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Data Science Seminar Series

Dynamical systems and machine learning: combining in a principled way data-driven models and domain-driven models

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Data-driven models such as those common in machine learning tend to be relatively domain-agnostic and thus are widely-applicable across many domains. It is a fundamental challenge how best to combine such data-driven models with fine-scale domain-driven models that are common in physics and other natural sciences and that make strong use of domain-specific insight. Among other things, a domain-informed model formulation should encode some degree of stability or robustness or well-conditioning (in that a small change of the input will not lead to drastic changes in the output), characteristic of the underlying scientific problem. Here, we describe recent work on using techniques from dynamical systems theory to combine these two types of models in a principled way. We'll describe how to develop physics-informed autoencoders using Lyapunov stability, leading to novel domain-driven regularization and to models that improve the generalization error and reduce prediction uncertainty for fluid flow problems. We'll also describe ContinuousNet, a variant of the popular residual neural network (ResNet) model that is meaningfully continuous-in-depth. By embedding discrete neural network models into higher-order numerical integration schemes, e.g., Runge Kutta schemes, ContinuousNet can learn to represent continuous dynamical systems (which ResNets and other nominally-continuous models cannot); and, by exploiting ideas from numerical integration theory, ContinuousNet have improved robustness properties as well as improved training and inference properties on standard (non-scientific) machine learning tasks.

Michael W. Mahoney is at the University of California at Berkeley in the Department of Statistics and at the International Computer Science Institute (ICSI). He works on algorithmic and statistical aspects of modern large-scale data analysis. Much of his recent research has focused on large-scale machine learning, including randomized matrix algorithms and randomized numerical linear algebra, geometric network analysis tools for structure extraction in large informatics graphs, scalable implicit regularization methods, and applications in genetics, astronomy, medical imaging, social network analysis, and internet data analysis. He received him PhD from Yale University with a dissertation in computational statistical mechanics.