Tian-Yi Zhou - Approximation of RKHS Functionals by Neural Networks

Motivated by the abundance of functional data such as time series and images, there has been a growing interest in integrating such data into neural networks and learning maps from function spaces to R (i.e., functionals). In this paper, we study the approximation of functionals on reproducing kernel Hilbert spaces (RKHS's) using neural networks. We establish the universality of the approximation of functionals on the RKHS's. Specifically, we derive explicit error bounds for those induced by inverse multiquadric, Gaussian, and Sobolev kernels. Moreover, we apply our findings to functional regression, proving that neural networks can accurately approximate the regression maps in generalized functional linear models. Existing works on functional learning require integration-type basis function expansions with a set of pre-specified basis functions. By leveraging the interpolating orthogonal projections in RKHS's, our proposed network is much simpler in that we use point evaluations to replace basis function expansions.

Savvas Sardelis - Statistical mechanics of of discrete nonlocal nonlinear lattices

In recent years, a groundbreaking statistical model, drawing inspiration from classical thermodynamics and statistical mechanics, has emerged as a powerful framework in describing complex phenomena within the field of optics. This talk delves into the intricacies of the generalized Aubry-André lattice, investigating how characteristics of eigenvectors—be they localized or extended—affect thermalization. Given the spectrum's capacity to accommodate both localized and extended states, we aim to discern their respective impacts on thermalization time and dynamics.

Yuchen Zhu - Quantum State Generation with Structure-Preserving Diffusion Model

We consider the generative modeling of the states of quantum systems, and an approach based on denoising diffusion model is proposed. The key contribution is an algorithmic innovation that respects the physical nature of quantum states. More precisely, the commonly used density matrix representation of mixed-state has to be complex-valued Hermitian, positive semi-definite, and trace one. Generic diffusion models, or other generative methods, may not be able to generate data that strictly satisfy these structural constraints, even if all training data do. To develop a machine learning algorithm that has physics hard-wired in, we leverage the recent development of Mirror Diffusion Model and design a previously-unconsidered mirror map, to enable strict structure-preserving generation. Both unconditional generation and conditional generation via classifier-free guidance are experimentally demonstrated efficacious, the latter even enabling the design of new quantum states when generated on unseen labels.

Lawan Wijayasooriya - Polyglot Entrainment for higher dimensional neuronal models

The entrainment of biological oscillators is a classic problem in the field of dynamical systems and synchronization. We explore a novel type of entrainment mechanism referred to as polyglot entrainment (multiple-disconnected 1:1 regions) for higher dimensional nonlinear systems. Polyglot entrainment has been recently explored only in two-dimensional slow-fast models in the vicinity of Hopf bifurcations (HB). Heading towards generality, we investigate the phenomenon of polyglot entrainment in higher-dimensional conductance-based models including the four-dimensional Hodgkin-Huxley (HH) model and its reduced three-dimensional version. We utilize dynamical systems tools to uncover the mechanism of entrainment and geometric structure of the null surfaces to explore the conditions for the existence of polyglot entrainment in these models. In light of our findings, in the vicinity of HB, when an unforced system acts as a damped oscillator and the fixed point is located near a cubic-like manifold, polyglot entrainment is observed.

Haniyeh Fattahpour - Mathematical Modeling of Cellular Proliferation in Tissue-Engineering Scaffold Pores

Examining the interplay of various factors on tissue growth within a tissue-engineering scaffold channel is crucial for optimizing cell proliferation. This study delves into the combined effects of nutrient flow rate, nutrient consumption, scaffold elasticity, and cell properties. A novel mathematical model is developed to describe the dynamics of nutrient flow, concentration, scaffold elasticity, and cell proliferation. Subsequently, the model is solved and employed to simulate the cell proliferation process. The ultimate aim is to optimize the initial configuration of scaffold channels to maximize cell growth. Our findings reveal that the rate of nutrient consumption by cells, referred to as the cell hunger rate, significantly impacts tissue growth, resulting in longer incubation periods for higher cell hunger rates. Additionally, the compliance of the scaffold material slightly affects overall growth. Notably, by reducing scaffold elasticity while maintaining a constant nutrient consumption rate, an optimal funnel-shaped channel geometry emerges. This geometry, with a larger upper part compared to the narrower channel downstream, promotes improved tissue integration and functionality.