

Sampling

from the *posterior* distribution

After training on *in silico* pairs:

$$\{(\mathbf{x}^{(m)}, \bar{\mathbf{y}}^{(m)})\}_{m=1}^M$$

posterior samples conditioned on *summarized* field data $\bar{\mathbf{y}}^0$ are drawn via

$$\mathbf{x} \sim p_{\hat{\phi}}^{-1}(\mathbf{x} \mid \bar{\mathbf{y}} = \bar{\mathbf{y}}^0) \iff \mathbf{x} = f_{\hat{\phi}}^{-1}(\mathbf{z}; \bar{\mathbf{y}}^0) \quad \text{with} \quad \mathbf{z} \sim N(\mathbf{0}, \mathbf{I})$$

► CNF is *amortized*

► training *marginalizes* forward KL divergence $\mathbb{E}_{\mathbf{y} \sim p(\mathbf{y})} \left[\mathbb{KL} \left(p(\mathbf{x} \mid \mathbf{y}) \parallel p_{\phi}(\mathbf{x}) \right) \right]$

Dynamic simulation-based inference