Learning Nonlinear Dynamics: Variational Autoencoders

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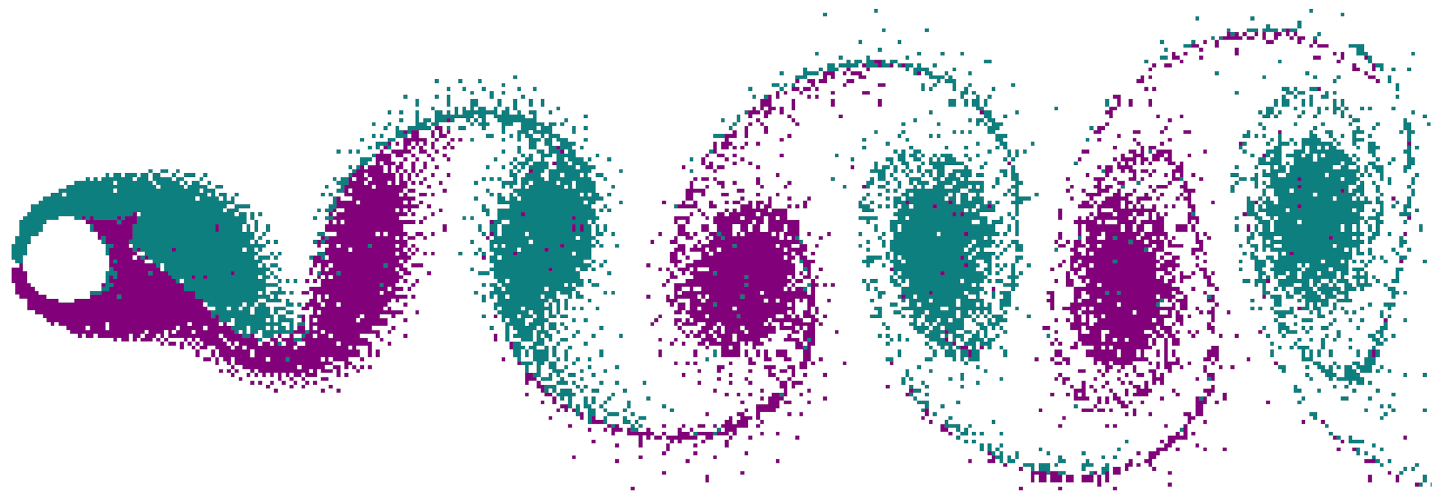
Motivation

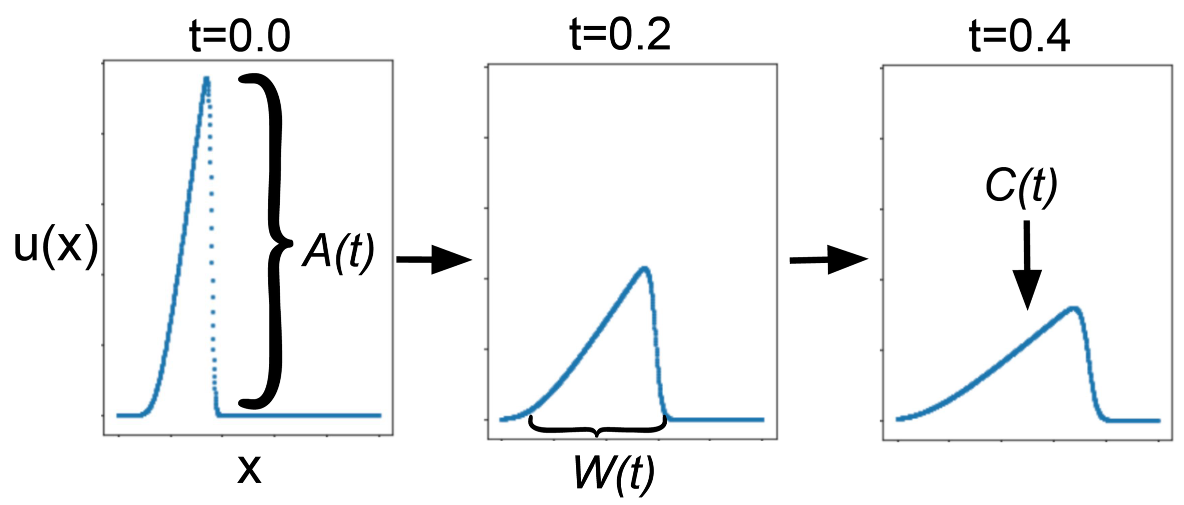
- For some time critical applications, current physics simulation methods are not fast enough.
- This is because they must resolve an enormous amount of microscopic features of the system.
- In practice, we would like a method for evolving only the macroscopic features of interest.
- We propose a data-driven technique for doing this based on Variational Autoencoders (VAEs).



Vortex shedding is shown above. Instead of calculating the position of every single fluid particle, it would be faster to keep track of the larger spirals. Image courtesy of Cesareo de La Rosa Siqueira.

Concept

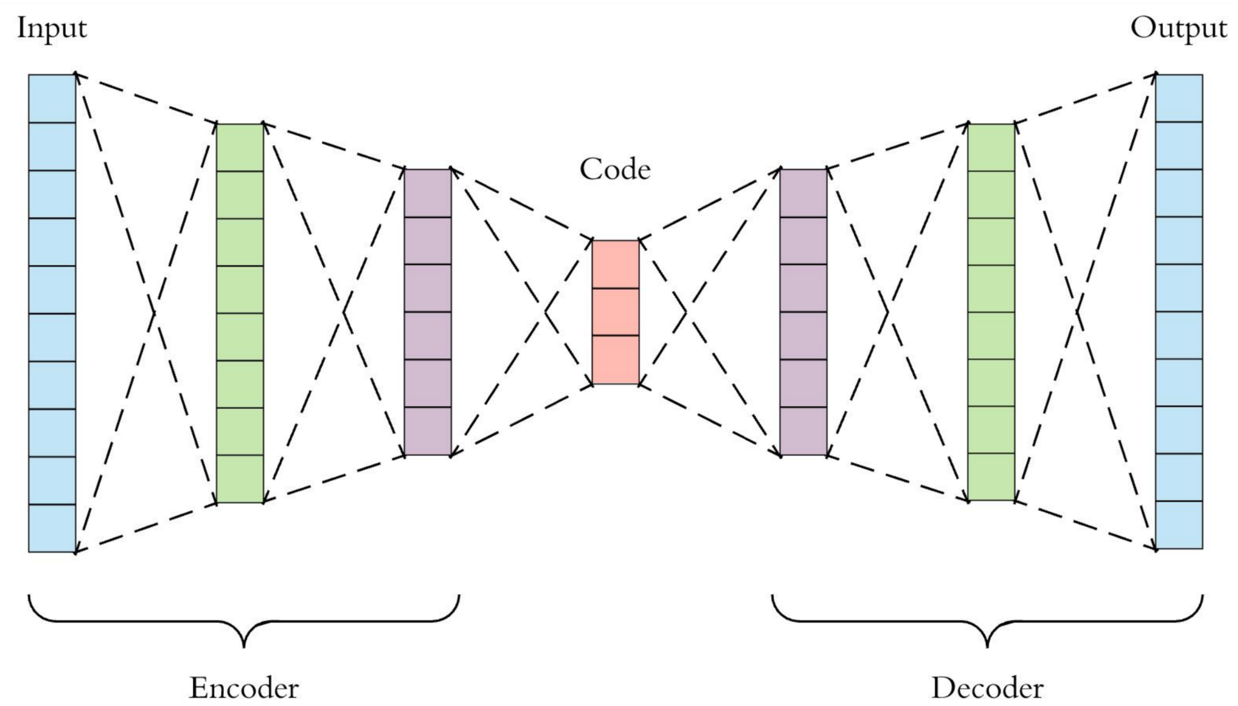
- High dimensional data can often be described by only a few key features.
- Consider the case of a traveling shock wave (shown below).



- This wave can be described by three latent variables: amplitude $A(T)$, width $W(t)$, and center $C(t)$.
- It is much easier to work with these latent variables than all the data points.

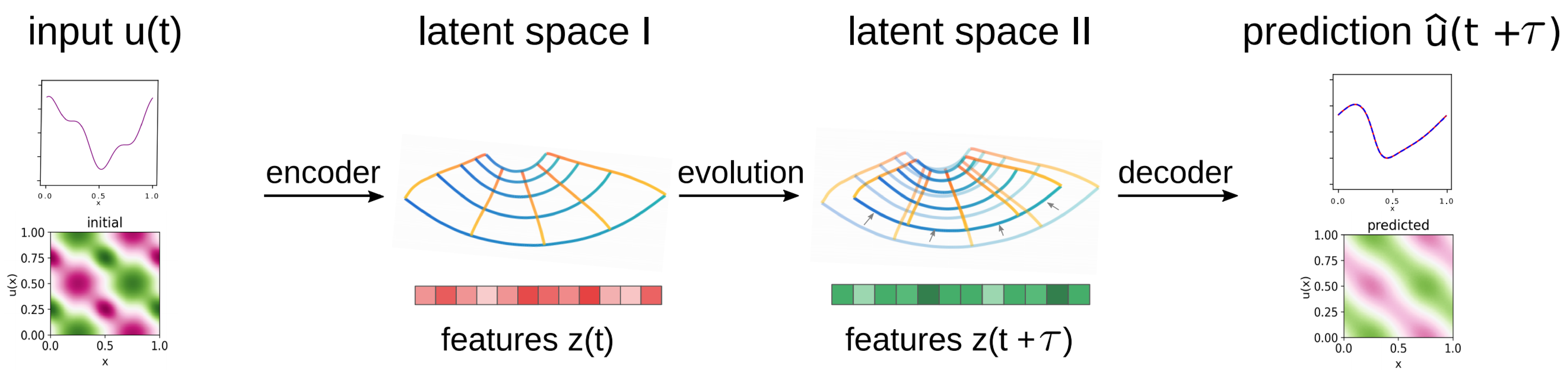
Method

- VAEs are a machine learning technique for dimensionality reduction.
- An Autoencoder (AE) is a bottlenecked neural network consisting of an encoder followed by a decoder. The AE is trained to reconstruct the input data, meaning the the latent code variables must completely describe the data.



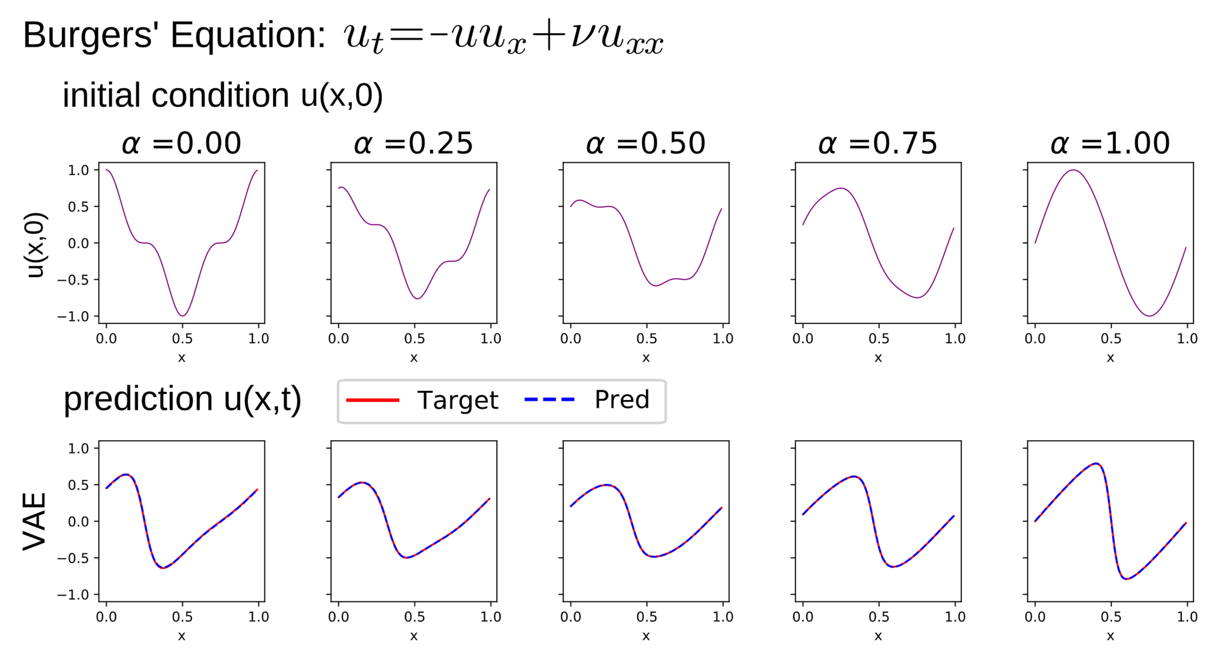
SRC: Arden Dertat, towardsdatascience.com

- Dynamics are modeled by first encoding the data, then performing time evolution in the low dimensional latent space, then decoding into the predicted evolved data.

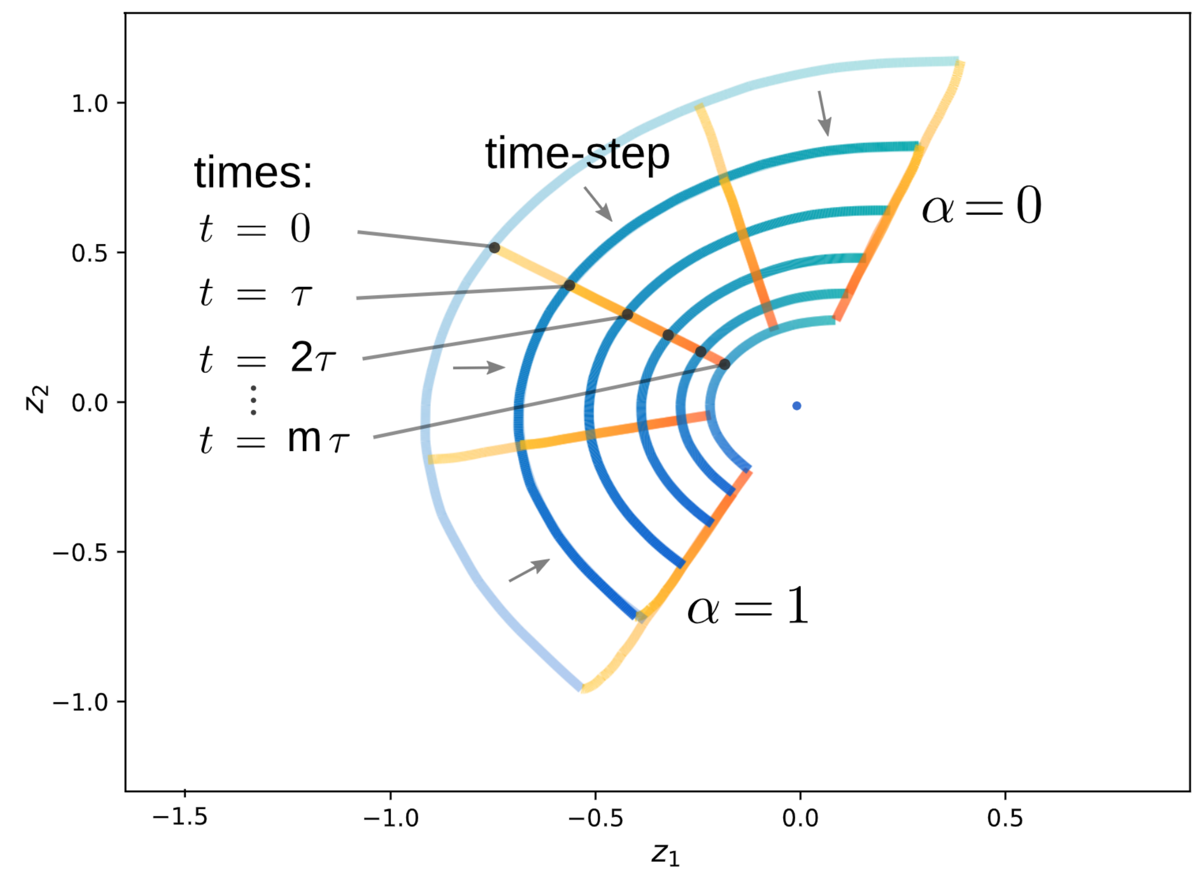


Results

Dynamics under the 1D nonlinear Burgers' PDE shown. Initial conditions are parameterized by α.



Plot of latent space shows that VAE learns a disentangled representation of the data.



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