Questions and answers - Francois Lanusse Lecture 1

The following questions were submitted through Google Form. Some may have been answered in the Q&A session already. Nevertheless, we request our lecturers to provide written answers here for the benefit of those who could not attend that session. Thank you!

Slide not specified. Your talk about Deep Priors remind me about a paper titled "Deep image prior" (DIP) (https://arxiv.org/abs/1711.10925) where the researchers use implicit regularization effect imposed from the CNN structure to solve the inverse problem in CV such as denoising and imprinting. I have seen researchers in geophysics using DIP to solve the inverse problem. Do you think there is a potential to apply DIP to the inverse problem you are working on? Also, I'd like to learn more about the implicit regularization effect in ML. The DIP paper only gives empirical explanation of the implicit regularization effect from the CNN, but not mathematical explanation. If you have any suggestions about the literature on this topic, I would be very appreciated. Thanks!

Answer: As yes, as you say "Deep Image Priors" was more about saying that CNNs provide a good inductive bias to discriminate between reconstruction artifacts and signals. You can certainly use that property to regularize the solution of an inverse problem, but, as you say, we do not know exactly what are the assumptions/priors on the signal that are leveraged this way.
This is a similar situation to classical regularization techniques for inverse problems such as sparsity in wavelet space and broader compressed sensing techniques. These worked well enough to regularize inverse problems, but the priors that they impose on the solution are not something we can motivate from a physics perspective.
The difference with using generative models as priors is that we train them explicitly on simulations or data that we understand to represent a physically motivated prior for the problem we are trying to solve.