



The Differentiation of Residents' Cultural Consumption Tendency and Consumption Recommendation System Based on Network Inference Algorithm

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Abstract: To address the issue of insufficient accuracy in consumer recommendation systems, a new biased network inference algorithm is proposed based on traditional network inference algorithms. This new network inference algorithm can significantly improve the resource allocation ability of the original one, thereby improving recommendation performance. Then, the performance of this algorithm is verified through comparative experiments with network-based inference algorithms, network inference algorithms with initial resource optimization, and heterogeneous network inference algorithms. The results showed that the accuracy of the new network inference algorithm was 24.5%, which was superior to traditional one. In terms of system performance testing, the recommendation hit rate of the new network inference algorithm increased by 13.97%, which was superior to the other three comparative algorithms. The experimental results indicated that a novel network inference algorithm with bias can improve the performance of consumer recommendation systems, providing new ideas for improving the performance of consumer recommendation systems.

Keywords: Recommendation system; Network inference algorithm; Bias; Accuracy

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1. Introduction

As the problem of information overload becomes increasingly severe, the role of recommendation systems in daily life is becoming increasingly important [10]. Consumer recommendation system is a system that recommends products or services that may be of interest to users based on their historical consumption records and preferences [19]. It can help users save search and purchase costs, improve shopping efficiency and satisfaction. Consumer recommendation systems typically provide users with personalized shopping experiences and conversion rates by analyzing their historical consumption records and preferences. Network inference algorithm is an artificial intelligence algorithm based on evidence theory, which analyzes and infers a large amount of historical data and input information to draw conclusions and make decisions. Network-based Inference (NBI) algorithms typically use techniques such as probability distribution, probability models, and statistical inference to support various application scenarios. NBI algorithms analyze input data and information, draw conclusions, and make decisions, thereby achieving inference and resolution of unknown problems. In recent years, due to the higher accuracy of NBI algorithm compared with collaborative filtering technology, it has gradually become popular in the recommendation field [5]. Traditional NBI algorithms are also used in consumer recommendation systems, but even if they are applied, the performance of the recommendation system cannot achieve the expected results [3]. To improve the accuracy of consumer recommendation systems and promote the development of residents' cultural consumption, it is of great value to explore a new algorithm applied to recommendation systems [7]. A new NBI algorithm is proposed to address the issue of low accuracy in traditional algorithms. This new NBI algorithm optimizes initial resources on traditional NBI algorithms, making the entire model biased. This algorithm is applied to the consumer recommendation system to design a new type of consumer recommendation system. The proposal of this new algorithm not only promotes the development of NBI algorithms, but also contributes to the development of cultural consumption among Chinese residents. The paper mainly consists of four parts. The first part of the content is an introduction to the related work of NBI algorithms and consumer recommendation systems, as well as the motivation for this research. The second part is an introduction to the specific methods of this study, mainly focusing on the introduction of new NBI algorithms and consumer recommendation systems. The third part is the performance comparison analysis of the new NBI algorithm and the comparison analysis of the consumer recommendation system. The fourth part summarizes the entire text and draws important conclusions from this study.

2. Related Works

With the rapid advancement of modern information technology, NBI algorithms have been applied in several fields because of their simplicity and efficiency. Trinh H C et al. proposed Boolean NBI algorithm for the problem of insufficient network structure and dynamics methods for inferring gene regulatory networks from steady-state gene expression data, which improved the accuracy of prediction models [14]. Zheng K team proposed to solve the problem of poor robustness and overfitting caused by large-scale data in collaborative filtering recommendation algorithms by using variational inference to construct recommendation networks, which can improve the performance of probabilistic recommendation models [20].

Ye J et al. proposed a subset structure fusion based on the problem of accurate topological inference in nonsmooth networks network topology inference method. The analysis and simulation results denoted that the method improved the accuracy of topology inference in nonsmooth networks [18]. Turabieh H's team proposed a dynamic adaptive network-based fuzzy inference system method to interpolate missing values in a simple and accurate way for the problem of Internet of Medical Things systems are prone to missing data. The outcomes indicated that the method improves the performance of the Internet of Medical Things system by 5% [15]. Cho Y J et al. proposed a new distance-based inference model for camera networks for the problem of efficient re-identification of people. The outcomes indicated that the method can effectively re-identify people in large-scale camera networks with different transition times identification [2].

There are also countless approaches applied to consumer recommendation systems. There are still problems in scalability and cold start. Xu H proposed a recommendation system based on user content consumption to address the lack of scalability of existing systems. The results showed that the method improved the hit rate of the recommendation system [17]. Chen X et al. for the lack of personalized recommendation in offline to online to offline e-commerce model proposed a rule-based semantic inference method. Examples expressed that the method can easily and quickly implement personalized recommendations [1]. Liu D's team proposed an improved LSH algorithm based on p-stable distribution to improve the performance of the system for the problem of low recommendation reliability of commodity. The experiments proved that the algorithm had a certain degree of optimization, which not only improved the check-all rate and error rate, and also optimized memory utilization and search efficiency [9]. Kumar and Reddy for the problem of inability to select travel destinations among the information accessible on the Internet, proposed to apply the C4.5 decision tree algorithm to travel recommendation system. The findings denoted that the algorithm not only improved the problem of inability to select destinations in the system, but also improved the recommendation accuracy of the system [8]. Wang D et al. addressed the problem of poor recommendation utility due to considering only the user's viewpoint in the recommendation system. They proposed the multi-objective model for recommender systems. Numerous experimental findings indicated that this model outperformed other models in average accuracy, diversity, novelty, provider coverage, and platform profit [16].

The above studies illustrate that NBI algorithms have been effectively utilized in several fields, and there are numerous methods applied to consumer recommendation systems, but there is a lack of research on applying NBI algorithms to consumer recommendation systems. Therefore, the study applies NBI algorithms to consumer recommendation systems to improve the problem of inaccurate recommendations of today's consumer recommendation systems by embedding optimized NBI algorithms into consumer recommendation systems.

3. The System of Residents' Consumption Tendency Based on NBI Algorithm

3.1. Traditional Network Recommendation Algorithm

Recommendation algorithms of network inference can be used in residential consumer recommendation systems because of their simplicity and efficiency, but traditional NBI algorithms are still deficient in resource allocation [12]. To address this problem, the study proposed a novel NBI algorithm model for use in consumer recommendation systems. This model improved the rationality of resource flow in the network by mining more available information, which in turn improved the model performance. The specific resource flow of the traditional NBI algorithm is shown in Figure 1.

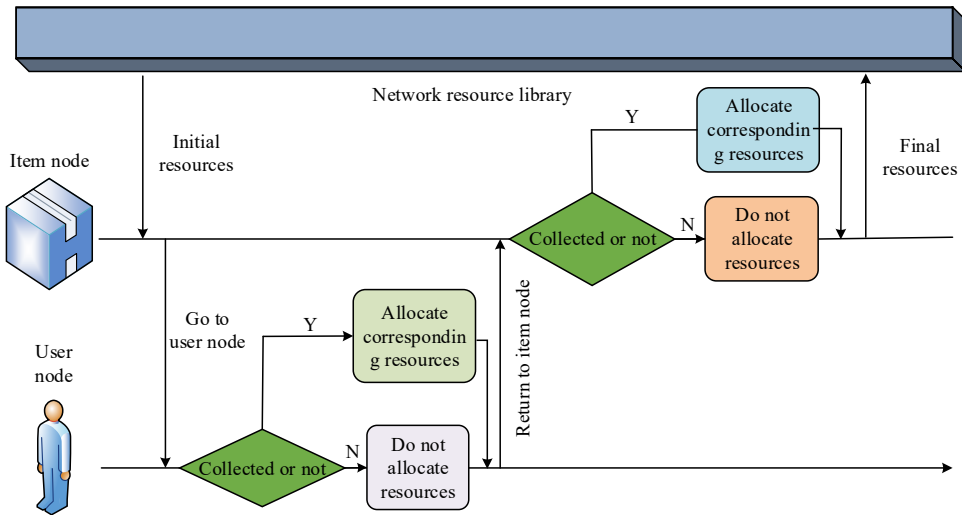


Figure 1. Flow Chart of Traditional NBI Algorithm Implementation

From Figure 1, the initial resource goes to the user node first, and if the user node collects the resource, the corresponding resource is allocated into the item node, otherwise no resource is allocated. When a resource passes through the item node, similar to passing through the user node, if the item node collects the resource, the corresponding resource amount is allocated as the final resource amount, otherwise the allocated resource is 0, i.e., the final resource amount is 0. The above resource flow can be expressed in the form of a matrix, and the expression is shown in equation (1).

$$f' = Wf \quad (1)$$

The resource flow matrix W in equation (1) denotes the causal relationship between items. The specific algorithm flow of traditional NBI is as follows. In the bidirectional network $G(X, Y, Z)$, the nodes in the set X and the set Y are represented by $x_1, x_2, \dots, x_n$ and

$y_1, y_2, \dots, y_n$, respectively. The initial resource $f(x_i) \geq 0$ of the first node is in the set i . The first step of the NBI algorithm is to flow all the resources owned by the set X to the set Y , so that the resource $f(y_l)$ owned by the l th node in the set Y is expressed as shown in equation (2).

$$f(y_l) = \sum_{i=1}^n \frac{a_{il} f(x_i)}{k(x_i)} \quad (2)$$

In equation (2), $k(x_i)$ denotes the degree of node x_i and a_{il} is an adjacency matrix of $n * m$, whose expression is given in equation (3).

$$a_{il} = \begin{cases} 1, & x_i y_l \in E \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

In the NBI algorithm, after flowing all the resources owned by the set X to the set Y , all the resources in the set Y are then returned to X . The expression of the resources $f'(x_i)$ owned by the final node x_i is shown in equation (4).

$$f'(x_i) = \sum_{l=1}^m \frac{a_{il} f(y_l)}{k(y_l)} = \sum_{l=1}^m \frac{a_{il}}{k(y_l)} \sum_{j=1}^n \frac{a_{jl} f(x_j)}{k(x_j)} \quad (4)$$

In equation (4), $k(y_l)$ expresses the degree of node y_l and a_{il} is an adjacency matrix of $n * m$. The expression of $f'(x_i)$ can be rewritten as equation (5).

$$f'(x_i) = \sum_{j=1}^n w_{ij} f(x_j) \quad (5)$$

In equation (5), w_{ij} denotes the flow of resources between nodes x_i and x_j in the set X . The expression is shown in equation (6).

$$w_{ij} = \frac{1}{k(x_j)} \sum_{l=1}^m \frac{a_{il} a_{jl}}{k(y_l)} \quad (6)$$

In equation (6), $k(x_j)$ and $k(y_l)$ denote the degree of nodes x_j and y_l , respectively. In the traditional NBI algorithm, the model construction is simple and straightforward, the computational complexity is low, and it has good generalizability [13]. However, the traditional NBI algorithm suffers from the problem of serious negative evaluation loss. In the information filtering, in addition to positive evaluations to uncover the user's hobby characteristics, negative evaluations are also important for analyzing the behavioral characteristics of users [6]. This is because negative evaluations are not only negative attitudes such as users expressing dissatisfaction and dislike of items, but also imply other behavioral information of users [4]. If the useful information from negative evaluations can be extracted correctly, it can be an important contribution to the construction of personalized models for users.

3.2. NBI Algorithm Based on Bias

To solve the problem of losing negative evaluations in traditional NBI algorithms without increasing the computational effort of the model. The study assigns different initial resource amounts to different negative evaluations of items to make the recommendation algorithm model biased and constitute a new Biased Network-based Inference (BNBI) algorithm. This does not affect the original resource flow, but also allows the initial resources to be combined with other methods to give the model a better scalability. In the rating system, the study proposes to make full use of the information in the negative evaluation by citing item similarity in the negative evaluation, thus reducing the adverse effect of item diversity on the results. For the user j , the initial resource allocation f_i^j expression is shown in equation (7).

$$f_i^j = a_{ij} f(\phi) \quad (7)$$

In equation (7), $f(\phi)$ is the decay function, where ϕ denotes the sum of the similarities of all items given negative ratings by the item i and the user j . The expression of ϕ is shown in equation (8).

$$\phi = \sum_{k=1}^{K_j} Sim_{ik} \quad (8)$$

In equation (8), K_j indicates the number of items given negative ratings by the user j , and Sim_{ik} means the similarity of items i and k . The exponential function is chosen as the decay function, then the expression of $f(\phi)$ is shown in equation (9).

$$f(\phi) = t^\phi \quad (0 < t < 1) \quad (9)$$

In summary, all items collected by the user j will have different recommendation weights. Those items that are similar to the items given negative ratings by users will have a lower recommendation weight. This method can also be combined with the method of reducing the recommendation weights of popular items. On this basis, for users j , f_i^j expressions are shown in equation (10).

$$f_i^j = a_{ij} f(\phi) k^\beta(o_i) \quad (10)$$

Under this algorithm, the recommendation weights of the items will all be reduced at the time of resource initiation. The flowchart of this BNBI algorithm implementation in the rating system is shown in Figure 2.


$$T = \mu - \tau * \sigma \quad (11)$$

In equation (11), μ indicates the average number of user views. σ denotes the standard variance of the number of user views. τ refers to the variable weights. The flowchart of BNBI algorithm implementation in the non-rating system is shown in Figure 3.

3.3. Construction of Residential Consumption Recommendation System Based on NBI Algorithm

Most of today's consumer recommendation systems are not very accurate. To enhance the performance of resident consumer recommendation systems, the study builds a novel consumer recommendation systems by embedding an NBI algorithm with bias into the consumer recommendation systems. The specific structure of the novel consumer recommendation systems is shown in Figure 4.

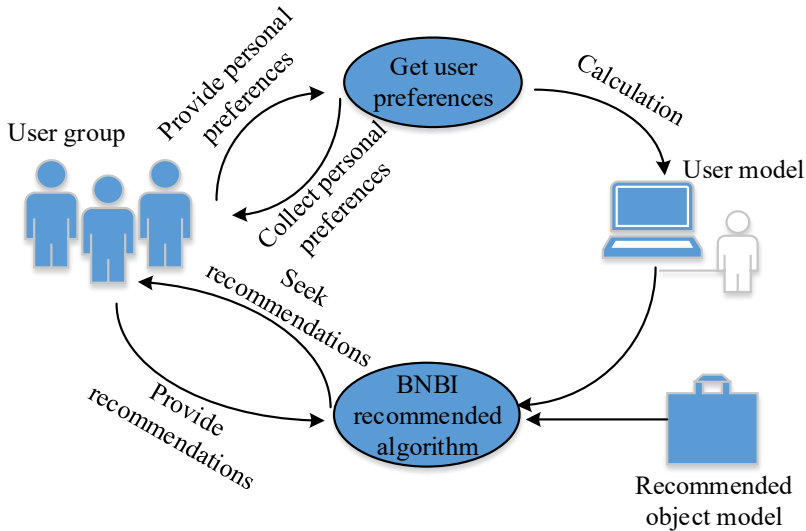


Figure 4. Structure Diagram of the New Consumer Recommendation Systems

In Figure 4, the whole consumer recommendation systems includes four modules: user, user model, recommendation object model and recommendation algorithm. The main role of the user is to improve the personal preferences to the subsequent process and facilitate the calculation of the exclusive user model. The user model and the recommendation object model are mainly used in the new NBI algorithm for calculation. The BNBI algorithm mainly calculates the model and then outputs the final recommended items. The specific operation of the recommendation system is that the system collects the user's personal preferences, calculates the user's exclusive model, then the exclusive user model and the recommendation object model are applied to the BNBI algorithm. The BNBI algorithm calculates and outputs the recommended items required by the user.

4. Algorithm Performance Parameters and Model Results Analysis

4.1. Performance Comparison of NBI Algorithms

To compare the performance of NBI algorithms, research was conducted on the rating system Movie Lens dataset and the non-rating system Last.FM dataset, respectively. Movie Lens is a

rating system where users vote on movies using discrete rating values of 1-5. The Movie Lens dataset contains 2113 users and 10197 movies (items), providing 855598 available reviews, and also includes 13222 tags. Last.FM is a non-rating system that includes 1892 users and 17632 songs (items), providing 92834 available reviews, and the dataset also contains 11946 tags. To test and compare the performance of the models designed in the study, different evaluation metrics were used in the comparison experiments. The study choose common metrics accuracy, recall and F1 metrics to test the performance of different models. Among them, the accuracy and recall represented the reliability of the recommendation, and the accuracy calculation expression is shown in equation (15).

$$P(L) = \frac{1}{m} \sum_{i=1}^m \frac{l_i(L)}{L} \quad (15)$$

In equation (15), L is the length of the recommendation list, and $l_i(L)$ is used to denote the number of items co-existing in the test set and the recommendation list. The expression for calculating the recall is shown in equation (16).

$$R(L) = \frac{1}{m} \sum_{i=1}^m \frac{l_i(L)}{Y} \quad (16)$$

The number of items in the test set collected by the user is denoted by Y in equation (16). F1 metrics can provide a more comprehensive evaluation of the model performance comparison. F1 metrics expression is shown in equation (17).

$$F1(L) = \frac{2P(L) \times R(L)}{P(L) + R(L)} \quad (17)$$

In addition to the common evaluation indicators, the study also chose diversity as well as novelty indicators that have been used in recent years to test the ability of unpopular items. The expression of the diversity indicator is shown in equation (18).

$$D(L) = \frac{1}{m(m-1)} \sum_{i \neq j} \left(1 - \frac{q_{ij}}{L} \right) \quad (18)$$

In equation (18), q_{ij} denotes the total number of recommended items in the recommendation list owned by both user i and user j . L denotes the length of the recommendation list. The expression for novelty is given in equation (19).

$$N(L) = \frac{1}{mL} \sum_{i=1}^m \sum_{l=1}^L k(o_l) \quad (19)$$

In equation (19), $k(o_l)$ indicates the degree of the item o_l . Among the above five evaluation metrics, larger values of precision, recall, F1 metric and diversity indicate better performance. Novelty, on the other hand, has a higher value indicating a worse performance. To better analyze the performance of BNBI algorithm, this study tested it with four inference algorithms: Heterogeneous Network-based Inference (HNBI) algorithm, traditional NBI algorithm, and Signed Network-based Inference (SNBI) algorithm in Matlab simulation environment. The precision, recall, F1 index, diversity, and novelty of the four inference

algorithms were compared. Among them, the precision results of the four inference algorithms in the two types of datasets are shown in Figure 5.

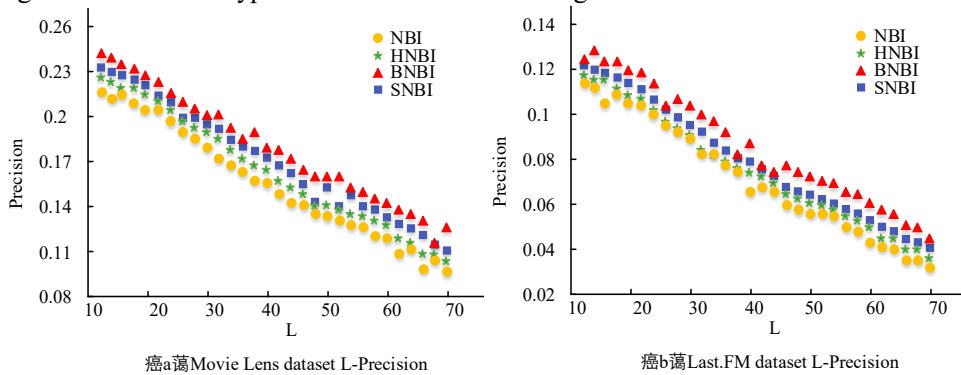


Figure 5. Precision Graph of Four Algorithms in Two Datasets

From Figure 5, the precision of the four algorithms in both datasets tended to decrease as the length of the recommendation list L increased. In the rating system Movie Lens, it was obvious that the accuracy of BNBI algorithm was higher than the other three algorithms, with the highest precision of 0.245. In the non-rating system Last.FM, the precision of BNBI algorithm was also higher than the other three algorithms, with the highest precision of 0.128. In summary, in precision dimension, both in the rating and non-rating systems, the BNBI algorithm performed better than the other three algorithms. The recall results of the four inference algorithms in the two types of data sets are shown in Figure 6.

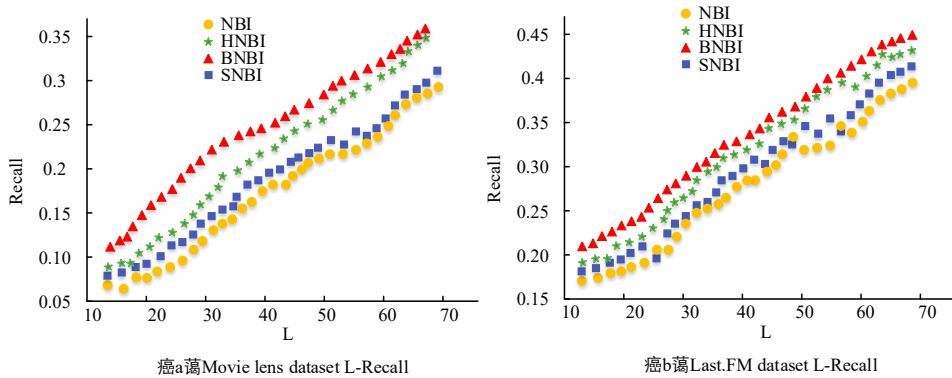


Figure 6. Recall Graph of Four Algorithms in Two Data Sets

From Figure 6, the recall of all four algorithms in both Movie Lens dataset and Last.FM dataset tended to increase with the growth of the recommendation list length L . In the rating system Movie Lens, when the recommendation list length was 70, the BNBI algorithm had the highest recall rate of 0.35, while the NBI algorithm had the lowest recall rate of 0.28. In the non-rating system Last.FM, when the recommendation list length was 70, the recall rate of the BNBI algorithm was higher than the other three algorithms, with a recall rate of 0.44. In

summary, the BNBI algorithm outperformed the other three algorithms in both the rating and non-rating systems in recall rate dimension. The F1 values of the four algorithms in the Movie Lens dataset and the Last.FM dataset are shown in Figure 7.

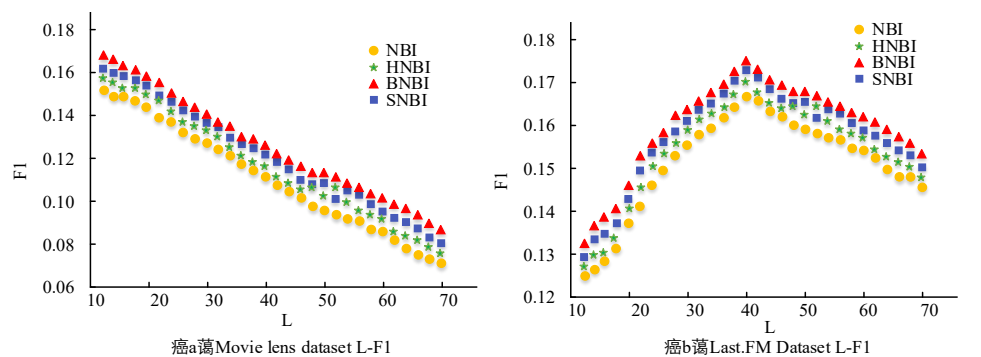


Figure 7 F1 Values of Four Algorithms in Two Data Sets

From Figure 7, the F1 values of the four algorithms in the Movie Lens dataset showed a decreasing trend with the growth of the recommendation list length L. The F1 value of the BNBI algorithm was significantly higher than the other three algorithms, with the highest value of 0.168. The F1 values of the four algorithms in the Last.FM dataset showed a trend of increasing and then decreasing with the increase of L, and there was a maximum value when L was 40. According to the equation for F1 value, F1 value was related to precision and recall. Due to the low decrease in precision and recall in the Last.FM dataset, F1 value reached its maximum at L=40. The F1 values of the BNBI algorithm were higher than those of the other three algorithms regardless of the value of L. Among them, the BNBI algorithm had the maximum value of F1 at L of 40, which was 0.178. This result indicated that the BNBI algorithm outperformed the other three algorithms in the Last.FM dataset. In summary, in terms of the F1 value dimension, the BNBI algorithm had the best performance in both systems. The diversity results of the four algorithms in the Movie Lens dataset and the Last.FM dataset are shown in Table 1.

Table 1. Diversity of the Four Algorithms on the Two Datasets

Diversity	NBI		HNBI		BNBI		SNBI	
	Movie Lens	Last.FM	Movie Lens	Last.FM	Movie Lens	Last.FM	Movie Lens	Last.FM
10	0.7321	0.8321	0.7412	0.8528	0.7637	0.8768	0.7528	0.8635
20	0.6812	0.7925	0.7135	0.8178	0.7421	0.8439	0.7367	0.8317
30	0.6537	0.7725	0.6987	0.7836	0.7139	0.8232	0.7025	0.8012
40	0.6378	0.7512	0.6759	0.7698	0.6922	0.8102	0.6811	0.7807
50	0.6117	0.7433	0.6537	0.7567	0.6817	0.7938	0.6635	0.7675
60	0.5978	0.7277	0.6421	0.7328	0.6634	0.7728	0.6513	0.7469
70	0.5765	0.7156	0.6278	0.7234	0.6436	0.7618	0.6378	0.7311

From the data in Table 1, in the Movie Lens dataset, the diversity of all four algorithms decreased as the length of the recommendation list L increased. Among the four algorithms, the BNBI algorithm had the highest diversity of 0.7637. In the non-rating system Last.FM dataset, the diversity of BNBI algorithm was also higher than that of NBI, HNBI and SNBI algorithms, and the highest diversity of BNBI algorithm was 0.8768. In summary, in terms of diversity dimension, BNBI algorithm outperformed both Movie Lens dataset and Last.FM dataset. The novelty values of the four algorithms in the Movie Lens dataset and the Last.FM dataset are denoted in Table 2.

Table 2. Novelty of the Four Algorithms on the Two Datasets

Novelty	NBI		HNBI		BNBI		SNBI	
	Movie Lens	Last. FM	Movie Lens	Last. FM	Movie Lens	Last. FM	Movie Lens	Last. FM
10	1126.32	174.38	1117.25	162.35	1102.35	168.39	1106.72	170.23
20	1035.78	147.75	1031.75	135.75	1017.93	143.74	1030.27	148.35
30	988.37	128.97	973.15	122.18	957.32	125.48	975.71	131.79
40	936.87	119.32	928.33	117.29	922.71	117.24	931.51	122.41
50	902.29	111.27	888.18	108.37	876.63	108.62	898.37	115.29
60	866.35	105.48	851.72	102.68	843.17	100.34	863.48	108.86
70	841.97	99.36	813.36	97.21	815.81	93.58	827.27	101.58

From the data in Table 2, in the Movie Lens dataset, the novelty of the four algorithms tended to decrease as the length of the recommendation list L increased. The BNBI algorithm had the lowest novelty among the four algorithms, with a value of 815.81. In the non-rating system Last.FM dataset, the novelty of BNBI algorithm was lower than the other three algorithms, with a value of 93.58. In summary, from the novelty dimension, the BNBI algorithm outperformed the other three algorithms in both Movie Lens dataset and Last.FM dataset. From the results of comparing the four algorithms in the above five dimensions, the performance of the BNBI algorithm was significantly better than the traditional NBI algorithm as well as the HNBI and SNBI algorithms, which has better recommendation results.

4.2. Comparison of the Results of Residential Consumption Recommendation System

After the consumer recommendation systems was designed and installed according to the actual situation of the community, the study conducted comparison experiments on the PC side and the APP side, respectively. The experimental subjects were the users in the community within one week, and the behavioral data of the users were used as the base samples for comparison. It divided user behavior data into four different experimental datasets, where Dataset 1 includes social network relationship information within the community, such as friend list, interests, geographic location, etc. Dataset 2 includes information on users' consumption behavior within the community, such as consumption amount, consumption frequency, etc. Dataset 3 includes information on users' consumption habits within the community, such as whether they frequently visit a particular merchant or purchase certain

products. Dataset 4 includes other behavioral data of users within the community, such as whether they frequently participate in an activity, whether they frequently visit a store, etc. By collecting this data, it could be used to train and test recommendation system, thereby improving their recommendation accuracy and precision. Different models of the consumer recommendation systems were used in the four experimental data sets, and the growth values of recommended hit rate (RHR), click-through rate (CTR), and return on investment (ROI) for each model were measured to compare the performance of each consumer recommendation systems. The study used Matlab simulation software to test four systems in four datasets, and the RHR results of the four systems in the experimental dataset are shown in Figure 8.

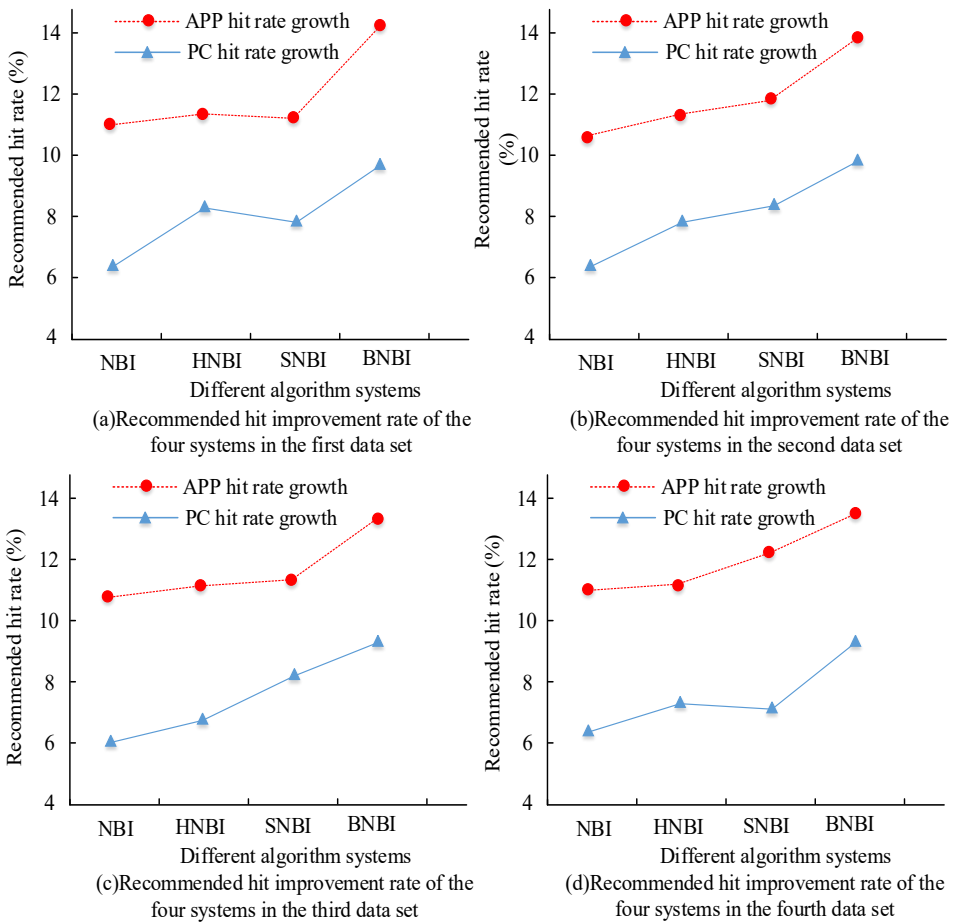


Figure 8. Comparison of RHR Growth Values for Different Systems

From the four-line graphs in Figure 8, the growth of RHR of all four systems in APP was higher than the growth of RHR in PC. The results showed that the highest RHR growth among the four systems in the APP side was the BNBI system with 13.97% growth in RHR, and the lowest RHR growth was the NBI system with 10.82% growth in RHR. This result showed that

the performance of BNBI system was much higher than the performance of traditional NBI system in APP side. In the PC side, the highest growth of RHR among the four systems was the research-designed BNBI system, with 9.27% growth of RHR. The lowest growth of RHR was the NBI system, with 6.13% growth of RHR. This result showed that the performance of BNBI system was also better than the performance of traditional NBI system in APP side. Combining these two results, the performance of BNBI system was better than the other three systems in the growth value of the RHR. The graphs of the CTR results of the four systems in the experimental dataset are shown in Figure 9.

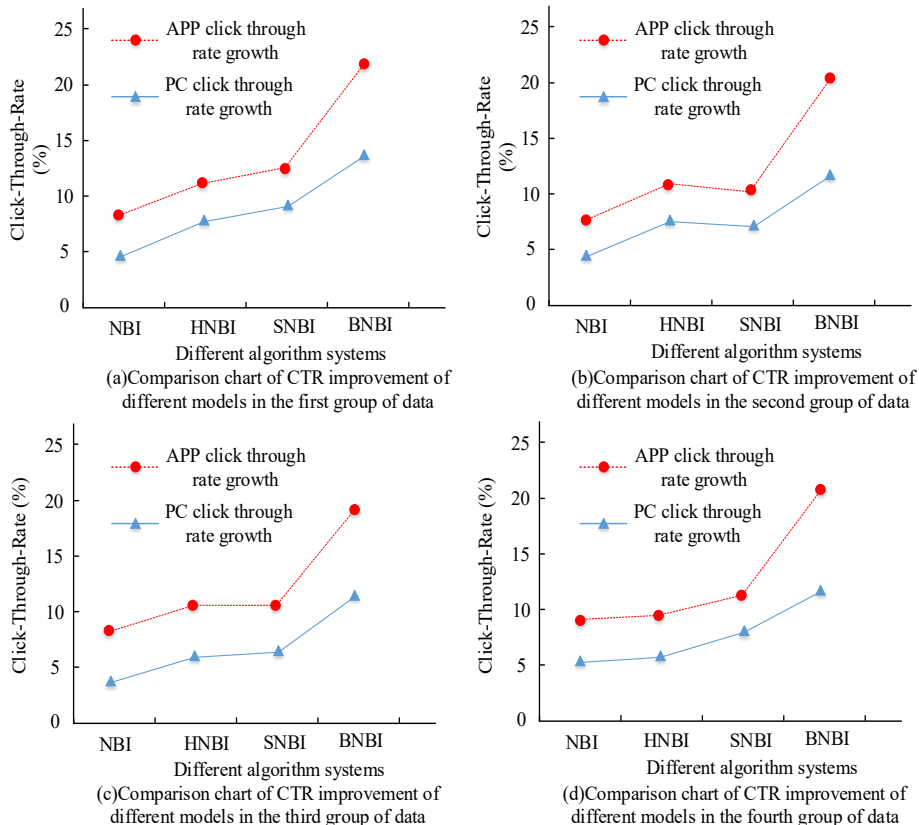


Figure 9. Comparison of Online CTR Growth Values for Different Models

From the four sets of line graphs in Figure 9, it was obvious that the growth rate of online CTR of all four systems in APP was higher than that of online CTR in PC. The average growth rate of the online CTR of the four systems in the four data sets was taken for comparison. The results showed that the highest growth rate of online CTR among the four systems in the APP side was the BNBI system designed by the study, with a growth rate of 20.85%. The lowest growth rate of online CTR was the NBI system, with a growth rate of 8.34%. This result denoted that the performance of BNBI system was much higher than that of traditional NBI system in the APP side. In the PC side, the highest growth of online CTR among the four systems was the research-designed BNBI system with 11.34% growth of online CTR. The

lowest growth of online CTR was the NBI system with 4.51% growth of online CTR. This result expressed that the performance of BNBI system was also better than that of traditional NBI system in APP side. Combining these two results, the BNBI system outperformed the other three systems in terms of the growth value of online CTR. The results of online ROI, another metric of the four systems in the experimental dataset, are shown in Figure 10.

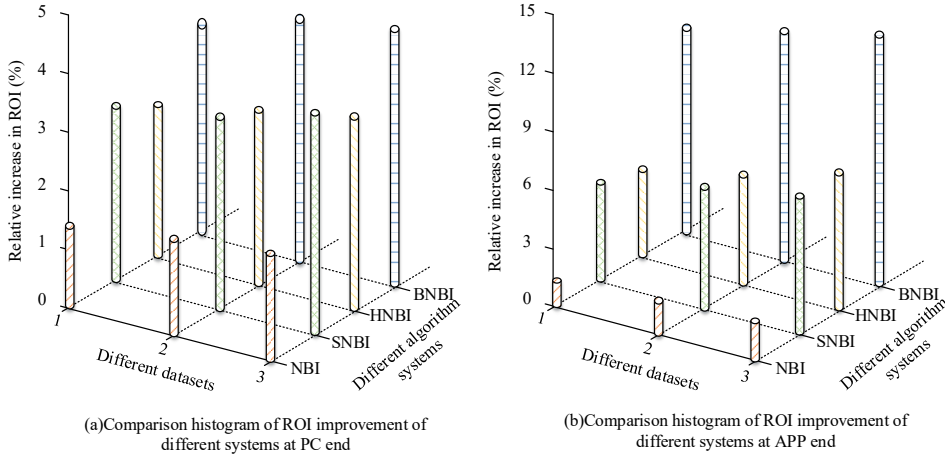


Figure 10. Comparison of Online ROI Growth Values for Different Models

Looking at Figure 10, the online ROI growth value of the BNBI recommendation system designed for the study was higher than the other three systems, both on the PC and the APP sides. Taking the average of the three sets of data, the online ROI growth value of BNBI recommendation system was 4.86% in PC, which was higher than that of NBI recommendation system (1.52%). This result indicated that in the PC side, the BNBI recommendation system had the best performance among the four different groups of systems. In the APP side, the online ROI growth value of BNBI recommendation system was 14.78%, which was 1.73% higher than NBI recommendation system. Combining these two results, the BNBI recommendation performance of the study design was indeed better than the other three recommendation system in the dimension of online ROI growth value. From the combined results of the three aspects of the comparison of the RHR, CTR and ROI growth values of the four systems, the BNBI recommendation system has the best performance among the four different systems.

5. Conclusion

The advent of the information explosion era has caused a big impact on recommendation system. Nowadays, recommendation system cannot give correct recommendations. To solve this problem, the study proposed to optimize the initial resources on the basis of the traditional NBI algorithm, so that the algorithm model was biased. The performance of this new algorithm was compared with the traditional NBI, HNBI and SNBI algorithms for experiments. The

results showed that the new BNBI algorithm outperformed the other three algorithms in the rating system with accuracy, recall, F1 index, diversity, and novelty of 24.5%, 6%, 0.168, 0.7637, and 815.81, respectively. This result indicated that the new NBI algorithm outperformed the traditional NBI algorithm. The study also verified the superiority of BNBI performance by comparing it with NBI, HNBI, and SNBI systems. The results showed that the RHR, CTR, and ROI growth rates of the BNBI system were 13.97%, 20.85%, and 14.78%, respectively, and the overall performance was better than that of the NBI, HNBI, and SNBI systems. The BNBI recommendation algorithm proposed in current research targeted a moderate dataset size. To increase the scale of its application dataset, optimization algorithms needed to be used to optimize its parameters to adapt to large-scale datasets. In addition, although the research designed system was superior to traditional recommendation system, the information mining in negative evaluations during resource allocation was not complete enough. How to fully mine the information in negative evaluations is the next research direction. Therefore, subsequent research needs to improve the depth of negative information mining in resource allocation and find appropriate optimization algorithms to optimize the proposed algorithm.

Acknowledgements: None.

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Received 20.07.2023, Accepted 02.12.2023