End Term (Fall 2024)
DA 626: Recommendation System Design

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Total Marks: 80 marks

Instructions:

- The Answers must be brief and to the point. Bullets or tables or charts are highly encouraged as representations for answers.
- There should be a clear indication of the sub-parts of the answers. Like 2a) instead of just a). If you answer a question with just a), you will be awarded 0 credits.
- In case of any ambiguity, please mention (any) assumption explicitly and then answer the questions.
- **Answer 1 question from Section 1 (Question 1-1), Answer 8 questions from Section 2 (Question 2-19) and Answer 2 questions from Section 3 (Question 20-25).**

Section 1 : This is compulsory. [10 marks]

1. Suppose we have a user-item interaction matrix R with the following ratings (where rows represent users and columns represent items):

$$R = \begin{bmatrix} 5 & 3 & 0 & 1 \\ 4 & 0 & 0 & 1 \\ 1 & 1 & 0 & 5 \\ 0 & 0 & 4 & 4 \\ 0 & 1 & 5 & 4 \end{bmatrix} \quad (1)$$

Decompose R into two matrices, P (user-feature matrix) and Q (item-feature matrix), with rank $k = 2$. Use the initial values,

$$P = \begin{bmatrix} 0.5 & 0.8 \\ 0.6 & 0.7 \\ 0.4 & 0.9 \\ 0.7 & 0.6 \\ 0.5 & 0.5 \end{bmatrix}_{5\times 2} \quad \begin{bmatrix} 0.6 & 0.8 & 0.5 & 0.6 \\ 0.4 & 0.3 & 0.7 & 0.5 \end{bmatrix}_{2\times 4} \quad (2)$$

$$Q = \begin{bmatrix} 0.6 & 0.4 \\ 0.8 & 0.3 \\ 0.5 & 0.7 \\ 0.6 & 0.5 \end{bmatrix} \quad (3)$$

$\begin{bmatrix} 0.62 \end{bmatrix}$ PQ^T $5\times 2 \;\; 2\times 4$ 4×1

(a) Perform one iteration of gradient descent with a learning rate of 0.01 and regularization term 0.1.

(b) Based on your decomposed matrices, calculate the predicted rating for User 1 on Item 3.

Section 2 : Answer 8 questions out of the following. [5 × 8 = 40 marks]

2. Suppose you have sparse interaction data for a new e-commerce platform. Describe a method to generate synthetic user-item interactions to address sparsity. What factors would you consider when generating synthetic data to ensure it reflects realistic user behavior?

3. Outline one approach to evaluate whether the synthetic data improves the model's recommendation accuracy or relevance.

4. Explain how graph-based data augmentation techniques (such as graph sampling, graph clustering, or random walks) can be applied to a recommendation system with a user-item graph.

5. What are potential limitations of using graph-based augmentation techniques in recommendation systems? Discuss at least two limitations.

6. Define cross-domain data augmentation in recommendation systems. How can cross-domain information (e.g., interactions from a music streaming service and a video streaming service) be leveraged to enhance recommendations?

7. Imagine you're building a recommendation system for an online bookstore, but you have access to user interaction data from a movie streaming platform. Describe a strategy for using cross-domain data augmentation to improve book recommendations.

8. What challenges might you face when implementing cross-domain data augmentation in this scenario? Suggest at least two potential solutions to these challenges.

9. Explain how data augmentation can help address the cold-start problem in recommendation systems, particularly for new users and items.

10. Suppose you have a new user who has no interaction history. Describe two data augmentation strategies that could be used to generate recommendations for this user.

11. Consider a new item that has just been added to the catalog and has no user interactions yet. Describe how you could use content-based or feature-based data augmentation to enhance initial recommendations for this item.

12. Evaluate the potential risks of using data augmentation to handle cold-start problems. What are the main considerations to keep in mind to ensure recommendations remain relevant and accurate?

13. Outline a process for evaluating the effectiveness of data augmentation in a recommendation system. What metrics would you use, and why?

14. Consider the scenario where data augmentation improves one metric (e.g., recall) but decreases another (e.g., precision). How would you decide whether to keep the augmentation strategy? Discuss how balancing these metrics impacts user experience.

15. Define temporal data augmentation and discuss its relevance to recommendation systems that handle dynamic user preferences (e.g., news, fashion).

16. Describe a method to use temporal patterns (such as day of the week, time of day, or season) to augment the user-item interaction data in a recommendation system.

17. Assume you are building a recommendation system for a social media platform where user preferences change over time. Explain how temporal data augmentation could improve the accuracy of recommendations in this setting. What challenges might arise, and how could they be addressed?

18. Discuss potential biases that could be introduced by data augmentation in recommendation systems. Provide an example of a data augmentation technique that could lead to biased recommendations if not carefully implemented.

19. Suggest two strategies to mitigate bias when using data augmentation techniques in recommendation systems. Explain how each strategy can help ensure fair and unbiased recommendations.

Section 3: Answer 2 questions out of the following. **[15 × 2 = 30 marks]**

20. **Situation:** You are building a recommendation system for an online retail platform. The platform collects implicit feedback such as clicks, time spent on pages, and purchases. However, your team wants to translate this into explicit ratings (e.g., 1 to 5 stars) for better model performance.

    (a) Propose a strategy to convert the implicit feedback into explicit ratings. Include the metrics you would use (e.g., time spent, number of clicks, etc.).

    (b) Explain how you would validate the reliability of the converted explicit ratings.

    (c) What assumptions would you need to make about user behavior for this conversion? Discuss the potential risks of these assumptions.

21. **Situation:** A music streaming platform tracks implicit feedback, including the number of times a song is played, skipped, or added to a playlist. Your goal is to generate explicit feedback scores (e.g., ratings out of 10) based on these interactions.

    (a) Develop a weighted scoring formula that combines the following implicit actions:
    - Play count ($W_{play} = 0.6$)
    - Skip count ($W_{skip} = -0.4$)
    - Add-to-playlist count ($W_{add} = 1.0$)

    (b) Calculate the explicit score for a song with the following interactions:
    - Played 10 times
    - Skipped 3 times
    - Added to playlists 2 times.

    (c) Discuss how the weights assigned to each action could influence the recommendations. How would you determine the optimal weights?

22. **Situation:** To improve the accuracy of your implicit-to-explicit conversion model, you decide to conduct a user survey to collect explicit ratings for a sample of items.

    (a) Design a process for comparing the explicit ratings collected from the survey to the scores generated from implicit feedback. How would you measure the accuracy of your conversion model?

    (b) Explain how the survey results could help you refine your conversion model.

    (c) Discuss potential biases in using survey data for this purpose. How would you address these biases?

23. **Situation:** In a news recommendation system, user preferences change over time. The system collects implicit feedback such as reading time and the number of article shares.

    (a) Describe how you would incorporate temporal information (e.g., recency) into the process of converting implicit feedback into explicit ratings.

    (b) Suggest a formula for adjusting the weight of older interactions when generating explicit scores.

    (c) Discuss the trade-offs between prioritizing recent feedback versus historical feedback in this conversion process.

24. (a) Identify two types of bias that could be introduced when converting implicit feedback to explicit feedback. Provide examples of how these biases might manifest in a recommendation system.

    (b) Discuss how you would detect and mitigate noise in the implicit feedback signals to ensure accurate explicit ratings.

    (c) If implicit feedback data are sparse for certain users, how would you handle this sparsity when performing the conversion?

25. Open-Ended Questions

    (a) What role do machine learning models (e.g., regression or classification) play in converting implicit feedback into explicit feedback? Design a simple machine learning workflow for this conversion.

    (b) Explore how contextual factors (e.g., time of day, device type) could improve the accuracy of converting implicit feedback into explicit ratings. Provide an example of how these factors could be used.

    (c) Discuss ethical considerations in converting implicit feedback to explicit feedback. How would you ensure user privacy and avoid misinterpreting user intent?