

Enabling Embedded Algorithms R&D Through Template-based Generic Programming

Eric Phipps

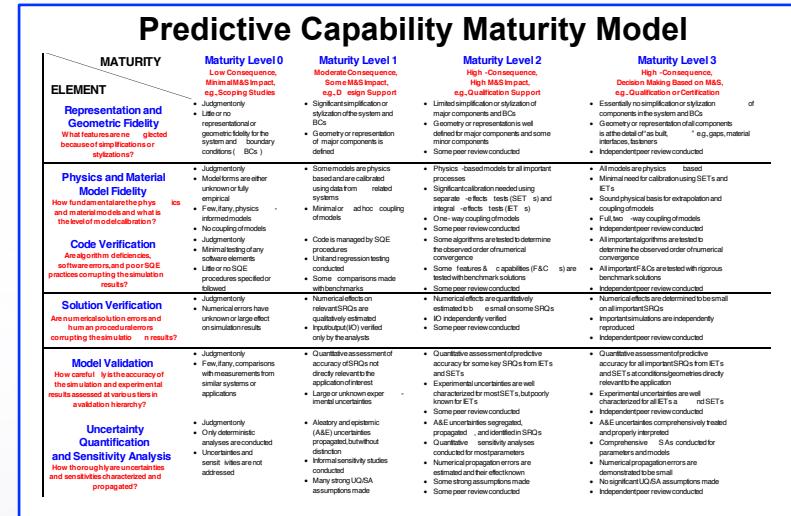
**Optimization and Uncertainty Quantification
Department 1441**

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Embedded Algorithms are Critical for Mission Success

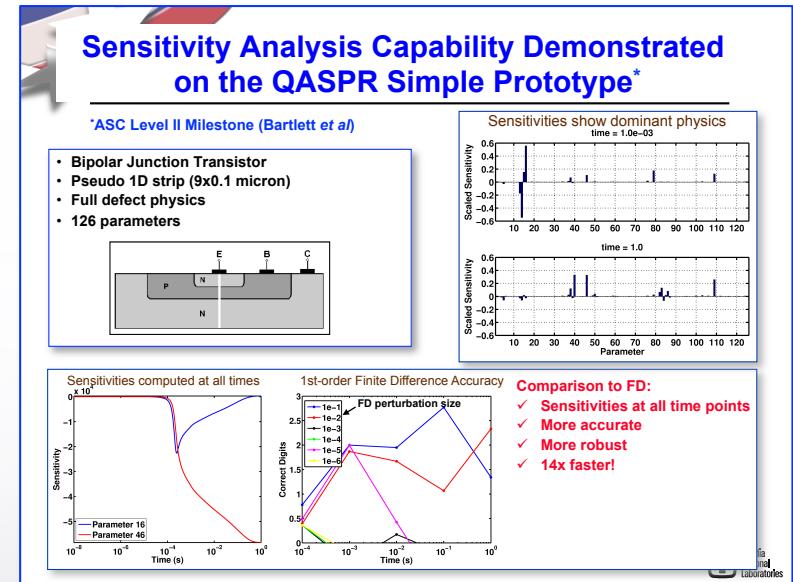
- V&V&UQ are crucial to today's mission
 - Foundation of predictive simulation
- Single-point forward simulations are insufficient
 - Sensitivities
 - Error estimates
 - Probability distributions
 - Epistemic uncertainties



- Embedded algorithms are critical to achieving success
 - Predictive science demands of complex, multiscale physics
 - Exascale

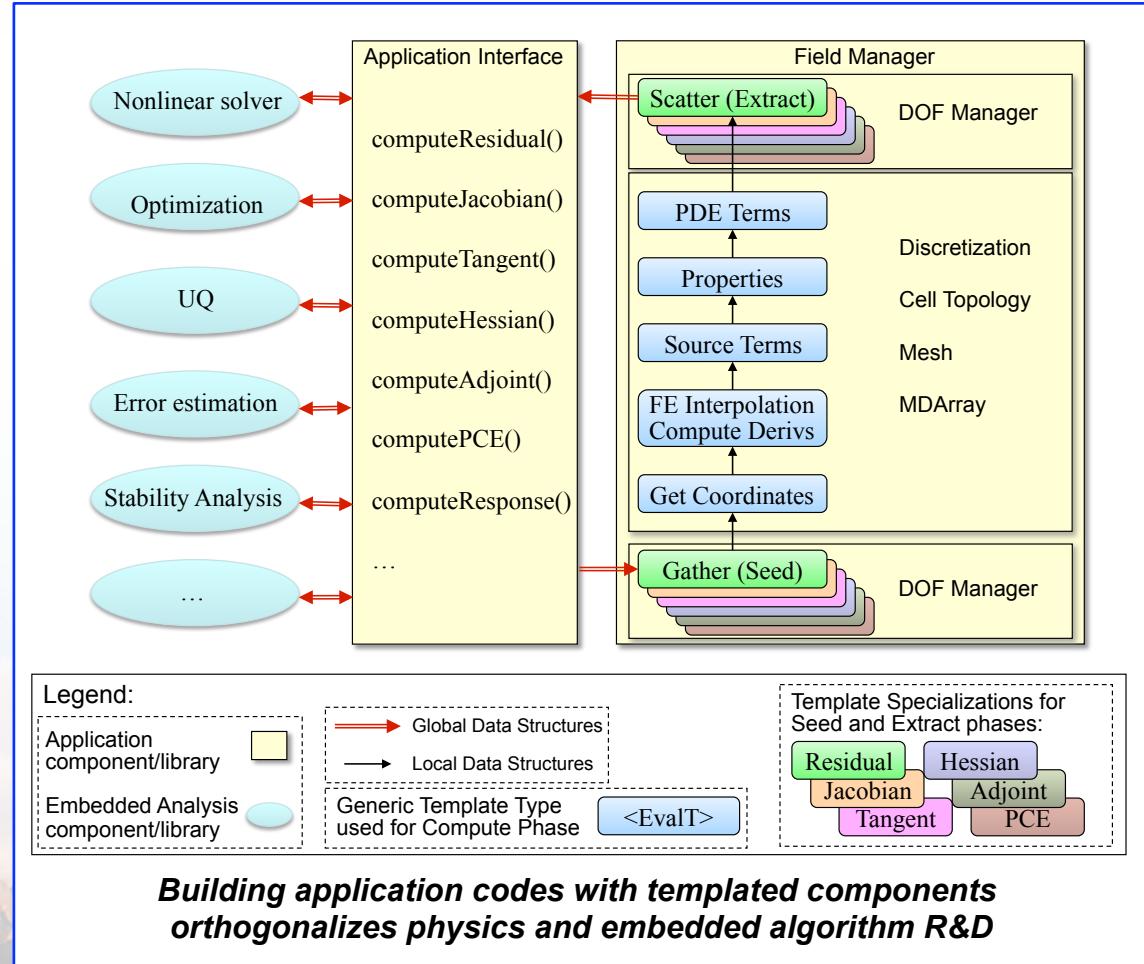
Addressing Embedded Algorithm Challenges through Templating & AD

- Embedded algorithms leverage simulation structure
 - Adjoint sensitivities/error estimates
 - Derivative-based optimization/stability analysis
 - Stochastic Galerkin or adjoint-based UQ methods
 - ...
- Incorporating directly requires significant effort
 - Developers must understand algorithmic requirements
 - Limits embedded algorithm R&D impact
- '06 and '08 external reviews
 - Automatic differentiation (AD)
 - C++ templating of physics at “element” level
 - Operator overloading-based AD tools
- Demonstrated success for QASPR project
 - Efficient Jacobian evaluation without hand-coding
 - Rapid physics development
 - Forward sensitivity analysis



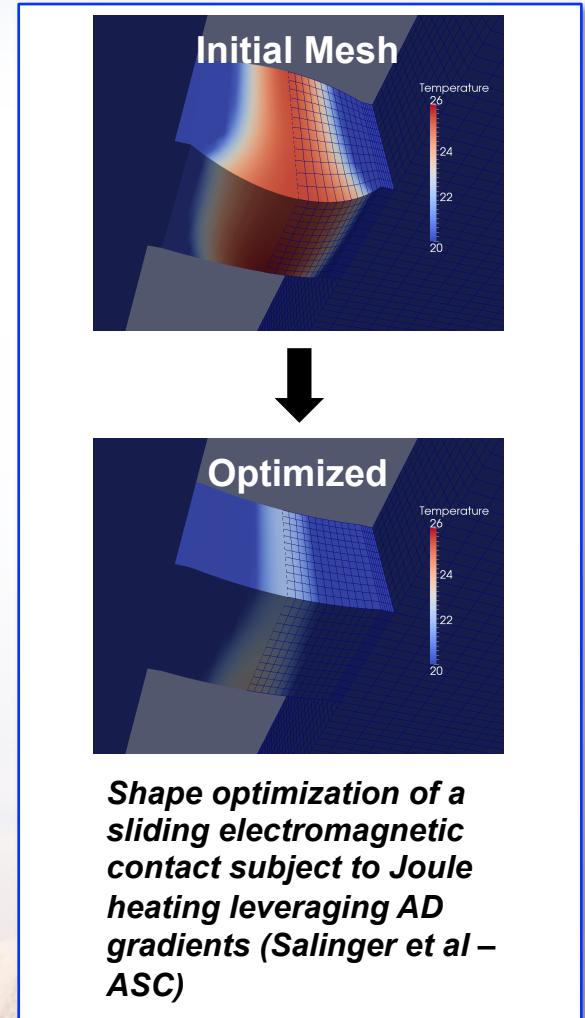
Unique Component Support of Embedded Algorithms via Templates

- **Templating on scalar type enables analysis abstraction**
 - **float** \rightarrow **forward simulation**
 - **FAD** \rightarrow **sensitivity**
 - **PCE** \rightarrow **probability**
 - **Fuzzy number** \rightarrow **epistemic**
 - **Template-based generic programming**
- **Templating components provides API to support embedded algorithms**
 - **Developers focus on component implementation**
 - **Embedded quantities are easily incorporated**
- **Our support of embedded algorithms through templates is unique**
 - **Libmesh, deal.II, FEniCS, Sundance, MASA**
 - **Template approach is scalable to many embedded techniques**



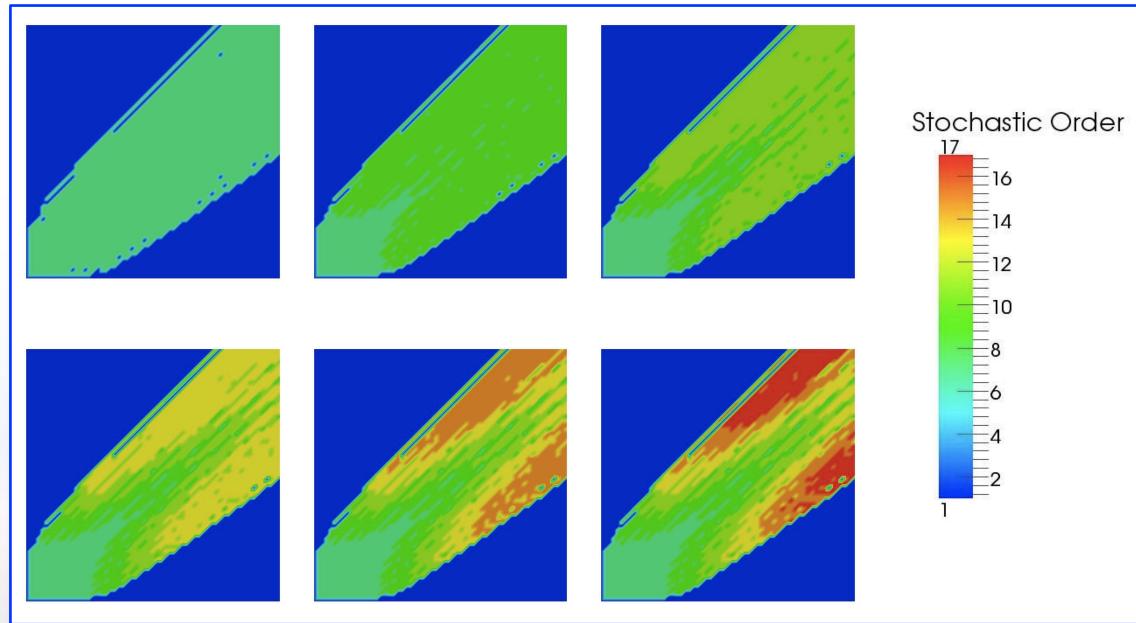
Spectrum of Impact for Template Component Approach

- **Derivatives – Mature capabilities**
 - Jacobians, parameter sensitivities, gradients
 - QASPR semiconductor device physics
 - Drekar MHD
 - CASL thermo-mechanics
 - QCAD quantum device modeling
 - SIERRA/Aria (fluids) and Adagio (solid mechanics)
 - LCM solid mechanics
 - Xyce electronic circuits
 - R&D focused on
 - Efficiency of AD tools (see slide #14)
 - Improving breadth of support (MPI, BLAS, ...)
- **Embedded UQ – Basic algorithmic R&D**
 - Collaboration with USC (ASCR)
 - Stochastic Galerkin solver/preconditioners
 - Multiphysics embedded UQ
 - Embedded sampling (ASC)
 - Spatially adaptive embedded UQ (LDRD)
 - Heterogeneous multicore embedded UQ (LDRD)



Templates Enable Unique Embedded UQ R&D

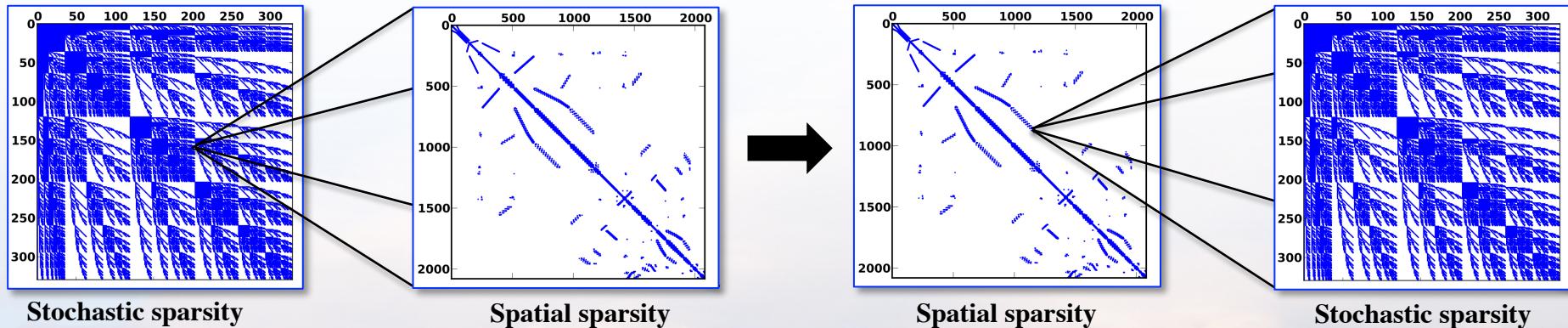
- Spatially adaptive UQ of a strongly convected field in Drekar
 - Eric Cyr – SNL LDRD
 - 2-D convection-diffusion with stochastically varying inlet angle
 - Intrusive stochastic Galerkin with spatially varying polynomial order



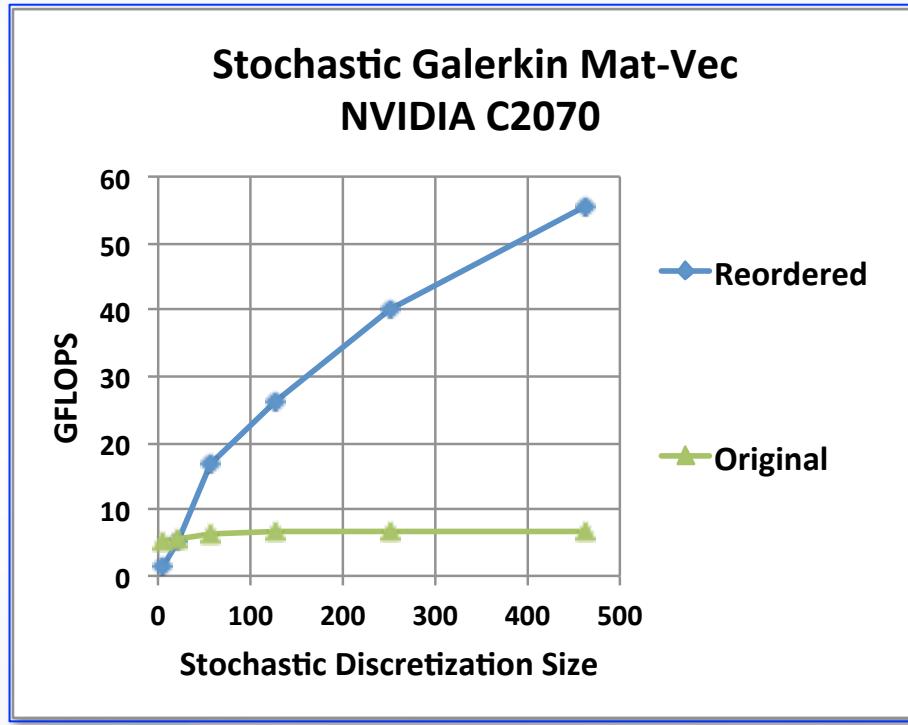
- *Possible only through embedded approaches*
- *Templated component approach makes this possible*

Unique Multicore R&D with Path to Impact

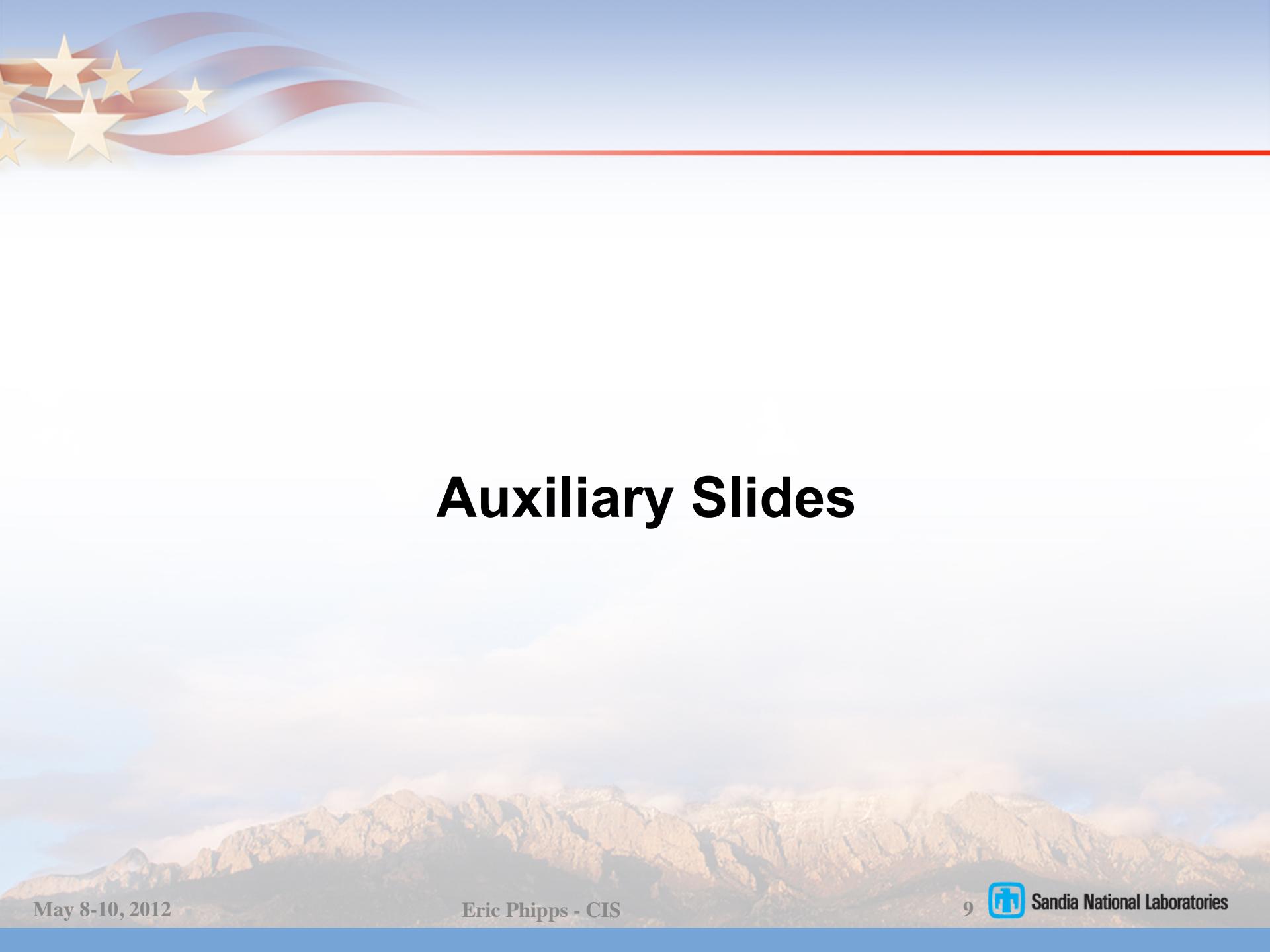
- UQ approaches implemented as an outer loop
 - Single-point forward simulations use very little available compute power
 - Emerging architectures leading to dramatically increased on-node parallelism
- Move UQ to the inner loop to leverage increased parallelism:
 - Phipps, Edwards, Hu – SNL LDRD
 - Embed UQ types in templated linear algebra data structures, solvers, preconditioners
 - Custom UQ-aware multicore linear algebra kernels



Unique Multicore R&D with Path to Impact



- *Realize exascale performance through embedded UQ*
- *Templated components make this possible*



Auxiliary Slides



Significant Visibility in External Community

- **Automatic differentiation**
 - 3 conference papers (ICCS 2006, AD 2008, AD 2012)
 - Program committee for AD 2008
 - Editor, organizing committee, program committee for AD 2012
- **Template-based generic programming**
 - 2 journal articles under revision
- **Embedded/multi-physics UQ**
 - 3 published/accepted journal articles, 2 under revision, 1 under review, 3 in preparation
- **Numerous conference and workshop presentations**

“Predictive Simulation of Complex Coupled Systems under Uncertainty”

Eric Phipps (SNL), Roger Ghanem (USC)

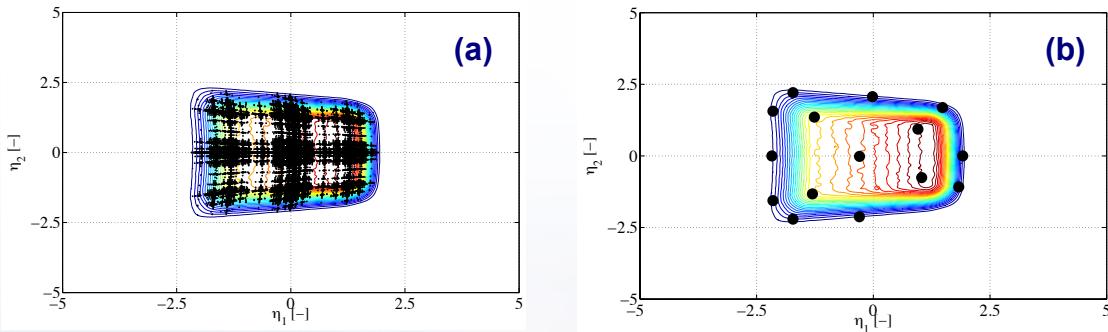
Objectives

- Develop techniques for accurate, efficient, and scalable uncertainty quantification (UQ) of complex, multiphysics, coupled systems

Impact

- Mitigate curse-of-dimensionality inherent in many large-scale multiphysics systems enabling rigorous UQ in large coupled systems

Stochastic Dimension Reduction in a Simplified Reactor Core



PDF and sample points before dimension reduction (a) and after (b) of uncertain input space for heat transfer in a coupled thermal-neutronics problem demonstrating 3 orders of magnitude reduction in computational cost

Accomplishments

- Developed computational framework for *embedded* UQ of coupled systems allowing adaptation of uncertainty representation
- Developed novel UQ approaches that leverage multiphysics structure to reduce dimensionality of uncertainty representations¹⁻³
- Developed stable method for computing stochastic expansion coefficients in high dimensions⁴

1. Arnst, Ghanem, Phipps, Red-Horse, “Elements of a computational framework for stochastic coupled-systems modeling: dimension reduction,” submitted to IJNME.
2. Arnst, Ghanem, Phipps, Red-Horse, “Measure transformation and efficient quadrature in reduced-dimensional stochastic analysis of coupled systems,” submitted to IJNME.
3. Constantine, Phipps, “A Lanczos Method For Approximating Composite Functions,” accepted to Appl. Math and Comp.
4. Constantine, Eldred, Phipps, “Sparse Pseudospectral Approximation Method,” accepted to CMAME.



AD Provides Analytic Derivatives Without Hand-Coding

- How does Automatic Differentiation (AD) work?
 - Derivatives at operation level known
 - Chain rule
- What does AD compute?
 - Forward mode derivatives (Jacobians, Jacobian-vector products)
 - Reverse mode derivatives (Gradients, Jacobian-transpose products)
 - High order univariate Taylor polynomials
- How is it implemented?
 - Source transformation (Fortran)
 - Operator overloading (C++)
- Multiple derivative components propagated simultaneously
 - Big cache benefit, potential for multi-core

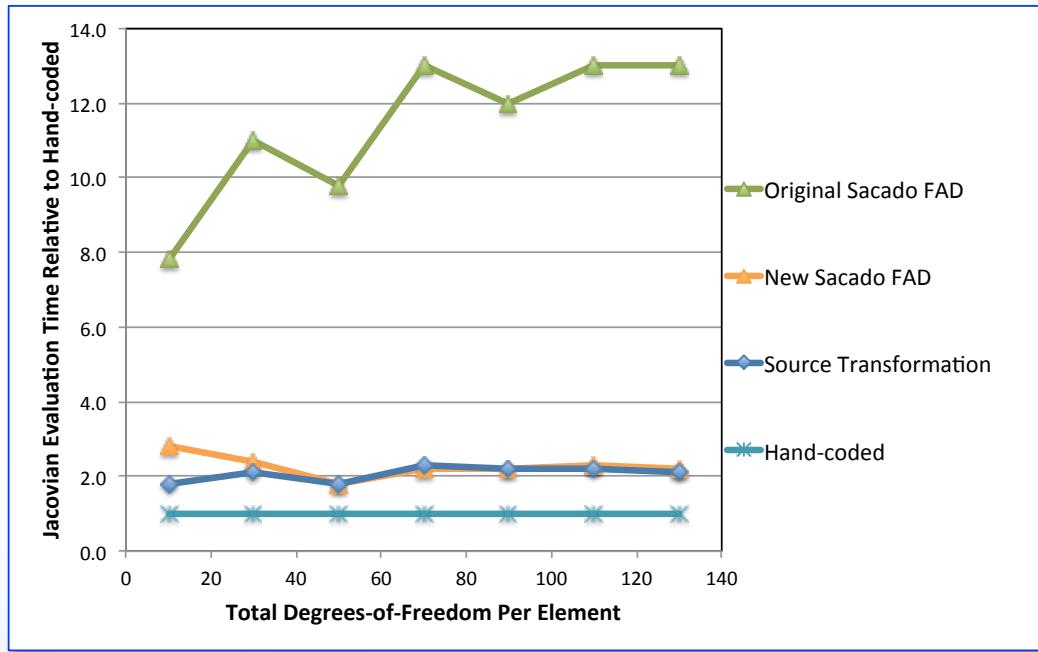


Our AD Research is Distinguished by Tools & Approach for Large-Scale Codes

- Many AD tools and research projects
 - ✗ Most geared towards Fortran (ADIFOR, OpenAD)
 - ✗ Most C++ tools are slow (ADOL-C)
 - ✗ Most applied in black-box fashion
- Sacado: Operator overloading AD tools for C++ applications
 - ✓ Multiple highly-optimized AD data types
 - ✓ Transform to template code & instantiate on Sacado AD types
 - ✓ Apply AD only at the “element level”
- This is the only successful, sustainable approach for large-scale C++ codes!
- Directly impacting QASPR through Charon
 - ✓ Analytic Jacobians and parameter derivatives



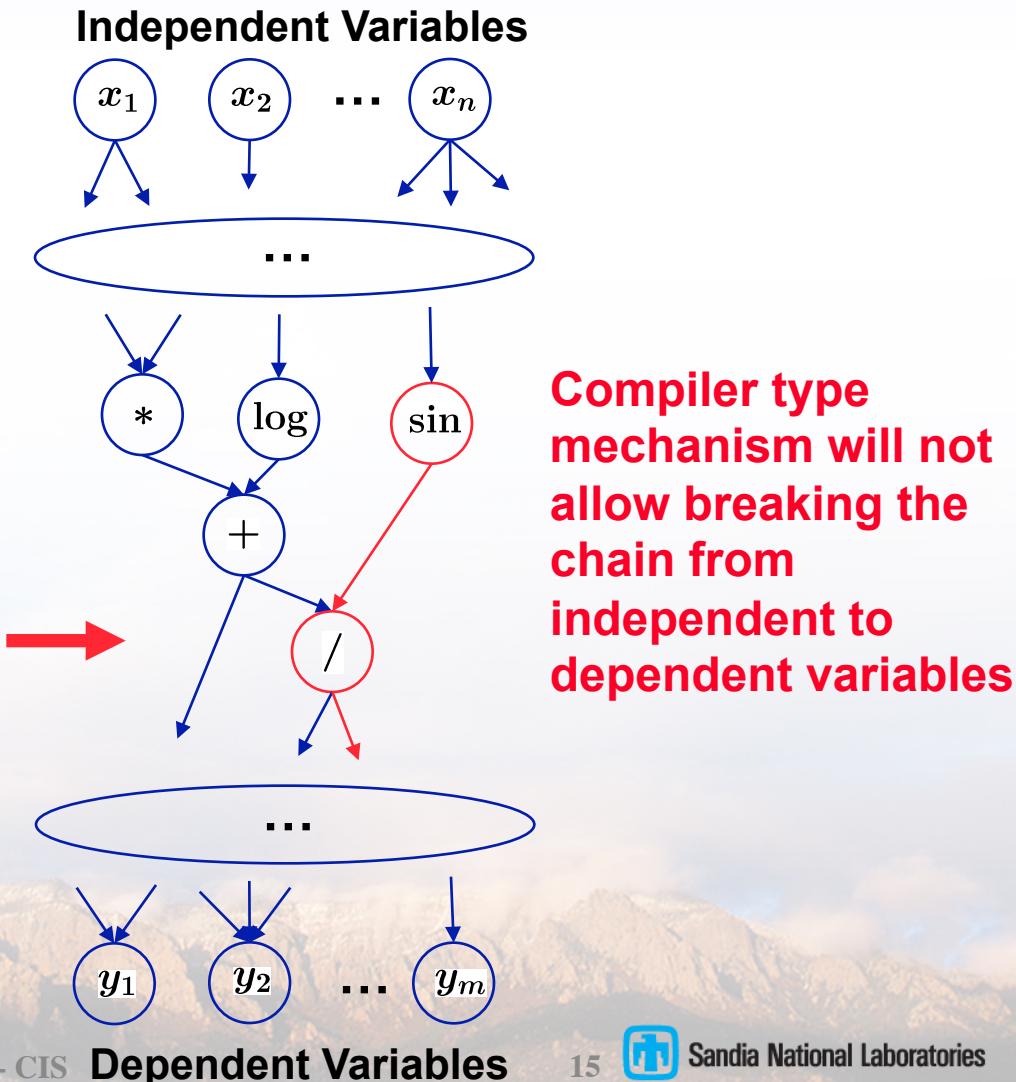
Our AD Tools Perform Extremely Well



- Comparison of Sacado element-based forward AD approach for computing analytic Jacobian to source transformation and hand-coding
- Simple set of representative PDEs
 - **Total degrees-of-freedom = number of nodes x number of PDEs for each element**
- 6x improvement in Sacado Forward AD tools (FAD) from 2004 to 2012
- Comparison to source transformation demonstrates operator overloading overhead is zero
- 2x cost relative to hand-coded, optimized Jacobian (very problem dependent)

Verification of Automatic Differentiation

- Verification of the AD tools
 - Unit-test with respect to known derivatives
 - Composite tests
 - Compare to other tools
 - Compare to hand-derived
 - Compare to finite differences
- Verification of AD in application code
 - Compiler drastically simplifies this
 - All of the standard hand-coded verification techniques
 - Compare to finite differences
 - Nonlinear convergence



Embedded Stochastic Galerkin UQ Methods

- Steady-state stochastic problem (for simplicity):

Find $u(\xi)$ such that $f(u, \xi) = 0$, $\xi : \Omega \rightarrow \Gamma \subset R^M$, density ρ

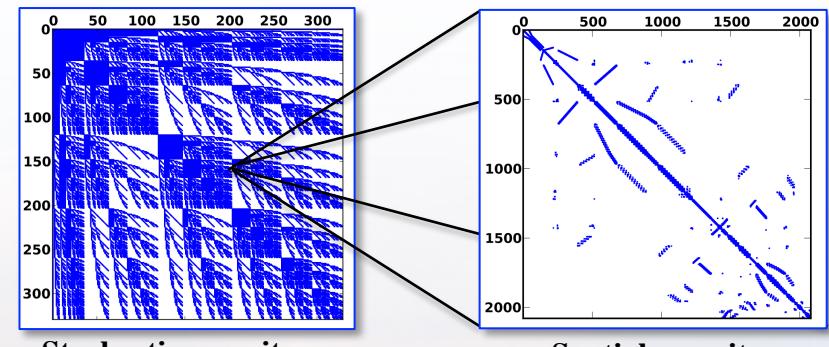
- Stochastic Galerkin method (Ghanem and many, many others...):

$$\hat{u}(\xi) = \sum_{i=0}^P u_i \psi_i(\xi) \rightarrow F_i(u_0, \dots, u_P) = \frac{1}{\langle \psi_i^2 \rangle} \int_{\Gamma} f(\hat{u}(y), y) \psi_i(y) \rho(y) dy = 0, \quad i = 0, \dots, P$$

– Multivariate orthogonal basis of total order at most N – (generalized polynomial chaos)

- Method generates new coupled spatial-stochastic nonlinear problem (intrusive)

$$0 = F(U) = \begin{bmatrix} F_0 \\ F_1 \\ \vdots \\ F_P \end{bmatrix}, \quad U = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_P \end{bmatrix} \quad \frac{\partial F}{\partial U} :$$



- Advantages:

– Many fewer stochastic degrees-of-freedom for comparable level of accuracy

- Challenges:

– Computing SG residual and Jacobian entries in large-scale, production simulation codes
– Solving resulting systems of equations efficiently, particularly for nonlinear problems

Stokhos: Trilinos Tools for Embedded Stochastic Galerkin UQ methods

- Eric Phipps, Chris Miller, Habib Najm, Bert Debusschere, Omar Knio
- Tools for describing SG discretization
 - Stochastic bases, quadrature rules, etc...
- C++ operator overloading library for automatically evaluating SG residuals and Jacobians
 - Replace low-level scalar type with orthogonal polynomial expansions
 - Leverages Trilinos Sacado automatic differentiation library

$$a = \sum_{i=0}^P a_i \psi_i, \quad b = \sum_{j=0}^P b_j \psi_j, \quad c = ab \approx \sum_{k=0}^P c_k \psi_k, \quad c_k = \sum_{i,j=0}^P a_i b_j \frac{\langle \psi_i \psi_j \psi_k \rangle}{\langle \psi_k^2 \rangle}$$

- Tools forming and solving SG linear systems
 - SG matrix operators
 - Stochastic preconditioners
 - Hooks to Trilinos parallel solvers and preconditioners
- Provides tools for investigating embedded UQ methods in large-scale applications



<http://trilinos.sandia.gov>

Generating SG Residual/Jacobian Entries Through Automatic Differentiation (AD)

- Trilinos package Sacado provides AD capabilities to C++ codes
 - AD relies on known derivative formulas for all intrinsic operations plus chain rule
 - AD data types & overloaded operators
 - Replace scalar type in application with Sacado AD data types
- Similar approach can be used to apply SG projections in an operation by operation manner

Given $a(y) = \sum_{i=0}^P a_i \psi_i(y)$, $b = \sum_{i=0}^P b_i \psi_i(y)$, find $c(y) = \sum_{i=0}^P c_i \psi_i(y)$

such that $\int_{\Gamma} (c(y) - \phi(a(y), b(y))) \psi_i(y) \rho(y) dy = 0$, $i = 0, \dots, P$

- Simple formulas for addition, subtraction, multiplication, division
- Transcendental operations are more difficult

SG Projections of Intermediate Operations

- Addition/subtraction

$$c = a \pm b \Rightarrow c_i = a_i \pm b_i$$

- Multiplication

$$c = a \times b \Rightarrow \sum_i c_i \psi_i = \sum_i \sum_j a_i b_j \psi_i \psi_j \rightarrow c_k = \sum_i \sum_j a_i b_j \frac{\langle \psi_i \psi_j \psi_k \rangle}{\langle \psi_k^2 \rangle}$$

- Division

$$c = a/b \Rightarrow \sum_i \sum_j c_i b_j \psi_i \psi_j = \sum_i a_i \psi_i \rightarrow \sum_i \sum_j c_i b_j \langle \psi_i \psi_j \psi_k \rangle = a_k \langle \psi_k^2 \rangle$$

- Several approaches for transcendental operations

- Taylor series and time integration (Fortran UQ Toolkit by Najm, Debusschere, Ghanem, Knio)
- Tensor product and sparse-grid quadrature (Dakota)

- These ideas allow the implementation of Sacado “AD” types for intrusive stochastic Galerkin methods
 - Easy transition once code is setup to use AD

Commuted SG Matrix Orthogonal Polynomial Multiply

- Two level algorithm
 - Outer: traditional CRS matrix-vector multiply algorithm
 - Inner: orthogonal polynomial multiply

$$w(i, \text{row}) = \sum_{t=A\text{row}(\text{row})}^{A\text{row}(\text{row}+1)-1} \sum_{j,k=0}^P A\text{value}(k, t)v(j, A\text{col}(t))C_{ijk}$$

stochastic basis stochastic bases sum stochastic basis stochastic basis triple product

FEM basis FEM bases sum FEM basis FEM basis

- Symmetric sparse tensor stored in compressed format:

$$w(i, \text{row}) = \sum_{t=A\text{row}(\text{row})}^{A\text{row}(\text{row}+1)-1} \sum_{n=C\text{row}(i)}^{C\text{row}(i+1)-1} (A\text{value}(C(n).k, t)v(C(n).j, A\text{col}(t)) + A\text{value}(C(n).j, t)v(C(n).k, A\text{col}(t)))C(n).\text{value}$$

- Opportunities for iteration concurrency: row , i , t , n

Manycore-GPU with Inner Polynomial Multiply: Two-level Concurrency

thread-block parallel

$$w(i, \text{row}) = \sum_{n=\text{Crow}(i)}^{\text{Crow}(i+1)-1} \sum_{t=\text{Arow}(\text{row})}^{\text{Arow}(\text{row}+1)-1}$$

thread-warp parallel

thread parallel

serial within a thread

thread-block shared memory

$(\text{Avalue}(C(n).k, t)v(C(n).j, \text{Acol}(t)) +$
 $\text{Avalue}(C(n).j, t)v(C(n).k, \text{Acol}(t)))C(n).value$

thread-block shared memory

GPU global memory

- **Multiple levels of concurrency:**
 - Each row owned by a thread-block
 - Each warp within a thread-block owns an “i”
 - Warps within a thread perform polynomial multiply in parallel, executing CRS loop serially
- **Currently sparse tensor stored in GPU global memory**