Uncovering mental and neural structure through data-driven ontology discovery

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Abstract

Despite a wealth of behavioral and neural findings, psychology and cognitive neuroscience lack integrative theories. One difficulty is the apparent multifuctional character of neural function (Anderson, 2016), a perspective ultimately founded on our neural and cognitive ontologies (Shine, Eisenberg, & Poldrack, 2016), and potentially ameliorated by their reconceptualization. While the progressive development of our neural ontology in terms of brain atlases and functional networks is the norm, commiserate refinement of a cognitive ontology has been lacking. We forward a data-driven framework to integrate multiple psychological literatures into a new cognitive ontology. We examine individual-differences across an unprecedented range of behavioral tasks, self-report surveys and real-world outcomes and use factor-analysis to reduce the dimensionality of these measurements, creating a "cognitive space" to serve as a common coordinate system to describe many cognitive constructs. Within the cognitive space measurements are structured, which is revealed through clustering. This new representation of cognitive measures provides a hypothesis for neural organization, which we pursue in an fMRI experiment where we scan participants completing a subset of the behavioral measures.

Keywords: Ontology; Cognition; Self-Regulation

Cognitive neuroscience has linked neural activity to a wealth of cognitive processes, yet struggles to produce a cumulative account of neural function(Yarkoni, Poldrack, Van Essen, & Wager, 2010). This slow progress has many causes, but is partially explained by the lack of systematic ontologies describing brain structure and mental function. While integrative brain atlases have been steadily improving, commensurate efforts to improve cognitive ontologies have been limited.

We address this by developing a data-driven cognitive ontology derived from individual differences across a broad range of behavioral tasks, self-report surveys, and real-world outcomes (see (Eisenberg et al., 2018) for an overview of the research program). 522 participants completed 63 different measures on Mechanical Turk related to decision-making, working memory, cognitive control, impulsivity, and personality, amongst other psychological constructs. Each of these measures was decomposed into multiple dependent variables (DVs; N=206) which reflect means of specific item sets, comparisons between task conditions, or model parameters thought to capture putative psychological constructs.

A particular question for this project was whether surveys and task DVs could be captured within a single space, given their different measurement characteristics. Because the battery included both surveys and tasks putatively related to the same cognitive constructs (e.g., impulsivity), one would predict significant relationships between the two sets of DVs that would support such a joint cognitive space. Interestingly, though subsets of the tasks and surveys putatively reflect similar constructs, we find that they are only weakly correlated, and thus bifurcate in the ontology. The independence of these two groups of measures suggests a top-level ontological distinction between the constructs underlying task and survey DVs and necessitated the creation of two cognitive spaces.

We thus analyzed tasks and surveys separately using identical pipelines. Using exploratory factor analysis, we identify two low-dimensional cognitive spaces that separately capture behavioral tasks and surveys. The task space was defined by five dimensions that are broadly related to drift-diffusion parameters (speed of information processing, caution, and perceptual/motor responses), temporal discounting, and strategic information processing. Survey factors largely reflected separate measurement scales (e.g., Social Risk Taking and Financial Risk Taking, DOSPERT subscores) or a combination of several closely related DVs (e.g., Sensation Seeking, which related to DVs derived from the Sensation Seeking Scale, UPPS-P, I7, and DOSPERT). A notable exception was the Goal-Directedness factor, which integrates a heterogeneous set of DVs related to goal-setting, self-control, future time-perspective, and grit.

To complement this dimensional approach, we employed hierarchical clustering within the task and survey spaces identify separable clusters. These clusters can be thought of as psychological "kinds", related to, but separate from, the dimensions identified with factor analysis. As an example, in the survey dendrogram a "self-control" branch composed of two separate clusters was apparent: one primarily related to impulsivity (but also reflecting goal-directedness, mindfulness and reward sensitivity), and one reflecting long-term goal attitudes, incorporating time-perspective and implicit theories of willpower. Overall, structure discovery reveals a simpler cognitive ontology than typically employed in the psychological sciences.

As real-world relevance is an essential feature of theoretical constructs(Yarkoni & Westfall, 2016), we also evaluated whether tasks and surveys can predict real-world outcomes. We reduced the self-reported real-world outcomes to 9 ”target” factors (e.g. mental health, binge drinking) and computed individual outcome factor scores, which represents real-world outcomes that have previously been related to behavioral tasks and surveys included in the measurement battery. We assessed predictive ability using cross-validated ridge regression. While surveys performed moderately well, tasks showed almost no predictive ability. For the surveys, the predictive psychological dimensions can be expressed as an ”ontological fingerprint”, which exemplifies the utility of a joint ontological language for describing diverse societally relevant outcomes. Each outcome measure was predicted by a heterogeneous set of survey factors, indicating that real-world outcomes are related to a diversity of underlying cognitive traits.

To link these cognitive structures to neural activity, we ran a followup fMRI study. Using a genetic algorithm, we identified a smaller number of behavioral tasks and survey questions that best captured the entire ontological space to use in an fMRI study. 100 participants completed 10 tasks and resting-state scans, from which we calculate 40 unique contrasts. Contrasts were subjected to dimensionality reduction and clustered to reveal a neural similarity space that complements that derived from behavioral individual differences. A subset of these participants completed the original behavioral battery, affording direct linkage between neural structures and ontological constructs. This research is ongoing.

In summary, cognitive ontologies describe the psychological constructs through which most human neuroscience is understood. We demonstrate that data-driven structure discovery techniques can profitably improve these ontologies, and that doing so helps to contextualize brain states identified using fMRI.

References

Anderson, M. L. (2016, January). Précis of after phrenology: Neural reuse and the interactive brain. *Behav. Brain Sci.*, *39*, e120.

Eisenberg, I. W., Bissett, P. G., Canning, J. R., Dallery, J., Enkavi, A. Z., Whitfield-Gabrieli, S., . . . Poldrack, R. A. (2018, February). Applying novel technologies and methods to inform the ontology of self-regulation. *Behav. Res. Ther.*, *101*, 46–57.

Shine, J. M., Eisenberg, I., & Poldrack, R. A. (2016, January). Computational specificity in the human brain. *Behav. Brain Sci.*, *39*, e131.

Yarkoni, T., Poldrack, R. A., Van Essen, D. C., & Wager, T. D. (2010, November). Cognitive neuroscience 2.0: building a cumulative science of human brain function. *Trends Cogn. Sci.*, *14*(11), 489–496.

Yarkoni, T., & Westfall, J. (2016). Choosing prediction over explanation in psychology: Lessons from machine learning. *FigShare, https://dx. doi. org/10. 6084/m9. figshare*, *2441878*, v1.