Modular analysis of brain and free word association networks

Theses of PhD dissertation

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ABSTRACT

Networks are used for exploring underlying relations in various datasets by defining nodes and edges corresponding to a certain logic of the observed system. In the recent decades, numerous parameters were developed to describe different properties of the networks. Modular organization is an important topological property, in which certain group of nodes have denser connectivity within themselves than between other regions of the network. Also the nodes constituting a given module probably share similar properties regarding the analyzed phenomenon. Modularity maximization is among the most popular network modularization algorithms, hence the number and size of the modules are not predefined. In the present thesis 1) I demonstrated a modularity value based improvement for the statistical evaluation of group-level brain networks and 2) I developed and validated a process for defining polarized opinions based on the modules of free word association networks. Although, the modular investigation of the networks creates a strong link between the two topic, the duality of the analyzed phenomena indicates the separate description of the modular brain network and the modular free word association analysis.

MODULAR ANALYSIS OF BRAIN NETWORKS

Introduction

Graph theoretical analyses of complex functional networks, obtained using fMRI and MEG (for review see (Stam & van Straaten, 2012)), has demonstrated that brain functional networks have a modular (sub-network) structure, where a module is defined as a highly integrated sub-network consisting of regions with much denser connectivity among themselves than between those regions and the rest of the brain. Although there is not a universal way for detecting the community structure in complex networks, the modularity (Q) value optimizing algorithms (M. Newman & Girvan, 2004) became the gold standard for identifying the functional brain modules. The aim of the current study was to present a method to evaluate differences in the community membership of the nodes between representative modular structures.

Representative community structures are derived from multiple subjects of a single clinical sample, or condition, thus it gives a unique, characteristic modular organization. The visual demonstration of different representative modular structures is hardly accompanied with their statistical evaluation. On one hand, the comparison of two, unique networks are not trivial, on the other hand, the non-linear nature of the community detection algorithms makes extremely difficult to statistically evaluate certain visual differences. For example, how can we prove that the merging of two modules have a higher impact on the differences between two representative modular structures than the altered community assignment of one single node? Considerable visual differences between representative modular structures may originate in the altered connections of a single node, which restructure the whole community structure.

We tested the method on resting-state fMRI data of young and elderly subjects. The elderly functional network was characterized by altered community structure (Geerligs, Renken, Saliasi, Maurits, & Lorist, 2015; Meunier, Achard, Morcom, & Bullmore, 2009) reduced modularity (Geerligs et al., 2015) and generally more between-module and less within-module connections than the young network (Chan, Park, Savalia, Petersen, & Wig, 2014). We expected that our method can detect the prominent regions whose modular memberships are crucial for the formation of the young and elderly brain networks.

Methods

Participants and fMRI processing

Data of healthy young (19-21 years; N = 20; SD= ±1; 9 women) and elderly (67-85 years; N = 20; SD= ±6; 10 women) individuals was analyzed in this study. Pairwise temporal correlations between all ROIs' time series were calculated, and used as measures of connectivity strengths. Correlation coefficients were converted into z-values using Fisher's transformation. Every subject was characterized by a weighted, undirected network, where the ROIs represented the nodes and the connectivity strengths defined the weights of edges.

Modularity and partition distance

In order to determine the modular structure, smaller functional subgraphs or modules were decomposed from the entire resting state network. The modularity (Q) of a graph describes the possible formation of communities in the network:

$$Q = \sum_{s=1}^{N}\left[\frac{k_s}{L} - \left(\frac{d_s}{2L}\right)^2\right],$$

where N is the number of modules, L is the total sum of all edge weights in the network, k_s is the sum of all weights in module s, and d_s is the sum of the strength of nodes (the sum of edge weights of a certain node) in module s (M. Newman & Girvan, 2004). The representative modular structure was determined by applying the modularity algorithm on the young and elderly subjects' average connectivity matrices respectively.

The distance between different partition representations of networks with identical nodes can be determined by the normalized mutual information (MIn):

$$MIn = 2 * \frac{H(Y) + H(E) - H(Y,E)}{H(Y) + H(E)}$$

where H(Y) and H(E) is the entropy of the young and elderly partitions respectively and H(Y,E) is the joint entropy of the two partitions (Meilă, 2007).

Local modularity and approximation node shifts

The relative importance of each region in the maintenance of the modular organization was measured by shifting each brain region to all possible extraneous modules. Shifting a node with an unstable community membership has less effect on the modularity value than shifting a node from its unique group (Rubinov & Sporns, 2011). Each transformation can be characterized by the change of the modularity value:

$$dQ_i = Q_{before\ transformation\ of\ node\ i} - Q_{after\ transformation\ of\ node\ i}$$

The average value of dQ_i is the local modularity for node i. It defines how strongly the node is connected to its own module. The local modularity value can also be interpreted as the correspondence of a given node to the modular organization of a network.

Beside the calculation of the local modularity we can mark certain node shifts between modules, which approximate one partition towards the other (approximation node shifts). The changes of the MIn (dMIn) can detect these node shifts:

$$dMIn = MIn(young, elderly) - MIn(young', elderly),$$

in which dMIn values with negative sign denote node shifts, which approximate the young partition towards the elderly.

It is important to emphasize that the presented analysis is not symmetric, thus the two age groups have different representative partitions. Therefore, it is necessary to perform it on the calculated networks both for the young and the elderly separately. The statistical evaluation of the local modularity and approximation node shifts based on a permutation procedure on the mixed groups.

Novel scientific results

The modularity of the young representative network (Q_{young}=0.25) was significantly higher than that of the mixed group (p=0.0036, 5000 permutations), while the modularity of the elderly representative network ($Q_{elderly}$=0.21) was significantly lower than that of the mixed group (p=0.016, 5000 permutations). The modularity algorithm detected 4 functional modules in the young and 3 modules in the elderly group. The occipital module showed the highest overlap between the two age groups, while the fronto-temporal and the default mode network (DMN) were merged to one single cluster in the elderly group.

Thesis Ia. I measured the extent of the modularity decrease caused by changing the community membership of brain regions. The occipital regions showed the highest local

modularity difference between the young and elderly group, but the local modularity value of the regions in the default mode network was slightly affected by aging. As the young group was characterized by a significantly higher modularity than the elderly group, the higher local modularity values were also found in this group. The most prominent increase of the local modularity in the young group compared to the mixed group was observed in the occipital regions (15 from the 18 occipital regions showed significantly higher local modularity). On the contrary, the local modularity of the structures of the default mode network was only slightly affected by aging. Increased local modularity was found only for 4 (right/left hippocampus, left parahippocampal gyrus, left angular gyrus) of the 13 regions of the DMN.

In contrast to the young group only a few regions of increased local modularity were observed in the elderly group. The medial frontal cortex (p=0.03), paracingulate gyri (p_{right}=0.03; p_{left}=0.001), superior parietal lobules (p_{right}=0.009; p_{left}=0.01) and inferior temporal gyri (p_{right}=0.004; p_{left}=0.05) showed an increased local modularity compared to the mixed group.

I found increased local modularity of the occipital module was found in the young, which is in line with the previously reported increased segregation of the visual cortex in the young (Geerligs et al., 2015). I determined that regions of the dorsal attention network were characterized with an increased local modularity in the elderly which suggest that these regions preserve the modular structure in advanced age.

Thesis Ib. I evaluated the group-level differences in the community membership of the brain regions between the two age groups by applying approximation node shifts. I showed that the changes of the community assignment of the young 'fronto-temporal' module have a significant impact on the modular organization of the brain networks in advanced age. There were 28 approximation node shifts from the young group toward the elderly, and 9 approximation node shifts from the elderly group toward the young. In case of the young group node transformations indicated shifts mainly from the fronto-temporal module, since this module was absorbed to other modules in the elderly group. The majority of the approximation node shifts caused a significant modularity decrease compared to the mixed group. In case of the elderly, transformation of the bilateral middle temporal gyri (p_{right}=0.05; p_{left}=0.05) and the right supramarginal gyrus (p=0.045) from the 'centro-parieto-temporal' module to the 'fronto-temporal + DMN' module resulted in a significant modularity decrease compared to the mixed age group. Changing of the modular assignment of the bilateral superior parietal lobules (p_{right}=0.02; pl_{eft}=0.04) from the elderly group's 'centro-parieto-temporal' to the young group's 'occipital' module also resulted in a significant modularity decrease compared to the mixed age group.

I identified 4 modules in the young and 3 in the elderly group. I found the merging of the DMN to the 'fronto-temporal' module in the elderly group. The method showed that the changes of the community assignment of these regions have a significant impact on the modular organization of the brain networks in advanced age.

MODULAR ANALYSIS OF FREE WORD ASSOCIATION NETWORKS

Introduction

As a measure of public opinions, the free association method can be viewed as a semi-structured alternative between traditional questionnaires producing highly structured data and web-mining algorithms collecting large quantities of unstructured data. Hence, the free association method can overcome the predefined scope of questionnaires (Bansak, Hainmueller, & Hangartner, 2016) since respondents can express freely their opinion, yet, it has the advantage of representative samples and fast data processing as opposed to several web-mining methods (Lazer, Kennedy, King, & Vespignani, 2014). Traditionally, free association analysis focuses on consensual meaning (i.e., most frequent words and rankings) regarding a social object (Abric, 1993; Moscovici, 1984; Wagner et al., 1999) and they do not focus on the polarization of opinions (Bradley, Mogg, & Williams, 1995; Halberstadt, Niedenthal, & Kushner, 1995; Joffe & Elsey, 2014; Niedenthal, Halberstadt, & Innes-Ker, 1999).

First, we mapped, the social representations of Hero and Everyday Hero in Hungary by representing them as networks constructed from free associations. We identify modules of the networks and categorize the associations based on their topological positions in the association networks. In order to do that, we define global hubs as the most dominant associations of the whole social representation and modular hubs as the characteristic associations in the different modules.

Second, we aimed to demonstrate that co-occurrence statistic of associations can identify polarized opinions in the perception of refugee/migrants. In this study we referred to our free association networks as networks of co-occurring opinions (CoOp networks). We constructed such CoOp networks from multiple response free associations to the cue “migrant” in case of two independent and comprehensive samples in Hungary. Subsequently, we identified modules (densely connected subnetworks) of the CoOp networks.

We hypothesized that frequently co-occurring associations have higher emotional similarity (Hypothesis 1). To test this, respondents were asked to evaluate their own associations with emotional labels. We calculated the correlation between emotional similarity values and co-occurrence connection values applying a permutation method (quadratic assignment procedure; QAP).

We assumed that the modules of the CoOp network reflect different opinions. Therefore, we statistically compared the attitude value (Perceived Group Threat) of participants whose associations belonged to different modules (Hypothesis 2).

We tested the robustness of the CoOp networks (Hypothesis 3). First, we aimed to test whether the LLR values were correlated between the randomly divided data in both samples (Hypothesis 3a). Second, we aimed to test whether the CoOp networks are more similar to each other—based on normalized mutual information—than a large number of randomized networks (null-models) with similar properties (Hypothesis 3b). Third, we aimed to test whether the exclusion of rare associations increase the robustness of our method due to the lower proportion of peripheral associations and the higher proportion of core associations (Hypothesis 3c).

Methods

Participants

Researches employed on nationally representative probability samples: 506 (in case of Hero) and 503 (in case of Everyday Hero) and two times (June 2016 (Sample 1) and in October 2016 (Sample 2)) 505 (in case of Migrant). The samples were nationally comprehensive in terms of gender, age, level of education, and type of residence for those Hungarians who use the Internet at least once a week.

Association task

The instruction was: "Please, write 5 words which first come into your mind about Hero/Everyday hero/Migrant!"

Additional tasks (Migrant study)

After providing all the 5 associations, respondents got back their associations one by one and were asked to provide two emotional labels to each of their own associations. We used the following 20 emotional labels (differences from the original ones can be seen in parentheses): interest- alarm (anxiety), empathy-contempt, surprise-indifference, hope-fear, gratitude-anger, joy-sadness, calmness- relief (frustration), pride-shame, generosity-envy and love (sympathy)-hate (antipathy).

Perceived threat from refugee/migrants were assessed using seven items (Sample 1 α = .96, Sample 2 α = .96) which were translated from an implementation (Kteily, Bruneau, Waytz, & Cotterill, 2015) of the Integrated Threat Theory (Stephan, Stephan, & Oskamp, 2000). The higher value indicates higher level of perceived threat from refugee/migrants.

Association network creation

We algorithmically set up two networks which stand for the social representations of Hero and Everyday Hero in Hungary. To create such networks, we had to determine the nodes and the edges. We listed the different associations from the total set of associations to a given cue. The nodes represented these different associations. There was an edge between two associations if they were mentioned together by at least one study participant. The weight of an edge between two associations was equal to the number of times they were mentioned together. Therefore, the construction of networks was only directed by the co-occurrences of associations in the individual representations.

In the analysis of the "Migrant" associations a more sophisticated, statistical method was applied for the measure repulsive and attractive co-occurrence. We used log-likelihood ratio (LLR) to assess co-occurrence connections between every possible association pairs (Dunning, 1993). LLR between two associations was positive (attractive) if their observed co-occurrence number was higher than the expected one and negative (repulsive) if their observed co-occurrence number was lower than the expected one.

Graph parameters

The scale-free topology of a network refers to the power-law function that the probability distribution function ($P(x)$) of the node strength (x) follows:

$$P(x) \sim x^{-\alpha},$$

where α is the scaling parameter (Barabási & Albert, 1999). The scaling parameter typically lies in the range $2 < \alpha < 3$ (Clauset, Shalizi, & Newman, 2009). The power-law distribution of the normalized node strengths was tested separately for the Hero and Everyday Hero networks. The Maximum Likelihood Estimation fitting model determined the scaling parameter (α) of the power-law function and the minimum node strength ($x_{\min}$) for which the power law holds.

We investigated the modular organization of the association networks. In order to do that, smaller subnetworks (modules) were decomposed from the entire networks and the modularity value (Q) was calculated (M. E. J. Newman, 2004). The Louvain algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008) with fine-tuning (Sun, Danila, Josić, & Bassler, 2009) was applied to identify the modular partition with the highest possible modularity. For the migrant association, we applied a modified version of the original modularity formula (Gomez, Jensen, Arenas, 2009) to deal with both the positive (attractive) and negative (repulsive) links:

$$Q = \frac{1}{v^{+} + v^{-}} \sum_{ij} [(w_{ij}^{+} + e_{ij}^{+}) - (w_{ij}^{-} + e_{ij}^{-})]\, \partial_{M_i M_j},$$

where Q denotes the modularity value of a given partition of a network, v^{+}/v^{-} denote the total positive/negative weights of the network, w_{ij}^{+}/w_{ij}^{-} denote the positive/negative weights between node *i* and j, e_{ij}^{+}/e_{ij}^{-} denote the chance-expected positive/negative connections between node *i* and j, $\partial_{M_i M_j}$ is an indicator function set to 1 if node *i* and *j* belong to the same module. Also, a consensus partition was determined in these samples for the sake of higher reliability (Lancichinetti & Fortunato, 2012).

Degree-, weight-, and strength-preserving randomization [48] was applied to generate 4999 independent null models (random networks) for the social representations of both Hero and Everyday Hero. The modular organizations of the two social representation networks were tested by comparing their maximal modularity values to the corresponding random networks.

CoOp modules as polarized opinions

To demonstrate the stability regarding co-occurrences of associations and the identified modular structure, we compared the LLR edges and modular structures of the two independent samples (Sample 1 and Sample 2). The similarity of the modular structures was measured with the normalized mutual information (nMI). To demonstrate that higher number of observations offer a higher stability of our method, we iteratively raised the threshold of the ignored associations. The similarity of the LLR edges and modular structures were calculated for each threshold between Sample 1 and Sample 2.

The affective similarity between every pair of associations was based on the L1-norm of the emotional vectors of the associations. Correlation between the LLR values and the corresponding affective similarity values was derived by the Quadratic Assignment Procedure (QAP) (Simpson, 2001). We evaluated the association modules in networks according to the attitudes toward refugee/migrants. Respondent were assigned to the modules to which the majority of their associations belonged. Respondents were compared by pairwise independent t-test on their attitude scores between every pair of modules.

Novel scientific results

Thesis IIa.: I constructed semantic networks from multiple free word associations for the cue "Hero/Everyday Hero". I experimentally evaluated global parameters of the networks to describe relevant socio-psychological constructs. Scale-free properties (scaling parameter (α), minimal normalized node strength (x_{min}), p-value of the line fitting) were determined for the Hero and Everyday Hero networks. In case of Hero, we found α=2.15 from x_{min}=.312. In case of Everyday Hero, we found α=2.21 from x_{min}=.8. In the range determined by x_{min}, the normalized node strength distributions showed a power law distribution (p(Hero)=.11, p(Everyday Hero)=.5). The modularity value of the Hero network (Q=.19) was not significantly higher than the corresponding modularity values of the null (random) models (p=0.19; mean=.17; standard deviation=0.027). In case of Everyday Hero, the modularity value of every (4999) independent null model was lower (p<.001; mean(random)=.15; standard deviation(random)=0.013) than the modularity value calculated for the social representation network (Q=.26). These results showed that the Hero network was non-modular and the Everyday Hero network was modular. The scale-free properties of the association networks correspond to the classical core/periphery social representation structure. In the statistically modular network, we determined the modules and their modular hubs, which may represent socio-cognitive patterns in the social representations.

Thesis IIb. I demonstrated in case of the "migrant" cue that the co-occurrence based relations of free word associations reflected emotional similarity and the modules of the association network were validated on well-established measures. Significant correlations were found between the co-occurrence and affective similarity values of Sample 1 (r_s *(64)* = .42, p_{QAP} = .018) and Sample 2 (r_s (62)= .39, p_{QAP} = .035) (Hypothesis 1). In case of Sample 1 and Sample 2, all pairwise comparisons of the modules showed significant differences in the POT score (Hypothesis 2).

Thesis IIc. I tested and showed the LLR and modular level robustness of the CoOp networks. Furthermore, I demonstrated that exclusion of rare associations increases the robustness of the modular structure, which suggesting the validity of the applied framework. I found a significant correlation between the LLR values of the equally separated data for 100 independent runs in Sample 1 (Hypothesis 3a) (mean r_s (2209) = .26, mean p_{QAP} < .001) and Sample 2 (mean r_s (2924) = .28., mean p_{QAP} < .001). The similarity between the modular structures of the divided data were significantly higher than the similarity of the corresponding null models (Hypothesis 3b) (for Sample 1: M_{real}=0.3, SD_{real}=0.056, M_{null}=0.21, SD_{null}=0.042, t(198)=12.52, p<.001; for Sample 2: M_{real}=0.26, SD_{real}=0.058, M_{null}=0.2,

SD_{null}=0.04, t(198)=8.9, p<.001). The robustness of the network was increased by the exclusion of rare association (Hypothesis 3c). The threshold was iteratively raised from the default 3 to 10. Strong and significant correlation was detected between the threshold and the LLR (for Sample 1 r_s (6) = .91, p = .002; for Sample 2 r_s (6) = .97, p < .001) and modular (for Sample 1 r_s (6) = .98, p < .001; for Sample 2 r_s (6) = .96, p < .001) level similarity.

Publications related to the present thesis

Papers:

-File, B., Klimaj, Z., Somogyvári, Z., Kozák, L. R., Gyebnár, G., Tóth, B., ... & Molnár, M. (2016). Age-related changes of the representative modular structure in the brain. In Pattern Recognition in Neuroimaging (PRNI), 2016 International Workshop on (pp. 1-4). IEEE.
-File, B., Keczer, Z., Vancsó, A., Bőthe, B., Tóth-Király, I., Hunyadi, M., ... & Orosz, G. (2019). Emergence of polarized opinions from free association networks. Behavior research methods, vol. 51, no. 1, p. 280-294.
-Keczer, Z., File, B., Orosz, G., & Zimbardo, P. G. (2016). Social Representations of Hero and Everyday Hero: A Network Study from Representative Samples. PloS one, vol. 11, no. 8, p. e0159354.

Oral presentations:

-Bálint File, Dániel Gerő, Marco Bueter, Zsolt Keczer, Gábor Orosz, Zoltán Somogyvári, Júlia Góth, Noreen Hinrichs, Matteo Müller, István Ulbert (2019): Véleménykinyerés szabad szó asszociációs hálózatok moduláris vizsgálatával, Doktoranduszok Országos Szövetsége, Debrecen
-File, B., Keczer, Z., Vancsó, A., Bőthe, B., Tóth-Király, I., Hunyadi, M., ... & Orosz, G. (2018). Polarized Opinions from Free Association Networks, Singapore Conference on Applied Psychology 2018, Singapore

Poster presentations:

-Bálint File, Zsolt Keczer, Gábor Orosz, Beáta Bőthe, István Tóth-Király, Anna Vancsó, Márton Hunyadi, Adrienn Ujhelyi, István Ulbert, Júlia Góth (2017): Attitudes toward migrants: free word association networks bridging social and cognitive representations. 18th General Meeting of the European Association of Social Psychology, Granada, Spain

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