International Journal of New Developments in Engineering and Society
ISSN 2522-3488 Vol. 4, Issue 1: 61-69, DOI: 10.25236/IJNDES.040109

Dynamic resource allocation recommendation algorithm based on popularity

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ABSTRACT. *Aiming at the unreasonable resource allocation problem of traditional mass diffusion and heat conduction algorithms, this paper proposes a dynamic resource allocation algorithm based on popularity. Taking into account the different degree of influence of the popularity of items in different periods, this paper proposes the concept of item weighting to improve the traditional algorithm, and design the non-equilibrium mass diffusion and heat conduction algorithm. The experimental results prove that compared with the original mass diffusion algorithm and heat conduction algorithm and some improved algorithms based on mass diffusion and heat conduction, the algorithm proposed in this paper can significantly improve the performance of the Recommender system.*

KEYWORDS: *Recommender systems, Heat conduction, popularity, Accuracy*

1. Introduction

The explosive development of information has led to a significant decrease in the utilization rate of information, causing serious information overload problems [1]. In order to solve the impact of information overload on people's access to the required information, researchers have proposed Recommender systems. Compared with search engines, Recommender systems make predictions by analyzing users' interests and preferences. As an active information acquisition tool, it can assist people to filter information without requiring additional operations by users.

With the continuous addition of new items, some obsolete items have less and less influence and will eventually be deleted by the system. Different types of items have different life cycles, and user preferences change dynamically over time. The main purpose of this paper is to analyze the trend of items through time-related data, and to help the Recommender system better understand the purchase behavior of users in different periods.

2. Related work

The Recommender system is dynamic, users' interests will change over time, and the popularity of items will also change over time. The purchase behavior that occurred a long time ago does not truly reflect the current interest of the target user, and the very popular products in the past may be forgotten, so the influence of the time factor on the Recommender system cannot be ignored. In recent years, many scholars have realized that time information should be regarded as one of the most useful contextual dimensions [2]. Adding the time factor can help the Recommender system track changes in users' interests, and help identify user habits and interest periodicity.Ding et al. [3] believe that users' purchases in different periods should be given different weights, and the recent purchase records should be more valuable than the past, and proposed a time-based weighted collaborative filtering algorithm. Zhou et al. [4] adjusted the strength of nodes in the network through the weighted method of time decay function to improve the popularity prediction performance. Li et al. [5] integrated the recent popularity into the recommendation algorithm based on heat conduction, which improved the recommendation performance. Song et al. [6] proved that using some recent information can improve the performance of the HHM algorithm. However, previous studies only considered the impact of recent popularity on the Recommender system, and did not consider the dynamic adjustment of the popularity of different time periods in resource allocation. Reasonable use of commodity popularity trends and time information can help recommender systems better understand user behavior and make more accurate recommendations.

3. Method

In the mass diffusion algorithm, the number of resources conforms to the law of conservation of energy, and the total number of resources obtained by the final item is equal to the number of original resources. However, in the actual system, due to the phenomenon of preference dependence of nodes, users tend to buy items with relatively high popularity. Predicting which items will be popular in the future can help the Recommender system make better decisions. Starting from the trend of item popularity, this paper studies how to use the dynamic characteristics of item popularity to improve the overall performance of the Recommender system.

3.1 Popularity prediction model

3.1.1 Recent popularity of items

Preference dependence is a well-known mechanism in network evolution theory[7]. Nodes have a preference dependency effect, which shows that the overall popularity of items can predict the future popularity trend to a certain extent. Merely considering the overall popularity of items will lead to an increase in the future popularity of some outdated and generous items. However, these items are no longer

ISSN 2522-3488 Vol. 4, Issue 1: 61-69, DOI: 10.25236/IJNDES.040109

popular, and the future popularity should decrease. Relative to the overall popularity of the item, the recent popularity can represent the popularity trend of the next period of time, and the fusion of the recent popularity information of the item can improve the performance of the popularity trend prediction algorithm. The recent popularity of an item is the total number of items in the time period $(t-T_P,t)$, that is, the increment of the item degree of the item from $t-T_P$ to t, which measures the dynamic evolution process of user interest in the item. Define the recent popularity of items as shown in formula 1.

$$k_\alpha^{recent}(t) = k_\alpha(t) - k_\alpha(t-T_P), \quad t > T_P \quad (1)$$

Where $k_a(t)$ represents the degree of item a at time t, and $k_a(t-T_p)$ is the degree of item a at time $t-T_p$.

3.1.2 Popularity calculation method based on time perception

This paper divides the user's purchase records according to the time node T_p, and calculates the past popularity and recent popularity of each item respectively. Existing studies have found that the popularity of a single object will decay exponentially over time [8-9]. In order to make better use of time information to predict the popularity trend, this paper adds an exponential time decay function when counting past popularity, and defines the past popularity of item a as shown in formula 2.

$$k_\alpha^{past}(t) = \sum_{i=1}^{|U|} A_{i\alpha}(t) e^{\lambda(T_{i\alpha}-t)}, \quad t < T_p \quad (2)$$

$A_{i\alpha}(t)$ represents the link relationship between user i and item a at time t (1 if user i purchases item a, otherwise 0). $T_{i\alpha}$ represents the time for user i to purchase item a, and the adjustable parameter λ represents the time decay weight, which is used to control the speed at which popularity decays with time.

3.1.3 Item popularity prediction algorithm

By determining the time window length T_p, the popularity of items in different time periods can be calculated according to the above formula. In order to benefit from the popularity of different intervals, it is proposed to introduce two parameters to fuse the past popularity and recent popularity of items to obtain the popularity trend prediction value k_α. The expression is shown in formula 3.

$$k_\alpha(t) = \alpha k_\alpha^{past}(t) + \beta k_\alpha^{recent}(t) + \varepsilon \quad (3)$$

ISSN 2522-3488 Vol. 4, Issue 1: 61-69, DOI: 10.25236/IJNDES.040109

3.2 Resource allocation recommendation algorithm integrating popularity trend

3.2.1 Analysis of the process of mass diffusion recommendation algorithm

The resource allocation recommendation algorithm based on the bipartite graph is mainly divided into the mass diffusion algorithm (MD) and the heat conduction algorithm (HC), and their transfer matrix is as follows.

$$W_{\alpha\beta}^{MD} = \frac{1}{k_\beta}\sum_{i=1}^{|U|}\frac{a_{i\alpha}a_{i\beta}}{k_i} \tag{4}$$

$$W_{\alpha\beta}^{HC} = \frac{1}{k_\alpha}\sum_{i=1}^{|U|}\frac{a_{i\alpha}a_{i\beta}}{k_i} \tag{5}$$

The above-mentioned transfer matrix can be divided into two steps, in which the mass diffusion process can be decomposed into:

Step 1: Item -> User

$$R_u = \sum_{i=1}^{|I|}\frac{a_{ui}e_i}{k_i} \tag{6}$$

Step 2: User->Resource

$$R_i = \sum_{u=1}^{|U|}\frac{a_{ui}e_u}{k_u} \tag{7}$$

Among them, U and I respectively represent the collection of users and items, k represents the degree of the node, e represents the number of resources of the node, and a_{ui} represents the purchase relationship between user u and item i. It can be seen from formulas 6 and 7 that when resources are passed from one end to the node at the other end, the number of resources received by the other end node depends on the degree of the incoming end node. This leads to the greater the degree of the node, the less the node allocates resources to the node connected to the other end. In practice, the greater the degree of an item, the more attractive it is to users. Therefore, it is necessary to improve the resource allocation process based on the item degree information.

3.2.2 Definition of item weight

Based on the process of mass diffusion and heat conduction, this paper introduces time perception and proposes the concept of item weighting. First, increase the number of resources spread by nodes with larger items. Secondly, by considering the popularity of different periods, predict the future trend of the

ISSN 2522-3488 Vol. 4, Issue 1: 61-69, DOI: 10.25236/IJNDES.040109

popularity of items, increase the number of resources allocated for items whose popularity will rise in the future, and reduce the number of resources allocated for items whose popularity will decline in the future.

First of all, this article defines U_{past} as the collection of items purchased in the time period of (T_0,T_P), T_0 as the earliest time of the training set, U_{recent} as the collection of items purchased by (t-T_P,t), and the collection of items with rising popularity as U_{rise}. The expression is shown in formula 8.

$$U_{\text{rise}} = \{c \mid \alpha k_c^{past} < \mid \beta \mid k_c^{recent}\} \tag{8}$$

In order to adjust the influence of popularity on the resource allocation process, this paper proposes the concept of item weighting degree, formula 9 defines the weighting degree *dpr* of each item. Item weighting is divided into two parts: when items are in a collection of items with increasing popularity or items have just been popular recently, the final popularity is 1, indicating that their resource allocation weight is the largest. When the item is not in the set of rising popularity, the predicted value of the popularity prediction algorithm proposed in this paper is used as the item weight. The specific formula is shown in 9.

$$dpr_i = \begin{cases} \alpha k_i^{past} + \beta k_i^{recent} + \varepsilon\ , & i \notin (U_{recent} - U_{past}) \cup U_{rise} \\ 1\ , & i \in (U_{recent} - U_{past}) \cup U_{rise} \end{cases} \tag{9}$$

Among them, the parameter α>0. When α<1, it means that the more popular items are, the more resources are allocated. The range of β is [-1,0). β<0 indicates that the more popular items are allocated more resources.

3.2.3 Improved resource allocation recommendation algorithm based on item weight

In order to study the role of item popularity in the mass diffusion and heat conduction recommendation algorithm, this paper combines item weighting to improve the recommendation scoring formula for mass diffusion and heat conduction. In the original mass diffusion algorithm, by replacing the original item degree as the weighting degree of the proposed item, the popularity-based mass diffusion algorithm (PB-MD) algorithm is obtained. The specific transition probability matrix WPB-MD is shown in formula 10.

$$W_{\alpha\beta}^{PB-MD} = \frac{1}{dpr_\beta} \sum_{i=1}^{|U|} \frac{a_{i\alpha} a_{i\beta}}{k_i} \tag{10}$$

The element $W_{\alpha\beta}^{PB-MD}$ of the transition matrix W^{PB-MD} represents the weight of the resource that item β assigns to item α. Similarly, by replacing the original degree

ISSN 2522-3488 Vol. 4, Issue 1: 61-69, DOI: 10.25236/IJNDES.040109

of the heat transfer matrix, the popularity-based heat transfer algorithm (PB-HC) can be obtained. The transfer matrix is shown in formula 11.

$$W_{\alpha\beta}^{PB-HC} = \frac{1}{dpr_{\alpha}} \sum_{i=1}^{|U|} \frac{a_{i\alpha} a_{i\beta}}{k_i} \tag{11}$$

4. Experiment and analysis

4.1 Dataset description

For the reliability of the experimental results, this article conducted experiments on two public datasets MovieLens and Netflix. The scoring records of the last month are selected as the test set, and the rest are the training set. The specific description is shown in Table 1.

Table 1 Dataset description

Dataset	Users	Items	Links	Sparsity	Date range
MovieLens	943	1682	100000	6.3×10^{-2}	19th Sep 1997—22nd Apr 1998
Netflix	4960	16599	1.2×10^{6}	1.5×10^{-2}	1st Jan 2000—31st Dec 2005

4.2 Evaluation Metric

This article uses accuracy, novelty and diversity to evaluate the performance of recommendation algorithms. Among them, Precision, Recall, and F1-Score are used for accuracy. If the Recommender system recommends all popular products, the value of the recommendation is not great and it cannot generate a personalized recommendation list. Novelty measures the ability of the recommender system to recommend non-hot items to users. It calculates the average degree of items in the user's recommendation list, the smaller the value of the novelty index, the less popular the items recommended by the recommender system, the more popular. Diversity is to calculate the Hamming distance between different users' recommendation lists (the top L items), the greater the Hamming distance, the higher the recommendation diversity. The recommendation diversity of the entire Recommender system is the average Hamming distance of all users.

4.3 Analysis of experimental results

In order to compare the performance of the algorithm proposed in this paper, we have compared the original mass diffusion algorithm and heat conduction algorithm, and compared with the latest algorithms based on recent popularity, HP-MD and HP-HC [10]. The dynamic adjustment process of the algorithm proposed in this paper is mainly performed by determining the recent popularity reference point T_P, and the long-term popularity weight α and the recent popularity weight β work together. For the parameters α and β, the experiment uses grid search to determine the optimal parameters. For the MovieLens data set, the experimental setting T_P=30, for the Netflix data set T_P=60.

Table 2 shows the performance of the comparison algorithm and the improved algorithm PB-MD and PB-HC proposed in this paper in Precision, Recall, F1-Score, diversity and novelty. In the table, the best performance of the same type of algorithm is shown in bold. For the improved algorithm proposed in this paper, the following parameters are set in the experiment. In the MovieLens dataset, the parameters of PB-MD are $\alpha = 0.3$, $\beta = -0.9$, and the parameters of PB-HC are $\alpha = 0.4$, $\beta = -0.5$. In the Netflix data set, the parameters of PB-MD are $\alpha = 0.9$, $\beta =-1$, and the parameters of PB-HC are $\alpha = 0.5$, $\beta =-0.5$. It can be seen from the results that the improved algorithm proposed in this paper is significantly better than the original algorithm in accuracy-related metrics Precision, Recall, and F1-Score. Specifically, on the MovieLens dataset, the PB-MD algorithm improves F1-Score by 27.5% compared to the original algorithm, and the improvement ratio on the Netflix dataset is 31.8%, and it is also superior to the original algorithm in novelty and diversity.

Table 2 The performance of MD, HC, PB-MD and PB-HC algorithms on two datasets

Dataset	Metric	Algorithms					
		MD	HP-MD	PB-MD	HC	HP-HC	PB-HC
MovieLens	Precision	0.13929	0.14167	**0.14881**	0.00476	0.00714	**0.05119**
	Recall	0.07714	0.07759	**0.11022**	0.00202	0.00723	**0.12355**
	F1-Score	0.09929	0.10026	**0.12664**	0.00284	0.00718	**0.07239**
	Diversity	0.78353	0.78629	**0.82172**	**0.86747**	0.73600	0.39719
	Novelty	310.6143	308.8524	**291.1667**	2.35357	**1.6904**	33.8559
Netflix	Precision	0.06092	0.06114	**0.06823**	0.00104	0.00151	**0.08563**
	Recall	0.01809	0.01843	**0.02698**	0.00066	0.00068	**0.06539**
	F1-Score	0.02789	0.02832	**0.03867**	0.00081	0.00094	**0.07415**
	Diversity	0.73939	0.74241	**0.78203**	**0.87655**	0.72247	0.25649
	Novelty	1883.37	1878.75	**1735.65**	1.11242	**1.09915**	385.300

The improved algorithm based on heat conduction, the PB-HC algorithm, has a very obvious improvement in the accuracy index. This is because the original heat conduction algorithm itself has the characteristics of low accuracy, but high novelty and diversity. It can be seen from the results that in the MovieLens dataset, the accuracy of the PB-HC algorithm is 25.5 times the original accuracy, and in the Netflix dataset it is 92.1 times the original algorithm. If the actual system requires high novelty, the PB-HC algorithm will be more suitable than the MD algorithm. Through the experimental results, it can be found that PB-MD and PB-HC can greatly improve the recommendation performance of the original algorithm, which shows that integrating the popularity of items in different time periods in the resource allocation algorithm can improve the performance of the original algorithm.

ISSN 2522-3488 Vol. 4, Issue 1: 61-69, DOI: 10.25236/IJNDES.040109

In terms of experimental parameters, β in [-1, -0.5] indicates that recently popular items should get a higher weight in the resource allocation process. The range of α in [0.3, 0.5] indicates that popular items should also receive higher resource allocation weights. The experimental results show that it is unreasonable for the original algorithm to divide resources equally by degree, which will cause the more popular items to allocate fewer resources to users. At the same time, the experimental results also prove that the node's preference attachment phenomenon is also well reflected in the real Recommender system data set. Users will be more inclined to buy more popular items, and reasonable use of users' preferences can improve the accuracy of the Recommender system.

5. Conclusion

This paper proposes an algorithm to predict the trend of item popularity based on the popularity of different periods, and introduces the trend of popularity into related algorithms based on resource allocation to improve the resource allocation process of the recommendation algorithm. Experiments prove that the improved algorithm is significantly better than the original algorithm in accuracy and novelty. The popularity-based resource allocation recommendation algorithm proposed in this paper only considers the influence of item popularity on the algorithm, and does not consider the influence of user degree on the algorithm. Active users and inactive users should have different weights in the resource allocation process. In future work, we should further study the integration of user activity in the resource allocation process.

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