Abstract: Technological advancements in recent years have enabled organizations to collect, organize, store and analyze very large amounts of data from variables that are available at different temporal frequencies - e.g. monthly, weekly, daily. Such data is commonly referred to as mixed frequency time series data. In the first part of the talk, we will focus on mixed frequency regression, where the response variable and the covariates are available at different frequencies (for example, quarterly vs. monthly). We will present novel Bayesian methodology for (sparse) estimation of the regression coefficients and of the (autoregressive) lag length using a Bayesian adaptation of the nested lasso framework. In the second part, we will focus on mixed frequency vector autoregressive (VAR) models, which aim to capture linear temporal interdependencies among multiple time series observed at different frequencies. The issue of overparameterization in a VAR model becomes more acute in high-dimensional settings where the number of variables is more than or comparable to the sample size. We present a Bayesian approach which achieves parameter reduction through a combination of sparsity and simple structural relationships between appropriate parameters. We will illustrate the efficacy of the proposed approach on simulated data and on real data from macroeconomics, and establish posterior consistency under high-dimensional scaling where the dimension of the VAR system grows with the sample size. The talk is based on joint work with Nilanjana Chakraborty, Satyajit Ghosh and George Michailidis.

Bio: I am an Associate Professor in the Department of Statistics at University of Florida. My primary research interests lie broadly in statistical methodology and applied probability. My current work focuses on the following areas: Statistical methodology for covariance estimation and high dimensional inference, Markov chain Monte Carlo (MCMC), Bayesian asymptotics for high-dimensional data.