Plain Language Summary

Machine learning techniqus applied to Monte Carlo integration

Niklas Götz

Generating predictions from the standard model, the well established theory of fundamental forces and particles, for what we can observe in detectors require multiple steps. Crucial for the precision of the prediction is an integration step. As experimental results become more and more precise, the theoretical predictions have to improve too.

The precision of an integration improves with the numerical work invested in it. However, due to the finite numerical resources available, it is crucial to improve the efficiency of numerical integration. A common way to perform numerical integration is the Monte Carlo method, for which the integrand is evaluated many times at random arguments and the integral is approximated by the mean of the generated values. Standard algorithms to improve the precision try to determine the values for which the integral has the highest values, in order to sample there more often - this strategy is called importance sampling.

Integrands in particle physics suffer from correlations as well as highly expensive evaluation. The standard algorithms of importance sampling fail to correctly identify regions of high values when correlations are present. This work evaluates a new strategy of importance sampling using machine learning. A neural network is trained to identify parameters of a distribution which approximates the integrand, using a method called normalizing flows. This allows to circumvent the issue of the correlations.

The standard approach and the approach using normalizing flows are tested for multiple standard integrals of particle physics. It is shown that the normalizing flows excel especially for high dimensional integrals and can outperform standard algorithms successfully.