THE UNIVERSITY OF CHICAGO | **DEPARTMENT OF STATISTICS**

PHD DISSERTATION PRESENTATION

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A Statistical Learning Theory for Models with High Complexity

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ABSTRACT

Understanding why high-dimensional estimators can generalize beyond finite training samples is a fundamental problem in statistical learning theory. The traditional intuition, as suggested by Occam's razor, is that models with low complexity tend to generalize better. We can often find simple models that explain the training data well if the high-dimensional data distribution has some hidden low-dimensional structure (for example, sparse linear regression and low-rank matrix recovery). However, contrary to our traditional intuition, complex models which interpolate noisy training labels can also enjoy good generalization in some settings. This phenomenon, which we refer to as "interpolation learning", has significantly challenged our theoretical foundation of statistical learning. In this thesis, we present a novel Moreau envelope generalization theory to establish the concentration of measure in high dimensions. Since our result can precisely quantify the role of model complexity in generalization error, we are able to establish strong consistency results even though the norm of the high-dimensional interpolants that we consider diverges. In addition to proving sharp non-asymptotic bounds for interpolants in various contexts, we also recover versions of classical results from the compressed sensing and high-dimensional statistics literature. Applications of our theory include kernel ridge regression, max-margin classification, matrix sensing, phase retrieval and some simple neural networks.