Statistical Physics of High Dimensional Inference[1] MADHU AD-
VANI, SURYA GANGULI, Stanford University — To model modern large-scale
datasets, we need efficient algorithms to infer a set of P unknown model parame-
ters from N noisy measurements. What are fundamental limits on the accuracy of
parameter inference, given limited measurements, signal-to-noise ratios, prior infor-
mation, and computational tractability requirements? How can we combine prior
information with measurements to achieve these limits? Classical statistics gives in-
cisive answers to these questions as the measurement density $\alpha = \frac{N}{P} \to \infty$. However,
modern high-dimensional inference problems, in fields ranging from bio-informatics
to economics, occur at finite α. We formulate and analyze high-dimensional infer-
ence analytically by applying the replica and cavity methods of statistical physics
where data serves as quenched disorder and inferred parameters play the role of
thermal degrees of freedom. Our analysis reveals that widely cherished Bayesian
inference algorithms such as maximum likelihood and maximum a posteriori are
suboptimal in the modern setting, and yields new tractable, optimal algorithms to
replace them as well as novel bounds on the achievable accuracy of a large class of
high-dimensional inference algorithms.

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