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Counterfactual Reasoning over Community Detection: A Case Study of the Public Science Day Community

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Abstract: With the rapid rise of new media platforms such as Weibo and Tiktok, communities with science communication characteristics have progressively grown on social networks. These communities pursue essential objectives such as increased visibility and influence. For the success of the public understanding of science in China, case studies of science communication communities on social media are becoming increasingly valuable as a point of reference. The authenticity of user influence plays an important role in the analysis of the final outcome during the process of community detection. By integrating counterfactual reasoning theory into a community detection algorithm, we present a novel paradigm for eliminating influence bias in online communities. We consider the community of Public Science Day of the Chinese Academy of Sciences as a case study to demonstrate the validity of the proposed paradigm. In addition, we examine data on science communication activities, analyze the key elements of activity communication, and provide references for not only augmenting the communication impact of similar types of popular science activities but also advancing science communication in China. Our main finding is that the propagation channel for the science communication experiment exhibits multi-point scattered propagation and lacks a continuous chain in the process of propagation.

Key words: causal inference; counterfactual reasoning; community detection; science communication; social networks

1 Introduction

Networks are powerful tools for representing relational information among data objects from social, natural, and academic domains[1]. One way to understand a network is to identify and analyze groups of vertices that have highly similar properties or functions. The groups of vertices are called communities in social networks. The characteristics and connections of the members of a community are different from those of other community members in the network. Community detection is of great significance in network analysis, which aims to group graph nodes into clusters with dense interconnection. It has been studied for decades and has found various real-world applications, such as recommendation[2, 3], anomaly detection[4], and scientific discipline discovery[5].

Most community detection algorithms currently focus on general domains; however, for specific domains, such as science communication, we cannot rely on common assumptions. Science communication on the Internet, which is the most important method for the Public Understanding of Science (PUS)[6] in China at present, has great research value and gradually forms a community with science communication as the main feature on social networks. As Chinese people increasingly incorporate multiple science social media

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accounts into their daily life, it is of great significance to detect influential nodes in the Chinese science communication community.

When we perform community detection for science communication communities, there is often a glaring bias. The traditional training paradigm always considers all the interaction influence between users as the final influence score, whereas it ignores a potential factor: In the case of the same data generated by user interaction behavior, do blog posts by Key Opinion Leaders (KOLs), i.e., individuals with a large number of followers on social media platforms, have the same real influence as those posted by ordinary users[7, 8]? By formalizing this scientific question into a well-defined causal estimand in an imaginary world, we can raise a counterfactual[9] question here: If KOLs with a wide fan base lose the biased influence generated by fan behavior on a topic, what will happen to their real influence?

To promote the PUS in China, Public Science Day is held by the Chinese Academy of Sciences in May every year. Each institute will be open to the public during the event. Currently, it has emerged as a crucial medium for the general public to comprehend the advancement of technology and explore science. Thus, it has made a significant contribution toward improving citizens' scientific literacy and piquing the interest of the youth in science, while trying to gradually transform traditional popular science into science communication. Each year, discussions on Public Science Day in social networks form a community that has a significant influence on science communication during a specific time period. The 17th Chinese Academy of Sciences Public Science Day was hosted on May 22–23, 2021♯. The main social platform for this event was Weibo, one of the biggest Chinese forum communities worldwide, which emphasizes the importance of fast information sharing, communication, and interaction as a social media platform centered on user relationships[10, 11]. Data records show that more than 167 million people have participated in Weibo's live broadcasts, interactions, short videos, voting, and other activities.

♯As the Public Science Day of 2022 was held online owing to COVID-19, we believe that if we want to study the communication effect of science popularization activities during the pandemic period, it is more meaningful to study how offline activities can be combined with Internet community dissemination. Therefore, the Public Science Day of 2021 was selected as our research object.

This study focuses on investigating the influence bias in the community during Public Science Day as well as analyzing the key nodes and transmission paths in the communication network. This study also explores the characteristics of key users and key blog posts, as well as the relationship between changes in the activity heat and activity measures. To this end, we adopt a variety of methods to examine the popular science activities of Public Science Day from multiple perspectives. The two core features of the investigation are transmission paths of key nodes and popularity analysis. This study aims to identify the most influential users in the communication network as well as analyze the communication paths, taken by information through the network. By examining the characteristics of key users and key blog posts, this study can provide insights into how information spreads through the network and which users are the most effective at disseminating information.

In addition, this study examines the relationship between changes in the activity heat and activity measures. This can help identify the types of activities that are the most effective in increasing engagement and interest in popular science topics.

Overall, this study provides a comprehensive overview of the popular science activities of Public Science Day and sheds light on the key factors that contribute toward the success of such events. The flowchart of our research is shown in Fig. 1.

The main contributions of this study are as follows:

- We apply the counterfactual theory of causal inference to the community detection algorithm, which provides a counterfactual paradigm for solving the user influence bias in the ranking. It is called Counterfactual Reasoning LeaderRank (CRLR), which is an attempt of causal inference in the field of social computing. This is one of the few studies in the field of community detection.
- We test our algorithm on the real science communication community and provide a sociological analysis of the experimental results.
- We find that the process of combining online and offline science communication activities has important implications for studying science communication during COVID-19. Through the study of the communication path, we find that science communication has the characteristics of multi-point

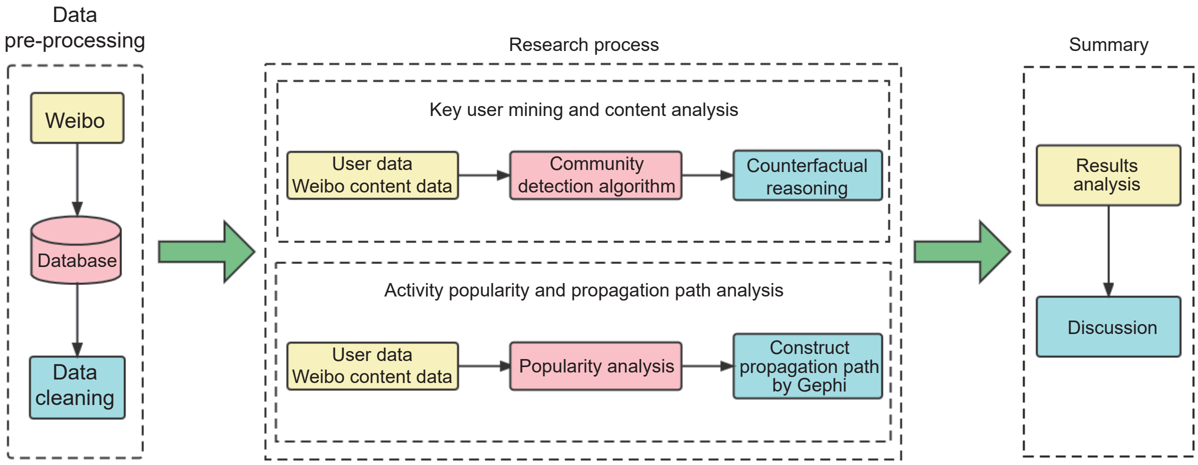

Fig. 1 Flowchart of this study. The research process stage consists of two parts: one is key user and content analysis, and the other is activity popularity and propagation path analysis.

and non-long chain transmission in the Internet. Finally, we provide suggestions for carrying out the PUS more effectively on social media in the future.

The remainder of this paper is organized as follows. Section 2 reviews the related work. Sections 3 and 4 describe our algorithm and approach. Finally, Section 5 concludes the paper and discusses the scope for future work.

2 Related Work

Identifying and tracking community structures in complex networks are among the cornerstones of network studies. They constitute the core algorithm for studying how science communication is carried out on social platforms. In this section, we review the research method of science communication in China, which is the most relevant to this study, the influence of KOLs in social networks, and existing studies on causal inference in community detection.

2.1 Science communication in China

The cause of science communication in China can be divided into five stages for which the connotation is constantly enriched and the concept is gradually updated: popularization of traditional science, public understanding of science, public reflection on science, public engagement in science, and public science service[12]. In the fifth stage, the continuous development of information science and technology promotes the emergence of a new scientific paradigm, namely citizen science[13]. With the rapid growth of “we media” social platforms, the public’s desire and demand for participating in science through “we media” have become increasingly strong in China, and it has far exceeded the ability of existing science popularization activities. Therefore, a new form and framework is urgently required to improve the scientific quality of citizens and promote the positive interaction between science and society[14]. Citizen science also gradually arouses the extensive attention of people from all walks of life in China.

Public Science Day is an exhibition of the science popularization resources of the Chinese Academy of Sciences and an important embodiment of its science popularization work. As one of the three most important science popularization activities in China, Public Science Day has witnessed rapid development over the past decade[15]. By organizing science popularization activities, we can effectively disseminate scientific and cultural knowledge, thereby enhancing the overall scientific and cultural literacy of the population. Conducting extensive science popularization events serves as an impactful means to promote and apply scientific theories and technologies within China. Such large-scale activities encompass a broad spectrum and are of significant relevance to people’s daily life, thereby eliciting a positive response from society. By fostering a robust scientific ecosystem and bolstering public scientific and cultural literacy, we can maximize the communicative impact.

During the COVID-19 pandemic, research on science communication has mainly focused on how to deal with relevant rumors[16] and how to carry out more effective online science communication[17]. However, research on the combination of offline and online activities, such as Public Science Day, has been ignored. The in-depth exploration of such activities has great significance.

2.2 Influence of KOLs in social networks

According to some existing studies in network theory, it is possible for people to be connected with each other over six edges, also known as the small world phenomenon[18]. Using the technology of modern social networks, we can exploit this phenomenon to connect to more people than ever before[19]. Studies in the field of sociology have also demonstrated that certain individuals inside networks have a propensity to dominate others and occupy a key position within the network. Such influential people are called opinion leaders or Key Opinion Leaders (KOLs). They represent a small amount of people with very deep knowledge on a certain topic or with a superior skill set in a specific field. Contagion by cohesion through KOLs acquires information into a group, while contagion by equivalence generates adoptions within the group. KOLs constantly promote the dissemination and diffusion of content by influencing their audiences[20].

In an increasingly fragmented media environment, socially shared information by KOLs may be more influential, as people are increasingly dependent on the suggestions and information provided by others in their social network[21] and tend to trust such information more than that received directly from media outlets[22].

The influence of KOLs in social networks, especially in the science communication community, is veritable[23, 24]. However, from previous science communication activities, we have found that the key users with the greatest influence in the community are not always KOLs with the largest number of fans. Although KOLs still play the most important role in the community, users with a small number of fans can also become key users in the community where a particular topic is located. In summary, there is no simple linear relationship between the amount of influence a user has and the number of the user's followers. The influence will present a state of virtual high, because the sources of influence of KOLs are divided into real influence generated by their own content and false influence generated by the behaviors of fans. Moreover, influence on social media is based on many factors. In this study, we focus on the interaction between users. If a KOL's User Generated Content (UGC) on a topic in a social network generates the same interactive data as a regular user, we expect the former to have lower true influence and popularity than the latter.

2.3 Causal inference in community detection

Causal inference is the science that aims to estimate the causal effects between variables. It is conducted via the study of systems, where the measure of one variable is suspected to affect the measure of another, and it has been widely used in natural language processing[25], computer vision[26], and recommendation[27]. Causal inference is being increasingly used by researchers in the main application area of machine learning; however, its discovery in the community is just beginning. Although the first methods for community detection date back to the 1970s[28–31], the area currently continues to attract the attention of researchers and data scientists in a broad range of disciplines, including monitoring pre-election political communication, racial protest rhetoric on Twitter, and hidden trendsetters in online media[32–34]. Existing studies usually combine causal inference with community detection from two directions. One is to mine causal relationships in the network by exploiting community detection algorithms; for example, Baltsou et al.[35] provided an algorithm-semi-agnostic framework for computing the causes and responsibility of belongingness to a community. The other is to incorporate the theory of causal inference into the community algorithm; Smith et al.[36] attributed the impact by accounting for narrative propagation over the network using a network causal inference framework applied to data arising from graph sampling and filtering.

3 Key User Mining and Content Analysis

When we rank user influence, the traditional paradigm (Fig. 2a) usually weighs the user's interaction behavior and includes it in the final user influence score. However, this approach ignores a key problem. If a user is a KOL with a large number of followers, then the real influence generated by this user's interaction pattern weighted should be low in the prediction score. Because fan groups have their own preferences, they

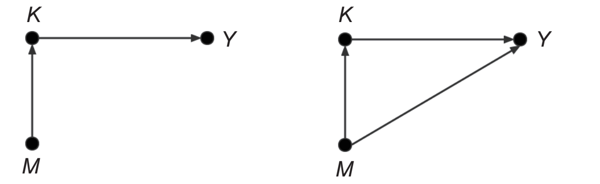

Fig. 2 Causal graph for traditional paradigm and incorporating interactive mode. *Y*: user influence prediction score. *K*: key user. *M*: interactive mode (interactive buttons in social networks that express how much a user likes a post, e.g., Like, Comment, and Repost).

frequently interact with their KOL. However, the user influence under independent topics generated by such interaction is not accurate, and the influence of content posted by users who do not have fan groups and eventually achieve the same influence score may be much higher than that of content posted by opinion leaders. For example, consider a user does not have a fan group, but the content that the user publishes on a certain topic has the same interaction mode data as an opinion leader with a strong fan group, such as likes, comments, and forwarding. Then, we can assume that the real influence generated by this user is higher than that of the KOL. Therefore, the fan group may produce an influence bias[37] when ranking the user influence (Fig. 2b). However, our research on this issue aims not to produce inequality between a KOL with a large number of fans and the influence of the content released under a certain topic but to fully return to the real influence of the user content.

To this end, we resort to causal inference[9] which is the science of analyzing the relationship between a cause and its effect. One of the main contributions of causal inference is the focus on clearly defined estimands before building models[38, 39]. By formalizing the aforementioned scientific question into a well-defined causal estimand in an imaginary world, we can raise a counterfactual[9] question here: If KOLs with a wide fan base lose the biased influence generated by fan behavior on a topic, what will happen to their real influence?

3.1 A causal view of bias amplification

To study bias amplification, we build a causal graph to explicitly analyze the causal relations in the community detection[40] algorithm.

3.1.1 Causal graph

The causal graph is a directed acyclic graph $G = \{V, E\}$, where V denotes the set of variables and represents the cause-effect relations among variables[9]. In a causal graph, a capital letter (e.g., K) denotes a variable whereas a lower-case letter (e.g., k) denotes its observed value. An edge implies that the ancestor node is a cause K and the successor node is an effect Y. Consider Fig. 2b as an example: $M \to Y$ implies that there is a direct effect from M to Y. Furthermore, the path $M \to K \to Y$ implies that M has an indirect effect on Y via a mediator K. According to the causal graph, the value of Y can be calculated from the values of its ancestor nodes, which are formulated as follows:

$$Y_{m,k} = Y(M = m, K = k) \tag{1}$$

where $Y(\cdot)$ denotes the value function of Y. We can predict the value of Y from inputs M and K.

3.1.2 Causal effect

Counterfactual reasoning is a comparison of the possible results caused by different assumptions under the same conditions, given the actual decision outcome (Fig. 3). The causal effect of M on K is the magnitude by which the target variable Y is changed by a unit change in an ancestor variable M. Then, we can define the Total Effect (TE) of $M = m$ on Y:

$$\text{TE} = Y_{m,K_m} - Y_{m^*,K_{m^*}} \tag{2}$$

which can be understood as the difference between two hypothetical situations, $M = m$ and $M = m^*$. Further, $M = m^*$ refers to a situation where the value of M is muted from reality; we typically set the value as the mean. K_{m^*} denotes the value of K when $M = m^*$. According to the theory of causal inference, TE can be decomposed into Natural Direct Effect (NDE) and Total Indirect Effect (TIE), which represent the effects through the direct path $M \to Y$ and the indirect path $M \to K \to Y$, respectively. NDE is defined as follows:

$$\text{NDE} = Y_{m,K_{m^*}} - Y_{m^*,K_{m^*}} \tag{3}$$

where $Y_{m,K_{m^*}} = Y(M = m, K = K(M = m^*))$. The

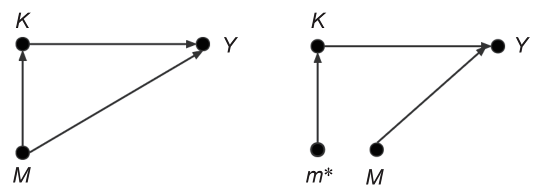

Fig. 3 Comparison between real-world and counterfactual-world causal graphs.

calculation of Y_m and K_{m^*} is a counterfactual reasoning, as it requires the value of the same variable M to be set with different values on different paths. In general, the total effect of a change is equal to the difference between the direct effect of the change and the indirect effect of the reverse change. TIE can be finally formulated as follows:

$$\mathrm{TIE} = \mathrm{TE} - \mathrm{NDE} = Y_{m,K_m} - Y_{m,K_{m^*}} \tag{4}$$

3.2 Reasoning strategy

As mentioned previously, we can obtain a counterfactual reasoning paradigm to remove user influence bias. Y can represent any known paradigm for traditional community discovery with key user detection at its core. In our study, we choose LeaderRank[41] as the basic algorithm. From the causal graph shown in Fig. 3a, we can get the final prediction score:

$$\hat{y} = \hat{y}_k \times \sigma(\hat{y}_m) \tag{5}$$

where $\hat{y}_k$ denotes the prediction score of LeaderRank in the last iteration, and $\sigma(\hat{y}_m) \in [0,1]$ denotes the weight index in the interactive mode.

3.2.1 LeaderRank

The algorithm introduces a background node based on PageRank[42], and the background node is bi-directionally connected to all the nodes in the network. Concretely, the basic prediction score can be expressed as follows:

$$\hat{y}_i(t+1) = \frac{\sum_{j=1}^{N+1} a_{ji}}{k_j^{\mathrm{out}}} \hat{y}_j(t) \tag{6}$$

$$\hat{y}_i = \hat{y}_i(t_c) + \frac{y_g(t_c)}{N} \tag{7}$$

where k_j^{out} denotes the out degrees, i.e., the number of leaders of j, and $y_g(t_c)$ denotes the score of the ground node in the steady state.

3.2.2 Weight function

In the activity dissemination network, the dissemination influences generated by Repost, Comment, and Like behavior are not equal. Formally,

$$\sigma(\hat{y}_m) = \frac{\sum_{i=1}^{n} (\alpha_1 \times m_{\mathrm{repost}_i} + \alpha_2 \times m_{\mathrm{comment}_i} + \alpha_3 \times m_{\mathrm{like}_i})}{N} \tag{8}$$

$$\alpha_1 + \alpha_2 + \alpha_3 = 1 \tag{9}$$

$$m = \begin{cases} 1, & \text{interactions between users are certain;} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where α_1, α_2, and α_3 denote the weight index on the basis of Repost, Comment, and Like in this research, respectively. At present, there are many methods for determining the weight coefficient. They are mainly categorized into subjective assignment and objective assignment methods[43].

Criteria Importance Through Intercriteria Correlation (CRITIC) is a type of objective evaluation method whereby the importance of indicators can be obtained according to the contrast strength and conflict between the indicators[44]. The greater the value of the weight index, the better the propagation effect; thus, CRITIC does not need to perform reverse data forward processing, and we can get $\alpha_1 = 0.52$, $\alpha_2 = 0.25$, and $\alpha_3 = 0.23$.

3.2.3 Counterfactual reasoning

As mentioned above, the key to eliminating the influence bias is to remove the direct effect via path $M \to Y$ from the ranking score $\hat{y}$. To this end, we perform ranking according to the following:

$$\hat{y}_k \times \sigma(\hat{y}_m) - \hat{y}_{k^*} \times \sigma(\hat{y_m}) \tag{11}$$

where $\hat{y}_{k^*}$ denotes the value of $\hat{y}_k$ with $K = K_{m^*}$. Intuitively, the inference can be understood as an adjustment of the ranking according to $\hat{y}$. Thus, we obtain the ranking schema for our study as Formula (11). Recall that $\mathrm{TIE} = \mathrm{TE} - \mathrm{NDE}$; the key difference between the proposed counterfactual paradigm and the traditional paradigm is using TIE instead of TE.

3.3 Dataset

In the Weibo community on Public Science Day 2021, considering the forwarding mechanism, there may be multiple forwarding relationships in a forwarded blog post. In this study, only the relationship between the original blog post and its first-level forwarding person, namely, the direct forwarding relationship, is retained, so as to avoid relationship redundancy. After removing irrelevant information, such as automatic replies of the system, a total of 32 003 user nodes participating in the topic were obtained.

3.4 Ranking results

To verify the effectiveness of the counterfactual reasoning method, we perform the community detection ranking process on the network constructed by the knowledge graph[45], and we use the original LeaderRank, PageRank, and Sort by In-Out Degree[46] methods for comparison. We select the top 20 results, as shown in Table 1. However, from the viewpoints of user privacy and better presentation of our study results in English, we use English tags instead of Chinese user names, as shown in Table 2.

The overall comparison indicates that most of the top 20 key users obtained by the four ranking algorithms are the same. The results of CRLR has some key user variations on the results of LR, such as SP3 is consistently ranked ahead of OF3 by the other algorithms, except for CRLR. After analyzing the account, we find that OF3 has a larger number of reposts and comments than the former, and these two indexes are important reference values for measuring the real influence of users in CRLR. Compared with the other three algorithms, SP6 ranks lower than the CRLR algorithm. After our analysis, we found that the total number of blog posts made by this user during the activity is 9; hence, it will rank higher in the algorithm relying on the link relationship between users. In other words, although the user has published many blogs, there are some blog posts with low interaction, and the real influence generated is extremely low. The CRLR algorithm considers the average and stable real influence of users. According to the results, the debias method introduced by CRLR is more in line with the original intention of the design of this experiment and the investigation idea of the science communication network.

Table 1 Top 20 key users in different algorithms.

No.	Counterfactual reasoning + LeaderRank	LeaderRank	PageRank	In-out degree
1	SP1	SP1	SP1	SP1
2	MM1	MM1	SP7	SP2
3	SP2	SP2	SP14	MM1
4	OF1	SP3	MM6	SP3
5	OF2	OF1	SP15	OF1
6	OF3	SP4	SP9	SP6
7	SP3	SP6	SP3	SP7
8	OF4	OF3	SP10	MM6
9	MM2	OF2	SP6	OF2
10	MM3	SP7	MM3	OF3
11	SP4	MM6	MM1	SP9
12	SP5	SP8	OF2	SP13
13	SP6	SP10	SP2	SP11
14	SP7	OF7	OF7	SP4
15	MM4	OF4	SP16	OF4
16	OF5	SP11	SP4	SP8
17	OF6	MM3	SP8	OF7
18	SP8	SP12	MM7	MM5
19	MM5	MM4	SP17	SP12
20	SP9	SP13	OF1	OF6

In the traditional paradigm, we have always believed that the correlation between the user's spread influence in the network and the popularity of blog posts has a simple linear relationship. However, as the research goes deeper, an increasing number of deviations indicate that the real influence of users is not so simple. We use Spearman's correlation coefficient[47] for ranking data to measure the correlation between two sets of data in Table 3. As can be seen, CRLR has the highest correlation between the importance of user nodes and the importance of blog posts, and the obtained results are conducive to the subsequent analysis.

3.5 Analysis of key user and content

Through the key nodes mined by our counterfactual paradigm, the features possessed by these nodes are analyzed.

We compare the ranking results of key users with their number of fans (Fig. 4), and we find that users with a large fan base are mainly concentrated in the top

Table 2 Tag for Weibo users.

Tag	Definition	Explanation
SP	Science popularization blogger	In the field of science communication, there is a wide range of fan bloggers who take science communication as the main attribute.
MM	Mainstream media	They are usually large-scale news media with strong influence and credibility in politics, economy, life, and other aspects.
OB	Ordinary being blogger	Individual users who do not have a fan base but may be recognized by other users for their unique ideas and opinions on a topic.
OF	KOL in other fields	KOLs in other fields, such as military, finance, and education, are attracted by a certain topic and engage in cross-disciplinary activities.

Table 3 Spearman's correlation coefficient for ranked data.

Algorithm	Spearman's correlation coefficient			
	@10%	@30%	@50%	@100%
Counterfactual reasoning+LeaderRank	0.7125	0.7090	0.7068	0.7034
LeaderRank	0.7081	0.7081	0.7063	0.6931
PageRank	0.5363	0.4169	0.4152	0.4016
In-out degree	0.6667	0.6788	0.6820	0.6837

Note: @10%, @30%, @50%, and @100% mean the Spearman's correlation coefficients of top 10%, 30%, 50%, and 100% users in different algorithms, respectively.

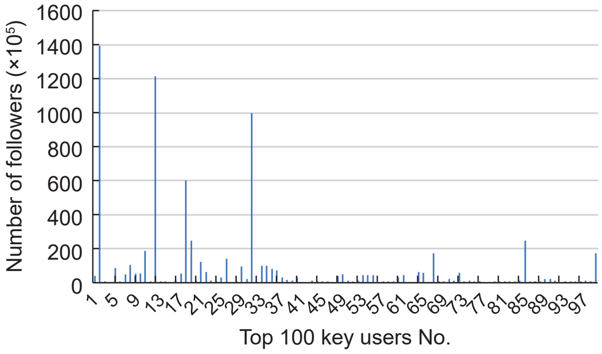

Fig. 4 Distribution of follower counts among the top 100 key users.

35; however, not all top users have a large number of fans, which shows that opinion leaders can still have a considerable degree of real influence after a certain topic goes down. Moreover, the CRLR algorithm determines high-influence users who do not have many fans. After the verification of users, our ranking results are fitted to the real influence of users on this topic. The influence generated by users with a small fan base can also be larger than the interaction influence generated by users with a large fan base.

KOLs in social networks can be categorized into two main types: Monomorphic KOLs and Polymorphic KOLs. The former refers to individuals who are influential and recognized in a single field or domain, while the latter refers to individuals who possess influence across multiple fields and topics[48]. In our Public Science Day communication community, the SP tag users belong to Monomorphic KOLs, whereas the MM and OF tag users belong to Polymorphic KOLs. From the viewpoint of the influence of the first five key users, SP1 as the initiator of the activity is the KOL in the field of science popularization. It is the most influential user in this activity, although from the viewpoint of the number of fans, it is far less influential than the Polymorphism KOLs; however, in terms of the fan audience, publication publicity frequency has advantages. Meanwhile, as Polymorphism KOLs, although MM1 and OF1 have a wide fan base, their influence is not as great as that of relevant bloggers who are popular in the field of science popularization but have relatively few fans, perhaps because the absolute number of their fans is not high. If this scope is expanded, then in the activities, the cross-subjective communication of opinion leaders in non-popular science fields enhances public similarity rather than specific differentiation. The polymorphism and cross-layer properties of Polymorphism KOLs make them have a stronger universal similarity with global diverse users, instead of being limited to vertical topics or subdivided fields. In other words, when Polymorphism KOLs are involved in the topic, the cross-layer communication influence will show an increasing trend. Although the real influence in the activity is not as high as that of Monomorphic KOLs with similar conditions, it plays a positive role in expanding the audience of communication.

From the viewpoint of the types of Weibo posts issued during key user activities obtained by CRLR (Fig. 5), propagandize accounted for a large proportion, i.e., 51%. The numbers of blog posts for both types of discussion and feedback are comparable. Further, we predicted before the event that the percentage of key users posting and forwarding lucky draw blog posts would be close to 20%. We believed that this type of blog post would account for a large proportion of the

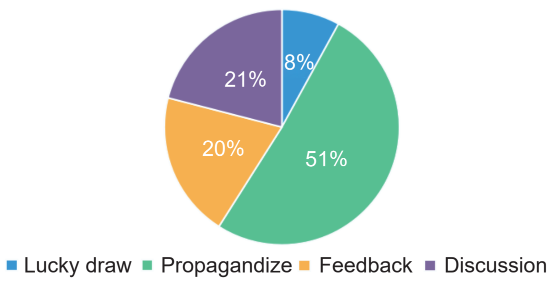

Fig. 5 Types of Weibo posts by key users.

popular blog posts in the pre-evaluation. However, the results show that this type of blog post only accounts for 8%. After our analysis, we find that this situation is related to many factors such as the fan preference of key users, the popularity of the event, and the value of the prize.

By introducing the counterfactual paradigm and related weight factors, we use the CRLR algorithm to determine the key users with real influence in the communication network of this activity, and we analyze the blog posts published by these users to obtain the relevant characteristics of key users and key blog posts, so as to comprehensively understand the communication situation of the activity.

4 Activity Popularity and Propagation Path Analysis

A comprehensive study of this campaign cannot be conducted only by analyzing the key users and blog content activities. Community members do not exist as individuals; building upon the above, in the context of science communication community, their interactions affect the popularity and propagation path of activities. This section aims to understand how certain activities or posts are popular, how they spread in the community, and what factors can cause them to spread. In other words, we can gain deeper insights into the mechanisms that drive engagement and information diffusion within the Public Science Day community.

4.1 Activity popularity analysis

Public Science Day can be divided into four stages according to the important time nodes, such as publicity warm-up, lucky draw, official propaganda film, People’s Daily publication, and special live broadcast: Warm-up Period (6 May–17 May), Lucky Draw Period (18 May–21 May), Offline Period (22 May–23 May), Webcast Period (23 May–28 May). Figure 6 shows the hot trend of the activities.

It can be seen from the activity hot trend curve that the overall hotness of the community does not change significantly during the Warm-up Period and Webcast Period. The first uptick in the overall hotness occurred during the Lucky Draw Period. The main reason for the rise in popularity at this stage is that the main activities must be carried out four days in advance of the warm-up of the Weibo forwarding and entering the Lucky Draw. Through the mechanism of forwarding the Lucky Draw, a broader audience is included in the communication network formed by the publisher, and a large number of data benefits can be gained in a short time. The hotness of the activity reaches the highest in the Offline Period, which leads to a large number of

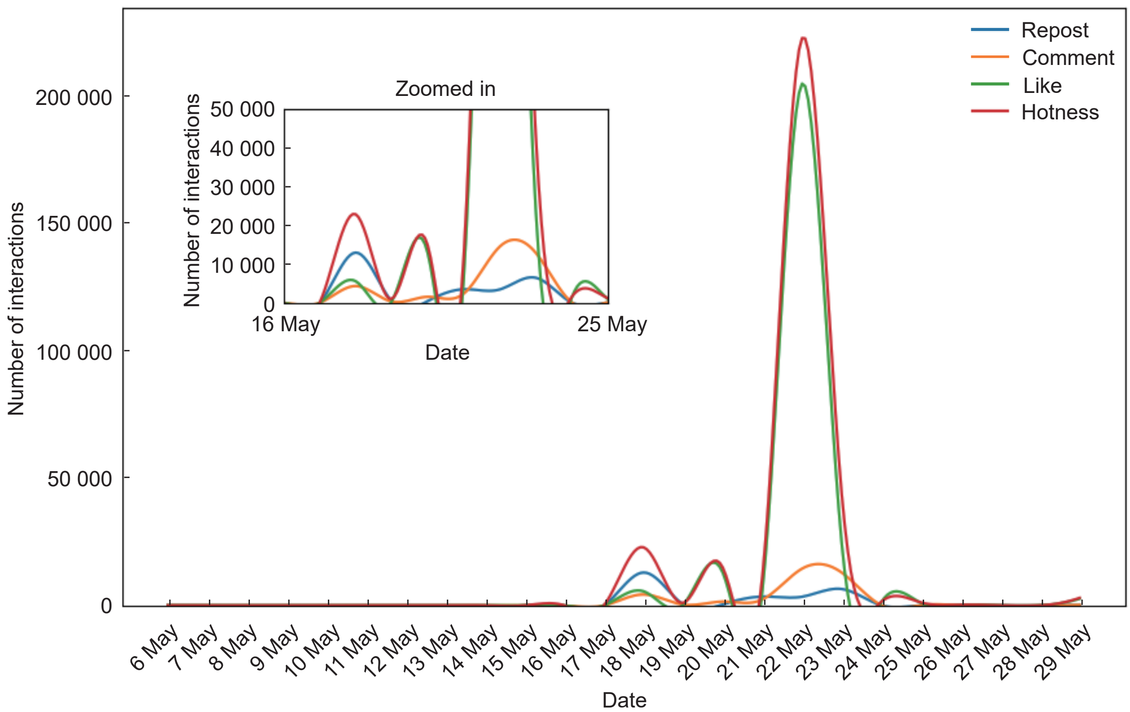

Fig. 6 Hot trend of Public Science Day.

user discussions in the community. The participation of key users drives the surrounding groups. In contrast to the low popularity in the Webcast Period, we believe that the reason is that offline interactions can promote the activity. Users will have a better experience and more engagement, and it will be easier to start a conversation about the event in the community.

We use CRLR to investigate and compare the key users with real influence in the community at different stages (Table 4), where KP is the key users at the current stage and A-KP is the key users up to this stage, including the current stage.

According to the hot trend of the activity and the comparison of key users under different time nodes, the total heat is low in the Warm-up Period. Starting from the opening of Lucky Draw and the release of the promotional video on 18 May, the total popularity of the activity increased rapidly. On 21 May, the popularity rose again after the KOLs promoted the activity on Weibo. On 22 May and 23 May, the popularity of the activity reached the highest point after MM1 started the live broadcast on Weibo. It can be seen from Fig. 6 that the repost data of this activity reached the peak on 18 May, 21 May and 23 May; the activities of repost Lucky Draw blog were carried out on these three days. On 22 May and 23 May, the comment data reached the peak, and the blogs published by MM1 and MM3, two major Chinese mainstream media, attracted more user comments.

4.2 Propagation path analysis

In the propagation process of Weibo events, the interactive mode between users is the most effective way to expand the propagation effect. In this study, the Weibo propagation network of Public Science Day was constructed on the basis of the relationship of Repost, Comment, and Like among users. If a user interacts with the users in the previous level but does not interact with the users in the next level, we say that the user is a level 1 user. In the propagation network constructed in this experiment, the level 1 users are not shown. Based on the collected data, the Gephi tool[49] was used to construct the dissemination network of this activity, as shown in Fig. 7. In the visual communication network, the sub-communities formed by the user groups radiated by different key users are represented by different colors.

From Fig. 7 and Table 4, SP1, MM1, SP2, and OF1 have the highest contribution, with more users interacting. Through the participation of KOLs in the field of science communication and mainstream media, as well as KOLs in other fields, the multi-point communication of the event was realized, and they constituted the key users of the event. After analyzing the propagation path of the activity, we find that the propagation mode of the activity is different from the propagation of public opinion[50], with characteristics of multi-point propagation and non-long chain propagation. We analyze multi-point transmission because the nature of scientific communication determines that content producers with high topic volumes have their own unique content, and the transmission chain is short because the nature of the Lucky Draw Period of the activity makes more users participate in a forwarding interaction. The information dissemination level of this activity is low, and the participants are the fans of key users.

5 Conclusion and Future Work

Social media platforms provide several pathways for

Table 4 Comparison of key users under different time nodes.

No.	Warm-up Period		Lucky Draw Period		Offline Period		Webcast Period	
	KP	A-KP	KP	A-KP	KP	A-KP	KP	A-KP
1	SP18	SP18	SP1	SP1	MM1	SP1	SP1	SP1
2	SP19	SP19	MM1	MM1	SP1	MM1	MM2	MM1
3	SP20	SP20	OF2	OF2	OF1	SP2	MM3	SP2
4	OB1	OB1	SP2	SP2	SP3	OF1	SP2	OF1
5	SP21	SP21	SP14	SP14	OF3	OF2	OF4	OF2
6	SP22	SP22	SP23	SP23	SP8	OF3	MM1	OF3
7	MM8	MM8	SP24	SP24	SP6	SP3	SP4	SP3
8	OF8	OF8	SP9	SP9	MM4	SP8	OF9	OF4
9	OB2	OB2	SP25	SP25	SP2	SP6	OF10	MM2
10	OB3	OB3	MM9	MM9	SP12	MM4	OB4	MM3

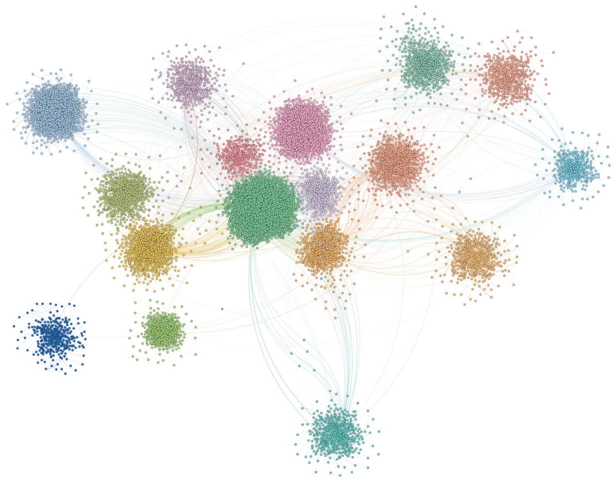

Fig. 7 Main propagation network of Public Science Day.

science communication. After all, such online modes are an extension and reflection of offline modes. How does science communication occur in different environments with different audiences matters, especially in the era of new media in the context of COVID-19? Online publicity and promotion, and both online and offline science communication activities, have gradually become the main forms of expression of PUS.

In this study, we considered the influence of fans' interactive behavior on the final influence of KOLs. The effects of this situation are often inflated in existing interactions. To this end, we used counterfactual theories to eliminate the influence bias of the traditional paradigm, and we employed LeaderRank by introducing a causal paradigm. This is called Counterfactual Reasoning LeaderRank (CRLR). We verified the validity of the proposed model on the real Weibo data of the Public Science Day of the Chinese Academy of Sciences. We presented and analyzed the word cloud formed by the key users and communication content in this science communication activity. Moreover, we considered the user engagement and other indicators in the four main stages of the activity.

By gaining a deeper understanding of the overall development of the activity, we conducted a social communication analysis of this activity from two aspects: activity popularity and propagation path. It is crucial to preheat science popularization activities in the early stages, and the quality of the early stages significantly determines how the popularity of the activities can reach the highest point. Finally, the characteristics of multi-point communication and non-long chain communication in science communication activities were also demonstrated.

This study presented an initial attempt to exploit counterfactual reasoning for community detection as well as a case study of how to effectively carry out science communication activities online and offline in the COVID-19 period. Based on our discoveries, we further discuss the following:

● Our method uses counterfactual reasoning theory to identify influential individuals in the science communication community; however, this approach has certain limitations. Even if we introduce a causal paradigm, the real influence of users is still determined by the presence of unmeasured confounders[9]. This study only discussed the influence of the most dominant interaction mode. We should consider more comprehensive user profiles in the future. In addition, the portability of the proposed model needs to be further verified.

● The development of scientific activities is significantly different from the dissemination of public opinion, which is not caused by a single user group but under the joint publicity of multiple user groups. However, our data of one year have certain limitations, and the expansion of the time range should be considered in the future in order to study the differences between scientific communication activities and other types of communication activities.

On the basis of this study and previous studies, we contend that causal inference is a solid theory for gaining a deeper understanding of communities, and that the related field of community detection can offer guidance on science communication. Technical studies on community detection and optimization in science communication domains are valuable for understanding the opportunities and challenges of engaging with the public, promoting scientific literacy, combating misinformation, and facilitating informed discussions about science-related topics in social networks. Our findings have the potential to guide the formulation of effective science communication strategies, bolster public engagement with science, and contribute toward evidence-based policy-making.

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