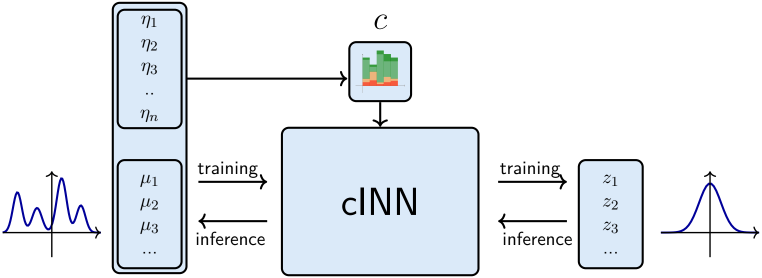

A Method for Inferring Signal Strength Modifiers by Conditional Invertible Neural Networks

CHEP 2023, Norfolk, Virginia

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for the CMS Collaboration

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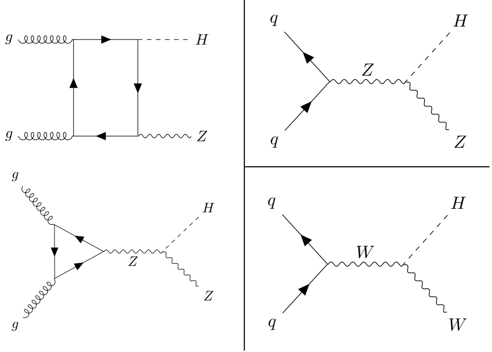
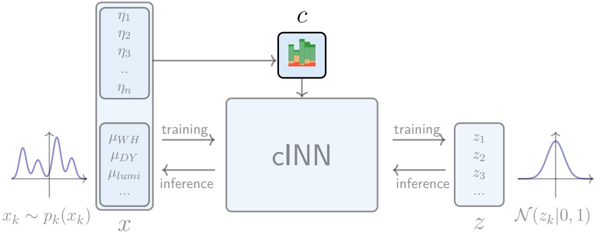
- Why conditional Invertible Neural Networks (cINNs)[1]?
  - Many parameter fits: time-consuming
    → Posterior inference with cINNs is time-efficient
  - cINN model preserve gradients
    → Applicable in differentiable workflows
- VH-Analysis at CMS:
  - 3 Signal processes:
    - $gg \to ZH$
    - $qq \to ZH$
    - $qq \to WH$
  - 13 Background processes:
    - Drell-Yan Process
    - $t\bar{t}$ production
    - Vector boson fusion Higgs production...
- Goal: infer the signal strength modifier parameters $\mu = \sigma/\sigma_{SM}$

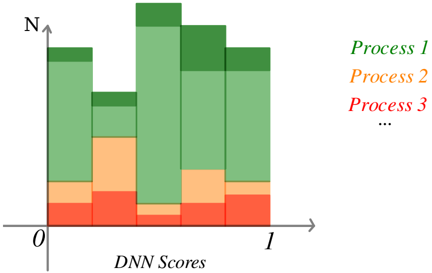
Gluon Fusion	Quark Initiated



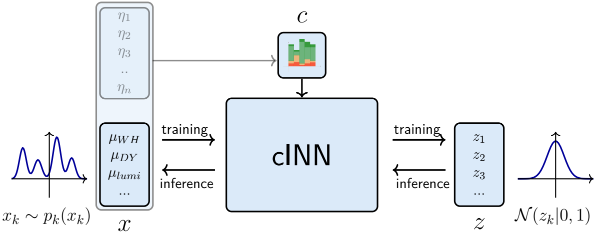
[1] 2003.06281

- Analysis performed at CMS
- Based on simulated MC samples
- Analysis workflow:
  1. Simulated events
  2. Final state object selection
  3. DNN process categorization
  4. Fit
- Maximum likelihood fit:
  - Histogrammed DNN scores
    $\rightarrow$ Used as condition c for the cINN





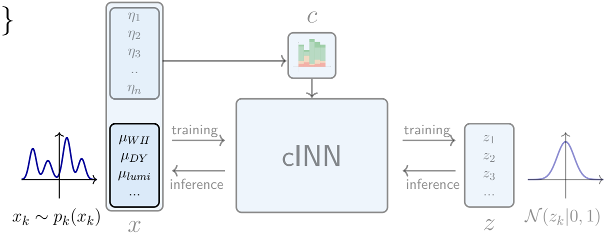
- cINN architecture:
  - Based on normalizing flows
    $\rightarrow$ invertibility and differentiability
  - Alternating network blocks:
    - Affine coupling blocks
    - Permutation blocks



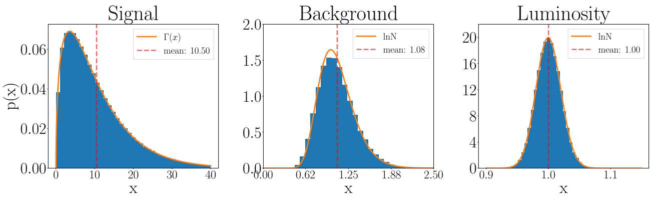
- Forward direction: training
  - Approximate the unknown true posteriors $p(x|c)$
  - Map inputs to a $\mathcal{N}(z|0,1)$

- Backward direction: inference
  - Sampling from $\mathcal{N}(z|0,1)$ and inversion
    $\rightarrow$ Posterior samples
    $\rightarrow$ Predictions

- Goal: infer signal modifier parameters $\{\mu_i\}$
  - Dataset contains expected $\{\mu_i\}$ and nuisance parameter effects
  - Scale processes with their μ_i
  - Model uncertainties



- μ Priors:
  - Signal: Γ-distribution
    - Finer sampling around expected μ
    - Sensitivity for $\mu \gtrsim 10$
  - Background:
    - Lognormal $\langle x \rangle = 1 \pm 27\%$
  - Luminosity:
    - Lognormal $\langle x \rangle = 1 \pm 2\%$
    - Affects all processes equally



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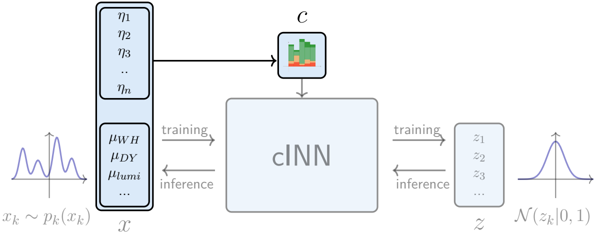
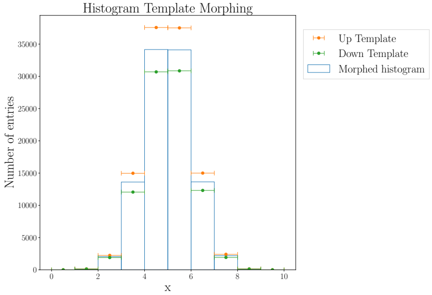
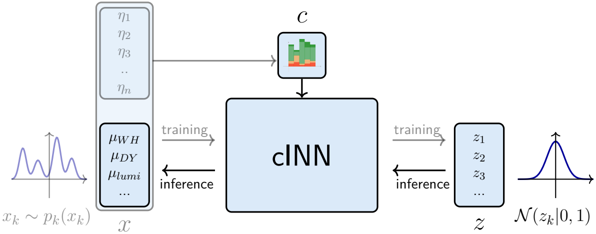
- Statistical uncertainties
  - Expected measurement uncertainty
  - MC sample size
  - Both follow a Poisson distribution
- Systematic effects:
  - Normalizing uncertainties
    $\rightarrow$ Process scaling
  - Shape-changing uncertainties
    $\rightarrow$ Histogram template morphing

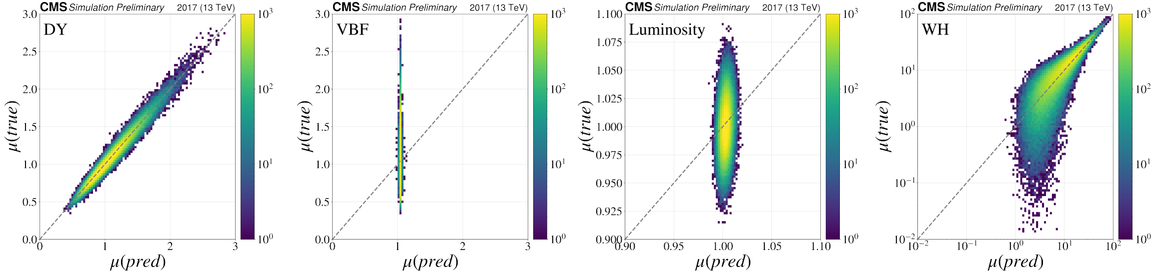




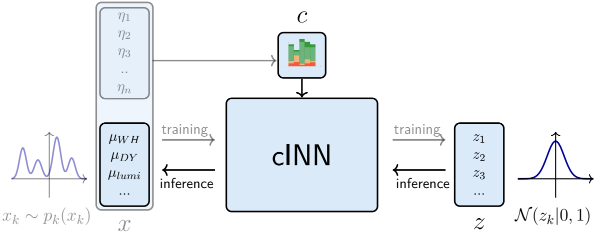
Signal Modifier Parameter Inference – Predictions

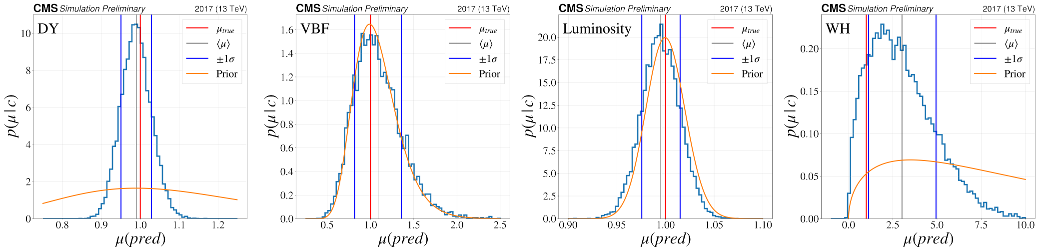
- 3 parameters groups per sensitivity:
  - well-reconstructed parameters (μ_{DY} ...)
  - unrecognized parameters (μ_{VBF} ...)
  - weakly-recognized parameters (μ_{lumi}...)
- Signal: sensitivity threshold for small μ



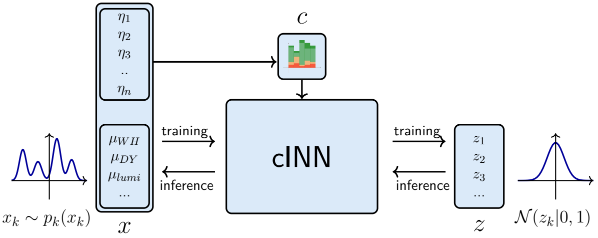


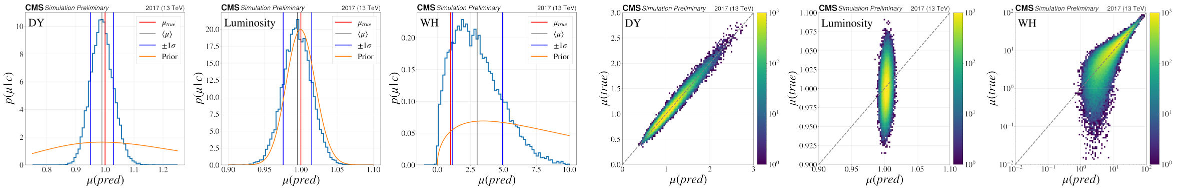
- Background (`DY`, ...):
  - narrow posteriors = high sensitivity
- Unrecognized (`VBF`, ...):
  - posteriors = priors
- Luminosity nuisance: weakly recognised
- Signal: broad posteriors → high uncertainty
- Comparable results to likelihood fit





- cINN is able to infer the signal strength modifiers
  $\rightarrow$ applicable in HEP
- Good prediction performance
  - Posterior width reflects network sensitivity
  - Signal: sensitivity drop for signal for small μ
  - Comparable results to likelihood fit

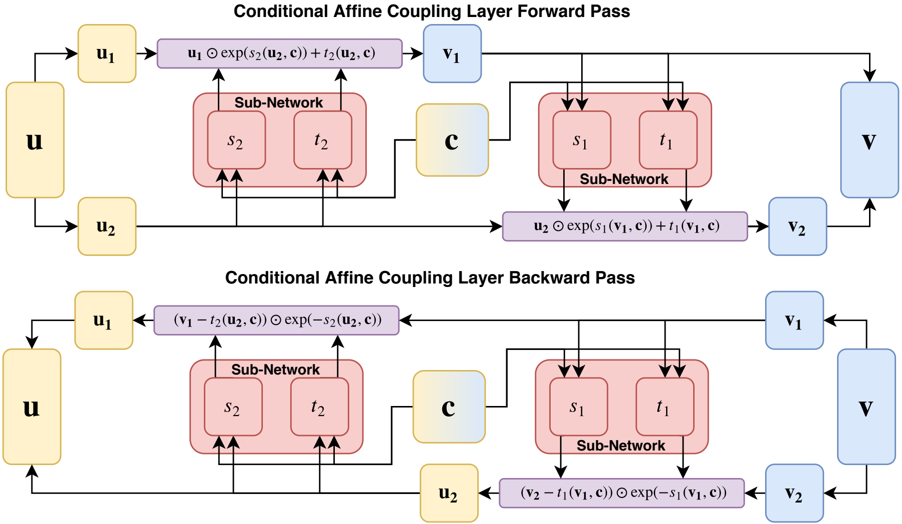




Backup

Network Setup – cINN Architecture

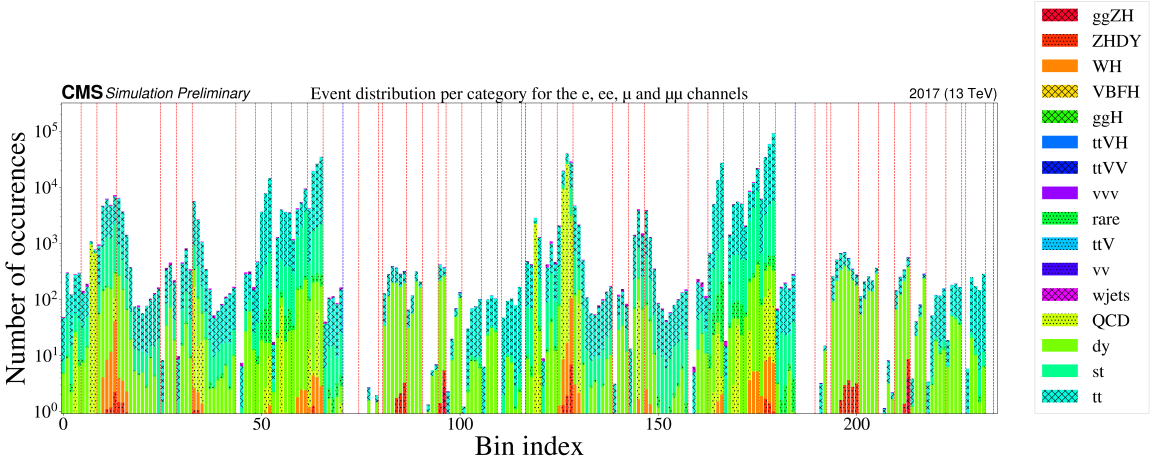
- $\dim c = 235$
- $\dim x = 17$
  - 3 signal modifier parameters
  - 13 background modifier parameters
  - 1 nuisance parameter (luminosity)
- 12 GLOW Blocks with permutation layers
- Subnetworks with 3 layers à 128 nodes with ReLU



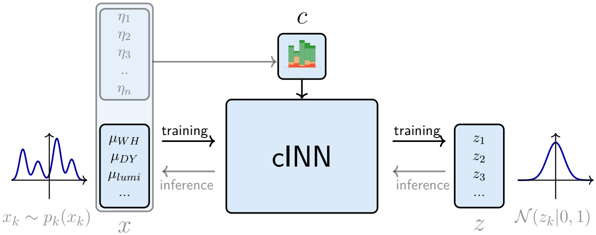
from [2007.08391]

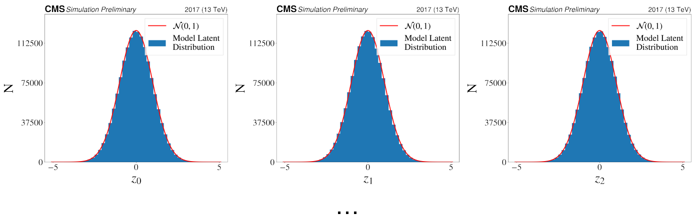
The Conditions – Nominal with $\mu = 1$

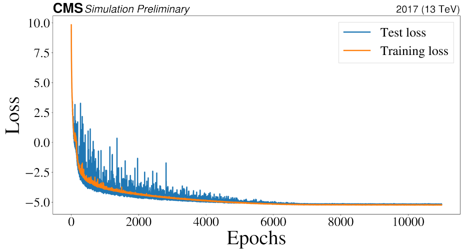
- 4 channels: 2 SL + 2 DL
- 13 subcategories



- 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

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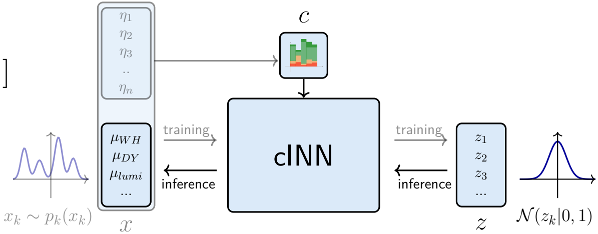
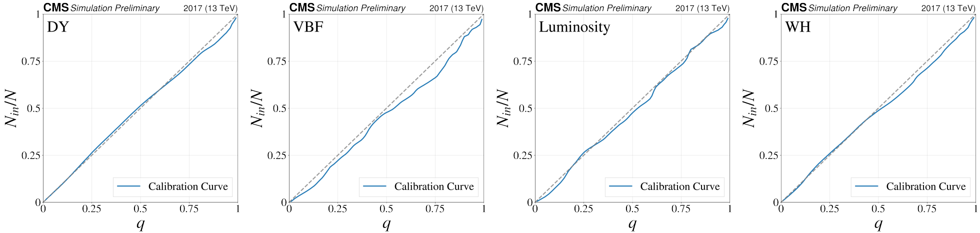
- Calibration error: measure of model bias

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

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



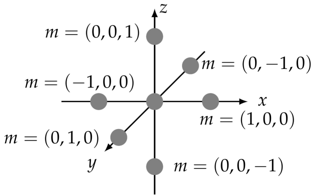


...

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

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

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



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

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