

THE DIFFUSION KERNEL FILTER

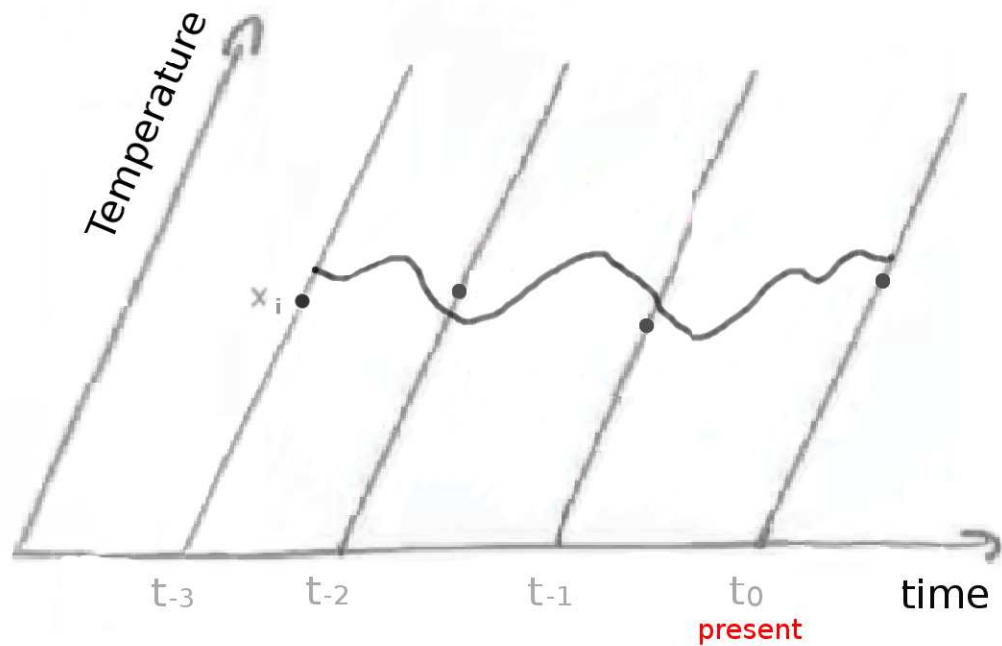
P. KRAUSE

In collaboration with J.M. Restrepo

University of Arizona
Mathematics

Sponsored by NSF

Bootstrap Filter

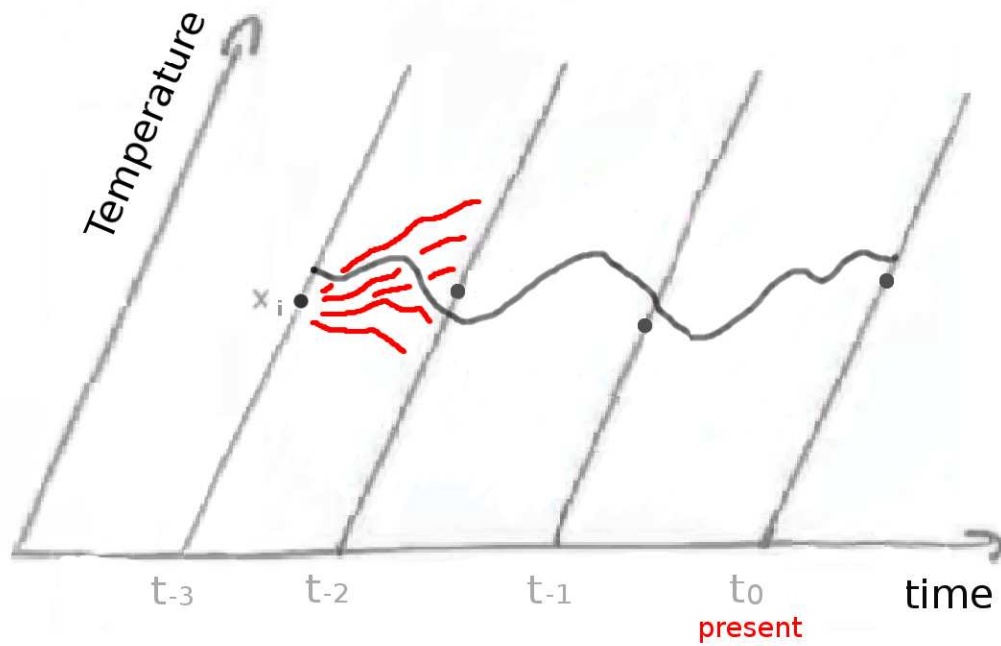


noisy measurements

Wish to sample $\Phi(x_i, t_0)$ corrected by past data, where Φ is the dynamics of a model

$$dT = f(T) dt + g(t, w) dw \text{ for temperature changes}$$

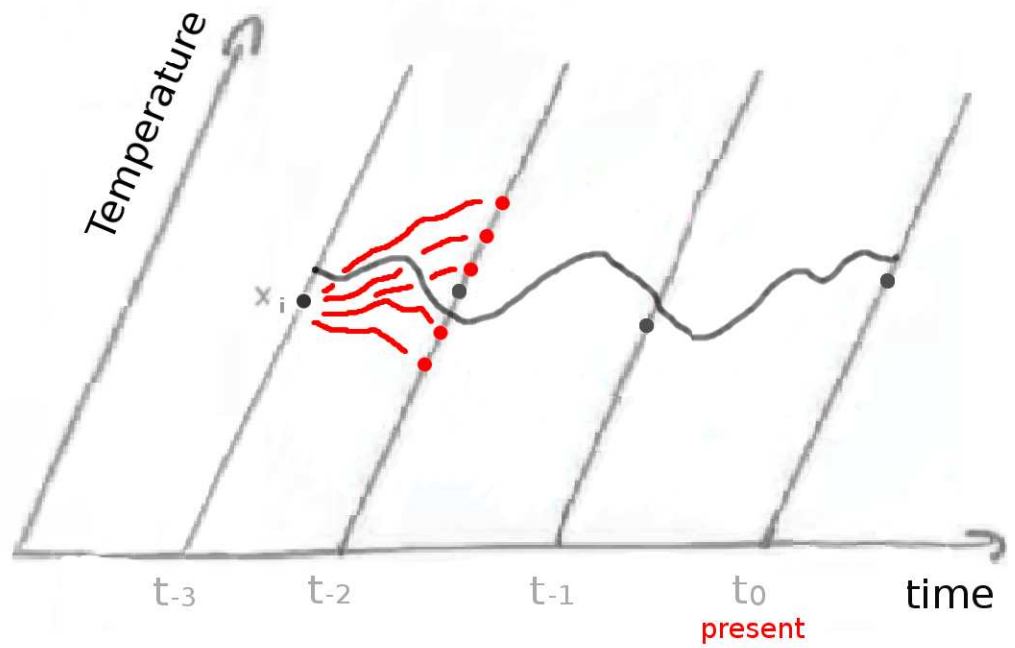
Bootstrap Filter



Prediction step:

$$dT = f(T) dt + g(t, w) dw$$

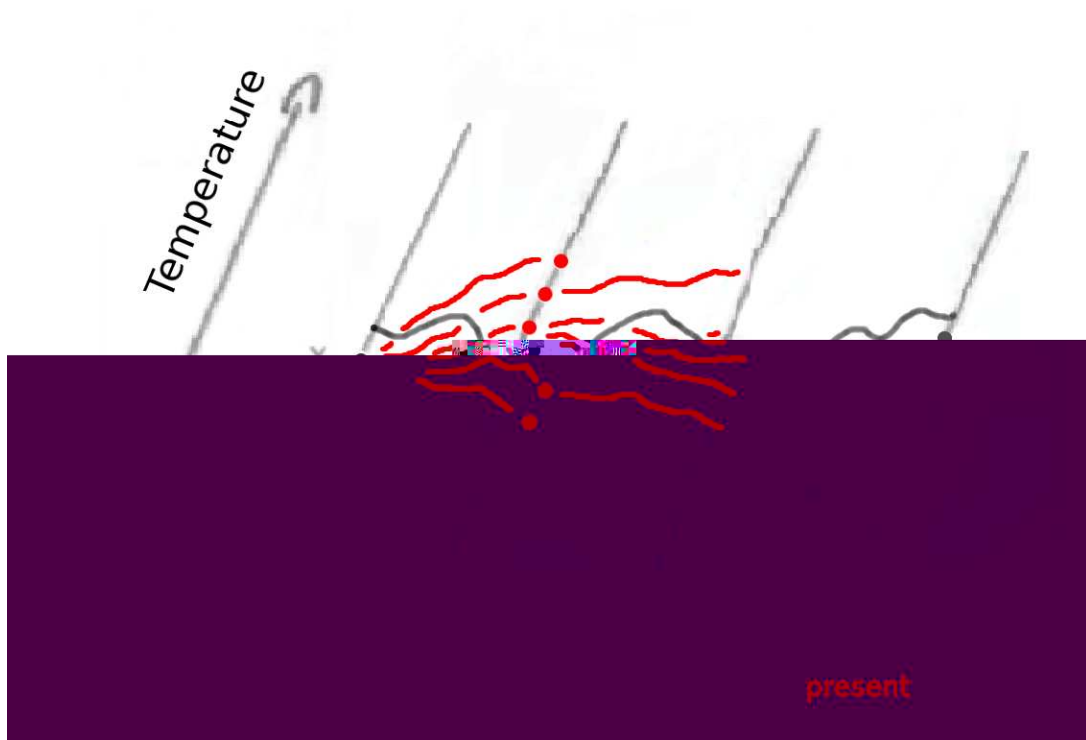
Bootstrap Filter



Filtering step:

weigh samples and define branching

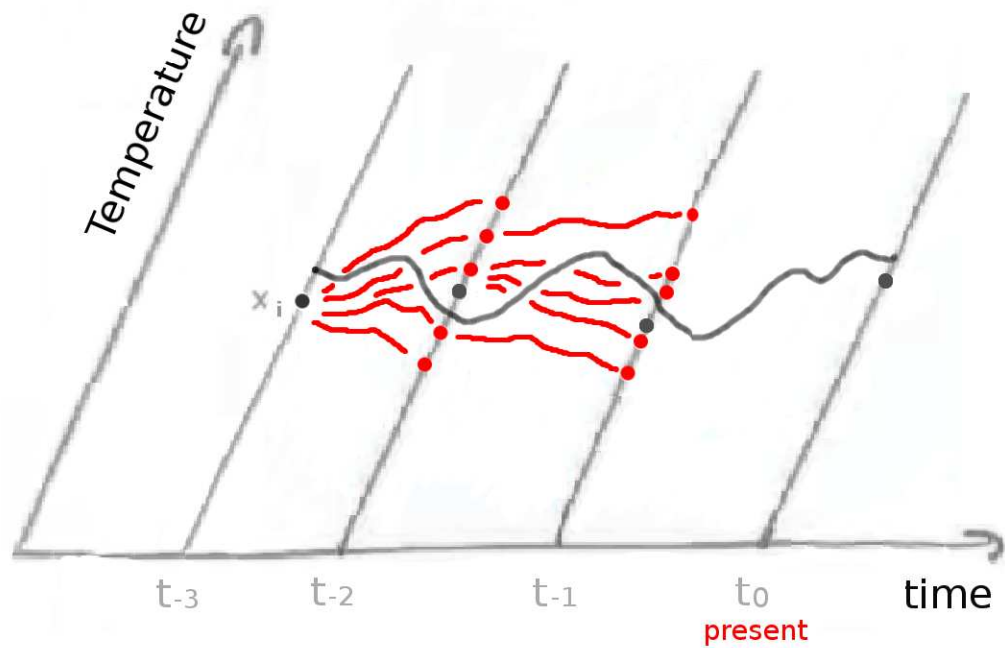
Bootstrap Filter



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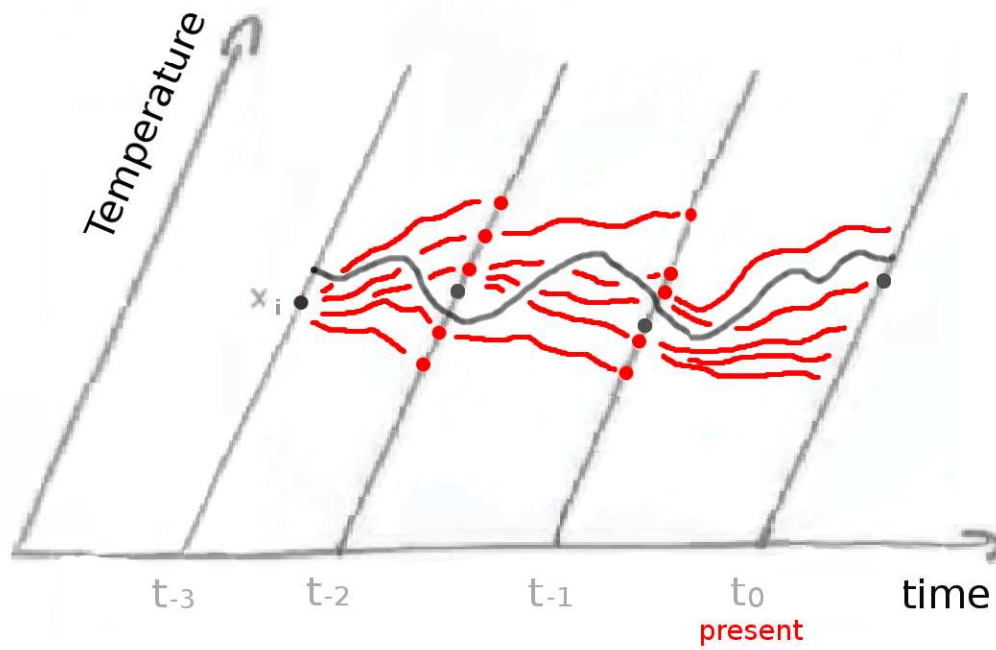
Bootstrap Filter



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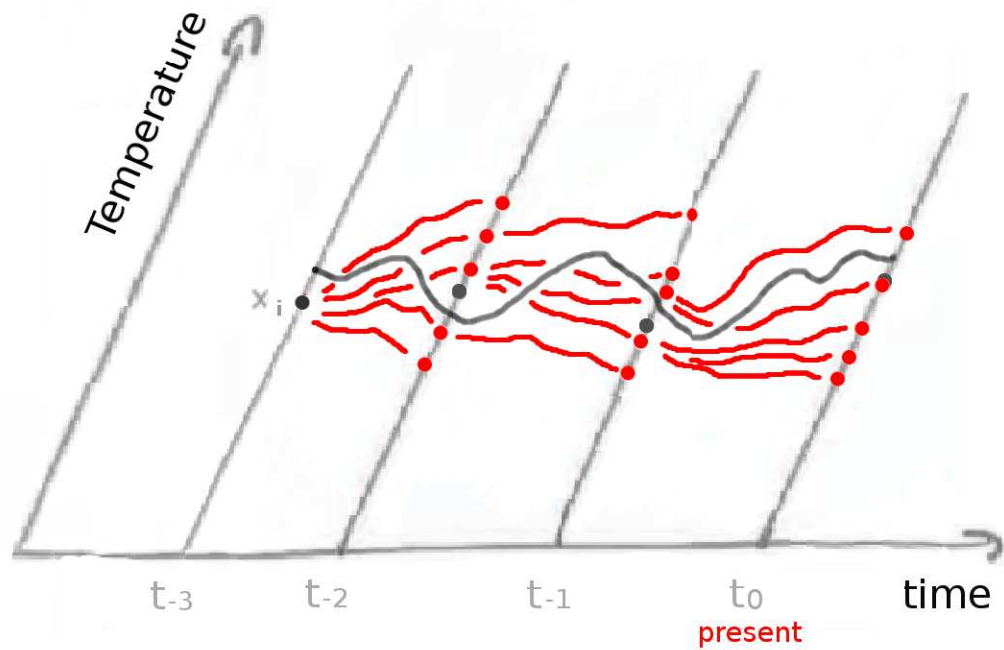
Bootstrap Filter



Prediction step:

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Bootstrap Filter



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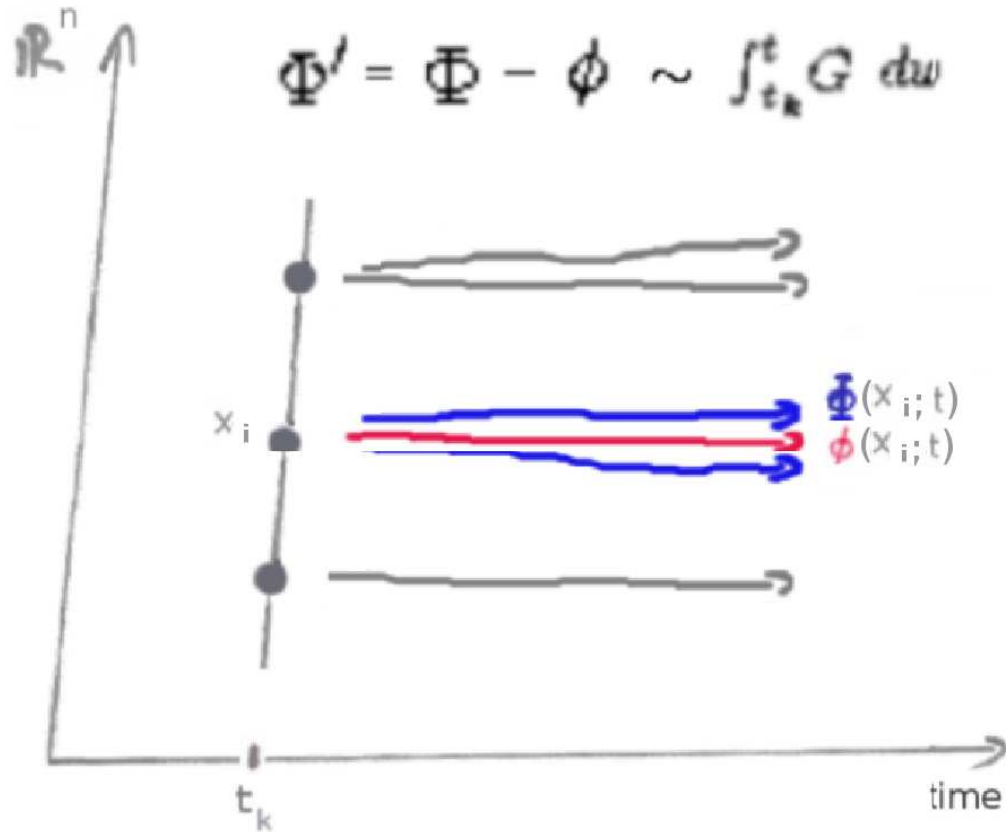
Bootstrap Filter

Drawbacks:

- (1) HUGE operations count: $O(I d)$
 - $I :=$ sampling size
 - $d :=$ model dimension
 - e.g.: $I = 500,000$ for capturing first 3 moments of noisy-Lorenz (fast increase with # moments)

- (2) Troubles defining prediction
 - e.g.: average estimates of (p, ρ, T) won't satisfy $p = R\rho T$ (gas eq.)

Diffusion Kernel Filter (DKF)



Parametrization:

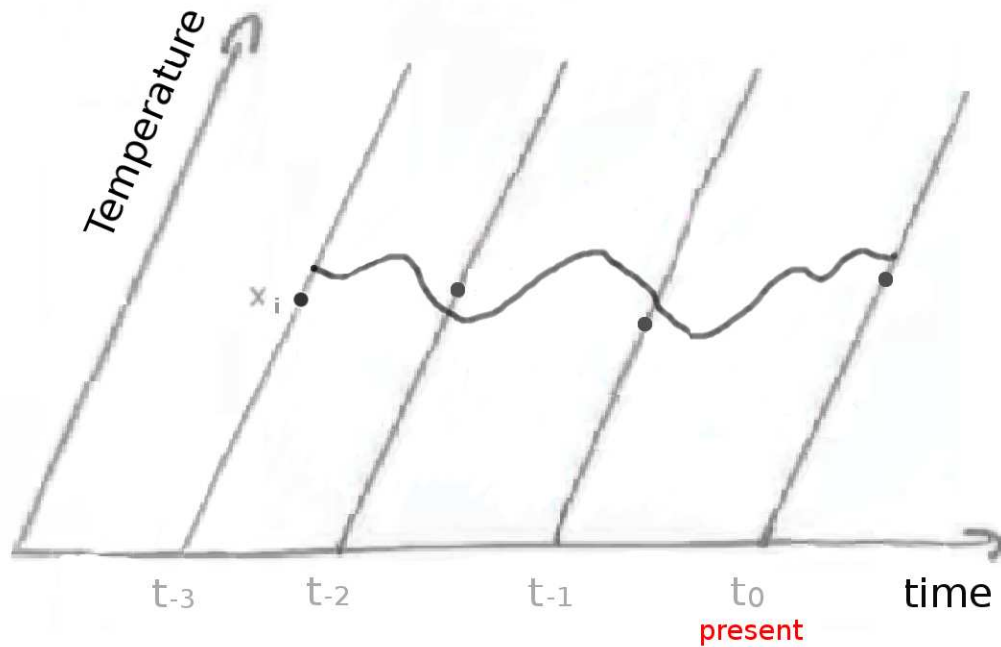
$$\Phi'(x_i, t) = \nabla \phi(x_i, t) \int_{t_k}^t g(s, w(s - t_k)) dw(s - t_k)$$

in distribution, while small,

where $\Phi' = \Phi - \phi$, Φ stoch. dynamics, ϕ determ. dynamics

$\nabla \phi$ determ. propagator of perturb., $\int_{t_k}^t ()$ accumulated noise

DKF

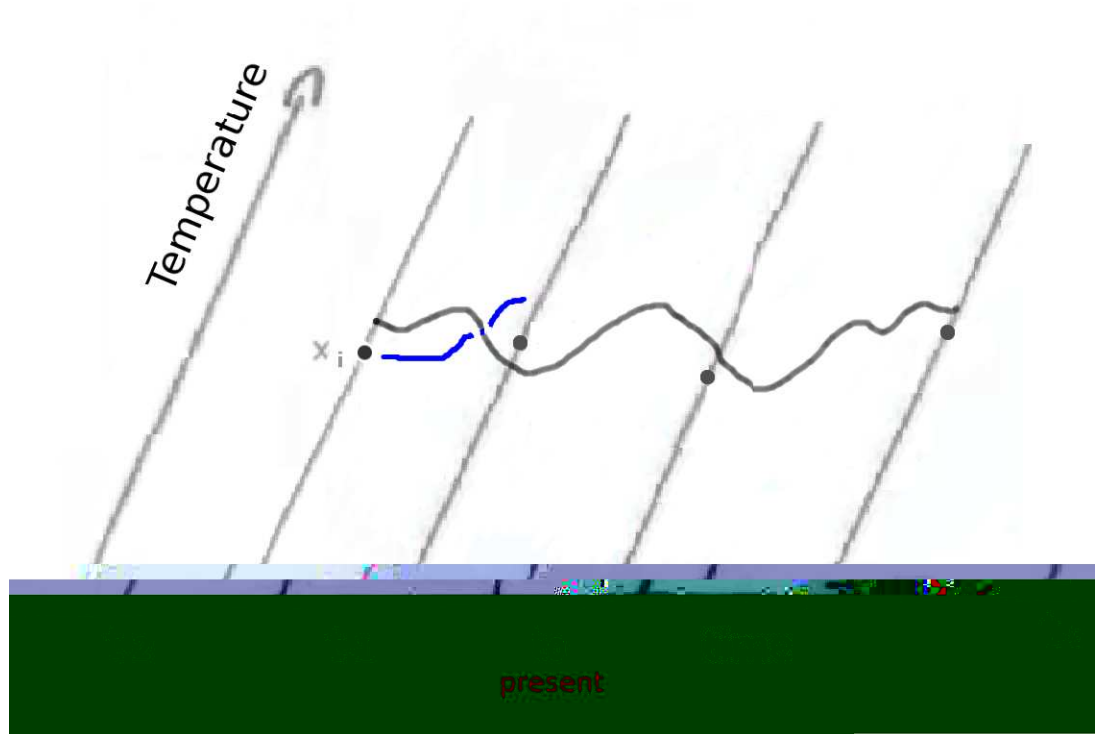


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Wish to sample $\Phi(x_i, t_0)$ corrected by past data, where Φ is the dynamics of a model

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DKF

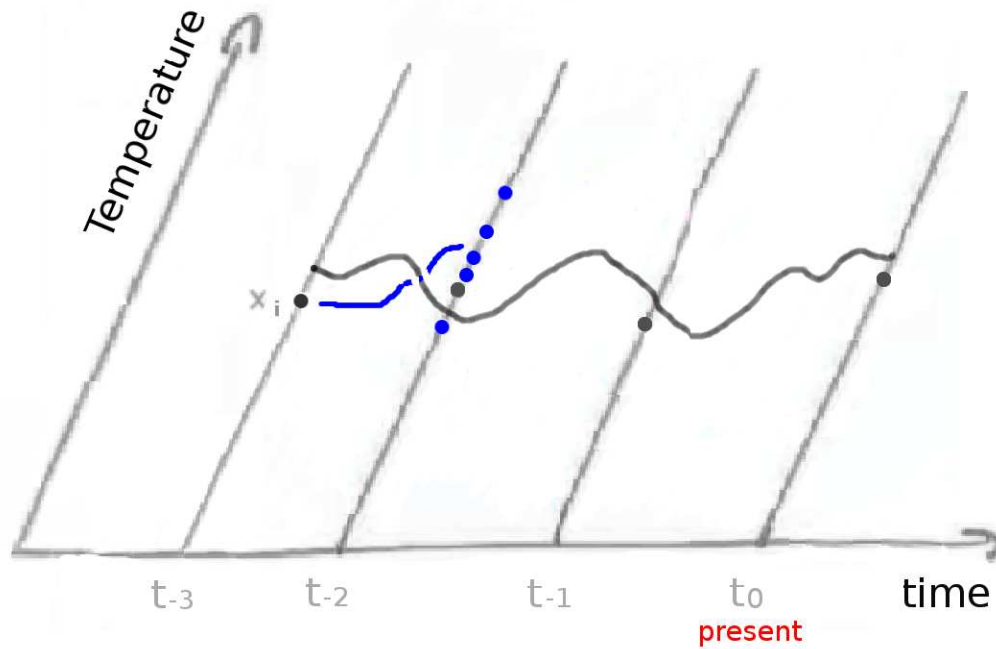


Prediction step:

$$(1) \frac{d}{dt}T = f(T)$$

$$(2) \frac{d}{dt}\nabla T = \nabla f(T) \nabla T$$

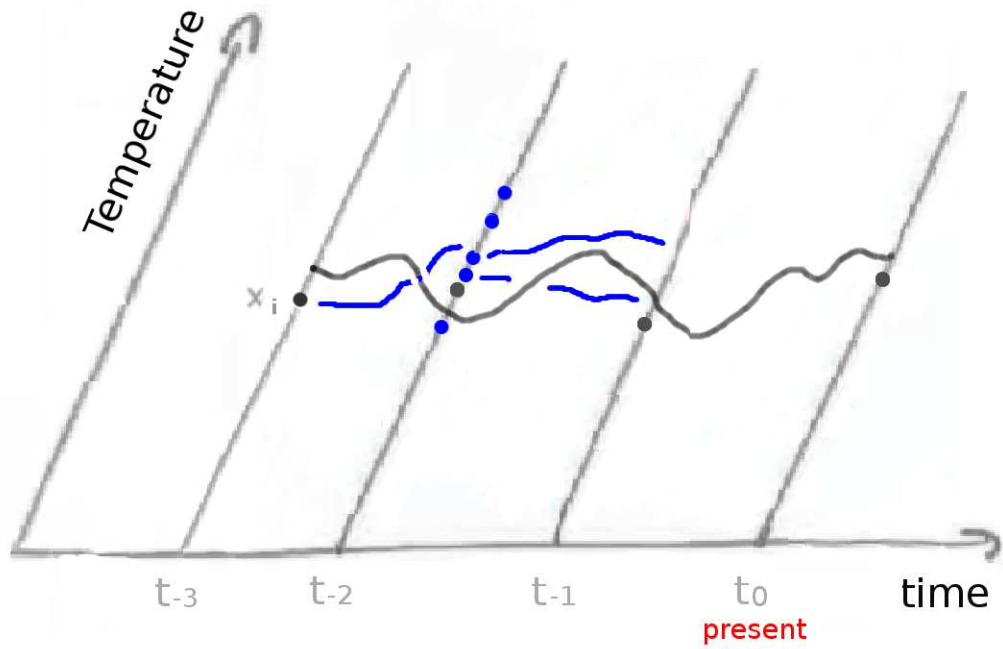
DKF



Filtering step:

- (1) draw samples from parametrization
- (2) weigh samples and define branching

DKF

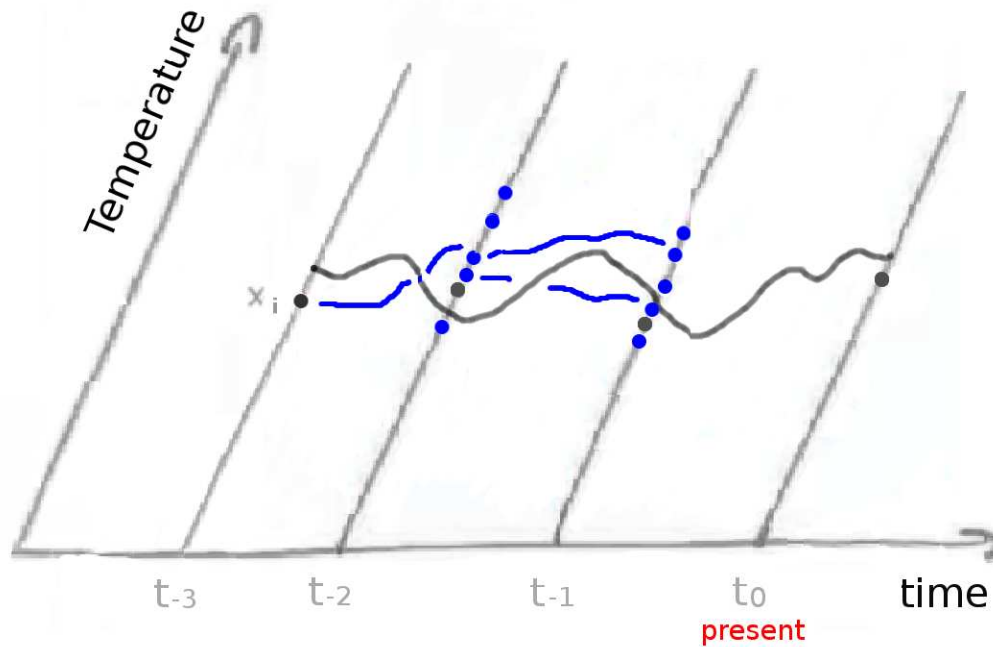


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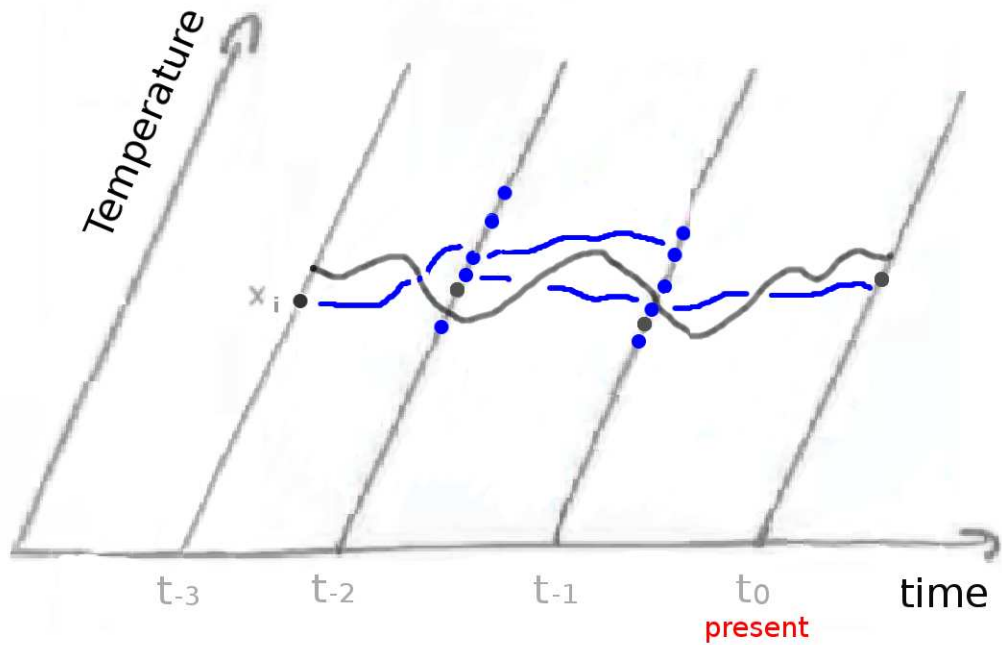
DKF



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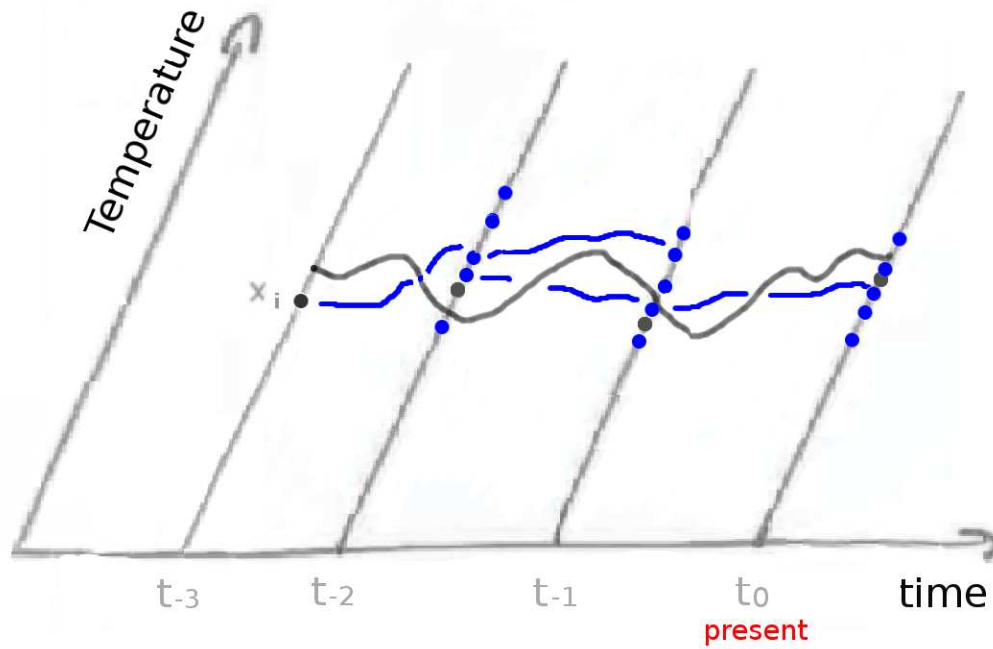


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DKF



Filtering step:

- (1) draw samples from parametrization
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DKF

Operations count:

$$O(I_k d^2) \text{ with } I_k \leq I$$

where I_k is # branches at time t_k

$$\frac{\text{DKF count}}{\text{Bootstrap count}} = O\left(\frac{I_k d}{I}\right)$$

Good job! for:

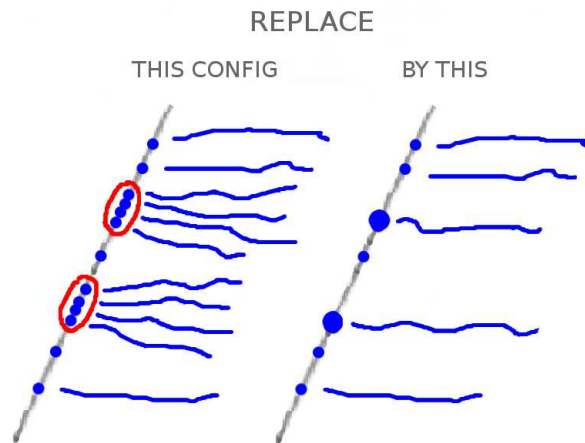
$$d < \text{const} \frac{I}{I_k}$$

(non-Gaussianity increases I_k)

Clustered DKF (cDKF)

Filtering step:

- (1) draw samples from parametrization
- (2) weigh samples
- (3) stick to samples that are cluster representatives:
the weights associated with them are taken to be the sum of the weights of their cluster members



- (4) define branching from the weighed cluster representatives

cDKF

Operations count:

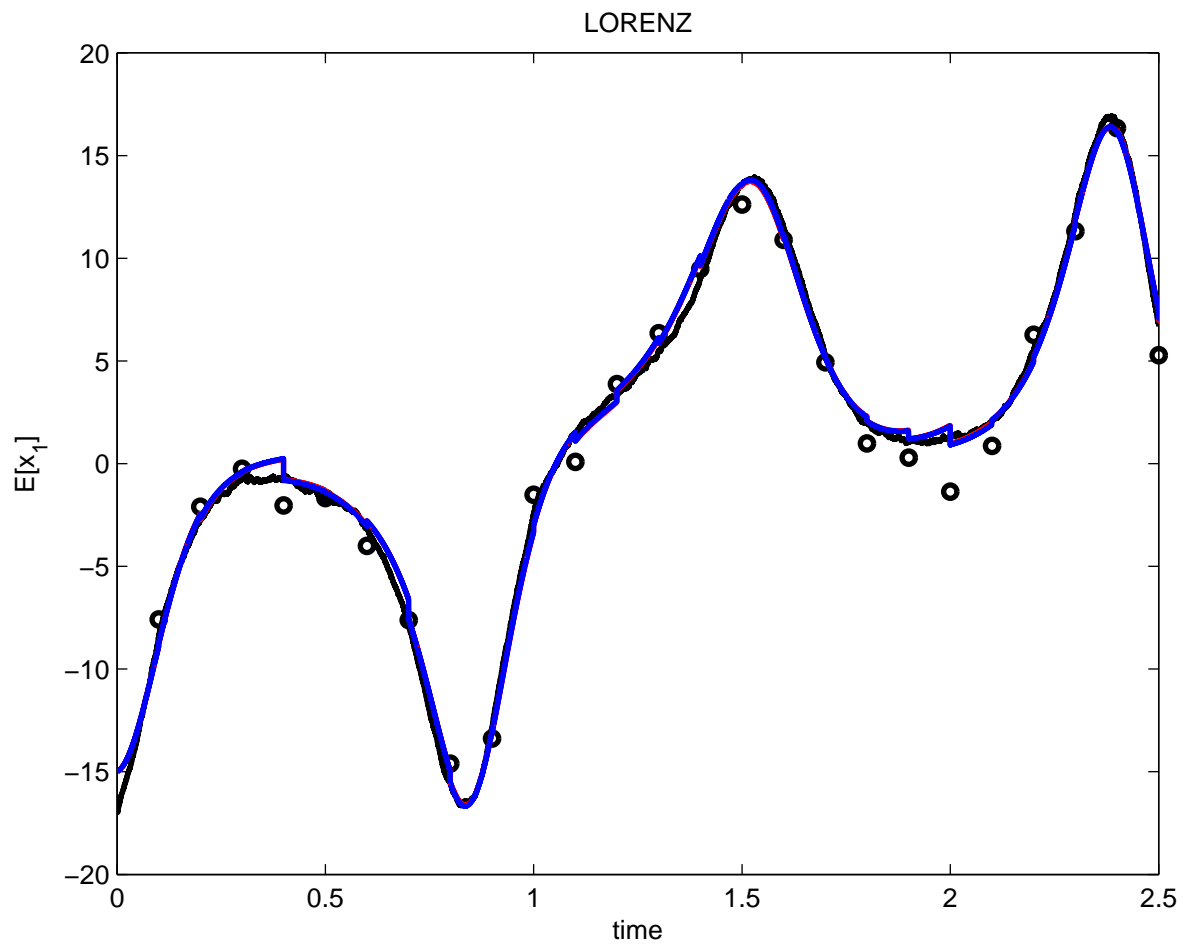
$$O(I_k d^2) \text{ with } I_k \leq 10^{-r} I$$

where I_k is # branches at time t_k

$$\frac{\text{cDKF count}}{\text{Bootstrap count}} = O\left(\frac{I_k d}{I}\right) \leq O(10^{-r} d)$$

Good job! for:

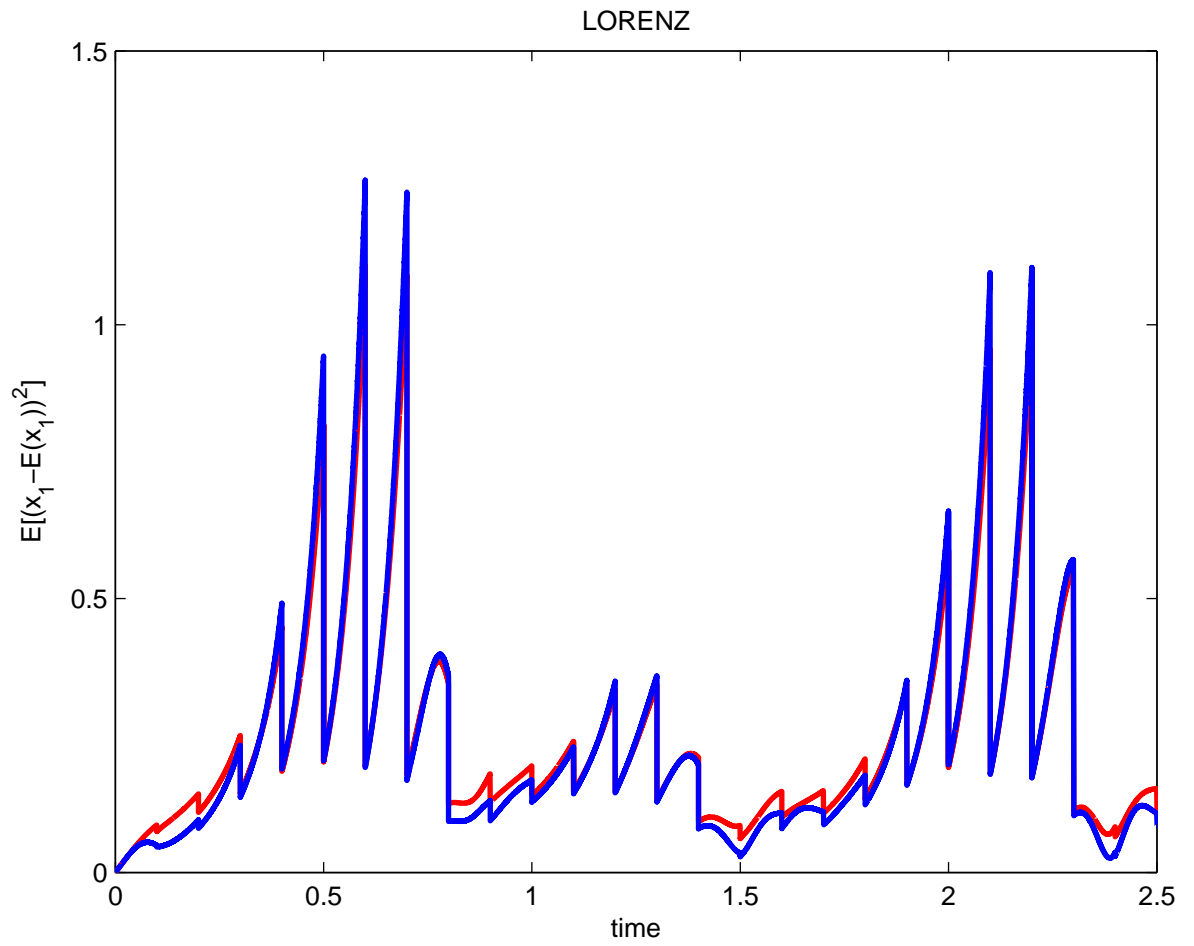
$$d < \text{const } 10^r$$



RED = Bootstrap

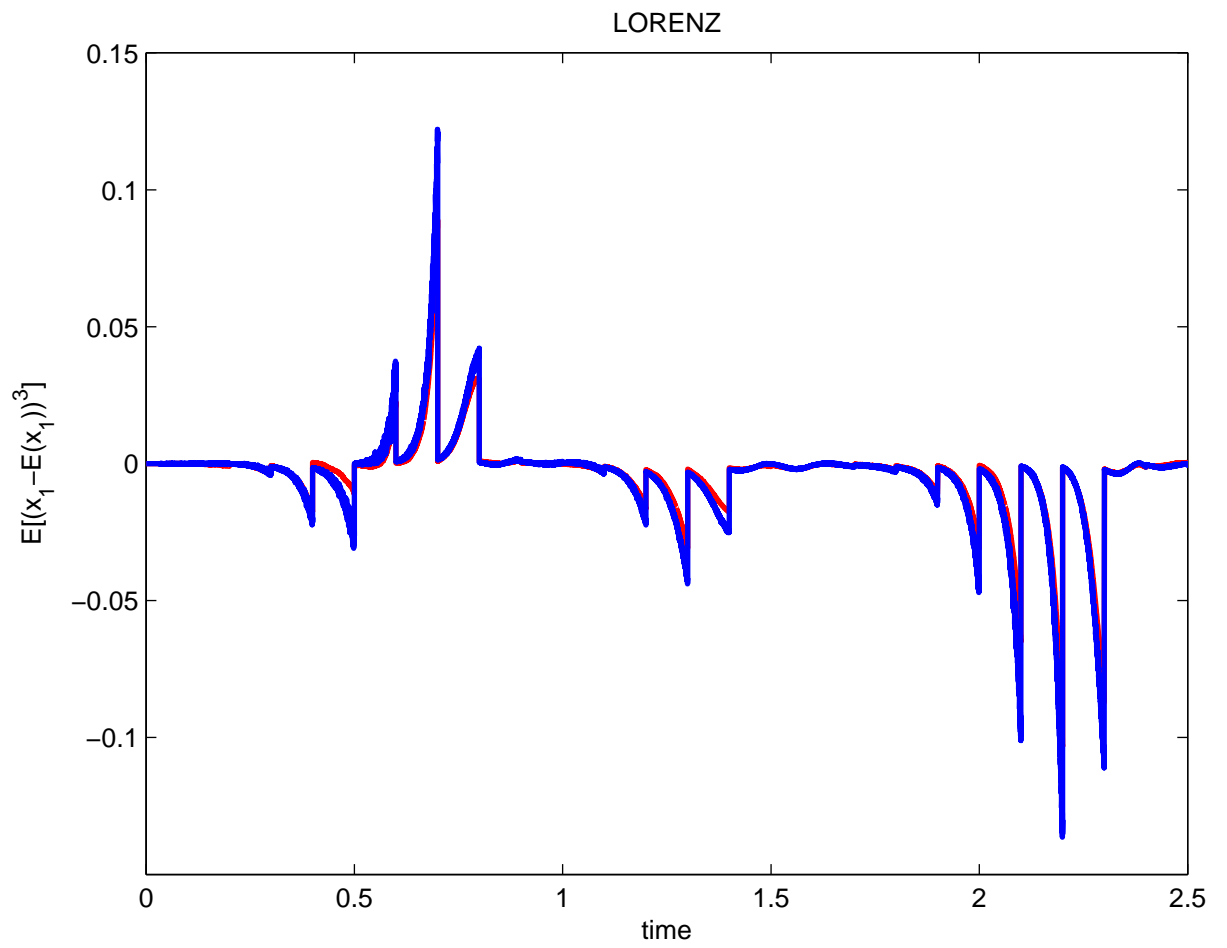
BLUE = DKF

BLACK = real path



RED = Bootstrap

BLUE = DKF



RED = Bootstrap

BLUE = DKF

Average-entropy prediction

Diffusion Kernel:

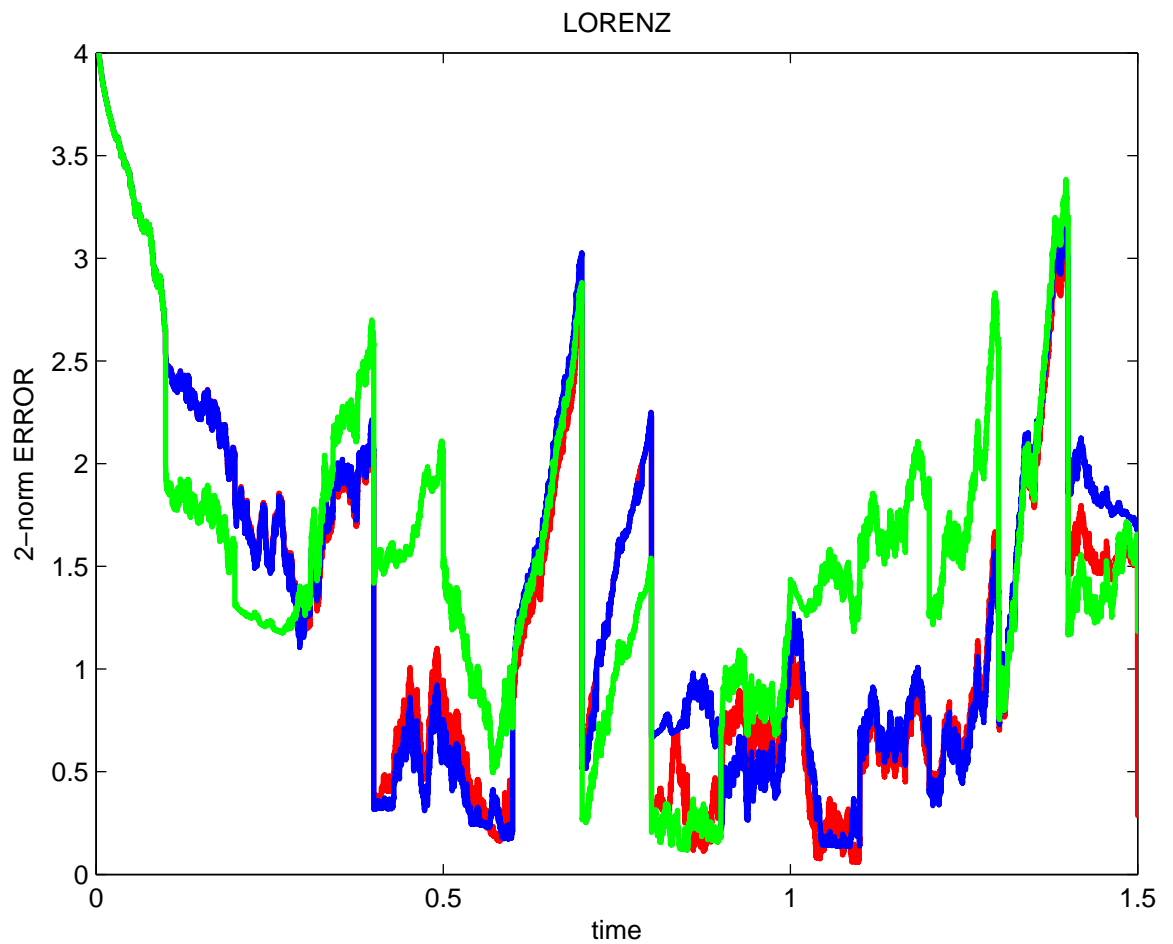
$$G(x_i; t, s) := \nabla \phi(x_i, t) g(s, w(s - t_k))$$

Uncertainty norm:

$$\text{entropy} \sim \|\text{Cov}(\Phi'(x_i; t))\|_\infty \leq \|G(x_i; t, \cdot)\|^2$$

Average-entropy prediction: deterministic path within the branch of prediction whose $\|G\|$ (or entropy) at the end of the prediction time-interval is closest to the average $\|G\|$ (or entropy) over all branches

Max-likelihood prediction: deterministic path emanating from most likely initial



RED = average estimate

BLUE = average-entropy prediction

GREEN = max-likelihood prediction

Derivation

- 1) Reformulation of problem into Liouville SPDE
- 2) Use of Duhamel to project onto OPEN SODE
- 3) Closure