



Absence of Barren Plateau in Quantum Convolutional Neural Networks

arXiv:2011.02966

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Is there a barren plateau problem in the quantum CNN?



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Map of The Noisy Hardware Efficient Ansatz



Credit: Marco Cerezo



Cong et al, *Quantum Convolutional Neural Network*, 2018, <u>arXiv:1810.03787</u> Grant et al., *Hierarchical quantum classifiers*, 2018, <u>arXiv:1804.03680</u>











Applications

Phase detection

Quantum error correction

1D Haldane Chain





Barren plateau for the QCNN: first intuition

Previous work: the hardware-efficient ansatz does **not** have barren plateau if:

- 1. We have a local-cost function
- 2. We have a logarithmic number of layers



Cerezo et al, Cost-Function-Dependent Barren Plateaus in Shallow Quantum Neural Networks, <u>arXiv:2001.00550</u>

Intuition: QCNN won't have any barren plateau because of the logarithmic number of layers **Problem:** the QCNN is **not** the hardware-efficient ansatz => we have to do some work

First simplification: modify the circuit to avoid conditional measurement between two blocks



Second simplification: remove the conditional measurements (doesn't change the statistics)



Reason: property of the Haar measure: $\mu_{\text{Haar}}(WV) = \mu_{\text{Haar}}(W)$

Third simplification: we decorrelate the unitaries



Reason: this should give a lower bound on the correlated version (mix of analytical and empirical evidence)

Fourth simplification: linear cost-function with respect to the input state



$$C(\theta) = \operatorname{Tr}[OU_{\theta}\rho_{\mathrm{in}}U_{\theta}^{\dagger}]$$

Example: classification (0 vs 1)

$$C(\theta) = \frac{1}{M_0} \sum_{\rho_i \in S_0} \operatorname{Tr}[U(\theta)\rho_i U^{\dagger}(\theta)O]$$
$$-\frac{1}{M_1} \sum_{\rho_i \in S_1} \operatorname{Tr}[U(\theta)\rho_i U^{\dagger}(\theta)O]$$

Result



Result









Gradient w.r.t this block



Gradient w.r.t this block

Problem: way too many terms to integrate



Gradient w.r.t this block

Idea: causal cone + module decomposition



Method: keep track of all the integrals in a graph



Result: variance = sum over all paths of length log(n) in the graph



Numerical experiments

Simulator: Cirq + TensorFlow Quantum



Future work

- How to study correlated architectures systematically?
- How to study non-linear cost-functions? (e.g. mean-squared error)
- Can we deduce the trainability of MERA from our result?
- Can we use GRIM to analyze other architectures
- How useful are QCNNs in practice?

Thanks for your attention