Data 612 Project 2 Content-Based and Collaborative Filtering

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Building simple movie recommender system using:

- Content-Based Filtering
- User-User Collaborative Filtering
- Item-Item Collaborative Filtering

We'll evaluate each method using RMSE on sampled MovieLens data.

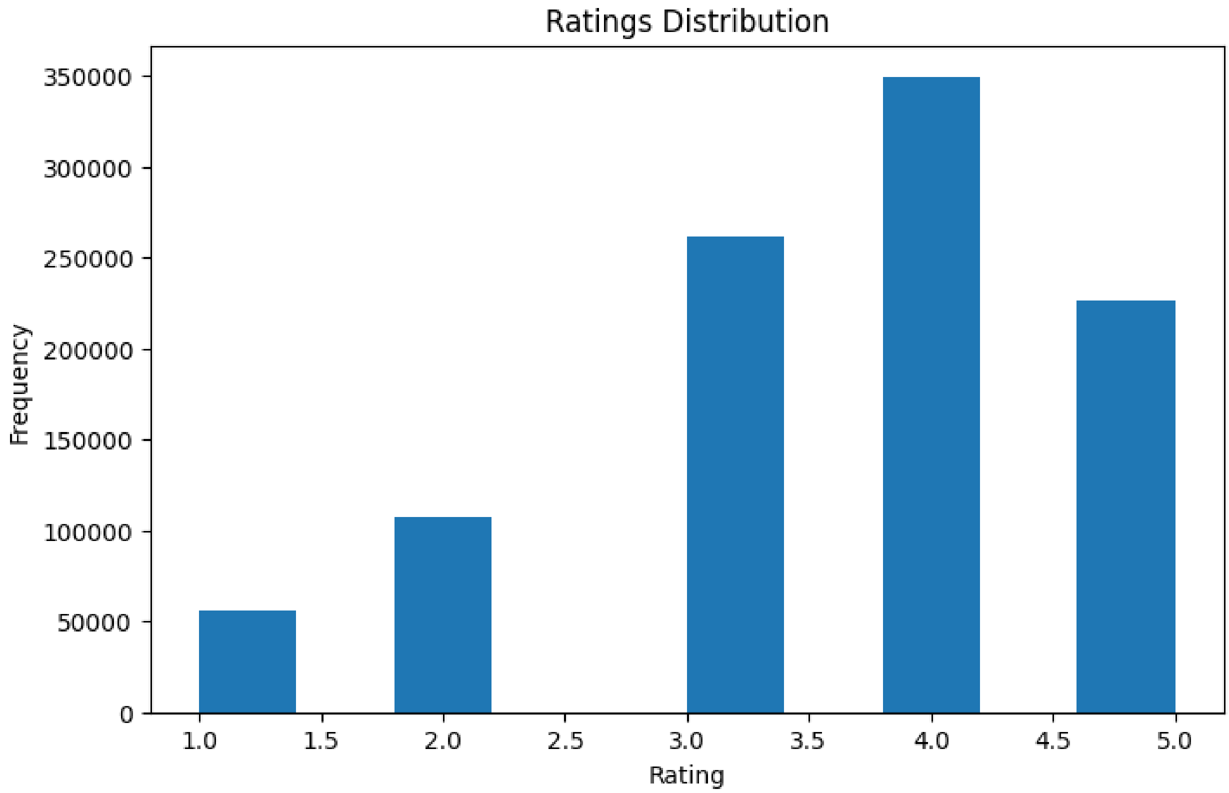
Import Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel, pairwise_distances
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from math import sqrt
```

Load and Prepare Data

```
ratings = pd.read_csv('ratings.csv', sep='\t', encoding='latin-1',
usecols=['user_id', 'movie_id', 'rating'])

users = pd.read_csv('users.csv', sep='\t', encoding='latin-1',
usecols=['user_id', 'gender', 'zipcode', 'age_desc', 'occ_desc'])

movies = pd.read_csv('movies.csv', sep='\t', encoding='latin-1',
usecols=['movie_id', 'title', 'genres'])

movies['genres'] = movies['genres'].fillna("").apply(lambda x: "
".join(x.split('|')))

def plot_ratings_distribution():
    plt.figure(figsize=(8, 5))
    ratings['rating'].hist(bins=10)
    plt.title('Ratings Distribution')
    plt.xlabel('Rating')
    plt.ylabel('Frequency')
    plt.grid(False)
    plt.show()
```

```
plot_ratings_distribution()
```



Content-Based Filtering

```
tfidf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2),
stop_words='english')
tfidf_matrix = tfidf.fit_transform(movies['genres'])
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
indices = pd.Series(movies.index, index=movies['title'])

def genre_recommendations(title, top_n=10):
    idx = indices[title]
    sim_scores = sorted(list(enumerate(cosine_sim[idx])), key=lambda
x: x[1], reverse=True)[1:top_n+1]
    movie_indices = [i[0] for i in sim_scores]
    return movies['title'].iloc[movie_indices]

genre_recommendations('Toy Story (1995)')
```

```
1050            Aladdin and the King of Thieves (1996)
2072                         American Tail, An (1986)
2073        American Tail: Fievel Goes West, An (1991)
2285                        Rugrats Movie, The (1998)
2286                             Bug's Life, A (1998)
```

```
3045                               Toy Story 2 (1999)
3542                            Saludos Amigos (1943)
3682                               Chicken Run (2000)
3685    Adventures of Rocky and Bullwinkle, The (2000)
236                             Goofy Movie, A (1995)
Name: title, dtype: object
```

Collaborative Filtering

```
small_data = ratings.sample(frac=0.02, random_state=42)
train_data, test_data = train_test_split(small_data, test_size=0.2,
random_state=42)

user_item_matrix = small_data.pivot_table(index='user_id',
columns='movie_id', values='rating').fillna(0)

user_similarity = 1 - pairwise_distances(user_item_matrix,
metric='cosine')
np.fill_diagonal(user_similarity, 0)

item_similarity = 1 - pairwise_distances(user_item_matrix.T,
metric='cosine')
np.fill_diagonal(item_similarity, 0)

def predict_ratings(ratings_matrix, similarity, type='user'):
    if type == 'user':
        mean_user_rating =
ratings_matrix.mean(axis=1).values.reshape(-1, 1)
        ratings_diff = ratings_matrix.values - mean_user_rating
        pred = mean_user_rating + similarity.dot(ratings_diff) /
np.array([np.abs(similarity).sum(axis=1)]).T
    elif type == 'item':
        pred = ratings_matrix.values.dot(similarity) /
np.array([np.abs(similarity).sum(axis=1)])
    return pred

def rmse(pred, actual):
    pred = pred[actual.nonzero()].flatten()
    actual = actual[actual.nonzero()].flatten()
    return sqrt(mean_squared_error(pred, actual))

train_matrix = user_item_matrix.values
user_pred = predict_ratings(user_item_matrix, user_similarity,
type='user')
item_pred = predict_ratings(user_item_matrix, item_similarity,
type='item')
```

```
<ipython-input-141-1156135249>:5: RuntimeWarning: invalid value
encountered in divide
  pred = mean_user_rating + similarity.dot(ratings_diff) /
```

```
np.array([np.abs(similarity).sum(axis=1)]).T
<ipython-input-141-1156135249>:7: RuntimeWarning: invalid value
encountered in divide
  pred = ratings_matrix.values.dot(similarity) /
np.array([np.abs(similarity).sum(axis=1)])

user_pred = np.nan_to_num(user_pred)
item_pred = np.nan_to_num(item_pred)

print("User-Based CF RMSE:", rmse(user_pred, train_matrix))
print("Item-Based CF RMSE:", rmse(item_pred, train_matrix))

User-Based CF RMSE: 2.9776070454569346
Item-Based CF RMSE: 3.3883378319551745
```

Conclusion

- **User-based Collaborative Filtering** performs better on this dataset with RMSE = 2.98.
- **Item-based CF** is slightly worse, possibly due to data sparsity.
- **Content-based recommendations** work well for giving similar genre-based suggestions.