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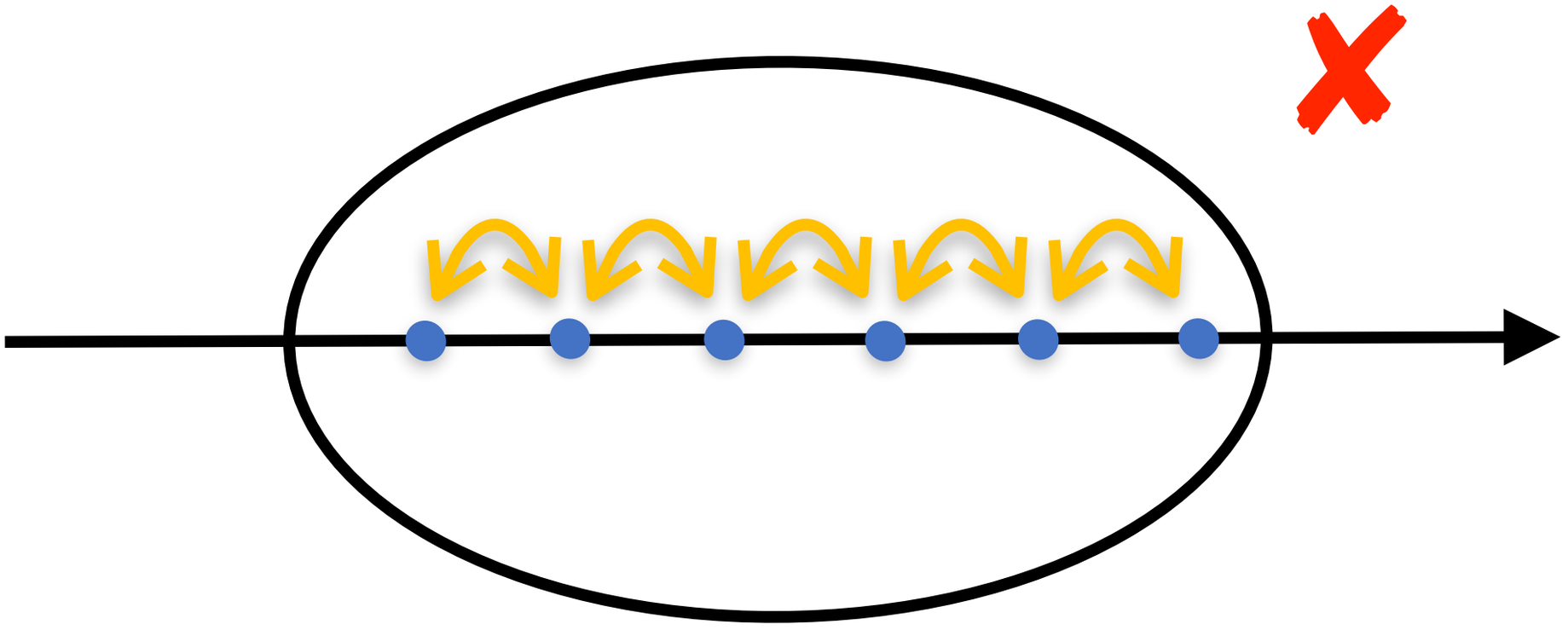
Gaussian Processes [Dynamic]



Goal: Find a filter L that

(1) matches with desired spectrum,

(2) is causal, i.e. future only depends on past.

Kalman filtering and smoothing solutions to temporal Gaussian process regression models

Publisher: IEEE

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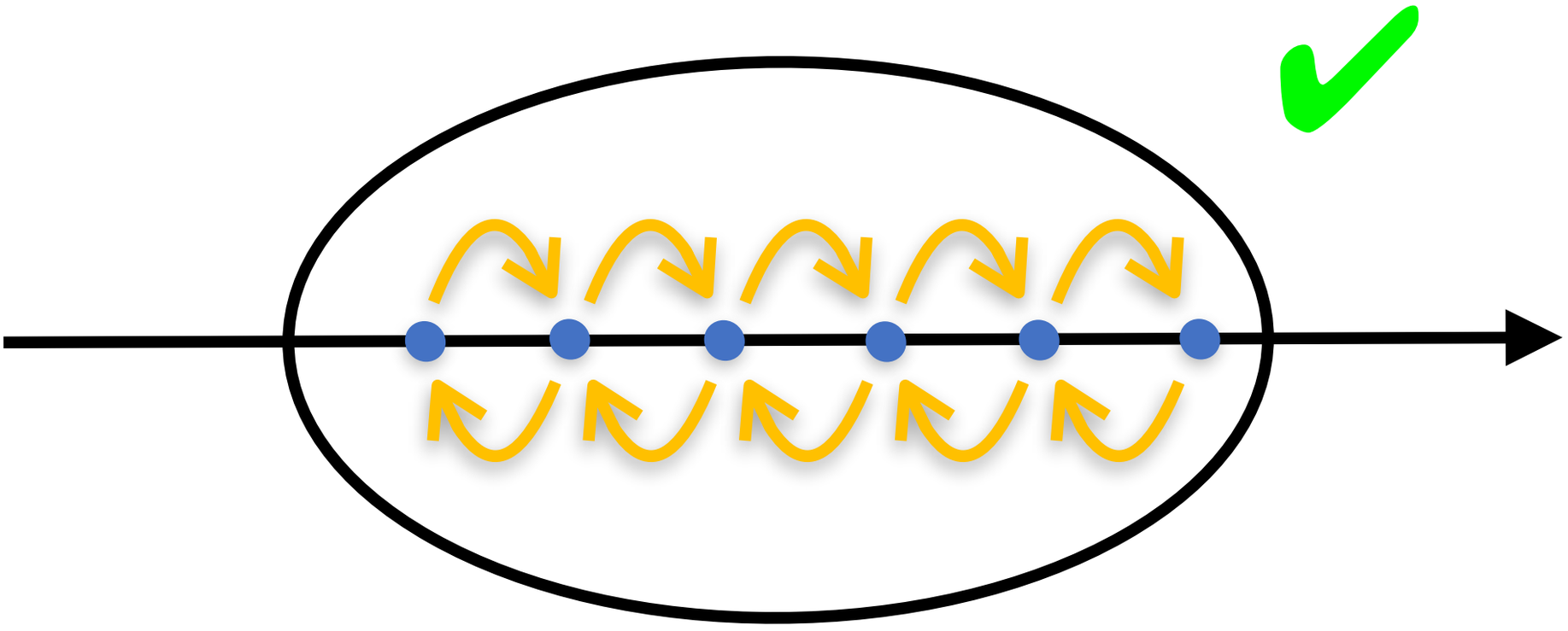
Jouni Hartikainen ; Simo Särkkä All Authors

The filter $(\lambda + \nabla)^{p+1}$ is causal and yields Matérn-$(p + 1/2)$ spectrum.

Example (Matérn-3/2): Solve for $f''(t) + 2\lambda f'(t) + \lambda^2 f(t) = \varepsilon(t)$.



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.

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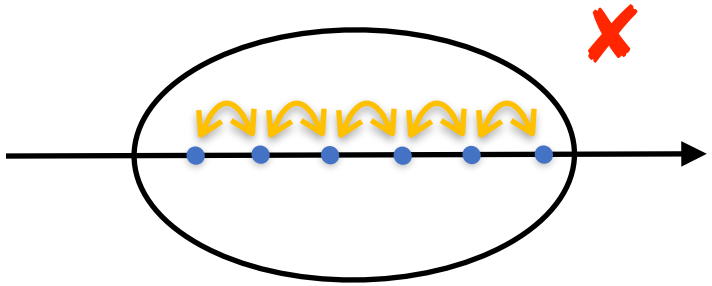

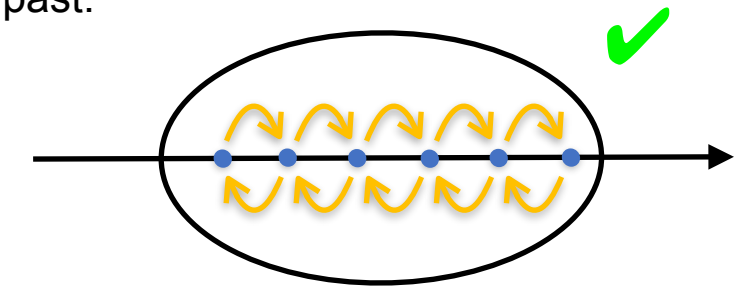

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