Monitoring with Sequential Bayesian Inference

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ML4Seismic Fall Meeting
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School of Earth and Atmospheric Sciences

3 Georgia Tech College of Engineering
School of Electrical and Computer Engineering

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Motivation

Uncertainties affect accuracy of digital twin model

- leakages, inaccurate permeability, **varying injection rate**

Benefits of sequential Bayesian inference

- prediction based on current observation and also all previous observations
- more information collected along the way
- uncertainty quantification

Wood et. al, Locked away – geological carbon storage, The Royal Society, October 2022
Ringrose, Philip. How to store CO2 underground: Insights from early-mover CCS Projects, 2020.

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Motivation

Goal: put general statements such as

> *"It is possible to forecast the likely plume behaviour within reasonable bounds of uncertainty. Precise predictions cannot however be expected, and an interactive modelling approach with model updates based on feedback from regular monitoring data is the right approach for developing CO2 storage projects."* by Ringrose

> *"The monitoring data are often combined with parameterised models of the various flow processes to restrict the range of possible scenarios consistent with the data, but significant uncertainties remain."* by Woods

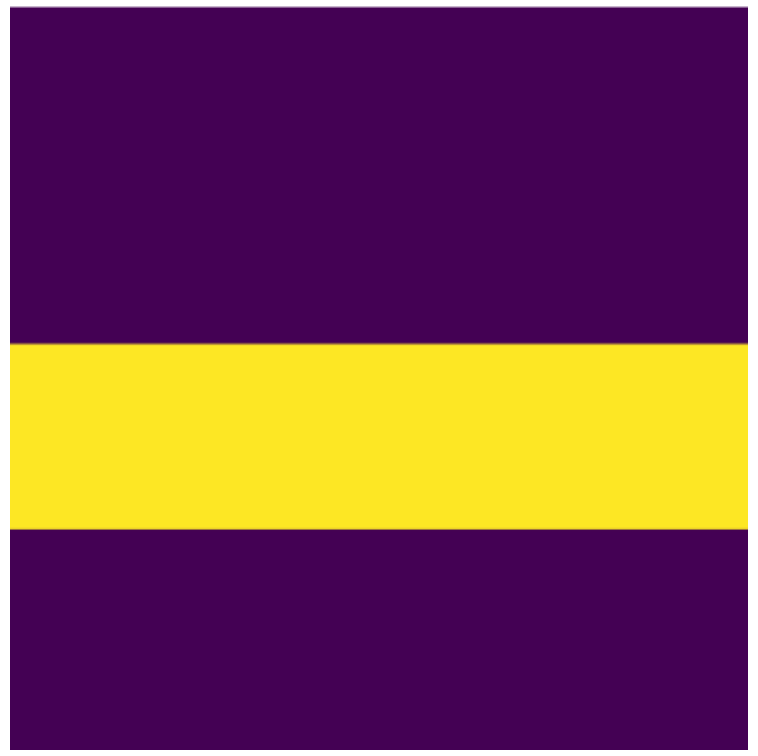
on a firmer theoretical footing.

Li, D., Xu, K., Harris, J. M., & Darve, E. (2020). Coupled time-lapse full-waveform inversion for subsurface flow problems using intrusive automatic differentiation. Water Resources Research, 56, e2019WR027032.

Forward Simulation

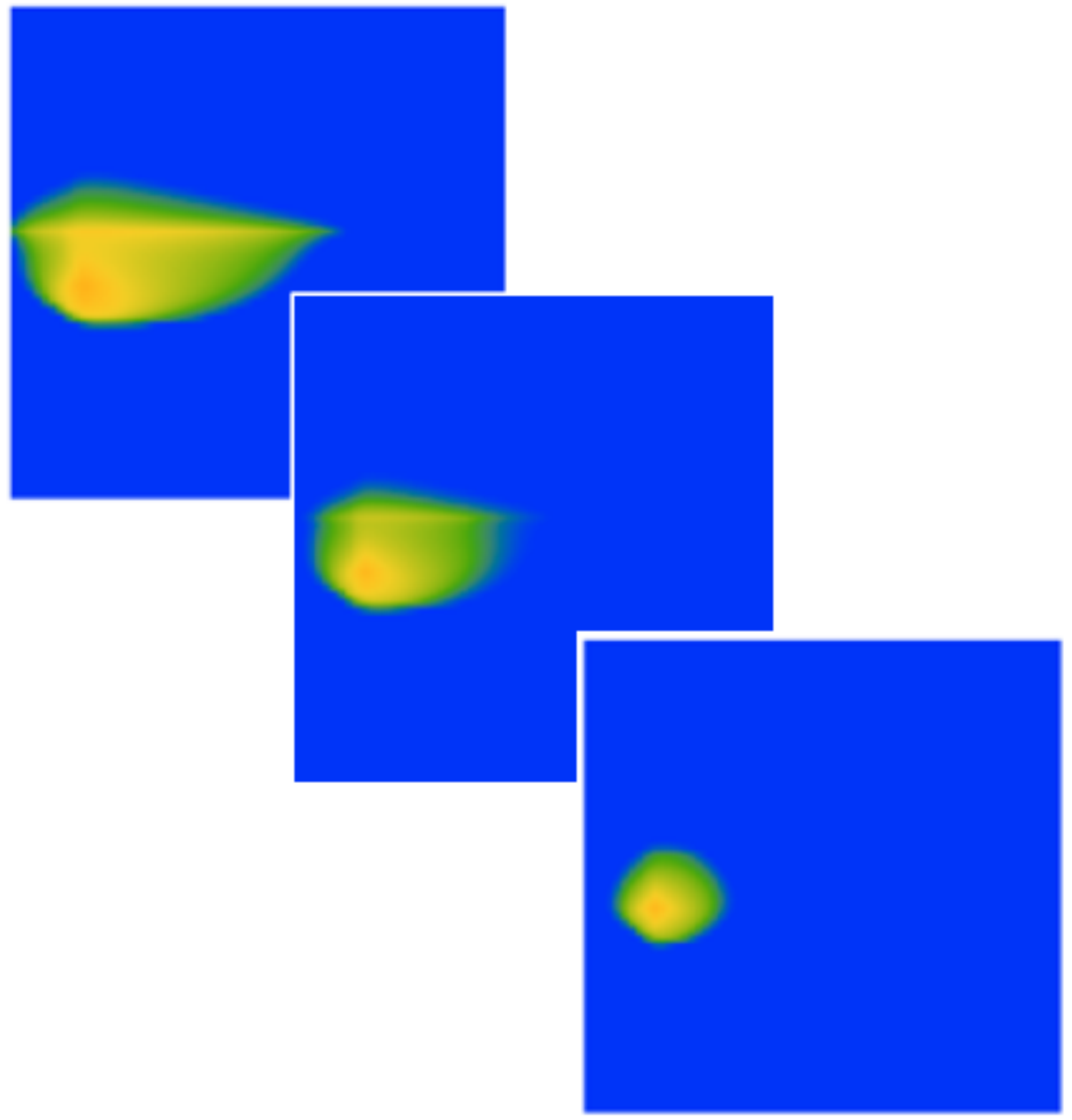
reservoir model

permeability



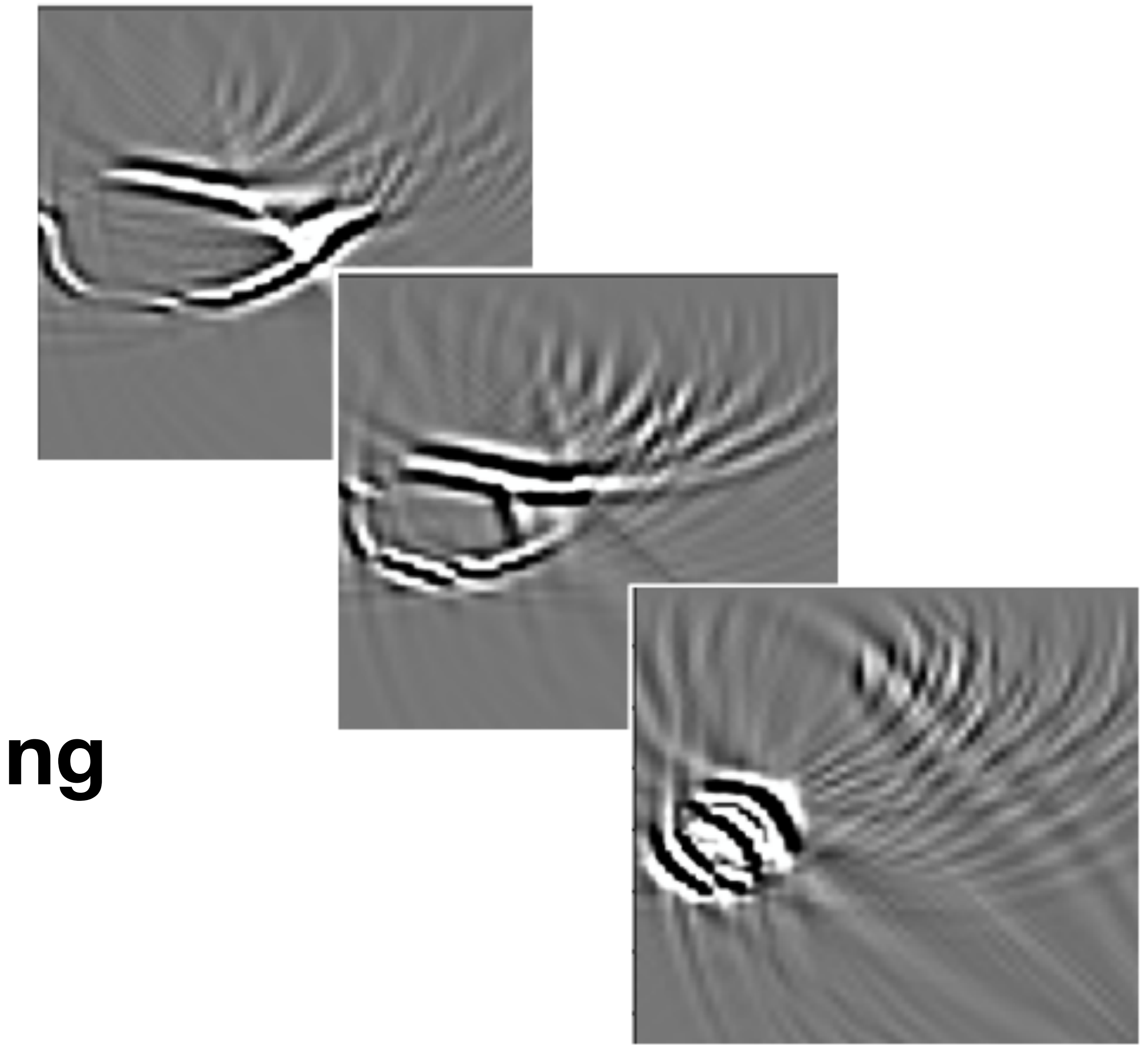
fluid-flow physics

CO_2 saturation



seismic imaging

seismic images



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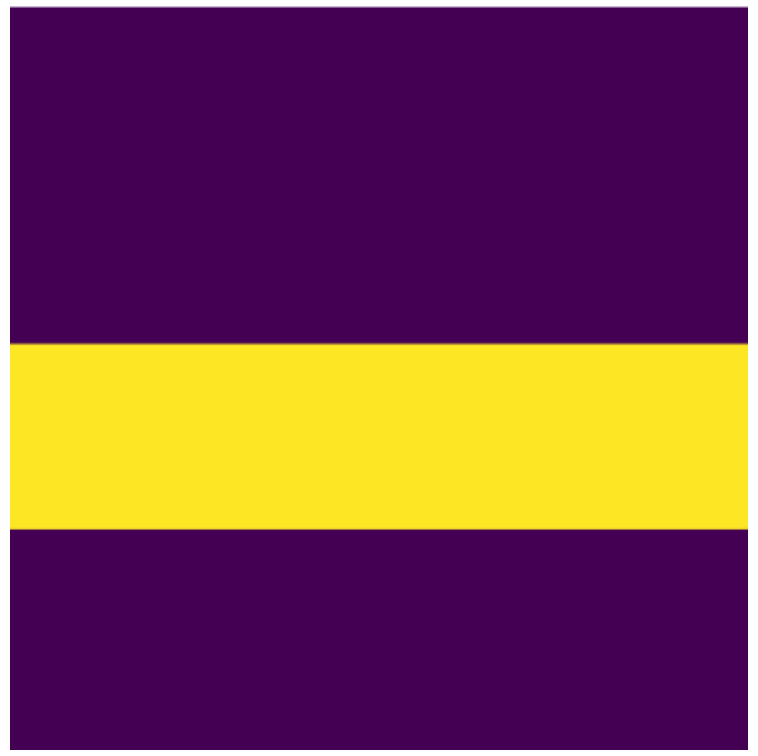

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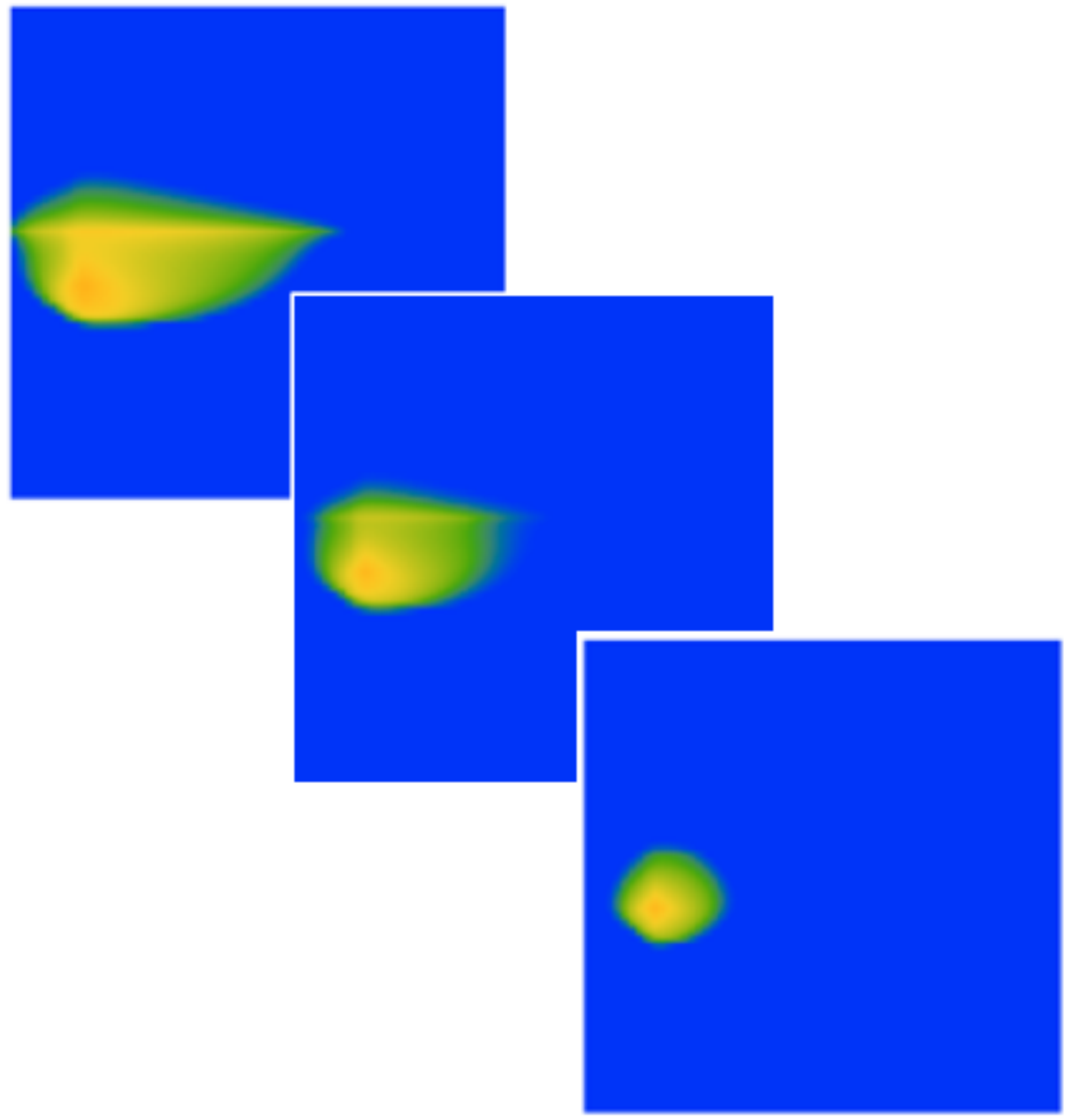

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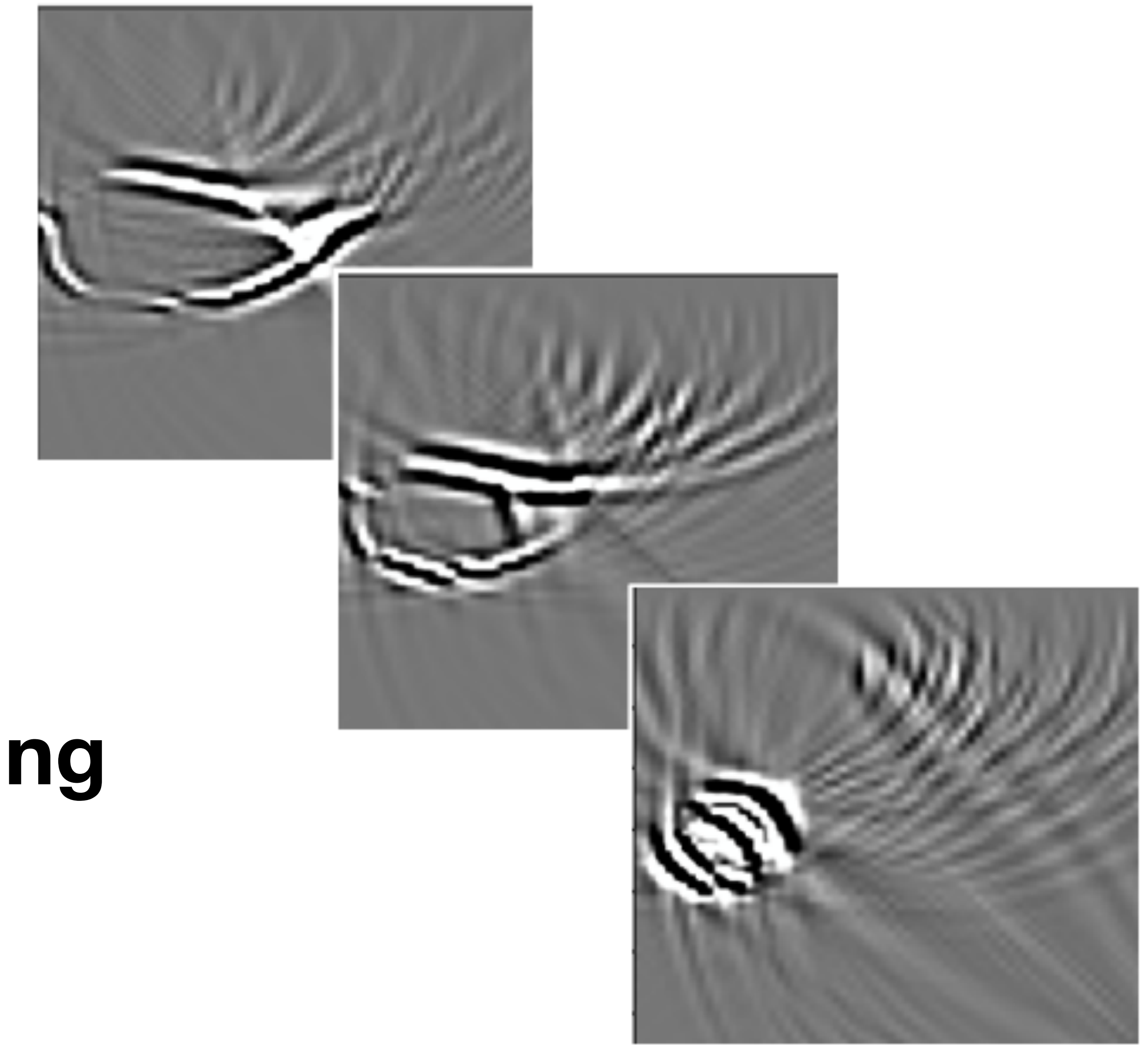

$\mathbf{x}$

$\mathbf{y}$

Numerical Experiments

Experiment Setup

Ground-truth data

Experiment groups

1. **Unconditioned**
   - sequential CO_2 saturation data
2. **Conditioned by seismic**
   - sequential Bayesian inference
   - train conditional normalizing flow

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Experiment Setup

Transition model $\mathcal{M}$ (fluid-flow equation)

- **stochasticity**

varying injection rate $\mathrm{I}\,[m^3/s]$

$$\mathrm{I} \sim \mathcal{N}(0, 0.2)$$

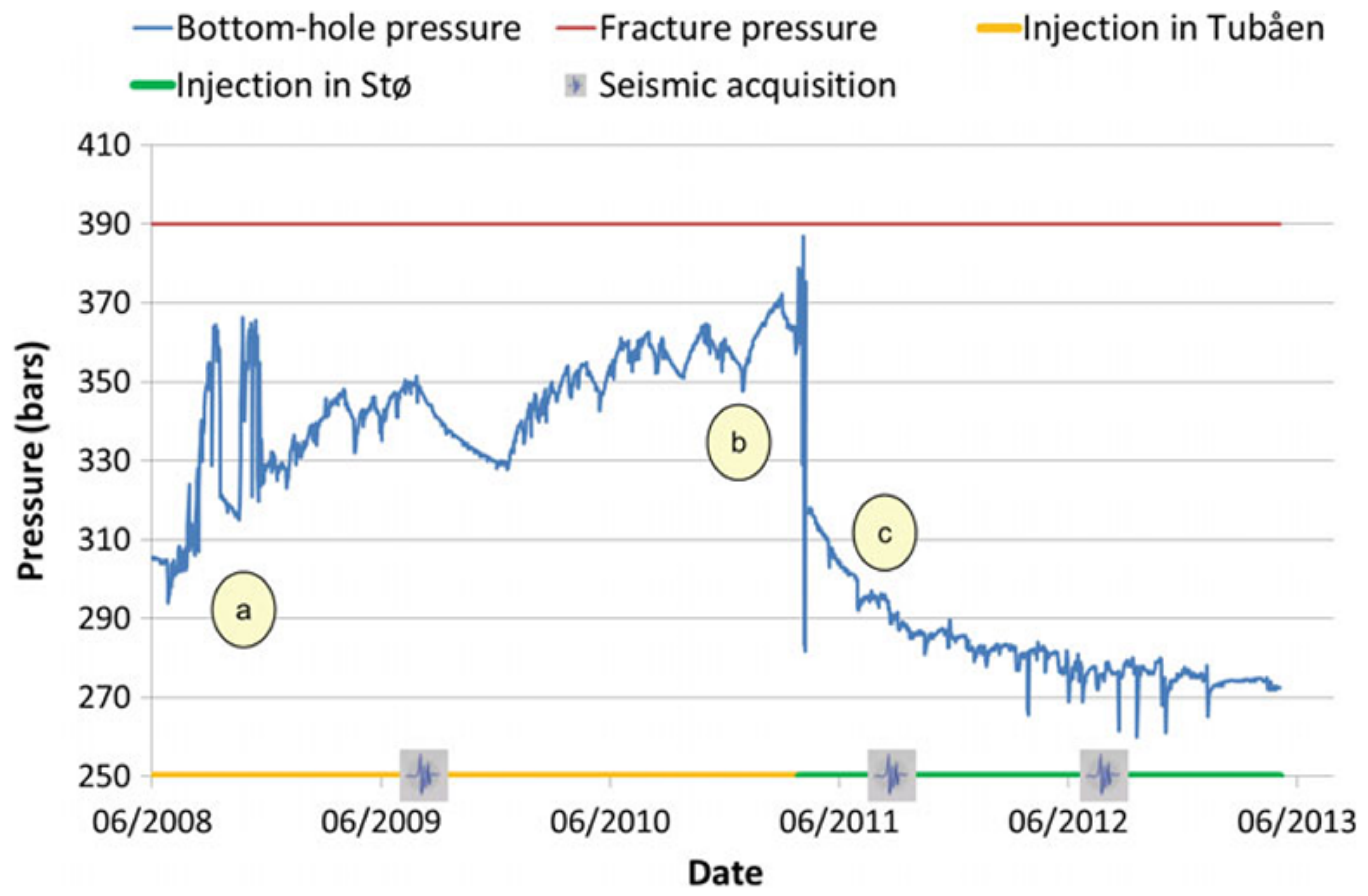


Figure taken from Ringrose's book Fig. 2.45. Part **b** shows a gradual rising trend in pressure due to geological flow barriers in Tubaen Fm.

Experiment Setup

Sequential experiment:

- 5 vintages for each group
- each time step is 200 days

Seismic setup:

- 8 sources / 200 receivers located on the top of the model
- generating linear data

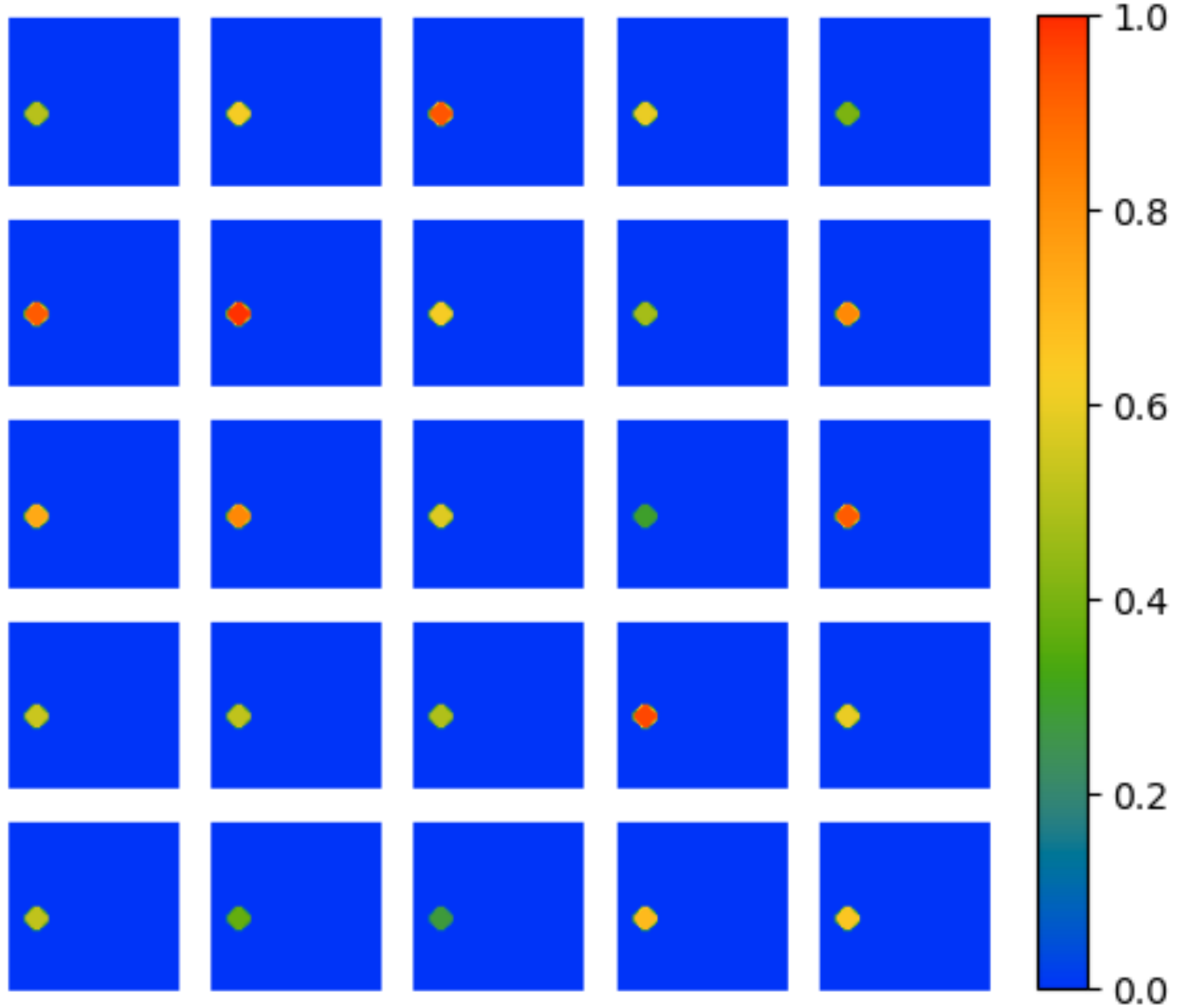
Generating Ground Truth

Model setup & prior generation

- constant acoustic velocity/density
- plumes initialized as circles with saturation $s \sim \mathcal{U}(0.2, 0.8)$

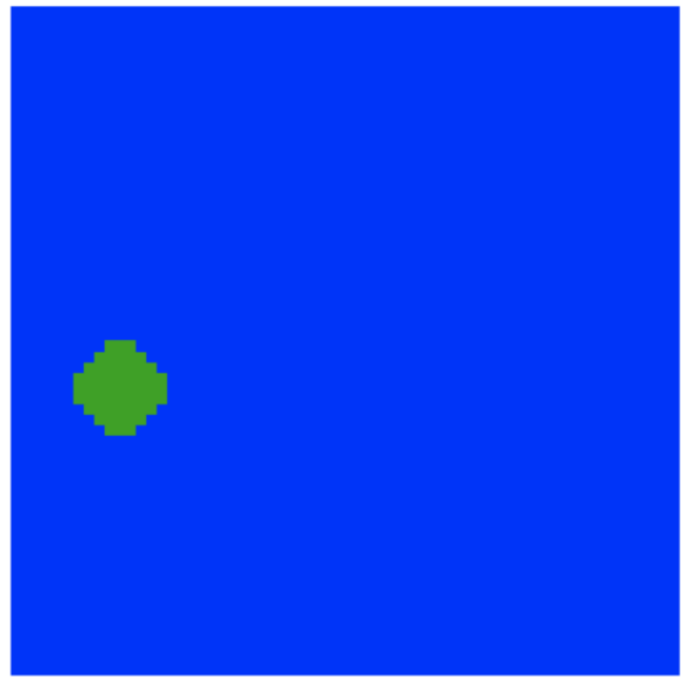
Prior

$$\mathbf{x} \sim P(\mathbf{x})$$

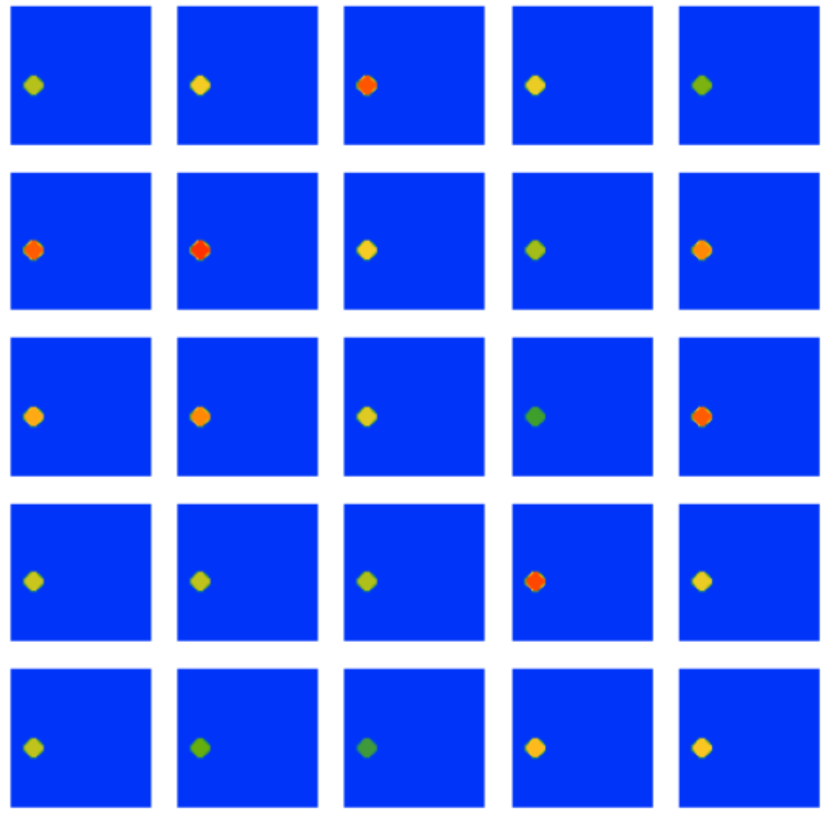


Generating Ground Truth

k = 0



$\mathbf{x} \sim P(\mathbf{x})$



Prior

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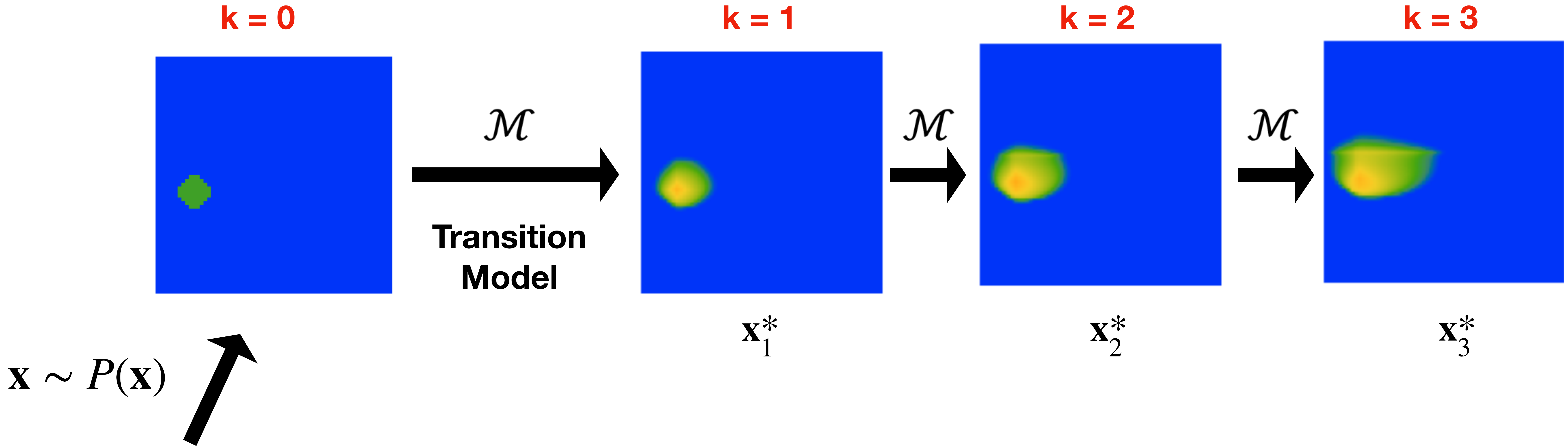
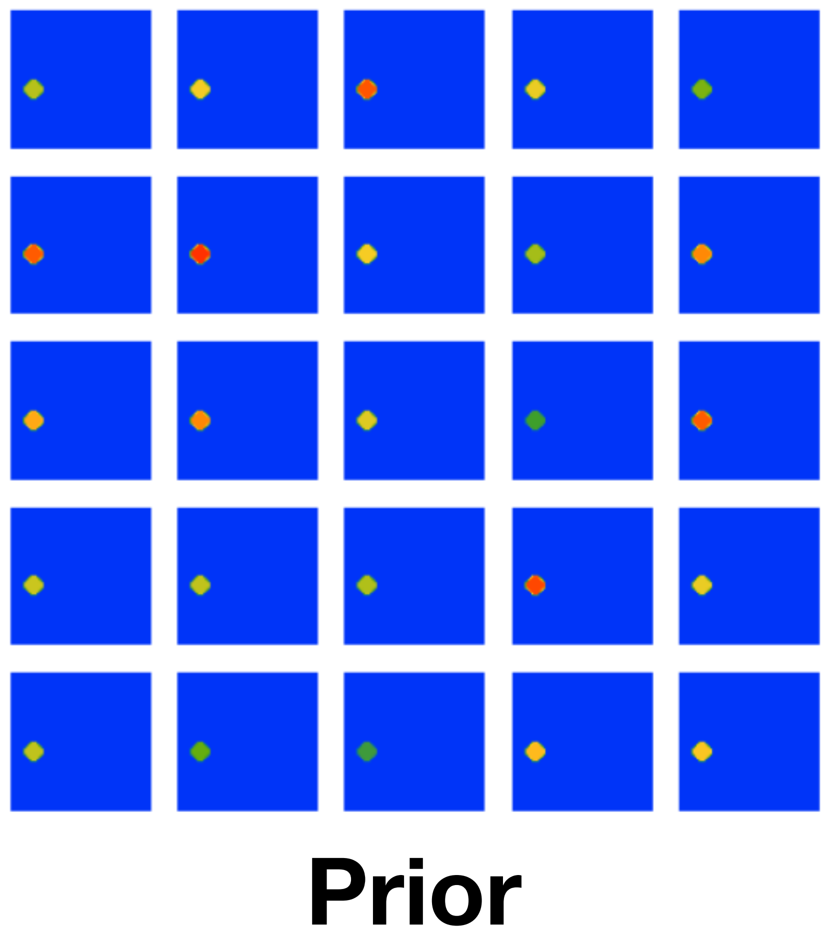
Generating Ground Truth





Transition model's stochasticity comes from varying injection rate

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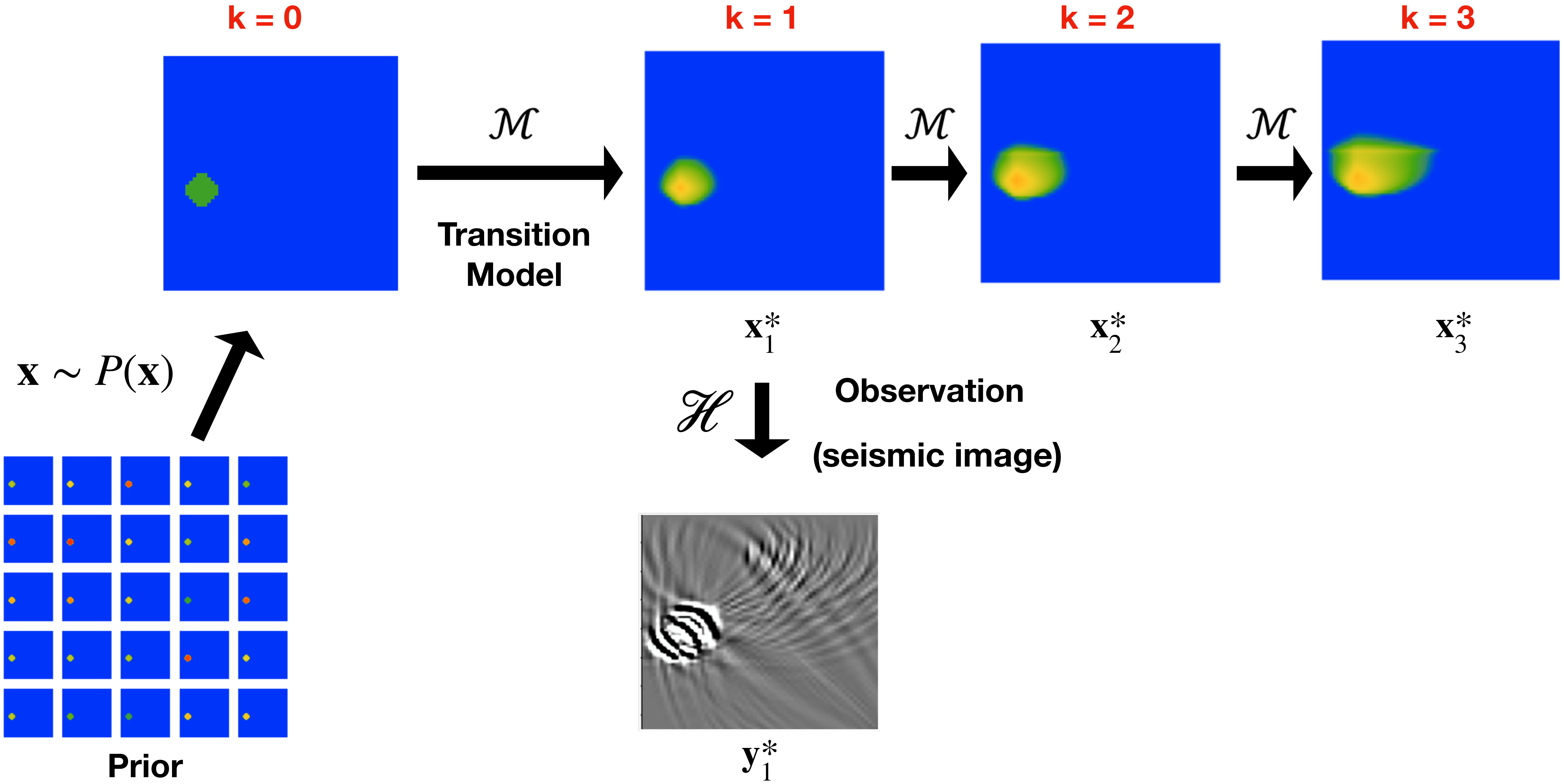
Generating Ground Truth



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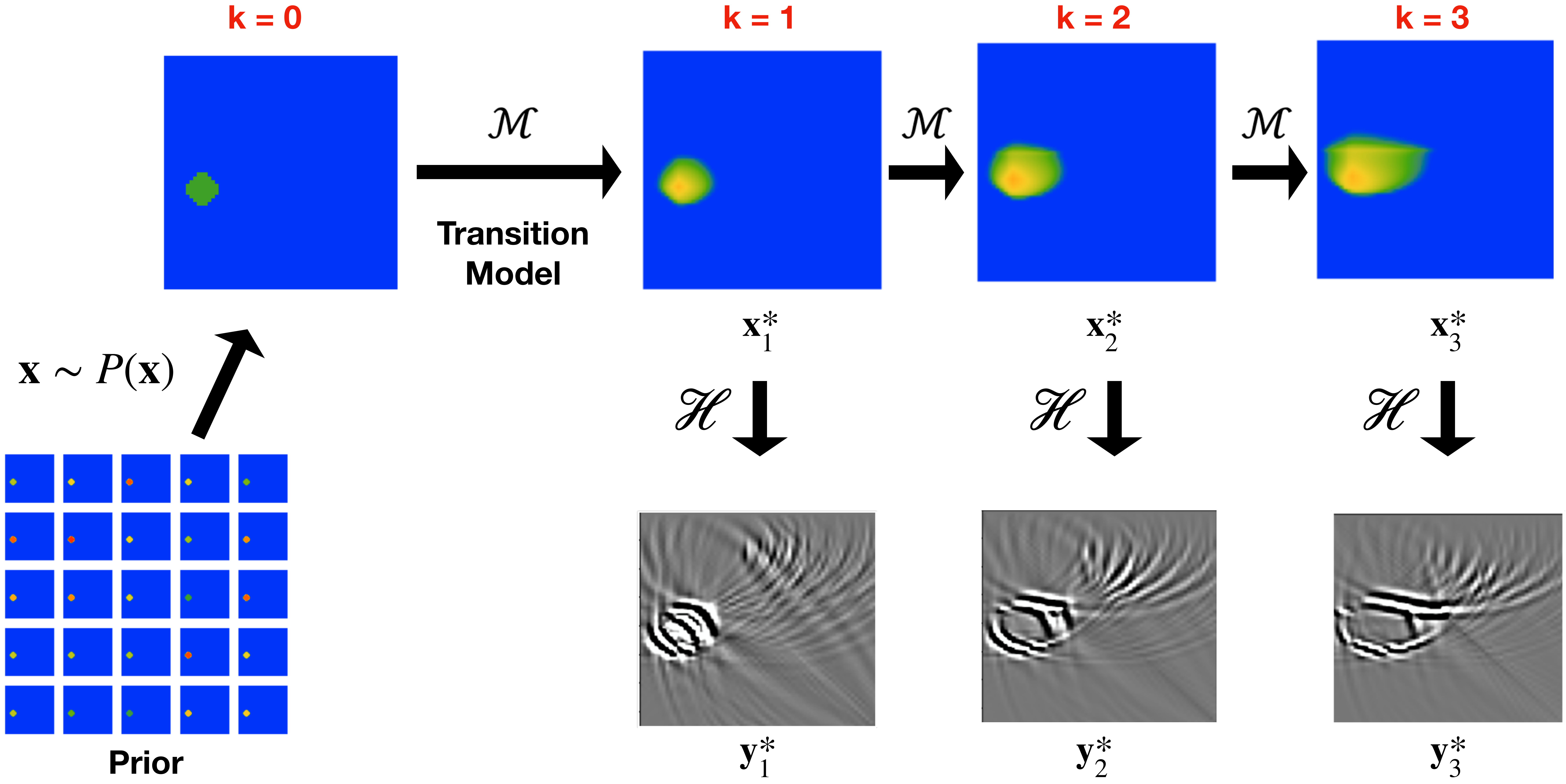
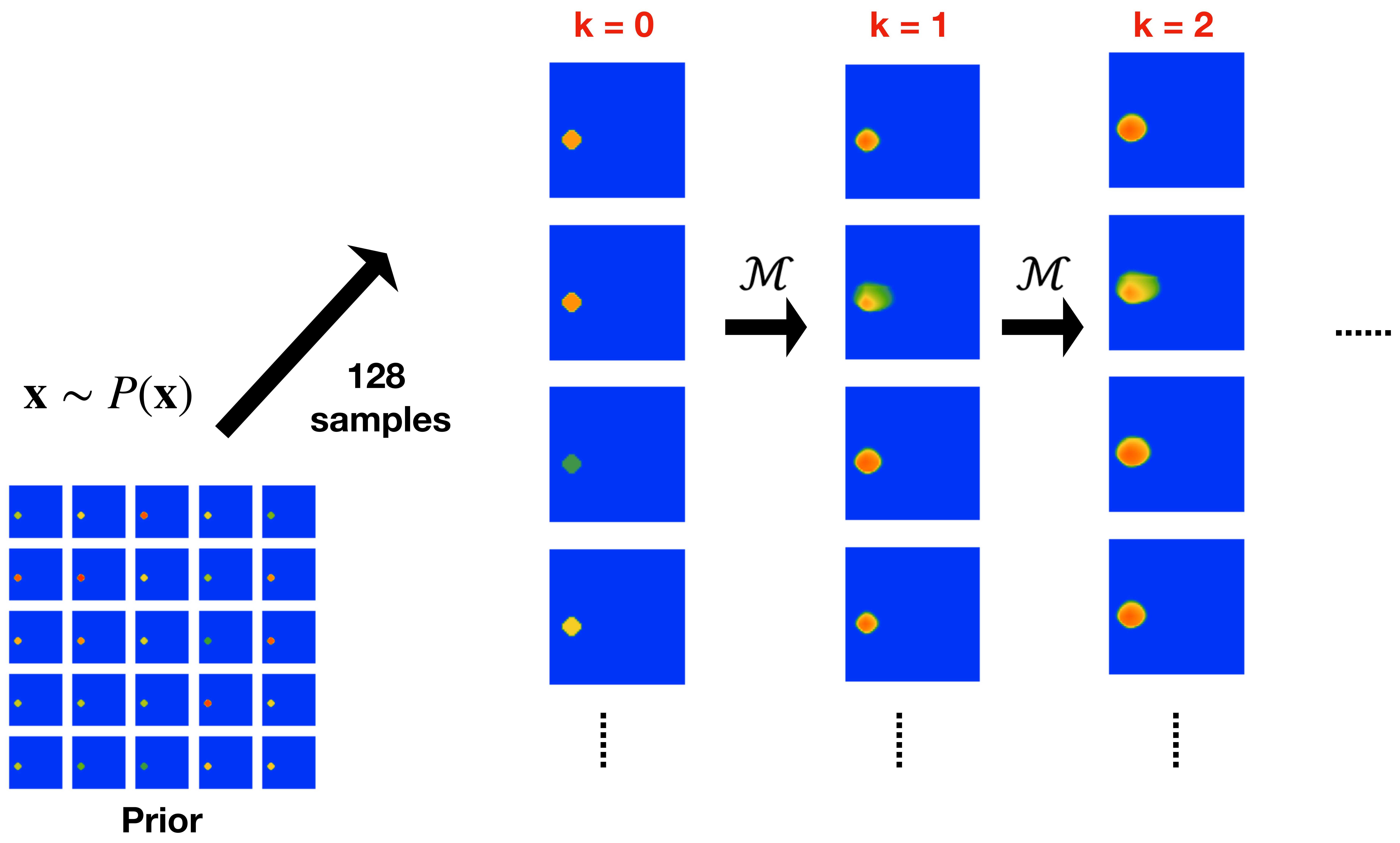


Unconditioned Simulation



Conditioned on Seismic

Conditional Normalizing Flow (CNF)

- learn to sample from conditional distribution $p(\mathbf{x} \mid \mathbf{y})$
- inverse problem: “Given data $\mathbf{y}$, which $\mathbf{x}$ corresponds to it?”

$$p(\mathbf{x} \mid \mathbf{y})$$

Conditioned on Seismic

Conditional Normalizing Flow (CNF)

- learn to sample from conditional distribution $p(\mathbf{x} \,|\, \mathbf{y})$
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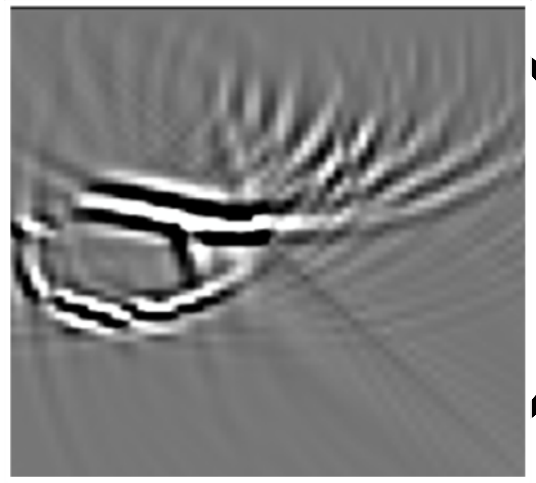
$\sim p(\ \mathbf{x} \mid$  $)$

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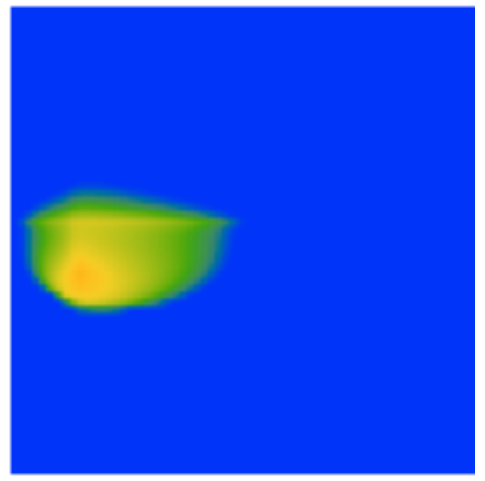
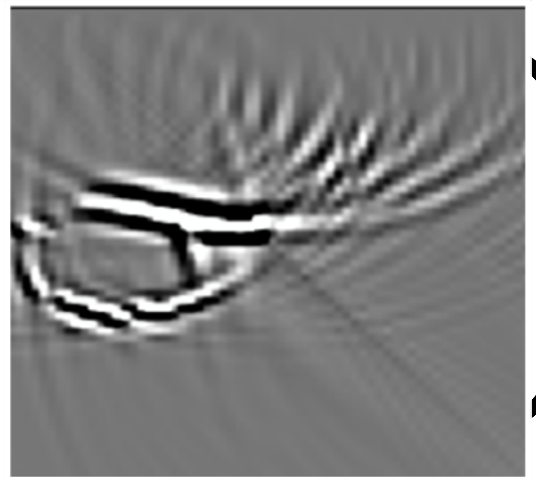
 $\sim p(\mathbf{x} \mid$  $)$

Conditioned on Seismic

Conditional Normalizing Flow (CNF)

- Learn to sample from conditional distribution $p(\mathbf{x} \mid \mathbf{y})$
- Inverse problem: "Given data $\mathbf{y}$, which $\mathbf{x}$ corresponds to it?"
- **CNF: "Given data $\mathbf{y}$, which distribution of data $\mathbf{x} \sim p(\mathbf{x} \mid \mathbf{y})$ matches y ?"**

$$p(\ \mathbf{x} \mid \mathbf{y}\ )$$

Generated by the trained CNF

Conditioned on Seismic

Conditional Normalizing Flow (CNF)

- learn to sample from conditional distribution $p(\mathbf{x} \mid \mathbf{y})$
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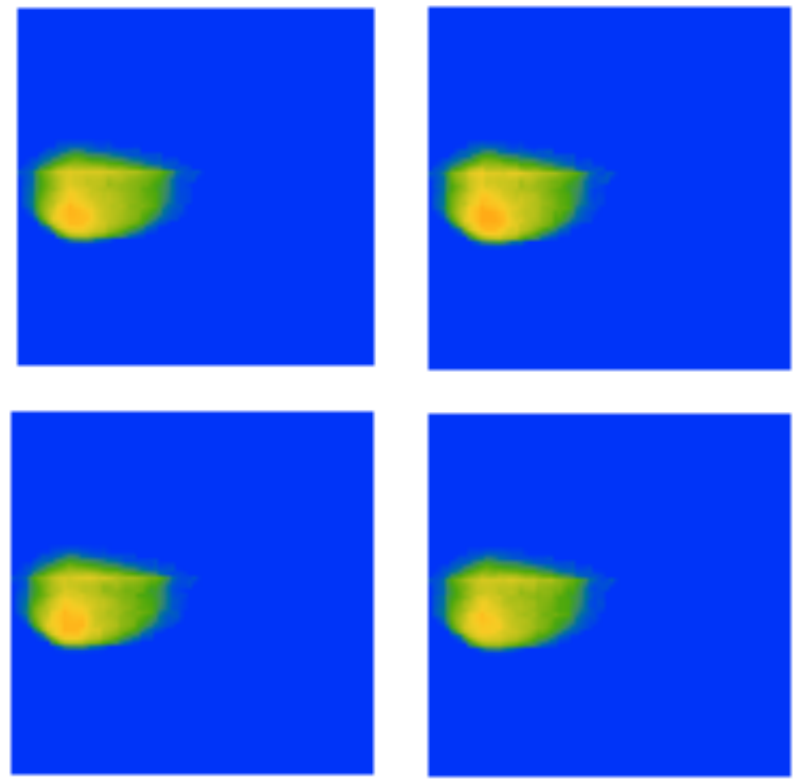
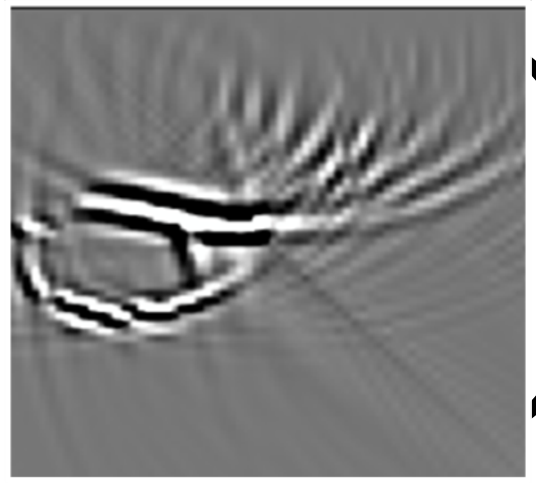
- **CNF: “Given data $\mathbf{y}$, which distribution of data $\mathbf{x} \sim p(\mathbf{x} \mid \mathbf{y})$ matches $\mathbf{y}$?”**



$\sim p(\mathbf{x} \mid$  $)$

Ardizzone, Lynton, et al. "Conditional Invertible Neural Networks for Guided Image Generation." (2019).

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Conditioned on Seismic

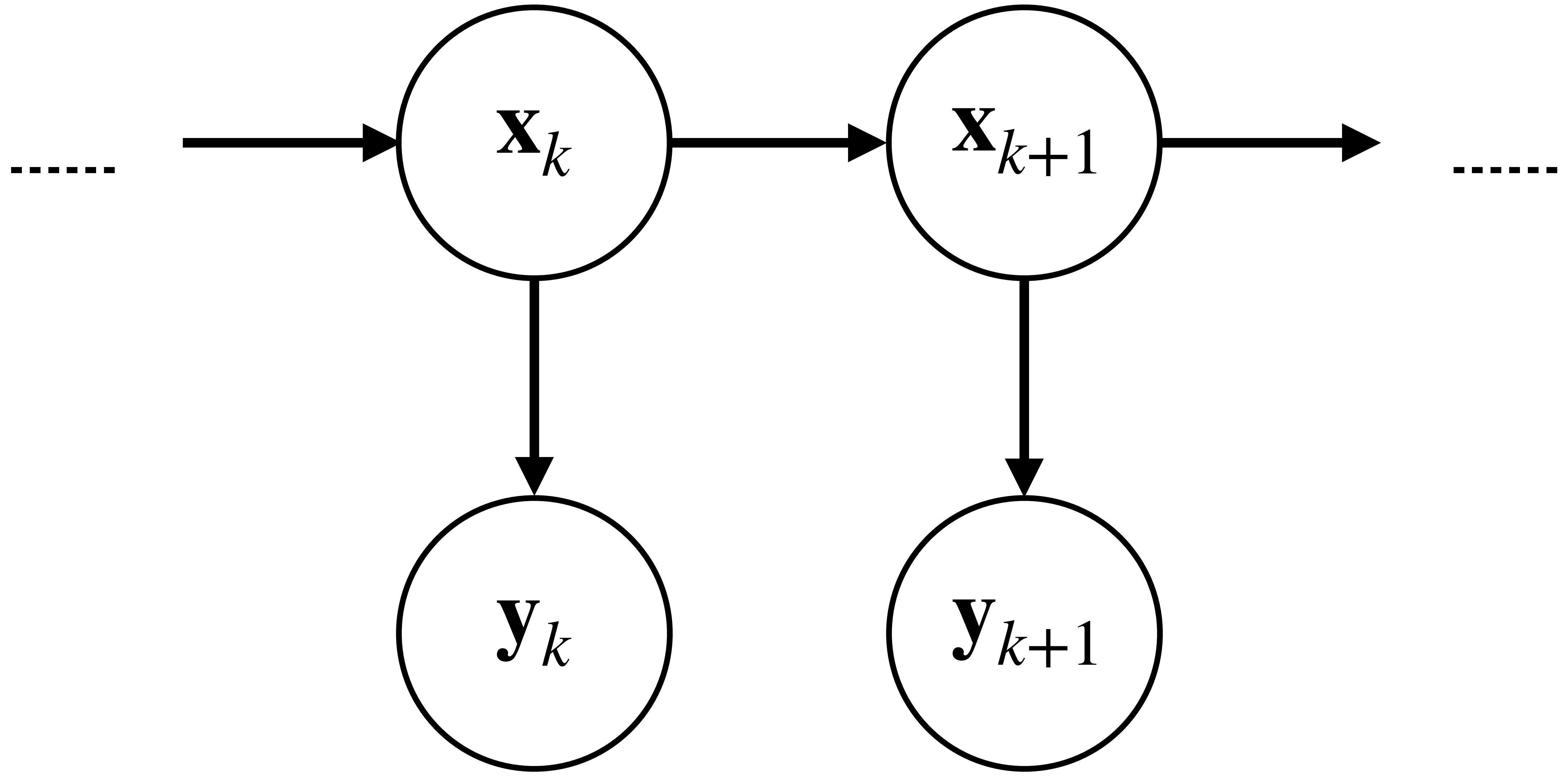
Conditional Normalizing Flow (CNF)

- learn to sample from conditional distribution $p(\mathbf{x} \,|\, \mathbf{y})$
- inverse problem: "Given data $\mathbf{y}$, which $\mathbf{x}$ corresponds to it?"
- **CNF: "Given data $\mathbf{y}$, which distribution of data $\mathbf{x} \sim p(\mathbf{x} \,|\, \mathbf{y})$ matches y?"**
    - neural network training:

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

Kruse, Jakob, et al. "HINT: Hierarchical invertible neural transport for density estimation and Bayesian inference." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 35. No. 9. 2021.

Sequential Bayesian Inference



Sample from posterior of previous time step, and use it as prior of current time step

Kruse, Jakob, et al. "HINT: Hierarchical invertible neural transport for density estimation and Bayesian inference." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 35. No. 9. 2021.

Conditioned - sequential Bayesian

k=1

$$
\begin{array}{ccc}
P(\mathbf{x}) & & \\
\big\downarrow & & \\
\mathbf{x}_0 & \xrightarrow{\mathcal{M}} & \mathbf{x}_1
\end{array}
$$

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Conditioned - sequential Bayesian

$P(\mathbf{x})$

k=1

$$\mathbf{x}_0 \xrightarrow{\mathcal{M}} \mathbf{x}_1$$

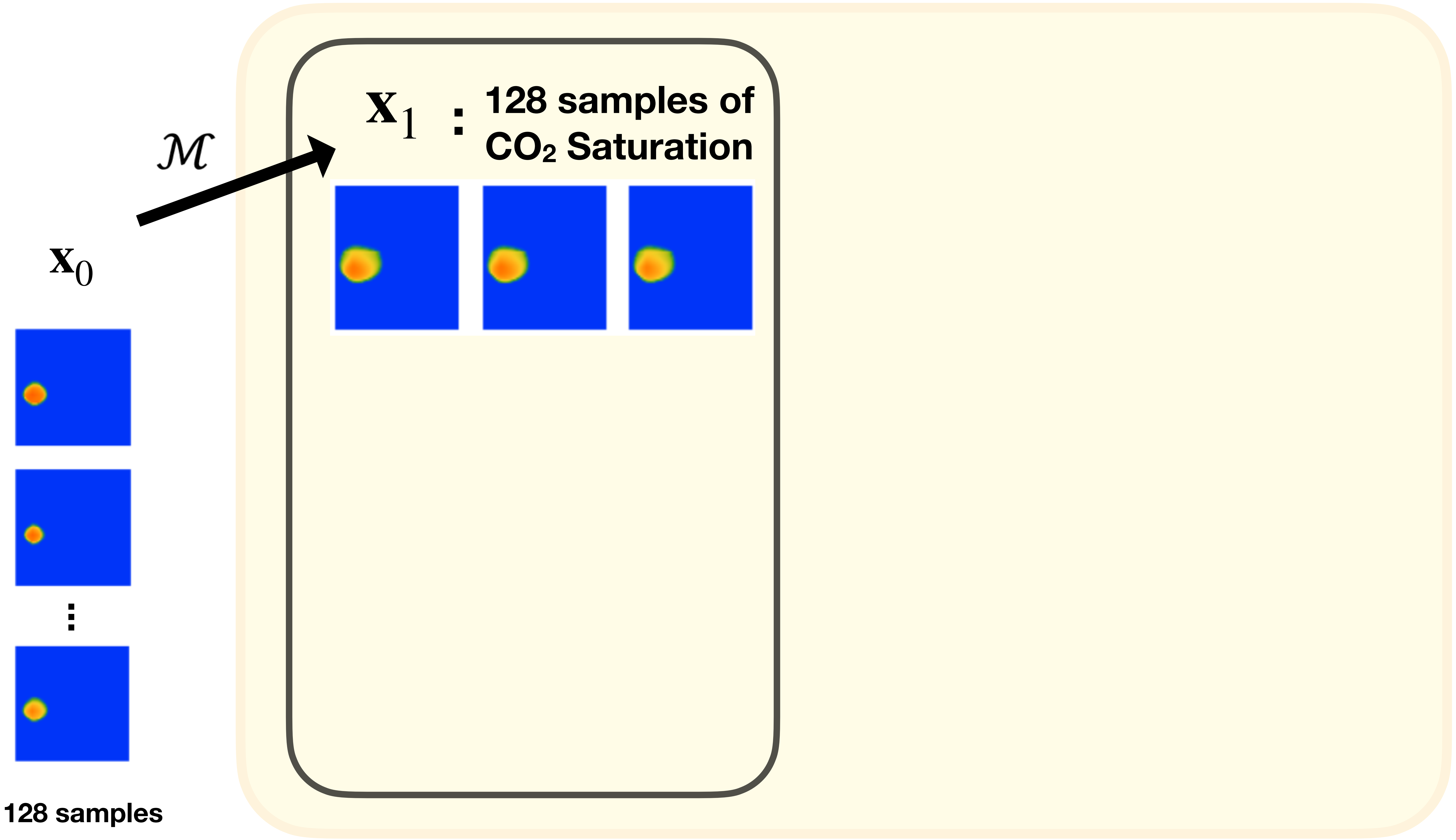
CNF Training Block

$$x_1 \sim p(\,\cdot \mid y_1^*)$$

Conditioned - sequential Bayesian

k=1

CNF Training Block



Conditioned - sequential Bayesian

k=1

CNF Training Block

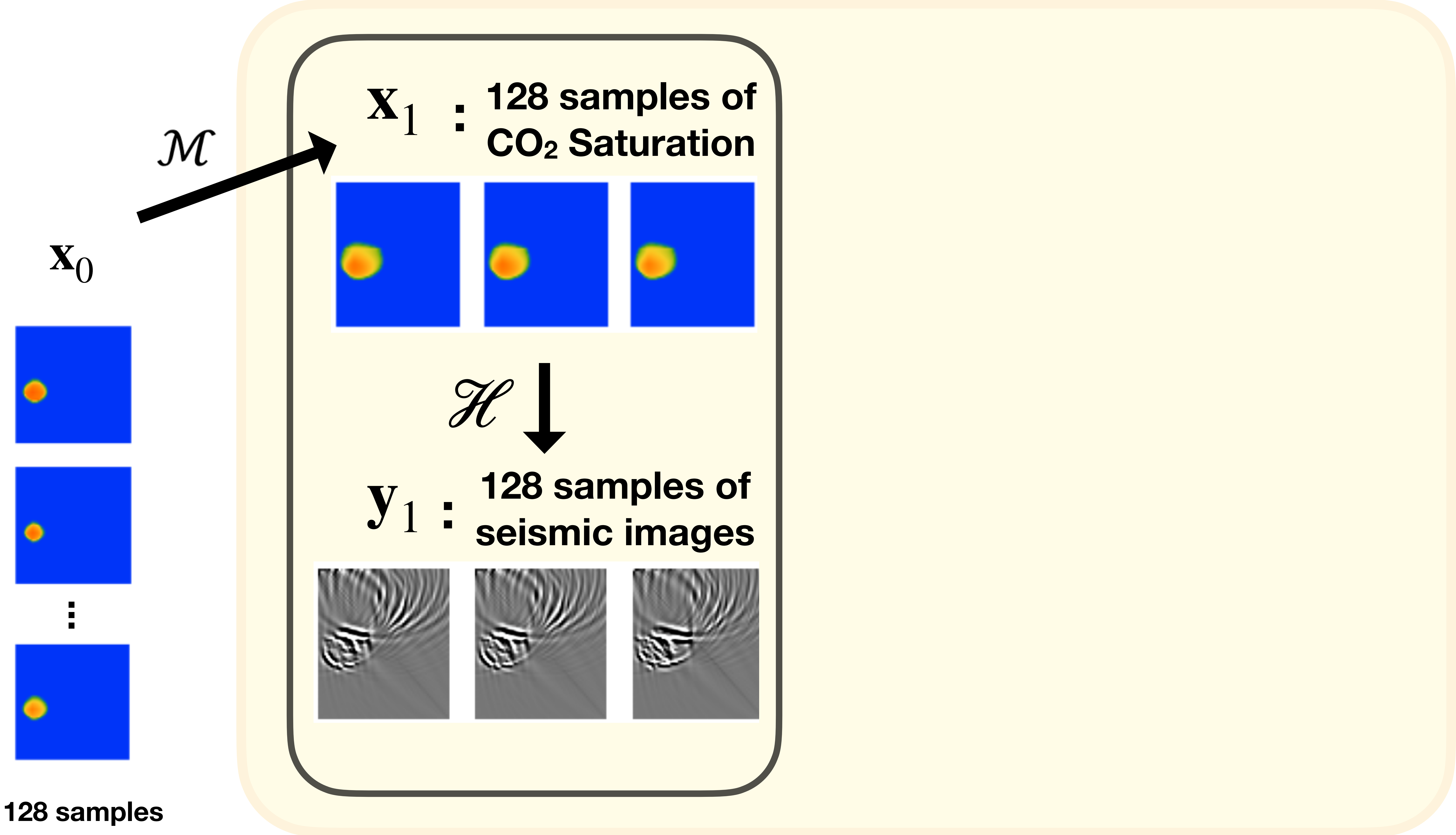


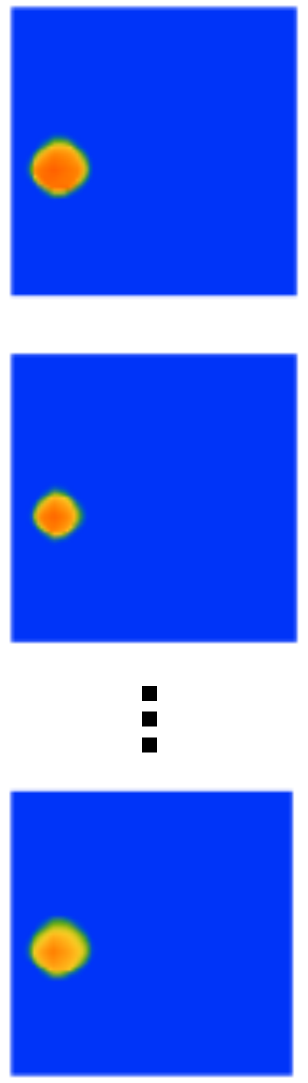
Image of the neural network is from: Image materials such as neural networks and Deep Learning [WTFPL] for presentations and seminars (http://nkdkccmbr.hateblo.jp/entry/2016/10/06/222245)

Conditioned - sequential Bayesian

k=1

CNF Training Block

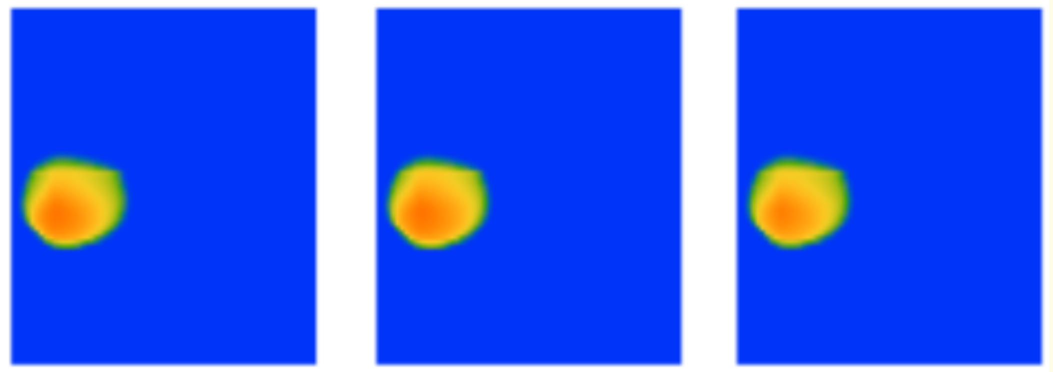
$\mathbf{x}_0$



128 samples

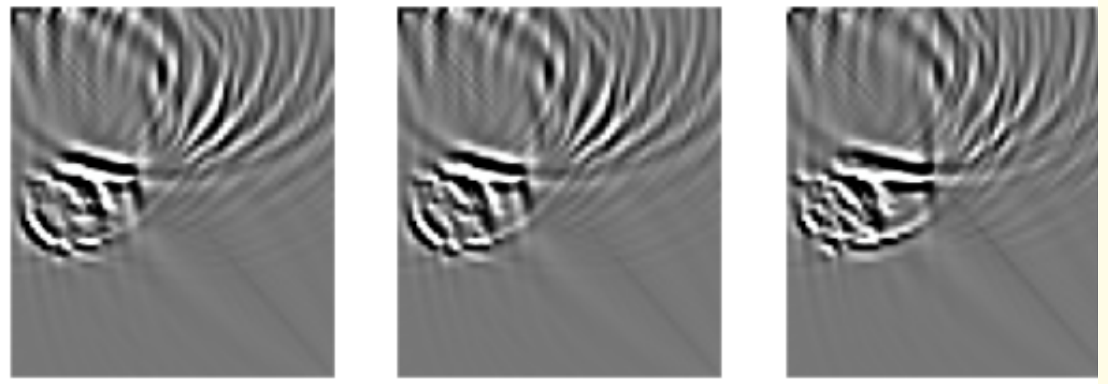
$\mathcal{M}$

$\mathbf{x}_1$: **128 samples of CO_2 Saturation**



$\mathscr{H}$

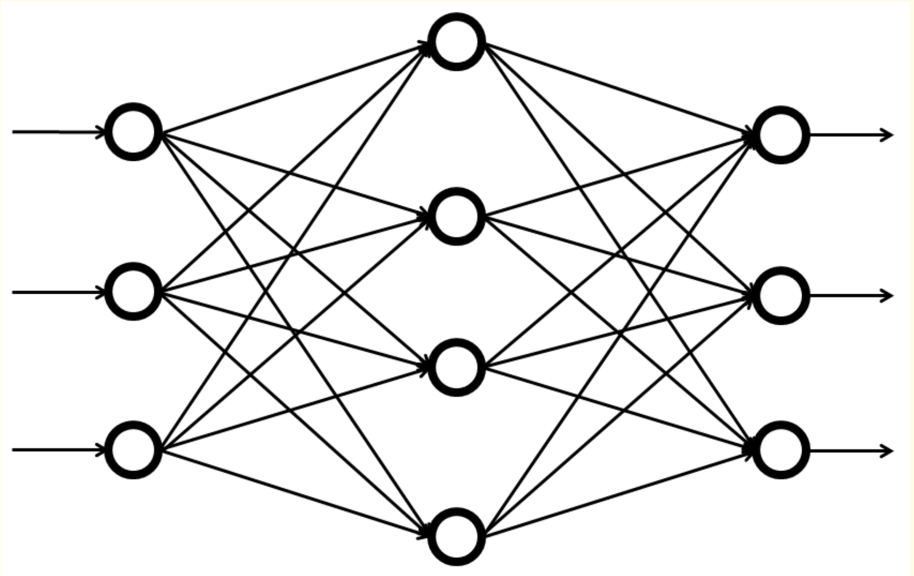
$\mathbf{y}_1$: **128 samples of seismic images**



$\{\mathbf{x}, \mathbf{y}\}$

$$p_\theta(\mathbf{x}_1 \,|\, \mathbf{y}_1) \approx p(\mathbf{x}_1 \,|\, \mathbf{y}_1)$$

Conditional Normalizing Flow (CNF)



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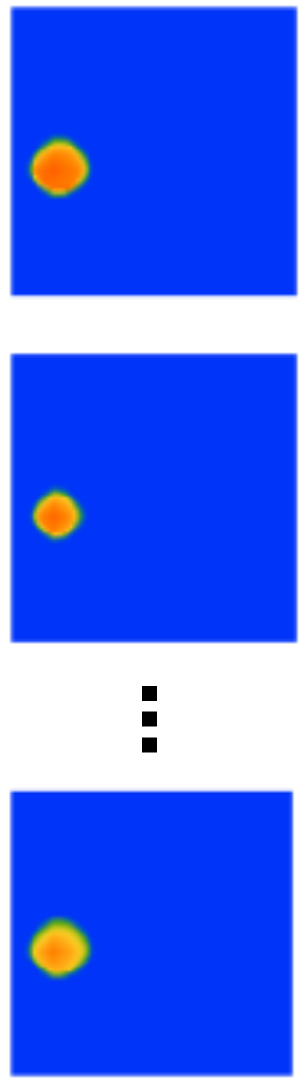
Conditioned - sequential Bayesian

k=1

CNF Training Block

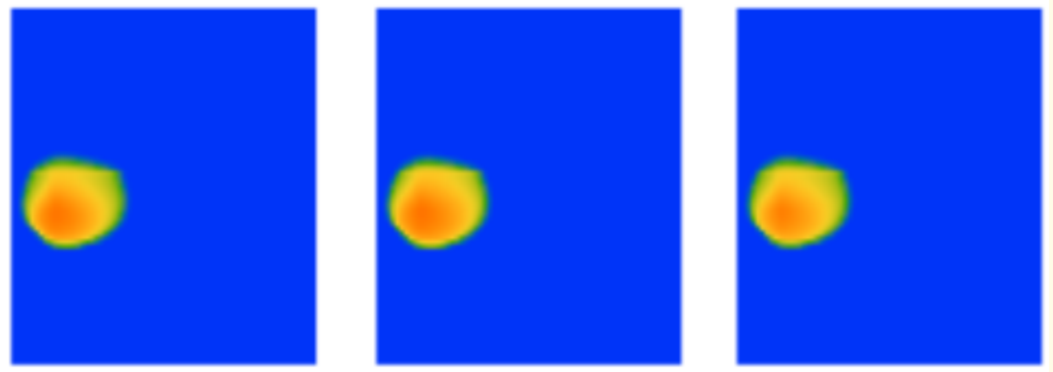
$\mathbf{x}_0$



128 samples

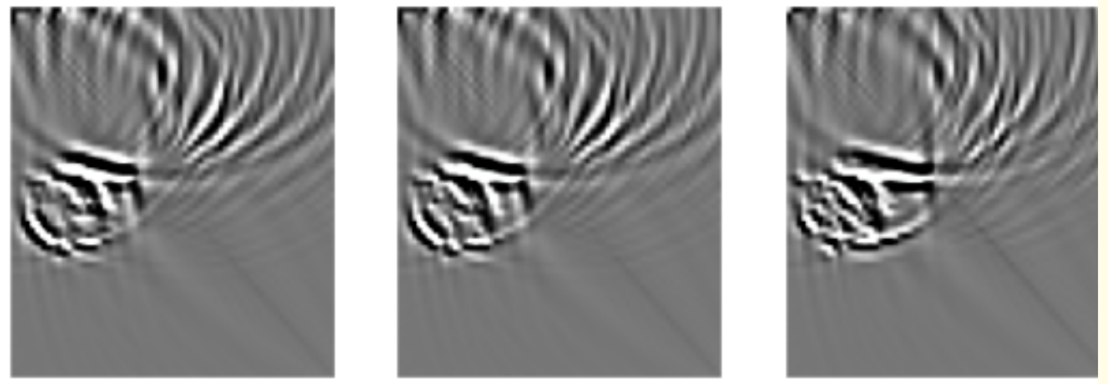
$\mathcal{M}$

$\mathbf{x}_1$: **128 samples of CO_2 Saturation**



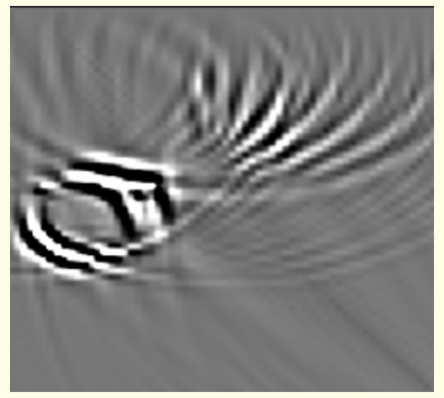
$\mathscr{H}$

$\mathbf{y}_1$: **128 samples of seismic images**



$\{\mathbf{x}, \mathbf{y}\}$

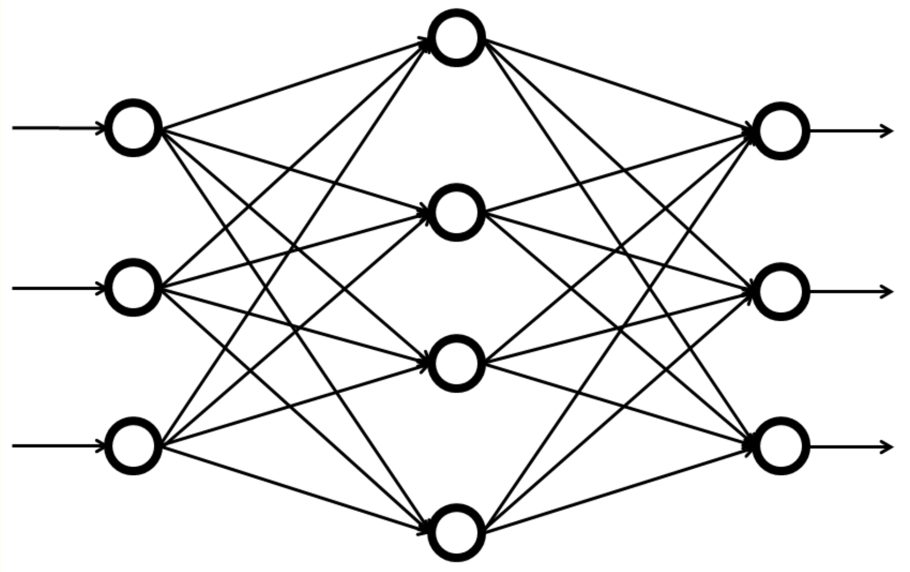
Field Observation



$\mathbf{y}_1^*$

$$p_\theta(\mathbf{x}_1 \,|\, \mathbf{y}_1) \approx p(\mathbf{x}_1 \,|\, \underline{\mathbf{y}_1})$$

Conditional Normalizing Flow (CNF)



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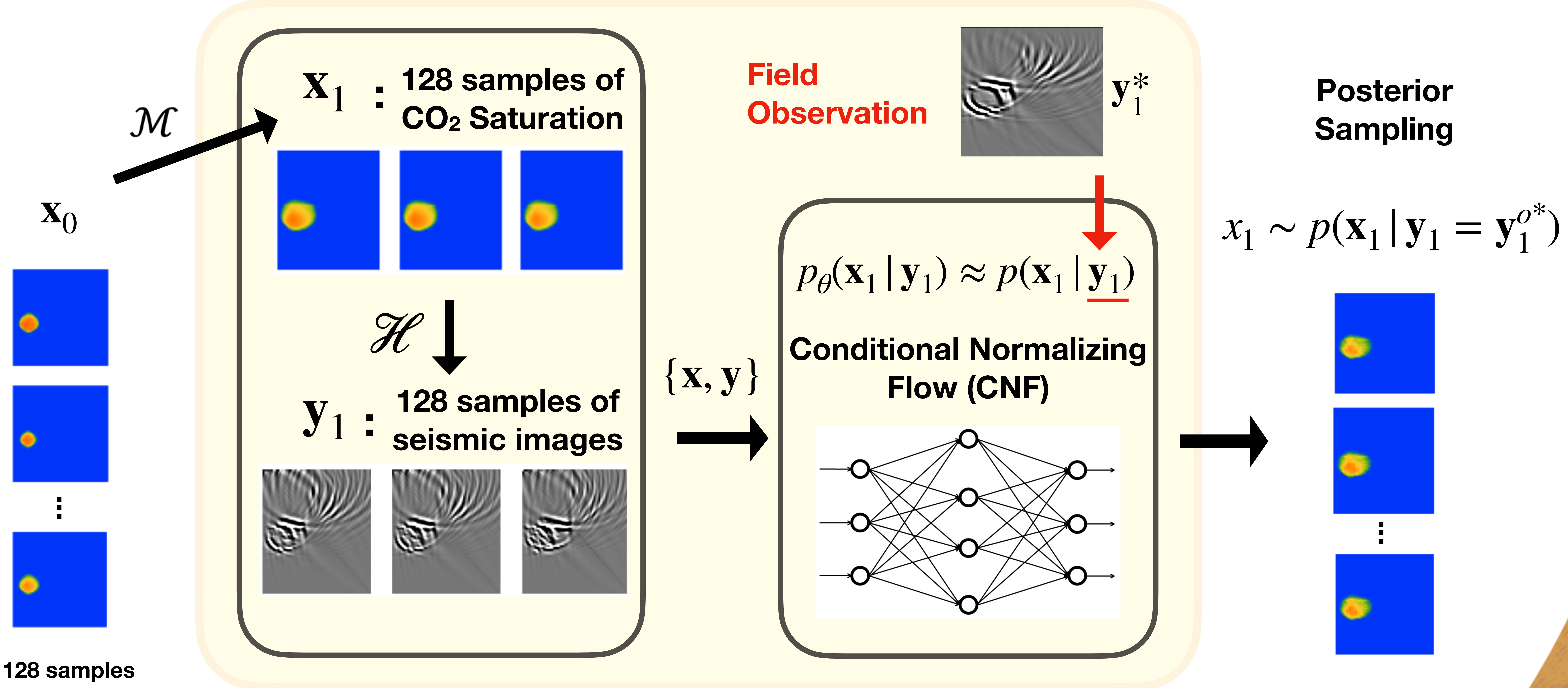
Conditioned - sequential Bayesian

k=1

CNF Training Block



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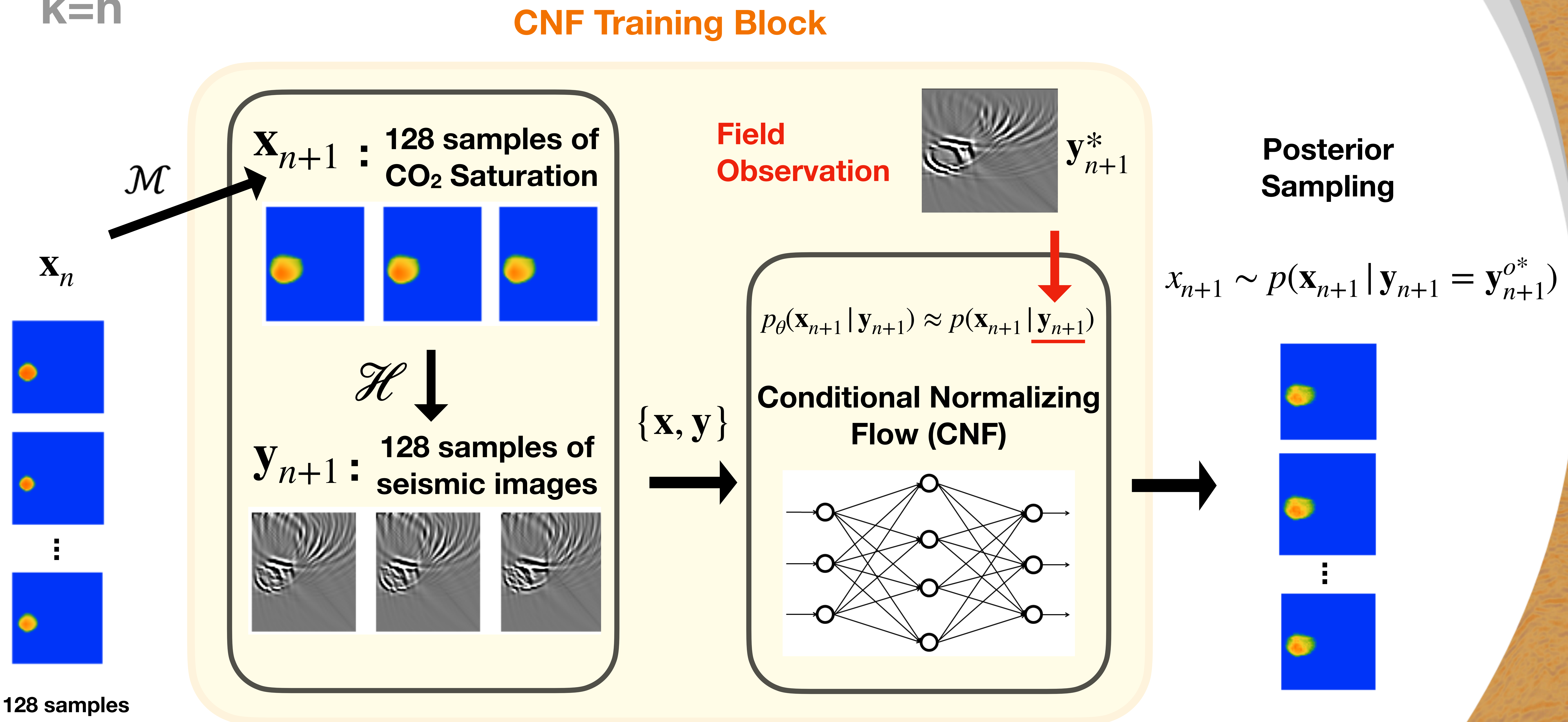
Conditioned - sequential Bayesian

k=n



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Conditioned - sequential Bayesian

$P(\mathbf{x})$

k=1

$$\mathbf{x}_0 \xrightarrow{\mathcal{M}} \mathbf{x}_1$$

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$$x_1 \sim p(\,\cdot \mid y_1^*)$$

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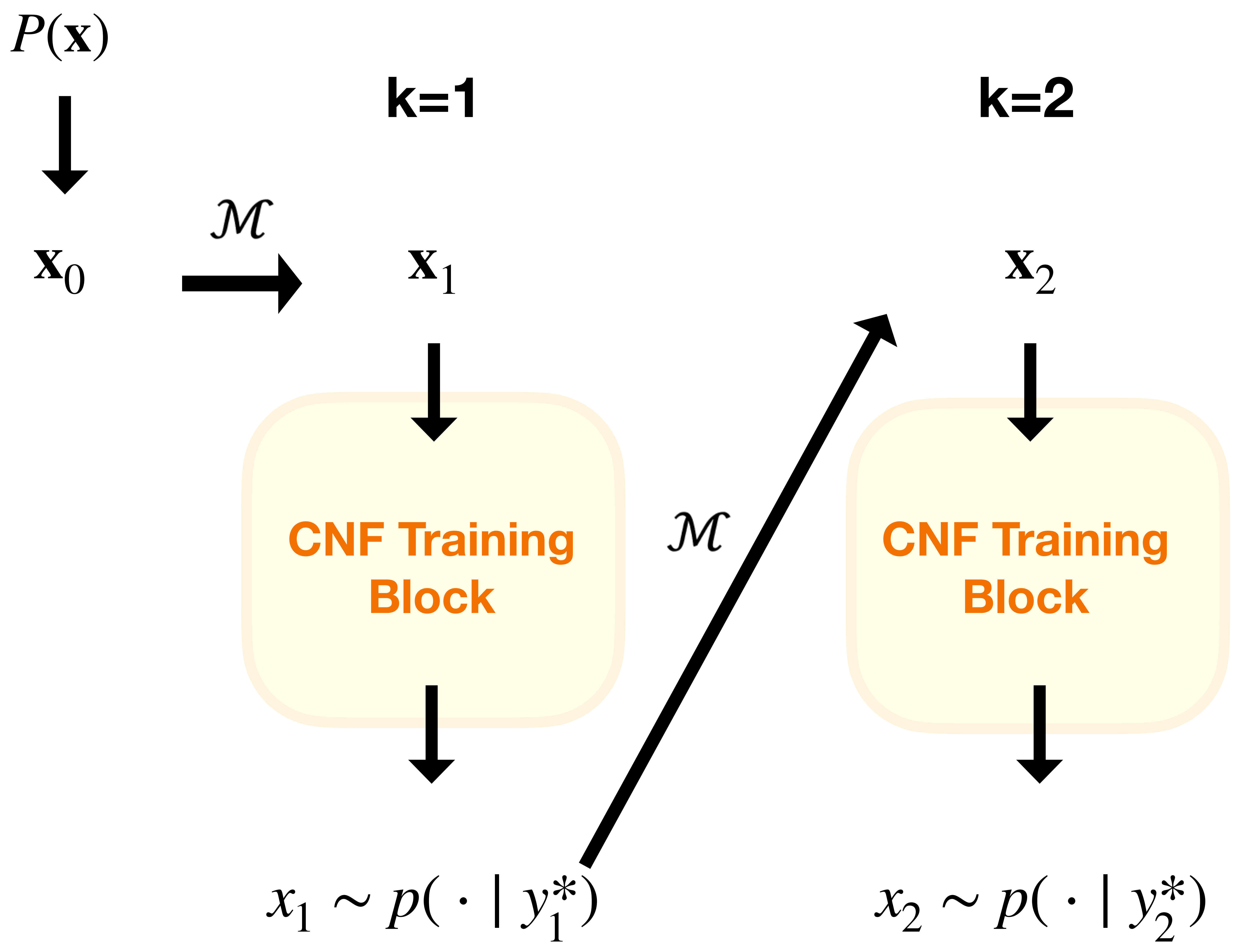

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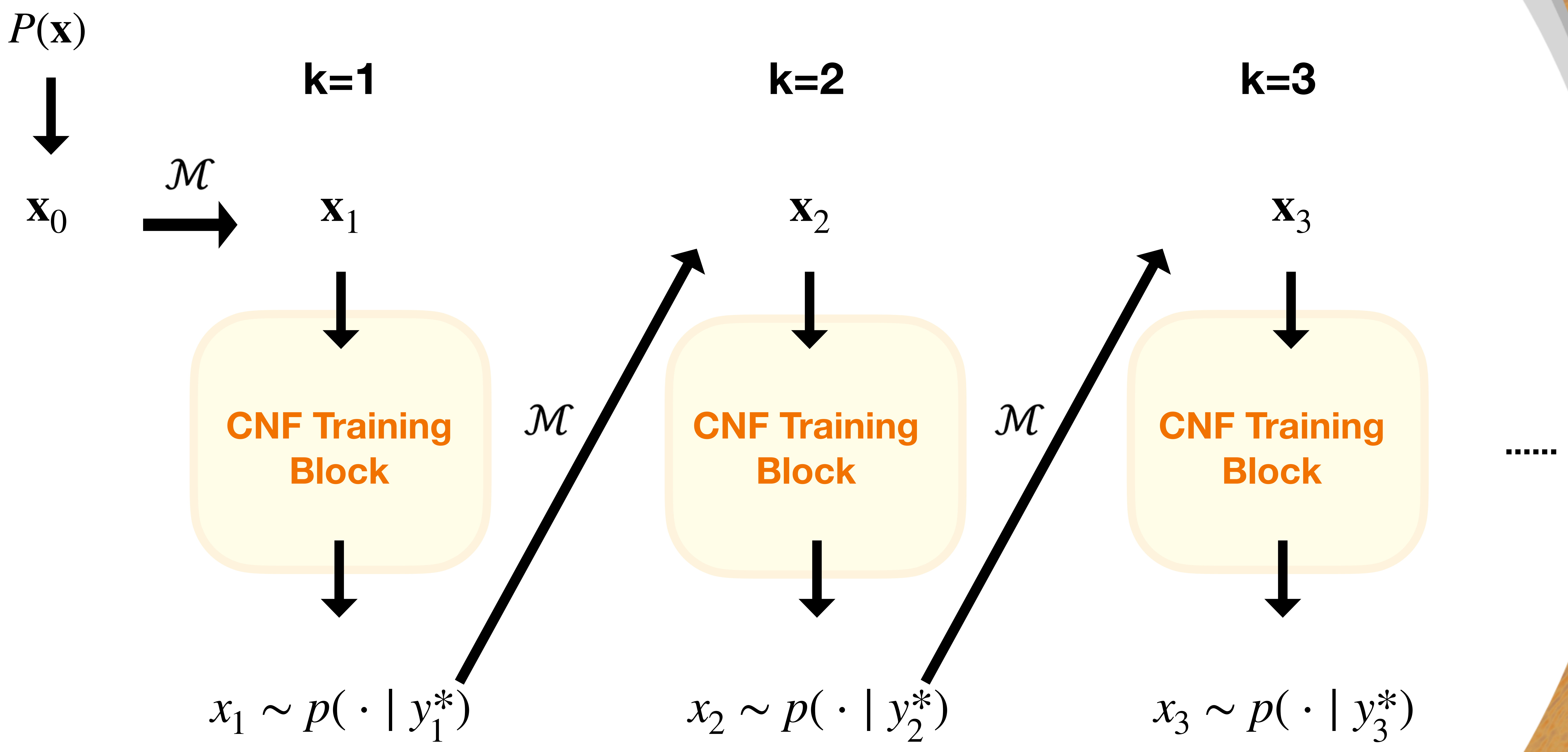
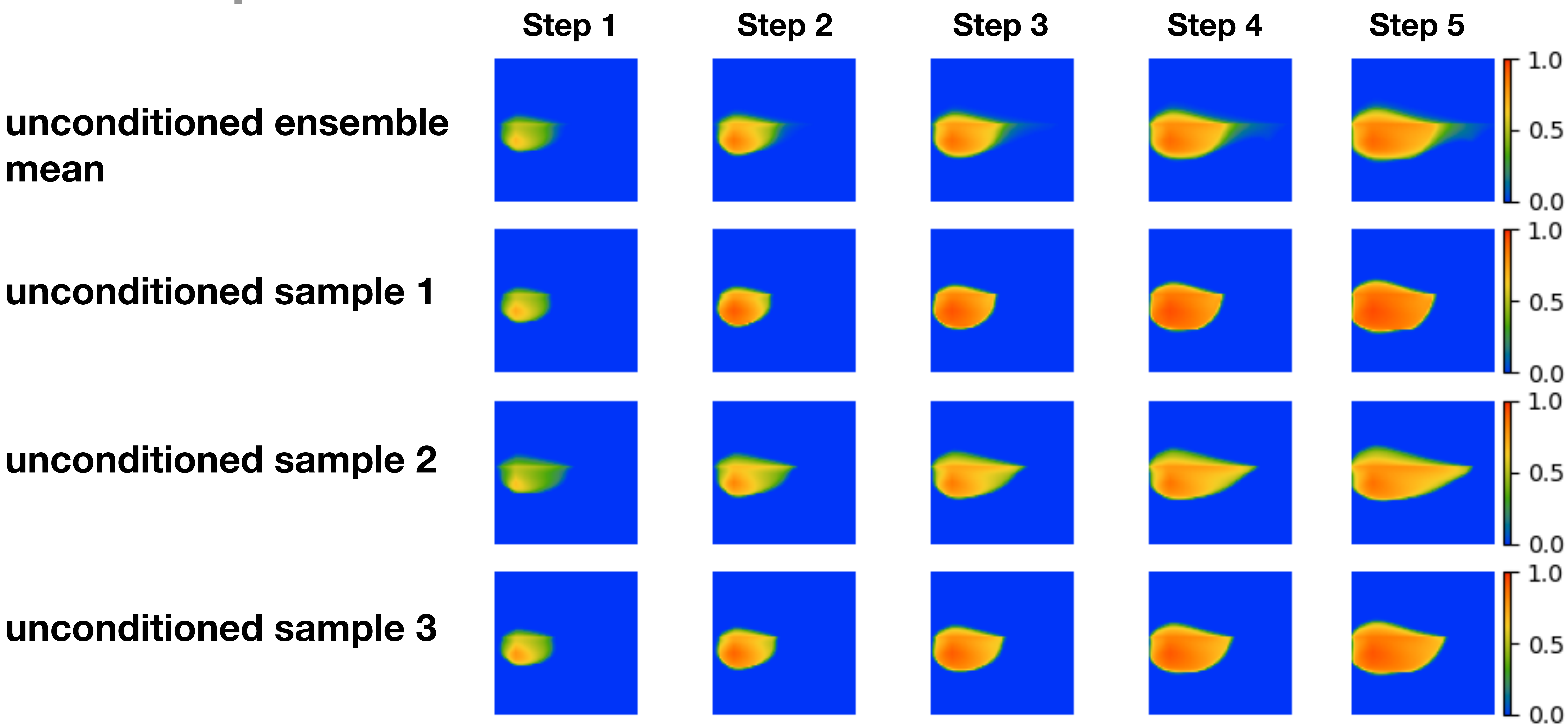


Results

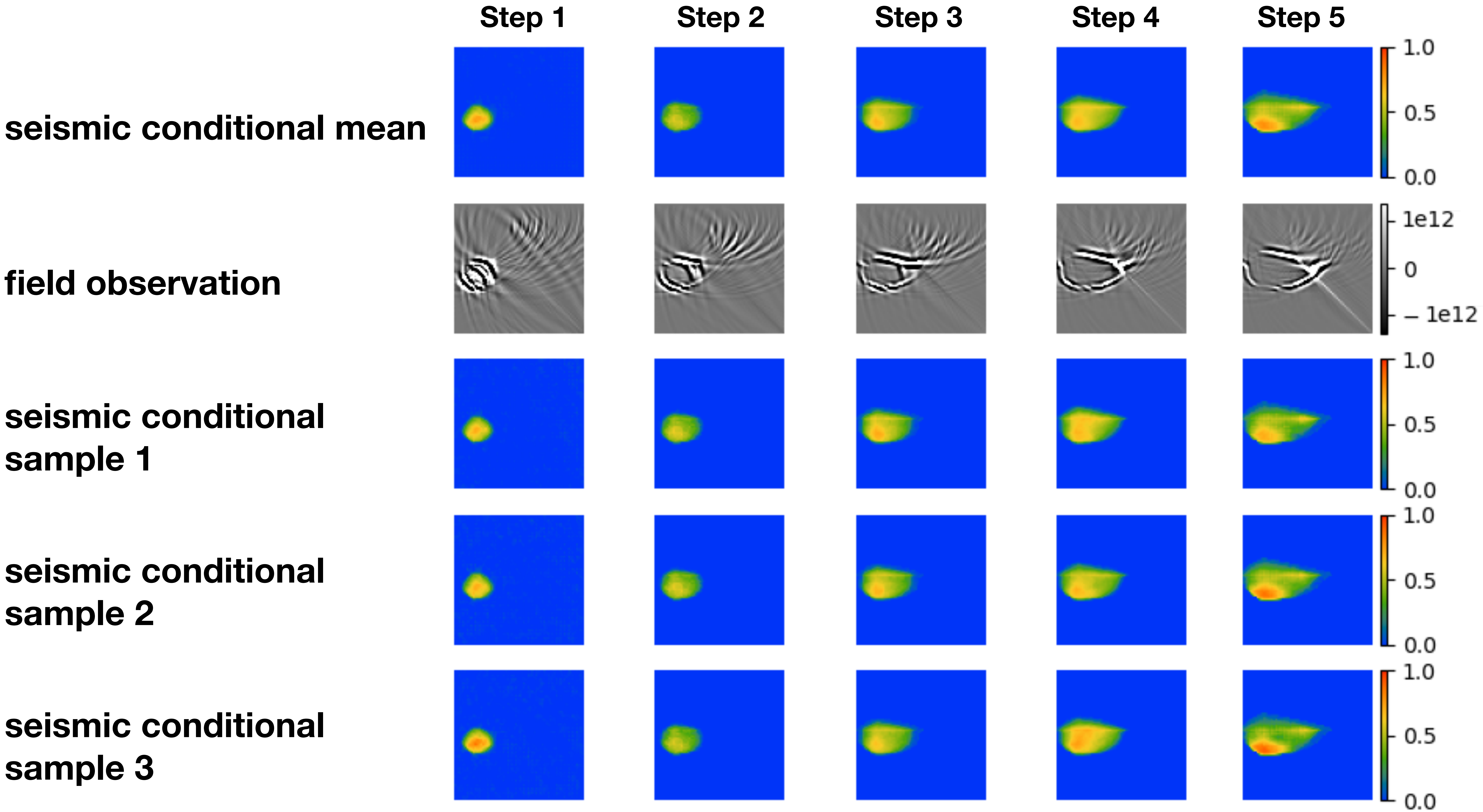
Unconditioned

predict CO_2 plume



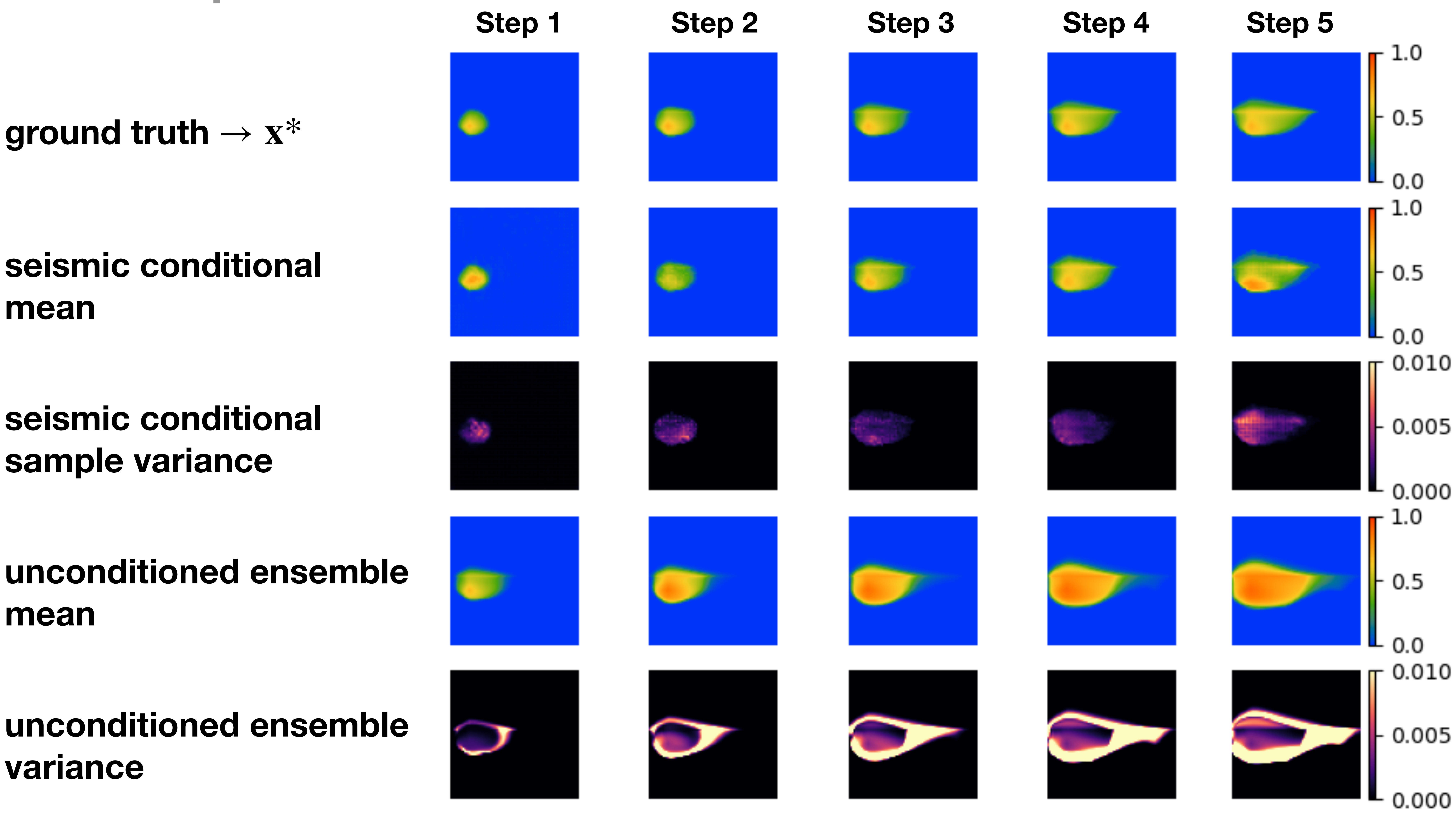
Conditioned on seismic

predict CO_2 plume



Conditioned on seismic

predict CO_2 plume



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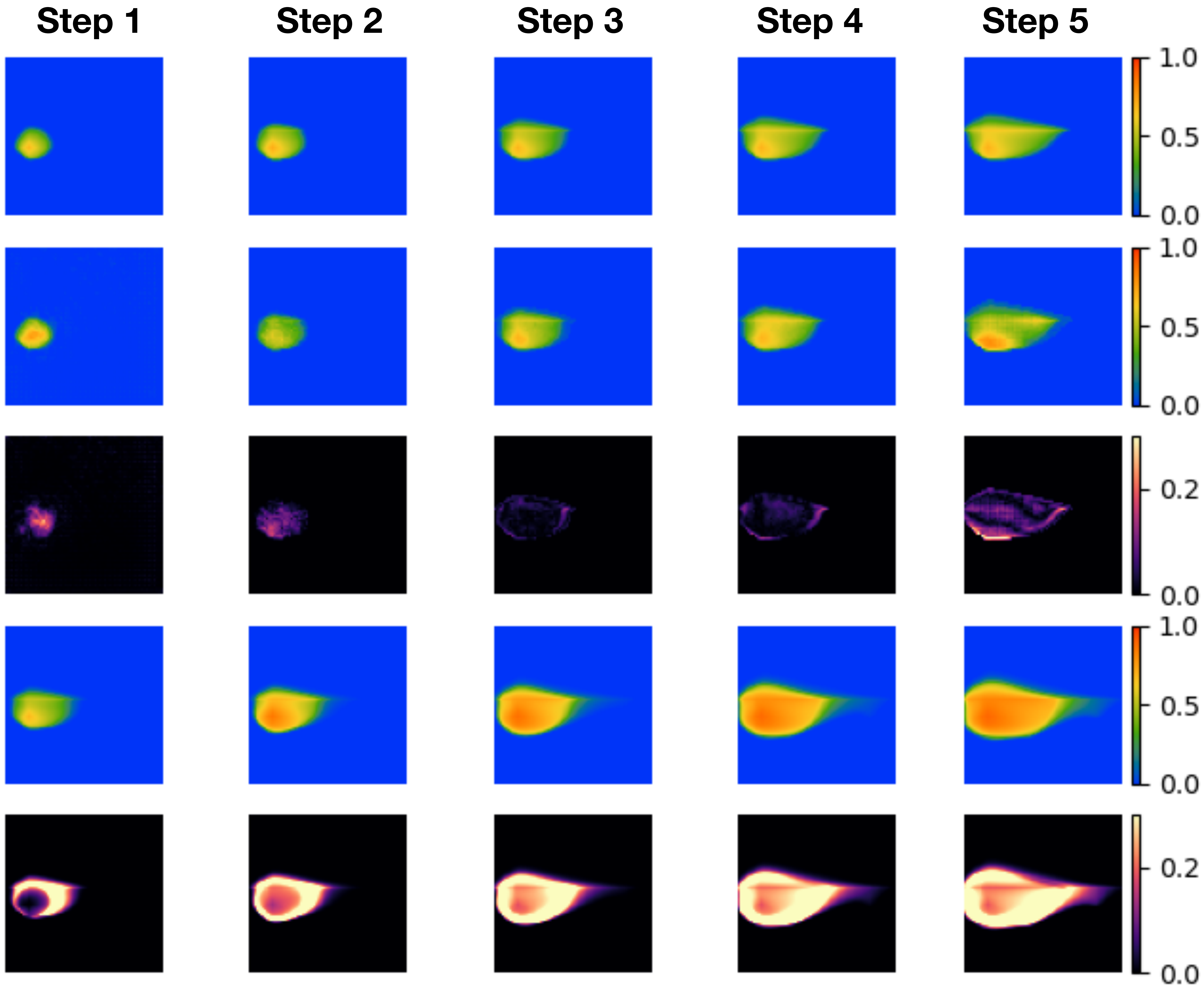
Conditioned on seismic

predict CO_2 plume



ground truth $\rightarrow \mathbf{x}^*$

seismic conditional mean $\rightarrow E(\mathbf{x}_c \sim p(\mathbf{x}\,|\,\mathbf{y}))$

$|\,\mathbf{x}^* - E(\mathbf{x}_c \sim p(\mathbf{x}\,|\,\mathbf{y}))\,|$

unconditional ensemble mean $E(\mathbf{x}_u)$

$|\,\mathbf{x}^* - E(\mathbf{x}_u)\,|$

Conclusions

Unconditioned simulation

- error increases with time

Conditioned on seismic with sequential Bayesian inference

- less variance
- assimilate information and learn along time
- characterize uncertainty

Future Work

Realistic setup of CO_2 reservoir model

- real Earth 3D permeability models
- more stochasticity: e.g. permeability which we assumed given and fixed

Conditioned on other observations

- pressure data from wells
- work with time varying permeability

Apply technique on scenario leakage for early detection

Acknowledgement

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