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Research Report

Simple dissociations for a higher-powered neuropsychology

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ABSTRACT

Dissociations in cognitive neuropsychology are often investigated at the level of the single-case, and formal criteria exist for the detection of dissociations, and their sub-classification into 'classical' and 'strong' types. These criteria require a patient to show a frank deficit on one task (for a classical dissociation) or both tasks (for a strong dissociation), and a significantly extreme difference between tasks. I propose that only the significant between-task difference is logically necessary, and that if this simple criterion is met, the patient should be said to show a dissociation. Using Monte Carlo simulations, I show that this simplification increases the power to detect dissociations across a range of practically-relevant conditions, whilst retaining excellent control over Type I error. Additional testing for frank deficits on each task provides further qualifying information, but using these test outcomes to categorise dissociations as classical or strong may be too uncertain to guide theoretical inferences reliably. I suggest that we might instead characterise the strength of the dissociation using a continuous index, such as the effect size of the between-task difference.

1. Introduction

Dissociations are a core concept in cognitive neuropsychology. If two putative mental functions can be disturbed, each without comparable consequences for the other, we may hypothesise some degree of independence between them (i.e. *double dissociation*; Teuber, 1955). At a practical level, dissociations and double-dissociations are empirical observations. These observations can support theoretical inferences about the functional architecture of cognition, provided that certain assumptions are met. The inferences that dissociations can license, and the plausibility of the assumptions required for them to hold, have been discussed and debated elsewhere (Caramazza, 1986; Caramazza & McCloskey, 1988; Coltheart, 2001, 2017; Dunn & Kirsner, 2003; Ellis & Young, 1988; Patterson & Plaut, 2009; Shallice, 1979, 1988, 2015). In this paper, I focus on a more limited, practical question: if neuropsychologists *are* interested in finding dissociations, what operational criteria should they use?

Dissociations are often investigated at the level of the individual 'case', in isolation or as part of a larger series, and a range of statistical tests have been developed to compare single cases against matched control samples, as a proxy for the patient's pre-morbid abilities (see McIntosh & Brooks, 2011, for a brief overview). These tests estimate how unlikely it would be to find performance more extreme than that

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of the single case, if testing a person from the healthy population. Case-control comparisons are inherently low-powered, a problem exacerbated by the common use of very small control samples ($n \leq 10$) (Crawford & Garthwaite, 2006a, 2006b; Crawford, Garthwaite, & Gray, 2003). The saving grace of cognitive neuropsychology is that the effects of brain damage are often severe, and thus visible to low-powered statistical microscopes. Without such large effects, single-case cognitive neuropsychology would barely be possible at all. Nonetheless, as Crawford, Garthwaite, and Ryan (2011) have argued, "*anything that can increase statistical power to detect deficits or dissociations should be encouraged (provided that it does not achieve this at the cost of failing to control the Type I error rate)*" (p. 1167).

I propose that a simple change could be made to current criteria that would increase the power to detect dissociations, under a range of practically-useful conditions, whilst retaining appropriate control over Type I error rate. I will explore these intuitions empirically, using Monte Carlo simulations. Before doing so, I provide a brief background on the operational definition of deficits and dissociations in cognitive neuropsychology, and recent statistical developments. Readers familiar with these ideas may wish to skip directly to the methodological proposal (Section 3).

2. Deficits and dissociations

The classical concepts of deficit and dissociation are easy to grasp: acquired brain-damage has impaired some aspect of a person's mental abilities (deficit), which is at odds with the preservation of some other aspect (dissociation). The modern framework for single-case dissociations, and the assumptions required for inferences on mental structure, was laid out most comprehensively by Shallice (1988). Amongst the contributions of his landmark book was the delineation of three forms of dissociation, of differing degrees of inferential strength (Shallice, 1988, Chapter 10).[1] The most powerful, *classical dissociation*, corresponds roughly to the stark contrast typical of the classical literature, with performance on one task (X) grossly impaired whilst another task (Y) is performed normally. Of intermediate strength, and thus perhaps misleadingly named, was the *strong dissociation*, defined by a striking discrepancy between the performance of tasks X and Y, but with deficits on both tasks. A more minor, *trend dissociation* was also suggested, in which two tasks are performed at different levels, yet without the striking discrepancy that characterises a strong or classical dissociation. Shallice noted that the distinction between the strong and trend forms, might be somewhat loose in practice, in part because "*it would be very difficult to calculate for any particular pair of tests what spread of performance would be expected to arise in the normal population*" (p240).

Fifteen years later, Crawford et al. (2003) enumerated three key problems with these criteria, as applied within the research field. First, there was yet no widely-agreed statistical test for a single-case deficit. A deficit might be demonstrated by reference to a standardised cut-off, by quantitative comparison (e.g. z-score) with a small to modestly-sized control group ($n = 5$–15), or just inferred from a qualitative contrast with one or more 'representative' controls. The second problem was that the definition of a classical dissociation requires preserved performance on one task, but this cannot be confirmed by conventional means, because it requires us to 'prove' the null hypothesis of no deficit, when at best we can fail to reject it. Third, and most crucially, classical and strong dissociations imply an abnormal discrepancy in the degree of impairment between tasks, but no validated method was available for testing this directly (see Shallice's comment, above). A positive test of the all-important *dissociation* between tasks was lacking.

Crawford and colleagues were able to suggest solutions for the first and third of these problems. They noted that estimating the rarity of a patient's score by reference to the z-distribution assumes that the control mean and standard deviation are population parameters, when very often they are biased estimates from a restricted, and often small, sample. In restricted samples ($n < 50$), the likelihood of extreme z-scores will be underestimated, promoting false positive findings of deficits (high Type I error rates). Their solution was instead to base the test of deficit on the t-distribution, taking account the size of the control sample. Crawford and Howell (1998) developed a modified *t*-test for case-control comparisons, which constrains Type I error rate robustly, even with very small control samples ($n < 10$), and which is also reasonably tolerant of departures from normality (Crawford, Garthwaite, Azzalini, Howell, & Laws, 2006).

Similarly, Crawford, Howell, and Garthwaite (1998) modified the *paired t*-test, to provide a parametric method for comparing the difference between a patient's performances on two tasks against the distribution of paired differences amongst controls. They devised an *Unstandardised Difference Test*, appropriate if the two tasks are on a common scale and performed with similar variances by controls, and a *Revised Standardised Difference Test* for the more usual scenario of two differently-scaled tasks, which standardises the scores on each task before the differences are assessed (Crawford & Garthwaite, 2005). Crawford and colleagues subsequently developed Bayesian counterparts for these tests. The Bayesian Test of Deficit gives similar outcomes to the modified *t*-test; the Bayesian Unstandardised Difference Test gives similar outcomes to the Unstandardised Difference Test; but the Bayesian Standardised Difference Test outperforms the Revised Standardised Difference Test (Crawford & Garthwaite, 2007; Crawford et al., 2011). These Bayesian tests have subsequently been extended further to allow for the inclusion of covariates (Crawford, Garthwaite, & Porter, 2010). Most importantly, for present purposes, the establishment of robust case-control tests of deficit and between-task difference enabled Crawford et al. (2003) to define formal criteria for Shallice's categories of *classical* and

[1] Shallice accompanied these definitions by a careful consideration of the assumptions required, and some recommendations for maximising the likelihood of valid inferences from dissociations. These included the use of multiple tasks to converge on the functions of interest, because, "*Inferences from individual patients that are based on only a single test findings are, in my opinion, highly suspect.*" (Shallice, 1988, p. 231). For simplicity of the present treatment, however, we consider the scenario of a single task X and single task Y.