Improvements and Discussion of "Explainable Classification of Brain Networks via Contrast Subgraphs"

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ABSTRACT

TODO

CCS CONCEPTS

• Mathematics of computing → Graph algorithms; **• Applied computing →** *Consumer health.*

KEYWORDS

graph analytics, graph algorithms, brain networks, densest subgraph

ACM Reference Format:

Tengkai Yu and Keanelek Enns. 2022. Improvements and Discussion of "Explainable Classification of Brain Networks via Contrast Subgraphs". In *Proceedings of ACM Conference (Conference'17).* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

The question we are asking is, "Can we translate a brain network into a vector/embedding in such a way that the embedding is intuitive *and* adequately separates different brain networks according to their classes?" If we could do this, we would have an explainable classification method for brain networks.

Lanciano *et al.* proposed a method that used contrast subgraphs to create two dimensional representations of brain networks [2]. A contrast subgraph is simply a subgraph, or set of nodes, that is dense (has high edge weight) in one group of networks and sparse in another, assuming that all analyzed graphs share a common vertex set.

2 RELATED WORK

Are you supposed to mention the paper you are replicating in the related works? Also, to what extent should we mention the papers that Lanciano built off of?

Talk about trend towards explainability in AI (xAI). A possible reference is https://doi.org/10.1016/j.inffus.2021.01.008

Dai and Wang worked on creating explanations that are built into a GNN [1] rather than trying to find an explanation after the GNN had made its classification. They found their method to be less biased and more computationally efficient when compared to using a post-hoc explainer such as GNN explainer.

Wang *et al.* recently proposed a method, named DHC-E, for embedding graphs in a generalizable way that does not require any hyperparameters [3]. The embedding has a moderate number of dimensions depending on the graph set analyzed and is based on the h-index values of each node in the graph. They used principal component analysis to present the graph embeddings in two dimensions.

Look into https://doi.org/10.1142/S0129183118400077, https://dl.acm.org/doi/abs/10.1145/3219819.3219980

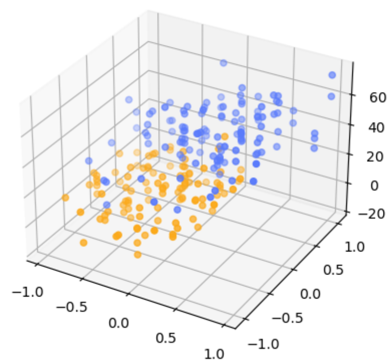

Figure 1: This is just a test image, we need to create proper images with proper labels

3 PROBLEM STATEMENT

This is a special case of graph classification where all considered graphs possess the same set of vertices (i.e. regions of the brain which are, naturally, common to all brains).

4 EXPERIMENTS

5 LIMITATIONS

This study was limited primarily by the data set used. In many machine learning applications, a large volume of data is needed to adequately train and test new models. With a small data set, it is difficult to know how generalizable any of the discussed methods are to new brain networks that we wish to classify. Additionally, the

Conference'17, July 2017, Washington, DC, USA

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

way the data set was created and the individuals that were studied have a large impact on the validity of the methods developed with respect to classifying brain networks with ASD. The limitations in data set quantity and size are likely due to the costly nature of developing such brain networks as the ones analyzed in this study [TODO: back that claim up and perhaps talk about the data preparation like Lanciano did].

Furthermore, Autism Spectrum Disorder is a very complex disorder with unclear definitions, and it may manifest in various different ways [perhaps this belongs in the intro when describing why the problem is hard?]. Above all this, the brain is a highly complex organ that is not fully understood. The brains of individuals are unique and develop in complex manners. There may be a plethora of confounding factors that have an effect on the classification of such networks with respect to identifying ASD in individuals.

6 DISCUSSION

Lanciano *et al.* showed that the degrees of each node in the studied brain networks did not vary significantly between the two classes [2], yet the contrast subgraphs are defined as a set of nodes, and every edge induced by these nodes is used for classification. Instead, we should look solely at edges that are important for distinguishing between the classes.

The discriminative edge method considers the most important edges in each class (defined as having the most positive and most negative weights in the difference network) when creating an embedding. Additionally, it considers the brain network as a whole in its third dimension, which likely captures more interesting information with respect to complex connections in the brain. However, it does not specifically identify higher order structures in the brain networks that may be leading to the DNN's success.

7 CONCLUSION

Future work should attempt to identify higher order structures (such as triangles, k-clusters, or graphlets of varying size and shapes) as a means of embedding. This could be done by identifying prominent structures in each summary graph (perhaps after thresholding the edge weights), eliminating structures common to both, and counting the number of overlapping structures that a new brain network has in common with each class. The challenge associated with this technique comes with the computational complexity of enumerating such high order structures.

As discussed in section 5, this study should be replicated on additional data sets to further test its validity.

REFERENCES

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[2] Tommaso Lanciano, Francesco Bonchi, and Aristides Gionis. 2020. *Explainable Classification of Brain Networks via Contrast Subgraphs*. Association for Computing Machinery, New York, NY, USA, 3308–3318. https://doi.org/10.1145/3394486.3403383

[3] Hao Wang, Yue Deng, Linyuan Lü, and Guanrong Chen. 2021. Hyperparameter-free and Explainable Whole Graph Embedding. *CoRR* abs/2108.02113 (2021). arXiv:2108.02113 https://arxiv.org/abs/2108.02113

APPENDICES

A ARTIFACTS

Project Repository:
https://github.com/keanelekenns/contrast-subgraph