A Computational Framework for Influence Networks: Application to Clergy Influence in HIV/AIDS Outreach

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¹Abstract— Strong social networks can encourage healthy behaviors. In this paper, we introduce a sociology-based computational framework for influence networks. The model construct is generic and is applicable to diverse social network analysis. We demonstrate its usage in calibrating the positive influence of church clergy in spreading HIV/AIDS information in a large metropolitan city. Five experiments are designed to contrast influence with respect to the interaction style between clergy and churchgoers. Competitive and non-competitive knowledge dissemination are also analyzed. The results show that when only one set of information exists, the spreading scope is directly proportional to the product of population size and the disease infection rate. When competing information is present, the importance of clergy in spreading the information decreases when the original propagation sources are ample. However, if sufficient interaction and trust are present among the clergy and the participants, the clergy's positive influence remains significant despite pre-existing knowledge. The generalized framework requires minimal regional data to establish the influence network. It provides useful policy insights for decision makers to determine effective avenues for information dissemination through community influencers.

Keywords—Sociology-based influence network, HIV/AIDS; influence calibration, influence optimization.

I. INTRODUCTION

Infectious diseases such as HIV/AIDS, tuberculosis and malaria pose challenges to global health. Although these contagious diseases have risen to the top of the international agenda in recent years, there remain major hurdles in combating and eradicating them effectively. In the United

States alone, more than 1.2 million people are living with HIV, with 1 out of 8 unaware of it [14]. Furthermore, statistics show that African Americans continue to bear the greatest burden of HIV: they represent 12% of the total population but account for 45% of the HIV diagnoses [14].

The spread of many of these contagious diseases can be mitigated through changes in human behavior. It is well-known that strong social networks can encourage healthy behaviors.

Realizing the importance of early intervention, the Centers for Disease Control and Prevention (CDC) and public health leaders design HIV outreach programs for early preventive measures and treatment, especially for the vulnerable population. Unfortunately, the HIV/AIDS stigma still asserts a significant barrier for people to voluntarily seek disease prevention and treatment information. Thus, public health practitioners seek various strategies to reach out to high-risk individuals to overcome this prejudice.

Exploiting strong social networks can help disseminate knowledge and shape positive health behavior. In particular religious community centers have long played significant roles in information dissemination. Hadaway et al. reported that about 20% of Americans go to church on a weekly basis [19]. In a survey conducted in 2007, Khosrovani, et al. concluded that for the highly vulnerable population, the involvement of churches in providing information and education is very crucial [21].

Although the importance of churches in spreading disease prevention knowledge and reducing the stigma has long been recognized, few investigations have been carried out to calibrate the value of the aid from church leaders. With only limited resources for congregational HIV/AIDS education programs, it is beneficial to identify influential churches and clergymen and effective outreach efforts.

II. RELATED WORKS AND OUR CONTRIBUTION

A. Related Works

Religion plays an important role in American life. Most Americans believe in a deity, three-fourths pray at least weekly,

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ASONAM '17, July 31-August 3, 2017, Sydney, Australia
© 2017 Copyright is held by the owner/author(s).
ACM ISBN 978-1-4503-4993-2/17/07.
<https://doi.org/10.1145/3110025.3125430>

and more than half attend religious services at least monthly [27]. Numerous studies focus on the influences churches and religious workers have on regular church attendants. Khosrovani et al. conducted a survey on African American churches in the metro Houston area in 2007 and concluded that although the attitude of churches has evolved over the last 25 years, the real disposition towards HIV remains passive and negative. On the other hand, 90% of church participants thought that churches should be involved in educating their congregation about HIV/AIDS prevention, helping ease the anxiety of HIV/AIDS carriers, and engaging high-risk individuals in counseling and seeking appropriate medical tests to learn of their health status [21]. Bluethenthal et al. found that while HIV and public health workers sought assistance from clergy (in Los Angeles County), educational outreach about HIV awareness and reducing HIV stigma were not high priorities for most religious congregations [24]. There are some positive findings as well. For example, Moore et al. reported that church leaders (in North Carolina) employed various approaches to communicate with congregants about HIV issues [4]. Religious leaders play an important role in society and can potentially have a broad impact on HIV education. With the aid of modern social media, clergy can communicate with many congregants simultaneously, and hence can potentially generate broad coverage and positive impact.

Graphs and networks have broad applications in science, engineering, mathematics and technology [8, 22, 28]. Within social science, early work of Newman et al. analyzed scientific collaboration networks where every researcher corresponds to a node, and two nodes are connected if the researchers coauthored a paper together [20]. Since the emergence of social networks and user data, there has been tremendous interest in the phenomenon of influence propagation [5, 7, 23]. Most of these studies require a social graph with edges labeled with probabilities of influence between users [3, 6]. Goyal et al. investigated where and how probabilities of influence between users were established from real social network data. The authors built models of influence from a social graph and a log of actions by its users using the Flickr data set consisting of a social graph with 1.3 million nodes, 40 million edges, and an action log consisting of 35 million tuples associated with 300 thousand distinct actions [2].

Besides these data-based approaches, notable results have been achieved in the field of sociology. Using a subset of the British population, Dunbar et al. first established the three social circle layers of individuals: the support clique, the sympathy group and the general acquaintance. He and his co-authors discussed the number of people in each group based on the number of kin and personality of the individual [25, 26]. Dunbar et al. also investigated how memory capacity and theory of mind are involved in determining the size of social circles [17].

B. Our Influence Network Design and Contributions

In this paper, we utilize sociology theory to design a general-purpose framework of a computational influence network. The model is flexible and can accommodate any type of data model analysis and model objectives. We present a scalable computational algorithm for determining a set of key

influencers who can assert the maximum influence/effect within the network.

To demonstrate its applicability, we apply our influence network model to the clergy HIV/AIDS education outreach in a large metropolitan city. The input includes a set of churches, the number of regular participants, and the regional HIV/AIDS infection rate, estimated by zip codes. Our model will rank the churches (hence their influence power) based on their capability of spreading HIV/AIDS information positively and successfully. The results show a tradeoff between choosing larger churches versus choosing the churches located at sites with higher HIV/AIDS infection rates.

The model can be applied to other contagious diseases and public health outreach, or in the analysis of news and/or information spreading (rumors or facts). Our approach offers some novel features: (i) While most research related to social network construction focuses on collecting the data from online sources and building the network based on the data, our approach does not rely on specific data. This enables modeling of the social network impact among all groups, including those that are not as active online. (ii) Although the importance of church for spreading information in certain communities has been recognized, there is little research focusing on calibrating its importance mathematically. Our study facilitates policy-and decision making.

III. METHODOLOGY

In this section, we first present the construction of a generic influence network model. The social network is a generalized framework that incorporates some fundamental sociology features. The influence model is then applied to calibrate the importance of church leaders in the HIV/AIDS outreach. In the model, we estimate the HIV/AIDS infection rate in each of the sub-regions covered by a church using zip code information. Finally, we simulate the effects of spreading educational outreach information within each church. We measure their influence based on the number of HIV/AIDS infected churchgoers who are influenced positively by the clergy-led HIV/AIDS educational outreach.

A. The Influence Network Construction

Our network consists of three elements: the node set N , the arc set A and the weights on the arcs $p(\cdot)$, which can be interpreted as the influence probabilities from the source nodes to the destination nodes. Here, the network is considered as directed: even though friendship is usually a mutual relationship. We note that the abilities for a friend pair to influence each other are sometimes different. This is especially true when one side is in a leadership role while the other is in a follower role. Given the number of nodes in a network, we can generate the set of arcs A and the influence probabilities $p(\cdot)$.

TABLE I SOCIAL NETWORK LAYERS AND THEIR SIZES

Layers	Mean	Std dev
Support clique	4.72	2.95
Sympathy group	11.6	5.64
General acquaintance	124.8	34.69

Dunbar et al. [25, 26] investigated the general social circle. The authors suggested that for most individuals, the social circle includes three layers: 1) *the support clique*, which only includes one's closest friends and certain kin. The individual would seek advice and help only within the support clique when facing difficulties; 2) *the sympathy group*, defined as all those whose sudden death would be upsetting, this is the principal group of one's social circle; and 3) *the general acquaintance*, these are the people that one would send a Christmas card. Table 1 shows the mean size, standard deviation for each of these three layers [25, 26].

Using the definition of these social circle layers, it can be deduced that one can assert only trivial influence on general acquaintance. In our construction, we first combine the support clique and the sympathy group together and assume that the combined group size is represented by a positive truncated normal distribution with mean μ and standard deviation σ . Specifically, let (μ_1, σ_1) and (μ_2, σ_2) be the mean and standard deviation of the support clique and the sympathy group respectively, then μ and σ of the positive truncated distribution satisfy $\mu = \mu_1 + \mu_2$ and $\sigma = \sigma_1 + \sigma_2$. Although the sum of two independent normal distributions is still normal, for positive truncated distribution this property does not hold. However, if we let $X_1 \sim N(\mu_1, \sigma_1)$, and $X_2 \sim N(\mu_2, \sigma_2)$, using the data in Table 1, we have $\Pr(X_1 < 0) = 0.055$ and $\Pr(X_2 < 0) = 0.020$. Hence the error of using the property of normal distribution herein would be quite small and acceptable.

The arcs in the support clique and those in the sympathy group will be distinguished when we generate the influence probabilities. Even though the arcs in our model are directed, friendship is usually mutual. Thus, we assign a value q to represent the percentage of arcs for which the relationship is mutual. When assigning arcs to a certain node v , we first consider connecting the nodes that are the source of an arc directed to v .

Research has also shown that in reality, people are more willing to build relationships with trustworthy partners and extroverted people tend to have a larger social circle [1, 9]. Thus, instead of generating a random number from the positive truncated normal distribution, we first generate a $U(0,1)$ random variable $S(v)$ to represent the trustworthiness and networking ability of an individual v ; we then use $F^{-1}(S(v))$ to find the number of outgoing arcs from node v . Here, F is the cumulative distribution function of positive truncated normal (μ, σ) distribution.

An arc (v_1, v_2) means that v_1 is able to influence v_2 with the probability $p(v_1, v_2)$. Given a set of nodes, Algorithm 1 generates the arcs and the resulting influence graph.

Algorithm 1: Influence Graph Construction

Input: Number of nodes n , mean μ and variance σ for the size of the support clique and the sympathy group.

Output: The arc set A (or the adjacency matrix A)

```

1 For each  $v$  in  $V$ :
2   Count=0;
3    $C = N^{in}(v)$  (The source of in-arcs of  $v$ )
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4   while (count <  $F^{-1}(S(v))$ ) {
5     if ( $C = \emptyset$ ) {
6       Uniformly randomly choose an unconnected node  $w$ ;
7       Generate  $u \sim \text{Bernoulli}(S(w))$ , if  $u=1$  then add  $(v, w)$  to
A and count++;
8     }
9     else {
10      Choose a node  $w \in C$ .
11      Generate  $u \sim \text{Bernoulli}(q)$ , if  $u=1$ , then add  $(v, w)$  to A
and count++; remove  $w$  from  $C$ ;
12    }
13  }
14 }
```

After generating the nodes, the influence probability on each arc is assigned. In our network, we only need to distinguish the arcs that represent the support cliques. To do this, a positive truncated normal distribution random number is used to fix the size of support cliques and then fit them into the existing arcs. We note that this algorithm generates a directed graph in which some of the weak relations in the social network are not included.

B. The Church Network

We apply our generalized social network to churches. First we divide the entire metropolitan area into divisions with each division centered on a megachurch. The geographical boundaries of the divisions can be represented spatially with known population information from actual census data. We divide the population in one parish into three groups:

- **Group 1 (The clergy):** This group represents the clergy in the church; they have a good reputation among church participants.
- **Group 2 (The regular church participants):** This group represents regular church participants. They usually go to church on a weekly or monthly basis.
- **Group 3 (Non-church participants):** This group represents the people who do not attend the center church on a regular basis, it includes people who never go to church and/or people attending other smaller churches.

To construct the specialized church network, we first construct the network between individuals in Group 2 and 3. Then we connect the clergy in Group 1 to church participants in Group 2. To account for uncertainties in the degree of influences clergy have on participants, multiple connecting methods can be explored. For example, we could connect each clergy to each participant, or we could first generate the number of clergy from which a participant is acquainted with; then choose among these the most influential clergy to connect to the participant. The transition probability on the arcs connecting Group 1 and Group 2 equals the probability on the arcs representing the support clique for weekly church participants and the arcs representing the sympathy group for monthly churchgoers.

TABLE II MODEL PARAMETERS

Parameter name	Value	Source
# of monthly participants/# of weekly participants	24/39	[12]
The rate of clergy/total population	0.002	[11]
Percentage of mutual friendships	0.9	assumption
Transition probability for support clique	0.2	assumption
Transition probability for sympathy group	0.05	assumption
Radius of the church influence circle	5 km	assumption
α in equation (1)	0.5	assumption

The independence cascade influence model, introduced by Goldenberg et al. in 2001 [15, 16], is chosen for our simulation. This model was mathematically investigated and used in influence maximization problem by Kempe et al. in [6].

Independent cascade model (IC): Given a weighted graph $G=(V,E)$ where the node set V represents the people in the social network and the directed arc set E represents the ability for the originating node to affect the end node. The weights $p(\cdot)$ on the arcs are the transition probabilities. Let the initial seed set be S_0 and for time $1 \leq t \leq T$, let S_t be the active set at t . At each t such that $1 \leq t \leq T$, for every inactive nodes $v \notin S_{t-1}$, each node $u \in N^{in}(v) \cap (S_{t-1} \setminus S_{t-2})$, u would initiate an activation attempt to v in the form of a Bernoulli trial with probability $p(u,v)$. If successful, v would be activated. Here, u is an in-node of v that was active at time $t-1$, but inactive at time $t-2$. Hence, in an IC model, each node would only perform the activation attempt to adjacent nodes once after they are activated. If the attempt fails, it would not try again.

Our experiments intend to i) prove (and confirm) that in the church clergy-participant network, the most influential nodes for maximizing the overall influence are the clergy nodes; and ii) evaluate the overall effects under various interactions. This will assist church clergy and decision makers in strategizing the rules of engagement with the participants to optimize their overall influence. The influence maximization problem can be formally stated as follow:

Influence maximization: Given a positive integer K , how to choose K nodes to form a seed set S such that the expected number of affected nodes denoted as $f(S)$, is maximized?

Kempe et al. proved that the influence maximization problem is *NP-hard* even for $K=1$ [6]. $f(\cdot)$ is called the influence function. The influence function for a set S is evaluated by Monte Carlo simulation. In each simulation, arcs are sampled based on their associated probability, then all the nodes that are still connected to S would be affected. Kempe et al. also proved that if the influence function is monotone and submodular, i.e. for any node sets $S \subseteq T$ and nodes $v \notin T$, we have $f(T) \geq f(S)$ and $f(S \cup \{v\}) - f(S) \geq f(T \cup \{v\}) - f(T)$, then the greedy algorithm which chooses the most influential node one by one until K nodes are chosen can give a solution whose influence function is greater than $(1-1/e)$ of the influence function of the optimal set. We use the lazy greedy method

improved by Leskovec et al. [18] to choose the most influential set.

We test three homogeneous models contrasting the different connection and interaction between clergy and participants. In model 1, each clergy member is connected to each participant. The subgraph connecting clergy and church participants is bipartite. In model 2, we randomly generate the number of clergy a participant knows and randomly assign them to an available clergy. The number of clergy a participant knows is a discrete uniform distribution from 1 to number of clergy. In model 3, each participant is only matched to one clergy member. This seems realistic since each churchgoer tends to have his/her trusted clergy. Each clergy member knows a binomial distributed number of participants. We also include two mixed / heterogeneous models (model 4 and 5). In model 4, the clergy and the participants are connected with equal proportion as in model 1, 2 and 3 respectively (i.e., 1/3 for each). In model 5, the mixing percentage of the three models are 25%, 25% and 50% respectively. In all models, only one kind of information is spreading on the network. In our test, the cardinality of our target set is equal to the number of clergy for each church. We run the test 1000 times for each church and take the average over the runs.

The test results show that the most influential set exactly contains all clergy members. The results are expected since clergy affect / influence many more people than others.

Fig. 3. shows the results for the 5 models. The two horizontal axes are the number of weekly participants and the HIV/AIDS density in the area where the church is located. The vertical axis shows the simulation results on the number of HIV/AIDS participants who are influenced / affected positively by clergy efforts in disseminating information. We observe that results from model 1 and model 2 are quite similar and the most effective, and the results from model 3 are the least effective. The mixed cases return results that are bounded above and below by model 1 and model 3, respectively.

Fig. 3. Affected HIV/AIDS population in each of the megachurches

In Fig. 4-6, we focus on the percentage of HIV/AIDS participants who are influenced / affected positively by clergy efforts across all the churches.

Fig. 4. shows the percentage of HIV/AIDS population influenced positively. The results show that regardless of the church population size, model 1 asserts the highest influence (55% versus 13% for model 3 respectively), due to the close relationship that participants have with each clergy. Model 2 (dark blue) shows that participants only need to know sufficient number of clergy (not all of them) to benefit from the outreach as well as in Model 1. Model 3 shows that if each participant only knows one clergy, the outreach will not be very successful. Mixed models probably present a more realistic connection pattern of the congregation. It is encouraging that they offer 27% to 43% positive outreach gain. These findings demonstrate that effective communication and interaction style must be explored to optimize clergy outreach efforts.

From these empirical results, especially results from model 1 and model 3, an interesting optimization problem will be *what is the minimal number of clergy that each participant should know / trust / interact in order for the outreach to reach its full potential (as in Model 1 and 2 results)?*

Our findings also suggest that regardless of the church size, the percentage of the HIV/AIDS population that is positively influenced remains rather steady. In fact, the percentage of all people (regardless of HIV/AIDS infection status) influenced by the church also remains relatively constant. If n denotes the population size in a certain church area with h the percentage of HIV/AIDS infected population; and p the size of HIV/AIDS population who are influenced positively at the end, our findings suggest that $p = \lambda n h$ for some positive scalar $\lambda < 1$. This leads to an interesting conclusion: we can estimate a rough ranking of the churches in any area by simply ranking the product of the number of participants and the HIV/AIDS infection rate in this area. Strategically, public health leaders can determine in this order the allocation of resources in reaching out to the churches.

Fig. 4. Percentage of positively affected HIV/AIDS population

B. Competitive Model

In reality, as with social media, where there are positive messages and misleading and/or negative messages, there may be opposite information countering the information that we want to spread. We would like to investigate the net effect of this competitive information messaging. We use a competitive independent cascade (CIC) model to model this competitive outreach environment. In a simplistic case, two types of information are labeled: one positive and one negative. The positive information is what we would like to spread and influence the community positively; while the negative information is countering our effort.

Each arc in the CIC model has two weights representing the positive and negative transition probabilities. Both follow the same transition rules as in the IC model. When a node is activated by both a positive attempt and a negative attempt, a proportional tie-breaking rule is applied to decide whether the node becomes positively or negatively affected. That is, if the sampling gives m positive arcs and n negative arcs to an inactive node v , v would become positive with probability $\frac{m}{m+n}$ and negative with probability $\frac{n}{m+n}$. Budak et al. [3] showed that when the positive transition probability equals to the negative transition probability for each arc, the influence function is still submodular and the Greedy method proposed by Kempe et al. [6] still applies.

There are usually stable groups holding the positive and negative opinions respectively. A node is said to be stable when it holds the positive or negative opinion before the information dissemination starts. In our simulation for the competitive model, we assume initially 1%, 5%, 10% and 15% population hold positive opinion while the similar number hold opposite opinion. Our aim is to compare the spreading effects with and without HIV/AIDS outreach by the clergy.

Fig. 5. contrasts the clergy effect against the rate of HIV/AIDS population that are positively influenced under the assumption of model 3 (that every participant only knows one clergy). When the endogenous percentages of people holding opposite opinions is relatively high (at 15%), the effect of the clergy outreach is minimal and dominated by the network effect of opposing stable groups. The clergy's influence becomes more significant when most participants have neutral opinion. When only one percent of population hold opposite opinion, the positive influence of the clergy has a two-fold increase. This affirms that religious leaders play an important role in society and can potentially have a broad impact on HIV education. We observe that the rates do not fluctuate much, showing that when other variables are fixed, the size of the church congregation does not play a leading role in the scope of information propagation. This again supports the linear relationship that we observe in the non-competitive case.

Fig. 6. analyzes the roles of the congregational workers as the size of the stable group varies. The horizontal-axis is the percentage of positive stable group in the population (same as the percentage of negative stable group) and the vertical-axis

is the percentage of HIV/AIDS population who are affected by positive information.

Recall that in model 4, 1/3 of the participants are connected to all clergy, another 1/3 of the participants are connected to a random number of clergy while the remaining 1/3 are connected to only one clergy. In model 5, the weights of the 3 become 0.25, 0.25 and 0.5.

The results for the 5 models without involvement of clergy (orange curves) are virtually identical. When clergy are not involved, the connection style is not important.

For the 5 models with clergy HIV outreach, model 1 and model 2 show a slight decreasing trend with respect to the stable group size. This means that in models 1 and 2 clergy are somewhat more influential when the stable group size is small. The gap between having clergy versus no clergy are very significant, although diminish as the size of the stable set increases. This clearly confirms the important role of clergy, especially when the church community is close-knit and participants and clergy know each other well.

Models 3, 4 and 5 show increasing trends, showing that clergy become important as the stable group becomes bigger. These models have looser interaction networks. This shows that when the participants have strong opinions, it starts to spill over with the clergy's outreach.

Contrasting the with (blue) and without clergy (orange) trend across all models, we can see from Fig. 6. that the gap between the two curves diminishes when the size of the stable set expands, which corresponds to our intuition that the importance of churches in spreading information decreases when the original propagation sources are ample. However, the positive role of clergy in disseminating knowledge remains significant (despite strong opinion) when participants know and interact with multiple clergy. The effect is most limiting when each participant only knows one clergy.

Fig. 5. Competitive model: Percentage of positively affected HIV/AIDS population with (solid curves) or without (dotted curves) clergy outreach (when each participant is connected to one clergy only)

Fig. 6. Competitive model: Percentage of affected HIV/AIDS population for the largest church in Atlanta. The x-axis corresponds to the endogenous percentage of people holding positive (and negative opinions).

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we propose an approach to rank churches based on their capability to spread HIV/AIDS information when limited data is available. Since the resources that public health leaders have for church educational programs are limited, choosing the sites to affect the maximum (positive) influence is practical and essential. Although we focus on HIV/AIDS experiments in our validation, the computational framework is generic and is applicable to diverse social network analyses, including public health disease trending and/or in spreading social or other information.

The method presented has three novelties. First, it builds a generalized influence network based on sociological human behavior theory. The model does not require specific group data and/or a local social network construct. Second it estimates the disease infection rate through spatial and census information. Third, it models the network effect among all people (clergy and participants) by coupling sociology theory of social circles. The computational algorithm simulates combination network effect and measures the net positive outcome.

We implement and analyze the model for effective HIV/AIDS knowledge dissemination for 12 megachurches in the city of Atlanta. When no competing information is present, we discover that while different connection/interaction structures between clergy and regular church participants would affect the degree of knowledge spread, the percentage of HIV/AIDS infected people who would eventually learn the disease information with the help of the church stays constant, regardless of the church size.

The same results apply to the competitive model (when both positive and negative information exist among the participants and the population). Thus, one can design a rough ranking by simply ranking the product of the church size and the local HIV/AIDS infection rate. This offers a practical policy for public health HIV intervention and education.

When there is competing information, it becomes clear that clergy assert more significant (and positive) influence among church participants when the church community is close-knit and participants know multiple clergy. Even when each participant knows only one trusted clergy, clergy does play an important role in the information spread, and their significance is more evident when the strong opinion group is small. Churches can organize social activities to facilitate active participants' interaction to a broad group of church members to optimize their effect. When participants interact with multiple churches, the overall impact of clergy in promoting HIV/AIDS knowledge becomes more significant.

Compared to previous results for influence networks, our algorithm is scalable and can be used to analyze any population size. We are currently exploring network effect in marketing and in investor and consumer choices.

ACKNOWLEDGEMENT

This work is partially supported by a grant from the National Science Foundation (IIP- 1361532).

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