Strategic Promotional Campaigns for Sustainable Behaviors: Maximizing Influence in Competitive Complex Contagions*

Arkadiusz Lipiecki[0000−0003−1118−0388]

Wrocław University of Science and Technology, Wrocław, Poland
arkadiusz.lipiecki@pwr.edu.pl

Abstract. We address the research gap in evaluating the effectiveness of network seeding strategies in maximizing the spread of beliefs within non-progressive competing complex contagions. Our study focuses on management perspective of devising promotional campaigns for sustainable and health behaviors. We conduct an extensive computational analysis on two empirical datasets, comparing four established strategies in two different scenarios. Our results show that it is possible to achieve widespread adoption of beliefs, even under very limited network information. However, this success requires a strategic approach that includes additional efforts to prevent the targeted influencers from abandoning these attitudes in the future.

Keywords: Influence Maximization · Complex Contagion · Networks · Seeding Strategies · Belief Dynamics · Adoption of Sustainable Behaviors

1 Introduction

In 2021 the International Energy Agency published the world's first comprehensive report studying how to achieve net-zero carbon dioxide emissions. *Net Zero by 2050* highlights behavioral change as a crucial factor in decarbonization. This raises a question of what factors can drive the collective adoption of sustainable behaviors and how to facilitate it. Kowalska-Pyzalska [7] notes that environmental behaviors are strongly connected to, i.a., environmental beliefs, norms and social influence. Similarly, social norms among close ties has been identified as strong predictors of vaccine intentions [11]. In view of this, our attention centers on harnessing the power of social contagion, with particular focus on belief spreading. Within the joint realms of complex systems, network science and social simulation, considerable attention has been focused on network seeding strategies – methods for optimal selection of early adopters that maximizes the spread of their influence. From the perspective of promotional campaigns, seeding strategies attempt to answer the question of who to target with the campaign to maximize its outreach potential. For example, one-hop strategy, which

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exploits the friendship paradox to find seed candidates, was shown to yield higher product adoption and health knowledge dissemination than targeting highly connected individuals [6]. Recently, in the face of empirical findings suggesting that social spreading is not a simple, but a complex contagion, i.e. it requires the influence of a group rather than a single individual, Guilbeault and Centola [4] introduced a new measure for identifying central nodes and shown its efficiency in maximizing influence across various progressive models. However, progressive models do not allow the individuals to revert to their previous states. While this limitation is justified in many cases, our beliefs and behaviors can be highly variable, and efforts to promote socially responsible attitudes are vulnerable to being undermined by uncertainty and competition between conflicting views. The need for influence maximization under reversible opinions has already been addressed for simple competing contagions within the voter model [3, 12]. Yet despite the great interest in spreading processes based on complex contagion, there is little to no research devoted to evaluating the effectiveness of network seeding strategies in the non-progressive case of competitive complex contagions [14]. In order to address this gap we perform a simulation study on two empirical social networks, providing a comparison of selected seeding strategies in facilitating collective change of beliefs within such a framework. The code is open-source and available on GitHub: `github.com/lipiecki/qvoter-seeding`.

2 Methods

Model. To model the non-progressive competing complex contagions we implement the q-Voter Model (qVM) [2] with n agents placed in nodes of a social network, where neighborhood $N(i)$ of node i corresponds to the set of k_i nodes directly linked to i. The qVM is a generalization of the voter model, in which an agent can change its state only when influenced by a unanimous group of q randomly selected neighbors. In our model each agent can be in one of two states: *adopter* or *rejecter*. We use the term *adopter* to refer to an agent in the state that we aim to promote, and *rejecter* for an agent in the opposite state. A single elementary update of the model consists of the following steps:

1. Choose a random agent i.
2. Form the q-panel – choose at random q neighbors of i.
3. If all agents in the q-panel are adopters – i becomes an adopter.
   Otherwise, if all agents in the q-panel are rejecters – i becomes a rejecter.

The general model of competing complex contagion studied in [14] corresponds to the qVM in which the q-panel is drawn with replacement. However, drawing with replacement allows an agent to change its state under the influence of less than q neighbors due to multiple selections of the same neighbor. In order to ensure that simple contagion dynamics do not affect the results of simulations, we adopt the approach of drawing without replacement. Additionally, we examine two settings of the model with respect to seed behavior: flexible seeds, which undergo an updating procedure and differ from non-seeds solely in their initial

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state, and inflexible seeds (zealots) [12], which are indefinitely fixed as adopters and do not change their state.

Seeding Strategies. To provide a concise but comprehensive picture of how susceptible the qVM is to various seeding methods, we have selected four distinct strategies, differing in computational complexity and information requirement. We will refer to the number of nodes that are seeded within a given experiment as the seeding budget.

High Degree (HD) – seeding nodes with the highest degree, which is one of the most straightforward node centrality measures. The number of direct neighbors is a simple proxy of node's importance and does not require full information of the network structure. Seeding high degree nodes was shown to be an optimal strategy for the simple voter model [3].

PageRank (PR) – seeding nodes with the highest PageRank centrality, which was initially introduced for identifying the most important web pages. Since then PageRank has gained an incredible amount of attention, also in the context of social influence. It is a promising candidate for evaluating the importance of nodes in the qVM. To understand why, consider the influence probability P_{ij}, i.e. the probability that node i selects $j \in N(i)$ as part of the q-panel during an elementary update. Since q sources are drawn, $P_{ij} = q/k_i$. Notice that P/q is a stochastic matrix of the random walk on the same network. PageRank centrality measure is closely tied to the stationary probability distribution of such a random walk.

Complex Centrality (CC) – seeding nodes with the highest complex centrality was proposed as an effective strategy in maximizing the spread of complex contagions [4]. Complex centrality of a node is defined as an average length of complex paths extending from that node, where the length of a complex path between nodes i and j is equal to the shortest path length between them in the subgraph induced by the spread of progressive complex contagion from the neighborhood of i to node j [4]. Complex centrality depends on the underlying dynamics of the contagion through thresholds T_i, corresponding to the number of adopters in $N(i)$ required to activate i within a progressive complex contagion. Hence, to adapt this method to the non-progressive case, we set T_i for each individual i as a minimal number of adopters in its neighborhood for which the probability of gathering a unanimous q-panel of adopters is greater or equal to the probability of gathering a unanimous q-panel of rejecters: $T_i = \max\{q, \lceil k_i/2 \rceil\}$.

One-hop – this strategy identifies seed nodes through a simple two-step process, in which we first select a random set of individuals with size equal to the seeding budget and then query them to nominate one of their neighbors (in simulations selected at random) as the seed [10]. If the number of nominated unique seeds is smaller than the budget, we randomly draw nodes from the initially selected random set. One-hop strategy works under very limited network information, as it does not require any prior knowledge about the network structure, and the number of links discovered during the querying is no greater than the seeding budget. Moreover, due to simplicity of the process, it can be readily implemented in field experiments, which is a significant advantage from the per-

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spective of promotional strategies. Finally, it is worth noting that the process of selecting seeds within the one-hop strategy corresponds to performing single-step random walks starting from random initial nodes, which relates one-hop to PR centrality and to the influence probability within the qVM.

Simulations. To evaluate the effectiveness of seeding strategies in maximizing the spread of beliefs, we perform simulation experiments on two empirical networks – Facebook dataset from the Stanford Network Analysis Project (SNAP) [9] and Facebook dataset of verified pages of politicians (Politicians) [13]. According to the model specification, in the process of updating a state of a node, its q random neighbors are selected. However, it may occur that the degree of a node is smaller than q. Then we can either omit such nodes and do not update their state, or assume a different size of the q-panel, equal to the the degree of a node. We adopt the latter approach, but this raises another issue. In the empirical networks we study there exist nodes with degree equal to one, which means that updating such nodes would correspond to a simple contagion dynamics. To avoid this, we conduct preprocessing of the network data to ensure that every node has at least two neighbors. For each node with a single neighbor we perform a *triad formation* step of the Holme-Kim algorithm [5], where we add a link between the single-neighbor node and one of its randomly selected next-nearest neighbors. Since this preprocessing introduces randomness to the networks, we conduct simulations on an ensemble of 10^2 networks generated this way. The agent systems are evolved for 10^5 Monte Carlo steps (each consisting of n elementary updates) or until the absorbing state (full adoption or full rejection) is reached.

3 Results

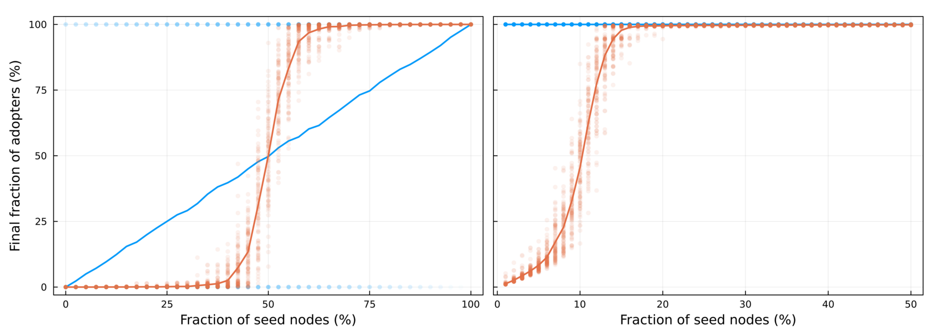

Fig. 1. The final fraction of adopters with respect to the fraction of randomly seeded nodes on the SNAP network within the qVM for $q = 1$ (blue) and $q = 2$ (orange). Colored lines represent the ensemble averages (10^3 networks), while colored circles mark the individual simulation outcomes. Left panel shows the results for flexible seeds, and the right panel – for zealots.

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The first question that ought to be answered in the context of maximizing influence within the qVM is whether there exists a substantial difference between the spreading behavior in the case of a simple voter model ($q = 1$) and the non-linear qVM with complex contagion ($q > 1$). Fig. 1. presents the comparison of the percentage of adopters for varying fraction of random seed nodes for $q = 1$ and $q = 2$. In the flexible seeds scenario, the simple voter model always evolves towards either full adoption or total absence thereof. The probability of adoption increases linearly with the number of seed nodes. The adoption within the 2VM is qualitatively different, the average number of adopters follows a sharp S-shape transition pattern with an inflection point at 50%.

Belief dynamics with zealots highlight that collective change is significantly more difficult if the voter-like dynamics follow complex contagion. For $q = 1$ agent systems reach full adoption for any non-zero seeding budget, while for $q = 2$ it is reached only after exceeding a sufficient fraction of seeds. These results show evident qualitative differences between the susceptibility to collective change of the simple voter system and the non-linear qVM, which motivates us to examine influence maximization strategies within complex contagions, i.e. $q > 1$.

Table 1. Network statistics (size n, average node degree $\langle k \rangle$, average clustering coefficient ρ, average shortest path length d) and a minimal seeding budget for which the ensemble median reached a specified adoption level τ within the 2VM.

						Flexible				**Zealots**			
Network	n	$\langle k \rangle$	δ	d	τ	HD	PR	CC	One-hop	HD	PR	CC	One-hop
SNAP	4039	43.7	0.62	3.7	80%	40%	25.0%	35.0%	47.5%	17.5%	5.0%	17.5%	10.0%
					90%	50.0%	27.5%	37.5%	47.5%	20.0%	7.5%	20.0%	10.0%
					95%	50.0%	32.5%	40.0%	50.0%	30.0%	15.0%	27.5%	12.5%
Politicians	5908	14.3	0.49	4.6	80%	25.0%	20.0%	27.5%	37.5%	7.5%	5.0%	10.0%	5.0%
					90%	47.5%	25.0%	47.5%	42.5%	10.0%	7.5%	15.0%	7.5%
					95%	67.5%	35.0%	67.5%	47.5%	60.0%	20.0%	60.0%	10.0%

We therefore proceed to analyze the seeding experiments for $q = 2$. Statistics of the network ensemble and the seeding budgets required for reaching specified adoption levels are presented in Table 1, while the entire adoption curves are shown in Fig. 2. Firstly, in the setting of flexible seeds, the strategy based on PR can be considered as the most efficient among the examined contenders. It significantly outperforms one-hop, and although HD and CC lead to higher fractions of adopters for low seeding budgets, they are more costly than PR in reaching the adoption levels close to 50% and higher (see left panels of Fig. 2.). However, simulations with zealots paint a different picture, with a surprising performance of the one-hop strategy. While PR is the most efficient at reaching 80% and 90% adoption levels (see Table 1.) and leads to highest adoption at small fractions of seed nodes (see right panels of Fig. 2.), one-hop strategy outperforms PR in achieving nearly full adoption. For zealots, seeding with HD and CC performs rather poorly when we aim for widespread adoption, requiring c.a. twice larger budgets to reach target levels of 80% and above in the SNAP network, and up to six times larger budget to reach 95% adoption in the Politicians network. More-

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over, one-hop is the only strategy that is consistently, i.e. across all fractions of seed nodes, no worse that random seeding in the case of zealots. One possible explanation for this result is the fact that random and one-hop strategies seed nodes in various parts of the network, while highly central nodes can cluster at the core of the network, thus leading to higher difficulty in affecting network's periphery. In general, given the same seeding budget, adoption levels are significantly higher when seed nodes behave as zealots, which is to be expected given that they serve as constant sources of pro-adoption influence.

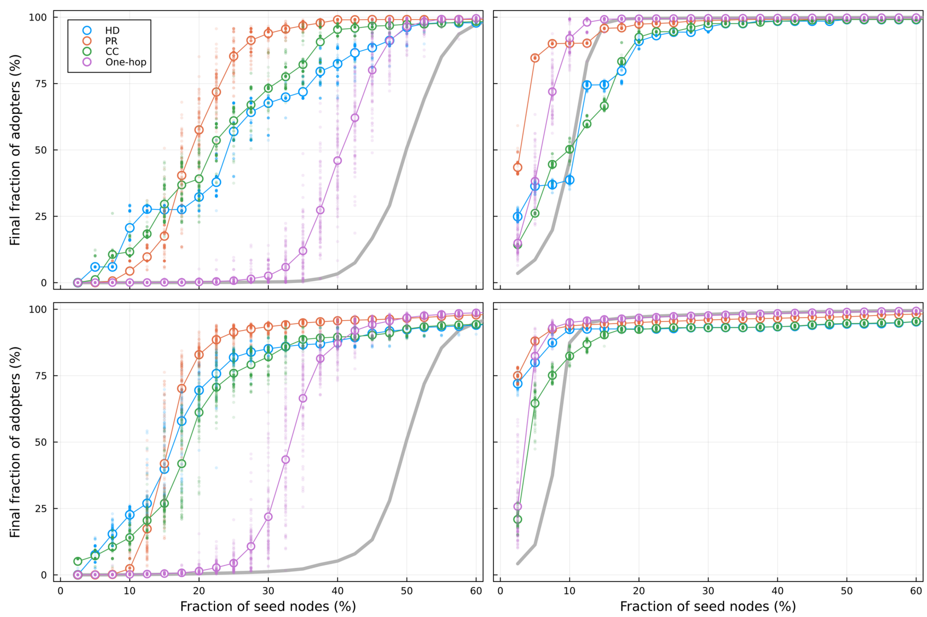

Fig. 2. The final fraction of adopters with respect to the fraction of seed nodes for selected seeding strategies within the 2VM. Empty colored circles correspond to ensemble averages (10^2 networks), while full colored markers correspond to individual simulation outcomes. Grey lines correspond to ensemble averages for random seeding. Top panels correspond to simulations on the SNAP network, while bottom panels – on the Politicians network. Left panel shows the results for flexible seeds, and the right panel – for zealots.

Finally, let us examine how the susceptibility of the social network to collective adoption varies for different sizes of influence group. Since the size of the q-panel affects the spreading of both adoption and rejection, it is difficult to form expectations of how it affects the efficiency of seeding strategies. Fig. 3 shows the comparison between the efficiency of selected strategies in seeding the Facebook SNAP network for $q = 2$, 3 and 4. For zealot seeds, all the adoption curves are visibly shifted to the right, which means that the network is less susceptible to

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seeding by all considered strategies. However, the main conclusion holds across the examined q values – PR performs best for small seeding budgets, but one-hop is most efficient in reaching nearly full adoption. Notably, in contrast to one-hop, final fraction of adopters resulting from PR and CC saturates below 100%, with the saturation level decreasing with q. Similar behavior is observed in the scenario with flexible seeds, with an exception of one-hop strategy exhibiting a strong resilience against increasing the complexity of the contagion processes. The adoption curves obtained from one-hop are not affected by the value of q.

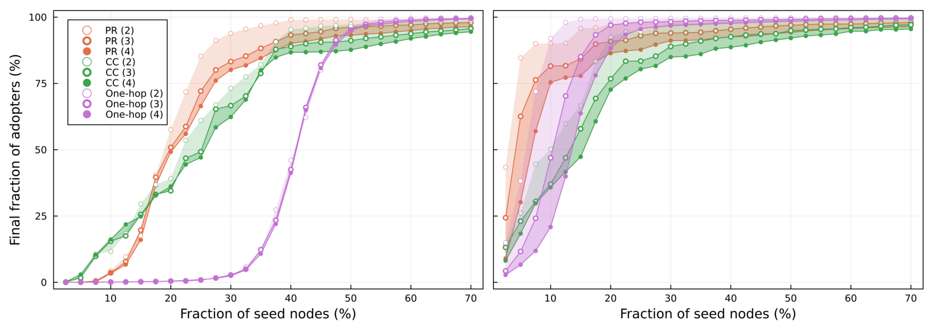

Fig. 3. Comparison of the final fraction of adopters with respect to the fraction of seed nodes on the SNAP network for selected seeding strategies within the qVM for $q = 2, 3$ and 4. Values presented on the plots are ensemble averages (10^2 networks). Left panel shows the results for flexible seeds, and the right panel – for zealots.

4 Discussion

In the face of current problems that require widespread collective action, such as reaching herd immunity or climate change mitigation, computational social science can provide valuable insights to support strategic promotion of environmental and health behaviors [7, 8]. Therefore, in this study we addressed the research gap in evaluating the effectiveness of network seeding strategies within the framework of competitive complex contagions, which accounts for both group influence and variability in opinions. Notably, many problems remain for future research. For example, considering the spreading behavior with the presence of zealots that oppose the promoted attitude [12] or examining the effects of network coevolution on the widespread belief adoption [1] can provide insights on how to facilitate collective change in the presence of high hesitancy and polarization. From the managerial perspective, an important next step is to evaluate more sophisticated strategies that work under limited network information [10].

Our results indicate that increasing the complexity of competing contagions decreases the susceptibility of social networks to seeding strategies. Yet influence maximization methods that do not account for contagion complexity emerged

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as promising solutions. PageRank centrality outperformed all other strategies in reaching adoption majority in the setting of flexible seeds. In the scenario of pro-adoption zealots, PageRank was most effective for small seeding budgets, but one-hop turned out as the best strategy for achieving nearly full adoption. Since one-hop requires very little information about the network and can be implemented by conducting a single round of surveys, our findings suggest that facilitating collective adoption of beliefs and behaviors through social influence is achievable in real-life scenarios. Moreover, zealot seeds required drastically smaller budgets than flexible ones. Therefore, the key recommendation for decision-makers managing promotional campaigns is that dedicating resources for maintaining consistency in the attitudes of targeted influencers can be more beneficial than acquiring additional network information.

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