On the Aggression Diffusion Modeling and Minimization in Online Social Networks

Marinos Poiitis
mpoiitis@csd.auth.gr
Aristotle University of Thessaloniki
Thessaloniki, Greece

Athena Vakali
avakali@csd.auth.gr
Aristotle University of Thessaloniki
Thessaloniki, Greece

Nicolas Kourtellis
nicolas.kourtellis@telefonica.com
Telefonica I+D
Barcelona, Spain

ABSTRACT
Aggression in online social networks has been studied up to now, mostly with several machine learning methods which detect such behavior in a static context. However, the way aggression propagates in the network has received little attention as it embeds modeling challenges. In fact, modeling how aggression propagates from one user to another, is an important research topic since it can enable effective aggression monitoring, especially in media platforms which up to now apply simplistic user blocking techniques.

In this paper, we focus on how to model aggression propagation on Twitter, since it is a popular microblogging platform at which aggression had several onsets. We propose various methods building on two well-known diffusion models, Independent Cascade (IC) and Linear Threshold (LT), to study the aggression evolution in the social network. We experimentally investigate how well each method can model aggression propagation using real Twitter data, while varying parameters, such as users selection for model seeding, weigh users' edges, users' activation timing, etc. Based on the proposed approach, the best performing strategies are the ones to select seed users with a degree-based approach, weigh user edges based on overlaps of their social circles, and activate users while considering their aggression levels. We further employ the best performing models to predict which ordinary real users could become aggressive (and vice versa) in the future, and achieve up to \( AUC=0.89 \) in this prediction task. Finally, we investigate methods for minimizing aggression, by launching competitive cascades to "inform" and "heal" aggressors. We show that IC and LT models can be used in aggression minimization, thus providing less intrusive alternatives to the blocking techniques currently employed by popular online social network platforms.

CCS CONCEPTS
- Information systems → Social networks; World Wide Web;
- Computing methodologies → Network science; Modeling and simulation.

KEYWORDS
social networks, information diffusion, aggression modeling, aggression minimization, cascades, immunization

1 INTRODUCTION
Online social media offer unprecedented communication opportunities, but also come with unfortunate malicious behaviors. Cyberbullying, racism, hate speech and discrimination are some of the online aggressive, abusive or inappropriate behaviors manifesting in such platforms, and often have devastating consequences for individual users, and the society as a whole. Aggression can be explicit or implicit in the way it is expressed, through posting of negative views and feelings (e.g., anger, distrust or sadness), inappropriate content (e.g., posting of embarrassing photos or videos), or unconsciously (e.g., through negative gossip spreading) hurting online users. This phenomenon is critical and vital since it challenges online trust in many ways. Online permanence, Hidden influence and Omnipresence are among the core traits of aggression, which are difficult to recognize, or even observe [24]. Overall, online social media users are often left exposed and vulnerable to potential aggression threats.

Inter-disciplinary studies have focused on cyberaggression and cyberbullying from the perspective of social psychology, social and computational sciences. They have proposed several theoretical formulations [1, 24] based on well-studied theories of social learning and bonding, as well as the theory of planned behavior [17]. Furthermore, several applied machine learning models have been proposed to detect such behavior, and help its mitigation in online platforms (e.g. [5, 9, 12, 32]). Even with all this body of earlier work, online aggression has not been uniformly defined, as remarked in [8]. Hence, online aggression is formulated under varying approaches, depending on the severity of the aggressive behavior, the type of platform and social interactions it facilitates, the power of the aggressor over the victim, etc. In the majority of the aforementioned works, machine learning approaches are used, emphasizing on the selection of particular user content and context features to detect the behavior under study.

Interestingly, aggression in real life has been found to spread in social circles, from one user to another due to aggressive peer influence, and even in a cascading fashion, possibly affecting multiple users at the same time (e.g., minors in a family with aggressive parenthood). Therefore, the aggression’s overall effect can be stronger
as it propagates through the network [14]. Surprisingly, and despite its severity in the online world, aggression propagation in the cyber space has gathered little attention, primarily due to the complexity of the problem. This is evident from the lack of automated processes in the popular media platforms to mitigate or completely eliminate aggression’s negative effects, by only going as far as blocking or reporting abusive users and removing inappropriate content [2].

The present work focuses on the online aggression propagation problem and studies the complexities of capturing and modeling aggression propagation. It considers the well known diffusion models of Independent Cascading (IC) and Linear Threshold (LT) as a basis for capturing the aggression evolution as it spreads in a social network [16]. We select these models as they provide the building blocks for studying the diffusion process at its two fundamental types of interactions: user-user (IC) and user-neighborhood (LT).

To this end, we define appropriate parameters for formulation of aggression-aware information diffusion models, and enabling a thorough study of the aggression dynamics, and how they are affected when controlling several user and network properties. Moreover, we show how IC and LT models can be used in aggression minimization, providing less intrusive alternatives to the techniques currently in use by various social media platforms.

In summary, the main contributions of this work are:

1. **C1: aggression cascading diffusion theoretical foundation**, by exploring IC and LT as the basic propagation models. Upon them, the theoretical notions of user-user interaction, initial user selection strategies and user propagation are introduced and adjusted accordingly. The same models are also adjusted as aggression minimization methods, and various healing approaches are formulated (Section 3).

2. **C2: aggression modeling and minimization experimentation on real data**, by identifying the best parameter configurations for both IC and LT through cosine similarity performance tests and statistical validation for modeling, as well as aggression reduction for minimization. Real data experimentation, extensive simulations, a modeling case study as well as comparison to the blocking minimization methods currently in use by social platforms support our findings (Section 4).

3. **C3: neighborhood importance and central user detection** are found as the most effective strategies which extend both IC and LT principles. Specifically, neighborhood similarity is shown to be the most appropriate criterion according to which user relationships are formed. Additionally, the initiation of the diffusion process by users who are located at the network’s core is shown to lead to the most effective aggression propagation model. Finally, IC and LT modeling could be effective aggression minimization techniques, achieving a reduction of ~50% for IC and ~15% for LT in comparison to the user banning methods currently in place by social platforms (Section 4).

4. **C4: Simulation framework release** for reproducibility purposes and further experimentation or extensions\(^1\).

The rest of this paper is organized as follows. In Section 2 the related works are reviewed. Section 3 provides the theoretical foundation of both aggression modeling and minimization. The experimental evaluation is presented in Section 4 and Section 5 provides a discussion of this work’s results and further improvements.

## 2 RELATED WORK

Information diffusion has been originally studied by probabilistic models [10, 23], which were advanced by considering a discrete optimization problem formulation driven by the well-known Independent Cascade (IC) and Linear Threshold (LT) diffusion models [16]. In these two models, the process unfolds in discrete time steps, where each user is affected by a specific neighbor only once, and each user can affect a set of users; hence the information spreads in a cascading manner. Thus, these methods capture not only the neighborhood influence, but also the cumulative influence of a user’s social circle where online aggression phenomena can occur [14].

**Opinion Dynamics (OD)** is another family of information diffusion models which studies the effects and conditions of information propagation over the network. Under OD, the well studied Voter model proposes that a user gets influenced by one of its neighbors through a random "voting" process [11]. However, in contrast to IC and LT, in Voter model a specific user can be activated multiple times. Hence, specific conditions should be satisfied to ensure opinion convergence or process termination. Another set of models are the well known Susceptible, Infected, Recovered (SIR) models from the field of epidemics. They are a generalization of IC, categorizing users into the above three states and studying the transitions from one state to another, under specific thresholds [30]. Both OD and SIR are useful in understanding the dynamics of diffusion process and determining proper aggression propagation models.

### 2.1 Influence Maximization

The above methods model information diffusion in a controlled environment with no specific limitations. However, in many real world scenarios there is scarcity in available resources, such as limited number of nodes that can be initially activated. Thus, another research topic emerged, called influence maximization. Its main goal is to maximize the expected influence in the network by discovering the most influential users [3] and hence mitigating the effect of the limitations. Under this context, the scarcity in resources is translated into a fixed number of seed nodes that the propagation process could be initiated from, to achieve maximum influence [27].

The main focus of influence maximization is the optimization of the seed selection process itself by minimizing the selection cost [6, 20], or even sustaining the spread of the cascade above a specified threshold [20]. In this context, it has been shown that a greedy algorithm outperforms methods based on network and node properties [16]. However, the simple greedy version is infeasible due to the high complexity that the inherent Monte Carlo simulations introduce when applied on large network. Therefore, many optimization methods have been proposed.

A significant improvement of the greedy algorithm is Cost-Effective Lazy Forward selection (CELF) that leverages the mathematical set property called submodularity - proposing that the difference an item makes when included in a set decreases as the

\(^1\)https://anonymous.4open.science/r/c11fd39b-f5cd-48eb-99e8-0b2384cdbe69/
size of the set increases - achieving an 700% improvement in execution time over the simple version [18]. Moreover, Single Discount (SD) and Degree Discount (DD) heuristics outperform CELF in terms of execution time by more than six orders of magnitude while maintaining a high influence spread, constituting them appropriate for big data analysis where time constraints are crucial [7]. In particular, SD finds the most central nodes based on an iterative selection and removal process, while DD is fine-tuned towards IC model and exploits its user activation probability.

The most significant efforts for influence maximization have exploited both types of cascading models - IC and LT - and thus these methods form a state-of-art baseline. However, beyond the basic IC and LT generic seed strategies, there are also methods inspired by natural phenomena. For example, Simulated Annealing is an approach that optimizes the spread function of the diffusion process both in terms of time and magnitude through a local search algorithm [15]. Likewise, information diffusion has been addressed through heat diffusion - a mechanism from the field of Ferromagnetism - emulating heat dissemination from higher to lower temperature objects [21]. The natural approaches have introduced the decaying effect of time on a user's influence and they have largely inspired the Decaying Aggression Transfer healing mechanism proposed in our work.

2.2 Competitive Cascades

In both information diffusion and influence maximization, the presence of a parallel, sometimes negative cascade has been mentioned. Under this scenario, each cascade selects a seed set to initiate its propagation. The two cascades evolve simultaneously and depending on the assumed hypotheses, they either compete to be the first to activate a node or affect a node regardless of the competitor and measure the impact at the end of both processes. These are known as Competitive Cascades and help us formulate the first part of our proposed aggression minimization process.

2.2.1 Competitive Influence Maximization. Considerable efforts in competitive cascades have proposed models which set the objective to find a positive seed set that minimizes the spread of a negative cascade [13, 33]. This problem is called Influence Blocking Maximization (IBM) and has been addressed with both IC and LT. However, in order to properly select the positive seed nodes, these methods retrace to the discussed greedy algorithm of influence maximization. To overcome the computational limitations, they either propose tailor-made problem variations of IBM [33], or improve the greedy version through model specific structures, such as the Local Directed Acyclic Graph, applicable only on LT [13].

Furthermore, misinformation containment on LT - different term to refer to IBM problem - has been addressed by introducing preference - a metric defined by the user thresholds and the in-neighbors' edge weights - to help a user decide which cascade to accept when both competitive cascades satisfy the threshold requirements [34]. Moreover, to find the most prevalent cascade in an IC simultaneous influence approach, the notion of authorities - users with high validity - has been proposed [4]. Specifically, it has been shown that the positive cascade is the dominant one as valid information spreads through authorities, while misinformation by less influential users. However, the negative cascade’s spread starts from a single node rather than a set of nodes. To overcome this obstacle, an optimized greedy algorithm has been proposed, but still lacks approximation guarantees of the optimal solution [33].

2.3 Immunization

Social media nowadays tend to address abusive behavior restriction by blocking abusive users or posts. This preference is grounded on either the simpler nature of those algorithms, or due to their more straightforward application. Hence, apart from the competitive cascades, the latest immunization or blocking algorithms are also reviewed in this work and compared to discover the most efficient approach in terms of aggression reduction.

State-of-the-art methods in the domain of immunization favor algorithms based on linear algebra manipulation to exploit the users who are responsible for the largest information spread in the network. Specifically, for a large family of diffusion processes, it has been shown that the only network parameter that determines whether this diffusion would become an epidemic or not is the largest eigenvalue \( \lambda \) of the adjacency matrix \( A \) [22]. By leveraging this observation, many methods have progressed such as the NetShield algorithm which introduces a ranking score called Shield score to detect the most important abusive users [29]. Furthermore, NetMelt transfers the problem to edge deletion, as node deletion is more radical and intrusive [28]. However, such methods operate offline, i.e., they capture the network state before the propagation process starts, in contrast to competitive cascades that we propose.

2.4 Aggression Modeling and Minimization

Aggression modeling and minimization has been studied mostly via machine learning approaches. Specifically, Twitter account features have been used to detect and categorize phenomena such as hate speech [32], while iterative and incremental crowdsourcing techniques have been proposed to annotate abusive tweets [12]. Apart from user content and context, graph features such as peer pressure and cumulative influence have also been highlighted [25]. Furthermore, a multi-class classifier has been used to study the classification among various types of abusive behavior such as racism and homophobia [9], while Random Forests have been exploited to detect other disturbing phenomena such as cyberbullying [5]. These efforts address online aggression using user content and context features without correlating them to the aggression diffusion process, thus neglecting its dynamics and effect on user behavior.

According to the authors knowledge, there is only a single approach which has examined the effect of online aggression diffusion and it exploits OD models [26]. However, in social networks aggression spreads through a user post based on this user’s social circle. Hence, cascade models are more suitable than OD for aggression modeling, as they simulate a mass information dissemination process rather than user-user interactions. Apart from aggression modeling through cascades, to the best of our knowledge, we are the first to address online aggression minimization. In particular, two different minimization methods are explored here using: (a) competitive cascades, (b) node/edge blocking. The second method - which is what social media such as Twitter use nowadays [2] - is compared to the proposed competitive cascades with respect to aggression reduction efficiency.
3 METHODOLOGY

In this section, we provide the theoretical foundations for user interactions, seed selection, aggression propagation and healing mechanisms, and connect them to the diffusion and minimization problems, as per Contribution 1.

3.1 Aggression Modeling

A social network is represented by a directed graph \( G = (V, E) \), where \( V \) is a set of \( n \) nodes or users, and \( E \) is a set of \( m \) edges, i.e., relationships between users. Each node is associated with an aggression score denoted by \( A_i \), \( \forall i \in V \). The aim is to find whether the IC and LT are able to model aggression diffusion and what are the important parameters that enable them to do so.

3.1.1 Seed Selection. Under aggression diffusion modeling, the seed selection process is the first crucial component to describe. Seed nodes are the ones the diffusion process starts. The ultimate result of the propagation model is tightly related to these initial seed nodes. The necessity for selecting seed nodes is due to the diffusion model being restricted by a given budget \( k \), meaning that we can only afford a specific amount of initial stimulation of \( k \) seed nodes. As a result, a sophisticated seed selection strategy could enable the diffusion process and lead to the increase of the number of activated nodes. The proposed strategies are presented below:

- **All Aggressive**: Set all aggressive users as seed nodes.
- **Top Aggressive**: Set top \( k \) aggressive users as seed nodes, where \( k \) is given by the user. If \( k > |\text{aggressive users}| \), use All Aggressive strategy.
- **Single Discount (SD)**: Use algorithm presented in [7]. Iteratively, place the user with the highest degree in seed nodes set, remove said node and proceed.
- **Degree Discount (DD)**: Also presented in [7]. It works like SD but it is fine grained towards IC model, taking advantage of the prior activation probability.
- **Random**: Choose users as seeds randomly.

3.1.2 Weighting Scheme. Next step is to define the various weighting schemes we apply on the network edges. Each scheme captures real world properties that can impact the aggression diffusion in a different way, as they can affect the probability of propagating aggression. In the following, we assume that the user is embedded in directional edges:

- **Jaccard overlap (Jaccard)**: In social media, the friends and followers of a user can heavily influence the user’s own beliefs. If two connected users appear to have similar or even identical social circles, this could point to very similar beliefs or behaviors. Therefore, given two connected nodes \( u \) and \( v \), and their corresponding sets of neighbors \( N_u \) and \( N_v \), the Jaccard overlap of their edge is defined as weight \( w_{uv} = \frac{|N_u \cap N_v|}{|N_u| + |N_v|} \in [0,1] \).
- **Power score (Power)**: Given a node \( u \), the Power score \( P_u \) is defined as the ratio of the in-degree (incoming edges) over out-degree (outgoing edges), \( P_u = \frac{\text{inDegree}_u}{\text{outDegree}_u} \in [0,1] \). The higher the Power score of a node, the more dominant the influence the node receives from its in-neighbors in comparison to the degree that it influences its out-neighbors.

However, for this measure to be applied as an edge weight, it has to be considered in a pairwise fashion. Therefore, given an edge from node \( u \) to \( v \), we define \( P_{uv} = \frac{P_u}{P_v} \in [0,1] \) to capture \( v \)'s in-neighbor and \( u \)'s out-neighbor influence.

- **Weighted overlap (Weighted)**: Given two nodes \( u \) and \( v \), their Jaccard overlap \( w_{uv} \) and their Power score \( P_{uv} \), the Weighted overlap is defined as \( P_{uv} = P_u * w_{uv} \in [0,1] \). This metric combines the previous two weights.

Next, and using the above notations and metrics, we describe the IC and LT diffusion models, given a constant seed budget \( k \).

3.1.3 Independent Cascade (IC). At time step \( t = 0 \) the process starts with an initial seed set \( S \) of active nodes with \( |S| \leq k \) and proceeds in discrete time steps according to the following stochastic rule. At each time step \( t \), a set of active nodes \( Active^t \) are present in the network. Each active node \( u \in Active^t \), that was activated in time step \( t \), has a single chance to activate each of its inactive neighbors, \( v \), with probability \( p \). This probability is defined with respect to the very same notions that were introduced in weighting schemes above. That is, node \( v \) is activated by node \( u \) with: \( p \leq w_{uv} \), \( p \leq P_{uv} \) or \( p \leq P_{uv} \\ w_{uv} \) when the activation criterion is Jaccard, Power or Weighted, respectively.

Under the aggressive IC model, activation means that \( u \) transfers its aggression score to user \( v \), that is \( A_u = A_{uv} \). However, there is a case where multiple nodes \( u \in N_v \), try to activate the same node \( v \) simultaneously, and succeed. Then, the decision of whose aggression score will be transferred follows one of the following strategies:

- **Random**: The activation order is arbitrary and the aggression score of a randomly selected node \( u \in N_v \), from the successful ones (i.e., \( N_v \cap Active^t \)), is transferred to the node being activated \( v \).
- **Top**: The most aggressive node among the successful ones transfers its aggression score to \( v \).
- **Cumulative**: The cumulative aggression score of all nodes is transferred according to their contribution, a metric capturing peer pressure, also verified in [25]. For example, if \( S = \{u_1, u_2, u_3\} \) the set of nodes that succeeded, then \( A_v = \sum_{i \in S} w_i * A_i \) with \( w_i = \frac{A_i}{\sum_{j \in S} A_j} \) and \( A_i \) their respective aggression scores.

If node \( u \) succeeds, then node \( v \) gets activated in step \( t + 1 \); but regardless of \( u \)'s success, it cannot make any further attempts to activate \( v \) in a following step. The IC process terminates when no more activations are possible.

3.1.4 Linear Threshold (LT). In the LT model, each node \( v \) is assigned a threshold \( \theta_v \). The process starts with an initially activated seed set \( S \) with \( |S| \leq k \), similarly to the IC process. In step \( t \), node \( v \) is influenced by each neighbor \( u \in N_v \), according to a weight which should respect the node threshold selection. Specifically, the alternative activation criteria at time step \( t \) are:

- **Aggression**: When aggression scores are used as node thresholds, that is: \( \theta_v = A_v \forall v \in V \), then \( \theta_v \leq \sum_{u \in N_v \cap Active^t} A_u \).
- **Power**: When power scores are used as node thresholds, that is \( \theta_v = P_v \forall v \in V \), then \( \theta_v \leq \sum_{u \in N_v \cap Active^t} P_u \).
Finally, under the aggressive \(LT\) model, in contrast to the \(IC\) case, activation has a single interpretation which is that the neighbors of node \(v\) transfer their average aggression score to \(v\):
\[
A_v = \frac{\sum_{w \in N_v} A_w}{|N_v|} \in [0, 1].
\]
In this context, the process unfolds until there are no nodes left to become active according to the thresholds.

### 3.2 Aggression Minimization

Given the two models (\(IC\) and \(LT\)), we address the problem of aggression minimization by means of two different approaches, called *competitive* and *blocking* aggression minimization, respectively.

#### 3.2.1 Competitive Aggression Minimization (CAM)

Under this minimization method, there are two competing diffusion processes, a negative - also called aggressive - and a positive or educational cascade. The goal of the later is to minimize the spread of the negative one. For the negative cascade and hence the aggression diffusion, we use the best model discovered in aggression modeling (as explained earlier), while for the positive or educational process, we use the corresponding cascading model, and test the alternative configurations.

**Problem 1 (CAM).** Given a directed network \(G = (V, E)\), with \(V\) and \(E\) denoting the node and edge sets, respectively, an integer budget \(k\) and two competing diffusion processes, the aggressive and educational, with the later having a set of parameters \(\theta(\cdot)\), the CAM problem is to find a positive seed set \(S\) with \(|S| \leq k\) and \(\theta(\cdot)\), s.t. \(\theta(\cdot) = \arg\min_{A(G)} v.\text{r.} S\), where \(A(G) = \sum_{v \in V} A_v\) is the overall aggression score in the network.

We now define the rules that describe the educational cascade. Under \(IC\), the activation probabilities follow the same notions of the negative cascade with respect to weighting schemes: Jaccard overlap, Power score or Weighted overlap. However, under \(LT\), the activation criterion as well as node thresholds should depend on Power only. Aggression would be an inappropriate threshold as the educational cascade intents to mitigate the effect of aggression on the network, instead of maximizing the overall aggression score.

Using a predefined negative seed set, and according to the best strategy of aggression modeling scenario, we allow the two processes unfold simultaneously. If at time step \(t\), both cascades reach the same node \(v\), then \(v\) gets positively activated, simulating the fact that most probably an educated or aware user would stop manifesting aggressive behavior.

Proceeding to the meaning of activation from the perspective of the positive cascade - the healing effect - , we discern four possible cases:

- **Vaccination**: activating user \(v\) results to \(A'_v \rightarrow 0\), i.e., the user becomes normal immediately. This hypothesis is strict.
- **Aggression transfer**: activating user \(v\) results to:
  - \(IC\): \(A'_u \rightarrow A_u\), with user \(u\) activating \(v\)
  - \(LT\): \(A'_u \rightarrow \frac{\sum_{w \in N_u} A_w}{|N_u|}\)
- **Decaying aggression transfer**: activating user \(v\) is affected by a decaying factor \(\lambda\) capturing the distance from the source of the information. Hence, \(\lambda = \frac{1}{\text{ hops}}\) and:
  - \(IC\): \(A'_u \rightarrow \lambda \ast A_u\), with user \(u\) activating \(v\)
  - \(LT\): \(A'_u \rightarrow \frac{\sum_{w \in N_u} \lambda \ast A_w}{|N_u|}\)

**Hybrid**: using a combination of cases 1 and 3:
\[
A'_v = \begin{cases} 
\text{Vaccination} & \text{if } p \geq A_v \\
\text{Decaying aggression transfer} & \text{otherwise}
\end{cases}
\]

It is clarified here that the seed nodes of the positive cascade are considered as the most sensitized as the educational piece of information initiates its propagation from them. Hence, the healing effect on them is drastic and depends on their respective aggression scores. More formally, the new aggression score of the positive seed nodes follows the below rule:
\[
A'_s = \begin{cases} 
0 & \text{if } p \geq A_s \\
A_s & \text{otherwise}
\end{cases}
\]

Finally, with respect to the seed strategy of the positive cascade, two alternatives are considered. On one hand, the seed strategy of the negative cascade can be used, but this scenario favors the negative cascade as the decision would be based on its own specifics. On the other hand, one of the other strategies proposed in aggression modeling section can be exploited, regardless of the seed strategy of the negative cascade.

#### 3.2.2 Blocking Aggression Minimization (BAM)

In contrast to CAM, in Blocking Aggression Minimization (BAM) there is only a single cascade, the aggressive one. The aim here is to target specific nodes or edges to immunize. That means removing them to optimally suppress aggression diffusion over the network. In the case of social networks, node removal is equal to banning a user which is a drastic measure. This is why we consider the case of edge removal also. Formally the problem is defined below:

**Problem 2 (BAM-N).** (node version)

*Given a directed network \(G = (V, E)\), with \(V\) and \(E\) denoting the node and edge sets, respectively, and an integer budget \(k\), the problem is to find a subset of nodes \(S \subseteq V\) with \(|S| = k\), s.t. \(S = \arg\min_{S \subseteq V} A(G)\), where \(A(G) = \sum_{v \in V} A_v\) is the overall aggression score in the network, and \(P(V)\) is the Power Set of \(V\).*

**Problem 3 (BAM-E).** (edge version)

*Given a directed network \(G = (V, E)\), with \(V\) and \(E\) denoting the node and edge sets, respectively, and an integer budget \(k\), the problem is to find a subset of edges \(S \subseteq E\) with \(|S| = k\), s.t. \(S = \arg\min_{S \subseteq V} A(G)\), where \(A(G) = \sum_{v \in V} A_v\) is the overall aggression score in the network, and \(P(E)\) is the Power Set of \(E\).*

Based on the major finding of [31] and [22], for a large family of diffusion processes, the only network parameter that determines whether this diffusion would become an epidemic or not is the largest eigenvalue \(\lambda\) of the adjacency matrix \(A\). For this reason, in our experiments next, we use NetShield [29] to solve the BAM-N problem, and NetMelt [28] for BAM-E problem. Motivated by the results of these two studies, coupled with the competitive minimization explained earlier, we also implement an aggression-related variation. In particular, instead of using the initial edge weights, we exploit the product of the aggression scores of source and destination nodes. That, is for pair \((u, v)\) in the adjacency matrix, the cell value now becomes \(A_{uv} \ast A_{vu}\). However, it should be noted that BAM is a problem that exploits offline methods, in contrast to CAM which adjusts to the dynamics of the aggression diffusion.
4 EXPERIMENTAL RESULTS

In this section, and as per our Contribution 2, we present the results of the experimental process, first with respect to aggression modeling using IC and LT methods (Sec. 4.2 and 4.3), and then aggression minimization using competing cascades or blocking (Sec. 4.4).

4.1 Experimental Setup

Dataset: In this work, we focus on the Twitter social network. The dataset used is an unlabeled Twitter network comprised of 81,306 users and 1,788,149 directed edges between them [19]. To reduce noise in the converging process, we use the strongly connected component of this network, which consists of 68,413 nodes and 1,685,163 directed edges. The edge weights are decided according to the proposed weighting schemes described in Section 3. The Twitter network used here is unlabeled, i.e., there is no indication which users are normal or aggressive. Such labels are needed to bootstrap our propagation algorithms. To that end, and using similar methodology as in [26], we apply the prediction algorithm proposed in [5], which provides a probability for a user to be aggressive or not, based on their characteristics in the network and their activity. We tune this algorithm to use only network-related features that are available in our dataset, and apply it to compute the initial user aggression scores of all users, which is equal to the probability of a user being aggressive. With this classifier, 5,594 users (or ~8% of the network) were given a non-zero aggression score.

Metrics used to measure aggression change:

Following similar methodology with past work [26], we measure the state of aggression of users, and how it changes through simulated time using a vector of 26 metrics. The 6 core metrics enlisted below capture the network state with respect to users and edges and their label at time $t_i$:

- $n$: portion of normal users in the network
- $a$: portion of aggressive users in the network
- $N-N$: portion of edges that both users $i$ and $j$ are normal
- $N-A$: portion of edges that user $i$ is normal & $j$ aggressive
- $A-N$: portion of edges that user $i$ is aggressive & $j$ normal
- $A-A$: portion of edges that $i$ and $j$ are aggressive users

By combining these core metrics, Table 1 presents 20 additional metrics capturing the transitions through simulated time between $t_i$ and initial state $t_0$.

| $t_0$     | $t_i$     |
|-----------|-----------|
| $n$       | $|n \parallel a|_i$  |
| $a$       | $|n \parallel a|_i$  |
| $N-N$     | $|N-N \parallel N-A \parallel A-N \parallel A-A|_i$  |
| $N-A$     | $|N-N \parallel N-A \parallel A-N \parallel A-A|_i$  |
| $A-N$     | $|N-N \parallel N-A \parallel A-N \parallel A-A|_i$  |
| $A-A$     | $|N-N \parallel N-A \parallel A-N \parallel A-A|_i$  |

Measuring metrics in ground truth: We were provided with the ground truth scores for the above metrics from [26], for both state of individual users and their edges, as well as change of state. This ground truth vector was computed on a smaller labelled Twitter network of 401 users, published by [5] and re-crawled in 2019 (i.e., two snapshots of state in 2016 and 2019, and provided by [26]). Comparing simulation and ground truth data: The above set of metrics is computed for all simulated models and all their time steps, and compared with the ground truth vector using Cosine Similarity, i.e., $\text{Cosine}(\text{ground truth vector, simulation vector})$. In fact, we tried other similarity metrics, such as Pearson and Spearman correlations, but Cosine Similarity produced the more stable results. This comparison establishes how closely a model’s changes to the state of aggression of the network (in both nodes and edges) match the ground truth data through the simulated time steps.

The careful reader will notice that the state of users is binary (normal and aggressive). Therefore, and in order to successfully compute the cosine of the two vectors at each simulated step, we need to dichotomize the users’ state. For this, we experimented with different thresholds ($T_A$) on the users’ aggression scores ($T_A = \{0.1, 0.2, ..., 0.9\}$) and then computed cosine similarity for each newly-dichotomized simulation vector. We concluded that results with $T_A = 0.4$ exhibit best overall similarity with ground truth data. Thus, all results presented next are focus on $T_A = 0.4$.

Statistical Tests: For the IC modeling, we run every experiment 10 times due to the inherent randomized nature of the activation process. Additionally, when Random is used as the seed strategy, each experiment is executed 10 more times, leading to a total of 100 executions. To present these results, we use Cumulative Distribution Functions (CDF). To validate whether there is significant difference in parameter values, we employ One-Way ANOVA, followed by a pairwise post-hoc Tukey’s HSD test, to spot the exact value of the significant parameter. We identify statistically significant differences at p-value < 0.001 for both tests. For the LT modeling, there is no probabilistic step to be taken, and thus, we run each experiment only once, except for the case of Random seed strategy, for which we execute each setup 10 times and acquire average performance. These results are presented in a table were appropriate.

Simulation Framework: We designed and implemented a modular and extensible simulation framework to execute the modeling and minimization experiments. It is written in Python, it is open sourced, and allows fine-grained control of simulation parameters, to enable reproducible experiments, and future extensions.

4.2 Aggression Modeling

In the next paragraphs, we present and analyze the results for selecting 1) Seed set strategy, 2) Weighting scheme, and 3) Activation criterion (for IC) and Threshold strategy (for LT).

4.2.1 Seed Selection Strategy. For the rest of the experimental process, we distinguish the results of IC and LT-based models due to the different presentation processes. We set the seed size (budget $k$) to 5594, to match the number of users with non-zero aggression score. Regarding seed strategy, Top Aggressive is unnecessary as the selected seed size allows the use of all aggressive users.

Figure 1 presents the results regarding IC-based models. For brevity, the exhaustive list of experiments is not presented, as similar patterns were observed. From these results, we note a small, yet statistically significant dominance of the network-feature strategies, Single Discount (SD) and Degree Discount (DD). Specifically, Tukey’s HSD test found that degree-based strategies (SD and DD)
are significantly better than others. Additionally, for Power- and Weighted-based graphs, SD and DD do not have significant differences, while in Jaccard, SD is prevalent. Hence, for the IC models, SD seems the appropriate seed strategy due to its reduced computation cost compared to DD.

Turning to LT-based configurations (Table 2), we note that DD, although applicable, is not compatible with the theoretical background of LT model. If we focus on the configurations of Jaccard, we see that similar to the case of IC, the most dominant strategy is SD. Also, Power and Weighted results do not show significant difference between the various seed strategies. Thus overall, SD is the most prevalent seed strategy for LT-based models too.

Table 2: Cosine similarity for LT models, with different weighting schemes (WS), seed strategies (SS) and threshold strategies (TS). * = all parameter values

| WS    | SS    | TS     | Cosine |
|-------|-------|--------|--------|
| Jaccard | Random | * | 0.690  |
| Jaccard | All Aggressive | * | 0.688  |
| Jaccard | SD     | A | 0.691  |
|       |       | P | 0.690  |
| Power  |       | * | 0.689  |
| Weighted |       | * | 0.689  |

4.2.2 Weighting Scheme. Given the selected seed strategy SD, we now analyze the results on different weighting schemes. Figure 2 shows that Jaccard is the best weighting scheme, regardless of the activation criterion, also confirmed statistically with ANOVA and Tukey tests.

Moving to the LT-based configurations, Table 2 again presents that the best performance is achieved when using Jaccard. Additionally, Weighted and Power as weighting schemes do not present any practical differences - deviations are observed on the sixth decimal point - constituting them inappropriate weighting schemes. Thus, we conclude with Jaccard as the weighting scheme for LT as well.

4.2.3 Activation Criterion and Threshold Strategy. Up to now, we investigated the various possible configurations from a macroscopic point of view, to conclude to SD as the best seed selection strategy and Jaccard as the best weighting scheme. Next, we look into activation criteria and threshold strategies to select best possible setups. Specifically, Figure 3 shows that Cumulative activation strategy is the best, while there is no clear distinction between Top and Random strategies, validated by ANOVA too. Also, Tukey’s HSD test highlights the superiority of Cumulative over Top and Random, whose results overlap. This prevalence is explained by the crucial effect that a user’s neighborhood has on them, as it is also pointed out by the General Aggression Model [1].

Proceeding to LT models, we also focus on the experiments regarding Jaccard with SD. Table 2 shows that Aggression-based thresholds perform slightly better and, hence, they should be used to model aggression propagation. This observation is intuitive, as it suggests that the higher the aggressiveness of a user, the easier to propagate it - a feature that enables the overall aggression diffusion process over LT.

4.2.4 Snapshot Evolution. In the previous experimental cases, the diffusion process was let to unfold until completion (i.e., after all possible time steps), and then the similarity with ground truth
we studied this trend with two more similarity metrics (Pearson and Spearman) with ground truth at each time step. In both cases, the IC was calculated. However, there could be an intermediate time step (snapshot) in the propagation that can better match the ground truth change of state. To investigate if this is the case, we created snapshots of the diffusion process at the end of every time step and track the corresponding results.

Figure 4 shows for the two modeling methods, the similarity with ground truth at each time step. In both IC and LT, the performance decreases rapidly within the first steps and gradually stabilizes in the last ones. This trend shows that aggression probably does not propagate that deeply into the network (remember that steps here mean graph hops), and that our models better match the ground truth in the first or second time steps of the diffusion process. Interestingly, the stable behavior for the last steps validates the integrity of the convergence value studied earlier. When we studied this trend with two more similarity metrics (Pearson and Spearman correlations), we found that Pearson behaves like Cosine, but Spearman presents an early increase with a steady drop afterwards. However, we decided to focus our analysis on Cosine, since the normality requirement for Pearson is not satisfied, and Cosine is more sensitive to subtle changes than Spearman.

**Takeaways:** Combining the above experimental observations, it is concluded that aggression diffusion over social networks can be modeled with a cascading model, such as IC or LT, fulfilling the first part of Contributions 2 and 3. For both models, the best seed strategy is SD, meaning that the most accurate models of aggression diffusion should initiate their process from the most central points in the network. Moreover, for both cases, the best performing weighting scheme is Jaccard which expresses that relations are formed based on users’ neighborhood similarity. Furthermore, specific to IC-based models, activation criterion should be set to Cumulative, enabling the whole neighborhood of a node to affect its aggression state, while for LT-based models, an Aggression-based threshold strategy is the best, as it enables the overall dissemination process. Lastly, the diffusion process should unfold until convergence to achieve a stable state.

### 4.3 Case Study: modeling aggression diffusion

To evaluate the best IC and LT models (as concluded earlier), we apply them to the small labeled Twitter network of the prediction algorithm [5]. There are labels for two network snapshots (for 2016 and 2019), while users are labeled as normal or aggressive in both. Using the user labels of the first snapshot, we run the IC and LT models and measure the AUC of the predicted labels, vs. the ones of the 2nd snapshot. The AUC achieved by IC (with SD, Jaccard, and Cumulative) is 0.82, while for LT (with SD, Jaccard and Aggression) is 0.89. Thus, both configurations perform well in modeling aggression diffusion, and LT seems to provide slightly better performance, with fewer false positives (aggressors).

### 4.4 Aggression Minimization

The second part of the experimental process pertains to aggression minimization (CAM and BAM problems). To address the CAM problem, a competitive cascade process is exploited aiming at decreasing the final aggression score of the network, while for BAM, the proposed node and edge blocking mechanisms select the nodes to remove before the launch of the aggressive cascade.

#### 4.4.1 Competitive Aggression Minimization

With respect to CAM, the positive cascade should be similar to the negative one, i.e., for both IC and LT models, and both positive and negative cascades the chosen weighting scheme is Jaccard. For the IC, the activation strategy is Cumulative, and for LT the threshold strategy is Aggression. Thus, the two cascades compete in equal terms and the rest of parameters are investigated. The experimentation comprises of the different seed strategies for the positive cascade, as well as the various healing mechanisms: Vaccination, Transfer, Decaying transfer, and Hybrid.

Here, we focus on the best configurations of the modeling phase mentioned earlier. Figure 5 presents aggression evolution during the competitive cascade process, for various seed and healing strategies on the IC models. Y-axis presents the ratio of loss or gain with respect to the case where no healing is applied. First, regarding the seed strategy of the positive cascade, it is shown that, Random presents the best results for every healing mechanism reaching 57.8% aggression reduction, while DD follows with 57.3%. Seed strategies SD and All Aggressive follow with 55.3% and 53.5%, respectively. Thus, Random is the best option when computational cost is important, while DD could be chosen if stability is necessary.

With respect to the healing strategies, regardless of the positive seed strategy, the Transfer healing presents the worst performance with a best-case reduction of 8%. This behavior is due to the simple aggression score transferring, regardless of the result on the corresponding node. The rest of the healing mechanisms perform similarly, no matter the seed strategy. In particular, Vaccination is the most dominant mechanism, achieving 57.3% aggression reduction, while Decaying transfer and Hybrid follow with ~57%. These results are intuitive, since Vaccination makes the strong assumption that nodes get completely healed, whereas Decaying transfer is a more relaxed and realistic version of Vaccination, and Hybrid lies in between them.

Another critical factor of a healing strategy’s efficiency is the number of nodes that get activated by the negative cascade. This is important since the same aggression reduction on a larger number of activated nodes expresses a more efficient mechanism. In particular, all healing mechanisms, except Transfer, activate about the same number of nodes (plots omitted for brevity). Combining the results on aggression reduction with number of activated nodes, we conclude that Vaccination is the best healing mechanism, but due to its mostly theoretical nature, Decaying transfer could be assumed to minimize aggression in IC-based models.
Proceeding to the LT models, Figure 6 presents a more interesting set of results than IC. Here, DD is not a viable option as it has been explained already. For the rest of the strategies, SD is dominant, achieving up to 92% reduction, with Random following closely with 90%. Moving to the healing strategies, Vaccination achieves the best reduction of approximately 92%, but, in contrast to the IC case, it is the only one that preserves the reduction during the whole process. This can be explained by the fact that Vaccination completely deactivates the touched nodes, and, thus, they have zero effect on their neighbors during the subsequent steps. On the contrary, the rest of methods can not preserve the reduced aggression levels suggesting a potential inefficiency of competitive cascades on LT models. Hence, we observe that in LT models, the most possible and realistic reduction starts from 5% and can raise up to 20% using as healing mechanism the Hybrid.

Regarding the activated nodes during each propagation process, Vaccination activates the least number of nodes, while Decaying transfer stimulates 2x more nodes compared to Hybrid in most cases. Also, considering the theoretical nature of Vaccination, Decaying Transfer should be prioritized as a healing mechanism.

4.4.2 Blocking Aggression Minimization. Moving to the second minimization problem (BAM), the results of four methods combining: 1) node or 2) edge blocking (removal), while using a) Jaccard as edge weight in the adjacency matrix A, or b) the modified version with the aggression scores (please see details in Sec. 4.4) are briefly discussed and compared to a no-immunization process as baseline. For node and edge blocking, NetShield [29] and NetMelt [28] algorithms were used, respectively, to select nodes or edges to remove.

For IC, the aggression-based variations do not present significant improvement over the baseline. Aggression reduction is possible - although smaller than competitive cascades - by exploiting node removal, achieving a reduction of 8%. We note that the number of removed nodes is 5594, equal to the seed size of the competitive cascade process. However, when edge blocking is examined, the overall aggression score is, in fact, doubled, regardless of the type of the matrix A. This unpredictable behavior is caused by the combination of significant edge removal and the degree-based seed strategy of the underlying diffusion process. Moreover, to let NetMelt reach the same number of nodes as NetShield, ~470k edges have to be removed, which is clearly unrealistic.

For LT, edge removal (with both types of A) presents a switching behavior of 1% increase and decrease in overall aggression, in relation to the baseline of no immunization. However, these fluctuations are small and do not lead to a significant outcome on aggression minimization. Regarding node removal, there is a better performance in terms of aggression minimization, since the reduction reaches 6% for the Jaccard-based A, and 8% for the aggression-based case. In general, the aggression alternative of the adjacency matrix seems to benefit the process, but more in-depth research is needed to understand its tradeoffs.

Lastly, regarding the number of activated nodes, in comparison to the competitive cascades, the immunization methods here tend to activate 4x times more nodes overall. Again, for brevity the respective results are omitted.

**Takeaways:** Aggression minimization through competitive cascades outperforms blocking techniques. Specifically, using IC models, we achieve a reduction of 57% of the initial total aggression score of the network, while with blocking methods up to a reduction of 8%. Using LT models, even though competitive cascades are more efficient in terms of aggression reduction, the gradual aggression score increase during the diffusion process suggests that node blocking should be preferred. These observations cover the second and last part of Contributions 2 and 3.
5 DISCUSSION & CONCLUSION

In this work, the dual problem of aggression modeling and aggression minimization in online social networks, and specifically Twitter, was examined. To the best of our knowledge, aggression modeling has been addressed only in [26], where it was approached through opinion dynamics instead of cascading models. Both approaches present comparable performance in modeling real Twitter data on aggression diffusion, while having some distinguishing features regarding the process and convergence conditions. We believe our work advances the community’s understanding on aggression diffusion one step further, while determining the most prevalent of the two methods is left for a follow-up work. Apart from aggression modeling, however, we are the first to address aggression minimization. We exploit models from the domains of competitive cascades and immunization and discover strategies to implement them as minimization methods.

In this paper, first, we showed that aggression diffusion can indeed be modeled with both IC- and LT-based propagation processes, as they can reach a good cosine similarity with ground truth of $\sim$70%. Our results showed that aggression diffusion benefits from starting the propagation from the most central, but not necessarily the most aggressive nodes in the network. Additionally, the weighting scheme for graph edges should utilize the Jaccard overlap between social circles of users, to capture the importance of neighborhood similarity. Regarding the specifics of each model, Cumulative was the best activation criterion for IC, as it engulfs the team influence on information propagation. For LT, Aggression was the best threshold strategy, suggesting that high aggressiveness is easier to propagate and hence enabling aggression diffusion.

With respect to aggression minimization, competitive cascades achieved a total of 57% reduction with IC, and 5-20% in LT models, while node blocking methods reached $\sim$8% reduction in both IC and LT. Edge blocking is inappropriate, as it interferes with the degree of nodes, making it incompatible with the degree-based SD seed strategy of the aggression cascade. Furthermore, in LT scenario, competitive cascades could not preserve their efficiency and hence the more stable blocking methods should be preferred.

Regarding competitive cascades, the similar behavior of the most prevalent seed strategies allows a tradeoff between stability and computational cost. Specifically, Random strategy achieved high performance with low computational cost, while DD presented similar performance with more stable behavior. In LT models, where DD is not applicable, SD was chosen. Moreover, Decaying Transfer was the most appropriate healing mechanism, despite Vaccination’s higher performance. This is because Vaccination presumes that users affected by a positive piece of information, such as a cyberbullying sensitizing campaign, will not switch back to abusive behavior. This assumption is rather theoretical, and not easily applicable or proven in a real-world scenario.

Combining the observations on competitive cascades and blocking techniques, and to reduce aggression in online social networks, we propose the use of awareness campaigns (e.g., sharing posts for eliminating racism or hate speech), instead of banning users. In this way, a less intrusive, but yet more effective minimization method can be implemented. Concluding, for aggression modeling and minimization, there are various extensions of this work that can be investigated in the near future:

1. Implement further theoretical aggression features in the diffusion models, to better capture aggression dynamics on real networks.
2. Investigate various thresholds that enable an epidemic spread of aggression under different virus-spreading models.
3. Examine ways to incorporate offline blocking methods into the diffusion process and dynamically minimize aggression.

REFERENCES

[1] J. J. Allen and C. A. Anderson. 2017. General aggression model. The International Encyclopedia of Media Effects (2017), 1–15.
[2] R. Basak, S. Sural, N. Ganguly, and S. K. Ghosh. 2019. Online public shaming on twitter: Detection, analysis, and mitigation. IEEE Transactions on Computational Social Systems 6, 2 (2019), 208–220.
[3] A. Borodin, Y. Filmus, and J. Oren. 2010. Threshold models for competitive influence in social networks. In WINE. Springer, 539–550.
[4] C. Budak, D. Agrawal, and A. El Abbadi. 2011. Limiting the spread of misinformation in social networks. In 20th WWW, 2011. Proceedings. ACM, 665–674.
[5] P. Chatzakou, N. Kourtellis, J. Blackburn, E. De Cristo, G. Strinhini, and A. Vakali. 2017. Mean birds: Detecting aggression and bullying on twitter. In ACM on WebSci, 2017. Proceedings. ACM, 13–22.
[6] N. Chen. 2009. On the approximability of influence in social networks. SIAM Journal on Discrete Mathematics 23, 3 (2009), 1400–1415.
[7] W. Chen, Y. Wang, and S. Yang. 2009. Efficient influence maximization in social networks. In 15th ACM SIGKDD, 2009. Proceedings. ACM, 199–208.
[8] L. Corcoran, C. Guckin, and G. Prentice. 2015. Cyberbullying or cyber aggression? A review of existing definitions of cyber-based peer-to-peer aggression. Societies 5, 2 (2015), 245–255.
[9] T. Davidson, D. Warmshly, M. Macy, and I. Weber. 2017. Automated hate speech detection and the problem of offensive language. In 11th IICWSM.
[10] P. Domingos and M. Richardson. 2001. Mining the network value of customers. In 7th ACM SIGKDD, 2001. Proceedings. ACM, 57–66.
[11] J. Fernández-Gracia, K. Suchecki, J. J. Ramasco, M. San Miguel, and V. Eguiluz. 2014. Is the voter model a model for voters? PLoS 11, 15 (2014), 158701.
[12] A. M. Founta, C. Djojvua, D. Chatzakou, I. Leontiadis, J. Blackburn, G. Strinhini, A. Vakali, M. Sirivianos, and N. Kourtellis. 2018. Large scale crowdsourcing and characterization of twitter abusive behavior. In 12th ICWSM.
[13] X. He, G. Song, W. Chen, and Q. Jiang. 2012. Influence blocking maximization in social networks under the competitive linear threshold model. In SDM, 2012. Proceedings. SIAM, 463–474.
[14] A. K. Henneberger, D. L. Coffman, and S. D. Gest. 2017. The effect of having aggressive friends on aggressive behavior in childhood: using propensity scores to strengthen causal inference. Social Development 26, 2 (2017), 295–309.
[15] P. Jiang, G. Song, C. Gao, Y. Wang, W. Si, and K. Xie. 2011. Simulated annealing based influence maximization in social networks. In 25th AAAI.
[16] D. Kempe, J. Kleinberg, and É. Tardos. 2003. Maximizing the spread of influence through a social network. In 9th ACM SIGKDD, 2003. Proceedings. ACM, 137–146.
[17] J. Lee and Y. Lee. 2002. A holistic model of computer abuse within organizations. IMCS 10, 2 (2002), 57–63.
[18] J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, C. Faloutsos, J. VanBriesen, and N. Glance. 2007. Cost-effective outbreak detection in networks. In 13th ACM SIGKDD, 2007. Proceedings. ACM, 420–429.
[19] J. Leskovec and J. J. McAuley. 2012. Learning to discover social circles in ego networks. In Advances in NIPS. 539–547.
[20] C. Long and R. C. Wong. 2011. Minimizing seed set for viral marketing. In 2011 IEEE 11th ICDM. IEEE, 427–436.
[21] H. Ma, H. Yang, M. R Lyu, and I. King. 2008. Mining social networks using heat diffusion processes for marketing candidates selection. In 17th ACM CIKM, 2008. Proceedings. ACM, 233–242.
[22] B. A. Prakash, D. Chatrabarti, N. C. Valver, M. Faloutsos, and C. Faloutsos. 2012. Threshold conditions for arbitrary cascade models on arbitrary networks. KAIS 33, 3 (2012), 549–575.
[23] M. Richardson and P. Domingos. 2002. Mining knowledge-sharing sites for viral marketing candidates selection. In 17th ACM CIKM, 2008. Proceedings. ACM, 420–429.
[24] N. Glance. 2007. Cost-effective outbreak detection in networks. In Advances in NIPS. 539–547.
[26] C. Terizi, D. Chatzakou, E. Pitoura, P. Tsaparas, and N. Kourtellis. 2020. Angry Birds Flock Together: Aggression Propagation on Social Media. *arXiv preprint arXiv:2002.10131* (2020).

[27] G. Tong, W. Wu, S. Tang, and D. Du. 2017. Adaptive influence maximization in dynamic social networks. *IEEE/ACM TON* 25, 1 (2017), 112–125.

[28] H. Tong, B. A. Prakash, T. Eliassi-Rad, M. Faloutsos, and C. Faloutsos. 2012. Gelling, and melting, large graphs by edge manipulation. In *21st ACM CIKM, 2012. Proceedings*. ACM, 245–254.

[29] H. Tong, B. A. Prakash, C. Tsourakakis, T. Eliassi-Rad, C. Faloutsos, and D. H. Chau. 2010. On the vulnerability of large graphs. In *2010 IEEE ICDM*. IEEE, 1091–1096.

[30] D. Trpevski, W. K. Tang, and L. Kocarev. 2010. Model for rumor spreading over networks. *PRE* 81, 5 (2010), 056102.

[31] Y. Wang, D. Chakrabarti, C. Wang, and C. Faloutsos. 2003. Epidemic spreading in real networks: An eigenvalue viewpoint. In *22nd SRDS, 2003. Proceedings*. IEEE, 25–34.

[32] Z. Waseem and D. Hovy. 2016. Hateful symbols or hateful people? predictive features for hate speech detection on twitter. In *NAACL SRW, 2016. Proceedings*. 88–93.

[33] P. Wu and L. Pan. 2017. Scalable influence blocking maximization in social networks under competitive independent cascade models. *Computer Networks* 123 (2017), 38–50.

[34] H. Zhang, H. Zhang, X. Li, and M. T. Thai. 2015. Limiting the spread of misinformation while effectively raising awareness in social networks. In *International CiSeNet*. Springer, 35–47.