

SNS COLLEGE OF ENGINEERING

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

Recommender System

8/17/2023

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RECOMMENDER SYS TEM



•Recommender systems are algorithms that make recommendations to users about the best option to choose from a set of options.

• Of course, the "best" option is going to vary from person to person, which is why recommender systems turn to data about products and users' preferences to generate individualized suggestions.

•Unlike supervised machine learning models, which will predict an exact answer to a question or problem, recommender systems are preference-based, Nitya says.

•"A recommender system is a combination of human and machine interaction that decides whether something is good or abad outcome," she adds.





- Matrix operations play a crucial role in building and understanding recommender systems, which are used to predict and suggest items that users might be interested in.
- Recommender systems rely on user- item interaction data, often represented in a user-item matrix, where rows correspond to users and columns correspond to items.
- Matrix operations help uncover patterns in this data to make accurate recommendations.





1. Matrix Factorization:

•One common approach involves decomposing the user-item matrix into two lower-dimensional matrices: a user matrix and an item matrix.

- By multiplying these matrices together, you reconstruct the original matrix and predict missing entries.
- •This technique helps in reducing noise and capturing latent features.





Example:

- Imagine a user-item matrix for a movie recommendation system.
- Each cell represents a user's rating for a movie.
- Matrix factorization aims to decompose this matrix into two lower- dimensional matrices a user matrix and an item matrix.
- The resulting matrices capture latent features, such as genres or themes.
- For instance, if User A and User B both liked action movies and comedies, the user matrix might have similar feature vectors for these users.





2.Gradient Descent:

•When optimizing matrix factorization, gradient descent is often employed to iteratively adjust the matrices to minimize the prediction error.
•It's a fundamental optimization technique used in training recommender

system s.





Example:

- Continuing with the movie recommendation system, after applying matrix factorization, you use gradient descent to adjust the user and item matrices iteratively.
- By minimizing the difference between predicted and actual ratings, the matrices become more accurate, leading to improved recommendations.





3.Collaborative Filtering

•This technique leverages matrix operations to identify users with similar preferences and items with similar attributes.

•By calculating similarity measures between user vectors or item vectors, collaborative filtering can suggest item sbased on the preferences of similarusers.





Example

•Consider a user-item matrix where users rate movies. Collaborative filtering calculates user similarities based on their ratings.

- If User A and User B have similar movie preferences, their vectors in the user matrix will be close.
- •The system then recommends movies liked by similar users to UserA.





4.Regularization:

- •Matrixoperations in recommender system sare proneto overfitting.
- •Regularization techniques like L2 regularization are used to prevent excessive emphasis on specific features or users/items, improving the generalization of recommendations.





Example

- In matrix factorization, regularization prevents overfitting. It adds a penalty term to the optimization process.
- For instance, using L2 regularization, you'd minimize the sum of squared values in the user and item matrices, discouraging extreme values and promoting a balanced representation.





5.Content Based Filtering:

•Matrix operations can also be used to combine user-item interaction data with item content information.

•By representing item features as vectors, you can calculate similarities between userpreferences and item features, enhancing the recommendation process





Example

- Now, let's include movie features like genre, director, and cast. Represent these features as vectors.
- Calculate cosine similarity between User A's preferences vector and movie vectors.
- Movies with higher cosine similarity are recommended since they align with User A's interests.



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