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Interpretable Learning of Effective Dynamics for multiscale systems

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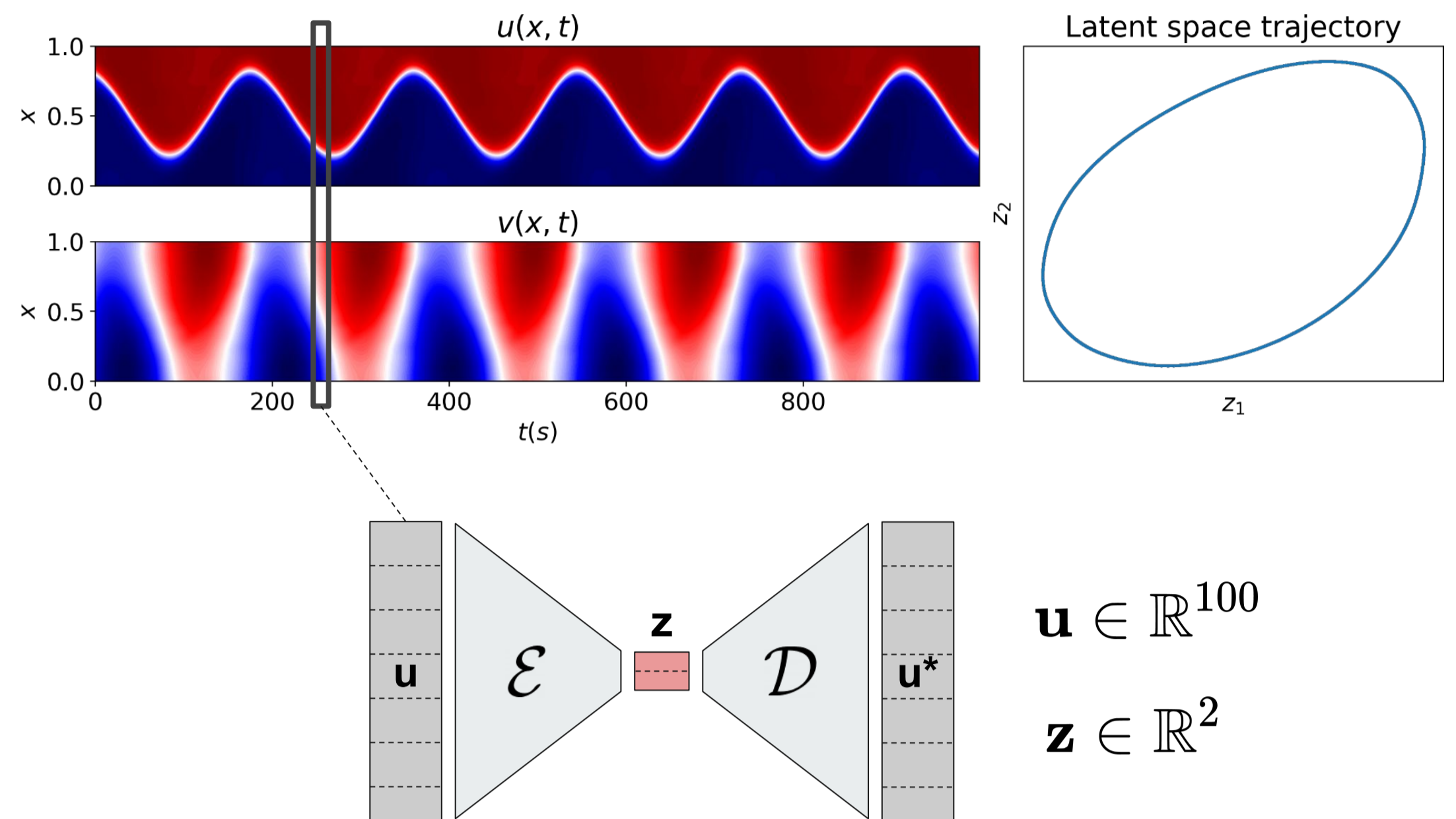
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Dimensionality Reduction

Neural AutoEncoders can be used to identify low dimensional representation spaces for dynamical systems. On the left, the 1D Fitz-Hugh Nagomo model is reduced from a representation on a 100 points spatial mesh to two latent coordinates (z_1 and z_2).

Unfortunately, the dynamics of this low dimensional representation are a-priori unknown :

$$\frac{dz}{dt} = ?$$



Form of the Dynamics

$$\frac{dz}{dt} = \mathbf{A}z + \mathbf{B}_\infty \int_0^t e^{\mathbf{D}_\infty s} \mathbf{C}_\infty \mathbf{z}_s ds + \mathbf{F}(t)$$

Results from dynamical systems theory, mainly the theory of the Koopman Operator (see [1]) can be used to derive an ansatz for the reduced dynamics.

The proposed form of the dynamics requires the learning of two linear operators (\mathbf{A} and $\mathbf{\Lambda}$) and two neural networks (Ψ_1 and Ψ_2).

$$\frac{dz}{dt} = \mathbf{A}_\theta z + \Psi_1 \left[\int_{-\infty}^t e^{\mathbf{\Lambda}_\theta(t-s)} \Psi_2(\mathbf{z}_s) ds \right]$$

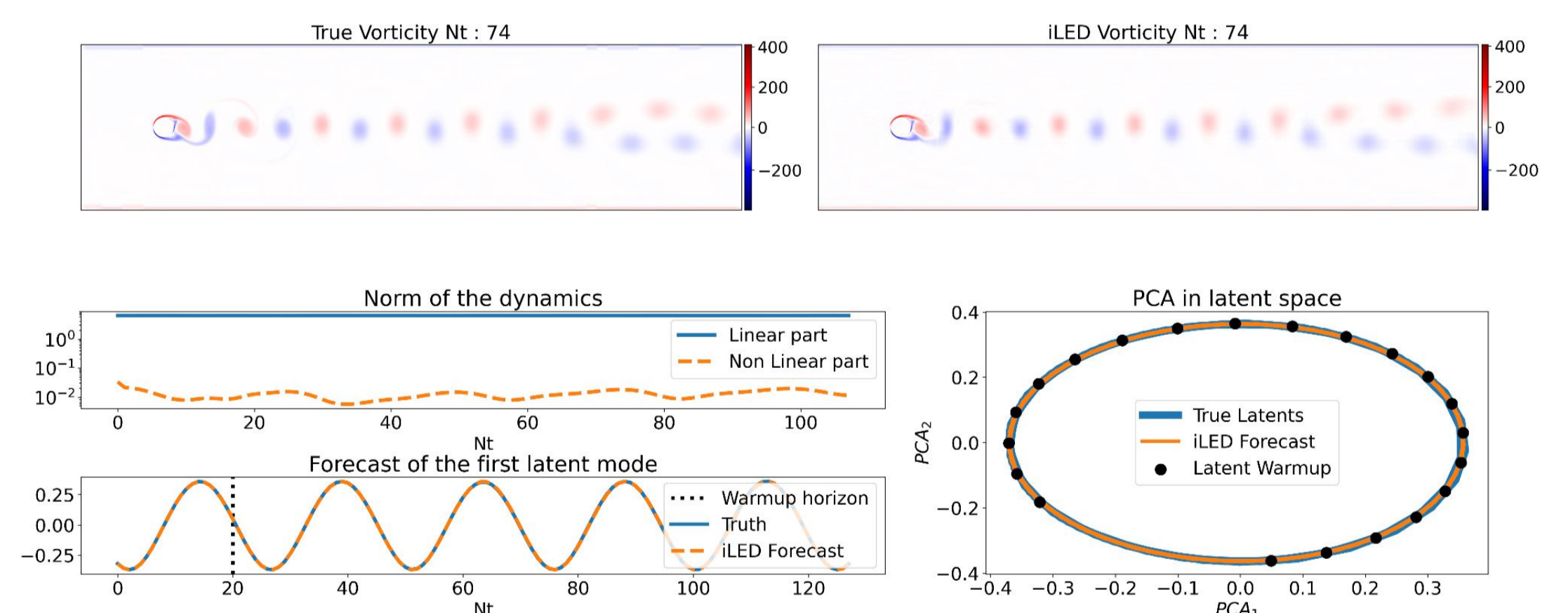
Markovian Part

Memory Effects

Application : Cylinder Flow

The 2D cylinder flow can also be reduced to a two dimensional representation. After training the proposed dynamical model, a model is obtained, able to forecast the state of the system efficiently and accurately for multiple periods of the system.

It is interesting to note that the dynamics are almost completely linear, yielding a highly interpretable model.



Application : Kuramoto-Sivashinsky

The method is able to learn chaotic dynamics as well. In these cases, the non-linear memory effects become critical to the model.

