
QUANTUM RESERVOIR PROCESSING

NOISY INTERMEDIATE-SCALE QUANTUM ARTIFICIAL INTELLIGENCE

Tomasz Paterek

Xiamen University Malaysia
& University of Gdańsk

tomasz@paterek.info

COLLABORATORS

Timothy Liew

Nanyang Technological University



Sanjib Ghosh

The Chinese University of Hong Kong



Tanjung Krisnanda

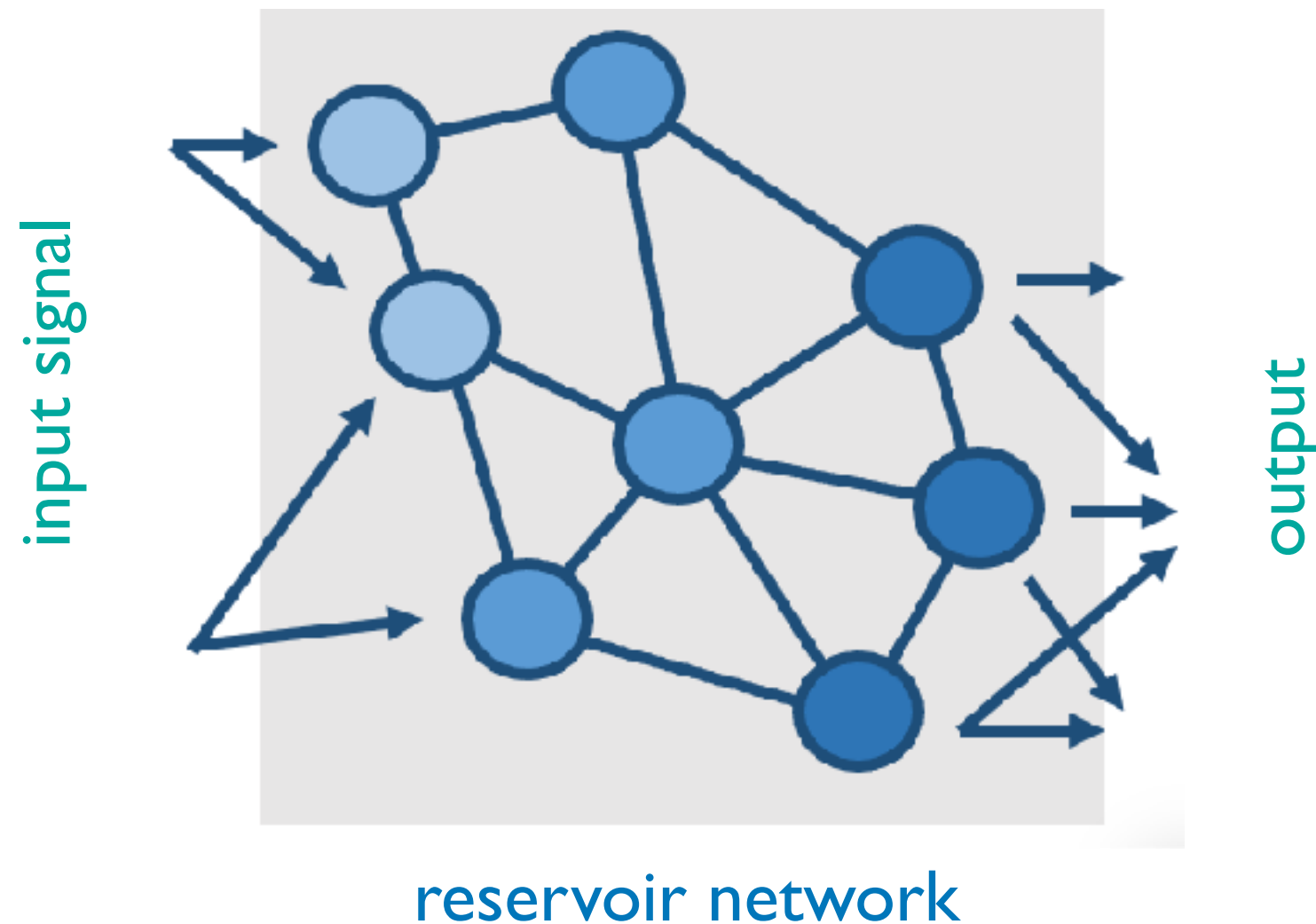
National University of Singapore



Yvonne Y. Gao

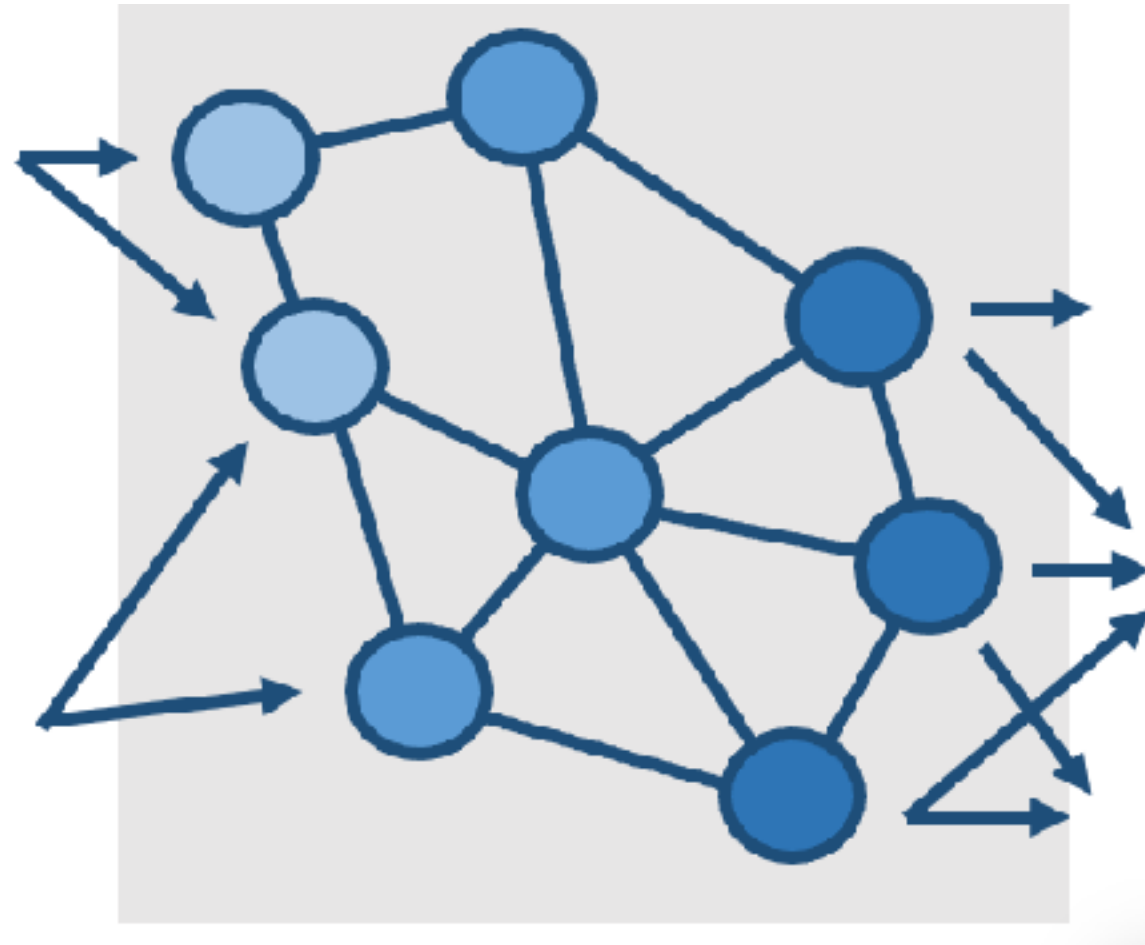
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RESERVOIR COMPUTER



- Random network
- Only output weights are adapted

Classical or quantum input



Classical or quantum output

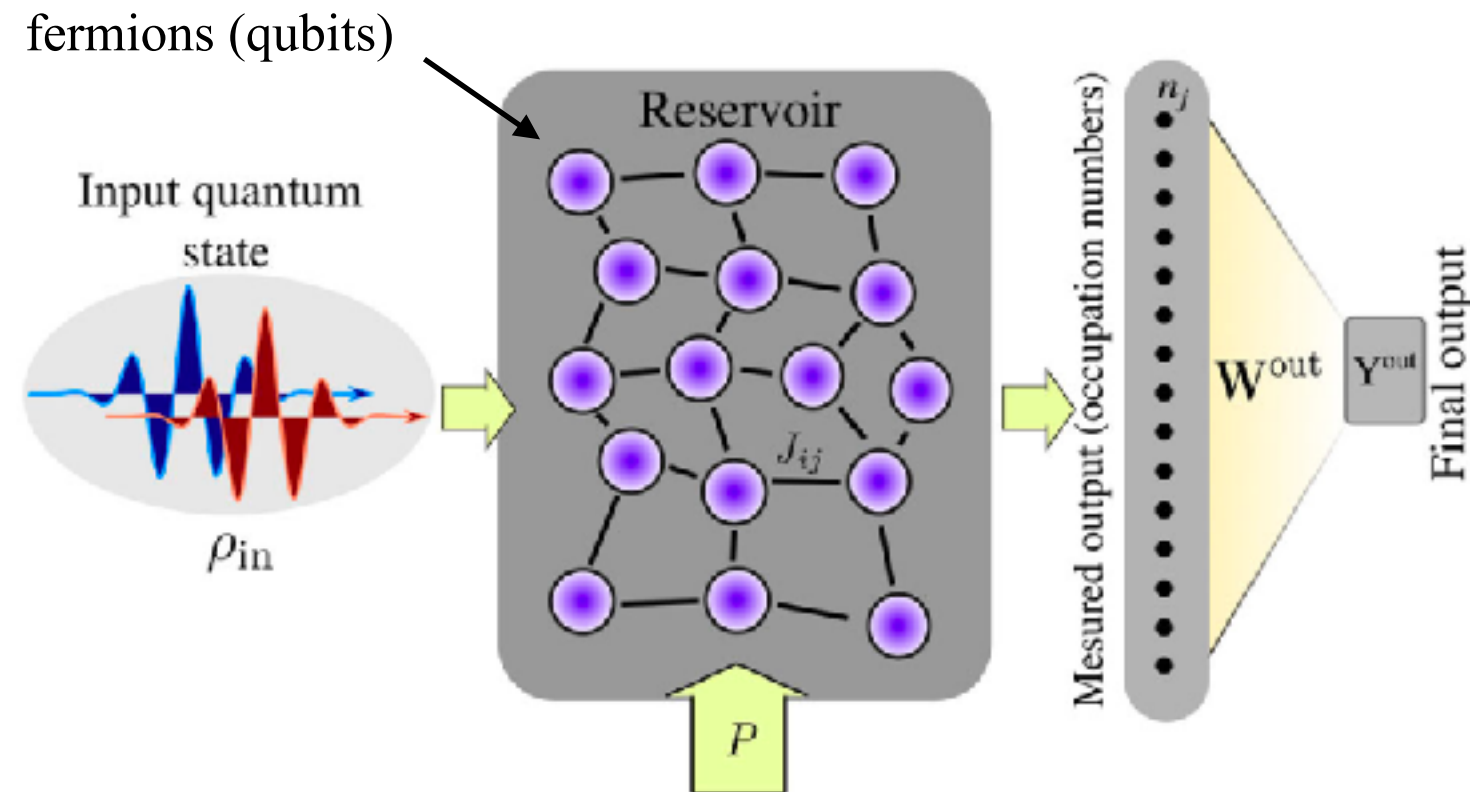
Network of randomly
connected quantum nodes

WHY IS THIS INTERESTING?

- Randomly connected networks model physical devices with manufacturing errors
 - It turns out this device operates successfully for a plethora of internal dynamics and couplings — suitable for hardware implementation
 - Training is conceptually simple and computationally inexpensive — essentially a linear map
 - Simple measurements on individual nodes, i.e. no need for correlated measurements
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QUANTUM INPUT — CLASSICAL OUTPUT

THE MODEL



1. Initial condition: steady state of the pumped and decaying reservoir
2. Input state coupled to the reservoir
3. Transient evolution
4. Measurement of the mean occupation of each node

WHAT CAN THIS DO?

- Witness entanglement of the input state
 - Estimate entanglement of the input state
 - Estimate entropy of the input
 - Estimate any function of the input
 - Estimate the input (quantum tomography)
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WITESSING ENTANGLEMENT

Problem: is input state entangled?

Setting for simulations:

Four reservoir nodes modelled as fermions (qubits).

Random nearest-neighbour coupling (Fermi-Hubbard model).

$$\hat{H}_R = \sum_{ij} J_{ij} (\hat{b}_i^\dagger \hat{b}_j + \hat{b}_j^\dagger \hat{b}_i)$$

Random: J_{ij} are uniformly distributed in $[-1, 1]$ and normalised to fix available energy.

Presented data will be averaged over these random realisations.

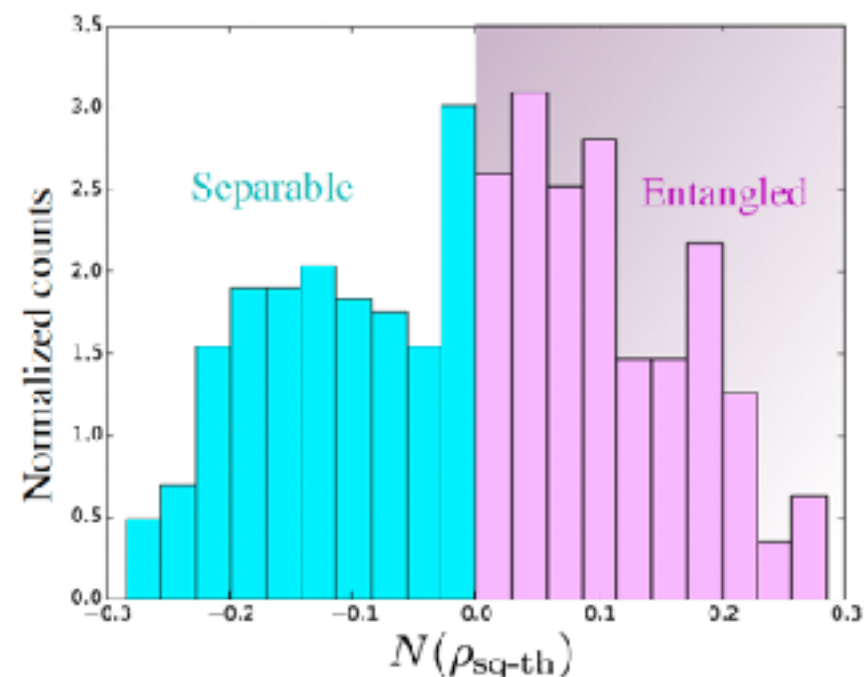
This shows that the method is insensitive to the details of the couplings.

TRAINING

Input states encoded in cv of optical two-mode fields.
For training we choose squeezed thermal states:

$$\rho_{\text{in}} = \hat{S}(\alpha) \rho_{\text{th}} \hat{S}^\dagger(\alpha)$$
$$\hat{S}(\alpha) = \exp(\alpha \hat{a}_1^\dagger \hat{a}_2^\dagger - \alpha^* \hat{a}_1 \hat{a}_2)$$

We randomise alpha such that 50% of input states are entangled.
Here we sampled 200 input states.



COUPLING TO THE RESERVOIR

It turns out this is not very important.
So it could be very simple, say just hoping:

$$\hat{H}_I = \sum_{kj} f_k(t) W_j^{\text{in}} \left(\hat{a}_k^\dagger \hat{b}_j + \hat{b}_j^\dagger \hat{a}_k \right)$$

We included possible decay and pumping via master equation:

$$i\hbar\dot{\rho} = [\hat{H}_{\text{tot}}, \rho] + \frac{i\gamma}{2} \sum_j \mathcal{L}(\hat{b}_j) + \frac{iP}{2} \sum_j \mathcal{L}(\hat{b}_j^\dagger)$$

MEASUREMENT ON THE RESERVOIR

Mean occupation numbers:

$$n_j = \langle \hat{b}_j^\dagger \hat{b}_j \rangle$$

We process them linearly as follows:

$$y_i^{\text{out}} = \sum_j W_{ij}^{\text{out}} n_j$$

where $\mathbf{y}^{\text{out}} = (1, 0)$ if input is entangled

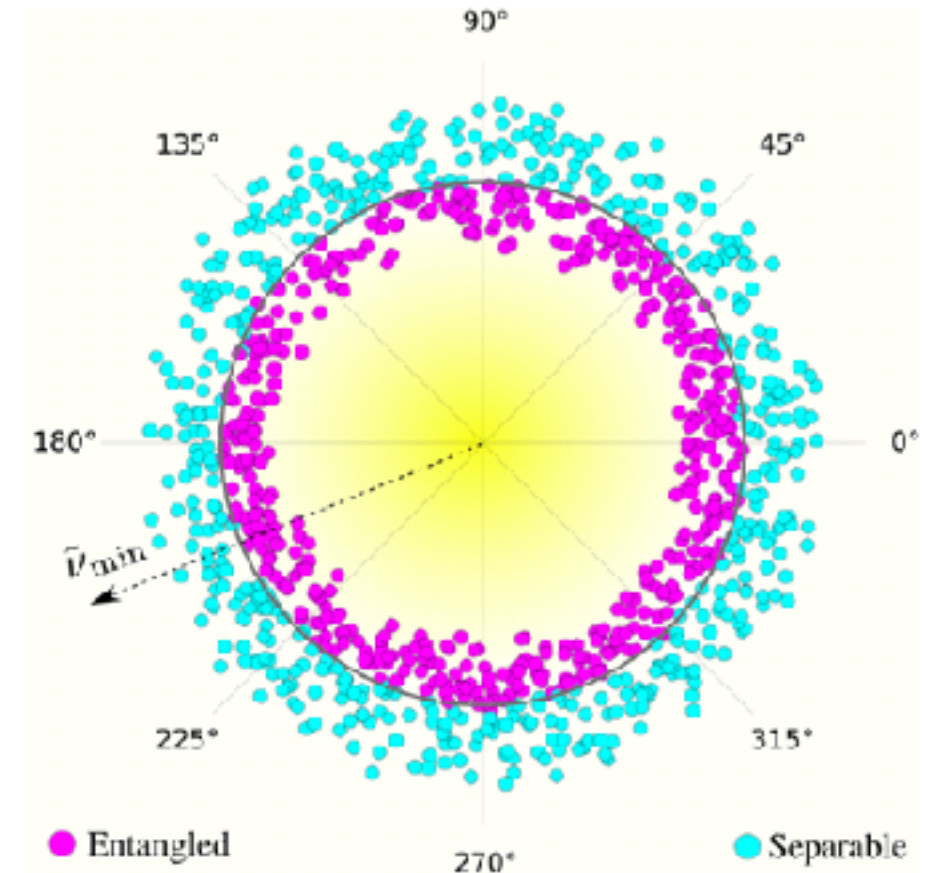
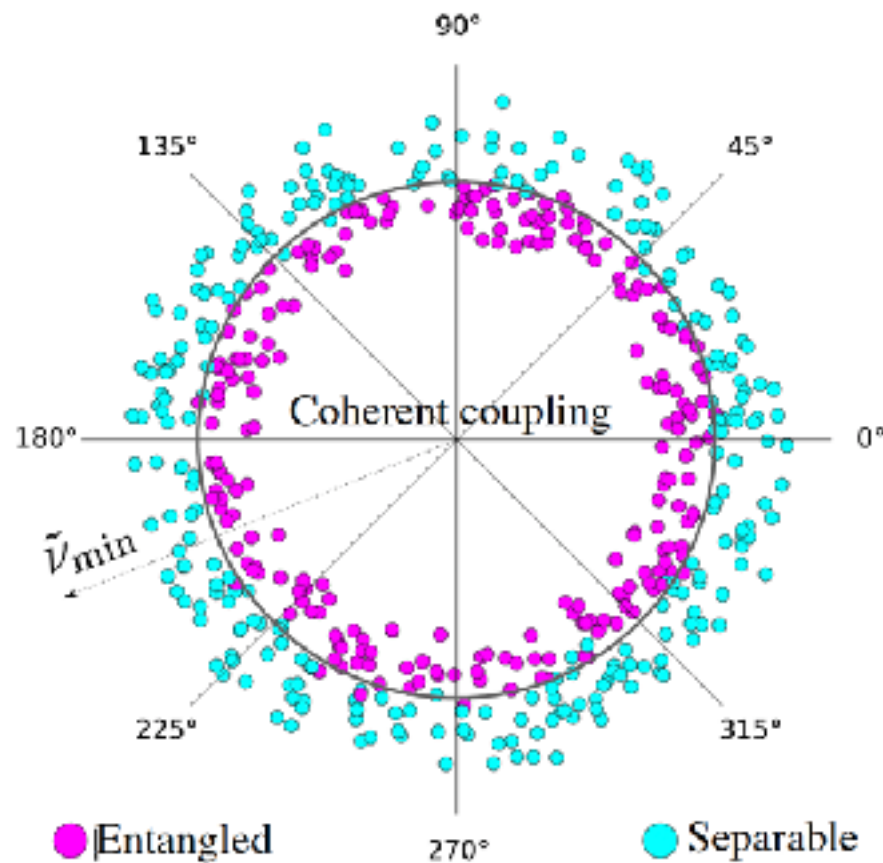
$\mathbf{y}^{\text{out}} = (0, 1)$ otherwise

\mathbf{W}^{out} from ridge regression

THIS WORKS!

Testing: another set of squeezed thermal states

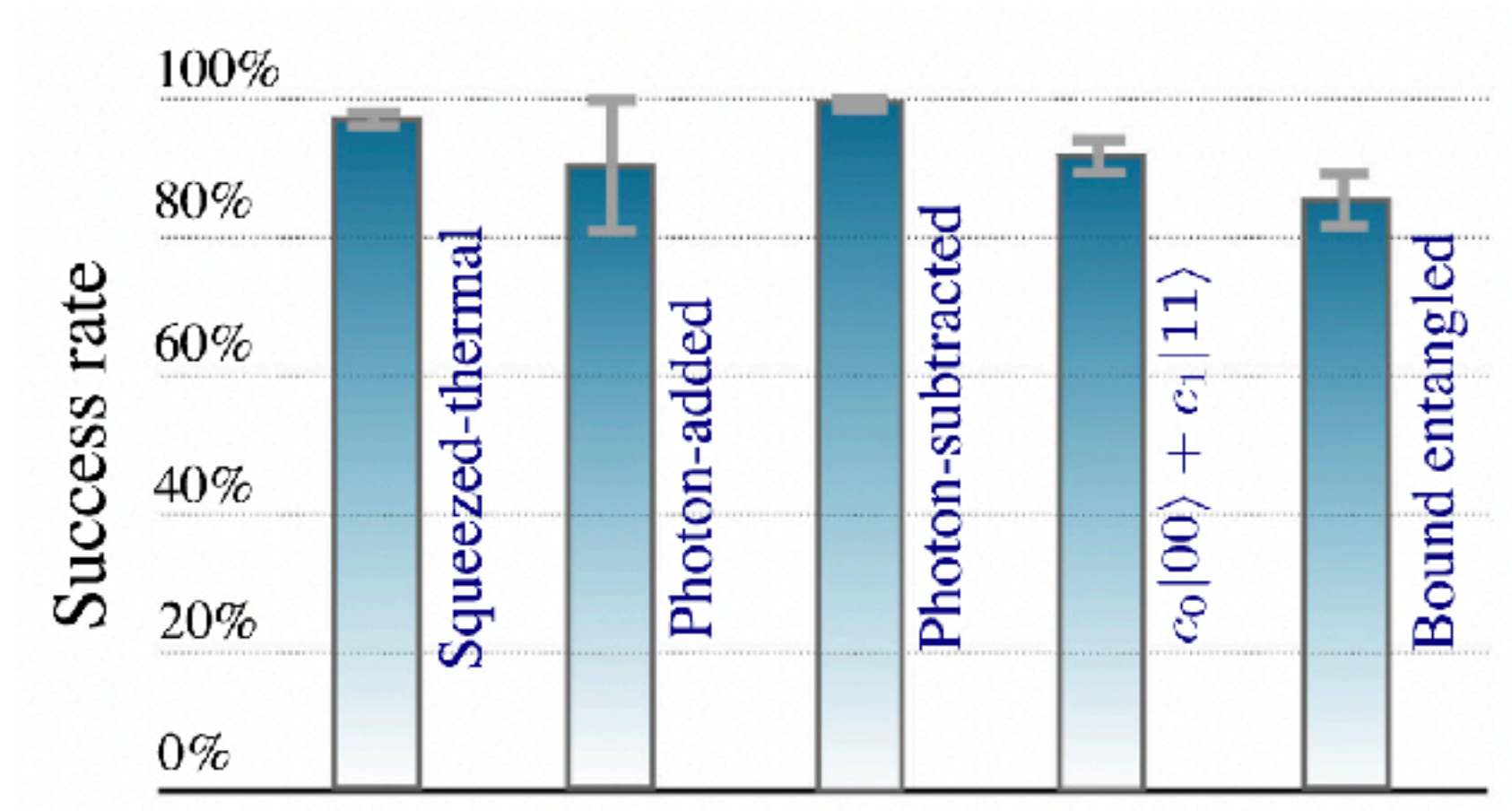
We use the trained Wout and say that input is entangled if upper entry of the output is larger than the lower entry.



Tested with 100 states, mistake in ~ 4 states.

AND WORKS UNEXPECTEDLY WELL...

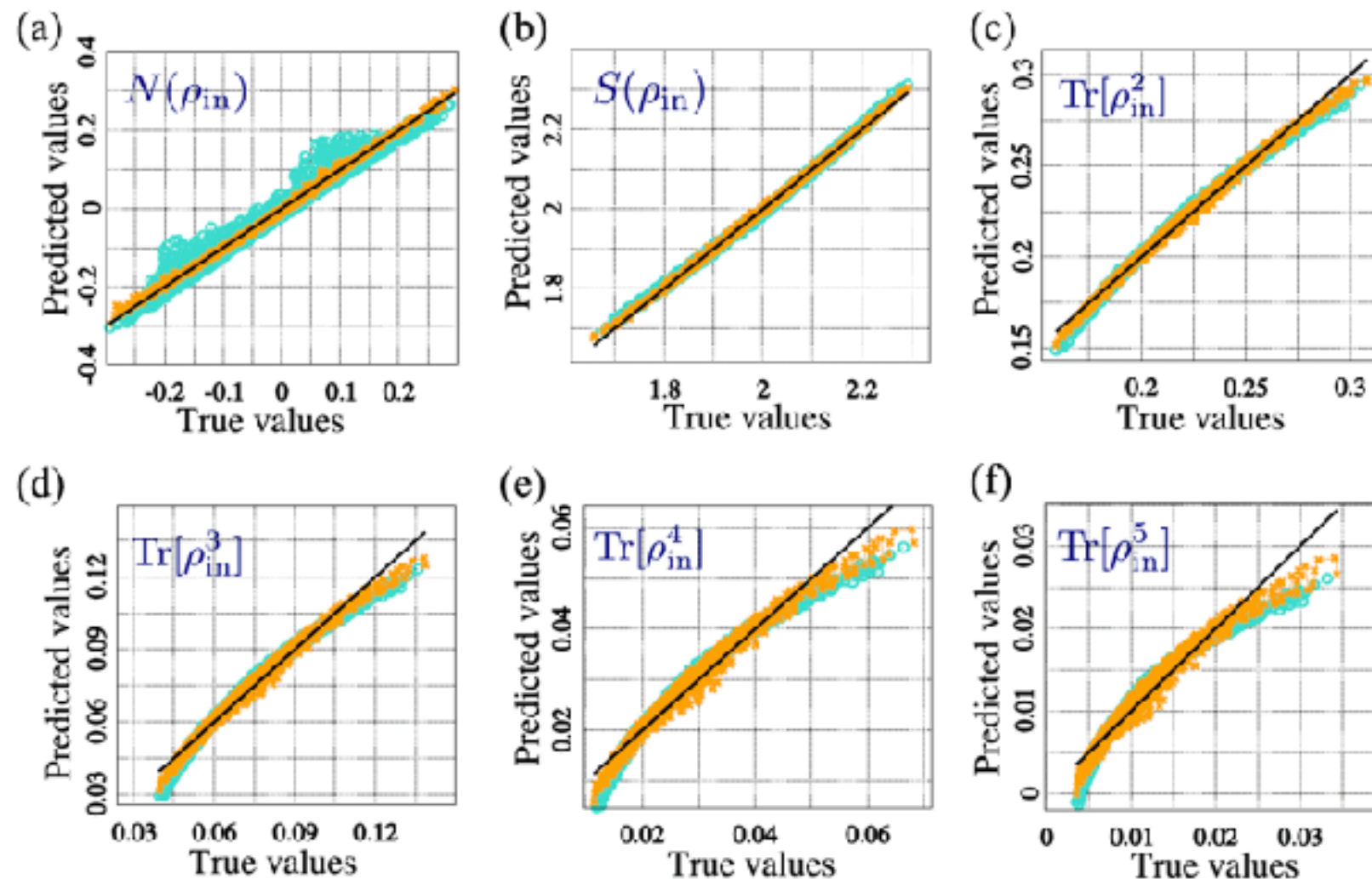
Testing with other classes of states



THE NON-LINEAR FUNCTIONS OF THE INPUT

Estimating non-linear functions of input state

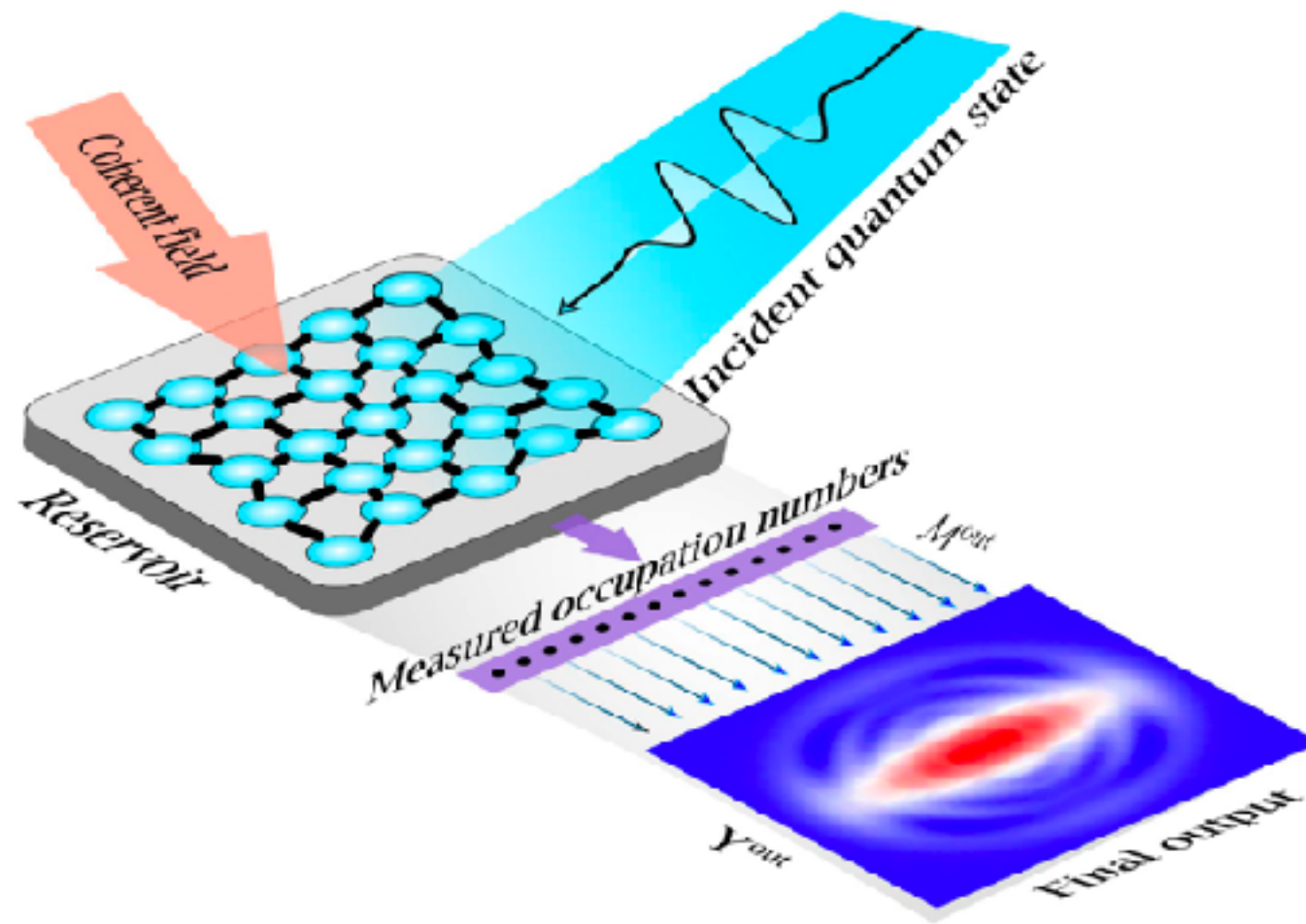
By having higher-dimensional output we may simultaneously estimate a number of parameters. Of course we need to train first, but only once!



Trained and tested on squeezed thermal states

Reservoir size: 2 (blue) and 4 (orange)

QUANTUM STATE TOMOGRAPHY



S. Ghosh et al. IEEE TNNLS 32, 3148 (2021)

WHAT IS LEARNING DOING?

It is solving a system of linear equations.

Any density matrix can be written as sum of D^2 linearly independent states:

$$\rho_{\text{in}} = \sum_i \alpha_i \rho_i, \quad \text{with} \quad \sum_i \alpha_i = 1$$

Training solves the following set of D^2 equations for D^2 random input states:

$$\mathcal{M}^{\text{out}} \vec{n}_i + \vec{m} = \vec{\rho}_i$$

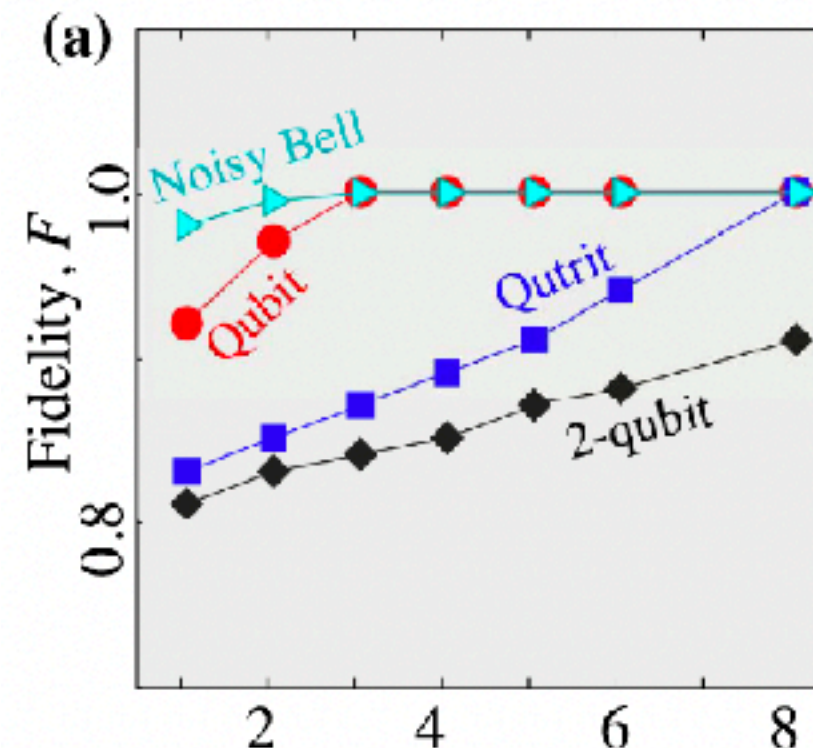
Since the occupation measurement is effectively a POVM on the input state, it is linear in this state and we have:

$$\vec{n} = \sum_i \alpha_i \vec{n}_i \quad \longrightarrow \quad \mathcal{M}^{\text{out}} \vec{n} + \vec{m} = \vec{\rho}_{\text{in}}$$

QRP is using a linear map

WE NEED D^2-I RESERVOIR NODES

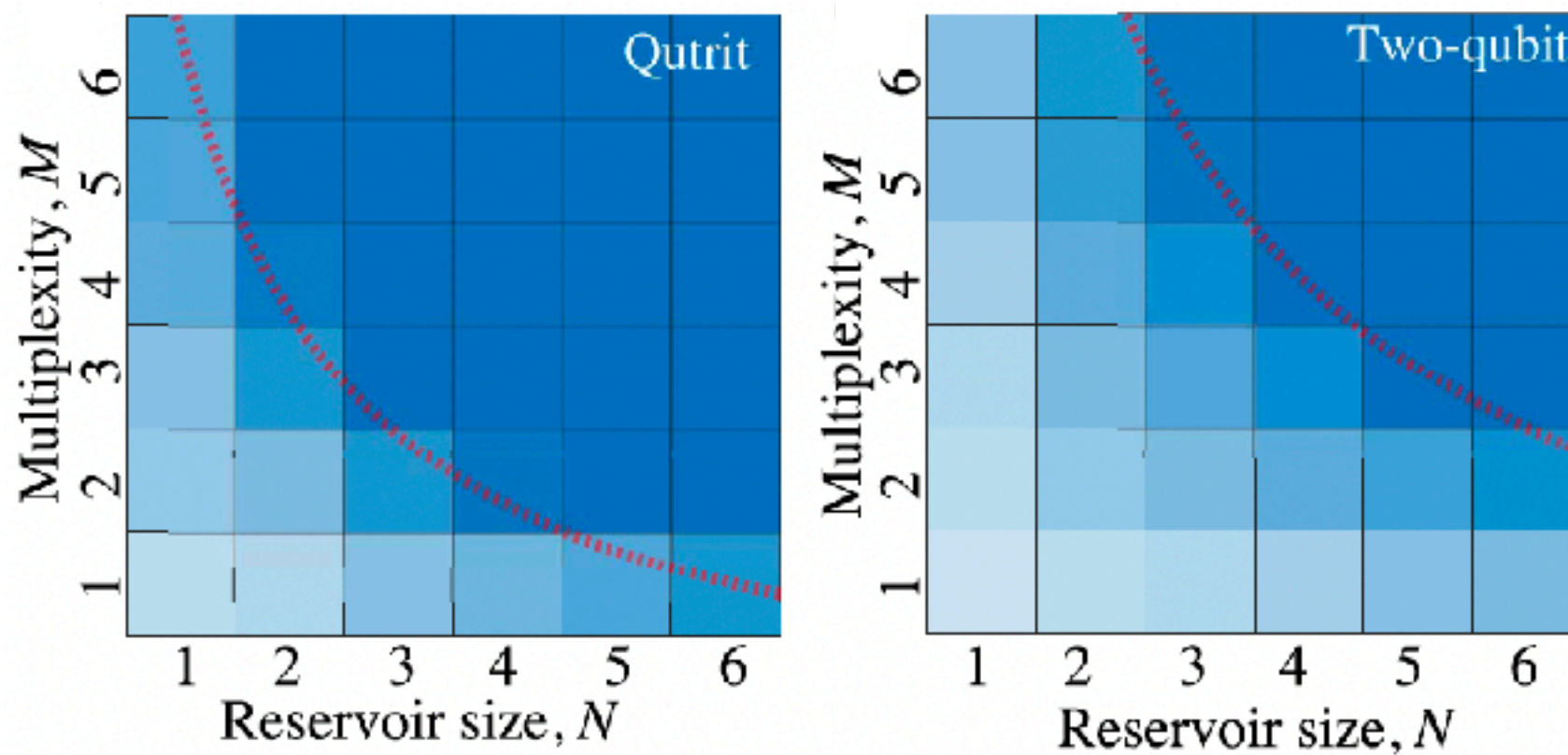
This is the number of independent real parameters



TIME MULTIPLEXING

D is exponential in the number of input systems.

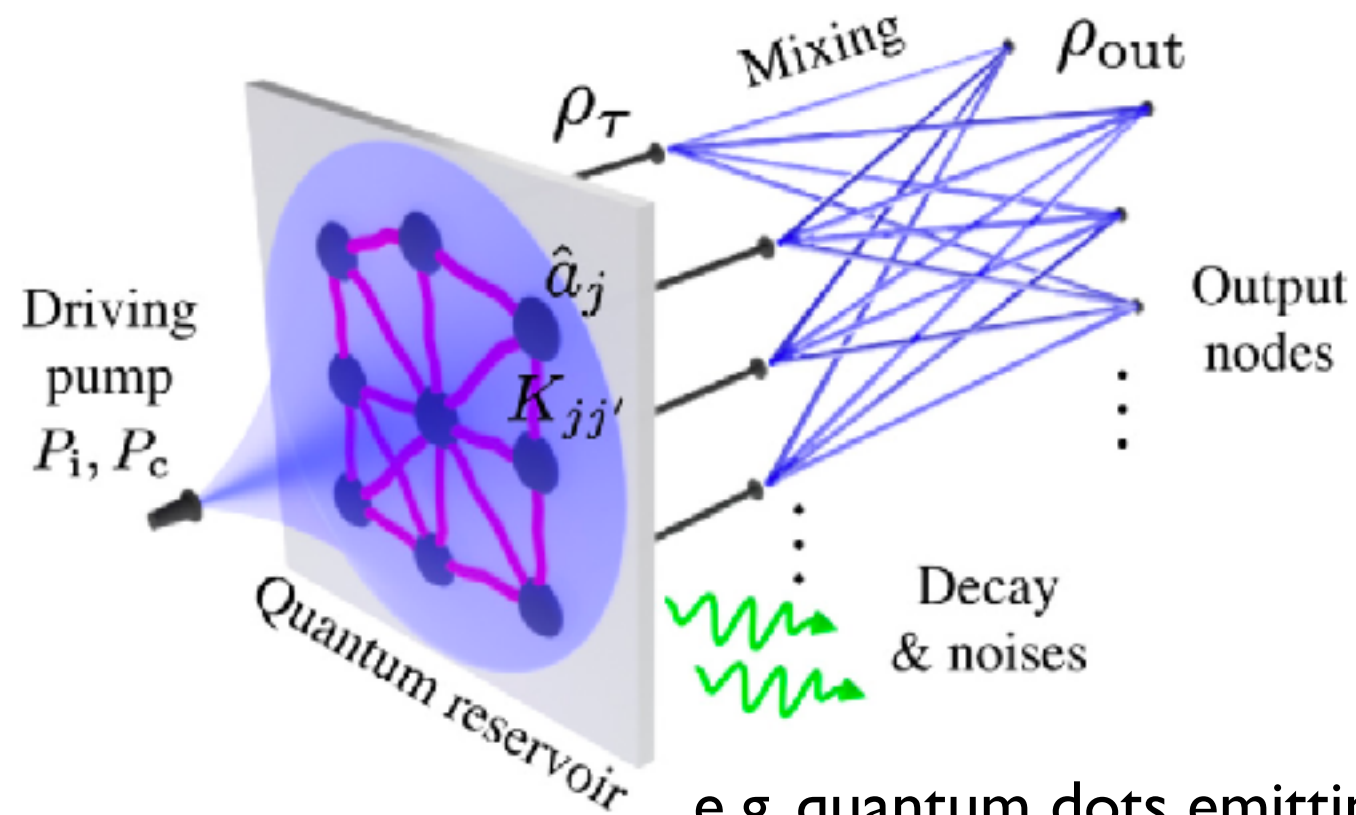
Yet, instead of exponentiating the number of reservoir nodes, we can measure them many times...



Dashed line shows relation $NM = D^2 - 1$

CLASSICAL INPUT — QUANTUM OUTPUT

From simple input to complex output



e.g. quantum dots emitting photons
 ρ_τ is the steady state

S. Ghosh et al. Phys. Rev. Lett. 123, 260404 (2019)

T. Krisnanda et al. Neu. Net. 136, 141 (2021)

THE MODEL

The reservoir and coherent pump: $\hat{H} = \sum_j E_j \hat{a}_j^\dagger \hat{a}_j + \sum_{\langle jj' \rangle} K_{jj'} (\hat{a}_j^\dagger \hat{a}_{j'} + \hat{a}_{j'}^\dagger \hat{a}_j) + \sum_j (P_{C,j} \hat{a}_j^\dagger + P_{C,j}^* \hat{a}_j),$

Decay and incoherent pump: $\dot{\rho} \equiv \mathcal{L}[\rho] = -\frac{i}{\hbar}(\hat{H}\rho - \rho\hat{H}) + \sum_j \frac{\gamma_j}{\hbar} L[\rho, \hat{a}_j] + \frac{P_{I,j}}{\hbar} L[\rho, \hat{a}_j^\dagger],$

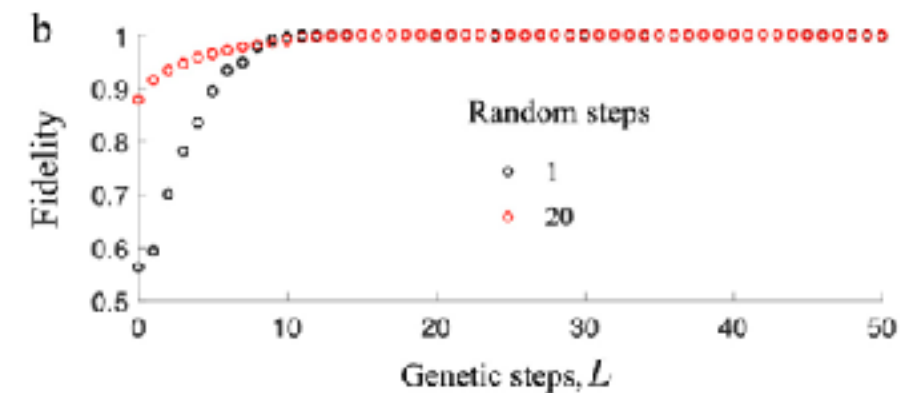
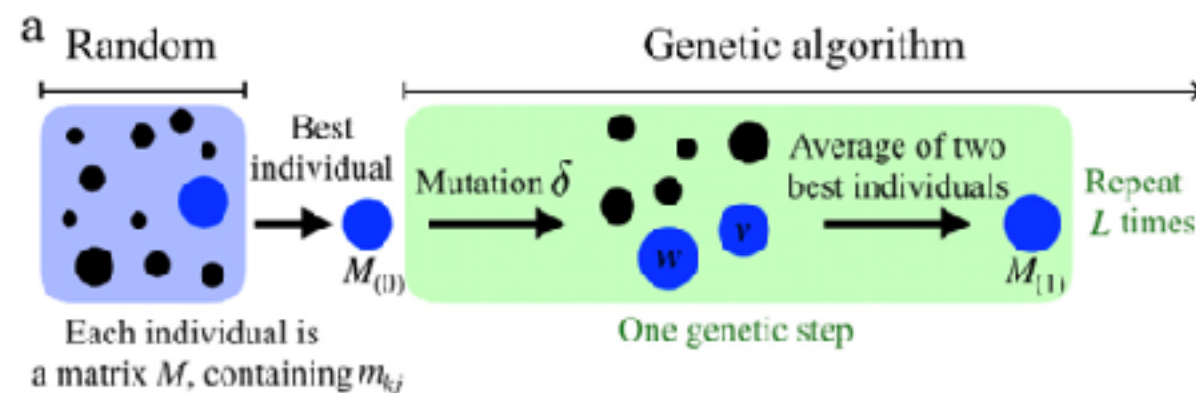
Noise: $\rho(t + \Delta t) = M_{dp} M_{ds} [\rho(t) + \Delta t \mathcal{L}[\rho(t)]]$

Linear mixing of the emissions:

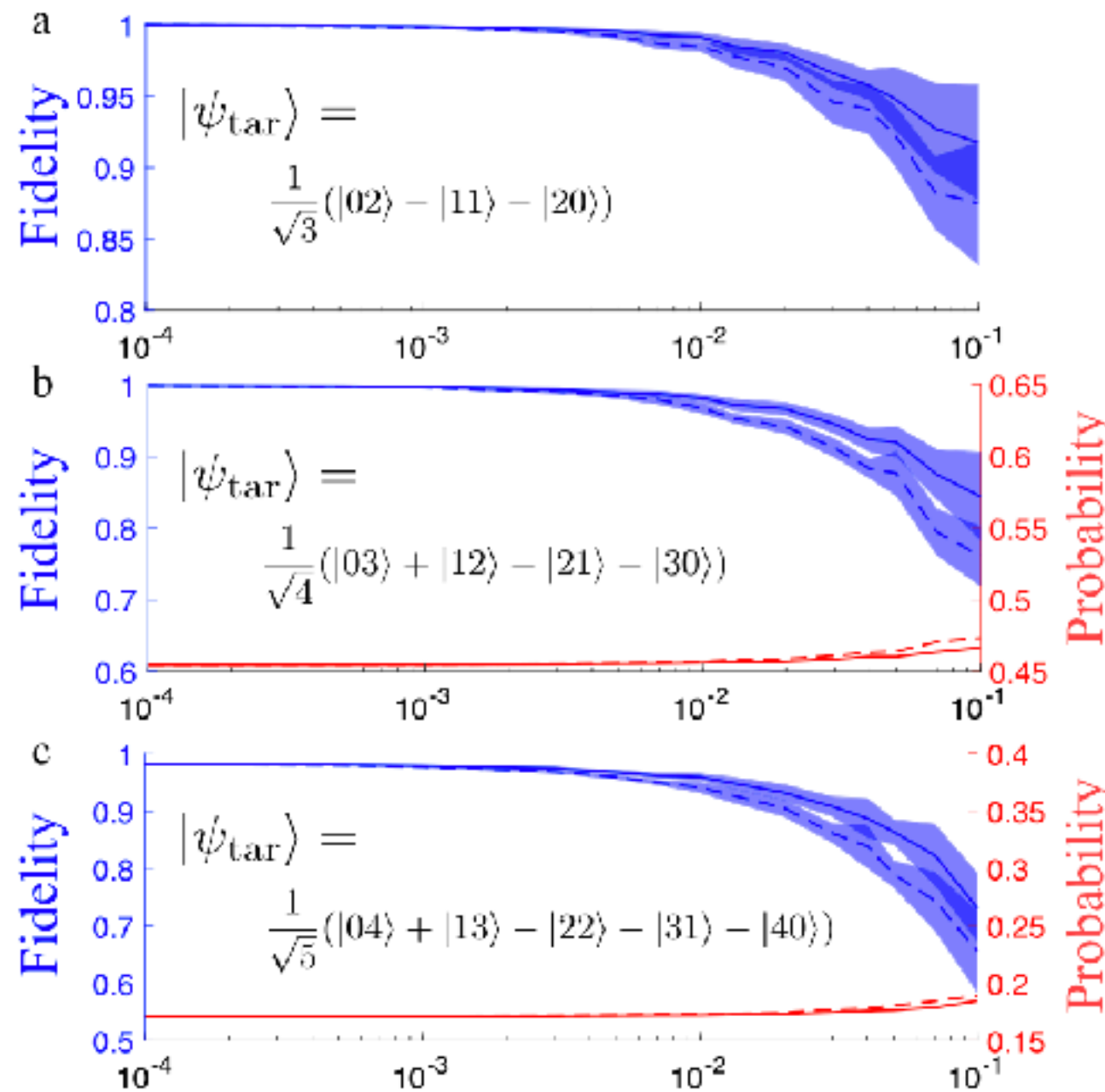
$$\hat{C}_k = \sum_j m_{kj} \hat{B}_j$$

final output modes
photonic modes

weights to be trained (by maximizing fidelity)



PREPARATION OF MAXIMALLY ENTANGLED STATES IN HIGHER D



reservoir with 2 nodes

reservoir with 4 nodes:
2 post-selected

reservoir with 4 nodes:
2 post-selected

highest decay rate $\rightarrow \Gamma/P$ \leftarrow each node pumped with the same strength

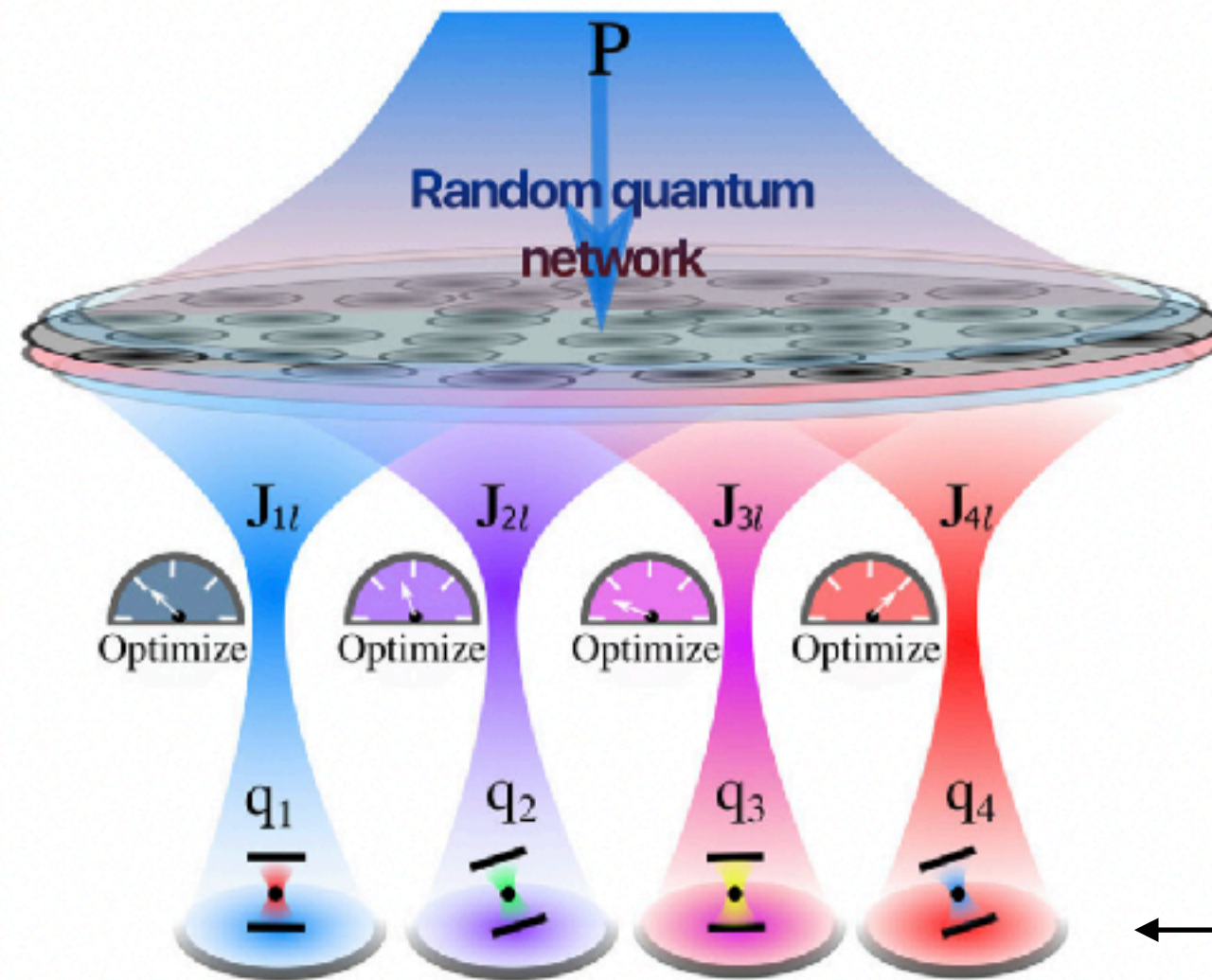
without noise
—
with noise
- - -

PREPARATION OF OTHER STATES

- NOON states — quantum metrology
- W states — multipartite entanglement
- Cluster states — universal quantum computing
- Single-photon states — quantum technologies

QUANTUM INPUT — QUANTUM OUTPUT

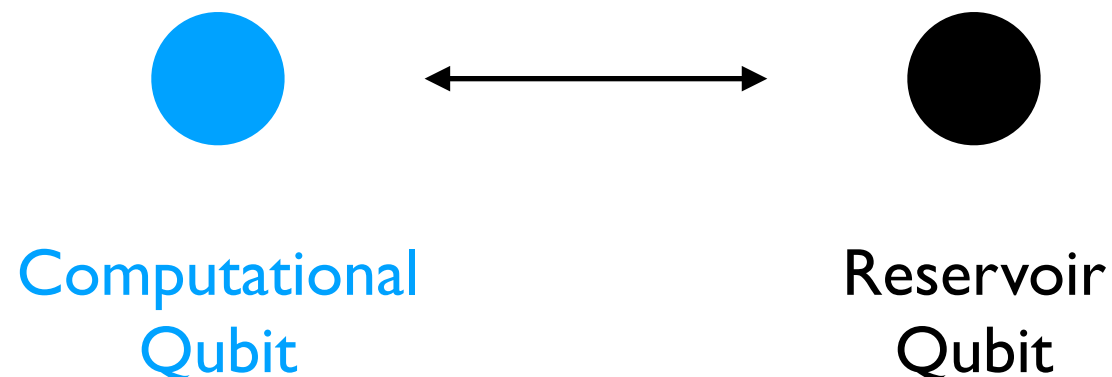
TOWARDS QUANTUM COMPUTING



← Computational Qubits

THE MODEL: SINGLE QUBIT OPERATIONS

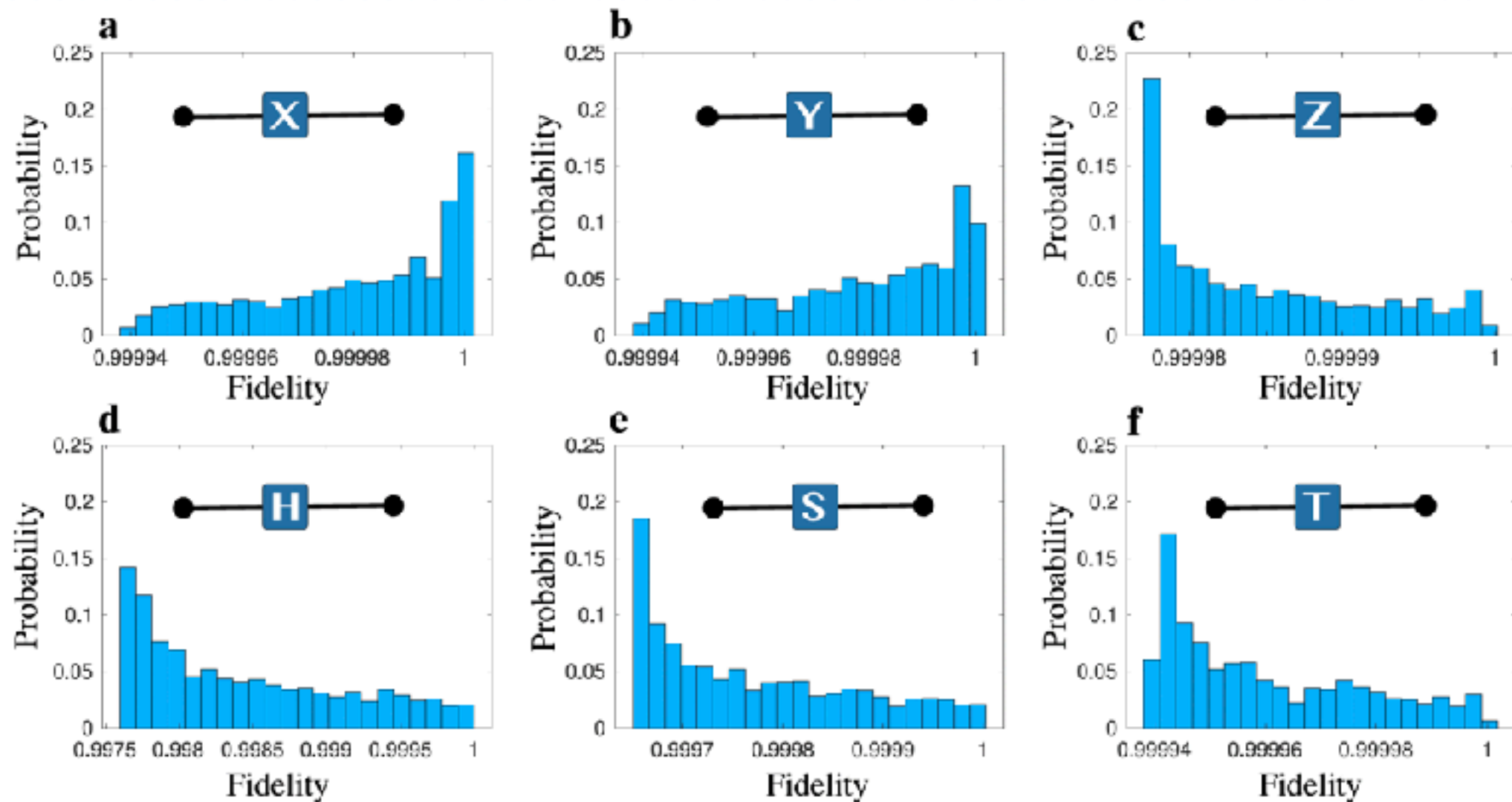
In toy examples learning can be done (almost) analytically



1. Compute Kraus operators on the computational qubit
2. Use closed form expression for gate fidelity
3. Maximise on a computer

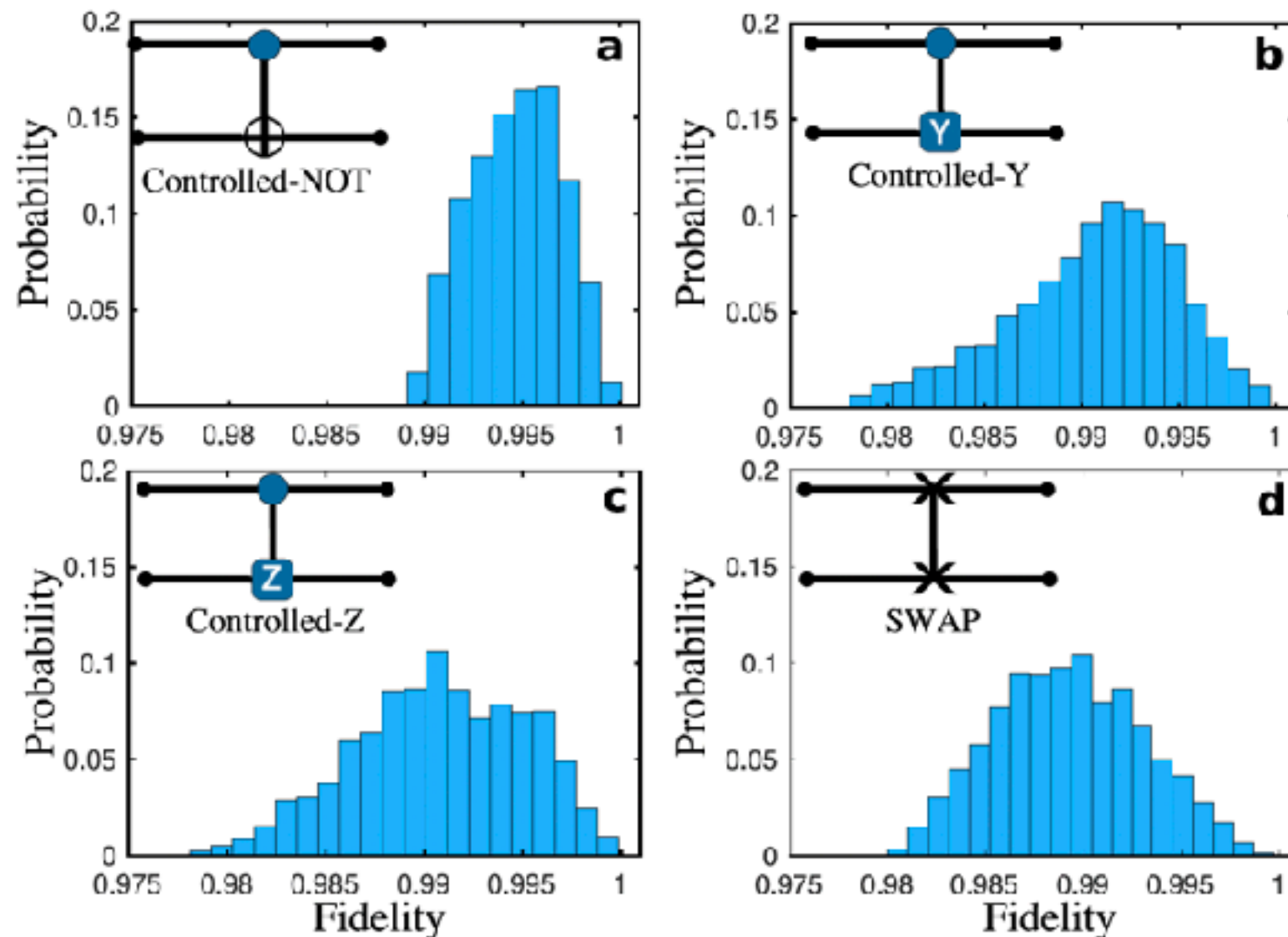
$$\begin{aligned} F &= \int_{S^{2n-1}} \langle \psi | U_0^\dagger \mathcal{G}(|\psi\rangle\langle\psi|) U_0 | \psi \rangle dV \\ &= \sum_k \int_{S^{2n-1}} |\langle \psi | M_k | \psi \rangle|^2 dV \\ &= \frac{1}{n(n+1)} \left\{ \text{Tr} \left(\sum_k M_k^\dagger M_k \right) + \sum_k |\text{Tr}(M_k)|^2 \right\} \end{aligned}$$

THIS WORKS WELL



Most of the gates on average above 0.999

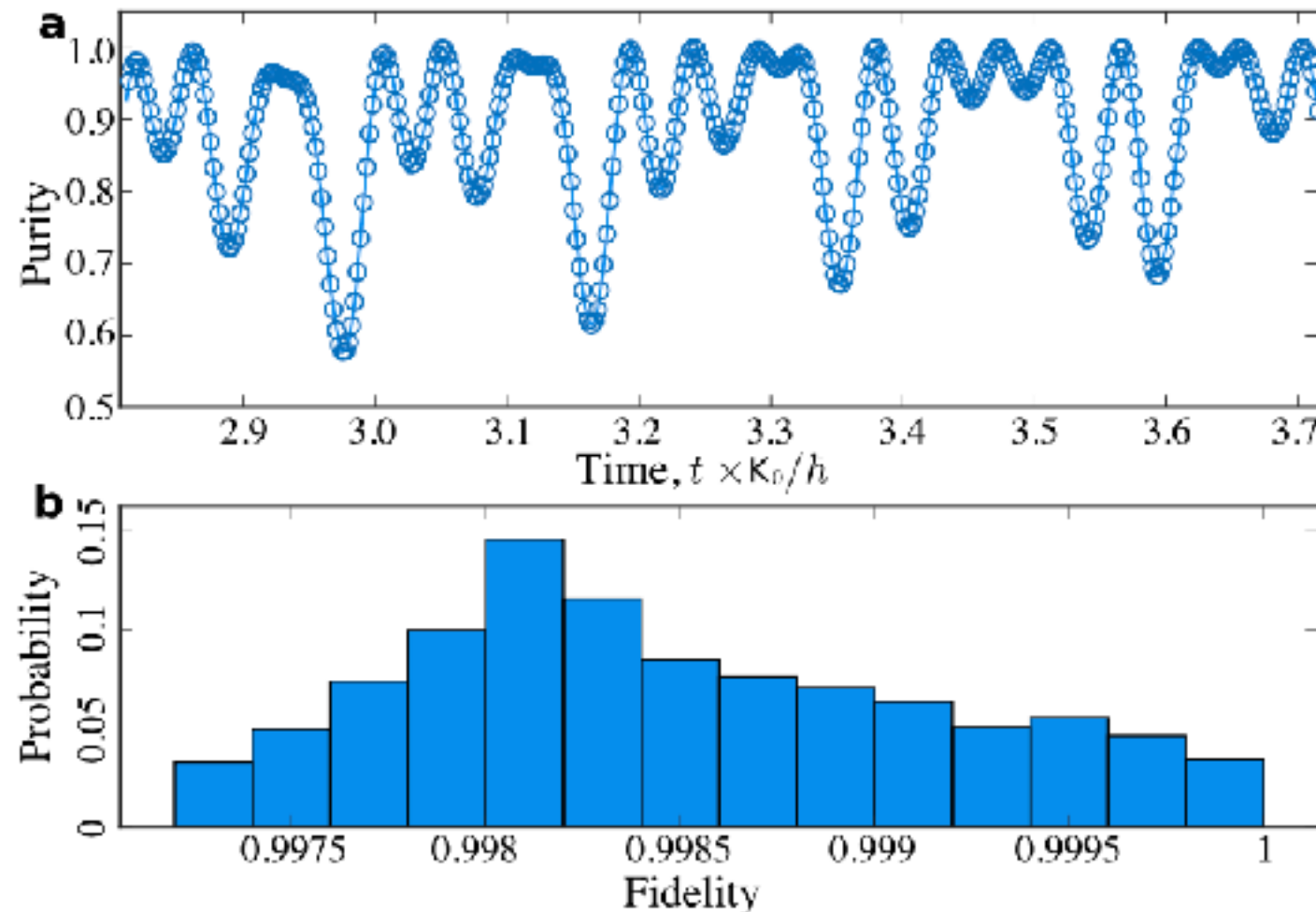
TWO-QUBIT GATES



Reservoir of 6 nodes. Fidelity of 2000 random states.
(10 random pure state for training — max of average fidelity)

Altogether this provides a universal set of gates.

TRAINING OF MAPS



Purity of a single qubit coupled to a single reservoir node

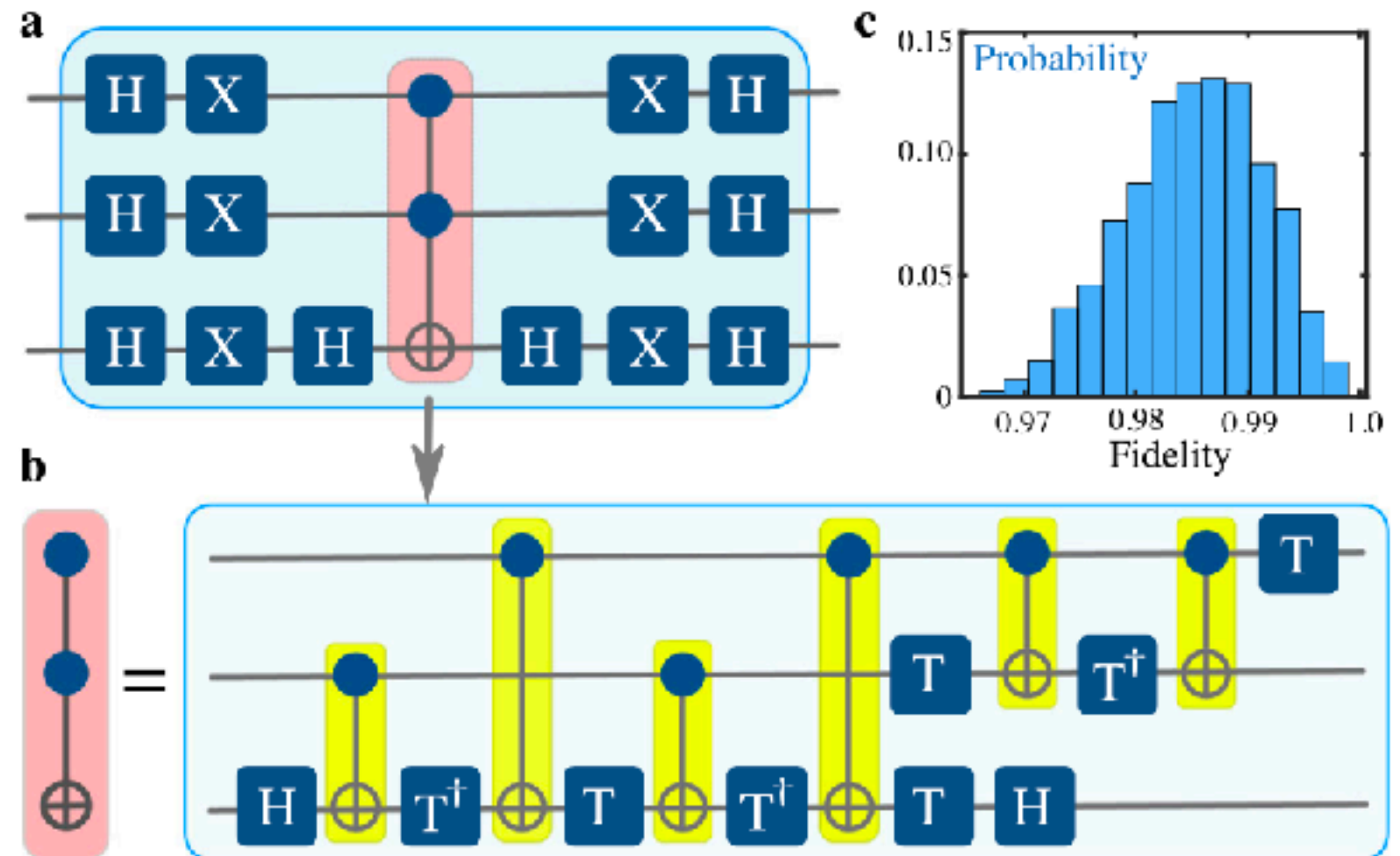
Fidelity between QRP operation and the map induced by the master equation:

$$\hbar \dot{\rho} = (\gamma/2)(2\sigma^- \rho \sigma^+ - \sigma^+ \sigma^- \rho - \rho \sigma^+ \sigma^-)$$

COMPRESSING QUANTUM CIRCUITS: TRAINING OF MULTIQUBIT UNITARIES

Three-qubit Grover's unitary

In conventional circuit model is requires 29 gates

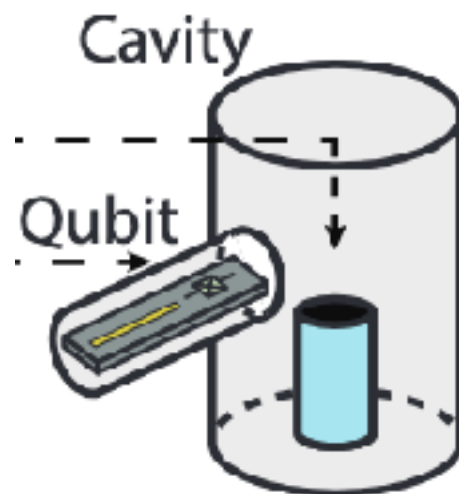


QRP trained with 10 random states gives mean $F > 0.98$

EXPERIMENT



Bosonic Circuit QED setup



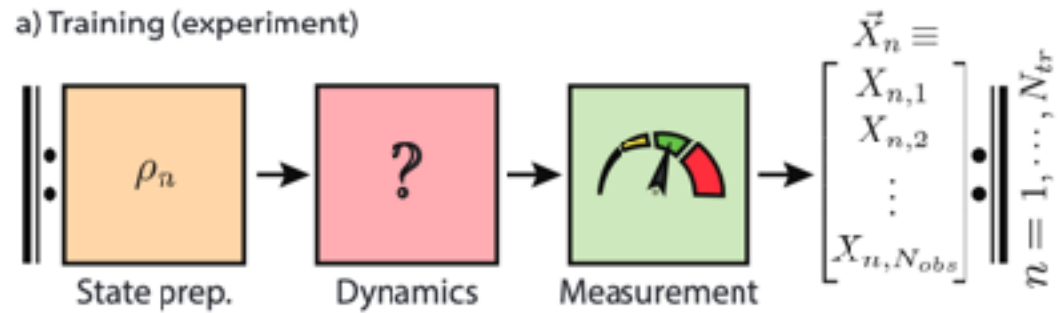
Cavity mode — reservoir
Qubit — readout device

$$\begin{aligned} \hat{H}_0/\hbar = & \sum_{k=q,c,r} \omega_k \hat{k}^\dagger \hat{k} - \frac{\chi_{kk}}{2} \hat{k}^\dagger \hat{k}^\dagger \hat{k} \hat{k} \\ & - \chi_{cq} \hat{c}^\dagger \hat{c} \hat{q}^\dagger \hat{q} - \chi_{qr} \hat{q}^\dagger \hat{q} \hat{r}^\dagger \hat{r} - \chi_{cr} \hat{c}^\dagger \hat{c} \hat{r}^\dagger \hat{r} \\ & - \chi'_{cq} \hat{c}^\dagger \hat{c}^\dagger \hat{c} \hat{c} \hat{q}^\dagger \hat{q}, \end{aligned}$$

$$\begin{aligned} \hat{H}_d/\hbar = & \epsilon_q(t) \hat{q} e^{i\omega_{dq}t} + \epsilon_q^*(t) \hat{q}^\dagger e^{-i\omega_{dq}t} \\ & + \epsilon_c(t) \hat{c} e^{i\omega_{dc}t} + \epsilon_c^*(t) \hat{c}^\dagger e^{-i\omega_{dc}t} \end{aligned}$$

THE PROTOCOL FOR PROCESS AND STATE TOMOGRAPHY

a) Training (experiment)

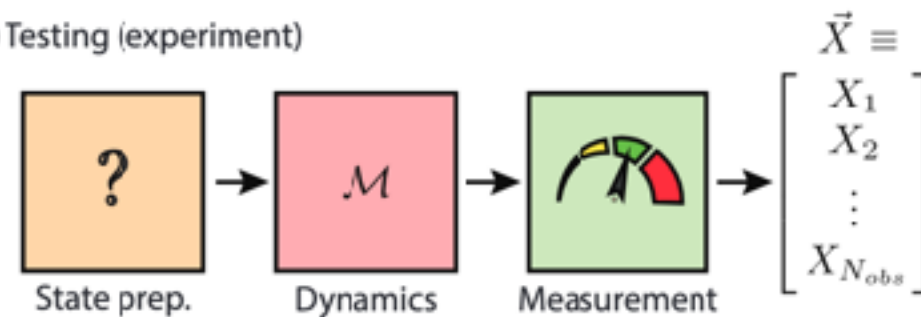


Process tomography

b) Learning the dynamics



c) Testing (experiment)



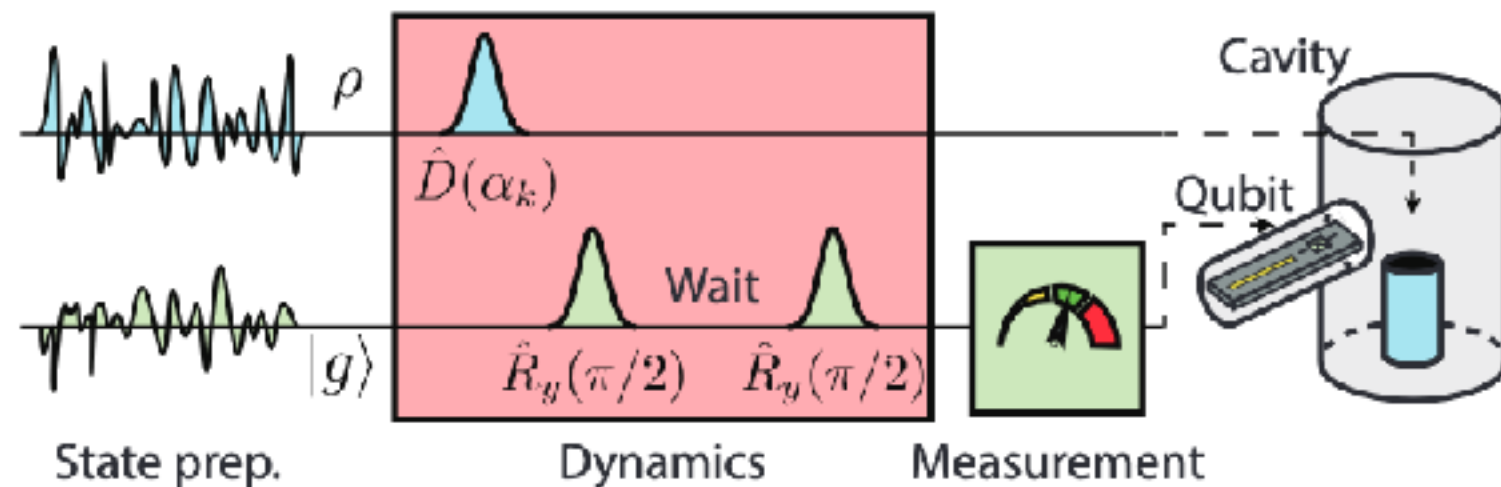
State tomography

d) Reconstructing the state



For reservoir dimensions 2 to 6.

PROCESS TOMOGRAPHY: LEARNING OF THE PROCESS MATRIX



Parity measurement — noisy translation from the reservoir to the qubit

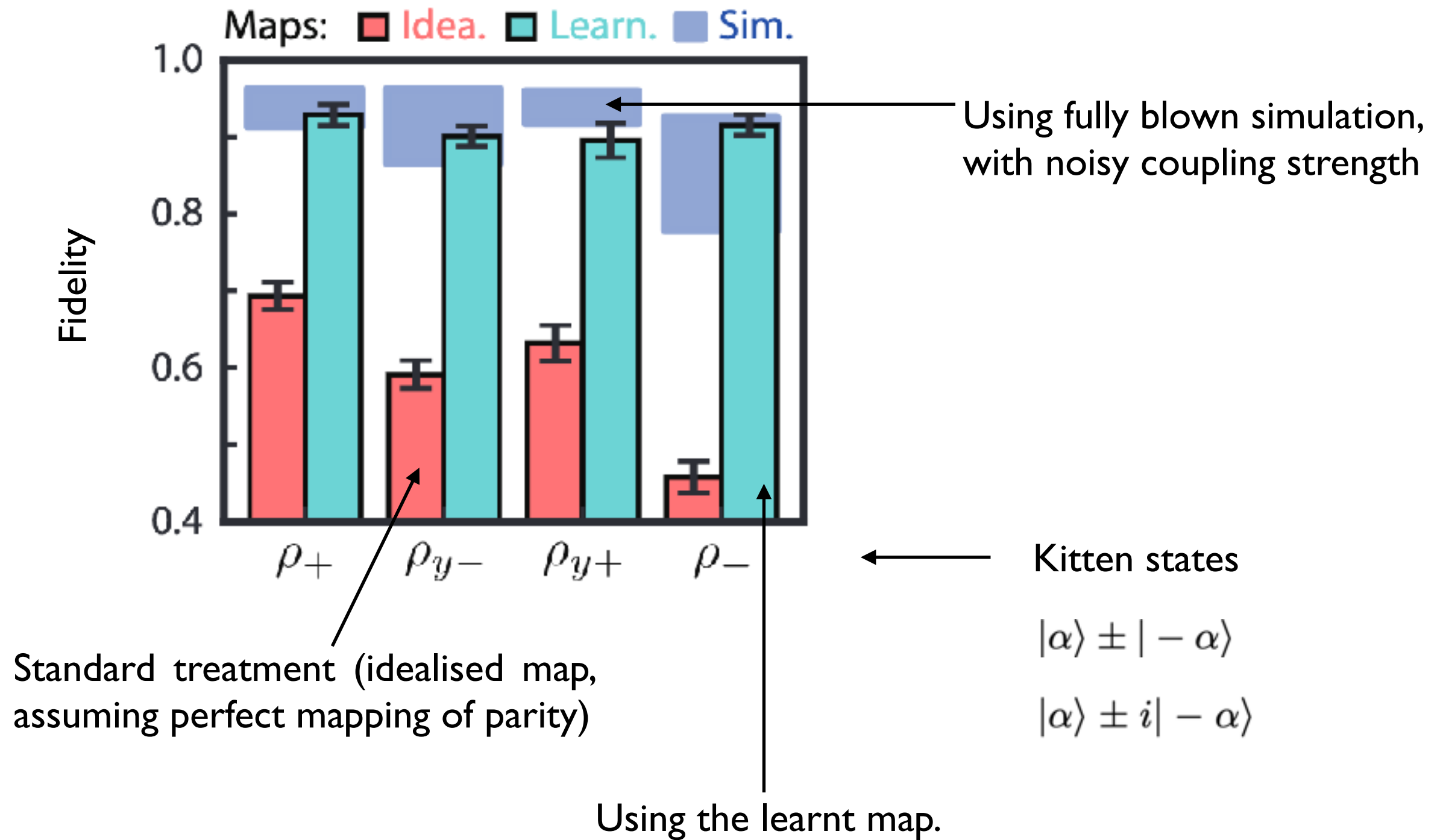
D^2 input states (independently verified to have average fidelity ~ 0.97):

D Fock states ($|0\rangle, |1\rangle, \dots, |D-1\rangle$)

$D^2 - D$ of their superpositions $(|l\rangle + e^{i\Phi}|m\rangle)/\sqrt{2}$ $l < m = 0, 1, \dots, D-1$ and $\Phi \in \{0, \pi/2\}$

For every input state the parity is measured after D^2-1 different displacements, 1000 times for each, to estimate the mean. Then ridge regression returns the map.

TESTING RESULTS



Elimination of systematic errors

In this setup it is the noisy parity mapping

Economic in terms of resources

For $D = 6$, we trained with 36 states and used a reservoir of ~ 2.5 qubits

Classical neural networks have already been used for this problem.

They utilised ~ 700 neurons and 7000 training states.

CONCLUSIONS

QRP: live long and prosper!



INTERSPECIES EDUCATION

