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Optimization with RAVEN

RAVEN Workshop



Outline

- Brief introduction on Optimization algorithms in RAVEN:
 - SPSA
- Optimization examples
 - Optimization of a deterministic model
 - Optimization of a stochastic model

Optimization algorithms in RAVEN

- RAVEN currently provides 2 optimizations schemes:
 - Gradient Descent (Finite Difference)
 - Simultaneous Perturbation Stochastic Approximation (SPSA)
- Embedded de-noising capabilities
- Multi-Objective Optimization can be performed with a blend of Optimization and Ensemble Modeling



Stochastic optimization

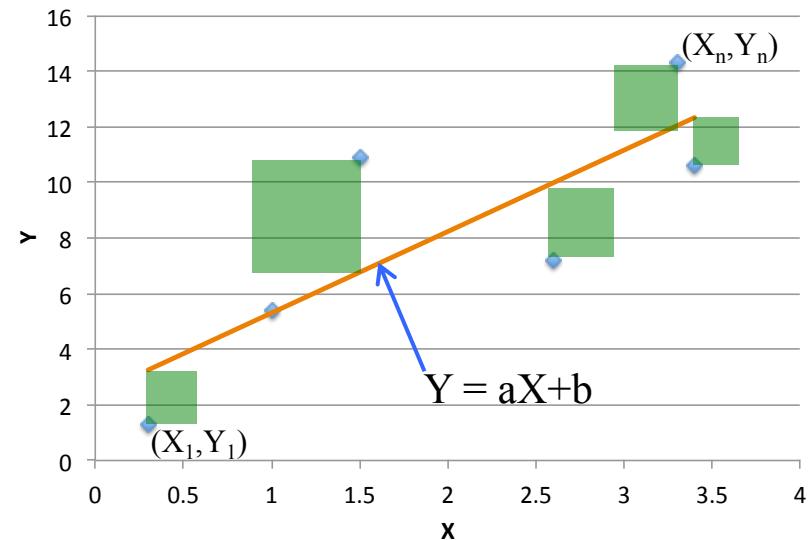
Try to fit straight line to a set of points (X_i, Y_i)

- Define target function to minimize
 - For example least squares

$$T(a,b) = \sum_{i=1}^n (aX_i + b - Y_i)^2$$

- Minimize with algorithm
 - Find “a” and “b” such that $T(a,b)$ is minimal
 - For example “gradient descent” algorithm – $\nabla T(a,b)$ move in direction
- What if lots of decision variables ($T=T(a,b,c, \dots)$) or system is stochastic ($X_i \rightarrow Y_i$ not unique)?
 - $\nabla T(a,b)$ may be difficult or impossible to evaluate

⇒ Stochastic optimization algorithms



Simultaneous Perturbation Stochastic Approximation (SPSA) Algorithm for Efficient Stochastic Optimization

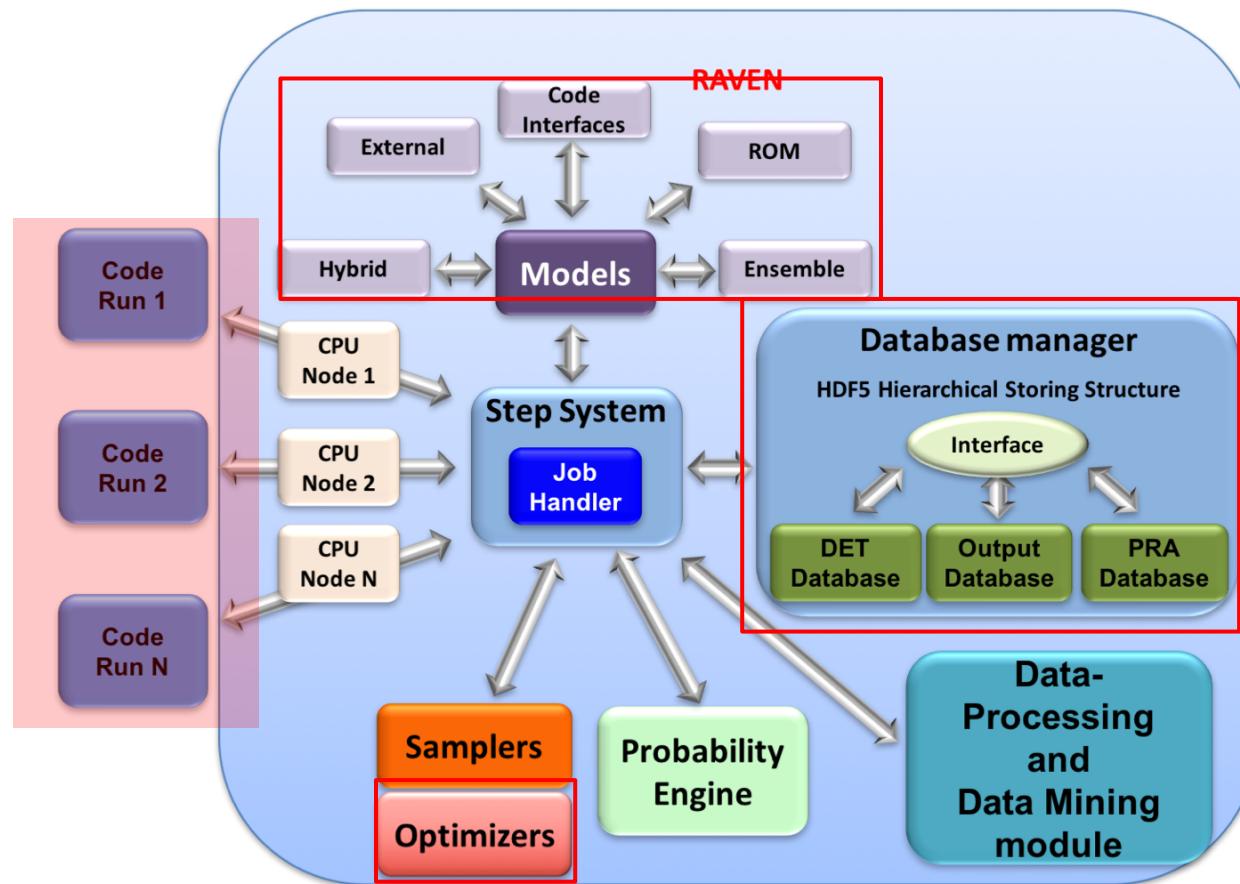
- No gradient formula or gradient measurements needed
- Approximate the gradient based on two function evaluations
 - Simultaneously approximate gradient for all variables
 - Regardless of the number of decision variables
- Converge to optimal in stochastic sense
 - Inaccurate estimation of gradient may temporarily lead to worse solution
- There has been a growing interest in stochastic optimization algorithms that do not depend on direct gradient information or measurements
 - Applicable in areas such as statistical parameter estimation, (nonlinear) feedback control, simulation-based optimization, signal and image processing, and experimental design

Advanced SPSA

- **Stochastic De-noising**
 - Find expected values of points and gradients
 - ⇒ Multiple evaluations of each sample taken, which will be used to calculate expected values and reduces the stochastic noise
- **Multi-trajectory**
 - avoid local minima
 - ⇒ Multiple initial starting points to be identified by the user. If one trajectory begins following another trajectory, the first is eliminated and only the second continues
- **Adaptive Stepping**
 - Slow convergence across a domain
 - ⇒ Adaptive step sizing determination algorithm in RAVEN's SPSA algorithm. Gradient for direction information only. Step size based on previous performance

Optimization Modeling Within RAVEN

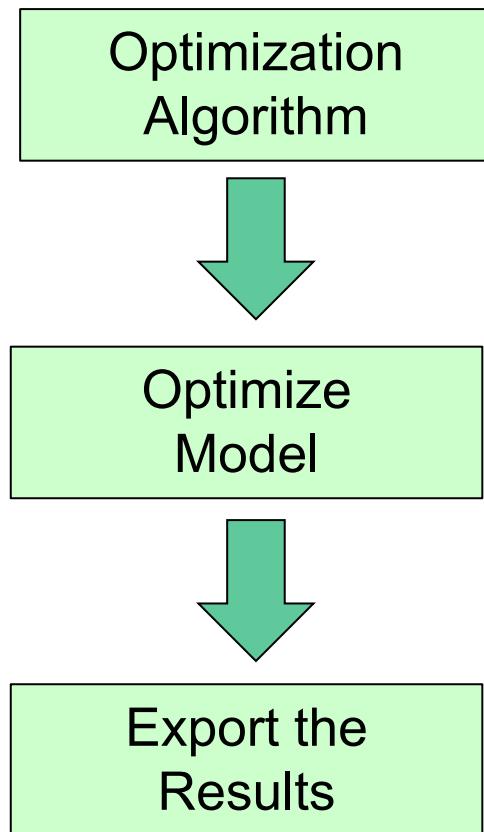
- All modeling steps that involve optimization are available in RAVEN
 - Set up the optimization problem
 - Perform optimization of the objective function



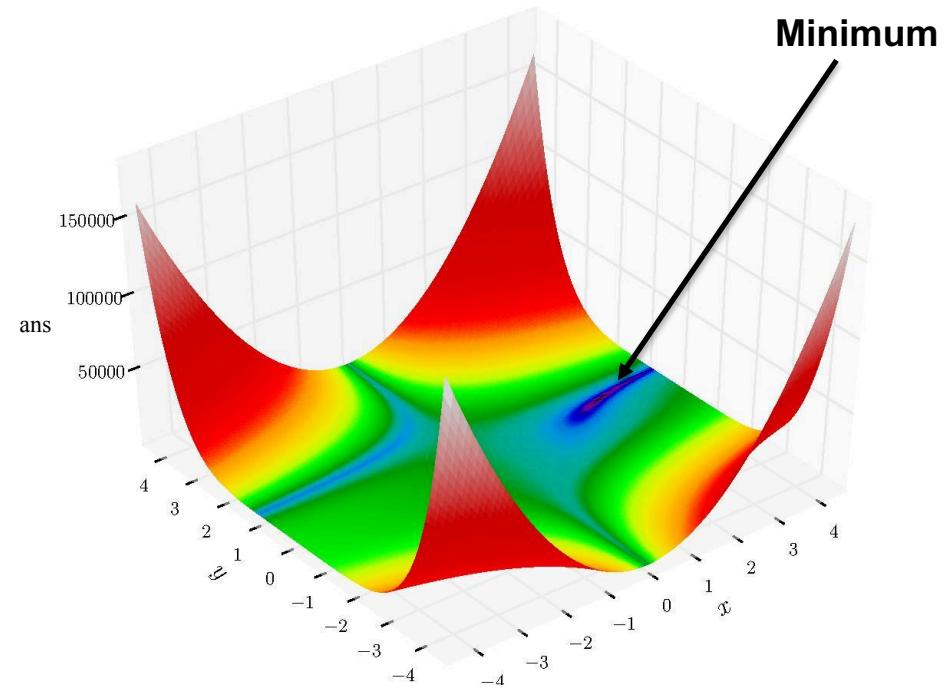
RAVEN Examples

Example 1 – No stochasticity

Workflow



External model employed:
beale.py



Optimal Minimum: $f(3.0, 0.5) = 0.0$

finite_difference.xml

Construct the Model to optimize

Models	Optimizers	Databases	DataObjects	Steps
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```
<Models>
  <ExternalModel ModuleToLoad="beale" name="beale" subType="">
    <variables>x,y,ans</Features>
  </ExternalModel>
</Models>
```

Beale model

beale.py model:

```
def evaluate(x,y):
    return (1.5 -x +x*y)**2 + (2.25 -x +x*y*y)**2 + (2.625 -x +x*y*y*y)**2
def run(self,inputs):
    self.ans = evaluate(self.x,self.y)
```

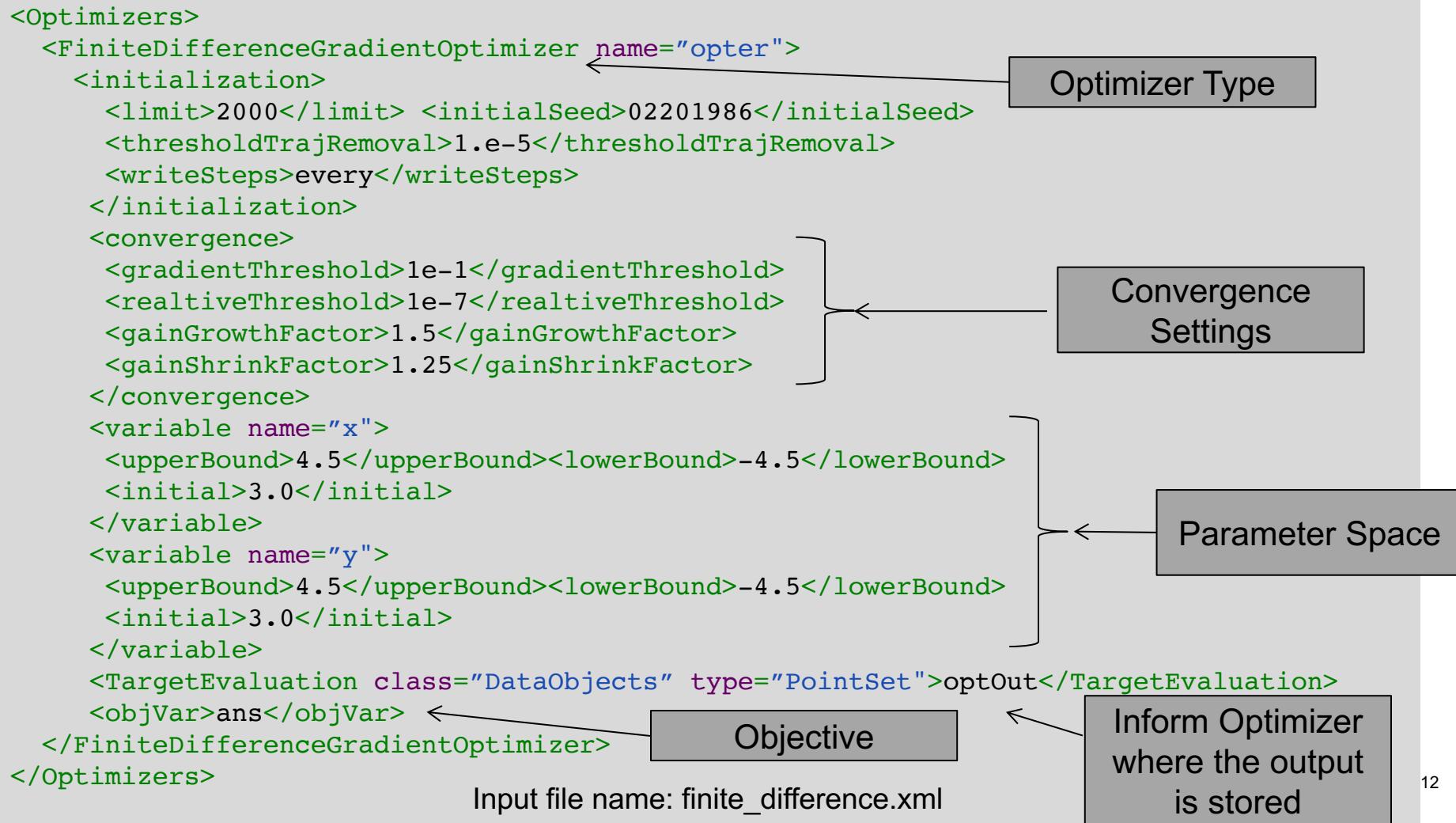
Select the optimization strategy

Models	Optimizers	Databases	DataObjects	Steps
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```

<Optimizers>
  <FiniteDifferenceGradientOptimizer name="opter">
    <initialization>
      <limit>2000</limit> <initialSeed>02201986</initialSeed>
      <thresholdTrajRemoval>1.e-5</thresholdTrajRemoval>
      <writeSteps>every</writeSteps>
    </initialization>
    <convergence>
      <gradientThreshold>1e-1</gradientThreshold>
      <relativeThreshold>1e-7</relativeThreshold>
      <gainGrowthFactor>1.5</gainGrowthFactor>
      <gainShrinkFactor>1.25</gainShrinkFactor>
    </convergence>
    <variable name="x">
      <upperBound>4.5</upperBound><lowerBound>-4.5</lowerBound>
      <initial>3.0</initial>
    </variable>
    <variable name="y">
      <upperBound>4.5</upperBound><lowerBound>-4.5</lowerBound>
      <initial>3.0</initial>
    </variable>
    <TargetEvaluation class="DataObjects" type="PointSet">optOut</TargetEvaluation>
    <objVar>ans</objVar>
  </FiniteDifferenceGradientOptimizer>
</Optimizers>

```

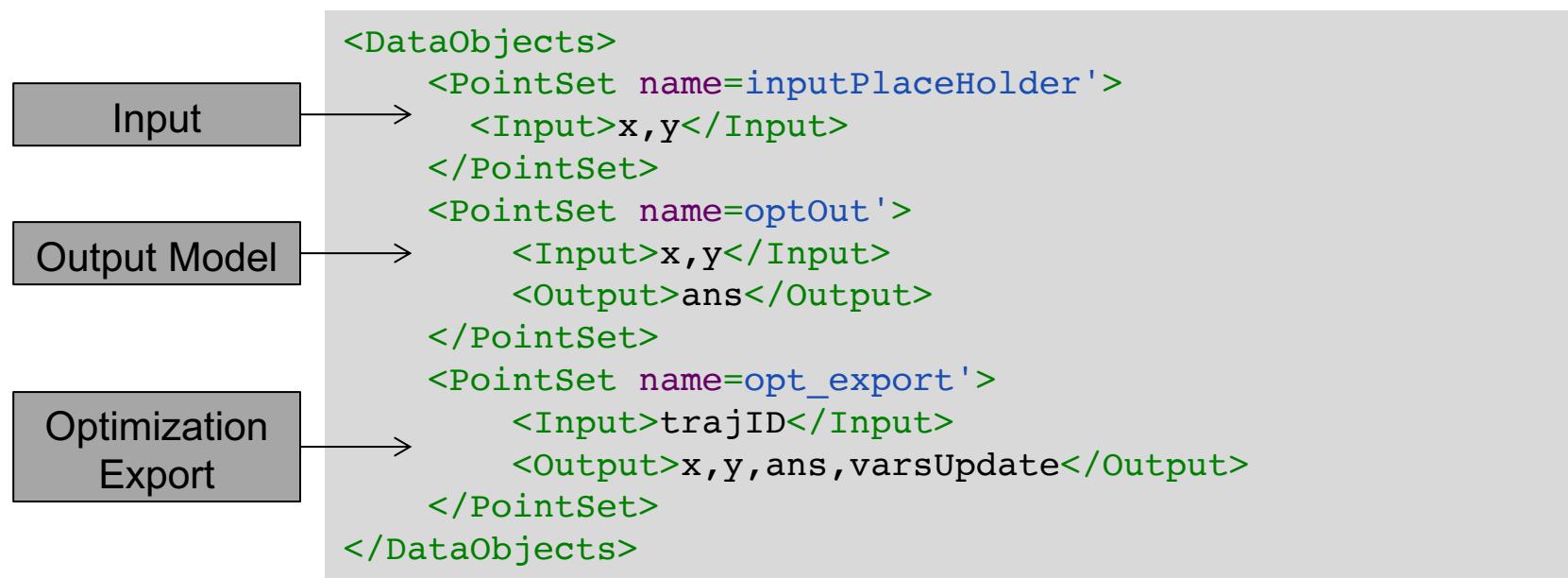


The diagram illustrates the structure of the XML configuration file. It highlights several sections with arrows pointing to callout boxes:

- Optimizer Type:** Points to the `<Optimizer name="opter">` element.
- Convergence Settings:** Points to the `<convergence>` section.
- Parameter Space:** Points to the `<variable>` sections for variables `x` and `y`.
- Objective:** Points to the `<TargetEvaluation>` section.
- Inform Optimizer where the output is stored:** Points to the `<objVar>` element.

Input file name: finite_difference.xml

Set up the data containers



Optimize a Model and Create a Database

Models	Optimizers	Databases	DataObjects	Steps
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```

<Steps>
  <MultiRun name="optimize">
    <Input          class="DataObjects" type="PointSet"      >inputPlaceHolder</Input>
    <Model         class="Models"      type="ExternalModel">beale</Model>
  <Optimizer     class="Optimizers"   type="FiniteDifferenceGradientOptimizer">opter</Optimizer>
    <SolutionExport class="DataObjects" type="PointSet">opt_export</SolutionExport>
    <Output        class="DataObjects" type="PointSet">optOut</Output>
  </MultiRun>
  <IOStep name="print">
    <Input          class="DataObjects" type="PointSet"      >opt_export</Input>
    <Output         class="OutStreams"  type="Print"       >opt_export_fd</Output>
    <Output         class="OutStreams"  type="Plot"        >
      optimization_history_input_space_fd
    </Output>
    <Output         class="OutStreams"  type="Plot"        >
      optimization_history_iterations_fd
    </Output>
  </IOStep>
</Steps>

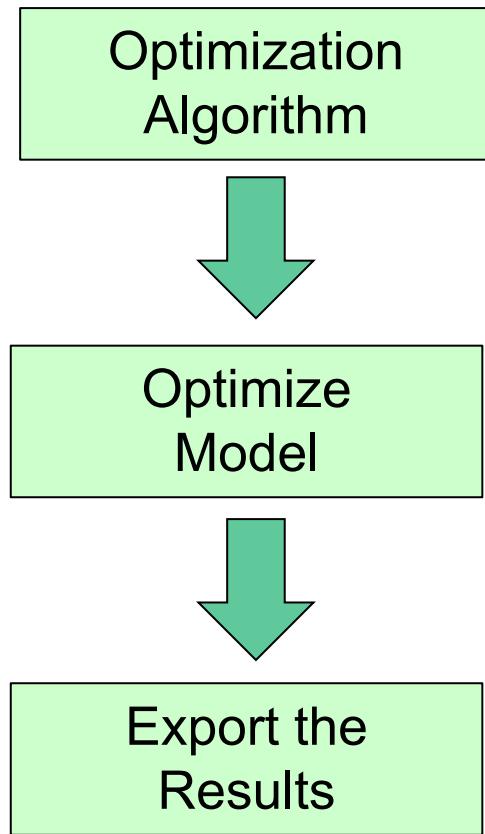
```

Ready to Run?

RUN?

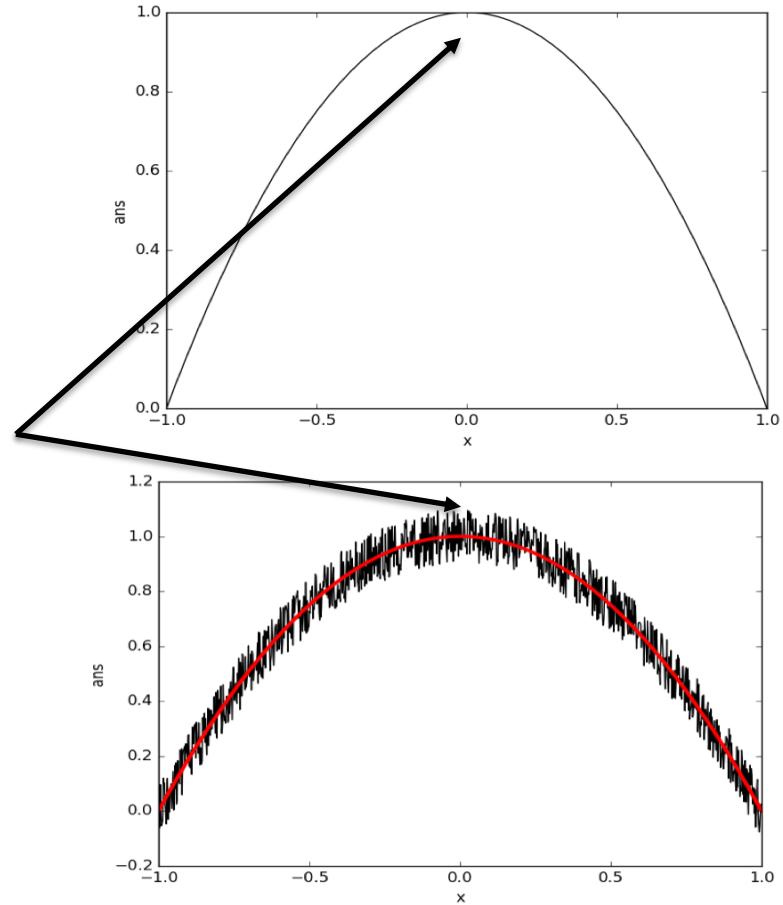
Example 2 – Intrinsic stochasticity

Workflow



spsa_stochastic.xml

**External model employed:
stoch_parabola.py**



Optimal Maximum: $f(0.0) = 1.0$

Construct the Model to optimize

Models	Optimizers	Databases	DataObjects	Steps
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```
<Models>
  <ExternalModel ModuleToLoad="stoch_parabola" name="parabola" subType="">
    <variables>x,ans</Features>
  </ExternalModel>
</Models>
```

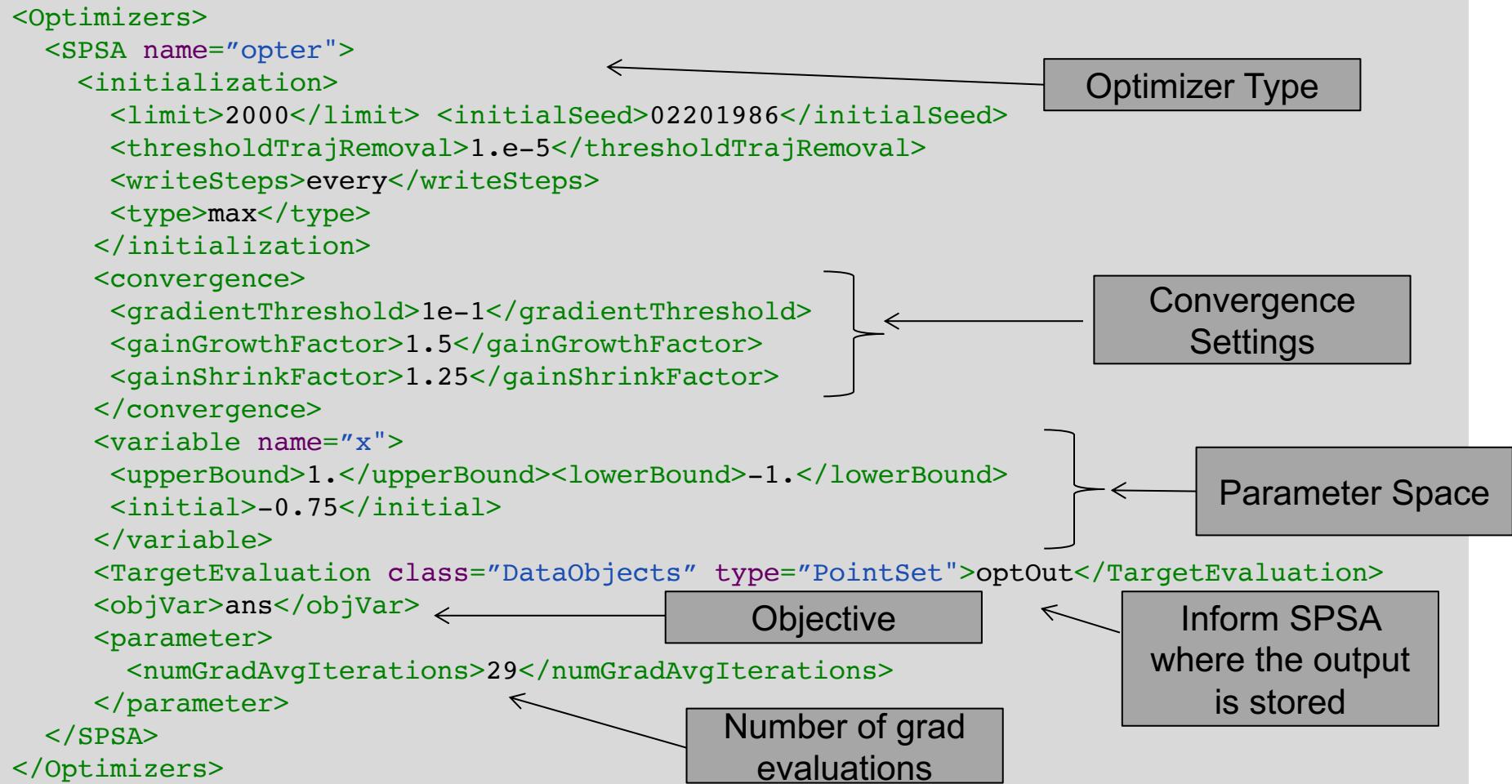
Parabola model

stoch_parabola.py model:

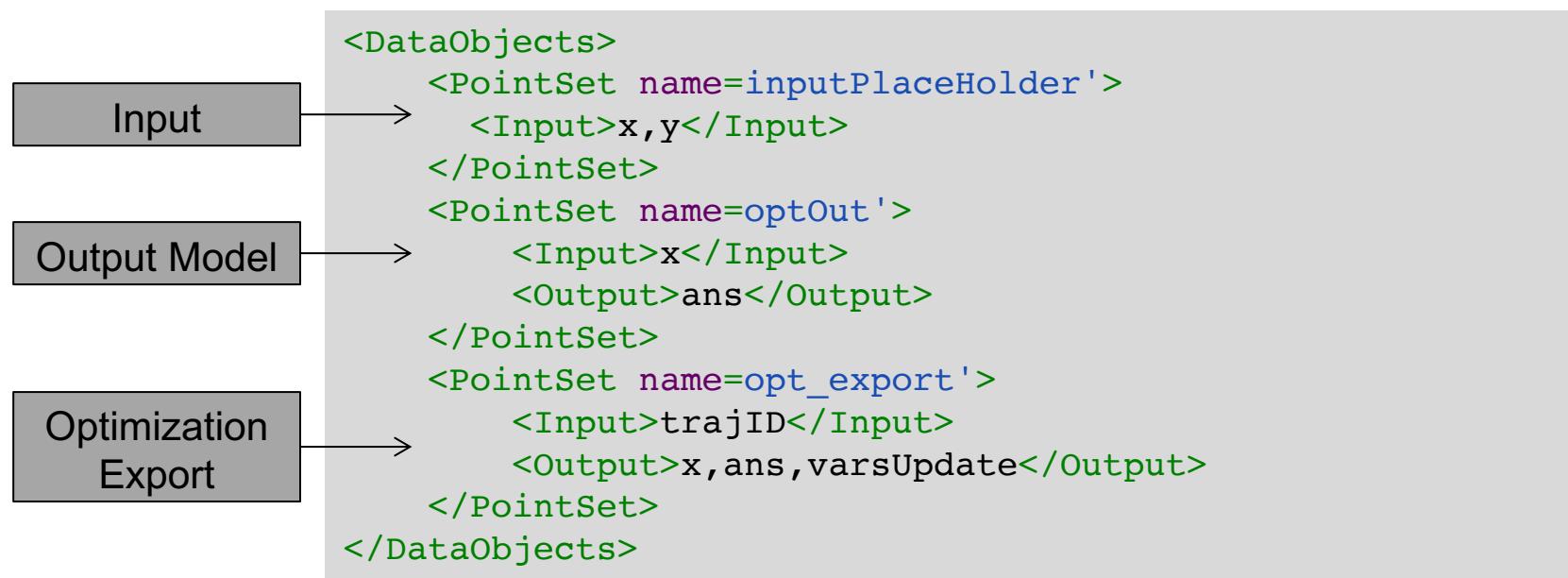
```
def evaluate(x,y):
  ran = random()/10.
  return ran -sum(l*l for l in values)+1.
def run(self,inputs):
  self.ans = evaluate(inputs.values())
```

Select the optimization strategy

Models	Optimizers	Databases	DataObjects	Steps
--------	------------	-----------	-------------	-------



Set up the data containers



Optimize a Model and Create a Database

Models	Optimizers	Databases	DataObjects	Steps
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```

<Steps>
  <MultiRun name="optimize">
    <Input class="DataObjects" type="PointSet"      >inputPlaceHolder</Input>
    <Model   class="Models"   type="ExternalModel">beale</Model>
    <Optimizer class="Optimizers" type="SPSA".     >opter</Optimizer>
    <SolutionExport class="DataObjects" type="PointSet". >opt_export</SolutionExport>
    <Output   class="DataObjects" type="PointSet".   >optOut</Output>
  </MultiRun>
  <IOStep name="print">
    <Input   class="DataObjects" type="PointSet"    >opt_export</Input>
    <Output  class="OutStreams"  type="Print"       >opt_export_spsa</Output>
    <Output  class="OutStreams"  type="Plot">
      optimization_history_input_space_spsa
    </Output>
    <Output   class="OutStreams"  type="Plot">
      optimization_history_iterations_spsa
    </Output>
  </IOStep>
</Steps>

```

Ready to Run?

RUN?