School of Mathematical
and Physical Sciences

Department of Mathematics and Statistics

Preprint MPS-2012-24

8 November 2012

Interventions in social networks: Impact on positive mood and network dynamics

by

Danica Greetham, Robert Hurling, Abhijit Sengupta, Joy Wilkinson

Interventions in social networks: Impact on positive mood and network dynamics

Danica Greetham[a]*, Robert Hurling[b], Abhijit Sengupta[c], Joy Wilkinson[b]

[a]*Centre for the Mathematics of Human Behaviour, Department of Mathematics and Statistics, University of Reading, RG6 6OW, UK*
[b]*Unilever R&D Colworth, UK, MK44 1LQ*
[c]*Essex Business School, University of Essex, Southend Campus, SS1 1LW*

Abstract

Results from two studies on longitudinal friendship networks exploring the impact of a positive psychology based gratitude intervention on the social network dynamics in relation to positive and negative affect are presented. The interventions are designed to increase positive affect and decrease negative affect in the subjects. The first study involves administering intervention to the whole network while the second study involves

We analyse the data using stochastic actor modelling techniques to identify resulting network changes, impact on positive and negative affect and potential contagion of mood within the population. The first study results in a significant increase in positive and decrease in negative affect between baseline and post intervention measures across the population. We find homophily with

Friendsh [3nF ( )]TJETBT1 0 0 1 111.98 287.81 Tm[o)-17(f)8( )-207(c

dynamics are ignored when evaluating the results of the interventions. Interventions through social networks in fact can be a powerful tool to induce the desired behavior (Valente, 2012; Cross and Parker, 2004). This paper aims to fulfill this gap in the literature, by reporting on the results from two intervention studies which take into account

Everett, 2006; Opsahl, et al., 2010)) for reviews. However, it is only recently that research has focused on centrality in dynamic, *evolving networks* (Grindrod, et al., 2011).

For static networks, *Katz centrality* (Katz, 1953) computes the relative influence of a node within a network by measuring the number of the immediate neighbors, *and* all the other nodes in the network that connect to the node under consideration through the immediate neighbors. Walks made to distant neighbors are penalized by an attenuation factor. This concept was recently revisited in (Estrada & Hatano, 2008) and (Grindrod, et al., 2011). Centrality across time-steps is based on the extension of Katz centrality to evolving networks. For example, if A and B interact on Monday and B and C interact on Tuesday then information can be passed from A to C but not vice versa, which is normally overlooked by looking at the aggregated networks and ignoring time dimension. This asymmetry gives rise to two types of centrality indices during a time-window the first quantifies the ability of an individual to pass a message onwards, and is called *broadcast index*, and the second, quantifies the ability to listen or receive message and is called *receiver index*.

As mentioned earlier, Positive Affect (PA) and Negative Affect (NA) are connected to mood and well-being in the social psychol

3. Methodology

We explain in more detail network modelling and analysis techniques that were used to analyze the results of the studies.

3.1. SIENA

As mentioned above, we used SIENA (Snijders, et al., 2010) (Ripley & Snijders, 2011), a *stochastic actor-based* framework to model the simultaneous evolution of network structure and behavior/individual characteristics of nodes in the network. SIENA is able to incorporate actor covariates and dyadic covariates as well as characteristics of the underlying network to statistically model the process of network evolution and behavior at the same time. As its input as far as network characteristics are concerned, SIENA requires network ties data from a number of ob
minimum number of such waves required is 2 and
a binary variable which takes value 1 if there exists a link *initiated by i* (the ego) to *j* (the alter) and 0

network is interpreted as a Markov process (i.e. stochastic process where the probability distribution of future states depends only on current state and not on the past states). The tie variables, represented by an
adjacency matrix for Ma52(04B7<004400570003>63<005 /P <</MCID 57>BDCF BTTm[T5606f)8(o)-5(r)-3(k(to606fD 767>BDp

guide a more detailed exploration. However,

reciprocity, which measures the tendency to reciprocate ties, in our case a recall of communication; **outdegree**, which measures the density of a network or the tendency to have ties at all; and **transitive triplets**, which measures the tendency toward network closure within groups of three. For the purpose of capturing network based selection effects, we also included **PA similarity** and **NA similarity**, which measure the tendency of preferring ti

To examine behavioural influence, we tested for **linear** and **quadratic shape**, **total** and **average similarity**, **indegree** and **outdegree**, and **average alter effect** for both PA and NA. Results reveal positive coefficients on the quadratic term and non-positive coefficient on the linear term for both PA and NA, which imply a general tendency towards extreme values i.e. high values of PA/NA tend to be pushed up and lower values are pulled down further. This result is similar to the one found in the pilot study (Greetham, et al., 2011). Moreover, no evidence of spill-over or contagion in either PA or NA were found in significant proportions, in terms of average similarity, alter, indegree or outdegree effects. Thus, we have two following results.

R1: PA and NA tend to be pushed towards extreme values, with the effect

Rank Sum test, which does not necessitate the strict assumptions of an underlying normal distribution. The results of the analysis done on the collected data is summarized in Table 3 in the form of p-values derived from each pair-wise comparison, where the null represents no change and the title of the columns two and three represent the alternate hypothesis.

Change from	**PA increase**	**NA decrease**
Day 1 to 2	0.1026	0.3734
Day 1 to 3	0.0978	0.0418
Day 1 to 4	0.0008***	0.0034***
Day 2 to 3	0.4689	0.0720
Day 2 to 4	0.0628*	0.0305**
Day 3 to 4	0.0087***	0.2857
Day 0 to 5	<0.0001***	0.9948

Table 3: Wilcoxon Rank Sum Test p-values for pairwise comparison between days for PA and NA

The p-values reported in Table 3

W

Figure 1: Katz centrality index (broadcast) of weighted Q versus an average value of NA over 4 days

5. Study II: Limited Intervention

to influence other group members, so we hoped that will make it easier to measure the difference between the two groups.

5.2. Results

Dynamics of entire study duration

Again we tested two types of effects, structural effects which have to do with the structure of a social network and influence effects that relate to the measured behaviours, in our case levels of recorded positive and negative affect.

R1: In the group A we found that the actors with higher values of positive affect had tendency to contact more people than average but they are contacted by less people. In the group B the actors with higher values of positive affect were contacted by less people, but there was no significant effect in them contacting more people.

This can be seen in table where in group A, positive affect alter and positive affect ego effects are both significant (at 0.05 level) with negative and positive value respectively, and in group B only negative value of positive affect alter is significant. The Tables 4 and 5 provide the parameter estimates and standard errors obtained for these effects, (all parameters in bold are significant at 0.05 level).

Effect	par	se
constant friends rate period 1	**4.3904**	**0.7179**
constant friends rate period 2	**5.0192**	

Table 5: Group B, structural effects (significant effects are in bold)

For influence effects, we tested for linear and quadratic shape, total and average similarity, indegree and outdegree and average alter effect for both positive and negative affect.

We found significant effect for the average similarity of positive affect in the group A which expresses the preference of actors to have similar levels of positive affect to their contacts (where the total influence of contacts does not depend on the number of contacts) so

positive affect levels between members in this social network. In the group B we found significant effect for the negative affect average similarity. Also results obtained by a Nayman-Rao type multiple-score tests confirmed t-type test results, with p-value of 0.0119 for PA average similarity in group A and p-value of 0.0023 for NA average similarity in group B.

Effects	par.est.	s.e.
rate pa period 1	3.3224	1.5836
rate pa period 2	2.44	0.6572
rate pa period 3	1.8881	0.5386
pa linear shape	-0.0668	0.0849
pa quadratic shape	-0.4353	0.0755
pa effect from SWLS	0.0425	

positive interaction) and two, matrices where interactions were given by their durations in minutes. Sorted broadcast indices of participants in group A and B are given on the Figure 2 below.

We were able to correctly predict (i.e. to pick them for the intervention based on their low NA on the first day of the study) the 1st, 2nd and 4th ranked individuals broadcast communicability indices in group A and avoid the top ranked people for intervention in the group B. We checked correlations between broadcast communicability indices and all the other properties that we measured and could not find any other predictor of high values. This validates our finding in Study I with regard to NA scores and broadcasting tendency.

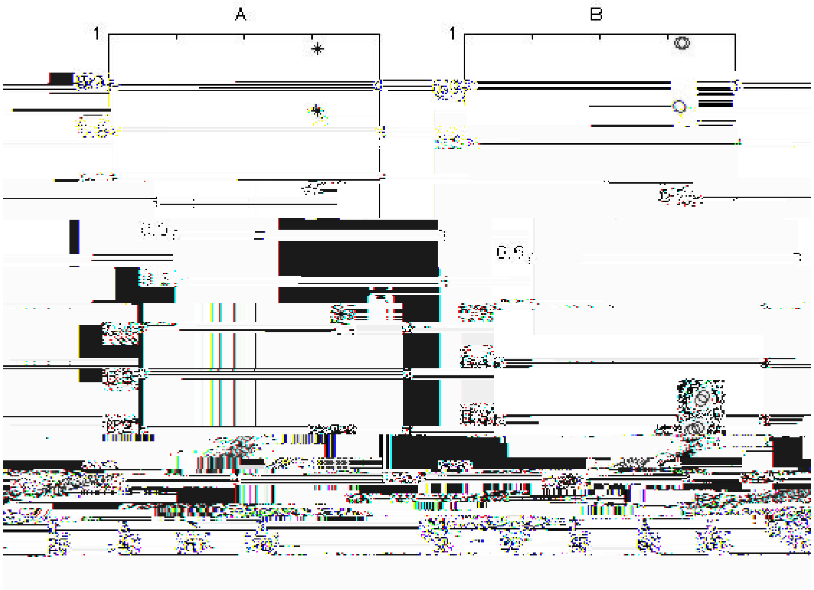

Figure 2: Sorted broadcast indices based on 4 days of group A and B

6. Discussion and Future Work

6.1. Discussion

The two studies presented above examine the effects of a gratitude based intervention on the overall mood of members of a social network firstly when the intervention is administered to all, and secondly, to a selected few. We found that the underlying network structure indeed has an impact on the network and behavior dynamics and on whether there was homophily and contagion of PA and NA over the network. Moreover, we found that the results of a positive psychology based intervention over a social network can vary dramatically depending on who the intervention was administered to, such as high NA individuals (causing contagion in NA) versus low NA individuals (resulting in contagion in PA) in Study II.

It is quite apparent that the results of Study I are more in line with what we would expect, but Study II threw up some surprising findings. While some of them do reflect the result of interventions within sub groups, we need to be careful in how we interpret the others. Although evidence of contagion could be detected using the SIENA analysis, our results from pairwise comparison of baseline and post intervention values provided some counter-intuitive results and the expected spill-over effects were not apparent. This could be a result of a number of confounding factors. First of all, the sample sizes were kept small in order to keep the study manageable resource-wise. This could be a key reason why some of the results especially those relating to comparison of data from days 1-2 versus days 3-4 did not appear statistically significant, and hence were not included. We had to resort to comparing the pre and post study values. However, as we have seen in prior studies (Golder and Macy, 2011), PA, NA and other mood based constructs do exhibit short and medium term cyclical patterns, and hence our results are subject to these background changes as well. Secondly, related to the size of the sample, the size of the intervention groups were kept at approximately one-quarter of the group as a whole. At this point, we have no way of judging *a priori* whether the size of the chosen intervention group is optimum for the intervention being considered as well as the underlying network characteristics. Further studies on this topic alone are required for greater understanding. And finally, we chose a 4 day period for the study under the assumption that individuals receiving the intervention are able to transfer PA and NA within this time period, given their interaction level and underlying social network structure. More thorough investigation is required in this regard as well.

6.2. Future work

It is increasingly being recognized that interventions within social can

Cohen, S. & Lemay, E., 2007. Why would social networks be linked to affect and health practices. *Health Psychology,* 26(4), pp. 410-417.
Cross, R. & Parker, A., 2006 . *R Cross, A Parker, The Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations.* Cambridge MA: Harvard Business School Press.
DeNeve, K. M. & Cooper, H., 1998. The happy personality: a meta-analysis of 137 personality traits and subjective well-being.. *Psychological Bulletin,* Volume 124, pp. 197-229.
Diener, E. & Emmons, R., 1984. The independence of positive and negative affect. *J Pers Soc Psychol.,* 47(5), pp. 1105-17.
Diener, E., Emmons, R. A., Larsen, R. J. & Griffin, S., 1985. The Satisfaction With Life Scale. *Journal of Personality Assessment,* Volume 49, pp. 71-75.
Emmons, R. & McCullough, M., 2003b. *The Gratitude Questionnaire-Six Item Form (GQ-6).* s.l.:s.n.
Estrada, E. & Hatano, N., 2008. Communicability in Complex Networks. *Physical Review E,* Volume 77.
Fordyce, M., 2005. A Review of Research on the Happiness Measures: A Sixty Second Index of Happiness and Mental Health. In: *SOCIAL INDICATORS RESEARCH SERIES.* Netherlands: Springer, pp. 373-399.
Golder, S. & Macy, M. W., 2011. Diurnal and Seasonal Mood Tracks Work Sleep and Daylength Across Diverse Cultures. *Science,* 333(6051), pp. 1878-1881.
Gray, E. & Watson, D., 2007. Assesing Positive and Negative Affect via Self-Report. In: J. A. Coan & J. J. B. Allen, eds. *Handbook of emotion elicitation and assessment.* New York: Oxford University Press, pp. 171--183.
Greetham, D., Linley, A., Hurling, R. & Osborne, G., 2011. Social networks and positive and negative affect. *Procedia-Social and Behavioural Sciences, Dynamics of Social Network Analysis ,* pp. 4-13.
Grindrod, P., Higham, D. J., Parsons, M. C. & Estrada, E., 2011. Communicability across evolving networks. *Physical Review E,* p. 83.
Katz, L., 1953. A new index derived from sociometric data analysis. *Psychometrika,* Volume 18, pp. 39-43.
McPherson, J., Smith-Lovin, L. & Cook, J., 2001. Birds of a feather: homophily in social networks. *Annual Review of Sociology,* Volume 27, p. 415 444.
Michie, S., 2008. Designing and implementing behaviour change interventions to improve population health.. *J Health Serv Res Policy,* 13(3), pp. 64-69.
Norman, G. et al., 2007. A Review of eHealth Interventions for Physical Activity and Dietary Behavior Change. *American Journal of Preventive Medicine,* 33(4), p. 336 345.
Opsahl, T., Agneessens, F. & Skvoretz, J., 2010. Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks,* 32(3), p. 245.
Quercia, D., Capra, L. & Crowcroft, J., 2012. *The Social World of Twitter: Topics, Geography, and Emotions.* Dublin, s.n.
Ripley, R. & Snijders, T., 2011. *Manual for SIENA version 4.0.,* Oxford: University of Oxford, Department of Statistics; Nuffield College.
Snijders, T. A., 2005. Models for longitudinal network data. In: P. Carrington, J. Scott & S. Wasserman, eds. *Models and methods in social network analysis.* s.l.:Cambridge University Press, pp. 215-247.
Snijders, T., Steglich, C. & Van de Bunt, G., 2010. Introduction to actor-based models for network dynamics. *Social Networks,* Volume 32, pp. 44-60.
Tellegen, A., 1985. Structures of mood and personality and their relevance to assessing anxiety, with an emphasis on self-report. In: A. H. Tuma & J. D. Maser, eds. *Anxiety and the Anxiety disorders.* s.l.:Hilsdale, pp. 681 -706.
Totterdell, P. et al., 2004. Affect networks: a structural analysis of the relationship between work ties and job-related affect. *Journal of Applied Psychology,* Volume 89, pp. 854-867.
Valente, T., 2012. Network Interventions. *Science,* 337(6090), pp. 49-53.
Valente, T. & Pumpuang, P., 2007. Identifying Opinion Leaders to Promote Behavior Change. *Health Educ Behav,* 34(6), pp. 881-896.
Watson, D., Clark, L., McIntyre, C. & Hamaker, S., 1992. Affect, personality, and social activity. *J Pers Soc Psychol.,* 63(6), pp. 1011-25.