Sequence Generative Modeling

Prof. Vincent Sitzmann

Sequences are everywhere…

“A busy street in Europe.
A small crowd of people are
walking…”

“A Gibson Les Paul Electric
Guitar in a case…”

“A pair of birds built from Lego…”

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Video Generative Modeling is an Essential Vision Problem

Optical flow tells us about 3D

Content of image from one moment to the next tells us about semantics (what things co-occur)

We can learn about processes (such as cooking) from video

Good candidate for representation learning

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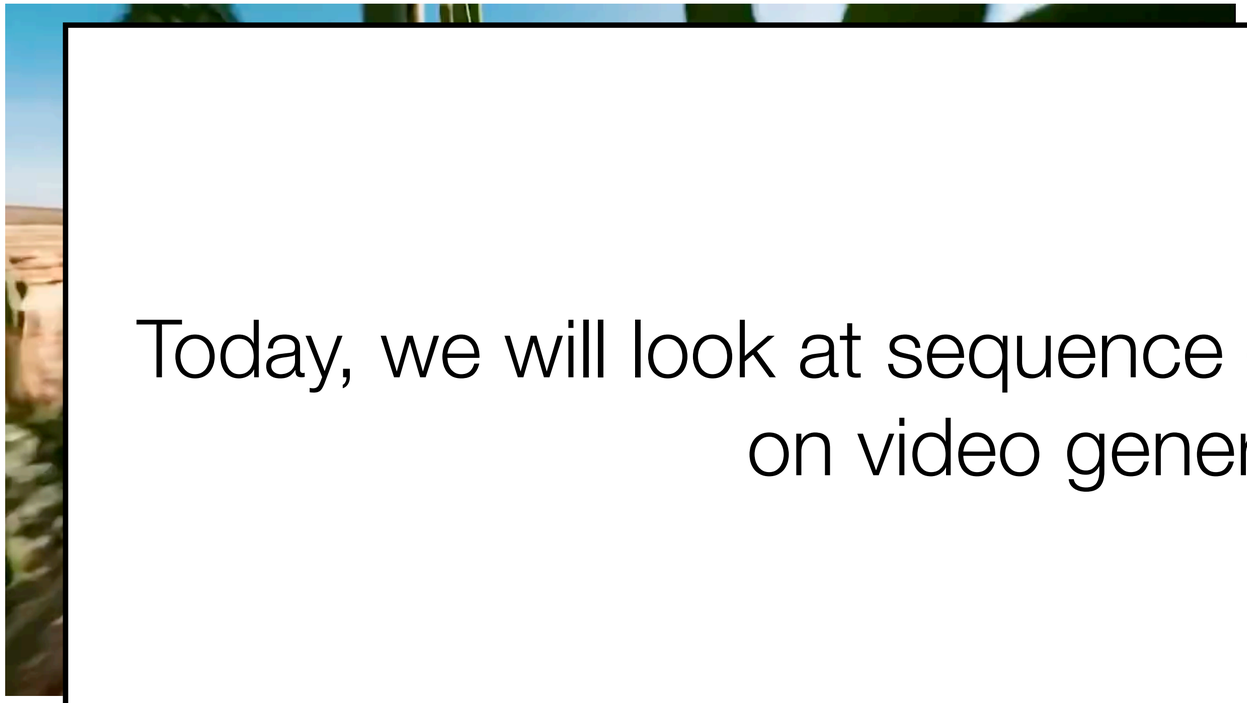

Optical flow tells us about 3D

Today, we will look at sequence generation with a particular focus on video generative modeling.

learning

Preliminaries: Distributions of Sequences

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As the name implies, we are modeling distributions of sequences, denoted as

$$p(x_1, x_2, x_3, \dots)$$

Causal Factorization of the Joint

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We can always model the joint auto-regressively:

$$p(x_1, x_2, x_3, \dots) = \prod_{i=1}^{N} p(x_i \mid x_{<i})$$

That is, the future only depends on the past, not on the future.

Note that this is just a re-writing of the joint -
this is a mathematical fact. Any distribution can be factorized in this way, even ones that aren't causal to begin with.

The Markov Property

The Markov Property

Some sequences can be factorized as:

$$p(x_1, x_2, x_3, \dots) = p(x_1) \prod_{i=1}^{N} p(x_{i+1} \mid x_i)$$

“Given the present, the future is independent of the past.”

This is *not* a re-writing of the joint, b/c we dropped a bunch of conditionals! I.e. if a sequence is not Markov to begin with, we can’t appropriately model it as such.

The Markov Property

The Markov Property

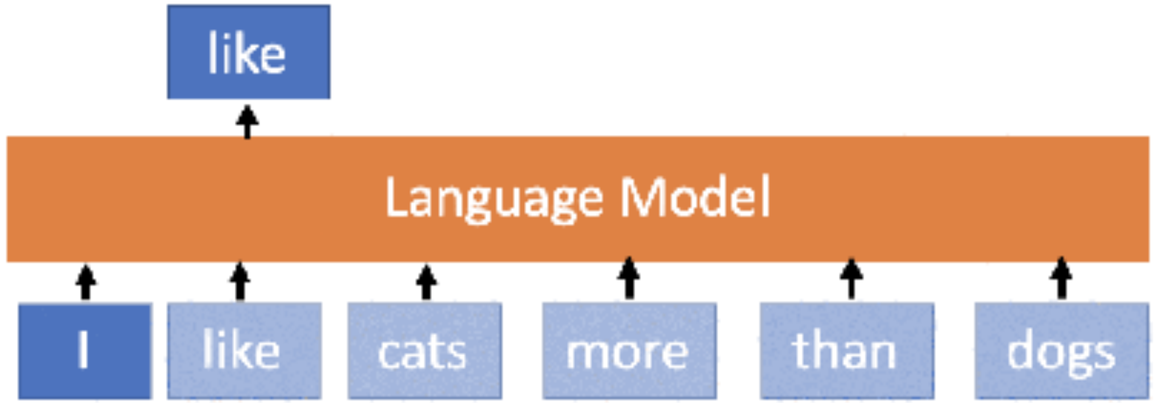
Varying degrees of “Markovianity” are possible:

$$p(x_1, x_2, x_3, \dots) = p(x_1) \prod_{i=1}^{N} p(x_{i+1} \mid x_i, x_{i-1})$$

Consider a video of a pendulum. Given just one frame, you cannot accurately predict the next - it could be swinging in either direction! Given two frames, you can.

Two major paradigms for sequence generation

Video generation generally trained with **Full-Sequence Diffusion**



LLMs generally trained with **Next-Token Prediction**

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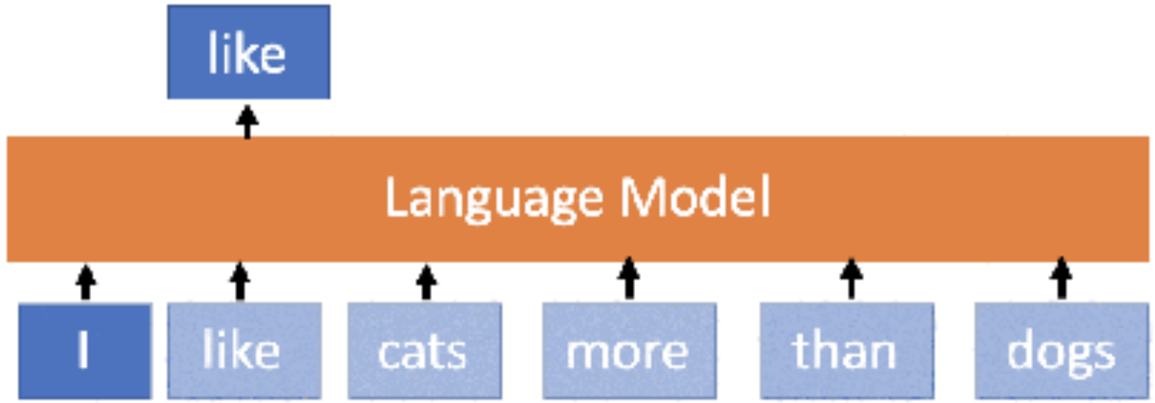

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Preliminaries: Noise as Masking

Unmasked

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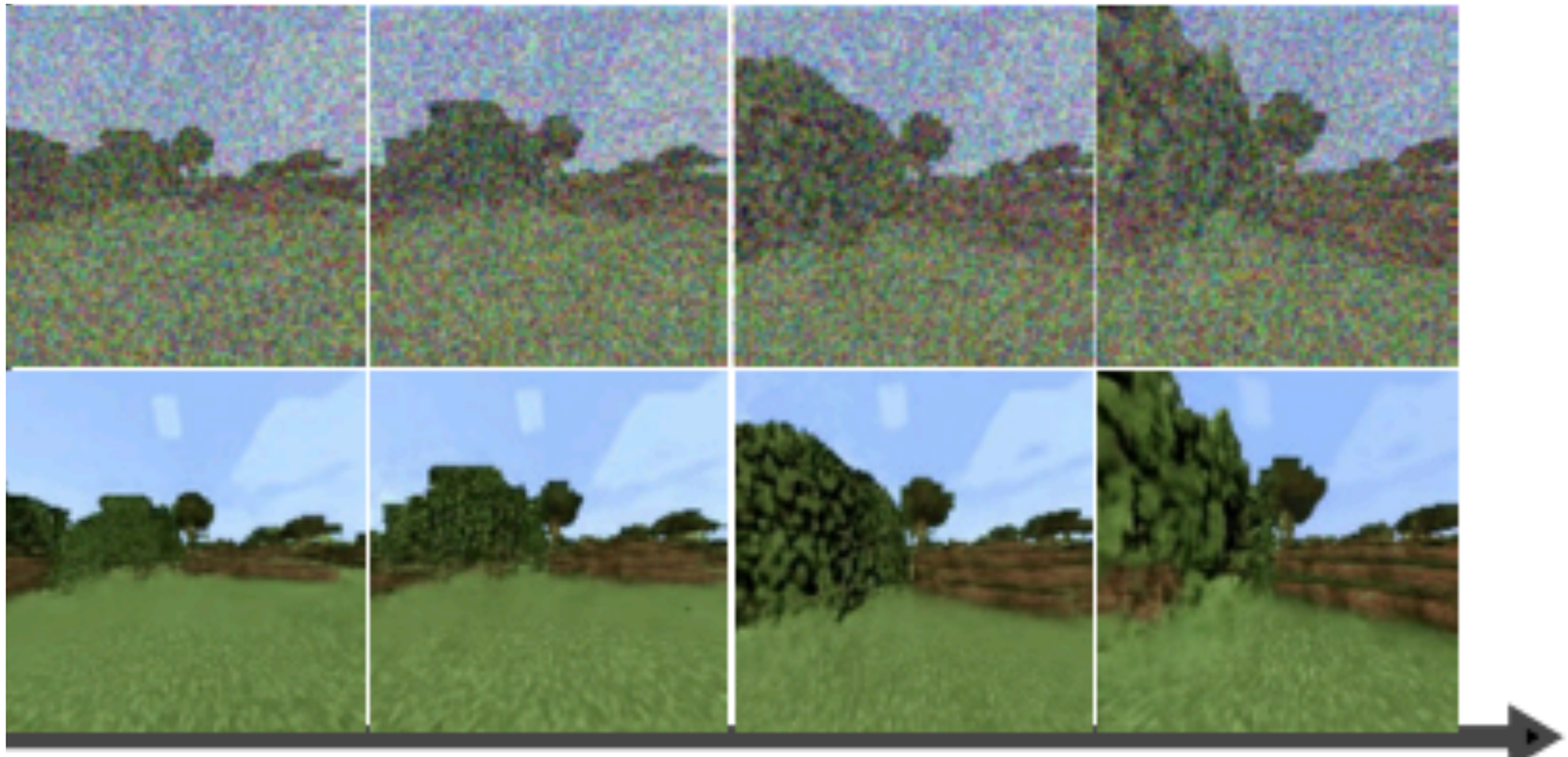
Slightly Masked

Unmasked



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Fully Masked

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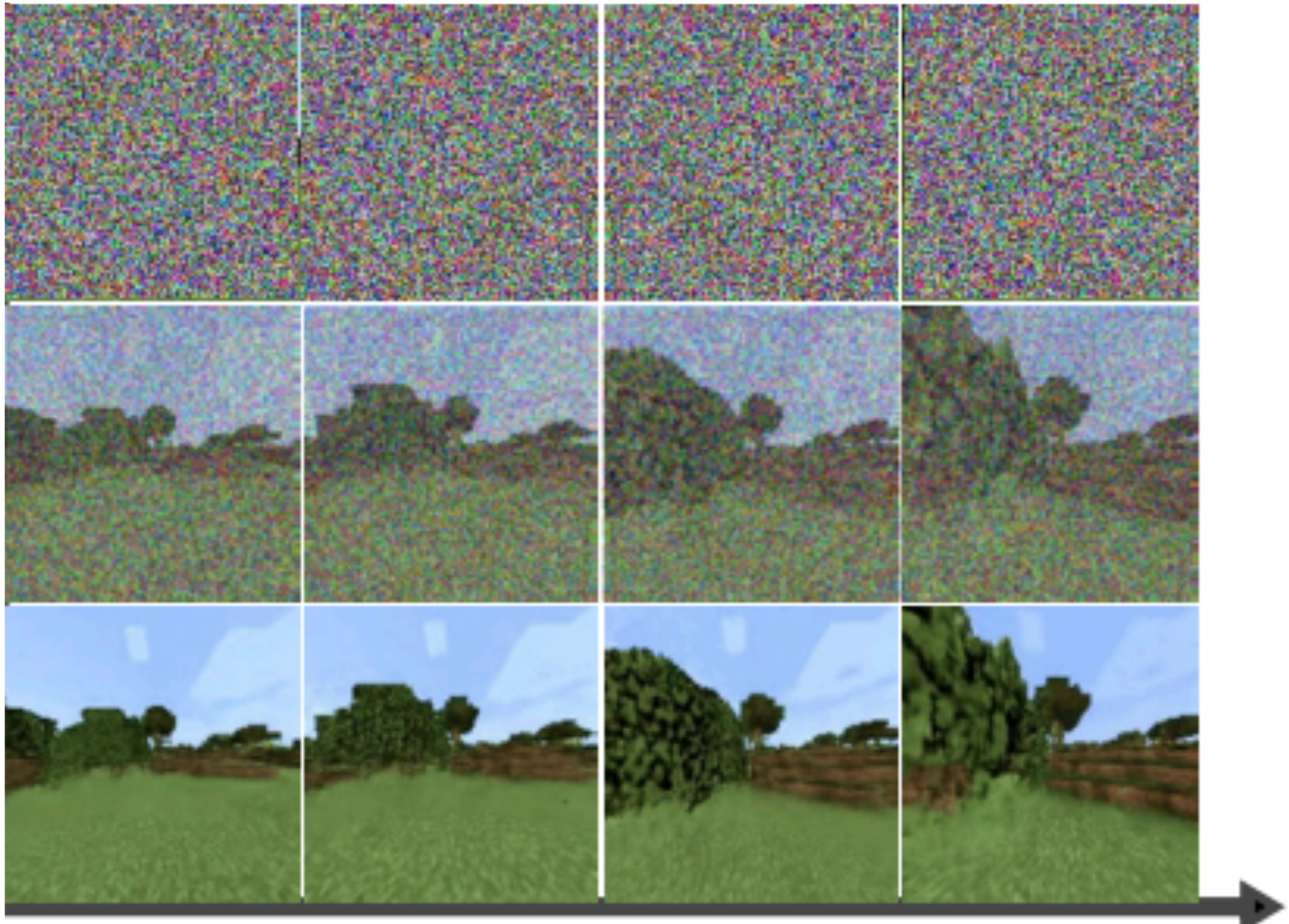

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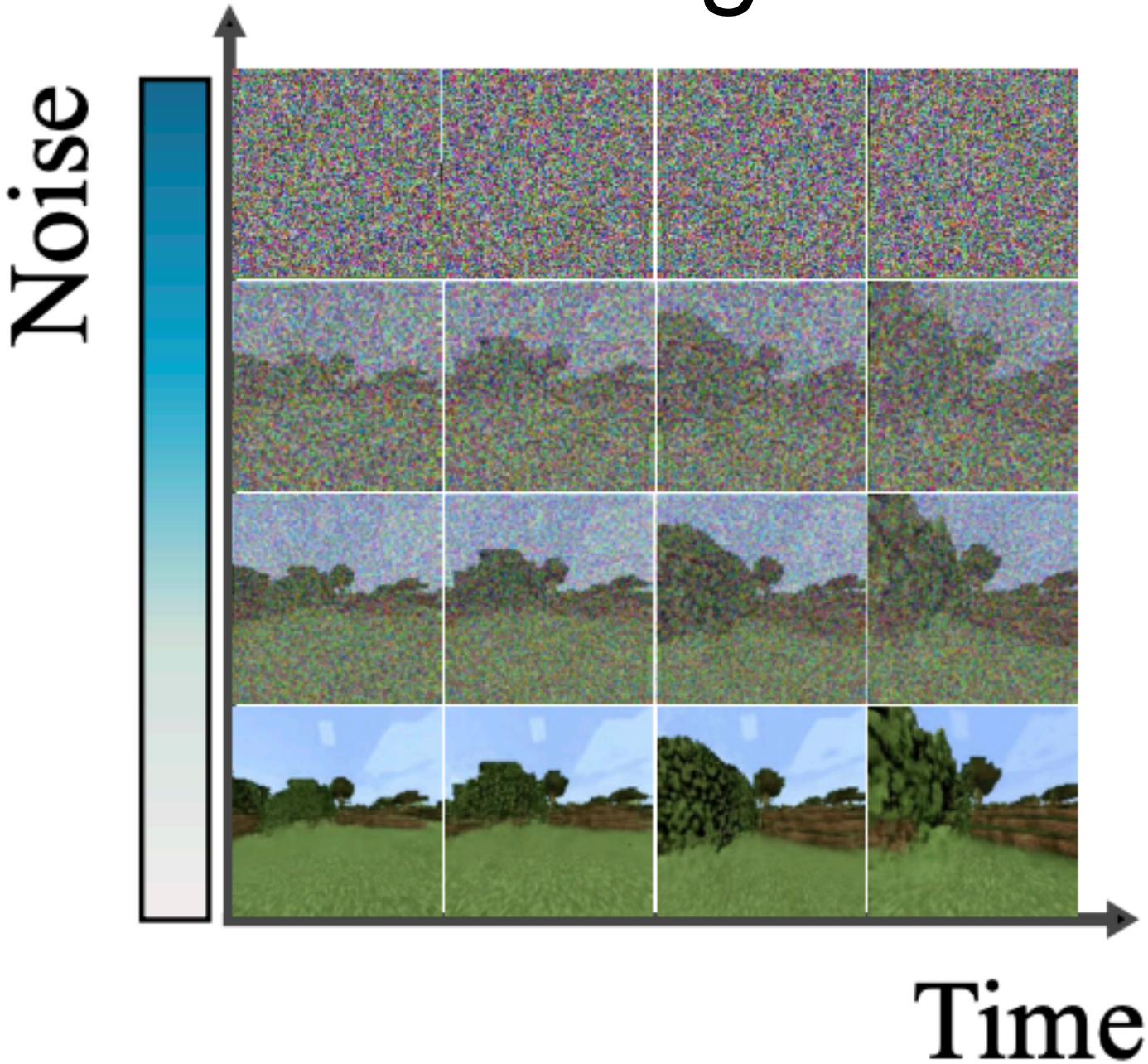
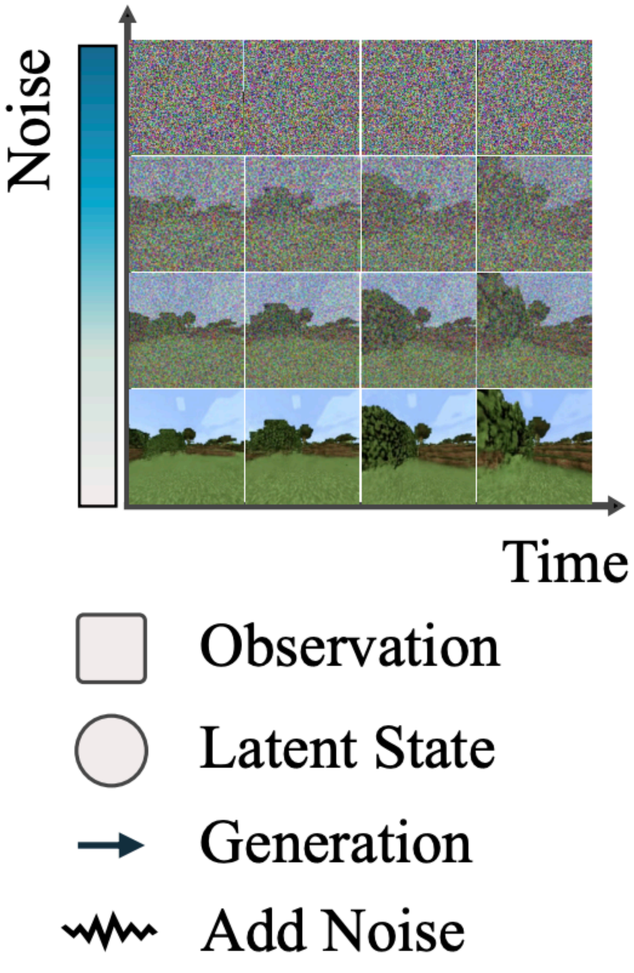
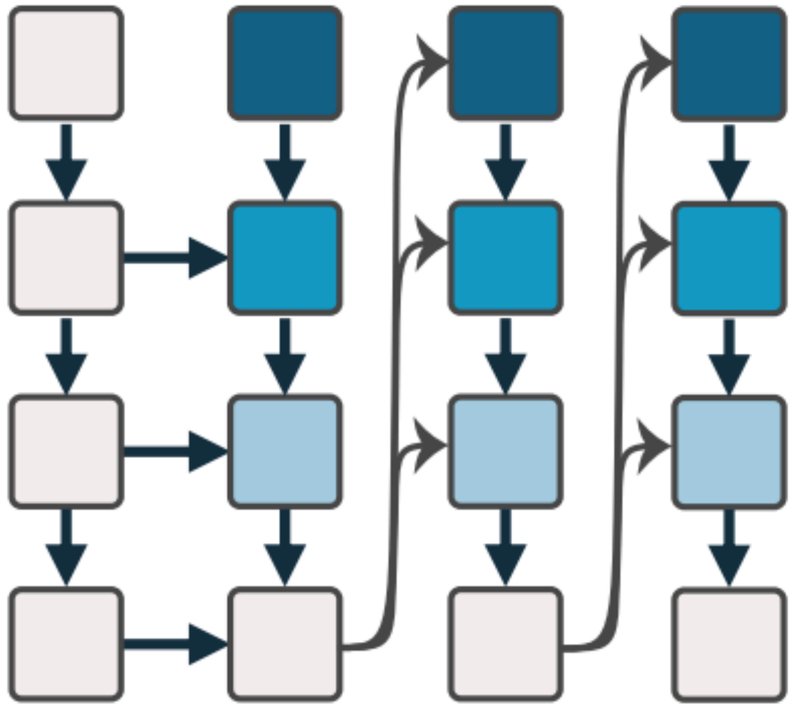


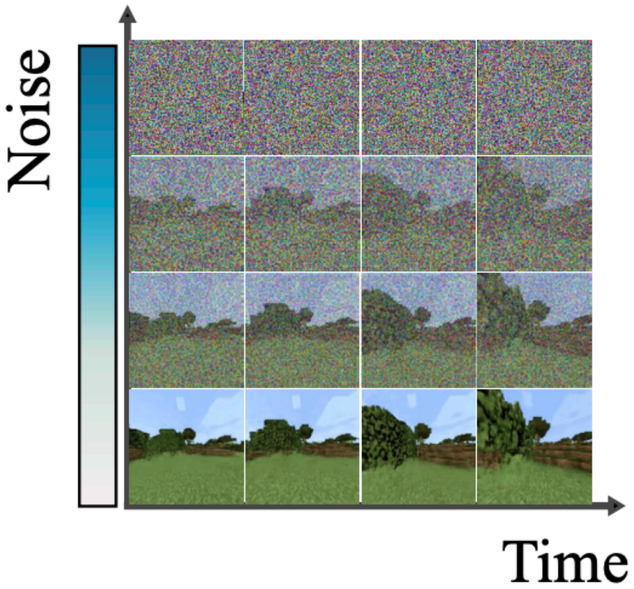
Two axes of
sequence generation

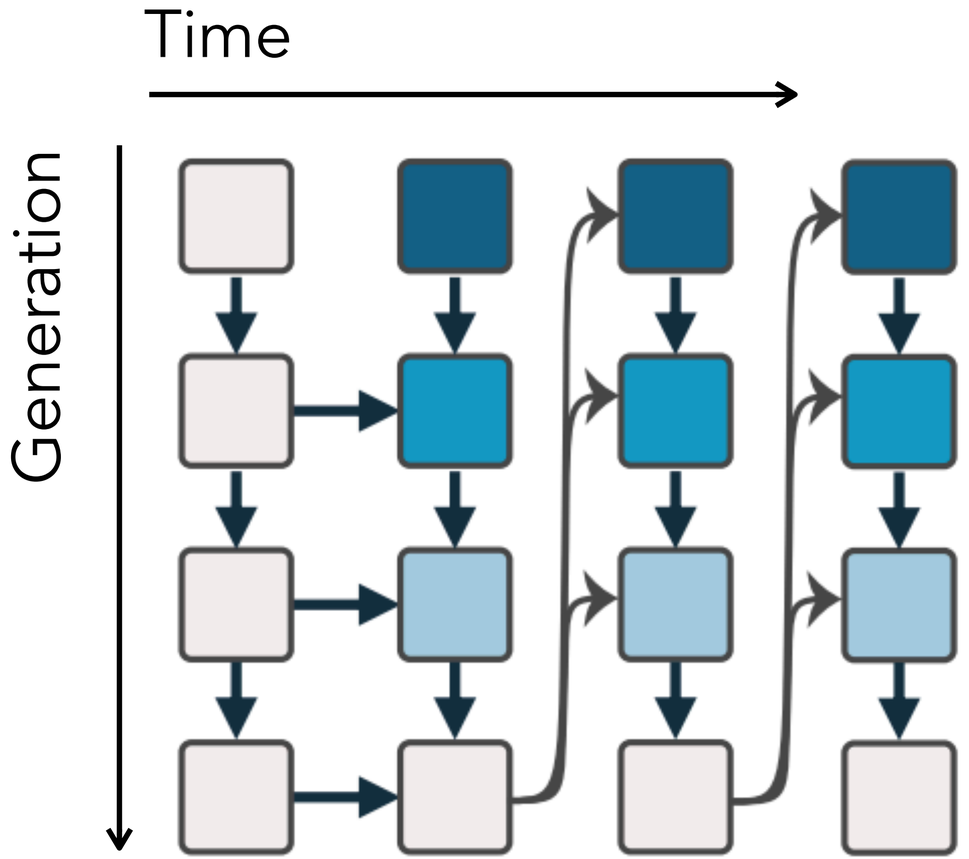
Next-Token Prediction





Next-Token Prediction





Observation

Latent State

Generation

Add Noise

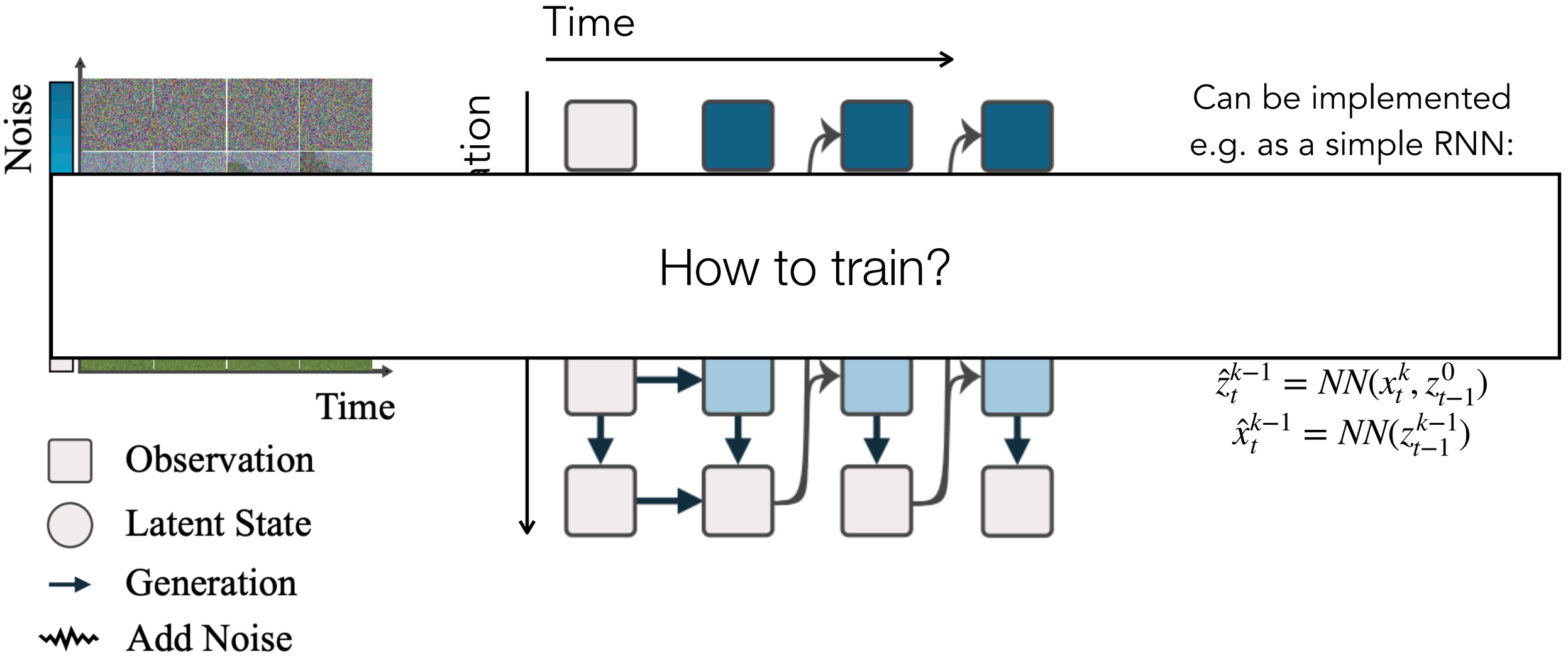
Can be implemented e.g. as a simple RNN:

$$\hat{x}_t^{k-1} = NN(x_t^k, x_{t-1}^0)$$

Or with latent states:

$$\hat{z}_t^{k-1} = NN(x_t^k, z_{t-1}^0)$$
$$\hat{x}_t^{k-1} = NN(z_{t-1}^{k-1})$$

Next-Token Prediction



$$\hat{z}_t^{k-1} = NN(x_t^k, z_{t-1}^0)$$
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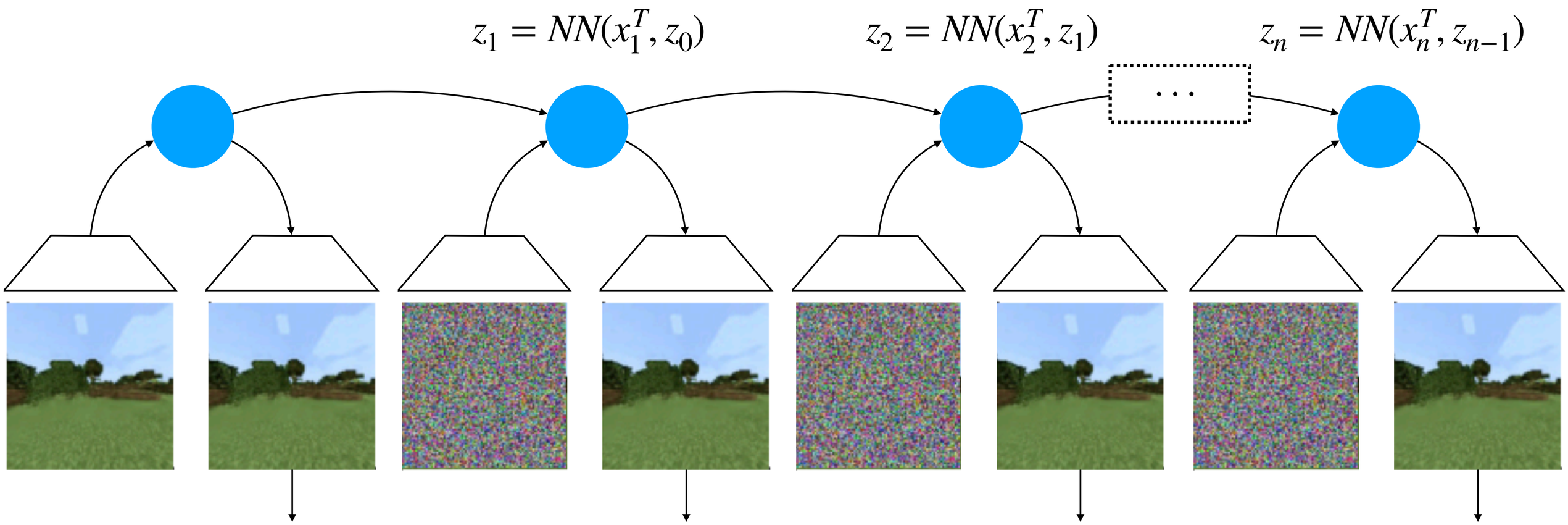
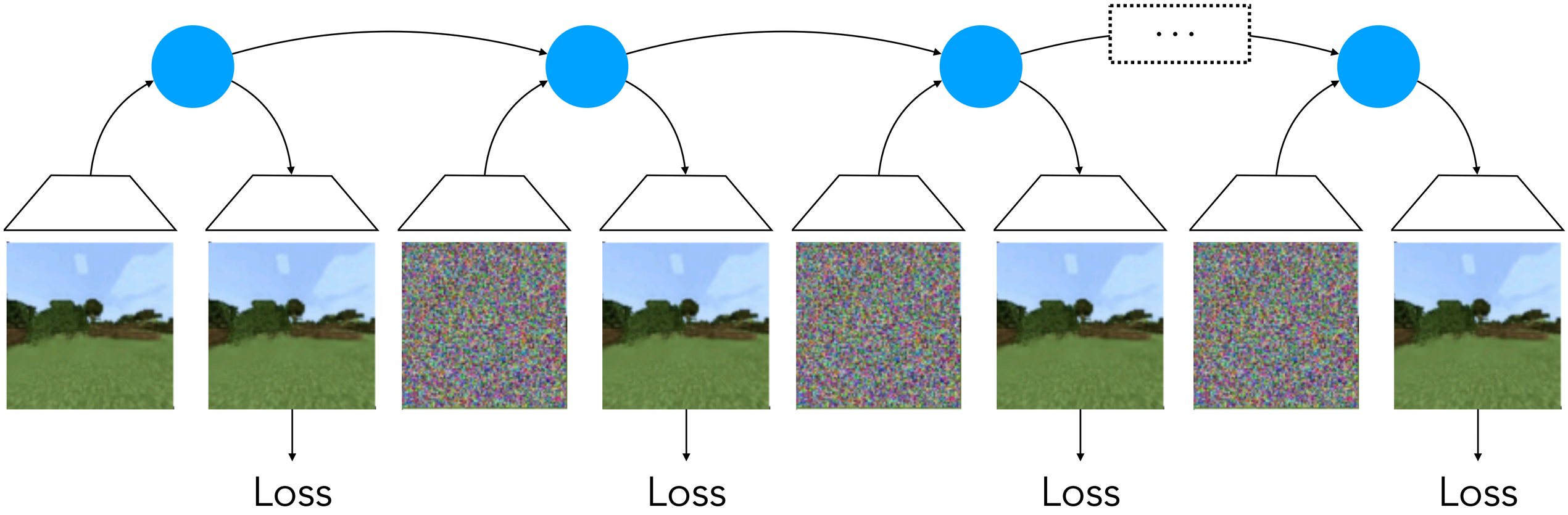
“Free Running” Training

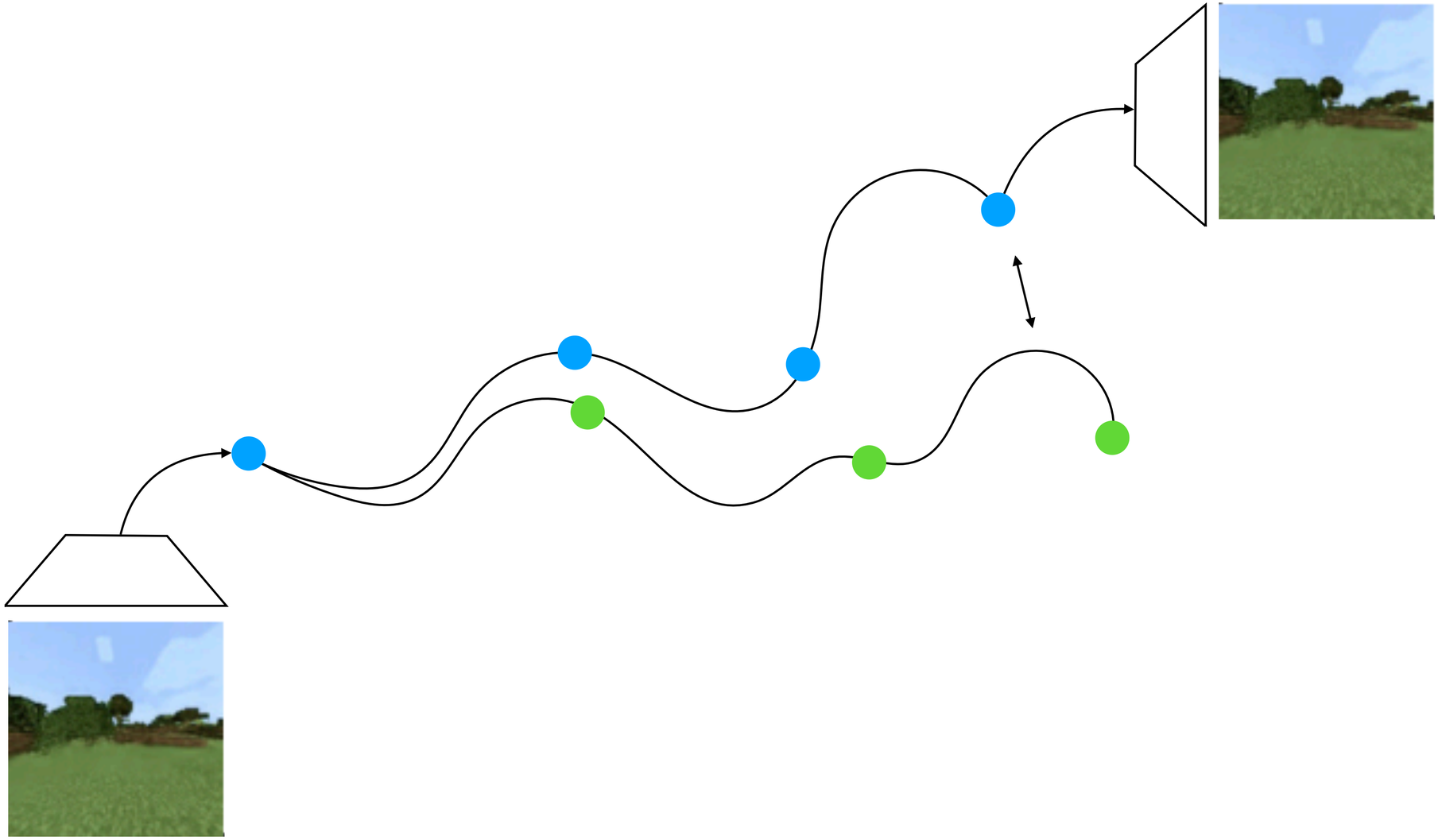


“Free Running” Training

$z_0 = NN(x_0^0)$ $z_1 = NN(x_1^T, z_0)$ $z_2 = NN(x_2^T, z_1)$ $z_n = NN(x_n^T, z_{n-1})$



The Problem with Free Running



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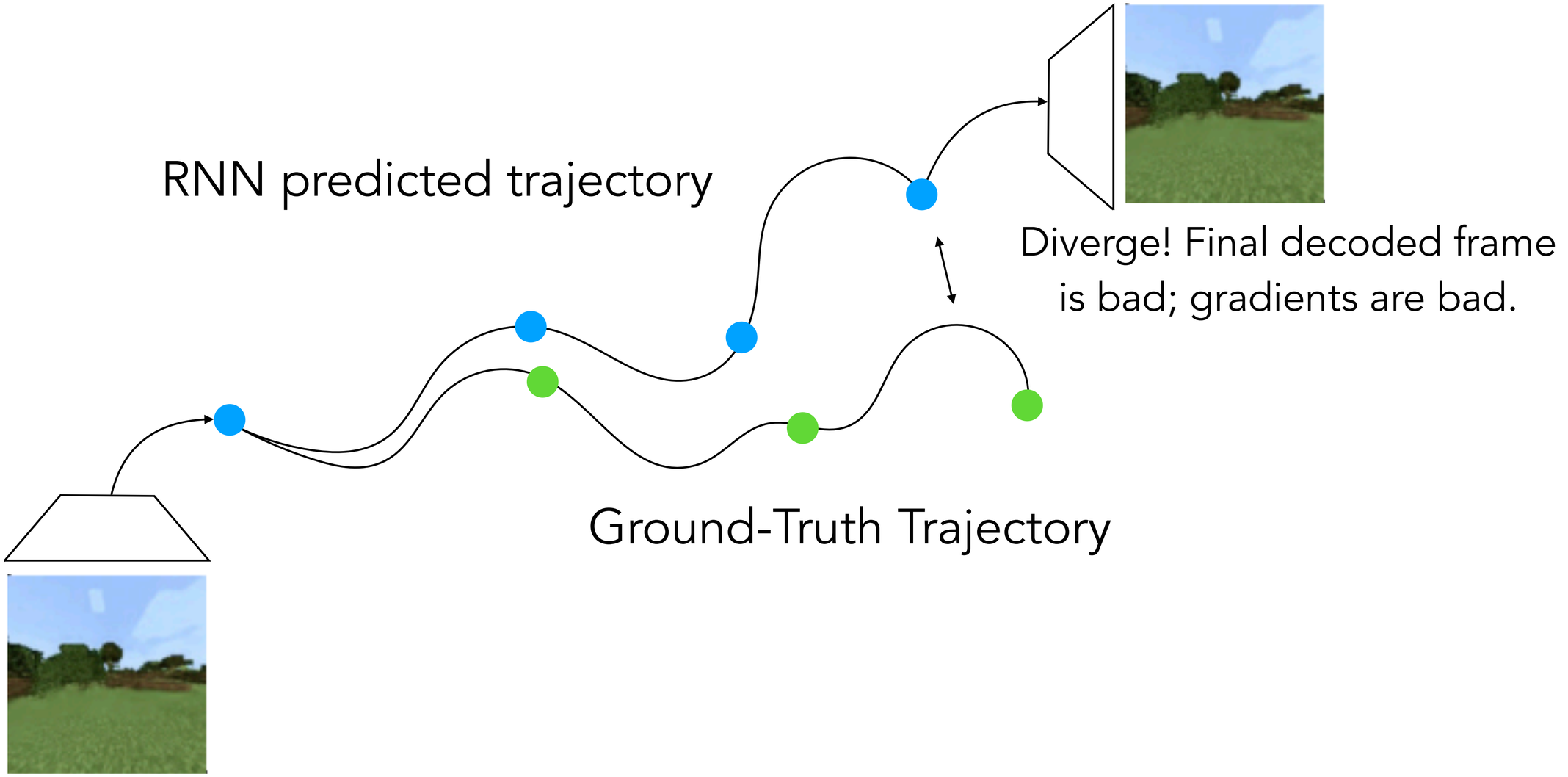
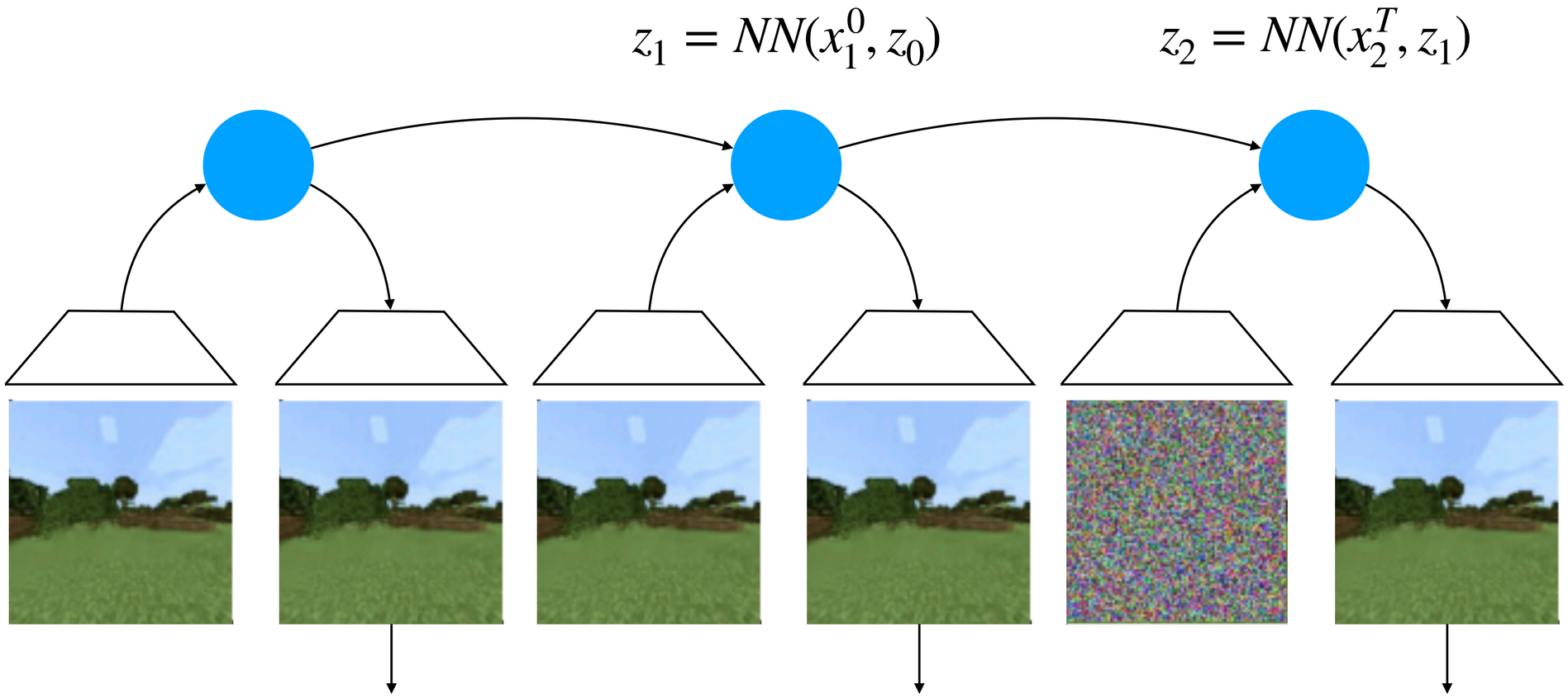


Teacher Forcing Training: Only Final Frame is masked, all intermediates are ground-truth



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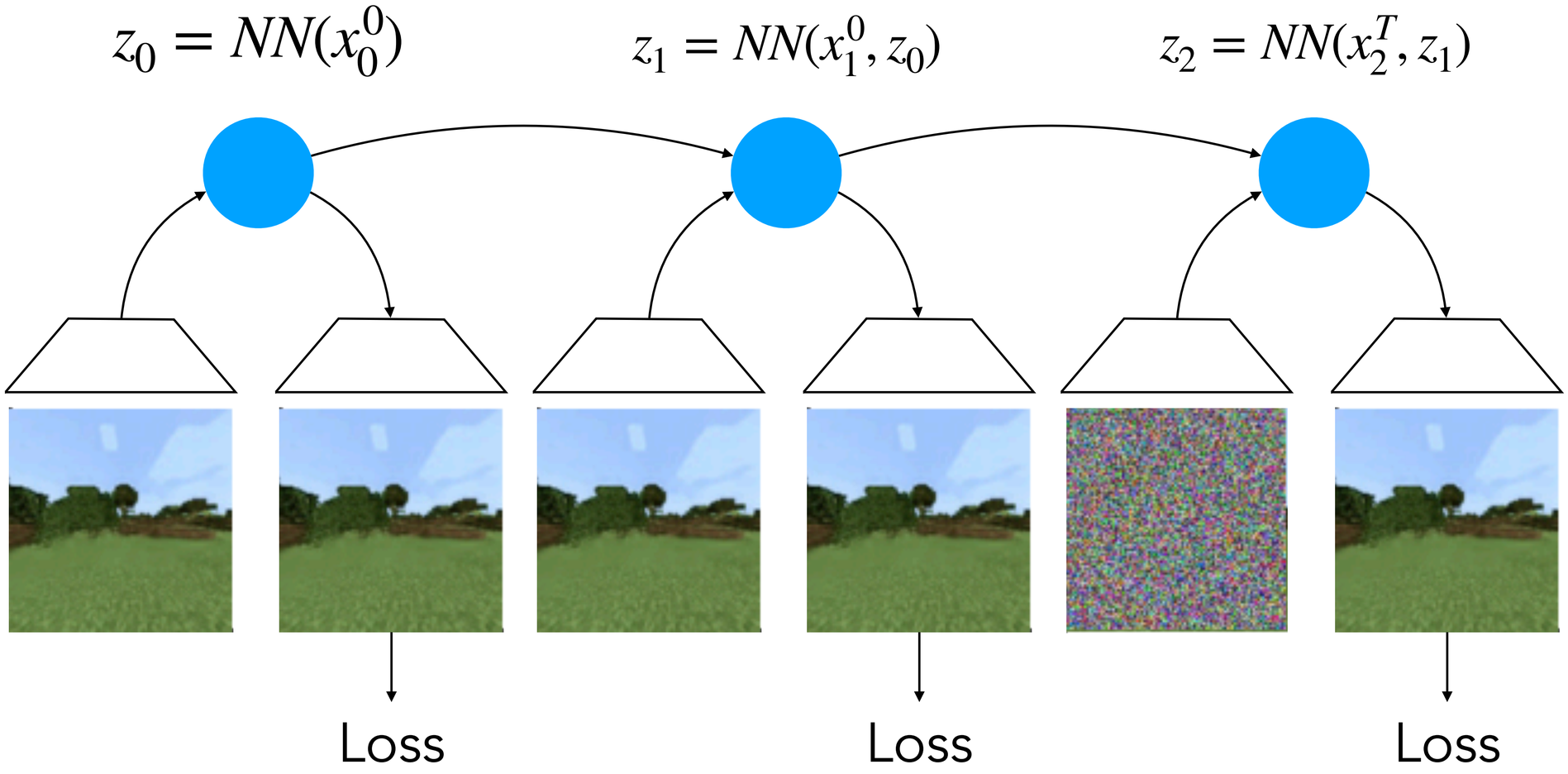

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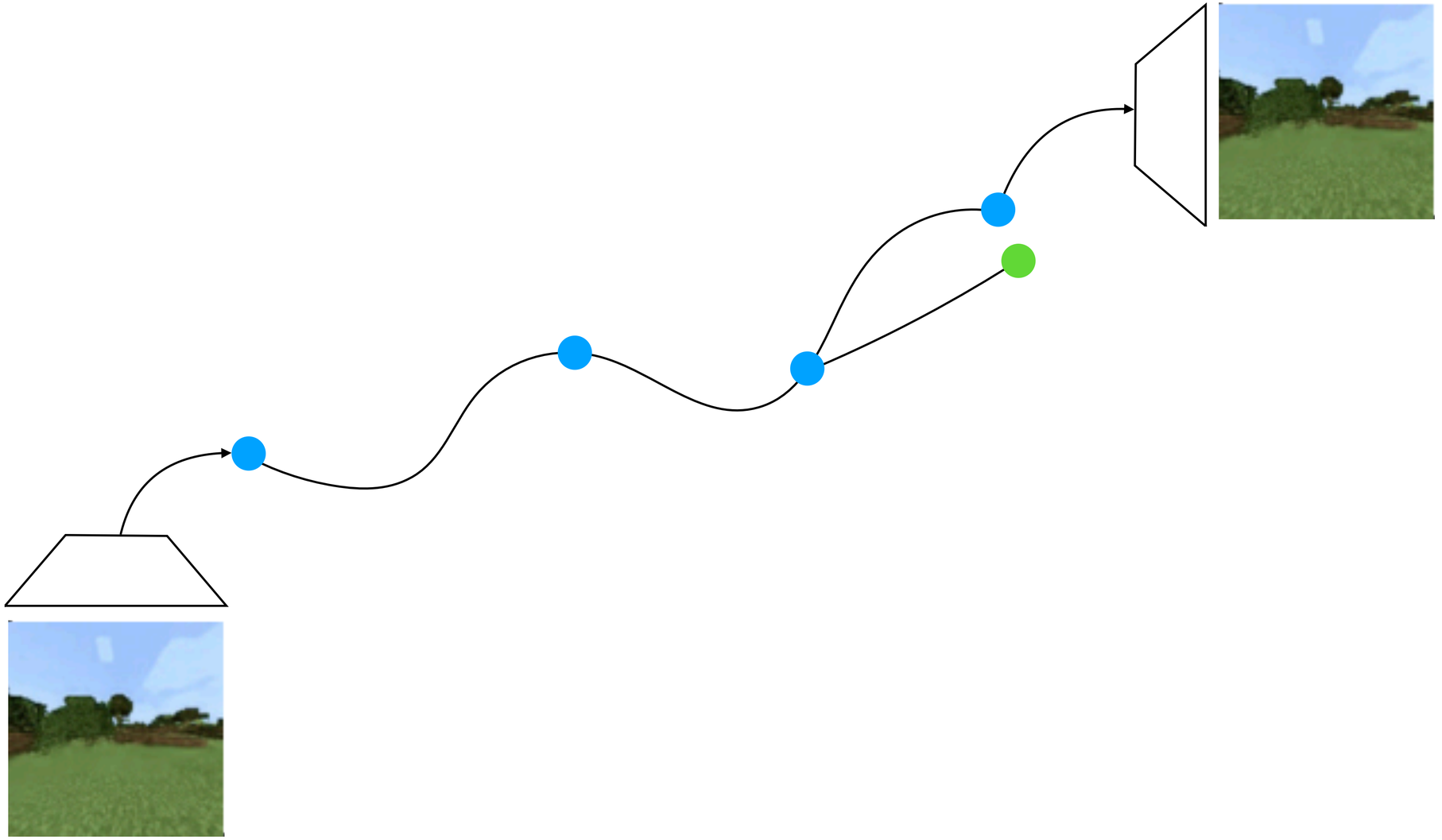

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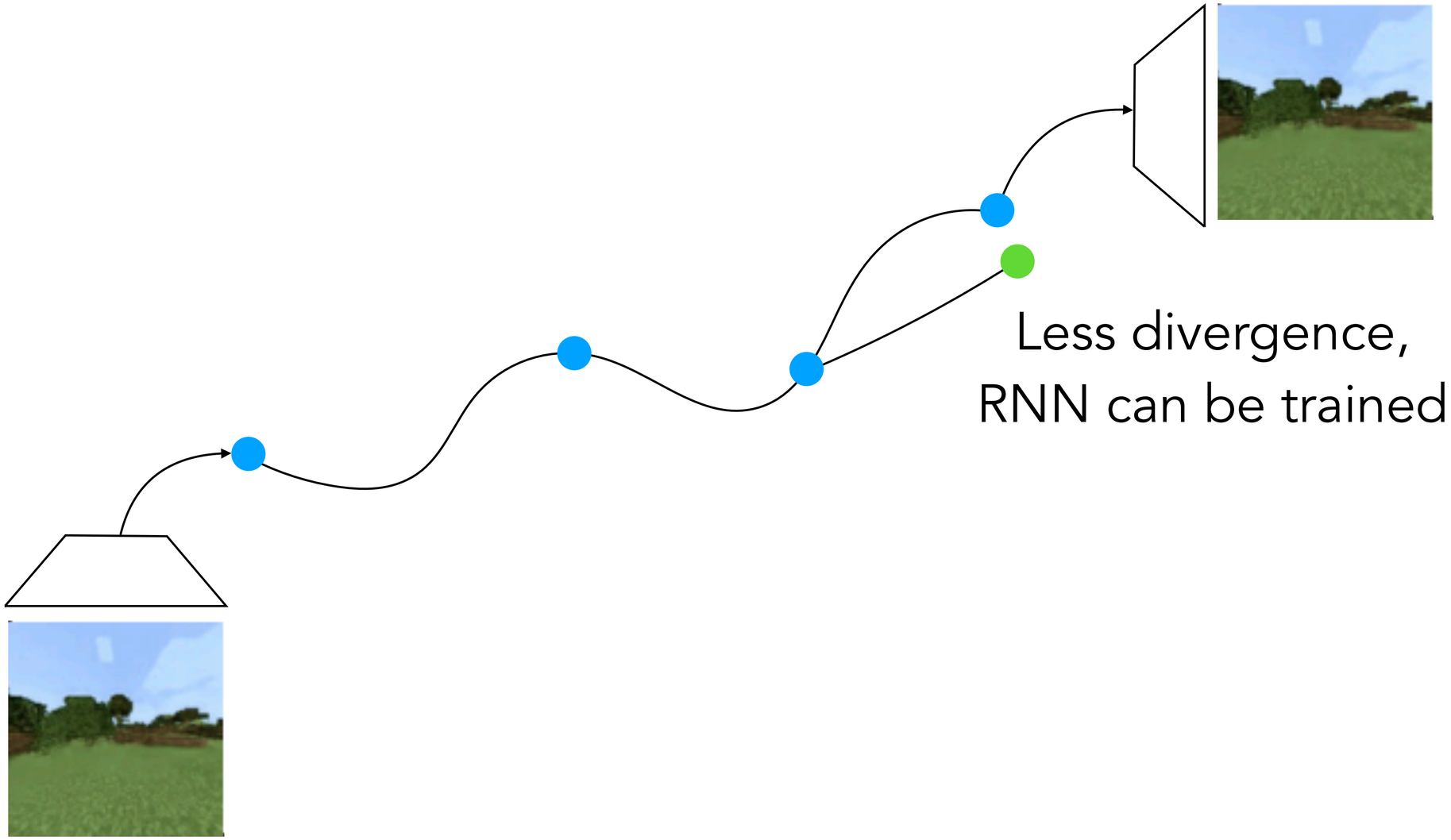

Problem with Teacher Forcing: Test-Time is OOD!

Next-token prediction

compounding error

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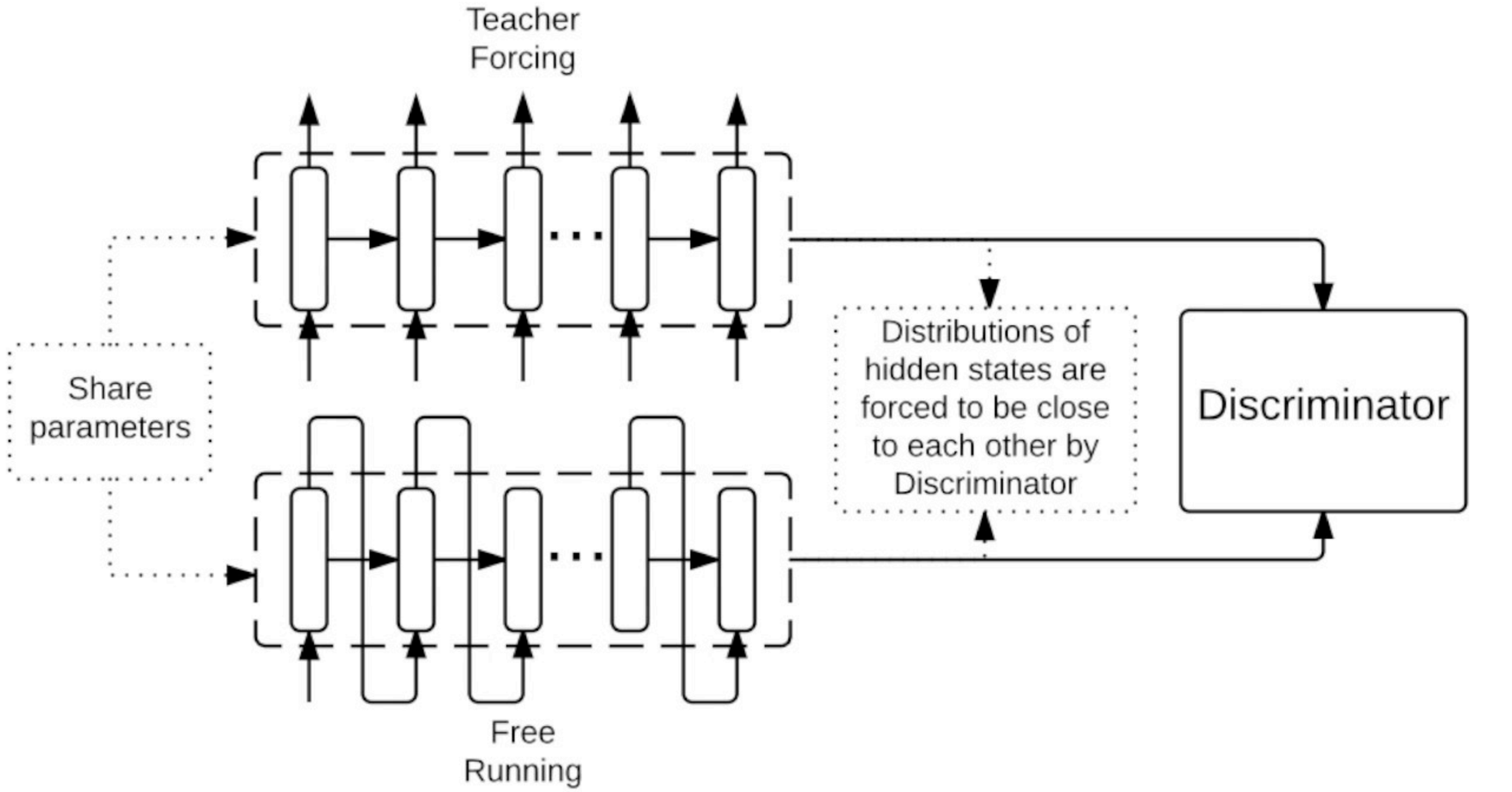
compounding error

Problem: at test time, *have* to use RNN predictions! Quickly diverges.

Prior attempts at fixing this



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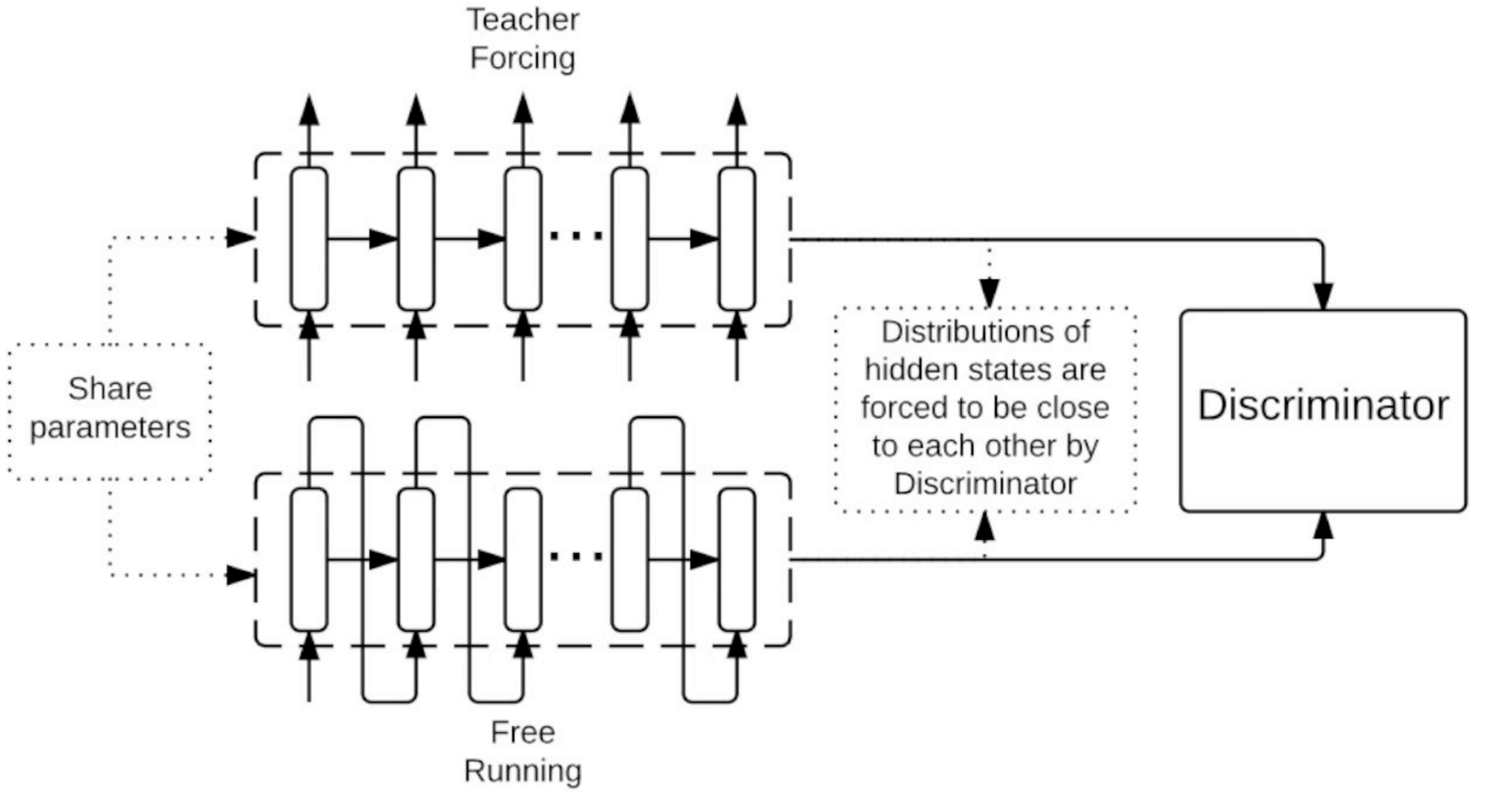
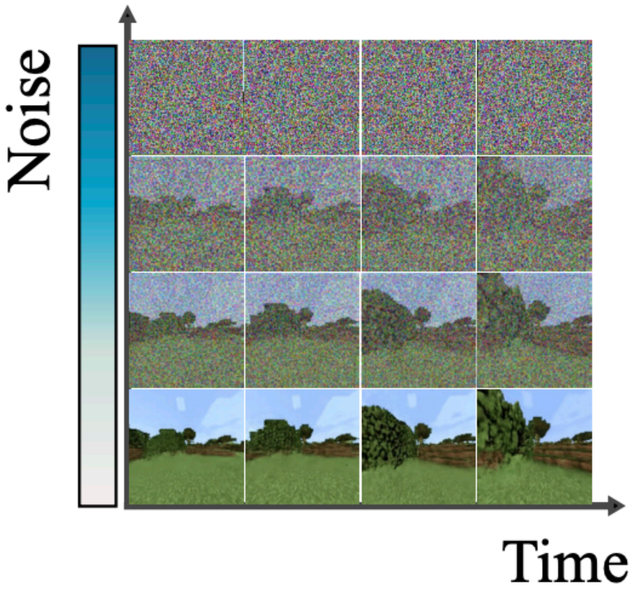


[Professor Forcing, Lamb et al. 2016]

Auto-Regressive Generation (Next-Token Prediction)



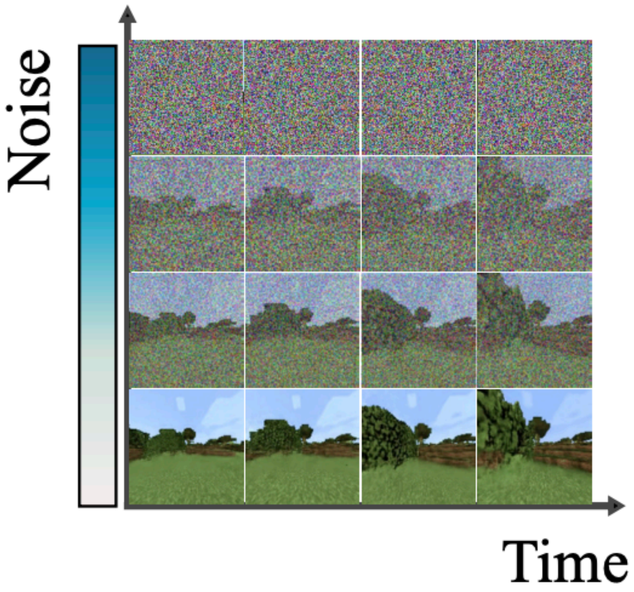
Observation

Latent State

Generation

Add Noise

Auto-Regressive Generation (Next-Token Prediction)



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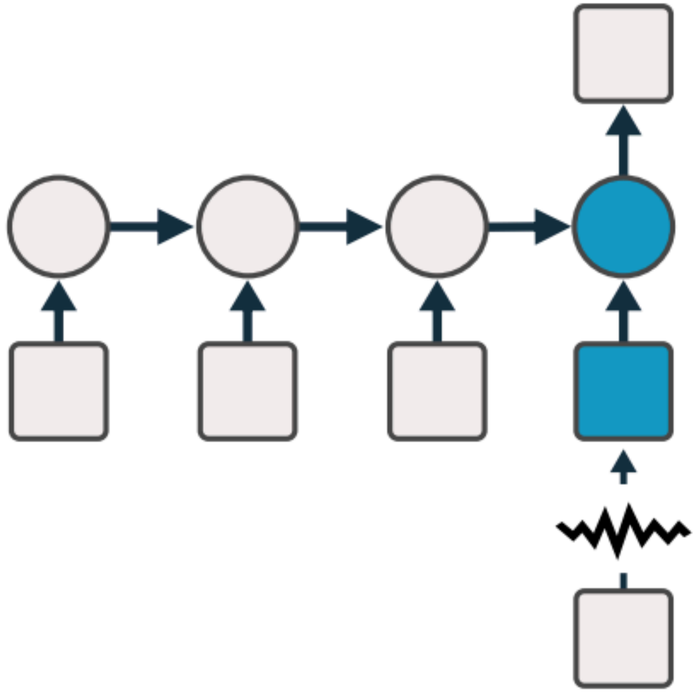
Training



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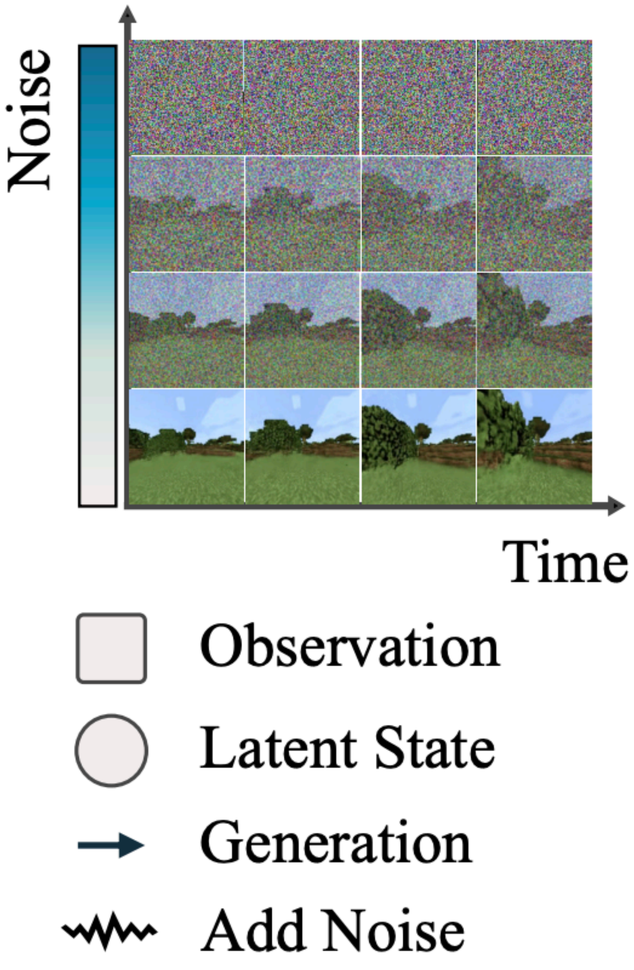
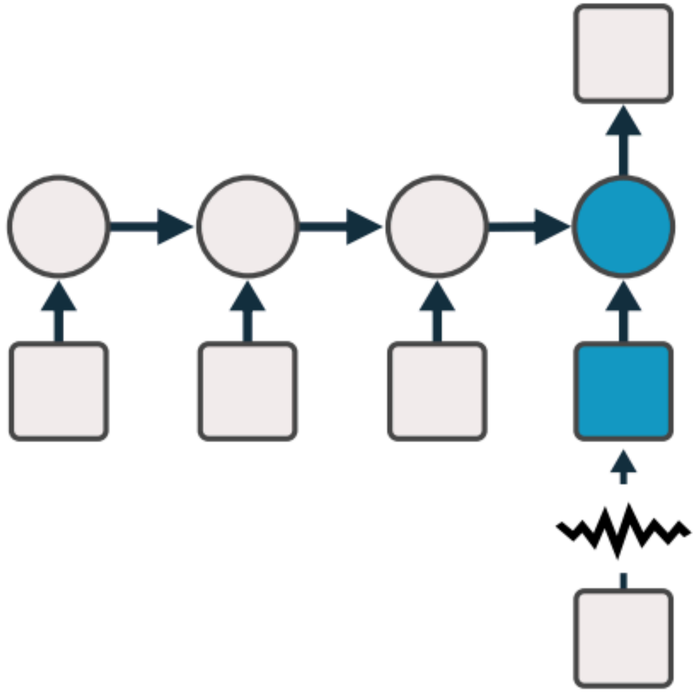
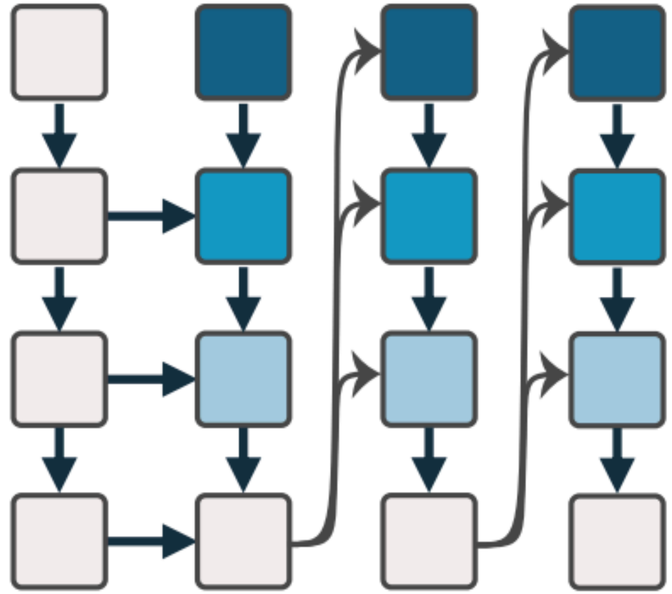


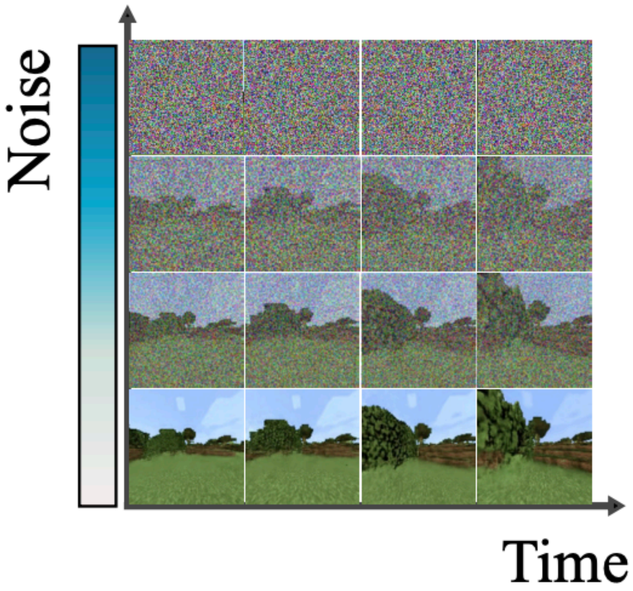
Training



Inference



Full-Sequence Diffusion



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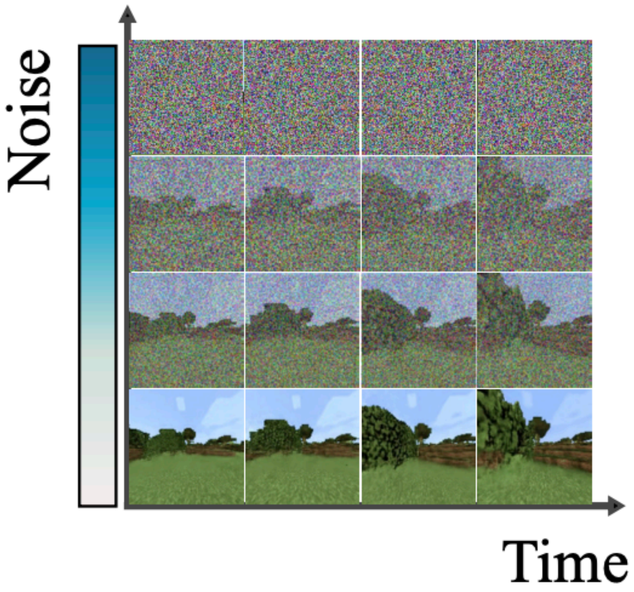

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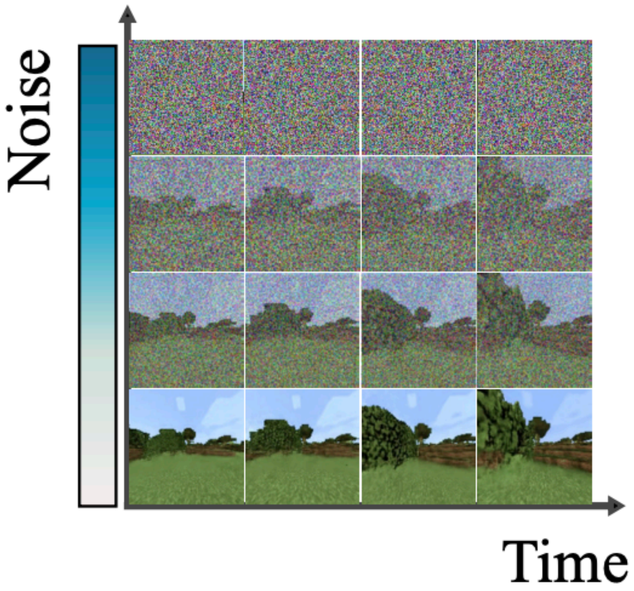

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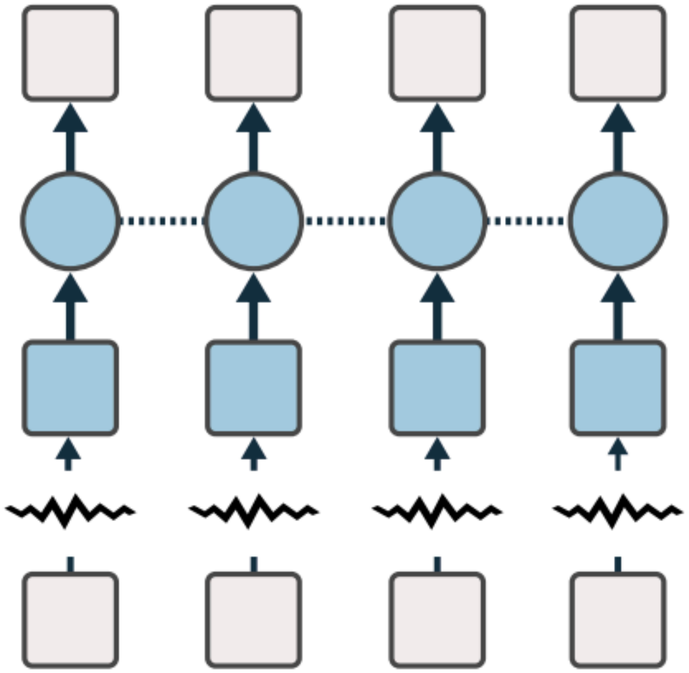

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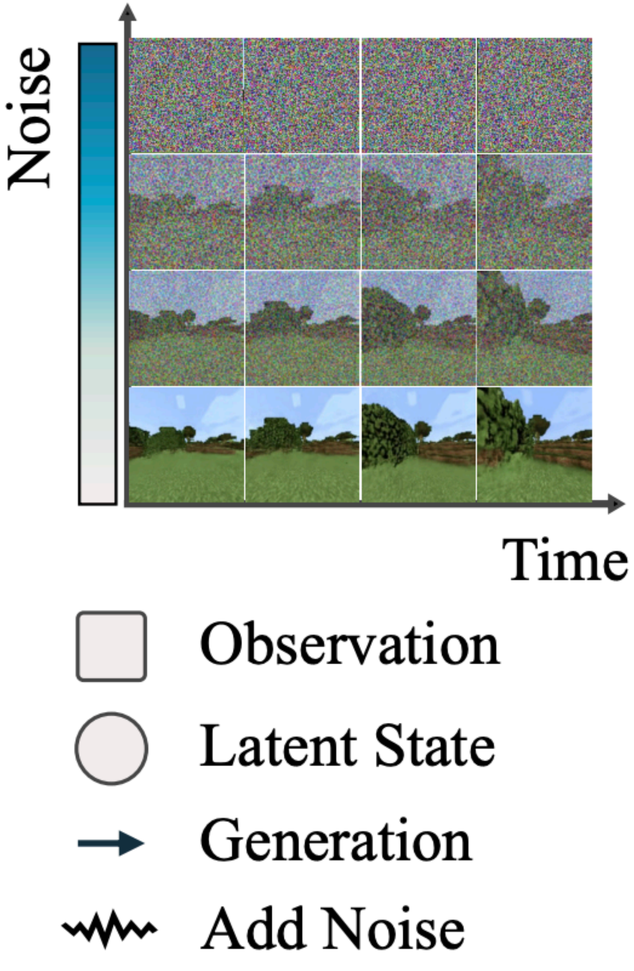
Full-Sequence Diffusion



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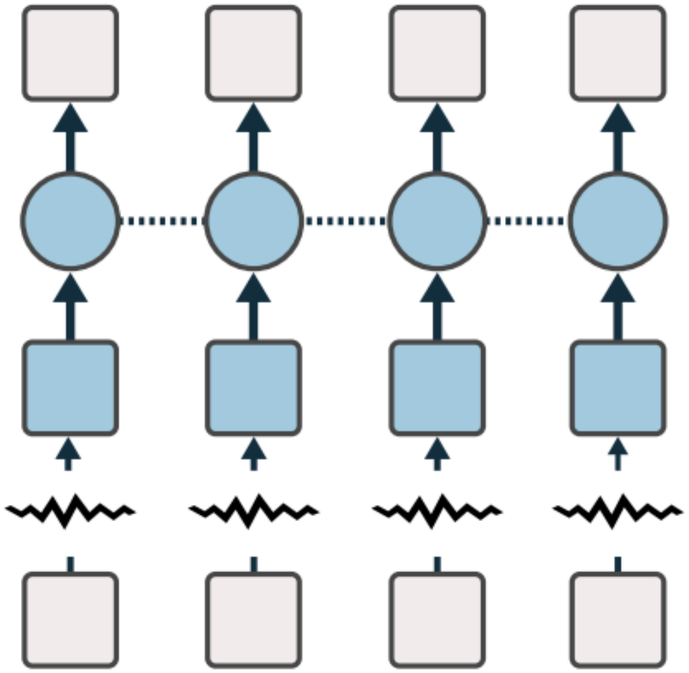

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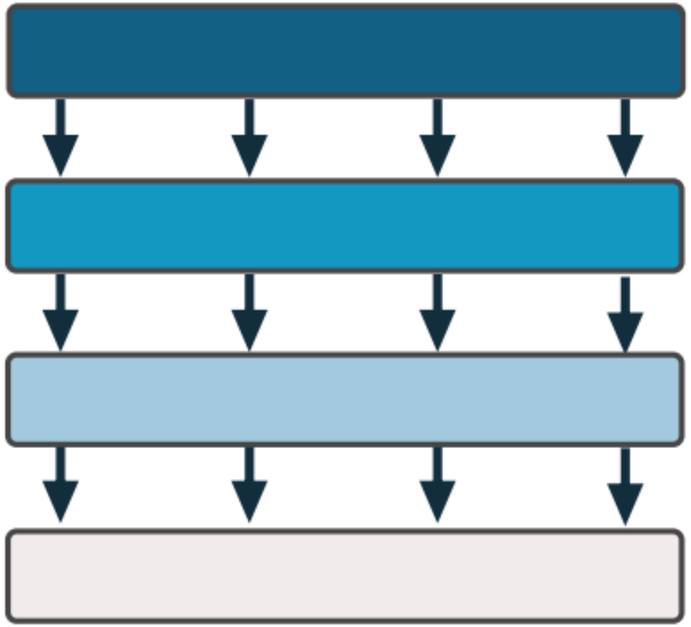

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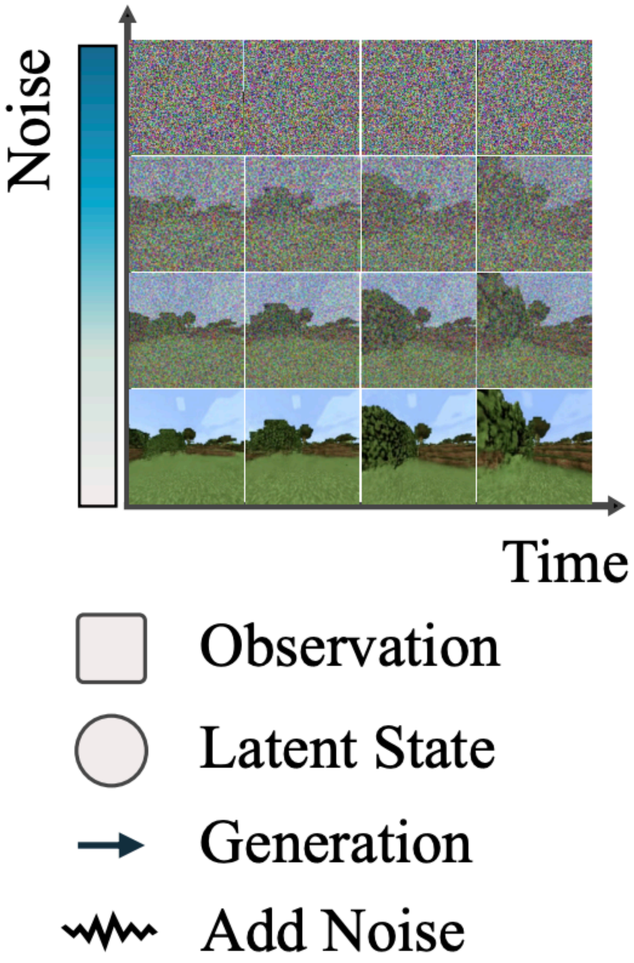

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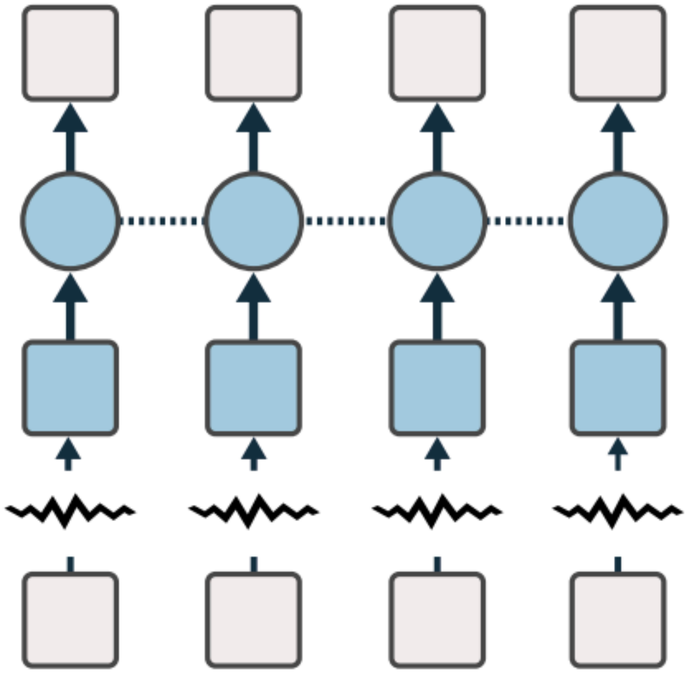
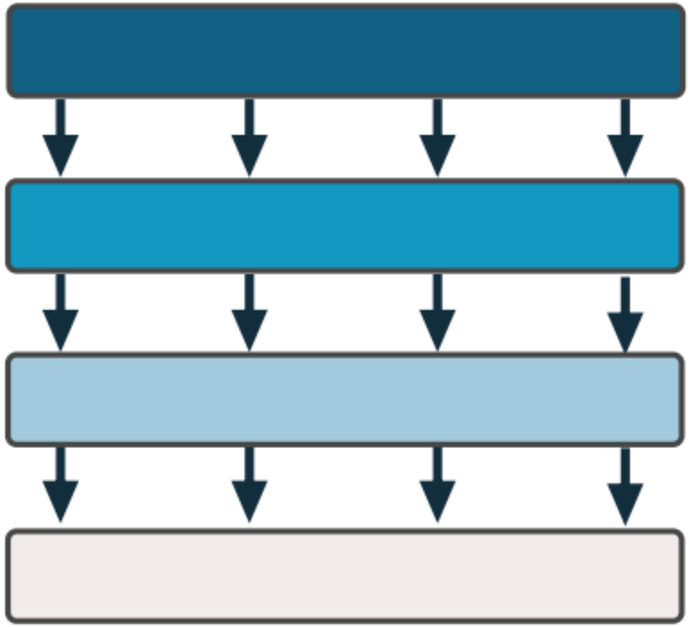


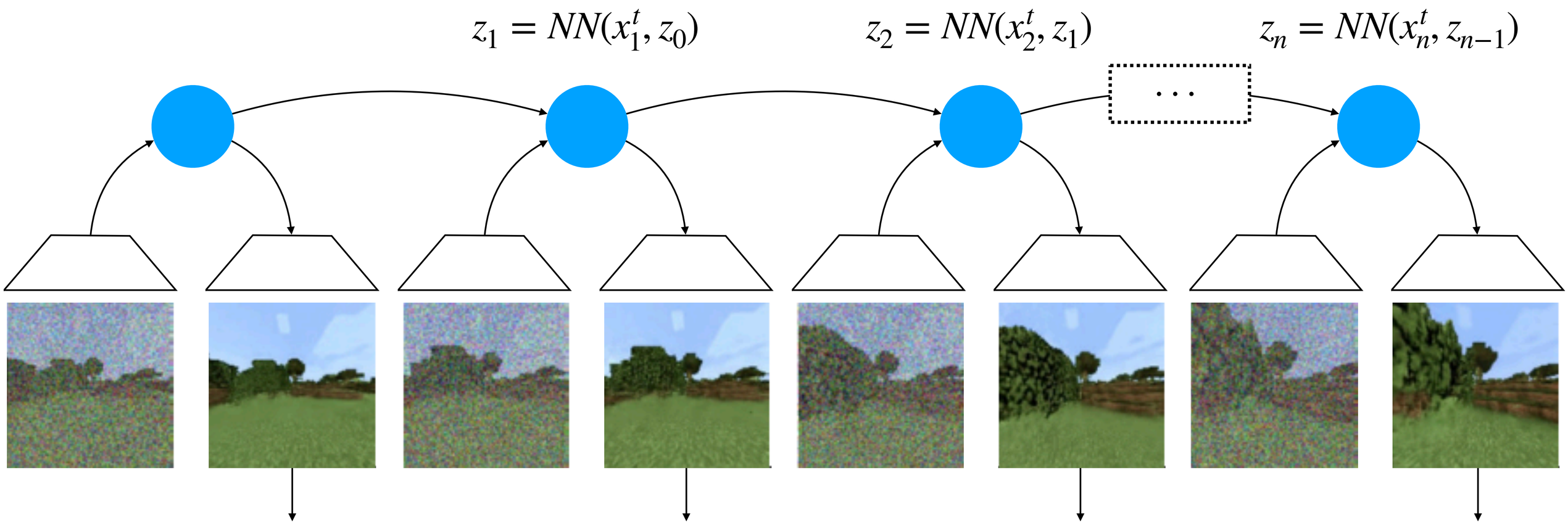
Inference



Examples: SORA, Meta Movie Gen, Diffusion Probabilistic Modeling for Video Generation, [Yang et al. 2022], Video Diffusion Models [Ho et al. 2022]

Full-Sequence Diffusion Training

With RNN



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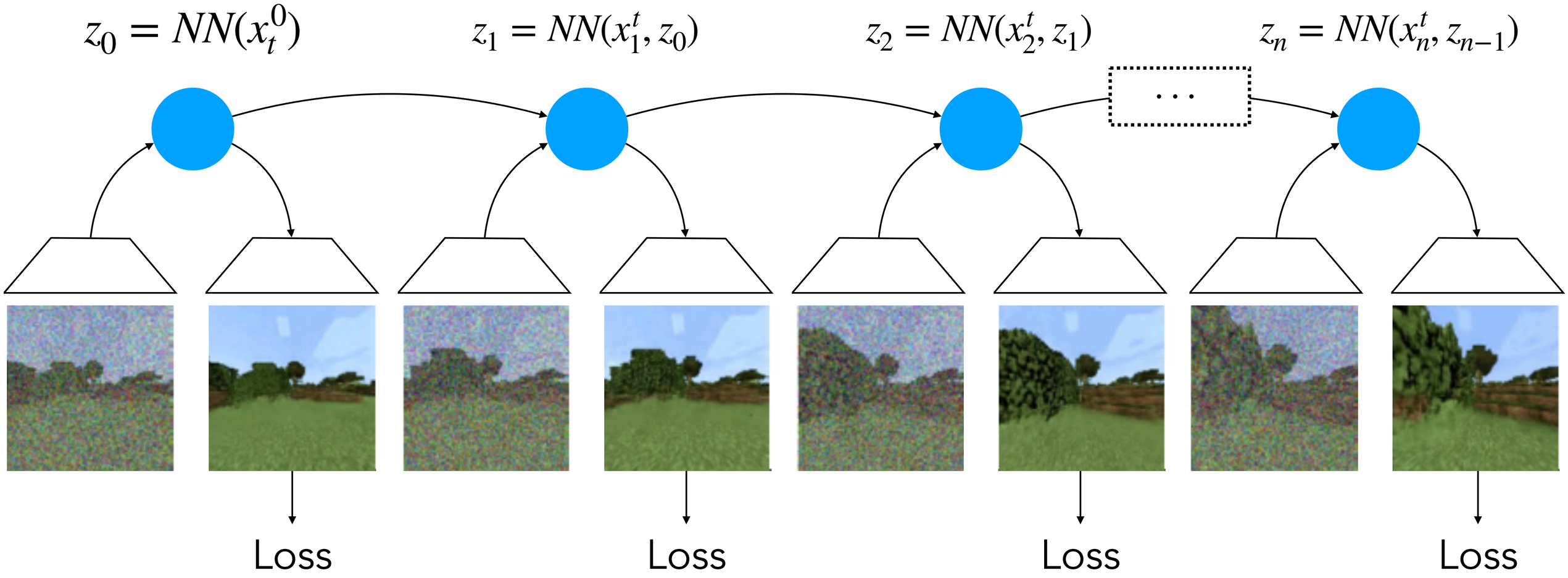
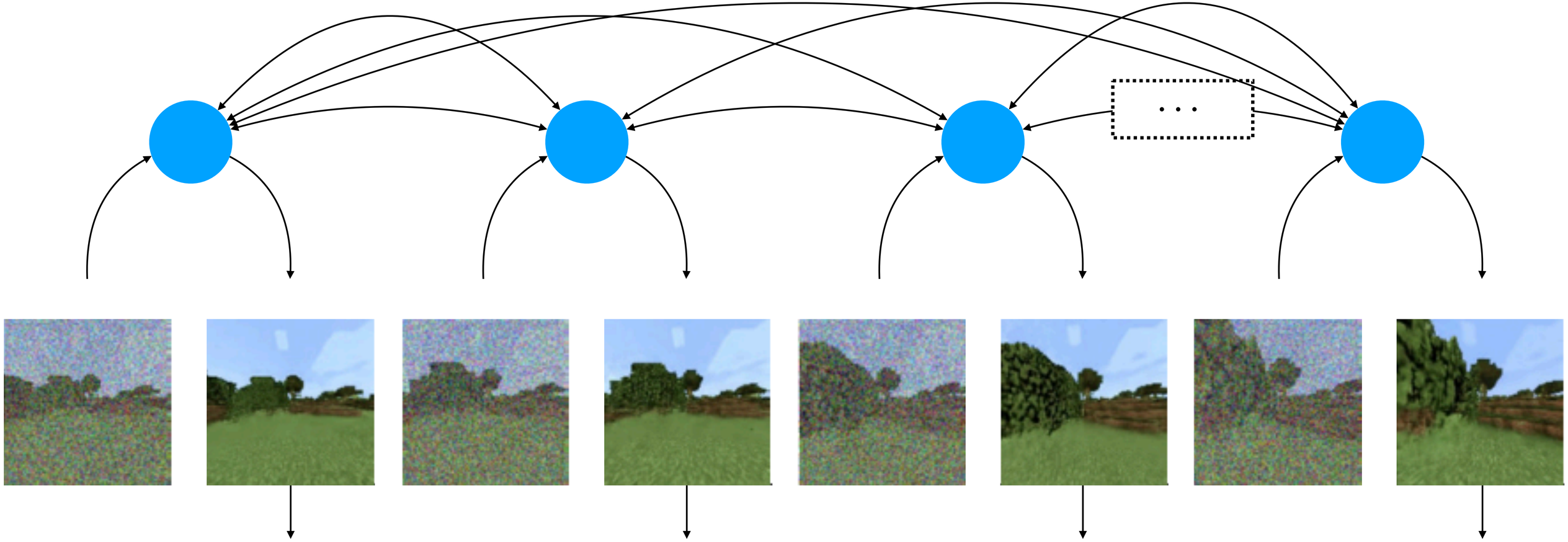


Full-Sequence Diffusion Training

With Transformers



Full-Sequence Diffusion Training

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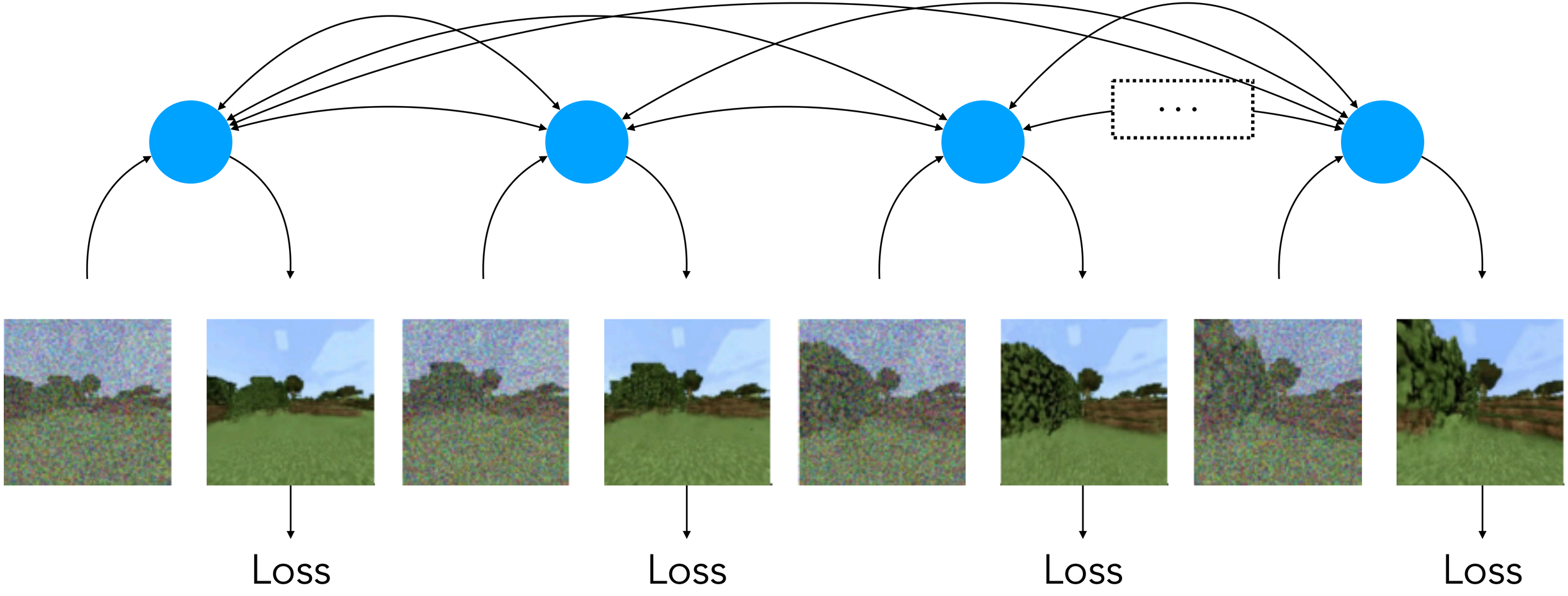

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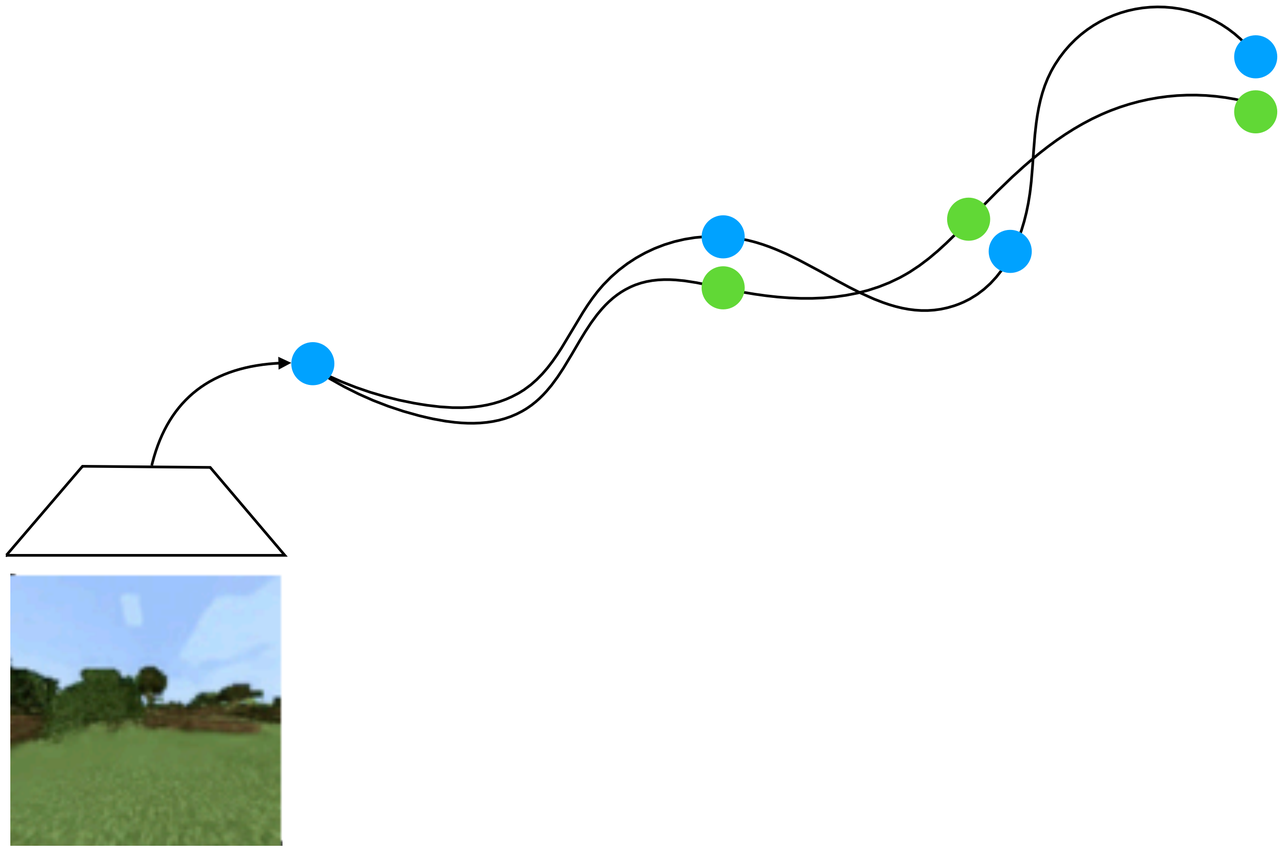
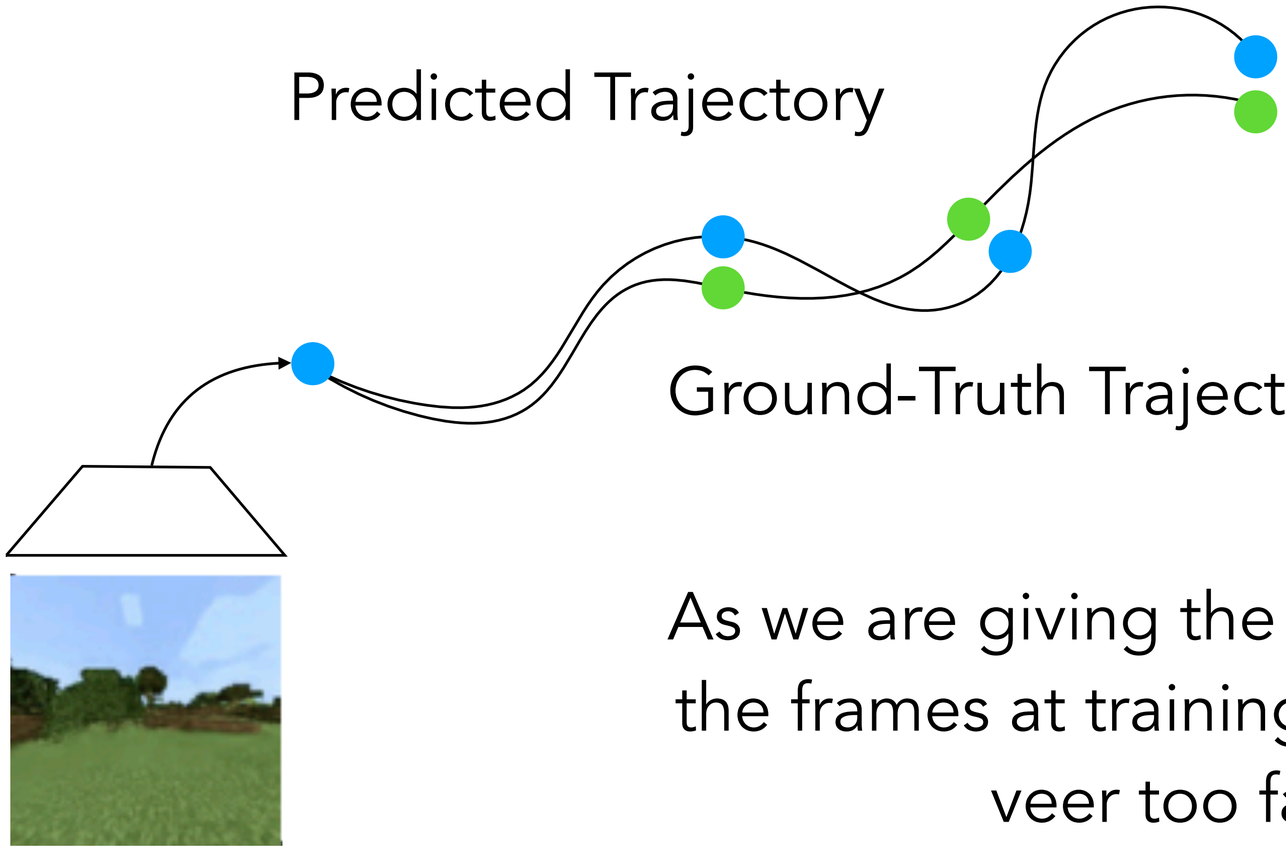
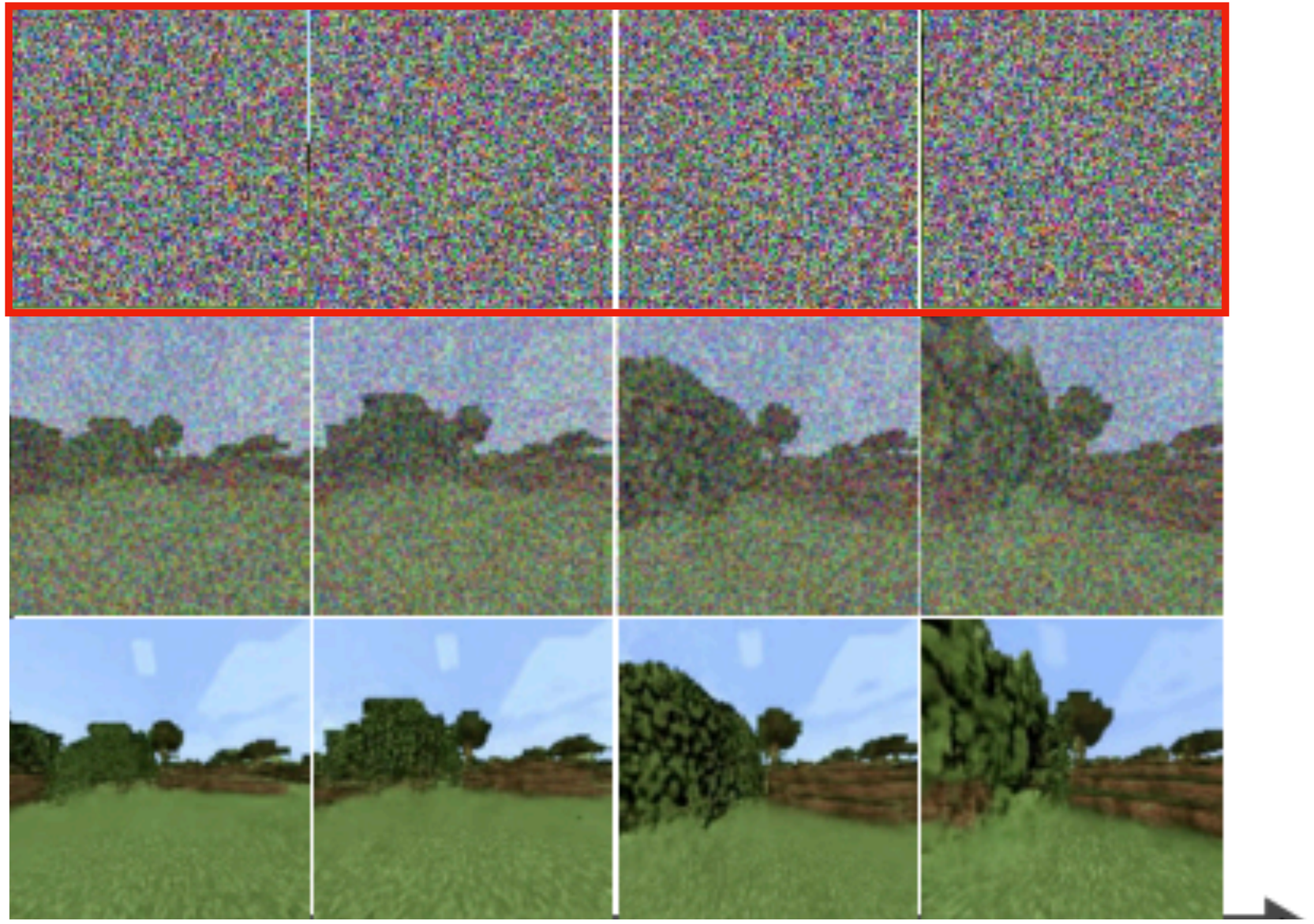


Full-Sequence Diffusion Training

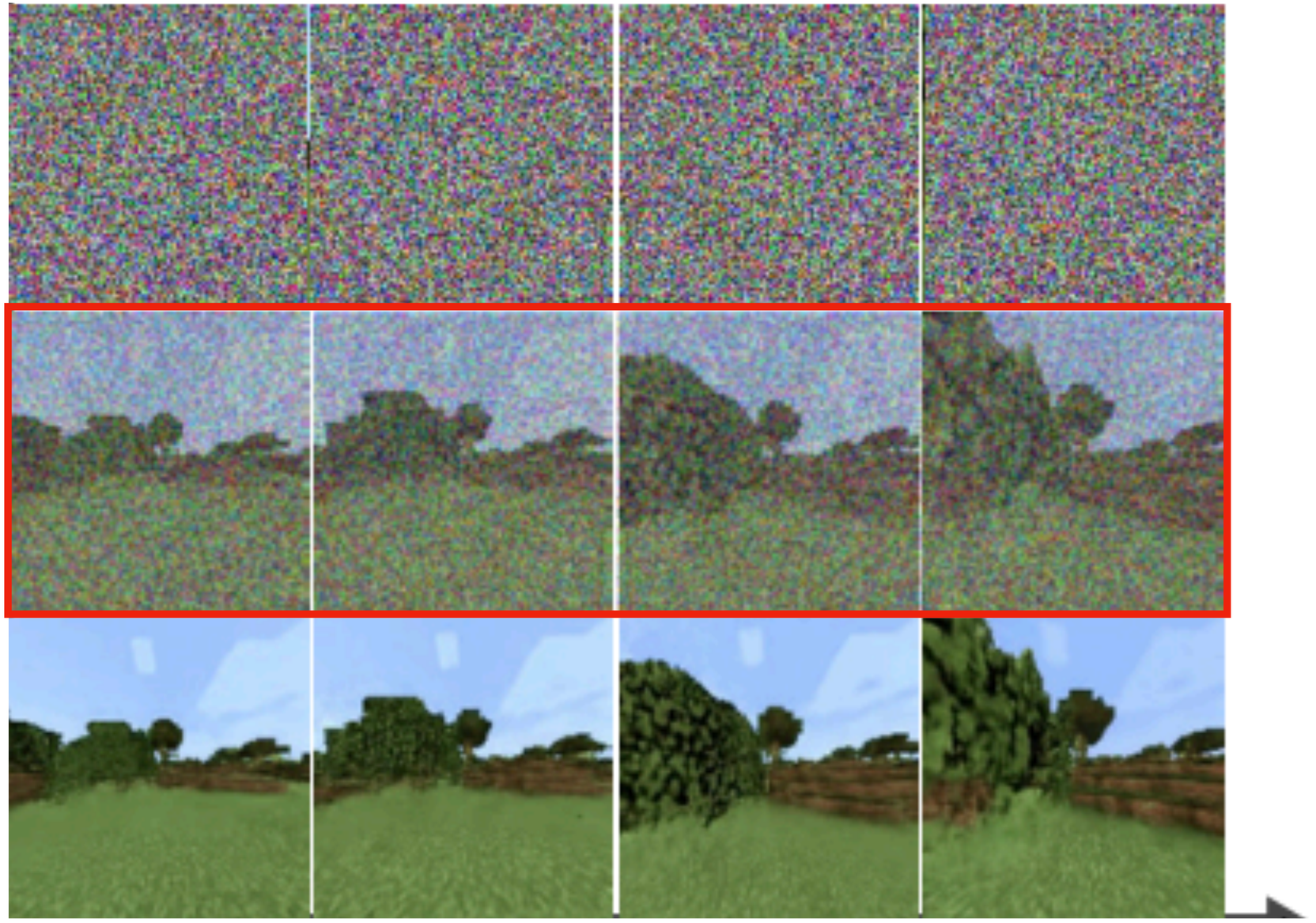


As we are giving the model a noisy version of all the frames at training time, its predictions won't veer too far from the truth.

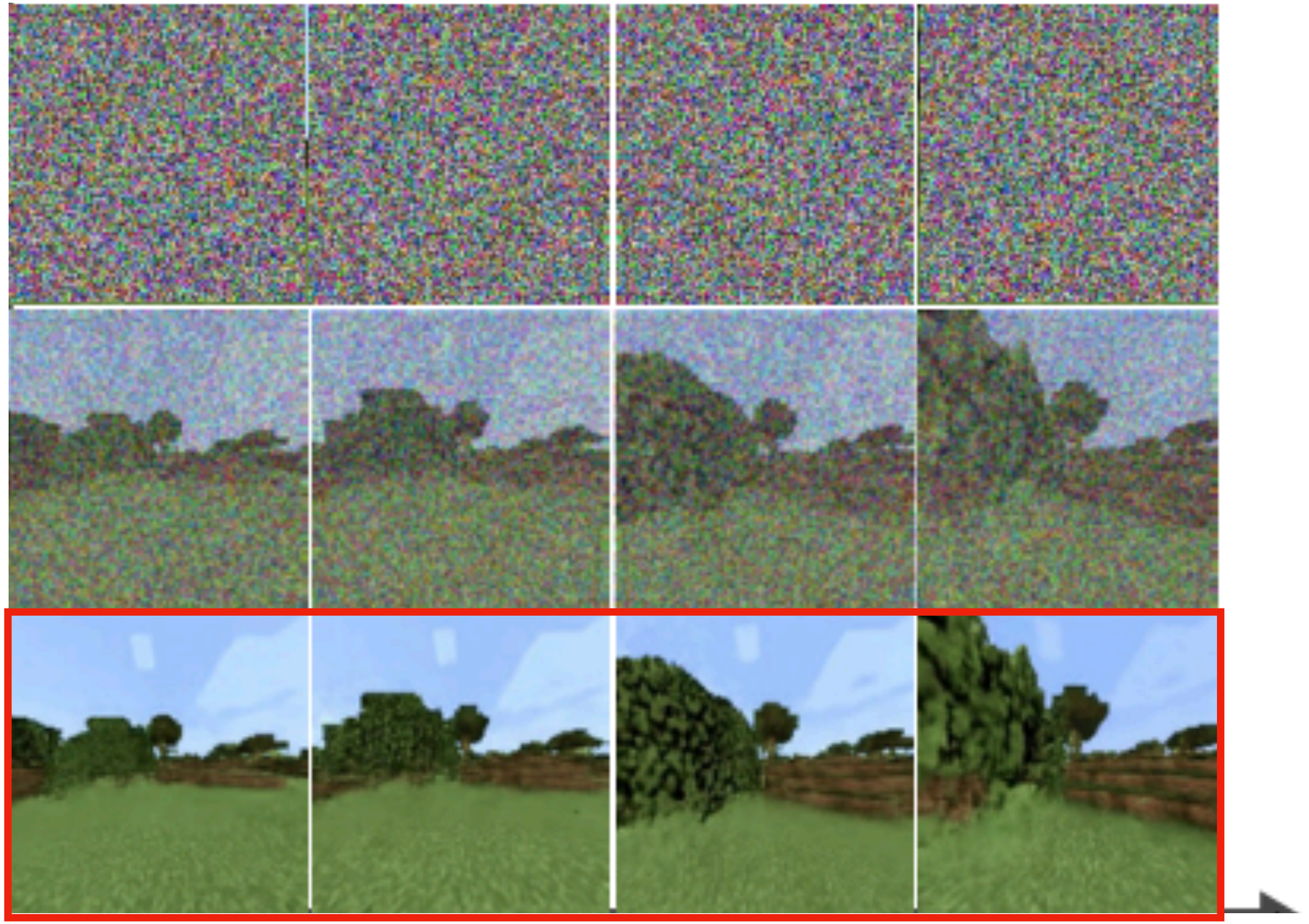
The problem with full-sequence Diffusion: Auto-Regressive Rollout



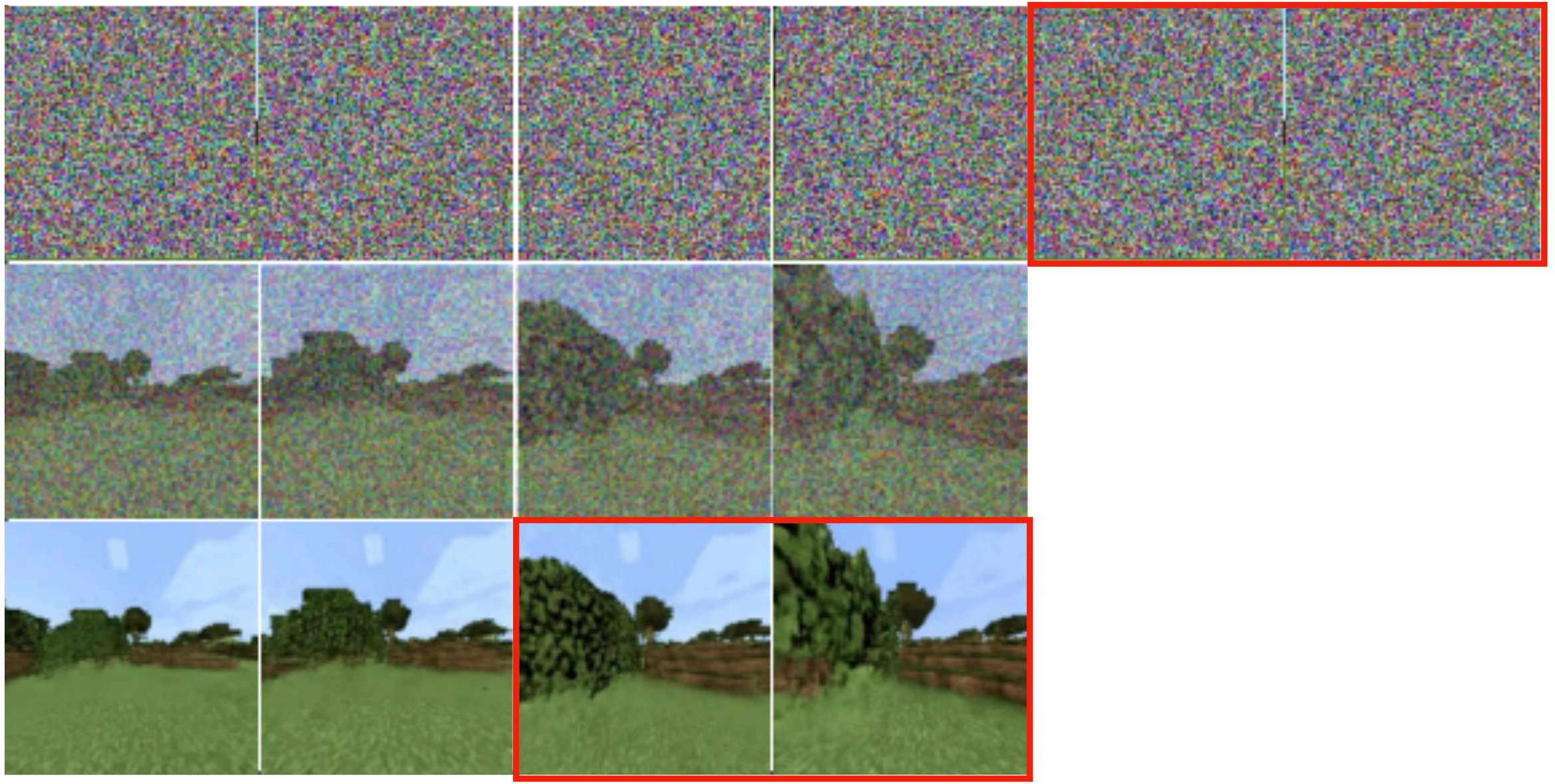
The problem with full-sequence Diffusion: Auto-Regressive Rollout



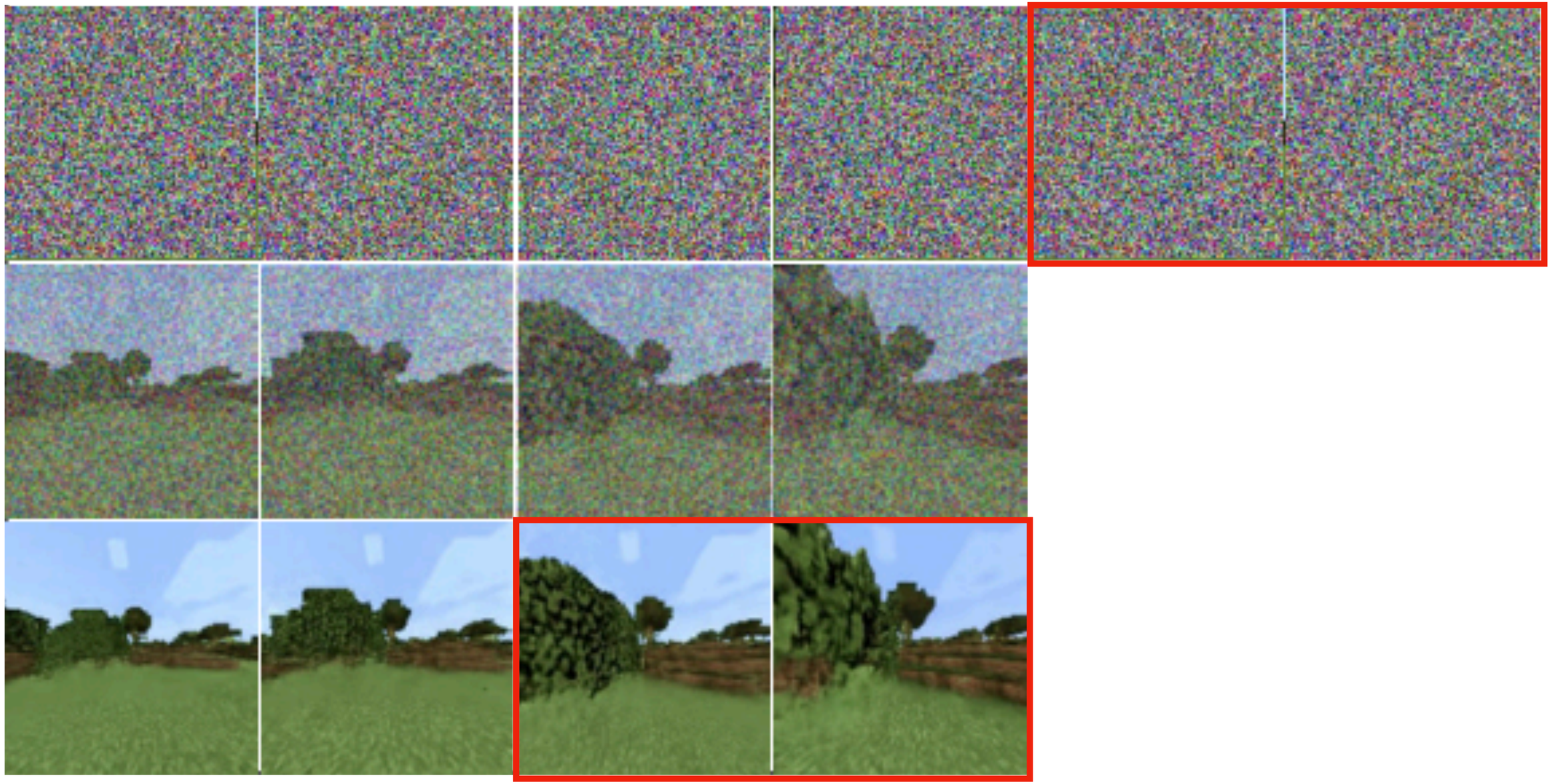
The problem with full-sequence Diffusion: Auto-Regressive Rollout



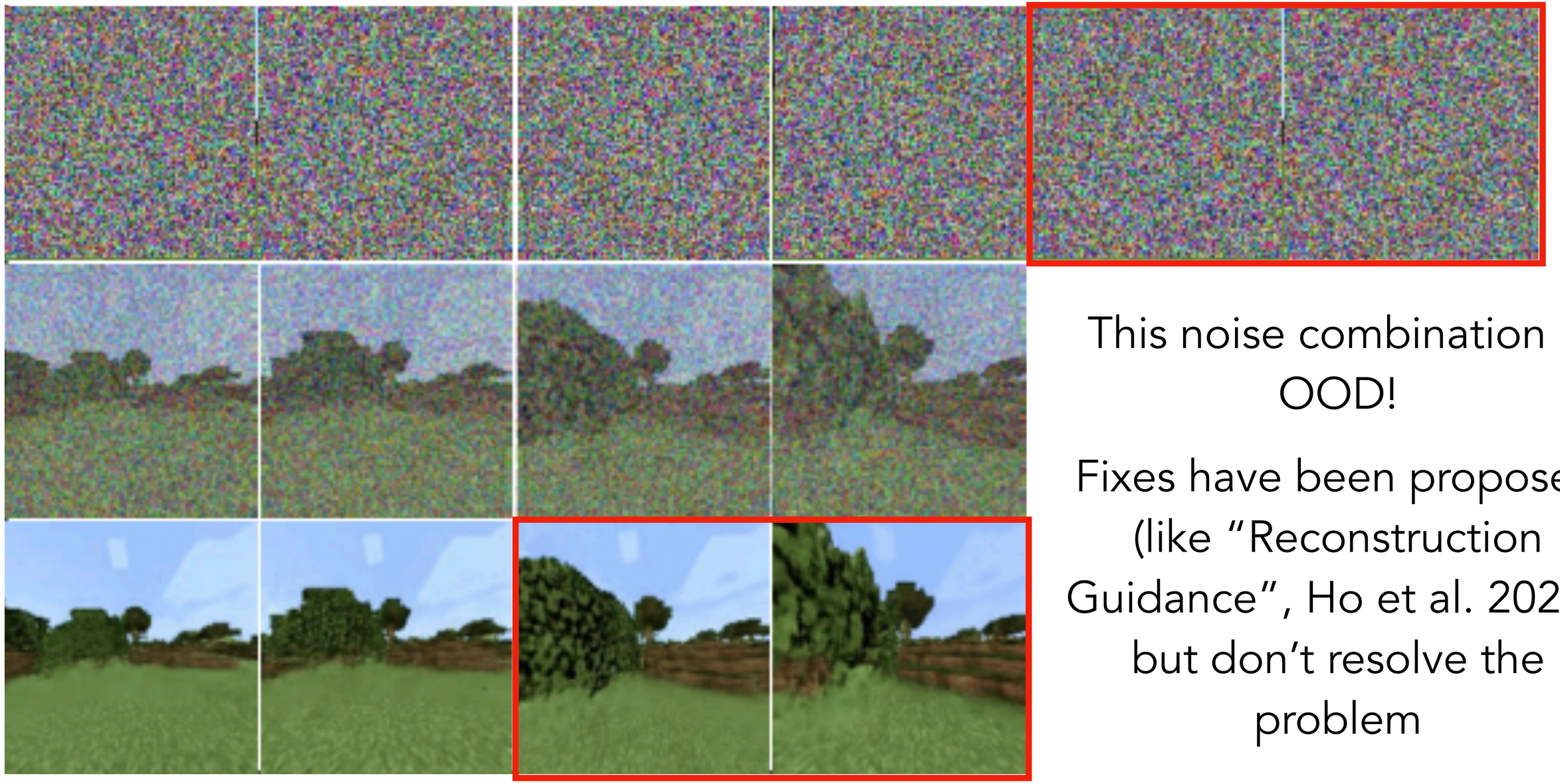
The problem with full-sequence Diffusion: Auto-Regressive Rollout



The problem with full-sequence Diffusion: Auto-Regressive Rollout



The problem with full-sequence Diffusion: Auto-Regressive Rollout



This noise combination is OOD!

Fixes have been proposed (like “Reconstruction Guidance”, Ho et al. 2020), but don’t resolve the problem

Auto-Regressive Rollout

Next-token prediction

compounding error

Full-Sequence Diffusion

consistency issues

Auto-Regressive Rollout

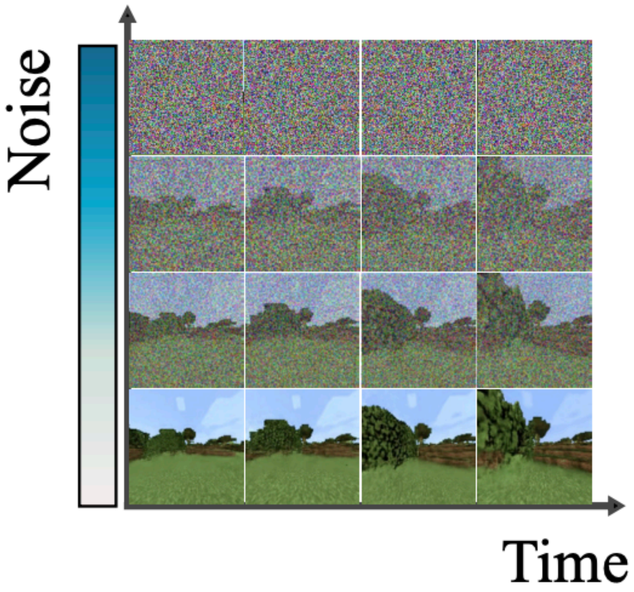
Next-token prediction

compounding error

Full-Sequence Diffusion

consistency issues

Full-Sequence Diffusion



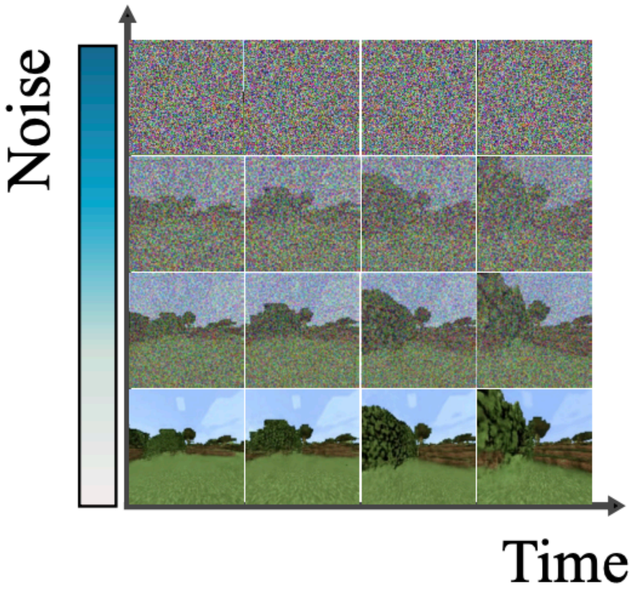
Observation

Latent State

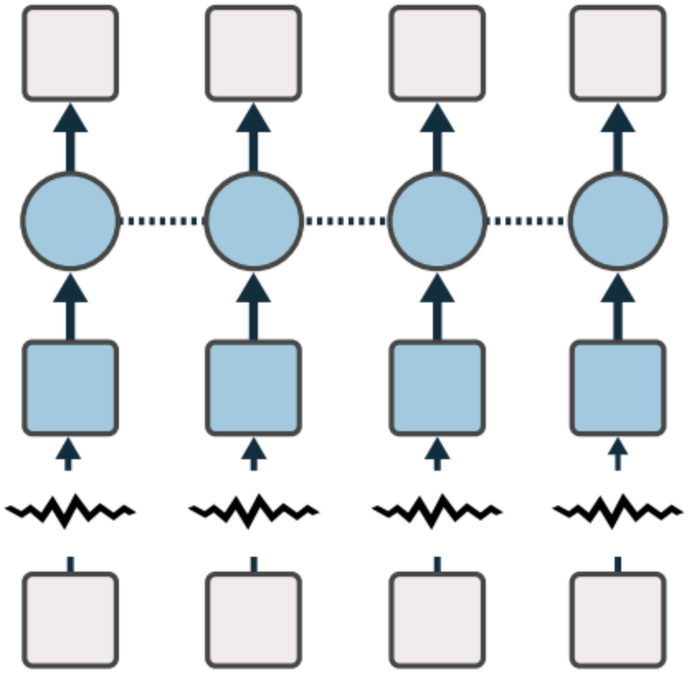
Generation

Add Noise

Full-Sequence Diffusion



Training



Observation

Latent State

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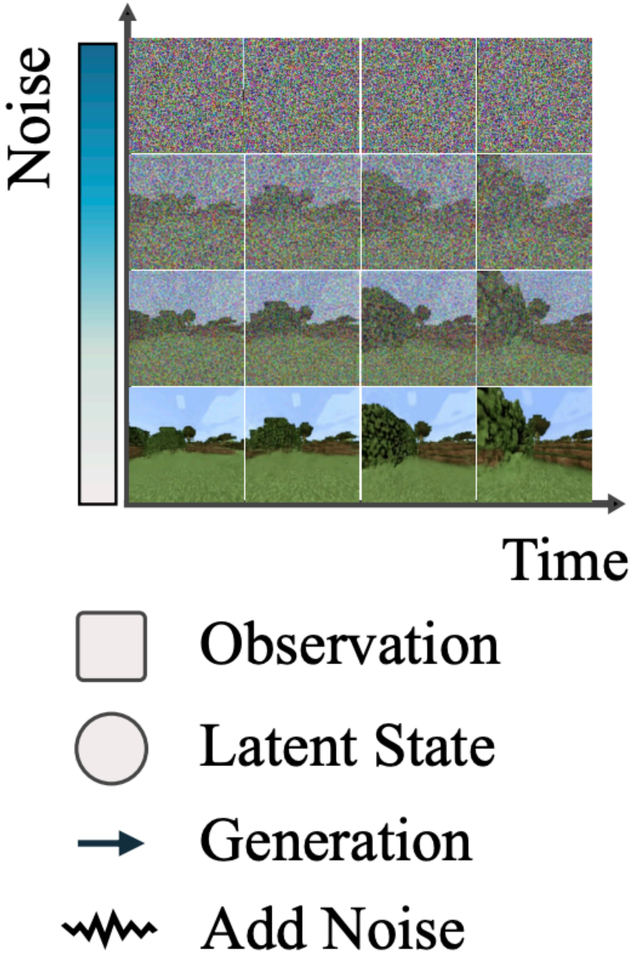
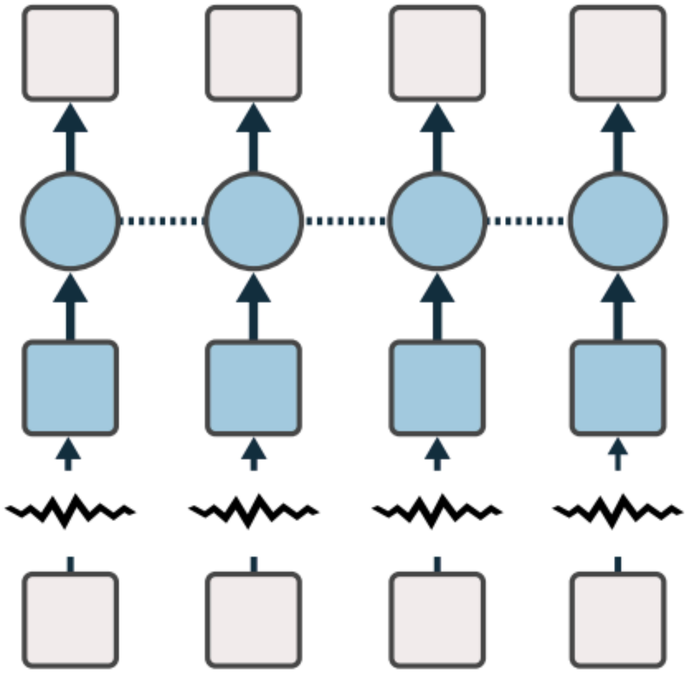
Add Noise

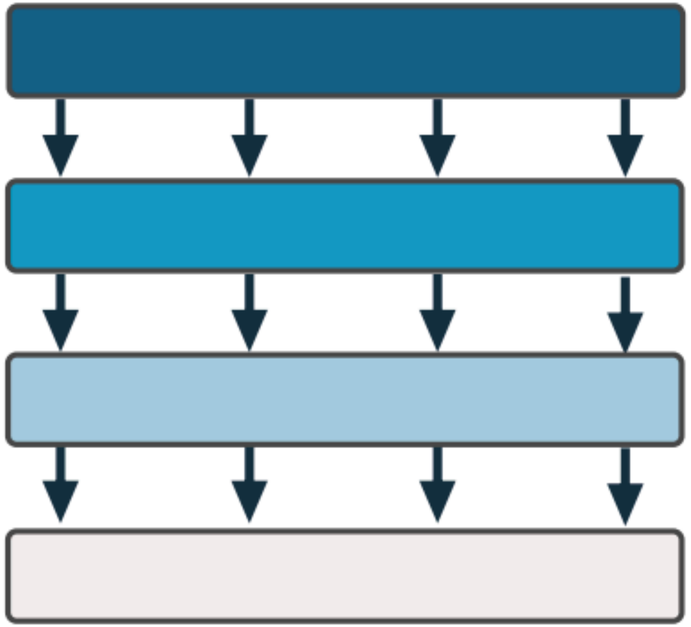
Full-Sequence Diffusion



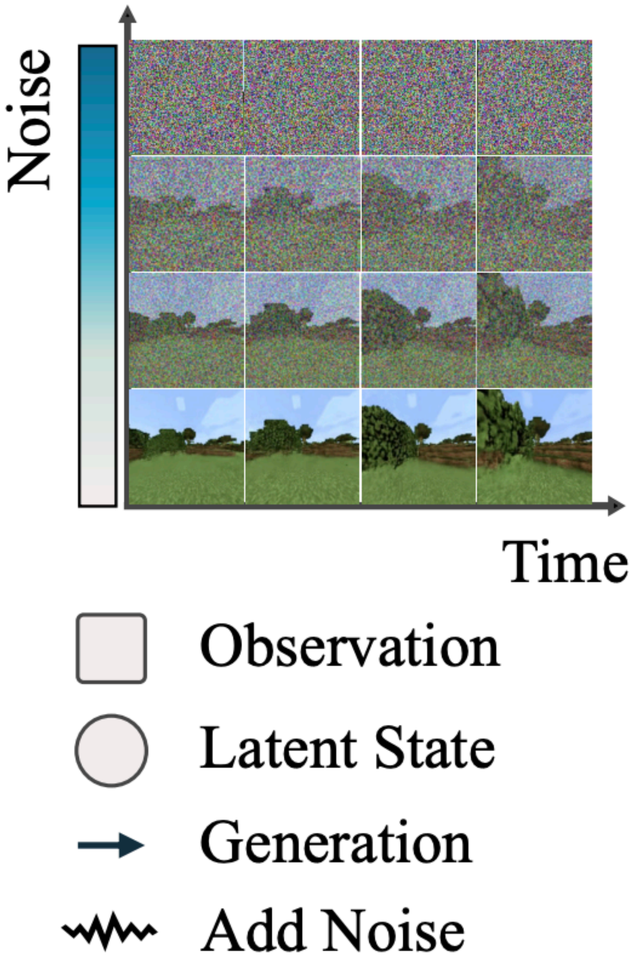
Training



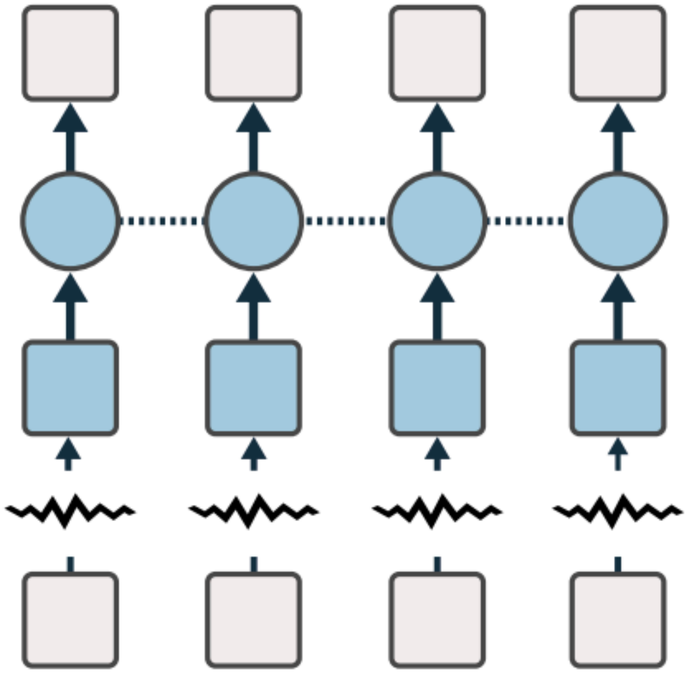
Inference



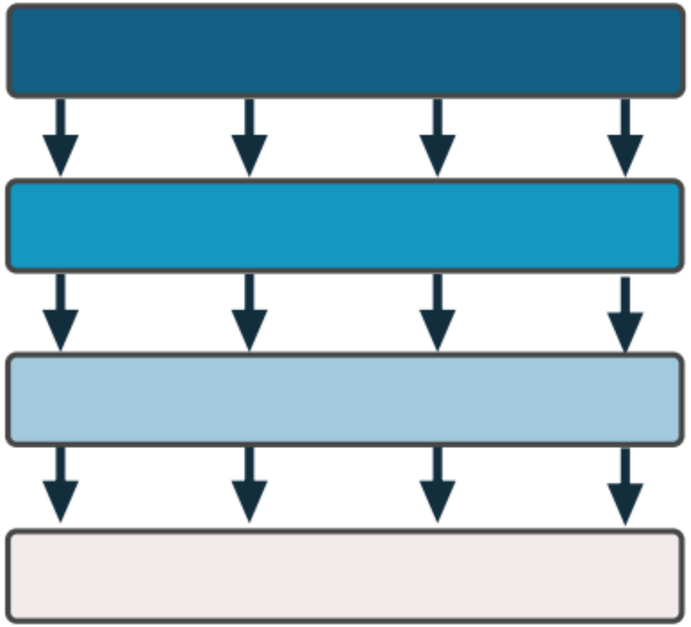
Full-Sequence Diffusion



Training



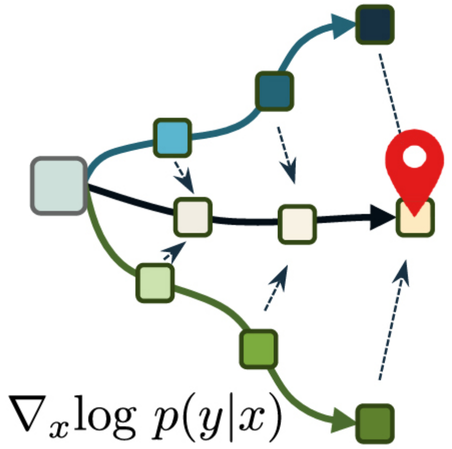
Inference



Examples: SORA, Meta Movie Gen, Diffusion Probabilistic Modeling for Video Generation, [Yang et al. 2022], Video Diffusion Models [Ho et al. 2022]

Capabilities of Existing Models

Guidance



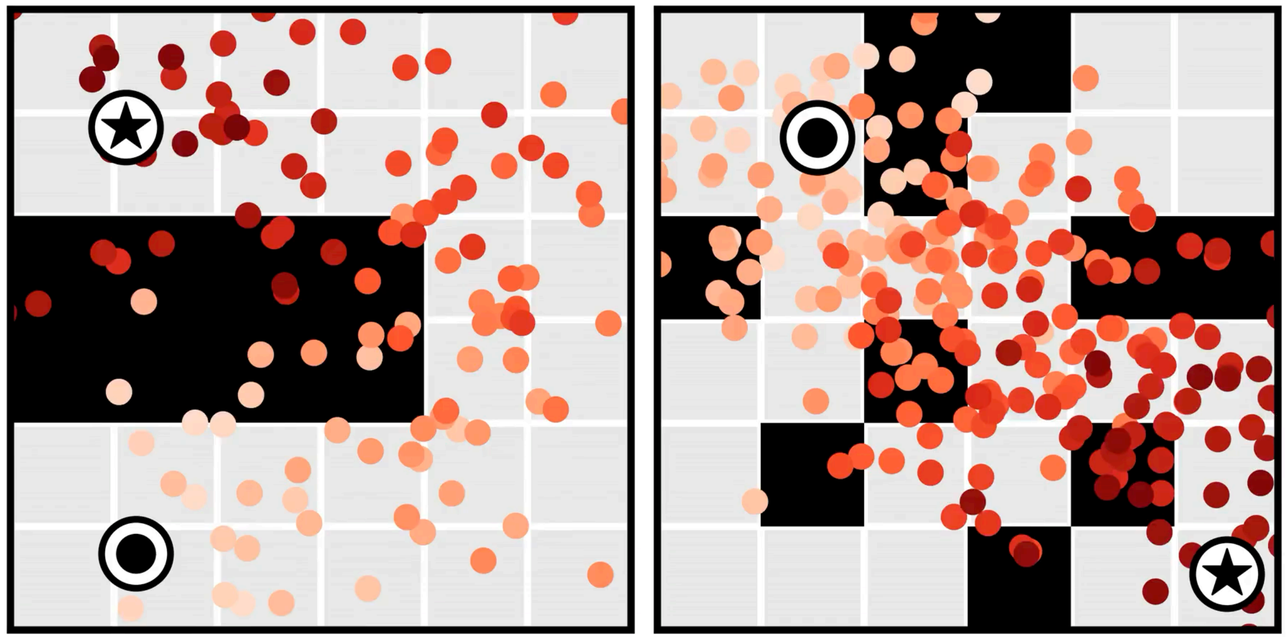
Teacher Forcing

Full-Seq. Diffusion

Planning: Sampling to Arrive at Particular Future

Full-Sequence Diffusion

Planning via **Guidance**



Compute loss on future state,
backdrop to past states
bias denoising

Trained on State, Action pairs

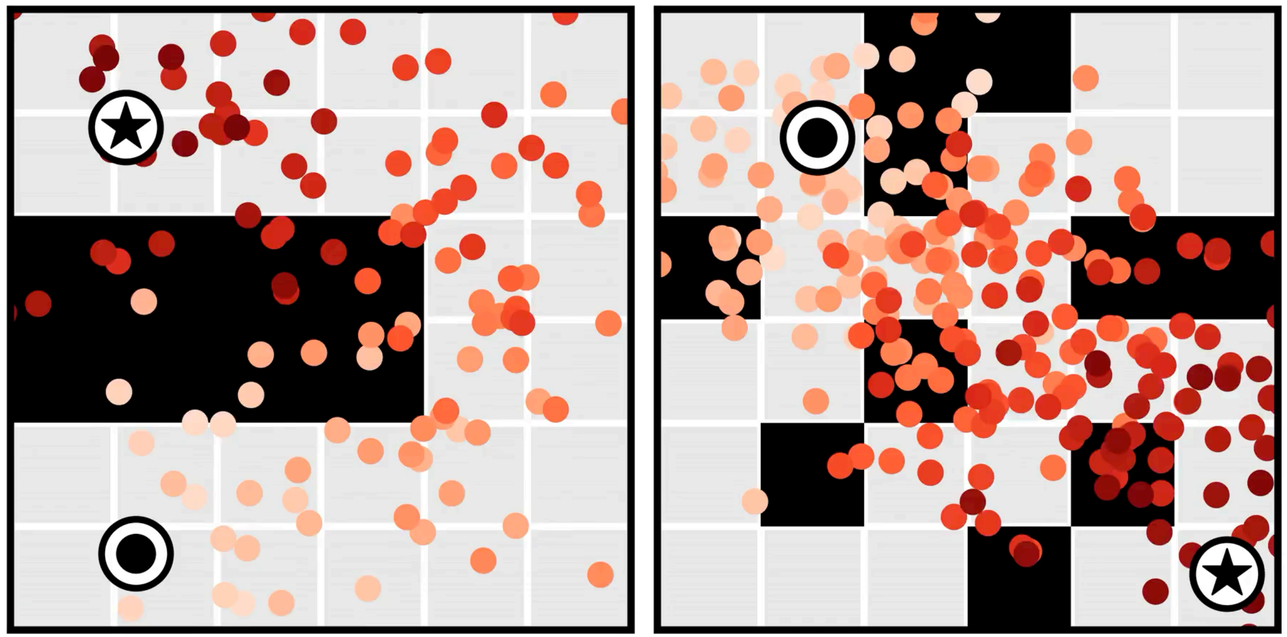
$$(S_0, a_0), \ldots, (S_n, a_n)$$

Planning with Diffusion for
Flexible Behavior Synthesis,
Tanner and Du et al., 2024

Planning: Sampling to Arrive at Particular Future

Full-Sequence Diffusion

Planning via **Guidance**



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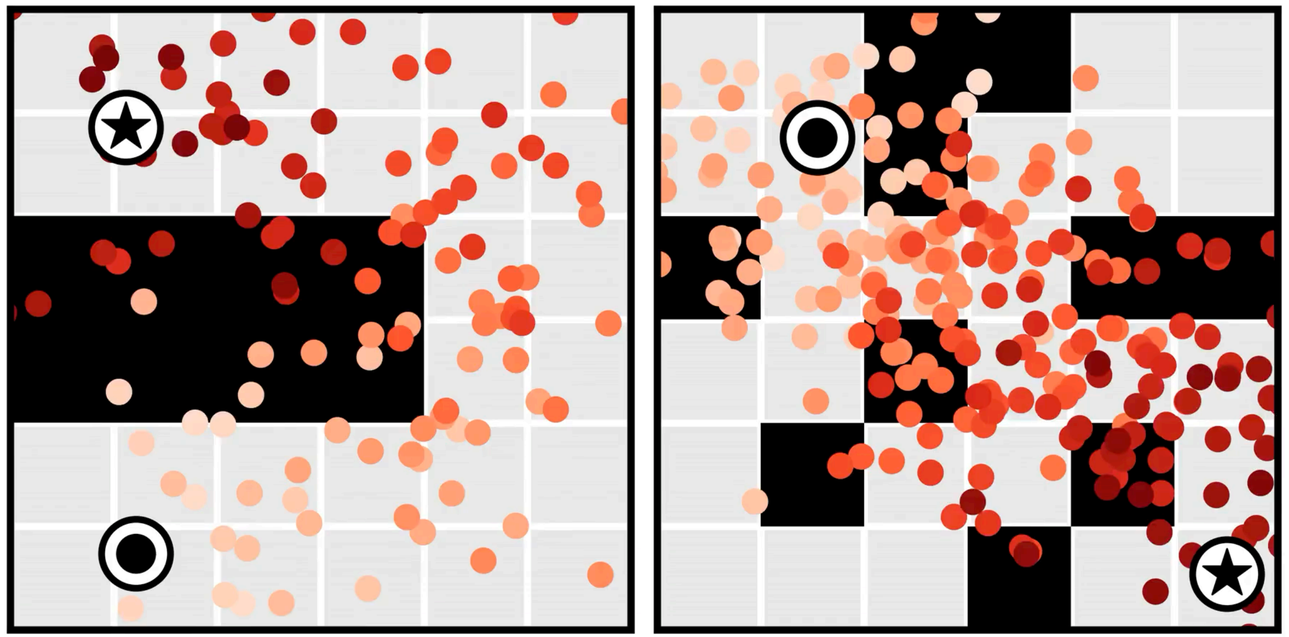
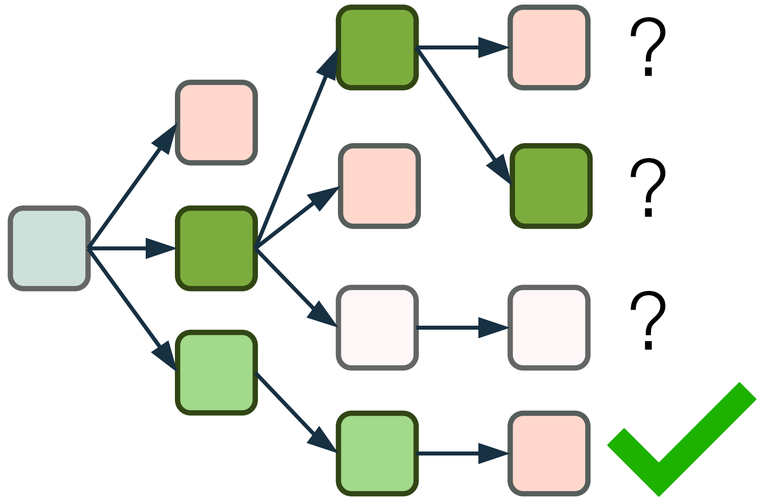


Compute loss on future state,
backdrop to past states
bias denoising

Next-Token Prediction

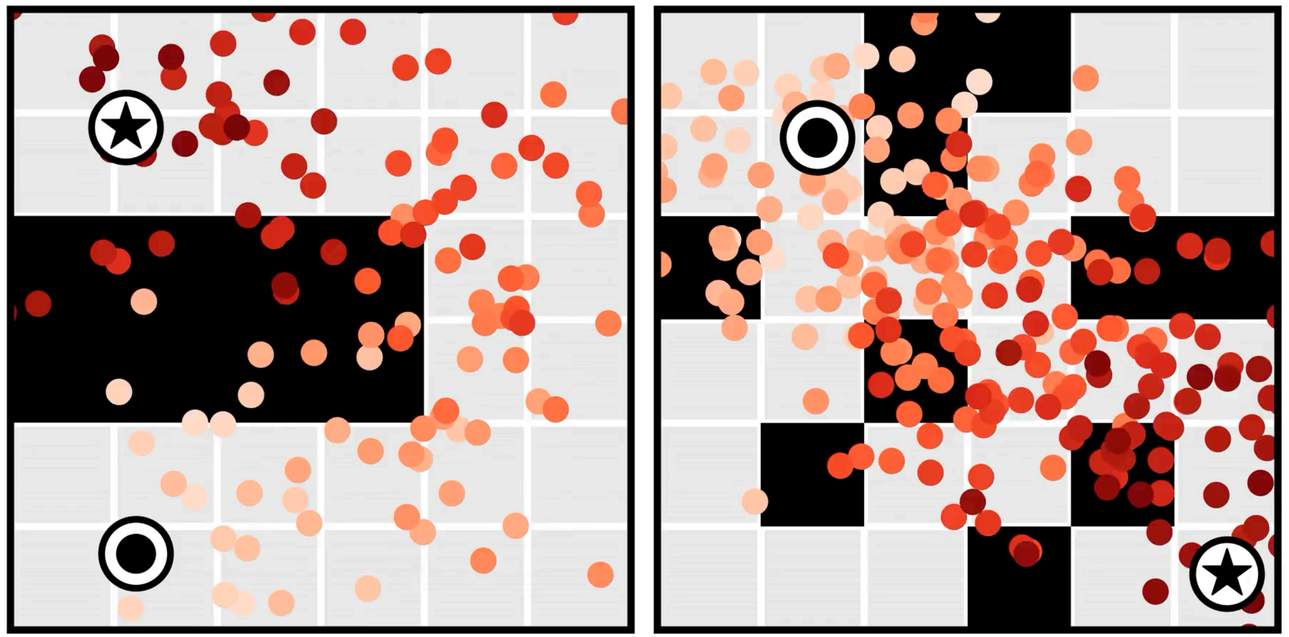
Planning via **Rollout & Search**



Planning: Sampling to Arrive at Particular Future

Full-Sequence Diffusion

Planning via **Guidance**



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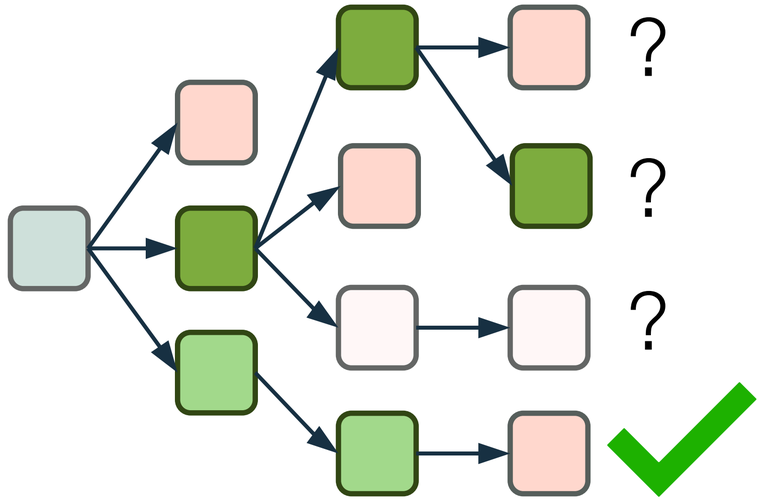
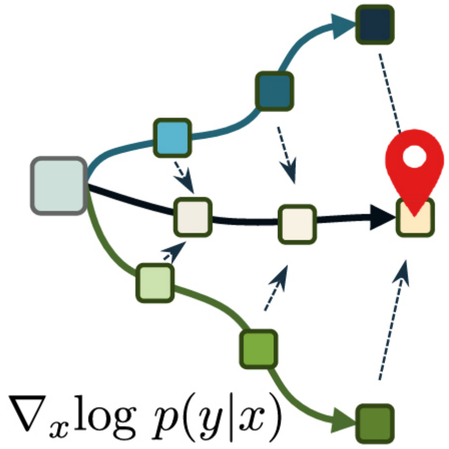
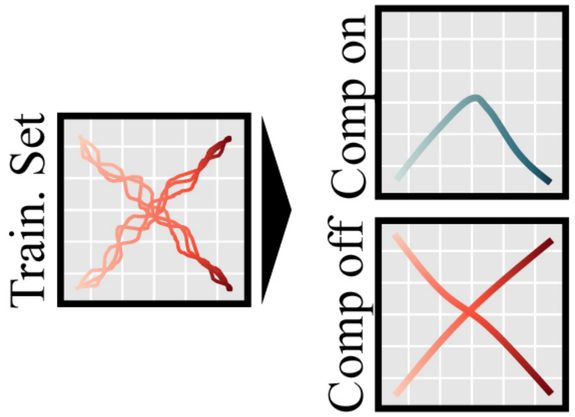


Capabilities of Existing Models

Guidance



Compositionality

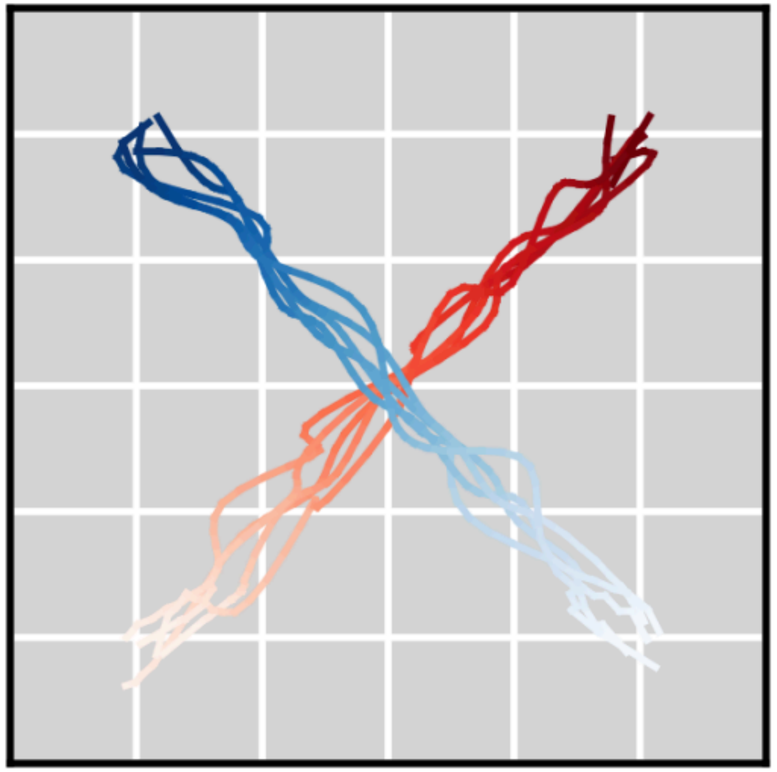


Teacher Forcing ✗ ✓

Full-Seq. Diffusion ✓ ✗

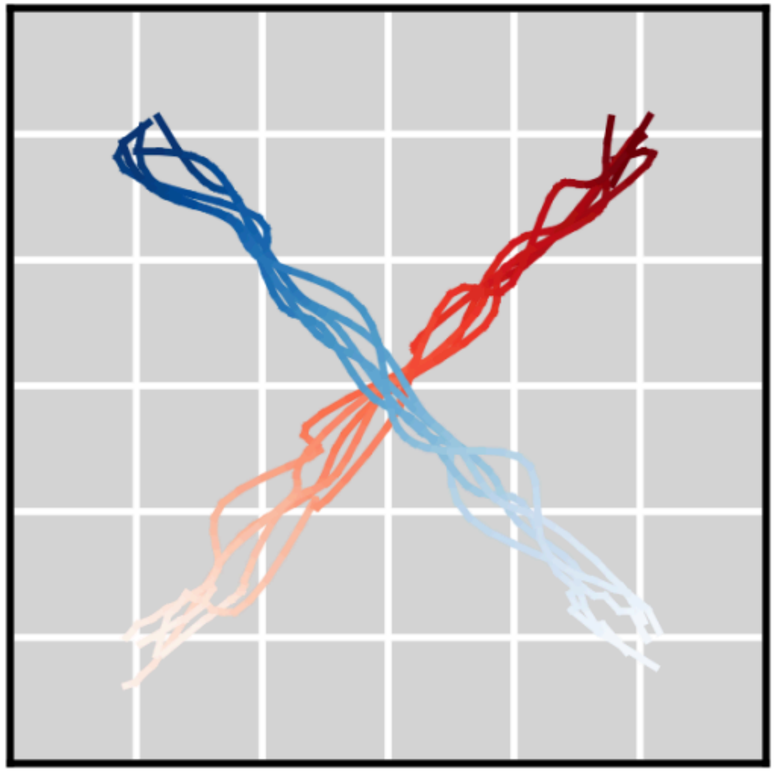
Compositionality and Conditioning on the Past

Training Set

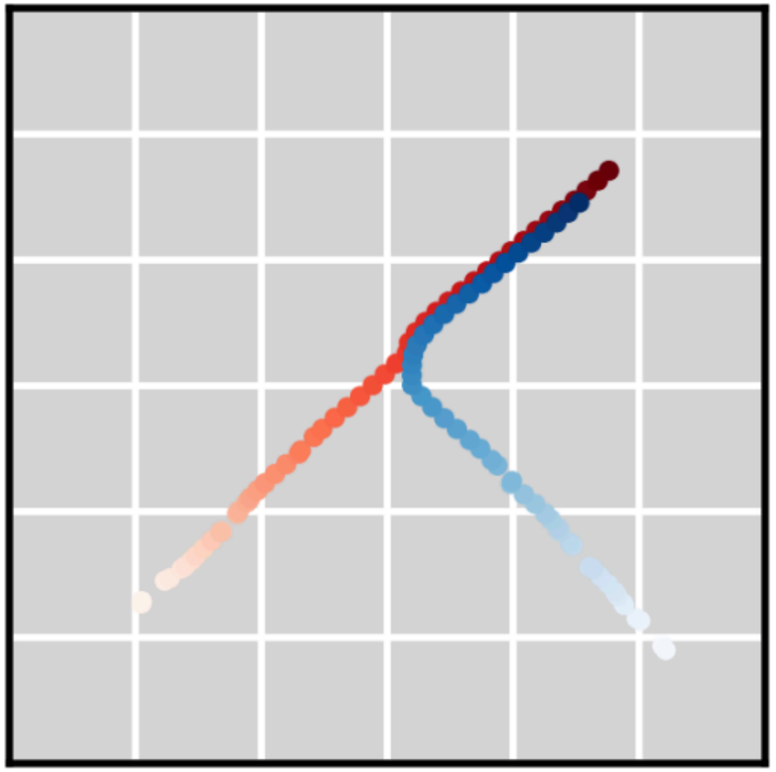


Compositionality and Conditioning on the Past

Training Set



What we often want



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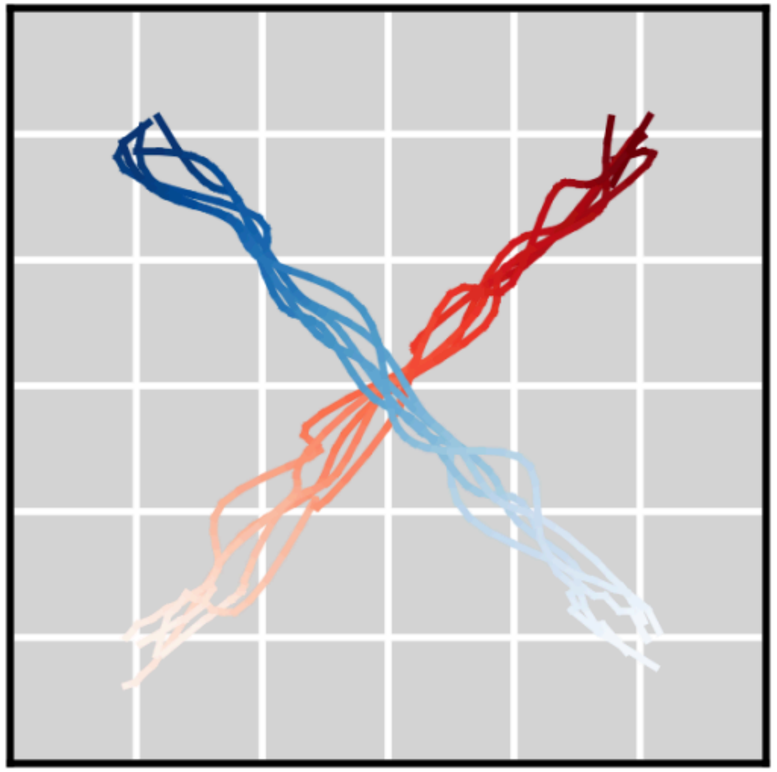
Training Set



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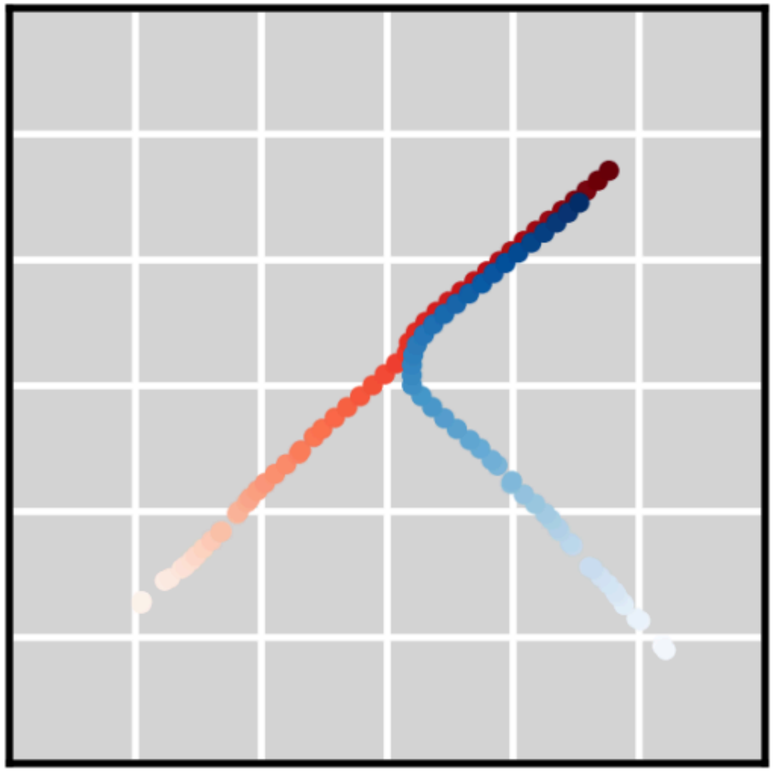
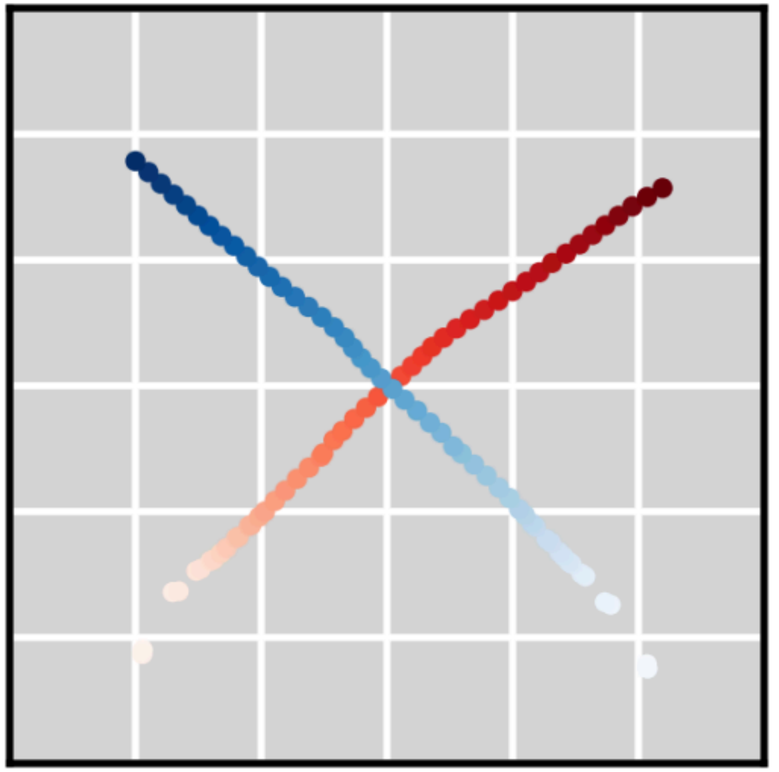
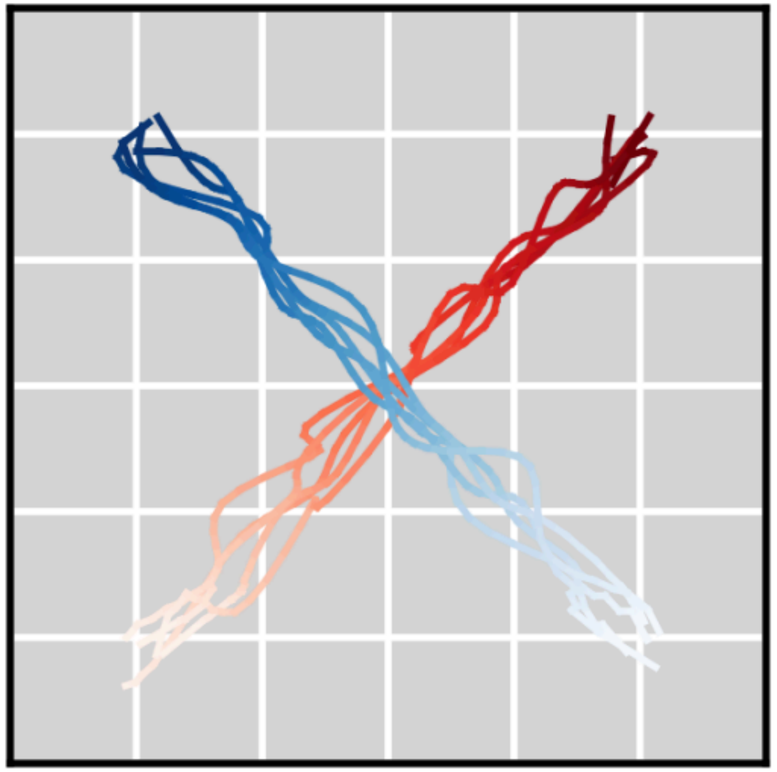


Full-Seq Diffusion



Compositionality and Conditioning on the Past

Training Set



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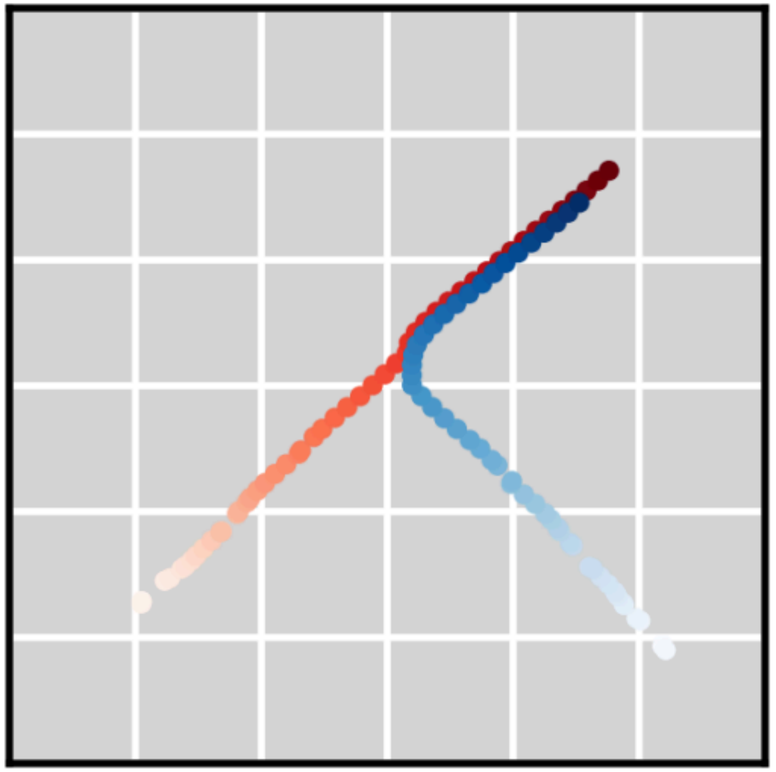
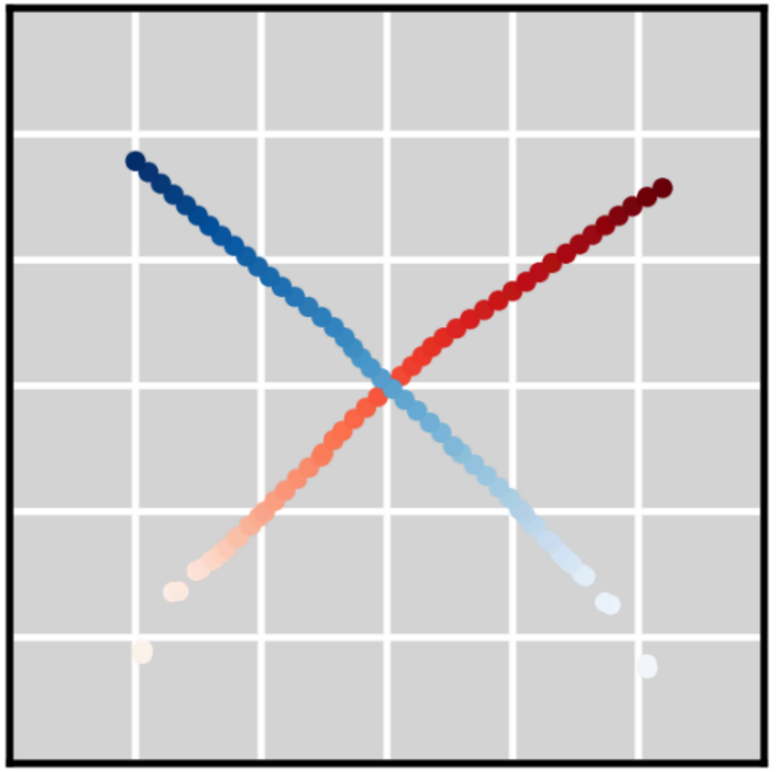


$p(x_2 \mid x_1)p(x_1 \mid x_0)p(x_0)$

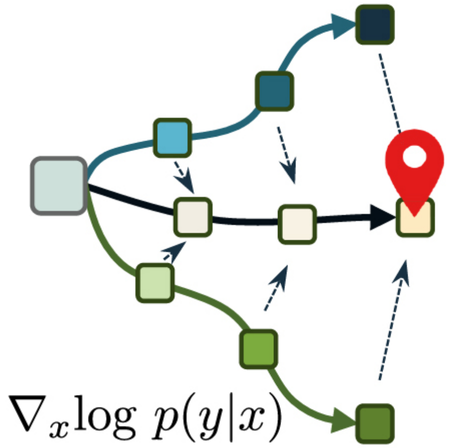
Full-Seq Diffusion



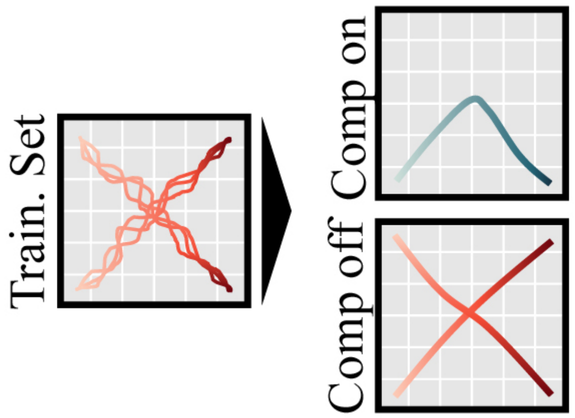
$p(x_0, \ldots, x_N)$

Capabilities of Existing Models

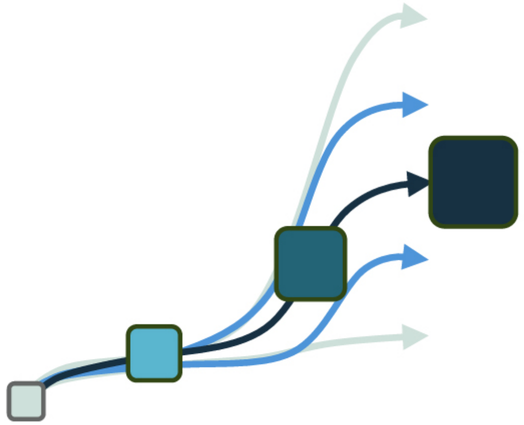
Guidance



Compositionality

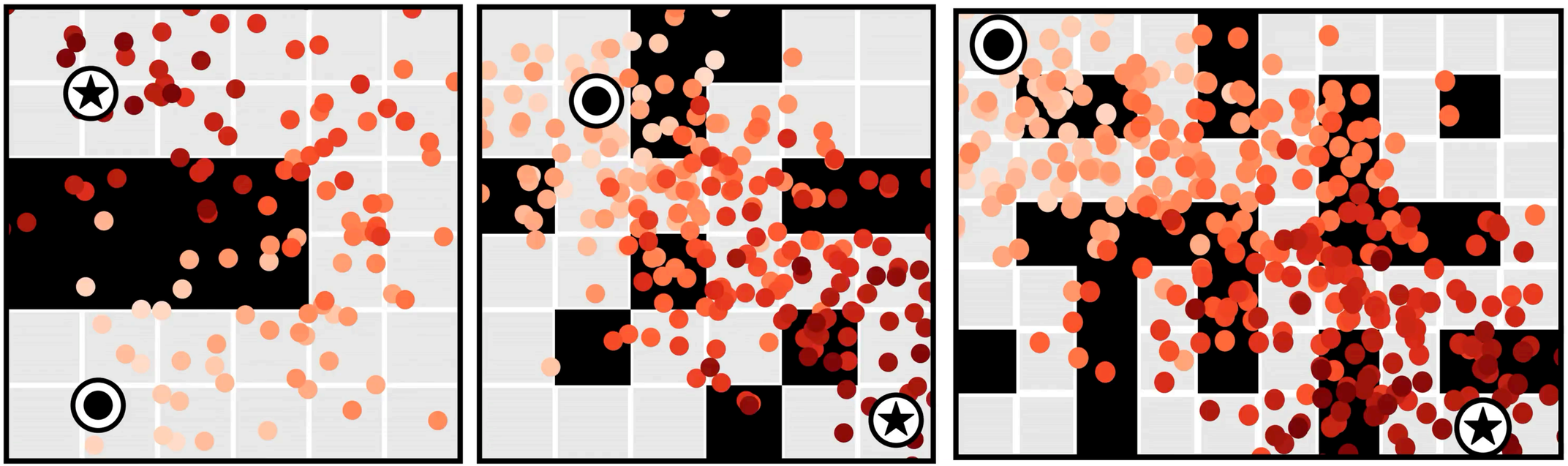


Causal Uncertainty



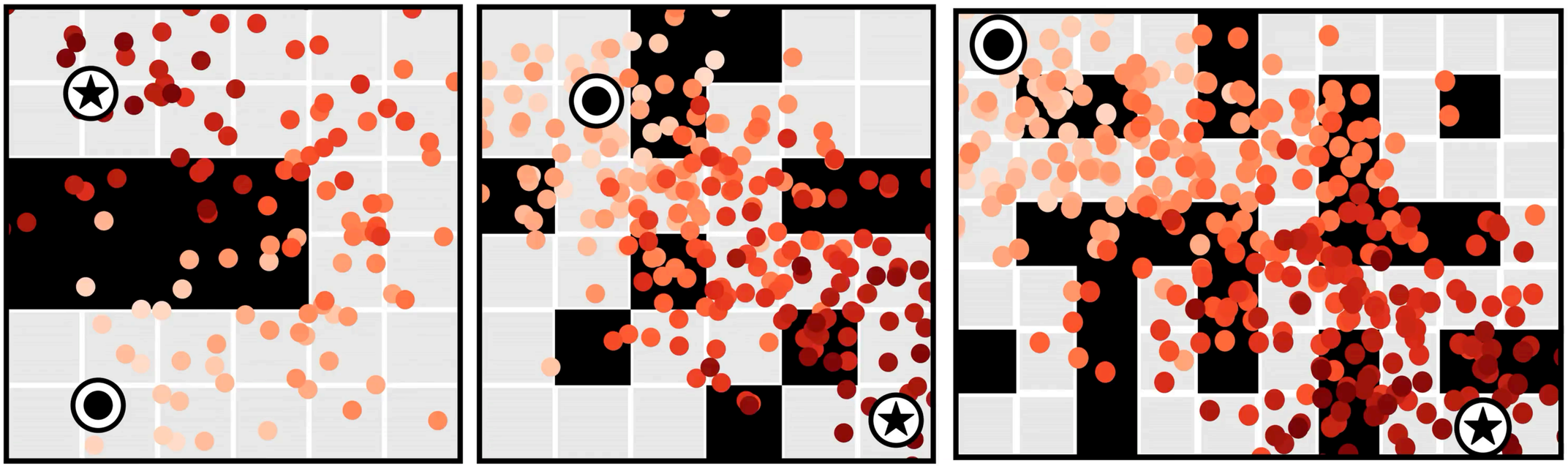
Teacher Forcing	✗	✓	✓
Full-Seq. Diffusion	✓	✗	✗

Causal Uncertainty



Full-Seq. Diffusion: uncertainty is removed from all states at the same speed. But a small difference in early states might lead to a *large* difference later! Doesn't work for planning…

Causal Uncertainty



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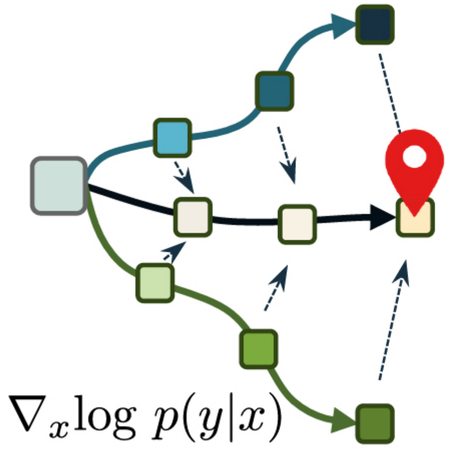
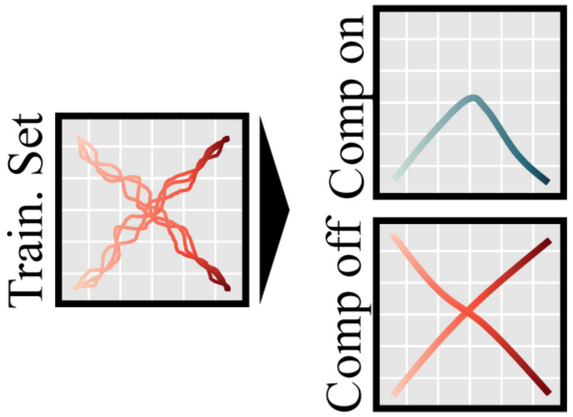
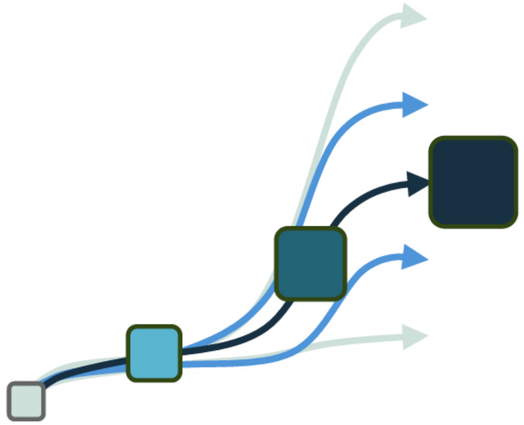
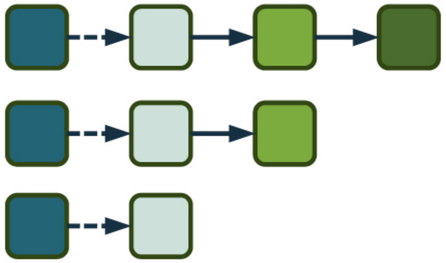
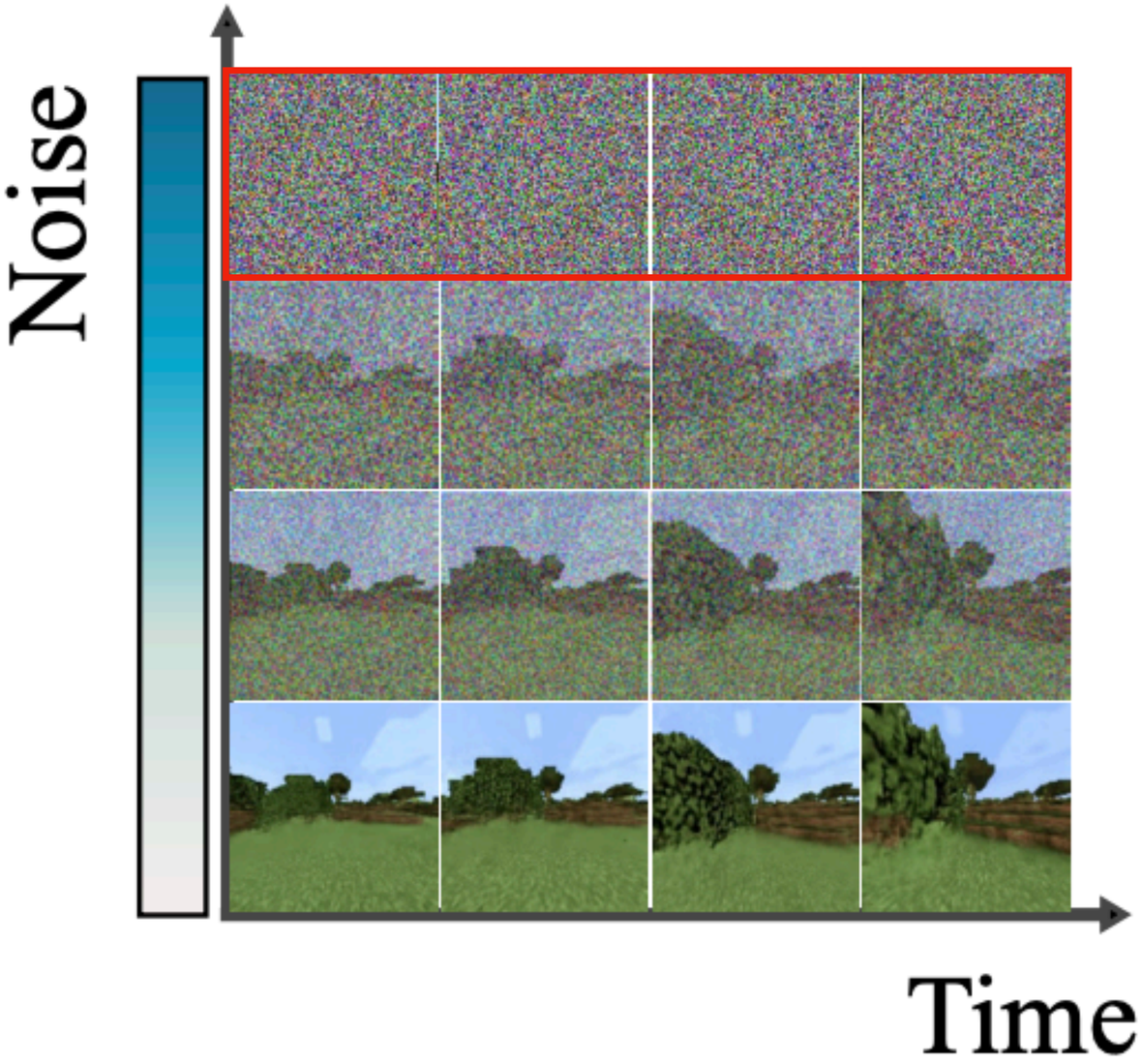
Capabilities of Existing Models

	Guidance	Compositionality	Causal Uncertainty	Flexible Horizon
				
Teacher Forcing	✗	✓	✓	✓
Full-Seq. Diffusion	✓	✗	✗	✗

Full-Seq. Diffusion: All Frames at Equal Noise Level



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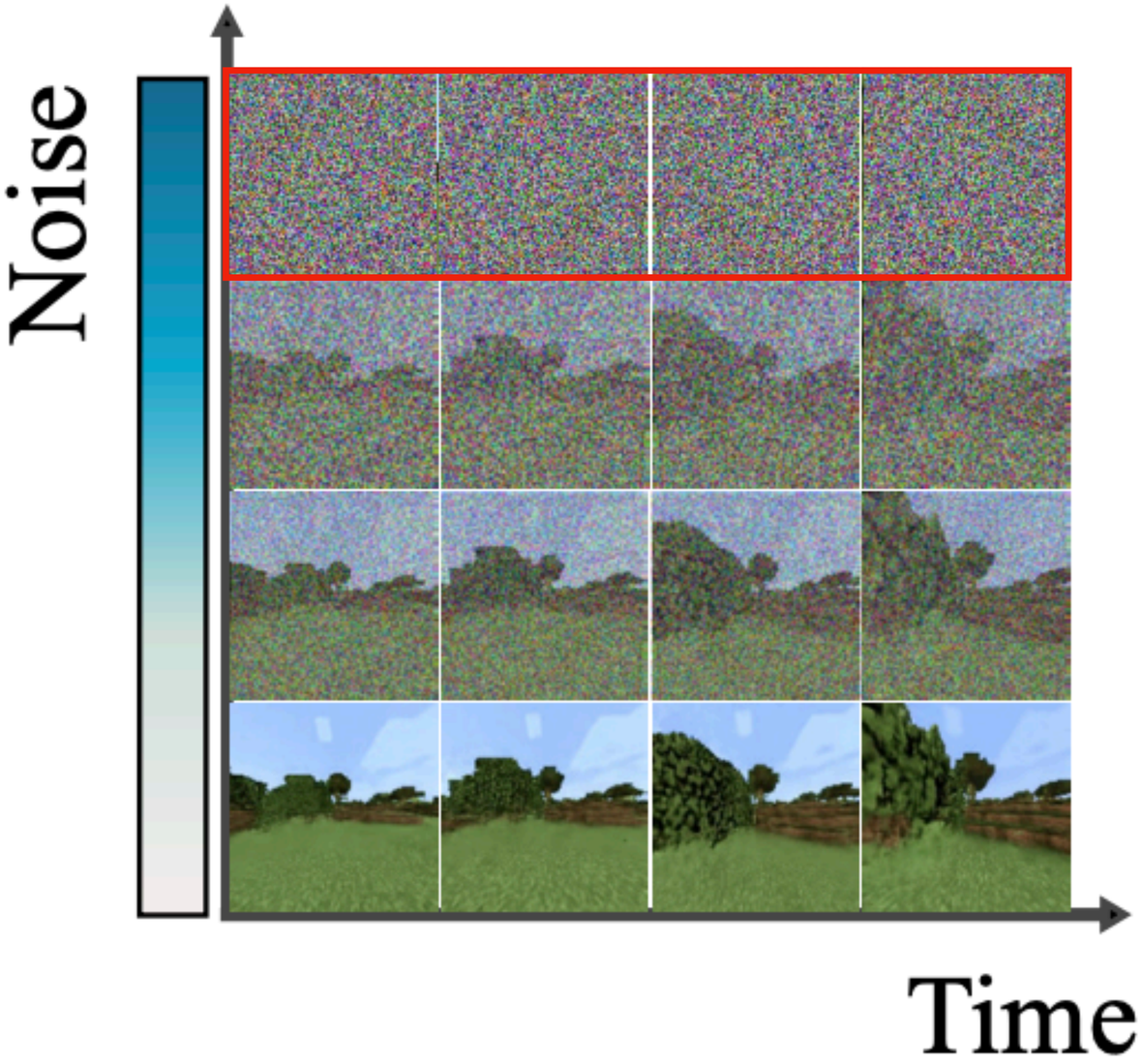

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