

Topological relationships between brain and social networks

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Abstract

Brains are complex networks. Previously, we revealed that specific connected structures are either significantly abundant or rare in cortical networks. However, it remains unknown whether systems from other disciplines have similar architectures to brains. By applying network-theoretical methods, here we show topological similarities between brain and social networks. We found that the statistical relevance of specific tied structures differs between social “friendship” and “disliking” networks, suggesting relation-type-specific topology of social networks. Surprisingly, overrepresented connected structures in brain networks are more similar to those in the friendship networks than to those in other networks. We found that balanced and imbalanced reciprocal connections between nodes are significantly abundant and rare, respectively, whereas these results are unpredictable by simply counting mutual connections. We interpret these results as evidence of positive selection of balanced mutuality between nodes. These results also imply the existence of underlying common principles behind the organization of brain and social networks.

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1. Introduction

Although brains are highly complex networks, it is unlikely that neurons and cortical areas are randomly connected (Felleman & Van Essen, 1991; Hilgetag, O’Neill, & Young, 1996; Song, Sjöstrom, Reigl, Nelson, & Chklovskii, 2005; Young, Scannell, & Burns, 1995). In order to comprehend their organization, it is likely to be important to quantify their architectures. Recently, it has been reported that specific connected structures are either significantly abundant or rare in mammalian cortical networks (Sakata, Komatsu, & Yamamori, 2005; Sporns & Kötter, 2004), and these tendencies are significantly similar across species (Sakata et al., 2005). However, it still remains unknown whether topological similarities between brain networks and systems from other disciplines exist or not. In neural development, specific molecules which are crucial in axonal growth toward specific targets function as “attractants” or “repellents” (Tessier-Lavigne & Goodman, 1996).

Positive and negative mutual interactions by activity-based competition in the axonal growth of retinal ganglion cells are also known (Hua, Smear, Baier, & Smith, 2005). These results suggest that both positive and negative influences among neurons and their targets critically contribute to the establishment of their connections. On the other hand, we intuitively know that explicit social evaluations among people, such as a positive or negative emotional attitudes, play a role in the establishments of social ties. This analogy between the role of explicit social attitudes in the establishment of social ties and that of molecular functions in the development of neuronal circuits raises an intriguing hypothesis that brain and social networks might contain similar connected structures. The goal of the present study is therefore to investigate the topological similarity between brain and social networks.

The emerged network theory has uncovered that many natural and artificial networks share global and local topological properties (Albert & Barabási, 2002; Barabási & Albert, 1999; Milo et al., 2002; Watts & Strogatz, 1998). Many networks display certain local connected structures, termed “network motifs”, at a much higher frequency than expected in randomized networks (Milo et al., 2002). Based on the Significance Profile (SP) of small

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Table 1
Collection of complex networks and their topological features

Network	Size	#m/#edge	l	l_{rand}	C	C_{rand}	r
Brain (macaque 1)	72	325/833	2.21	1.96 ± 0.01	0.497	0.163 ± 0.005	-0.127
Brain (macaque 2)	30	121/311	1.72	1.66 ± 0.01	0.561	0.358 ± 0.011	-0.047
Brain (macaque 3)	41	104/426	1.48	1.79 ± 0.01	0.799	0.259 ± 0.008	-0.037
Brain (cat)	65	409/1139	1.86	1.73 ± 0.00	0.582	0.274 ± 0.004	0.015
Brain (rat)	23	59/212	1.66	1.59 ± 0.01	0.526	0.419 ± 0.014	-0.143
Neuron (<i>C. elegans</i>)	197	256/1974	2.91	2.54 ± 0.00	0.185	0.051 ± 0.002	0.060
Social +1	25	19/75	2.56	2.78 ± 0.14	0.427	0.103 ± 0.030	-0.007
Social +2	32	37/192	2.18	2.07 ± 0.02	0.393	0.192 ± 0.019	0.154
Social +3	67	40/182	4.63	3.99 ± 0.16	0.170	0.031 ± 0.011	0.190
Social +4	35	22/97	4.57	3.26 ± 0.16	0.371	0.063 ± 0.020	0.131
Social +5	32	21/81	4.20	3.37 ± 0.23	0.214	0.059 ± 0.021	-0.016
Social +6	17	23/85	1.69	1.83 ± 0.04	0.541	0.305 ± 0.037	0.021
Social +7	29	123/405	1.52	1.50 ± 0.00	0.579	0.499 ± 0.008	-0.085
Social -1	17	14/85	1.81	1.83 ± 0.03	0.400	0.307 ± 0.036	-0.222
Social -2	32	2/90	2.87	3.13 ± 0.16	0.091	0.071 ± 0.022	-0.023
Social -3	28	9/110	2.39	2.46 ± 0.07	0.117	0.134 ± 0.027	-0.183
Bipartite model 1	505	25/307	3.56	4.38 ± 0.38	0.000	0.001 ± 0.001	-0.971
Bipartite model 2	200	102/1255	3.24	3.08 ± 0.01	0.000	0.031 ± 0.003	-0.011
Electronic circuit 1	122	0/189	6.02	6.91 ± 0.86	0.000	0.006 ± 0.004	0.058
Electronic circuit 2	252	0/399	7.28	8.83 ± 0.78	0.000	0.003 ± 0.002	0.060

#m, number of pairs of edges involving mutual connections. l , average shortest path length. C , average clustering coefficient. r , assortative coefficient (Newman, 2002). rand, topological features of an ensemble ($n = 1000$) of randomized networks that have the same number of edges and size as the real network. Data represent average \pm s.d.

subgraphs in the real network compared to randomized networks, some networks from different systems have very similar SPs, which are categorized as a “superfamily” (Milo, Itzkovitz, Kashtan, Levitt, Shen-Orr, et al., 2004). This methodology is not only mathematically stringent but also effective for analyzing network architectures of different sizes. However, topological similarities between cortical networks and systems from other disciplines have not yet been systematically compared. Thus, in the present study, by applying this network-theoretical approach to connectivity data from networks of cortical areas and other disciplines, we show an unexpected topological similarity between brain and specific social networks.

2. Methods

2.1. Database of unweighted directed networks

All unweighted directed networks collected in this study and their basic properties are summarized in Table 1. Although many of the original data matrices represent weighted directed networks, we employed them as unweighted directed networks.

We used macaque cortical connectivity data from Young (1993) for “Brain (macaque 1)”. Area 14 was excluded because it has very few connections. “Brain (macaque 2)” was derived from results summarized by Felleman and Van Essen (1991). For “Brain (macaque 3)”, we used connectivity data related to the orbitofrontal cortex reported by Carmichael and Price (1995a, 1995b, 1996). Cat cortical connectivity data reported by Scannell, Blakemore, and Young (1995) were used for “Brain (cat)”. “Brain (rat)” comprised connectivity data associated with rat hippocampus, taken from Burns and Young (2000). These networks are thought to be involved

in spatial memory. “Neuron (*C. elegans*)” was available at <http://www.wormbase.org>. We used data for chemical synapses only.

For social networks, detailed descriptions of nodes and ties are summarized in Table 2. We first collected data from six published papers (Jennings, 1937; MacRae, 1960; Moreno, 1934; Nordlie, 1958; Wolman, 1937; Zeleny, 1950) in the social sciences, in which people positively and/or negatively selected other people (Fig. 1(a) and Table 2). Then, we considered positive and negative choices as positive and negative social attitudes, respectively. In constructed social networks, a node and a directed edge represent a person and a social tie from one person to another, respectively (Fig. 1(a)). In the present analysis, we distinguished these social networks depending on the types of relationship, that is, these networks were divided into “friendship” and “disliking” networks (Fig. 1(a) and Table 2). Detailed procedures are as follows: “Social +1” was derived from “sociogram II” analyzed by Jennings (1937). “Social +2” and “Social -2” were derived from “matrix I” given by Zeleny (1950). Although original data represent a weighted directed graph ($w = -2, 0, 1, 2$), we distinguished positive weighted edges ($w = 1, 2$) from negative ones ($w = -2$) as belonging to different networks. “Social +3” was derived from “Table 1” presented by MacRae (1960). “Social +4” and “Social +5” were derived from “sociogram I” and “sociogram II” given by Wolman (1937), respectively. “Social +6” and “Social -1” were originated by Nordlie (1958) and were derived from “Table 2.14.” in Doreian, Batagelj, and Ferligoj (2005). The top and the lowest six ranks were considered to be positive and negative edges, respectively. “Social +7” and “Social -3” were derived from “Table 1” given by McKinney (1948). Although original data represent a weighted directed graph ($w = -1, 0, 1$), we distinguished

Table 2
Collection of social networks

Network name	Sources	Description
Social +1	Jennings (1937)	Sociometric analysis for "Community in the New York State Training School for Girls". Three choices expressing degrees of preference for "eating at the same table" were allowed for each girl.
Social +2	Zeleny (1950)	Sociometric analysis of a college classroom. After 6 weeks of 1 hour of daily contact, each student was asked to choose persons whom she/he wants and does not want to work with.
Social +3	MacRae (1960)	Sociometric analysis of prison inmates. Each inmate was asked the following question: "What fellows on the tier are you closest friends with?"
Social +4	Wolman (1937)	Sociometric analysis of families in Centerville. Each family in Centerville was asked to submit a secret ballot indicating three neighbors in order of preference.
Social +5	Wolman (1937)	The same as Social +4.
Social +6	Nordlie (1958)	Sociometric analysis of students in the final week of a semester. The students were asked to assign attractiveness rankings to other students.
Social +7	McKinney (1948)	Sociometric analysis of a ninth grade classroom. The students in the class were asked to express their attitude toward participating in a discussion group with other members of the class.
Social -1	Nordlie (1958)	The same as Social +6.
Social -2	Zeleny (1950)	The same as Social +2.
Social -3	McKinney (1948)	The same as Social +7.

Persons involved in each study were required to choose particular persons positively and/or negatively. In studies carried out by Zeleny (1950), Nordlie (1958) and McKinney (1948), both positive and negative relationships were simultaneously surveyed. In the present study, these two relationships were distinguished to construct different types of networks.

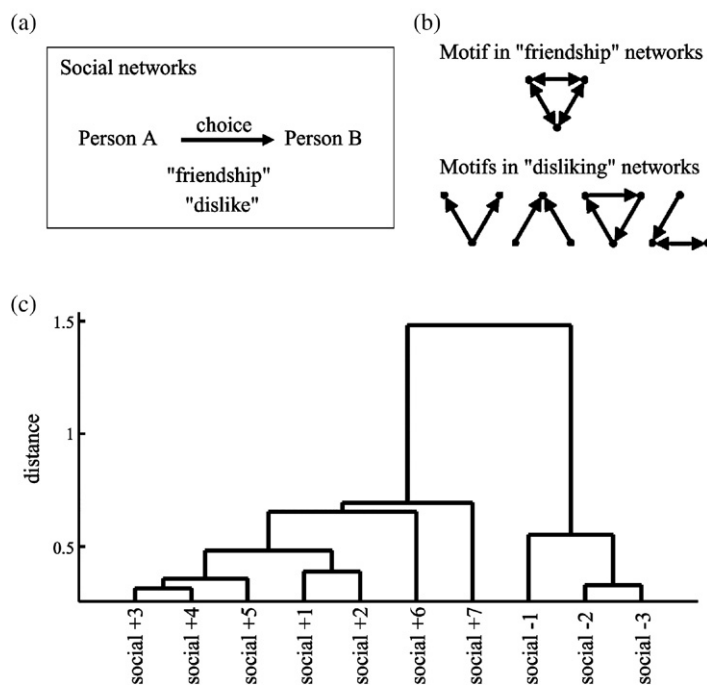


Fig. 1. Relation-type specificity in social networks. (a) Classification of social networks. We considered social networks that consisted of positive and negative evaluations as friendship and disliking networks, respectively. (b) Network motifs in friendship and disliking networks. Network motifs, defined as an overrepresented subgraph ($SP > 0.2$), are shown. (c) Hierarchical clustering of TSPs of social networks.

positive weighted edges ($w = 1$) from negative ones ($w = -1$) as belonging to different networks.

In bipartite models, nodes belong to two groups and connections are formed between these groups but not within groups. We generated two bipartite networks: "Bipartite model 1" with two groups of nodes of sizes $N_1 = 500$ and $N_2 = 5$ and "Bipartite model 2" with $N_1 = 100$ and $N_2 = 100$. Connection probabilities of a directed or reciprocal connection between nodes of different groups were $p = 0.06$ and $q =$

0.003, respectively. For electronic circuits, data are available at <http://www.weizmann.ac.il/mcb/UriAlon/>.

2.2. Database of weighted directed networks

All weighted directed networks collected in this study are summarized in Table 3. Social +2, Social -2, Social +1, Social +4, Social +5, Brain (macaque 3), and Brain (cat), in all of which weights of edges were classified into four degrees

Table 3
Collection of weighted networks

Network	Size	#edge		
		$w = 1$	$w = 2$	$w = 3$
Brain (macaque 3)	41	151	71	204
Brain (cat)	65	534	483	122
Social (+2)&(-2)	32	90	96	96
Social (+1)	25	25	25	25
Social (+4)	35	29	34	34
Social (+5)	32	21	28	32

#edge, the number of weighted edges, is presented by each weight value.

($w = 0, 1, 2, 3$), were used. For Social +2 & -2, we replaced edge weights $w = -2, 1, 2$ in the original data with $w = 1, 2, 3$.

2.3. Analysis of significance profiles

All analyses were carried out with custom-written LabVIEW (National Instruments, Austin, TX), MATLAB (Mathworks Inc., Natick, MA), C++ (Microsoft, Redmond, WA), and Perl software.

The network motif detection algorithm is described elsewhere (Milo, Itzkovitz, Kashtan, Levitt, Shen-Orr, et al., 2004; Milo et al., 2002; Sakata et al., 2005). Briefly, we started with the real network, and repeatedly switching randomly chosen pairs of connections (e.g., $X1 \rightarrow Y1, X2 \rightarrow Y2$ are replaced by $X1 \rightarrow Y2, X2 \rightarrow Y1$). To control the appearances of 2-node motifs, we generated a series of randomized network groups ($n = 1000$), each of which preserved the numbers of incoming and outgoing degrees per node, as well as the number of mutual edges per node, as in the real network. We scanned all combinations of M -node subgraphs (in this study, $M = 3$) of real and randomized networks and determined the appearances of all possible motifs. The procedure used to detect higher-order cliques ($M = 4, 5, 6, 7, 8, 9$) was the same as in this method. The concentration of subgraph i is the number of times it appears in the network divided by the total number of counts of all possible connected subgraphs (13 subgraphs). For each subgraph i , the statistical significance is evaluated by the Z score:

$$Z_i = \frac{N_{\text{real}_i} - \langle N_{\text{rand}_i} \rangle}{\text{std}(N_{\text{rand}_i})},$$

where N_{real_i} is the number of times the subgraph appears in the network, and $\langle N_{\text{rand}_i} \rangle$ and $\text{std}(N_{\text{rand}_i})$ are the mean and the standard deviation of its appearances in the randomized network group, respectively. When subgraph i never appeared in randomized networks, Z_i was set at zero. SP is the vector of Z scores normalized to length 1.

$$\text{SP}_i = \frac{Z_i}{\sqrt{\sum Z_i^2}}.$$

This allows us to compare the locally connected structure of networks from different data, even if network sizes are different.

The algorithm used to detect weighted motifs was essentially the same as in the above method. First, the network was

scanned for nine possible connected subgraphs ($M = 2$). Using the switching algorithm, we then generated an ensemble of 1000 randomized networks, which had the same numbers of incoming and outgoing weighted connections per nodes, and compared them with the real network. Methods for the evaluation of the statistical significance of each subgraph and comparisons of their profiles among different networks were the same as those in the analyses for unweighted networks. Imbalance indices were defined as the differences in weights between connections.

2.4. Robustness experiment

This analysis was conducted on the supercomputer at our institute. “mfinder” (<http://www.weizmann.ac.il/mcb/UriAlon/>) and “R” (<http://www.r-project.org/>) software were also used. First, a node was randomly chosen and added to a subgraph based on connectivity data from the real network, and Triad Significance Profiles (TSPs) from the subgraph were compared with those from the real network by calculating the correlation coefficient r . These processes were repeated until the size of the subgraph grew to the same as that of the real network. We started these experiments from a subgraph size of $N = 5$, and over 5500 sessions were conducted. We adopted two strategies to select nodes: (1) The “random selection” condition: a new node was randomly chosen and added to the subgraph. (2) The “neighbor selection” condition: a new node which was a “neighbor” to the subgraph in the real network was randomly chosen and added to the subgraph. Note that directions of edges were not considered in choosing the new node.

3. Results

3.1. Relation-type specificity in social networks

Since the types of social relationships (i.e., the types of edges in social networks) are quite varied, topological features of social networks might differ depending on the types of explicit social attitudes. To test this possibility, collected social networks were divided into “friendship” and “disliking” networks (Fig. 1(a) and Methods). Many of these networks showed the small-world phenomenon (Watts & Strogatz, 1998). Compared with the Erdős–Rényi random networks (Erdős & Rényi, 1960), these social networks had similar average shortest path lengths l (Table 1). Many of the analyzed networks had a significantly larger average clustering coefficient C than those of the random networks (Table 1). In all of the analyzed friendship networks, “clique”, where all persons are reciprocally interconnected, was significantly abundant (Fig. 1(b)). On the other hand, “V-shape” and “loop” subnetworks were network motifs in the disliking networks (Fig. 1(b)). Furthermore, we analyzed the Significance Profile (SP) of 13 possible triads (TSP) for 10 social networks. For comparison of these TSPs, we constructed a dendrogram with hierarchical clustering (Fig. 1(c)). We found structural diversity of social networks and their clear distinction depending on the type of relationship (Fig. 1(c)).

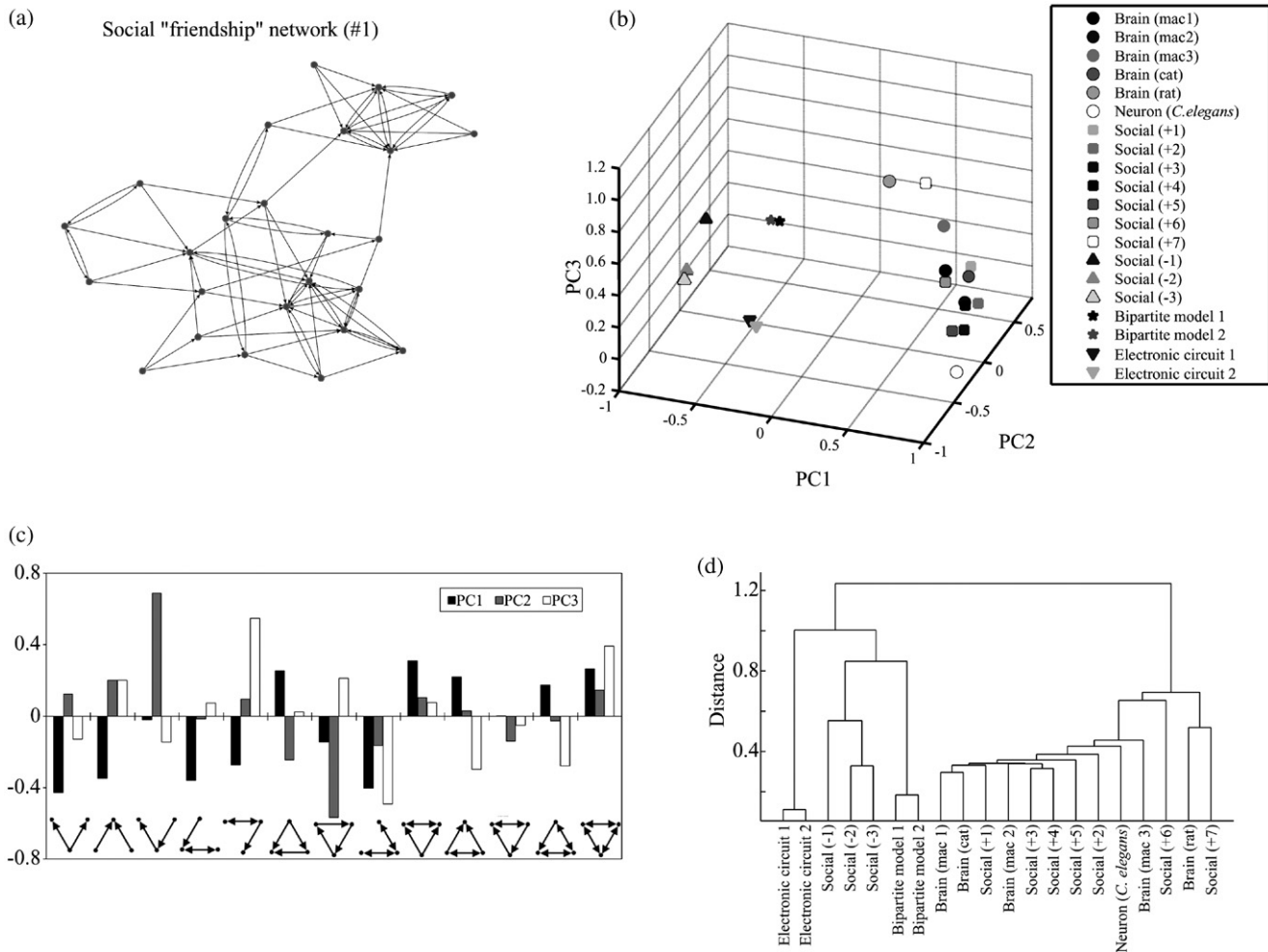


Fig. 2. Topological similarity and dissimilarity among complex networks. (a) Global topology of a friendship network. The distributed analytical software, "Pajek" (<http://vlado.fmf.uni-lj.si/pub/networks/pajek/>), was used to draw this network architecture. (b) Principal Component (PC) Analysis (PCA) of TSPs of complex networks. TSPs from each network were projected into the top three PCs. (c) The top three PCs in this analysis. Each PC represents variability of TSPs. (d) Hierarchical clustering of TSPs of complex networks. Note that brain and friendship networks fell into the same cluster. Abbreviations: mac, macaque; PC, principal component.

3.2. Topological similarity between brain and friendship networks

To evaluate topological similarity between brain and social networks, we first drew networks using the Kamada–Kawai algorithm (Kamada & Kawai, 1989). Some features (such as modularity) of the cat cortical network (see Fig 1(b) in Sakata et al. (2005) seemed to be similar to those of the specific social network (Fig. 2(a)). This tendency implies topological similarity between brain and social networks although global features (e.g., the average shortest path length l , assortative coefficient r , etc.) seem to be different between brain and social networks (Table 1).

To elucidate the extent to which the topologies of brain and social networks are statistically similar, TSPs of five mammalian brain networks were compared with those of social networks, neuronal networks, bipartite models, and electronic circuits (Table 1). To analyze similarities and dissimilarities among the TSPs, we adopted the Principal Component Analysis (PCA) (Fig. 2(b) and (c)) and constructed

a dendrogram with hierarchical clustering (Fig. 2(d)). Brain networks, including neuronal networks, were more similar to the friendship networks than to other networks (Fig. 2). These similarities and dissimilarities were unpredictable from the relationship between densities of reciprocal connections and average clustering coefficient, and the concentration of subgraphs (data not shown). In the present PCA, the top three Principal Components (PCs) could account for 86.7% of the variance of the TSPs; these three PCs individually accounted for 61.6%, 18.3%, and 6.7% of the variance. The first PC (PC1) mainly contributed to explaining the variability of the TSPs between brain and friendship networks and other networks, and the second PC (PC2) mainly contributed to explaining the variability between the bipartite models and electronic circuits. PC2 and the third PC (PC3) contributed to explaining the variability within the brain and friendship networks. We also found higher-order cliques were significantly abundant in both brain and friendship networks but not in other networks (Table 4).

Table 4
Number of higher-order cliques

Network	Clique size						
	3	4	5	6	7	8	9
Brain (macaque 1)	440 (17.2)	251 (17.8)	60 (18.4)	4 (12.6)	0	0	0
Brain (macaque 2)	170 (6.8)	112 (6.2)	36 (7.0)	4 (8.1)	0	0	0
Brain (macaque 3)	231 (8.7)	255 (7.1)	144 (6.3)	39 (6.2)	4 (5.8)	0	0
Brain (cat)	973 (21.1)	1182 (24.5)	847 (43.7)	396 (156)	126 (1260)	24 (n.d.)	6 (n.d.)
Brain (rat)	53 (2.4)	20 (3.0)	3 (3.8)	0	0	0	0
Neuron	50 (14.0)	5 (49.9)	0	0	0	0	0
Social +1	5 (5.8)	1 (n.d.)	0	0	0	0	0
Social +2	8 (3.4)	0	0	0	0	0	0
Social +3	5 (11.3)	0	0	0	0	0	0
Social +4	3 (5.6)	0	0	0	0	0	0
Social +5	1 (3.6)	0	0	0	0	0	0
Social +6	10 (2.5)	1 (1.4)	0	0	0	0	0
Social +7	181 (4.2)	127 (4.5)	41 (3.9)	5 (2.9)	0	0	0
Social -1	1 (0.4)	0	0	0	0	0	0
Social -2	0	0	0	0	0	0	0
Social -3	0	0	0	0	0	0	0
Bipartite model 1	0	0	0	0	0	0	0
Bipartite model 2	0	0	0	0	0	0	0
Electronic circuit 1	0	0	0	0	0	0	0
Electronic circuit 2	0	0	0	0	0	0	0

A “clique” is a fully mutually connected subgraph. The number in parentheses indicates the Z score. n.d.: the Z score could not be calculated because no clique appeared in the ensemble of randomized networks.

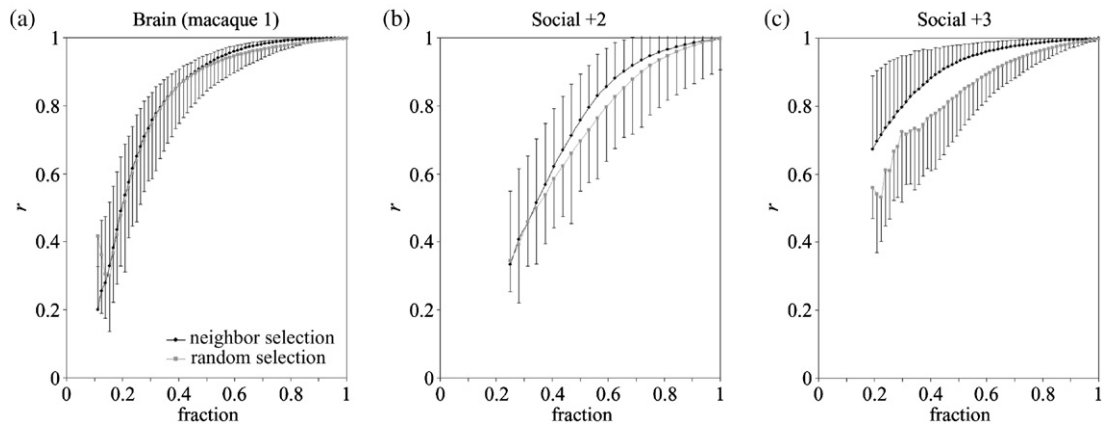


Fig. 3. Robustness of TSPs. Relationship between network reconstructions and TSPs in a macaque cortical network (a), Social +2 (b), and Social +3 (c). Filled circles and grey squares represent the “neighbor selection” and “random selection” strategies, respectively. The x axis represents a fraction defined as the size of subgraphs divided by the size of the real network. The y axis represents the correlation coefficient r between the TSP of the subgraph and that of the real network. Data indicate mean \pm s.d.

3.3. Robustness

To determine how many nodes are sufficient to represent TSPs similar to those from real networks, we conducted robustness experiments for several networks including brain and friendship networks (Fig. 3). In these analyses, we adopted two strategies: “neighbor selection” and “random selection” (see also Methods). Since we could expect that outcomes of these two strategies might be affected by global features (such as average shortest path lengths l , network sizes, etc.) of analyzed networks, we decided to analyze networks of Brain (macaque1), Social +2, and Social +3. The former two networks have similar l , but they have different network sizes

(Table 1). On the other hand, Brain (macaque1) and Social +3 have similar network sizes, but they have different l and C (Table 1). As shown in Fig. 3, about 30 to 40 nodes were sufficient to represent TSPs similar to those from real networks if “neighbor selection” was adopted. However, more nodes seemed to be required to represent TSPs similar to those from real networks in Social +3 which had larger l if “random selection” was adopted.

3.4. Balance of reciprocity

Since brain and friendship networks are communication networks and have more mutual connections than other

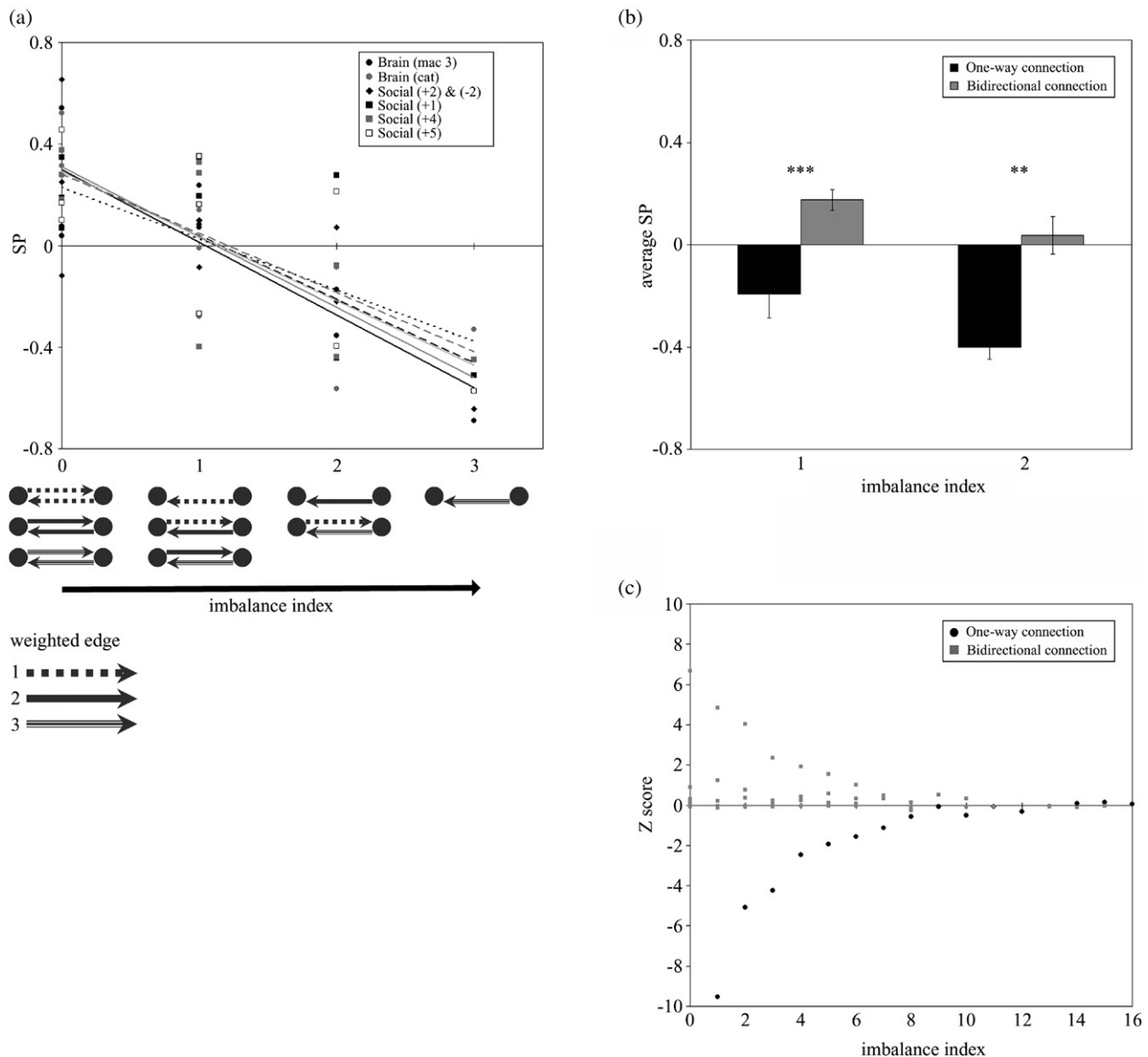


Fig. 4. Statistical significance of balanced reciprocity. (a) Balanced and imbalanced mutual connections were significantly abundant and rare, respectively. The x axis represents an imbalance index defined as the difference between the weights of two edges, and also, possible connected weighted dyads (2-node subgraphs) are shown. The y axis represents normalized Z scores. (b) Difference of average SPs between one-way and bidirectional connections. Data indicate mean \pm s.e. ***: $p < 0.005$, **: $p < 0.01$ (two-tailed t -test). (c) Significant profile of dyads in a worm's weighted network. Filled circles and grey squares represent Z scores of one-way and bidirectional connections, respectively.

networks (Table 1), we hypothesized that a balance of the mutual connections might be crucial to their functionality as communication systems. To verify this hypothesis, we investigated the abundance of mutual connections in weighted directed networks in which the connection weight w was represented by four degrees ($w = 0, 1, 2, 3$) (Table 3). We found that Weighted Dyad SPs (wDSPs) negatively correlated to “imbalance indices”, defined as the difference in weights between connections (Fig. 4(a)). These features were unpredictable by merely analyzing the concentration of weighted dyads (data not shown). In addition, wDSPs of bidirectional dyads were significantly higher than those of one-way dyads (Fig. 4(b)).

Based on this observation (Fig. 4(b)), we hypothesized that bidirectional connections might be more positively selected than one-way connections. To test this possibility in more differentiated weighted networks, we analyzed the Z score of weighted dyads in the worm's weighted network, in which the connection weight was represented by 16 degrees. As we expected, Z scores of bidirectional connections (0.60 ± 0.19 , mean \pm s.e.) were significantly higher than those of one-way connections (-1.82 ± 0.69) (two-tailed t -test, $p < 0.005$, Fig. 4(c)). Thus, the bidirectional connection was significantly more abundant than the one-way connection. In addition, bidirectional connections were negatively correlated with

imbalance indices (Fig. 4(c)) whereas one-way connections were positively correlated with those (Fig. 4(c)).

4. Discussion

We showed relation-type-specific topological features in social networks and topological similarities between brain and friendship networks, for which TSPs were similar, and also balanced and imbalanced reciprocal connections between actors (i.e., persons or cortical areas) were significantly abundant and rare, respectively. These results suggest that brain and friendship networks share similar principles of organization.

Recently, there have been hot debates on the origin of network motifs (overrepresented subgraph) in real networks and whether or not the network motifs arise solely from geometric constraints (Artzy-Randrup, Fleishman, Ben-Tal, & Stone, 2004; Itzkovitz & Alon, 2005; Milo, Itzkovitz, Kashtan, Levitt, & Alon, 2004). In the present study, to calculate SPs, we adopted randomized networks as the null hypothesis, in each of which the numbers of incoming, outgoing and mutual connections per node were preserved similar to those in the real network. Since friendship and brain networks had high densities of mutual connections (Table 1), our adopted null hypothesis is more stringent than others. Itzkovitz and Alon (2005) showed that network motifs in many real world networks cannot be captured solely by examined geometric models. In general, the adopted null hypothesis governs the decision as to whether specific subgraphs are overrepresented. This might lead to different conclusions concerning the network motif (Artzy-Randrup et al., 2004; Milo, Itzkovitz, Kashtan, Levitt, & Alon, 2004; Sakata et al., 2005). However, in the case of comparing TSPs among different networks, this problem is not serious (Milo, Itzkovitz, Kashtan, Levitt, & Alon, 2004; Sakata et al., 2005). Thus, our findings are unlikely to be affected by the adopted null hypothesis.

We also showed that small fractions of networks were sufficient to represent local topological features (i.e., TSPs) in robustness experiments (Fig. 3). Our present results suggest that we may have a good chance to uncover local design principles of larger networks only if we could effectively analyze a small fraction of the entire networks. We adopted two strategies in robustness experiments. As we expected, varied outcomes of these two strategies (Fig. 3) seem to depend on global features of the network topology shown in Table 1. That is, two strategies would not give different outcomes in networks with smaller l since selected nodes can be easily connected in such networks even if these nodes were randomly selected. However, failure rates were higher with “random selection” compared to those with “neighbor selection” (data not shown). The failure rate was defined as the number of failure populations, in which TSPs could not be analyzed because specific triads were not generated in the ensemble of randomized networks, divided by the total number of analyzed datasets. In order to estimate TSPs of all the networks, it would be necessary to analyze more combinations if random selection is adopted.

We previously predicted that TSPs might be similar between brain and social networks (Sakata et al., 2005) because both cortical networks and social networks have abundant cliques and related subgraphs according to results from previous studies (Milo, Itzkovitz, Kashtan, Levitt, Shen-Orr, et al., 2004; Sakata et al., 2005). The importance of the present study is that we directly confirmed this prediction. Brain networks might form a superfamily with social networks and World Wide Web (www) hyperlink networks (Milo, Itzkovitz, Kashtan, Levitt, Shen-Orr, et al., 2004). However, since sets of network motifs are different within brain networks, our collection of brain and friendship networks does not strictly form the superfamily defined by previous studies (Milo, Itzkovitz, Kashtan, Levitt, Shen-Orr, et al., 2004), in which, for example, the worm neuronal network was distinguished from social and www networks. In our analysis, the worm neuronal network is more similar to highly evolved cortical networks and friendship networks than to disliking networks, bipartite models, and electrical circuits.

Despite similarities of TSPs between brain and friendship networks, global features, such as the assortative coefficient r (Newman, 2002; Newman & Park, 2003), tend to be different between these networks (Table 1). Since the sizes of the analyzed networks were small, this tendency is still inconclusive (Newman, 2002). As larger social networks have already been analyzed extensively (Newman, 2002; Newman & Park, 2003), further study exploring more detailed maps of mammalian cortical networks is required to address this issue.

Why do brain and friendship networks have similar TSPs? One possibility is an accidental coincidence. However, it is unlikely that this occurs in most analyzed brain and friendship networks, even if this coincidence could occur in some networks. Another possibility is that brain and friendship networks might have developed to achieve similar aims (e.g., interactive communication among actors). Mutual interactions between nodes would be more prominent in these networks compared with other systems. Our findings in Fig. 4 quantitatively emphasize this feature. This “reciprocity” might be a general principle in the organization of these two systems (Bronfenbrenner, 1943; Wasserman & Faust, 1994) and would have functional roles in information processing. It is also likely that the reciprocity leads to an overrepresentation of clique and related structures. In addition, abundant cliques might enhance the functional flexibility to perform various tasks because network topology confers strong constraints on computational ability and the clique could possess various structural repertoires (Sporns & Kötter, 2004). Interestingly, it has been revealed that these tendencies in terms of abundant reciprocity are also observed in cortical microcircuitry. (Markram, Lubke, Frotscher, Roth, & Sakmann, 1997; Song et al., 2005). In a rodent’s visual cortex, local networks of pyramidal neurons are far from random, and bidirectional connections are more common than expected in a random network (Song et al., 2005). Furthermore, the strengths of synaptic connections between mutually connected neurons are positively correlated. However, interlaminar connections in the cortical microcircuit are not always reciprocal and it is also likely that there is tradeoff with overall wiring costs

required to possess abundant cliques, particularly in the whole brain (Buzsáki, Geisler, Henze, & Wang, 2004; Cherniak, Mokhtarzada, Rodriguez-Esteban, & Changizi, 2004; Klyachko & Stevens, 2003). The relationships that exist between spatial factors (e.g., edge length, node location) and network motifs remain to be determined in future studies.

We applied the motif detection method and calculated the imbalance index to devise methods of quantifying the balance of mutual connections and of evaluating the statistical significance of the number of balanced mutual connections. Importantly, our results (Fig. 4) could not be predicted simply by counting each subgraph, suggesting positive selection of balanced connections in brain and friendship networks. Although molecular mechanisms behind the development of corticocortical connections still remain to be elucidated, our findings predict that connectivity among cortical areas might develop to maintain the balance of their reciprocal connectivity. We also revealed that wDSPs of bidirectional dyads were significantly higher than those of one-way dyads (Fig. 4(b) and (c)), suggesting that different selections occurred in one-way and bidirectional connections. Unexpectedly, a profile of one-way connections in the worm network (Fig. 4(c)) was different from those in other analyzed networks (Fig. 4(a) and (b)). Although types of chemical synapse (excitatory or inhibitory synapse) in the worm's neuronal networks still remain to be identified, it would be interesting to analyze wDSPs of the worm network taking such types of chemical synapse into account because our present results have a uncovered relation-type-specific topology of social networks.

In summary, explicit social attitudes were found to crucially affect the contents of local structures in social networks, and an unexpected topological similarity between mammalian cortical networks and social friendship networks was reported. In these two systems, balanced reciprocal connections seem to be positively selected compared with random networks. Because it is unlikely that each actor directly obtains global information about the network topology, each actor is apt to establish connections to more attractive actors rather than less attractive ones, resulting in an abundance of clique and balanced structures. Together with the importance of information processing in brain and friendship networks, our findings suggest that these two networks developed and evolved on the basis of common principles, such as attractive interaction, in order to achieve similar purposes.

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