IBMQ-연세대 밋업 발표회

단일측정기반 양자학습
Single-Shot Measurement Learning (SSML)

2023.09.14

ETRI 양자컴퓨팅연구실 / 방정호

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Quantum State Learning via Single-Shot Measurements

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A novel machine-learning algorithm based on single-shot measurements, named single-shot measurement learning, is demonstrated achieving the theoretical optimal accuracy. The method is at least as efficient as existing tomographic schemes and computationally much less demanding. The merits are attributed to the inclusion of weighted randomness in the learning rule governing the exploration of diverse learning routes. These advantages are explored experimentally by a linear-optical setup that is designed to draw the fullest potential of the proposed method. The experimental results show an unprecedented high level of accuracy for qubit-state learning and reproduction exhibiting (nearly) optimal infidelity scaling, $O(N^{-0.983})$, for the number N of unknown state copies, down to $< 10^{-5}$ without any compensation for experimental nonidealities. Extension to high dimensions is discussed with simulation results.

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양자 상태 정밀 평가·측정 가능해진다...표준연 5배 이상 정확한 측정기술 개발

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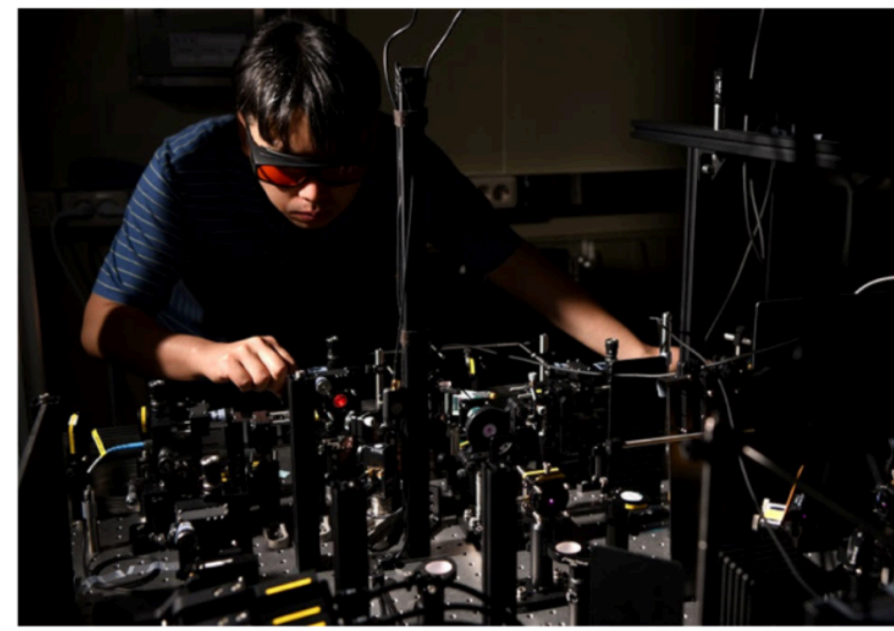
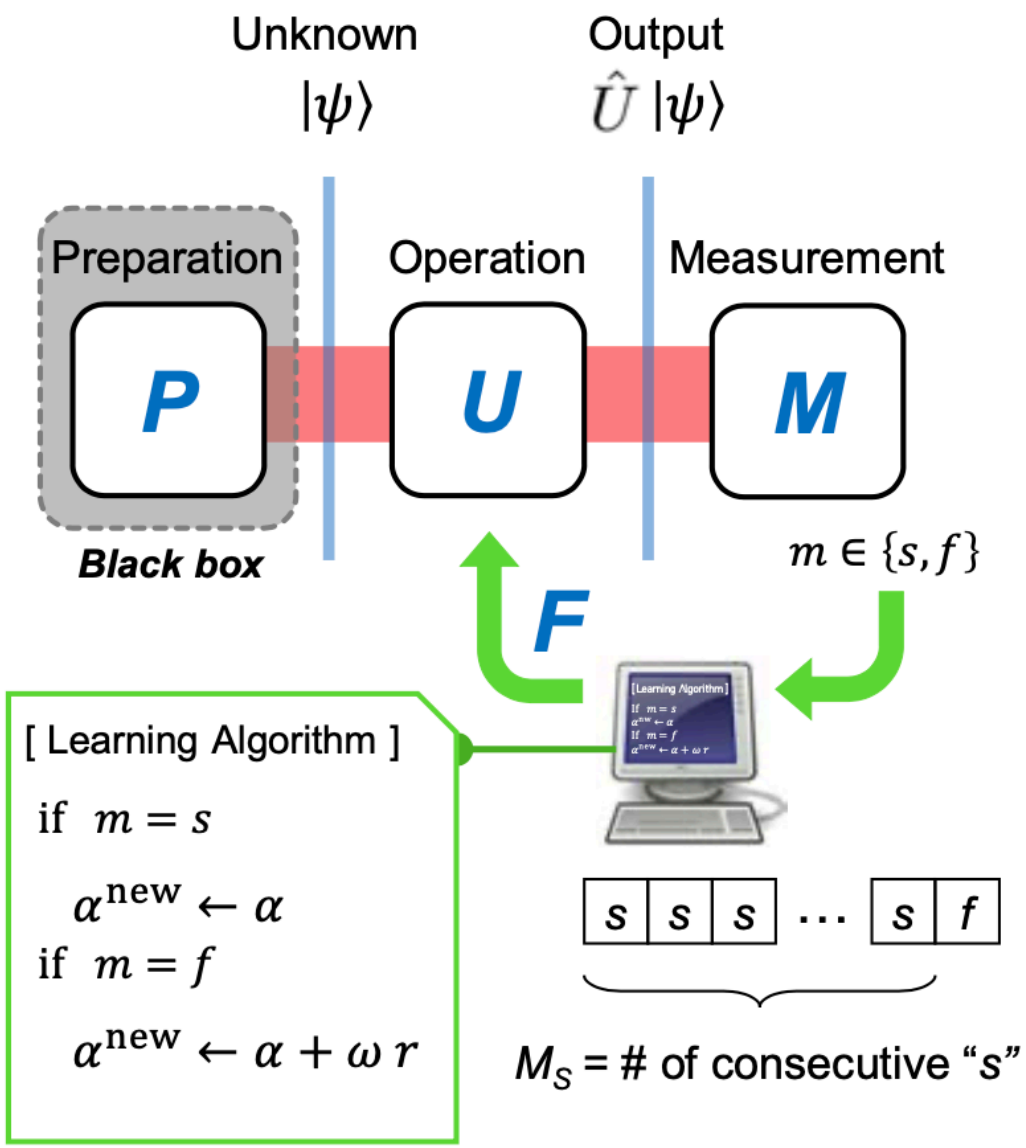


<이상민 표준연 책임연구원이 양자 상태 평가 실험을 하는 모습>

국내 연구진이 양자통신과 양자컴퓨팅에 쓰이는 정보 단위인 큐비트(양자입자에 저장된 정보) 상태를 평가하는 기술을 개발, 세계 최고 수준 정확도를 달성하는 데 성공했다.

한국표준과학연구원은 이상민 책임연구원과 박희수 양자기술연구소장이 이진형 한양대 교수, 김재완 고등과학원 교수, 방정호 한국전자통신연구원(ETRI) 선임연구원과 함께 이와 같은 기술 개발에 성공했다고 25일 밝혔다.

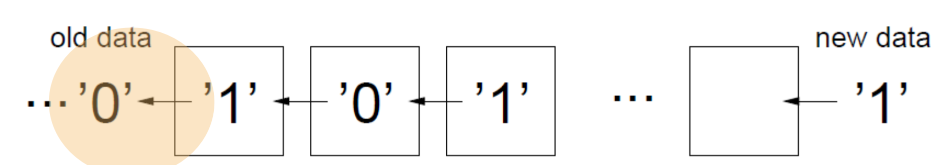
Single-shot measurement learning (SSML) algorithm



*SSML algorithm

Repeat
Perform the single-shot measurement
Record the measurement result
Counting the number of events : *Ns, Nf*
If 'fail' event **then**
$p \leftarrow p + f(Ns, Nf)\, r$
EndIf
Until Satisfying the halting condition

• Classical memory storage and halt condition



※ If it is fully occupied, the oldest data is deleted.

If the storage is all filled by success, F terminates th e learning process ➔ "***Halt condition***"

* An iteration step : one measurement

Learning probability and Survival probability

A primitive model analysis (random search)

Learning probability *P(s)* : A probability that learning is completed before or at the number of iteration step *s*

$$P(s) = \sum_{j=1}^{s} p_s (1-p_s)^j = 1-(1-p_s)^s$$

where the probability p_s : a randomly generated parameters to be inside the acceptable region, i.e. $= \gamma$

$$\boxed{P(s) \simeq 1 - e^{-\gamma s}}$$

Noting that *P(s)* can be considered as a cumulative distribution function of *s*, then $1/\gamma$ characterizes how many iterations are needed for the completion of learning. We define this a characteristic constant

Learning probability and Survival probability

① The probability that the learning is completed with a parameter set (using delta-function trick):

$$P(0|\mathbf{a})_{\text{avg}}^{N_L} \simeq \int da_1 \xi_1(a_1)^{N_L} \int da_2 \xi_1(a_2)^{N_L} \cdots \int da_{d^2-1} \xi_{d^2-1}(a_{d^2-1})^{N_L}$$
$$\approx \prod_{j=1}^{d^2-1} \int_{-\infty}^{\infty} da_j \exp\left[-\frac{(a_j - a_{j,\text{opt}})^2}{2\Delta^2}\frac{N_L}{K}\right] \approx \left(\frac{K 2\pi \Delta^2}{N_L}\right)^{\frac{d^2-1}{2}} .$$

② The probability that the learning is completed at n iteration step:

$$\left(1 - P(0|\mathbf{a}^{(1)})^{N_L}\right)\left(1 - P(0|\mathbf{a}^{(2)})^{N_L}\right) \cdots \left(1 - P(0|\mathbf{a}^{(n-1)})^{N_L}\right) P(0|\mathbf{a}^{(n)})^{N_L}$$

⇨ An approximation of the learning probability with ① + ②

$$\begin{aligned}
P_L(n) \approx\ & P(0|\mathbf{a}^{(1)})_{\text{avg}}^{N_L} \\
& + \left(1 - P(0|\mathbf{a}^{(1)})_{\text{avg}}^{N_L}\right) P(0|\mathbf{a}^{(2)})_{\text{avg}}^{N_L} \\
& + \left(1 - P(0|\mathbf{a}^{(1)})_{\text{avg}}^{N_L}\right)\left(1 - P(0|\mathbf{a}^{(2)})_{\text{avg}}^{N_L}\right) P(0|\mathbf{a}^{(3)})_{\text{avg}}^{N_L} \\
& \vdots \\
& + \left(1 - P(0|\mathbf{a}^{(1)})_{\text{avg}}^{N_L}\right)\left(1 - P(0|\mathbf{a}^{(2)})_{\text{avg}}^{N_L}\right) \\
& \cdots \left(1 - P(0|\mathbf{a}_{\text{avg}}^{(n-1)})^{N_L}\right) P(0|\mathbf{a}_{\text{avg}}^{(n)})^{N_L} \\
\approx\ & \sum_{i=0}^{n-1} \left(1 - P(0|\mathbf{a})_{\text{avg}}^{N_L}\right)^i P(0|\mathbf{a})_{\text{avg}}^{N_L} = 1 - \left(1 - P(0|\mathbf{a})_{\text{avg}}^{N_L}\right)^n ,
\end{aligned}$$

$$\boxed{P_L(n) \approx 1 - e^{-\frac{n}{n_c}}, \text{ or equivalently, } P_S(n) \approx e^{-\frac{n}{n_c}},}$$

Stability, Accuracy, and Efficiency of SSML

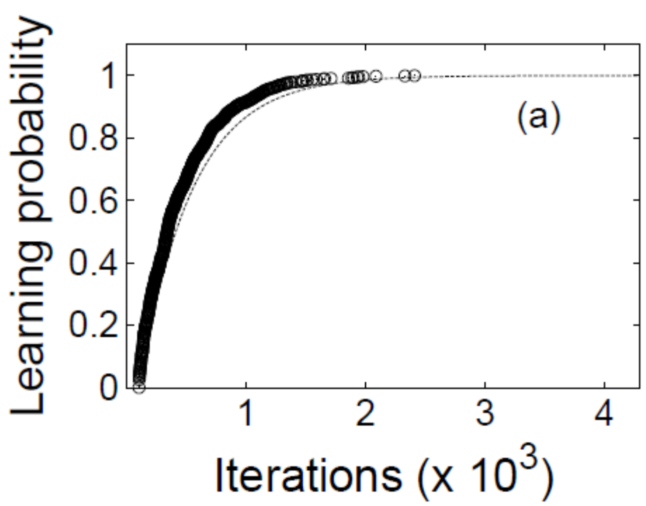
Learning probability, $\mathcal{P}_L \approx 1 - e^{-\frac{n}{n_c}}$,

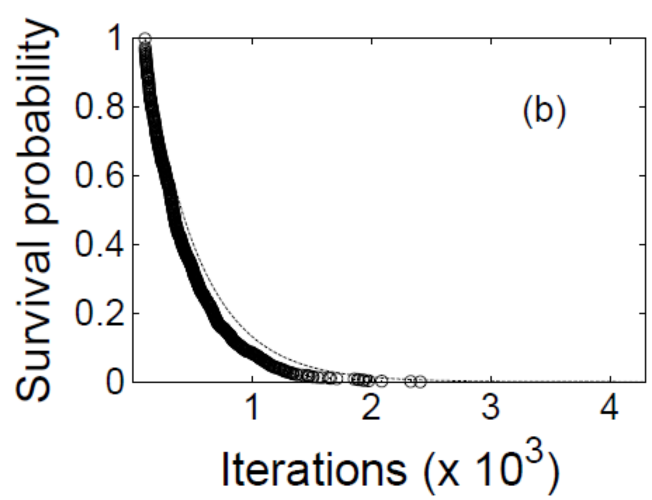
Survival probability, $\mathcal{Q}_L \approx e^{-\frac{n}{n_c}}$

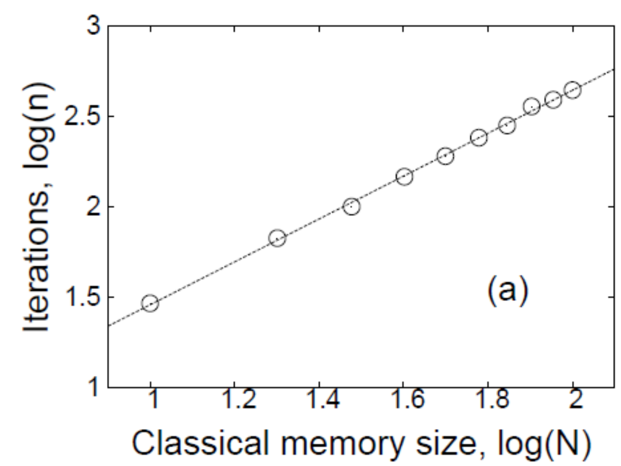
where $n_c = AN^D$ is "characteristic constant."

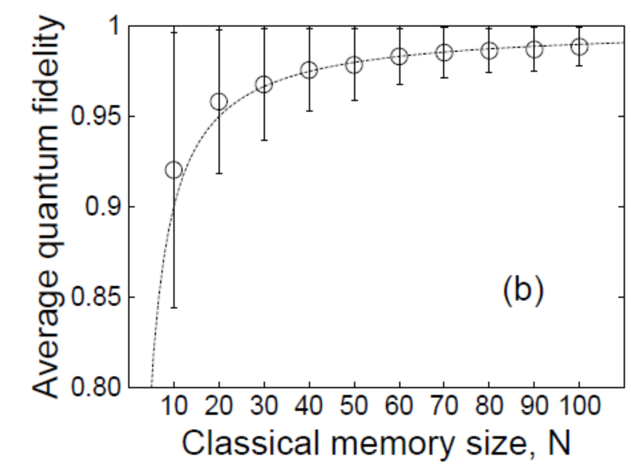
- Stability : exponentially decay of survival probability
- Accuracy : average fidelity
- Efficiency : the characteristic constant for a given N

Numerical Simulations









Robustness of SSML

Error model due to the photon loss

Full erasure super-operator:

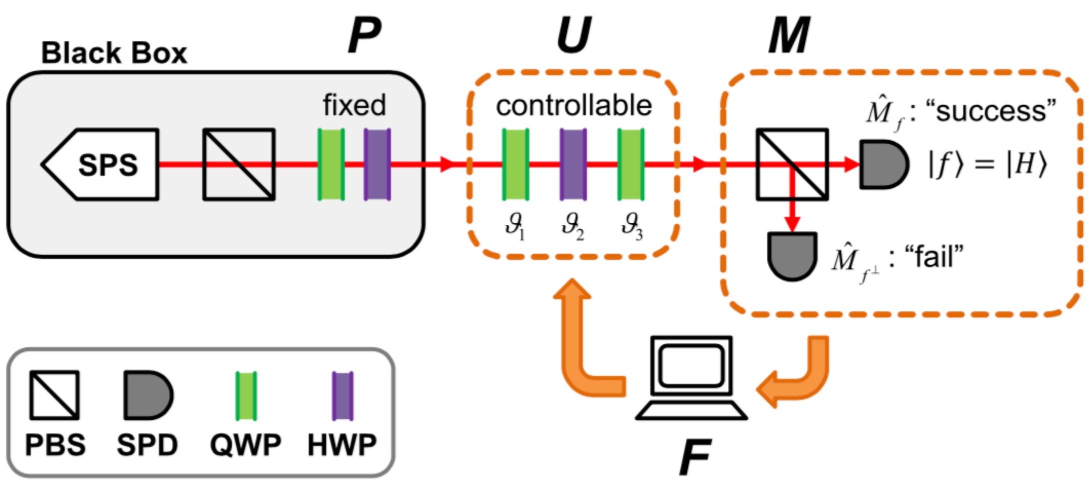
$$\mathbb{E}(\rho) = \frac{1}{2}\mathbb{1} = \frac{1}{4}(\rho + \mathbf{X}\rho\mathbf{X} + \mathbf{Z}\rho\mathbf{Z} + \mathbf{Y}\rho\mathbf{Y}).$$

If a photon is not detected on either mode, a measurement failure has occurred, and we may replace the qubit with a fresh qubit in a known state. This is fundamentally different from the depolarizing channel, where there is no *a priori* knowledge of the position of the errors

Learning efficiency

$$n_c = AN^D \rightarrow n_c' = A(1+\eta)N^D$$

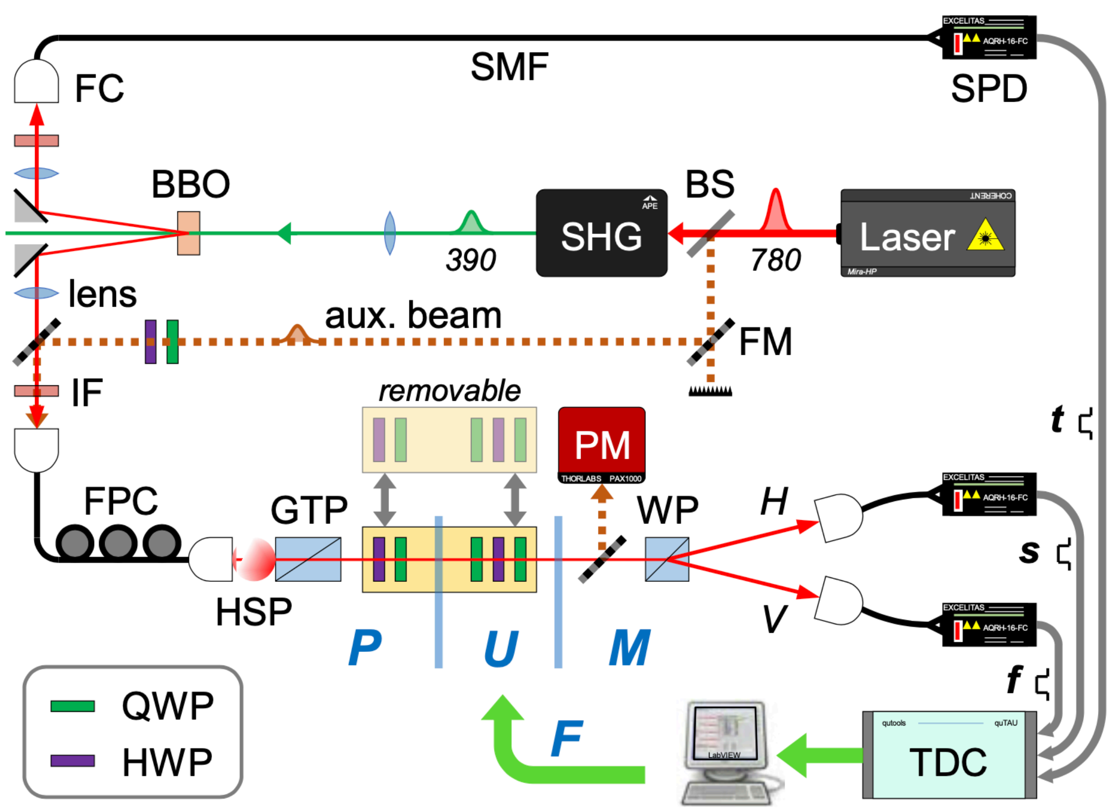
Linear-optical experiment of SSML



Step 1: Setting (unknown) U

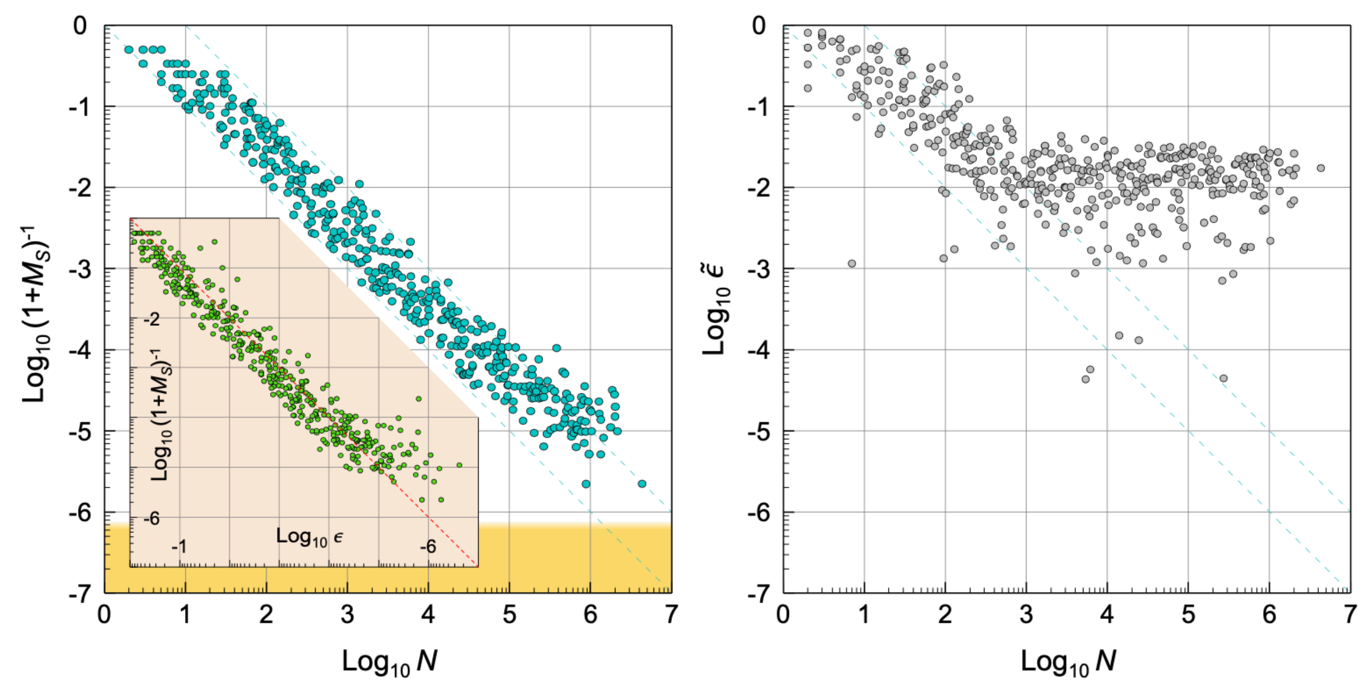
Step 2: Learning U: $\hat{U}\,|\psi\rangle = |H\rangle$

Step 3: Identify $|\psi\rangle$ with (learned) U: $|\psi\rangle = \hat{U}^\dagger\,|H\rangle$



Single-shot + randomness

Statistical updates



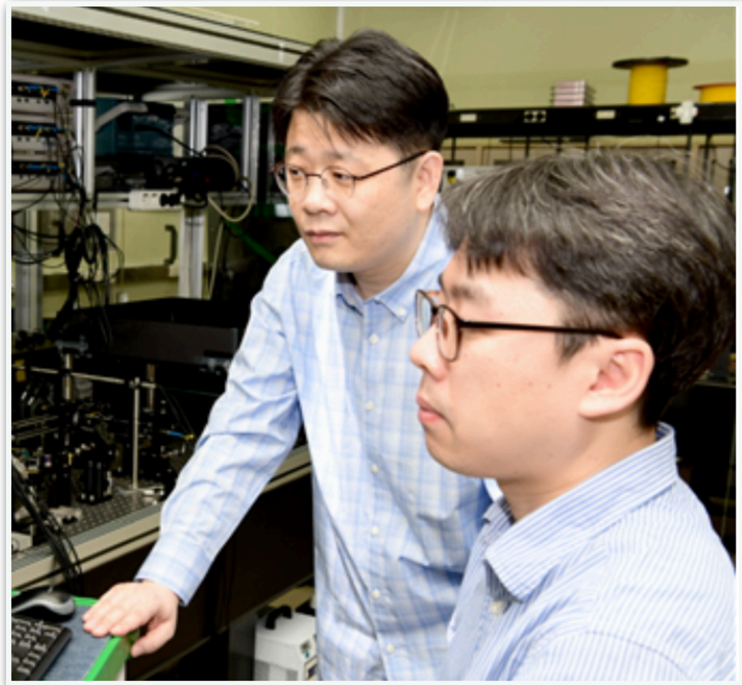
Our Learning-based Method

Standard Tomographic Method

Ultra High-Precision Learning Estimation: Single-Shot Measurement Learning (SSML) → $\simeq 10^{-3}$ Error (QST) / $\simeq 10^{-8}$ Error (SSML)

The intrinsic statistical errors in quantum hardware can be mitigated through software techniques.

양자 하드웨어에 본질적으로 수반될 수 밖에 없는 통계적 에러가 소프트웨어를 통해 극복될 수 있다는 연구사례



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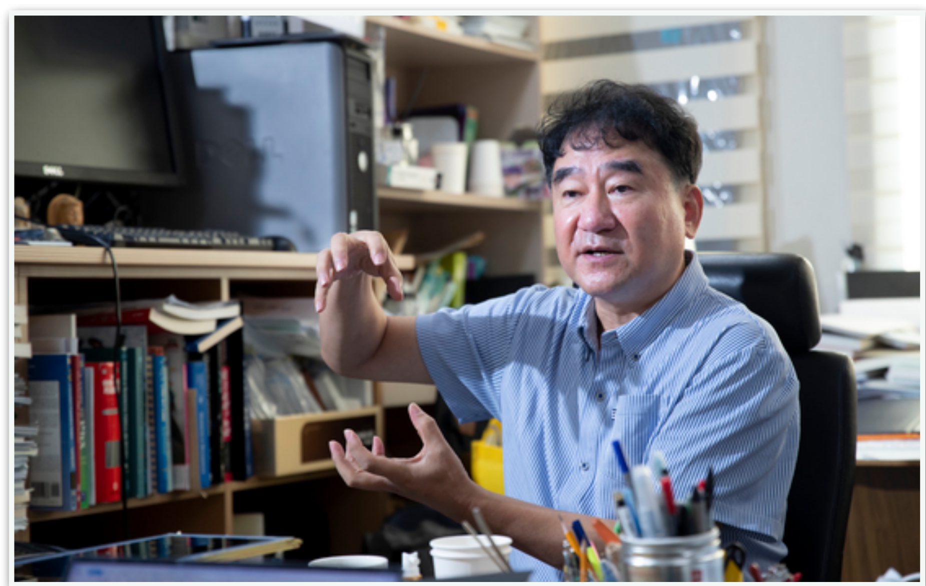

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감사합니다