

Time-Resolved Shadow Tomography of Open Quantum Systems

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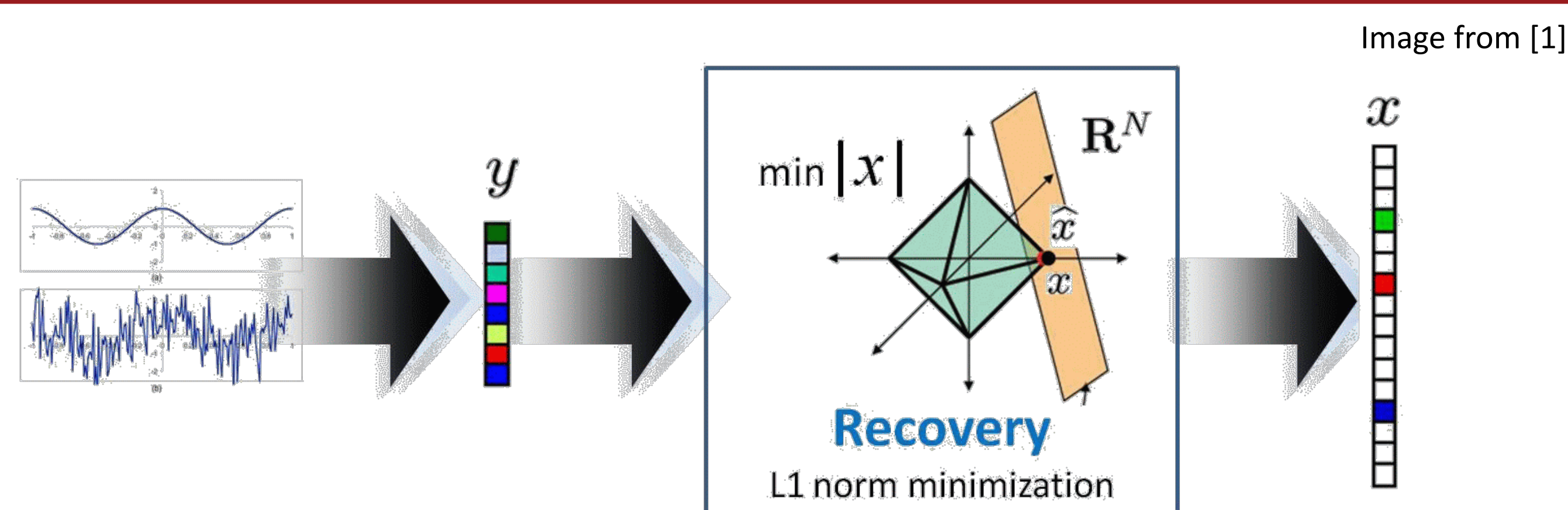
Motivation for Open Quantum Systems (OQS)

- ❖ The time evolution of an expectation value in an OQS is

$$S(t) = \langle O, \rho(t) \rangle = \text{Tr}(O\rho(t)) = \text{Tr}(Oe^{\mathcal{L}t}(\rho_0)) \\ = \langle \langle O | e^{\mathcal{L}t} | \rho_0 \rangle \rangle = \sum_k e^{\lambda_k t} \langle \langle O | v_k \rangle \rangle \langle \langle v_k | \rho \rangle \rangle$$

- ❖ How efficiently can we estimate $S(t)$ and extract some of the λ_k s?
- ❖ Applications include spectroscopy, device characterization, algorithm verification, etc.

Prior Work – Compressed Sensing (CS)



- ❖ CS poses that a signal $x \in \mathcal{R}^n$, the measurement $y \in \mathcal{R}^m$ of x , and the sparse representation $\alpha \in \mathcal{R}^d$ of x , are related via

$$y = \Phi x = \Phi \mathcal{D} \alpha \equiv \Psi \alpha$$

where $\mathcal{D} \in \mathcal{R}^{n \times d}$ is the dictionary matrix, $\Phi \in \mathcal{R}^{m \times n}$ is the measurement matrix, and we are given that α is k -sparse

- ❖ Recovery of α (or x) from y is possible if $\Psi \in \mathcal{C}^{m \times d}$ obeys the restricted isometry property (RIP) of order k and some constant δ_K , which means that for every k -sparse vector $\alpha \in \mathcal{C}^d$, we have

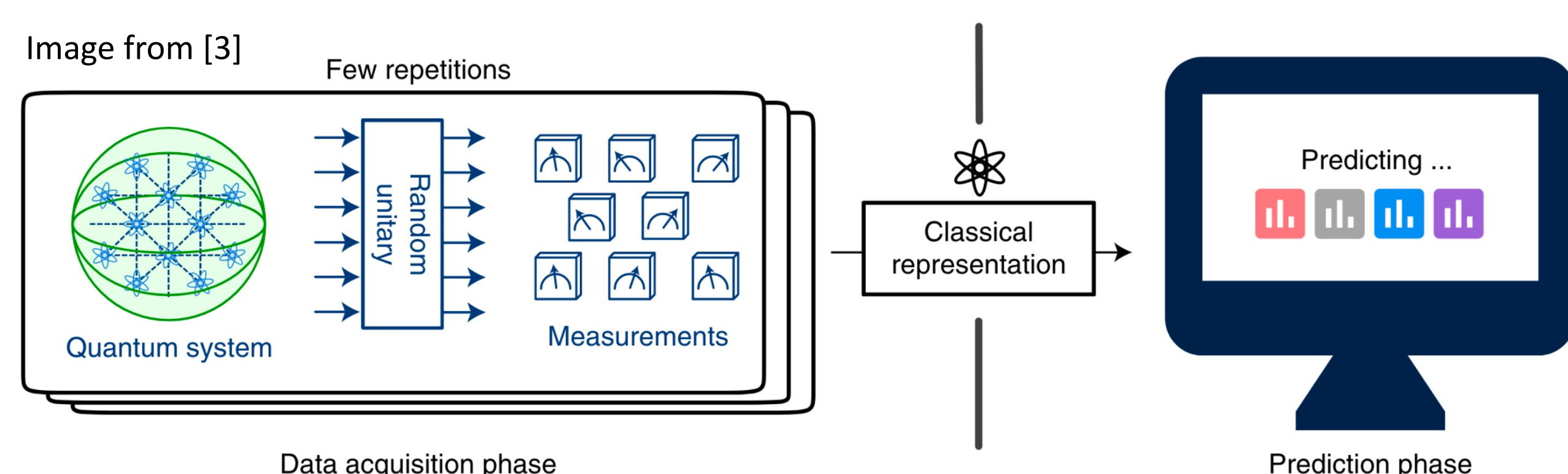
$$(1 - \delta_k) \|\alpha\|_2^2 \leq \|\Psi \alpha\|_2^2 \leq (1 + \delta_k) \|\alpha\|_2^2$$

- ❖ If x_k is the restriction of x to its k largest values (in magnitude) and $y = Ax + e$ is a noisy measurement of x obeying $\|e\|_2 \leq \epsilon$, then^[2] the solution x^* to the l_1 -minimization

$$\min \|x\|_1 \text{ s.t. } \|Ax - y\|_2 \leq \epsilon$$

- ❖ obeys $\|x^* - x\|_2 \leq C_{1k}\epsilon + C_{2k} \cdot \|x^* - x\|_1 / \sqrt{k}$
If the signal is exactly k -sparse and noiseless, then this works perfectly

Prior Work – Shadow Tomography (ST)



- ❖ ST^[3] is an efficient method for estimating an arbitrary set of expectation values from a classical dataset of shadows which approximate a given quantum state
- ❖ ST promises that given $N \cdot K$ shadows of ρ , we can estimate a set of M expectation values $\text{Tr}(\rho O_i) \equiv o_i$ such that

$$|\hat{o}_i - o_i| \leq \epsilon \text{ if } K = 2 \log(2M/\delta), N = \frac{34}{\epsilon^2} \cdot 4^w$$

where O_i is a Pauli string of max weight w , δ is the probability that at least one error exceeds ϵ , and each estimate is produced via median-of-means (MoM) over K sets of N shadows each.

- ❖ Other than its size and max weight, the shadow dataset is independent of the observable set $\{O_i\}$

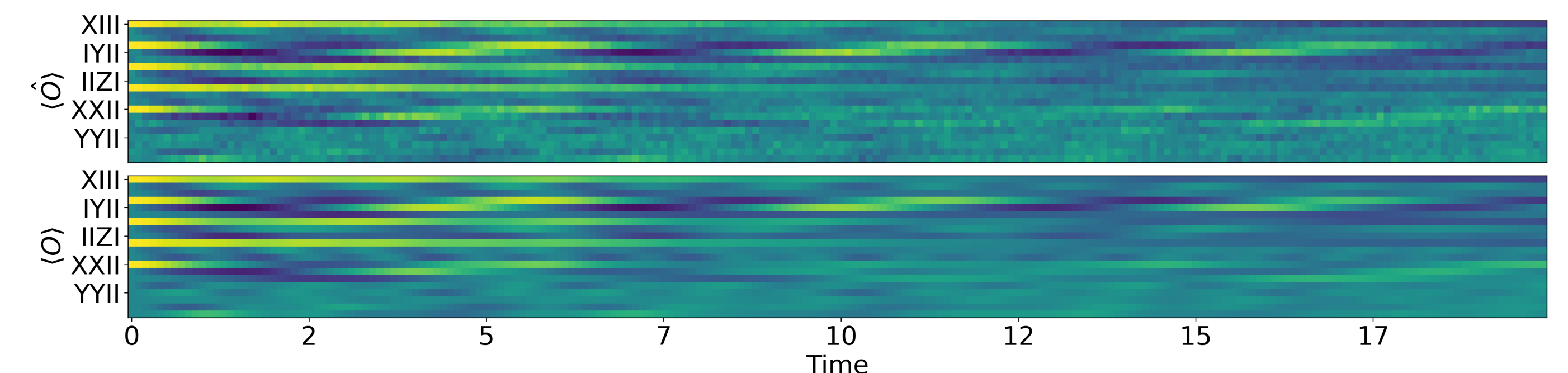
Data processing pipeline

- ❖ For time-domain signals of length n which are k -sparse in frequency space, it is known that for a unitary matrix $U \in \mathcal{C}^{n \times n}$ and a sufficiently small $\delta_k > 0$, the following holds^[4]:

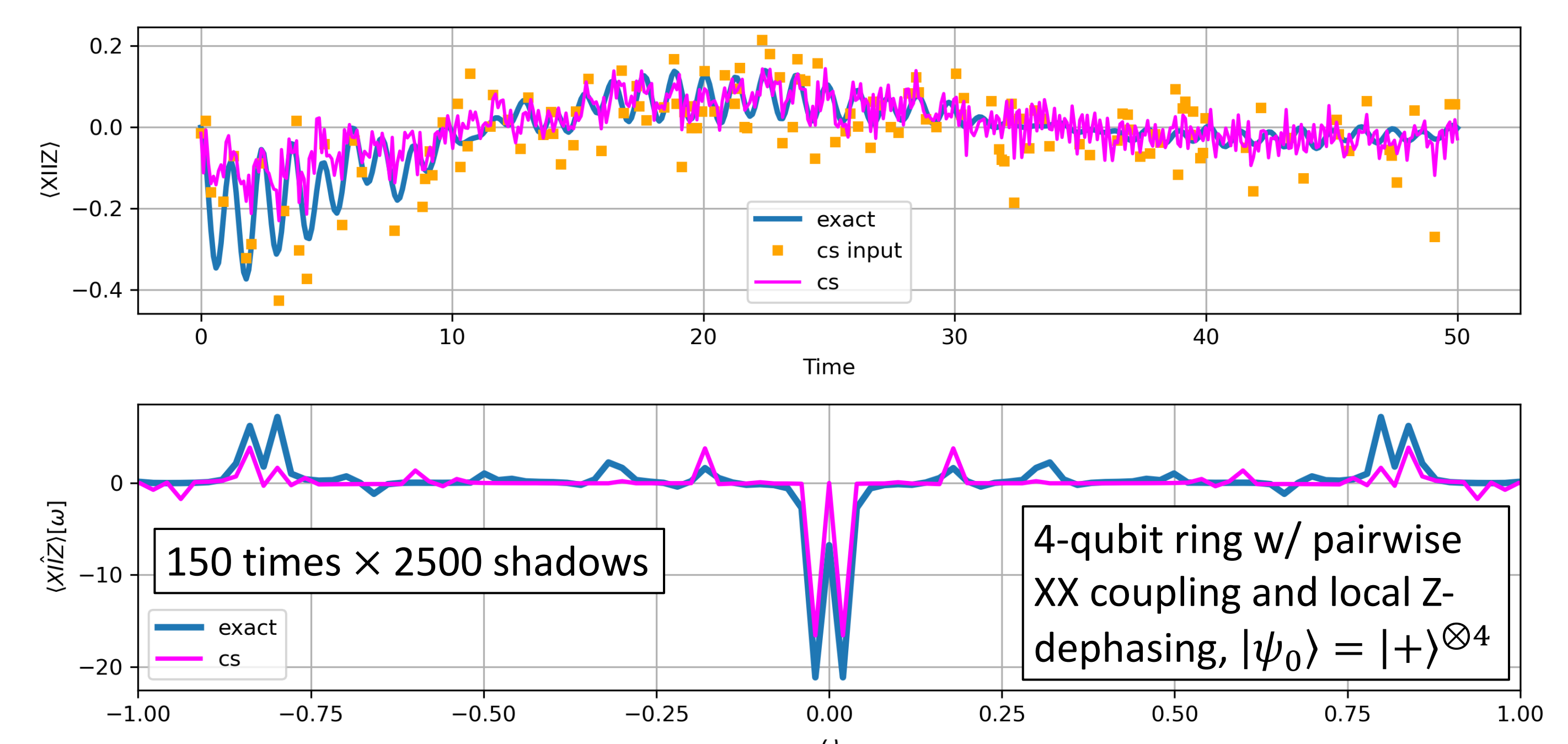
For some $q = O(\delta_k^{-4} \cdot k \cdot \log^2(k/\delta_k) \cdot \log n)$, let $\Psi \in \mathcal{C}^{q \times n}$ be a matrix whose q rows are chosen uniformly and independently from the rows of U . Then, with probability $1 - 2\exp[-\Omega(\delta_k^{-2} \cdot \log n \cdot \log(k/\delta_k))]$, the matrix Ψ satisfies the restricted isometry property of order k with constant δ_k

- ❖ Thus, with $\mathcal{D} = U$ (the $n \times n$ DFT transform), and Φ a subset of the rows of the identity matrix, we can compose them to obtain a subsampled Fourier matrix $\Psi = \Phi U$ which obeys the RIP

- 1) Perform ST at random times



- 2) Solve the CS problem with a subsampled Fourier sensing matrix



- ❖ Components beyond the Nyquist limit are recoverable
- ❖ Shot noise from ST is mitigated by enforcing sparsity
- ❖ Some weak components are missed

Summary & next steps

- ❖ Total number of shots needed to reconstruct all M signals of length n which are at most k -sparse

$$N_{tot} \sim O(k \log M \log^2 k \log n / \epsilon^2)$$

where the l_2 -reconstruction error is bounded by $O(\epsilon \sqrt{n})$ for decay-less signals of weight- w Pauli strings

- ❖ Use a harmonic inversion algorithm to fit the reconstructed signal to a sum of decaying sinusoids to extract the evolution parameters, and quantify the effect of shot noise from ST on these estimates^[5]
- ❖ Combine the various observable signals in a clever way to process more components in parallel^[6]
- ❖ Can we upper bound the number of components λ_k given ρ_0 ? Are there better sensing matrices for weakly-decaying signals?

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