Linear State-Space Model with **Time-Varying Dynamics**

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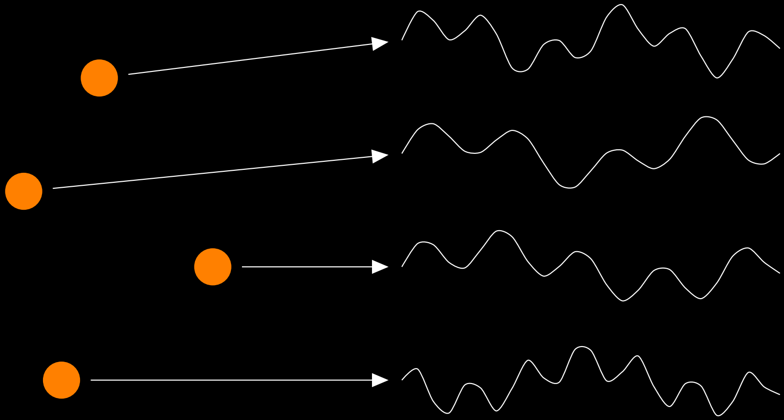
Spatio-temporal data



arbitrary
locations

equispaced
time instances

Statistical modelling
of
physical processes
with
changing parameters

Stochastic advection-diffusion process

Simulated process: $$\frac{\partial f}{\partial t} = \delta \nabla^2 f - \mathbf{v} \cdot \nabla f + R,$$

Stochastic advection-diffusion process

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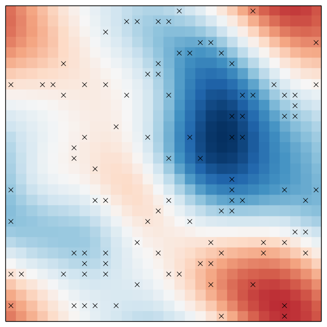
velocity field
varies in time

Video



Linear state-space model

Observations: $\mathbf{y}_n = \mathbf{C}\mathbf{x}_n + \text{noise},$

Latent states: $\mathbf{x}_n = \mathbf{W}_n\mathbf{x}_{n-1} + \text{noise},$

Linear state-space model

Observations: $\mathbf{y}_n = \mathbf{C}\mathbf{x}_n + \text{noise},$

Latent states: $\mathbf{x}_n = \mathbf{W}_n\mathbf{x}_{n-1} + \text{noise},$

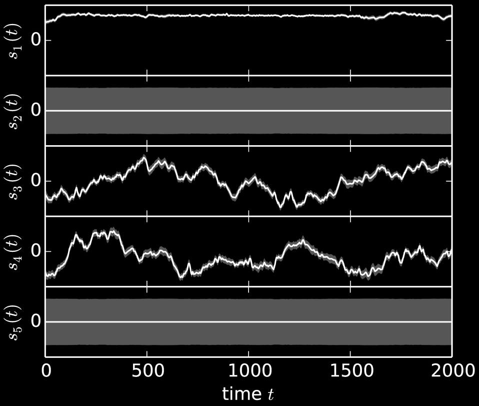
with time-varying dynamics

State dynamics: $\mathbf{W}_n = \sum_{k=1}^{K} s_{kn}\mathbf{B}_k,$

Mixing weights: $\mathbf{s}_n = \mathbf{A}\mathbf{s}_{n-1} + \text{noise},$

Variational
Bayes

Posterior of **the mix weights**



Predictive **RMSE**

	Experiment				
Dynamics	1	2	3	4	5
Constant	104	107	102	94	104
Switching	106	117	113	94	102
Time-varying	**73**	**81**	**75**	**67**	**82**

Implementation available

BayesPy

Python package

Conclusion

Efficient modelling of time-varying dynamics