KU LEUVEN

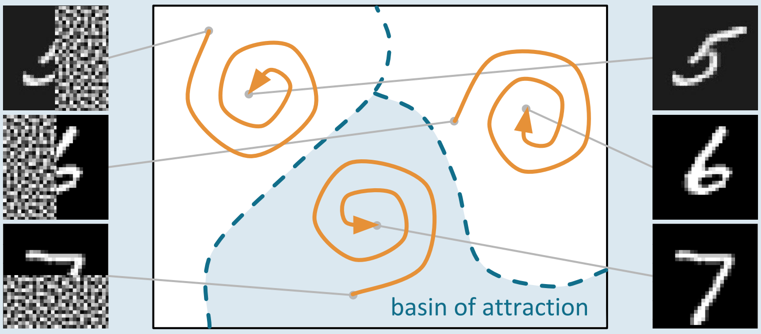
Deep Contractive Least Squares Support Vector Machines for associative memory

Goal - Modelling auto-associative memory

We model memory with a discrete dynamical system

$$\boldsymbol{x}^{(k+1)} = f(\boldsymbol{x}^{(k)}),$$

whose stable equilibria are the memories to store. This way, as the state evolves, it gradually converges to a memory, and thereby reconstructs it.



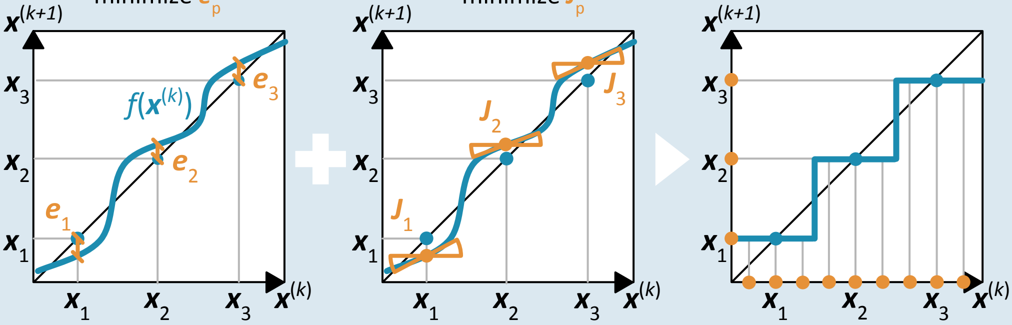
Proposed solution - Combining LS-SVMs[1] and C-AEs[2] into C-LS-SVMs

[1]Least Squares SVMs
[2]Contractive autoencoders

We describe the dynamical system by the update equation

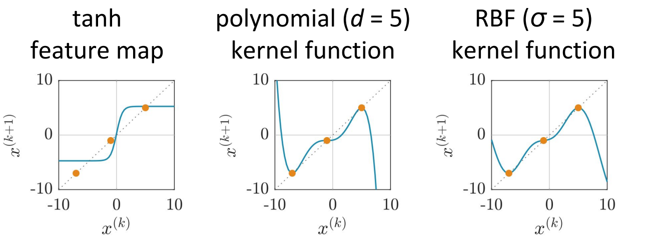
$$\boldsymbol{x}^{(k+1)} = f(\boldsymbol{x}^{(k)}) = \boldsymbol{W}^\top \varphi(\boldsymbol{x}^{(k)}) + \boldsymbol{b}.$$

The parameters $\boldsymbol{W}$ and $\boldsymbol{b}$ result from a convex optimization problem that balances an **equilibrium objective**, and a **local stability objective**.



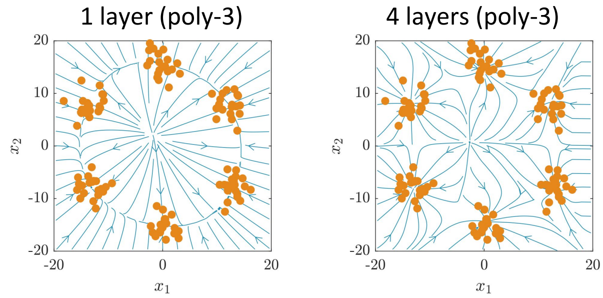
Results

Shallow C-LS-SVMs



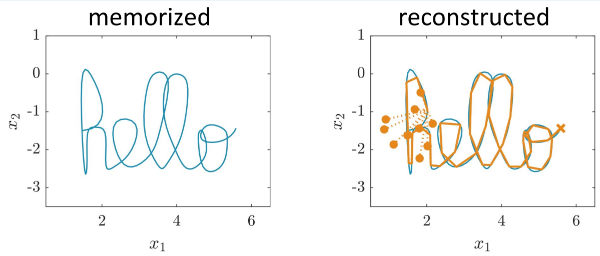
A C-LS-SVM can use a wide range of feature maps $\varphi(\boldsymbol{x})$, either defined explicitly, such as the tanh feature map, or defined implicitly by a positive definite kernel function.

Deep C-LS-SVMs



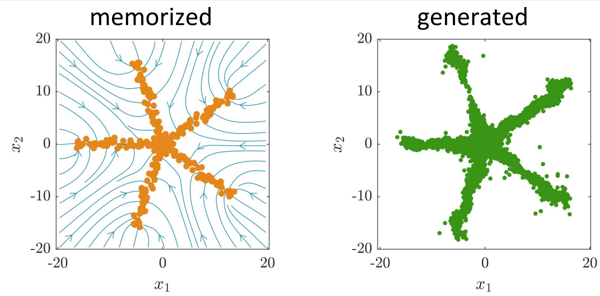
Deep C-LS-SVMs more accurately store the memories (•).

C-LS-SVMs that memorize movements



The C-LS-SVM reconstructs the memorized movement well from noisy initial conditions (•) up to the end (×).

Generative C-LS-SVMs



The generated points precisely populate the data manifold.

Master of Science in **Mathematical Engineering**

Master Thesis **Octave Oliviers**

Thesis supervisor **Prof. dr. ir. Johan Suykens**

Mentors **Ir. Henri De Plaen** **Ir. Arun Pandey**