



THE UNIVERSITY OF
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DEPARTMENT OF STATISTICS

PhD Dissertation Presentation

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“Problems in modern inference: distribution free prediction and goodness of fit testing”

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Abstract

In the modern era of machine learning, increasingly complex models are used to analyze complex data and guide scientific and real-world decision-making, making reliable statistical inference both more important and more challenging. This motivates assumption-lean methods that reduce reliance on distributional assumptions and model correctness while aiming to remain statistically valid. This talk focuses on two central aspects of modern statistical inference: distribution-free prediction and goodness-of-fit testing.

The first part of the talk studies conformal prediction, a framework for constructing prediction sets with distribution-free coverage guarantees. Full conformal prediction is statistically attractive but computationally prohibitive. Common computational shortcuts, such as grid-based approximations, are much faster but may lack marginal coverage guarantees and can fail in practice. We place these approximations within a unified framework and introduce a tournament correction that restores finite-sample, distribution-free marginal coverage without imposing additional assumptions.

The second part of the talk studies flexible goodness-of-fit testing. Resampling-based tests are powerful because they allow the analyst to use essentially any test statistic, provided the artificial data sets are exchangeable with the observed data under the null. Existing approaches condition on exact or approximate sufficient statistics, but can be limited in scope, power, or computational tractability. We propose approximately co-sufficient sampling via Bayes, or aCSS-B, which conditions on samples from a Bayesian posterior distribution as a flexible approximate sufficient

statistic. This expands the applicability of resampling-based goodness-of-fit testing to structured models while retaining frequentist validity guarantees.