

Retraction

Retracted: Research on Maximizing Influence of Blockchain Social Network Based on BCLT Model

Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] C. Liu and S. Bin, "Research on Maximizing Influence of Blockchain Social Network Based on BCLT Model," *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 7335390, 8 pages, 2022.

Research Article

Research on Maximizing Influence of Blockchain Social Network Based on BCLT Model

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In the blockchain social network, the traditional influence maximization algorithm has the problem of insufficient accuracy of the influence spread. To solve the above problem, a BCLT model including the characteristics of the blockchain is established based on the linear threshold model. The BC-RIS algorithm is proposed based on the reverse reachable set. The BC-RIS algorithm's influence spread and running time and the traditional algorithm is compared using the real blockchain social network data set. The experimental results show that the BC-RIS algorithm can obtain a larger influence spread range, which is more in line with the influence propagation law of the blockchain social network.

1. Introduction

Many blockchain social networks have emerged with the rapid development of blockchain technology. Such social networks save the information and its transmission channels through blockchain, and the content sent or transmitted by users is difficult to be tampered with and erase. At the same time, such social networks provide tokens and reputation incentives/penalties for excellent/false content to promote users to be more rational when facing information with economic incentives. The higher the quality and credibility of the content sent by the users, the more forwards they will get, which will bring more financial rewards. Therefore, blockchain social networks have different communication mechanisms from traditional social networks. It can play an essential role in the in-depth research on the recommendation mechanism and social communication mechanism of blockchain.

Influence maximization is a hot topic in social network influence research. Richardson et al. [1] first proposed the problem of maximizing influence. Its content is to find K initial seed nodes under a specific information propagation model to maximize the influence propagation range after the information propagation process. The research of influence

maximization mainly includes two areas: the influence propagation model and the influence maximization algorithm. Goldenberg et al. [2, 3] proposed two main types of influence propagation models: the independent cascade model (IC) [2] and the linear threshold model (LT) [3]. Bazgan et al. [4] expanded the IC and LT models and realized the mutual transformation of the latter two models. Literature [5, 6] studied the influence propagation model on symbolic networks with polarity. Reference [7] studied the phenomenon of inactive nodes and homogeneous competition in communities and proposed a new communication model. Weng Kerui et al. [8] learned that the integer programming model was maximizing social influence under the determined threshold.

Kempe [9] proved in 2003 that the influence maximization problem based on IC and LT model is an NP-hard problem and proposed a greedy algorithm. It is an iterative selection of the maximum marginal revenue node, with an approximate solution of $((1 - 1/E) - \epsilon)$. However, the algorithm has low efficiency and is unsuitable for large-scale social networks. Leskovec et al. [10] optimized the efficiency of the greedy algorithm and proposed CELF (cost-effective lazy forwards) algorithm. The running speed of this algorithm is about 700 times that of the traditional greedy

algorithm. Goyal et al. [11] further improved the algorithm's time efficiency and proposed CELF ++ algorithm. Although the scholars optimize the above algorithms for the operation efficiency of the greedy algorithm, it still takes a lot of time to select the most influential node, which makes many scholars to choose to study heuristic algorithms with higher operational efficiency. References [12, 13] have proposed heuristic algorithms based on degree centrality. Chen et al. [14] proposed a PMIA algorithm based on the maximum influence propagation path in the network in 2010, which is also a heuristic algorithm. In addition, Jiatang Tian et al. [15] and Cao Jiuxin et al. [16] proposed new heuristic algorithms according to the propagation and structural characteristics of the network. The above heuristic algorithm runs faster, but there are some defects in inaccuracy. In 2015, Borgs et al. [17] proposed a RIS (reverse influence sampling) algorithm to generate a set of reverse reachable nodes and judge the importance of nodes by the number of nodes in the group. Zhao Yufang et al. [18] studied the influence maximization of a multi-subnet composite complex network model. It proposed an MR-RRset algorithm based on a reverse reachability set. Deng Xinhui et al. [19] studied and improved the RIS algorithm and proposed the D-RIS influence maximization algorithm, which reduced the algorithm's time complexity. Yu Lei et al. [20] consider the influence propagation problem in the case of co-marketing of two commodities and propose a corresponding greedy algorithm. Zhu Jianming et al. [21] model the influence diffusion process under the influence of the echo chamber effect and study the influence maximization problem of the echo chamber effect. He Qiang et al. [22] obtain better impact diffusion and running time by First-Last Allocating Strategy and Apical Dominance. Ma Lianbo et al. [23] propose an influence evaluation model that measures the propagation range of combined nodes in an independent cascade model.

Most studies on blockchain social networks focus on the characteristics of blockchain social networks and their impact on information propagation mechanisms. However, there are relatively few research results on maximizing the influence of blockchain social networks. Among them, Wang Xiwei and others studied the identification of opinion leaders in the blockchain environment [24] and the screening of network rumors based on blockchain [25] and research on the contribution mechanism of blockchain-based on consensus [26]. Therefore, it is of great practical significance to study the maximization of the influence of blockchain social networks. This paper proposed the BCLT model based on the linear threshold model and the characteristics of blockchain social networks. Compared with the traditional model [27–29], the model can better simulate the influence propagation on blockchain social networks. The author proposes an algorithm based on the reverse reachable set and BCLT model.

The main contributions of this study are as follows:

- (1) The factors that affect the propagation of blockchain social network influence are discussed and analysed, and the influence propagation mechanism of blockchain social network that is different from traditional social networks is summarized

- (2) Aiming at the influence propagation in the blockchain environment, the linear threshold model (LT) is improved, and the blockchain social network influence propagation model is established
- (3) Based on the blockchain social network influence propagation model, combining the existing RIS algorithm with the blockchain social network influence propagation characteristics, an influence maximization algorithm applied to the BCLT model is proposed

2. Influence Maximization Based on BCLT Model

2.1. Definition of BCLT Model. The positive and negative votes cast by users in the blockchain social network will have positive and negative influences. Therefore, the blockchain social network can be abstractly expressed as a directed network graph $G_B = (V, P, C, E)$, where $V = \{v_1, v_2, \dots, v_n\}$, which represents the nodes (users) in the network. Set $E = \{e_1, e_2, \dots, e_n\}$, meaning the set of edges between nodes (that is, the relationship between users); $P \in (0, 1)$, the weight of each edge of the network, that is, the influence between nodes probability. For each directed edge e_{uv} in the graph, there is an attribute $P(u, v)$. The literature [24] gave the evaluation criteria of the node acceptance degree and the weight of each index. In this paper, the node acceptance degree is used as the influence parameter of the node. The symbol C represents the influence parameter of the node. The influence parameter is defined as:

$$C = \begin{cases} \alpha * NR + \beta * NT + \gamma * NP, & \text{cred} > 0, \\ 0, & \text{cred} \leq 0. \end{cases} \quad (1)$$

Among them, α , β , and γ are the weights of the node reputation (NR), the number of node tokens (NT), and the number of issued documents in the influence parameters (NP), respectively. It can be inferred from the literature [23]: $\alpha \cong 0.5816$, $\beta \cong 0.3431$, $\gamma \cong 0.0750$. Taking Steemit, the most popular blockchain social network platform, as an example, according to the Steemit white paper [24], when the node reputation is less than or equal to 0, its voting result will be invalid, and its influence parameter C is 0. After normalizing the influence parameters, the value range of the influence parameters of node i is obtained as $C_i \in [0, C_i - \min(C)/\max(C) - \min(C)]$. Table 1 shows the symbols commonly used in this paper.

2.2. Influence Propagation Rules of the BCLT Model.

Unlike the general symbolic network, in the blockchain social network, the negative votes cast by users will have a more significant negative impact on the spread of influence, and it is not possible to remove the negatively affected nodes in the process of influence spread. And after the node accepts the positive influence, there is a certain probability of producing a negative opinion, and it turns into a negatively influencing node. In this model, there are three node states, namely, (1) inactive state, (2) positive active state, and (3)

TABLE 1: Frequently used notations.

Symbol	Description
G_B	Blockchain network diagram
V	Set of nodes
E	Set of directed edges
P	Influence probability between nodes
C	Node's influence parameters
θ^+	Positive activation threshold
θ^-	Negative activation threshold
R	Type of influence the node exerts
q_0	Information quality factor
$sp(v)$	The proportion of positive active nodes in the node's in-degree neighbor nodes
$in(v)$	The set of activated in-degree neighbor nodes of the node
S	Seed nodes set
$RRset$	Reverse reachable nodes set

negative active state. $R(u, v)$ represents the type of influence node u exert on v , $R(u, v) \in \{+1, 0, -1\}$. When the node u is in the inactive state, $R(u, v) = 0$, the node has no propagation ability. When the node u is in the positive active condition, $R(u, v) = +1$, the node u exerts a positive influence on the node v at this time.

When node u is negatively activated, $R(u, v) = -1$, node u exerts a negative effect on node v at this time. The probability of influence between nodes, the type of influence exerted by nodes, the influence parameters of nodes, and the quality of the transmitted information jointly determine the state transition of nodes. Suppose the influence received by node v in the model satisfies the negative activation condition. In that case, the node will be affected by "negative bias" [23], and node v becomes a negative activation node. Suppose the influence received by node v satisfies the positive activation condition about the influence of herd mentality on information propagation in reference [25]. In that case, the probability of making v a positive activation node is $q_v = q_0 * e^{-\ln q_0 * sp(v)}$. There is a probability of $1 - q_v$ Make v a negatively active node, where q_0 is the information quality factor [23]. The information quality factor represents the initial probability of the node maintaining a positive activation state after being positively influenced, and $sp(v)$ is the proportion of active positive in-degree neighbor nodes of node v .

Figure 1 depicts the state transitions between inactive nodes and active nodes.

Similar to the traditional linear threshold model, the BCLT model reflects the cumulative effect of influence. In the BCLT model, there are two threshold values θ^+ and θ^- for each node, which indicate the degree of positive influence and negative influence, respectively, $\theta^+ \in (0, 1)$ and $\theta^- \in (-1, 0)$. The closer the θ^+ and θ^- values are to 0, the more susceptible the node is to the influence of its neighbor nodes. After normalization, the influence parameter C_u of node U represents the weight of influence exerted by this node on its outdegree neighbor node. $in(v)$ represents the set of activated entry nodes of node V . The average value of influence parameter C_u and influence probability P between nodes is the new activation probability. It decides positive and negative activation conditions of node V , as shown in formula (2) and formula (3).

$$\sum_{u \in in(v), in(v) \neq \emptyset} \text{Average}(C_u + P(u, v)) * R(u, v) \geq \theta_v^+, \quad (2)$$

$$\sum_{u \in in(v), in(v) \neq \emptyset} \text{Average}(C_u + P(u, v)) * R(u, v) \leq \theta_v^-. \quad (3)$$

This part describes the propagation rules of the BCLT model as follows: (1) At the initial time $t = 0$, only the nodes in the seed set S are in the active forward state, and the rest of the nodes in the network are in the inactive state. (2) At each step, t ($t > 0$), the activated node tries to activate its inactive out-degree neighbor nodes. When the influence of positive neighbor nodes that a node accepted is more significant than the threshold θ^+ ($\sum_{u \in in(v), in(v) \neq \emptyset} \text{Average}(C_u + P(u, v)) * R(u, v)$), the node will change to a positive activation state with a probability of $q_v = q_0 * e^{-\ln q_0 * sp(v)}$, and a negative activation state with a possibility of $1 - q_v$. When the influence of the negative neighbor node is less than the threshold θ^- , the node will turn into a negative activation state; when the neighbor node's influence accepted by the node is more significant than the threshold θ^- and less than the threshold θ^+ , the node will still be in an inactive state. (3) When no inactive nodes can be activated in the network, the propagation process ends.

The spread of influence on the BCLT model is shown in Figure 2:

2.3. BC-RIS: Influence Maximization Algorithm Based on Reverse Reachable Sets Applied to BCLT Model. The influence maximization problem requires finding a set of seed nodes S in a given social network G to obtain the widest spread. In the traditional influence maximization algorithm: the greedy algorithm cannot be applied to large-scale social networks due to the high cost of solving time; the heuristic algorithm has the problem of insufficient accuracy. The reverse influence sampling algorithm RIS replaces the Monte Carlo simulation used in the greedy algorithm with the reverse reachable set $RRset$ (Reverse Reachable Set), which solves the problem that the calculation speed and accuracy of the influence maximization algorithm cannot be achieved at the same time. Based on the reverse influence sampling algorithm, this paper proposes a reverse influence sampling

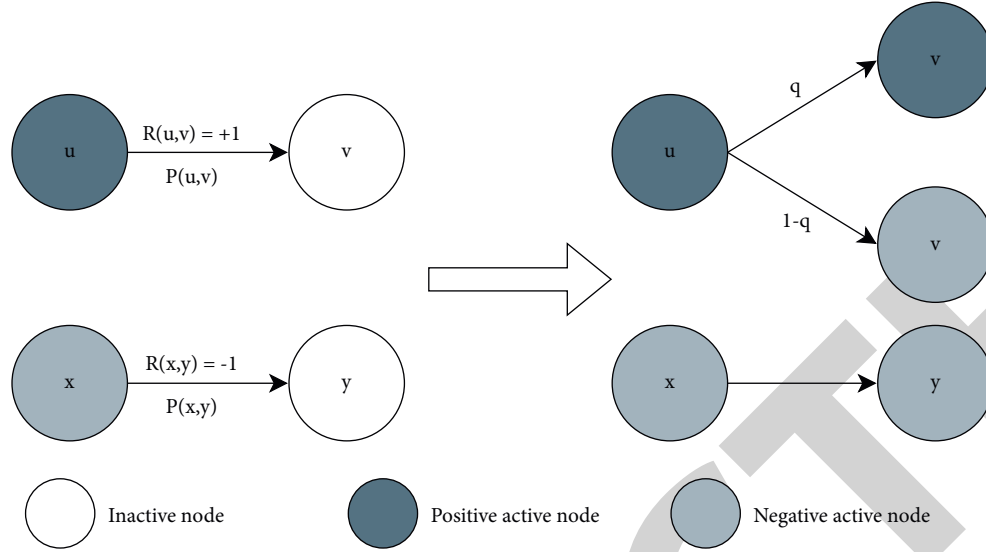


FIGURE 1: Node state transition diagram in BCLT model.

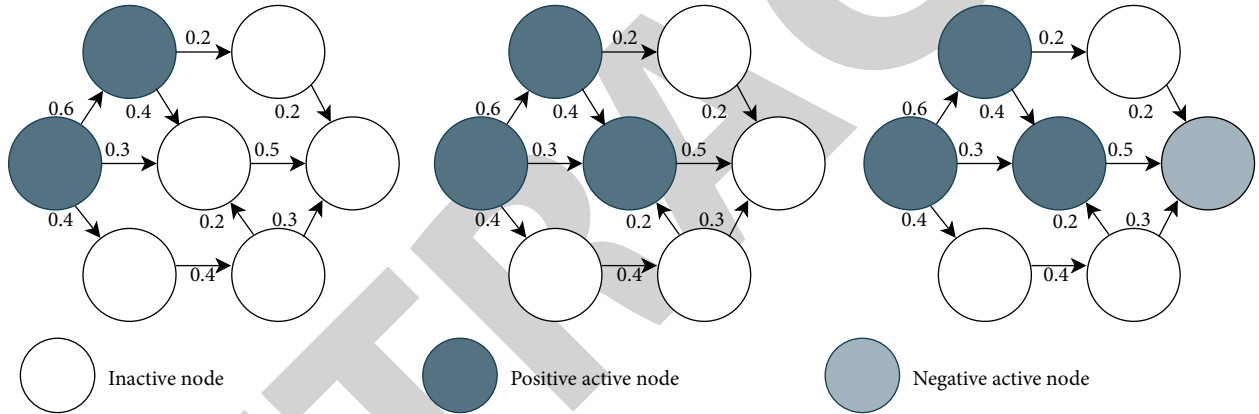


FIGURE 2: The spread of influence on the BCLT model.

algorithm BC-RIS on the blockchain social network. The algorithm is mainly divided into two parts: (1) Generate a certain number of reverse reachable sets according to the sampling graph of the network; (2) Use the maximum coverage method to find k nodes covering more reverse reachable sets in the generated reverse reachable set, and use these k nodes as the seed nodes of the influence maximization problem. Reference [17] gives two basic definitions of the reverse influence sampling algorithm.

Definition 1. Sampling graph

Sampling graph g refers to a random graph obtained by deleting edge e according to the probability of $1 - P(e)$ for all edges $e \in E$ in a given graph $G = (V, P, E)$.

Definition 2. Reverse reachable set.

The reverse reachable set refers to the set of nodes that can reach the node v in the sampling graph g .

According to Definition 1, the generation of the sampling graph g is only related to the propagation probability p between nodes. The larger the p corresponding to the edge, the greater the probability of the edge appearing in the

sampling graph. This method of generating sampling graphs is insufficient to reflect the characteristics of blockchain social networks. In this paper, the propagation probability p between nodes and the influence parameter C of the node determine the probability of an edge appearing in the sampling graph. The larger the influence parameter of the out-degree node in the directed edge, the more likely the edge will appear in the sampling graph. This method can eliminate nodes with negative reputation values and reduce the probability of low reputation value nodes appearing in the reverse reachable set. In addition, this paper uses the method in literature [6] to limit the sampling depth of the reverse reachable set, which improves the algorithm's efficiency. Figure 3 shows a sampling graph on a blockchain social network and an example of a reverse reachability set:

A directed graph G can randomly generate various sampling graphs, such as g_1 and g_2 . For node G in the directed graph, its reverse reachability set in the sampling graph g_1 is $\{A, C, G\}$, and the reverse reachability set in the sampling graph g_2 is $\{A, B, C, G\}$. Algorithm 1 shows the pseudo-code description of the algorithm. `new_nodes` is the set of newly added nodes in the reverse reachable set after

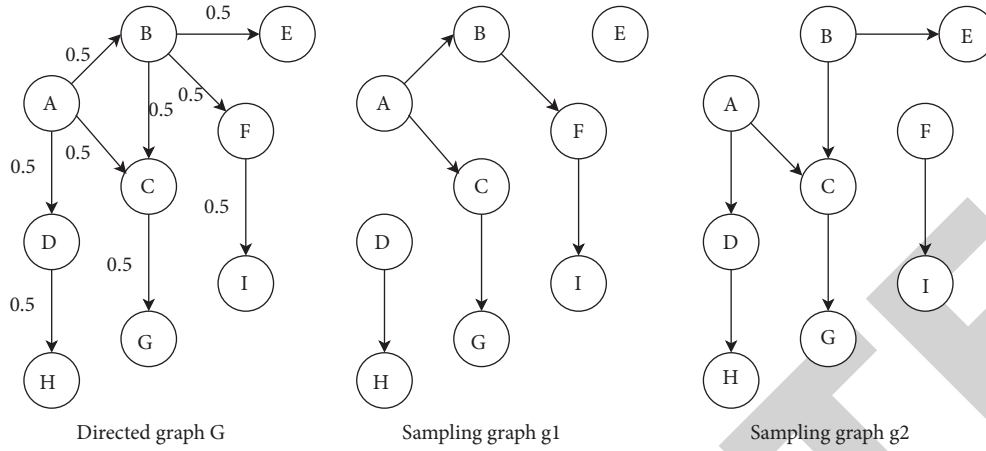


FIGURE 3: Sampling graph and reverse reachable set on blockchain social network.

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Initialize: tempRRset $\leftarrow v$ , new_nodes $\leftarrow v$ , depth $\leftarrow 1$ 
Input: the blockchain social network  $G_B = (V, P, C, E)$ 
# Generate the sampling graph  $g$  of  $G_B$  according to  $P$  and  $C$ 
# Random select a node  $v$  from the sampled graph  $g$ 
for new_nodes  $\neq \emptyset$  do
# random select  $u$  in new_nodes
new_nodes $\leftarrow \{u_{in}\}$  //The in-degree neighbor node, if it does not exist, new_nodes =  $\emptyset$ 
RRset = tempRRset + new_nodes , tempRRset $\leftarrow$ RRset , depth = depth + 1
if depth > sample_depth then
Break
end if
end for

```

ALGORITHM 1: Generate reverse reachable set.

```

Initialize:  $S \leftarrow \emptyset$ 
Input: number of seed nodes  $k$ , reverse reachable set RRset
for  $i = 1$  to  $k$  do
 $v \leftarrow \text{max\_coverage}(\text{RRset})$  //get the seed nodes by the maximum coverage method
 $S \leftarrow S + v$  //add the seed node to the seed node set
RRset = RRset - RRset( $v$ ) //delete the RRset containing the seed node
end for

```

ALGORITHM 2: choose k seed nodes.

each traversal; tempRRset represents the reverse reachable set obtained after the last traversal, and sample_depth is the maximum sampling depth when generating the reverse reachable set.

According to the literature [17], a node appears in the reverse reachable set many times. It means this node can activate multiple nodes to be considered a node with strong influence, so it can use the maximum coverage method to select a seed node. The process of choosing k seed nodes is (1) Through the maximum covering strategy, find a node that appears the most times in the existing reverse reachable set and use it as a seed node; (2) Add this node to the seed node set S ; (3) Eliminate the reverse reachable set containing the

node; (4) Iterate the above process k times to obtain k seed nodes. The solution obtained by using the maximum coverage method in 1) is an optimal local solution, and the algorithm can finally get an approximate resolution of $((1 - 1/E) - \epsilon)$. The algorithm's time complexity is related to the number k of the selected seed nodes. Algorithm 2 shows the pseudocode description of the algorithm.

There are two main parts of the BC-RIS algorithm: when generating reverse reachable set, the time complexity of developing a single inverse reachable set is $O(\theta)$, θ refers to the number of nodes v_i , edge in sampling graph G , and the time complexity of generating n inverse reachable sets is $O(n * \theta)$. When selecting seed nodes, the maximum

coverage method used by the BC-RIS algorithm reflects the greedy idea, and the time complexity of finding the seed node-set composed of K nodes is $O(k)$. Finally, the time complexity of the BC-RIS algorithm is $O(n * \theta + k)$. Greedy algorithm's time complexity is $O(k * |V| * |E| * m)$, in which $|V|$ says the number of the nodes in network $|E|$ noted in the network edge number, m noted the number of Monte Carlo simulation. Large social networks often have larger $|V|$ and $|E|$ and m . Therefore, compared with the greedy algorithm, the BC-RIS algorithm is more suitable for large blockchain social networks.

3. Simulation Experiment and Result Analysis

3.1. Experimental Dataset and Experimental Design. This paper conducts simulation experiments based on the user data and user attention data set of the Steemit platform. Steemit is one of the most widely used blockchain social network platforms. Users of the website can check the reputation value, the number of posts, and the number of existing tokens of others, to judge whether the posts of others are credible. Table 2 shows the specific parameters of the dataset.

V in the table indicates the number of nodes in the directed graph, E shows the number of directed edges in the directed graph, D_{outMAX} indicates the out-degree value of the node with the largest out-degree in the directed graph, and d denotes the network diameter of the graph. This experiment uses the method of comparing the positive influence propagation range and algorithm running time of the BC-RIS algorithm and the traditional influence maximization algorithm (Random, DegreeDiscount, and CELF, RIS) to analyze the accuracy and operating efficiency of the BC-RIS algorithm. The value of the information quality factor (q_0) is 0.5, and the influence probability (P) of the edge in the network is the reciprocal of the out-degree value of the starting point of the edge. The influence parameter C of a node is jointly determined by the reputation value of each node, the number of tokens, and the number of issued documents.

3.2. Result Analysis. This paper uses Monte Carlo simulations 1000 times to simulate influence propagation in the BCLT model. It takes the average value of the propagation range of influence obtained from 1000 Monte Carlo simulations as the final propagation range of influence.

As can be seen from Figures 4 and 5, for different influence maximization algorithms, the influence propagation range decreases with the increase of activation threshold θ . The reason is that the activation threshold θ represents the degree of difficulty for nodes to be activated. The larger the activation threshold is, the more difficult it is for unactivated nodes to be activated, and finally obtained a smaller propagation range of influence. At the same activation threshold, the influence propagation range accepted by the BC-RIS algorithm is superior to other algorithms. In addition, when the activation threshold is the same, increasing the number of initial seed nodes can obtain a more extensive spread range of influence.

TABLE 2: Parameters of experimental datasets.

V	E	D_{outMAX}	d
7242	273942	1590	4

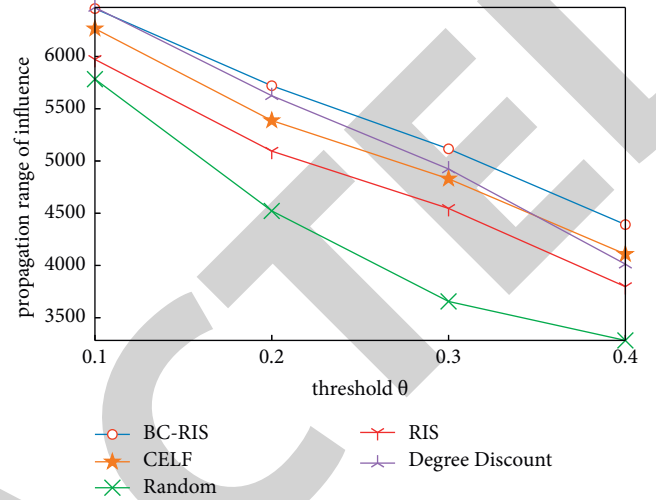


FIGURE 4: Positive influence propagation range of different influence maximization algorithms, and number of seed nodes is 20.

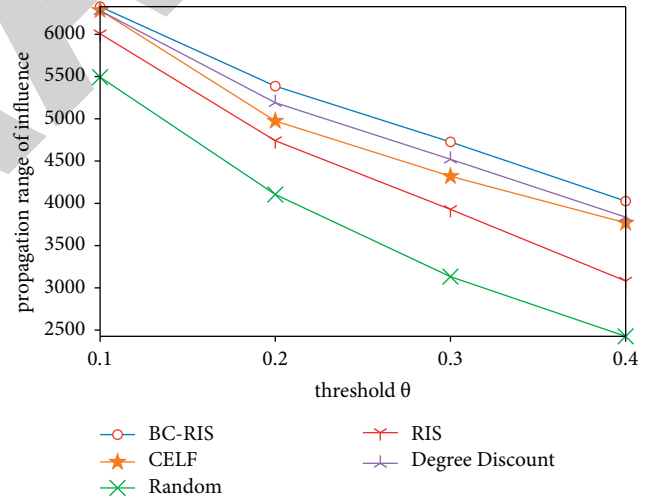


FIGURE 5: Positive influence propagation range of different influence maximization algorithms, and number of seed nodes is 10.

This part of the experiment compares the running time of the BC-RIS algorithm and some traditional algorithms when the positive and negative activation threshold θ^+ and θ^- values are 0.1, 0.2, 0.3, and 0.4, respectively. Figures 6 and 7 respectively, represent the running time of different influence maximization algorithms when the initial seed node number is 10 and 20.

As can be seen from Figures 6 and 7, the running time of the CELF algorithm and CELF++ algorithm decreases significantly with the increase of activation threshold θ . In contrast, the BC-RIS algorithm proposed in this paper has a slight variation with the activation threshold θ . This result is because the increase of the activation threshold θ will reduce

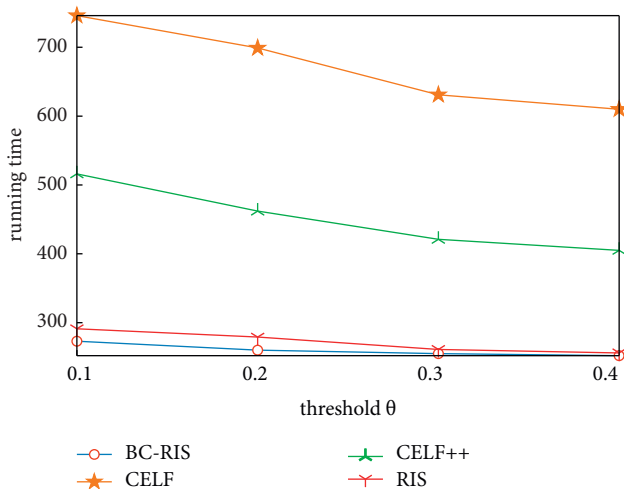


FIGURE 6: The running time of different influence maximization algorithms, when number of seed nodes is 20.

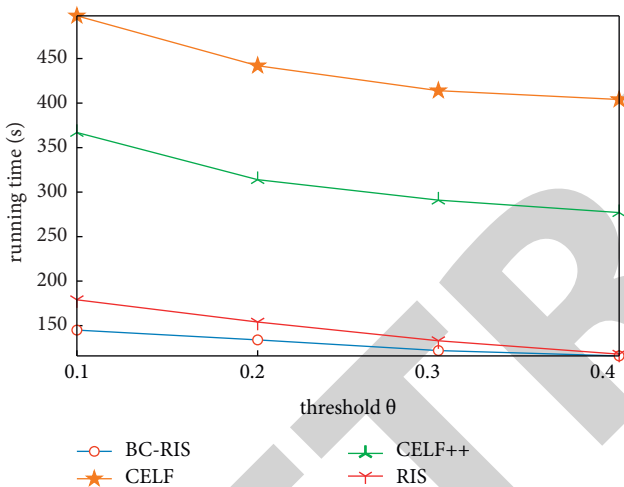


FIGURE 7: The running time of different influence maximization algorithms, when number of seed nodes is 10.

the candidate node set during the operation of the greedy algorithm. The maximum coverage method used in the BC-RIS algorithm is not affected by the activation threshold θ and has better stability. Under the condition of the same activation threshold and the same initial seed node-set, the running time of the proposed algorithm is significantly smaller than that of the CELF algorithm. In addition, the activation threshold is unchanged, and the running time of both algorithms increases with the increase of seed nodes.

4. Conclusions

Most of the current work related to influence maximization focuses on traditional social networks. There are few studies on maximizing the influence of blockchain social networks. This paper proposes a blockchain social network influence propagation model BCLT based on a linear threshold model (LT). A positive influence maximization algorithm (BC-RIS) based on a reverse reachable set is proposed based on this

model. The algorithm considers the unique properties of blockchain social networks in generating reverse reachable sets. In the simulation experiment, based on the accurate Steemit social network data set, the BC-RIS algorithm is compared with other classical algorithms to verify its effectiveness. The experimental results show that compared with the classical algorithm: (1) the BC-RIS algorithm can select the seed node-set more accurately and obtain a more extensive influence propagation range; (2) the BC-RIS algorithm has an ideal running time. Therefore, the BC-RIS algorithm can effectively solve the problem of maximizing influence in the social blockchain. This study does not consider the impact of time factors on the influence spread of blockchain social networks. Next, we will study the effect of time on the propagation of blockchain social networks.

Data Availability

Previously reported Steemit data were used to support this study and are available at <https://doi.org/10.1145/3292500.3330965>. These prior studies (and datasets) are cited at relevant places within the text as references [30].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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