

MLQ 2021

Improving Quantum Sensing with Variational Methods

JOHANNES JAKOB MEYER, FU BERLIN & QMATH

 @jj_xyz

arxiv:2006.06303

A variational toolbox for quantum multi-parameter estimation

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(Dated: June 11, 2020)



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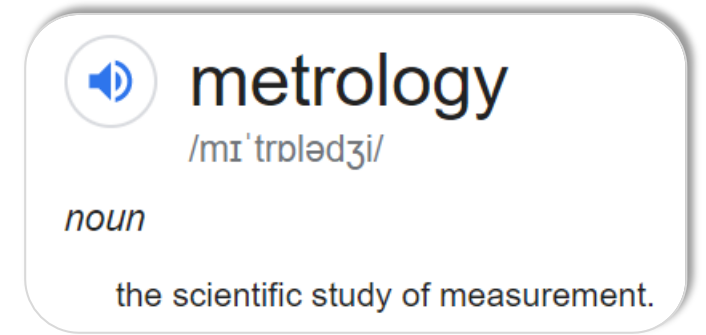
Quantum Metrology

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Physical quantities (magnetic fields, energies, ...)
need to be **measured** accurately

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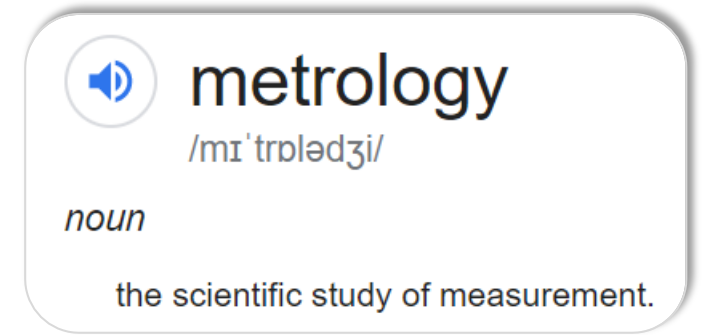
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Probe
State




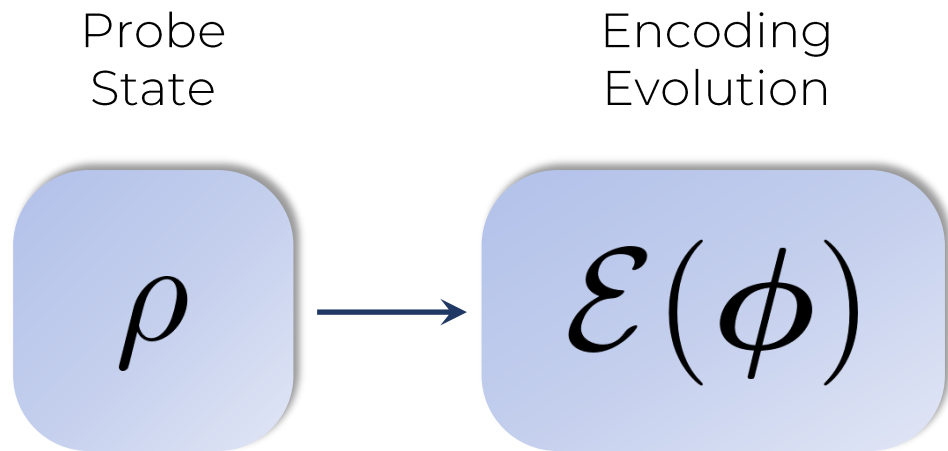
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the scientific study of measurement.

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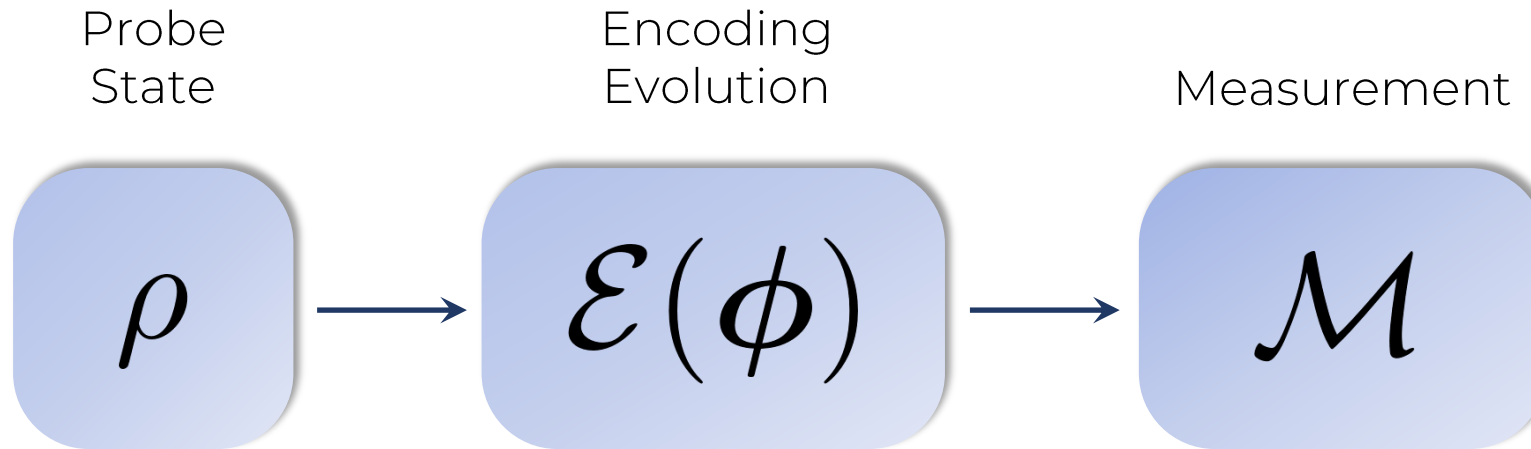


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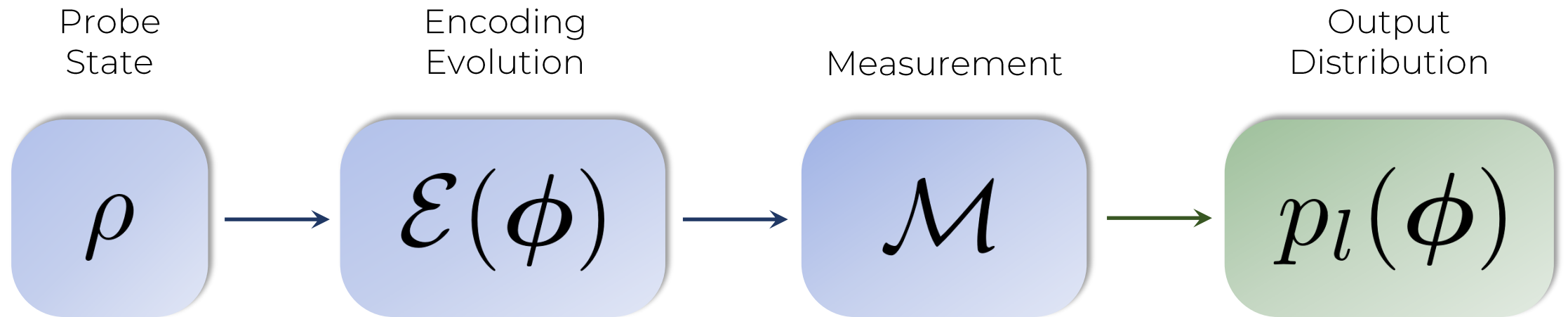
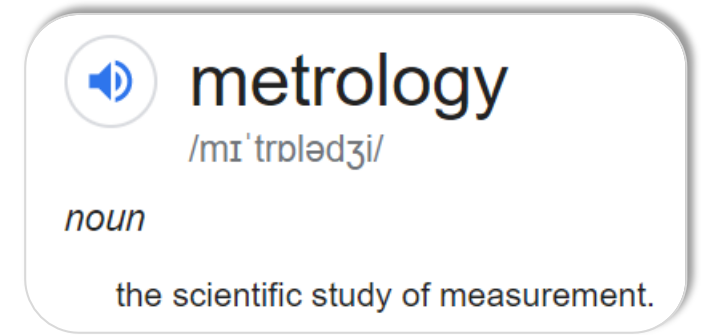
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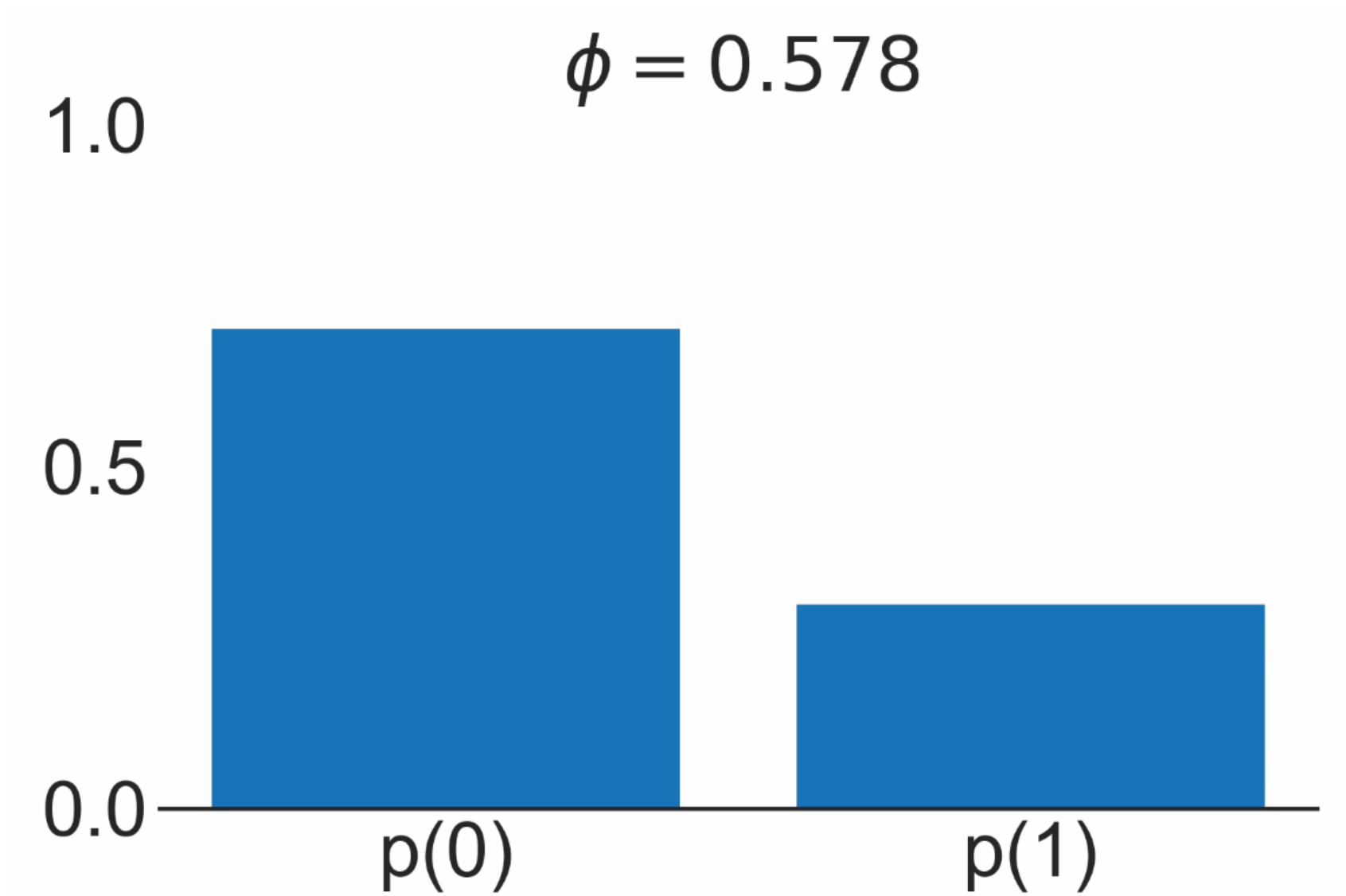
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Gathering Intuition

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Measuring Performance

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Task: Compute an **estimator** from the output distribution

$$p_l(\phi) \rightarrow \hat{\varphi} : \mathbb{E}\{\hat{\varphi}\} = \phi$$

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→ Classical Fisher information should be used to judge sensing quality!

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Complicated under noise and device limitations

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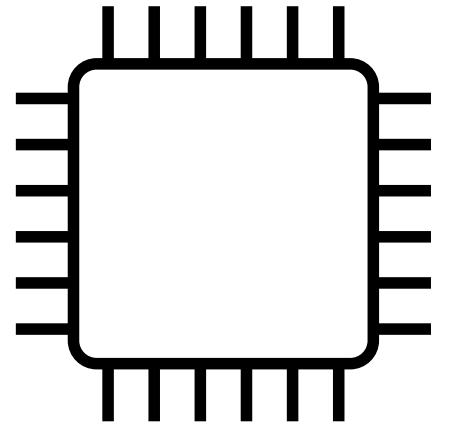
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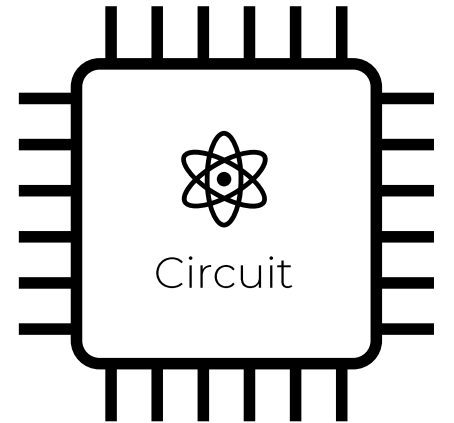


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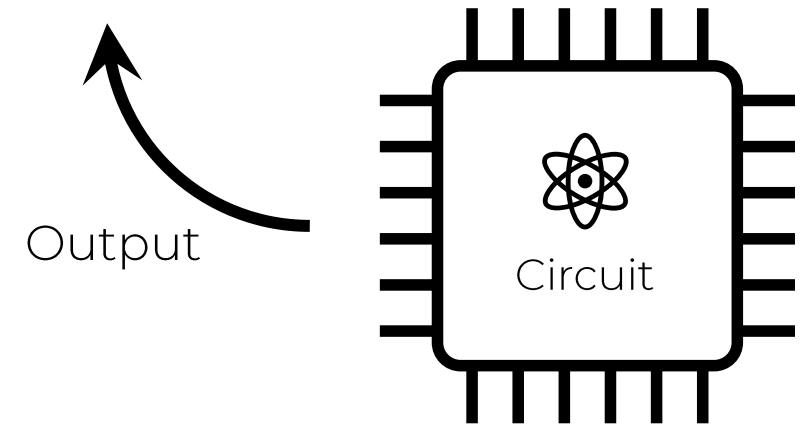


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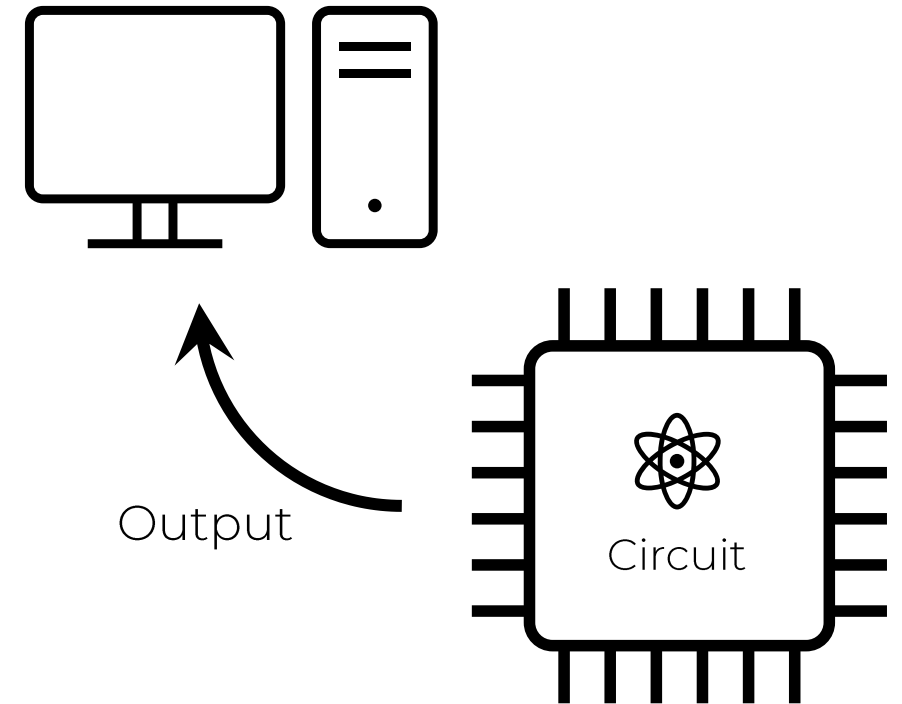


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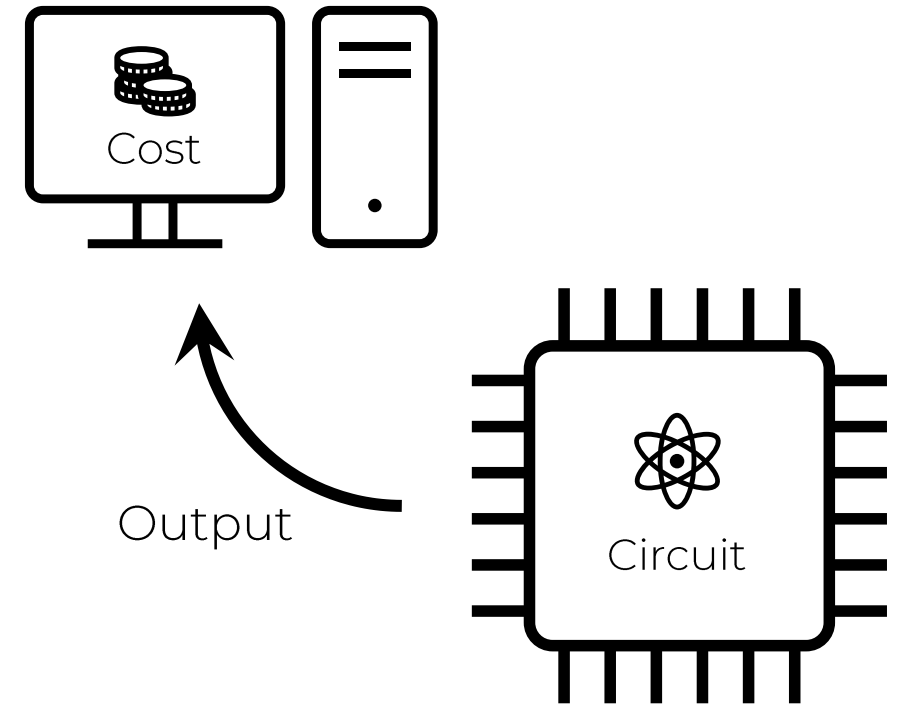


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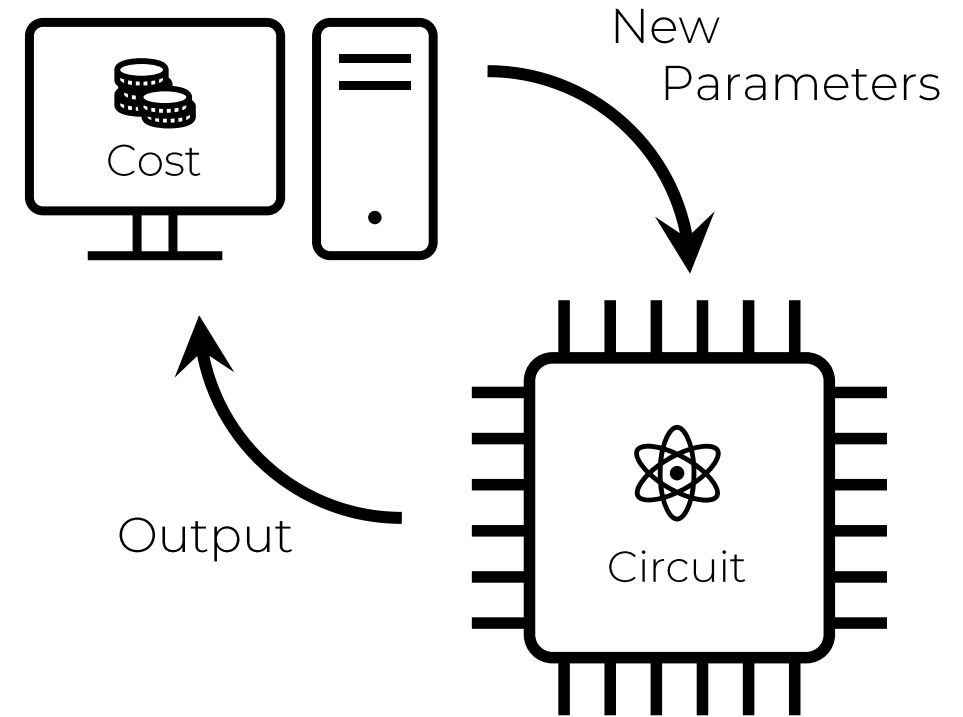


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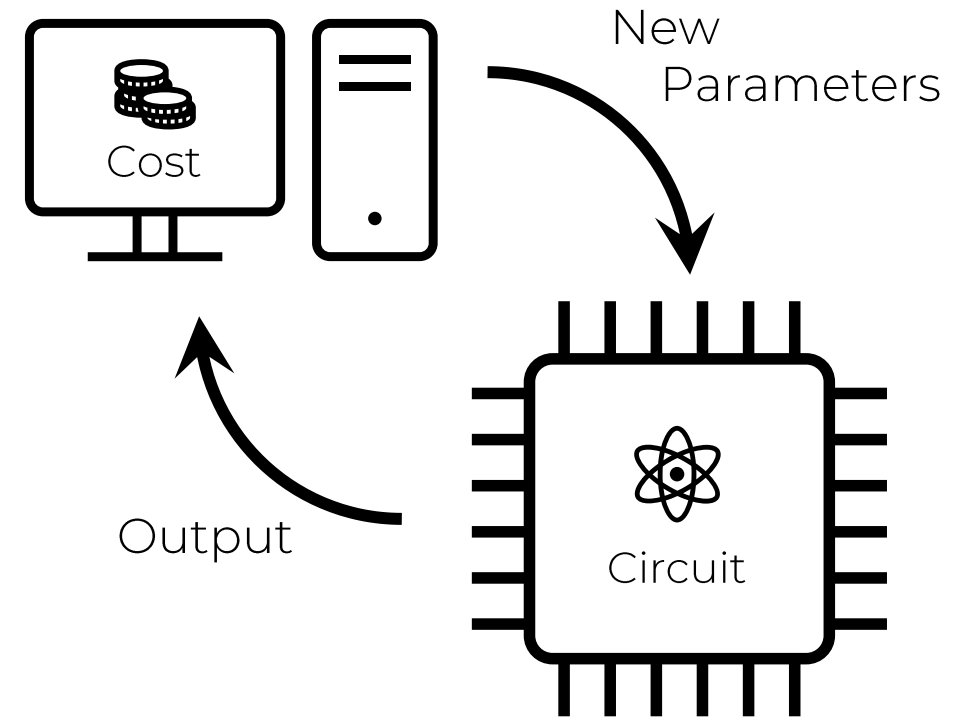
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Prior work^{1,2} focused on single-parameter metrology and surrogates for the Quantum Fisher Information



¹Kaubrügger, Raphael, et al. *Physical Review Letters* 123.26 (2019): 260505.

²Koczor, Bálint, et al. "Variational-State Quantum Metrology." *New Journal of Physics* (2020).

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$$\text{Tr}\{W \text{Cov}(\hat{\mathbf{f}})\} \geq \frac{1}{n} \text{Tr}\{W I_{\mathbf{f}}^{-1}\} = \frac{1}{n} C_W$$

Calculation of Fisher Information

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Fisher Information Matrix w.r.t. the physical parameters

$$[I_{\phi}]_{jk} = \sum_l \frac{1}{p_l} \frac{\partial p_l}{\partial \phi_j} \frac{\partial p_l}{\partial \phi_k}$$

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Exploit parameter-shift rule^{1,2} to calculate derivatives

$$\partial_j p_l(\phi) = \frac{1}{2} \left[p_l \left(\phi + \frac{\pi}{2} \mathbf{e}_j \right) - p_l \left(\phi - \frac{\pi}{2} \mathbf{e}_j \right) \right]$$

¹Schuld, Maria, et al. *Physical Review A* 99.3 (2019): 032331.

²Banchi, Leonardo, and Gavin E. Crooks. arXiv preprint arXiv:2005.10299 (2020).

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The cost function is obtained from a weighted trace of the Cramér-Rao bound

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Numerical experiments that showcase the performance of the approach

Take-Home Message

Variational methods on near-term quantum computers can be used to improve quantum sensors

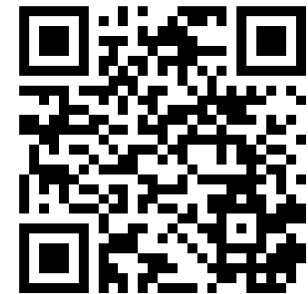
Thank you for your attention!



Paper



Demo



Slides

The Algorithm Landscape

The Algorithm Landscape



Single Parameter



Multiparameter



The Algorithm Landscape

■ Single Parameter ■ Multiparameter

Kaubrügger et al.

COST FUNCTION

Spin Squeezing

STATE PREPARATION

Fixed Circuit

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Koczor et al.

COST FUNCTION

Fidelity

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Parametrized Circuit

MEASUREMENT

N/A

The Algorithm Landscape

■ Single Parameter ■ Multiparameter

Kaubrügger et al.

COST FUNCTION

Spin Squeezing

STATE PREPARATION

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MEASUREMENT

Fixed

Ours

COST FUNCTION

Classical Fisher Info

STATE PREPARATION

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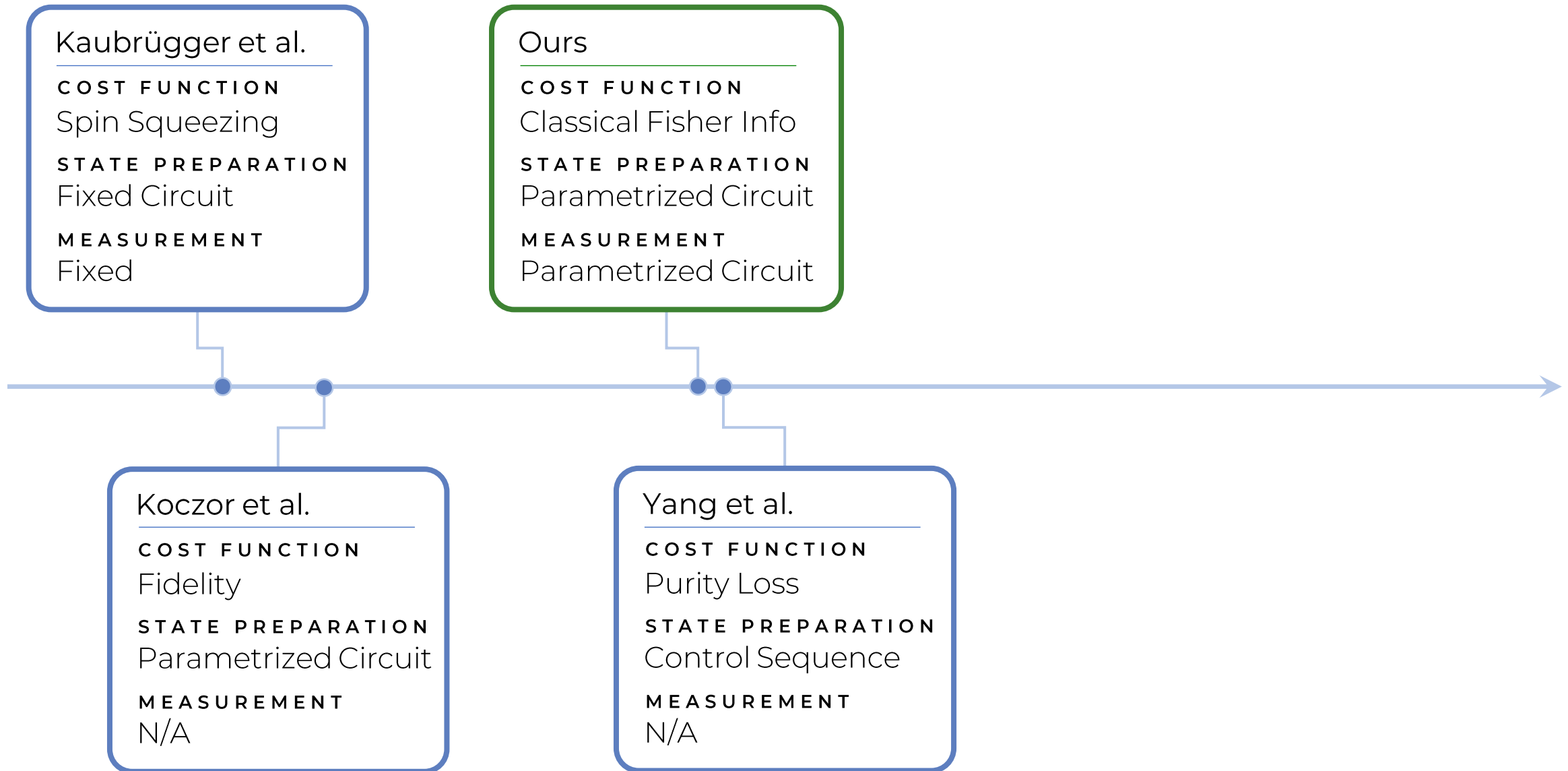
Parametrized Circuit

MEASUREMENT

N/A

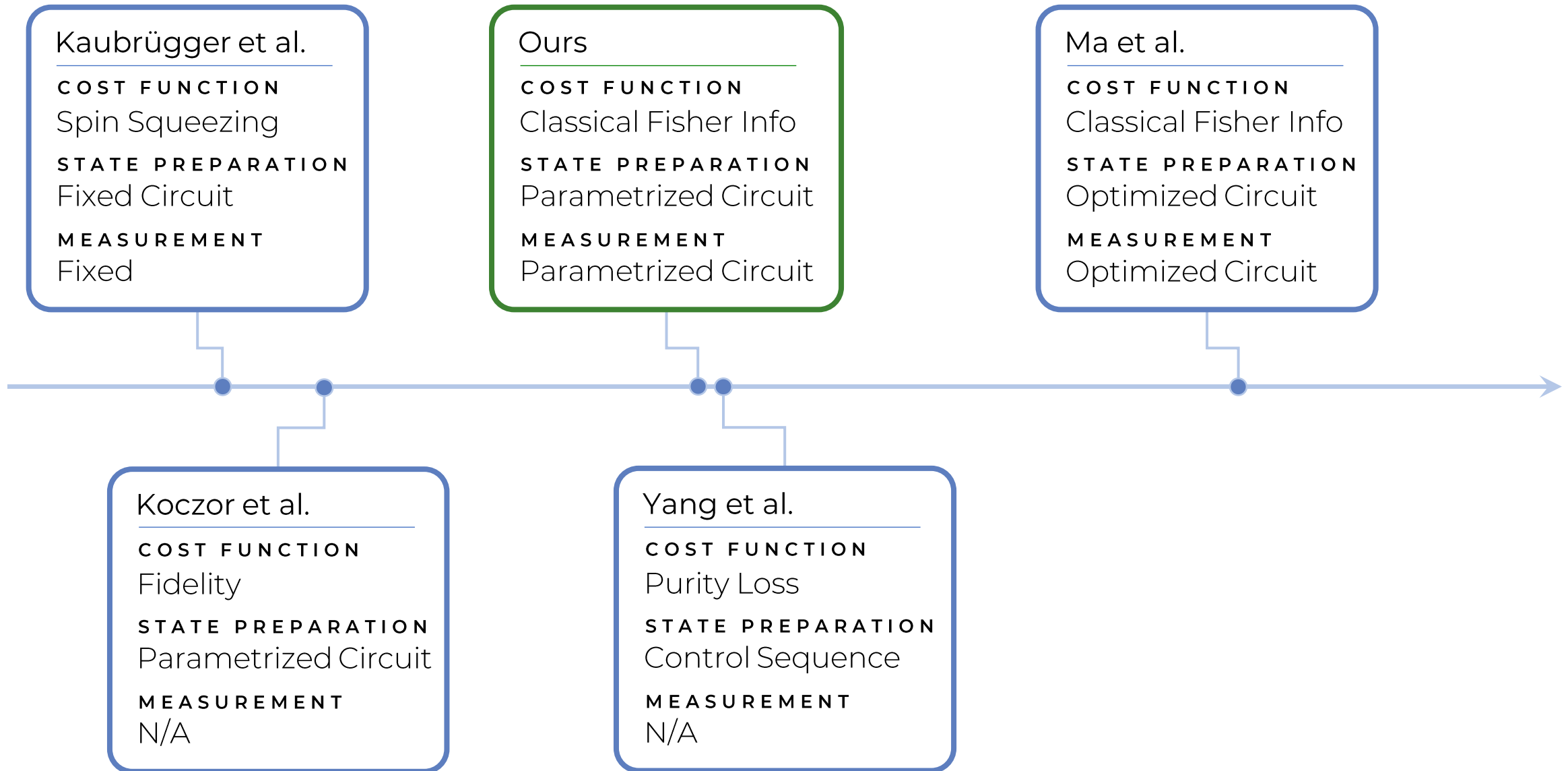
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