

Poster Presenters	
P1	Sofia Agostoni , University of Genoa <i>Automatic regularisation approaches for 2D/3D Image Scanning Microscopy</i>
P2	Harshit Bajpai , Indian Institute of Technology Roorkee (IIT Roorkee) <i>Graph Laplacian Assisted Iterative Regularization for Ill-Posed Problems with Applications to Medical Imaging</i>
P3	Cristian Bonato , Heriot-Watt University <i>Reconstructing magnetisation of complex magnetic textures</i> <i>We are an experimental physics group using a quantum sensor based on a single spin to image magnetic textures in novel magnetic materials, with a particular interest on topological structures (i.e. skyrmions, bimerons). Reconstructing magnetisation from magnetic stray fields is an ill-posed inverse problem. We are currently tackling this with a simple fitting and regularisation but we would be very interested in exploring generative-AI approaches.</i>
P4	Arwa Dabbech , Heriot-Watt University <i>A deep-learning approach for joint calibration and imaging in radio astronomy</i>
P5	Zeljko Kereta , University College London <i>Trajectory Stitching for Solving Inverse Problems with Flow-Based Models</i>
P6	Teresa Klatzer , University of Edinburgh <i>Mirror Langevin Dynamics with Plug-and-Play Priors for Poisson Inverse Problems</i>
P7	Arthur Leclaire , Telecom Paris <i>Controllable Blind Deblurring with Diffusion Models</i>
P8	Cristiano Parenti , University of Modena and Reggio Emilia <i>An Inexact-Proximal Plug-and-Play Method with Line Search for Nonconvex Inverse Problems</i> <i>This is a joint work with Professors Silvia Bonettini and Marco Prato.</i>
P9	Gabriele Scrivanti , MaLGA center, DIBRIS, Università di Genova <i>A self-supervised approach for quantitative parameter estimation in fluorescence microscopy for stable design of photovoltaic materials</i>
P10	Jonathan Spence , Heriot-Watt University <i>Deep Unfolding of MCMC Kernels</i> <i>Markov chain Monte Carlo (MCMC) methods are fundamental to Bayesian computation, but can be computationally intensive, especially in high-dimensional settings. Push-forward generative models, such as generative adversarial networks (GANs), variational auto-encoders and normalising flows offer a computationally efficient alternative for posterior sampling. However, push-forward models are opaque as they lack the modularity of Bayes Theorem, leading to poor generalisation with respect to changes in the likelihood function. In this work, we introduce a novel approach to GAN architecture design by applying deep unfolding to Langevin MCMC algorithms. This paradigm maps fixed-step iterative algorithms onto modular neural networks, yielding architectures that are both flexible and amenable to interpretation. Crucially, our design allows key model parameters to be specified at inference time, offering robustness to changes in the likelihood parameters. We train these unfolded samplers end-to-end using a supervised regularized Wasserstein GAN framework for posterior sampling. Through extensive Bayesian imaging experiments, we demonstrate that our proposed approach achieves high sampling accuracy and excellent computational efficiency, while retaining the physics consistency, adaptability and interpretability of classical MCMC strategies.</i>
P11	Bernardin Tamo Amougou , Heriot-Watt University <i>An Equivariant Self-Supervised VAE for Uncertainty Quantification in Bayesian Imaging Problems</i>

P12	<p>Pierre-Antoine Thouvenin, Centrale Lille</p> <p><i>CARDS: a Python library of Composable Algorithms for Reproducible Distributed Sampling</i></p> <p><i>Implementing efficient distributed samplers to address high-dimensional inverse problems is a challenging task. This is especially difficult for samplers combining different transition kernels to fully exploit parallel computing opportunities inherent to the target posterior distribution. To address this issue, this poster introduces CARDS, a Python library aimed at facilitating the implementation of distributed samplers over multiple CPUs or GPUs. The main software design choices and features currently implemented in the library will be emphasized. Joint work with Maxime Bouton, Stéphane Despieres and Pierre Chainais.</i></p>
P13	<p>Xiaoyu Wang, Heriot-Watt University</p> <p><i>Scalable training of stochastic spiking neural networks</i></p>
P14	<p>Lingyi Yang, University of Nottingham</p> <p><i>Distilling score-based diffusion models with path signatures</i></p>