What Becomes of the Broken Hearted?

An Agent-Based Approach to Self-Evaluation, Interpersonal Loss, and Suicide Ideation

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ABSTRACT

Social surroundings greatly affect how we perceive ourselves. Examining the network of social relations may help us reveal important information about our psyche. We build on this idea and propose a model that is consistent with social psychological theories and connects individuals' emotional states with their social relations. The model consists of a social network of agents. Using a centrality-based measure of self-evaluation, the model quantifies the amount of interpersonal loss experienced by agents as their social relations change. Applying this model, we analyze interpersonal loss of agents in standard network structures under different conditions. We then draw a link to suicide and discuss two real-world suicide incidents. Finally, we simulate dynamics of large random networks and investigate how network structures affect suicide ideation and its possible cascades.

Keywords

Social network; self-evaluation; interpersonal loss; suicide; agent-based model; ego network

1. INTRODUCTION

Social relations greatly shape our roles as individuals in the society. Important personal attributes – such as statues, identity, and self-worthiness – may all be understood through observing our relationship with others. A major part of our daily activities thus involves cultivating and preserving ties with others. Inevitably, social relations evolve as life circumstances change. We feel uplifted when forging new links, while feeling hurt when losing existing bonds. An important question then arises: *How is our emotional state affected by the changing social relations?*

One can approach this question from two perspectives. Firstly, there is a micro perspective which focuses on the impact of social surroundings to an individuals' mental state. This perspective consists of a long line of studies in psychology [34]. As suggested by both theoretical analysis and empirical evidence, mental health and social relations are closely linked; the risk factor that social isolation and the loss of social relations poses to a person's health is comparable to common risk factors such as smoking, alcohol consumption and obesity [26, 25, 7, 15, 40].

Secondly, there is also a macro perspective which focuses on the complex network of interpersonal ties. The key question here is how the structure of our social network may give rise to collective behaviors and social facts. Sociology has long been studying the complex social networks and its dynamics since the pioneering works of Himmel, Durkheim and Moreno [19, 43, 33, 22]. More recently, studies on complex social networks has been incorporated into the new paradigm of *network science*, with a stronger emphasis on simulations and predicative modeling [35, 47, 20]. A current theme in this endeavor concerns with promoting health and well-beings through network analysis [12, 13].

In this paper, a third pathway is adopted; We aim to bring both directions above together by theorizing the link between the micro and the macro perspectives. Agent-based models provide a natural venue for such an investigation: One can build a network of agents who are able to perceive their social relations and internalize their surroundings into emotional states. Such a model will help us to understand how structural changes in social network affect self-reflection and give rise to emotional loss. More importantly, our model also provides a link to suicide ideation.

Suicide is one of the most serious global problems nowadays, accounting for around one million casualties globally per year [41]. In the US, suicide is the leading cause of injury mortality, surpassing motor vehicle crashes [36]. Studies on suicide sits at the confluence between psychology and sociology. Durkheim first addressed suicide from a social perspective and pointed out that factors such as integration, religion and family greatly impact on suicide [18]. Several suicide models have been proposed [9, 29, 42, 6]. Despite decades of intensive research, suicide remains challenging; deriving a overarching theory that fits all existing evidences while being useful in detection and prediction is extremely difficult due to the problem's complex nature [14].

We summarize the main contribution of the paper:
(1) We present an agent-based model on a dynamic social network which captures i) agents self-evaluation; and ii) their interpersonal loss due to structural changes.
(2) We mathematically analyze our model in several standard social structures (See Sec. 3).

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(3) We draw a link among network dynamics, interpersonal loss and suicide ideation and analyze this link on two real-world suicide incidents. Through the case studies, we also demonstrate a mechanism in which suicide behaviors might cascade through a social network (See Sec. 4).
(4) We simulate our model on a number of random network models in the hope of discovering attributes and patterns with predictive value (See Sec. 5).

Background and Related Work. Our model is consistent with several established theories in social psychology.

Firstly, Zubin and Spring's stress-vulnerability model states that a person's mental states are controlled by the dual effect of stressful life events and inherent vulnerability [49]. Bonner and Rich further extended this model to suicide and tested it using real suicide data [10, 39]. Our model naturally captures this dual effect: stressful life events are reflected in changes to social ties, while vulnerability is embodied by self-loops on agents (see below).

Secondly, Tesser's *self-evaluation maintenance model* addresses the intimate relation between people's reflections on themselves (self-evaluation) and their relations [45]. Here self-evaluation is largely defined through social interactions; People will try to maintain their self-evaluation through social interactions. In fact, *homeostasis*, a much earlier concept proposed by Stagner, already characterized people's mental states by certain equilibria; Evaluation of oneself, or ego, should be kept at a certain *perceptual constancy* which, if disturbed, will lead to tension and mental breakdown [44].

Thirdly, Durkheim's theory of suicide presents social relation has a major factor in suicide; Societies where people are loosely connected (e.g. Denmark) tends to have a higher rate of suicide than societies where people are closer (e.g. Italy) [18]. Recently, Bearman and Moody studied relations between social isolation and suicide in teenagers [8]. The interpersonal theory of suicide attempts to explain suicidal thoughts as the outcome of several factors that could be measured in the context of social relations [27, 38]. This paper presents a computational realization of this theory through a network-based formalization.

Lastly, we mention several recent related works on suicide that adopted a data-driven approach: [48] applies linear regression between suicide rate and other personal attributes; [1] describes an auto-detection system of suicide-risky behaviors on Twitter using text classification and mining techniques; [16] focuses on the spread of suicidal ideas among Twitter users also using text mining; [5] analyzes data of suicide attempts in Korea using decision trees. This paper differs from all these works in that an agent-based approach is adopted. Nevertheless, it would be an interesting future work to incorporate the agent-based and data-driven approaches to provide prediction systems of suicide behaviors.

2. THE MODEL

Our model consists of a population of networked agents who are able to perceive and internalize social surroundings.

Definition 1. A *social network* $G = (V, E, w)$ consists of a set V of agents who are connected by directed edges $E \subseteq V^2 \setminus \{(u, u) \mid u \in V\}$ which represent interpersonal ties; a *weight function* $w : E \to [0, 1]$ assigns a real-valued weight to each tie $(u, v) \in E$.

The highest weight $w(u, v) = 1$ implies that u is strongly attached to v while smaller weights indicate weaker attachments. If $(u, v) \in E$ we say that u, v are *adjacent*; we use N_v to denote the set $\{v\} \cup \{u \mid (u, v) \in E \text{ or } (v, u) \in E\}$.

We need a notion that captures how agents internalize their own value within their social surroundings. More specifically, we define *self-evaluation* as a measure of how high an agent perceives its own social position, i.e., how much value the agent perceives in itself within its own social circle.

In order to obtain self-evaluation, agents must perceive their social surroundings, that is, any agent $v \in V$ has knowledge about all adjacent agents as well as ties between them. For each $v \in V$, we define a set of edges $E_v = \{(u, v) \in E \mid u \in N_v, v \in N_v\} \cup \{(v, v)\}$. Note that E_v includes a loop (v, v) which is not present in E; this loop will be used to capture the attention that v pays to itself.

Definition 2. The *ego network* of v is $G_v = (N_v, E_v, w_v)$ where the weight function $w_v : E_v \to [0, 1]$ is defined by $w_v(e) = w(e)$ for any $e \in E_v \cap E$ and $w_v(v, v) = a$ for a fixed value $a \in [0, 1]$. Here v is called the *ego* in G_v and any other node $u \in N_v$ is called an *alter*.

The value a in the definition obviously depends on the agent v. In a sense it measure the agent v's inherent *vulnerability*; a lower value of a means that the agent v is more vulnerable. The ego network has been intensively investigated [11, 30]; It embodies an agent's subjective view of its social surroundings, and thus should be used as a basis when calculating the emotional states of the agent [24].

The self-evaluation of an agent v depends on social relations in G_v. A higher number of attachments to v boosts v's self-evaluation, while a lower number worsens self-evaluation. Based on this idea, to define self-evaluation, we imagine that each agent in the ego network gives out an amount of "support" to adjacent nodes. The amount of attention sent along an edge depends on the edge weight. More formally, let $c(u)$ denote the amount of attention held by any agent $u \in N_v$, then

$$c(u) = \frac{1}{\lambda} \sum_{(u', u) \in E_v} w(u', u)c(u') \tag{1}$$

where $\lambda \in \mathbb{R}$ is a constant. In other words, if we let M denote the weighted adjacency matrix of the ego network G_v and let $\vec{c}$ denote the vector $(c(u_1), \ldots, c(u_k))$ where $u_1, \ldots, u_k$ represents a fixed enumeration of N_v, then $\vec{c}M = \lambda\vec{c}$. Thus $\vec{c}$ is an eigenvector of the matrix M corresponding to the eigenvalue λ. Here we pick λ as the largest eigenvalue in terms of absolute value, i.e., the *dominating eigenvalue*; this value is important as it reflects a *collective gain* of the ego network G_v. We further assume that the total amount of attentions equals λ, i.e.,

$$\sum_{v \in N_v} c(v) = \lambda \tag{2}$$

The above definition $\vec{c}$ coincides with the notion of *eigenvector centrality* in the weighted network G_v [2]. There is, however, a crucial difference between centrality and $\vec{c}$: While centrality measures the position of nodes in the global network, here the vector $\vec{c}$ is calculated within the ego network which is subjectively defined for the agent v. In this way, $\vec{c}$ reflects not centrality but rather v's subjectivity.

Definition 3. The *self-evaluation* of the ego v is $\varepsilon(v) = c(v)$, v's eigenvector centrality in its ego network G_v.

Note that the self-evaluation of v depends on the structure of the current social network G. As G changes, the self-evaluation may also change. We consider changes to a social network as discrete events. Such changes may be the addition or removal of agents or ties between agents, or change to weights of existing ties.

Let G be the starting network and G' be the changed network. Correspondingly let $\varepsilon(v)$ denote the self-evaluation of v prior to the change and $\varepsilon'(v)$ after the change. As the ego network changes, $\varepsilon'(v)$ may be reduced.

Definition 4. The *interpersonal loss* experienced by v during the change from G to G' is $\gamma_{G,G'}(v) = 1 - \frac{\varepsilon'(v)}{\varepsilon(v)}$ if $\varepsilon'(v) < \varepsilon(v)$, and 0 otherwise; if the networks G and G' are clear, we omit the subscript writing simply $\gamma(v)$.

The interpersonal loss $\gamma(v)$ captures a negative change in the emotional state of v as the social structure evolves from G to G'. If $\gamma(v)$ is positive, it means that v has a lower self-evaluation in the new social structure.

3. STANDARD SOCIAL STRUCTURES

We use a few examples to illustrate self-evaluation and interpersonal loss defined above and mathematically analyze these notions on standard network structures.

3.1 Dyads

A *dyad* is a network consisting of two agents v, u with mutual ties. We set $w(v,u) = 1$ and $w(u,v) = \ell \in [0,1]$. This means that v is fully attached to u and the parameter ℓ represents how much u attaches to v. The adjacency matrix of the ego network of v is $M_{\mathsf{dyad}} = \begin{bmatrix} a & 1 \\ \ell & 0 \end{bmatrix}$. We are then able to compute the self-evaluation of v. The dominating eigenvalue of M_{dyad} is $\lambda = 1/2(a+\sqrt{a^2+4\ell})$. An eigenvector corresponding to λ is (λ, ℓ). Applying the fact that $c(u) + c(v) = \lambda$, we get

$$\varepsilon(v) = \frac{\lambda^2}{\lambda+\ell} = \frac{a^2+2\ell+a\sqrt{a^2+4\ell}}{a+2\ell+\sqrt{a^2+4\ell}}.$$

We now fix a scenario for a possible change to the dyad: Suppose the value of $w(u,v)$ in the dyad drops from ℓ to 0. In other words, this scenario assumes that the bond from u to v diminishes. As a result of this change, v naturally experiences interpersonal loss. This is consistent with our calculation: The interpersonal loss experienced by v is

$$\begin{aligned}\gamma(v) &= 1 - \frac{\varepsilon'(v)}{\varepsilon(v)} = 1 - \frac{a^2+a^2}{a+a} \div \frac{a^2+2\ell+a\sqrt{a^2+4\ell}}{a+2\ell+\sqrt{a^2+4\ell}} \\ &= \frac{2\ell(1-a)}{a^2+2\ell+a\sqrt{a^2+4\ell}}\end{aligned}$$

Fig. 1 displays the self-evaluation and interpersonal loss of v in the scenario above. A larger ℓ or a implies a higher self-evaluation of v; $\varepsilon(v)$ varies considerably with changing ℓ when a is large. In general, a smaller a leads to a higher interpersonal loss; when a is small, even very small drop on ℓ leads to a large $\gamma(v)$. Thus a reflects a kind of 'vulnerability' of v: The lower a gets, the higher an impact will be felt by the ego due to social relation changes; This is consistent with the vulnerability-stress model [49].

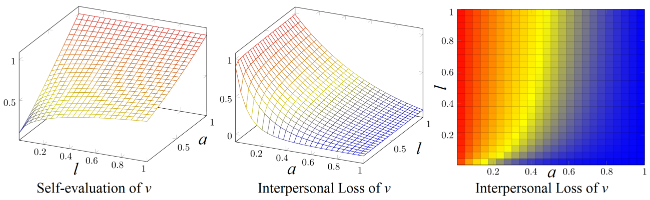

Figure 1: Self-evaluation and interpersonal loss of ego in a dyad with $a \in [0,1]$ and $\ell \in [0,1]$.

3.2 Triads

A *triad* consists of three agents v, u, s. Triads form a fundamental social structure intensively studied in sociology. *Triadic closure*, a long established principle, states that when strong ties exist between v and both u and s, u and s tend to form a (strong or weak) relation [20, 23]. Here we provide an alternative interpretation of this principle from the point of view of v. Suppose that the three agents start off strongly attach to each other, but then the relation between two of them, say u and s, is cut. By triadic closure, it is reasonable that the third agent v will experience interpersonal loss (i.e., a latent stress) as a result of this change.

Guided by this intuition, we fix the following setup: Let $w(v,x) = w(x,v) = 1$ for $x \in \{u,s\}$, and let $w(u,s) = w(s,u) = \ell$. The adjacency matrix of the ego network of v in the triad is

$$M_{\mathsf{tri}} = \begin{bmatrix} a & 1 & 1 \\ 1 & 0 & \ell \\ 1 & \ell & 0 \end{bmatrix}.$$

This matrix has dominating eigenvalue

$$\lambda = \frac{a+\ell+\sqrt{(a-\ell)^2+8}}{2}. \tag{3}$$

An eigenvector corresponding to eigenvalue λ_1 is $(1/(\lambda - a), 1, 1)$. Since $c(v) + c(u) + c(s) = \lambda$, we have

$$\varepsilon(v) = \frac{2\lambda/(\lambda-a)}{2/(\lambda-a)+2} = \frac{(a+\ell)+\sqrt{(a-\ell)^2+8}}{\sqrt{(a-\ell)^2+8}-a+\ell+2}.$$

We can now quantify the amount of interpersonal loss experienced by v as ℓ drops to 0. The interpersonal loss experienced by v is

$$\gamma(v) = 1 - \frac{(a^2+4+a\sqrt{a^2+8})(\sqrt{(a-\ell)^2+8}-a+\ell+2)}{4((a+\ell)+\sqrt{(a-\ell)^2+8})}$$

Fig. 2 plots the self-evaluation and interpersonal tie of v with varying values of $a \in [0,1]$, $\ell \in [0,1]$. For small a, a larger ℓ leads to mild increase in self-evaluation of v. The interpersonal loss is especially evident (more than 10%) when a is small (meaning that v is vulnerable) and ℓ is large (meaning that u, s start off closely bonded). The interpersonal loss, however, gets smaller as a increases.

3.3 Star Networks

An *n-star* consists of $n+1$ agents $v, u_1, \ldots, u_n$; here v is the ego and connects to u_i via mutual ties, while no tie exists between any pair of u_i's. We fix $w(v, u_i) = 1$ for all $1 \le i \le n$ and let $w(u_i, v)$ be a variable $k \in [0,1]$; the variable a is $w(v,v)$.

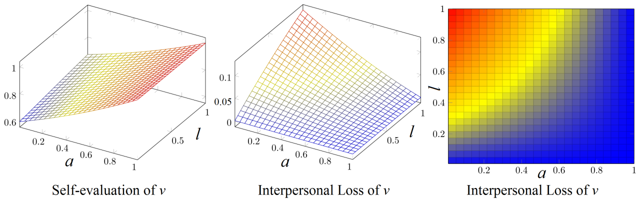

Figure 2: Self-evaluation and interpersonal loss of ego in a triad with $a \in [0,1]$ and $\ell \in [0,1]$.

THEOREM 1. *The self-evaluation of v in an n-star is $\frac{\lambda^2}{\lambda+n}$ where $\lambda = \frac{1}{2}a + \sqrt{a^2+4nk}$.*

PROOF. The adjacency matrix of an n-star is

$$M_{\mathsf{star}} = \begin{bmatrix} a & 1 & \cdots & 1 \\ k & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ k & 0 & \cdots & 0 \end{bmatrix}$$

To compute the eigenvalue λ, we compute the determinant of $A = M_{\mathsf{star}}^{\mathrm{T}} - \lambda I_{n+1}$ where I_{n+1} is the identity matrix:

$$\det(A) = \det\left(\begin{bmatrix} a-\lambda & k & \cdots & k \\ 1 & -\lambda & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 1 & 0 & \cdots & -\lambda \end{bmatrix}\right)$$
$$= \sum_{\sigma \in S_{n+1}} \operatorname{sgn}(\sigma) \prod_{i=1}^{n+1} A_{i,\sigma_i}$$

where S_{n+1} is the set of permutations of $\{1,\ldots,n+1\}$, $\sigma \in S_{n+1}$ is a permutation with sign $\operatorname{sgn}(\sigma) \in \{-1,1\}$ and A_{i,σ_i} is the (i,σ_i)-entry of matrix A.

We now analyze all non-zero terms $\Pi_{i=1}^{n+1} A_{i,\sigma_i}$ in the determinant $\det(A)$: Such a term is either the product of all diagonal entries $(a-\lambda)(-\lambda)^n$, or $A_{i,1}A_{1,i}(-\lambda)^{n-2} = k(-\lambda)^{n-2}$ for some $2 \leq i \leq n+1$, which corresponds to the permutation $(i, 2, \ldots, i-1, 1, i+1, \ldots, n+1)$. This is an odd permutation and thus has sign -1. Overall, we get

$$\det(A) = (a-\lambda)(-\lambda)^n - nk(-\lambda)^{n-1}. \tag{4}$$

The required λ satisfies $(a-\lambda)(-\lambda)^n - nk(-\lambda)^{n-1} = 0$. The (non-zero) dominant eigenvalue thus satisfies

$$(a-\lambda)(-\lambda) - nk = 0. \tag{5}$$

Thus the dominant eigenvalue is $\lambda = \frac{1}{2}a + \sqrt{a^2+4nk}$. An eigenvector that corresponds to λ is $(\lambda, 1, \ldots, 1)$. Setting $c(v) + c(u_1) + \cdots + c(u_n) = \lambda$, we obtain

$$\varepsilon(v) = c(v) = \frac{\lambda^2}{\lambda+n} \tag{6}$$

as required. $\square$

We now fix the following scenario: Suppose all alters u_i start off attaching to v with weight 1 (i.e., the ego and alters are strongly mutually bonded), but then $w(u_i, v)$ drops to $k \in [0,1]$. We calculate the interpersonal loss experienced by v for three fixed values of $a = 0, 0.5, 1$ using k and n as parameters; See Fig. 3. As expected, as k gets smaller, v experience a higher interpersonal loss. For any fixed value of n, the interpersonal loss is roughly proportional to k. Furthermore, when n is small, the interpersonal loss is significantly smaller when a is larger.

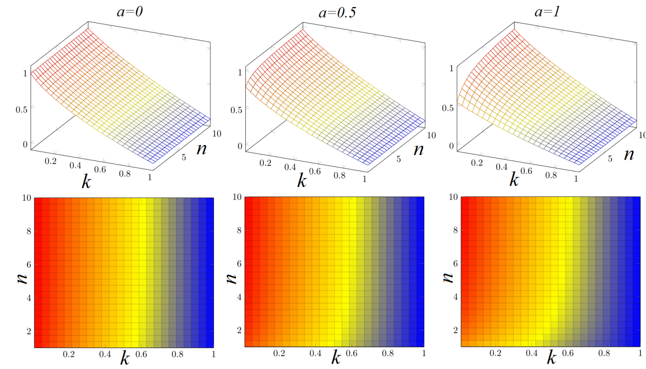

Figure 3: Interpersonal loss experienced by v in an n-star when the weight of the ties from alters to v changes from 1 to $k \in [0,1]$. The figure shows respectively the cases when $a = 0, a = 0.5, a = 1$.

3.4 Complete Networks

A *complete network* is a tightly-knitted social group that contains an edge between any pairs of agents. Consider a complete network containing $n+1$ agents $v, u_1, u_2, \ldots, u_n$. Let's also assume that the (positive) weight of any edges between two different agents are the same, which is denoted by ℓ. Furthermore, assume $w(v,v) = 0$.

We now fix the following scenario which we call $\mathsf{downsize}$: Start from the complete network. Pick one agent u_n and change the weights of the ties between u_n and all other agents to 0; this may be due to the fact that u_n has left the group, resulting in the group reducing its size by one person. Naturally we would expect that v will experience an interpersonal loss due to $\mathsf{downsize}$. It turns out that the amount of this interpersonal loss does not depend on the weight ℓ, and is in an inverse-square relation to n.

THEOREM 2. *The interpersonal loss experienced by v due to the process* $\mathsf{downsize}$ *is n^{-2}.*

PROOF. The adjacency matrix of the complete network with $n+1$ agents is the $(n+1) \times (n+1)$ matrix

$$M_{\mathrm{K}} = \begin{bmatrix} 0 & \ell & \cdots & \ell \\ \ell & 0 & \cdots & \ell \\ \vdots & \vdots & & \vdots \\ \ell & \ell & \cdots & 0 \end{bmatrix}$$

Note that all nodes in this ego network would get the same centrality, and thus the eigenvector $\vec{c}$ that we look for is $\vec{c} = (c, c, \ldots, c)^{\mathrm{T}}$ for some $c \in \mathbb{R}$. Since $M_{\mathrm{K}}^{\mathrm{T}}\vec{c} = (n\ell c, \ldots, n\ell c)^{\mathrm{T}} = n\ell\vec{c}$, the eigenvalue $\lambda = n\ell$ and the self-evaluation is

$$\varepsilon(v) = \frac{n\ell}{n+1}.$$

After $\mathsf{downsize}$, as the updated network contains n agents, the updated self-evaluation of v is $\varepsilon'(v) = \frac{(n-1)\ell}{n}$.

Hence the interpersonal loss is $\gamma(v) = 1 - \frac{\varepsilon'(v)}{\varepsilon(v)} = 1 - \frac{n^2-1}{n^2} = n^{-2}$. $\square$

4. A SOCIAL ASPECT OF SUICIDE

Our next goal is to develop a link from interpersonal loss to suicide ideation. We hypothesize that suicidal thoughts arise from an excessive level of interpersonal loss. This hypothesis is supported by several guiding principles. The first principle is that social relation amounts to an important factor in suicide ideation. The second principle, as supported by the stress-vulnerability model, states that suicide ideation is influenced by both stressful life events and agents' inherent vulnerability. The third is that stressful life events, such as breaking-up with partners or loss of loved ones, are often reflected by changes to social relations. To analyze our hypothesis, we discuss two real-world suicide incidents.

4.1 Incident I: The Suicide of Jiang Yan

Background. *The suicide of Jiang Yan* is a high-profile incident in China, attracting much attention of both domestic and international medias in 2008 [1]. The incident involves 31 years-old Jiang Yan, an office worker in Beijing, discovering an adultery affair between her husband, Wang Fei, and one of his office mates. This was followed by a painful break-up and conflicts between the Jiang and Wang families, which ended in Jiang committing suicide on December 29, 2007 by jumping off from a 24-story building. During the last two months of her life, Jiang documented her husband's infidelity and her emotional turmoil in her online blog (on the now defunct MSNSpace). The disturbing blog – referred to as the "death blog"– was made public days before her suicide which was widely circulated through Chinese online social medias posthumously [17]. This incident triggered a big Internet phenomenon, arousing huge public anger, condolence, and debates on moral values and marriage.

While it is undeniable that Jiang's suicide is directly attributed to her husband's infidelity, we would like to understand the cause of the suicide from a computational perspective and provide a quantifiable explanation.

Methodology. We analyze Jiang's death blog which contains detailed accounts of her daily life in her last days. The blog mentioned 27 individuals who interacted with Jiang in various ways during the period. Apart from Wang and his mistress, the people mentioned were either relatives or friends of Jiang and Wang. We assume mutual ties between family members of Jiang, and also between family members of Wang. We assume ties between the friends only when the blog explicitly states so. We classify ties into three types: strong, weak and awareness ties. Strong ties exist between close relatives such as between Jiang and her parents and her sister. As Jiang's husband Wang is a persistent source of her misery, Jiang has a strong tie towards Wang; However the relation may not be mutual. To any acquaintance whom Jiang did not interact with in a specific period but is surely recognized by Jiang, we draw an awareness tie; this represents a weaker form of tie than the weak ties. Notice also that the classification of ties are not necessarily objective but are made from the subjective view of the ego, Jiang.

The temporal nature of the blog allows the analysis of network dynamics. We divide the period into four stages which reflect major shifts to Jiang's social relations. The first stage (Oct. 28) is when Jiang just became aware of the affair. Jiang and Wang still enjoyed mutual strong ties. The second (Oct. 29 – Nov. 11) is when Jiang and Wang had several confrontations until Wang moved out from their apartment. Here the relation from Wang to Jiang became a weak tie. The third (Nov. 12 – Dec. 20) is when Jiang lived alone and gradually lost contact with her friends. It is evident that by this stage, Jiang had seriously considered committing suicide, yet she still kept regular interaction with her work mates. The fourth (Dec. 21 – Dec. 27) is when Jiang started her holiday and spent the days either visiting family or shutting herself out from the outside world. This stage immediately precedes her death.

For each stage above, we construct an ego network of Jiang. In the networks, we assign a weight of 1 to all strong ties, and a variable weight ℓ to all weak ties. We assume a weight of 1/2 to the self-loop on Jiang herself. See Fig. 4. In each network, undirected edges represent mutual weak ties. The grey nodes indicate those agents to whom Jiang has an awareness tie; The weight of an awareness tie is set to 0.1.

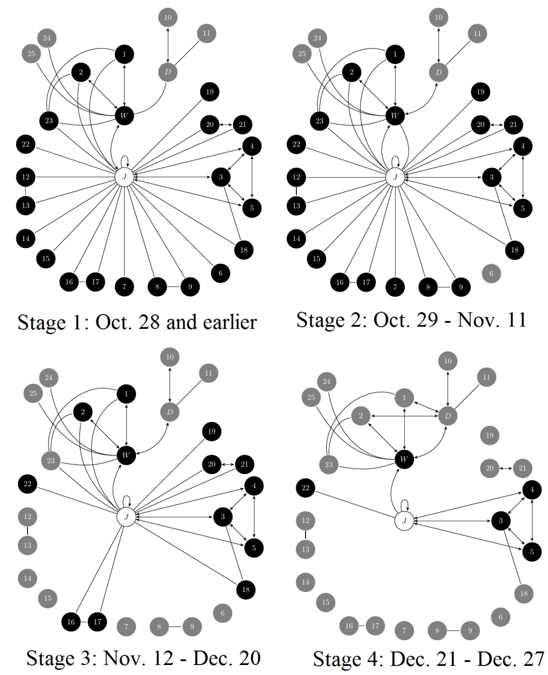

Figure 4: Jiang Yan's ego network in four stages from Oct. 28 to Dec. 27, 2007. The white node in the middle of each graph is Jiang.

Results. Using the power iteration method, we are able to compute eigenvalues for all networks above to obtain self-evaluation of Jiang. We then measure the interpersonal loss experienced by Jiang at each stage where the self-evaluation in that stage is compared against Stage 1. Fig. 5 displays the self-evaluation and interpersonal loss across all four stages, and with varying values of the parameter ℓ. As shown by the figure, Jiang's self-evaluation consistently and significantly dropped as her life progressed from Stage 1 to Stage 4, resulting in a high (around 0.7) interpersonal loss during these two months for any values of $\ell \in [0, 1]$. The result thus suggests a strong evidence that excessive levels of interpersonal loss amount to a potential cause to suicidal ideation.

[1] https://zh.wikipedia.org/wiki/%E5%A7%9C%E5%B2%A9 %E8%87%AA%E6%9D%80%E4%BA%8B%E4%BB%B6 (in Chinese)

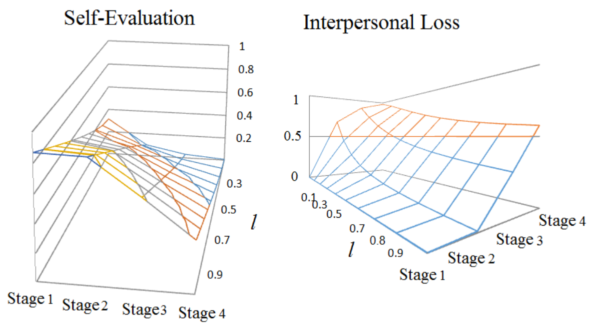

Figure 5: Jiang Yan's self-evaluation and interpersonal loss across all four stages. ℓ indicates the weight of the weak ties.

4.2 Incident II: The Case at Shuangcheng

Background. *The Case at Shuangcheng* is a story reported by Chai Jing, a renowned Chinese journalist, in her collection of autobiographic investigative reports "*Kanjian* (Insights)[2]". Shuangcheng is a small rural village situated in the remote Gansu province. In May 2003, a group of five close friends in a local elementary school aged between 13 and 14 consecutively attempted suicide by taking pesticide during a four-day period; four children subsequently survived the incident. Interviews of the local residents and the survivors revealed that the incident started when a girl in the group, Miao, was bullied at school, publicly humiliated by her boyfriend, Yang, and then took her own life. This was followed by the attempted suicide of her nearest friend, Cai and two days later, another friend Sun. A fourth child, Ni, who considered Sun as her best friend, committed suicide the next day. Miao's boyfriend Yang, having been interrogated by police after Miao's death, committed suicide a day later. Due to silence of the survivors, the exact reason behind the series of suicides remains mysterious to this day.

Methodology. The story involves several interrelated suicides incidents. After one person attempted suicide, we hypothesize that the interpersonal loss experienced by others may trigger subsequent suicidal behaviors, leading to further network changes. As such process cascades through the network, we theorize the "spreading effect" of suicide ideation from a network perspective, which has been the subject of intensive debates in social sciences [4].

To define the networks, we carefully examine the investigative report by Chai Jing, and order the victims according to the time of their suicide. We consider only the first four, Miao, Cai, Sun, Ni, for whom we are able to extract ego networks. We assign strong ties between the children with their close family members and identify several strong ties between the children. All the children have expressed strong attachments and empathy towards Miao, who was the first to commit suicide. Fig. 6 displays the ego networks of all four children. For Miao, we show her ego networks before (i.e., the initial stage) and after she was bullied at school. For each other child, we show the initial ego network and the network after the previous child committed suicide.

[2]`https://en.wikipedia.org/wiki/Chai_Jing`

The directed edges represent strong ties and the undirected edges represent mutual weak ties. The persons who have committed suicide are shown in grey, to whom we assume an awareness tie from the ego.

Results. Note that each person's ego network is modified by the suicide of the previous person, and this affects the ego's self-evaluation. We calculate the self-evaluation of all four children from the first stage (before Miao's bullying) to when the child committed suicide. As in the previous case study, the strong ties have a weight of 1, while the weak ties have a weight of ℓ. The self-loop has a weight 0.5. The interpersonal loss at any stage is computed by comparing self-evaluation of that stage with the first stage. Fig. 7 displays the interpersonal loss of all four children when $\ell = 0.2, 0.5$. It is clear that the children consecutively experience high levels of interpersonal loss just before committing suicide; the rise of interpersonal loss is clearly attributed to previous suicides of others. Moreover, this effect is especially evident when ℓ is relatively low, when the interpersonal loss of all children all reach 50% or higher.

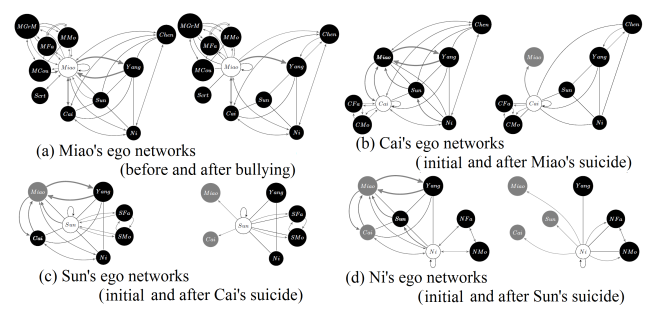

Figure 6: The ego networks of the children who committed suicide. The white node is the ego.

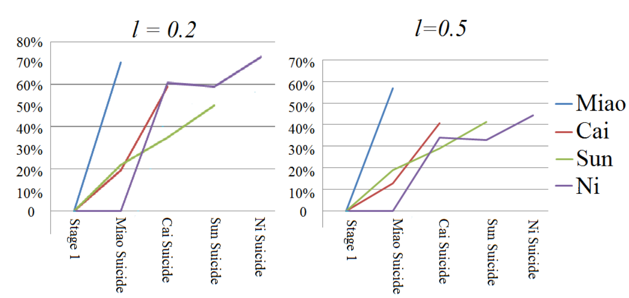

Figure 7: The interpersonal loss of the children who committee suicide in different stages, with $\ell = 0.2, 0.5$

Summarizing the two case studies discussed, we posit the following properties that link interpersonal loss with suicide:

1. Suicide ideation may be affected (or caused) by high levels of interpersonal loss; and
2. While it is common knowledge that suicide spreads, the exact mechanism of spreading is largely unclear. Merely exposure to suicide activities does not necessarily lead to suicide of an individual [31]. This work illustrates a sociological tradition where suicide is not contagious, but rather cascades due to structural changes.

5. SIMULATIONS AND EXPERIMENTS

Our next goal is to investigate how social network influence suicide ideation. In particular, we want to pinpoint structural properties with potential predictive value on suicidal behaviors. The link between interpersonal loss and suicide allows us to simulate suicidal behaviors on networked agents. Our underlying assumption is that *interpersonal loss can be seen as an estimate of the probability of suicide.*

The simulation comprises the following steps: Firstly a random social network is generated. Then a scenario changes the network structure in a certain way, affecting agents' self-evaluation. Agents' interpersonal loss imply how likely they will commit suicide, which may trigger more structural changes to the network.

Random network models. We need a simple yet general framework of social network simulation. To this end, we adopt a strong-weak dichotomy of ties between agents in the network; the weak ties represent mutual acquaintance relations and strong ties represent directional relations such as trust, love or emotional dependence. Firstly, we generate undirected ties using three well-known types of random graph models:

(1) The first (ER) is the Erdös-Rényi random graph model [21]. The model starts with a number n of agents and adds edges between pairs of agents uniformly random with probability $p \in [0, 1]$. (2) The second type (BA) is Barabási-Albert's scale-free graph model [3] which generates graphs with power law degree distribution. The model starts with a cycle of n nodes and from each node, adds at most $m < n$ edges to others using a preferential attachment scheme. (3) The third type (KM) is Kleinberg's small world graph model that builds a network with small average path length and high clustering coefficient [28, 20]. The model starts from an $n \times n$ grid and adds random edges to each pair of nodes u, v with a probability proportional to $d^{-q}(u, v)$, where $q \in \mathbb{R}$ is called the *clustering exponent*. The higher q gets, the more clustered the nodes are in the resulting network.

Strong ties. We need a formal device that generates directed ties between agents. Two people's shared social circle often reveals their closeness. In particular, the *neighborhood overlap* between any pairs of agents u, v refers to the ratio of the number of common friends of u and v against the total number of friends of u or v, i.e., $P(u, v) = \frac{|N_u \cap N_v|}{|N_u \cup N_v|}$. The notion has been used to measure *tie strength* [37]. Therefore, we view $P(u, v)$ as a probability and generate directed strong ties (u, v) and (v, u) with probability $P(u, v)$. The overall procedure for network generation is given in Proc. 1.

We then assign weights to ties in the network: The directed ties receive a weight of 1 and undirected weak ties a weight of 0.5. Each agent in the network will get a random self-loop weight (vulnerability) uniformly chosen from [0, 1].

Network dynamics. Our simulation requires a fixed scenario that directs network dynamics. For this, we assume the following: The network starts with the topology as generated above, and then, an event occurs which results in a random sub-population disappearing from the network. In other words, agents are removed from the network with a probability $p_{\mathsf{die}} \in [0, 1]$ (i.e., the agent v "dies" with death probability p_{die}). This may correspond to the real-life situation such as natural disaster, war or political turmoil which results in significant casualties or migration.

Procedure 1 NetworkGeneration

```
Generate an undirected network G = (V, E) using ER, BA
or KM
for (u, v) ∈ V², u ≠ v do
    Compute neighborhood overlap P(u, v)
    Add directed edges (u, v) with probability P(u, v)
    Add directed edge (v, u) with probability P(u, v)
    Remove undirected edge between u, v if any directed
edge is added
end for
```

Experiments. Let G_0 denote the original generated network and G_1 denote the resulting network after the node removals. For each remaining agent v, we compute the self-evaluation in both G_0 and G_1, which gives us the interpersonal loss $\gamma(v)$. The value of $\gamma(v)$ clearly falls in the range $[0, 1]$. According to discussions in the previous sections, it is reasonable to assume that $\gamma(v)$ influences the likelihood that agent v would commit suicide. We therefore implement a randomized procedure that removes v from the network with probability $\gamma(v)$. If no agent further dies, the process is terminated; otherwise, let G_2 be the resulting network and we repeat the process on G_2. The process continues until either all agents are removed from the network, or no survived agents are further removed. We perform three types of tests:

(1) Firstly, we look at how initial self-evaluation affects interpersonal loss by measuring the distribution of the interpersonal loss of agents (in G_1) against their initial self-evaluation in G_0. To visualize the results, we will use a color map with horizontal axis indicating the ranges of initial self-evaluations and the vertical axis indicating the ranges of interpersonal losses. The colors of cells (from red to blue) indicate the number of agents whose attributes fall into the respective ranges (as in e.g. Fig. 8 left column).

(2) Secondly, we look at the effect of agents' vulnerability by measuring the distribution of the interpersonal loss of agents (in G_1) against their self-loop weights. We also use color maps for this test by indicating the ranges of self-loop weights horizontally and indicating interpersonal loss vertically. The colors of cells represent also the numbers of agents in the respective ranges (as in e.g. Fig. 8 middle column).

(3) Thirdly, we look at the effect of the death probability by comparing the ratio of agents who committed suicide in G_1 against different p_{die}. This requires running the procedure several times using different p_{die} values. We visualize the results of this measurement by indicating the death probability p_{die} horizontally and the rate of suicide vertically. We then apply a standard regression method (kNN regression) to derive a clearer correlation between the measured indices (as in e.g. Fig. 8 right column).

Results. The results for each type (ER, BA, KM) of random networks are summarized below:
ER networks. We generate 10 ER networks each containing 1000 agents with edge probability $p = 0.07, 0.47$, which indicate sparsity of the networks. See Fig. 8 for the results of all three tests. The top row shows the case with $p = 0.07$ (sparse networks) and the bottom row for $p = 0.47$ (denser

networks). Due to high skewness, the color maps are log-transformed. A few facts stand out from the plots: (a) sparsity of the network clearly affects agents interpersonal loss – the fewer ties exist among the agents, the higher their loss will become; (b) agents' vulnerability does not significantly impact their interpersonal loss; (c) the suicide ratio in the sparser network is slightly higher as p_{die} rises.

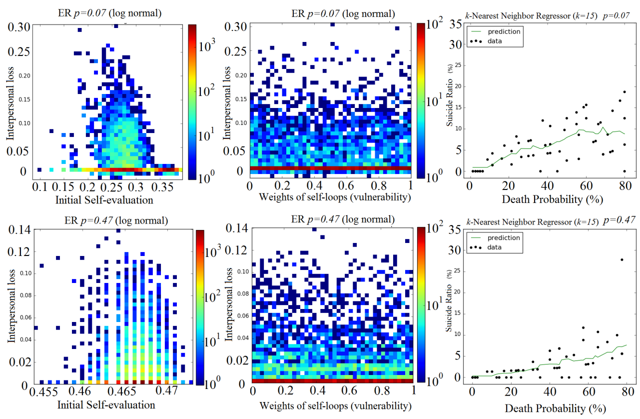

Figure 8: Experimental results for ER networks.

BA **networks.** We generate 50 BA networks each containing 1000 nodes and $m = 2$. See Fig. 9 for the results. Cells with negative vertical values indicate that agents' self-evaluation increased due to node removal. Just like for ER networks, agent's vulnerability does not exhibit a clear impact on interpersonal loss. The first figure is considerably different from the same plot for ER networks, where a vast majority of agents have both low initial self-evaluation and low interpersonal loss. This may be due to the uneven degree distribution of scale-free networks. Moreover, the suicide ratio is proportional to the death probability p_{die}.

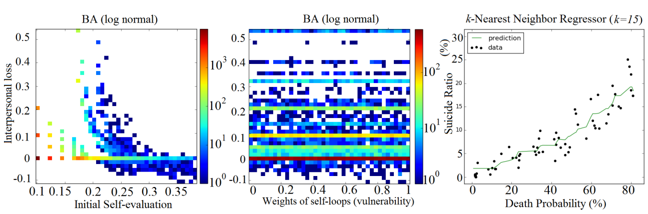

Figure 9: Experimental results for BA networks.

KM **networks.** We generate 50 KM networks containing 1225 nodes each where the clustering exponent $q = 2, 10$. See Fig. 10 for the results. The top row shows the case with $q = 2$ (low level of clustering) and the bottom row for $q = 10$ (higher level of clustering). Observe that (a) in the network with a higher level of clustering, agents generally enjoy higher self-evaluation, however, this also means that they are more sensitive to change as they tend to have higher interpersonal loss. (b) A higher clustering exponent leads to a higher suicide rate.

6. CONCLUSION AND OUTLOOK

In this work we initiate an agent-based study on the link between social network structures and agents' emotion states. In particular, our model can be used to compute the

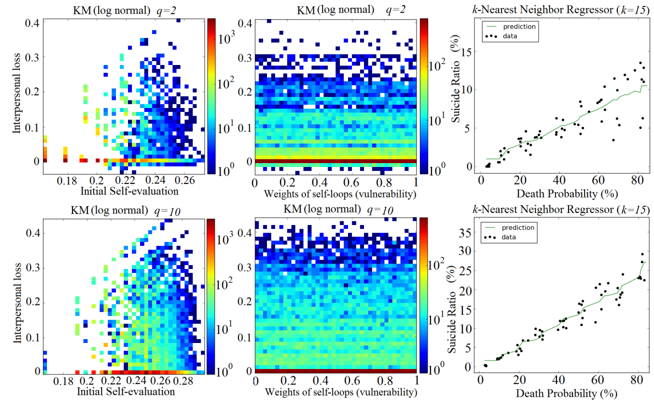

Figure 10: Experimental results for KM networks.

evolving self-evaluations in dynamic networks and simulate, using a randomized process, suicidal behaviors of agents. Our conclusions are:

1. Echoing sociological theories on suicide, our model shows through case studies that network structures and dynamics strongly influences suicide.
2. Through simulations on random networks, we observe that sparsity of interpersonal ties attributes to increased interpersonal loss. As a result, the population is more sensitive to random events causing agents disappearing from the network. In other words, *sparse networks tend to have high suicidal ratio.*
3. Through simulations on small-world networks, we observe that clustering attributes to both higher self-evaluation and higher interpersonal loss. In particular, *high levels of clustering in the network tends to result in high suicidal ratios.*

Naturally, analysis could be carried out to illustrate a more precise link between clustering, density, and degree distribution of the network, and to pinpoint the exact affect of vulnerability and interpersonal loss.

Other future works consist of enriching the model with more dimensions. For example, as changes to the social network reduces self-evaluation, the agent may initiate actions, such as establishing new ties, to counteract the interpersonal loss and "re-balance" self-evaluation. A different type of enrichment is to introduce negative ties (e.g. adversarial relations) between agents.

To apply discoveries of the work, one would consider ways to utilize data-driven technologies (such as social media mining) for mental health intervention [32]. This path naturally faces numerous challenges (e.g. privacy issues, false positives). While this work does not focus on these challenges per se, insights provided by our model may nevertheless help to guide novel solutions, e.g., establishing social platforms that facilitate supportive network building, which in turn benefits mental health. As suggested by numerous research [46], social relations play a crucial and prevalent role in people's mental health. It is thus reasonable to explore applicability of interpersonal loss to other mental problems such as depression or aging. The eventual aim of the work is to quantify the impact of social relations and their dynamics to the mental health.

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