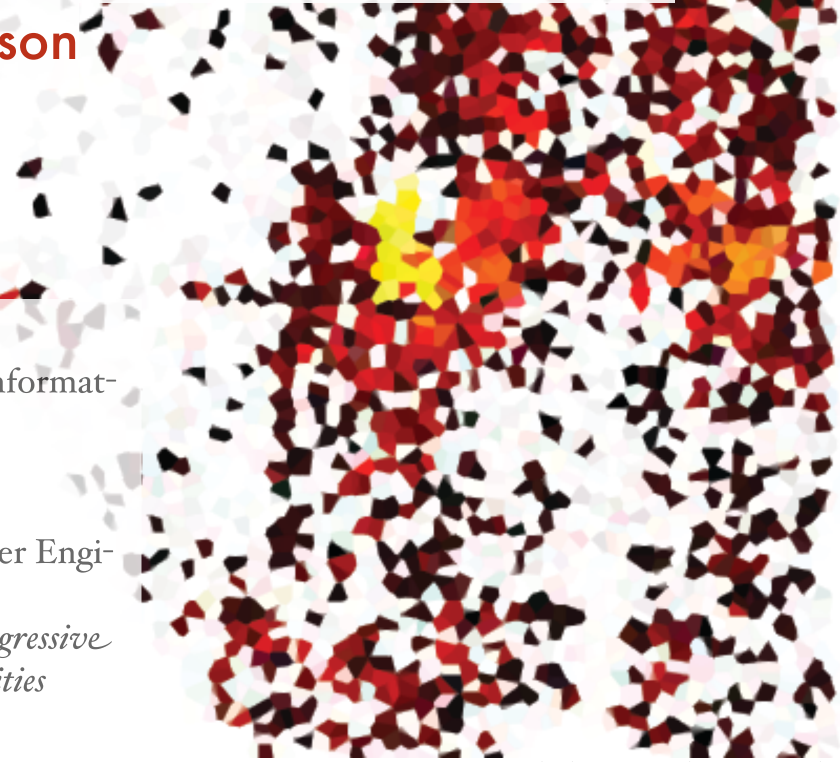
# Workshop on Sparse Data Recovery and its Application to Brain Imaging

## University of Wisconsin, Madison

## April 4, 2011   408 SMI



Node degrees in a brain network

### Sparse Data Recovery 1:00-3:30PM

Sijian Wang, Dept. of Biostatistics and Medical Informatics
*Random Lasso*

Barry D. Van Veen, Dept. of Electrical & Computer Engineering
*Estimation of High Dimensional Multivariable Autoregressive Models of EEG/MEG Data: Challenges and Opportunities*

Julia Velikina, Department of Medical Physics
*Constrained Reconstruction in Rapid Serial MR Imaging*

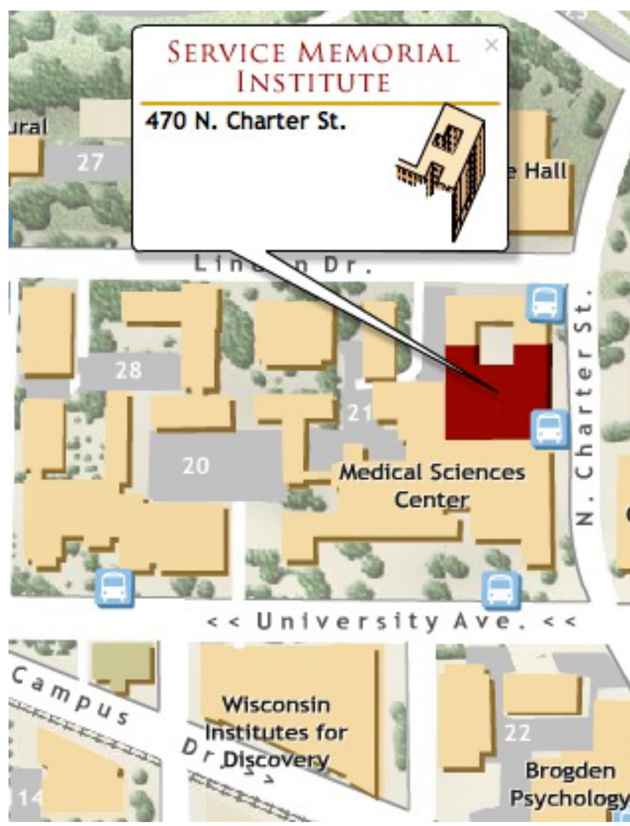
Jong Chul Ye, Dept. of Bio. and Brain Engineering, KAIST, Korea
*Compressive MUSIC for Joint Sparse Recovery and Its Applications*

### Brain Imaging and Networks 3:45-5:30PM

Robert Nowak, Dept. of Electrical & Computer Engineering
*Association and Causation in Network Inference*

Moo K. Chung, Dept. of Biostatistics and Medical Informatics
*Sparse Topological Data Recovery and its Application to Brain Network Modeling*

Chris Hinrichs, Dept. of Computer Science
*Learning Disease Patterns in Medical Imaging: Applications to Alzheimer's Disease Research*





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# Program 1:00-3:30pm

## Sijian Wang, Dept. of Biostatistics and Medical Informatics

### *Random Lasso*

We propose a computationally intensive method, the random lasso method, for variable selection in linear models. The method consists of two major steps. In Step 1, the lasso method is applied to each of the bootstrap samples for a set of randomly selected covariates. A measure of importance is yielded from this step for each covariate. In Step 2, a similar procedure to the first step is implemented with the exception that for each bootstrap sample, a subset of covariates is randomly selected with unequal selection probabilities determined by covariates' importance measures. The final set of covariates and their coefficients are determined by averaging bootstrap results obtained from Step 2. The proposed method tends to remove highly correlated variables altogether or select them all, and maintains maximal flexibility in estimating their coefficients, particularly with different signs.

## Barry D. Van Veen, Dept. of Electrical & Computer Engineering

### *Estimation of High Dimensional Multivariable Autoregressive Models of EEG/MEG Data: Challenges and Opportunities*

The high temporal resolution of EEG or MEG data relative to typical neural time scales strongly suggests the need for memory in EEG/MEG brain network models. A multivariable autoregressive (MVAR) model models the electrical signal at each location of interest as a linear combination of past values of signals at all locations and thus can be used to infer both functional and effective connectivity measures such as coherence and Granger causality. MVAR models are well-suited to application of group sparse estimation techniques. Challenges to the identification of cortical MVAR models include the inherent nonstationarity of the brain and the difficulties of model validation. Furthermore, scalp EEG/MEG measurements are blurred due to forward problem physics and usually have low SNR. This talk reviews progress toward addressing these issues and the potential role of sparse recovery methods.

## Julia Velikina, Department of Medical Physics

### *Constrained Reconstruction in Rapid Serial MR Imaging*

In many MRI applications, the amount of time available for data acquisition is limited by physiological factors such as contrast arrival and breath hold or considerations of patient comfort. As a result, images may need to be reconstructed from incomplete data. Compressed Sensing provides an efficient way to reconstruct images from undersampled data sets. However, at high accelerations, the level of sparsity in MR images may be insufficient to support the requisite acceleration factors, resulting in residual artifacts and loss of spatial resolution. In serial imaging, availability of a non-spatial dimension, e.g. a time variable, can facilitate the task of achieving sparsity. Indeed, correlations between images in the series can be exploited to achieve a higher level of sparsity, therefore, allowing higher acceleration factors or a more accurate reconstruction. We will describe our approach to reconstruction of MR image series from highly undersampled data using constrained reconstruction in the parametric dimension and demonstrate applications of the proposed technique to time-resolved angiography and quantitative relaxometry.

## Jong Chul Ye, Dept. of Bio and Brain Engineering, Korea Advanced Institute of Science and Technology (KAIST), Korea

### *Compressive MUSIC for Joint Sparse Recovery and its Applications*

The joint sparse recovery problem addresses the identification of unknown input vectors that share common sparse support. Recent trend is to apply compressive sensing (CS) due to its capability to estimate sparse support even with an insufficient number of snapshots, in which case classical array signal processing fails. However, CS guarantees the accurate recovery in a probabilistic manner, which often shows inferior performance in the regime where the traditional array signal processing approaches succeed. The main contribution of the present article is a unified approach that unveils a missing link between CS and array signal processing. The new algorithm, which we call compressive MUSIC, identifies the parts of support using CS, after which the remaining supports are estimated using a novel generalized MUSIC criterion. We demonstrate how compressive MUSIC can be used to improve resolution for biomedical imaging problems such as diffuse optical tomography.

# Program 3:45-5:30pm

## Robert Nowak, Dept. of Electrical & Computer Engineering

### *Association and Causation in Network Inference*

The term "brain network" means many things to many people. Much of the work I have seen uses it in a rather loose sense; a brain network is simply a summary statistic (often referred to as the "functional connectivity") with little or no direct relation to physical structure or signaling in the brain. The term "effective connectivity" refers to causal interactions between brain components, and seems to be a more concrete notion of a brain network. I will discuss three probabilistic approaches to modeling and inferring networks from data: correlation thresholding, graphical modeling, and causal/interventional calculus. The latter seems to come closest to potentially capturing effective connectivity, while the former may be at best loosely associated with effective connectivity and could even be misleading.

## Moo K. Chung, Dept. of Biostatistics and Medical Informatics

### *Sparse Topological Data Recovery and its Application to Brain Network Modeling*

Motivated by Rips complex in persistent homology, we present a new framework of modeling functional measurements as topological objects. The level set associated with the measurements can be approximated using a simplicial complex consisting of nodes and links. The existence of links basically determine the underlying topological structure of the signal. The strength of links can be modeled using an underdetermined linear model. By incorporating sparsity into the model, the links can be sparsely obtained making interpretation and visualization of the simplicial complex easier. We will explore the relationship between sparse topological structures to the sparse regression framework. We apply the proposed framework in constructing various brain networks.

Chris Hinrichs, Dept. of Computer Science

## *Learning Disease Patterns in Medical Imaging: Applications to Alzheimer's Disease Research*

Alzheimer's Disease (AD) affects over 5 million people in the United States, and is the most common form of age-related dementia. Symptoms include loss of memory and executive function, ultimately depriving patients of their capacity for basic day-to-day activities. Because the brain is so robust to neuronal damage, neuropathology can precede outward signs of cognitive impairment by as much as several decades; yet once brain matter is lost, it is irrecoverable. Therefore, treatment must also precede clinical dementia. Non-invasive indicators such as MRI and PET scans, or Cerebrospinal Fluid (CSF) measures can provide early clues, but the sheer volume of data, surprising levels of subject heterogeneity, and subtlety of the disease patterns (relative to normal aging) mean that traditional statistical group analyses have difficulties predicting at an individual level which patients are most likely to develop AD. In particular, my research focuses on combining multiple heterogeneous data modalities into a single integrated machine learning framework without compromising model complexity or generalizability. Recent results have applied kernel methods such as Multi-Kernel Learning (MKL) to the problem, showing gains over single-modality methods. In addition, we have extended the MKL model to allow both prior-based and empirical modulation of interactions between kernels / modalities by means of non-isotropic norm regularization of kernel combination weights. Ongoing work includes applications to clinical trial enrichment and further development of multiple kernel methods.