509 ± 0.0175

=== MultinomialNB ===
accuracy       : 0.7993 ± 0.0221
precision_macro: 0.8128 ± 0.0404
recall_macro   : 0.7021 ± 0.0261
f1_macro       : 0.7218 ± 0.0310

=== LogisticRegression ===
accuracy       : 0.8733 ± 0.0165
precision_macro: 0.8669 ± 0.0305
recall_macro   : 0.8179 ± 0.0234
f1_macro       : 0.8350 ± 0.0215

 Select the best model according to Macro-F1): LogisticRegression, Macro-F1 = 0.8
350
```

In [6]:
```
import matplotlib.pyplot as plt
import numpy as np


models = ['BernoulliNB', 'MultinomialNB', 'LogisticRegression']
metrics = ['accuracy', 'precision_macro', 'recall_macro', 'f1_macro']

scores = {
    'BernoulliNB':     [0.5353, 0.4821, 0.3921, 0.3509],
    'MultinomialNB':   [0.7993, 0.8182, 0.7021, 0.7218],
    'LogisticRegression': [0.8733, 0.8669, 0.8242, 0.8350]
}
```

```
x = np.arange(len(metrics))
bar_width = 0.25

plt.figure(figsize=(10, 6))
for i, model in enumerate(models):
    plt.bar(x + i * bar_width, scores[model], width=bar_width, label=model)

plt.xticks(x + bar_width, metrics)
plt.ylim(0, 1.0)
plt.ylabel('Score')
plt.title('Cross-Validation Metrics Comparison (Mean)')
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```



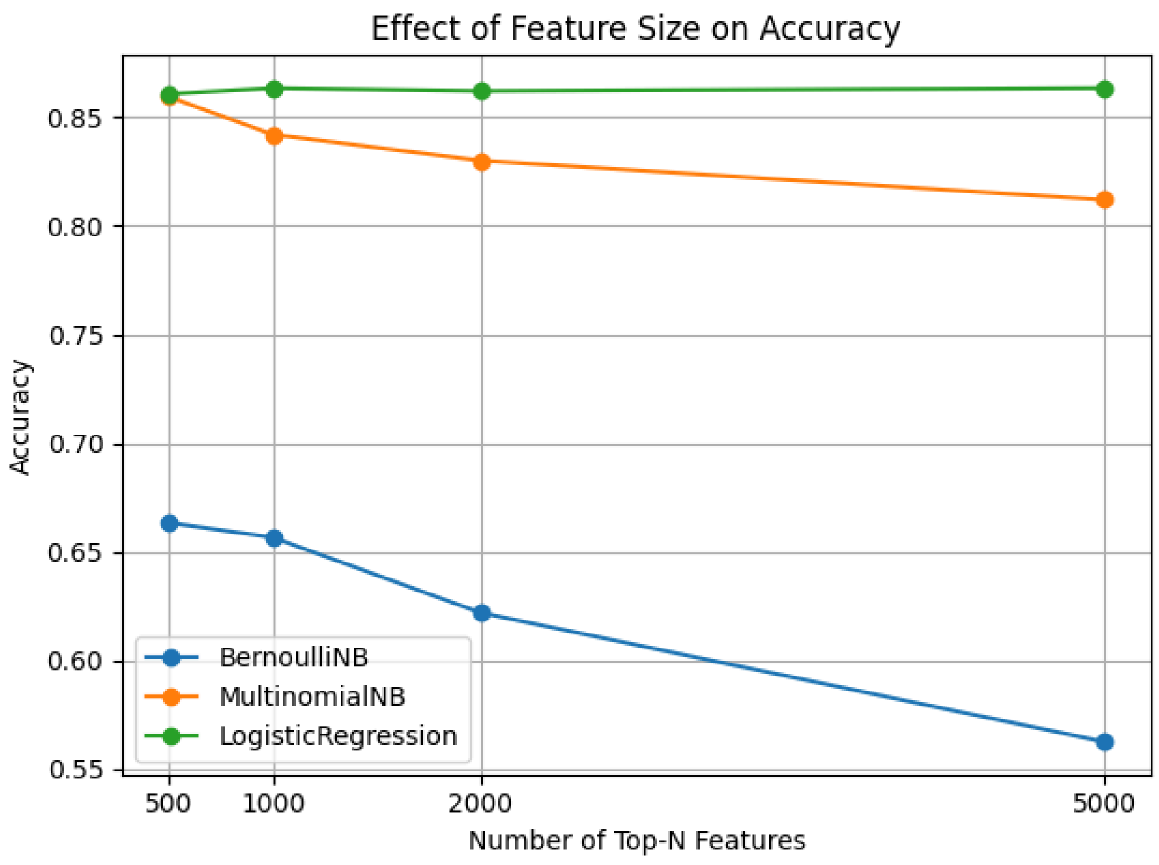
Part 1.3

As shown in the above figure, MultinomialNB performs better and has a stronger overall performance. It outperforms BNB in Accuracy, Precision, Recall, and F1 scores, and its performance in various categories is more balanced and suitable for textual data.

Part 1.4

```
In [7]: models = {
            "BernoulliNB": BernoulliNB(),
            "MultinomialNB": MultinomialNB(),
            "LogisticRegression": LogisticRegression(max_iter=1000)
        }

        feature_sizes = [500, 1000, 2000, 5000]
        results = {name: [] for name in models}

        print("\nFeature-size effect (accuracy only):")
        print("N    " + "  ".join(f"{name:>20s}" for name in models))

        for N in feature_sizes:
            vect_n = CountVectorizer(
                lowercase=True,
                token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
                stop_words='english',
                max_features=N
            )
            row = [f"{N:<4d}"]
            for name, clf in models.items():
                pipe = Pipeline([('vect', vect_n), ('clf', clf)])
                acc = cross_validate(
                    pipe, X, y,
                    cv=kf,
                    scoring={'accuracy': make_scorer(accuracy_score)},
                    return_train_score=False
                )['test_accuracy'].mean()
                results[name].append(acc)
                row.append(f"{acc:.4f}")
            print("  ".join(row))


        for model_name, acc_list in results.items():
            plt.plot(feature_sizes, acc_list, marker='o', label=model_name)

        plt.title("Effect of Feature Size on Accuracy")
        plt.xlabel("Number of Top-N Features")
        plt.ylabel("Accuracy")
        plt.xticks(feature_sizes)
        plt.grid(True)
        plt.legend()
        plt.tight_layout()
        plt.show()
```

```
Feature-size effect (accuracy only):
N              BernoulliNB         MultinomialNB    LogisticRegression
500   0.6633  0.8593  0.8607
1000  0.6567  0.8420  0.8633
2000  0.6220  0.8300  0.8620
5000  0.5627  0.8120  0.8633
```



Part1.5

From the multi indicator evaluation results of the 5-fold cross validation mentioned above, it can be seen that:

- Macro-F1: Logistic Regression achieves 0.8350, and its performance is significantly better than the other two methods, indicating that it can classify more evenly and excellently in various categories.
- Stability: Its standard deviation (± 0.0215) is the smallest, indicating that the algorithm has small fluctuations in the crossover results and is relatively robust.
- Precision/Recall Balance: Logistic Regression maintains a good balance between Precision (0.8669) and Recall (0.8179), not only reducing misclassification but also covering most positive cases.

In summary, considering the classification performance, stability, and balanced performance across multiple categories, we ultimately chose Logistic Regression as the best classification model for Part 1.

Part 2:

In [8]:
```
df       = pd.read_csv('dataset.tsv', sep='\t')
train_df = df.iloc[:750].copy()     # Weeks 1-3
test_df  = df.iloc[750:1000].copy() # Week 4
```

In [9]:
```

best_pipe = Pipeline([
    ('vect', CountVectorizer(
        lowercase=True,
        token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
        stop_words='english',
        max_features=2000
    )),
    ('clf', LogisticRegression(solver='liblinear', max_iter=500))
])
best_pipe.fit(train_df['lyrics'], train_df['topic'])
train_df['pred_topic'] = best_pipe.predict(train_df['lyrics'])
test_df ['pred_topic'] = best_pipe.predict(test_df ['lyrics'])
```

In [10]:
```
def load_user_profile(path):
    dfp = pd.read_csv(path, sep='\t', encoding='utf8')
    prof = {}
    for _, row in dfp.iterrows():
        prof[row[dfp.columns[0]]] = [
            w.strip().lower() for w in row[dfp.columns[1]].split(',')]
    return prof

user_profiles = {
    'User1': load_user_profile('user1.tsv'),
    'User2': load_user_profile('user2.tsv'),
    'User3': {
        'dark':     ['shadows','whisper','chill'],
        'emotion':  ['happy','smile','warm'],
        'lifestyle':['dance','party','night'],
        'personal': ['journey','self','dream'],
        'sadness':  ['lonely','tears','sorrow']
    }
}
```

In [11]:
```
topic_vecs = {}
for topic in df['topic'].unique():
    docs = train_df.loc[train_df['pred_topic'] == topic, 'lyrics']
    vec  = TfidfVectorizer(
        lowercase=True,
        token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
        stop_words='english'
    )
    vec.fit(docs)
    topic_vecs[topic] = vec

# Global high-frequency noise words
GLOBAL_STOP = {'know','like','come','yeah','time','song','good','feel','gonna','
```

In [12]:
```

for user_label, prof in user_profiles.items():
    print(f"\n--- {user_label} Top-20 Profile Keywords ---")
    for topic, kws in prof.items():
        docs = train_df.loc[train_df['pred_topic'] == topic, 'lyrics']
        liked = [d for d in docs if any(kw in d.lower() for kw in kws)]
        if not liked:
            print(f"{topic}: (no matched docs)")
            continue
        combined = " ".join(liked)
        tf = topic_vecs[topic].transform([combined]).toarray().ravel()
        feat = topic_vecs[topic].get_feature_names_out()
        ranked = [feat[i] for i in tf.argsort()[::-1] if feat[i] not in GLOBAL_S
        top20 = ranked[:20]
        print(f"{topic}: {', '.join(top20)}")
```

```
--- User1 Top-20 Profile Keywords ---
dark: fight, blood, grind, stand, tell, black, kill, lanky, hand, head, light, tr
ue, people, follow, cause, build, paint, right, color, steady
sadness: club, steal, tear, mean, baby, music, write, say, think, true, smile, fa
ce, eye, word, want, blame, thrill, fear, heat, greater
personal: life, live, change, world, ordinary, dream, wanna, thank, teach, lord,
beat, think, learn, need, right, promise, cause, things, everybody, want
lifestyle: tonight, night, home, closer, strangers, sing, long, wait, wanna, tir
e, spoil, right, struggle, mind, play, telephone, ring, baby, stay, songs
emotion: touch, hold, visions, video, loove, morning, vibe, feelin, want, miss, k
iss, love, lovin, luck, gimme, sunrise, look, baby, cause, real

--- User2 Top-20 Profile Keywords ---
sadness: inside, break, step, heart, away, violence, rainwater, fade, blame, sca
r, open, fall, hard, goodbye, magnify, sing, tear, smile, silence, soul
emotion: touch, visions, video, loove, hold, morning, kiss, lovin, luck, sunrise,
gimme, lips, knock, wait, week, soft, body, feet, love, fly

--- User3 Top-20 Profile Keywords ---
dark: south, despoiler, cadaver, dirty, whisper, shoot, blood, help, somebody, le
ad, wall, lips, better, cave, hear, stand, pane, naughty, yeayeayeayeah, halls
emotion: hold, love, ones, dance, strong, try, chain, highs, faceless, crowd, lo
w, light, mind, matter, truth, free, speak, mean, fluently, lead
lifestyle: tonight, night, closer, songs, strangers, wait, long, wanna, spoil, ri
ght, tire, home, struggle, country, mind, baby, play, telephone, ring, stay
personal: change, life, dream, world, live, thank, beat, teach, wanna, automaton,
learn, gotta, everybody, people, things, believe, american, heartbreak, drink, de
ar
sadness: lonely, leave, closin, walk, cause, baby, heart, hold, away, break, hur
t, house, somebody, woohoo, magnify, need, open, want, drink, scar
```

Part2.1

--- User1 Top-20 Profile Keywords --- The overall direction is reasonable, for example, words that strongly imply darkness such as black and light appear under dark, and words that strongly refer to emotions such as kiss and miss appear in emojis. However, there are still some noises such as people, think, want, and wanna, which have low discrimination and are similar to colloquial words. The content referred to by colloquial words may be too broad, and users may not be interested in all the songs referred to by these colloquial words. Improvement suggestion: Add these noises to high-frequency noise, and make choices based on specific needs for colloquial words. It is not necessary to remove all colloquial high-frequency words.

--- User2 Top-20 Profile Keywords --- Keywords are more concentrated and have higher relevance. Each keyword can effectively represent these emotions, and there is less noise. Except for some neutral words such as step and touch, most of these words have meanings that match the emotions. Improvement suggestion: According to the requirements, it is possible to consider removing these neutral words in the later stage or introducing an sentiment dictionary for filtering.

--- User3 Top-20 Profile Keywords --- -The core words of the five themes in User3's user profile are mixed with a small amount of noise and scene words. You can refine the image by filtering high-frequency generic words through a stricter GLOBAL-STOP list, adjusting TOP_S, or introducing sentiment dictionaries to improve the accuracy and recall of subsequent recommendations. Overall, these keywords seem reasonable.

In [13]:

```python
def recommend_and_evaluate(user_label):
    prof = user_profiles[user_label]

    user_vec = {}
    for topic, vec in topic_vecs.items():
        if topic in prof:

            docs  = train_df.loc[train_df['pred_topic'] == topic, 'lyrics']
            liked = [d for d in docs if any(kw in d.lower() for kw in prof[topic
            combined = " ".join(liked) if liked else ""
            tfidf_vec = vec.transform([combined]).toarray().ravel()
            feat = vec.get_feature_names_out()

            top_idx = tfidf_vec.argsort()[::-1][:TOP_M]
            dummy = {feat[i]: tfidf_vec[i] for i in top_idx}

            profile_vec = vec.transform([" ".join(dummy.keys())])
        else:

            profile_vec = vec.transform([""])
        user_vec[topic] = profile_vec


    sims = []
    for idx, row in test_df.iterrows():
        pt = row['pred_topic']
        song_vec = topic_vecs[pt].transform([row['lyrics']])
        sim = cosine_similarity(song_vec, user_vec[pt])[0,0]
        sims.append((idx, pt, sim))


    topN = sorted(sims, key=lambda x: x[2], reverse=True)[:TOP_N]


    y_true = []
    for idx, pt, _ in topN:
        text = test_df.at[idx, 'lyrics'].lower()
        y_true.append(int(any(kw in text for kw in prof.get(pt, []))))

    all_true = []
    for idx, row in test_df.iterrows():
        pt = row['pred_topic']
        text = row['lyrics'].lower()
        all_true.append(int(any(kw in text for kw in prof.get(pt, []))))

    prec = sum(y_true) / TOP_N
    rec  = sum(y_true) / sum(all_true) if sum(all_true)>0 else 0.0

    print(f"{user_label} Precision@{TOP_N} = {prec:.3f}, Recall@{TOP_N} = {rec:.
TOP_M = 15
TOP_N = 10

for TOP_M in [15,20,25, 30, 50,None]:
    for TOP_N in [10]:
        print(f"\n>>> Grid search: TOP_M={TOP_M}, TOP_N={TOP_N} <<<")
        for user in user_profiles:
            recommend_and_evaluate(user)
```

```
>>> Grid search: TOP_M=15, TOP_N=10 <<<
User1 Precision@10 = 0.500, Recall@10 = 0.060
User2 Precision@10 = 0.300, Recall@10 = 0.300
User3 Precision@10 = 0.500, Recall@10 = 0.143

>>> Grid search: TOP_M=20, TOP_N=10 <<<
User1 Precision@10 = 0.400, Recall@10 = 0.048
User2 Precision@10 = 0.300, Recall@10 = 0.300
User3 Precision@10 = 0.400, Recall@10 = 0.114

>>> Grid search: TOP_M=25, TOP_N=10 <<<
User1 Precision@10 = 0.600, Recall@10 = 0.071
User2 Precision@10 = 0.400, Recall@10 = 0.400
User3 Precision@10 = 0.400, Recall@10 = 0.114

>>> Grid search: TOP_M=30, TOP_N=10 <<<
User1 Precision@10 = 0.700, Recall@10 = 0.083
User2 Precision@10 = 0.200, Recall@10 = 0.200
User3 Precision@10 = 0.400, Recall@10 = 0.114

>>> Grid search: TOP_M=50, TOP_N=10 <<<
User1 Precision@10 = 0.700, Recall@10 = 0.083
User2 Precision@10 = 0.100, Recall@10 = 0.100
User3 Precision@10 = 0.500, Recall@10 = 0.143

>>> Grid search: TOP_M=None, TOP_N=10 <<<
User1 Precision@10 = 0.700, Recall@10 = 0.083
User2 Precision@10 = 0.400, Recall@10 = 0.400
User3 Precision@10 = 0.200, Recall@10 = 0.057
```

In [14]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer

best_pipe_rf = Pipeline([
    ('vect', CountVectorizer(
        lowercase=True,
        token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
        stop_words='english',
        max_features=2000
    )),
    ('clf', RandomForestClassifier(
        n_estimators=100,
        random_state=42,
        n_jobs=-1
    ))
])


best_pipe_rf.fit(train_df['lyrics'], train_df['topic'])
```

```
train_df['pred_topic_rf'] = best_pipe_rf.predict(train_df['lyrics'])
test_df ['pred_topic_rf'] = best_pipe_rf.predict(test_df ['lyrics'])
```

In [15]:
```
def print_top20_profiles(pred_col, topic_vecs, user_profiles, TOP_M, GLOBAL_STOP

    for user_label, prof in user_profiles.items():
        print(f"\n--- {user_label} Top-20 Profile Keywords (using {pred_col}) --
        for topic, kws in prof.items():
            docs = train_df.loc[train_df[pred_col] == topic, 'lyrics']
            liked = [d for d in docs if any(kw in d.lower() for kw in kws)]
            if not liked:
                print(f"{topic}: (no matched docs)")
                continue

            combined = " ".join(liked)
            tf = topic_vecs[topic].transform([combined]).toarray().ravel()
            feat = topic_vecs[topic].get_feature_names_out()

            ranked = [feat[i] for i in tf.argsort()[::-1] if feat[i] not in GLOB
            top20 = ranked[:TOP_M]
            print(f"{topic}: {', '.join(top20)}")


def build_topic_vecs(pred_col):
    vecs = {}
    for topic in df['topic'].unique():
        docs = train_df.loc[train_df[pred_col] == topic, 'lyrics']
        vec  = TfidfVectorizer(
            lowercase=True,
            token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
            stop_words='english'
        )
        vec.fit(docs)
        vecs[topic] = vec
    return vecs

topic_vecs_lr = build_topic_vecs('pred_topic')
topic_vecs_rf = build_topic_vecs('pred_topic_rf')


GLOBAL_STOP = {'know','like','come','yeah','time','song','good',
               'feel','gonna','dilly','oohoohoohoooh','lalala','oohooh','oohooho
TOP_M = 30

print_top20_profiles('pred_topic',    topic_vecs_lr, user_profiles, TOP_M, GLOBAL
print_top20_profiles('pred_topic_rf', topic_vecs_rf, user_profiles, TOP_M, GLOBA
--- User1 Top-20 Profile Keywords (using pred_topic) ---
dark: fight, blood, grind, stand, tell, black, kill, lanky, hand, head, light, tr
ue, people, follow, cause, build, paint, right, color, steady, drown, shoot, pai
n, bone, leave, oouuu, fall, woah, death, story
sadness: club, steal, tear, mean, baby, music, write, say, think, true, smile, fa
ce, eye, word, want, blame, thrill, fear, heat, greater, regret, forever, leave,
place, wear, lift, read, stay, darling, body
personal: life, live, change, world, ordinary, dream, wanna, thank, teach, lord,
beat, think, learn, need, right, promise, cause, things, everybody, want, automat
on, believe, gotta, place, grow, ways, young, look, people, leave
lifestyle: tonight, night, home, closer, strangers, sing, long, wait, wanna, tir
e, spoil, right, struggle, mind, play, telephone, ring, baby, stay, songs, lose,
ready, cause, girl, think, goodnight, oohoohooh, make, late, depression
emotion: touch, hold, visions, video, loove, morning, vibe, feelin, want, miss, k
iss, love, lovin, luck, gimme, sunrise, look, baby, cause, real, right, lips, lig
ht, control, wait, knock, feet, wanna, doin, week

--- User2 Top-20 Profile Keywords (using pred_topic) ---
sadness: inside, break, step, heart, away, violence, rainwater, fade, blame, sca
r, open, fall, hard, goodbye, magnify, sing, tear, smile, silence, soul, leave, w
anna, drift, think, crash, wave, icecold, longneck, someday, mind
emotion: touch, visions, video, loove, hold, morning, kiss, lovin, luck, sunrise,
gimme, lips, knock, wait, week, soft, body, feet, love, fly, laughter, strong, ha
nd, remember, control, try, break, yeahah, goodbye, arm

--- User3 Top-20 Profile Keywords (using pred_topic) ---
dark: south, despoiler, cadaver, dirty, whisper, shoot, blood, help, somebody, le
ad, wall, lips, better, cave, hear, stand, pane, naughty, yeayeayeayeah, halls, p
illow, body, crazy, follow, window, dance, answer, need, thoughts, start
emotion: hold, love, ones, dance, strong, try, chain, highs, faceless, crowd, lo
w, light, mind, matter, truth, free, speak, mean, fluently, lead, heart, shake, h
eaven, leave, break, fake, hearts, night, play, bruise
lifestyle: tonight, night, closer, songs, strangers, wait, long, wanna, spoil, ri
ght, tire, home, struggle, country, mind, baby, play, telephone, ring, stay, los
e, need, ready, goodnight, sing, make, cause, late, girl, depression
personal: change, life, dream, world, live, thank, beat, teach, wanna, automaton,
learn, gotta, everybody, people, things, believe, american, heartbreak, drink, de
ar, away, grow, try, realize, habit, years, cause, young, look, alright
sadness: lonely, leave, closin, walk, cause, baby, heart, hold, away, break, hur
t, house, somebody, woohoo, magnify, need, open, want, drink, scar, tell, memorie
s, ocean, think, road, stay, wish, crabb, oatmeal, rescue

--- User1 Top-20 Profile Keywords (using pred_topic_rf) ---
dark: fight, blood, grind, stand, tell, black, kill, lanky, hand, head, light, tr
ue, people, follow, cause, build, paint, right, color, steady, drown, shoot, pai
n, bone, leave, oouuu, fall, woah, death, story
sadness: club, steal, tear, mean, baby, music, write, say, think, true, smile, fa
ce, eye, word, want, blame, thrill, fear, heat, greater, regret, forever, leave,
place, wear, lift, read, stay, darling, body
personal: life, live, change, world, ordinary, dream, wanna, thank, teach, lord,
beat, think, learn, need, right, promise, cause, things, everybody, want, automat
on, believe, gotta, place, grow, ways, young, look, people, leave
lifestyle: tonight, night, home, closer, strangers, sing, long, wait, wanna, tir
e, spoil, right, struggle, mind, play, telephone, ring, baby, stay, songs, lose,
ready, cause, girl, think, goodnight, oohoohooh, make, late, depression
emotion: touch, hold, visions, video, loove, morning, vibe, feelin, want, miss, k
iss, love, lovin, luck, gimme, sunrise, look, baby, cause, real, right, lips, lig
ht, control, wait, knock, feet, wanna, doin, week

--- User2 Top-20 Profile Keywords (using pred_topic_rf) ---
```

```
sadness: inside, break, step, heart, away, violence, rainwater, fade, blame, sca
r, open, fall, hard, goodbye, magnify, sing, tear, smile, silence, soul, leave, w
anna, drift, think, crash, wave, icecold, longneck, someday, mind
emotion: touch, visions, video, loove, hold, morning, kiss, lovin, luck, sunrise,
gimme, lips, knock, wait, week, soft, body, feet, love, fly, laughter, strong, ha
nd, remember, control, try, break, yeahah, goodbye, arm

--- User3 Top-20 Profile Keywords (using pred_topic_rf) ---
dark: south, despoiler, cadaver, dirty, whisper, shoot, blood, help, somebody, le
ad, wall, lips, better, cave, hear, stand, pane, naughty, yeayeayeayeah, halls, p
illow, body, crazy, follow, window, dance, answer, need, thoughts, start
emotion: hold, love, ones, dance, strong, try, chain, highs, faceless, crowd, lo
w, light, mind, matter, truth, free, speak, mean, fluently, lead, heart, shake, h
eaven, leave, break, fake, hearts, night, play, bruise
lifestyle: tonight, night, closer, songs, strangers, wait, long, wanna, spoil, ri
ght, tire, home, struggle, country, mind, baby, play, telephone, ring, stay, los
e, need, ready, goodnight, sing, make, cause, late, girl, depression
personal: change, life, dream, world, live, thank, beat, teach, wanna, automaton,
learn, gotta, everybody, people, things, believe, american, heartbreak, drink, de
ar, away, grow, try, realize, habit, years, cause, young, look, alright
sadness: lonely, leave, closin, walk, cause, baby, heart, hold, away, break, hur
t, house, somebody, woohoo, magnify, need, open, want, drink, scar, tell, memorie
s, ocean, think, road, stay, wish, crabb, oatmeal, rescue
```

In [16]:
```python
import pandas as pd
from sklearn.metrics.pairwise import cosine_similarity

def recommend_and_evaluate(pred_col, user_label, TOP_N, TOP_M):

    prof = user_profiles[user_label]

    user_vec = {}
    for topic, vec in topic_vecs[pred_col].items():
        docs = train_df.loc[train_df[pred_col] == topic, 'lyrics']
        liked = [d for d in docs if any(kw in d.lower() for kw in prof.get(topic
        combined = " ".join(liked) if liked else ""

        if TOP_M is None:
            profile_vec = vec.transform([combined])
        else:
            tfidf_vec = vec.transform([combined]).toarray().ravel()
            feat      = vec.get_feature_names_out()
            top_idx   = tfidf_vec.argsort()[::-1][:TOP_M]
            profile_text = " ".join(feat[i] for i in top_idx)
            profile_vec  = vec.transform([profile_text])

        user_vec[topic] = profile_vec


    sims = []
    for idx, row in test_df.iterrows():
        pt = row[pred_col]
        song_vec = topic_vecs[pred_col][pt].transform([row['lyrics']])
        sim = cosine_similarity(song_vec, user_vec[pt])[0,0]
        sims.append((idx, pt, sim))
    topN = sorted(sims, key=lambda x: x[2], reverse=True)[:TOP_N]


    y_true = [int(any(kw in test_df.at[idx,'lyrics'].lower() for kw in prof.get(
              for idx, pt, _ in topN]
    precision = sum(y_true) / TOP_N


    all_true = [int(any(kw in row['lyrics'].lower() for kw in prof.get(row[pred_
                for _, row in test_df.iterrows()]
    recall    = sum(y_true) / sum(all_true) if sum(all_true)>0 else 0.0

    return precision, recall


def build_topic_vecs(pred_col):
    vecs = {}
    for topic in df['topic'].unique():
        docs = train_df.loc[train_df[pred_col]==topic, 'lyrics']
        vec  = TfidfVectorizer(
            lowercase=True,
            token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
            stop_words='english'
        )
        vec.fit(docs)
        vecs[topic] = vec
    return vecs

topic_vecs = {
    'pred_topic':    build_topic_vecs('pred_topic'),
    'pred_topic_rf': build_topic_vecs('pred_topic_rf')
}



records = []
for model_col in ['pred_topic','pred_topic_rf']:
    for TOP_M in [15,20,25,30,50,None]:
        for TOP_N in [10]:
            for user in user_profiles:
                prec, rec = recommend_and_evaluate(model_col, user, TOP_N, TOP_M
                records.append({
                    'Model':    'LogReg' if model_col=='pred_topic' else 'RandFo
                    'User':     user,
                    'TOP_M':    'All' if TOP_M is None else TOP_M,
                    'TOP_N':    TOP_N,
                    'Precision':prec,
                    'Recall':   rec
                })

df_results = pd.DataFrame(records)

df_results['F1'] = df_results.apply(
    lambda r: 2*r['Precision']*r['Recall']/(r['Precision']+r['Recall'])
    if (r['Precision']+r['Recall'])>0 else 0.0,
    axis=1
)

pd.set_option('display.max_rows', None)
from IPython.display import display
display(df_results)
```

	Model	User	TOP_M	TOP_N	Precision	Recall	F1
0	LogReg	User1	15	10	0.5	0.059524	0.106383
1	LogReg	User2	15	10	0.3	0.300000	0.300000
2	LogReg	User3	15	10	0.5	0.142857	0.222222
3	LogReg	User1	20	10	0.4	0.047619	0.085106
4	LogReg	User2	20	10	0.3	0.300000	0.300000
5	LogReg	User3	20	10	0.4	0.114286	0.177778
6	LogReg	User1	25	10	0.6	0.071429	0.127660
7	LogReg	User2	25	10	0.4	0.400000	0.400000
8	LogReg	User3	25	10	0.4	0.114286	0.177778
9	LogReg	User1	30	10	0.7	0.083333	0.148936
10	LogReg	User2	30	10	0.2	0.200000	0.200000
11	LogReg	User3	30	10	0.4	0.114286	0.177778
12	LogReg	User1	50	10	0.7	0.083333	0.148936
13	LogReg	User2	50	10	0.1	0.100000	0.100000
14	LogReg	User3	50	10	0.5	0.142857	0.222222
15	LogReg	User1	All	10	1.0	0.119048	0.212766
16	LogReg	User2	All	10	0.1	0.100000	0.100000
17	LogReg	User3	All	10	0.7	0.200000	0.311111
18	RandForest	User1	15	10	0.7	0.093333	0.164706
19	RandForest	User2	15	10	0.3	0.375000	0.333333
20	RandForest	User3	15	10	0.4	0.117647	0.181818
21	RandForest	User1	20	10	0.7	0.093333	0.164706
22	RandForest	User2	20	10	0.2	0.250000	0.222222
23	RandForest	User3	20	10	0.4	0.117647	0.181818
24	RandForest	User1	25	10	0.9	0.120000	0.211765
25	RandForest	User2	25	10	0.3	0.375000	0.333333
26	RandForest	User3	25	10	0.3	0.088235	0.136364
27	RandForest	User1	30	10	0.8	0.106667	0.188235
28	RandForest	User2	30	10	0.2	0.250000	0.222222
29	RandForest	User3	30	10	0.2	0.058824	0.090909
30	RandForest	User1	50	10	1.0	0.133333	0.235294
31	RandForest	User2	50	10	0.1	0.125000	0.111111
32	RandForest	User3	50	10	0.6	0.176471	0.272727

	Model	User	TOP_M	TOP_N	Precision	Recall	F1
33	RandForest	User1	All	10	1.0	0.133333	0.235294
34	RandForest	User2	All	10	0.2	0.250000	0.222222
35	RandForest	User3	All	10	0.5	0.147059	0.227273

Part2.2

Based on the above output information, logistic regression algorithm performs the best for these three users. For the comparison between these three users, User 2's interest keywords are relatively concentrated and can produce good results under both algorithms. However, User 1 and User 3's interests are relatively scattered, and there are some words with broad meanings in the keywords. Therefore, logistic regression can produce more balanced data while filtering out some noise. However, the random forest algorithm requires the use of all words to produce a good result, so in this regard, the random forest algorithm is slightly inferior to the logistic regression algorithm. Based on the above results and the specific performance of parameters, logistic regression algorithm is the most suitable for matching user profiles and songs. The reason is that the logistic regression algorithm has the best average F1 score among three users. At the same time, this algorithm has a small size, is faster to train, and saves more computing resources.

Part 3:

```
In [17]: N = 10
TOP_M = 25
TOP_N = 10
np.random.seed(42)

weeks = [
    (   0, 250),
    ( 250, 500),
    ( 500, 750)
]
```

```
In [18]: df = pd.read_csv('dataset.tsv', sep='\t')
print(df.columns)
```

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

```
In [19]: N = 10
weeks = [(0, 250), (250, 500), (500, 750)]

week_batches = []


for i, (start, end) in enumerate(weeks, start=1):
    batch = df.iloc[start:end] \
        .sample(n=N, random_state=start) \
        [['artist_name', 'track_name', 'lyrics', 'topic']]

    batch.index.name = 'orig_idx'
    week_batches.append(batch)

    print(f"\n=== Week {i} Batch (rows {start}-{end-1}) ===")
    display(batch[['artist_name', 'track_name', 'topic']])
```

```
=== Week 1 Batch (rows 0-249) ===
```

orig_idx	artist_name	track_name	topic
225	all them witches	internet	personal
122	derek b	bullet from a gun	dark
92	mike ryan	the rewrite	lifestyle
157	billie eilish	all the good girls go to hell	dark
154	black lips	crystal night	lifestyle
161	uncle kracker	rescue	sadness
198	guts	peaceful life	dark
83	l'indécis	the god behind the pines	dark
63	banes world	you say i'm in love	sadness
155	buczer	hip hop prod. crackhouse	dark

```
=== Week 2 Batch (rows 250-499) ===
```

orig_idx	artist_name	track_name	topic
306	khalid	this way	sadness
278	black pistol fire	wake the riot	dark
286	high valley	i be u be	personal
457	jo mersa marley	point of view	lifestyle
340	dreamville	1993 (with j. cole, jid, cozz & earthgang feat...	sadness
318	seckond chaynce	i miss you bae	emotion
265	kings of leon	walls	dark
445	kash'd out	gimme love	lifestyle
473	aaron watson	trying like the devil	dark
282	imagine dragons	whatever it takes	sadness

```
=== Week 3 Batch (rows 500-749) ===
```

	artist_name	track_name	topic
orig_idx			
735	josh turner	never had a reason	personal
684	the dear hunter	cascade	dark
700	dean lewis	waves	sadness
558	skarra mucci	the song	lifestyle
626	nahko and medicine for the people	runner	personal
547	robert plant	carry fire	sadness
555	chris stapleton	the ballad of the lonesome cowboy	lifestyle
662	jesse royal	modern day judas	dark
636	novelists	under different welkins	personal
702	rex orange county	loving is easy	personal

In [20]:
```python
train_feedback_df = df.iloc[:30].copy()

# Real user Liked tags
train_feedback_df['Liked'] = [
    1, 0, 1, 1, 0, 1, 0, 1, 0, 1,
    0, 1, 1, 0, 0, 0, 0, 1, 0, 1,
    1, 1, 0, 1, 0, 0, 0, 1, 1, 0
]
```

In [21]:
```python
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression

vectorizer = TfidfVectorizer(
    lowercase=True,
    token_pattern=r"(?u)\b[a-zA-Z]{2,}\b",
    stop_words="english",
    max_features=5000
)

X_train = vectorizer.fit_transform(train_feedback_df['lyrics'].fillna(""))
y_train = train_feedback_df['Liked'].values

clf = LogisticRegression(max_iter=1000, random_state=42)
clf.fit(X_train, y_train)
```

Out[21]:
```
▾ LogisticRegression
LogisticRegression(max_iter=1000, random_state=42)
```

In [22]:
```python
week4_df = df.iloc[750:1000].copy()
week4_df.index = range(750, 1000)

X_week4 = vectorizer.transform(week4_df['lyrics'].fillna(""))
like_probs = clf.predict_proba(X_week4)[:, 1]
week4_df['like_score'] = like_probs
```

```
In [23]: recommendations = week4_df.sort_values(by='like_score', ascending=False).head(10
         print("The recommended songs are as follows:")
         display(recommendations[['track_name', 'artist_name', 'like_score']])
```

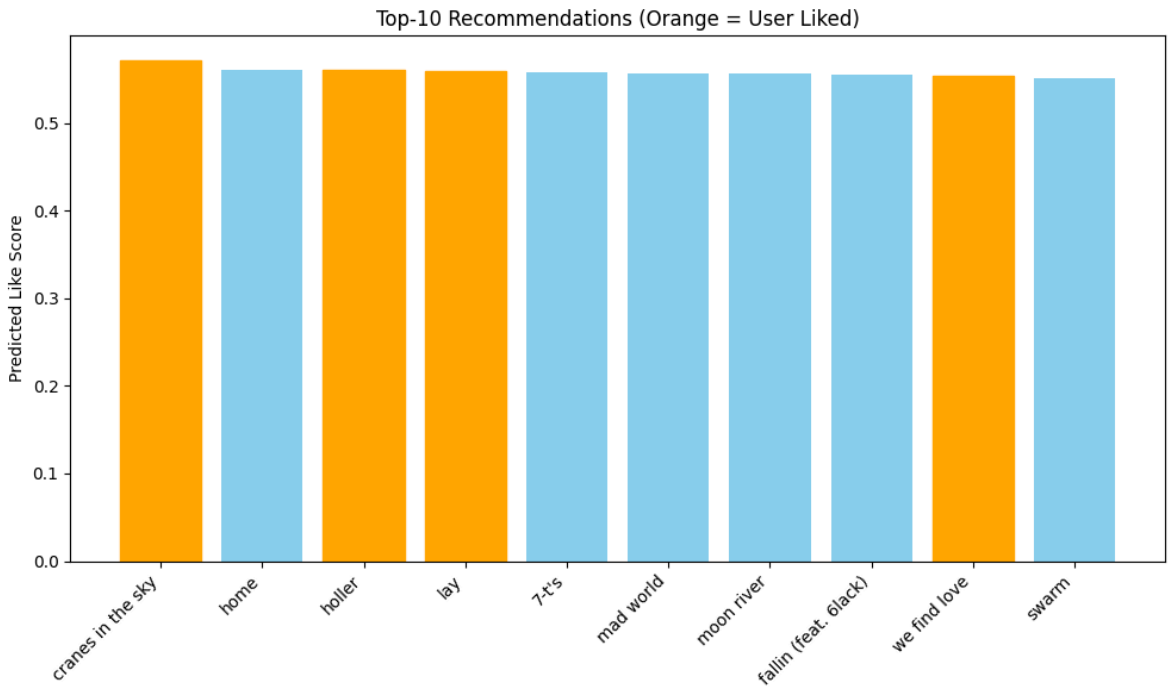
```
The recommended songs are as follows:
```

	track_name	artist_name	like_score
989	cranes in the sky	solange	0.570909
988	home	the movement	0.561122
905	holler	band of rascals	0.560005
828	lay	the blue stones	0.559316
775	7-t's	marcus miller	0.557820
777	mad world	jordan rakei	0.556119
902	moon river	nicole henry	0.555872
970	fallin (feat. 6lack)	bazzi	0.554723
798	we find love	daniel caesar	0.553591
975	swarm	thank you scientist	0.551353

```
In [24]: import matplotlib.pyplot as plt


         week4_df['orig_idx'] = week4_df.index


         recommendations = week4_df.sort_values(by='like_score', ascending=False).head(10


         user_feedback_raw = [1, 0, 1, 1, 0, 0, 0, 0, 1, 0]
         user_feedback = {}


         for idx, label in zip(recommendations['orig_idx'], user_feedback_raw):
             user_feedback[int(idx)] = int(label)


         recommendations['is_liked'] = recommendations['orig_idx'].map(user_feedback.get)


         precision_at_10 = recommendations['is_liked'].sum() / len(recommendations)


         num_user_likes = sum(user_feedback.values())
         recall_at_10 = recommendations['is_liked'].sum() / num_user_likes if num_user_li


         f1_at_10 = 2 * precision_at_10 * recall_at_10 / (precision_at_10 + recall_at_10)


         map_score = 0
         hit_count = 0
         for rank, is_liked in enumerate(recommendations['is_liked'], start=1):
```

```
    if is_liked:
        hit_count += 1
        map_score += hit_count / rank
map_at_10 = map_score / hit_count if hit_count else 0


print("Recommended system evaluation indicators:")
print(f"Precision@10: {precision_at_10:.4f}")
print(f"Recall@10:    {recall_at_10:.4f}")
print(f"F1@10:        {f1_at_10:.4f}")
print(f"MAP@10:       {map_at_10:.4f}")


plt.figure(figsize=(10, 6))
bars = plt.bar(recommendations['track_name'], recommendations['like_score'], col
for i, is_liked in enumerate(recommendations['is_liked']):
    if is_liked:
        bars[i].set_color('orange')

plt.xticks(rotation=45, ha='right')
plt.ylabel("Predicted Like Score")
plt.title("Top-10 Recommendations (Orange = User Liked)")
plt.tight_layout()
plt.show()
```

```
Recommended system evaluation indicators:
Precision@10: 0.4000
Recall@10:    1.0000
F1@10:        0.5714
MAP@10:       0.7153
```



User feedback (the user has not registered for comp9727 and is not familiar with this type of model construction):

Among the recommended 10 songs, only 4 songs are more in line with personal preferences, but some of the recommended songs have an overall style that matches personal preferences but not every segment is very suitable. It can only be said that the model captures my overall preferences, but the control over details is still inadequate. For example, although I prefer certain songs, the duration of the songs does not quite match my preferences.