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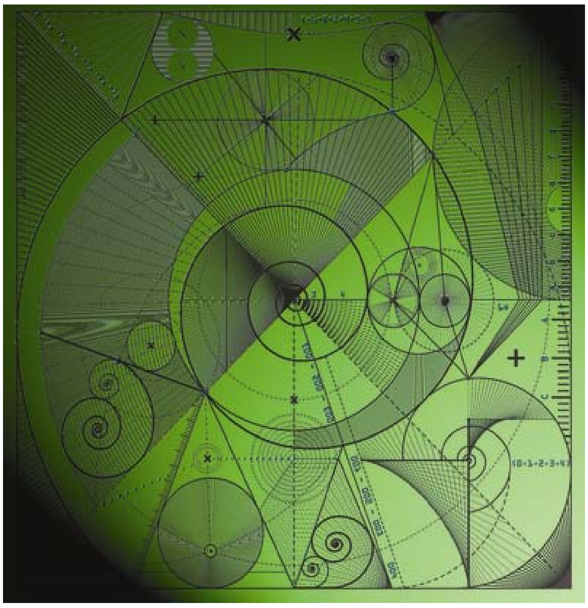

Interventions in social networks: Impact on positive mood and network dynamics

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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 selecting a subgroup of individuals as 'agents of change'. 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 regard to positive and negative affect but no evidence of contagion is found. Network became more volatile along with a fall in rate of change of negative affect. The best broadcasters in the population tended to be the ones with least negative affect levels. The second study involved two groups, and in each group a certain number of individuals were chosen as recipients of the intervention. There was evidence of positive affect contagion in the group with low initial level of negative affect and contagion in negative affect in the group with high initial level. Also, different positive and negative affect dynamics in intervention and non-intervention part of the networks were observed in the two groups.

Keywords: Network interventions, Longitudinal networks, Friendship networks, Katz centrality, Positive affect, Negative affect

1. Introduction

Collective mood of individuals in a social group and its relationship with the dynamics of network(s) in such groups is a fascinating topic from a research point of view, but which has mostly proved very challenging in terms of a precise explanation of its mechanisms. However, recent availability of large data-sets of human to human communication obtained from online social networking platforms such as Twitter and Facebook reveal evidence of correlation between levels of positive and negative emotion of individuals and those they are directly connected to (Quercia, et al., 2012). Analysis of a large amount cross-cultural Twitter data (Golder & Macy, 2011) confirmed the existence of a daily and weekly rhythm of aggregated mood, and indicated correlation between friendship/follower relationships and positive/negative emotions of Twitter users across different cultures.

Mood is a complex phenomenon which is difficult to measure in individuals (Fordyce, 2005) (Gray & Watson, 2007). Social psychology literature often sees the use of Positive Affect (PA) and Negative Affect (NA) to relate moods to well-being (DeNeve & Cooper, 1998) (Tellegen, 1985). These are constructs which are relatively easy to measure, have been established as independent (Diener & Emmons, 1984) and follow different short-term dynamics (Greetham, et al., 2011). Some limited amount of research has also been carried out involving PA and NA, and its spread through networks – for instance, through organizational networks (Totterdell, et al., 2004).

In this work, we present results from two independent studies, which aim to investigate how *interventions* within socially networked groups impact PA and NA, not just directly, but also through the resulting network dynamics within the groups. Positive psychology based interventions (Michie, 2008) (Abraham & Michie, 2008) (Norman, et al., 2007) are increasingly being investigated as incentives to induce certain desired behaviors in groups of individuals – but in most cases, the impact of the underlying social network structure and 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 underlying network structure and dynamics, and examine how they in turn impact the levels of desired behavior (in this case levels of PA and NA) within the population. Additionally, we recognize that it may not be feasible to administer an intervention to all members of a group forming the social network – for instance, in case of large scale policy interventions carried out on whole populations. To that end, we also investigate the impact of first identifying the optimal intervention nodes (agents of change) and providing only these agents with the intervention. The results are encouraging but also point towards a large number of possible avenues that can extend the research presented here. As we witness the development of this "emerging science of network based interventions" (Valente, 2012), we recognize that there is still lot of work to be done in measuring short and long term impact of these interventions within social networks and optimization of the same. The main aims of this paper are summarized as follows:

- Investigate the results of a gratitude based intervention on an evolving social network and relationship between the network's structure and dynamics on mood related constructs of the individuals, viz. Positive Affect and Negative Affect.
- Explore the impact of choosing target individuals (agents of change) for limited intervention and test the choice of low negative affect as a predictor for high evolving network centrality.
- Attempt to detect evidence of mood transfer (contagion) and corresponding spill-over effects, by comparing the results from interventions on the whole and on parts of networks.

The rest of the paper is organized as follows. In Section 2, we provide a brief background on the underlying theory on both social network analysis as well as on the PA and NA constructs used as the basis of evaluating the effects of intervention. In Section 3, we explain our methodology and estimation procedures used in analyzing the results from the studies. In Section 4, we provide the description and results of Study I, which examines the impact of providing an intervention to the whole population. Subsequently, in Section 5, the results are provided from Study II, which restricts the intervention to a minority of individuals in the network, with the aim of detecting contagion, if any, of the benefits of intervention. Finally, we will conclude with discussions of results and some directions for the future work

2. Theoretical Background

A *network intervention* uses social network data to accelerate behavior change or make it more sustainable across the targeted population. In a very recent review (Valente, 2012), four main strategies of network interventions are identified: *individual* – picking agents of change based on their position in network (central, peripheral, ability to bridge two communities, etc.) or their behavioral characteristics (e.g. extrovert, smoker/non-smoker etc.); *segmentation* – simultaneous behavior change for subgroups, thus requiring community detection, but allowing application of different interventions on the different parts of network (e.g. intervening in core versus periphery); *induction* – stimulating or enforcing new ties in order to propagate a message or behavior through the network; *alteration* – creating or deleting network nodes and/or ties and/or re-wiring existing ties.

Depending on context, availability and character of network data, the nature of the network itself and the intervention being considered, each of these strategies offers a wide choice of algorithms and processes. In this work we use the first strategy, picking individuals on the network as the agents of change while assuming knowledge about the whole network on part of the mechanism designer. The aim is then to optimize the choice of individuals, or more precisely to measure the influence of choice on the intervention results.

Previous work (Valente & Pumpuang, 2007) indicates that identification and recruitment of opinion leaders/key players who can act as champions for the desired intervention in order to accelerate behavior, is key. And for this purpose, one has to compute the appropriate centrality measures (local or global) across the network. It is this measure of centrality, which quantifies the relative importance of a node and determines its involvement within a network. The literature in social network analysis has proposed a number of different centrality measures, and has tested and compared them on undirected, directed and weighted networks. See (Borgatti &

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 psychology literature (DeNeve & Cooper, 1998) (Tellegen, 1985). In a study involving emotional contagion of small working groups of 2 to 4 members (Barsade, 2002), the author reports “a robust finding of group contagion”, and also that there was no difference in the degree of contagion of negative and positive moods/emotions. The emotion contagion was also shown to influence subsequent group dynamics. In two studies investigating the relationship between organizational networks and employees' affect (Totterdell, et al., 2004) PA and NA were shown to spread within work groups. Similarity of affect between employees depended on the presence of work ties and structural equivalence. Affect was also related to the size and density of employees' work networks. Furthermore, they investigated a merger of two organizational groups, and found that negative changes in employees' affect were related to having fewer cross-divisional ties and to experiencing greater reductions in network density. On a similar note, a recent study analyzing large amount of Twitter and Facebook data (Quercia, et al., 2012) shows correlation between friendship/follower relations and positive/negative mood of Twitter users.

In an interesting piece of work examining the daily and seasonal dynamics of PA and NA, obtained from a large cross-cultural set of Twitter data (Golder & Macy, 2011), the authors identified individual-level diurnal and seasonal mood rhythms that are common across different cultures. In accordance with previous small-scale lab studies, they found that individuals are most positive in the morning but mood deteriorates as the day progresses. People are overall happier on weekends, and diurnal rhythms over weekdays are nearly identical for both PA and NA. While there is not much difference within the weekdays, PA is higher significantly on weekends. This difference between weekend and weekdays is confirmed in countries where weekend is on Fridays and Saturdays as well. Seasonal change in baseline positive affect varies with change in day-length which supports previous findings that ‘winter blues’ is related to diminished PA but not increased NA.

There exists a lot of on-going research and debate on correlation versus causation in every discipline involving empirical research. This is especially relevant in the case of research involving data from social networks. It is often relatively easy to identify correlations between constructs involving network dynamics, but it is more difficult to tease out the direction of causality within these constructs and their interplay with the underlying network structure. This is compounded if the structure is dynamic, i.e. evolving through the time. Fortunately, the recent development of empirical methods based on stochastic actor-based models for network dynamics implemented in SIENA – Simulation Investigation for Empirical Network Analysis (Snijders, et al., 2010; Snijders, 2005) have enabled study of co-evolving network dynamics *and* behaviour of its members, allowing us to differentiate between two types of processes: *social selection* and *social influence*. Selection processes describe how actors choose other actors and form ties, based on their assigned attributes. Influence processes describe dynamics of actors' observed qualities or attributes (PA and NA, in our case) and its influence on other members of the network, connected either directly or indirectly. Both our studies use SIENA to analyse network dynamics and behaviour, and the inter-relationships between the two.

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 observation moments, where each moment is labeled as a 'panel wave'. The minimum number of such waves required is 2 and is generally kept below 10. A 'tie' in SIENA is represented as a binary variable $\boldsymbol{x_{ij}}$ which takes value 1 if there exists a link *initiated by i* (the ego) to *j* (the alter) and 0 otherwise. The term 'initiation' is key and hence the reason behind calling these models 'actor based'. The term stochastic arises from the fact that network ties are considered as 'states' and hence, the dynamic nature of the 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 $\boldsymbol{n} \times \boldsymbol{n}$ adjacency matrix for a given time period, represents a panel wave and the key input into the model. For model identification, SIENA uses a stepwise procedure whereby, independent covariates are either included or excluded from the final model based on its contribution to the overall goodness of fit and statistical significance. Since the stochastic model itself is too complex for classical estimation methods, simulation based procedure was devised which uses method of moments to model the network *change* process. The references mentioned above contain all the details of the estimation procedure, its strengths and weaknesses in great detail and would be useful to the interested reader.

3.2. Centrality in evolving networks - communicability

We used recently developed concept of communicability in evolving networks (Grindrod, et al., 2011) to try to identify the most important members of the analysed social network. For an evolving (longitudinal) network, we assume that a set of nodes is fixed, i.e. stays the same during all time steps, and edges evolve (they are created, deleted or stay the same) in any time step. For a time step *i* we denote by A_i the adjacency matrix of the network in time step *i.* Based on adjacency matrices we compute communicability matrix$Q = \prod_{i=0}^{M}(I - \alpha A_i)^{-1}$, where I is identity matrix, $\alpha = \frac{1}{2\max(\rho(A_i))}$, $i = 0, \cdots, M$ consecutive time-steps and $\rho(A_i)$ is the largest eigenvalue ofA_i[1].

The main idea of Q is to compute the number of walks of all possible lengths between each two vertices, where longer walks are penalized. Once computed for a set of given time-step matrices, $Q_{i,j}$ gives us a summary how well information can be passed between two actors *i* and *j*. The k^{th} row and column sums are new centrality measures for each actor *k*: *broadcast* and *receive*. They measure how well an actor can broadcast and receive message respectively.

4. Study I: Uniform Intervention

This study examines the impact of an intervention within a dynamic social network, where *all actors* in the social network receive an intervention aimed at improving their well-being. The aim is to identify the key attributes of a network and the individuals within the network, which influence how the intervention impacts the overall mood (PA and NA) of all individuals. It also aims to identify the impact of the intervention on the network structure itself, in terms of the number and nature of ties at various nodes of the network. Note that, given the nature of the study, there is no explicit control group to benchmark the results against, but the pre-intervention measures of behavioural traits are used as a baseline against the post intervention measures. It is intended to provide an initial understanding of network dynamics in the presence of interventions, which can

[1] Note that $\alpha < \frac{1}{(\rho(A_i))}, \forall i = 0, \dots, M$, for the inverse to exist.

guide a more detailed exploration. However, Study II detailed below, follows the more standard intervention group versus control group study design.

4.1. Study Design

This study consisted of 89 participants, who were all second year students from a UK University located in the midlands. The study itself ran for 4 consecutive days (Days 1 to 4, Monday to Thursday) with pre (baseline) and post study measures taken on separate days (Day 0 and Day 5 respectively, Wednesdays before and after the week in which the intervention took place). The intervention on the afternoon of Day 3 and 4 consisted of writing up three things that one is grateful for that day, while eating an ice-cream. Participants were given an ice-cream voucher which could be exchanged for an ice-cream in the campus café, where a drop-box for filled out questionnaires was also located.

A number of background, behavioural and network related measures were taken before, during and after the study. First of all, the gender, age and ethnicity of participants were recorded. During the 4 main days of the study, the participants were also asked to record their respective PA and NA using a 10 item Positive Affect and Negative Affect Scale (PANAS) twice, once in the afternoon and once in the evening. On days 3 and 4, this was done in conjunction with the positive psychology gratitude intervention – i.e. the participants were asked to complete a "Three Good Things" exercise while eating the ice cream during the afternoon and later on again in the evening. Additionally, the baseline and post study measures, taken on days 0 and 5, consisted of the following: trait Gratitude using a 6 item Gratitude questionnaire (Emmons & McCullough, 2003b), subjective Happiness using the 4 item Subjective Happiness Scale, Satisfaction with Life Scale (SWLS) using the 5 item scale (Diener, et al., 1985) and PA and NA using 20 item PANAS scale.

Secondly, all participants were asked to record their daily interactions (frequency and duration) with others within the network, which would provide the data to estimate ties within the participants. A limit of 10 interactions was given during the day to constrain the task for participants and to ease data analysis (and this limit was reached on five occasions during the main 4 days of the study). Each recorded interaction detailed the name and description (friend or acquaintance) of the contact, the time and duration of interaction, the type of interaction (face to face, phone, SMS, email or online) and finally, a rating on the interaction from very negative to very positive (5 point scale). Due to the extensive nature of the study, students were compensated at the end of the study. The study was approved by University Ethical Committee.

4.2. Aims and Hypotheses

The data generated from Study 1 was used to examine two types of phenomena. The first relates to the effect of the intervention on the network dynamics, particularly how it impacts communication between individuals within the network and whether there is evidence of spill-over effects relating to overall behavioural traits PA and NA, such as homophily[2] and contagion in these. This also involved examining the evolving nature of communications within the social network over time. The second phenomenon relates to the actual impact on PA and NA within individuals – i.e. whether this intervention, which aimed at improving well-being could actually do so, measured through overall levels of PA and NA.

4.3. Results

All network based analysis was done using the SIENA package, which uses method of moments to test for both *social selection effects* (network dynamics) and *social influence effects* (behavior dynamics). We used 2000 iterations for the estimation of the covariance matrix and all t-ratios were less than 0.1 indicating excellent convergence properties. For more details on the explanation of the methodology used in SIENA, see (Snijders et. al. 2010; Ripley & Snijders, 2011). Jaccard coefficients between the 4 consecutive days were 0.417, 0.351 and 0.322 respectively, all well within accepted limit of expected network change.

Dynamics entire study duration

To test for structural effects, we included the following controls variables: **network rate**, a basic characteristic of network evolution which models the speed by which each actor gets an opportunity to change ties;

[2] Homophily is the tendency of individuals to make links and associate with similar others. See *(McPherson, et al., 2001)*

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 ties with others who have similar levels of PA and NA respectively (homophily). Among other related covariates or exogenous effects, we included gender, age, ethnicity, Satisfaction with Life (SWLS), Happiness, Trait Gratitude, Relatedness and Loneliness on network structure.

For the purpose of testing social influence, we included **network rate, linear shape, quadratic shape, PA average similarity, PA ego, PA alter, PA indegree, PA outdegree, NA average similarity, NA ego, NA alter, NA indegree, NA outdegree** and exogenous effects mentioned above**.**

Effect	par. est.	s.e.
Social Selection Effects		
network rate period1	**3.7854**	0.5326
network rate period2	**6.7361**	1.1085
network rate period3	**6.0325**	0.9878
Outdegree	**-3.2496**	0.1418
Reciprocity	**2.8383**	0.1625
transitive triplets	**0.5293**	0.0548
SWLS alter	**0.1498**	0.0717
PA similarity	**1.0274**	0.5098
NA similarity	**1.7299**	0.8313
Social Influence Effects		
PA rate period1	**3.0714**	0.7974
PA rate period2	**2.4594**	0.6358
PA rate period3	**3.5815**	1.3245
PA linear shape	-0.3576	0.0871
PA quadratic shape	**0.0558**	0.0683
Relatedness on PA	**0.1908**	0.0795
NA rate period1	**2.527**	0.9604
NA rate period2	**2.0307**	0.9311
NA rate period3	**1.4484**	0.5072
NA linear shape	**-2.1642**	0.2589
NA quadratic shape	**0.4405**	0.1506
Gratitude on **NA**	**-0.4797**	0.2291

Table 1: Parameter estimates and standard errors for main effects included in the model, as analysed by SIENA

We used repeatedly SIENA to keep or remove variables within the models built to estimate effects on network and behaviour dynamics. Table 1 reports the parameter estimates and standard errors for all variables with potential impact on both the network dynamics and the behaviour related measures. The variable names and estimate values marked in bold represent significance at $\alpha = 0.05$.

In terms of overall network dynamics, all three network effects – reciprocity, outdegree and transitivity – were revealed to be significant in the data. With respect to the baseline measures, only Satisfaction with Life Scale Score (SWLS) had a significant influence on the network structure, with a positive coefficient for SWLS-alter. This indicates a tendency for participants with higher values of SWLS to have been reported as contacted by other people more often. In terms of the exogenous variables, significant positive coefficients were obtained for PA and NA *similarity* as well, which imply that people preferred ties with others who have similar values of PA and NA independently (homophily). Interestingly, homophily in NA seems to be stronger than homophily in PA, i.e. people are more drawn to each other by their levels of negative affect than positive affect.

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 stronger in NA than in PA.

R2: The underlying social network induces homophily with respect to PA and NA, but no contagion could be observed in the same. Homophily is stronger with respect to NA than PA.

Intervention versus Baseline

Although there was no control group in the study, we used the first two days (pre-intervention) as baseline in order to identify the changes in social network characteristics brought about as a result of the intervention. SIENA based models were built including all the above covariates independently for the baseline and for the post intervention days. Each set of models included two time steps, and a standard t-test was used to compare the differences in estimated coefficients between the two models. Table 2 provides the estimates, standard errors and the corresponding T-statistics. The only parameters which significantly changed between the pre and post intervention periods are the *Basic network rate* and *Rate NA*, giving us the following result:

R3: The intervention days brought about increased volatility in the interaction dynamics, along with a fall in the rate of change in NA.

Effect	**Par. est. 1**	**S.E.1**	**Par.est. 2**	**S.E.2**	**T**
basic network rate	**3.6549**	**0.5702**	**5.616**	**0.7696**	**-2.04747**
Outdegree	-3.9247	0.7726	-3.2655	0.2254	-0.81908
Reciprocity	3.3711	0.58	2.5436	0.2598	1.302067
Transitive triplets	0.619	0.1966	0.4255	0.0805	0.910835
PA alter	-0.3849	0.3417	-0.1318	0.1642	-0.66763
PA ego	-0.2831	0.3394	0.0514	0.1645	-0.88688
PA similarity	0.0973	1.4105	0.3209	1.0528	-0.12704
NA alter	-0.626	0.3357	0.0487	0.2433	-1.62737
NA ego	-0.187	0.6095	-0.1334	0.254	-0.08117
NA similarity	1.2313	3.0287	2.9046	1.3546	-0.50434
Rate PA	3.643	1.4003	3.14	0.7072	0.320638
PA linear shape	0.0657	0.0957	0.1045	0.1016	-0.27799
PA quadratic shape	-0.2045	0.0714	-0.1682	0.0737	-0.35375
Rate NA	**2.493**	**0.5474**	**1.0837**	**0.2591**	**2.327024**
NA linear shape	-0.1646	0.1447	-0.4856	0.2478	1.118644
NA quadratic shape	-0.4104	0.1983	-0.3617	0.3339	-0.1254
NA effect from gratitude	-0.213	0.3191	0.1797	0.4772	-0.68408

Table 2: Comparison between baseline and post intervention network dynamics. Results in bold represent a significant *change* between baseline and intervention days.

Apart from the SIENA based analysis, we carry out a standard statistical comparison of means between pre and post intervention levels of PA and NA within the population. This is done in order to see if we can detect changes as a result of the intervention by measuring overall levels of PA and NA without resorting to network based analysis (in essence, ignoring any network dynamics within the underlying population). We carry out a pair-wise comparison of each measure across Days 1 to 4. Additionally, we compare Days 0 and 5 as well, to get an idea of the underlying trend. For making the comparisons, we use the non-parametric Wilcoxon Signed

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 3Table 3 indicate that there is a significant increase Positive Affect post intervention, especially when the first and the last days of the study are compared (day 1 to 4). There is no evidence of increase in PA between days 1 and 2 or between 2 and 3. However, there is clear evidence of an increase in PA between days 3 and 4 -- which can be linked to the repeated intervention on the last two days -- hence supporting our hypothesis that the intervention results in improved well-being. This is borne out by the pre and post study measures of PA as well (last row in Table 3).

However, the effect on Negative Affect is more complicated. Whereas there is some significant drop in NA between days 1 and 4, supporting the hypothesis, it is difficult to attribute this to the effect of the intervention as the evidence from the intermediate days is weak. However, there is a significant *increase* in NA between the pre and post study measures (with a p-value of 0.0001 when tested), which may be attributed to external confounding factors. Hence, the fact that there is some evidence of decrease in NA during the intermediate days is significant, which leaves us with the following result:

R4: The intervention on days 3 and 4 causes an increase in PA and decrease in NA overall.

Evolving Katz centrality vs. NA

In order to compute evolving Katz centrality indices, we created the communicability matrices, from the 4 daily interaction adjacency matrices were interactions were given only as 0 and 1 and also for interaction matrices where interactions were given by their durations in minutes. We computed both broadcast and receive indices for both binary (Q) and weighted matrices (Q_dur), where the weights were equal to the duration of communication in minutes.

The broadcast and receive indices were strongly correlated (~87%). This can be explained by the lack of hierarchy in the group (i.e. there was no designated "receivers" and "broadcasters", such as e.g. directors and secretaries in the firms). There was no significant correlation with the degree (which is defined as a total number of intercommunication for an actor), betweeness (all minimum paths between any two actors that pass through a particular actor), normalized degree or normalized betweeness of the friendship, acquaintanceship or friendship and acquaintanceship matrices obtained before and after study. Also there was no significant correlation with average positive or negative affect were the averages of positive and negative affect are taken for each person over 4 days.

However, when we looked at the broadcast and receive indices of the weighted, the majority of actors had both broadcast_dur and receive_dur indices equal to zero. Interestingly, the individuals with the top 5 broadcast_dur indices were also the ones with the minimum average NA (see Figure 1. This implied – that at least as far as this data was concerned, when the duration of communication is taken into account the best "broadcasters" were people with the smallest possible levels of negative affect (note that the majority of the reported communication – i.e. on the average 70-80% each day – were face-to-face, approximately 5% was by phone, and the rest was digital). This finding, although statistically not significant enough in terms of numbers to form an independent result, is still strong enough for us to use in the next study, where we choose a selected few to who we administer the intervention.

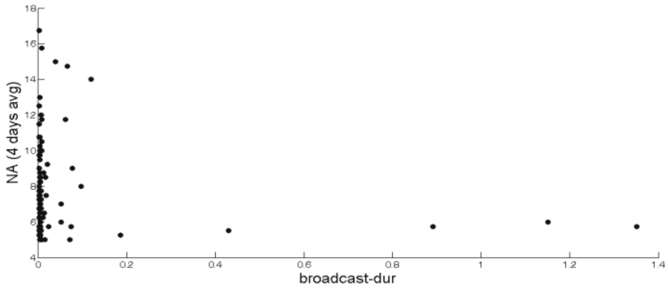

Figure 1: Katz centrality index (broadcast) of weighted Q versus an average value of NA over 4 days

5. Study II: Limited Intervention

This study extends Study I by investigating the effect on network dynamics and resulting implications on well-being, when an intervention is administered to only a subset of individuals in a group, rather than targeting it to everyone. Administering an intervention to everyone in a population maybe optimum in terms of ensuring the desired outcome (as seen in Study 1) but is usually not feasible for a number of reasons – costs, unavailability, lack of resources being the most obvious ones. This study provides the groundwork to facilitate efficiency when administering intervention within a network with the aim of spreading the effect through contagion. It also develops a paradigm and provides directions for future study designs involving interventions in networks. Additionally, it might help to identify factors to take note of when using limited interventions within closed groups.

In the previous study, the gratitude and ice-cream intervention proved successful short-term, raising overall well-being (increasing positive affect daily and a week after, and decreasing negative affect daily) when applied to the whole group. We also saw evidence of homophily in the contact network where individuals choose others with similar levels of both positive and negative affect to communicate to, but we did not find any significant evidence for contagion (transfer of positive/negative affect within a group). In this study a limited number of individuals were targeted with the intervention in order to measure significant spill-over effects, if there are any. Our finding in Study I, that the best broadcasters are always low NA individuals, is used in this study to devise an alternative method of targeting the so called "agents of change" – individuals receiving the intervention in order to pass on the benefits through the network.

5.1. Study Design

We recruited two groups of second year students enrolled in a degree course from a university in the south east of United Kingdom. Students in each of these groups, which are labeled as A and B, were chosen so that they participate in similar activities/courses inside the group, but the two groups do not overlap. Participants were asked for their consent, and were paid for their participation, given the intense requirements of the study. Ethical approval was obtained from the University's ethics committee. In group A, 62 participants completed the study and in the group B, 65 participants. All baseline, pre, post-study and daily measures were the same as in the Study I. The only difference was that PANAS was measured just in the evening, and that *not* all participants got the intervention. The same intervention was administered on the third and the fourth day of study but only to approximately quarter of each group. The main study ran for 4 days (Monday to Thursday), while pre and post measurements were taken on the Wednesday the week before, and a post study measure taken on the Wednesday the week after. Fifteen individuals were chosen for the intervention in group A (approx. 24%) and these were specifically individuals with the *smallest levels of negative affect* on the first day of the study. In the group B, 13 individuals were chosen for the intervention (approx. 20%) and these were individuals with the *highest levels of negative affect*. It was hypothesised in (Barsade, 2002) that when people are feeling low energy, and unpleasant, they become more internally oriented, withdrawn from the group, with less opportunity 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**	**0.8462**
constant friends rate period 3	**5.279**	**1.188**
outdegree	**-2.9286**	**0.1564**
reciprocity	**2.5754**	**0.2358**
transitive triplets	**0.4185**	**0.0439**
SWLS similarity	-0.0569	0.3106
gratitude similarity	0.247	0.36
happiness similarity	0.0842	0.3657
positive affect similarity	-0.5067	0.3021
negative affect similarity	0.0748	0.2796
positive affect alter	**-0.3975**	**0.1554**
positive affect ego	**0.3032**	**0.1402**

Table 4: Group A, structural effect, (significant effects are in bold)

Effect	**par.est.**	**s.e.**
constant friends rate period 1	**4.6426**	**0.7028**
constant friends rate period 2	**3.751**	**0.7048**
constant friends rate period 3	**9.2069**	**1.9737**
outdegree	**-3.1796**	**0.137**
reciprocity	**3.388**	**0.1994**
transitive triplets	**0.4127**	**0.0564**
SWLS similarity	-0.2714	0.2827
gratitude similarity	-0.1327	0.3756
happiness similarity	-0.1435	0.297
PA similarity	-0.2225	0.283
NA similarity	0.102	0.265

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 there is an evidence of an influence (or “contagion”) of 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**	**0.0205**
pa effect from gratitude	0.0142	0.0328
pa effect from happiness	-0.0152	0.0232
pa effect from pa	0.0132	0.0152
pa effect from na	0.0237	0.0163
rate na period 1	**2.3716**	**0.9301**
rate na period 2	**2.162**	**0.7333**
rate na period 3	8.1388	5.0364
na linear shape	-0.113	0.1082
na quadratic shape	-0.3287	0.1718
na average similarity	**5.6398**	**1.8365**
na effect from SWLS	0.0196	0.0351
na effect from gratitude	-0.0942	0.061
na effect from happiness	-0.0133	0.0429
na effect from pa	-0.0421	0.0274
na effect from na	0.0298	0.0261

Table 6: Influence effects, group A (significant effects are in bold)

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**	**0.0205**
pa effect from gratitude	0.0142	0.0328
pa effect from happiness	-0.0152	0.0232
pa effect from pa	0.0132	0.0152
pa effect from na	0.0237	0.0163

rate na period 1	**2.3716**	**0.9301**
rate na period 2	**2.162**	**0.7333**
rate na period 3	8.1388	5.0364
na linear shape	-0.113	0.1082
na quadratic shape	-0.3287	0.1718
na average similarity	**5.6398**	**1.8365**
na effect from SWLS	0.0196	0.0351
na effect from gratitude	-0.0942	0.061
na effect from happiness	-0.0133	0.0429
na effect from pa	-0.0421	0.0274
na effect from na	0.0298	0.0261

Table 7: Influence effects, group B (significant effects are in bold)

This creates complex picture of inter-group affect dynamics and gives us two following results which we will discuss in more details later.

R2: Contagion of positive affect is seen in group A.
R3: Contagion of negative affect is seen in group B.

In terms of the other covariates, SWLS had a very small, but significant (at 0.05 level) influence on the positive affect dynamics. However it had a negative sign in the group A and a positive sign in the group B. Participants with higher levels of SWLS thus had stronger tendency toward higher positive affect values in group B and lower positive affect values in group A. The opposite signs do seem a bit surprising but a possible explanation may be found when we look at changes in PA, NA and the covariates in various groups and relate it to the initial levels of before the intervention was administered (see section 6.3). Happiness and Gratitude had small but significant (at$\alpha = 0.05$) positive effect on PA in group A, but no such effect was found in B.

Intervention versus Baseline

Although there was no control group in the study design, we used the fact that there was no intervention in the first two days as the baseline against which all comparisons were made, post intervention. Hence in order to make detailed comparisons between the baseline and intervention days, we ran the SIENA based network analysis on each consecutive pair of days 1 to 4 and compared the results from the 4 separate estimates for each group.

Interestingly, in the group A we could pinpoint the time when the influence effect switches on for PA - the *PA average similarity* variable is significant for the analysis done on the days 2 and 3, but not for any other pair of days (p-value of 0.0037 for days 2-3, 0.5874 for days 1-2 and 0.6562 for days 3-4). Thus the influence effect in group A nicely coincides with actual administration of the intervention. On the other hand, the corresponding p-values for influence in negative affect in group B were 0.03, 0.04, and 0.15 for days 1-2, 2-3 and 3-4 respectively. Hence, this effect is significant during both the baseline and on the first day of intervention, so we could not relate them to the beginning of intervention exclusively.

Following Study I, we used standard statistical techniques to determine the direct effects of intervention on the various measures of well-being. The aim was also to see if we could detect spill-over effects from people receiving the intervention to those not receiving it via network interactions. We applied the non-parametric Wilcoxon Signed Rank test to assess changes in mean values of SWLS, Gratitude, Happiness, PA and NA between pre and post intervention time points for both groups A and B. We compared these values for those who received the intervention against those who did not, within each group. We expected the intervention to have a greater impact on measures of well-being, for those who received it, in group A than in group B, due to the recipients in A having a lower level of NA overall, which is more suited for such interventions. We also expected an impact of intervention to be more effectively transferred to the rest, in group A than in group B, due to group A intervention recipients also being better broadcasters than their counterparts in B.

Our focus was on the difference between pre (Day 0) and post (Day 5) study measures, but similar to Study I, we examined the patterns within the 4 main days of the study as well. However, there were no significant differences in the PA and NA levels across these 4 days, i.e. there was no evidence for the changes in well-being for those receiving the interventions to be significantly different to those not receiving it. On the other hand, there were definite changes in the pre and post study measures, which are reported in Tables 8 and 9. For convenience, from hereon we refer to the people in the sub-group receiving the intervention as "Int", those not receiving the intervention as "Non" and each group as a whole as "All".

	SLWS		**Gratitude**		**Happiness**		**Positive Affect**		**Negative Affect**	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
All	24.2	24.2	31.0**	30.2**	19.2	19.0	32.3	27.8	21.3	19.3
Non	23.9	21.6	30.9***	27.4***	19.3	17.2	31.3***	26.3***	21.9	18.7
Int	25.1	26.1	31.5	31.1	19.1	19.6	35.3	32.9	19.7***	16.1***

Table 8. Changes in well-being measures for Group A. 2 and 3 stars represent significant difference between pre and post levels at 0.05 and 0.01 respectively.

	SLWS		**Gratitude**		**Happiness**		**Positive Affect**		**Negative Affect**	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
All	25.4	25.0	31.3**	30.4**	19.9	19.8	32.4	28.7	21.6***	19.4***
Non	25.5	24.8	31.8**	29.9**	20.0	19.0	31.8***	28.1***	21.1***	18.3***
Int	25.9**	24.0**	31.0	30.5	19.4	19.2	34.7**	31.2**	23.3	24.0

Table 9. Changes in well-being measures for Group B. 2 and 3 stars represent significant difference between pre and post levels at 0.05 and 0.01 respectively.

Unlike Study 1, the effects of intervention in a sub-group are more complex in nature. Within Group A (with overall lower levels of NA), NA of Int tracks the *downward* trend in NA of Non, although it is only the former which is significant (at $= 0.01$) . Also, the Int do not exhibit a significant change in PA, while Non exhibits a significantly fall (at $\alpha = 0.01$) between Days 0 and 5. Here we take the view that any interpretation of changes in well-being measures in certain people in a group requires a comparison to those changes seen in other people within the same group. This implies the following – ice cream and gratitude intervention worked well for those receiving it in Group A (in the sense of reducing the *loss* in PA relative to the 'background decline'), but the direct benefits of the intervention have not spread to the others in the group.

The results for Group B (where intervention was administered to the high NA individuals) were different. Int in Group B actually *increased* their NA by a small amount (24.0 – 23.3 = 0.7) whereas Non *decreased* their NA between the start and end of the study. These high NA individuals, to whom the intervention was administered to, also did not benefit in terms of PA either, which fell significantly (31.2 – 34.7 = - 3.5), and was matched by a similar fall in the Non individuals (28.1 – 31.8 = -3.7). Hence it can be said that administering an intervention to the high NA individuals not only *did not* help in improving their wellbeing, but actually made matters worse for them as well as others in their network (as witnessed in the significant average NA similarity parameter in Table 7).

In terms of Gratitude, there was a significant drop in the Non for both groups A and B, whereas there was no such 'background drop' for Int – implying that, the intervention was successful in creating resilience against it. Happiness itself did not exhibit any significant change for either group, irrespective of whether we consider the Int or Non individuals. SWLS on the other hand, reduces significantly for the Int in Group B where no such drop is observed in Group A – which provides further evidence of the fact that Gratitude interventions may cause undesirable effects if administered to individuals with high NA. Additionally, direct and sustained spillover effects of well-being from the Int to others in their network do not seem to be present in any significant amount when we compare the absolute changes of attributes between people who got the intervention versus those who didn't.

We computed the communicability matrix, broadcast and receive indices from the 4 daily interaction matrices. Two types of matrices were used – one, where interaction was a binary variable (0 for no interaction and 1 for 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.

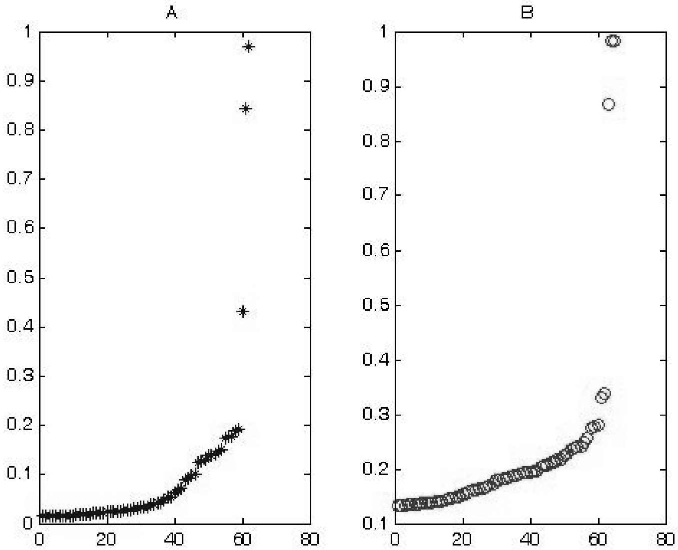

Figure 2: Sorted broadcast indices based on 4 days of group A and B

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 offer significant potential benefits in inducing sustainable behavior change. The most relevant examples are in the health wellbeing sector (Valente, 2012). However, additional applications can lie within organizations (improving work culture, motivation etc.), in education (in schools), in encouraging pro-environmental sustainable behavior, tackling crime and many others. This is an emerging field which is developing rapidly and we see the direction of our future work shaping in two complementary streams:

1) Designing small-scale controlled experiments in order to investigate optimal designs and contexts of networks based interventions in more depth and disentangling complex confounding influences that might emerge while interventions are being administered.

2) Validating our results on large-scale data-sets involving many participants and more dense networks.

We mentioned a few areas earlier where further optimization is required as far as delivering interventions is concerned to a subset of nodes within a network. Related to that, further investigation is required on *how* to choose the agents of change. Our study found a weak relationship between NA and broadcasting, but it is not a well-established principle which can be relied upon. Hence more work is necessary to understand this relationship more thoroughly. Another related area to explore is within the temporal axis – related to our finding of low NA being a predictor of high communicability indices. Further work could be done in relation to larger/finer time-scales and the length of the time-window in which these observations stay valid etc. Moreover, we have only chosen the 'individual' based intervention strategy – whereas at least three more strategies exist (and many more if they are combined) which can be used to deliver the intervention.

We are also aware of the design limitation of the studies presented here – in that, they have been carried out in student based environments exclusively (although in different universities and not with psychology students exclusively) and they rely on self-reporting, so due caution is called for when interpreting the results (as in every other study with self-reported behaviour).

In terms of validation using large scale data sets, one straight forward step would be to examine large online social networks data where positive and negative affect measures are not self-reported but obtained through statistical measurements. Although explicit creation of network ties is difficult to gauge, using 'mentions' and 'friends' as a proxy for contact networks would allow us to conduct a similar experiment on a much large scale. If large-scale validation support the conclusions presented here, it would then be interesting to further explore what kind of mechanisms are responsible for the observed phenomena and how they relate to personality traits.

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