Abstract:

In real-world supervised learning problems, accurate and trustworthy labels are often elusive, with label noise being a pervasive challenge. In this talk, we will delve into the inherent robustness of conformal prediction—a powerful tool for quantifying predictive uncertainty—to label noise. We will address both regression and classification problems and characterize how and when we can generate uncertainty sets that include the true labels that are hidden from us. By navigating between theory and practice, we will showcase the conservative coverage of clean ground truth labels achieved by employing conformal prediction with noisy labels and commonly used score functions, except in adversarial cases.