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ICE-8
Quantum Information in Spain
Santiago de Compostela

Neural-network-assisted quantum magnetometers

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Fundación Tecnalia Research & Innovation

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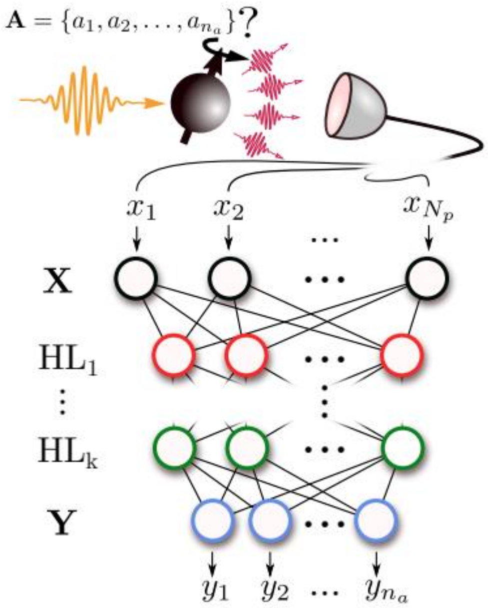
Y. Chen, Y. Ban, R. He, *et. al.*, npj Quantum Inf. 8, 152 (2022).

Y. Ban, *et. al.*, Quantum Sci. Technol. 6, 045012 (2021).

Y. Ban, *et. al.*, arXiv: 2212.12058 (2022).

Neural networks are valuable in distinct quantum sensing scenarios.



Phase estimation,

Phys. Rev. Appl. 10, 044033 (2018);
Phys. Rev. A 100, 012106 (2019);

Parameter estimation,

npj Quntuam Inf. 5, 82 (2019);
PRX Quantum 2, 020303 (2021);
npj Quantum Inf. 8, 2 (2022).

Sensors calibration

Phys. Rev. Lett. 123, 230502 (2019);
npj Quantum Inf. 7, 169 (2021);
Adv. Photon. 5, 016005 (2023).

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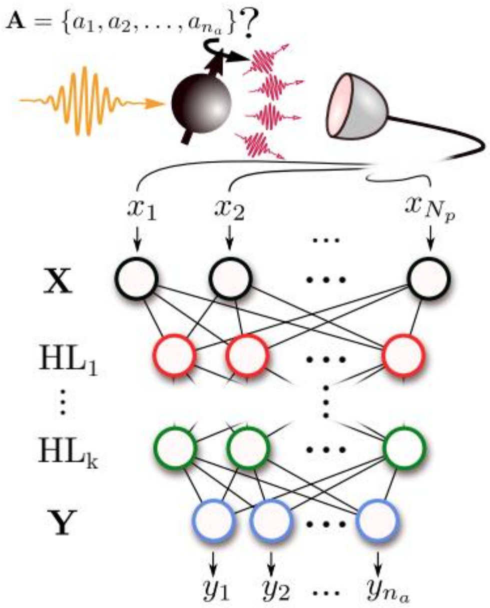

✓ A Neural Network Assisted $^{171}Yb^{+}$ Quantum Magnetometer

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✓ Neural networks for Bayesian quantum many-body magnetometry

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A Neural Network Assisted $^{171}Yb^{+}$ Quantum Magnetometer

In collaboration with

the experimental group from the University of Science and Technology of China(USTC)

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USTC, Hefei

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UC3M, Madrid

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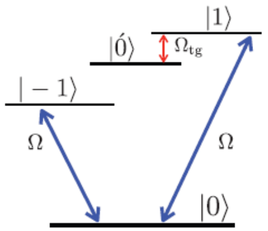
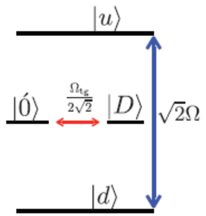
$^{171}\mathrm{Yb}^{+}$ Quantum Magnetometer

a target RF field

$\Omega_{\rm tg}\cos(\omega_{\rm tg}t+\phi_{\rm tg})$



$^2S_{\frac{1}{2}}$ manifold of $^{171}\mathrm{Yb}^{+}$



Dressed state basis

$$|u\rangle=(|B\rangle+|0\rangle)/\sqrt{2}$$
$$|d\rangle=(|B\rangle-|0\rangle)/\sqrt{2}$$
$$|D\rangle=(|-1\rangle-|1\rangle)/\sqrt{2}$$
$$|B\rangle=(|-1\rangle+|1\rangle)/\sqrt{2}$$

$\Omega_{\rm tg}\ll\Omega\ll\omega_{\rm tg}$

RWA

$$H=-\frac{\Omega_{\rm tg}}{2\sqrt{2}}(|D\rangle\langle\acute{0}|+|\acute{0}\rangle\langle D|).$$

$$P_D(t)=\cos^2(\pi t/t_{\rm R})\quad t_{\rm R}=2\pi\sqrt{2}/\Omega_{\rm tg}$$

Detection of radio frequency fields

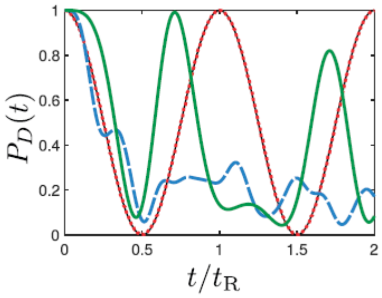
Phys. Rev. Lett. 116, 240801 (2016).

Dressed state qubit, a robust register

Nature 476, 185 (2011); Phys. Rev. Lett. 117, 220501 (2016).

Dressed state qubit approach is restricted to a narrow working regime

harmonic sensor responses



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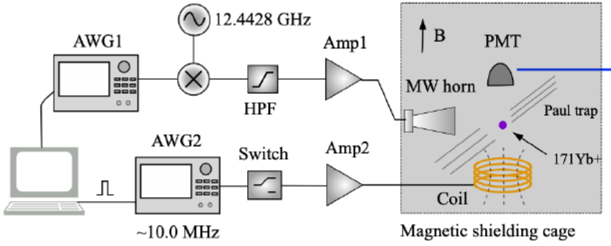

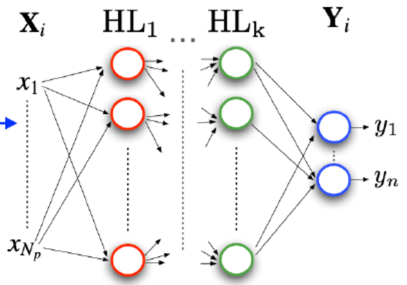

$$\mathbf{X} = \{P_1, P_2, ..., P_{N_p}\} \;\overset{?}{\longrightarrow}\; \mathbf{Y} \approx \mathbf{A} = \{\Omega_{\mathrm{tg}}, \xi\}$$

an $^{171}Yb^{+}$ atomic sensor

+

adequately trained neural networks

A versatile magnetometer enables the characterization of target fields.

Scenario I: a reduced number of measurements.

Scenario II: Continuous data acquisition.

the working regime: responses beyond the harmonic behavior!

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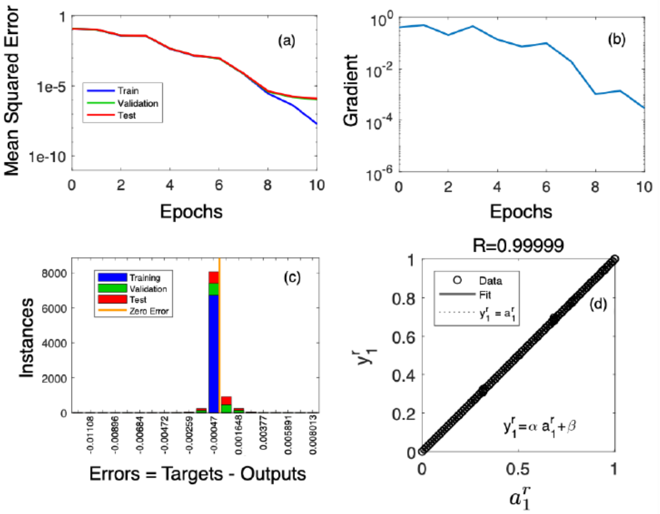
Scenario I: A reduced number of measurements.

Training results:



$$\phi_{\rm tg} = 0 \quad \omega_{\rm tg} = (2\pi) \times 10.56 \ \text{MHz}$$

Outputs obtained from the NN, when the input data are the experimental responses

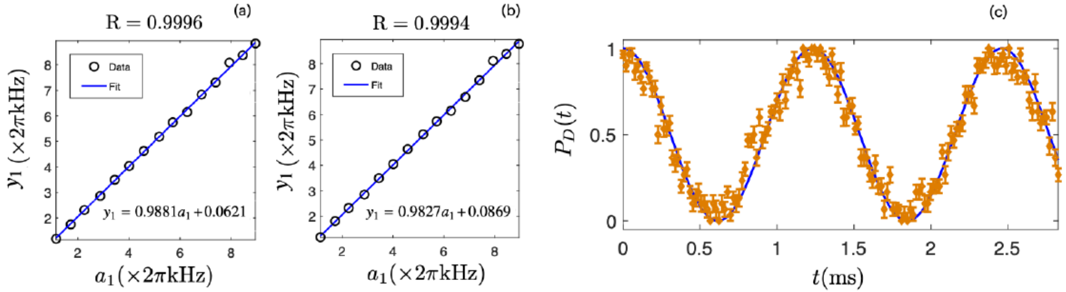
$a_1 (\times 2\pi$ kHz)	y_1 ($\times 2\pi$ kHz) with $N_m = 100$	y_1 ($\times 2\pi$ kHz) with $N_m = 30$
1.1487	1.1827	1.1731
1.7229	1.7473	1.8060
2.2566	2.3109	2.3207
2.8760	2.8616	2.8527
3.4429	3.4961	3.4947
4.0098	4.0391	4.0502
4.5778	4.6283	4.6386
5.1834	5.1856	5.2208
5.7140	5.7448	5.7297
6.2797	6.1482	6.2134
6.8397	6.8358	6.6896
7.3927	7.3086	7.3471
7.9319	8.0864	8.1129
8.4527	8.3775	8.3870
8.9493	8.8414	8.7825

$$\bar{F} = \frac{1}{N}\sum_{j=1}^{N} F_j \quad F_j = 1 - |y_1^j - a_1^j|/a_1^j \quad a_1 = \Omega_{\rm tg}$$

$N_m = 100 \quad \bar{F} = 98.76\% \quad \text{SD} = 0.7762\%$

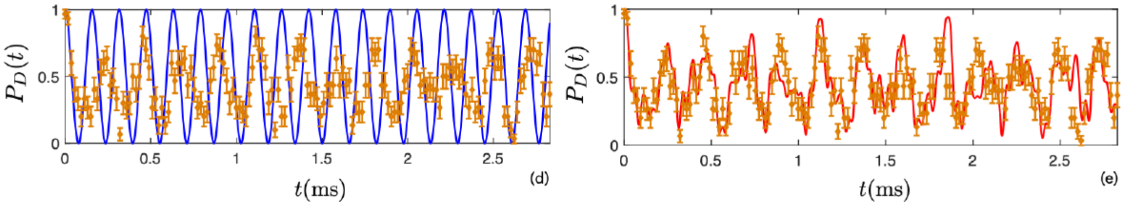
$N_m = 30 \quad \bar{F} = 98.31\% \quad \text{SD} = 1.1483\%$

$\omega_{\mathrm{tg}} = (2\pi) \times 10.56 \;\mathrm{MHz} \qquad \phi_{\mathrm{tg}} = 0 \qquad \Omega = (2\pi) \times 5.5\mathrm{kHz}$



$N_m = 100$ $\qquad$ $N_m = 30$ $\qquad$ $N_m = 30 \quad \Omega_{\mathrm{tg}} = (2\pi) \times 1.1487 \;\mathrm{kHz} \quad y_1 = (2\pi) \times 1.1731 \;\mathrm{kHz}$

$P_D(t) = \cos^2(\pi t / t_{\mathrm{R}})$



$N_m = 30 \quad \Omega_{\mathrm{tg}} = (2\pi) \times 8.9493 \;\mathrm{kHz} \quad y_1 = (2\pi) \times 8.7825 \;\mathrm{kHz}$

Scenario II: Continuous data acquisition.

no reinitialization of the RF field is possible; $N_m = 1$

RF source is always on.

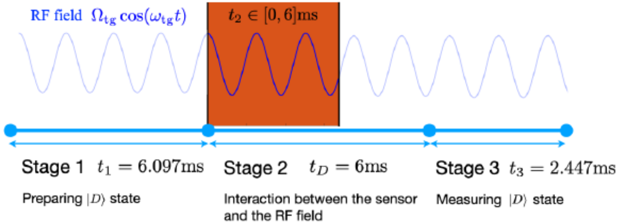
To get one input string:

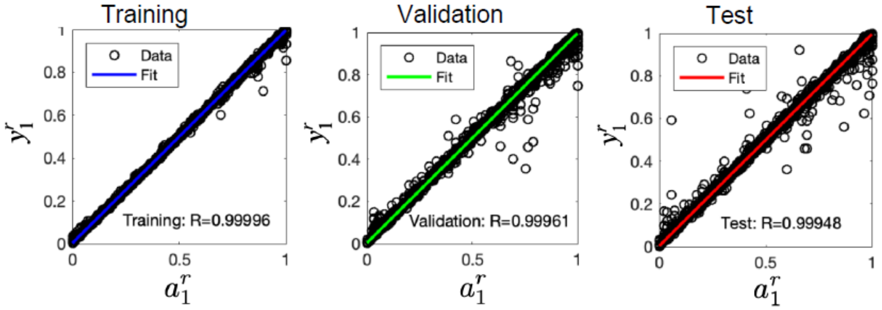
251 times of repetition for three stages

96 Ω_{tg} values $\in 2\pi\times[0.5, 10]$ kHz

To get training/validation/test datasets

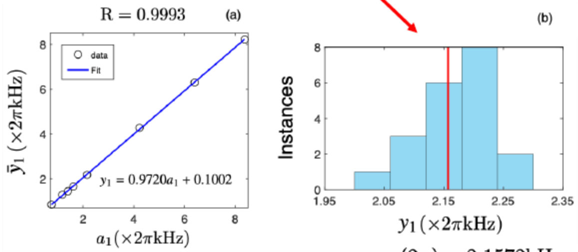
1800 times of repetition for each Ω_{tg}





Targets $a_1(\times 2\pi$ kHz)	Average values $\bar{y}_1$ $(\times 2\pi$ kHz)	Standard deviation SD $(\times 2\pi$ kHz)
0.7542	0.8417	0.0690
1.1840	1.2759	0.0833
1.4044	1.4384	0.0222
1.6206	1.6542	0.0660
2.1572	2.1720	0.0543
4.2265	4.2761	0.0594
6.3960	6.2988	0.0776
8.3689	8.2255	0.1531

For each Ω_{tg}, 20 experimentally obtained strings



$a_1 = (2\pi) \times 2.1572$kHz

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Other estimators: e.g. Bayesian inference.

$$p(\theta|\mathbf{X}) \propto p(\mathbf{X}|\theta)p(\theta)$$

$\mathbf{X}$: data obtained by interrogating quantum sensor at different time instants

Versatile Atomic Magnetometry Assisted by Bayesian Inference

R. Puebla, Y. Ban, J.F. Haase, M.B. Plenio, M. Paternostro, and J. Casanova

Phys. Rev. Applied **16**, 024044 (2021).

A Bayesian analysis and a NN provide a comparable precision for the estimators.

	Bayesian estimator	Neural Networks
Accurate microscopic model	Necessary	Not necessary
Prior knowledge	More	Less
Operation time	Long	Short (once trained)
Computational cost	More	Less

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Neural networks for Bayesian quantum many-body magnetometry

arXiv > quant-ph > arXiv:2212.12058

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Quantum Physics

[Submitted on 22 Dec 2022]

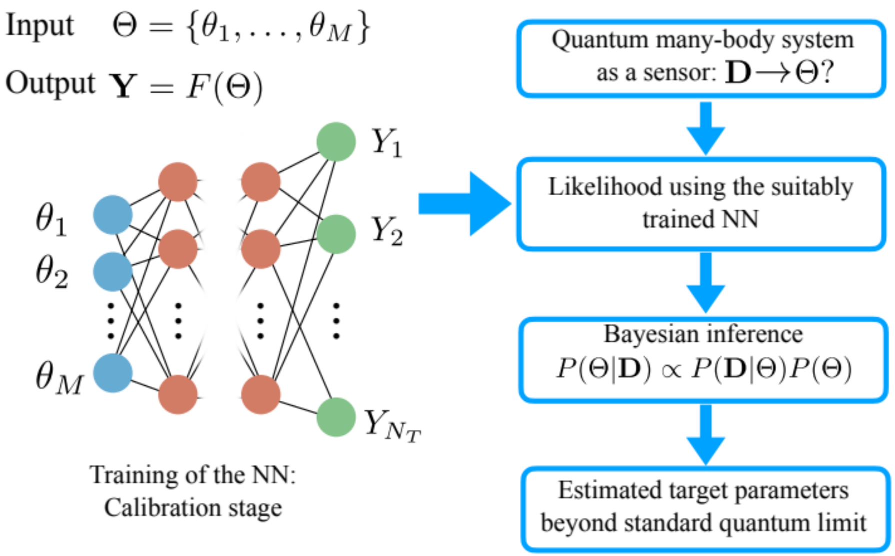
Neural networks for Bayesian quantum many-body magnetometry

Yue Ban, Jorge Casanova, Ricardo Puebla

Entangled quantum many-body systems can be used as sensors that enable the estimation of parameters with a precision larger than that achievable with ensembles of individual quantum detectors. Typically, the parameter estimation strategy requires the microscopic modelling of the quantum many-body system, as well as a an accurate description of its dynamics. This entails a complexity that can hinder the applicability of Bayesian inference techniques. In this work we show how to circumvent these issues by using neural networks that faithfully reproduce the dynamic of quantum many-body sensors, thus allowing for an efficient Bayesian analysis. We exemplify with an XXZ model driven by magnetic fields, and show that our method is capable to yield an estimation of field parameters beyond the standard quantum limit scaling. Our work paves the way for the practical use of quantum many-body systems as black-box sensors exploiting quantum resources to improve precision estimation.

Neural networks faithfully reproduce the dynamics of quantum many-body sensors, thus allowing for an efficient Bayesian analysis.

Bayesian Inference Assisted by Neural Networks



$$P(\mathbf{D}|\Theta) = \Pi_{j=1}^{N_T} f(X_j, N_m, \langle A(t_j;\Theta)\rangle).$$

$$\langle \hat{A}(t;\Theta)\rangle = \mathrm{Tr}\left[\hat{A}\hat{U}(t)\hat{\rho}_0\hat{U}^\dagger(t)\right]$$

$$\mathbf{Y}_{j=1,\ldots,N_T} \equiv F(\Theta)_{j=1,\ldots,N_T} \approx \langle \hat{A}(t_{j=1,\ldots,N_T};\Theta)\rangle$$

$$P(\mathbf{D}|\Theta) = \Pi_{j=1}^{N_T} f(X_j, N_m, F(\Theta)_{j,\ldots,N_T}).$$

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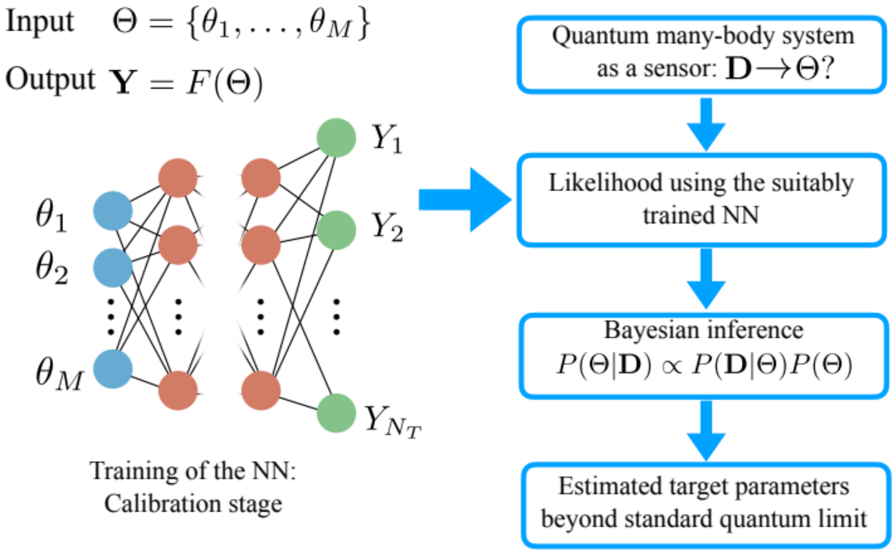
Simulation of quantum many-body dynamics by neural networks

XXZ spin-1/2 chain



1D external magnetic field

$$\hat{H}_1(g_x) = -\sum_{i=1}^{N-1}(\hat{\sigma}_i^x\hat{\sigma}_{i+1}^x + \hat{\sigma}_i^y\hat{\sigma}_{i+1}^y + J_z\sigma_i^z\sigma_{i+1}^z) + g_x\sum_{i=1}^{N}\hat{\sigma}_i^x.$$

$$F_1(g_x)_{j=1,\dots,N_T} \approx \langle \hat{A}_1(t_{j=1,\dots,N_T}; g_x)\rangle$$

$$\hat{A}_1 = (\hat{\sigma}^x_{N/2} + 1)/2$$

$$P(\mathbf{D}|\Theta) = \Pi_{j=1}^{N_T} f(X_j, N_m, F(\Theta)_{j,\dots,N_T}).$$

Estimation on 2D, 3D external magnetic fields also work!

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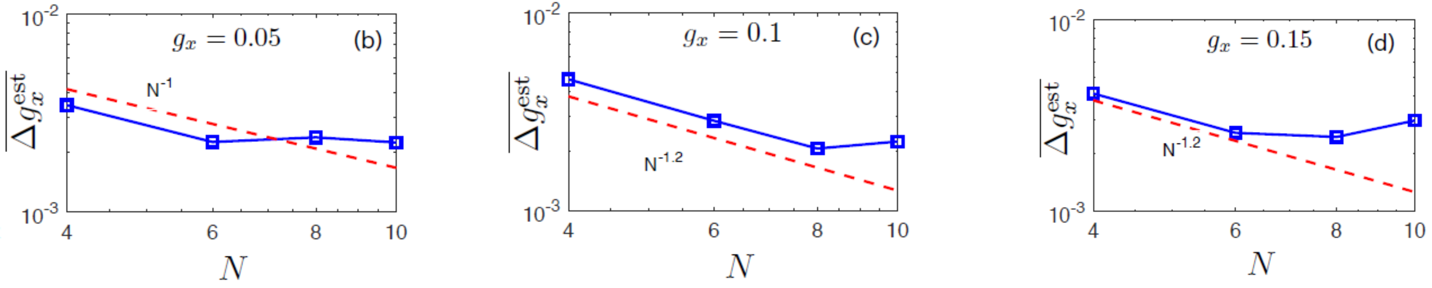
Simulation of quantum many-body dynamics by neural networks

XXZ spin-1/2 chain

Bayes' theorem

$$P(\Theta|\mathbf{D}) \propto P(\mathbf{D}|\Theta)P(\Theta)$$

$$\theta_j^{\rm est} = \int d\theta_j \theta_j P(\theta_j|\mathbf{D}) \qquad (\Delta\theta_j^{\rm est})^2 = \int d\theta_j (\theta_j - \theta_j^{\rm est})^2 P(\theta_j|\mathbf{D}),$$



Standard quantum limit $\Delta\theta \propto N^{-1/2}$ Heisenberg limit $\Delta\theta \propto N^{-1}$

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Conclusion and outlook

- ✓ the benefits to integrate neural networks to decipher the information contained in the sensor responses.
- ✓ Continuous data acquisition and precision
- ✓ Reproduction of microscopic modelling of the quantum many-body system by neural networks
- ✓ opening the door to employ experimental quantum many-body systems as sensors beyond the classical simulation capabilities.