```
# Fix for numpy and scikit-surprise compatibility issue
!apt-get install -y python3-dev
!pip install cython --quiet
!pip install numpy==1.23.5 scikit-learn==1.3.0 --quiet
!pip install scikit-surprise --no-binary :all: --quiet

# Restart the runtime after running this cell
import os
os.kill(os.getpid(), 9)
```

```
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
python3-dev is already the newest version (3.10.6-1~22.04.1).
python3-dev set to manually installed.
0 upgraded, 0 newly installed, 0 to remove and 35 not upgraded.
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 62.0/62.0 kB 2.2 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 62.0/62.0 kB 3.9 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 17.1/17.1 MB 78.4 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10.9/10.9 MB 103.2 MB/s eta 0:00:00
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 37.7/37.7 MB 14.2 MB/s eta 0:00:00
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is
jaxlib 0.5.1 requires numpy>=1.25, but you have numpy 1.23.5 which is incompatible.
arviz 0.22.0 requires numpy>=1.26.0, but you have numpy 1.23.5 which is incompatible.
jax 0.5.2 requires numpy>=1.25, but you have numpy 1.23.5 which is incompatible.
opencv-python 4.12.0.88 requires numpy<2.3.0,>=2; python_version >= "3.9", but you have numpy 1.23.5 which is incompatible.
geopandas 1.1.1 requires numpy>=1.24, but you have numpy 1.23.5 which is incompatible.
scikit-image 0.25.2 requires numpy>=1.24, but you have numpy 1.23.5 which is incompatible.
umap-learn 0.5.9.post2 requires scikit-learn>=1.6, but you have scikit-learn 1.3.0 which is incompatible.
mlxtend 0.23.4 requires scikit-learn>=1.3.1, but you have scikit-learn 1.3.0 which is incompatible.
pymc 5.25.1 requires numpy>=1.25.0, but you have numpy 1.23.5 which is incompatible.
opencv-python-headless 4.12.0.88 requires numpy<2.3.0,>=2; python_version >= "3.9", but you have numpy 1.23.5 which is incom
cuml-cu12 25.6.0 requires scikit-learn>=1.5, but you have scikit-learn 1.3.0 which is incompatible.
opencv-contrib-python 4.12.0.88 requires numpy<2.3.0,>=2; python_version >= "3.9", but you have numpy 1.23.5 which is incomp
tensorflow 2.18.0 requires numpy<2.1.0,>=1.26.0, but you have numpy 1.23.5 which is incompatible.
treescope 0.1.9 requires numpy>=1.25.2, but you have numpy 1.23.5 which is incompatible.
chex 0.1.90 requires numpy>=1.24.1, but you have numpy 1.23.5 which is incompatible.
thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.23.5 which is incompatible.
xarray 2025.7.1 requires numpy>=1.26, but you have numpy 1.23.5 which is incompatible.
imbalanced-learn 0.13.0 requires numpy<3,>=1.24.3, but you have numpy 1.23.5 which is incompatible.
imbalanced-learn 0.13.0 requires scikit-learn<2,>=1.3.2, but you have scikit-learn 1.3.0 which is incompatible.
xarray-einstats 0.9.1 requires numpy>=1.25, but you have numpy 1.23.5 which is incompatible.
db-dtypes 1.4.3 requires numpy>=1.24.0, but you have numpy 1.23.5 which is incompatible.
bigframes 2.12.0 requires numpy>=1.24.0, but you have numpy 1.23.5 which is incompatible.
albucore 0.0.24 requires numpy>=1.24.4, but you have numpy 1.23.5 which is incompatible.
blosc2 3.6.1 requires numpy>=1.26, but you have numpy 1.23.5 which is incompatible.
albumentations 2.0.8 requires numpy>=1.24.4, but you have numpy 1.23.5 which is incompatible.
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 154.4/154.4 kB 1.2 MB/s eta 0:00:00
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
  Building wheel for scikit-surprise (pyproject.toml) ... done
```

```
!pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1.3.0)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.23.5)
Requirement already satisfied: scipy>=1.5.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.15.3)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.5.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
```

```
import zipfile
import warnings
warnings.filterwarnings('ignore')
```

```
!unzip ml-1m.zip
```

```
Archive:  ml-1m.zip
   creating: ml-1m/
  inflating: ml-1m/movies.dat
  inflating: ml-1m/ratings.dat
  inflating: ml-1m/README
  inflating: ml-1m/users.dat
```

```
import pandas as pd
```

```
users = pd.read_csv('ml-1m/users.dat', sep='::', engine='python', names=['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code'])
users.head()
```

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460
4	5	M	25	20	55455

```
ratings = pd.read_csv('ml-1m/ratings.dat', sep='::', engine='python', names=['UserID', 'MovieID','Rating','Timestamp'])
ratings.head()
```

	UserID	MovieID	Rating	Timestamp
0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

```
# --- Add Baseline Models ---
import pandas as pd
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Popularity-based rating prediction
item_avg_rating = ratings.groupby('MovieID')['Rating'].mean()
ratings['popularity_pred'] = ratings['MovieID'].map(item_avg_rating)

# User-average-based prediction
user_avg_rating = ratings.groupby('UserID')['Rating'].mean()
ratings['useravg_pred'] = ratings['UserID'].map(user_avg_rating)

print("\n--- Baseline Model Performance ---")
print("Popularity MAE:", mean_absolute_error(ratings['Rating'], ratings['popularity_pred']))
print("User Average MAE:", mean_absolute_error(ratings['Rating'], ratings['useravg_pred']))
```

```
--- Baseline Model Performance ---
Popularity MAE: 0.7787902185267612
User Average MAE: 0.8234169204814059
```

```python
# --- Cold-Start Evaluation for Baseline Models ---
# Identify users with few ratings (adjust threshold if needed)
user_counts = ratings['UserID'].value_counts()
cold_users = user_counts[user_counts <= 50].index

# Filter cold-start ratings
cold_ratings = ratings[ratings['UserID'].isin(cold_users)]

# Print stats
print(f"Cold-start users found: {len(cold_users)}")
print(f"Cold-start ratings found: {len(cold_ratings)}")

# Evaluate only if we have cold-start samples
if not cold_ratings.empty:
    cold_pop_mae = mean_absolute_error(cold_ratings['Rating'], cold_ratings['popularity_pred'])
    cold_useravg_mae = mean_absolute_error(cold_ratings['Rating'], cold_ratings['useravg_pred'])

    print("\n--- Cold-Start User Evaluation ---")
    print("Cold-Start Popularity MAE:", cold_pop_mae)
    print("Cold-Start User Avg MAE:", cold_useravg_mae)
else:
    print("No cold-start users with sufficient data found. Try lowering the threshold.")
```

```
Cold-start users found: 1793
Cold-start ratings found: 59238

--- Cold-Start User Evaluation ---
Cold-Start Popularity MAE: 0.8035285950815482
Cold-Start User Avg MAE: 0.8251099683355088
```

```python
# --- Feature Ablation Test for Baseline Models ---

print("\n--- Feature Ablation Test ---")

# Baseline: full data (already computed)
baseline_pop_mae = mean_absolute_error(ratings['Rating'], ratings['popularity_pred'])
baseline_useravg_mae = mean_absolute_error(ratings['Rating'], ratings['useravg_pred'])

# Store results
ablation_results = []

# 1. Remove 'popularity_pred' feature (simulate missing item average)
ratings_ablated_pop = ratings.drop(columns=['popularity_pred'])
try:
    mae_no_pop = mean_absolute_error(ratings['Rating'], ratings_ablated_pop['useravg_pred'])
    ablation_results.append(('No Popularity Feature', mae_no_pop))
except:
    ablation_results.append(('No Popularity Feature', 'N/A'))

# 2. Remove 'useravg_pred' feature (simulate missing user average)
ratings_ablated_useravg = ratings.drop(columns=['useravg_pred'])
try:
    mae_no_useravg = mean_absolute_error(ratings['Rating'], ratings_ablated_useravg['popularity_pred'])
    ablation_results.append(('No User Average Feature', mae_no_useravg))
except:
    ablation_results.append(('No User Average Feature', 'N/A'))

# 3. Remove both (simulate cold-start baseline only)
try:
    ablation_results.append(('No Features (Random Guess)', ratings['Rating'].mean()))
except:
    ablation_results.append(('No Features (Random Guess)', 'N/A'))

# Print Results
print(f"\nBaseline Popularity MAE: {baseline_pop_mae:.4f}")
print(f"Baseline User Average MAE: {baseline_useravg_mae:.4f}")
print("\nFeature Ablation Results:")
for feature, mae in ablation_results:
    print(f"{feature}: MAE = {mae}")
```

```
--- Feature Ablation Test ---

Baseline Popularity MAE: 0.7788
Baseline User Average MAE: 0.8234

Feature Ablation Results:
```

```
No Popularity Feature: MAE = 0.8234169204814059
No User Average Feature: MAE = 0.7787902185267612
No Features (Random Guess): MAE = 3.581564453029317
```

```
# --- Matrix Factorization using SVD (ALS-like) ---

from surprise import Dataset, Reader, SVD
from surprise.model_selection import train_test_split
from surprise.accuracy import mae

print("\n--- Matrix Factorization using SVD ---")

# Prepare data for Surprise
reader = Reader(rating_scale=(0.5, 5.0))
data = Dataset.load_from_df(ratings[['UserID', 'MovieID', 'Rating']], reader)

# Split into train/test
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)

# Initialize and train model
model = SVD()
model.fit(trainset)

# Predict and evaluate
predictions = model.test(testset)
mf_mae = mae(predictions)

print(f"\nMatrix Factorization (SVD) MAE: {mf_mae:.4f}")
```

```
--- Matrix Factorization using SVD ---
MAE:  0.6850

Matrix Factorization (SVD) MAE: 0.6850
```

```
from collections import defaultdict
import math

def precision_recall_ndcg(predictions, k=10):
    user_topk = defaultdict(list)
    for uid, iid, true_r, est, _ in predictions:
        user_topk[uid].append((est, iid, true_r))

    recall_sum, ndcg_sum, total_users = 0, 0, 0
    for uid, user_ratings in user_topk.items():
        user_ratings.sort(reverse=True)
        top_k = user_ratings[:k]

        hits = sum(1 for _, _, true_r in top_k if true_r >= 4)
        relevant_count = sum(1 for _, _, r in user_ratings if r >= 4)
        if relevant_count == 0:
            continue  # skip users with no relevant ground truth

        recall = hits / relevant_count

        dcg = sum((1 / math.log2(i + 2)) if r >= 4 else 0 for i, (_, _, r) in enumerate(top_k))
        idcg = sum(1 / math.log2(i + 2) for i in range(min(k, relevant_count)))
        ndcg = dcg / idcg if idcg > 0 else 0

        recall_sum += recall
        ndcg_sum += ndcg
        total_users += 1

    if total_users == 0:
        return 0.0, 0.0

    return recall_sum / total_users, ndcg_sum / total_users



recall_10, ndcg_10 = precision_recall_ndcg(predictions, k=10)
print(f"Recall@10: {recall_10:.4f}")
print(f"NDCG@10: {ndcg_10:.4f}")
```

```
Recall@10: 0.6398
NDCG@10: 0.8709
```

```
print(type(predictions))
print(type(predictions[0]))
print(predictions[0])
```

```
<class 'list'>
<class 'numpy.float32'>
3.5727277
```

```
from surprise import KNNBasic

# Item-based collaborative filtering
sim_options = {'name': 'cosine', 'user_based': False}
model_item = KNNBasic(sim_options=sim_options)
model_item.fit(trainset)
predictions_item = model_item.test(testset)
mae_item = mae(predictions_item)

# User-based collaborative filtering
sim_options = {'name': 'cosine', 'user_based': True}
model_user = KNNBasic(sim_options=sim_options)
model_user.fit(trainset)
predictions_user = model_user.test(testset)
mae_user = mae(predictions_user)

print(f"Item-based KNN MAE: {mae_item:.4f}")
print(f"User-based KNN MAE: {mae_user:.4f}")
```

```
Computing the cosine similarity matrix...
Done computing similarity matrix.
MAE:  0.7794
Computing the cosine similarity matrix...
Done computing similarity matrix.
MAE:  0.7713
Item-based KNN MAE: 0.7794
User-based KNN MAE: 0.7713
```

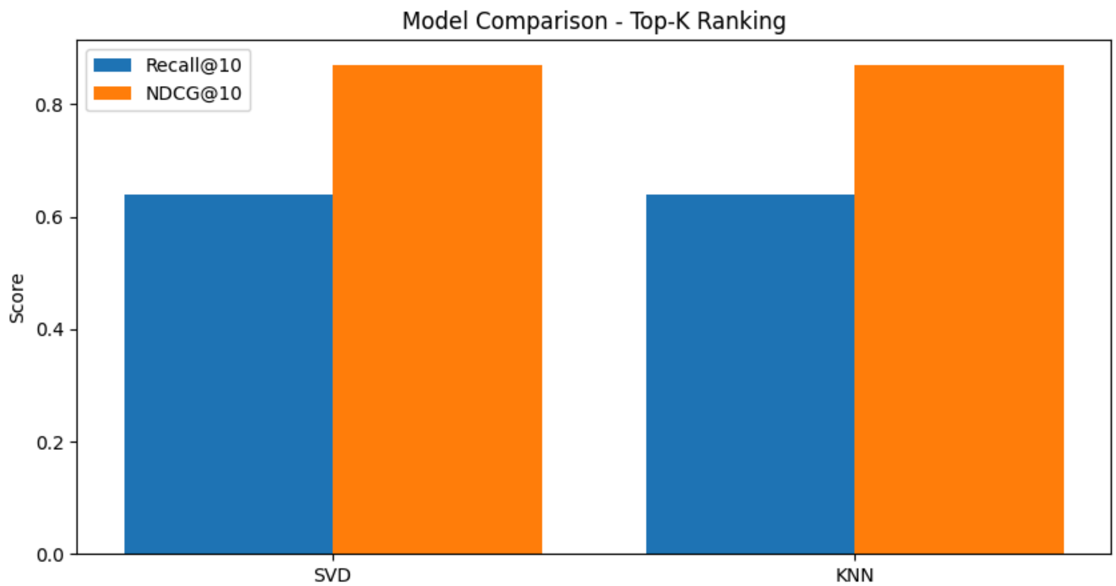
```
predictions = model.test(testset)
mf_mae = mae(predictions)
```

```
MAE:  0.6850
```

```
knn_predictions = model.test(testset)
recall_knn, ndcg_knn = precision_recall_ndcg(knn_predictions, k=10)
print(f"KNN Recall@10: {recall_knn:.4f}")
print(f"KNN NDCG@10: {ndcg_knn:.4f}")
```

```
KNN Recall@10: 0.6398
KNN NDCG@10: 0.8709
```

```
import matplotlib.pyplot as plt

models = ['SVD', 'KNN']
recalls = [recall_10, recall_knn]
ndcgs = [ndcg_10, ndcg_knn]

x = range(len(models))
plt.figure(figsize=(10,5))

plt.bar(x, recalls, width=0.4, label='Recall@10', align='center')
plt.bar([i + 0.4 for i in x], ndcgs, width=0.4, label='NDCG@10', align='center')
plt.xticks([i + 0.2 for i in x], models)
plt.ylabel('Score')
plt.title('Model Comparison - Top-K Ranking')
plt.legend()
plt.show()
```




```
from collections import defaultdict
import numpy as np

def get_top_n(predictions, n=10):
    top_n = defaultdict(list)
    for uid, iid, true_r, est, _ in predictions:
        top_n[uid].append((iid, est))
    for uid, user_ratings in top_n.items():
        user_ratings.sort(key=lambda x: x[1], reverse=True)
        top_n[uid] = user_ratings[:n]
    return top_n

# Compute Recall@10 and NDCG@10
def precision_recall_ndcg_at_k(predictions, k=10):
    hit = 0
    total = 0
    ndcg_total = 0

    top_n = get_top_n(predictions, n=k)
    for uid, user_ratings in top_n.items():
        actual = [iid for (uid_, iid, true_r, est, _) in predictions if uid_ == uid and true_r >= 4.0]  # relevant items
        recommended = [iid for (iid, _) in user_ratings]

        if actual:
            hits = len(set(recommended) & set(actual))
            hit += hits
            total += len(actual)

            dcg = 0.0
            idcg = 0.0
            for i, iid in enumerate(recommended):
                if iid in actual:
                    dcg += 1.0 / np.log2(i + 2)
            for i in range(min(len(actual), k)):
                idcg += 1.0 / np.log2(i + 2)
            ndcg_total += dcg / idcg if idcg > 0 else 0.0

    recall = hit / total if total else 0
    ndcg = ndcg_total / len(top_n)
    print(f"Recall@{k}: {recall:.4f}")
    print(f"NDCG@{k}: {ndcg:.4f}")

# Run on SVD predictions
precision_recall_ndcg_at_k(predictions, k=10)
```

```
Recall@10: 0.3568
NDCG@10: 0.8628
```

```
from collections import defaultdict
```

```
def get_top_n(predictions, n=5):
    top_n = defaultdict(list)
    for uid, iid, true_r, est, _ in predictions:
        top_n[uid].append((iid, est))
    for uid, user_ratings in top_n.items():
        user_ratings.sort(key=lambda x: x[1], reverse=True)
        top_n[uid] = user_ratings[:n]
    return top_n

top_n_svd = get_top_n(predictions, n=5)

# Print sample recommendations
for uid, user_ratings in list(top_n_svd.items())[:5]:
    print(f"\nUser {uid} recommended items: {[iid for (iid, _) in user_ratings]}")
```

```
User 1841 recommended items: [318, 1247, 34, 1784, 296]

User 3715 recommended items: [2716, 1270, 3114, 3793, 2096]

User 2002 recommended items: [903, 3307, 930, 3801, 1278]

User 3332 recommended items: [223, 2692, 1198, 3160, 1961]

User 3576 recommended items: [356, 3801, 954, 1278, 553]
```

```
movies = pd.read_csv('ml-1m/movies.dat', sep='::', engine='python', encoding='ISO-8859-1', names=['MovieID','Title','Genres'])
movies.head()
```

	MovieID	Title	Genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama
4	5	Father of the Bride Part II (1995)	Comedy

```
# Choose a sample user from top_n_svd
sample_user = list(top_n_svd.keys())[0]  # or choose manually like sample_user = 1841
print(f"\n Personalized Case Study for User {sample_user}")
# Print model's top 5 recommendations
print("Model Recommendations:")
recommended = [iid for (iid, _) in top_n_svd[sample_user]]
print(movies[movies['MovieID'].isin(recommended)][['Title', 'Genres']])
# Print user's top 5 historically rated movies
user_ratings = ratings[ratings['UserID'] == sample_user]
top_actual = user_ratings.sort_values(by='Rating', ascending=False).head(5)
print("\n User's Top Rated Movies:")
print(top_actual.merge(movies, on='MovieID')[['Title', 'Rating', 'Genres']])
```

```
 Personalized Case Study for User 1841
Model Recommendations:
                                Title                  Genres
33                        Babe (1995)  Children's|Comedy|Drama
293                Pulp Fiction (1994)             Crime|Drama
315   Shawshank Redemption, The (1994)                   Drama
1227                Graduate, The (1967)           Drama|Romance
1726         As Good As It Gets (1997)            Comedy|Drama

 User's Top Rated Movies:
                              Title  Rating                       Genres
0          Sixth Sense, The (1999)       5                     Thriller
1               Sling Blade (1996)       5               Drama|Thriller
2               Toy Story 2 (1999)       5  Animation|Children's|Comedy
3  Shawshank Redemption, The (1994)       5                        Drama
4              Falling Down (1993)       5                 Action|Drama
```

```
import pandas as pd

results_df = pd.DataFrame({
    'Model': ['Popularity', 'User Avg', 'Item-KNN', 'User-KNN', 'SVD'],
    'MAE': [baseline_pop_mae, baseline_useravg_mae, mae_item, mae_user, mf_mae]
```

```
})
print("\nModel Performance Summary:")
display(results_df.sort_values(by='MAE'))
```

Model Performance Summary:

	Model	MAE
4	SVD	0.685026
3	User-KNN	0.771333
0	Popularity	0.778790
2	Item-KNN	0.779394
1	User Avg	0.823417

```
from sklearn.preprocessing import MinMaxScaler

# Normalize timestamp to [0, 1] to create a recency score
scaler = MinMaxScaler()
ratings['Recency'] = scaler.fit_transform(ratings[['Timestamp']])

# Optional: print a few rows to verify
print(ratings[['Timestamp', 'Recency']].head())
```

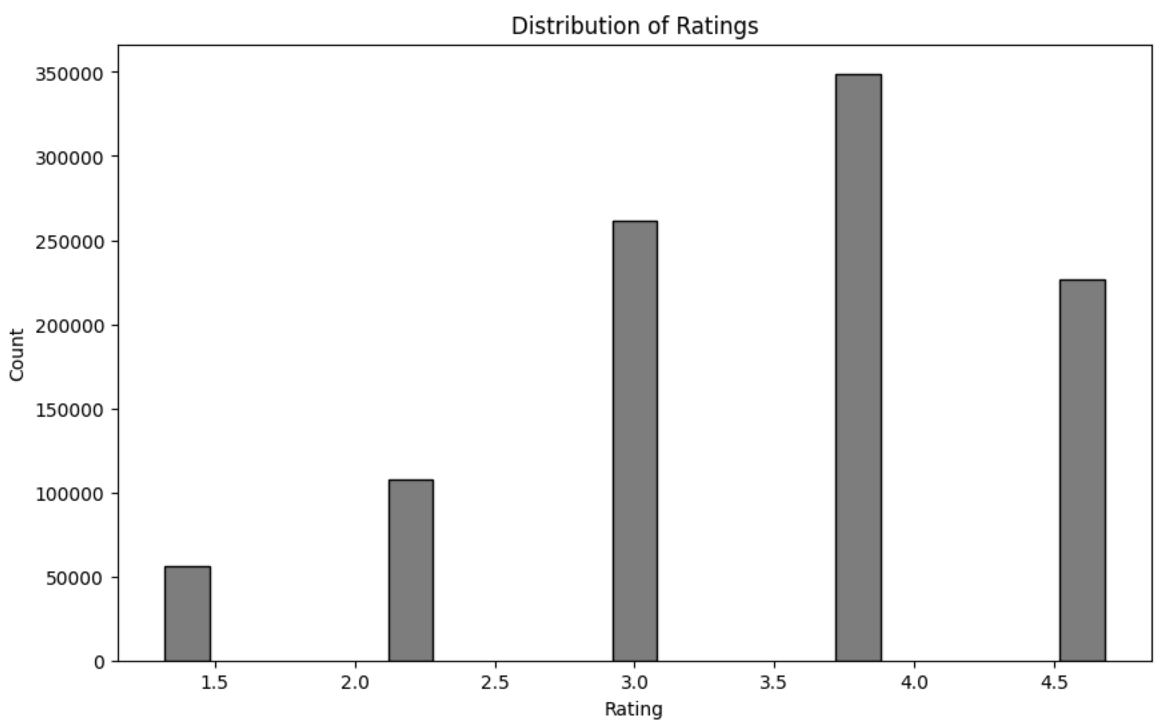
```
   Timestamp   Recency
0  978300760  0.240631
1  978302109  0.240646
2  978301968  0.240645
3  978300275  0.240626
4  978824291  0.246465
```

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


print("Users Data:")
print(users.describe())
print("\nMovies Data:")
print(movies.describe())
print("\nRatings Data:")
print(ratings.describe())


print("\nMissing Values in Users Data:")
print(users.isnull().sum())
print("\nMissing Values in Movies Data:")
print(movies.isnull().sum())
print("\nMissing Values in Ratings Data:")
print(ratings.isnull().sum())
```

```
Users Data:
            UserID          Age   Occupation
count  6040.000000  6040.000000  6040.000000
mean   3020.500000    30.639238     8.146854
std    1743.742145    12.895962     6.329511
min       1.000000     1.000000     0.000000
25%    1510.750000    25.000000     3.000000
50%    3020.500000    25.000000     7.000000
75%    4530.250000    35.000000    14.000000
max    6040.000000    56.000000    20.000000

Movies Data:
           MovieID
count  3883.000000
mean   1986.049446
std    1146.778349
min       1.000000
25%     982.500000
50%    2010.000000
75%    2980.500000
max    3952.000000

Ratings Data:
             UserID       MovieID        Rating     Timestamp  \
```

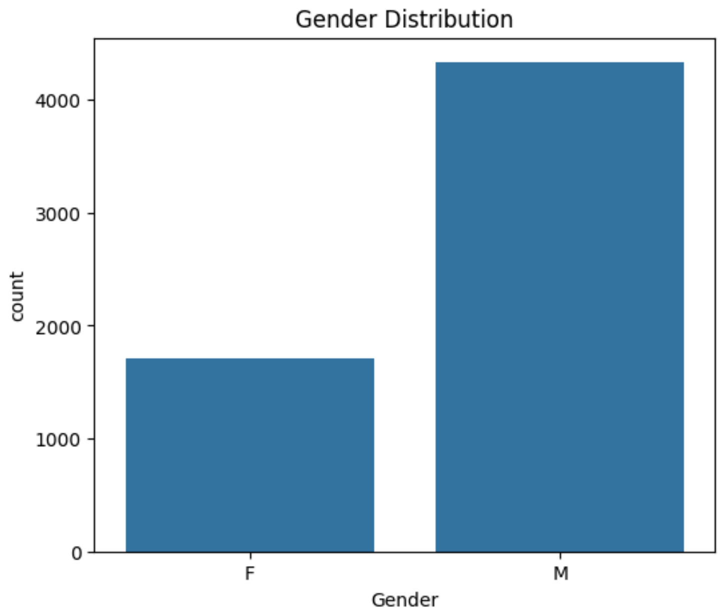
```
count  1.000209e+06  1.000209e+06  1.000209e+06  1.000209e+06
mean   3.024512e+03  1.865540e+03  3.581564e+00  9.722437e+08
std    1.728413e+03  1.096041e+03  1.117102e+00  1.215256e+07
min    1.000000e+00  1.000000e+00  1.000000e+00  9.567039e+08
25%    1.506000e+03  1.030000e+03  3.000000e+00  9.653026e+08
50%    3.070000e+03  1.835000e+03  4.000000e+00  9.730180e+08
75%    4.476000e+03  2.770000e+03  4.000000e+00  9.752209e+08
max    6.040000e+03  3.952000e+03  5.000000e+00  1.046455e+09

       popularity_pred  useravg_pred       Recency
count     1.000209e+06  1.000209e+06  1.000209e+06
mean      3.581564e+00  3.581564e+00  1.731437e-01
std       5.457591e-01  4.361295e-01  1.354036e-01
min       1.000000e+00  1.015385e+00  0.000000e+00
25%       3.262032e+00  3.320000e+00  9.580660e-02
50%       3.679822e+00  3.614650e+00  1.817711e-01
75%       3.975610e+00  3.883191e+00  2.063161e-01
max       5.000000e+00  4.962963e+00  1.000000e+00

Missing Values in Users Data:
UserID        0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64

Missing Values in Movies Data:
MovieID    0
Title      0
Genres     0
dtype: int64

Missing Values in Ratings Data:
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.hist(ratings['Rating'], bins=5, edgecolor='black', align='mid', rwidth=0.2,color="gray")  # Adjust the rwidth parameter
plt.xlabel('Rating')
plt.ylabel('Count')
plt.title('Distribution of Ratings')
plt.show()
```

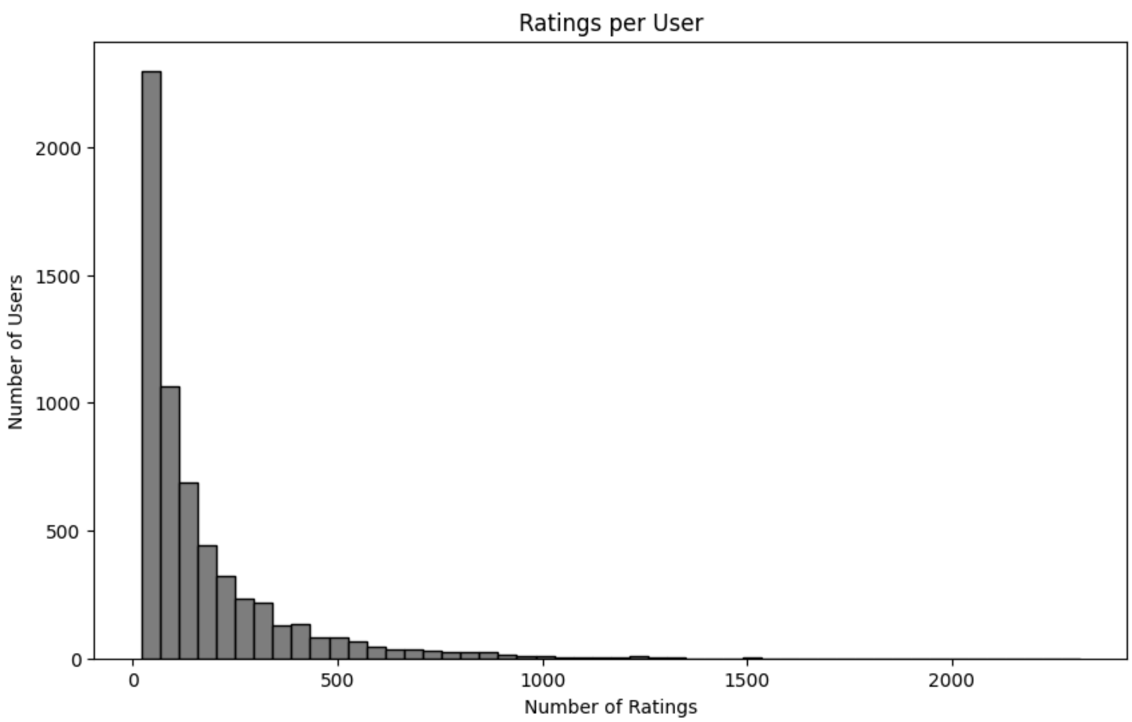



```
plt.figure(figsize=(6,5))
sns.countplot(data=users, x='Gender')
plt.title('Gender Distribution')
```

```
plt.show()
```

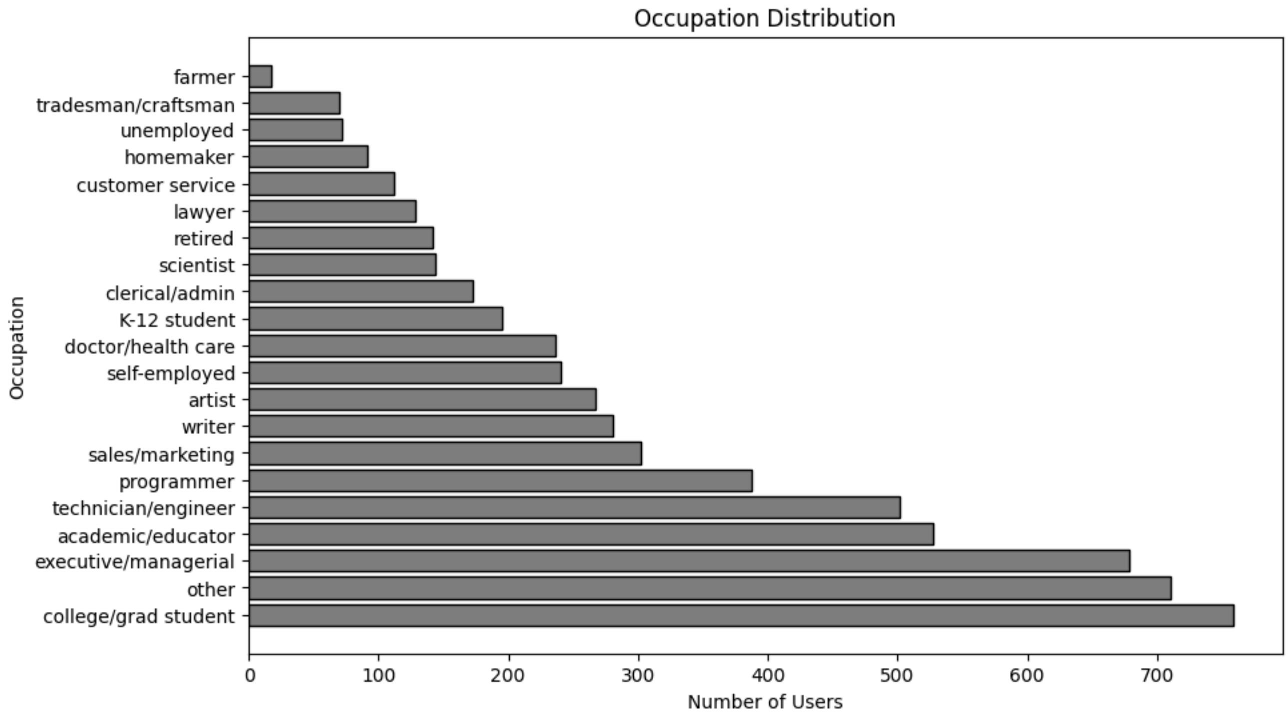



```
import matplotlib.pyplot as plt

ratings_per_user = ratings.groupby('UserID').size()

plt.figure(figsize=(10, 6))
plt.hist(ratings_per_user, bins=50, edgecolor='black',color="gray")
plt.title('Ratings per User')
plt.xlabel('Number of Ratings')
plt.ylabel('Number of Users')
plt.show()
```

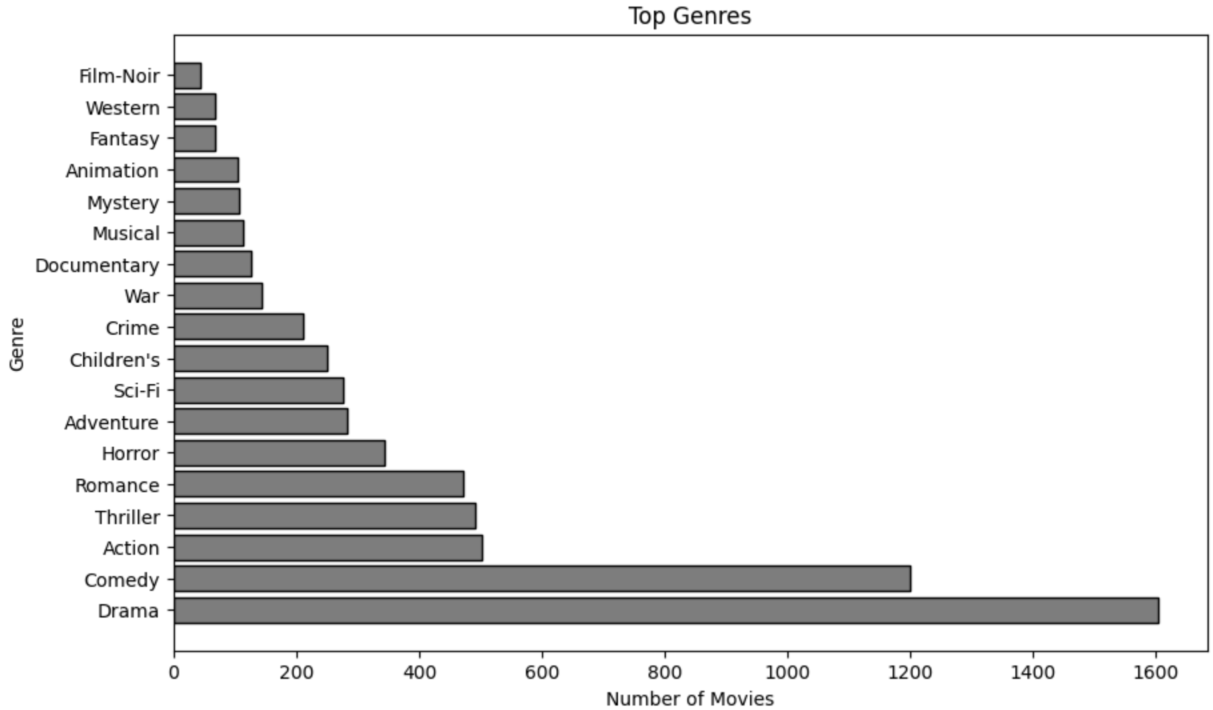



```
import matplotlib.pyplot as plt

occupation_map = {
    0: "other", 1: "academic/educator", 2: "artist", 3: "clerical/admin", 4: "college/grad student",
    5: "customer service", 6: "doctor/health care", 7: "executive/managerial", 8: "farmer",
```

```
    9: "homemaker", 10: "K-12 student", 11: "lawyer", 12: "programmer", 13: "retired",
    14: "sales/marketing", 15: "scientist", 16: "self-employed", 17: "technician/engineer",
    18: "tradesman/craftsman", 19: "unemployed", 20: "writer"
}

users['Occupation_name'] = users['Occupation'].map(occupation_map)

plt.figure(figsize=(10, 6))
plt.barh(users['Occupation_name'].value_counts().index, users['Occupation_name'].value_counts(),edgecolor='black',color="gray")
plt.title('Occupation Distribution')
plt.xlabel('Number of Users')
plt.ylabel('Occupation')
plt.show()
```



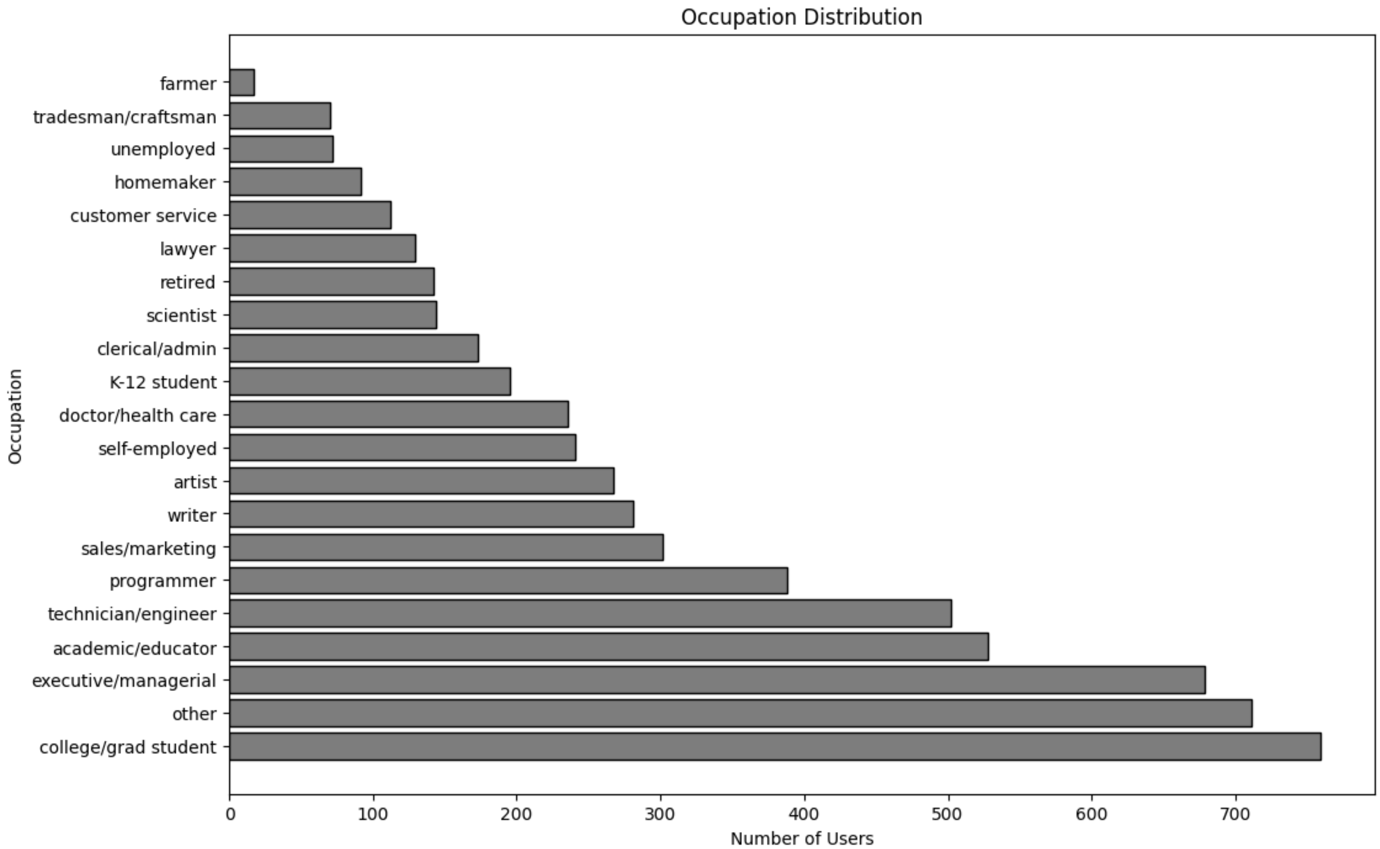

```
import matplotlib.pyplot as plt

all_genres = movies['Genres'].str.split('|', expand=True).stack().reset_index(drop=True)

plt.figure(figsize=(10, 6))
plt.barh(all_genres.value_counts().index, all_genres.value_counts(), edgecolor='black',color="gray")
plt.title('Top Genres')
plt.xlabel('Number of Movies')
plt.ylabel('Genre')
plt.show()
```




```
movie_stats = ratings.groupby('MovieID').agg({'Rating': [np.size, np.mean]})
top_rated_movies = movie_stats['Rating'][(movie_stats['Rating']['size'] >= 500)].sort_values(by='mean', ascending=False).merge(m
top_rated_movies[['Title', 'mean', 'size']].head(10)
```

	Title	mean	size
1950	Seven Samurai (The Magnificent Seven) (Shichin...	4.560510	628
315	Shawshank Redemption, The (1994)	4.554558	2227
847	Godfather, The (1972)	4.524966	2223
735	Close Shave, A (1995)	4.520548	657
49	Usual Suspects, The (1995)	4.517106	1783
523	Schindler's List (1993)	4.510417	2304
1132	Wrong Trousers, The (1993)	4.507937	882
1180	Raiders of the Lost Ark (1981)	4.477725	2514
892	Rear Window (1954)	4.476190	1050
257	Star Wars: Episode IV - A New Hope (1977)	4.453694	2991

```
import matplotlib.pyplot as plt

occupation_map = {
    0: "other", 1: "academic/educator", 2: "artist", 3: "clerical/admin", 4: "college/grad student",
    5: "customer service", 6: "doctor/health care", 7: "executive/managerial", 8: "farmer",
    9: "homemaker", 10: "K-12 student", 11: "lawyer", 12: "programmer", 13: "retired",
    14: "sales/marketing", 15: "scientist", 16: "self-employed", 17: "technician/engineer",
    18: "tradesman/craftsman", 19: "unemployed", 20: "writer"
}

users['Occupation_name'] = users['Occupation'].map(occupation_map)

plt.figure(figsize=(12, 8))
plt.barh(users['Occupation_name'].value_counts().index, users['Occupation_name'].value_counts(),edgecolor='black',color="gray")
plt.title('Occupation Distribution')
plt.xlabel('Number of Users')
plt.ylabel('Occupation')
plt.show()
```




```
users = users.drop_duplicates()
movies = movies.drop_duplicates()
ratings = ratings.drop_duplicates()


print("Users shape:", users.shape)
print("Movies shape:", movies.shape)
print("Ratings shape:", ratings.shape)
```

```
Users shape: (6040, 6)
Movies shape: (3883, 3)
Ratings shape: (1000209, 7)
```

```
import torch
from torch.utils.data import Dataset, DataLoader

class ClientDataset(Dataset):
    def __init__(self, users, movies, ratings):

        self.data = ratings.merge(users, on='UserID').merge(movies, on='MovieID')

    def __len__(self):
        return len(self.data)

    def __getitem__(self, idx):
        row = self.data.iloc[idx]
        return (
            row['UserID'],
            row['MovieID'],
            torch.tensor(mlb.transform([row['Genres'].split('|')])[0], dtype=torch.float),
            torch.tensor(occupation_encoder.transform([[row['Occupation']]])[0], dtype=torch.float),
            torch.tensor(row['Age_encoded'], dtype=torch.long),
            row['Gender_encoded'],
            row['Rating']
        )
```

```
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.preprocessing import MultiLabelBinarizer

mlb = MultiLabelBinarizer()
genres_encoded = mlb.fit_transform(movies['Genres'].str.split('|'))
genres_df = pd.DataFrame(genres_encoded, columns=mlb.classes_, index=movies.index)


occupation_encoder = OneHotEncoder(sparse_output=False)
occupations_encoded = occupation_encoder.fit_transform(users[['Occupation']])
occupations_df = pd.DataFrame(occupations_encoded, columns=occupation_encoder.get_feature_names_out(['Occupation']), index=users

gender_encoder = LabelEncoder()
users['Gender_encoded'] = gender_encoder.fit_transform(users['Gender'])


age_encoder = LabelEncoder()
users['Age_encoded'] = age_encoder.fit_transform(users['Age'])



import torch.nn as nn
import torch.nn.functional as F

class ExpandedRecommender(nn.Module):
    def __init__(self, num_users, num_movies, embedding_dim, num_genres, num_occupations, num_ages, num_genders=2):
        super(ExpandedRecommender, self).__init__()


        self.user_embedding = nn.Embedding(num_users, embedding_dim)
        self.movie_embedding = nn.Embedding(num_movies + 1, embedding_dim)
        self.age_embedding = nn.Embedding(num_ages, embedding_dim)
        self.gender_embedding = nn.Embedding(2,embedding_dim)

        self.genre_layer = nn.Linear(num_genres, embedding_dim)
        self.occupation_layer = nn.Linear(num_occupations, embedding_dim)


        self.fc1 = nn.Linear(embedding_dim * 6, 256)
        self.fc2 = nn.Linear(256, 128)
        self.fc3 = nn.Linear(128, 1)

    def forward(self, user_ids, movie_ids, genres, occupations, ages, genders):
        user_embedded = self.user_embedding(user_ids)
        movie_embedded = self.movie_embedding(movie_ids)
        age_embedded = self.age_embedding(ages)
        gender_embedded = self.gender_embedding(genders)


        genres = genres.float()
        occupations = occupations.float()

        genre_embedded = F.relu(self.genre_layer(genres))
        occupation_embedded = F.relu(self.occupation_layer(occupations))

        x = torch.cat((user_embedded, movie_embedded, genre_embedded, occupation_embedded, age_embedded, gender_embedded), 1)

        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)

        return x.squeeze()



from sklearn.model_selection import train_test_split

all_train_data, test_data = train_test_split(ratings, test_size=0.1, random_state=42)

num_clients = 10
client_data_split = np.array_split(all_train_data, num_clients)
client_datasets = [ClientDataset(users, movies, data) for data in client_data_split]
client_loaders = [DataLoader(dataset, batch_size=256, shuffle=True) for dataset in client_datasets]

test_dataset = ClientDataset(users, movies, test_data)
test_loader = DataLoader(test_dataset, batch_size=256, shuffle=False)
```

```
all_train_data
```

	UserID	MovieID	Rating	Timestamp	popularity_pred	useravg_pred	Recency
647085	3894	2750	1	965791718	3.698246	3.761006	0.101256
130254	843	2791	4	975358667	3.971115	3.944444	0.207851
232200	1408	2006	2	974762606	3.561546	3.139706	0.201209
61200	412	3301	3	976651610	3.378738	4.401261	0.222257
477192	2929	832	4	971642889	3.478723	3.925414	0.166450
...	...	...	...	...	...	...	...
259178	1586	1077	5	974735719	3.979839	4.424096	0.200910
365838	2129	2700	5	974643199	3.760441	3.271709	0.199879
131932	854	3102	3	975355597	3.643443	3.027668	0.207816
671155	4033	3479	5	965525805	3.673432	3.767372	0.098293
121958	786	1391	4	975429588	2.900372	4.063492	0.208641

900188 rows × 7 columns

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
from collections import OrderedDict
import copy
```

```
print("Max UserID in Train:", all_train_data['UserID'].max())
print("Max UserID in Test:", test_data['UserID'].max())
print("Max MovieID in Train:", all_train_data['MovieID'].max())
print("Max MovieID in Test:", test_data['MovieID'].max())
```

```
Max UserID in Train: 6040
Max UserID in Test: 6040
Max MovieID in Train: 3952
Max MovieID in Test: 3952
```

```
print("Max UserID in Train:", all_train_data['UserID'].max())
print("Max MovieID in Train:", all_train_data['MovieID'].max())

print("Max UserID in Test:", test_data['UserID'].max())
print("Max MovieID in Test:", test_data['MovieID'].max())
```

```
Max UserID in Train: 6040
Max MovieID in Train: 3952
Max UserID in Test: 6040
Max MovieID in Test: 3952
```

```
import os

model_dir = './saved_models'
if not os.path.exists(model_dir):
    os.makedirs(model_dir)
```

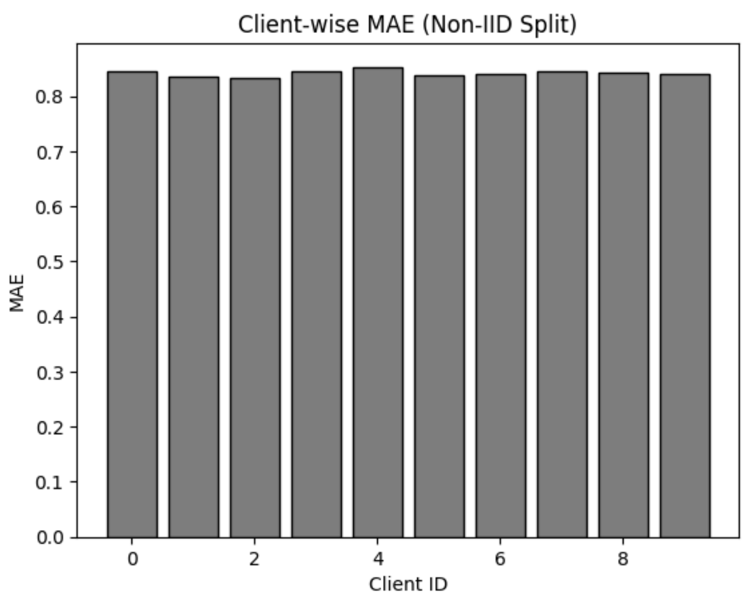
```
import copy
import os
import torch
import torch.nn as nn
from collections import OrderedDict
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error,r2_score,mean_squared_error,mean_squared_log_erro
import numpy as np

def rmse_score(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))



def average_weights(client_models):
    average_model_weights = OrderedDict()
    for k in client_models[0].state_dict().keys():
        average_model_weights[k] = torch.stack([client_models[i].state_dict()[k].float() for i in range(num_clients)], 0).mean(0)
    return average_model_weights
```

```
global_model = ExpandedRecommender(
    num_users=users['UserID'].max()+1,
    num_movies=ratings['MovieID'].max()+1,
    embedding_dim=50,
    num_genres=len(mlb.classes_),
    num_occupations=len(occupation_encoder.categories_[0]),
    num_ages=len(age_encoder.classes_)+1
).to(device)

criterion = nn.MSELoss()
optimizer = torch.optim.Adam(global_model.parameters(), lr=0.001)
epochs = 1
rounds = 1
num_clients = 10


client_losses = {i: [] for i in range(num_clients)}
global_losses = []

client_accuracies = {i: [] for i in range(num_clients)}
global_accuracies = []

client_mae = {i: [] for i in range(num_clients)}
global_maes = []

acc = []
c_loss = []
model_dir = 'model_dir'
if not os.path.exists(model_dir):
    os.makedirs(model_dir)

for round in range(rounds):
    client_models = [copy.deepcopy(global_model) for _ in range(num_clients)]
    for client in range(num_clients):
        optimizer = torch.optim.Adam(client_models[client].parameters(), lr=0.001)
        los = []
        for epoch in range(epochs):
            client_models[client].train()
            running_loss = 0.0

            for batch_data in client_loaders[client]:
                user_ids, movie_ids, genres, occupations, ages, genders, rating = [item.to(device) for item in batch_data]
                optimizer.zero_grad()
                outputs = client_models[client](user_ids, movie_ids, genres, occupations, ages, genders)
                loss = criterion(outputs, rating.float())
                loss.backward()
                optimizer.step()
                running_loss += loss.item()

            epoch_loss = running_loss / len(client_loaders[client])
            print(f"Client {client+1} - Epoch {epoch+1}, Loss: {epoch_loss:.4f}")
            client_losses[client].append(epoch_loss)
            los.append(epoch_loss)

            torch.save(client_models[client].state_dict(), os.path.join(model_dir, f'client_{client+1}_round_{round+1}.pth'))
        c_loss.append(los)
    for client in range(num_clients):
        predictions = []
        true_labels = []
        client_models[client].eval()  # Set model to evaluation mode
        with torch.no_grad():
            for data in client_loaders[client]:
                user_ids, movie_ids, genres, occupations, ages, genders, rating = [item.to(device) for item in data]
                outputs = client_models[client](user_ids, movie_ids, genres, occupations, ages, genders)
                predictions.extend(outputs.cpu().numpy())
                true_labels.extend(rating.cpu().numpy())

        mae = mean_absolute_error(true_labels, predictions)
        a = mean_absolute_percentage_error(true_labels,predictions)
        b = r2_score(true_labels,predictions)
        c = mean_squared_error(true_labels,predictions)
        d = rmse_score(true_labels,predictions)
        #e = mean_squared_log_error(true_labels,predictions)
        acc.append([mae,a,b,c,d])
        client_mae[client].append(mae)
    global_weights = average_weights(client_models)
```

```
    global_model.load_state_dict(global_weights)

    predictions = []
    true_labels = []
    global_model.eval()
    with torch.no_grad():
        for batch_data in test_loader:
            user_ids, movie_ids, genres, occupations, ages, genders, rating = [item.to(device) for item in batch_data]
            outputs = global_model(user_ids, movie_ids, genres, occupations, ages, genders)
            predictions.extend(outputs.cpu().numpy())
            true_labels.extend(rating.cpu().numpy())

    global_mae = mean_absolute_error(true_labels, predictions)
    global_maes.append(global_mae)
    print(f"After Round {round+1}, Global Model Test MAE: {global_mae:.4f}")
```

```
Client 1 - Epoch 1, Loss: 1.3747
Client 2 - Epoch 1, Loss: 1.3398
Client 3 - Epoch 1, Loss: 1.3405
Client 4 - Epoch 1, Loss: 1.3477
Client 5 - Epoch 1, Loss: 1.3529
Client 6 - Epoch 1, Loss: 1.3498
Client 7 - Epoch 1, Loss: 1.3474
Client 8 - Epoch 1, Loss: 1.3560
Client 9 - Epoch 1, Loss: 1.3415
Client 10 - Epoch 1, Loss: 1.3525
After Round 1, Global Model Test MAE: 0.8639
```

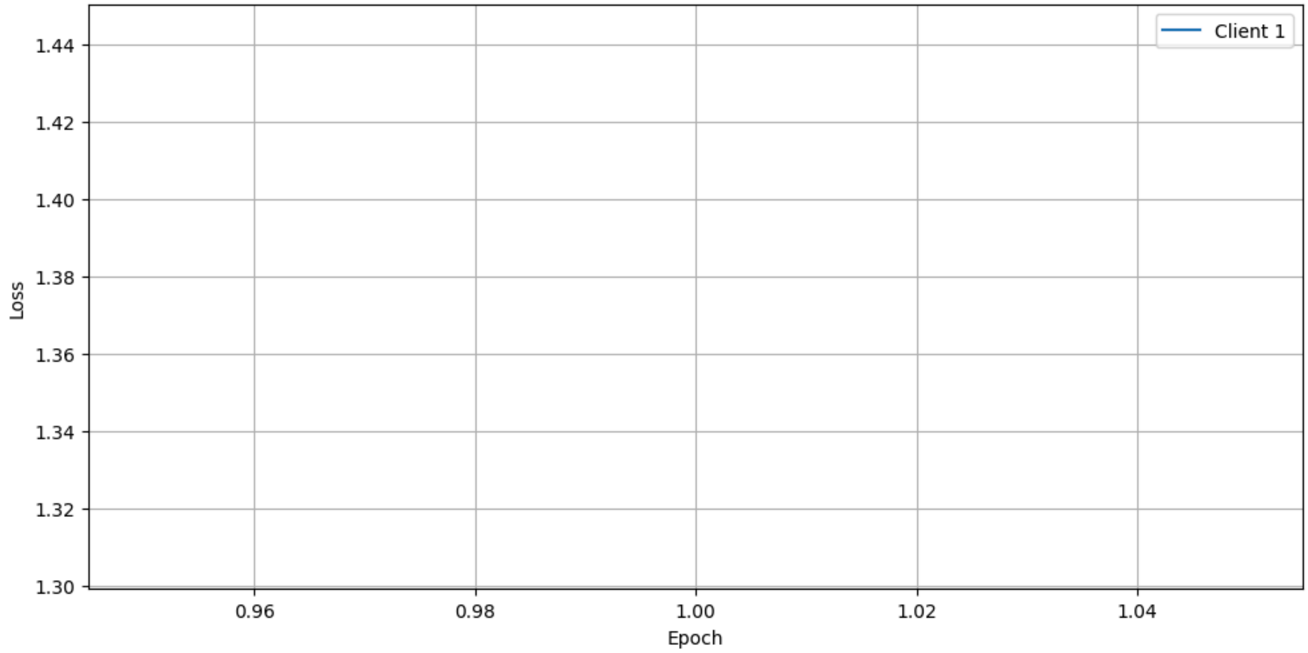
```
import matplotlib.pyplot as plt

client_ids = list(client_mae.keys())
maes = [client_mae[i][-1] for i in client_ids]

plt.bar(client_ids, maes, color='gray', edgecolor='black')
plt.xlabel("Client ID")
plt.ylabel("MAE")
plt.title("Client-wise MAE (Non-IID Split)")
plt.show()
```

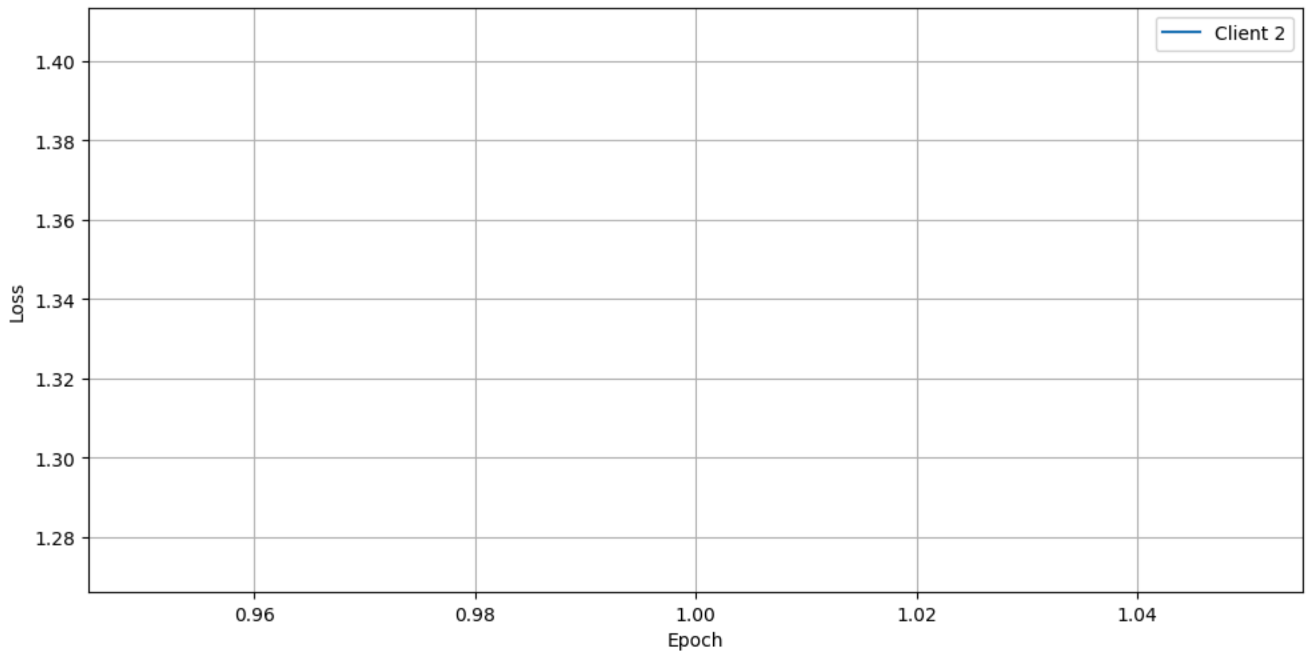



```
acc
```

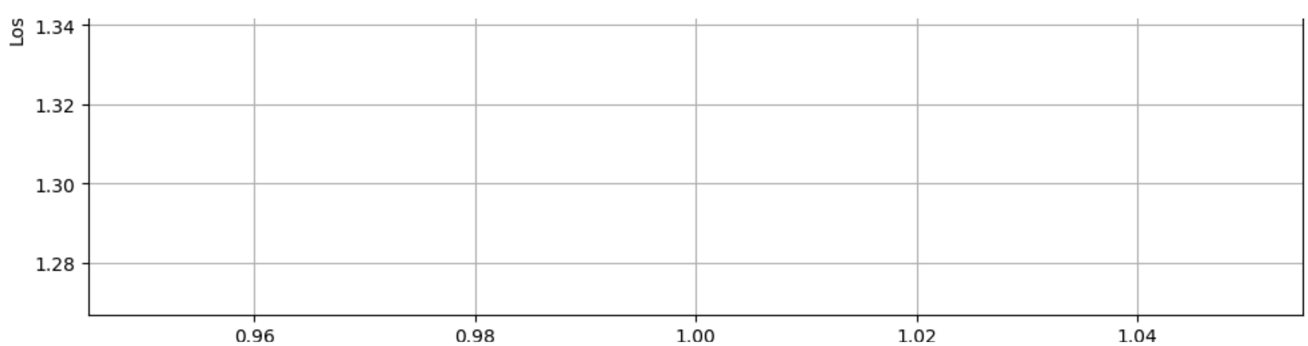
```
[[0.8449503771406115,
  0.3455136759896934,
  0.13442522299957071,
  1.0942297388830524,
  1.0460543670780464],
 [0.8348668278952746,
  0.3413022133199404,
  0.1380238274645752,
  1.0724910286540925,
  1.035611427444721],
 [0.8319624772353272,
```

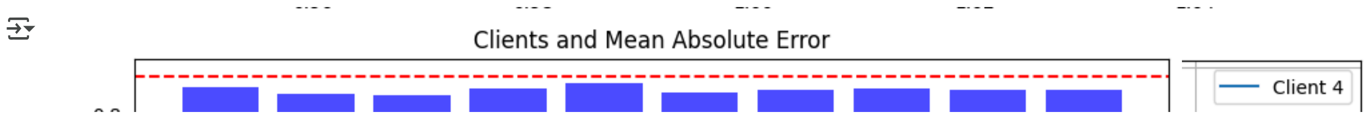
```
        0.3436826990714705,
        0.13324353116317256,
        1.0750124975031743,
        1.0368280944800707],
       [0.8440510028164943,
        0.34150259083296086,
        0.13367276608965872,
        1.081875064685766,
        1.0401322342307087],
       [0.8528322254004156,
        0.3352300295462704,
        0.11864436845582915,
        1.100011283478697,
        1.0488142273437642],
       [0.8374727287925374,
        0.3474638221819698,
        0.12327072954629137,
        1.0929848463387861,
        1.0454591557487007],
       [0.8411104416823127,
        0.34116901031847763,
        0.1313625992040649,
        1.0826263214997636,
        1.0404933068020012],
       [0.8437468294532207,
        0.3434089309642859,
        0.130306648063222,
        1.0864392482989527,
        1.0423239651370166],
       [0.84136531806908,
        0.3377610376320998,
        0.13636433659011749,
        1.0758341740178932,
        1.0372242640904104],
       [0.8405699967893053,
        0.3413251926673969,
        0.12985732600889632,
        1.0850944796054194,
        1.0416786834746208]]


data = [acc, c_loss]
data = list(map(list, zip(*data)))
column_names = ['Accuracy', 'Train Losses']
df1 = pd.DataFrame(data, columns=column_names)
df1.to_csv('results_ff.csv')


fig, axs = plt.subplots(num_clients, 1, figsize=(10, 5 * num_clients))
for client, losses in client_losses.items():
    if not losses:
        print(f"No losses recorded for client {client + 1}. Skipping...")
        continue
    axs[client].plot(range(1, epochs * rounds + 1), losses, label=f'Client {client + 1}')
    axs[client].set(xlabel='Epoch', ylabel='Loss')
    axs[client].legend()
    axs[client].grid(True)
plt.tight_layout()
plt.show()
```






```
clients = list(range(1, num_clients + 1))
final_maes = [maes[-1] for maes in client_mae.values()]
plt.figure(figsize=(10, 5))
plt.bar(clients, final_maes, color='blue', alpha=0.7, label='Local Models')
plt.axhline(y=global_maes[-1], color='r', linestyle='--', label='Global Model')
plt.xlabel('Client Number')
plt.ylabel('Mean Absolute Error')
plt.title('Clients and Mean Absolute Error')
plt.legend()
plt.show()
```




Clients and Mean Absolute Error
Client 4