Unfolding with conditional invertible networks

[2006.06685]

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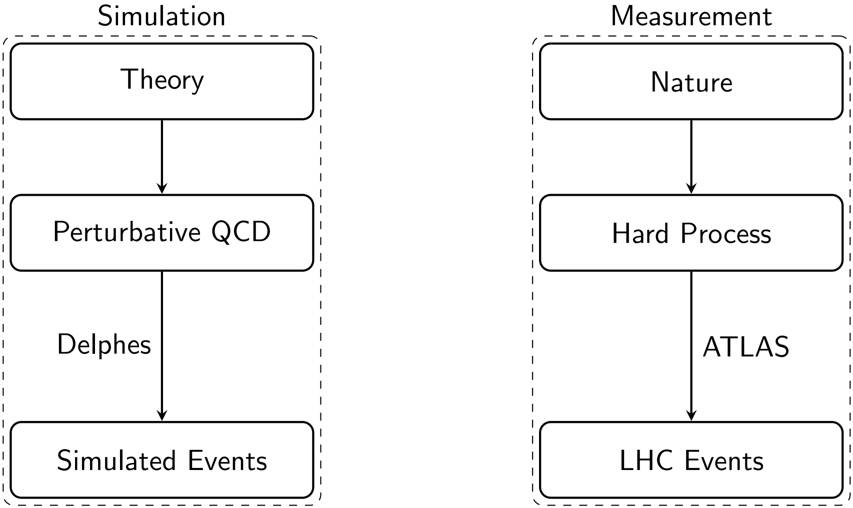
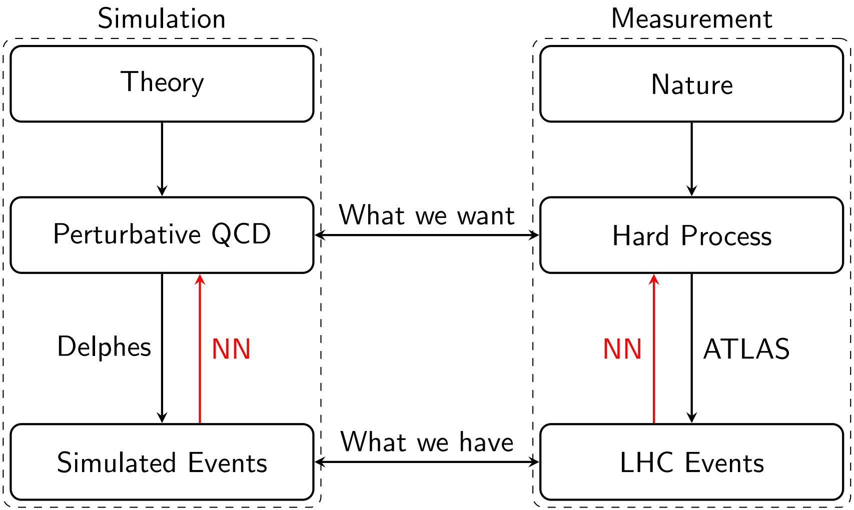
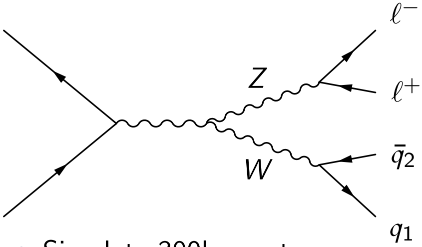
Inverting the simulation



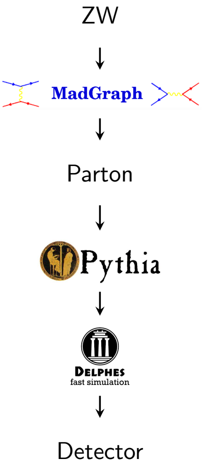
Inverting the simulation



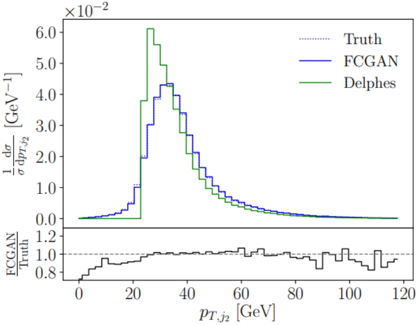
Simulating and Inverting Detector Effects

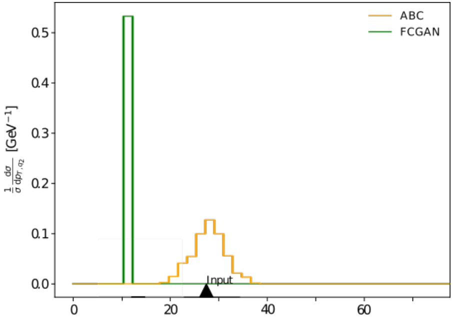


- Simulate 300k events
- Learn detector $\rightarrow$ parton
- Want **probabilistic** mapping



"Just GAN it"



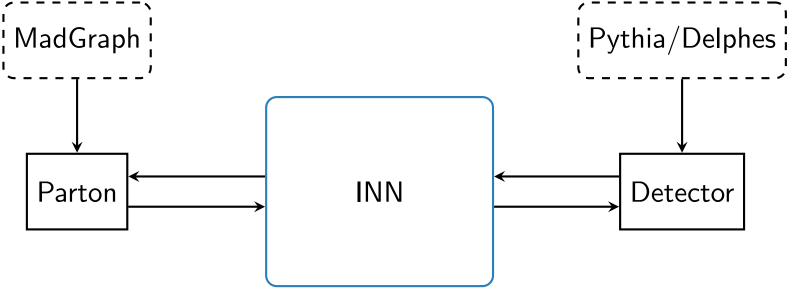


- Good results on full phase space

- Unfold single event 3200 times
- Compare to closest dataset events

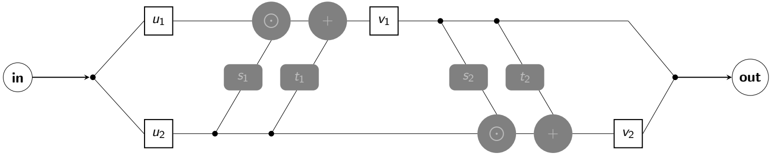
Details: [1912.00477]

Invertible Neural Networks



- Learn bijective mapping → inverse direction for free
- Same dimensionality for both sides
- Extra noise for probabilistic application → extend with noise (eINN)

Coupling Blocks

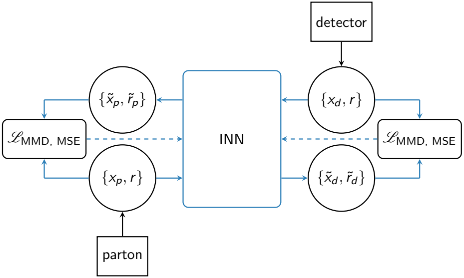


Forward: $v_1 = u_1 \times e^{s_1(u_2)} + t_1(u_2)$ $\quad v_2 = u_2 \times e^{s_2(v_1)} + t_2(v_1)$

Backward: $u_2 = (v_2 - t_2(v_1)) \times e^{-s_2(v_1)}$ $\quad u_1 = (v_1 - t_1(u_2)) \times e^{-s_1(u_2)}$

- Split input in u_1, u_2
- Invertible for arbitrary s, t
- Jacobian triangular $\rightarrow$ easily tractable

INN Training



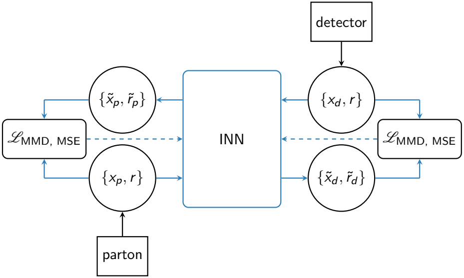
INN Training

Detector → Parton

$$\mathscr{L}_y = \mathscr{L}_{MMD}(x_p, \tilde{x}_p) + \mathscr{L}_{MSE}(x_p, \tilde{x}_p)$$

Parton → Detector

$$\mathscr{L}_x = \mathscr{L}_{MMD}(x_d, \tilde{x}_d) + \mathscr{L}_{MSE}(x_d, \tilde{x}_d)$$



Invariant mass distribution

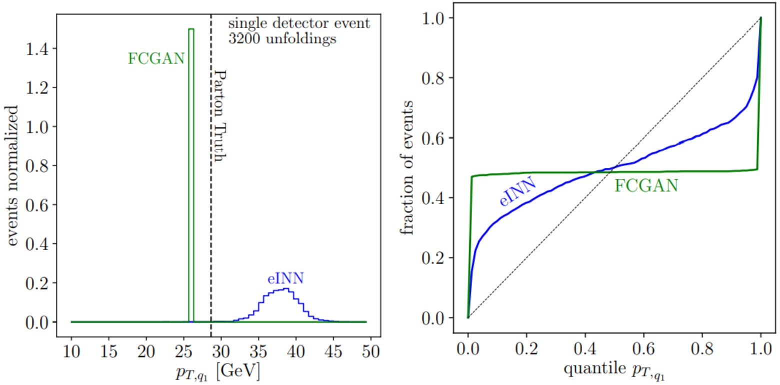
$$\mathscr{L}_M = \mathscr{L}_{MMD}(M(x_d), M(\tilde{x}_d)) + \mathscr{L}_{MMD}(M(x_p), M(\tilde{x}_p))$$

Gaussian latent distribution

$$\mathscr{L}_z = \mathscr{L}_{MMD}(r, \tilde{r}_p) + \mathscr{L}_{MMD}(r, \tilde{r}_d)$$

Maximum Mean Discrepancy: $\mathscr{L}_{MMD} = k(X, X) + k(Y, Y) - 2k(X, Y)$

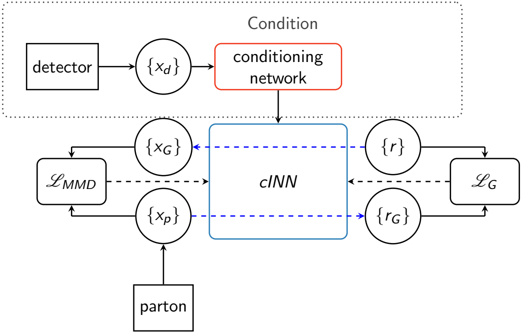
INN Results



Calibration Curves

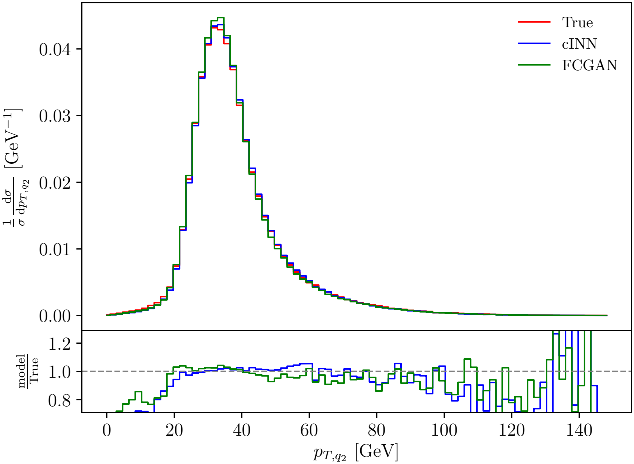
- Get parton distribution for fixed detector-level (noise sampling)
- Plot frequency of ground truth appearing in quantile x
- Expect diagonal → Noise parton correlation incorrect

Conditional Invertible Neural Networks



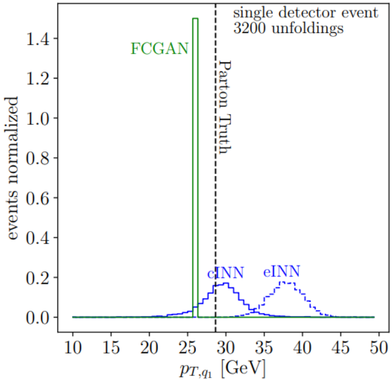
- Network conditioned on detector information
- Map parton to normal distribution
- Minimize $\mathscr{L}_G = \mathbb{E}_{i\in 1,\ldots,N}\left[\frac{||f(x_{p,i}|x_{d,i},\theta)||_2^2}{2} - \log|J_i|\right] + \tau||\theta||_2^2$

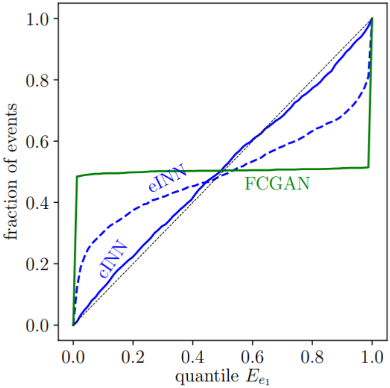
cINN Results



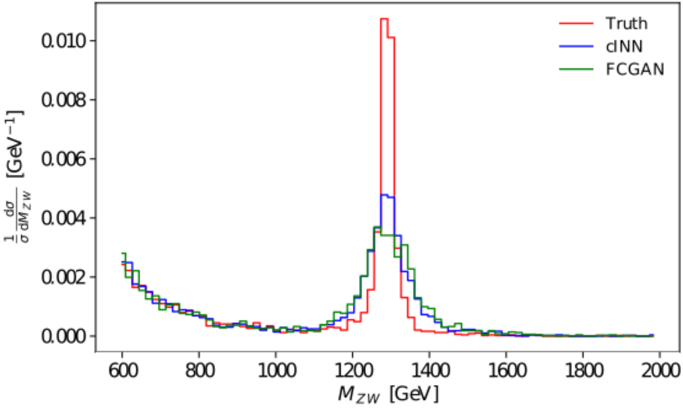
cINN and cGAN both perform well on full phase space

Calibration



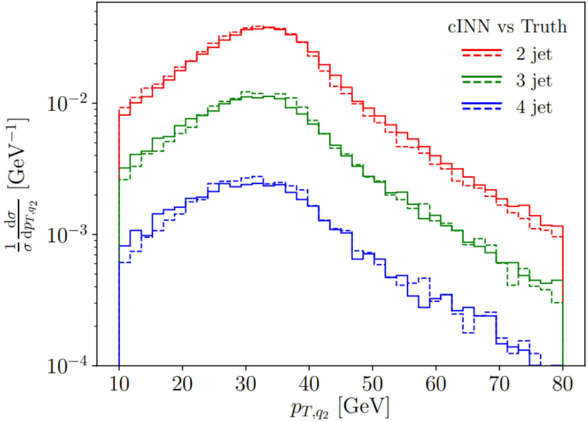


Hidden Mother Particle



- Introduce new W' particle into test data → decays into W and Z
- Adding their four-vectors results in distinct mass peak

Include Initial State Radiation



Train on inclusive channel
Evaluate on exclusive 2/3/4 jets

Conclusion

- Unfolding of ZW Process works with cGAN/eINN/cINN
- Statistically coherent results with cINN
- Can reconstruct unseen structures on parton level (e.g. W' particle)
- Simultaneous unfolding of different numbers of jets