Post-doctoral project

Bayesian inference for cosmology: Inferring initial conditions of the local cosmic web

Postdoc Jan.2024 – Dec. 2025

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Dates: 24 months; the starting date around January or February 2024, can be adjusted depending on the availability of the successful candidate.

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Keywords: Inverse problem, cosmological simulation model, physics-informed training, Bayesian inference, MCMC algorithms.

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1 Project overview

According to the standard cosmological model, about 95% of the Universe is dark. Recent large survey analyses reveal tensions with this model. For instance, the local measurement of the expansion rate and the estimate of the Universe homogeneity differ by more than three standard deviations from those inferred with the first light of the Universe. The cosmological heated debate is to work out whether these tensions are a signature of new physics or of systematic biases in the observation processing pipeline. Part of this pipeline relies on cosmological simulations to act as the missing ground truth. However, the simulations only statistically reproduce the local cosmic web. A new type of simulations, qualified as constrained, is emerging. Initial velocity and density fields of such simulations stem from observational constraints.

This post-doctoral project is aimed at inferring the initial velocity and density fields of the local cosmic web from today's luminosity distances and observational redshifts measurements. This high-dimensional astrophysical inverse problem is challenging. In particular, it will leverage a large number of measurements (Bayer et al. 2023; Prideaux-Ghee et al. 2023). The absence of ground truth data calls for reliable estimators with associated uncertainty quantification. This motivates the use of Markov chain Monte-Carlo (MCMC) algorithms to access posterior distributions. The hierarchical model relies on a costly cosmological simulator to describe the evolution of cosmological objects from the initial conditions. A first step will be to replace the black-box simulator in the inference algorithm by a tractable surrogate model trained on a grid of simulations, in the spirit of (Dai et al. 2023; Jindal et al. 2023; Raissi et al. 2019). The second step will focus on the design of a high-dimensional MCMC algorithm to infer the parameters of interest (Coeurdoux et al. 2023a,b; Durmus et al. 2018; Vono et al. 2020).

Keywords. Inverse problem, cosmological simulation model, Bayesian inference, MCMC algorithms.

2 Scientific context

The project is part of the *ANR Chaire IA SHERLOCK* (*Fast inference with controlled uncertainty: application to astrophysical observations*) led by Pierre Chainais (co-funded by Agence Nationale de la Recherche (ANR), I-SITE, Centrale Lille Institut and Région Haut-de-France). The successful candidate will be jointly supervised by Jenny Sorce (CNRS Researcher in cosmology), Pierre Chainais (Professor, Centrale Lille) and Pierre-Antoine Thouvenin (Assoc. Prof., Centrale Lille) in the CRIStAL lab (UMR 9189), Lille, France.

Access to the medium scale computing center from the Universtiy of Lille is acquired, with the possiblility to apply for computing resources from the national flagship Jean Zay supercomputer. In addition, 7 million cpu.hours have been secured at TGCC on the Irene/Rome partition. They will be used to produce the simulations required to trained the surrogate model.

3 Profile and requirements

PhD in signal/image processing, computer science or applied mathematics. The project requires a strong background in data science and/or machine learning (statistics, optimization), signal & image processing. Very good Python coding skills are expected. A B2 English level is mandatory.

Knowledge in C++ programming, as well as experience or interest in parallel/distributed code development (MPI, OpenMP, CUDA, ...) will be appreciated.

4 Application procedure

Applicants are invited to email the following documents as a single `.pdf` file to all the co-advisors:

- a detailed curriculum, including a list of publications;
- link to the PhD manuscript (or PhD project if upcoming defense);
- reports from PhD reviewers if available;
- a cover letter;
- references: recommendation letters or names of 2 researchers/professors recommending your application.

For further information, please contact the co-advisors of the project:

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- Pierre Chainais, pierre.chainais@centralelille.fr.

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