Abstract:
Many computer vision and medical imaging problems are faced with learning from large datasets, with millions of observations and features. In this talk I present a novel efficient algorithm for variable selection and learning on such datasets, optimizing a likelihood with sparsity constraints. The iterative algorithm alternates parameter updates with tightening the constraints by gradually removing variables based on a criterion and a schedule. I present a generic approach for optimizing any differentiable loss function and applications to regression and classification. By using one dimensional piecewise linear response functions we introduce nonlinear dependence on the selected variables and a second order prior on the response functions to avoid overfitting. The approach has theoretical guarantees of convergence and variable selection consistency for regression and logistic regression. Experiments on real and synthetic data show that the proposed method compares very well with other state of the art methods in regression and classification while being computationally very efficient.

Bio:
Adrian Barbu received his BS degree from University of Bucharest, Romania, in 1995, a Ph.D. in Mathematics from Ohio State University in 2000 and a Ph.D. in Computer Science from UCLA in 2005. From 2005 to 2007 he was a research scientist and later project manager in Siemens Corporate Research, working in medical imaging. He received the 2011 Thomas A. Edison Patent Award with his co-authors for their work on Marginal Space Learning. From 2007 he joined the Statistics department at Florida State University, first as assistant professor, and since 2013 as associate professor. His research interests are in computer vision, machine learning and medical imaging.