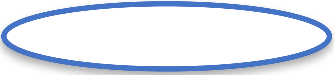
Lancaster University



For separable kernel $k = k_{space}k_{time}$, the spectral density is the product $S(\omega_1, \omega_2) = S_{space}(\omega_1)S_{time}(\omega_2)$.

When k_{time} admits the SDE form, we have $S(\omega_1, \omega_2) = \dfrac{\sigma^2 S_{space}(\omega_1)}{L(e^{i\omega_2})L(e^{-i\omega_2})}$.

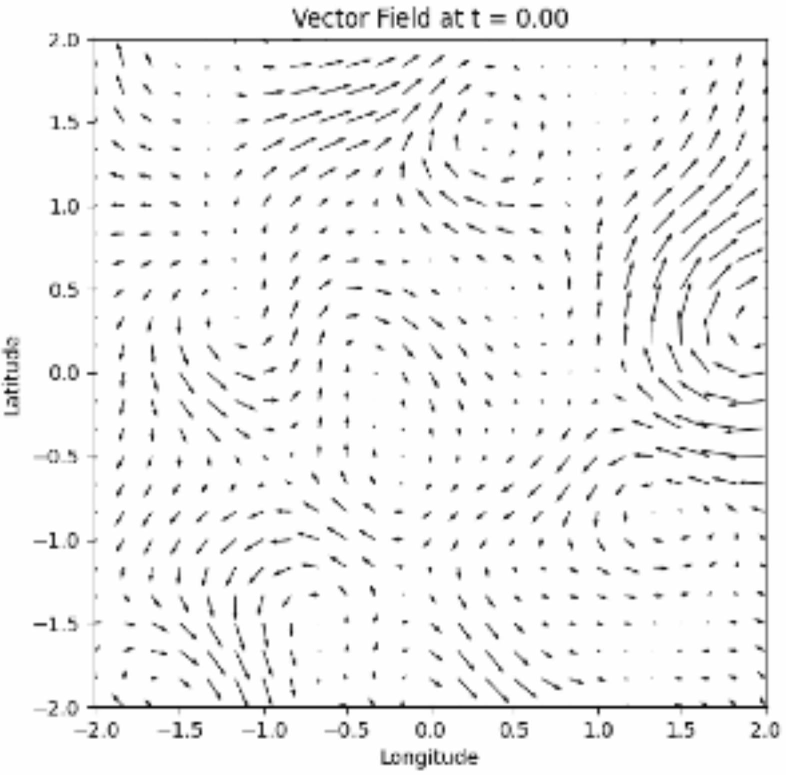
same dynamics

different white noise

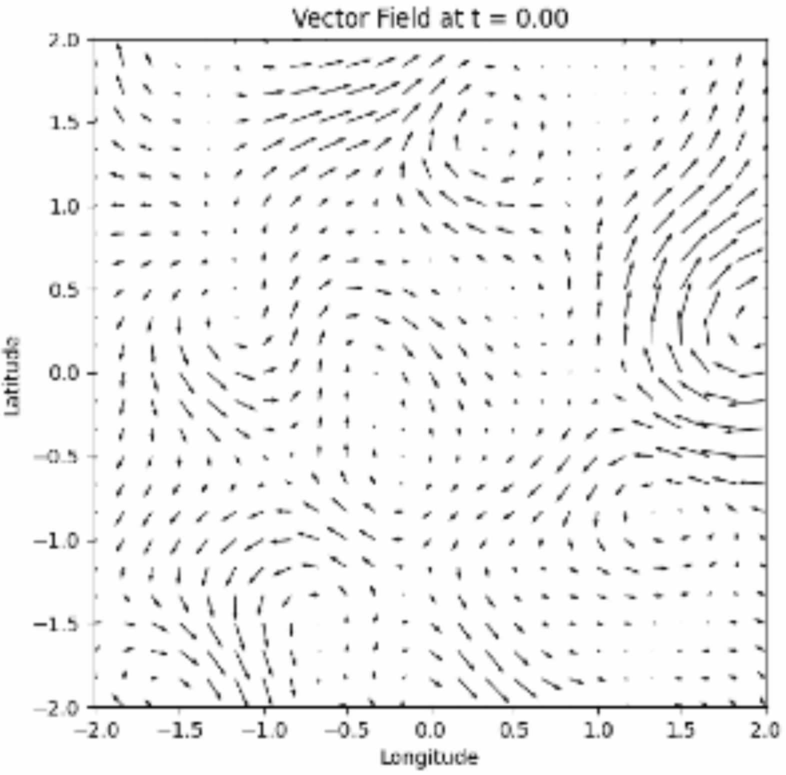
$$\nabla_t \boldsymbol{f}(\boldsymbol{x}, t) = F_{full} \boldsymbol{f}(\boldsymbol{x}, t) dt + L_{full} d\boldsymbol{w}(x, t)$$

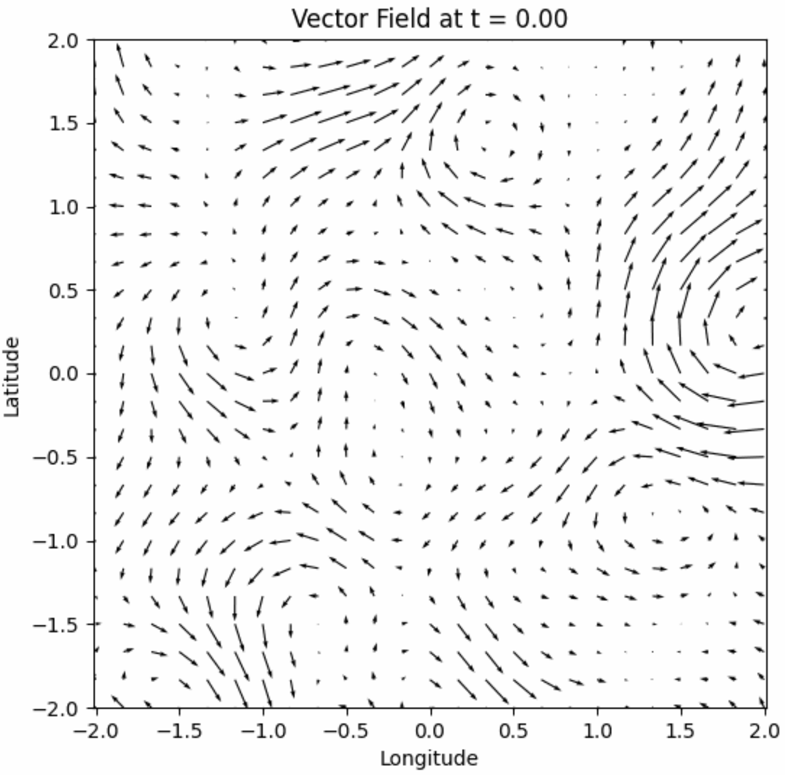
Sarkka, S., Solin, A. and Hartikainen, J. (2013). Spatio-Temporal learning via infinite-dimensional Bayesian filtering and smoothing: A look at Gaussian process regression through Kalman filtering, *IEEE Signal Processing Magazine* 30(4): 51–61.

Gaussian Processes [Dynamic]



Vector Field at t = 0.00
Latitude
Longitude
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

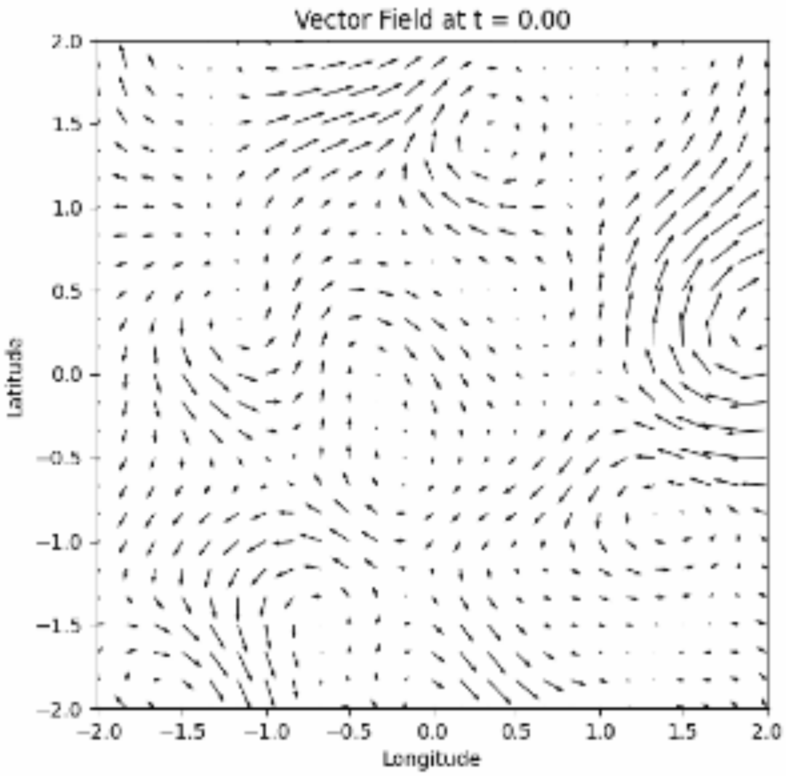

Vector Field at t = 0.00
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
Latitude
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Longitude



Vector Field at t = 0.00
Latitude
Longitude
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

Sarkka, S., Solin, A. and Hartikainen, J. (2013). Spatio-Temporal learning via infinite-dimensional Bayesian filtering and smoothing: A look at Gaussian process regression through Kalman filtering, *IEEE Signal Processing Magazine* 30(4): 51–61.

Gaussian Processes [Dynamic]



$_{ie}$, the spectral density is the product $S(\omega_1, \omega_2) = S_{space}(\omega_1)S_{time}(\omega_2)$.

different white noise

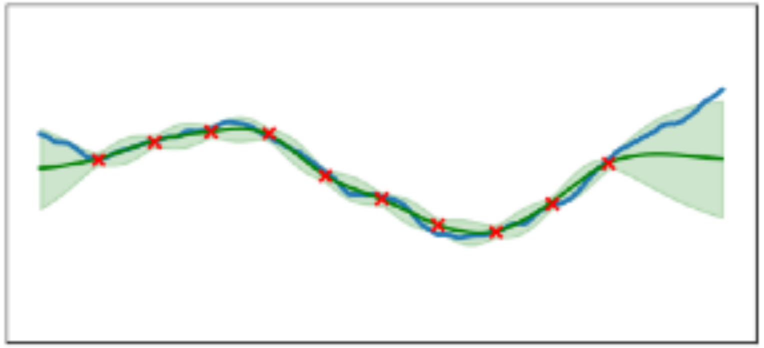
the SDE form, we have $S(\omega_1, \omega_2) = \dfrac{\sigma^2 S_{space}(\omega_1)}{L(e^{i\omega_2})L(e^{-i\omega_2})}$.

same dynamics

$_t\, \boldsymbol{f}(\boldsymbol{x}, t) = F_{full}\boldsymbol{f}(\boldsymbol{x}, t)dt + L_{full}d\boldsymbol{w}(x, t)$

Vanilla-SPDE Exchange (VASE)

Static



Dynamic