Improving *Sequential Latent Variable Models* with **Autoregressive Flows**

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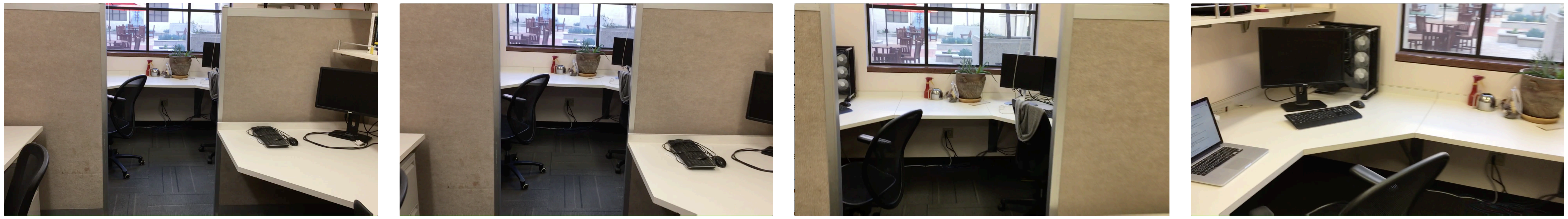
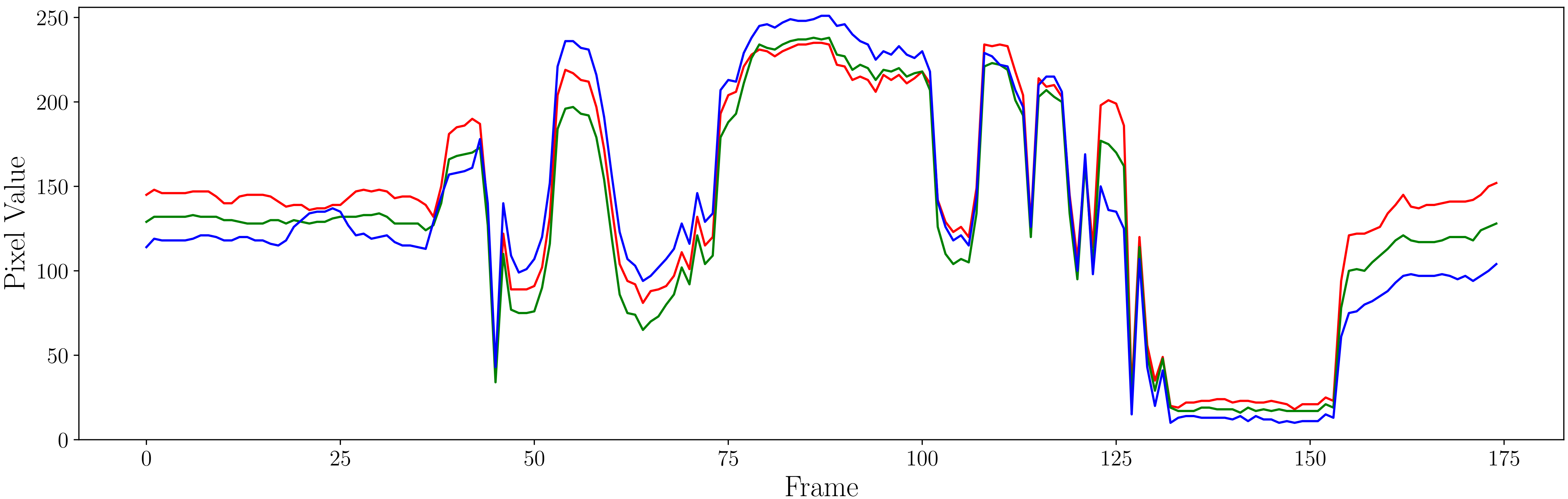
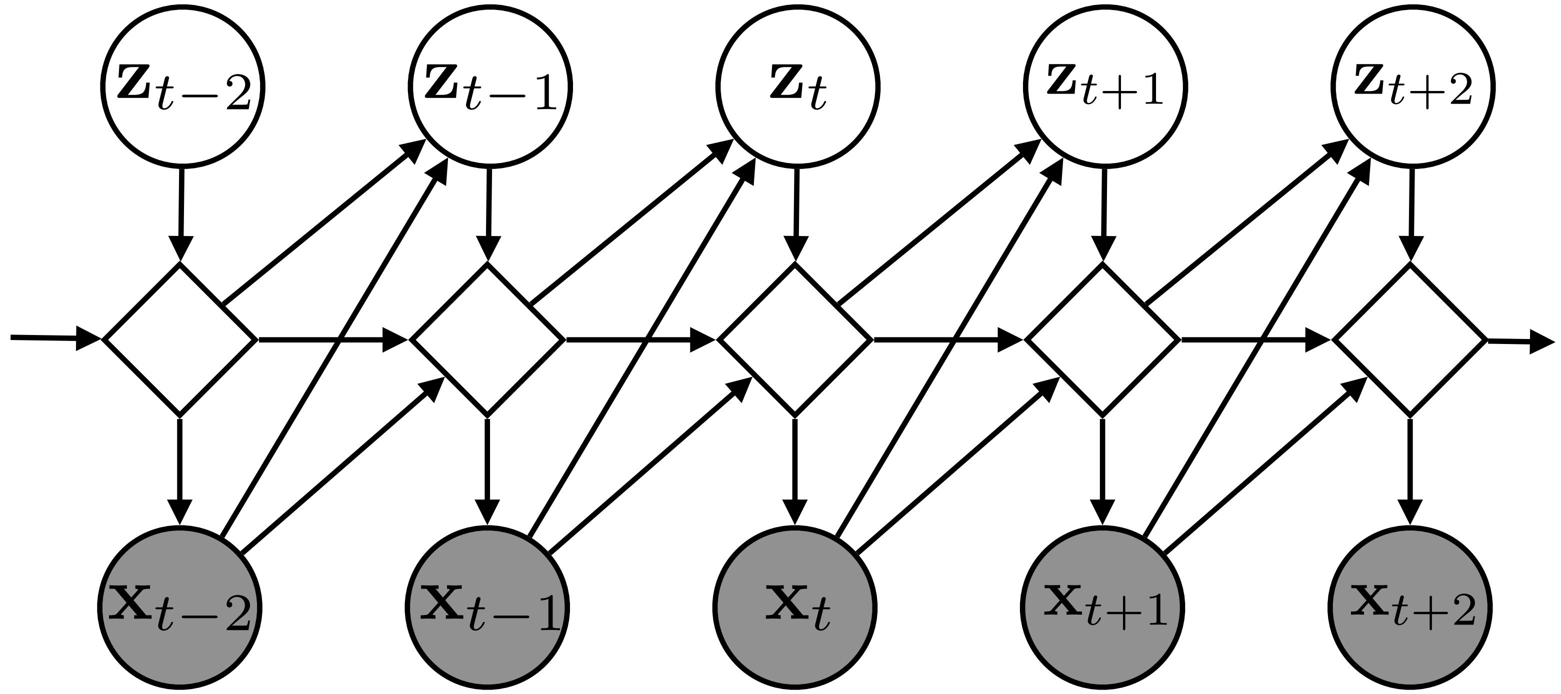
MOTIVATION





sequences in the natural world
are typically highly ***dependent in time***

MOTIVATION



sequential latent variable model

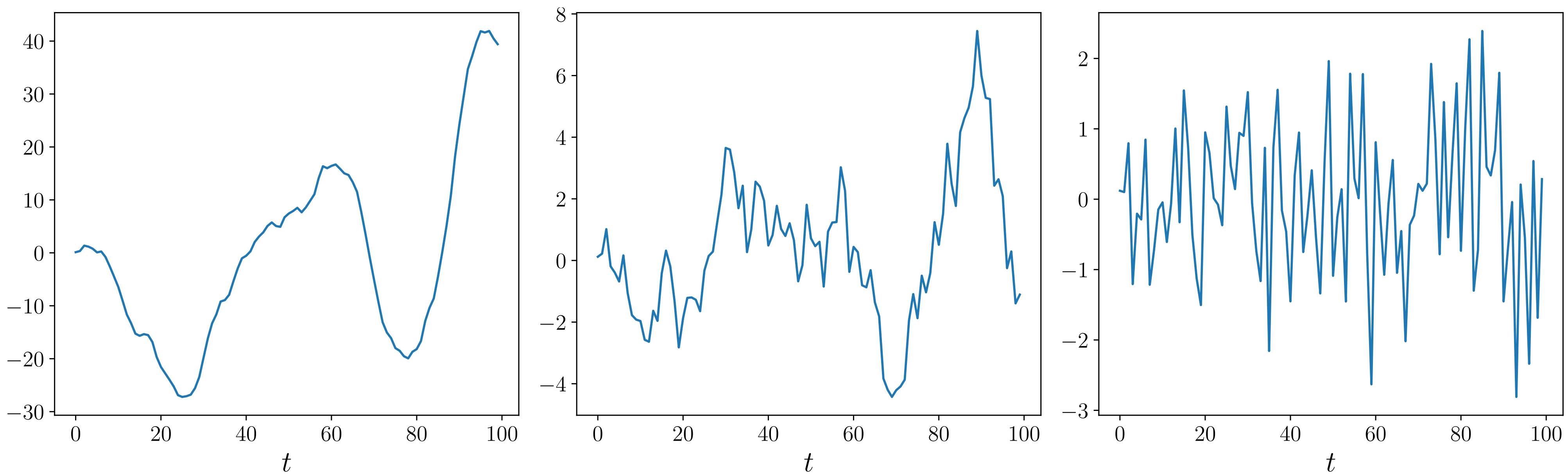
$$p_\theta(\mathbf{x}_{1:T}, \mathbf{z}_{1:T}) = \prod_{t=1}^{T} p_\theta(\mathbf{x}_t | \mathbf{x}_{<t}, \mathbf{z}_{\leq t}) p_\theta(\mathbf{z}_t | \mathbf{x}_{<t}, \mathbf{z}_{<t})$$

how can we simplify the estimation of dynamics in $\mathbf{z}$*?*

⟶ *reduce the degree of temporal dependence*

TEMPORAL DECORRELATION

position $\mathbf{x}$ → **velocity** $\mathbf{u} = \Delta \mathbf{x}$ → **noise** $\mathbf{w} = \Delta \mathbf{u}$



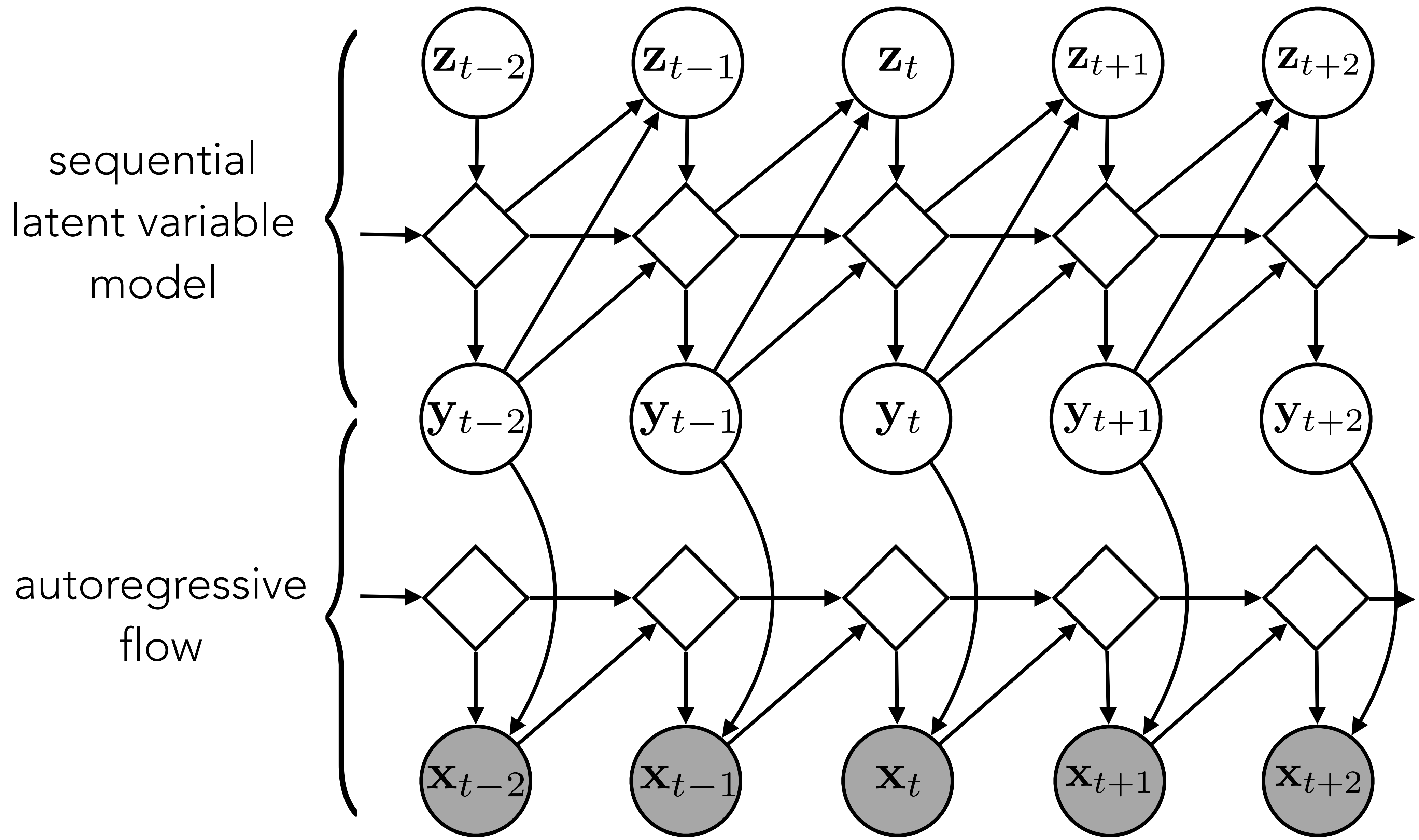
high temporal dependence

no temporal dependence

generalize temporal differences to $\mathbf{y}_t = \dfrac{\mathbf{x}_t - \boldsymbol{\mu}_\theta(\mathbf{x}_{<t})}{\boldsymbol{\sigma}_\theta(\mathbf{x}_{<t})}$

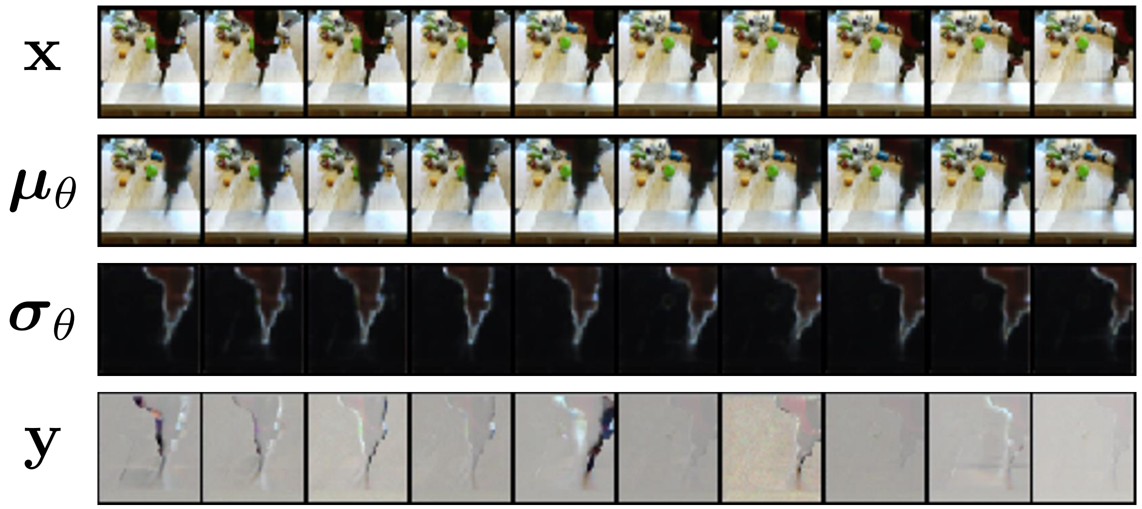
autoregressive flow across time

APPROACH

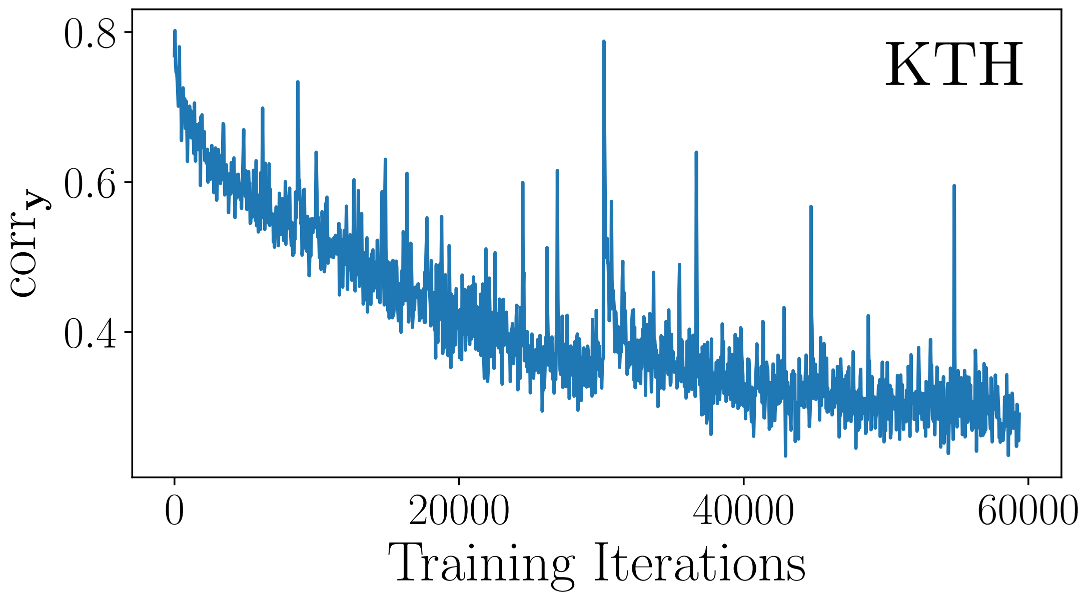


sequential
latent variable
model
autoregressive
flow
$\mathbf{z}_{t-2}$
$\mathbf{z}_{t-1}$
$\mathbf{z}_{t}$
$\mathbf{z}_{t+1}$
$\mathbf{z}_{t+2}$
$\mathbf{y}_{t-2}$
$\mathbf{y}_{t-1}$
$\mathbf{y}_{t}$
$\mathbf{y}_{t+1}$
$\mathbf{y}_{t+2}$
$\mathbf{x}_{t-2}$
$\mathbf{x}_{t-1}$
$\mathbf{x}_{t}$
$\mathbf{x}_{t+1}$
$\mathbf{x}_{t+2}$

visualize flows



quantify decorrelation



performance improvements

test negative log-likelihood in *nats / dim*

	M-MNIST	BAIR	KTH
1-AF	2.15	3.05	3.34
2-AF	2.13	2.90	3.35
SLVM	$\leq$ 1.92	$\leq$ 3.57	$\leq$ 4.63
SLVM w/ 1-AF	$\leq$ **1.86**	$\leq$ **2.35**	$\leq$ **2.39**