Master internship and thesis offer

Neural network prior and full Bayesian sampling for inverse problems

Scientific context: Inverse problem, deconvolution, deep learning, Bayesian strategy.

Signal-image-vision issues: Prior learning, posterior sampling, conditional generators,...

Involved tools: Invertible networks, normalizing flow, stochastic sampling, MCMC, Langevin/Hamilton.

Possible application fields: Imaging in physics, astronomy, medicine, remote sensing, industry,...

Computing environment: Matlab, PC.

Location: Groupe Signal – Image, IMS, Talence, France.

Duration internship: Five or six months starting in January or February 2022.

Supervisors: J.-F. Giovannelli and G. Bourmaud, Groupe Signal – Image, IMS, Talence and collaboration with F. Champagnat, DTIM / Unité Image, Vision, Apprentissage, ONÉRA, Palaiseau.

Doctoral study: The internship will open to a PhD thesis on the subject.

Contact: J.-F. Giovannelli (`Giova@IMS-Bordeaux.fr`).

The fast development of neural networks and deep learning methodologies [1] opens the way to new solutions for large scale inverse problems [2–4]. In particular, in the Bayesian framework [5, 6], the prior distribution can be learned from a bunch of examples characteristic of the considered field of interest. This contrasts with the standard methods based on general all-purpose priors (see figure) usually designed within restricted parametric distribution families [3, 4, 7]. Whatever the approach, standard or neural network, the Bayesian strategy provides a tool of choice for uncertainty quantification and statistical analysis, in particular *via* posterior sampling of the unknowns given the measurements. See [8, 9] for the neural network approach or [5, 6] for a more general view.

The designed prior will be next combined to the distribution of the measurements (likelihood) to provide the posterior, the latter being sampled by means of an MCMC algorithm, for instance in the AGEM framework [10]. On the methological side, this framework is presently tied to a particular class of networks (the denoising autoencoders) and we plan to generalize to invertible network architectures [9, 11] that enable explicit manipulation of sample likelihood, a potential asset for sampling algorithms, such as Langevin or Hamilton MCMC samplers.

A first instance of this methodology (learning, sampling, imaging including uncertainties) will be developed in the context of the internship: select a simple network architecture, gather a first learning database (already available), learn and test the model. The objective of the thesis is to proceed on the design, implementation and assessment of such approaches on cases of increasing complexity.

In addition, the AGEM framework presents another essential interest in practice: it affords adaptive tuning to operating conditions not met during the learning phase. In particular, it enables to consider different extensions toward hyperparameter estimation. Besides, AGEM exploits a Monte

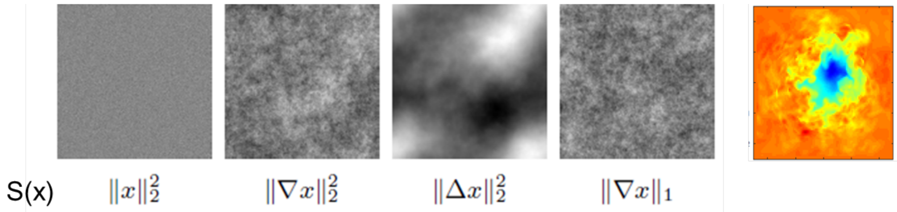

Figure 1: Typical sample of prior. On the left: four samples of “all purpose” prior with various Gibbs energy (from [8]) and on the right: a typical image of gas distribution (from [13]).

Carlo EM approach for hyperparameter estimation, and it is potentially more efficient to develop fully Bayesian approaches where hyperparameters themselves are attributed a prior [7, 12].

Such tools for image reconstruction and uncertainty quantification are of major interest in a wide range of modalities for various fields: physics, astronomy, medicine, remote sensing, industry,. . . A focus could be put on the domain of aerospace and the field of fluid mechanics, more specifically turbulent flows, for example tomography of gas density for aerodynamics and propulsion [13, 14] or particle image velocimetry [15]. In the latter, the methodology could be demonstrated on experimental data gathered from various experimental facilities developed at ONÉRA, *e.g.,* multiview holographic bench [14] or particle image velocimetry [15]. In such cases, the realism of the bunch of examples can be ensured by numerical simulations thanks to exactly-controlled physical models. In order to improve the generalization capability of our networks to experimental data, the bunch of example could be enriched with high resolution measurements for complex flows and constrained observation conditions (turbulent flows, scarcer measurements).

References

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