Pasqal Defining the quantum reality

Limitations of measure-first protocols in quantum ML

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Introduction & Research question

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Recently: "randomized measurement toolbox" utilized with great success in ML!

- *e.g., predicting complex properties of physical systems (Huang et al, Science 2022)*

Idea: Use measurement protocol to "preprocess" quantum data → classical data

→ which is then fed into (classical) ML algorithm.

Slogan: "Measure first, ask questions later".

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Research question: *are there ML tasks where full quantum states are required?*

- I.e., can't obtain succinct classical descriptions containing enough information.

Our result: Yes, we construct ML task where measure-first preprocessing is insufficient!

While limitations of measurement protocols are known (Grier et al, Quantum 2024, Gong & Aaronson, PMLR), they do not directly apply to their usefulness in machine learning tasks.

- Apply only to worst-case, whereas ML is concerned with average-case.
- Consider "unphysical states" (i.e., not eff. preparable) hindering practical applicability.

The ML problem: predicting outcomes of POVMs

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Main ingredients: (i) set of quantum states S, (ii) set of POVM measurements $\{\boldsymbol{\Lambda}_x\}$.

- Data given to learner: $T_x = \{ (\rho^{\otimes k}, z) \}$, where $z \sim \pi_x(\rho)$:= "measuring $\boldsymbol{\Lambda}_x$ on ρ".
  - **Important**: learner is not aware of which $\boldsymbol{\Lambda}_x$ is producing the samples!
- Goal of learner: Find/learn hypothesis h that *given* $\rho^{\otimes k}$ *produces sample from* $\pi_x(\rho)$.
  - In other words, find a way to reproduce measurement of *unknown* $\boldsymbol{\Lambda}_x$.

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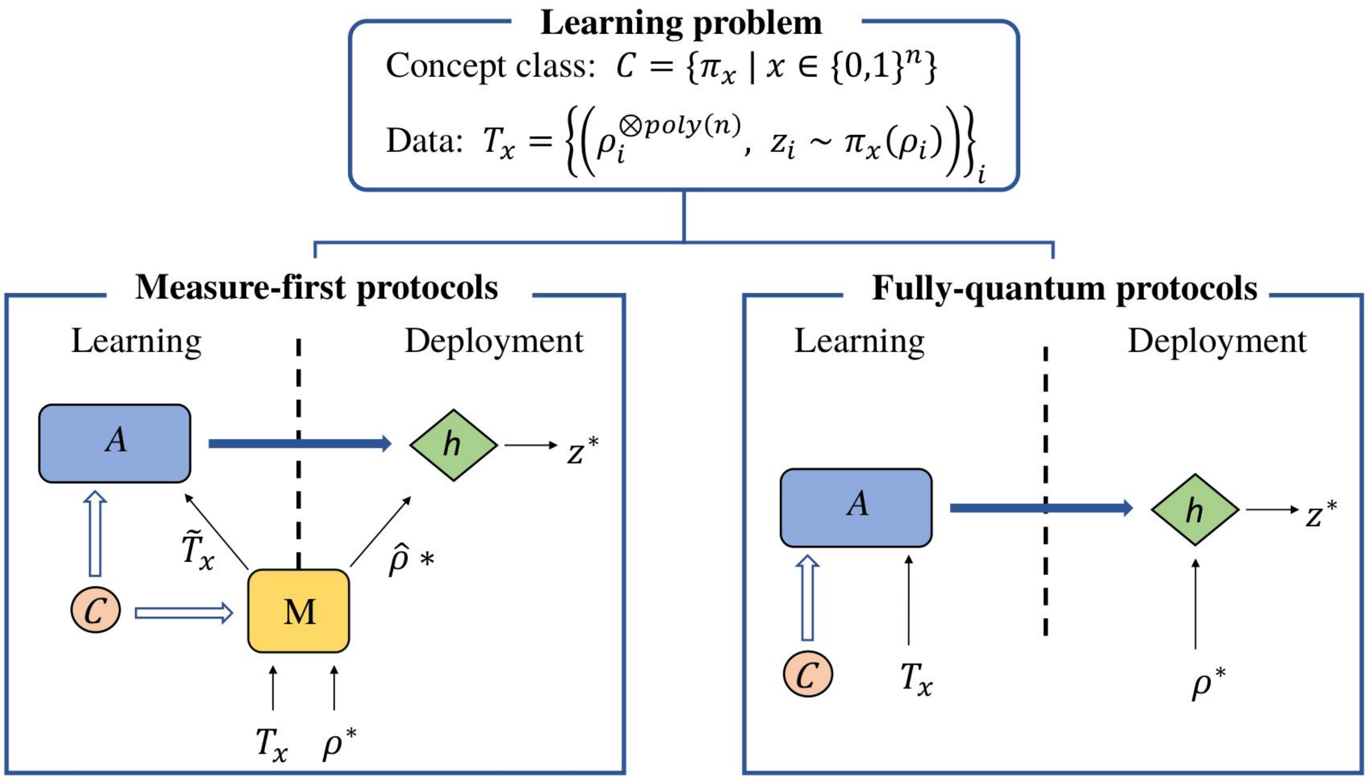
Next: we study two possible learning scenarios for this task

1. <u>Fully quantum</u>: learning & deployment can utilize *full quantum state* $\rho^{\otimes k}$.
2. <u>Measure-first</u>: learning & deployment have to use *classical representation* of $\rho^{\otimes k}$ obtained from first applying a (randomized) measurement protocol.
   - **Importantly**: choice of measurement protocol can depend on $\{\Lambda_x\}$, but not on individual Λ_x

ML protocols: Measure-first & Fully-quantum



Our result

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<u>Learning criteria</u>

We say that $\{\boldsymbol{\Lambda}_x\}$ is $(\boldsymbol{\epsilon}, \boldsymbol{\delta}, p_{succ})$-measure-first/fully-quantum learnable on S if there exists a measure-first/fully-quantum protocol A such that for every x with prob. at least p_{succ}:

$$\Pr_{\rho\in S}\left(||h(\rho/M(\rho)) - \pi_x(\rho)||_{TV} < 1-\epsilon\right) \geq \delta$$

where given training data of size T_x = O(poly(n)) and h = A(T_x).

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Theorem (Main result)

There exists a set of efficiently preparable quantum states S and POVMs $\{\boldsymbol{\Lambda}_x\}$ such that:

- $\{\boldsymbol{\Lambda}_x\}$ is ***not*** ($\boldsymbol{\epsilon}$, $\boldsymbol{\delta}$, 1/2)-measure-first learnable on S for all $\boldsymbol{\epsilon\delta}$ > 7/8.
- $\{\boldsymbol{\Lambda}_x\}$ is (0, 0, 1)-fully-quantum learnable on S.

Proof-sketch:

1) Hidden-Matching problem: $\{\boldsymbol{\Lambda}_x\}$, S s.t. measure-first protocol cannot achieve $\boldsymbol{\epsilon\delta}$=1 (i.e., worst-case).
2) Yoa's principle: worst-to-average case reduction (i.e., hardness for $\boldsymbol{\epsilon\delta}$ > ⅞).
3) Pseudo-random quantum states: separation persists on efficiently preparable quantum states.

Summary / Conclusion

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- We propose a machine learning framework contrasting two learning protocols:
    - "fully-quantum", allowed to adaptively/coherently process quantum data.
    - "measure-first", restricted by fixed initial (randomized) measurement protocol.

- We provided example of learning task efficiently solvable by fully-quantum protocol, whereas measure-first protocol *cannot* do so efficiently.
    - considers "average-case performance" on "physical" (i.e., eff. preparable) states.

These findings underscore crucial role of coherent processing of quantum data in ML!

- Certain learning tasks inherently require the "exponential capacity" of quantum states.