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RAVEN Workshop

Advanced UQ With Collocation Methods

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Table of Contents

Overview	. :
Motivations	. !
Methods	. 8
Sparse Grid Collocation	. 9
Sobol Decomposition	1
Demonstration	1



Overview



Overview: Session Goal

Use advanced methods to accelerate UQ

- For low dimensionality, far fewer runs
- For smooth respones, provides accurate ROMs
- ROMs contain analytic mean, variance, sensitivities



Motivations



Motivations: Monte Carlo

Gold standard in UQ is Monte Carlo, Latin Hypercube

- Consistently convergent (central limit theorem)
- Easy to develop
- · Error diminishes slowly
- Requires $1/\epsilon^2$ samples to achieve error ϵ



Motivations: Alternatives to Monte Carlo

Some structured samplers can improve greatly on Monte Carlo Example: Stochastic Collocation for generalized Polynomial Chaos

- Expand model in orthogonal polynomials
- Use integration to determine expansion coefficients
- Quadrature methods perform polynomial integrations

Input dimensions need to be orthogonalized before running



Methods



Methods: generalized Polynomial Chaos expansion

$$f(x) \approx G(x) = \sum_{k \in \Lambda} c_k \Phi_k(x),$$
 (1)

where

- f(x) is the original model,
- x are the uncertain inputs in f(x),
- G(x) is the generalized Polynomial Chaos expansion,
- k is a multi-index to a polynomial, e.g. (3,1,2),
- A is a pre-determined set of polynomial indices,
- ck are expansion coefficients,
- $\Phi_k(x)$ are multidimensional orthogonal polynomials



Methods: gPC Coefficients

$$f(x) \approx G(x) = \sum_{k \in \Lambda} c_k \Phi_k(x),$$
 (2)

 $\Phi_k(x)$ are orthogonal,

$$c_k = \int_{\Omega} \rho(x) f(x) \Phi_k(x) dx \tag{3}$$

where $\rho(x)$ is the joint probability distribution. Numerically, use quadratures for c_k

$$c_k \approx \sum_{\ell=1}^L w_\ell f(x_\ell) \Phi_k(x_\ell)$$
 (4)

where w_{ℓ} are the weights and x_{ℓ} are the points



Methods: Large Dimensionality

Tensor SCgPC only efficient if N < 4Fight curse of dimensionality using Sparse Grids

- Hyperbolic Cross
- Total Degree
- Smolyak Quadrature



Methods: SCgPC in RAVEN

TODO add code: ROM, Sampler, RomTrainer, MultiRun



Methods: Interpolation Node

What if I want to use a different quadrature? What if some dimensions require higher-order polynomials than others? Specify through an interpolation node TODO example



Methods: Adaptive

What if I don't know what dimensions are higher order? Use the Adaptive SCgPC sampler! TODO code



Methods: Sobol Decomposition



Methods: Sobol Decomposition

Another kind of expansion

$$f(x, y, z) = f_0$$
+ $f_1(x) + f_2(y) + f_3(z)$
+ $f_{1,2}(x, y) + f_{1,3}(x, z) + f_{2,3}(y, z)$
+ $f_{1,2,3}(x, y, z)$,

where $f_1(x) = \int \int f(x, y, z) dy dz$, etc. Benefits:

- Many problems dominated by low-order interacations
- Provides easy access to Sobol sensitivities
- Each sub-term can be modelled as SCgPC ROM
 - Most are dimension 2 or less!
- Can also be constructed adaptively
 - Highest efficiency: Adaptive Sobol with Adaptive SCgPC



Demonstration: Attenuation Problem



Reminder: the Model

$$f(x) = \prod_{n=1}^{N} \exp(-x_n/N),$$
 (5)

$$x_n \sim \mathcal{U}(0,1).$$
 (6)

Taylor expansion suggests many combinations of high-order terms

$$\exp(-x) = 1 - x + \frac{x^2}{2!} - \frac{x^3}{3!} + \cdots$$
 (7)

Expected:

- · Tensor Product, Total Degree, Adaptive perform well
- Hyperbolic Cross should struggle