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# An Uncertainty Quantification System for Tabular Equations of State

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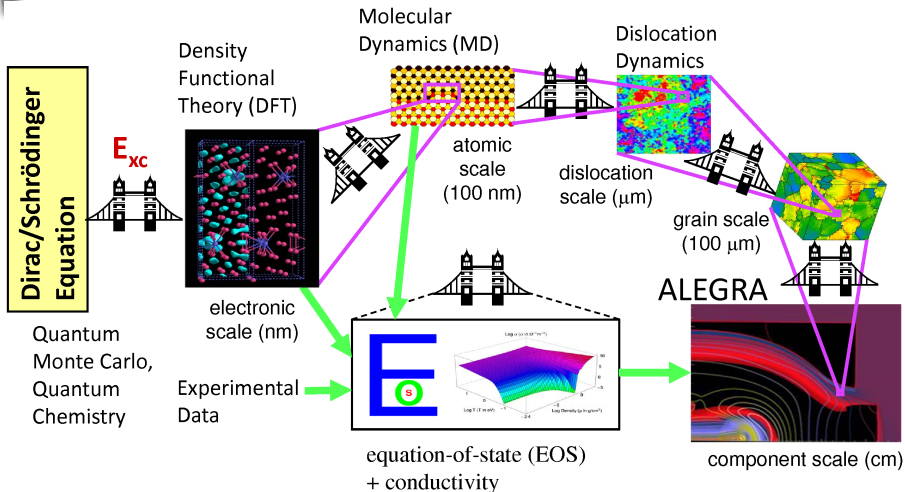
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# Motivation



Goal: Provide quantitative error estimates to the continuum analysts based upon fundamental measurements and calculations of the EOS.



# Tabular EOS UQ System

Software Package	Output
EOS model library and data	Proposal model (XML input deck)
Bayesian inference using Markov Chain Monte Carlo	Extensive sampling of Posterior Distribution Function (PDF)
EOS Table building	Topologically equivalent tables for each sample
PCA analysis	Mean EOS table + most significant table perturbations
Hydrocode + Dakota	Cumulative Distribution Function for quantities of interest

- ▶ First half of system utilizes **analytic** EOS models.
- ▶ Last half of system utilizes **tabulated** EOS models.

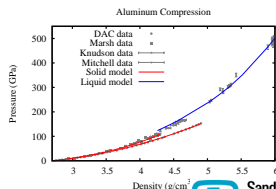
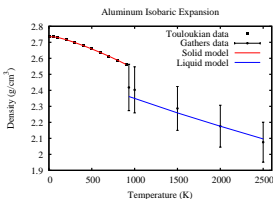
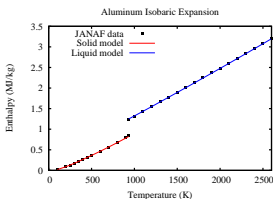
# EOS Data and Model

## Test multi-phase aluminum model:

- ▶ Semi-empirical solid-liquid-gas model
  - ▶ Cold curve uses polynomial expansion form
  - ▶ FCC solid phase uses the Debye model
  - ▶ Fluid phase uses Bushman-Lomonosov-Fortov model
- ▶ 30 parameters in total
- ▶ Range of interest to 40 kK and 10 g/cm<sup>3</sup>

## Multiple sets of data used for calibration:

- ▶ Isobaric enthalpy and density for solid and liquid
- ▶ Shock data for solid and liquid
- ▶ Isothermal compression data for solid
- ▶ QMD calculations of critical point plus melt and vaporization data



# Bayesian Inference of Parameters

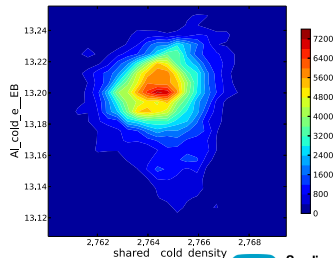
$$p(\lambda|D) = \frac{p(D|\lambda)p(\lambda)}{p(D)}$$

Diagram illustrating the components of Bayes' rule:

- posterior:  $p(\lambda|D)$
- likelihood:  $p(D|\lambda)$
- prior:  $p(\lambda)$
- normalization:  $p(D)$

## Bayes' rule gives posterior distribution function (PDF):

- ▶ Represents belief in parameter values  $\lambda$  given data  $D$ .
- ▶ Adaptive Markov Chain Monte Carlo used to sample the PDF.
- ▶ Starting point obtained via optimization.
- ▶ Difficult due to ill-constrained and magnitude differences of parameters.
- ▶ Must enforce stability and physicality constraints on model via priors
- ▶ Successfully applied on the 30 parameter example aluminum model.
- ▶ Marginal distribution of two cold curve parameters indicate their lack of correlation

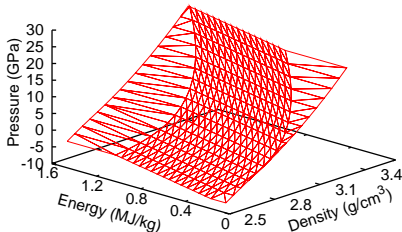
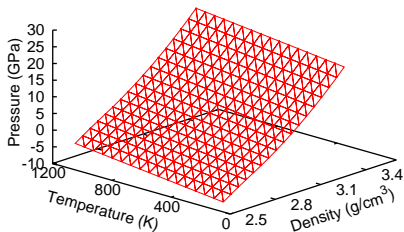


# Tabular Representation

## New unstructured triangular (UTri) format essential:

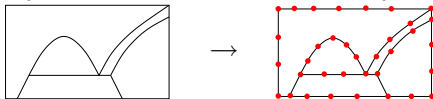
- ▶ Uses linear interpolation on triangles
- ▶ Non-rectangular grid easily follows phase boundaries capturing derivative discontinuities
- ▶ Adaptation allows for storage efficiency while ensuring a desired tabulation accuracy
- ▶ Tabulates in both the  $(\rho, T)$  and  $(\rho, E)$  phase spaces
- ▶ All desired variables tabulated simultaneously

## Example pressure surfaces in $(\rho, T)$ and $(\rho, E)$ spaces:

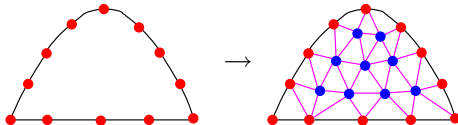


# Smooth Mesh Generation

N sample tables with **consistent** topologies:



**Adaptively mesh boundaries:** linear map of node locations between sample tables



**Adaptively mesh phase regions:** interior nodes mapped using a Laplace-Beltrami smoother with phase boundary points as boundary conditions

$$\frac{1}{\sqrt{g}} \frac{\partial}{\partial \xi^\alpha} \left( \sqrt{g} g^{\alpha\beta} \frac{\partial x^i}{\partial \xi^\alpha} \right) = 0$$

Smoothing of mesh points **eliminates noise** from PCA.

# Tabular UQ Analysis

Use **Principal Component Analysis (PCA)** to look for a tabular representation with reduced dimensionality:

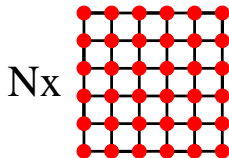
- ▶ Start with representative sample of tables (e.g. MCMC chain states)
- ▶ Perform PCA:

$$\bar{z} = ZH^{1/2}\mathbf{1}/\mathbf{1}^T H\mathbf{1}$$

$$G^{1/2}(Z - \bar{z}\mathbf{1}^T)H^{1/2} = \tilde{U}\Sigma\tilde{V}^T$$

$$z = \bar{z} + U\Sigma\xi = \bar{z} + G^{-1/2}\tilde{U}\Sigma\xi = \bar{z} + (Z - \bar{z}\mathbf{1}^T)H^{1/2}\tilde{V}\xi$$

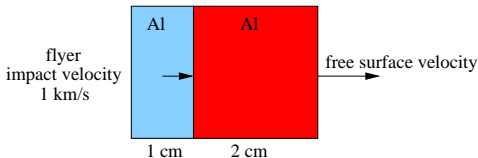
- ▶ Choose a truncated set of modes to export in tabular form
- ▶ In the hydrocode, **an EOS table is generated at start up** for each sample run with the user selecting the number of modes to be used:  $T = \bar{T} + \sum_k \xi_k T_k$
- ▶ Random variables  $\xi_k$  are uncorrelated, zero mean, unit variance, but not necessarily independent



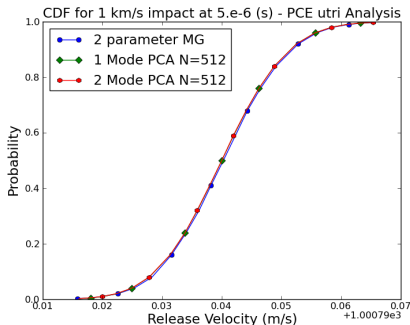


# Example Results

## Simple flyer plate impact problem:



- ▶ Measure free surface velocity at back of target
- ▶ Results shown for a two parameter Mie-Grüneisen model





## Summary

- ▶ Tabular EOS UQ system developed
- ▶ Supports multi-phase EOS models with many uncertain parameters
- ▶ Enabled by underlying unstructured triangular table format
- ▶ Robustness issues need to be worked out before realizing full production system
  - ▶ Stable and physical behavior of models for arbitrary parameter choices
  - ▶ Determining good starting points for the MCMC chain
  - ▶ More efficient table generation
  - ▶ Proper conditioning of variables for the PCA step
  - ▶ Examine the assumption of Gaussian distributions