

Contrasting Discrete and Continuous Time Methods for Bayesian System Identification

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Often we want to identify models governed by stochastic differential equations, but usually we use discrete time models for learning.

$$\begin{aligned} \mathbf{x}_{t+\delta} &= \mathbf{f}_{DT}(\mathbf{x}_t) + \mathbf{L}_{DT}\kappa_t \quad \text{or} \quad d\mathbf{x}_t = \mathbf{f}_{CT}(\mathbf{x}_t) \, dt + \mathbf{L}_{CT} \, d\beta_t \\ \mathbf{y}_i &= \mathbf{g}(\mathbf{x}_{t_i}) + \rho_i \end{aligned}$$

Each $\kappa_t \sim \mathcal{N}(0, I)$ independently, each $\rho_i \sim \mathcal{N}(0, R)$ independently. β_t is standard *D*-dimensional Brownian motion.



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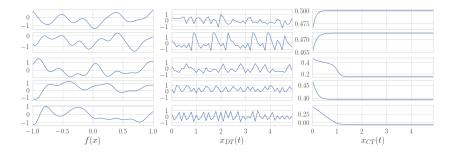
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Bayesian modelling: $f \sim \mathcal{GP}(m, k)$



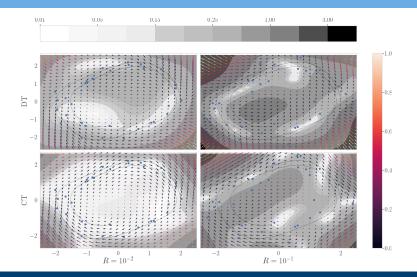
Contrasting priors



The prior samples are qualitatively different unless f_{DT} is a diffeomorphism.



Contrasting posteriors





Conclusions

- Discrete and continuous time priors have important differences
- These impact the quality of posteriors in challenging learning scenarios
- But CT models are expensive and challenging–a good way of constructing diffeomorphic DT priors would be appealing.

