



Improving Classical Shadows with Grouping Strategies

Marçal Herraiz Bayó

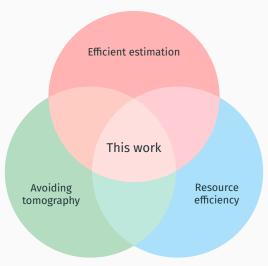
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Motivation

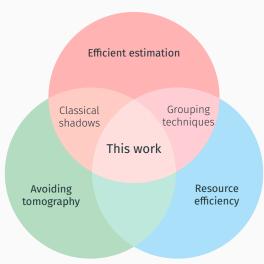
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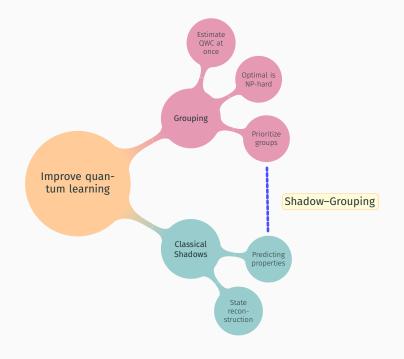
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Grouping via Qubit-wise Commutativity

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Two tensor-product observables

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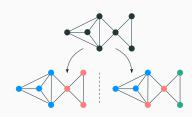
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Formulated as a Minimum Clique Cover (MCC) problem on a *graph*:

- Nodes: observables
- Edges: QWC relation
- Find minimal number of complete subgraphs (NP-hard [1])



Classical Shadows

Classical Shadows — Basics

Given a quantum state ρ :

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Procedure

Given a state ρ , choose an ensemble \mathcal{U} of unitaries. Then:

- 1. Randomly choose $U \in \mathcal{U}$ and evolve ρ by U. $\parallel \rho \longmapsto U \rho U^{\dagger}$
- 2. **Measure** rotated state in the comp. basis. $||b\rangle = |0110\dots 101\rangle$
- 3. **Undo** rotation and **store** result. **snapshot**

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If $\mathcal{U} = \{\text{single-qubit Clifford gates}\}\$, then step 2 is equivalent to measuring in a Pauli basis P_{U} .

Suppose we want to estimate a Pauli word $O = P_1 \otimes \cdots \otimes P_n$.

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$$\langle {\it O} \rangle = {\rm Tr}({\it O}\rho) = \prod_{j: \mathbb{I} \neq P_j = P_{\it U_j}} 3(1-2b_j).$$

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Calculating $\langle O \rangle$ reduces to:

- Count the matches between Pauli components of O and random Pauli bases in the shadow.
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Problem:

no matches \implies measurements are discarded! [3]

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Suppose we want to estimate the energy $\langle H \rangle$ of a state ρ , where

$$H = \sum_{i=1}^{M} h_i O^{(i)}, \quad h_i \in \mathbb{R}, \text{ and } O^{(i)} \text{ are Pauli words.}$$

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Adaptively choose measurement bases that QWC with multiple Hamiltonian terms [4, 5].

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Prioritize terms in *H* by weights:

weight
$$(O^{(i)})$$
 $\begin{cases} \uparrow \text{ with } |h_i|, \\ \downarrow \text{ with the number of times } O^{(i)} \end{cases}$ has been measured

Algorithm Sketch and Numerical

Demonstrations

Algorithm Sketch

Inputs: Hamiltonian decomposition $H = \sum_{i=1}^{M} h_i O^{(i)}$, measurement budget N.

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For each shot $k \in \{1, \dots, N\}$:

- 1. Compute weights based on $|h_i|$ and previous measurements.
- 2. Sort terms by decreasing weight.
- 3. Construct a measurement setting that QWC with as many terms as possible.
- 4. Measure and estimate.

Numerical Demonstrations

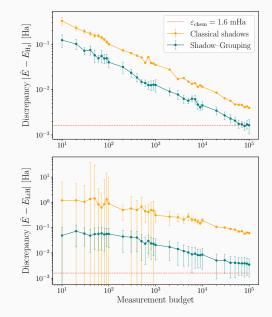
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Results

- Up to 18x improvement in accuracy for a fixed measurement budget.
- Reached chemical precision with orders of magnitude fewer measurements.



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All code and data are publicly available in a GitHub repository [8].

Acknowledgements

Acknowledgements

- Berta Casas, Sergi Masot, Dr. Bruno Juliá.
- Family, friends.

References

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References

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Backup Slides

Problem: more settings Q that QWC with $O^{(i)} \Longrightarrow$ better estimation of $\langle O^{(i)} \rangle$. But what about other terms?

Possible solution: prioritize QWC-settings .

Assign a weight to each term and update it after every shot.

Recall: $H = \sum_{i=1}^{M} h_i O^{(i)}$, with $O^{(i)} \in \mathcal{P}$.

Desirable properties of weight $(O^{(i)})$:

- 1. Should be **proportional** to $|h_i|$.
- 2. Should decrease if we have estimated $\langle O^{(i)} \rangle$ many times. In [4], authors propose:

weight
$$(O^{(i)}) := |h_i| \frac{\sqrt{N_i + 1} - \sqrt{N_i}}{\sqrt{N_i(N_i + 1)}},$$

where $N_i \equiv \#$ times we have estimated $\langle O^{(i)} \rangle$ before.

How do we construct a measurement setting Q?

Recall: Q is a Pauli word and has to QWC with as many terms of H as possible.

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Algorithm ([4]): 4-qubit system. At a certain shot $k \in \{1, ..., N\}$:

		Terms				eas.	set		
					I	\mathbb{I}	I	I	← Initialize
w_1	X	${\mathbb I}$	Y	\mathbb{I}					
w_2	Y	$egin{array}{c} Z \ Z \ Y \ \mathbb{I} \end{array}$	${\mathbb I}$	\mathbb{I}					
w_3	X	Z	${\mathbb I}$	\mathbb{I}					
w_4	Z	Y	${\mathbb I}$	X					
w_5	X	${\mathbb I}$	${\mathbb I}$	Y					

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		Terms				S. S	etting	Q_k	
w_1 w_2 w_3 w_4 w_5	$\begin{array}{c} X \\ Y \\ X \\ Z \\ Y \end{array}$	$egin{array}{c} \mathbb{I} & & & & & & & & & & & & & & & & & & &$	$\begin{bmatrix} Y \\ \mathbb{I} \\ \mathbb{I} \\ \mathbb{I} \end{bmatrix}$	$\begin{bmatrix} \mathbb{I} & \mathbb{I} $	X	I	Y	\mathbb{I}	← Initialize ← Change matches
ω5	21		ш	1					

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		Terms				s. sett	ing	Q_k	
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w_1	X	\mathbb{I}	Y	\mathbb{I}	X	I	Y	\mathbb{I}	← Change matches
w_2	Y	Z	${\mathbb I}$	\mathbb{I}	X	$\overline{\mathbb{I}}$	Y	${\mathbb I}$	← No changes
w_3	X	\overline{Z}	${\mathbb I}$	\mathbb{I}					
w_4	Z	Y	${\mathbb I}$	X					
w_5	X	${\mathbb I}$	${\mathbb I}$	Y					

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Algorithm ([4]): 4-qubit system. At a certain shot $k \in \{1, ..., N\}$:

$$\Longrightarrow \boxed{Q_k = X_1 \otimes Z_2 \otimes Y_3 \otimes Y_4.}$$

Now update weights of terms that QWC with Q_k and compute setting for shot k+1.

We programmed this algorithm:

$$H = h_1 X_1 Z_2 + h_2 Y_1 Z_3 + h_3 Z_2 Z_3 + h_4 X_1 Y_2 Z_3, \quad 0 < h_1 < h_2 < h_3 < h_4.$$

