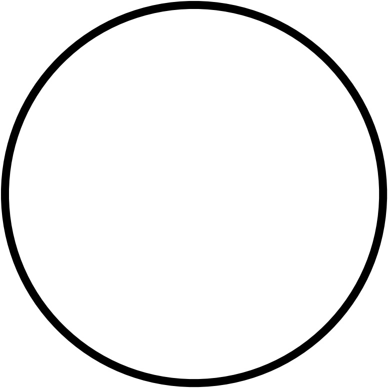
SLIM

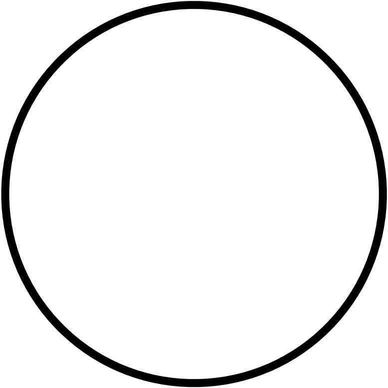
ML4Seismic

Learned Sequential Bayesian Inference

Train conditional NF on samples $(\mathbf{x}_k, \mathbf{y}_k) \sim p(\mathbf{x}_k, \mathbf{y}_k)$ **via**

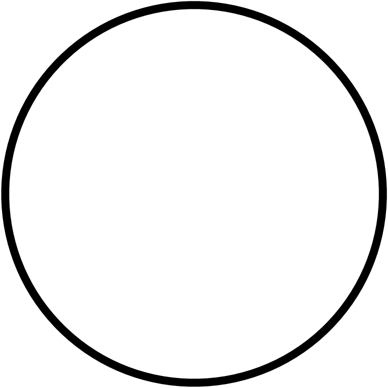
$$\hat{\phi} \ = \arg\min_{\phi} \frac{1}{N} \sum_{m=1}^{M} \left(\|f_\phi(\mathbf{x}_k^{(m)}; \mathbf{y}_k^{(m)})\|_2^2 - \log \left| \det \mathbf{J}_{f_\phi} \right| \right)$$

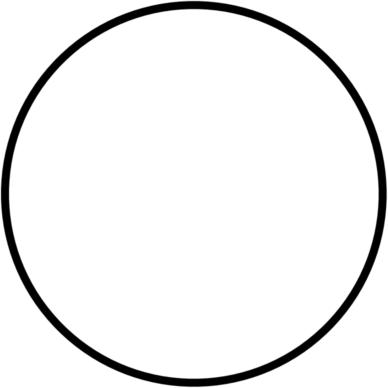




$$\mathbf{x}_{k-1}$$

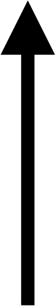
$$\mathbf{x}_k$$

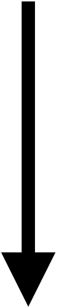




$$\mathbf{y}^{\mathrm{o}}_{k-1}$$

$$\mathbf{y}_k$$





[redacted] [redacted] [redacted] [redacted] [redacted] [redacted]

given $\mathbf{y}^{\mathrm{o}}_{k-1}$ generate training samples $(\mathbf{x}_k, \mathbf{y}_k) \sim p(\mathbf{x}_k, \mathbf{y}_k)$

Create training ensemble by sampling

- prev. state $\mathbf{x}_{k-1} \sim p(\mathbf{x}_{k-1} \,|\, \mathbf{y}^{\mathrm{o}}_{k-1})$
- permeability $\mathbf{K} \sim p(\mathbf{K})$

Apply dynamics $\mathbf{x}_k = \mathscr{M}_{k-1}(\mathbf{x}_{k-1}, \mathbf{K})$

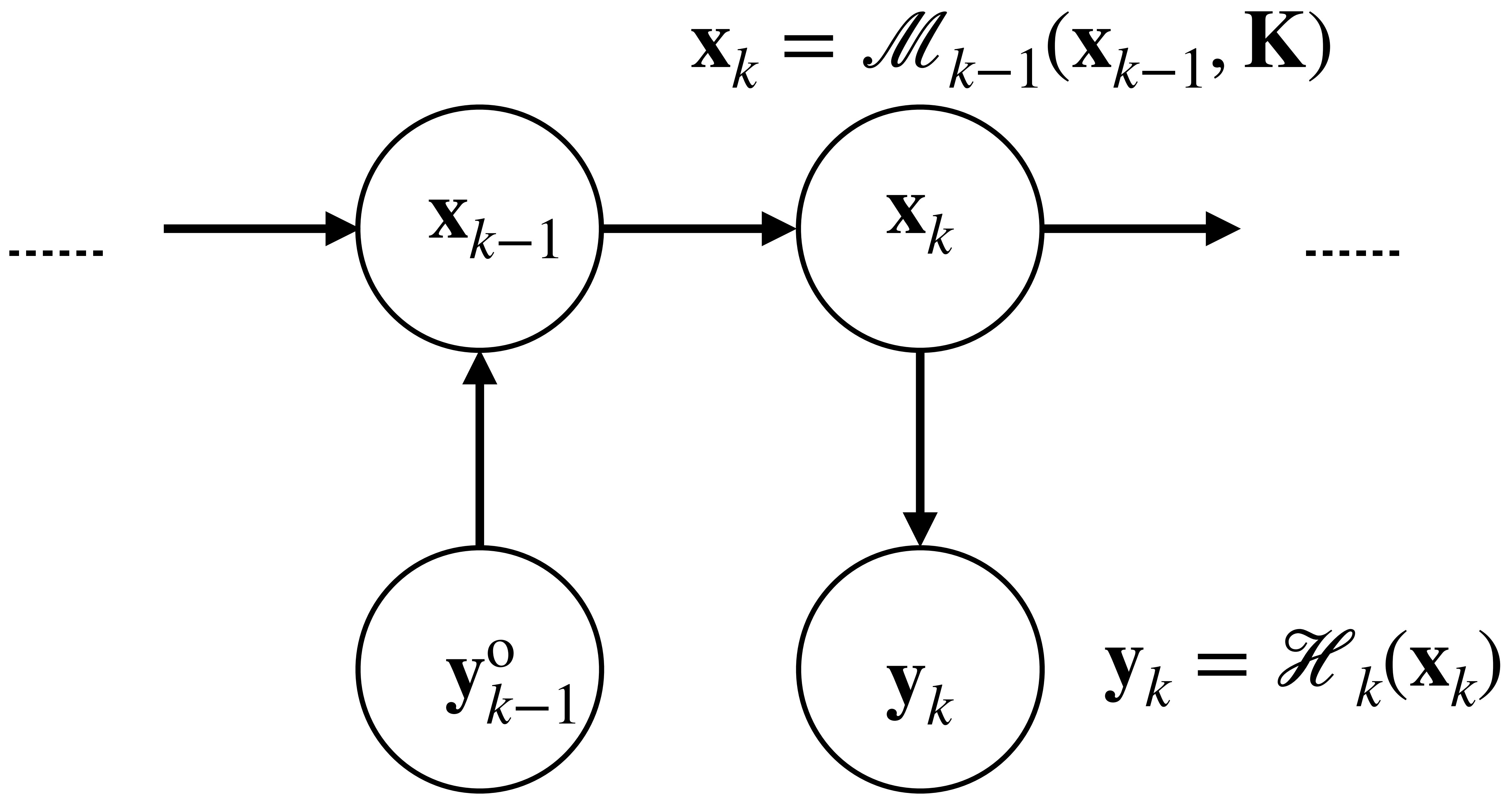
Simulate data $\mathbf{y}_k = \mathscr{H}_k(\mathbf{x}_k)$

$$\mathbf{x}_k = \mathscr{M}_{k-1}(\mathbf{x}_{k-1}, \mathbf{K})$$

$$\mathbf{y}_k = \mathscr{H}_k(\mathbf{x}_k)$$

Learned Sequential Bayesian Inference

given $\mathbf{y}^{\mathrm{o}}_{k-1}$ generate training samples $(\mathbf{x}_k, \mathbf{y}_k) \sim p(\mathbf{x}_k, \mathbf{y}_k)$



Create training ensemble by sampling

- prev. state $\mathbf{x}_{k-1} \sim p(\mathbf{x}_{k-1} \,|\, \mathbf{y}^{\mathrm{o}}_{k-1})$
- permeability $\mathbf{K} \sim p(\mathbf{K})$

Apply dynamics $\mathbf{x}_k = \mathscr{M}_{k-1}(\mathbf{x}_{k-1}, \mathbf{K})$

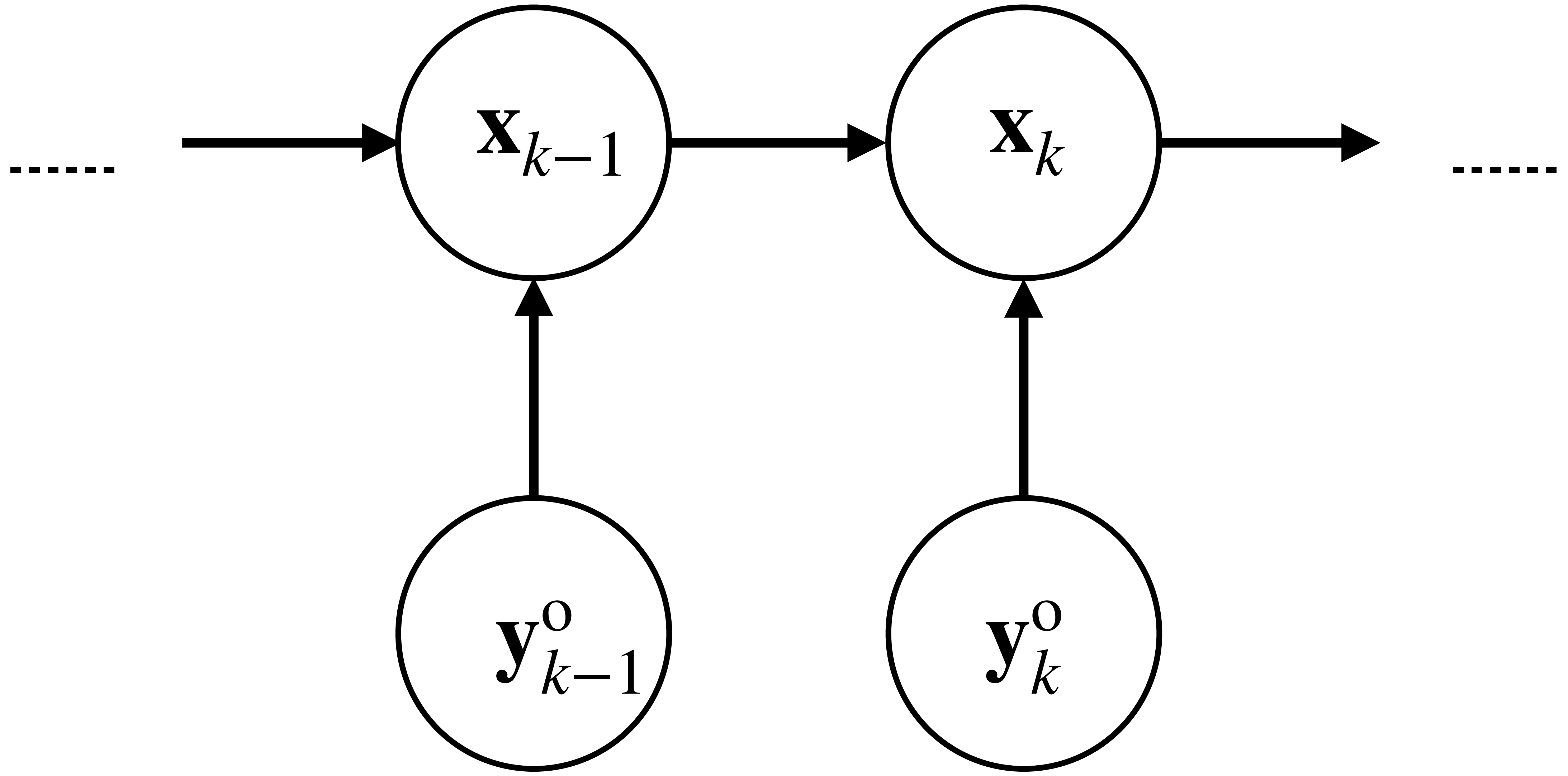
Simulate data $\mathbf{y}_k = \mathscr{H}_k(\mathbf{x}_k)$

Train conditional NF on samples $(\mathbf{x}_k, \mathbf{y}_k) \sim p(\mathbf{x}_k, \mathbf{y}_k)$ via

$$\hat{\phi} = \underset{\phi}{\arg\min} \frac{1}{N} \sum_{m=1}^{M} \left(\|f_\phi(\mathbf{x}_k^{(m)}; \mathbf{y}_k^{(m)})\|_2^2 - \log \left| \det \mathbf{J}_{f_\phi} \right| \right)$$

Learned Sequential Bayesian Inference

sample from posterior $\mathbf{x}_k \sim p(\mathbf{x}_k \mid \mathbf{y}_k^{\mathrm{o}})$



Sample from posterior $\mathbf{x}_k \sim p(\mathbf{x}_k \mid \mathbf{y}_k^{\mathrm{o}})$ via $\mathbf{x}_k = f_{\hat{\phi}}^{-1}(\mathbf{z}; \mathbf{y}_k^{\mathrm{o}})$

with $\mathbf{z} \sim N(\mathbf{0}, \mathbf{I})$.

HINT: Hierarchical Invertible Neural Transport for General and Sequential Bayesian inference, Detommaso, et. al., arXiv:1905.10687