Personalized Recommendation via Suppressing by Users and Items

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Abstract. An efficient recommendation system is fundamental to solve the problem of information overload in modern society. In physical dynamics, material diffusion based on binary networks has a wide range of applications in recommendation systems. However, material diffusion has the disadvantage of excessive diffusion and excessive attention to high-prevalence items. Most of the previous studies focused on reducing the popularity of the item. This paper suppresses the excessive diffusion between people and objects by simultaneously adjusting popular users and items. It evaluates the algorithm through two real datasets (Movielens and Netflix), which proves the method is superior to other algorithms in accuracy, diversity and novelty.

1. Introduction  
The Internet and smart mobile devices have been making our lives more convenient. People are getting used to reading news, watching movies, shopping, making friends and so on through various network systems. At the same time, they are also exposed to various information provided by these websites. The explosive information makes it difficult to retrieve quickly the objects of interest on the Internet. Therefore, people launched an information recommendation system to recommend the things they are interested in based on their behaviours on the network, such as Amazon \cite{1}, Twitter \cite{2}, Taobao.

There are many models in kinds of literature, including dimensionality reduction techniques, social matrix filtering, diffusion-based methods, and hybrid recommendation models. However, people find accuracy and diversity seem to be a seesaw. Whenever the side rises, the other side will fall, such as the model of heat conduction and mass diffusion. They are based on the physics of the binary network \cite{3-5}, using diffusion to transmit information. Now the heat conduction model \cite{6} can provide diversified recommendations, but less precision. The mass diffusion model \cite{7} provides more accuracy, but less diversity.

2. Related Work  
This diversity-accuracy dilemma has attracted wide attention in recommendation systems. Researchers improved the accuracy of the heat conduction model by considering bias heat conduction, weighted heat conduction \cite{8}. On the other hand, mass diffusion-based models \cite{9-12} also improve the diversity of the model with multichannel diffusion, removing redundant correlation, using clustering and other ways. Besides, to simultaneously combine the advantages of the two models, a hybrid model based on mass diffusion and heat conduction is proposed \cite{12,13}. A balanced diffusion algorithm is presented according to the mixed idea.
3. Method

In the e-commerce system, each user collects some objects according to actual needs. In the recommendation system, a binary network is used for $G(U, O, E)$. $U = \{u_1, u_2, u_3, \ldots, u_m\}$, $O = \{o_1, o_2, o_3, \ldots, o_n\}$ and $E = \{e_1, e_2, e_3, \ldots, e_m\}$ are users, items, and relationship sets, respectively. $A_{n \times n}$ represents the adjacency matrix. If the user $U_i$ purchases the item $O_j$, the $a_{ij}$ value is 1, otherwise it is 0.

The original diffusion-based recommendation algorithm become Network-Based Inference (NBI) [7], which is the Probs algorithm in the reference. The NBI passes the initial resource $f$ owned by the object (where $f_{\alpha}$ represents the initial resource owned by User $\alpha$), and then redistribute resources through diffusion $f' = Wf$, where:

$$w_{ij} = \frac{1}{k_{ij}} \sum_{l=1}^{m} \frac{a_{il}a_{lj}}{k_{ul}}$$  \hspace{1cm} (1)

is the resource transfer matrix. $k_{oj} = \sum_{i=1}^{m} a_{ij}$ and $k_{ul} = \sum_{j=1}^{m} a_{lj}$ represent the degree of the item $o_j$ and the user $u_l$ respectively. For the target user $u_t$, for the sake of simplicity, a unit of resources are allocated for the items collected by $u_t$.

The user's recommendation list is sorted and made according to the collected final resources in descending order for all objects the user does not collect.

As mentioned before, the model based on material diffusion [11] has poor diversity and high accuracy. Most other improved algorithms focus on adjusting the degree of items, and suppressing the popularity of overly popular items to achieve suppression. For the purpose of diffusion, to improve this situation, the researchers set two hyperparameters $a$ and $\beta$:

$$w_{ij} = \frac{1}{(k(o_j)k(o_j))^{\beta}} \sum_{l=1}^{m} \frac{a_{il}a_{lj}}{k(u_l)}$$  \hspace{1cm} (2)

Then in the case of $a = b > 0$, the effect is better than HHP [15]. This is the BD algorithm, namely:

$$w_{ij} = \frac{1}{(k(o_j)k(o_j))^{\beta}} \sum_{l=1}^{m} \frac{a_{il}a_{lj}}{k(u_l)}$$  \hspace{1cm} (3)

where $\beta > 0$.

Also, we consider punishing users who are too popular to suppress the spread of substances, and try to increase diversity and novelty as much as possible without compromising accuracy.

Two hyperparameters $\beta$ and $\delta$ are set. The model is optimized by adjusting these two hyperparameters:

$$w_{ij}^{MBD} = \frac{1}{(k(o_j)k(o_j))^{\beta}} \sum_{l=1}^{m} \frac{a_{il}a_{lj}}{(k(u_l))^{\delta}}$$  \hspace{1cm} (4)

It is called a mixed balanced diffusion algorithm (MBD for short). This model becomes the model of the balanced diffusion when $\delta = 1$.

4. Data and Evaluation

4.1. Dataset.

To test the model, two popular datasets are used: Movielens and Netflix. They are publicly available and can be downloaded for free at http://www.netflixprize.com/ and https://grouplens.org. The data set contains all the ratings users have for movies they watched, ranging from 1 to 5 stars. The records with ratings $<3$ will be discarded because only rating $\geq 3$ means users like the items.

| Data    | Users | Objects | Links  | Sparsity |
|---------|-------|---------|--------|----------|
| Movielens | 943   | 1682    | 82520  | $6.3 \times 10^{-1}$ |
| Netflix  | 1000  | 6000    | 701947 | $1.17 \times 10^{-2}$ |

To evaluate the performance of different models, each dataset is randomly divided into two subsets according to a 9:1 ratio. The training set $E^T$ contains 90% of the data. The test set $E^P$ contains 10% of the data. The training set is considered as known information for model recommendation. And the
test set is used to test the model recommendation performance.

4.2. Evaluation indicators.

(1) Improved precision (Precision, denoted as P): The recommended accuracy rate for the user $U_i$ is $T_i(L)/L$. By averaging the accuracy of all users, the accuracy of the entire system can be obtained as:

$$P = \frac{1}{|U|} \sum_{U \in U} \frac{T_i(L)}{L}.$$  

(2) Recall [12]: Recall is the proportion of the number of all hitting links in testing set and the size of testing set, as

$$\text{Recall}(L) = \frac{1}{|E^P|} \sum_{j=1}^{m} T_i(L).$$

(3) Averaged ranking score $\langle r \rangle$ [16]: $\langle r \rangle$ measures the ability of ranking users’ preferable object. The averaged ranking score is denoted as:

$$\langle r \rangle = \frac{1}{|E^P|} \sum_{ij \in E^P} \frac{\text{rank}_{ij}}{N_j}$$

where $|E^P|$ represents the number of elements in testing set.

(4) Hamming distance [13] Suppose $L$ items are recommended to the user, as well as the number of the same items in the recommended list of the user $u_i$ and the user $u_j$ is $Q_{ij}$. Then the Hamming distance between the user $u_i$ and the user $u_j$ is:

$$H_{ij} = 1 - \frac{Q_{ij}}{L}.$$ 

The Hamming distance of the recommendation algorithm as a whole is:

$$H = \frac{1}{|U|(|U| - 1)} \sum_{i \neq j} H_{ij}.$$ 

(5) Average degree $\langle k \rangle$ [13,14]. Suppose the jth recommended item recommended to the user $u_i$ is $o_{ij}$, and the recommendation list has a length of $L$. Then the average popularity of all recommended items is:

$$\langle k \rangle = \frac{1}{mL} \sum_{j=1}^{m} \sum_{t=1}^{L} k(o_{ij})$$

(6) Self-information (U), For item $\alpha$, the probability a randomly selected user selects it is:

$$k_{a} = \frac{k_{a}}{M}$$

So the self-information amount of the commodity can be expressed as:

$$U_{a} = \log_{2} \frac{M}{k_{a}}.$$ 

The system’s self-information quantity $U(L)$ is also the mean value of the self-information quantity of the items in the recommendation list of all users.

4.3. Benchmark methods. For comparison, five recommendation algorithms are briefly introduced,

(1) Network-Based Inference (NBI) [7] has been introduced before.

(2) Balanced diffusion algorithm (BD) [12] has been introduced before.

(3) Heterogenous Network-Based Inference (HNBI) [11]

$$w_{ij}^{HNBI} = \frac{[k(o)]^{\beta}}{k_{ij}} \sum_{l=1}^{m} \frac{a_{il}a_{lj}}{k_{ul}}.$$ 

(4) Hybrid ProbS and HeatS (HHP) [15]

$$w_{ij}^{HHP} = \frac{1}{k(o)\beta(k(o))^{1-\beta}} \sum_{l=1}^{m} \frac{a_{il}a_{lj}}{k(u_l)}.$$ 

(5) Biased Heat Conduction (BHC) [16]

$$w_{ij}^{BHC} = \frac{1}{k(o)\beta} \sum_{l=1}^{m} \frac{a_{il}a_{lj}}{k_{ul}}.$$
Fig. 1 Algorithm performance under different recommendation lengths for different datasets.

Table 2: Algorithm performances on two datasets with $L = 50$. The optimal $\beta$’s of ranking score $\langle r \rangle$ for BD, BHC, HHP, HNBI are $(0.7, 0.5, 0.3, 1)$ in Movielens and Netflix. And the optimal $\beta$ and $\delta$’s of ranking score $\langle r \rangle$ for MBD are $(0.5, 1.4)$.

| Movielens | H   | $<k>$   | P      | R      | U      | $\langle r \rangle$ |
|-----------|-----|---------|--------|--------|--------|-------------------|
| BD        | 0.8117 | 242.5  | 0.1746 | 0.5515 | 2.502  | 0.0913            |
| BHC       | 0.8045 | 196.1  | 0.1698 | 0.5360 | 2.531  | 0.09591           |
| HHP       | 0.7854 | 207.9  | 0.1710 | 0.5395 | 2.385  | 0.09720           |
| HNBI      | 0.7122 | 238.6  | 0.1560 | 0.4922 | 2.138  | 0.1101            |
| NBI       | 0.6437 | 254.9  | 0.1523 | 0.4804 | 1.981  | 0.1170            |
| MBD       | **0.8212** | **197** | **0.1764** | **0.5572** | **2.501** | **0.09182** |

| Netflix    | H   | $<k>$   | P      | R      | U      | $\langle r \rangle$ |
|------------|-----|---------|--------|--------|--------|-------------------|
| BD         | 0.6412 | **1987** | 0.5300 | 0.4794 | **2.943** | 0.04923          |
| BHC        | 0.5972 | 2058   | 0.5136 | 0.4645 | 2.682  | 0.04809           |
| HHP        | 0.8986 | 2177   | 0.5151 | 0.4658 | 2.364  | **0.04608**       |
| HNBI       | 0.8394 | 2058   | 0.4461 | 0.4035 | 2.592  | 0.04890           |
| NBI        | 0.4014 | 2349   | 0.4652 | 0.4207 | 2.141  | 0.05002           |
| MBD        | **0.9326** | 2014   | **0.5440** | **0.4921** | **2.659** | **0.05242** |

5. Results:
To get reliable data, two real datasets are used to verify the algorithm. Besides five indicators are used to compare the six methods of the two datasets. The specific data is in Table 2.

As shown in Table 2, for the two datasets, MBD performs almost best on all six metrics. MBD surpasses the original mass diffusion-based algorithm NBI in almost all aspects. H increased by 27.5%.
\( \langle k \rangle \) decreased by 22.7%. P increased by 15.8%. R increased by 16.0%. U increased by 26.2%. RS decreased by 21.5% in Movielens. H increased by 132%. \( \langle k \rangle \) decreased by 14.3%. P increased by 16.9%. And R increased 17%. U increased by 24.2% in Netflix. MBD is superior to other algorithms in accuracy, novelty and diversity mostly.

At the same time, to display the algorithm performance of the recommended list of different lengths, a line chart of the recommended list is drawn from 5 to 100. As shown in the figure, mostly, the performance of MBD is significantly better than other algorithms. For those indicators that are higher and better, MBD is at the top. And for those indicators that are smaller and better, MBD is at a lower position, which further supports the conclusions in the table. Limiting the popularity between different popular items and users can effectively improve the recommended effect.

6. Conclusion and Discussion
In commercial applications, MBD can more accurately target users and their favorite items match. In this case, the user's loyalty will be further improved. So the merchant can increase the profit and keep the old users. MBD has a wide range of applications, such as recommending users according to the consumption record items, recommendations for news, TV shows, and user ratings based on user browsing news history, and some other improvements. Although MBD has improved the original benchmark algorithm, there are many other ways to discuss. For example, improving the diffusion of the bipartite graph by improving the relationship between material diffusion and heat diffusion. Some other information can also be considered to further improve the dimensions of the recommendation system, such as the user's occupation and birthplace.

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