Revolutionizing Legal Responsibility and Governance in C2C Online Platforms with Collaborative CAD

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Abstract. To improve the fairness and justice of the online trading platform under the C2C mode, it combines the intelligent method to identify the fraudulent behavior of the online trading platform under the C2C mode and studies its legal responsibility and governance. Moreover, starting from the characteristics of ICLA, this paper discusses the feasibility of its application to fraud gang detection and constructs an ICLA fraud detection model (FD_ICLA).In addition, this paper takes the model structure as the main line, expounds the definition and design of its components, combs through the working principle of the model as a whole, and explains the FD_ICLA model to classify the trustworthy state of the cell and identify the fraudulent gang. The research shows that the recognition methods of fraudulent behaviors in the online trading platform under the C2C mode proposed in this paper have a certain effect.

Keywords: C2C model; online trading platform; legal responsibility; governance; Collaborative CAD
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1 INTRODUCTION

The rapid development and brand effect of the B2C electronic trading market have had a significant impact on the C2C electronic trading market. The trading platform plays a key role in stabilizing and increasing the transaction scale of the C2C market. In addition to the most basic business logic implementation, the main development direction of the C2C platform is the diversification of transaction methods, the improvement of user experience, and the design of the trust mechanism. If it does not have a robust trust system, other means are impossible [2]. While the new shopping mode is convenient for people, a crisis of trust that rarely exists in face-to-face transactions is quietly lurking in the online transaction market, which creates a certain degree of obstacle to the development of e-commerce [17]. The C2C trading platform plays the role of supervisory administrator and maintains the order of the electronic trading market. Traders can log in to this platform to trade if they have buying and selling needs, and different platforms have corresponding trading mechanisms, resulting in different reputation rules. Designing a reasonable trust mechanism and applying the existing reputation rules can constrain the behavior of both parties to enhance the trust relationship between buyers and sellers so as to regulate the C2C electronic trading market [19]. Moreover, people's trust in C2C websites is different from their trust in B2C websites, which is determined by two different online transaction modes [10]. The influence of the brand-name effect of a B2C website as a merchant on trust is different from that of a C2C website as a platform. At the same time, the design of a good trust mechanism will play a full role in the role of reputation rules in the C2C electronic trading market. As people's trust in the C2C platform increases, users' shopping satisfaction also increases, increasing the confidence of buyers and sellers in the success of the transaction. Furthermore, more and more users will participate in transaction activities and gradually increase the online shopping transaction volume, thus ensuring the healthy development of the C2C electronic trading market [12]. Collaborative CAD technology has unveiled a pivotal shift in the landscape of e-commerce. This study has delved into the intersection of technology, regulation, and accountability, underscoring the profound implications for both platform operators and users.

In the C2C platform, one of the characteristics is that both buyers and sellers do not know the identity of the other party, and buyers cannot effectively verify the quality and other attributes of online products. Due to this information asymmetry, there are widespread serious reverses. The problems of choice and the prisoner's dilemma[11], coupled with the imperfect legal system related to the online trading market, make it easy for the fraudulent behavior of the transaction party to occur in the practice of online trading. At this time, it needs to rely on the spontaneous order of the market, and one of the important factors is the reputation rule. Reputation is generated invisibly in the online trading market and acts as a signaling role to help users better understand the transactions of other users [1]. Reputation rules are a kind of system used to build trust relationships between people, and reputation has existed for a long time in the electronic trading market. A seller with a low reputation, no matter how low the price of the product, will be ignored, and a seller with a high reputation, even if his product price is higher than the average, will still attract a large number of customers, there is a reputation premium here. It can be seen that in the online trading market, establishing a good reputation is very important for both buyers and sellers [14]. However, quantitatively measuring reputation is not easy, mainly because it is difficult to collect data. However, the emergence of a credit evaluation system brings the possibility of measuring reputation. After the transaction is completed, both buyers and sellers will evaluate each other's transaction behavior. According to the feedback results, the website records the evaluation of the counterparty obtained by each user in past transactions. These ratings are converted into a reputation score in some way. It represents the user's experiential reputation in the network environment, and this accumulated reputation is more rapid than word of mouth [7].

Fraud detection techniques based on statistics and machine learning have been successfully applied to activities such as anti-money laundering, credit card fraud, wire fraud, and computer intrusion [8]; a literature review of financial transaction fraud. Reference [3] summarizes the identification and classification methods on the application of data mining techniques to detect financial fraud. The literature [5] clearly shows that in the financial field, data mining techniques have been widely used to detect insurance fraud, corporate fraud, and credit card fraud, and there is a lack of research on mortgage fraud, money laundering, securities, and commodity fraud in academia. The main data mining techniques used for FFD are logistic regression models, neural networks, Bayesian belief networks, and decision trees.

Reference [16] proposed a fake website identification system based on statistical learning theory and developed a prototype system to demonstrate the potential utility of such a system. Reference [15] shows that systems based on statistical learning theory can utilize richer fraud potential information and combine the feature information of fraud problems to detect various types of fake websites more accurately. The results have important implications for e-commerce and online safety, given the enormous costs that fake websites have inflicted on online transactions in the past. The researchers derived a comprehensive model and a set of theories for identifying fraudulent merchants from a theoretical perspective, addressing why consumers are deceived by various types of deceptive information and summarizing the behavioral characteristics of three fraudulent merchants: Automatic elimination of negative reviews, the product information is not detailed, and the positive reviews are faked [6]. A method based on the Self-Organizing Map Neural Network (SOMNN, Self-Organizing Map Neural Network) is proposed to detect online transaction fraud, and it also provides a specific method and technology for feature engineering in collecting fraud data. It is dynamically updated with new transactions and self-learning, independent of statistical distribution assumptions [18]. It has been verified that telecom operators can suspend services through detection and stop the losses caused by fraudulent users. This method has proved its trial performance for the network fraud caused by Routing Information Protocol (RIP, Routing information Protocol01) attack [13].

Some scholars proposed an unsupervised learning method based on a finite mixture model to identify [4]. Considering the two states of normal and fraudulent for each item, the two states of the observed item are modeled as hidden variables, and the proposed model estimates the states using the Expectation Maximization (EM) algorithm. Experimental results show that the proposed model is more effective than existing outlier detection methods in identifying pricing fraud. Furthermore, it is shown that exploiting the number of clusters helps improve pricing fraud detection performance.

Reference [9] proposes a cost-effective method for identifying fraudulent behaviors. It is mainly to apply PCA (Principal Component Analysis) to reduce the characteristics of traders and eliminate repetitive and worthless information. Generally speaking, the fewer features used, the less computational workload of the recognition algorithm, and the faster the online recognition response. A post-analysis method is also proposed to identify fraudsters by the behavior of traders in the final stages of shopping.

To improve the fairness and justice of the online trading platform under the C2C mode, it combines the intelligent method to identify the fraudulent behavior of the online trading platform under the C2C mode and studies its legal responsibility and governance so as to improve the operation effect of the online trading platform under the C2C mode.

2 TRANSACTION BEHAVIOR RECOGNITION IN NETWORK PLATFORM BASED ON CELLULAR AUTOMATA

2.1 Definition of Cellular Automata

v is the state of the cell, and its value belongs to the finite set S, V represents the set of cell states, V^K represents the set of k consecutive cell states, V^Z represents the set of all cell states, d is the cell space dimension, r is the cell neighbor radius, and t is the time (or iteration number).

It takes one-dimensional cellular space (d=1) as an example. Based on the above description, the evolution process of cellular automata can be expressed by formula (1). The local rule set f can be flexibly defined and expressed uniformly as formula (2).

$$F : V_t^Z \to V_{t+1}^Z \tag{1}$$

$$f : V_t^{2r+1} \to V_{t+1} \tag{2}$$

It takes the set of neighboring cells and its own state as the input, takes the state of a single cell as the output, and applies the local rules to the cells one by one. The overall evolution of the cellular automaton is obtained, as shown in formula (3):

$$F\left(V_{t+1}^{i}\right)=f\left(V_{t}^{i-r},\ldots,V_{t}^{i},V_{t}^{i+r}\right) \tag{3}$$

V^{i} represents the cell at position i. In this way, we have defined a one-dimensional cellular automatic model

A tuple automaton consists of four parts: 1) cell space, The cells are distributed in the cell space (Figure 1);2) the cell state set, which is a finite set of discrete values, including all the values of the cell state; 3) local rules (or state transition rules), which define the conditions and results of cell state changes; 4) cell neighbors (or neighborhoods, as shown in Figure 2). The details of each part are as follows.

For any sequence consisting of 1/0, the corresponding 0/1 sequence can be generated at the next moment. For example, if the layout of the cellular automaton at a given time t is V_{t}, as shown in formula (4), then driven by the rules described in Table 1, the layout of cellular automata at time t+1 should be V, as shown in formula (5).

$$V_{t}=\{01011111110001100000110\} \tag{4}$$

$$V_{t+1}=\{01111111001010010011010 0\} \tag{5}$$

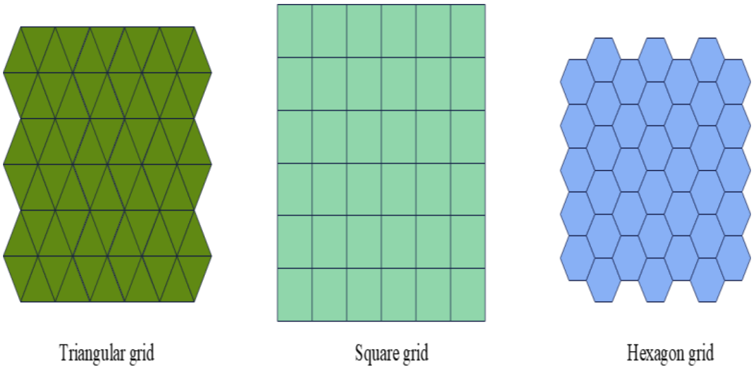
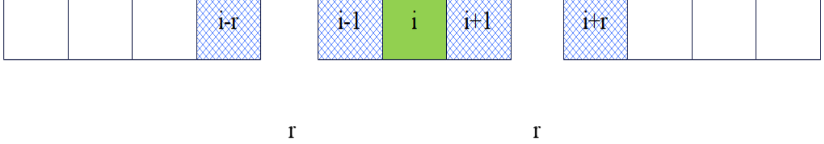
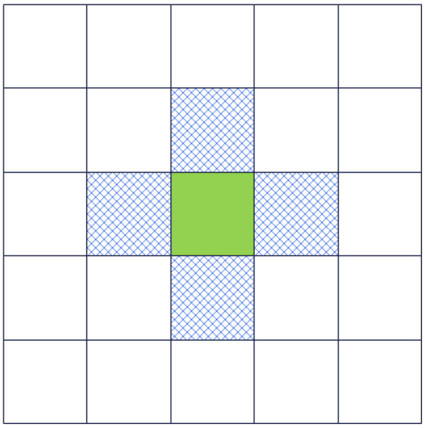


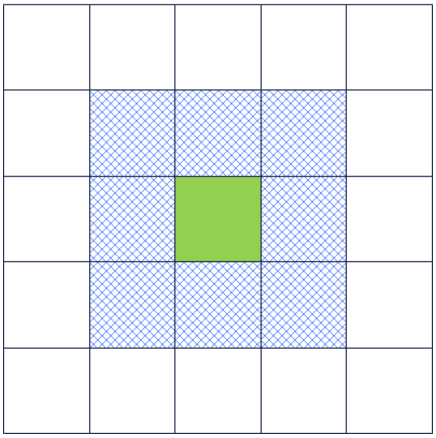
Figure 1: Three common two-dimensional cell spaces.



a. One-dimensional cell-space neighborhood



b. Von Neumann style



c. Moore style

Figure 2: Common neighborhood models of 1D and 2D cellular automata.

2.2 Irregular Cell Learning Automata

A learning automaton (LA) is a simple automaton working in an unknown stochastic environment, which can be represented as a quaternion $LA=\{\alpha,\beta,\mathrm{p},\mathrm{T}\}$. Among them, α represents the action set, β is the environmental feedback set, and p is the action probability vector $P(n+1)=T(\alpha(n),\beta(n),p(n))$. Therefore, T refers to the learning algorithm that updates the action probability vector.

An environment can be represented by a triple $E=\{\alpha,\beta,\mathrm{c}\}$, which $\alpha=\{\alpha_1,\alpha_2,\ldots,\alpha_r\}$ represents a finite set of inputs, $\beta=\{\beta_1,\beta_2,\ldots,\beta_r\}$ is defined as the set of outputs, and

$c=\{c_1,c_2,\ldots,c_r\}$ is a set of penalty probabilities, where each element c_i in c corresponds to an input action.

For example, when action α_i is selected, and good feedback is obtained, the action probability vector is updated according to the formula (6). Otherwise, it is updated according to formula (7).

$$\begin{cases} p_i(n+1)=p_i(n)+a(1-p_i(n)) \\ p_j(n+1)=p_j(n)-ap_j(n) \quad \forall j \;\; j\neq 1 \end{cases} \tag{6}$$

$$\begin{cases} p_i(n+1)=(1-b)\,p_i(n) \\ p_j(n+1)=b+(1-b)\,p_j(n) \quad \forall j \;\; j\neq i \end{cases} \tag{7}$$

In the above two sets of equations, a and b represent the reward and punishment parameters, respectively. If a=b, the learning algorithm T is called L_{R-P}. If $a \square\ b$ it is called $L_{R\xi P}$ an algorithm, and when b=0, it is called L_{R-I} an algorithm.

Irregular cellular learning automata is a combination of irregular cellular automata and learning automata, as shown in Figure 3. We define an irregular cellular learning automaton as an irregular cellular automaton mapped by an undirected graph.

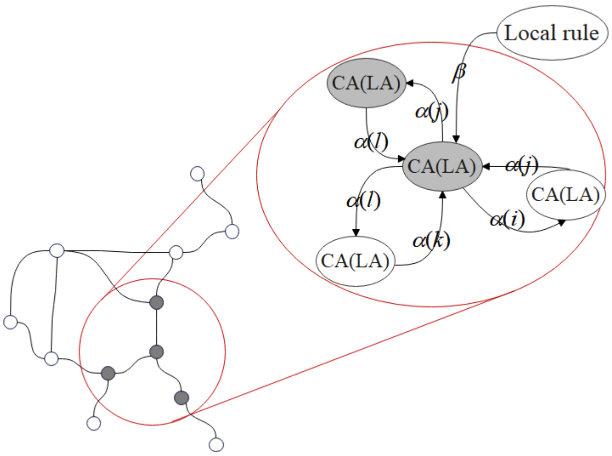


Figure 3: Structure and principle of Irregular cellular learning automata.

2.3 Relevant Elements of Detection Models for Irregular Cell Learning Automata

Irregular cell learning automata can be represented in the form of a quintuple with mathematical notation. In the study of e-commerce gang fraud, the FD_ICLA detection model can be represented by the quintuple shown in formula (8):

$$FD\_ICLA=\{G<B,C,E>,\Phi,N,A,F\} \tag{8}$$

1. Cellular space
The standard CA model is based on the rule division of research objects. The cell space of FD_ICLA is an irregular graph and an abstract concept. The FD_ICLA fraud detection model maps the bipartite graph $G < B, C, E >$ to the cell space.

2. Cell

Nodes in the transaction graph consist of buyers and sellers. To this end, the FD_ICLA model divides the cells into two categories: one is used to represent buyers, called C cells, and the other is used to represent sellers, called B cells. Figure 4 is a bipartite graph consisting of users and transactions. If it is mapped to an irregular cellular automaton, the cells are divided into two types. The grey cells represent sellers, which belong to set B, and the green cells represent buyers, which belong to set C. Meanwhile, the set of edges E represents the transaction relationship between buyers and sellers.

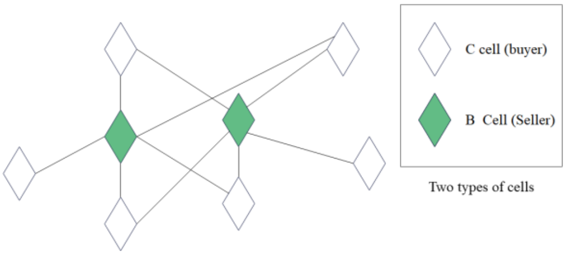


Figure 4: Two types of cells in the FD_ICLA fraud detection model.

The research content of this paper is the identification of fraudulent gangs. Considering that there are two types of cells in the FD_ICLA model, this paper defines the neighborhood of two different types of cells, as shown in formulas (9) and (10).

$$N_{bi} = \left\{ c_j \mid e_{ij} \in G(E), b_i \in B, c_j \in C \right\} \tag{9}$$

$$N_{ci} = \left\{ b_j \mid e_{ij} \in G(E), b_i \in B, c_j \in C \right\} \tag{10}$$

Figure 5 is an example of the definition of neighbors in the FD_ICLA model. According to formula (9), the neighbors of cell 2b in the figure have been highlighted. Similarly, according to formula (10), the neighbors of other cells can be deduced by analogy.

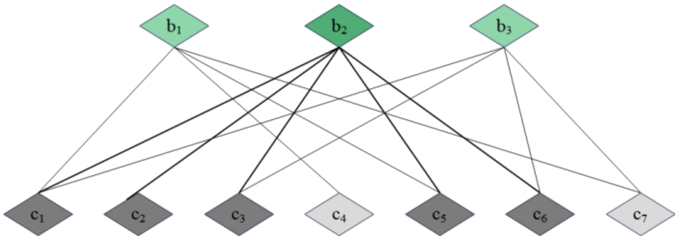


Figure 5: Example of definition of neighbor for FD_ICLA fraud detection model.

The above definition of neighbors is reasonable, and there is a direct transaction relationship between buyers and sellers. However, this relationship is not obvious and is usually ignored.

Fraud gangs include two key players, namely fraudulent sellers and a number of fake buyers who aim to disguise the identities of fraudulent sellers, also known as alliances. In addition, there are also a large number of honest and credible buyers and sellers on e-commerce platforms. Therefore, we determine that the valid state set Φ of the FD_ICLA model contains at least three states, namely fraud (F), alliance (A), and trustworthy (T). There is also an important state, which is between trusted and untrusted; that is, a trusted state that cannot be directly identified by the system is called unknown (U). Finally, the cell state set Φ of the FD_ICLA model is defined as $\Phi = \{F, A, T, U\}$.

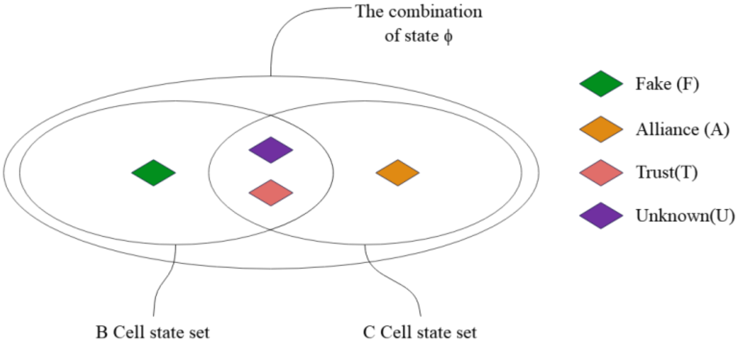


Figure 6: Cell state set Φ of FD_ICLA model.

Figure 6 depicts the state set Φ and the possible states of different types of cells.

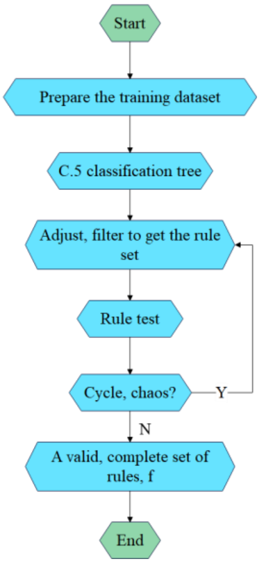
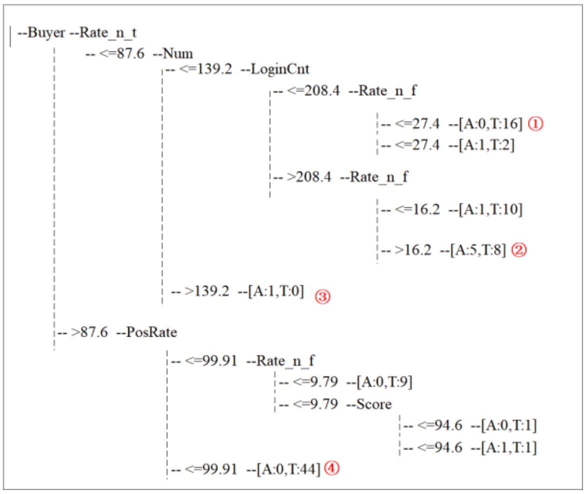


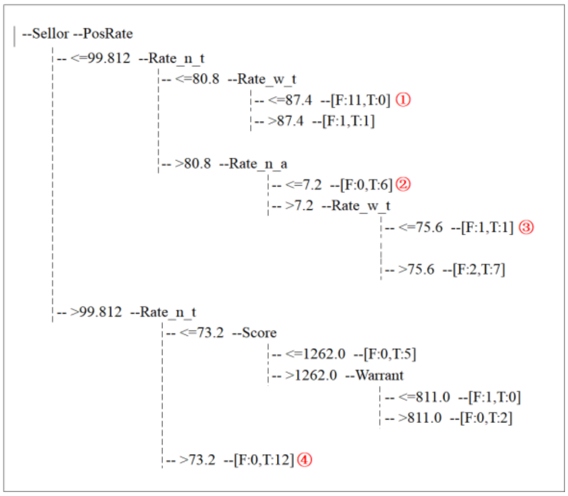
Figure 7: Local rule mining process.

Before determining the members of the rule set, we need to check the rules to ensure their validity and integrity. If the cellular automata cannot reach a stable state during the inspection process, the rule set needs to be adjusted, or the classification tree needs to be reconstructed. The complete process of rule definition is shown in Figure 7.

This paper uses the C4.5 decision tree algorithm to try to divide the continuous attribute x into two sections at four split points and select the optimal split point to discretize the attribute based on the information gain rate. The number of samples for buyer decision tree construction is 100 (91 credible and 9 allies), and the resulting decision tree is shown in Figure 8. The number of input samples for the seller decision tree is 50 (34 credibles and 16 frauds).



a. Buyer C4.5 Decision classification tree



b. Seller C4.5 Decision classification tree

Figure 8: C4.5 Decision classification tree for local rule mining.

This paper defines the priority for the rules, assigns a higher priority to the rules with less calculation amount, and executes the matching operation first. If there is a match, the matching conclusion is returned, and the subsequent rules (if any) are ignored. The specific rule chain and matching process are shown in Figure 9.

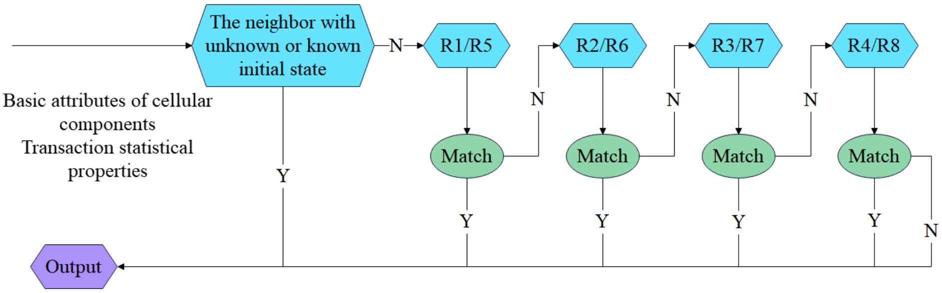


Figure 9: Rule chain and rule application process.

The defined linear learning operator includes formula (11) and formula (12). When the reinforcement signal obtained by the learning automaton A is Reward, formula (11) is applied, and if the reinforcement signal is Punish, formula (12) is applied.

$$\begin{cases} p_i(n+1) = p_i(n) + a\left(1 - p_i(n)\right) \\ p_j(n+1) = p_j(n) - a p_j(n) \qquad \forall j \quad j \neq 1 \end{cases} \tag{11}$$

$$\begin{cases} p_i(n+1) = (1-b)\, p_i(n) \\ p_j(n+1) = b + (1-b)\, p_j(n) \qquad \forall j \quad j \neq 1 \end{cases} \tag{12}$$

The state transition methods of cell B and cell C are shown in formula (13) and formula (14), respectively:

$$\Phi_I(k) = \begin{cases} U, Entropy\left(p_i(k)\right) \geq \delta \\ F, Entropy\left(p_i(k)\right) < \delta \text{且} p_{iF}(k) \geq p_{iT}(k) \\ T, Entropy\left(p_i(k)\right) < \delta \text{且} p_{iF}(k) < p_{iT}(k) \end{cases} \tag{13}$$

$$\Phi_I(k) = \begin{cases} U, Entropy\left(p_i(k)\right) \geq \varepsilon \\ \mathrm{A}, Entropy\left(p_i(k)\right) < \varepsilon \text{且} p_{iA}(k) \geq p_{iT}(k) \\ T, Entropy\left(p_i(k)\right) < \varepsilon \text{且} p_{iA}(k) < p_{iT}(k) \end{cases} \tag{14}$$

Among them, $Entropy\left(p_i(k)\right)$ represents the information entropy of the action selection event of cell *i* at time k, and δ and ε are the threshold parameters set by the entropy of the action selection event of cell B and cell C, respectively. When the event entropy is larger than the threshold, the cell state is defined as unknown U. Otherwise, the action (state) corresponding to the larger value in the probability vector is used as the cell state. It is set to $\delta = \varepsilon = 0.75$ when it is not described in this paper.

In the FD_ICLA model, the cell state is represented by an action probability vector, and the concept of information entropy can be used to measure the degree of uncertainty of the event that a cell chooses an action (state), as shown in the formula (15):

$$H_i(k) = -\sum_{j=1}^{3} p_{ij}(k) \cdot \ln\left(p_{ij}(k)\right) \tag{15}$$

Among them $p_{ij}(k)$ refers to the probability that cell i selects the j-th action at the k-th iteration. $H_i(k)$ represents the degree of uncertainty about the event of choosing an action.According to the meaning of entropy, the larger the entropy value, the more uncertain the state of the cell, that is to say, the greater the possibility of the automaton choosing different actions. Conversely, a smaller entropy value indicates that the cell has a more certain trusted state.

$$H(k) = \frac{1}{N}\sum_{j=1}^{N} H_j(k) \tag{16}$$

In order to evaluate the degree of certainty of all cell states of the whole model, this paper takes the average value of the information entropy of the selected action of the learning automaton after each iteration as the evaluation index (formula (16)), where N is the cell in the model The total amount. When the value of $H(k)$ is less than or the threshold λ, the model state is defined as convergent.

In this paper, the proportion of rewarded cells in each iteration is 1% as a measure, and its formula is shown in formula (17):

$$I_k = \frac{\sum_{j=1}^{N} 1, \beta_{jk} = '\mathrm{Re}\,ward'}{N} \tag{17}$$

Among them, N is the total number of cells, and β_{jk} is the reinforcement signal received by the learning automaton embedded in cell j at the k-iteration. The faster I_k approaches 1, the stronger the learning ability of the learning automaton, and the faster the FD_ICLA model can reach the convergence state driven by the learning operator. On the contrary, the weaker the self-adjustment ability of the model, the longer the convergence process.

The second step in the figure is the application of the cellular automata local rule F, and the process is similar to the standard CA. However, the result of the rule application does not directly modify the cell state but first obtains the feedback state $R_{out}(k)$ of a neighbour. The detailed process is shown in Figure 11. After obtaining $R_{out}(k)$, according to the mapping matrix, it is converted into the reinforcement signal of the learning automaton, and then the action probability vector representing the cell state is updated by the learning algorithm.

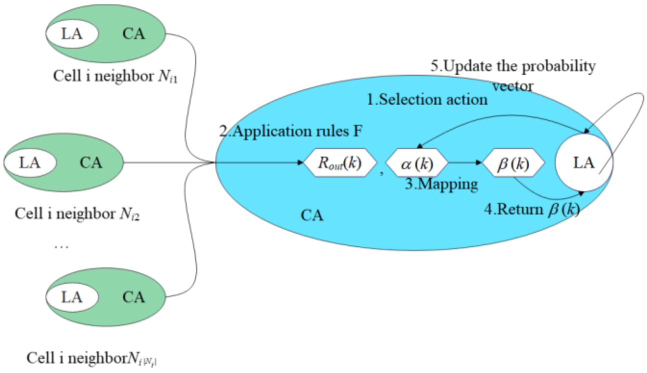


Figure 10: Flow chart of the k-th iteration of the FD_ICLA model.

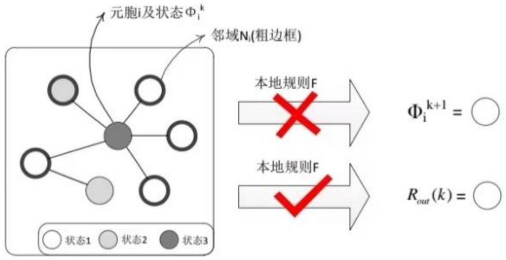


Figure 11: Application of 1 local planning in the FD_ICLA model.

Among them $R_{out}(k)$, it refers to the feedback from the cell neighbors. The state Φ_i^k of cell i at time k is state 3, and its neighbors are marked with thick borders. The neighbor feedback $R_{out}(k)$ that can be obtained by applying local rule F is state 1, but its state Φ_i^{k+1} at time d is not modified to state 1.

3 RESEARCH ON LEGAL RESPONSIBILITY AND GOVERNANCE OF ONLINE TRADING PLATFORMS UNDER C2C MODE

The second part constructs the identification of legal problems that can be used in online trading platforms under C2C. After that, this paper mainly studies the fraudulent behavior of the online trading platform in the C2C mode and verifies the recognition effect of the algorithm in this paper on the fraudulent behavior in the online trading platform in the C2C mode. The evaluation results are shown in Table 1.

Num	*Transaction identification*	*Num*	*Transaction identification*	*Num*	*Transaction identification*

1	*75.4381*	*15*	*71.2278*	*29*	*71.5707*
2	*76.3217*	*16*	*73.0390*	*30*	*74.8997*
3	*77.2907*	*17*	*75.3266*	*31*	*72.7553*
4	*78.3816*	*18*	*78.6626*	*32*	*76.0104*
5	*78.5158*	*19*	*72.2141*	*33*	*72.1045*
6	*71.8019*	*20*	*77.1875*	*34*	*78.5232*
7	*72.5180*	*21*	*73.1825*	*35*	*77.2365*
8	*76.0586*	*22*	*77.7023*	*36*	*75.6144*
9	*76.2365*	*23*	*71.8157*	*37*	*76.3384*
10	*77.7811*	*24*	*71.0701*	*38*	*78.0956*
11	*77.3699*	*25*	*73.2689*	*39*	*72.8025*
12	*72.0750*	*26*	*75.9586*	*40*	*76.6191*
13	*78.5225*	*27*	*77.5031*	*41*	*73.8710*
14	*73.9587*	*28*	*77.7445*	*42*	*77.0919*

Table 1: The recognition effect of the algorithm on the fraudulent behavior in the online trading platform under the C2C mode.

Through the above research, it can be seen that the recognition methods of fraudulent behaviors in the online trading platform under the C2C mode proposed in this paper have certain effects. On this basis, the following points are proposed:

The self-discipline of relevant online trading platforms should be carried out from the following aspects. First, it is necessary to establish an industry self-discipline system to correct and guide the behavior of participants in online trade. Second, it is necessary to carry out integrity publicity and set a model. The electronic trading industry of online trading platforms can adopt the advanced compensation fund system, unconditional returns, and other related behaviors to expand its influence and set up role models. Moreover, operators, whether it is goods advertising, quality standards, payment environment, protection of personal privacy, or related after-sales services, all need to take pride in establishing the value of integrity and be ashamed of violating it. Third, it is necessary to intensify the publicity of credit and establish the legal thinking of citizens. It is necessary to invite lecturers, professors, and other scholars to give lectures to form a certain scale. At the same time, it is necessary to strengthen the legal awareness and honest thinking of operators according to such methods. Fourth, it is necessary to carry out follow-up after-sales consumer reviews and tracking inquiries. The sellers and platform providers of the C2C network trading platform must constantly improve their work and respect users' comments. Moreover, it is necessary to conduct follow-up surveys on consumers to understand the real needs of buyers for quality and versatility, humbly absorb suggestions and actively correct deficiencies, and report the results of the survey and improvement to the industry's self-regulatory organizations. In addition, it is necessary to conduct sampling visits by industry self-discipline, thereby accelerating the improvement of the defects of electronic trade and finally achieving a comprehensive improvement of the quality of website services. Fifth, it is necessary to commend trustworthy operators and punish those who violate credit. At the same time, it is necessary to rely on rewards and undertakings to enhance the recognition of electronic trade operators, make them self-aware, keep a sense of integrity in mind, and protect a good transaction order. In addition, it is necessary to build a new order with integrity as the leading concept, establish a virtuous circle of online trade, and ensure the healthy and orderly development and progress of electronic trade.

4 CONCLUSIONS

As a fashionable transaction mode, C2C electronic transactions have brought a lot of opportunities to people. Among them, anyone can become a seller in the C2C electronic trading market, which makes full use of the surplus domestic labor and relieves the employment pressure. The user group of the C2C electronic trading market is increasing day by day, and the online trading volume hits a new high year by year, in which reputation plays a huge role. Reputation can reduce people's skepticism about the transaction mode of online shopping, build trust between traders, and promote the continuous improvement of these online trading platforms, thus playing a virtuous cycle for the development of the electronic trading market. In order to improve the fairness and justice of the online trading platform under the C2C mode, this paper combines the intelligent method to identify the fraudulent behavior of the online trading platform under the C2C mode. The research shows that the recognition methods of fraudulent behaviors in the online trading platform under the C2C mode proposed in this paper have a certain effect.

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