

Analysis of the EnKF for inverse problems

Plan

- Inverse problems (and ways to solve them)
- Adapting the EnKF method
- The twist! (*)
- Results (theoretical & numerical)

Goals

me	you
keep your awake	stay awake
get you excited about (*)	keep big picture in mind.
you learn something	

Inverse problems

$$y = g(u) + \eta \quad (\text{IP})$$

with $y \in Y$, $u \in X$, $\eta \sim N(0, \Gamma)$.

How well can we reconstruct u from y ?

Key element.

$$\Phi(u; y) = \frac{1}{2} \|\Gamma^{-1}(y - g(u))\|_Y^2, \quad \text{the least squares functional}$$

Optimization

$$u^* = \arg\min_{u \in X} \Phi(u, y) + \|u - u_0\|_C^2$$

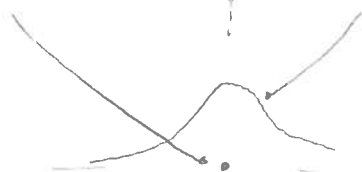
Often solved by some form
of gradient descent.

Bayesian

$$u \sim \mu_0, \quad \eta \sim N(0, \Gamma) \quad \text{indep.}$$

$$u^* = u | y \sim \mu$$

$$\text{with } \mu(du) \propto \exp(-\Phi(u, y)) \mu_0(du)$$

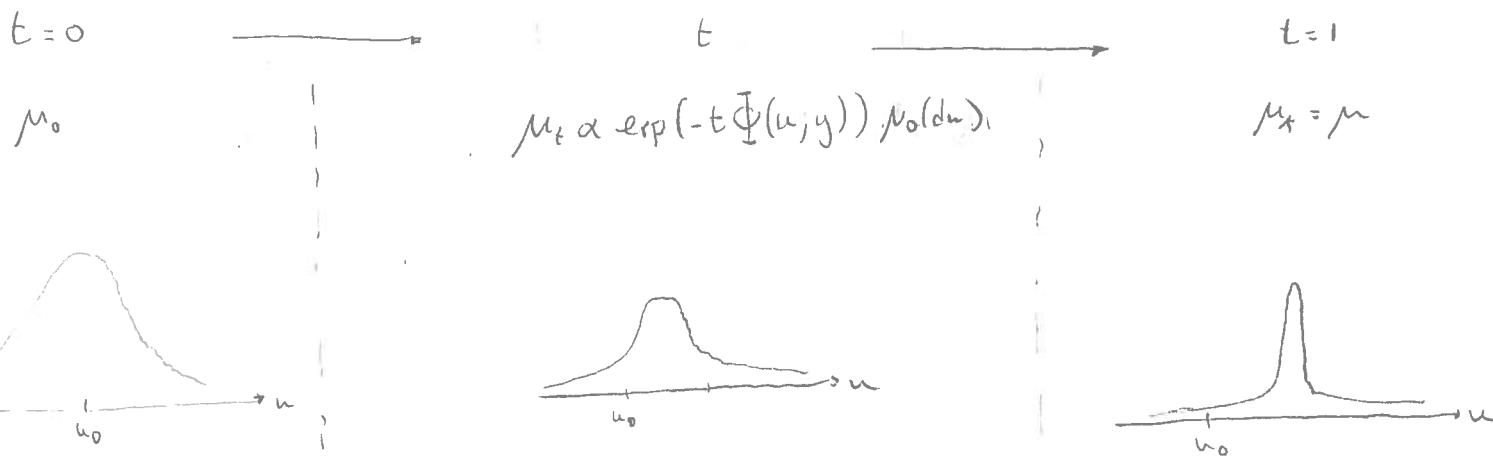


NOTE. For $\mu_0 = N(u_0, C)$, we get
 $\mu(du) \propto \exp[-(\Phi(u, y) + \|u - u_0\|_C^2)] du$

Examples

EnKF Approximate a partially, noisily observed dynamical system by an evolving ensemble of particles $\{u_n^{(j)}\}_{j=1}^J$

Idea. Interpolate between μ_0 and μ .



Define a step size h , and approximate this dynamics using the EnKF for the first $N=1/h$ steps.

Plug in the artificial dynamics.

$$u_{n+1}^{(j)} = u_n^{(j)} + C^{up}(u_n) [C^{pp}(u_n) + h^{-1} \Gamma]^{-1} (y_{n+1}^{(j)} - g(u_n^{(j)})) \quad j=1, \dots, J$$

where $y_{n+1}^{(j)} = y + \epsilon_{n+1}^{(j)}$ $\{\epsilon_n^{(j)}\} \text{ iid } N(0, \Sigma)$

$$C^{up}(u) = \hat{\text{cov}}(u, g(u)) = \frac{1}{J} \sum_{j=1}^J (u^{(j)} - \bar{u})(g(u^{(j)}) - \bar{g})^T$$

$$C^{pp}(u) = \hat{\text{cov}}(g(u), g(u))$$

How good is it?

- linear + gaussian noise: convergence as $J \rightarrow \infty$
- otherwise: complicated

What about letting J fix (realistic) and $h \rightarrow 0$?

Continuous limit

Revisiting update rule, and letting $h \rightarrow 0$ we obtain an Euler-Maruyama discretization of

$$\frac{du^{(j)}}{dt} = \underbrace{C^{up}(u) \Gamma^{-1} (y - g(u^{(j)}))}_{\text{deterministic}} + \underbrace{C^{up}(u) \Gamma^{-1} \sqrt{\Sigma}}_{\text{random}} \frac{dW^{(j)}}{dt} \quad (\text{SDE})$$

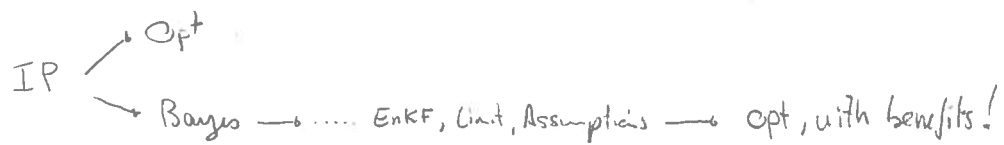
Assumptions! $g(\cdot) = A \cdot$ is linear, $y = \mathbb{R}^k$, $\Sigma = 0$

Then (SDE) becomes

$$\begin{aligned} \frac{du^{(j)}}{dt} &= C^{up}(u) \Gamma^{-1} (y - Au^{(j)}) = \hat{\text{cov}}(u, Au) \Gamma^{-1} (y - Au^{(j)}) \\ &= \hat{\text{cov}}(u, u) A^T \Gamma^{-1} (y - Au^{(j)}) = \boxed{-\hat{\text{cov}}(u, u) D_u \Phi(u, y)} \quad (\text{ODE}) \end{aligned}$$

(the twist)

Each particle performs a preconditionized gradient descent for Φ ! (Demo)



The Analysis (noise free: $y = Au^+$)

i) (ODE) has an unique solution

ii) The ensemble collapses to its mean for $t \rightarrow \infty$

iii) The EnKF converges to the best approx of the sol } we will prove jointly

Defs $e^{(j)} = u^{(j)} - \bar{u}$, $r^{(j)} = u^{(j)} - u^+$, $(E)_{ij} = \langle Ae^{(i)}, Ae^{(j)} \rangle_r$

Lemma: $E \xrightarrow{t \rightarrow \infty} 0$

Proof Mossgang: $\frac{dE}{dt} = -\frac{2}{J} E^2$ with $E(0) = Q^T \Lambda(0) Q$ $\Lambda(t) = \text{diag}(\lambda^{(1)}(t), \dots, \lambda^{(J)}(t))$

$$\Rightarrow E(t) = Q^T \Lambda(t) Q \text{ and } \frac{d\lambda^{(j)}}{dt} = -\frac{2}{J} \lambda^{(j)}$$

$$\Rightarrow \lambda^{(j)}(t) = \begin{cases} \left(\frac{2}{J}t + \frac{1}{\lambda^{(j)}(0)}\right)^{-1} & \text{for } \lambda^{(j)}(0) \neq 0 \\ 0, & \text{otherwise} \end{cases} = O(t^{-1}) \text{ as } t \rightarrow \infty$$

we're not allowed to do this, yet!

Existence (I) One can show $\frac{d u^{(j)}}{dt} = -\frac{1}{J} \sum_{k=1}^J \langle A r^{(j)}, A e^{(k)} \rangle_r e^{(k)}$

rhs is locally Lipschitz in u (polynomial) \Rightarrow sol exists on some $[0, T)$

$e^{(k)}$ is bounded? \checkmark

$r^{(j)}$ is bounded? Yes, with similar proof as $e^{(k)}$ $\checkmark \Rightarrow$ rhs is bounded, no blow up, \checkmark
sol exists in \mathbb{R}_+ .

Collapses to mean (II) Trivially follows from existence (I) and lemma.

We note $\lambda^{(j)}(t) = O(t^{-1}) \Rightarrow \|E\|_2 = O(t^{-1/2})$

Best approx (III) One can show that $u^{(j)}(t) \in \text{span}\{u^{(j)}(0)\}_{j=1}^J =: X_0$ with

We can decompose $r^{(j)}(t)$ as $r_0^{(j)} \in AX_0$ and $r_\perp^{(j)} \in AX_0^\perp$

Then $\dim AX_0 = \min\{J-1, \dim V\}$

and $r_0^{(j)}(t) = O(t^{-1})$ for $t \rightarrow \infty$.