ICMS Edinburgh 3-7 June

Location: Bayes Centre 5th floor (turn right out of the lift)

Modelling particle-laden turbulent flows with neural stochastic differential equations

Speaker: **Josh Williams**, STFC Hartree Centre

Large eddy simulation/ Navier-Stokes equation

timescale for the friction?? What is this?

Feed-forward Neural Network

Network inference in a stochastic multi-population neural mass model via approximate Bayesian computation

Speaker: **Irene Tubikanec**, Johannes Kepler University Linz

Paper: https://arxiv.org/abs/2306.15787

Solving 6N-dimensional SDEs

stochastic Hamiltonian type of SDEs:

Numerical method:

Mean-square convergent of order

Splitting method

Fourier Transform in nSMC-ABC algorithm maybe link the Memory friction

High Rank Path Development: an approach of learning the filtration of stochastic processes

Speaker: **Hao Ni**, University College London

Hilbert-Schmidt distance: (distance of two matrices)

Too theoretical for me. So many notation about space. Couldn't follow during the talk.

Learning mean field models from data

Speaker: **Grigoris Pavliotis**, Imperial College London

Papers: Related to Non-Markovian and Mean Field Limit in SDE

Mean field limits

McKean–Vlasov process: wiki or Mean Field Limit in SDE (Fokker-Planck equation of a interacting parcticles process)

We consider the following system of one-dimensional interacting particles over the time interval $[0,T]$

$$\begin{aligned} \mathrm{d}X_t^{(n)} &= f(X_t^{(n)};\alpha)\,\mathrm{d}t + \frac{1}{N}\sum_{i=1}^{N} g(X_t^{(n)} - X_t^{(i)};\gamma)\,\mathrm{d}t + \sqrt{2h(X_t^{(n)};\sigma)}\,\mathrm{d}B_t^{(n)}, \\ X_0^{(n)} &\sim \nu, \qquad n = 1,\dots,N, \end{aligned} \tag{1}$$

where N is the number of particles, $\{(B_t^{(n)})_{t\in[0,T]}\}_{n=1}^N$ are standard independent one dimensional Brownian motions, and ν is the initial distribution of the particles, which is assumed to be independent of the Brownian motions $\{(B_t^{(n)})_{t\in[0,T]}\}_{n=1}^N$. We remark that we assume chaotic initial conditions, meaning that all the particles are initially distributed according to the same measure. The functions f, g and h are the drift, interaction, and diffusion functions, respectively, which depend on some parameters $\alpha \in \mathbb{R}^{J+1}$, $\gamma \in \mathbb{R}^{K+1}$ and $\sigma \in \mathbb{R}^{L+1}$.

We focus our attention on large systems, i.e., when the number of interacting particles is $N \gg 1$, and therefore it is reasonable to look at the mean field limit (see, e.g., \cite{Daw83,Gar88}), which provides a good approximation of the behavior of a single particle in the system. In particular, letting $N \to \infty$ in (1) we obtain the nonlinear, in the sense of McKean, SDE

$$\begin{aligned} \mathrm{d}X_t &= f(X_t;\alpha)\,\mathrm{d}t + (g(\cdot;\gamma) * u(\cdot,t))(X_t)\,\mathrm{d}t + \sqrt{2h(X_t;\sigma)}\,\mathrm{d}B_t, \\ X_0 &\sim \nu, \end{aligned} \tag{2}$$

where $u(\cdot;t)$ is the density with respect to the Lebesgue measure of the law of X_t, and satisfies the nonlinear *Fokker--Planck equation* named **McKean--Vlasov equation**

$$\begin{aligned} \frac{\partial u}{\partial t}(x,t) &= -\frac{\partial}{\partial x}(f(x;\alpha)u(x,t) + (g(\cdot;\gamma) * u(\cdot,t))(x)u(x,t)) + \frac{\partial^2}{\partial x^2}(h(x;\sigma)u(x,t)) \\ u(x,0)\,\mathrm{d}x &= \nu(\mathrm{d}x). \end{aligned}$$