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Omnifold uncertainties

How statistical uncertainties propagate through unbinned unfolding

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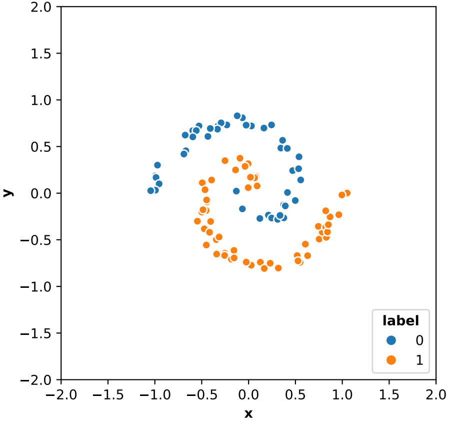
U.S. DEPARTMENT OF ENERGY
Office of Science

Multi-Layer Perceptron (MLP) - Toy Example



Dataset: 100 samples from 2 gaussian-smeared spirals, “0” (upper spiral / blue points) and “1” (lower spiral / orange points)
Task: classify the blue and orange points

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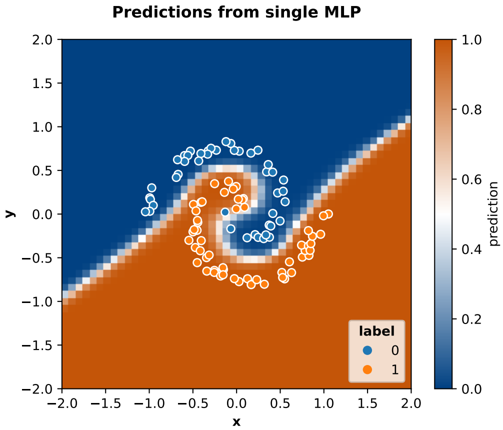
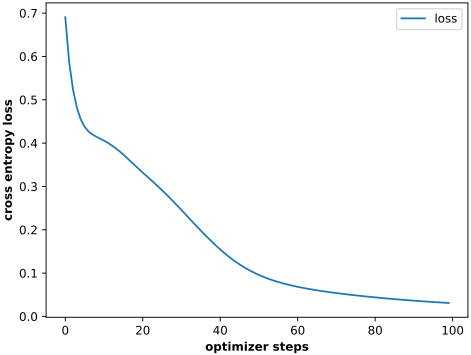


Attempt 1: A single Multi-Layer Perceptron (MLP)



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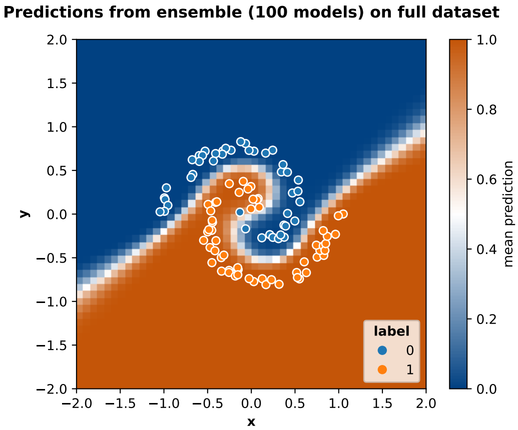
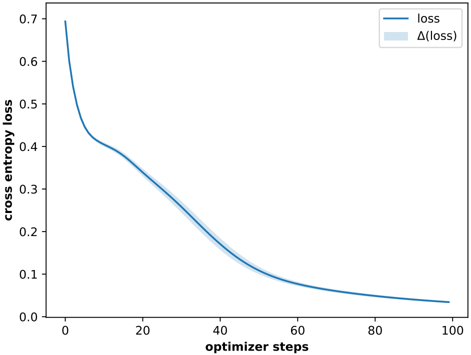


Attempt 2: 100 MLPs, each initialized differently, but sees the whole dataset



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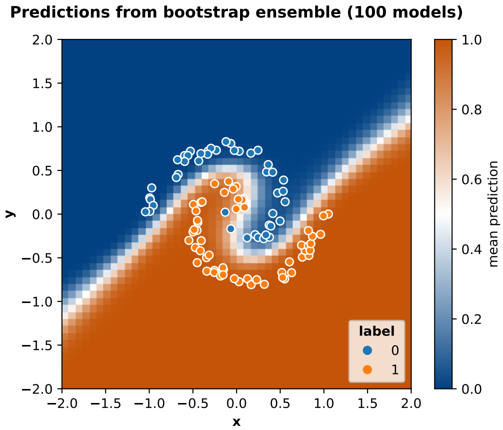
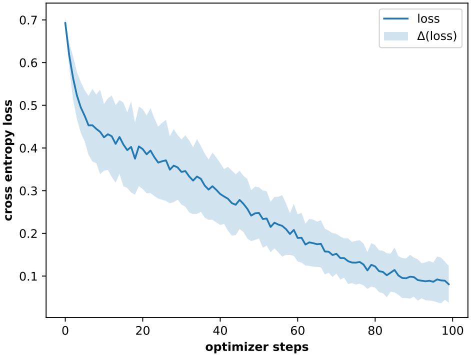
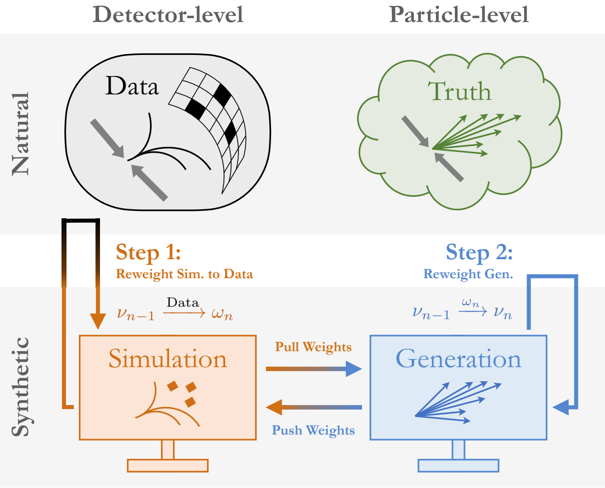


Attempt 3: 100 MLPs, each sees different bootstrap sampling of the dataset



Omnifold : Basics



- Iterative unfolding using unbinned data

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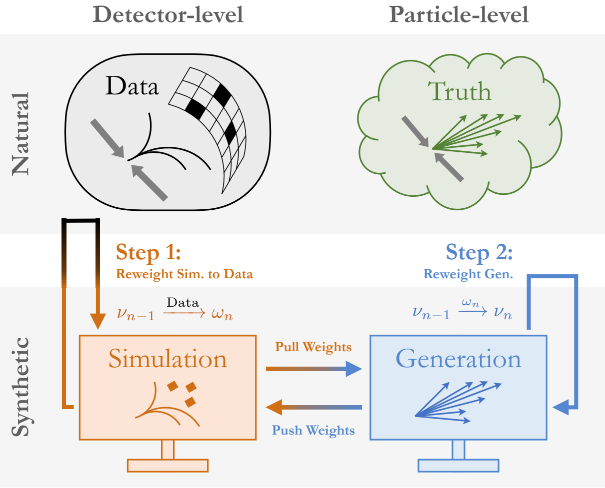

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- Steps 1 and 2 each uses MLP classifier to calculate per-sample conditional probabilities

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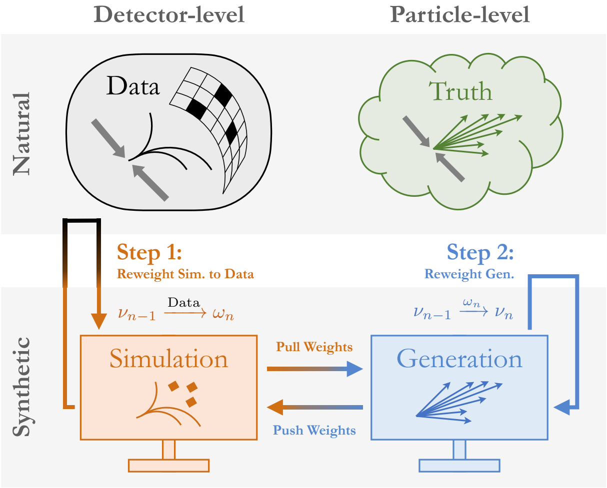

- Iterative unfolding using unbinned data
- Steps 1 and 2 each uses MLP classifier to calculate per-sample conditional probabilities
- Step 1 reweights reco to data and Step 2 propagates them to the gen

Generalized angularities

$$\lambda_\beta^\kappa = \sum_{\text{const}\in\text{jet}} \overbrace{\left(\frac{p_{\text{T,const}}}{p_{\text{T,jet}}}\right)^\kappa}^{\text{soft/hard radiation}} \times \overbrace{r(\text{const},\text{jet})^\beta}^{\text{collinearity sensitive}}$$

$$r(\text{const},\text{jet}) = \sqrt{(\eta_{\text{jet}} - \eta_{\text{const}})^2 + (\phi_{\text{jet}} - \phi_{\text{const}})^2}$$

- **LHA angularity** $\lambda_{0.5}^1 = \frac{\sum_{\text{trk}\in\text{jet}} p_{\text{T,trk}}\sqrt{\Delta R}}{p_{\text{T,jet}}}$,
- **Jet girth:** $\text{g} = \lambda_1^1 = \frac{\sum_{\text{trk}\in\text{jet}} p_{\text{T,trk}}\Delta R}{p_{\text{T,jet}}}$, measure of jet broadening
- **Thrust** $\lambda_2^1 = \frac{\sum_{\text{trk}\in\text{jet}} p_{\text{T,trk}}\Delta R^2}{p_{\text{T,jet}}}$, related to jet mass
- **Momentum dispersion :** $p_T^D = \lambda_0^2$
- Done for both inclusive jets and hard-core component of the inclusive jets
- Hard-core component calculated by vector summing constituents with $p_T > 2.0$ GeV/c

Dataset and Simulations

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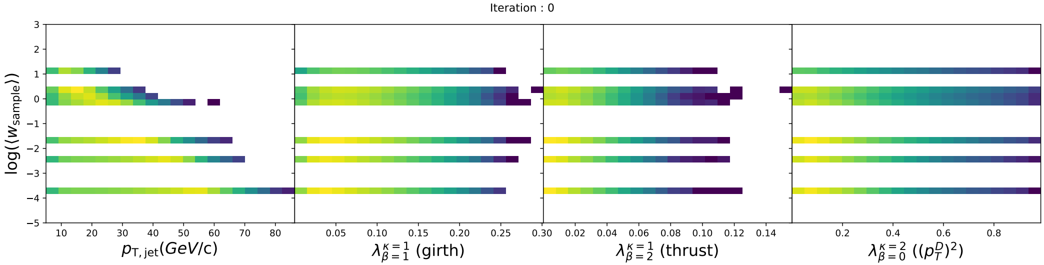
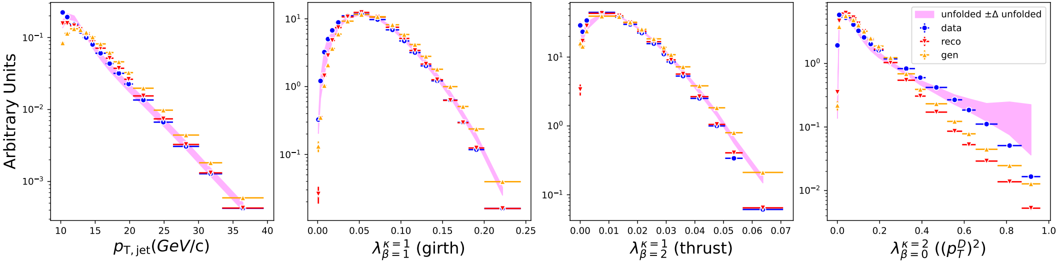
- Each model runs for 10 unfolding iterations

Bootstrapped Omnifolding : Mean Model Prediction



Bootstrapped Omnifolding : Unfolded Histograms



Conclusions and Outlook

- Bootstraped ensembling results in better predictions which depend on phase space distribution of the features
- Omnifolded weights from bootstraped ensemble results in smoothing of sample-weights distributions
- Unfolded distributions from bootstraped omnifold show uncertainties that increase with decrease in data statistics
- Need to run bigger ensembles to get better convergence of histograms with iterations