# Some recent work inspired by Le Cam's Theory

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**Abstract**

The key idea of Le Cam's theory is to approximate a complicated statistical problem by a more tractable one. In my talk, I will describe some of my recent work which was directly inspired by Le Cam's theory. The talk will attempt to shed light on how Le Cam's theory can be applied to high-dimensional models. Firstly, I will discuss how Le cam's theory has inspired me and my coauthors to propose new statistical procedures for models such as robust nonparametric regression (with the noise distribution is unknown and possibly heavy-tailed) and generalized nonparametric regression in exponential families (Poisson regression, binomial regression, and Gamma regression and so on). We took a unified approach of using a transformation to convert each of these problems into a standard homoskedastic Gaussian regression problem to which any good nonparametric Gaussian regression procedure can be applied. Secondly, I will discuss minimax rates of convergence for estimating the Toeplitz covariance matrix under the spectral norm. The minimax lower bound is derived by constructing a more informative and tractable model (in the Le Cam's sense) for which it is easier to derive a minimax lower bound. Finally, (if time permits ) I will discuss minimax rates of convergence for estimating an infinite-dimensional parameter in functional regression for general exponential families. An estimator that achieves the minimax upper bound is constructed by maximum likelihood on finite-dimensional approximations with parameter dimension that grows with sample size. The Le Cam's distance provides the key technical tool for bounding the error of the approximations.