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Event classification using Graph Network

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After the Higgs boson discovery, the main interest in the elementary particle physics is the discovery of beyond the Standard Model. LHC, which is the most energetic collider in the world, continues to be the leading experiment in the energy frontier. While LHC does not increase the center of mass energy beyond 14 TeV over a few decades, the amount of collision data will be significantly increased by the upgrade to High-Luminosity LHC. We need to leverage the observed data to the fullest extent in such an era.

One of the most attractive ways to utilize observed collision data is deep learning. Deep learning can represent a complex correlation between the input variables, and it is known to have better sensitivity than the traditional analysis method in some real examples. Although deep learning has a very significant capability to represent any complicated functions, such a representation ability leads to the overfitting of the training data. To use deep learning more effectively, we need to embed our domain knowledge in the deep learning model as inductive bias. Graph Network could accomplish such a requirement. Graph Network handles a graph, which has nodes and edges. By using a graph structure, we can assign a grouped element as a node and the known relation between elements as an edge. Additionally, a graph structure could produce interpretable results than the typical one-row representation.

We apply Graph Network to an event classification problem to embed a domain knowledge as an inductive bias in the model. Implementation of inductive bias is expected to avoid the unphysical calculation of the input variables in the neural network. We expect to avoid overfitting and accomplish better classification performance than the traditional multilayer perceptron model, in particular, when the number of training data is insufficient. We construct the Graph Network model for the event classification for a typical physics process and compare the performance between the Graph Network and traditional analysis methods.

Additionally, it is important to consider the known constraint in the experimental data. Usually, experimental data has symmetries, e.g., spatial rotation invariance. A generic deep learning model does not consider such a rule, resulting in the over-fitting. By giving such a known rule, we can improve the performance of deep learning.

We will report the latest results and the issues in the implementation of the high-level domain knowledge.

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