

Neuroimaging data association with behavioral variables: A class of multivariate methods and their comparison using multi-task fmri data.

Luke Morgan*

Editorial Office, Journal of Neuroinformatics and Neuroimaging, London, United Kingdom

Abstract

It is becoming more typical to gather numerous linked neuroimaging datasets from different modalities or activities and situations. We also have nonimaging data, such as cognitive or behavioural variables, and it is only by combining these two types of data—neuroimaging and non-neuroimaging—that we can understand and explain the evolution of neural and cognitive processes, as well as predict outcomes for intervention and treatment. There are several ways for combining or fusing various neuroimaging datasets or modalities; however, approaches for combining imaging and non-imaging data are still in their infancy. Current techniques for finding brain networks associated to cognitive evaluations are still mostly focused on simple one-to-one correlation analyses and do not take advantage of cross-dataset information. This paper presents two methodologies based on Independent Vector Analysis (IVA) to concurrently evaluate imaging datasets and behavioural variables in order to identify multivariate correlations between imaging data and behavioural aspects. The simulation findings suggest that our proposed methods outperform current approaches in discovering relationships across imaging and behavioural components. Using Functional Magnetic Resonance Imaging (fMRI) task data from 138 healthy controls and 109 patients with schizophrenia, researchers discovered that the Central Executive Network (CEN) estimated in multiple datasets has a strong correlation with the behavioural variable that measures working memory, a finding that traditional approaches do not detect. The majority of the detected fMRI maps also reveal substantial changes in activations between healthy controls and patients, suggesting that they might provide a valuable hallmark of mental illnesses.

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Introduction

In cognitive neuroimaging, the availability of various datasets that give complementary information is becoming more prevalent. The creation of fusion methods in which the datasets may completely interact with and inform each other when selecting interesting characteristics for further investigation is a key difficulty when studying such datasets. Latent variable models are used in matrix and tensor decomposition methods, allowing for such interactions across datasets. Because these approaches ensure uniqueness with few assumptions, the estimated latent variables (components) are immediately interpretable, that is, they can be used to explain the link between datasets and populations. Because these approaches ensure uniqueness with few assumptions, the estimated latent variables (components) are immediately interpretable, that is, they can be used to explain the link between datasets and populations.

Independent Component Analysis (ICA), a prominent matrix decomposition-based approach on which we focus in this study, offers an appealing basis for completely multivariate data fusion. The use of ICA and its extensions developed for the fusion of multiple datasets can help explain the underlying relationship across datasets by starting from the assumption of latent variable independence (component independence) and are successful when there is a good model match, that is, the model's assumptions are satisfied. Independent Vector Analysis (IVA), for example, generalises ICA across many datasets by using existing statistical information inside and across datasets, which is crucial for multivariate data fusion. IVA enables

datasets to completely interact with each other in a symmetric manner by allowing them to play a comparable function in the decomposition and build association only when it is accessible. As a result, IVA offers a completely multivariate strategy for analysing various neuroimaging datasets.

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*Correspondence to:

Luke Morgan
Editorial Office
Journal of Neuroinformatics and Neuroimaging
London
United Kingdom
Email: info@alliedacademies.org