Referee Report for the Paper Pattern classification of fMRI data: applications for analysis of spatially distributed cortical networks

Jiaxu Han

This referee report is based on the paper titled “Pattern classification of fMRI data: applications for analysis of spatially distributed cortical networks” by Yourganov and colleagues (2014). The paper used “NPAIRS framework” (Yourganov, 2014, p9) to evaluate a set of pattern classification algorithms on both simulated and experimental fMRI data sets (Yourganov, 2014, p4).

Analyzing fMRI data has been a “challenging task” because “the signal of interest is typically weak, distributed among various spatial locations, and confounded by complex spatially correlated high-variance noise” (Yourganov, 2014, p1). There are a variety of methods that can perform classification of fMRI data: “probabilistic vs. non-probabilistic”, “univariate vs. multivariate”, and “linear vs. non-linear” (Yourganov, 2014, p2). Several studies assessed the classifiers based only on the accuracy of the classification, but had inconsistent findings (Yourganov, 2014, p2 and p3). Therefore, besides prediction accuracy, the authors proposed additional evaluation matrices, such as “reproducibility” matrices, to test classification algorithms (Yourganov, 2014, p3).

In the introduction (p1-p4), Yourganov et al. (2014) provided a thorough literature review of the background of the problem. Though not explicitly stated in the paper, it is still implied that a broad research question in this area is how to select the best classification algorithm among a large group of methods to perform binary classification of fMRI data (Yourganov et al., 2014, p2.).

To investigate the research question, they used the NPAIRS framework to evaluate four types of algorithms: LD, QD, Linear SVM, and GNB (Yourganov, 2014, p9). The evaluation was based on “out-of-sample classification accuracy”, “reproducibility of spatial maps” and “area under ROC curve” (Yourganov, 2014, p9 & p10). To get “reproducibility of spatial maps” (Yourganov, 2014, p3), Yourganov and colleagues proposed a modified method of “sensitive map construction” based on an earlier work on this topic (Yourganov, 2014, p3). In the section “Materials and methods” (Yourganov, 2014, p5-p18), the paper provided a detailed explanation about how they simulated data, processed experimental data, computed performance metrics and various classification algorithms, as well as evaluating the performance of the classifiers (Yourganov, 2014, p5-p18). After conducting a thorough statistical analysis, the paper concluded that “the best performers were linear and quadratic discriminants”, and “in some rare situations, a nonlinear Gaussian naive Bayes classifier” (Yourganov, 2014, in the Abstract section of the published version of this paper).

The study applied affective computational techniques to address the research question. They evaluated the classifiers not only on the experimental data set but also on a simulated data set. Having a simulated data set would allow researchers to actually know “the underlying parameters of active signal” (Yourganov, 2014, p4). They also used machine learning by splitting up the data set into two subsets; one subset is used to train the classifier and the other subset “serves as an independent test set to evaluate classification accuracy” (Yourganov, 2014, p5).

The methods used in the paper were necessary to answer the research question. Acquiring fMRI data is expensive; although there are some open source websites that would allow researchers to contribute and share data, the consistency of the data cannot be verified. By simulating data, the authors could have a large data set while ensuring the standards of the study would be met. Building on that, using a large data set to train the classifier and evaluate models in the following step would enhance the validity of the study.

However, it is too strong to conclude that the methods were “sufficient” to answer a relatively broad research question. As pointed out in the paper, the study did not consider classifier models that require more than one tuning parameter (Yourganov, 2014, p4) and only "focus on binary classification problems" (Yourganov, 2014, p4). Still, the study applied sophisticated computational techniques to evaluate the chosen models and also provided findings that compellingly answered the research question.

The authors put their paper in the context of the broader literature with no unnecessary citations. I would suggest that the authors provide additional information on why they chose that specific experimental fMRI data set. If relevant, they may provide additional citations for the justification of that choice. Also, on page 4, the paper mentioned that "Metrics are computed by splitting the data set into two independent subsets of approximately same size…" if possible, the authors may attach additional citations about the algorithms that they applied to split data sets and train classifiers. For example, Pereira, Mitchell, and Botvinick wrote a paper that summarized the use of machine learning classifier on fMRI data (2010).

There are some minor style and grammar errors that need further revision:

1. On page 1, there is an extra space between the sentence "…under which individual brain volumes were acquired" and the sentence "Classification of brain volumes…"

2. On page 2, there is an extra space between the sentence "Yet another distinction between classifiers is whether they are linear or non-linear" and the sentence "Linear classifiers separate the classes with…".

3. On page 4, in the last sentence, "Another limitation in our analysis is our focus on binary classification problems…, an on within-subject classification", "an" should be replaced with "and".

4. If possible, please change the alignment of all the equations presented in the paper as "centered."

5. On page 35, please remove the doi number attached to the reference "Berman, M., Yourganov, G., Askren, M. K., Ayduk, O., Casey, B. J., Gotlib, I. H., Kross, E.,

McIntosh, A.R., Strother, S.C., Wilson, N.L., Zayas, V., Mischel, W., Shoda, Y., & Jonides, J. (2013). Dimensionality of brain networks linked to life-long individual differences in self-control. Nature Communications, Article # 1373".

6. Please consider adding headers on Table 1 through Table 5.

Extension

Yourganov et al.'s study focused on binary classification problems (2014, p4). I would like to propose an extension of their research question to multi-class classification problems. More specifically, the research question is "how to select the best classification algorithm among a group of classification algorithms to perform the multi-class classification of fMRI data."

Multi-class classification is "the problem of classifying instances into one of three or more classes" (https://en.wikipedia.org/wiki/Multiclass_classification). There may be some differences between binary classification problems and multi-class classification problems, and we need to make adjustments accordingly in the new study. It is still possible to apply similar methods used in Yourganov et al.'s paper on multi-class problems. For example, we would simulate a data set and split it into two data sets. We would possibly use one data set to train the multi-class classifier and then test the trained classifier on the other data set and evaluate them using adjusted evaluation matrices.

References

Yourganov, Grigori, Tanya Schmah, Nathan W. Churchill, Marc G. Berman, Cheryl L. Grady, and Stephen C. Strother, "Pattern Classifi- cation of fMRI Data: Applications for Analysis of Spatially Distributed Cortical Networks," NeuroImage, August 2014, 96 (1), 117–132.

Pereira, F., Mitchell, T., & Botvinick, M. (2008). Machine learning classifiers and fMRI: a tutorial overview. *NeuroImage*, *45*(1 Suppl), S199-209.

https://en.wikipedia.org/wiki/Multiclass_classification