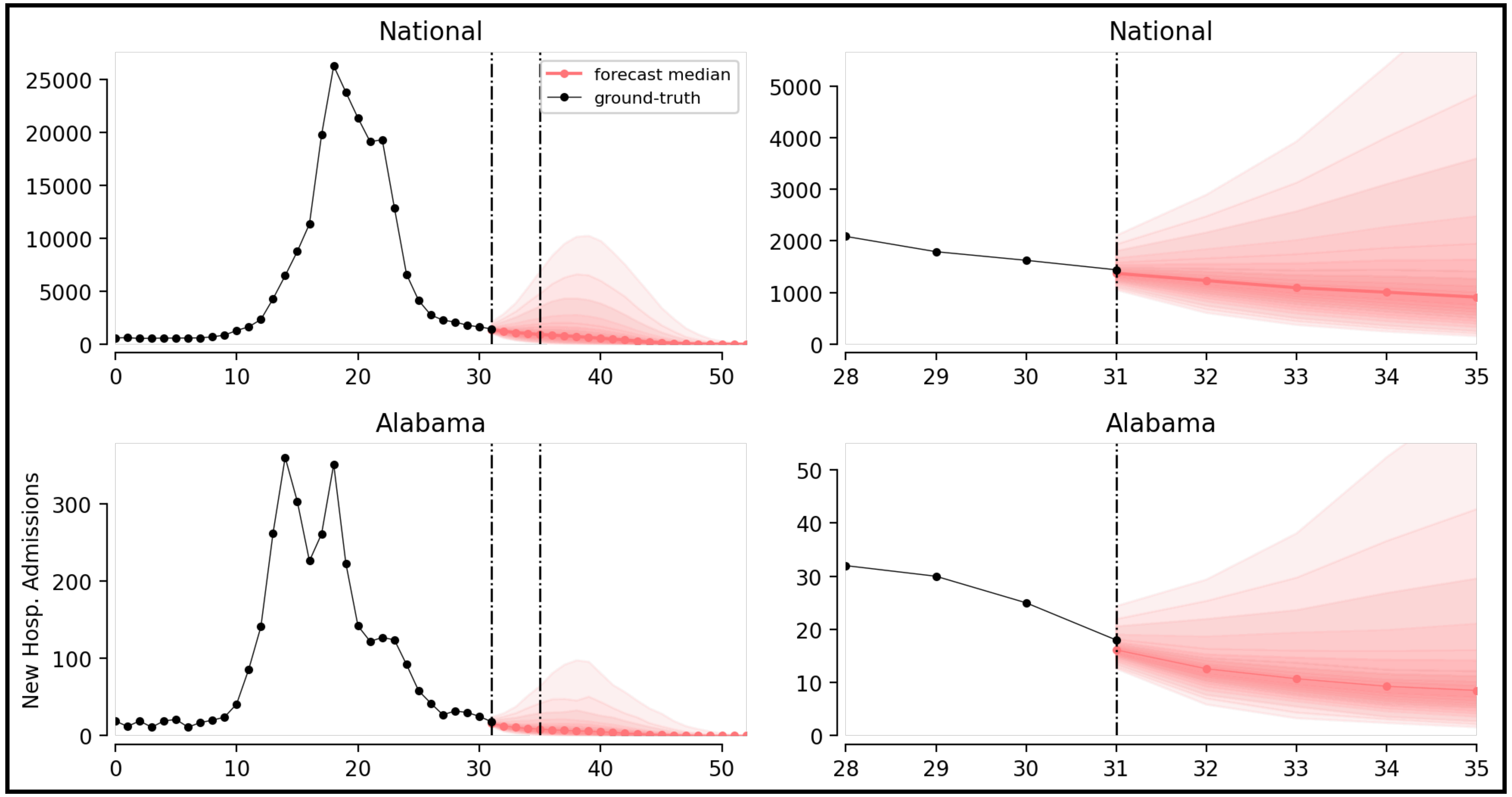
INFLUPAINT: GENERATIVE ARTIFICIAL INTELLIGENCE TO FORECAST SEASONAL INFLUENZA IN THE U.S.

Joseph Lemaitre, Jess K. Edwards, Justin Lessler

The University of North Carolina at Chapel Hill



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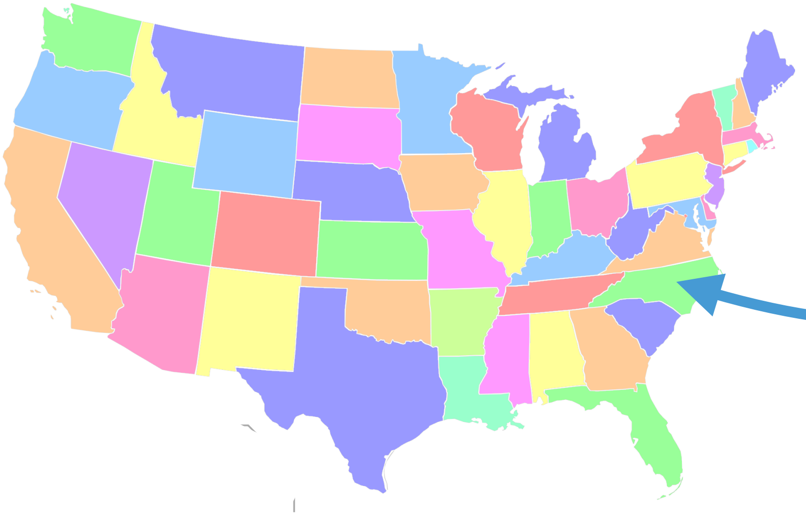
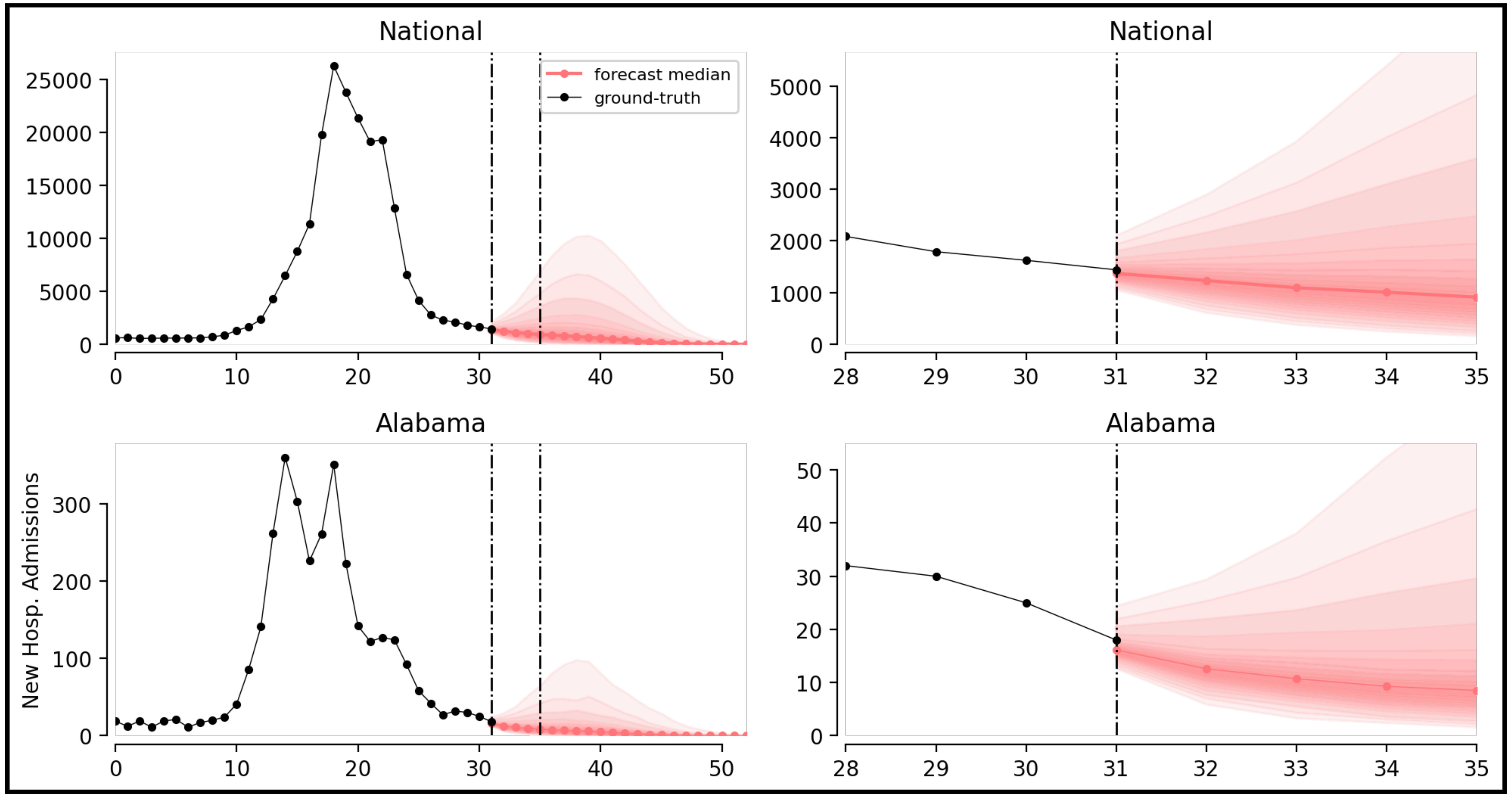




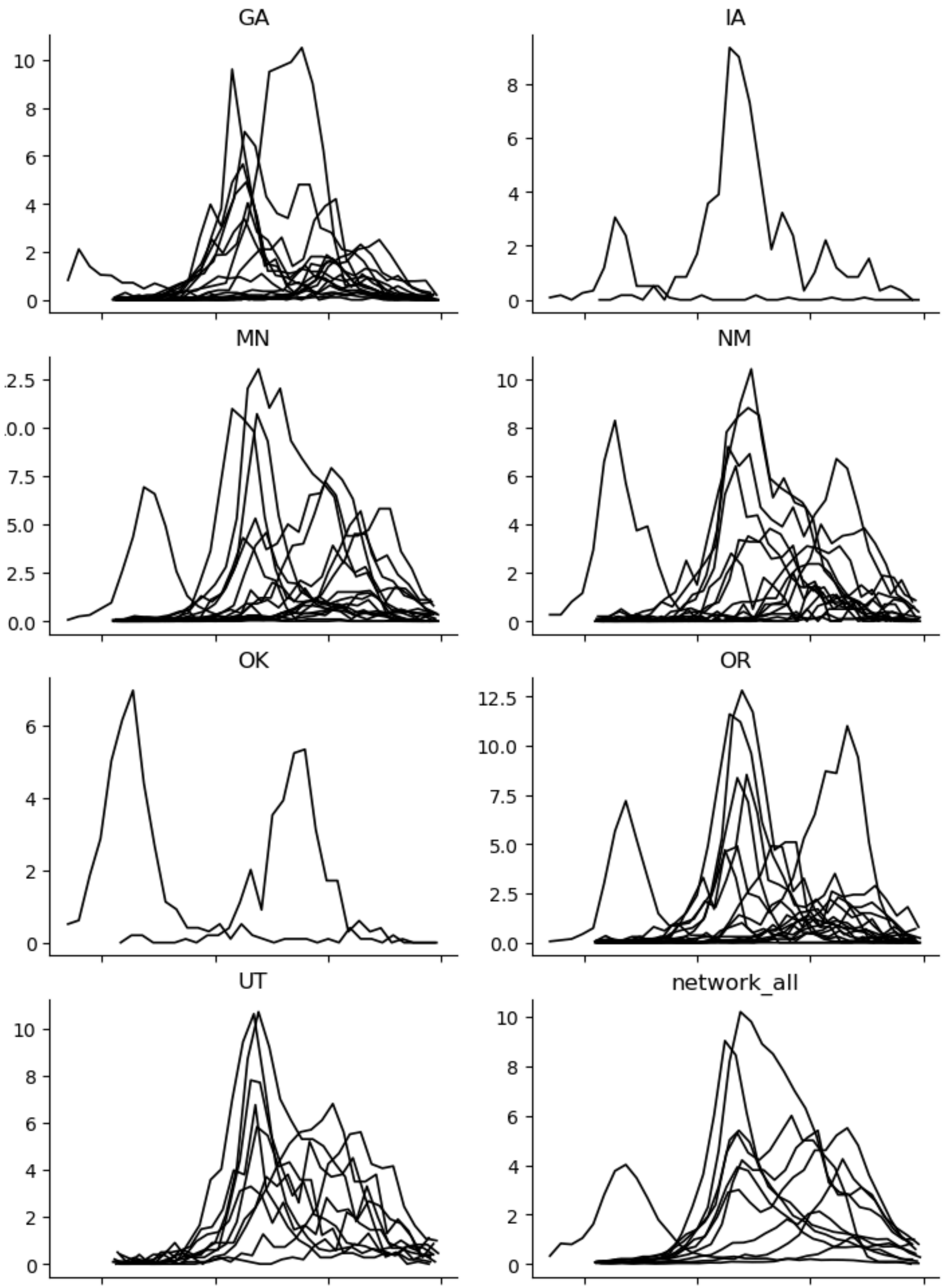
BROADER GOALS

A. **Produce forecasts of infectious disease transmission that reflect the diversity of the observed patterns**

- How many “modes” has the FluSurv data →

B. **Build hybrid statistical/mechanistic models**

- So flexible statistical modeling framework



DEEP GENERATIVE ~~AI~~ MODELING

- **Generative models:** generate new data; builds a representation of the data generating process

- Denoising Diffusion Probabilistic Models (DDPM) provide high-quality samples with **good diversity and mode coverage** (no mode collapse like GANs). Think DALL-E 2 🎨

- Other methods: variational autoencoders (VAE), autoregressive models (ARM), generative adversarial networks (GAN)

$$\underbrace{\Pr(\boldsymbol{\theta}|\boldsymbol{x})}_{\text{posterior}} = \frac{\overbrace{\Pr(\boldsymbol{x}|\boldsymbol{\theta})}^{\text{likelihood}}\ \overbrace{\Pr(\boldsymbol{\theta})}^{\text{prior}}}{\Pr(\boldsymbol{x})}$$

Very useful

Denoising Diffusion Probabilistic Models

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Diffusion Models Beat GANs on Image Synthesis

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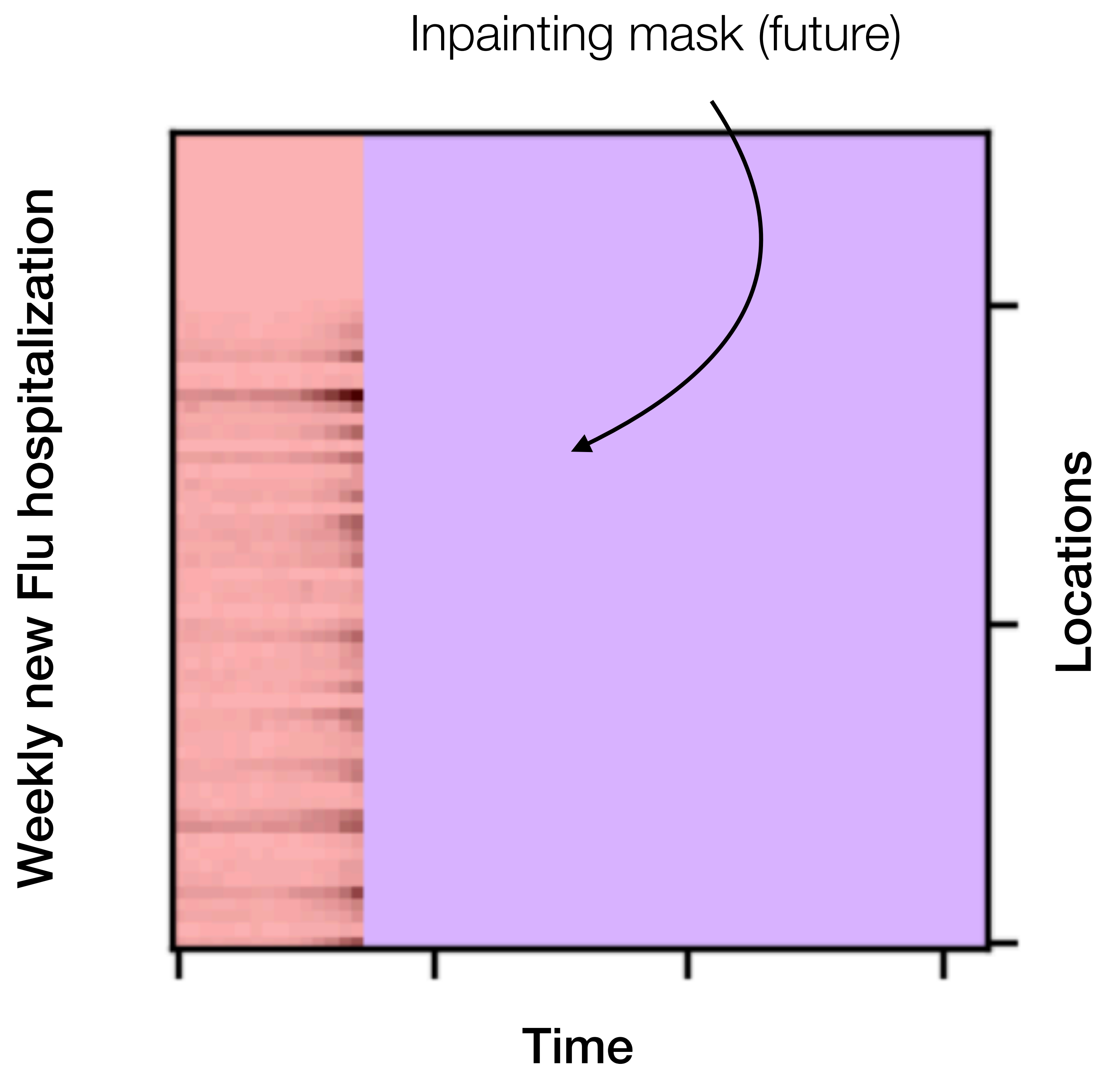
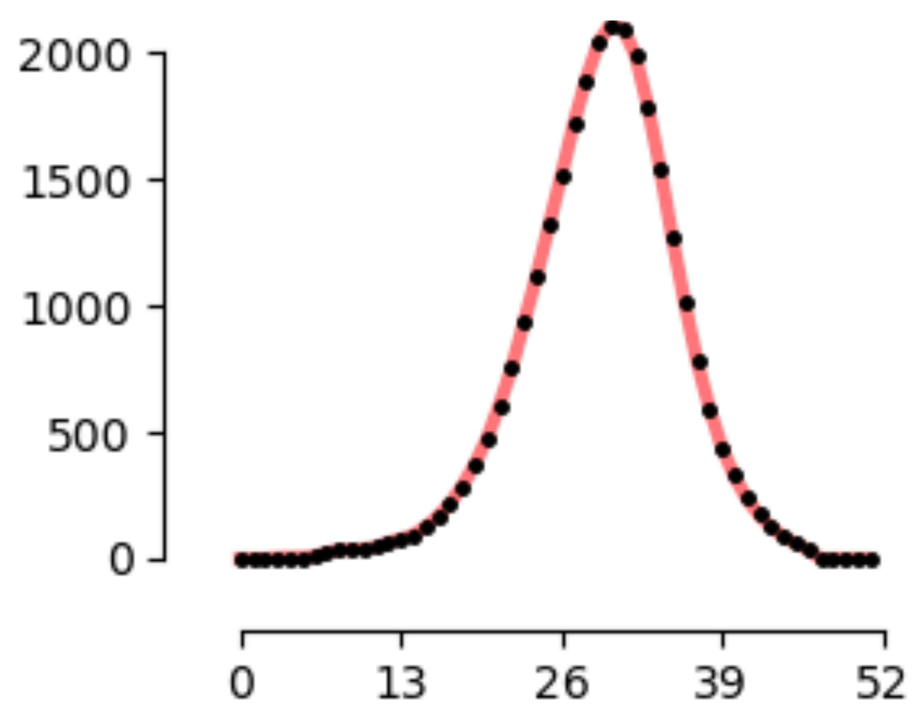
DEEP GENERATIVE ~~AI~~ MODELING

- We **treat influenza epidemic curves as images** (axes are time and location, pixel value is e.g incident hospitalization). We generate epidemic trajectories using a DDPM…



DENOISING DIFFUSION PROBABILISTIC MODELS 101

Pure signal



“diffusion time”

DENOISING DIFFUSION PROBABILISTIC MODELS 101

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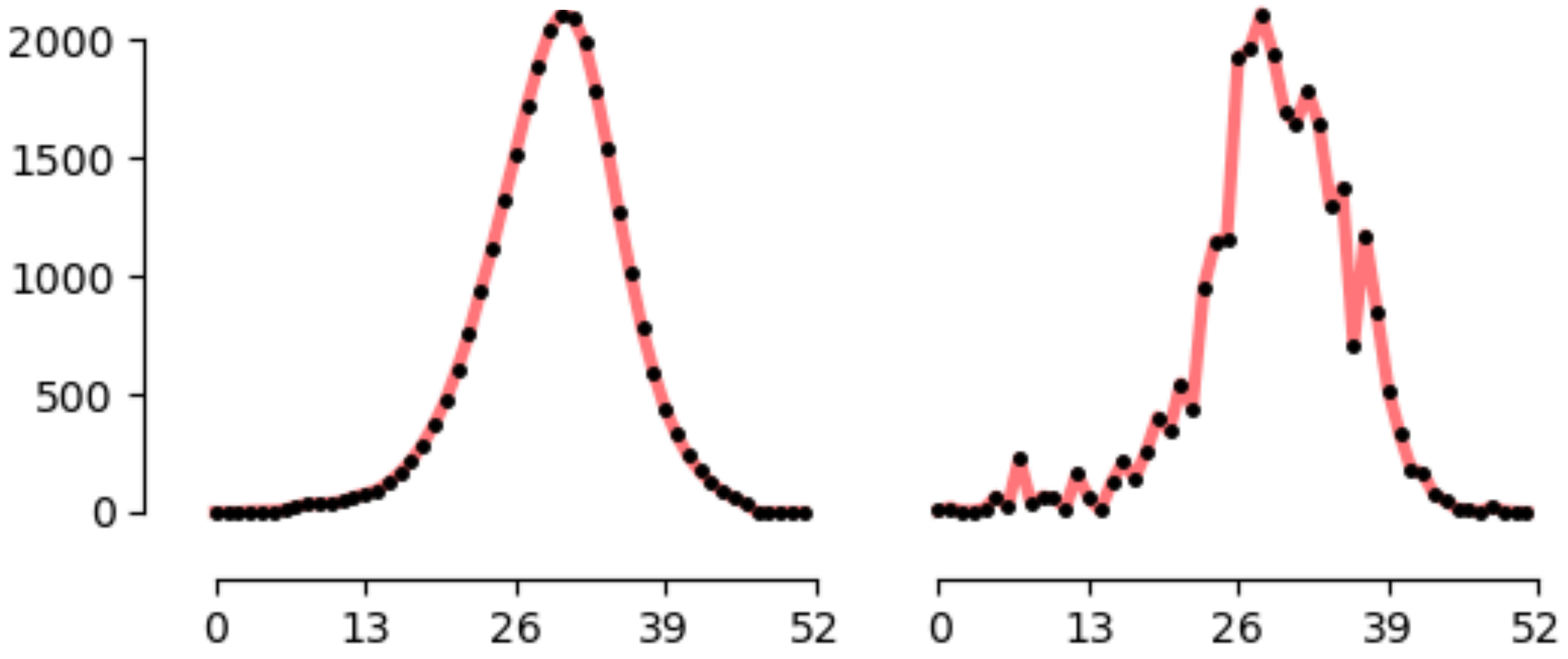

“diffusion time”

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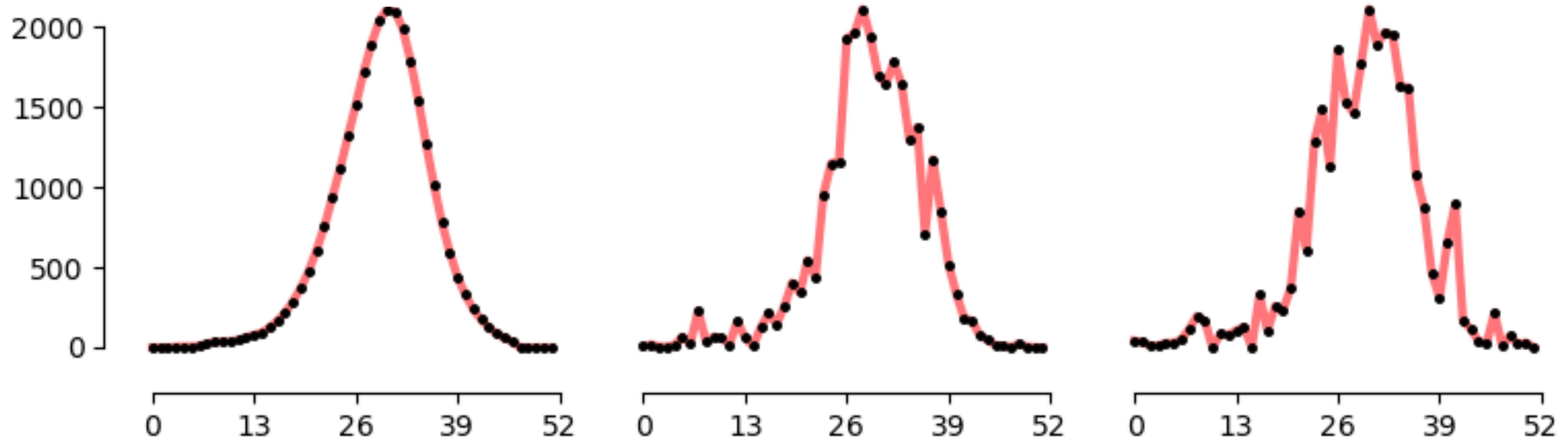
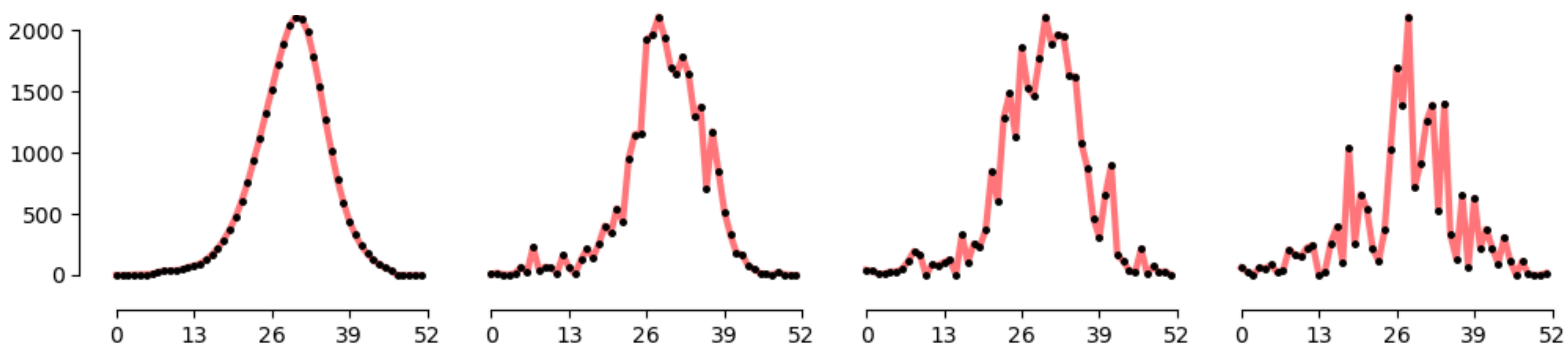


"diffusion time"

DENOISING DIFFUSION PROBABILISTIC MODELS 101

$$q(\mathbf{x_t} \mid \mathbf{x_{t-1}})$$

Pure signal



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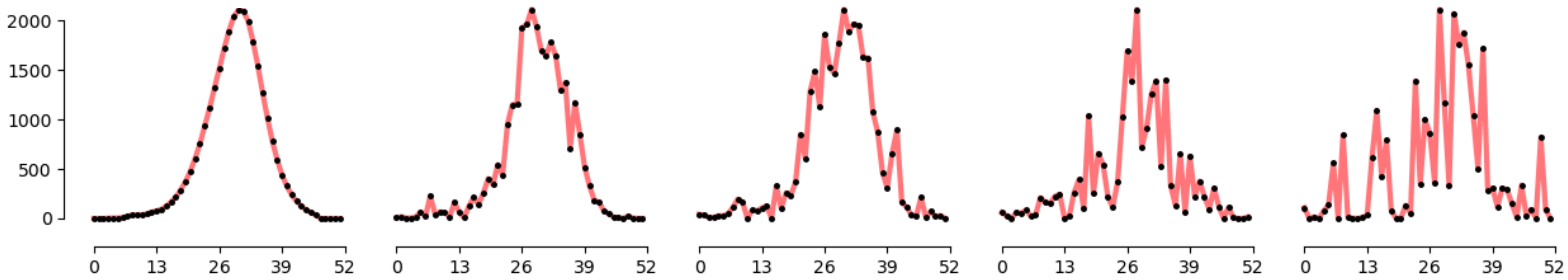

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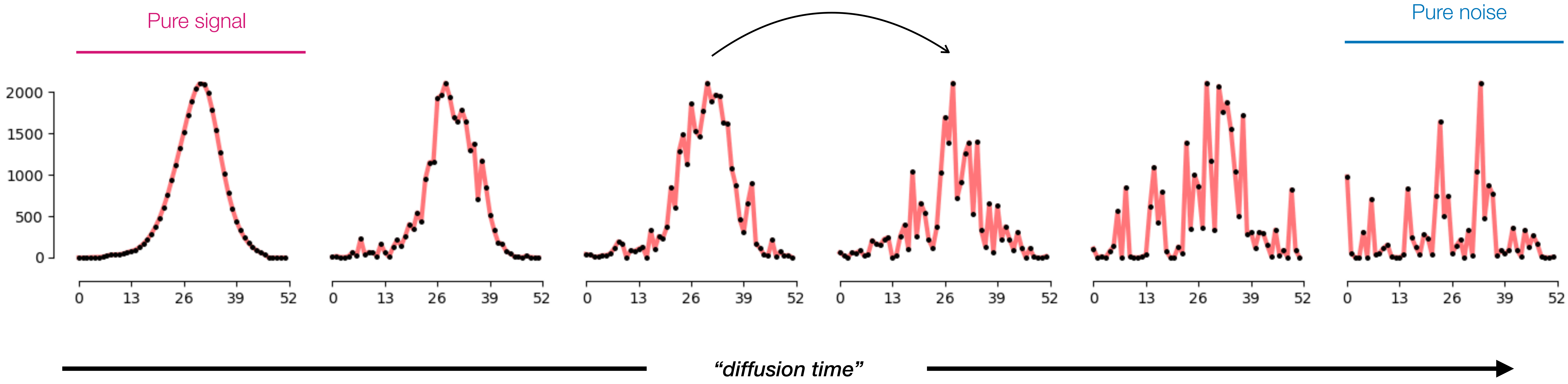

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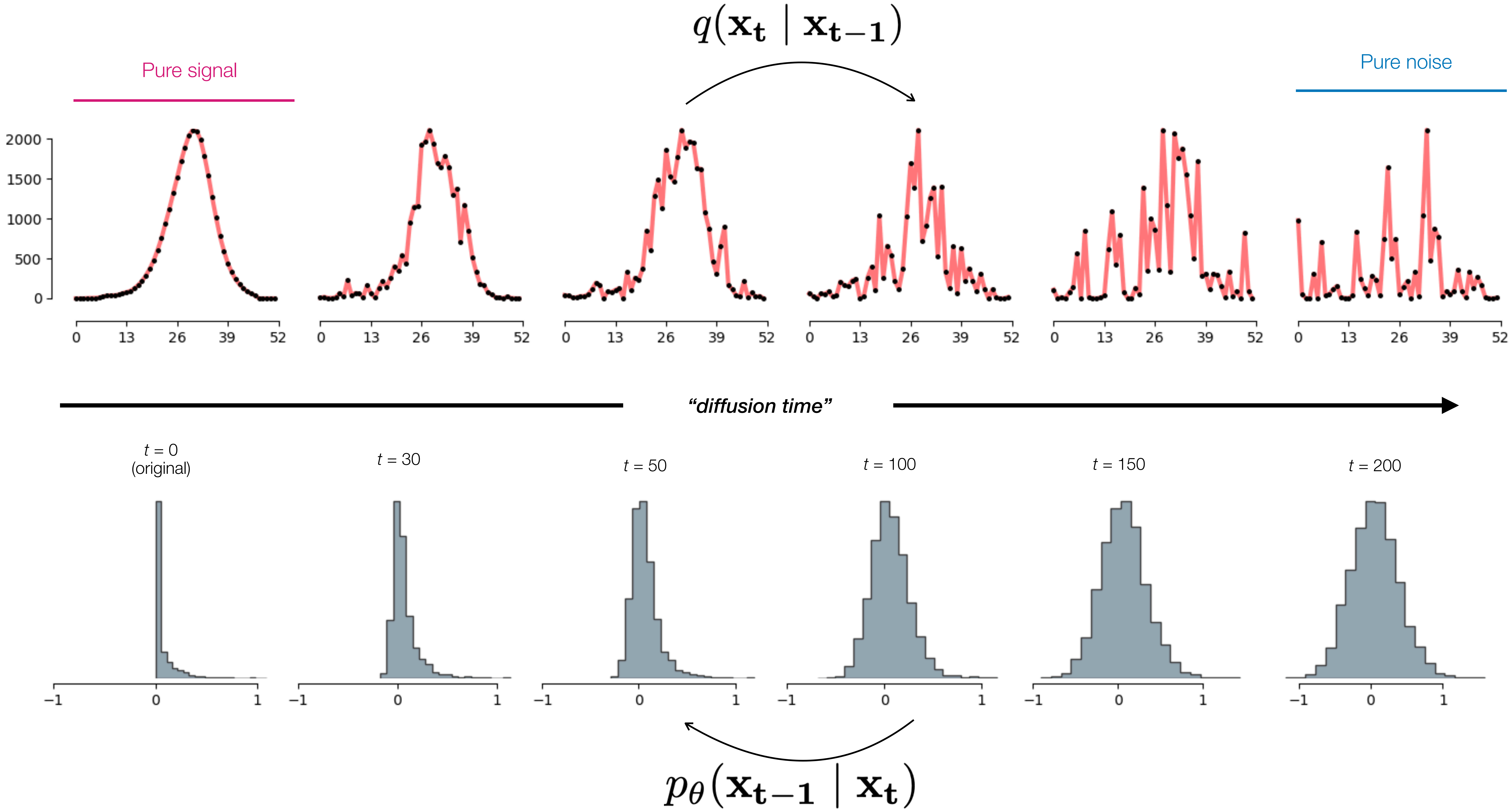
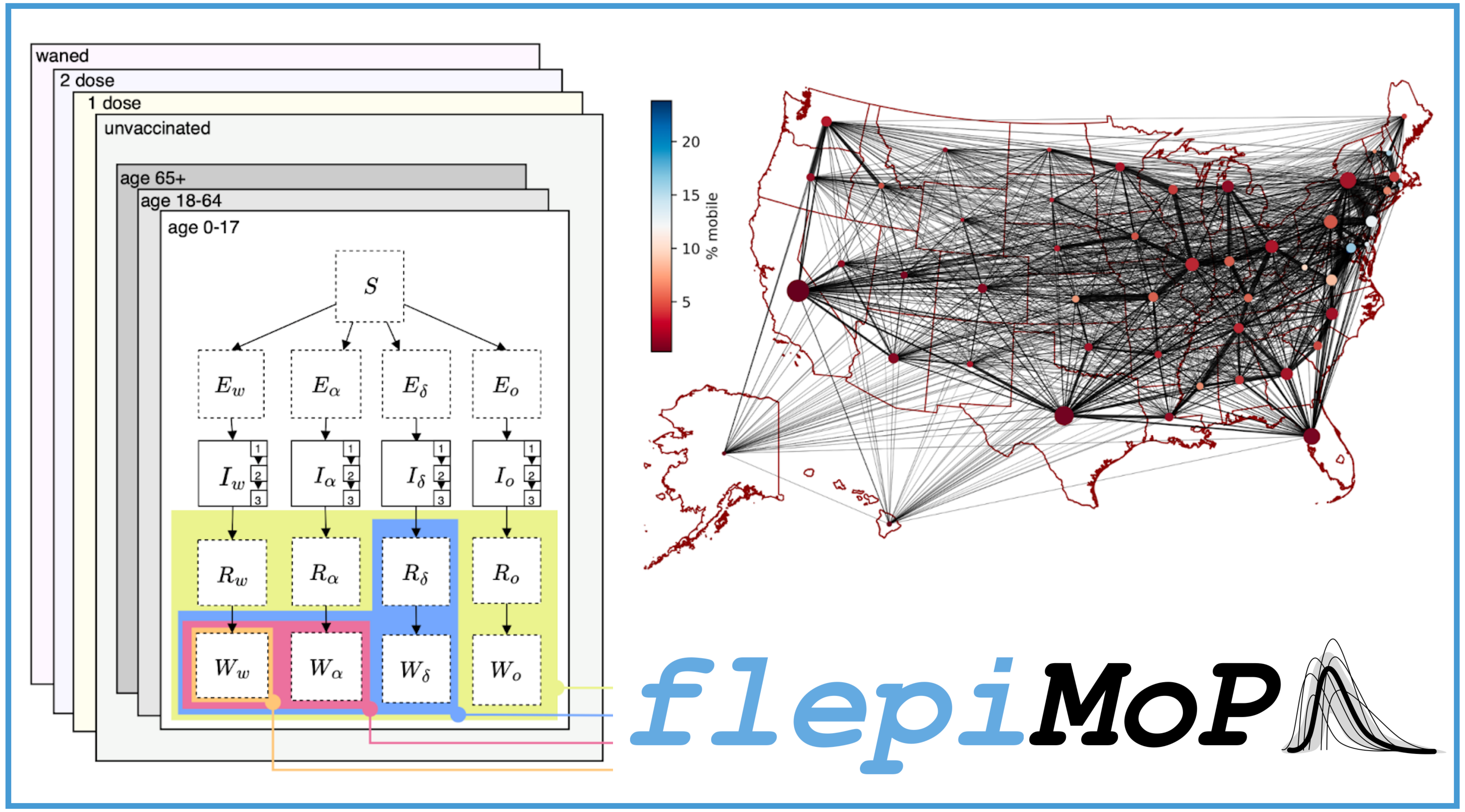
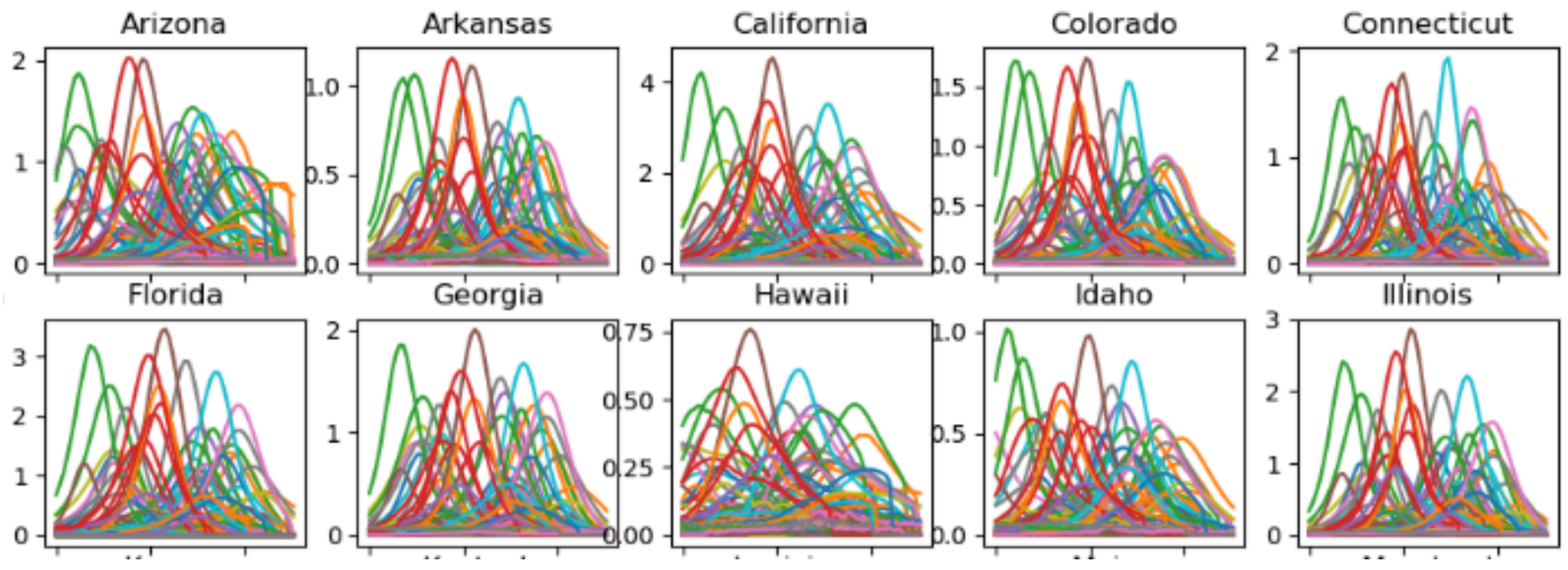


TRAINING DATA

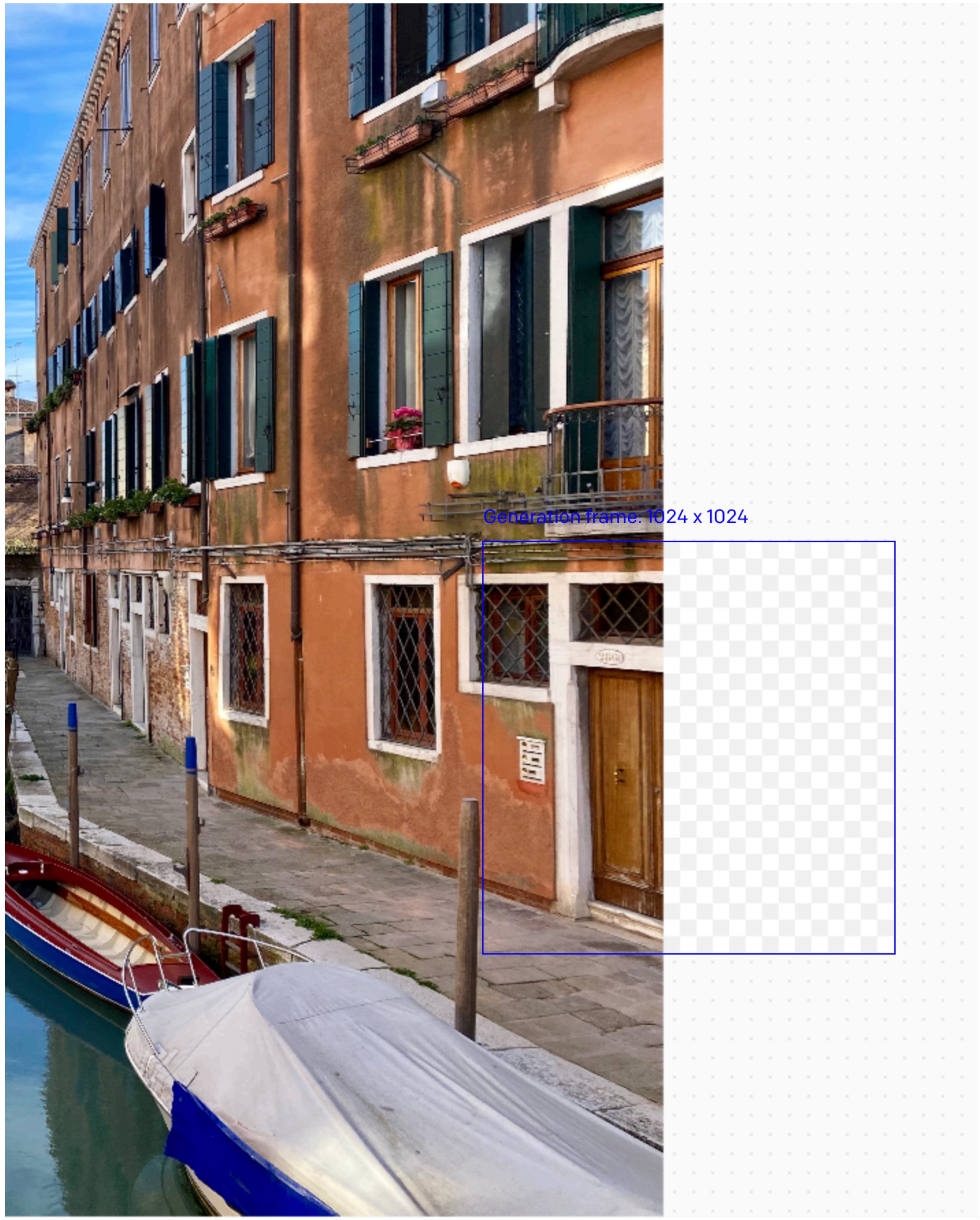
- **No dataset corresponds to what we want to model** (New Hospital Admission at the state level). We mix 👨🏻‍🍳:
    - Outputs from a **mechanistic influenza transmission** model (flepiMoP.org 👀)
    - **Reported US influenza data** (Fluview, FluSurv) at different locations (very small datasets, dozen of samples),
- **Augmented** & scaled





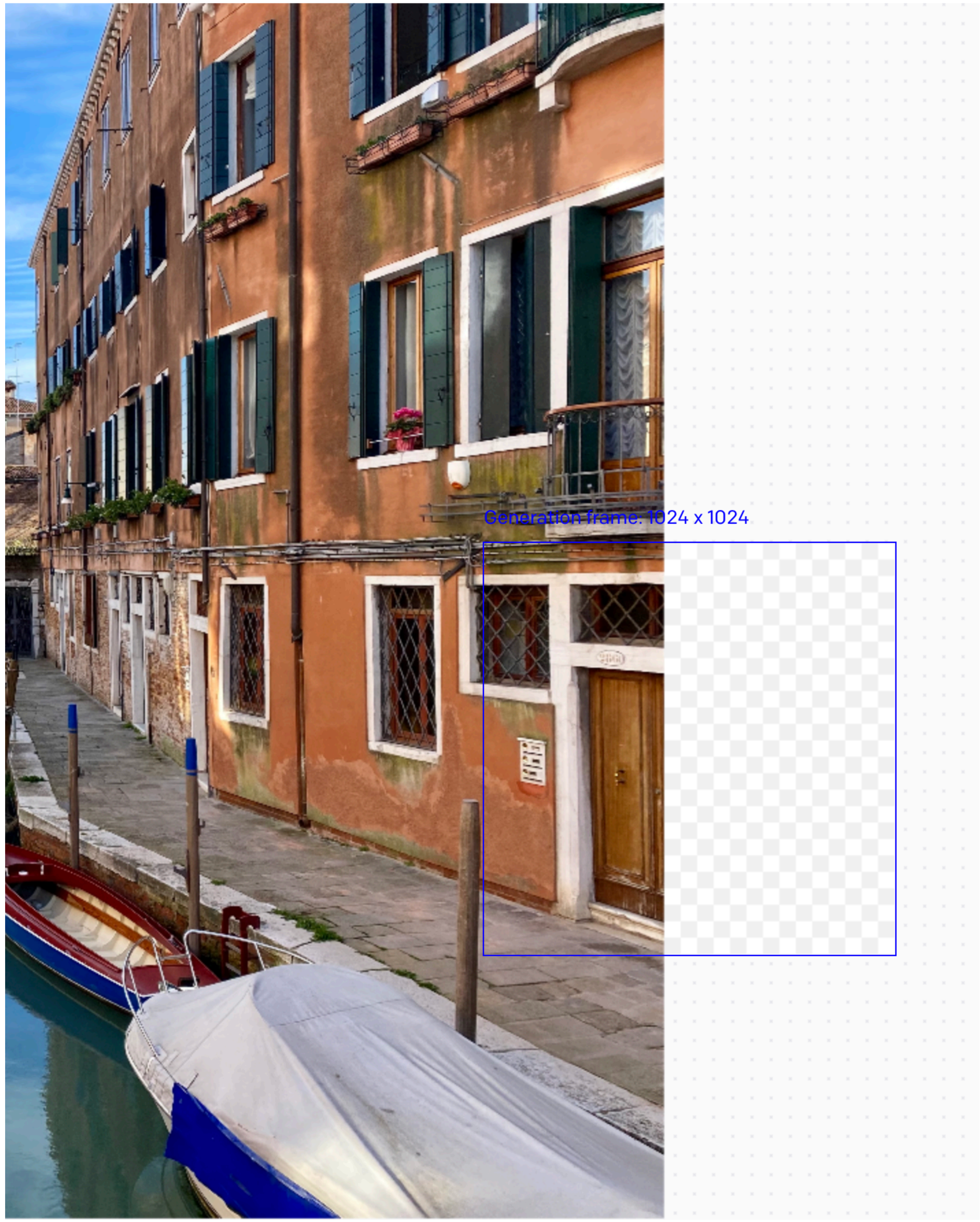
Transformed training data sample

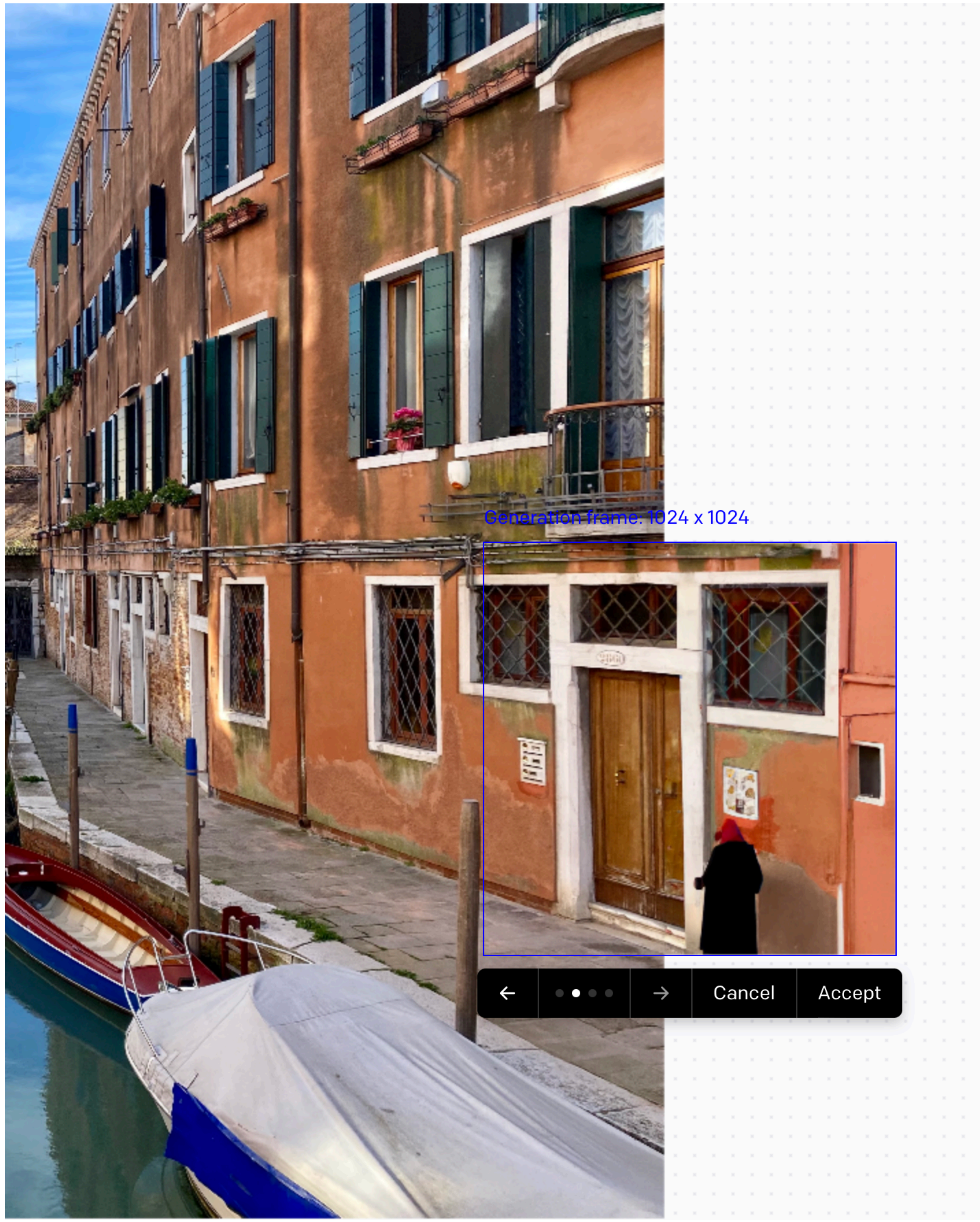
CONDITIONING DENOISING DIFFUSION MODELS



DALL-E 2 from OpenAI, 2022. Try it !

CONDITIONING DENOISING DIFFUSION MODELS





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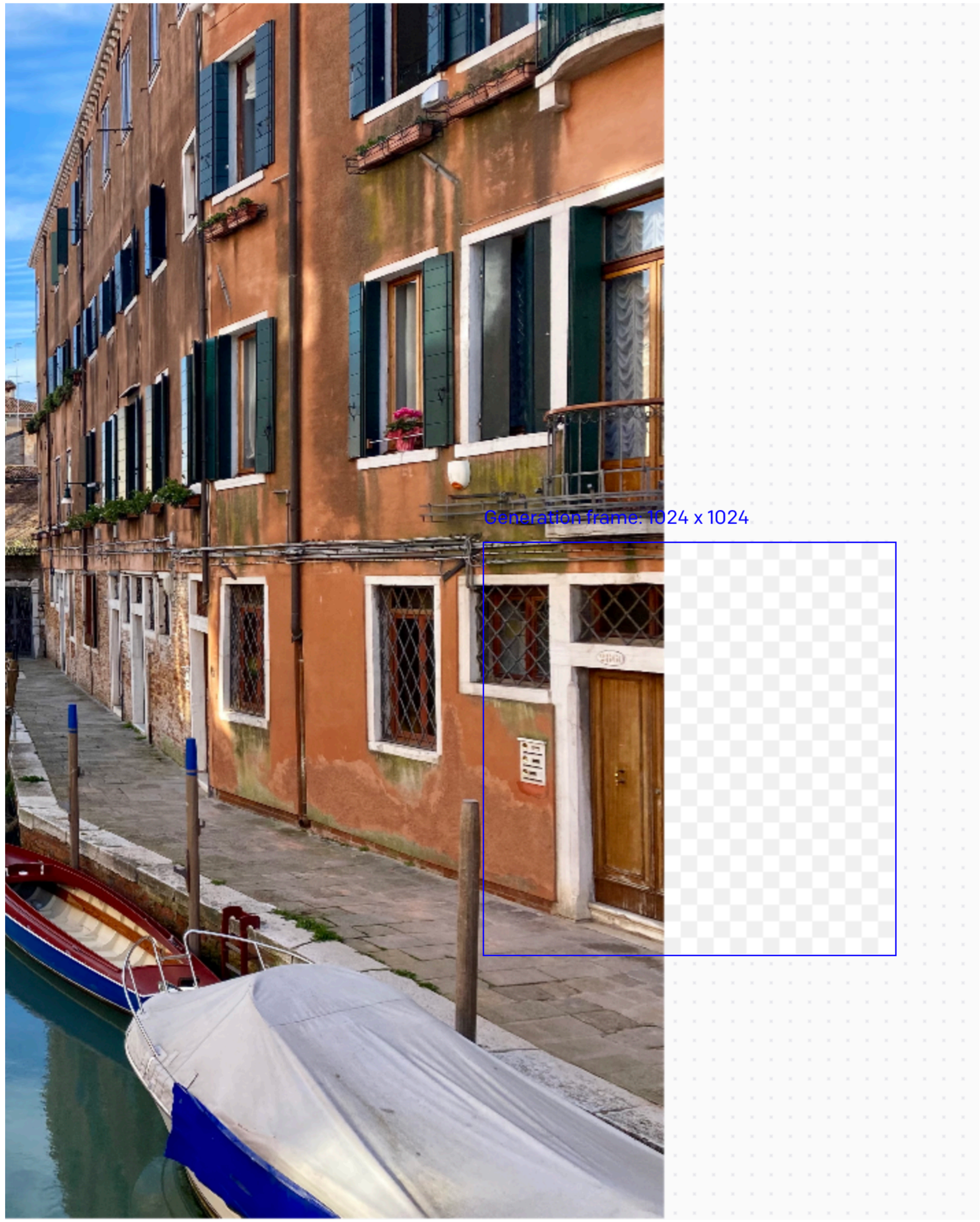

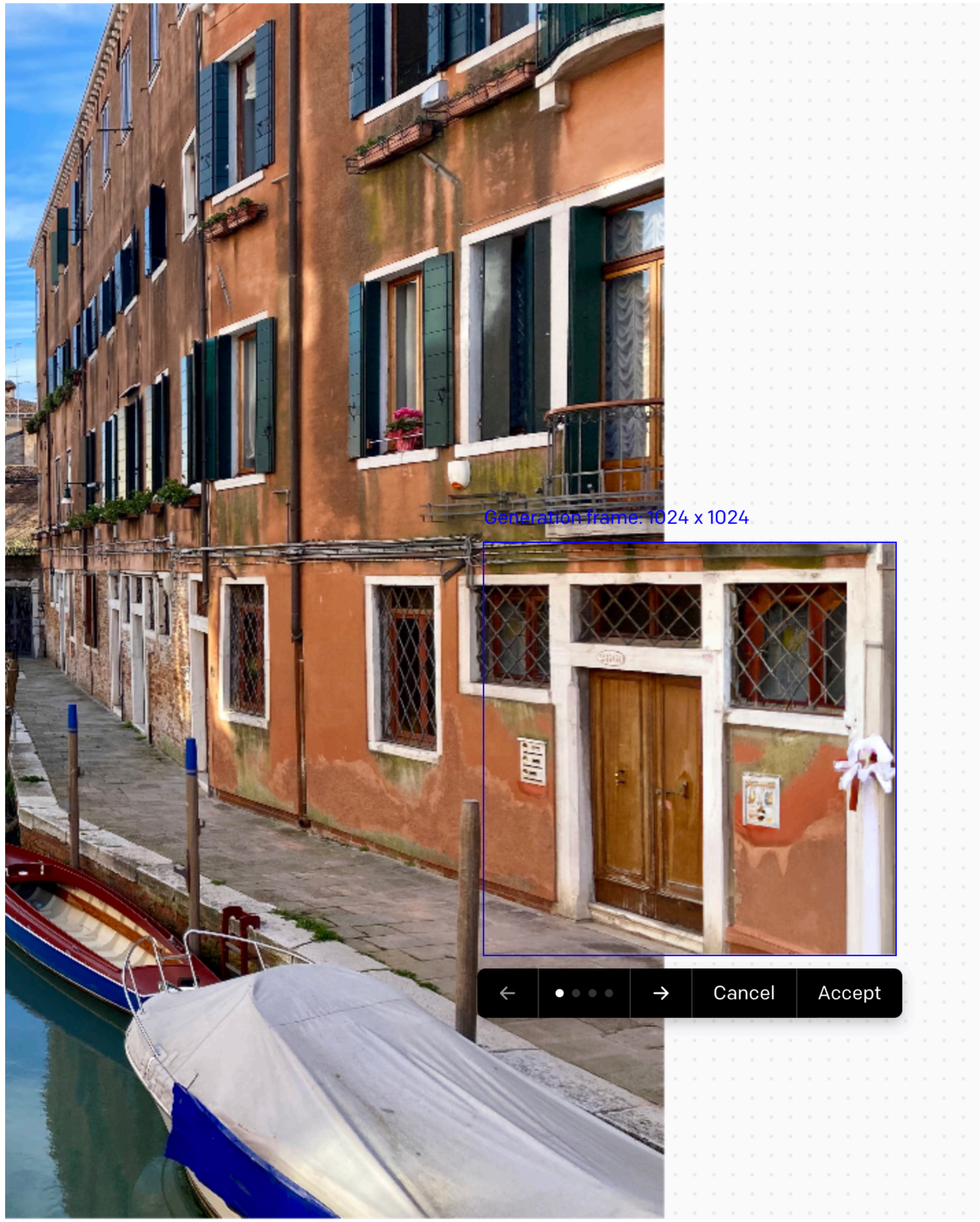

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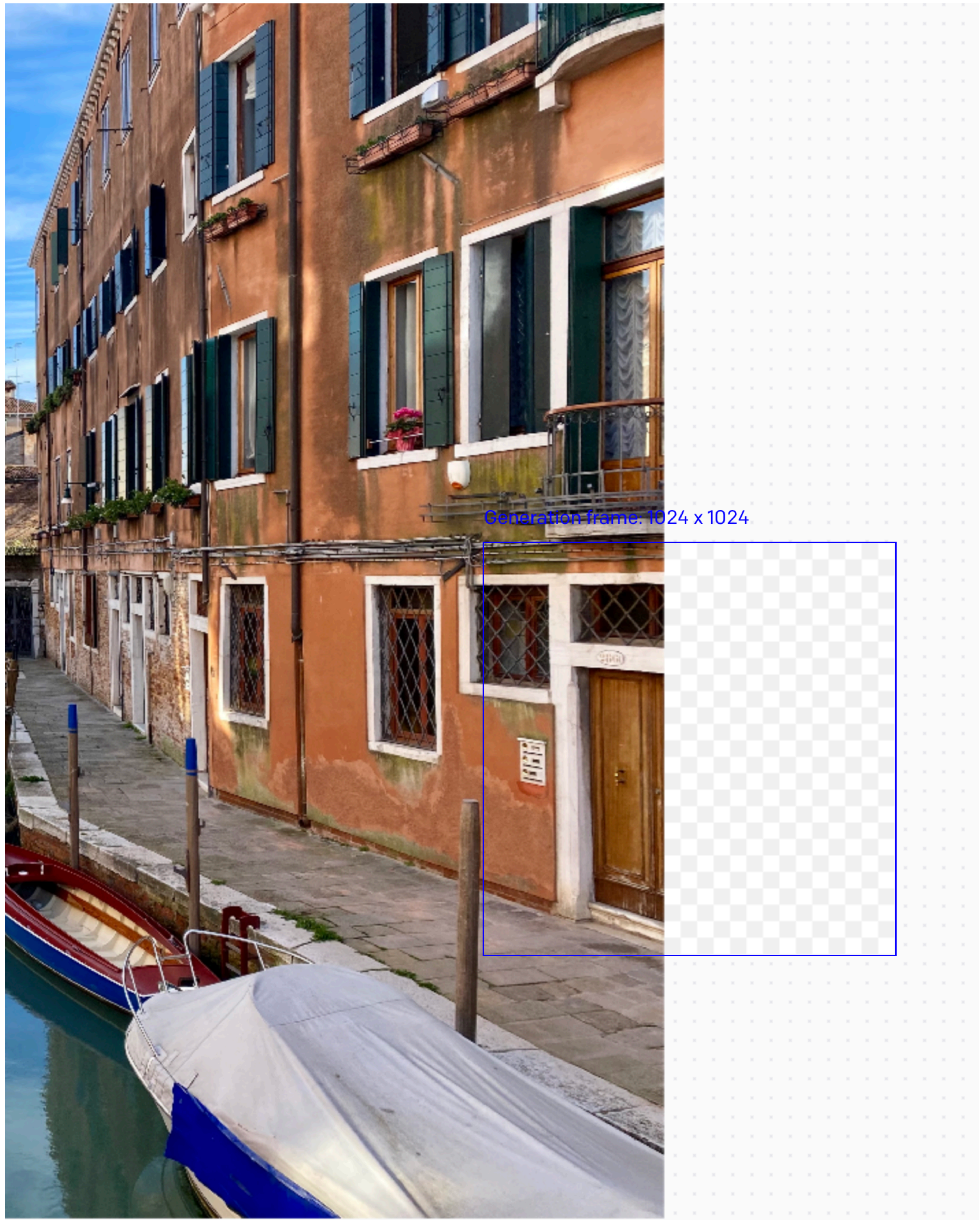

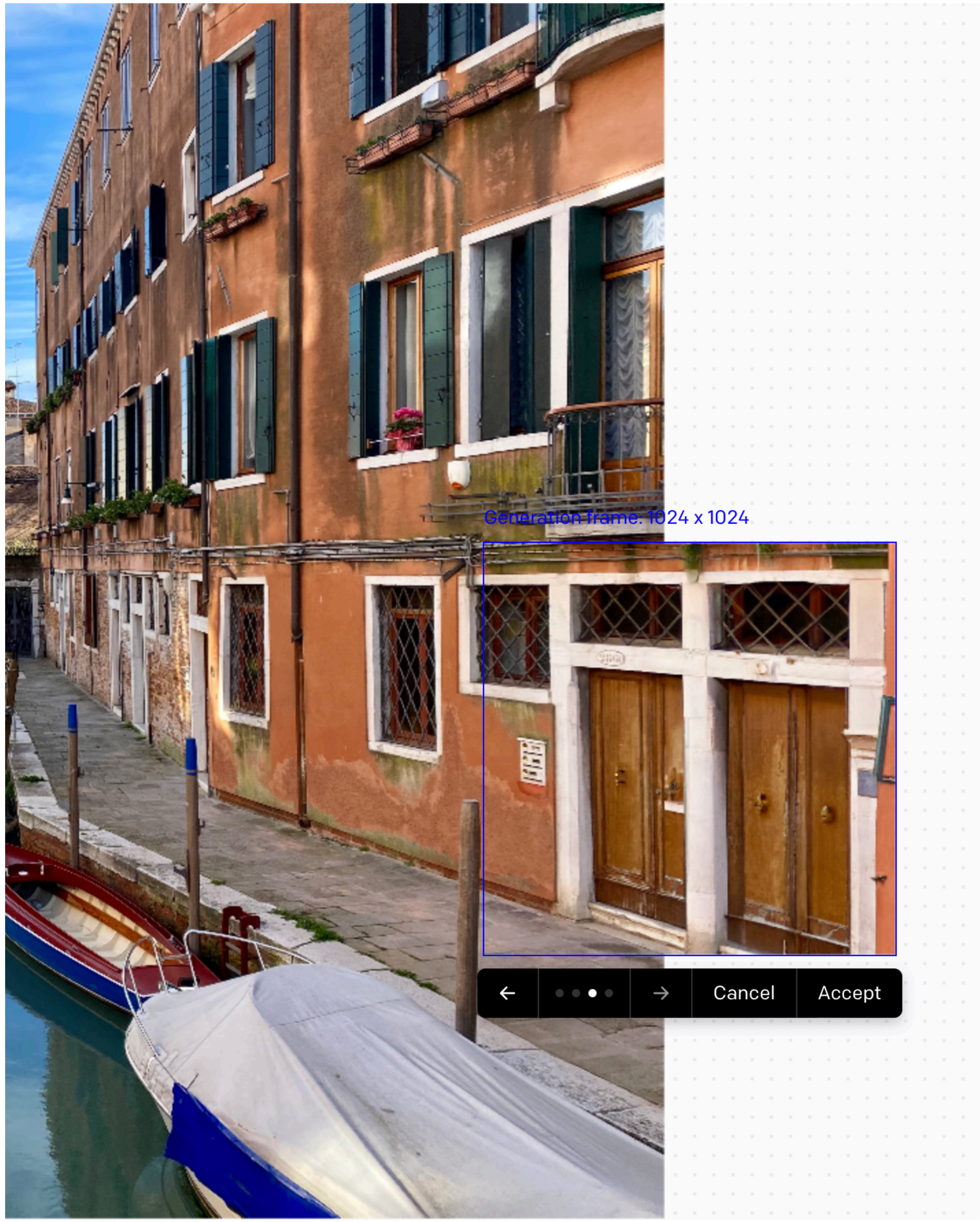

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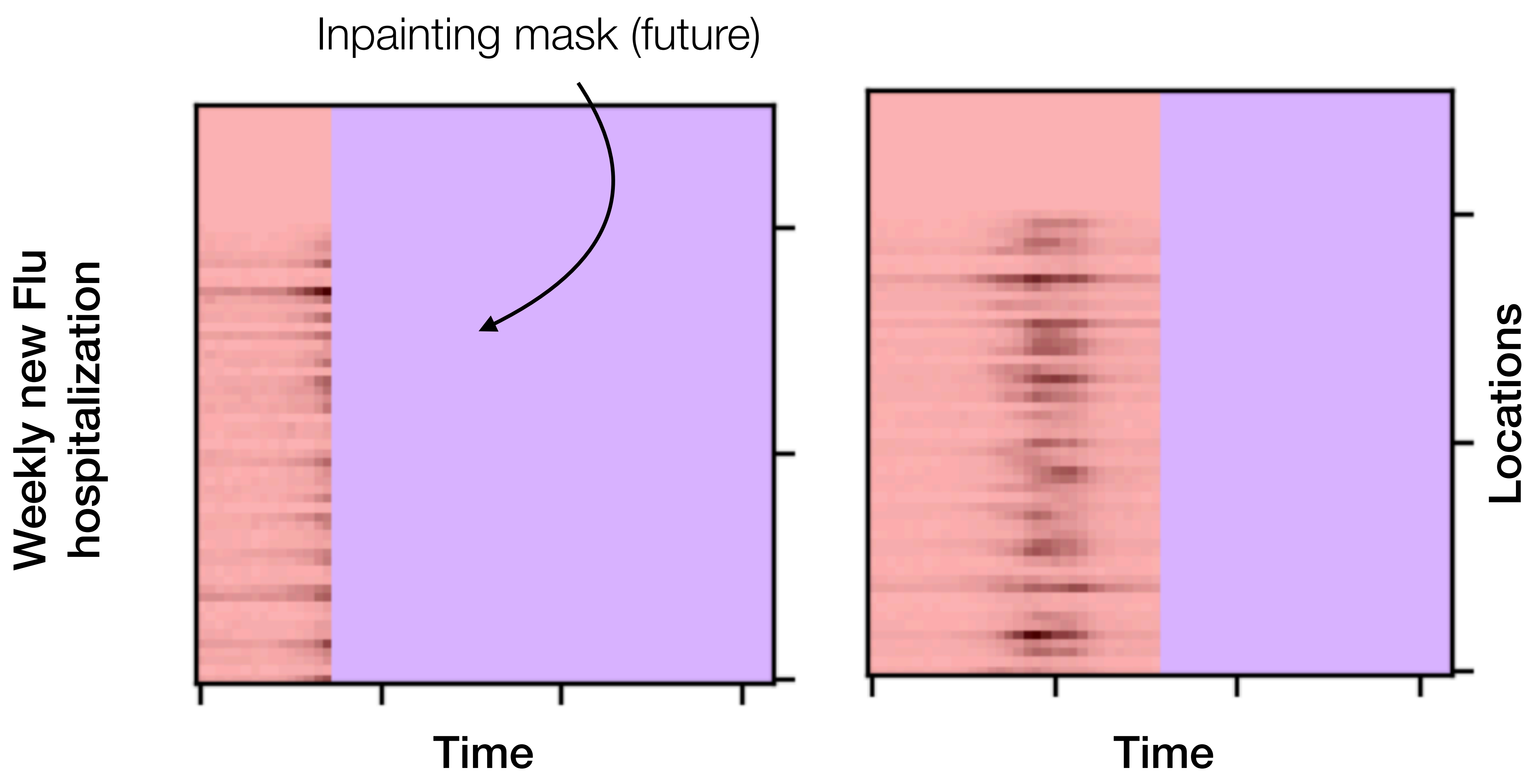
INPAINTING

- Inpainting alter the reverse diffusion by sampling the unmasked regions using ground-truth
- REpaint outperforms SOTA for inpainting
- Parameters: the global harmonization is defined by the resampling schedule
- The mask can have any shape

RePaint: Inpainting using Denoising Diffusion Probabilistic Models

Andreas Lugmayr Martin Danelljan Andres Romero Fisher Yu Radu Timofte Luc Van Gool
Computer Vision Lab
ETH Zürich, Switzerland



INPAINTING

- **Inpainting** alter the reverse diffusion by sampling the unmasked regions using ground-truth
- **REpaint** outperforms SOTA for inpainting
- Parameters: the **global harmonization** is defined by the resampling schedule
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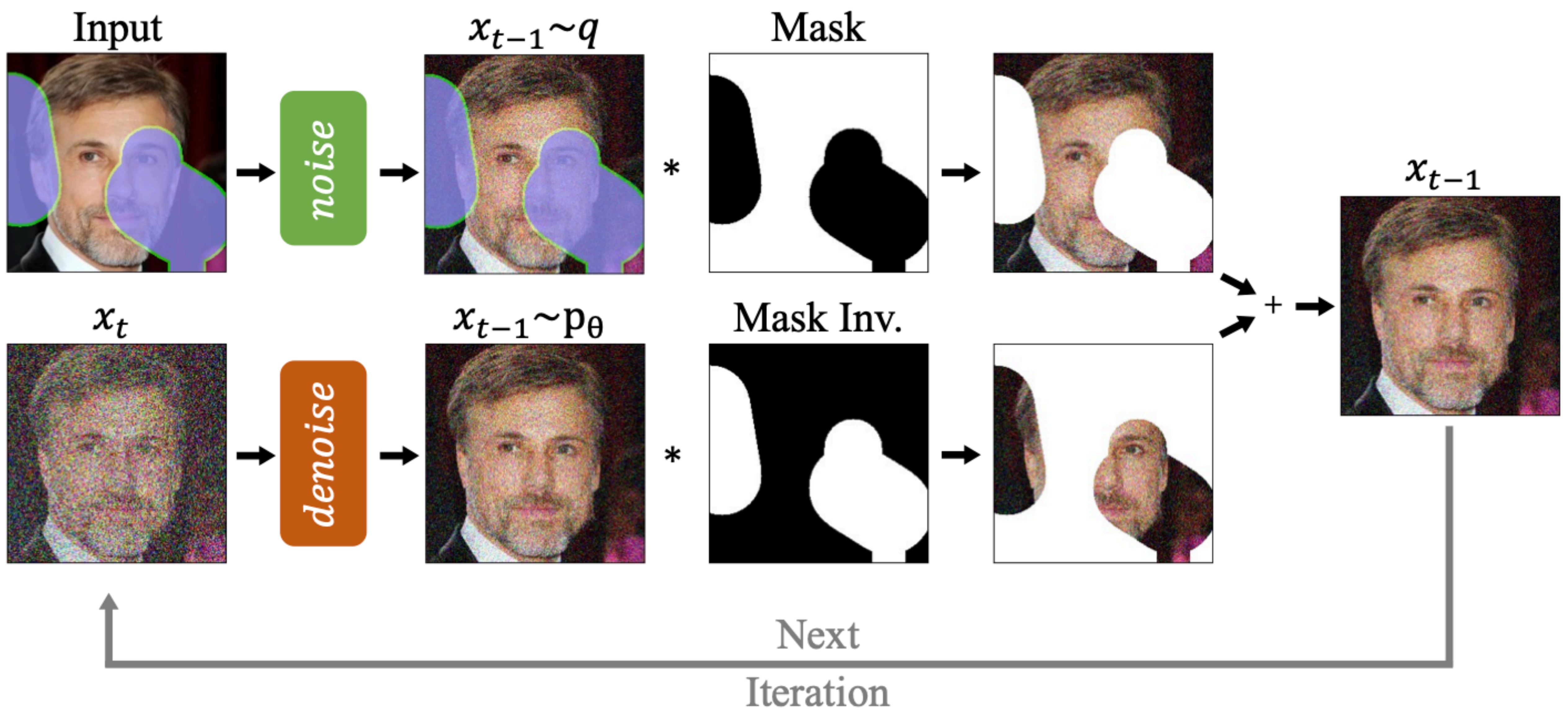
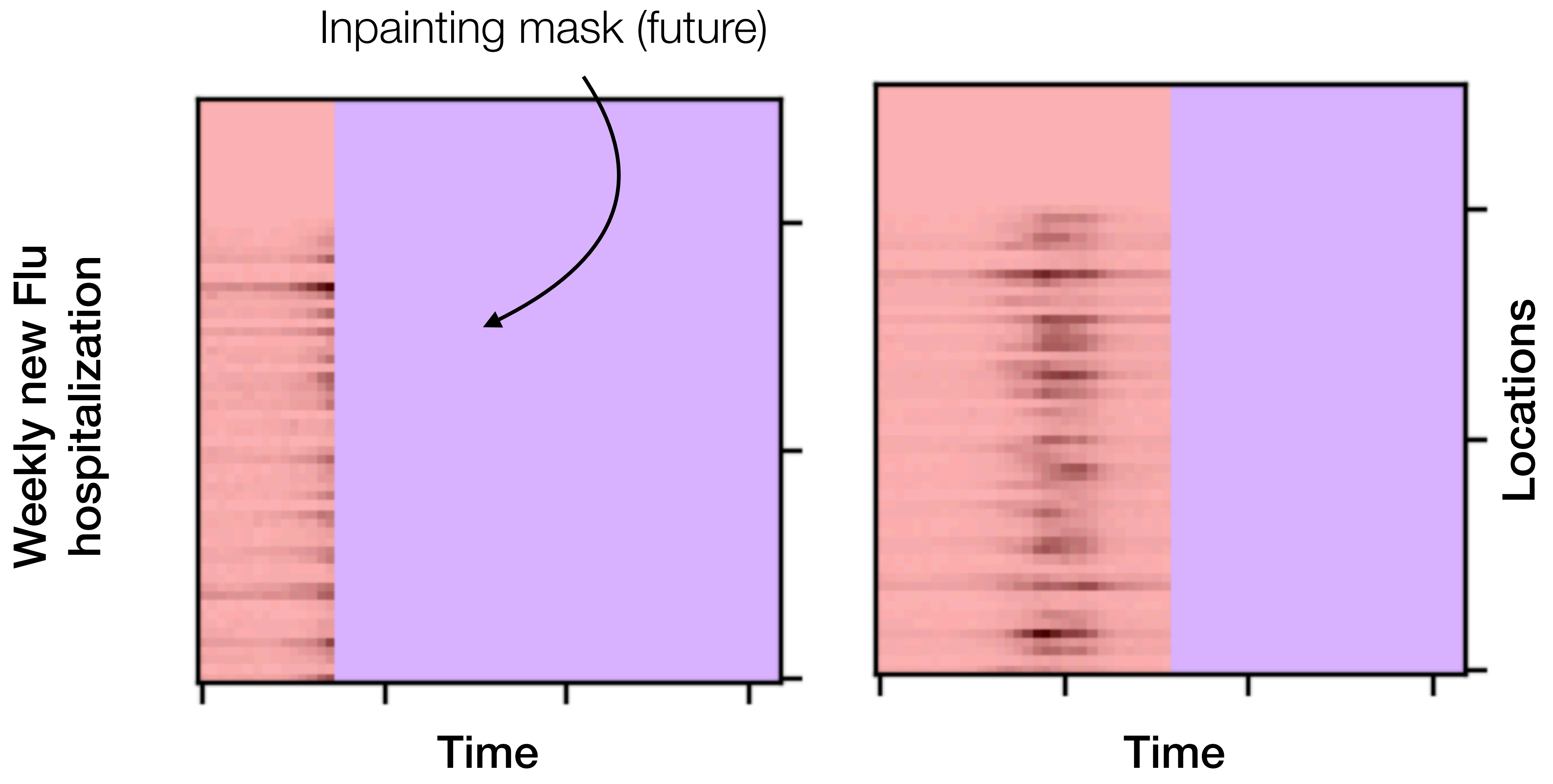
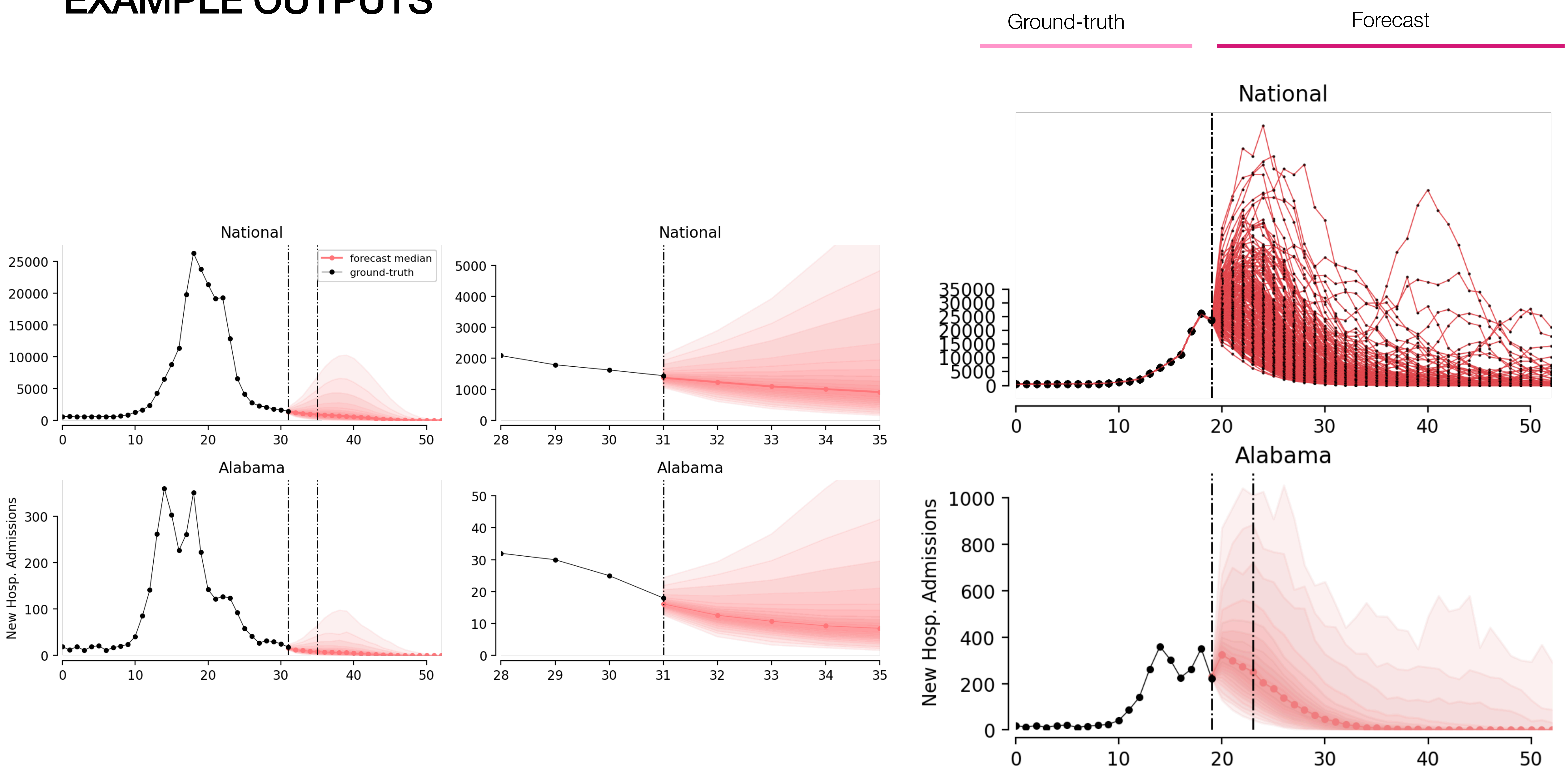
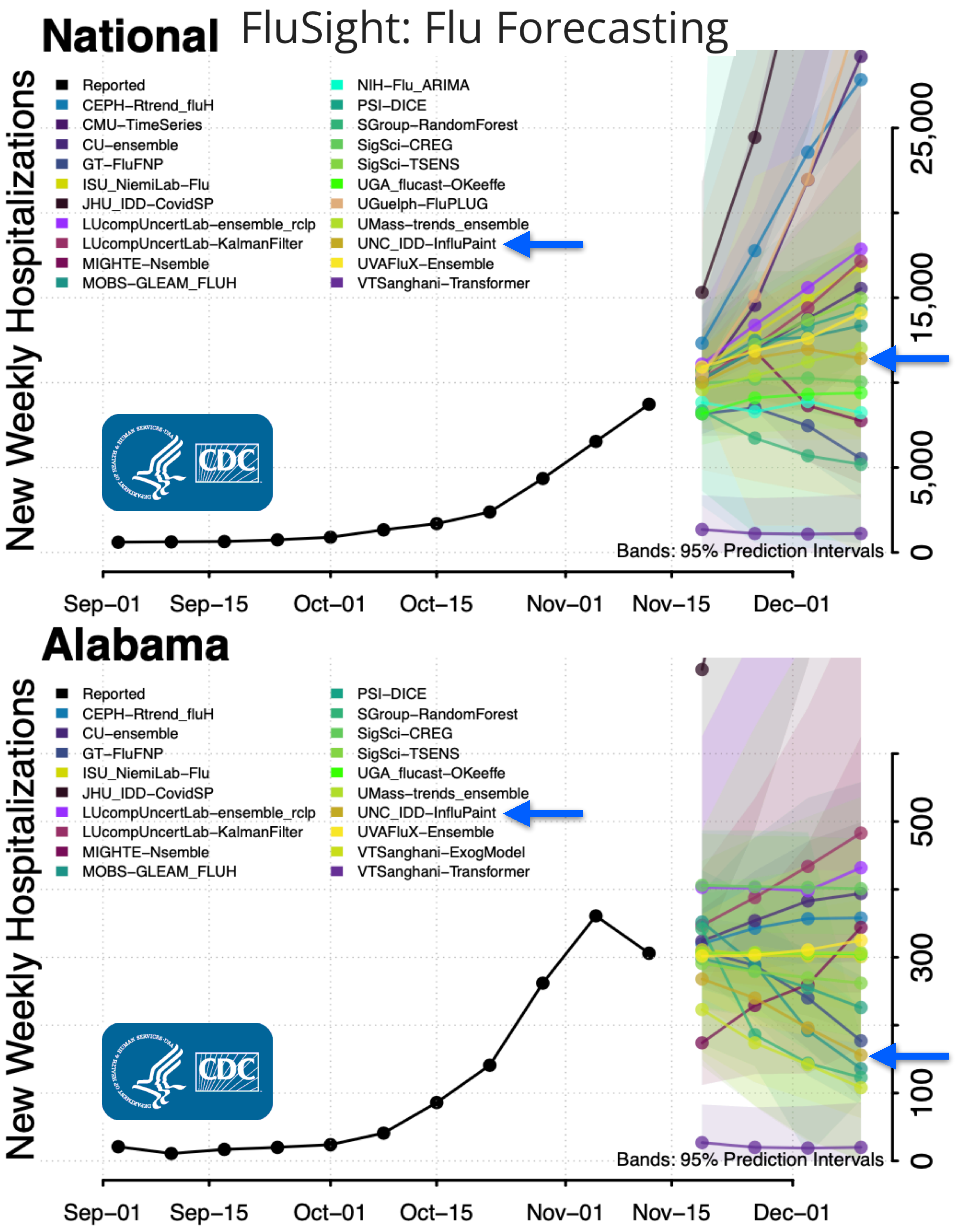




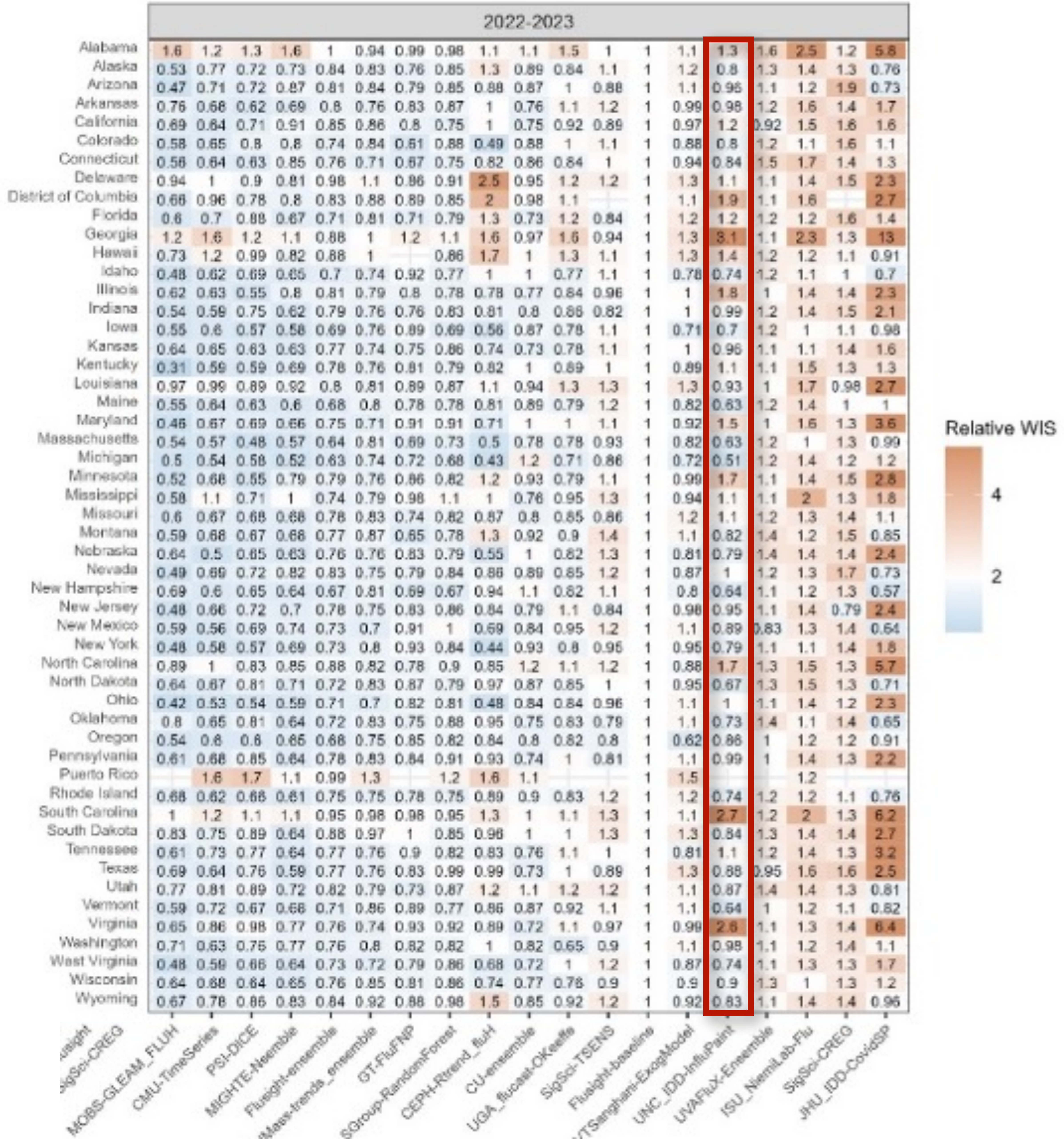
EXAMPLE OUTPUTS



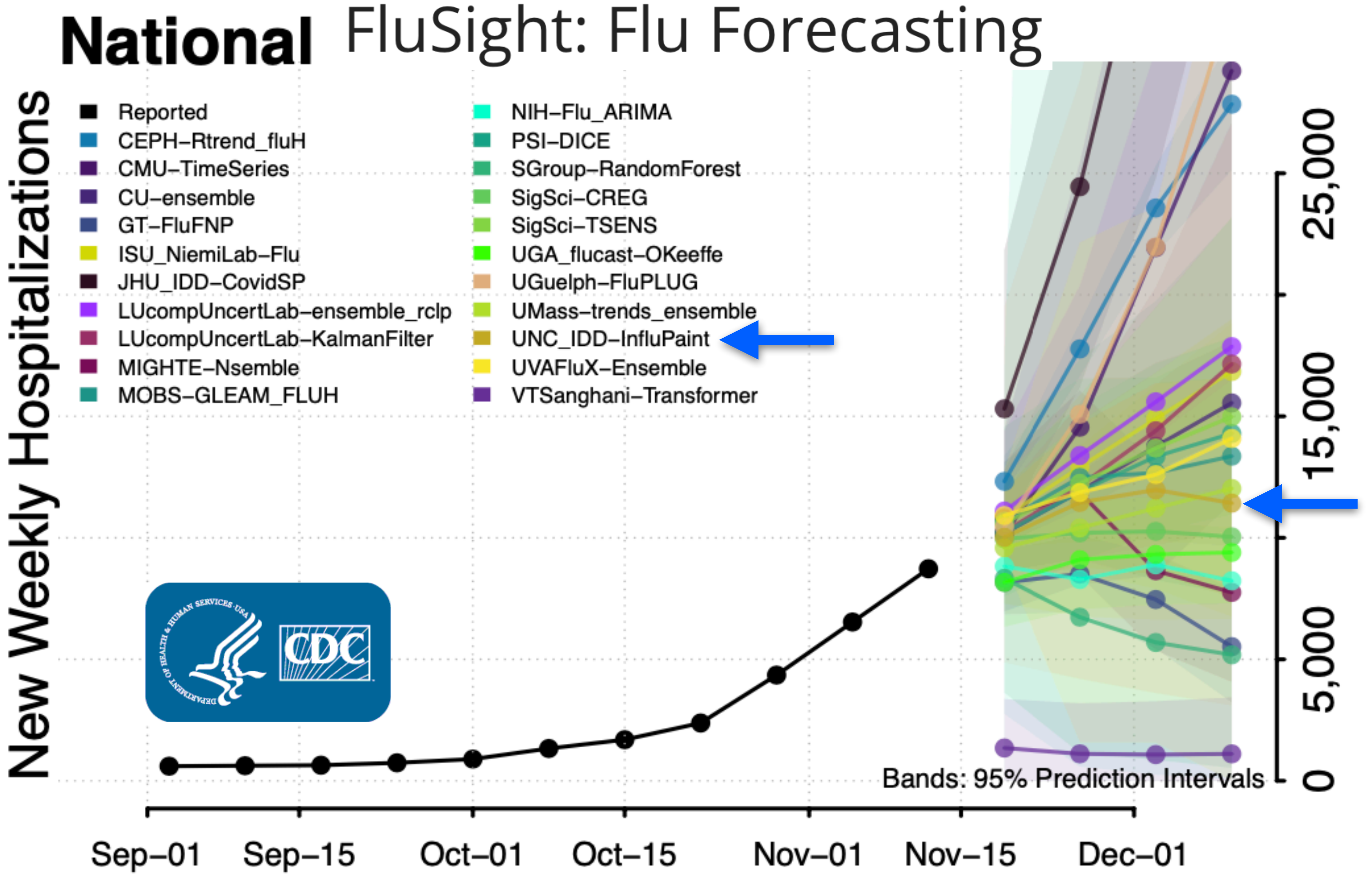
FLUSIGHT FORECASTING CHALLENGE

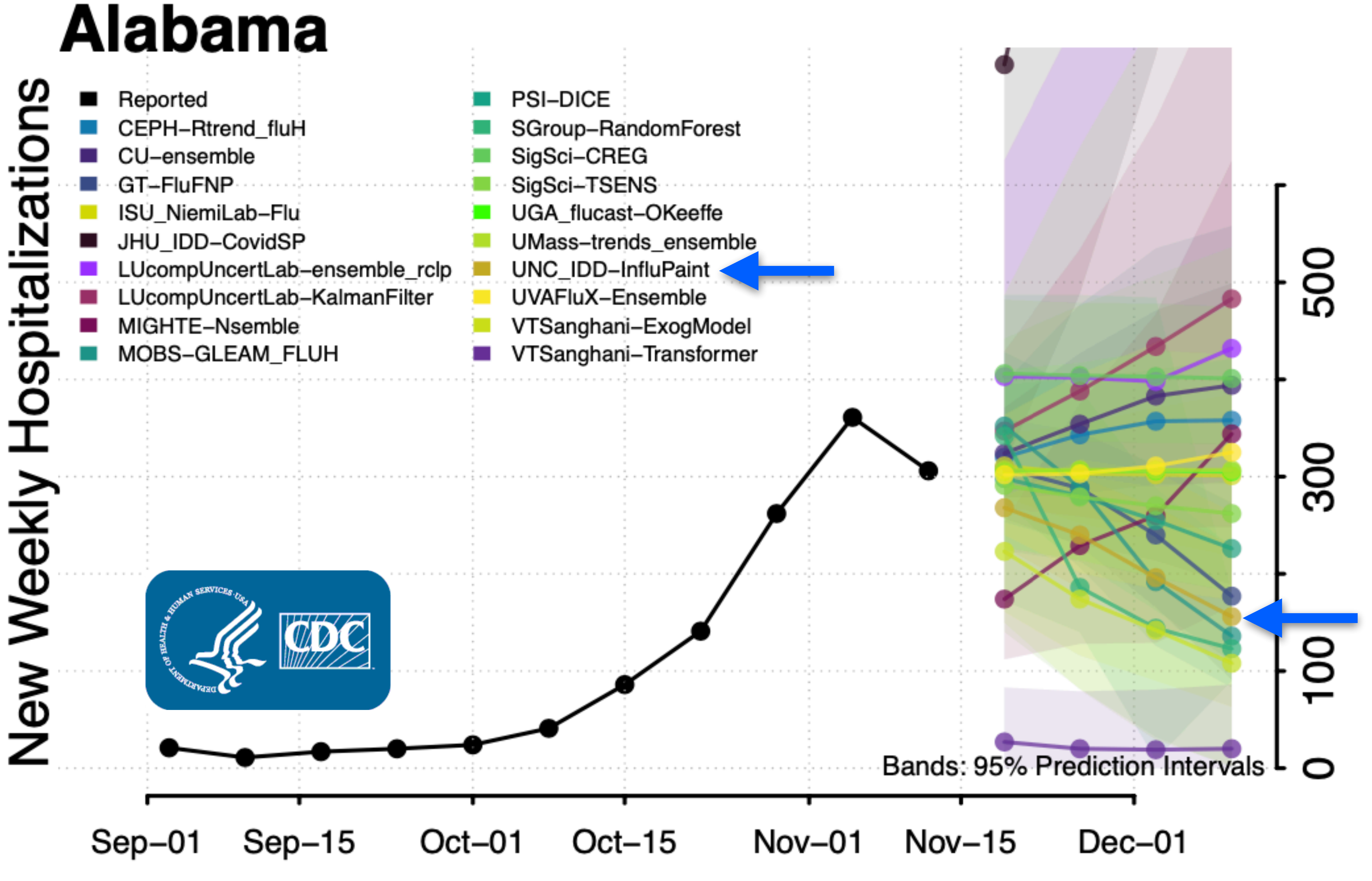


FLUSIGHT FORECASTING CHALLENGE



FluSight: Flu Forecasting





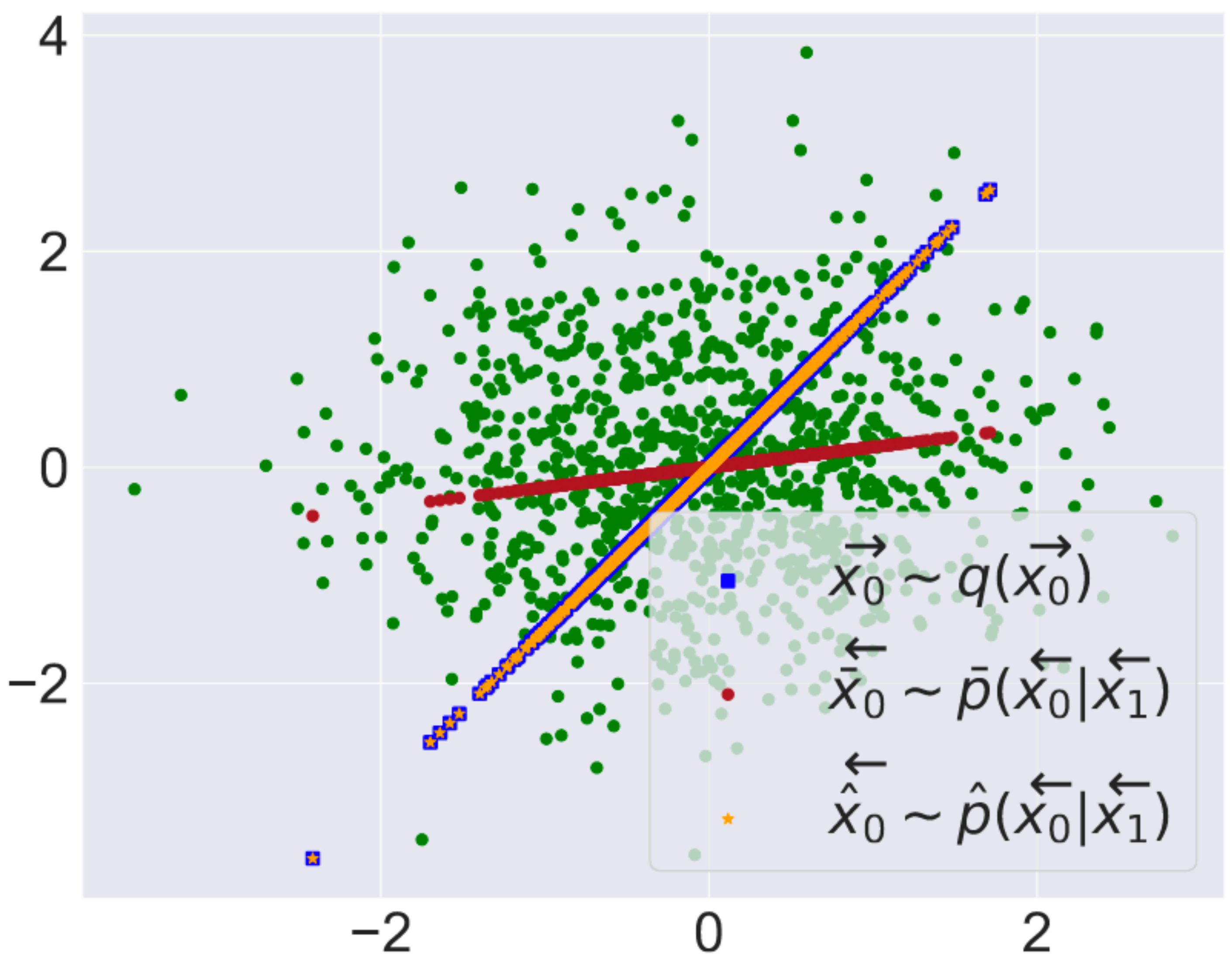
SO WHAT ?

- **Theory**
  - *“You can't just treat forecasts as images, the incidence and time axes have completely different semantics (even if e.g locality is important)”*
  - Some very nice **theoretical properties** — e.g DDPMs as SDEs, proof that *Repaint* generalizes well to unseen masks without retraining
- **Practice**
  - Surprisingly works
  - Good diversity: double peaks and single peaks, little bumps …
  - **Poor forecasting performance**

A Theoretical Justification for Image Inpainting using Denoising Diffusion Probabilistic Models

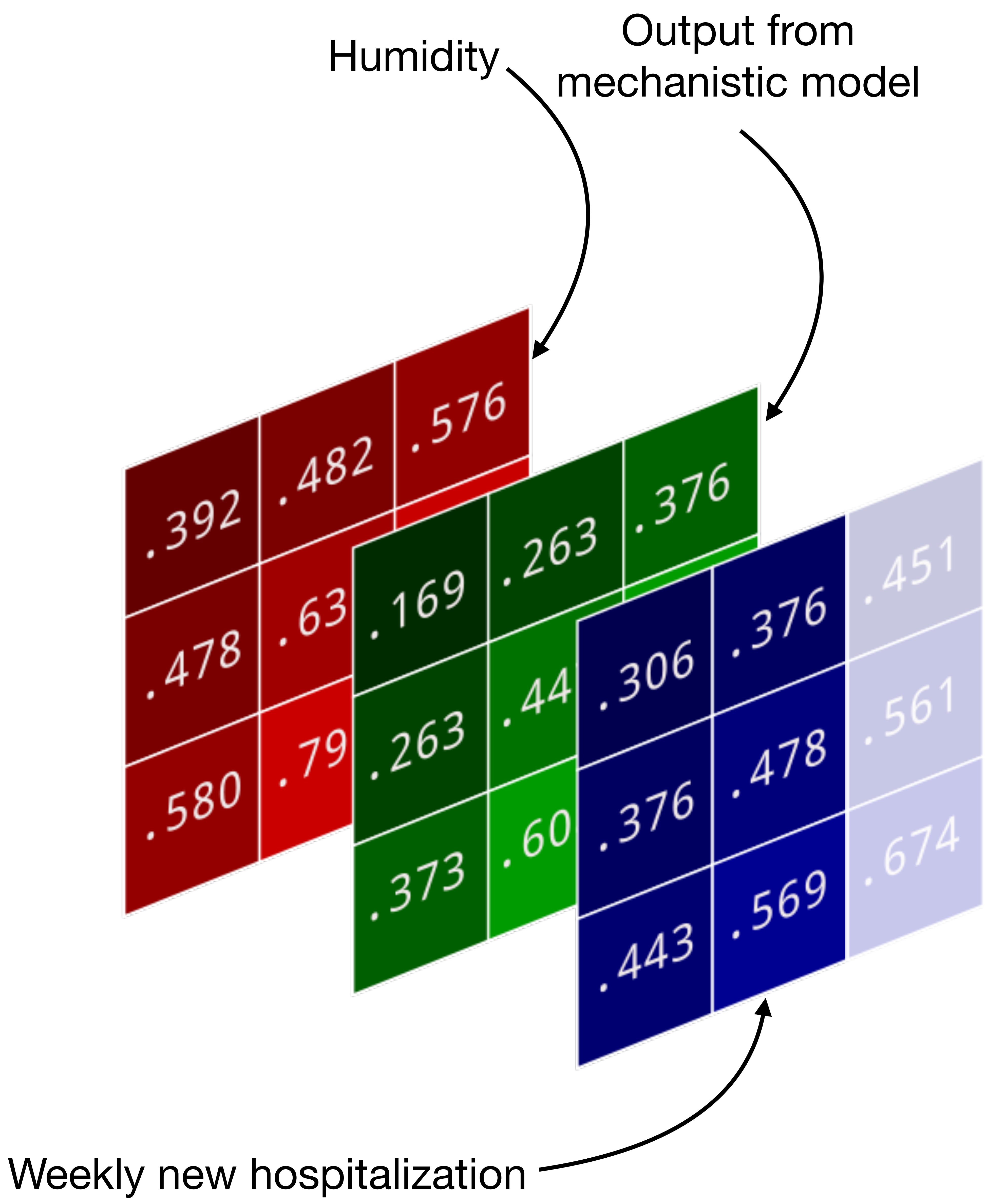
Litu Rout*, Advait Parulekar†, Constantine Caramanis‡ and Sanjay Shakkottai§

The University of Texas at Austin



CURRENT WORK

- Covariates (humidity, Flu strains…) as additional image channels.
  - But also **mechanistic model outputs**, leveraging the masking flexibility
- Broader applicability of knowing p(**x**): imputation, structure discovery, density estimation



THANK YOU FOR YOUR ATTENTION 👀

💻 **Code** github.com/jcblemai/inpainting-idforecasts

📈 **Forecasts** github.com/cdcepi/Flusight-forecast-data

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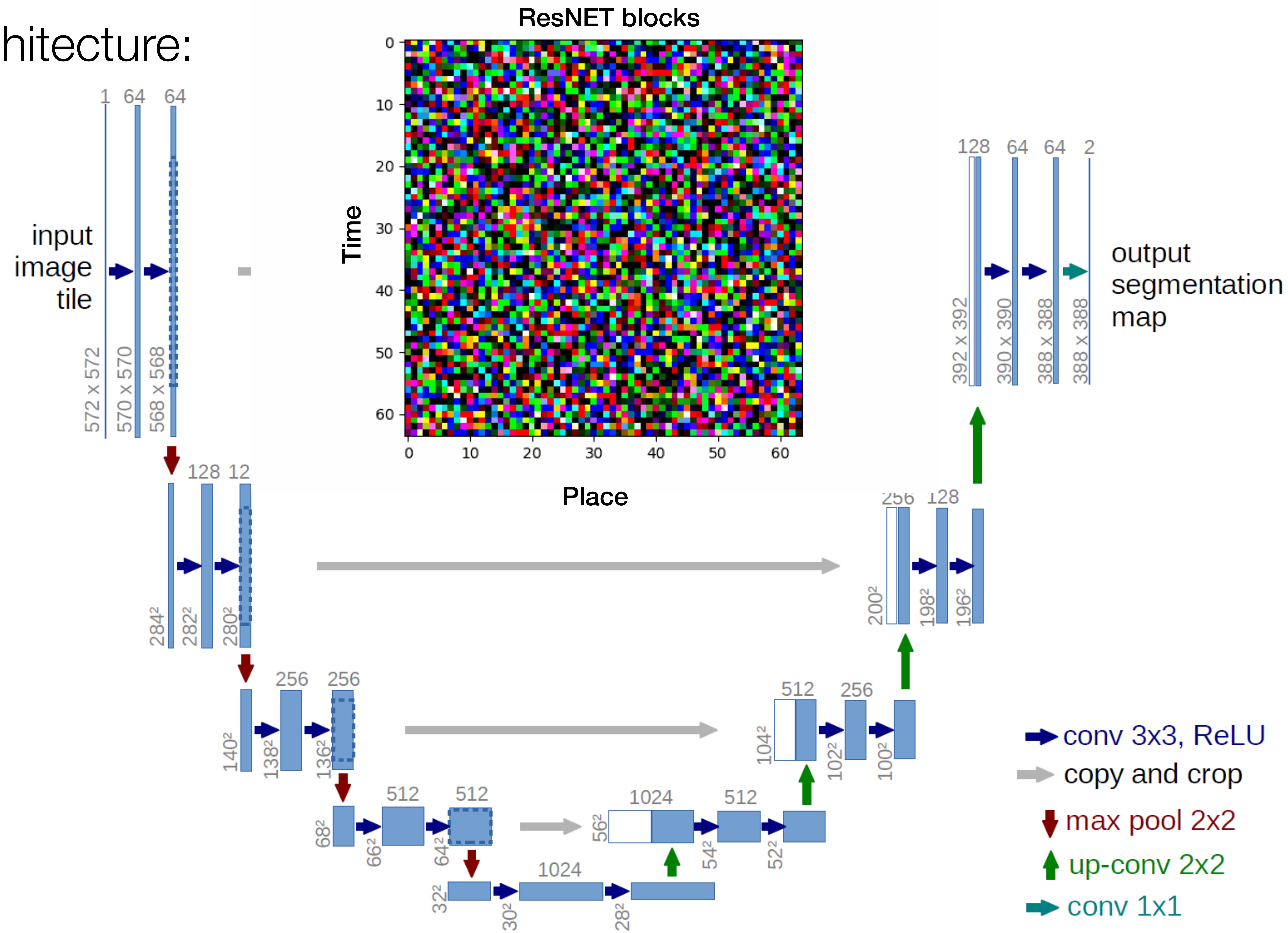
@JosephLemaitre_

A DDPM ARCHITECTURE FOR INFECTIOUS DISEASE

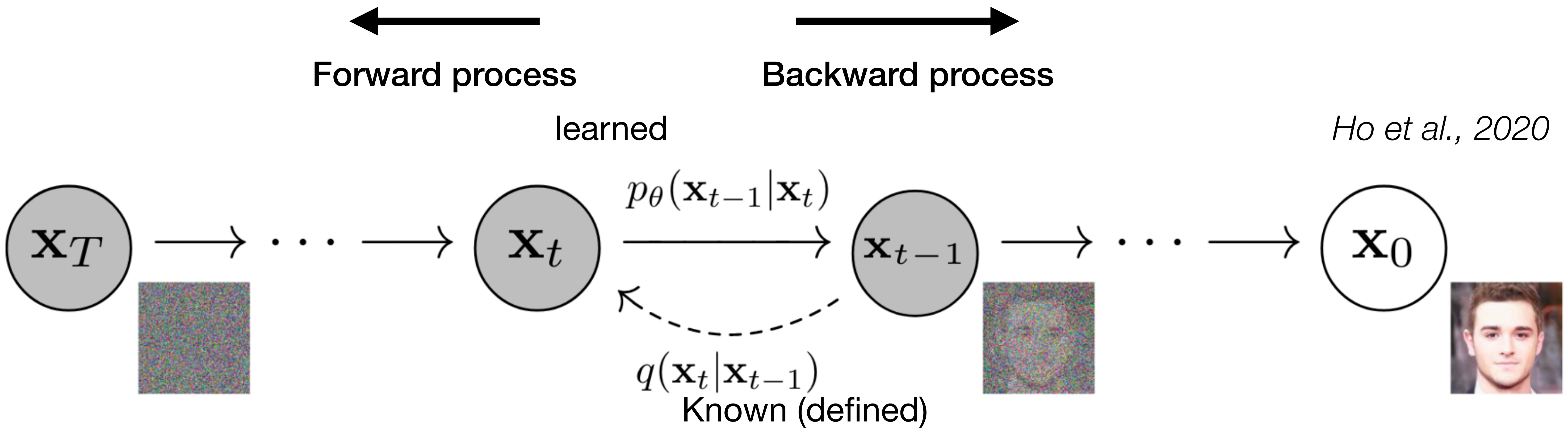
- Backward process network architecture:
  - **U-net** with
    - Wide ResNet block
    - + Attention module
    - + Group normalization
    - + Residual connections
    - + **many tricks** 🪄



DENOISING DIFFUSION PROBABILISTIC MODELS

- DDPM consists of two transforms:
  - **Forward**: Markov chain that gradually adds noise to the data until the signal is destroyed;
  - **Backward**: trained neural network that denoises an image for one step.
- **Training** of the neural net is done on forward-transformed samples from the dataset.
- **Sampling** consists of generating gaussian random noise images and transforming them with the backward transform.
- We stay very close to the literature for image generation.

Ho et al., 2020



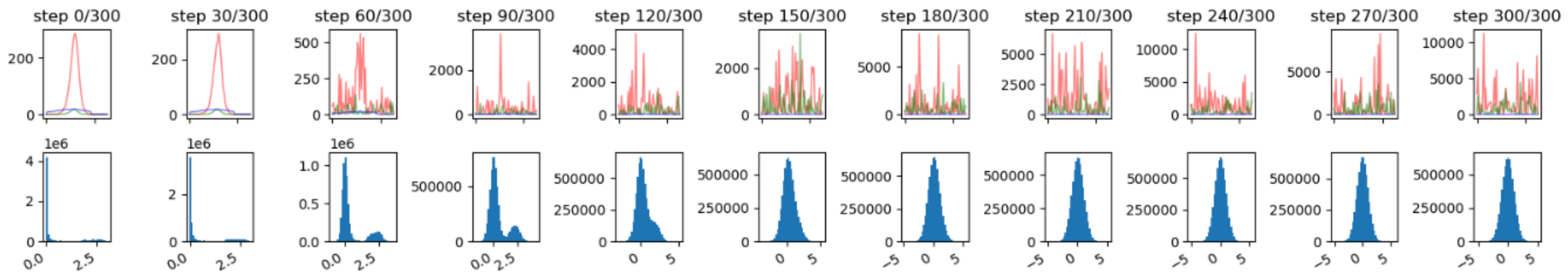
Algorithm 1 Training

repeat
  $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
  $t \sim \mathrm{Uniform}(\{1, \dots, T\})$
  $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  Take gradient descent step on
    $\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$
until converged

Algorithm 2 Sampling

$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
for $t = T, \dots, 1$ **do**
  $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
  $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
end for
return $\mathbf{x}_0$

Example forward diffusion process of an epidemic curve:



DENOISING DIFFUSION PROBABILISTIC MODELS 101

$$q(\mathbf{x_t} \mid \mathbf{x_{t-1}})$$

Pure signal

Pure noise

🚂 Training Algorithm

repeat

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$\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

Take gradient descent step on

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✨ Sampling Algorithm

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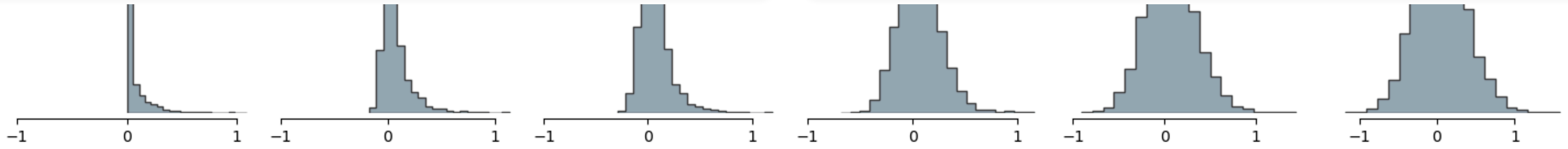
return $\mathbf{x}_0$



$$p_\theta(\mathbf{x_{t-1}} \mid \mathbf{x_t})$$