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Editorial

Multivariate decoding and brain reading: Introduction to the special issue

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ABSTRACT

In recent years, the scope of neuroimaging research has been substantially extended by multivariate decoding methodology. Decoding techniques allow us to address a number of important questions that are frequently neglected in more conventional analyses. They allow us to focus on storage of "mental content" in brain regions, rather than on overall levels of activation. They directly address the question how much information can be "read out" of brain activity patterns, thus inverting the classical direction of inference that attempts to explain brain activity from mental state variables. At the same time, they provide a much higher sensitivity to detection of effects than conventional approaches. This special issue is a showcase of research in this emerging field. Besides five invited review papers by key experts in the field, it presents a representative selection of work showing the diversity and power of multivariate decoding analyses ranging from methodological foundations to cognitive and clinical studies.

Introduction multivariate decoding

Traditionally, neuroimaging has been dominated by mass-univariate analyses based on the general linear model (GLM; see Friston et al., 1995). In this approach, univariate statistical tests are applied at each location of the brain individually and the statistical parameters are then plotted at each position of the brain (hence "statistical parametric mapping," SPM). The GLM/SPM approach is highly suitable when the aim of a study is to assess whether the activity level at a single location in the brain is modulated by a specific mental operation. However, an important question has frequently remained unclear: how and where is information about specific mental contents represented in the brain? To date content-specific research has typically relied on markers for content-specific processing such as frequency tags (Tononi et al., 1998) or semantic tags like activity in the fusiform face area during processing of faces and in the parahippocampal place area during processing of visual scenes and buildings (Epstein & Kanwisher, 1998; Kanwisher, McDermott & Chun, 1997; Moutoussis & Zeki, 2002; Tong et al., 1998).

It has long been established that the brain encodes most mental contents using populations of cells (Georgopoulos, Schwartz & Kettner, 1986; Tanaka, 1998) and that the covariance structure between multiple individual units is of essential importance in neural coding (Averbeck et al., 2006). For example, in motor cortex the direction of movement of a cursor is coded in the population vector that is a sum of the preferred movement directions of each individual motor cortex cell (Georgopoulos, Schwartz & Kettner, 1986). This importance of distributed "population" activity on the neuronal level is paralleled in neuroimaging by a seminal study by Haxby and colleagues (2001) who presented subjects with images of objects. These images were different exemplars taken from eight different categories (faces, houses, cats, chairs, scissors, shoes, bottles and phase-scrambled noise). The fMRI responses in object-selective cortex were determined for each category and accumulated separately for odd and even acquisition runs. Haxby and colleagues found that each object category evoked a spatial pattern of fMRI activity that was unique for this category only. They then attempted to classify the objects viewed during even runs based on the knowledge of patterns of responses for the different categories during odd runs. The classification rule was to assign a given fMRI response pattern in the even runs to the category that had evoked the most similar response pattern in the odd runs. Following this approach they were able to determine which object the subject had been viewing with an accuracy of 96% (based on pairwise classifications). Interestingly, there was only a minor reduction in accuracy if the classification was based on voxels that did not respond maximally to the corresponding objects. This is an important finding, because it suggests the existence of category-specific information outside the regions that would be considered most relevant for this category in a conventional GLM analysis.

The study by Haxby and colleagues (2001) was the first widely perceived study using classification approaches for the analysis of fMRI data. Since then a tremendous extension has happened and the approach has had a large impact on the way scientists think about fMRI data. Most importantly, it has become apparent that even single samples of neuroimaging data contain much more information than was previously believed possible. And it has become obvious that the smoothing employed in traditional GLM-based approaches throws away a major source of information that is contained in the fine-grained spatial patterning of fMRI signals. This has sparked debates regarding the neurophysiological sources of pattern-information that have not been finally resolved yet, but have helped clarify potential shortcomings in existing theories (Boynton, 2005; Haynes & Rees, 2006; Kamitani & Tong, 2005; Kriegeskorte, Cusack & Bandettini, 2010; Op de Beeck, 2010; Swisher et al., 2010).

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The full breadth of applications of multivariate decoding is only gradually becoming apparent. It ranges from basic cognitive and clinical neuroscience all the way to “neurotechnological” applications where decoding of neuroimaging signals is used as a basis for clinical and commercial technologies. This volume provides an overview of this exciting novel field.

Overview of papers in the special issue

The volume starts off with five invited reviews by major protagonists in the field. Lemm and colleagues provide an introduction to machine learning in neuroimaging and provide hints how to avoid common mistakes. Two reviews, one by Naselaris and colleagues and one by Kriegeskorte, demonstrate the importance of model-based approaches and encoding models for multivariate classification. A review by Ashburner and Klöppel presents approaches to classification of structural MRI data that can assess variability across subjects. LaConte provides an introduction to real-time classification and Krishnan and colleagues discuss the link between classification and partial least squares.

The review section is followed by a number of papers on methodological aspects of machine learning in neuroimaging. This includes methodological basics such as a comparison of various classifiers (Pereira & Botvinick; Langs et al.; Björnsdotter, Rylander & Wessberg), sensitivity to physiological noise, task reordering, and across-scan classification (Anderson et al.), the link between response amplitude and decoding accuracy (Smith, Kosillo & Williams), dimensionality estimation (Yourganow et al.) and dimensionality reduction (Douglas et al.; Remes et al.). It also includes novel approaches such as Gaussian process methods for the analysis of cortical maps (Macke et al.), surface-based versus volumetric searchlights approaches (Chen et al.; Oosterhof et al.), links between DCM and classification (Brodersen et al.) and decoding from brain connectivity graphs (Richiardi et al.). This section also contains two papers on the link between fMRI pattern signals and the underlying neural and vascular architecture (Chaimow et al.; Thompson, Correia & Cusack). Two studies present different but related approaches to optimize “brain reading”, both based on the Pittsburgh Brain Activity Interpretation Competition (PBAIC) and both using relevance vector machines (Valente et al.; Chu et al.).

The next section contains a number of applications of multivariate decoding, starting with several cognitive neuroscience studies using pattern classification approaches. This includes studies on number processing (Zorzi, Bono & Fias), motion perception (Wolbers, Zahorik & Giudice; Schwarzkopf, Sterzer & Rees), decision making and reward (Clithero et al.; Kahnt et al.), generative models of object representation (Chang, Mitchell & Just), action observation and mirroring (Ogawa & Inui), cognitive ageing (Carp et al.), rule representation (Woolgar et al.), and emotional processing (Sitaram et al.). Then, there are a number of studies that demonstrate classification of diseases such as Alzheimer’s (Cuingnet et al.; Markiewicz et al.), Huntington's (Rizk-Jackson et al.), vegetative state and locked-in (Phillips et al.) and depression (Nouretdinov et al.). Finally, there are four studies that use machine learning for the analysis of EEG signals. Two studies present approaches for single-trial EEG-decoding analyses (Blankertz et al.; DeMartino et al.), one study investigates the role of gamma oscillations and sensorimotor rhythms for brain computer interfaces (Grosse-Wentrup, Schölkopf & Hill) and the final study shows that EEG can be used for the decoding of music (Schaefer et al.).

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