Mitigate Echo Chamber Problem by Adding User-Centric Features to Collaborative Filtering Based Recommender System

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Abstract

An increasing number of products and information offerings are tailored for users via recommender systems (RS). However, growing concerns have risen towards these systems, especially since that RS might result in narrower exposure of user interest, issues known as "echo chambers."In this paper, we build two recommender systems with user historical behavior data and user-centric feature data. We simulate the recommendations given by negative matrix factorization (NMF) and collective matrix factorization (CMF) with the MovieLens data set and compare the content diversity. We find that based solely on users' historical behavior data, prolonged exposure to system-generated recommendations decreases content diversity. However, adding user-centric features data mitigated the echo chamber problem to some extent.

1 Introduction

An increasing number of products and information offerings are tailored for users via recommender systems (RS). However, growing concerns have risen towards these systems despite theăenormous financial success, especially since that RS might result in narrower exposure of user interest, issues known as "echo chambers." [7, 13, 10]

Most recommender systems are data-driven and based on consumer behavior, such as ratings andăpurchases [5]. Using user-generated behavioral data has naturally intrinsic drawbacks the RS would be penalized for generating new preferences which are not in the user's historical data. McNee et al. [15] highlight the importance of user-centric features and metrics that emphasize recommendation quality, such as content diversity.

In this paper, we meet these challenges by comparing two kinds of RS: behavior-oriented RS, which is the RS based on the user's historical behavior, and user feature-centric RS, which values user-centric characteristics, such as gender, age, and occupation. We frame two specific research questions:

- $RQ1$: Do behavior-oriented recommender systems reduce content diversity and contribute to echo chamber formation over time?
- $RQ2$: Is the echo chamber problem mitigated by adding user-centric characteristics?

2 Related work

A significant amount of research has been done to determine whether echo chambers and filter bubbles exist by detecting or quantifying them.[3, 4, 17] Regarding the dataset, we utilized in this

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study, MoviLens, Nguyen et al.[16] discovered that the variety of recommended items and those users engage with narrows with time. Other studies that looked at other platforms also came to varied conclusions[20, 2]. For instance, to determine if personalization fragments the population, Hosanagar et al. [12] examined data from an online music service and concluded that it did not.

Another thread of research aims to clear up factors contributing to the formation of echo chambers[1, 6, 8], as well as strategies to mitigate the problem.[14, 11, 9] Badami et al. found that matrix factorization models are easier to lead to echo chambers and proposed a new recommendation model. Others tried to mitigate echo chambers with specific factors, such as source position indicators, user-specific metrics, etc.

3 Data and Methods

3.1 Data

We use a subset of the MovieLens dataset, which contains 100,000 ratings from 943 users on 1,682 movies. In addition to user ratings, this dataset also provides user demographic features, including gender, age, and occupation. We only keep users with complete information on gender, age, and occupation. Based on the user and item's id, we constructed a user-item matrix where rows represent users, columns represent movies, and entries represent user ratings.

3.2 Methods

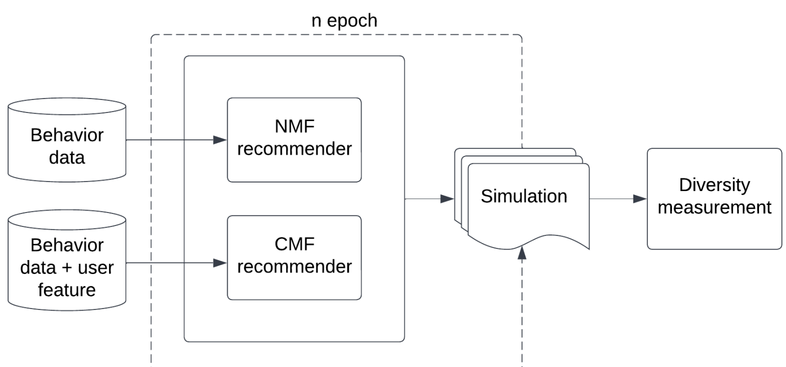

Figure 1: Working flow. We build two RSs based on non-negative matrix factorization(NMF) with historical behavior data and collective matrix factorization (CMF) with historical behavior plus users' features data. By simulating users' prolonged exposures to each of the RS, we compare the content diversity of output recommended movies tags

3.2.1 Building recommender systems

We use matrix factorization to build collaborative filtering RS. In its basic form, matrix factorization represents users and items by vectors of latent factors inferred from the user-item rating matrix. Since we are interested in which components contribute to the formation of an echo chamber, we constructed two RSs using two different matrix factorization techniques.

Behavior-oriented recommender system We first consider building an RS completely relying on movie ratings. The algorithm we use is non-negative matrix factorization (NMF).

Given matrix V with n observations denoted as $x_{i,i=1,2,...n}$, each vector x has m dimensions. NMF decomposes matrix V into two non-negative matrices W and H, such that W is a $n \times k$ matrix and H is a $k \times m$ matrix. In this way, $V \approx WH$. [19]

We treat the previous user-item movie rating matrix as V, and applied the NMF model in the scikit-learn package to build our RS based on movie ratings.

Adding user-centric features In addition to users' taste in movies, users' demographic features may also play roles in designing RSs. Therefore, we constructed our second RS, which incorporates user attributes in age, gender, and occupation as side features to previous user-item movie rating matrix. Since NMF is unsuitable for multiple relationships, we applied collective matrix factorization (CMF).

Given two relational matrix X and Y, we could decompose these two matrices into three matrices U, V, and Z such that $X \approx f_1(UV^T)$ and $Y \approx f_2(VZ^T)$. [18]

In this paper, we see X as user-item movie rating matrix, Y as user attribute matrix that represents users with user features. We then applied the CMF model in cmfrec package to build our RS based on movie ratings with user features.

3.2.2 Simulation of prolonged exposure

To study and compare the echo chamber effect of the two RSs we build above, we set up an experimental approach by simulating the recommendation engine's working process over time.

First, we fit all historical data from the MovieLens dataset into our recommender models above as the initial state. Second, we randomly sample 10 percent of the users and append the corresponding predicted movie rates to the original dataset. Then, we model the interaction between users and the RS by iteratively appending new recommendations and refitting the new appended dataset to the engines, assuming that users take the recommendations and give the exact ratings that the engine predicts. We ran 30 epochs in the experiment to see how prolonged RS exposure affects the recommended content's diversity.

3.2.3 Content diversity measurement

We compute the Jaccard similarity d between users' historical top 10 rating movie genres $h_{i,i=1,2,..10}$, and recommended top 10 rating movie genres $p_{i,i=1,2,..10}$. Each movie genre is represented by a vector space of length N consisting of binary values. We calculate each user's content diversity score u_i by averaging the Jaccard similarity between each unique movie genres pairs:

$$u_j(h_i, p_i) = \frac{\sum_{i=1}^{100} \frac{|h_i \cap p_i|}{|h_i| + |p_i| - |h_i \cap p_i|}}{100}.$$

Smaller similarities represent less similar movies and are more diversified to one another based on their movie type. For recommended results per epoch, we calculate diversity $D(j)$, where j denotes the number of users per epoch, by averaging the average Jaccard similarity of each user's recommended content:

$$D(j) = \frac{\sum_{i=1}^{j} u_j(h_i, p_i)}{j}.$$

4 Results and discussion

After running simulations of the two RSs and measuring the diversity of recommended contents correspondingly, we can compare the performance of the two RSs in terms of the echo chamber effect.

In figure A, the users' exposure to the systems enlarges as we increase the epoch from 1 to 30. The average diversity for each epoch in the NMF model gradually decreases, while the average diversity in the CMF model is improved as the iteration continues.

Figures B and C explicitly add the user's average density for both RSs. For CMF-based RS shown in B, the user's average diversity is lower and clustered under the epoch of 15, indicated by the density plot; With prolonged exposure, the user's average diversity gets larger with more variance. Comparatively, for NMF-based RS, the user's average diversity declines along with the prolonged exposure and clustered in a lower range of diversity of 0.15-0.18.

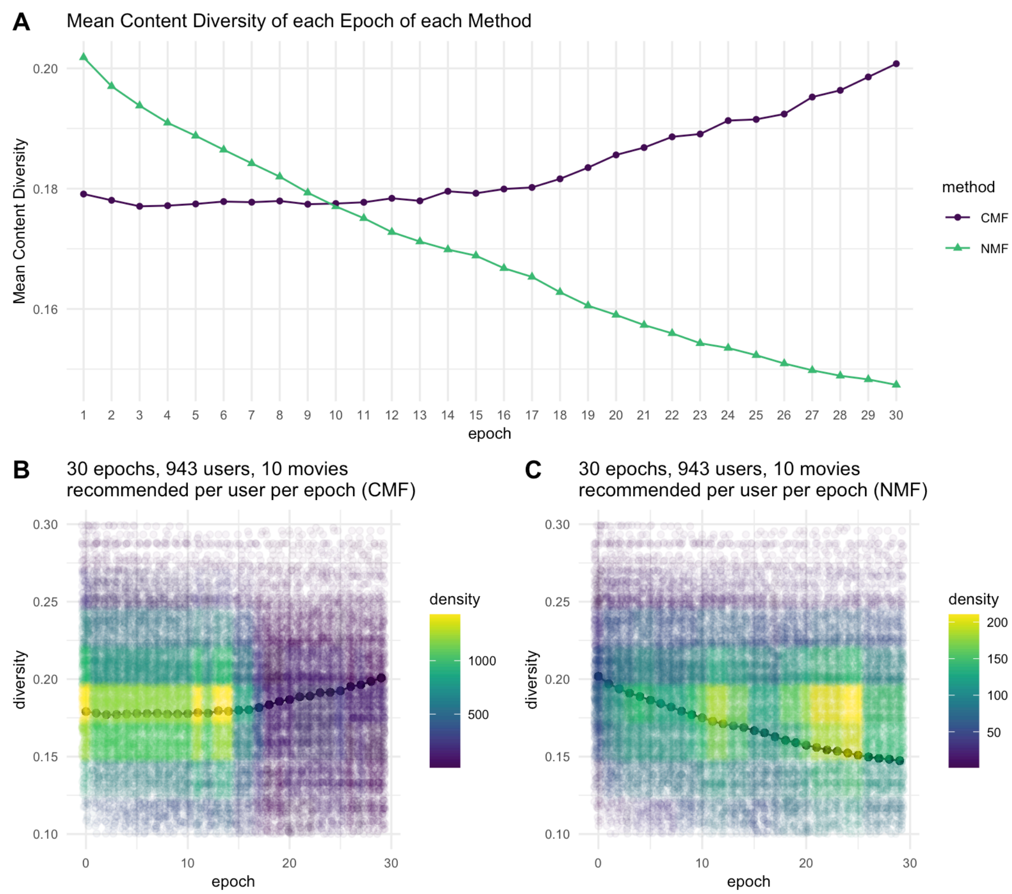

Figure 2: Simulation results

From the above results, we can conclude that the traditional RS using movie ratings based on Non-negative Matrix Factorization and historical behavior data would lead to the echo chamber effect, which shrinks the diversity of movies recommended to users. After adding the user features to build a CMF model, the problem of echo chamber is mitigated to some extend, illustrated by a higher average content diversity score and a sparser distribution of the user's average content diversity.

5 Conclusion

We analyzed the echo chamber problem of collaborative filtering RSs. Traditional collaborative filtering algorithms such as NMF mainly rely on user-item interactions to make recommendations. We find that such collaborative filtering algorithms will gradually reduce the content diversity as the exposure to recommenders prolongs, which results in echo chamber. We then applied a more creative collaborative filtering algorithm CMF. CMF considers both user-item interactions and user-user interactions. Adding user features could increase content diversity as the exposure to recommenders prolongs. Our findings provide empirical results to the formation of echo chamber in RSs, also some insights for solving echo chamber problems.

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