

**University of California, Irvine  
Statistics Seminar**

***Robust Inference in High-dimensional Models –  
Going Beyond Sparsity Principles***

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(Bldg. #314 on campus map)**

In high-dimensional linear models the sparsity assumption is typically made, stating that most of the parameters are equal to zero. Under the sparsity assumption, estimation and, recently, inference have been well studied. However, in practice, sparsity assumption is not checkable and more importantly is often violated, with a large number of covariates expected to be associated with the response, indicating that possibly all, rather than just a few, parameters are non-zero. A natural example is a genome-wide gene expression profiling, where all genes are believed to affect a common disease marker. We show that existing inferential methods are sensitive to the sparsity assumption, and may, in turn, result in the severe lack of control of Type-I error. In this article, we propose a new inferential method, named CorrT, which is robust and adaptive to the sparsity assumption. CorrT is shown to have Type I error approaching the nominal level and Type II error approaching zero, regardless of how sparse or dense the model. In fact, CorrT is also shown to be optimal whenever sparsity holds. Numerical and real data experiments show a favorable performance of the CorrT test compared to the state-of-the-art methods.