Tuesday, January 26th, 2:30 pm

Speaker: Jay Pina

Institution: York University

Title: Unknotting the brain: Some simple approaches to modeling neural circuits and their dynamics

Abstract: Mammalian brains have enormous numbers of neurons. Even mice have ~1e8 neurons, with ~1e12 connections between them. These neurons form intricate feedforward and recurrent circuits with connection strengths that evolve in time, enabling the animals to learn and respond adaptively to their environments. Such circuits lead to complicated neuronal dynamics across many spatial and temporal scales, providing enormous challenges in untangling how these vast networks of neurons work together to process and adapt to incoming stimuli. As a result, numerous mathematical and computational modeling approaches have been developed to elucidate various aspects of these neuronal networks, ranging from ultra-detailed biophysical PDEs to ultra-simple networks of binary, discrete-time neurons. As the adage advises us, all of these models are wrong, yet some may be useful.

Here, we describe two simplified approaches that may provide insight into dynamical and computational properties of mammalian brains. In one approach, we show that modeling populations of neurons as recurrent nonlocal integrodifferential equations *with fixed connection strengths* leads to mathematically tractable neuronal networks with dynamics that qualitatively match experimental data. In particular, we use this neural field approach to model spatially resonant dynamics that are relevant to pattern-sensitive epilepsy, a condition in which static visual stimuli with wavenumbers within a critical range can induce seizures. Consistent with experimental results, we find that only wavenumbers within a critical range induce network activity.

In the second approach, we show that so-called “deep” feedforward neural networks *with connection strengths that can vary*, ubiquitous in machine learning applications such as object recognition, may provide a framework with which to model learning in the brain. While much doubt has surrounded the biological plausibility of such models, recent work has addressed many of the fundamental criticisms. Here, we show experimental evidence that suggests that the part of mammalian brains that is responsible for vision may instantiate such a feedforward model that learns to predict features of visual stimuli.