

Entanglement-induced provable and robust quantum learning advantages

Haimeng Zhao

Caltech

haimeng@caltech.edu

Dong-Ling Deng

Tsinghua

Caltech



清华大学

Tsinghua University



[arXiv:2410.03094](https://arxiv.org/abs/2410.03094)

Motivation

Can we find practical and provable quantum advantage in **classical** ML tasks?

(Most applications are classical, not quantum!)

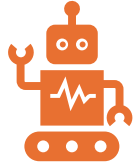
Known obstacles:

1. Hard to unconditionally prove lower bounds.
2. More expressive QML models are harder to train.
3. Data-loading overheads lead to dequantization.
4. NISQ devices limit heuristic exploration.

Our work:

A machine learning task demonstrating
noise-tolerant unconditional linear quantum advantage in
representation power, inference speed, and training efficiency!

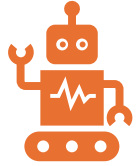
Our work:



practically relevant: seq-seq translation

A machine learning task demonstrating
noise-tolerant unconditional linear quantum advantage in
representation power, inference speed, and training efficiency!

Our work:



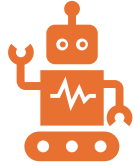
practically relevant

A **machine learning** task demonstrating noise-tolerant unconditional linear quantum advantage in representation power, inference speed, and training efficiency!



tolerate $O(1)$ depolarize noise

Our work:



practically relevant

A **machine learning** task demonstrating **noise-tolerant** unconditional linear quantum advantage in representation power, inference speed, and training efficiency!

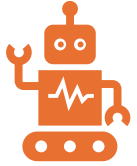


tolerate $O(1)$ depolarize noise



provable w/o conjectures

Our work:



practically relevant

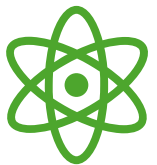
A **machine learning** task demonstrating **noise-tolerant unconditional linear quantum advantage** in representation power, inference speed, and training efficiency!



tolerate $O(1)$ depolarize noise



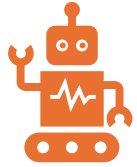
provable w/o conjectures



quantum $O(1)$ vs classical $\Omega(n)$

exp. improve SOTA $\Omega(\log n)$

Our work:



practically relevant

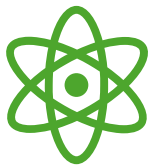
A **machine learning** task demonstrating
noise-tolerant unconditional linear quantum advantage in
representation power, inference speed, and training efficiency!



tolerate $O(1)$ depolarize noise



provable w/o conjectures



quantum $O(1)$ vs classical $\Omega(n)$

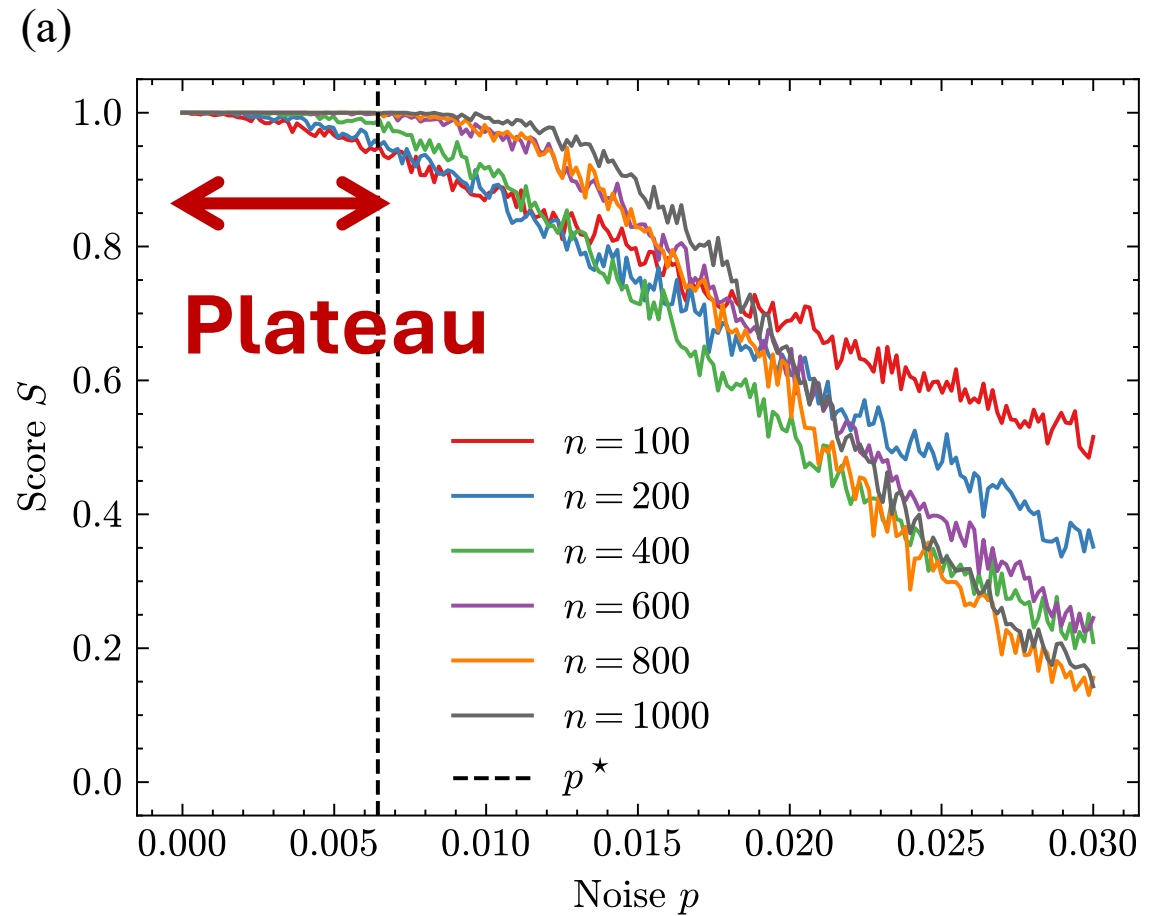
exp. improve SOTA $\Omega(\log n)$



fewer parameters
faster inference & train
smaller sample size

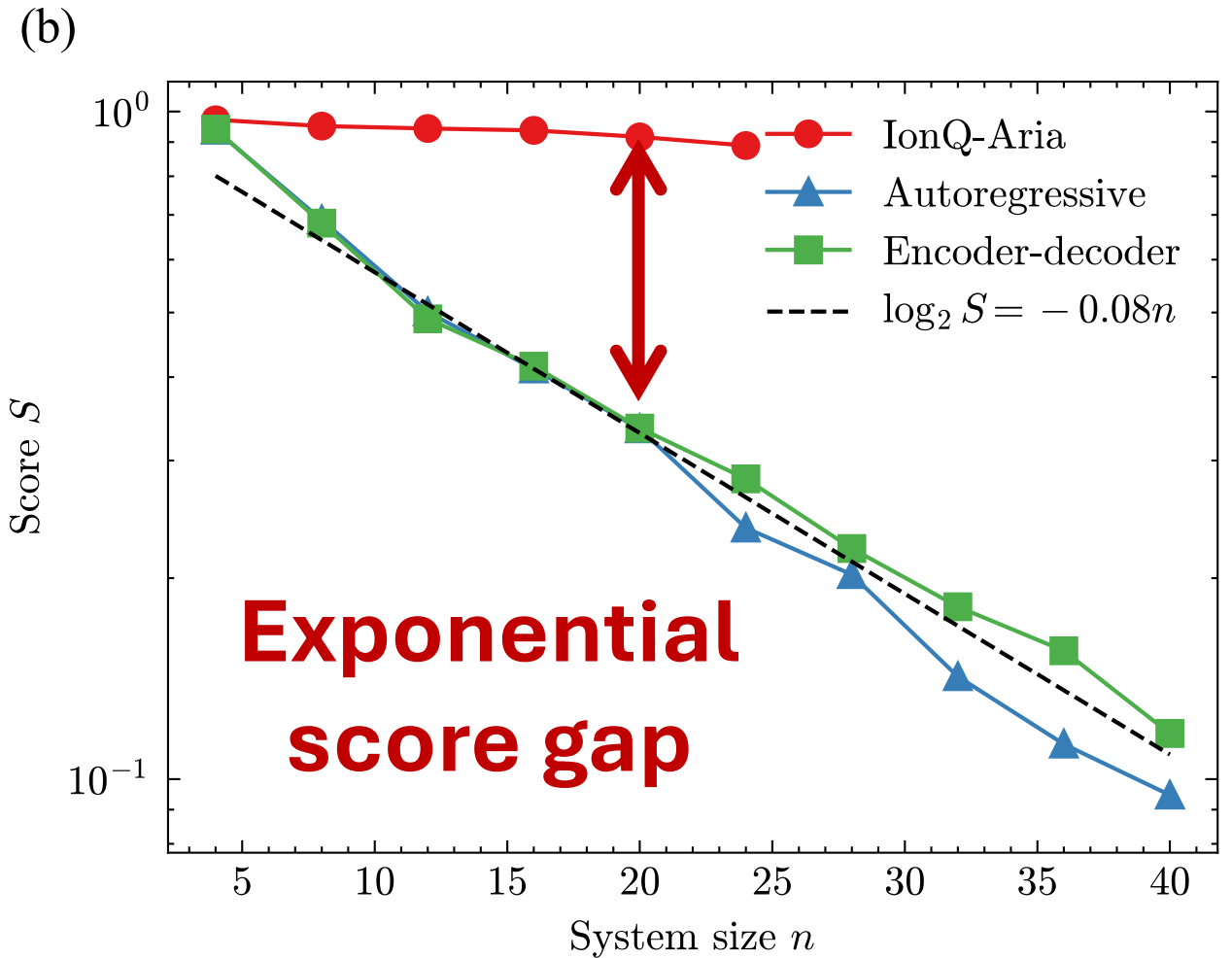
Numerics & Ion trap

- Noise tolerance
- Exponential separation in score
- Classical models suffer from q advantage + overfitting



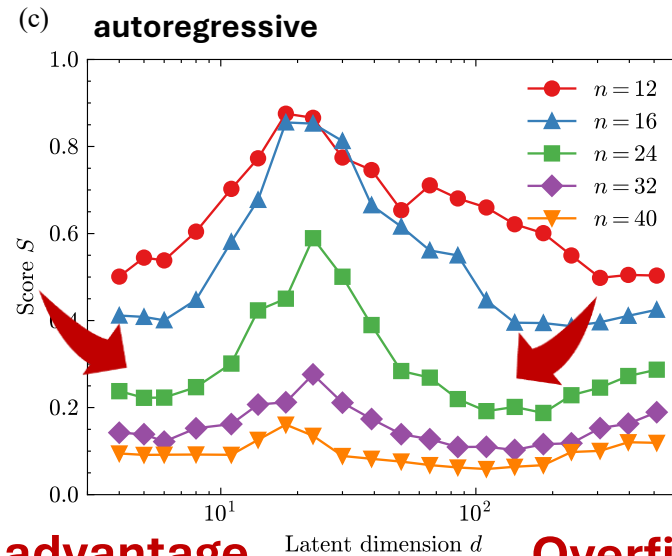
Numerics & Ion trap

- Noise tolerance
- Exponential separation in score
- Classical models suffer from q advantage + overfitting



Numerics & Ion trap

- Noise tolerance
- Exponential separation in score
- Classical models suffer from q advantage + overfitting

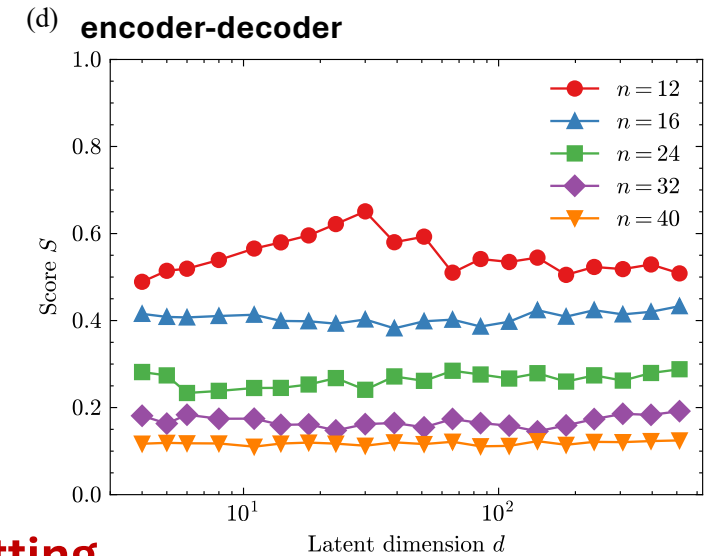


q. advantage

≪

Overfitting

≫ #



Conclusions & Future directions

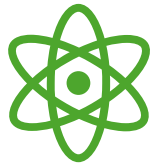
A quantum advantage in ML



provable w/o conjectures



tolerate $O(1)$ depolarize noise



quantum $O(1)$ vs classical $\Omega(n)$
exp. improve SOTA, $\Omega(\log n)$



fewer parameters
faster inference & train
smaller sample size



visible on small size!
(q. advantage + overfit)



boost advantage w/
many-body Bell inequalities?



against more general classical
models?



non-locality in real-world?
e.g., natural language?