Research on User Influence Weighted Scoring Algorithm Incorporating Incentive Mechanism

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Abstract. Overall product ratings are an important basis for users when shopping online or using online services. However, some sellers and web service providers put a large amount of false rating data into the rating system to improve their own rankings, which seriously damages the interests of users. In this paper, two methods are used to reduce the impact of false ratings on overall ratings. First, a user influence weighted scoring algorithm is proposed to analyze user behavior and build a user influence model. The influence of different users on the rating is considered when calculating the overall rating to improve the accuracy of the project's overall rating. Secondly, a blockchain-based rating incentive mechanism is designed to correlate users' rating behavior with their interests, effectively constraining their rating behavior and making them consciously and proactively provide more authentic ratings. Simulations comparing the proposed algorithm with the rating algorithms used on Douban and IMDB show that the algorithm performs best in terms of resistance to interference. The experimental results also show that the rating incentive mechanism can reward high-impact users and punish low-impact malicious users, and can effectively defend against malicious users.

Keywords: User influence model, Weighted scoring algorithm, Incentive mechanism, Blockchain.

1 Introduction

In recent years, a series of online services represented by online shopping, online movie viewing, and online reading has risen rapidly. When users use online websites or mobile apps, they will take the comprehensive score of goods or virtual services as an important basis [1]. According to the survey data of Jupiter Research, an American market research company, 77% of Internet users will refer to product reviews written by other people on the Internet before purchasing a product [2]. Online ratings are a form of credit guarantee that emerged at the beginning of the construction of Internet platforms [3]. The establishment of a rating mechanism not only proves the commercial value of the information but is also an important means to overcome the "lemon puzzle" [4]. However, some sellers and online service providers are putting a lot of untrue rating data into the rating system in order to improve the rating and ranking of their products. This seriously harms the interests of users and other merchants.The lack of constraints has led to a serious decline in the accuracy and authenticity of rating data on virtual service sites and e-commerce sites. The issue of trust in the Internet is one of the most important issues that need to be urgently addressed for the continued healthy development of online services today.

Currently, major websites with evaluation needs have established their own set of evaluation systems to provide online reviews and rating functions [5]. Douban uses a simple weighted rating algorithm where the weight is a percentage of the number of users rating the site; the rating algorithm used in the IMDB TOP250 is a Bayesian statistical algorithm. To a certain extent, it has alleviated the credit crisis of online transactions and increased the confidence of users in online transactions [6]. However, there are still some problems with the current scoring algorithms and evaluation rules. It lacks a mechanism to discern whether users' ratings are genuine and objective. It also does not take into account the impact that different users have on the overall rating.It is not possible to effectively constrain user behavior and motivate users to make realistic evaluations. Therefore, it is necessary to construct a user influence model by analyzing users' evaluation behavior. The influence of the different users is used as a weight in the weighting algorithm when calculating the overall rating.

Improving the overall accuracy and authenticity of ratings requires not only a weighting algorithm, but also an effective rating incentive mechanism.Current traditional scoring incentives are based on the system giving users tokens or financial rewards when they rate a project. To a certain extent, this incentive policy has served to encourage users to rate. However, due to the drawback of its undifferentiated rewards, it also brings a large number of low-quality ratings to the rating system. As blockchain technology continues to mature, blockchain incentives are also widely used in privacy protection [7-10], data sharing [11-14], and supply chains [15-18]. The characteristics of blockchain technology, such as non-tamperability and openness and transparency, can guarantee the reliability of the scoring incentive mechanism.

To solve the above problems, the following research and work are carried out in this paper.(1) Constructing a user influence model, analyzing the characteristics of user evaluation behavior in four aspects: authenticity, objectivity, honesty, and user participation enthusiasm of user ratings. And using the Analytic Hierarchy Process to select appropriate weights for these four factors. (2) A user influence weighted evaluation algorithm is proposed to calculate the comprehensive rating taking into account the influence of different users on the rating. It effectively solves the problem of malicious users injecting a large amount of false evaluation information and improves the accuracy of the comprehensive rating of the project.(3) Propose a rating incentive mechanism to closely link the quality of users' ratings with their interests. Effectively restrain users' rating behaviour, guide users to consciously and actively maintain the network ecological environment of the rating system and improve the authenticity of comprehensive project ratings.

2 User Influence Model

By analyzing the characteristics of user rating behavior, the influence of users is modeled in terms of four factors: authenticity, objectivity, honesty, and active participation of users. The weights of these four factors were determined using the AHP (Ana-lytic Hierarchy Process). This is used to distinguish between users who are more influential in the overall rating of the project and those who are less influential. Table 1 summarises commonly used parameters in the algorithm.

Table 1. Important parameters and meanings in the algorithm.

Variables	Implication
U	The set of users involved in the evaluation, $U_i \in U$
S	The set of categories of evaluation items, $S_j \in S$
$P(U_i, S_j)$	Degree of preference of user U_i for items of category S_j
N_i	Total number of times user U_i has reviewed all items
$N(U_i, S_j)$	Number of times user U_i has evaluated category S_j items
$M_{i,j}$	Average rating of items in category S_j by user U_i
M_i	Average rating of all items by user U_i
$M_{i,a}$	Average rating of user U_i for the item with the highest type of preference
M_a	Average rating of all users of this item
$M_{i,b}$	Average rating of user U_i for the item with the lowest type of preference
M_b	Average rating of all users of this item

2.1 Authenticity of user ratings

There are differences in user preferences for different types of projects, and this difference is reflected in the user ratings for different types of projects. The authenticity of users' ratings of items has a direct impact on the authenticity of the overall item ratings. The degree of truthfulness of user ratings is indicated by calculating the dispersion of user ratings for different types of items. If a user's scores for different types of items are relatively concentrated, it means that the user's scores for all items are relatively single, and the range of score changes is relatively small. Whether or not they like the item, the ratings are relatively close. In this case, the ratings of users of this type are less informative. In contrast, if a user's ratings vary significantly between the different types of items, they are based on their preferences and the real situation of the items. These user ratings are of high reference value to other users who have not used the item. The authenticity of the rating of user U_i is denoted as $F(U_i)$, which is calculated by the formula (1).

$$F(U_i) = \frac{\sum_{j \in S} \left(M_{i,j} - M_i\right)^2}{|S|} \tag{1}$$

2.2 Objectivity of user ratings

Some users rate items more subjectively, and some users rate items more objectively. User ratings with more objective ratings are more valuable for reference. Therefore, the objectiveness index is used to measure whether the user's rating of the item is objective. To evaluate the objectivity of user ratings, users' preferences for various types of items should be considered. By calculating the number of user evaluations for different types of items, users' preferences can be more intuitively understood. A user preference calculation formula is introduced to show a user's preference for different types of items, and the preference degree of user U_i for items of category S_j can be calculated by the formula (2). If the average rating of the user for the item with the highest type of preference and the item with the lowest type of preference is closer to the average rating scored by all users of the item, it means that the user's rating is more accurate and objective. The user's rating has a higher reference value. The objectivity of the user's rating is noted as $C(U_i)$, which is calculated by the formula (3).

$$P\left(U_i, S_j\right) = \frac{N\left(U_i, S_j\right)}{\left|N_i\right|} \tag{2}$$

$$C\left(U_i\right) = \frac{1}{\ln\left(\frac{\sqrt{\left(M_{i,a} - M_a\right)^2 + \left(M_{i,b} - M_b\right)^2}}{2} + 2\right)} \tag{3}$$

2.3 Honesty of user ratings

The honesty of user ratings is calculated based on the user's last eight rating behaviors. The design of the honesty vector draws on the P2P credit vector mechanism proposed by A.A.Selcuk, E.Uzun, etc. [19]. The integrity vector is represented as an eight-bit binary vector of integrity from left to right, depending on the order in which the evaluation actions occur. The initial value of the eight bits is 0. This design can pay more attention to the user's recent rating behavior. Set a threshold for extreme evaluations, and determine whether the number of users who rated the item accounts for less than 30% of the total number of users who rated the item. If it is less than 30%, it is judged as a malicious evaluation. The non-malicious evaluation behavior is recorded as 1, and the malicious evaluation behavior is recorded as 0. After a non-malicious evaluation by the user, the leftmost binary bit is marked as 1. The honest vector is updated as shown in Figure 1. The flag bit represents the subscript of the user's first recorded evaluation.

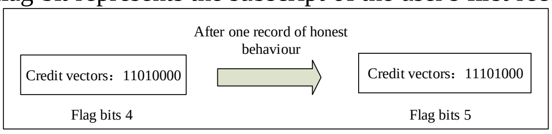


Fig. 1. Update of the credit vector after one honest act by the user

m is the sign bit. Converts the honest vector from the first m binary digits of the left digit to decimal, denoted by the parameter $(\gamma)_2$. The converted decimal number is used as the numerator and 2^m as the denominator. The two are divided to obtain a number in the range [0,1), which is the user's honesty coefficient. The honesty of the user's rating is written as $H(U_i)$ and is calculated by the formula (4).

$$H(U_i) = \frac{(\gamma)_2}{2^m} \tag{4}$$

2.4 Active participation of user ratings

Actually, some users are more active and willing to express their opinions and feelings about projects. And others who rarely or hardly ever evaluate the project, these users tend to have low engagement motivation and gradually lose the trust of other users. User participation enthusiasm is considered from two aspects: the total number of user evaluations of all items and the number of user evaluation item types. Suppose user A has watched 50 movies of the same type, and user B has watched 5 different types of movies, 10 of each type. At this time, only considering the total number of user evaluations cannot distinguish the user's participation enthusiasm. The user's participation enthusiasm is recorded as $I(U_i)$, and it is calculated by the formula (5).

$$I(U_i) = 1 - \frac{1}{\ln\left(\sum_{j \in S} |S| \times N(U_i, S_j)\right)} \tag{5}$$

2.5 User influence

The user influence is composed of the above four factors, i.e. the authenticity, objectivity, honesty, and active participation of the user's rating, which is denoted as $T(U_i)$ and calculated by the formula (6). The value of λ has the property as in formula (7).

$$T(U_i) = \lambda_1 F(U_i) + \lambda_2 C(U_i) + \lambda_3 H(U_i) + \lambda_4 I(U_i) \tag{6}$$

$$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1 \tag{7}$$

Use AHP to obtain the weight λ. Firstly, a hierarchical structure model is established, with the target level being user influence, represented by A1. The four criteria of the criterion layer are the authenticity of user rating B1, the objectivity of user rating B2, the honesty of user rating B3, and the active participation of user B4. The method of constructing the judgment matrix in AHP is the consensus matrix method. Make a pairwise comparison of each scheme under a certain criterion and rate it according to the degree of importance. The pairwise comparison matrix P between the criterion layer and the target layer is constructed by pairwise comparison, as shown in the formula (8).

$$P = \begin{bmatrix} 1 & 3 & 5 & 4 \\ \frac{1}{3} & 1 & 5 & 4 \\ \frac{1}{5} & \frac{1}{5} & 1 & 2 \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{2} & 1 \end{bmatrix} \tag{8}$$

Because the construction of the judgment matrix is greatly affected by subjective factors, it is necessary to check the consistency of the calculation results [20]. Among them, the random consistency index *RI* is related to the order of the judgment matrix. The larger the order of the matrix, the greater the possibility of random deviation of consistency [21]. The corresponding index *RI* of the fourth-order matrix is 0.9. Considering that deviations from consistency may be due to random reasons, it is also necessary to compare the *CI* with the random consistency indicator *RI* when testing whether the judgment matrix has satisfactory consistency, to derive the test coefficient *CR*, as in the formula (9).

$$CR = \frac{CI}{RI} \tag{9}$$

When the consistency ratio $CR<0.1$, the judgment matrix passes the consistency test. The maximum characteristic root λ_{max} of the judgment matrix and its corresponding eigenvector were solved by the arithmetic mean method and judged for consistency. The eigenvector was normalized and noted as W_1. Matrix P: $\lambda_{max}=4.261$, $W_1=(0.5231,0.3003,0.0984,0.0782)$, $CI=0.0872$, calculated as $CR=0.0968< 0.10$, and the consistency test passed. Therefore, the judgment matrix constructed is considered reasonable and feasible. The weights corresponding to the four influencing factors of the user influence model were calculated as shown in Table 2 below.

Table 2. The corresponding weights of the four factors that affect the user's credit.

Influencing factors	Authenticity of user ratings	Objectivity of user ratings	Accuracy of user ratings	Active participation of user ratings
Weighting	0.508	0.303	0.106	0.083

The user influence calculation is therefore communicated as shown in formula (10).

$$T(U_i) = 0.508F(U_i) + 0.303C(U_i) + 0.106H(U_i) + 0.083I(U_i) \tag{10}$$

3 User influence weighting algorithm

To minimize the impact of malicious users on the overall rating, this paper proposes a user influence weighted scoring algorithm. The design of the weighting in terms of user influence is intended to prevent users with lower quality ratings from having a disproportionate impact on the ratings. The numerator of the formula is the sum of the product of the users' ratings and their influence, and the denominator is the sum of each user's influence. The final settlement score for the tth cycle is denoted as W_t, which represents the overall rating of *n* users for the item at moment *t*, as in formula (11). $T(i)$ is the influence of user *i*, G_i is the rating of the item by user *i*.

$$W_t = \frac{\sum_{i=1}^{n} T(i) \times G_i}{\sum_{i=1}^{n} T(i)} \tag{11}$$

The rating cycle begins with the user rating the item. After a user submits a rating, the rating cannot be modified and the rating cycle ends. At the end of a rating cycle, the settlement of this period begins. Analyze the user's rating behavior, and update the user's influence according to the user's influence calculation formula. The blockchain issues corresponding rewards to users according to their influence. According to the updated user influence, the item score is updated through the influence weighted rating algorithm, and the next rating cycle begins.

4 Ratings incentive mechanism

To constrain user behavior, this paper proposes a differentiated rating incentive mechanism based on blockchain. Unlike traditional centralized rating systems, blockchain technology is immutable, open and transparent, making the distribution of scoring rewards more credible. Each user is associated with a unique Ethereum account address, and the smart contract issues token rewards to users at intervals of each rating cycle. The total amount of rewards issued by the blockchain to users in a cycle consists of two parts: each rating user pays an admission fee of 5 tokens to the blockchain prize pool; the blockchain provides the same number of tokens as the total entry fee paid by all participating scoring users in a cycle.

The advantage of this design is that the number of ratings in a rating cycle is proportional to the total amount of rewards issued by the blockchain, saving the overhead of the rating system. The number of rewards issued by the blockchain to users is determined by the proportion of user influence to the total influence of rated users. Users with large influence will receive higher rewards than paying the admission fee. And users with low influence will have a portion of the admission fee confiscated. The reward obtained by user U_i is shown in the formula (12). R_i denotes the number of rewards received by user U_i in a cycle, $T(i)$ is the influence of user i, and n denotes the number of users participating in rating in a cycle. The total amount of rewards issued by the blockchain to users consists of an entrance fee of 5 tokens paid by each user and an equal amount of tokens provided by the system, which is 10n in total.

$$R_i = \frac{T(i)}{\sum_{i=1}^{n} T(i)} \times 10n \tag{12}$$

5 Experiments and Analysis

To verify the validity and universality of the user influence weighting algorithm and the blockchain rating incentive mechanism proposed in this paper. This section designs relevant experiments based on the algorithms proposed in the previous section.

5.1 Experimental Environment

The experiment selects the public dataset MovieLens 1M, which contains 1,000,209 ratings of 3,900 movies by 6,040 users, with a score ranging from 1 to 5, and also includes movie genre information. The dataset required for this paper is constructed in the following ways: (1) filter out the movie with the largest number of ratings (2) calculate the number of ratings owned by all users who rated the movie and filter out the 100 users with the largest number of ratings. (3) Traverse the database and filter out all the movies reviewed by these 100 users. The filtered normal user data set contains 101,559 ratings of 3,462 movies by 100 users.

5.2 Experimental Protocols

The performance of the influence weighted scoring algorithm in real scenarios is tested by gradually adding abnormal users among normal users. The following typical non-normal users were added to give an initial insight into the resistance of the rating algorithm to interference. Add 5 to 50 abnormal users to the data in 10 times, and divide the data into 11 groups. The non-normal users are divided into three categories: (1) Rated 2 for all movies (2) Rated 10 for all movies (3) Rated only one type of movie with a score of 2. Take ten types of movies, the one with the largest number of ratings for each type, and the arithmetic average of the comprehensive scores of ten movies in total, and compare them with the evaluation algorithms of mainstream websites (take Douban movie scoring algorithm and IMDB TOP250 movie scoring algorithm as examples). Compare the experiment and analyze the trend of score change. Douban movie scoring algorithm is calculated according to formula (13).

$$W = \sum_{i=1}^{10} N_i \times i \tag{13}$$

Where i denotes the different scores given to the film from 1 star to 5 stars (the number of stars correspondingly multiplied by 2 to convert to a ten-point scale), and N_i denotes the percentage of people who scored i out of the total number of people who scored the film. The scoring algorithm used in the IMDB TOP250 is the Bayesian statistical algorithm, with the formula (14).

$$W = \frac{V}{V+m} \times R + \frac{m}{V+m} \times C \tag{14}$$

R is the arithmetic mean score of the movie. V is the total number of people who reviewed the movie. m is the minimum number of reviews needed to enter the IMDB Top 250. C is the arithmetic mean score of all movies so far.

5.3 Analysis of experimental results

Ratings immunity test results and analysis

(1) Add 5 to 50 users who rated all movies as 2 to the data in 10 steps, and divide the data into 11 groups. The movie scores calculated by different rating algorithms in 11 groups of experiments are shown in Table 3 below, and the trend of movie scores is shown in Fig.2(a). The experimental data shows that before adding non-normal users, the movie scores calculated by the influence weighting algorithm were similar to those calculated by the Douban rating algorithm, with a difference of only 0.015. It shows that the movie score calculated by the influence weighting algorithm is almost equal to

the score calculated by the current mainstream movie scoring websites, and has a certain authority. After adding non-normal users to the group, the movie score calculated by the influence weighted algorithm decreased from 8.29 at the beginning to 7.702, a drop of only 0.588. While the score calculated by the Douban algorithm decreased by 2.375 and the IMDB algorithm decreased most significantly, with a 2.414 decrease. From Fig.2(a), it can be seen that the influence weighted scoring algorithm (red line) has a gentle downward trend with the increase in the number of non-normal users. While the downward trend of the Douban scoring algorithm (black line) and the IMDB scoring algorithm (blue line) is steeper. This shows that the influence weighted scoring algorithm has better anti-interference characteristics than the Douban scoring algorithm and the IMDB scoring algorithm. The calculated score is more realistic.

Table 3. Experiment 1 Movie Scoring Score.

Data sets	1	2	3	4	5	6	7	8	9	10	11
Proposed	8.290	8.241	8.185	8.128	8.069	8.006	7.943	7.882	7.812	7.761	7.702
Douban	8.305	7.943	7.619	7.331	7.070	6.837	6.622	6.428	6.247	6.085	5.930
IMDB	7.550	7.059	6.678	6.369	6.112	5.895	5.704	5.539	5.390	5.258	5.136

(2) Add 5 to 50 users who rated all movies as 10 to the data in 10 steps. The movie scores calculated by different scoring algorithms are shown in Table 4 below. The trend of movie scores is as follows shown in Fig.2(b). The experimental data shows that the movie score calculated by the influence weighting algorithm increased from 8.29 at the beginning to 8.49 after adding non-normal users to the group, which only increased by 0.2. While the score calculated by the Douban scoring algorithm increased by 0.693. The IMDB scoring algorithm changed most significantly, with a 1.372 increase in score. As can be seen from Fig.2(b), the influence weighted scoring algorithm (red line) has a significantly slower score increase trend than the Douban scoring algorithm (black line) and the IMDB scoring algorithm (blue line) as the number of abnormal users increases. This shows that the increase in the proportion of non-normal users has the least impact on the influence weighted scoring algorithm.

Table 4. Experiment 2 Movie Scoring Score.

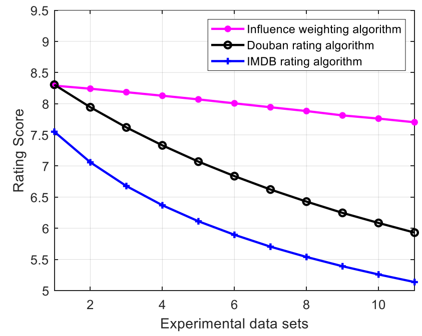
Data sets	1	2	3	4	5	6	7	8	9	10	11
Proposed	8.290	8.314	8.333	8.354	8.372	8.394	8.413	8.432	8.452	8.470	8.490
Douban	8.305	8.420	8.518	8.603	8.680	8.748	8.807	8.862	8.913	8.958	8.998
IMDB	7.550	7.920	8.087	8.266	8.414	8.535	8.635	8.723	8.798	8.862	8.922

(3) Add 5 to 50 users who only rated one type of movie to the data in 10 steps, and the score is 2 points. The movie scores calculated by different scoring algorithms are shown in Table 5 below, and the trend of movie scores is shown in Fig.2(c). The experimental results show that the influence weighted scoring algorithm reduces the score from 8.29 to 7.742, only 0.53, with the increase in the proportion of non-normal users. While the Douban scoring algorithm and the IMDB scoring algorithm decreased by 1.375 and 1.506, respectively. As shown in Fig.2(c), when the number of non-normal users gradually increases, the influence weighted scoring algorithm (red line) has the most gentle

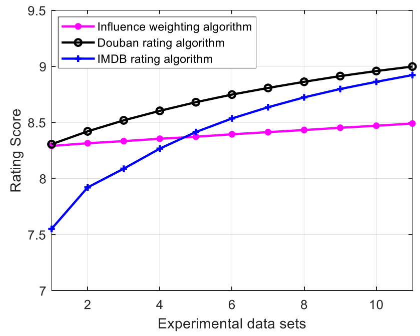
decreasing trend and the strongest anti-interference. The three different scoring algorithms in the three experiments with the increase of the proportion of non-normal users and the comparison of score changes are shown in Fig.2(d). The influence weighted scoring algorithm (blue) showed the least change in score.

Table 5. Experiment 3 Movie Scoring Score.

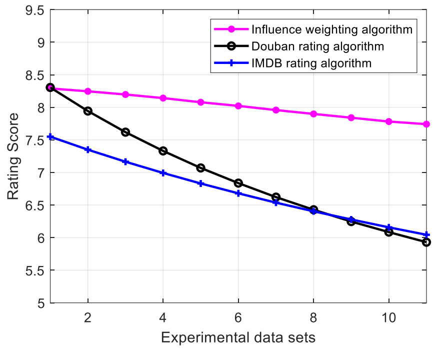
Data sets	1	2	3	4	5	6	7	8	9	10	11
Proposed	8.29	8.246	8.197	8.142	8.078	8.022	7.958	7.899	7.841	7.782	7.742
Douban	8.305	7.943	7.619	7.331	7.07	6.837	6.622	6.428	6.247	6.085	5.93
IMDB	7.55	7.35	7.165	6.993	6.831	6.68	6.537	6.404	6.279	6.158	6.044



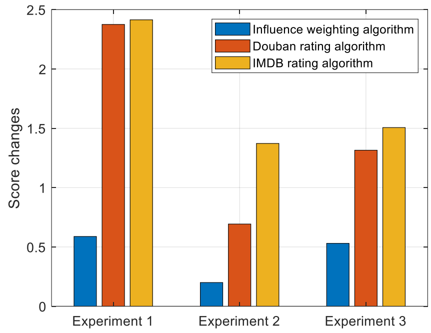
(a) Experiment 1 movie score change chart



(b) Experiment 2 movie score change chart



(c) Experiment 3 movie score change chart



(d) Comparison of fraction changes in three experiments

Fig. 2. Graph of the change in score for the three experiments

Results and analysis of the ratings incentive mechanism experiment

According to the above incentive mechanism and experimental method design, use Python for data visualization. Add 10 non-normal users of three different types to the 100 normal users. Do three experiments to compare and analyze the income of normal and abnormal users. This proves the feasibility and effectiveness of the incentive mechanism. The income amount of different users are shown in Fig.3. The experimental results show that in the three experiments, the income amount of normal users (blue histogram) is higher than that of non-normal users (red histogram), and the income amount of normal users is 5 tokens higher than the admission fee. In contrast, the non-normal users all gained less than 5 tokens, suggesting that the incentive mechanism effectively constrains non-normal rating behavior and improves the quality of the overall score.

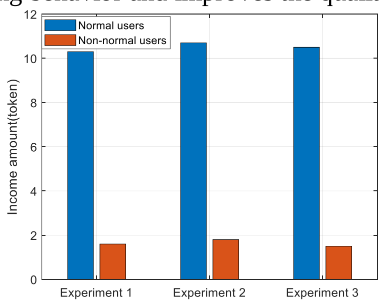


Fig. 3. Amount of revenue for different users in three experiments

6 Conclusion

This paper proposes a user influence weighted rating algorithm, which takes into account the influence of different users on the scoring when calculating the overall score of an item. It effectively improves the anti-interference capability of the rating algorithm. A user influence weighted rating algorithm that includes an incentive mechanism is proposed. While rewarding users who rate seriously, malicious users who interfere with the normal operation of the system are punished. The quality of the ratings is improved to ensure the healthy development of the system ecology. And the effectiveness and feasibility of the algorithm are proved through experiments. The next step can be to carry out research work in the following two aspects: (1) The current influence model in this paper is based on AHP to design the weights of the four factors. But the user rating behavior is greatly influenced by subjective factors, which can be studied with the help of machine learning in the future. (2) The evaluation algorithm only considers the user's rating of the item, for not considering the textual content of the user's comments on the item. The next step needs to use a neural network model to identify the textual content and classify it to improve the system's ability to identify malicious users.

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