Applications of AI/ML from Nuclear Data to Reactor Design

Vladimir Sobes

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KNOXVILLE

Machine Learning
in Nuclear Data Evaluation

Artificial Intelligence
for Reactor Design

Machine Learning
in Nuclear Data Evaluation

Key take-aways:

1. Hyper-parameter tuning
2. Learning new functions which are difficult to derive

Artificial Intelligence
for Reactor Design

Key take-aways:

1. Autonomous optimization – *beyond human capabilities*
2. Surrogate models – *cautionary tales*

We need to solve the engineering problem

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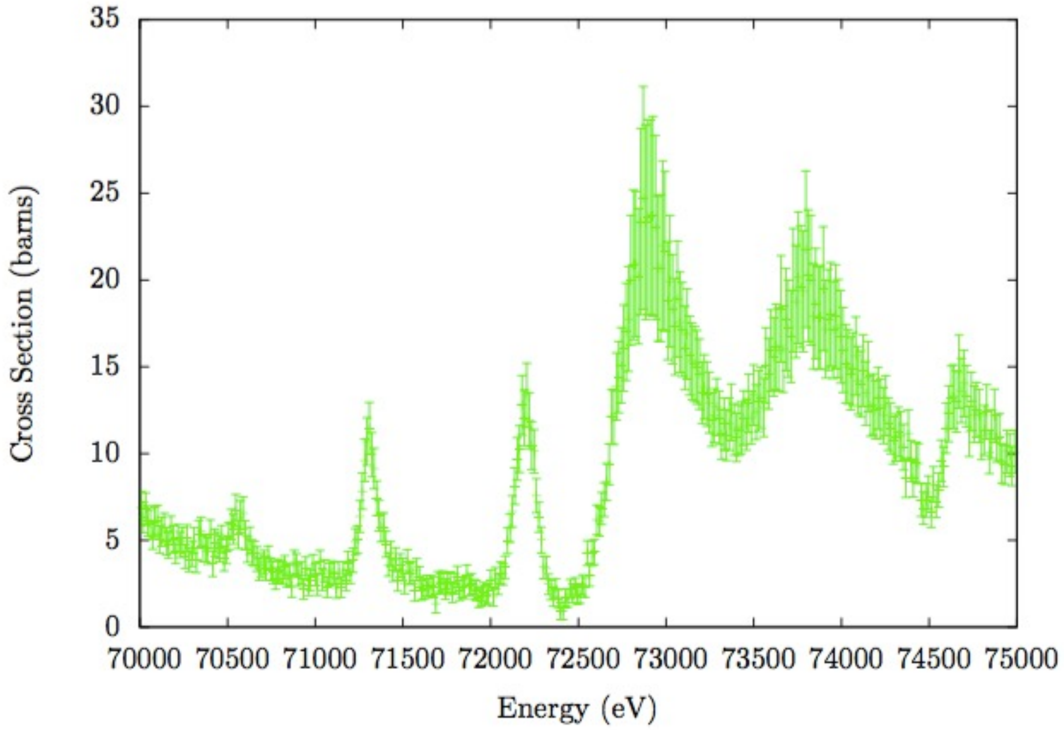
Motivation for automation



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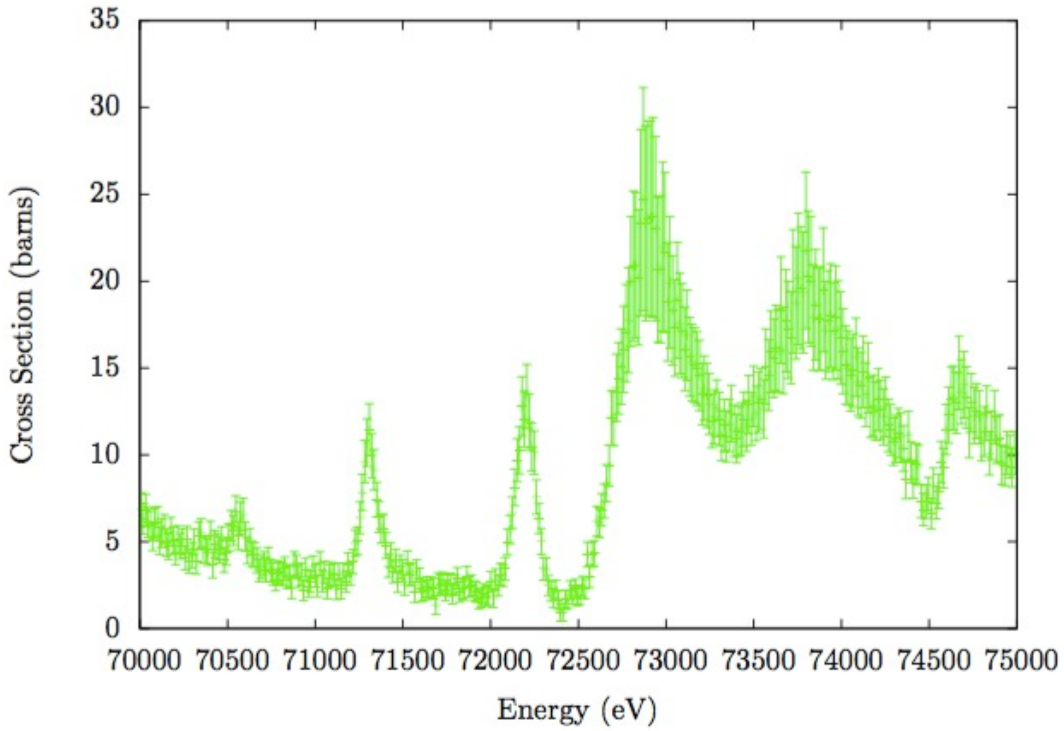

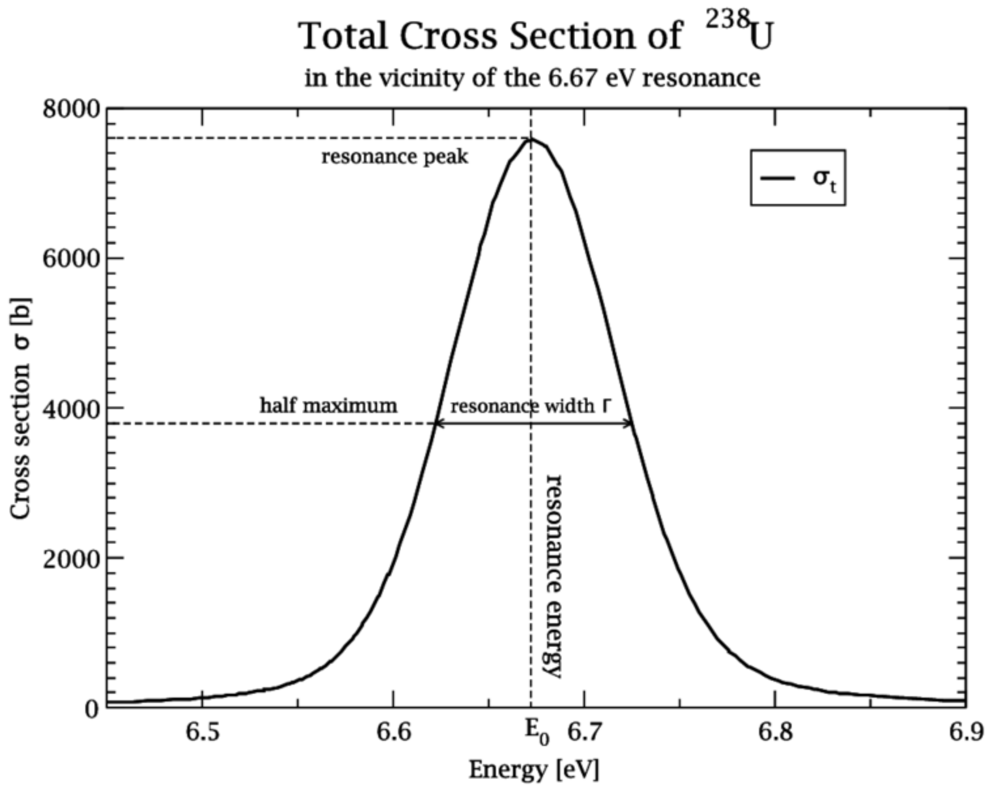

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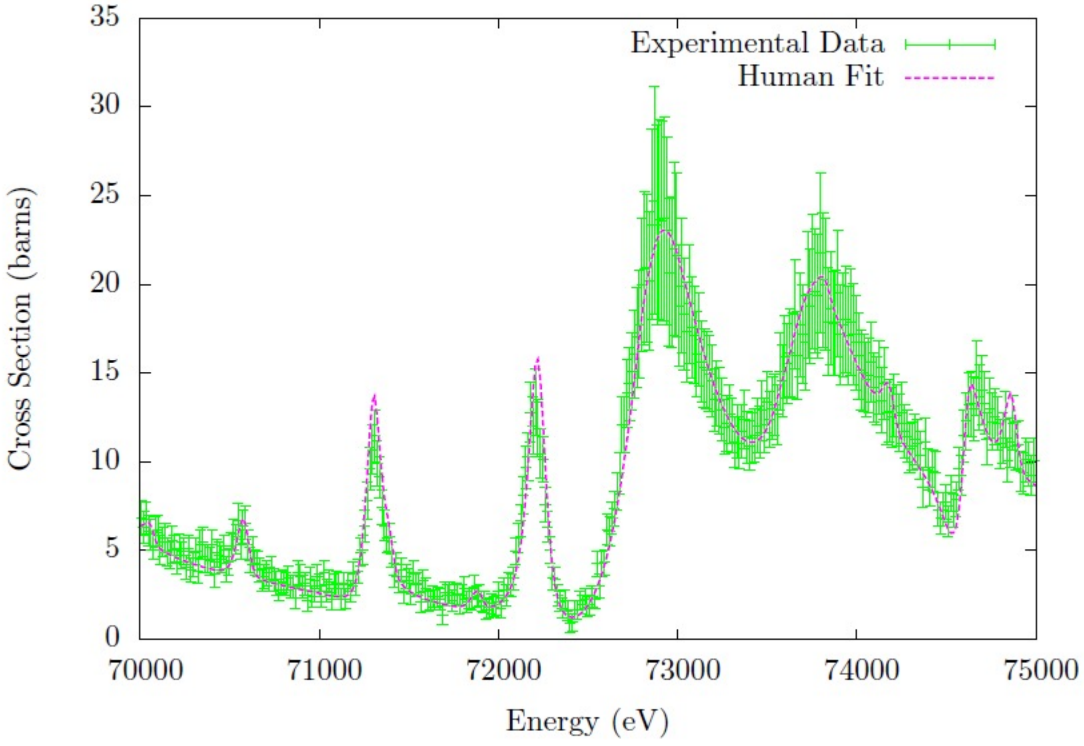
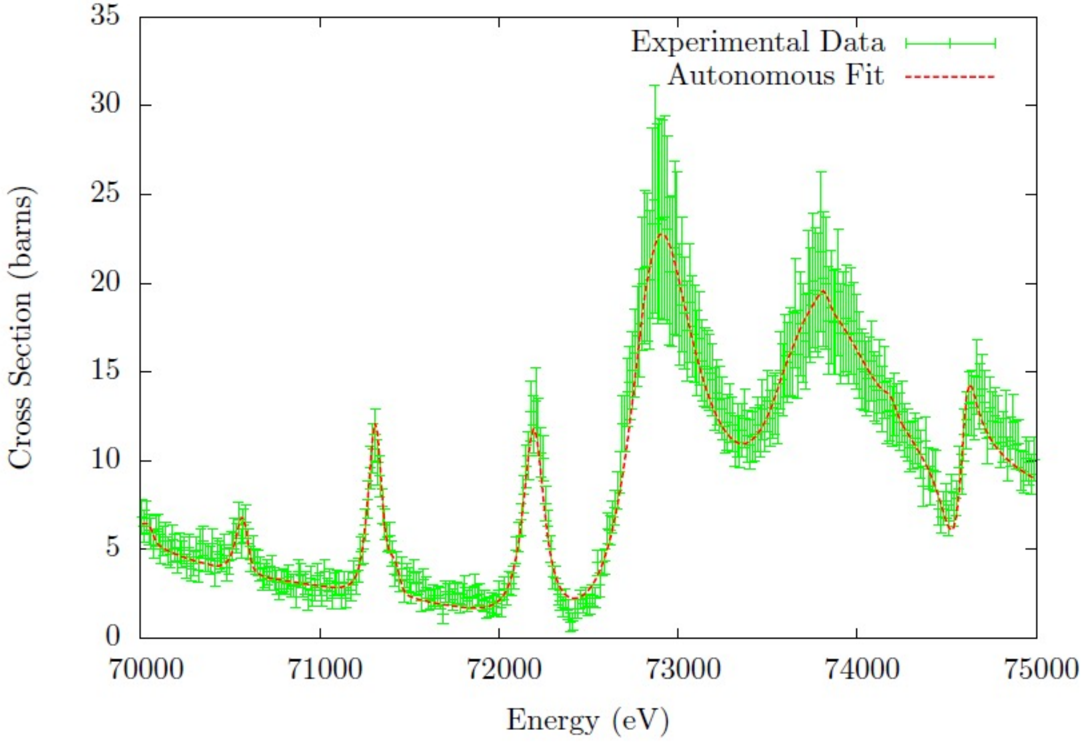
Motivation for automation





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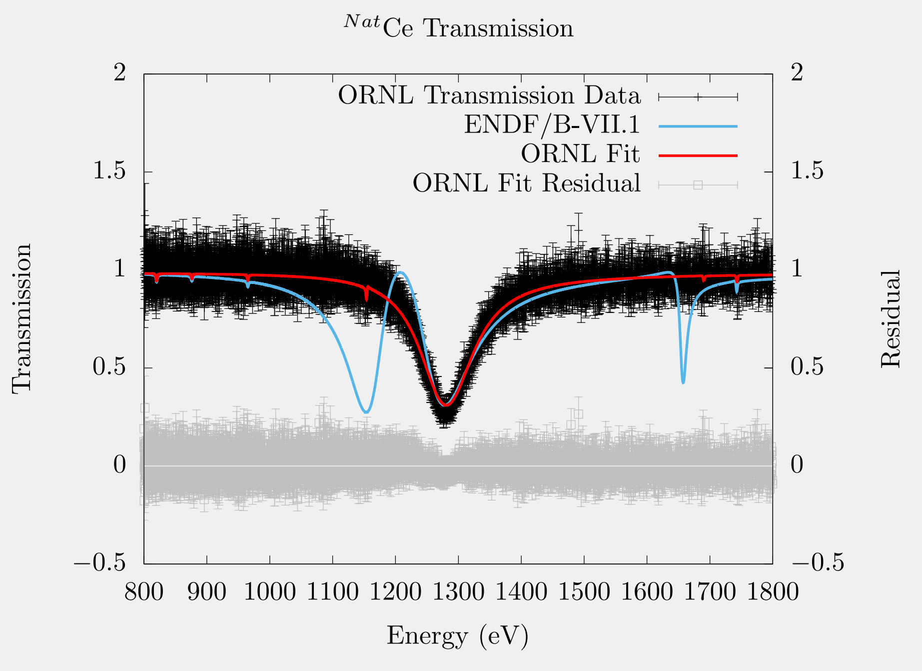

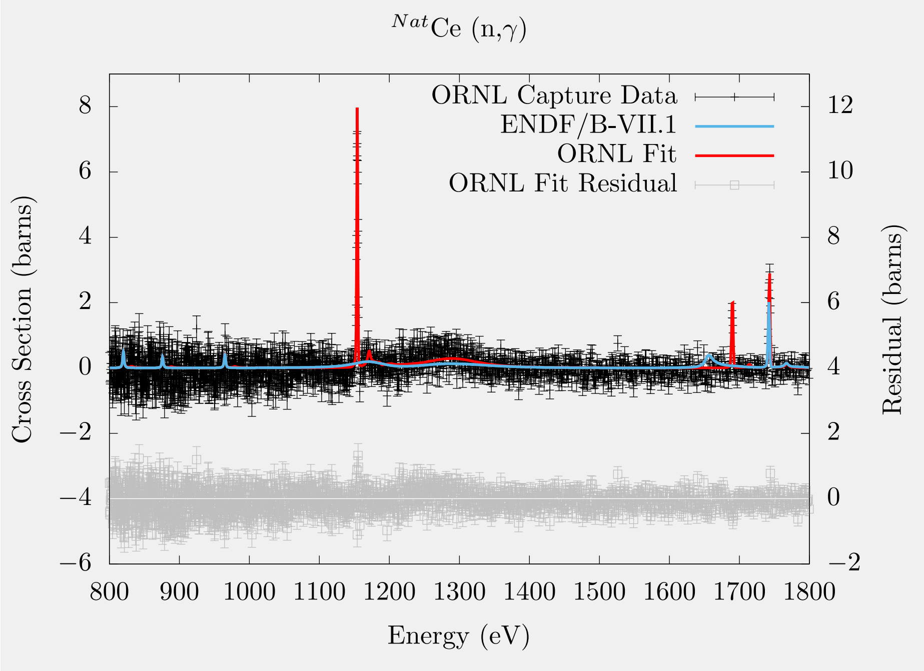

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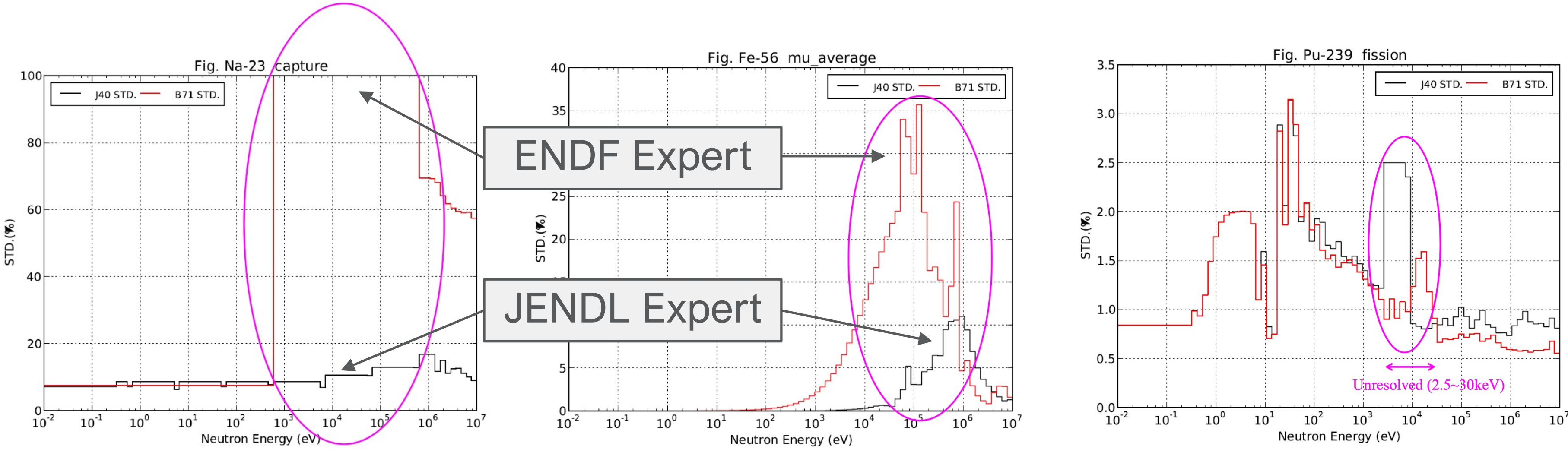

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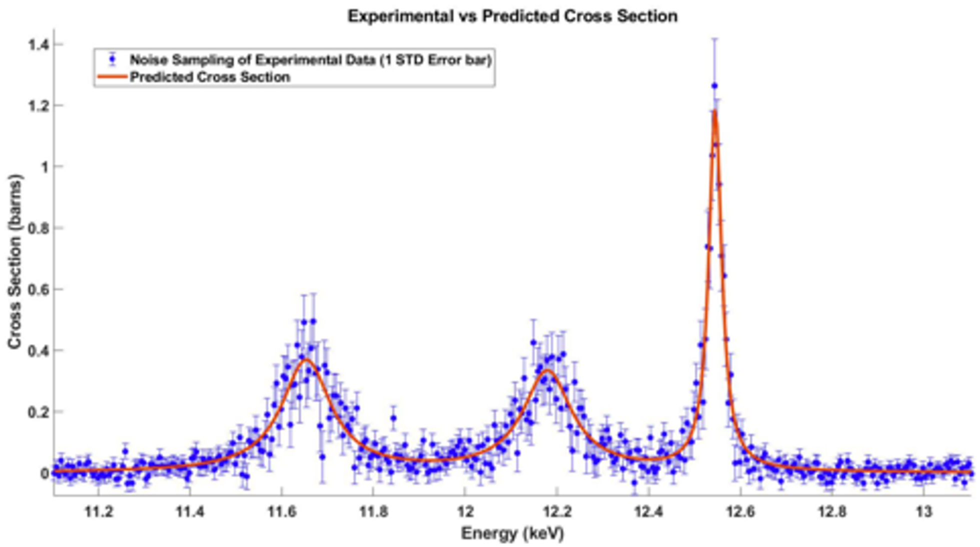

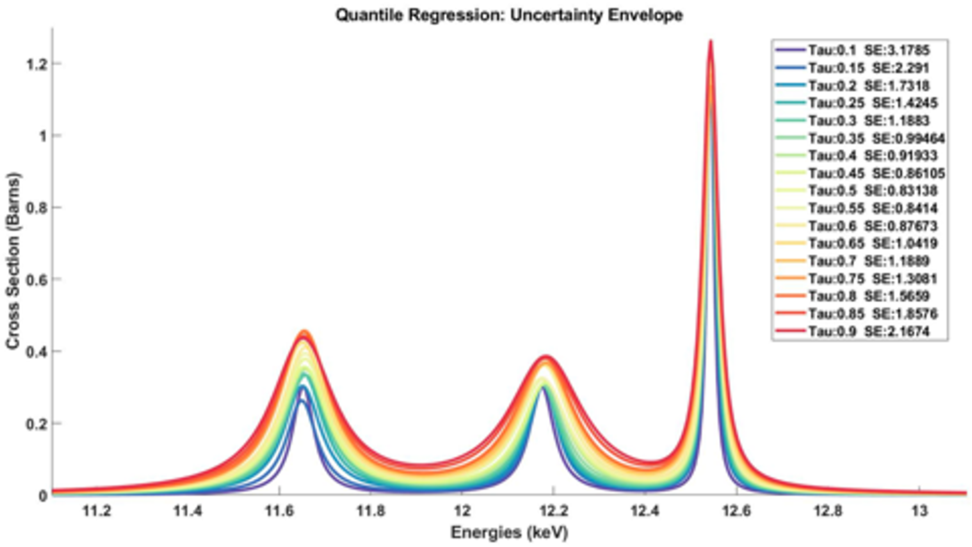

J. Armstrong, Decomposition Approach to Parametric Nonconvex Regression; Nuclear Resonance Analysis, UTK MS Thesis, (2021).

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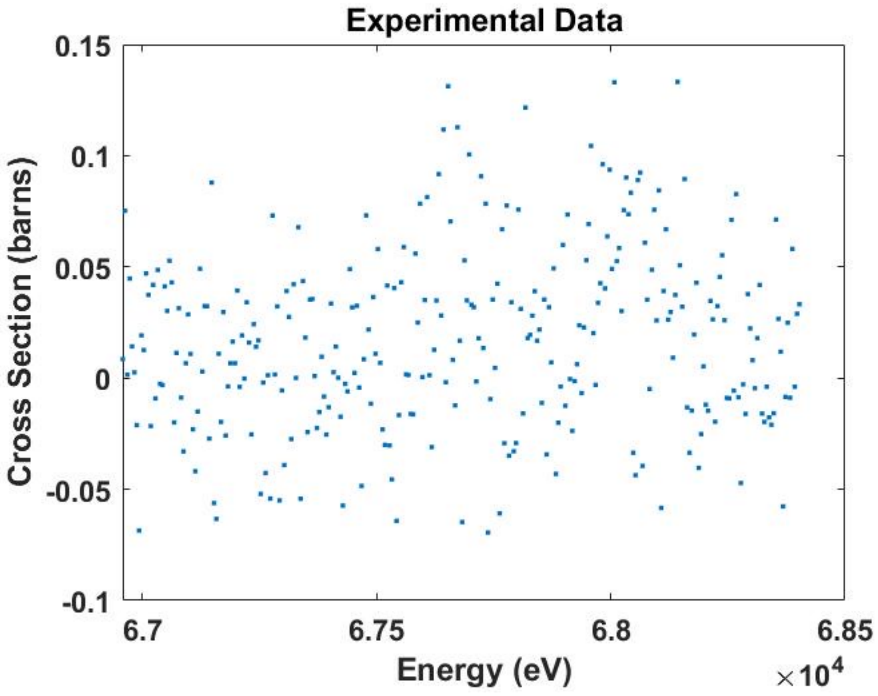

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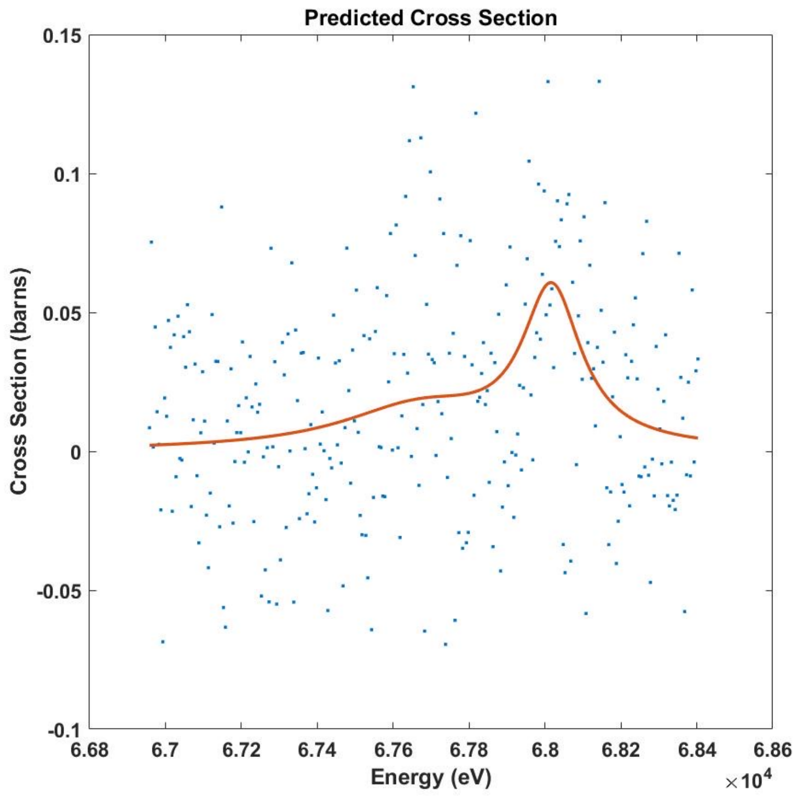

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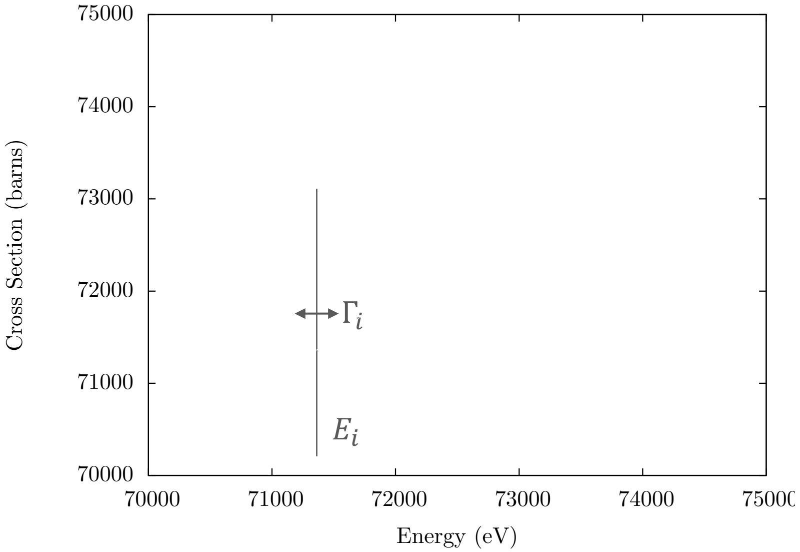
The Future of Human Involvement in Nuclear Data Evaluation

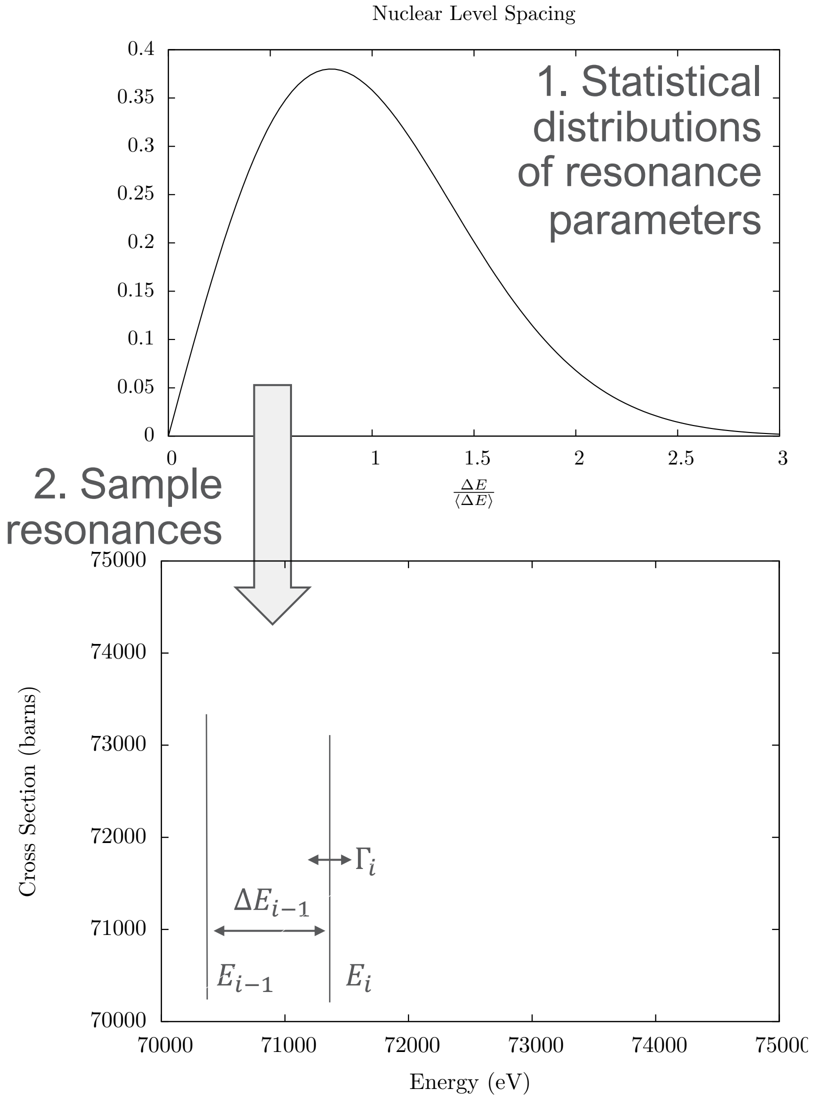
Machine Learning in Nuclear Data Evaluation

Key take-aways:

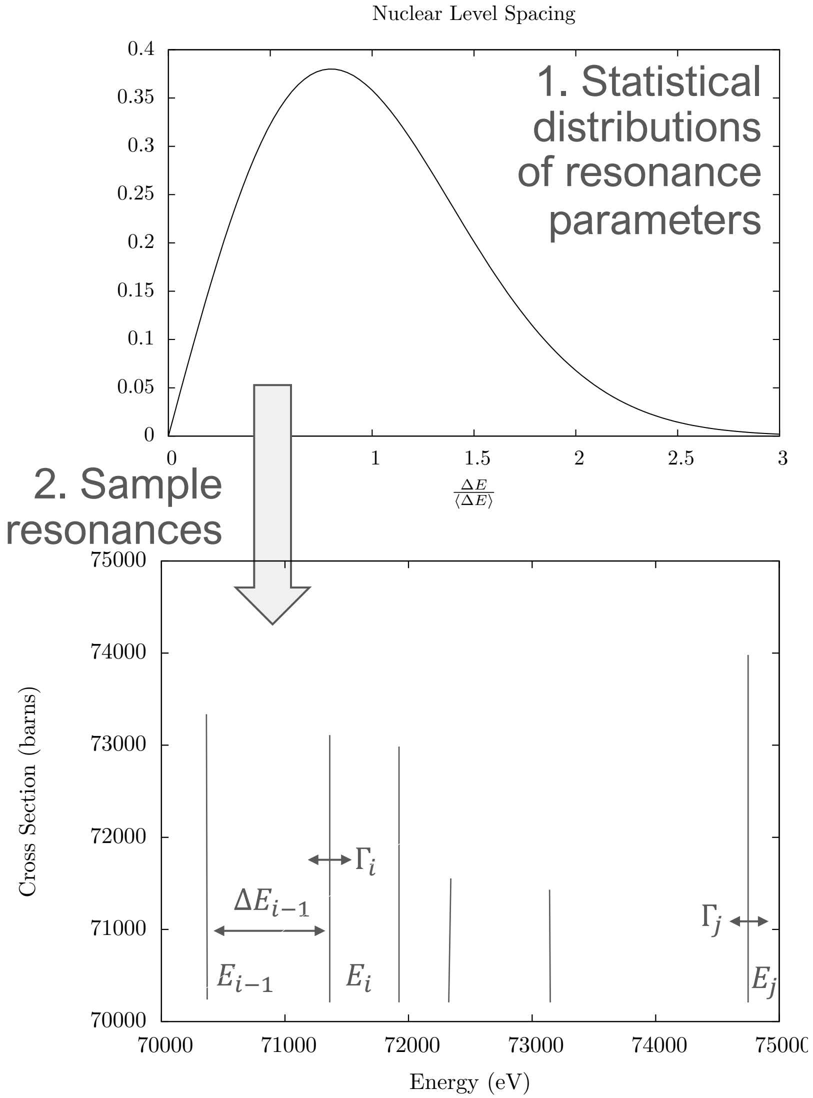
1. Hyper-parameter tuning
2. Learning new functions which are difficult to derive

Generation of Synthetic Training Data





Nuclear Level Spacing
1. Statistical distributions of resonance parameters
2. Sample resonances
$\frac{\Delta E}{\langle \Delta E \rangle}$
Cross Section (barns)
Energy (eV)
Γ_i
ΔE_{i-1}
E_{i-1}
E_i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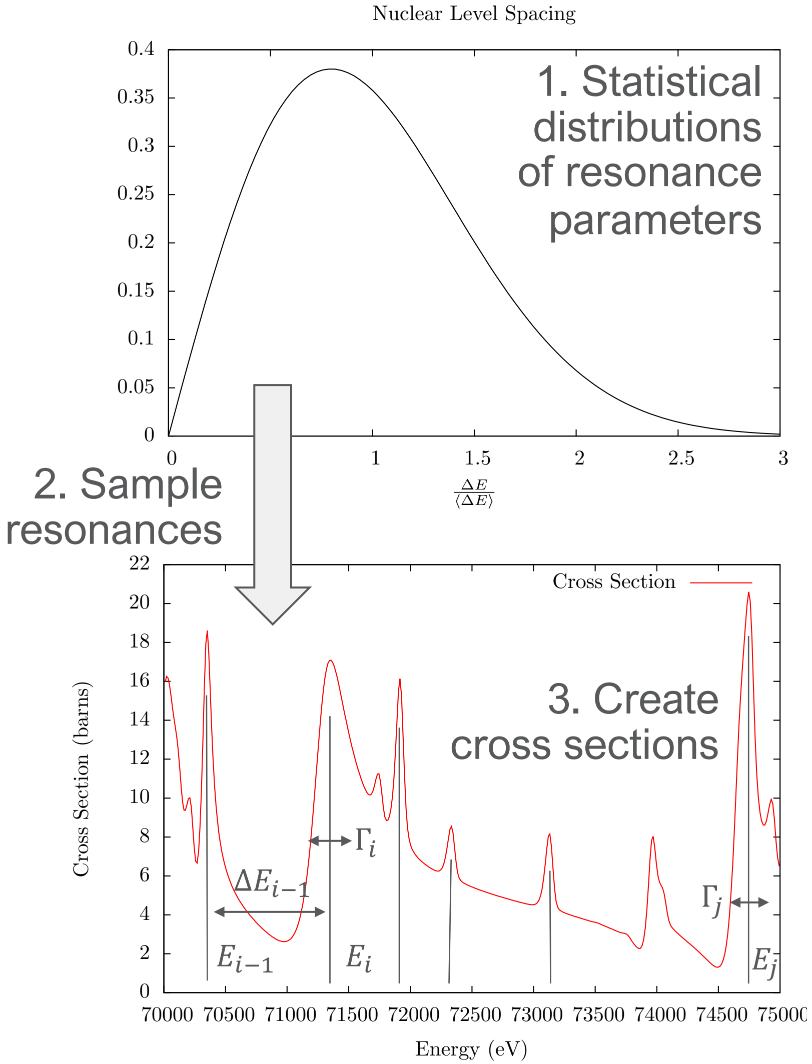
Nuclear Level Spacing
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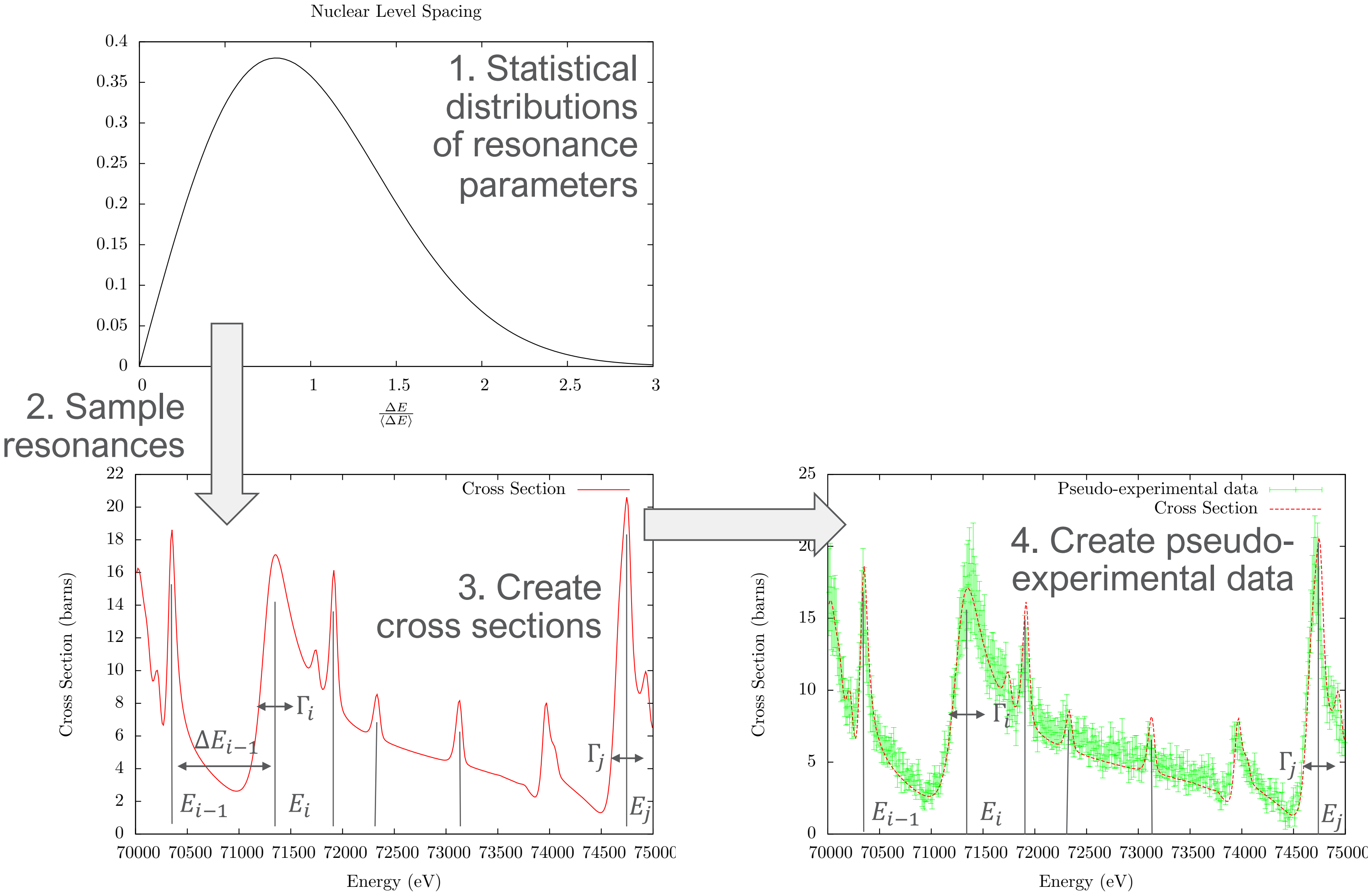

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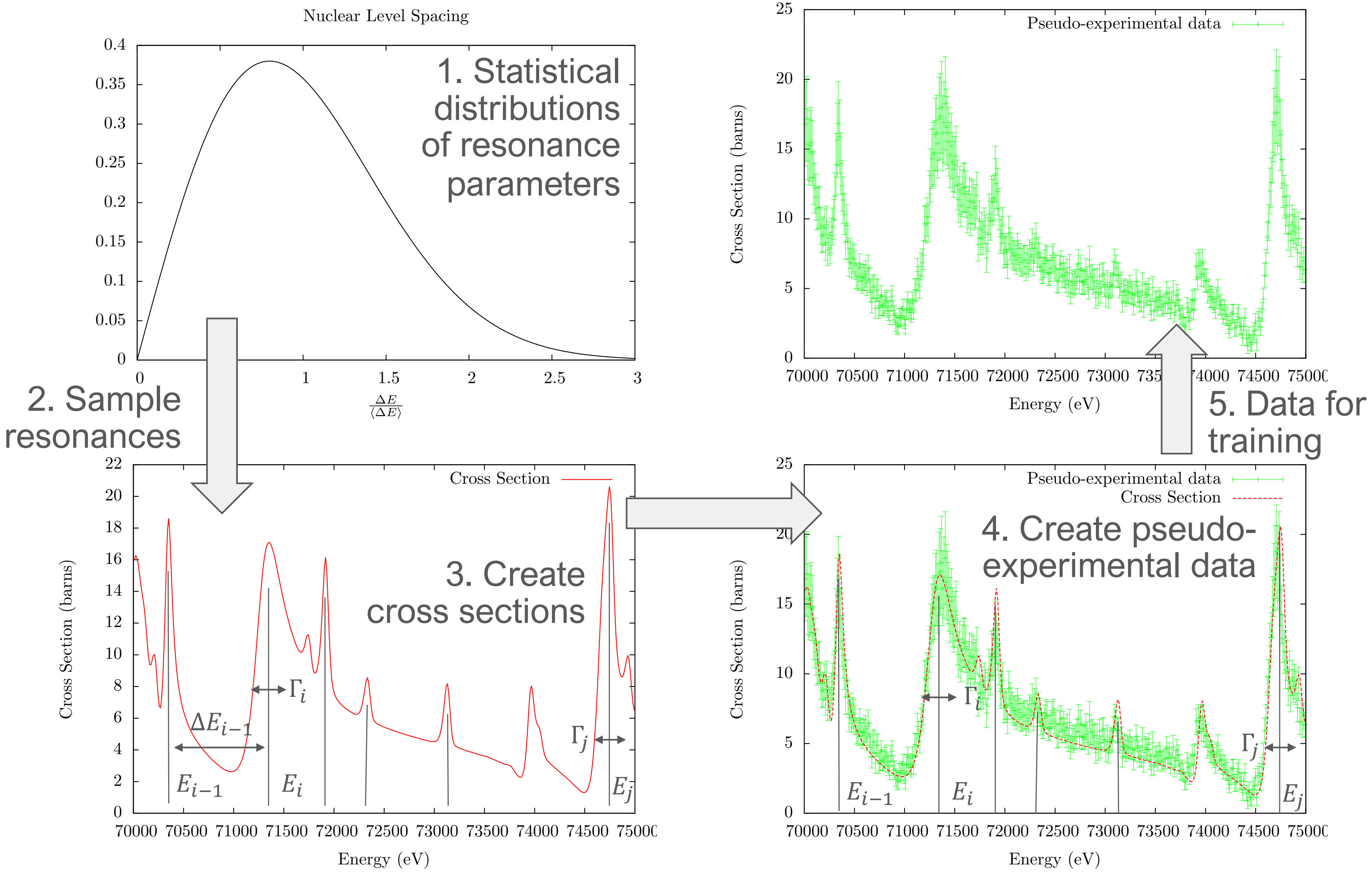
Cross Section (barns)
Energy (eV)
ΔE_{i-1}
Γ_i
Γ_j
E_{i-1}
E_i
E_j
Pseudo-experimental data
Cross Section
4. Create pseudo-experimental data
Cross Section (barns)
Energy (eV)


Nuclear Level Spacing
1. Statistical distributions of resonance parameters
2. Sample resonances
3. Create cross sections
4. Create pseudo-experimental data
5. Data for training
Cross Section
Pseudo-experimental data
Cross Section (barns)
Energy (eV)
$\frac{\Delta E}{\langle \Delta E \rangle}$
E_{i-1}
E_i
E_j
ΔE_{i-1}
Γ_i
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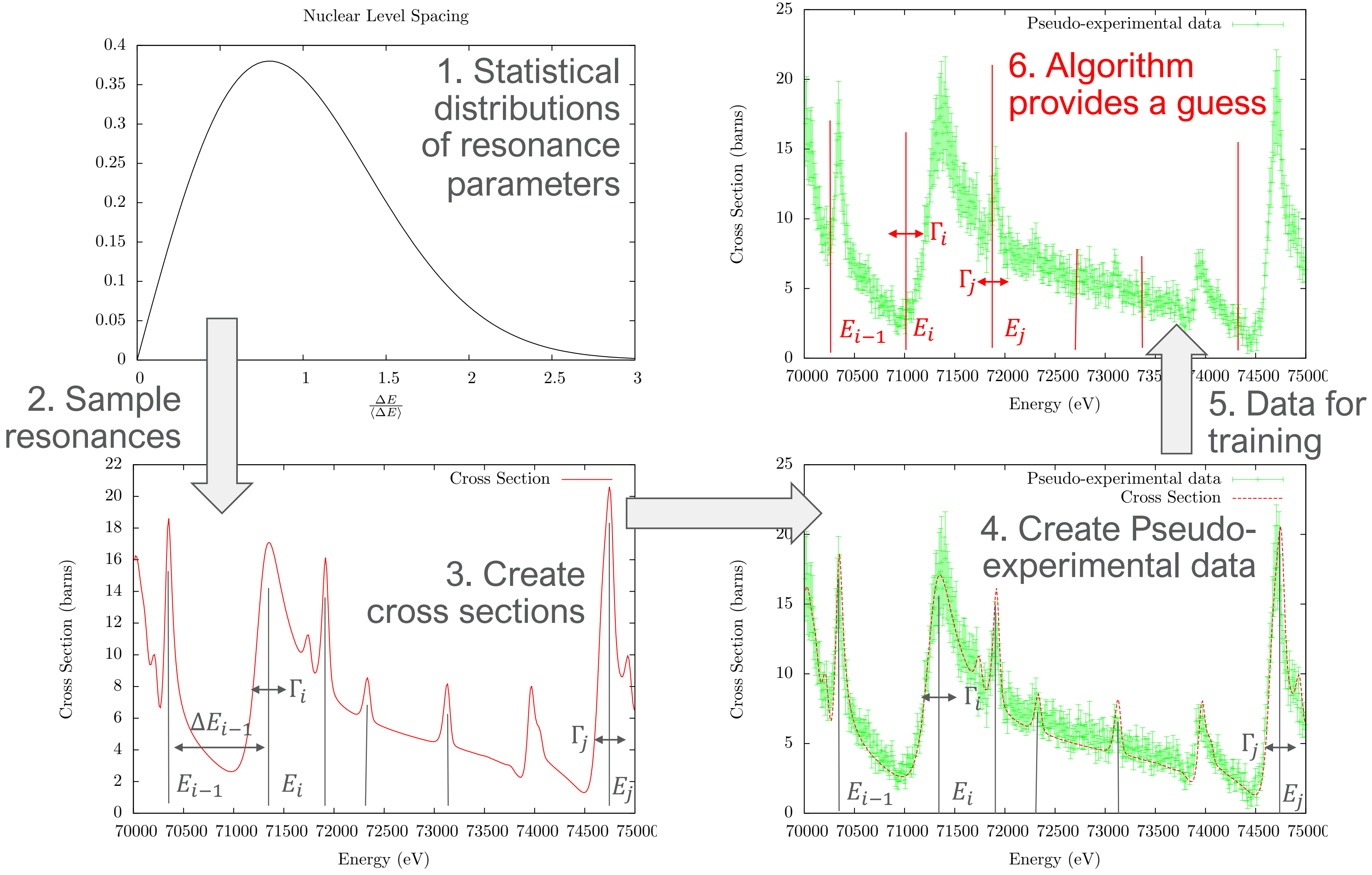
Nuclear Level Spacing
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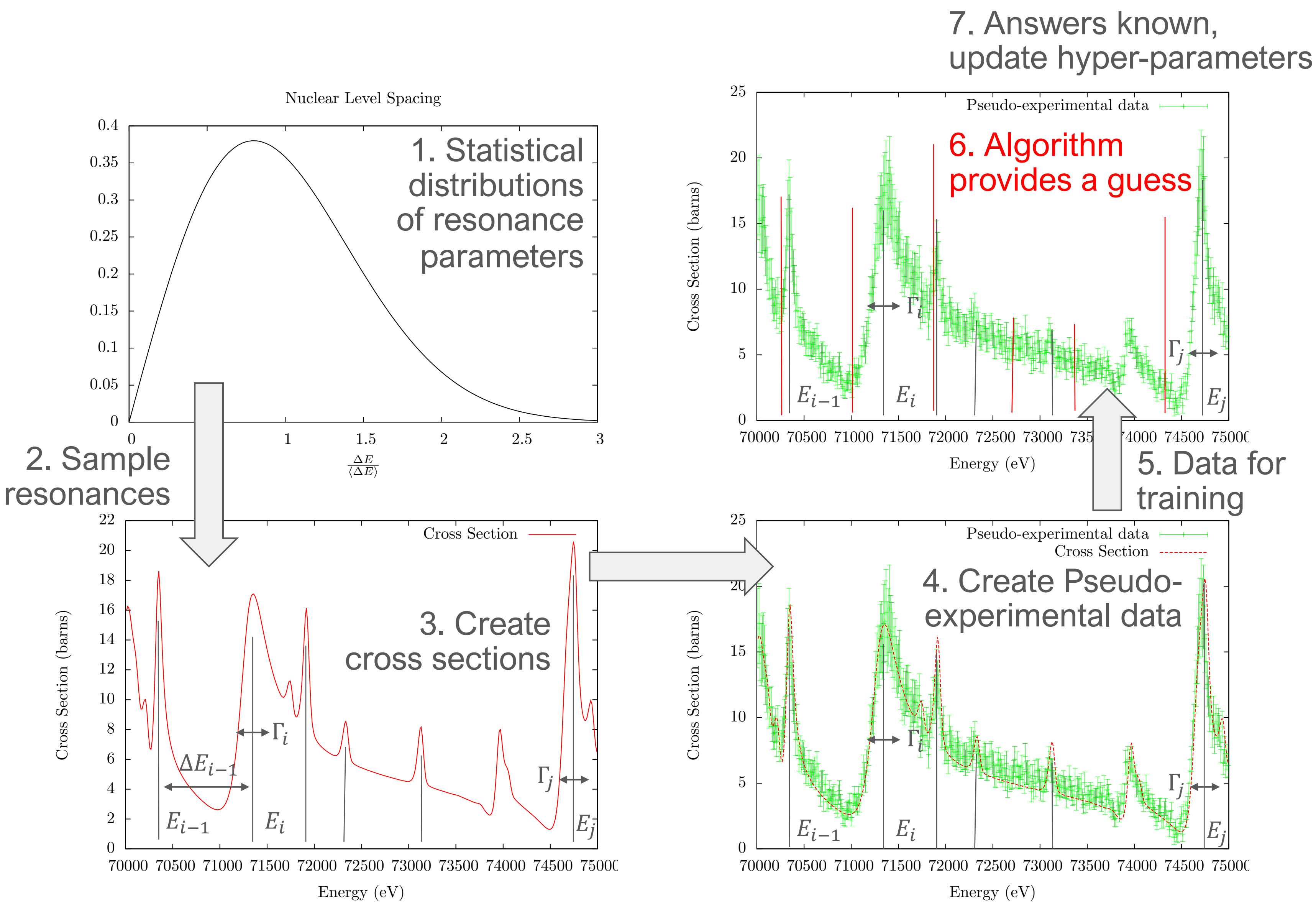
E_i
E_j
Cross Section (barns)
Energy (eV)
Pseudo-experimental data
4. Create Pseudo-experimental data
5. Data for training
6. Algorithm provides a guess



7. Answers known,
update hyper-parameters
Nuclear Level Spacing
1. Statistical distributions of resonance parameters
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3. Create cross sections
Cross Section
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Pseudo-experimental data
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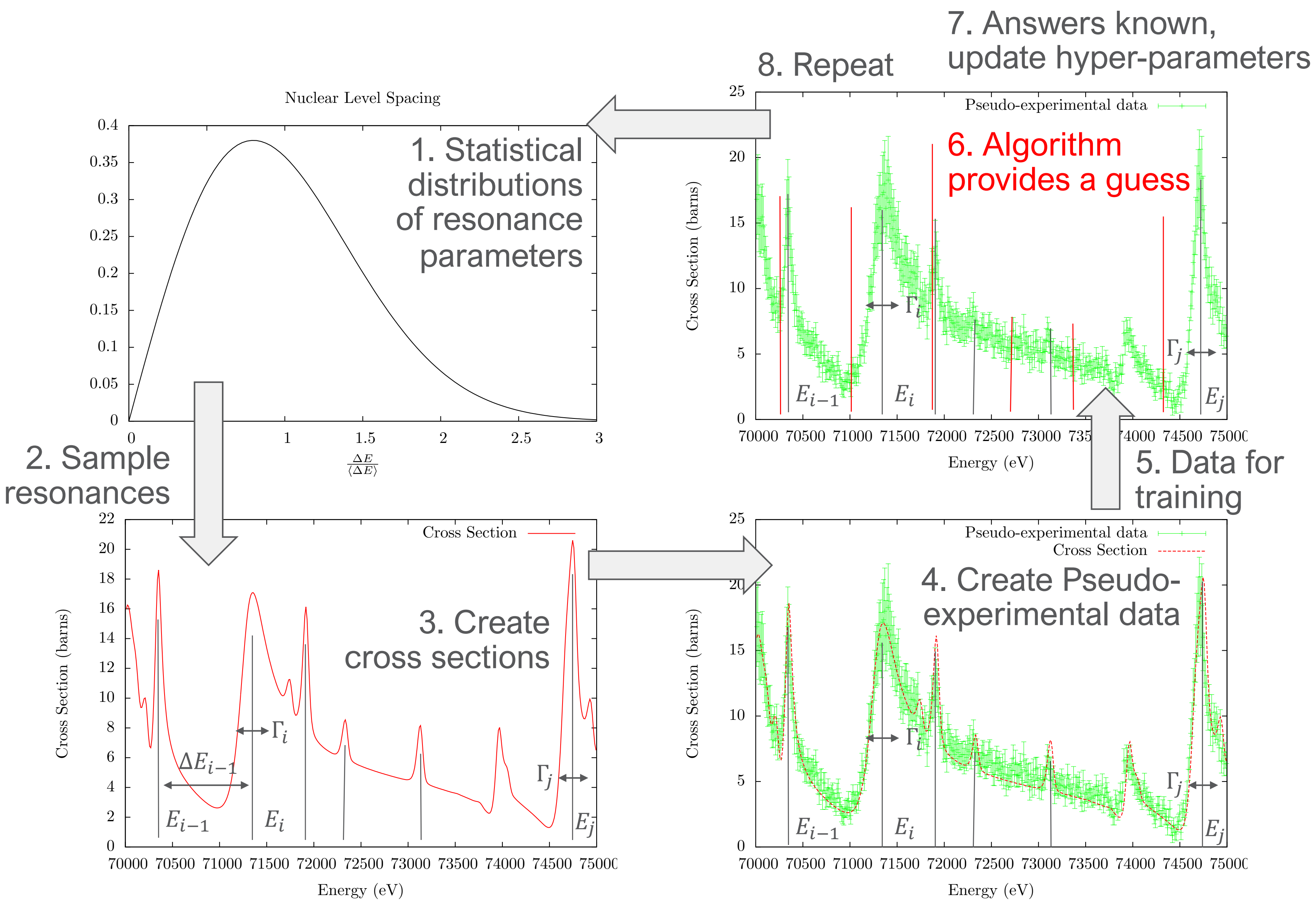
Cross Section (barns)
Energy (eV)



1. Statistical distributions of resonance parameters
2. Sample resonances
3. Create cross sections
4. Create Pseudo-experimental data
5. Data for training
6. Algorithm provides a guess
7. Answers known, update hyper-parameters
8. Repeat
Nuclear Level Spacing
$\frac{\Delta E}{\langle \Delta E \rangle}$
Cross Section
Pseudo-experimental data
Cross Section (barns)
Energy (eV)
E_{i-1}
E_i
E_j
Γ_i
Γ_j
ΔE_{i-1}

Machine Learning in Nuclear Data Evaluation

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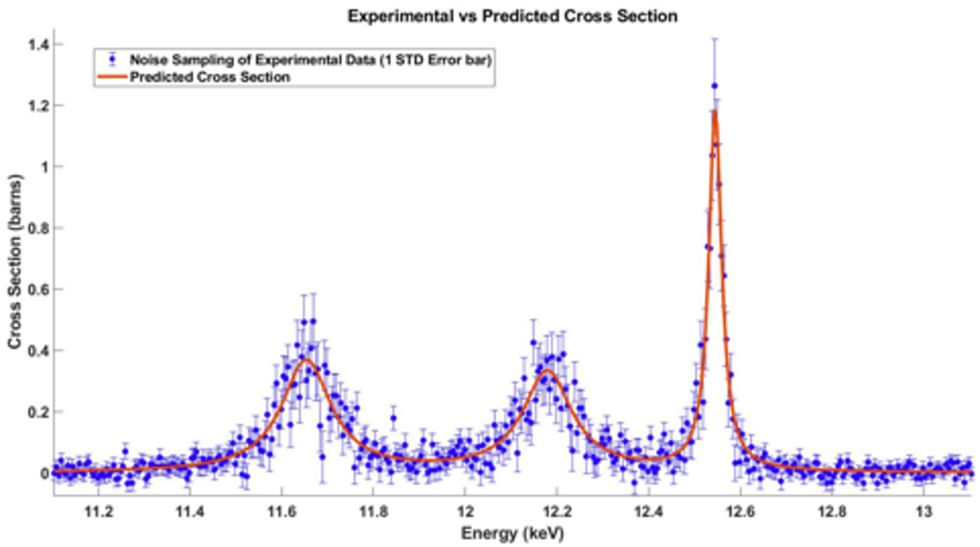
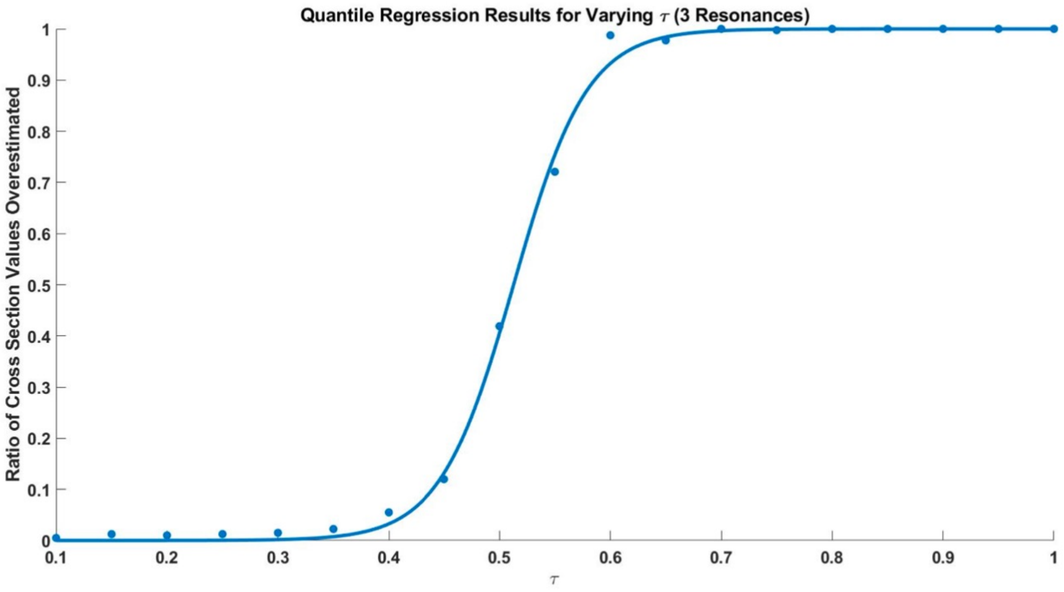
Learning the Function for Uncertainty Quantification





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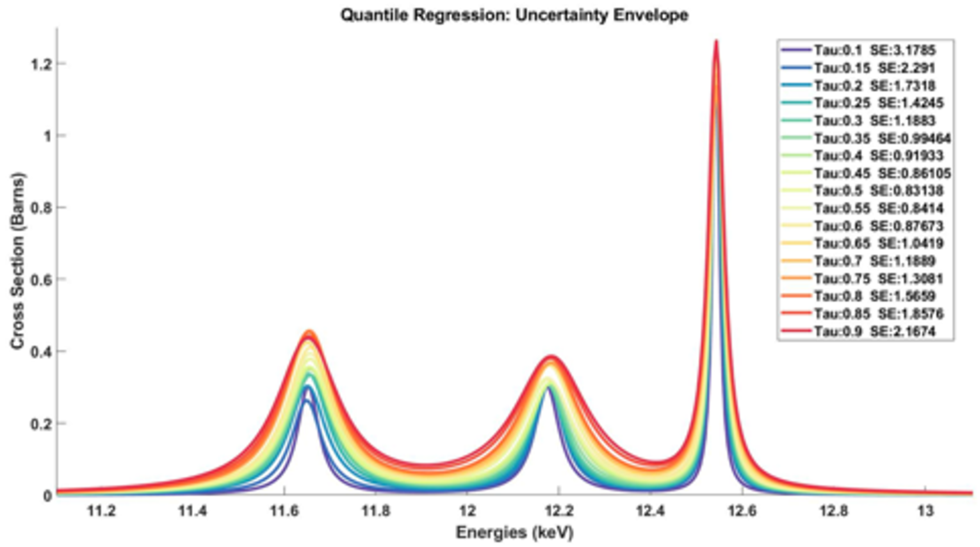
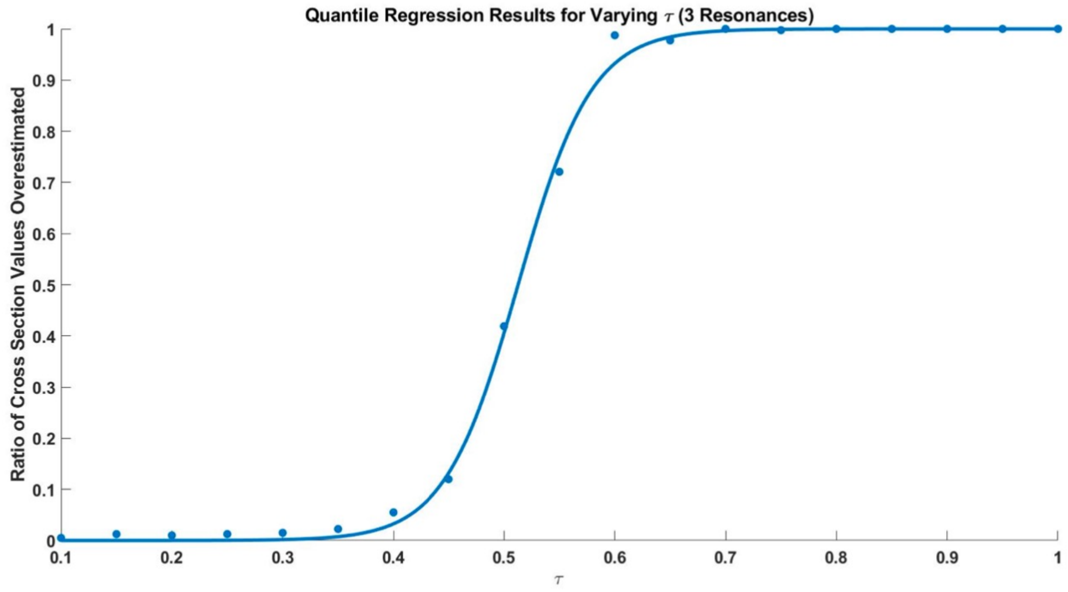
Learning the Function for Uncertainty Quantification





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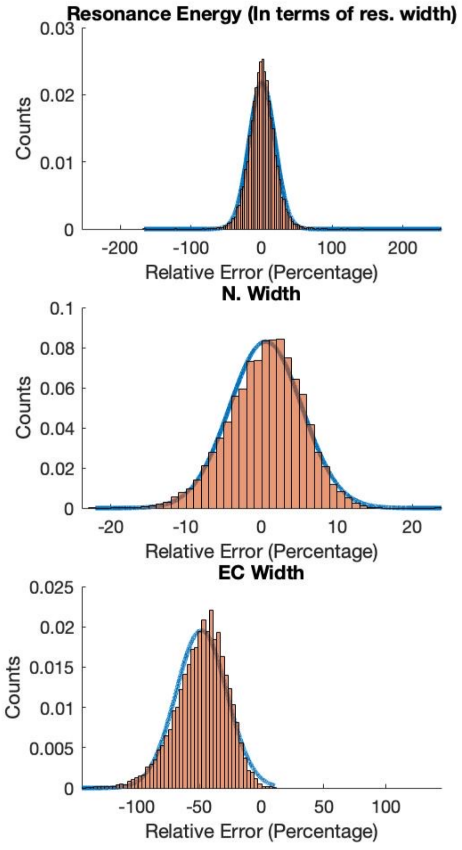

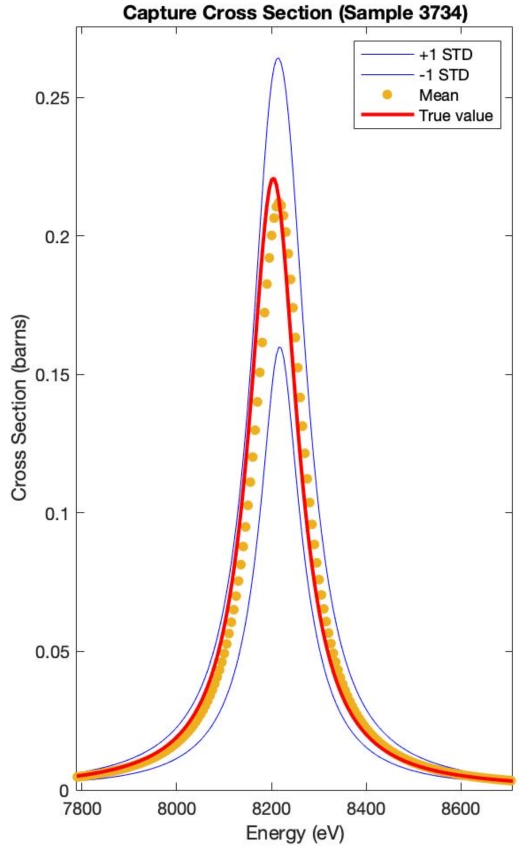

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Artificial Intelligence for Reactor Design

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1. Autonomous optimization – *beyond human capabilities*
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Artificial Intelligence for Reactor Design

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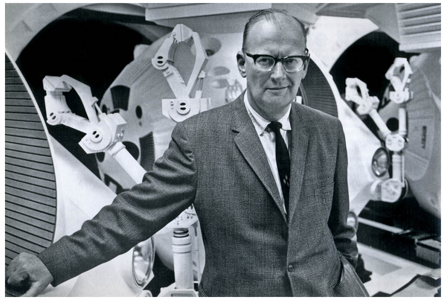
“Any sufficiently advanced technology is indistinguishable from magic.”

Arthur C. Clarke

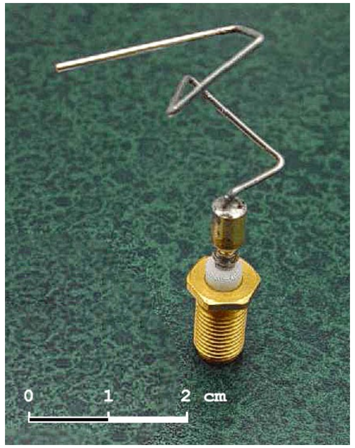


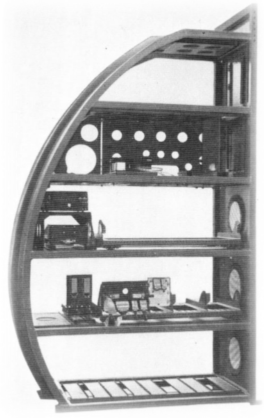
Motivation for automation

Motivation for automation

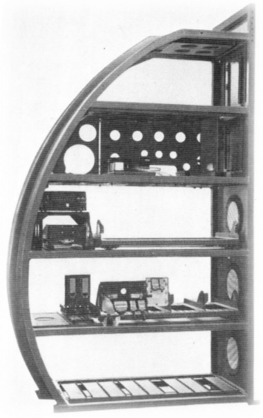
Imagine an antenna

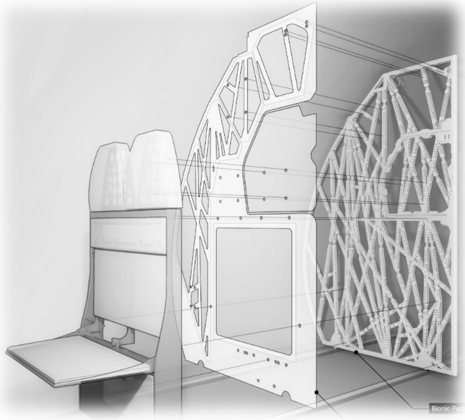
Motivation for automation


0 1 2 cm

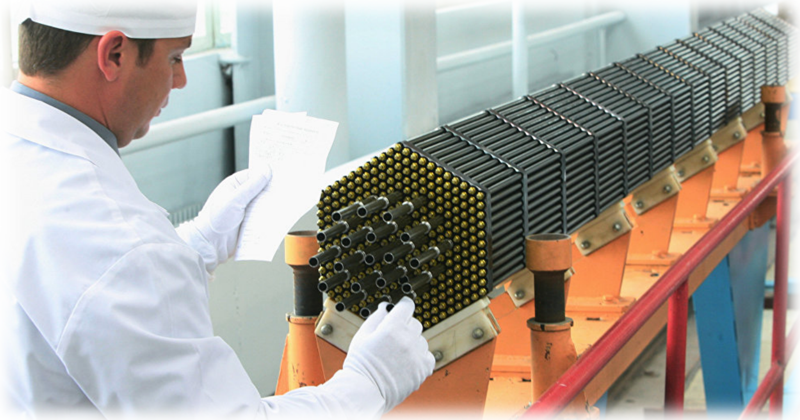


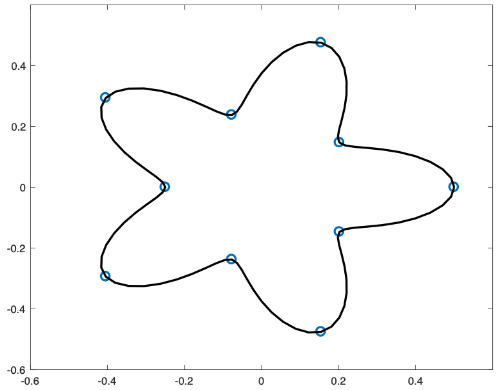
Airplane Partition Wall



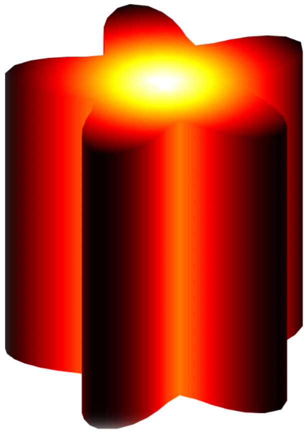


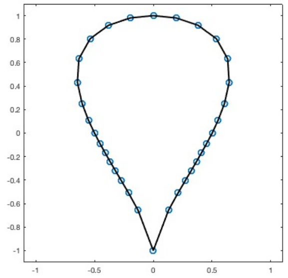
Airplane Partition Wall

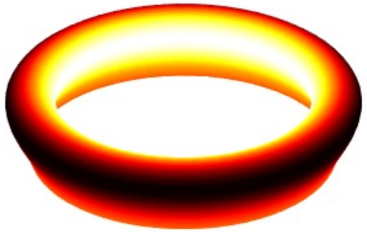


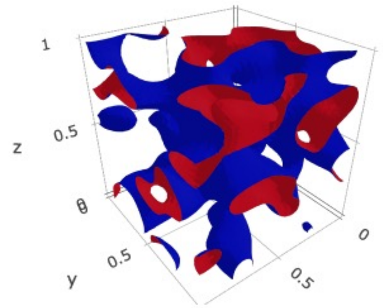


0.4
0.2
0
-0.2
-0.4
-0.6
-0.6
-0.4
-0.2
0
0.2
0.4




1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1
-0.5
0
0.5
1

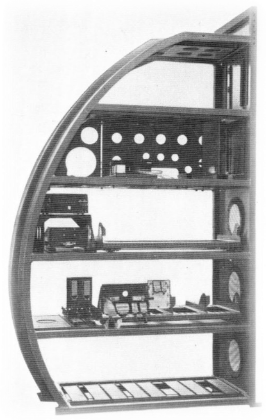



1
0.5
z
0
0.5
y
0
0.5

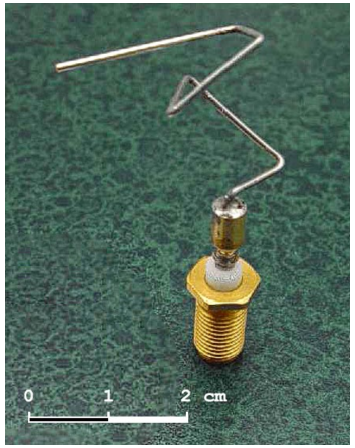
The Future of Human Involvement in Reactor Design

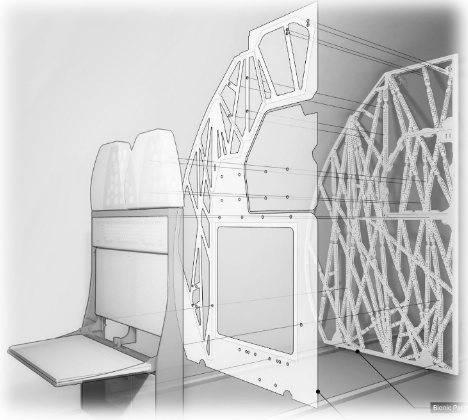
Spacecraft Antenna | Airplane Partition Wall | Nuclear Systems

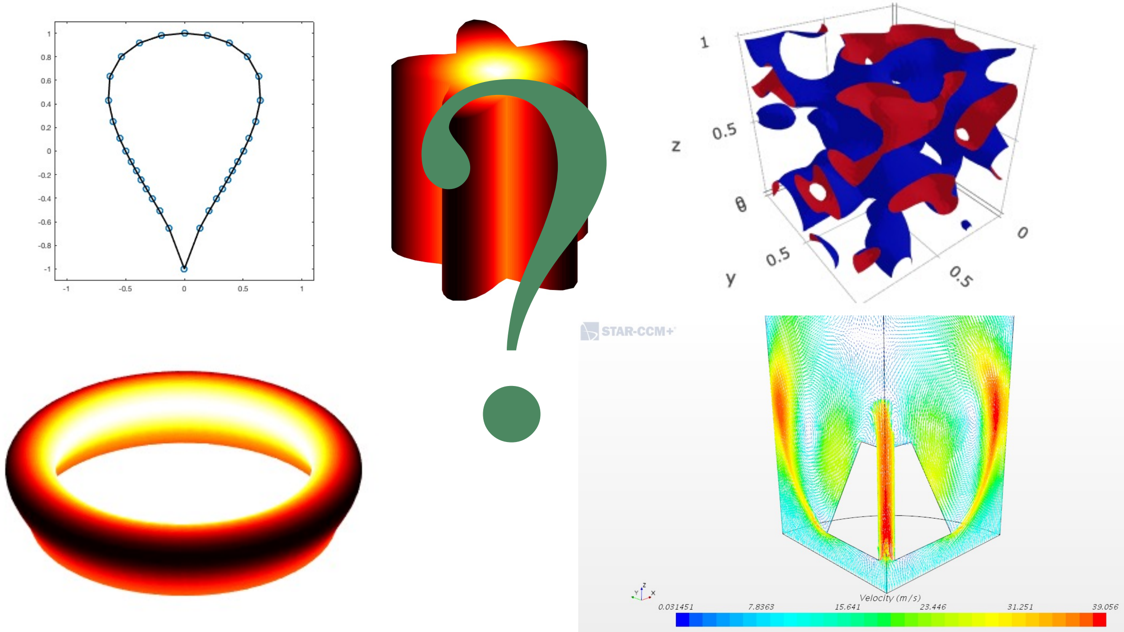
Human Design



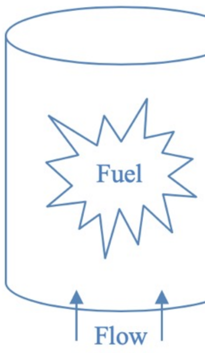
AI Design







Motivation for automation



V. Sobes, et. al., Artificial Intelligence Design of Nuclear Systems Empowered by Advanced Manufacturing, PHYSOR 2020, Mar. (2020)

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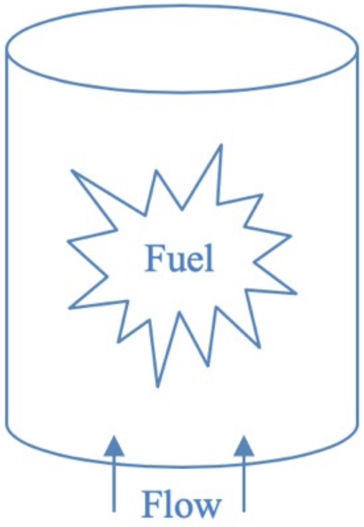

Fuel: UO_2

Enrichment	19.75%
Density	10.8 g/cc
Thermal conductivity	4 W/mK

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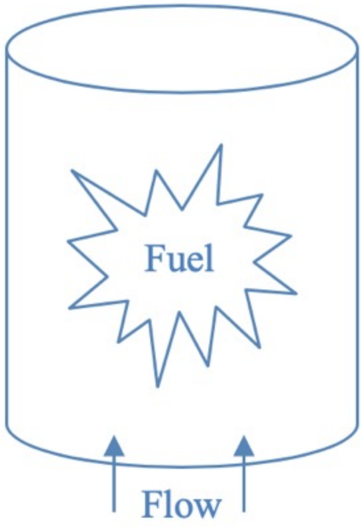

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Coolant: He

Inlet pressure	6 MPa
Inlet flow velocity	10 m/s
Inlet temperature	425 °C

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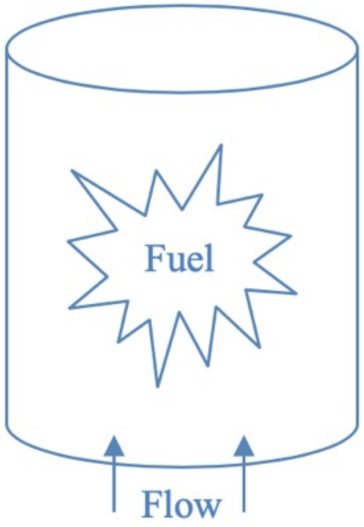
Constraints	
Min. excess reactivity	1500 pcm
Max. fuel temperature	618 C
Component power	10 kW



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Objective: Minimize Fuel Mass

Constraints	
Min. excess reactivity	1500 pcm
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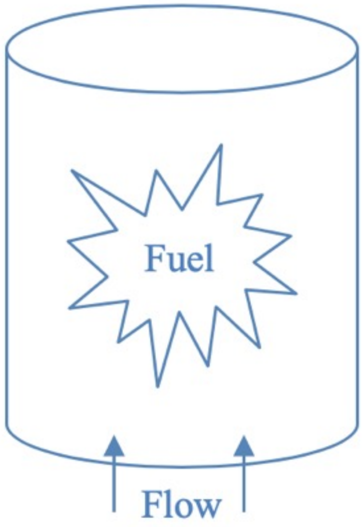
Component power	10 kW



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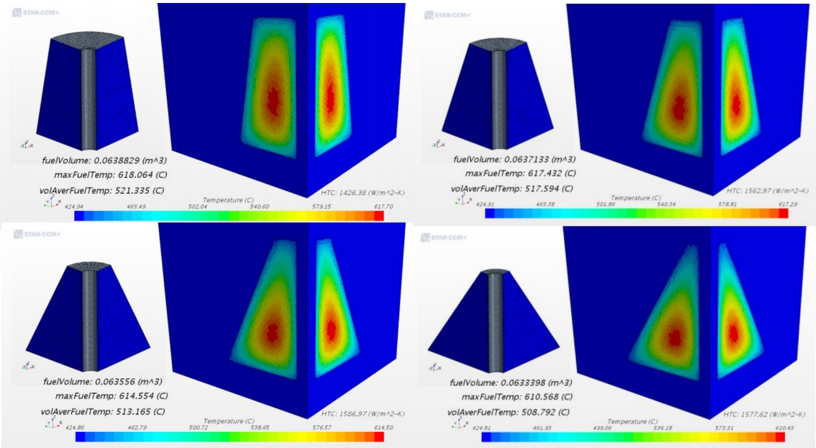
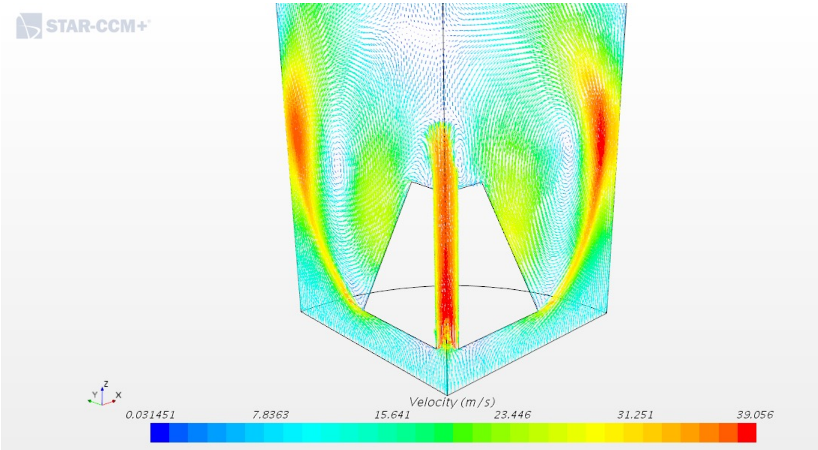
High Fidelity (Full) Physics Model





Cylinder Core

Constraints

$k > 1.01500$

$T_{max} < 618$ C

$P = 10$ kW

Shape must a cylinder

Cylinder Core

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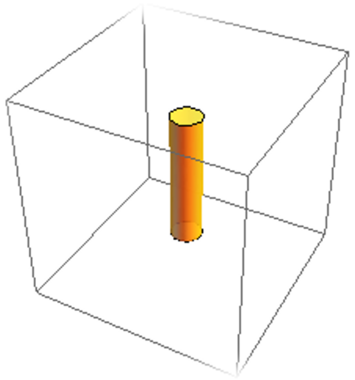
k > 1.01500

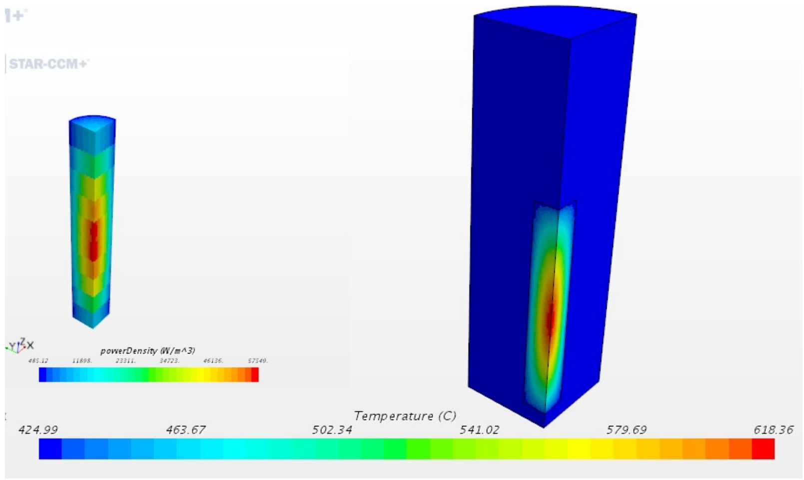
T_{max} < 618 C

P = 10 kW

Shape must a cylinder

Fuel Rod





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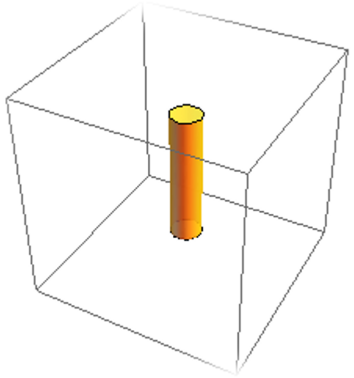
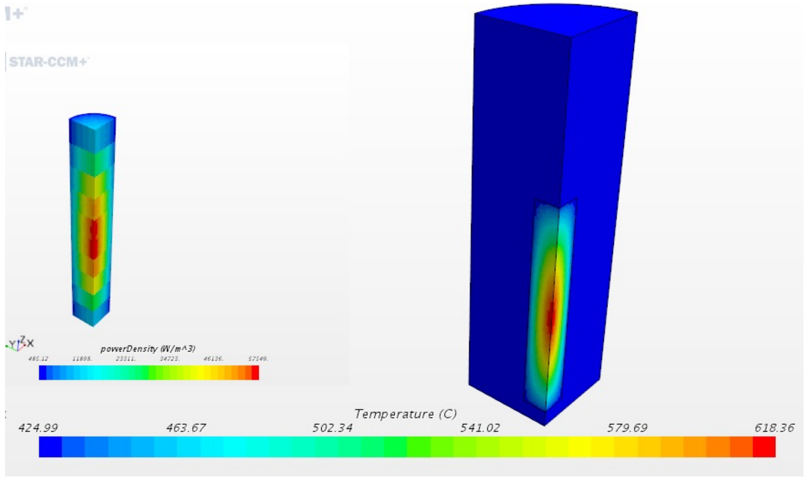
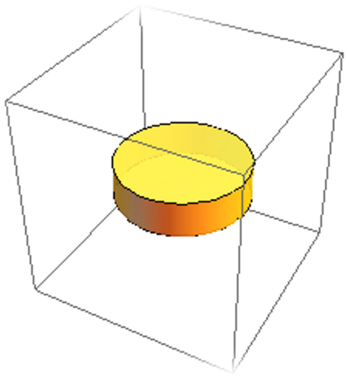
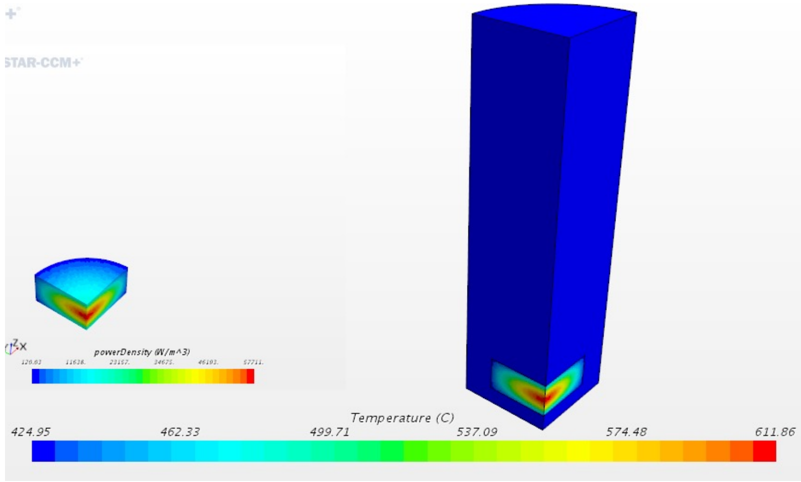




Fuel Disk





Cylinder Core

Constraints

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$T_{max} < 618$ C

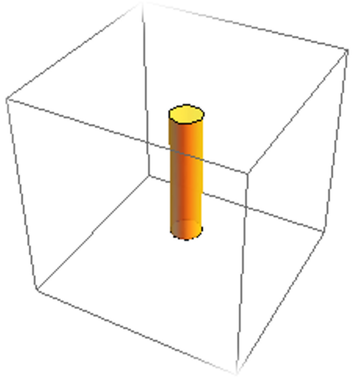
P = 10 kW

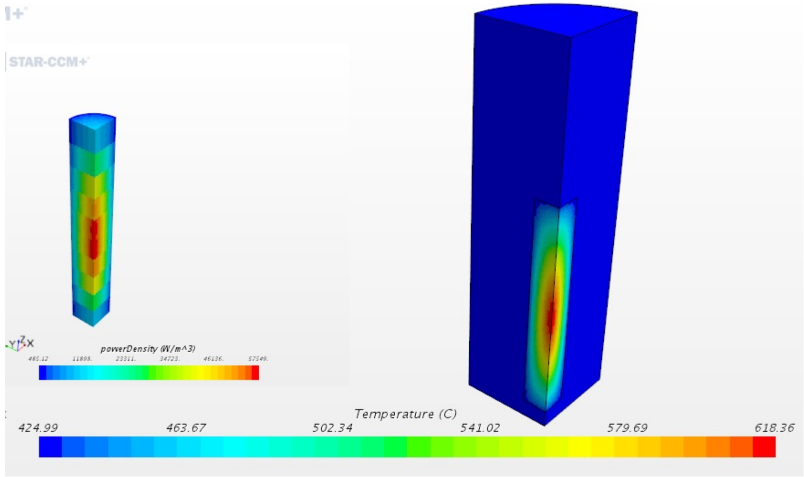
Shape must a cylinder

Volume 0.52 m^3

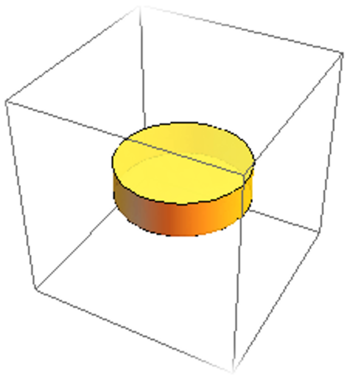
Surface area 4.4 m^2

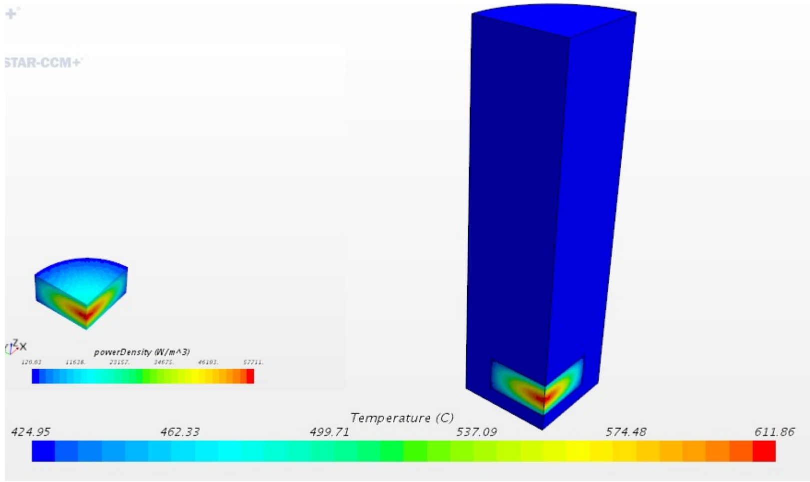
Fuel Rod





Fuel Disk





Annulus Core

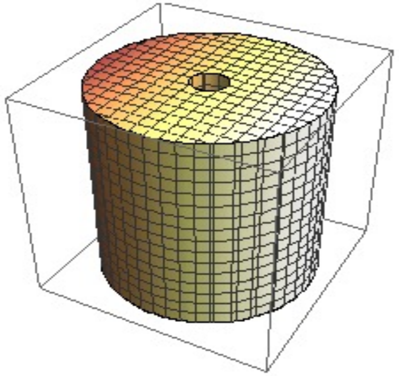
Constraints

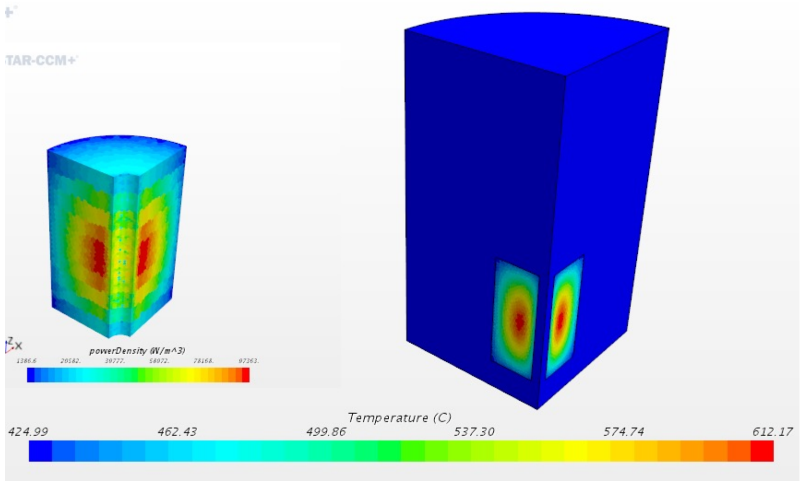
$k > 1.01500$

$T_{max} < 618$ C

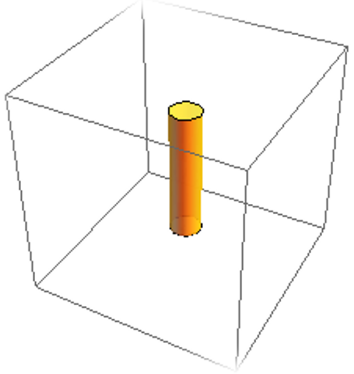
$P = 10$ kW

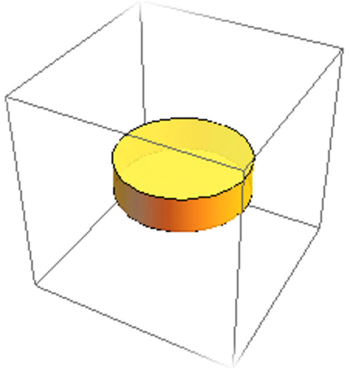
Annulus Solution





Cylinder Solution





Annulus Core

Constraints

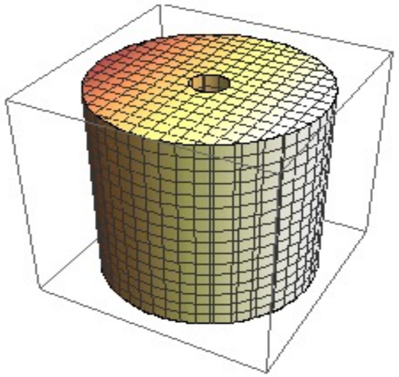
k > 1.01500

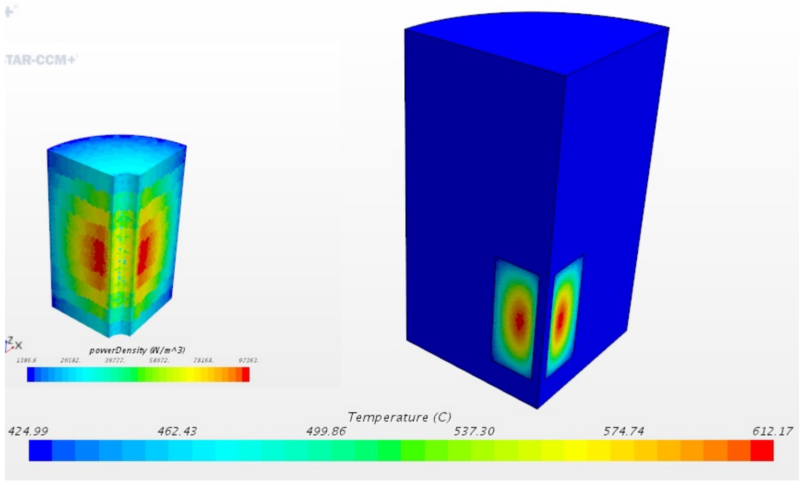
T_{max} < 618 C

P = 10 kW

Minimal critical volume 0.19 m^3

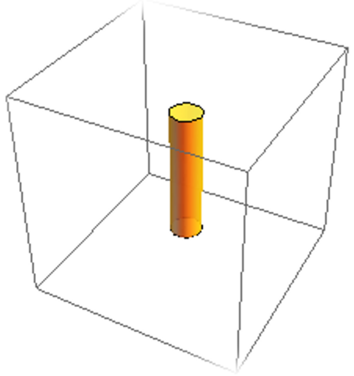
Annulus Solution

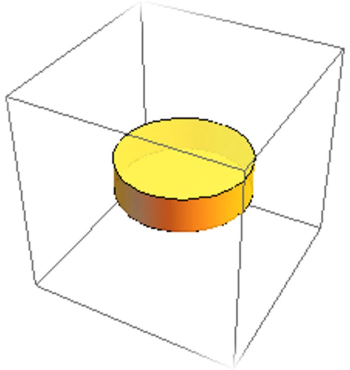




Volume 0.25 m^3
Surface area 2.5 m^2

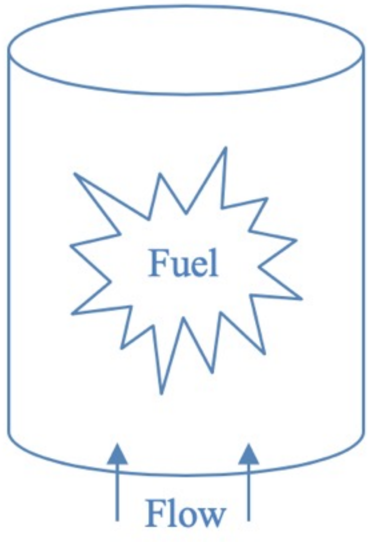
Cylinder Solution





Volume 0.52 m^3
Surface area 4.4 m^2

Cone Core



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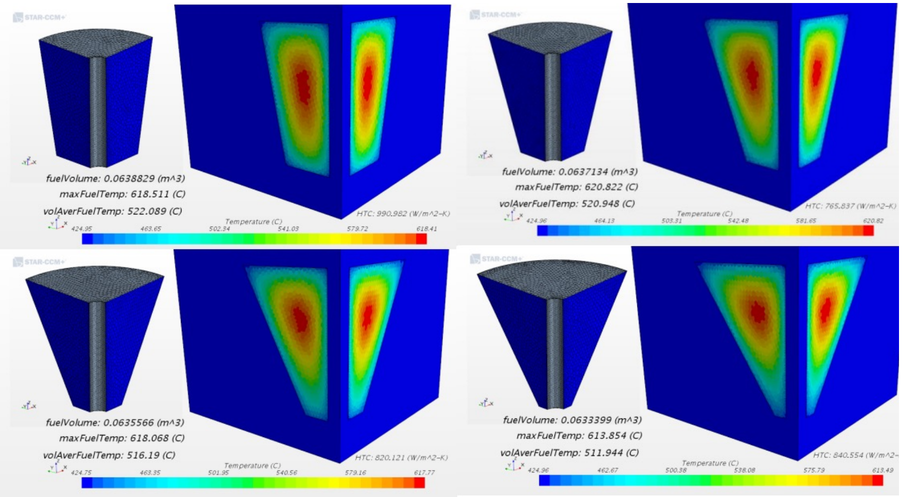
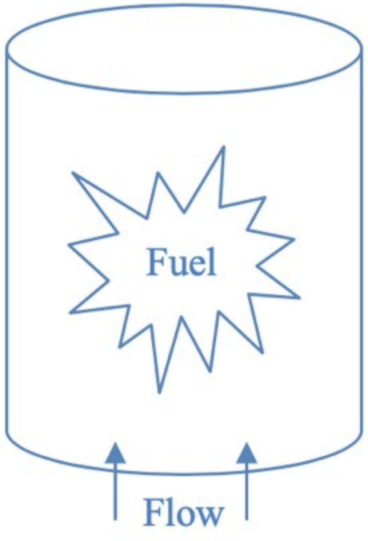
Cone Core

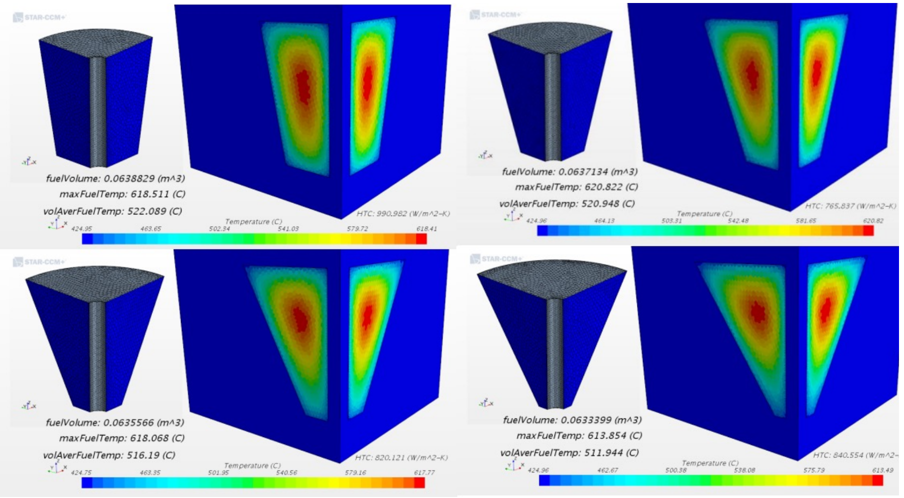
Tapered Design

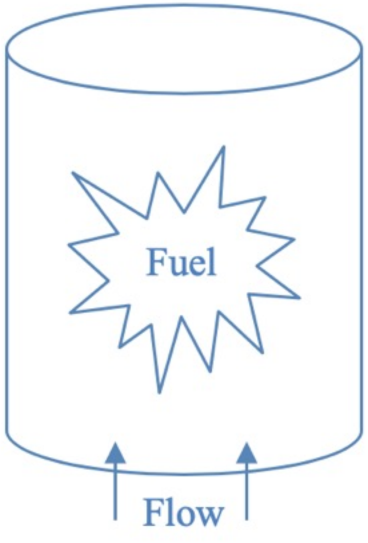




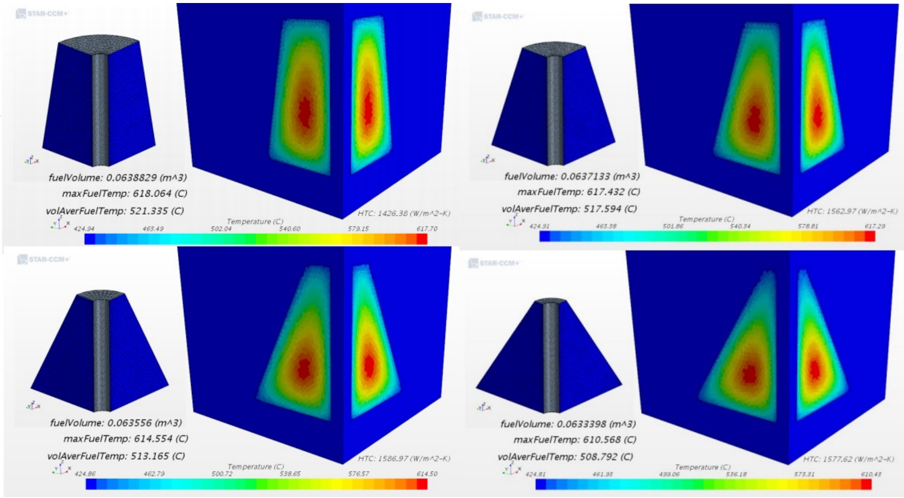
Cone Core

Tapered Design



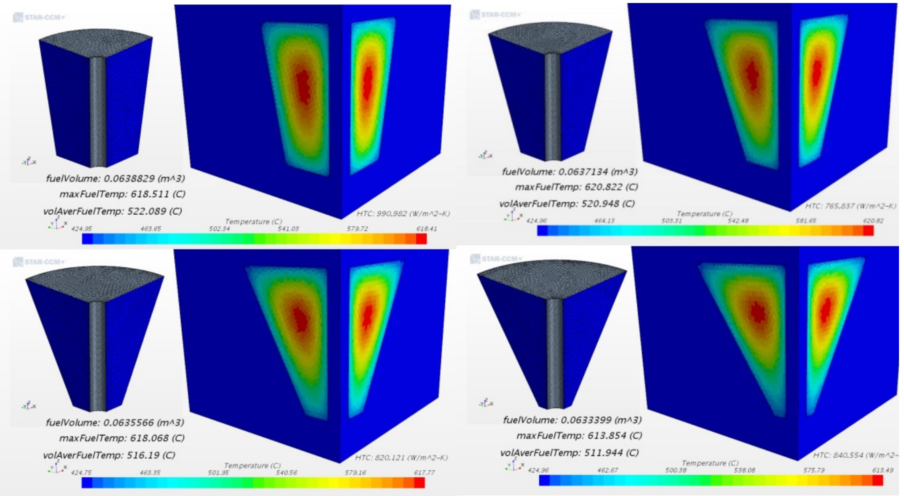


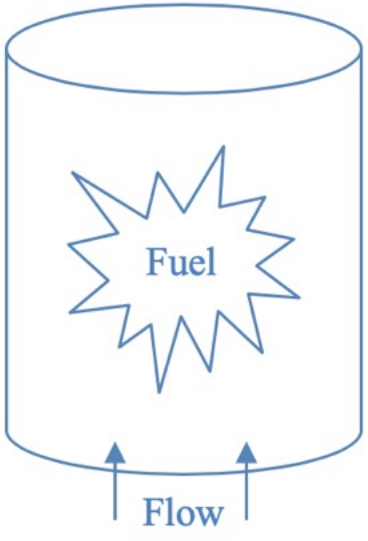
Blunted Design



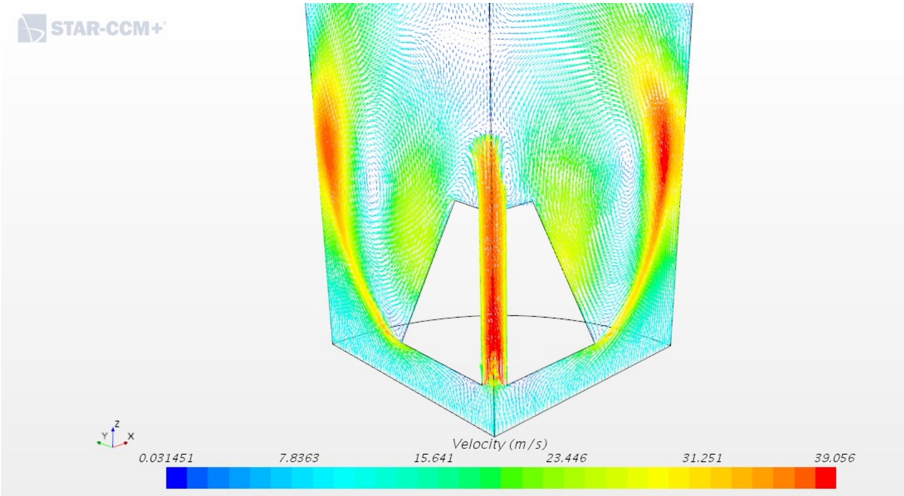
Cone Core

Anticipated Tapered Design

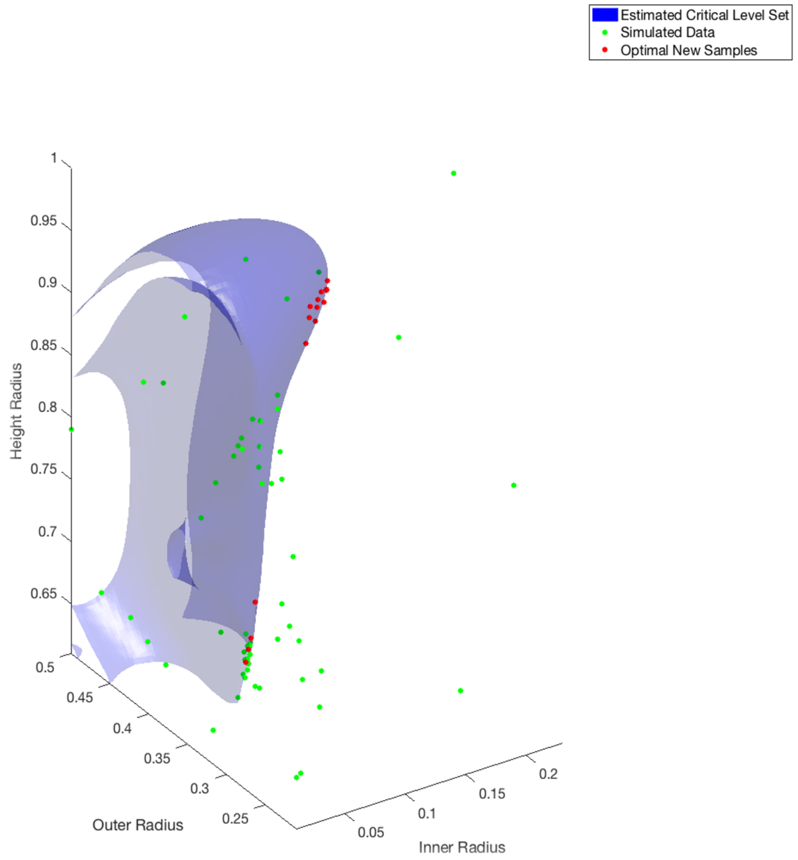




Optimal Blunted Design



Design Algorithm
Gaussian Process Learning



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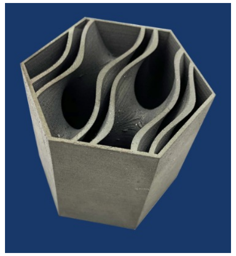
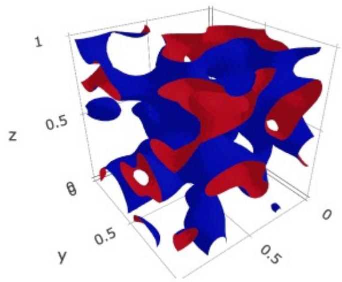
The Curse of Dimensionality in Design Space

10



100
Parameters



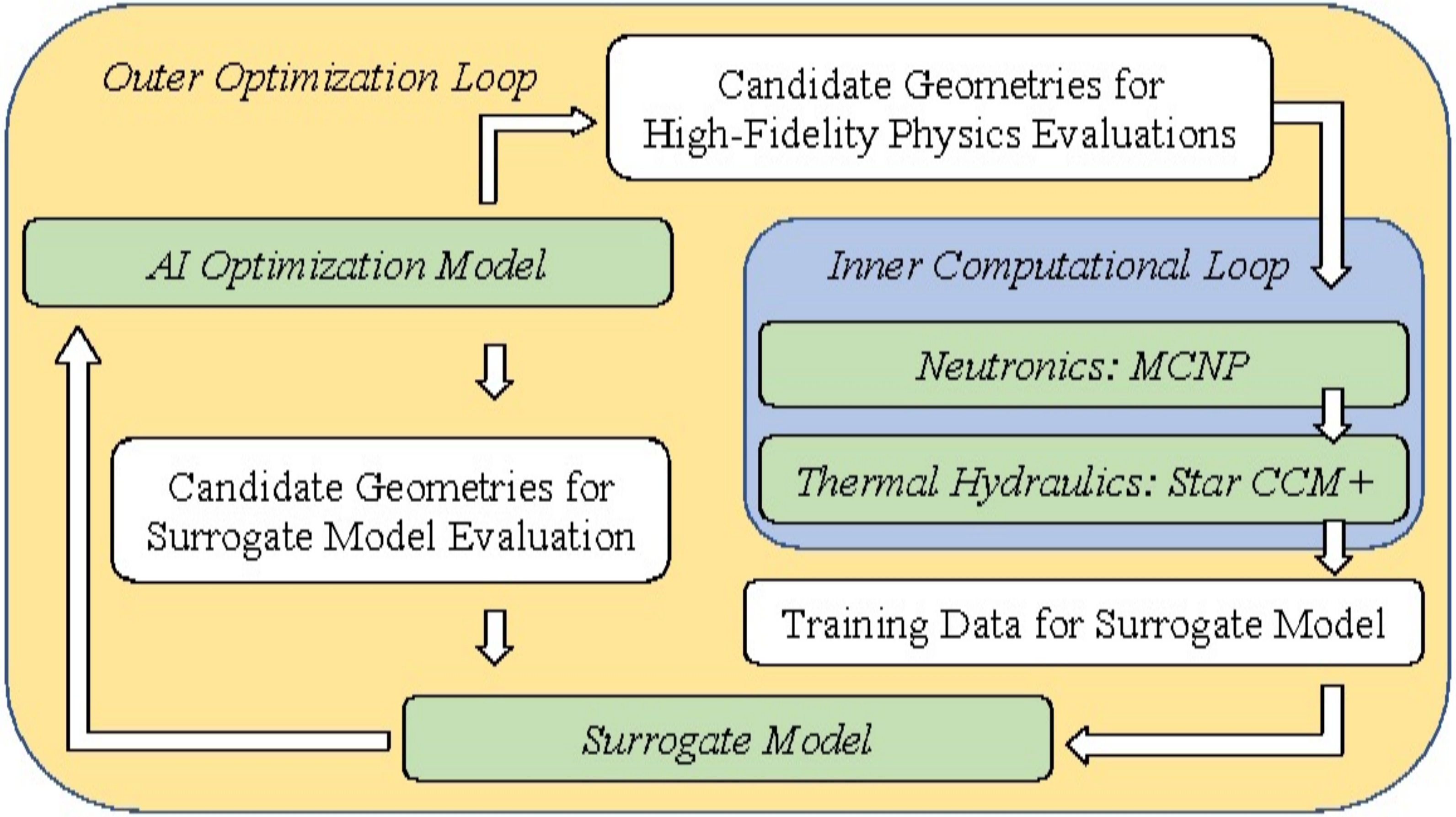
1000+

Artificial Intelligence for Reactor Design

Key take-aways:

1. Autonomous optimization – *beyond human capabilities*
2. Surrogate models – *cautionary tales*

A Modular Framework



V. Sobes, B. Hiscox, E. Popov, et al. AI-Based Design of a Nuclear Reactor Core, Nature Scientific Reports, DOI: 10.1038/s41598-021-98037-1 (2021).

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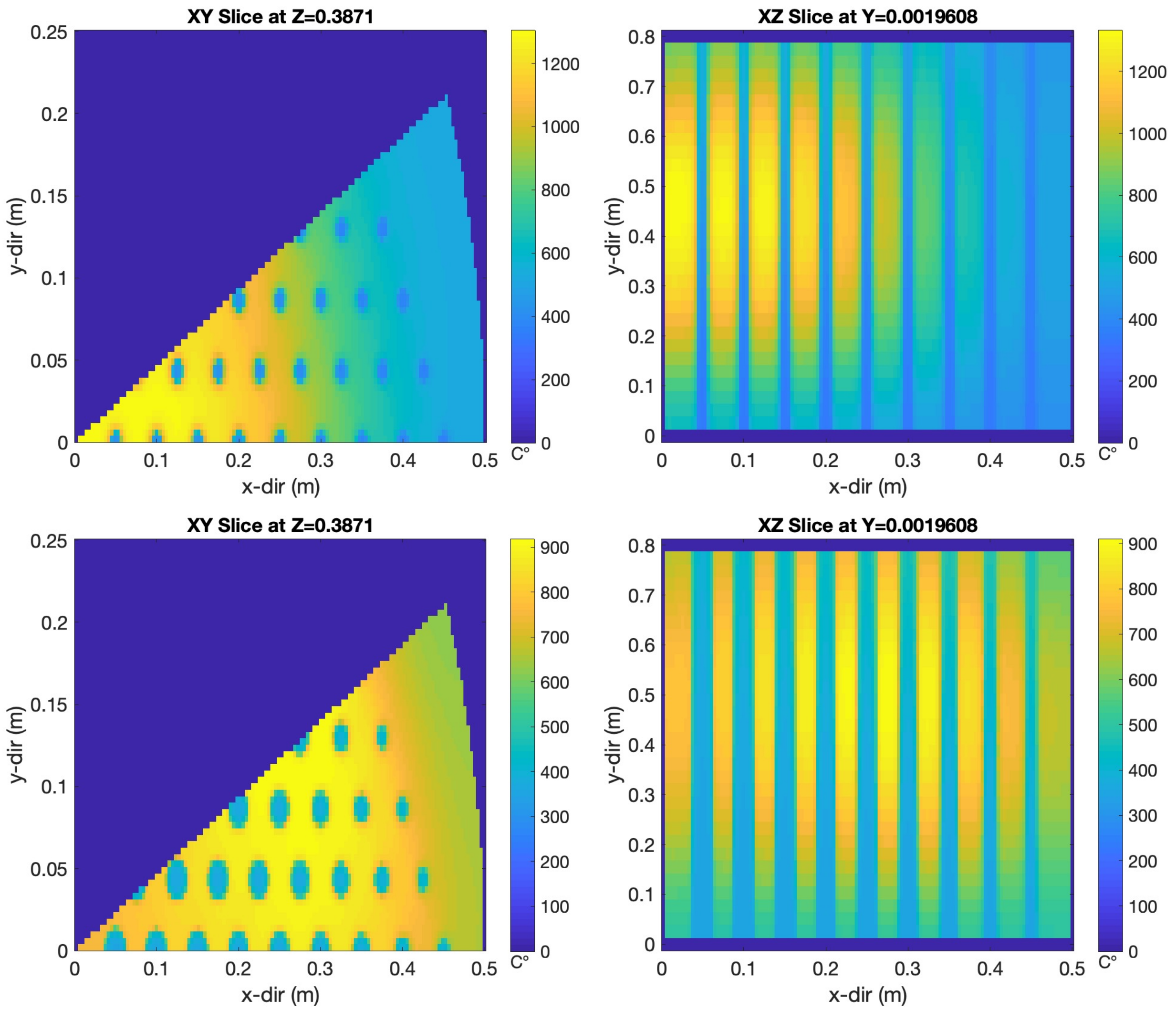
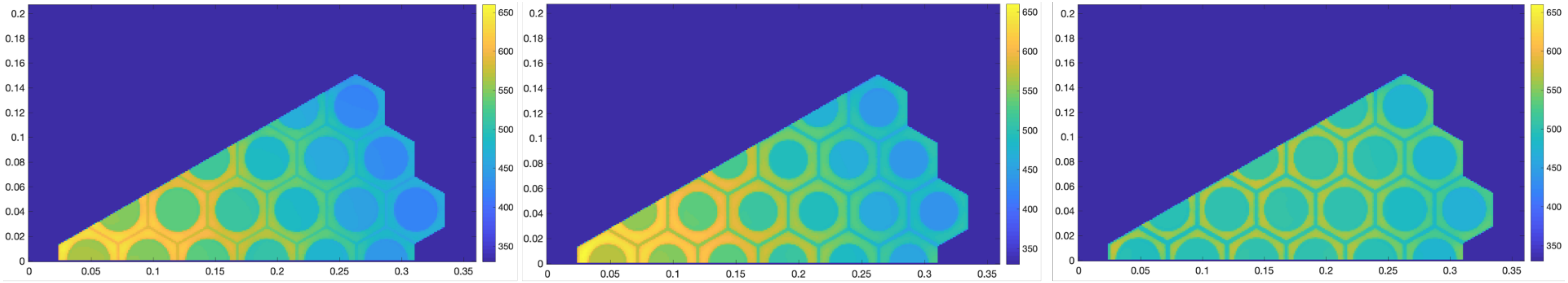
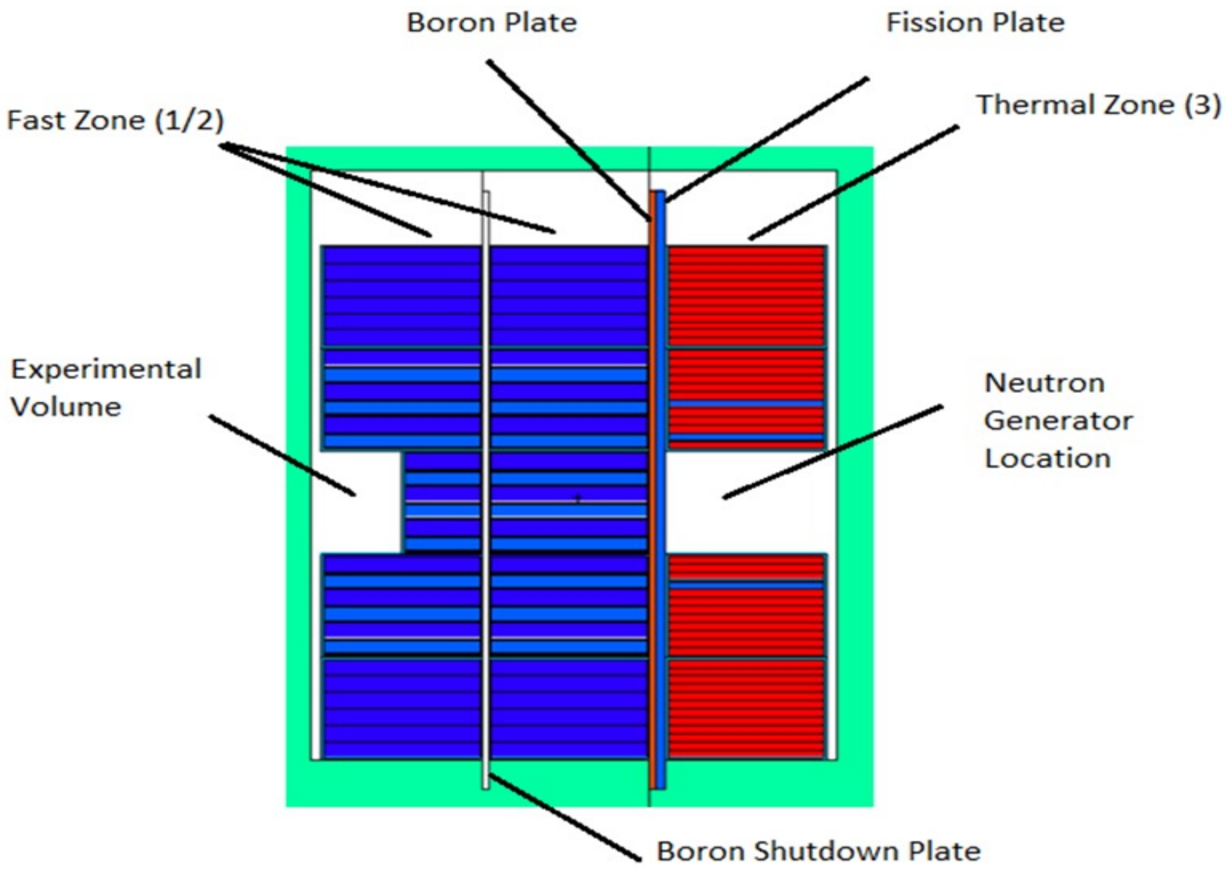
Full Core Optimization

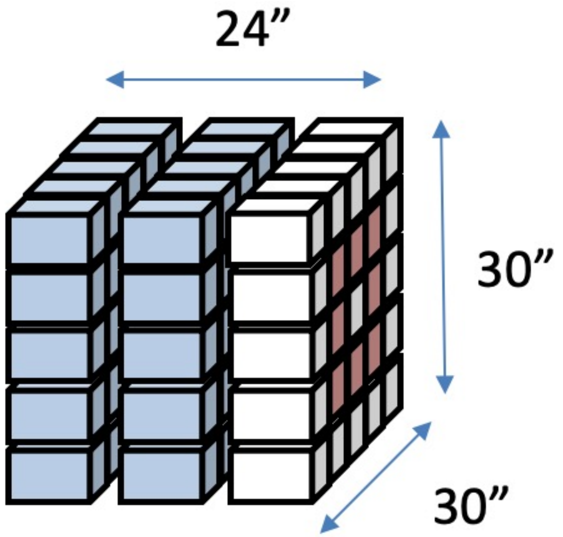


Full Core Optimization



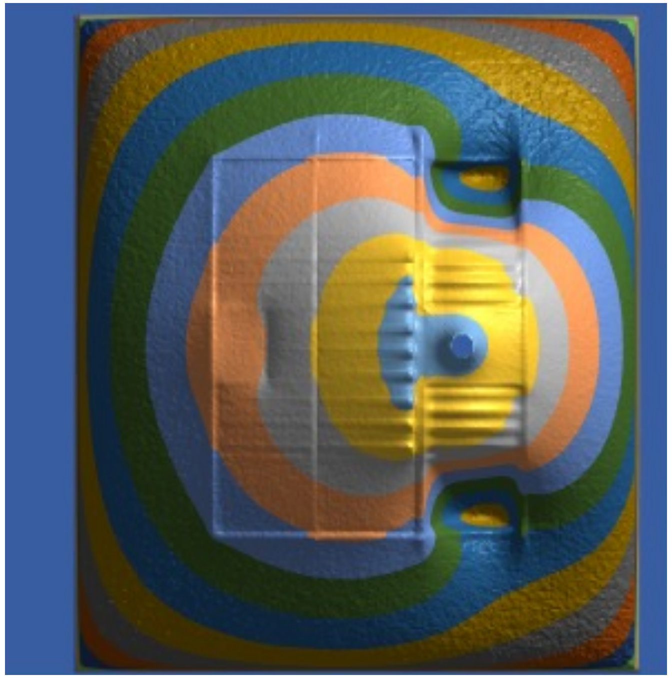
FNS Design Concept



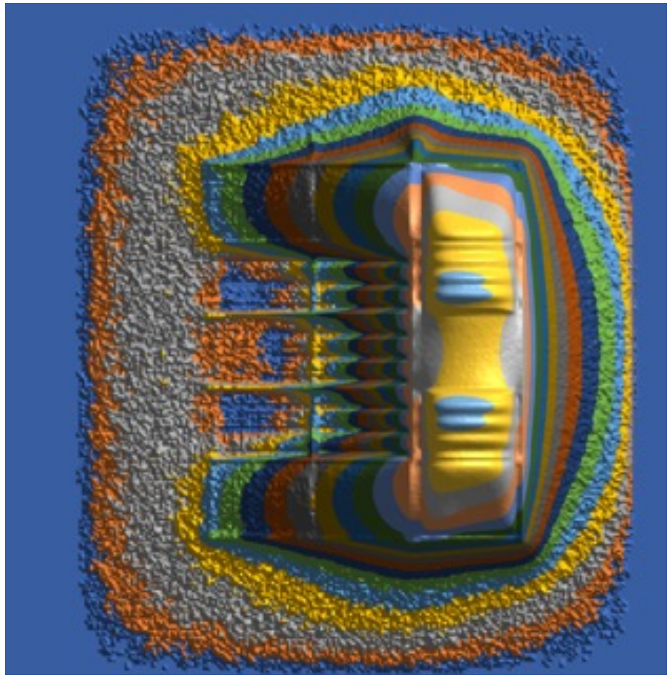


J. Pevey, V. Sobes, W. Hines, Neural Network Acceleration of Genetic Algorithms for the Optimization of A Coupled Fast/Thermal Nuclear Experiment, Frontiers in Energy Research-Nuclear Energy (accepted), (2022).

Simulation Results



Fast Flux



Thermal Flux

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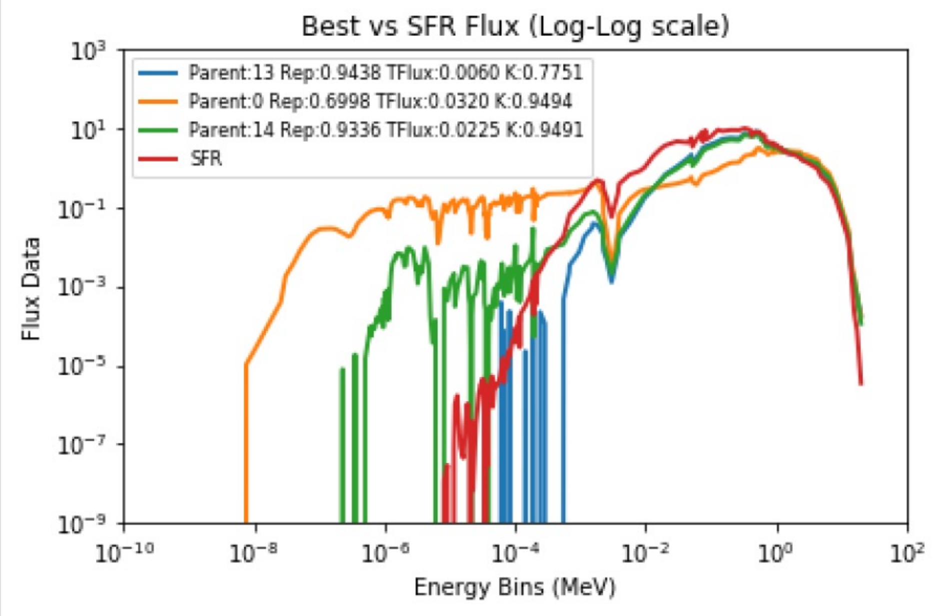
Heuristic Design Objectives

Maximize flux representativity

Improves the relevance



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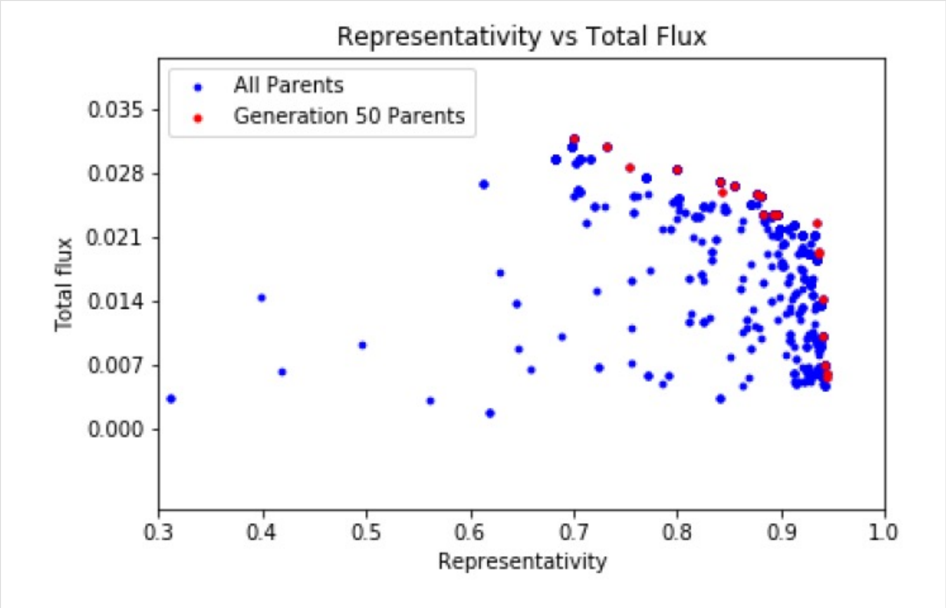
Heuristic Design Objectives

Maximize flux representativity

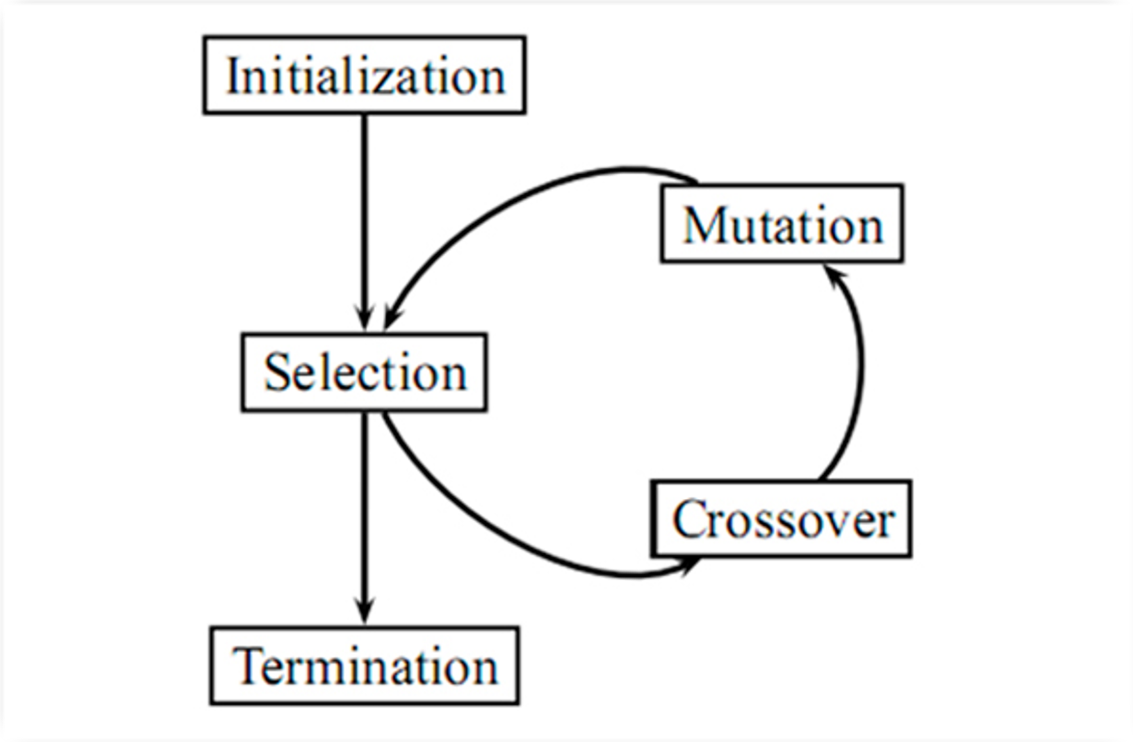
Improves the relevance

Maximize flux magnitude

Decreases measurement time



Design Algorithm
NSGA2 Genetic Algorithm



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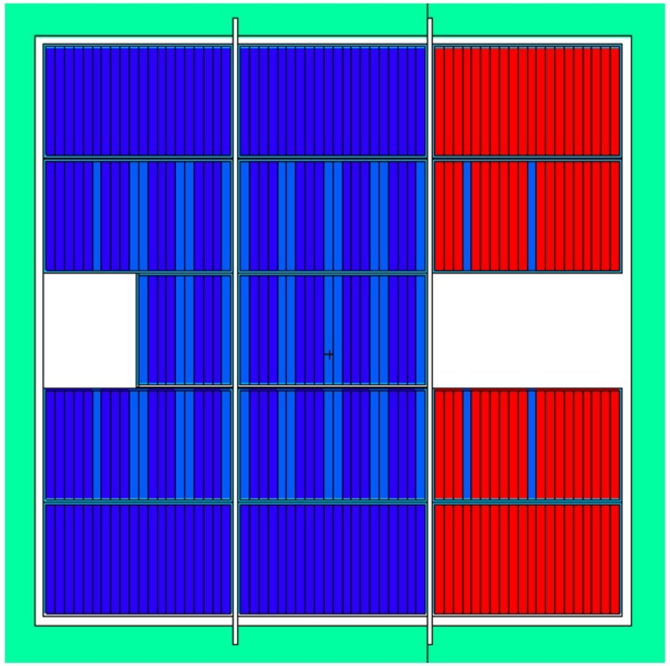
Human Design



Color Key:

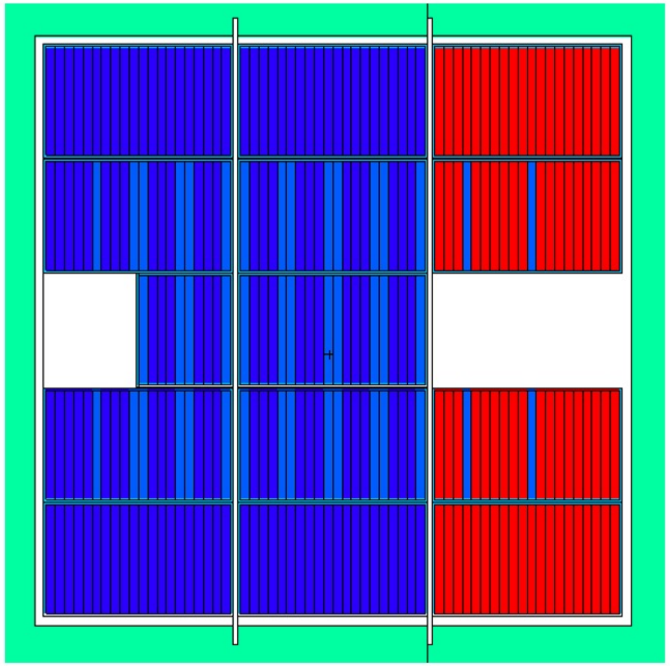
Uranium

Lead

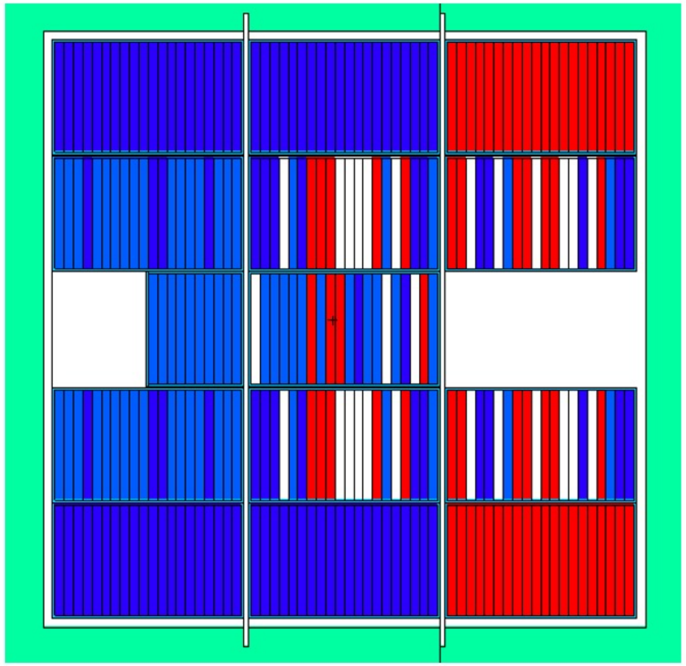
Polyethylene

Void

Human Design



AI Design

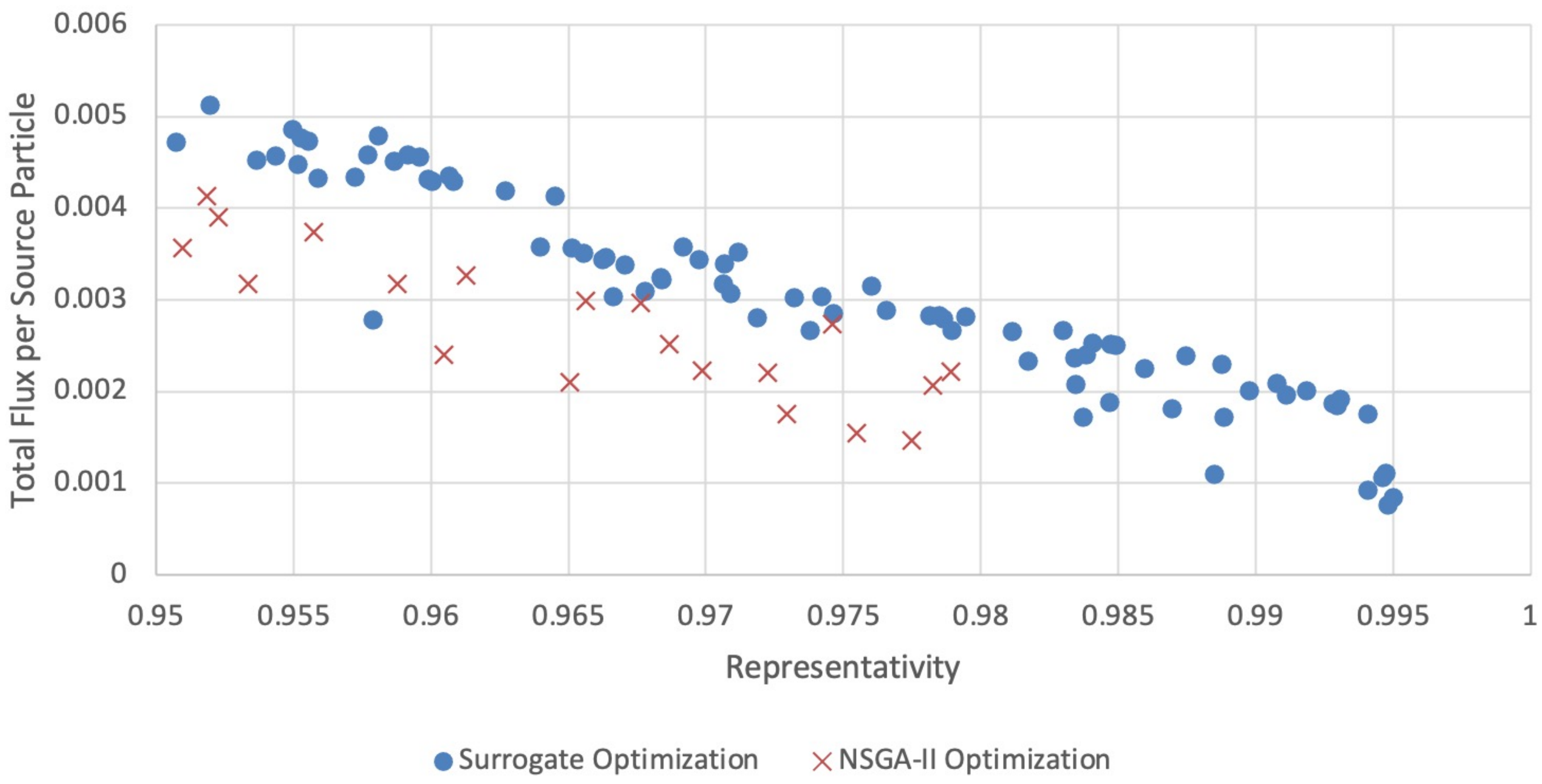


Color Key:

- Uranium
- Lead
- Polyethylene
- Void

2X Performance
on Design Objectives

Neural Network Acceleration of Genetic Algorithms



Massimo Salvatores

Massimo Salvatores

“Simple is beautiful”

John Lloyd

John Lloyd

“Not only have they not created artificial intelligence, they haven't yet created artificial stupidity.”