# HARPY AEROSPACE SUMMER INTERNSHIP

AIoT Project

RECOMMENDATION SYSTEM

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## MODEL 1: Collaborative filtering model using k-Nearest Neighbors (k-NN)

## SOURCE CODE:

```
#installing requirements.txt

!git clone https://github.com/tensorflow/examples
%cd examples/lite/examples/recommendation/ml/
!pip install -r requirements.txt

#important libraries

!pip install surprise
import pandas as pd
from surprise import Dataset, Reader, SVD
from surprise.model_selection import train_test_split
from surprise import accuracy

# Download and unzip the dataset
DATASET_LINK = 'http://files.grouplens.org/datasets/movielens/ml-100k.zip'
!wget -nc $DATASET_LINK
!unzip -n ml-100k.zip

# Load the dataset
column_names = ['user_id', 'item_id', 'rating', 'timestamp']
data = pd.read_csv('ml-100k/u.data', sep='\t', names=column_names)

# Load item information
item_info = pd.read_csv('ml-100k/u.item', sep='|', header=None, encoding='latin-1')
item_info = item_info[[0, 1]]
item_info.columns = ['item_id', 'title']

# Display basic info
print("Dataset info:")
print(data.info())
print("\nFirst few rows of the dataset:")
print(data.head())
```

```
DATASET_LINK='http://files.grouplens.org/datasets/movielens/ml-100k.zip'
!wget -nc http://files.grouplens.org/datasets/movielens/ml-100k.zip
!unzip -n ml-100k.zip

#loading movielens dataset

overall_stats = pd.read_csv('ml-100k/u.info', header=None)
print("Details of users, items and ratings involved in the loaded movielens dataset:
",list(overall_stats[0]))

## same item id is same as movie id, item id column is renamed as movie id
column_names1 = ['user id','movie id','rating','timestamp']
ratings_dataset = pd.read_csv('ml-100k/u.data', sep='\t',header=None,names=column_names1)
ratings_dataset.head()

# Load the dataset
column_names = ['user_id', 'item_id', 'rating', 'timestamp']
data = pd.read_csv('ml-100k/u.data', sep='\t', names=column_names)

# Load item information
item_info = pd.read_csv('ml-100k/u.item', sep='|', header=None, encoding='latin-1')
item_info = item_info[[0, 1]]
item_info.columns = ['item_id', 'title']

# Display basic info
print("Dataset info:")
print(data.info())
print("\nFirst few rows of the dataset:")
print(data.head())

# NCF MODEL

from scipy.sparse import csr_matrix
from sklearn.neighbors import NearestNeighbors

# Create a pivot table
user_item_matrix = data.pivot(index='user_id', columns='item_id', values='rating').fillna(0)
user_item_sparse_matrix = csr_matrix(user_item_matrix.values)

# Fit the k-NN model
knn = NearestNeighbors(metric='cosine', algorithm='brute')
knn.fit(user_item_sparse_matrix)
```

```
# Define the Recommendation Function
def recommend_movies(user_id, num_recommendations=5):
    distances, indices = knn.kneighbors(user_item_matrix.loc[user_id, :].values.reshape(1, -1),
n_neighbors=num_recommendations+1)
    indices = indices.flatten()
    distances = distances.flatten()
    recommendations = []
    for i in range(1, len(indices)):
        movie_id = user_item_matrix.columns[indices[i]]
        recommendations.append((item_info[item_info['item_id'] == movie_id]['title'].values[0],
distances[i]))

    return recommendations

# Get recommendations for a user
user_id = 3
num_recommendations = 15
recommendations = recommend_movies(user_id, num_recommendations)

print(f"Top {num_recommendations} recommendations for User {user_id}:")
for i, (title, distance) in enumerate(recommendations):
    print(f"{i+1}: {title} (distance: {distance})")
#visualising rating distribution
import matplotlib.pyplot as plt

# Rating distribution
plt.figure(figsize=(10, 6))
data['rating'].value_counts().sort_index().plot(kind='bar', color='orange')
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()

#visualisng top recommendations
def recommend_movies_visual(user_id, num_recommendations=5,clr='skyblue'):
    distances, indices = knn.kneighbors(user_item_matrix.loc[user_id, :].values.reshape(1, -1),
n_neighbors=num_recommendations+1)
    indices = indices.flatten()
    distances = distances.flatten()
```

```
 recommendations = []
  for i in range(1, len(indices)):
      movie_id = user_item_matrix.columns[indices[i]]
      title = item_info[item_info['item_id'] == movie_id]['title'].values[0]
      recommendations.append((title, distances[i]))

  # Plotting recommendations
  plt.figure(figsize=(10, 8))
  y_pos = range(len(recommendations))
  plt.barh(y_pos, [distance for _, distance in recommendations], align='center', color=clr)
  plt.yticks(y_pos, [title for title, _ in recommendations])
  plt.xlabel('Distance')
  plt.title(f'Top {num_recommendations} Recommendations for User {user_id}')
  plt.gca().invert_yaxis()  # Invert y-axis to show highest distance at the top
  plt.show()

  return recommendations

# Get recommendations and visualize for user_id 3
user_id = 3
num_recommendations = 15
recommendations = recommend_movies_visual(user_id, num_recommendations)
# Get recommendations and visualize for user_id 3
user_id = 15
num_recommendations = 15
recommendations = recommend_movies_visual(user_id, num_recommendations, 'purple')
# Get recommendations and visualize for user_id 3
user_id = 8
num_recommendations = 8
recommendations = recommend_movies_visual(user_id, num_recommendations, 'yellow')
```

**OUTPUT:**

```
Archive:  ml-100k.zip
   creating: ml-100k/
  inflating: ml-100k/allbut.pl
  inflating: ml-100k/mku.sh
  inflating: ml-100k/README
  inflating: ml-100k/u.data
  inflating: ml-100k/u.genre
  inflating: ml-100k/u.info
  inflating: ml-100k/u.item
  inflating: ml-100k/u.occupation
  inflating: ml-100k/u.user
  inflating: ml-100k/u1.base
  inflating: ml-100k/u1.test
  inflating: ml-100k/u2.base
  inflating: ml-100k/u2.test
  inflating: ml-100k/u3.base
  inflating: ml-100k/u3.test
  inflating: ml-100k/u4.base
  inflating: ml-100k/u4.test
  inflating: ml-100k/u5.base
  inflating: ml-100k/u5.test
  inflating: ml-100k/ua.base
  inflating: ml-100k/ua.test
  inflating: ml-100k/ub.base
  inflating: ml-100k/ub.test
Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
```

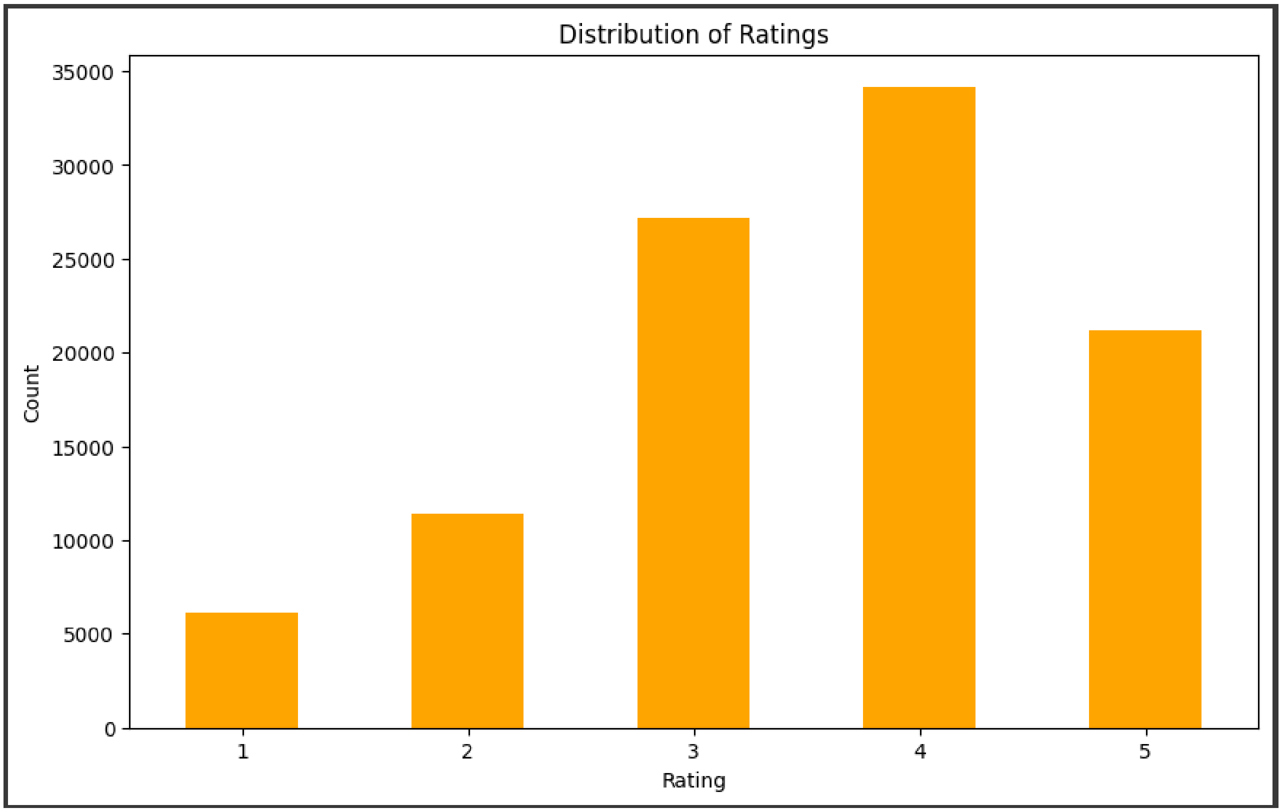
```
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   user_id    100000 non-null  int64
 1   item_id    100000 non-null  int64
 2   rating     100000 non-null  int64
 3   timestamp  100000 non-null  int64
dtypes: int64(4)
memory usage: 3.1 MB
None

First few rows of the dataset:
   user_id  item_id  rating  timestamp
0      196      242       3  881250949
1      186      302       3  891717742
2       22      377       1  878887116
3      244       51       2  880606923
4      166      346       1  886397596
```

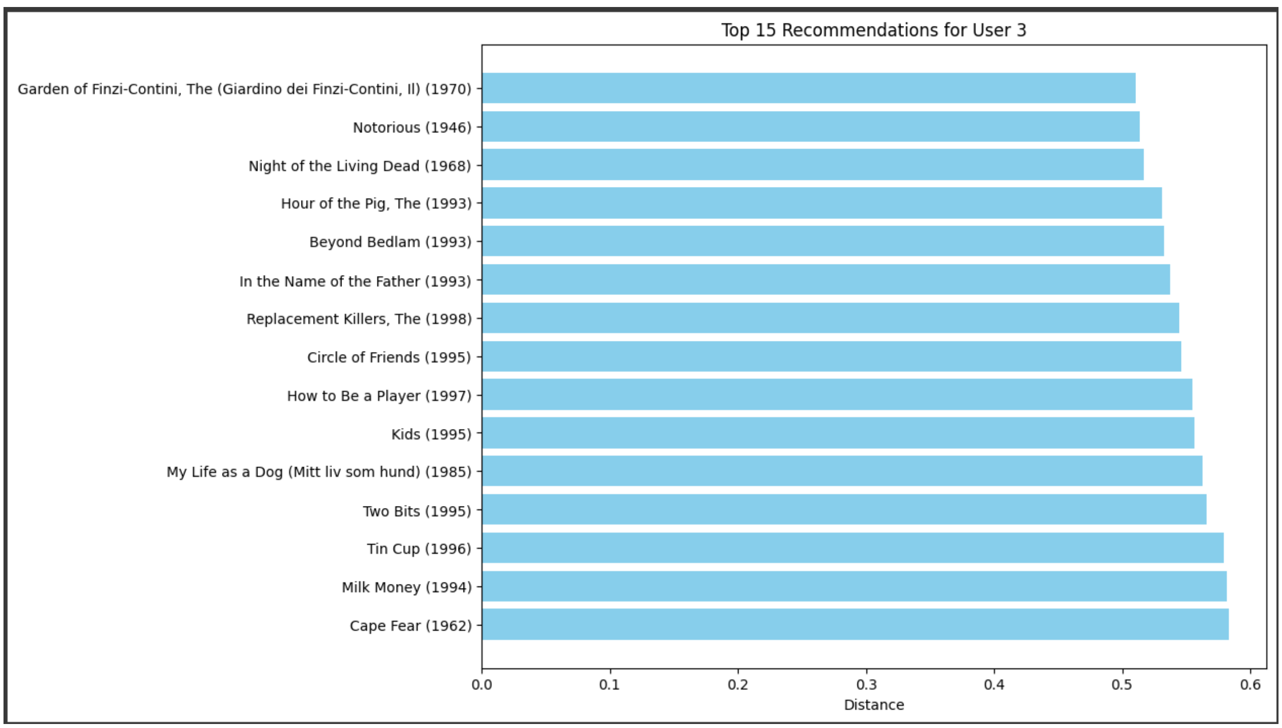
| | user id | movie id | rating | timestamp |
|---|---|---|---|---|
| 0 | 196 | 242 | 3 | 881250949 |
| 1 | 186 | 302 | 3 | 891717742 |
| 2 | 22 | 377 | 1 | 878887116 |
| 3 | 244 | 51 | 2 | 880606923 |
| 4 | 166 | 346 | 1 | 886397596 |

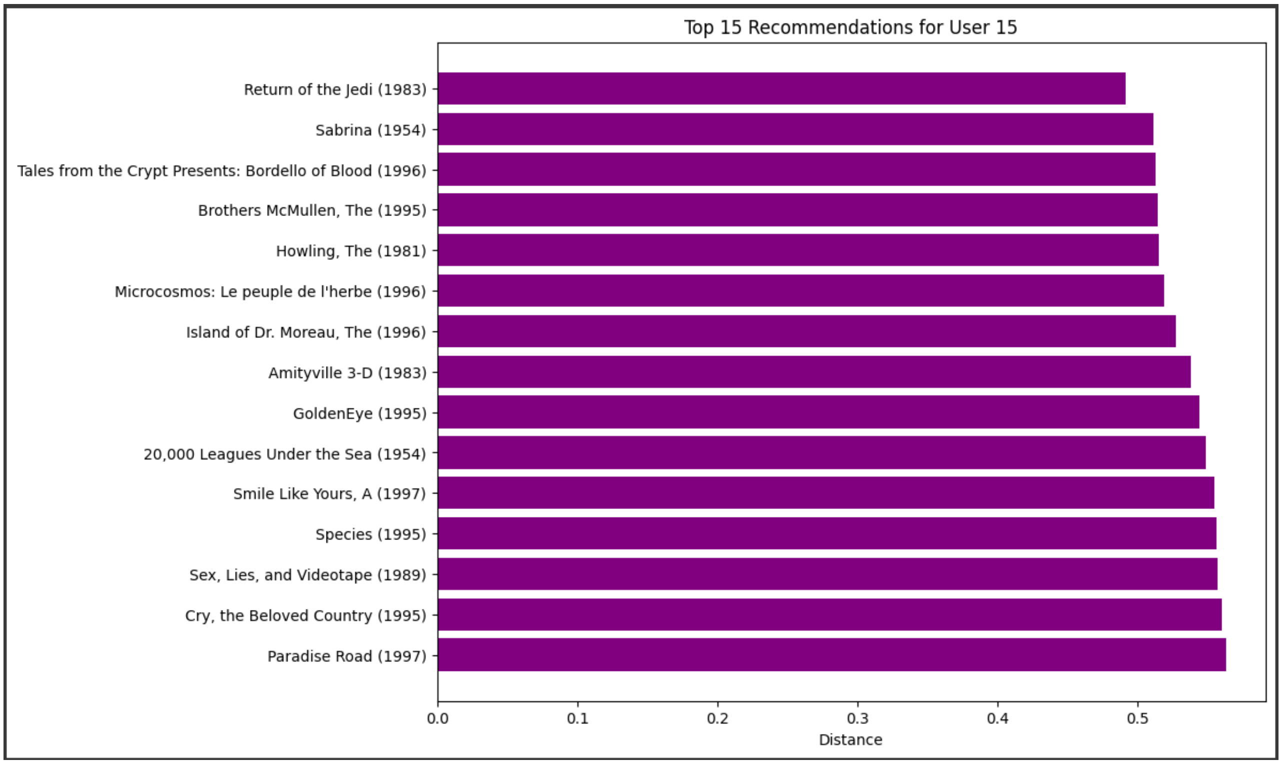
```
Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   user_id    100000 non-null  int64
 1   item_id    100000 non-null  int64
 2   rating     100000 non-null  int64
 3   timestamp  100000 non-null  int64
dtypes: int64(4)
memory usage: 3.1 MB
None

First few rows of the dataset:
   user_id  item_id  rating  timestamp
0      196      242       3  881250949
1      186      302       3  891717742
2       22      377       1  878887116
3      244       51       2  880606923
4      166      346       1  886397596
```

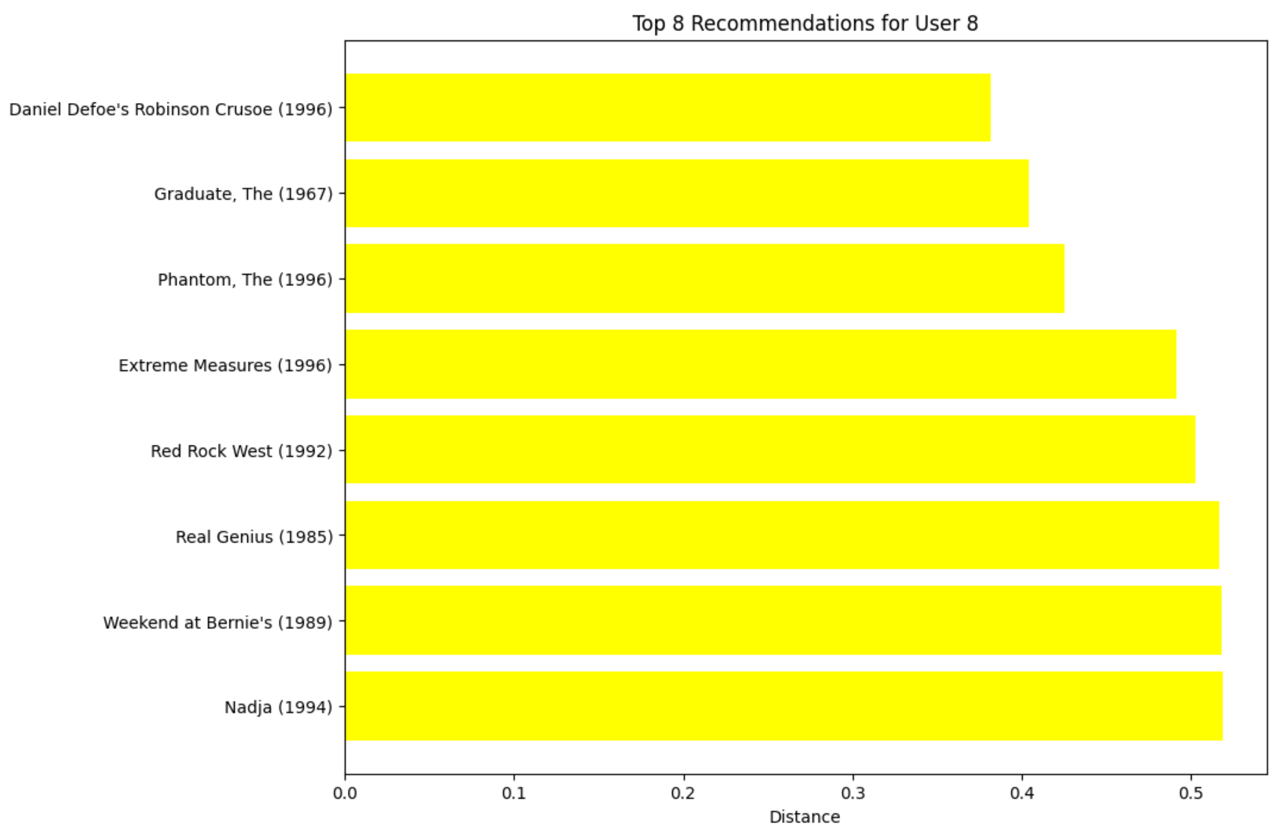
```
NearestNeighbors
NearestNeighbors(algorithm='brute', metric='cosine')
```

```
Top 15 recommendations for User 3:
1: Garden of Finzi-Contini, The (Giardino dei Finzi-Contini, Il) (1970) (distance: 0.5109682057285196)
2: Notorious (1946) (distance: 0.514075473740512)
3: Night of the Living Dead (1968) (distance: 0.5170790656883248)
4: Hour of the Pig, The (1993) (distance: 0.531165810609274)
5: Beyond Bedlam (1993) (distance: 0.5325576087248058)
6: In the Name of the Father (1993) (distance: 0.5372323649899484)
7: Replacement Killers, The (1998) (distance: 0.5449485329842954)
8: Circle of Friends (1995) (distance: 0.5460269903577735)
9: How to Be a Player (1997) (distance: 0.5545039809855525)
10: Kids (1995) (distance: 0.5561300816166361)
11: My Life as a Dog (Mitt liv som hund) (1985) (distance: 0.5626145279273538)
12: Two Bits (1995) (distance: 0.5656209837704875)
13: Tin Cup (1996) (distance: 0.5793654168793101)
14: Milk Money (1994) (distance: 0.5816611039544359)
15: Cape Fear (1962) (distance: 0.5835093530673334)
```


Distribution of Ratings
35000
30000
25000
20000
15000
10000
5000
0
Count
1
2
3
4
5
Rating


Top 15 Recommendations for User 3
Garden of Finzi-Contini, The (Giardino dei Finzi-Contini, Il) (1970)
Notorious (1946)
Night of the Living Dead (1968)
Hour of the Pig, The (1993)
Beyond Bedlam (1993)
In the Name of the Father (1993)
Replacement Killers, The (1998)
Circle of Friends (1995)
How to Be a Player (1997)
Kids (1995)
My Life as a Dog (Mitt liv som hund) (1985)
Two Bits (1995)
Tin Cup (1996)
Milk Money (1994)
Cape Fear (1962)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Distance


Top 15 Recommendations for User 15
Return of the Jedi (1983)
Sabrina (1954)
Tales from the Crypt Presents: Bordello of Blood (1996)
Brothers McMullen, The (1995)
Howling, The (1981)
Microcosmos: Le peuple de l'herbe (1996)
Island of Dr. Moreau, The (1996)
Amityville 3-D (1983)
GoldenEye (1995)
20,000 Leagues Under the Sea (1954)
Smile Like Yours, A (1997)
Species (1995)
Sex, Lies, and Videotape (1989)
Cry, the Beloved Country (1995)
Paradise Road (1997)
0.0
0.1
0.2
0.3
0.4
0.5
Distance


Top 8 Recommendations for User 8
Daniel Defoe's Robinson Crusoe (1996)
Graduate, The (1967)
Phantom, The (1996)
Extreme Measures (1996)
Red Rock West (1992)
Real Genius (1985)
Weekend at Bernie's (1989)
Nadja (1994)
0.0
0.1
0.2
0.3
0.4
0.5
Distance

## MODEL 2: Collaborative filtering model using Matrix Factorization

### SOURCE CODE:

```
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

#load the dataset
url = 'http://files.grouplens.org/datasets/movielens/ml-100k/u.data'
columns = ['userId', 'movieId', 'rating', 'timestamp']
ratings_data = pd.read_csv(url, sep='\t', names=columns)

ratings_data['userId'] = ratings_data['userId'].astype('category').cat.codes.values
ratings_data['movieId'] = ratings_data['movieId'].astype('category').cat.codes.values
# Split data into training and testing sets
train, test = train_test_split(ratings_data, test_size=0.2, random_state=42)

# Build recommendation model
num_users = len(ratings_data['userId'].unique())
num_movies = len(ratings_data['movieId'].unique())
embedding_size = 50

user_input = tf.keras.layers.Input(shape=(1,), name='user_input')
movie_input = tf.keras.layers.Input(shape=(1,), name='movie_input')

user_embedding = tf.keras.layers.Embedding(input_dim=num_users,
output_dim=embedding_size, input_length=1, name='user_embedding')(user_input)
movie_embedding = tf.keras.layers.Embedding(input_dim=num_movies,
output_dim=embedding_size, input_length=1, name='movie_embedding')(movie_input)
```

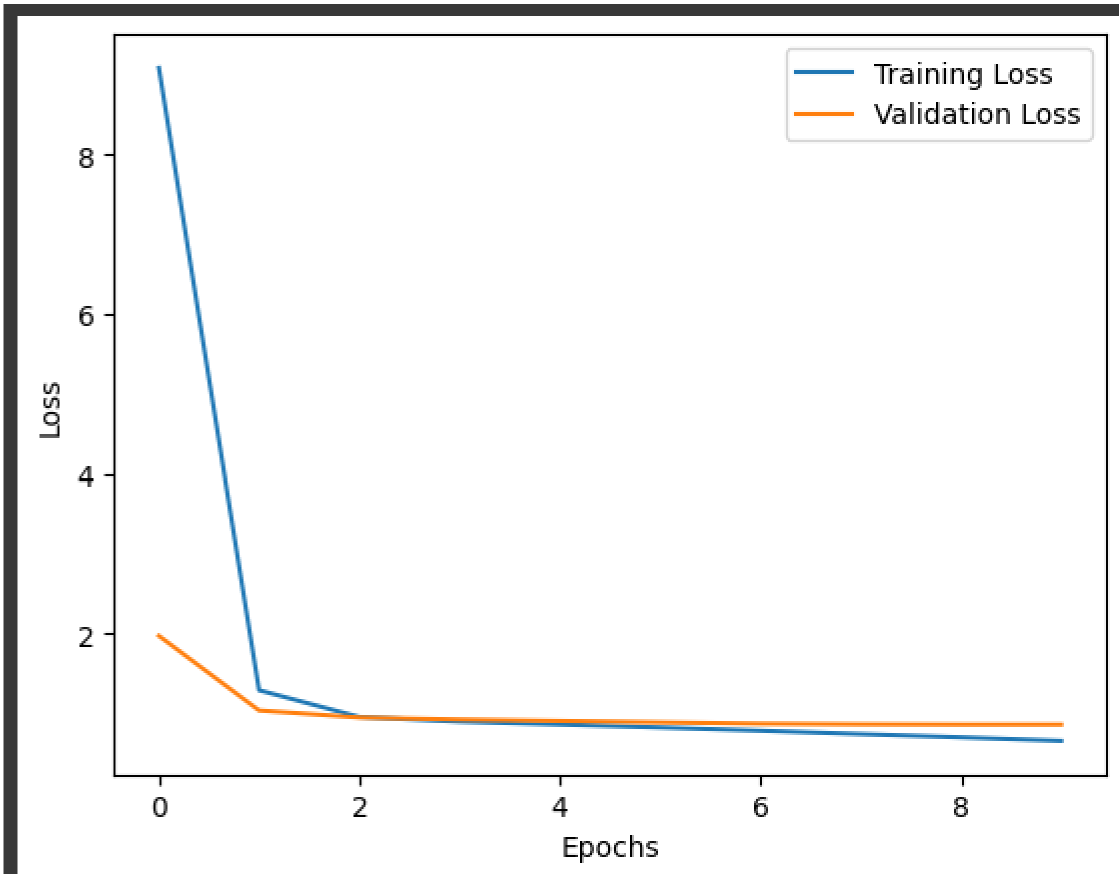
```
user_flatten = tf.keras.layers.Flatten()(user_embedding)
movie_flatten = tf.keras.layers.Flatten()(movie_embedding)

prod = tf.keras.layers.Dot(axes=1)([user_flatten, movie_flatten])

model = tf.keras.Model(inputs=[user_input, movie_input], outputs=prod)
model.compile(optimizer='adam', loss='mean_squared_error')
# Train the model
history = model.fit([train['userId'], train['movieId']], train['rating'],
                    batch_size=64, epochs=10,
                    validation_data=([test['userId'], test['movieId']], test['rating']))

# Visualize training history
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Example prediction
user_id = 5  # Example user ID
movie_id = 12  # Example movie ID
predicted_rating = model.predict([np.array([user_id]), np.array([movie_id])])
print(f'Predicted rating for user {user_id} and movie {movie_id}: {predicted_rating[0][0]}')

# Rating distribution
plt.hist(ratings_data['rating'], bins=10, edgecolor='brown')
plt.title('Rating-Frequency Distribution')
plt.xlabel('Rating')
```

```
plt.ylabel('Frequency')
plt.show()

# Number of ratings per user
ratings_per_user = ratings_data.groupby('userId').size()
plt.hist(ratings_per_user, bins=100, edgecolor='black')
plt.title('Ratings per User')
plt.xlabel('Ratings')
plt.ylabel('Users')
plt.show()

# Number of ratings per movie
ratings_per_movie = ratings_data.groupby('movieId').size()
plt.hist(ratings_per_movie, bins=100, edgecolor='black')
plt.title('Ratings per Movie')
plt.xlabel('Ratings')
plt.ylabel('Movies')
plt.show()

# Average rating per user
avg_rating_per_user = ratings_data.groupby('userId')['rating'].mean()
plt.hist(avg_rating_per_user, bins=10, edgecolor='black')
plt.title('Average Rating per User')
plt.xlabel('Average Rating')
plt.ylabel('Users')
plt.show()

# Average rating per movie
avg_rating_per_movie = ratings_data.groupby('movieId')['rating'].mean()
plt.hist(avg_rating_per_movie, bins=75, edgecolor='black')
```

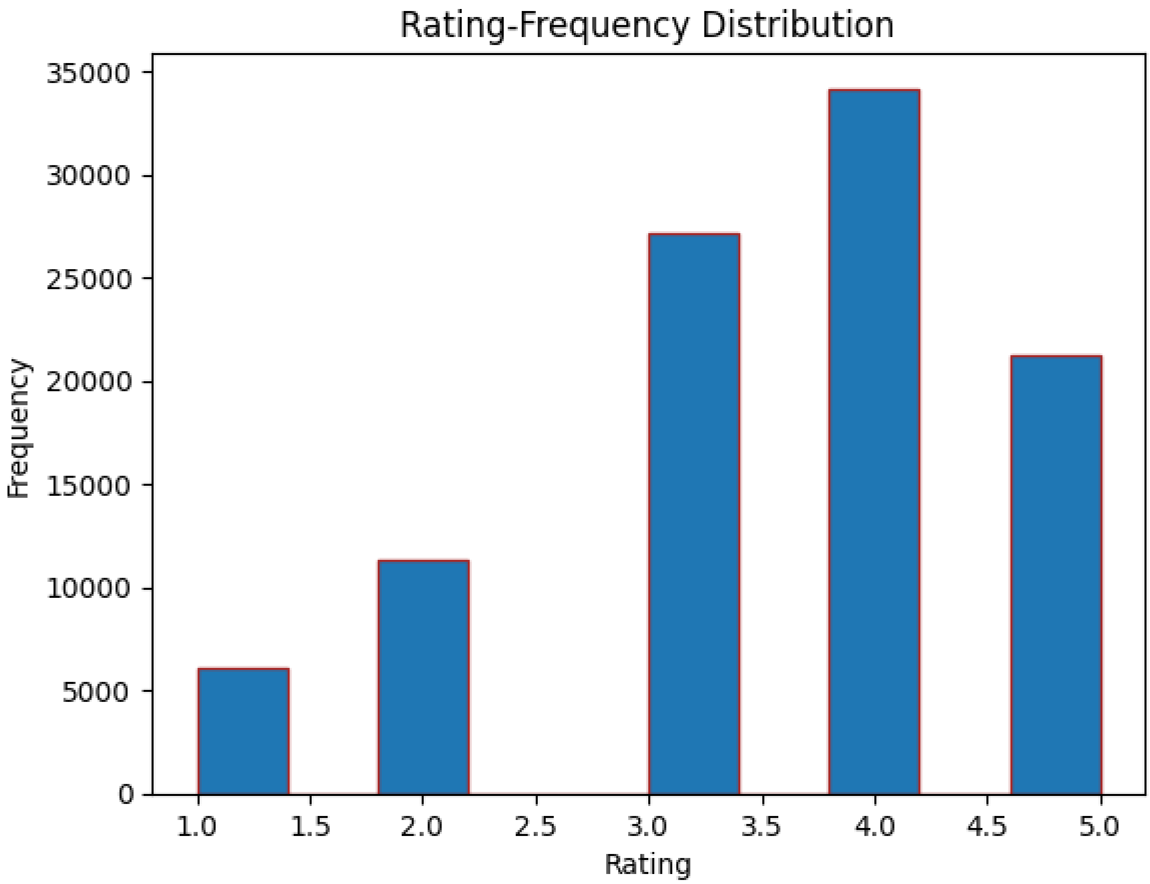
```
plt.title('Average Rating per Movie')
plt.xlabel('Average Rating')
plt.ylabel('No. of Movies')
plt.show()

# Pie chart of ratings
rating_counts = ratings_data['rating'].value_counts()
plt.pie(rating_counts, labels=rating_counts.index, autopct='%2.3f%%', startangle=270)
plt.title('Rating Distribution')
plt.show()

# Bar plot of top 10 most rated movies
top_25_movies = ratings_data['movieId'].value_counts().head(25)
plt.bar(top_25_movies.index, top_25_movies.values, color='darkgreen')
plt.title('Top 25 Most Rated Movies')
plt.xlabel('Movie ID')
plt.ylabel('Count of Ratings')
plt.show()

# Bar plot of top 10 highest average rating movies
top_50_avg_rated_movies = ratings_data.groupby('movieId')['rating'].mean().nlargest(50)
plt.bar(top_50_avg_rated_movies.index, top_50_avg_rated_movies.values, color='indigo')
plt.title('Top 50 Highest Average Rating Movies')
plt.xlabel('Movie ID')
plt.ylabel('Average Rating')
plt.show()
```

**OUTPUT:**

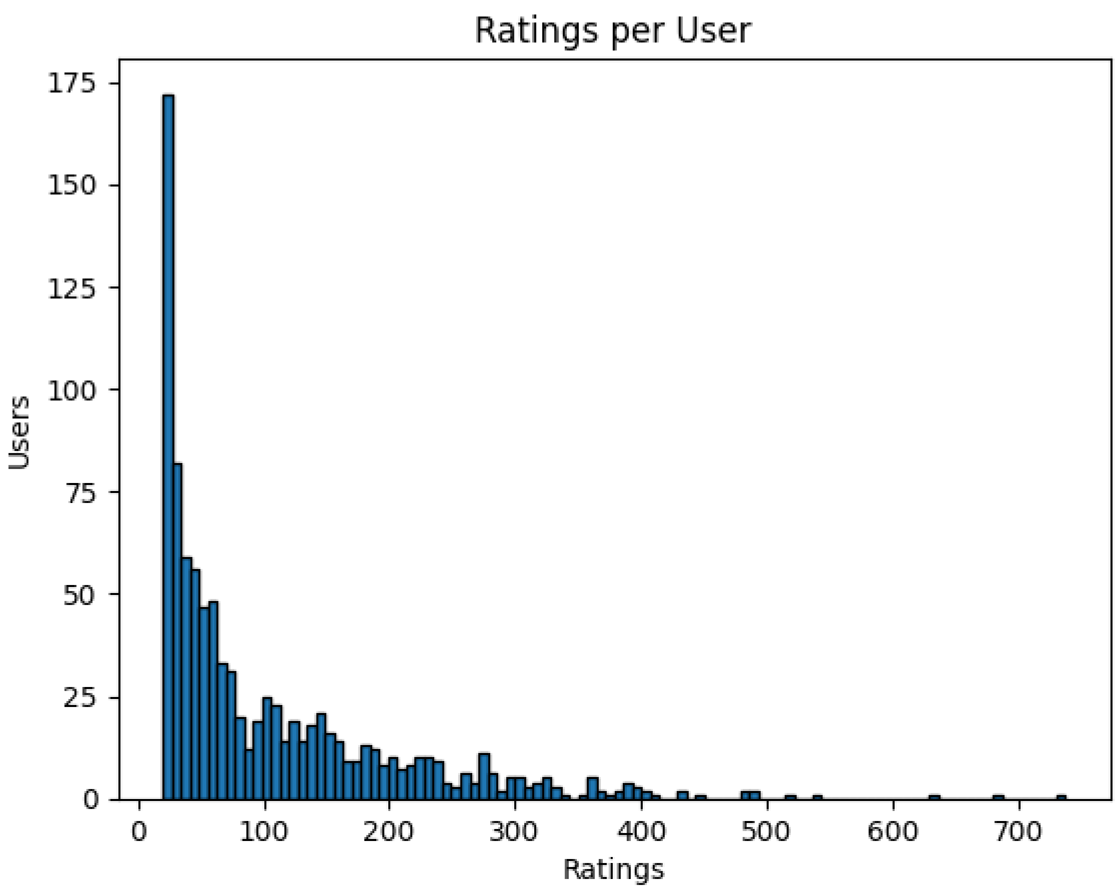
```
Epoch 1/10
1250/1250 [==============================] - 5s 3ms/step - loss: 9.0913 - val_loss: 1.9742
Epoch 2/10
1250/1250 [==============================] - 4s 3ms/step - loss: 1.2915 - val_loss: 1.0375
Epoch 3/10
1250/1250 [==============================] - 6s 5ms/step - loss: 0.9556 - val_loss: 0.9489
Epoch 4/10
1250/1250 [==============================] - 5s 4ms/step - loss: 0.8972 - val_loss: 0.9238
Epoch 5/10
1250/1250 [==============================] - 7s 6ms/step - loss: 0.8614 - val_loss: 0.9059
Epoch 6/10
1250/1250 [==============================] - 7s 6ms/step - loss: 0.8237 - val_loss: 0.8883
Epoch 7/10
1250/1250 [==============================] - 5s 4ms/step - loss: 0.7835 - val_loss: 0.8711
Epoch 8/10
1250/1250 [==============================] - 7s 6ms/step - loss: 0.7409 - val_loss: 0.8640
Epoch 9/10
1250/1250 [==============================] - 9s 7ms/step - loss: 0.7002 - val_loss: 0.8610
Epoch 10/10
1250/1250 [==============================] - 6s 5ms/step - loss: 0.6560 - val_loss: 0.8608
```



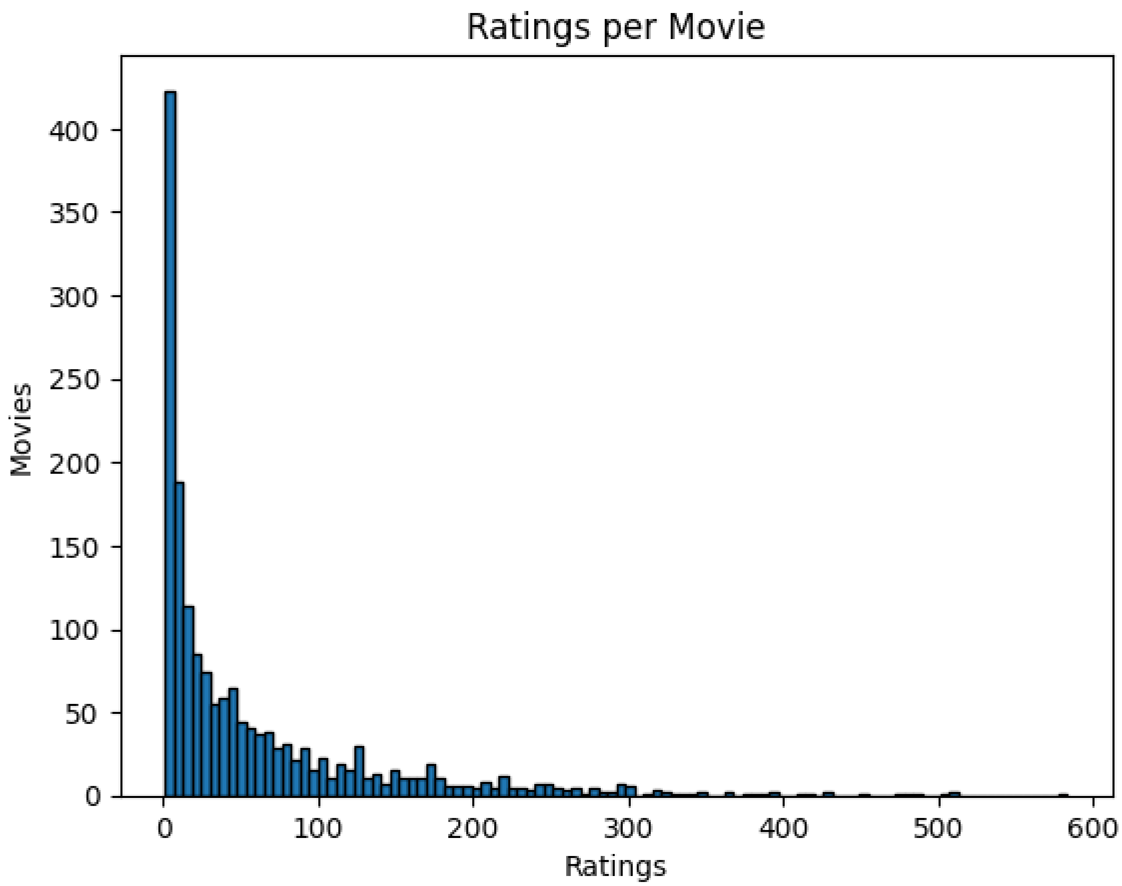

```
1/1 [==============================] - 0s 32ms/step
Predicted rating for user 5 and movie 12: 3.4013187885284424
```

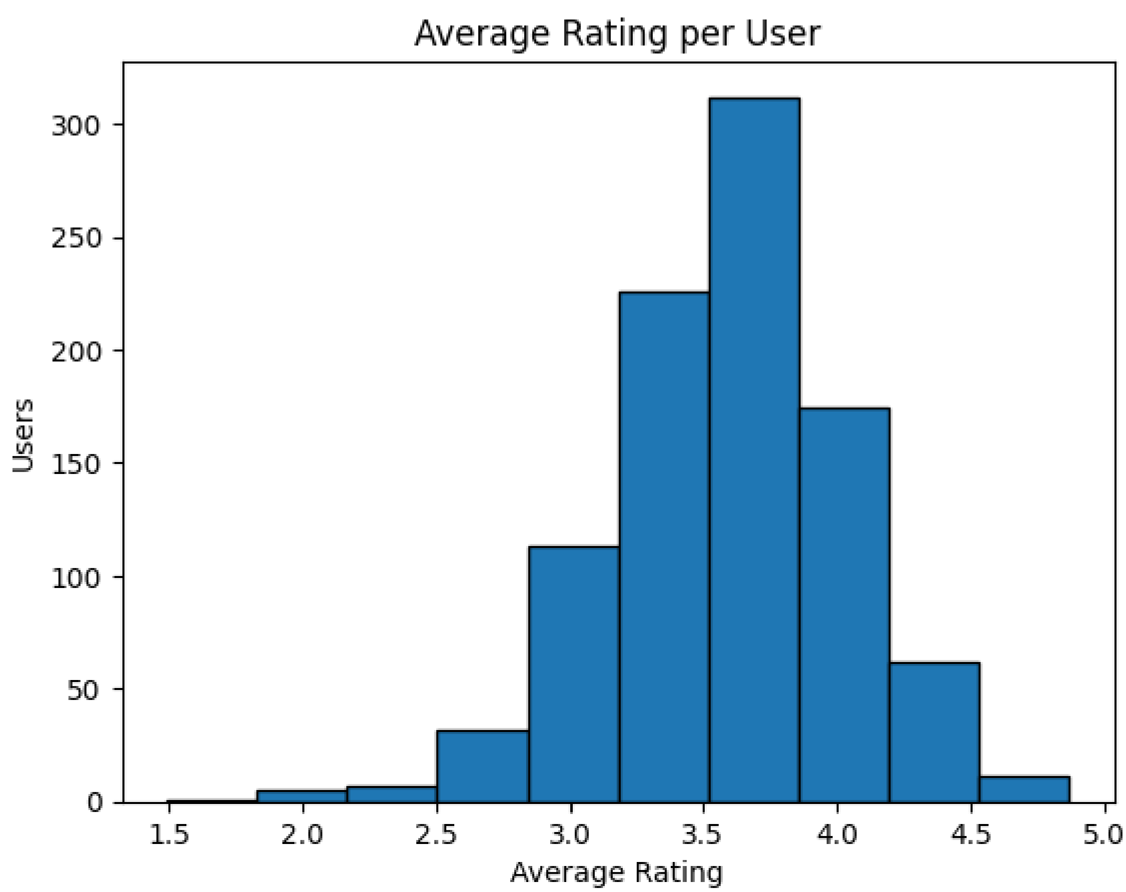


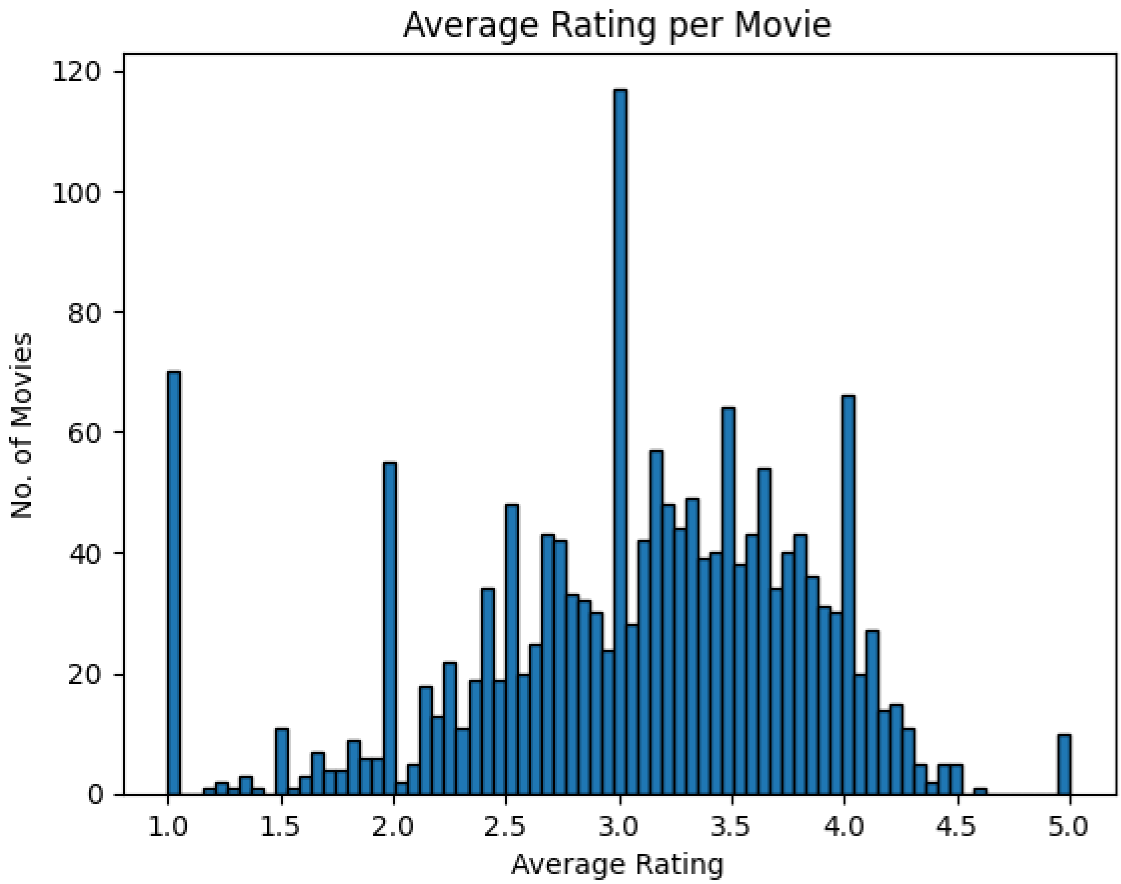
Rating-Frequency Distribution
Frequency
Rating
0
5000
10000
15000
20000
25000
30000
35000
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

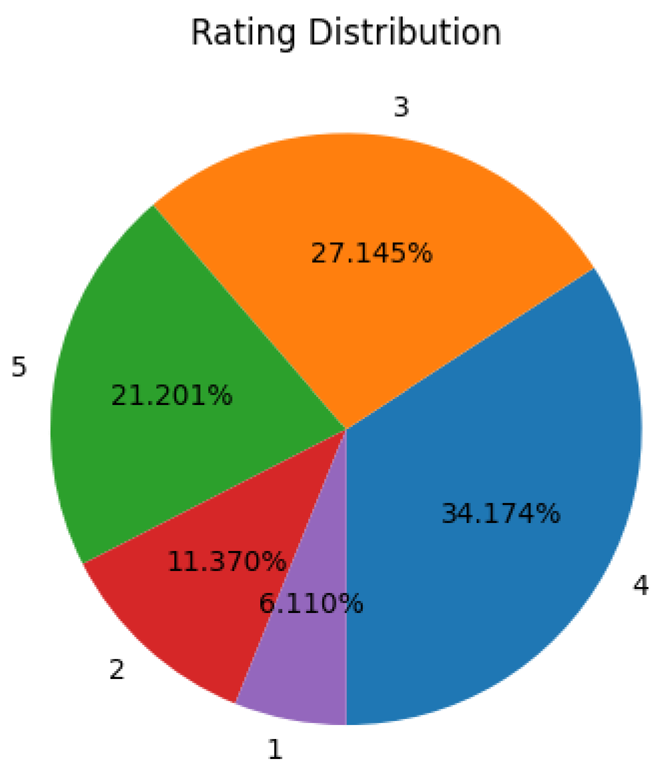
Ratings per User
Users
Ratings
0
25
50
75
100
125
150
175
0
100
200
300
400
500
600
700


Ratings per Movie
Movies
Ratings
0
50
100
150
200
250
300
350
400
0
100
200
300
400
500
600

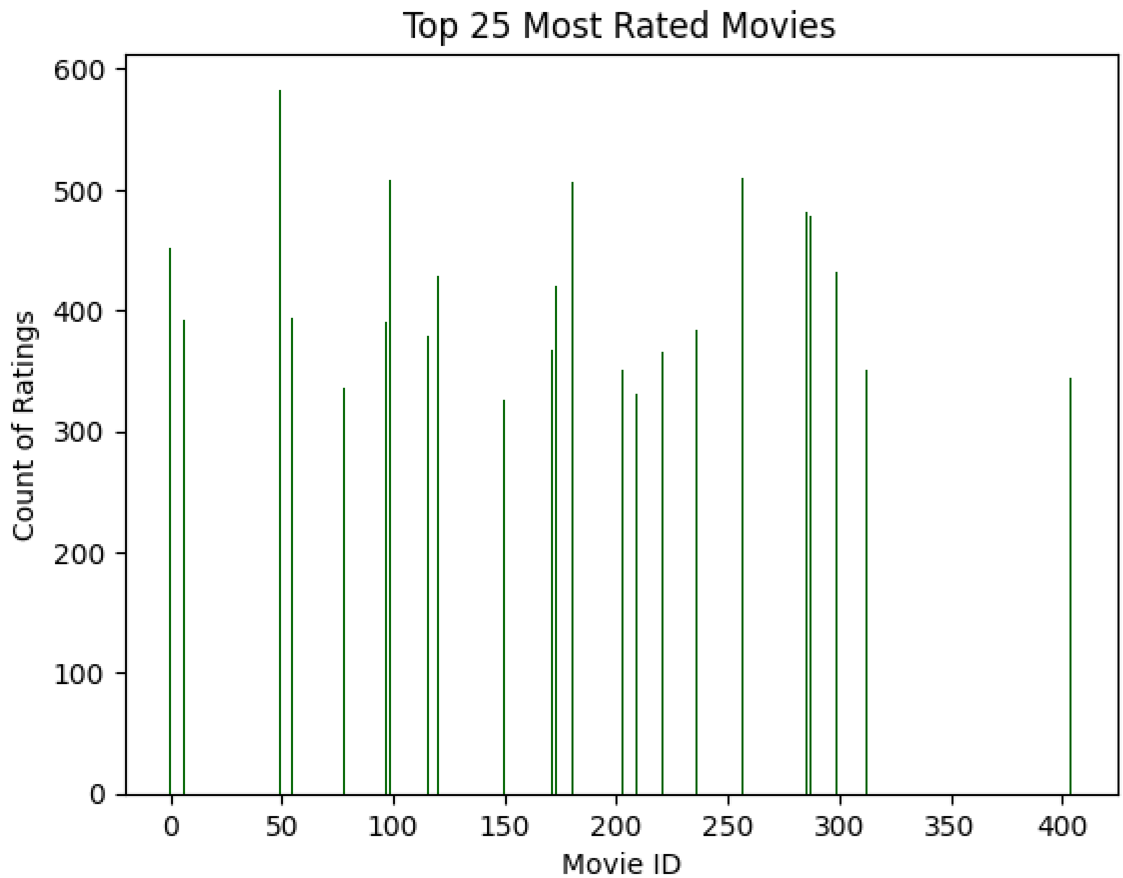

Average Rating per User
Users
Average Rating
0
50
100
150
200
250
300
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0



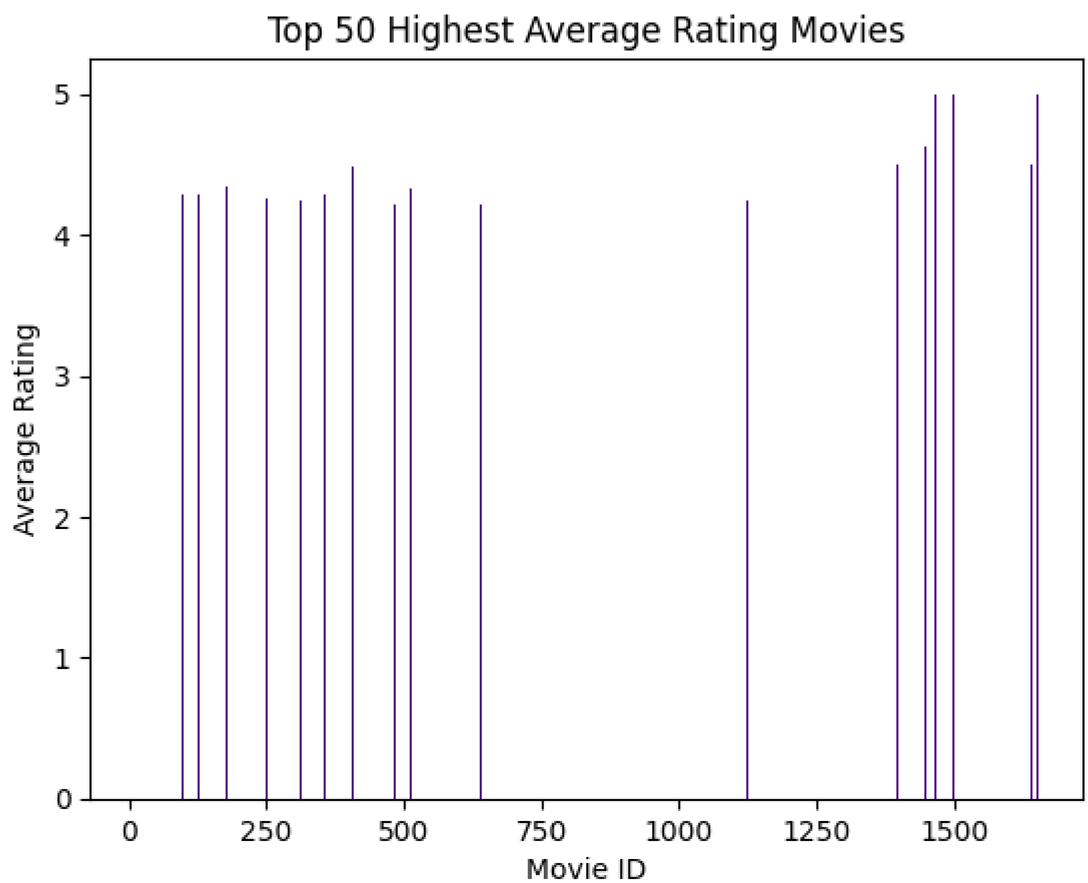
Average Rating per Movie
No. of Movies
Average Rating
0
20
40
60
80
100
120
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

Rating Distribution
3
27.145%
5
21.201%
34.174%
4
11.370%
6.110%
2
1



Top 25 Most Rated Movies
Count of Ratings
Movie ID
0
100
200
300
400
500
600
0
50
100
150
200
250
300
350
400

Top 50 Highest Average Rating Movies
Average Rating
Movie ID
0
1
2
3
4
5
0
250
500
750
1000
1250
1500

## MODEL 3: Graph Neural Network

### SOURCE CODE:

```
!pip install -q tensorflow-recommenders matplotlib scikit-learn tabulate

import tensorflow as tf
import tensorflow_datasets as tfds
import tensorflow_recommenders as tfrs
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras import layers
from sklearn.manifold import TSNE
from tabulate import tabulate


# Load the MovieLens dataset
ratings = tfds.load("movielens/100k-ratings", split="train")
movies = tfds.load("movielens/100k-movies", split="train")

# Prepare the data
ratings = ratings.map(lambda x: {
    "movie_title": x["movie_title"],
    "user_id": x["user_id"],
    "timestamp": x["timestamp"]
})

movies = movies.map(lambda x: x["movie_title"])
```

```
# Define the user and movie model with additional features.
user_ids_vocabulary = tf.keras.layers.StringLookup()
movie_titles_vocabulary = tf.keras.layers.StringLookup()

user_ids_vocabulary.adapt(ratings.map(lambda x: x["user_id"]))
movie_titles_vocabulary.adapt(movies)

# Convert the movie titles to a TensorFlow Dataset
movies = tf.data.Dataset.from_tensor_slices(list(movies))

# Define the GNN layer
class GNNLayer(layers.Layer):
    def __init__(self, units):
        super(GNNLayer, self).__init__()
        self.units = units
        self.dense = layers.Dense(units)

    def call(self, inputs, edge_index):
        x = inputs
        row, col = edge_index[:, 0], edge_index[:, 1]
        out = tf.math.unsorted_segment_sum(x[col], row,
num_segments=tf.shape(x)[0])
        return self.dense(out)
```

```
class GNNModel(tfrs.Model):
    def __init__(self, user_model, movie_model, task):
        super().__init__()
        self.user_model = user_model
        self.movie_model = movie_model
        self.task = task

    def call(self, features):
        user_embeddings = self.user_model(features["user_id"])
        movie_embeddings = self.movie_model(features["movie_title"])
        edge_index = tf.convert_to_tensor([features["user_id"],
features["movie_title"]])
        gnn_layer = GNNLayer(64)
        user_embeddings = gnn_layer(user_embeddings, edge_index)
        movie_embeddings = gnn_layer(movie_embeddings, edge_index)
        return self.task(user_embeddings, movie_embeddings)

    def compute_loss(self, features, training=False):
        user_embeddings = self.user_model(features["user_id"])
        movie_embeddings = self.movie_model(features["movie_title"])
        return self.task(user_embeddings, movie_embeddings)

# Define user and movie models
user_model = tf.keras.Sequential([
    user_ids_vocabulary,
    tf.keras.layers.Embedding(user_ids_vocabulary.vocabulary_size(), 64),
    tf.keras.layers.Dense(32, activation="relu")
])
```

```
movie_model = tf.keras.Sequential([
    movie_titles_vocabulary,
    tf.keras.layers.Embedding(movie_titles_vocabulary.vocabulary_size(), 64),
    tf.keras.layers.Dense(32, activation="relu")
])

# Define the task
task = tfrs.tasks.Retrieval(metrics=tfrs.metrics.FactorizedTopK(
    candidates=movies.batch(128).map(movie_model),
    ks=[5, 10]
))

# Create and compile the model
model = GNNModel(user_model, movie_model, task)
model.compile(optimizer=tf.keras.optimizers.Adam(0.01))

# Train the model and capture the training history
history = model.fit(ratings.batch(4096), epochs=10, verbose=1)

# Set up brute-force search for retrieval
index = tfrs.layers.factorized_top_k.BruteForce(model.user_model)
index.index_from_dataset(
    movies.batch(100).map(lambda title: (title, model.movie_model(title)))
)
```

```
def print_recommendations(user_id):
    _, titles = index(np.array([user_id]))
    top_titles = titles[0, :10].numpy()
    print(f"\nTop 10 recommendations for user {user_id}:")
    print(tabulate(enumerate(top_titles, 1), headers=["Rank", "Movie Title"],
tablefmt="fancy_grid"))
# Get and print recommendations for a specific user
print_recommendations("5")


# Get and print recommendations for another user
print_recommendations("28")


# Plot the training loss and top-k accuracy
plt.figure(figsize=(18, 8))


# Plot training loss
plt.subplot(1, 3, 1)
plt.plot(history.history['loss'], label='Loss')
plt.title('Training Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()


# Plot top-5 and top-10 accuracy
plt.subplot(1, 3, 2)
plt.plot(history.history['factorized_top_k/top_5_categorical_accuracy'], label='Top-5
Accuracy')
plt.plot(history.history['factorized_top_k/top_10_categorical_accuracy'], label='Top-
10 Accuracy')
```

```
plt.title('Top-K Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Extract embeddings for visualization
user_embeddings = []
movie_embeddings = []
for user_id in ratings.map(lambda x: x["user_id"]).take(100):
    user_embeddings.append(model.user_model(np.array([user_id.numpy()])))

for movie_title in movies.take(100):

movie_embeddings.append(model.movie_model(np.array([movie_title.numpy()])))

user_embeddings = np.vstack(user_embeddings)
movie_embeddings = np.vstack(movie_embeddings)
# Use t-SNE for dimensionality reduction
user_tsne = TSNE(n_components=2).fit_transform(user_embeddings)
movie_tsne = TSNE(n_components=2).fit_transform(movie_embeddings)

# Plot embeddings using t-SNE
plt.subplot(1, 3, 3)
plt.scatter(user_tsne[:, 0], user_tsne[:, 1], label='Users', alpha=0.6)
plt.scatter(movie_tsne[:, 0], movie_tsne[:, 1], label='Movies', alpha=0.6)
plt.title('t-SNE of User and Movie Embeddings')
plt.legend()
plt.show()
```

## OUTPUT:

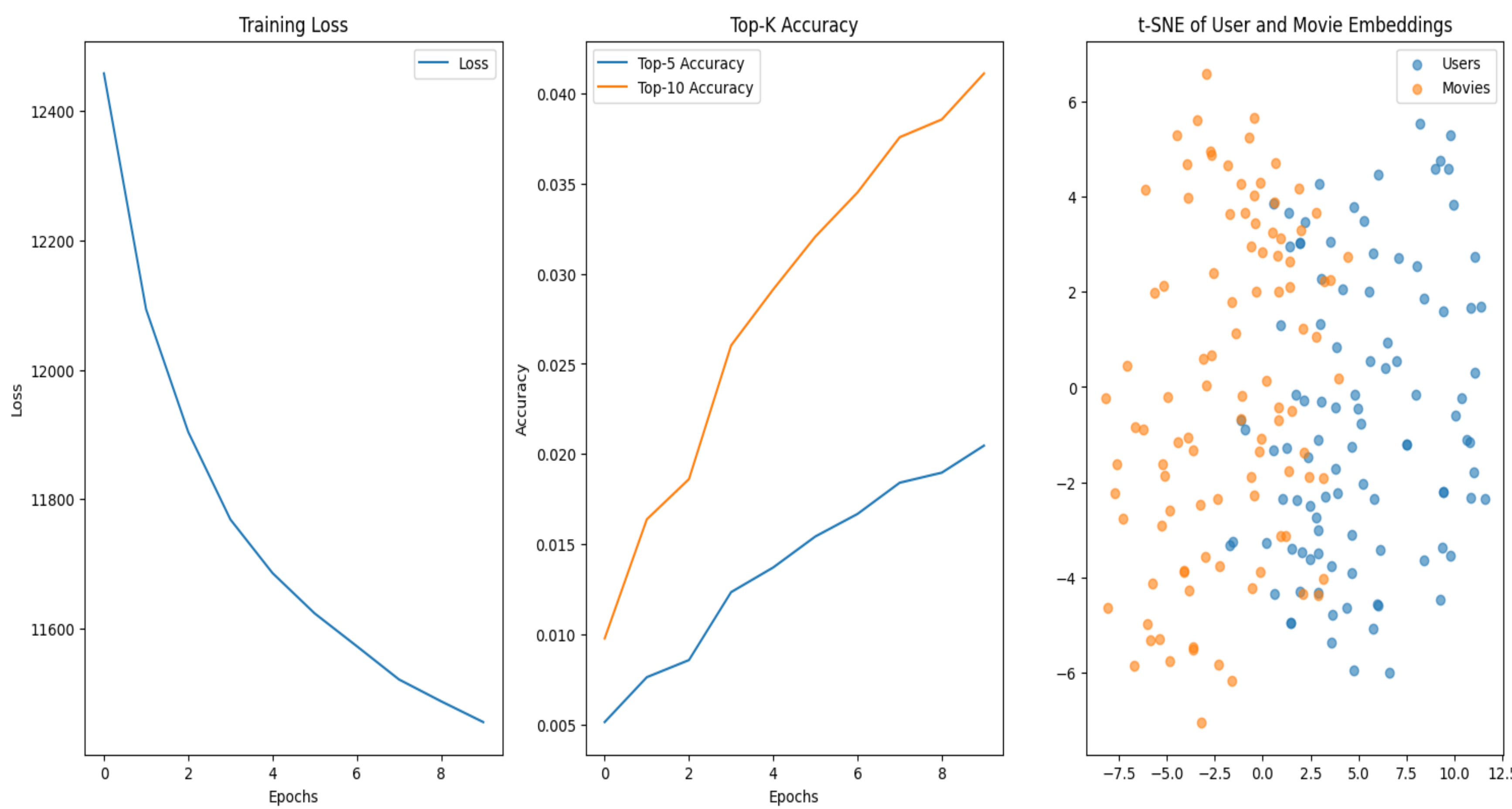
```
Epoch 1/10
25/25 [==============================] - 28s 1s/step - factorized_top_k/top_5_categorical_accuracy: 0.
Epoch 2/10
25/25 [==============================] - 22s 875ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 3/10
25/25 [==============================] - 16s 630ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 4/10
25/25 [==============================] - 16s 630ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 5/10
25/25 [==============================] - 16s 650ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 6/10
25/25 [==============================] - 16s 639ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 7/10
25/25 [==============================] - 16s 639ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 8/10
25/25 [==============================] - 20s 797ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 9/10
25/25 [==============================] - 21s 787ms/step - factorized_top_k/top_5_categorical_accuracy:
Epoch 10/10
25/25 [==============================] - 16s 642ms/step - factorized_top_k/top_5_categorical_accuracy:
<tensorflow_recommenders.layers.factorized_top_k.BruteForce at 0x7faa990bfe50>
```

Top 10 recommendations for user 5:

| Rank | Movie Title |
|---|---|
| 1 | Amityville Curse, The (1990) |
| 2 | Amityville 1992: It's About Time (1992) |
| 3 | NeverEnding Story III, The (1994) |
| 4 | Amityville: A New Generation (1993) |
| 5 | Lassie (1994) |
| 6 | Burnt Offerings (1976) |
| 7 | Calendar Girl (1993) |
| 8 | Flintstones, The (1994) |
| 9 | Jaws 3-D (1983) |
| 10 | Beverly Hillbillies, The (1993) |

Top 10 recommendations for user 28:

| Rank | Movie Title |
|---|---|
| 1 | Wes Craven's New Nightmare (1994) |
| 2 | Body Snatchers (1993) |
| 3 | Body Snatchers (1993) |
| 4 | Blob, The (1958) |
| 5 | Omen, The (1976) |
| 6 | Star Trek: Generations (1994) |
| 7 | Candyman (1992) |
| 8 | Body Snatcher, The (1945) |
| 9 | Shining, The (1980) |
| 10 | Lawnmower Man, The (1992) |



Training Loss
Loss
12400
12200
12000
11800
11600
0
2
4
6
8
Epochs
Top-K Accuracy
Top-5 Accuracy
Top-10 Accuracy
Accuracy
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0
2
4
6
8
Epochs
t-SNE of User and Movie Embeddings
Users
Movies
6
4
2
0
−2
−4
−6
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5