

L3 – Quantum Technologies for GW detection

Amaldi Research Center



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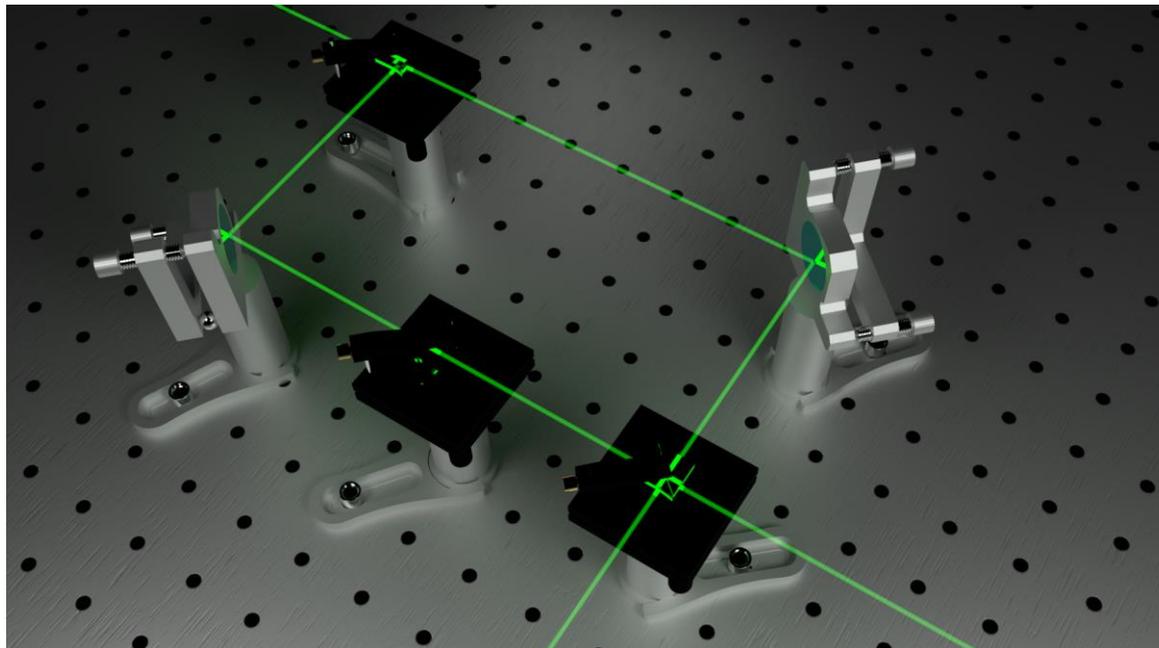
Quantum technologies for quantum sensing

Aim: improved precision in the estimation of an unknown physical quantity by adopting quantum resources

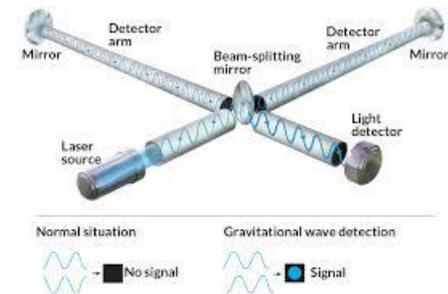
Optical phase estimation:



Unknown parameter ϕ phase difference between interferometer arms



Applications:

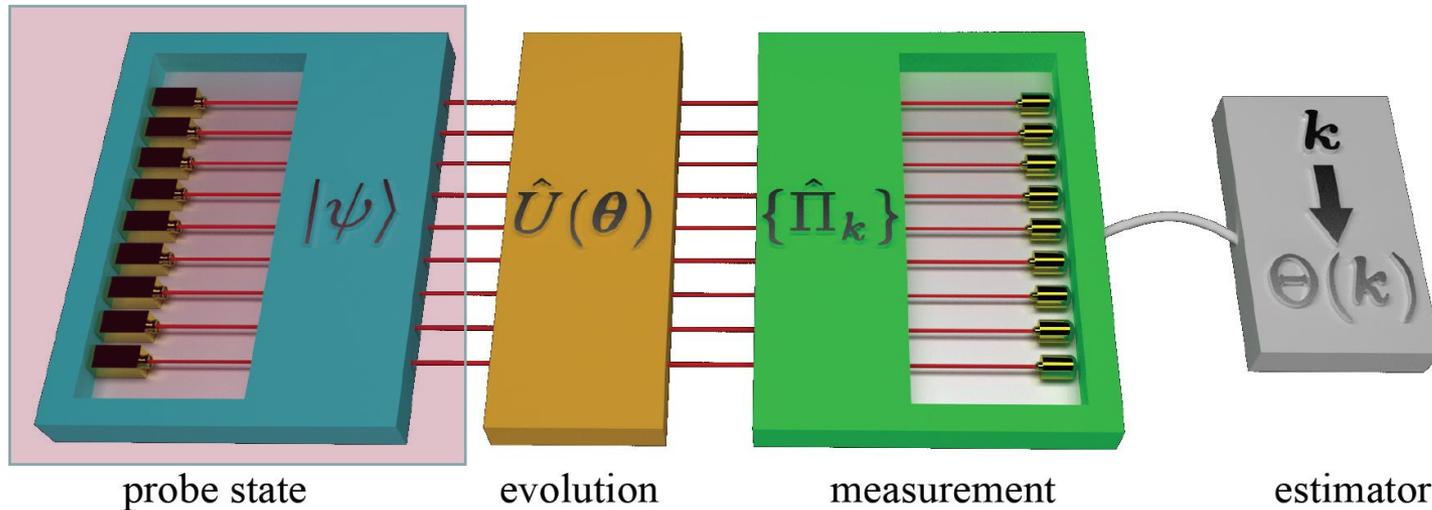


-) Gravitational wave detection
-) Imaging
-) Quantum communications
-) Biological systems measurements

E. Polino, M. Valeri, N. Spagnolo, F. Sciarrino, AVS Quantum Science **2**, 024703 (2020)

Quantum metrology

General quantum framework for estimation problems



Key element: preparation of the probe state

Ultimate limits for optical phase estimation

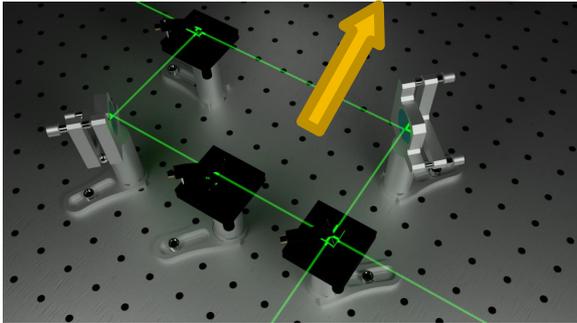
$\Delta\phi \geq \frac{1}{\sqrt{\nu N}}$  Standard quantum limit (SQL), achievable with classical resources

$\Delta\phi \geq \frac{1}{\nu\sqrt{N}}$  Heisenberg limit (HL), achievable with quantum resources (entangled states, squeezed states)

Optical phase estimation and quantum approach

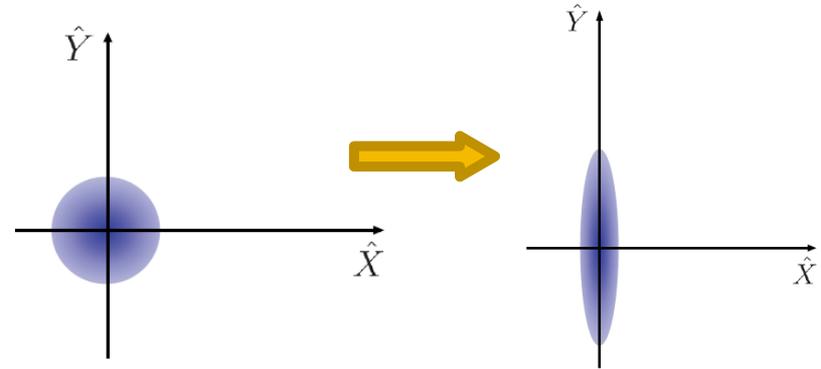
Maximally entangled states

$$|\psi\rangle = \frac{1}{\sqrt{2}} (|2\rangle|0\rangle + e^{i2\phi}|0\rangle|2\rangle)$$

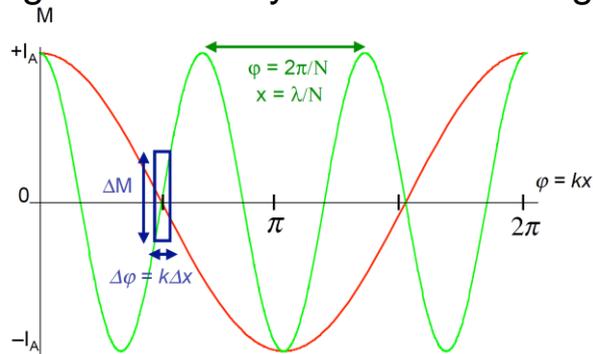


Squeezed light

Reduced noise in one phase quadrature

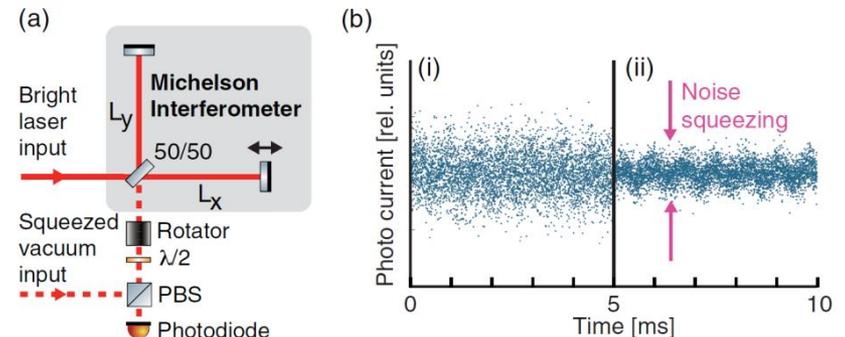


Higher sensitivity than classical light



First unconditional violation of the standard quantum limit:
S. Slussarenko, et al., Nature Photonics **11**, 700-703 (2017)

Application for GW detection



Recent review:
L. Barsotti, et al., Rep. Prog. Phys. **82**, 016905 (2019)

Quantum estimation: open issues

1. Estimation with limited data

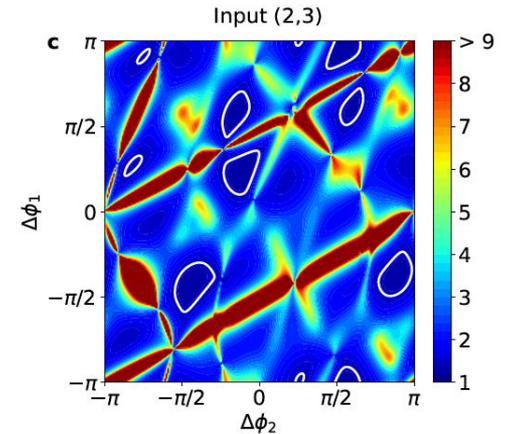
➔ Can we improve convergence rate to SQL or HL with limited data?

➔ Robustness to noise in the estimation process?

Sensitivity may depend on the parameters value



Same precision is required



2. Calibration of large scale quantum sensors

Precise calibration of the system response function



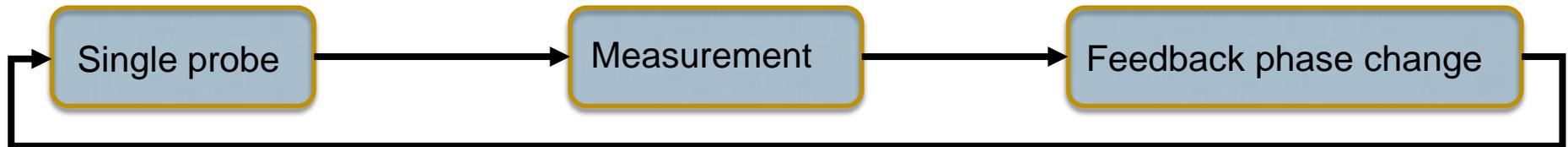
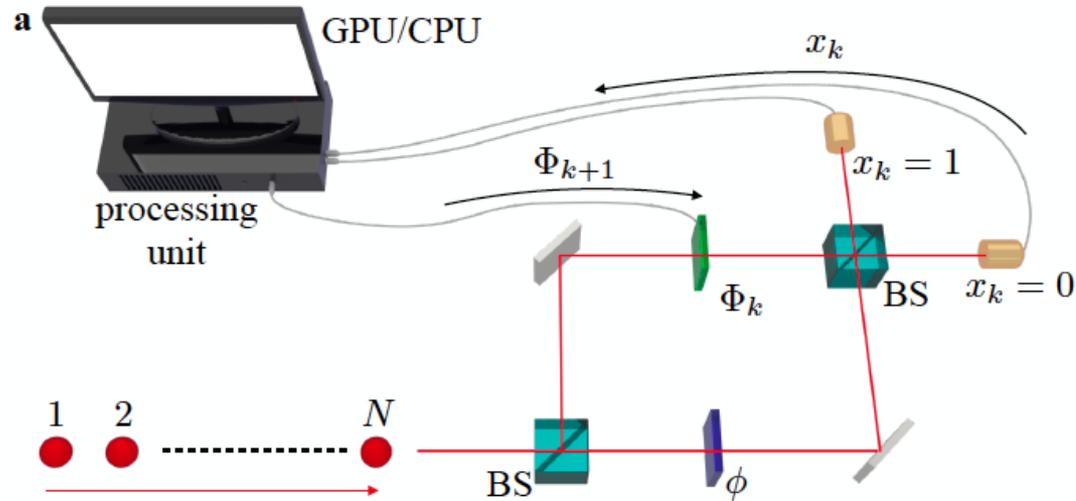
can we reduce the number of measurements?



can we soften the need for system modeling?

➔ **our approach: devising algorithms based on machine learning**

Adaptive estimation with limited data



-) **Online approaches:** feedback phase is evaluated at each run by the processing unit

-) **Offline approaches:** feedback phase is changed from a list of pre-calculated rules

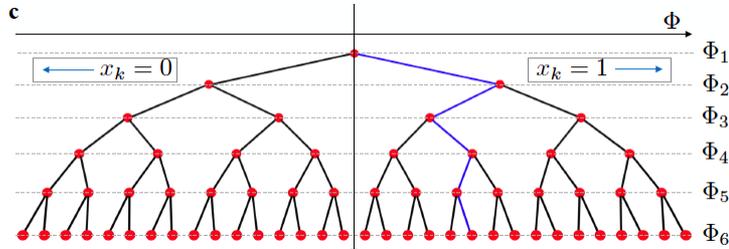


Machine learning techniques can be employed

Adaptive estimation with limited data

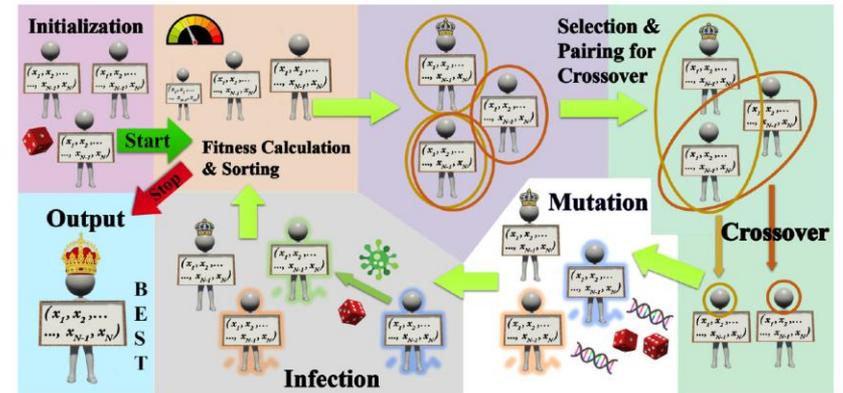
OFFLINE APPROACHES

Particle Swarm Optimization



maps the problem to particle evolution

Genetic Algorithm

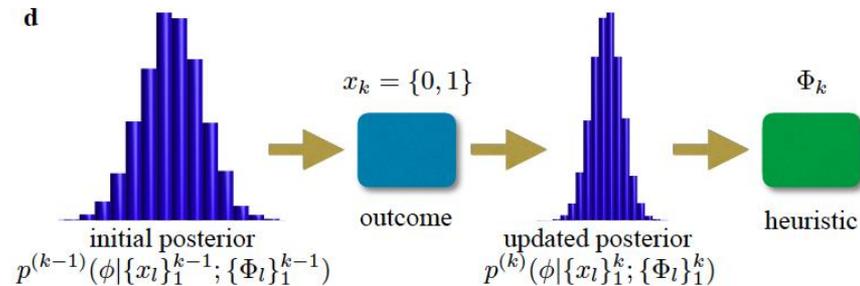


inspired by the principles of natural selection

A. Lumino, et al., Phys. Rev. Applied **10**, 064028 (2018)
 K. Rambhatla, et al., Phys. Rev. Research **2**, 033078 (2020)

ONLINE APPROACHES

Optimized adaptive Bayesian approach

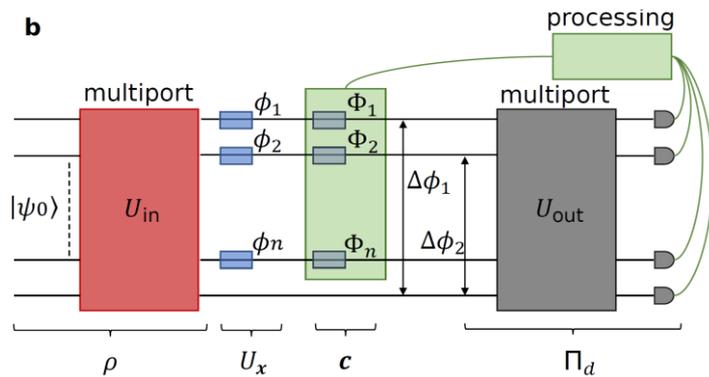


At each step the feedback is applied to minimize the variance of the posterior distribution

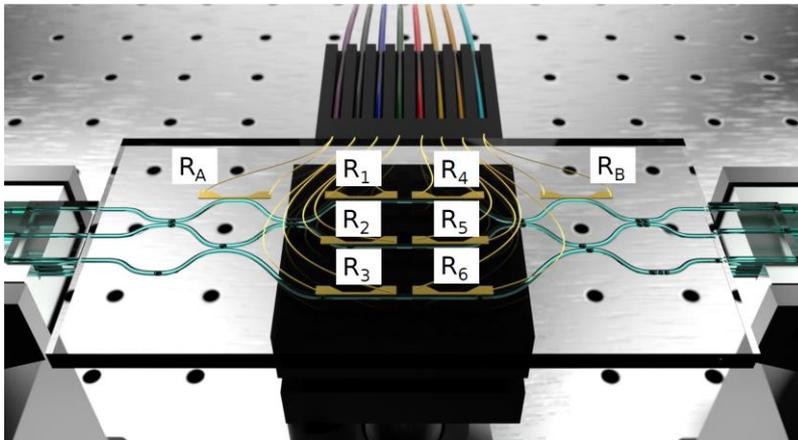
A. Lumino, et al., Phys. Rev. Applied **10**, 064028 (2018)
 M. Valeri, et al., npj Quantum Information **6**, 92 (2020)

Extension to multiparameter estimation

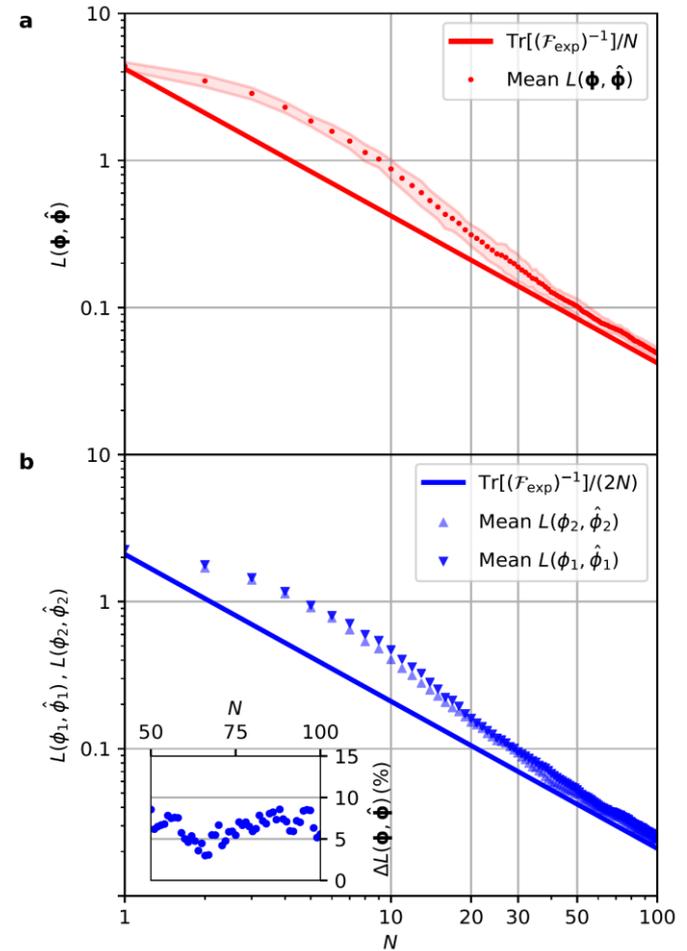
Optimized adaptive Bayesian approach



Requires multiple feedback phases:



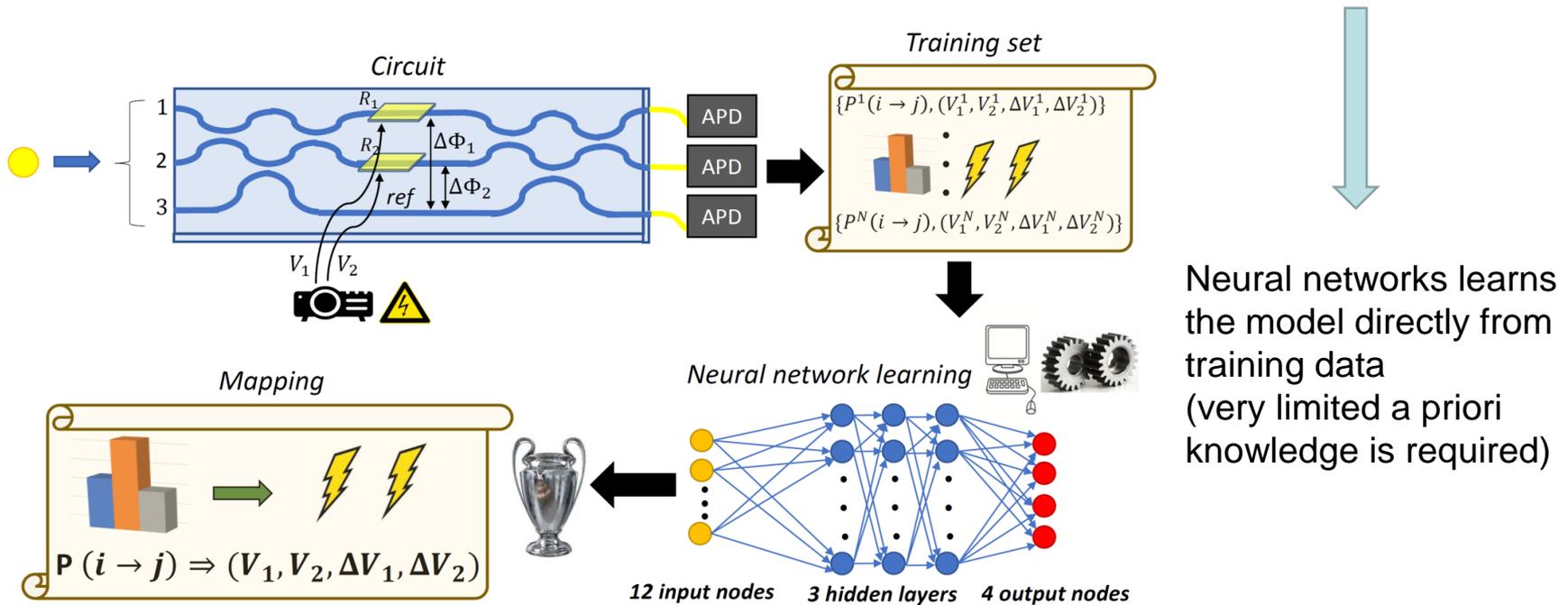
M. Valeri, et al., npj Quantum Information **6**, 92 (2020)



Calibration of quantum sensors via neural networks

New approach for calibration - machine learning for quantum sensors

Advantage: Neural networks do not rely on knowledge of the device model

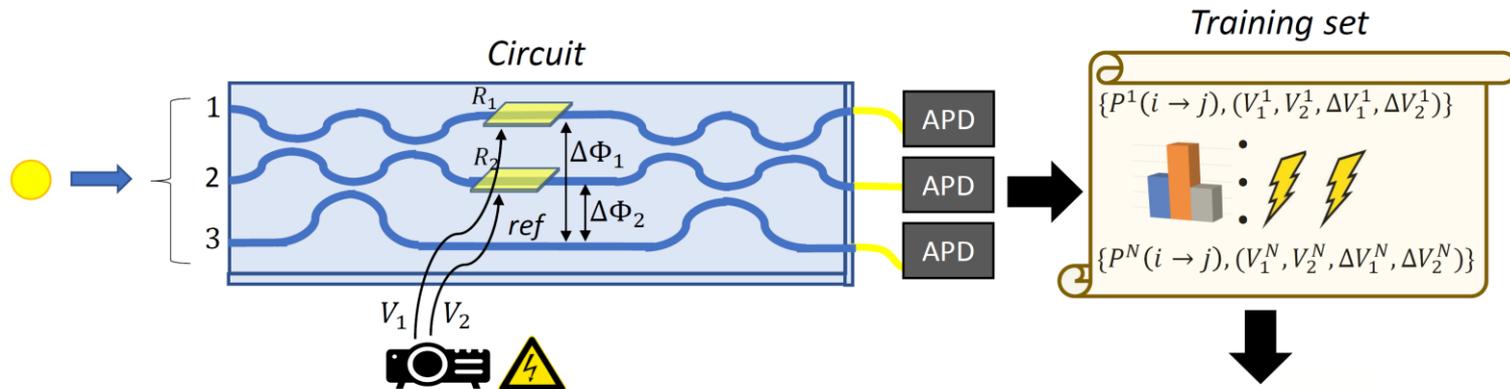


V. Cimini, et al., Phys. Rev. Lett. **123**, 230502 (2019)

V. Cimini, et al., Phys. Rev. Appl. **15**, 044003 (2020)

Calibration of quantum sensors via neural networks

Concept of the approach



(1) A series of input-output data are generated from the apparatus

$$\{\vec{x}, \vec{y}\}_k = \{P(i \rightarrow j), (V_1, V_2)\}_k \text{ for } i, j = 1, 2, 3.$$

output probabilities

input parameters tuned by the user

$$\Delta\phi_i = \sum_{j=1}^2 (\alpha_{ij} P_{R_j} + \alpha_{ij}^{\text{NL}} P_{R_j}^2)$$

Requires additional calibration of $(V_1, V_2) \leftrightarrow (\Delta\phi_1, \Delta\phi_2)$

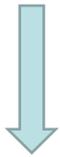
V. Cimini, et al., Phys. Rev. Lett. **123**, 230502 (2019)
V. Cimini, et al., Phys. Rev. Appl. **15**, 044003 (2020)

Calibration of quantum sensors via neural networks

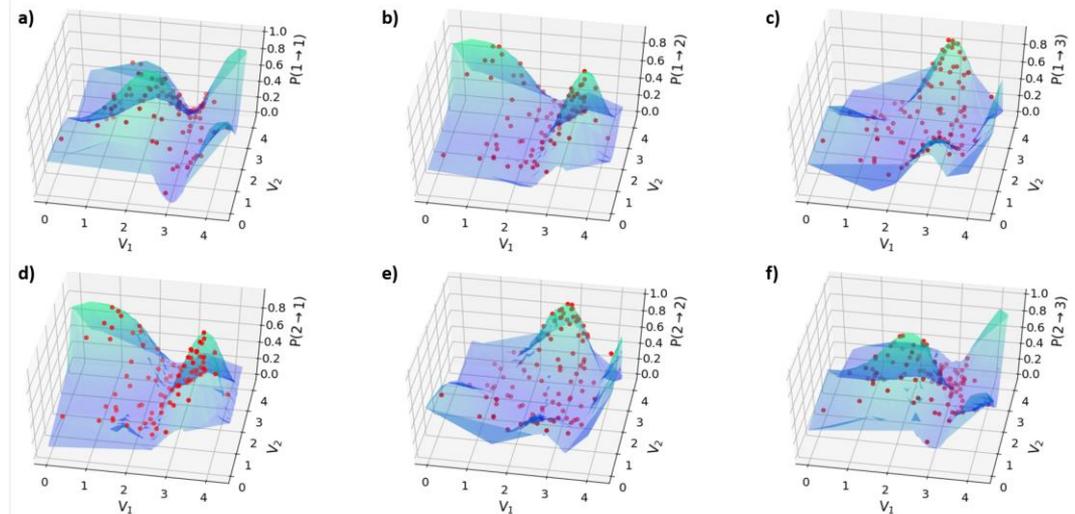
Concept of the approach

(2) The training set is used to train a neural network to learn the mapping between $P(i \rightarrow j)$ and (V_1, V_2)

No a priori knowledge on the functional form of the model/mapping is generally required, including noise



(3) After training, the network is capable of predicting the correspondence between $P(i \rightarrow j)$ and (V_1, V_2) on new sets of data



V. Cimini, et al., Phys. Rev. Lett. **123**, 230502 (2019)
V. Cimini, et al., Phys. Rev. Appl. **15**, 044003 (2020)

Results and Perspectives

Other results

A. Z. Goldberg, et al., Phys. Rev. A **102**, 022230 (2020)

V. Cimini, et al., Phys. Rev. Applied **13**, 024048 (2020)

V. Cimini, et al., arXiv:2110.02908 (2021)

ML for adaptive estimation

ML for sensors calibration



ongoing and future work

Quantum phase estimation with squeezed light



Development in progress of a squeezing apparatus

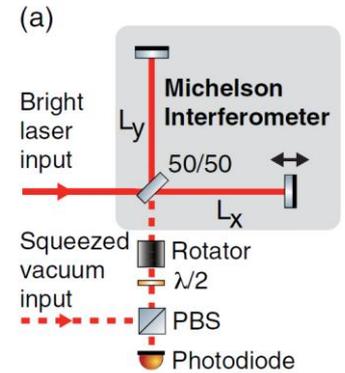
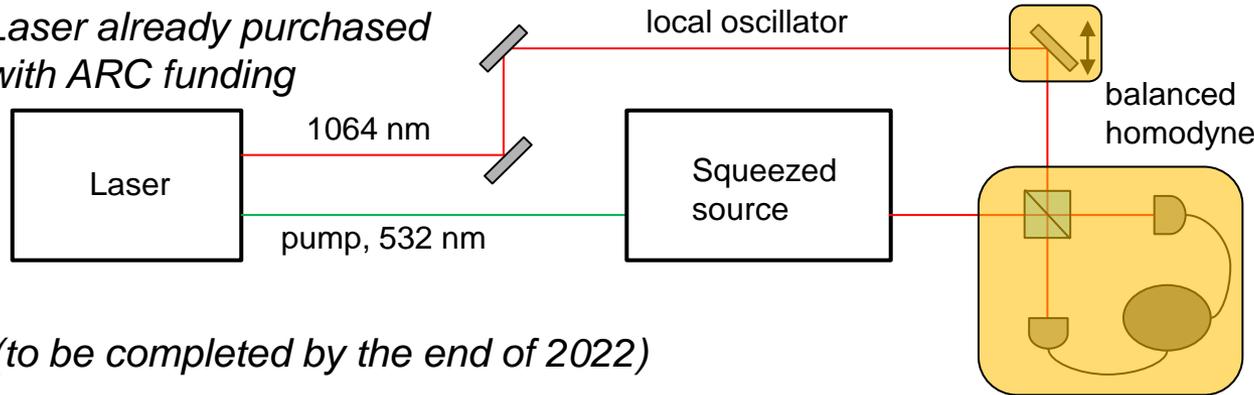


Testing of protocols for phase estimation with squeezed light for GW detection

Results and Perspectives

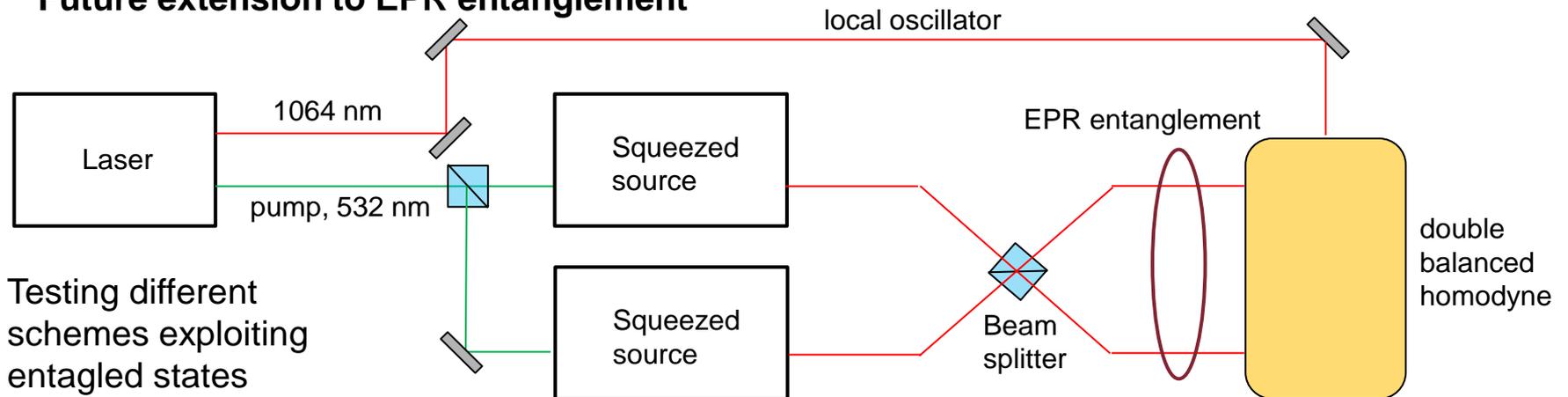
Development of a squeezed single-mode light source

Laser already purchased with ARC funding



Testing protocols for phase noise reduction in GW interferometers

Future extension to EPR entanglement



People



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Marco Barbieri
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Roberto Osellame
Andrea Crespi
Giacomo Corrielli



Vittorio Giovannetti
Federico Beliaro



Aaron Goldberg
Aephraim Steinberg



Marco G. Genoni



Nathan Wiebe