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Activating Intelligent Commenting using Extricate of Tweets

Prachi Kulkarni, D.K.Chitre

Student, Department of Computer Engineering, Terna Engineering College, Maharashtra, India

Professor, Department of Computer Engineering, Terna Engineering College, Maharashtra, India

ABSTRACT: In existing approach we can't retweet or intelligence comment to a particular word , but in proposed approach that examines the practice of retweeting as a way of intelligence commenting in a group likewise digital marketing by which participants can be "in a conversation." While retweeting has become a convention inside Twitter, participants embrace it for diverse reasons and using varying styles. Our data and analysis reveal the messiness of retweeting by highlighting how issues of authorship, attribution, and communicative fidelity are negotiated in diverse ways. Using a series of case studies and empirical data, this paper maps out different conversational aspects of retweeting digital intelligence commenting.

I. INTRODUCTION

A conversation is most commonly bounded in time, space and social context. Whether sitting around a table or talking on the telephone, conversations typically include a known, fixed set of participants who are assembled in real time in a particular social context for the purpose of talking to one another. The growth of computer-mediated communication, social media and networked publics has shown that conversations can take place asynchronously and unbounded in space or time, but they are most often nevertheless bounded by a reasonably well-defined group of participants in some sort of shared social context.

One kind of conversation that does not have a bounded set of participants is the kind described by marketers, celebrities, and politicians when they seek to be "in conversation" with their customers, fans, or constituents. These conversations do not typically involve direct dialogue, but a public interplay of voices that gives rise to an emotional sense of shared conversational context. Thus, the participants are no longer bounded except by a loosely shared social context.

Because of Twitter's structure, which disperses conversation throughout a network of interconnected actors rather than constraining conversation within bounded spaces or groups, many people may talk about a particular story at once, such that others have a sense of being surrounded by the story, despite perhaps not being an active contributor in the conversation. The stream of messages provided by Twitter allows individuals to be peripherally aware of discussions without being contributors.

Various behavioral conventions have arisen over time and come to be inscribed in the Twitter technology, such as public yet directed messages using the @ symbol and hashtags (#'s) to mark tweets with topical keywords. Both conventions have clear conversational purposes. Honeycutt and Herring [8] examine the conversational aspects of messages with the @ symbol. However, a third behavioral convention known as the "retweet", or the copying and rebroadcasting of another participant's message, enables conversations in a different manner. In this article, we argue that, as with link-based blogging [3], retweeting can be understood both as a form of information diffusion and as a structure within which people can be part of a conversation. The spread of tweets is not simply about getting messages out to new audiences, but also about validating and engaging with others. As a result of retweeting, some users get a sense of being a part of a broader conversation even when they themselves do not contribute.



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1.1 Background

Retweeting is also an important practice to analyse because of the issues it raises concerning authorship, attribution, and communicative fidelity. In an environment where conversations are distributed across the network, referents are often lost as messages spread and the messages themselves often shift. What participant's value and the strategies they use when

Retweeting reveal salient aspects of the conversations they seek to create on Twitter. In this paper, we develop, study, and validate via experimentation on real data from Twitter, an epidemic model of the information propagation temporal dynamics for specific topics. Several works [3]–[5] have studied information propagation in Twitter using principles of epidemic theory [6]. More papers have studied the information propagation speed and the influence of users in Twitter [1]. In general, previous works consider that knowledge about a topic stops propagating at the node that last tweeted with a specific hashtag. However, Twitter users are surrounded by conversations determined by such hashtags, being aware of their topics but not necessarily acting or interacting with other participants [1]. To address this aspect, our approach considers for the first time the set of followers of nodes that initiated or reproduced tweets with a specific hashtag as part of the set of informed nodes, thus capturing more realistically the behaviour of information propagation in Twitter. Under this consideration, we show that information spreads in a great part of the Twitter network in relatively short time compared with Twitter's scale. As this is also the case in the real world, this paper contributes toward exemplifying Twitter as a virtual testbed [12] for accurately tracking social trends and behaviors.

1.2 Motivation

Twitter is a microblogging service that was founded in early 2006 to enable people to share short textual messages—"tweets"—with others in the system. Because the system was originally designed for tweets to be shared via SMS, the maximum length of a tweet is 140 characters. Though the service evolved to include more uses besides SMS, such as web and desktop clients, this limitation persisted, and so was re-narrated as a feature. Twitter's Creative Director Biz Stone argues, "Creativity comes from constraint" [6]. The approach followed in this paper with respect to the set of the informed users prevents underestimating the extent of information propagation of specific topics within Twitter network, as it will be shown via the numerical evaluations. Furthermore, we thoroughly examine several hashtag categories studying the adaptation of the epidemic model for each one of them. Specifically, there exist hashtag types that require time-varying infection rates for properly describing them, whereas others require constant rates for capturing more precisely the real information propagation taking place in the Twitter network. Our model is shown via evaluations to be well adapted to all hashtag categories, if the "Social Web" is the latest evolution of the Web where information is generated very quickly, consumed by millions of users, and updated quickly by others through commenting, replying, transferring, etc. This is practiced by people who differ in culture, knowledge, background, ideology, etc.

II. PROBLEM STATEMENT

In existing approach we can't retweet or intelligence comment to a particular word In but in proposed approach that examines the practice of retweeting as a way of intelligence commenting in a group likewise digital marketing by which participants can be "in a conversation." While retweeting has become a convention inside Twitter, participants embrace it for diverse reasons and using varying styles. Our data and analysis reveal the messiness of retweeting by highlighting how issues of authorship, attribution, and communicative fidelity are negotiated in diverse ways. Using a series of case studies and empirical data, this paper maps out different conversational aspects of retweeting digital intelligence commenting.

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III. PRESENT INVESTIGATION

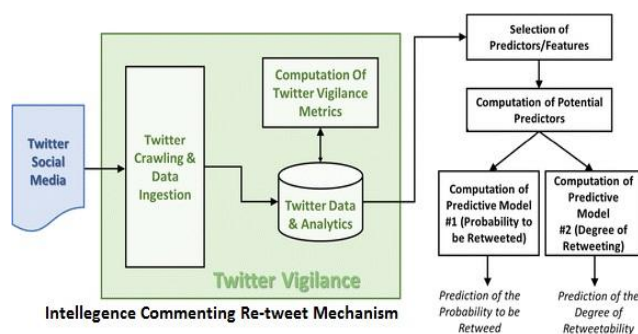


Fig. 1. Proposed System Architecture

According to the above presented state of the art, retweeting is a powerful mechanism to diffuse information on Twitter. The number of retweets of a tweet can be considered as a measure of how much the produced tweet has been effective in propagating the information, which is one of the major motivations for tweeting on Twitter.com. The proposed study aims at identifying the values of tweets' features which may determine the *degree of retweeting* and, as a side effect to understand the mechanisms which may determine retweeting in Twitter. The main goal is to create a predictive model for assessing the *degree of retweeting*, and thus to classify tweets in terms of certain classes for their *degree of retweeting*. The computational process at the end is performed through the following steps as depicted in Fig.3.1 and better described as follows:

1. Collection of the data from Twitter.com by crawling them by using Twitter Vigilance platform and tools on the basis *searches* and *channels*. The platform allows computing simple metrics for counting tweets/retweets for search and channel, extracting relationships among users, etc. Selection of predictors/features from collected data and metrics.
2. Computation of potential predictors: a statistical criterion is applied to identify the statistically significant features. The use of an exploratory method is a crucial issue not only for ranking the variables before the construction of a prediction model, but also to give the phenomenon's first interpretation and to understand the underlying data structure.
3. Computation of a predictive model for the assessment of the binary probability to be retweeted or not.
4. Computation of a model to predict the *degree of retweeting*. The results have been obtained by comparing several different computational alternatives and approaches and selecting the better ranked and the most relevant metrics as described in the following.

According to the previous statements, we have adopted Classification and Regression Tree (CART) models to understand the relevance of variables and to construct a model for predicting the probability to be retweeted and the *degree of retweeting*.

Our approach models the diffusion of a topic as cascades and thus adopts a sender-centric vision. We use the Twitter follower graph as a basis and consider three dimensions: (i) semantics, (ii) social, and (iii) time. To make use of the third dimension, we leverage the AsIC meta-model, an extension for a continuous time axis of the broadly used IC model by adding a time-delay parameter on each edge. This allows us to model the propagation as an asynchronous process and therefore capture the temporal dynamics more accurately.

Failures:

1. Huge database can lead to more time consumption to extract tweet and classification process of that tweets.
2. Hardware failure.
3. Software failure.

Twitter doesn't allow to have tweets at same time more than 60 tweets for on single # tag or search word.it may block user for suspecting the data attack or fishing shown



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Your account has been locked.



What happened?

Your account appears to have exhibited unusual behavior that violates the [Twitter Rules](#). To unlock your account, please complete the steps below and confirm that you are the valid account owner.

What you can do:

To unlock your account, you must do the following:

- Pass a Google reCAPTCHA challenge
- Verify your phone number

When you tap 'Start', Google may collect and use information about you, your device, and browser. View [Google's Privacy Policy](#).

Start

Success:

1. User tweets the message and after detect the data set by using verifying user's tweets.
2. User gets result very fast according to their needs.

Our project is NP-Complete

Our project comes into the NP Complete, because time it will not give the result. For the decision problem, so that it will give the solution for the problem within polynomial time. The set of all decision problems whose solution can be provided into polynomial time by using the attribute enhanced index.

V. RESULTS & DISCUSSIONS

In this section, we compare the numerical results obtained via base paper on the evolution of the number of searched Twitter users over time and the corresponding evolution derived from our data set for each hashtag. In order to determine the suitable commenting with existing data sets rates' values, λ_1 and λ_2 , for each hashtag, we trained our proposed model on the collected data set for the corresponding hashtag, for both the cases of constant. The training is performed based on both the least squares and the least absolute deviations (LAD) methods, as the most popular fitting methods. For each hashtag, we divided the collected data set in two parts, using the first for training purposes in order to obtain the parameters of given inputs and the other for testing the predicting behavior of our model over unknown data. Note that since we do not know explicitly the average number of followers of a Twitter user (to the best of our knowledge, we have not found a relevant result in the literature). Our aim to reduce time complexity of the present system.

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