**Speakers: Xinle Tian and Dan Miles (University of Bath)**

**Date: 07/05/2024 at 13:15 in 1 West 2.01**

## Talk 1: Multi-response linear regression estimation based on low-rank pre-smoothing

**Abstract:**
Pre-smoothing is a technique aimed at increasing the signal-to-noise ratio in data to improve subsequent estimation and model selection in regression problems. However, pre-smoothing has thus far been limited to the univariate response regression setting. Motivated by the widespread interest in multi-response regression analysis in many scientific applications, this article proposes a technique for data pre-smoothing in this setting based on low rank approximation. We establish theoretical results on the performance of the proposed methodology, and quantify its benefit empirically in a number of simulated experiments. We also demonstrate our proposed low rank pre-smoothing technique on real data arising from the environmental sciences..

## Talk 2: Encouraging sparsity and similarity across multiple covariate-influenced Gaussian Graphical Models

**Abstract:**
Across various modern applications, many data sets are high-dimensional in nature and can often be represented through a Markovian conditional dependence graph upon a sparse adjacency matrix, where sparsity manifests itself through a high proportion of zero-valued off-diagonal elements. Classical likelihood-based approaches do not account for sparsity well, thus requiring some form of heuristic or penalty. A multivariate Gaussian graphical model is a standard choice for continuous data, where a LASSO one-norm penalty can be employed to shrink the off-diagonal precision matrix elements. However, a complication arises when the distribution is derived from sparse covariates, and further, there may be multiple instances of the model, as adjacent samples, each having their own parameter set. A Fused-LASSO-based penalty is proposed to additionally encourage parameter similarity across such adjacent samples, utilising the conditional covariate dependence structure as a regression. Fortunately, through a novel block-matrix formulation, it is shown that

the conditional model can be transformed and estimated via the Generalised LASSO. Both theoretical and computational results show that the prescribed optimisation offers accurate shrinkage for different dimensionalities and sample sizes, where increasing the latter also demonstrates asymptotic selection consistency when adapting the penalty weights. This presentation aims to outline the theoretical underpinnings, an example simulation study, and application considerations.