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A Role for Network Science in Social Norms Intervention

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Abstract
Social norms theory has provided a foundation for public health interventions on critical issues such as alcohol and substance use, sexual violence, and risky sexual behavior. We assert that modern social norms interventions can be better informed with the use of network science methods. Social norms can be seen as complex contagions on a social network, and their propagation as an information diffusion process.

We observe instances where the recommendations of social norms theory match up to theoretical predictions from information diffusion models. Conversely, the network science viewpoint highlights aspects of intervention design not addressed by the existing theory. Information about network structure and dynamics are often not used in existing social norms interventions; we argue that these factors may be contributing to the lack of efficacy of social norms interventions delivered via online social networks. Further, delivery via online social networks may enable novel intervention designs employing realtime feedback.

Keywords: Network Science, Social Norms, Contagion Models, Complex Contagion, Behavior Change

1 Introduction

About one in ten deaths among working-age adults in the US are attributable to excessive drinking [27]. The CDC reports nearly 1 in 5 women reported experiencing rape at some time in their lives, with more than 40% of those victims having been raped before age 18 [3]. The CDC estimates that nearly 20 million new sexually transmitted infections occur every year in the US, resulting in nearly $16 billion in health care costs [8]. With such massive impacts, these issues of alcohol and substance use, sexual violence, and sexually transmitted infections are targets for public health interventions in the US.

Due to the social nature of substance use and sexual relationships, harms reduction strategies have included *social norms interventions*. Social norms refers to what is perceived to be "normal" behavior of peers, and these beliefs influence our behavior in turn [2]. Individuals often overestimate the prevalence of risky behaviors amongst their peers, which can lead to

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increased risky behavior in the individual [22]. The social norms approach to intervention seeks to correct these misperceptions, reducing peer pressure and consequently the frequency of these behaviors [2, 4, 18, 20]. For example, President Obama's recent "It's On Us" campaign uses the language of social norms theory:

> Most men are not comfortable with violence against women, but often don't speak out because they believe that other men accept this behavior. By getting men involved, we can change this way of thinking and create new social norms [29].

While the social norms approach is based in a rich theory, the theory does little to illuminate implementation details of interventions such as specifically who to target and for how long. The current body of best practices is largely informed by empirical results, and a common criticism of the social norms approach is the lack of rigorous scientific support for its claims [2, 14]. The classic theory of social norms also seems to produce poor outcomes when applied to online social networks (OSNs), leading to debate about its applicability and usefulness going forward [6, 24]. Since intervention recommendations are largely based on empirical results, social norms interventions are largely discussed in particular contexts. As a result, lessons learned in a substance use intervention, for example, are often of limited use when applied to a sexual violence intervention. Leaders in the field have recently begun calling for better methods for comparing and evaluating interventions across application domains [1, 6, 18].

This position paper proposes filling these gaps by using network models to test, refine, and recommend intervention strategies based on social norms. Recent research on information diffusion in social networks provides a way forward for designing interventions on OSNs, illuminating dynamics that the classic theory of social norms fails to capture. Network models of intervention also open the door to novel designs utilizing realtime feedback mechanisms. Finally, a key feature of network models is their domain-independence. By focusing on the information diffusion and dynamics of underlying social networks, network models of intervention will allow for better, more principled recommendations across application domains.

2 Background

2.1 Models of Human Behavior

The *theory of reasoned action* is a framework to describe human behavior, widely used in social science and public health contexts [15]. It states that an individual's behavioral intentions are controlled by a combination of attitude and social norms [15]. In this context, attitude refers to the cost-benefit analysis of the situation based on the individual's beliefs.

Interventions targeting social norms can focus on the injunctive norm: "your peers think that inappropriately touching someone in a bar is wrong, so you shouldn't do it", and/or the descriptive norm: "inappropriately touching someone in a bar is not something that your peers do, so you shouldn't either" [20].

These types of interventions are based on the *theory of social norms* popularized by Alan Berkowitz and H. Wesley Perkins. The theory describes situations in which individuals misperceive the attitudes and/or behavior among a group of peers or community members. Alcohol, tobacco, and illegal substance use have long been the targets of social norms interventions [2, 20]. Recently, social norms interventions have been gaining momentum as tools for targeting sexual violence and risky sexual behaviors, presumably due to increased attention [4, 18].

2.2 Contagion Models of Information Diffusion

A *meme* is defined as "an idea, behavior, or style that spreads from person to person within a culture."[1] The diffusion of a meme through a social network is often likened to the spread of a virus or contagion – hence the phrase "going viral." Among theoretical models of social contagion, the simplest and most widely studied is the independent cascade model (ICM) [17, 19]. In this class of models, each exposure to a meme leads to an independent chance of a target individual adopting that meme. Once a node adopts the meme, it can expose all of its neighbors. The neighbors can also spread the meme, and so on, potentially leading to large information cascades. In the context of behavior-change models, nodes in the network are people, and behaviors are the memes being transmitted.

While the ICM models are useful, we assert that they are inadequate to model social norms as they lack mechanisms to account for social reinforcement. Previous studies of behavior spreading on OSNs have suggested social reinforcement as being important to the diffusion process [9, 28]. As compared to the simple contagion models of ICM, *complex contagion* models require multiple sources of exposure for a node to adopt a meme [10]. The linear threshold model incorporates a simple form of social reinforcement by linking the probability of adopting a meme to the proportion of neighbors exhibiting the meme [17, 19].

3 Model: Social Norms as Complex Contagion

Let us conceptualize social norms as a linear threshold model (LTM) with a concrete example of binge drinking.[2] Consider a target node on a network connected to other nodes via a friendship relation. The target node might perceive binge drinking to be "normal" if most ($> 50\%$) friends exhibit binge drinking behavior. At that point, the target node may exhibit binge drinking behavior. This is illustrated in Figure 1 where, given this example, pink could represent binge drinking behavior.

To this simple instance of an LTM, one can add model features. The 50% of normality in the example is a model parameter, one that may well differ between individuals. Past the threshold, the strength of the effect may depend on the proportion of peers exhibiting the given behavior, *i.e.* via peer pressure.

While the actual modeling of interventions is proposed work, empirically-derived recommendations for social norms interventions match up in several ways with theoretical predictions of this class of network models with social reinforcement. These matches are described in the intervention design sections of this paper.

4 Case Study: STI Reduction in Young Adults

As a case study in how the proposed work could be effective, we offer the following motivating example of reducing sexually transmitted infection (STI) incidence among young adults.

As mentioned in the introduction, the CDC estimates that nearly 20 million new STIs occur each year in the US, resulting in nearly $16 billion in health care costs. Not mentioned above is the fact that young adults aged 15-24 are disproportionally likely to acquire one of these infections. This age group represents a quarter of the sexually active population but contracts

[1] "meme." Mirriam-Webster.com. 2015.

[2] The National Institute on Alcohol Abuse and Alcoholism defines binge drinking as a pattern of drinking that brings a person's blood alcohol concentration (BAC) to 0.08 grams percent or above. This typically happens when men consume 5 or more drinks, and when women consume 4 or more drinks, in about 2 hours.

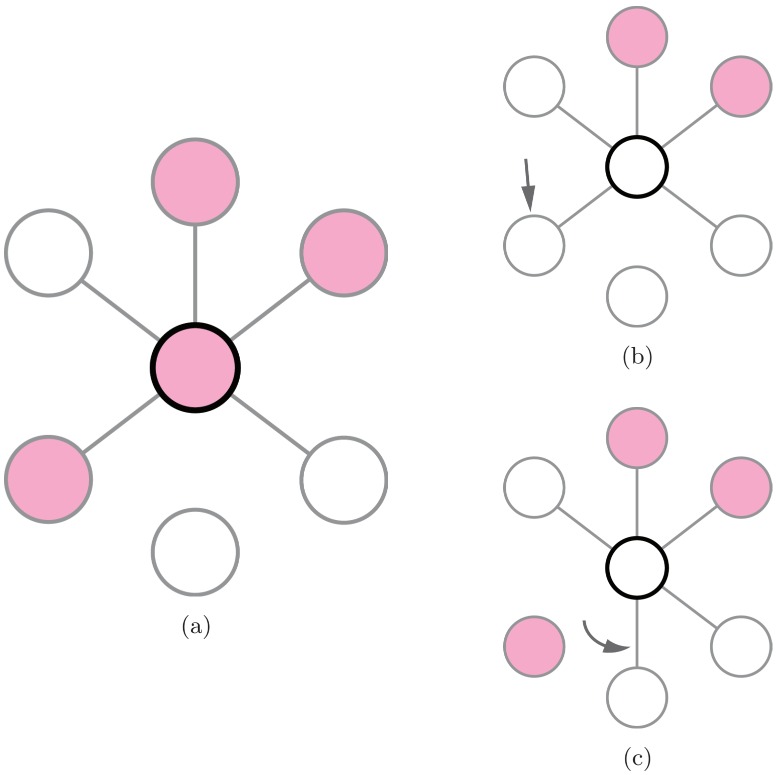

Figure 1: A given node can change state in a linear threshold model due to either node (b) or edge (c) dynamics. Arrows in (b) and (c) highlight changes from (a).

half of all new STIs [8]. While harmful on their own, STIs increase a person's risk for acquiring and transmitting HIV and can lead to severe reproductive health complications. All of these factors combine to make STI prevention among young adults a high priority.

Efforts toward reducing STI incidence focus on encouraging protective behaviors and/or discouraging risky ones. Protective behaviors include discussing condom use with potential partners and wearing condoms during sex; risky behaviors include early sexual debut, having multiple concurrent sexual partners, using drugs and/or alcohol during sex, and pressuring or being pressured into having sex [4, 18].

Given the high importance members of this age group place on the perception of their peers, focusing on social norms is a natural choice when targeting this subpopulation [11]. Social norms are an established target for adolescent substance use prevention efforts, but recent research has suggested it as a useful intervention strategy in the context of sexual behavior [13]. Sheana Bull *et al.* demonstrated the existence of misperceptions in both types of STI risk factors: youth and young adults underestimate the frequency of protective behaviors amongst their peers whilst overestimating the incidence of risky behaviors [4]. This twofold misperception makes the social norms approach particularly applicable because interventions can possibly target both norms simultaneously. Young and Jordan show that OSN users' perceptions of social norms – and their behavioral intentions – regarding risky sexual practices are influenced by their peers' OSN activity [35].

Given the age group and scope of the problem, interventions taking place on OSNs are particularly desirable. Unfortunately, previous attempts at OSN social norms interventions to reduce STI risk have not resulted in lasting behavior change, with effect returning to baseline at the six-month follow-up [16, 34]. As detailed in the following section on intervention design, we assert that classical social norms theory is inadequate for this type of intervention, and that a network science approach to the problem can provide a way forward.

5 Intervention Design

Given a contagion model of social norms, an intervention is defined as intentionally changing the behavior of some subset of nodes and then observing the evolution of the network. *In silico* simulation of these interventions allows for repeatedly tweaking and testing intervention strategies, eventually deciding on the strategy that presents the best result.

The success or failure of a modeled intervention is evaluated by criteria such as persistence and virality. A persistent intervention creates a lasting impact on the collective state of the network. Ideally, this would mean that nodes changed from undesirable behaviors to desirable ones and did not subsequently return to their previous undesirable state. A viral intervention would cascade through the network, spreading the desired behavior to many more nodes beyond the initial targets.

5.1 Community Structure and Composition

One of the more concrete recommendations of the "classic" theory of social norms is that interventions should be concentrated on tight social groups, *e.g.* a sports team, as opposed to looser ones like that of a college dorm [2, 14]. This matches with predictions from complex contagion models of behavior change [9].

Tight social communities are defined qualitatively as having more intra-community links than inter-community links. In the case of a simple contagion, tight communities can have the effect of "trapping" a spreading contagion by keeping it inside the community, repeatedly exposing the same people [31, 32]. In the case of complex contagion, communities can have the opposite effect. Since complex contagions require multiple exposures to spread, strong community structures can serve to incubate complex contagions with their local, intra-community spreading [21]. A complex contagion on a network without community or cluster structure is more likely to die out without spreading to many other nodes; however, complex contagions can still fall victim to trapping, presenting a tradeoff to be optimized.

With a model of the contagion and the social network, practitioners could simulate interventions targeting different social communities in order to optimize the spread of the desired behavior. The converse is also possible: if a specific community group needs to be targeted, this allows practitioners a principled way to tweak the intervention messaging, *i.e.* contagion, in order to optimize its spread.

5.2 Network Dynamics

Another key feature made measurable by OSNs is the structure and dynamics of the social network itself. By structure, we mean the network structure of nodes and edges, and by dynamics we mean the creation/destruction of edges in the network over time.

Most efforts at social norms interventions taking place on OSNs have not taken advantage of the underlying structure of the social network [5, 7, 16]. When OSN structure has been considered in the literature, the researchers are treating the network connectivity as static when in reality OSN structure is quite dynamic [6, 9, 25].

As previously described in the case study section, previous sexual health interventions delivered via OSNs have failed to produce lasting results, their effectiveness dropped off by the six-month follow-up [16, 34]. A linear threshold model of social norms leads to novel hypotheses about the source of this phenomenon. Figure 1 shows the two ways by which node state can change in a linear threshold model: in response to other node state changes, as in 1(b), or in response to changes in the network configuration, as in 1(c). Note that Fig. 1(c) demonstrates how network dynamics can cause a change in node state even when all other node states remain constant. This observation suggests a hypothesis as to how OSN-delivered social norms interventions can fail to engender persistent change. The classic hypothesis is that the message fails to "stick" and people simply return to pre-intervention baselines. Instead one might posit that once the intervention messaging stops spreading, the dynamics of the network take over, and the natural mixing of OSNs is responsible for driving the return of the previous social norm misperception.

The dynamic nature of networks, and OSNs in particular, is well-studied in network science. In social networks, not only do dynamics influence the node state as illustrated in Fig. 1, but Weng has demonstrated the converse: that node state also influences dynamics [33].

An intervention taking dynamics into account would recognize and plan for the social mixing that happens during and after the intervention. Such an intervention could even take advantage of network dynamics by seeking to create reinforcing social links between individuals demonstrating the desired behavior. These aspects of intervention design are traditionally ignored in the social norms literature, except perhaps in the case of campus alcohol use: these interventions sometimes provide alternatives to "the party scene," thereby having a homophilous effect [20].

5.3 In-situ Evaluation

Whether or not an intervention is designed based on network principles, the idea of intervention can be described in terms of network state. When planning an intervention, practitioners have knowledge about initial state of the network, *i.e.* information about the social network and of the expression of the target behavior. The goal of the intervention is then to drive the network to a desired state with respect to behavior exhibited by the network nodes. Thus an intervention strategy consists of a plan of which nodes to target with which messages and for how long.

Traditionally, when interventions are staged, either surveys or interviews are used to measure the behavior of members of the target population. These "active" measurements are usually done before the and after the intervention, then usually again for a follow-up after a few months. The classic theory does little to illuminate what a target population should look like during the course of an intervention. As a result, traditional social norms interventions are largely restricted to staging an intervention, stopping to evaluate, and repeating if necessary and/or possible.

Staging interventions on OSNs and/or using OSN data for measuring behavior opens up a whole new space of possibilities by using constant "passive" observation of OSN behavior. These measurements can be taken of large swathes of the target population in real- or near-real time. This real-time picture of the intervention as it is taking place in the real world allows for *in-situ* evaluation of intervention progress. Since network simulations of interventions can show temporal dynamics, practitioners can compare the measurements from the real-life network to the simulations in order to evaluate whether or not the intervention is on track to meet its goals. If desired, this could allow practitioners to make strategic adjustments to an ongoing intervention when necessary.

For example, suppose practitioners were performing a sexual health intervention on a college campus aimed at encouraging protective behaviors including condom use. The designers of the intervention select the swim team as a good target for intervention due to their strong community ties and co-ed composition. After the intervention messaging was delivered, real-time observation of OSN behavior indicates that the swim team was receptive to the message but attitudes towards condom use have not changed among non-team peers. Instead of having to wait to perform surveys and collect results, campus health professionals are instead able to respond quickly and target another related group with the intervention messaging. This time they target a dorm where many swim team members live. Because the swim team is already exhibiting the desired behavior, the intervention messaging spreads much more easily in the large dorm than it would have otherwise, and the desired behavior "breaks out" and begins to spread to the campus at large.

The advantage that *in-situ* evaluation provided in this hypothetical situation is that the follow-up effort could be made before the effect of the initial intervention wore off, thus making the two efforts mutually reinforcing. With a traditional intervene-evaluate-revise cycle, the practitioners may have had to start again from baseline, costing more money, time, and effort.

Theoretical support for *in-situ* evaluation of intervention comes from Lilian Weng's work on predicting successful memes in social networks [32]. Her work defines key features based on network structure that predict virality such as audience size, community structure, and speed of growth. Measuring and targeting these kinds of metrics may allow practitioners to maximize the chance of an intervention going viral and producing the desired culture change.

5.4 Real-time Feedback

Classic social-norms interventions rely on discrete interventions and discrete measurement of effect. The previous section describes how continuous measurement can enable more effective discrete interventions. Naturally one is led to consider the corresponding possibility of continuous intervention.

Berkowitz describes how *individualized normative feedback* – feedback to the participant based on his or her behavior/beliefs/state – is the gold standard of intervention techniques [2]. It produces good results but has traditionally been difficult and/or costly to implement.

With continuous and centralized behavior measurement available via OSNs, a practitioner simultaneously observe the behaviors of large numbers of intervention targets without the traditional survey-response cycle. Even if a survey is necessary to better measure the state of a participant, online surveys can often be completed in minutes or less and feedback provided just as fast. This low cost and quick turnaround potentially allows for more opportunities for individualized normative feedback.

Advances in content and sentiment analysis may even allow practitioners to provide individualized normative feedback algorithmically, without a human in the loop [12]. At this point, the engineering definition of feedback comes into view. Recall the network conception of intervention described in the previous subsection; a comprehensive social norms intervention taking place on an OSN could include feedback mechanisms that continually measure and respond in order to drive the network state towards the desired configuration.

A hypothetical example of this kind of feedback could be constructed around mental health services and stigma. Major depression is one of the most common mental disorders in the US, affecting almost 7% of US adults in 2012 [26]. Despite the prevalence of mental health disorders in general and depression in particular, significant stigma exists in the US with respect to mental health care [23]. Recent results have demonstrated how it may be possible to predict depression in people via their OSN behavior [12, 30]. One could imagine a system that observes the OSN behavior of a target population, looking for signs of depression. When the system detects an individual displaying these signs, it would send a PSA-style message to the individual. This message would not identify the individual, but would instead provide information about the prevalence of mental health issues among the population, seeking to correct the misperception of that social norm. The aim would be to reduce the perceived stigma of seeking treatment. Messaging could also potentially be delivered to peers of the individual, so as to increase peer support and decrease stigma. IRB issues abound in this hypothetical, but it demonstrates the idea.

Current models and theories for intervention are ill-equipped for *in-situ* evaluation and modification, much less this kind of control via real-time feedback [24]. By conceptualizing and simulating these novel types of intervention, network models of intervention can help move the theory forward.

6 Conclusion

Social norms theory has provided a foundation for public health interventions on critical issues such as alcohol and substance use, sexual violence, and risky sexual behavior. We assert that modern social norms interventions, often taking place at least partly on OSNs, can be better informed with the use of tools from network science.

In support of this position, we frame social norms as a type of complex contagion on a social network, and the propagation of social norms as an information diffusion process. Interventions are then conceptualized as attempts to create lasting and wide-ranging change in the state of the network. With a model of the social contagion and the underlying network, practitioners could ideally experiment with simulations each representing different intervention strategies, selecting the best for implementation.

In so doing, we observe instances where the recommendations of social norms theory match up to theoretical predictions from information diffusion models, such as targeting interventions to community groups. In these instances where network science predictions match the traditional advice, the network models offer explanations as to the reason for the effectiveness of the strategies.

The network science viewpoint also highlights aspects of intervention design that the classic theory does not address, including the potential role of network dynamics in decreasing intervention effectiveness over time. The ability to simulate network models of intervention, coupled with increased monitoring and measuring abilities offered by OSNs, enable more detailed evaluation during the course of an intervention. Real-time monitoring via OSNs also opens the door to real-time feedback mechanisms.

Additionally, network models of intervention would be more amenable to comparison across application domains, answering a demand expressed by leaders in the field. In order to highlight the cross-domain applicability of these ideas, hypothetical examples from multiple different application domains were used in this position paper to illustrate the concepts at hand.

With President Obama's "It's On Us" campaign, increasing numbers of young people contracting STIs, and increasing numbers of campus campaigns against alcohol use and sexual violence, there has never been more attention focused on these public health issues. We argue that social norms interventions can continue to contribute to their solutions; however in order to do so we must update the theory with tools from social networks and information diffusion.

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