

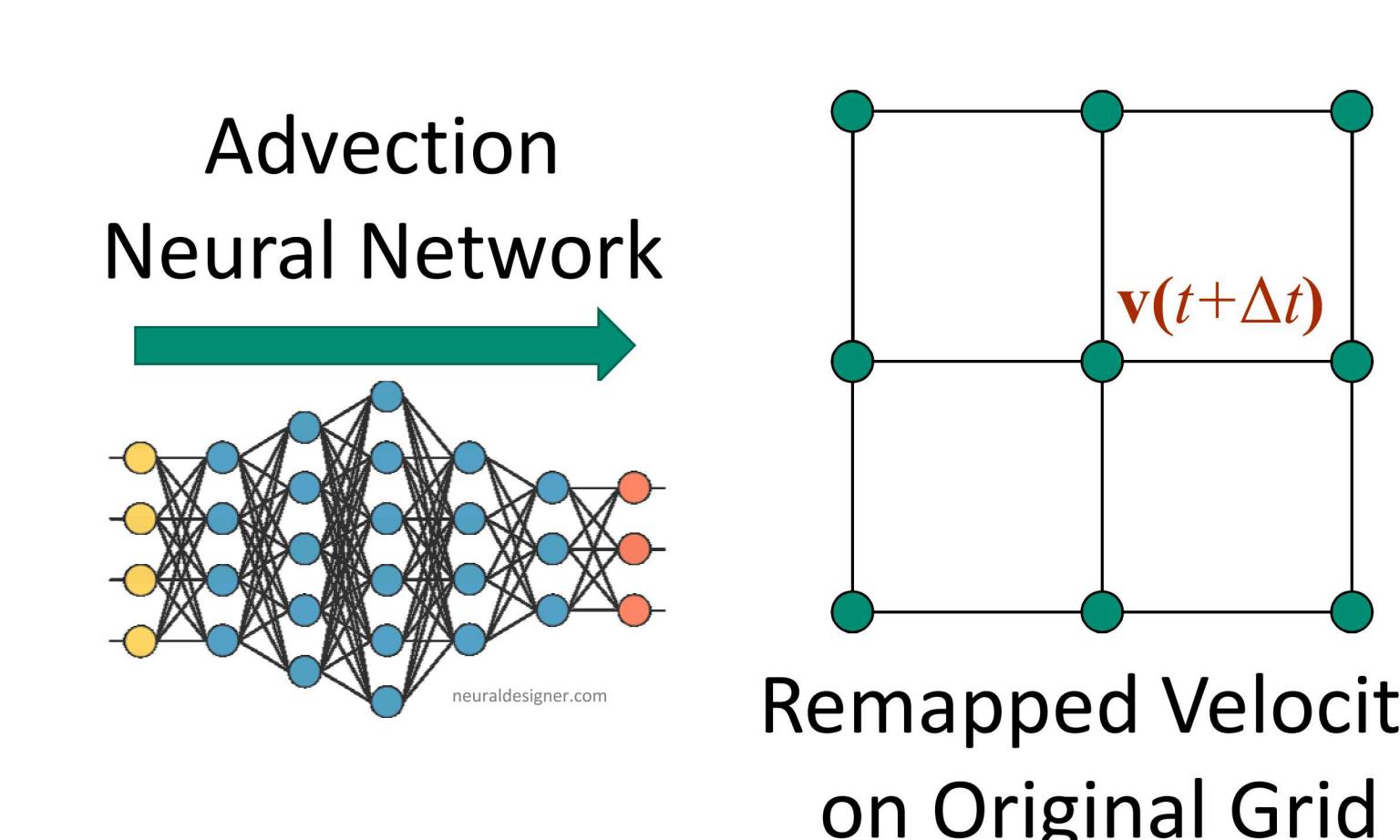


Deep Learning the Advection in Eulerian Hydrocodes

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Problem

- Can we **substitute** traditional components of a simulation algorithm with **data-driven models**?
- **2 steps of hydrocode**
 - Lagrangian step: Deform mesh
 - Remap/Advection Step: Remap nodal velocities back onto original mesh
- **Objective is to approximate the remap step using a neural network**



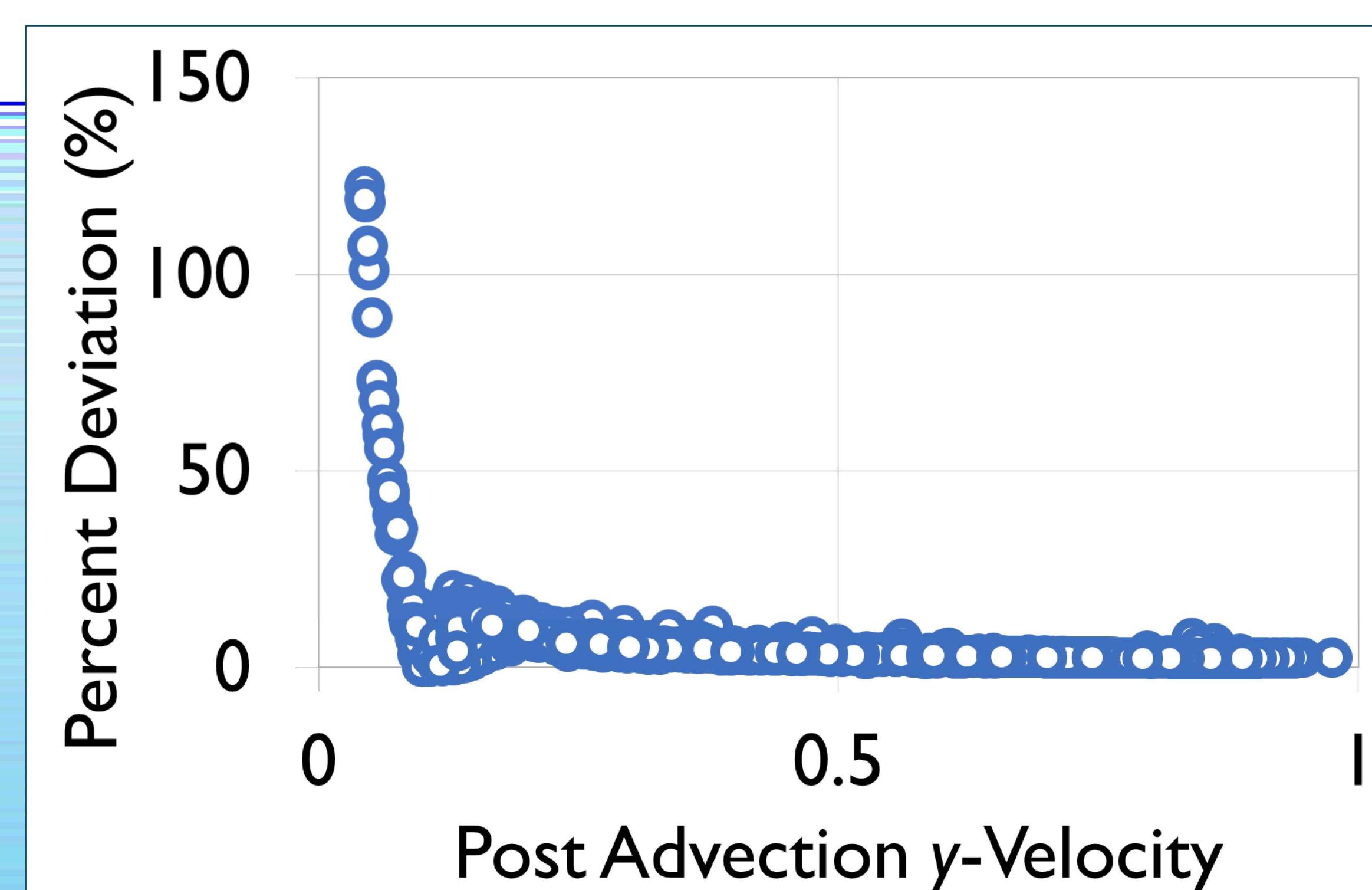
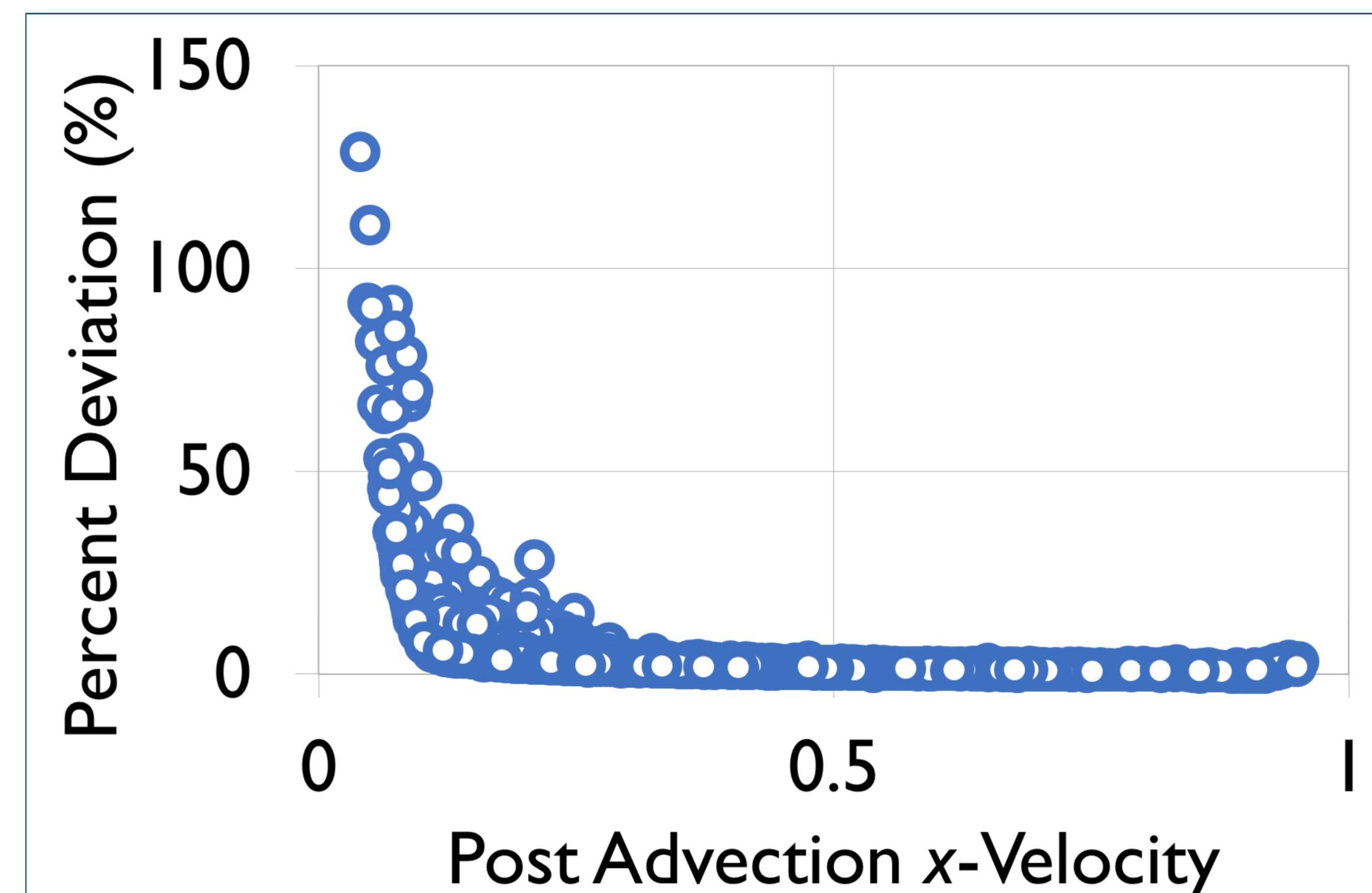
Training Data

$\mathbf{v}_{i,j} \approx f(\Delta\mathbf{r}_{i,j}, \Delta\mathbf{r}_{i-1,j}, \Delta\mathbf{r}_{i+1,j}, \Delta\mathbf{r}_{i,j-1}, \Delta\mathbf{r}_{i,j+1})$

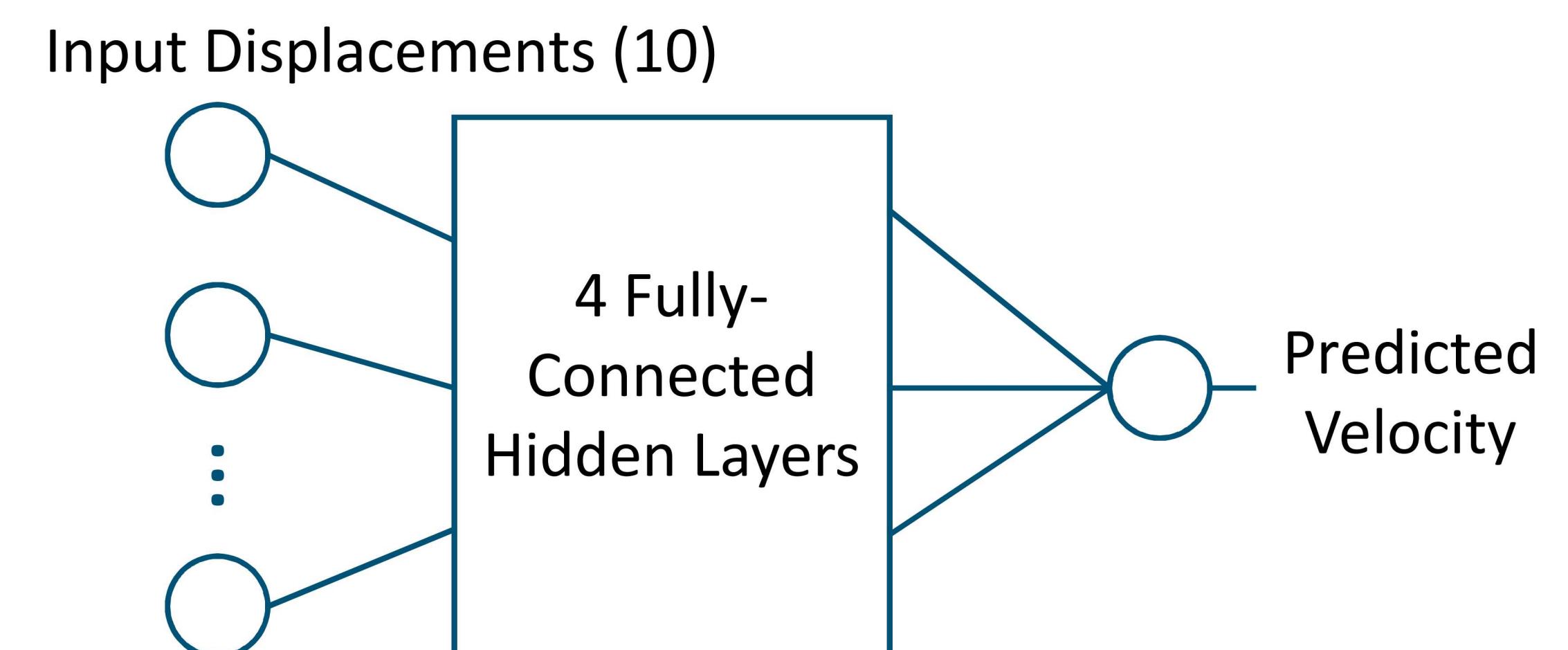
- **~100,000 data points** of post advection velocity vs. displacement at nodes and immediate neighbors
- Randomly initialized, normally distributed velocities on 2D grid (normalized between 0 and 1)

Results

- Average predicted velocities **within 4%**
- Larger deviations near zero velocities due to divide-by-zero effect



Network Architecture



- Multi-layer perceptron, Leaky ReLU activation
- Smooth L1 loss optimized using SGD
- Two separate networks trained to predict x and y velocity components

Significance & Outlook

- This exploratory work shows promise in accurately predicting advection velocity
 - More advanced models and/or more data will likely improve accuracy
 - Other algorithms in computational solvers should be explored
- An advanced DNN-remap algorithm trained on high resolution simulations or exact solutions may be possible

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