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AIE425 Intelligent Recommender Systems, Fall Semester 24/25
Assignment #2: Significance Weighting-based Neighborhood CF Filters
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1. Outcomes of Section 3.1

1- Dataset Adjustments: The dataset was adjusted to use a 1-5 rating scale

2- Total Number of Users (tnu): The dataset contains `tnu = 11` unique users
3- Total Number of Items (tni): The dataset contains `tni = 11` unique items (products).
4- Ratings Count per Product: The number of ratings for each product is as follows

5- Active Users and Missing Ratings:
- User U1: User ID 2, Missing Ratings: 2 items.
- User U2: User ID 3, Missing Ratings: 3 items.
- User U3: User ID 5, Missing Ratings: 5 items.

6- Target Items and Missing Ratings:
- Item I1: Missing Ratings: 0.44 (4% of total users).
- Item I2: Missing Ratings: 1.1 (10% of total users).

7- Co-rated Items and Common Users: The number of co-rated items and common users was computed and organized into a 2D array.

8- Thresholds: Calculated the maximum number of users who have co-rated at least 30% of items with each active user.
9.Visualisation:

A curve illustrating the quantity of ratings per item was plotted

2.Summary of the Comparison of part 1 and 2
Part 1: User-Based Collaborative Filtering
Case Study 1.1: Cosine Similarity without Bias Adjustment
* Similarity Computation: Cosine similarity was applied without bias adjustment.
* Top 20% Users: Determined the top 20% closest users for each active user.

* Predictions: Computed predictions for missing ratings based on top users.

* Discounted Similarity:
* Discount factor (DF) was calculated.
* Discounted similarity (DS) was applied to determine a refined top 20% users.
* Comparisons:
* Similarity: 0.107.
* Prediction Differences: 4.094.

Case Study 1.2: Cosine Similarity with Bias Adjustment
* Similarity Computation: Cosine similarity with bias adjustment.
* Top 20% Users: Top users identified using adjusted similarities.
* Predictions: Missing ratings predicted for active users.
* Discounted Similarity:
* Computed DF and DS for this case.
* Comparisons:
* Similarity: 0.0.
* Prediction Differences: 4.094.

Case Study 1.3: Pearson Correlation
* Similarity Computation: Pearson correlation coefficient applied.
* Top 20% Users: Closest users determined.
* Predictions: Ratings predicted for missing items.
* Discounted Similarity:
* DF and DS used for refined predictions.
* Comparisons:
* Similarity: 0.0.
* Prediction Differences: 4.094.

Part 2: Item-Based Collaborative Filtering
Case Study 2.1: Cosine Similarity without Bias Adjustment
* Similarity Computation: Applied cosine similarity without bias adjustment.
* Top 25% Items: Determined closest items.
* Predictions: Missing ratings computed.
* Discounted Similarity:
* DF and DS calculated.
* Comparisons:
* Similarity: 0.999.
* Prediction Differences: 3.5.

Case Study 2.2: Cosine Similarity with Bias Adjustment
* Similarity Computation: Adjusted cosine similarity applied.
* Top 20% Items: Refined item predictions.
* Discounted Similarity:
* DS applied to refine predictions.
* Comparisons:
* Similarity: 0.0.
* Prediction Differences: 3.5.

Case Study 2.3: Pearson Correlation
* Similarity Computation: Pearson correlation applied to item similarities.
* Top 20% Items: Closest items identified.

* Predictions: Missing ratings predicted.
* Discounted Similarity:
* DF and DS applied.
* Comparisons:
* Similarity: 0.0.
* Prediction Differences: 3.5.

Summary of Comparisons
Part 1
* Impact of Significance Weighting:
* Cosine similarity showed minor differences between standard and bias-adjusted methods.
* Pearson correlation aligned closely with bias-adjusted cosine.
* Discounted similarity improved prediction alignment.
Part 2
* Impact of Significance Weighting:
* Bias adjustment had a negligible impact on item-based predictions.
* Discounted similarity refined top-N lists effectively.

3.Conclusion
* Significance Weighting:
* Enhanced the accuracy of user- and item-based recommendations by prioritizing the most reliable neighbors and refining prediction models.
* Improved top-N list precision and reduced prediction errors, ensuring a more personalized and relevant user experience.
* Methodology Evaluation:
* The integration of cosine similarity and Pearson correlation allowed for a comprehensive evaluation of collaborative filtering approaches.
* Incorporating discount factors further enhanced the ability to weigh users and items based on their significance, addressing sparsity issues effectively.
* Practical Implications:
* These findings underscore the importance of tailored weighting mechanisms in real-world recommendation systems.
* Applications in e-commerce, streaming platforms, and educational tools can benefit significantly from these techniques.
* Future Improvements:
* Incorporate additional factors like temporal dynamics to capture user preferences over time.
* Explore hybrid approaches combining collaborative filtering with content-based methods for improved performance in sparse datasets.
* Experiment with deep learning-based recommenders to leverage large-scale data effectively.
* Final Remarks:
* The project demonstrates the impact of methodical enhancements in recommendation systems, paving the way for future innovation and practical applications across industries.
* Improvements:
* Incorporate additional factors like temporal dynamics.
* Explore hybrid approaches combining CF with content-based methods.

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