Emotions as infectious diseases in a large social network: the SISa model

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Human populations are arranged in social networks that determine interactions and influence the spread of diseases, behaviours and ideas. We evaluate the spread of long-term emotional states across a social network. We introduce a novel form of the classical susceptible–infected–susceptible disease model which includes the possibility for 'spontaneous' (or 'automatic') infection, in addition to disease transmission (the SISa model). Using this framework and data from the Framingham Heart Study, we provide formal evidence that positive and negative emotional states behave like infectious diseases spreading across social networks over long periods of time. The probability of becoming content is increased by 0.02 per year for each content contact, and the probability of becoming discontent is increased by 0.04 per year per discontent contact. Our mathematical formalism allows us to derive various quantities from the data, such as the average lifetime of a contentment 'infection' (10 years) or discontentment 'infection' (5 years). Our results give insight into the transmissive nature of positive and negative emotional states. Determining to what extent particular emotions or behaviours are infectious is a promising direction for further research with important implications for social science, epidemiology and health policy. Our model provides a theoretical framework for studying the interpersonal spread of any state that may also arise spontaneously, such as emotions, behaviours, health states, ideas or diseases with reservoirs.

Keywords: social networks; happiness; emotional contagion; SIS model; depression; social contagion

1. INTRODUCTION

Social network effects are of great importance for understanding human behaviour. People interact with different numbers of individuals and with some individuals more than others, and this affects behaviour in fundamental ways. Investigations from diverse fields, including sociology, economics, physics, mathematics and public health, have studied social networks, both to understand their structure and their affect on social dynamics. Economic behaviour, such as purchasing decisions (Lazarsfeld & Katz 1955), employment prospects (Marmaros & Sacerdote 2002; Calvo-Armengol & Jackson 2004), bankruptcy (Uzzi 1996), investment (Cohen *et al.* 2008) and productivity (Oswald *et al.* 2009) have been shown to be influenced by network contacts (reviewed in Jackson 2009). Other behaviours such as college GPA (Sacerdote 2001) and crime (Glaeser *et al.* 1996; Haynie 2001) have been related to peer effects. Recently, social networks have been studied as determinants of health (reviewed by Smith & Christakis 2008), ranging from determining the patterns of infectious disease spread (Keeling & Eames 2005) to the

propagation of behaviours such as smoking cessation (Christakis & Fowler 2008), obesity (Christakis & Fowler 2007) and suicidal ideation (Bearman & Moody 2004). Networks also play an important role in evolutionary biology, where population structure determining interactions can facilitate the evolution of cooperative behaviour (Ohtsuki *et al.* 2006; Tarnita *et al.* 2009*a,b*; Nowak & May 1992; Fu *et al.* 2007).

Human emotions are strongly influenced by social contacts. 'Emotional contagion' (Hatfield *et al.* 1994) is known to occur over short timesscales between people in frequent close contact, such as families (Larson & Almeida 1999), roommates (Howes *et al.* 1985) and team-mates (Barsade 2002), and even occurs in experimental situations (Fowler & Christakis 2010). Positive and negative moods also spread during workplace interactions such as cooperation (Barsade 2002), negotiation (Van Kleef *et al.* 2004) and successful leadership (Bono & Ilies 2006). The spread of positive mood is a common technique in interpersonal relations, and the 'service with a smile' technique is a well-known example (Pugh 2001). Depressive moods and symptoms have been found to be contagious both by media and by personal contact with strangers or acquaintances (Joiner & Katz 1999). Over longer timesscales, clinically relevant depressive states can also spread between social contacts (Ueno 2005). Unlike most of these previous studies, in the present work we demonstrate the interpersonal

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spread of long-lasting emotional states over protracted timescales.

Recently, Fowler & Christakis (2008) have studied the properties of happiness in relation to a network of social contacts, extracted from the Framingham Heart Study (Dawber 1980). They observe correlations in happiness between individuals who are connected in a social network. If your friends are happy, then you are more likely to be happy in the future. This correlation, they suggest, is caused in part by an inductive effect of happiness spreading from person to person. Thus, happiness could be thought of as a form of social infection. Here, we evaluate this conceptual approach to emotional transmission in a mathematically rigorous way, by formally modelling the spread of positive and negative emotions using theoretical tools from epidemiology.

Mathematical models for the spread of microbial infections help us to understand and predict the spread of disease (Anderson & May 1991). Such models have also been used to explore the spread of non-microbial infections, such as rumours (Daley & Kendall 1964) or computer viruses (Pastor-Satorras & Vespignani 2001). Studying the dynamics of epidemiological models on social networks is currently an active area of research. Many models have been developed to study how the structure of networks affects disease spread (Keeling & Eames 2005). These models have been used to understand contagious diseases where the network describes contacts in geographical proximity (for example severe acute respiratory syndrome (SARS), Meyers et al. 2005; foot-and-mouth disease, Ferguson et al. 2001) or for studying sexually transmitted diseases where the network consists of sexual partnerships (Eames & Keeling 2002).

Here, we introduce a novel approach for studying the spread of emotions in a social network. We can think of emotions at three levels: 'moods', 'states' or 'traits'. These levels have increasing duration and permanence, and differ in terms of the extent to which they are deeply characteristic of the individual, and therefore the extent to which they are mutable or immutable. We will use the word 'long-term emotional states' to describe the phenomena of interest to us here, lying in between fleeting moods and permanent traits (like personality traits). We use the terms *content* and *discontent* for these phenomena that have been characterized, in prior work, as akin to happiness and depression, with validated scales. We modify a classical infectious disease model to represent the spread of emotions, to account for the fact that emotions can be contracted both spontaneously and through transmission. We then use this model to ask whether emotional states in the Framingham Heart Study dataset (Dawber 1980) do indeed act like infectious diseases. For an emotional state such as content to fit the classical definition of an infectious disease, (i) the probability of becoming content must depend on the number of content contacts (and not on the number of non-content contacts), and (ii) the probability of switching from content back to neutral ('recovering' from content) should be independent of any properties of social contacts. The particular structure of the Framingham Heart Study dataset, with a social network, reliable emotional evaluation and longitudinal follow-up, allows application of our model to the spread of content and discontent over long timescales. We find that both content
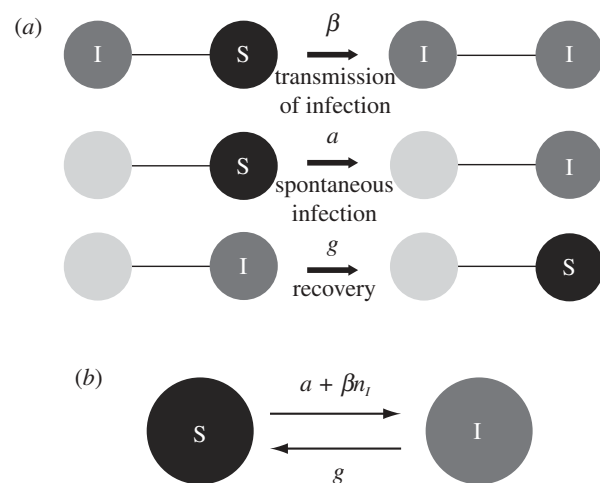
Figure 1. The SISa model of infection. (*a*) There are three processes by which an individual's state can change. (i) An infected individual transmits infection to a susceptible contact with rate β. (ii) A susceptible individual spontaneously ('automatically') becomes infected at rate a, regardless of the state of her contacts. (iii) An infected individual returns to being susceptible at rate g, independent of the state of her contacts. (*b*) The rates of movement for an individual between the susceptible and infected states. n_I is the number of infected contacts.

and discontent behave like infectious diseases. The data allow us to then estimate values for model parameters, and to calculate derived quantities which give insight into the dynamics of emotional contagion.

2. MATERIAL AND METHODS

(a) *Basic infectious disease model*
In the simplest infectious disease models (Anderson & May 1991), individuals are classified as occupying one of two states: 'susceptible', meaning they do not have the disease, and 'infected', meaning they do have the disease. The disease can be transmitted to a susceptible person when they come into contact with an infected person. The rate of this disease transmission from infected to susceptible is defined as β, the *transmission rate*. Once an individual is infected, he/she recovers from the disease at a constant rate g, regardless of his/her contact with susceptible or infected others. In one class of disease models (susceptible–infected–recovered (SIR)), recovered individuals become immune to further infection and enter a 'recovered' state. However, an emotion can occur many times over an individual's life, and therefore we use assume infected individuals return to the susceptible state after recovering. This form of susceptible–infected–susceptible (SIS) model is used to model infectious diseases that do not confer immunity, such as many sexually transmitted diseases.

In the standard SIS model, infection can only be transmitted by having a contact between an infected and a susceptible individual. Emotional 'infections', however, can also arise owing to spontaneous factors other than transmission. Therefore, we extend the SIS model by adding a term whereby uninfected individuals spontaneously (or 'automatically') become infected at a constant rate a, independent of infected contacts. A diagrammatic representation of our modified SIS model, which we will call SISa, is shown in figure 1.

The corresponding differential equations for a well-mixed population are described in equation (2.1). When the population is not well-mixed but instead constrained on a social network, the transmission rate for each individual depends on the number of infected contacts (n_I) instead of the total number of infected individuals (I).

$$
\left.
\begin{aligned}
\frac{dS}{dt} &= -\beta SI + gI - aS, \\
\frac{dI}{dt} &= \beta SI - gI + aS
\end{aligned}
\right\}
\qquad (2.1)
$$
$$
\text{and} \quad I + S = N,
$$

where S is the number of susceptible individuals, I the number of infected individuals β the transmission rate, g the recovery rate, and a the rate of spontaneous infection. This model assumes a constant population size, neglecting birth and death.

(b) *Parameter estimation*

The classical definition of an infectious disease in the SIS/SIR context is that (i) the probability of an individual transitioning from susceptible to infected is an increasing function of the number of infected contacts, while (ii) the probability of a transition from infected to susceptible (i.e. recovery) is independent of the number or state of contacts. Exposure to infected individuals makes you more likely to become sick, but once you are infected you recover at a constant rate regardless of contacts. In addition to infectious contagion, the SISa model has an additional spontaneous mode of acquiring disease. To both test that a behaviour displays infectious-disease-like dynamics, and to estimate values for the model parameters a, β and g, we can use dynamic information about transitions between states based on multiple time points in longitudinal data. For data points separated by time intervals (Δt) smaller than the average time between transitions, the transition probabilities can be linearized. The probability of a transition from susceptible to infected after a time Δt can be given by $P(S \rightarrow I, \Delta t) \sim (a + \beta n_I)\Delta t$, and the probability of transition from infected to susceptible after time Δt, by $P(I \rightarrow S, \Delta t) \sim g\Delta t$. It is necessary for the time between measurements to not be comparable to or greater than the average lifetime of a state to keep the probability of double transitions within a time interval low.

(c) *Dataset*

In this study, we evaluate the assumption that emotions behave like infectious agents. We use data from the Framingham Heart Study (Dawber 1980) and the framework discussed above to test whether content and discontent fit the dynamics of infectious diseases. The Framingham study was initiated in 1948 in Framingham, Massachusetts and has continued enrolling subjects till the present. Subjects were examined at regular intervals of approximately three years. They were administered a psycho-social exam called the CES-D, which allowed us to classify each individual as *content*, *discontent* or *neutral*. We used the well-defined cut-off of a score of 16 on the full CES-D scale to classify subjects as *discontent*. This measure has previously been called 'depression', though it is not specific to clinical depression and represents general distress or depressive symptoms (Rush 2007). *Content* was defined as a score of 12 on the positively worded questions of the CES-D, and is the same subscale used by others and called 'positive affect', 'well-being' or 'happiness' (Moskowitz 2003; Ostir *et al.* 2000; Pressman & Cohen 2005; Fowler & Christakis 2008). The terms 'content', 'discontent' and 'emotional state' as used in this paper represent long-term states reflecting general life satisfaction, as opposed to short-lived moods evinced in response to stimuli. Additionally, social networks were constructed for each subject based on recorded information on friends, family, co-workers and residential neighbours. For details, see the electronic supplementary material.

We hypothesize that a neutral emotional state may act like a susceptible state, and that content and discontent act like 'infected' states (figure 1). We validate this classification using the data analysis presented below. Note that we exclude the possibility of *coinfection* by both content and discontent simultaneously, as this doubly infected state very rarely appears in the data (see the electronic supplementary material, figure S1). However, *superinfection* may be possible: individuals could potentially move directly between being content and discontent without passing through neutral. The data are used to validate the model assumptions and estimate values for the parameters β, a and g. These parameters are then used to calculate derived quantities of interest, such as the average lifetime of an emotional infection, the probability an infected person passes the infection to a given contact sometime during the course of her infection, and the average frequency with which infections arise spontaneously. Additionally, agent-based simulations are used to compare model dynamics and clustering with the observational data.

(d) *Measuring transmission of emotions*

To study the transmission of emotions, we examine changes in emotional state between the two sequential exams of the Framingham Heart Study in which the CES-D was administered (exams 6 and 7). The average fraction of the network that was classified as content or discontent was very similar between the two exams, suggesting the transmission process is at steady state (exam 6: 65% content, 9% discontent; exam 7: 62% content, 9% discontent). Additionally, these exams were closely and consistently spaced ($\Delta t = 3 \pm 1$ year). We include only subjects who answered all questions on the CES-D in both exams.

Subjects were initially classified as first as either 'content' or 'not content', and then separately as 'discontent' or 'not discontent'. Individuals who are neither 'content' nor 'discontent' are classified as 'neutral'. As expected, very few people who are classified as 'content' are also classified as 'discontent' (less than 1/1000). Thus we have three possible emotional states. A diagram of the distribution of subjects between emotional states in included in the electronic supplementary material, figure S1.

A given state x is considered infectious if having more contacts in state x makes you more likely to switch to state x. That is, a positive relationship between the number of contacts in state x and the probability to

transition from state y to state x indicates that state x is infectious with respect to state y. Therefore, to test whether a given state x is infectious with respect to another state y, we perform an ordinary least squares (OLS) linear regression as follows. Each subject in state y in exam 6 is coded as either having transitioned to state x (transition = 1) or not (transition = 0) in exam 7. We then regress this binary transition variable for each subject against that subject's number of contacts in state x during exam 6. A significant positive correlation indicates that having more friends in state x at the earlier exam makes you more likely to switch to state x in the later exam. If state x is infectious (a significant positive correlation exists), then the value of β can be calculated from the slope of the regression line, and the value of a can be calculated from the intercept. If state x is not infectious (no significant correlation exists), then the value of g can be calculated from the intercept. Δt was taken as the average time between examinations, which was 2.5 years. Using logistic regression as opposed to OLS regression gives very similar results, as the datapoint line is within the linear range of the logistic model.

It is important for our analysis that subjects do not change emotional states rapidly (days or weeks), but instead on the timescale of years or longer. While the CES-D asks subjects to evaluate feelings in the last week, it is known to be a reliable measure of long-term emotions, as opposed to short-lived moods evinced in response to stimuli. Several studies have shown that CES-D scale scores to be stable for up to 12 months, with high intra-individual test–retest correlations (Radloff 1977; Roberts 1980). Furthermore, we find a strong positive correlation between each subject's emotional state in the two measurement periods ($r = 0.47$). This suggests that emotional states are not fluctuating on the timescale of weeks or months, but rather on the timescale at which we are measuring: if they were changing faster than 3–5 years, then a subject's state in exam 6 would not be strongly predictive of her state in exam 7. Note that this correlation is also confirmed by a more detailed analysis (Fowler & Christakis 2008). Thus, there is strong evidence that the emotions we are measuring change only on the timescale we are measuring, as opposed to fluctuating much more rapidly.

Our epidemiological approach to social contagion has important differences from other models which look at correlations in present and past states of connected individuals (Christakis & Fowler 2007, 2008; Fowler & Christakis 2008). Here, we look at how contacts influence the transitions between states, which better captures the nature of contagion. Since we use pre-existing social ties, we do not see effects from selection bias in choosing friends with similar emotional states. Additionally, confounding events that lead to concurrent changes in connected individuals will not show up as contagion effects in this model.

3. RESULTS

In the Framingham Heart Study network, individuals may be connected to neighbours, co-workers, first-degree relatives and self-nominated friends. An individual's degree is the number of contacts that individual has to other people in the network. Restricting to only individuals who had been administered the CES-D at

both exams 6 and 7, and their connections that exist at exam 6, gives a population of size $n = 1880$, with an average degree of 3.1. The network is approximately Poisson distributed, with a long tail, although with some subjects having no connections. It has been previously found that family and friends living more than 2 miles away are not significantly associated with emotional influence (Fowler & Christakis 2008), suggesting that face-to-face contact is important for transmission. Thus, we restrict our analysis to connections involving only friends and relatives living closer than 2 miles away, next-door or same address neighbours and co-workers. With these further constraints, the degree of the network was reduced to 1.25 ± 1.35.

The results of the infectiousness analysis for the spread of content and discontent between exams 6 and 7 are shown in figure 2. Consistent with the SISa model formulation, we find a significant positive correlation between the probability of transitioning from neutral to content and the number of content contacts (figure 2a, coeff. = 0.052, $p=0.024$), and no significant relationship between the transition from content to neutral and the number of neutral contacts (figure 2b, coeff. $=- 0.011$, $p=0.59$). Additionally, we find no significant relationship between the probability of transitioning from neutral to content and the number of neutral contacts (coeff. = 0.48, $p = 0.10$), or the probability of transitioning from content to neutral and the number of content contacts (coeff. = 0.22, $p = 0.98$). This suggests that content can indeed be modelled as an infectious process in the SISa framework, with neutral susceptibles more likely to become content infecteds with each content contact they have. The parameters for the SISa model can be calculated from the transition probabilities using equations mentioned previously, by dividing slope and intercept values by Δt, the average time between exams. The transmission rate, β, is found to be 0.02 yr^{-1}. The spontaneous infection parameter a is found to be 0.18 yr^{-1}. The recovery parameter g is found to be 0.088 yr^{-1}. These results are dependent on restricting analysis to contacts who had exams separated by less than three-and-a-half years (75%). For longer times it becomes increasingly probable that more than one transition has been made between exams.

We now repeat this analysis for discontent. We find that discontent can be also described in the SISa framework as a contagious emotion with neutral as the susceptible state. The probability of transitioning from neutral to discontent is positively correlated with the number of discontent contacts (figure 2c, coeff. = 0.097, $p = 0.027$), and the probability of transitioning from discontent back to neutral is independent of the number of neutral contacts (figure 2d, coeff. = 0.032, $p = 0.56$). Additionally, we find no significant relationship between the probability of transitioning from neutral to discontent and the number of neutral contacts (coeff. = 0.11, $p = 0.75$), or the probability of transitioning from discontent to neutral and the number of discontent contacts (coeff = 0.002, p = 0.99). The model parameters are $\beta = 0.04$ yr^{-1}, $a = 0.040$ yr^{-1}, $g = 0.13$ yr^{-1}. Interestingly, the rate of transmission through a contact is similar for both content and discontent, while the rate of spontaneous infection is much larger for content and the rate of recovery is larger for discontent.
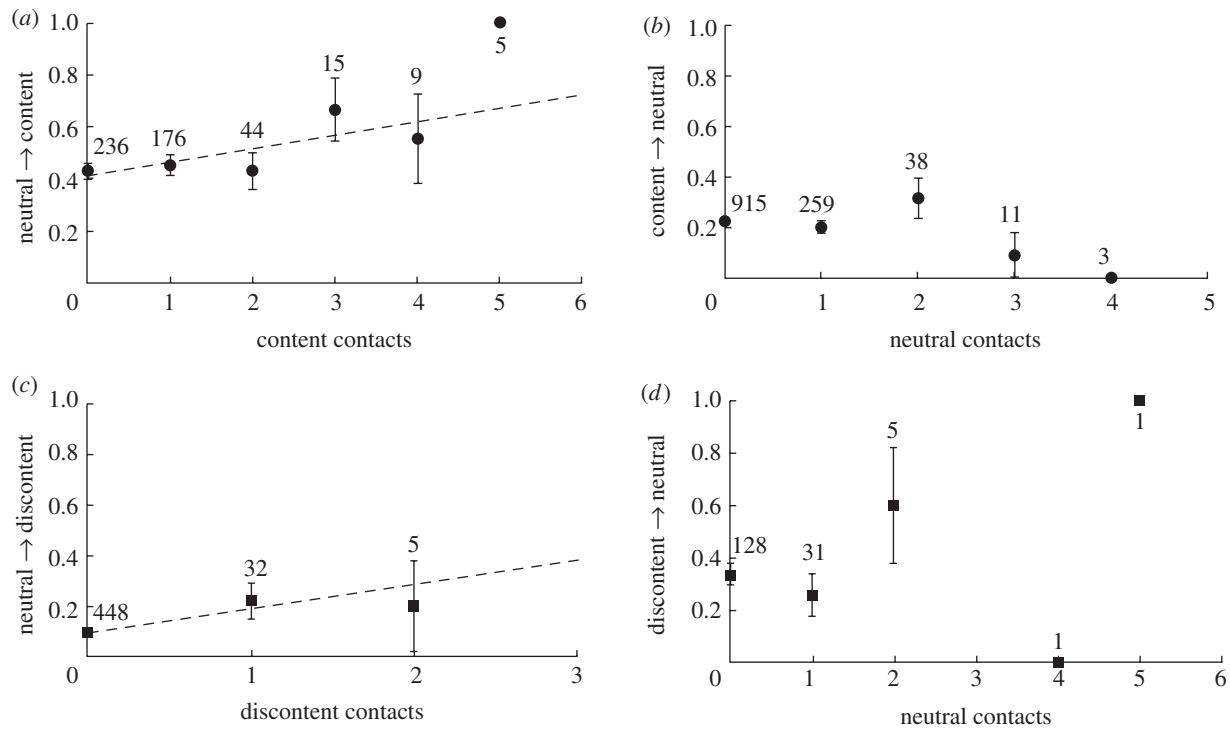
Figure 2. Both content and discontent behave like disease agents, infecting those in a susceptible neutral emotional state. (*a*) Becoming content: the probability of transitioning from neutral to content increases in the number of content contacts (slope = 0.052, $p = 0.024$, intercept = 0.42). (*b*) Recovering from content: the probability of recovering from content to the neutral state does not depend on the number of neutral contacts (slope = −0.011, $p = 0.59$, intercept = 0.22). (*c*) Becoming discontent: the probability of transitioning from neutral to discontent increases in the number of discontent contacts (slope = 0.097, $p = 0.027$, intercept = 0.095). (*d*) Recovering from discontent: the probability of recovering from discontent to the neutral state does not depend on the number of neutral contacts (slope = 0.032, $p = 0.56$, intercept = 0.32). Error bars represent the standard error of the mean, and labels are the number of individuals averaged for each data point. We also find no significant dependence of these transitions on age, sex or education ((*a*): age, coeff = 0.0014, $p = 0.52$; education, coeff = 0.0024, $p = 0.81$; sex, coeff = −0.0074, $p = 0.87$. (*b*): age, coeff = 0.0016, $p = 0.21$; education, coeff = −0.0095, $p = 0.08$; sex, coeff = 0.0109, $p = 0.64$. (*c*): age, coeff = 0.0001, $p = 0.93$; education, coeff = 0.0008, $p = 0.90$; sex, coeff = 0.0485, $p = 0.08$. (*d*): age, coeff = −0.0006, $p = 0.88$; education, coeff = −0.0165, $p = 0.35$; sex, coeff = −0.024, $p = 0.77$).

We also include for the possibility of direct transitions between content and discontent ('superinfection'), which are sometimes observed. We calculate the rate of direct transitions from content to discontent to be $s_{cd} = (0.009 \pm 0.003)$ per year and the rate from discontent to content to be $s_{dc} = (0.07 \pm 0.02)$ per year. See the electronic supplementary material for details. The estimated rates of all transitions are visualized in figure 3.

From the SISa model parameter estimates, various quantities of interest can be calculated. The average lifetime of an emotional state is the average length of time an individual spends in this state before recovering. For both content and discontent, 'recovering' usually means going to the neutral state (g_c or g_d), but also includes the possibility of transitioning directly to the other 'infected state' (s_{cd} or s_{dc}). The total recovery rate (g_T) is the sum of both these rates. The average lifetime of a contentment infection is 10.1 years, and for discontentment it is 5.0 years. Thus, the average contentment infection appears to last twice as long as the average discontentment episode. The 'influence' of an emotion is the cumulative probability that the infection will be passed from an infected to a susceptible connection before the infected individual recovers. This is calculated as $1 - e^{-\beta/g_T} \simeq \beta/g_T$. For both content and discontent, this value is 0.18. The 'cycle length' is the average length of time between spontaneous infections, and is
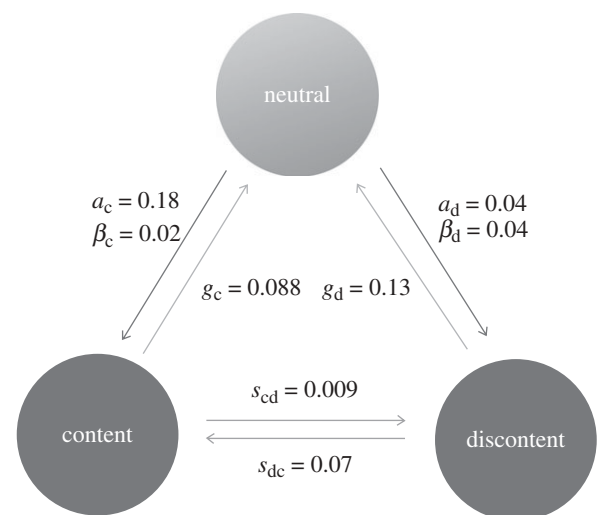

Figure 3. Parameter estimates for content and discontent using the SISa model framework. From these results, derived from figure 2, we show that content and discontent are infectious emotions that can be 'caught' by neutral (susceptible) individuals from content or discontent (infected) contacts. There is also some 'superinfection' present: direct transitions between content and discontent. a_c (a_d) = rate of spontaneously becoming content (discontent), g_c (g_d) = rate of recovery from content (discontent), β_c (β_d) = transmission rate of content (discontent), s_{cd} (s_{dc}) = rate of spontaneous superinfection from content to discontent (discontent to content).

5.6 years for content and 25 years for discontent. This suggests that an individual may spontaneously become content many times throughout life.

In the regular SIS or SIR models, the average number of secondary infections caused before recovery is called the *basic reproductive ratio*, R_0. An epidemic only occurs for $R_0 > 1$. In the SISa model, there is no thresholding behaviour as seen in traditional models, because of the spontaneous infection term. Even if there are no individuals initially infected and no contagion ($\beta = 0$), spontaneous infection will nonetheless lead to a non-zero steady-state level of infected. In the absence of spontaneous infection, the effective R_0 can be estimated as $\beta n/g$, where n is the average degree. For content, R_0 is 0.28 and for discontent it is 0.39. Since for both R_0 is less than one, self-sustained epidemics of either emotion could not be sustained if people did not become spontaneously infected.

We also perform further analysis to examine differences in local network structure for individuals in different emotional states. Content individuals have on average 1.26 connections to other people in the data, neutral individuals 1.37 connections and discontent individuals 0.97 connections. The smaller number of connections among discontent individuals suggests isolation, which could be contributing to or secondary to depressive symptoms. We can also ask whether people in a given state tend to cluster. Clustering is a measure of the spatial correlation (in the network sense) between individuals in the same emotional state. Clustering is defined as the ratio of the observed number of connections between two types of individuals to the number of connections expected if the positioning of individuals in the network was random. Clustering of like individuals can be caused by an infective process spreading within a network ([Keeling 1999](#)), but may also be caused by confounding environmental factors influencing behaviour, or selection of contacts based on similar behaviour. In a purely infectious process on a network, the average correlation between two infected individuals will be greater than one, and the average correlation between an infected and a susceptible individual will be less than one. To compare observed clustering to that expected from a pure infection, we perform agent-based simulations of SISa epidemics on networks with the FHS network topology and calculate the predicted clustering ([table 1](#)). For content, there is good agreement between observed and predicted clustering, suggesting that the inductive spread of content can explain the observed clustering of content individuals. For discontent, however, there is less clustering in the data than predicted by the infectious disease simulations. Thus discontent people are more isolated in the network than predicted by the infectious model, which is consistent with the reduced average degree observed above. This could be explained by a tendency for depression to cause people to interact less with others, or for social isolation to lead to depression ([Beck & Alford 2009](#)).

4. DISCUSSION

Here, we have shown that long-term emotional states can spread between socially connected individuals. The transmission rate for content is found to be $\beta = 0.02$ yr^{-1},

Table 1. Network structure dependence on emotional states, and comparison with epidemic simulations. Discontent individuals have a significantly lower number of contacts (degree) than others. C_{xy} is the clustering between individuals of type x and y. c, content; d, discontent, n, neutral. The clustering of like individuals that arises from an infectious process can explain the clustering of content individuals, but discontent individuals are less clustered than expected for the transmission rate.

	content	discontent	neutral
average degree	1.26	0.97	1.37
observed clustering	$C_{cc} = 1.04$	$C_{dd} = 1.07$	—
	$C_{cn} = 0.91$	$C_{dn} = 0.77$	—
simulated clustering	$C_{cc} = 1.09$	$C_{dd} = 1.92$	—
	$C_{cn} = 0.95$	$C_{dn} = 1.0$	—

and the spontaneous infection parameter is found to be $a = 0.18$ yr^{-1}, thus each content contact increases the probability per year of becoming content by 11%. For discontent, the rate of spontaneous infection is $a = 0.040$ yr^{-1} and the rate of transmission is $\beta = 0.04$ yr^{-1}, so each discontent contact makes an individual 100% more likely to become discontent each year. The average lifetime of a contentment 'infection' is measured to be 10 years, and a discontentment 'infection', 5 years. We have introduced a novel framework for formalizing social contagion derived from the study of infectious diseases, which can be used to study the spread of emotions or other social phenomena. This infectious disease approach has several advantages over methods which examine correlations in behaviours of connected individuals. Our method controls for selection bias in choosing contacts with similar behaviour, as well as confounding environmental factors synchronously affecting contacts. Moreover, we find no dependence of the probability of changing emotional state on age, sex or education, which have been found in previous studies of content and discontent to affect the propensity for emotions and confound the correlations between contacts ([Fowler & Christakis 2008](#); [Angst 1992](#)). This lack of dependence when we focus on transitions suggests that our approach is more robust to variation across individuals than previous methods.

Much of the appeal of our approach is the significance of our results despite the great simplicity of the model used, and the assumptions made about the dataset. Determining the various transition rates for the model requires the implicit assumption that all individuals are identical in their susceptibility to various emotional states. These rates therefore represent ensemble averages over the population. In reality, individuals are likely to differ in their predispositions to various emotional states.

The ability to observe transmission of emotional states over long time frames requires some particular properties of the Framingham Heart Study. These include large sample sizes, longitudinal follow-up, extensive information on social contacts and various relationships, closely and consistently spaced exams, and reliable measures of emotions and behavioural states. This study was not designed to study social networks or mental health, and so there are some drawbacks that could be improved upon in more specifically designed projects.

For example, we only examine changes between two time points, which give us stationary values for the rates of transmission, although it is plausible that these rates themselves change over time. Future work exploring the dynamic spread of emotions with higher resolution data collection is called for. This may also allow for more complex and perhaps realistic models, such as modeling emotions as continuous variables rather than discrete states, with transmission depending on the severity of infection.

One possible limitation of this study is the social network dataset used. We have also assumed that the social network collected through the Framingham Heart Study is the same as the contact network for the spread of emotions, which is almost certainly not true given the sparseness of the Framingham network. Because the Framingham Heart Study was not designed as a study of social networks, no attempt was made to capture all of a person's important contacts. Many close friends of a person could be missing (usually only one was recorded) and family and co-workers who are not part of ones actual social network may have been counted. Even if under-sampling of real-world contacts did occur, it does not change our results qualitatively: our data clearly show that rates of becoming 'content' or 'discontent' increase with the number of 'infected' contacts (i.e. are contagious) while the rates of 'recovery' to a 'neutral' state do not depend on contacts. However, it could change the measured rate constants. If we missed a constant number of contacts for each person, the intercept of the transition graphs would be shifted to the right, then the actual a would be smaller than the a we measured. If we missed a constant fraction of contacts for each person, then the x-axis would be compressed and the slope would be increased, so then the actual value of β would be smaller than the β we measured. However, while it is probable that the Framingham network underestimates the total number of contacts, the relationship to the number of 'influential' contacts is unclear. In this sense, the observed value of the transmission rates, β, are network dependent. Additionally, network connections may be weighted differently according to their ability to transmit emotions. It would be ideal to design longitudinal study with the intent of measuring social networks and health and carefully define contacts, such as by amount of time spent together per day, influence, etc.

A CES-D score of greater than 16 (which we defined as 'discontent') can occur with major depression (94% specific) as well as alcohol or drug dependence, anxiety, dysthymia or bipolar disorder. Thus, it is a measure of depressive symptoms or general distress and not necessarily clinical depression (Rush 2007; Radloff 1977). The 10 year prevalence of all affective disorders is close to 30 per cent (Angst 1992) which suggests that a large portion of the population is susceptible to depressive symptoms. This fact is consistent with our ensemble treatment, and with the observed cycle length for discontent of 25 years. Treating discontent as a spontaneously acquired or transmitted infection has one major drawback: it assumes that the probability of becoming discontent is independent of an individual's history of depressive episodes. In reality, depression is known to be a recurrent condition, with relative risk increasing with history of illness (Angst *et al.* 2003). It has been found that 72 per cent of people with major or minor depression experience recurrent episodes (Kessler *et al.* 1997). No comparable data exist for the CES-D measurement of content, which is less routinely used. Relevant data for comparison will probably become available as the study of 'positive psychology', and especially its relation to health (Pressman & Cohen 2005), becomes more widespread. There have been no studies to our knowledge which examine the lifetime or cycle of discontent or content in the general population, as defined by the CES-D.

Our study provides evidence for a transmissive component to the dynamics of the emotions of content and discontent. However, this dataset does not give insight into the mechanism of infection. It is possible that displayed emotions are directly contagious (via mimicry, pheromones, etc.), or that emotions spread indirectly, for example by sharing some type of good fortune. While short-term emotional states have been suggested as a mechanism for systemically coordinating body functions to react in the most favourable way to an environmental stimulus, and as a means of 'quick-and-dirty' communication of this stimulus to others (Lewis & Haviland-Jones 2004), it is not obvious how this argument extends to the contagion of long-term emotional states. The observed fact that 'catching' content and discontent depends on social contacts, while 'recovering' to a neutral state does not, suggests that infection involves a process similar to teaching a life skill that can then persist without a constant stimulus. The mechanisms behind the transmission of long-term emotional states merit further study.

We have formally demonstrated that emotions can be thought of as infectious diseases spreading across social networks. We have introduced a novel form of mathematical infectious disease model for describing the spread of emotions which has advantages over previous methods. We have validated this model by studying content and discontent propagating across a large social network. Our results give insight into the transmissive nature of positive and negative emotions, and our model provides a theoretical framework for studying the spread of other emotions, as well as a wide range of other social phenomena. Determining to what extent particular emotions or behaviours are infectious is a promising direction for further research with important implications for social science, epidemiology and health policy.

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Emotions as infectious diseases in a large social network: the SISa model

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Supplementary Material

Framingham Heart Study Dataset

In this study, we evaluate the assumption that emotions behave like infectious agents. We use data from the Framingham Heart Study (Dawber, 1980) and the framework discussed above to test whether positive and negative emotions fit the dynamics of an infectious disease. The Framingham study was initiated in 1948 in Framingham, Massachusetts and has continued enrolling subjects through the present. We examined individuals in the Offspring Cohort, enrolled starting in 1971. Subjects come to a central facility at regular intervals (approximately every 3 years) for medical examination and collection of other survey data. In additional to information on mental and physical health, subjects were asked to name at least one close friend at each exam, and were also connected to all first-order relatives, coworkers, and residential neighbours.

For each subject, the following social connection data is available: (i) each other person to whom they were connected, (ii) the dates of initiation and termination of that relationship, (iii) the type of relationship (neighbour, coworker, first-degree relative, or friend), and (v) the geographic distance between the two subjects. The social network for each exam was constructed by creating a network matrix G, where $G_{ijk} = 1$ if subject i nominated subject j as a connection before or during the time that subject i was administered exam k. All relationship types are mutual except for friendships, which are self-nominated, such that $G_{ijk} \neq G_{jik}$ is possible for friendships.

Individuals in the Framingham Heart Study were administered a widely validated psycho-social exam called the CES-D (The Center for Epidemiologic Studies Depression Scale, (Radloff, 1977)) at exams 6 and 7 (administered on average in 1997 and 2000). The full version of this survey style exam is commonly used to classify depressive symptoms (Rush, 2007; Radloff, 1977; Schroevers et al., 2000) and a subscale which comprises a distinct factor (Thorson and Powell, 1993; Joseph and Lewis, 1995; Pressman and Cohen, 2005; Radloff and Teri, 1986; Sheehan et al., 1995) has also been validated as a measure of positive affect (Moskowitz, 2003; Ostir et al., 2000; Pressman and Cohen, 2005). Similar measures of positive affect using subjective surveys have been shown to be highly correlated with objective measures of well-being (Oswald and Wu, 2010). We have chosen to call this positive state measured by the CES-D *content*, though it has been called 'happiness' by others. It is also related to optimism and self-esteem. The negative emotion measured by the full CES-D scale is generally called 'depression', though as described in (Rush, 2007), this measure is generally agreed to represent a long-term emotional state of depressive symptomology that is distinct from (and less severe than) the mental illness state of clinical depression. To prevent confusion, we have called this measure *discontent* throughout the paper.

A content score and a discontent score were calculated for each subject from the raw responses to 20 multiple choice questions from the CES-D. The questions asked subjects to judge the frequency with which they experienced a particular feeling or behaviour, with available answers being 0=(rarely or none of the time, <1 day per week), 1=(some or a little of the time, 1-2 days per week), 2=(occasionally or a moderate amount of the time, 3-4 days per week) and 3=(most of the time, 5-7 days per week). Subjects are classified as *content* if they scored the maximum value of 3 on each of four particular questions related to positive feelings. Summing the answers to the 16 CES-D questions related to negative feelings and adding inverted answers to the 4 positive questions, subjects are classified as *discontent* if they have a total score greater than 16 (out of a possible 60). Individuals who are neither content nor discontent are classified as *neutral*. The distribution of emotional states among our subjects is shown in Figure S1A. We find that less than 1 out of every 1000 subjects are both content and discontent, validating our classification of emotions into the three states content, discontent and neutral. Figure S2B shows the number of people who made each transition between the two examinations.
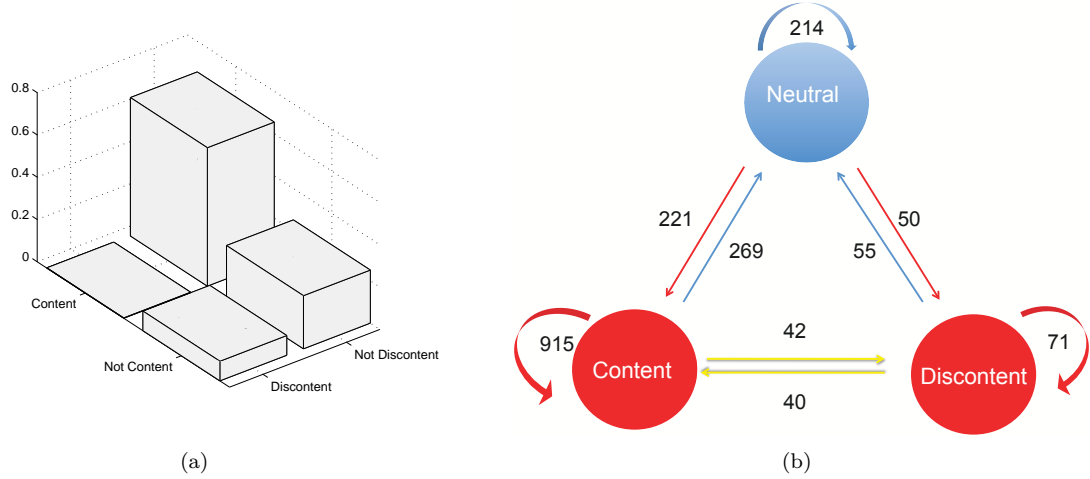
Figure S1. A) The distribution of subjects between four emotional states measured by the CES-D. Subjects were classified as first as either 'content' or 'not content', and then separately as 'discontent' or 'not discontent'. Individuals who are neither 'content' nor 'discontent' are classified as 'neutral'. As expected, very few people who are classified as 'content' are also classified as 'discontent', while those that are 'not content' may be 'discontent' or 'not discontent'. Fraction content=0.63, discontent=0.09, neutral=0.28. B) Each circle represents an emotional state, and the arrows and numbers display the number of transitions that occurred between each state.

Super-infection: Direct transitions between content and discontent infected states

Figure S1B shows that direct transitions between the content and discontent states are sometimes observed. There are two possibles explanations for these transitions. Firstly, because exams are only every 3 years, it is possible that some of these individuals actually moved through the neutral state, and thus made two transitions between observations (ie content to neutral to discontent). The second explanation is that these individuals actually moved directly between these states via 'super-infection'. We can predict how often we would expect double transitions to occur within the 3 year window, based on the estimates for each individual transition. These predictions are lower than the observed number of direct transitions. Thus the difference between the observed and expected can be interpreted as the rate of actual direct transitions. This is explained in detail below. The estimated rates of all transitions are visualized in Figure 3 in the main text.

For a Markov process, if an event occurs at a rate a, then the probability that this event has occurred after a time Δt is $1 - e^{-a\Delta t}$. If two events occur at rates a_1 and a_2, and must occur in that sequential order, then in a time period Δt the probability that both occur is :

$$\int_0^{\Delta t} a_1(1 - e^{-a_2(\Delta t - t)})\, dt = a_1\Delta t - \frac{a_1}{a_2}(1 - e^{-a_2\Delta t}) \tag{1}$$
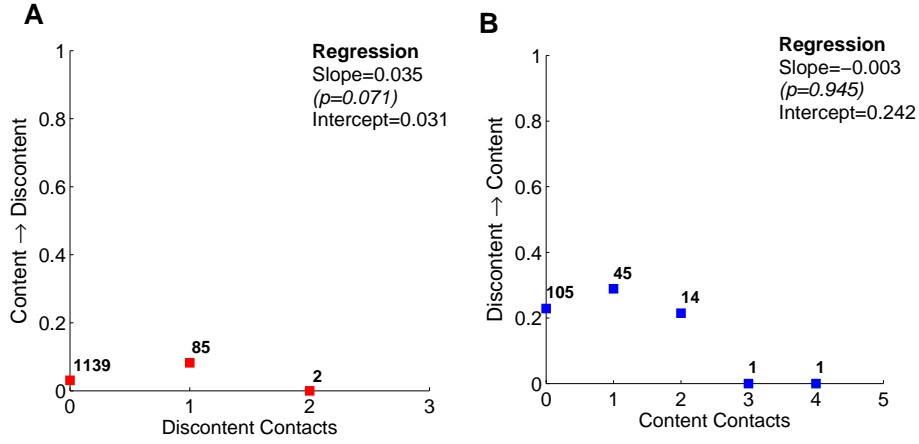
3

Figure S2. Observed rates of direct transitions between content and discontent and vice versa. We see no significant dependance on the number of infected contacts for these direct transitions.

From this expression we can calculate the expected rate of double transitions between content and discontent (going through the neutral state) in a single time period between exams.

For content $\rightarrow$ discontent, the two transitions that must occur are : content to neutral $(a_1 = g_c)$ and neutral to discontent $(a_2 = a_d + \beta_d n_d)$. There values are:

- $g_c = 0.088 \pm 0.006$ /year

- $a_d = 0.040 \pm 0.006$ /year

- $\beta_d = 0.04 \pm 0.02$ /year

For discontent $\rightarrow$ content, the two transitions that must occur are : discontent to neutral $(a_1 = g_d)$ and neutral to content $(a_2 = a_c + \beta_c n_c)$. There values are:

- $g_d = 0.13 \pm 0.02$ /year

- $a_c = 0.18 \pm 0.01$ /year

- $\beta_c = 0.02 \pm 0.01$ /year

4

Using Equation 1, the expected rate of double transitions are (with standard deviations included):

- content to discontent: $c_{expected} = (0.004 \pm 0.001) + (0.004 \pm 0.001) * n_d$ /year

- discontent to content: $c_{expected} = (0.025 \pm 0.004) + (0.003 \pm 0.002) * n_c$ /year

Observed double transition, from Figure S2:

- content to discontent: $c_{observed} = (0.013 \pm 0.002) + (0.014 \pm 0.019) * n_d$ /year

- discontent to content: $c_{observed} = (0.097 \pm 0.016) + (-0.0013 \pm 0.043) * n_c$ /year

Note that the contact dependent terms for the double transition are observed to be non-significant, and also expected to be overlapping with zero due to the margins of error on the calculated rates. We hence ignore them for the reported rates of double transitions. The rate of direct bypass transitions is the extra number of transitions that cannot be accounted for by double transitions. This is found by subtracting the expected rates ($c_{expected}$) from the observed rates ($c_{observed}$)

Rate of direct bypass transition:

- content to discontent: $s_{cd} = (0.009 \pm 0.003)$ /year

- discontent to content: $s_{dc} = (0.07 \pm 0.02)$ /year

It is interesting to note that in Figure S1B, the number of individuals transitioning directly from content to discontent is very similar to number transitioning from discontent to content. The same is true of the transitions between content and neutral, and between discontent and neutral. Thus the system is in *detailed balance*, suggesting a unique subset of the population may be responsible for the direct transitions between content and discontent. For example, it could be those suffering from bipolar disease, who represent about 1% of the population and switch between manic and discontent episodes on the order of months.

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CES-D Questions.
Questions #4, 8, 12 and 16 were used to construct the 'content' scale.

1. I was bothered by things that don't usually bother me.
- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

2. I did not feel like eating; my appetite was poor.
- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

3. I felt that I could not shake off the blues even with the help of my family or friends.
- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

4. I felt that I was just as good as other people.
- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

5. I had trouble keeping my mind on what I was doing.
- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

6. I felt depressed.
- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

7. I felt everything I did was an effort.
- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

8. I felt hopeful about the future.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

9. I thought my life had been a failure.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

10. I felt fearful.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

11. My sleep was restless.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

12. I was happy.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

13. I talked less than usual.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

14. I felt lonely.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

15. People were unfriendly.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

16. I enjoyed life.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

17. I had crying spells.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

18. I felt sad.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

19. I felt that people disliked me.

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

20. I could not get "going".

- ○ Rarely or none of the time (<1 day)
- ○ Some or a little of the time (1-2 days)
- ○ Occasionally or a moderate amount of the time (3-4 days)
- ○ Most or all of the time (5-7 days)

Scoring for All Except Questions 4, 8, 12, and 16:
- 0 points Rarely or none of the time (< 1 day)
- 1 point Some or a little of the time (1-2 days)
- 2 points Occasionally or a moderate amount of the time (3-4 days)
- 3 points Most or all of the time (5-7 days)

For questions 4, 8, 12, and 16, the scoring is exactly the same except that it is reversed: "Most or all of the time" is scored 0 points, "Rarely or none of the time" is scored 3 points, etc.