Inference Of Tokamak Transport Profiles Through Machine Learning

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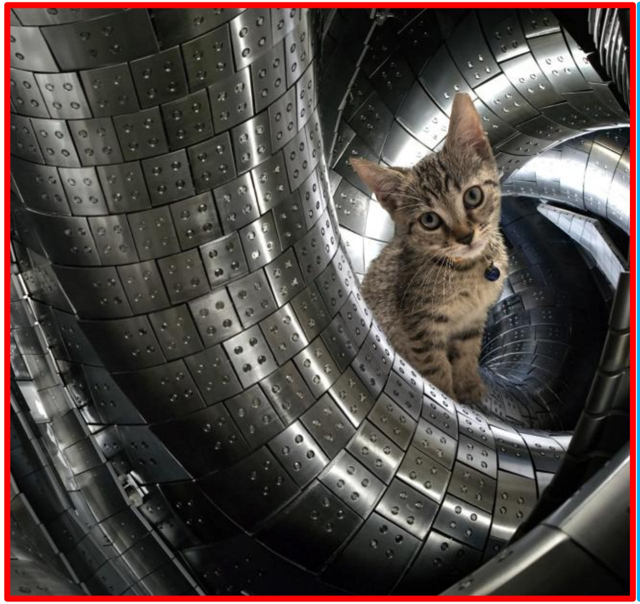
Research Retreat 2025
Group Talk
June 4th, 2025

William & Mary
Arts & Sciences

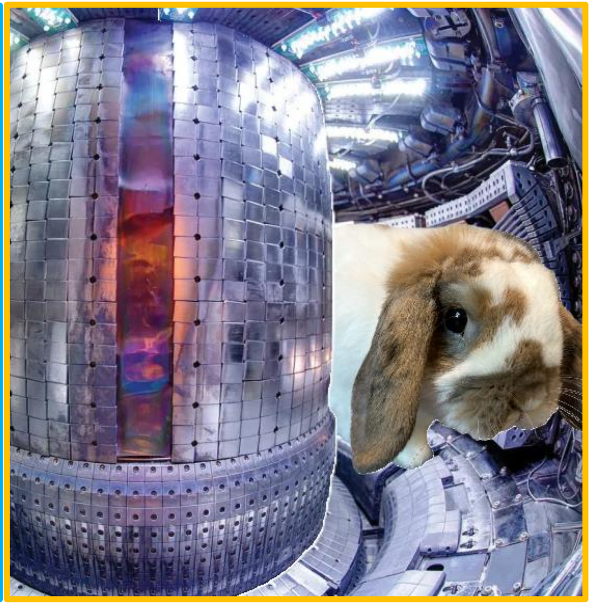
A Bit About Me…

Project Mascots



Leo, age 10mo.

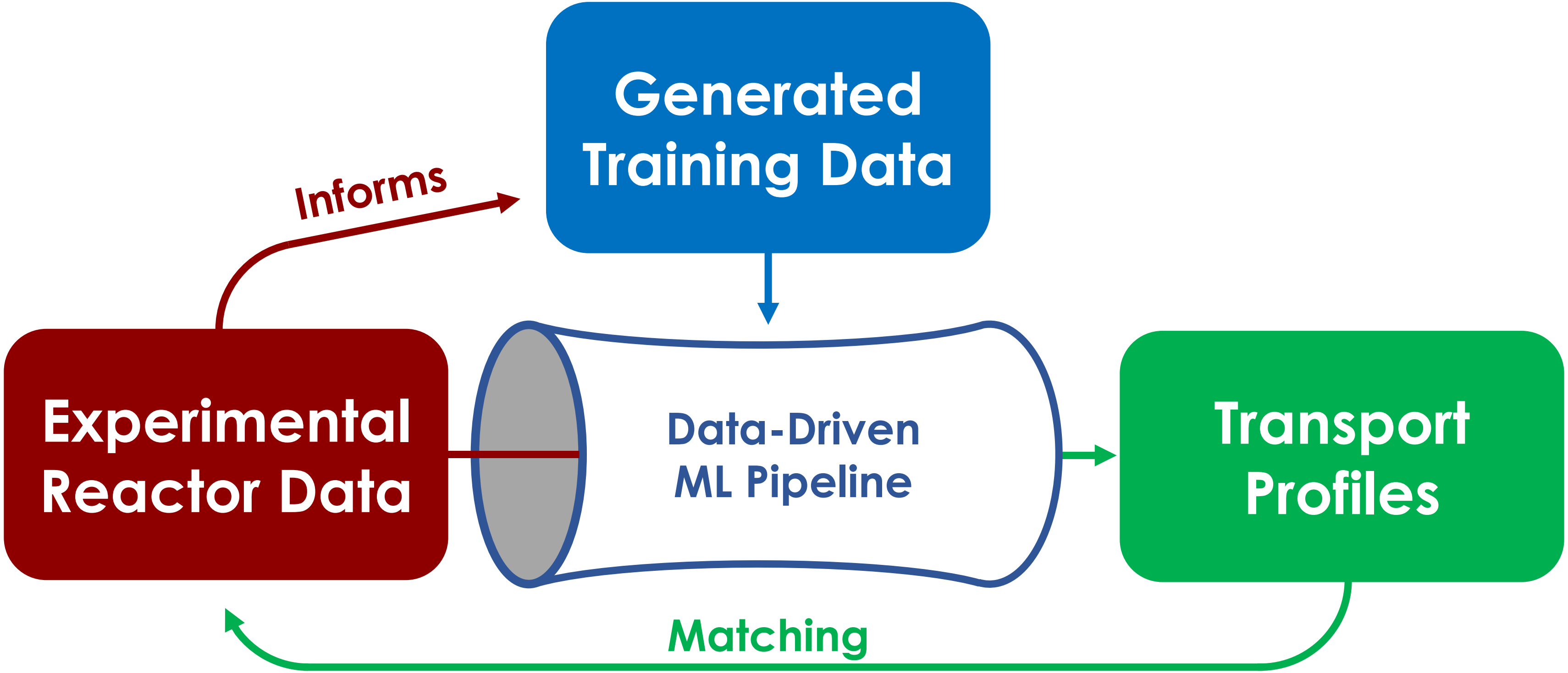
Houdini, age 1.5yr.



Peanut, age 7mo.

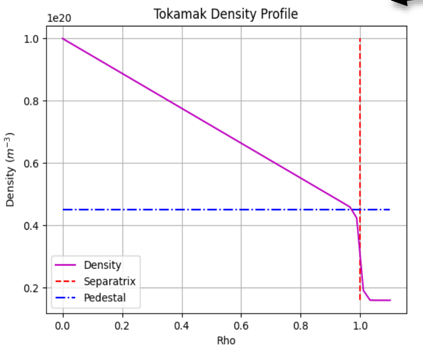
Very helpful when coding…

Project Overview

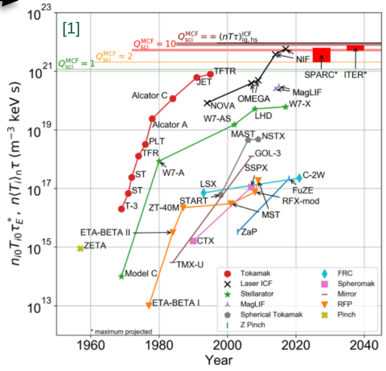


Why Does This Matter?

Physics Importance



Knowledge of Transport Conditions and their effect on Pedestal Formation is key to improving performance and will only become more important on future machines.



Implementation Benefits

Current SOTA

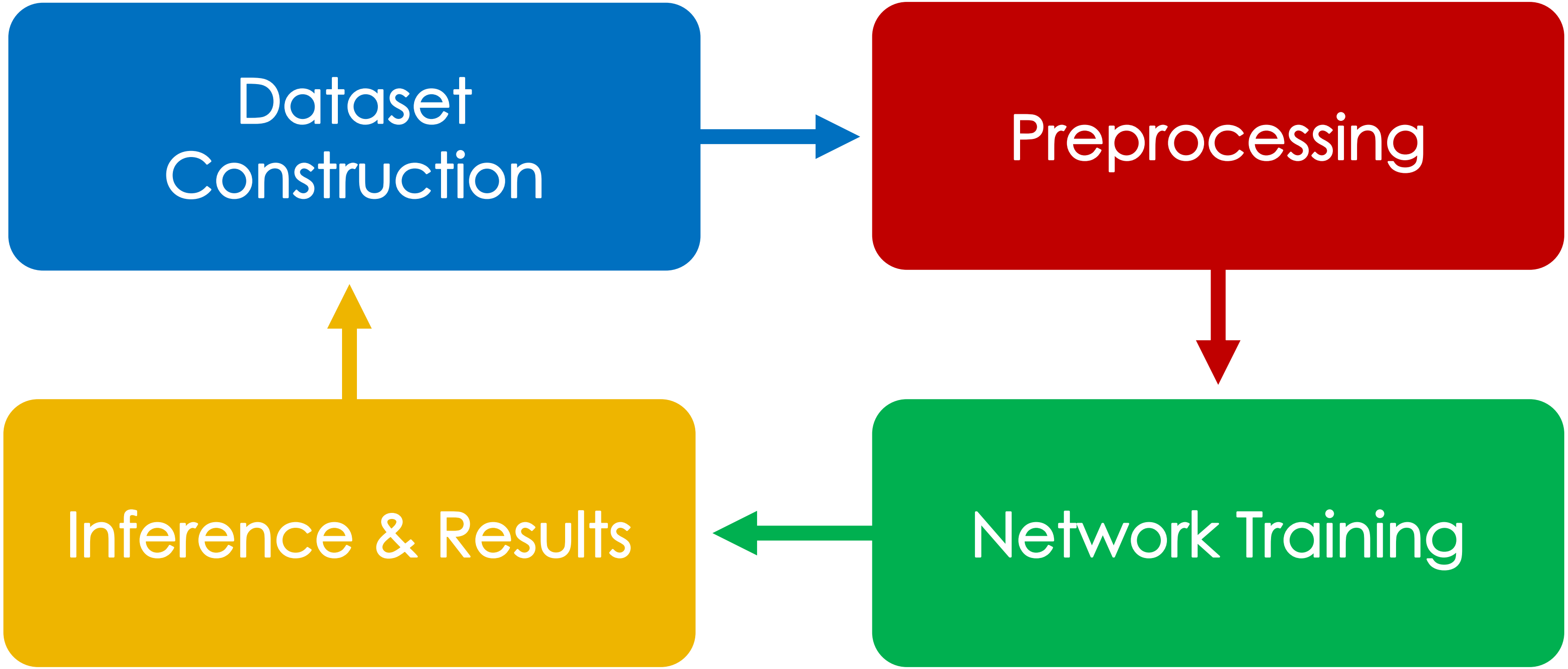
Complicated, Opaque, Slow, Rigid, Bespoke

→

ML Benefits

Simple, Accessible, Modular, Fast, Generalized

Project Structure



Questions?

Dataset Construction Overview

Data Challenges

- Largest hurdle is a lack of data
- Transport Profiles not able to be measured directly
- On the scale of data required, performance becomes essential

Transport Parameters

Continuity

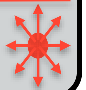
$$\frac{\partial n}{\partial t} = -\frac{1}{r}\frac{\partial}{\partial r}(r\Gamma) + S$$

D-V Ansatz

$$\Gamma = -D\frac{\partial n}{\partial r} + vn$$

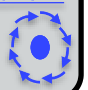
Diffusion(D)

Spreading Out
No "Direction"



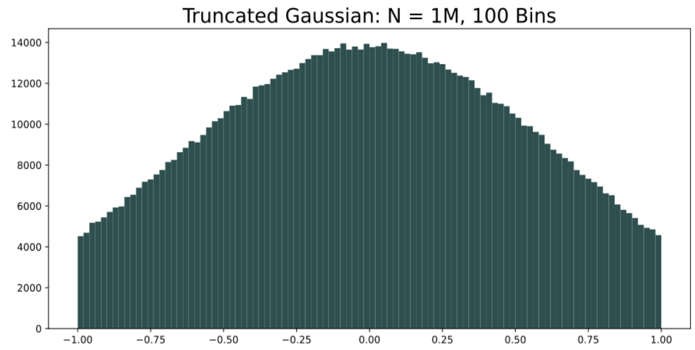
Convection(V)

Moving Around
One "Direction"



The Strengths of D&V Determine Plasma Behavior

Generation Distribution



Types of Profiles

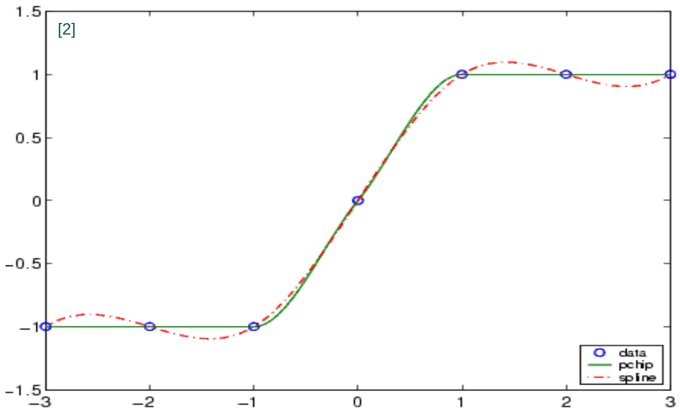
- Source(ρ,t)
- Initial Density(ρ)
- Diffusion(ρ)
- Convection(ρ)

Dataset Construction

Selecting Free Params.

- Source & Initial Density fit to known functional forms, varying function input parameters
- Diffusion and Convection created by interpolating between varying knot points (PCHIP Interpolation)

PCHIP Interpolation

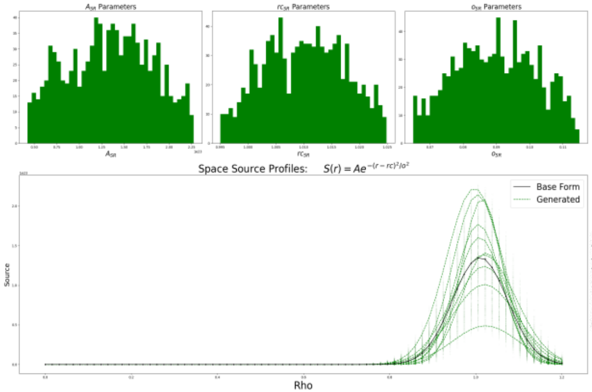


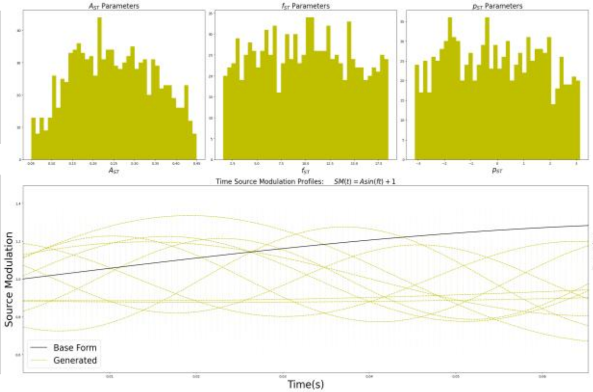
Generation Process

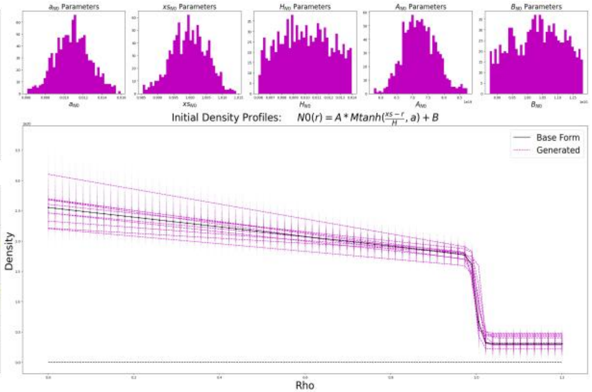
Determine Spanning Parameter Boundaries → Select Distribution Parameters → Generate Randomized Free Params. → Construct Initial Profiles

Dataset Construction

Example Generated Parameter Spaces

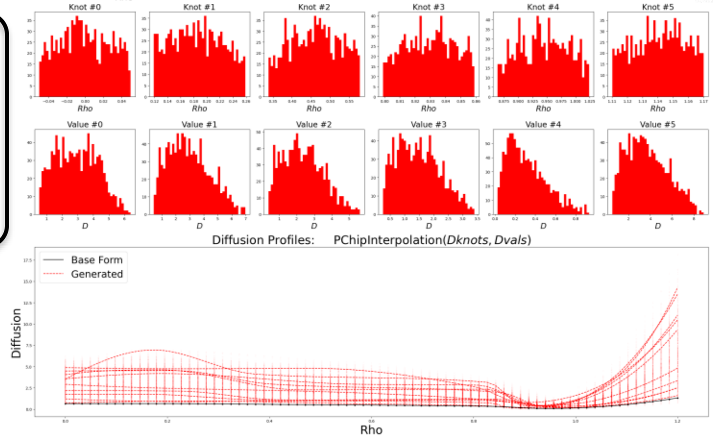


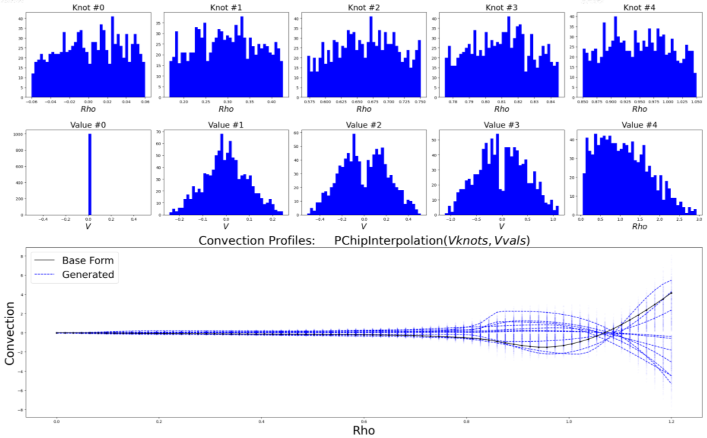




Modeled After

Alcator C-Mod





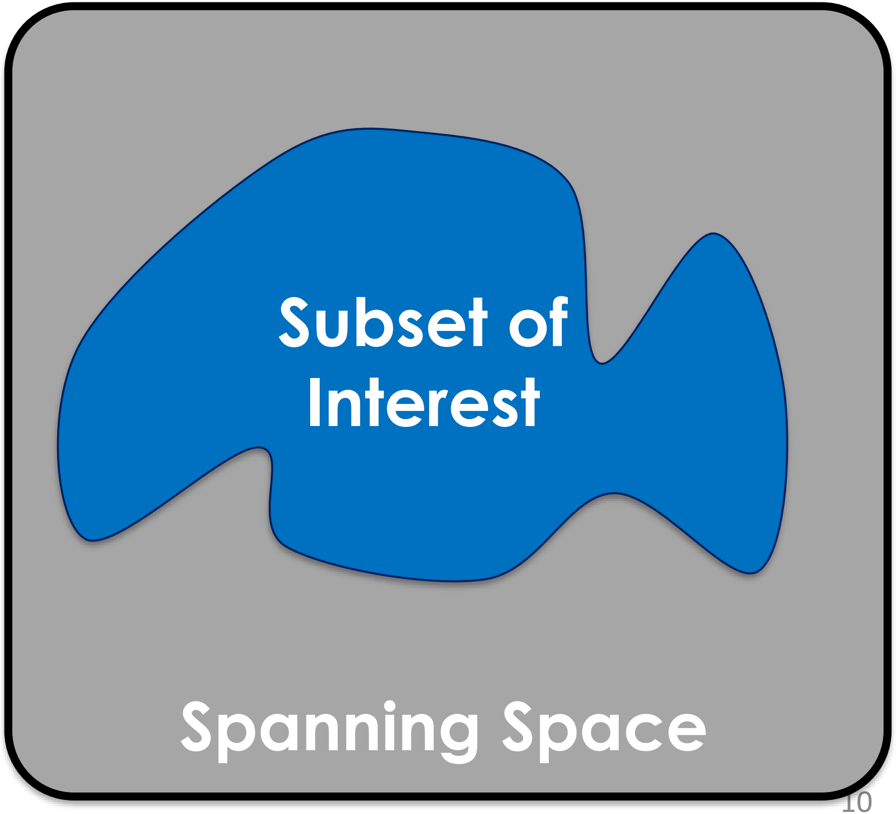
Dataset Construction

Goals Behind Process

- Form a spanning space of all reasonable experimental conditions.
- Enforce reasonable bounds, but keep dataset broad
- 'Map Out' experimental transport parameter space

Need To Ensure Alignment With Realistic Conditions

Spanning Spaces



Preprocessing

Needed Before Model Training

What We Have

Initial Condition Database

→

What We Need

Solved Density Evolutions

Solver Framework

Continuity

$$\frac{\partial n}{\partial t} = -\frac{1}{r}\frac{\partial}{\partial r}(r\Gamma) + S$$

D-V Ansatz

$$\Gamma = -D\frac{\partial n}{\partial r} + vn$$

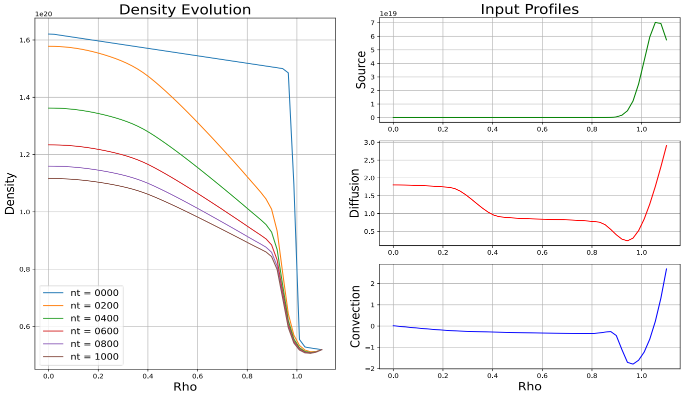
Implementation

1. Finite Diff. Method
2. 1D Radial C-D Ansatz
3. Solved In Matrix Form
4. GPU Accelerated

Behavior Validation

- Benchmarked to numerical errors against existing finite diff PDE solvers
- Achieves ~2000x faster results than naïve CPU SciPy approach
- Accepts all uniform grid shapes for rho & time, stability verified within reason

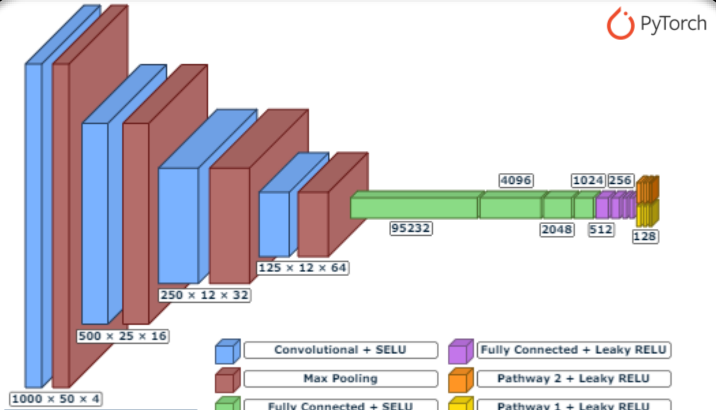
Example Density Evolution



Questions?

Network Training Overview

Network Architecture



Network Inputs

Rho: 1D
Time: 1D
Source: 1D
Density: 2D

Network Outputs

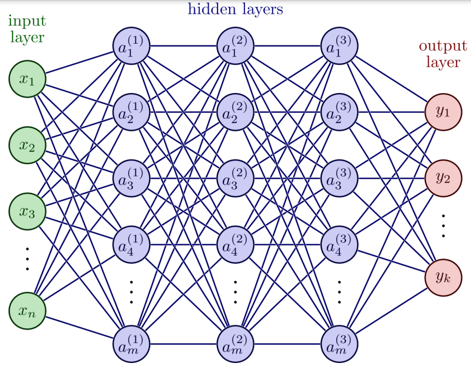
Diffusion: 1D
Convection: 1D

Network Characteristics

- ❑ Non-Linear Activation Functions
- ❑ Split Output Data Pathways
- ❑ Learning-Rate Scheduler
- ❑ Huberloss Criterion (delta = 0.75)
- ❑ AdamW optimizer function
- ❑ Data Standard Scaling
- ❑ Optimized Runtime

A Primer on Neural Nets

Structure



Training

Process Inputs
Infer Outputs
Score Model
Update Weights

Convolutions

- Enforced Locality
- Useful for Spatial or Temporal Data
- Often on Images

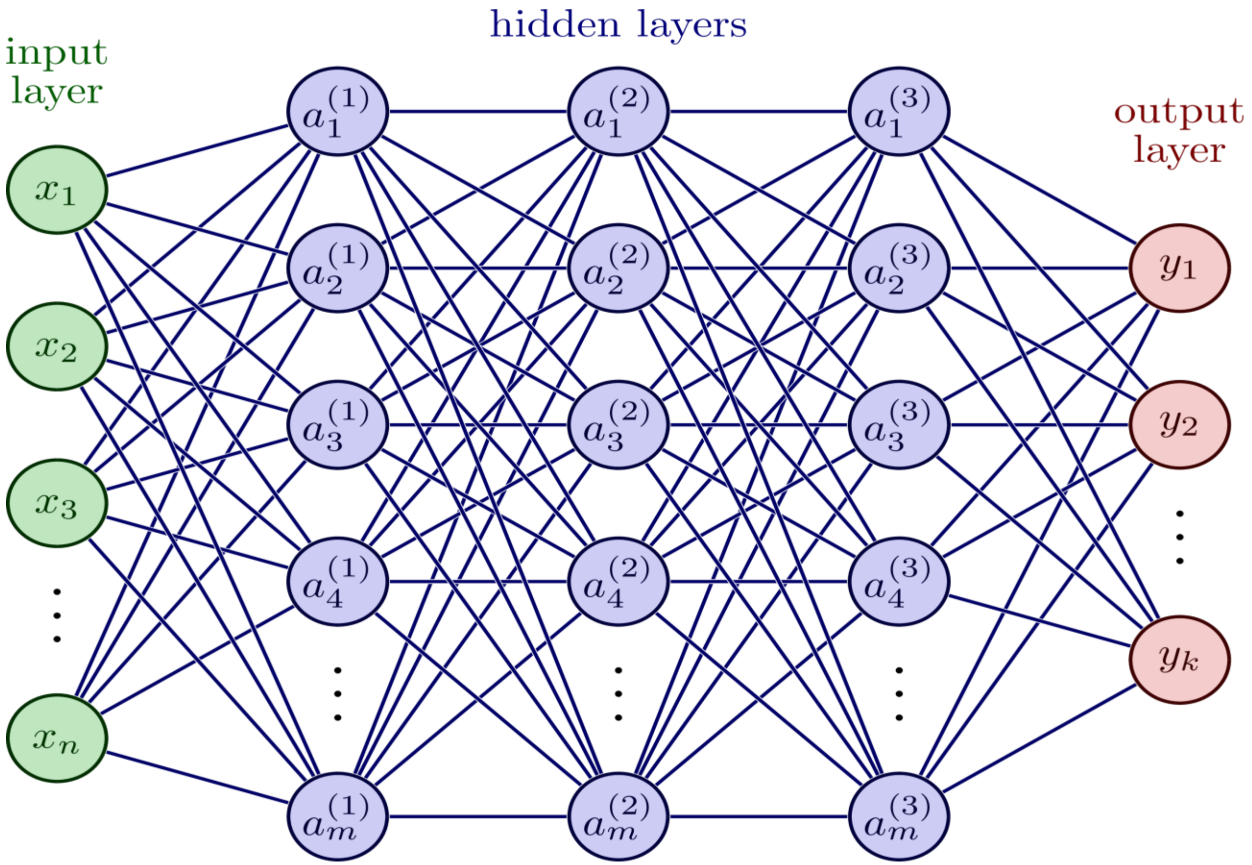
Parameter Tuning

Iterative Hypothesis Testing

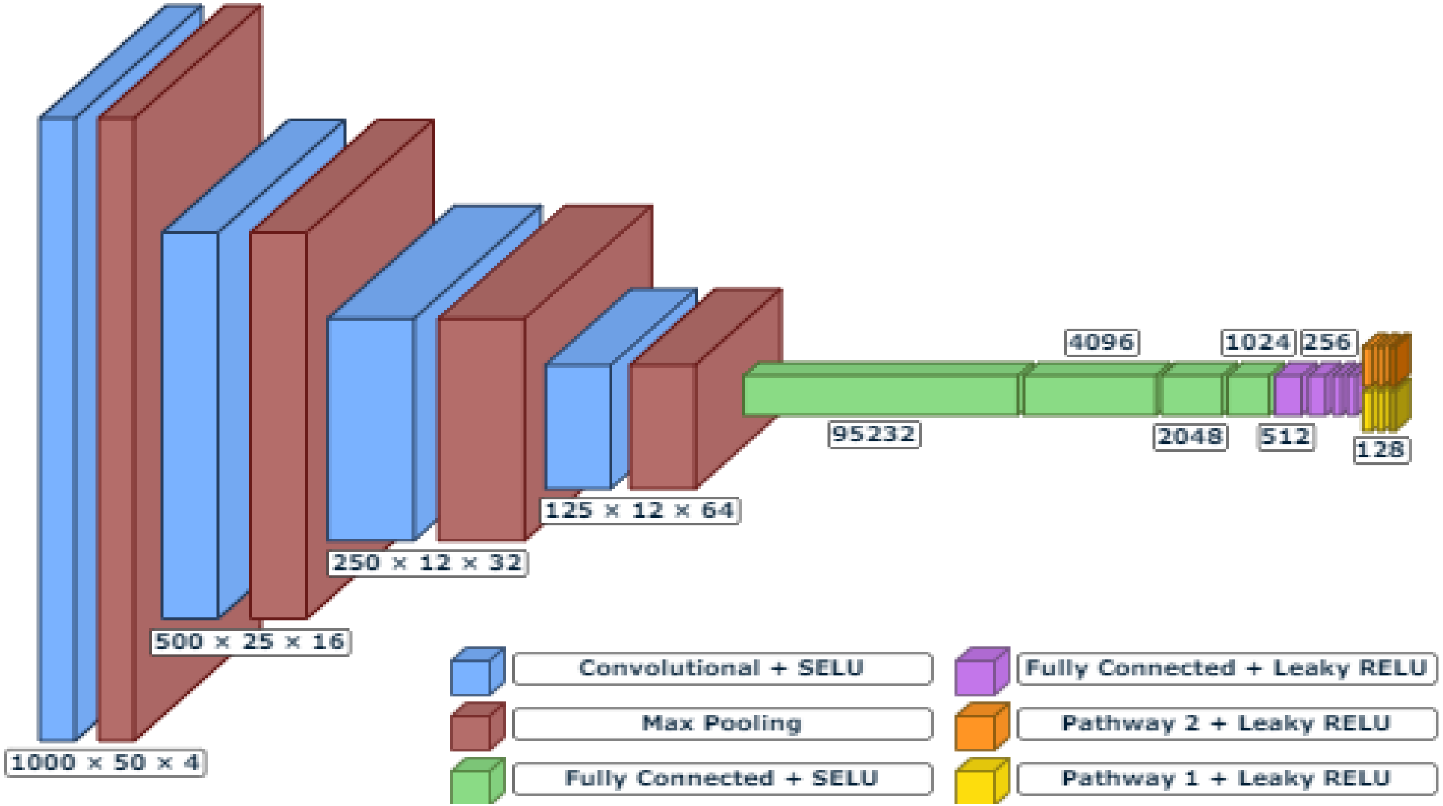
OR

Optimization Schemes

Network Training



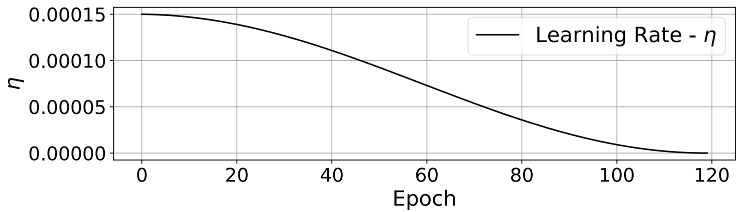
Network Training



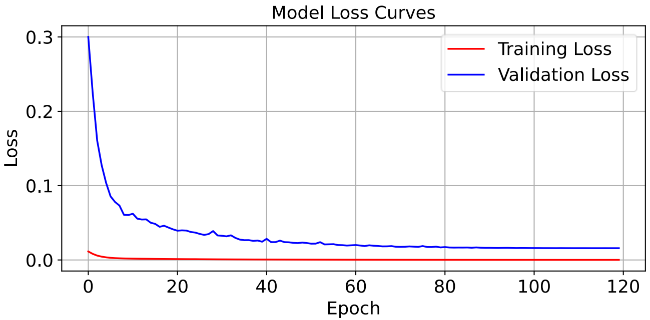
Network Training

Training Process

- Training/Validation/Test Split of 70/10/20 Implemented
- Trains in ~1hr, 120 epochs (RTX 4090, 7950x3d, 128GB RAM)



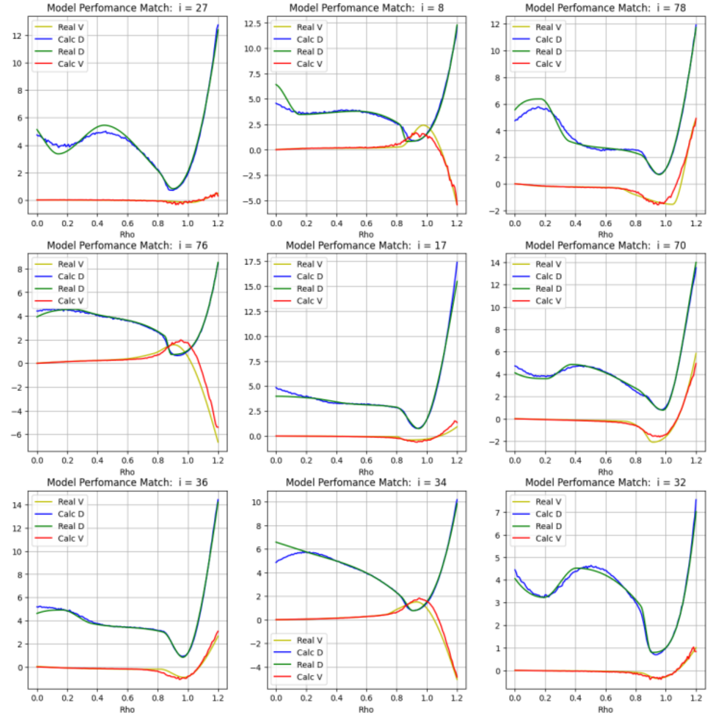
Training Loss	Validation Loss	Test Loss
0.0042	0.0159	0.0168



- Gap between losses suggests overfitting
- Saturated at ~60 epochs training
- Model error is exceedingly low

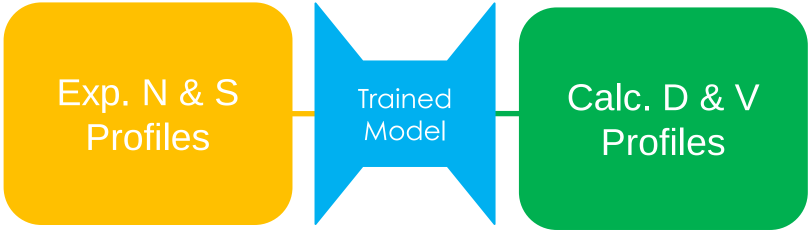
Results

All samples below selected at random from testing set (Model has not seen this data before)



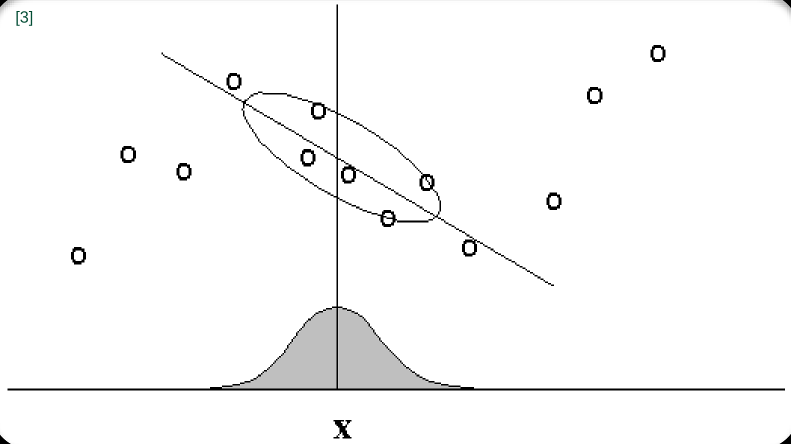
Inference of Exp. Transport

Inference Process

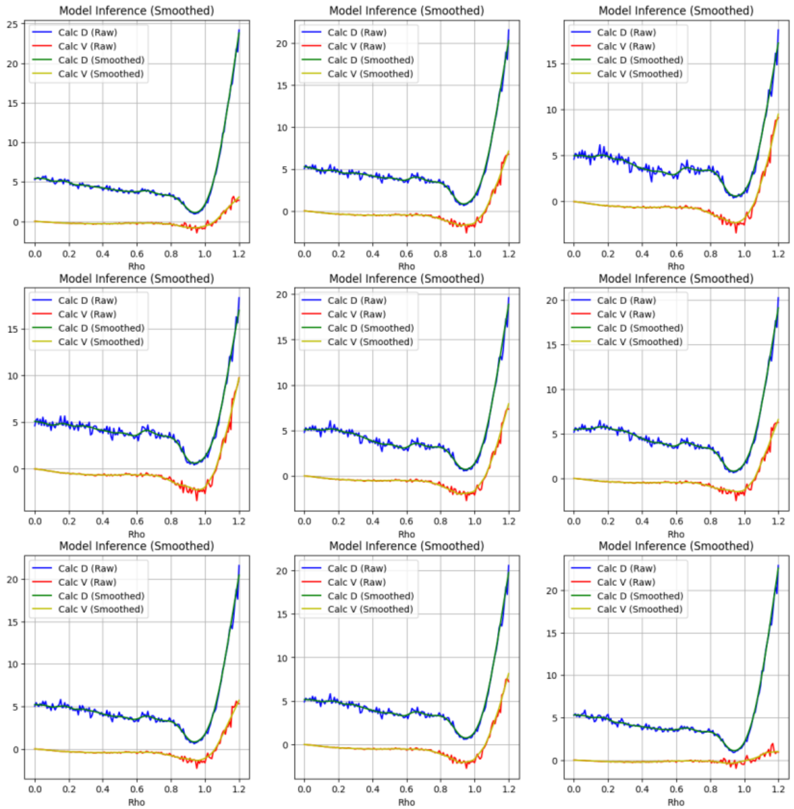


Locally Weighted Regression

[3]

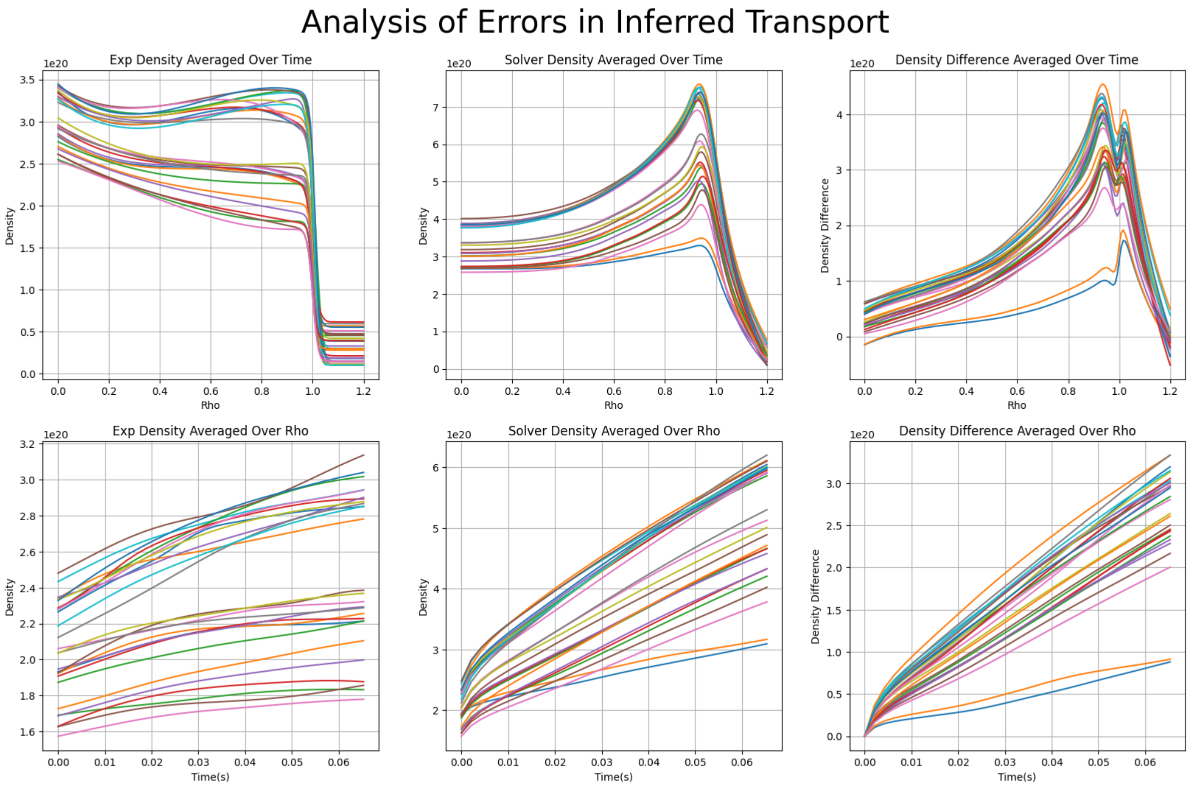


Example Profiles



Scoring Inference Results

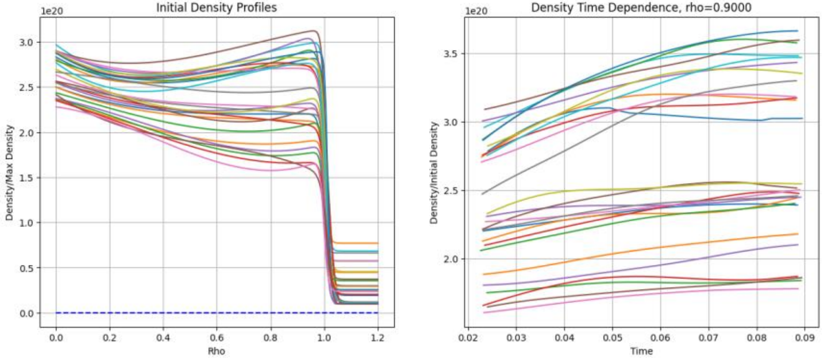
Inferred transport profile & exp. Initial conditions time-evolved using solver and compared to exp. data



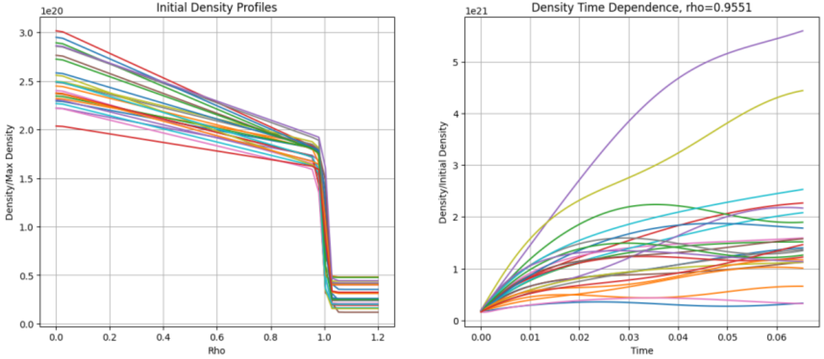
Questions?

Fixing Data Alignment

Experimental Density Evolution

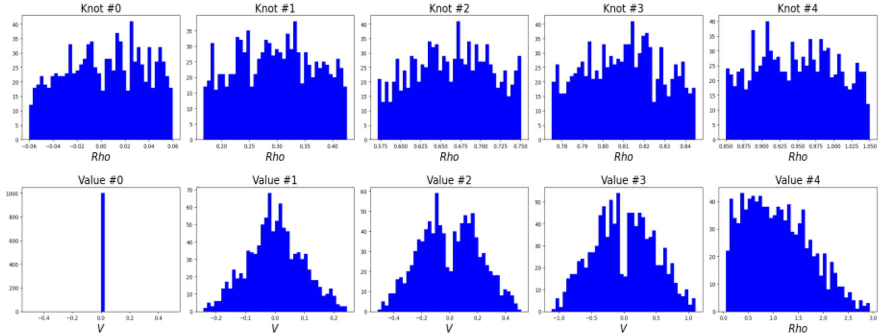


Generated Density Evolution

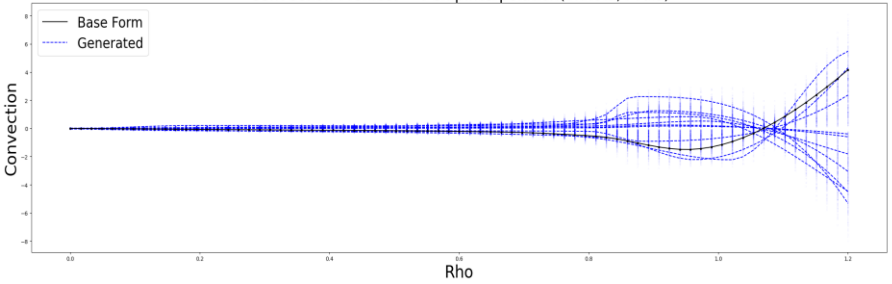


Generation Modifications

- Add a Sink Term to solver past the Separatrix
- Move Convection crossing point inward
- Widen parameter space, more samples



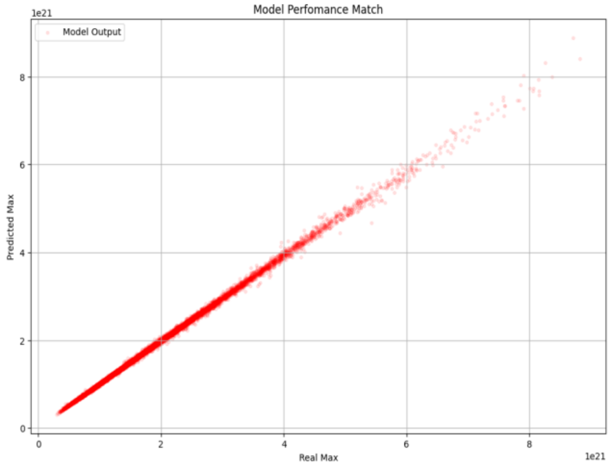
Convection Profiles: PChipInterpolation(*Vknots*, *Vvals*)



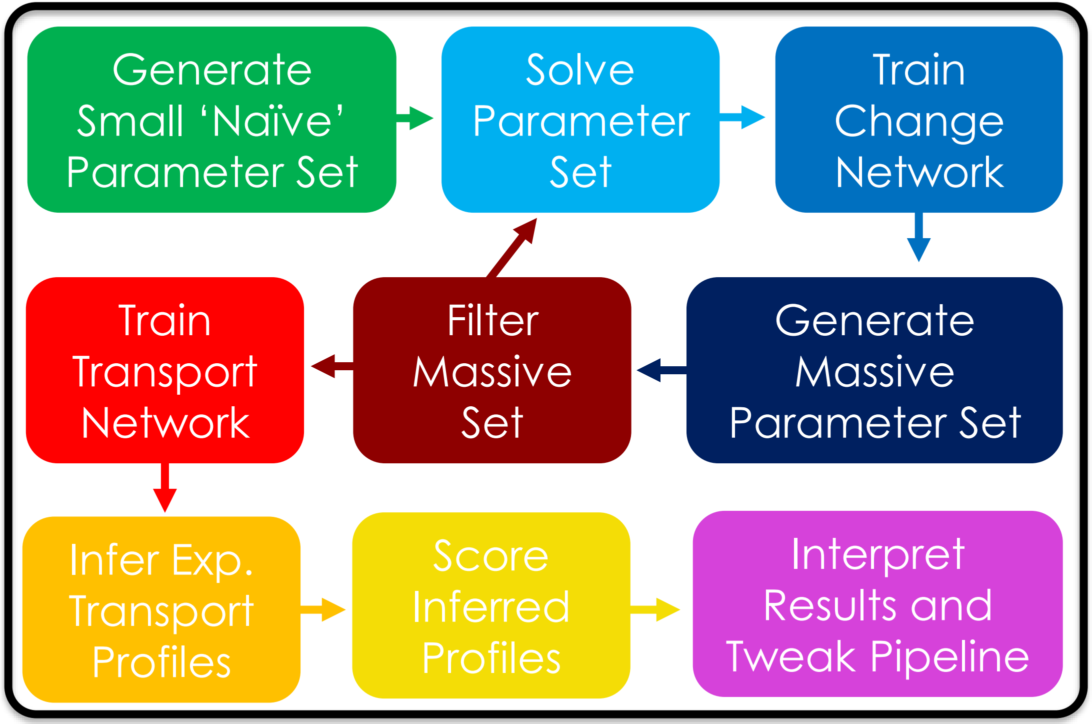
Fixing Data Alignment

Filtering

- Use another NN to ‘predict’ evolution of initial conditions
- Use these results to filter the ‘naïve’ parameter choices
- Just predict a few statistics to optimize performance



Filtering Process Diagram

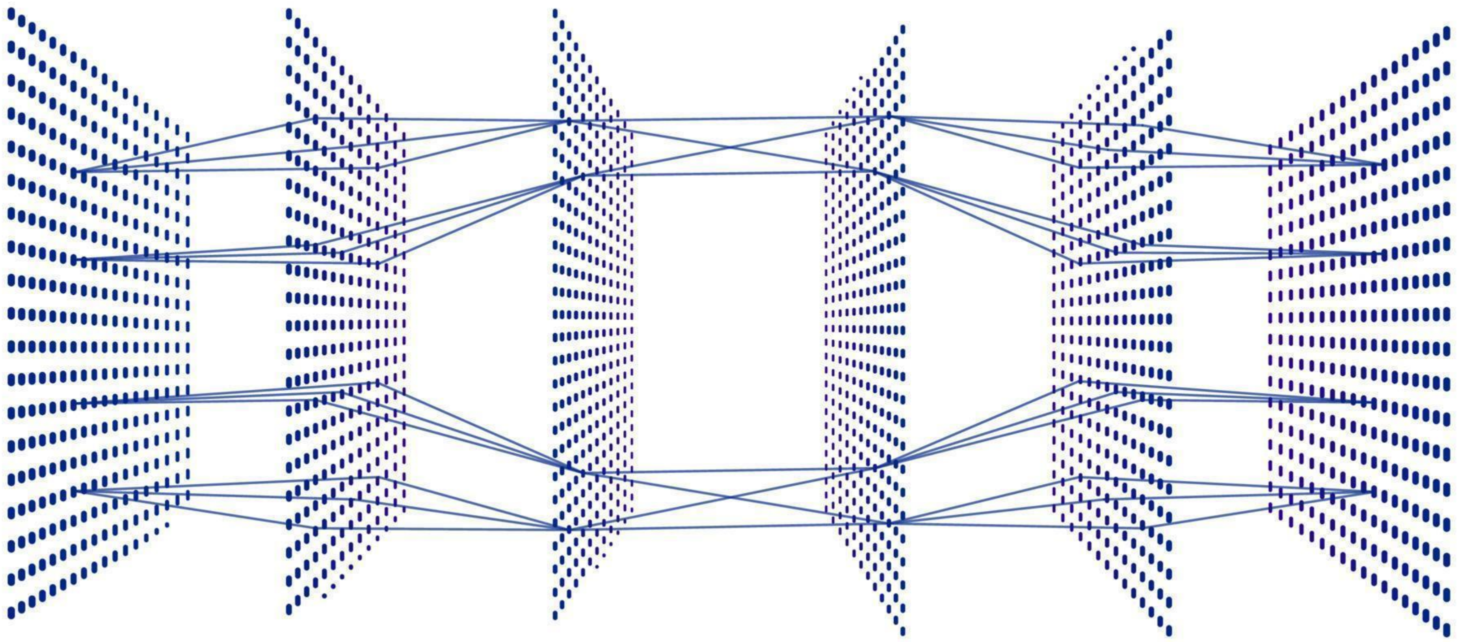


Not all subprocesses included

Future Work

- Finalize Filtering Process
- Tune Data Generation
- Allow Time-Dependent Transport
- Add Transport Density Link
- Examine Parameter Map and Region Deviance
- Incorporation Dimensionless Parameters
- & Much more…

Thanks For Listening!



References

Figures

[1]: Wurzel 22, Progress toward fusion energy breakeven and gain as measured against the Lawson criterion

[2]: Northwestern, Matlab Function Reference

[3]: Carnegie Mellon University, Locally Weighted Regression

Resources

- PPPL Intro to Plasma Course
- A Short Introduction to Plasma
- Github Site (Under Construction)

Papers

[1]: *S. Mordijck 2020 Nucl. Fusion 60 082006*

[2]: *E. Stefanikova et al 2016 Rev. Sci. Instrum. 11E536*

[3]: *A.M. Rosenthal et al 2024 Nucl. Fusion 64 036006*

[4]: *F. Sciortino 2021 MIT Libraries 142810*

Acknowledgement

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