

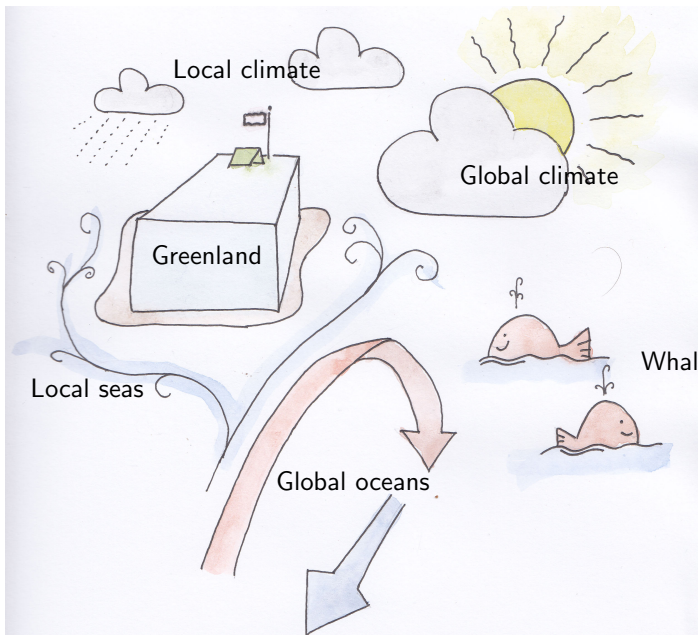
Model limitations: Sequential data assimilation with uncertain static parameters

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Illustration: the Greenland ice-sheet



Simplest interesting example

Conditional on θ :

$$x_0 \sim \pi_{x_0}(\theta) \quad (\text{init. cond. unc.})$$

$$x_t = g(x_{t-1}; \theta) + Q(x_{t-1}; \theta) \omega_t \quad (\text{state eqn.})$$

$$y_t = f(x_t; \theta) + \nu_t \quad (\text{obs. eqn.})$$

where

$$\omega_t \stackrel{\text{iid}}{\sim} \text{N}(0, I) \quad (\text{structural uncertainty})$$

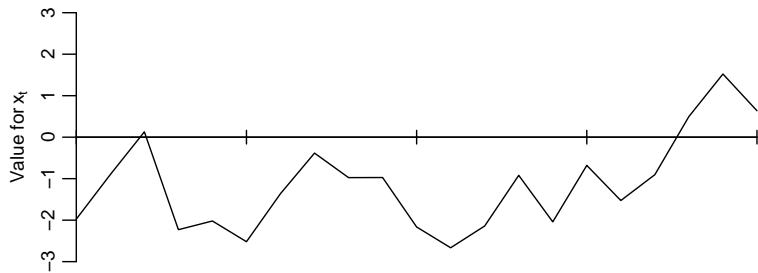
$$\nu_t \stackrel{\text{iid}}{\sim} \text{N}(0, v^2) \quad (\text{measurement unc.})$$

and then let $\theta \sim \pi_\theta$, to account for **parametric uncertainty**. The functions f , g , and Q are given, likewise the measurement uncertainty standard deviation, v .

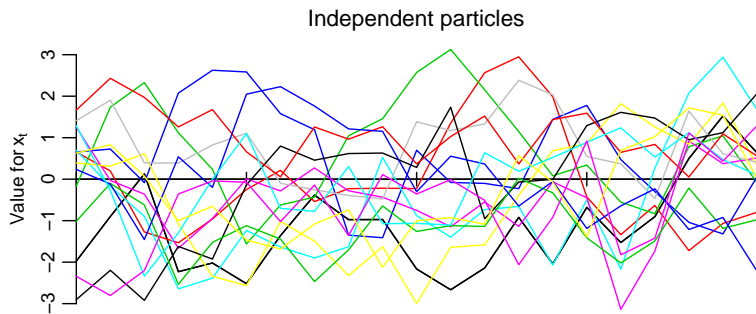
Sampling from $\{x_{0:T}, \theta\} \mid y_{1:T}$ “intractable and unsolved”
(C. Andrieu)

Particle filters, for given θ

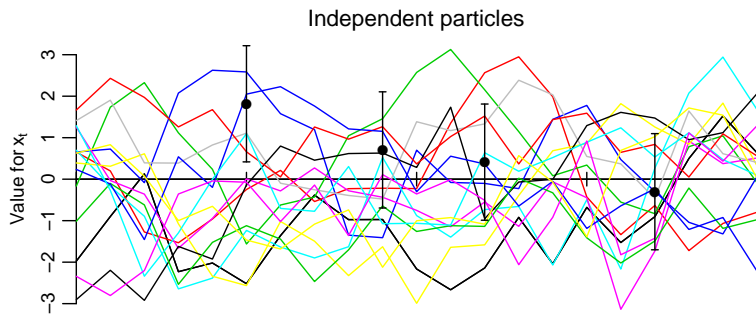
Independent particles



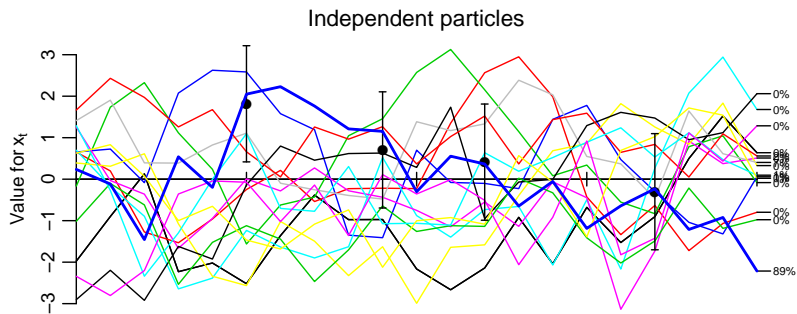
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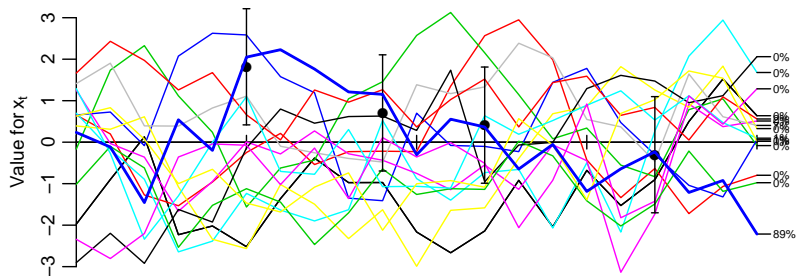


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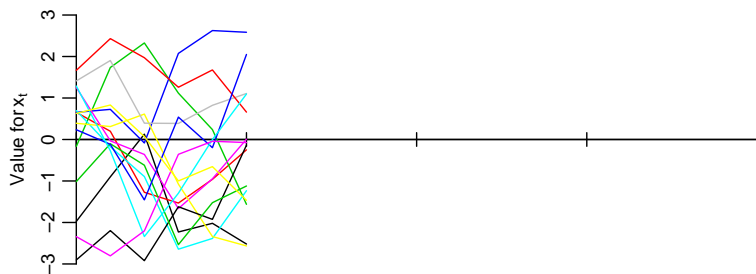


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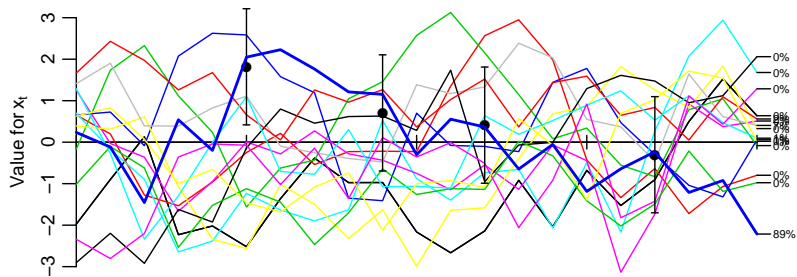


Interacting particles

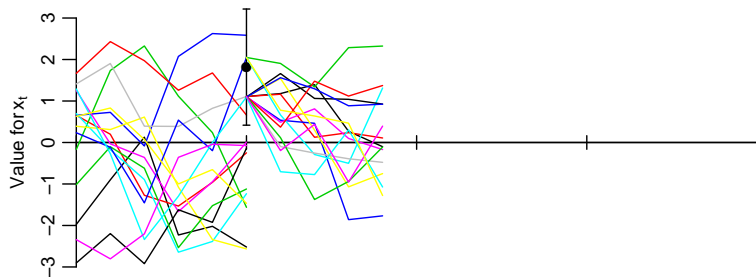


Particle filters, for given θ

Independent particles

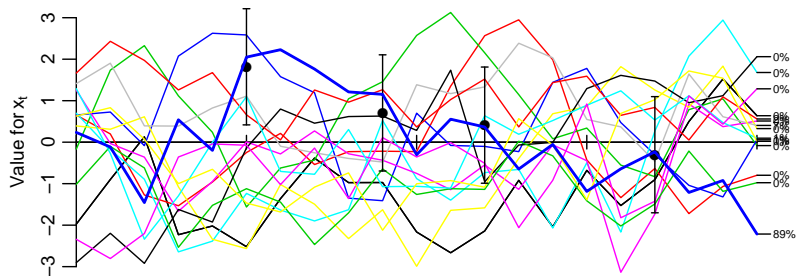


Interacting particles

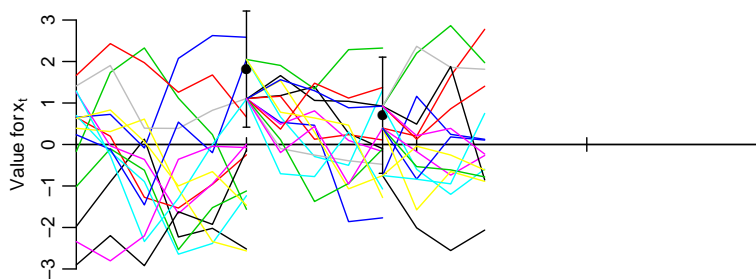


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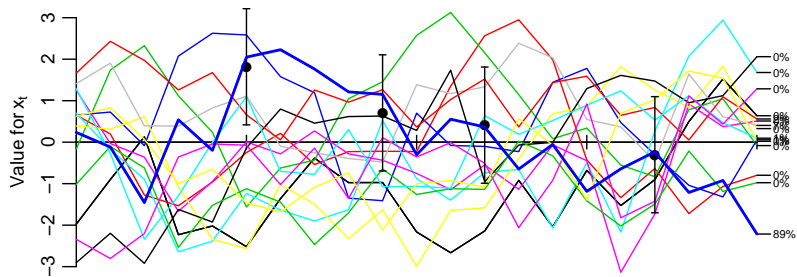


Interacting particles

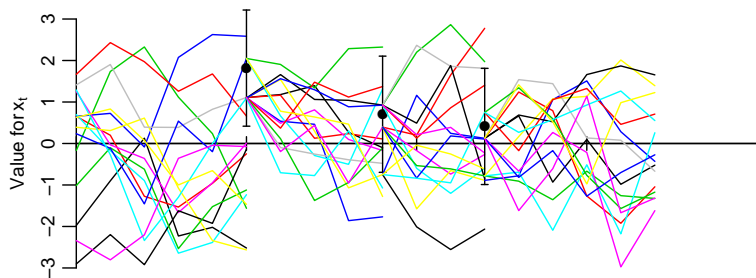


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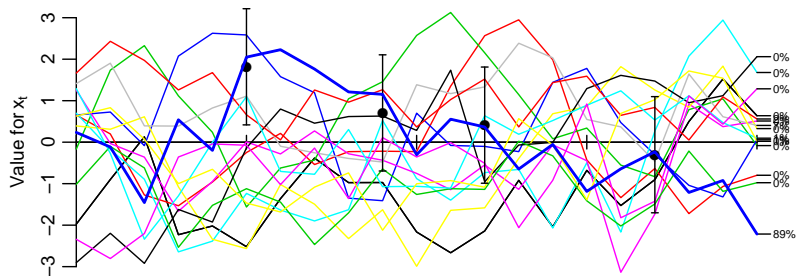


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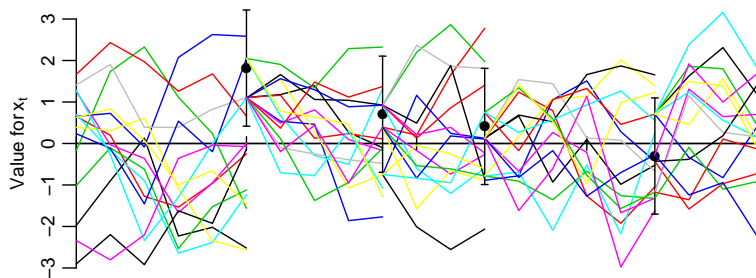


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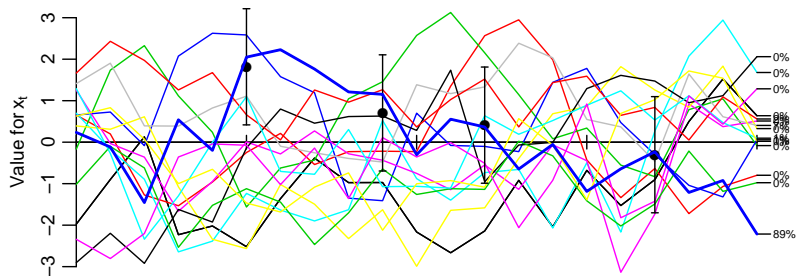


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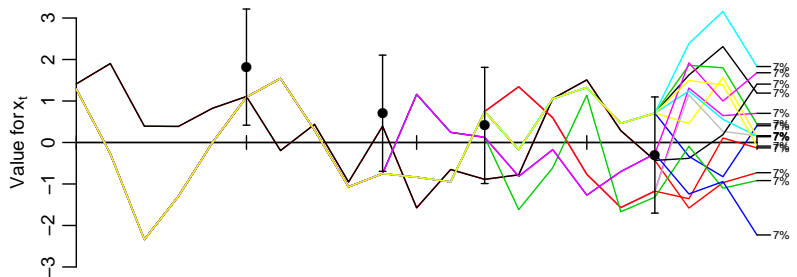


Particle filters, for given θ

Independent particles



Interacting particles



The difficulties with uncertainty θ

- ▶ One simple idea is to attach a realisation from π_θ to each particle, in order to sample jointly from $\{x_{0:T}, \theta\} \mid y_{1:T}$.

However, static parameters do not evolve in time, so every interaction reduces the resolution of the θ distribution. Too many observations, and the θ distribution becomes degenerate, unless we have `<DrEvil>one million</DrEvil>` particles.

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- ▶ The solution is to 'integrate out' the state vector in some form. The two approaches are
 1. Gaussian (Laplace) approximation for $x_{1:T} | \{\theta, y_{1:T}\}$ turning a high-dimensional integration into a high-dimensional optimisation;
 2. Particle Markov chain Monte Carlo (P-MCMC), which uses a Gibbs sampler to swap between sampling $x_{1:T} | \{\theta, y_{1:T}\}$ and $\theta | \{x_{1:T}, y_{1:T}\}$.

Summary

In inference for environmental systems, 'high dimensional data' is ~ 1000 observations. This is at the limit of what we can compute.

- ▶ Particle filters, the most general tool for sampling from $x_{1:T} \mid \{\theta, y_{1:T}\}$, adapt naturally to parallel implementation;
- ▶ MCMC for $\theta \mid y_{1:T}$ or $\theta \mid \{x_{1:T}, y_{1:T}\}$, can also be implemented in parallel, using the approach of Cui *et al.*

Small state vectors, though!

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Two useful references

C. Andrieu *et al*, 2009, Particle Markov chain Monte Carlo methods, forthcoming in the *Journal of the Royal Statistical Society, Ser. B*, available at

http://www.rss.org.uk/pdf/Andrieu_et_al._14.10.09.pdf

T. Cui *et al*, 2009, Using MCMC Sampling to Calibrate a Computer Model of a Geothermal Field, available at <http://www.stats.ox.ac.uk/~nicholls/linkfiles/papers/cui09.pdf>

<http://www.stats.ox.ac.uk/~nicholls/linkfiles/papers/cui09.pdf>