ID de Contribution: **14**

Type: **Non spécifié**

E. Moulines : Solving Bayesian Inverse Problems Using Denoising Diffusion Models

jeudi 12 septembre 2024 16:40 (40 minutes)

Solving Bayesian Inverse Problems Using Denoising Diffusion Models

joint work with: Alain Oliviero-Durmus, Yazid Janati-El-Idrissi (post-doc), Badr Moufad (PhD), Mehdi Abou El Qassime (PhD), Ahmed Ghorbel (Ing), Lisa Bedin (Ing), Ecole polytechnique & FX-Conseil, J. Olsson, KTH, S. Le Corff, Sorbonne Université.

The growing interest in the use of Denoising Diffusion Models (DDMs) as fundamental elements for solving inverse Bayesian problems has recently marked a significant trend. The application of DDMs in this context offers a promising way to harness complex prior distributions. However, one of the major hurdles in this approach is the difficulty of sampling from the posterior distribution that arises when DDMs are used as priors. This challenge is primarily due to the complicated dynamics and high-dimensional nature of the diffusion processes involved.

To overcome this obstacle, previous research efforts have focused on developing strategies to modify the drift term within the diffusion process. These modifications aim to better approximate the true posterior distribution, albeit often at the cost of introducing bias or increased computational complexity. While useful, such methods do not target the “true” posterior.

Our work introduces a novel paradigm that takes advantage of the unique structural properties of DDMs. We propose a systematic decomposition of the posterior sampling into a sequence of more manageable intermediate tasks. Each of these tasks is designed to progressively refine the approximation of the posterior distribution, utilizing the structure of the DDM prior to effectively guide the sampling process. With this methodology, we can achieve a more accurate approximation of the posterior distribution and significantly reduce the approximation error compared to previous approaches.

Our empirical investigations emphasize the effectiveness of our proposed method in a wide range of applications, ranging to image restoration, ECG reconstruction to urban mobility simulation.
This work therefore sets a new benchmark for the use of denoising-diffusion models in solving inverse Bayesian problems and provides both theoretical insights and practical advances in the field.