
Recent Advances in Model-Order Reduction for Radiation Transport Simulations

Jean Ragusa

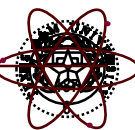
Department of Nuclear Engineering
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Center for Large-Scale Scientific Simulations



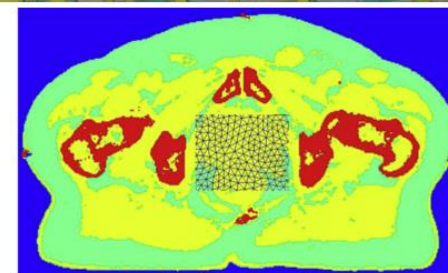
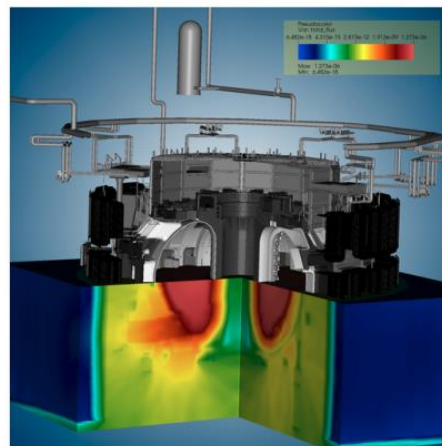
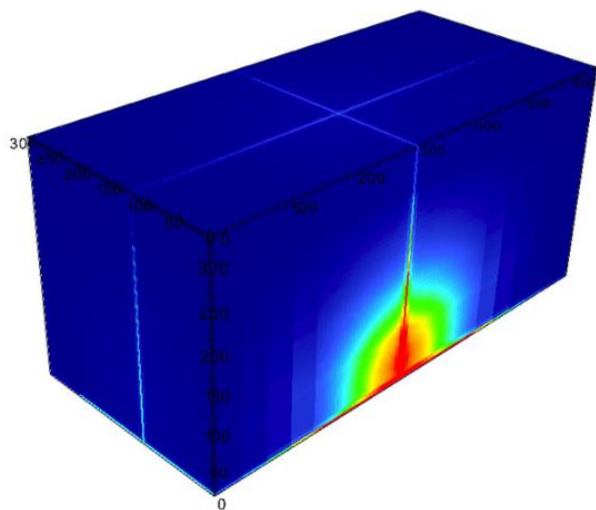
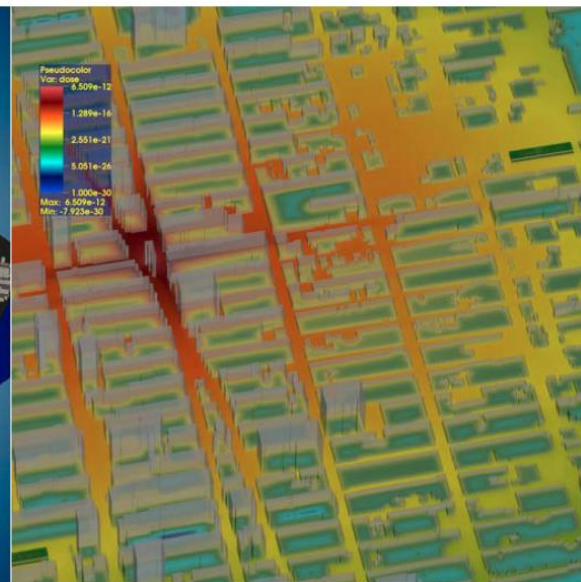
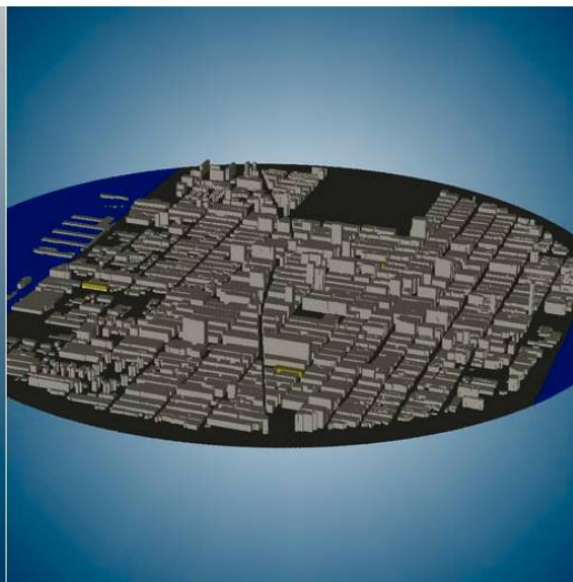
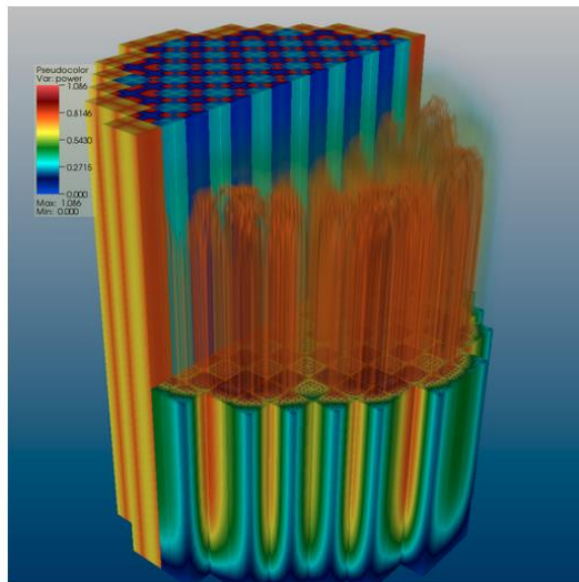
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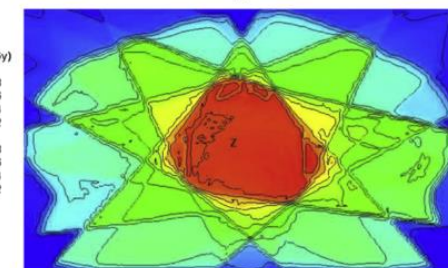
Brown Univ., ICERM Computational Learning for Model Reduction, Jan. 6-10, 2025



Radiation Transport Is Ubiquitous



a



b



Outline

1. Background on Radiation Transport
 - A. Motivations for (*p*arametric) ROM for Radiation Transport
 - B. Crash course on Radiation Transport

2. Reduced-Order Models for Radiation Transport
 - A. Projection-based *p*ROM:
 - i. Minimally-invasive approach
 - ii. Affine decomposition of operators
 - B. Non-intrusive *p*ROM
 - i. Gaussian process regression, MARS
 - C. Operator inference for *p*ROM
 - i. Linear and Nonlinear Frameworks
 - D. Operator inference for *time-d*ependent ROM (linear manifolds)
 - E. Diffusion-based ROM + Discrepancy Emulation (*if time permits*)

3. Conclusions and Outlook



Outline

1. Background on Radiation Transport

- A. *Motivations for (parametric) ROM for Radiation Transport*
- B. *Crash course on Radiation Transport*

2. Reduced-Order Models for Radiation Transport

- A. *Projection-based pROM:*
 - i. Minimally-invasive approach
 - ii. Affine decomposition of operators
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- C. *Operator inference for pROM*
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3. Conclusions and Outlook



The Linear Boltzmann Transport Equation

- Integro-differential equation

$$\left(\vec{\Omega} \cdot \vec{\nabla} + \sigma_t(\vec{r}, E)\right) \Psi(\vec{r}, \vec{\Omega}, E) = \frac{1}{4\pi} \int_{4\pi} d\Omega' \int dE' \sigma_s(\vec{r}, E' \rightarrow E) \Psi(\vec{r}, \vec{\Omega}', E') + S_{\text{fixed}}(\vec{r}, \vec{\Omega}, E)$$

- Conversation statement in phase space (**losses = gains**)

- 6-dimensional phase-space**: space($\vec{r}, 3$) + energy($E, 1$) + direction($\vec{\Omega}, 2$)

- $\Psi(\vec{r}, \vec{\Omega}, E)$: energy-dependent angular “flux” (“flux” \rightsquigarrow particle/energy density)

- neutral particles** = neutrons; photons; coupled neutrons/photons

- can be amended to include time dependence, production from fission

$$\frac{1}{v(E)} \frac{\partial \Psi(t, \vec{r}, \vec{\Omega}, E)}{\partial t}$$

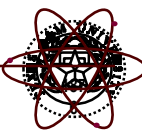
$$\frac{\chi(E)}{4\pi} \int_{4\pi} d\Omega' \int dE' \nu \sigma_f(\vec{r}, E') \Psi(\vec{r}, \vec{\Omega}', E')$$

- can be amended (Boltzmann-Fokker-Planck) for charged particles

- Outcome of particle interactions (cross-section material properties)

$$\sigma_t(\vec{r}, E), \quad \sigma_s(\vec{r}, E), \quad \sigma_s(\vec{r}, E' \rightarrow E) = \sigma_s(\vec{r}, E) P_s(E' \rightarrow E)$$

total , scattering, differential scattering = scattering \times transfer probability



Parametric Radiation Transport

$$\left(\vec{\Omega} \cdot \vec{\nabla} + \sigma_t(\vec{r}, E)\right) \Psi(\vec{r}, \vec{\Omega}, E) = \frac{1}{4\pi} \int_{4\pi} d\Omega' \int dE' \sigma_s(\vec{r}, E' \rightarrow E) \Psi(\vec{r}, \vec{\Omega}', E') + S_{\text{fixed}}(\vec{r}, \vec{\Omega}, E)$$

■ **Parametric** full-order model (FOM):

➤ **Parameters:**

- Volumetric + boundary sources
- Material properties (cross sections)

➤ **Multi-query problems**

• **Design optimization**

- Shielding
- Detection
- Therapeutics
- Power

• **Uncertainty Quantification**

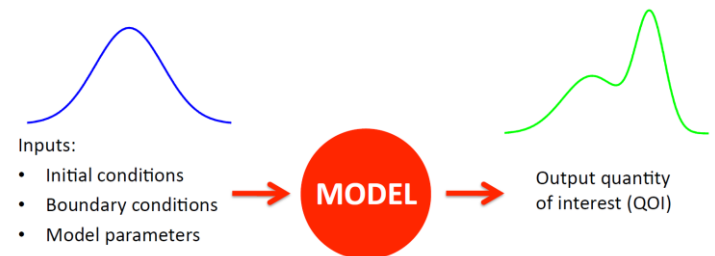
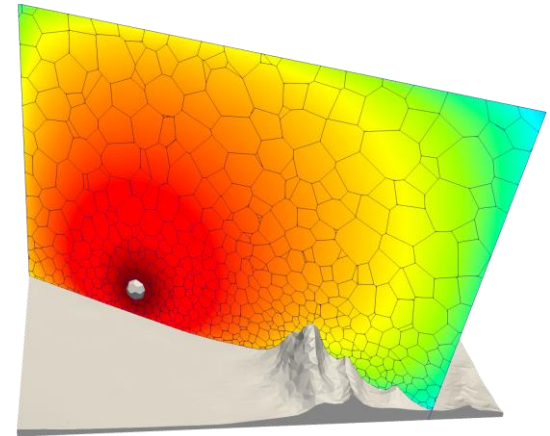
- Cross-section error
- Manufacturing uncertainty

• **Real-time applications**

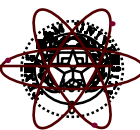
- Reactor monitoring
- Defense applications

• **Design of Experiments**

➤ **Ideally suited for parametric ROM (pROM)**



- Quantify the impact of input uncertainties on output QOI
- Propagate input uncertainty through the computational model
- Nonlinear transformation of input uncertainty



Phase-space Discretization

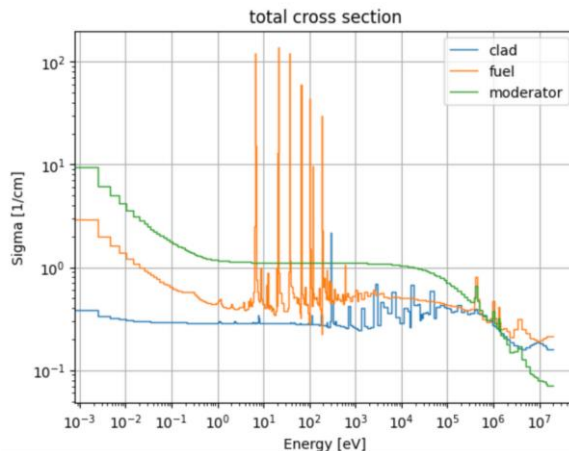
- **Energy variable:** $E \in \mathcal{E} = [0, E_{\max}] = \bigcup_{g=1}^G [E_{g+1}, E_g]$
- G : **10's to 100's** groups
- **Introduce** $\Psi^g(\vec{r}, \vec{\Omega}) = \int_{E_{g+1}}^{E_g} dE \Psi(\vec{r}, \vec{\Omega}, E)$ **and perform** $\int_{E_{g+1}}^{E_g} dE$ (Transport Eq.)

$$\left(\vec{\Omega} \cdot \vec{\nabla} + \sigma_t^g(\vec{r}) \right) \Psi^g(\vec{r}, \vec{\Omega}) = \frac{1}{4\pi} \sum_{g'=1}^G \int_{4\pi} d\Omega' \sigma_s^{g' \rightarrow g}(\vec{r}) \Psi^{g'}(\vec{r}, \vec{\Omega}') + S_{\text{fixed}}^g(\vec{r}, \vec{\Omega})$$

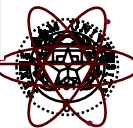
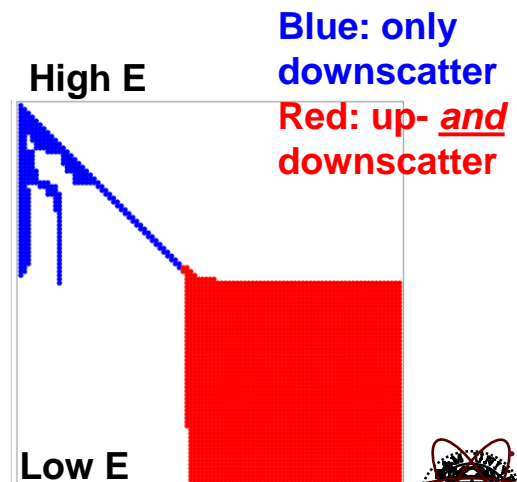
$$1 \leq g \leq G$$

- G coupled Transport eqs.
- **Energy** coupling occurs on the RHS. LHS is **diagonal** in groups

**Material properties:
log-log scale!**



Sparsity pattern of energy transfers:



Phase-space Discretization

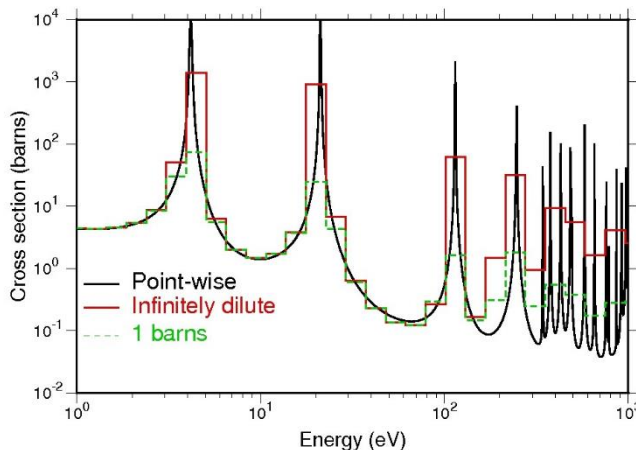
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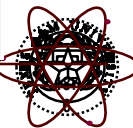
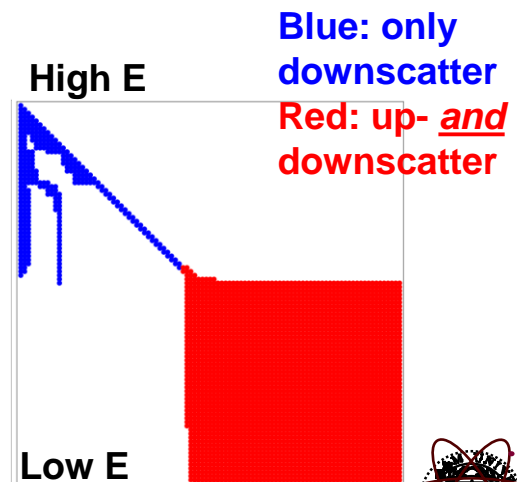
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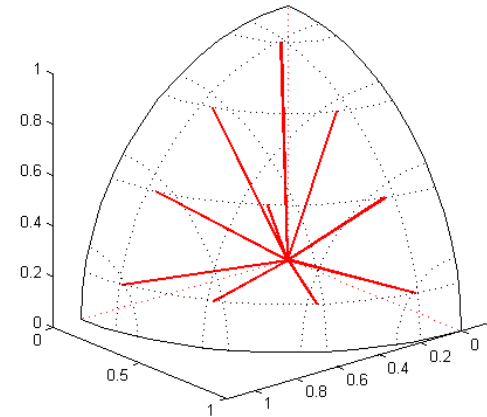


Sparsity pattern of energy transfers:



Phase-space Discretization

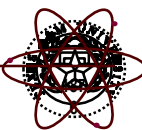
- **Angular variable:** $\vec{\Omega} \in \mathcal{S}^2$
- **Collocation (angular quadrature)** $(w_d, \vec{\Omega}_d)_{1 \leq d \leq N_\Omega}$
- N_Ω : 100's to 1000's directions
- **Solve for** $1 \leq g \leq G$ **and** $1 \leq d \leq N_\Omega$



$$\left(\vec{\Omega}_d \cdot \vec{\nabla} + \sigma_t^g(\vec{r}) \right) \Psi^g(\vec{r}, \vec{\Omega}_d) = \frac{1}{4\pi} \sum_{g'=1}^G \sigma_s^{g' \rightarrow g}(\vec{r}) \underbrace{\sum_{d'=1}^{N_\Omega} w_{d'} \Psi^{g'}(\vec{r}, \vec{\Omega}_{d'})}_{=\Phi^{g'}(\vec{r})} + S_{\text{fixed}}^g(\vec{r}, \vec{\Omega}_d)$$

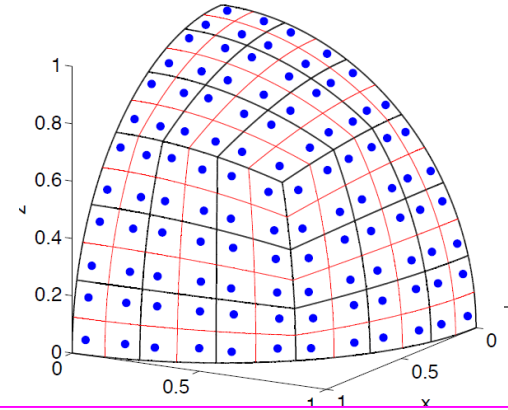
with: $\Psi_d^g(\vec{r}) = \Psi^g(\vec{r}, \vec{\Omega}_d)$ and the angle-integrated solution $\Phi^g(\vec{r}) = \sum_{d'=1}^{N_\Omega} w_{d'} \Psi_{d'}^g(\vec{r})$

- $G \times N_\Omega$ coupled Transport eqs.
- **Angular** coupling occurs on the RHS.
- LHS is still **diagonal** in groups and directions



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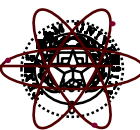
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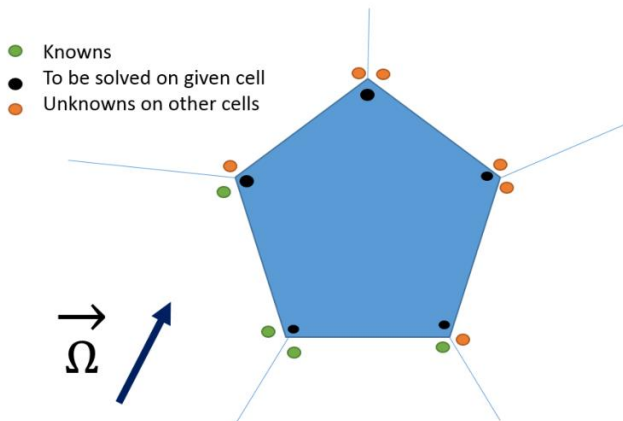
Phase-space Discretization

- Solving for a given group g (omitted below) and a given direction d :

$$\left(\vec{\Omega}_d \cdot \vec{\nabla} + \sigma_t(\vec{r}) \right) \Psi_d(\vec{r}) = \frac{\sigma_s(\vec{r})}{4\pi} \Phi(\vec{r}) + S_{\text{fixed+inscattering into } g}$$

- **Conundrum:** the unknown and its angular integral appear on both sides.
- **Lag the angular redistribution** (~fixed-point iterative process):
- **Spatial** variable: DGFEM with upwinding ↑

$$\left(\Psi_d, -(\vec{\Omega}_d \cdot \vec{\nabla} + \sigma_t) b_i \right)_K + \langle \Psi_d, \vec{\Omega}_d \cdot \vec{n} b_i \rangle_{\partial K^+} = (q, b_i)_K + \langle \Psi_d^\uparrow, |\vec{\Omega}_d \cdot \vec{n}| b_i \rangle_{\partial K^-}$$



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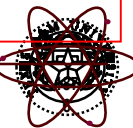
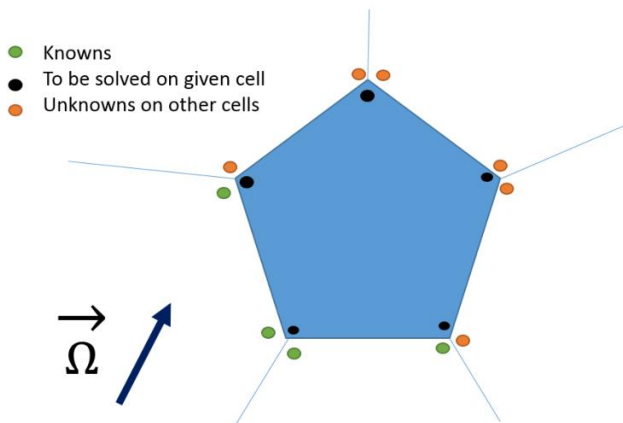
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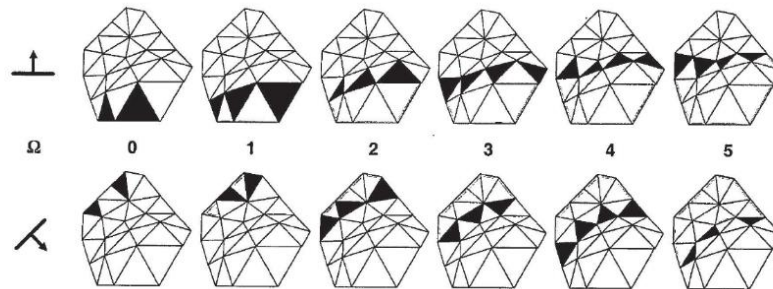
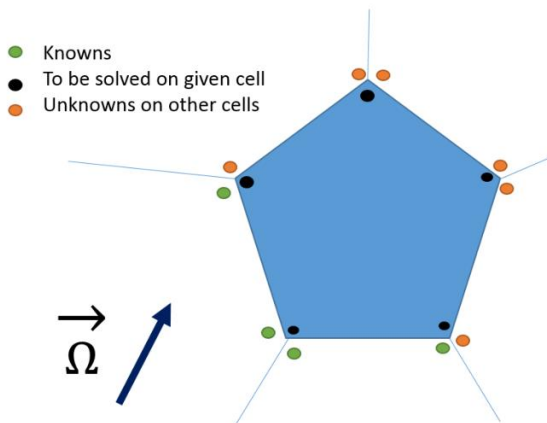
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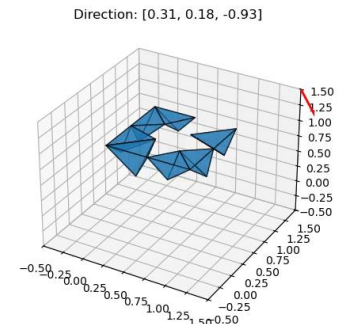
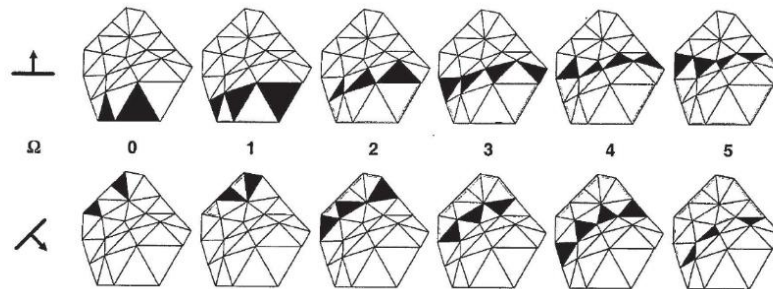
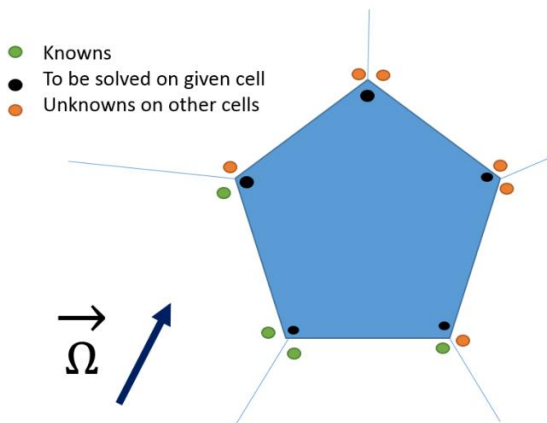
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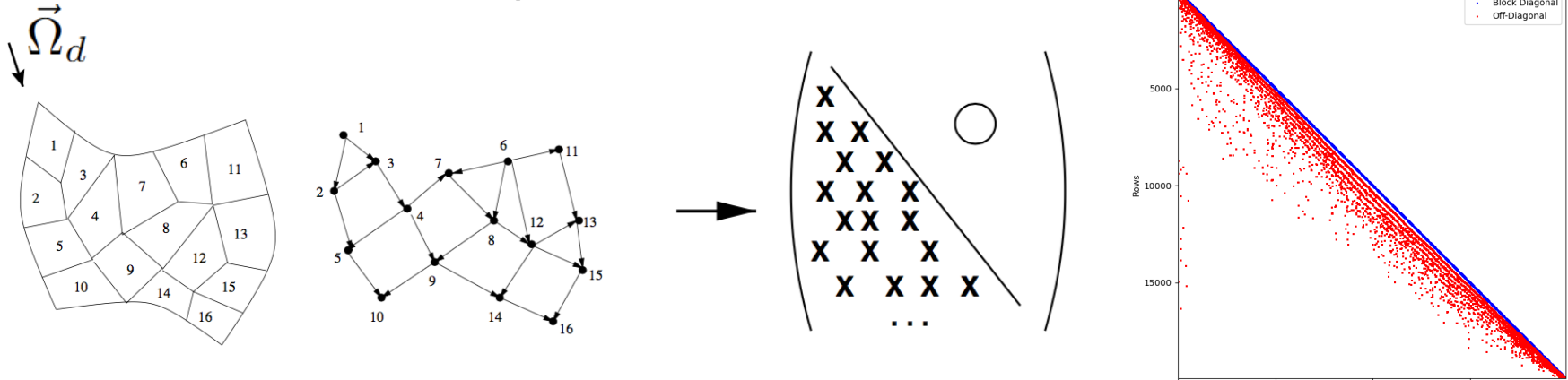
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Transport Sweeps: a Matrix-free Process

- The “transport sweep” is a **task-directed graph** that makes the advection-reaction operator block lower triangular



Formidable computational problem:

- Space: $N_x \times N_y \times N_z$ cells (say $100 \times 100 \times 100 = 1$ million spatial cells)
- Angle: 50 - 5,000 directions (say 1,000)
- Groups: several dozens and up (say 100)
- 8 spatial degrees of freedom/cell (discontinuous finite elements)
- Total: **about 1 trillion (10^{12}) unknowns**, (figures > 1 trillion are not infrequent ...)

Key Points:

- Radiation transport is a linear problem $Ax = b$
- The number of unknowns per vertex of a mesh is gigantic ($> 10,000$)
- Due to the size of the problem, matrix A is not available (not built nor stored)

Transport Sweeps: a Matrix-free Process

- The “transport sweep” is a **task-directed graph** that makes the advection-reaction

Equivalent to U.S. debt

On MIRA (BQ/G):

| dofs/cells | spatial cells/core | angles | groups | cores | total dofs |
|------------|--------------------|--------|--------|-------|------------|
| 8 | 4,096 | 80 | 3 | 1.5M | 12T |
| dofs/cells | spatial cells/core | angles | groups | cores | total dofs |
| 8 | 1 | 31,104 | 99 | 768k | 19T |



...2018 numbers ...

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Notation

- Parametric Transport Equation**

$$\left(\vec{\Omega} \cdot \vec{\nabla} + \sigma_t(\vec{r}, E) \right) \Psi(\vec{r}, \vec{\Omega}, E) = \frac{1}{4\pi} \int_{4\pi} d\Omega' \int dE' \sigma_s(\vec{r}, E' \rightarrow E) \Psi(\vec{r}, \vec{\Omega}', E') + S_{\text{fixed}}(\vec{r}, \vec{\Omega}, E)$$

- Angular integration:** $\Phi = D\Psi$

- Hence, the Transport Equation is:**

$$L(\sigma_t)\Psi = \Sigma(\sigma_s)\Phi + q_{\text{fixed}}$$

- Where is $Ax = b$?**

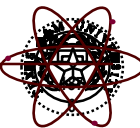
➤ **Standard solution procedure** (radiation codes implement L^{-1} in a **matrix-free** manner):
Moment form of the eqs.:

$$\begin{cases} \Psi^{(\ell+1)} = L^{-1}(\Sigma\Phi^{(\ell)} + q_{\text{fixed}}) \\ \Phi^{(\ell+1)} = D\Psi^{(\ell+1)} \end{cases}$$

$$\Rightarrow \underbrace{(I - DL^{-1}(\sigma_t)\Sigma(\sigma_s))}_{=A(\mu)} \Phi = \underbrace{DL^{-1}q_{\text{fixed}}}_{=b(\mu)}$$

➤ **Another acceptable view for MOR:**
Angular form of the eqs.:

$$\underbrace{(L(\sigma_t) - \Sigma(\sigma_s)D)}_{=A(\mu)} \Psi = \underbrace{q_{\text{fixed}}}_{=b(\mu)}$$



Angular Form vs. Moment Form ROM?

- Governing law: $L\Psi = \Sigma \underbrace{D\Psi}_{=\Phi} + q$

- The FOM solves always involve Ψ : $\begin{cases} \Psi^{(\ell+1)} = L^{-1}(\Sigma\Phi^{(\ell)} + q) \\ \Phi^{(\ell+1)} = D\Psi^{(\ell+1)} \end{cases} \implies (I - DL^{-1}\Sigma)\Phi = DL^{-1}q$

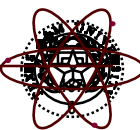
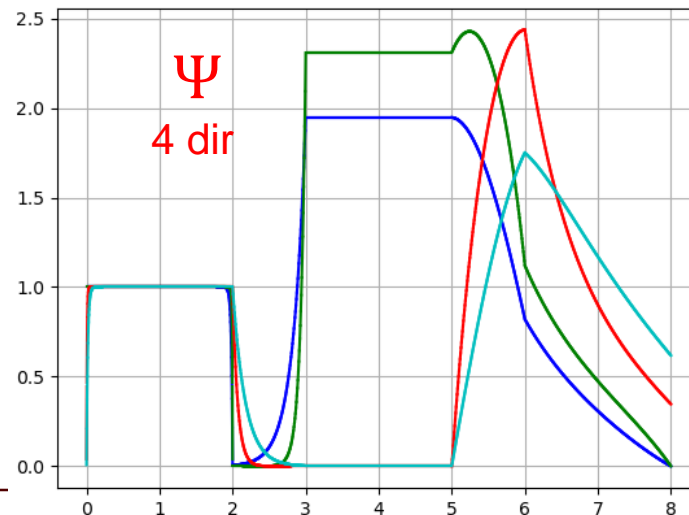
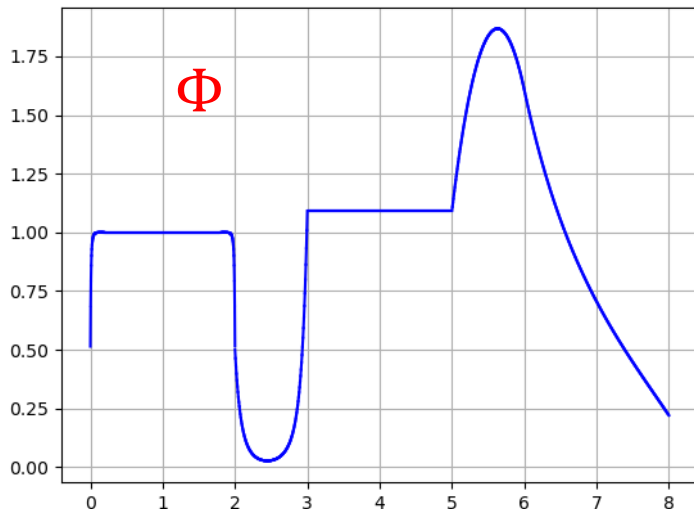
- However, the ROM is either built considering

$L\Psi = \Sigma D\Psi + q$ (angular form ROM) or $(I - DL^{-1}\Sigma)\Phi = DL^{-1}q$ (moment form)

- If one only reconstructs Φ , only angle-integrated quantities can be calculated

$$RR = \int_V d^3 \int dE \int_{4\pi} d\Omega \sigma(\vec{r}, E) \Psi(\vec{r}, E, \vec{\Omega}) = \int_V d^3 \int dE \sigma(\vec{r}, E) \Phi(\vec{r}, E)$$

- Ψ and Φ can be vastly different:



Why Transport and Not Diffusion?

- Under some circumstances (**low absorption, distributed sources, high scattering**), a Diffusion approximation is a suitable representation for Φ :

$$\left(-\vec{\nabla} \cdot D_g \vec{\nabla} + \sigma_t^g - \sigma_s^{g \rightarrow g} \right) \Phi^g = \sum_{g'=1, g' \neq g}^G \sigma_s^{g' \rightarrow g} \Phi^{g'} + S_{\text{fixed}}^g$$

- **“physics-guided” reduction: 4D problem (space (3) + energy (1)) instead of a 6D problem**
- **Then perform ROM on the multigroup diffusion eqs.**
 - **elliptic operators,**
 - **affine decomposition**
- But diffusion is not suitable for all transport problems:
 - **Problems with strong absorption, localized sources, low scattering**
 - **Problems that exhibit a streaming limit (hyperbolic nature)**
 - **→ low decay of singular values**
 - **Large Kolmogorov width**



Parametric MOR

- Model-order reduction (MOR) reduces the computational complexity of mathematical models in numerical simulations
- Model + input parameters (*in*) \rightarrow PDEs \rightarrow discretization \rightarrow system with large # unknowns, N (degrees of freedom, DoFs)

Full Order Model (FOM): Solve $\mathbf{A}(\mathit{in})\vec{x} = \vec{b}(\mathit{in}), \quad \vec{x} \in \mathbb{R}^N$

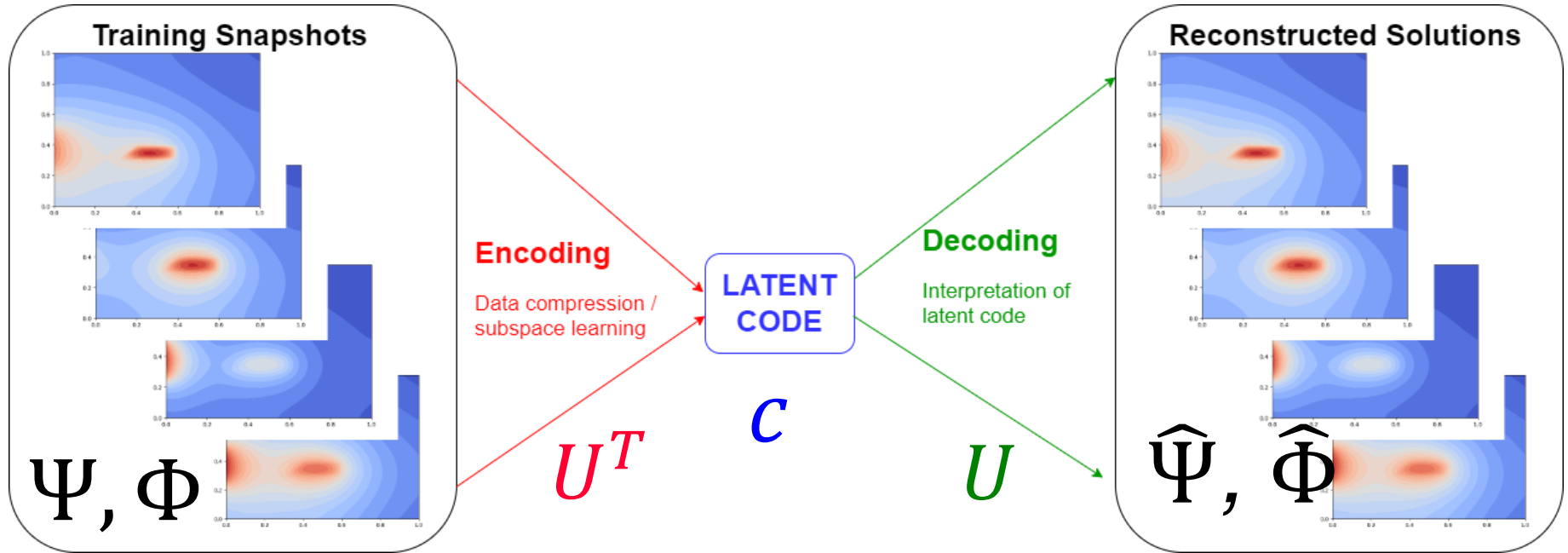
- Model order reduction reduces the computational complexity of a model by reducing the number of DoFs

Reduced Order Model (ROM): Solve $\mathbf{A}_r(\mathit{in})\vec{c} = \vec{b}_r(\mathit{in}), \quad \vec{c} \in \mathbb{R}^r, \quad (r \ll N)$
such that $\|\vec{x} - \mathbf{U}_r\vec{c}\| \leq C_r(\mathit{in})$ with $\lim_{r \rightarrow N} C_r = 0$.

- \mathbf{U}_r = reconstruction operator
- Data-driven, projection-based ROMs with linear manifolds
 - ROM solution linear combination of r size N basis vectors
 - Offline training phase and online prediction phase



Principle of MOR



$$c = U^T \Phi$$

$$\hat{\Phi} = U c$$

- Linear manifolds: e.g., subspace is obtained via SVD, greedy RB, ...
- Nonlinear manifolds: encoding/decoding learning (Willcox, Maday, ...)



Data-driven Subspace Learning: Principles

Offline phase:

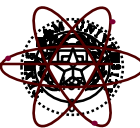
- Parameters: $\vec{\mu} = (\sigma_t, \sigma_s, q)$
- Solve FOM: $\mathbf{A}(\vec{\mu}_i)\vec{x}(\vec{\mu}_i) = \vec{b}(\vec{\mu}_i)$
 - $\mathbf{X} = (\vec{x}(\vec{\mu}_1), \vec{x}(\vec{\mu}_2), \dots, \vec{x}(\vec{\mu}_{n_{\text{snap}}}))$
- Proper orthogonal decomposition (POD)
 - Singular value decomposition (SVD): $\mathbf{X} = \mathbf{U}\mathbf{\Lambda}\mathbf{V}^T$
 - Information content $I(r) = \frac{\sum_{i=1}^r \lambda_i^2}{\sum_{i=1}^{n_{\text{snap}}} \lambda_i^2}$
 - Restrict subspace to the first r columns of \mathbf{U} as basis vectors \mathbf{U}_r

Online phase:

Unseen parameter $\vec{\theta}$

- Approximate solution
$$\vec{x}(\vec{\theta}) = \sum_{j=1}^r \vec{u}_j c_j(\vec{\theta}) = \mathbf{U}_r \vec{c}(\vec{\theta})$$
- Projection
$$\underbrace{\mathbf{W}^T(\vec{\theta})\mathbf{A}(\vec{\theta})\mathbf{U}_r}_{\mathbf{A}_r(\vec{\theta})} \vec{c}(\vec{\theta}) = \underbrace{\mathbf{W}^T(\vec{\theta})\vec{b}(\vec{\theta})}_{\vec{b}_r(\vec{\theta})}$$

Galerkin: $\mathbf{W} = \mathbf{U}_r$
Petrov-Galerkin: $\mathbf{W}(\vec{\theta}) = \mathbf{A}(\vec{\theta})\mathbf{U}_r$
- ROM solve
$$\mathbf{A}_r(\vec{\theta})\vec{c}(\vec{\theta}) = \vec{b}_r(\vec{\theta})$$



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1. Background on Radiation Transport
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 - B. Crash course on Radiation Transport

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 - A. **Projection-based *p*ROM:**
 - i. Minimally-invasive approach
 - ii. Affine decomposition of operators
 - B. *Non-intrusive p*ROM
 - i. Gaussian process regression, MARS
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3. Conclusions and Outlook



Minimally-invasive Transport ROM: Procedure

- Based on moment form of transport

$$\text{FOM: } \underbrace{(I - \mathbf{DL}(\vec{\theta})^{-1}\Sigma(\vec{\theta}))}_{\mathbf{A}(\vec{\theta})} \underbrace{\vec{\Phi}(\vec{\theta})}_{\vec{x}(\vec{\theta})} = \underbrace{\mathbf{DL}(\vec{\theta})^{-1}\vec{Q}}_{\vec{b}(\vec{\theta})}$$

$$\text{ROM: } \underbrace{\mathbf{W}^T(\vec{\theta})(I - \mathbf{DL}(\vec{\theta})^{-1}\Sigma(\vec{\theta}))\mathbf{U}_r}_{\mathbf{A}_r(\vec{\theta})} \vec{c}(\vec{\theta}) = \underbrace{\mathbf{W}^T(\vec{\theta})\mathbf{DL}(\vec{\theta})^{-1}\vec{Q}}_{\vec{b}_r(\vec{\theta})}$$

- Matrix-free $\mathbf{L}^{-1}(\vec{\theta})$ contained in \mathbf{A} and \vec{b} , need transport sweep for each POD mode + one for RHS

- Repeat for each NEW $\vec{\theta}$; Bottleneck due to full-order operation
- Minimally intrusive

GMRes: action of mat on vec

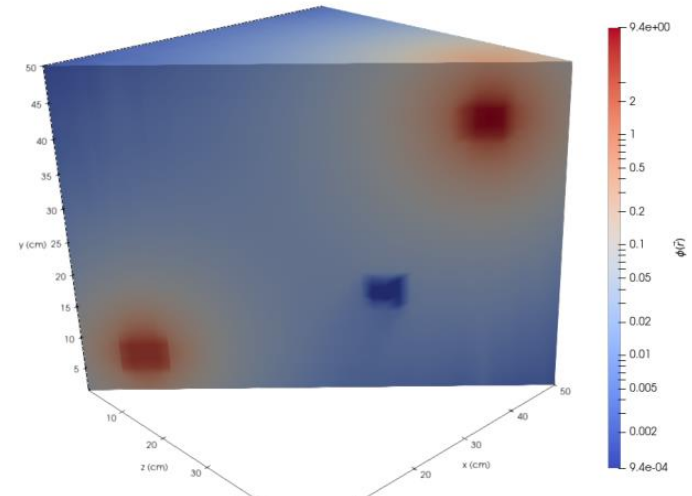
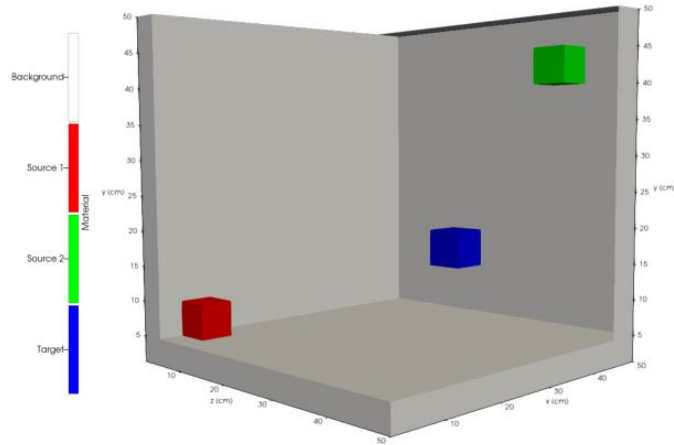
Offline phase

1. Generate $\{\vec{\Phi}(\vec{\mu}_i)\}_{i=1}^{n_{\text{snap}}}$ snapshots
2. Compute SVD, obtain POD modes \mathbf{U}_r

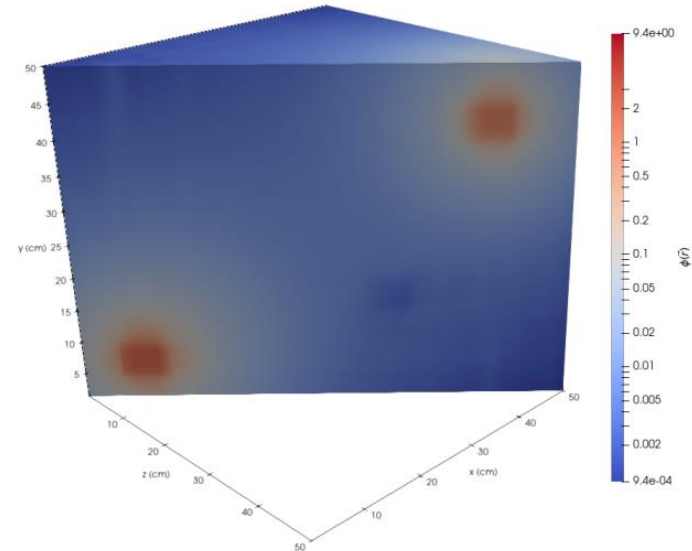
Online phase; For each $\vec{\theta}$:

1. Sweep $\mathbf{L}^{-1}(\vec{\theta})\Sigma(\vec{\theta})\vec{u}_j$, $j \in [1, r]$, assemble $\mathbf{A}(\vec{\theta})\mathbf{U}_r$
2. Sweep $\mathbf{L}^{-1}(\vec{\theta})\vec{Q}$, assemble $\vec{b}(\vec{\theta})$
3. Define test subspace $\mathbf{W}(\vec{\theta})$
 - Galerkin: $\mathbf{W} = \mathbf{U}_r$
 - Petrov-Galerkin: $\mathbf{W}(\vec{\theta}) = \mathbf{A}(\vec{\theta})\mathbf{U}_r$
4. Compute $\mathbf{A}_r(\vec{\theta}) = \mathbf{W}(\vec{\theta})^T \mathbf{A}(\vec{\theta})\mathbf{U}_r$ and $\vec{b}_r(\vec{\theta}) = \mathbf{W}(\vec{\theta})^T \vec{b}(\vec{\theta})$
5. Solve reduced system $\mathbf{A}_r(\vec{\theta})\vec{c}(\vec{\theta}) = \vec{b}_r(\vec{\theta})$
6. Reconstruct full-order solution from reduced coordinate $\vec{\Phi}^{\text{ROM}}(\vec{\theta}) = \mathbf{U}_r \vec{c}(\vec{\theta})$

Minimally-invasive Transport ROM: Results (1/2)



Some snapshots

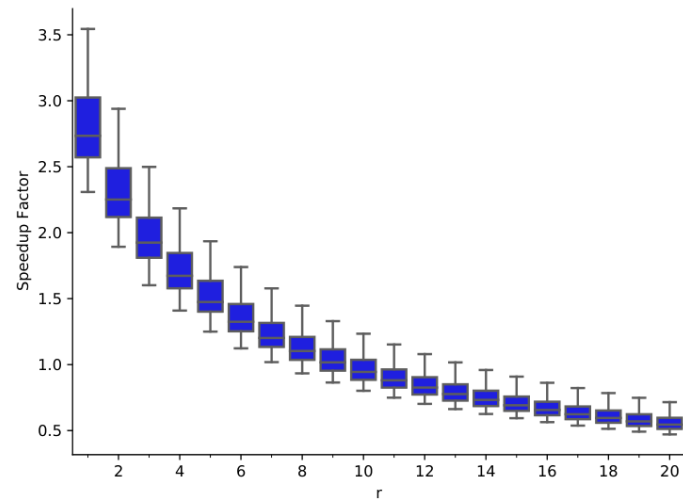
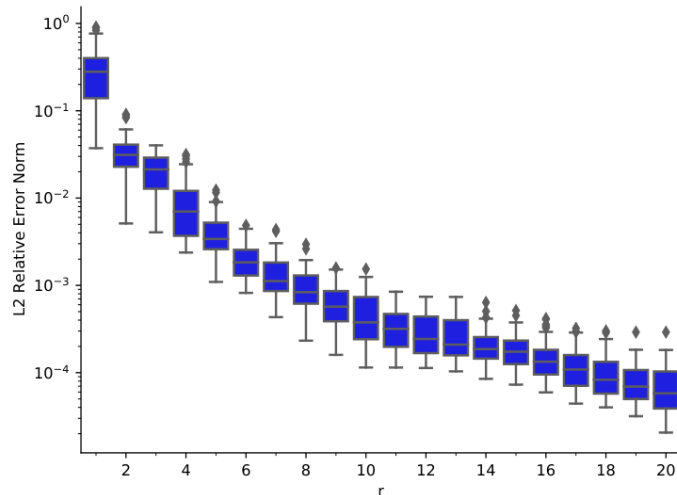
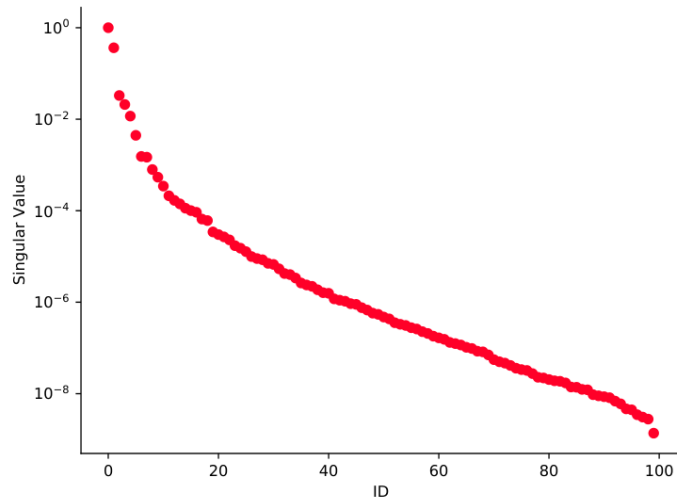


| Parameter | Material | | | |
|-------------------------------------|-------------------------|-------------------------|--------------------------|--------------------------|
| | Background | Target | Source 1 | Source 2 |
| $\Sigma_t \text{ (cm}^{-1}\text{)}$ | $\mathcal{U}(0.0, 0.1)$ | $\mathcal{U}(0.0, 2.0)$ | 2.0 | 0.3 |
| $c \text{ (cm}^{-1}\text{)}$ | $\mathcal{U}(0.5, 1.0)$ | $\mathcal{U}(0.0, 0.5)$ | 1.0 | 0.6 |
| $Q \text{ (par cm}^{-3}\text{)}$ | 0.0 | 0.0 | $\mathcal{U}(0.0, 10.0)$ | $\mathcal{U}(0.0, 10.0)$ |

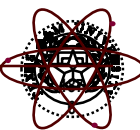
- $N \approx 1.14 \times 10^9$
- 100 snapshots
- 50 test cases



Minimally-invasive Transport ROM: Results (2/2)

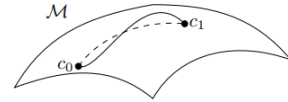
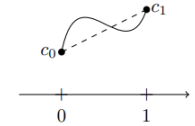


- Minimally invasive but low-speedups due to the need to perform a full-order operation (L^{-1} “transport sweep”) for each new parameter realization



Minimally-invasive Transport ROM: a way forward

- Interpolate the reduced operator using training data: (**OMMI**: Offline Maximizing Minimally Invasive)
- Linear interpolation vs. Grassmann manifold interpolation



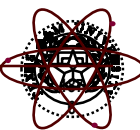
WIP

Offline phase

- Generate $\{\vec{\Phi}(\vec{\mu}_i)\}_{i=1}^{n_{\text{snap}}}$ snapshots
- Compute SVD, obtain POD modes \mathbf{U}_r
- Sweep $\mathbf{L}^{-1}(\vec{\mu}_i)\Sigma(\vec{\mu}_i)\vec{u}_j$, $i \in [1, n_{\text{snap}}]$ and $j \in [1, r]$, assemble $\mathbf{A}(\vec{\mu}_i)\mathbf{U}_r$
- Sweep $\mathbf{L}^{-1}(\vec{\mu}_i)\vec{Q}$, $i \in [1, n_{\text{snap}}]$, assemble $\vec{b}(\vec{\mu}_i)$
- Define test subspace $\mathbf{W}(\mu_i)$
 - Galerkin: $\mathbf{W} = \mathbf{U}_r$
 - Petrov-Galerkin: $\mathbf{W}(\mu_i) = \mathbf{A}(\vec{\mu}_i)\mathbf{U}_r$
- Compute $\mathbf{A}_r(\vec{\mu}_i) = \mathbf{W}(\vec{\mu}_i)^T \mathbf{A}(\vec{\mu}_i)\mathbf{U}_r$ and $\vec{b}_r(\vec{\mu}_i) = \mathbf{W}(\vec{\mu}_i)^T \vec{b}(\vec{\mu}_i)$ for $i \in [1, n_{\text{snap}}]$

Online phase; For each $\vec{\theta}$:

- Interpolate $\mathbf{A}_r(\vec{\theta})$ and $\vec{b}_r(\vec{\theta})$ using $\mathbf{A}_r(\vec{\mu}_i)$ and $\vec{b}_r(\vec{\mu}_i)$
- Solve reduced system $\mathbf{A}_r(\vec{\theta})\vec{c}(\vec{\theta}) = \vec{b}_r(\vec{\theta})$
- Reconstruct full-order solution from reduced coordinate $\vec{\Phi}^{\text{ROM}}(\vec{\theta}) = \mathbf{U}_r\vec{c}(\vec{\theta})$

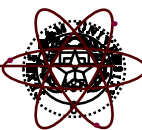


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3. Conclusions and Outlook



Affine-decomposed Radiation Transport: 1/3

- Based on angular form of transport:

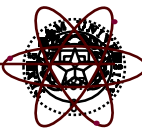
$$\underbrace{\left(\underbrace{\vec{\Omega}_d \cdot \vec{\nabla}}_{G_d} + \underbrace{\sigma_t^g(\vec{r})}_{T(\vec{\theta})} \right) \underbrace{\psi_d^g(\vec{r})}_{\vec{\Psi}} - \frac{1}{4\pi} \sum_{g'=1}^G \underbrace{\sigma_s^{g' \rightarrow g}(\vec{r})}_{\Sigma(\vec{\theta})} \sum_{d'=1}^{n_\Omega} w_{d'} \underbrace{\psi_{d'}^{g'}(\vec{r})}_{\vec{\Psi}}}_{L(\vec{\theta})} = \underbrace{Q_d^g(\vec{r})}_{\vec{Q}}$$

$$(G + T(\vec{\theta}) - \Sigma(\vec{\theta})D)\vec{\Psi} = \vec{Q}(\vec{\theta})$$

All reaction operators are **affine** w.r.t parameters. Let k denote material k :

$$M^k = \text{mass matrix, } \vec{f}^k = \text{load vector, } T^g(\vec{\theta}) = \sum_{k=1}^{N_{\text{mat}}} \sigma_t^{g,k} M^k,$$

$$\Sigma_{g,g'}(\vec{\theta})D_{d'} = \sum_{k=1}^{N_{\text{mat}}} \sigma_s^{g' \rightarrow g,k} M^k D_{d'}, \quad \vec{Q}_d^g(\vec{\theta}) = \sum_{k=1}^{N_{\text{mat}}} Q_d^{g,k} \vec{f}^k$$



Affine-decomposed Radiation Transport: 2/3

FOM:
$$\underbrace{(\mathbf{G} + \mathbf{T}(\vec{\theta}) - \Sigma(\vec{\theta})\mathbf{D})}_{\mathbf{A}(\vec{\theta})} \underbrace{\vec{\Psi}(\vec{\theta})}_{\vec{x}(\vec{\theta})} = \underbrace{\vec{Q}}_{\vec{b}(\vec{\theta})}$$
 Recall:
not solved as is in codes

ROM:
$$\underbrace{\mathbf{W}^T(\vec{\theta})(\mathbf{G} + \mathbf{T}(\vec{\theta}) - \Sigma(\vec{\theta})\mathbf{D})\mathbf{U}_r}_{\mathbf{A}_r(\vec{\theta})} \vec{c}(\vec{\theta}) = \underbrace{\mathbf{W}^T(\vec{\theta})\vec{Q}}_{\vec{b}_r(\vec{\theta})}$$

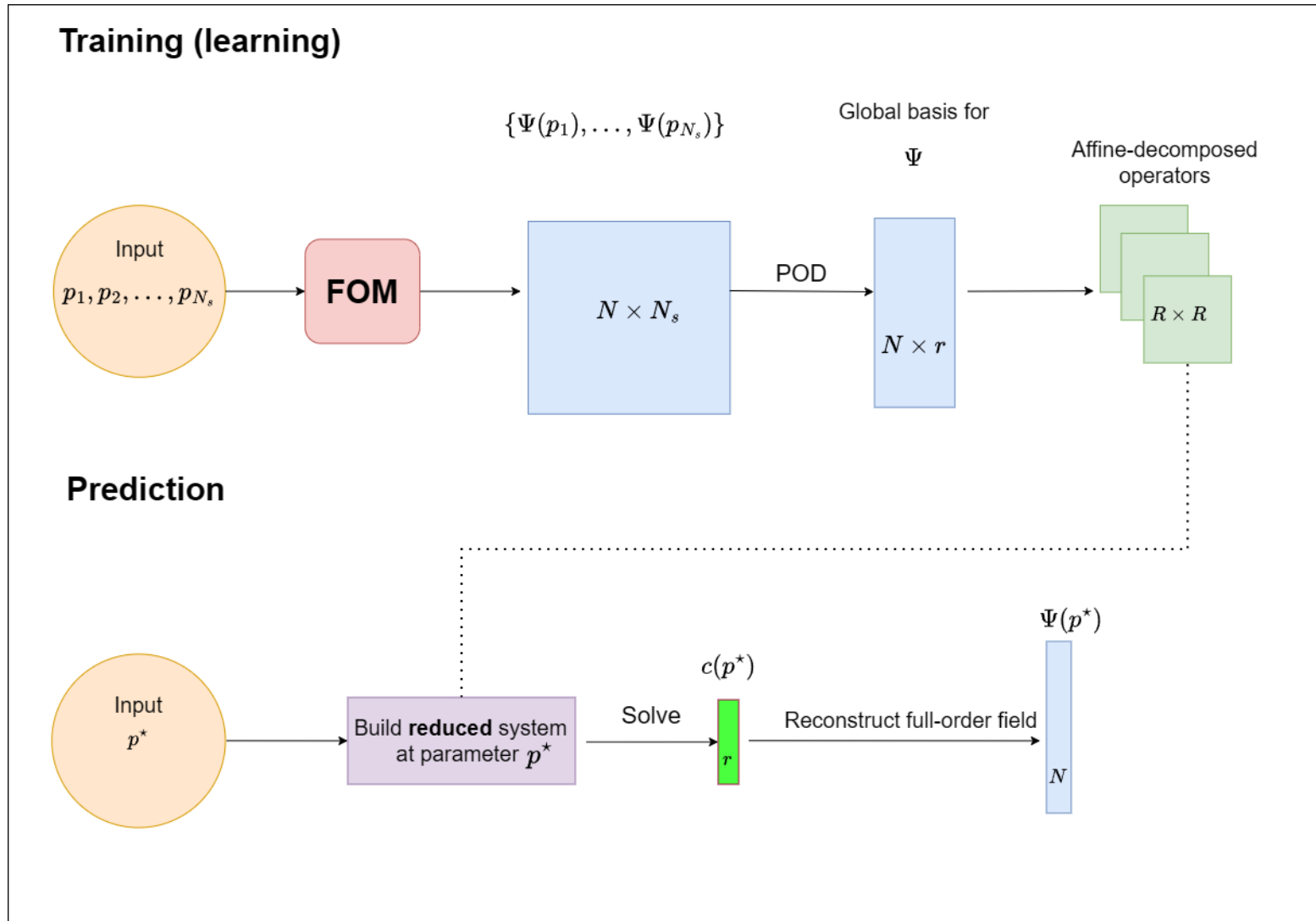
$$\mathbf{A}(\vec{\theta}) = \sum_k \theta_k \mathbf{A}^k, \quad \vec{b}(\vec{\theta}) = \sum_k \theta_k \vec{b}^k, \quad \mathbf{W}(\vec{\theta}) = \sum_{k'} \theta_{k'} \mathbf{W}^{k'}$$

$$\mathbf{A}_r(\vec{\theta}) = \sum_k \sum_{k'} (\theta_k \theta_{k'}) \underbrace{\left(\mathbf{W}_{k'}^T \mathbf{A}_k \mathbf{U}_r \right)}_{=\mathbf{A}_r^{kk'}}, \quad \vec{b}_r(\vec{\theta}) = \sum_k \sum_{k'} (\theta_k \theta_{k'}) \underbrace{\left(\mathbf{W}_{k'}^T \vec{b}_k \right)}_{=\vec{b}_r^{kk'}}$$

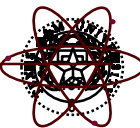
- **Code-intrusive** to precompute components $\mathbf{A}_r^{kk'}$ and $\vec{b}_r^{kk'}$ of reduced systems
- **Does not required full-order operations**
 - Potential for very large speedup



Affine-decomposed Radiation Transport: 2/3



– Potential for very large speedup



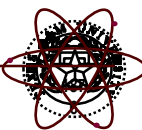
Affine-decomposed Radiation Transport: 3/3

Offline phase

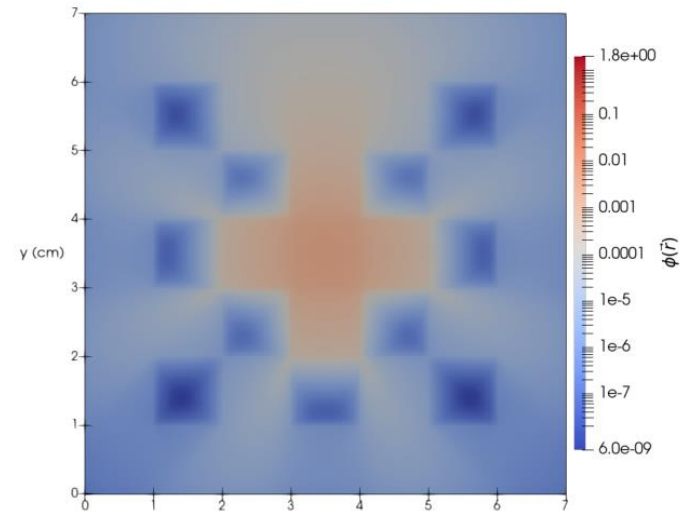
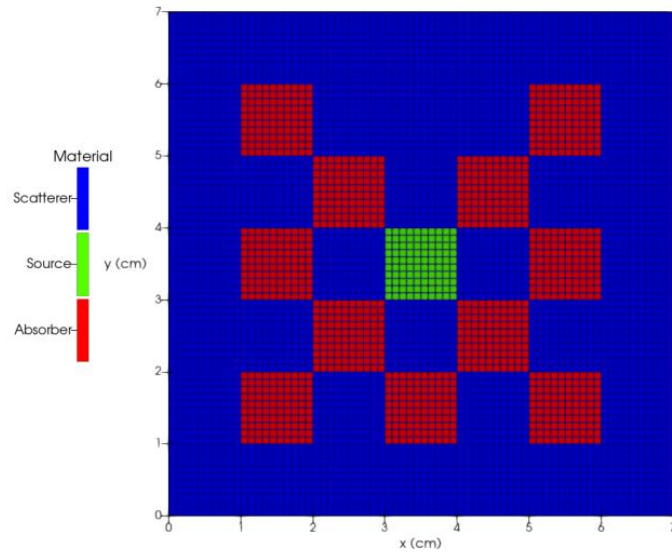
1. Generate snapshots $\{\vec{\Psi}(\vec{\mu}_i)\}_{i=1}^{n_{\text{snap}}}$
2. Compute SVD, get POD modes \mathbf{U}_r
3. Compute small projection terms $\mathbf{A}_r^{kk'} = \mathbf{W}_{k'}^T \mathbf{A}_k \mathbf{U}_r$, $\vec{b}_r^{kk'} = \mathbf{W}_{k'}^T \vec{b}_k$ from affine decomposition

Online phase; For each $\vec{\theta}$:

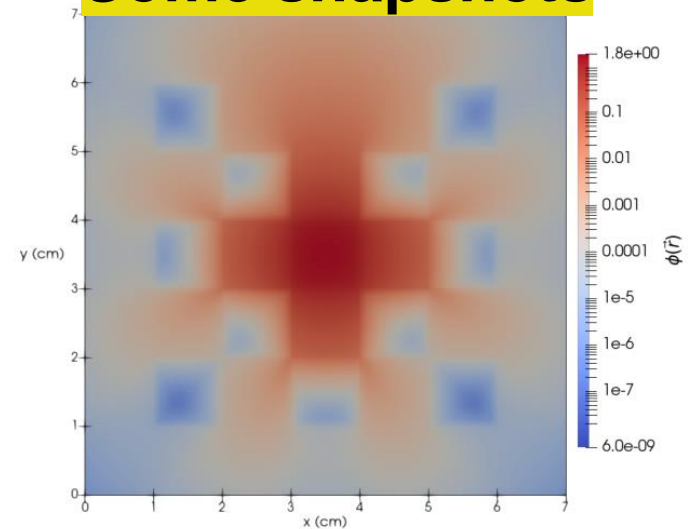
1. Define test subspace $\mathbf{W}(\vec{\theta})$
 - Galerkin: $\mathbf{W} = \mathbf{U}_r$
 - Petrov-Galerkin: $\mathbf{W}(\vec{\theta}) = \mathbf{A}(\vec{\theta}) \mathbf{U}_r$
2. Construct $\mathbf{A}_r(\vec{\theta}) = \sum_k \sum_{k'} (\theta_k \theta_{k'}) \mathbf{A}_r^{kk'}$
3. Construct $\vec{b}_r(\vec{\theta}) = \sum_k \sum_{k'} (\theta_k \theta_{k'}) \vec{b}_r^{kk'}$
4. Solve reduced system $\mathbf{A}_r(\vec{\theta}) \vec{c}(\vec{\theta}) = \vec{b}_r(\vec{\theta})$
5. Reconstruct solution from reduced coordinates $\vec{\Psi}^{\text{ROM}}(\vec{\theta}) = \mathbf{U}_r \vec{c}(\vec{\theta})$



Checkerboard bench.: Sweep-based vs. Affine-decomposed ROMs



Some snapshots

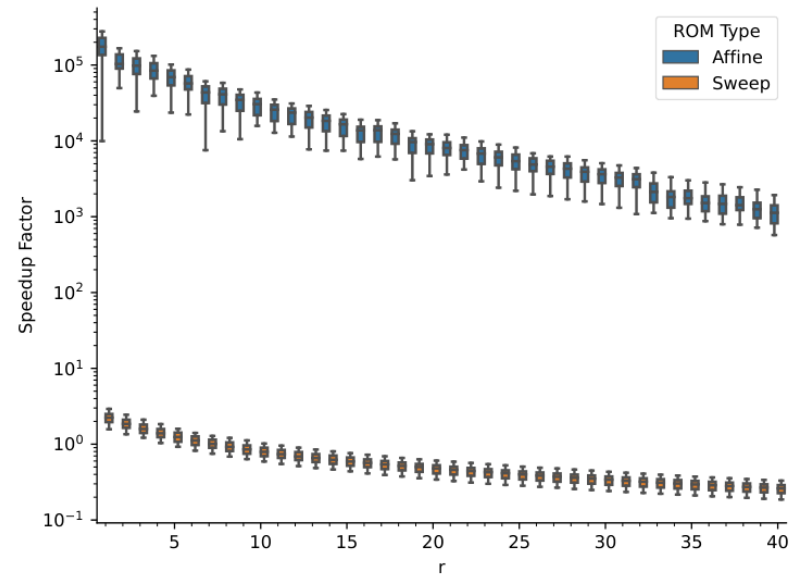
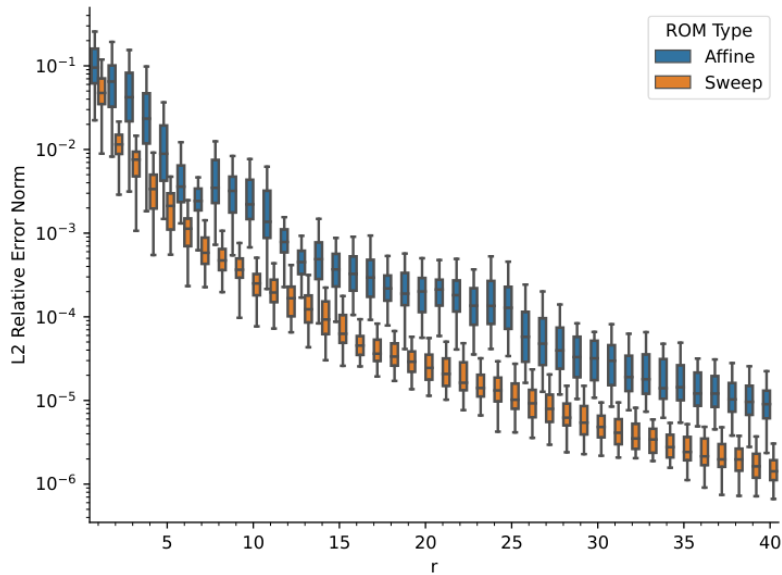
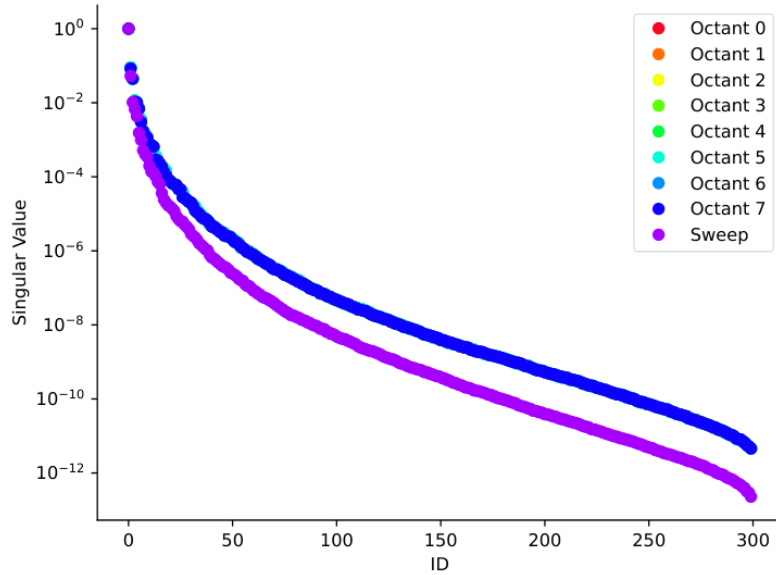


| Parameter | Material | |
|--------------------------|--------------------------|-------------------------|
| | Absorber | Scatterer |
| Σ_a (cm^{-1}) | $\mathcal{U}(7.5, 12.5)$ | $\mathcal{U}(0.0, 0.5)$ |
| Σ_s (cm^{-1}) | $\mathcal{U}(0.0, 5.0)$ | $\mathcal{U}(0.5, 1.5)$ |
| Q ($par\ cm^{-3}$) | 0 | $\mathcal{U}(0.0, 2.0)$ |

- $N \approx 2.01 \times 10^7$
- 300 snapshots
- 50 test cases

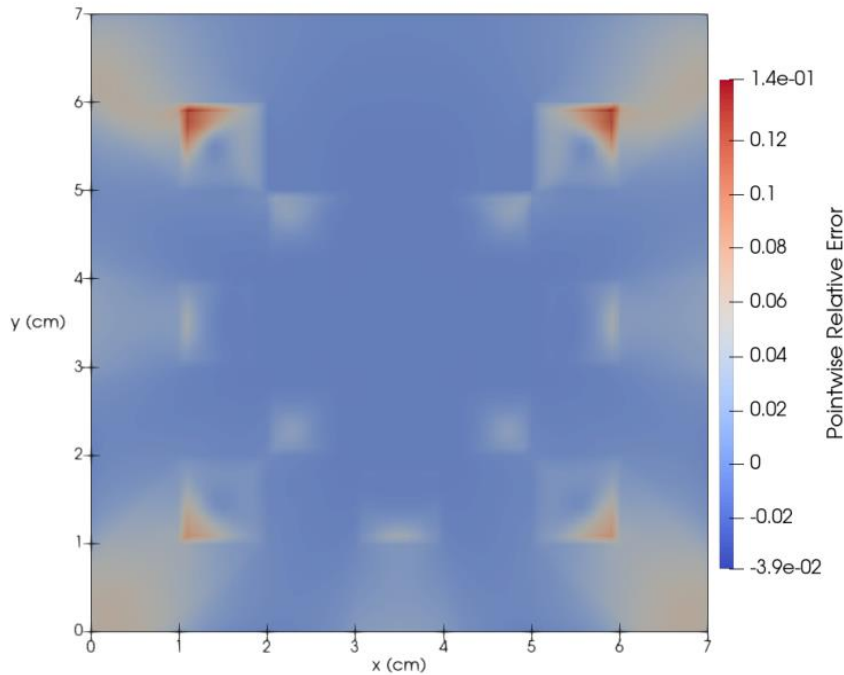


Checkerboard bench.: Sweep-based vs. Affine-decomposed ROMs

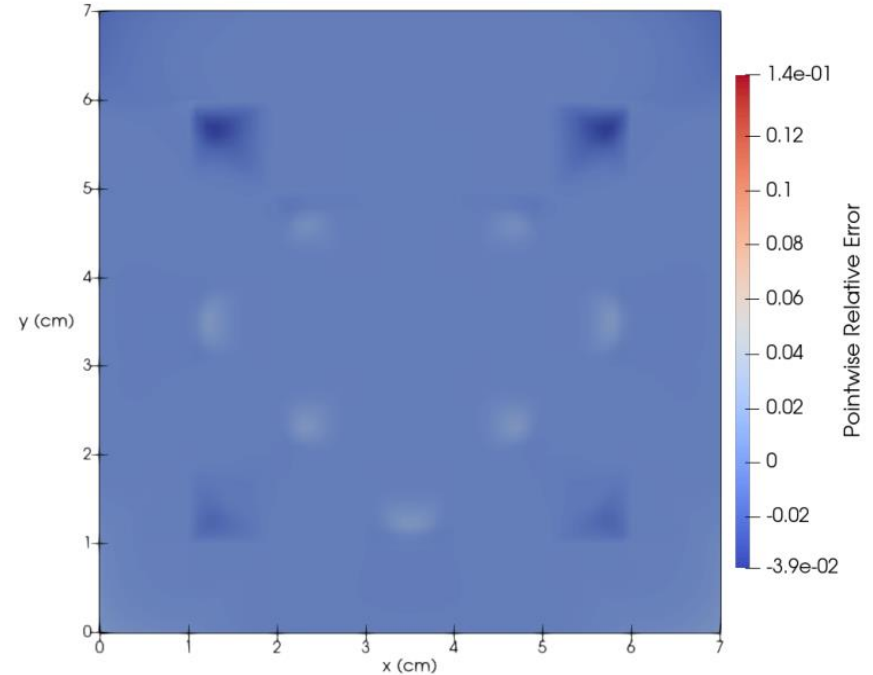


Checkerboard bench.: Sweep-based vs. Affine-decomposed ROMs

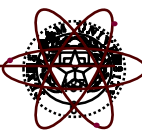
Pointwise errors



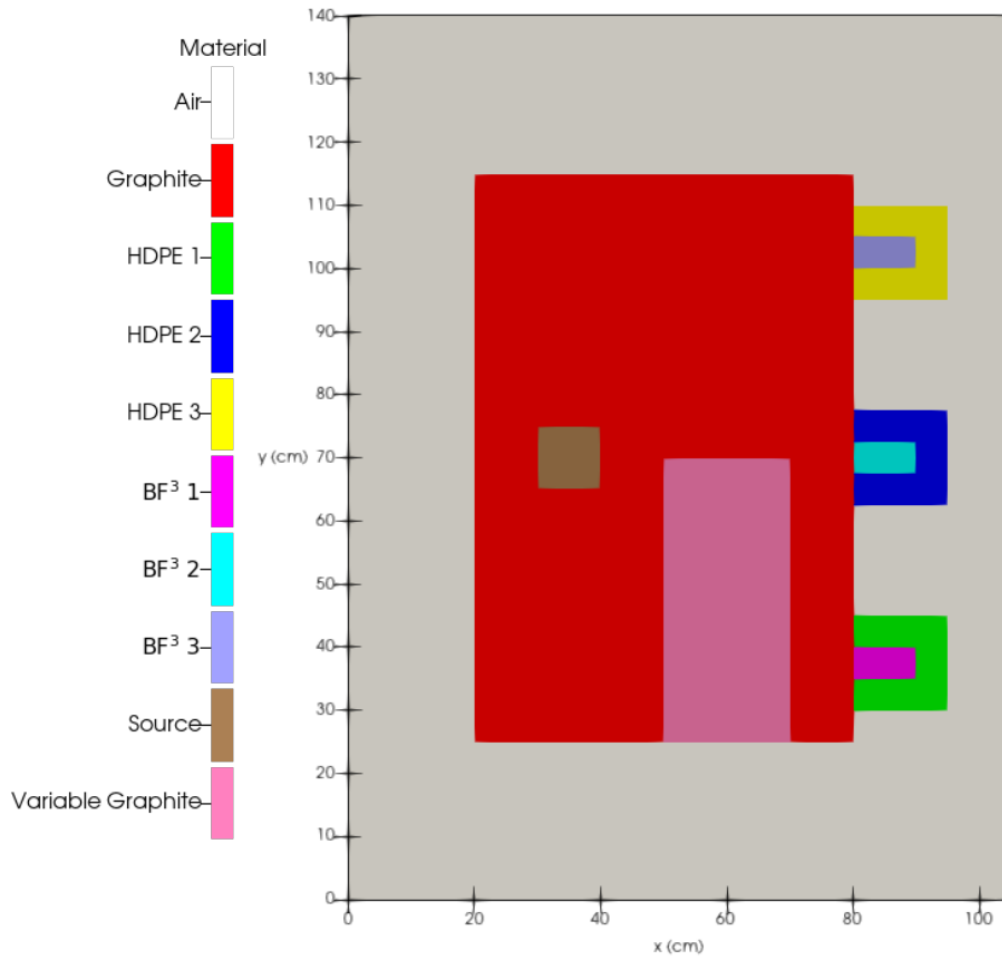
26 POD modes (affine)



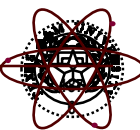
40 POD modes (affine)



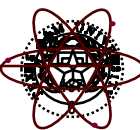
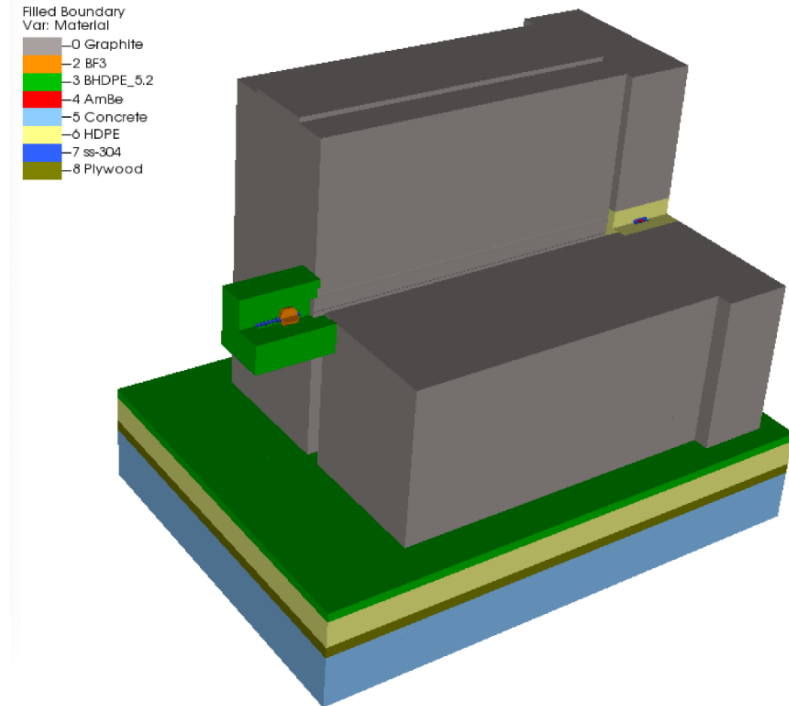
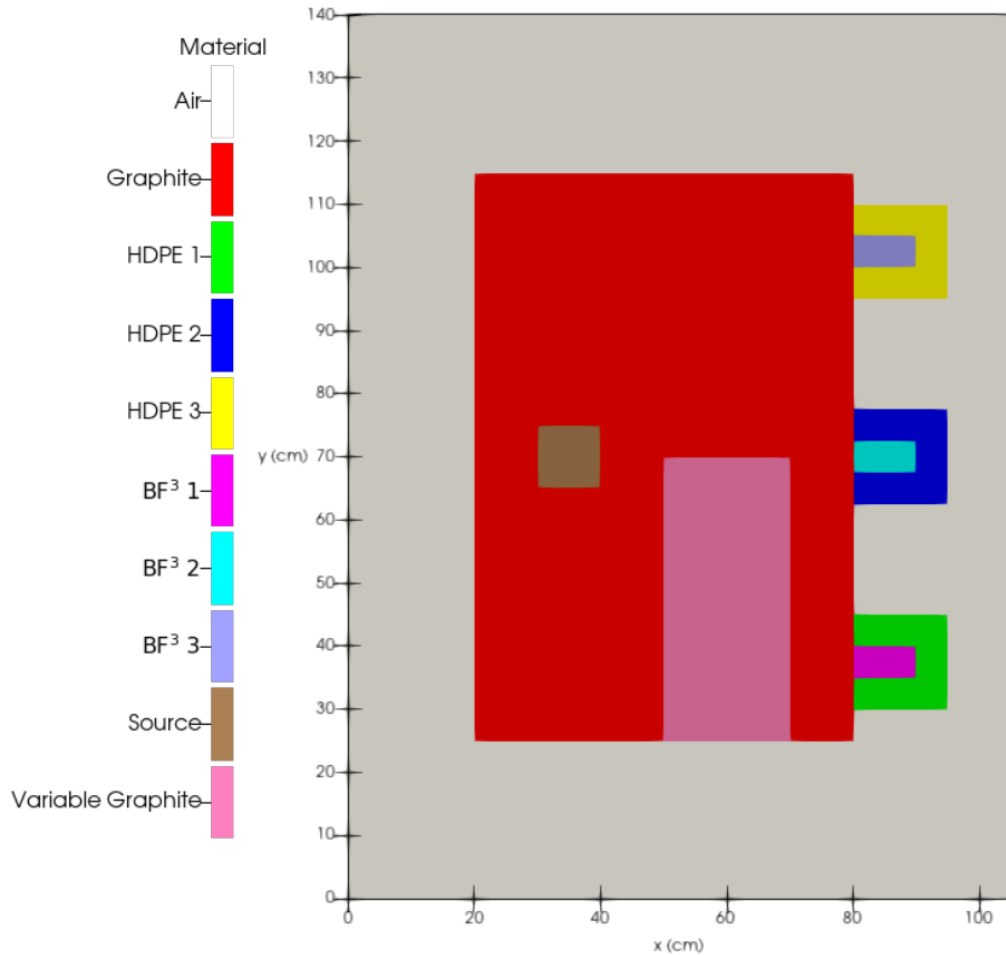
3-D graphite matrix with HDPE shrouds (affine ROM only)



- 4 parameters
 - Mass fraction of boron in HDPE 1-3 ($\mathcal{U}(0, 7.2)\%$)
 - Variable graphite density ($\mathcal{U}(0, 2.26) \text{ g/cm}^3$)
- 13 energy groups
- $N \approx 2.46 \times 10^8$
- 200 snapshots
- 100 test cases

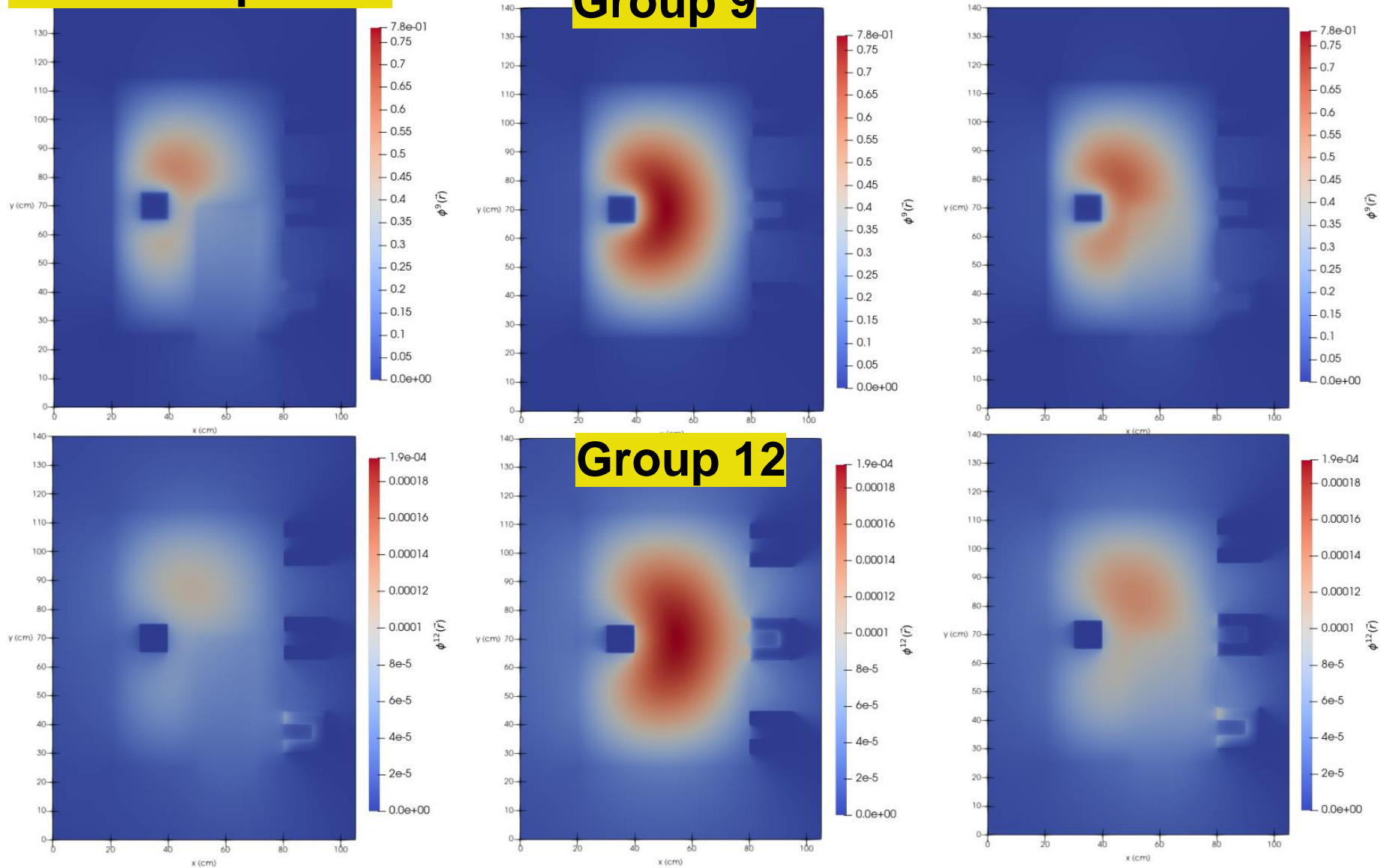


3-D graphite matrix with HDPE shrouds (affine ROM only)

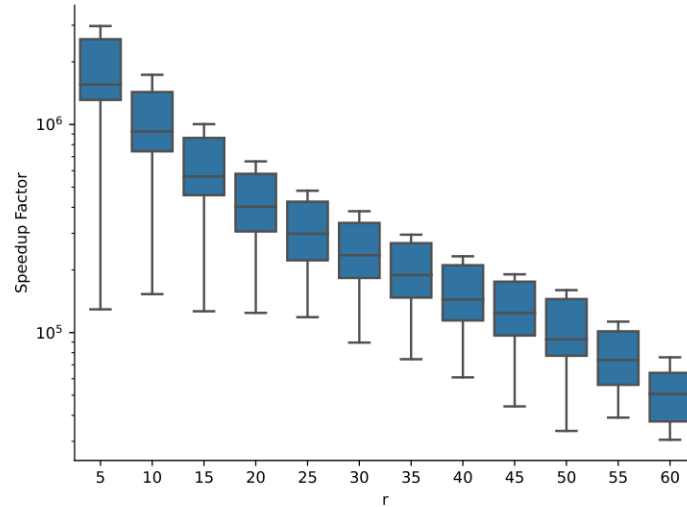
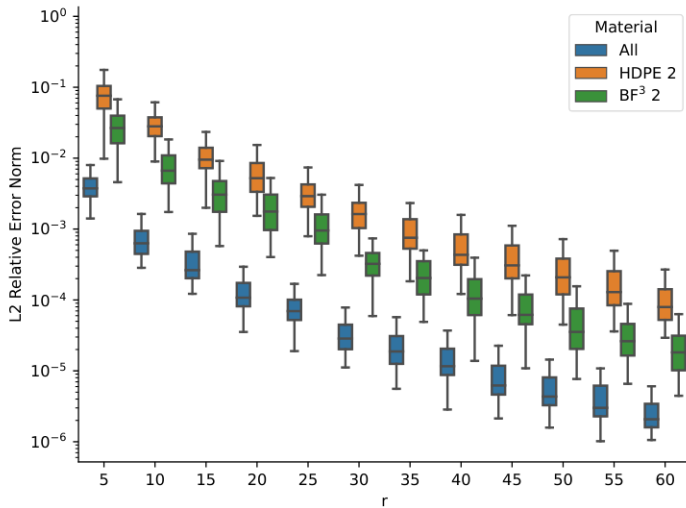
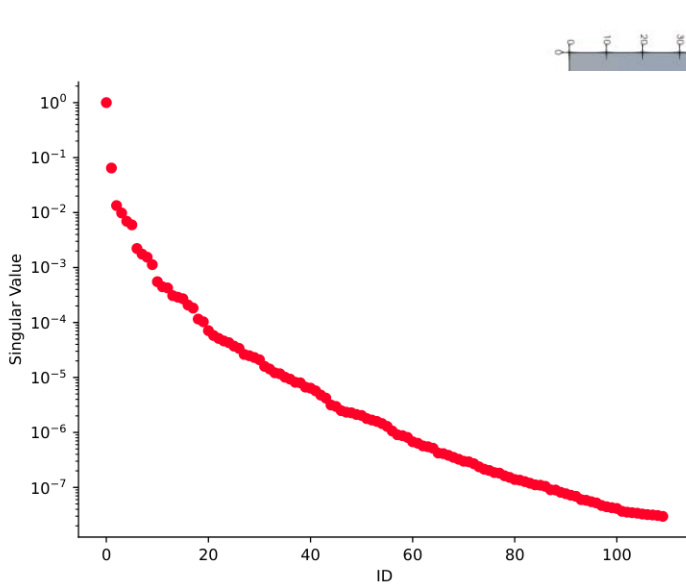


3-D graphite matrix with HDPE shrouds (affine ROM only)

Some snapshots



3-D graphite matrix with HDPE shrouds (affine ROM only)



60 POD modes

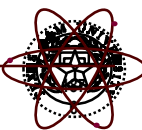


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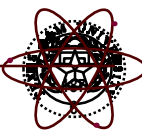
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 - i. Gaussian process regression, MARS
 - C. Operator inference for *p*ROM
 - i. Linear and Nonlinear Frameworks
 - D. Operator inference for *time-d*ependent ROM (linear manifolds)
 - E. Diffusion-based ROM + Discrepancy Emulation (*if time permits*)

3. Conclusions and Outlook



Motivation for Operator Inference

- Minimally-invasive 😊 ROM based on the moment form of the TE requires L^{-1} , a full-order operation 😞.
- Affine-decomposition of the angular form of the TE is very code-invasive 😞 but very effective 😊.
- Non-intrusive 😊 black-box schemes
 - such as POD + coefficient interpolation / regression / kriging
 - Only uses snapshot data and bypasses projection of the PDE.
 - Are we still adequately encoding the physics? 😊
- Can we effectively **infer the reduced operator** from snapshot data **without code intrusiveness**?
 - **Operator inference** [Willcox/Peherstorfer/Geelen/...]



Operator inference, with linear manifolds

- Start with the angular form, seen previously:

$$\underbrace{\left(\underbrace{\vec{\Omega}_d \cdot \vec{\nabla}}_{G_d} + \underbrace{\sigma_t^g(\vec{r})}_{T(\vec{\theta})} \right) \underbrace{\psi_d^g(\vec{r})}_{\vec{\Psi}} - \frac{1}{4\pi} \sum_{g'=1}^G \underbrace{\sigma_s^{g' \rightarrow g}(\vec{r})}_{\Sigma(\vec{\theta})} \sum_{d'=1}^{n_\Omega} w_{d'} \underbrace{\psi_{d'}^{g'}(\vec{r})}_{\vec{\Psi}} = \underbrace{Q_d^g(\vec{r})}_{\vec{Q}}$$

$$L(\vec{\theta}) \quad \quad \quad (G + T(\vec{\theta}) - \Sigma(\vec{\theta})D)\vec{\Psi} = \vec{Q}(\vec{\theta})$$

- Recognize reaction terms (T and Σ) are affine in the parameters:

$$T^g(\vec{\theta}) = \sum_{k=1}^{N_{\text{mat}}} \sigma_t^{g,k} M^k, \quad \Sigma_{g,g'}(\vec{\theta}) D_{d'} = \sum_{k=1}^{N_{\text{mat}}} \sigma_s^{g' \rightarrow g,k} M^k D_{d'}, \quad \vec{Q}_d^g(\vec{\theta}) = \sum_{k=1}^{N_{\text{mat}}} Q_d^{g,k} \vec{f}^k$$

- Recall that we use **DGFEM**, so the reaction terms are also **block diagonal matrices**

➤ **Terms are computable, even without access to source code**

- Need: Mesh (connectivity, material block IDs), and elemental mass matrices/load vectors

➤ **Material-independent FOM matrices/vectors do not depend on groups or directions**

- But their small ROM counterparts (because of the POD modes) will be group- and direction-dependent

- Seek solution as: $\psi_d^g(\vec{\theta}) = U_r^{g,d} c_d^g(\vec{\theta})$ (recall, snapshots often are centered)



Operator inference, with linear manifolds

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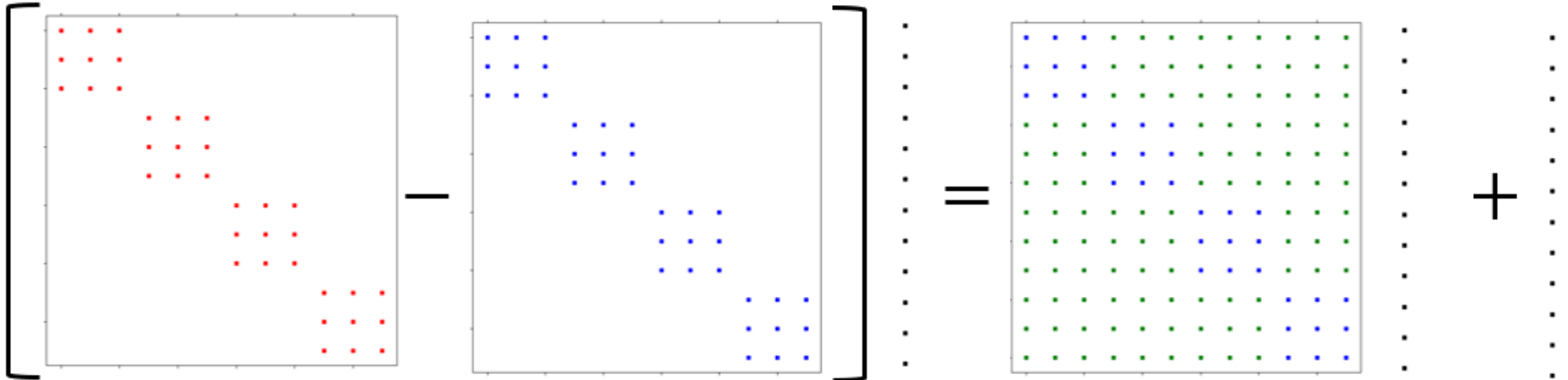


Operator inference, with linear manifolds

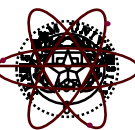
- After Galerkin projection, the reduced-order system is:

$$(G_r + T_r(\vec{\mu}) - \Sigma_r(\vec{\mu}))\vec{c}(\vec{\mu}) = \vec{Q}_r(\vec{\mu})$$

➤ where only G_r is **unknown**



Note: can G_r be inferred per group and per direction independently

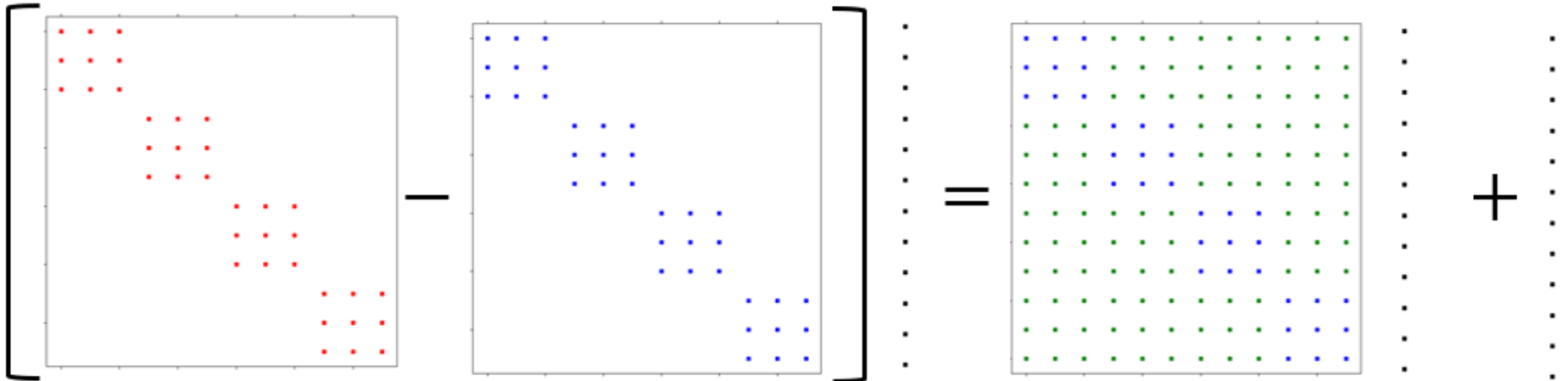


Operator inference, with linear manifolds

- After Galerkin projection, the reduced-order system is:

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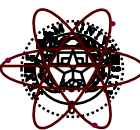
Note: can G_r be inferred per group and per direction independently

with

$$C = \begin{bmatrix} \vdots & & \vdots \\ \vec{c}(\mu_1), & \dots, & \vec{c}(\mu_{N_{\text{snap}}}) \\ \vdots & & \vdots \end{bmatrix} \quad R = \begin{bmatrix} \vdots & & \vdots \\ \vec{r}(\mu_1), & \dots, & \vec{r}(\mu_{N_{\text{snap}}}) \\ \vdots & & \vdots \end{bmatrix}$$

and

$$\vec{r}(\mu_i) = \vec{Q}_r(\mu_i) - (T_r(\vec{\mu}_i) - \Sigma_r(\vec{\mu}_i))\vec{c}_i$$

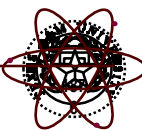


Operator Inference, with nonlinear manifolds

$$\psi_d^g = \underbrace{\mathbf{U}_r^{g,d} c_d^g}_{=\text{linear}} + \underbrace{\overline{\mathbf{U}}_q^{g,d} \mathbf{X}^{g,d} f_p(c_d^g)}_{=\text{nonlinear}}$$

with

- $\mathbf{U}_r^{g,d} \in \mathbb{R}^{N \times r}$: linear subspace of dimension r
- c_d^g : reduced coordinates
- $f_p(c) = [c^2, \dots, c^p]$: polynomial representation from degree 2 up to p
- $\overline{\mathbf{U}}_q^{g,d} \in \mathbb{R}^{N \times q}$: q -dimensional subspace. Requiring $[\mathbf{U}_r, \overline{\mathbf{U}}_q]^T [\mathbf{U}_r, \overline{\mathbf{U}}_q] = \mathbf{I}_{r+q}$ suggests an easy choice for $\overline{\mathbf{U}}_q$: the next q POD modes.
- $\mathbf{X}^{g,d} \in \mathbb{R}^{q \times (p-1)r}$: a mapping of the polynomial expansion of the reduced state vector onto $\overline{\mathbf{U}}_q$



Operator Inference, with nonlinear manifolds

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- $\mathbf{X}^{g,d} \in \mathbb{R}^{q \times (p-1)r}$: a mapping of the polynomial expansion of the reduced state vector onto $\overline{\mathbf{U}}_q$

$$\mathbf{X}^{g,d} = \operatorname{argmin}_{\mathbf{X} \in \mathbb{R}^{q \times (p-1)r}} \left(\frac{1}{2} \sum_{i=1}^{N_{\text{snap}}} \left\| \psi_d^g(\vec{\mu}_i) - [\mathbf{U}_r^{g,d}, \overline{\mathbf{U}}_q^{g,d}]^T \begin{bmatrix} c_d^g \\ \mathbf{X} f_p(c_d^g) \end{bmatrix} \right\|_2^2 + \frac{\lambda}{2} \|\mathbf{X}\|_F^2 \right)$$



Operator Inference, with nonlinear manifolds

■ **LS solution** $\mathbf{X}^{g,d} = [\bar{\mathbf{U}}_q^{g,d}]^T \underbrace{[\Psi_d^g - \mathbf{U}_r^{g,d} \mathbf{c}_d^g]}_{=\text{proj.error}} \mathbf{F}^T (\mathbf{F} \mathbf{F}^T + \lambda \mathbf{I})^{-1}$

with

$$\mathbf{F} = \begin{bmatrix} \vdots & & \vdots \\ f(c_d^g(\mu_1)), & \dots, & f(c_d^g(\mu_{N_{\text{snap}}})) \\ \vdots & & \vdots \end{bmatrix}$$

Performing OpInf using the nonlinear representation:

$$\mathbf{G}_r \vec{c}(\vec{\mu}) + \mathbf{P}_r \vec{f}(\vec{\mu}) = \underbrace{\vec{Q}_r(\vec{\mu}) - (\mathbf{T}_r(\vec{\mu}) - \Sigma_r(\vec{\mu})) \vec{c}(\vec{\mu}) - (\mathbf{T}_r^f(\vec{\mu}) - \Sigma_r^f(\vec{\mu})) \vec{f}(\vec{\mu})}_{\vec{r}(\mu)}$$

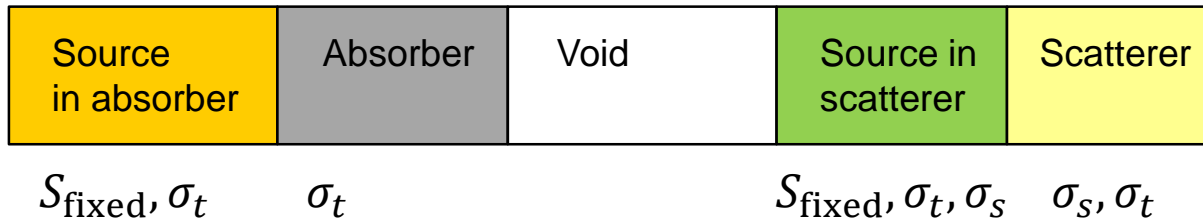
$$\mathbf{G}_r = \mathbf{U}_r^T \mathbf{G} \mathbf{U}_r \quad , \quad \mathbf{P}_r = \mathbf{U}_r^T \mathbf{G} \bar{\mathbf{U}}_q \mathbf{X} \quad , \quad \mathbf{T}_r^f(\vec{\mu}) = \mathbf{U}_r^T \mathbf{T} \bar{\mathbf{U}}_q \mathbf{X} \quad , \quad \Sigma_r^f(\vec{\mu}) = \mathbf{U}_r^T \Sigma \bar{\mathbf{U}}_q \mathbf{X}$$

Finding \mathbf{G}_r and \mathbf{P}_r in a least-square sense over all snapshots μ_i

$$(\mathbf{G}_r, \mathbf{P}_r) = \operatorname{argmin}_{\mathbf{G}_r \in \mathbb{R}^{r \times r}, \mathbf{P}_r \in \mathbb{R}^{r \times (p-1)r}} \left(\frac{1}{2} \sum_i \left\| \mathbf{G}_r \vec{c}(\vec{\mu}_i) + \mathbf{P}_r \vec{f}(\vec{\mu}_i) - \vec{r}(\vec{\mu}_i) \right\|_2^2 + \frac{\lambda^G}{2} \|\mathbf{G}_r\|_F^2 + \frac{\lambda^P}{2} \|\mathbf{P}_r\|_F^2 \right)$$

Coupled system: alternating directions (solve for \mathbf{G}_r with **old** \mathbf{P}_r , then solve for \mathbf{P}_r using **updated** \mathbf{G}_r , ...)

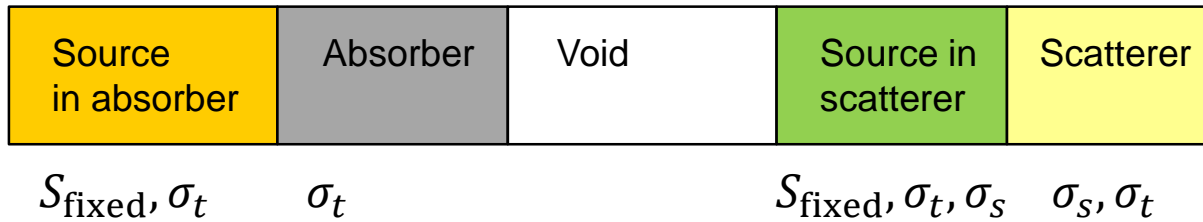
Problem Set-up



Solution in 8 discrete directions at nominal values of the parameters

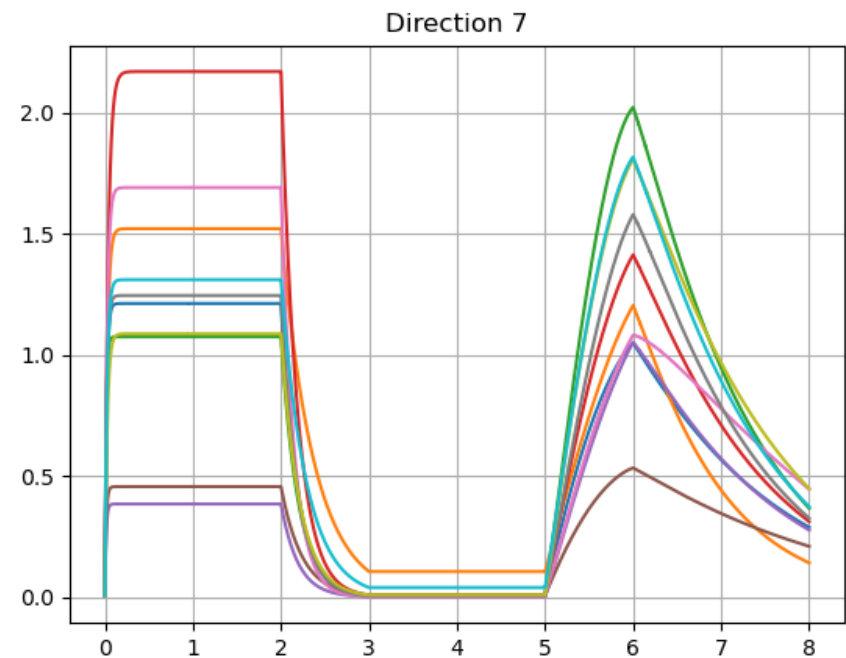
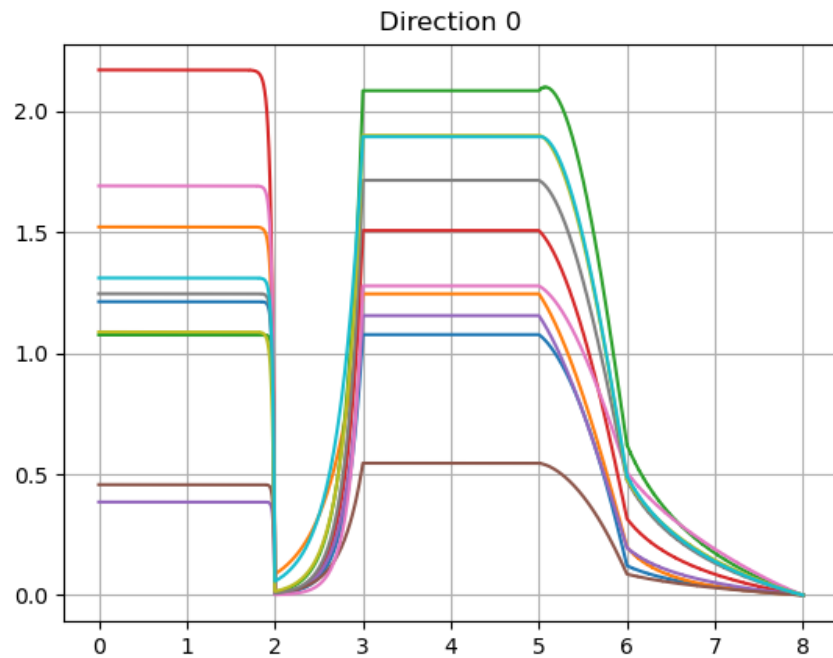


Sample snapshots

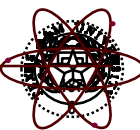
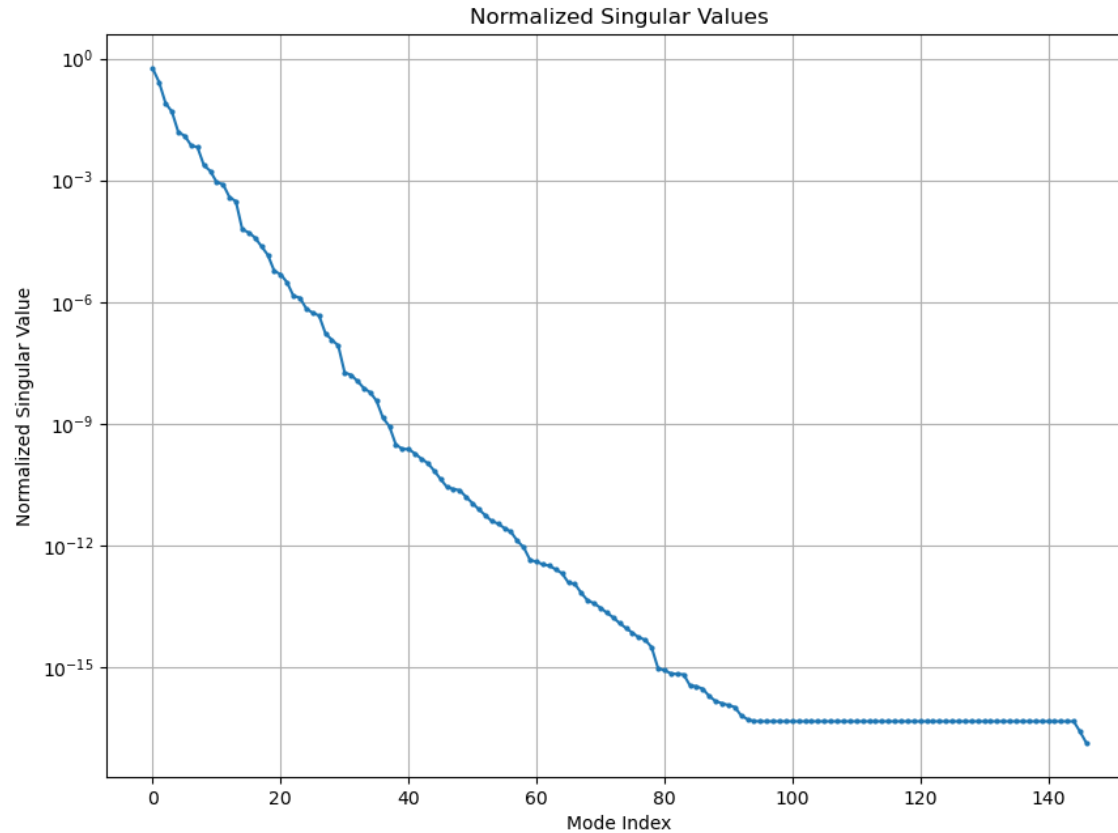


6 params

- Parametric range +/- 50% of nominal values
- Sample snapshots for first and last directions:



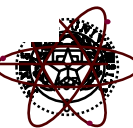
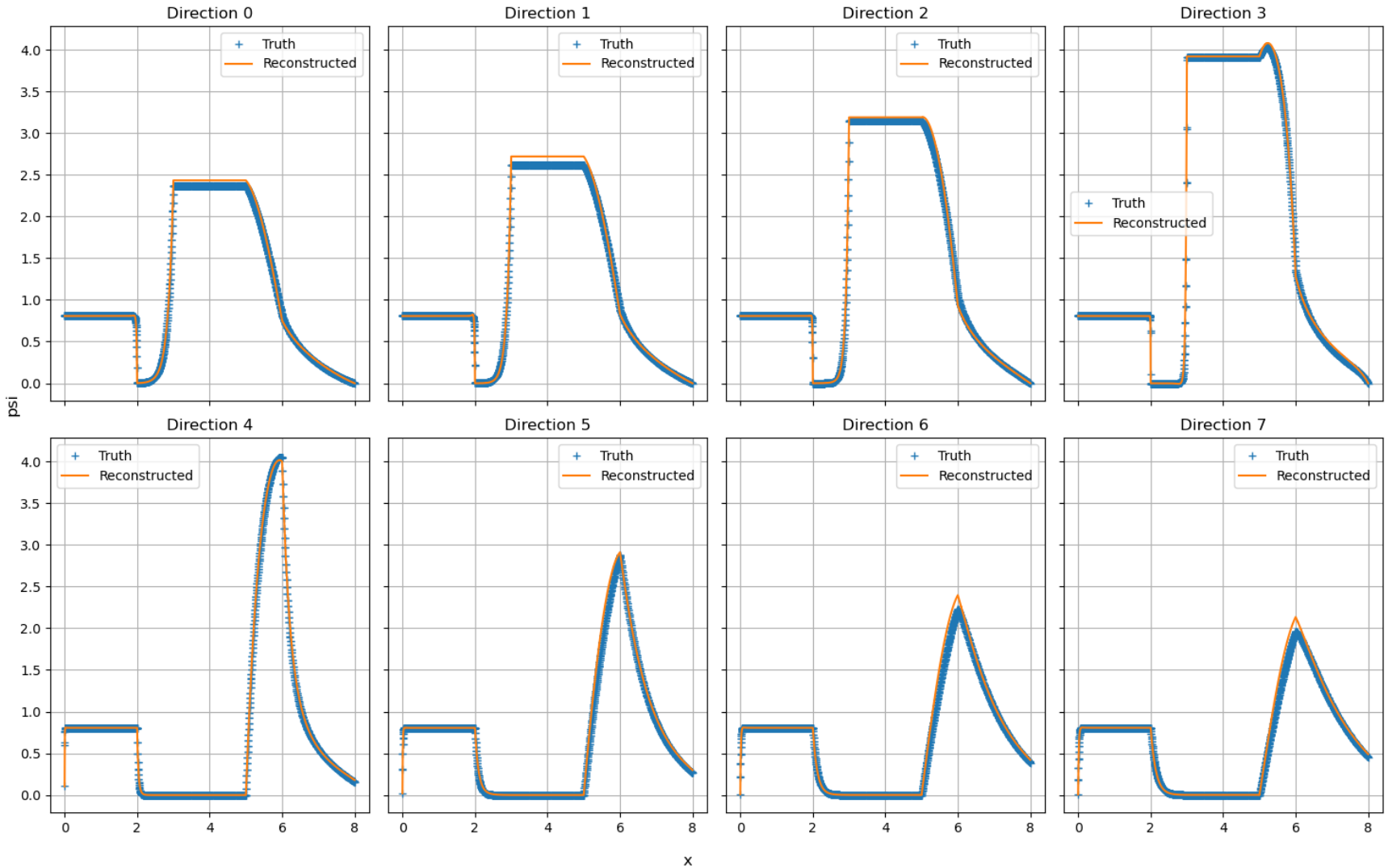
Oplnf reconstruction, with **linear** manifolds



Oplnf reconstruction, with **linear** manifolds

Comparison for Sample 2

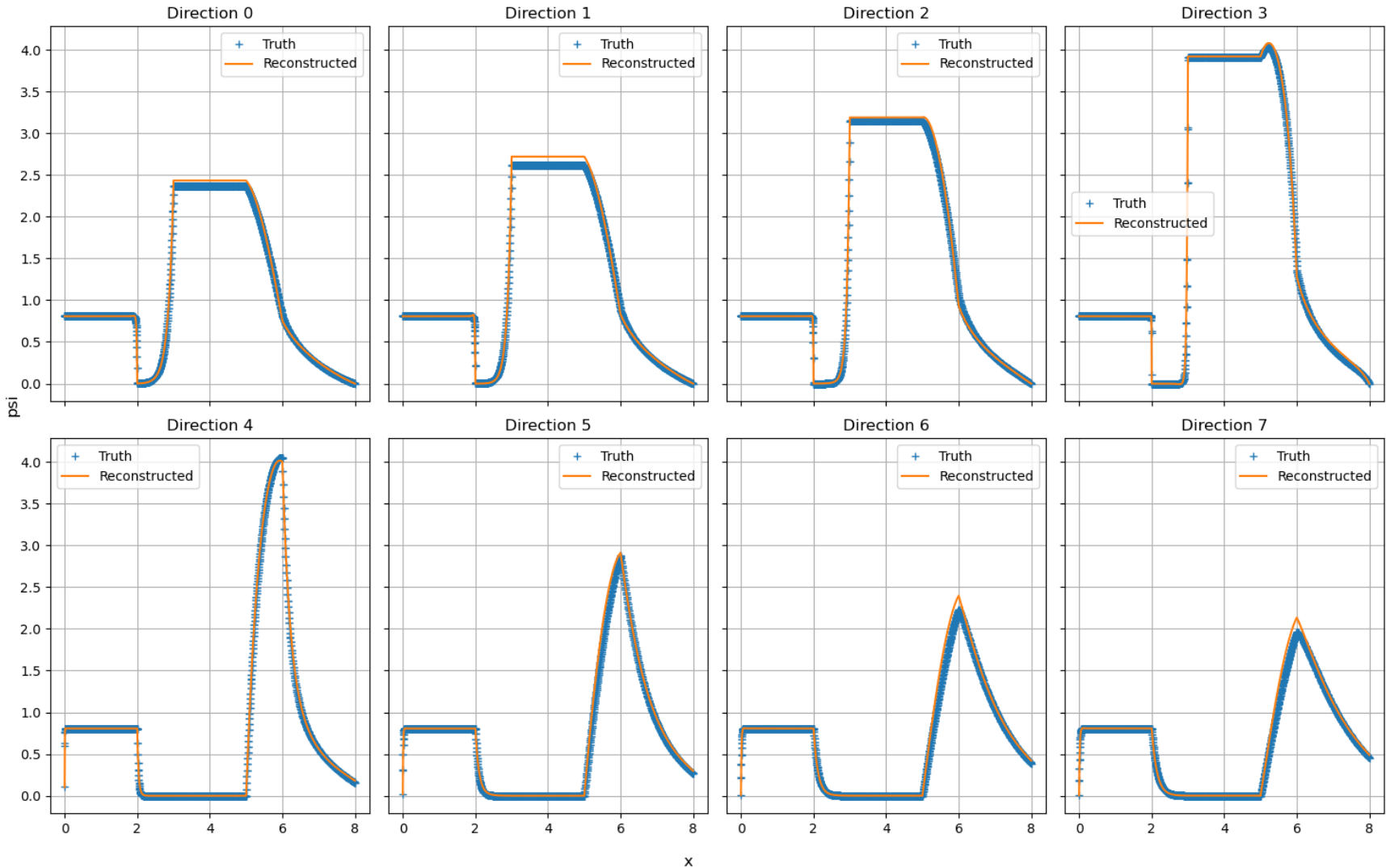
rank=4



Oplnf reconstruction, with **linear** manifolds

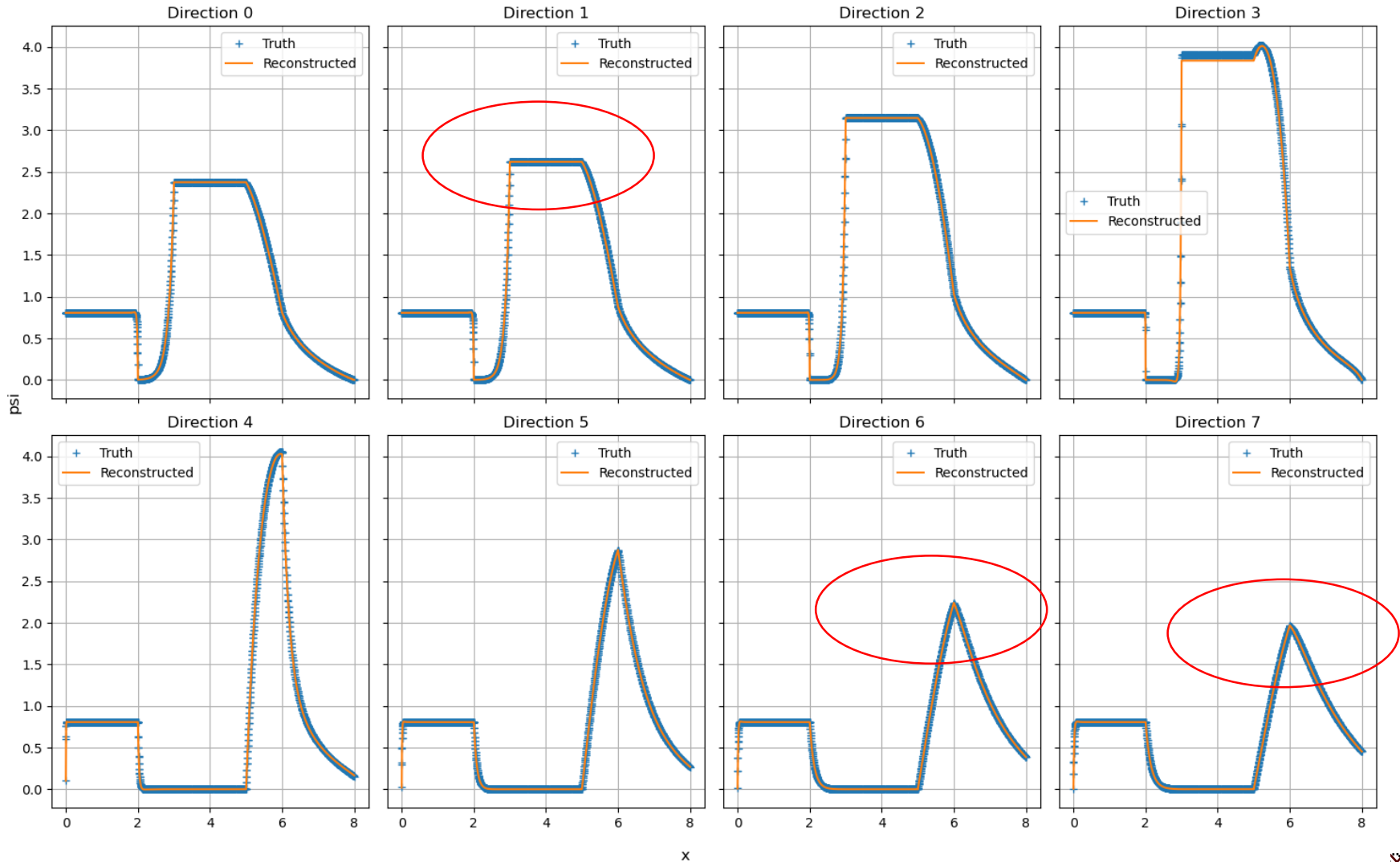
Comparison for Sample 2

rank=4



Oplnf reconstruction, with **linear** manifolds

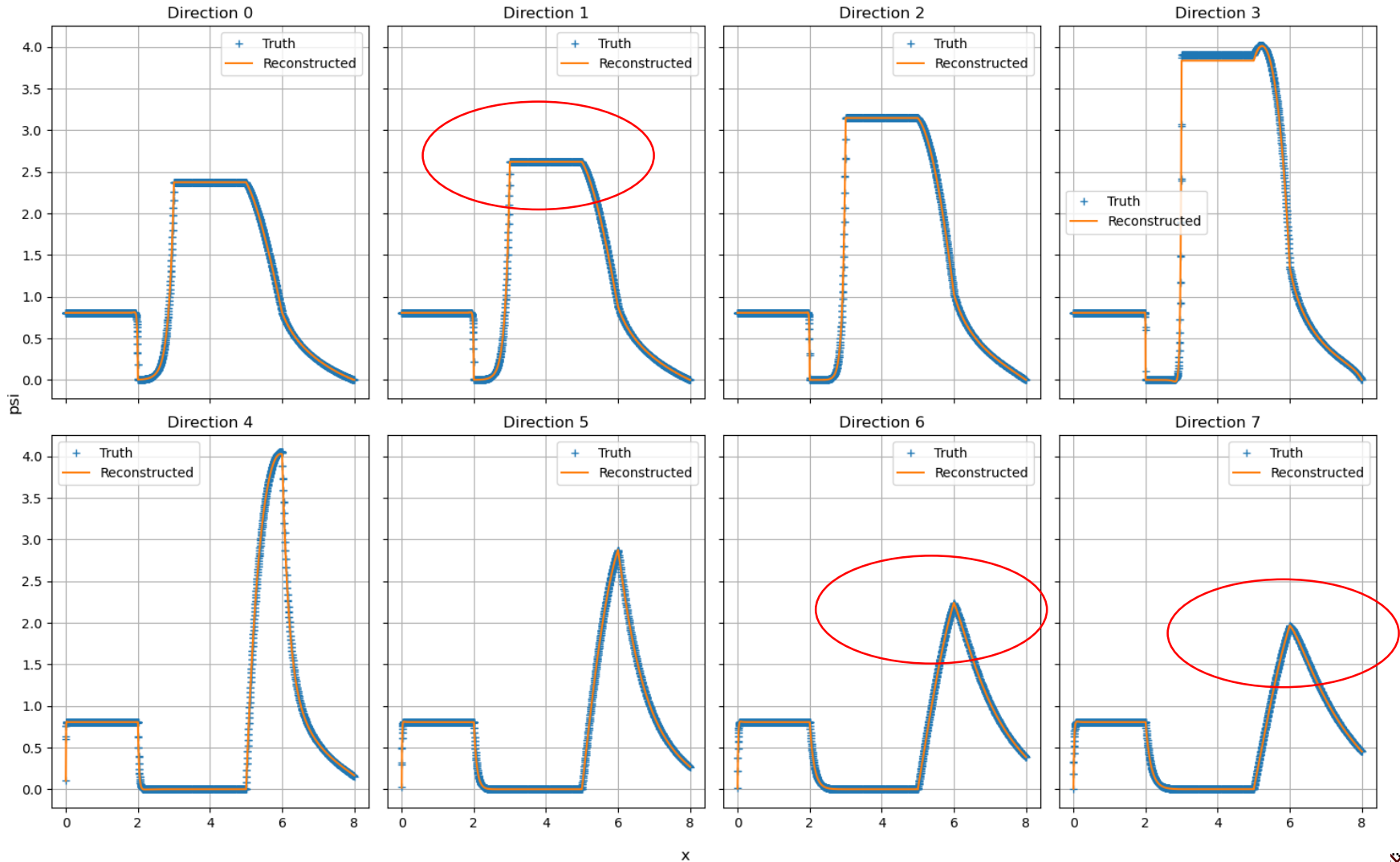
Comparison for Sample 2



Oplnf reconstruction, with **linear** manifolds

Comparison for Sample 2

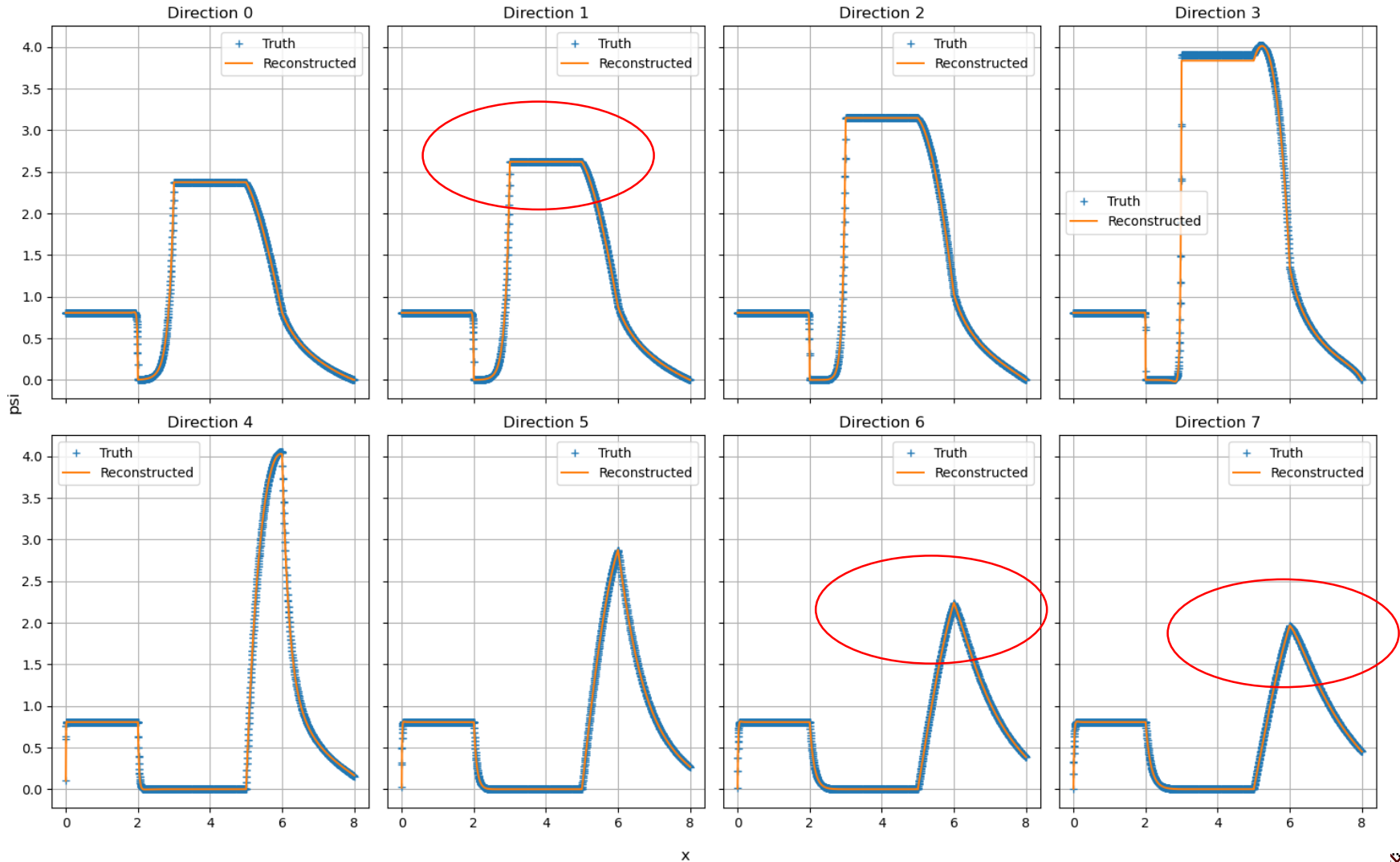
rank=8



Oplnf reconstruction, with **linear** manifolds

Comparison for Sample 2

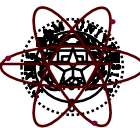
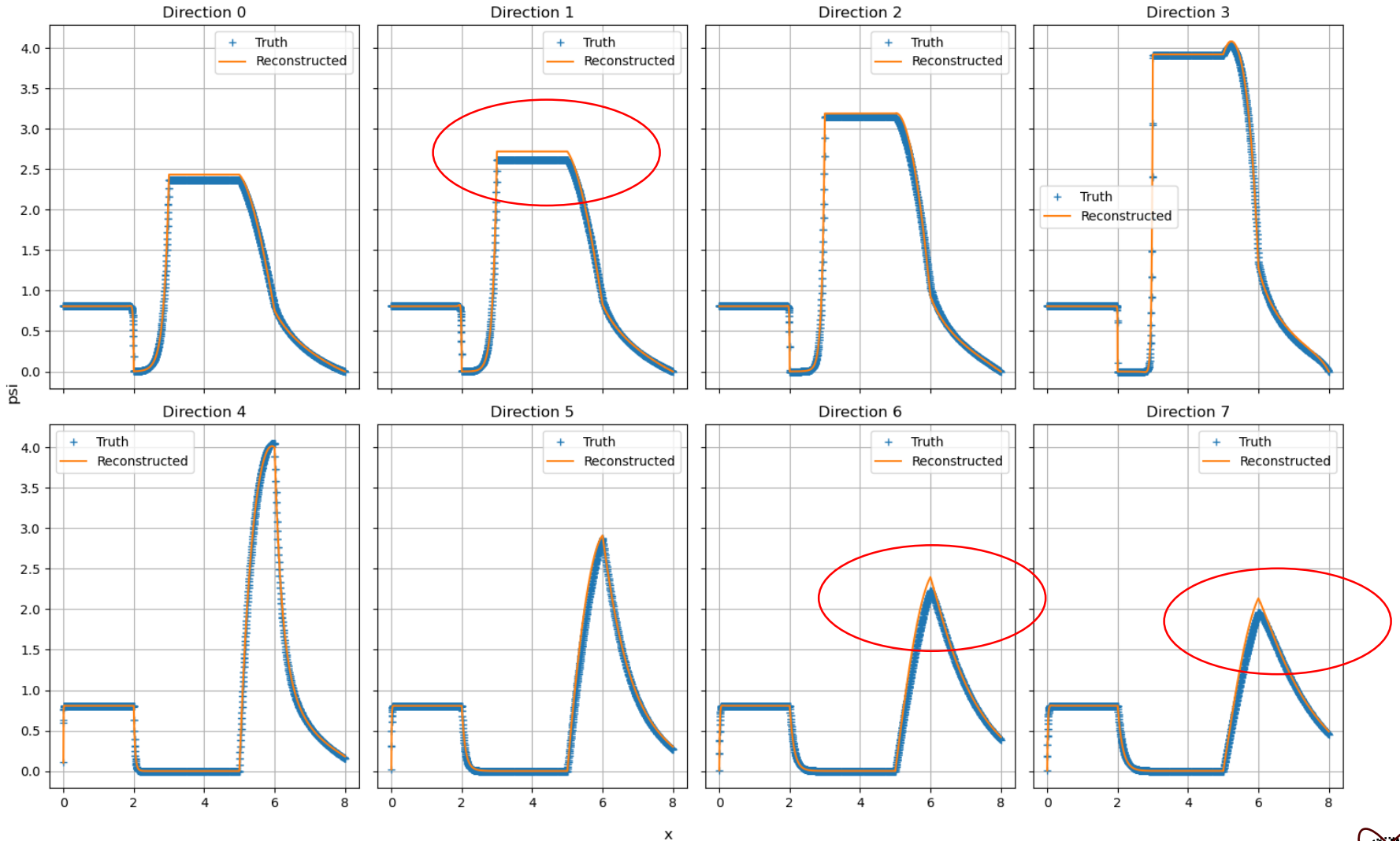
rank=8



Oplnf, with linear and nonlinear manifolds

rank=4

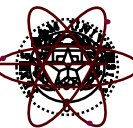
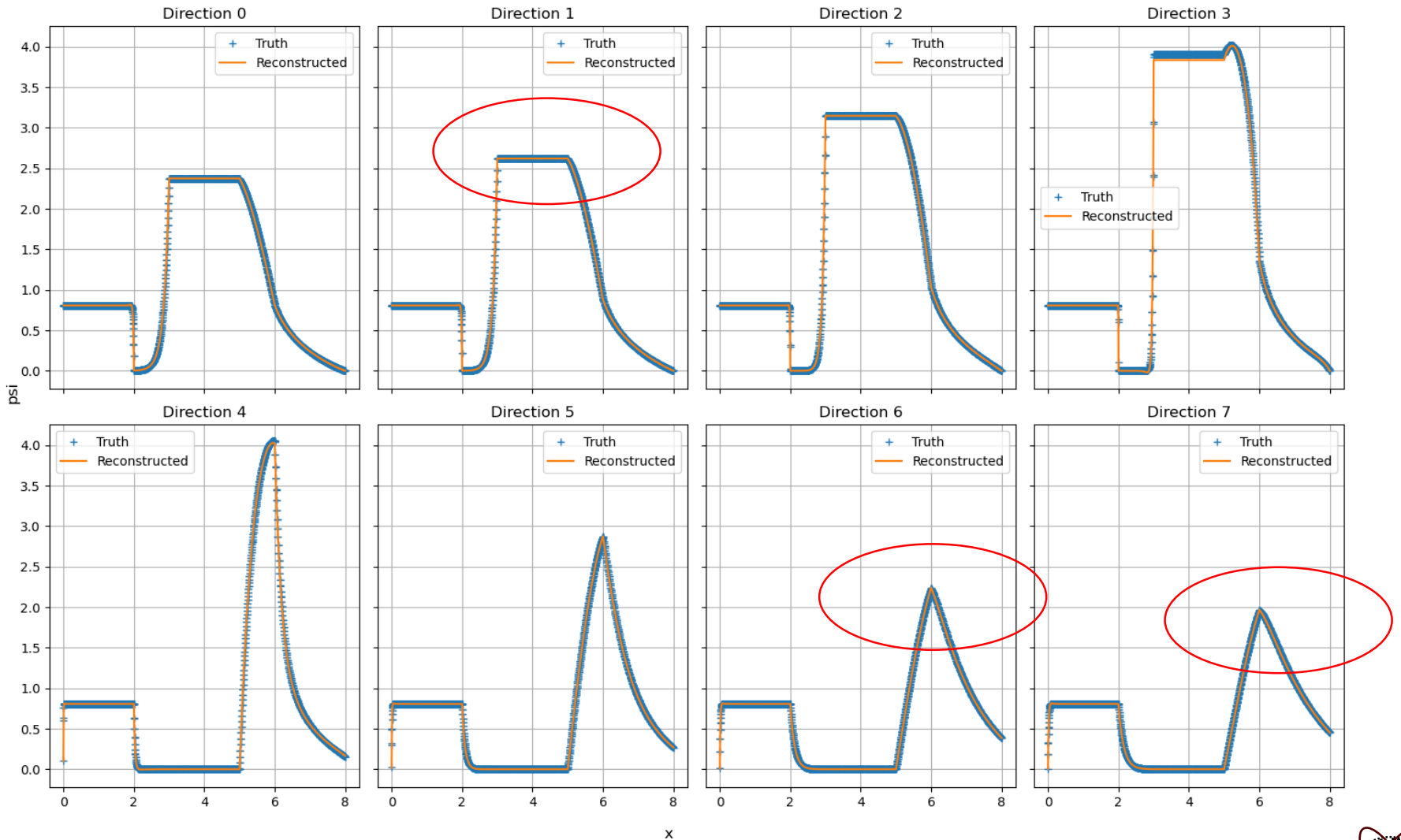
Comparison for Sample 2



Oplnf, with linear and nonlinear manifolds

rank=4

Comparison for Sample 2

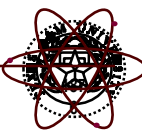


Outline

1. Background on Radiation Transport
 - A. Motivations for (*p*arametric) ROM for Radiation Transport
 - B. Crash course on Radiation Transport

2. Reduced-Order Models for Radiation Transport
 - A. Projection-based *p*ROM:
 - i. Minimally-invasive approach
 - ii. Affine decomposition of operators
 - B. Non-intrusive *p*ROM
 - i. Gaussian process regression, MARS
 - C. Operator inference for *p*ROM
 - i. Linear and Nonlinear Frameworks
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3. Conclusions and Outlook



Operator inference: Time-dependent problems

- Time-evolution FOM:

$$\frac{1}{v} \partial_t \Psi + (G + T - \Sigma D) \Psi = Q$$

- Same philosophy:

- All reaction terms are affine-decomposable, hence computable easily
- G_r is the only **unknown**

- Using **training data** and form a least-square system (with Tikhonov regularization)

$$G_r = \operatorname{argmin}_{G_r \in \mathbb{R}^{r \times r}} \left(\frac{1}{2} \sum_{n=1}^{N_\tau} \left\| \frac{1}{v} \frac{d}{dt} \vec{c}_n + G_r \vec{c}_n + (T_r - \Sigma_r) \vec{c}_n - \vec{Q}_r \right\|_2^2 + \frac{\lambda}{2} \|G_r\|_F^2 \right)$$

- $\frac{d}{dt} \vec{c}_n$: computed using high-order finite-differences from the collected temporal snapshots

- LS solve (same as before):

$$G_r = RC^T \left(CC^T + \lambda I \right)^{-1}$$

with

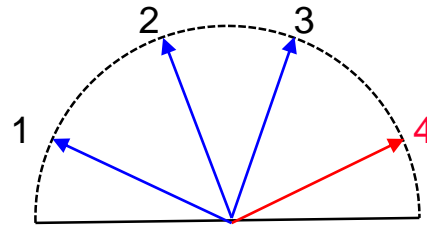
$$C = \begin{bmatrix} \vdots & \vdots \\ \vec{c}(t_1), \dots, \vec{c}(t_{N_\tau}) & \\ \vdots & \vdots \end{bmatrix} \quad R = \begin{bmatrix} \vdots & \vdots \\ \vec{r}(t_1), \dots, \vec{r}(t_{N_\tau}) & \\ \vdots & \vdots \end{bmatrix}$$

and

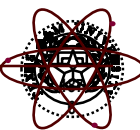
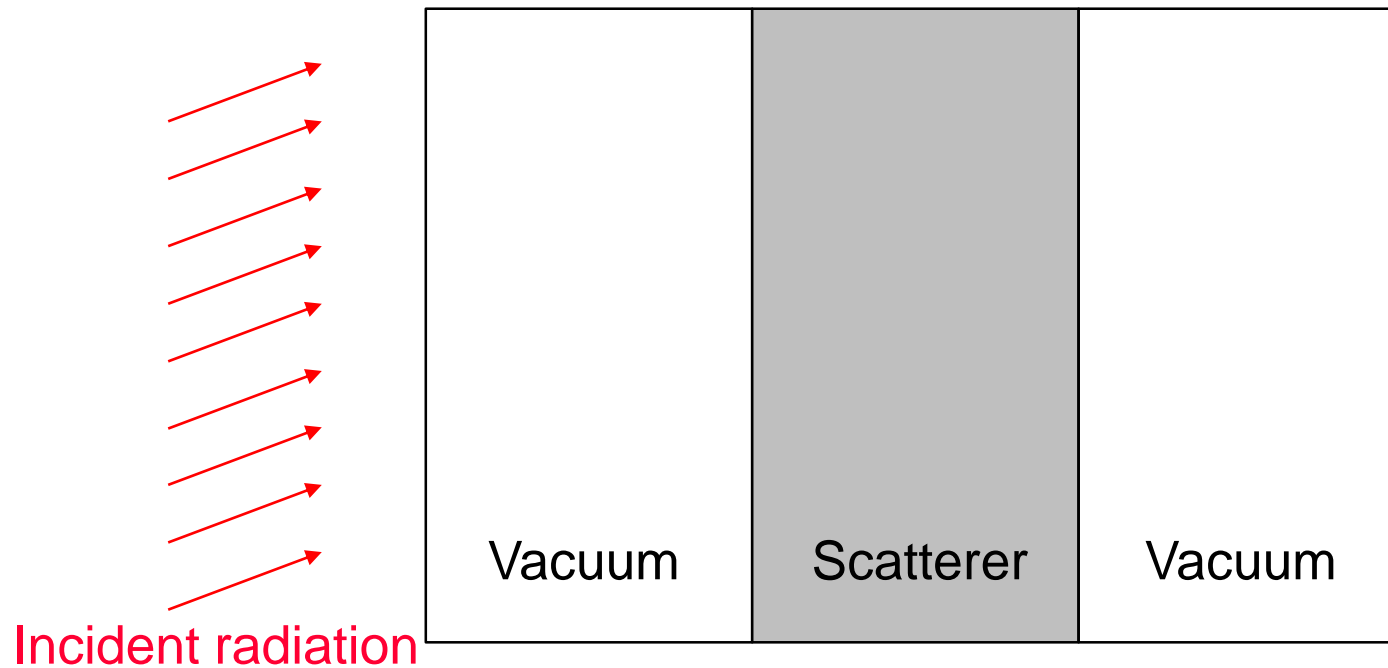
$$\vec{r}(t_n) = \vec{Q}_r - (T_r - \Sigma_r) \vec{c}(t_n) - \frac{1}{v} \frac{d}{dt} \vec{c}(t_n)$$



Problem Set-up



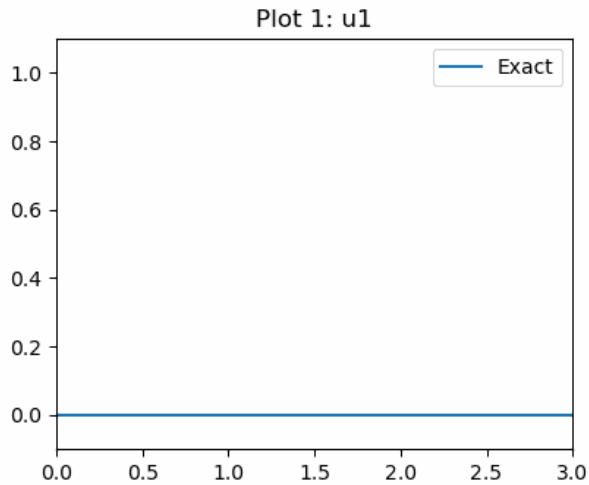
Tracking radiation in
4 directions (cones)



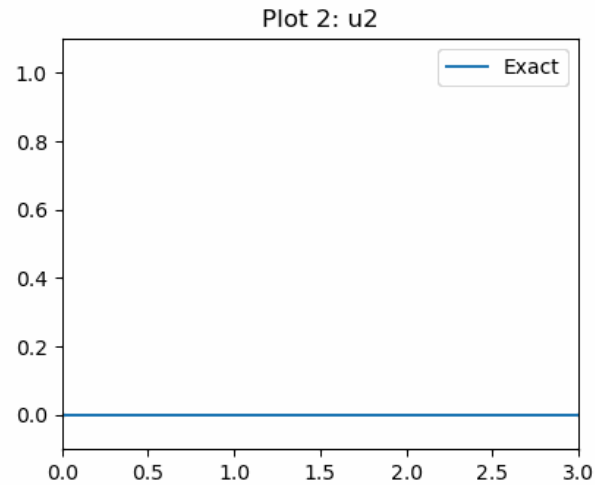
Exact (reference) Solution

Time Step: 0

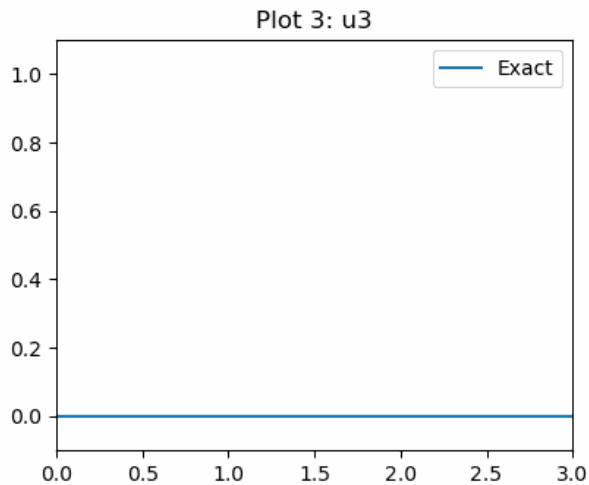
d = 1



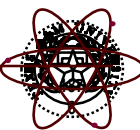
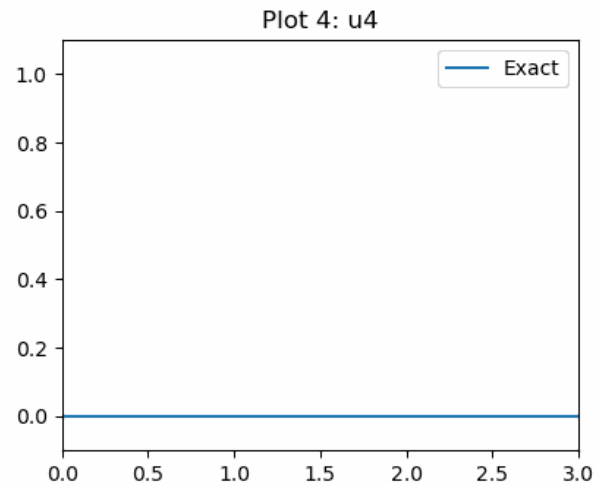
d = 2



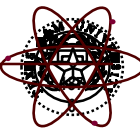
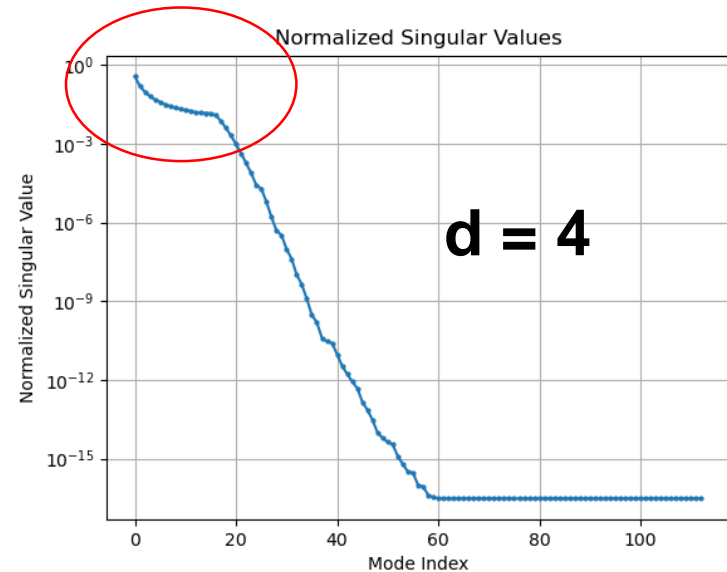
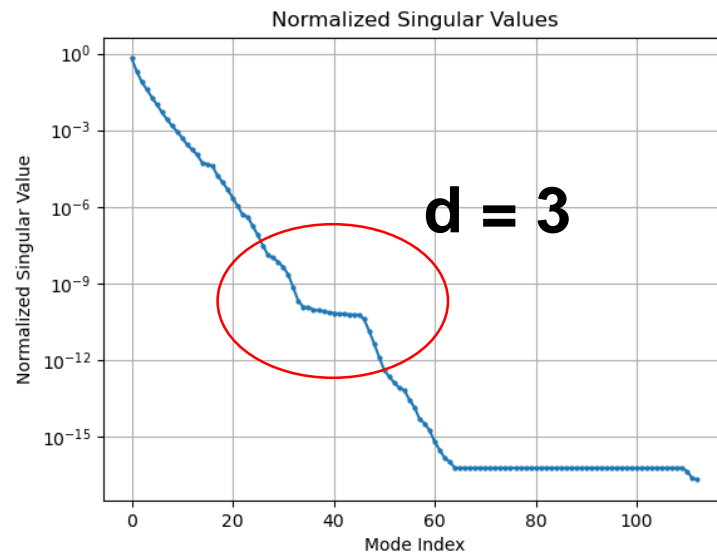
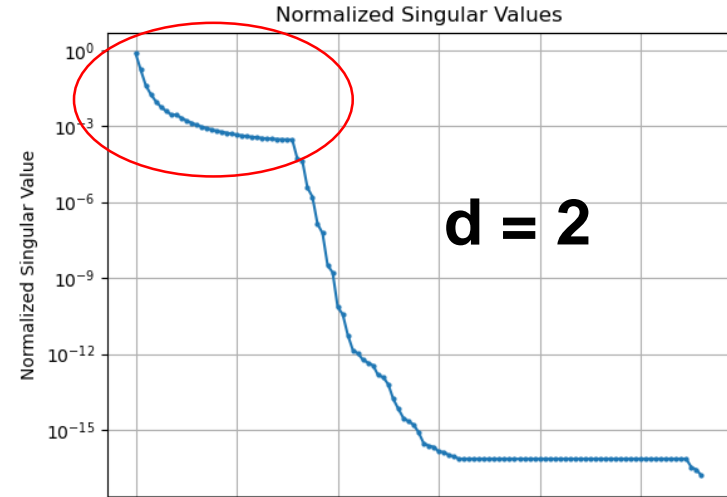
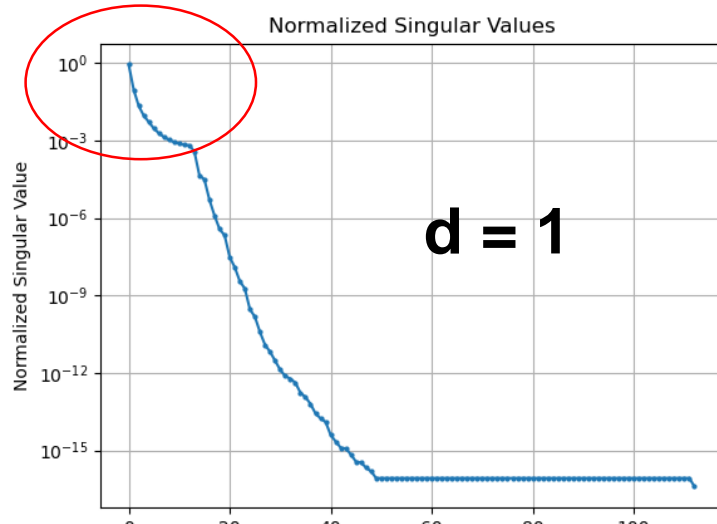
d = 3



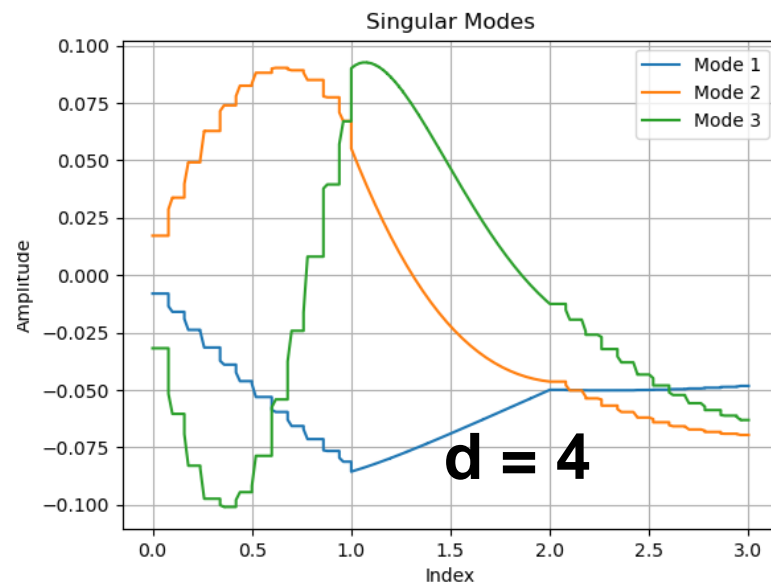
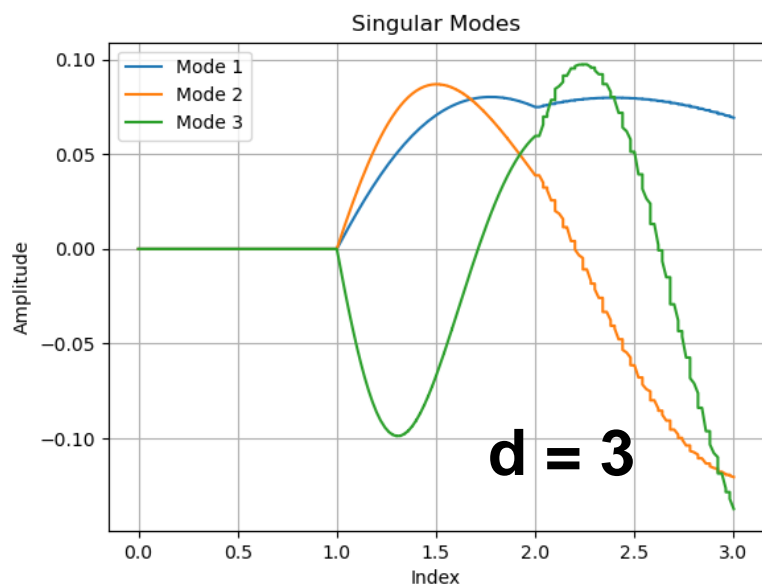
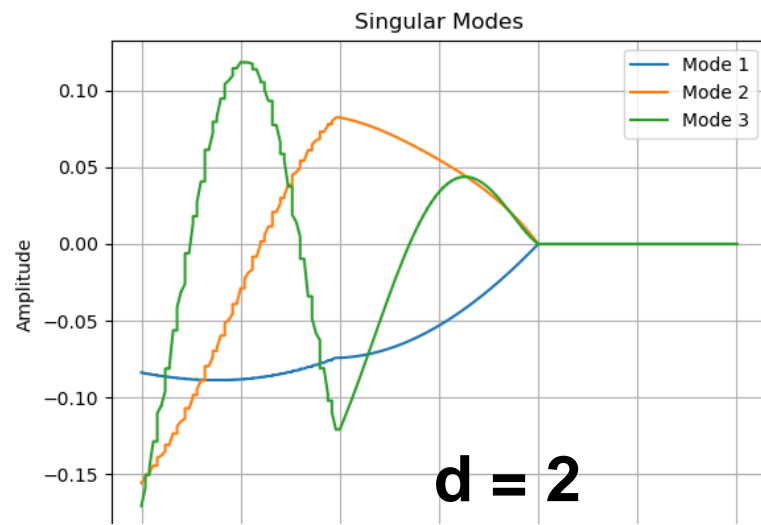
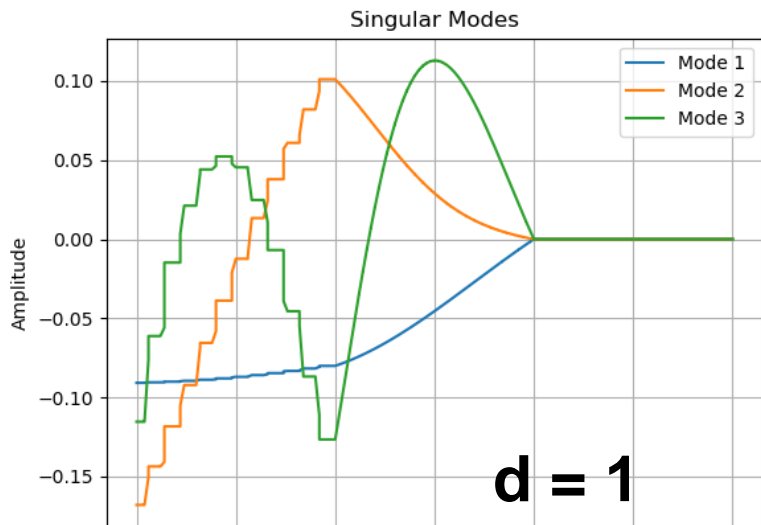
d = 4



Singular values plots per direction

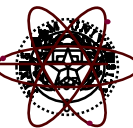
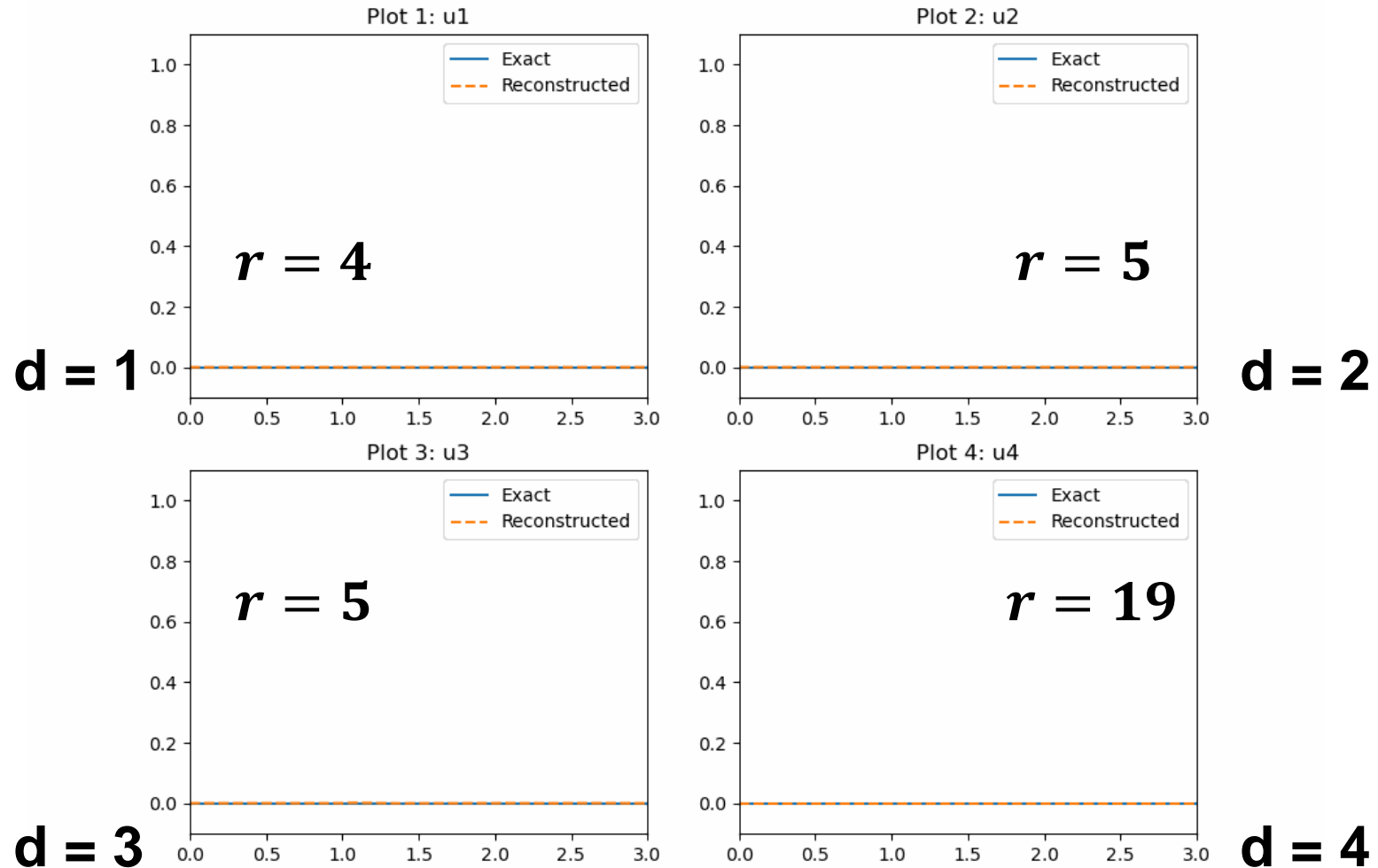


POD modes



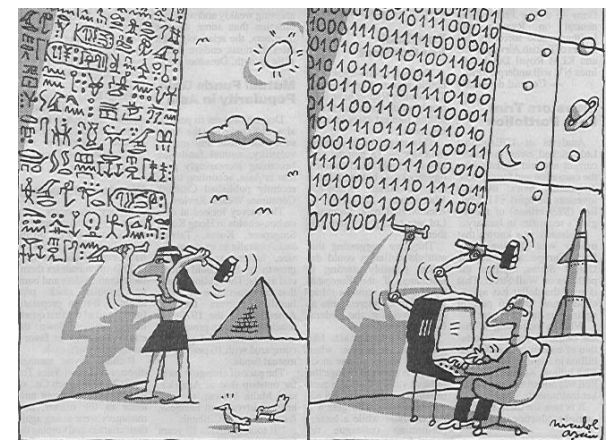
Reconstruction with OpInf

Time Step: 0



- **Parametric ROM for radiation transport**
 - *Minimally-invasive approach*
 - *Affine Decomposition*
 - *Non-intrusive POD+regression (Gaussian process, sparse-grid interpolant, MARS)*
 - *Operator inference with **linear and nonlinear** manifolds*
- **Operator inference for time-dependent problems (with linear manifolds)**
- **Next:**
 - *Operator inference for TD with **nonlinear manifolds***
 - *Low-rank approximation in the 6D phase-space (space+energy+direction)*
 - Tensor decomposition
- **Open-source Software: OpenSn**
 - <https://github.com/Open-Sn/OpenSn>
 - **Massively parallel Linear Boltzmann solver**
 - **No physics: user supplies interaction properties σ**

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Thanks and EOF

- **Students and Post-docs:** Patrick Behne (INL), Ian Halvic (X-energy), Peter German (INL), Dominic Caron (LLNL), Mauricio Tano (INL), Ian Aranda (LANL), Quincy Huhn (2025)
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 - DOE/NEUP (Nuclear Energy)
 - DOD/DTRA (Defense Threat Reduction Agency)
 - LLNL

