Abstract: The unprecedented prediction accuracy of modern machine learning beckons for its application in a wide range of real-world applications, including autonomous robots, medical decision making, scientific experiment design, and many others. A key challenge in such real-world applications is that the test cases are not well represented by the pre-collected training data. To properly leverage learning in such domains, especially safety-critical ones, we must go beyond the conventional learning paradigm of maximizing average prediction accuracy with generalization guarantees that rely on strong distributional relationships between training and test examples.

In this talk, I will describe a robust learning framework that offers rigorous extrapolation guarantees under data distribution shift. This framework yields appropriately conservative yet still accurate predictions to guide real-world decision-making and is easily integrated with modern deep learning. I will showcase the practicality of this framework in an application on agile robotic control. I will conclude with a survey of other applications as well as directions for future work.

Friday, October 25, 2019, 10:30 am
Mathematics and Science Center: MSC W201