RUTGERS
School of Arts and Sciences

Department of Statistics

DEPARTMENT OF STATISTICS

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Scalable Bayesian Inference and Summarization for Functional Data

November 13, 2019
11:45am – 12:45pm
Light refreshments will be served
110 Frelinghuysen Road
Hill Center, Room 552

Abstract: Modern scientific monitoring systems, such as wearable and implantable devices, commonly record data over a continuous domain at high resolutions. These *functional data* are high-dimensional, strongly correlated, and usually measured concurrently with other variables of interest. Bayesians models for functional data are particularly appealing: they accommodate multiple dependence structures, handle missing or irregularly-spaced data, and provide regularization via shrinkage priors. However, these models are often complex, computationally intensive, and difficult to interpret. This talk will focus on two fundamental challenges for Bayesian functional data analysis: (1) constructing sufficiently flexible and scalable functional regression models and (2) extracting interpretable posterior summaries. The proposed modeling framework is nonparametric and uses an unknown functional basis to learn prominent functional features, which are associated with scalar predictors within a regression model. A customized projection-based Gibbs sampler provides posterior inference with linear time complexity in the number of predictors, which is empirically faster than existing frequentist and Bayesian alternatives. Using the posterior distribution, a decision theoretic approach for Bayesian variable selection is developed, which identifies a subset of covariates that retains nearly the predictive accuracy of the full model. The methodology is applied to actigraphy data to investigate the association between intraday physical activity and responses to a sleep questionnaire.

Bio: Dr. Daniel Kowal is an assistant professor in the Department of Statistics at Rice University. Dr. Kowal develops statistical methodology and algorithms for massive data sets with complex dependence structures, such as functional, time series, and spatial data. His recent work focuses on Bayesian models for prediction and inference, as well as scalable approximations to complex models. He received his PhD from Cornell University in 2017.