Bahçeşehir University, Istanbul, Turkey
Analysis & PDE Center, Ghent University, Ghent, Belgium
Institute Mathematics & Math. Modeling, Almaty, Kazakhstan

"Analysis and Applied Mathematics"

Weekly Online Seminar

Seminar leaders:
Prof. Allaberen Ashyralyev (BAU, Istanbul),
Prof. Michael Ruzhansky (UGent, Ghent),
Prof. Makhmud Sadybekov (IMMM, Almaty)

Date: **Tuesday, January 17, 2023**
Time: 14.00-15.00 (Istanbul) = 12.00-13.00 (Ghent) = 17.00-18.00 (Almaty)

Zoom link: https://us02web.zoom.us/j/6678270445?pwd=SFNmQUIvT0tRaH-lDaVYrN3l5bzJVQT09, **Conference ID:** 667 827 0445, **Access code:** 1

Speaker:
Prof. Dr. Boumediene Hamzi
Johns Hopkins University (USA) and Alan Turing Institute (UK)

Title: **Machine Learning and Dynamical Systems Meet in Reproducing Kernel Hilbert Spaces**

Abstract: Since its inception in the 19th century through the efforts of Poincaré and Lyapunov, the theory of dynamical systems addresses the qualitative behavior of dynamical systems as understood from models. From this perspective, the modeling of dynamical processes in applications requires a detailed understanding of the processes to be analyzed. This deep understanding leads to a model, which is an approximation of the observed reality and is often expressed by a system of Ordinary/Partial, Underdetermined (Control), Deterministic/Stochastic differential or difference equations. While models are very precise for many processes, for some of the most challenging applications of dynamical systems (such as climate dynamics, brain dynamics, biological systems or the financial markets), the development of such models is notably difficult. On the other hand, the field of machine learning is concerned with algorithms designed to accomplish a certain task, whose performance improves with the input of more data. Applications for machine learning methods include computer vision, stock market analysis, speech recognition, recommender systems and sentiment analysis in social media. The machine learning approach is invaluable in settings where no explicit model is formulated, but measurement data is available. This is frequently the case in many systems of interest, and the development of data-driven technologies is becoming increasingly important in many applications.

The intersection of the fields of dynamical systems and machine learning is largely unexplored and the objective of this talk is to show that working in reproducing kernel Hilbert spaces offers tools for a data-based theory of nonlinear dynamical systems.

In this talk, we use the method of parametric and nonparametric kernel flows to predict some chaotic dynamical systems. When trained on geophysical observational data, for example, the weekly averaged global sea-surface temperature, considerable gains are also observed by the proposed technique in comparison to classical partial differential equation-based models in terms of forecast computational cost and accuracy. When trained on publicly available re-analysis data for the daily temperature of the North-American continent, we see significant improvements over classical baselines such as climatology and persistence-based forecast techniques. Although our experiments concern specific examples, the proposed approach is general, and our results support the viability of kernel methods (with learned kernels) for interpretable and computationally efficient geophysical forecasting for a large diversity of processes. We also consider microlocal kernel design for detecting critical transitions in some fast-slow random dynamical systems.

We then show how kernel methods can be used to approximate center manifolds, propose a data-based version of the center manifold theorem and construct Lyapunov functions for nonlinear ODEs.

We also introduce a data-based approach to estimating key quantities which arise in the study of nonlinear autonomous, control and random dynamical systems. Our approach hinges on the observation that much of the existing linear theory may be readily extended to nonlinear systems-- with a reasonable expectation of success- once the nonlinear system has been mapped into a high or infinite dimensional Reproducing Kernel Hilbert Space. In particular, we develop computable, non-parametric estimators approximating controllability and observability energies for nonlinear systems. We apply this approach to the problem of model reduction of nonlinear control systems. It is also shown that the controllability energy estimator provides a key means for approximating the invariant measure of an ergodic, stochastically forced nonlinear system. We also show how kernel methods can be used to detect critical transitions for some multi scale dynamical systems.

This is joint work with Jake Bouvrie (MIT, USA), Matthieu Darcy (Caltech), Edward DeBrouwer (KU Leuven), Peter Giesl (University of Sussex, UK), Christian Kuehn (TUM, Munich/Germany), Jonghyeon Lee (Caltech), Romit Malik (ANNL), Sameh Mohamed (SUTD, Singapore), Houman Owhadi (Caltech), Martin Rasmussen (Imperial College London), Kevin Webster (Imperial College London), Bernard Hasasdonk and Dominik Wittwar (University of Stuttgart), Gabriele Santin (Fondazione Bruno Kessler).

Biography:

Boumediene Hamzi is currently a Visiting (Full) Professor at the department of Applied Mathematics and Statistics at Johns Hopkins University. He held multiple positions including Visiting Senior Scientist at the department of Computational and Mathematical Sciences at Caltech, Marie Curie Fellow at Imperial College London and Koc University, Visiting Assistant Professor at Duke University and Research Assistant Professor at UCDavis. He is currently also an External Researcher and Coordinator of the Research Interest Group on “Machine Learning and Dynamical Systems” at the Alan Turing Institute in London/UK. His current research interests are the interface of Machine Learning and Dynamical Systems in view of developing a qualitative theory of dynamical systems in Reproducing Kernel Hilbert Spaces.