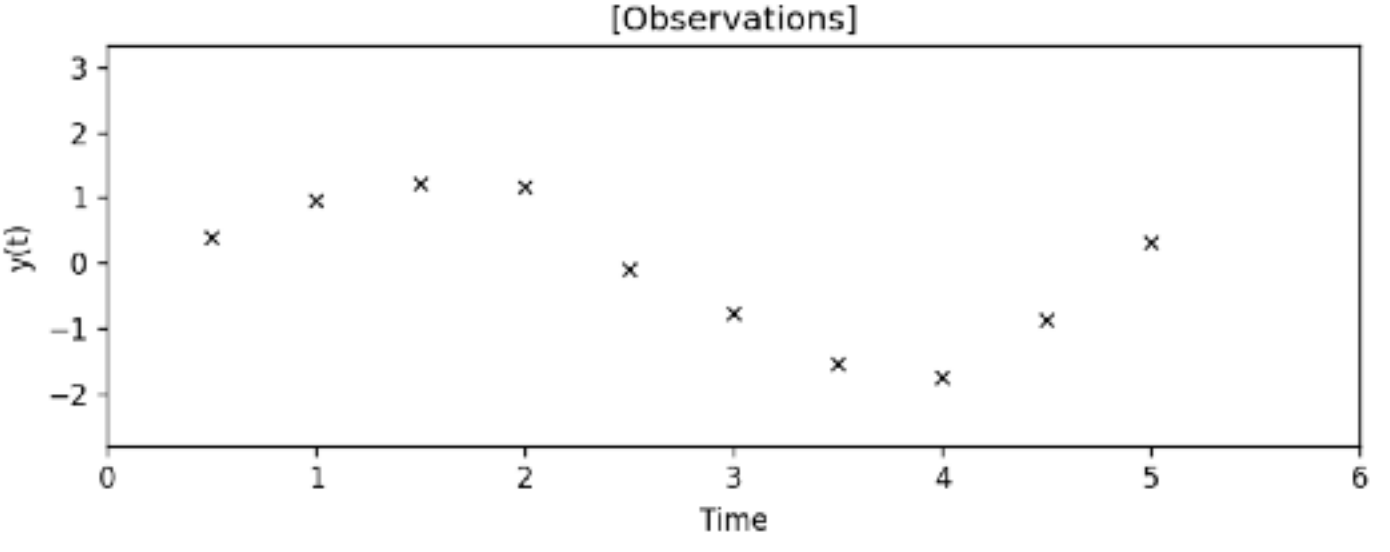

Lancaster
University

# Gaussian Processes [Dynamic]

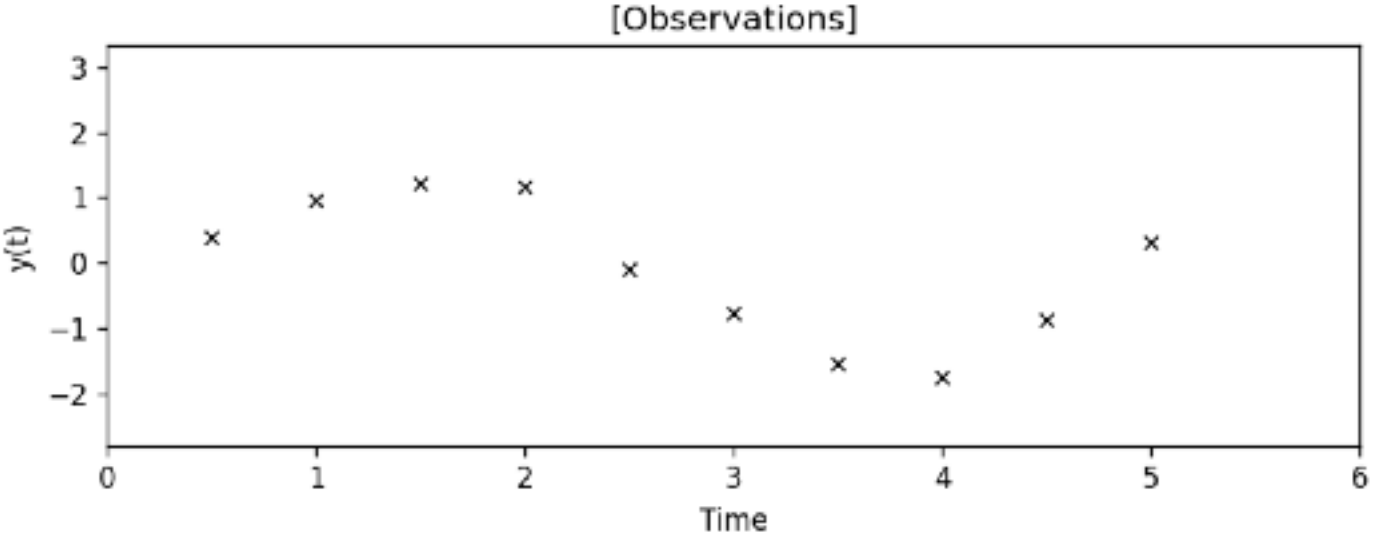
$$f''(t) + 2\lambda f'(t) + \lambda^2 f(t) = \varepsilon(t)$$

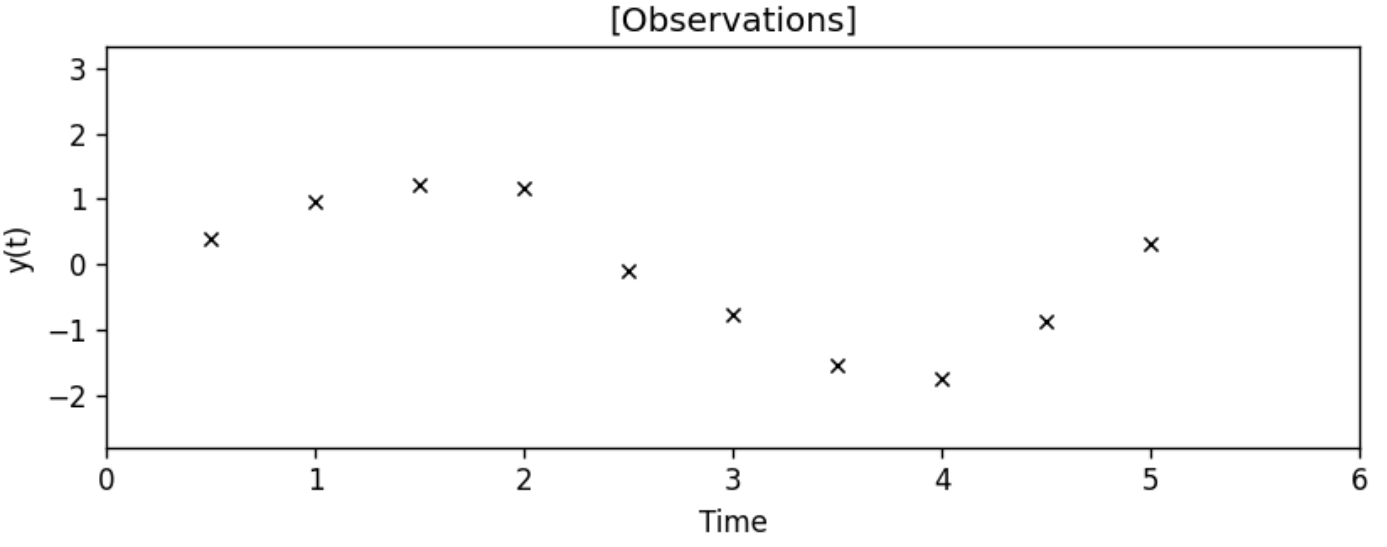
**Linear SDE**

- produce exact transition density
- observations are linear emission
- admit sequential inference via Kalman filter & smoother


[Observations]
y(t)
Time
3
2
1
0
−1
−2
0
1
2
3
4
5
6

Hartikainen, J. and Särkkä, S. (2010). Kalman filtering and smoothing solutions to temporal Gaussian process regression models, *2010 IEEE international workshop on machine learning for signal processing*, IEEE, pp. 379– 384.


[Observations]
y(t)
Time
3
2
1
0
−1
−2
0
1
2
3
4
5
6


[Observations]
y(t)
Time
3
2
1
0
−1
−2
0
1
2
3
4
5
6

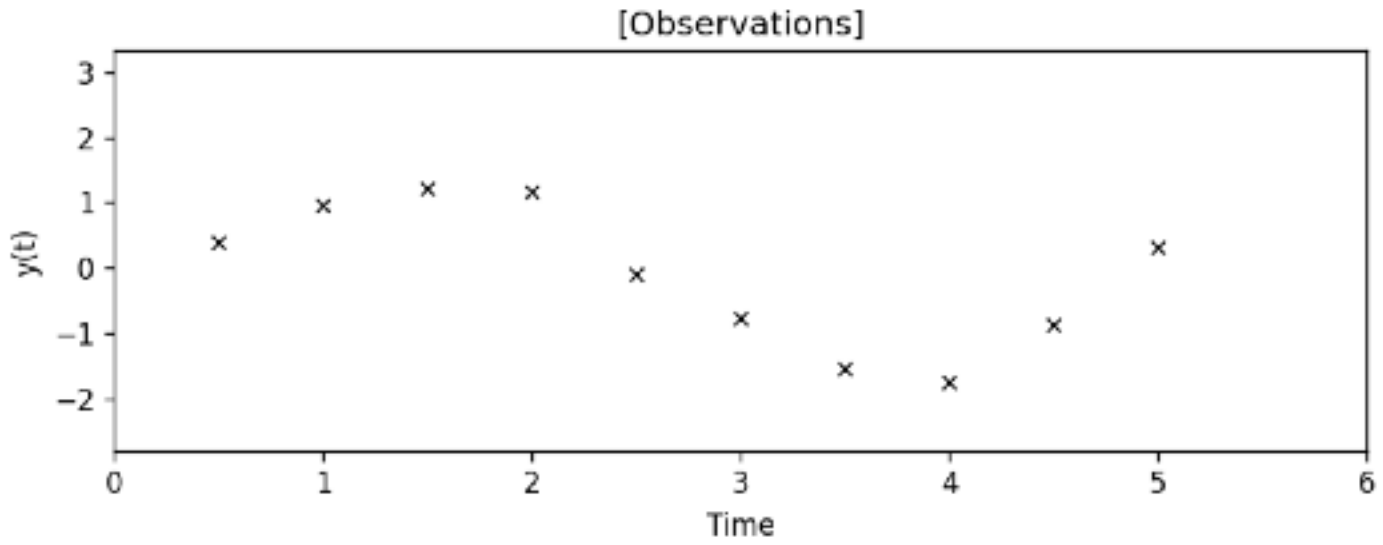
Hartikainen, J. and Särkkä, S. (2010). Kalman filtering and smoothing solutions to temporal Gaussian process regression models, *2010 IEEE international workshop on machine learning for signal processing*, IEEE, pp. 379– 384.

# Gaussian Processes [Dynamic]

Lancaster University

$$f''(t) + 2\lambda f'(t) + \lambda^2 f(t) = \varepsilon(t)$$

**Linear SDE**
- produce exact transition density
- observations are linear emission
- admit sequential inference via Kalman filter & smoother



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]

Lancaster University