Tensor Networks in Quantum Generative Adversarial Learning

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Quantum machine learning (QML) [1] explores the interaction between quantum computing and machine learning, investigating how results and techniques from one field can be used to solve the problems of the other. With an ever-growing amount of data, current machine learning systems are rapidly approaching the limits of classical computational models. In this regard, quantum computational power can offer advantage in such machine learning tasks. The field of quantum machine learning explores how to devise and implement quantum software that could enable machine learning that is faster than that of classical computers. Fuelled by increasing computing power and algorithmic advances, machine learning techniques have become powerful tools for finding patterns in data. Quantum systems produce peculiar patterns that classical systems are thought not to produce efficiently, so it is reasonable to postulate that quantum computers may outperform classical computers on machine learning tasks. Last, but not least, since many machine learning algorithms are naturally robust to noise, which can actually be a resource instead of a problem [2], QML is a promising application for near-term imperfect quantum devices.

Set in this landscape this research project builds upon the following two main ingredients: Quantum Generative Adversarial Networks (QuGANs) and Tensor Networks (TNs).

1) Generative Adversarial Networks (GANs) are a major recent breakthrough of classical machine learning. Adversarial learning has its roots in game theory, and exploits the competition between two agents, namely a discriminator and a generator, to train the latter to exactly reproduce the statistics of some process-generated data. Achieved results are outstanding, and their quantum generalization (QuGANs) [3, 4], on top of possibly implementing exponential speedups for classical tasks, open the way to new methods for studying quantum many-body states and encoding their properties.

2) Tensor Networks [5] are, in brief, a mathematical tool that offers efficient descriptions of quantum many-body states that are based on the entanglement content of the wave function. Mathematically, the amount and structure of entanglement is a consequence of the chosen network pattern and the number of parameters in the tensors.

During the last years, the field of Tensor Networks has lived an explosion of results in several directions. This is specially true in the study of quantum many-body systems, both theoretically and numerically. But, perhaps more fascinating, also in the direction of quantum gravity, thanks to its relation to the holographic principle and the AdS/CFT correspondence [6].

While we plan to delve deeper in the quantum foundations and applications of QuGANs, and of QML techniques in general, we aim at exploiting these techniques to find optimal methods to encode more general quantum states in TN structures, departing from the nowadays known and tractable examples. Attracted by the connection between the emergent spatial geometry of the networks and holography, this research may also shed additional light on our comprehension of how spacetime may emerge from entanglement.

References

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