Real-Time and Cost-Effective Limitation of Misinformation Propagation

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Abstract—Online Social Networks (OSNs) constitute one of the most important communication channels and are widely utilized as news sources. Information spreads widely and rapidly in OSNs through the word-of-mouth effect. However, it is not uncommon for misinformation to propagate in the network. Misinformation dissemination may lead to undesirable effects, especially in cases where the non-credible information concerns emergency events. Therefore, it is essential to timely limit the propagation of misinformation. Towards this goal, we suggest a novel propagation model, namely the Dynamic Linear Threshold (DLT) model, that effectively captures the way contradictory information, i.e., misinformation and credible information, propagates in the network. The DLT model considers the probability of a user alternating between competing beliefs, assisting in either the propagation of misinformation or credible news. Based on the DLT model, we formulate an optimization problem that aims in identifying the most appropriate subset of users to limit the spread of misinformation by initiating the propagation of credible information. Through extensive experimental evaluation we demonstrate that our approach outperforms its competitors.

I. INTRODUCTION

An intriguing behavior of users of Online Social Networks (OSNs) is information sharing, where often users further propagate information of interest to their friends. An interesting study reveals that more than 45.1% of the messages published by a user are further propagated by his/her followers and over 37.1% are propagated by followers up to 4 hops away from the original publisher [1]. However, it is not uncommon for false news to propagate through social networks, causing significant repercussion outside the network, e.g., a tweet stating that there was an explosion in the White House caused stocks to temporarily plunge\(^1\). It becomes therefore clear that it is vital to detect and timely block the propagation of deceptive information.

Misinformation is defined as any malicious, deceptive or irrelevant information regarding an event, that is spread either deliberately or unintentionally in the social network [2, 3]. Manifold factors contribute to the complexity of the task of misinformation blocking. Sources of misinformation are multiple and varying, as is the users’ susceptibility to the news they are exposed. Furthermore, the longer the deceptive information propagates in the network without contradiction from a reputable source, the greater is the effect of the misleading information and it is thus crucial to timely notify users about the credible information. For the effective and efficient solution of the problem, a set of interesting research questions should be addressed: (i) how can a user’s susceptibility be estimated, in order to efficiently approximate the degree to which the user is willing to adopt or renounce an idea, (ii) how can we identify the sources of misinformation, (iii) how can we estimate the influence of the users across the network, and finally, (iv) given a desired number of sources to contradict misinformation, which is the most appropriate subset of users to initiate the cascade to timely limit the misinformation dissemination?

The problem of limiting misinformation or rumors in OSNs, commonly referred as misinformation or rumor blocking, is the subject of study in [2], [4], [5], however, none of the proposed schemes considers propagation times and therefore, fail to capture any time constraints during the dissemination of the information. Furthermore, the susceptibility of a user related to the propagation of content is ignored. Finally, they assume that users remain loyal to adopted belief as the propagation unfolds, an assumption that is not always correct. There are multiple examples of users that apologized after unintentionally contributing to the spread of false news\(^2\).

The objective of this work is to minimize the misinformation spread while overcoming the above limitations. Our approach is two-fold: First, we propose a novel propagation model, namely the Dynamic Linear Threshold (DLT) model, where each user is associated with a renouncement threshold that expresses her susceptibility to adopt an idea. We define the threshold to be dynamically adjusted after a user adopts an idea and allow the user to renounce a previously adopted belief. However, adopting a different opinion regarding the validity of the information is less likely after the user is convinced on a specific piece of information. Additionally, the proposed model considers the impact of competing ideas to the users’ choice of adopting an idea. Finally, we consider that the influence of a user over any other user in the network varies over time and there is a certain time frame that a user is more likely to be influenced by a specific neighbor. To limit the spread of misinformation, in the second part of our approach, we propose an algorithm that aims at selecting an appropriate subset of users to initiate the propagation of credible information. Our goal is to identify a subset of users to act as seeds for the dissemination of credible news and minimize the number of users infected during the spread of non-credible information.

\(^1\)http://www.cnbc.com/id/100646197  
\(^2\)http://twitchy.com/2015/05/04/we-screwed-up-shep-smith-apologizes-for-false-report-on-baltimore-shooting-video/
The contribution of this work is summarized as follows:

- We introduce a novel propagation model where users' susceptibility to news dynamically adapts over time. The model captures the hesitance of users to renounce their beliefs, making it appropriate to realistically describe the spread of information in OSNs. Furthermore, while previous works ignore time constraints during the propagation process, we capture time as an actual unit.
- We suggest a greedy approach that efficiently solves the problem of misinformation limitation by selecting an appropriate subset of users to decontaminate the network. Our proposed model for seed selection is efficient and independent of the structure of the underlying network.
- We illustrate through extensive experimental evaluation that our approach achieves notably better results than its competitors with respect to misinformation limitation.

II. MODEL AND PROBLEM DEFINITION

In this section we describe the network model and formally define the problem of misinformation blocking.

A. Network Model

A social network is commonly represented as a directed weighted graph $G(V, E)$. Users of the network constitute the nodes and a directed edge from user $u$ to $v$ denotes the flow of information. For example, in the Twitter network, the edge $u \rightarrow v$ denotes that user $u$ has replied to or retweeted messages published by $v$. We associate each edge $u \rightarrow v$ with a weight $w_{uv}$, which expresses the influence of $u$ over $v$.

Each node $u$ is assigned a credibility score $c_u$ and a renouncement threshold $r_u$. The credibility score $c_u$ expresses the trustworthiness of user $u$. Effectively estimating the users' credibility is out of the scope of this work, however, there are approaches suggested by former studies on how to identify sources of misinformation [2], [6], [7]. The renouncement threshold $r_u$ denotes the incredulity of the user $u$ in renouncing an already adopted opinion, either credible or misinformation. Users that present high renouncement are characterized as skeptical in adopting and propagating information, while users with low renouncement are less reluctant. We assume that users have an initial reluctance regarding information sharing, but after they are convinced on disseminating the information, their renouncement threshold increases, as they become hesitant in later switching their beliefs. Following the terminology of [4], we distinguish between three different user roles, namely infected, protected and inactive.

Infected users (I): Non-credible users or users that adopt and propagate false news, either deliberately or unintentionally. Infected users are considered negatively influenced users.

Protected users (C): Users that adopt the credible information and therefore are able to further propagate it to the network are referred to as Protected users or positively influenced users. Unlike the work in [4] that assumes that the protected users remain protected throughout the propagation process, we define them to be susceptible to misinformation.

Inactive users (R): Users that are unaffected by the propagation of either credible or false news. It holds that $R = V \setminus (I \cup C)$, where $V$ is the set of all users.

An example of the social graph is presented in Figure 1a, where negative, positive and non-signed users represent the infected, protected and inactive users respectively. The values on the edges denote the weights, with $c$ and $r$ values denoting the renouncement threshold and credibility scores respectively.

B. Problem Definition

Given (i) a social graph $G(V, E)$, (ii) the weight of the edges $w_{uv}, \forall u \in V \rightarrow v \in E$ among users of the network, denoting the influence of user $u$ over $v$, (iii) the set of initially non-credible users before the propagation unfolds (referred as misinformation originators $I_0$), and (iv) a parameter $k$ denoting the desirable number of user in the network to act as initiators of credible news propagation, our goal is to select a subset of users $S$ with $|S| \leq k$, so that the number of infected users $I$ during the propagation is minimized. $I_0$ constitutes a subset of the infected users and the seed subset $S$ of the credible users, hence $I_0 \subset I$ and $S \subset C$. We aim at providing a cost-effective solution where we define the cost for the seed selection process as the amount of messages exchanged among users. Thus, it could be monetary (for an SMS) or resource allocation cost.

We refer to users in $S$ as seeds. The role of the seeds is to decontaminate the infected users by propagating the credible information. We assume that seeds are convinced about the credible information, regardless of their renouncement threshold. The aforementioned problem is referred in the bibliography as the Influence Blocking problem [4], [8] and can be proven to be NP-Complete.

III. PROPAGATION MODEL

In this section we introduce our Dynamic Linear Threshold (DLT) propagation model and later present our methodology for computing the influence and the updated renouncement scores.

A. The Dynamic Linear Threshold Model

The most common propagation models in Social Networks are the Independent Cascade (IC) model and the Linear Threshold (LT) model [9]. Both the IC and the LT propagation models express the information dissemination of a single campaign and hence ignore the way conflicting propagation may impact one another. Furthermore, traditional IC and LT models ignore propagation times. Variations of the above models consider time limitations [10]–[13], yet none of them takes into account opposing campaigns that may be propagated simultaneously. To overcome the above limitations, we propose the Dynamic Linear Threshold (DLT). The DLT model differs from the traditional LT model in the following ways:

- The DLT model considers competing ideas that simultaneously propagate in the network and evolve over time.
- We estimate the influence of a user $u$ to a neighbor $v$ not solely based on the weight of the edge $u \rightarrow v$, but also based on the time frame, i.e., there is a time window that a neighbor is most likely to be influenced.
- Contrary to the LT model, DLT assumes that a user may renounce an adopted idea, based on the input influence of its neighbors.
- The threshold of user $v$, denoted as renouncement $r_v$, is dynamically updated whenever a user $v$ adopts an idea.
Similarly to the LT model, we consider that a user $v$ adopts a belief when the influence from the incoming neighbors exceeds the renouncement threshold $r_v$. To estimate the probability that a user $u$ influences a user $v$ at time $t$ we exploit the Poisson Distribution. User $v$ adopts either the misinformation or the credible information, depending on the beliefs of the incoming neighbors. The propagation process unfolds at discrete steps as follows: (i) At step $\tau - 1$ each user $u$ that is either negatively or positively influenced (infected or credible respectively), influences the currently inactive neighbors $v \in \text{out}(u)$ with a probability $IF(v|t)$ that is estimated based on the weight of the edge and the time window $t$. (ii) A user $v$ adopts a belief based on the influence of the incoming neighbors $u \in \text{in}(v)$. In case that the negative/positive influence exceeds the renouncement threshold $r_v$, then user $v$ becomes infected/credible. We assume that, if both conflicting propagation reach the renouncement threshold $r_v$, then user $v$ adopts neither of them. This is based on the fact that when a user is convinced on both conflicting information, due to the high ambiguity presented for the specific information, he remains hesitant concerning the adoption of either. (iii) At step $\tau$, each node that is either positively or negatively influenced at step $\tau - 1$ is added to the credible or infected set and the renouncement thresholds are updated. The aforementioned propagation steps are repeated until no more users can be influenced. The existence of conflicting influences at node $v$ is taken into consideration when deciding whether $v$ will adopt a specific belief (see Section III-B). In Figure 1 we illustrate with an example the propagation, where newly influenced users at step $\tau$ have their renouncement thresholds updated.

### B. Influence and renouncement computation

In the DLT model we consider that the propagation unfolds over time and the transmission times between any two users vary. To estimate the probability of a user $u$ influencing user $v$ at time $t$ we assume a Poisson Distribution, that is,

$$p_{uv}(t; \lambda) = \frac{\lambda^t e^{-\lambda}}{t!}$$

where $$\lambda = Var(T_{uv}) = \frac{1}{n} \sum_{i=1}^{n} (t_i - \mu)$$ (1)

In the above equation $T_{uv} = \{t_1, t_2, ..., t_n\}$, is the set of time intervals between any two subsequent interactions of user $u$ with $v$, $t_i$ is the $i-th$ interval, $n$ is the total number of subsequent interactions and $\mu$ is the mean of all values in $T_{uv}$. By exploiting the above distribution to model the propagation times between nodes, each neighbor $u \in \text{in}(v)$ is given a different probability for influencing user $v$. Hence, the influence of $v$ from his neighbors changes dynamically over time. This is a reasonable assumption considering the way updates are presented to users in Online Social Networks, i.e., a timeline presentation with the more recent update on top. As time elapses, the influence of user $u$ on user $v$ gradually fades, since the probability of the update of $u$ presented in the timeline of $v$ decreases. However, updates may not necessarily appear in the most recent way in the news feed of the user [14], [15], hence the Poisson Distribution captures the fact that between each two users $u$ and $v$, with edge $u \rightarrow v$, there is a different time window within which the probability of $u$ influencing $v$ increases. Note that more sophisticated methods that predict whether a user will view a message within a certain time window from its publication may be exploited [16].

We define that a user $v$ at time $t$ is influenced by his/her neighbors according to the following Influence Function:

$$IF(v|t) = \sum_{u \in \text{in}(v)} B(u|t) \cdot p_{uv}(t; \lambda) \cdot w_{uv}$$ (2)

where $\text{in}(v)$ denotes the incoming neighbors of user $v$, $B(u|t)$ equals $-1$ if user $u$ has adopted the non-accurate belief at time $t$, $B(u|t)$ equals $1$ if user $u$ is convinced on the credible information at time $t$, or is $0$ otherwise. In the above equation $p_{uv}(t; \lambda)$ denotes the probability that user $u$ influences $v$ at time $t$ and $w_{uv}$ denotes the influence of $u$ over $v$ as expressed by the weight of the edge $u \rightarrow v$. User $v$ adopts a belief if $|IF(v|t)| \geq r_v$ and $B(v|t)$ at time $t$ is set to $1$ if $IF(v|t) > 0$, or $-1$ if $IF(v|t) < 0$. In case $|IF(v|t)| < r_v$ we assume that no belief can be adopted either because none of the credible or non-credible exceeds the threshold or both exceed it.

The above function considers the co-existence of conflicting cascades, since the misinformation decreases the sum while the credible information increases it. Therefore, unless either the positive or negative influence is strong enough, the user becomes hesitant on which one to adopt. Intuitively, when a user is exposed to both the negative and the positive propagation, the influence of the one is counterbalanced by the influence of the other. Whenever user $v$ adopts a belief $B_i$, then the renouncement score $r_v(t)$ of user $v$ at time $t$ is
updated as follows:
\[ r_v(t) = 1 - (1 - r_v(0))^{y+1} \]  
(3)
where \( 1 - r_v(0) \) denotes the inherited reluctance of user \( v \) regarding the adoption of a cascade, and \( y \) the number of times a user switched believes. The above equation intuitively expresses that the renouncement of user \( v \) increases whenever he/she adopts a belief, hence, the user becomes more reluctant renouncing an adopted belief.

IV. MISINFORMATION BLOCKING

In order to limit the spread of false news, and therefore the number of infected users, we suggest the selection of a limited subset of users that will assist the decontamination of infected users by cascading the credible news. Since the problem of finding the appropriate subset of users for misinformation blocking is NP-Complete, we develop a greedy algorithm that iteratively adds nodes to the seed set \( S \), until the desired number \( k \) of seeds is reached, or no more seeds can be added. The Algorithm exploits simulated annealing at each iteration in order to determine the most appropriate seed.

Based on Equation 2, for a node \( v \) not to be infected, it should hold \( IF(v|t) \geq 0 \) or \( |IF(v|t)| < r_v \) otherwise, that is:
\[
\sum_{u \in \text{in}(v)} B(u|t) \cdot p_{uv}(t; \lambda) \cdot w_{uv} \geq 0, \text{ or } \left| \sum_{u \in \text{in}(v)} B(u|t) \cdot p_{uv}(t; \lambda) \cdot w_{uv} \right| < r_v
\]  
(4)

Given the set of misinformation originators \( I_0 \), the nodes likely to be infected at step belong to the neighborhood of \( I_0 \). In order to identify the misinformation originators, we exploit the credibility scores of the users, denoting as misinformation originators the users with the lower credibility scores. Therefore, for nodes with incoming edges from \( I_0 \), i.e., \( v \in \text{out}(I_0) \) we have to maximize \( IF(v|t) \) of user \( v \), while considering the number of nodes \( I_k \) infected after \( k \) seeds are selected. Hence we define the function \( g(S_k) \) as follows:
\[
g(S_k) = \sum_{v \in \text{out}(I_k)} IF(v|t) - (|I_k| - |I_0|) = \sum_{v \in \text{out}(I_k)} \sum_{u \in \text{in}(v)} B(u|t) \cdot p_{uv}(t; \lambda) \cdot w_{uv} - (|I_k| - |I_0|) \]  
(5)

In the above equation \((|I_k| - |I_0|)\) denotes the additional nodes infected given the seed set \( S_k \). We need not only to maximize the positive influence, but also minimize the set of infected nodes. Therefore, by maximizing \( g(S_k) \) we either increase positive influence by maximizing \( \sum_{v \in \text{out}(I_k)} \sum_{u \in \text{in}(v)} B(u|t) \cdot p_{uv}(t; \lambda) \cdot w_{uv} \) or decrease the set of infected nodes at time \( t \) by minimizing \((|I_k| - |I_0|)\). Since \( B(u|t) \) equals 1 when the node \( u \) is credible, -1 if \( u \) is infected or 0 otherwise, the above equation may be written as follows:
\[
g(S_k) = \sum_{v \in \text{out}(I_k)} \left( \sum_{u \in W_k} p_{uv}(t; \lambda) \cdot w_{uv} - \sum_{u \in I_0} p_{uv}(t; \lambda) \cdot w_{uv} \right) - (|I_k| - |I_0|) \]  
(6)

where \( W_k = C \cup S_k \), \( W_k \) denotes the neighbors of node \( v \) that are protected and therefore have a positive influence and \( I_0 \) are the infected nodes and have negative impact. In Algorithm 1 we present the simulated annealing approach for achieving the maximization of \( g(S_k) \). Parameters \( \alpha \), \( T \) and \( T_{\text{min}} \) are tunable, depending on the refinement required in the solution. However, these can effect the execution times. For the experiments the values are set as in Algorithm 1.

Algorithm 1: REACT

Data: \( G(V, E) \), \( I_0 \), \( C \), \( \text{seedsSize} \), \( t \)
\( S \leftarrow \emptyset \);
while \( |S| < \text{seedsSize} \) do
  \( T \leftarrow 1.0; \)
  \( T_{\text{min}} \leftarrow 0.0001; \)
  \( \alpha \leftarrow 0.7; \)
  \( g(S_k) \leftarrow \text{null}; \)
  while \( T > T_{\text{min}} \) do
    \( u_k \leftarrow \text{randomSeed}(V); \)
    \( S_k \leftarrow S \cup u_k; \)
    \( I_k \leftarrow \text{getInfected}(I_0, C, S_k); \)
    \( g_{\text{new}}(S_k) = \sum_{v \in \text{out}(I_k)} \left( \sum_{u \in C \cup S_k} p_{uv}(t; \lambda) \cdot w_{uv} - \sum_{u \in I_0} p_{uv}(t; \lambda) \cdot w_{uv} \right) - (|I_k| - |I_0|); \)
    if \( g(S_k) = \text{null} \) then
      \( g(S_k) \leftarrow g_{\text{new}}(S_k); \)
      \( \text{ap} \leftarrow e^{\frac{g_{\text{new}}(S_k) - g(S_k)}{T}}; \)
      if \( \text{ap} \geq \text{random()} \) then
        \( u \leftarrow u_k; \)
        \( g(S_k) \leftarrow g_{\text{new}}(S_k); \)
      end
    end
    \( T = T \cdot \alpha; \)
  end
  \( S \leftarrow S \cup u; \)
end

The algorithm computes the seed set \( S \) as follows:
1: Initially a random seed \( u_k \) is selected at step \( k \).
2.1: Given \( u_k \), seed set \( S \) and the misinformation originators \( I_0 \), the set of infected users \( I_k \) when \( u_k \) is added to the seed set \( S_k \) = \( S \cup u_k \) and the value of the \( g(S_k) \) function are estimated. \( I_k \) is computed by simulating the propagation under the DLT model given the seed set \( S_k \). At each iteration in the value of the prior best seed as well as seed \( u \). Hence, \( g(S_k) \) expresses the value of the best candidate seed at step \( k \) and \( u \) the best candidate, and \( g_{\text{new}}(S_k) \) the value of the \( u_k \) candidate investigated at the current iteration of the simulated annealing process.
2.2: After the \( k \) th iteration completes the best candidate \( u \) is added to the seed set \( S \), i.e., \( S = S \cup u \).
3: Steps 1 through 2 are repeated until the required number of seeds is selected or no more nodes may be protected by the selection of additional seeds.

In this work we only aim at identifying the appropriate seeds set and do not consider streaming data to estimate the evolution of the propagation process.

V. EXPERIMENTAL EVALUATION

We conducted a set of experiments on a real world emergency related dataset, namely the Sandy Dataset. The Sandy
dataset is related to tweets regarding the Sandy Hurricane, a major emergency event that unfolded in 2012, from October 22 to November 2, and severely affected the area of New York City [17]. We choose this dataset as it is indicative of the way emergency related information flows in the network.

In order to form the graph, we used the replies a tweet received. For each reply an edge is formed between the user that published the tweet and the user that replied implying that the influence flows from the publisher to the responder. We refer to the publisher of the tweet as source. Users that presented no interactions are excluded from the social graph. The final graph $G(V, E)$ consists of 25838 users and 23913 edges. The influence of a source $u$ to a user $v$, i.e., the weight of the edge, is calculated as $influence_{u \to v} = \max \{R_e(u): v \in V \}$, where $R_e(u)$ is the total number of replies of user $v$ to user $u$. Intuitively, the influence of $u$ to $v$ is estimated based on the maximum number of interactions of $v$ with any other user $u' \in V$ in the network.

To assess the performance of our approach, we implemented and compared three seed selection techniques.

**Degree:** Under the Degree seed selection technique, nodes are added to the seed set based on their out-Degree, i.e., nodes with the highest number of outgoing edges are selected.

**Greedy Viral Stopper (GVS):** The GVS technique constitutes a modification of the algorithm suggested by Nguyen et al. [2]. Instead of searching the minimum seed set for the decontamination of nodes, seeds are selected until a desired number of seeds is reached. The GVS model iteratively selects seeds. At each step $k$ a node $u$ that results in the greatest number of users protected from seed set $S_k \cup u$ is selected.

**REACT:** REACT (REal-time And CoST-effective misinformation blocking) constitutes the implementation of our approach, that exploits simulated annealing to determine the appropriate set of seeds to decontaminate the network.

Concerning propagation times between users, since these are not provided, we randomly generate a set of 10 time intervals $t_i \in T_{uv}$ between any two user $u$ and $v$, where $u, v \in V$ and $e_{u \to v} \in E$ in the social graph $G(V, E)$ of the network. Every $t_i$ ranges between 0 to 5 minutes, i.e., 0 to 300 seconds. For the experimental evaluation, we assign the initial renouncement thresholds and credibility scores of the users uniformly at random.

### A. Decontamination Performance

We initially estimate the number of nodes decontaminated under varying sizes of misinformation originators. For these experiments we ignore any time constraints by setting $p(t \leq 5 \text{min}; \lambda)$ for all nodes, that results to 1, since all times are generated between 0 and 5 minutes. The misinformation originators are set to 10% and 15% of the nodes with the lower credibility scores. We choose 10 in accordance to [4] and 15% in accordance to [2].

In Figures 2a and 3a we present the number of infected after the propagation process is completed, given seed sets of different sizes, with 10% and 15% misinformation originators respectively. In Figure 2b we present the percentage of nodes sheltered by the selected seeds with 10% misinformation originators and in Figure 3b we present the percentage of nodes sheltered with 15% misinformation originators. We define as sheltered the nodes that are infected during the propagation of misinformation when protectors (i.e. seeds) are absent. Overall, REACT outperforms the Degree approach for seed selection, by managing to decontaminate a larger portion of users in the network. Contrary, the GVS approach seems to perform poorly under all cases, as it only considers the number of nodes informed on the credible information rather the minimization of nodes infected. Same trends are observed when we set the misinformation originators to either 10% or 15%, with a slightly drop at the number of nodes protected when the misinformation originators increase.

### B. Nodes protected under different time requirements

In Figures 4a and 4b we present the percentage of nodes sheltered under different propagation time requirements in the Sandy network with 10% and 15% misinformation originators respectively. We set the propagation time between any two nodes in the network to be either tight, i.e., 2 minutes or relaxed, i.e., 5 minutes. Constraining the time requirements between any two users affects the adoption probability (Equation 2) and the constraint of 2 minutes expresses the emergency of a user informing her neighbors, as opposed to 5. The results are similar for both 10% and 15% misinformation originators and suggest that when time requirements are relaxed, the number of users sheltered increases.

### VI. RELATED WORK

**Competition using Independent Cascading and Linear Thresholds.** In [18], authors exploit a Game-Theoretic approach to estimate the best strategy players should deploy...
in competitive environments, so as to maximize their influence in the network. They propose the Dynamic Influence in Competitive Environments (DICE) propagation model, where each user has the ability to hold multiple ideas with different probability. In [8] the authors study the Influence Blocking Maximization (IBM) problem. They suggest the Competitive Linear Threshold (CLT) propagation model. Each vertex in the social graph is assigned a threshold and each edge is associated with a negative and a positive weight. Users may be positively or negatively activated, depending on which activation is triggered first. In [19] authors study the problem of influence maximization under the Competitive Linear Threshold (CLT) model, but define CLT slightly differently than in [8]. A node is activated by the party that has the highest overall influence and exceeds the threshold of the user. They assume that if a node is activated by a party, it cannot be activated again by another party. Players select seeds interchangeably. Fan et al. in [4] study the rumor blocking problem in OSNs. Their goal is to select the minimal subset of users, referred as Protectors, in order to minimize the propagation achieved by Rumor Originators. Similar to [4], authors in [2] aim at identifying the smallest set of protectors to contain the spread of misinformation to a desired ratio. In [5] authors aim in the limitation of misinformation in OSNs under the Multi-Campaign Independent Cascade model. In [20] authors suggest an approach to limit misinformation while maximizing the spread of good information in the network. Borotin et al. in their work [21] propose extensions of the Linear Threshold propagation model to formulate competitive influence cascades in the network. Time-constraints are ignored in their model and a user that adopts a specific technology may not switch state afterwards. Pathak et al. in [22] suggest a Generalized Linear Threshold Model for multiple cascades in social networks that allows users to switch states regarding the adopted cascade.

VII. CONCLUSIONS

In this paper, we propose an approach for misinformation limitation that is aware of two important dimensions, currently neglected by the related work. The first one is that propagation time differs among the users. The second is that users’ susceptibility to new information should dynamically adapt over time. We further demonstrate the efficiency and effectiveness of our approach. Our research agenda includes a number of challenging problems like taking into account the dynamic nature of the social graph, the handling of multiple competing ideas flooding the network and the identification of non-credible users in real time.

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