Bayesian Data Assimilation within the AOML-UMD Ensemble Prediction System

Jonathan Poterjoy

University of Maryland
NOAA Atlantic Oceanographic and Meteorological Laboratory

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Regional modeling framework

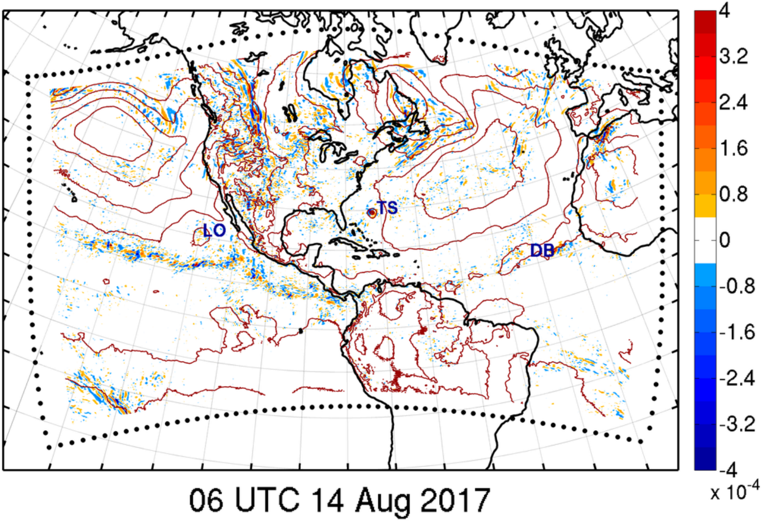
AOML-UMD Ensemble Prediction System

Main collaborators: Gus Alaka (AOML), Henry Winterbottom (I. M. Systems Group)

- Ensemble analysis and prediction system for the NOAA HWRF model using GSI EnKF.
- Sequential data assimilation is performed over a regional domain using GFS to provide boundary conditions.
- Conventional and clear-air satellite radiance measurements are assimilated every 6 h.
- Bias correction for radiances performed online.

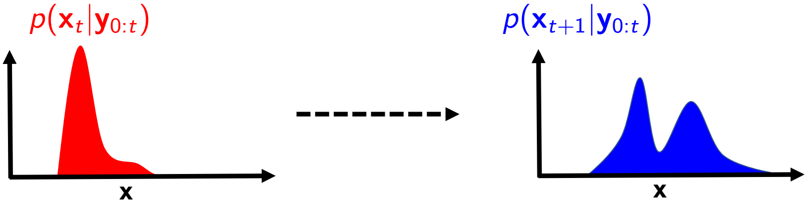
Regional modeling framework

MSLP (contours) and 850-mb vorticity increments (shading) for member 1



Bayesian filtering problem

The goal is to estimate a model state's pdf conditioned on observations.

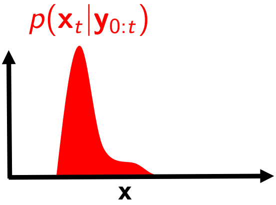


$\mathbf{x}_t$ and $\mathbf{y}_t$ are given by:

$$
\begin{aligned}
\mathbf{x}_{t+1} &= M(\mathbf{x}_t) + \eta_t, \\
\mathbf{y}_t &= H(\mathbf{x}_t) + \epsilon_t.
\end{aligned}
$$

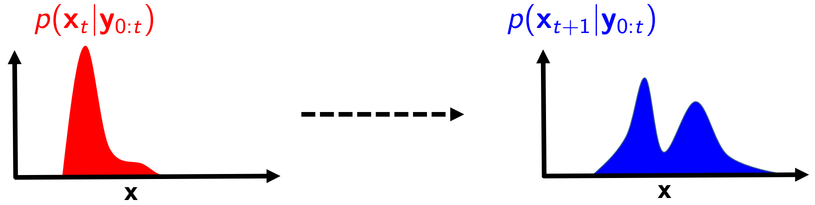
Monte Carlo approach: DA step

Draw $\mathbf{x}_t^n$ for $n = 1, 2, ..., N_e$, from $p(\mathbf{x}_t|\mathbf{y}_{0:t})$.



Monte Carlo approach: prediction step

Pass samples through forecast model.



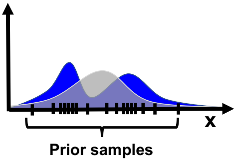
$\mathbf{x}^n_{t+1} = M(\mathbf{x}^n_t) + \eta^n_t$, are then samples from $p(\mathbf{x}_{t+1}|\mathbf{y}_{0:t})$.

Moving beyond EnKF/Var for DA step

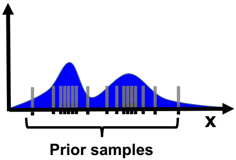
Particle filters (PFs) use ensemble members ("particles") to approximate prior and posterior distributions.

In the context of DA schemes currently used for NWP:

- EnKFs apply a sample estimate of mean and covariance – parameters needed for Gaussian density estimation.
- PFs use samples to apply a Dirac delta function approximation of probability densities.



vs.



Moving beyond EnKF/Var for DA step

Particle filters (PFs) use ensemble members ("particles") to approximate prior and posterior distributions.

- Even for nonlinear $M(\mathbf{x})$ and $H(\mathbf{x})$, and non-Gaussian errors PFs converge to the Bayesian solution as
  i. ensemble sizes increase.
  ii. model and observation errors become more reliable.
- Like EnKFs, PFs require ensemble sizes that increase with the problem size.
- Approximations are needed to prevent ensemble variance from collapsing to zero for NWP; namely, localization and inflation.

A particle filter for large problems

Poterjoy (2016) proposes a localized PF algorithm that fits easily into community software packages for ensemble DA:

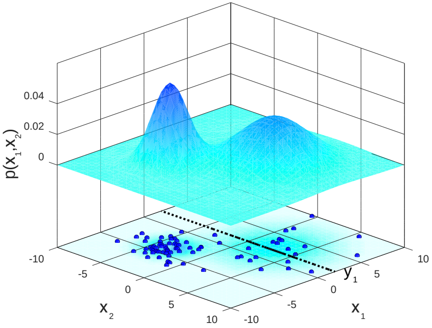
- Data Assimilation Research Testbed (DART) maintained by the Data Assimilation Research Section of NCAR
- Ensemble component of operational Gridpoint Statistical Interpolation (GSI) system maintained by DTC
- JEDI?

Serial ensemble square root filters

DART and GSI process obs serially, performing parallel obs- and state-space updates (Anderson and Collins 2007).

For example, consider the 2-D problem:

- **Blue shading**: $p(x_1, x_2)$
- **Blue markers**: samples from $p(x_1, x_2)$
- **Dashed line**: direct observation of x_1, denoted y_1



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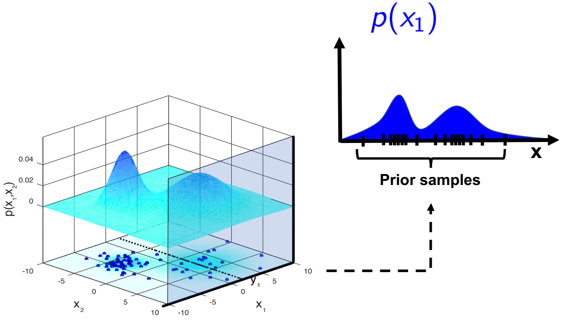
Observation Space



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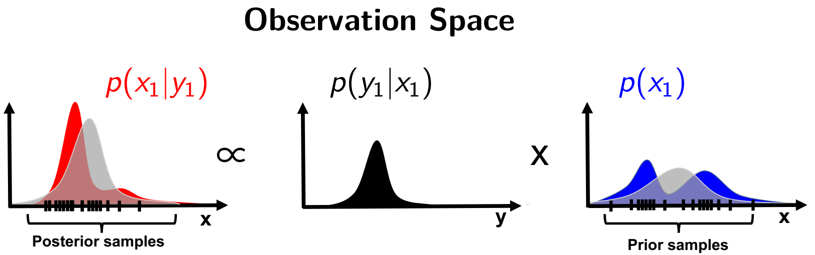

$p(x_1|y_1) \approx N(\overline{x}_{post}, \sigma^2_{post}),$ $\qquad$ $p(x_1) \approx N(\overline{x}_{prior}, \sigma^2_{prior})$

Serial ensemble square root filters

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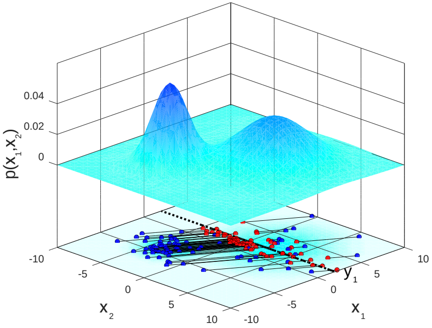
State Space

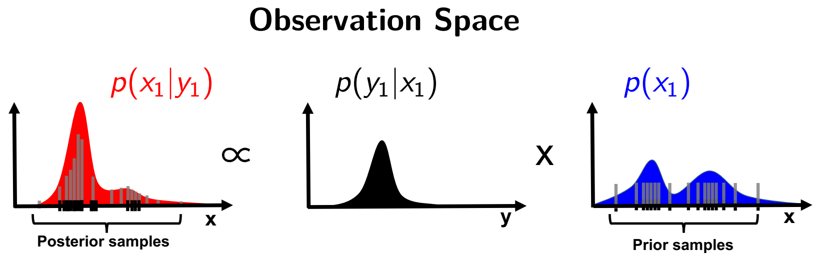
Each $\mathbf{x}^n$ is updated via a linear regression from obs-space update:

$$\color{red}{\bar{\mathbf{x}}} \leftarrow \bar{\mathbf{x}} + \mathbf{K}(y_1 - x_1)$$
$$\color{red}{\mathbf{x}^{n'}} \leftarrow \tilde{\mathbf{K}}\mathbf{x}^{n'}, \text{ for } n = 1, ..., N_e$$



Local particle filter

The algorithms described in Poterjoy (2016) and Poterjoy et al. (2019) follow a similar strategy.



$$p(x_1|y_1) \approx \sum_{n=1}^{N_e} w^n \delta(x_1 - x_1^n),$$
$$w^n \propto p(y_1|x_1^n)$$

$$p(x_1) \approx \frac{1}{N_e} \sum_{n=1}^{N_e} \delta(x_1 - x_1^n)$$

Local particle filter

The algorithms described in Poterjoy (2016) and Poterjoy et al. (2019) follow a similar strategy.

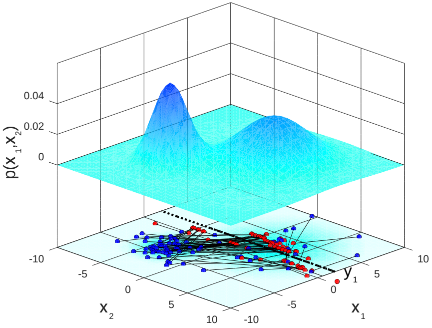
State Space

Original EnKF update of each $\mathbf{x}^n$ is replaced by:

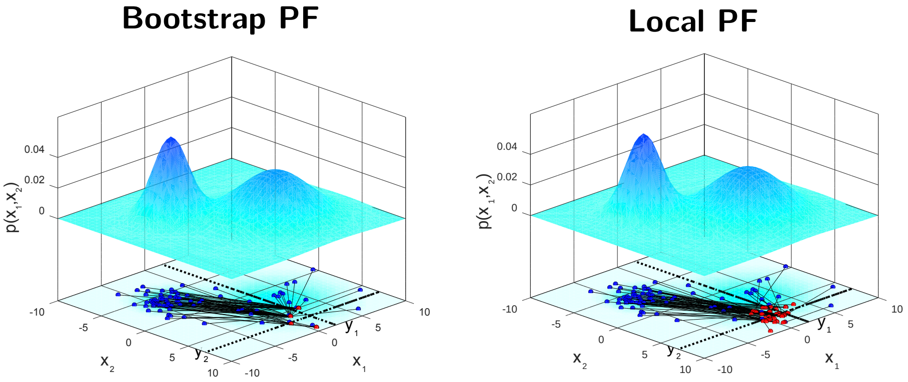
$$\color{red}{\overline{\mathbf{x}}} \leftarrow \sum_{n=1}^{N_e} \omega^n \circ \mathbf{x}^n,$$

$$\color{red}{\mathbf{x}^{n'}} \leftarrow \mathbf{r}_1 \circ \mathbf{x}^{n'} + \mathbf{r}_2 \circ \mathbf{x}^{k'_n},$$

where ω^n, $\mathbf{r}_1$, and $\mathbf{r}_2$ are formulated to reflect a mix of PF and prior solutions.



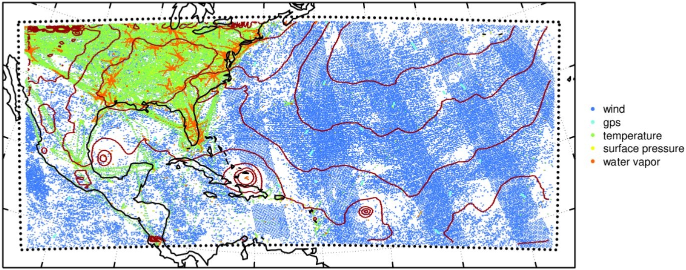
Failure of PF without ρ and β



In its standard form, the Bootstrap PF collapses easily for example problem with $N_y = 2$ and $N_e = 80$.

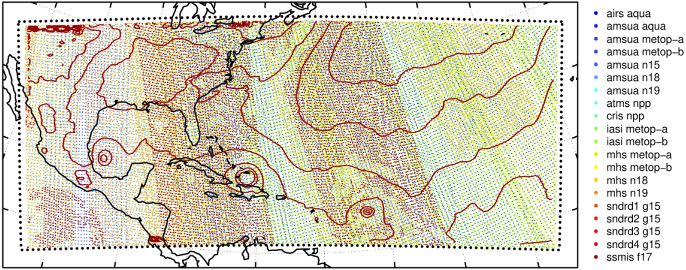
Month-long experiments from Sept. 2017

MSLP and conventional ob locations every 6 h



00 UTC 8 Sep 2017

MSLP and radiance ob locations every 6 h



00 UTC 8 Sep 2017

Experiment setup and verification

Cycling data assimilation tests:

- **Model grid spacing**: 18 km
- **Observation frequency**: 6 h
- **Ensemble DA schemes**: EnKF (Whitaker and Hamill 2002) and a variant of the Poterjoy (2016), Poterjoy et al. (2018) local PF
- **Ensemble size**: 60

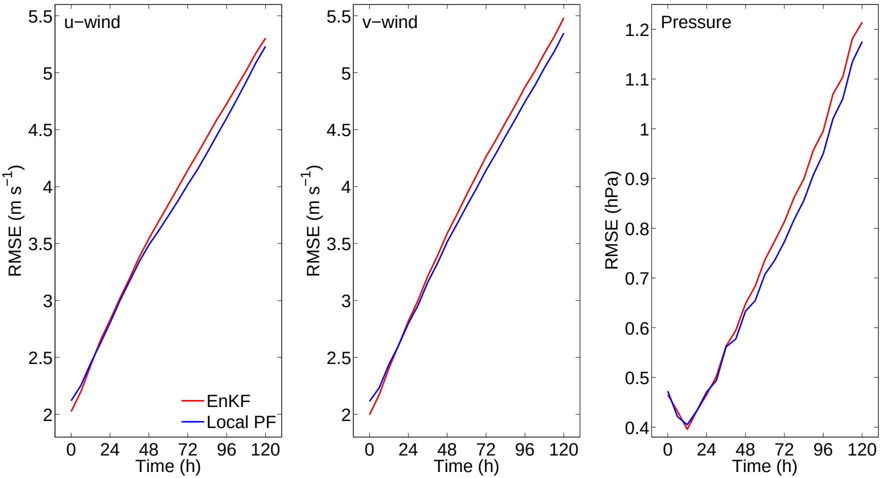
Experiment setup and verification

Verification:

- **Forecasts**: 20-mem ensemble 120-h forecasts initialized twice a day
- **Spin up**: verification begins 5 d into cycling DA experiments
- **Verifying metric**: volume-average root mean square difference between ensemble mean forecasts and GFS analysis

Ensemble mean forecast RMSE

RMSEs averaged over 52 sets of ensemble forecasts



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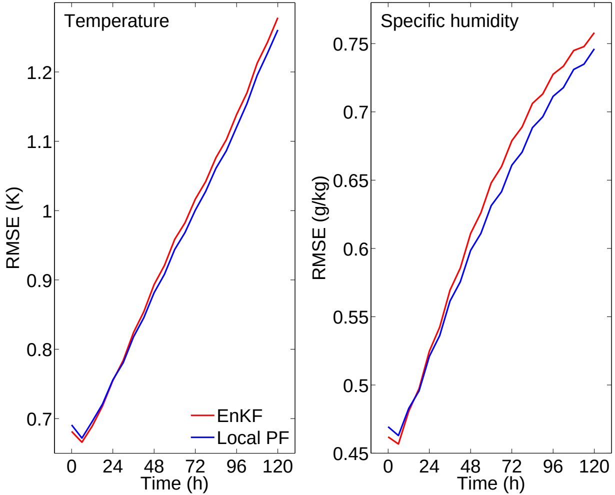

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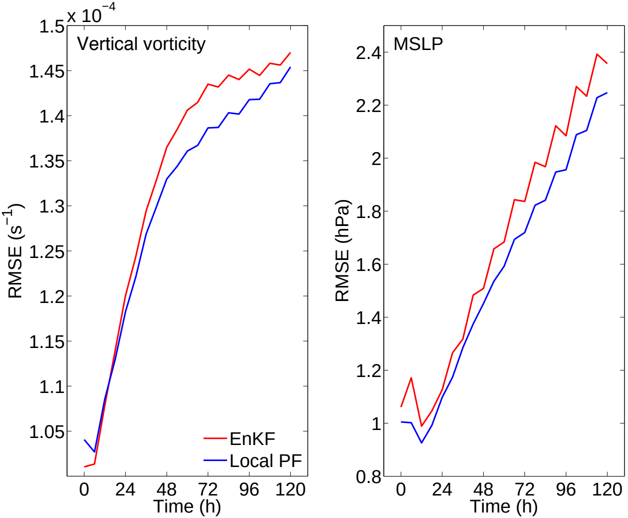
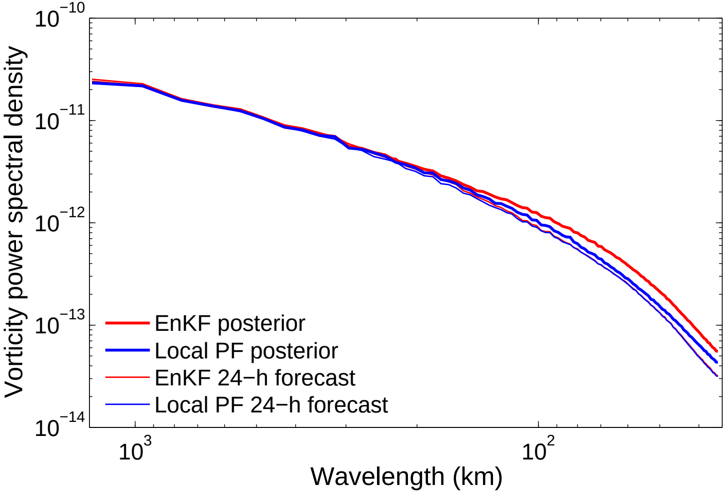
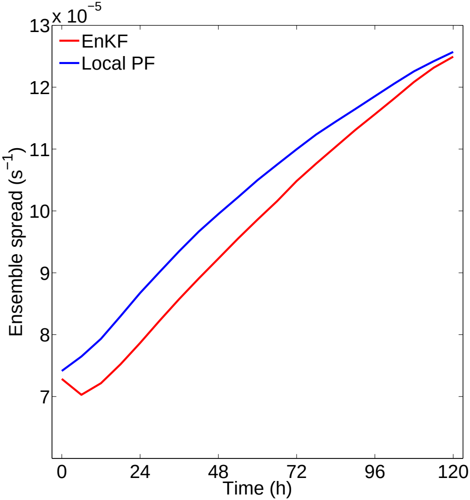


Impact of data assimilation on wind field



Impact on uncertainty estimate from ensemble



Average ensemble spread in domain-mean vertical vorticity from 0 – 120 h.

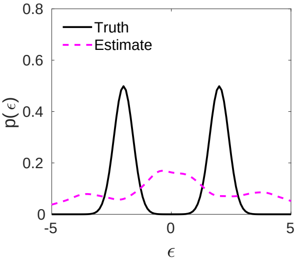
Summary of progress

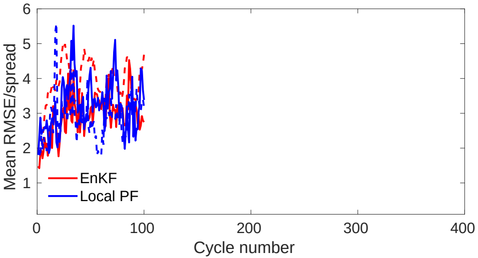
Formulating PF algorithms that operate efficiently for high-dimensional problems remains an active area of research.

- Poterjoy et al. (2019) highlight some (but not all) recent advancements for filter discussed here.
- Results from month-long regional experiments are encouraging:
  i. First real test for synoptic-scale NWP.
  ii. Large room for improvement.
- Some national centers are already exploring the use of PFs for NWP; e.g., Potthast et al. (2019).

Looking forward

Let's start re-thinking Gaussian assumptions for obs errors.





- Obs errors estimated online using Gaussian mixture approximation: early tests with Lorenz (1996) model.
- $N_x = 40$, $N_y = 20$, $\Delta t = 0.05$ time units (~ 6 h)

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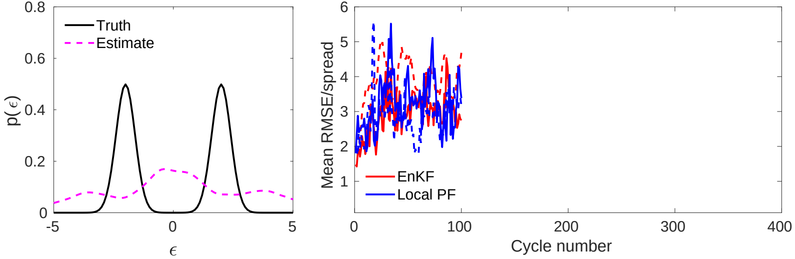

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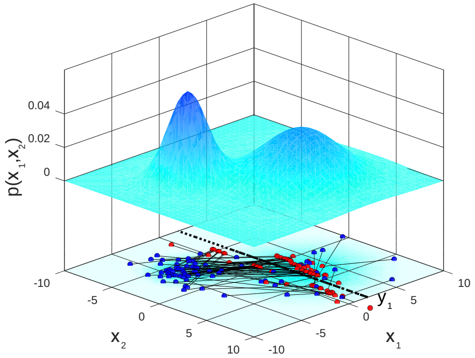
Looking forward

Localization for PFs is still an evolving idea.



- Current strategy: generate localized particle updates through a single step.

$$\color{red}{\bar{\mathbf{x}}} \leftarrow \sum_{n=1}^{N_e} \omega^n \circ \mathbf{x}^n,$$

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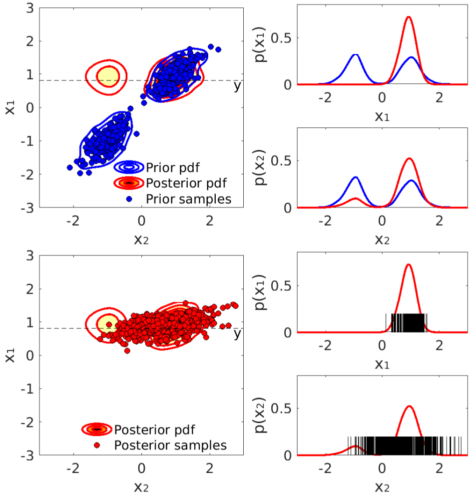

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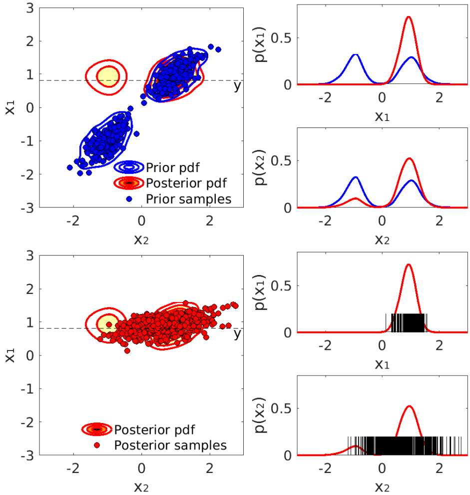

- New approach: break original update into a series of intermittent steps.
- Each intermittent step uses particle weights with larger "effective ensemble size" than one single update.

Looking forward

Outstanding PF questions relevant to this meeting:

- What are the implications for assimilating all-sky radiance measurements?
- What can be done with larger ensembles?
- Can nonlinear DA provide additional benefits for modeling systems configured to use rapid updates?

My contact info

email: poterjoy@umd.edu
url: https://poterjoy.com

References

Other PF-based strategies using localization

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