2022

Point Cloud-based Mapper for QCD Analysis

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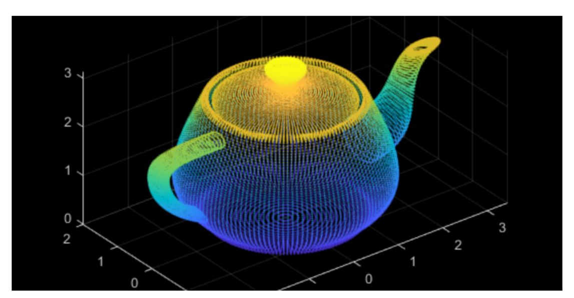
Introduction

- Many developing applications demand perception of 3D environments or interaction with 3D objects.
- The most common and promising 3D visual representation models in many heterogeneous fields is "point clouds" (from raw sensor input).
- What is point cloud?
  The data in its rawest form is known as a "point cloud". It is a set of data points in space, and these points represent a 3D shape or object as shown in Figure,1. Each point has its own set of X, Y, and Z coordinates.
- The Point cloud is being utilized in a variety of applications, such as robotics.
- Our application of point cloud-based is in physics, mapping event level to parameter level.



Challenges with point cloud: Irregularity, unstructuredness, and unorderdness. A deep learning neural network model that can directly address point clouds' issues is called *"PointNet"*.

Figure 1. 3D point cloud representation

PointNet Approach (Architecture and Application)

- The key to the PointNet approach for adopting this architecture for our application in physics is the use of a symmetric function and a multi-layered transformation-alignment network (T-Net)
- A symmetric function is used to aggregate global information from all the points in the point cloud, which is embedded with local and global information to capture relationships between points at the low-level and high-level structure of the object
- The T-Net is used to help make the network invariant to rigid transformations such as rotations, which do not modify the structure of the object.

ML-based Optimization in Nuclear Femtography

- At the Electron-Ion Collider (EIC), we constructed a toy scenario as a simplistic proxy for lepton-proton collisions to demonstrate the possibility of integrating event-based learning for nuclear femtography.
- Two QCFs presenting up and down parton distribution functions (PDFs):

$$u(x) = x^{a_u}(1-x)^{b_u}$$

$$d(x) = 0.1^x a_d (1-x)^{b_d}$$

- And two toy physical observables have been made to simulate inclusive DIS on the proton and neutron, respectively:

$$\sigma 1 = 4u(x) + d(x)$$

$$\sigma 2 = 4d(x) + u(x)$$

- The pdfs can be created as:

$$p_{1,2}(x) = \frac{\sigma_{1,2}(x)}{\int_0^1 dx\ \sigma_{1,2}(z)}$$

- The event samples are determined by the specified parameter values, and we construct "true" event samples by using a certain value for the parameter as the ground "truth". Consequently, the aim is to estimate parameter values from these event samples and quantify an uncertainty quantification for the associated toy (up and down) PDFs.

Method of Point Cloud-based Mapper for QCD Analysis

- Figure. 2 shows that the Point Cloud-based Variational Autoencoder adopts the architecture of PointNet and Variational Autoencoder.

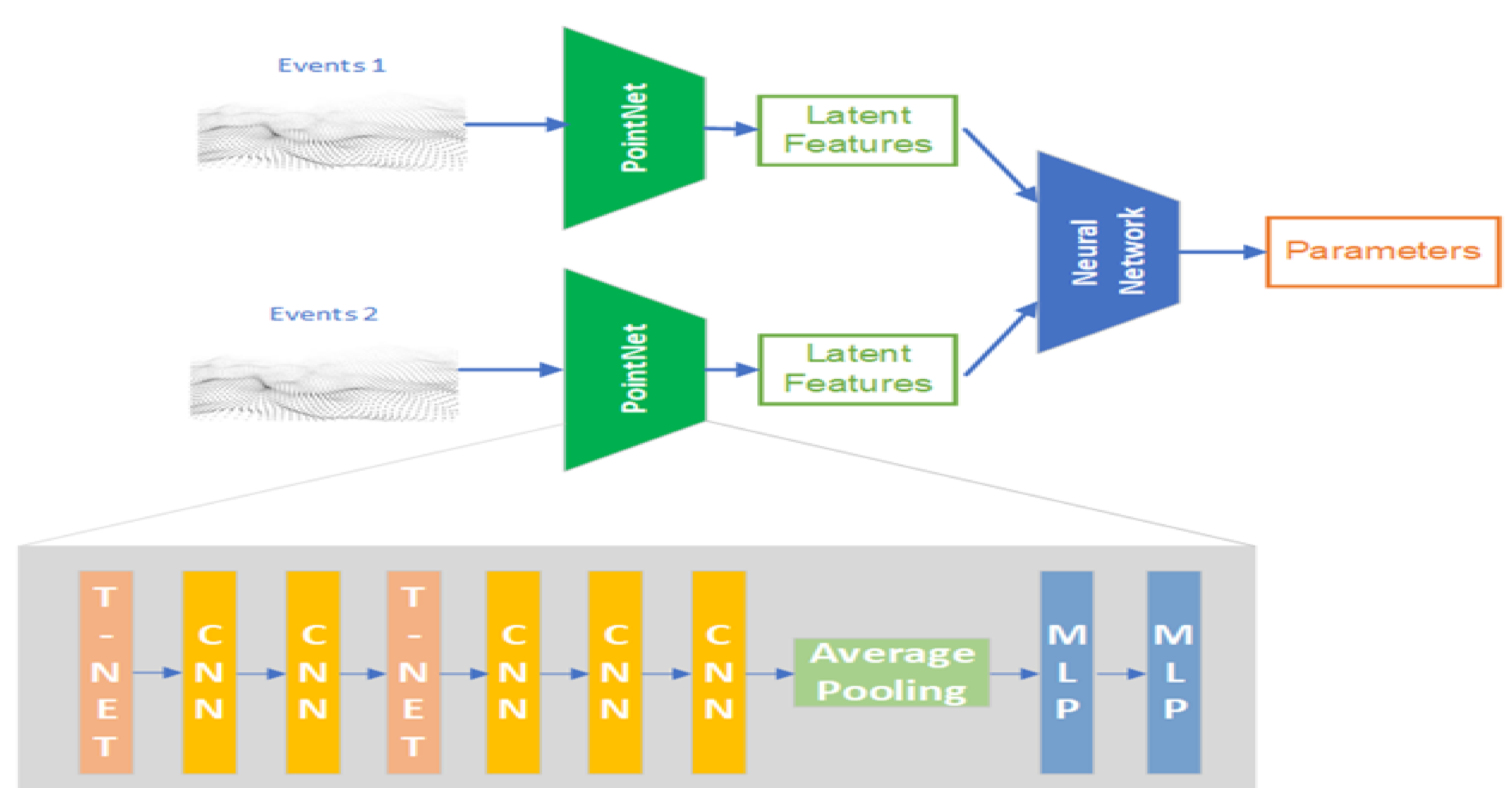


Figure 2. Point cloud-based Mapper architecture

- Combined architectures are selected to learn the mapping from event space to parameter space ($\sigma 1$ and $\sigma 2$).
- A set of events is represented as a point cloud,which retains the permutation invariant property and geometric correlations of the events while being flexible with the amount of events in the input.
- The point cloud-based neural network is made up of two main components:
  (A) *Convolutional neural networks* to generate/select the orderless features.
  (B) *Transformer networks* to learn the representations of the geometry of the events.
- The PointNet network in our application accepts n points as input, executes input and feature transformations.
- By average pooling, it aggregates point features. After average pooling, Multi-layer perceptron is used to enable the learning of a spatial encoding for each point.
  - The first phase of the PointNet network involves a sub-network that is named *T-Net* for "transformation network". T-Net attempts to learn an affine transformation matrix from its own mini network.
  - T-Net in our application is applied twice and trained alongside PointNet.
  - Its first job is to transform the input features (n, 1000,1) into a canonical representation and then as an affine transformation for alignment in feature space (n, 1000,1). As a second job, the transformation is constrained to be near to an orthogonal matrix, i.e. $\|\ \mathbf{XX}^T - I\| = 0$.
  - A latent layer is included between the PointNet neural network and the Dense Layer neural network, which is deeply connected with its preceding layer, to learn the features of data and simplify data representations for the purpose of finding patterns.

Result

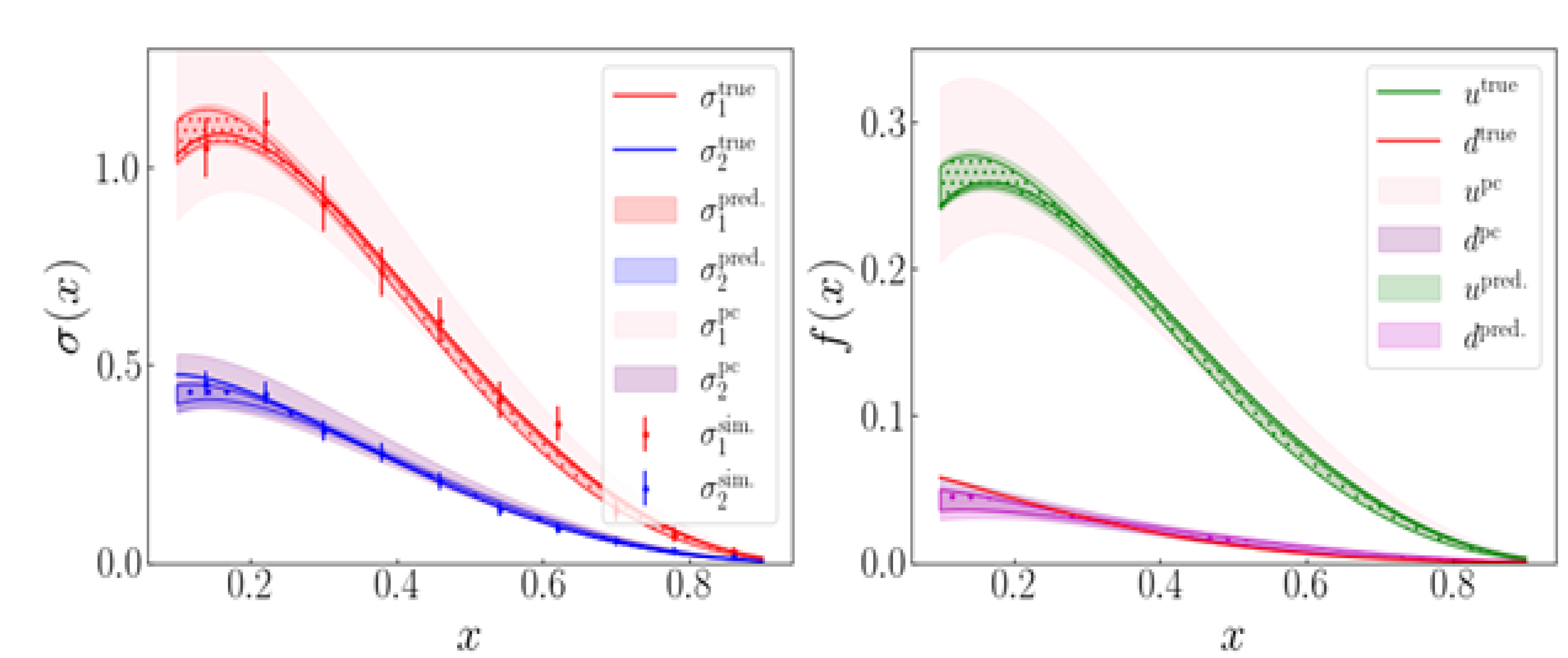


Figure 3. Point cloud-based Mapper Result

- Our results show that σ_1^{true} and σ_2^{true} are respectively within one standard division of predicted $\sigma_1^{\rm pc}$ and $\sigma_2^{\rm pc}$ using point cloud-based variational autoencoder.
- Our trained point cloud-based variational autoencoder model acts as an effective inverse function from detector level events to parameter space which can be used as the final step to infer the QCFs model parameters from the experimental detector level events.
- The point cloud model can be extended to high-dimensional events with permutation-invariant features.

References

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