Likelihood-informed subspace for high-dimensional particle filters

Master research internship proposal

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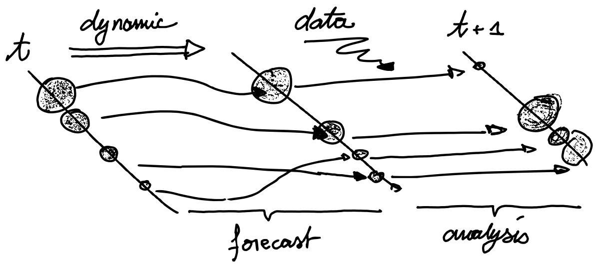
Context. One of the many achievements of computer aided simulations has been the sharp improvement in the human prediction capabilities of weather and climate, with undeniable benefits for society: agricultural planning, extreme weather preparedness, mitigation of climate change effects, etc. The quality of the simulations rely on the ability to acquire data about the present state and the past state and to assimilate these data in the numerical model to make reliable predictions. This is referred as data assimilation.

Data assimilation can be viewed as a large-scale Bayesian inverse problem. It requires the estimation of the probability probability distribution of the state variables, at a given time, conditionned on all the previously observed measurement data. Particle filter algorithms receive a growing attention from the data assimilation community [1]. They consists in sampling the state space in places where the data could appear. However they perform poorly for large state space dimension [2,3].

Goals. Particle filter methods rely on a collection of state space point (the particles) associated with weights which are used to represent the probability distribution of a dynamical system of state variables. Going from time t to $t+1$ requires a two-steps update: (i) the *forecast*, which transports the particle according to the dynamic of the model, and (ii) the *analysis*, which assimilates the data observed at time $t+1$. The performance of the method strongly relies on the efficiency of the second stage, that is how the new particles/weights properly accounts for the conditioning on the data. In order to guaranty stable analysis step, standard approaches (reweighting and/or resampling) require the number of particles to growth exponentially with the state space dimension [3], which is unfeasible for high-dimensional problems.



The goal of this internship is to leverage novel gradient-based dimension reduction techniques [4] in order to design effective particle filter methods in high-dimension. The idea is to find a low-dimensional subspace of the state space where the data *will be* informative. This will allow the reduction of the analysis space and, hopefully, yield better performances.

After a literature study, the intern will test the feasibility of the idea on academic models (Lorentz for example). Extension to problems of larger dimension will be eventually considered. This internship can lead to a PhD, where an application to realistic ocean models is foreseen. This work is part of an ongoing collaboration with Monash University and MIT (https://team.inria.fr/unquestionable/).

Prerequisites. Applied math skills (optimisation, numerical analysis, probability / statistics) and programming skills (Matlab, python, C or Fortran)

Bibliography

[1] P.J. van Leeuwen. Data Assimilation for the Geosciences. chapter Particle filters for the Geosciences. Oxford University Press Blue Book Series, 2014.
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[3] Snyder, C., Bengtsson, T., Bickel, P. and Anderson, J., 2008. Obstacles to high-dimensional particle filtering. Monthly Weather Review, 136(12), pp.4629-4640.
[4] Zahm, O., Cui, T., Law, K., Spantini, A. and Marzouk, Y., 2018. Certified dimension reduction in nonlinear Bayesian inverse problems. arXiv preprint arXiv:1807.03712.