Simulation-based inference

Cranmer, Kyle, Johann Brehmer, and Gilles Louppe. "The frontier of simulation-based inference." PNSA 117.48 (2020): 30055-30062.
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Neural posterior estimation

Likelihood-free inference

Train a *conditional* neural network w/ *in silico* simulations on pairs $\{(\mathbf{x}^{(m)}, \mathbf{y}^{(m)})\}_{m=1}^{M}$

$$\mathbf{y} \sim p(\mathbf{y} \,|\, \mathbf{x}) \quad \Longleftrightarrow \quad \mathbf{y} = \mathrm{g}(\mathbf{x}, \zeta)$$

where $\zeta \sim p(\zeta \,|\, \mathbf{x})$ with $\mathbf{x} \sim p(\mathbf{x})$

Given these pairs train via

$$\underset{\phi, \psi}{\text{minimize}} \frac{1}{M} \sum_{m=1}^{M} \left(\frac{1}{2} \left\| f_\phi \left(\mathbf{x}^{(m)}; h_\psi(\mathbf{y}^{(m)}) \right) \right\|_2^2 - \log \left| \det J_{f_\phi}^{(m)} \right| \right)$$

- f_ϕ is the *inference network* defined by a *Conditional Normalizing Flow* (CNF)
- h_ψ is a learned *summary* statistic yielding $MI\left(\mathbf{x}, h_\psi(\mathbf{y})\right) \approx MI\left(\mathbf{x}, \mathbf{y}\right)$