Research on the differentiation of residents’ cultural consumption tendency and consumption recommendation system based on network inference algorithm

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Abstract

In order to solve the problem of insufficient accuracy of consumer recommendation systems, the study proposes to design a new network inference algorithm with bias based on the traditional network inference algorithm. Then the performance of this algorithm is verified by means of comparison experiments with NBI, SNBI and HNBI algorithms. The results show that the new network inference algorithm has an accuracy rate of 24.5%, which is better than the traditional network inference algorithm. In terms of the constituted system performance test, the recommendation hit rate of the novel network inference algorithm increases by 13.97%, which is better than NBI, SNBI, and HNBI. The experimental results indicate that the novel network inference algorithm with bias can improve the performance of the consumer recommendation system, which provides a new idea for the performance improvement of the consumer recommendation system.

1 Introduction

As the problem of information overload becomes more and more serious, the role of recommendation systems in life is becoming more and more important (Liu Y et al. 2020) [1]. However, the performance of recommendation systems needs to be improved urgently because most of the existing recommendation systems use collaborative filtering and the accuracy of recommendation systems is not high (Zheng G et al. 2020) [2]. In recent years, network inference algorithms have started to become popular in the field of recommendation due to their higher accuracy compared to collaborative filtering techniques (Han X et al. 2021) [3]. Traditional network inference algorithms are also used in consumer recommendation systems, but even the performance of recommendation systems that apply traditional network inference algorithms does not reach the expected results (Fukushima A et al. 2018) [4]. To improve the accuracy of consumer recommender systems, it is of great value to explore a novel algorithm to be applied to recommender systems (Jayashree R et al. 2018) [5]. For the problem of low accuracy of traditional network inference algorithm, a novel network inference algorithm is proposed in the study. This novel network inference algorithm optimizes the initial resources on the traditional network inference algorithm and makes the whole model biased. And the algorithm is applied to the consumer recommendation system to design a new type of consumer recommendation system.

2 Related Works

With the rapid development of modern information technology, network inference algorithms have been applied in several fields because of their simplicity and efficiency. Trinh H C et al. proposed Boolean network inference algorithm for the problem of insufficient network structure and dynamics methods for inferring gene regulatory networks from steady-state gene expression data, which improves the accuracy of prediction models (Trinh H C et al. 2021) [6]. 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 (Zheng K et al. 2021) [7]. Ye J et al. proposed a subset structure fusion based on the problem of accurate topological inference in nonsmooth networks network topology inference method, and the analysis and simulation results show that the method improves the accuracy of topology inference in nonsmooth networks (Ye J et al. 2020) [8]. 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 IoMT systems that are prone to missing data. The results show that the method improves the performance of the IoMT system by 5% (Turabieh H et
al. 2020) [9]. Cho Y J et al. proposed a new distance-based inference model for camera networks for the problem of efficient re-identification of people, and the results show that the method can effectively re-identify people in large-scale camera networks with different transition times identification (Cho Y J et al. 2019) [10].

There are also countless approaches applied to consumer recommendation systems. There are problems in scalability and cold start. Xu H proposed a recommendation system based on user content consumption based on viewing time patterns and interest objects to address the lack of scalability of existing systems. The results showed that the method improved the recommendation hit rate of the recommendation system (Xu H 2018) [11]. Chen X et al. for the lack of personalized recommendation in O2O e-commerce model proposed a rule-based semantic reasoning method. Examples show that the method can easily and quickly implement personalized recommendations (Chen X et al. 2020) [12]. 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 recommendation system, and the experiments proved that the algorithm has a certain degree of optimization, which not only improves the check-all rate and error rate of, and also optimized memory utilization and search efficiency (Liu D et al. 2019) [13]. Kumar M R R B S For the problem of inability to select travel destinations among the information accessible on the Internet in travel recommendation systems, proposed to apply the C4.5 decision tree algorithm to travel recommendation systems, and the results showed 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 (Kumar M R R B S 2021) [14]. Wang D et al. addressed the problem of poor recommendation utility due to considering only the user’s viewpoint in the recommendation system. proposed the NBHXMAOEA similarity model for recommender systems. Numerous experimental results show that this model outperforms other models in terms of average accuracy, diversity, novelty, provider coverage and platform profit (Wang D et al. 2020) [15].

The above studies illustrate that network inference 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 network inference algorithms to consumer recommendation systems. Therefore, the study applies network inference algorithms to consumer recommendation systems to improve the problem of inaccurate recommendations of today’s consumer recommendation systems by embedding optimized network inference algorithms into consumer recommendation systems.

3 Research On The System Of Residents’ Consumption Tendency Based On Network Inference Algorithm

3.1 Optimization of network inference algorithms

Recommendation algorithms of network inference can be used in residential consumer recommendation systems because of their simplicity and efficiency, but traditional network inference algorithms are still deficient in resource allocation (Shi X et al. 2019) [16]. To address this problem, the study proposes a novel NBI (Biased NBI, BNBI) model for use in consumer recommendation systems. This model improves the rationality of resource flow in the network by mining more available information, which in turn improves the model performance. The specific resource flow process of the traditional network inference algorithm is shown in Fig. 1.
As can be seen from Fig. 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 process can be expressed in the form of a matrix, and the expression is shown in Eq. (1).

$$f' = Wf$$  \tag{1}$$f' = Wf$$

The resource flow matrix in Eq. (1) represents 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 and the set are represented by $x_1, x_2, \ldots x_n$ and $y_1, y_2, \ldots y_n$, respectively. The initial resource $f(x_i) \geq 0$ of the first node in the set in the set. The first step of the network inference algorithm is to flow all the resources owned by the set to the set, so that the resource $f(y_l)$ owned by the th node in the set is expressed as shown in Eq. (2).

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

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

$$a_{il} = \begin{cases} 1, & x_iy_l \in E \\ 0, & \text{otherwise} \end{cases}$$  \tag{3}$$a_{il} = \begin{cases} 1, & x_iy_l \in E \\ 0, & \text{otherwise} \end{cases}$$

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

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

In Eq. (4), $k(y_i)$ represents the degree of node $y_i$ and $a_{il}$ is an adjacency matrix of $n \times m$. $f'(x_i)$ The expression of Eq. (5) can be rewritten as Eq.

$$f'(x_i) = \sum_{j=1}^{n} w_{ij} f(x_j)$$  \tag{5}$$f'(x_i) = \sum_{j=1}^{n} w_{ij} f(x_j)$$
In Eq. (5), $w_{ij}$ represents the flow of resources between nodes $x_i$ and $x_j$ in the set. The expression is shown in Eq. (6).

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

In Eq. (6), $k(x_j)$ denotes the degree of node $x_j$ and $k(y_l)$ denotes the degree of node $y_l$. In the traditional NBI algorithm, the model construction is simple and straightforward, the computational complexity is low, and it has good generalizability (Tao J 2019) [17]. However, the traditional NBI algorithm suffers from the problem of serious negative evaluation loss. In the information filtering process, in addition to positive evaluations to uncover the user's hobby characteristics, negative evaluations are also important for analyzing the behavioral characteristics of users (Ivek I et al. 2021) [18]. 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 (Geukens F et al. 2022) [19]. 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. To solve the problem of losing negative evaluations in traditional network inference 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 BNBI model. This does not affect the process of 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, the initial resource allocation $f^j_i$ expression is shown in Eq. (7).

$$f^j_i = a_{ij}f(\phi)$$

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

$$\phi = \sum_{k=1}^{K_j} Sim_{ik}$$

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

$$f(\phi) = t^\phi (0 < t < 1)$$
In summary, all items collected by the user 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, expressions are shown in Eq. (10).

\[ f^j_i = a_{ij} f(\phi) k^\alpha (o_i) \]

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 Fig. 2.

As can be seen from Fig. 2, compared to the traditional NBI algorithm, the BNBI algorithm incorporates an optimization step for the initial resources, and the optimized initial resources are fed backward, which can improve the performance of the model. It is also necessary to study the application of the model in non-rated systems because they are often found in daily life. In non-rated systems, users’ interests are generally less intuitive to see and need to be derived from the analysis of users’ browsing and clicking behaviors (Saba W E et al. 2021) [20]. However, non-rating systems generally represent users’ behaviors that are stable over time and are more representative of their true preferences. Since items with negative ratings cannot be accurately identified in non-rating systems, while items that are particularly liked are easily identified. Therefore, the study uses item similarity to enhance the amount of resources for items with similar user liking items, so that the recommendation list into which these item items enter can be optimized for the final amount of resources. In the non-rating system, the user’s preferences are expressed through the user’s usual browsing, etc. Therefore, it is important to determine the threshold value of the user’s favorite items, and the expression of is shown in Eq. (11).

\[ T = \mu - \tau \ast \sigma \]

In Eq. (11), \( \mu \) denotes the average number of user views, \( \sigma \) denotes the standard variance of the number of user views, and \( \tau \) denotes the variable weights. The flowchart of BNBI algorithm implementation in the non-rating system is shown in Fig. 3.

In the BNBI algorithm in a non-rated system, for a given user, the final resource \( f^j_i \) is defined as shown in Eq. (12).

\[ f^j_i = f^j_i \ast f(\phi) \]

In Eq. (12), \( f(\phi) \) is the reinforcement function and \( \phi \) is defined as shown in Eq. (13).

\[ \phi = \sum_{k=1}^{K_j} Sim_{ik} \]
In Eq. (13), $K_j$ represents the number of items rated by the user, represents the similarity between items $Sim_{ik}$ and items, and $\phi$ represents the sum of similarities between items and items rated by the user. The exponential function is chosen as the strengthening function and the expression of $f(\phi)$ is shown in Eq. (14).

$$f(\phi) = t^\phi$$

The algorithm is similar to the content-based filtering approach, but the difference between the two is that even if an item is extremely similar to an item that a user likes, but too few resources are acquired in the BNBI algorithm process, the item still does not make it to the recommendation list.

### 3.2 Construction of residential consumption recommendation system based on network inference algorithm

Most of today's consumer recommender systems are not very accurate. In order to enhance the performance of residential consumer recommendation systems, the study builds a novel consumer recommendation system by embedding a network inference algorithm with paranoia into the consumer recommendation system. The specific structure of the novel consumer recommendation system is shown in Fig. 4.

As shown in Fig. 4, the whole consumer recommendation system 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 network inference algorithm for calculation; the BNBI recommendation algorithm mainly calculates the model and then outputs the final recommended items. The specific operation process 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 recommendation algorithm, and the BNBI recommendation algorithm calculates and outputs the recommended items required by the user. In order to test and compare the performance of the models designed in the study, different evaluation metrics will be used in the comparison experiments. The study will choose common metrics accuracy, recall and F1 metrics to test the performance of different models. Among them, the accuracy and recall represent the reliability of the recommendation, and the accuracy calculation formula is shown in Eq. (15).

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

In Eq. (15), $l_i(L)$ 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 formula for calculating the recall is shown in Eq. (16).

$$R(L) = \frac{1}{m} \sum_{i=1}^{m} \frac{l_i(L)}{Y}$$
The number of items in the test set collected by the user is denoted by in Eq. (16). F1 metrics can provide a more comprehensive evaluation of the model performance comparison. F1 metrics expression is shown in Eq. (17).

\[
F1(L) = \frac{2P(L) \times R(L)}{P(L) + R(L)}
\]

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 Eq. (18).

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

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

\[
N(L) = \frac{1}{mL} \sum_{i=1}^{m} \sum_{l=1}^{L} k(o_l)
\]

In Eq. (19), \(k(o_l)\) indicates the degree of the item \(o_l\). Among the above five evaluation metrics, larger values of accuracy, recall, F1 metric and diversity indicate better performance. Novelty, on the other hand, has a higher value indicating a worse performance.

4 Algorithm Performance Parameters And Model Results Analysis

4.1 Performance Comparison of Network Inference Algorithms

To compare the performance of the network inference algorithms, the study was tested on the Movie Lens dataset, a rating system, and the Last.FM dataset, a non-rating system, respectively. The accuracy, recall, F1 metrics, diversity, and novelty of the four inference algorithms were compared, respectively. Among them, the accuracy results of the four inference algorithms in the two types of datasets are shown in Fig. 5.

As can be seen from Fig. 5, the accuracy of the four algorithms in both datasets tends to decrease as the length of the recommendation list \(L\) increases. In the rating system Movie Lens, it is obvious that the accuracy of BNBI algorithm is higher than the other three algorithms, with the highest accuracy of 0.245. In the non-rating system Last.FM, the accuracy of BNBI algorithm is also higher than the other three algorithms, with the highest accuracy of 0.128. In summary, in terms of accuracy dimension, both in the rating system and in the non-rating system, the BNBI algorithm performs better than the other three algorithms. The recall results of the four inference algorithms in the two types of data sets are shown in Fig. 6.
It is obvious from Fig. 6 that the recall of all four algorithms in both Movie Lens dataset and Last.FM dataset tends to increase with the growth of the recommendation list length L. In the rating system Movie Lens, the NBI algorithm has the highest recall rate and the BNBI algorithm has the lowest recall rate of 0.06. This indicates that BNBI has the best performance in the Movie Lens dataset. In the non-rating system Last.FM, the recall rate of BNBI algorithm is also lower than the other three algorithms, with the lowest recall rate of 0.173. In summary, the BNBI algorithm outperforms the other three algorithms in both the rating and non-rating systems in terms of recall rate dimension. The F1 values of the four algorithms in the Movie Lens dataset and the Last.FM dataset are shown in Fig. 7.

As can be seen from Fig. 7, the F1 values of the four algorithms in the Movie Lens dataset show a decreasing trend with the growth of the recommendation list length L. The F1 value of the BNBI algorithm is significantly higher than the other three algorithms, with the highest value of 0.168, indicating that the BNBI algorithm has the best performance in the Movie Lens dataset. The F1 values of the four algorithms in the Last.FM dataset show a trend of increasing and then decreasing with the increase of L, and there is a maximum value when L is 40. The F1 values of the BNBI algorithm are higher than those of the other three algorithms regardless of the value of L. Among them, the BNBI algorithm has the maximum value of F1 at L of 40, which is 0.178. This result indicates that the BNBI algorithm outperforms the other three algorithms in the Last.FM dataset. In summary, in terms of the F1 value dimension, the BNBI algorithm has 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>
<thead>
<tr>
<th>Diversity</th>
<th>NBI Movielens</th>
<th>NBI Last.FM</th>
<th>HNBI Movielens</th>
<th>HNBI Last.FM</th>
<th>BNBI Movielens</th>
<th>BNBI Last.FM</th>
<th>SNBI Movielens</th>
<th>SNBI Last.FM</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.7321</td>
<td>0.8321</td>
<td>0.7412</td>
<td>0.8528</td>
<td>0.7637</td>
<td>0.8768</td>
<td>0.7528</td>
<td>0.8635</td>
</tr>
<tr>
<td>20</td>
<td>0.6812</td>
<td>0.7925</td>
<td>0.7135</td>
<td>0.8178</td>
<td>0.7421</td>
<td>0.8439</td>
<td>0.7367</td>
<td>0.8317</td>
</tr>
<tr>
<td>30</td>
<td>0.6537</td>
<td>0.7725</td>
<td>0.6987</td>
<td>0.7836</td>
<td>0.7139</td>
<td>0.8232</td>
<td>0.7025</td>
<td>0.8012</td>
</tr>
<tr>
<td>40</td>
<td>0.6378</td>
<td>0.7512</td>
<td>0.6759</td>
<td>0.7698</td>
<td>0.6922</td>
<td>0.8102</td>
<td>0.6811</td>
<td>0.7807</td>
</tr>
<tr>
<td>50</td>
<td>0.6117</td>
<td>0.7433</td>
<td>0.6537</td>
<td>0.7567</td>
<td>0.6817</td>
<td>0.7938</td>
<td>0.6635</td>
<td>0.7675</td>
</tr>
<tr>
<td>60</td>
<td>0.5978</td>
<td>0.7277</td>
<td>0.6421</td>
<td>0.7328</td>
<td>0.6634</td>
<td>0.7728</td>
<td>0.6513</td>
<td>0.7469</td>
</tr>
<tr>
<td>70</td>
<td>0.5765</td>
<td>0.7156</td>
<td>0.6278</td>
<td>0.7234</td>
<td>0.6436</td>
<td>0.7618</td>
<td>0.6378</td>
<td>0.7311</td>
</tr>
</tbody>
</table>

From the data in Table 1, it can be seen that in the Movie Lens dataset, the diversity of all four algorithms decreases as the length of the recommendation list L increases; among the four algorithms, the BNBI algorithm has the highest diversity of 0.7637. This indicates that BNBI has the best performance in the Movie Lens dataset. In the non-rating system Last.FM dataset, the diversity of BNBI algorithm is also higher than that of NBI algorithm, HNBI algorithm and SNBI algorithm, and the highest diversity of BNBI algorithm is 0.8768. In summary, in terms of diversity dimension, BNBI algorithm outperforms both Movie Lens dataset and Last.FM dataset. NBI
algorithm, HNBI algorithm, and SNBI algorithm. The novelty values of the four algorithms in the Movie Lens dataset and the Last.FM dataset are shown in Table 2.

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

From the data in Table 2, it can be obtained that in the Movie Lens dataset, the novelty of the four algorithms tends to decrease as the length of the recommendation list L increases; the BNBI algorithm has the lowest novelty among the four algorithms, with a value of 815.81. This result indicates that BNBI has the best performance in the Movie Lens dataset. In the non-rated system Last.FM dataset, the novelty of BNBI algorithm is lower than the other three algorithms, with a value of 93.58. In summary, from the novelty dimension, the BNBI algorithm outperforms 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, it can be concluded that the performance of the BNBI algorithm is significantly better than the traditional NBI algorithm as well as the HNBI algorithm and SNBI algorithm through the improved BNBI algorithm, which has better recommendation results.

### 4.2 Comparison of the results of residential consumption recommendation system

After the consumer recommendation system 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, and 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. Different models of the consumer recommendation system 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. (ROI) to compare the performance of each consumer recommendation system. The graphs of the recommendation hit rate results for the four systems in the experimental dataset are shown in Fig. 8.

From the four line graphs in Fig. 8, we can see that the growth of recommendation hit rate of all four systems in APP is higher than the growth of recommendation hit rate in PC. Taking the average of the recommendation hit rate growth values in the four data sets, the results show that the highest recommendation hit rate growth
among the four systems in the APP side is the BNBI system with 13.97% growth in recommendation hit rate, and the lowest recommendation hit rate growth is the NBI system with 10.82% growth in recommendation hit rate. This result shows that the performance of BNBI system is much higher than the performance of traditional NBI system in APP side. In the PC side, the highest growth of recommendation hit rate among the four systems is the research-designed BNBI system, with 9.27% growth of recommendation hit rate; the lowest growth of recommendation hit rate is the NBI system, with 6.13% growth of recommendation hit rate. This result shows that the performance of BNBI system is also better than the performance of traditional NBI system in APP side. Combining these two results, the performance of BNBI system is better than the other three systems in terms of the growth value of the recommended hit rate. The graphs of the click-through rate results of the four systems in the experimental dataset are shown in Fig. 9.

From the four sets of line graphs in Fig. 9, it is obvious that the growth rate of online click-through rate of all four systems in APP is higher than that of online click-through rate in PC. The average of the online click-through growth rate of the four systems in the four data sets was taken for comparison. The results show that the highest growth rate of online click-through rate among the four systems in the APP side is the BNBI system designed by the study, with a growth rate of 20.85%; the lowest growth rate of online click-through rate is the NBI system, with a growth rate of 8.34%. This result shows that the performance of BNBI system is much higher than that of traditional NBI system in the APP side. In the PC side, the highest growth of online click-through rate among the four systems is the research-designed BNBI system with 11.34% growth of online click-through rate; the lowest growth of online click-through rate is the NBI system with 4.51% growth of online click-through rate. This result shows that the performance of BNBI system is also better than that of traditional NBI system in APP side. Combining these two results, the BNBI system outperforms the other three systems in terms of the growth value of online click-through rate. The results of online ROI, another metric of the four systems in the experimental dataset, are shown in Fig. 10.

Looking at Fig. 10, it is clear that the online ROI growth value of the BNBI recommendation system designed for the study is higher than the other three systems, both on the PC and the APP side. Taking the average of the three sets of data, it can be analyzed that the online ROI growth value of BNBI recommendation system is 4.86% in PC, which is higher than that of NBI recommendation system (1.52%). This result indicates that in the PC side, the BNBI recommendation system has the best performance among the four different groups of systems. In the APP side, the online ROI growth value of BNBI recommendation system is 14.78%, which is much higher than the 1.73% of NBI recommendation system. Combining these two results, it can be analyzed that the BNBI recommendation performance of the study design is indeed better than the other three recommendation systems in terms of the dimension of online ROI growth value. From the combined results of the three aspects of the comparison of the recommendation hit rate growth value, click-through rate growth value, and ROI growth value of the four systems, it can be concluded that 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 systems. Nowadays, recommendation systems cannot give correct recommendations. To solve this problem, the study proposes to optimize the initial resources on the basis of the traditional network inference algorithm so that the algorithm model is biased. The performance of this new algorithm is compared with the traditional NBI algorithm, HNBI
algorithm and SNBI algorithm for experiments. The results show that the new BNBI algorithm outperforms 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 indicates that the new network inference algorithm outperforms the traditional network inference algorithm. The study also verified the superiority of BNBI performance by comparing it with NBI, HNBI, and SNBI systems. The results show that the recommendation hit growth rate, click-through growth rate, and return-on-investment growth rate of the BNBI system are 13.97%, 20.85%, and 14.78%, respectively, and the overall performance is better than that of the NBI, HNBI, and SNBI systems. Although the system designed by the study is better than the traditional recommendation system, the information mining in the negative evaluation in the resource allocation process is not complete, and how to completely mine the information in the negative evaluation is the next research direction.

**Declarations**

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**Contribution of individual authors:**

Naiyu Lian: conception and design of the manuscript and interpretation of data, literature searches and analyses, clinical evaluations, manuscript preparation and writing the paper;

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Comparison of online ROI growth values for different models