

A quantum-assisted algorithm for sampling applications in machine learning

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An increase in the efficiency of sampling from Boltzmann distributions would have a significant impact in deep learning and other machine learning applications. Recently, quantum annealers have been proposed as a potential candidate to speed up this task, but several limitations still bar these state-of-the-art technologies from being used effectively. One of the main limitations is that, while the device may indeed sample from a Boltzmann-like distribution, quantum dynamical arguments suggests it will do so with an instance-dependent effective temperature, different from the physical temperature of the device. Unless this unknown temperature can be unveiled, it might not be possible to effectively use a quantum annealer for Boltzmann sampling. In this talk, we present a strategy to overcome this challenge with a simple effective-temperature estimation algorithm. We provide a systematic study assessing the impact of the effective temperatures in the learning of a kind of restricted Boltzmann machine embedded on quantum hardware, which can serve as a building block for deep learning architectures. We also provide a comparison to k-step contrastive divergence (CD-k) with k up to 100. Although assuming a suitable fixed effective temperature also allows to outperform one step contrastive divergence (CD-1), only when using an instance-dependent effective temperature we find a performance close to that of CD-100 for the case studied here. We discuss generalizations of the algorithm to other more expressive generative models, beyond restricted Boltzmann machines.