Measuring the Dynamics of Information Processing on a Local Scale in Time and Space

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Abstract. Studies of how information is processed in natural systems, in particular in nervous systems, are rapidly gaining attention. Less known however is that the local dynamics of such information processing in space and time can be measured. In this chapter, we review the mathematics of how to measure local entropy and mutual information values at specific observations of time-series processes. We then review how these techniques are used to construct measures of local information storage and transfer within a distributed system, and we describe how these measures can reveal much more intricate details about the dynamics of complex systems than their more well-known "average" measures do. This is done by examining their application to cellular automata, a classic complex system, where these local information profiles have provided quantitative evidence for long-held conjectures regarding the information transfer and processing role of gliders and glider collisions. Finally, we describe the outlook in anticipating the broad application of these local measures of information processing in computational neuroscience.

1 Introduction

Analysis of directed information transfer between variables in time-series brain imaging data and models is currently gaining much attention in neuroscience. Measures of information transfer have been computed, for example, in fMRI measurements in the human visual cortex between average signals at the regional level [38] and between individual voxels [8], as well as between brain areas of macaques from local field potential (LFP) time-series [48]. A particularly popular topic in this domain is the use of information transfer measures to infer effective network connectivity between variables in brain-imaging data [39, 91, 49, 88, 69, 54, 63], as well as studying modulation of connection strength with respect to an underlying task

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[94]. Furthermore, measures of information transfer are used to reveal differences between healthy and diseased states in neural data (e.g. for EEG measurements of epilipsy patients in [10]) and in models (e.g. for Parkinson's disease in [43]).

Much of this work quantifies information transfer from a source variable to a target variable using the information-theoretic measure known as the *transfer entropy* [82], or its equivalent under linear-Gaussian conditions, the Granger causality [28]. This information-theoretic approach to studying directed interactions in neural systems can be viewed as part of a more broad effort to study distributed computation in complex systems in terms of how information is stored, transfered and modified (e.g. [59, 60, 62]). The approach is highly appropriate in computational neuroscience, and indeed for complex systems in general, because:

- these concepts of computation are meaningful and well-understood (e.g. information transfer as reflecting directed coupling between two variables, information storage as predictability or structure in a time-series process);
- the quantities measured (e.g. transfer entropy for measuring information transfer) are well-defined and can be measured on any type of time-series data (continuous or discrete-valued);
- the quantities are at heart model-free (in contrast to the Granger causality linearisation)[1] and detect non-linear interactions and structure; and
- distributed computation is the language in which dynamics are often described in neuroscience (e.g. "the brain represents and processes information in a distributed fashion and in a dynamical way" [27]) and complex systems in general (e.g. claims that small-world structures have "maximum capability to store, process and transfer information" [42]).

Now, such work on distributed computation to date typically focuses on the (time) *average* information transfer, which is how the transfer entropy and other information-theoretic measures are traditionally defined. Yet the *dynamics* of transfer from a source to a target can also be quantified at individual observations or configurations of the variables using the *local* transfer entropy [59]. Such local measures can be defined for any traditional information-theoretic variable, including for related measures of information storage and processing (e.g. [62]). To be explicit, local information-theoretic measures characterise the information attributed with specific measurements x and y of variables X and Y, rather than the average information associated with these variables.

This local perspective can reveal dynamical structure that the average cannot. Applied to time-series data, local measures tell us about the *dynamics* of information in the system, since they vary with the specific observations in time, and local values are known to reveal more details about the system than the averages alone [16, 83, 84]. To be specific, a measured average of transfer entropy does not tell us about how the directed relationship between two variables fluctuates through time, how

[1] This also contrasts with dynamic causal modeling, a model-based approach that compares a set of a priori defined neural models and tests how well they explain the experimental data [25].