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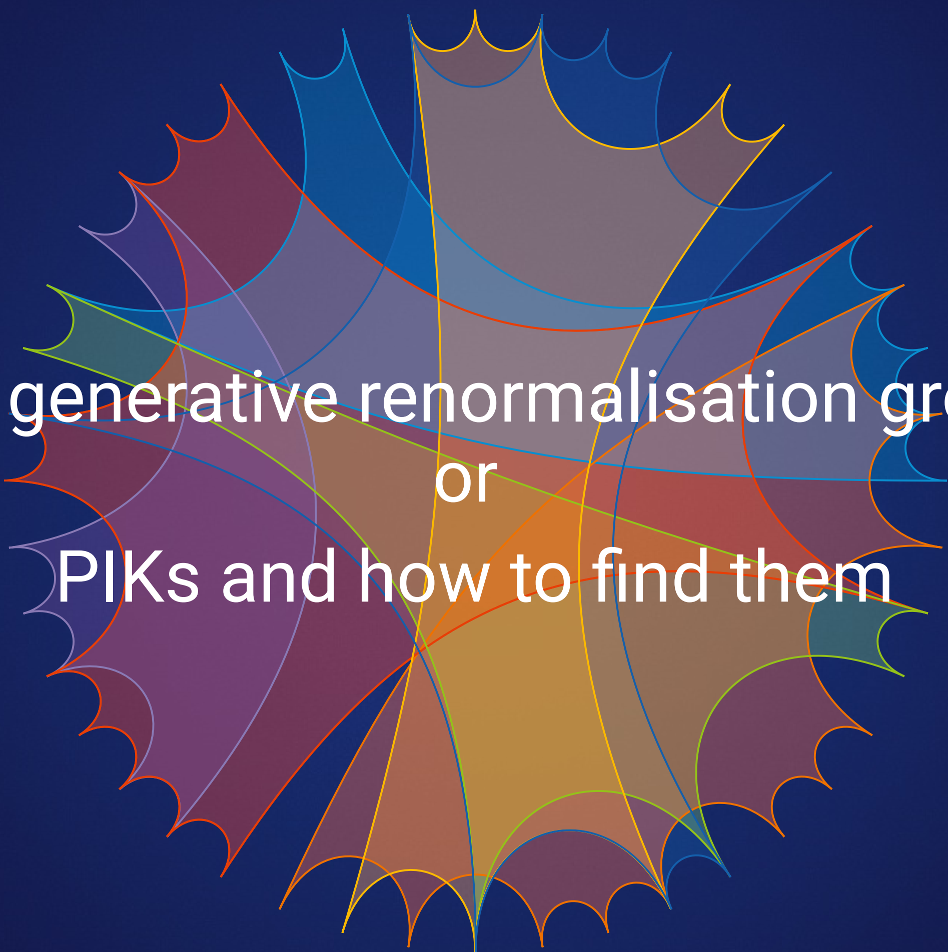

The generative renormalisation group
or
PIKs and how to find them

January 30, 2026, 1:30 PM, Phil 12 GHs

COFFEE & SNACKS IN ROOM 106

ZOOM: Meeting ID: 935 6549 3662, Code: 928036

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ABSTRACT

Renormalisation group (RG) maps can be understood as general reparametrisations of a given statistical distribution or data set. Moreover, RG-flows provide an analytic access to the reparametrisation map. This can be used to simplify sampling tasks in large dimensional (data) spaces with non-Gaussian distributions: In general, these sampling tasks are numerically expensive and show a bad scaling with the size of the data space. Specifically interesting and well-defined examples for such tasks are lattice field theories, the discete formulations of quantum field theories.

We use the analytic form of the RG-map (or rather its kernel) to recast the sampling task with a given distribution as one with a 'simple' distribution that can be efficiently sampled, combined with the task of solving a linear partial differential equation for the map. Then, the kernel encodes the non-trivial information (physics) of the distribution and is hence called a physics-informed kernel (PIK).
While this is similar to Machine Learning architectures such as normalisation flows or diffusion models it avoids the out-of-domain problems present in these architectures.

The application of the architecture is illustrated within simple low dimensional examples, also discussing briefly the extension to complex distributions. There we aim at the solution of sign problems, and a comparison of our setup with standard sampling methods for complex distributions (Complex Langevin, Lefschetz thimbles and alikes) reveals that our architectures avoids the problems encountered there.

Sources:

(1) Generative sampling with physics-informed kernels: https://arxiv.org/abs/2510.26678
(2) Solving sign problems with physics-informed kernels: in preparation
(3) talks at Noto-Workshop on Machine Learning and Physics 2025: http://www.thphys.uni-heidelberg.de/~pawlowsk/talks/talksNoto2025_Pawlowski.pdf

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