

Analyzing Characteristics of Nontrivial Information Diffusion via Implicit Links on Social Media

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Abstract. On social media, information spreads primarily through explicit relationships, such as follow connections, among users. However, information diffusion isn’t limited to explicit relationships alone. Users may come across posts from others via external websites or searches and subsequently repost them. The characteristics of such information diffusion, which bypass explicit social relationships, have not been thoroughly examined to date. In this paper, we examine the characteristics of non-trivial information diffusion facilitated by implicit-links among social media users. We define information diffusion that occurs without explicit social relationships as dissemination through implicit links. Utilizing three Twitter datasets, we investigate how users engage in information diffusion through implicit-links. Our findings suggest that users situated farther from the source are more inclined to involve in information diffusion via implicit-links, contrasting with those in closer proximity. This implies that implicit-links originate from sources beyond direct social connections among users. Additionally, we observe that while implicit-links have a weaker influence on diffusion size compared to explicit-links, they tend to distribute information across diverse communities distinct from the source user.

Keywords: Social networks · Social media · Information diffusion · Implicit links.

1 Introduction

Social media platforms are utilized by a large number of users across diverse contexts. The number of users on social media such as Twitter (currently X), Facebook, and Instagram has been increasing [9, 24]. Social media platforms play crucial roles to disseminate important information for people under several contexts such as political elections [10], natural disasters [16], and pandemic of infectious viruses [23].

Analyzing and understanding the characteristics of information diffusion on social media has been an important research topic for facilitating various applications, such as limiting the spread of misinformation, and optimizing viral marketing strategies. Information posted by companies or individuals on social media has the potential to spread extensively. Consequently, social media is utilized as a platform for implementing viral marketing strategies that leverage word-of-mouth [12]. In contrast, the ease of information dissemination inherent in social media also leads to the proliferation of fake news, posing significant challenges [23]. Therefore, there is a growing body of research aimed at understanding the characteristics of information diffusion on social media and intervening to either enhance or suppress information dissemination by leveraging these characteristics. For instance, there exist several studies on identifying influencers [1, 14], and adding or removing links within social networks [7, 19] to control the scale of information diffusion.

Existing studies assume that information is disseminated through explicit relationships (i.e., follow relationships) among social media users, and use a cascade graph for representing the paths of information diffusion on social media [9]. In a cascade graph, nodes represent social media users, and link (u, v) represents that information is disseminated from user u to user v . Most social media platforms allow users to explicitly specify receiving information from other users by following them. If user u follows user v and user u reposts user v 's post, it is natural to consider that information is disseminated from user v to user u . With such assumptions, cascade graphs are constructed. Figure 1 shows an example of a follow network and a cascade graph that represents information diffusion on the follow network.

In contrast, information diffusion does not necessarily occur only among users in a explicit follow relationship. For instance, users may encounter posts from other users through external websites or searches and may repost those posts. In such cases, it is difficult to estimate the paths of information diffusion solely from follow relationships, which produces a disconnected cascade graph. Figure 2 illustrates an instance of such a disconnected cascade graph. In this example, despite node A having no direct paths to node D, it reposts node D's post. In such cases, it is not obvious how node A came to know about node D's post. We hypothesize that in such follow networks, where paths are not readily apparent, information diffusion occurs via implicit links. Existing studies have shown that when constructing cascade graphs from the history of information diffusion on social media and the social graph among users, the resulting cascade graph often becomes disconnected [13, 15, 17, 18]. This observation suggests that real information diffusion cascades comprise nontrivial information diffusion paths via implicit links that cannot be directly inferred from a follow network representing explicit relationships among users.

However, the characteristics of such nontrivial information diffusion via implicit links have not been examined before. Understanding the characteristics of nontrivial diffusion, which are prevalent in many real information diffusion cascades, is valuable for constructing realistic information diffusion models. Most ex-

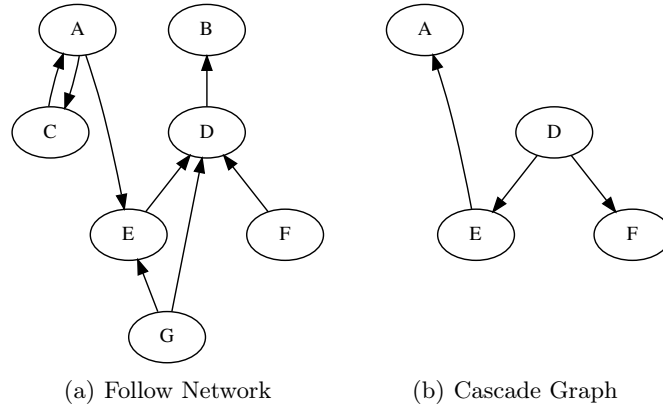


Fig. 1. Example of a follow network and cascade graph: (a) An illustration of a follow network where each directed link represents a follow relationship. (b) An example of a cascade graph when a post by node D is reposted by nodes A, E, and F. Given that nodes E and F follow node D (as depicted in Fig. 1(a)), the post is considered to be disseminated from node D to nodes E and F, thus resulting in the cascade graph having links (D, E) and (D, F) . Similarly, since node A follows node E, the post is considered to be disseminated from node E to A, and the cascade graph has link (E, A) .

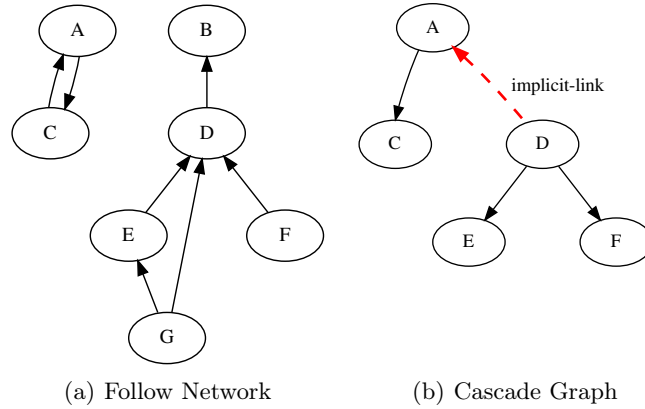


Fig. 2. Example of a follow network and a cascade graph demonstrating nontrivial information diffusion via an implicit link: (a) An illustration of a follow network where each directed link represents a follow relationship. (b) An example of a cascade graph when a post by node D is reposted by nodes A, C, E, and F. Given that nodes E and F follow node D, the post is considered to be disseminated from node D to nodes E and F, resulting in the cascade graph containing links (D, E) and (D, F) . However, since node A lacks an explicit path to node D, the route through which node D's post reaches node A is not readily apparent. Such nontrivial pathways of information diffusion are inferred to have occurred via implicit links.

isting information diffusion models assume that information spreads only through explicit relationships between users. In other words, existing models of information diffusion do not account for the existence of nontrivial diffusion paths. Understanding the characteristics of nontrivial diffusion is expected to contribute to the development of more realistic information diffusion models that incorporate nontrivial diffusion paths.

In this paper, we investigate the characteristics of nontrivial information diffusion paths, which cannot be directly inferred from a social graph, utilizing datasets of retweet cascades from Twitter. Specifically, we address the following research questions:

- **(RQ1)**: How does nontrivial information diffusion, which does not rely on explicit relationships between users, occur on social media?
- **(RQ2)**: To what extent does nontrivial information diffusion affect the size of the diffusion cascade?
- **(RQ3)**: Which users receive information through nontrivial information diffusion?

To address these research questions, we analyze the characteristics of nontrivial information diffusion using multiple datasets related to information diffusion on Twitter [1, 4, 20]. Using datasets of retweet cascades among users constituting the social network, which represents the follow relationships among Twitter users, we analyze the characteristics of nontrivial diffusion. We investigate the distance between the source of information and users engaging in nontrivial reposting to analyze how nontrivial information diffusion occurs (**RQ1**). Furthermore, we examine how the subsequent sizes of information diffusion differ after trivial reposts through the follow network and nontrivial reposts that cannot be inferred from follow relationships, aiming to analyze the impact of nontrivial information diffusion on diffusion sizes (**RQ2**). Finally, by examining the communities of users who originated posts and those who reposted them, we analyze which users receive information through trivial and nontrivial reposts (**RQ3**).

The rest of this paper is structured as follows. Section 2 introduces related work on information diffusion on social media. In Section 3, we define the terms used in this paper and describe the datasets. Section 4 shows the results, and Section 5 discusses their implications. Finally, Section 6 concludes this paper.

2 Related Work

Researchers have been actively investigating the dynamics of information diffusion on social media [1, 4, 5, 10, 14, 16, 21, 22]. For instance, Vosoughi et al. [22] found that false information often spreads more extensively than accurate information. Similarly, Tsugawa and Ohsaki [21] revealed that negative posts have a tendency to disseminate more rapidly and widely compared to positive or neutral content on social media. Moreover, researchers have investigated the characteristics of information diffusion within specific contexts. For example, Domenico et

al. [4] examined how information about the discovery of the Higgs boson propagated. Additionally, investigations have focused on understanding information diffusion patterns during significant events such as elections, hurricanes [10], earthquake disasters [16], and the COVID-19 pandemic [23].

Insights into information diffusion on social media have led to practical applications, including methods for identifying influential users and strategies for controlling information diffusion. The identification of influencers, who can spread information to many users, has been a hot research topic. Techniques for influencer identification utilizing the network structure of follow relationships [14] and leveraging the historical patterns of information diffusion [1] have been proposed. Tong et al. [19] proposed a method to limit the size of information diffusion by manipulating network connections. Furukawa and Tsugawa [7] evaluated the effectiveness of link deletion strategies in limiting the size of information diffusion using social media data. Their findings suggest that link deletion strategies are not effective in limiting the sizes of actual information diffusion cascades. Moreover, their findings suggest that one contributing factor to the ineffectiveness of the link deletion strategies is the prevalence of nontrivial information diffusion paths that do not rely on social ties within the follow network.

While there has been limited research on nontrivial information diffusion paths that do not rely on explicit social ties, a few pioneering studies have addressed this issue. Numann and Fischer [15] highlighted that constraints imposed by the API used for data acquisition and user privacy settings may influence the observation of nontrivial information diffusion. Taxidou et al. [18] found that approximately 50% of information diffusion can be attributed to reposts by users with explicit social ties, with an additional 13% explained by other forms of interaction, such as quotes. Myers et al. [13] reported that 29% of diffusion was influenced by diffusion outside the follow network. Shioda and Nakajima [17] defined users involved in information diffusion through nontrivial paths as untraceable users and demonstrated a negative correlation between the number of untraceable users involved in information diffusion and the number of followers of the source of that information.

While most existing studies have primarily reported the occurrence frequency of nontrivial information diffusion, this study goes beyond by analyzing the impact of nontrivial diffusion on the dynamics of information diffusion through a comparison with conventional information diffusion facilitated by social ties. Additionally, we explore the implications of these findings for the mechanisms underlying nontrivial diffusion.

3 Preliminaries

3.1 Terminologies and Notations

A follow network $G = (V, E)$ is a directed network, where V denotes a set of nodes representing social media users and E denotes a set of links indicating follow relationships between users. The set of users followed by user u is denoted

as $\Gamma(u)$. The author of post t is represented as $a(t)$, and a repost of post t by user v is denoted as $r(t, v)$. Each original post t and its subsequent reposts form a diffusion cascade.

A diffusion graph representing the diffusion paths of a cascade of post t is denoted as $H_t = (R_t, E_t)$. The set of nodes in H_t comprises users who posted or reposted post t . The link $(u, v) \in E_t$ in H_t represents the spread of post t from user u to user v . In the diffusion graph, $(u, v) \in E_t$ if user v follows user u ($u \in \Gamma(v)$) and the timing of $r(t, v)$ precedes the timing of repost $r(t, u)$ or the author of the tweet t , $a(t)$ is user u .

To differentiate between reposts facilitated by explicit social ties and those occurring through implicit connections, we introduce the terms “explicit-link” and “implicit-link”. When the diffusion path of a repost $r(t, u)$ explicitly exists in the diffusion graph H_t (i.e., when node $u \in V_t$ has an incoming link, denoted as $(v, u) \in E_t$, where node v exists), we refer to the spread of repost $r(t, u)$ as being facilitated by an explicit-link. Conversely, when node $u \in V_t$ does not have an incoming link (i.e., when there is no node v such that $(v, u) \in E_t$), we consider the spread of repost $r(t, u)$ as being facilitated by an implicit-link.

3.2 Datasets and Methodology

We employed Twitter datasets comprising follow networks representing user relationships, along with users’ posts and their reposts, for our analyses. Each repost in the dataset was categorized as disseminated either by an implicit-link or an explicit-link, and differences between these categories were examined. We determined whether a repost is disseminated by an implicit-link using information regarding who follows whom and who reposted which post and when.

The three Twitter datasets utilized in this study are referred to as Higgs [4], Nepal [1], and Ordinary [20] datasets. The Higgs dataset was collected following the announcement of the discovery of the Higgs boson, the Nepal dataset was gathered after the 2015 Nepal earthquake, and the Ordinary dataset comprises randomly selected English reposts from 2018. Basic statistics of these datasets are presented in Table I. The datasets contain approximately 10,000 to 50,000 posts and associated reposts, along with follow relationships between users who posted and reposted them.

Firstly, we examine the distance between the source and reposting users on the follow network to analyze the characteristics of users who reposted through implicit-links (Sec. 4.1). Secondly, we investigate the impact of reposts through implicit-links on the sizes of diffusion cascades by comparing the number of reposts following a repost through an implicit-link and an explicit-link (Sec. 4.2). Finally, we explore differences in communities between post authors and users who reposted them to identify which users receive information through implicit-links (Sec. 4.3).

Table 1. Overview of the Datasets

	Higgs	Nepal	Ordinary
Number of users	456,626	273,213	111,000
Number of follow links	14,855,842	17,818,902	3,130,963
Number of posts	41,426	49,098	10,000
Number of reposts	354,930	472,840	116,826

4 Analysis

4.1 Distance between Source and Reposting Users

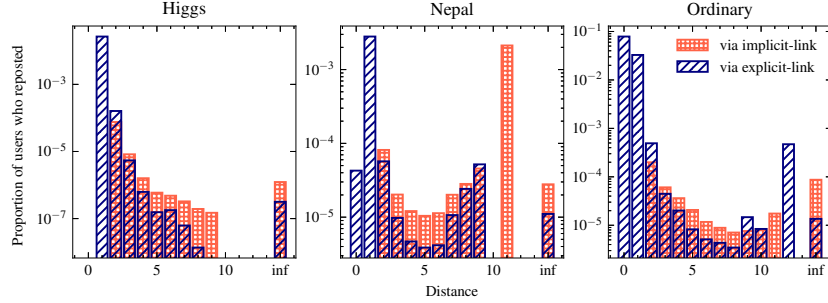


Fig. 3. The proportion of reposting users among users located at a certain distance from the source

First, we analyze how non-trivial information diffusion occurs through reposts facilitated by implicit-links (**RQ1**). To examine which users engage in reposting via implicit-links, we investigate the distances on the follow network between the author of the original post and the users who reposted it. The distance on the follow network is presumed to reflect the closeness of relationships between users. For example, users with similar interests are likely to be closer to each other, whereas those with differing interests are expected to be more distant. Therefore, we hypothesize that users who are closer to the original post’s author on the follow network are more inclined to repost. By evaluating repost frequency relative to user distance, we aim to characterize the attributes of users involved in creating implicit-links.

Figure 3 shows the proportion of users who performed reposts via explicit-links and implicit-links among users located at a certain distance from the post’s author. In contrast, Fig. 4 shows the proportion of reposts made via implicit-links among users at a given distances from the post’s author. Note that, by definition, reposts via implicit-links cannot occur at a distance of 1. As anticipated, Fig. 3

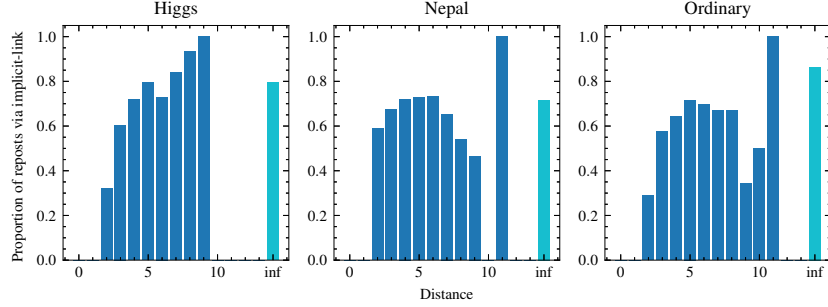


Fig. 4. The proportion of reposts via implicit-link by distance from the source

demonstrates that users in closer proximity to the author are more likely to repost. In contrast, Fig. 4 indicates that users farther from the source are more likely to engage in information diffusion via implicit-links compared to users at closer distances.

The increasing proportion of implicit-links across larger distances between the source and reposting users implies that some implicit-links may originate outside the follow network. If we hypothesize that implicit-links exclusively occur within the follow network and are the result of user privacy settings or unrecorded interactions like likes and mentions, the proportion of implicit-links would remain constant regardless of the distance between the source and reposting users. However, the proportion of implicit-links varies depending on the distance. Therefore, it is suggested that reposts via implicit-links occur due to information obtained through avenues other than social ties among users. For instance, users may acquire information through external websites, trending features, or searches. These external factors outside the follow network may potentially influence information diffusion via implicit-links.

4.2 Effects of Reposting on Future Cascade Sizes

To clarify the effects of reposts via implicit-links on the dynamics of information diffusion, we investigate how such reposts influence the final size of information diffusion cascade (**RQ2**). Previous studies on information diffusion dynamics and modeling have either implicitly or explicitly assumed that information spreads solely through the follow network. However, if information spreads extensively via implicit-links, it becomes imperative to incorporate them into models of information diffusion. Conversely, if information is seldom disseminated through implicit-links and diffusion is primarily driven by explicit-links, it suggests that there may be no necessity to include implicit-links in diffusion models.

We define the repost contribution index (RCI) and use it to measure the contribution of each repost on the final cascade size of a post. The RCI is defined as follows. Let $B(r(t, v))$ denote a set of reposts made prior to repost $r(t, v)$ by users followed by user v . Similarly, let $F(r(t, v))$ represent a set of reposts $r(t, w)$

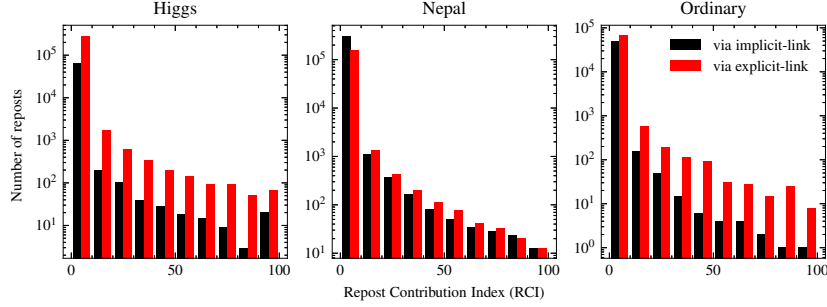


Fig. 5. Distribution of the repost contribution index (RCI)

that fulfill the condition $r(t, v) \in B(r(t, w))$. The RCI of repost $r(t, w)$ to the final cascade size of post t is determined by the following equation.

$$\text{RCI}(r(t, w)) = \sum_{r(t, v) \in F(r(t, w))} \frac{1 + \text{RCI}(r(t, v))}{|B(r(t, v))|} \quad (1)$$

Figure 5 compares the distribution of the RCI for reposts via implicit-links and reposts via explicit-links. The horizontal axis of the figure represents the RCI, while the vertical axis indicates the number of reposts associated with each RCI. From Fig. 5, we can find that majority of reposts, whether via explicit or implicit-links, have a low RCI. This finding aligns with the results of Goel et al. [8]. When comparing reposts via implicit-links and reposts via explicit-links, it is observed that reposts via explicit-links tend to have higher RCI. Consequently, this suggests that implicit-links may be less effective in disseminating information compared to explicit-links.

4.3 Effects of Reposting on Inter-Community Diffusion

To examine the recipients of information through diffusion via implicit-links, we calculate the fraction of posts reposted by users belonging to communities different from the post’s author. The findings from the previous section suggest that information diffusion via implicit-links has a weak effect on the diffusion scale. However, if implicit-links facilitate information dissemination across different communities, it can be deemed effective in reaching a diverse range of users.

For community detection, we utilized the Louvain algorithm [2], a method commonly employed in previous studies analyzing information diffusion on social media [20]. Community detection involves partitioning nodes within a network into multiple communities, characterized by a higher density of links among nodes within the same community [6]. It is expected that communities identified from social networks will reflect real-world groupings and node interests.

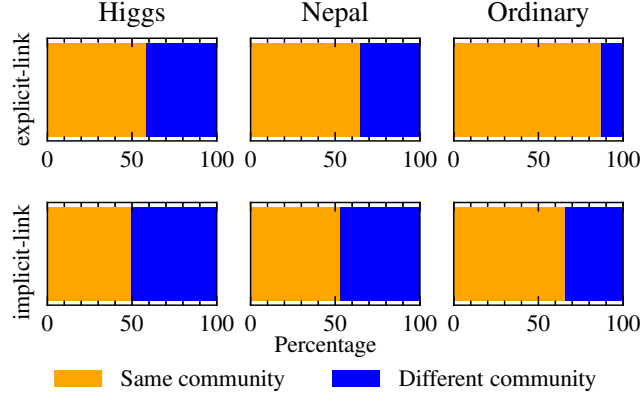


Fig. 6. The percentage of reposts where the author of the original post and reposting user belong to the same community and the percentage where they belong to different communities. The upper charts show the results for explicit-links whereas lower charts show the results for implicit-links.

Figure 6 shows the proportion of reposts where the original post’s author and the reposting user belong to the same community, alongside the proportion where they belong to different communities. In all results, reposts within the same community constitute the majority. However, the proportion of reposting users belonging to different communities from the post’s author is higher for users reposting via implicit-links compared to those reposting via explicit-links. Consequently, it is suggested that while implicit-links may play a lesser role in large-scale diffusion, they have a tendency to disseminate information to users across diverse communities distinct from the source user.

5 Discussion

Our findings suggest that many information diffusion models, which assume only explicit links, may not adequately replicate the characteristics of real-world information spread. More than half of the reposts by users located three or more distances away from the original source are due to implicit links. Therefore, when using information diffusion models like the independent cascade model [11] or the linear threshold model [11] to simulate the spread of information, the probability of distant users receiving the information might diverge from real data. The insights from this study could be valuable in developing new information diffusion models that account for implicit links.

The results indicating that information can reach different communities through implicit links offer valuable insights for mitigating biased information spread, such as the echo chamber effect [3]. While it is known that most reposted information tends to stay within a single community [20], our findings suggest that

implicit link diffusion helps spread information across different communities. If information recommendation systems can increase diffusion through implicit links, it might be possible to enhance information spread across communities. This could be beneficial for reducing the echo chamber effect and for implementing viral marketing strategies that reach a diverse audience.

Despite shedding light on these aspects of nontrivial diffusion via implicit-links, our study presents several limitations, suggesting the future works. While we have demonstrated that some implicit-links extend beyond the follow network, the precise factors driving nontrivial diffusion via implicit-links remain unclear. By incorporating interaction data beyond reposts and examining users' behavior outside of social media platforms, we anticipate clarifying the dynamics underlying the occurrence of implicit-links. Furthermore, our study solely analyzed the characteristics of nontrivial diffusion without deliberating on how to incorporate it into information diffusion models. Proposing novel information diffusion models that account for diffusion via implicit-links and exploring intervention strategies based on these models represent critical future works.

6 Conclusion

In this paper, we investigated the characteristics of nontrivial information diffusion via implicit-links among users of social media. Leveraging three Twitter datasets, we examined the characteristics of users who engage in reposts via implicit-links and investigated the subsequent impact of these reposts on diffusion. Our findings indicate that users located farther from the source are more inclined to involve in information diffusion via implicit-links, contrasting with those at closer proximities, suggesting that implicit-links arise from sources beyond direct social ties among users. Moreover, our results reveal that while implicit-links have a smaller effect on diffusion size compared to explicit-links, whereas implicit-links tend to disseminate information to users across diverse communities distinct from the source user. These observations suggest that future research should focus on developing information diffusion models that incorporate implicit links and clarifying the fundamental mechanisms underlying them.

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