

**University of California, Irvine  
Statistics Seminar**

*A Few Recovery Problems from Noisy Observations*

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In this talk, I will discuss the following three classical problems on the recovery of hidden signals from noisy observations, and present our solutions using statistical methods. I will also highlight the key proof strategies and the intuition behind them, with the help of a lot of pictures.

- 1) The recovery of hidden nearest neighbor (NN) graphs from noisy random networks. The observed network is a weighted complete graph, whose edge weights are independent and distributed according to  $P$  for edges in the hidden NN graph and  $Q$  otherwise. Our model incorporates the celebrated Watts-Strogatz small-world graph as a special case. For both exact and almost exact recovery, we characterize the sharp information-theoretic limits, which are governed by two divergence measures between  $P$  and  $Q$ .
- 2) The recovery of convex support from noisy measurements. A popular class of problem in statistics deals with estimating the convex support of a density from  $n$  observations drawn at random from a  $d$ -dimensional distribution. We consider the more realistic model that allows for the observations to be contaminated with additive noise. We show that the minimax rate of estimation in Hausdorff distance is polylogarithmic in  $n$ . We will focus on the case where the additive noise is distributed according to a multivariate Gaussian distribution, even though our techniques could easily be adapted to other noise distributions.
- 3) The recovery of individual coordinates in the high-dimensional linear model. It is well known that high-dimensional procedures such as the LASSO provide biased estimators of parameters in a linear model. To remove the bias is an extensively studied problem in frequentist statistics, but much needs to be done in the Bayesian analogue. In this talk, I will present a prior construction that removes the bias from a Bayesian sparse prior. Moreover, a Bernstein-von Mises theorem is obtained under this prior, meaning that the rescaled posterior distribution converges to a Gaussian distribution in total variation distance.

*If you are not part of the ICS community and would like to attend, please contact Lisa Stielor, [lstieler@uci.edu](mailto:lstieler@uci.edu), for access*