Title: Stochastic Control & Learning

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Proposal for Special Topic Math577-001 UArizona course in the Fall of 2023

Description:
This course is aimed at the students interested in learning about theoretical and practical approaches associated with the following four inter-related topics in contemporary applied mathematics:
- stochastic processes of non-equilibrium statistical mechanics;
- stochastic optimal control;
- deep reinforcement learning;
- diffusion models of deep generative learning.

In this course you will learn theoretical concepts, will develop mathematical and common sense intuition, and will also become familiar with modern applications of the four topics and related approaches. This course will be rich on examples in sciences and engineering. Our two major examples through out the course will be (a) dynamics and control of particles/swimmers/sensors in stochastic environments (e.g. thermal bath and fluid flows), (b) thermal control in buildings subject to exogenous (such as outside temperature and price of electricity) as well as internal (e.g. related to fluctuations in occupancy) uncertainties.

Prerequisites:
This course should be of interest to graduate students in the School of Mathematical Sciences (Mathematics, Applied Mathematics, Statistics / Data Science) as well as in other Departments and Schools across UArizona. Working knowledge of the basic undegraduate mathematics (algebra, analysis, differential equations) is required. Some prior experience in Stochastic Processes and/or Statistical Mechanics (at least one graduate level course, such as Math581b) is highly recommended.

Assignments & Credits:
There will be 3 homework assignments, and an individual project. No exam(s). Grade structure: Lecture Attendance 10%; HW 40%; Project presentation 50%. List of projects (and related research papers) will be given (30+ options). Students are required to pick up one of the suggested projects or choose their own paper/project relevant to the course (negotiable) by September 15. Projects may be theoretical or may include software implementation component. Any modern scientific software will be acceptable for completing the projects, e.g., matlab, mathematica, julia or python. Project presentations will be scheduled (possibly multiple sessions) for late November- early December.

Topics and Textbooks:
- 3 introductory lectures will be based on Mark Levi, "Classical Mechanics with Calculus of Variations and Optimal Control: An Intuitive Introduction", 2014, ISBN 978-0-8218-9138-4.
- 5-6 lectures devoted to stochastic differential equations and stochastic optimal control, will follow online course (and lecture notes) of B. Kappen, available at `http://www.snn.ru.nl/~bertk/control/madrid2012january.html`and `http://www.snn.ru.nl/~bertk/control/timeseriesbook.pdf`.
- 9-10 following lectures on the deep reinforcement learning will be based on R S. Sutton and Andrew G. Barto book "Reinforcement Learning", 2018 (second edition), ISBN 978-0-262-19398-6; as well as lecture notes of S. Levine (UC Berkley) on "Deep Reinforcement Learning", `http://rail.eecs.berkeley.edu/deeprlcourse-fa21/`; and on-line book of A. Agarwal, N. Jiang, S. M. Kakade, and W. Sun on "Reinforcement Learning: Theory and Algorithms", `https://rltheorybook.github.io/`.
- 5-6 lectures devoted to generative diffusion models of deep learning will be based on a number of recent

papers, including the review by Y. Lee, et al, “Diffusion Models: A Comprehensive Survey of Methods and Applications", `http://arxiv.org/abs/2209.00796`.

Expected learning outcomes:
After completion of the course students will know
• Basic approaches and methodology describing and resolving problems stated in terms of stochastic processes (stochastic ODEs, path-integral, Kolmogorov-Fokker-Planck);
• How to formulate and solve stochastic optimal control problems (Pontrygin Minimal Principe, Hamilton-Jacobi-Bellman) for an application of interest;
• When and how to use one of many reinforcement learning approaches to interpret data streams;
• How to utilize methods from stochastic processes and statistical mechanics to devise diffusion models of deep learning to represent unlabeled data.