Acceleration of UQ and PRA with RAVEN Hybrid Model

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Outline

- RAVEN overview:
    - General Code Infrastructure
    - UQ and PRA capability needs
- Surrogate Modeling:
    - Overview
    - Validation
    - Optimization
- Hybrid Modeling
    - Automated model selection
- Future Work

RAVEN overview

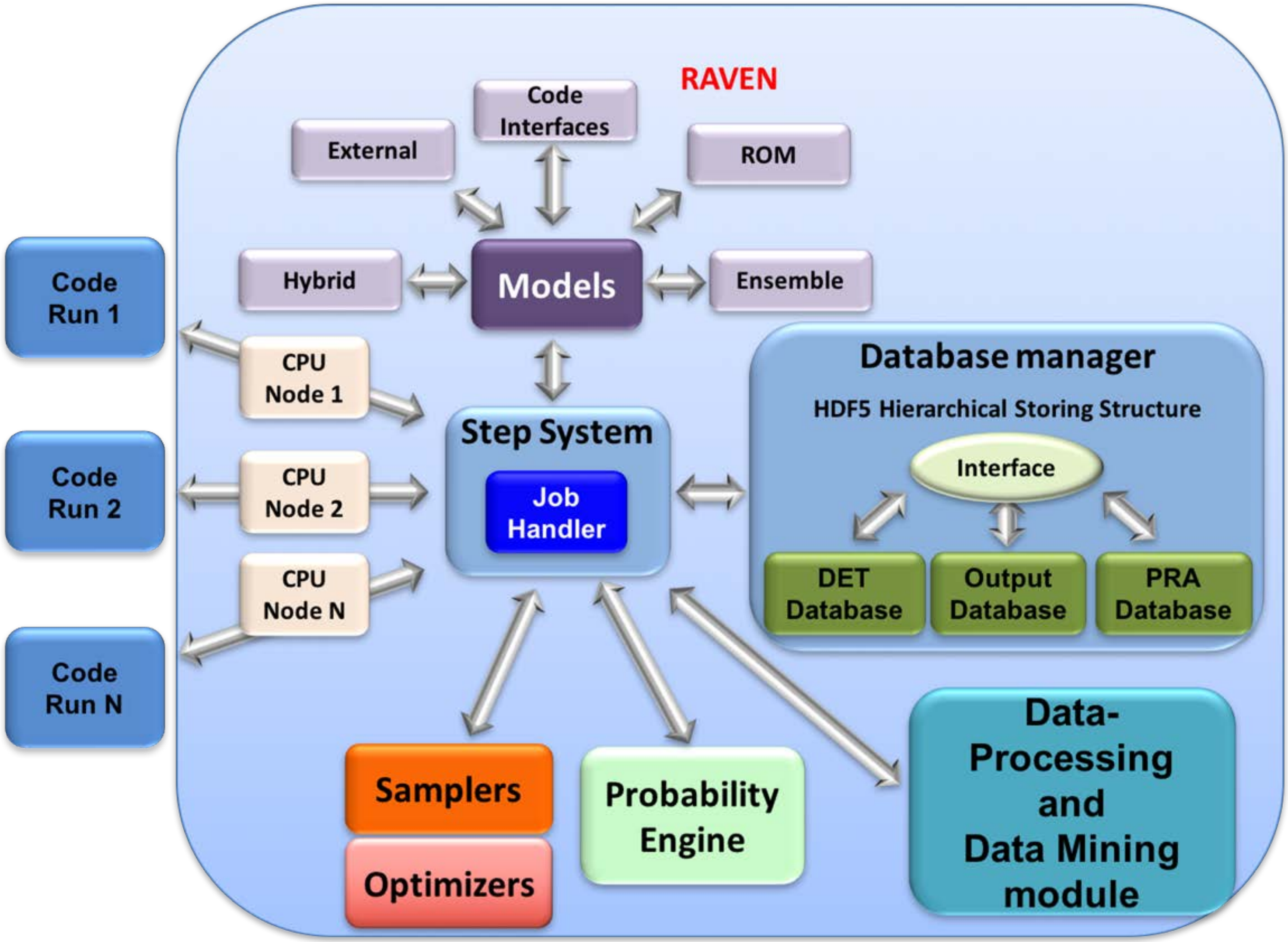
RAVEN overview

Project Background

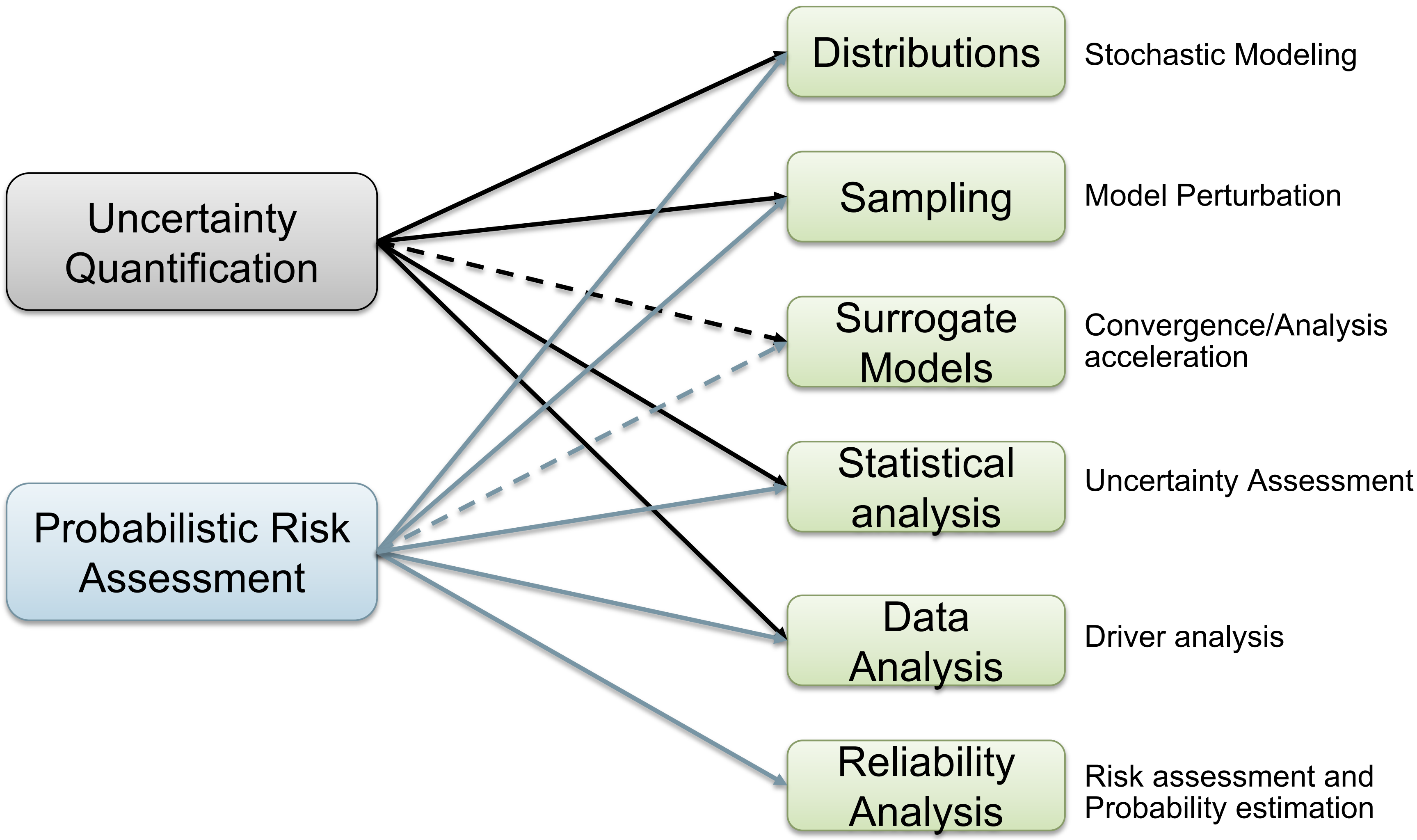
- RAVEN development has begun in early 2012. Been supported by:
  - Light Water Reactor Sustainability (LWRS), under the RISMC path-way
  - Nuclear Energy Advanced Modeling and Simulation Program (NEAMS)
  - Nuclear-Renewable Hybrid Energy Systems (NHES)

- The overall goal was to conceive a tool to enable Risk Informed Safety Margin Characterization (RISMC)
  - Evaluating risk (uncertainty propagation)
  - Understanding risk (limit surface, ranking, sensitivity, data mining)
  - Mitigating risk (optimization)

RAVEN Infrastructure



UQ and PRA: Capabilities vs. Needs



DPRA and UQ methodologies

Dynamic PRA and UQ common methodologies

Samplers (Forward)

RAVEN supports many forward samplers

- Monte Carlo
- Grids:
  - equal-spaced in probability and/or in value or custom
  - mixed (probability, custom, value)
- Stratified (LHS type)
  - equal-spaced in probability and/or in value or custom
  - mixed (probability, custom, value)
- Factorial Designs:
  - 2-Level Fractional-Factorial
  - Plackett-Burman
- Response Surface Designs:
  - Box-Behnken
  - Central Composite
- Generalized stochastic collocation polynomial chaos

A different sampling strategies can be associated to each variable separately

Models

RAVEN support five different models' entities:

- ROM (Reduced Order Models). This type of models are constitute by already trained supervised learning algorithms (RAVEN can use data sets for their training)
- External Models. External models are made of python code that use directly the "model" class
- External codes. These are classical third parties codes. The API requires the implementation of writing/reading to/from the input/output files
- Ensemble Model. Assemble of multiple models
- Hybrid Model. Smart Assemble of Surrogate and "high-fidelity" models

ROMs: a Quick Introduction

- Consider a set of *N* data points

Data

$$\left(x_i, F(x_i)\right) \quad i = 1, \ldots, N$$

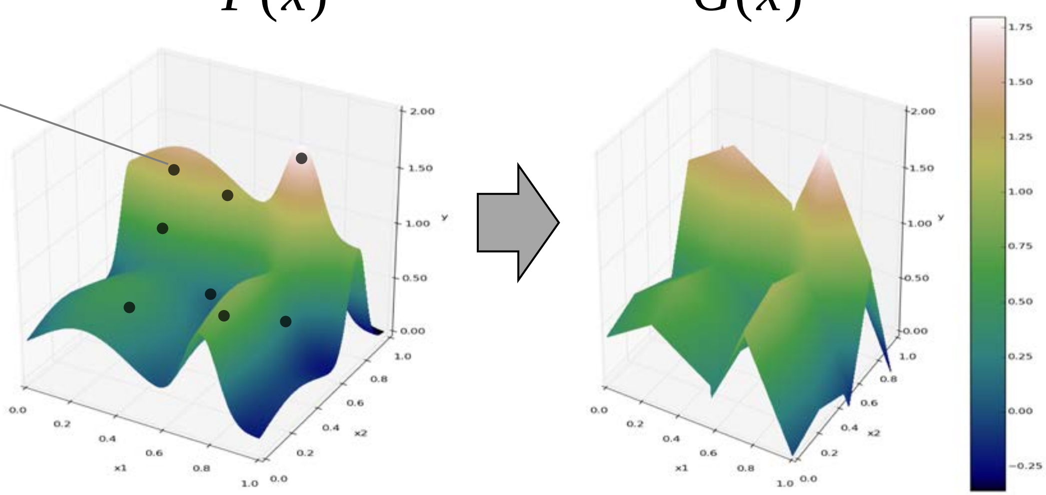
Output: Simulation outcome (success/failure, max clad temperature)

Inputs: Initial and boundary conditions

- Build a surrogate model
  - Reduced Order Model $G(x): x_i \longrightarrow G(x_i) \cong \mathrm{F}(x_i)$

$F(x)$ $\qquad\qquad$ $G(x)$

$\left(\boldsymbol{x}_i, F(\boldsymbol{x}_i)\right)$



ROMs: a Quick Introduction

- Basically we are trying to reduce the complexity of the original model

ROM (e.g., quadratic regressor)

$$G(x): x_i \longrightarrow G(x_i) \cong \mathrm{F}(x_i)$$

Original data (e.g., RELAP5)

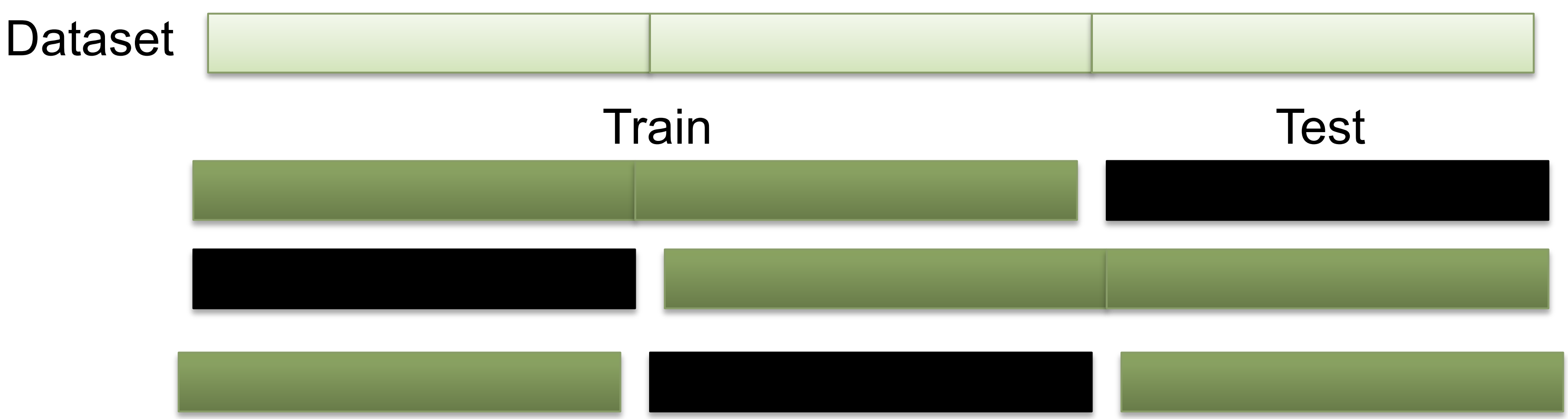
- Pros:
  - Much faster computation of the output variable

- Cons:
  - Presence of error in the ROM computed values

Cross-Validation for assessing Surrogate Models validity

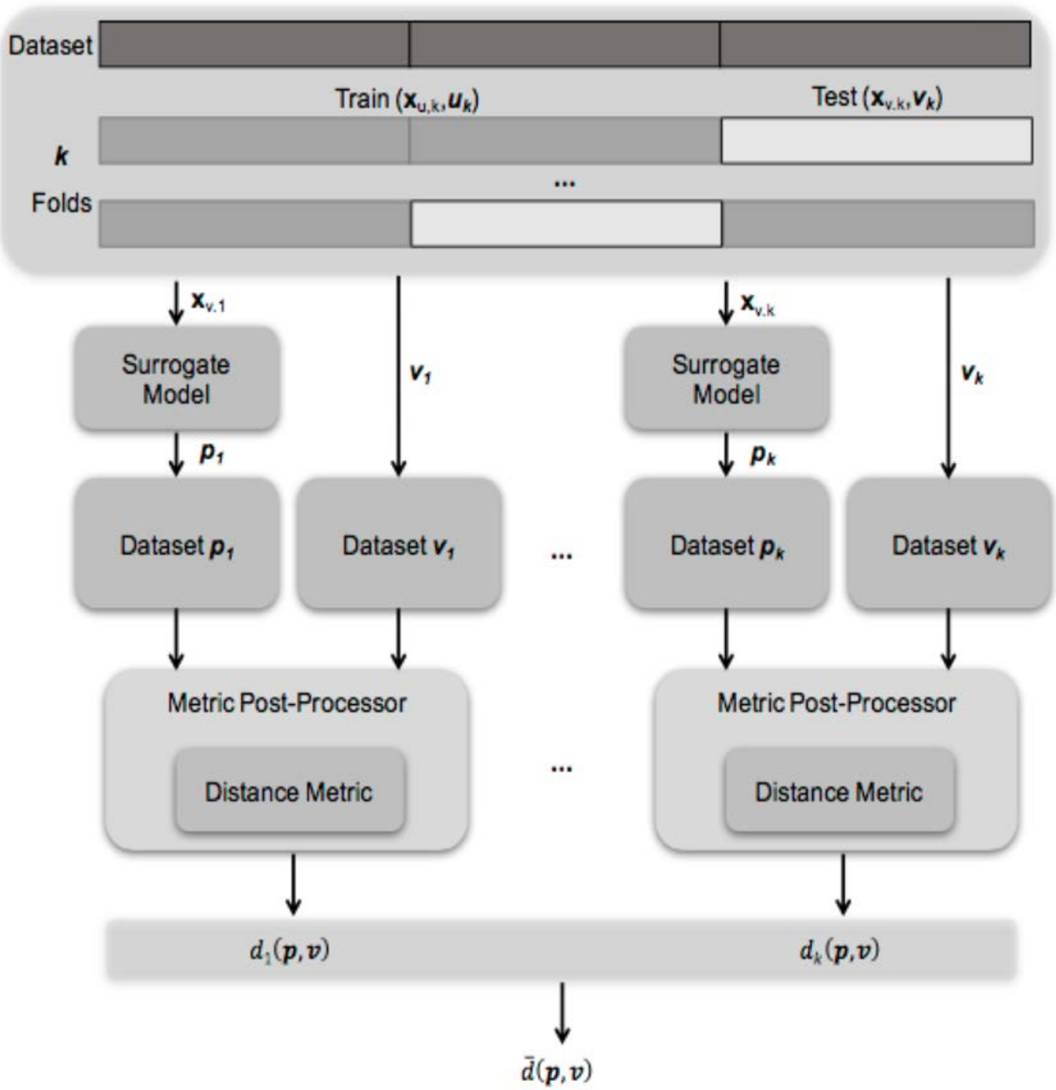
- Take out some of the training set
  - Train on the remaining training set
  - Test on the excluded instances
  - *Cross-validation*

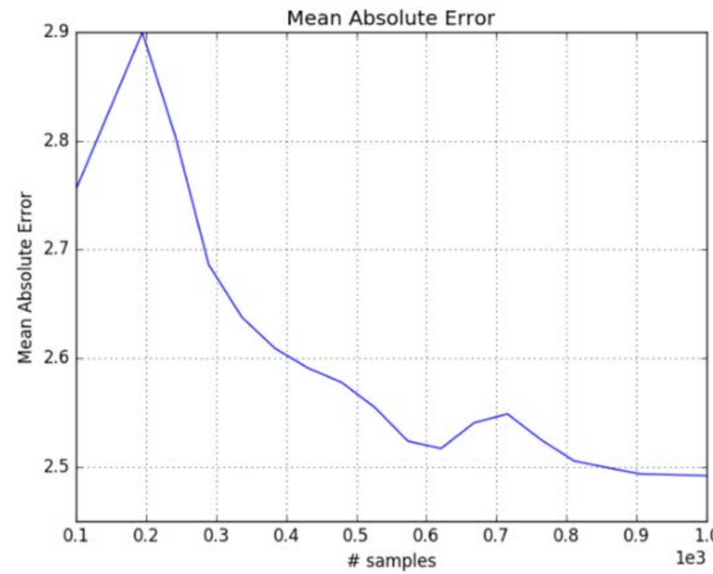
- Cross Validation



- Compute a score (e.g. R^2)

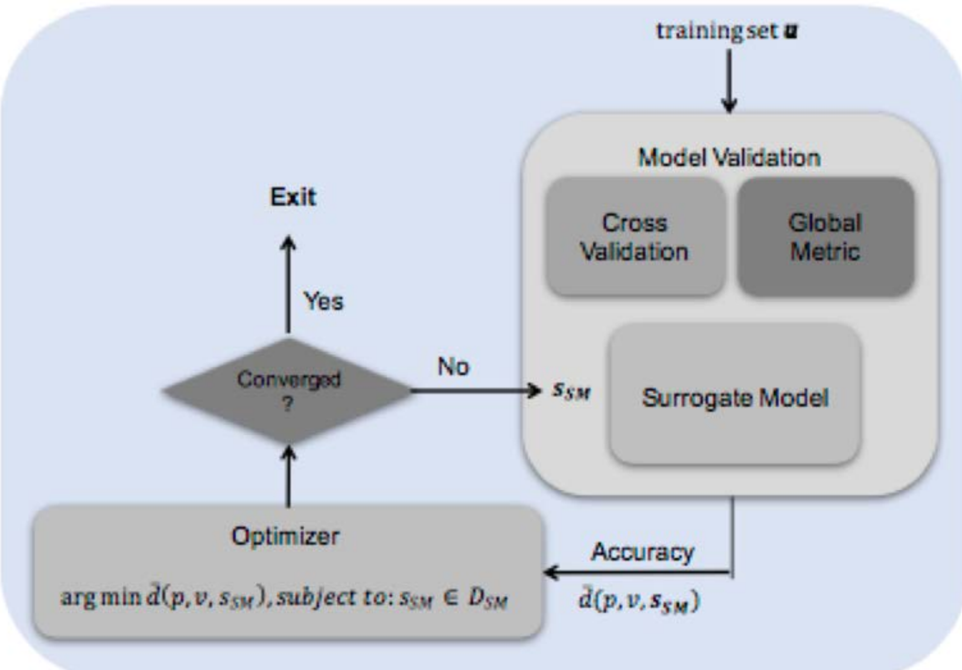
Model validation RAVEN scheme

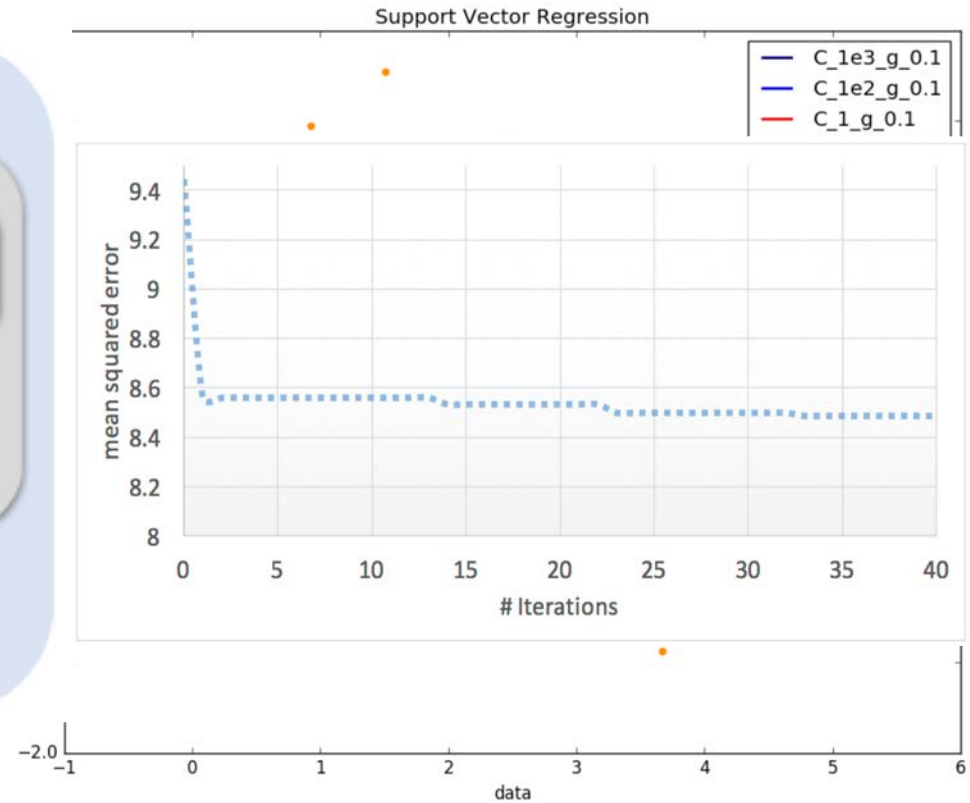




Mean Absolute Error score (Cross-validation) as function of # samples

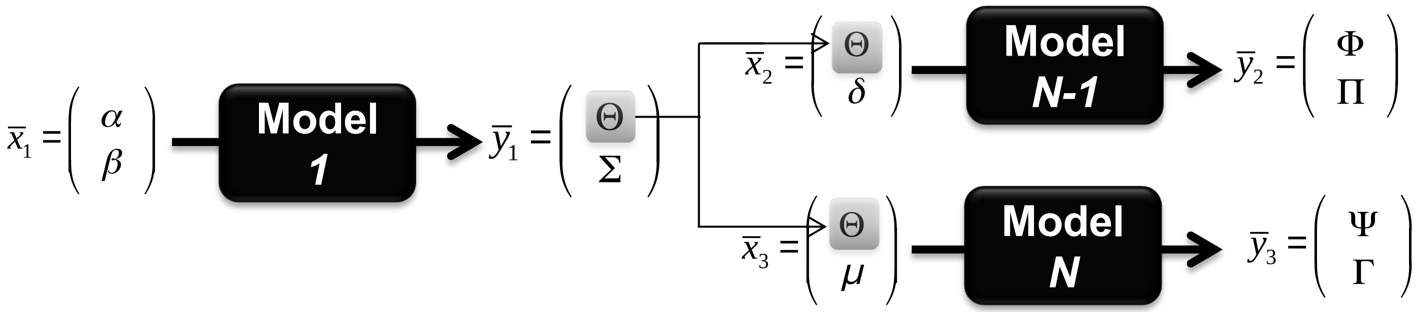
Surrogate Model Optimization





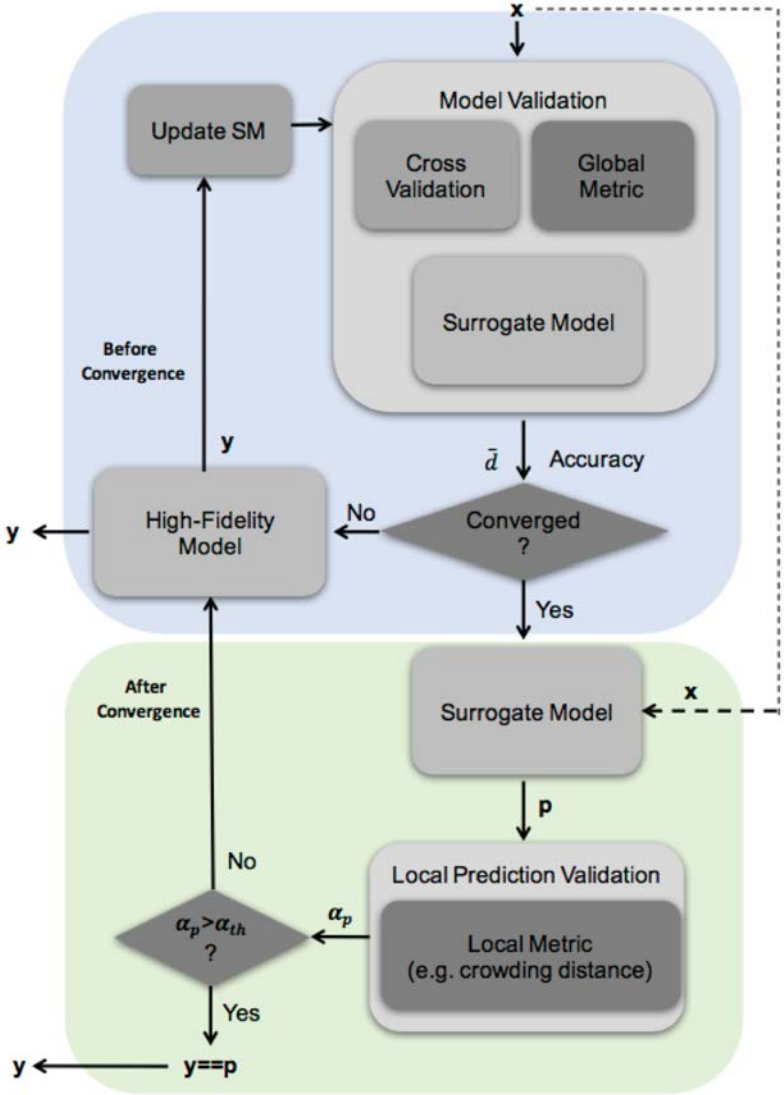
Ensemble model

- Multiple "models" can be assembled together and treated as a single one
- Models can be completely heterogeneous (code, external models, ROM)
- RAVEN acts as a hub for the information exchange
- Information passed between "models" could be:
  - Set of lump values
  - *Set of time series or fields*



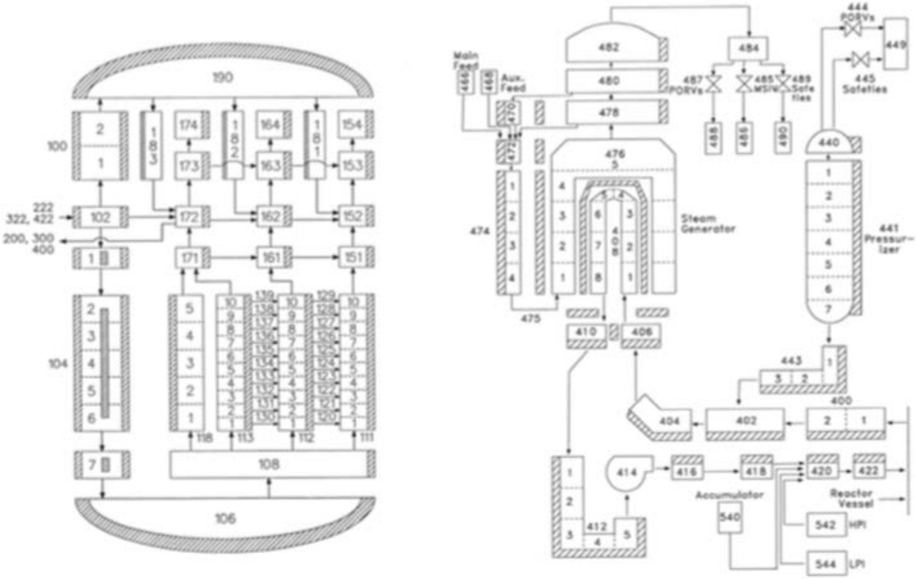
$$\bar{x}_1 = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} \quad \bar{y}_1 = \begin{pmatrix} \Theta \\ \Sigma \end{pmatrix} \quad \bar{x}_2 = \begin{pmatrix} \Theta \\ \delta \end{pmatrix} \quad \bar{y}_2 = \begin{pmatrix} \Phi \\ \Pi \end{pmatrix} \quad \bar{x}_3 = \begin{pmatrix} \Theta \\ \mu \end{pmatrix} \quad \bar{y}_3 = \begin{pmatrix} \Psi \\ \Gamma \end{pmatrix}$$

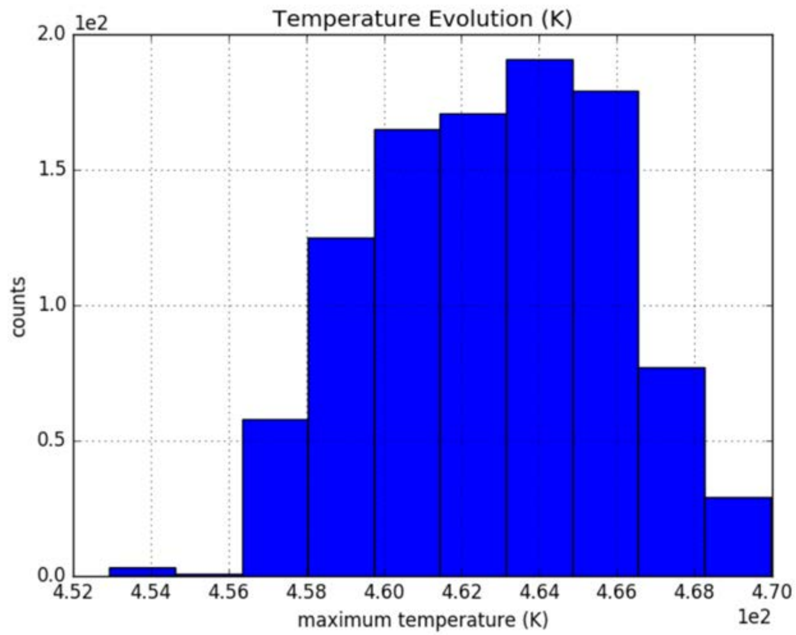
Hybrid-Model (automatic selection ROM/physical model)



- The *HybridModel* is designed to combine multiple surrogate models and any other Model (i.e. high-fidelity model) leveraging the *EnsembleModel* infrastructure, deciding which of the Model needs to be evaluated based on the model validation score.

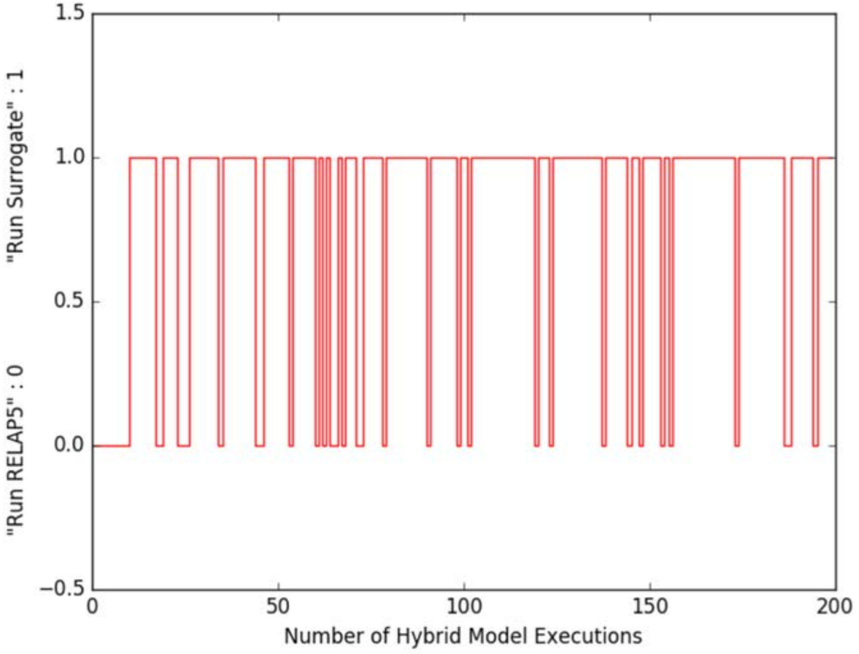
Application of the Hybrid Model on a PWR SBO using RELAP5-3D





1000 Monte Carlo samples

Application of the Hybrid Model on a PWR SBO using RELAP5-3D



200 RELAP5 evaluations over 1000 MC Samples

RELAP5-3D

Parameter	Result
mean	462.64
Minimum	458.57
Maximum	467.32
Median	462.64

HYBRID MODEL

Parameter	Result
mean	462.65
Minimum	458.03
Maximum	467.53
Median	462.64

Future work on the Hybrid Model

- Identification of Time-dependent validation metrics
- Extension of the Hybrid Model in the time-domain
- Development of model-based local validation metrics

Thank you