Deep Contractive Least Squares Support Vector Machines for associative memory

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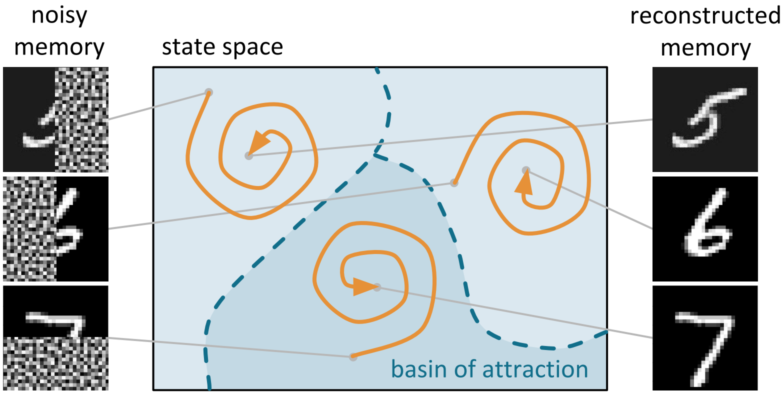
Goal - Modelling auto-associative memory

We model memory with a discrete dynamical system

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

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



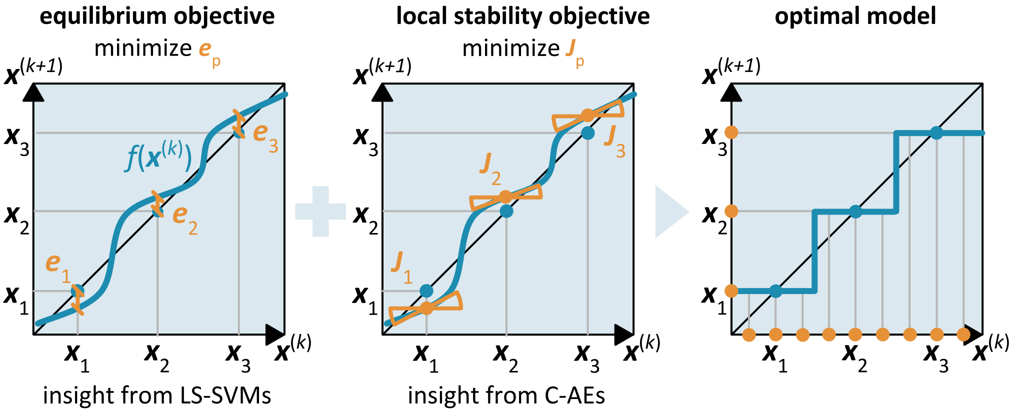
Proposed solution - Combining LS-SVMs[1] and C-AEs[2] into C-LS-SVMs

[1]Least Squares SVMs
[2]Contractive autoencoders

We describe the dynamical system by the update equation

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

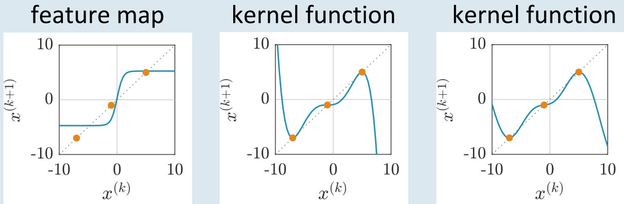
The parameters W and b result from a convex optimization problem that balances an **equilibrium objective**, and a **local stability objective**.



Results

Shallow C-LS-SVMs

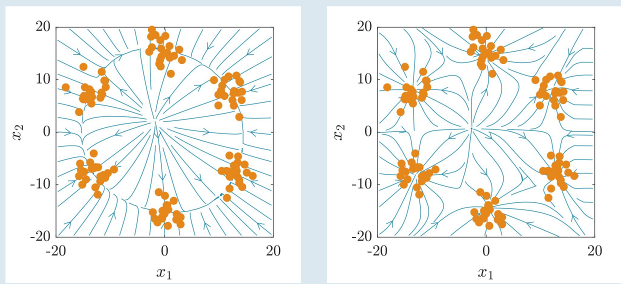
tanh feature map | polynomial (d = 5) kernel function | RBF (σ = 5) kernel function



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

Deep C-LS-SVMs

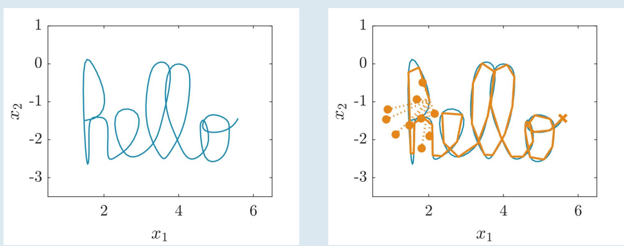
1 layer (poly-3) | 4 layers (poly-3)



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

C-LS-SVMs that memorize movements

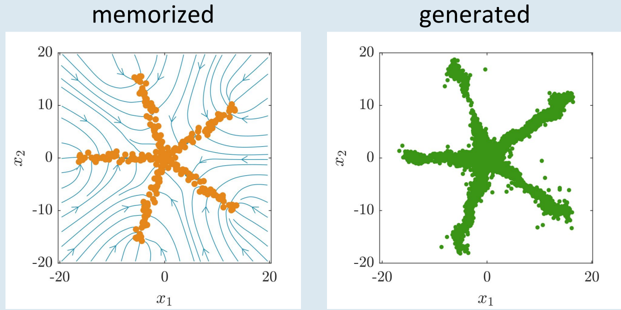
memorized | reconstructed



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

Generative C-LS-SVMs

memorized | generated



The generated points precisely populate the data manifold.

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