The Computational Trade-offs of the Functional Organization of the Human Brain

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Abstract

The human brain is capable of producing a vast range of useful and complex computations. Yet, limited resources imply that excelling in one cognitive function should come at the expense of another one, resulting in a trade-off. If so, how can we systematically discover the computational goals that drive the functional design of human cognition? In this work we utilize Pareto optimality theory to map the computational trade-offs that drive individual differences in the functional organization of the human brain. We suggest that individual differences in resting-state fMRI-based functional connectivity can be explained by a trade-off between three competing goals: 1) energy cost minimization 2) cognitive control and goad directed attention 3) memory and internal processing.

Keywords: Pareto Optimality; Individual Differences; Resting-state Functional Connectivity

Introduction

The human brain has the capacity to process enormous amounts of information and produce a vast range of useful and complex behaviors. Yet, the brain's computational capacity is not limitless (Buschman, Siegel, Roy, & Miller, 2011; Lieder & Griffiths, 2020), suggesting that no one brain can solve all cognitive tasks optimally. Previous works have shown how specific trade-offs between functional goals are apparent in the design of neuronal mechanisms at several levels. Those include trade-offs such as speed-accuracy in decision making (Ivanoff, Branning, & Marois, 2008; Wenzlaff, Bauer, Maess, & Heekeren, 2011) and robustness-efficiency of neuronal code (Pryluk, Kfir, Gelbard-Sagiv, Fried, & Paz, 2019). Understanding the brain's architecture in terms of trade-offs has the potential to uncover the core computations that neuronal circuits evolved to serve (Pallasdies, Norton, Schleimer, & Schreiber, 2021).

Pareto optimality theorem suggests that for an organism (or system) that needs to optimize several competing tasks, all optimal solutions lie in the convex-hull of the solutions that optimized those tasks (called archetypes)(Shoval et al., 2012). This strong geometrical constraint limits the solution space - with two tasks, the Pareto front is a line, with three tasks it is a triangle, and so on... One can then reverse this argument - If a high-dimensional dataset is structured into a low-dimensional polytope, the vertices of this convex-hull may represent archetypes optimizing specific tasks. Under this framework, individual differences represent different balancing choices between the optimization of competing tasks. The Pareto Task Inference (ParTI) method (Hart et al., 2015) has been fruitful in employing this rationale to extract the tasks and trade-offs driving biological organisms (Tendler, Mayo, & Alon, 2015; Korem et al., 2015). In this work we map the possible tradeoffs between cognitive goals.We applied Pareto analysis on individual differences in the functional connectivity patterns between predefined cortical networks (Van Den Heuvel & Pol, 2010; Yeo et al., 2011) to find the competing computational goals of human brain functional connectivity.

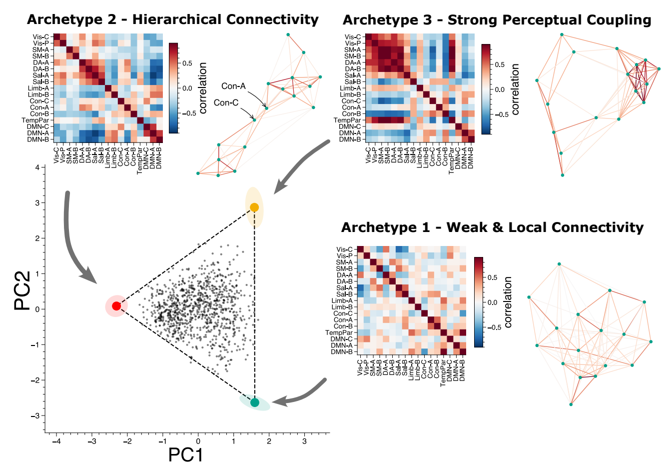

Figure 1: Individual differences in functional connectivity are explained by a trade-off between three archetypal connectomes. The projection of the functional connectomes on the first two PCs and re-projection of the archetypes.

Results

Human functional connectivity data is well described by a triangle with three archetypes We analyzed fMRI resting state data of 1200 healthy young adults from the Human Connectome Project (HCP(Van Essen et al., 2013)). We calculated the pairwise Pearson correlations between the mean BOLD signal timecourse of each of the 17 cortical networks (defined by Yeo et al.(Yeo et al., 2011)) to obtain 136 connectivity features. Next, we applied the Pareto Task Inference method (ParTI (Hart et al., 2015)) on the connectivity features of all individuals. We found that a triangle with 3 archetypes fits the data well (t-ratio test, $p < 10^{-4}$). We note that this result is robust to preprocessing pipeline, cortical parcellations, fMRI data format, scan-rescan locations, and Pareto simplex algorithm. If the Pareto assumption is correct, each archetype of a specific connectivity pattern represents a core cognitive-computational goal that the functional connectivity aims to optimize.

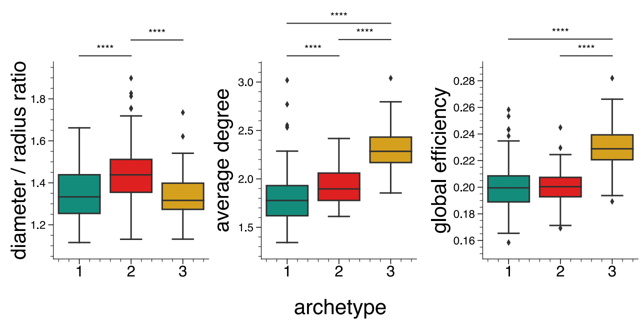

Figure 2: The connectomes of individuals near the three archetypes show distinct topological properties.

Individuals near the three archetypes have distinct connectivity topology, cognitive, psychiatric and demographic characteristics. To better understand the trade-offs that induce the triangular structure, we analyzed the connectivity patterns of the three archetypes. We found three distinct computational patterns: 1. Local, inter-network computations 2. A hierarchical structure of two computing clusters linked by a central hub and 3. A densely connected perceptual cluster linked through several links to a second cluster of higher cognitive function (Fig. 1). These connectivity patterns suggest specific roles of the different archetypes: Archetype 1 involves lower cognitive function and processing, archetype 2 involves goal-directed cognitive function (Keller et al., 2023), and archetype 3 involves integration of information and memory (Westphal, Wang, & Rissman, 2017; Vatansever, Menon, Manktelow, Sahakian, & Stamatakis, 2015). We further extracted the functional connectomes of 10% of the individuals that are closest to each of the archetypes to compute graph measures for these networks (Fig. 2). We found that individuals near archetype 1 have lower average weighted degree indicative of lower energetic cost (Tomasi, Wang, & Volkow, 2013). We found that archetype 2 has a tree-like structure, indicating a more hierarchical structure compared to archetypes 1 and 3 as indicated by the graph radius to diameter ratio.Finally, archetype 3 is characterized by a more dense all-to-all connected network as indicated by the global efficiency (Latora & Marchiori, 2001) of the graph. We further used enrichment analysis(Hart et al., 2015) on a set of behavioral, demographic and psychiatric features described in the HCP dataset. We found that archetype 1 was enriched with high self-reported aggression and hostility, high impulsivity, and higher scores for antisocial behavior. Archetype 2 was enriched with higher agreeableness and higher performance in sustained attention task. Lastly, archetype 3 was enriched with higher accuracy and slower response times in memory tests (but which did not pass an FDR correction).

Brain connectivity patterns during task engagement further characterize the optimized cognitive goals

If a location on the Pareto front of brain connectivity patterns reflects a specific balance between competing cognitive functions, one would expect that engaging in a cognitive task will require reconfiguration of the network to best fit the demands of the new context. Therefore, the connectivity patterns of individuals within a specific task can indicate the function of the different computational goals (archetypes). To that aim, we computed the functional connectivity patterns for HCP participants during the EMOTION task with its two conditions (Face/Shape) and the LANGUAGE task with its two conditions (Story/Math). We found that the distribution of participants' location within the triangle varied between the four conditions (Fig. 3). In the EMOTION task, We found that distances from archetype 3 were farther away compared to resting-state and data mainly resides near the archetype 1 - archetype 2 edge. On this trade-off axis, there was a significant shift towards archetype 1 and away from archetype 2 in the emotional condition blocks compared to the neutral condition. For the LANGUAGE task we found that the distances to archetype 1 significantly decrease indicating a rise in its importance. In addition, the trade-off between archetype 2 and archetype 3 was significant, with a closer distribution to archetype 2 in the math condition compared to the story condition ($p < 10^{-8}$ for all comparisons with Mann-Whitney test).

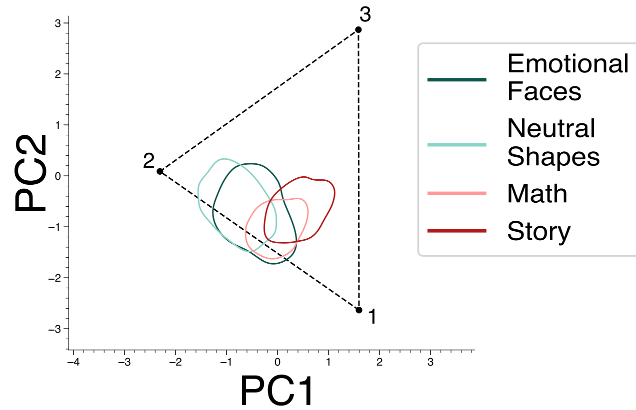

Figure 3: The effects of task condition on locations within the Pareto optimal triangle. Contours show 50% high-density regions of the population distribution in each condition.

Discussion

This work probes the computational goals and trade-offs in the functional organization of the human brain, as depicted by resting-state cortical functional connectivity. Our results suggest that individual differences in the brain's functional connectivity stem from different balancing choices between competing computational goals. As such, they provide a new integrative perspective over the functional role of individual differences in macroscale brain activity patterns.

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