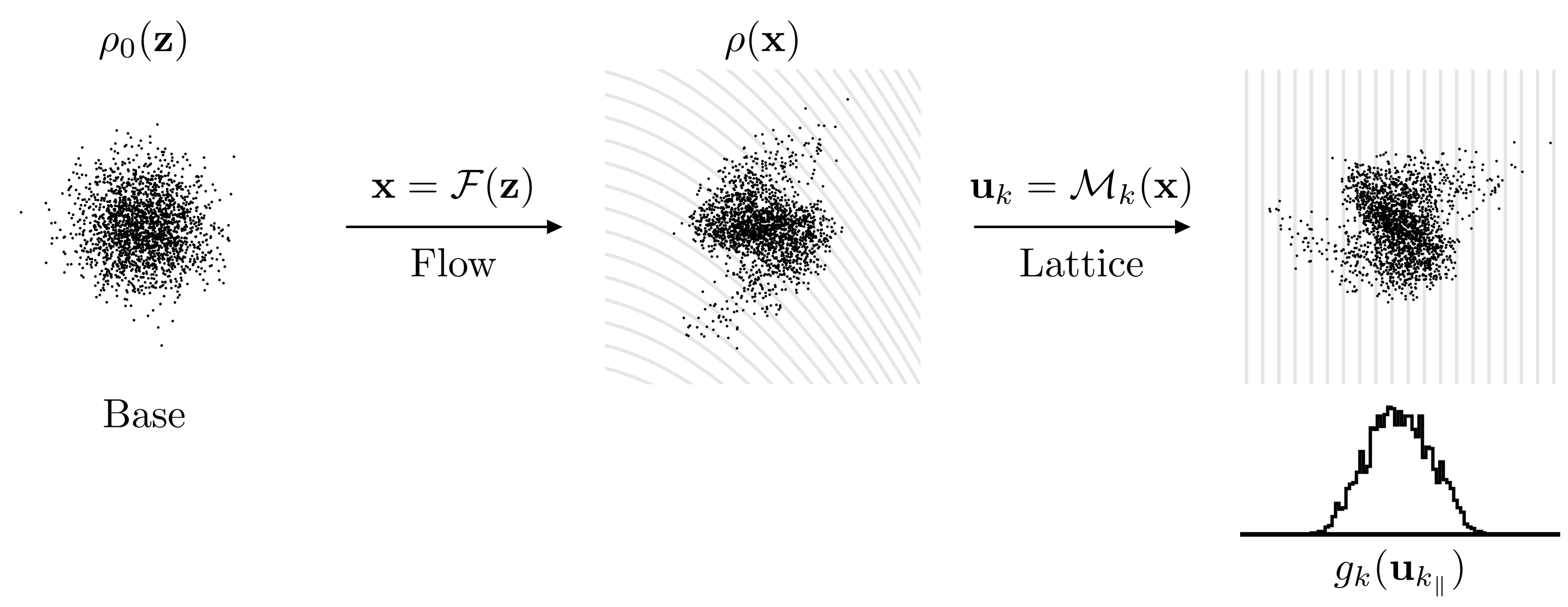
MENT-Flow: Maximum-Entropy Phase Space Tomography Using Normalizing Flows

Austin Hoover (Oak Ridge National Laboratory), Jonathan C. Wong (Institute of Modern Physics)

Normalizing flows for projection-constrained entropy maximization



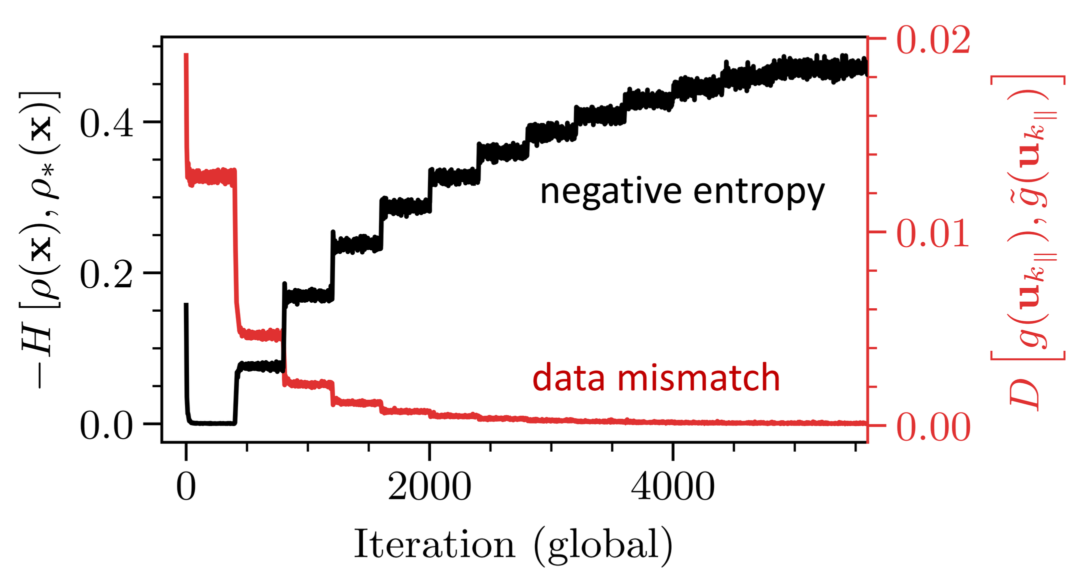
A *normalizing flow is* an invertible, differentiable map (represented by a neural network) between distributions. The probability density obeys

$$\log \rho(\mathbf{x}) = \log \rho_0(\mathbf{z}) - \log |J_{\mathcal{F}}(\mathbf{z})| \longleftarrow \text{volume change}$$

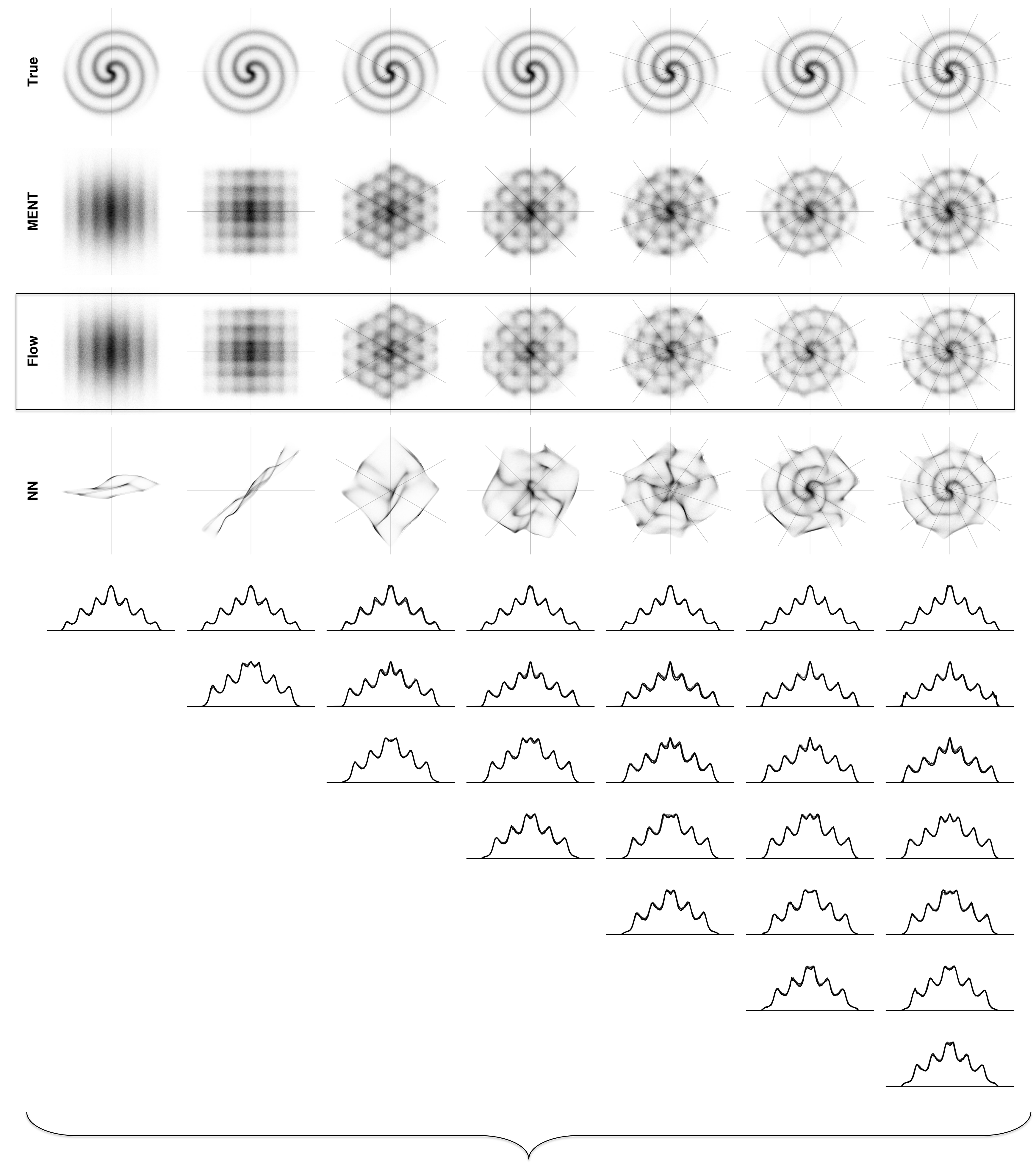
We obtain an unbiased, differentiable entropy estimate by sampling N particles from the base distribution and pushing them through the flow:

$$-H[\rho(\mathbf{x}), \rho_*(\mathbf{x})] = \int \rho(\mathbf{x}) \log(\rho(\mathbf{x})/\rho_*(\mathbf{x})) d\mathbf{x} \approx \frac{1}{N} \sum_{i=1}^{N} \log(\rho(\mathbf{x}_i)/\rho_*(\mathbf{x}_i))$$

We maximize the entropy via stochastic gradient descent [arXiv:1701.03504]. We enforce projection constraints using differentiable beam physics simulations and projected density estimation [arXiv:2209.04505]. We perform the constrained maximization using a penalty method.

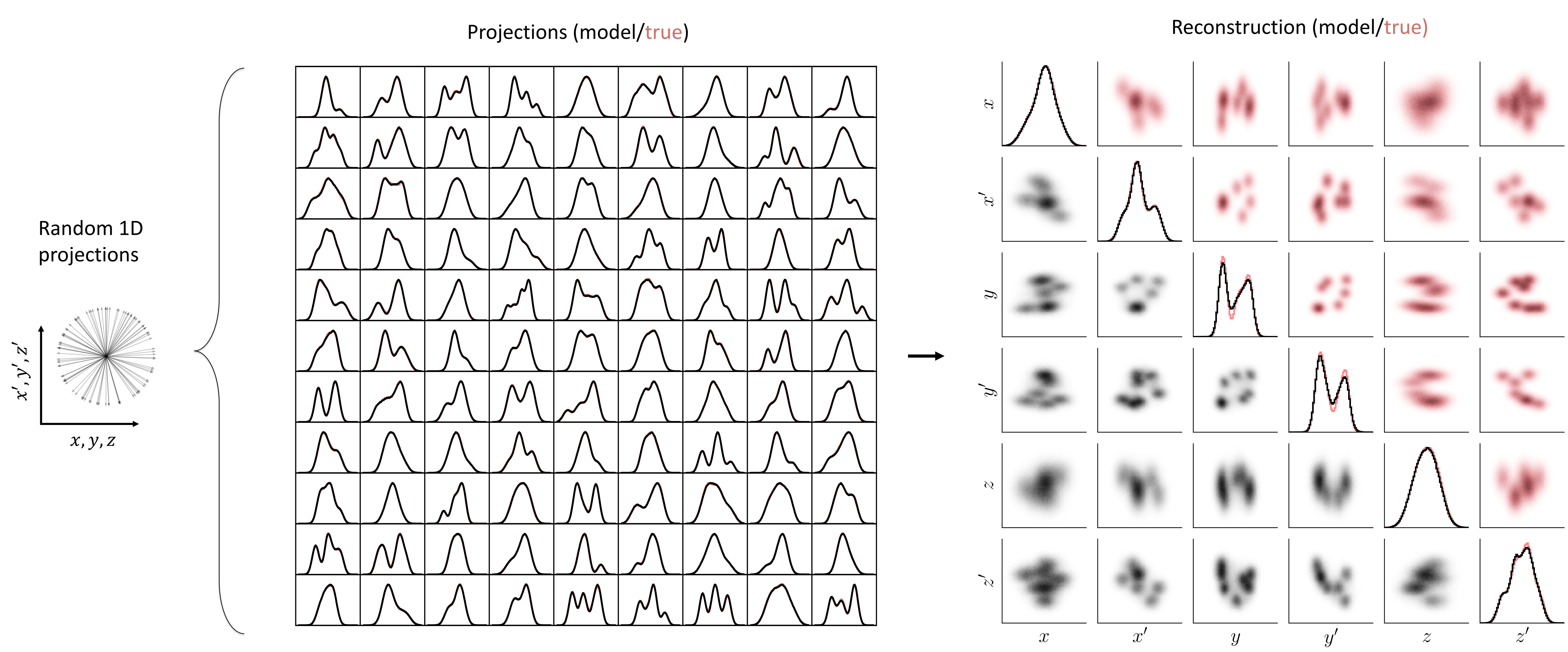


MENT-Flow approaches 2D MENT (exact) solutions



MENT enforces logically consistent inference. While all solutions fit the data in these examples, the MENT solutions are as simple as possible.

Normalizing flows can fit complex 6D distributions to large measurement sets



This work has been authored by UT-Battelle, LLC, under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy.