Less is More: Predicting Creativity with Function Connectivity of Rest-fMRI using Feature Selection Methods

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Abstract : Creativity is the source of national scientific and technological progress and economic development. However, there is little research using machine learning method to study the relationship between the functional connectivity and verbal creativity. In this paper, we proposed a prior-knowledge-based and data-driven based method (PDM) to explore the most relevant functional connections (FC) for the prediction of creativity. Specifically, we classify 289 participants into high and low creation group by using their resting state function nuclear magnetic resonance (fMRI) data. A total of 34,716 functional connections (FC) were analyzed in the whole brain. The PDM selected 13 FCs out of the 34,716FCs, which consists of rank sum test, random forest, and backward selection algorithm. The selected13 FCs can effectively distinguish high and low creation groups with an accuracy of 85.6% in training dataset and 67.2% in test dataset, much higher than the accuracy achieved by using the 134FCs selected by traditional statistics method. The contribution of each FC to the prediction has been also studied. The results suggest that less number of FCs can produce better prediction results, and that less important FCs may contribute more in the prediction. The finding of this paper may help us to better understand the neural mechanisms of creative brain networks. And the proposed method could be useful in any other researches that intensively explore the relationship between neuroimaging metrics and behavior scores.

Key Words: machine learning, creativity prediction, fMRI, functional connection, feature selection, PDM.

Introduction

Creativity is the ability to produce something both novel and useful (Runco & Jaeger, 2012; Stein, 1953) and is central to the progression of human civilization, prosperity, and well-being (Diedrich, Benedek, Jauk, & Neubauer, 2015; Runco & Jaeger, 2012). Individuals with high creativity usually have some important traits and unusual cognitive abilities. For instance, they appear to have a specific semantic associative network and exhibit a flexible thinking way, which contributes to building linkages between apparently unrelated things or concepts (Fink et al., 2009; Kenett, Anaki, & Faust, 2014).

These complex cognitive abilities may not depend on a single brain region but require the interaction between multiple brain regions (Beaty, Benedek, Silvia, & Schacter, 2016). Although researchers earlier stressed that the default mode network (DMN) and the control network show an antagonistic relation at rest and during externally directed attention tasks, more evidence suggests that creativity is closely related to the coupling of several core regions that mainly located in the two networks (Beaty, Benedek, Kaufman, & Silvia, 2015; Pinho, Ullen, Castelo-Branco, Fransson, & de Manzano, 2016; Zhu et al., 2017). The DMN is mainly composed of the medial prefrontal cortex, posterior cingulate cortex, and lateral temporal cortex (Buckner, Andrews-Hanna, & Schacter, 2008; Raichle, 2015) and has often been observed to be deactivated in some external goal-oriented tasks but increased in response to various creative tasks such as verbal divergent thinking, musical improvisation, and visual art design (Beaty, Christensen, Benedek, Silvia, & Schacter, 2017; Ellamil, Dobson, Beeman, & Christoff, 2012; Pinho et al., 2016). The DMN has been considered to play a key role in the generation of candidate ideas (potentially useful information derived from long-term memory) (Beaty et al., 2016). The control network, such as the frontoparietal network (FPN), exhibits enhanced activities in a wide variety of cognitive tasks that require externally directed attention (e.g., working memory, inhibitory control, cognitive flexibility) (Dosenbach, Fair, Cohen, Schlaggar, & Petersen, 2008; Power et al., 2011; Zanto & Gazzaley, 2013), and is also related to creative thinking. Unlike the DMN, researchers suggest that the control network aims to evaluate the efficacy of candidate ideas and modify them to meet the constraints of task-specific goals (Beaty et al., 2016). Cooperation between the DMN and the control network supports the dynamic cognitive processes of idea generation and selection.

Many studies have recently investigated the possibility of predicting individual creative ability from brain connectivity by using functional connections (FC), because the FC can describe the interaction between different brain regions. A connectome-based predictive model (CPM) (Shen et al., 2017) was used to predict the scores of alternate uses task, which is a common way for accessing creativity of individuals. The FCs that are highly correlated with the scores are selected as the independent variable of the CPM and it is proved that the FCs can reliably predict the individual creativity (Beaty et al., 2018). FCs and genes were used as independent variables in a linear regression model to predict individual creativity. The genes and FCs used together can improve the prediction performance (Z. Liu et al., 2018). All these studies used cross-validation for evaluating the model, which is important to ensure the generalization of the models (Shen et al., 2017).

Although these previous studies have investigated the possibility of predicting creativity by using neuroimaging data (fMRI in particular), all the work employed large amount of FCs as the independent variables and did not evaluate the contribution of every selected FC to the prediction. A common agreement in statistics and machine learning is that the number of causal or relevant

features is only a few (Burges, 2010; Chen et al., 2016; Fan & Lv, 2010; Hussein et al., 2001; Li et al., 2017; Yu & Liu, 2004), i.e. the number of FCs that help to predict creativity is limited. The large amount of FCs (i.e. features) used in the previous studies may easily lead to lower prediction accuracy and high computation load (Chen et al., 2016; Li et al., 2017; Yu & Liu, 2004). On the other hand, though the contribution of each FC may be presented by the significance of association (P value) or correlation coefficient to the creativity. The results in this research show that P values or correlation coefficients are vague and could be weak in terms of determining the contribution of individual FC to the prediction.

To select most relevant FCs for the prediction and also make each FC's contribution evaluable, we employed a classification model in this research instead of CPM or regression model. In regression models, all the FCs' correlation values are summed to produce one index as the independent variable (Beaty et al., 2018; Z. Liu et al., 2018); therefore the final prediction performance can only reflect the contribution of all the input FCs as a whole. In this paper, we take each FC as a feature into the classification model, and classify the creativity scores. The purpose of this research is not only prediction/classification but also evaluation of the contribution of each FC, which may give us more understanding on how creative brain functions.

To make the evaluated FCs most representative, this research focused on the task of classifying high and low creative groups (binary classification). Cross-validation was employed in the classification (Shen et al., 2017). We divided 289 participants' data into dataset1 and dataset2, trained the model in data1 and tested it on data2 to ensure the generalization of the model. The FCs input to classification model have been rigorously selected through three steps by using a prior-knowledge-based and data-driven-based method (PDM) consisting of feature selection methods in statistics and machine learning, i.e. firstly rank sum test was used, then random forest was used, and finally backward selection algorithm was used. After each step, the number of FCs became smaller.

The experimental results show that less number of FCs can produce better prediction results, and that less important FCs may contribute more in the prediction. Specifically, the number of FCs after the first step of feature selection is 134, and after the third step of feature selection is 13; The 13 FCs can produce much higher classification accuracy than 134 FCs. A FC alone can produce low classification accuracy, but makes very large contribution in the group of 13 FCs.

To sum up, this research proposed a PDM method for intensively investigating the FC selection in predicting creativity. The binary classification was performed to locate the most representative FCs. The method has found the group of FCs that can give the best prediction results. The contribution of each FC to the prediction has been studied, which suggest that less FCs may contribute more in the prediction.

Materials and Methods

Data

Ethics statement

The MRI and behavioral protocols were approved by the local ethics committee of Southwest University, Chongqing, China. A written informed consent was received from each participant before experiment, which was approved by the Institutional Human Participants Review Board of Southwest University Imaging Center for Brain Research. All methods were conducted according

to the approved guidelines.

Participants

The database used in the article has a total of 435 participants, all of whom are students of China Southwest University (Chen et al., 2018). The database is available through the International Data-sharing Initiative (http://fcon_1000.projects.nitrc.org/). We first removed 35 subjects' data, whose head motion is greater than 2 mm and 2 degrees, and had 400 subjects' data for analysis. Since we analyzed creativity in two categories, i.e. high creative group and low creative group, 111 subjects whose creative scores were near the mean were removed, and 289 subjects were left for further analysis. We divided the data into two datasets, dataset1 and dataset2 without overlapping to each other. Dataset 1 had 144 subjects (72 women, mean age = 19.67y, SD = 1.28), of which 62 were highly creative group and 82 were low creative group. Dataset2 had 145 subjects (80 women, mean age = 20.01, SD = 1.14), of which 62 were highly creative group and 83 were low creative group.

All subjects were right-handed, without mental and psychological disorders, drug or alcohol dependence. All the resting-state fMRI data were collected in the Southwest University Center for Brain Imaging, Chongqing, China by using a 3.0-TSiemens Trio MRI scanner (Siemens Medical, Erlangen, Germany).

Resting-state FMRI

During scanning, subjects were asked to close their eyes, not think about a particular object, and not fall asleep. The 8- min scan of 242 contiguous whole-brain resting-state functional images was obtained by using gradient choplanar imaging (EPI) sequences with the following parameters: slices =32, repetition time (TR)/echo time (TE)=2000/30 ms, field of view (FOV)=220 × 220 mm, flip angle=90, voxel size=3.4 × 3.4 × 3 mm³, and thickness/slice gap=3/1 mm

Creativity Assessment

Two items from the verbal form of the Torrance Tests of Creative Thinking were used to assess creativity (Torrance, 1974; Ye & Hong, 1988), i.e. the alternate uses task (AUT) and the product improvement task (PIT). The AUT required participants to generate as many interesting and unusual uses as possible for a cardboard box. The PIT asked participants to generate as many ways as possible to change a toy elephant to make it more interesting and attractive. Both tasks were limited to 10 minutes. The creativity score is the sum of originality (the degree of originality of the ideas) and fluency (the number of meaningful and relevant ideas) (Chen et al., 2018). Three trained raters evaluated the answers of all participants based on standard guidance (Chen et al., 2018; F. Zhu, Zhang, & Qiu, 2013), and the inter rater correlation coefficient was high (ICC >0.9).

Method

Image Pre-processing

All resting-fMRI data were preprocessed using SPM12 (<http://www.fil.ion.ucl.ac.uk/spm>) and the Data Processing Assistant for Resting-State fMRI (DPABI) (Yan & Zang, 2010) under MATLAB2016b. The first 10 EPI scans were discarded to suppress the equilibration effects. The remaining scans were then slice timing corrected, realigned and normalized by DARTEL with

linear transformation and re-sampled to $3 \times 3 \times 3 \text{ mm}^3$. 35 patients were then excluded due to the head motion, who had $<2.0 \text{ mm}$ maximum displacement in the x, y, or z plane and $<2.0^\circ$ of angular rotation about each axis. A 264 putative functional area template was employed to locate nodes in the whole-brain network. The time series of these 264 regional were extracted by averaging voxel time series within each region. For each subject, the Pearson cross-correlation between two regional BOLD signals (time series) was calculated to reflect a FC between these two region pairs. A brain network consisting of the 264 brain regions therefore produced 34,716 FCs.

Creativity Label

The creative scores of our subjects ranged from 10 to 97.25. This paper focuses on binary classification, i.e. individuals are classified into high creative individuals and low creative individuals. However, we cannot simply divide creative individuals into two categories based on the mean of creative scores, such as individuals whose creative scores are higher than the mean are called highly creative individuals, and those whose creative scores are lower than the mean are called low creative individuals. Such division method cannot find the individuals in the two extreme of creativity. Locating the two groups of peoples in the extreme of creativity is the first step of finding the most representative FCs that helps to differentiate high and low creative groups. Therefore, this paper used affinity propagation clustering method (Frey & Dueck, 2007) to automatically cluster the creative score into 8 groups (the 8 is given by the method, not the user), and then excluded the subjects in the category, whose creative score is near the average values (the fourth group, creative scores of these subjects are between 37.25 and 45.25 in this research). By performing this automatic clustering method, the individuals with a creative score above 45.25 were regarded as high creative individuals, and individuals with a creative score below 37.25 were regarded as low creative individuals in this research.

Feature selection

There are 34,716 FCs in the whole brain and 289 subjects to be investigated, which easily leads to the problem of “small n , large p ”, where n is the size of samples ($n=289$) and p is the number of features ($p=34,716$). Simply using the large amount of features to classify the small samples will easily cause spurious accuracy and extremely long computing time. A common agreement in statistics is that the number of causal or relevant features is only a few, i.e. the number FCs that help to differentiate high and low creative groups is limited. To find the related FCs in the large amount of FCs, researchers have used statistic test, i.e. the significance of the association between FC and creativity was calculated, the FCs with its P value smaller than a threshold were selected as the causal features (Beaty et al., 2018; Z. Liu et al., 2018). This method is based on a prior knowledge that the causal FC must be highly related to the creativity score. However, the prior-knowledge-based feature selection method could be not enough and often be combined with other data-driven-based feature selection method to further strengthen and selection power and select the most related features thus improve the prediction performance (Chen T., 2016). Based on the understanding above, we proposed a FC selection method by combining prior knowledge and data-driven method (PDM).

The PDM is a three-step feature selection method. The first step is a rough selection that selects the FCs associated with verbal creativity by using rank sum test. The second step is based

on the result of the first step, and the FCs that are important in predicting creativity are selected by using random forest. The third step feature selection is based on the second step, and further selection is made to select a group of FCs that better predicting creativity by using backward selection. Each step of PKDD and its results are described in the following sections.

The first step of PDM: Statistic Test

We first use the rank sum test to roughly select FCs that distinguish between high and low creativity. The reason why the rank sum test is selected instead of the t test is that t test requires two groups of samples to obey normal distribution and the variance is the same. The rank sum test does not make special assumptions about the data distribution, and thus can be applied to more complex data distribution. The process of the first step of PDM is shown in Figure 1. We extract all non-repetitive FCs of high and low creative individuals in data1, and get two feature matrices (seen second block in Figure 1), i.e. High Creative Functional Connection Matrix 62 (subject, rows)*34716 (FC, cols) and Low Creative Functional Connection Matrix 82 (subject, rows) * 34716 (FC, cols). Then the rank sum test was performed on the FCs of the high and low creative groups. Finally we selected 134 FCs ($p < 0.005$). The third block diagram in Figure 1 shows the location of these 134 FCs in the brain. The brain network map is drawn by the BrainNet Viewer tool (Xia, Wang, & He, 2013).

Figure 1 the process of first step of PDM.

The second step of PDM: Single FC Assessment

In the second step, we extract the corresponding 134 functional connections for each subject to form a large feature matrix 144 (subject, rows) * 134 (FC, cols). Then the random forest (Breiman, 2001) was used to classify the two groups of individuals. The importance of each FC is calculated by using out-of-bag error. According to random forest, the importance of a feature X is calculated as follows:

1. For each decision tree in random forest, the error of out-of-bag data is calculated by using corresponding out-of-bag (OOB) data, which is recorded as err_{OOB1} .
2. Noise is added randomly to X of all samples of OOB data (the value of the sample at the X can be changed randomly), and the error of the OOB data is calculated again, which is recorded as err_{OOB2} .
3. Assuming that there are N trees in a random forest, the importance of feature X is evaluated by $\sum (err_{OOB1} - err_{OOB2}) / N$.

For a feature that has a great impact on the classification result, the accuracy outside the bag will be greatly reduced if noise is added to the feature.

Since the importance of the characteristics of each random forest is different, the general distribution of the importance of the features will be slightly different. We thus used random forests to calculate the importance of FCs for 10 times and averaged the results. The average importance is ranked and the top 20 FC are selected. These 20 FCs are shown in Table 1, where P is the P values of the rank sum test, R is the correlation coefficient between FC and creativity score, mean_imp is the average importance. Sorting is based on the order of importance from high to low. Figure 2 shows the spatial location of these 20 FCs in the brain. Different color of the nodes or the color bar indicates different regions of brain. From the blue to red, the color represents Uncertain, Sensory/somatomotor hand, Sensory/somatomotor mouth, Cingulo-opercular task control, Auditory, Default mode, Visual, Fronto-parietal task control, Salience, Cerebellar, and Dorsal attention, respectively.

Table 1 the selected 20 FCs with P, R values and mean importance values

ROI	Network	ROI	Network	P	R	Mean_imp
12	Uncertain	176	Fronto-parietal Task Control	0.00384	0.241	0.020275
62	Auditor	131	Default mode	0.002604	0.231	0.01701
13	Sensory/somatomotor Hand	261	Dorsal attention	0.000336	-0.275	0.016026
77	Default mode	245	Cerebellar	0.003964	-0.237	0.015721
199	Fronto-parietal Task Control	245	Cerebellar	0.004568	0.264	0.015133
38	Sensory/somatomotor Hand	177	Fronto-parietal Task Control	0.002648	-0.162	0.014709
70	Auditory	116	Default mode	0.003434	0.241	0.014384
38	Sensory/somatomotor Hand	192	Fronto-parietal Task Control	0.002398	-0.155	0.01371
13	Sensory/somatomotor Hand	253	Uncertain	0.00037	-0.235	0.013666
86	Default mode	260	Dorsal attention	0.004713	0.239	0.013405
121	Default mode	200	Fronto-parietal	0.001713	0.181	0.012853

Task Control						
115	Default mode	256	Dorsal attention	0.003219	-0.225	0.012745
160	Visual	193	Fronto-parietal Task Control	0.004713	-0.236	0.01196
45	Sensory/somatom otor Hand	47	Cingulo-opercul ar Task Control	0.002438	-0.223	0.011876
13	Sensory/somatom otor Hand	141	Uncertain	0.000349	-0.243	0.010989
32	Sensory/somatom otorHand	50	Cingulo-opercul ar Task Control	0.002781	-0.211	0.010703
31	Sensory/somatom otor Hand	87	Default mode	0.001713	-0.259	0.010674
13	Sensory/somatom otorHand	177	Fronto-parietal Task Control	0.002479	-0.289	0.010638
144	Visual	209	Salience	9.86E-06	-0.229	0.010618
121	Default mode	187	Fronto-parietal Task Control	0.002359	0.209 562	0.010301

Figure 2 the location of the selected 20 FCs.

The third step of PDM: Group of FC Assessment

The selected 20 FCs will be further selected in the third step. The purpose of this step is to find the best combination of FCs within the 20 FCs, so that this group of FC can give the best predictive performance. The number of FCs in the group and which FC is in the group are decided by the final performance. Backward feature selection and support vector machine (SVM) are used in this step. The flowchart of this step is illustrated in Figure 3. At first, all the features that selected in the second step are taken as the features of SVM with ten-fold cross validation, and an average classification rate of ten folds is obtained and stored. Next, a feature is discarded and 20 feature subsets are formed, the discarded features in the figure 3 is marked as 0, and the kept features are marked as 1. Each feature subset produces a 10-fold average classification rate. The feature subset with the highest classification rate will be saved. On the basis of this subset, another feature is discarded again, i.e. 19 feature subsets and corresponding 10-fold average classification rate are obtained, and the feature subset with the highest 10-fold average classification rate is selected. The above steps are continuously conducted until only one feature remains. All the feature subsets with their classification rates in each round will be recorded. Finally, the feature subset with the highest average classification rate is selected as the output.

Figure 3 the flowchart of the third step of PDM

Validation using independent data set

After three steps of feature selection, we obtained a group of FCs that can effectively distinguish high and low creativity. We used independent dataset2 to verify whether these FCs combinations can effectively predict high and low creation groups in the new data. Firstly, we extract the FCs of dataset2 and then perform a 10-fold cross-validation in data2 with SVM.

Permutation analysis

To determine whether the prediction result is significantly better than random, a non-parametric permutation analysis was performed. We ran a 10,000 permutation test on both dataset1 and dataset2, i.e. randomly confusing the creative labels, and then using SVM to perform 10-fold cross-validation to obtain the classification rate. The p-value of the Permutation test is the number of times that the classification rate is higher than the true classification rate divided by 10,000.

Result

FCs selected by PDM

Table 2 shows the final results of the PDM. We finally selected 13 FCs from the 34,716 FCs. These 13 FCs together can effectively predict the high and low creation. The 13 FCs are given in Table 2, where ROI indicates the node number in Power template, Network indicates the network where each node lies in, P indicates the P value of the rank sum test, and R is the Pearson correlation coefficient. Figure 4 shows the location of the 13 FCs in the brain space. The color of the each node represents the network, which the node belongs to. From blue to red, the color represents Sensory/somatomotor hand , Sensory/somatomotor mouth , Cingulo-opercular task control, Default mode, Uncertain, Visual, Fronto-parietal task control, Cerebellar, and Dorsal attention, respectively.

Table 2 the final selected 13 FCs

ROI	Network	ROI	Network	P	R
13	Sensory/somatomotor Hand	261	Dorsal attention	0.000336	-0.275
77	Default mod	245	Cerebellar	0.003964	-0.237
199	Fronto-parietal Task Control	245	Cerebellar	0.004568	0.264
38	Sensory/somatomotor Hand	177	Fronto-parietal Task Control	0.002648	-0.162
38	Sensory/somatomotor Hand	192	Fronto-parietal Task Control	0.002398	-0.155
86	Default mode	260	Dorsal attention	0.004713	0.239
121	Default mode	200	Fronto-parietal Task Control	0.001713	0.181
160	Visual	193	Fronto-parietal Task Control	0.004713	-0.236
45	Sensory/somatomotor Hand	47	Cingulo-opercular Task Control	0.002438	-0.223
13	Sensory/somatomotor Hand	141	Uncertain	0.000349	-0.243
31	Sensory/somatomotor Hand	87	Default mode	0.001713	-0.259
13	Sensory/somatomotor Hand	177	Fronto-parietal Task Control	0.002479	-0.289
121	Default mode	187	Fronto-parietal Task Control	0.002359	0.209562

Figure 4 the location of the selected 13 FCs.

Prediction results

In Table 3, the classification rates and F1-Scores in dataset1 and dataset2 are shown. For dataset1 the value are mean values of ten folds test. After the FCs and model are determined in the dataset1, they are applied to dataset2 directly without any training. The classification rate and F1-Scores of every fold in dataset1 are given in figure 5. Blue bar indicates the accuracy and red indicates F1-Score. The F1-score is used in the dataset that the samples are unbalanced. In Table 3, we can observe that the F1-score and classification rate is very close to each other, which suggests the dataset is well balanced and the classification rate is good enough for indicating the prediction performance. Therefore, we will use the classification rate as the only index for assessing the classification performance.

Table 3 Classification rate and F1-score of the final selected FCs

	Dataset1	Dataset2
Classification rate	0.8556	0.6722
F1-score	0.8507	0.6741

Figure 5 Classification rate and F1-score of every fold in dataset1

To illustrate the effectiveness of the FCs selected by PDM, we compare the classification results obtained by the final selected 13 FCs and obtained by other FCs. The 134 FCs ($p < 0.005$) selected in the first step of PDM are often used in the prediction methods (Shen et al 2017, Beaty et al. 2018, Liu et al. 2018). The classification rates obtained by these 134 FCs are given in the second row in Table 4. It is seen from Table 4 that the final 13 FCs selected by PDM can produce much higher recognition rate than 134 FCs, though 13 is much less than 134.

We also further selected another 13 FCs from the 134 FC by using other methods instead of PDM. The 13 FCs can be found by using the least 13 p values, the largest 13 R values (all R values are positive, the FCs are positively related to the creativity), the smallest 13 R values (all R values are negative, the FCs are negatively related to the creativity), the largest absolute 13 R values (R can be positive or negative, FCs can be negatively or positively related to the creativity). The classification rates of these sets of FCs are also given in Table 4.

Table 4 Comparison of classification rates under various settings

	Dataset1	Dataset2
134 FCs ($p < 0.05$)	0.7611	0.5739
13 FCs with least p value	0.6194	0.5724
13 FCs with largest R value	0.6944	0.5862
13 FCs with smallest R value	0.6639	0.5448
13 FCs with largest absolute R value	0.6694	0.5862
13 FCs selected by PDM	0.8556	0.6722

The contribution of single FC to the prediction

To investigate the contribution of every single FC to the classification/prediction, we conducted two measurements: 1. discarding each FC, and calculating the classification rate obtained by the remaining 12 FCs; 2. inputting every FC as the only feature to the classification model, and calculating the classification rate. The first measurement is to investigate FC's Contribution in the Group (to what extent every single FC contribute in the group of 13 FCs), the less the classification rate, the more important the discarded FC is in the group. The second

measurement is to investigate FC's Importance in Prediction Alone (to what extent the FC alone can predict the creativity), the larger the recognition rate, the more important the single FC is in the prediction.

For the convenience of expression, we numbered the final 13 FCs in Table 2 from 1 to 13. The number of each FC is shown in the first column of Table 5. The effect of removing every FC on the classification is given in the second column in Table 5. It represents the classification rates on dataset 1 obtained by discarding the corresponding FC (whose number is in the first column) and taking the remaining 12 FCs as features. The third column of Table 5 gives the rank of the corresponding classification rate in the second column, e.g. the '5' in third column of second row indicates that '0.8056' in the second column of the same row is the fifth smallest number in all numbers in the second column and also that the corresponding FC makes the fifth most important contribution in the group. The fifth column in Table 5 is the classification rate obtained by the FC numbered in the first column. The sixth column in Table 5 gives the rank of the classification rate in the fifth column, e.g. the '6' in sixth column of second row indicates that '0.6583' in the second column of the same row is the sixth largest number in all numbers in the sixth column and also that the corresponding FC alone is the sixth most important FCs.

It is observed in Table 5 that for some FCs, Importance in Prediction Alone (IPA) coincides with Contribution in the Group (CIP), such as the No.1, No. 5, No. 6, and No. 7 FCs. For these FCs, if the IPA is high, so does the CIP.

However, for other FCs, the IPA and CIP do not agree with each other, such as No. 3, No 4, and No. 9 FCs. The IPA shows that the No. 4 (IPA=1) and No. 3 (IPA=2) FC are the most important FC if they are used alone to predict the creativity. The No.4 FC itself can produce a 0.7278 classification rate, and No. 3 can produce 0.7028, which are fairly high rates. However, the No. 4 and No.3 FC makes the 12th and 10th contribution in the group (CIP=12 and CIP=10). The situation for No. 8 FC is opposite. The No.8 FC is the 9th important FC, but makes the 3rd contribution in the group. This indicates that more important FC in prediction alone could make less contribution in the group, while less important FC could make more important contribution.

Table 5 Importance and Contribution of individual FC in Prediction of Creativity

Number	Classification rates by removing the FC	Rank (Contribution in the Group, CIP)	Classification rates of the FC	Rank (Importance in Prediction Alone, IPA)
1	0.7167	1	0.6806	3
2	0.8056	5	0.6583	6
3	0.8250	10	0.7028	2
4	0.8403	12	0.7278	1
5	0.8083	6	0.6750	4
6	0.8222	9	0.5667	10
7	0.8397	11	0.4833	13
8	0.7778	3	0.5750	9
9	0.7889	4	0.6028	7
10	0.8167	8	0.5139	11
11	0.7639	2	0.6667	5
12	0.8423	13	0.5944	8
13	0.8083	7	0.5139	12

Discussion

The present study examined whether robust classification of high-creativity and low-creativity participant rely on several brain area's cooperation by using PDM method. We used dataset1 to determine related FCs, and dataset1 and dataset2 to validate whether our result is reliable and could be generalized. The results show that the effective identification of high and low creative individuals mainly depends on the cooperation of several networks of Fronto-parietal Task Control Network, Sensory/somatomotor Hand Network, Default mode Network, Visual Network, Cerebella Network, Dorsal attention Network, Cingulo-Opercular Network. The present study confirms the effectiveness of recognizing individuals with high or low creativity ability by machine learning approach.

In the present study, we used the rank sum test to select the most significant edges in the connectivity matrices and 134 FCs ($p < 0.005$) were selected. Then, the random forest was used to compute the importance of 134 FCs and 20 edges whose importance ranked in the top 20 were retained. Last, we used backward selection algorithm and SVM to select a combination of 13 FCs that made the classification rate the highest. Our method greatly reduced feature dimensions and computational complexity. And the result can be easily generalized to new data. The classification rate and F1-scores of dataset1 and dataset2 were shown in table 3. As can be seen from Table 3, the average classification rate of the ten-fold cross-validation on dataset1 is 0.8856, while the classification rate on dataset2 also reaches 0.6722. Since the classification rate cannot be used as a good indicator to measure our classification results under the condition of unbalanced samples, F1-Score is introduced as a more comprehensive index in Table 3 to evaluate whether our results are valid. As can be seen from Table 3, the F1-score of the corresponding dataset 1 and dataset 2 are 0.8507 and 0.6741, respectively, which is almost the same as the classification rate, so that our classification rate is effective. It is observed in Figure 3 that the accuracies of each fold are well balanced, indicating that our results do not depend on the grouping of the dataset. And each group of accuracy and its F1-Scores are basically flat, what improved the result is effective again.

It is seen from Table 4 that the final 13 FCs selected by PDM can produce much higher classification rate than 134 FCs selected by using statistic test, though 13 is much less than 134. This indicates that PDM is more powerful method for selecting causal features than statistic test used in previous studies (Shen et al. 2017, Beaty et al. 2018, Liu et al. 2018) and the PDM has picked the most representative FCs that help to predict creativity. It is also seen from Table 4 that the 13 FCs selected by PDM can produce much higher classification rate than all other set of 13 FCs selected by using P values or correlation coefficients (R values). The classification rates on dataset2 obtained by 13 FCs selected using P values or R values and the classification rate obtained by 134 FCs are similar to each other, which indicates relying P value or R value can only give rough selection results. To further select the most relevant FCs, PDM is required.

It is observed in Table 5 that for some FCs, Importance in Prediction Alone (IPA) coincides with Contribution in the Group (CIP), such as the No.1, No. 5, No. 6, and No. 7 FCs. For these FCs, if the IPA is high, so does the CIP. However, for other FCs, the IPA and CIP do not agree with each other, such as No. 3, No 4, and No. 9 FCs. The IPA shows that the No. 4 (IPA=1) and No. 3 (IPA=2) FC are the most import FC if they are used alone to predict the creativity. The No.4 FC itself can produce a 0.7278 classification rate, and No. 3 can produce 0.7028, which are fairly

high rates. However, the No. 4 and No.3 FC makes the 12th and 10th contribution in the group (CIP=12 and CIP=10). The situation for No. 8 FC is opposite. The No.8 FC is the 9th important FC, but makes the 3rd contribution in the group. This indicates that more important FC in prediction alone could make less contribution in the group, while less important FC could make more important contribution. The results suggest that we may need to understand the creativity as a result of cooperating of different FCs. The FCs play an important role in the group of FCs may need to be investigated more.

We selected 13 FCs from 34,716 FCs, the results were shown in Table 2. These FCs are involved in default mode network, fronto-parietal task control network, dorsal attention network, cingulo-opercular task control network sensory/somatomotor hand network, visual network and cerebella. Among these FCs, the FCs between default mode network (DMN) and Fronto-parietal task control network positively predict creativity. Recent viewpoint highlights the role of the DMN and the control network (CN) in the neural basis of creativity (Beaty et al., 2016; Jung, Mead, Carrasco, & Flores, 2013). The DMN is active during rest and deactivates during most externally-oriented tasks (Greicius, Krasnow, Reiss, & Menon, 2003; Raichle et al., 2001). The CCN is engaged in attention-demanding cognitive tasks (Aron, 2007; Dreher & Berman, 2002). During creative tasks, these networks correspond to blind variation and selective retention components of creative cognition, respectively (Jung et al., 2013). The DMN reflects the blind variation mechanism that is related to creative thinking generation and CCN reflects the selective retention which is related to the top-down cognitive control (Abraham, 2014; Jung et al., 2013; Mok, 2014). Creative idea involves the dynamic interactions of these brain networks (Beaty et al., 2016).

The FCs between default mode network (DMN) and dorsal attention network (DAN) also positively predict creativity. The DAN is responsible for maintaining and re-orienting attention (Christoff, et al., 2016). This is supported by the finding that high variability of the FCs between the DMN and the DAN is related to high verbal creativity, which indicates that the dynamic interaction between the DMN and DAN is related to creative thinking (Sun et al., 2019). According to a dynamic framework of spontaneous thought, creative thinking can be defined as a special type of spontaneous thought that is intermediate between mind-wandering and goal-directed thought (Christoff, et al., 2016). That means deliberate constraints at various levels are needed from time to time in creative thinking processes. The DMN may provide sustained internally oriented cognition for creative thinking, while it couples with attention networks. This may lead to a frequently shifting focus of thoughts to externally oriented cognition for exploring task-related cues from environment, which favors high creativity (Sun et al., 2019).

We also found the interaction between networks involves in high level cognitive ability and networks involves in primary sensory/motor or cerebellar can predict creativity. The activity of region in these networks has been observed in previous task-based fMRI study. For example, Sagger et al. found that higher creative content in drawing task was associated with increased engagement of bilateral cerebellum (Saggar et al., 2015). Creativity is complex and is involved in the integration of information from different sensory channel.

The present study also has some limitation. Although the accuracy of our prediction model has achieved 0.8556 for distinguishing high and low creative individuals, this classification rate still needs to be improved when facing practical application. We only considered the high and low creative groups and not the ordinary group. In the future, we hope to introduce the more advanced

models to make a quantitative prediction of each individual's creative ability in order to further explore the neural mechanism of the brain network related to creativity and further improve the accuracy of the prediction of individual's creative ability.

Conclusion

In conclusion, this research proposed a PDM method for intensively investigating the FC selection in predicting creativity. The binary classification was performed to locate the most representative FCs. The method has found the group of FCs that can give the best prediction results. The contribution of each FC to the prediction has been studied, which suggest that less FCs may contribute more in the prediction. By using these most relevant FCs, the high and low divergent thinking individuals can be predicted. These FCs involve in default mode network, fronto-parietal task control network, dorsal attention network, cingulo-opercular task control network sensory/somatomotor hand network, visual network and cerebella. Our work provides a method for other similar works that need to intensively explore the relationship between neuroimaging metrics and behavior scores. The finding of this research will help us to better understand the neural mechanisms of creative brain networks and provide brain imaging indicators to distinguish high and low creative groups.

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