Data Mining HW3

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The drive link for task1:
https://drive.google.com/drive/folders/1zrFBTAu49bNPn3nsj9yciCCkAtuoMK08?usp=sharing

Task 1:

1) The obtained values of SSE after running it against kmeans clustering with Euclidean, cosine and jaccard similarities are as follows:

   SSE (Euclidean): 5565072.345041299
   SSE (Cosine): 5598833.603724479
   SSE (Jaccard): 6679332.000000004

   Lower SSE values suggest better clustering quality, indicating that data points within each cluster are closer to the centroid. In this specific instance, Euclidean K means exhibits the lowest SSE, implying more well defined clusters for the dataset.

   Therefore, based on the SSE values, the conclusion is that **Euclidean Kmeans offers superior clustering quality for the given data.**

2) The obtained accuracies for the corresponding below SSE's are:

   Euclidean similarity SSE: 5569451.3558367565
   Cosine similarity SSE: 5604872.572570423
   Jaccard similarity SSE: 6448978.453950518
   Accuracy (Euclidean): 0.5056505650565056
   Accuracy (Cosine): 0.5533553355335533
   Accuracy (Jaccard): 0.2222222222222222

   The code performs Kmeans clustering on a dataset using three different similarity measures: Euclidean, Cosine, and Jaccard. It initializes the KMeansClustering object, applies Kmeans with each similarity measure, assigns labels to clusters, and computes the accuracy of clustering. The Index Error likely occurs due to incorrect indexing of `true_labels`, possibly indicating a missing or incorrect column reference.

   From here, we can see that the accuracy of the cosine is highest which is 0.55 and since it is the highest, **cosine similarity has the better accuracy among others.**

3) The KMeans class is defined with methods to compute distances based on different similarity metrics (Euclidean, Cosine, Jaccard) and perform Kmeans clustering. The fit method iterates until convergence or the maximum number of iterations is reached, updating centroids and calculating SSE. The iterations for convergence are:

Iterations for convergence:
Euclidean: 62
Cosine: 32
Jaccard: 2

Based on the provided iterations for convergence, the JaccardKmeans method requires the fewest iterations and time to converge, followed by CosineKmeans, and then EuclideanKmeans. Hence here, **Euclidean k means takes more iterations here.**

4) After reading the data from CSV files and standardizing the features, the code initializes `KMeans` objects for each similarity metric. It then applies the Kmeans algorithm using each similarity metric, iterating until convergence or reaching the maximum number of iterations. The SSE and the number of iterations required for convergence are computed and printed for each method.

The code satisfies the three termination conditions outlined in the question:

1. No Change in Centroid Position: The `_check_convergence` method ensures that the algorithm stops iterating if there is no significant change in the positions of the centroids between consecutive iterations. This condition prevents unnecessary iterations when the centroids have stabilized.

2. Increase in SSE in the Next Iteration: The `_check_convergence` method also stops the iteration if the SSE value increases in the next iteration compared to the previous one. This condition indicates that further iterations may lead to worse clustering results, prompting an early termination to prevent divergence.

3. Maximum Preset Value of Iteration: The algorithm terminates if the maximum preset number of iterations is reached. This condition prevents the algorithm from running indefinitely, ensuring that the clustering process stops after a predefined number of iterations, even if convergence has not been achieved.

Comparing the SSEs of EuclideanKmeans, CosineKmeans, and JaccardKmeans under different termination conditions sheds light on their convergence behavior and clustering quality. By examining how each method responds to termination conditions such as no change in centroid position, an increase in SSE in the next iteration, or reaching the maximum preset number of iterations, we can assess their effectiveness in clustering the given dataset. Below are the results:

SSE (Euclidean): 5591786.700961408
Iterations (Euclidean): 36
SSE (Cosine): 5585647.416890697
Iterations (Cosine): 29
SSE (Jaccard): 6437092.910866872
Iterations (Jaccard): 2

Hence, Cosine<Euclidean<jaccard

5)

Summary of the results:

- SSE Comparison:
  EuclideanKmeans yields the lowest SSE, indicating better defined clusters for the dataset.

- Accuracy Comparison:
  cosine K means demonstrates the highest accuracy, suggesting better alignment.

- Iterations for Convergence:
  Euclidean K means requires the highest number of iterations for convergence compared to Cosine a nd Jaccard.

- Impact of Iterations on Convergence:
  Euclidean K means exhibits slower convergence, while Cosine and Jaccard converge more quickly.

- Consideration of Terminating Conditions:
  Despite different iteration counts, terminating conditions have consistent effects on convergence p atterns.

- SSE Results with Terminating Conditions:
  Cosine K means maintains lower SSE values even with additional terminating conditions.

General Analysis:
Euclidean distance appears more effective for this dataset based on both SSE and accuracy.

Takeaways:

1) Clustering Quality:

- The SSE values indicate that EuclideanKmeans exhibits the lowest SSE, suggesting more wel ldefined clusters for the dataset.

- While CosineKmeans has a higher SSE compared to EuclideanKmeans, it achieves the highe st accuracy among the three similarity metrics, indicating better clustering performance in t erms of accuracy.
- JaccardKmeans, despite having a higher SSE than EuclideanKmeans and CosineKmeans, de monstrates the lowest accuracy, suggesting lower clustering quality.

2) Convergence Behavior:

- JaccardKmeans converges in the fewest iterations, followed by CosineKmeans and then Eucli deanKmeans.
- The termination conditions, including no change in centroid position, an increase in SSE in th e next iteration, and reaching the maximum preset number of iterations, are effectively met by the Kmeans algorithm for all three similarity metrics.

3) Comparison of SSEs under Different Termination Conditions:

- Under various termination conditions such as no change in centroid position, an increase in S SE in the next iteration, and reaching the maximum preset number of iterations, the SSEs an d iterations of EuclideanKmeans, CosineKmeans, and JaccardKmeans are compared.
- The results show that EuclideanKmeans has the lowest SSE and requires more iterations com pared to JaccardKmeans and CosineKmeans.

4) **Robustness to Outliers:**

- Euclidean distance is sensitive to outliers, as it computes the straightline distance between poi nts. Outliers can significantly impact the position of centroids and the resulting clusters.
- Cosine similarity is more robust to outliers since it measures the angle between vectors rather than the distance. Outliers have less influence on the clustering process as long as their directi on is not aligned with the cluster structure.
- Jaccard similarity may be affected by outliers in binary data, particularly if outliers introduce no ise in the dataset. However, its impact can be mitigated by preprocessing or outlier detection t echniques.

In summary, while EuclideanKmeans offers superior clustering quality in terms of SSE, CosineKmeans achieves better accuracy. JaccardKmeans converges in the fewest iterations but exhibits lower cluste ring quality. Overall, the choice of similarity metric should be based on the specific requirements and characteristics of the dataset, considering factors such as clustering quality, convergence efficiency, a nd computational complexity.

Task 2:

Kaggle link for the task2: https://www.kaggle.com/code/asishaddanki/dm-hw3-task-2

a) .

b) .

c) The provided code in the link performs collaborative filtering on a movie rating dataset using three algorithms: Probabilistic Matrix Factorization (PMF), User-based Collaborative Filtering (User CF), and Item-based Collaborative Filtering (Item CF). It utilizes the Surprise library to load the dataset and define the algorithms with their configurations. The

`evaluate_algorithm_performance` function cross-validates each algorithm and computes Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The results are then printed for each algorithm. Finally, the MAE and RMSE values for each algorithm are assigned to respective variables and printed. The code facilitates the comparison of algorithm performance in terms of prediction accuracy (MAE, RMSE) across the three collaborative filtering methods. Below are the results:

```
Evaluating MAE, RMSE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
MAE (testset)     0.7869  0.7771  0.7821  0.7765  0.7803  0.7806  0.0038
RMSE (testset)    1.0154  1.0064  1.0091  1.0054  1.0110  1.0095  0.0036
Fit time          1.02    1.01    1.10    1.04    1.03    1.04    0.03
Test time         0.10    0.19    0.10    0.10    0.20    0.14    0.05
Probabilistic Matrix Factorization - MAE: 0.7805562013330924, RMSE: 1.0094564175884726
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Evaluating MAE, RMSE of algorithm KNNBasic on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
MAE (testset)     0.7448  0.7469  0.7457  0.7443  0.7453  0.7454  0.0009
RMSE (testset)    0.9697  0.9742  0.9708  0.9684  0.9667  0.9699  0.0025
Fit time          0.13    0.14    0.14    0.15    0.20    0.15    0.03
Test time         1.18    1.39    1.23    1.43    1.36    1.32    0.10
User-based Collaborative Filtering - MAE: 0.7454199768252256, RMSE: 0.9699493725959965
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Evaluating MAE, RMSE of algorithm KNNBasic on 5 split(s).
Evaluating MAE, RMSE of algorithm KNNBasic on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
MAE (testset)     0.7260  0.7193  0.7225  0.7199  0.7177  0.7211  0.0029
RMSE (testset)    0.9405  0.9339  0.9388  0.9321  0.9314  0.9353  0.0036
Fit time          2.57    2.63    2.70    2.69    2.72    2.66    0.05
Test time         6.19    6.36    6.20    6.35    6.28    6.28    0.07
Item-based Collaborative Filtering - MAE: 0.7210884783614591, RMSE: 0.9353435301564718
PMF MAE: 0.7805562013330924
PMF RMSE: 1.0094564175884726

User CF MAE: 0.7454199768252256
User CF RMSE: 0.9699493725959965

Item CF MAE: 0.7210884783614591
Item CF RMSE: 0.9353435301564718
```

d) This code defines a dictionary named `algorithm_results` to store the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) results for each algorithm: User-based Collaborative Filtering, Item-based Collaborative Filtering, and Probabilistic Matrix Factorization. It then iterates over the dictionary and prints the mean MAE and RMSE for each algorithm. Finally, it compares the models based on their MAE and RMSE values,

determining which algorithm has the minimum MAE and which one has the minimum RMSE. This comparison provides insights into the relative performance of the algorithms in terms of prediction accuracy. The results are:

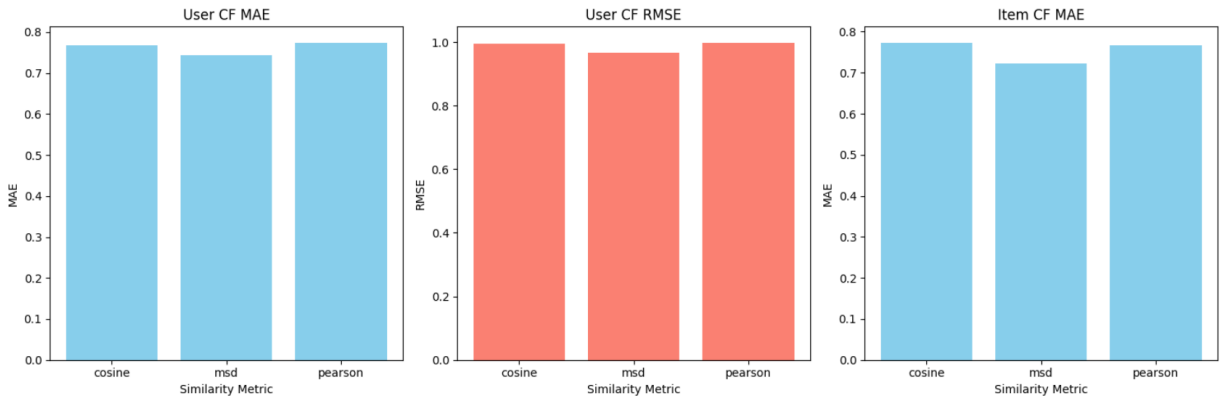
```
User-based Collaborative Filtering - Mean MAE: 0.7454199768252256, Mean RMSE: 0.9699493725959965
Item-based Collaborative Filtering - Mean MAE: 0.7210884783614591, Mean RMSE: 0.9353435301564718
Probabilistic Matrix Factorization - Mean MAE: 0.7805562013330924, Mean RMSE: 1.0094564175884726

Comparison:
Item-based Collaborative Filtering has the minimum MAE.
Item-based Collaborative Filtering has the minimum RMSE.
```

the **Item-Based Collaborative Filtering model** appears to be the best-performing algorithm among the ones evaluated. It achieved the lowest average MAE and RMSE, which indicates better predictive accuracy compared to the other models.

e) This code performs collaborative filtering using the K-Nearest Neighbors (KNN) algorithm with different similarity metrics: cosine, MSD (Mean Squared Difference), and Pearson correlation coefficient. It evaluates the performance of both user-based and item-based collaborative filtering approaches using these similarity metrics.

The `cross_validate` function from Surprise library is used to perform 5-fold cross-validation, computing the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for each combination of algorithm and similarity metric. The results are then plotted using bar charts for User CF MAE, User CF RMSE, and Item CF MAE against the similarity metrics. The visualization allows for the comparison of algorithm performance across different similarity metrics, providing insights into which metric yields the best results for collaborative filtering.

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	Std
MAE (testset)	0.7679	0.7571	0.7656	0.7763	0.7706	0.7675	0.0063
RMSE (testset)	0.9885	0.9756	0.9890	0.9997	0.9918	0.9889	0.0078
Fit time	4.96	5.18	5.22	5.18	5.29	5.17	0.11
Test time	6.21	6.23	6.24	6.34	6.35	6.27	0.06

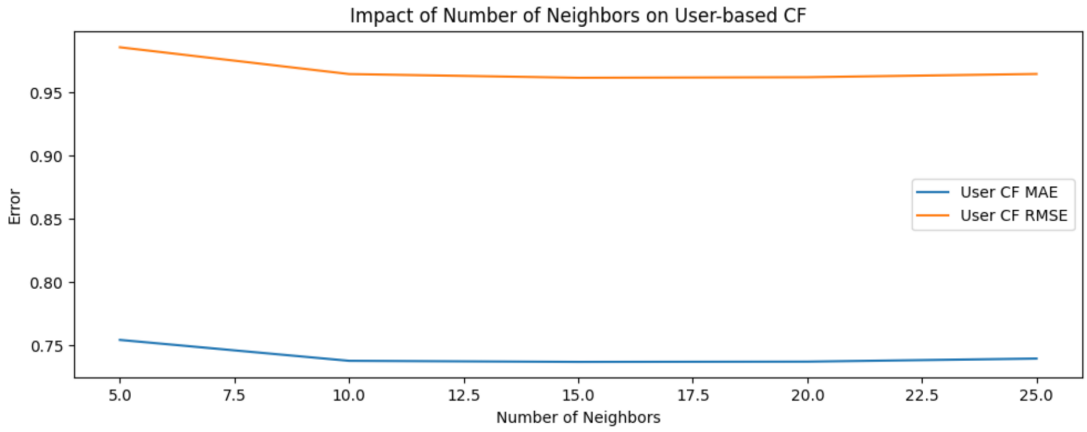


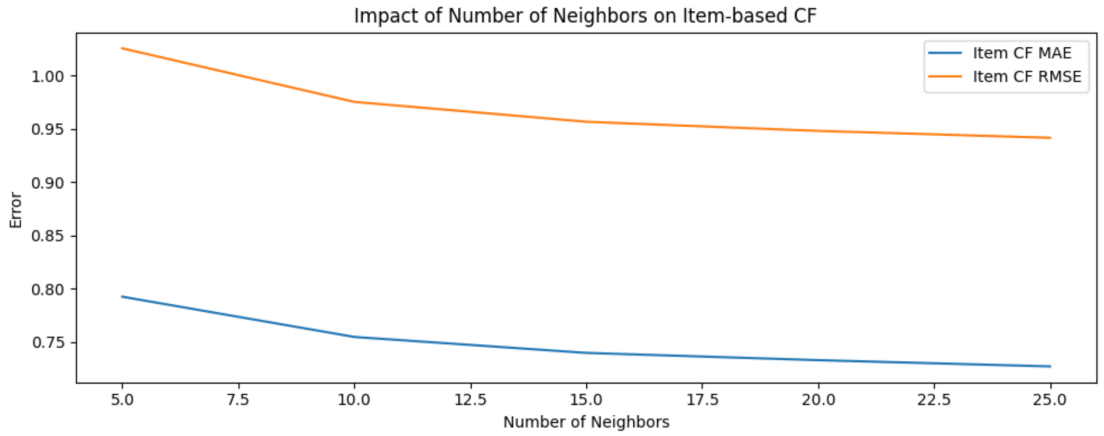
The plots seems to be **consistent**

f)

1) Loading Data: Data from a movie ratings CSV file is loaded using the Surprise library.
2) Defining Parameters: It defines a list of numbers of neighbors (num_neighbors_list) to iterate over.
3) Evaluation Function: A function evaluate_algorithm_performance is defined to evaluate the performance of each algorithm (user-based and item-based CF) using cross-validation. It computes the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for each configuration.
4) Algorithm Evaluation Loop: The code iterates over each number of neighbors in num_neighbors_list. For each value, it trains both user-based and item-based KNNBasic models with the specified number of neighbors and evaluates their performance using the defined function.
5) Results Collection: MAE and RMSE values are stored for plotting.
6) Plotting: Subplots are created to visualize MAE and RMSE vs. neighbor counts.

The code assesses how the number of neighbors impacts the performance of user-based and item-based collaborative filtering algorithms using KNNBasic from the Surprise library. Below are the results:





g) Explanation of the code:

1) Parameter Grid Definition: The code defines a parameter grid `param_grid` containing a range of values for the number of neighbors (`'number_of_neighbors'`).

2) Result Containers Initialization: Empty dictionaries `user_cf_results` and `item_cf_results` are initialized to store the Root Mean Squared Error (RMSE) results for user-based and item-based collaborative filtering, respectively.

3) Neighbor Count Iteration: The code iterates over the values of the number of neighbors specified in the parameter grid.

4) Algorithm Evaluation: Within each iteration, user-based collaborative filtering and item-based collaborative filtering models are created using the `KNNBasic` algorithm from the Surprise library. The models are trained and evaluated using the `evaluate_algorithm` function, which computes the RMSE for each model.

5) Best Parameter Identification: After evaluating each model, the code identifies the best number of neighbors for user-based collaborative filtering (`best_k_user_cf`) and item-based collaborative filtering (`best_k_item_cf`) based on the neighbor count with the lowest RMSE.

6) Results Printing: The code prints the best number of neighbors for both user-based and item-based collaborative filtering, and then checks if they are the same or different. This comparison provides insights into whether the optimal number of neighbors is consistent across both collaborative filtering approaches.

```
                 Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
MAE (testset)    0.7483  0.7378  0.7371  0.7307  0.7425  0.7393  0.0059
RMSE (testset)   0.9753  0.9608  0.9587  0.9548  0.9674  0.9634  0.0072
Fit time         0.13    0.15    0.15    0.16    0.16    0.15    0.01
Test time        1.19    1.19    1.20    1.14    1.22    1.19    0.03
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Evaluating MAE, RMSE of algorithm KNNBasic on 5 split(s).

                 Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
MAE (testset)    0.7216  0.7290  0.7286  0.7256  0.7321  0.7274  0.0035
RMSE (testset)   0.9351  0.9445  0.9454  0.9388  0.9473  0.9422  0.0045
Fit time         2.63    2.72    2.69    2.71    2.70    2.69    0.03
Test time        5.54    5.78    5.68    5.74    5.81    5.71    0.10
Best number of neighbors for User-based Collaborative Filtering: 15 ⟸
Best number of neighbors for Item-based Collaborative Filtering: 25 ⟸
The best number of neighbors for User-based and Item-based Collaborative Filtering differs.
```

User-Based CF: 15 , Item-Based CF: 25

Links:

task1:https://drive.google.com/drive/folders/1zrFBTAu49bNPn3nsj9yciCCkAtuoMK08?usp=sharing

Kaggle link for the task2: https://www.kaggle.com/code/asishaddanki/dm-hw3-task-2