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Q4 Sparse canonical correlation analysis relates network-level atrophy to 2 multivariate cognitive measures in a neurodegenerative population

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ABSTRACT

This study establishes that sparse canonical correlation analysis (SCCAN) identifies generalizable, structural 23 MRI-derived cortical networks that relate to five distinct categories of cognition. We obtain multivariate 24 psychometrics from the domain-specific sub-scales of the Philadelphia Brief Assessment of Cognition 25 (PBAC). By using a training and separate testing stage, we find that PBAC-defined cognitive domains of language, 26 visuospatial functioning, episodic memory, executive control, and social functioning correlate with unique and 27 distributed areas of gray matter (GM). In contrast, a parallel univariate framework fails to identify, from the training 28 data, regions that are also significant in the left-out test dataset. The cohort includes 164 patients with 29 Alzheimer's disease, behavioral-variant frontotemporal dementia, semantic variant primary progressive aphasia, 30 non-fluent/agrammatic primary progressive aphasia, or corticobasal syndrome. The analysis is implemented 31 with open-source software for which we provide examples in the text. In conclusion, we show that multivariate 32 techniques identify biologically-plausible brain regions supporting specific cognitive domains. The findings are 33 identified in training data and confirmed in test data. 34

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Q5 Introduction

Multivariate methods have advantages over univariate methods in 41 genomics (Hibar et al., 2011; Le Floch et al., 2012; Parkhomenko et al., 42 2009), pattern recognition (Bishop, 1995; Roberts, 1997; Tipping, 2001) 43 and neuroimaging (De Martino et al., 2008; Fan et al., 2008; McIntosh 44 et al., 1996; Shamy et al., 2011; Tosun et al., 2012) due to the high dimensionality 45 and latent structure within these types of datasets. Various forms 46 of multivariate pattern analysis (MVPA) (Habeck et al., 2008; Hanke et al., 47 2009; Kloeppel et al., 2008; Norman et al., 2006; Stonnington et al., 2010) 48 are frequently used in (often functional) magnetic resonance imaging 49 (MRI) studies to increase detection power (McIntosh et al., 1996; 50 Norman et al., 2006; O'Toole et al., 2007; Yamashita et al., 2008). Recently, 51 multivariate analysis of structural MRI has gained more attention 52 (Grosenick et al., 2013; Ryali et al., 2010; Sabuncu and Van Leemput, 53 2011). The large majority of these techniques relate a multivariate 54 pattern to a univariate outcome. 55

Modern datasets allow the opportunity to relate two independent 56 multivariate patterns. Neuroimaging and psychometric batteries describe 57 cognition and the brain itself, respectively, with a matrix of quantitative 58 measurements. These types of datasets may be analyzed with methods 59 such as canonical correlation analysis (CCA) (Cherry, 1996) which is 60 closely related to multivariate regression and partial least squares (Sun 61 et al., 2009). Partial least squares (PLS), without sparseness, has been 62 used for several years in multivariate brain mapping studies (Addis 63

et al., 2004; Chen et al., 2009; Leibovitch et al., 1999; Lin et al., 2003; 64 McIntosh et al., 1996). Ridge and related penalties allow these methods 65 to be applied even when the number of subjects is far fewer than the 66 number of measurements (Nestor et al., 2002b). However, a caveat of 67 these approaches is that the resulting solution vectors have global extent 68 i.e. cover the entire brain with basis vectors that are non-zero and may 69 have both positive and negative values. Traditional approaches are more 70 clearly directional: a long neurological history is founded on relating 71 behavioral deficits (losses) associated with destruction of brain tissue by 72 stroke or related disorders. Perhaps the most famous example is H.M. 73 This epilepsy patient lacked the ability to form new memories after anterior 74 temporal lobe resection. That is, loss of a specific part of the brain 75 resulted in a specific deficit. 76

Tools such as independent component analysis and principal 77 components analysis (PCA) (Borroni et al., 2012; Comon, 1994; Mansfield 78 et al., 1977; Shamy et al., 2011; Yeung and Ruzzo, 2001) increase 79 power by efficiently describing data. However, PCA solutions provide 80 signed basis vectors with global support and therefore lose the specificity 81 of classical region of interest approaches or lesion studies. Sparse multi- 82 variate methods have advantages of interpretability (Lee and Seung, 83 1999; Suykens et al., 2002) and, potentially, improved generalizability 84 (Elad, 2006; Ryali et al., 2010; Yamashita et al., 2008; Zhang, 2008; 85 Zibulevsky and Elad, 2010). In this paper, we use the cognitive variance 86 induced by a spectrum of neurodegenerative conditions to examine 87 how new, sparse multivariate analysis techniques more powerfully 88

89 reveal relationships between brain and behavior. At the same time, sparse methods achieve a degree of specificity that cannot naturally be
 90 obtained by dimensionality reduction tools such as PCA (Lee and Seung, 1999). Here, we apply sparse multivariate methods to find cortical
 91 networks that vary with cognition in a mixed group composed of controls and phenotypes related to Alzheimer's disease (AD) and frontotemporal
 92 lobar degeneration (FTLD) pathology. An example of the difference between sparse solutions and more traditional approaches appears in
 93 Fig. 1.

94 Like AD, FTLD is a progressive neurodegenerative condition that is accompanied by changes in behavior. Unlike AD, which typically
 95 presents atrophy in the precuneus and temporal lobes, FTLD's pathology occurs more frequently in frontal and temporal lobes (Rabinovici et al.,
 96 2007; Whitwell et al., 2007). FTLD phenotypes include patients with a disorder of social compartment and executive functioning (bvFTD); a
 97 non-fluent/agrammatic variant of primary progressive aphasia (naPPA), also known as progressive non-fluent aphasia; a semantic variant of
 98 primary progressive aphasia (svPPA), also known as semantic dementia; and corticobasal syndrome (CBS). A common test for cognitive deficits in
 99 dementia is the Mini-Mental State Examination (Hill and Baeckman, 1995). However, the MMSE does not assess the behavioral and cognitive
 100 deficits associated with FTLD (Hutchinson and Mathias, 2007). Other tests have been developed to screen and compare patients with
 101 dementia syndromes, including the Frontal Assessment Battery (Dubois et al., 2000) (FAB); the Addenbrooke Cognitive Examination
 102 (Galton et al., 2005) (ACE); and the Montreal Cognitive Assessment (MoCA) (Nasreddine et al., 2005).

103 The Philadelphia Brief Assessment of Cognition (Libon et al., 2007, 2011) (PBAC) provides an economical means to screen and assess im-
 104 portant domains of cognitive and behavioral impairment associated with AD and FTLD spectrum phenotypes. The PBAC requires about
 105 12 min for administration and scoring. An important component of the PBAC is the construction of sub-scales designed to assess specific
 106 cognitive and behavioral/compartment deficits that typify AD and FTLD syndromes, including executive/working memory, language,
 107 visuospatial/constructional skills, verbal/visual episodic memory, and behavior/social compartment. Dementia severity is assessed by summing
 108 all PBAC sub-scales. Recent research with the PBAC has demonstrated that AD and FTLD patients present with specific areas of impairment on
 109 sub-scales that correspond to phenotypic syndromes (Libon et al., 2011) i.e. clinical diagnosis.

110 The current study extends previous research with the PBAC (Libon et al., 2011) by examining the gray matter neuroimaging correlates of
 111 PBAC's cognitive and social measurements in a large number of AD and FTLD patients. From a neurological perspective, the purpose, here,
 112 is to use the variance within these patients to assess brain and behavior relationships across multiple behavioral loci, as opposed to diagnosis.
 113 From a technical perspective, the goal is to contrast univariate and multivariate techniques. To test the hypothesis that PBAC indirectly

138 measures the integrity of different cortical networks (versus individual voxels), we employ a new data-driven machine learning technique,
 139 sparse canonical correlation analysis for neuroimaging (SCCAN), to associate high-dimensional imaging measurements with the full infor-
 140 mation provided by a multivariate psychometric battery such as PBAC. Specifically, this approach allows an optimal weighting of psychometric
 141 sub-scales (as opposed to averaging their values) such that the relationship with neuroimaging is maximized. At the same time, SCCAN opti-
 142 mizes and selects regions of gray matter (GM) to maximize correlation with psychometrics. This results in a set of gray matter regions that
 143 may be interpreted as the network most-associated with the given psychometric domain. SCCAN previously identified covariation between
 144 GM and diffusion tensor imaging white matter (WM) changes that optimally discriminate between CSF- and autopsy-defined patients with AD
 145 and FTLD (Avants et al., 2010b). The purpose of the current research is to test the hypothesis that SCCAN may employ individual PBAC sub-scales
 146 to extract GM networks that are reproducibly associated with variation in cognition. This would provide additional criterion validity for both
 147 the PBAC and multivariate techniques such as SCCAN, in contrast to univariate techniques, and establish a novel strategy for performing
 148 multivariate analyses of brain and behavior.

149 Methods

150 An overview of our study is in Fig. 2. We first discuss the core dataset and measurements. We then discuss the PBAC and SCCAN methods. We
 151 proceed with an evaluation framework, including a comparison against a univariate approach.

152 Patients

153 Individuals participating in the current research were drawn from a corpus of 270 patients, as previously described (Libon et al., 2011).
 154 Dementia patients were evaluated by experienced behavioral neurologists (AC, HBC, RGG, MG) and classified clinically on the basis of previ-
 155 ously published criteria (Gorno-Tempini et al., 2011; McKhann et al., 2001; Rascovsky et al., 2011). A research diagnosis was made on the
 156 basis of an independent review of a semi-structured history obtained from patients and their families and a detailed neurologic examination.
 157 At least two trained reviewers from a consensus committee (inter-rater reliability, $r = 0.91$, $p < 0.001$) confirmed patients' clinical diagnosis and
 158 the presence of a specific dementia syndrome involving AD or FTLD. Discrepancies were resolved based on group discussion and follow-up
 159 assessment. The PBAC was not used for the initial diagnosis of research participants.

160 The clinical diagnosis of dementia was consistent with serum studies, clinical studies of cerebrospinal fluid (when available), clinical
 161 imaging studies such as MRI or CT, and functional neuroimaging studies such as SPECT or PET (these studies were not available to the consensus
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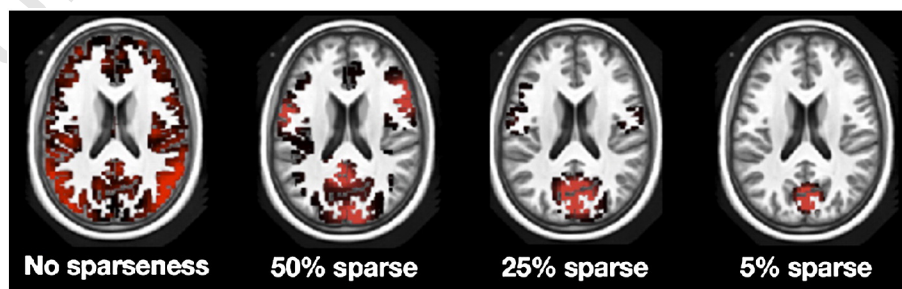


Fig. 1. Sparse canonical correlation analysis solution vectors are overlaid on a slice of the brain where the brightness of the red-hued overlay is related to the solution's weighting at the local voxel. A traditional canonical correlation analysis produces component vectors with global extent (to reader's far left). Sparse solutions (increasingly sparse to the reader's right) seek to extract controllably focal information thereby, in the context of this paper, isolating "networks" of voxels that collectively relate to cognition. This enables component vectors to be more easily interpreted in terms of traditional neuroscientific coordinate systems.

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