The critical effect of social grooming costs on structures of social relationships

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May 25, 2016

Abstract

The number of possible social relationships a single human being can be involved in is limited, and the distribution of strengths of such relationships show significant skew. This skewness suggests that costs and benefits of the social interactions required to bond with others (social grooming) depend on the strength of the social relationships: if it involved uniform costs and benefits, the distribution would not be skew. In this paper, we show that the cost of social grooming increases with the strength of social relationships, and its gradient increases the width and shallowness of these relationships as evident from an analysis of data from six communication systems. We show that narrow and deep social relationships require higher costs per relationship than do wide and shallow ones, using a comparison with a null model where social grooming costs were assumed to be independent of the strength of social relationships. This may be due to increase in communication volumes, such as number of characters and duration of calls, along with an increase in the strength of social relationships. We test this hypothesis using an individual-based simulation where social grooming costs are assumed to increase linearly with the strength of social relationships; this is the simplest assumption. The results of this simulation suggest that the gradient of social grooming costs increases the width and shallowness of social relationships.

Social grooming is used to construct and maintain social relationships. This behavior is important in complex human societies. Close social relationships lead to mutual cooperation. A high sociability among baboon mothers, for example, increases the probability of their children’s survival, thanks to increased cooperation from others; similarly, humans who frequently participate in social grooming obtain cooperation through social networking games (SNGs). On the other hand, having many weak social relationships helps in obtaining a variety of information which is advantageous in a complex society.

Social relationships provide humans with various advantages. However, they face cognitive constraints (e.g. memory and processing capacity) and time constraints (i.e. time costs) in constructing and maintaining social relationships. These time costs are not negligible, as humans spend a fifth of their day in social grooming and maintaining social relationships. Therefore, the mean strength of existing social relationships has a negative correlation with the number of social relationships.

Humans must construct and maintain social relationships within the constraints of this trade-off. Thus, it is expected that they employ strategies to distribute the limited time resources to maximize benefits from their social relationships. As a result of such strategies, relationship strengths (as measured
by frequency of social grooming [14, 17, 18, 19, 20] may often show a much skewed distribution [21, 19] (distributions following a power law [18, 17, 20] or a power law with exponential cut-off [22, 23]). The Yule-Simon process may cause such distributions [24, 25, 26], i.e. humans’ strategies may lead them to distribute limited time resources in proportion to the strength of social relationships, thus leading to further strengthening of strong social relationships [16].

This study aims to discover how time constraints in social grooming affect social structures. We analyze the following six data sets (see the Data sets section in Materials and Methods and SI Table S1 for details): 1) Twitter data [27], recording interactions among 2,585 users with 278,475 relationships, where an act of social grooming is defined as using the “mention” or “reply” functions to communicate with others; 2) and 3) Data from a Japanese social networking site (SNS) 755, published by 7gogo, Inc. (http://7gogo.jp/), which provides two types of communication systems (see SI Fig. S1 for specifications). We treated these as different data sets, namely group chats and wall communications. The former data records interactions among 17,796 users with 238,611 relationships. We defined an act of social grooming as communicating in a chat limited to two members. The latter data records interactions among 20,000 users with 534,475 relationships. Here we defined an act of social grooming as posting a comment on another’s wall; 4) Data from a Japanese avatar chat system, Ameba Pigg, published by CyberAgent, Inc. (https://pigg.ameba.jp/), which records interaction among 76,379 users with 1,610,710 relationships (see SI Fig. S2 for specifications), where we defined an act of social grooming as communicating in a chat limited to two members; 5) Mobile phone call data [28] recording mobile phone calls among 73 people with 7,801 relationships, where we defined an act of social grooming as a phone call; 6) Data from a short message service (SMS) [28], recording messages among 61 people with 2,266 relationships, where we defined an act of social grooming as sending a message to another. These data sets of human behavior enable us to analyze social interactions quantitatively among many users, which is useful for the construction of theoretical models of social phenomena. Studies [17, 18, 20, 22, 21, 23, 6] previously cited in this paper also analyzed data from SNSs, SNGs, mobile phones, or SMSs.

Results

In the six communication systems considered in this study, the distributions of the strength of social relationships showed power law with exponential cut-off distributions (Fig. 1), similar to that found in
Figure 2: Probability $p$ of social grooming on next days in each strength of social relationship $d$. The data periods are from the first thirty days. These show that those power law distributions were generated by a Yule-Simon process because the $p$ was proportional to $d$. The $p$ of 755 wall communications and 755 group chats in strong social relationships tended to be higher. We did not observe these linear trends in mobile phone and SMS data sets due to the small amount of data. The number of data is given in SI Table S1.

Previous studies [17, 18, 23, 20, 22]. The distributions were generated by a Yule-Simon process (Fig. 2). As above, these skew distributions seem to be caused by individuals’ time cost distribution strategies. Here, we consider a simple model as a null model. If the daily social grooming cost is independent of the strength of the relationship then an individual’s total social grooming cost $C$ is $\sum_{i=1}^{N} d_i$, where $d_i$ is the number of social-grooming-days from the individual to individual $i$, and $N$ is the total number of social grooming partners. If $m$ is mean number of social-grooming-days (i.e. $\sum_{i=1}^{N} d_i/N$), then $C = \sum_{i=1}^{N} d_i = Nm$. Therefore, under this assumption, $N$ should be inversely proportional to $m$. We conducted the following regression analysis to confirm this hypothesis in the data sets:

$$\log N \sim \text{Normal}(\mu),$$

$$\mu = -a \log m + b \log u,$$

where $u$ is a individual’s number of use-days, i.e. $C = u^b$. If this hypothesis is correct, then $a$ (the coefficient of $\log m$) should be 1.

Figure 3 shows that all data sets obey $C = Nm^a$ ($a > 1$) (see SI Table S2 for the regression results). That is, the null model did not fit the data sets. $a > 1$ shows that for $C = Nm^a$, the stronger the social relationship $d$, the more social grooming costs increased per day because the effect of $m$ on $C$ increases with $m$.

To determine how strength $d$ affects social grooming costs $c$, we analyzed the effect of communication volumes $v$ by the strength of social relationships $d$. The results of this analysis (Fig. 4) show that communication volumes, denoted by $v$, increased with increases in the strengths, denoted by $d$, and their gradients were independent of the number of days in the data period $t$ (Fig. 5). That is, the social grooming cost $c$ should increase with an increase in social grooming density ($d/t$) under the assumption that social grooming costs are proportional to communication volume $v$.

To explain $a > 1$ for $C = Nm^a$, we constructed a simulation model of social grooming cost distribution strategies based on the assumption that social grooming costs increase with an increase in social grooming.
Figure 3: Relationships between $N$ (total number of social grooming partners) and $m$ (mean number of social grooming days). These user behavior data (black points) did not obey the null model ($C = Nm$; orange lines), where the assumed social grooming cost is independent of the strength of the relationship, but obeyed $C = Nma$ (green and dash lines). Therefore, individuals who had a few strong relationships (i.e., large $m$) invested more in the relationships than individuals who had many weak relationships (i.e., small $m$), where $a = 1.19$ (Twitter), $a = 1.21$ (755 group chat), $a = 1.56$ (755 wall communication), $a = 1.10$ (Ameba Pigg), $a = 1.07$ (mobile phone) and $a = 1.24$ (SMS), where user use-days $u$ were 75th percentile, estimated by the regression models (Eq. 1), where adjusted R-squares were 0.990 (Twitter), 0.974 (755 group chat), 0.959 (755 wall communication), 0.997 (Ameba Pigg), 0.994 (mobile phone) and 0.990 (SMS) (see SI Table S2 for details). The number of data is given in SI Table S1.

Figure 4: The relations of communication volumes per day $v$ by strengths of social relationships $d$. The strengths increased volumes of communication per day, that is, social grooming costs also probably increase with an increase in the strengths, where the volumes were number of characters per day in Twitter, 755 and Ameba Pigg, duration per day in mobile phones and frequency of messaging per day in SMS because no information regarding number of characters in the SMS data set was considered. The orange lines are the 25th percentile, green and dotted lines are the 50th percentile and blue and dashed lines are the 75th percentile. These are shown for cases where the number of samples is more than 20 (the ranges of $d$ of mobile phone and SMS are short because the sizes of these data sets were small). The number of data is given in SI Table S1.
Figure 5: Compaction of the medians of \( v \) for each social grooming density \( (d/t) \) for different periods (\( t \) is number of days of the data periods), which are entire periods (orange lines), nine-tenths of the periods (green and dotted lines), and eight-tenths of the periods (blue and dashed lines). These similar gradients are analogized, i.e. this shows gradients depending on social grooming density as distinct from those depending on social grooming frequency. These are shown when the number of samples is more than 20 (the ranges of \( d \) of mobile phone and SMS are short because the sizes of these data sets were small). The number of data is given in SI Table S1.

Figure 6: The results of fits by the simulation model to the regression lines of all data sets (i.e. green and dashed lines in Fig. 3). Very good fits were observed between the simulation results (orange triangles) and the regression lines (green lines); that is, the simulation model has explanation capacity for the phenomenon \( a > 1 \) for \( C = Nm^a \). The parameters of the cost functions were \( \alpha = 1.34 \) and \( \beta = 0.24 \) (a: Twitter), \( \alpha = 1.27 \) and \( \beta = 0.39 \) (b: 755 group chat), \( \alpha = 3.89 \) and \( \beta = 0.23 \) (c: 755 wall communication), \( \alpha = 1.62 \) and \( \beta = 0.64 \) (d: Ameba Pigg), \( \alpha = 0.05 \) and \( \beta = 0.31 \) (e: mobile phone) and \( \alpha = 5.05 \) and \( \beta = 0.34 \) (f: SMS). The number of data is given in SI Table S1.
density $d/t$ (see The simulation model in the Materials and Methods section for details). We used a linear social grooming cost function $c(d) = \alpha d/t + \beta$ as the simplest assumption (if $\alpha = 0$ then it is the null model). In the model, individuals construct social relationships using their limited resources (i.e. time), based on this assumption and the Yule-Simon process. This model fits all data sets (Fig. 6), that is, it had explanation capacity for the phenomenon $a > 1$ for $C = Nm^a$; furthermore, the $a$ was determined by the cost function gradient $\alpha$ (Fig. 7a). Here we analyzed the effect of the gradient $\alpha$ to the structure of social relationships by using the model. As the result (Fig. 7b and 7c) demonstrates, the increase of the gradient $\alpha$ increased the power law coefficients of the strength of social relationships, i.e. the gradient increased width and shallowness of social relationships.

**Discussion**

There is a trade-off between the number of social relationships (i.e. $N$) and the mean strength of social relationships (i.e. $m$) [15, 16] as humans must perform frequent social grooming to maintain close relationships [13, 14]. Here, we found a simple law where $N$ was inversely proportional to $m^a$ ($a > 1$). The $a$ was due to the increase in social grooming costs; the increase gradient increased with the strengths of social relationships. This cost increase may be due to the fact that strong social relationships tend to be the site of complex and frequent communications.

We also found that the gradient was an important factor to determine the structure of social relationships. In communication systems with the large gradient of social grooming costs, people tend to construct wide and shallow social relationships. In contrast, people tend to maintain close social relationships with limited partners in the communication system with a small gradient of social grooming costs. The gradient, which represents a time cost distribution strategy, may depend on social environments such as the degrees of conflict. Human beings invest greatly in strong social relationships to compete for the cooperation of others [29, 30]. Strong social relationships exist for acquiring cooperation from oth-
ers \cite{29, 30}. However, cooperators cannot cooperate with everyone because there are costs to cooperation \cite{31, 32}. As a result, human beings should need to compete on the strength of social relationships with the cooperators’ friends, and it may generate a skew distribution of the strength of social relationships. On the other hand, widespread investments may lead to a lot of cooperation from many cooperators. Therefore, human beings should change their investments according to their time cost distribution strategy (i.e., the gradient of social grooming costs) depending on the social environment.

The difference of the gradient may generate various kinds of social relationships. In text communications over the Internet, such as on Twitter, users tend to construct wide and shallow social relationships which are used for acquiring and diffusing information \cite{10, 33}, and the gradient of social grooming costs increases should be high in the communication systems. On the other hand, for strong social relationships, users prefer face to face or telephone communications \cite{34}, and the gradient should be low in the communication systems.

Based on the social brain hypothesis, the explanation of the evolution of humanity’s signature social structures is expected to offer knowledge about human origins \cite{1}. We believe that our findings contribute to the explanation of humanity’s signature social structures such as the limitation on the number of social relationships \cite{1, 13, 35, 36} and the skewness of social relationships \cite{21, 22, 18, 23, 19, 20}.

Materials and Methods

Data sets

We used six data sets: 1) Twitter data (used as test set in \cite{27}) recording interactions among 2,585 people with 278,475 relationships, from 6/23/2007 to 3/17/2010, where an act of social grooming is defined as using the “mention” or “reply” functions to communicate with others; 2) and 3) Data from the Japanese SNS 755, published by 7gogo, Inc. (https://7gogo.jp/), which provides two types of communication systems data, dating from 1/1/2015 to 3/31/2015, which we treated as two different sets (see SI Fig. S1 for specifications), namely data from group chats and that from wall communications. The former data records interactions among 17,796 users with 238,611 relationships, where we defined an act of social grooming as communicating in a chat limited to two members. The latter data record interactions among 20,000 users with 534,475 relationships, where we defined an act of social grooming as posting a comment on another’s wall. We removed data relevant to official users from both data sets; 4) Data from Japanese avatar chat Ameba Pigg, published by CyberAgent, Inc. (https://pigg.ameba.jp/), which records interactions among 76,379 users with 1,610,710 relationships, from 10/1/2014 to 12/31/2015 (see SI Fig. S2 for specifications), where we defined an act of social grooming as communicating in a chat limited to two members; 5) Data from mobile phone calls \cite{28}, recording mobile phone calls among 73 people with 7,805 relationships from 9/5/2008 to 6/29/2009, where we defined an act of social grooming as a call to another; 6) Data from SMS \cite{28}, which records SMSs among 61 people with 2,266 relationships from 1/1/2008 to 6/27/2009, where we defined an act of social grooming as sending a message to another.

In the data sets from Twitter, 755 (group chat and wall communication) and Ameba Pigg, we limited the targets of analysis to active users who had more number of social grooming days than the 50th percentile among Twitter users and the 75th percentile among 755 and Ameba Pigg users because these internet service data sets included many inactive users.

The Simulation Model and Experiments

To determine how the strength of relationship \(d\) affects social grooming costs, we analyzed the relation of communication volumes \(v\) to the strength of social relationships \(d\). The results of the analysis (Fig. \ref{fig:4}) show that communication volumes \(v\) increased along with relationship strength \(d\) and the gradients were independent of the number of days of the data periods \(t\) (see Fig. \ref{fig:4}). That is, social grooming cost
should increase with an increase in social grooming density \((d/t)\), under the assumption that social grooming costs are proportional to communication volume \(v\).

We conducted the following simulation. At each step \(t\), individual \(i\) repeats the following for \(R > 0\). Each \(i\) has a resource \(R\) that is spent when \(i\) performs social grooming with others. However, each \(i\) does not perform the act of social grooming twice with same individuals in each step \(t\). \(R\) is reset before each step \(t\). Each \(i\) creates a social relationship with a stranger \(j\) based on probability \(q_i\), where the strength of social relationship \(d_{ij}\) is 1 and \(i\) pays the cost \(\beta\) from its resource \(R\) (if \(R < \beta\), then \(d_{ij}\) is \(R/\beta\) and \(R\) becomes 0). In contrast, \(i\) reinforces its social relationships based on probability \(1 - q_i\). Each \(i\) selects a social grooming partner \(j\) based on a probability proportional to the strength of the social relationships between \(i\) and \(j\) \((d_{ij})\), then \(i\) adds 1 to the strength of its social relationship \(d_{ij}\) and \(R\) becomes 0).

We conducted two experiments that fit the actual data (i.e. Fig. 3), analyzing the effect of parameter \(\alpha\). In the former experiment, we tested the fit of this model. That is, we optimized parameters \(\alpha, \beta\) to fit the regression lines of Fig. 3, where the evaluation function was mean square error between simulation results and regression lines, \(T\) was period of each data set, \(R\) was the 75th percentile of user use-days \(u\) divided by \(T\) \((R = 0.126\) and \(T = 998\) (Twitter), \(R = 0.258\) and \(T = 120\) (755 group chats), \(R = 0.225\) and \(T = 120\) (755 wall communications), \(R = 0.164\) and \(T = 456\) (Ameba Pigg), \(R = 0.589\) and \(T = 297\) (mobile phone) and \(R = 0.107\) and \(T = 543\) (SMS)). In the latter experiment, we observed the effect of \(\alpha\) on \(C = Nm^\alpha\) and the distribution of social relationship strengths, where we used \(T, R\) and \(\beta\) of the Twitter data set, as with the former experiment.

End Notes

Acknowledgement We are grateful to assistant Professor Genki Ichinose at Shizuoka University, who provided valuable comments and suggestions throughout this study.

Author Contributions M.T. designed the research. M.T. conducted data analysis. I.F. contributed analysis tools. I.F. constructed a data analysis platform for our data. M.T. wrote the main manuscript text. All authors reviewed the manuscript.

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Supporting Information Figure S1: Basic specification of 755. Users have two roles, namely chat member (User A, B and C) or commenter (User X, Y and Z). This application provides two types of interactions, those between chat members and those between chat members and commenters. We term the former a group chat and the latter a wall communication. We treat these as different data sets. Users can perform either role at any time. A chat member creates chat rooms where they chat with other chat members (this is an interaction between chat members). To join a chat room as a chat member, users have to be invited by other chat members. On the other hand, all users can read all chat rooms, and they can post comments to chat rooms as commenters, without limits. Comments are limited to 200 characters (almost all users use Japanese); in contrast, chat members’ posts can use unlimited number of characters. Chat members can respond to comments (an interaction between chat members and commenters); however, other users can only read the comments. That is, wall communications are open platforms where users can talk to someone they do not know. On the other hand, group chats are semi-closed platforms where users can speak with acquaintances who were invited by chat members.
Supporting Information Figure S2: The basic specification of the avatar chat Ameba Pigg. Users chat in a room where more than one user can belong. They can enter or leave the room any time. Their utterances are limited to 37 characters (almost all users use Japanese), and an unlimited number of utterances can be used. That is, users can talk to anyone at any time.
Supporting Information Table S1: Summaries of data sets. \( N \) and \( m \) were tallied for each individual, \( d \) was tallied for each relationship and \( v \) was tallied for each combination between relationship and day.

| Communication System    | Variable | Size | min | 2.5%ile | 25%ile | 50%ile | 75%ile | 97.5%ile | max |
|-------------------------|----------|------|-----|---------|--------|--------|--------|----------|-----|
| Twitter                 | \( N \)  | 2,585| 7   | 28      | 65     | 94     | 136    | 264      | 736 |
|                         | \( m \)  | 2,585| 1.25| 1.84    | 2.79   | 3.55   | 4.66   | 8.61     | 25.23 |
|                         | \( d \)  | 278,475| 1   | 1       | 1      | 1      | 3      | 20       | 166 |
|                         | \( v \)  | 943,719| 2   | 21      | 54     | 94     | 136    | 383      | 14,120 |
| 755 Group chat          | \( N \)  | 17,796| 1   | 1       | 5      | 9      | 17     | 51       | 187 |
|                         | \( m \)  | 17,796| 1.00| 1.43    | 2.44   | 3.53   | 5.60   | 18.00    | 112.00 |
|                         | \( d \)  | 238,611| 1   | 1       | 1      | 2      | 4      | 18       | 112 |
|                         | \( v \)  | 901,212| 1   | 1       | 17     | 48     | 143    | 1,072    | 31,990 |
| 755 Wall communication  | \( N \)  | 20,000| 1   | 1       | 6      | 11     | 24     | 159      | 1,372 |
|                         | \( m \)  | 20,000| 1.00| 1.02    | 1.53   | 2.45   | 4.39   | 15.67    | 103.00 |
|                         | \( d \)  | 534,475| 1   | 1       | 1      | 1      | 2      | 13       | 121 |
|                         | \( v \)  | 1,270,546| 3   | 6       | 17     | 33     | 73     | 452      | 17,565 |
| Ameba Pigg              | \( N \)  | 156,222| 1   | 1       | 3      | 5      | 13     | 64       | 689 |
|                         | \( m \)  | 156,222| 1.00| 1.00    | 1.33   | 2.00   | 3.92   | 19.32    | 454.00 |
|                         | \( d \)  | 1,911,139| 1   | 1       | 1      | 1      | 2      | 13       | 22 |
|                         | \( v \)  | 6,989,307| 13  | 143     | 358    | 652    | 1,289  | 4,588    | 87,281 |
| Mobile phone            | \( N \)  | 73    | 2   | 16      | 47     | 94     | 126    | 279      | 688 |
|                         | \( m \)  | 73    | 1.81| 2.06    | 3.34   | 3.95   | 4.75   | 7.45     | 8.07 |
|                         | \( d \)  | 7,801| 1   | 1       | 1      | 1      | 1      | 2        | 32 |
|                         | \( v \)  | 32,728| 0   | 0       | 24     | 60     | 223    | 10,261   | 328,031 |
| SMS                     | \( N \)  | 48    | 1   | 1       | 4      | 11     | 19     | 194      | 283 |
|                         | \( m \)  | 48    | 1.00| 1.00    | 1.68   | 2.85   | 4.03   | 11.35    | 30.5 |
|                         | \( d \)  | 1,233| 1   | 1       | 1      | 1      | 1      | 2        | 30 |
|                         | \( v \)  | 4,942| 1   | 1       | 1      | 3      | 7      | 36       | 168 |
Supporting Information Table S2: The results of the regression analysis (Eq. 1) of each communication system. The coefficient $-a$ were smaller than $-1$, that is, the user behaviour data did not obey the null model ($C = Nm; a = 1$). Their adjusted R-squared values were 0.990 (Twitter), 0.974 (755 group chat), 0.959 (755 wall communication), 0.997 (Ameba Pigg), 0.994 (mobile phone) and 0.990 (SMS).

| Communication System | Coefficient | Estimate | Standard Error | t-value | p-value       |
|----------------------|-------------|----------|----------------|---------|---------------|
| Twitter              | $-a$        | -1.189567| 0.023256       | -51.15  | Less than 2.0 × 10^{-16} |
|                      | $b$         | 1.309346 | 0.006815       | 192.12  | Less than 2.0 × 10^{-16} |
| 755 Group chat       | $-a$        | -1.214229| 0.004640       | -261.7  | Less than 2.0 × 10^{-16} |
|                      | $b$         | 1.269766 | 0.002294       | 553.5   | Less than 2.0 × 10^{-16} |
| 755 Wall communication| $-a$       | -1.562142| 0.006250       | -249.9  | Less than 2.0 × 10^{-16} |
|                      | $b$         | 1.476393 | 0.002769       | 533.2   | Less than 2.0 × 10^{-16} |
| Ameba Pigg           | $-a$        | -1.0954104| 0.0007440      | -1472   | Less than 2.0 × 10^{-16} |
|                      | $b$         | 1.0939529| 0.0003137      | 3487    | Less than 2.0 × 10^{-16} |
| Mobile phone         | $-a$        | -1.07332 | 0.15756        | -6.812  | 2.59 × 10^{-9} |
|                      | $b$         | 1.25628  | 0.04689        | 26.795  | Less than 2.0 × 10^{-16} |
| SMS                  | $-a$        | -1.24089 | 0.07815        | -15.88  | Less than 2.0 × 10^{-16} |
|                      | $b$         | 1.21949  | 0.02995        | 40.72   | Less than 2.0 × 10^{-16} |