Abstract: The Bayesian paradigm offers a flexible modeling framework for statistical analysis, but relative to penalization-based methods, little is known about the consistency of Bayesian model selection methods in the high dimensional setting. I will present a new framework for understanding Bayesian model selection consistency, using sample size dependent spike and slab priors that help achieve appropriate shrinkage. More specifically, strong selection consistency is established in the sense that the posterior probability of the true model converges to one even when the number of covariates grows nearly exponentially with the sample size. Furthermore, the posterior on the model space is asymptotically similar to the L0 penalized likelihood. I will also introduce a new Gibbs sampling algorithm for posterior computation, which is much more scalable for high dimensional problems than the standard Gibbs sampler, and yet retains strong selection consistency. The new algorithm and the model selection consistency theory work for a variety of problems including linear and logistic regressions, and a more challenging problem of censored quantile regression where a non-convex loss function is involved.

Bio Naveen Narisetty is a PhD Candidate in Statistics at the University of Michigan. He obtained his Bachelor’s and Master’s degrees also in Statistics from the Indian Statistical Institute, Kolkata. He has broad research interests in Bayesian methods, theory, computational algorithms, nonparametric methods, and interdisciplinary scientific research. He received research and teaching awards including two student paper awards from the American Statistical Association, a pre-doctoral fellowship and an outstanding teaching award from the University of Michigan.