Financial and Risk Management
Interdisciplinary Speaker Series for AY18/19

About the Speaker: Professor Weinan E, Princeton University

Weinan E received his Ph.D. from UCLA in 1989. After being a visiting member at the Courant Institute of NYU and the Institute for Advanced Study at Princeton, he joined the faculty at NYU in 1994. He is now a professor of mathematics at Princeton University, a position he has held since 1999.

Weinan E's work centers around multi-scale modeling and machine learning. Most recently, he has been working on integrating machine learning and physical modeling to solve problems in traditional areas of science and engineering, such as molecular dynamics, PDEs, control theory, etc. Weinan E is the recipient of the SIAM R. E. Kleinman Prize, von Karman Prize and the ICIAM Collatz Prize. He is a member of the Chinese Academy of Sciences, a fellow of the American Mathematical Society, a SIAM fellow and a fellow of the Institute of Physics.

Research Seminar - Monday 10 June (10.00am to 12.00pm)

The Mathematical Theory of Neural Network-based Machine Learning

(suitable for graduate students)

Colloquium Lecture - Wednesday 12 June (2.00pm to 3.00pm)

Machine Learning: Mathematical Theory and Scientific Applications

Both lectures are held @Department of Mathematics, Seminar Room 1, (S17, #04-06)

The Mathematical Theory of Neural Network-based Machine Learning

The task of supervised learning is to approximate a function using a given set of data. In low dimensions, its mathematical theory has been established in classical numerical analysis and approximation theory in which the function spaces of interest (the Sobolev or Besov spaces), the order of the error and the convergence rate of the gradient-based algorithms are all well-understood. Direct extension of such a theory to high dimensions leads to estimates that suffer from the curse of dimensionality as well as degeneracy in the over-parametrized regime.
In this talk, we attempt to put forward a unified mathematical framework for analyzing neural network-based machine learning in high dimension (and the over-parametrized regime). We illustrate this framework using kernel methods, shallow network models and deep network models. For each of these methods, we identify the right function spaces (for which the optimal complexity estimates and direct and inverse approximation theorems hold), prove optimal generalization error estimates and study the behavior of gradient decent dynamics.

Machine Learning: Mathematical Theory and Scientific Applications

Modern machine learning has had remarkable success in all kinds of AI applications, and is also poised to change fundamentally the way we do physical modeling. In this talk, I will give an overview on some of the theoretical and practical issues that I consider most important in this exciting area. The first part of this talk will be focused on the following question: How can we make use of modern machine learning tools to help build reliable and practical physical models? Here we will address two issues (mostly using the example of molecular dynamics):
(1) building machine learning models that satisfy physical constraints;
(2) using microscopic models to generate the optimal data set.

The second part of the talk will be devoted to some of the theoretical issues. Serious difficulties arise due to the fact that the underlying dimensionality is high, the neural network models are non-convex and highly over-parametrized. We don't yet have a complete mathematical picture about neural network-based machine learning but we will discuss the current status. Specifically, we will discuss the representation of high dimensional functions, optimal a priori estimates of the generalization error for neural networks, and gradient decent dynamics.

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