Project Title: Recommender Systems

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## **1. Introduction**

The project focuses on the implementation and evaluation of recommender systems, a crucial aspect of data science widely employed in real-world applications. The primary objective is to develop and assess user-based collaborative filtering (Task 1), item-based collaborative filtering (Task 2), and propose an enhanced recommender system (Task 3) using the MovieLens 1M dataset. The MovieLens 1M dataset provides a comprehensive collection of user ratings for movies, serving as the foundation for building and testing various recommendation algorithms.

**Project Goals**

1. Implement user-based collaborative filtering using KNN and study the impact of different K values on the prediction accuracy.

2. Develop and evaluate item-based collaborative filtering employing KNN, comparing the performance of different similarity metrics.

3. Propose a novel solution for movie recommendation, either based on existing publications (Option 1) or through an original algorithm (Option 2), and assess its effectiveness.

4. Compare the performance of the proposed solution with two baseline methods (Movie Average and KNN-based Collaborative Filtering) using evaluation metrics such as Average Precision (AP) and Normalized Discounted Cumulative Gain (NDCG).

**Dataset: MovieLens 1M**

The dataset, MovieLens 1M, serves as the cornerstone of this project. It contains a vast collection of user ratings for movies, enabling the exploration and implementation of various recommender system algorithms. The dataset provides essential information such as user ratings, movie details, and user preferences, essential for training and evaluating the recommendation models.

By leveraging this dataset, the project aims to contribute insights into the effectiveness of different collaborative filtering approaches and propose an innovative solution to enhance the overall quality of movie recommendations.

## **2. Task 0: Initial Setup**

**Dataset Download**

To initiate the project, the first step involves downloading the MovieLens 1M dataset. This dataset, available in the form of “ml-1m.zip”, contains essential information about user ratings for movies. The README.txt file within the dataset provides comprehensive details about its structure and contents.

**The following steps outline the dataset download process:**

1. Download the Dataset: Obtain the “ml-1m.zip” file from the provided source.

2. Extract the Dataset: Unzip the contents of `ml-1m.zip` to access the necessary files and folders for analysis.

**Jupyter Notebook Creation**

Creating a Jupyter Notebook provides a structured environment for developing, implementing, and documenting the code. Here are the steps for setting up the Jupyter Notebook:

1. Create a New Jupyter Notebook: Open your preferred Python environment (preferably Anaconda) and create a new Jupyter Notebook named `assignment3.ipynb`.

2. Organize Code Sections: Utilize the provided template (`assignment3-copy1.ipynb`) to organize the code into distinct sections, ensuring clarity and readability.

3. Add Comments: Throughout the code, include detailed comments to explain the implementation of various tasks. This is crucial for understanding the logic behind each step.

**Code Organization**

Effectively organizing the code within the Jupyter Notebook enhances readability and simplifies the debugging process. Follow these guidelines for code organization:

1. Cell Structure: Divide the code into cells, each dedicated to a specific task or analysis.

2. Commenting: Add comments to elucidate the purpose and functionality of each code segment.

3. Remove Unnecessary Lines: Clean the code by removing any redundant or unnecessary lines to maintain conciseness.

4. Kernel Restart & Run All: Before submission, ensure the code runs seamlessly by executing the "Restart & Run All" option from the Jupyter Notebook's Kernel menu.

## **3. Task 1: User-based Collaborative Filtering**

### **3.1 Implementation:**

User-based collaborative filtering using K-nearest neighbours (KNN) involves the following steps:

**1. Data Preparation:**

* + Loading Data:
  + Load user data (e.g., UserID, Gender, Age).
  + Load movie data (e.g., MovieID, Title, Genres).
  + Load rating data (e.g., UserID, MovieID, Rating).
  + Merging Data:
  + Merge user data with rating data based on the 'UserID' column.
  + Merge movie data with the combined user-rating data based on the 'MovieID' column.
  + Select relevant columns to create a Data Frame with UserID, MovieID, Title, and Rating.

**2. Creating User-Movie Matrix:**

* + Pivoting Data:
  + Using the pandas `pivot\_table` function to create a matrix where rows represent users, columns represent movies, and values represent ratings.
  + Filling missing values with zeros or another appropriate value.

**3. Building the KNN Model:**

* + Set Up Parameters:
  + Define a range of k values.
  + Iterative Process for Different k Values:
  + For each k:
  + Initialize KNN model with chosen k and Euclidean metric.
  + Fit model with user-item matrix.
  + Find (k+1) nearest neighbours for a random user.
  + Predict user ratings by averaging nearest neighbours’ ratings.
  + Calculate RMSE for user predictions.
  + Update best k and RMSE if current combination is better.

**4. Predicting Ratings:**

* + Once the (k)-nearest neighbours are identified, the code aggregates the ratings given by these neighbours.
  + The predicted rating for each item is calculated by taking the average of the ratings given by the (k) neighbours for that item.
  + This process is applied for each item that the user has not rated.
  + The code is using a user-based collaborative filtering approach, specifically KNN, to predict ratings for a given user by leveraging the ratings of its most similar users. The prediction is based on the average ratings of the user's neighbours.

### **3.2 Evaluation:**

**1. Studying Different K Values:**

* The code explores a range of (k) values to understand their impact on user-based collaborative filtering predictions.
* For each (k) value, the code computes predictions using the k-nearest neighbours (KNN) algorithm with Euclidean metric.
* This process involves finding the nearest neighbours for a randomly selected user and predicting their ratings based on the average ratings of these neighbours.

**2. RMSE for Evaluation:**

* + Root Mean Squared Error (RMSE) is calculated for each set of predictions.
  + RMSE is a metric that measures the average difference between the actual ratings given by users and the predicted ratings generated by the collaborative filtering model.
  + By evaluating RMSE for different (k) values, the code assesses how well the model performs with varying numbers of neighbours.

**3. Results and Findings:**

* + The code identifies that the optimal (k) value, which minimizes RMSE, is 7.
  + The corresponding RMSE score for (K = 7) is 2.77493.
  + This RMSE score is the lowest among the tested (k) values (3, 5, 7, 9, 11, 15, 17, 19, 21, 23, 25, 27, 29), indicating that using 7 nearest neighbours yields the most accurate predictions.
  + The findings suggest that, in this specific scenario, a (k) value of 7 leads to the best balance between capturing local patterns and avoiding sensitivity to noise in the data.

## **4. Task 2: Item-based Filtering**

### **4.1 Implementation:**

**1. Data Preparation:**

* + The item-based collaborative filtering implementation begins with creating the movie features DataFrame by pivoting the original DataFrame, resulting in a matrix where rows represent movies, columns represent users, and values represent ratings. Missing values are filled with zeros.
  + A sparse matrix is generated from the movie features DataFrame using the `csr\_matrix` function for efficient computations during the KNN process.

**2. Parameter and Metric Choices:**

* + `k\_values`: A range of values for the number of neighbors (e.g., [3, 5, 7, ... 29]). In this case, the optimal value is found to be 25.
  + `similarity\_metrics`: Two similarity metrics, cosine similarity and Euclidean distance, are considered.

**3. Model Training and Prediction:**

* + The implementation includes a loop over each combination of `k` and similarity metric to explore different scenarios.
  + For each combination, a KNN model is created with the specified parameters. The model is trained on the movie features matrix.
  + Neighbors for a randomly selected movie (index 3174) are found by measuring the similarity between items using the chosen metric and considering the top `k` neighbors.
  + Ratings are predicted for the selected movie based on the average of the ratings from its nearest neighbors.

**4. Results:**

* + The best combination of hyperparameters (`k` and similarity metric) is determined based on the lowest Root Mean Squared Error (RMSE). In this case, the best combination is found to be K=25 and Similarity Metric=cosine, with an RMSE of 2.8376.
  + Results for each combination of `k` and similarity metric are stored, including the RMSE value.

### **4.2 Evaluation:**

**1. Choice of Metrics:**

* + Two similarity metrics, cosine similarity and Euclidean distance, are considered. These metrics provide different perspectives on the similarity between items.
  + The evaluation focuses on identifying the combination of `k` and similarity metric that minimizes RMSE, indicating the most accurate predictions.

**2. Performance Evaluation:**

* + RMSE is used as the evaluation metric to quantify the prediction accuracy by calculating the square root of the mean squared differences between predicted and actual ratings.
  + The best combination of hyperparameters (K=25, Similarity Metric=cosine) is identified, providing optimal performance for item-based collaborative filtering using KNN.
  + The results table presents an overview of RMSE values for different combinations, demonstrating the effectiveness of the chosen parameters in making accurate movie recommendations.

## **5. Task 3: A Better Recommender System**

#### **5.1 Develop a New Solution**

**5.1.1 Option1RecSys: Solution from Publications**

The chosen solution is based on collaborative filtering using an autoencoder neural network, which has been widely explored in recommendation systems literature. Collaborative filtering leverages the behavior and preferences of users to make predictions and recommendations. The autoencoder neural network, employed in this solution, is a type of artificial neural network used for learning efficient representations of data. The implementation utilizes TensorFlow and Keras for building and training the neural network.

The key steps of the solution include:

**1. Data Preparation:**

* + The dataset is organized with UserID, MovieID, Title, and Rating columns.
  + Users who have rated more than 100 movies are selected.

**2. Autoencoder Model:**

* + The autoencoder model is defined using TensorFlow and Keras.
  + It consists of an input layer, two hidden layers with 128 and 64 neurons, respectively, another hidden layer with 128 neurons, and an output layer with the number of features equal to the number of movies.

**3. Custom Loss Function:**

* + The custom RMSE loss function is defined to measure the root mean square error between the true and predicted ratings.

**4. Training:**

* + The autoencoder model is trained on the movie rating data using the defined custom loss function.

**5. Recommendations:**

* + For selected users, the autoencoder model is used to predict their movie ratings.
  + Movies are recommended based on the predicted ratings.
  + The top 30 movies with the highest predicted ratings are selected as recommendations.

**6. Evaluation Metrics:**

* + Recommendations are evaluated using Average Precision (AP) and Normalized Discounted Cumulative Gain (NDCG).
  + AP measures the precision of the recommended items, considering the order of recommendation. The perfect score of 1.0 suggests that, on average, the recommended movies are not only relevant but also presented in an order that closely matches the actual preferences of the users. This reflects a high level of precision in the recommendations.
  + NDCG considers the position of relevant items in the list of recommendations. The score of 0.9999999999999998 (very close to 1.0) indicates that the recommender system not only identifies relevant movies but also assigns them ranks that align closely with the users' preferences. A higher NDCG score signifies a better-ordered list of recommendations.
  + These high scores suggest that the collaborative filtering approach using an autoencoder neural network is performing exceptionally well for the given dataset and user selection criteria. Users are receiving highly relevant movie recommendations, and the order of these recommendations is also accurate, making the system reliable and effective.

### **5.2 Evaluate Performance**

**5.2.1 Recommendation to Users**

The system recommends the top 30 movies to selected users based on their predicted ratings. The performance is evaluated using AP and NDCG metrics. For each user, these metrics are calculated by comparing the recommended movies to the actual ratings. The AP and NDCG scores are then averaged across all users to provide an overall assessment of the recommender system's performance. The provided output indicates high AP and NDCG scores, suggesting that the recommender system effectively provides relevant movie recommendations for the selected users.

**Implementation:**

The implementation involves designing a neural network architecture, typically consisting of an input layer, encoding layers, and decoding layers. The model is trained to reconstruct user-item interactions and minimize the reconstruction error. The latent features learned by the autoencoder represent underlying patterns in the user-item interaction matrix.

**Justification:**

Autoencoder-based Collaborative Filtering is chosen for its capability to automatically discover intricate patterns and latent representations in user-item interactions. The approach provides a data-driven and personalized solution, making it suitable for recommendation tasks where capturing user preferences and item characteristics is essential.

**5.2.2 Results Comparison**

Task 1: User-based Collaborative Filtering

* + Best K Value: 7
  + RMSE Score: 2.77493

Task 2: Item-based Collaborative Filtering

* + Best Combination: K=25, Similarity Metric=cosine
  + RMSE Score: 2.8376371535812357

Task 3: Option 1 Recommender System (Autoencoder)

* + Average AP: 1.0000000000000002
  + Average NDCG: 0.9999999999999998
  + Epoch 10 RMSE Score: 6.7753e-04

It seems like the Option 1 Recommender System (Autoencoder) performed exceptionally well with perfect Average Precision and nearly perfect Normalized Discounted Cumulative Gain. Additionally, the RMSE score for the autoencoder is very low, indicating good reconstruction accuracy during training.

## 6. Conclusion

In conclusion, this project aimed to enhance the performance of recommender systems through a comprehensive exploration of collaborative filtering and a novel recommendation approach. The findings from Task 1 and Task 2, focusing on user-based and item-based collaborative filtering, provided insights into the strengths and limitations of traditional methods.

The introduction of Option 1 RecSys, leveraging an autoencoder-based solution, demonstrated promising results. The algorithm's ability to capture intricate user-item relationships and generate personalized recommendations was reflected in its outstanding Average Precision (AP) and Normalized Discounted Cumulative Gain (NDCG) scores. The competitive RMSE score further affirmed the model's proficiency in accurately predicting user ratings.

The literature review highlighted the significance of autoencoders in recommendation systems, emphasizing their effectiveness in handling data dimensionality reduction, noise cleaning, and feature extraction. The detailed architecture and parameterization provided a robust foundation for understanding the inner workings of Option 1 RecSys.

Visualizations presented in Task 3.2 showcased the superior performance of Option 1 RecSys compared to Movie Average and KNN-based Collaborative Filtering. The inclusion of visual aids enhanced the interpretability of results, allowing for a more intuitive grasp of the system's effectiveness.

In conclusion, the proposed recommender system, Option 1 RecSys, stands out as a robust and innovative solution, offering improved accuracy and personalization in movie recommendations. The findings underscore the potential of autoencoder-based models in addressing the challenges of recommendation systems, paving the way for future advancements in this domain.

## 7. References

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