Communication versus computation: The hidden costs, shaping the brain's architecture

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Abstract

Large-scale human brain networks exhibit complex topological characteristics, likely reflecting a balance among competing objectives such as minimizing wiring cost and maximizing communication efficiency. Interestingly, computational modelling has suggested that the connectivity of the brain is biased towards enhanced communication rather than a minimized wiring cost. Yet, the relationship between such communication efficiency and the functional capacity of the brain, e.g., to solve computational problems, remains unclear. To address this question, we used a game-theoretical framework in which individual brain regions establish connections only if it improves their signalling efficiency, given the wiring cost. We show that, firstly, complex network architectures naturally emerge from these local interactions, capturing some hallmarks of the brain. Secondly, resulting networks have both superior communication and reduced wiring cost compared to empirical brain networks. However, these optimal networks exhibited diminished memory capacity relative to empirical networks. Our findings suggest that efficient communication does not necessarily translate to improved computation. Instead, functional capacity may have played an essential role in shaping brain network architecture, potentially even at the expense of communication efficiency.

Keywords: Brain networks; Communication efficiency; Brain-inspired reservoir computing; Game theory; Optimality.

Introduction

The architecture of the human brain is highly organized, incorporating interconnected clusters, functional hierarchies, influential hubs, and selective shortcuts among those hubs [Sporns et al., 2004]. A key driver of this organization is the *wiring cost*, since the brain is confined within the skull and maintaining connections is metabolically expensive [Chklovskii et al., 2002]. Another contributing factor is *communication efficiency* that is conventionally captured via the shortest path distance between regions. Computational modelling suggests the brain may have prioritized communication efficiency over strict wiring cost minimization, leading to sub-optimal wiring patterns [Kaiser and Hilgetag, 2006, Hayward et al., 2023]. Although this communication-centric configuration is well-supported, its implications for the brain's computational capacity remain largely unexplored. Recent studies instantiating recurrent neural networks (RNNs) and echo state networks (ESN) from the brain's architecture show that these networks achieve a performance on par with randomly wired networks, at best [Damicelli et al., 2022, Goulas et al., 2021, Hadaeghi et al., 2024, Suárez et al., 2021]. These paradoxical findings prompt two questions: "**Is communication in brain networks, in fact, optimal?**" and subsequently, "**If it is, does enhanced communication promote better computational capacity?**" We address both questions using a game-theoretical framework, combined with generative modelling, to construct networks with both optimal communication and minimal wiring cost.

Methods

Empirical brain networks were based on diffusion spectrum imaging data from 70 healthy adults (average age 28.8 years), comprising 114 cortical regions defined by the Cammoun atlas [Cammoun et al., 2012]. Null networks (randomised and latticised) were generated by rewiring the empirical connectomes while preserving the degree distribution and network density [Rubinov and Sporns, 2011]. In our generative model, brain regions connect only if doing so increases their influence over other regions. Specifically, each region aims to maximize its own communication efficiency while minimizing its wiring cost. This contrasts with previous approaches that either rely on predefined wiring rules [Vértes et al., 2012] or globally optimise the entire network [Avena-Koenigsberger et al., 2014]. We modelled communication using three signalling modes: routing, propagation, and diffusion. Routing assumes signalling occurs strictly along the shortest path; propagation allows recruitment of parallel pathways, penalizing longer routes; diffusion models information as random walkers traversing the network [Seguin et al., 2023]. Additionally, as an alternative to signalling, we included homophily, where regions connect to expand their local clusters [Akarca et al., 2021, Vértes et al., 2012]. The model started from the three-dimensional embedding of the brain regions as nodes, connected minimally following a ring topology, and evolved over $T = 5000$ iterations. At each step, $N = 16$ nodes were randomly selected to "play". Edges among these nodes were flipped (connected nodes disconnected, and vice versa; Fig. 1, left panel). Players compared their new *payoff* to their previous state and retained new connections only if their payoff improved. The payoff function was defined as:

$$P_i(t) = -\alpha\left(\sum_j \frac{\Omega_{ij}}{\Omega_0}\right) - \left(\sum_j \frac{D_{ij}}{D_0} A_{ij}\right)$$

where $\frac{\Omega_{ij}}{\Omega_0}$ represents normalized communication efficiency between regions i and j, $\frac{D_{ij}}{D_0}$ the normalized Euclidean distance, and A the binary adjacency matrix. The trade-off parameter α was fine-tuned so generated networks matched empirical network densities. The final 70 networks from each model were used as representative instances once evolution reached steady-state. Similarity with empirical brain networks was quantified using portrait divergence, a measure that takes both local and global characteristics of networks into account [Luppi et al., 2024, Bagrow and Bollt, 2019], with smaller values corresponding to "more similar" and vice versa. The functional repertoire of networks was assessed by treating them as ESNs, solving a memory capacity (MC) task [Damicelli et al., 2022].

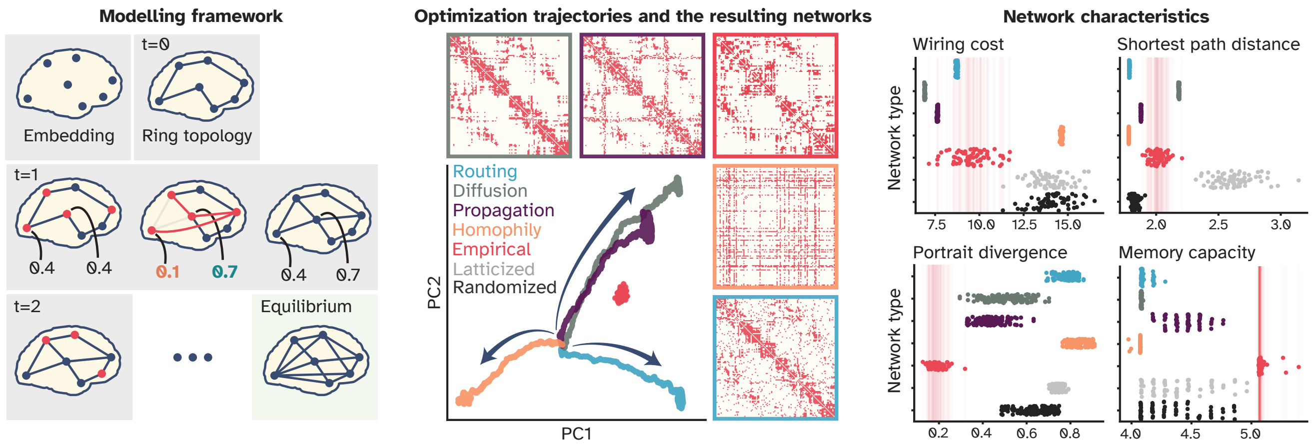

Figure 1: Visual summary of the modelling framework, trajectory of the game, and characteristics of all networks.

Results and Discussion

Brain-like network architecture emerges from competitive local interactions

The middle panel of Fig. 1 demonstrates that optimal networks surpass empirical brain networks, moving towards the Pareto fronts of the optimization space. However, portrait divergence between simulated and empirical brain networks (Fig. 1, right panel) indicates that brain-like organization naturally arises when regions maximize influence under diffusion and propagation regimes. This aligns with prior evidence showing, in addition to the shortest path, brain regions utilize longer parallel pathways to optimize signalling [Fakhar et al., 2024, Griffa et al., 2023]. Optimizing for routing communication created precisely located shortcuts, steering the network architecture towards randomness instead. Maximizing homophily led to dense local clustering around regional hubs. Inter-individual differences among empirical connectivity patterns were captured by comparing portrait divergence of each subject's network with a consensus network derived from all 70 networks, following [Betzel et al., 2019].

Human brains exhibit sub-optimal communication and wiring economy but enhanced memory capacity

As Fig. 1 right panel shows, optimal networks tend to have lower wiring costs and superior communication efficiency. Compared to null models, optimal networks broadly maintained random-network-level communication efficiency but at significantly reduced wiring cost. Together, these findings reveal that the current configuration of the human brain is sub-optimal in both wiring cost and communication efficiency. Yet despite this suboptimal cost-efficiency trade-off, empirical brain networks displayed the greatest functional repertoire (memory capacity), followed by networks optimized for propagation efficiency. Although networks optimized for diffusive dynamics were most topologically similar to the brain, both these and those optimized for routing dynamics exhibited markedly lower functional capacities. This suggests the additional wiring cost observed in empirical brain networks likely results from a third objective: maximizing functional capacity [Gilson et al., 2020, Achterberg et al., 2023].

In summary, our findings indicate brain networks are wired, not only to enhance communication and minimize wiring cost, but also to expand their functional capabilities. Balancing communication efficiency against wiring costs appear as bottom-up outcomes, emerging naturally from local interactions among regions. Conversely, expanding functional capacity likely serves as a top-down constraint, shaping network architecture beyond purely local interactions.

Acknowledgments

This work was in part funded by the Templeton World Charity Foundation, Inc. (funder DOI 501100011730) under grant TWCF-2022-30510 and the German Research Foundation (DFG) SPP 2041/GO 2888/2-2.

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