UNIVERSITÄT HEIDELBERG ZUKUNFT SEIT 1386

KIRCHHOFF-INSTITUT FÜR PHYSIK

IMPRS for Precision Tests of Fundamental Symmetries INTERNATIONAL MAX PLANCK RESEARCH SCHOOL

ML Unfolding based on conditional Invertible Neural Networks using Iterative Training

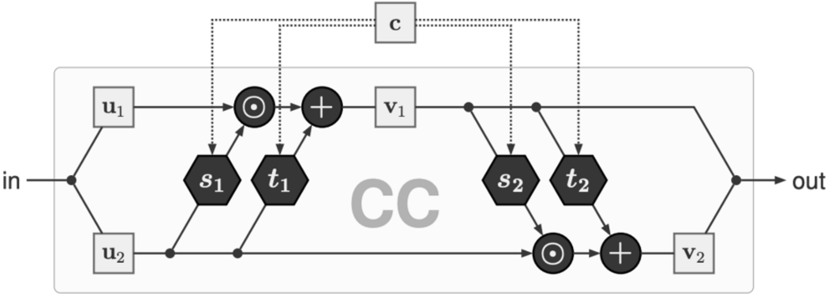
Mathias Backes (KIP)

with Anja Butter (LPNHE, ITP), Monica Dunford (KIP) and Bogdan Malaescu (LPNHE).

Based on [2212.08674]

Conditional Invertible Neural Networks (cINN)

$\vec{u}$



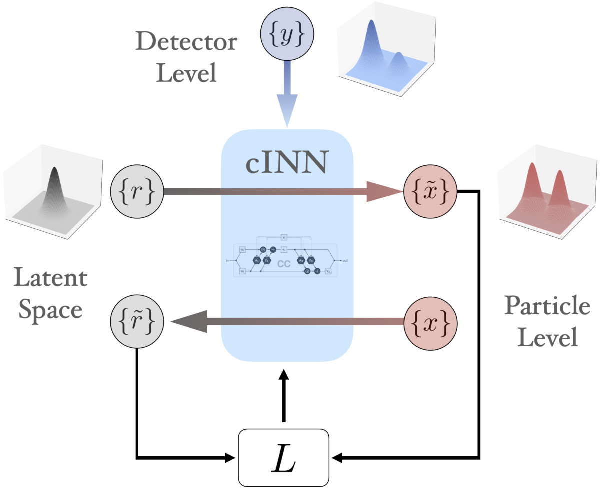
$\vec{v}$

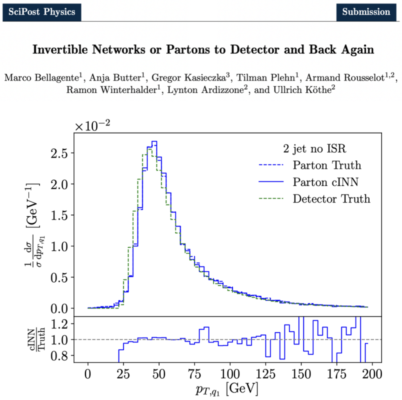
$$u_1 = (v_1 - t_1(u_2, c)) \oslash \exp(s_1(u_2, c))$$
$$u_2 = (v_2 - t_2(v_1, c)) \oslash \exp(s_2(v_1, c))$$

$$v_1 = u_1 \odot \exp(s_1(u_2, c)) + t_1(u_2, c)$$
$$v_2 = u_2 \odot \exp(s_2(v_2, c)) + t_2(v_1, c)$$

Source: arXiv [1907.02392]

cINN Unfolding



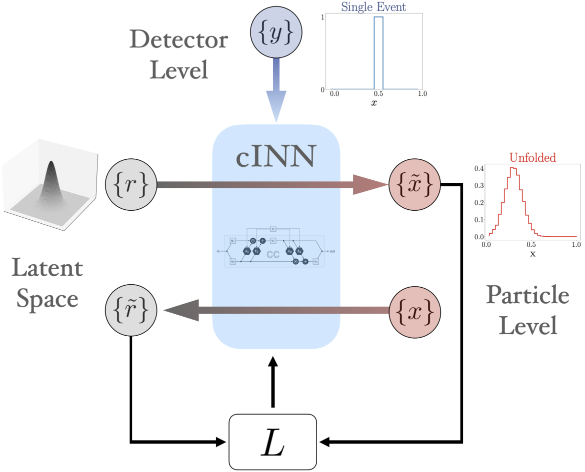

SciPost Physics Submission

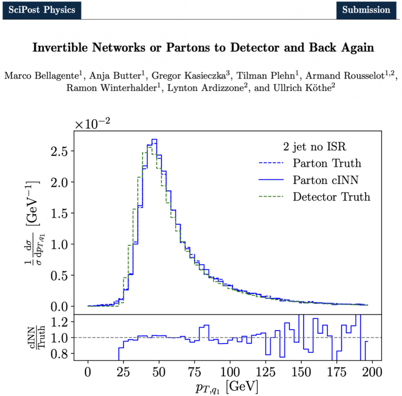
Invertible Networks or Partons to Detector and Back Again

Marco Bellagente[1], Anja Butter[1], Gregor Kasieczka[3], Tilman Plehn[1], Armand Rousselot[1,2], Ramon Winterhalder[1], Lynton Ardizzone[2], and Ullrich Köthe[2]

Source: arXiv [2006.06685]

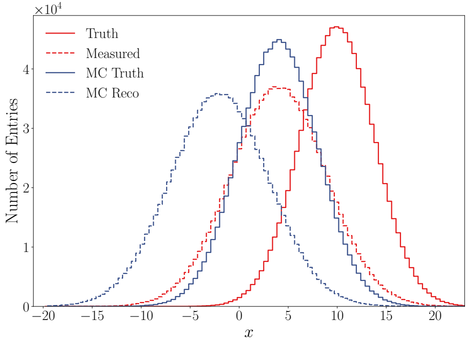
cINN Unfolding

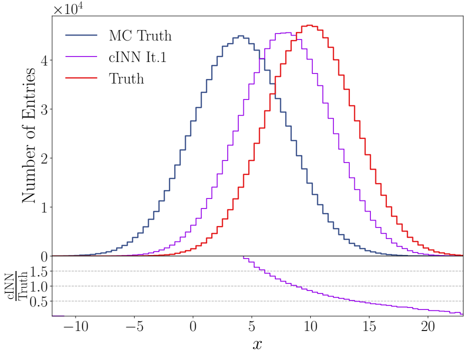




Source: arXiv [2006.06685]

cINN Unfolding



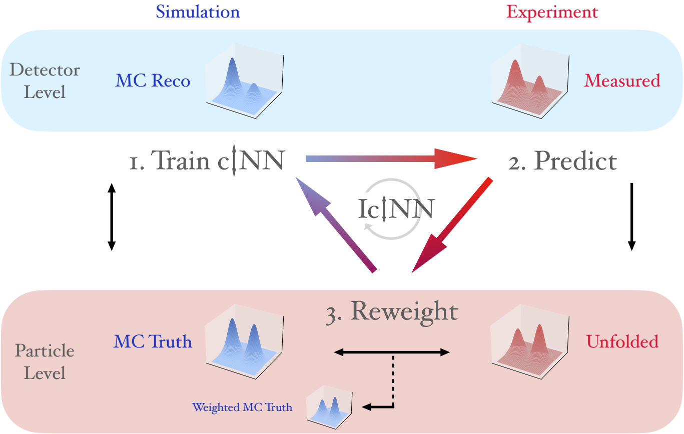


- Extreme toy example with large MC-data-differences and significant detector effects
- cINN unfolded distribution shows a strong bias towards the MC truth

$$p(t|r) = \frac{p(r|t) \cdot p(t)}{p(r)}, \quad \text{with} \quad t = \text{truth}, \quad r = \text{reco}$$

$\Rightarrow$ Iterative approach needed

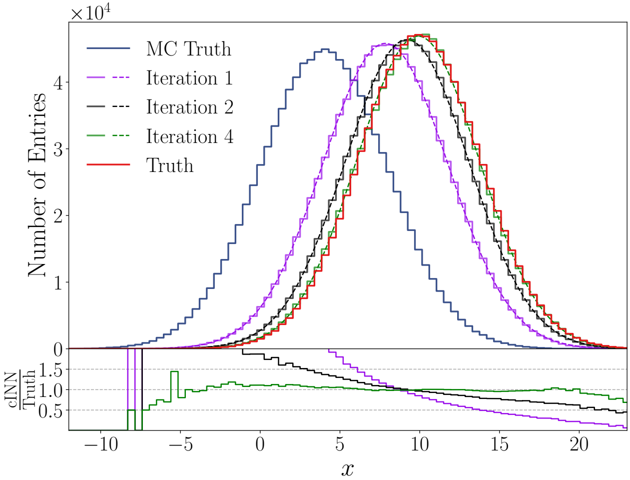
Iterative Approach



Advantages:

- Structures present in the data are encoded implicitly in the MC Truth
- General similarities to matrix based iterative bayesian-like unfolding
- Maintain event-wise probabilistic distributions

Results for the Iterative Approach



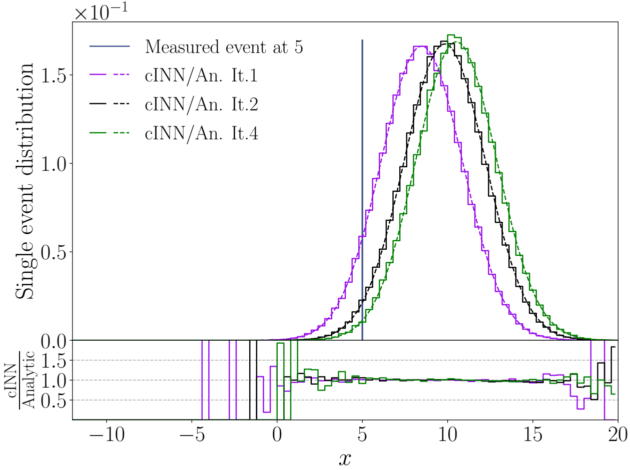
- Construct an analytically solvable toy model
- Use Bayes theorem to construct pseudo-inverse:

$$p(t|r) = \frac{p(r|t) \cdot p(t)}{p(r)}$$

- Apply pseudo-inverse to measured distribution:

$$p_u(t) = \int p(t|r) p_M(r) \mathrm{d}r$$

Results for the Iterative Approach



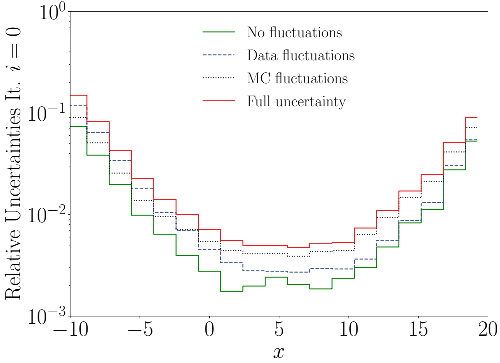
- Construct an analytically solvable toy model
- Use Bayes theorem to construct pseudo-inverse:

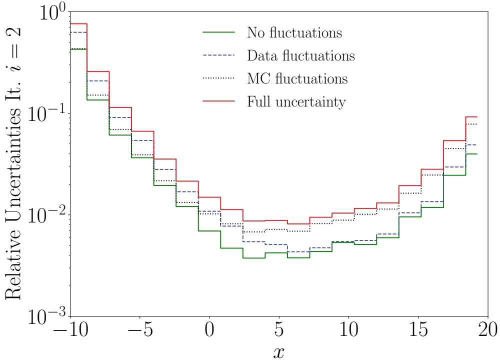
$$p(t|r) = \frac{p(r|t) \cdot p(t)}{p(r)}$$

- Apply pseudo-inverse to measured distribution:

$$p_u(t) = \int p(t|r) p_M(r) \mathrm{d}r$$

Uncertainties



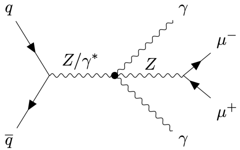


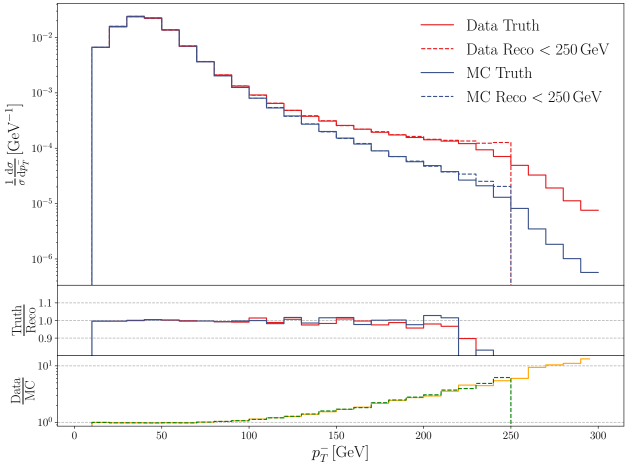
- Calculation of covariance matrices with toys:

$$\text{cov}_{ij} = \frac{1}{N_{\text{toys}}} \sum_{1}^{N_{\text{toys}}} (u_i - \overline{u}_i)(u_j - \overline{u}_j), \qquad \sigma_i = \sqrt{\text{cov}_{ii}}$$

Unfolding an EFT Process

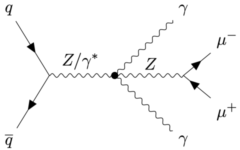
- Simulating the process
  $pp \to Z\gamma\gamma$ with $Z \to \mu^- \mu^+$
- MC $\to$ pure SM
- Data $\to$ SM + EFT contribution of
  $\mathcal{L}_{T,8} = \frac{C_{T,8}}{\Lambda^4} B_{\mu\nu} B^{\mu\nu} B_{\alpha\beta} B^{\alpha\beta}$
  with $\frac{C_{T,8}}{\Lambda^4} = \frac{2}{\mathrm{TeV}^4}$
- Applied detector smearing:
  $\Delta p_T = p_T \cdot \sqrt{0.025^2 + p_T^2 \cdot 3.5 \cdot 10^{-8}}$

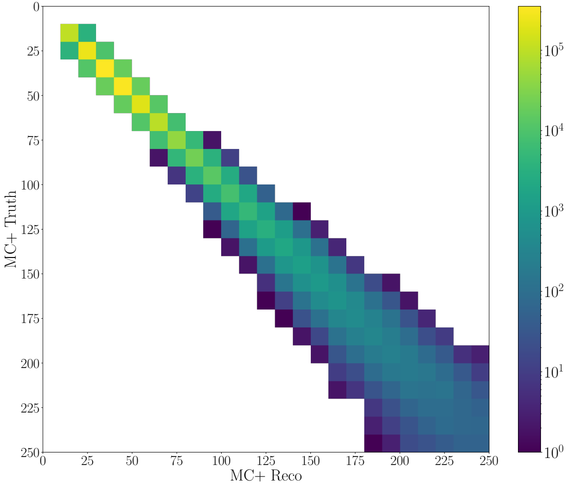




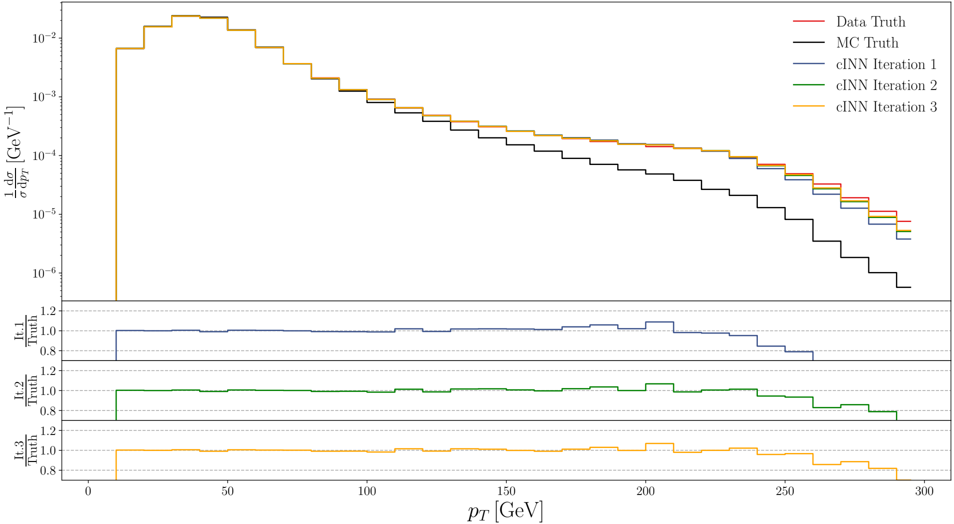
Unfolding an EFT Process

- Simulating the process
  $pp \to Z\gamma\gamma$ with $Z \to \mu^- \mu^+$
- MC $\to$ pure SM
- Data $\to$ SM + EFT contribution of
  $\mathcal{L}_{T,8} = \frac{C_{T,8}}{\Lambda^4} B_{\mu\nu} B^{\mu\nu} B_{\alpha\beta} B^{\alpha\beta}$
  with $\frac{C_{T,8}}{\Lambda^4} = \frac{2}{\text{TeV}^4}$
- Applied detector smearing:
  $\Delta p_T = p_T \cdot \sqrt{0.025^2 + p_T^2 \cdot 3.5 \cdot 10^{-8}}$

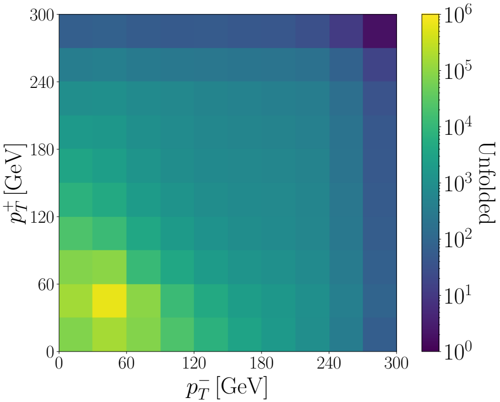


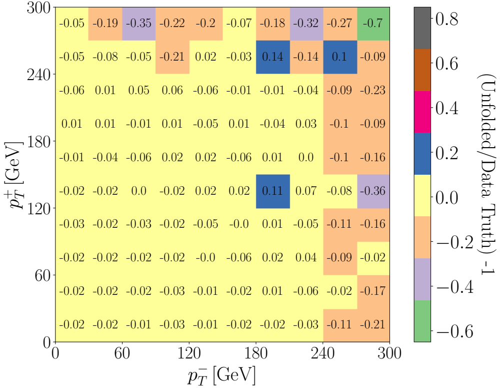


Unfolding an EFT Process



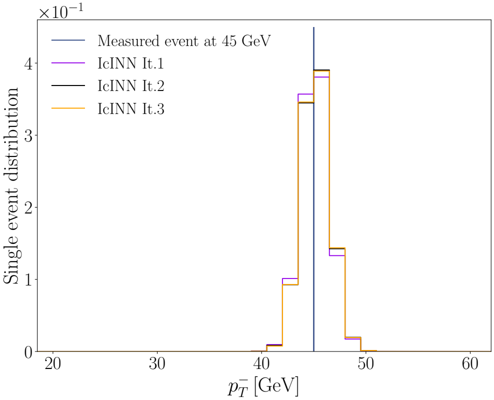
Unfolding an EFT Process

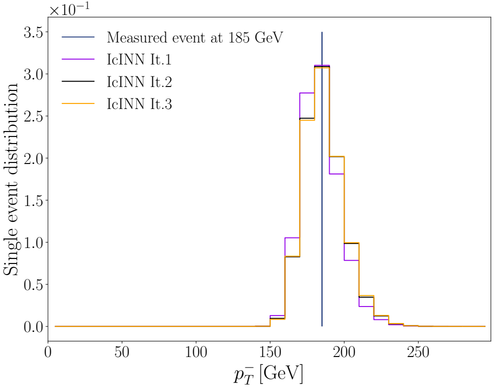




⇒ Unfolding of the p_T distributions of both muons simultaneously is possible

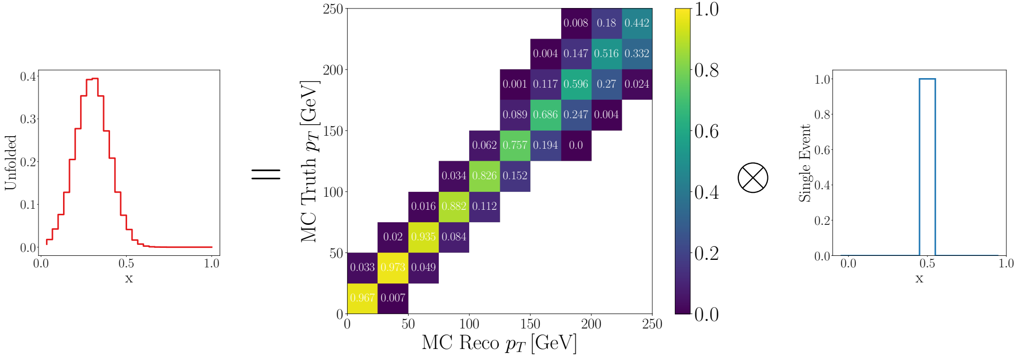
Unfolding an EFT Process





$\Rightarrow$ Single event unfolded distributions match the overall unfolding result

Matrix-based Single Event Unfolding



$\Rightarrow$ Possibility for cross-checks with IcINN Unfolding

Conclusion / Outlook

- Implementation of an iterative cINN unfolding algorithm and application to a physical example
- Central Idea: still obtain the cINN result of a probabilistic unfolded **distribution** while iteratively reducing the bias towards the MC simulation
- Next steps: single event unfolded distribution cross-checks; application of IcINN to real experimental data

Thank you for your attention!

Additional Material

Analytic Toy Example

- Gaussian smearing:

$$p(r|t) = \frac{1}{\sqrt{2\pi\sigma_s^2}} \exp\left(-\frac{(r-(t+\mu_s))^2}{2\sigma_s^2}\right).$$

- Bayes theorem:

$$p(t|r) = \frac{p(r|t)\cdot p(t)}{p(r)}.$$

- Unfolding a measured distribution $p_M(r)$ using Gaussian functions for $p(r)$, $p(t)$ and $p_M(r)$:

$$p_u(t) = \int p(t|r)p_M(r)\mathrm{d}r = \frac{1}{2\pi}\sqrt{\frac{\sigma_r^2}{\sigma_t^2\sigma_s^2\sigma_M^2}} \int \mathrm{d}r \exp\left(-\frac{(r-(t+\mu_s))^2}{2\sigma_s^2} - \frac{(t-\mu_t)^2}{2\sigma_t^2} + \frac{(r-\mu_r)^2}{2\sigma_r^2} - \frac{(r-\mu_M)^2}{2\sigma_M^2}\right)$$

- Evaluating leads to gaussian unfolded distribution with:

$$\mu_u = \frac{\mu_m\sigma_t^2 + \mu_t\sigma_s^2 - \mu_s\sigma_t^2}{\sigma_s^2+\sigma_t^2}, \qquad \sigma_u = \frac{\sqrt{\sigma_t^2\sigma_M^2 + \sigma_t^2\sigma_s^2 + \sigma_s^4}\sigma_t}{\sigma_s^2+\sigma_t^2}.$$

cINN Loss function

Minimize loss function:

$$\begin{aligned}\mathcal{L} &= -\langle \log p(\theta|x,y)\rangle_{x\sim f,y\sim g} \\ &= -\langle \log p(x|\theta,y)\rangle_{x\sim f,y\sim g} - \langle \log p(\theta|y)\rangle_{y\sim g} + \langle \log p(x|y)\rangle_{x\sim f,y\sim g} \\ &= -\langle \log p(x|\theta,y)\rangle_{x\sim f,y\sim g} - \lambda\theta^2 + \text{const.} \\ &= -\langle \log p(z(x)|\theta,y)\rangle_{x\sim f,y\sim g} - \langle \log \left|\frac{\mathrm{d}z}{\mathrm{d}x}\right|\rangle_{x\sim f,y\sim g} - \lambda\,\theta^2 + \text{const.}\end{aligned}$$

θ = cINN parameter, x = Parton Level, y = Detector level, z = Latent space variable

Source: arXiv [1907.02392]