Efficient event generation in high energy physics with Normalizing Flows and Optimal Transport

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Project description

In high energy physics, we study the interaction of the smallest particles using scattering experiments to explore the nature of these particles. While experimental data are provided by huge collider experiments like the Large Hadron Collider, numerical simulation is the backbone that provides reliable theoretical predictions. Based on first principles, a simulation software (called an event generator) generates independent events that describe the physical properties, like energy and direction of motion, of incoming and outgoing particles of a collision. The probability of occurrence for an event is encoded in a quantity called differential cross-section. It defines a probability distribution and the objective of an event generator is to provide samples that truthfully follow this distribution. The density function can have a complicated structure and its numerical evaluation time grows extremely fast with the number of particles involved. This makes the sampling in event generators a complex task that requires dedicated tools, which build on detailed physics knowledge. For challenging scattering processes, the generation of large event samples, as needed for the analysis of experimental data, reaches the limit of what is computationally possible with current approaches. More efficient sampling techniques are highly desirable to increase the physics reach.

In this project, I will study the use of generative models to design an efficient phase space sampler for event generation. While contemporary generative models are certainly powerful, it remains to be demonstrated that they are able to significantly increase the efficiency of event generation up to large numbers of final state particles. The process of event generation matches the use of generative models for machine learning tasks: Take a sample from a simple known distribution and transform it into a sample from the desired distribution. Normalizing Flows are especially well suited for this task since they provide a tractable likelihood and guarantee that every possible scattering event can be generated. Their continuous formulation through an ordinary differential equation is particulary powerful. Recent research reduced the training costs significantly and revealed connections to stochastic models, like diffusion, which have shown impressive results in various tasks. The problem is also fundamentally linked to Optimal Transport, since we are constructing a transport map between two probability densities and we can improve the sampler by optimising this map. During this project, I will furthermore consider various methods for incorporating the available prior physics knowledge into the sampling model.