Deep Learning of Quantum Entanglement

Dominik Koutný
Miroslav Ježek

Department of Optics, Palacký University, 17. listopadu 12, 77146 Olomouc, Czech Republic

koutny@optics.upol.cz

Entanglement quantification is of paramount importance to fundamental research as well as to many cutting-edge applications. Various approaches of entanglement detection have been proposed, but they usually provide only a witness or require the interference of multiple copies of the system under test [1]. It was shown that quantum tomography is necessary [2] for the exact determination of the entanglement in an unknown quantum state. The tomography yields complete information with a drawback of unfeasible scaling with the complexity of the system. Recently, artificial neural networks were exploited for the tomography by approximating the state wavefunction [3], and for entanglement witnessing. Despite these achievements, the question of how precisely the entanglement can be estimated directly from the incomplete measured data remains open. We approach this problem using deep convolutional neural networks for measurement independent strategy and with fully connected deep neural network for the measurement specific approach. We focus on the characterization of two- and three-qubit entanglement sources with imminent applications in quantum communications. We demonstrate significantly lower errors of quantum concurrence estimation from heavily undersampled Pauli measurements compared to state-of-the-art quantum tomography. We verified our approach on experimental data from quantum dot sources and parametric generators, showing the robustness to experimental errors.

References

[1] R. Islam, et al., Nature 528 (2015) 77
[2] D. Lu, et. al., Phys. Rev. Lett. 116 (2016) 230501
[3] G. Torlai, et al., Nat. Phys. 14 (2018) 447

Figures

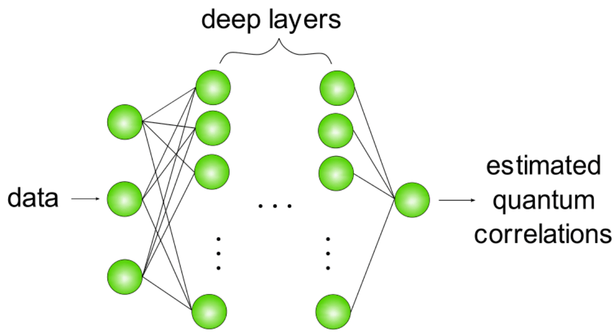

Figure 1: Schematics of measurement specific deep neural network (DNN). Informationally incomplete data from measurement projections are fed into DNN to estimate the concurrence and mutual information.

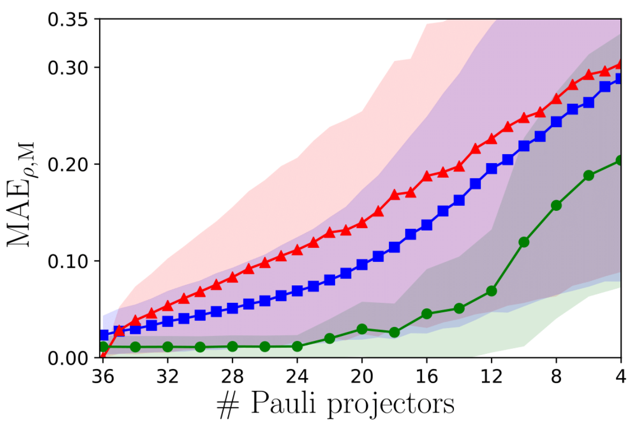

Figure 2: Depicted the mean average error of the concurrence (MAE) as a function of a number of measurement settings for the neural networks and tomographic approach. Both device independent (blue) and measurement specific (green) DNN's outperform the maximum likelihood (red) approach.