

Modulated Neural ODEs

I.A. Auzina, Ç. Yıldız, S. Magliacane, M. Bethge and E. Gavves



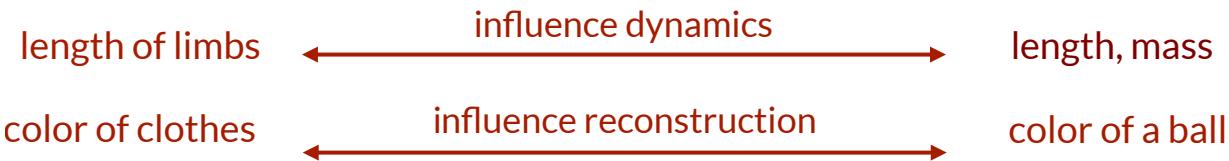
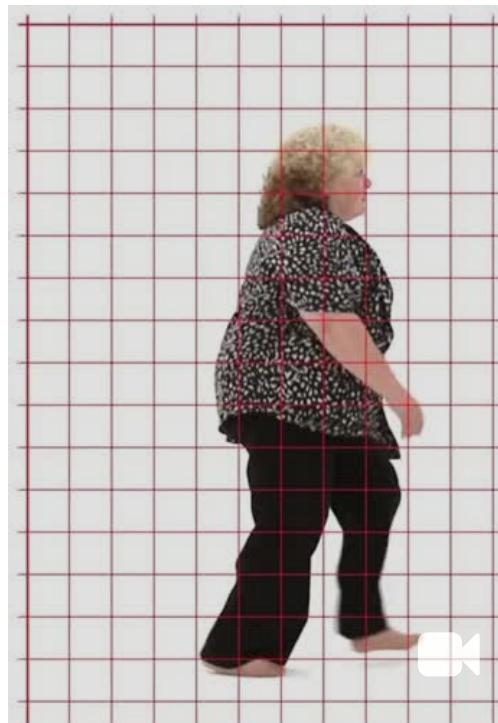
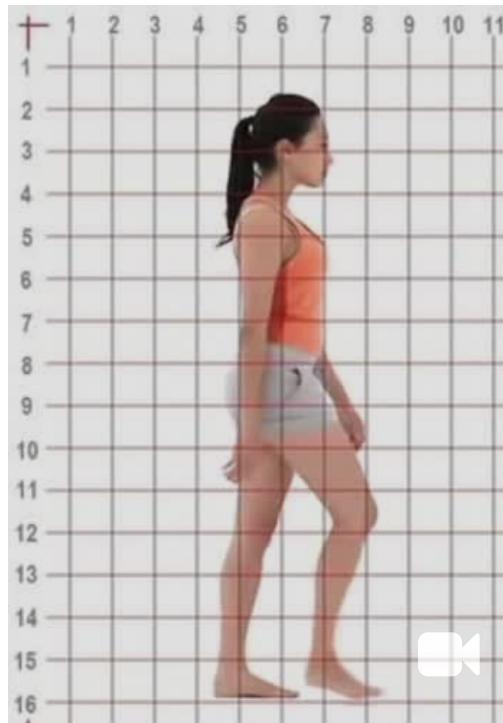
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Modulated NODEs

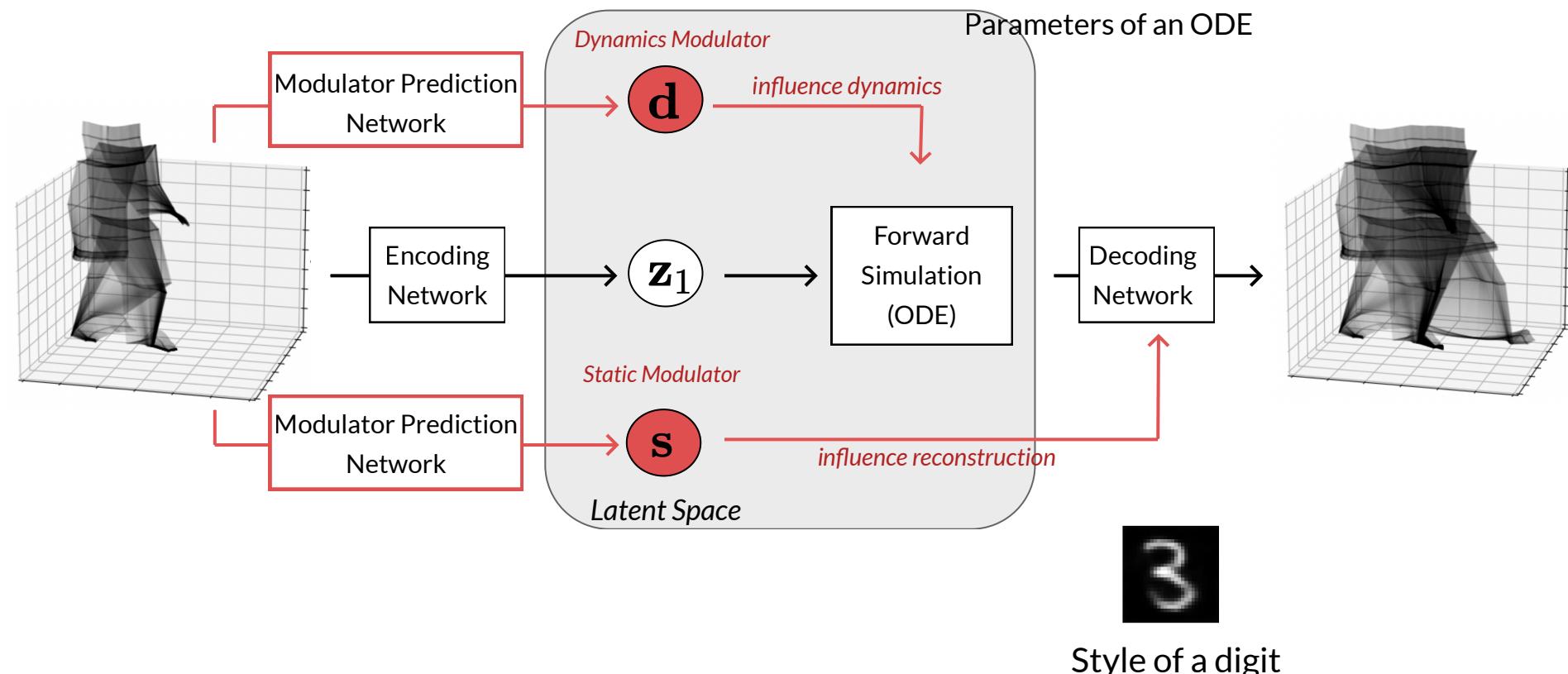
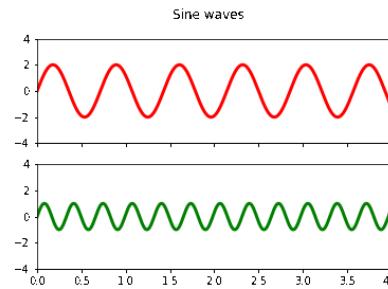
Key Idea:
does setting apart **dynamic states** from
underlying **static factors of variation** improve existing model performance?



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Modulated NODEs

Generative Model

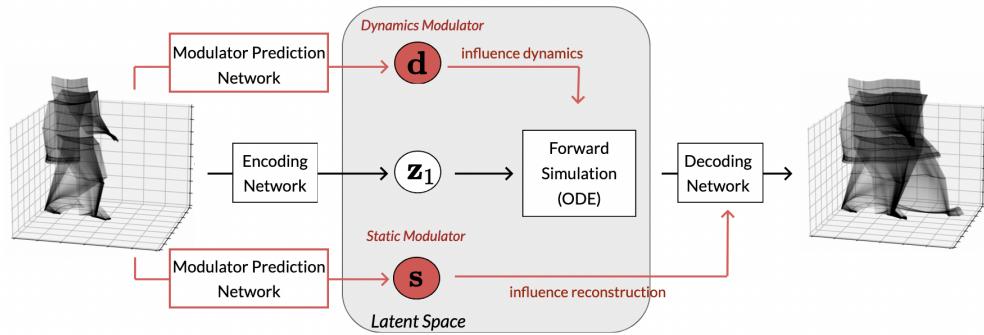
$\mathbf{d} \sim p(\mathbf{d}) \quad // dynamics\ modulator$

$\mathbf{s} \sim p(\mathbf{s}) \quad // static\ modulator$

$\mathbf{z}_1 \sim p(\mathbf{z}_1) \quad // latent\ ODE\ state$

$$\mathbf{z}_i = \mathbf{z}_1 + \int_{t_1}^{t_i} \mathbf{f}_{\theta}(\mathbf{z}(\tau); \mathbf{d}) d\tau$$

$$\mathbf{x}_i \sim p_{\mathbf{x}_i}(\mathbf{x}_i \mid \mathbf{z}_i; \mathbf{s}).$$



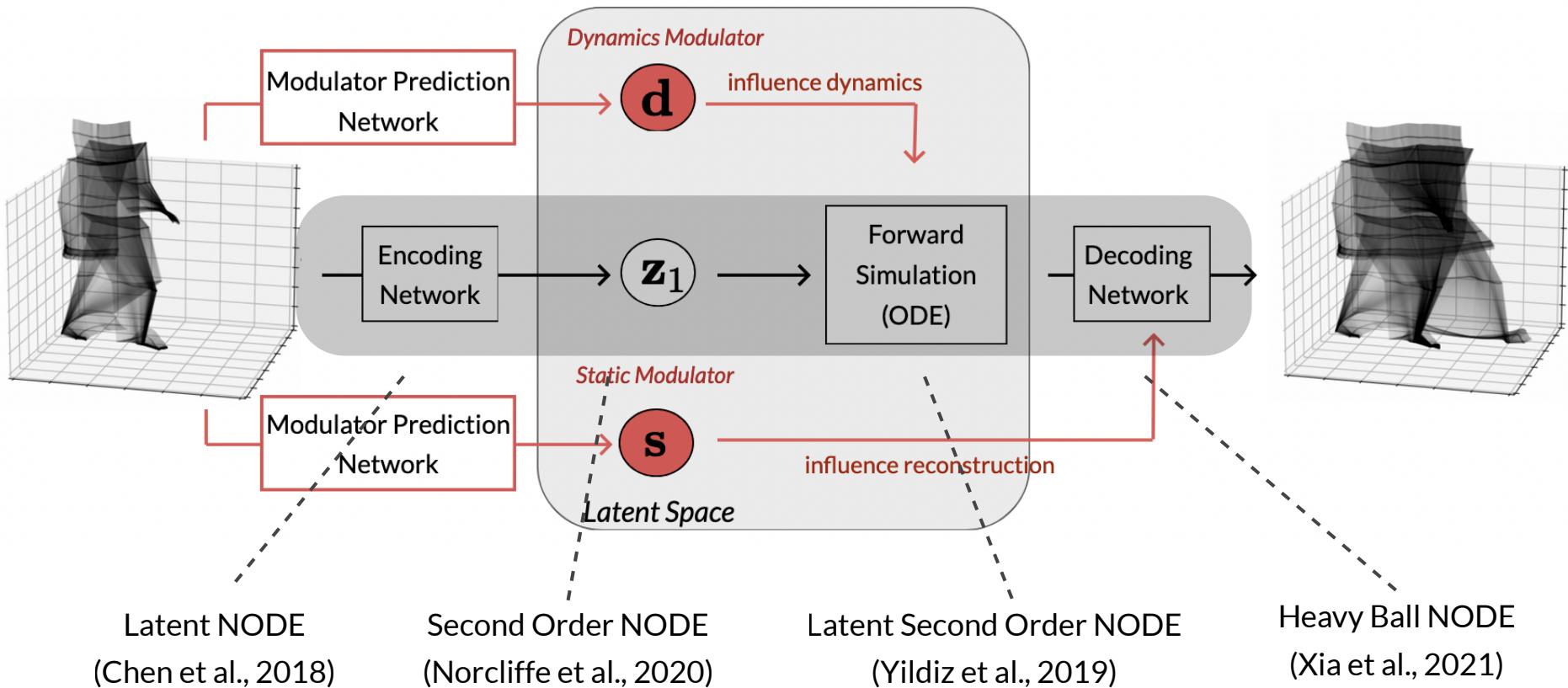
ELBO (Chen, 2018)

implicit, point-estimates



Modulated NODEs

A general framework



can be applied to most x-NODE

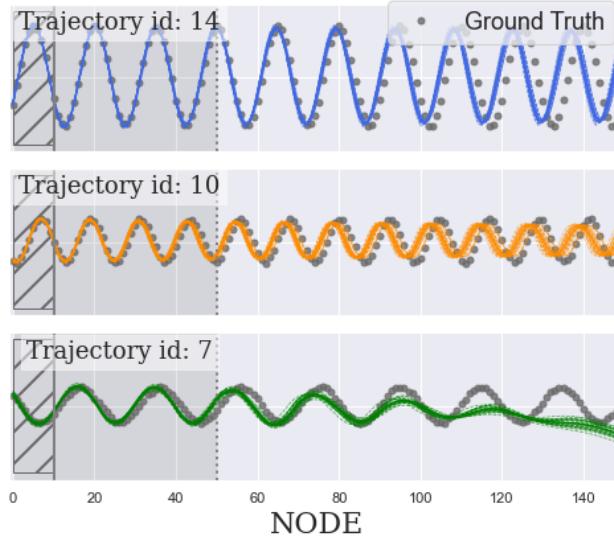


Modulated NODEs

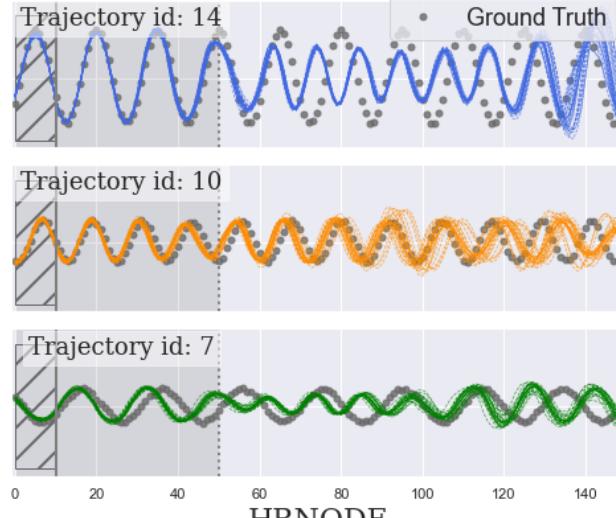
A general framework that improves forecasting and generalization

Sinusoidal Data

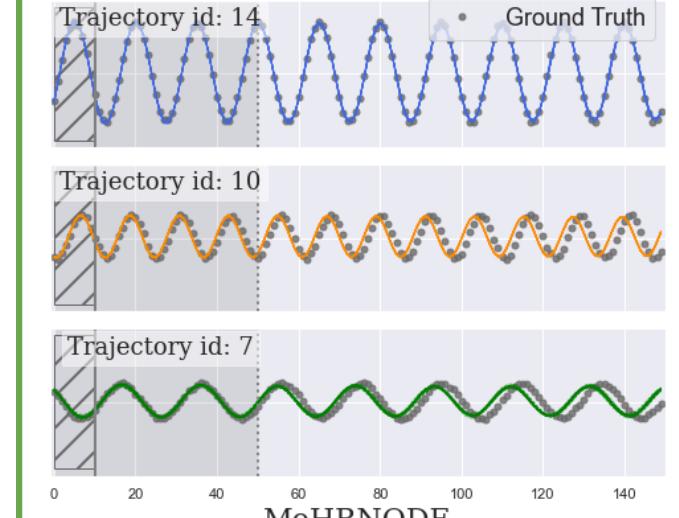
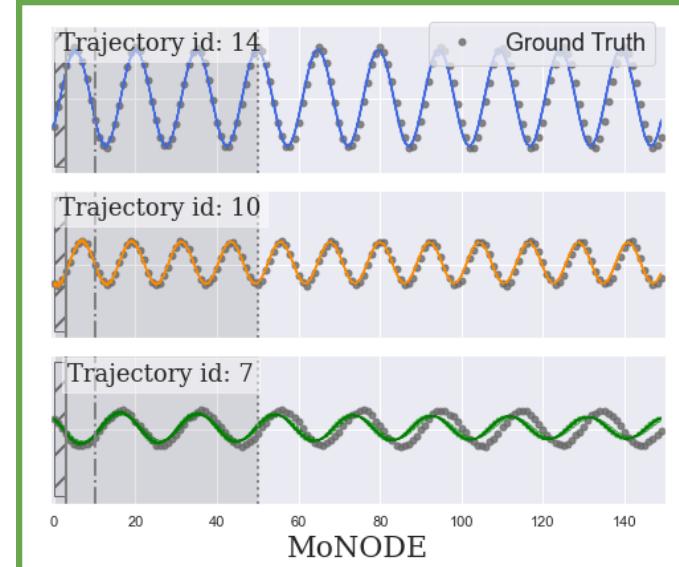
Latent NODE
(Chen et al., 2018)



Heavy Ball NODE
(Xia et al., 2021)



ours Mo-xNODE

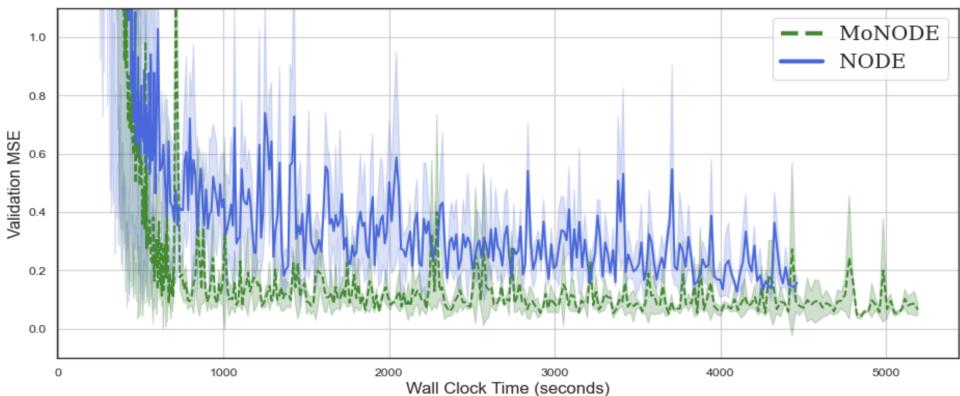


Modulated NODEs

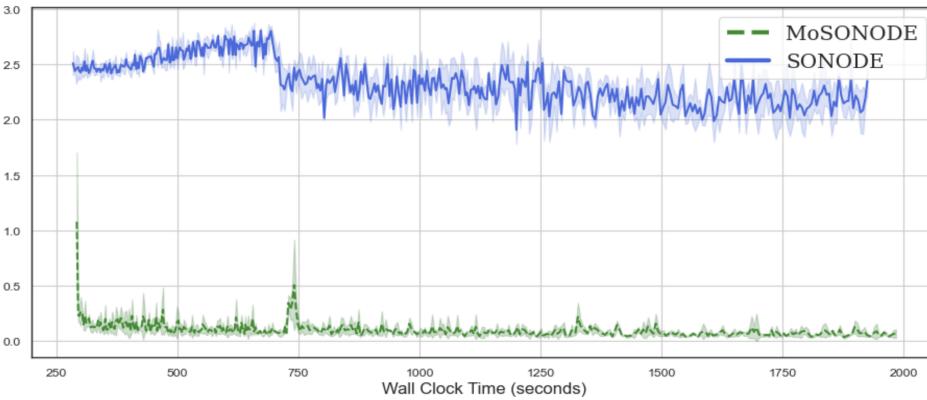
A general framework that is easier to train

Sinusoidal Data

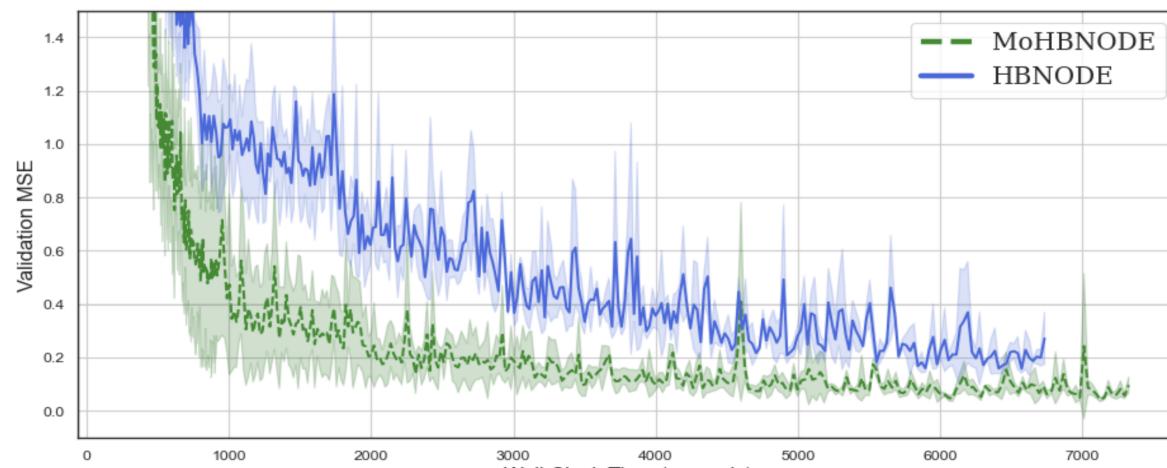
ours: Mo-xNODE



NODE (Chen et al., 2018)



SONODE (Norcliffe et al., 2020)



HBNODE (Xia et al., 2021)



Modulated NODEs

A general framework that disentangles underlying factors

PP parameters

$$d \sim \begin{aligned} \frac{dx}{dt} &= \alpha x - \beta xy \\ \frac{dy}{dt} &= \delta xy - \gamma y \end{aligned}$$

dynamics modulator

Table 2. R^2 scores to predict the unknown Factors of Variation from inferred latents. Higher is better.

	NODE	MoNODE
Sine	0.90	0.99
PP	-1.35	0.39
BB	-0.29	0.58



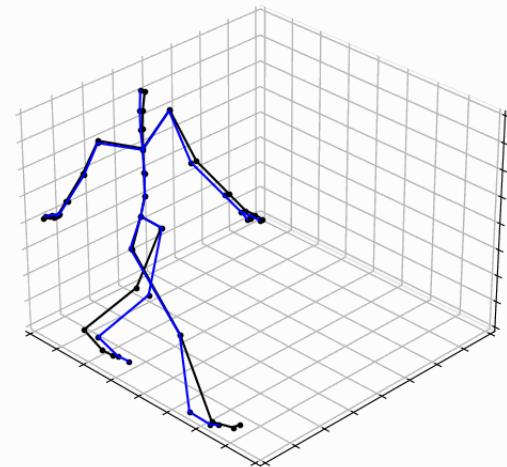
Modulated NODEs

that improves performance on real world data

Table 3. Test MSE and standard deviation. Lower is better.

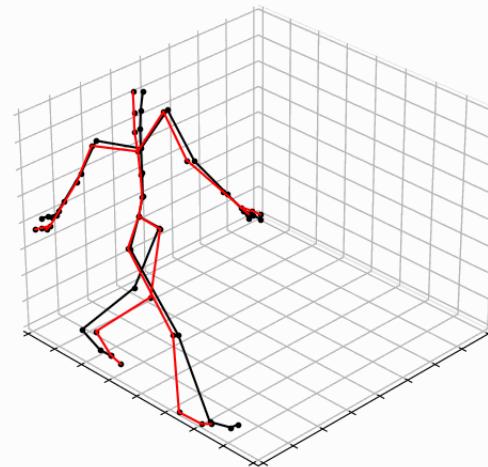
	BOUNCING BALL	ROT.MNIST	MOCAP	MOCAP-SHIFT
NODE	0.0199(0.001)	0.039 (0.003)	72.2(12.4)	61.6(6.2)
MoNODE	0.0164(0.001)	0.030 (0.001)	57.7(9.8)	58.0(10.7)

Mo-NODE vs GT (t=0)



MoNODE

NODE vs GT (t=0)



NODE



Thank you for your attention

All experiments and models publicly available at:

<https://github.com/IuzeAmandaA/MoNODE>

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