Tool Improvements for Simulation-Based Inference

Henning Bahl, Victor Bresó, Giovanni De Crescenzo, Tilman Plehn
g.de.crescenzo@thphys.uni-heidelberg.de

UNIVERSITÄT HEIDELBERG
ZUKUNFT SEIT 1386

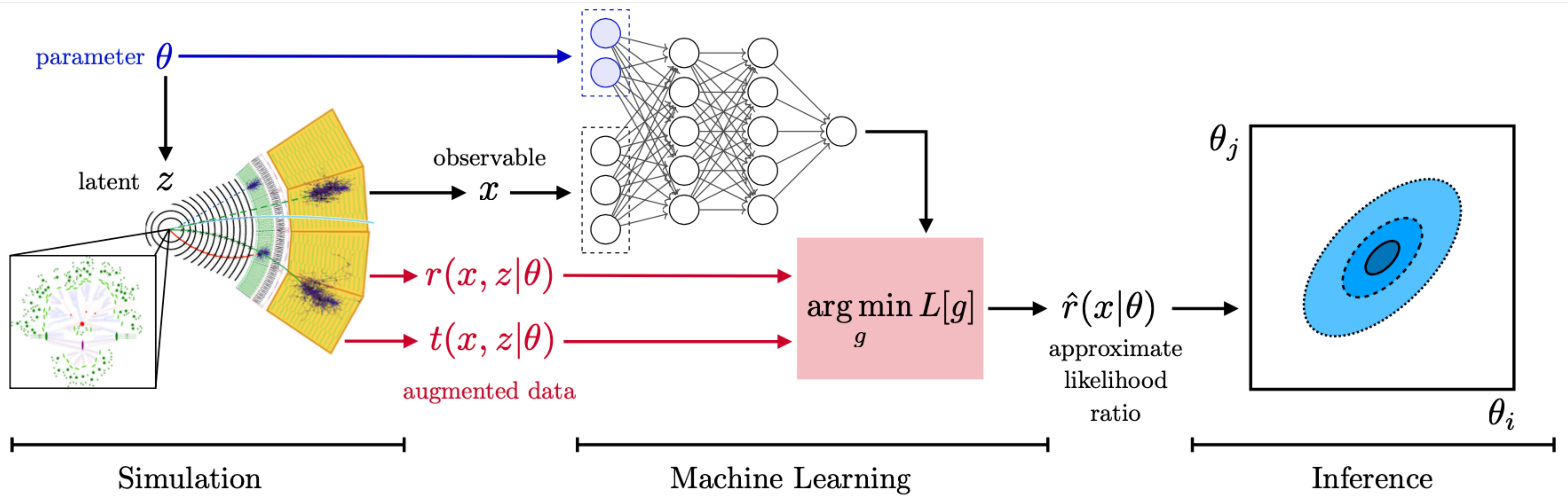


Image taken from "Constraining Effective Field Theories with Machine Learning" by J. Brehmer et al.

Learning, toy model, multi smearing

Learning approaches

- Derivative learning: $(x,z)_0 \sim p(x,z\,|\,\theta_0)$, [arXiv:2205.12976v1]

$$R_\alpha(z) = \frac{\partial_\alpha d\sigma(z, \theta=\theta_0)}{d\sigma(z,\theta=\theta_0)};$$

$$L := \int dxdz\, p(x,z\,|\,\theta_{SM}) \Big(R_\alpha(z) - \hat{R}_\alpha(x) \Big)^2$$

- Morphing aware: $(x,z)_i \sim p(x,z\,|\,\theta_i,\theta_0)$, $s(z) := \dfrac{1}{1+r(z)}$;

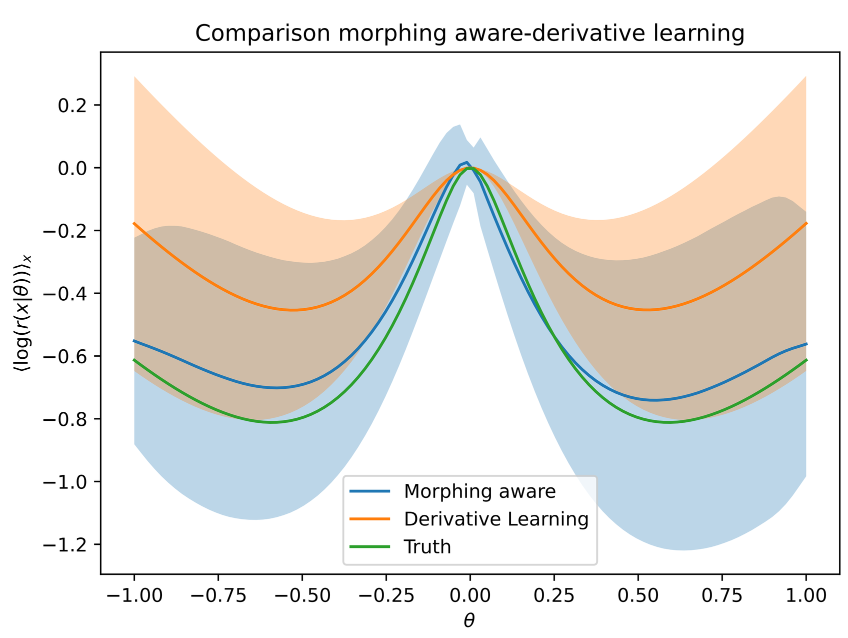
$$L := \int dxdz\, p(x,z\,|\,\theta_i,\theta_0) \Big[s(z) \log\big(\hat{s}(x)\big) + \big(1 - s(z)\big) \log\big(1 - \hat{s}(x)\big) \Big]$$

Toy model setup

Toy model simulator with same θ structure as SMEFT

$$p(x\,|\,z) = \mathcal{N}(x, \mu = z, \sigma = 0.7)$$

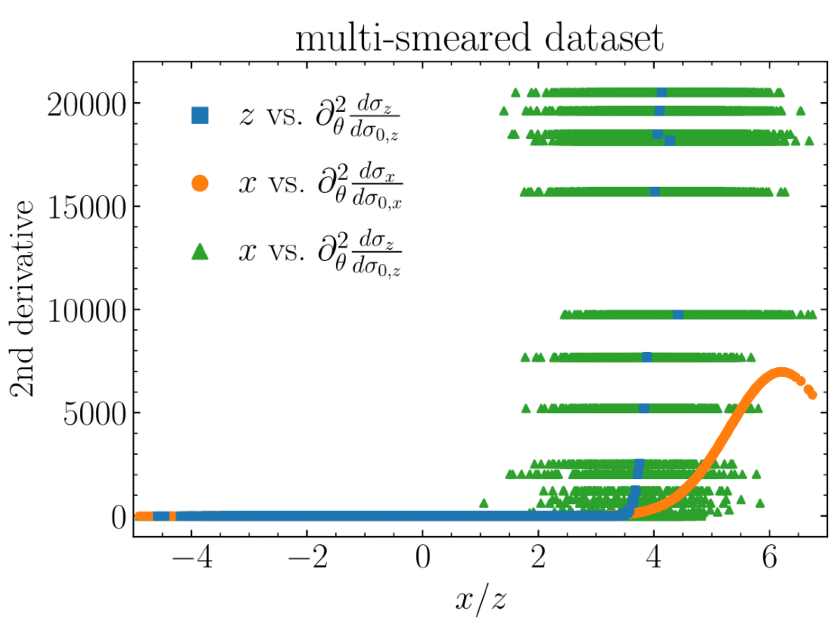
$$p(z\,|\,\theta) = \big(\mathcal{N}(z, \mu=0, \sigma=1) + \theta^2 \mathcal{N}(z, \mu=3, \sigma=0.1)\big)/(1+\theta^2)$$

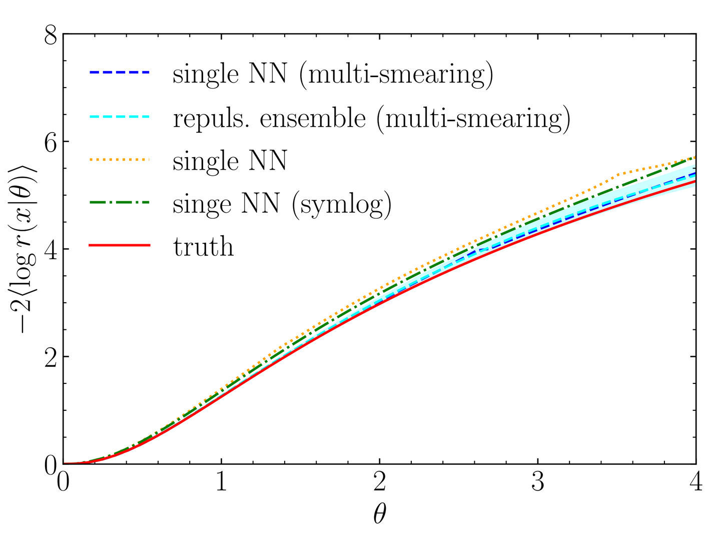


Repulsive ensembles: ensemble of networks with repulsive force to account for uncertainty. Show lack of training data depending on phase space region

Multi-smearing

Stabilize training sample by reweighting z events and sampling multiple x events accordingly





Physics case

- Standard Model Effective Field Theory (SMEFT)
- $\mathscr{L}_{SMEFT} = \mathscr{L}_{SM} + \sum_i \dfrac{\theta_i}{\Lambda^2} \mathcal{O}_i$
- $\mathscr{L}_{SMEFT} \to p(z\,|\,\theta) = \dfrac{d\sigma(z,\theta)}{\sigma(\theta)}$
- Linear θ dependence in $\mathscr{L}$ $\to$ quadratic in $d\sigma$
- $d\sigma(z,\theta) = \sum_{\alpha=0}^{2} \dfrac{(\theta-\theta_0)^\alpha}{\alpha!} \partial_\alpha d\sigma(z,\theta_0)$, θ 1D
- $r(x\,|\,\theta,\theta_0) = \dfrac{\int dz p(x\,|\,z) p(z\,|\,\theta)}{\int dz p(x\,|\,z) p(z\,|\,\theta_0)}$, same θ dependence
- $r(x,z\,|\,\theta,\theta_0) = r(z\,|\,\theta,\theta_0)$
- Two approaches:
  - Learn coefficient functions: derivative learning
  - Learn functions at fixed benchmark points: morphing aware

Physics results: $pp \to WZ$

- WZ production at $\sqrt{s} = 13.6$ TeV, 300 fb^{-1}
- Constrain 3 Wilson coefficients jointly
- Derivative learning
- Correct hierarchy of confidence ellipses