

Higher order QMC integration for Bayesian estimations

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Outline

- 1 Introduction
- 2 Parametric Bayesian posterior
- 3 Higher order QMC method
- 4 Combined error bound results
- 5 Numerical experiments

An example

- Consider

$$\begin{aligned} -\nabla \cdot (u(\mathbf{x}; \mathbf{y}) \nabla q(\mathbf{x}; \mathbf{y})) &= F(\mathbf{x}) \text{ in } D \subset \mathbb{R}^d \\ q(\mathbf{x}; \mathbf{y}) &= 0 \text{ on } \partial D, \end{aligned}$$

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- We are interested in the inverse problem of finding u from δ where

$$\delta_j = \mathcal{G}_j(q) + \eta_j, \quad j = 1, \dots, K.$$

Here \mathcal{G}_j is a continuous linear functional and η_j is a noise.

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Here \mathcal{G}_j is a continuous linear functional and η_j is a noise.

- Problem:** The unknown u is a function (infinite dimensional) whereas the data $\eta \in \mathbb{R}^K$ is finite dimensional.

General setup

Let

- the uncertainty $u \in X$, e.g. $X = L^\infty(D)$, be parametrized by

$$u(\mathbf{x}; \mathbf{y}) = u_0(\mathbf{x}) + \sum_{j \geq 1} y_j \psi_j(\mathbf{x}), \quad y_j \in [-1/2, 1/2].$$

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- the forward response map $G : X \times \mathcal{X}' \rightarrow \mathcal{X}$

$$q = G(u; F)$$

be given, e.g. G is the solution operator of the above elliptic PDE.

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where η is an additive noise with law $\mathbb{Q}_0 \sim \mathcal{N}(0, \Gamma)$ with covariance matrix $\Gamma \in \mathbb{R}_{\text{spd}}^{K \times K}$.

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- **Goal:** to compute a Bayesian estimate of QoI ϕ , given measurements of the observations.

Bayesian Estimation

Theorem 1

Assume that the potential $\Phi_{\Gamma}(u; \delta) = \frac{1}{2} \|\delta - \mathcal{G}(u)\|_{\Gamma}^2$ is, for fixed data $\delta \in \mathbb{R}^K$, π_0 measurable and that, for \mathbb{Q}_0 -a.e. data $\delta \in \mathbb{R}^K$ there holds

$$Z := \int_U \exp(-\Phi_{\Gamma}(u; \delta)) \pi_0(du) > 0 .$$

Then the conditional distribution of $u|\delta$ (u given δ) exists and is denoted by π^{δ} . It is absolutely continuous with respect to π_0 and there holds

$$\frac{d\pi^{\delta}}{d\pi_0}(u) = \frac{1}{Z} \exp(-\Phi_{\Gamma}(u; \delta)) . \quad (1.1)$$

With the QoI ϕ we associate parametric map

$$\begin{aligned}\Psi(\mathbf{y}) &= \Theta(\mathbf{y})\phi(q(u)) \\ &= \exp(-\Phi_{\Gamma}(u; \delta))\phi(q(u)) .\end{aligned}\tag{2.1}$$

Then the Bayesian estimate of the QoI ϕ , given noisy data δ , takes the form

$$\mathbb{E}^{\pi^{\delta}}[\phi] = Z'/Z, \quad Z' := \int_U \Psi(\mathbf{y}) \pi_0(d\mathbf{y}) .\tag{2.2}$$

An approximation strategy

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- The solution $q = G(u)$ is approximated by q_h via a Galerkin method
- The high dimensional integrals Z, Z' are approximated by higher order QMC method

Higher order QMC method

We approximate the s -dimensional integral

$$I_s(F) := \int_{[0,1]^s} F(\mathbf{y}) \, d\mathbf{y} \quad (3.1)$$

by an N -point QMC method, i.e., an equal-weight quadrature rule of the form

$$Q_{N,s}(F) := \frac{1}{N} \sum_{n=0}^{N-1} F(\mathbf{y}_n), \quad (3.2)$$

Digital net

Definition 1 (Digital net)

Let b be prime and $\alpha, s, m \in \mathbb{N}$. Let C_1, \dots, C_s be $\alpha m \times m$ matrices over \mathbb{Z}_b ; these are known as the generating matrices. For each integer $0 \leq n < b^m$, let $n = \xi_0 + \xi_1 b + \dots + \xi_{m-1} b^{m-1}$ be the b -adic expansion of n . For each $1 \leq j \leq s$ we compute

$$(\zeta_1, \zeta_2, \dots, \zeta_{\alpha m})^\top = C_j (\xi_0, \xi_1, \dots, \xi_{m-1})^\top,$$

set

$$y_j^{(n)} = \frac{\zeta_1}{b} + \frac{\zeta_2}{b^2} + \dots + \frac{\zeta_{\alpha m}}{b^{\alpha m}}$$

and set $\mathbf{y}_n = (y_1^{(n)}, y_2^{(n)}, \dots, y_s^{(n)})$.

Then, the resulting point set $\mathcal{S} = \{\mathbf{y}_n\}_{n=0}^{b^m-1} \subset [0, 1]^s$ is called a digital net.

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- Given $s \geq 1$, select s polynomials $q_1(x), \dots, q_s(x)$ from the set $G_{b,m}$ and write collectively

$$\mathbf{q} = \mathbf{q}(x) = (q_1(x), \dots, q_s(x)) \in G_{b,m}^s; \quad (3.4)$$

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$$n(x) = \sum_{r=0}^{m-1} \xi_r x^r \in \mathbb{Z}_b[x].$$

Polynomial lattice rule

- Denote by v_m the map from $\mathbb{Z}_b((x^{-1}))$ to the interval $[0, 1)$ defined for any integer w by

$$v_m \left(\sum_{\ell=w}^{\infty} t_{\ell} x^{-\ell} \right) = \sum_{\ell=\max(1,w)}^m t_{\ell} b^{-\ell} .$$

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- The QMC point set $S_{P,b,m,s}(\mathbf{q})$ of a (classical) polynomial lattice rule comprises the points

$$\mathbf{y}_n = \left(v_m \left(\frac{n(x)q_1(x)}{P(x)} \right), \dots, v_m \left(\frac{n(x)q_s(x)}{P(x)} \right) \right) \in [0, 1)^s, \\ n = 0, \dots, b^m - 1.$$

Interlaced polynomial lattice rules

- A *digit interlacing function* with interlacing factor $\alpha \in \mathbb{N}$ is given by

$$\begin{aligned} \mathcal{D}_\alpha : [0, 1)^\alpha &\rightarrow [0, 1) \\ (\mathbf{x}_1, \dots, \mathbf{x}_\alpha) &\mapsto \sum_{a=1}^{\infty} \sum_{j=1}^{\alpha} \xi_{j,a} \mathbf{b}^{-j-(a-1)\alpha}, \end{aligned} \quad (3.5)$$

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- For vectors, set

$$\begin{aligned} \mathcal{D}_\alpha : [0, 1)^{\alpha s} &\rightarrow [0, 1)^s \\ (\mathbf{x}_1, \dots, \mathbf{x}_{\alpha s}) &\mapsto (\mathcal{D}_\alpha(\mathbf{x}_1, \dots, \mathbf{x}_\alpha), \dots, \mathcal{D}_\alpha(\mathbf{x}_{(s-1)\alpha+1}, \dots, \mathbf{x}_{s\alpha})). \end{aligned} \quad (3.6)$$

Proposition 1

Let $s \geq 1$ and $N = b^m$ for $m \geq 1$ be integers and b be prime. Let $\beta = (\beta_j)_{j \geq 1}$ be a sequence of positive numbers. Assume that

$$\exists 0 < p \leq 1 : \sum_{j=1}^{\infty} \beta_j^p < \infty . \quad (3.7)$$

Define, for $0 < p < 1$ as in (3.7),

$$\alpha := \lfloor 1/p \rfloor + 1 . \quad (3.8)$$

Consider $F(\mathbf{y})$ whose mixed partial derivatives of order α satisfy
 $\forall \mathbf{y} \in U \forall \mathbf{s} \in \mathbb{N}$

$$\forall \boldsymbol{\nu} \in \{0, 1, \dots, \alpha\}^s : \quad |(\partial_{\mathbf{y}}^{\boldsymbol{\nu}} F)(\mathbf{y})| \leq c(F) \boldsymbol{\nu}_{E!} \prod_{j \in E} \beta_j^{\nu_j} \times |\boldsymbol{\nu}_{E^c}|! \prod_{j \in E^c} \beta_j^{\nu_j} \quad (3.9)$$

for some fixed integer $J \in \mathbb{N}$ where $E = \{1, 2, \dots, J\}$ and $E^c = \mathbb{N} \setminus E$, and where $c(g) > 0$ is independent of \mathbf{y} , \mathbf{s} and of $\boldsymbol{\nu}$. Then, for every $N \in \mathbb{N}$, one can construct an interlaced polynomial lattice rule of order α with N points such that there holds the error bound

$$\forall \mathbf{s}, N \in \mathbb{N} : \quad |I_s(F) - Q_{N,\mathbf{s}}(F)| \leq C_{\alpha,\beta,b,p} N^{-1/p}, \quad (3.10)$$

where $C_{\alpha,\beta,b,p} < \infty$ is a constant independent of \mathbf{s} and N .

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- Parametric regularity of solutions: $\exists \beta \in \ell^1(\mathbb{N})$,

$$\forall \mathbf{y} \in U : \|(\partial_{\mathbf{y}}^{\nu} q)(\mathbf{y})\|_{\mathcal{X}} \leq C_0 |\nu|! \beta^{\nu} \|f\|_{\mathcal{Y}}, \quad \forall \nu \in \mathbb{N}^{\mathbb{N}}, |\nu| < \infty.$$

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- Approximation properties

$$\forall v \in \mathcal{X}_t : \inf_{v^h \in \mathcal{X}^h} \|v - v^h\|_{\mathcal{X}} \leq C_t h^t \|v\|_{\mathcal{X}_t},$$

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- The sparsity condition imposed on the KL expansion of u

$$\{\|\psi_j\|_{\mathcal{X}}\}_{j \geq 1} \in \ell^p(\mathbb{N})$$

Theorem 2

The QMC-Petrov Galerkin approximation of the Bayesian estimate $\mathbb{E}^{\pi^\delta}[\phi]$ in (2.2) obtained as $Z'_{N,s,h}/Z_{N,s}$ with QMC-PG approximations $Z'_{N,s,h}$ and $Z_{N,s}$ of the integrals Z' and Z in (2.2), the error bound

$$\left| \mathbb{E}^{\pi^\delta}[\phi] - Z'_{N,s,h}/Z_{N,s} \right| \leq C(\Gamma, p) \left(h^t + s^{-(1/p-1)} + N^{-1/p} \right) .$$

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- QoI: parametric solution $q(x, \mathbf{y})$ evaluated at $x = \bar{x} = 0.25$.

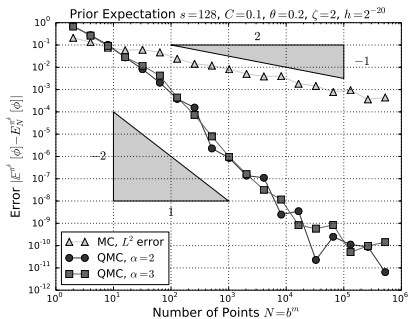
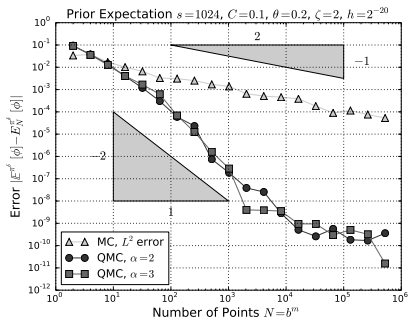
(a) $s = 128$ (b) $s = 1024$

Figure: Convergence of the error of the prior mean approximation vs. the number of samples $N = b^m$ for $s = 128, 1024, \zeta = 2, \alpha = 2, 3, h = 2^{-20}$.

Observation operator: evaluation of the solution $q(\mathbf{y})$ at $\mathbf{x}_{obs} = (0.2, 0.5, 0.7)$.

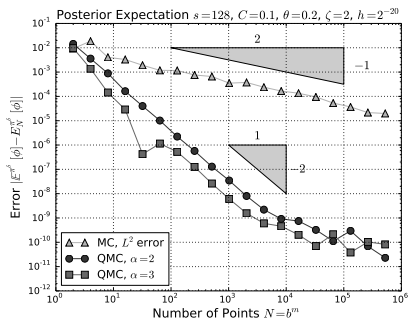
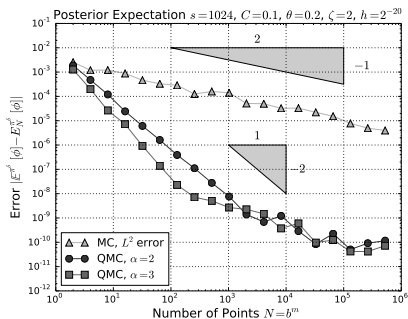
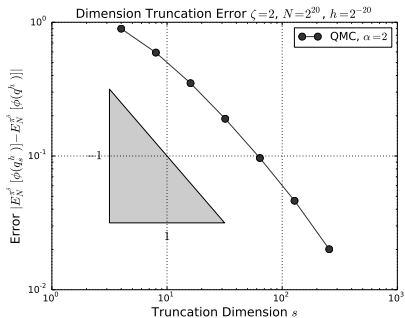
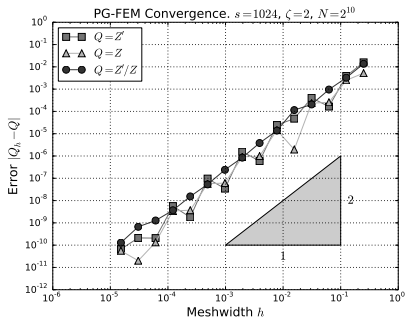
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(a) Dimension truncation error



(b) FEM error, KL basis

Figure: Dimension truncation and FEM errors. Reference solutions were obtained using $s = 1024$ dimensions for (a) and $h = 2^{-20}$ for (b).

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- **Future work:** A multi-level QMC approach for Bayesian estimates

References

- J.Dick, F.Y.Kuo, Q.T.Le Gia, D. Nuyens, Ch. Schwab: Higher order QMC Galerkin discretization for parametric operator equations, SINUM, 2014.

References

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THANK YOU FOR YOUR ATTENTION

Infinite-Dim Parametric Operator Equations

Let $f \in \mathcal{Y}'$ be given, for every $\mathbf{y} \in U$, find

$$q(\mathbf{y}) \in \mathcal{X} : A(\mathbf{y})q(\mathbf{y}) = f$$

Assume that for every $\mathbf{y} \in U$, there is a sequence $\{A_j\}$

$$A(\mathbf{y}) = A_0 + \sum_{j \geq 1} y_j A_j \tag{5.1}$$

In the previous example, we can define $A_0 = -\nabla \cdot (u \nabla)$ and $A_j = -\nabla \cdot (\psi_j \nabla)$

We associate with the operator A_j the bilinear forms $\alpha_j(\cdot, \cdot) : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$ via

$$\forall v \in \mathcal{X}, w \in \mathcal{Y} : \alpha_j(v, w) = \mathcal{Y} \langle w, A_j v \rangle_{\mathcal{Y}}, \quad j = 0, 1, 2, \dots .$$

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- ① The nominal operator $A_0 \in \mathcal{L}(\mathcal{X}, \mathcal{Y}')$ is boundedly invertible, i.e., there exists $\mu_0 > 0$ such that

$$\inf_{0 \neq v \in \mathcal{X}} \sup_{0 \neq w \in \mathcal{Y}} \frac{\alpha_0(v, w)}{\|v\|_{\mathcal{X}} \|w\|_{\mathcal{Y}}} \geq \mu_0, \quad \inf_{0 \neq w \in \mathcal{Y}} \sup_{0 \neq v \in \mathcal{X}} \frac{\alpha_0(v, w)}{\|v\|_{\mathcal{X}} \|w\|_{\mathcal{Y}}} \geq \mu_0. \quad (5.2)$$

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- 2 The fluctuation operators $\{A_j\}_{j \geq 1}$ are small with respect to A_0 : there exists a constant $0 < \kappa < 2$ s.t. for μ_0 as in (5.2) and some $s \geq 1$ we have

$$\sum_{j \geq s+1} \beta_j \leq \kappa < 2, \quad \text{where } \beta_j := \|A_0^{-1} A_j\|_{\mathcal{L}(\mathcal{X}, \mathcal{Y}')} , \quad j = 1, 2, \dots \quad (5.3)$$

Go back...