

Research Article

Crowd-Sourcing Information Dissemination Based on Spatial Behavior and Social Networks

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Received 6 November 2020; Revised 17 December 2020; Accepted 12 March 2021; Published 24 March 2021

Academic Editor: Nicola Bicocchi

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In the context of today's network era, rich social networks and convenient network communication make different individuals and groups interact and transmit information in more diversified ways, which also bring new dissemination in information of crowd-sourcing tasks. The paper analyzes mobile behavior characteristics of users from different perspectives, such as spatial activity behavior and location type preference, and constructs a user space mobile behavior model based on the physical world. At the same time, it analyzes the social influence of users in social networks and mode of information transmission. In the paper, real data sets are adopted, mathematical modeling and computer simulation are combined to build an information communication model around the social influence of users in social networks, and the rules of information communication in new environment of social networks are depicted in combination with users' spatial movement.

1. Introduction

With the development of mobile communication technology, social network has changed a lot. Crowd-sourcing is a way to use the power of the group to solve complex problems. Traditional crowd-sourcing distributing task is usually in the form of open bidding or competition, and the task is distributed to different execution groups by the crowd-sourcing platform. In recent years, the progress of the Internet has promoted the rapid development of social network services (SNS) [1]. Crowd-sourcing is widely regarded as emerging human-powered sensing power [2] and plays crucial role in different areas, such as indoor, sharing urban environment data [3], participant recruitment [4], automatically measuring organizational behavior [5], collaborative crowd density estimation with mobile phones [6], use of Bluetooth for analyzing of human movement [7], quantification of the level of crowdedness for pedestrian movements [8], localization [9], Pollen onsets detection [10], and relative research [11, 12]. The world has ushered in the era of the Internet. The cost of communication between people is getting lower and lower. Such as Facebook and Weibo, more and more users get the latest news and share

information with their friends through these online social platforms. In June 2017 alone, the number of users of Facebook exceeded 2.01 million [13].

With the popularity of social networks, crowd-sourcing task distribution has also ushered in a new way, that is, using a wide range of social networks to quickly spread crowd-sourcing task information and collect enough executioners and users in a short period of time. Due to the characteristics of social networks such as strong integration and complex structure, the interaction mode and information transmission mode among individuals are more diversified. Compared with the traditional platform-user [13, 14] crowd-sourcing mode, the crowd-sourcing task information transmission mode based on social networks is more efficient, faster, and more adaptable to the new social environment. Wang et al. [15] considered the effect of the mutual influence between message transmission nodes on information transmission. Xu et al. [16] established a new propagation model by considering the transition probability of nodes as a variable and studied nonlinear phenomena in social networks according to the equilibrium field equation. Literature [17] proposed a mobile crowd-sourcing employee recruitment scheme based on mobile social network. First,

some users on the social network were selected as the initial seed, and the task was pushed to them. Then, the affected users would accept and spread it to their friends. To some extent, the problem of the above definition is similar to that of maximizing influence in the social network research community [18–21]. In the literature [22], Zhang proposed a smart evolution model based on evolutionary game theory by introducing the reputation mechanism. And literature introduced strategy without reciprocity principle and with the indirect reciprocity principle individually, which is research influence of malicious users. However, the paper adopts evolutionary game theory to research reputation mechanism, which does not take relationship between physical and social into account. Influence maximization (IM) is the problem of finding a seed vertex set which is various applications such as approach to disseminate information, news, or ad within a social network [23]. Scholars adopt fused sampling, memorization, and vectorization to restructure, parallelize, and boost their performance on undirected networks. The proposed approach reduces the number of edge traversals; hence efficiency is promoted significantly. Obviously, the paper does not think of disseminating information with user preference and POI attributes. Social networks can provide huge data and, however, social information on social networks is not catching the changes in the entire network over time [24]. For highly influential users and posts, the paper introduces a novel dynamic social sensing model, named dynamic PageRank (DPRank) model, to evaluate the dynamic topical influence on social networks during the social information evolution. The paper pays more attention to dynamic social sensing model but ignores information relationship between mobile track and social network. In literature [25], social media feeds are novel platform for providing and dissemination of geographic information, which is positive to urban emergency events. In this paper, spatial and temporal information from the social media are extracted to detect the real-time event with GIS detecting system. The paper has not researched interactivity between user physical information and disseminating message model. The intelligence of Smart Cities (SC) is represented by its ability in mining multisource data for valuable insights [26]. Nevertheless, this paper has not harnessed data of user to explore match degree with their location attributes.

Based on the existing research, in distributing task of crowd-source, most researches pay more attention to mechanism and model of information dissemination or ignore individual physical location with social network. It can be concluded that most scholars ignore relationship research between user spatial behavior and social influence in information transmission. Nevertheless, social behavior is relevant to individual POI and personal behavior trace, which will influence distribution of crowd-sourcing task obviously. Consequently, the contribution of this paper is as follows:

- (1) This paper harnesses objective and subjective viewpoint in distributing mechanism of crowd-sourcing, in which it is called two dimensions structure. Objective factor is defined as pattern of

user space mobile behavior and subjective factor is defined as social centrality. This paper introduces two dimensions model, which combine user space mobile behavior with social networking based on user's mobile behavior patterns and interest preference, which is objective condition in distributing task of crowd-sourcing. For each user in the user-centered social network, this paper also studies the information transmission task of social network, which is the user's subjective social influence.

- (2) This paper analyzes similarity between user behavior and crowd-source task, which show probability of success. The match degree, therefore, is adopted between user behavior attribute and task POI, which reveal significant and latent sign in task distribution probability of success.

This paper designs a crowd-sourcing information transmission model based on spatial behavior and social network. Section 1 introduces the research on crowd-sourcing and information transmission on social networks. Section 2 firstly analyzes the spatial movement rules of users based on existing data, obtains the location of user activity center, uses the POI access frequency of location points as users' interest preference, and analyzes the users' physical task execution probability from the spatial location distance and task POI type similarity. Then, social networks are used to analyze users' social influence. Finally, the influence attenuation model of task information transmission is constructed. In Section 3, a task information communication model is constructed based on the objective implementation rate of the physical world and the subjective influence in the social network, respectively, to predict the effect of crowd-sourcing task information communication. Section 4 simulated the experiment on the real data set, compared the information transmission effects under the two modes, and analyzed and compared the average user completion rate, average influence, and audience degree in the communication subnetwork under the two information transmission models. The results show that the user completion rate and the average user influence are higher than random propagation.

2. Related Work

2.1. Problem Statement. In social network field, there are many different methods to explore social potential relationship in solving crowd-source problem and so on. The published literature takes into account information on one aspect, which is comprised of maximizing influence in the social network research community [16–19], mechanism on transmission of personal information [20–22] or urgent information dissemination [23], and mining multisource data for SC [26]. In view of sociological perspective, it is generally accepted that information is always influenced not only by the potential social network but also personally in the process of social transmission. In other words, physical attributes of users is affected by themselves and social

relationship. Consequently, most papers isolate user physical information and social network, which will hardly reveal potential social information transmission mechanism completely and comprehensively, since they have acquired rich achievements in specific research fields. In this paper, a novel viewpoint is introduced, which will not only harness individual physical information such as POI preference but also adopt social centrality.

The dissemination of task information relies on social structure, and social influence factors are affecting users' execution of tasks. Nevertheless, space location of the user and the distance from the task location impact the individual task execution, which affects their execution as importantly as individual interest and preference styles match the task styles. Therefore, the objective conditions are used to measure the user's task execution probability. Define $T_k: \langle \text{lat}_k, \text{lon}_k, \text{poi}_k, n_k \rangle$ as existing crowd-sourcing task information with latitude and longitude position, POI type. This paper also adopts historical check-in data of spatial movement behavior of users, which reveal POI styles of users with their check-in times. With historical distance data, user's activity center location and the task location are counted, which reflect execution probability under distance function $P_1 = e^{-\gamma * \text{dis}}$. $P_2 = \cos_{\text{poi}}$ is harnessed to reflect the similarity between the POI type of the task and the user's POI preference type, which is a crucial parameter to user's physical task execution probability in (1). At the same time, social influence of users can be focused on what is called the centrality of individual, which is based on graph theory. Obviously, centrality of individual reflects the degree between different nodes. Information transmission is timely, in which the effect of task information will gradually reduce with gradually increasing distance. Distance, therefore, will affect the attenuation process of task message, which is defined as model $y_i = e^{-\alpha * x_i * n}$. Two types of information construct two dimensions structure to research crowd-source problem, which is verified by real data test.

2.2. User Execution Probability. The dissemination of task information depends on social networks, and social influence factors are the subjective factors affecting users' performance of tasks. However, the objective factors affecting the user's task execution depend on the space location of the user and the distance from the task location as well as whether the user's interest and preference types match the task types. Therefore, the objective conditions are used to measure the user's task execution probability.

2.2.1. Definition Explanation. Currently, the existing crowd-sourcing task information generally includes $T_k: \langle \text{lat}_k, \text{lon}_k, \text{poi}_k, n_k \rangle$, crowd-sourcing task location, crowd-sourcing task type, required number of tasks, and other information, where $\text{lat}_k, \text{lon}_k$ are the latitude and longitude position point corresponding to the task, and poi_k is the POI type corresponding to the task. The historical check-in data of users are used to analyze the spatial movement behavior of users. Among them, the clustering method of DBSCAN is used to obtain the activity center point from the numerous

check-in spatial locations of users, and the check-in frequency of each user on different POI types is counted as the user's access interest and preference.

2.2.2. Distance Function. Obtain the user's activity center by clustering the historical data, and calculate the distance between the user's activity center location and the task location. Figure 1 shows the distance distribution between the user activity center and a task point on the left, and the distance distribution between the user and the task by using the distance function $P_1 = e^{-\gamma * \text{dis}}$ on the right. As the distance increases, the user is less likely to perform the task. There is an influence of different values of the parameters γ on the results. In combination with the actual situation, it is possible for the user to perform the task within 20 km of the task location (i.e., the probability P_1 is greater than 0.5). Therefore, in the experiment, $\gamma = 0.03$.

2.2.3. POI Type Similarity Function. $P_2 = \cos_{\text{poi}}$ is used to express the similarity between the POI type of the task and the user's POI preference type, that is, to calculate the cosine similarity between the user's POI interest preference and the task type. The similarity distribution of user and task POI types in a task is shown in Figure 2, where the x-coordinate is 1–3170 users, and the y-coordinate is the similarity between each user and the task POI type.

2.2.4. User's Physical Task Execution Probability. In combination with (1) and (2), the similarity between each user and the task POI and space distance loss of the task execution can be calculated, and physical execution probability of user can be constructed by combining the two:

$$P = \beta_1 * p_1 + \beta_2 * p_2 = \beta_1 * \cos_{\text{poi}} + \beta_2 * e^{-\gamma * \text{dis}}, \quad (1)$$

where \cos_{poi} is the similarity between the task POI type and the user's POI preference type and $e^{-\gamma * \text{dis}}$ is the distance function formed by the user's current activity center location and the task location distance. Fasting γ is the adjustment parameter, and β_1, β_2 are the weight. Equation (1) is used to calculate the physical world matching degree between tasks and users. As the predicted value of user task execution rate, its distribution is shown in Figure 2(b), which basically conforms to the normal distribution. That is, the number of users with the completion probability in the middle reaches is large, while the number of users at both ends of the probability is relatively small. The number of users with probability of $P > 0.04$ is 1790, accounting for 57%.

2.3. Analysis of User Social Centrality. The social influence of users in social networks can be expressed according to the centrality of users in graph theory. Among them, the centrality commonly used by users in undirected social networks can be measured in the following ways:

(1) Degree centrality D_i measures the degree to which one node in the network is related to all other nodes. The standardized measurement formula is as follows:

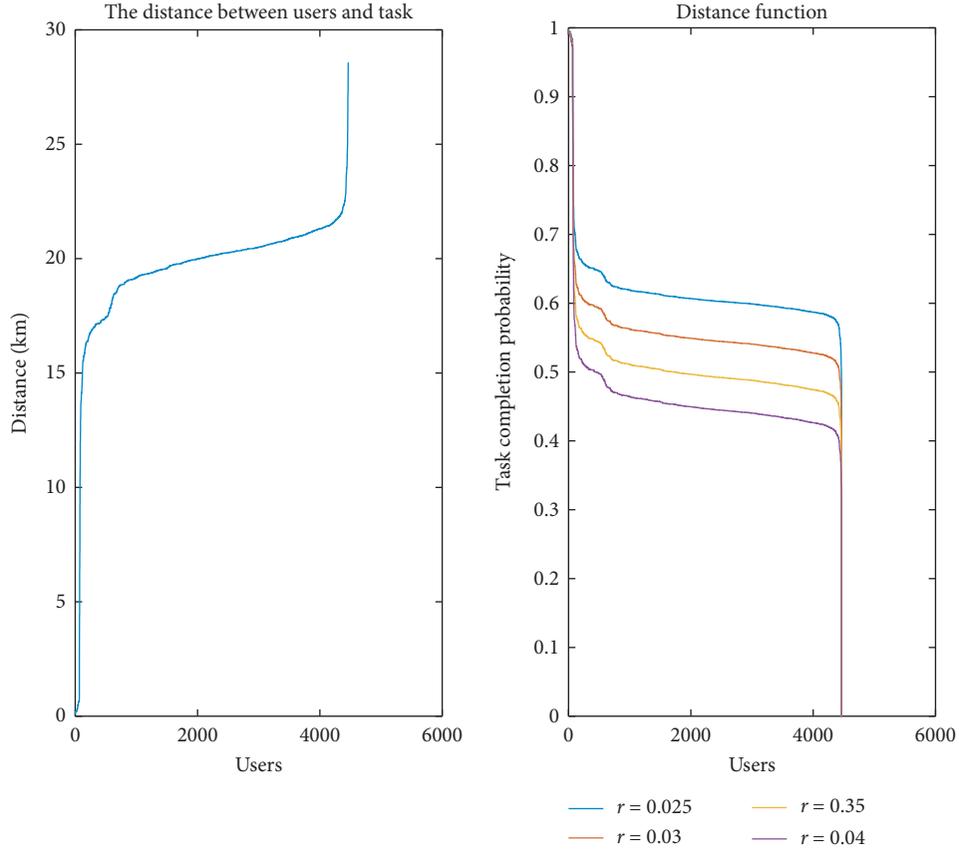


FIGURE 1: Distance distribution between user and task and parameter selection of distance function.

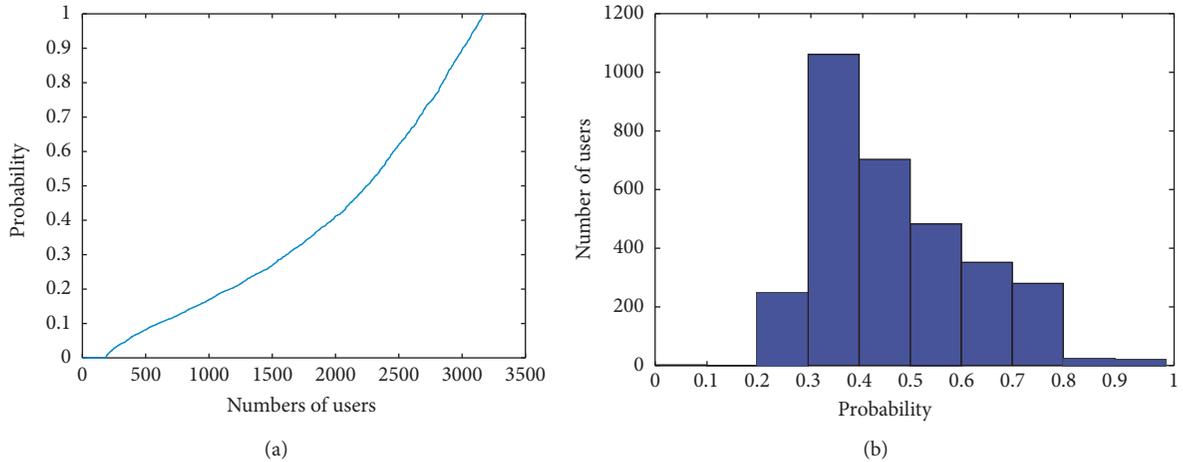


FIGURE 2: Distance distribution between user and task and parameter selection of distance function. (a) Similarity distribution of user and task POI types. (b) Number of users with completion probability.

$$D_i = \frac{\sum_{j=1}^g m_{ij}}{g-1} \quad (i \neq j), \quad (2)$$

where m_{ij} represents whether node i and node j are directly connected. If they are directly connected, then $m_{ij} = 1$; otherwise, $m_{ij} = 0$, $\sum_{j=1}^n m_{ij}$ is the total number of nodes connected to each node i (node degree), and g is the total number of nodes. Since degree centrality can directly

determine the scale of users involved in nodes (i.e., audience degree), it should be used as one of the indicators to determine the influence of users' information in the process of information transmission.

(2) Betweenness B_i is the number of the shortest paths between a node and other nodes. It is an indicator to describe the importance of a node in terms of the number of the shortest paths that pass through it.

$$B_i = \sum_{s \neq t \neq i} \frac{\sigma_{st}(i)}{\sigma_{st}}, \quad (3)$$

where $\sigma_{st}(i)$ represents the number of the shortest paths from node s to node t passing through node i , and σ_{st} represents the number of the shortest paths from node s to node t . If the centrality of a node is high, it will have a great influence on the information transmission of the whole graph. The control ability of a node over the information transmission of other nodes is investigated, so it should also be used as one of the indicators to determine the social influence of users.

Combined with the calculated user-degree centrality and media centrality distribution, the importance of users in the social network can be expressed. Therefore, $x_i = w_1 d_i + w_2 b_i$ is used to measure the social centrality of users. Since the two functions are the same and the values are similar, the parameter value set in the experiment is $w_1 = w_2 = 0.5$.

2.4. Information Influence Attenuation Model. In the process of information dissemination, it has timeliness and the same task information spread in different times, which have different effects with the longer distance task release. The influence of task information will gradually decay and thus will influence the spread of the attenuation process of task information and users, using the exponential decay build information influence in the process of information transmission attenuation model: $y_i = e^{-\alpha * x_i * n}$,

where y_i is defined as the influence of task information published with user i as the initial node, which decreases as the propagation time increases. x_i is defined as the social influence of users, namely, the social centrality, which can be calculated from the centrality D_i (Formula 2) and the centrality B_i (Formula 3) of users' social network degree. Since it is impossible to describe the propagation duration quantitatively, the paper replaced it with propagation algebra, in which n is the propagation algebra (in $a \rightarrow b \rightarrow c \rightarrow d$, a is the first generation of propagation, b is the second generation, c is the third generation, and d is the fourth generation), and beam is the regulating parameter. The larger the beam is, the faster the attenuation of propagation effect will be (see Figure 3 for the effect of beam on attenuation).

User influence follows the attenuation function $y_i = e^{-\alpha * x_i * n}$, and the value of α has a great influence on the attenuation effect of information influence. As the value of α increases, the information attenuation speed increases (the attenuation of information influence of the same user under different values of beam, as shown in Figure 3). In order to more accurately simulate the real world in the information dissemination process, the experiment set task information dissemination to stop times should be big enough, so should the premise of considering complexity and accuracy, and set up task information dissemination stop for 10 times, so choosing of α follows the following principle: calculate α as 10 to 50 conditions, respectively, the influence of the information transmission attenuation $y_i < 0.1$ how much need to spread the algebra, statistics number of each phase

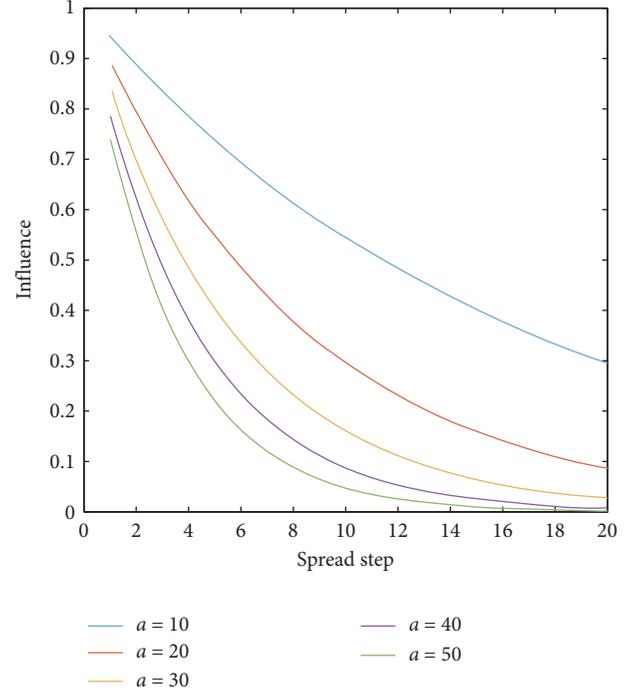


FIGURE 3: Influence of α on information attenuation effect.

distribution (see Figure 4). For example, when $\alpha = 20$, when it reaches the 10th generation, the number of users whose influence decreases below 0.1 is the largest, so in this experiment, $\alpha = 20$ is selected.

Figure 5 shows the attenuation of users' information influence in different propagation algebras due to the influence of attenuation function. Among them, the x -coordinate is 1–3170 users, the y -coordinate is the information influence of users, and ABCD is the current information influence distribution of users in the 1st, 7th, 14th, and 20th generation of propagation, respectively. It can be seen that, with the increase of the transmission time, that is, the transmission step length, the information transmission influence of users gradually declines. After 14 generations of transmission, about 1/3 of the user influence attenuation value is below 0.5.

3. Task Information Transmission Model

Task release process is adopted in the information dissemination independent cascade model, and this model is based on the theory of communication: assuming that a node in the network after u is activated, it will be at $p_{u,v}$ certain probability to activate it and connects it to the v -th node. In independent cascade model, each activation process is regarded as an independent activate event. If two users activate the user v at the same time, the two processes are regarded as the activation of two separate events, not affecting each other. If the node activation failed, influence disappears immediately and is not retained. If each is activated in the experiments, the user will be $y_i = e^{-\alpha * x_i * n}$ information influence value to activate their friends users, and activation processes are independent of each other, so

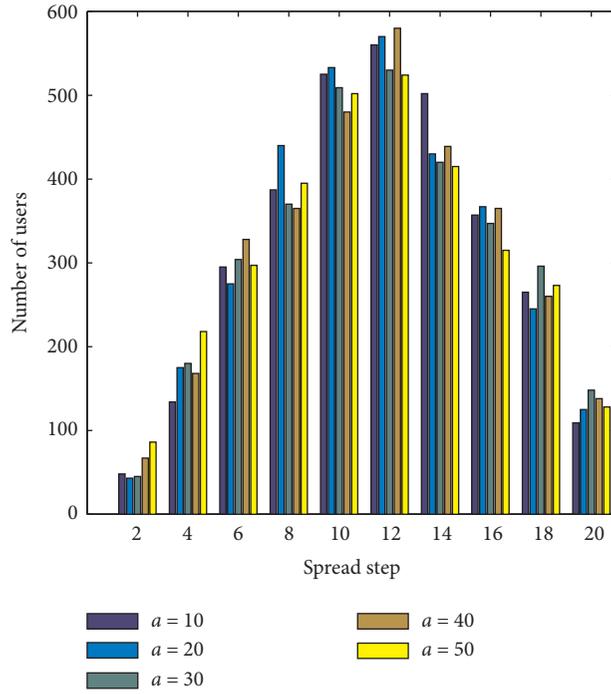


FIGURE 4: Number distribution under different attenuation effects.

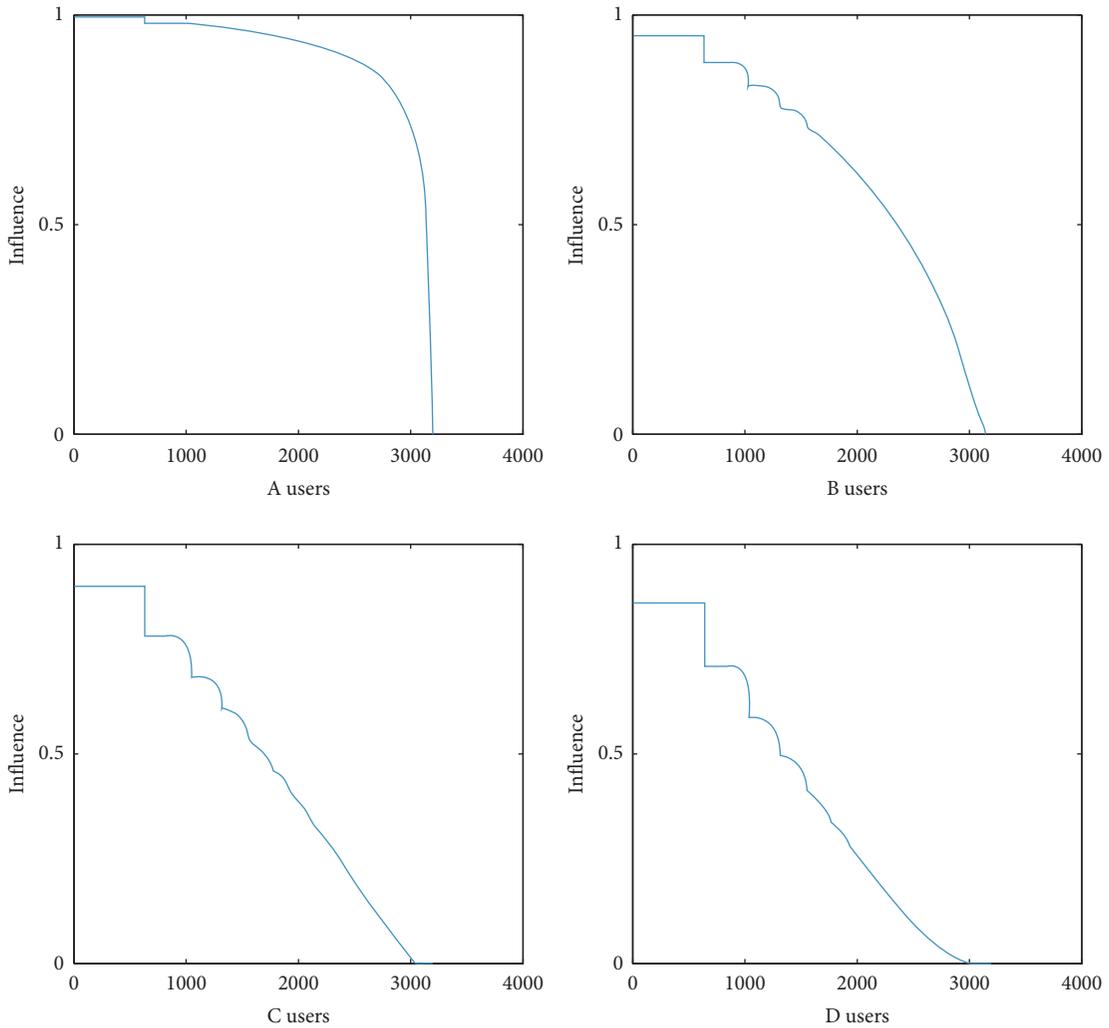


FIGURE 5: Information influence of users in different propagation algorithms.

when the task information is in $a > b > c > d$ order, each time only consider the influence of task information disseminates activation, only calculate such as b, c, b influence at that time, and no longer consider other factors. Therefore, in the case of transmission of $a \rightarrow b \rightarrow c \rightarrow a$, since each activation process is independent, the secondary enhancement of task effect is no longer considered. The flowcharts of the two transmission models are shown in Figure 6.

(1) *Random Transmission*. All friends of the communicator I receive the information. When the current influence of the communicator i is $y_i > 0.5$, it is believed that the friend can be inspired to spread the information; otherwise the information will stop spreading. As shown in Figure 7, each line in Figure 7 represents a user. The abscissa is the step size of the task information propagation, and the ordinate is the number of people in the subnetwork propagated by each user. The number of users affected in the initial stage of task propagation will increase rapidly. As time goes on (that is, the propagation algebra increases), the influence of user information will decline, and the number of users that can be affected will gradually decrease until the end of task propagation.

(2) *Purposeful Spread (Purposeful)*. Gives preference to its friends in the network the user set as the candidate for the task completion $P > 0.5$ practitioners to perform a task, in addition to choose influence $y_i > 0.5$ transmission of user tasks, namely each user influence in the collection consists of two parts} {candidate executives, main mongers, other processes and spread without a purpose is the same, until the information influence of 0 or spread to 10 generations.

In the process of purposeful communication, the communicator knows enough about the receiver to make different decisions according to different situations. Therefore, under the above conditions, due to the influence of the user's interest and location, the communicator will spread the task information in the following three situations:

If the current influence of user i is greater than the threshold value α_1 , i.e., $y_i = e^{-\alpha_1 * x_i * n} > \alpha_1$.

If the distance between user i 's activity center and task j is less than the threshold value α_2 , i.e., $dis_{i,j} < \alpha_2$.

If the similarity between user i 's interest preference and task type j is greater than the threshold value α_3 , i.e., $poi_{i,j} > \alpha_3$.

In the experiment, the selection principle of the values of α_2 and α_3 is as follows: the number of users meeting the conditions accounts for more than 10% of the total number of users, that is, according to the distance distribution or POI similarity distribution of all users, α_2 corresponding to 10% of users meeting conditions (b) and α_3 corresponding to 10% of users meeting conditions (c) are selected.

Analysis of each task: 3170 users spread the information of the network and are compared with the different users in the network, which are involved to the total number of audience and the distribution of the network users in the average influence AI , the network user average completion rate of AP (completion probability), for example, a user is, in a crowd-sourcing task with the process of information transmission, . Through the spread of the i -th user, the total number of information involved is n and involved each user

is P_j . Each user in every spread of the network has influence of I_j , and audience degree is n in the network formed by user i .

Average user influence is as follows:

$$AI = \frac{1}{n} \sum_{j=1}^n I_j. \quad (4)$$

Average user completion rate is as follows:

$$AP = \frac{1}{n} \sum_{j=1}^n P_j. \quad (5)$$

4. Experimental Results

This paper uses the data sets of New York's 2009–2011 of 3170 users signing in the data; in order to ensure the accuracy of the experiment, set the task information number to 50,100,150, respectively, to take users spread in the network task completion, influence the data such as on average comparing the results of the propagation model, experiments prove that under the condition of 50,100,150 missions, access to the distribution of the experimental results is very close, so only show the effect of 100 cases task contrast figure.

4.1. Comparison of All User Results. Figure 8 shows the task of 100 cases, compared to all users to spread after the formation of the network number distribution: Figure 8 is all user audience fragmentation distribution; the abscissa, respectively, is 1–3170 users; ordinate corresponds in the user's communication network and finally comes to the number of users, compared with purpose to spread and spread randomly, and purposeful communication involved is significantly less than random transmission.

Figure 9 shows the average influence distribution, where RI represents the average influence under random transmission and PI represents the average influence under purposeful transmission. In random transmission and purposeful spread two modes, almost all users have a purpose spread influence that is greater than the average random transmission influence on average, but considering purposeful spread in which users perform tasks of objective factors, about 50% of the average user purposeful spread influence is equal to the average influence approximation and random.

Figure 10 shows all user distribution, the average completion rate among them, the RP on behalf of the random transmission under the average completion rate, and mean completion of PP on behalf of purposeful spread. In the case of purposeful spread, communicator will give full consideration to the child in the network users to perform a task objective conditions; combining with the physical world in the user's demand in the task location, the types of tasks is targeted communication task information. Therefore, the average completion rate of all users since network transmission is greater than random transmission.

The number of users affected by random dissemination is more than that of purposeful people. However, in the case

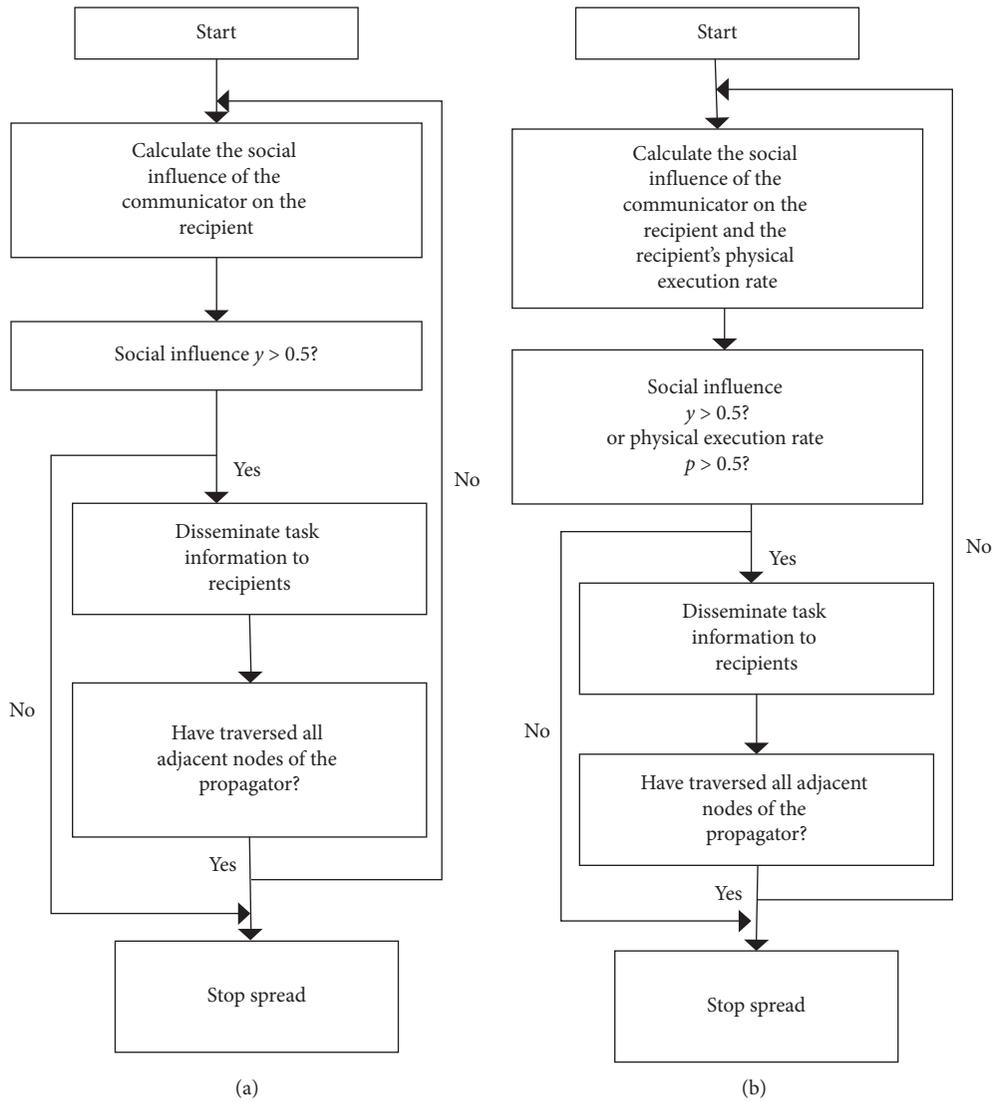


FIGURE 6: Flowcharts of the two transmission models.

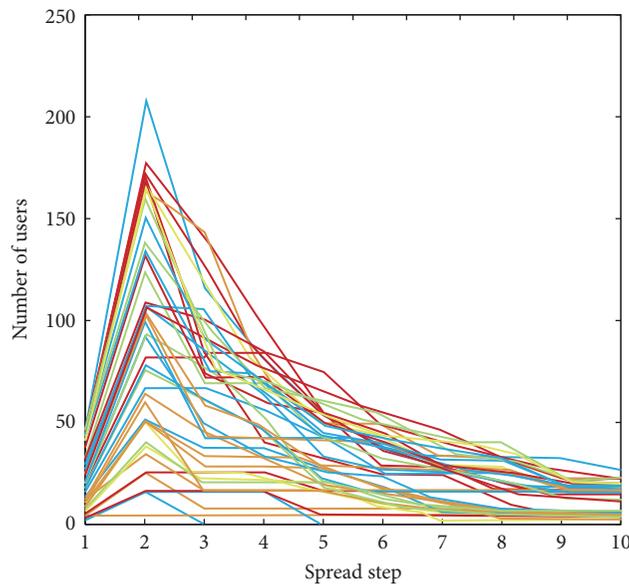


FIGURE 7: The distribution of the number of users affected by user propagation tasks.

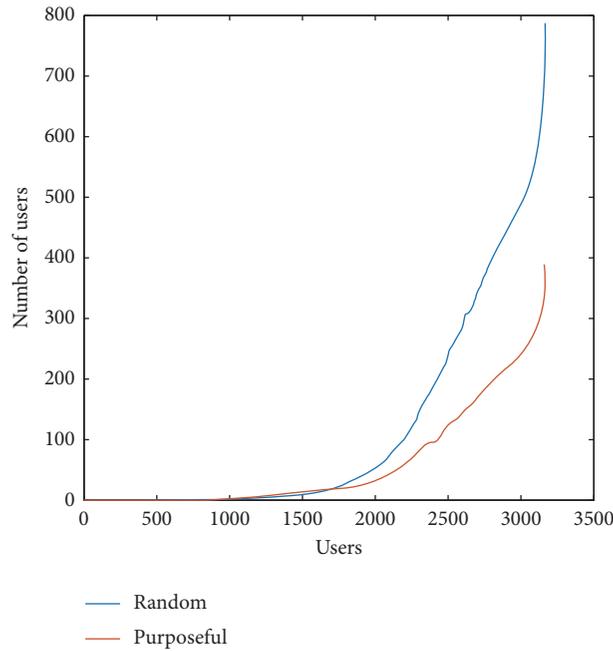


FIGURE 8: Audience distribution of the executor under the user information transmission network.

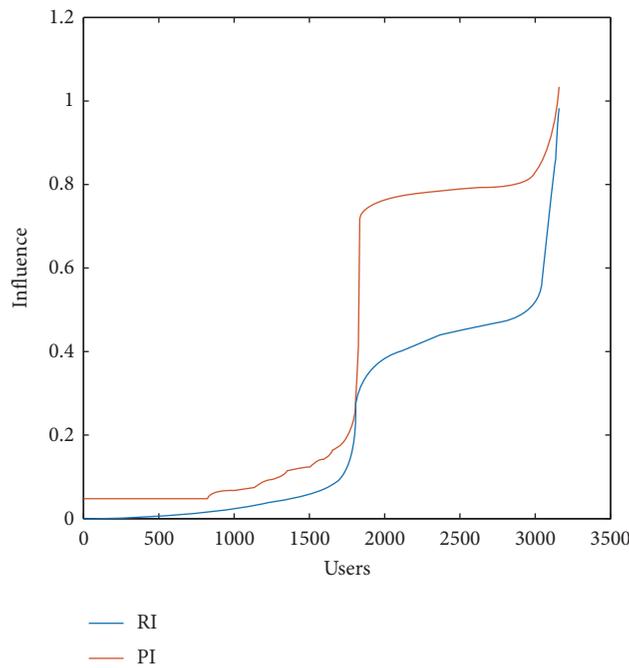


FIGURE 9: Distribution of the average influence of executors under the user information transmission network.

of random transmission and access by Internet users, the average impact is less complete than the average transmission. It can be understood that, in the process of random transmission, the user consumes more resources (time, mobile phone traffic, electricity, etc.) to invite users to be of low quality. In general, in the two crowd-sourcing task information transmission models used in this paper, random propagation has lower consumption and higher

efficiency than purposeful propagation. And purposeful dissemination can get a sufficient number of performers to users faster and more accurately.

4.2. Comparison of Some User Experiments with the Highest Audience. According to different task requirements, the spreaders and their subnetworks are selected differently. The

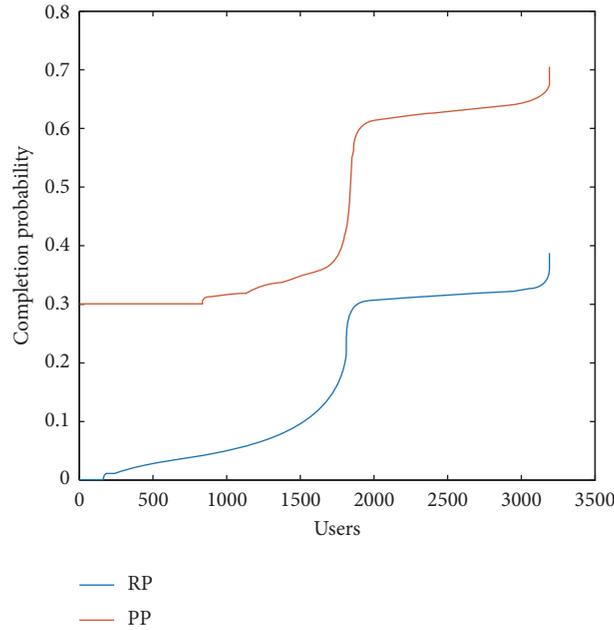


FIGURE 10: Distribution of the average completion rate of executors under the user information transmission network.

first four users with the largest number of spreaders are selected as the observation objects and their communication effects are compared: as shown in Figures 11–13 below.

Figure 11 shows the audience distribution of the first four users with the largest number of users in the communication subnetwork, where the x -coordinate represents 1–4 users and the y -coordinate represents the number of users in the subnetwork generated in the process of random transmission and purposeful transmission. It can be clearly seen that the number of random transmissions of subnetworks is much larger than that of purposeful transmission, which is about 2–2.5 times that of purposeful transmission.

Figure 12 is spread in the network users before the largest number of four executives average power distribution in the network. Among the four subfigures ABCD, four groups of corresponding users, in which the spread of the abscissa represents 1–10 generations, are described by their influence on average value of the user of transmission network. It can be clearly seen that the spread of the random network influence is on average less than purposeful spread: the average user is random influential in spreading rate of about 80% to 90%.

Figure 13 is the number of users in communication subnet of the top four executives on average completion rate distribution in the user's network, including the ABCD four corresponding users, the spread of the abscissa representing 1–10 generations, and ordinate in transmission network for its user value; the average completion rate is obvious, the spread of the random network is less than the average completion rate purposeful spread, and the average user in a purposeful spread more random transmission rate is about 80%.

4.3. Comparison of Partial User Experiments with the Highest Completion Rate. In practice, in addition to obtaining

enough executor users in a short period of time, the crowd-sourcing task pays most attention to the execution rate of users. Therefore, this paper analyzes the situation of user propagation subnetwork when the task requires a high completion rate. The top four users with the highest average completion rate in the communication network are taken out, and their communication effects are compared as shown in Figures 14–16.

Figure 14 shows the distribution of the first four users with the highest average completion rate in the communication subnetwork, in which the x -coordinate represents 1–4 users, and the y -coordinate represents the number of subnetworks generated in the process of random transmission and purposeful transmission. Compared with attracting enough users, these communicators pay more attention to the implementation of users. Therefore, the number of people in the communication subnetwork is small, and there is not much difference between random transmission and purposeful transmission. In the purposeful transmission, there will be more people spreading than random transmission.

Figure 15 shows the average influence distribution of the top four users with the highest average completion rate in the communication subnetwork. Among them, ABCD corresponds to four users, the x -coordinate represents the 1–10 generation of communication, and the y -coordinate is the average influence value of users in the communication network. Influenced by task requirements, communicators pay more attention to the execution rate of users, which may be directly transmitted to the executor. Therefore, in the purposeful communication network, the average influence of users is slightly higher than that of random communication.

Figure 16 is spreading in the network before the completion of the highest average four executives on average

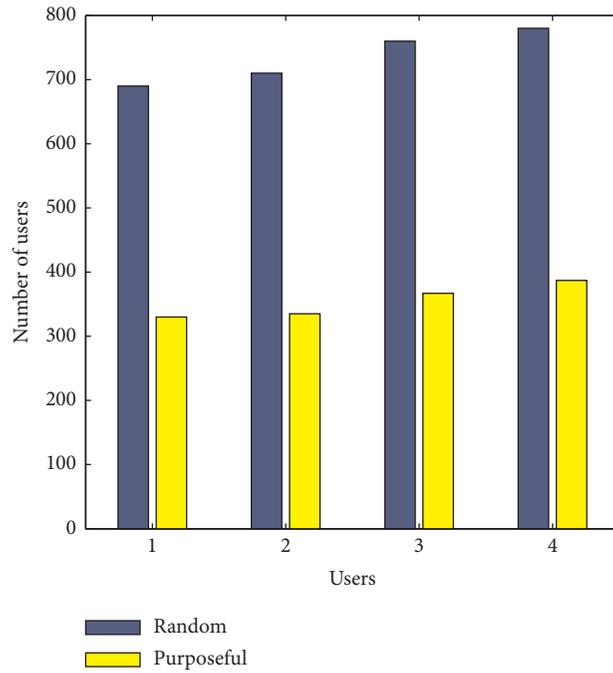


FIGURE 11: Distribution comparison of the top four users with the largest number of subnetwork users.

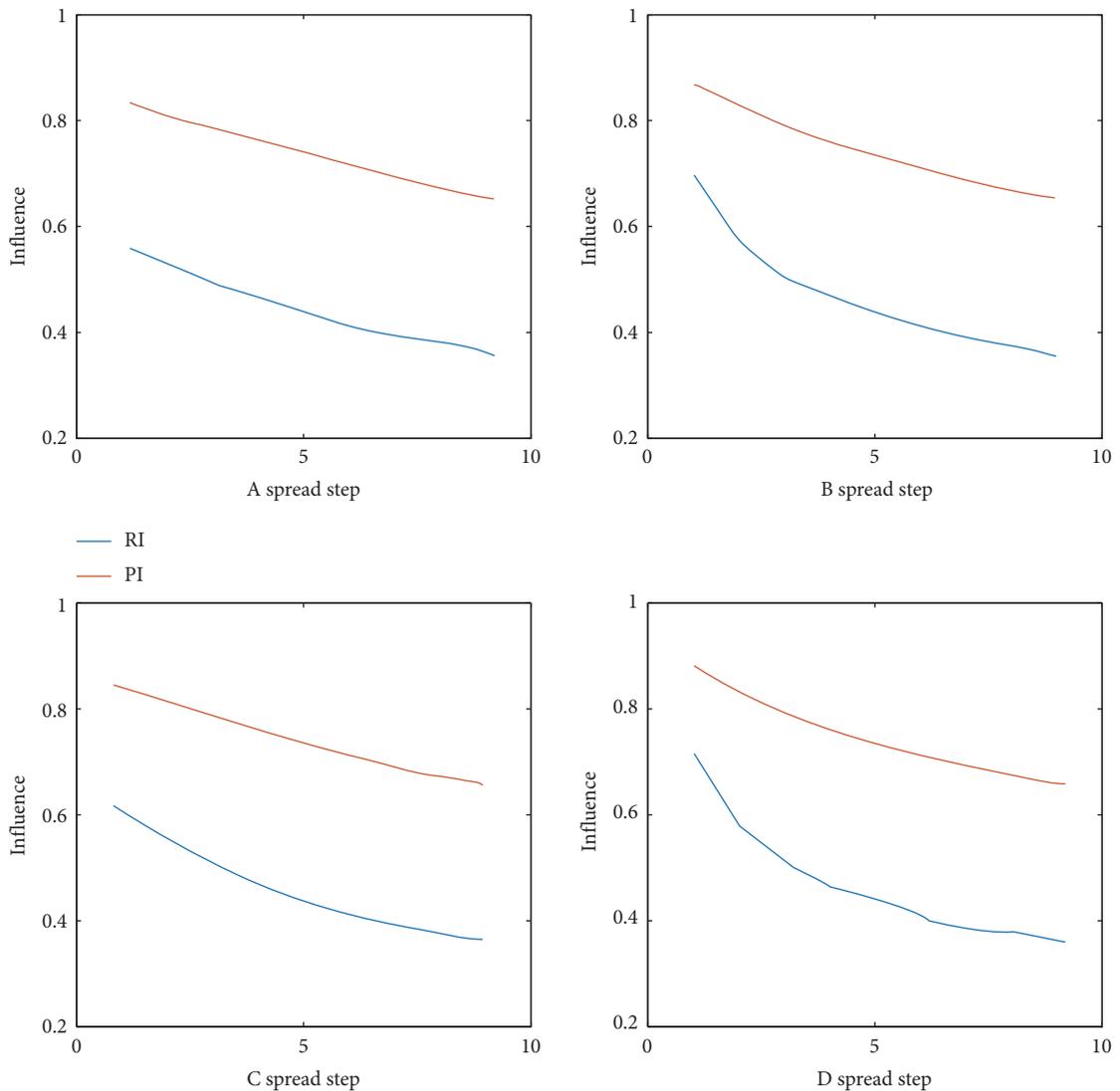


FIGURE 12: Comparison of the average influence distribution of executives in the top four user networks with the most subnetworks.

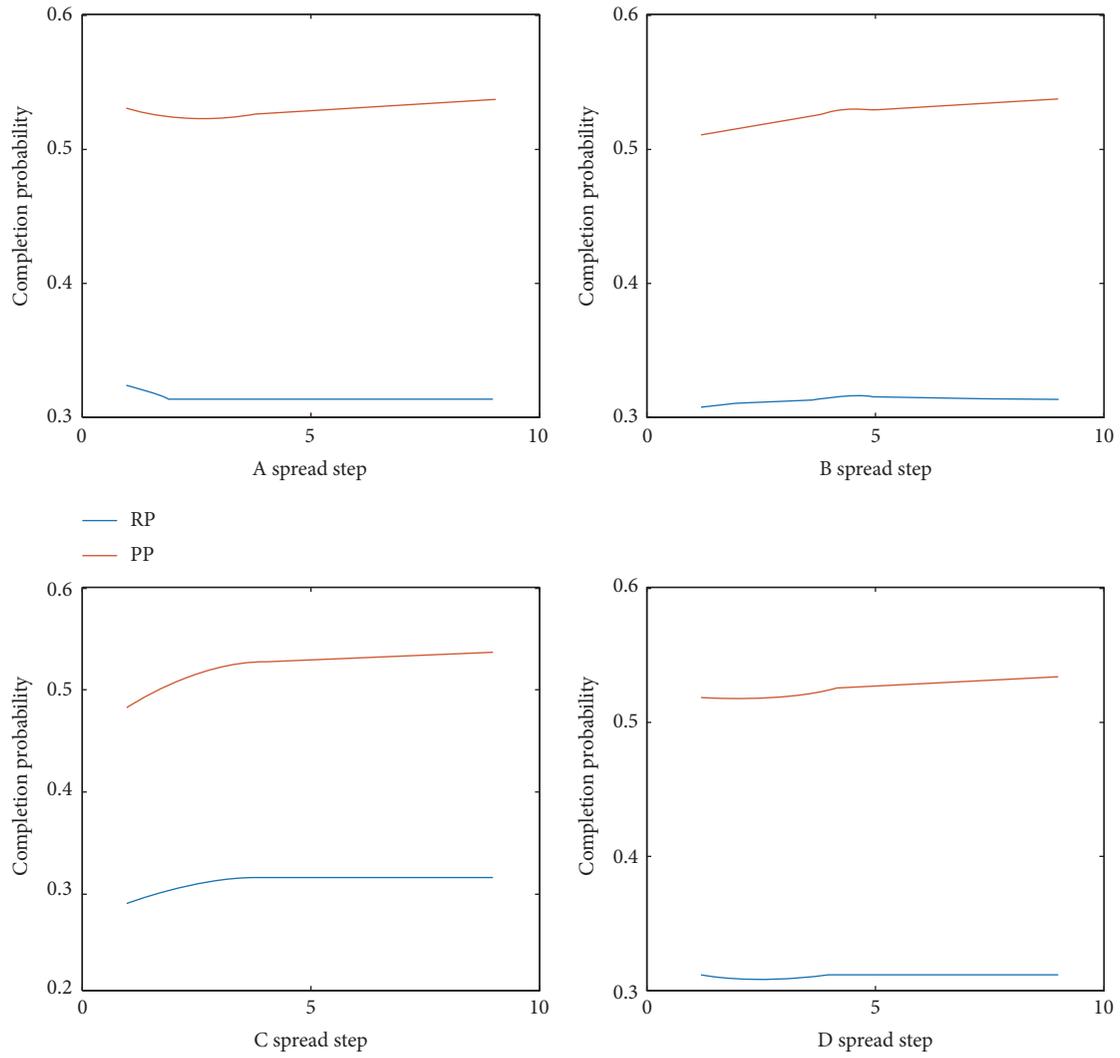


FIGURE 13: Distribution comparison of the average completion rate of executives in the top four user networks with the largest number of users.

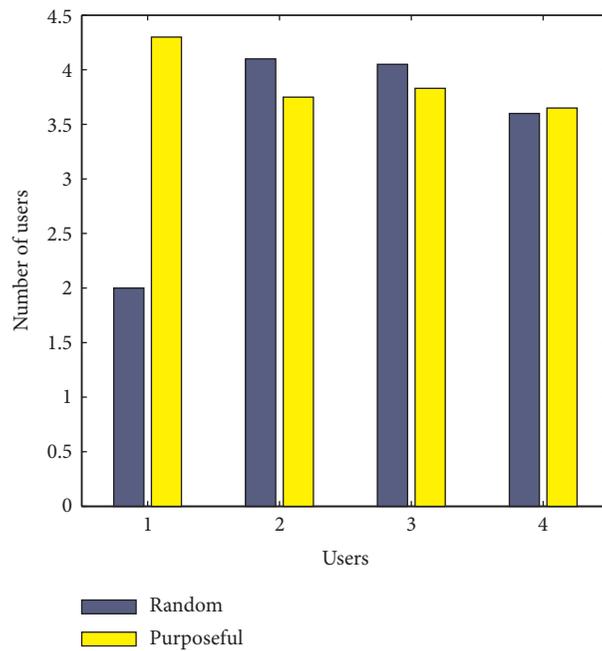


FIGURE 14: Audience degree distribution in the user communication network with the highest average completion rate.

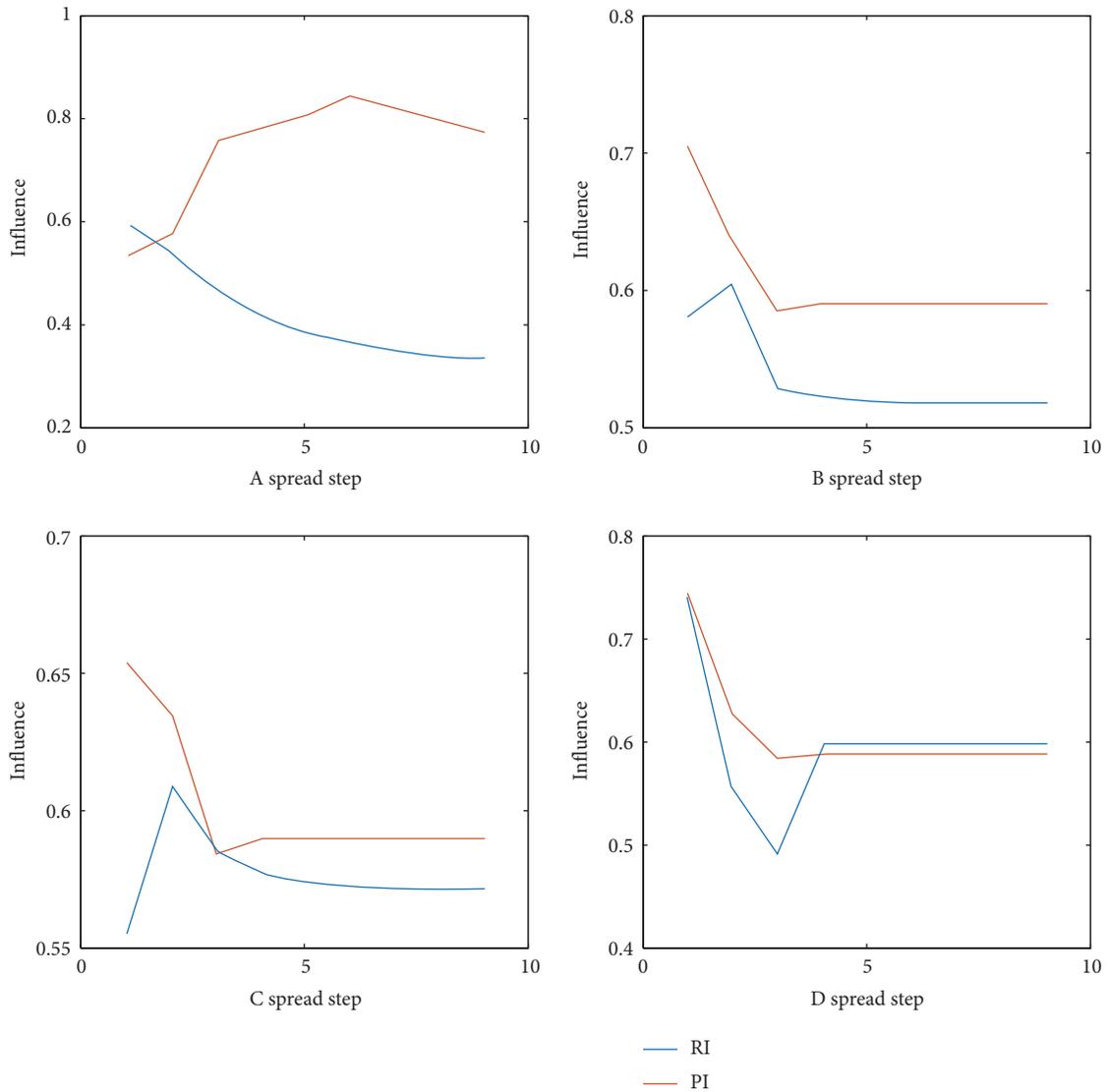


FIGURE 15: Comparison of the average influence distribution of executives in the network of the top 4 users with the highest average completion rate.

completion rate distribution in the user’s network, including the ABCD four corresponding user, the spread of the abscissa representing 1–10 generations, and ordinate in transmission network for its user value; the average completion rate is obvious, the spread of the random network is less than the average completion rate purposeful spread, and the average user in a purposeful spread more random transmission rate is about 80%.

4.4. Comparison of Running Time. The random transmission mode pays more attention to acquiring enough executors in a short time, while the purposeful transmission takes into account the user’s execution probability and communication ability and then carries out the transmission of task information. Therefore, the random transmission is faster and more efficient than the purposeful transmission. The experiment compares the running time of the two information

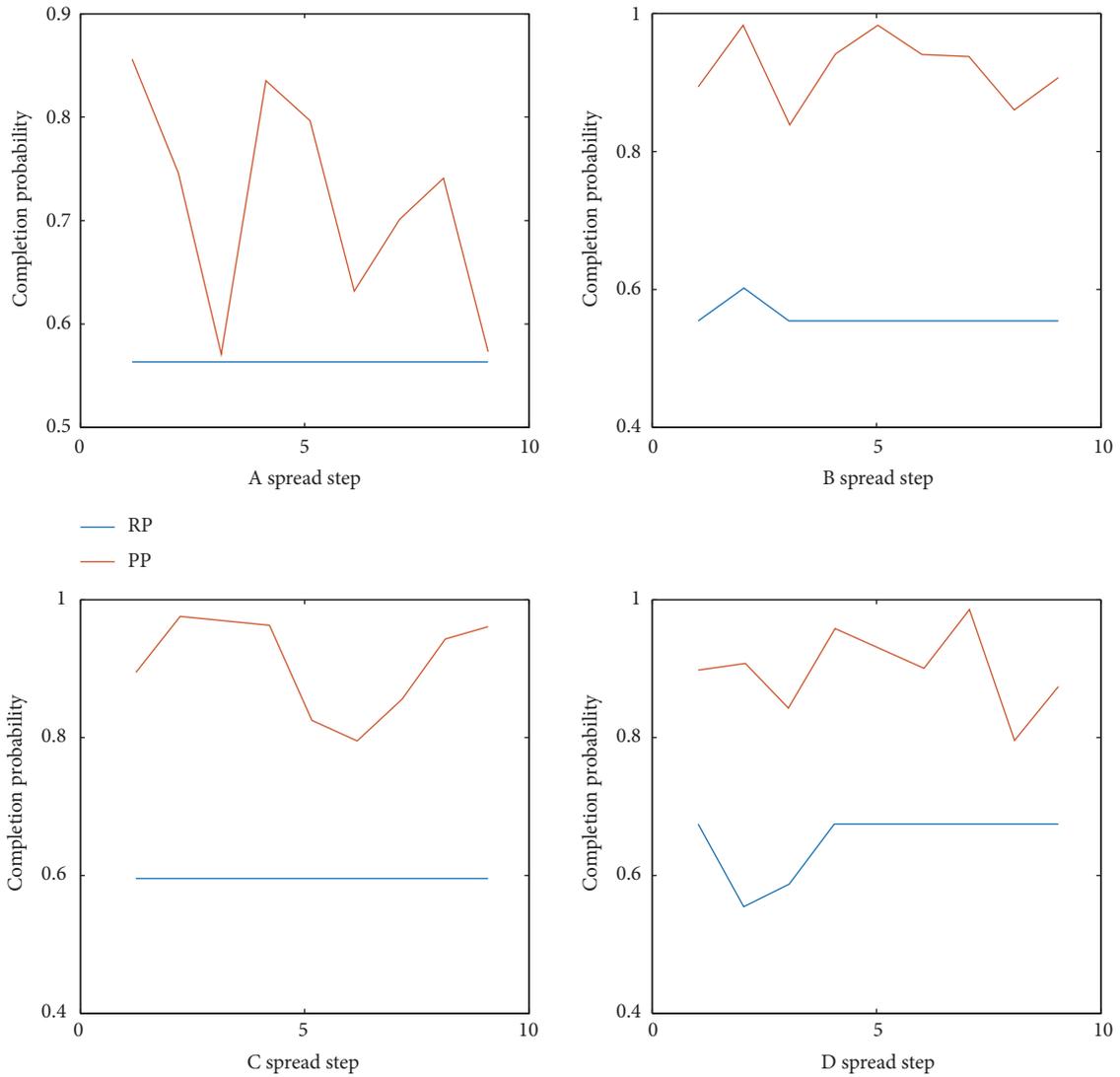


FIGURE 16: Distribution comparison of the average completion rate of executives in the top 4 user networks with the highest average completion rate.

TABLE 1: Comparison of the running time of the two propagation modes.

Number of tasks	Running time	
	Random transmission (s)	Purposeful transmission (s)
50	474.075	1382.758
100	805.579	2734.369
150	1137.922	4085.982

transmission models when the number of tasks is 50, 100, and 150, as shown in Table 1 and Figure 17. It can be seen that the running speed of random transmission is much

higher than that of purposeful transmission, and with the increase of the number of tasks, the running time of both transmission modes doubles.

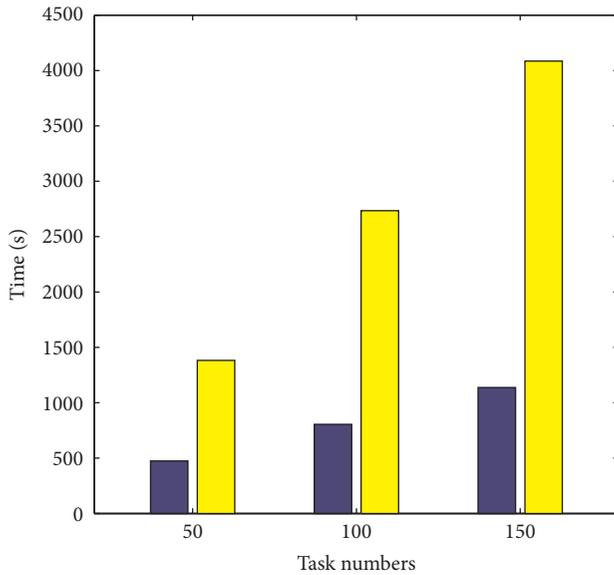


FIGURE 17: Comparison of running time.

5. Conclusion

This paper combines user space mobile behavior and social networking, in light of the user's mobile behavior patterns and interest preference analysis, in which we get the user to perform the task of crowd-sourcing objective conditions. The proposed algorithm uses the social network information transmission task and analyzes each user in a social network of social centrality, which is treated as the user subjective social influence. In the proposed strategy, social centrality of users is applied to the task with the process of information dissemination, random spread, and purposeful spread model. These introduced models were applied respectively to predict the spread of communicators subnetwork. The existing data, meanwhile, is employed to verifying these algorithm. Final experiment proves that, according to different mission requirements, this paper has a higher accuracy with proposed scheme.

Data Availability

The processed data required to reproduce these findings cannot be shared at this time as the data also form part of an ongoing study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the Science and Technology Department Industrial Public Relations of Shaanxi Province, Grant no. 2016GY064, Subsidy Fund of Key Laboratory of Shaanxi Province, Grant no. 2014SSJ2002, and Special Project of Shaanxi Provincial Department of Education, Grant no. 2013JK1002.

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