Unraveling Quantum Scrambling with Neural Networks

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Abstract

Quantum scrambling is the process by which quantum information is spread within the degrees of freedom of many-body quantum systems. As such, understanding what are the features of a quantum system that maximise this information spreading has become a recent topic of interest of crucial importance. Graph theory provides a natural mathematical framework to encode the interactions of a quantum many-body system, and we thus employ it to study the properties of quantum scrambling as we vary the underlying graph of interactions.
Predicting when a particular quantum many-body system features either strong quantum scrambling (chaotic system) or not (integrable system) is a delicate issue where sophisticated computationally expensive methods are needed. Using the adjacency matrix of the underlying graph of interactions we set up a supervised classification problem that we solve using (i) A standard 2D Convolutional Neural Network, and (ii) A Graph Neural Network. We show that well-known graph-theoretic quantities such as clustering coefficients control the quantum scrambling properties of the system. This suggests that far simpler quantities than previously thought might be needed in order to understand quantum scrambling.
While very much a work in progress, we believe our results pave the way for a better understanding of how to maximize the spreading of quantum information.

References

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2. J.Kim, J.Murugan, J.Olle, D.Rosa, Phys.Rev.A 105 (2022) 1, L010201

Figures

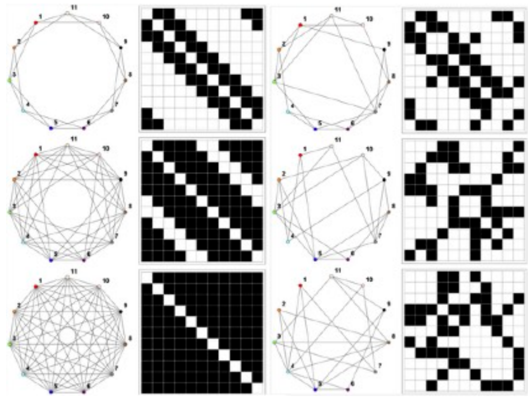

Figure 1: Examples of graphs with their associated adjacency matrix, here represented by an N × N array coded black where a connection exists and white otherwise.

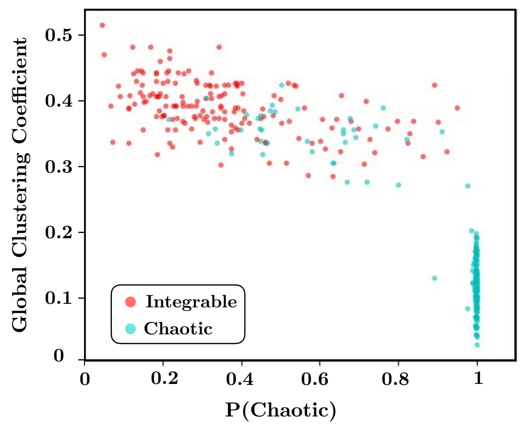

Figure 2: Global clustering coefficient as a function of the probability to be chaotic as predicted by the NN. Different colors correspond to the different labels used in the supervised training.