COMPUTATIONAL NEUROSCIENCE

Untangling network information flow

Determining how information flows throughout a network of interconnected components is a challenging task in many scientific domains. A framework is presented to deconstruct the flow of signals that are transmitted across any two areas (such as brain areas) and define how each area represents these signals.

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Multiple populations of neurons are organized into distinct brain areas that continuously exchange information with one another. Due to the physiological properties of axons and synapses, inter-areal communication is not instantaneous. These delays provide a useful definition of signal flow: the signal flow from area A to area B corresponds to the appearance of a signal initially in area A and later in area B. Signaling patterns are fundamental to understand how the brain processes information and generates functions, but until recently, scientists lacked the tools to decipher this cross-area information flow. Writing in *Nature Computational Science*, Evren Gokcen and colleagues[1] propose a framework, called delayed latents across groups (DLAG), that can dissect the neural activity into systematic patterns, clarify which pattern is transmitted forward or backward along a hierarchical flow, and, most importantly, determine the delay with which different patterns are communicated (Fig. 1).

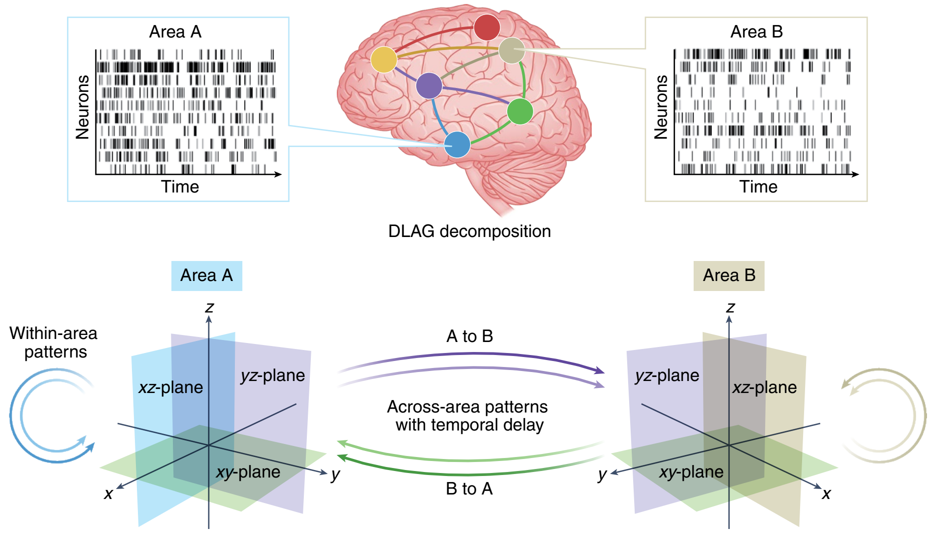

Fig. 1 | **DLAG computational flow.** Top: example of an interaction network connecting multiple brain areas. The two panels display example recordings from two areas (see ref. [1]). Bottom: DLAG output description. The methodology enables the examination of activity in each area as a multiplexed set of patterns that represent intra- and across-area communication. DLAG also returns the direction and associated temporal delay for each mode that spans multiple areas. Credit: adapted from ref. 1, Springer Nature America.

Previous inter-areal studies have either focused on determining the patterns conveyed between areas[2–6] or on carefully estimating the temporal delay across areas by exploiting pairwise spiking correlations[5–7]. These timing-based techniques have increased our understanding of how signals flow from one brain area to another. However, since these approaches primarily focused on pairs of neurons, they couldn't at once return both the signaled pattern and the associated delay across areas with high resolution. Therefore, much remains unclear about how neuronal populations organize their activity into patterns for inter-areal signaling and the latency associated with the signaling of these patterns.

DLAG, on the other hand, permits the identification of concurrent, bidirectional interactions between brain areas based on the recorded activity of neural populations. For each area, a high-dimensional population activity space can be defined such that each axis reflects the activity of a single neuron. Within this population activity space, DLAG reveals two types of latent variables: across-area and within-area low-dimensional subspaces. Each subspace dimension depicts a population activity pattern (Fig. 1). With the concept of a population activity space, the link between within- and across-area latent variables and observed population activity in each area can be depicted and interpreted geometrically. Additionally, and most importantly, DLAG predicts the latency of the across-areas information flow.

Technically, DLAG can be conceptualized as a time series extension of probabilistic canonical correlation analysis (pCCA) or as a multi-area extension of Gaussian process factor analysis with the capacity to estimate temporal delays between two areas. Using an exact expectation-maximization approach, all of the DLAG model parameters, including the Gaussian process timescales and time delays, are determined from the neural activity. After the DLAG model parameters have been estimated from neural activity, the trial-by-trial time courses of within- and across-area latent variables may be investigated in the context of behavioral studies. In addition, DLAG can identify whether the majority of the observed patterns are the result of feedback interactions between two areas. This was the case when DLAG was used to reveal the interaction between areas of the primary and secondary macaque visual cortex — a finding that warrants further investigation in the future, as it is commonly believed that these two brain areas interact primarily through feedforward, rather than feedback, interactions.

Although DLAG was primarily used on visual cortical areas, it holds great promise for a number of brain circuits where untangling the information flow across various areas is important.

For instance, determining where in the brain a signal relevant to a certain choice originates requires identifying and tracking specific neural patterns across several brain areas involved in decision making[8]. Similarly, the planning and execution of a movement includes a precise cascade of communication across numerous brain areas[9]. DLAG allows researchers to decipher and trace signals conveyed back and forth across various brain areas and, in theory, to determine where these signals originate. This may shed light on how information is mechanically transmitted and gated along brain circuits, making it a promising area for research in decision-making paradigms as well as in motor planning and execution.

But DLAG, and allied statistical techniques, are not only crucial to the study of neuroscience; they also have great potential for revealing directed interaction in the dynamics of all different kinds of graphs. Wherever numerous groups interact simultaneously, DLAG has the ability to identify significant links between the latent patterns that drive the dynamics of these groups. This is essentially true for all systems involving a complex network, including ecology, economics, social behavior, and communications networks. Consequently, DLAG awaits application in numerous contexts across numerous scientific domains, and these extensions are potential possibilities made available by this work.

Future extensions to DLAG may include the development of machine-learning-based techniques equivalent, in power, to it. Indeed, DLAG is an extension of pCCA, an algorithm that can be generalized by neural network approaches[10]. Additionally, it would be advantageous to expand DLAG so that it can execute the inference of latent variables using spiking patterns without preprocessing (smoothing or binning). Due to recent developments in machine learning, this is now possible[11]. These lines of inquiry are crucial for improving our understanding of how neural circuits process information. ❐

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Competing interests

The author declares no competing interests.