

# Adaptive Stochastic Galerkin Methods

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## Summary

## A model problem

$D \subset \mathbb{R}^d$  Lipschitz, for  $\omega \in \Omega$ ,

$$\begin{aligned} -\nabla \cdot (a(\omega, x) \nabla u(\omega, x)) &= f(x) & x \in D, \\ u(\omega, x) &= 0 & x \in \partial D. \end{aligned}$$

Weak formulation: Find  $u(\omega, x) \in H_0^1(D)$  such that

$$\int_D a(\omega, x) \nabla u(\omega, x) \cdot \nabla v(x) dx = \int_D f(x) v(x) dx$$

for all  $v \in H_0^1(D)$ .

Assume  $a(\omega, x)$  is uniformly bounded,

$$0 < a_- \leq a(\omega, x) \leq a_+ < \infty \quad \forall x \in D, \forall \omega \in \Omega.$$

## Series expansion

Let  $\bar{a}(x)$  be some approximation of  $a(\omega, x)$ , e.g.  $\bar{a}(x) := (a_- + a_+)/2$ .

Let  $(\psi_m, \psi_m^*)_{m \in \mathbb{N}}$  be a **biorthogonal basis** of  $L^2(D)$ . For  $m \in \mathbb{N}$ ,

$$Y_m(\omega) := \int_D (a(\omega, x) - \bar{a}(x)) \psi_m^*(x) dx \in [-1, 1].$$

By Hölder's inequality,  $Y_m$  is bounded for all  $m \in \mathbb{N}$ . Without loss of generality,  $\psi_m, \psi_m^*$  are scaled such that  $|Y_m| \leq 1$ .

Then

$$a(\omega, x) = \bar{a}(x) + \sum_{m=1}^{\infty} Y_m(\omega) \psi_m(x),$$

with convergence in  $L^2(D)$  for all  $\omega \in \Omega$ .

Under stronger assumptions, e.g.  $\sum_{m=1}^{\infty} \|\psi_m\|_{L^\infty(D)} < \infty$ , also convergence in  $L^\infty(D)$ , uniformly in  $\omega \in \Omega$ .

## Transformation to a product parameter domain

The coefficients  $Y_m(\omega)$  of  $a(\omega, x) - \bar{a}(x)$  constitute a map

$$Y : \Omega \rightarrow \Gamma := [-1, 1]^\infty, \quad \omega \mapsto (Y_m(\omega))_{m \in \mathbb{N}}.$$

Define the parametric diffusion coefficient

$$a(y, x) := \bar{a}(x) + \sum_{m=1}^{\infty} y_m \psi_m(x), \quad y = (y_m)_{m \in \mathbb{N}} \in \Gamma.$$

Then  $a(Y(\omega), x) = a(\omega, x)$  for all  $\omega \in \Omega$ .

For all  $y \in \Gamma$ , let  $u(y) \in H_0^1(D)$  solve

$$\int_D a(y, x) \nabla u(y, x) \cdot \nabla v(x) dx = \int_D f(x) v(x) dx \quad \forall v \in H_0^1(D).$$

Then  $u(Y(\omega), x) = u(\omega, x)$  for all  $\omega \in \Omega$ .

## Weak formulation on the parameter domain

Let  $\pi_m$  be a probability measure on  $[-1, 1]$  for all  $m \in \mathbb{N}$ , and

$$\pi := \bigotimes_{m=1}^{\infty} \pi_m \quad \text{on} \quad (\Gamma, \mathcal{B}(\Gamma)).$$

If  $Y \sim \pi$ , then  $(Y_m)_m$  are independent, and  $Y_m \sim \pi_m$ .

Weak formulation: Find  $u \in L^2_{\pi}(\Gamma; H_0^1(D))$  s.t.  $\forall v \in L^2_{\pi}(\Gamma; H_0^1(D))$ ,

$$\int_{\Gamma} \int_D a(y, x) \nabla u(y, x) \cdot \nabla v(y, x) dx d\pi(y) = \int_{\Gamma} \int_D f(x) v(y, x) dx d\pi(y).$$

Continuous and coercive bilinear form on  $L^2_{\pi}(\Gamma; H_0^1(D))$ .

Product structure:  $L^2_{\pi}(\Gamma; H_0^1(D)) \cong L^2_{\pi}(\Gamma) \otimes H_0^1(D)$ .

- deterministic space  $H_0^1(D)$ ,
- stochastic space  $L^2_{\pi}(\Gamma)$ .

## Orthonormal polynomials

Orthonormal polynomials w.r.t.  $\pi_m$  satisfy a recursion  $P_0^{(m)} = 1$ ,

$$\beta_{n+1}^{(m)} P_{n+1}^{(m)}(\xi) = (\xi - \alpha_n^{(m)}) P_n^{(m)}(\xi) - \beta_n^{(m)} P_{n-1}^{(m)}(\xi).$$

Tensor product orthonormal polynomials

$$P_\mu := \bigotimes_{m=1}^{\infty} P_{\mu_m}^{(m)}, \quad \mu \in \Lambda := \{ \mu \in \mathbb{N}_0^{\mathbb{N}} ; \# \text{supp } \mu < \infty \},$$

$$\text{i.e. } P_\mu(y) = \prod_{m=1}^{\infty} P_{\mu_m}^{(m)}(y_m) = \prod_{m \in \text{supp } \mu} P_{\mu_m}^{(m)}(y_m) \text{ for } y \in \Gamma.$$

### Theorem

$(P_\mu)_{\mu \in \Lambda}$  is an orthonormal basis of  $L_\pi^2(\Gamma)$ .

## Infinite system of equations

Expand the solution  $u$  w.r.t. the basis  $(P_\mu)_{\mu \in \Lambda}$  of  $L^2_\pi(\Gamma)$ ,

$$u(y, x) = \sum_{\mu \in \Lambda} u_\mu(x) P_\mu(y), \quad (u_\mu)_{\mu \in \Lambda} \in \ell^2(\Lambda; H_0^1(D)).$$

Define  $a_{\nu\mu}(x) := \int_\Gamma a(y, x) P_\mu(y) P_\nu(y) d\pi(y)$ ,  $\mu, \nu \in \Lambda$ ,

and  $f_\nu(x) := f(x) \int_\Gamma P_\nu(y) d\pi(y)$ ,  $\nu \in \Lambda$ .

Then for all  $\nu \in \Lambda$ , using test functions  $v(x) P_\nu(y)$ ,

$$\sum_{\mu \in \Lambda} \int_D a_{\nu\mu}(x) \nabla u_\mu(x) \cdot \nabla v(x) dx = \int_D f_\nu(x) v(x) dx \quad \forall v \in H_0^1(D).$$

**Infinite system of deterministic equations** for the **coefficients** of  $u$ , **equivalent** to the weak formulation by Parseval's identity.



# Infinite system of equations

Recall

- $a_{\nu\mu}(x) = \int_{\Gamma} a(y, x) P_{\mu}(y) P_{\nu}(y) d\pi(y), \quad \mu, \nu \in \Lambda,$
- $\xi P_n^{(m)}(\xi) = \beta_{n+1}^{(m)} P_{n+1}^{(m)}(\xi) + \alpha_n^{(m)} P_n^{(m)}(\xi) + \beta_n^{(m)} P_{n-1}^{(m)}(\xi),$
- $a(y, x) = \bar{a}(x) + \sum_{m=1}^{\infty} y_m \psi_m(x).$

Therefore,  $a_{\nu\mu} = 0$  except for

$$a_{\mu\mu}(x) = \bar{a}(x) + \sum_{m=1}^{\infty} \alpha_{\mu_m}^{(m)} \psi_m(x),$$

$$a_{\mu, \mu+\epsilon_m}(x) = a_{\mu+\epsilon_m, \mu}(x) = \beta_{\mu_m+1}^{(m)} \psi_m(x), \quad m \in \mathbb{N}.$$

In particular, no integrals over  $\Gamma$  need to be computed.

## Galerkin projection

Define a nested sequence of finite element spaces

$$\{0\} = V_0 \subset V_1 \subset \dots \subset V_\ell \subset V_{\ell+1} \subset \dots \subset H_0^1(D) .$$

For each  $\mu \in \Lambda$ , select a space  $V_{\ell(\mu)}$ , and define

$$\mathcal{V}_\ell := \{(v_\mu)_{\mu \in \Lambda} ; v_\mu \in V_{\ell(\mu)} \forall \mu \in \Lambda\} \subset \ell^2(\Lambda; H_0^1(D)) .$$

Assume  $\#\{\mu \in \Lambda ; \ell(\mu) \neq 0\} < \infty$ , then  $\dim \mathcal{V}_\ell < \infty$ .

Galerkin projection: replace  $\ell^2(\Lambda; H_0^1(D))$  by  $\mathcal{V}_\ell$  in the infinite system of equations for  $(u_\mu)_{\mu \in \Lambda}$ .

- **finite** system of equations since  $\mathcal{V}_\ell$  is finite dimensional.
- **well-posed** by Lax–Milgram since the bilinear form is coercive.
- **quasi-optimal** approximation in  $\ell^2(\Lambda; H_0^1(D)) \cong L_\pi^2(\Gamma; H_0^1(D))$ .

## Operator matrix perspective

Semidiscrete setting  $\mathcal{V}_N := \ell^2(\Lambda_N; H_0^1(D))$  for a  $\Lambda_N \subset \Lambda$ ,  $\#\Lambda_N = N$ .

Define the operator matrix  $\mathbf{A}_N \in \mathcal{L}(H_0^1(D), H^{-1}(D))^{N \times N}$ ,

$$\mathbf{A}_N := (A_{\nu\mu})_{\nu, \mu \in \Lambda_N}, \quad A_{\nu\mu} v := -\nabla \cdot (a_{\nu\mu} \nabla v),$$

and the vector  $\mathbf{f}_N := (f_\nu)_{\nu \in \Lambda_N} \in H^{-1}(D)^N$ .

The Galerkin projection  $\mathbf{u}_N \in H_0^1(D)^N$  is the solution of

$$\mathbf{A}_N \mathbf{u}_N = \mathbf{f}_N.$$

Iterative solution, e.g. by PCG, with preconditioner  $\bar{\mathbf{A}}_N := \text{diag}(\bar{A})$ ,  $\bar{A} v := -\nabla \cdot (\bar{a} \nabla v)$  consists of applications of  $A_{\nu\mu}$  and  $\bar{A}^{-1}$ .

The matrix  $\mathbf{A}_N$  is sparse,

$$\text{nnz}(\mathbf{A}_N) \leq (1 + 2\bar{\lambda}(\Lambda_N))N$$

for the average index length  $\bar{\lambda}(\Lambda_N) := \frac{1}{N} \sum_{\mu \in \Lambda_N} \#\text{supp } \mu$ .

## Adaptive Method

Iterative adaptive method  $\mathbf{u}_N^{(0)} := \mathbf{0}$ ,  $\Lambda_N^{(0)} := \emptyset$

1.  $\mathbf{r}_N^{(k)} := \text{Residual}(\mathbf{u}_N^{(k)})$  approximate  $\mathbf{f} - \mathbf{A}\mathbf{u}_N^{(k)}$
2.  $\Lambda_N^{(k+1)} := \text{Refine}(\Lambda_N^{(k)}, \mathbf{r}_N^{(k)})$  refine the discretization
3.  $\mathbf{u}_N^{(k+1)} := \text{Galerkin}(\Lambda_N^{(k+1)})$  Galerkin sol. in  $\ell^2(\Lambda_N^{(k+1)}; H_0^1(D))$

### Lemma

If  $\left\| (\mathbf{f} - \mathbf{A}\mathbf{u}_N^{(k)}) \Big|_{\Lambda_N^{(k+1)}} \right\|_{\ell^2(\Lambda; H^{-1})} \geq \vartheta \left\| \mathbf{f} - \mathbf{A}\mathbf{u}_N^{(k)} \right\|_{\ell^2(\Lambda; H^{-1})}$ , then

$$\left\| \mathbf{u} - \mathbf{u}_N^{(k+1)} \right\|_{\mathbf{A}} \leq \sqrt{1 - \kappa(\mathbf{A})^{-1}\vartheta^2} \left\| \mathbf{u} - \mathbf{u}_N^{(k)} \right\|_{\mathbf{A}}.$$

In particular, the iteration converges in the energy norm.

# Approximation of the residual

## Goal

For  $w = \sum_{\mu \in \Lambda_N} w_\mu P_\mu$ , approximate the residual

$$r(w) := f + \nabla \cdot (\bar{a} \nabla w) + \sum_{m=1}^{\infty} \nabla \cdot (\psi_m \nabla w).$$

## Partition

$$\Lambda_N = \Lambda_N^{[1]} \sqcup \Lambda_N^{[2]} \sqcup \dots \sqcup \Lambda_N^{[J]},$$

where  $\Lambda_N^{[1:J]}$  contains  $\mu \in \Lambda_N$  with the largestsmallest  $|w_\mu|_{H_0^1(D)}$ .

For  $w^{[j]} := w|_{\Lambda_N^{[j]}}$  and  $M_1 \geq M_2 \geq \dots \geq M_J \geq 0$ ,

$$r(w) \approx r_N(w) := f + \nabla \cdot (\bar{a} \nabla w) + \sum_{j=1}^J \sum_{m=1}^{M_j} \nabla \cdot (\psi_m \nabla w^{[j]}).$$

# Computational example

## Model problem

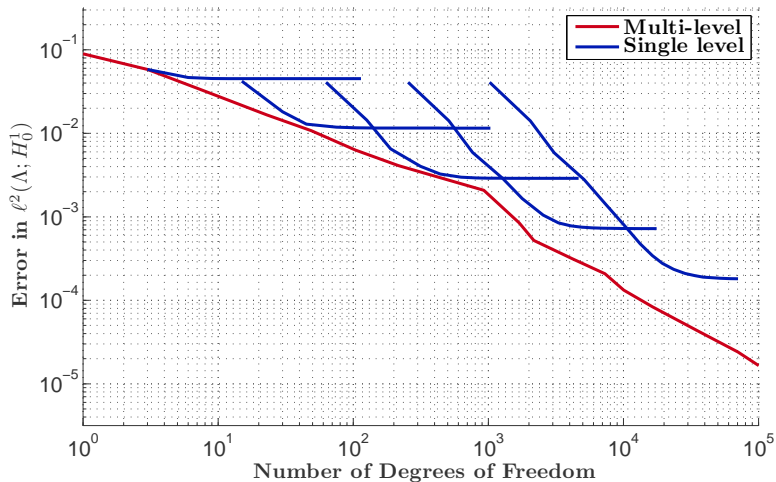
- $D = (0, 1)$
- $f(x) = x$
- $\bar{a}(x) = 1$ , i.e.  $\bar{A} = -\Delta$
- $\psi_m(x) = cm^{-4} \sin(m\pi x)$ , scaled such that  $c \sum_{m=1}^{\infty} m^{-4} = \frac{5}{6}$
- $\pi_m$  is the uniform distribution on  $[-1, 1]$ , i.e.  $d\pi_m(y_m) = \frac{1}{2}dy_m$
- $P_n^{(m)}$  are Legendre polynomials

## Linear finite element discretization,

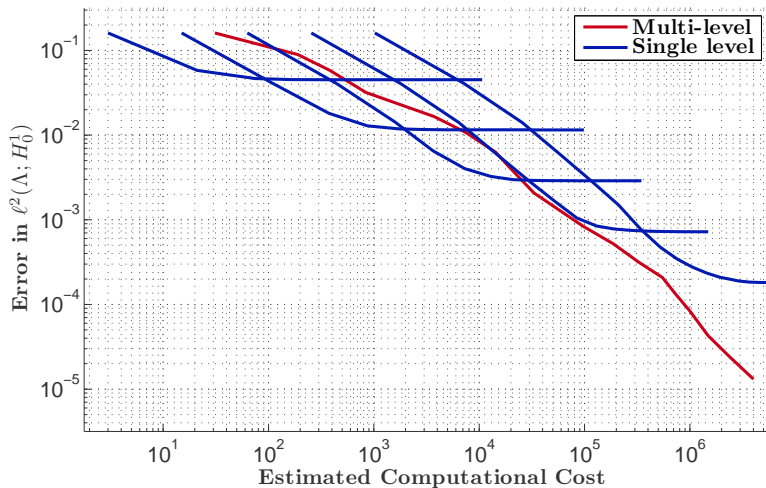
**Single level** fixed finite element space  $V_\ell \subset H_0^1(D)$  for all  $\mu \in \Lambda_N$  and all iterations  $k$

**Multi-level** different  $V_\ell$  for each  $\mu \in \Lambda_N$  and  $k \in \mathbb{N}$ , determined a posteriori in the refinement step

# Computational example



# Computational example





## Summary

- Tensor products of orthonormal polynomials form an orthonormal basis  $(P_\mu)_{\mu \in \Lambda}$  of  $L^2_\pi(\Gamma)$  for the infinite product domain  $\Gamma = [-1, 1]^\infty$  and infinite product measure  $\pi = \bigotimes_{m=1}^\infty \pi_m$ .
- Expanding the solution  $u$  w.r.t. this basis, a stochastic boundary value problem is recast as an infinite system of deterministic equations.
- Galerkin projections can be computed by standard iterative methods applied to a sparse operator matrix.
- Adaptive wavelet techniques applied to the basis  $(P_\mu)_{\mu \in \Lambda}$  can be used to determine appropriate sets  $\Lambda_N$  of active indices and finite element spaces  $V_{\ell(\mu)}$ ,  $\mu \in \Lambda_N$ , during the solution process.

Thank you for your attention!