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Structure-preserving Graph Kernel for Brain Network Classification

Jun Yu, Zhaoming Kong, Aditya Kendre, Hao Peng, Carl Yang, Lichao Sun, Alex Leow, Lifang He

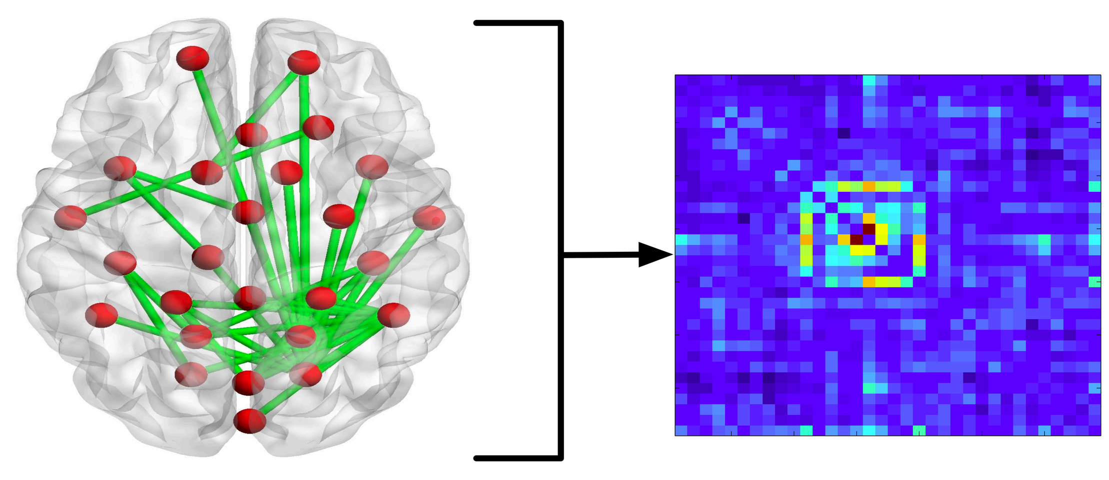
Abstract

Brain network analysis is of great importance in the clinical diagnosis and treatments. In this paper, we present a novel graph-based kernel learning approach for brain network classification. Specifically, we demonstrate how to exploit the natural graph structure of brain networks to encode prior knowledge in the kernel using the tensor product operator. For each brain network, we first proposed to apply sparse matrix factorization with a symmetric constraint to extract tensor product based approximation. We then used them to derive a structure-persevering symmetric graph kernel to be fed into the support vector machine (SVM). Quantitative evaluations on challenging EEG-based emotion recognition tasks with respect to different frequency bands demonstrate the superior performance of our proposed method, compared with the state-of-the-art traditional and deep learning methods. Together, results show that relevant EEG signals are primarily encoded in the alpha and theta bands during the emotion regulation task, which is consistent with previous findings.

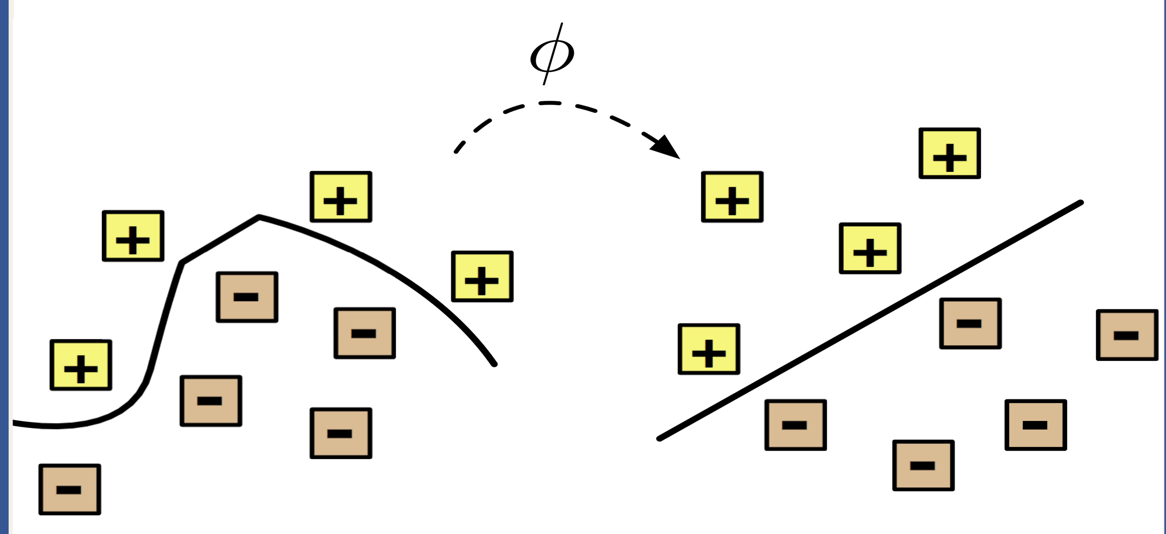
Background

The brain is a complex network from the perspective of neurons connected to each other. Thus, it is a fundamental mathematic tool for the connectome matrix to represent all possible pairwise anatomical connections between neural elements of the brain. In this symmetric matrix, the row or column dimension represents the number of nodes in the brain network, and the non-zero values are relevant importance among every pair of nodes (i.e., edges). Brain network analysis, enriched by the advances of neuroimaging technologies such as electroencephalography (EEG) and diffusion tensor imaging (DTI), has been an appealing research topic in recent years in neuroscience. Furthermore, the information encoded by the connectome can promote critical understanding on how the brain manages cognition, what signals the connections convey, and how these signals affect brain regions.

Framework



As mentioned in the background, the brain network is encoded as a symmetric matrix.



Then, we can use a graph-based feature mapping function $\phi(\cdot)$ to transform the graph data into a higher dimensional feature space (Hilbert space).

Structure-Preserving Symmetric Graph Kernel (SSGK) Model

Try to approximate the original matrix $\mathbf{X}$ and preserve essential information as much as possible:

$$\min_{\mathbf{a}_r} \|\mathbf{X} - \sum_{r=1}^{R} \mathbf{a}_r \otimes \mathbf{a}_r\|_F^2 + \lambda \sum_{r=1}^{R} \|\mathbf{a}_r\|_1$$

Solve the optimization problem above to obtain the matrix:

$$\widetilde{\mathbf{X}} \approx \sum_{r=1}^{R} \mathbf{a}_r \otimes \mathbf{a}_r$$

Map the matrix factorization into the outer product feature space:

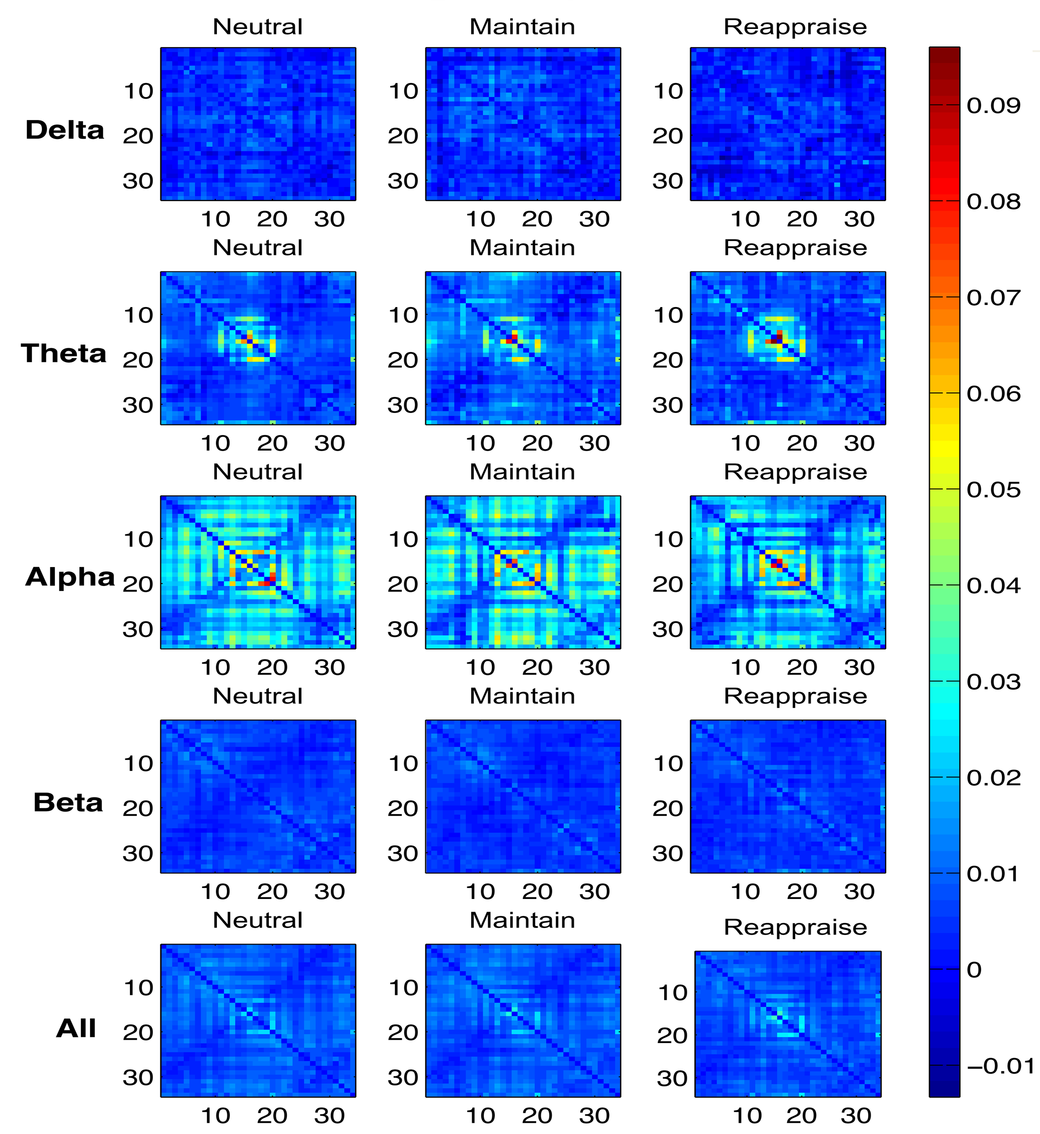
$$\phi: \sum_{r=1}^{R} \mathbf{x}_r \otimes \mathbf{x}_r \rightarrow \sum_{r=1}^{R} \phi(\mathbf{x}_r) \otimes \phi(\mathbf{x}_r)$$

Use kernel function to simplify the computation during the mapping:

$$\begin{aligned} \kappa(\mathbf{X}, \mathbf{Y}) &= \kappa\Big(\sum_{r=1}^{R} \mathbf{x}_r \otimes \mathbf{x}_r, \sum_{r=1}^{R} \mathbf{y}_r \otimes \mathbf{y}_r\Big) \\ &= \Big\langle \sum_{r=1}^{R} \phi(\mathbf{x}_r) \otimes \phi(\mathbf{x}_r), \sum_{r=1}^{R} \phi(\mathbf{y}_r) \otimes \phi(\mathbf{y}_r) \Big\rangle \\ &= \sum_{p=1}^{R} \sum_{q=1}^{R} \kappa(\mathbf{x}_p, \mathbf{y}_q) \kappa(\mathbf{x}_p, \mathbf{y}_q). \end{aligned}$$

Visualization & Results

The average EEG-connectome during neutral, maintain, and reappraise in the five different frequency bands:



The classification accuracy in percentage (%) by competing methods and the proposed method for five tasks:

Category	Method	Frequency Band				
		Delta	Theta	Alpha	Beta	All
Traditional	Edge	42.42	54.55	51.52	51.52	45.45
	CC	54.55	54.55	42.42	51.52	42.42
	CPL	48.48	42.42	45.45	48.48	39.39
	gSpan	39.39	51.52	39.39	54.55	48.48
	DuSK–2D	51.52	63.64	51.51	51.52	54.55
	DuSK–3D	57.58	57.58	57.58	54.55	48.48
	DuSK–4D	54.55	54.55	51.52	54.55	57.58
Deep Learning	CNN–2D	51.11	43.71	43.07	42.54	41.48
	CNN–3D	46.67	45.93	41.48	57.04	44.44
	GCN	41.31	48.08	41.01	40.61	37.37
Ours	$\text{SSGK}_{\text{w/o sparse}}$	57.58	66.67	63.64	54.55	57.58
	SSGK	**63.64**	**69.70**	**72.73**	**60.61**	**57.58**

Conclusion

This paper proposes a graph-based kernel learning approach called Structure-preserving Symmetric Graph Kernel (SSGK) for brain network classification task. The proposed method mainly follows two consecutive steps: first, a sparse-inducing symmetric matrix factorization strategy is applied to extract structural features from the natural symmetric graph representations of the brain network data, then the extracted structural features are directly used to define the SSGK function and further fed into the support vector machine for the classification. Experimental results on challenging EEG-based emotion recognition task demonstrates the effectiveness of the proposed method.

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Corresponding author: Lifang He

E-mail: lih319@lehigh.edu

Address: Department of Computer Science & Engineering, Lehigh University