

Disentangled Generative Models for Robust Prediction of System Dynamics

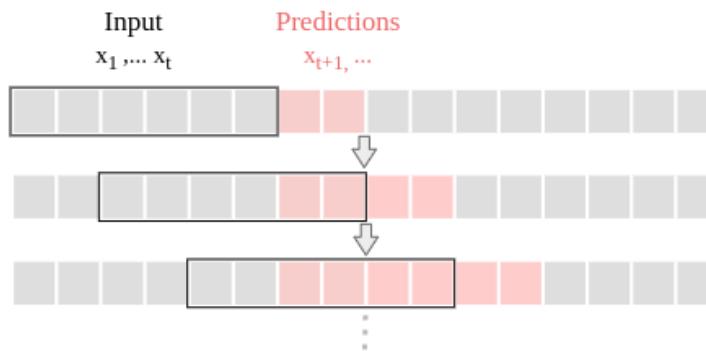
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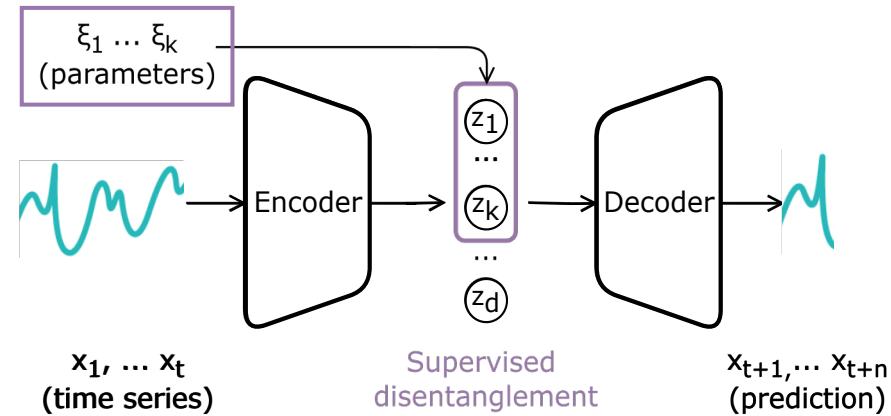
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Dynamical systems modelling

- Differential Equations (ODEs/PDEs)
- Data-driven prediction using neural networks
 - Long-term accuracy
 - OOD Robustness



Disentangling parameters from dynamics



Deterministic system with
observation noise

$$P(x_{>t}; x_{<t}, \xi) \sim f(x_{<t}, \xi) + \epsilon$$

$$P(x_{>t}; z) \sim Dec(z) + \epsilon \quad \rightarrow$$

VAE

$$P(x_{>t}; z_{<t}, z_\xi) \sim Dec(z_{<t}, z_\xi) + \epsilon$$

SD-VAE

Training SD-VAE

Supervised disentanglement as constrained optimization

$$z_i = \xi_i$$

Under KKT conditions constraint becomes a regularizer

$$\mathcal{L}_\xi(\mathbf{z}_{1:N_\xi}, \boldsymbol{\xi}) = \|\mathbf{z}_{1:N_\xi} - \boldsymbol{\xi}\|_2^2$$

SD-VAE objective: Combination of beta-VAE ELBO and regularizer

$$\mathbb{E}_{\mathbf{x}} \left[\mathbb{E}_{Q_\phi(\mathbf{z} | \mathbf{x})} \left[\log P_\theta(\mathbf{x} | \mathbf{z}) + \delta \mathcal{L}_\xi(\mathbf{z}_{1:N_\xi}, \boldsymbol{\xi}) \right] - \beta D_{KL} (Q_\phi(\mathbf{z} | \mathbf{x}) || P(\mathbf{z})) \right]$$

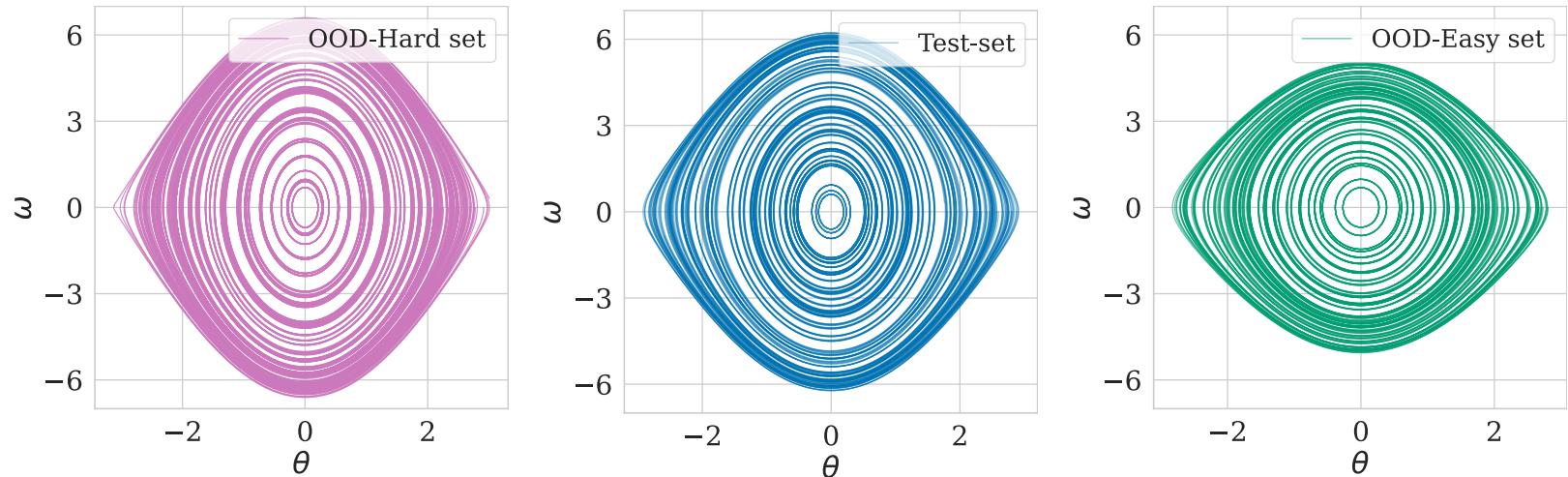
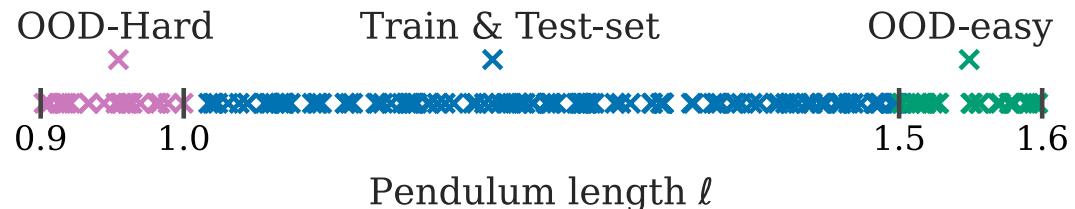
Datasets

Dynamical Systems

- Pendulum
- Lotka-Volterra
- 3-body system

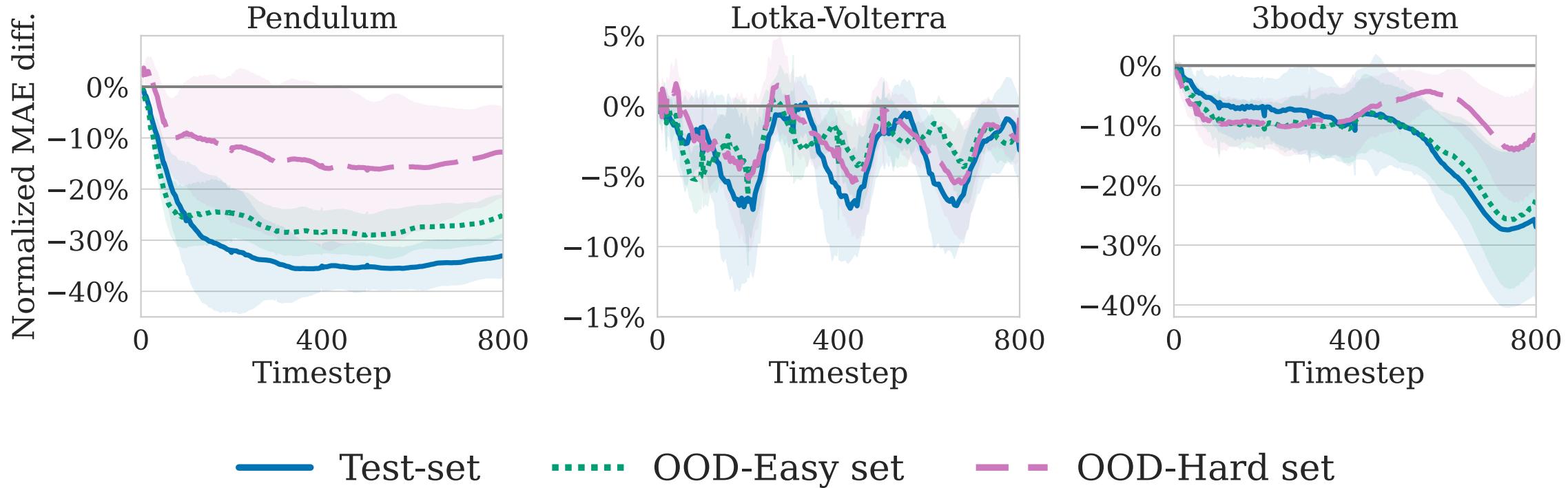
Datasets

- Train / Test set
- Two OOD Test sets
 - OOD-Easy
 - OOD-Hard



Prediction error

Error reduction of SD-VAE vs VAE

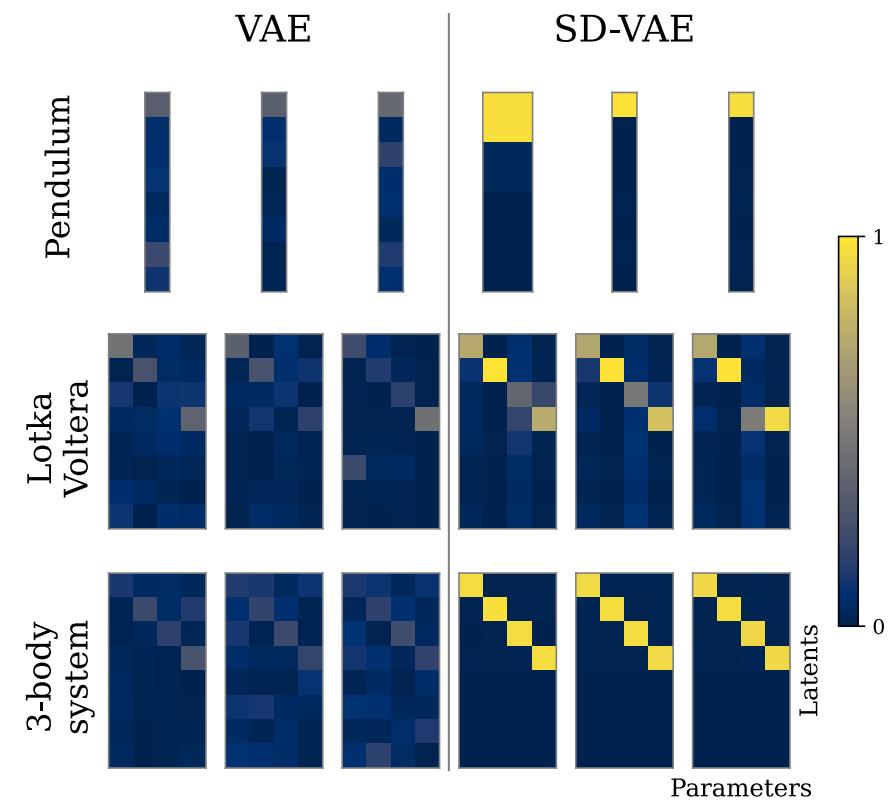


Disentangled representations

Disentanglement Metrics

	Pendulum		Lotka-Volterra		3 body system	
	VAE	SD-VAE	VAE	SD-VAE	VAE	SD-VAE
Disentanglement	-	-	0.27	0.53	0.20	0.90
Completeness	0.17	0.90	0.20	0.57	0.13	0.90
Informativeness	0.94	0.99	1.00	1.00	1.00	1.00
SAP	0.03	0.87	0.04	0.21	0.01	0.67
MIG	0.01	0.17	0.00	0.03	0.00	0.08

Predictive power
of latents



Thank you!

