The Ranking Problem of Socio-Economic Systems Based on GR Algorithm

Hua Guo, Mingzhen Shao

***Abstract*—In the current environment of increasing complexity and dynamics of socio-economic systems, effective ranking and evaluation of socio-economic systems have become increasingly important. According to the characteristics and demands of socio-economic systems, a new ranking model based on Group-based Reputation Ranking algorithm is proposed. In the process of model design, the multiplicity and dynamics of the socio-economic system are fully considered, so that the model can be better adapted to the needs of the socio-economic system. In the model validation and experimental part, the accuracy of the Group-based Reputation Ranking algorithm again shows a stable trend when the scoring threshold is 258 and is 6 percentage points higher than the Closeness Ranking algorithm. The MovieLens dataset, when dealing with maliciously rated cheating users, the Group- based Reputation Ranking algorithm results in an area under the curve line of 0.997, which shows a clear lead over the Closeness Ranking algorithm's 0.967. The Closeness Ranking algorithm guides the resolution index to 0.941. Through the area under the curve evaluation metric, the Iterative Group-based Reputation Ranking algorithm presents a more detailed global ranking with an area under the curve line value of about 0.95. The Iterative Group-based Reputation Ranking and Group-based Reputation Ranking both algorithms have the highest ranking accuracy, while the Iterative Group-based Reputation Ranking algorithm shows more significant robustness at increasing p-values. Overall, utilizing the Group-based Reputation Ranking algorithm provides a novel and effective approach for solving the ranking problem of socio-economic systems. This not only helps to improve our understanding and control of socio-economic systems, but also provides important theoretical support for decision making in socio-economic systems.**

***Index Terms*—cluster clustering, network structure, reputation ranking, ranking algorithms, socio-economic systems**

I. Introduction

With the rapid development of science and technology, socio-economic systems have deeply affected our daily lives, and in today's digitalized socio-economic environment, traditional rating and ranking systems are facing great challenges due to the fact that they are largely focused on the specific status of a single matter while ignoring the larger socio-economic context. Therefore, there is a need to develop a system that is capable of rating and ranking in an orderly manner from micro to macro and from detail to global [1], [2]. With the continuous evolution of technology and rapid changes in the socio-economic environment, how to make the rating and ranking system better adaptable and flexible to the complex and changing socio-economic environment has become the focus of current research [3]. Therefore, the study proposes a research on the ranking problem of socio-economic system based on Group-based Reputation Ranking (GR) algorithm for group clustering in view of the group interaction and overall influence, as well as the operation of socio-economic system. The study innovatively judges the reputation of these entities based on the interrelationships within and among clusters, aiming to better understand and measure the operation of socio-economic systems, with a view to the maintenance and development of socio-economic order [4], [5]. In addition, the adaptability and flexibility of the GR algorithm are quite outstanding. With the continuous progress of science and technology and the rapid changes in the socio-economic environment, the GR algorithm can be flexibly adapted and optimized according to different environments and needs in order to adapt to the ever-changing socio-economic environment. The research will be carried out in four parts, the first part is an overview of the socio-economic system sequencing problem based on GR algorithm, the second part is the study of the socio-economic system sequencing problem based on GR algorithm, the third part is the experimental validation of the second part, and the fourth part is the summary of the research and points out the shortcomings.

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II. Related Work

Network sorting algorithms are realized to infer the state of socio-economic systems as a whole by modeling the interactions as a network. Cluster-based clustering methods have been researched quite a lot, and many scholars have expanded their research on this to several fields and directions. Askari improved the Fuzzy C-Means (FCM) fuzzy clustering algorithm and amended the algorithm to use an adaptive exponential function to eliminate the effects of noise and outliers on the center of the clusters in order to prevent larger or heavier clusters from attracting the center of the smaller clusters. However, the algorithm suffers from these problems and has received a great deal of research and development, but improvements are still rare. The results of the study showed that the algorithm is suitable for data with unequal clusters [6]. Ezugwu et al. presented an up-to-date systematic and comprehensive review of traditional and state-of-the-art clustering techniques for different domains, which considered clustering from a more practical point of view, showing the prominent role of clustering in various disciplines. The applications of clustering in different fields, which have attracted considerable efforts from the scientific community, are also discussed. The results of the study show that the methodology is beneficial to practitioners and researchers. A good reference point for researchers and practitioners to design improved and efficient state-of-the-art clustering algorithms [7]. Rezaee et al. proposed a new k-mean clustering variant of the original algorithm, which utilizes the power established in the k-mean clustering algorithm to cluster data. The realization attracts the maximum number of similar targets or entities to their clusters. To demonstrate the superiority and efficiency of the proposed algorithm over traditional clustering algorithms, a two-dimensional syntactic dataset and benchmark datasets from different clustering studies were used. The results of the study showed that the algorithm was able to cluster the data more accurately than the classical algorithm for eight evaluation metrics such as normalized mutual information and normalized information variance [8]. Aldino et al. grouped potential maize producing areas based on to find out which areas produce large quantities of maize and which ones produce small quantities of maize. A k-mean clustering algorithm was used to group the data in one or more clusters so that the data in a cluster has a small degree of variability. The feasibility of the algorithm was verified for each district [9].

Socio-economic system is an important complex system, unlike inanimate physical systems, which encompasses human economic activities and the social environment in which they are embedded, and many scholars have gained considerable insights into analyzing and understanding the structure and dynamics of socio-economic systems. Bozzeda et al. investigated the characteristics of the distribution of plastic litter on Mediterranean beaches, and used a simple heterogeneous growth model in order to estimate the beach plastic litter quantity and size. The results showed a power-law distribution relationship between size and abundance of plastic products, which can support decision makers in estimating the total amount of plastic on beaches by applying a simple model [10]. Elena et al. proposed a natural based solution that can transform a water intensive economic model. By analyzing the water scarcity and drought issues in the case of Del Campo in Medina, Spain, a framework based on institutional economics was constructed to reveal the logic of action and values. The research results indicate that the framework emphasizes the potential of natural conservation programs, which can promote more adaptive system development to climate change through ecological and social value driven territorial transformation. In addition, the framework integrates comprehensive solutions for ecosystem services, transforming water scarcity into development opportunities and providing long-term climate adaptation development space for decision-making [11]. Brown Annuzzi et al. proposed the possible impact of (dehumanization) of high socioeconomic status groups on income redistribution attitudes. The research results indicate that when high socio-economic status groups are humanized, that is, their wealth is viewed as an internal attribute (such as ambition) rather than an external factor (such as corruption), people's support for income redistribution or high tax rates towards this group decreases. This finding suggests that humanized high socio-economic status groups may unintentionally contribute to the maintenance of the status quo, thereby providing rationalization for income inequality in society [12]. Friesen et al. used principal component analysis to identify the weights of the principal components and contributing variables from the various datasets, which were used to determine socio-economic between community disparities. The experiment outcomes denote that the practicality of the raised method also contributes to the improvement of socio-economic measurement and calculation methods and can make this method applicable to other regions [13].

In summary, traditional ranking and rating systems tend to rely on specific facts and individual conditions, and are limited in that they cannot adequately capture and reflect the complex interactions and overall influence of socio-economic entities. In addition, these systems are often difficult to adapt to rapidly changing socioeconomic environments, and thus, the accuracy and rationality of these systems have been seriously questioned. In contrast, the cluster clustering-based GR) algorithm proposed in the study combines the characteristics of group dynamics and influence, and fully takes into account the interactions between entities within a cluster and between clusters when rating and ranking entities. As a result, the algorithm is more adaptable and flexible, and it is able to respond to changes in socioeconomic conditions in a timely manner. A clearer measurement and understanding of the operation of socioeconomic entities is of significant theoretical and practical values in maintaining and developing the socioeconomic order.

III. Research on Ranking of Socio-Economic Systems Based on Reputation Ranking Algorithm of Cluster Clustering Author List

Traditional ranking and rating algorithms focus only on the behavior of individuals and ignore the overall socio-economic context and interactions in groups, which have certain limitations and cannot effectively adapt to changes in a complex socio-economic environment. The study of the proposed GR algorithm takes full account of the dynamics of groups and their influence. Algorithms for fairer and more transparent measurement and ranking of the reputation of socio-economic entities are provided for the operation of socio-economic systems to meet the demand for new rating and ranking methods.

A. Reputation Ranking Algorithm Based on Cluster Clustering

With the development of the Internet economy, e-commerce platforms carry out the public vision and are widely used. However, tens of thousands of goods and services data, effective identification methods need to be designed for users to maintain the healthy operation of the scoring system. However, in socio-economic systems, there are complex interactions between different subjects, which means that the behavioral characteristics of each subject, as well as the interaction dynamics and relative relationships need to be considered when predicting system conditions [14], [15]. Therefore, the study uses the online rating dataset to propose a GR algorithm, in which cluster clustering is the process of clustering the parts that are common to all aspects into groups, the manifestation of which is shown in Fig. 1.

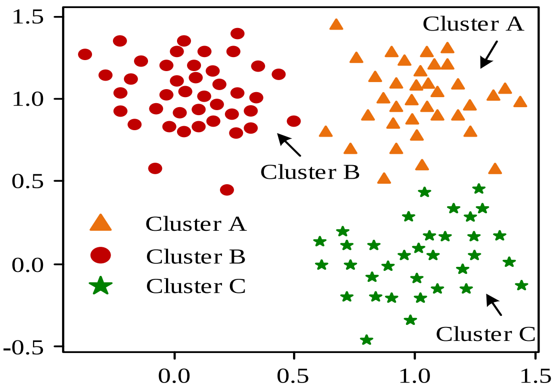

Fig. 1. Group clustering diagram.

Using cluster clustering can well extract the common features in user ratings, so as to clearly screen out the cheating users. However, there are serious cheating scoring behaviors in the traditional reputation ranking algorithm, which is based on the quality of the products for reputation ranking. Each product α has a unique quality score to reflect its real quality Q_α, and in the absence of benchmark information, the quality score is estimated by the average rating received by the product, the expression of which is shown in (1).

$$\hat{Q}_\alpha = \frac{\sum_{i\in U_\alpha} R_i A_{i\alpha}}{\sum_{i\in U_\alpha} R_i} \tag{1}$$

In (1), $A_{i\alpha}$ denotes the rating of user i on product α, R_i denotes the reputation of user i, and U_α denotes the user who rated product α. In the traditional reputation ranking algorithm based on product quality, the similarity-based ranking (Closeness Ranking, CR) algorithm realizes the calculation of user reputation based on the similarity between the user rating vector and the estimated quality of the product. Its mathematical expression is shown in (2).

$$TR_i = \frac{1}{k_i}\sum_{\alpha\in O_i}\left(\frac{A_{i\alpha}-\mu(A_i)}{\sigma(A_i)}\right)\left(\frac{\hat{Q}_\alpha-\mu(\hat{Q}_i)}{\sigma(\hat{Q}_i)}\right) \tag{2}$$

In (2), $\mu(A_i)$ and $\sigma(A_i)$ denote the mean and standard deviation of the rating quality, respectively, and the robustness of the algorithm in dealing with the cheating rating attack is improved to a larger extent. And in order to enhance the influence of reputation users in reputation evaluation, then for the user i, based on the framework of the CR algorithm, a nonlinear way is added in the iterative process. Its mathematical expression is shown in (3).

$$IARR_i = CR_i^\theta \cdot \frac{\sum_j CR_j}{\sum_j CR_j^\theta} \tag{3}$$

In (3), θ represents the adjustable parameter. However, when $\theta = 1$ is used, the method degrades to a CR method. Therefore, the traditional reputation ranking method based on product quality is difficult to accomplish online tasks with different difficulties. The traditional reputation ranking algorithm that relies on product unique quality construction is no longer applicable nowadays, so this research proposes a GR algorithm. The algorithm is calculated using multiple clusters and the process is shown in Fig. 2.

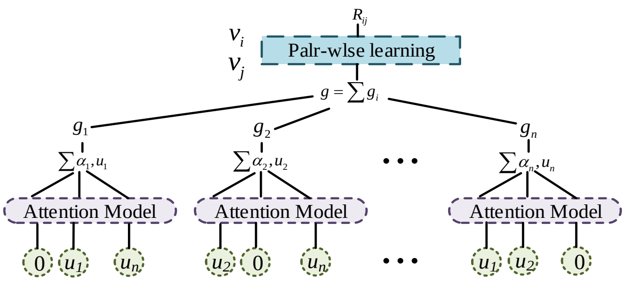

Fig. 2. Schematic diagram of the calculation process for multiple groups.

The GR algorithm divides the users into clusters based on the ratings and then the clusters are calculated. This method for any product α, put the users with rating value in the group ω_s $\Gamma_{s\alpha}$ and the expression is shown in (4).

$$\Gamma_{s\alpha} = \{U_i | a_{i\alpha} = \omega_s, i = 1, 2, \cdots, m\} \tag{4}$$

The size of all clusters is calculated through (4) to obtain the cluster size matrix as shown in (5).

$$\Lambda_{s\alpha} = |\Gamma_{s\alpha}| \tag{5}$$

The original rating matrix is followed by the rating feedback matrix through (5) to obtain the reputation feedback matrix. In order to avoid instability such as too small mean and too large variance of the reputation feedback obtained by the user, the defined equation for the user i reputation is shown in (6).

$$R_i = \frac{\mu(A_i')}{\sigma(A_i')}. \tag{6}$$

In (6), μ and σ are denoted as the mean and standard deviation of the reputation vector A_i'. In the face of the user i, the formula for calculating the mean value is shown in (7).

$$\mu(A_i') = \sum_\alpha \frac{A_{i\alpha}'}{k_i} \tag{7}$$

And the standard deviation is calculated as shown in (8).

$$\sigma(A_i') = \sqrt{\frac{\sum_\alpha (A_{i\alpha}' - \mu(A_i'))^2}{k_i}} \tag{8}$$

Through (8), all the users are finally sorted according to the reputation value to get the user with the lowest reputation ranking, thus detecting the presence of cheating ratings. The cluster clustering-based online user reputation algorithm's schematic diagram is shown in Fig. 3.

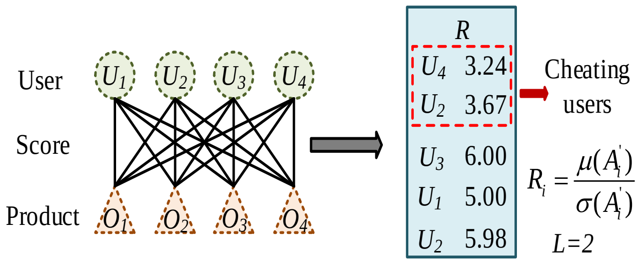

Fig. 3. Cluster clustering-based online user reputation algorithm's schematic diagram.

The algorithm maps the original scoring matrix according to the scoring feedback matrix to get the reputation feedback matrix in, and finally sorts the reputation ranking of all users. In Fig. 3, the reputation values of U_2 and U_4 are 3.24 and 3.67, which are the users with low reputation values and are determined as cheat rating users. Therefore, the online user reputation algorithm based on cluster clustering clusters user groups according to their reputation values, thus forming different user groups. The rating of each user within the cluster is then evaluated using specific criteria. The reputation value received by each user is calculated based on their reputation feedback matrix within the cluster, and these reputation values are then combined to form a final score that comprehensively evaluates the user's reputation. In this way, a comprehensive score can be evaluated more accurately for each user, so as to achieve effective management of user reputation.

B. Cluster Clustering Reputation Ranking Algorithm Based on Iterative Process

The reputation ranking algorithm based on cluster clustering evaluates the trustworthiness of users based on the size of the clusters formed by the ratings, the size of the clusters formed by the ratings is used to assess the trustworthiness of the users, taking into account the similarity and conformity tendency of the users' ratings. However, in practice, different users have different ability to estimate product quality, which leads to their credibility level [17], [18-19]. Therefore, an iterative process is introduced in calculating the cluster size, which not only improves the accuracy of the reputation ranking algorithm, but also enhances its robustness in the face of attacks from users with cheating ratings. In order to minimize the mutual reinforcement and mutual influence among the pages, iterative optimization is introduced to crack this influence. The clustering calculation process based on iterative process is shown in Fig. 4.

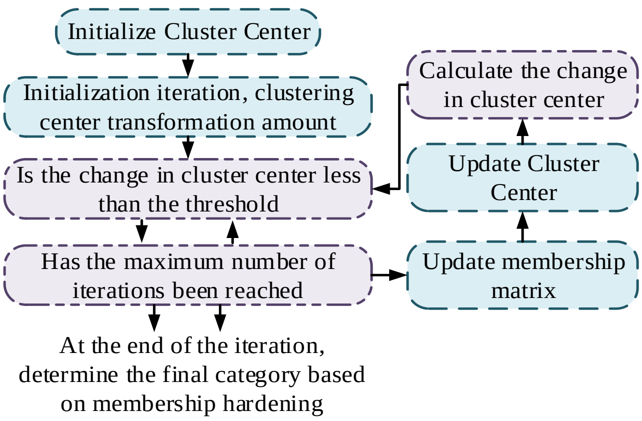

Fig. 4. Schematic diagram of clustering calculation process based on iterative process.

In the iterative process, the weights of each page need to be maintained and updated at the same time, and this iterative optimization process is widely used in online socio-economic system ranking. Before the initial assignment, the weights for each page need to be normalized. Formula (9) shows how to update the weight of the core page, where, represents the organization page of the core page, the weight of the organization page can be updated according to this core weight, and the expression for updating the weights of the core page i $x^{(i)}$ is shown in (9).

$$x^{(i)} \leftarrow \sum_{\alpha \in Y^{(i)}} y^{(\alpha)} \tag{9}$$

In (9), $Y^{(i)}$ represents the organization page of the core page i, and the weights of the organization page can be updated according to the core weights. For the organization page α, the expression for updating its weight $y^{(\alpha)}$ is shown in (10).

$$y^{(\alpha)} \leftarrow \sum_{i \in X^{(\alpha)}} x^{(i)} \tag{10}$$

In (10), $X^{(\alpha)}$ denotes the core page to which the update points. The other iterative optimization search process is composed of a two-part user-product base process. The first is to initialize the resources of any product α to f_α, and allocate the initialized resources as shown in (11).

$$f_\alpha^{'} = W \cdot f_\alpha \tag{11}$$

In (11), $f_\alpha^{'}$ denotes the number of products or resources obtained, W denotes the transformation matrix of resources in the network, 1 and the element $\omega_{\alpha\beta}$ of its transformation matrix is expressed as shown in (12).

$$\omega_{\alpha\beta} = \sum_{i=1}^{m} \frac{A_{i\alpha} A_{i\beta}}{k_i} \tag{12}$$

In (12), $A_{i\alpha}$ and $A_{i\beta}$ denote the ratings of user i on product α and product β respectively, k_i denotes the degree of user i, and $\omega_{\alpha\beta}$ can measure the similarity between product α and product β. Based on the similarity of user rating behaviors on online social platforms and the variability of user reputation levels within groups, an Iterative Group-based Reputation Ranking (IGR) algorithm based on the iterative process is improved. Therefore, the schematic diagram of the Iterative Group-based Reputation Ranking algorithm is shown in Fig. 5.

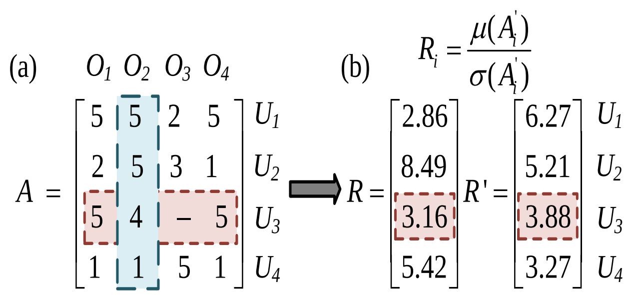

Fig. 5. Schematic diagram of a group clustering user reputation ranking algorithm based on iterative process.

The goal of IGR algorithm is to improve the accuracy of evaluation and ranking of user reputation by utilizing cluster size to process different ratings of users. First, all users are divided into clusters based on the ratings, and the product rating matrix $B^{(i)}$ obtained from the rating vector A_i of users i, whose mathematical expression is shown in (13).

$$B_{s\alpha}^{(i)} = \begin{cases} 1 & if\ A_{i\alpha} = \omega_s \\ - & otherwise \end{cases} \tag{13}$$

In (13), $A_{i\alpha}$ denotes the rating value ω_s given by the user i to the product α, s denotes the total number of different discrete ratings, and the symbol "$-$" denotes the null value. The users who give the same rating ω_s to the product α belong to the same group $\Gamma_{s\alpha}$, whose mathematical expression is shown in (14).

$$\Gamma_{s\alpha} = \left\{ U_i \middle| B_{s\alpha}^{(i)} = 1 \right\} \tag{14}$$

In (14), $B_{s\alpha}^{(i)}$ denotes the element in the product rating matrix of user i. The user's group affiliation and the user's reputation score for the user group size $\Lambda_{s\alpha}$ are defined as shown in (15).

$$\Lambda_{s\alpha} = \sum_{i=1}^{m} R_i B_{s\alpha}^{(i)} \tag{15}$$

In (15), $B^{(i)}$ is the product rating matrix of user i, R_i represents the reputation score of user i, and m is the total number of users in the system. The user i gets the reputation feedback $A_{i\alpha}^{'}$ from its rating $A_{i\alpha}$, which is defined as shown in (16).

$$A_{i\alpha}^{'} = \begin{cases} \Lambda_{s\alpha}^{*} & if \ A_{i\alpha} = \omega_s \\ - & otherwise \end{cases} \tag{16}$$

In (16), $A_{i\alpha}$ is the rating of the user i for the product α and ω_s is the corresponding rating value. After the introduction of the iterative optimization process, the reputation score of the user i is updated during the iteration process and its expression is shown in (17).

$$R_i = \frac{\mu(A_i^{'})}{\sigma(A_i^{'})} \tag{17}$$

In (17), μ and σ denote the calculation of mean and standard deviation, respectively. All users are ranked in descending order based on their reputation scores, and the top L users with the lowest rankings are rated as cheat score users. This algorithm degrades the IGR algorithm to GR algorithm after not using iterative process [20]. Through the above analysis, IGR algorithm improves the accuracy of evaluating user reputation by introducing iterative optimization process, and can effectively identify the users who cheat the rating. This provides a powerful tool to manage user reputation more effectively, thereby improving the operational efficiency of socio-economic systems.

IV. Performance and Sorting Effect Analysis of Reputation Sorting Algorithm Based on Cluster Clustering

In order to validate the performance of the algorithm in terms of performance and ranking when dealing with large-scale real-world data, as well as to measure its performance and effectiveness more accurately, the study chose three widely used datasets for testing: The MovieLens dataset, the Netflix dataset, and the Amazon dataset. The MovieLens dataset, which is provided by the University of Minnesota's GroupLens Research Lab and is particularly suitable for recommender system research.

A. Comparison of Algorithm Performance and Analysis of Experimental Results

To comprehensively evaluate the ranking effect of GR, three indexes Precision, Recall and F1 Score were introduced. To make a more comprehensive evaluation of the accuracy and robustness of the algorithm. Specifically, the Netflix dataset comes from Netflix's public competitions, which provide scores for a large number of movies. Amazon. Specifically, the Netflix dataset is derived from Netflix's public contests, which provides a large amount of movie rating data. The Amazon dataset, on the other hand, contains user ratings and scoring information for a variety of products, which is very suitable for complex data mining operations because of its huge amount of data and high diversity. The experimental environment for the study, an Intel Xeon processor, a server with 32GB RAM and a 1TB hard disk, was programmed in Python, with library functions from NumPy, Pandas, and Scikit-Learn. MovieLens' and Netflix's datasets mainly contain movie ratings, while Amazon's dataset mainly contains merchandise ratings. ratings, these datasets all follow a rating scale of 1 to 5, where 1 is the lowest rating and 5 represents the best rating. To ensure the accuracy and credibility of the rating data, only users who have rated products more than 20 times in the dataset, and the products rated, are included. Key data information for the three datasets is shown in Table I.

TABLE I
BASIC STATISTICAL INFORMATION OF REAL ONLINE RATING DATASETS

Data set	Number of users	Number of products	User average	Product average	Network sparsity
MovieLens	951	1765	114	79	0.078
Netflix	1043	1323	66	56	0.057
Amazon	681	1624	57	28	0.039

In Table I, there are 951 subscribers in the MovieLens dataset, while there are 1,043 and 681 subscribers in the Netflix and Amazon datasets, respectively. Indicates that MovieLens and Netflix datasets have more active users, while Amazon has relatively few. The number of products in MovieLens has the largest number of products in 1765; Netflix has 1,323; Amazon has 1,624 products. The three datasets averaged 114, 66, and 57 participants, respectively. Due to the diversity of products, its user ratings are also fragmented, its MovieLens products have an average of 79 ratings, while Netflix products have an average of 56 ratings, and Amazon products have the lowest average rating at 28. Finally, the network sparsity is used to describe the sparsity of the interaction between users and products. The network sparsity of the three data sets is 0.078, 0.057, and 0.039, respectively. A lower value indicates a closer interaction between the user and the product. As a result, MovieLens has high user engagement and product ratings, while Amazon shows greater product diversity and a tighter network of user product interactions. The specific ranking results are shown in Fig. 6.

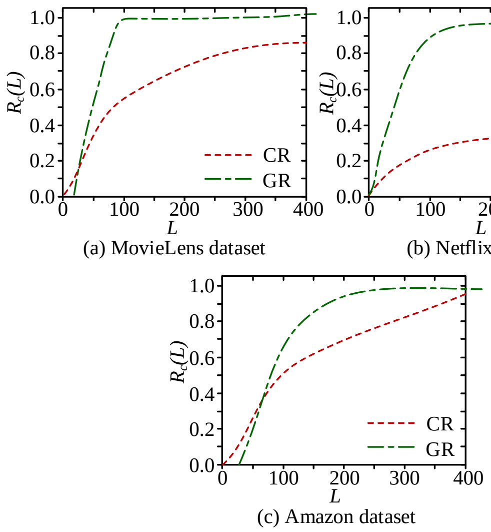

Fig. 6. The change of recall rate of sorting algorithm with the length of detection list under three datasets.

In Figure 6, the precision rate represents the proportion of fraud raters identified by the algorithm in all identified users, and the recall rate represents the proportion of fraud raters identified by the algorithm in all real fraud raters. F1 Score is the harmonic average of accuracy rate and recall rate, which can reflect the performance of the algorithm more comprehensively by considering accuracy rate and recall rate comprehensively. Fifty experiments were conducted for each type and their average values were taken. The results show that the GR algorithm outperforms the CR algorithm in terms of accuracy at all scoring thresholds, especially when dealing with malicious fraudulent scoring users, and its sorting results are more accurate. Specifically, the GR algorithm outperforms the CR algorithm by 19 percentage points, 37 percentage points, and 6 percentage points at scoring thresholds of 71, 153, and 258, respectively. This indicates that the GR algorithm significantly outperforms the CR algorithm in detecting fraudulent scoring users regardless of the type of fraudulent scoring users. The AUC results of the CR algorithm and the GR algorithm for ranking malicious and random type of fraudulent scoring users are shown in Table II.

TABLE II
AUC RESULTS OF REPUTATION ALGORITHM FOR RANKING CHEATING SCORING USERS

Test Data set	Malicious	Malicious	Stochastic	Stochastic
	CR	GR	CR	GR
MovieLens	0.967	0.997	0.943	0.974
Netffix	0.614	0.982	0.781	0.956
Amaon	0.931	0.953	0.903	0.972

In Table II, according to different data sets, the accuracy of reputation algorithm for cheating users is quite different. In MovieLens data set, the classification rate (CR) and packet rate (GR) of malicious users perform well, with GR as high as 0.997 and CR as high as 0.967, indicating that the algorithm can efficiently identify malicious users. For the Netflix dataset, the CR was only 0.614, indicating poor ability to identify malicious users in this dataset. However, its GR value reached 0.982, which performed well in the overall group level. The accuracy of Amaon data set is relatively average, with CR and GR values above 0.9, showing good recognition ability. By comparing these metrics in different online scoring environments, the reputation algorithm is significantly different in identifying cheating users and generally performs better at the group level than at the individual classification level.

B. Sorting Effectiveness Analysis of Reputation Sorting Algorithm for Cluster Clustering

As the advancement of big data and cloud computing, data mining and information sorting have become increasingly important. This paper discusses the performance of this algorithm on large data sets, including its ranking efficiency and stability, in order to better reveal the advantages and limitations of reputation ranking algorithm for clustering, and provide valuable thinking for subsequent research and optimization. In evaluating the effect of the reputation ranking algorithm, the reputation score obtained by the algorithm is analyzed for its ability to distinguish between users, using the IGR algorithm algorithm, CR algorithm and GR algorithm. Based on the results obtained from the MovieLens dataset calculation, the distribution of user reputation scores obtained by different reputation sorting algorithms is shown in Fig. 7**.**

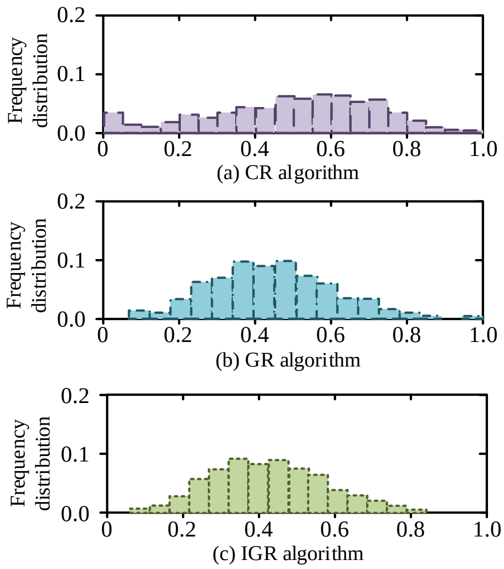

Fig. 7. Calculate the reputation frequency distribution of all users under different sorting algorithms.

In Figure 7, the user reputation scores calculated using the IR algorithm follow a Poisson-like distribution, while the scores obtained using the GR and IGR algorithms show a normal-like distribution, in addition to a large number of users with scores of 0. The three algorithms perform differently on different data sets. For example, on the MovieLens dataset, the IR algorithm outperformed the other two algorithms, while on the Netflix and Amazon datasets, the GR and IGR algorithms performed better. This may be related to the characteristics of the data set and the parameter Settings of the algorithm. In Figure 7(a), the CR algorithm guides the resolution index up to 0.941. In Figures 7(b) and (c), the resolution indices of the GR and IGR algorithms are very close to each other, respectively, at 0.911 and 0.913. The scores calculated using the CR algorithm, the GR algorithm and the IGR algorithm are able to better distinguish the characteristics of user groups. In the ranking algorithm, the influence of user activity on reputation ranking needs to be analyzed, and the user activity program is estimated by the user degree k. The results are shown in Figure 8.

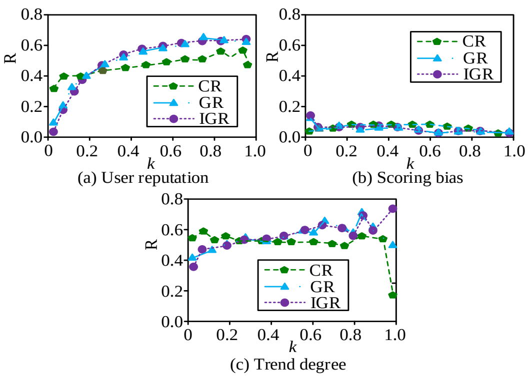

Fig. 8. The relationship between user reputation, rating bias, and trend under three sorting algorithms.

In Figure 8, the CR algorithm can better calculate the R score and user activity k, while the other two ranking algorithms do not reflect a clear preference for user activity. The correlation between R score and k is almost zero, which is proof. In Figure 8 (a), as user activity increases, reputation ranking shows an upward trend. The GR and IGR algorithms increased steadily from the initial values of 0.136 and 0.092 to 0.591 and 0.587, respectively. In Figure 8 (b), as user activity increases, the overall rating bias decreases. GR and IGR decreased to 0.058 and 0.064, respectively. In Figure 8 (c), as user activity increases, the trend level fluctuates significantly. Among them, the CR algorithm has the largest fluctuation, decreasing from 0.586 to 0.177; The fluctuation of the GR algorithm is significantly smaller, only increasing from 0.411 to 0.437, while the IGR algorithm has increased from 0.372 to 0.769. It can be seen that the GR algorithm more accurately evaluates the impact of user activities and has the best ranking effect on user reputation. The results of the ranking accuracy of the reputation ranking algorithms in response to malicious type of cheating rating users are shown in Fig. 9.

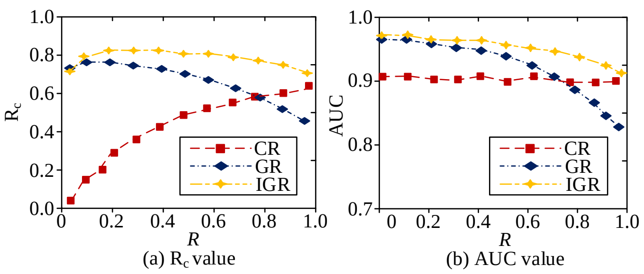

Fig. 9. Accuracy of three sorting algorithms in scoring users for malicious cheating.

As shown in Figure 9, when p value is large, IGR algorithm shows stronger sorting accuracy and robustness than GR algorithm; at relatively small p-values, the IGR algorithm and the GR algorithm have higher sorting accuracy. This shows that for malicious cheating users, IGR algorithm can better identify these users when their cheating behavior is more obvious (that is, the p value is larger). However, when cheating is difficult to detect (that is, the P-value is small), the performance of GR and IGR algorithms is comparable. 9(b), the AUC evaluation metrics, the IGR algorithm presents a more detailed global sorting, with an AUC value of about 0.95; if the p-value is large, the IGR algorithm proves to be better than the robustness of the GR algorithm; at the same time, the robustness of CR and RR algorithms is also quite reliable, with their AUCs maintained around 0.92. This shows that the IGR algorithm and GR algorithm are more effective than the general traditional algorithm in ranking when facing malicious rating users. The sorting accuracy results of the reputation sorting algorithms to cope with random type of cheating rating users are shown in Fig. 10.

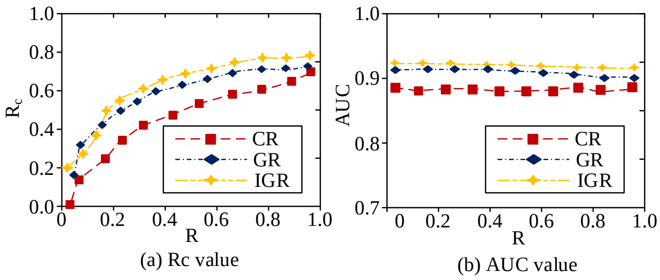

Fig. 10. The accuracy of three sorting algorithms in facing random cheating rating users.

In Figure 10, IGR algorithm and GR algorithm have the highest ranking accuracy, while the robustness of IGR algorithm increases with the increase of p-value. Although the cheating behavior is more random, the well-designed IGR and GR algorithms can still effectively identify these users. This proves that IGR and GR algorithms are very robust in dealing with various types of cheating. In Figure 10(a), the recall improves as p increases. The rapid increase in accuracy is observed as the p-value gradually approaches 0.05 from 0. The upward trend of accuracy starts to become slow when the p-value exceeds 0.05. In Figure 10(b), IGR and GR algorithms have the best sorting efficiency, and the AUC value is close to 0.96. The AUC of the CR algorithm is slightly lower, about 0.92. It can be seen that these two cluster-based algorithms perform better than other traditional algorithms when dealing with random types of users who cheat scores. The ranking robustness results of CR and GR reputation ranking algorithms are shown in Table III.

TABLE III
THE RANKING ROBUSTNESS RESULTS OF CR AND GR REPUTATION RANKING ALGORITHMS

Test Data set	Malicious	Malicious	Stochastic`	Stochastic
	CR	GR	CR	GR
Precision	0.961	0.979	0.972	0.953
Recall	0.54	0.81	0.64	0.85
Sorting accuracy	86.57%	94.42%	82.36%	97.59%
NDCG	0.31	0.53	0.28	0.62

As shown in Table III, GR algorithm performs better than CR algorithm on multiple evaluation indicators when dealing with malicious and random cheating users. The accuracy of CR algorithm is 0.961 and that of GR algorithm is 0.979, but the accuracy of CR algorithm (0.972) is higher than that of GR algorithm (0.953) when dealing with users who cheat on the model. This shows that both algorithms have high performance in the ability to accurately identify user ratings, but the specific advantages and disadvantages are affected by the type of cheating. In terms of sorting accuracy, GR algorithm is also superior to CR algorithm. Regardless of the type of cheating users, the ranking accuracy of more than 90% was achieved. When facing malicious cheating users, the ranking accuracy of GR algorithm is 94.42%, and when facing random cheating users, the ranking accuracy reaches 97.59%. For NDCG value, GR algorithm is 0.53 when dealing with malicious cheating users and 0.62 when dealing with random cheating users, both of which are significantly higher than CR algorithm's 0.31 and 0.28. This shows that GR algorithm does a better job than CR algorithm in giving higher weight to highly relevant users. It can be seen that although CR algorithm performs well on some indicators, GR algorithm shows stronger performance in terms of comprehensiveness and robustness, especially when dealing with users who cheat on the model, all indicators show advantages. The accuracy results of evaluating the actual cases of socio-economic system ranking under different algorithms are shown in Table IV.

TABLE IV
ACCURACY RESULTS OF SORTING ACTUAL CASES IN SOCIO ECONOMIC SYSTEMS UNDER DIFFERENT ALGORITHIMS

Project/ Evaluation Method	PCA	DEA	MDMM	GR
Corporate credit rating	85.23%	88.47%	82.15%	95.76%
Social media influence ranking	75.68%	70.34%	80.21%	96.89%
Ranking of urban competitiveness	80.56%	83.92%	78.48%	91.12%
Online Market Seller Sorting	82.39%	79.04%	85.77%	97.53%
Evaluation of the Influence of Academic Journals	77.85%	74.32%	81.65%	93.27%

According to Table IV, the GR algorithm performs the best in all indicators by comparing the effects of different evaluation methods. Among them, in corporate credit rating, the GR algorithm achieves an accuracy of 95.76%, which is higher than the PCA algorithm's 85.23%, DEA algorithm's 88.47%, and MDMM algorithm's 82.15%. This indicates that the GR algorithm has stronger accuracy and adaptability when dealing with complex and multivariate datasets. For the ranking of social media influence, the GR algorithm has an accuracy of 96.89%, which is much higher than other methods, indicating the efficiency of the GR algorithm in analyzing and understanding social media data. When evaluating the influence of academic journals, the GR algorithm is 93.27%, which is significantly higher than other methods. The lowest is the DEA algorithm, which is only 74.32%. From this, it can be seen that the GR algorithm has the best performance in different practical application cases, verifying the effectiveness of the algorithm in social and economic system rankings.

V. Conclusion

Social and economic systems contain complex hierarchical and functional structures that make inferring their state of operation and trends extremely difficult. However, traditional algorithms pay too much attention to the behavior of individuals, ignoring the interaction between groups and the impact of changes in the socio-economic environment on the reputation of entities. Thus, to address this issue, a ranking study of socioeconomic systems was proposed based on GR algorithm, which classifies entities in the cluster unit and fully considers the interaction between entities in the cluster in the measurement and ranking. The results show that the MovieLens, Netflix, and Amazon datasets have 951, 1,043, and 681 users, 1,765, 1,23-year-old, and 1,624 products, respectively, and average user engagement is 114, 66, and 57, respectively. The network sparsity was 0.078, 0.057, and 0.039, respectively, with MovieLens showing higher engagement while Amazon was more interactive. The CR and GR values of malicious users in MovieLens data set are 0.967 and 0.997 respectively, indicating efficient identification capability. The CR and GR of Netflix were 0.614 and 0.982 respectively. Amazon CR and GR both exceeded 0.9. This shows that the algorithm has a significant difference in the recognition ability of cheating users in different data sets, and the performance of grouping is usually better than that of individual classification. The study used three test datasets, each containing 50 different types of fake rating users, and averaged 50 experiments for each type. When dealing with randomly rated fraudulent users, the CR algorithm performed 0.943, while the GR algorithm was still better than the CR algorithm, but the difference was smaller, at 0.974. The resolution indexes of GR and IGR algorithms are very similar, 0.911 and 0.913 respectively. When p value is large, IGR algorithm shows higher sorting accuracy and robustness than GR algorithm. In addition, the IGR algorithm shows high accuracy when dealing with fraudulent users with malicious ratings, which further proves the validity and reliability of IGR algorithm in the study of ranking of socio-economic systems. It can be seen that the IGR algorithm has good adaptability and can quickly adapt to changes in the social and economic environment and update the ranking results in real time. The ranking results can be updated in real time to provide a more real and accurate reputation measurement. The research plays a pivotal role in advancing theoretical knowledge, but it also has a significant impact on the real-world decisions that shape social and economic outcomes.

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