Inferring Experimental Transport Parameters Through Machine Learning

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Motivations

- Transport Parameters (& Fueling) constrain pedestal structure, reactor performance. [1]
- Seek methods for inferring these parameters faster and with more accuracy than at present.

[4] Basic Project Structure

Generate Training Dataset
P = {D(r), V(r), N0(r), S(r,t)}
~10-100k Param. Sets

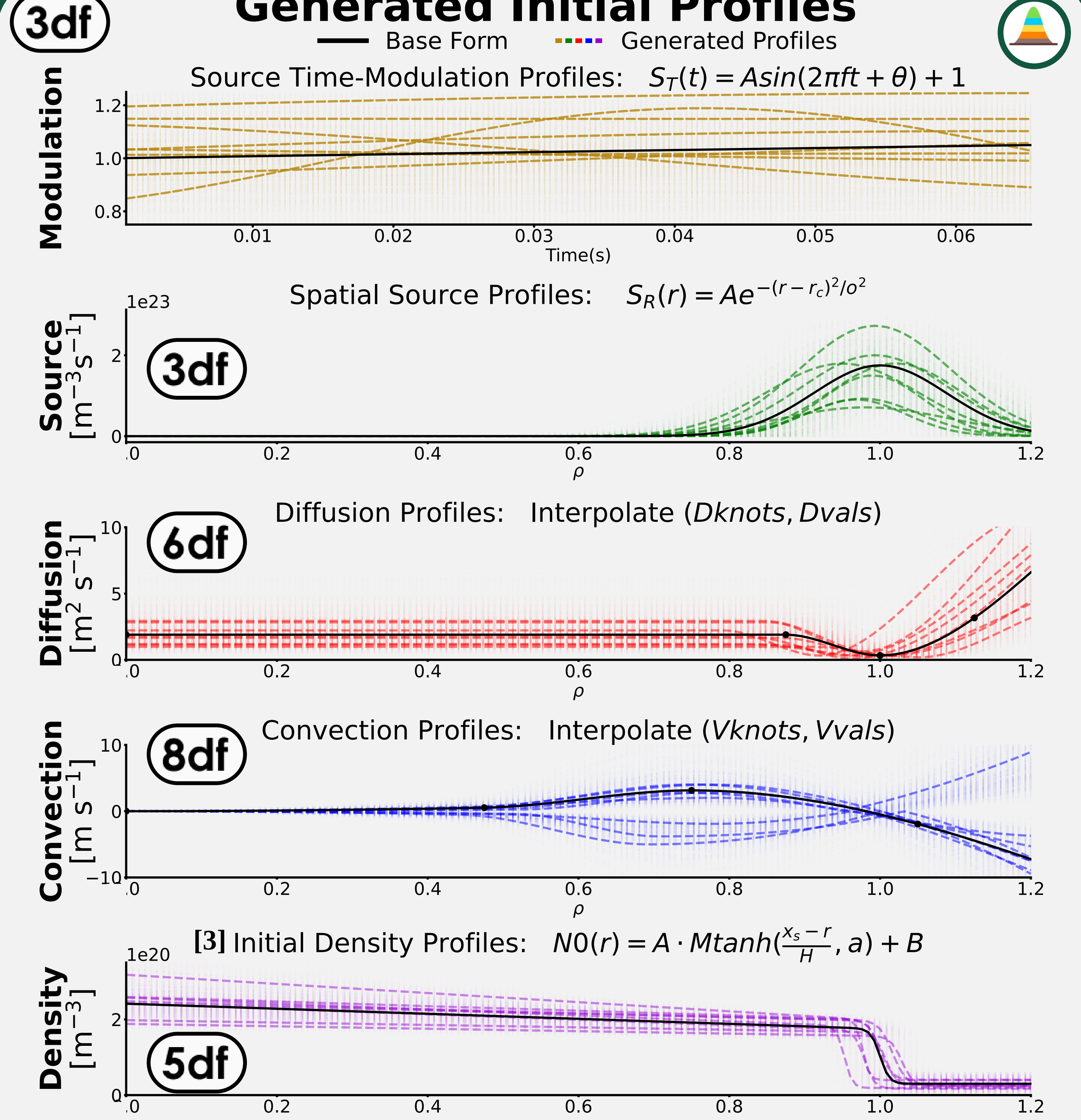
Construct Numerical Model
[2] 1D Radial D-V Ansatz
Finite Vol. CN: NVIDIA CUDA

Train Transport Neural Network
High Generated Perf.
Nonlinear Conv. NN:

Infer Exp. Transport, Score
Exp. Shot Data:
Compare N Data

Basic Data-Gen.

Generated Initial Profiles



Each input profile type is generated **independently**, with its free parameters pulled from some distribution (a broad **Truncated Gaussian** in this case)

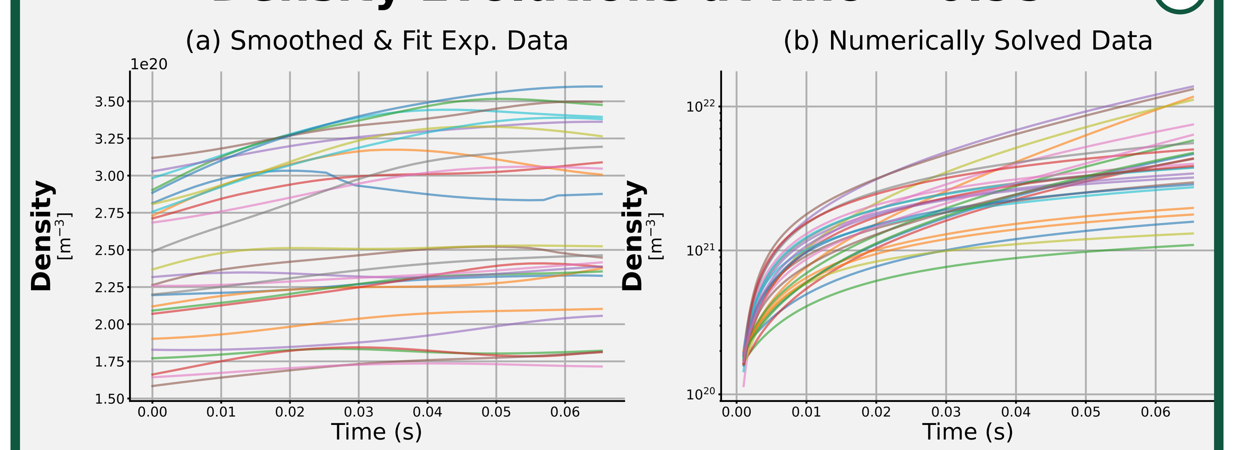
Source S(r,t) is constructed as SR(r)ST(t) (separable) for easier parameterization

Numerical Model

$$\frac{\partial n}{\partial t} = -\frac{1}{r}\frac{\partial}{\partial r}(r\Gamma) + S$$
$$\Gamma = -D\frac{\partial n}{\partial r} + vn \quad [2]$$

- Put the generated profiles into numerical model to get the time-evolved N.
- Majority not aligned.

Density Evolutions at Rho = 0.95



Selecting input profiles in a **broad & independent** manner causes nearly all sampled density evolutions to be **unfeasible (explode)**.

Quantifying 'Feasibility'

- Seek to define metrics to score the alignment of density evolutions with realistic conditions.
- Should have a defined 'threshold' and be dimensionless for easy comparisons.

Metric 1: Maximum Density

Constrain the **maximum density** across all rho & time points. **Greenwald Density** is a good choice for the feasibility threshold.

$$0 > N_G M_1 = \max(N(r, t)) - N_G$$

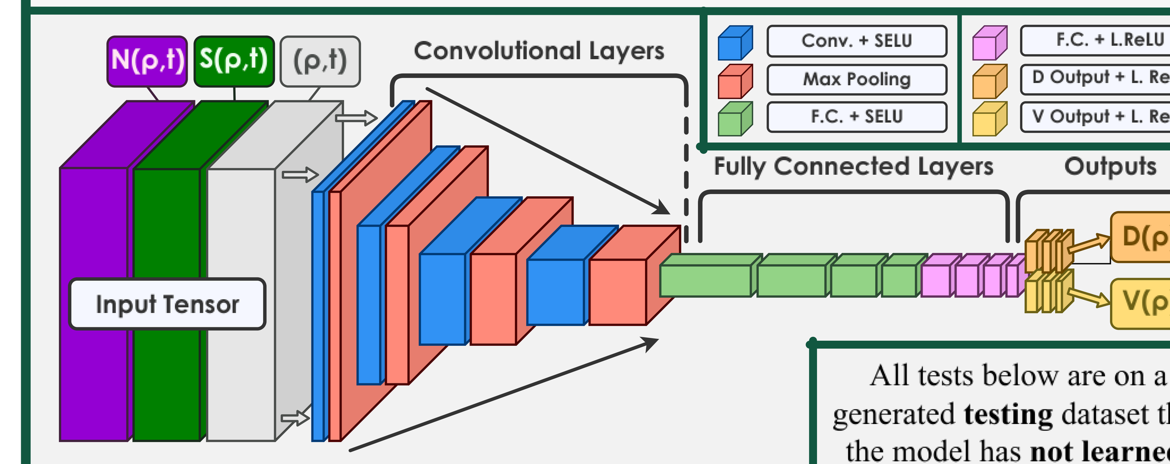
Metric 2: Maximum Edge Density

Constrain the **maximum edge density** at the SOL. The threshold for this metric is less exactly grounded, must be chosen.

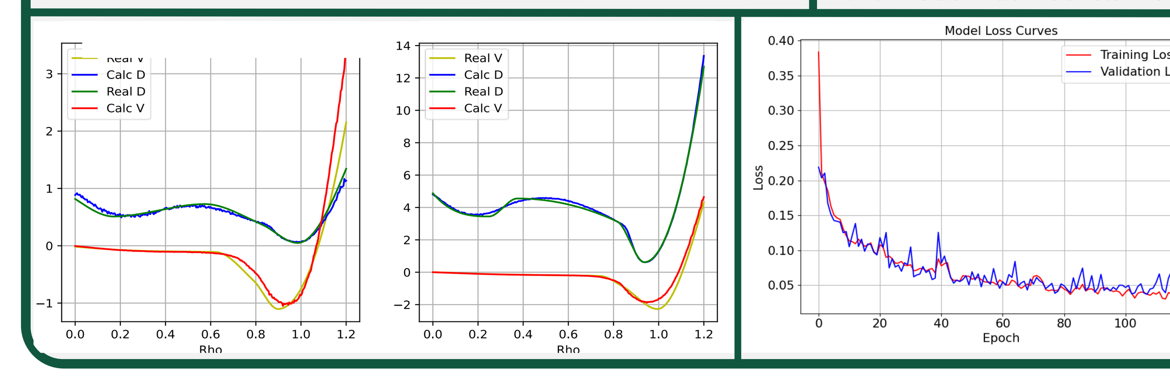
$$0 > N_{Thresh} M_2 = \max(N(r = r_{max}, t)) - N_{Thresh}$$

Transport Network

Network Architecture & Performance



All tests below are on a generated **testing** dataset that the model has **not learned.**



Mapping Out The Parameter Space

Construct Prequisites

Parameter Space
- Free Parameters
- Boundaries
- Scale (log/lin)

27d

Score Metrics
- Measure "Feasibility"
- Dimensionless
- Explicit Threshold N ⟹ μ

[5] Pareto Archive
- Multi-Obj. Opt.
- Stores Mapping
- No Weighting

[5] Multi-Fidelity Pipeline Structure

Quasi MC (Cold Start)
- 'Easy' Metrics
- 'Naïve' Method
- Get 3 ✓'s

SOBOL

Diag. TPE (Warmup)
- No Covariance
- Uses Archive
- Get df + 1 ✓'s

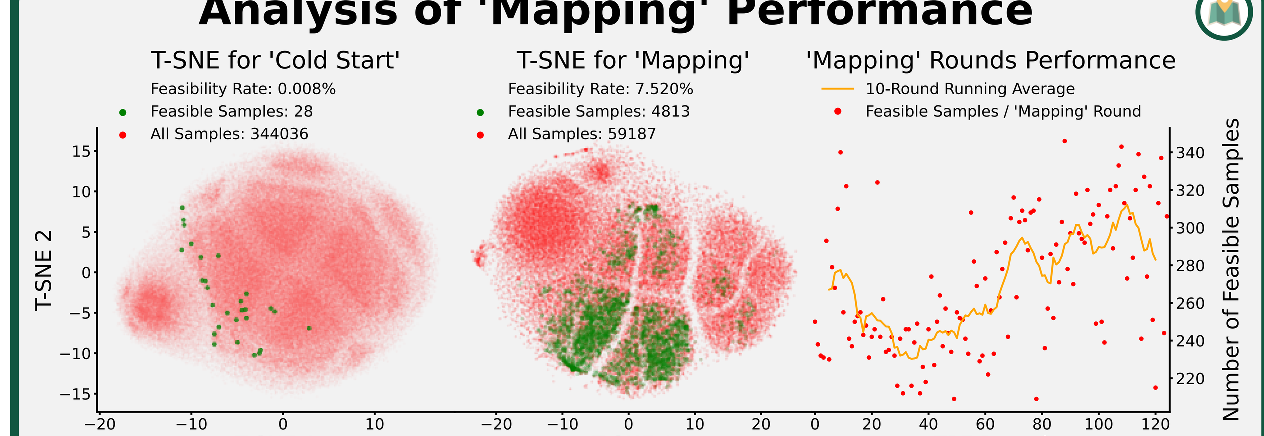
MV TPE (Mapping)
- Full Covar.
- Sparse Metrics
- Gets ✗/✓ Maps

TPE
$A \propto \frac{✓(P)}{✗(P)}$

Analyzing Mapping

- We use the T-SNE metric to evaluate similarity for high dimensional data
- Maps regions by density in parameter space.
- Each phase refines region.

Analysis of 'Mapping' Performance



Mapping appears effective at locating regions of feasibility. These regions have an **underlying structure** and seem to come in **clusters.**

Score %

Cold Start:
0.008%/
344,036

'Mapping':
7.520%/
59,187

Planned Future Work

- Sample parameters from mapping and examine change in the network's learning.
- Incorporate time-dependent transport.
- Map areas in transport parameter space to specific reactors, pedestal conditions. [4]
- Build adaptive pipeline for any metrics and sparsity / dimensionality.
- Analyze complete latent mapping when done to identify 'well-behaved' areas.

Acknowledgements

[1]: S. Mordijck 2020 *Nucl. Fusion* **60** 082006
[2]: A.M. Rosenthal *et al* 2024 *Nucl. Fusion* **64** 036006
[3]: E. Stefanikova et al. 2016 Rev. Sci. Instrum. 11E536
[4]: F. Sciortino 2021 MIT DSpace Libraries
[5]: J. Knowles & D. Corne 2004 Springer 10.1007
[6]: S. Watanabe 2025 Arxiv: 2304.11127v4 [cs.LG]

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