Name	Talk Title	Abstract
Colin Fox	Advances in computational inference for inverse problems	We discuss advances in computational inference for inference is tough.
Lutz Gross	Quasi-Newton methods with multi-grid preconditioning for solving large-scale 3D geophysical data inversion problems on parallel computers	The inversion of geophysical data is an optimization problem which is constraint by a set partial differential equations (PDEs) providing predictions of observations (e.g. electric potentials at certain locations) for a given distribution of the unknown physical properties (e.g. electric conductivity). The cost function is comprised of a measure of the data misfit and a regularization term. In contrast to conventional approaches introducing a discretization prior to optimization we apply the a quasi-Newton method, in this case the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method, in an appropriate function space for the unknown physical properties. The iteration process requires the solution of PDEs for the constraints and their adjoint problems which can be effectively implemented on parallel computers using the finite element method (FEM). The BFGS scheme constructs a low dimensional approximation of the Hessian which is inverted to be used as preconditioner. The efficiency of this self-preconditioning can hugely be improved by applying an algebraic multigrid (AMG) step to the degree that mesh independence of the convergence rate can be achieved. Moreover, the assemblage and inversion of a large and dense matrix to update the physical properties is avoided and the entire inversion scheme can be parallelized using domain decomposition. These are the two key features of the method that achieve weak scalability with the number of mesh cells across large parallel computers. We discuss the application of the method for the (virtual) monitoring of CO_2 injection using Electrical Resistivity Tomography (ERT) and gravity. Synthetic data generated from a multiphase, multicomponent CO_2 simulator provides predictions on the evolution of saturation, which is the target of the inversion. Electric conductivity and saturation are linked via a generalized Archie's law.
Janosch Rieger	Recent advances in domain reconstruction from electrical impedance	Electrical impedance tomography is an emerging budget-priced, non-invasive medical imaging technique that is very likely to complement computerised tomography in important applications such as pulmonary function control and breast cancer screening in the future. The main difficulty associated with this technology is that the arising inverse problem is strongly ill-posed. In this talk, I will discuss an alternative approach to domain reconstruction from electrical impedance tomography data, which is based on the concept of the convex source support introduced by Kusiak and Sylvester, as well as an appropriate numerical discretisation of the resulting problem.
Josef Dick	Quasi-Monte Carlo Methods in Uncertainty Quantification	In this talk we consider quasi-Monte Carlo rules which are based on (higher order) digital nets and their use in approximating expected values of solutions of partial differential equations (PDEs) with random coefficients. In particular, so-called interlaced polynomial lattice rules have attractive properties when approximating such integrals. These are applied for PDEs with uniform random coefficients, but can also be used in Bayesian inversion. In this talk we give an overview of recent
Benjamin Peherstorfer	Multifidelity Monte Carlo methods for rare event simulation	
Jesse Adams	MCMC-based Deconvolution with Reduced Boundary Artifacts and Non-negativity Constraints	Computationally efficient numerical methods for deconvolution algorithms often require choices for boundary conditions of the signal. The traditional choices, e.g. periodic, Dirichlet, and Neumann, make assumptions about the data outside of the signal domain which are often inconsistent with the physics of the data. Additionally, these methods for deconvolution can produce physically invalid reconstructions when the data has physically motivated constraints such as non-negativity. A regularized data-driven MCMC-based deconvolution in a Bayesian framework which allows for uncertainty quantification in the reconstruction with reduced boundary artifacts in the field of view. In this presentation i discuss additional progress I have implemented for this work, including the addition of an iterative approach to non-negativity constraints via Projected Newton, and optimizations that allow us to process larger images.
Tianhai Tian	Bayesian inference of stochastic models models using early rejection	
John Bardsley	Bayesian Methods and Uncertainty Quantification for Inverse Problems	

Elvar Bjarkason	Randomized Truncated SVD Methods for Accelerated Inversion and Approximate Uncertainty Quantification of Geothermal Reservoir Models	Geothermal reservoir simulations are typically slow and models made up of a few tens of thousands of model blocks can easily take hours to run. This is a considerable hindrance to model development since numerous simulations are required to invert a geothermal model with outputs governed by a large number of uncertain model parameters. Accurate uncertainty quantification of model parameters and outputs is hindered to an even larger degree since it requires significantly more simulations. The first issue of the time spent on a single inversion is addressed here by applying randomized low-rank matrix approximation methods to speed up model inversions using the Levenberg-Marquardt (LM) approach. Then we look at a randomized maximum likelihood (RML) approach as an inexpensive way of approximately quantifying uncertainty in model predictions. The RML method applied here uses the LM approach to minimize a stochastic objective function for an ensemble of model realizations. The LM method is commonly used for inverting models used to describe geothermal, groundwater, or oil and gas reservoirs. However, the standard LM approach requires explicitly forming and solving the linear LM update equations which is computationally impractical for highly parameterized inverse problems. For such problems matrix factorization methods or iterative inexact linear solvers are used to approximately solve the update equations Previous studies have shown that basing model updates on the truncated singular value decomposition (TSVD) of a dimensionless sensitivity matrix, achieved using Lanczos iteration, can speed up the inversion of reservoir models. The Lanczos method only requires the sensitivity matrix and its transpose times vectors, which are found efficiently using adjoint and direct simulations without the expense of forming a large sensitivity matrix. Nevertheless, this approach has the drawback of being a serial process, requiring an adjoint solve and a direct solve every Lanczos iteration. Randomized methods developed for low-rank approximation of large matrices are discussed as more efficient alternatives to the standard Lanczos method. LM variants are discussed here which use randomized methods to find a TSVD of the dimensionless sensitivity matrix at every inversion iteration. The randomized approach offers improved efficiency by simultaneous solution of the adjoint and direct simulations required at every inversion iteration. We look at comparing randomized TSVD methods against the Lanczos approach for a test case, based on matching the natural state and production history of a high enthalpy geothermal reservoir. The results show that inversions using the proposed non-iterative randomized methods resulted in very similar convergence characteristics to runs using Lanczos iteration, but required much less computational time. Finally a similar test case is used to look at the RML method for forecasting under uncertainty, when the model prior is described by a multivariate Gaussian distribution. The RML realizations are generated by applying the LM method speeded up by using randomized TSVD. The future behaviour of the true reservoir is then compared with the RML model predictions.
Kody Law	Multilevel Monte Carlo methods for Bayesian inference	The Bayesian posterior distribution is known only point-wise (possibly with an intractable likelihood) and up to a normalizing constant. Monte Carlo methods have been designed to sample such distributions, such as Markov chain Monte Carlo (MCMC) and sequential Monte Carlo (SMC) samplers. Recently, the multilevel Monte Carlo (MLMC) framework has been extended to some of these cases, so that approximation error can be optimally balanced with statistical sampling error, and ultimately the Bayesian inverse problem can be solved for the same asymptotic cost as solving the deterministic forward problem. This talk will concern the recent development of multilevel SMC (MLSMC) samplers and the resulting estimators for standard quantities of interest as well as normalizing constants. MLMC data assimilation methods, which combine dynamical systems with data in an online fashion, will also be presented, includingâ€‹ â€‹ML particle filters and ensemble Kalman filters. This class of algorithms are expected to become prevalent in the age of increasingly parallel emerging architecture, where resilience and reduced data movement will be crucial algorithmic considerations.
Marko Laine	Dimension reduction for remote sensing and data fusion	Remote sensing of vertical profiles of green house gases from satellites and ground based instruments typically results in ill-posed inverse problems, where the degrees of freedom of the signal is low and prior information has a significant role. To be able to efficiently extract the information content of the observations, likelihood informed dimension reduction is applied. Further, when observations from different sources are assimilated together, the procedure can be seen as high dimensional time series analysis. If the underlying fields to be modeled are smooth, we can utilize similar dimension reduction techniques. This will result as an efficient Kalman smoother algorithm. The talk will explain the theory behind the algorithms and give application examples in the field of environmental monitoring.

Kate Lee	weakly informative prior for mixture models	While mixtures of location-scale distributions have been studied for more than a century, the construction of a reference Bayesian analysis of those models still remains unsolved, with a general prohibition of the usage of improper priors due to the ill-posed nature of such statistical objects. By creating a new parameterisation cantered on the mean and variance of the mixture distribution itself, we are able to develop here a genuine weakly-informative prior for location-scale mixtures with an arbitrary number of components. We demonstrate that the posterior distribution associated with this prior is almost surely proper and provide MCMC implementations that exhibit the expected exchangeability.
Shev MacNamara	Robustness and sensitivity of stochastic models	Successful applications of stochastic modeling and simulation in biology are showcased by example. Random walks on a graph Laplacian provide a unifying framework. Markov processes with exponential waiting times are compared to non-Markov processes with non-exponential waiting times and with memory. Mittag-Leffler waiting times receive special attention. A Mittag-Leffler exclusion process is introduced. The sensitivity of a stochastic model to extrinsic variability is discussed. Attractive open questions and opportunities for future research are highlighted. Shev MacNamara, Bruce Henry, Bill McLean, "Fractional Euler Limits and their Applications," SIAM Applied Math Andreas Hellander, Jan Klosa, Per Lotstedt and Shev MacNamara, "Robustness analysis of spatiotemporal models in the presence of extrinsic fluctuations" SIAM Applied Math Gilbert Strang and Shev MacNamara "Functions of Difference Matrices are Toeplitz plus Hankel," SIAM Review. Arieh Iserles and Shev MacNamara "Magnus expansions and pseudospectra of master equations" https://arxiv.org/abs/1701.02522
Ellen B Le	1. Model Reduction via Domain Decomposition-based Methods for Large-Scale Inverse Problems	We present two computationally-efficient domain decomposition-based methods for solving inverse problems in high-dimensional parameter spaces. The methods are particularly relevant for problems with spatially concentrated observations and/or dynamics. For a synthetic PDE-constrained inverse problem we show the methods result in 1) an improved reconstruction over the full domain reconstruction and 2) in a reduced number of PDE solves over existing truncated domain methods and the full domain inversion. The key to both methods is a careful construction of the low-rank basis for the approximated Dirichlet-to-Neumann operator via a goal-oriented, model-constrained approach.
Hans De Sterck	Accelerated optimisation methods for matrix and tensor decompositions	
Qinian Jin	Regularisation of inverse problems by the alternating direction	
Heikki Haario	Assimilation and estimation for chaotic systems	
Ruanui Nicholson	Hierarchical Off-Diagonal Low-Rank Approximation for Hessians in Bayesian Inference	We address the problem of quantifying uncertainty in the solution of inverse problems governed by Stokes models of ice sheet flows within the framework of Bayesian inference. Computing the general solution of the inverse problem---i.e., the posterior probability density---is intractable with current methods on today's computers, due to the expense of solving the forward model (3D full Stokes flow with nonlinear rheology) and the high dimensionality of the uncertain parameters (which are discretizations of the basal sliding coefficient field). In this talk, we exploit the local sensitivity of data to parameters and build a hierarchically off-diagonal low-rank approximation for the Hessian (of the log posterior). This approximation will be applied as a preconditioner for a Newton-CG type method and for Hessian-based sampling in the inference of basal boundary conditions for ice sheet models. Preliminary results indicate that the HODLR pre-conditioner can be constructed using a significantly reduced number of modes of Hessian
Hoang Viet Ha	Multilevel MCMC for Bayesian Inverse Problems (this is a tentative title)	