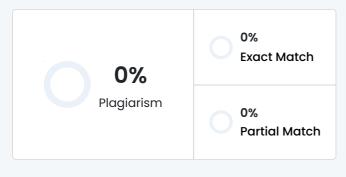


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AIE425 Intelligent Recommender Systems, Fall Semester 24/25 Assignment #2: Significance Weighting-based Neighborhood CF Filters Student ID: A20000021, Full Name: Ahmed Ashraf Mohamed Ali

- 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 II: 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.

Page 2 of 2

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