**End-To-End Latent Variational Diffusion Models for Inverse Problems in High Energy Physics**

Paper Review by Tyler Kim

**Motivation**

* Current detectors do not perfectly reconstruct particle properties, so a simulation-based inference was used to account for the effects. However, high fidelity simulation-based inferences are computationally expensive and generally inaccessible.
* *unfolding* is one approach yet there is no true inverse function, works in only a few dimensions, and requires binning the data.
  + *Unfolding*: mapping observed detector signatures directly to unobserved *truth-level* information

**Proposal**

* The paper proposes a novel generative unfolding method utilizing a diffusion model

**Variational Latent Diffusion (VLD)**

* The paper proposes a unified variational model that combines the conditional encoder, data VAE, and diffusion process into a single loss function and uses a supportive physics-informed consistency loss.
  + The conditioning encoder is simultaneously trained with other generative terms and is restricted to a deterministic mapping
    - Two exploration approaches
      * Extend encoder and decoder with conditional probabilistic models
      * Explore intermediate value that estimates VAE posterior but employs an unconditional decoder during generation
  + ELBO:
  + Physics-Informed consistency loss

**Unfolding Semi-Leptonic**  **Events**

* A Monte Carlo simulation is used to generate pairs of events at both the detector and parton level.
* The parton level events is taken as the data distribution and the detector level events is taken as the conditional distribution
* The generative model follows a procedure to unfold observed events
  + Sample parton configuration from distribution governing the process of interest:
  + Sample possible detector observations
  + Train generative model to approximate the inverse distribution
  + Produce new samples for inference data with unknown parton configurations

A diagram of a model

Description automatically generated

**Key Findings**

* Multiple baselines were used for experimenting
  + Traditional conditional variational autoencoder
  + Conditional invertible neural network
  + Variational diffusion model
  + Latent diffusion model
  + Variations of the VLD model
* The latent diffusion detector encoder uses SPANet’s jet transformer encoder where the authors extract fixed-size event embedding vector from the central transformer mapping variable-length, unordered detector observations in to a fixed-size real vector
* The encoder and decoder network uses a ConvNeXt-sinpired block structure for hidden layers.
  + Partons are represented as a single 55-dimensional vector for each event.
  + The latent space may be a higher dimensionality than the original space.
  + Encoder produces two outputs, the mean () and standard deviation ().
  + Decoder accepts latent parton representation and produces a deterministic estimate of the original parton configuration

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* **Dataset**
  + Pythia8 simulated parton showering and hardonization and DELPHES simulated the detector level responses.
  + Event selection was applied to reconstructed objects at detector-level.
  + The kinematics of the six final state partons, intermediate resonance particles, and entire system used as unfolding targets
* **Training Specs**
  + MSE and physics-informed consistency loss with used for reconstruction and noise loss.
  + 500k – 1M gradient steps for each model

A graph of a function

Description automatically generated with medium confidence

* **Results**
  + The VLD models with unconditional decoders (VLD and UC-VLD) performed best while VLD’s with conditional decoders worsened reconstruction.
  + The latent models performed better than CINN and VDM.
  + The end-to-end training procedure did better than the pre-trained LDM model

A diagram of a mass event

Description automatically generated with medium confidence

* The unfolded distributions were compared to the brute-force approach.