Bay Area Environmental Research Institute

Deep Generative Modeling of Periodic Variable Stars Using Physical Parameters

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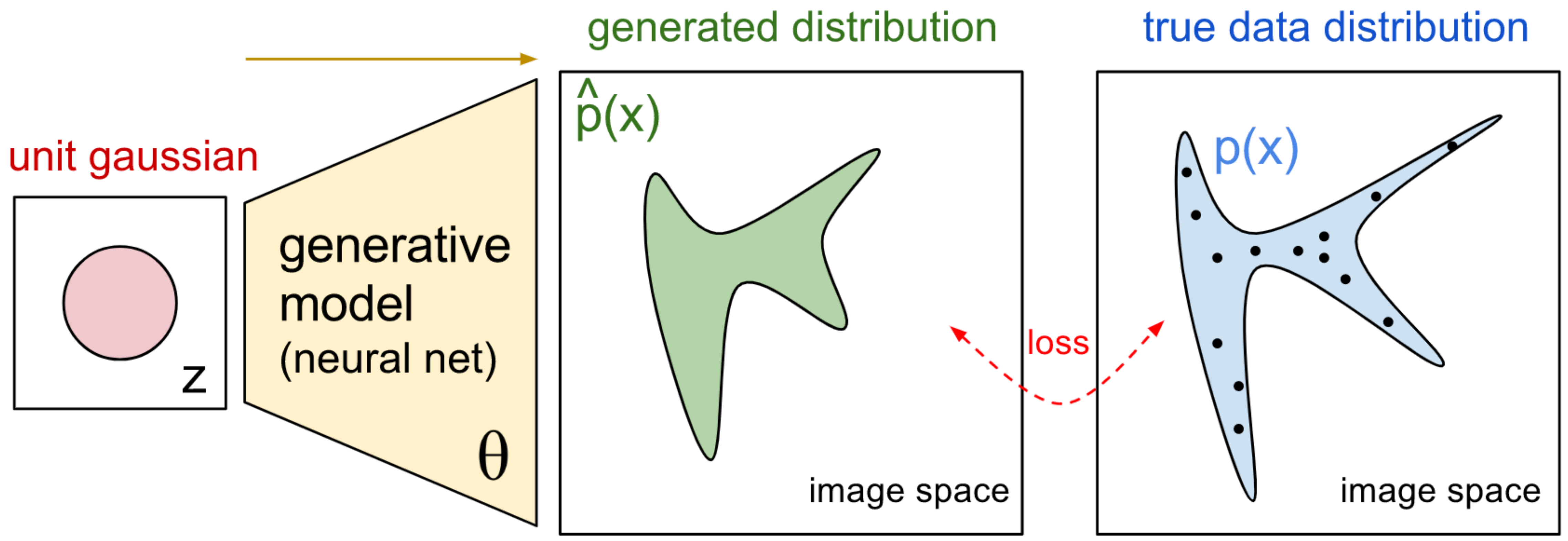
Main Goal

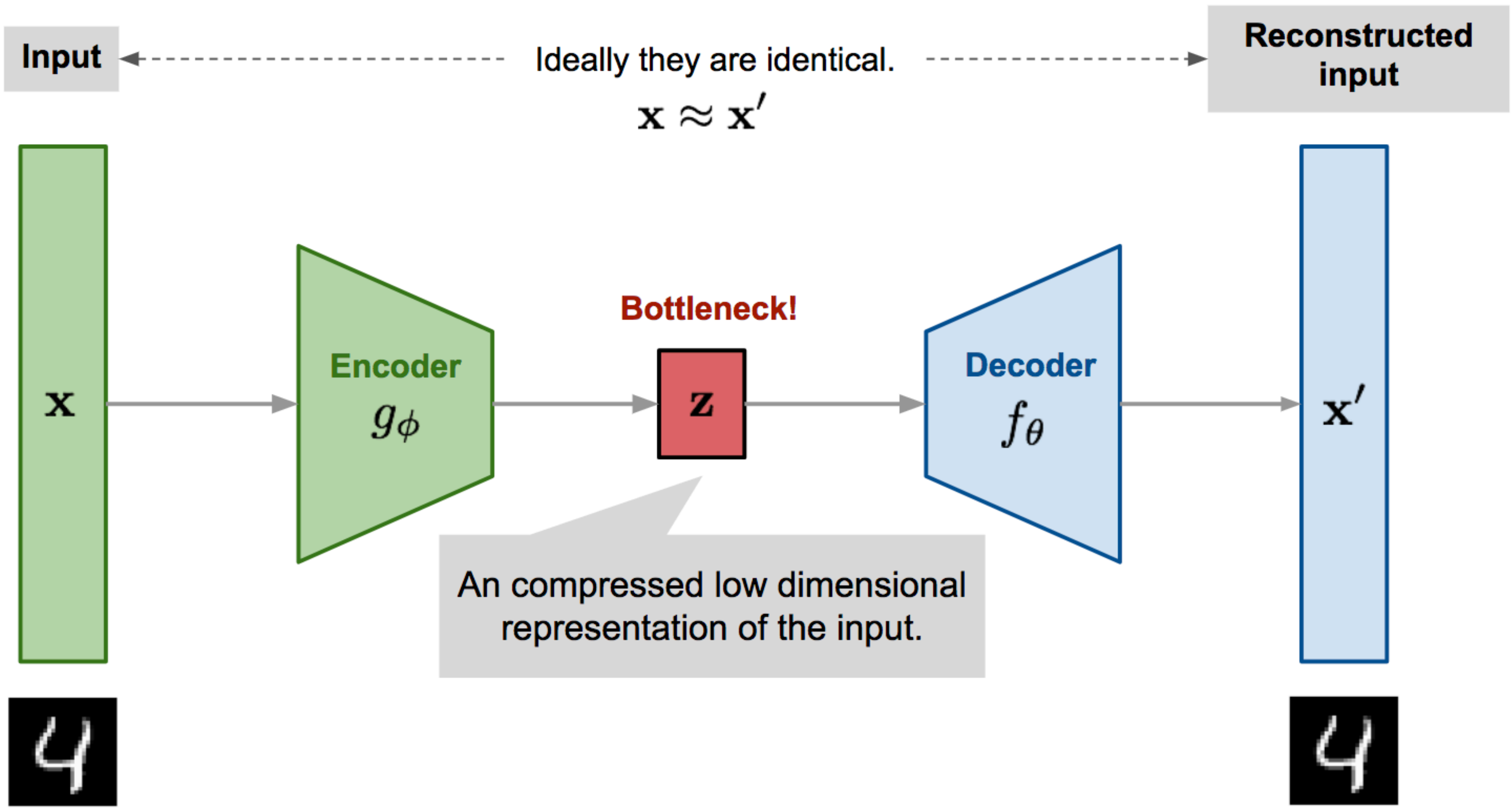
- Build a Generative Model that is able to create realistic observations of different types of variable stars.
- The model should consider stellar parameters and the variability class as inputs to generates a time series.
- Useful to:
    - Build training sets for supervised classification.
    - Explore how observing cadences impact variability studies at large scale including a wide variety of variability types.

What is a Deep Generative Model?

- A generative model describes how a dataset is generated, in terms of a probabilistic model. By sampling from this model, we are able to generate new data.
- A Deep Generative model (DGM) uses deep neural networks as functions.
- Examples of DGM are:
  - Generative Adversarial Networks (GAN)
  - Variational Autoencoders (VAE)
  - Normalizing Flows



AutoEncoder



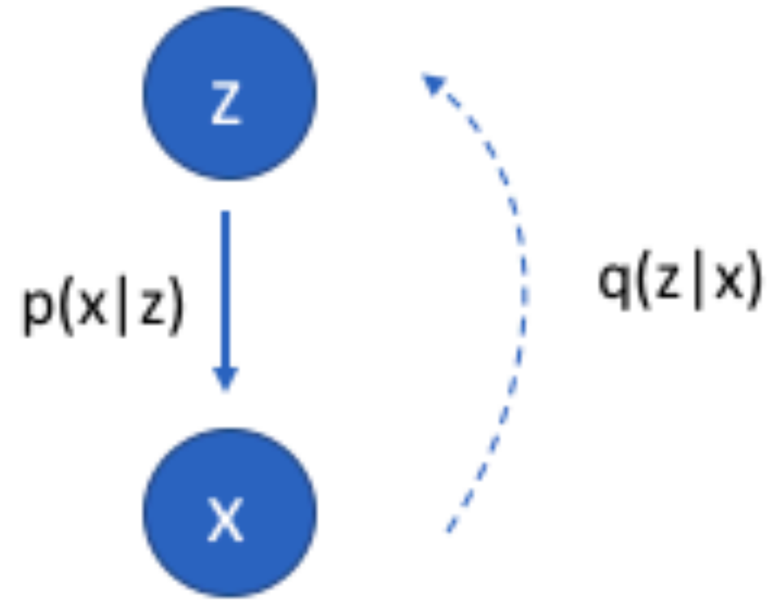
Figures by lilianweng.github.io/lil-log

Useful for:

- Data compression
- Feature extraction (Naul et al 2018, Jamal & Bloom 2020)
- Dimensionality reduction

Variational AutoEncoder

Generative Process



We wants to know

$$p(z|x) = \frac{p(x|z)p(z)}{p(x)}$$

But computing p(x) is intractable, then using Variational inference we can approximate

$$p(z|x) \approx q_\theta(z|x)$$

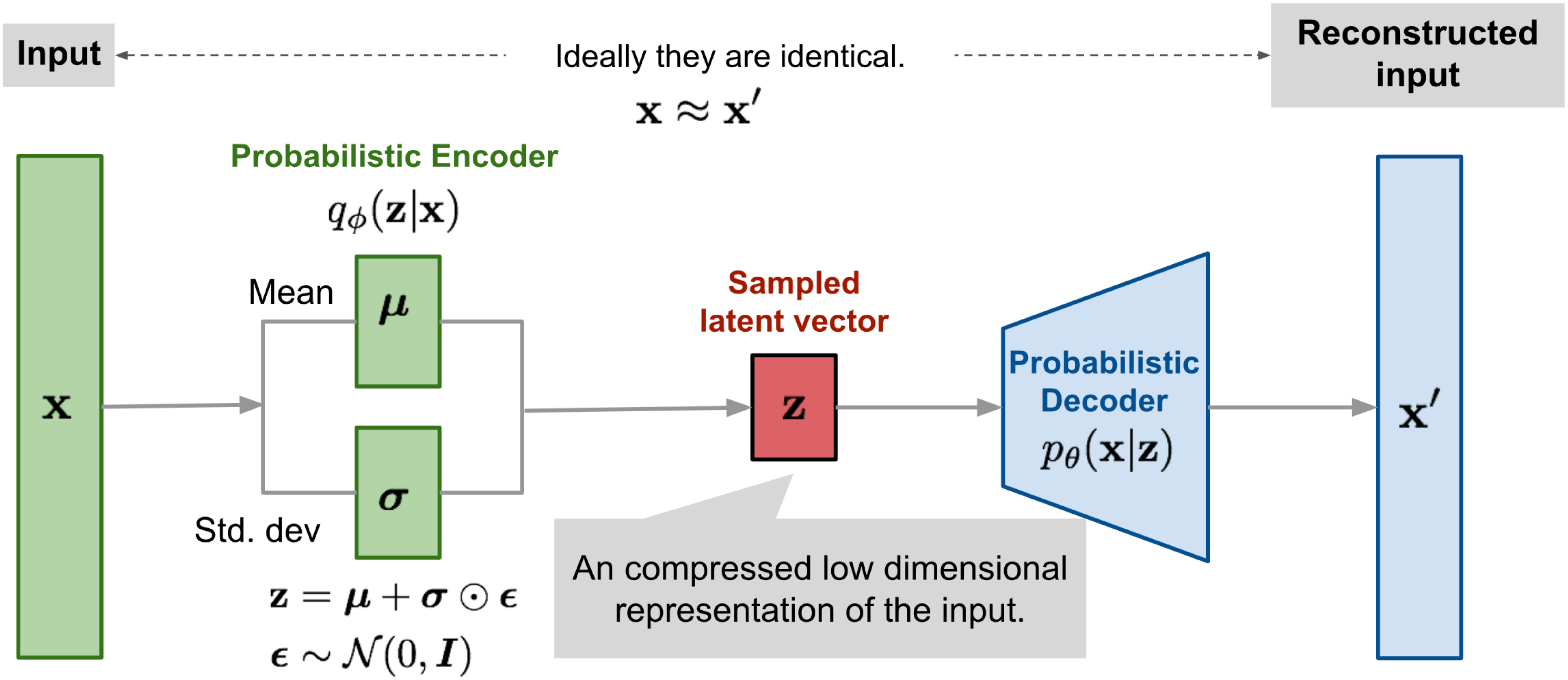
And minimize the KL Divergence between them

$$minKL(q_\theta(z|x)||p(z|x))$$

Which leads us to the known expression for the VAE's loss

$$E_{q(z|x)}logp(x|z) - KL(q(z|x)||p(z))$$

Variational AutoEncoder



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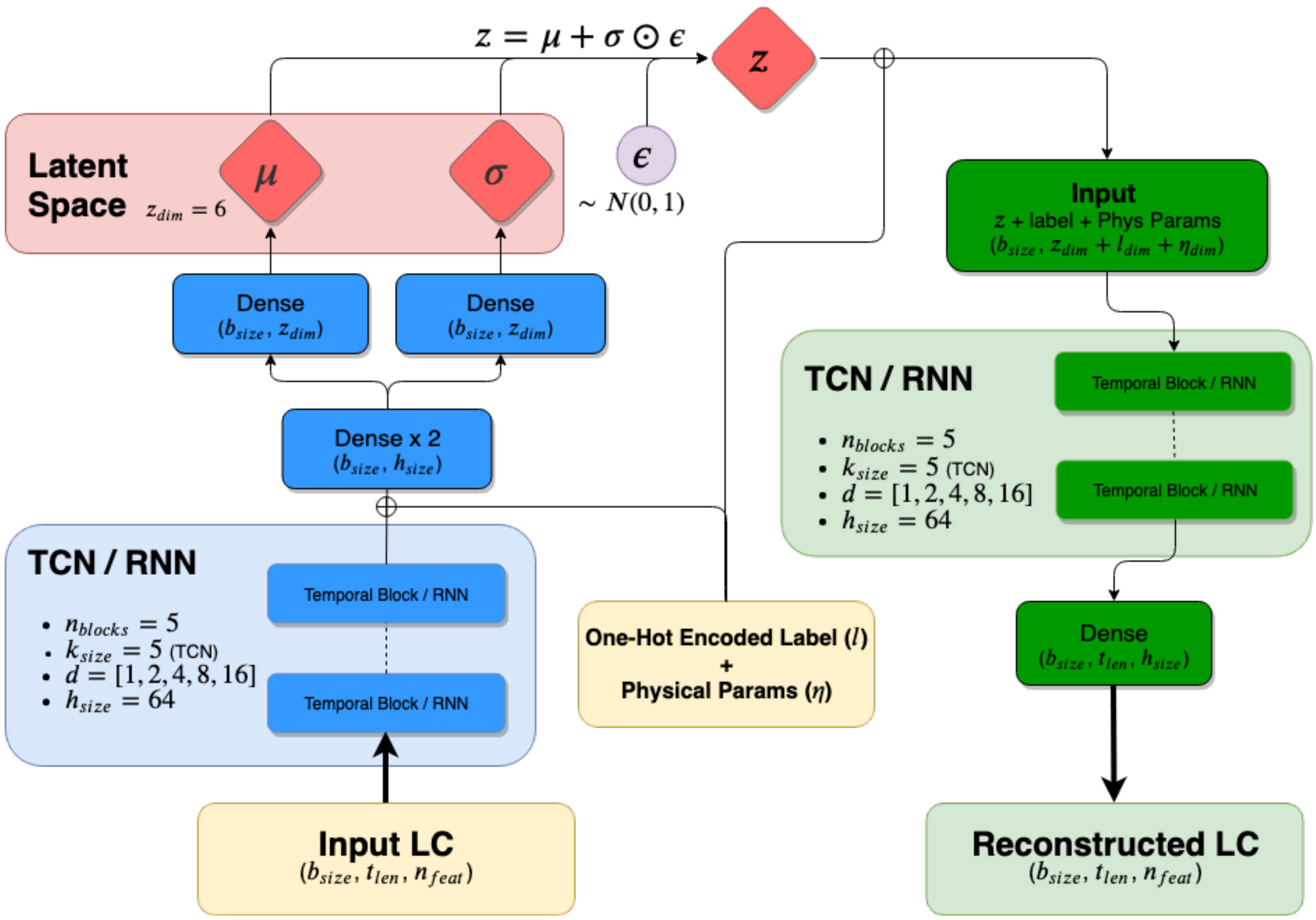
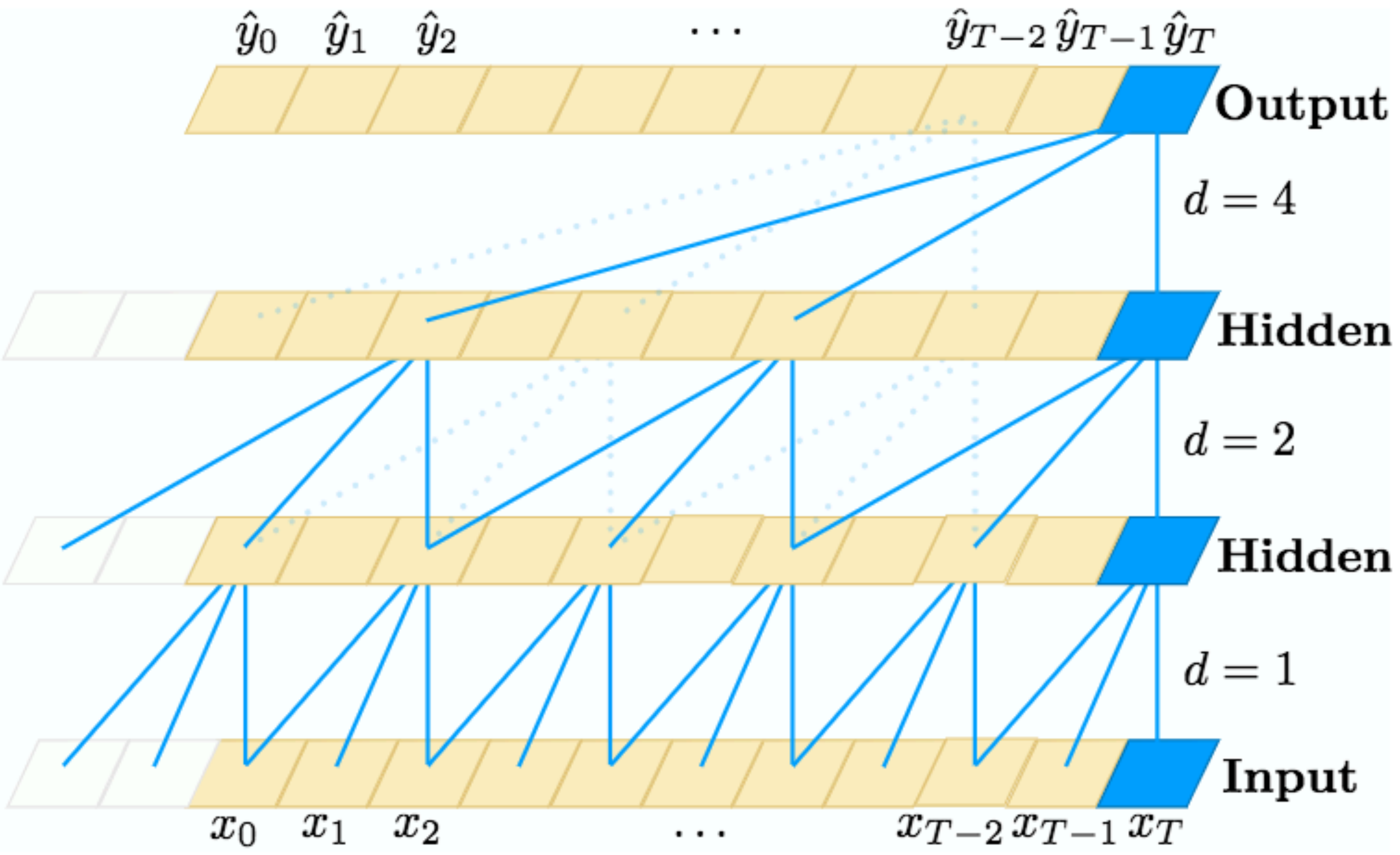
VAE Architecture

Martinez-Palomera et al. 2020

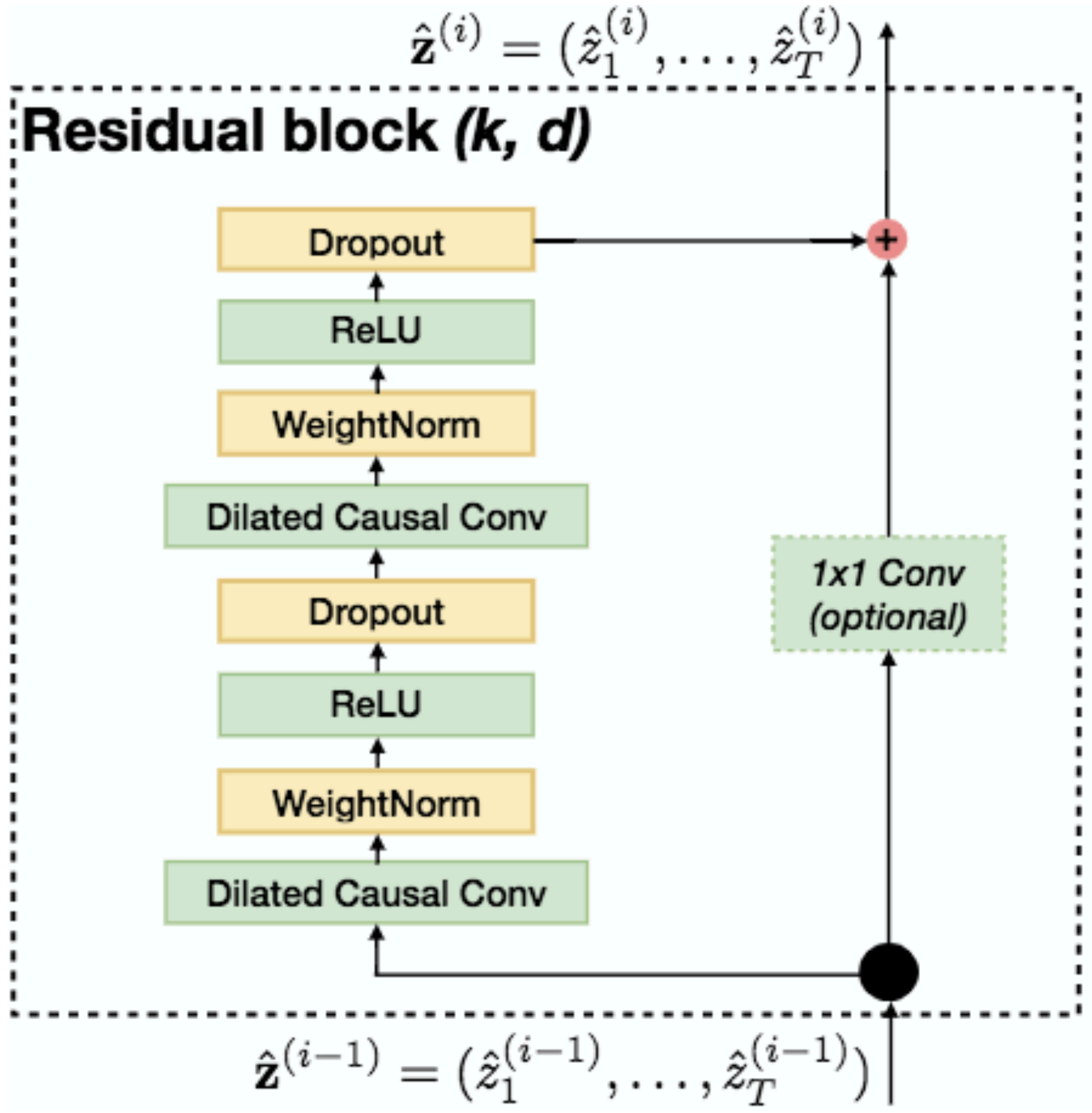


Temporal Convolutional Networks (TCN)

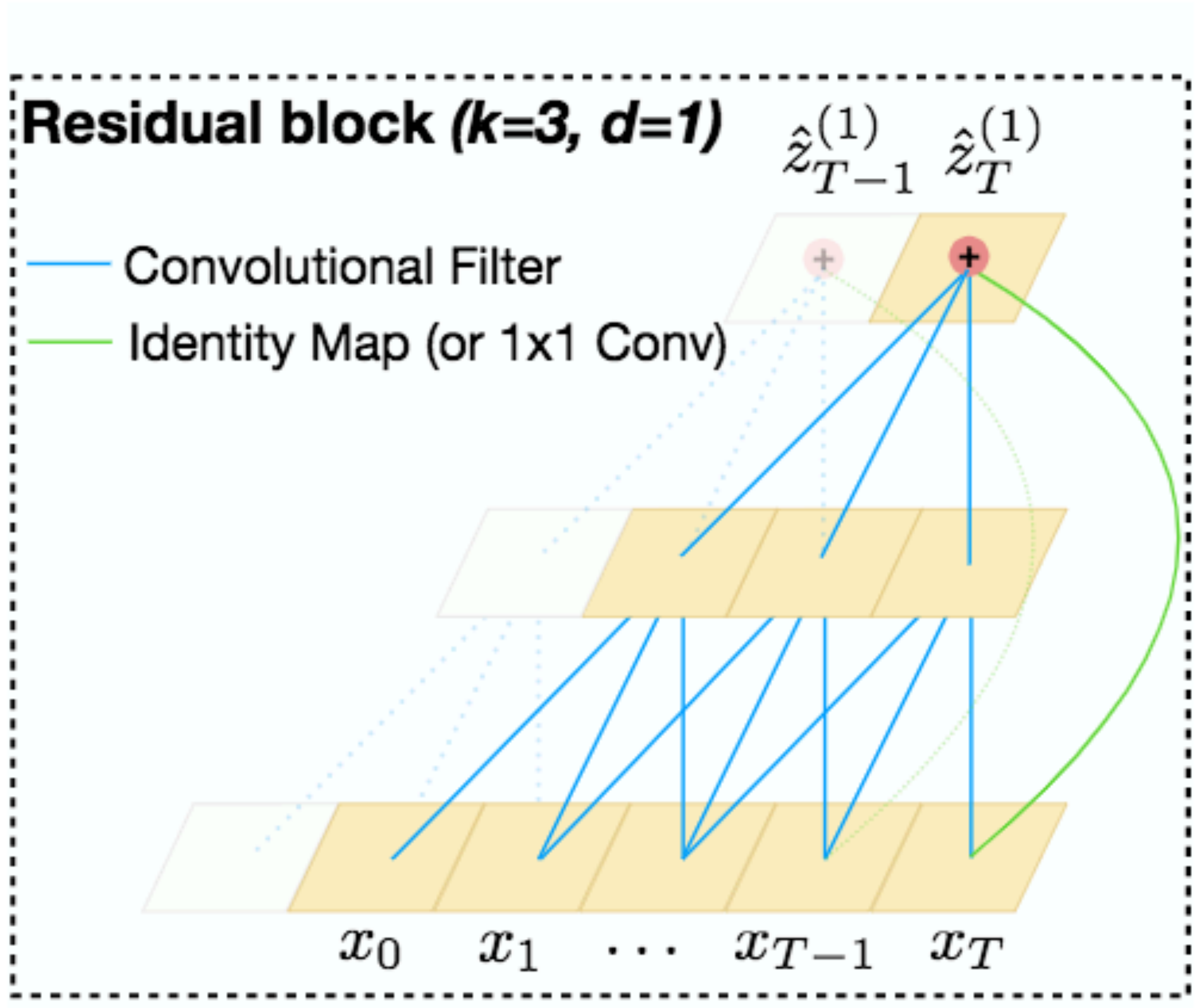
- Causal convolutions (a)
- Dilated convolutions (a)-> improve receptive field
- Residual connections (b,c)-> improve convergence and stability of deeper models



(a)



(b)



(c)

Bai et al., 2018

VAE
Objective function

$$\mathscr{L} = \underbrace{\mathbb{E}_{q(z|x)}[\log p(x\,|\,z)]}_{\text{Reconstruction Likelihood}} - \beta \underbrace{D_{KL}(q(z\,|\,x)\,||\,p(z))}_{\substack{\text{KL-Divergence} \\ \text{between encoder's} \\ \text{distribution and prior} \\ \text{latent distribution} \\ p(z) \sim \mathcal{N}(0,1)}} + D_{KL}(\hat{\sigma}_{mag}\,||\,\sigma_{mag})$$

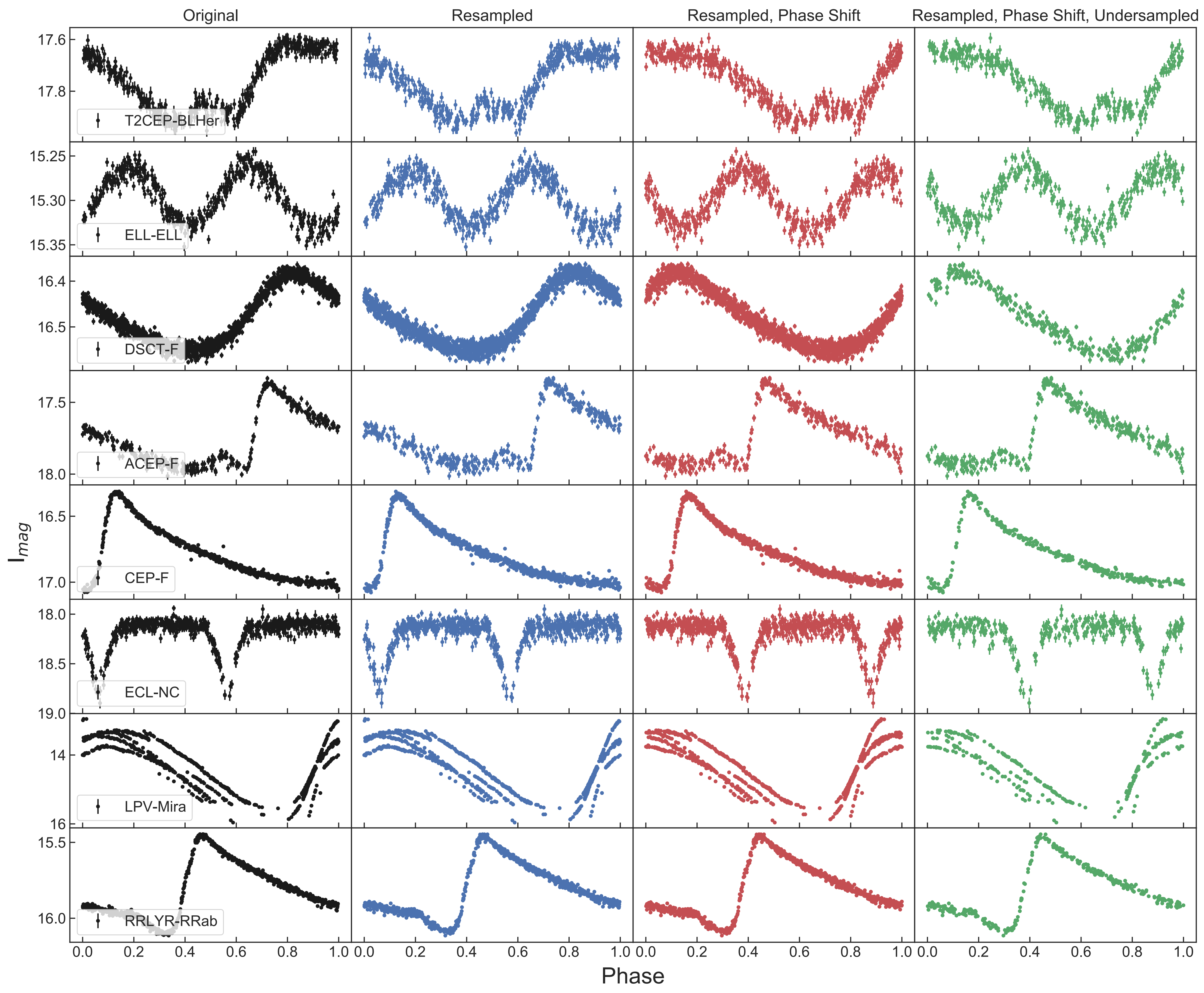
KL-Divergence
between reconstructed
and real errors
distributions

β: tunes the importance of an orthogonal/disentangled latent space

Dataset

Martinez-Palomera et al. 2020

OGLE III



65k Light curves

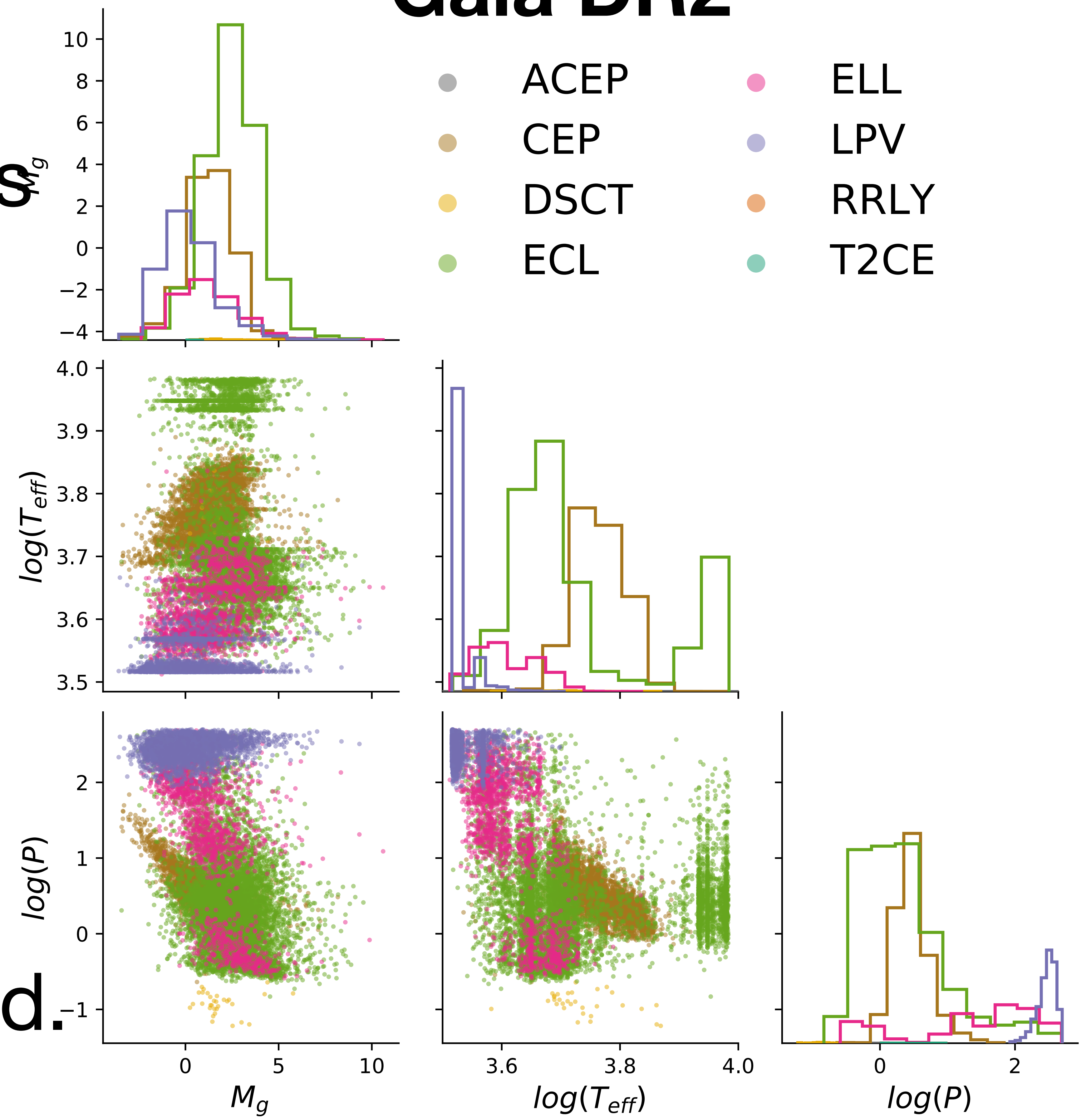
8 Variability classes (periodic only)

70% with Temp

5 % with stellar radius, luminosity and metallicity

-> we only used Teff, Mg, and Period.

Gaia DR2

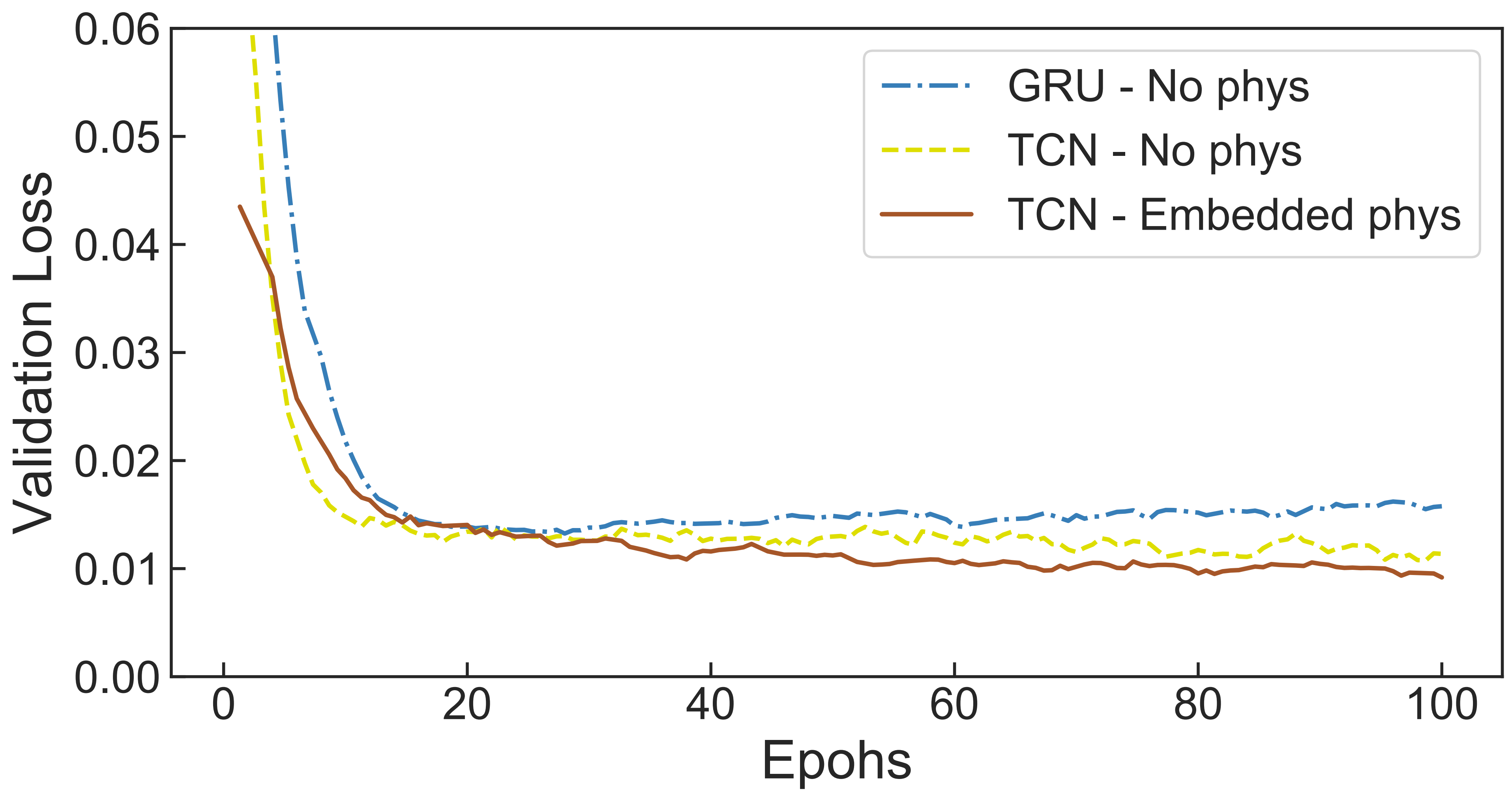


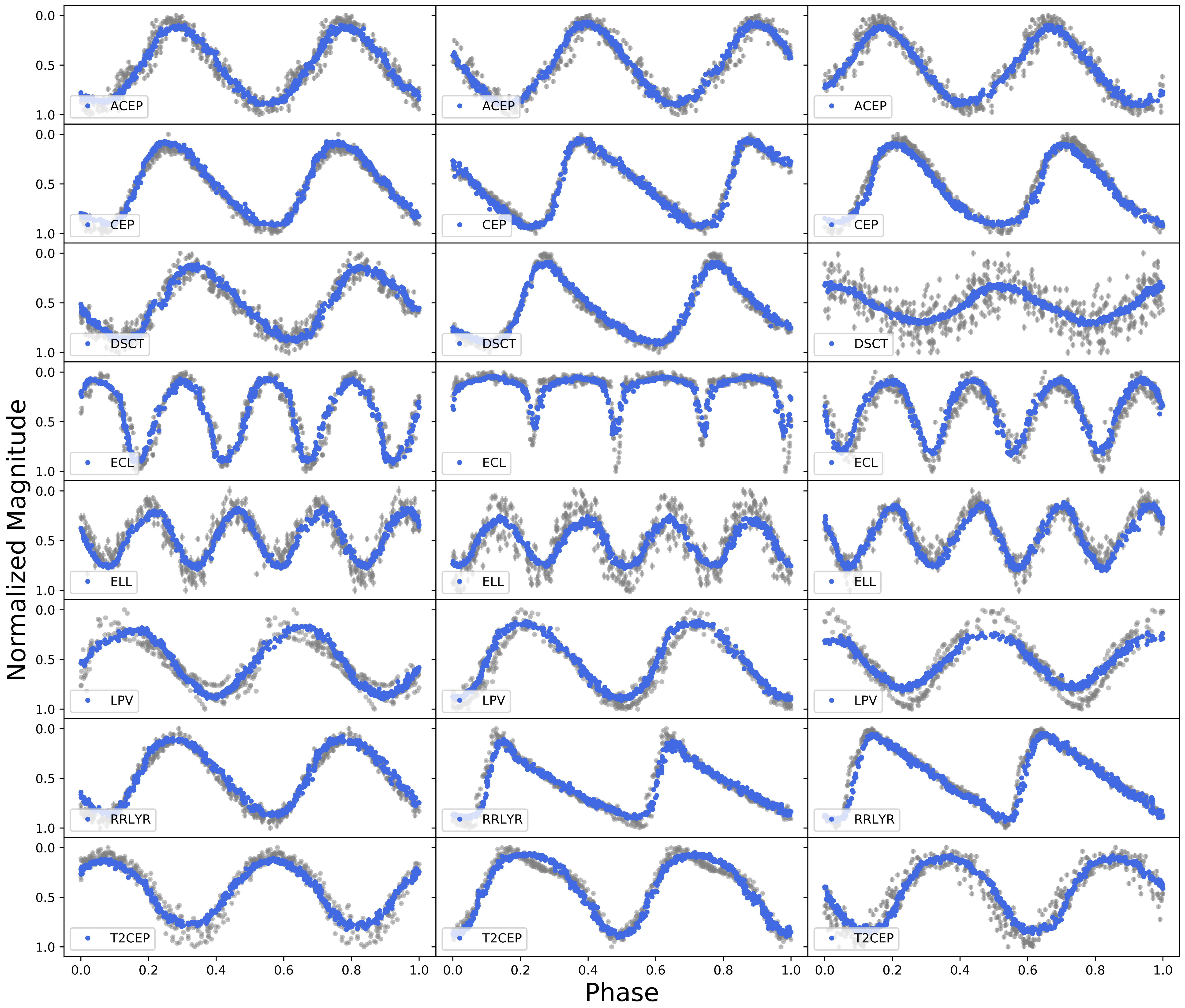
Training and LC reconstruction

Martinez-Palomera et al. 2020

TCN layers:

- converge marginally faster
- Reached a smaller loss values w/r to GRU





Generating new light curves

Martinez-Palomera et al. 2020

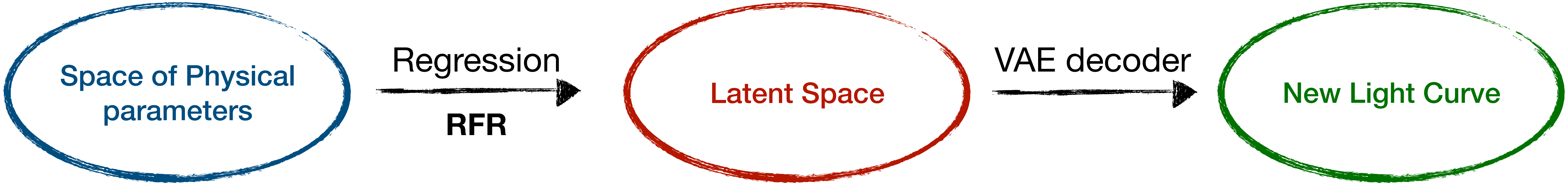
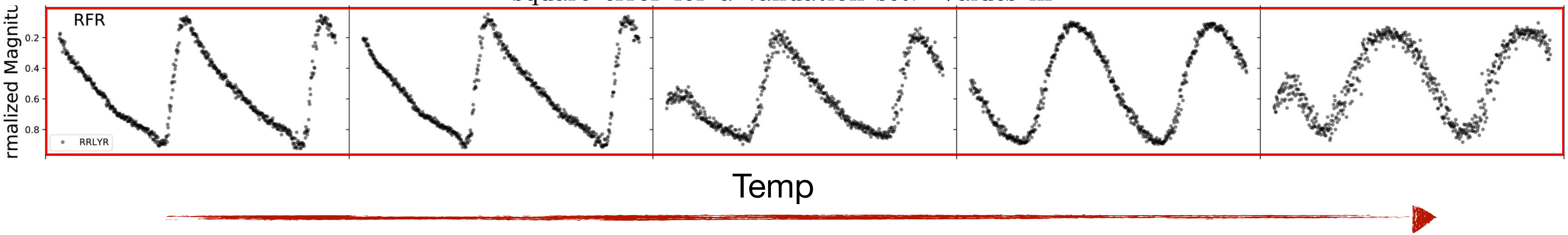


Table 3. Latent-Physical space regression

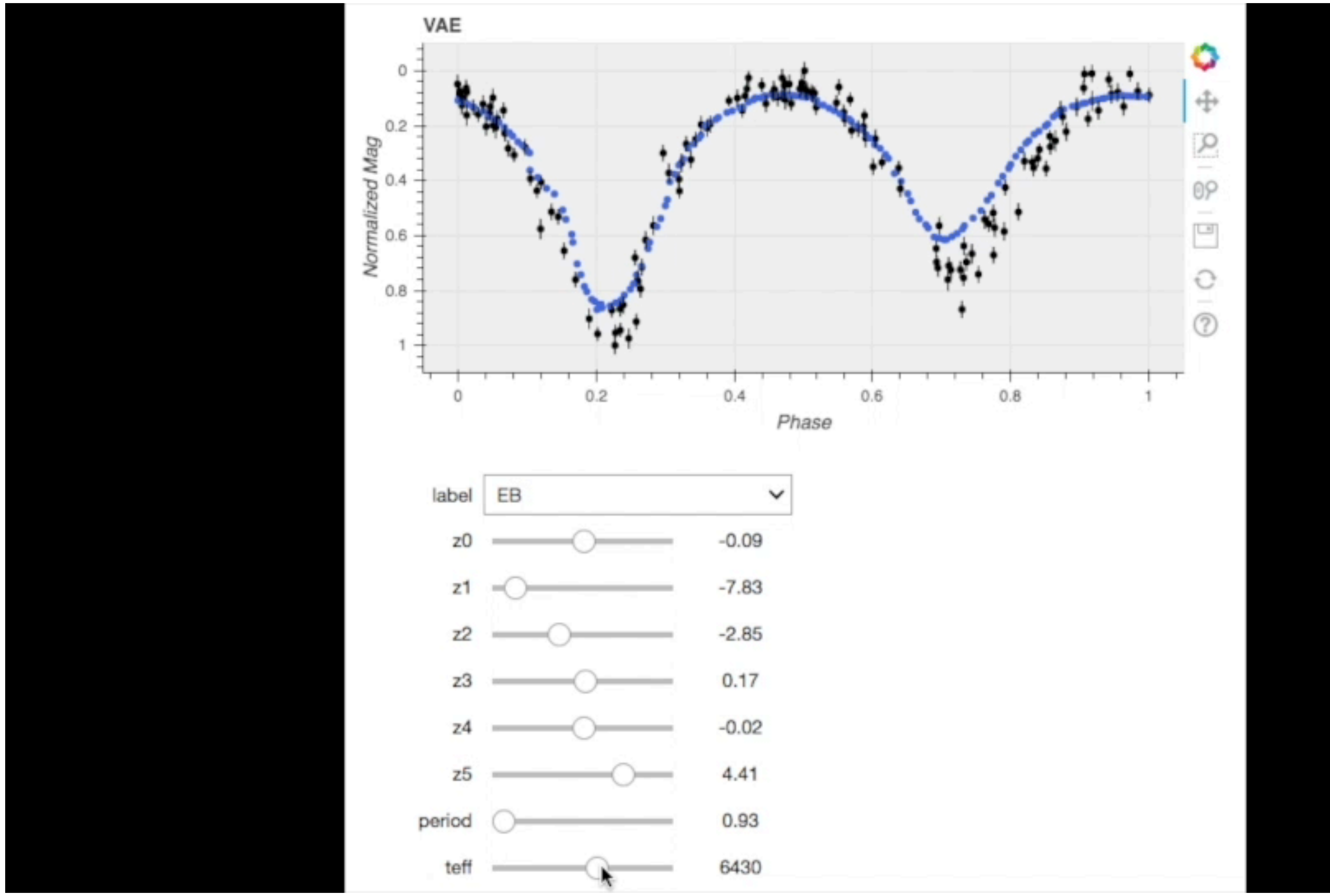
Generative Model	cVAE	cVAE-P
Linear	0.863	0.794
Random Forest	**0.299**	**0.289**
Multi-Layer Perceptron	0.863	0.798

NOTE—Values correspond to the root-mean-square error for a validation set. Values in



Summary

- We successfully trained a VAE able to reproduce periodic time series
- Embedded physical parameters into the latent space
- Mapping (regression) between the Latent and Physical space enables to generate new light curves for a given set of stellar parameters.
- Generated light curves are conditioned to the variability class
- Generated light curves are “tagged” with the observing time, allowing to mimic different survey observing cadences
- Unfortunately, the training set did not allow for exploration of more stellar parameters.



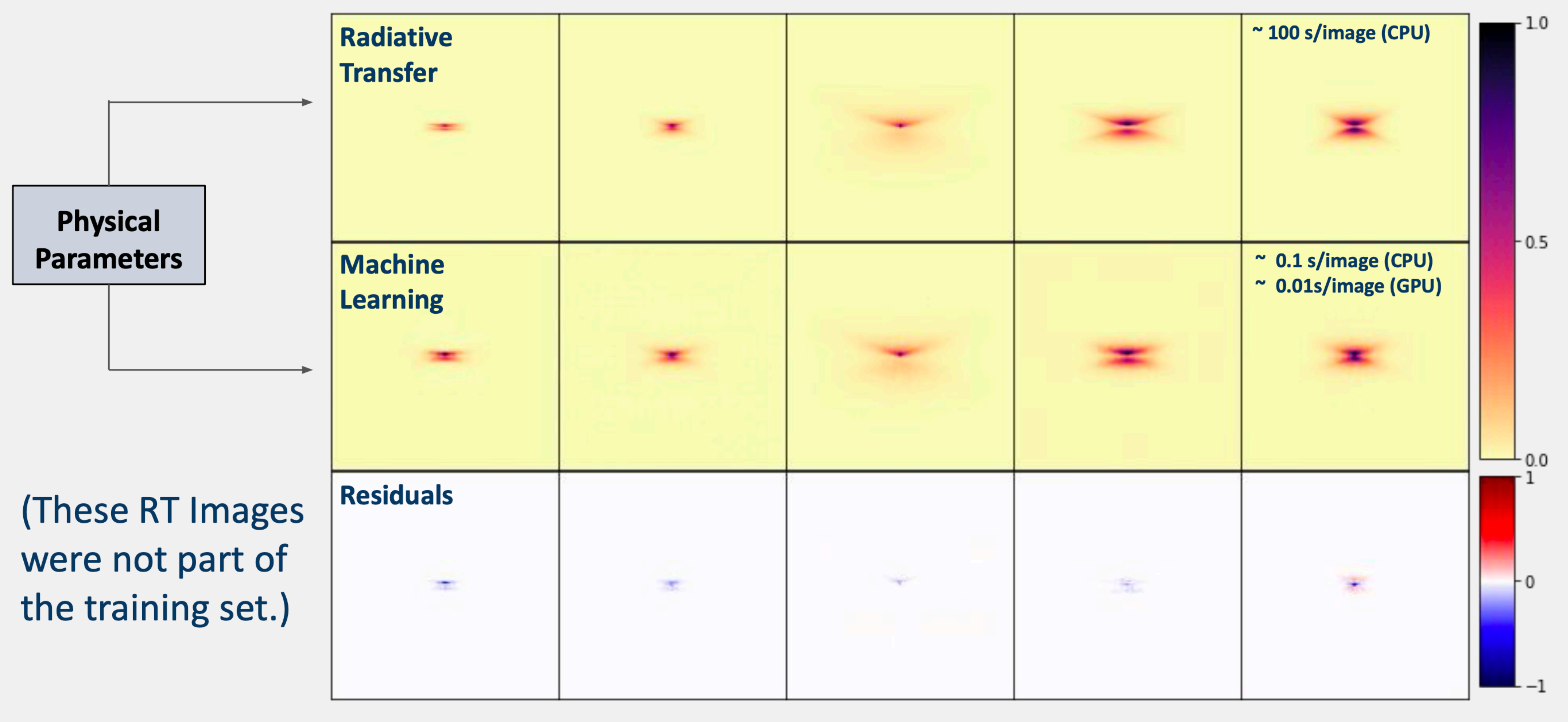
Advertising

Bay Area Environmental Research Institute

We are applying a similar approach of generative modeling with physical parameters to images of edge-on protoplanetary disks

To hear more about it, tomorrow (Thu 18th), **Zoie Telkamp** (UCB grad) will present about this work during the lunch talks at the Astro Department (3:30 pm)

“Developing a physics-aware neural network to generate edge-on protoplanetary disk images”



Thanks