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## **S1704. Bayesian uncertainty quantification in pore-scale imaging: how to robustly infer porous media morphological properties through reactive inverse problems?**

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Pore-scale modelling and simulation of reactive flows are usually built upon X-ray microtomography experiments that provide the internal and complex geometries of the porous media. Although these models offer the opportunity to study the evolution of the macroscale properties in the context of CO<sub>2</sub> storage, they suffer from measurement uncertainties arising from the pore-scale imaging process. Image artefacts, including noise and unresolved morphological features, are such limitations and require data-driven methods with uncertainty quantification. This aims to improve the reliability of the numerical modelling through better identification of the morphological properties using reactive inverse problems.

However, developing an efficient data-assimilation framework that robustly addresses such multi-objective and multi-scale inverse problems remains challenging. Therefore, we propose a novel adaptive strategy for unbiased uncertainty quantification in Bayesian Physics-Informed Neural Networks, which relies on an automatic weighting of the target distribution parameters and objectives. It benefits from enhanced convergence and stability compared to conventional formulations and reduces sampling bias by avoiding manual tuning of the critical weights. The adjusted weights also bring information on the task uncertainties and improve the reliability of the noise-related and model adequacy estimates.

In this presentation, we focus on the improvements and efficiency of this new approach on various benchmarks, including comparisons with an analytical baseline, and Computational Fluid Dynamics applications. We also apply this auto-weighting in Bayesian Physics-Informed Neural Networks on pore-scale imaging uncertainty quantification. In this direction, we aim to quantify unresolved features in porous media X-ray microtomography and capture morphological uncertainties on the porosity field.

