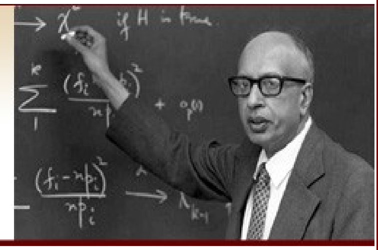
BAHADUR
MEMORIAL LECTURES

In honor of Raj Bahadur's fundamental contributions to statistics and to our department.



The University of Chicago, Department of Statistics, presents the

Twenty-Second Annual Bahadur Memorial Lectures

Sara van de Geer

Department of Mathematics, ETH Zürich

"Logistic regression with small Bayes error"

MONDAY, MAY 1, 2023 at 4:30 PM

Jones 303, 5747 S. Ellis Avenue

Refreshments before the seminar at 4:00 PM in Jones 303.

ABSTRACT

It is well-known that in binary classification the logistic regression estimator is unstable when the Bayes error σ is small. Yet, a small Bayes error should in fact be helpful and result in an improved rate for estimating the direction of the regression coefficients. We show that this is indeed the case, at least in a low-dimensional situation where the number of variables d is smaller than the number of observations n. If σ is small, but not too small ($\sigma \gtrsim d \log n/n$) we obtain the rate $\sqrt{\sigma d \log n/n}$. If σ is very small ($\sigma \lesssim d \log n/n$) the logistic regression estimator might not exist as there might be perfect separation. A ridge penalty on the regression coefficients however prevents interpolation and one finds the rate $\sqrt{\sigma d \log n/n} \asymp d \log n/n$ also in this very low noise case. Up to the log-term, this rate coincides with the one for interpolation in the noiseless case. The results rely on the assumption of Gaussian design and additive sub-Gaussian noise.

THURSDAY, MAY 4, 2023 at 3:30 PM
Jones 303, 5747 S. Ellis Avenue
Refreshments before the seminar at 3:00 PM in Jones 303.

"Small noise, no regularization"

ABSTRACT

We consider interpolation in regression and classification. Basis Pursuit estimates the vector of regression coefficients by choosing the interpolator of the data that has the smallest ℓ_1-norm. For the case of i.i.d. Gaussian design independent of the noise, Wang et al. [2021] show the intriguing result that noisy Basis Pursuit is consistent. By cleverly exploiting the Gordon Min-Max Theorem, they derive tight bounds. We will address the question whether consistency can be established in a more direct way using geometric insights and standard empirical process theory. For the classification problem, we compare error bounds for interpolation and various other estimation methods.

References

G. Wang, Donhauser K., and F. Yang. Tight bounds for minimum ℓ_1-norm interpolation of noisy data, 2021. arXiv:2111.05987.