

AN ELLIPTIC INVERSE PROBLEM ARISING IN GROUNDWATER FLOW

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BIRS Stochastic Multiscale Workshop
Banff, March 28th 2011

Outline

- 1 ELLIPTIC INVERSE PROBLEM
- 2 PRIOR MEASURE
- 3 BAYESIAN FRAMEWORK
- 4 MCMC APPROXIMATION
- 5 EXAMPLE
- 6 SPARSE APPROXIMATION
- 7 CONCLUSIONS
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Forward Problem

- **Darcy Law.** p pressure, k permeability.
- Let $D \subset \mathbb{R}^d$ be a bounded open set.
- Define $X = L^\infty(D)$ and $V = H_0^1(D)$.
- Let $k \in X$ with $\text{ess\,inf}_{x \in D} k(x) > 0$ and $f \in V^*$.
- Consider the (weak) elliptic PDE

$$\int_D k(x) \nabla p(x) \nabla v(x) \, dx = \int_D f(x) v(x) \, dx, \quad \forall v \in V.$$

- Unique solution p by Lax-Milgram.

Observation Operator

- Assume that $k = K(u)$ for $K : U \subseteq \ell^p \rightarrow K$.
- Define $G : U \rightarrow V$ by $G(u) = p$.
- Let $\mathcal{O} : V \rightarrow \mathbb{R}^K$ denote K linear functionals on V .
- Define $\mathcal{G} : X \rightarrow \mathbb{R}^K$ by $\mathcal{G} = \mathcal{O} \circ G$.
- We call \mathcal{G} the **OBSERVATION OPERATOR**.

Inverse Problem

- **FIND u GIVEN $y = \mathcal{G}(u) + \eta$.**
- Only **DENSITY ρ** of random variable η is known.
- **PRIOR** measure μ_0 on u .
- would like **BAYES THEOREM** in infinite dimensions.
- This would give the **POSTERIOR** measure μ^y on $u|y$:

$$\frac{d\mu^y}{d\mu_0}(u) \propto \rho(y - \mathcal{G}(u)).$$

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Log-Normal Prior

- $\{\varphi_j\}_{j \geq 1}$ an orthonormal sequence in $L^2(D)$.
- $\{\lambda_j\}_{j \geq 1}$ a positive ℓ^2 sequence of real numbers.
- $\{u_j\}_{j \geq 1}$ independent random variables with $u_j \sim \mathcal{N}(0, \lambda_j^2)$.
- $k(\mathbf{x}) = \exp\left(\sum_{j=1}^{\infty} u_j \varphi_j(\mathbf{x})\right)$.
- Defines a measure μ_0 on $U = \ell^2$, and push forward onto X .

Uniform Prior

- $\{\varphi_j\}_{j \geq 1}$ normalized sequence in X with $\|\psi_j\|_X = \lambda_j$.
- $\{\lambda_j\}_{j \geq 1}$ a positive ℓ^1 sequence of real numbers.
- $\{u_j\}_{j \geq 1}$ independent random variables with $u_j \sim \mathcal{U}(-1, 1)$.
- $k(\mathbf{x}) = \mathbf{a}(\mathbf{x}) + \sum_{j=1}^{\infty} u_j \varphi_j(\mathbf{x})$
- $\text{essinf}_{\mathbf{x} \in D} \mathbf{a}(\mathbf{x}) > \sum_{j=1}^{\infty} |\lambda_j|$.
- Defines a measure μ_0 on $U = [-1, 1]^{\mathbb{N}} \subset \ell^\infty$, and push forward onto X .

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Concrete Setting

- Study concrete case $y = \mathcal{G}(u) + \eta$, $\eta \sim \mathcal{N}(0, \Gamma)$.
- Define $\Phi(u) = \frac{1}{2} \|\Gamma^{-\frac{1}{2}}(\mathcal{G}(u) - y)\|^2$.
- **BAYES THEOREM** gives

$$\frac{d\mu^y}{d\mu_0}(u) \propto \exp(-\Phi(u)).$$

- **UNCERTAINTY QUANTIFICATION** consists of evaluating $\mathbb{E}^{\mu^y} \psi(u)$ for certain $\psi : U \rightarrow S$.
- We consider $\psi(u) = p$ and $S = V$ or $\psi(u) = p \otimes p$ and $S = \mathcal{L}(V, V)$.

Well-Posed Inverse Problem

Cotter, Dashti, Robinson, Stuart 2009.

Theorem

For both priors:

- *the posterior μ^y is absolutely continuous with respect to the prior measure μ_0 with density proportional to $\exp(-\Phi(u))$;*
- *posterior expectation of ψ is then*

$$\mathbb{E}^{\mu^y} \psi(u) = \frac{1}{Z} \mathbb{E}^{\mu_0} \exp(-\Phi(u)) \psi(u)$$

$$Z = \mathbb{E}^{\mu_0} \exp(-\Phi(u));$$

- *there is $C = C(r) > 0$ such that, for all y_1, y_2 with $\max\{\|y_1\|, \|y_2\|\} \leq r$,*

$$\|\mathbb{E}^{\mu^{y_1}} \psi(u) - \mathbb{E}^{\mu^{y_2}} \psi(u)\| \leq C \left(\mathbb{E}^{\mu} \|\psi(u)\|^2 + \mathbb{E}^{\nu} \|\psi(u)\|^2 \right)^{\frac{1}{2}} \|y_1 - y_2\|.$$

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Karhunen-Loeve Approximation

- Let $D = [0, 1]^d$ and $\varphi_{\mathbf{k}} = \exp(2\pi i \mathbf{k} \cdot x)$. **Fourier basis.**
- Let $\lambda_{\mathbf{k}} = (4\pi^2 |\mathbf{k}|^2)^{-s/2}$. **decay of standard deviations.**
- Let $P^N : U = \ell^2 \rightarrow \{u_{\mathbf{k}}, |\mathbf{k}| \leq N\}$.
- Let $U^N = P^N U$ and $\# = |U^N| \asymp N^d$

Measure on \mathbb{R}^\sharp

- $C^N : U^N \rightarrow U^N$ with $C^N = \text{diag}(\lambda_{\mathbf{k}})$ and $\mu_0^N = \mathcal{N}(0, C^N)$.
- Let $\mu^{y,N}$ denote the measure on U^N

$$\frac{d\mu^{y,N}}{d\mu_0^N} \propto \exp\left(-\Phi(P^N u)\right).$$

- In coordinates have Lebesgue density

$$\exp\left(-\Phi(P^N u) - \frac{1}{2}\langle u, (C^N)^{-1} u \rangle\right)$$

on \mathbb{R}^\sharp , amenable to MCMC.

- New MCMC: number of steps K independent of $\sharp(N)$.

Approximation Theorem

Dashti and Stuart 2010.

Theorem

Let $\psi(u) = p$ and $S = V$ or $\psi(u) = p \otimes p$ and $S = \mathcal{L}(V, V)$.
Assume that $s > \frac{d}{2}$ and let $t < s - \frac{d}{2}$. There is $C > 0$ such that,

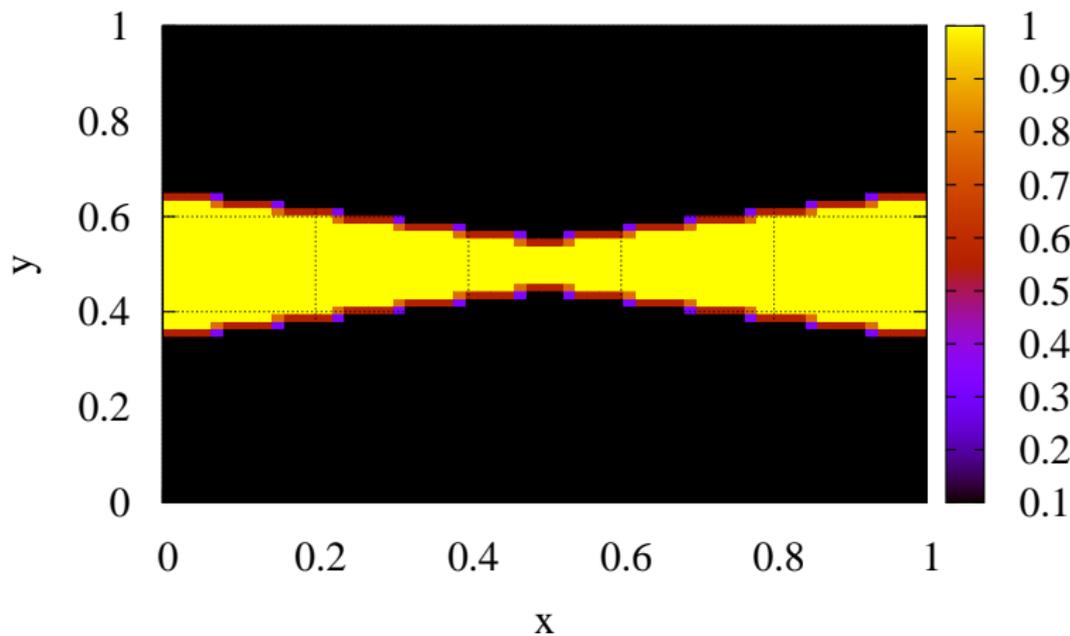
$$\|\mathbb{E}^{\mu^y} \psi(u) - \mathbb{E}^{\mu^{y,N}} \psi(P^N u)\|_S \leq CN^{-t}.$$

This error must be traded against MCMC error $M^{-\frac{1}{2}}$.

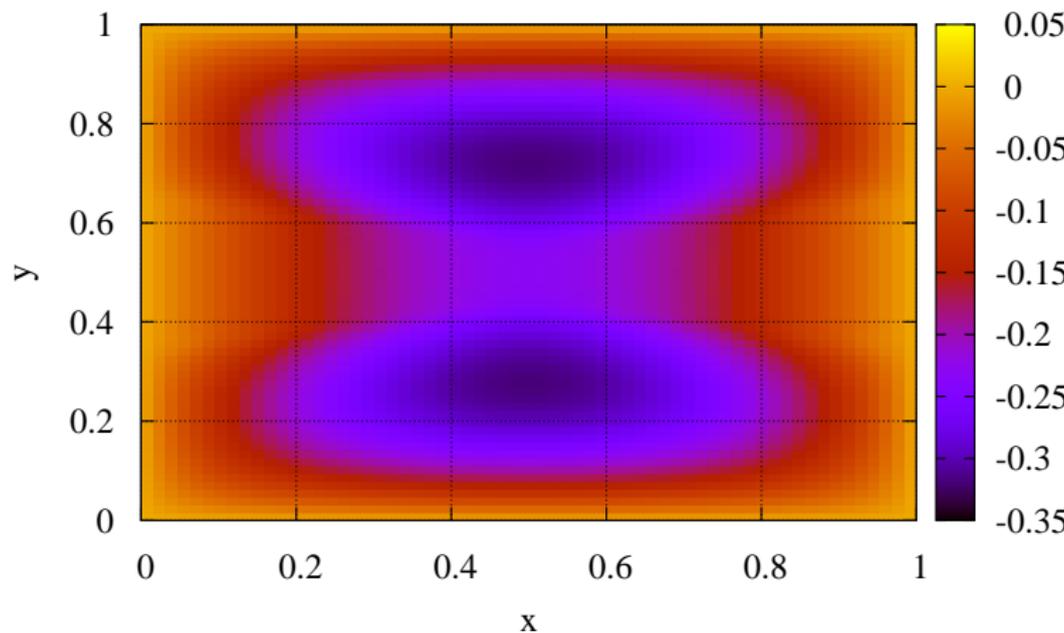
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True Diffusion Coefficient



True Pressure



MCMC Sampling

MOVIE

(Stuart and White 2011, in preparation)

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Polynomial Chaos

- Legendre polynomials $\int_{-1}^1 (L_k(t))^2 \frac{dt}{2} = 1$, $k = 0, 1, 2, \dots$
- $\mathcal{F} = \{\nu \in \mathbb{Z}^{\mathbb{N}} : |\nu|_1 < \infty\}$.
- Such multiindices have compact support.
- $L_\nu(\mathbf{z}) = \prod_{j \in \mathbb{N}} L_{\nu_j}(z_j)$, $\mathbf{z} \in \mathbb{C}^{\mathbb{N}}$, $\nu \in \mathcal{F}$.
- $\{L_\nu : \nu \in \mathcal{F}\}$ is orthonormal basis for $L^2(U, \mu_0(du))$.
- If $\Theta \in L^2(U, \mu_0(du); \mathbb{S})$ then $\Theta(u) = \sum_{\nu \in \mathcal{F}} \theta_\nu L_\nu(u)$.

Approximating Posterior Expectations

- We consider $\psi(u) = p$ and $S = V$ or $\psi(u) = p \otimes p$ and $S = \mathcal{L}(V, V)$.
- Recall that posterior expectation of ψ requires calculation of two integrals in infinite dimensions:

$$\mathbb{E}^{\mu^y} \psi(u) = \frac{1}{Z} \mathbb{E}^{\mu_0} \exp(-\Phi(u)) \psi(u)$$
$$Z = \mathbb{E}^{\mu_0} \exp(-\Phi(u));$$

- Both $\Theta_1(u) := \exp(-\Phi(u))$ and $\Theta_2(u) := \exp(-\Phi(u))\psi(u)$ are in $L^2(U, \mu_0(du))$.
- Suggests approximating integrals by $\Theta^M(u) = \sum_{\nu \in \Lambda_M} \theta_\nu L_\nu(u)$ for some index set $\Lambda_M \subset \mathcal{F}$ of cardinality M .

Approximation Theorem

Let $\mathbb{E}^{\mu^{y,M}} \psi(u)$ denote the resulting approximation.

Schwab and Stuart 2011

Theorem

Let $\psi(u) = p$ and $S = V$ or $\psi(u) = p \otimes p$ and $S = \mathcal{L}(V, V)$. Assume that, for some $\sigma \in (0, 1]$, $\sum_{j=1}^{\infty} \lambda_j^\sigma < \infty$. There is an index set Λ_N of cardinality M such that,

$$\|\mathbb{E}^{\mu^y} \psi(u) - \mathbb{E}^{\mu^{y,M}} \psi(P^M u)\|_S \leq CM^{\frac{1}{2} - \frac{1}{\sigma}}.$$

- If $\sigma < 1$ then this rate beats $M^{-\frac{1}{2}}$ from MCMC.
- Challenge is to realize this approximation so that cost/per unit error trade-off beats MCMC.

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- BAYESIAN approach to inverse problems allows for a natural approach to quantify uncertainty in the presence of data.
- KARHUNEN-LOEVE truncation leads to tractable MCMC methods with quantifiable error.
- POLYNOMIAL CHAOS representation of the posterior density affords the possibility of beating MCMC cost/unit error.

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Two Main Papers

- “Uncertainty quantification and weak approximation of an elliptic inverse problem”, M. Dashti and A.M. Stuart, submitted 2010. <http://arxiv.org/abs/1102.0143>
- “Sparse deterministic approximation of Bayesian inverse problems”, Ch. Schwab and A.M. Stuart, submitted 2011. <http://arxiv.org/abs/1103.4522>

Other Related Papers

All papers can be found at:

<http://www.warwick.ac.uk/~masdr/>

- 16c “Inverse Problems: A Bayesian Perspective”, A.M. Stuart, Acta Numerica **19**(2010).
- 80 “Bayesian inverse problems for functions and applications to fluid mechanics”, S.L. Cotter, M. Dashti, J.C. Robinson, A.M. Stuart, Inverse Problems, **25**(2009), 115008.
- 81 “Approximation of Bayesian inverse problems for PDEs”, S.L. Cotter, M. Dashti and A.M. Stuart, SIAM J. Num. Anal, **48**(2010), 322–345.
- 68 “A Bayesian approach to data assimilation”, A. Apte, M. Hairer. A.M. Stuart, J. Voss, PhysicaD, **230**(2007), 50–64.