Analyzing the Dynamics of Social Norms: Positive vs Negative Emergence

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***Abstract*—Gaining a deep understanding of descriptive positive and negative norms, such as their propagation speed, is crucial due to their significant impact on shaping individuals' attitudes and actions towards specific beliefs. Unfortunately, conducting in-depth analysis related to the diffusion of descriptive norms is a complex and context-dependent phenomenon that is influenced by various factors over time. To address this gap, this paper presents a comprehensive analysis of norm propagation in online communities. The study encompasses structural and temporal analyses. Through these analyses, our objective is to uncover the dynamics of norm diffusion, comprehend the patterns of different norms within communities. This will provide valuable insights into the social context and dynamics surrounding positive and negative norms, ultimately enhancing our understanding of norm diffusion and social influence processes. This understanding also offers valuable insights for developing effective campaigns that promote positive norms.**

***Index Terms*—COVID-19, Social Network Analysis, Norms**

I. Introduction

The rise in popularity of social media platforms has facilitated the dissemination of various social norms, such as positive and negative descriptive norms. Positive descriptive norms are social beliefs that define desirable behaviors within a particular context [1]. These norms operate by communicating what actions are considered socially appropriate and are enforced through positive sanctions such as praise or reward [2], serving as standard codes of conduct. Conversely, the negative descriptive norms define behaviors that are considered inappropriate or undesirable within a particular context [1]. These norms communicate what actions are not socially acceptable and are enforced through negative sanctions such as criticism or ostracism [1]. In the context of social media during the COVID-19 pandemic, positive descriptive norms involve promoting social distancing, and wearing masks, whereas negative norms involve the spread of conspiracy theories, misinformation, and disinformation.

Investigating descriptive positive and negative norms in the context of social media during the COVID-19 pandemic is crucial for several reasons. First, these norms play a significant role in shaping individuals' behaviors and attitudes towards public health guidelines [3]. Understanding how positive descriptive norms could influence public health campaigns and initiatives focused on minimizing COVID-19 spread. Conversely, investigating negative descriptive norms, such as the spread of conspiracy theories, could provide insights for developing strategies to combat the dissemination of false information and its detrimental effects on public. Second, investigating the propagation of norms, which follow a hierarchical structure (Figure 1), can provide valuable insights into the spread of these norms within online communities over time. Such structures show the spread of descriptive norms to a broader audience and can reveal the impact of influential users on norm diffusion.

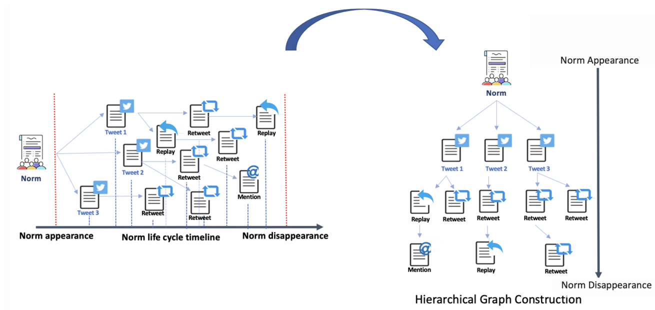

Fig. 1: An illustration of the hierarchical propagation network within a social media platform depicts a norm's progression from its initial emergence to its eventual termination.

Unfortunately, conducting in-depth analyses related to the diffusion of descriptive norms is a complicated and context-dependent phenomenon that is influenced by variables across time. Despite the extensive research in analyzing norms, most experiments have been conducted in the physical world [4], [5] or in virtual scenarios [6], limiting the applicability of findings to the online environment. Moreover, there is a lack of research exploring the differences in the propagation of negative and positive norms. To address these gaps, this study aims investigate a distinction between the propagation of positive and negative norms within hierarchical networks throughout the life cycle of social norms? What are these norms' temporal patterns and characteristics?

Organization. The remainder of the paper is structured as

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TABLE I: Positive Norms

Topics	Keywords
Maintaining social distance during Pandemic	“distance”, “keep distance”, “6 feet”, “distancing”, “6-foot rule”, “social distancing”, “physical distancing”
Individuals after the spread of COVID-19	“Wear a mask”, “keep mask on”, “Mask On”, “FaceMaskMaskUP”, “wearing mask”, “mandatory masks”, “mandatory face mask”, “Wear-Mask”

TABLE II: Negative Norms

Topics	Keywords
Bill Gates played a role in the creation COVID-19 for the purpose of microchipping people	“Bill Gates”,”microchipping+Bill Gates”,”Gates+pandemic simulations”
COVID-19 is genetically modified organism (GMO)	“GMO”,”genetically modified”,”big pharma”,”Fauci pharma”,”Gates pharma”,”genetically modified organism”
COVID-19 is biological weapon	“COVID19+weapon”,”biological weapon”,”weapon covid=19”
COVID-19 vaccines have not passed trials and are poisonous	“haven’t been tested”,”doesn’t be tested”,”not tested”,”poison”,”skip+trail”,”isn’t tested”,”aren’t tested”,”didn’t be tested”,”wasn’t tested”

follows. Section II presents the related works. Our hierarchical graph construction is introduced in section III while the in-depth analysis is discussed in section IV. Finally, section V concludes the paper.

II. Related Work

A. *Norm Propagation Analysis*

The analysis of social norms, positive and negative, within communities has gained significant attention in recent research efforts, especially after the COVID-19 pandemic. Kevin *et al* in [7] investigates how social distance norms present the dangers of increasing social rejection, whereas Sidney *et al* investigates the impacts of mask-wearing on social anxiety [8]. Romer *et al*, in contrast, focuses on showing how conspiracy theories are barriers to controlling the spread of COVID-19 in the USA [9]

Despite the recognized significance of social norms and the effectiveness of such analysis, several knowledge gaps and challenges remain. Firstly, while studies have identified the extensive analysis of various norms in different physical worlds, it is unclear what the norm life cycle looks like in online communities and whether they follow specific patterns. Secondly, to our knowledge, no existing studies have investigated the temporal analysis of positive and negative norms for diffusion-based models, which typically focus on modeling how norms spread or diffuse in the social network.

III. Hierarchical Graph Construction

This section presents our investigation into how to construct negative and positive norms’ hierarchical propagation networks. The formulation of the life cycle of a norm in our study consists of several stages, as shown in Figure 1. The first stage is the norm’s appearance, which refers to the initial observation of the norm. Subsequently, the tweets that follow the norm’s appearance are referred to as supporters, as they express agreement of a specific norm, either positive or negative. Finally, the retweets that follow the supporters’ tweets are referred to as distributors, as they disseminate the norms expressed by the supporters to a wider audience.

Due to the importance of the dataset preparation for building the graph, we first describe it in section III-A. Section III-B presents the overall picture of the hierarchical propagation networks of negative and positive norms.

A. *Dataset Preparation*

This paper utilizes the Twitter Streaming API to collect a basic dataset pertaining to COVID-19 vaccines. The data collection period spanned from January 1, 2021, to September 30, 2021, during which tweets related explicitly to COVID-19 vaccinations were gathered. To achieve this objective, we employ various relevant keywords, including ”vaccine,” ”sputnik,” and ”vaccination,” as well as brand names of COVID-19 vaccines, such as ”moderna” and ”Pfizer,” to filter out irrelevant tweets. By doing so, we were able to obtain a robust dataset of tweets that exclusively pertained to COVID-19 vaccinations. These data served as the foundation for subsequent analyses in this study.

The COVID-19 pandemic has led to the emergence of various new positive descriptive norms, including social distancing [10] and wearing masks [11], which have been widely embraced by individuals across the globe. The impact of these norms is reflected on social media platforms, where many people have been promoting such positive behaviors. However, the pandemic has also given rise to a set of negative norms that have been propagated on social media. These include beliefs [12] such as (i) Bill Gates played a role in the creation and distribution of COVID-19 for the purpose of microchipping people, (ii) COVID-19 is a genetically

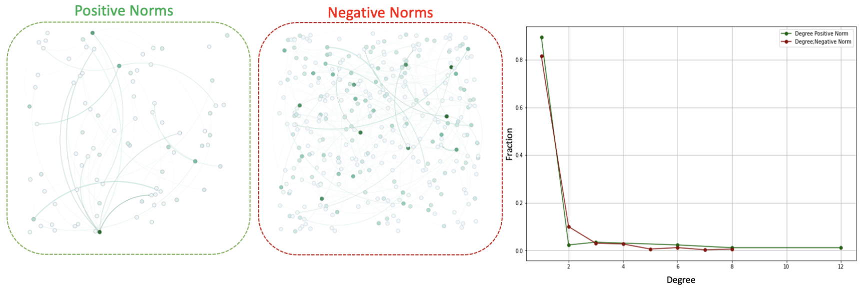

Fig. 2: The propagation network of positive and negative norms, along with the degree distribution.

modified organism (GMO), (iii) COVID-19 is a biological weapon, and (iv) COVID-19 vaccines have not passed trials and are poisonous. In our methodology, we employ a pattern of "word A + word B" as the basis for selecting relevant positive and negative norms, as shown in Table I and Table II, respectively. Specifically, a tweet is considered relevant to a given topic if both "word A" and "word B" appear in its main text. We finally extract $2,378$ tweets and $9,410$ retweets containing the keywords about the negative and positive norms from a total of $138,578$.

B. Propagation Networks

We introduce a hierarchical propagation network to examine the dissemination patterns of positive and negative norms. This network is designed to operate at various granularity levels, tracing the norm propagation process from its emergence to termination through cascades of retweets. To construct the propagation network, we utilize a weighted edge list that connects users in our dataset. We establish a directed edge from distributors to supporters, where the weight of the edge indicates the frequency at which distributors share behaviors written by supporters. This represents the spread of norms.

By analyzing the structure of norm diffusion, the propagation network enables us to identify influential users and communities in the propagation process. The propagation network can be modeled as a directed graph $G = (V, E)$, where V is the set of nodes representing Twitter users and E is the set of edges representing retweet relationships between them. The weight of an edge (u, v) reflects the number of times user u retweeted user v in our dataset.

IV. Norms Analysis

This section aims to employ various analytical approaches to investigate different aspects of norm dynamics and provide insights into the development of effective strategies for promoting positive norms and compacting negative norms. In the first section, structural analysis, we focus on revealing the fundamental structural attributes associated with the development and spread of norms. In the following section, temporal analysis, as the name suggests, investigates social norms' temporal patterns and dynamics, shedding light on how norms evolve and change over time between positive and negative norms, allowing us to understand the temporal sequences and transitions of various norms.

A. Structural Analysis

The constructed propagation network can capture the dissemination patterns of positive and negative norms in our dataset, including information about who shares these patterns. We perform a structural analysis of the network to understand the global spreading pattern of a norm from its emergence to its termination. This analysis allows us to investigate the network's structural aspects, such as the degree distribution, which can shed light on the propagation dynamics and the role of influential users in the process. By analyzing the structure of the propagation network, we can gain insights into the overall spreading pattern of the norms and the factors that affect their diffusion in the dataset.

The propagation network of positive and negative norms is illustrated in Figure 2, with the right graph representing negative norms and the left graph representing positive norms. In these graphs, nodes with darker shades indicate a higher degree, while darker edges indicate frequent sharing behavior occurring more than four times (strong connections). Analyzing the graphs, we can observe that the negative norms network exhibits a greater presence of influencers compared to the positive norms network in terms of their degrees. On the positive norms graph, we notice that strong connections primarily occur between influencers and individual nodes, whereas in the negative norms graph, the influencers establish more frequent weak connections with other nodes in the community. This discrepancy indicates that positive norms rely on receiving information from authoritative sources [13] such as the CDC. In contrast, communities promoting negative norms, such as conspiracy theories, tend to reinforce and support each other within their respective small groups [14].

To further investigate the structure of the propagation networks, we examine the degree distribution of the influential nodes for both positive and negative norms. The degree distribution, denoted by $P_deg(k)$, is defined as the fraction of nodes in the graph with degree k. This distribution provides important insights into the network structure. Our analysis reveals that most nodes have a relatively small degree, while positive norms exhibit a higher degree than negative ones. These findings indicate that positive norms may have a more centralized network structure, while negative norms tend to be more decentralized.

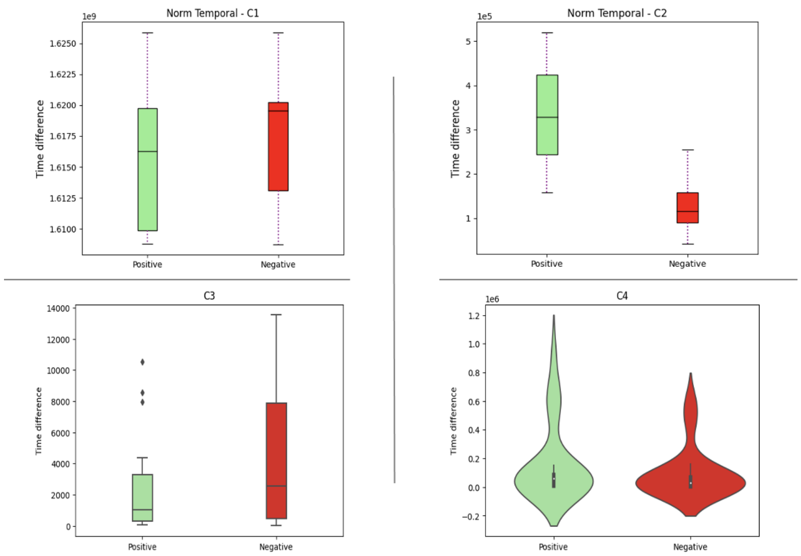

Fig. 3: Temporal Analysis of Positive and Negative Norms

B. *Temporal Analysis*

Analyzing temporal user engagements within the propagation network offers significant insights into the dynamics of norm dissemination. By investigating the frequency of user postings over time, we can gain a deeper understanding of how norms spread through online communities. Although neural networks can effectively capture temporal dynamics, the interpretability of the learned features and the underlying rationale behind their effectiveness remain unclear.

To address this limitation, we propose the extraction of several explicit temporal features from the propagation networks, enhancing the explainability of our analysis. These features aim to shed light on the distinct characteristics of norm propagation and whether they exhibit variations across different norms. In this paper, we focus on the propagation network and extract the following temporal features:

- C1: The average time elapsed between the appearance of a norm and the subsequent tweets that support it. This feature provides insights into the occurrence of short-term support in relation to the emergence of the norm. Understanding the time delay between the norm's appearance and its initial support can offer valuable indications of the immediate response from users.
- C2: The average time span between the norm-supporting tweets and the initial distribution that disseminated those norms. By capturing the time it takes for norms to be disseminated, this feature provides a measure of the speed at which the norms are distributed throughout the network. It offers valuable insights into the efficiency of the propagation process.
- C3: The interval between adjacent distributors reflects the time gap between consecutive instances of distributors sharing supporting tweets during the norm propagation process. This feature provides valuable information on the pace at which distributors are actively engaged in sharing supporting tweets. It highlights the rapidity of information flow within the network.
- C4: Time difference between the first supporting post for a norm and the last distributor of that norm. This feature represents the life cycle of a norm, capturing the time span from its initial support to its eventual cessation. Examining this temporal duration allows us to understand the overall dynamics of norm propagation, including its duration and longevity.

Figure 3 shows the temporal characteristics of positive and negative norm graphs. The graph C4 in Figure 3 reveals that negative norms exhibit a shorter life cycle compared to positive norms. This finding suggests that, on average, negative norms persist for a shorter duration within our datasets. Additionally, examination of C2 indicates that the reaction from the distributors to the supporters is fast and shorter for negative norms.

Turning our attention to C1, we observe that the initiation of support for both positive and negative norms occurs promptly. However, positive norms tend to endure for a longer duration, whereas negative norms exhibit a relatively shorter lifespan. Furthermore, in C3, we observe that distributors associated with the same supporter engage for a longer period in the case of negative norms. This observation may signify the presence of bots targeting specific users as they engage in multiple instances of sharing.

These findings shed light on the contrasting dynamics between positive and negative norms in terms of temporal characteristics. The shorter life cycle and rapid response of negative norms, coupled with the lengthy engagement of distributors in the propagation process, highlight unique patterns within the dissemination of negative norms.

C. Activity-Based Norm Life Cycle Analysis

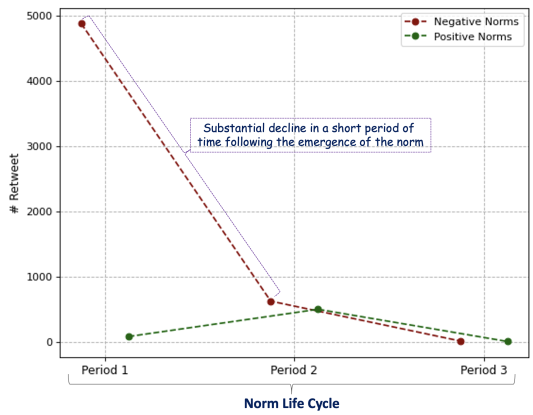

Fig. 4: The propagation speed of positive and negative norms during a norm's life cycle.

Analyzing the life cycle of a norm in relation to various factors, such as the speed of propagation across different levels, offers several significant advantages. Firstly, it provides a comprehensive understanding of the varying rates at which different norms spread. Secondly, employing consistent time intervals, as depicted in Figure 4, establishes a standardized framework for comparative analysis. This approach enables the identification of patterns, and the period-based approach can help us capture short-term dynamics and facilitate the detection of potential shifts within specific timeframes.

We present a comprehensive analysis of sharing behaviors across different time periods, as depicted in Figure 4. To gain deeper insights into the relative speed of descriptive norms, we have divided the life cycle of norms into three distinct periods. Period 1 marks the emergence of the norms, capturing the initial phase of norm establishment. The second period spans three months, representing a period of norm stability. Finally, the last period focuses on the disappearance of the norms, highlighting their gradual decline or cessation. Throughout these periods, we assess the influence of descriptive and positive norms by examining the sharing activity of the original norm-related posts. By systematically examining the norms' life cycle in this manner, we can clarify the temporal dynamics and measure the impact of these norms within each period.

Our analysis in Figure 4 reveals distinct patterns in the life cycle of positive and negative norms. Positive norms exhibit a consistent trajectory of growth followed by a decline throughout their life cycle. In contrast, negative norms experience a substantial and rapid decline within a relatively short period of time. These observations highlight the differential dynamics and temporal behaviors exhibited by positive and negative norms. The sustained increase and subsequent decline of positive norms suggest a gradual acceptance and adoption followed by a decrease in user engagement. On the other hand, the sharp decline of negative norms indicates a rapid loss of interest or a decline in their influence within the given time frame. This discrepancy underscores the contrasting trajectories and dynamics between positive and negative norms, shedding light on their distinct patterns of emergence, propagation, and eventual decline.

V. Conclusion

Understanding descriptive positive and negative norms is crucial since they play a significant role in shaping individuals' behaviors toward public health guidelines. Unfortunately, conducting in-depth analyses related to the diffusion of descriptive norms is a complicated and context-dependent phenomenon that is influenced by variables. To fill the gap, this paper presents a comprehensive analysis of norm propagation in social networks. Through these analyses, we aim to uncover the dynamics of norm diffusion, enhancing our understanding of norm diffusion and social influence processes.

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