POEM

Release 0.1

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Aug 20, 2024

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CHAPTER

ONE

INTRODUCTION

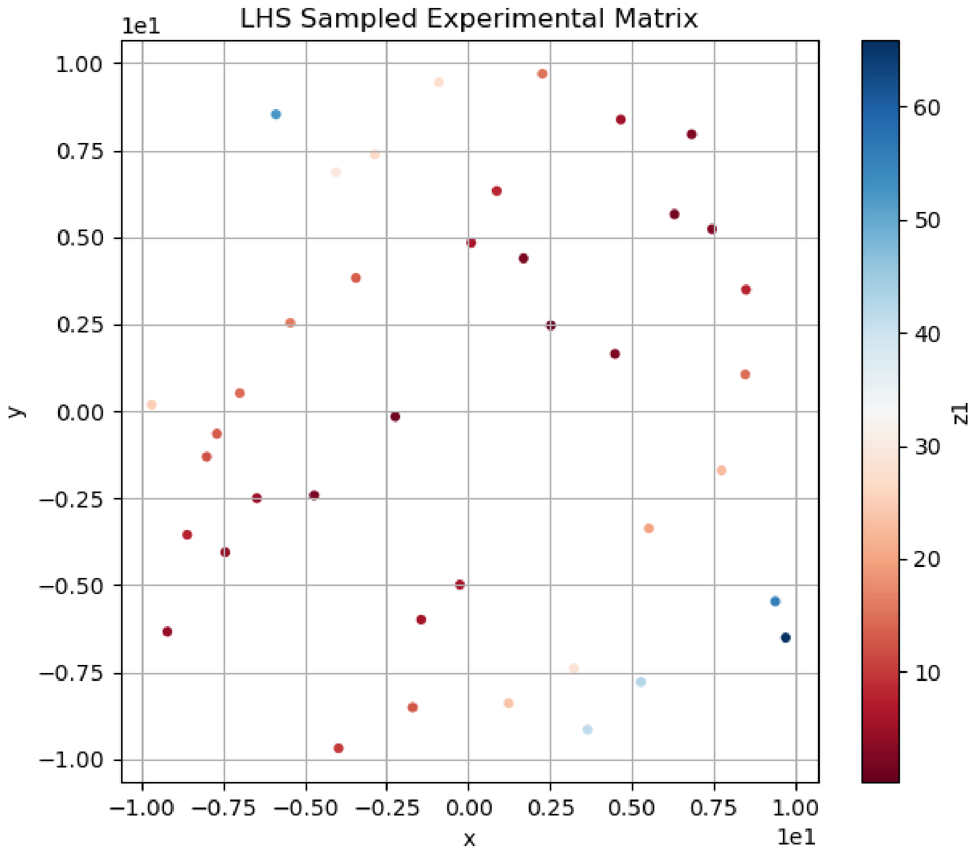
1.1 What Is POEM?

POEM is a platform for optimal experiment management, powered with automated machine learning to accelerate the discovery of optimal solutions and to automatically guide the design of experiments to be evaluated. POEM currently supports (1) random model explorations for experiment design, (2) sparse grid model explorations with the Gaussian polynomial chaos surrogate model to accelerate experiment design, (3) time-dependent model sensitivity and uncertainty analyses to identify importance features for experiment design, (4) model calibrations via Bayesian inference to integrate experiments in order to improve model performance, and (5) Bayesian optimization for optimal experimental design. POEM is also intended to simplify the experimental design process for users, enabling them to analyze the data with minimal human intervention, while also improving the technological output from research activities.

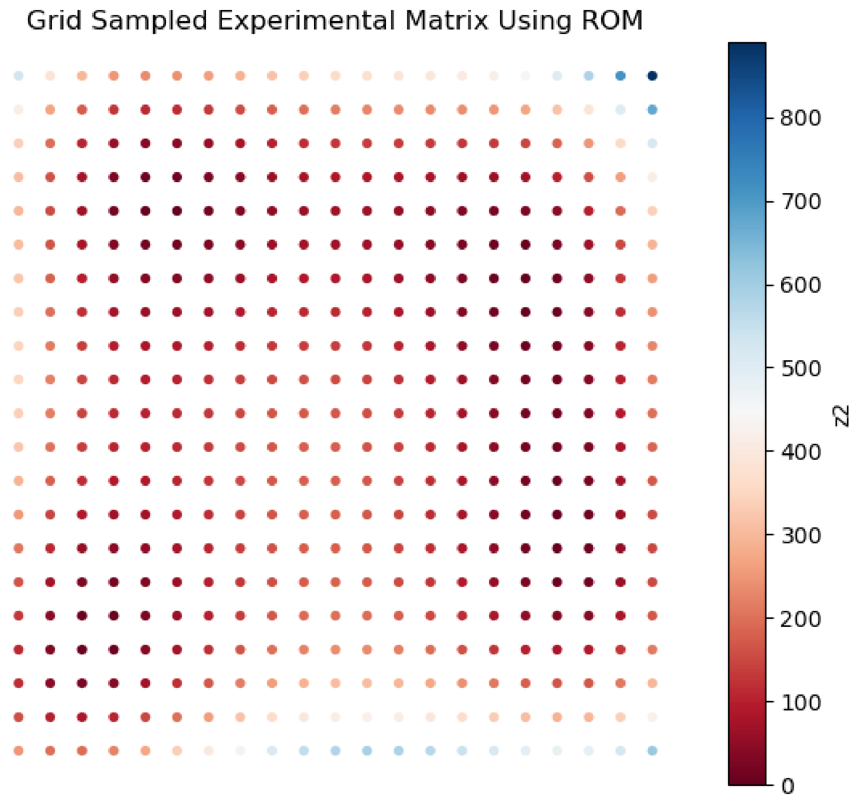
POEM leverages the Risk Analysis Virtual Environment (RAVEN), which is a robust platform that supports model explorations and decision making, to enable large scalability, reduce computational costs, and provide access to complex physical models when performing optimal experimental design.

1.2 Capabilities

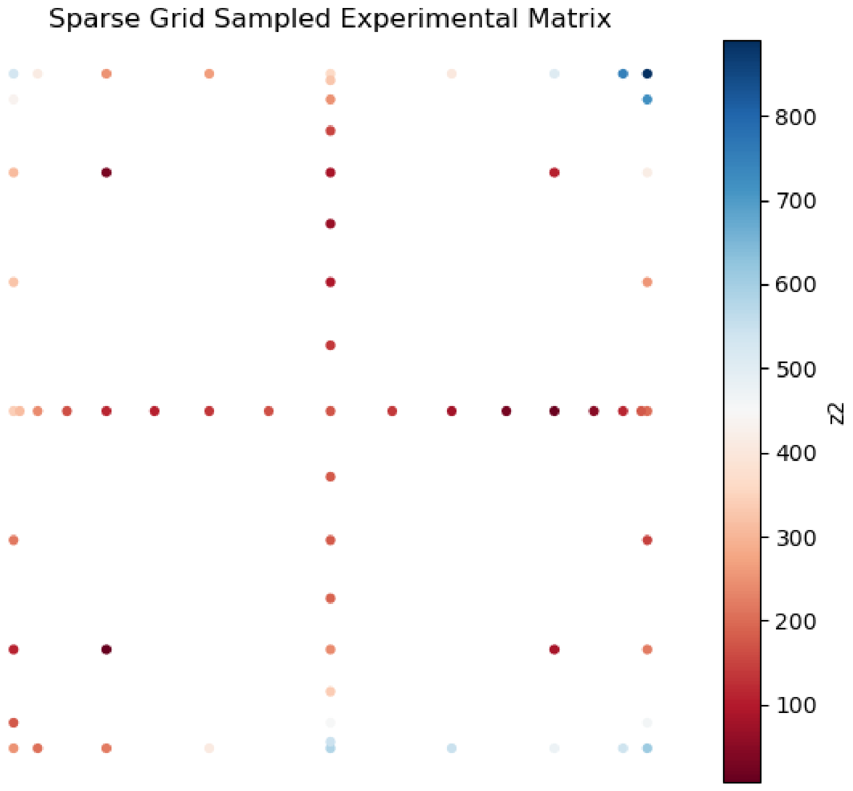
- Random model explorations for experiment design
  - See *Monte Carlo Sampling*
  - See *Latin Hypercube Sampling*

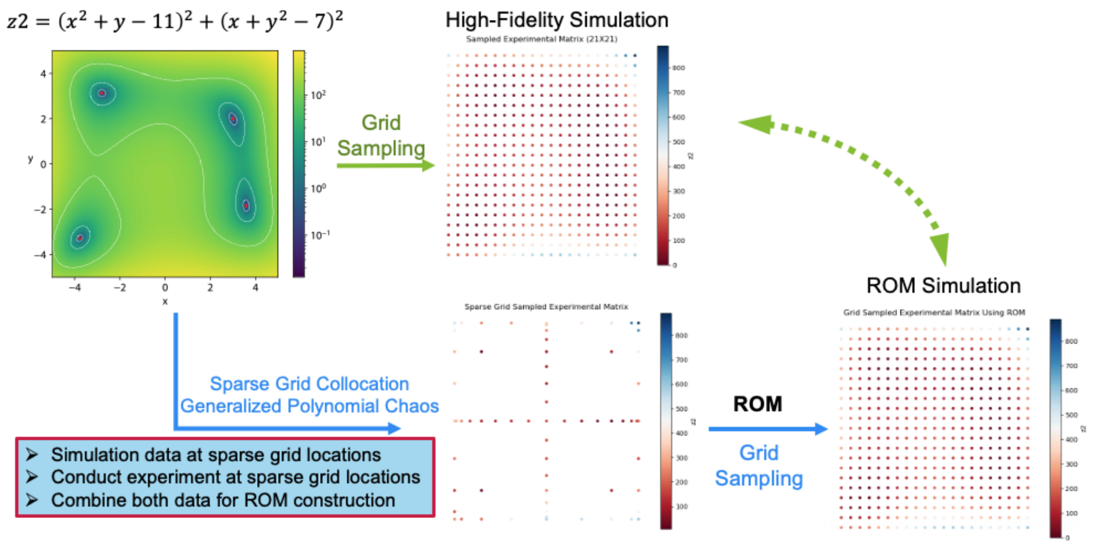


- Machine-learning-aided parameter space exploration
  - See *Train ROM*

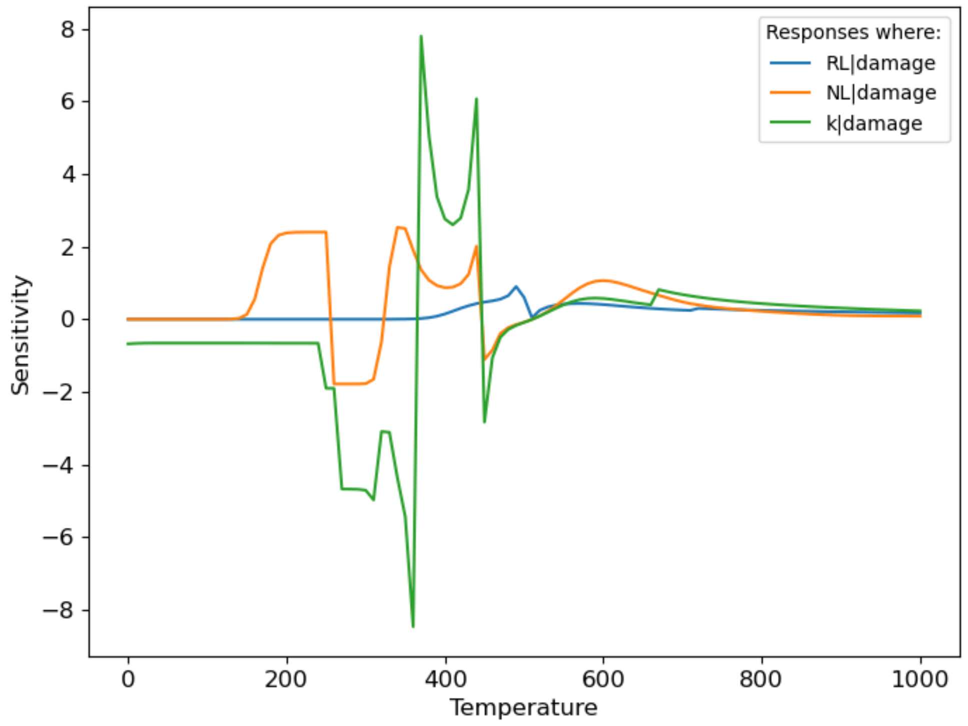


- Sparse grid stochastic collocation with Gaussian polynomial chaos expansion models to accelerate experimental design
  - See *Generate Sparse Grid Locations*

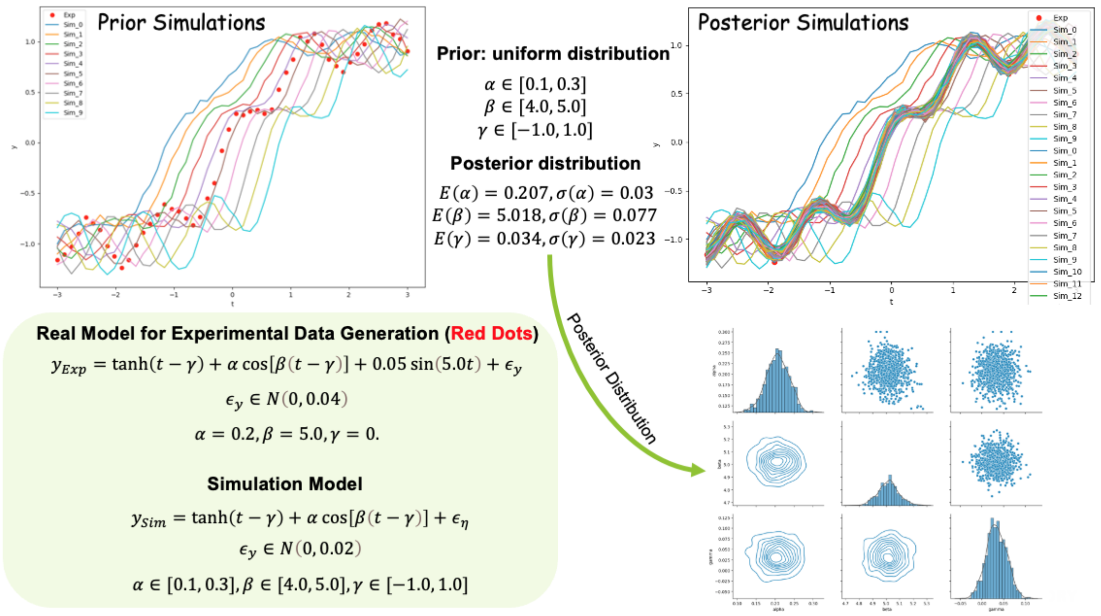



$z2 = (x^2 + y - 11)^2 + (x + y^2 - 7)^2$
High-Fidelity Simulation
Sampled Experimental Matrix (21X21)
Grid Sampling
ROM Simulation
Grid Sampled Experimental Matrix Using ROM
Sparse Grid Sampled Experimental Matrix
Sparse Grid Collocation
Generalized Polynomial Chaos
ROM
Grid Sampling
➢ Simulation data at sparse grid locations
➢ Conduct experiment at sparse grid locations
➢ Combine both data for ROM construction

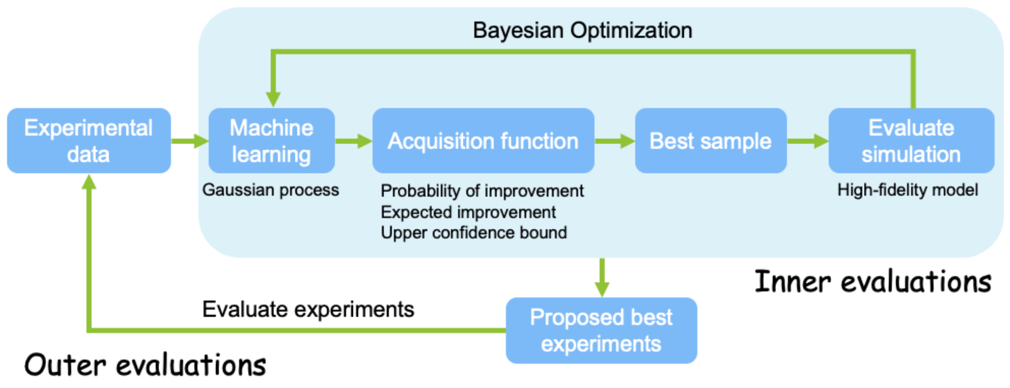
- Dynamic sensitivity and uncertainty analysis
  - See *Sensitivity Analysis*

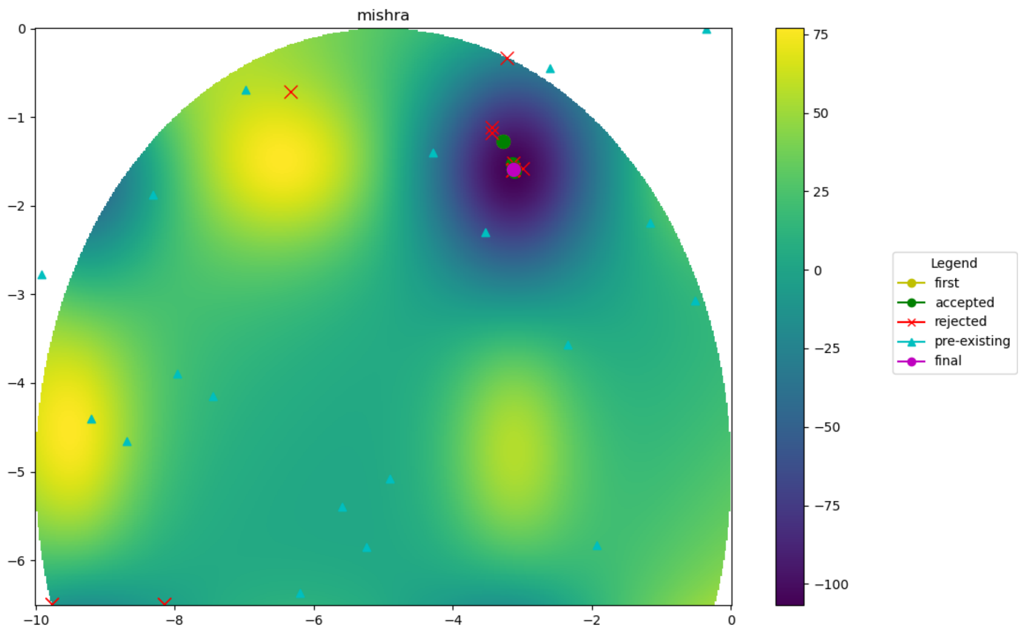


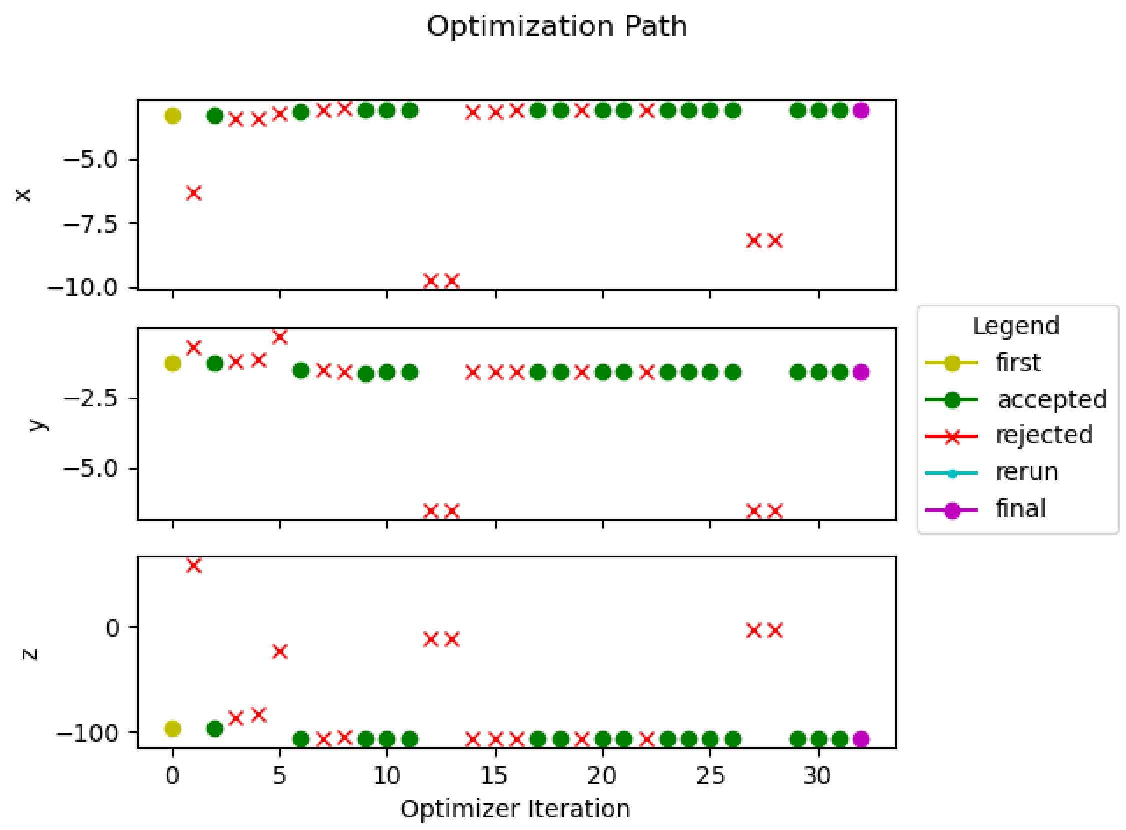
- Model calibration through Bayesian inference
  - See *Model Calibration*



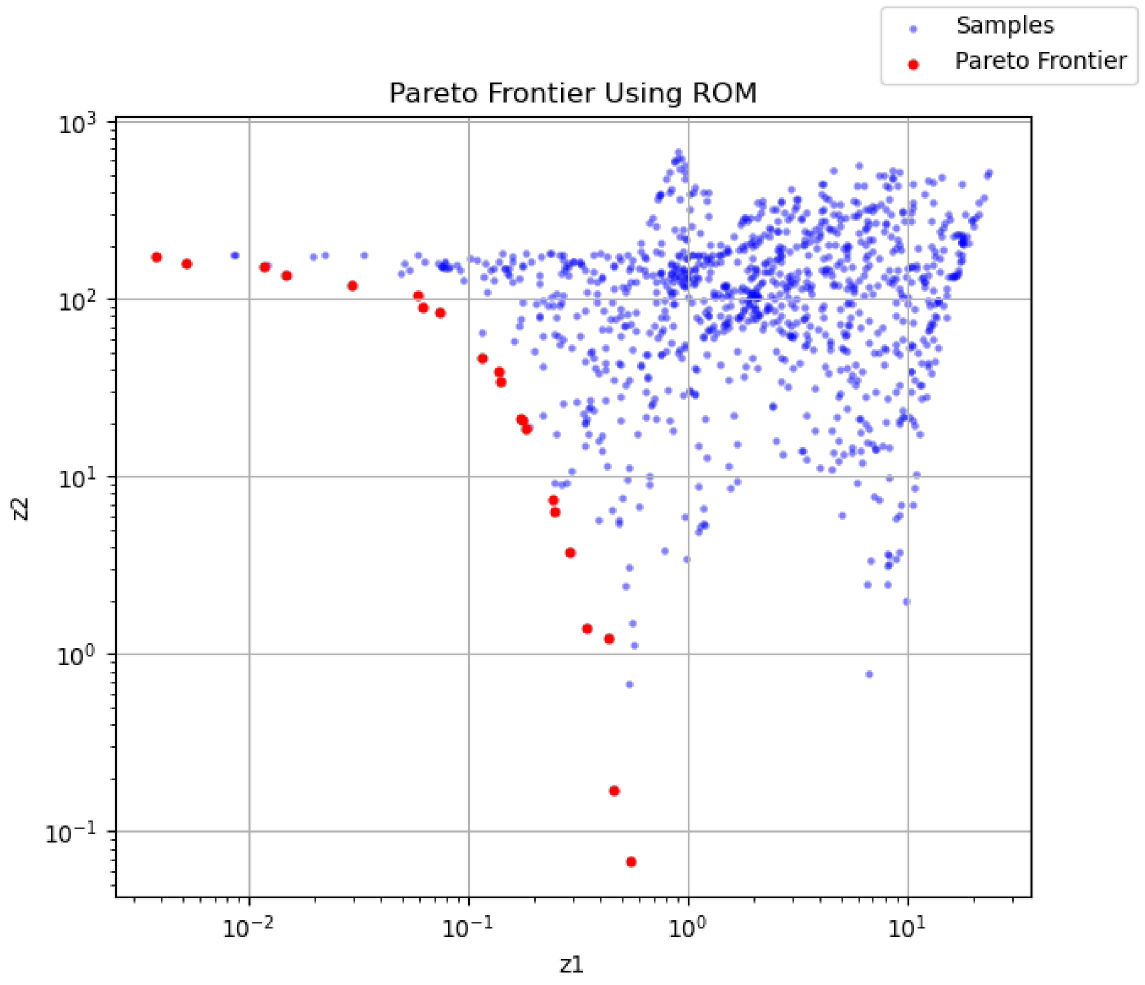
- Bayesian optimization for optimal experimental design
  - See *Bayesian Optimization*


Bayesian Optimization
Experimental data
Machine learning
Gaussian process
Acquisition function
Probability of improvement
Expected improvement
Upper confidence bound
Best sample
Evaluate simulation
High-fidelity model
Inner evaluations
Evaluate experiments
Proposed best experiments
Outer evaluations


mishra
Legend
first
accepted
rejected
pre-existing
final



- Pareto frontier to guide the design of the experiment to be evaluated


Samples
Pareto Frontier
Pareto Frontier Using ROM
10^3
10^2
10^1
10^0
10^{-1}
z2
10^{-2}
10^{-1}
10^0
10^1
z1

CHAPTER

TWO

INSTALLATION

2.1 How Is POEM Installed?

2.1.1 Installation

```
conda create -n poem_libs python=3.10
conda activate poem_libs
pip install poem-ravenframework
```

2.1.2 Clone

```
git clone git@github.com:idaholab/POEM.git
```

2.1.3 Test

```
cd POEM/tests
poem -i lhs_sampling.xml
```

CHAPTER THREE

QUICK START

3.1 Input Structure

POEM utilizes XML to define its input structure. The main input blocks are covered in the following sections.

3.1.1 Simulation block

The root node containing the entire input, all of the following blocks fit inside the `Simulation` block.

```
<Simulation>

  <RunInfo>
    ...
  </RunInfo>

  <GlobalSettings>
    ...
  </GlobalSettings>

  <Distributions>
    ...
  </Distributions>

  <Models>
    ...
  </Models>

  <Files>
    ...
  </Files>

  <Functions>
    ...
  </Functions>

  <LikelihoodModel>
    ...
  </LikelihoodModel>

</Simulation>
```

3.1.2 GlobalSettings block

This block specifies the global settings for the calculations. For example:

```
<GlobalSettings>
  <!-- Required Nodes -->
  <AnalysisType>LHS</AnalysisType>
  <limit>10</limit>
  <Inputs>x, y</Inputs>
  <Outputs>OutputPlaceHolder</Outputs>

  <!-- Optional Nodes -->
  <pivot>time</pivot>
  <dynamic>True</dynamic>

  <!-- Optional Nodes, uses for certain analysis -->
  <SparseGridData>path/to/data.csv</SparseGridData>
  <data>path/to/data.csv</data>
  <InitialInputs>0.1, 4.0, -1.0</InitialInputs>
  <PolynomialOrder>3</PolynomialOrder>
</GlobalSettings>
```

In general, this block accepts the following subnodes:

- Required Nodes
  - `AnalysisType`: The type of analysis, it accepts the following keywords:
    - `mc`: Simple Monte Carlo analysis for a given model. See *Monte Carlo Sampling*.
    - `lhs`: Sample the given model by using a Latin hypercube sampling (LHS) strategy. See *Latin Hypercube Sampling*.
    - `sensitivity`: Perform sensitivity analysis for the given model. The `mean, variance, 95/95 percentile, correlation, Spearman correlation, sensitivity coefficients, etc.` will be computed. See *Sensitivity Analysis*.
    - `sparse_grid_construction`: Generate sparse grid locations to guide experiments. These locations can be used to efficiently construct a high-order Gaussian polynomial chaos surrogate model. See *Generate Sparse Grid Locations*.
    - `sparse_grid_rom`: Train a multivariate high-order Gaussian polynomial chaos reduced-order model (ROM)/surrogate based on user-provided experimental data. See *Train ROM*.
    - `train_rom`: Train a Gaussian process ROM based on user-provided data. See *Train ROM*.
    - `bayesian_optimization`: Perform Bayesian optimization based on user-provided data and the simulation model. See *Bayesian Optimization*.
    - `model_calibration`: Perform model calibration by utilizing Bayesian inference, based on user-provided data and the simulation model. See *Model Calibration*.
  - `limit`: The total number of model executions or the number of samples to generate
  - `Inputs`: List of input variables
  - `Outputs`: List of output variables (if no output variables exist, `OutputPlaceHolder` can be used)
- Optional Nodes
  - `dynamic`: True if the user wants to perform a type of time-dependent analysis such as time-dependent ROM construction, sensitivity analysis, or model calibration

  - pivot: Required if dynamic is True. The pivot variable for dynamic analysis (the default is time).
- Optional Nodes for Certain Analysis
  - SparseGridData: The experimental data usable for training the Gaussian polynomial chaos ROM (only used by sparse_grid_construction and sparse_grid_rom)
  - PolynomialOrder: The highest order for the Gaussian polynomial chaos ROM (only used by sparse_grid_construction and sparse_grid_rom)
  - data: The experimental data usable to train the Gaussian process chaos ROM. Only used by train_rom and bayesian_optimization
  - InitialInputs: The initial values for the input variables listed by <Inputs> in <GlobalSettings>.

3.1.3 RunInfo block

This block specifies the calculation settings (e.g., working directory and number of parallel simulations).

```
<RunInfo>
  <WorkingDir>LHS</WorkingDir>
  <batchSize>1</batchSize>
</RunInfo>
```

In general, this block accepts the following subnodes:

- WorkingDir: Specifies the absolute or relative path to a directory that will store all the calculation results
- batchSize: Specifies the number of parallel executed simultaneously
- JobName: Specifies the name to use for the job when submitting to a PBS queue.

RunInfo for Cluster Usage

```
<RunInfo>
  <WorkingDir>FirstMF</WorkingDir>
  <batchSize>3</batchSize>
  <clusterParameters>-W block=true</clusterParameters>
  <NumThreads>4</NumThreads>
  <mode>
    mpi
    <runQSUB/>
  </mode>
  <NodeParameter> </NodeParameter>
  <NumMPI>2</NumMPI>
  <expectedTime>0:10:00</expectedTime>
  <JobName>test_qsub</JobName>
</RunInfo>
```

3.1.4 Files block

This block specifies the files to be used as input for the <Models> block. Users can specify as many input files as they need, and utilize the <Input> node to specify the name and path/to/file.

```
<Files>
  <Input name="sauq" type="">../../models/sauq.m</Input>
  <Input name="rt" type="">../../models/RateTheory.m</Input>
  <Input name="kc" type="">../../models/KlemensCallawayModel.m</Input>
</Files>
```

3.1.5 Distributions block

POEM leverages the RAVEN (https://github.com/idaholab/raven) input structure to build customized workflows for model explorations and optimal experimental design. In this case, POEM provides support for all the probability distributions available in RAVEN. The following is an example for the <Distributions> block:

```
<Distributions>
  <Uniform name='x'>
    <lowerBound>-10</lowerBound>
    <upperBound>0</upperBound>
  </Uniform>
  <Uniform name='y'>
    <lowerBound>-6.5</lowerBound>
    <upperBound>0</upperBound>
  </Uniform>
</Distributions>
```

In this block, users must define the distribution for each variable listed in the GlobalSettings Inputs node, and the name for the distribution should match the variable name listed under <GlobalSettings><Inputs>VariableList</Inputs></GlobalSettings>.

3.1.6 Models block

As with the <Distributions> block, POEM leverages the RAVEN (https://github.com/idaholab/raven) <Models> input structure. In this case, POEM provides support for all the models available in RAVEN. The following is an example for the <Models> block.

```
<Models>
  <ExternalModel ModuleToLoad="../../models/mishraBirdConstrained.py" name="mishra"␣
↪subType="">
    <inputs>x, y</inputs>
    <outputs>z</outputs>
  </ExternalModel>
</Models>
```

As its name suggests, an external model is an entity that is embedded at run time. This object allows the user to create a Python module that will be treated as a predefined internal model object.

The specifications of an external model must be defined within the XML block <ExternalModel>. This blocks accepts the following subnodes:

- inputs: Each variable name must match a variable used/defined in the external Python model.

- `outputs`: Each variable name must match a variable used/defined in the external Python model.

Each variable defined in the `<ExternalModel>`, `<inputs>`, and `<outputs>` blocks is available in the module (each method implemented) as a Python `self.` member.

3.1.7 Functions block

POEM leverages the RAVEN (https://github.com/idaholab/raven) `<Functions>` input structure. In this case, POEM provides support for using user-defined external functions. These functions are Python modules, with a format automatically interpretable by RAVEN software.

The following is an example for the `<Functions>` block:

```
<Functions>
  <External file="../../models/mishraBirdConstrained.py" name="constraint1">
    <variables>x,y</variables>
  </External>
</Functions>
```

In this section, the XML input syntax and the format of the accepted functions are fully specified. The specifications of an external function must be defined within the XML `<external>` block. This XML node requires the following attributes:

- `name`: User-defined name of this function
- `file`: Absolute or relative path specifying the code associated with this function.

To make the code aware of the variables the user will manipulate/use in their own Python function, the variables must be specified in the `<variables>` subnode input block. Within this block, the user must input only the variables directly used by the external function.

When the external function variables are defined, the code will initialize them at runtime and keep track of their values throughout the simulation. Each variable defined in the `<variables>` block is available in the function as a Python `self.` member. Below, an example of a user-defined external function is reported; the method `evaluate` needs to be defined in the function file:

```
def evaluate(self):
  return self.a * self.c
```

3.1.8 LikelihoodModel block for model calibration

This node is only used for model calibration analysis. The following is an example:

```
<LikelihoodModel>
  <simTargets>eta</simTargets>
  <expTargets shape="1,50" computeCov='False' correlation='False'>
    -1.16074224 -1.10303445 -1.02830511 -0.89782965 -0.73765453 -0.7989537
     -0.86163706 -1.02209944 -1.12444044 -1.23657398 -1.16081758 -1.01219869
     -0.890747   -0.80444122 -0.70893668 -0.61012531 -0.65670863 -0.6768583
     -0.74732441 -0.81448647 -0.73232671 -0.54989334 -0.39796749 -0.07894291
      0.13067378  0.28999998  0.27418965  0.313329    0.32306704  0.2885684
      0.32736775  0.52458854  0.69446572  0.82419521  1.04393683  1.00435818
      1.0810376   0.97245373  0.82406522  0.76067559  0.70145544  0.79479965
      0.88035895  0.97750307  1.11524353  1.17159017  1.18299222  1.07255006
```

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```
      1.02835909  0.90784132
  </expTargets>
  <expCov diag="True">
      0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
      0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
      0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
      0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
      0.02, 0.02, 0.02, 0.02, 0.02, 0.02
  </expCov>
  <!-- <biasTargets></biasTargets>
  <biasCov diag="False"></biasCov> -->
  <!-- <romCov diag="True"></romCov> -->
</LikelihoodModel>
```

The `<LikelihoodModel>` node accepts the following subnodes:

- `simTargets`: Targets of simulations used in the calibration.
- `expTargets`: Targets of experiments used in the calibration. Either variables or list of values. This node accepts the following attributes:
  - `shape`: Determines the number of targets and number of experimental observations for each target. For example, `shape="3,2"` indicates two targets, with three observations for each; whereas `shape="10"` indicates one target with 10 observations. Omitting this optional attribute will instead result in a single target with multiple observations.
  - `computeCov`: Indicates whether the experiment covariance matrix is provided or is instead computed based on the given experiment observations. If True, we will compute the covariance based on the given observations; otherwise, the user must provide the covariance matrix.
  - `correlation`: Indicates whether the targets are correlated. If True, and `compute` is True, we will compute the covariance matrix. If False, but `compute` is True, we will only compute the variance of each target.
- `expCov`: Experiment covariance (i.e., measurement noise). This node accepts the following attribute:
  - `diag`: If True, only the variance for each target must be provided; otherwise, the user needs to provide the full covariance matrix.
- `biasTargets`: Models uncertainty/discrepancy/bias/error in Targets that are used in calibration.
- `biasCov`: Models covariance, model bias/discrepancy, or model inadequacy caused by missing physics or numerical approximation. This node accepts the following attribute:
  - `diag`: If True, only the variance for each target must be provided; otherwise, the user needs to provide the full covariance matrix.
- `romCov`: Models uncertainty caused by the surrogate model, such as interpolation. This node accepts the following attribute:
  - `diag`: If True, only the variance for each target must be provided; otherwise, the user needs to provide the full covariance matrix.
- `reduction`: Allows reduction on likelihood model construction. This node accepts the following attributes:
  - `type`: This is the reduction method, and its default is **PCA**.
  - `basis`: User-provided basis vector for reduction.
  - `shape`: Determines the basis vectors for reduction. For example, `shape="10,2"` indicates two basis vectors with dimension 10.

CHAPTER

FOUR

MONTE CARLO SAMPLING

Monte Carlo sampling was utilized to perform random model explorations for experiment design. For this analysis, set <AnalysisType>MC</AnalysisType>. For example, the following input utilizes Monte Carlo sampling to generate 10 random samples of input variables x,y with associated Uniform distributions.

```
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>MC</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>MC</AnalysisType>
    <limit>10</limit>
    <Inputs>x, y</Inputs>
    <Outputs>OutputPlaceHolder</Outputs>
  </GlobalSettings>

  <Distributions>
    <Uniform name='x'>
      <lowerBound>-10</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
    <Uniform name='y'>
      <lowerBound>-6.5</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
  </Distributions>

</Simulation>
```

When a dynamic model is provided, the users need to set the <pivot> and <dynamic> nodes in <GlobalSettings>, as illustrated in the following example:

```
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>MC</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

```

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```
  <GlobalSettings>
    <AnalysisType>MC</AnalysisType>
    <limit>10</limit>
    <Inputs>x0, y0, z0</Inputs>
    <pivot>time</pivot>
    <dynamic>True</dynamic>
    <Outputs>x,y,z</Outputs>
  </GlobalSettings>

  <Distributions>
    <Normal name="x0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="y0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="z0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/lorentzAttractor.py" name="lorentzAttractor"␣
↪subType="">
      <inputs>inputGroup</inputs>
      <outputs>outputGroup</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

Users can can also employ `inputGroup` and `outputGroup` to represent the input and output variable lists, respectively, as illustrated in the example `<ExternalModel>` node above.

CHAPTER

FIVE

LATIN HYPERCUBE SAMPLING

LHS was utilized to perform random model explorations for experiment design. For this analysis, set <AnalysisType>LHS</AnalysisType>. For example, the following input utilizes LHS to generate 10 random LHS samples of input variables x,y with associated Uniform distributions:

```
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>LHS_mishra</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>LHS</AnalysisType>
    <limit>10</limit>
    <Inputs>x, y</Inputs>
    <Outputs>z</Outputs>
  </GlobalSettings>

  <Distributions>
    <Uniform name='x'>
      <lowerBound>-10</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
    <Uniform name='y'>
      <lowerBound>-6.5</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../../models/mishraBirdConstrained" name="mishra"␣
↪subType="">
      <inputs>x, y</inputs>
      <outputs>z</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

When a dynamic model is provided, the users need to set the <pivot> and <dynamic> node in <GlobalSettings>, as illustrated in the following example:

```xml
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>LHS</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>LHS</AnalysisType>
    <limit>10</limit>
    <Inputs>x0, y0, z0</Inputs>
    <pivot>time</pivot>
    <dynamic>True</dynamic>
    <Outputs>x,y,z</Outputs>
  </GlobalSettings>

  <Distributions>
    <Normal name="x0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="y0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="z0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/lorentzAttractor.py" name="lorentzAttractor"␣
↪subType="">
      <inputs>inputGroup</inputs>
      <outputs>outputGroup</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

Users can also employ `inputGroup` and `outputGroup` to represent the input and output variable lists, respectively, as illustrated in the example `<ExternalModel>` node above.

CHAPTER

SIX

TRAIN ROM

ROMs or machine learning models can be trained based on experiment data or a mix of experiment data and simulation data.

6.1 Train Gaussian Process Model

For this analysis, set `<AnalysisType>train_rom</AnalysisType>`. For example, the following input utilizes data provided by the `<data>` node to train the Gaussian process model. After training, the Gaussian process model inputs will be sampled via an LHS algorithm, along with their associated distributions, and the number of samples will be equal to the value of `<limit>`.

```xml
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>GP</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>train_rom</AnalysisType>
    <data>../LHS/sampling_dump.csv</data>
    <limit>10</limit>
    <Inputs>x, y</Inputs>
    <Outputs>z1</Outputs>
  </GlobalSettings>

  <Distributions>
    <Uniform name='x'>
      <lowerBound>-10</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
    <Uniform name='y'>
      <lowerBound>-6.5</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
  </Distributions>

</Simulation>
```

6.2 Train the Dynamic Gaussian Process Model

When a dynamic model is provided, the users need to set the `<pivot>` and `<dynamic>` nodes in `<GlobalSettings>`, as illustrated in the example below. In addition, set `<AnalysisType>train_rom</AnalysisType>`. For example, the following input will utilize data provided by the `<data>` node to train the Gaussian process model. After training, the Gaussian process model inputs will be sampled via an LHS algorithm, along with their associated distributions, and the number of samples will be equal to the value of `<limit>`.

```xml
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>GP_dynamic</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>train_rom</AnalysisType>
    <data>../LHS/sampling_dynamic_dump.csv</data>
    <limit>10</limit>
    <Inputs>x0, y0, z0</Inputs>
    <pivot>time</pivot>
    <dynamic>True</dynamic>
    <Outputs>x,y,z</Outputs>
  </GlobalSettings>

  <Distributions>
    <Normal name="x0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="y0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="z0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/lorentzAttractor.py" name="lorentzAttractor"␣
↪subType="">
      <inputs>inputGroup</inputs>
      <outputs>outputGroup</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

6.3 Train Gaussian Polynomial Chaos Model with Sparse Grid

For this analysis, set `<AnalysisType>sparse_grid_rom</AnalysisType>`. As an example, the following input utilizes data provided by the `<SparseGridData>` node to train a Gaussian polynomial chaos model. After training, the Gaussian process model inputs will be sampled via a Monte Carlo sampling algorithm, along with their associated distributions, and the number of samples will be equal to the value of `<limit>`.

```
<?xml version="1.0" ?>
<Simulation>

  <GlobalSettings>
    <AnalysisType>sparse_grid_rom</AnalysisType>
    <Inputs>x, y</Inputs>
    <Outputs>z1</Outputs>
    <PolynomialOrder>2</PolynomialOrder>
    <limit>10</limit>
    <SparseGridData>dump_SparseGrid.csv</SparseGridData>
  </GlobalSettings>

  <Distributions>
    <Uniform name="x">
      <lowerBound>-10</lowerBound>
      <upperBound>10</upperBound>
    </Uniform>
    <Uniform name="y">
      <lowerBound>-10</lowerBound>
      <upperBound>10</upperBound>
    </Uniform>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/matyas" name="externalModel" subType="">
      <inputs>x, y</inputs>
      <outputs>z1</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

For this ROM, users can also set the highest order of the Gaussian polynomial chaos expansions by simply setting `<PolynomialOrder>` in `<GlobalSettings>`.

6.4 Train Dynamic Gaussian Polynomial Chaos Model with Sparse Grid

When a dynamic model is provided, the users need to set the `<pivot>` and `<dynamic>` nodes in `<GlobalSettings>`, as illustrated in the example below. For this analysis, set `<AnalysisType>sparse_grid_rom</AnalysisType>`. As an example, the following input utilizes data provided by the `<SparseGridData>` node to train a Gaussian polynomial chaos model. After training, the Gaussian process model inputs will be sampled via a Monte Carlo sampling algorithm, along with their associated distributions, and the number of samples will be equal to the value of `<limit>`.

```xml
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>SparseGridDynamic</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>sparse_grid_rom</AnalysisType>
    <Inputs>x0, y0, z0</Inputs>
    <pivot>time</pivot>
    <dynamic>True</dynamic>
    <Outputs>x,y,z</Outputs>
    <PolynomialOrder>2</PolynomialOrder>
    <limit>10</limit>
    <SparseGridData>../SparseGrid/SparseGrid_dynamic_dump.csv</SparseGridData>
  </GlobalSettings>

  <Distributions>
    <Normal name="x0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="y0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="z0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/lorentzAttractor.py" name="lorentzAttractor"␣
↪subType="">
      <inputs>inputGroup</inputs>
      <outputs>outputGroup</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

For this ROM, the users can also set the highest order of the Gaussian polynomial chaos expansions by simply setting `<PolynomialOrder>` in `<GlobalSettings>`.

CHAPTER

SEVEN

GENERATE SPARSE GRID LOCATIONS

Sparse grid model explorations can be performed with a Gaussian polynomial chaos surrogate model so as to accelerate the experiment design.

When generating sparse grid locations, users can also set the highest order of the Gaussian polynomial chaos expansions by simply setting <PolynomialOrder> in <GlobalSettings>. The higher the polynomial order, the more sparse grid locations will be generated.

Once the experiment data are generated at the given sparse grid locations, the Gaussian polynomial chaos surrogate model can automatically be constructed. See the Train ROM section of this document for how to train the Gaussian polynomial chaos surrogate model.

7.1 Static Model

```
<Simulation>
  <RunInfo>
    <WorkingDir>SparseGrid</WorkingDir>
    <Sequence>SparseGridSampler, print</Sequence>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>sparse_grid_construction</AnalysisType>
    <Inputs>x, y</Inputs>
    <Outputs>z1</Outputs>
    <PolynomialOrder>3</PolynomialOrder>
  </GlobalSettings>

  <Distributions>
    <Uniform name="x">
      <lowerBound>-10</lowerBound>
      <upperBound>10</upperBound>
    </Uniform>
    <Uniform name="y">
      <lowerBound>-10</lowerBound>
      <upperBound>10</upperBound>
    </Uniform>
  </Distributions>

  <Models>
```

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```
    <ExternalModel ModuleToLoad="../models/matyas" name="externalModel" subType="">
      <inputs>x, y</inputs>
      <outputs>z1</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

7.2 Dynamic Model

When a dynamic model is provided, the users need to set the `<pivot>` and `<dynamic>` nodes in `<GlobalSettings>`, as illustrated in the following example:

```
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <WorkingDir>SparseGrid</WorkingDir>
    <Sequence>SparseGridSampler, print</Sequence>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>sparse_grid_construction</AnalysisType>
    <Inputs>x0, y0, z0</Inputs>
    <pivot>time</pivot>
    <dynamic>True</dynamic>
    <Outputs>x,y,z</Outputs>
    <PolynomialOrder>3</PolynomialOrder>
  </GlobalSettings>

  <Distributions>
    <Normal name="x0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="y0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="z0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/lorentzAttractor.py" name="lorentzAttractor"␣
↪subType="">
      <inputs>inputGroup</inputs>
      <outputs>outputGroup</outputs>
```

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```
    </ExternalModel>
  </Models>

</Simulation>
```

CHAPTER

EIGHT

SENSITIVITY ANALYSIS

8.1 Static Sensitivity Analysis

For this analysis, set `<AnalysisType>sensitivity</AnalysisType>`. A Monte Carlo method will be utilized to sample the given model with `limit` number.

```xml
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <JobName>sauq</JobName>
    <WorkingDir>sauq_runs</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>sensitivity</AnalysisType>
    <limit>10</limit>
    <Inputs>x, y</Inputs>
    <Outputs>z1</Outputs>
  </GlobalSettings>

  <Distributions>
    <Uniform name='x'>
      <lowerBound>-10</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
    <Uniform name='y'>
      <lowerBound>-6.5</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/matyas" name="externalModel" subType="">
      <inputs>x, y</inputs>
      <outputs>z1</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

8.2 Dynamic Sensitivity Analysis

Time-dependent model sensitivity and uncertainty analyses will be employed to identify the importance features for experiment design. For this analysis, set `<AnalysisType>sensitivity</AnalysisType>`. A Monte Carlo method will be utilized to sample the given model with `limit` number. When a dynamic model is provided, the users need to set the `<pivot>` and `<dynamic>` nodes in the `<GlobalSettings>`, as illustrated in the following example:

```xml
<?xml version="1.0" ?>
<Simulation>
  <RunInfo>
    <JobName>sauq</JobName>
    <WorkingDir>sauq_dynamic_external</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>sensitivity</AnalysisType>
    <limit>10</limit>
    <Inputs>x0, y0, z0</Inputs>
    <pivot>time</pivot>
    <dynamic>True</dynamic>
    <Outputs>x,y,z</Outputs>
  </GlobalSettings>

  <Distributions>
    <Normal name="x0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="y0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
    <Normal name="z0">
      <mean>4</mean>
      <sigma>1</sigma>
    </Normal>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/lorentzAttractor.py" name="lorentzAttractor"␣
↪subType="">
      <inputs>inputGroup</inputs>
      <outputs>outputGroup</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

CHAPTER

NINE

BAYESIAN OPTIMIZATION

This chapter covers Bayesian optimization for optimal experimental design.

9.1 Example

For this analysis, set `<AnalysisType>bayesian_optimization</AnalysisType>`. The existing experiment data can be provided through `<data>` in `<GlobalSettings>`. For example:

```
<?xml version="1.0" ?>
<Simulation verbosity="debug">
  <RunInfo>
    <WorkingDir>Optimization</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>bayesian_optimization</AnalysisType>
    <data>../LHS_mishra/sampling_dump.csv</data>
    <limit>10</limit>
    <Inputs>x, y</Inputs>
    <Outputs>z</Outputs>
  </GlobalSettings>

  <Distributions>
    <Uniform name='x'>
      <lowerBound>-10</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
    <Uniform name='y'>
      <lowerBound>-6.5</lowerBound>
      <upperBound>0</upperBound>
    </Uniform>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../../models/mishraBirdConstrained.py" name="mishra"␣
↪subType="">
      <inputs>x, y</inputs>
      <outputs>z</outputs>
    </ExternalModel>
```

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```
  </Models>

  <Functions>
    <External file="../../models/mishraBirdConstrained.py" name="constraint1">
      <variables>x,y</variables>
    </External>
  </Functions>

</Simulation>
```

9.2 Python External Model and Constrain

```
import numpy as np

def evaluate(x,y):
  """
    Evaluates Mishra bird function.
    @ In, x, float, value
    @ In, y, float, value
    @ Out, evaluate, value at x, y
  """
  evaluate = np.sin(y)*np.exp(1.-np.cos(x))**2 + np.cos(x)*np.exp(1.-np.sin(y))**2 + (x-
↪y)**2
  return evaluate

def constraint(x,y):
  """
    Evaluates the constraint function @ a given point (x,y)
    @ In, x, float, value of the design variable x
    @ In, y, float, value of the design variable y
    @ Out, g(x,y), float, $g(x, y) = 25 - ((x+5.)**2 + (y+5.)**2)$
            the constraint is designed such that
            the constraint function must be >= 0,
            so if:
            1) f(x,y) >= 0 then g = f
            2) f(x,y) >= a then g = f - a
            3) f(x,y) <= b then g = b - f
            4) f(x,y)  = c then g = 0.001 - (f(x,y) - c)
  """
  condition = 25.
  g = condition - ((x+5.)**2 + (y+5.)**2)
  return g

###
# RAVEN hooks
###

def run(self,Inputs):
  """
```

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```
    RAVEN API
    @ In, self, object, RAVEN container
    @ In, Inputs, dict, additional inputs
    @ Out, None
  """
  self.z = evaluate(self.x,self.y)

def constrain(self):
  """
    Constrain calls the constraint function.
    @ In, self, object, RAVEN container
    @ Out, explicitConstrain, float, positive if the constraint is satisfied
          and negative if violated.
  """
  explicitConstrain = constraint(self.x,self.y)
  return explicitConstrain
```

CHAPTER

TEN

MODEL CALIBRATION

Model calibrations are performed via Bayesian inference to integrate experiments so as to improve model performance. For this analysis, set <AnalysisType>model_calibration</AnalysisType>. When a dynamic model is provided, the users need to set the <pivot> and <dynamic> nodes in <GlobalSettings>, as illustrated in the below example. In addition, the initial values for the input variables can be provided via <InitialInputs>.

```xml
<?xml version="1.0" ?>
<Simulation verbosity="debug">

  <RunInfo>
    <WorkingDir>calibration_dynamic</WorkingDir>
    <batchSize>1</batchSize>
  </RunInfo>

  <GlobalSettings>
    <AnalysisType>model_calibration</AnalysisType>
    <pivot>time</pivot>
    <dynamic>True</dynamic>
    <limit>100</limit>
    <Inputs>alpha, beta, gamma</Inputs>
    <InitialInputs>0.1, 4.0, -1.0</InitialInputs>
    <Outputs>eta</Outputs>
  </GlobalSettings>

  <LikelihoodModel>
    <simTargets>eta</simTargets>
    <expTargets shape="1,50" computeCov='False' correlation='False'>
      -1.16074224 -1.10303445 -1.02830511 -0.89782965 -0.73765453 -0.7989537
      -0.86163706 -1.02209944 -1.12444044 -1.23657398 -1.16081758 -1.01219869
      -0.890747   -0.80444122 -0.70893668 -0.61012531 -0.65670863 -0.6768583
      -0.74732441 -0.81448647 -0.73232671 -0.54989334 -0.39796749 -0.07894291
        0.13067378  0.28999998  0.27418965  0.313329    0.32306704  0.2885684
        0.32736775  0.52458854  0.69446572  0.82419521  1.04393683  1.00435818
        1.0810376   0.97245373  0.82406522  0.76067559  0.70145544  0.79479965
        0.88035895  0.97750307  1.11524353  1.17159017  1.18299222  1.07255006
        1.02835909  0.90784132
    </expTargets>
    <expCov diag="True">
        0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
        0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
        0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
```

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```
        0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02, 0.02,
        0.02, 0.02, 0.02, 0.02, 0.02, 0.02
    </expCov>
    <!-- <biasTargets></biasTargets>
    <biasCov diag="False"></biasCov> -->
    <!-- <romCov diag="True"></romCov> -->
  </LikelihoodModel>

  <Distributions>
    <Uniform name='alpha'>
      <lowerBound>0.1</lowerBound>
      <upperBound>0.3</upperBound>
    </Uniform>
    <Uniform name='beta'>
      <lowerBound>4</lowerBound>
      <upperBound>6</upperBound>
    </Uniform>
    <Uniform name='gamma'>
      <lowerBound>-1</lowerBound>
      <upperBound>1</upperBound>
    </Uniform>
  </Distributions>

  <Models>
    <ExternalModel ModuleToLoad="../models/model_cal" name="model" subType="">
      <inputs>inputGroup</inputs>
      <outputs>outputGroup</outputs>
    </ExternalModel>
  </Models>

</Simulation>
```

CHAPTER ELEVEN

SUPPORT

The easiest way to get help with the project is to open an issue on Github.

The mailing list at ... is also available for support.

11.1 Developer

- Congjian, Wang: congjian.wang@inl.gov

11.2 Copyright

CHAPTER

TWELVE

CONTRIBUTORS

CHAPTER THIRTEEN

API REFERENCE

This page contains auto-generated API reference documentation[1].

13.1 src

13.1.1 Subpackages

13.1.1.1 src.poem

Subpackages

src.poem.templates

Attributes

configFileName	
path	
templateConfig	

Package Contents

`src.poem.templates.`**`configFileName = 'config.toml'`**

`src.poem.templates.`**`path`**

`src.poem.templates.`**`templateConfig`**

[1] created with sphinx-autoapi

Submodules

src.poem.PoemTemplate

Created on April 1, 2024 @author: wangc

This module inherits from the base Template class for Input Templates, which use an established input template as an accelerated way to write new RAVEN workflows.

Attributes

RAVEN_FRAMEWORK_LOC
logger

Classes

PoemTemplate	POEM: Template Class

Module Contents

`src.poem.PoemTemplate.`**`RAVEN_FRAMEWORK_LOC`**

`src.poem.PoemTemplate.`**`logger`**

class `src.poem.PoemTemplate.`**`PoemTemplate`**

Bases: `ravenframework.InputTemplates.TemplateBaseClass.Template`

POEM: Template Class

`_validEntities = ['RunInfo', 'Files', 'Models', 'Distributions', 'Samplers', 'Optimizers', 'DataObjects',...`

`loadTemplate`(*filename*)

Loads template file statefully. @ In, filename, str, name of file to load (xml) @ Out, None.

`createWorkflow`(*inputs*, *miscDict*)

Creates a new RAVEN workflow based on the information in dicitonary "inputs." @ In, inputs, dict, dictionary that contains XML node info that needs to be appended (i.e., {RavenXMLNodeTag: ListOfNodes}). @ In, miscDict, dict, dictionary that contains XML node text info that needs to be updated (i.e., {RavenXMLNodeTag: value}) @ Out, xml.etree.ElementTree.Element, modified copy of template ready to run.

`writeWorkflow`(*template*, *destination*, *run=False*)

Writes a template to file. @ In, template, xml.etree.ElementTree.Element, file to write @ In, destination, str, path and filename to write to @ In, run, bool, optional, if True then run the workflow after writing? good idea? @ Out, errors, int, 0 if successfully wrote [and run] and non-zero if there was a problem.

runWorkflow(*destination*)

Runs the workflow at the destination @ In, destination, str, path and filename of RAVEN input file @ Out, res, int, system results of running the code.

src.poem.PoemTemplateInterface

Created on April 1, 2024 @author: wangc

This module is the POEM template interface, which uses the user-provided input XML file to construct the corresponding RAVEN workflows (i.e., the RAVEN input XML file).

Attributes

logger
fh
formatter
ravenFrameworkPath

Classes

PoemTemplateInterface	POEM Template Interface

Module Contents

src.poem.PoemTemplateInterface.**logger**

src.poem.PoemTemplateInterface.**fh**

src.poem.PoemTemplateInterface.**formatter**

src.poem.PoemTemplateInterface.**ravenFrameworkPath**

class src.poem.PoemTemplateInterface.**PoemTemplateInterface**(*filename*)

Bases: object

POEM Template Interface

uniformDistNode

samplerVarNode

externalModelNode

lhExternalModelNode

`lhModelNode`

`reductionNode`

`basisNode`

`validAnalysis = ['sensitivity', 'sparse_grid_construction', 'sparse_grid_rom', 'lhs', 'mc', 'train_rom',...`

`analysisRequired`

`analysisOptions`

`_inputFile`

`_filenameRoot`

`_inputVarList = []`

`_outputVarList = []`

`_externalModelList = []`

`_externalModelInputDict`

`_externalModelOutputDict`

`_distList = []`

`_samplerList = []`

`_ensembleModelList = []`

`_dsList = []`

`_printList = []`

`_variableGroupsList = []`

`_inputDict`

`_pivot = 'time'`

`_limit = 1000`

`_initSamples = 20`

`_templateFile = None`

`_analysisType = None`

`_ravenNodeDict`

`_statsPrefix = ['skewness', 'variationCoefficient', 'mean', 'kurtosis', 'median', 'max', 'min', 'var', 'sigma']`

`_statsVectorPrefix = ['nsen', 'sen', 'pearson', 'cov', 'vsen', 'spearman']`

`_polynomialOrder = '2'`

`_sparseGridData = None`

`_data = None`

`_expTargets = None`

`_expCov = None`

`_dynamic = False`

`_initInputs = None`

`_globalSettings`

`_miscDict`

`getTemplateFile()`

`getOutput()`

Obtains the processed outputs from this class: PoemTemplateInterface @ In, None @ Out, (outputDict, miscDict), tuple, first dictionary contains the whole element that needs to be appended in the templated input, while the second dictionary contains only the values that need to be replaced.

`readInput()`

Reads the POEM input files and constructs corresponding ET elements @ In, None @ Out, None.

`readGlobalSettings(`*xmlNode*`)`

Reads the RunInfo XML node from the input root @ In, xmlNode, xml.etree.ElementTree.Element, the input root xml @ Out, None.

`checkInput()`

Checks the consistency of user-provided inputs @ In, None @ Out, None.

`static buildPointSet(`*name*, *inputs*, *outputs*`)`

Builds a single PointSet XML node @ In, name, str, the name for the PointSet @ In, inputs, str, string that contains the list of input variables @ In, outputs, str, string that contains the list of output variables @ out, pointSet, xml.etree.ElementTree.Element, the constructed PointSet XML node.

`static buildHistorySet(`*name*, *inputs*, *outputs*, *pivot='time'*`)`

Builds a single HistorySet XML node @ In, name, str, the name for the PointSet @ In, inputs, str, string that contains the list of input variables @ In, outputs, str, string that contains the list of output variables @ out, historySet, xml.etree.ElementTree.Element, the constructed HistorySet XML node.

`static buildPrint(`*name*, *source*`)`

Builds a single OutStream Print XML node @ In, name, str, the name for the PointSet @ In, source, str, string that contains name of Data Object @ out, printObj, xml.etree.ElementTree.Element, the constructed print XML node.

`buildSamplerVariable(`*inputs*, *distNode*, *limit=20*, *grid=False*, *init=None*`)`

Builds the sampler variable block.

`static buildSparseGridSampler(`*name='SparseGrid'*`)`

`static buildMonteCarloSampler(`*name*, *limit*`)`

`static buildVariableGroup(`*name*, *varList*`)`

Builds the variable group node @ In, name, str, the name for the variable group @ In, varList, list, list of variables @ out, group, xml.etree.ElementTree.Element, the constructed variable group XML node.

buildStatsGroup(*name*, *inputs*, *outputs*)

Builds the basic statistic variable group node @ In, name, str, the name for the variable group @ In, inputs, list, list of input variables @ In, outputs, list, list of output variables @ out, group, xml.etree.ElementTree.Element, the constructed variable group XML node.

static **findRequiredNode**(*xmlNode*, *nodeTag*)

Finds the required XML node @ In, xmlNode, xml.etree.ElementTree.Element, xml element node @ In, nodeTag, str, node tag that is used to find the node @ Out, subnode, xml.etree.ElementTree.Element, xml element node.

src.poem.plotUtils

Attributes

markerMap
markers

Functions

addPoint(ax, x, y, accepted)	
plotFunction(fig, title, method, constraint, xscale, ...)	Plots a 2D function as a colormap. Returns parameters suitable to plotting in a pcolormesh call.
animate(n, ax, x, y, a)	
animatePlot(x, y, a, fig, title, method, constraint, ...)	
optPath(x, y, a, fig, title, method, constraint, ...)	

Module Contents

src.poem.plotUtils.**markerMap**

src.poem.plotUtils.**markers**

src.poem.plotUtils.**addPoint**(*ax*, *x*, *y*, *accepted*)

src.poem.plotUtils.**plotFunction**(*fig*, *title*, *method*, *constraint*, *xscale*, *yscale*, *cscale=None*, *log=False*, *samps=500*, *xp=None*, *yp=None*)

Plots a 2D function as a colormap. Returns parameters suitable to plotting in a pcolormesh call @ In, title, string, title name for figure @ In, method, function, method to call with x,y to get z result @ In, constraint, function, boolean method that determines acceptability @ In, xscale, tuple(float), low/hi value for x @ In, yscale, tuple(float), low/hi value for y @ In, cscale, tuple(float), optional, low and high values for the color map @ In, log, bool, optional, if False will not lognormalize the color map @ In, samps, int @ In, extData, pandas.Dataframe @ Out, X, np.array(np.array(float)), mesh grid of X values @ Out, Y, np.array(np.array(float)), mesh grid of Y values @ Out, Z, np.array(np.array(float)), mesh grid of Z (response) values.

`src.poem.plotUtils.`**`animate`**`(`*n*, *ax*, *x*, *y*, *a*`)`

`src.poem.plotUtils.`**`animatePlot`**`(`*x*, *y*, *a*, *fig*, *title*, *method*, *constraint*, *xscale*, *yscale*, *cscale=None*, *log=False*, *samps=500*, *xp=None*, *yp=None*`)`

`src.poem.plotUtils.`**`optPath`**`(`*x*, *y*, *a*, *fig*, *title*, *method*, *constraint*, *xscale*, *yscale*, *cscale=None*, *log=False*, *samps=500*, *xp=None*, *yp=None*`)`

src.poem.poemUtils

Created on April 1, 2024 @author: wangc

Attributes

logger

Functions

convertNodeTextToList(nodeText[, sep])	Converts a space- or comma-separated string to list of string
convertNodeTextToFloatList(nodeText[, sep])	Converts a space- or comma-separated string to list of float
convertStringToFloat(xmlNode)	Converts XML node text to float
convertStringToInt(xmlNode)	Converts XML node text to integer
toString(s)	Method aimed at converting a string in type str
convertStringToBool(nodeText)	Converts string to bool

Module Contents

`src.poem.poemUtils.`**`logger`**

`src.poem.poemUtils.`**`convertNodeTextToList`**`(`*nodeText*, *sep=None*`)`

Converts a space- or comma-separated string to list of string @ In, nodeText, str, string from XML node text @ Out, listData, list, list of strings.

`src.poem.poemUtils.`**`convertNodeTextToFloatList`**`(`*nodeText*, *sep=None*`)`

Converts a space- or comma-separated string to list of float @ In, nodeText, str, string from xml node text @ Out, listData, list, list of floats.

`src.poem.poemUtils.`**`convertStringToFloat`**`(`*xmlNode*`)`

Converts XML node text to float @ In, xmlNode, xml.etree.ElementTree.Element, xml element @ Out, val, float, value of xml element text.

`src.poem.poemUtils.`**`convertStringToInt`**`(`*xmlNode*`)`

Converts XML node text to integer @ In, xmlNode, xml.etree.ElementTree.Element, xml element @ Out, val, integer, value of xml element text.

`src.poem.poemUtils.`**`toString`**`(`*s*`)`

Method aimed at converting a string in type str @ In, s, string, string to be converted @ Out, s, string, the casted value.

`src.poem.poemUtils.`**`convertStringToBool`**`(`*nodeText*`)`

Converts string to bool @ In, nodeText, str, string from XML node text @ Out, val, bool, True or False.

13.1.2 Submodules

13.1.2.1 src._utils

Utilities for use within POEM

Attributes

argvs

Functions

get_raven_loc()	Return RAVEN location: read from POEM/.ravenconfig.xml.
get_plugin_loc(plugin[, raven_path])	Get plugin location in installed RAVEN.

Module Contents

`src._utils.`**`get_raven_loc`**`()`

Return RAVEN location: read from POEM/.ravenconfig.xml @ In, None @ Out, loc, string, absolute location of RAVEN.

`src._utils.`**`get_plugin_loc`**`(`*plugin*, *raven_path=None*`)`

Get plugin location in installed RAVEN @ In, plugin, string, the plugin name @ In, raven_path, string, optional, if given then start with this path @ Out, plugin_loc, string, location of plugin.

`src._utils.`**`argvs`**

13.1.2.2 src.main

Created on April 1, 2024 @author: wangc

This module is the POEM template interface, which uses the user-provided input XML file to construct the corresponding RAVEN workflows (i.e., RAVEN input XML file).

Attributes

RAVEN_FRAMEWORK_LOC
logger
fh
formatter

Functions

runWorkflow(destination)	Runs the workflow at the destination.
main()	

Module Contents

src.main.**RAVEN_FRAMEWORK_LOC**

src.main.**logger**

src.main.**fh**

src.main.**formatter**

src.main.**runWorkflow**(*destination*)

Runs the workflow at the destination @ In, destination, str, path and filename of RAVEN input file @ Out, res, int, system results of running the code.

src.main.**main**()

13.2 PoemTester

Tests by running an executable.

13.2.1 Attributes

POEM_LOC
RAVEN_FRAMEWORK_LOC
TESTER_LOC

13.2.2 Classes

PoemRun	A POEM standalone test interface.

13.2.3 Module Contents

`PoemTester.POEM_LOC`

`PoemTester.RAVEN_FRAMEWORK_LOC`

`PoemTester.TESTER_LOC`

class `PoemTester.`**`PoemRun`**(*name*, *param*)

Bases: `RavenFramework.RavenFramework`

A POEM standalone test interface.

static get_valid_params()

Returns a list of valid parameters and their descriptions for this type of test @ In, None @ Out, params, _ValidParameters, the parameters for this class.

poem_driver

get_command()

Returns the command this test will run @ In, None @ Out, cmd, string, command to run.

CHAPTER

FOURTEEN

CONTRIBUTIONS

All contributions are welcome. You can help this project grow in multiple ways, from creating an issue, to reporting an improvement or a bug, to submitting a pull request to the development branch. The people who have been involved in the development of the package are listed on the *contributors page*.

PYTHON MODULE INDEX