Generating muonic force carriers events with classical and quantum neural networks

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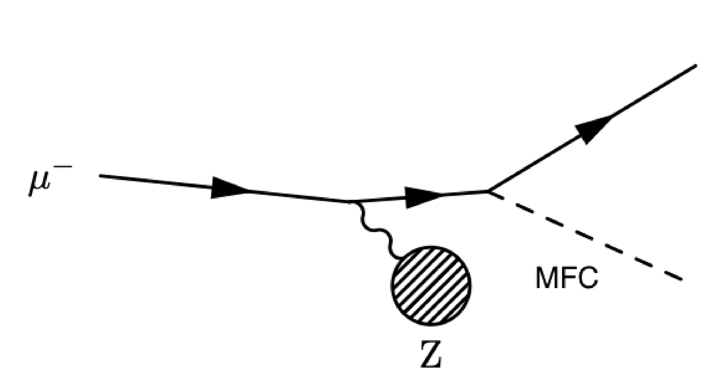
Abstract

We propose to use **(quantum) machine learning** to generate muon force carriers (MFC) events.

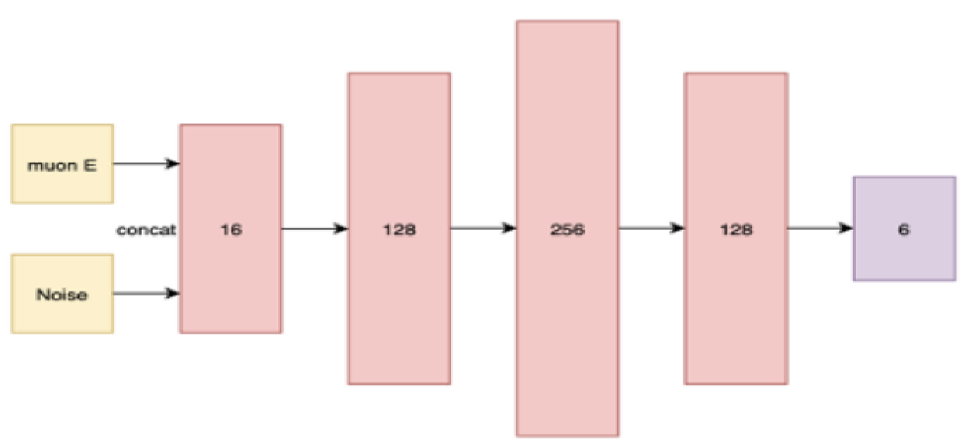
We consider a muon fixed-target collison between muons produced at the high-energy collisions of the LHC and the detector material of the ForwArd Search ExpeRiment (FASER) or the ATLAS calorimeter. In the ATLAS case, independent muon measurements performed by the inner detector (ID) and muon system (MS) can help to observe new force carriers coupled to muons, which are usually not detected. In the FASER experiment, the high resolution of the tungsten/emulsion detector is used to measure the muons trajectories and energies.

Physical Process

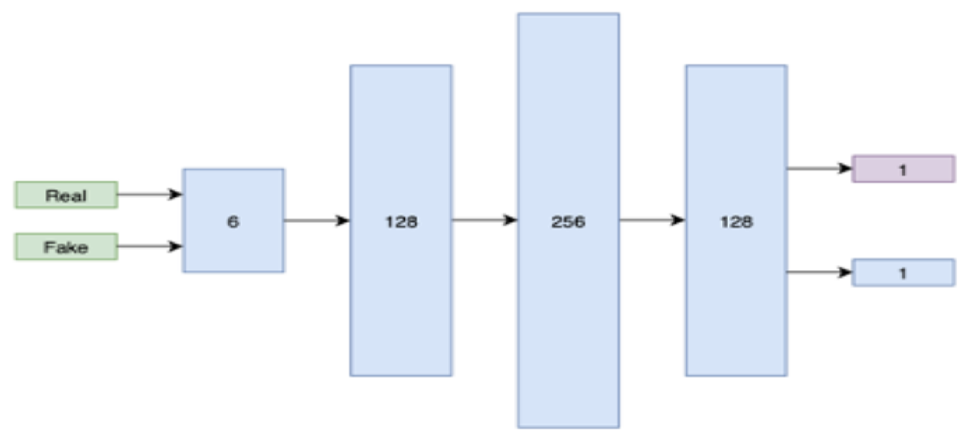


Muon scattering with the nucleus resulting in a muon and a MFC.

Classical C-GAN Architecture



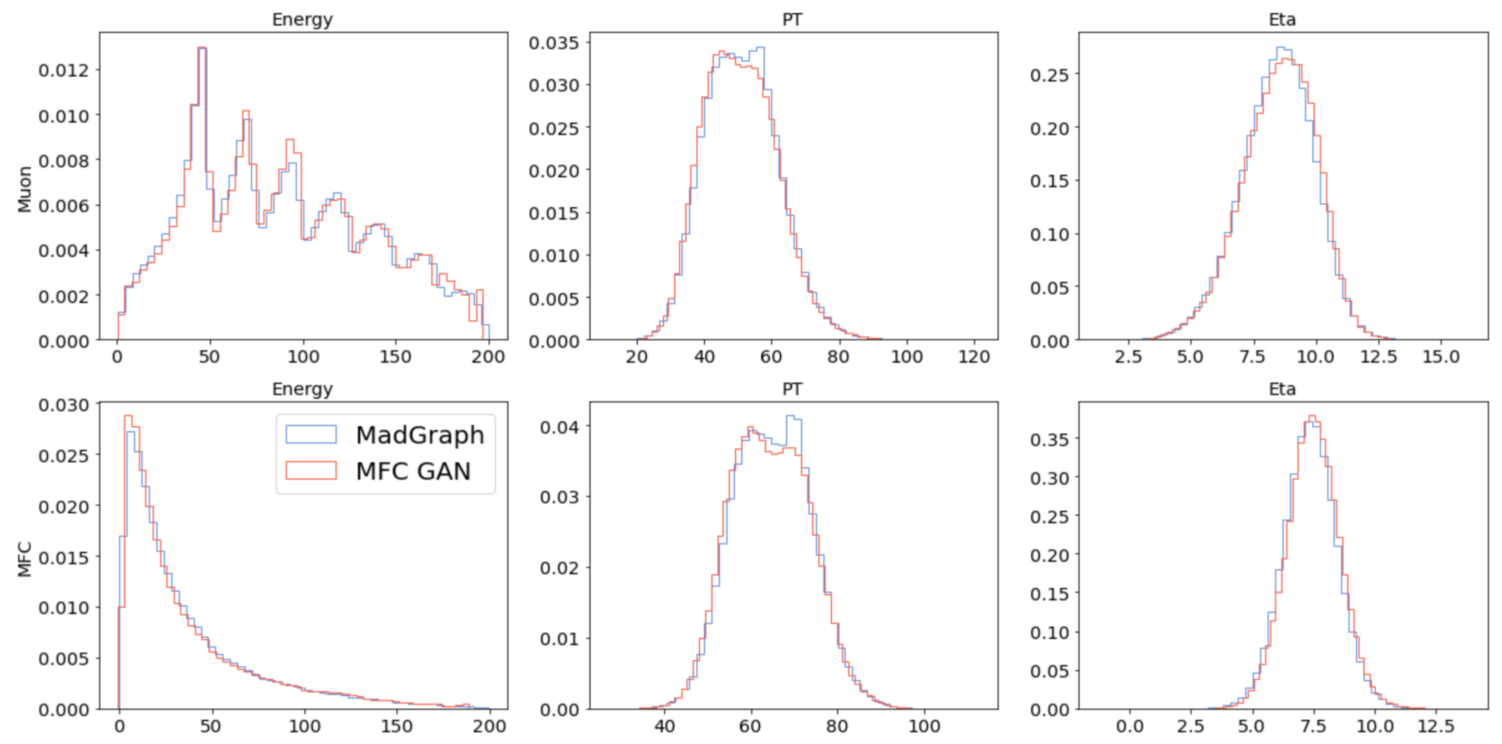
(a) Generator



(b) Discriminator

G Layer: FC + BatchNorm + Sigmoid
D Layer: FC + Sigmoid
$\hat{x} = G(e, z)$, where $z \sim \mathcal{N}(0, 1)$
$L_G = \text{BCE}(\hat{x})$
$L_D = \text{BCE}(x, \hat{x}) + \lambda(\text{MSE}(e, \hat{e}) + (\sigma_e - \sigma_{\hat{e}})^2)$

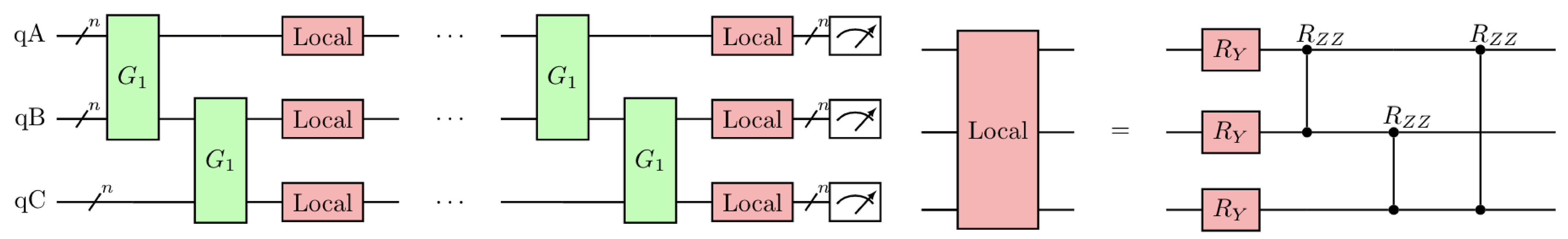
Classical C-GAN Results



Generated energy, transverse momentum (pt) and rapidity (η) of the outgoing muon and MFC compared to the reference MC simulations.

$\text{TV}_{\text{GAN}} = 0.189$

Generating multiples features with the Born machine



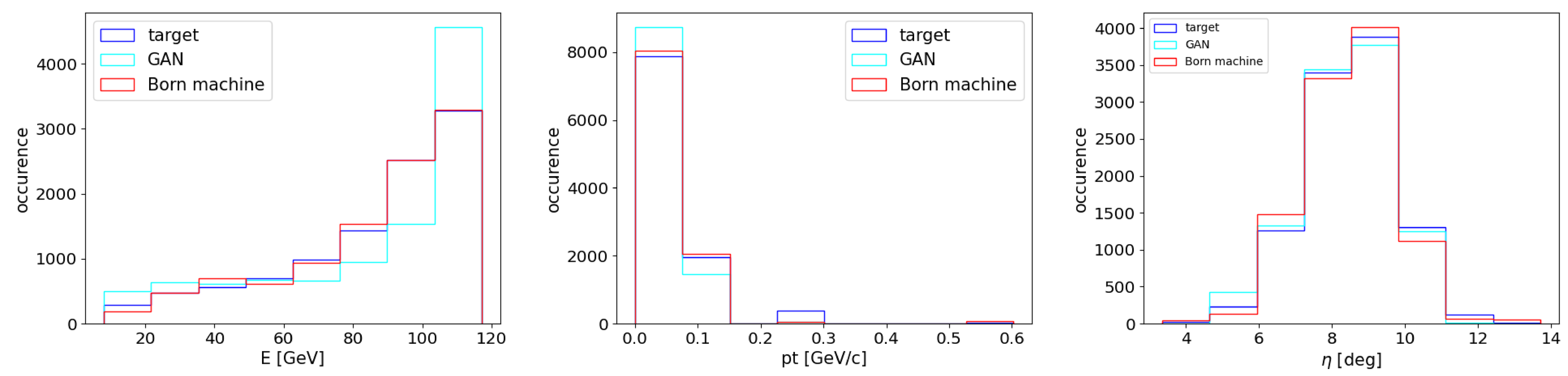
G_1: creates a Bell state between the first qubit in the registers • entangles the registers
Local: learns the 1 dimensional PDFs • takes the form of an Ising Hamiltonian
Legend: green: fixed gates (Hadamard and CNOTs) • red: trainable gates ($R_Y(\theta)$ and $R_{ZZ}(\theta)$)

QGM: Born machine

- sample from a variational quantum state $|\psi(\theta)\rangle$ with $p_\theta(x) = |\langle x|\psi(\theta)\rangle|^2$.
- fit target PDF using MMD loss with Gaussian kernel K: $\textbf{MMD}(P, Q) = ||\mathbb{E}_{X\sim P}[K(X)] - \mathbb{E}_{Y\sim Q}[K(Y)]||$.
- use one quantum register per feature.

Results: outgoing muon with an inital energy of 125 GeV

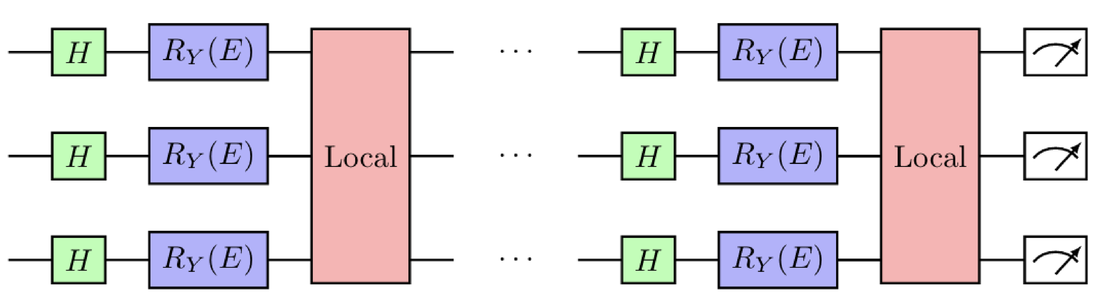
architecture: 5 reps • **preprocessing:** min-max scaling



a) energy b) transverse momentum (pt) c) pseudo rapidity (η)

Total Variance(P,Q)$= \frac{1}{2} \cdot \sum_{i,x} |P_i(x) - Q_i(x)|$: $\text{TV}_{\text{GAN}} = 0.28$, $\text{TV}_{\text{Born}} = 0.1$

Conditional Born machine



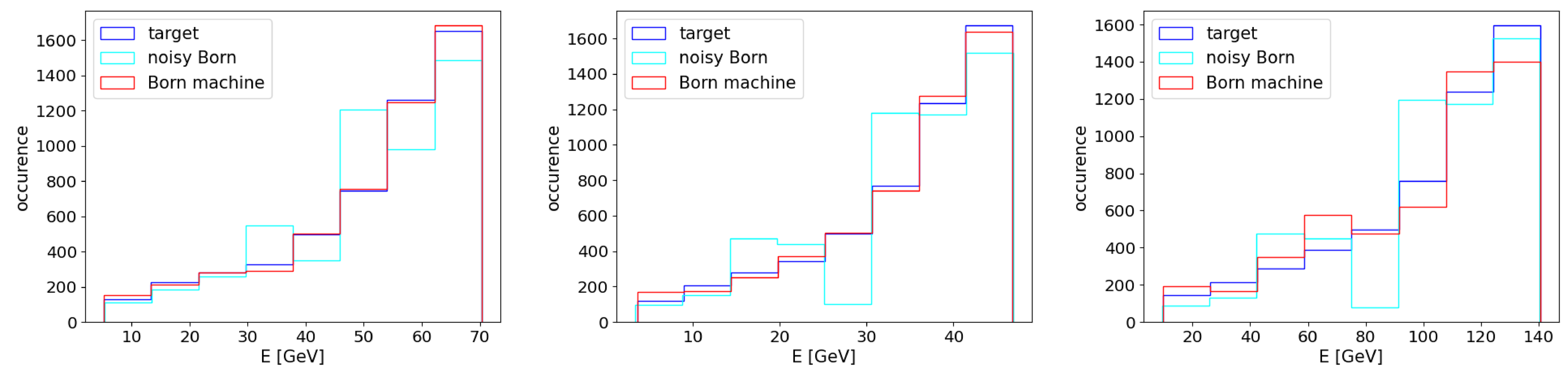
green: fixe • red: trainable • blue: encoding
Input: binning energy scaled between $[-\pi, \pi]$

Conclusion and Future work

- Both models have been successfully implemented for experiment simulation; Born machine has shown lower Total Variance.
- Enhance the Born machine and compare with initial results of the CGAN

Results: Conditional Born machine, outgoing muon energy

architecture: 4 reps • **preprocessing:** min-max scaling • **noise:** IBMQ casablanca



a) train: 150 GeV b) train: 200 GeV c) test: 175 GeV

a) TV $= 0.08$, $\text{TV}_{\text{noise}} = 0.25$ b) TV $= 0.16$, $\text{TV}_{\text{noise}} = 0.52$ c) TV $= 0.33$, $\text{TV}_{\text{noise}} = 1.4$

References

[1] Galon, I, Kajamovitz, E et al. "Searching for muonic forces with the ATLAS detector". In: *Phys. Rev. D 101, 011701* (2020)
[2] Coyle, B., Mills, D. et al, "The Born supremacy". In: *npj Quantum Inf 6, 60* (2020)