

Collaborative Filtering: Applications and Main Challenges

Collaborative Filtering is mainly used by recommendation systems. Aside from collaborative filtering, there is also content-based filtering used by recommendation systems. In this technical review, we will dive into the applications and challenges of collaborative filtering. Compared to content-based filtering, collaborative filtering can predict what a user will be interested in by finding users with similar interest and recommending them a product that has been liked by those users. Content-based filtering on the other hand only recommends based on what can be retrieved from product and finding similar products. In content-based filtering, the assumption is if a user likes 'comedy' genre, the user will like movies with the same genre. But that is not always accurate, so for movie recommendation, which is very subjective, a collaborative filtering will provide a more relevant movie recommendation.

There are multitude of applications that uses collaborative filtering today. From Netflix to TikTok, Facebook, and Spotify. The biggest tech companies use collaborative filtering to recommend products to its users based on what other similar users' preference. A successful recommendation system will keep its users engaged in the application thus increasing their time spent on the application. One example of a successful use of collaborative filtering is TikTok's "FYR" or For You Page. A large amount of their users spends their time watching videos after videos due to the success of their recommendation system. Other applications that use collaborative filtering are Spotify and Last.fm, which uses collaborative filtering to recommend music. Also, Netflix uses collaborative filtering to recommend movies. Lastly, TikTok and Youtube uses collaborative filtering to recommend videos, which increases user engagement.

Although collaborative filtering is being used by the top tech companies, there are still challenges that requires more research to find a more sophisticated solution. One of the challenges of collaborative filtering is data sparsity. It could stem from what is called a "cold start" where a user has no data available, thus no matching similar users to predict possible products that they may be interested in. This can also happen when a new product is added to the application and lacks rating from other users. The product will not be recommended to any user. In turn, only more established products will get recommended and the new product can fade into obscurity.

Another challenge to collaborative filtering is scalability. As the number of users and products to recommend grow, the dataset can get significantly bigger and processing the recommendation can take longer. A true and precise recommendation should use all possible data to recommend relevant products to the user, but as the dataset grows, too much resource must be used to precisely give a relevant recommendation. This can be countered by limiting the dataset or using clustering methods.

Another challenge that has been identified is synonymy. It happens when words that are similar in context are treated by the algorithm as completely different. This can occur because collaborative filtering does not put the content of the product in consideration. To combat this disadvantage, a topic model can be applied to collaborative filtering.

Another challenge to collaborative is gray sheep. It happens when a user's interest does not match with other users. Thus, any recommendation can be irrelevant for the user. Similarly, not having enough diversity of users in the application can also be a challenge. There have been complaints that such algorithms of Facebook were politically leaning, thus shaping the user's political views.

In collaborative filtering there can also be shilling attacks. It occurs when users manipulate and game the system in their favor. This can be done by users lowly rating their competitor's products and highly rating their product, as a result their product will be recommended more to other users. It can be difficult to remediate the issue, but it is possible.

Lastly a challenge for collaborative filtering is evaluation. Evaluating collaborative filtering can be subjective and thus require manual user evaluation to whether an algorithm is performing precisely. Such evaluation can be costly.

Although there are challenges to collaborative filtering, it has become popular in recommendation system as it provides adequately positive user experience for its users. The challenges can be combatted by tweaking the models and/or using a hybrid system of content-based and collaborative filtering. Overall, collaborative filtering is powerful and has become an integral part today. Whether it's recommending news, music, movies, or videos, collaborative filtering will be likely to recommend relevant content to the users.

Reference:

https://en.wikipedia.org/wiki/Collaborative_filtering

<http://datasadak.com/what-makes-tiktok-recommendation-system-so-powerful/>

<https://analyticsindiamag.com/collaborative-filtering-vs-content-based-filtering-for-recommender-systems/>

<https://grouplens.org/site-content/uploads/evaluating-TOIS-20041.pdf>

<https://fardapaper.ir/mohavaha/uploads/2019/03/Fardapaper-Recommender-Systems-Issues-Challenges-and-Research-Opportunities.pdf>