



DEPARTMENT OF INFORMATICS + TELECOMMUNICATIONS



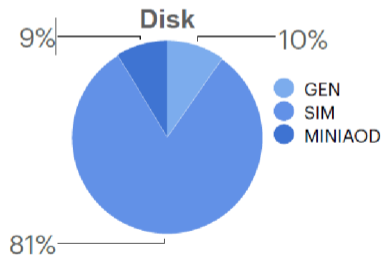
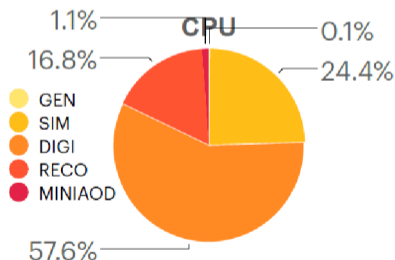
Particle-based Fast Jet Simulation at the LHC with Variational Autoencoders

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5th Inter-experiment Machine Learning Workshop - 10/05/2022

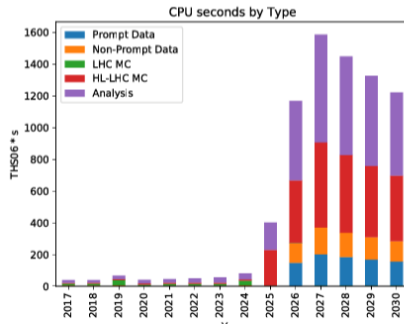
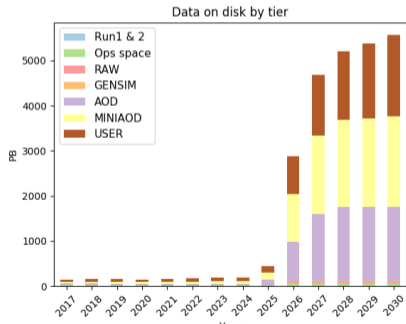
Motivations

- HEP data analysis heavily relies on the production and the storage of large datasets of simulated events
- Current HEP solutions are very accurate, but also very slow
 - Costly in time resources
 - Costly in storage (as data needs to be saved till researchers need it)
 - Cannot be used as on-demand services



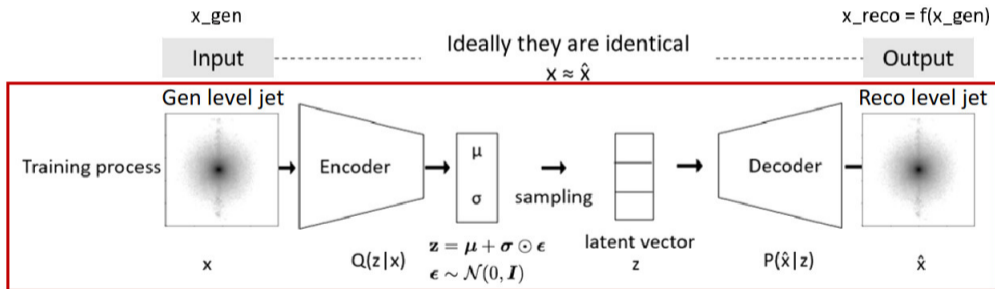
Motivations

- Foreseen upgrade for the High-Luminosity phase of the LHC will increase the number of collisions and the need of more accurate, synthetic data for analysis
- Current solutions do not scale with fixed budget → Deep Generative models proposed as a tool for speeding up HEP workflows



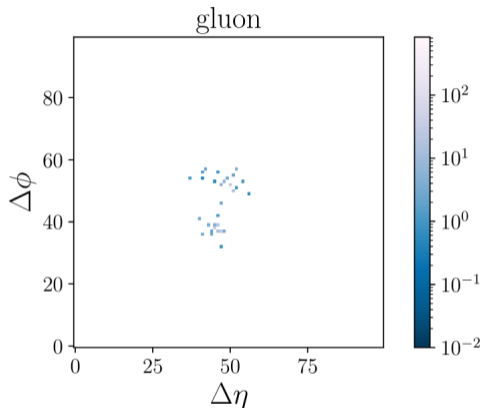
Particle-based Fast Jet Simulation with Variational Autoencoders

- Starting from a simulation of the jet before detector effects, we train a Variational Autoencoder (VAE) to return the corresponding list of constituents after detection
- Run end-to-end VAE (from GEN to RECO) to learn a parametric description of the detector response



Data Representation of Jets

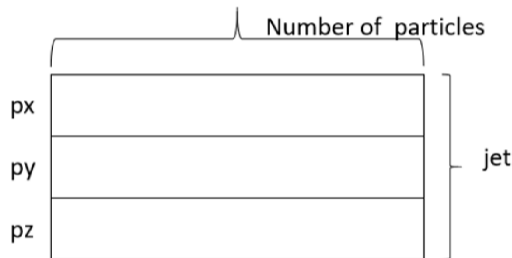
- Jets can be characterized as sparse sets of particles that are intrinsically unordered
- Jets can be represented as a list of constituents characterized by their momenta:
 - In cartesian coordinates p_x, p_y, p_z
 - In hadronic coordinates p_T, η, ϕ
- Although, sometimes, an ordering might be given to the data (e.g. ordering particles by decreasing p_T), it is also important to preserve the permutation invariance in it (depending on application-specific requirements)



Graphical representation of a gluon jet
[arXiv:1908.05318](https://arxiv.org/abs/1908.05318)

Data Representation of Jets

- We represent jets as a list of N highest p_T constituents, characterized by their momenta p_x , p_y , p_z . If less than N particles are present in the jet, zero-padding is applied.
 - Avoids sparsity of data dealing only with useful information
 - Fits well on the convolutional layers of our network
- We apply feature-dependent standardization such that each feature (p_x , p_y , p_z) has zero mean and unit variance.
- Our dataset consists of W boson jets with up to 50 particles.



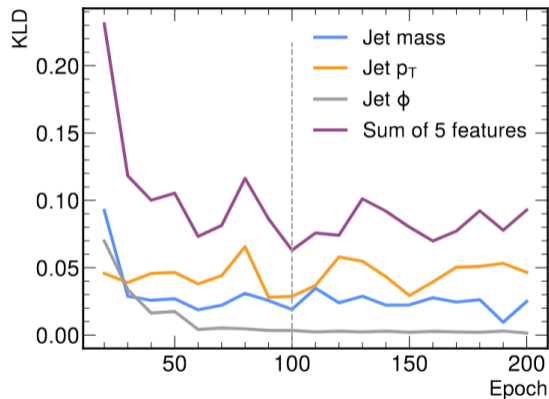
Reconstruction Loss Function

- Use of a permutation-invariant, pairwise Nearest Neighbour Distance (NND) known as the Chamfer distance ([arXiv:1906.02795](https://arxiv.org/abs/1906.02795)) for the reconstruction loss
- Customization of the reconstruction loss by adding two extra terms, the jet mass and the jet p_T to enforce the model to learn jet kinematics
- The jet mass and the jet p_T (target and reconstructed) are computed from the sum of the momenta of the particles on the jet

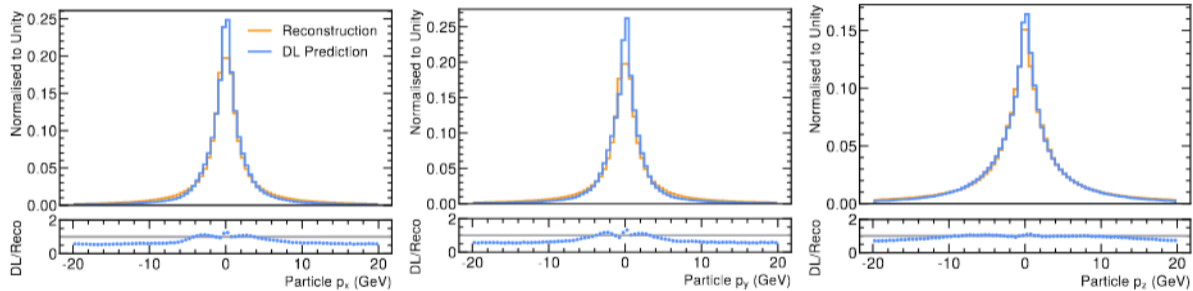
$$L_{reco} = \frac{1}{N} \sum_{i=0}^N \left[\sum_j \min_k (p_j^i - \hat{p}_k^i)^2 + \sum_k \min_j (p_j^i - \hat{p}_k^i)^2 \right. \\ \left. + \alpha_m (m_{jet}^i - \hat{m}_{jet}^i)^2 + \alpha_{p_T} (p_T^{jet,i} - \hat{p}_T^{jet,i})^2 \right]$$

Model Detection & Evaluation

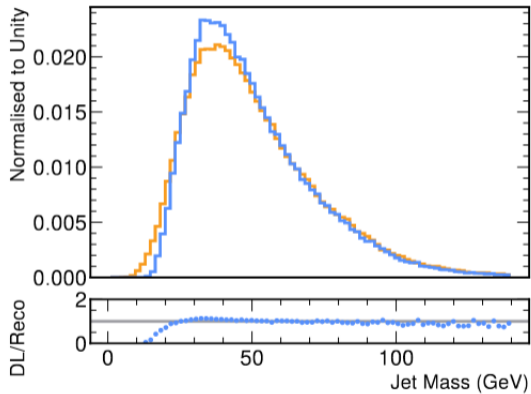
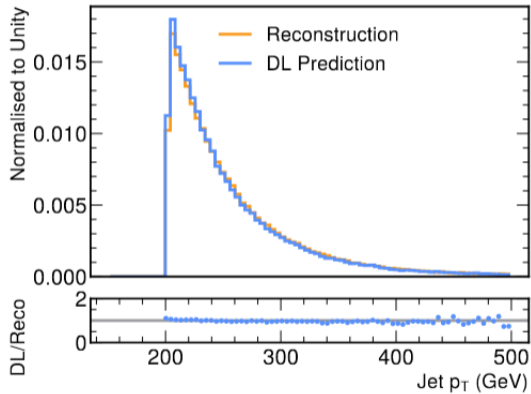
- KL divergence (KLD) between the output (DL) and the target (Reco) jet features histograms used as a quantitative metric to select the best model for analysis
- Define as best the model that satisfies joint conditions for KLD metrics:
 - minimizes KLD sum of all jet features
 - keeps the KLD sum of jet mass and jet p_T below an empirically-set threshold
- KLD as a figure of merit to find a compromise between the multi-objective reco loss



Results: Constituents Properties



Results: Jets Properties

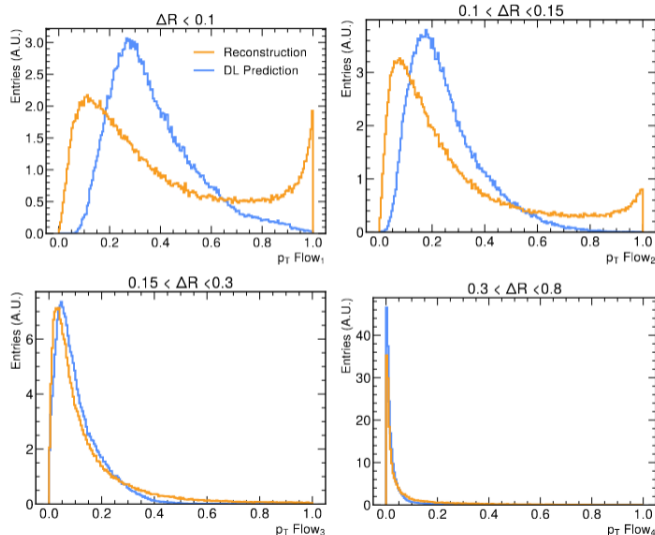


Results: Jets Substructure

- Jet substructure computed using momentum flows

$$Flow_n = \sum_p \frac{p_t^p}{p_T^{\text{jet}}}$$

- The sum runs over all particles with $\Delta R = \sqrt{\Delta\phi^2 + \Delta\eta^2}$ from jet axis, within $(n-1)/4 \times R$ and $n/4 \times R$



□ CNN VAE

- Working baseline model with a permutation-invariant loss
- Achieved fast-simulation precision on jets (constituents) properties
 - Retained fast simulation time of 10^{-3} s per event
 - Could already be used to generate events for most LHC physics analysis
- Main challenge: fixed-length tensors and zero-padding
- Possible solutions: learnable masking feature to deal with zero-padding, or Graph NNs.

□ Graph VAE

- Moving into a graph implementation of the VAE
- Permutation-invariant architecture + permutation-invariant loss → Replace CNN VAE with a Graph VAE + Chamfer loss
- Varied length tensors instead of fixed length → Avoid zero-padding

Backup

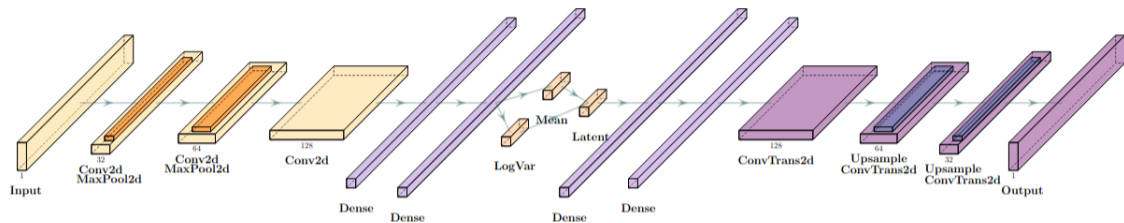
- The loss function of a VAE consists of two terms:
 - The reconstruction loss (e.g. traditionally a generic loss function such as the MSE) – the error between the original samples (inputs/targets) and the produced outputs (reconstructed inputs).
 - The Kullback-Leibler (KL) divergence used as a loss function between the encoder's distribution $q_{\phi}(z|x)$ and the $p_{\theta}(z)$ that optimizes the probability distribution parameters (μ and σ) to closely resemble those of the target distribution.

$$L^{VAE} = \beta D_{KL} + (1 - \beta) L_{reco}$$

where

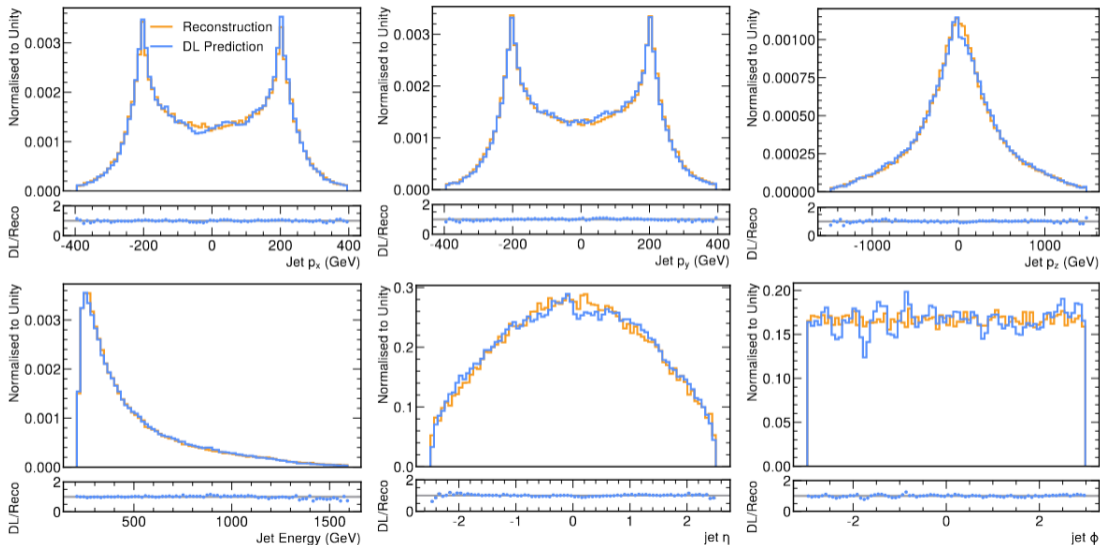
$$D_{KL}(q_{\phi}(z|x) || p_{\theta}(z))$$

VAE Architecture

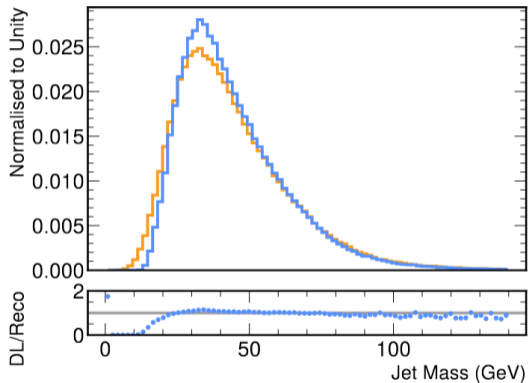
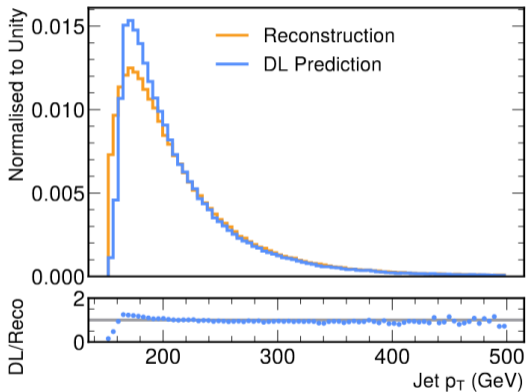


- Leaky ReLU (negative slope = 0.1) is being used as the activation function on all layers except for encoder and decoder output layers where linear activation is used.
- Adam optimization with a learning rate = 0.0001, latent space dimension = 20, and loss function tuned with $\beta = 1/9$, $\alpha_m = 1.0$, $\alpha_{p_T} = 0.1$
- Max pooling (Upsampling) with kernel size 1×2 and stride 2 is used after (before) the first (last) two Conv2D (ConvTrans2D) layers

Results: Jets Properties



Results: Jets Properties (before 200 GeV cut)



Results: Jets Properties (before 200 GeV cut)

