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Federated Learning Strategies of Generative Adversarial Networks for High Energy Physics Calorimeter Simulation

Thursday, 27 October 2022 11:00 (30 minutes)

Particle physics experiments spend large amounts of computational effort on Monte Carlo simulations. Due to the computational expense of simulations, they are often executed and stored in large distributed computing clusters. To lessen the computational cost, physicists have introduced alternatives to speed up the simulation. Generative Adversarial Networks (GANs) are an excellent Deep-Learning-based alternative due to their ability to imitate probability distributions. Concretely, one of the more tackled problems is calorimeter simulations since they involve a large portion of the computing power. GANs simulate calorimeter particle showers with good accuracy and reduced computational resources. Previous works have already explored the generation of calorimeter simulation data with GANs, but in most cases as a centralized perspective (i.e., where the dataset is present on the training node).
This separation creates a disparity between the training data generation (i.e., in distributed clusters) and training (i.e., centralized), introducing a limiting factor to the amount of data the centralized node can use to train. Federated Learning has arisen as a successful decentralized training solution where data is non-necessarily balanced, independent, and identically distributed (IID). Federated Learning is a training method where a group of \textit{collaborators} trains a model by sharing training updates with an \textit{aggregator}. The sparsity and distributed nature of the simulated data pairs favorably with the features of Federated Learning. In this work, we introduce new federated learning-based approaches for GAN training and test them on the 2DGAN model*. This work covers different training schemes for GANs with FL (e.g., centralized discriminator or centralized generator). Our work provides insights into the various architectures by performing model training and extracting performance metrics. The results permit the evaluation of the effectiveness of the different strategies.

- Rehm, F., Vallecorsa, S., Borras, K., & Krücker, D. (2021). Validation of Deep Convolutional Generative Adversarial Networks for High Energy Physics Calorimeter Simulations. doi:10.48550/ARXIV.2103.13698

Significance

Monte-Carlo Simulations are classically used in High-Energy Physics to simulate particle interactions in detectors. These simulations are often performed in distributed computing grids, creating an inherent dispersion of resulting data. Generative Adversarial Networks have emerged as a potential solution to these expensive simulations. However, they still enforce the centralization of data. Federated Learning is a novel decentralized deep learning model training approach. We combine Federated Learning with GANs for calorimeter simulation. We aim to provide different data architectures where data training is not uniformly distributed or balanced. Furthermore, we want to test diverse network configurations to understand the advantages, disadvantages, and differences between the classical centralized approaches and federated learning.

References

Experiment context, if any

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