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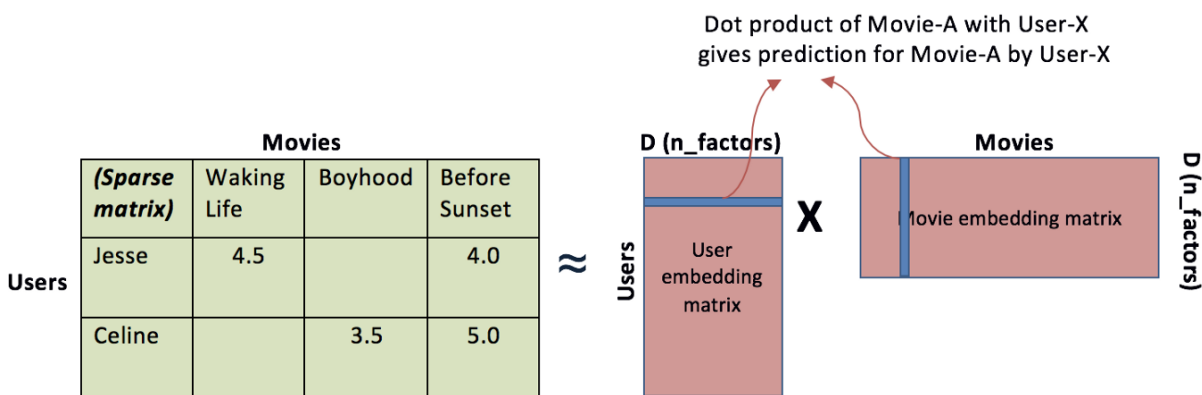
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Collaborative Filtering Algorithms

Recommendation systems are essential to many of the popular services used on a daily basis. From a user's perspective, this includes recommended styles of clothing while browsing through the website of an online retailer, a potential list of movies to watch from a streaming service, or curated playlists composed of artists similar to those a user has already listened to created by a music streaming application. These systems are most effective when maximizing the ability to predict what a new user would enjoy through calculated comparison to the current user base. This technique, known as collaborative filtering, works under the assumption that users with similar profiles and interests will have interest in and can be recommended similar items. Modern applications have implemented collaborative filtering using various algorithms.

One approach of collaborative filtering is memory-based, meaning that recommendations are calculated based on previous activity, such as user's purchases or likes. There are two types of filtering within the memory-based approach: user-item filtering and item-item filtering. User-item filtering identifies users with similar activity to a particular user and recommends items liked by that group of users, whereas item-item filtering finds users that liked a particular item and recommends other items liked by those users. In addition to different filtering types, there are multiple ways to measure the similarity between users and items. Both cosine similarity and the Pearson correlation coefficient are commonly used to quantify the distance between users based on their likes and item history. Since memory-based filtering does not require many optimizations, the approach is easy to use; however, it is not realistic to use when there is not enough data on certain users or items.

The model-based approach is a popular and more effective approach to collaborative filtering. By applying machine learning techniques to evaluate whether an item should be recommended to a particular user, model-based filtering can predict user interest more accurately than memory-based filtering when there is not enough information between a user's liked items. A prominent model-based approach is matrix factorization. The idea behind matrix factorization is that the recommendations for a particular user can be determined based on a smaller number of features. These features, known as embeddings, are determined mathematically and can be calculated by combining, deleting, or modifying existing characteristics into valuable factors that can show hidden patterns in the existing data. Here is an example of how the factorized matrices are formed:



Opting to use embedding instead of the original set of features reduces a large user-item correlation matrix into two smaller matrices for users and items that can be used to compute the corresponding correlations quickly. Model-based filtering like matrix factorization may require more fine-tuning and training than the memory-based approach but can be rewarding by providing an efficient way to calculate user similarities.

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There are various methods in which collaborative filtering can be implemented into a system to recommend the right items to certain users. Not only is there a memory-based approach that focuses on user ratings and likes to form recommendations, but there is a model-based approach that can be optimized and tuned such that sparse matrices are no longer a problem and computation time can be decreased monumentally. It is easy to see why new approaches and algorithms are constantly explored in relation to collaborative filtering since these techniques are so important to execute recommendation systems within services that are central to day-to-day living.

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References

Chen, Denise. “Recommender System — Matrix Factorization.” *Towards Data Science*, 8 Jul.

2020,

[https://towardsdatascience.com/recommendation-system-matrix-factorization-d61978660b](https://towardsdatascience.com/recommendation-system-matrix-factorization-d61978660b4b)

4b.

Grover, Prince. “Various Implementations of Collaborative Filtering.” *Towards Data Science*, 28

Dec. 2017,

[https://towardsdatascience.com/various-implementations-of-collaborative-filtering-100385](https://towardsdatascience.com/various-implementations-of-collaborative-filtering-100385c6dfe0)

c6dfe0.