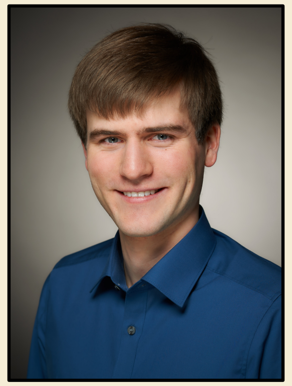
Latent SDEs on Homogeneous Spaces


Sebastian Zeng, Florian Graf & Roland Kwitt

University of Salzburg, Austria

Problem setting

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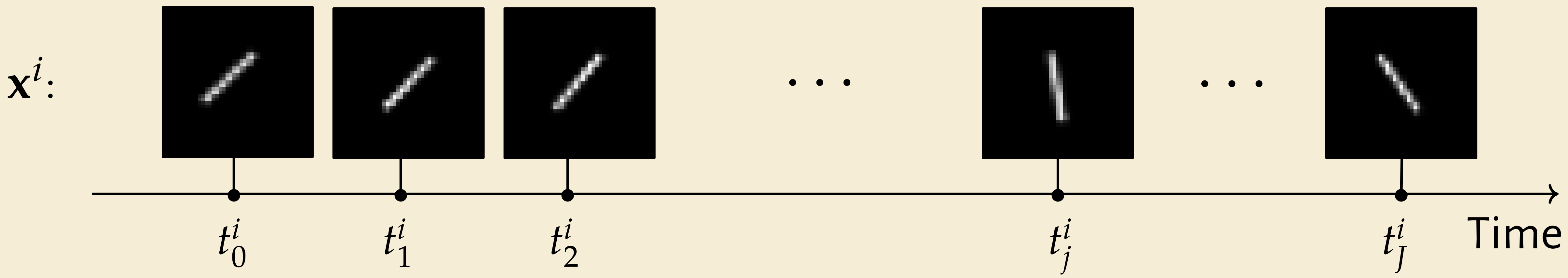

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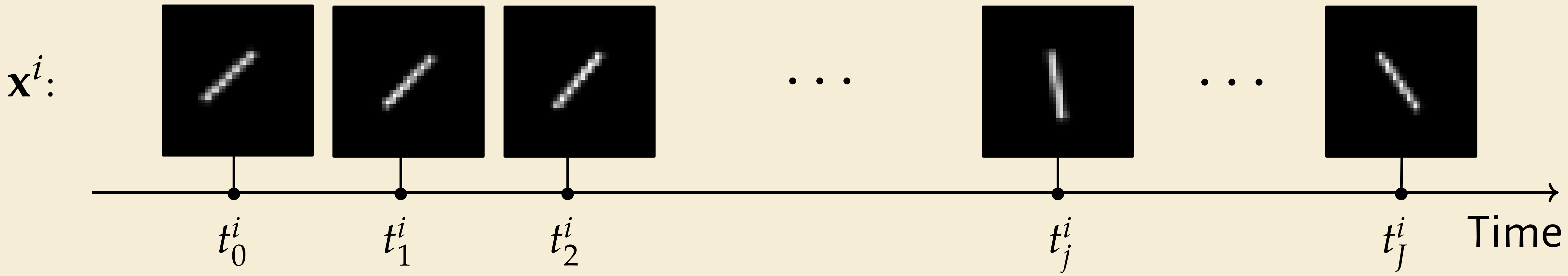


We assume

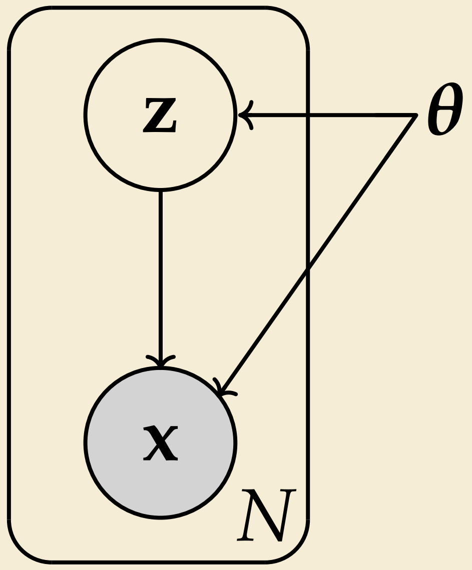
(1) $\mathbf{x}^i$ to be a **partially observed** continuous path from a **stochastic process** $X : \Omega \times [0, T] \to \mathbb{R}^d$, and

(2) that this process is governed by some **latent stochastic process** Z (with paths $\mathbf{z}^i$).

$\boxed{\text{We seek to learn } X\text{!}}$

Fitting a process to data

We follow a **Variational Bayes** approach with the following **directed graphical model**:



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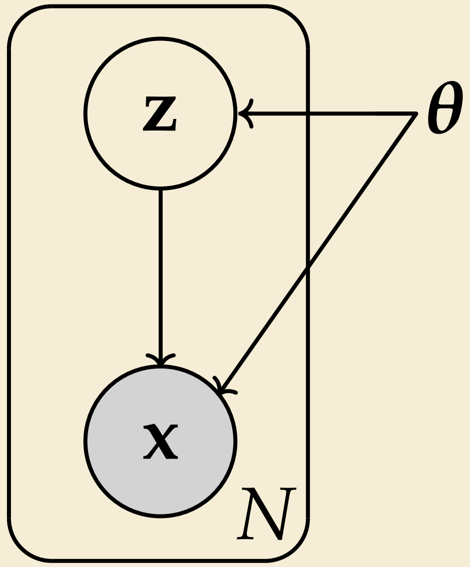

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$\boldsymbol{\theta}^*$ - true (unknown) parameter

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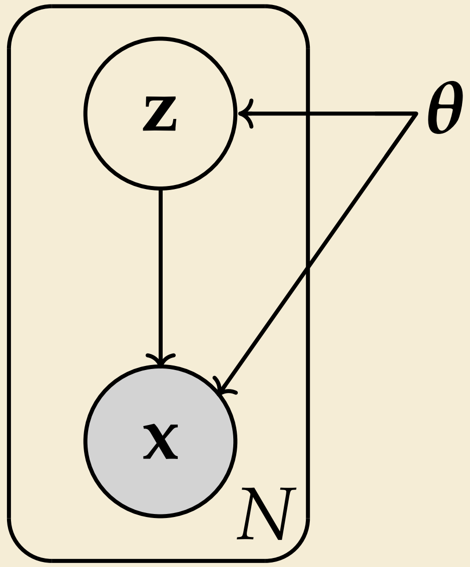

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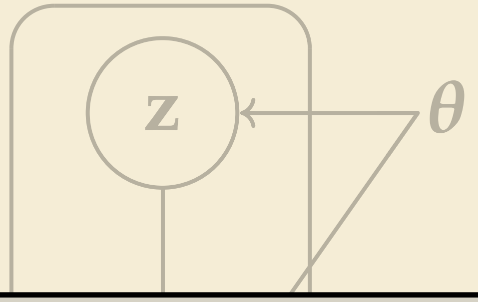

💡 Well-explored in the **vector-valued** setting (e.g., $\mathbf{x}^i \in \mathbb{R}^d$).

❓ Less well-explored in the **path-valued** setting (e.g., $\mathbf{x}^i \in \mathcal{C}([0,T],\mathbb{R}^d)$) — **Ours**!

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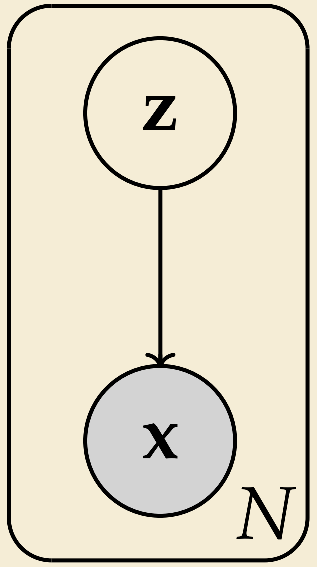
Approximate variational inference

Learning directed probabilistic models in case of intractable posterior path distributions $p_{\boldsymbol{\theta}}(\mathbf{z}|\mathbf{x}^i)$,



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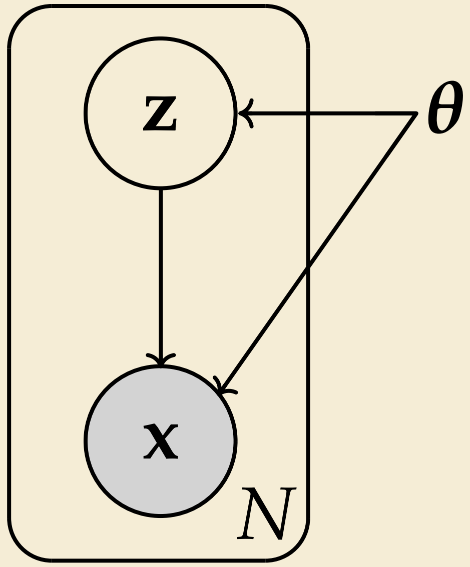

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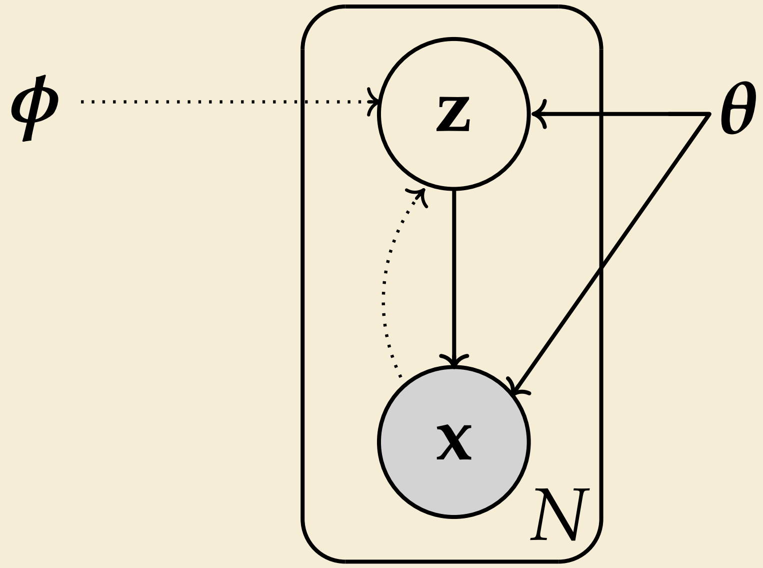

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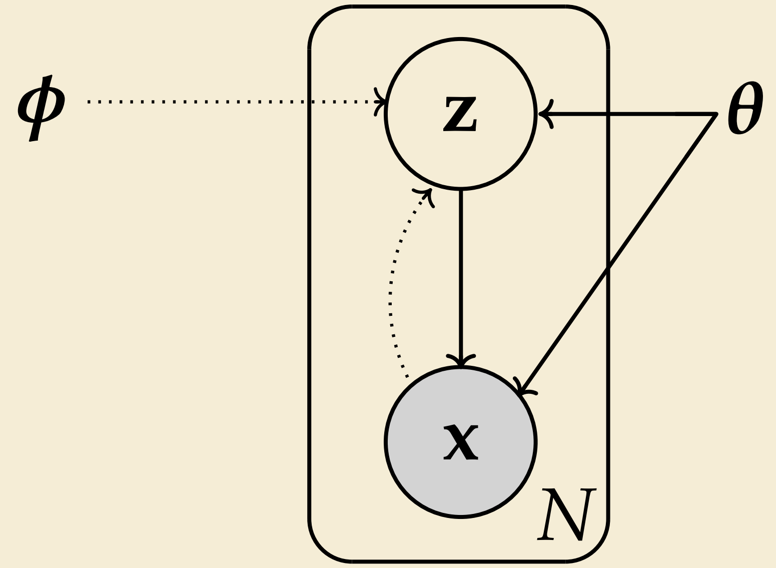

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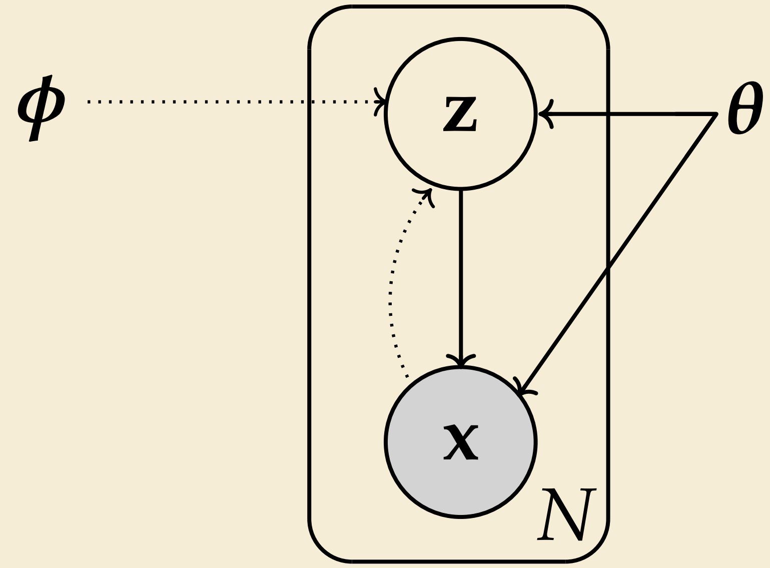

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Model **evidence**

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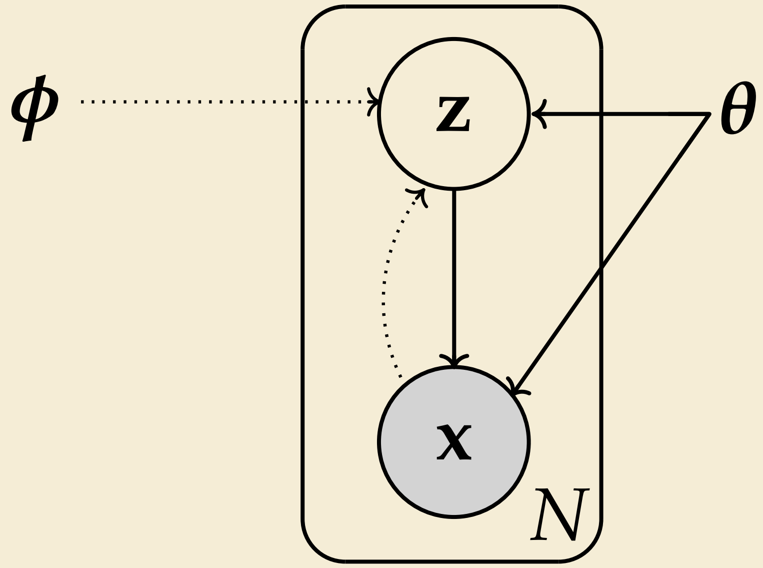

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KL divergence between **approximate posterior** and the **prior** path distribution

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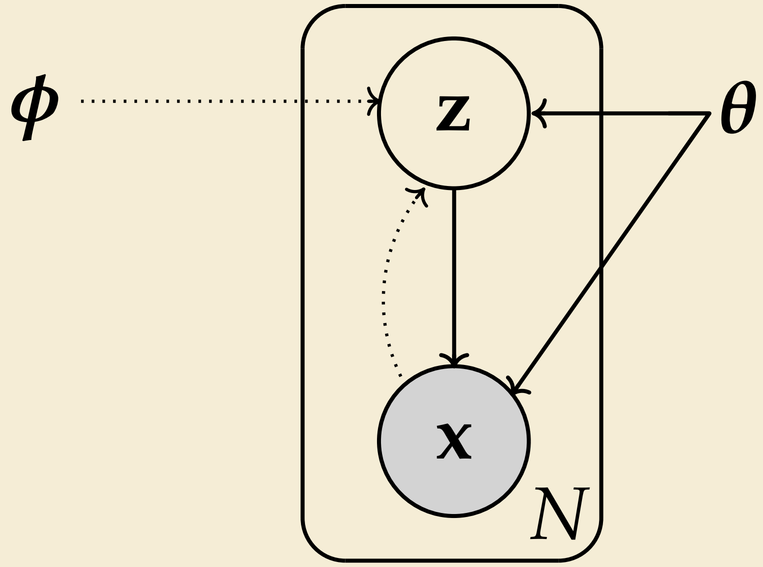

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Expected log-likelihood of **observed path** given the **latent path**

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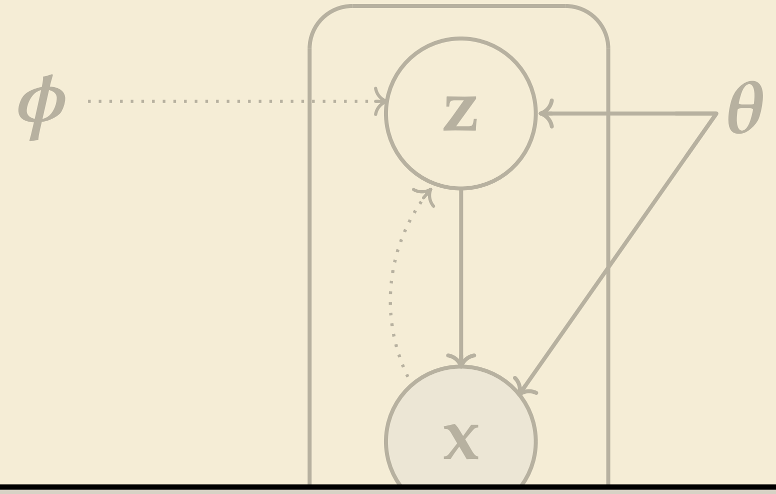

In this work, we consider **path distributions** of stochastic processes that are solutions to **SDEs**.

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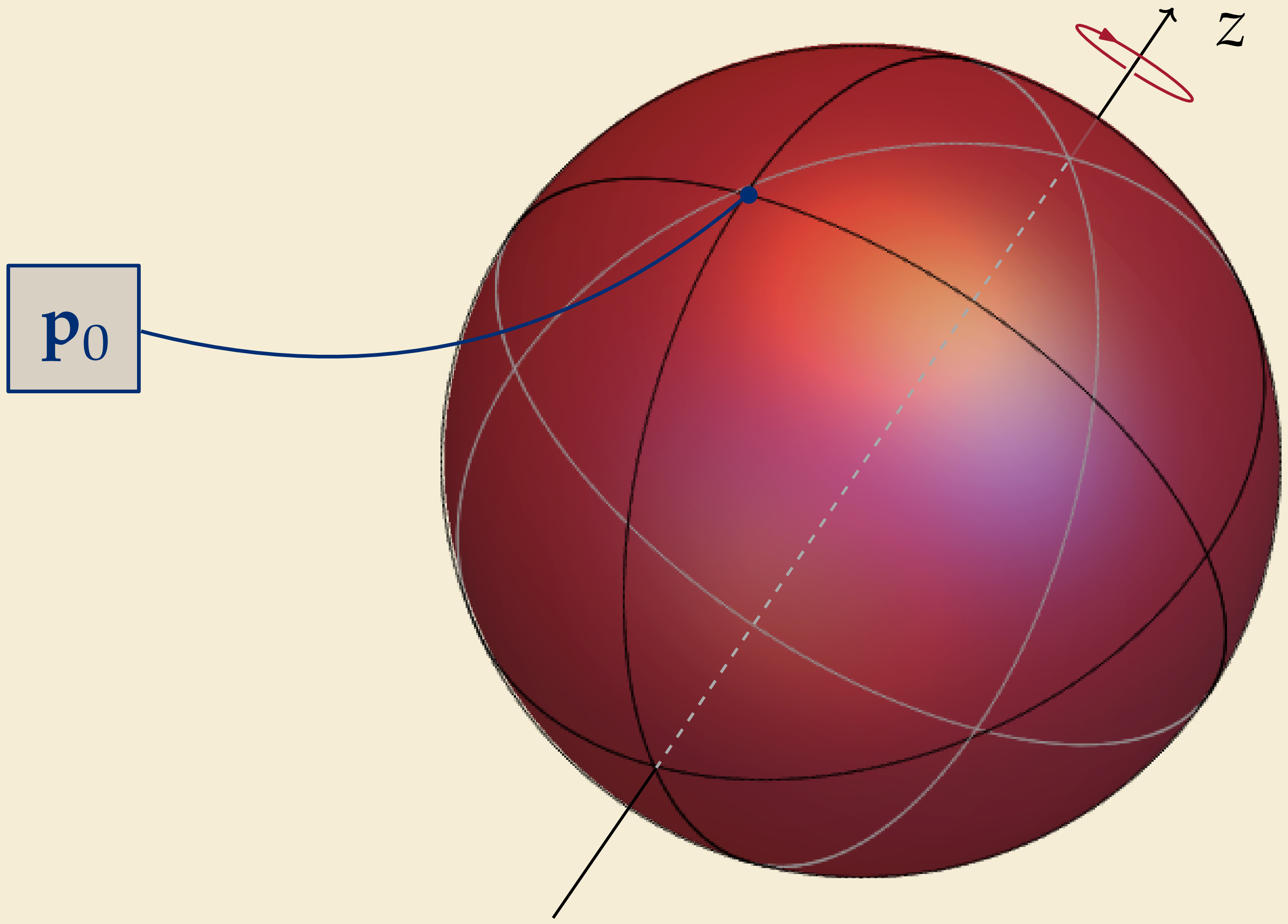
Considering these aspects, choosing SDEs that evolve on a **homogeneous space** as the consequence of some **(matrix) Lie group action** appears to be a reasonable choice.

Choice of latent space

Example: $\mathbb{S}^2$ with (quadratic) matrix Lie group $\mathrm{SO}(3)$.



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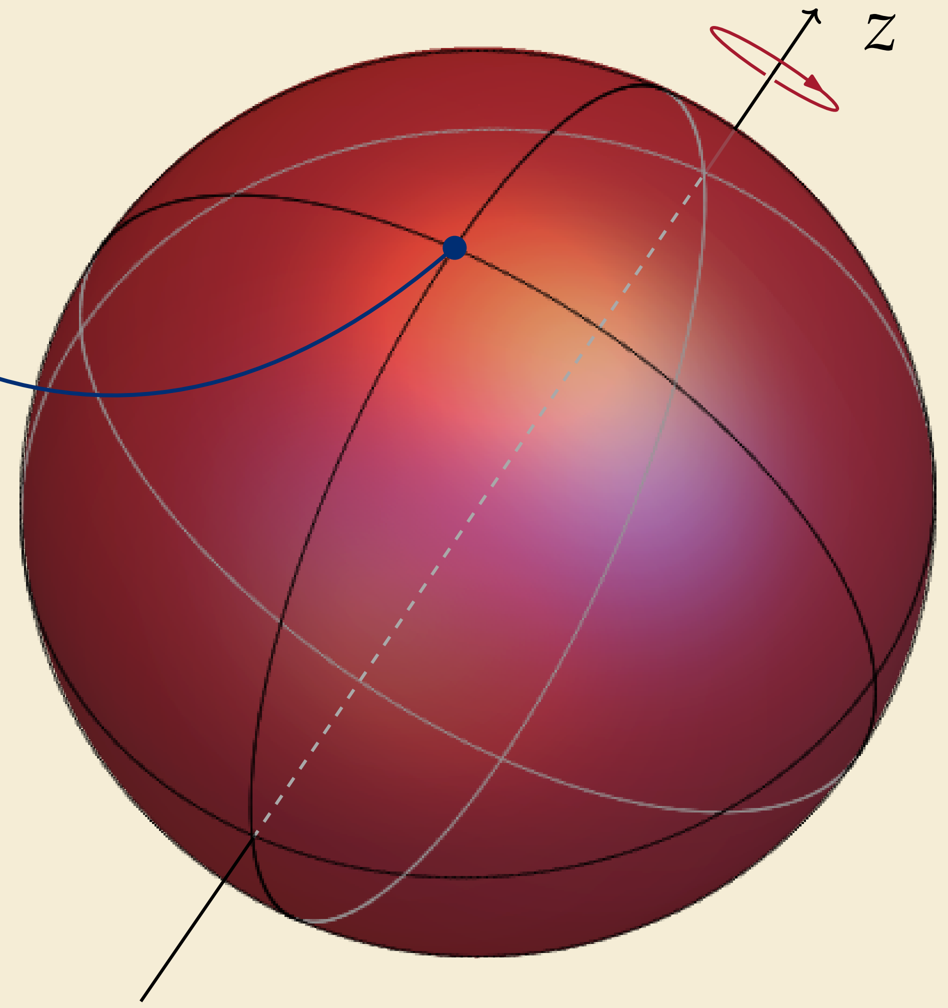

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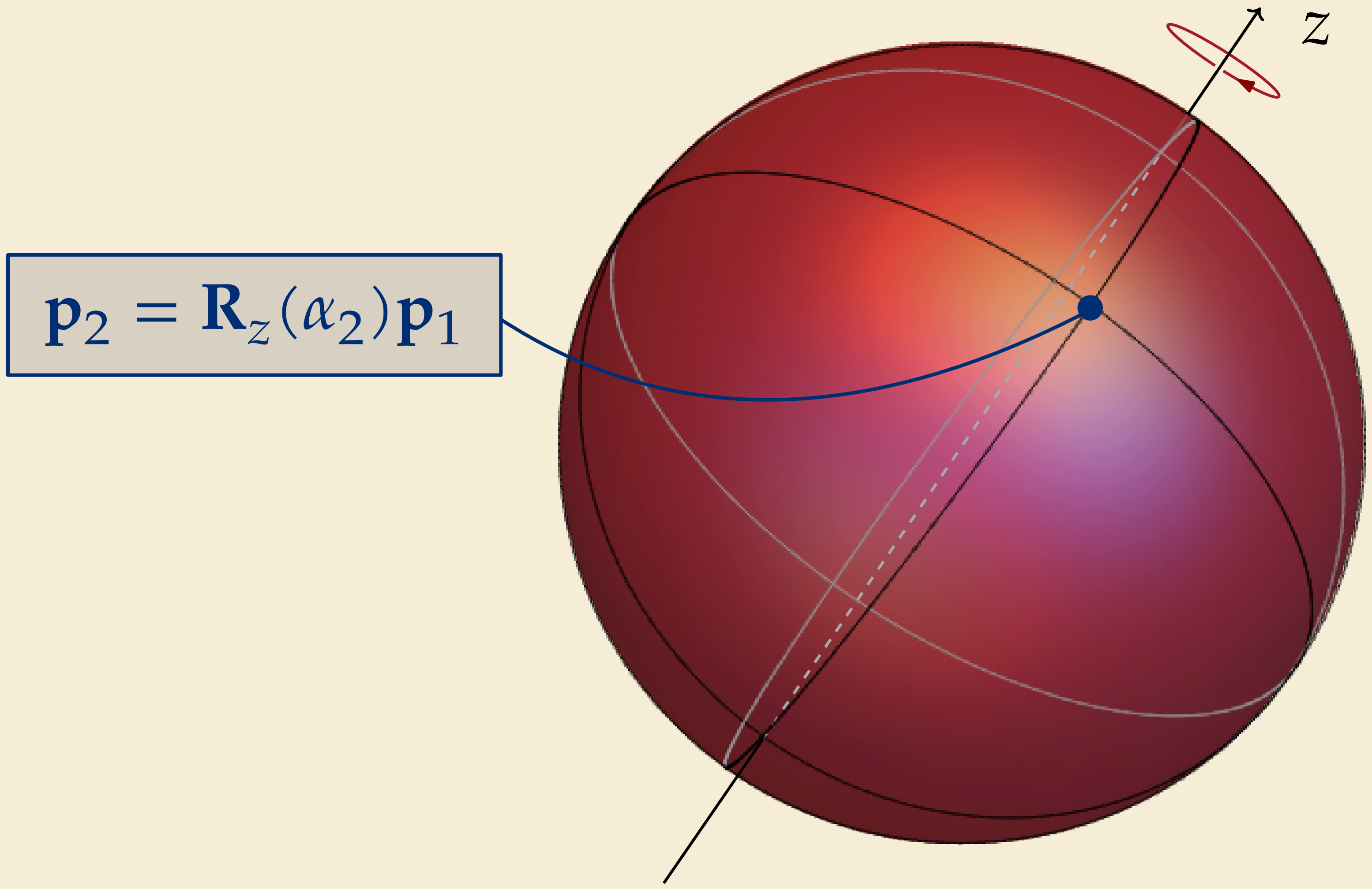

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Dynamics in homogeneous spaces

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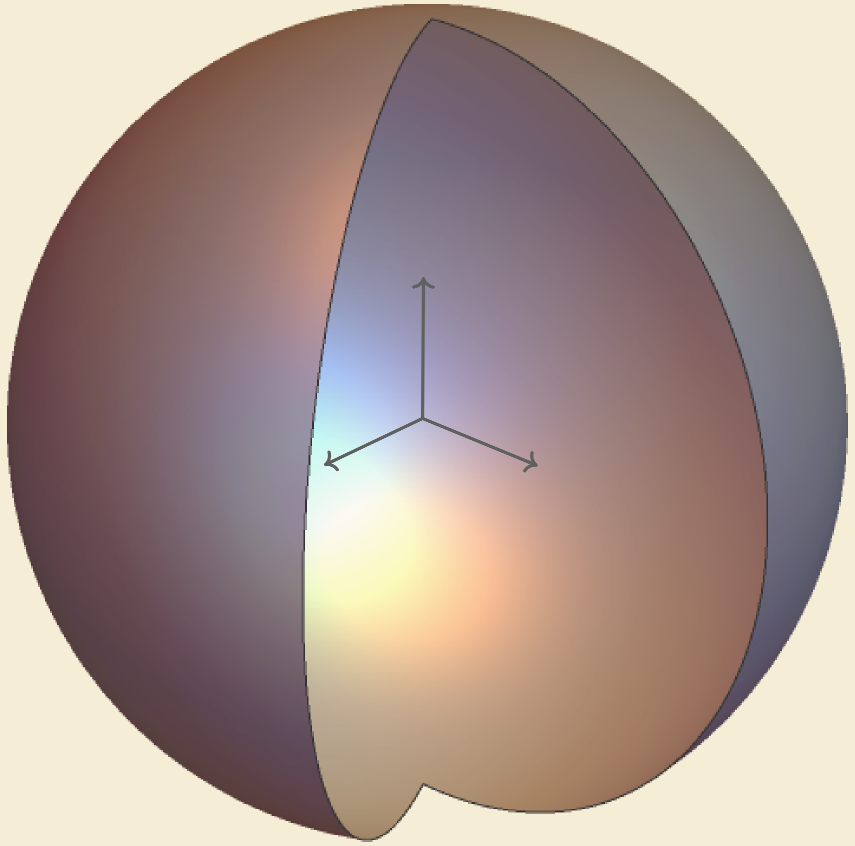

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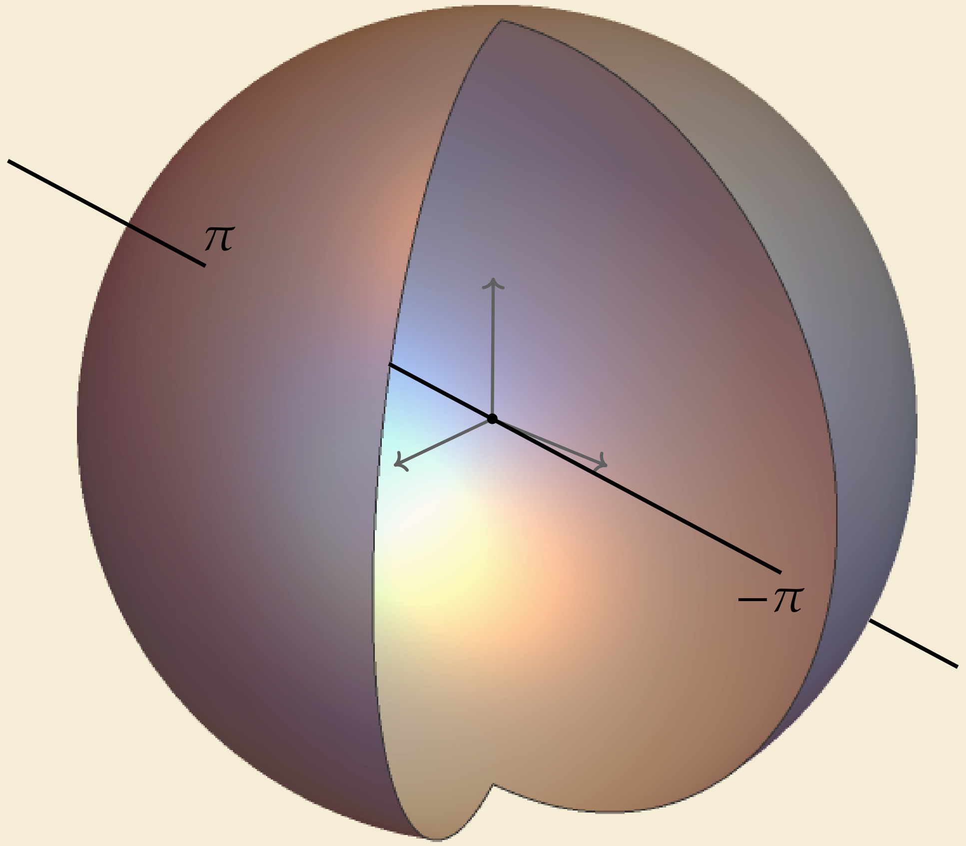

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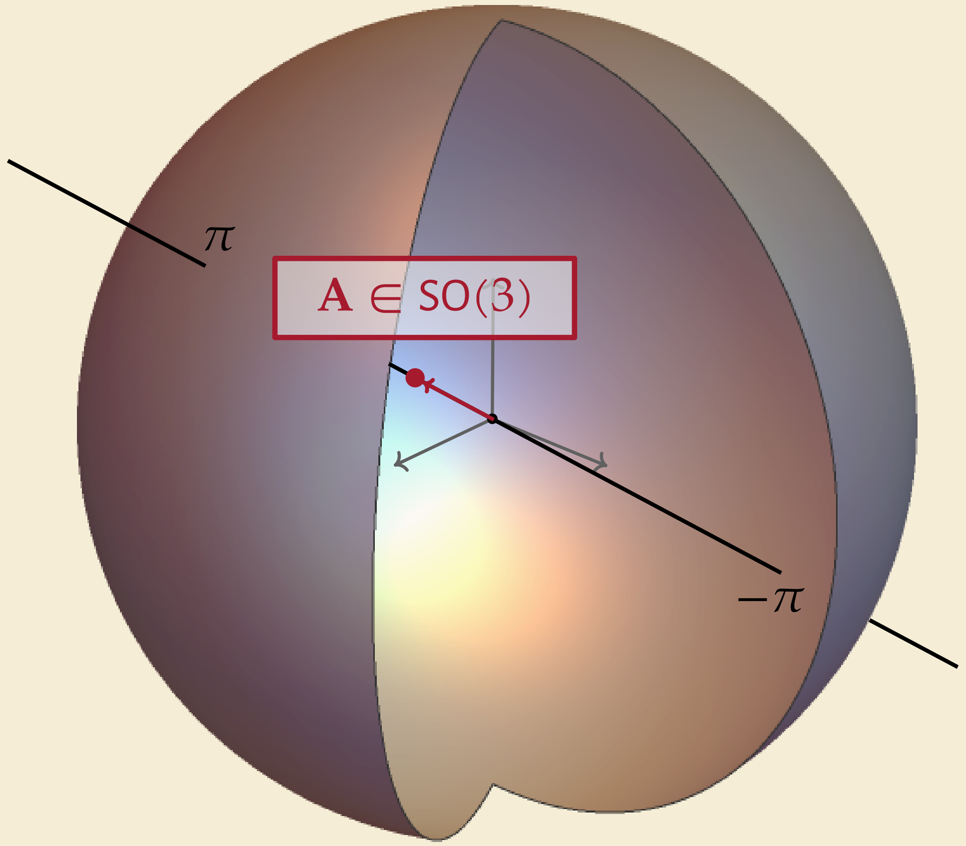

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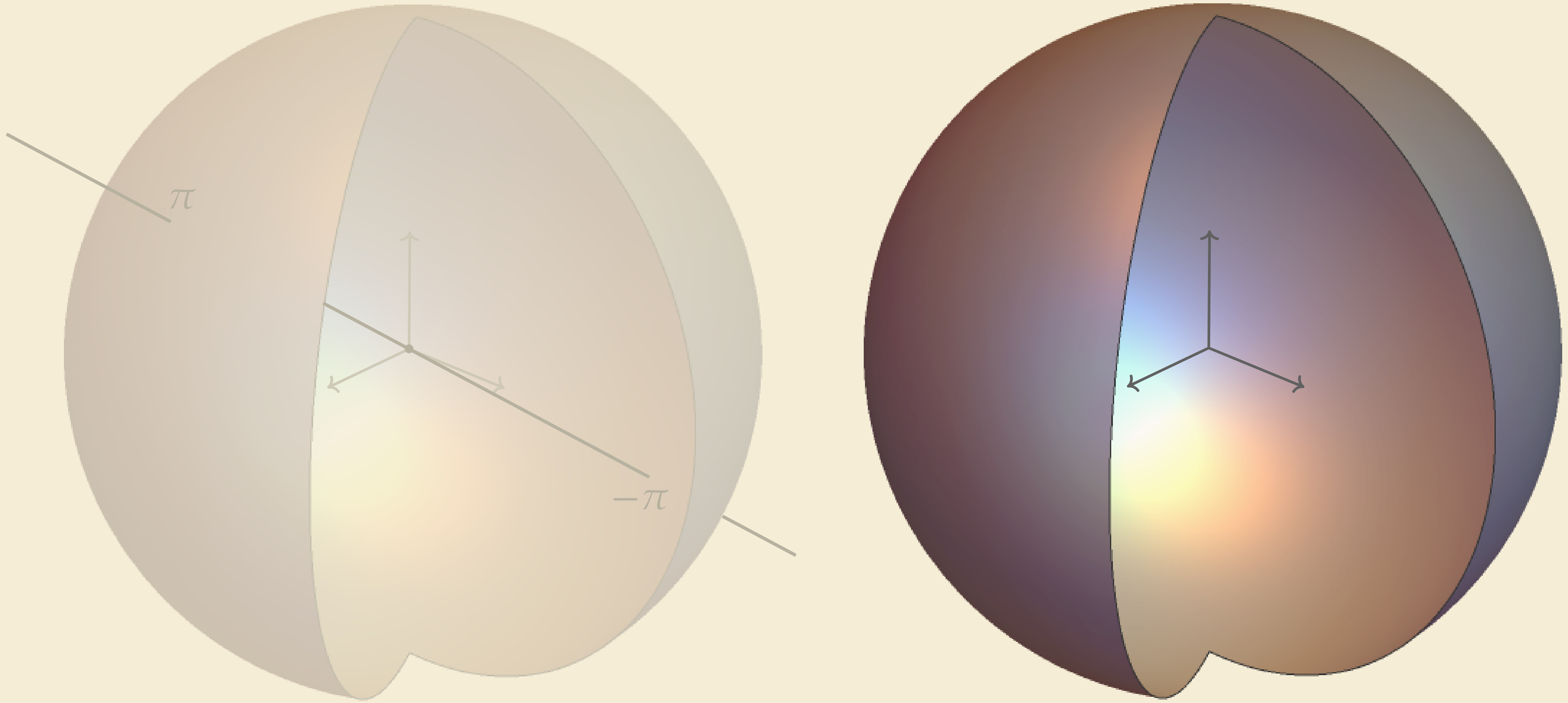

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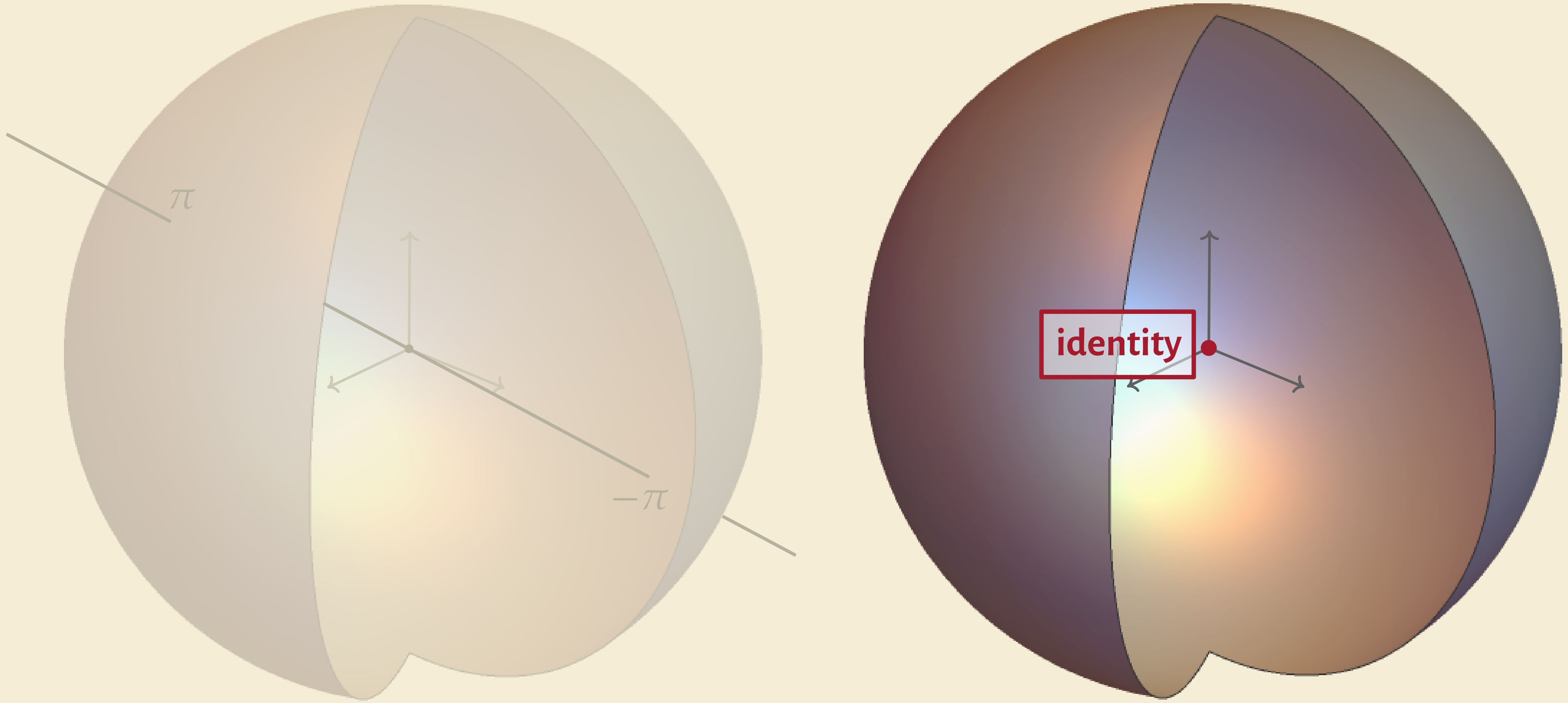

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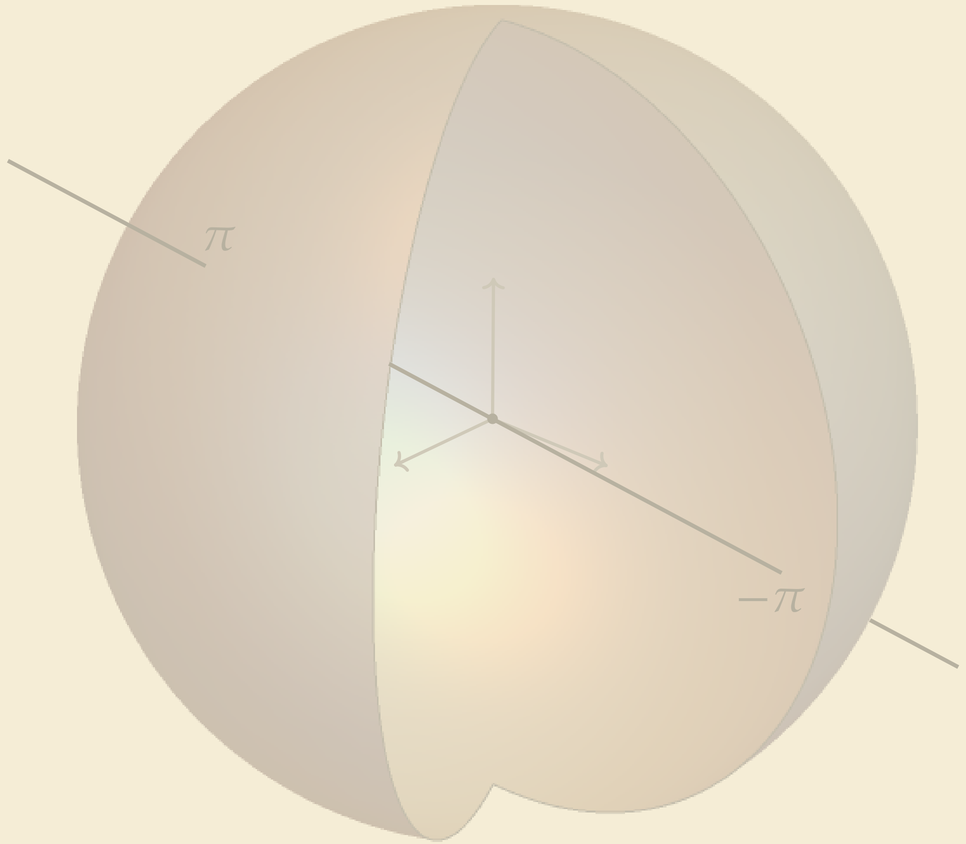

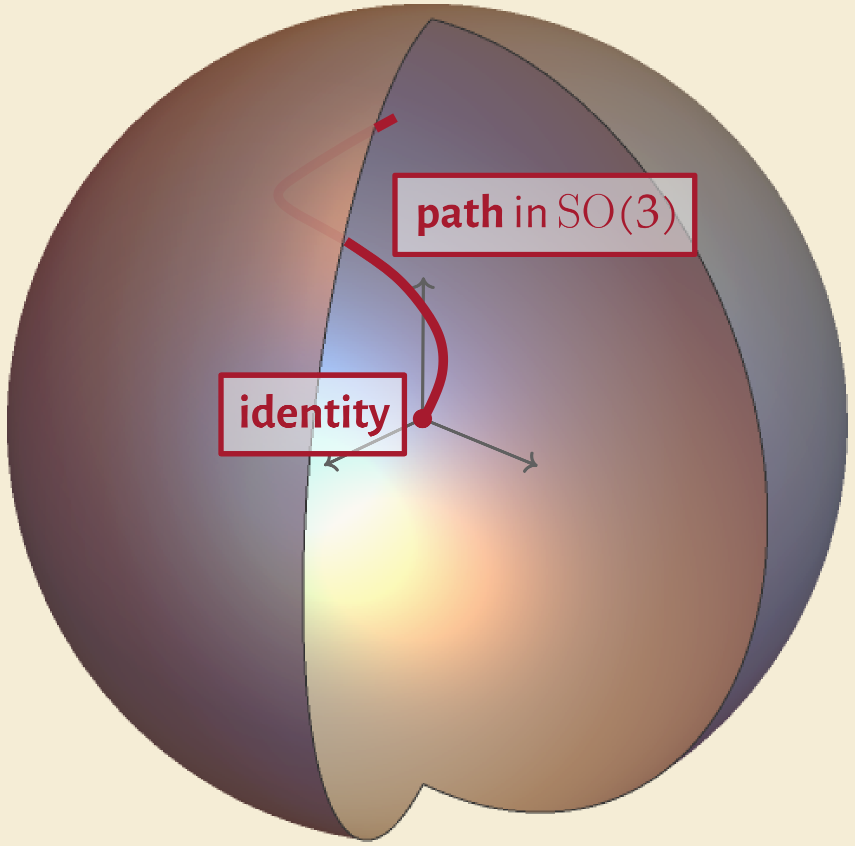

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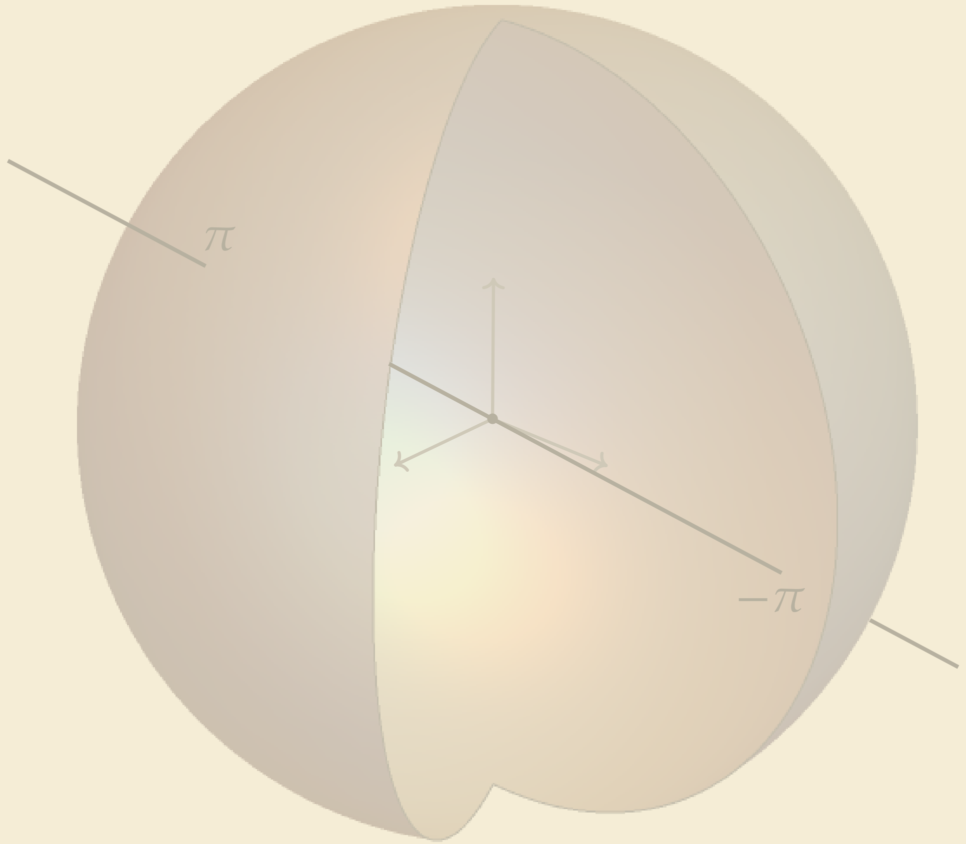

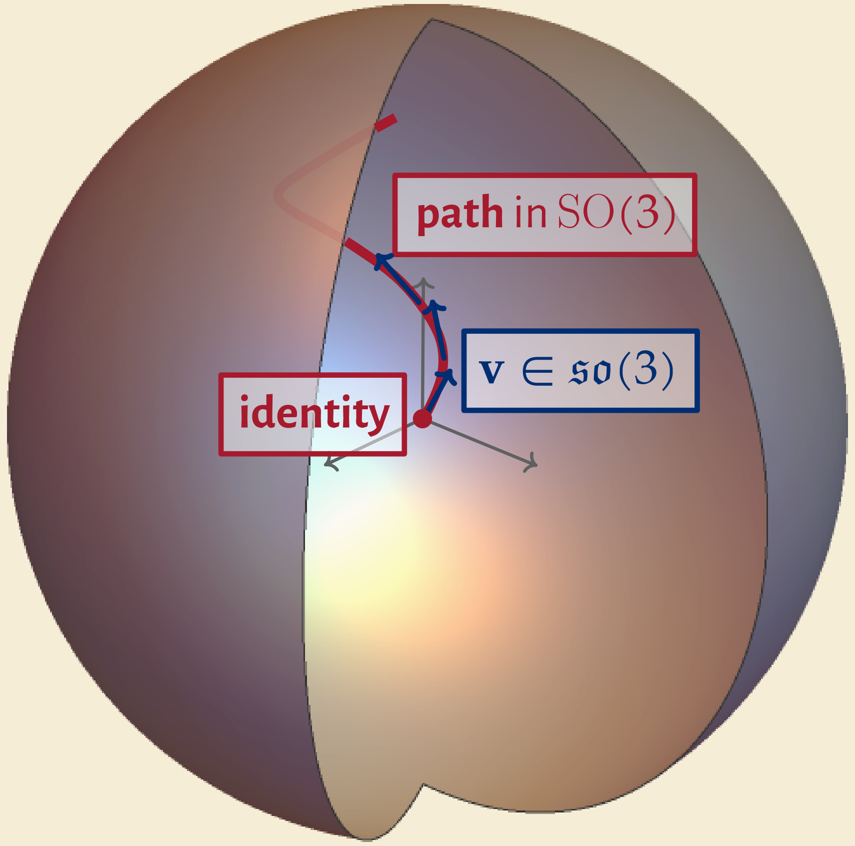

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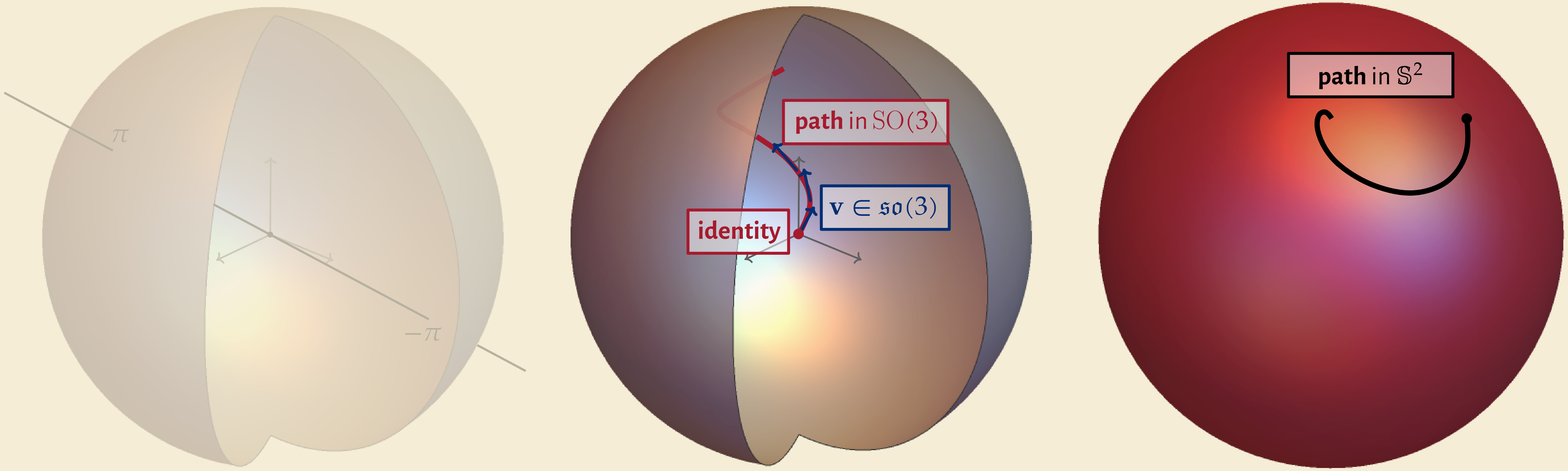

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SDEs in (quadratic) matrix Lie groups

Leveraging the Lie algebra $\mathfrak{g}$, we can define (Itô) SDEs in a (quadratic) matrix **Lie group** $\mathcal{G}$ of the form

$$\boxed{\mathrm{d}G_t = \left(\mathbf{V}_0(t)\mathrm{d}t + \sum_{i=1}^{m} \mathrm{d}w_t^i \mathbf{V}_i\right) G_t\,, \quad G_0 = \mathbf{I}_n\,.}$$

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Diffusion

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$$\mathbf{V}_0(t) = \mathbf{K}(t) + \frac{1}{2}\sum_{i=1}^{m} \mathbf{V}_i^2$$

$$\mathrm{d}G_t = \left(\mathbf{V}_0(t)\mathrm{d}t + \sum_{i=1}^{m} \mathrm{d}w_t^i \mathbf{V}_i\right) G_t\,, \quad G_0 = \mathbf{I}_n\,.$$

$\mathbf{K}(t), \mathbf{V}_1, \dots, \mathbf{V}_m \in \mathfrak{g}$

This induces an SDE for $Z = G \cdot Z_0$ in the **homogeneous space**:

$$\mathrm{d}Z_t = \left(\mathbf{V}_0(t)\mathrm{d}t + \sum_{i=1}^{m} \mathrm{d}w_t^i \mathbf{V}_i\right) Z_t\,, \quad Z_0 \sim \mathcal{P}\,.$$

$\mathcal{P}$ ... distribution over the initial state.

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$\mathcal{P}$ … distribution over the initial state.

The **prior** $p_{\boldsymbol{\theta}}(\mathbf{z})$ and **approximate posterior** $q_{\boldsymbol{\theta}}(\mathbf{z}|\mathbf{x})$ are determined by an SDE of this form!

To implement a drift parameterization depending on $\mathbf{x}$, we realize $\mathbf{K}^{\Phi}(\mathbf{x})(t) : [0, T] \to \mathfrak{g}$ via Chebyshev polynomials with **learnable coefficients**.

Learning objective

The **overall objective** (for our example of latent paths on $\mathbb{S}^{n-1}$):

$$\begin{aligned}\mathcal{L}(\boldsymbol{\phi},\boldsymbol{\theta};\mathbf{x}^i) = D_{\mathsf{KL}}\left(\mathcal{P}_0^{\boldsymbol{\phi}}\left(Z_0|\mathbf{x}^{\mathbf{i}}\right)\|\,\mathcal{U}_{\mathbb{S}^{n-1}}\right) \\ +\frac{1}{2}\int_0^T\int_{\mathbb{S}^{n-1}} q_{Z_t}(\mathbf{z})\|\mathbf{K}^{\boldsymbol{\phi}}(\mathbf{x}^i)(t)\mathbf{z}\|^2\mathrm{d}\mathbf{z}\mathrm{d}t \\ +\mathbb{E}_{\mathbf{z}\sim q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x}^i)}\left[\log p_{\boldsymbol{\theta}}\left(\mathbf{x}^i|\mathbf{z}\right)\right]\end{aligned}$$

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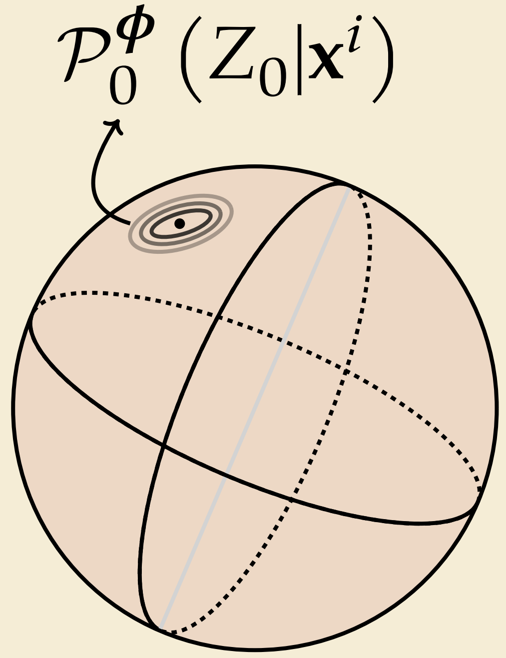

KL-div. to **uniform distribution** on $\mathbb{S}^{n-1}$

Learning objective

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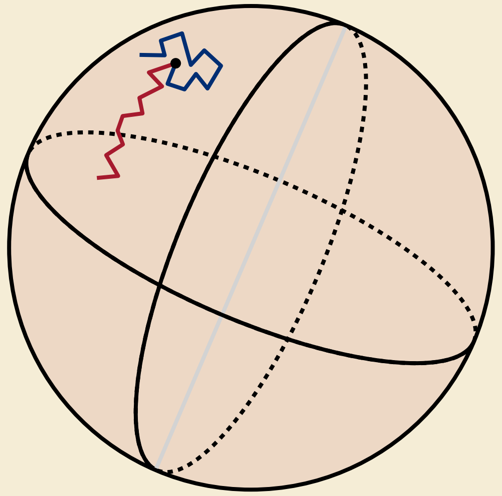

KL-div. between **approximate posterior** and a **driftless prior**

(essentially penalizes large rotations)

Learning objective

The **overall objective** (for our example of latent paths on $\mathbb{S}^{n-1}$):

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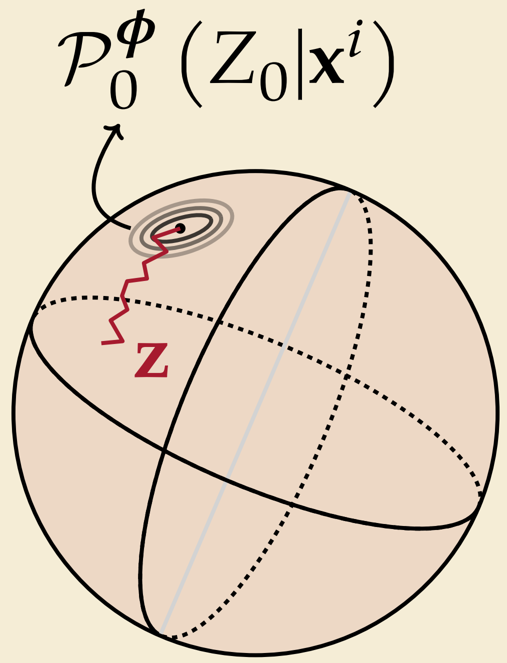
Expected **log-likelihood** of observed path given the latent path

Learning objective

The **overall objective** (for our example of latent paths on $\mathbb{S}^{n-1}$):

$$
\begin{aligned}
\mathcal{L}(\boldsymbol{\phi}, \boldsymbol{\theta}; \mathbf{x}^i) = D_{\mathrm{KL}} \left(\mathcal{P}_0^{\boldsymbol{\phi}} \left(Z_0 | \mathbf{x}^{\mathbf{i}} \right) \| \, \mathcal{U}_{\mathbb{S}^{n-1}} \right) \\
+ \frac{1}{2} \int_0^T \int_{\mathbb{S}^{n-1}} q_{Z_t}(\mathbf{z}) \| \mathbf{K}^{\boldsymbol{\phi}}(\mathbf{x}^i)(t) \mathbf{z} \|^2 \mathrm{d}\mathbf{z} \mathrm{d}t \\
+ \mathbb{E}_{\mathbf{z} \sim q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x}^i)} \left[\log p_{\boldsymbol{\theta}} \left(\mathbf{x}^i | \mathbf{z} \right) \right]
\end{aligned}
$$



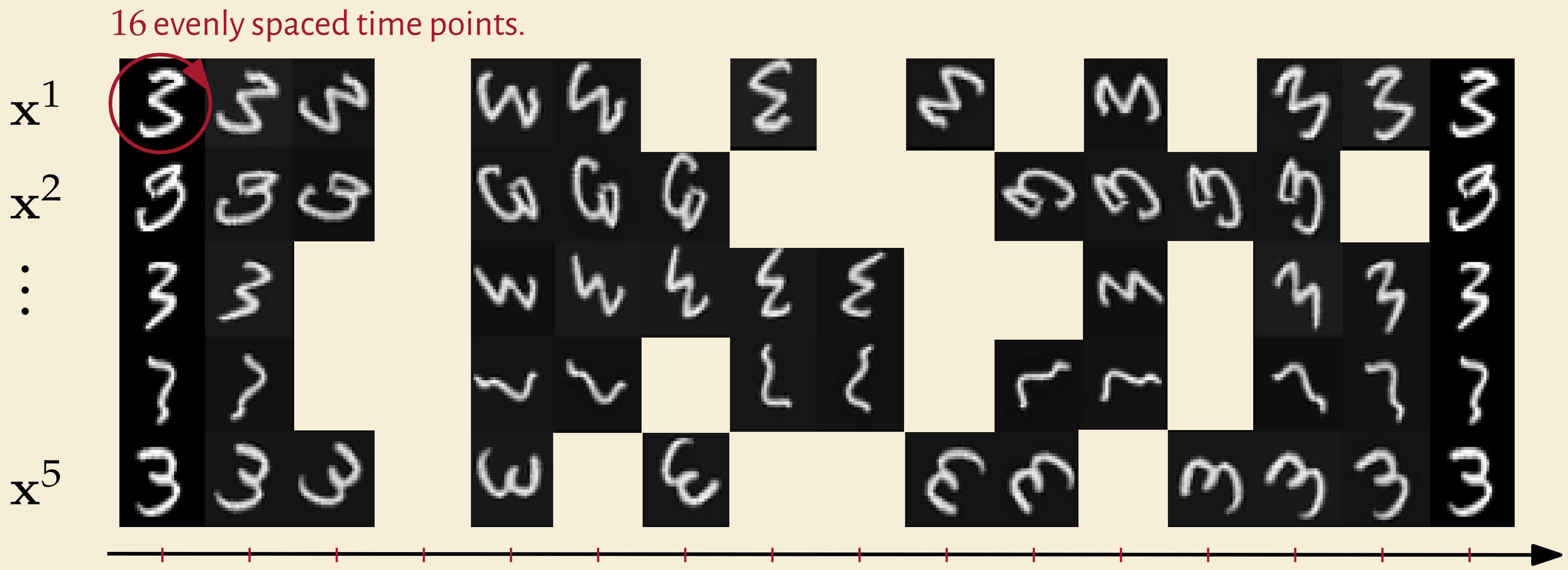
- **Sampling** from the approximate posterior:

  We use a one-step **geometric** Euler-Maryuama SDE solver, that is particularly easy to implement!

  [Marjanovic & Solo 2015; Muniz et al., 2022]

Some results

Five training samples of handwritten **rotating 3's** from `Rotating MNIST`

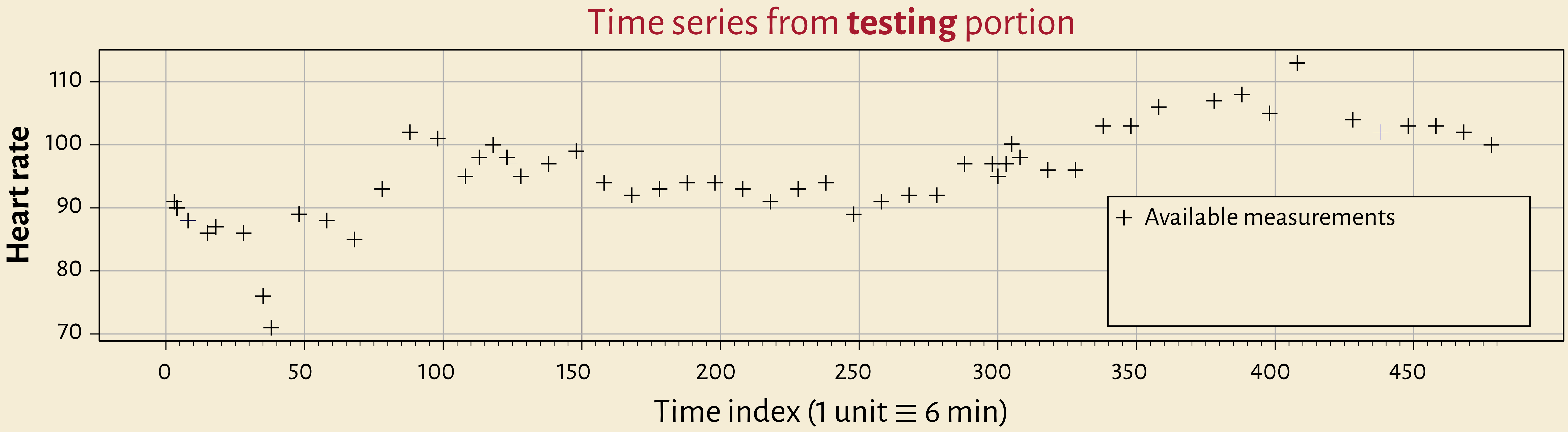


	$\downarrow$**MSE** $(\times 10^{-3})$
†GPPVAE-dis	30.9 ± 0.02
†GPPVAE-joint	28.8 ± 0.05
†ODE^{2}VAE	19.4 ± 0.06
†ODE^{2}VAE-KL	18.8 ± 0.31
CNN-ODE	14.5 ± 0.73
Ours	$\mathbf{11.8 \pm 0.25}$

† indicates results from [Yildiz et al., 2019].

Some results

`PhysioNet (2012)` **interpolation task** (see [Shukla & Marlin, 2021]):



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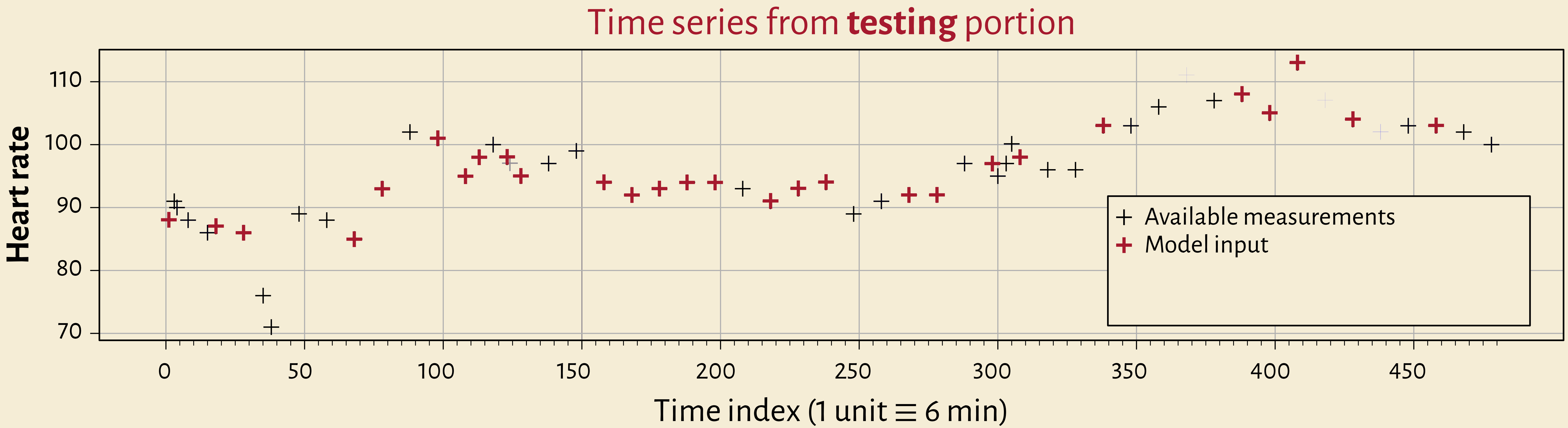

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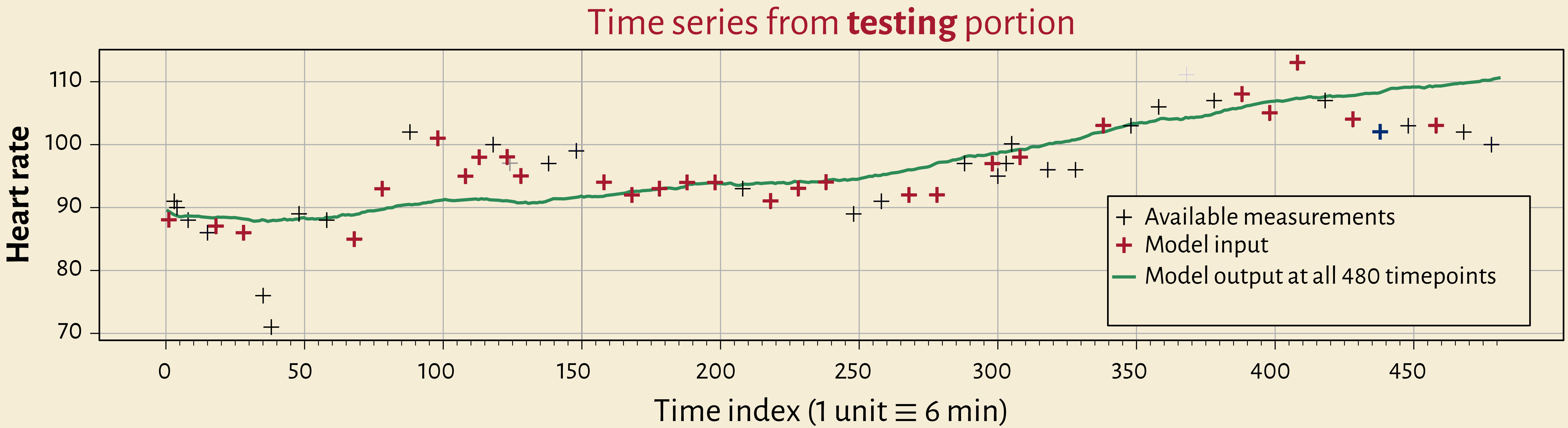

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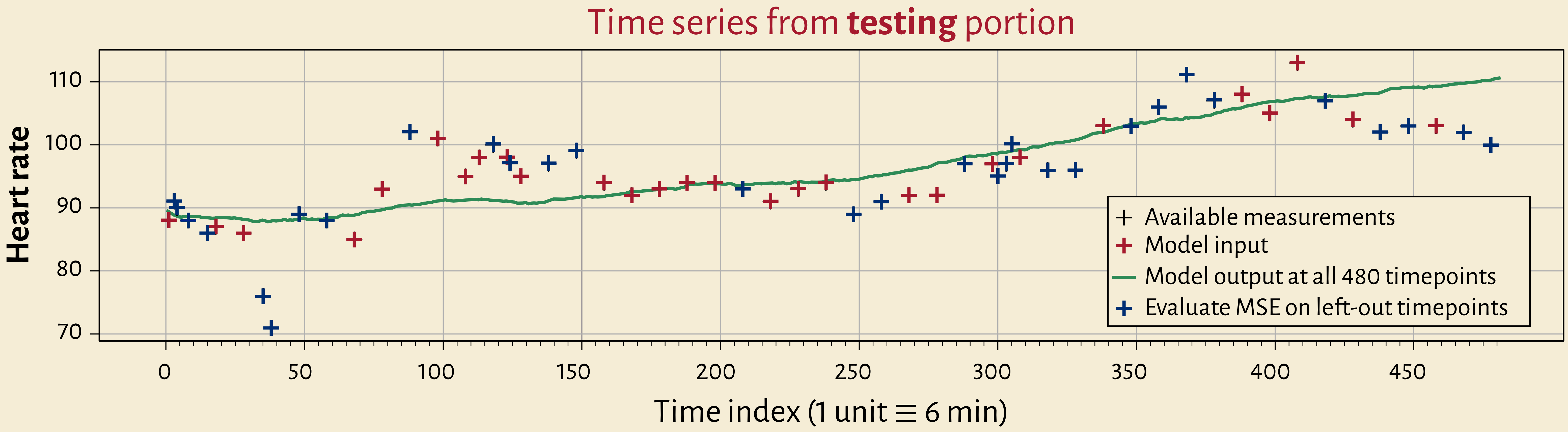

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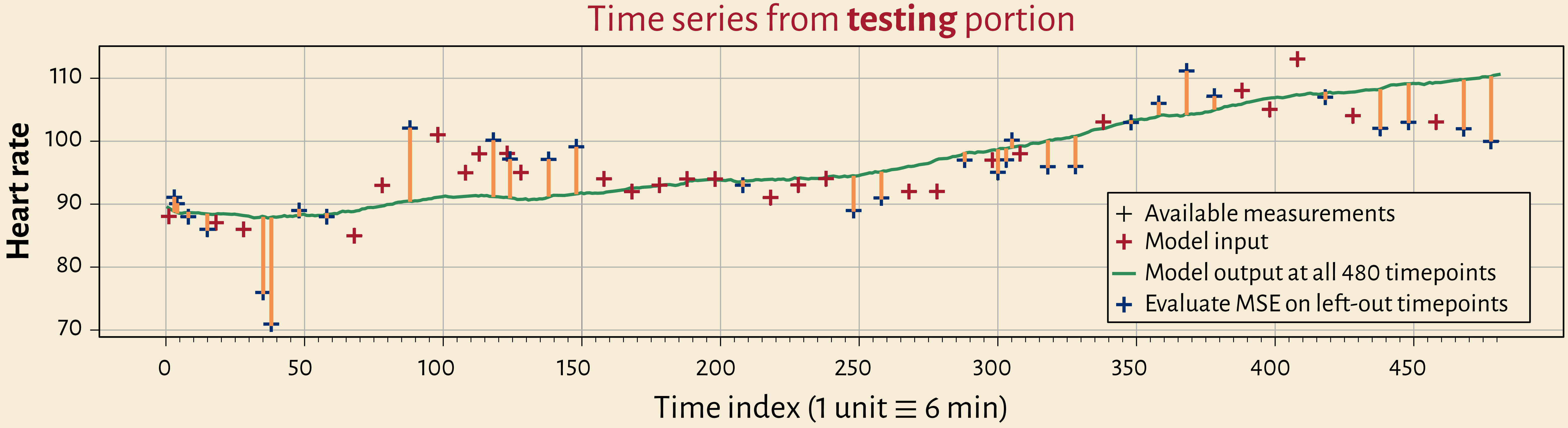

	↓**MSE** $(\times 10^{-3})$	
CRU	5.11 ± 0.40	[Schirmer et al., 2022]
f-CRU	5.24 ± 0.49	[Schirmer et al., 2022]
mTAND-Full	3.61 ± 0.08	[Shukla & Marlin, 2021]
mTAND-ODE	3.38 ± 0.03	[Shukla & Marlin, 2021] (*with added ODE*)
Ours	$\mathbf{3.11 \pm 0.02}$	

Thanks for your attention!

Come see us at our **poster # 1400**
Wed 13 Dec 5 p.m. CST @ Great Hall & Hall B1+B2

Full source code available at
`https://github.com/plus-rkwitt/LatentSDEonHS`

References

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