Adaptive Quantum State Tomography with Neural Networks

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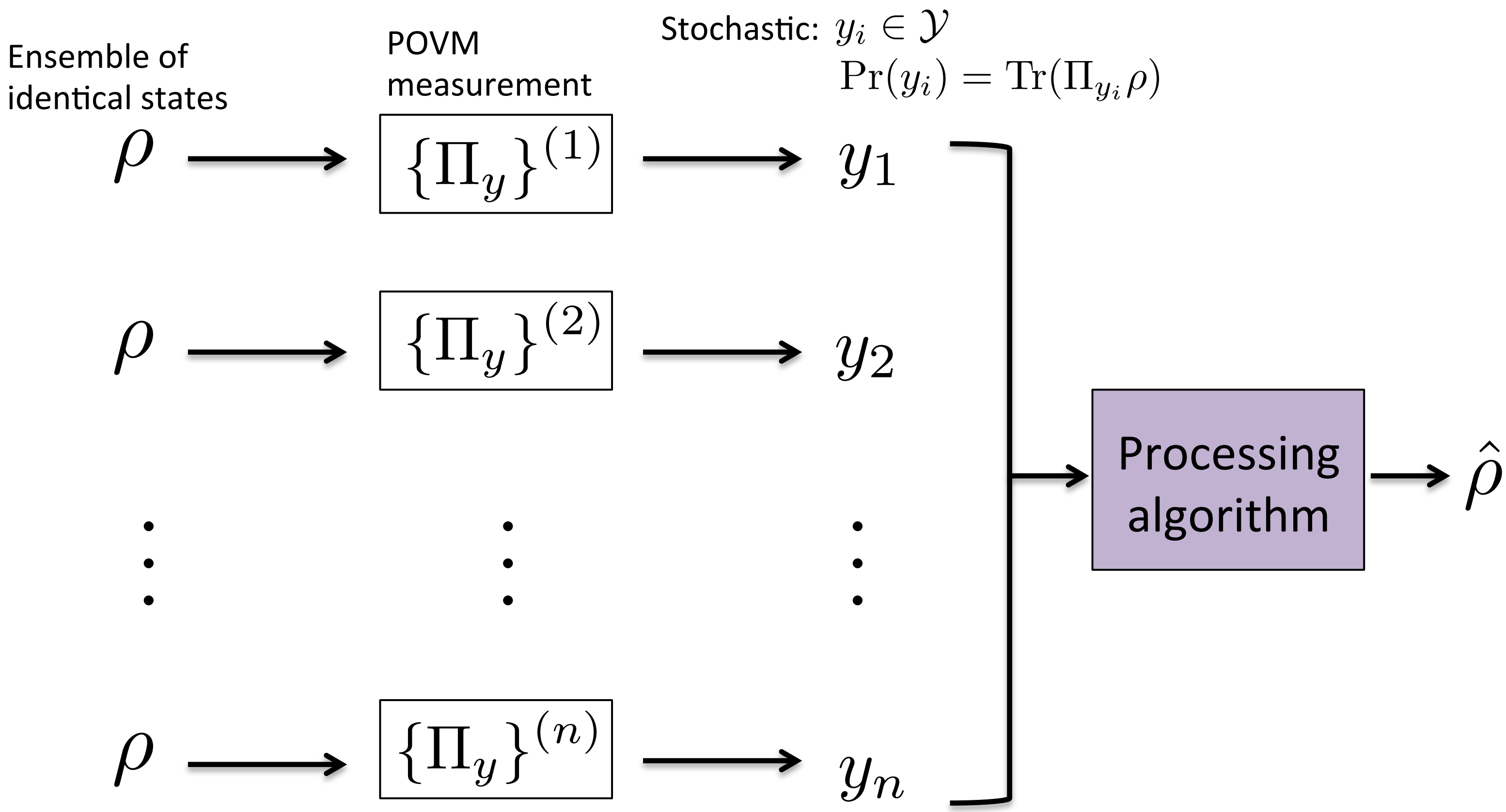
arxiv 1812.06693

Joint work with Stanislav Fort* and Hui Khoon Ng

* These two authors contributed equally

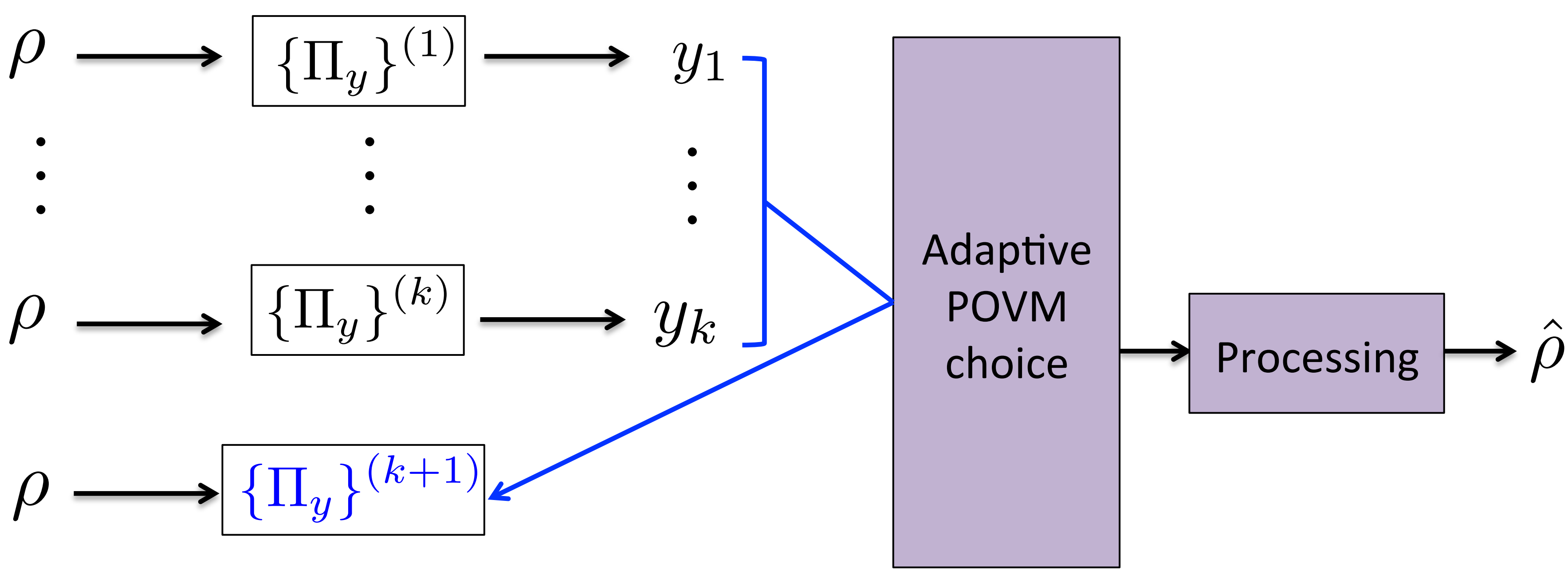
Quantum State Tomography



Adaptive Quantum Tomography

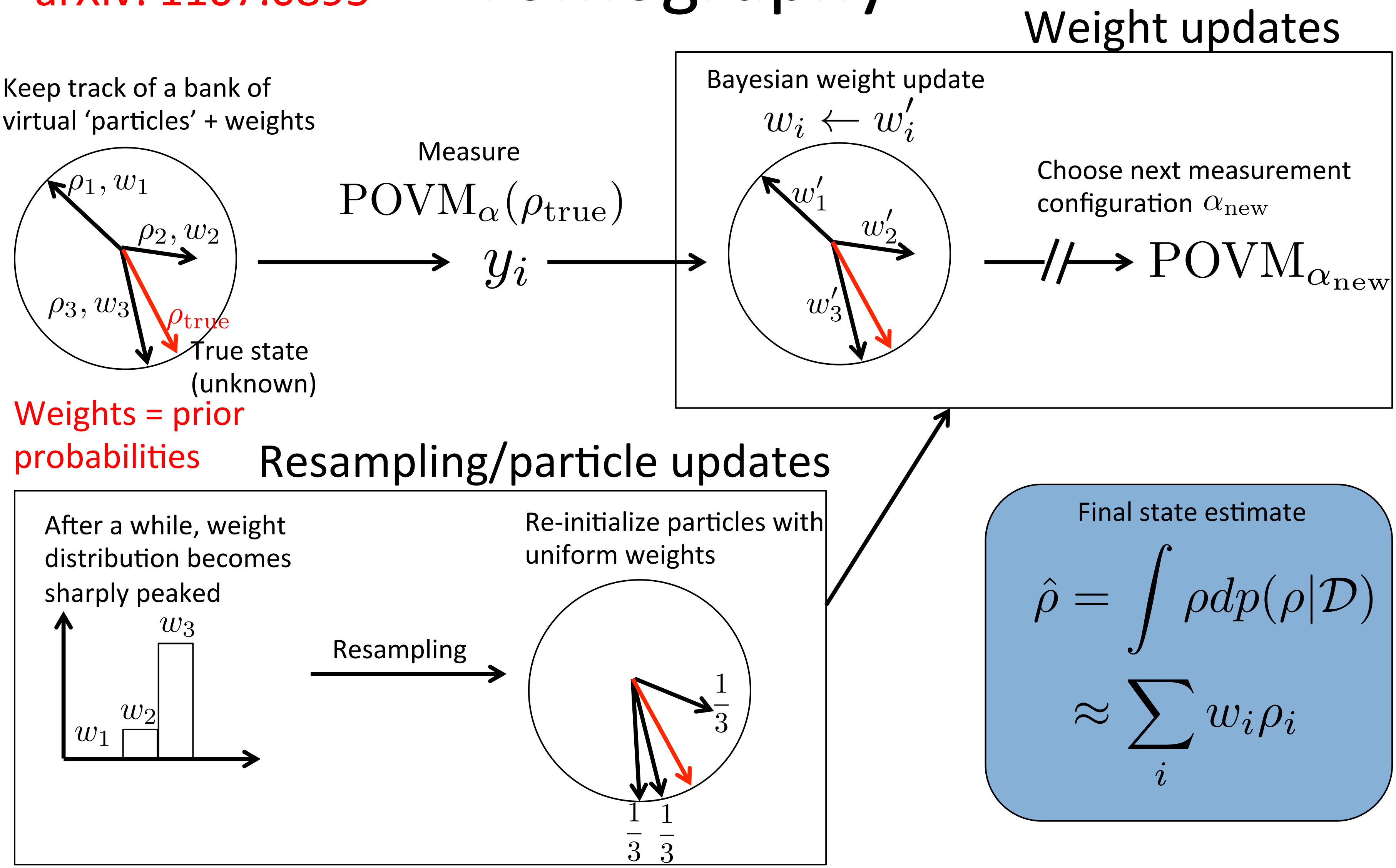
Problem: Expensive to prepare states for measurements.
Solution: Minimize measurements by choosing them adaptively based on past information.

On (k+1)-st iteration:



Adaptive Bayesian Quantum Tomography

arXiv: 1107.0895

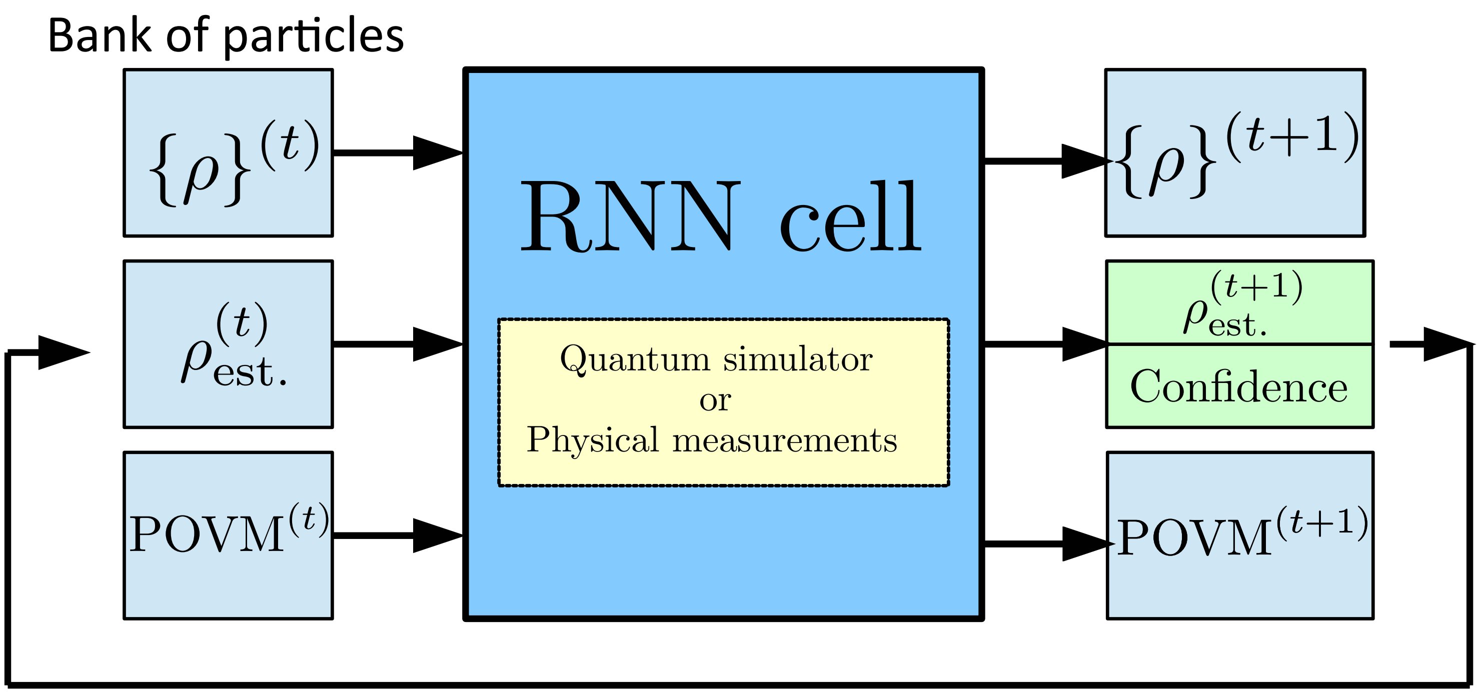


ABQT in more detail

- Basic idea: modified particle filter
- Weight decay problem → **resampling, costly**
  - Metropolis-Hastings algorithm (need to compute extensive probabilities)
  - Runtime for 100 particles, 1000 copies measured~ 4 hr
- Adaptivity: optimizing an entropy decrease heuristic
  - Maximizing mutual information between the label of bank states and the outcome of the next POVM

Our solution

Off-the-shelf deep learning architectures don't work for our purposes!



During training: simulate POVM

During deployment: experimenter supplies physical measurements

Within the RNN cell

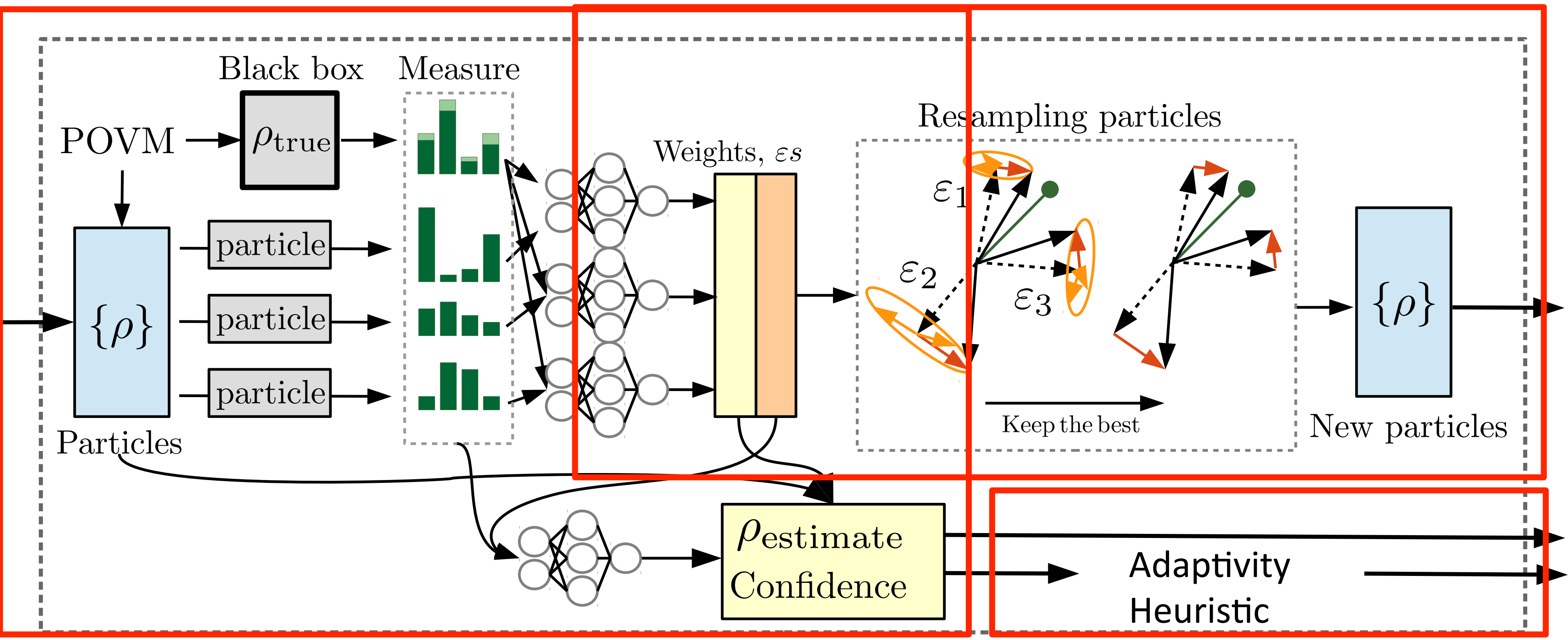
- **Takeaway: If you have an expensive function, approximate it with a neural network.**

- Input: old particle bank $\{\rho_i, w_i\}$

1. Update weights **using NN** $w_i \leftarrow w_i'$
2. Update particles **using NN** $\rho_i \leftarrow \rho_i'$
3. (optional) Output new POVM configuration α'

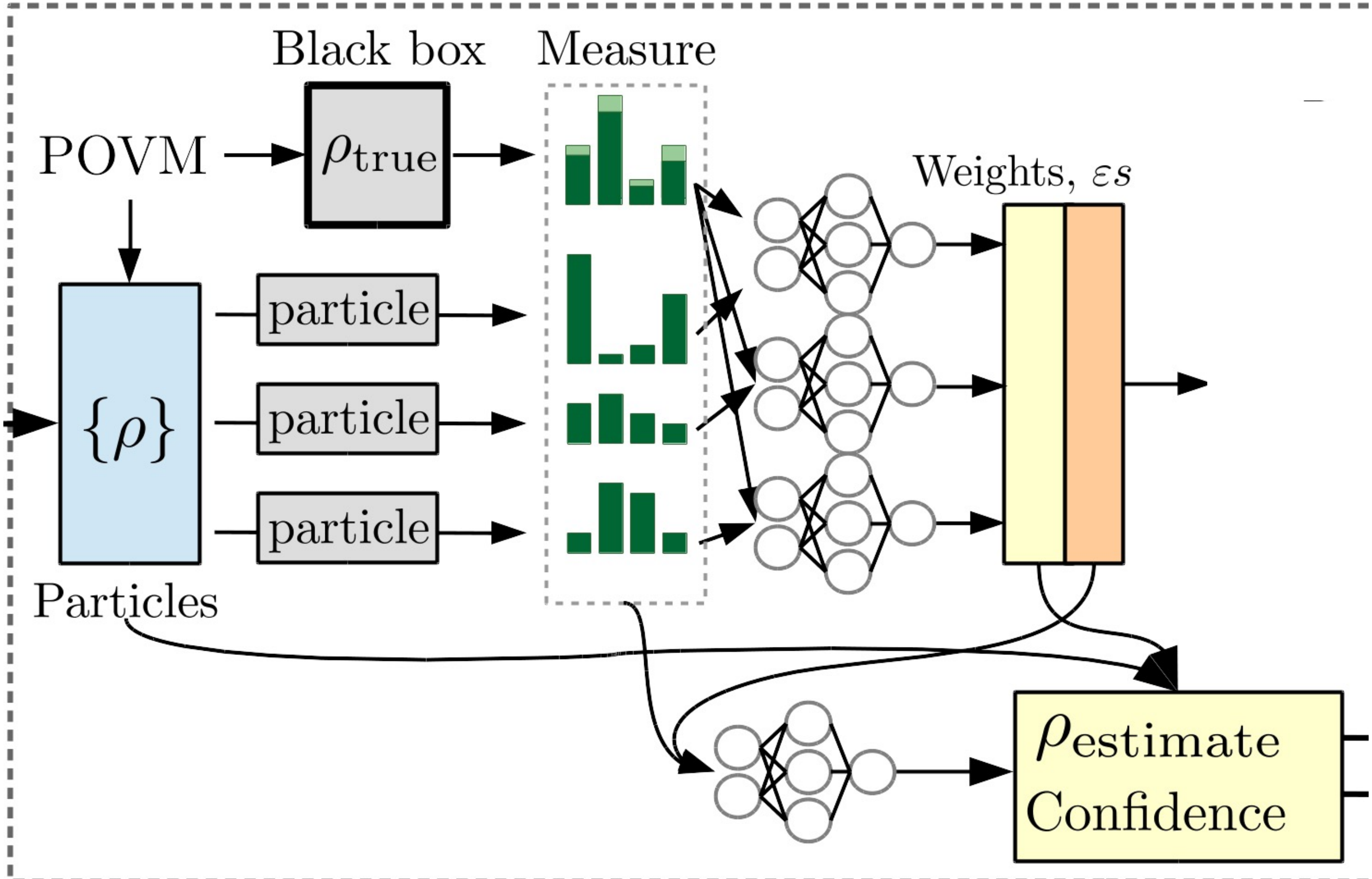
Within the RNN cell

- Stage 1: update weights and state estimate
- Stage II: update particles

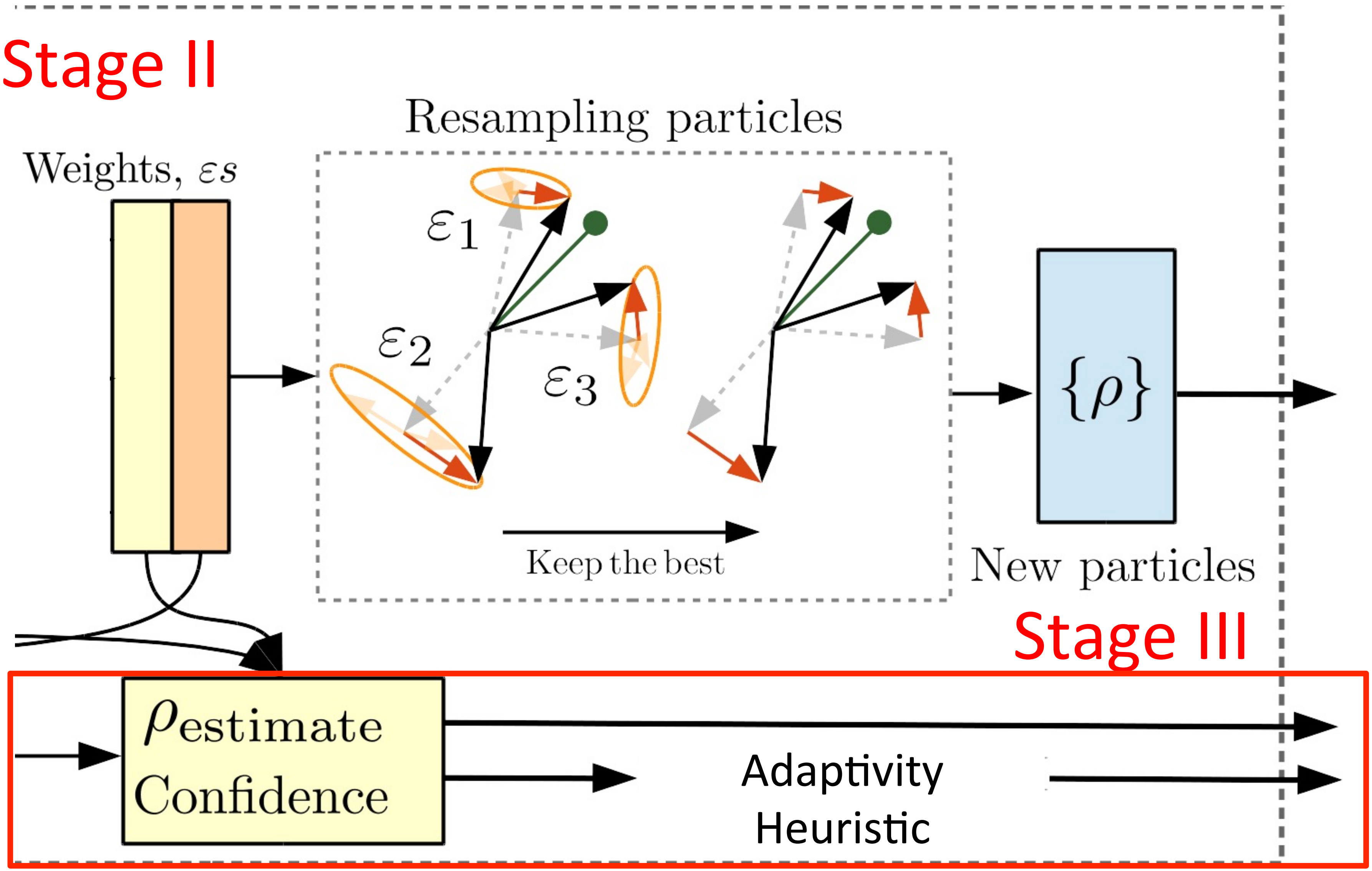


Stage III: measurement adaptivity

Stage I: update weights



Stages II and III



Different paradigm from ABQT

- In NA-QST:
  - Weights not interpreted as probabilities. No Bayesian weight updates → no weight decay.
  - NN **learns own similarity metric** to propose weight updates and resampling.
  - Resampling is fast!
  - Measurement adaptivity step influences earlier steps of weight updates and resampling, as they are trained using same signal.

Results

- With our rapid algorithm, we were able to perform experiments to understand the limits of usefulness of measurement adaptivity.
- Compared performance of NA-QST against ABQT and standard tomography implemented on same platform.
- Performance metric: Scaling of Bures distance with number of copies of true state measured.

Numerical experiments

- Parameters of variation:

  - **Reconstruction algorithm:** \`Standard' quantum tomography, ABQT or NA-QST

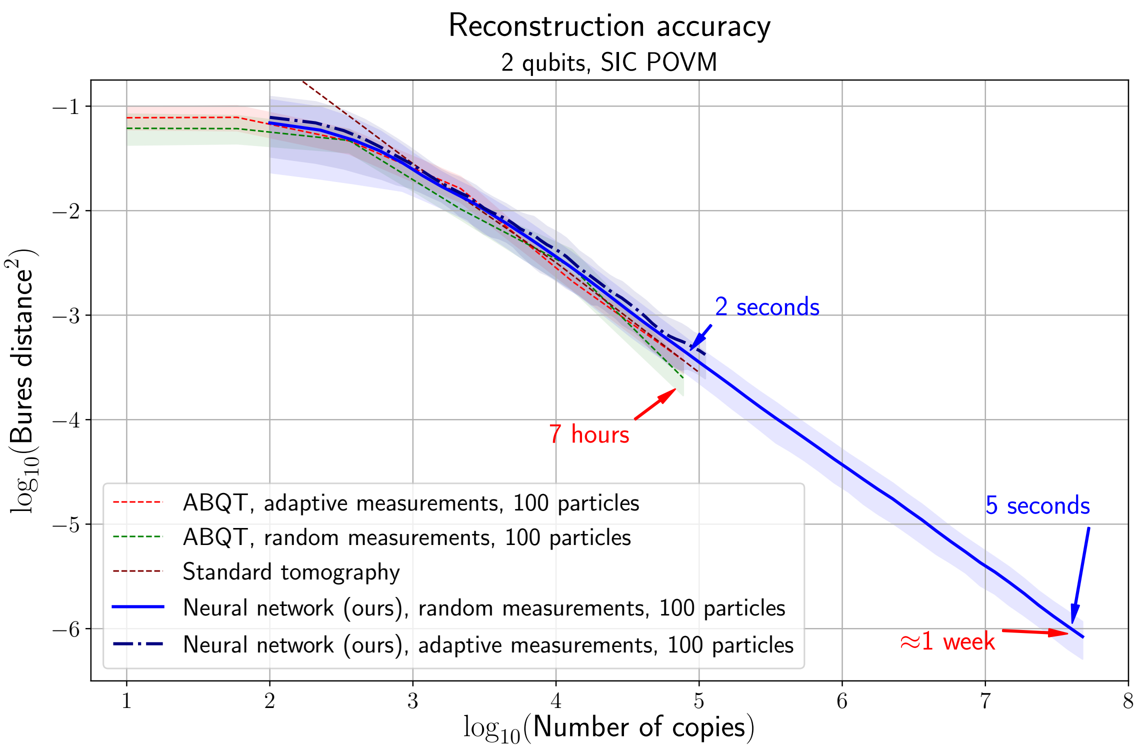
  - **Type of single-qubit POVM:** two (basis POVMs), three, four or six legs per subspace

  - **Adaptive or random measurements**

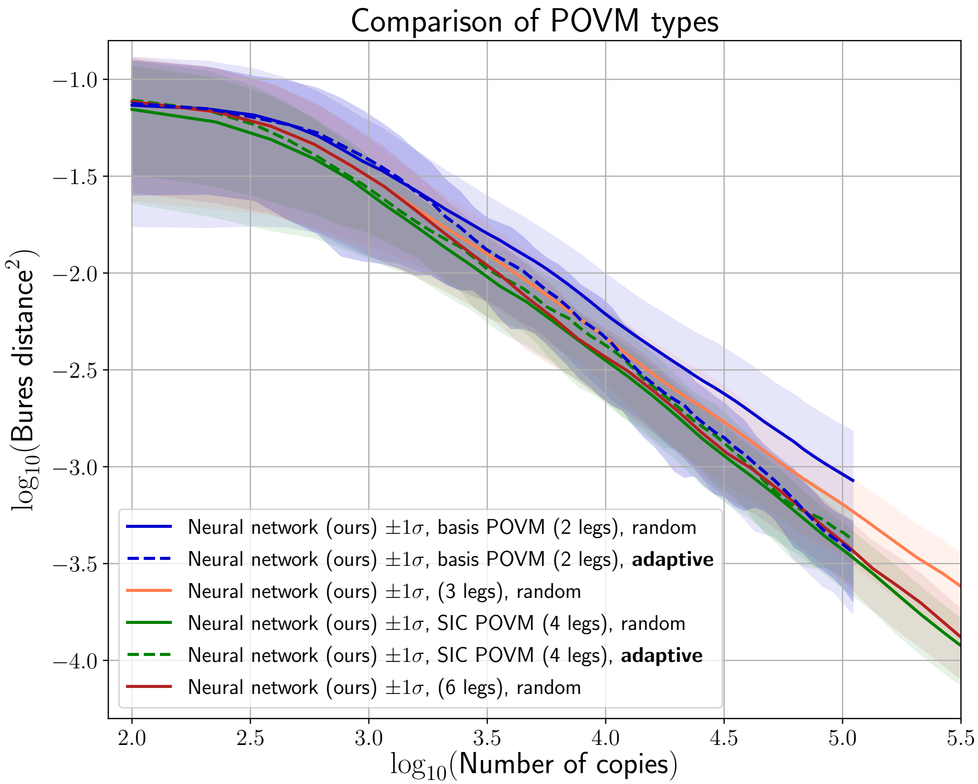
  - **Size of particle bank:** more particles means finer sampling and a higher quality approximation

Part I: Adaptivity with SIC-POVMs

- Adaptive algorithms vs non-adaptive ones for SIC-POVMs: no difference in performance!

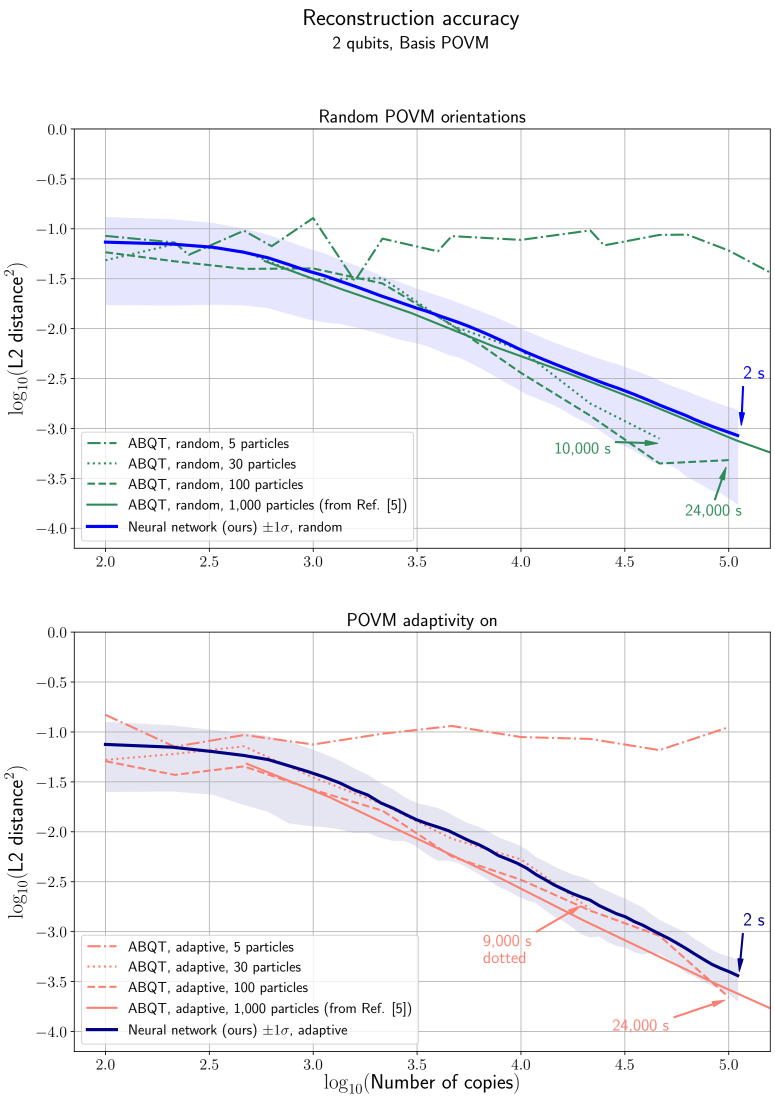


Part I: When is adaptivity helpful?



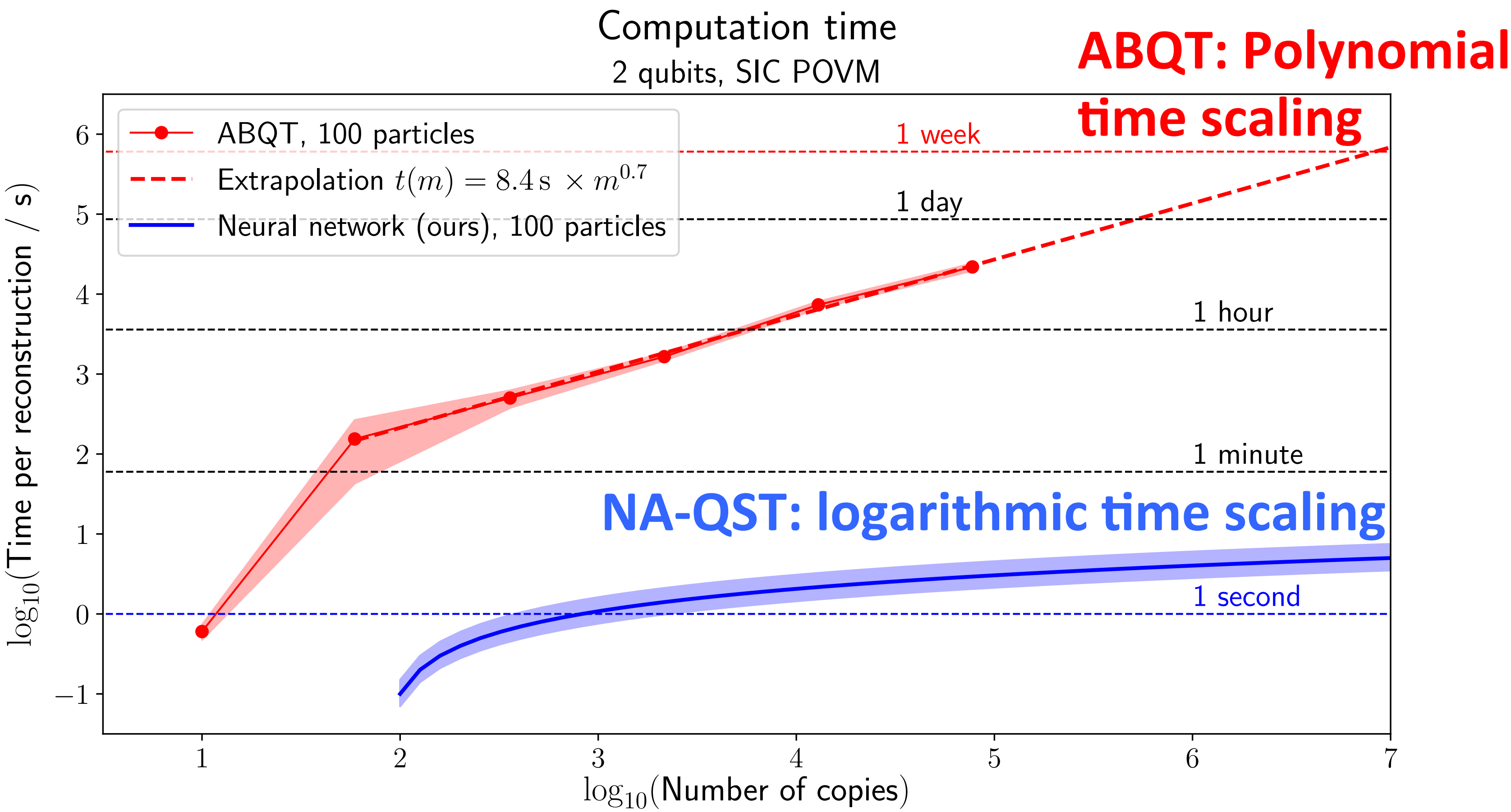
- Only for basis POVMs
- With >4 legs, adaptivity makes no difference

Part II: ABQT vs NA-QST (basis POVMs)



- Tweakable parameter for ABQT: Number of particles. More particles = better approximation of posterior.
- NA-QST with 100 particles performs comparably to ABQT with 10, 100, 1000 particles, but runs significantly faster!

Part III: Computation time for adaptive algorithms



Discussion

- NA-QST is fast, accurate and flexible – can be easily retrained for specific applications (low-rank states, etc).
- Huge potential for machine learning to solve design problems in experimental physics (for instance 1706.00868)
- Method can be extended to other modified particle filter algorithms.

Collaborators

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