**Special Seminar**

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**Visiting ATS from the Lawrence Berkeley National Laboratory**

# Deep Learning and Novel Data Analytics for Climate Science

**Hosted by Ben Toms and Aryeh Drager**

**Monday, Sept. 17, 2018**
**ATS room 101**
**Discussion will begin at 3 p.m.**

In this talk we discuss how machine learning, deep learning and novel data-driven analytics from applied math and physics can be used for two fundamental challenges in climate and weather sciences: (i) pattern recognition, pattern discovery and pattern tracking in large climate datasets, and (ii) emulation of complex dynamical processes that are critical for modeling Earth's weather and climate.

Part-1: Detecting, classifying and characterizing weather and climate patterns is a fundamental requirement to improve our understanding of extreme events, their formation and how they may change with global warming. These tasks, however, remain challenging across all classes of weather and climate patterns, and especially for extreme events. Deep Learning has revolutionized solutions to pattern recognition problems resulting in tremendous advances in computer vision, speech recognition, robotics and control systems. Topological data analysis is providing new and insightful ways of recognizing and characterizing the "shape" of data. Physics-based unsupervised pattern discovery is the next frontier of learning algorithms for scientific applications. In this presentation, we show how deep learning, applied topology and physics-based unsupervised discovery can be impactful in climate science. We present results on the methodology and lessons learned both on the science and the computations. We also highlight some challenges and opportunities.

Part-2: Predictive modeling of complex, nonlinear, high-dimensional dynamical processes such as atmospheric convection are crucial for improving the reliability and accuracy weather and climate models. Deep generative models have recently been successful in learning the underlying statistics of complex physical processes from large amounts of data. However, their success in predicting physical systems have been limited, primarily because they do not require physical consistency. By integrating physics constraints and desirable statistical properties into an emerging class of deep generative model called Generative Adversarial Networks (GANs), we develop a new paradigm for modeling complex dynamical systems. We present preliminary results on the methodology and performance of this model in simple test cases and more complex chaotic processes of relevance to weather and climate modeling.