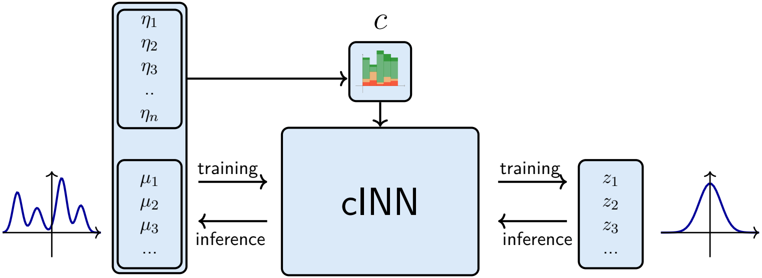

A Method for Inferring Signal Strength Modifiers by Conditional Invertible Neural Networks

ACAT Conference 2022

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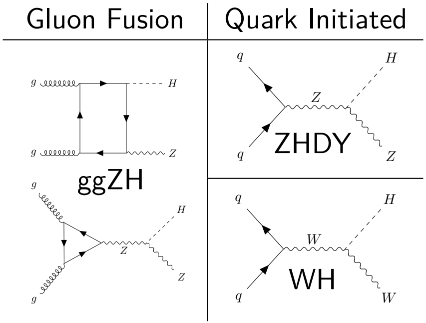
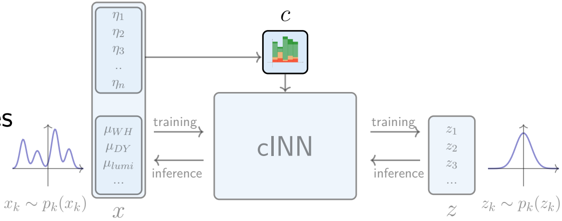
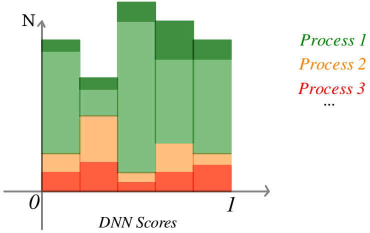
- Goal: inference of signal strength modifier parameters with cINNs
- Motivation:
  - Posterior inference with cINNs is time-efficient
  - Normalizing flows preserve gradients
- Analysis:
  - Signal processes: ggZH, ZHDY, WH
  - 13 Background processes: DY, VBF ...



Analysis Strategy and -Setup

- Analysis is based on simulated MC samples
- Multi-process classification:
  1. MC simulation
  2. Final state object selection
  3. DNN categorization
- Fit observables: histogrammed DNN scores
  - used as condition for the cINN





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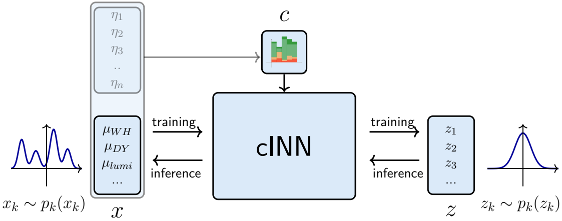
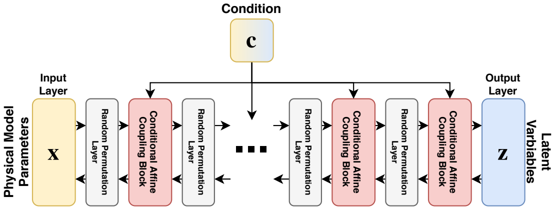
- Fit model posteriors $p_\phi(x|c)$ to the true posteriors $p(x|c)$
- Training: Map inputs to a $\mathcal{N}(z|0,1)$
- Inference: Sampling from $\mathcal{N}(z|0,1)$ and Inversion $\rightarrow$ posterior



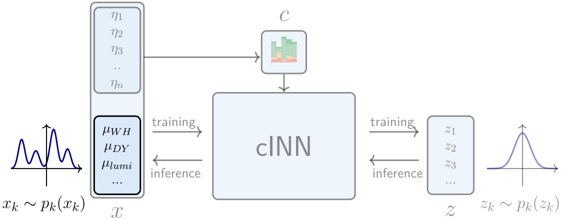
- Network:
  - Affine blocks and permutation layers
  - Conditions c input for each affine block

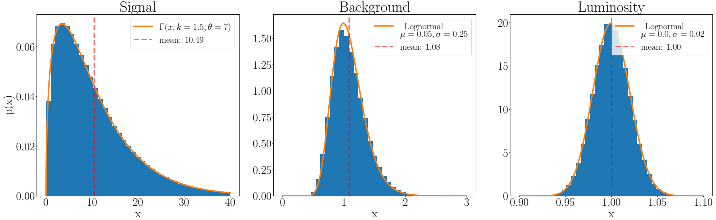


from [2007.08391]

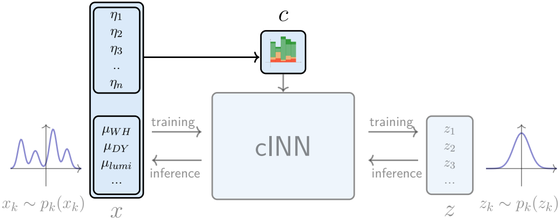
Network Setup – Data Preparation

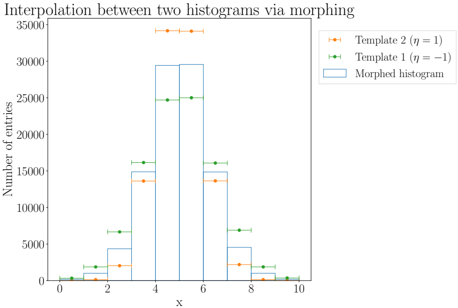
- Goal: infer signal modifier parameters $\{\mu_i\}$
  $\rightarrow$ dataset contains expected $\{\mu_i\}$ and nuisance parameter effects
- Priors:
  - Signal: $\Gamma(x; k = 1.5; \theta = 7)$
    $\rightarrow$ finer sampling around expected μ
  - Background:
    - Lognormal with mean $1 \pm 27\%$
  - Luminosity nuisance:
    - Lognormal around $1 \pm 2\%$





- Statistical uncertainties
  - Expected measurement uncertainty
  - MC sample size
- Systematic effects:
  - Normalizing uncertainties
  - Shape-changing uncertainties
    $\rightarrow$ Histogram template morphing





Signal Modifier Parameter Inference – Latent Distributions

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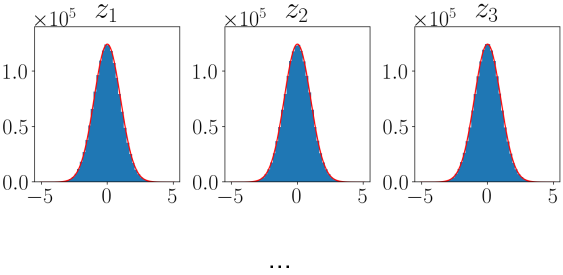
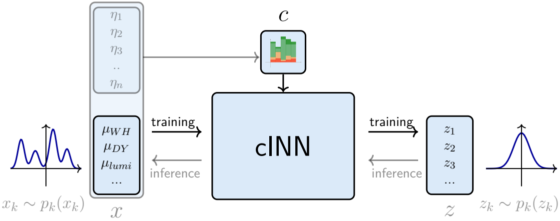
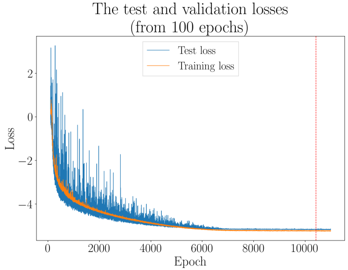
- Training: loss converges
- Latent space distribution follows $\mathcal{N}(0,1)$
- Sampling from $\mathcal{N}(0,1)$ yields well-approximated posteriors





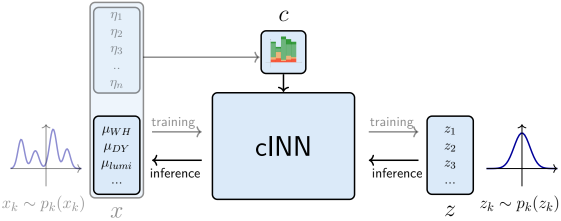


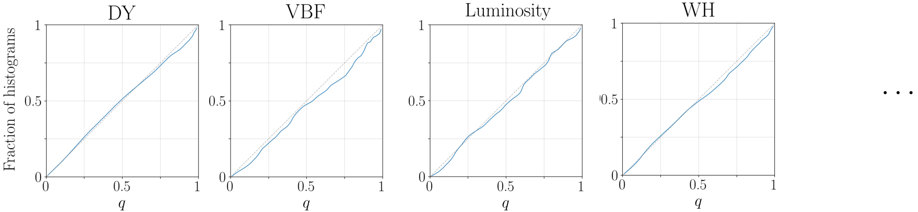
Signal Modifier Parameter Inference – Calibration Curves

- Calibration error: measure of model bias

$$e_{cal}(q) = \frac{N^{in}}{N} - q, \qquad q \text{ quantile}; q \in [0,1]$$

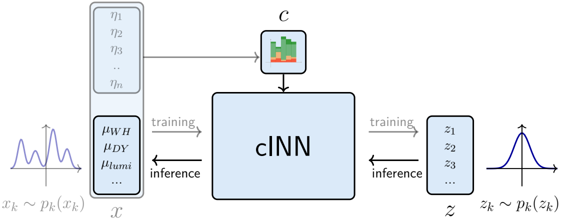
- N^{in}: number of posteriors containing the true MC value in their q quantile
- Ideal calibration: $e_{cal}(q) = 0$

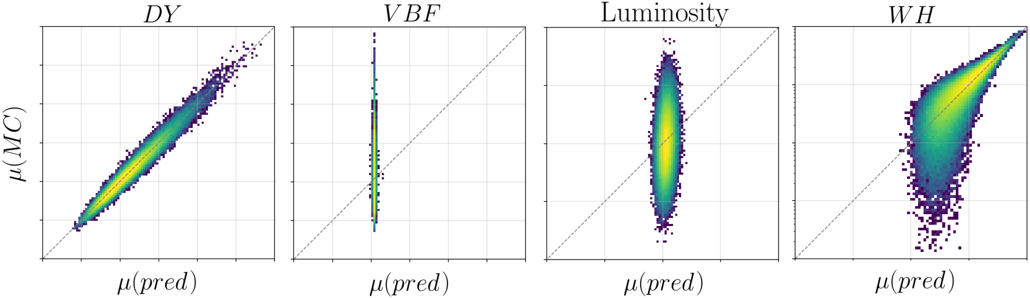




- Max median absolute calibration error $\lesssim \mathcal{O}(0.04)$
  $\Rightarrow$ No strong biases in the network model

- 3 parameters groups per sensitivity:
  - well-reconstructed parameters (μ_{DY} ...)
  - unrecognized parameters (μ_{VBF} ...)
  - weakly-recognized parameters (μ_{lumi}...)
- Signal: sensitivity threshold for small μ





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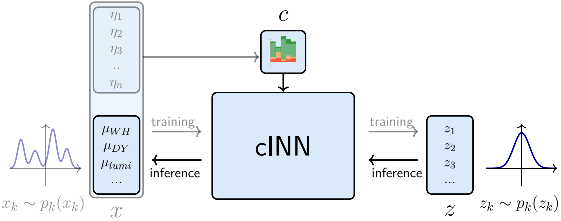
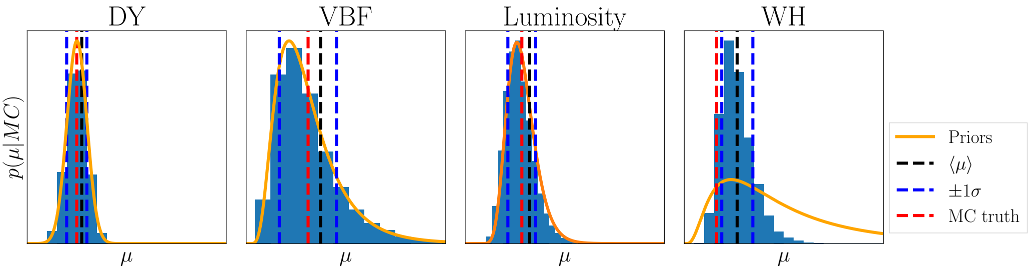
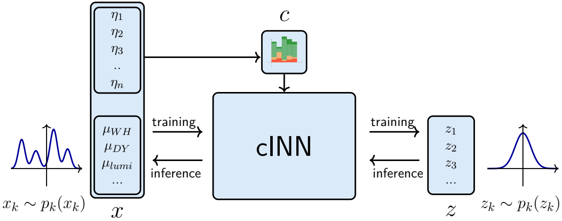
- Background (`dy`, ...):
  - narrow posteriors = high sensitivity
- Unrecognized (`VBF`, ...):
  - posteriors = priors
- Luminosity nuisance: weakly recognised
- Signal: highest sensitivity for `WH`
- Comparable results to likelihood fit

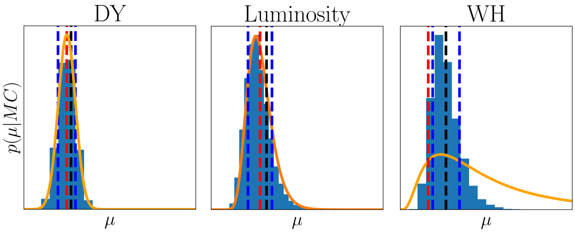


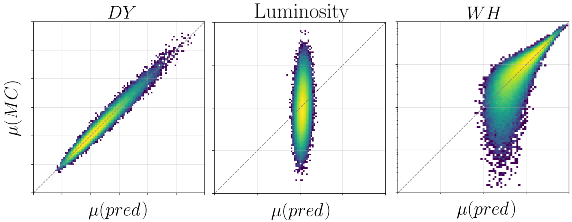


Conclusion

- cINN is able to infer the signal strength modifiers
- Good prediction performance
  - Latents follow $\mathcal{N}(0,1)$
  - No strong biases in the model
  - Sensitivity drop for signal for small μ
  - Comparable results to likelihood fit







Backup

Network Setup – cINN Architecture

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- $\dim c = 235$
- $\dim x = 17$
  - 3 signal modifier parameters
  - 13 background modifier parameters
  - 1 nuisance parameter (luminosity)
- 12 GLOW Blocks with permutation layers
- Subnetworks with 3 layers à 128 nodes with ReLU

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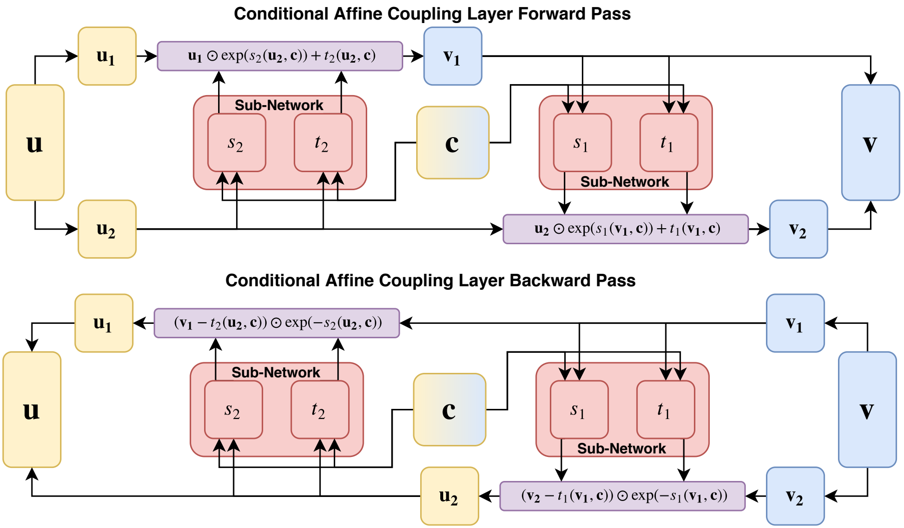

from [2007.08391]

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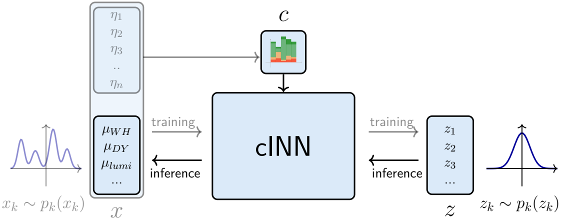
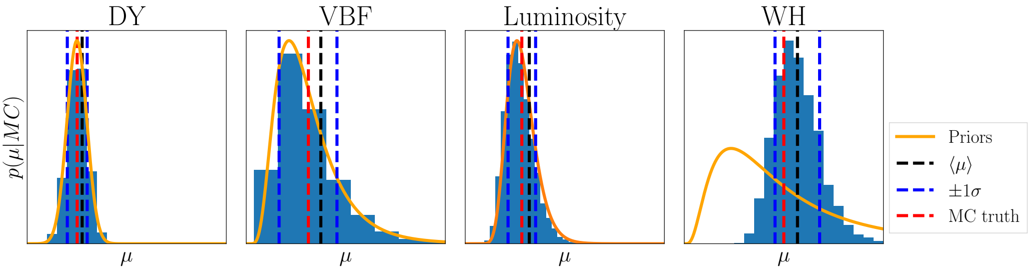
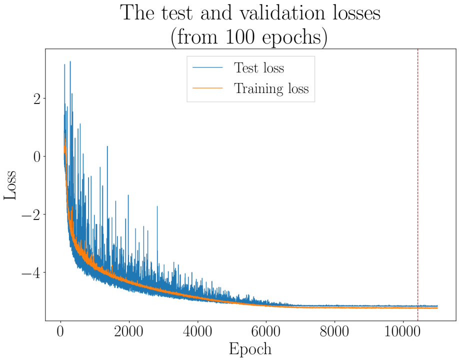
- Now:
  - High-signal, small-background scenerio
- Signal:
  - Symmetric distribution for sensitive processes
- Well- and weakly-reconstructed parameters: similar sensitivity
- Comparable results to likelihood fit

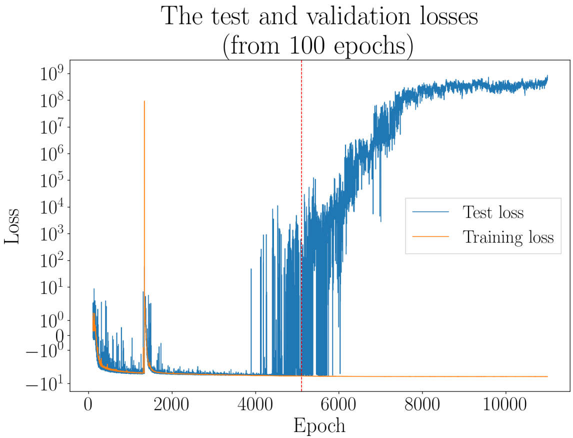




Signal Modifier Inference – Network Losses

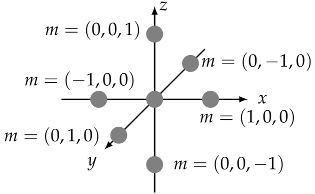
- Network converges
- Summary-Network extended cINN tends to overtrain





$$f(x|\mathbf{m}_i) = \underbrace{f(x|0)}_{f_0} + \sum_{j=1}^{T} \underbrace{\left.\frac{\partial f(x|\mathbf{m})}{\partial m_j}\right|_{\mathbf{m}=0}}_{f'_j} (m_i)_j + \sum_{j=1}^{T} \underbrace{\frac{1}{2!} \left.\frac{\partial^2 f(x|\mathbf{m})}{\partial m_j^2}\right|_{\mathbf{m}=0}}_{f'_{jj}} (m_i)_j^2 + \mathcal{O}\left((m_i)_j^3\right)$$

- Express the unknown derivatives f'_j, f'_{jj}
- 24 templates: 24 shape changing uncertainties



$$
\begin{pmatrix}
f\Big(x|(0, \;\; 0, 0\,, ..., \;\; 0)\Big) \\
f\Big(x|(0, \;\; 1, 0\,, ..., \;\; 0)\Big) \\
f\Big(x|(0, -1, 0\,, ..., \;\; 0)\Big) \\
\vdots \\
f\Big(x|(0, \;\; 0, 0\,, ..., \;\; 1\Big) \\
f\Big(x|(0, \;\; 0, 0\,, ..., -1\Big)
\end{pmatrix}
=
\underbrace{\begin{pmatrix}
1 & 0 & 0 & 0 & & 0 & 0 \\
1 & 1 & 1 & 0 & \cdots & 0 & 0 \\
1 & -1 & 1 & 0 & & 0 & 0 \\
 & & \vdots & & \ddots & \vdots & \\
1 & 0 & 0 & 0 & & 1 & 1 \\
1 & 0 & 0 & 0 & \cdots & -1 & 1
\end{pmatrix}}_{M}
\begin{pmatrix}
f_0 \\ f'_1 \\ f'_{11} \\ \vdots \\ f'_T \\ f'_{TT}
\end{pmatrix}
$$

$$f(x|\mathbf{m}) = (1, m_1, m_1^2, ..., m_T, m_T^2)M^{-1}\mathbf{f}$$