Virality of Information Diffusion on WhatsApp

Keywords: information diffusion, structural difference, breadth, depth, WhatsApp

Introduction: WhatsApp is the world's most popular messaging app, with over 2.78 billion monthly active users across 180 countries. Some of these messages are widely spread, forming viral patterns, often containing false information, polarizing content, hate speech, and conspiracy theories [1, 2]. Groups are a primary channel for the large-scale spread of information on WhatsApp. More and more political parties, conspiracy theorists, and marketers use WhatsApp groups to spread information widely for their own purposes. India, home to over 600 million WhatsApp users — the app's largest user base — has experienced significant use of WhatsApp for propagating information. The Bharatiya Janata Party, India's major political party, notably employs group messaging extensively to strengthen its engagement with voters [3]. To combat the spread of rumors, WhatsApp has imposed strict limits on message forwarding. Now, a message can only be forwarded to up to five chats at a time. If a message has been forwarded by others, it can only be shared with one group chat [4].

In this paper, we focus on two structural features of WhatsApp and measure information spread: breadth and depth. The former measures the maximum number of groups to which a message is sent simultaneously, while the latter measures the maximum number of times a message is forwarded. On public platforms like Twitter, these two structural features have been widely studied, with most scholars finding that breadth is the main factor leading to the large-scale spread of information [5]. However, little is known about the dissemination behavior of messages on private messaging apps. A further question arises: Do different types of information spread differently on WhatsApp? For instance, regarding three different types of information (text, image, video), which type spreads deeper, and which type spreads broader? Our research aims to address these two questions, filling the gaps in existing studies. By examining the dissemination patterns of various types of information on WhatsApp, we seek to provide insights into the structural characteristics of message propagation and contribute to a better understanding of information dissemination dynamics on private messaging platforms. These insights offer potential to comprehend, simulate, and eventually develop solutions to address challenges such as misinformation and hate speech.

Dataset: Our analysis utilizes a large dataset gathered from WhatsApp groups, which are a key medium for mass information dissemination on the platform. This dataset was collected through a field survey conducted in India, where our research team obtained informed consent from participants. These participants were offered the choice to contribute data from the WhatsApp groups they were comfortable sharing, ensuring ethical compliance. The dataset includes comprehensive metadata such as the list of all groups a user is a member of and the size of these groups. Additionally, it encompasses content from a subset of these groups, as authorized by the users, along with the contact lists from the users' phones. Although our dataset is extensive and novel, it does not encapsulate the complete WhatsApp network. However, it allows for a diverse representation of the network in different forms: a network based on common group memberships, a network formed by users sharing common groups, and a network based on shared contacts among users. These varied perspectives provide a multifaceted view of the network dynamics. Over a period of 13 months, from December 2022 to January 2024, we collected data from 1,600 groups, which included a variety of message types such as text, images, and videos, totaling over 760,000 messages. This extensive and diverse collection of data offers a rich resource for analyzing communication patterns and the spread of content within

WhatsApp groups, providing valuable insights into the role of digital platforms in information dissemination.

Method: To identify and analyze the propagation of messages within our dataset, we first utilized hashing techniques to track multiple instances of the same message (allowing for minor alterations), in a privacy-preserving manner. For images and videos, we used PDQ hashing [6], while for text, we applied Locality Sensitive Hashing [7]. This approach enabled us to detect variations in content, such as cropping or changes in encoding. We then filtered our dataset to include only messages that were shared at least twice, resulting in a subset of 112,383 messages. The next step involved measuring the cascade size of these messages. This entailed examining the number and size of distinct groups that each message reached. We refined this analysis by excluding overlapping users across groups. This allowed us to estimate the maximum reach of each message, defining this as its cascade size. This metric was crucial in understanding the extent of information dissemination across the network. Next, we further investigated the dissemination characteristics of different types of data. Specifically, for each data type, we quantified two important structural indicators, breadth and depth. The former characterizes the maximum number of groups a message was sent simultaneously, while the latter depicts the maximum forwarding times of a message. Subsequently, we further assessed the differences in breadth and depth features for different message types under varying cascade sizes; specifically, we grouped different types of data based on their cascade sizes and then calculated the proportions of different breadth and depth features within each cascade size range (Figure 2).

Results: The findings from our analysis of message cascades shed light on crucial dynamics and differences in information dissemination behavior across modalities (text, image and video). Figure 1 illustrates a notable distinction: text and video messages tend to generate larger cascade sizes compared to images. This distinction prompts further investigation into the underlying mechanisms driving cascade propagation. Moreover, our examination of cascade size in relation to breadth and depth, as depicted in Figure 2, unveils intriguing insights. From left to right, the bars are: message, text, image, and video. Here, 'message' represents the overall messages (the majority of which consist of text), without distinguishing their types. Contrary to the emphasis on breadth in public platforms, our study reveals that depth emerges as the primary driver behind widespread information dissemination[5]. This observation underscores the significance of understanding the structural characteristics of cascades in different message types. Specifically, the marked increase in multiple forwarding behaviors as cascade size escalates signifies the pivotal role of depth in facilitating large-scale information spread. While changes in breadth are less pronounced, the influence of depth remains consistently significant across varying cascade sizes. This is primarily due to WhatsApp's strict limitations on message breadth, indicating that structural constraints effectively regulate the large-scale spread of information. Additionally, this result suggests that delving deeper into the cascade structure, rather than merely focusing on the breadth of dissemination, is essential for comprehensively understanding information spread dynamics.

Furthermore, our investigation into structural disparities among message types—text, images, and videos—reveals distinct differences. While both breadth and depth contribute significantly to the large-scale spread of information in image cascades, text and video cascades exhibit a distinct pattern. In these cases, depth emerges as the decisive factor governing the spread process, with less pronounced changes in breadth characteristics across cascade sizes. Our findings underscore the importance of considering depth alongside breadth in analyzing information cascade dynamics. In ongoing work, we are building detailed representations of the cascades in the data to enable more dynamic measurements of network spread, e.g., the changing forward behaviors over time and correlated structure of depth and breadth.

References

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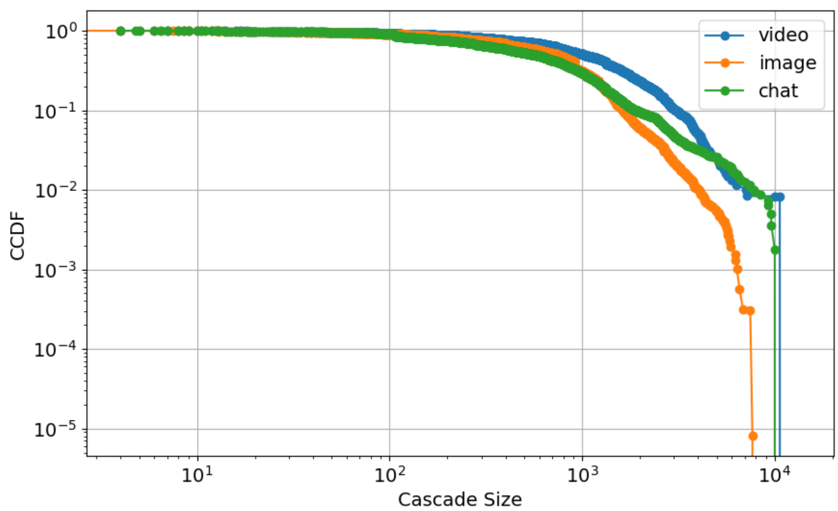
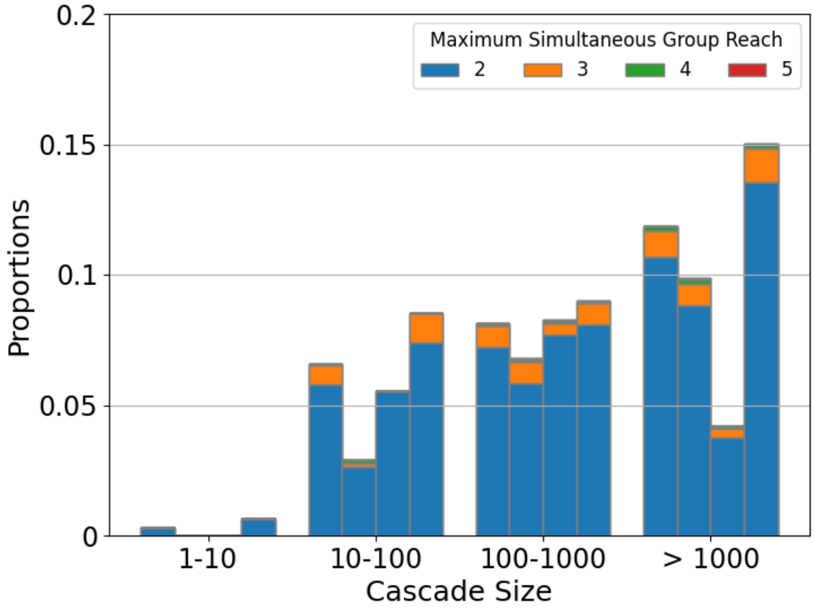
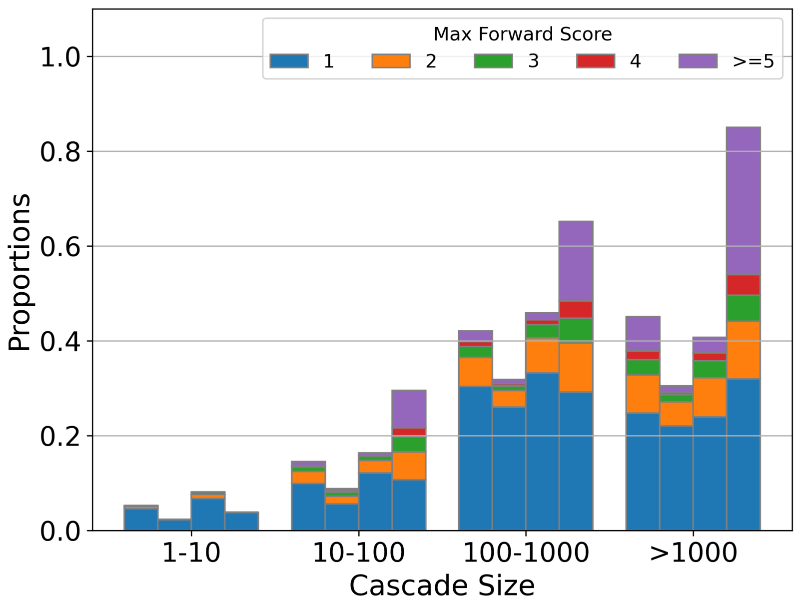


Figure 1: CCDF of Cascade Sizes by Modality



(a) Breadth



(b) Depth

Figure 2: Stacked Bar Chart for Structural Features

Note: For each cascade size, from left to right, the bars are: message, text, image, and video