Biology and Medicine Through Mathematics Conference

2019

May 15th, 11:30 AM - 12:00 PM

Predicting dynamics from hardwiring in canonical low-dimensional coupled networks

Anca R. Radulescu
State University of New York at New Paltz, radulesa@newpaltz.edu

Predicting dynamics from hardwiring in canonical low-dimensional coupled networks

Anca Rădulescu, SUNY New Paltz, radulesa@newpaltz.edu
Simone Evans, SUNY New Paltz, evanss3@hawkmail.newpaltz.edu

A point of great interest in computational neuroscience has been to explain how the hardwired *structure* of a network (such as the brain) affects its temporal *function*. The question has crucial applications and has earned its own subfield of study (currently known as "dynomics"). However, the task of translating connectivity patterns to ensemble temporal behavior presents the difficulty of simultaneously addressing the complexity of the graph and the richness of the coupled dynamics. This may be computationally intractable, even for relatively small network sizes and for reduced models of node-wise neural dynamics.To shed light on this relationship, a recent strategy has been to investigate it in basic theoretical models, where one may more easily identify and pair specific structural patterns to their effects on dynamics. For example, in threshold linear networks (TLN), complex ensemble behavior emerges from simple, almost linear node-wise dynamics. This makes it feasible to identify relationships between specific configurations and corresponding dynamic patterns [1]. While this represents remarkable progress, it would be important to establish whether this type of predictive analysis can be applied to other classes of models.

We use quadratic maps as a canonical way to model a neural response function in each of the network nodes. In this case, one can conveniently use the system's asymptotic (Julia and Mandelbrot) sets to calculate, visualize and interpret the long-term behavior of the system (in both phase and parameter spaces, with the network structure acting as a bifurcation parameter [2, 3]). The advantage is that of using clear topological markers (e.g., connectedness of a set) as the signature for the global dynamics of the system, amenable for prediction and classification. For example, we were able to identify an optimal parameter locus for which configurations which have identical Julia sets for one node-wise function (determined by the parameter c) do so for all c. This suggests means to produce robust classifications of ensemble behavior based entirely on the network architecture, independently on the node-wise dynamics (described by c). In this scenario, it is sufficient for the network to know in advance which hardwired structure is most effective to use in order to obtain a desired effect or avoid another, and then it can plastically modify its structure on a continuous basis, adapting online to new behavioral requirements.

We compare our results with those in other simplified models, proposing that some aspects may be universal to nonlinear networks, and hence could be further applied to physiological models with more complex dynamics. By the intrinsic properties of the quadratic node-wise dynamics, as well as by the nature of the methods and measures used in conjunction with these dynamics, our approach is fundamentally different from those being currently used to address other network types. One of our main directions of interest is to investigate how our results compare with predictions and classifications in other small networks with basic node dynamics. To fix our ideas, we will look at classification of attractor sets in threshold linear networks (studied by Curto et. al [1]) and at synchronization and clustering in inhibitory Hodgkin-Huxley neuronal networks (studied by Rinzel [4]). In each case, we will use the appropriate measures of synchronization and stability to assess and classify long-term dynamics; then we will check if there is any overlap (universality) in these classifications.

References

[1] C. Curto, K. Morrison. Pattern completion in symmetric Threshold-Linear Networks, *Neural Computation* 28 (12) pp. 2825–2852, 2016.

[2] A. Rădulescu, A. Pignatelli. Real and complex behavior for networks of coupled logistic maps, *Nonlinear Dynamics*, 87(2) 12951313, 2017.

[3] A. Rădulescu, S. Evans. Asymptotic sets in networks of coupled quadratic nodes, *Journal of Complex Networks*, 2018.

[4] D. Golomb, J. Rinzel. Clustering in globally coupled inhibitory neurons, *Physica D: Nonlinear Phenomena* 72 (3) pp. 259–282, 1994.