**Course Abstracts**

* **Deep Reinforcement Learning:** In recent years, Deep Reinforcement Learning (Deep RL) has seen several breakthroughs like AlphaGo. This lecture will cover basic concepts and algorithms in reinforcement learning, as well as approaches to scale these algorithms to powerful function approximation techniques such as deep neural networks. We will start by introducing markov decision processes (MDPs), and basic algorithms in tabular settings such as value iteration, policy iteration, and Q-learning. We will then dive into more advanced topics, where we introduce modern deep RL algorithms. The lecture will also include hands-on exercises and practical recommendations for tuning reinforcement learning algorithms.
* **Principles of functional Neuroimaging:** Understanding the brain is arguably among the most complex, important and challenging issues in science today. Neuroimaging is an umbrella term for an ever-increasing number of minimally invasive techniques designed to study the brain. These include a variety of rapidly evolving technologies for measuring brain properties, such as structure, function and disease pathophysiology.  The analysis of neuroimaging data is an example of a modern ‘big data’ problem, and the data is not only large but also has a complex correlation structure in both space and time.  Statistics plays a crucial role in understanding the nature of the data and obtaining relevant results that can be used and interpreted by neuroscientists. In this talk we will focus on methods for performing functional neuroimaging (e.g., functional MRI) and discuss how these techniques can be used to detect areas of the brain activated by a task, determine how different brain regions are connected and communicate with one another, and how brain measurements can be used for prediction and classification purposes.
* **Geometric and Graph methods for high-dimensional data:** We will discuss problems and constructions for analyzing large, high-dimensional data sets with techniques that estimate and exploit internal geometric properties of the data. We will start by discussing Diffusion Geometry, a widely used technique for transforming high-dimensional data into graphs, and studying random walks and spectral properties of those graphs to reduce the dimensionality of data, and to perform statistical and machine learning tasks, such as regression and clustering. Applications to the study of certain high-dimensional stochastic systems will be presented. We will then discuss multiscale techniques for the approximation and compression of high-dimensional data, and their connections with the above and to certain problems in statistical signal processing, such as dictionary learning. We will discuss the analysis of these ideas, and their applications to regression on manifolds and optimal transportation problems in high-dimensions. Finally, we will discuss multiscale techniques for model reduction of high-dimensional stochastic systems, that capture rare events. Computational aspects of all of the above will be discussed.

Background: strong linear algebra, basic probability required. Numerical linear algebra, advanced probability, Markov processes and stochastic processes will be helpful.

* **Optimization for Machine Learning: Convex and Nonconvex:**

**AIM:** To provide students a quick introduction to main topics in optimization, with a bias towards topics more relevant to machine learning.

This short course will cover the following main **topics:**

 - Introduction to basics of optimization

 - Convex sets, functions, duality

 - First-order optimization methods

 - Stochastic gradient based methods

 - Beyond stochastic gradients and convexity

 - Some techniques from nonconvex optimization

 - Insights into parallel and distributed optimization

 - Perspectives

In addition, the instructor will mention a few challenging problems during the course. Students are encouraged to attempt them. Moreover, there will be some programming questions that the students are also highly encouraged to work out.

**Programming languages:** Matlab, Python, or Julia (or any other)

* **Probabilistic Graphical Models: Inference, Learning, and Case Studies:** Graphical models provide a unified framework to describe statistical dependencies for a large-scale number of random variables. They have been widely used in many scientific domains, including information retrieval, computational biology, social science, and communication theory among others. In this course, we will discuss basics of graphical models in terms of their representation and characterization, the problem of inference and parameter estimation in graphical models, and how to learn the structure of graph from the data if it is unknown. Case studies from various application areas will be used to illustrate the key concepts.