Mitigation of measurement noise on quantum devices

Filip Maciejewski, Flavio Baccari, Zoltán Zimborás, Michał Oszmaniec

Kraków Quantum Informatics Seminar (KQIS), 2020.11.03

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Outline of presentation

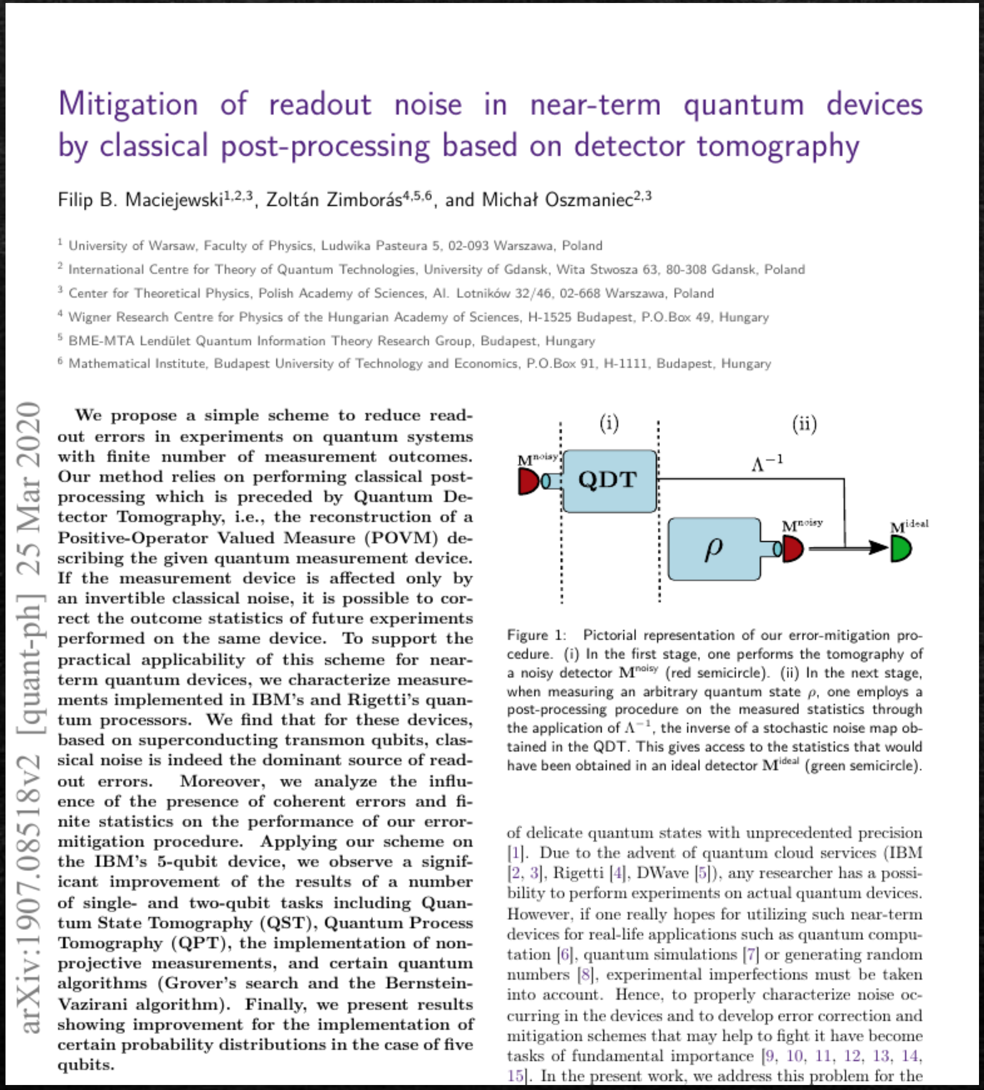
Measurement noise + mitigation

PART I – on small systems

PART II – on big systems

PART I is based on:

- Quantum 4 257 (2020)



Mitigation of readout noise in near-term quantum devices by classical post-processing based on detector tomography

Filip B. Maciejewski[1,2,3], Zoltán Zimborás[4,5,6], and Michał Oszmaniec[2,3]

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We propose a simple scheme to reduce readout errors in experiments on quantum systems with finite number of measurement outcomes. Our method relies on performing classical post-processing which is preceded by Quantum Detector Tomography, i.e., the reconstruction of a Positive-Operator Valued Measure (POVM) describing the given quantum measurement device. If the measurement device is affected only by an invertible classical noise, it is possible to correct the outcome statistics of future experiments performed on the same device. To support the practical applicability of this scheme for near-term quantum devices, we characterize measurements implemented in IBM's and Rigetti's quantum processors. We find that for these devices, based on superconducting transmon qubits, classical noise is indeed the dominant source of readout errors. Moreover, we analyze the influence of the presence of coherent errors and finite statistics on the performance of our error-mitigation procedure. Applying our scheme on the IBM's 5-qubit device, we observe a significant improvement of the results of a number of single- and two-qubit tasks including Quantum State Tomography (QST), Quantum Process Tomography (QPT), the implementation of non-projective measurements, and certain quantum algorithms (Grover's search and the Bernstein-Vazirani algorithm). Finally, we present results showing improvement for the implementation of certain probability distributions in the case of five qubits.

Figure 1: Pictorial representation of our error-mitigation procedure. (i) In the first stage, one performs the tomography of a noisy detector $\mathbf{M}^{\text{noisy}}$ (red semicircle). (ii) In the next stage, when measuring an arbitrary quantum state ρ, one employs a post-processing procedure on the measured statistics through the application of Λ^{-1}, the inverse of a stochastic noise map obtained in the QDT. This gives access to the statistics that would have been obtained in an ideal detector $\mathbf{M}^{\text{ideal}}$ (green semicircle).

of delicate quantum states with unprecedented precision [1]. Due to the advent of quantum cloud services (IBM [2, 3], Rigetti [4], DWave [5]), any researcher has a possibility to perform experiments on actual quantum devices. However, if one really hopes for utilizing such near-term devices for real-life applications such as quantum computation [6], quantum simulations [7] or generating random numbers [8], experimental imperfections must be taken into account. Hence, to properly characterize noise occurring in the devices and to develop error correction and mitigation schemes that may help to fight it have become tasks of fundamental importance [9, 10, 11, 12, 13, 14, 15]. In the present work, we address this problem for the

Outline of PART I

Measurement noise + mitigation on small systems

1. Basic definitions
2. Noise model and mitigation.
3. Quantum Detector Tomography.
4. Some error analysis.

Basic definitions – measurements

- Quantum measurement with *n* outcomes is a vector of operators:

$$\vec{M} = (M_1, \dots, M_n)$$

s.t.

$$\forall_i \; M_i \geq 0 \,, \quad \sum_i M_i = \mathbb{1}$$

Basic definitions – projective measurements

- Projective measurements fulfill additional requirement:

$$\vec{P} = (P_1, \dots, P_n)$$

s.t.

$$\forall_i \; P_i \geq 0, \quad \sum P_i = \mathbb{1}$$

Basic definitions – projective measurements

- Projective measurements fulfill additional requirement:

$$\vec{P} = (P_1, \ldots, P_n)$$

s.t.

$$\forall_i \; P_i \geq 0 \,, \quad \sum P_i = \mathbb{1} \,, \quad \forall_i \; P_i^2 = P_i$$

Basic definitions – Born’s rule

- If we perform measurement $\vec{M}$ on quantum state ρ, probability of obtaining outcome „i” is given by:

$$p(i \mid \vec{M}, \rho) = \mathrm{Tr}(\rho M_i)$$

Outline of PART I

Measurement noise + mitigation on small systems

1. ~~Basic definitions~~
2. Noise model and mitigation.
3. Quantum Detector Tomography.
4. Short error analysis.

Classical measurement noise

- We want to perform projective measurement:

$$\vec{P}$$

Classical measurement noise

- Our device performs noisy measurement:

$$\vec{p} \xrightarrow{\text{NOISE}}$$

Classical measurement noise

- Our device performs noisy measurement:

$$\vec{p} \xrightarrow{\text{NOISE}} \Lambda \vec{p}$$

Classical measurement noise

- Our device performs noisy measurement:

$$\vec{P} \xrightarrow{\text{NOISE}} \Lambda \vec{P}$$

STOCHASTIC MAP

Classical measurement noise

- On the level of probability vectors:

Classical measurement noise

- On the level of probability vectors:

$\vec{q}$ $\swarrow$ $\vec{p}$

Classical measurement noise

- On the level of probability vectors:

PROBABILITY VECTOR ON IDEAL DEVICE

$\vec{q}\ \vec{p}$

Classical measurement noise

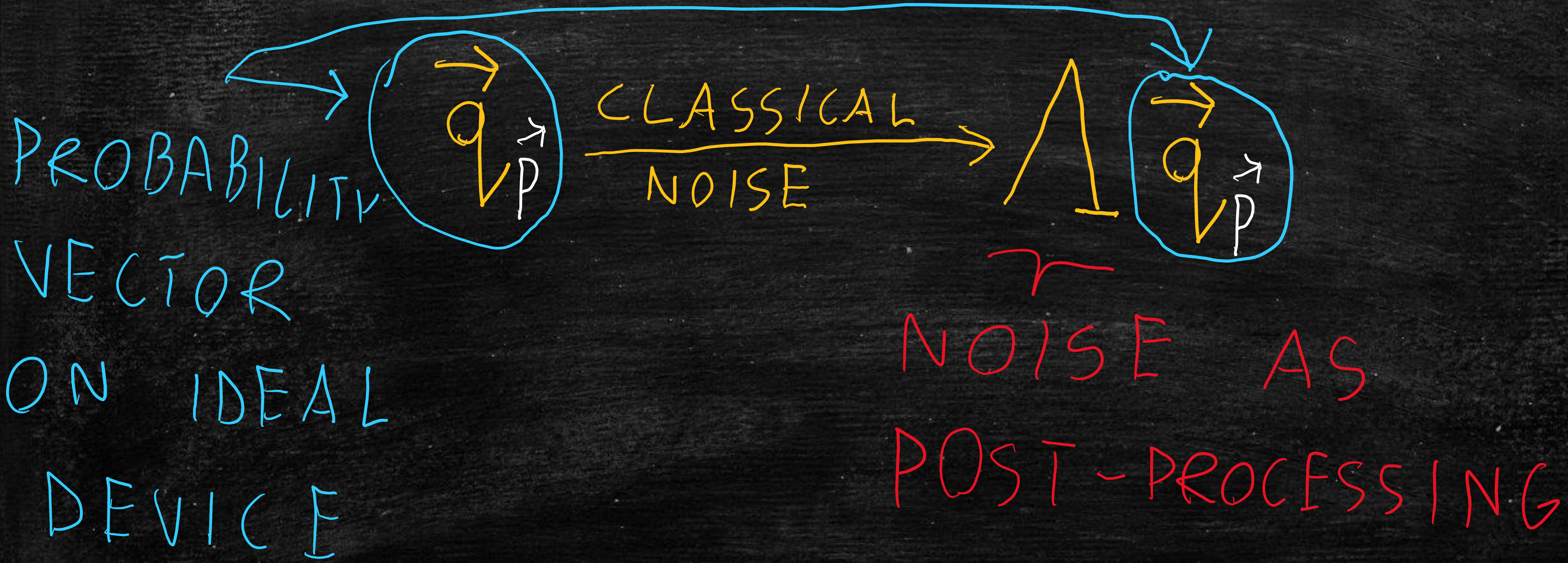
- On the level of probability vectors:

PROBABILITY VECTOR ON IDEAL DEVICE

$$\vec{q}_{\vec{p}} \xrightarrow[\text{NOISE}]{\text{CLASSICAL}} \Lambda \vec{q}_{\vec{p}}$$

Classical measurement noise

- On the level of probability vectors:



Classical noise as post-processing

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Classical noise as post-processing

$|0\rangle \xrightarrow{\text{MEASURE}}$

0

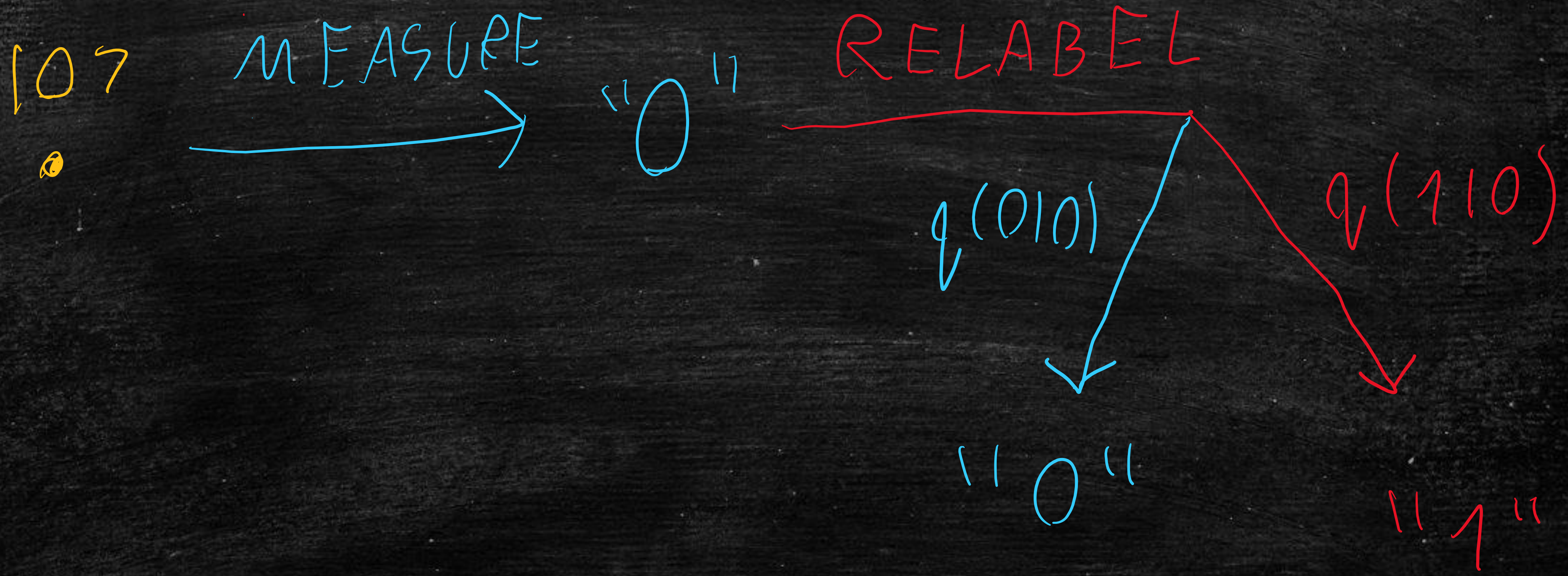
Classical noise as post-processing

$$|0\rangle \xrightarrow{\text{MEASURE}} \text{"0"}$$

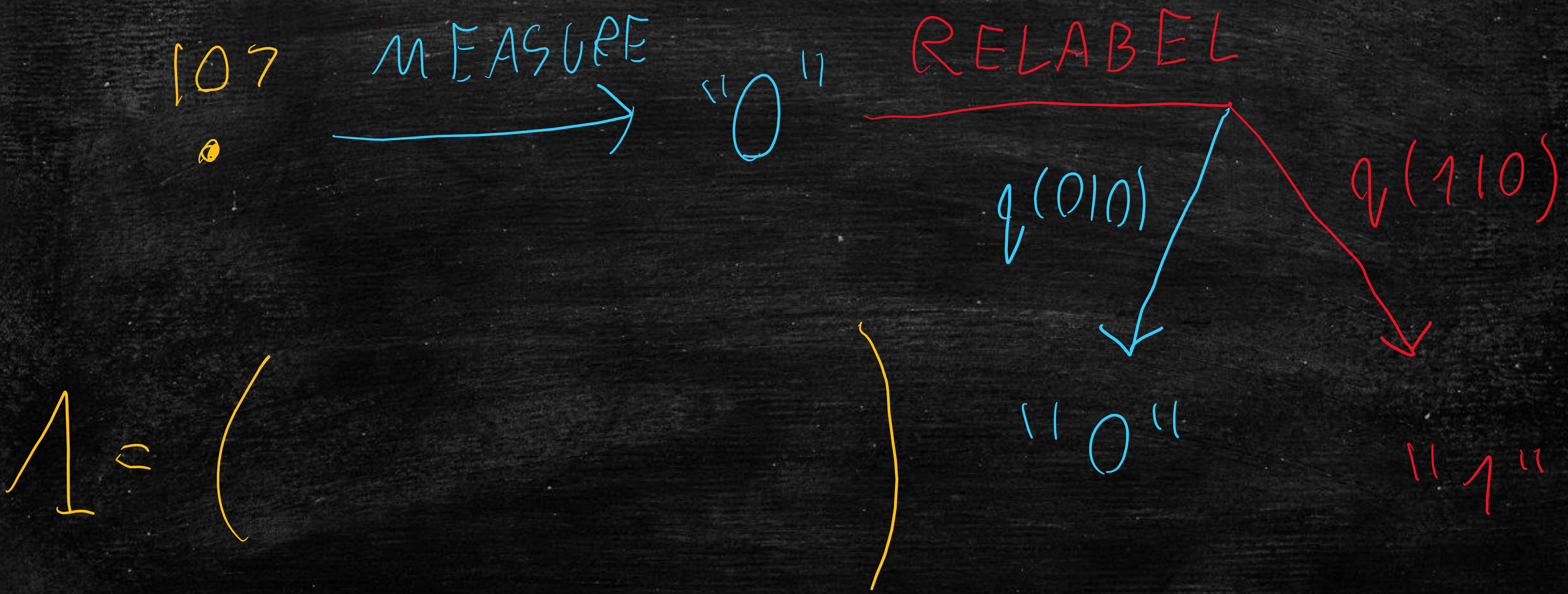
Classical noise as post-processing

$|0\rangle \xrightarrow{\text{MEASURE}}$ "0" RELABEL

Classical noise as post-processing



Classical noise as post-processing



Classical noise as post-processing

$$|0\rangle \xrightarrow{\text{MEASURE}} \text{"0"} \xrightarrow{\text{RELABEL}}$$

$$\text{"0"} \xrightarrow{q(0|0)} \text{"0"} \qquad \text{"0"} \xrightarrow{q(1|0)} \text{"1"}$$

$$\Lambda = \begin{pmatrix} q(0|0) & \\ q(1|0) & \end{pmatrix}$$

Classical noise as post-processing

$$|1\rangle \xrightarrow{\text{MEASURE}} \text{"1"} \xrightarrow{\text{RELABEL}}$$

$$\text{"1"} \xrightarrow{q(0|1)} \text{"0"} \qquad \text{"1"} \xrightarrow{q(1|1)} \text{"1"}$$

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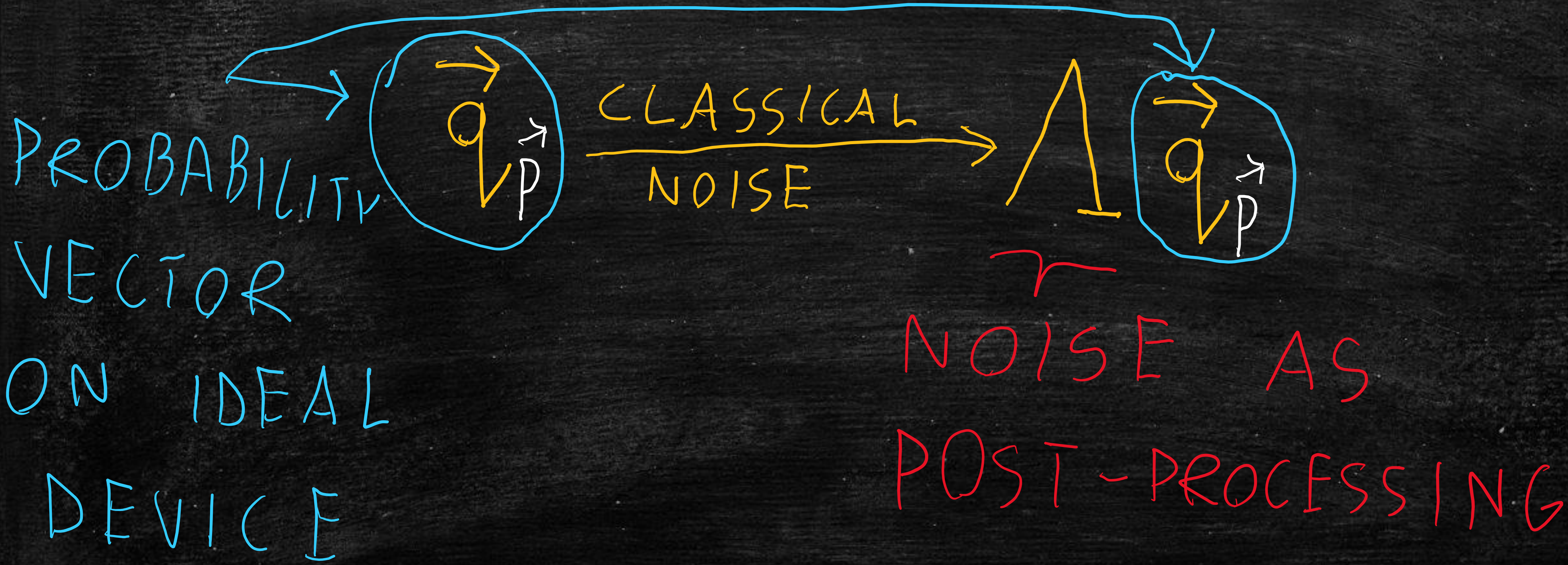
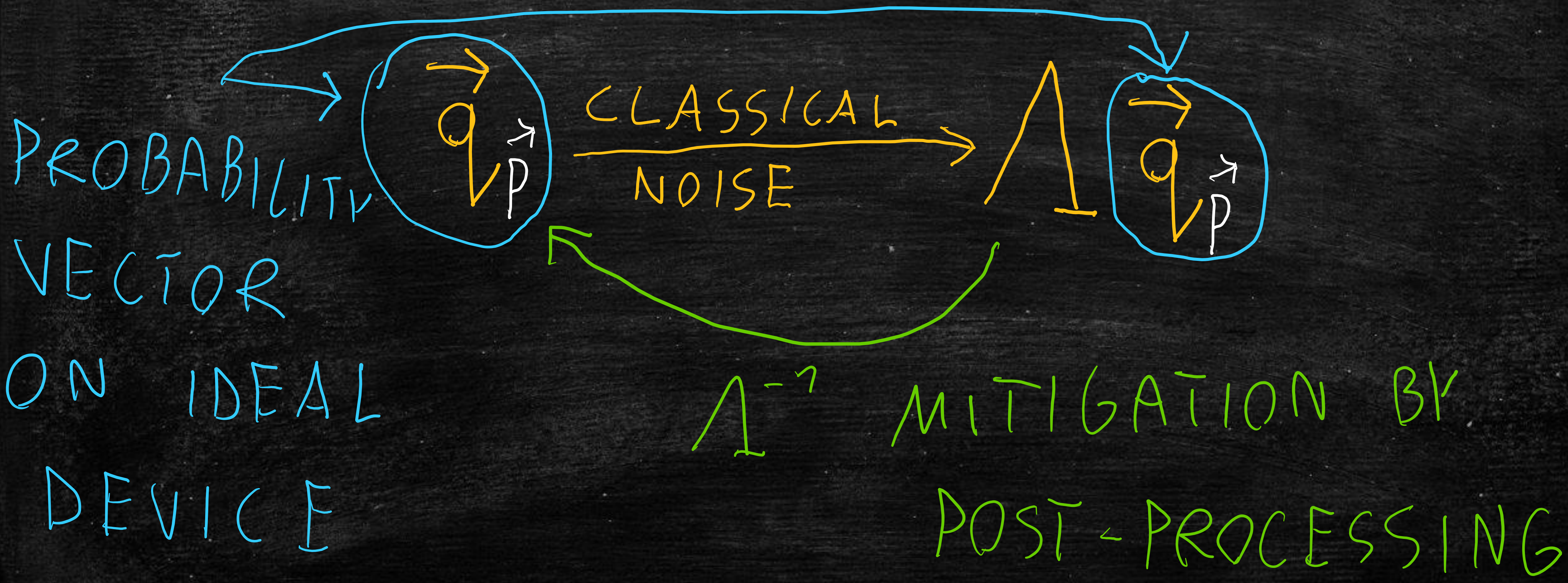
Classical measurement noise

- On the level of probability vectors:



Mitigation of classical noise

- On the level of probability vectors:



Mitigation of classical noise

- This is possible provided we know noise matrix Λ!

Mitigation of classical noise

- This is possible provided we know noise matrix Λ!
- How to reconstruct it (and verify noise model)?

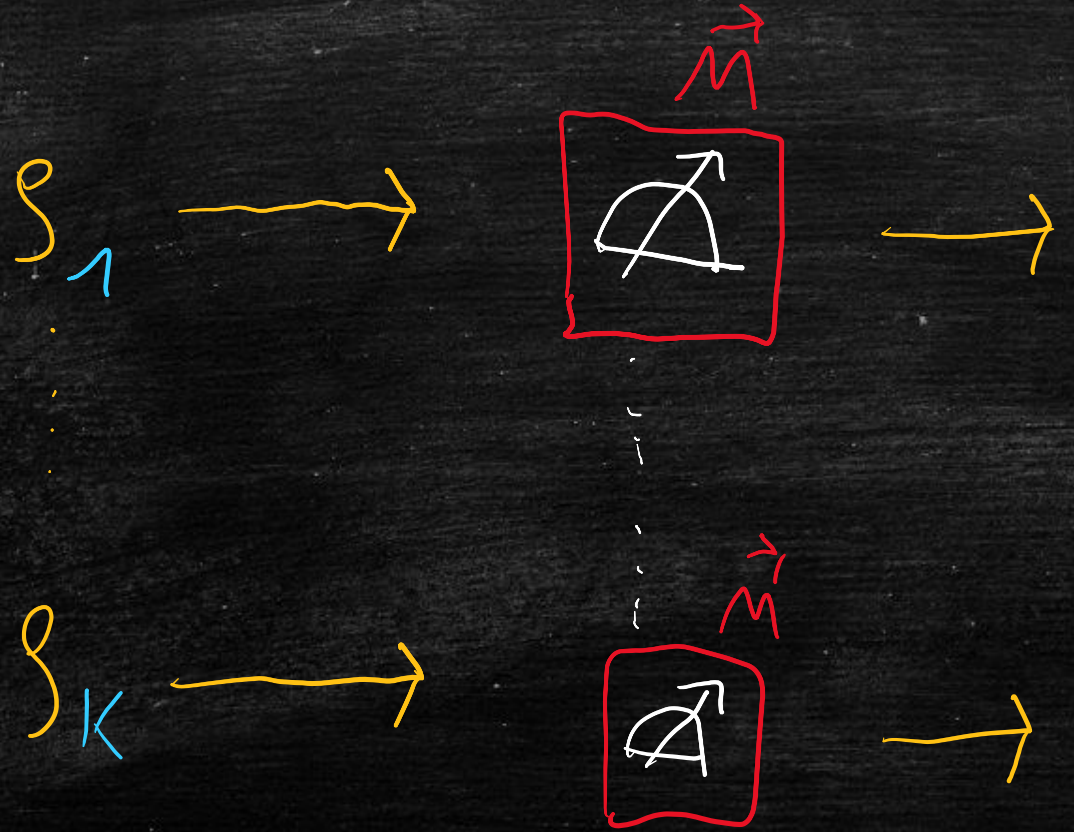
Outline of PART I

Measurement noise + mitigation on small systems

1. ~~Basic definitions~~
2. ~~Noise model and mitigation.~~
3. Quantum Detector Tomography.
4. Some error analysis.

Quantum Detector Tomography (QDT) – basic idea

- Put inside a measurement device various quantum states,



Quantum Detector Tomography (QDT) – basic idea

- Put inside a measurement device various quantum states, estimate probabilities...

$$\rho_1 \longrightarrow \overset{\vec{M}}{\boxed{}} \longrightarrow \forall_i \; p(i \mid \rho_1, \vec{M})$$

$$\vdots$$

$$\rho_K \longrightarrow \overset{\vec{M}}{\boxed{}} \longrightarrow \forall_i \; p(i \mid \rho_K, \vec{M})$$

Quantum Detector Tomography (QDT) – basic idea

- ...and use Born's rule to reconstruct measurement operators:

$$\forall_i \; p(i \mid \rho_1, \vec{M}) = \mathrm{Tr}(\rho_1 M_i)$$

Quantum Detector Tomography (QDT) – basic idea

- ...and use Born's rule to reconstruct measurement operators:

$$\forall_i \; p(i \mid \rho_1, \vec{M}) = \underbrace{\mathrm{Tr}(\rho_1 M_i)}_{\sim \text{Hilbert-Schmidt inner product}}$$

Quantum Detector Tomography (QDT) – experiments

- How it looks in practice?

Classical measurement noise

- Recall:

$$\vec{p} \xrightarrow{\text{NOISE}} \Lambda \vec{p}$$

STOCHASTIC MAP

Classical measurement noise

- Single-qubit example:

$$P_1 = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$$

$$P_2 = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

Classical measurement noise

- Single-qubit example:

$$P_1 = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \xrightarrow{\Lambda}$$

$$P_2 = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

Classical measurement noise

- Single-qubit example:

$$P_1 = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \xrightarrow{\Lambda} M_1 = \begin{pmatrix} p(0|0) & 0 \\ 0 & p(0|1) \end{pmatrix}$$

$$P_2 = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

Classical measurement noise

- Single-qubit example:

$$P_1 = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \xrightarrow{\Lambda} M_1 = \begin{pmatrix} p(0|0) & 0 \\ 0 & p(0|1) \end{pmatrix}$$

$$P_2 = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \xrightarrow{\Lambda} M_2 = \begin{pmatrix} p(1|0) & 0 \\ 0 & p(1|1) \end{pmatrix}$$

Quantum Detector Tomography (QDT) – experiments

- Hence if classical noise model is accurate, we expect reconstructed operators to be diagonal…

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- Yesterday evening, the measurement on qubit number 9 on Melbourne device looked like this:

Quantum Detector Tomography (QDT) – experiments

- Hence if classical noise model is accurate, we expect reconstructed operators to be diagonal…
- How it looks in practice?
- Yesterday evening, the measurement on qubit number 9 on Melbourne device looked like this:

$$M_1 = \begin{pmatrix} 0.943 & 0.001(1-i) \\ 0.001(1+i) & 0.101 \end{pmatrix}, \quad M_2 = \begin{pmatrix} 0.057 & -0.001(1-i) \\ -0.001(1+i) & 0.909 \end{pmatrix}$$

Quantum Detector Tomography (QDT) – experiments

- Hence if classical noise model is accurate, we expect reconstructed operators to be diagonal…
- How it looks in practice?
- Yesterday evening, the measurement on qubit number 9 on Melbourne device looked like this:

SMALL BUT NOT ZERO

$$M_1 = \begin{pmatrix} 0.943 & 0.001(1-i) \\ 0.001(1+i) & 0.101 \end{pmatrix}, \quad M_2 = \begin{pmatrix} 0.057 & -0.001(1-i) \\ -0.001(1+i) & 0.909 \end{pmatrix}$$

Quantum Detector Tomography (QDT) – experiments

- Hence classical noise model is good, but not perfect…

Quantum Detector Tomography (QDT) – experiments

- Hence classical noise model is good, but not perfect…
- How coherent noise affect error mitigation?

Outline of PART I

Measurement noise + mitigation on small systems

1. ~~Basic definitions~~
2. ~~Noise model and mitigation.~~
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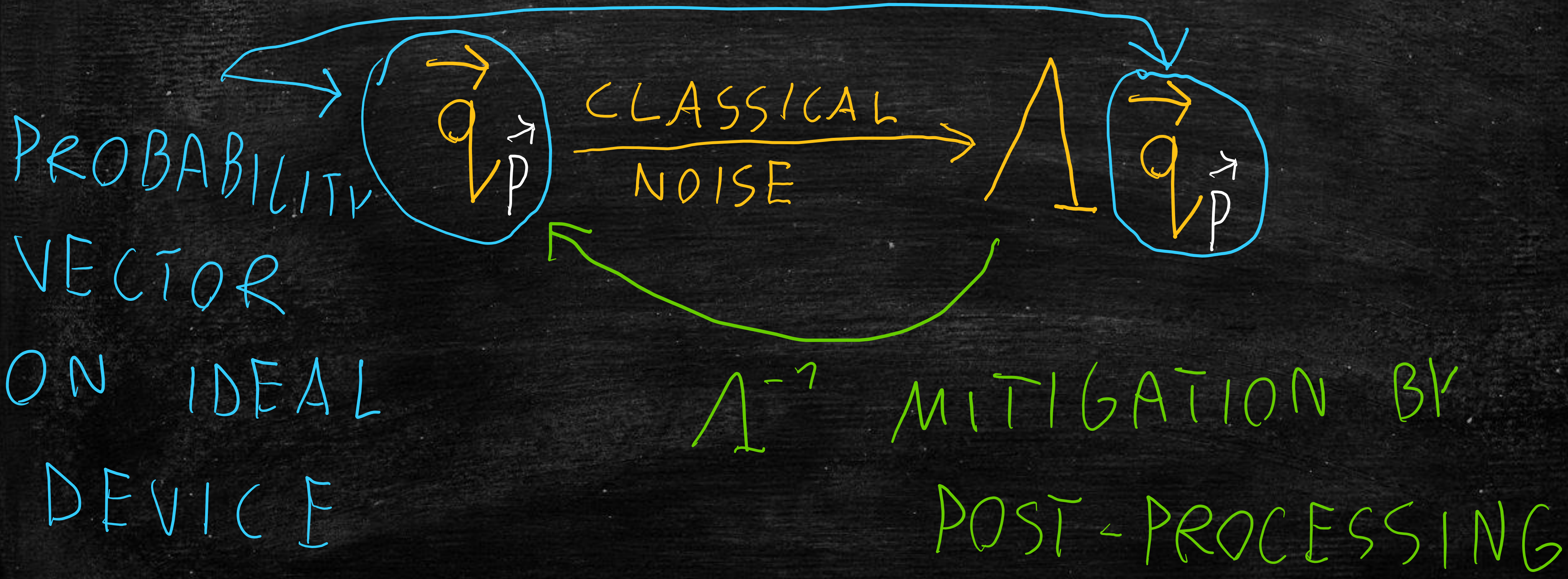
4. Some error analysis.

Mitigation of classical noise

- On the level of probability vectors:



What can go wrong?

- Presented error mitigation method is not perfect because:

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Effects of coherent errors

$\vec{M} =$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} =$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \Lambda \vec{P}$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \underbrace{\Lambda}_{\text{CLASSICAL NOISE}} \vec{P}$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \underbrace{\Lambda \vec{P}}_{\text{CLASSICAL NOISE}} + \vec{\Delta}$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \underbrace{\Lambda \vec{P}}_{\text{CLASSICAL NOISE}} + \underbrace{\vec{\Delta}}_{\text{COHERENT NOISE}}$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \underbrace{\Lambda \vec{P}}_{\text{CLASSICAL NOISE}} + \underbrace{\vec{\Delta}}_{\text{COHERENT NOISE}}$$

$$\underbrace{\vec{p}^{\,noisy}}_{\text{NOISY PD}} =$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \underbrace{\Lambda \vec{P}}_{\text{CLASSICAL NOISE}} + \underbrace{\vec{\Delta}}_{\text{COHERENT NOISE}}$$

$$\underbrace{\vec{p}^{\,noisy}}_{\text{NOISY PD}} = \Lambda \underbrace{\vec{p}^{\,ideal}}_{\text{IDEAL PD}} + \underbrace{\vec{\lambda}}_{\text{DEVIATION}}$$

Effects of coherent errors

$$\underbrace{\vec{p}^{\,noisy}}_{\text{NOISY PD}} = \Lambda\, \underbrace{\vec{p}^{\,ideal}}_{\text{IDEAL PD}} + \underbrace{\vec{\lambda}}_{\text{DEVIATION}}$$

Effects of coherent errors

$$\underbrace{\Lambda^{-1} \vec{n}^{\,noisy}}_{\text{CORRECTED PD}} = \underbrace{\vec{n}^{\,ideal}}_{\text{IDEAL PD}} + \underbrace{\Lambda^{-1} \vec{\lambda}}_{\text{DEVIATION}}$$

Effects of coherent errors

$$\underbrace{\Lambda^{-1}\vec{p}^{\,noisy}}_{\text{CORRECTED PD}} = \underbrace{\vec{p}^{\,ideal}}_{\text{IDEAL PD}} + \underbrace{\Lambda^{-1}\vec{\lambda}}_{\text{DEVIATION}}$$

$$\delta = D_{TV}\left(\Lambda^{-1}\vec{p}^{\,noisy}, \vec{p}^{\,ideal}\right)$$

Effects of coherent errors

$$\underbrace{\Lambda^{-1}\vec{p}^{\,noisy}}_{\text{CORRECTED PD}} = \underbrace{\vec{p}^{\,ideal}}_{\text{IDEAL PD}} + \underbrace{\overrightarrow{\Lambda^{-1}\lambda}}_{\text{DEVIATION}}$$

$$\delta \leq \| \Lambda^{-1} \|_{1\to 1} \, D_{op}(M, \Lambda \vec{p})$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \underbrace{\Lambda \vec{P}}_{\text{CLASSICAL NOISE}} + \underbrace{\vec{\Delta}}_{\text{COHERENT NOISE}}$$

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  - estimated statistics are not probabilities.

Illustration of statistical errors

NOISY PD

IDEAL PD

Illustration of statistical errors

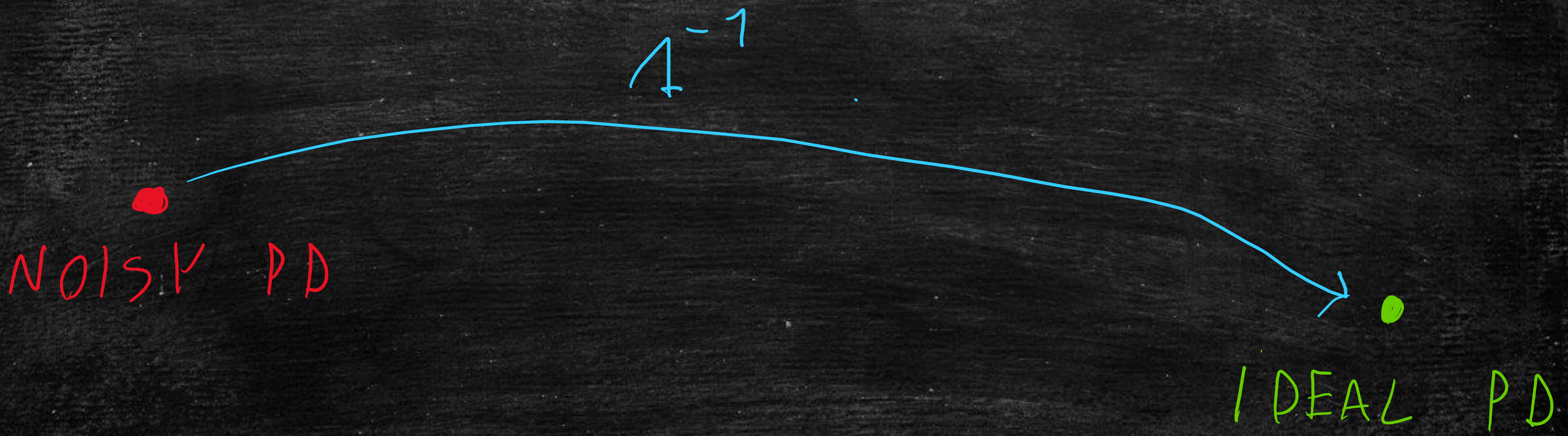


Illustration of statistical errors

NOISY PD

IDEAL PD

Illustration of statistical errors

ESTIMATED PD

NOISY PD

IDEAL PD

Illustration of statistical errors

ESTIMATED PD

ε^2

NOISY PD

IDEAL PD

Illustration of statistical errors

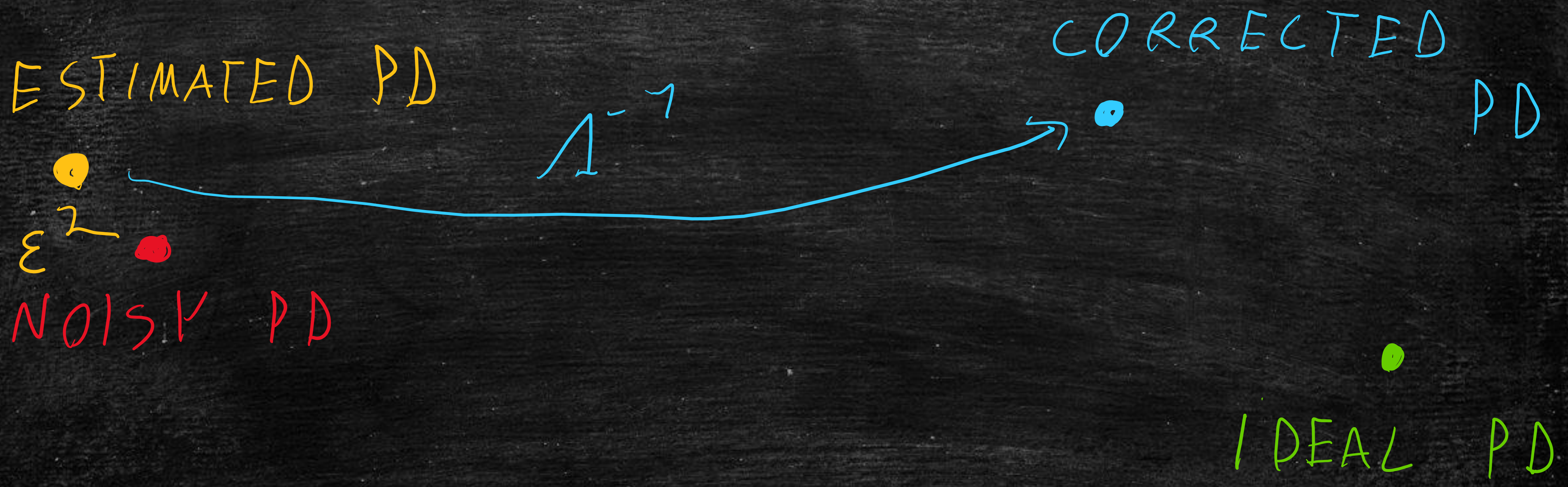


Illustration of statistical errors

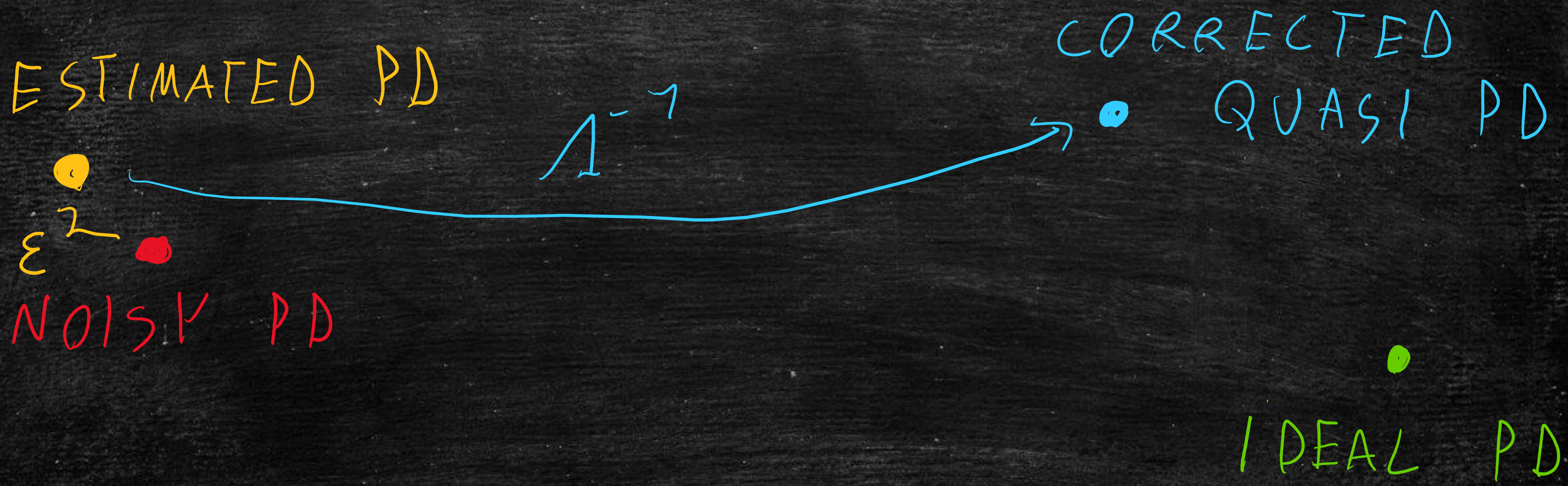


Illustration of statistical errors

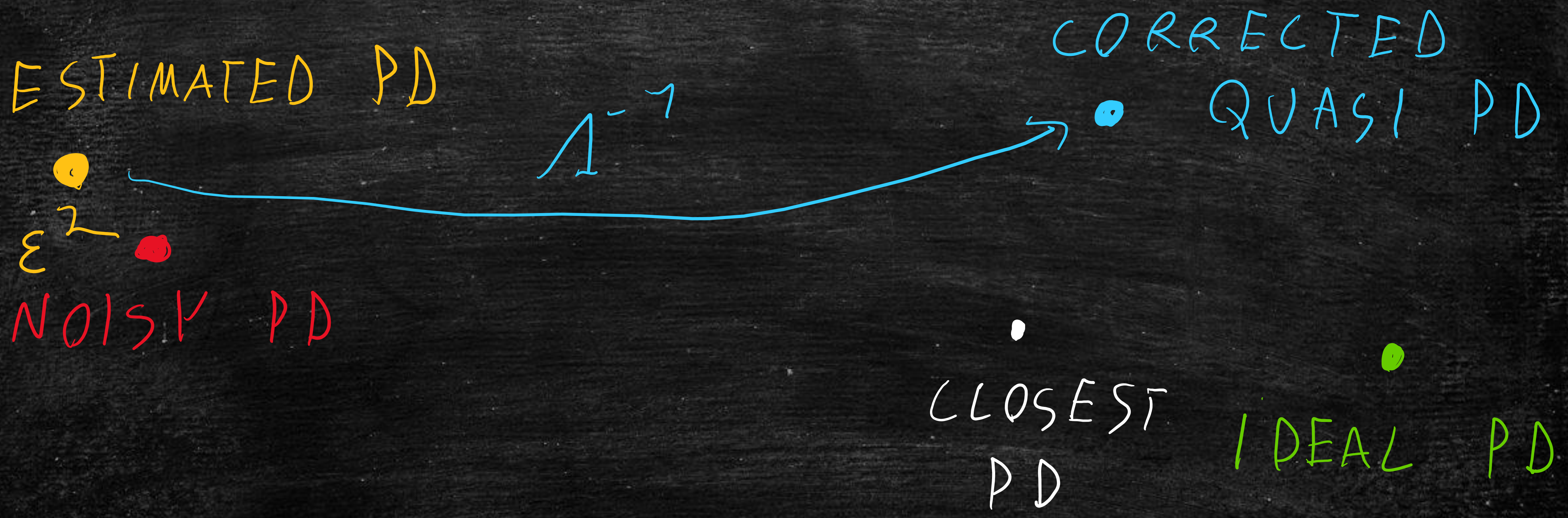


Illustration of statistical errors

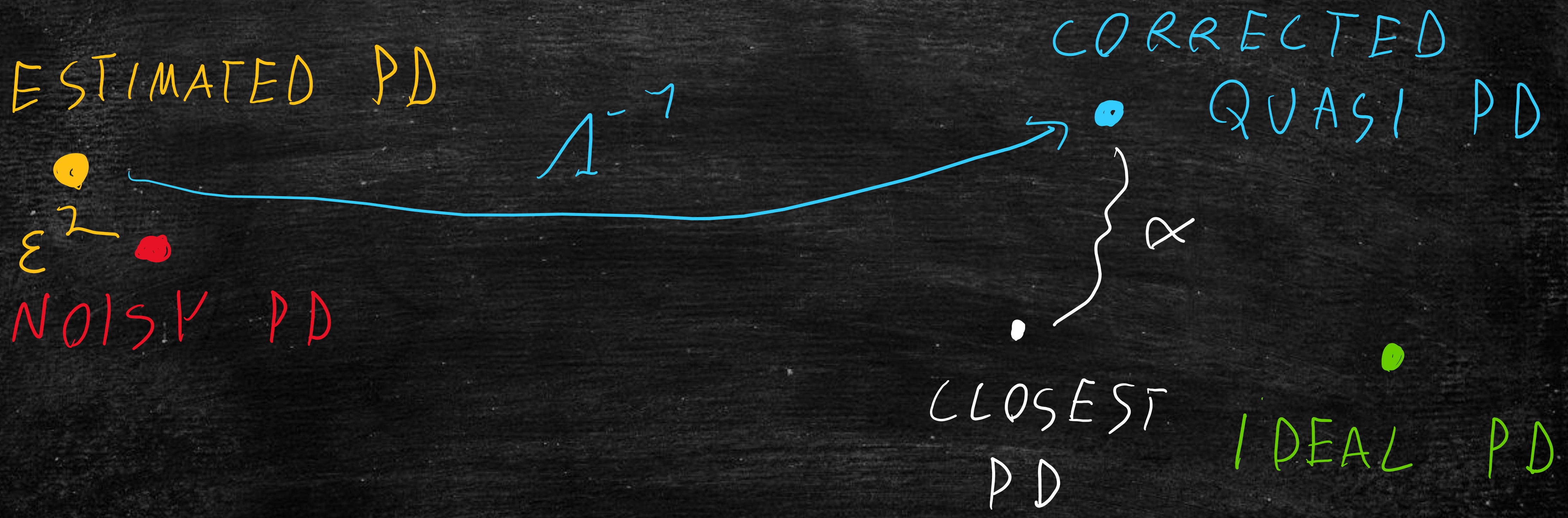


Illustration of statistical errors

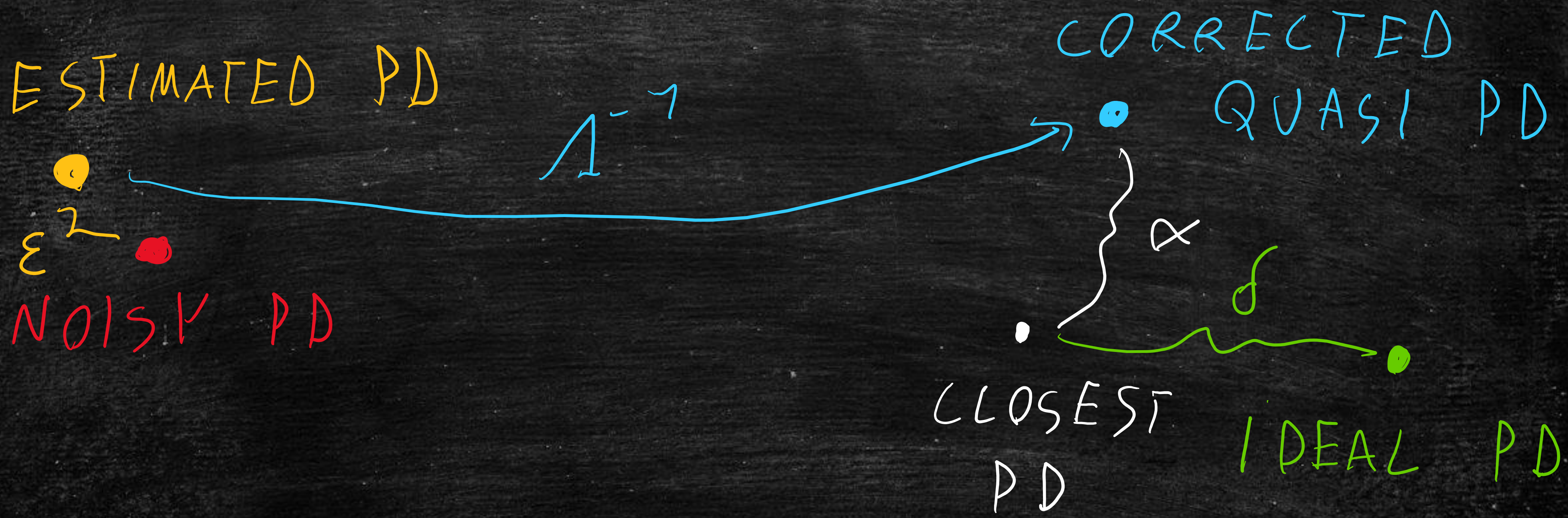
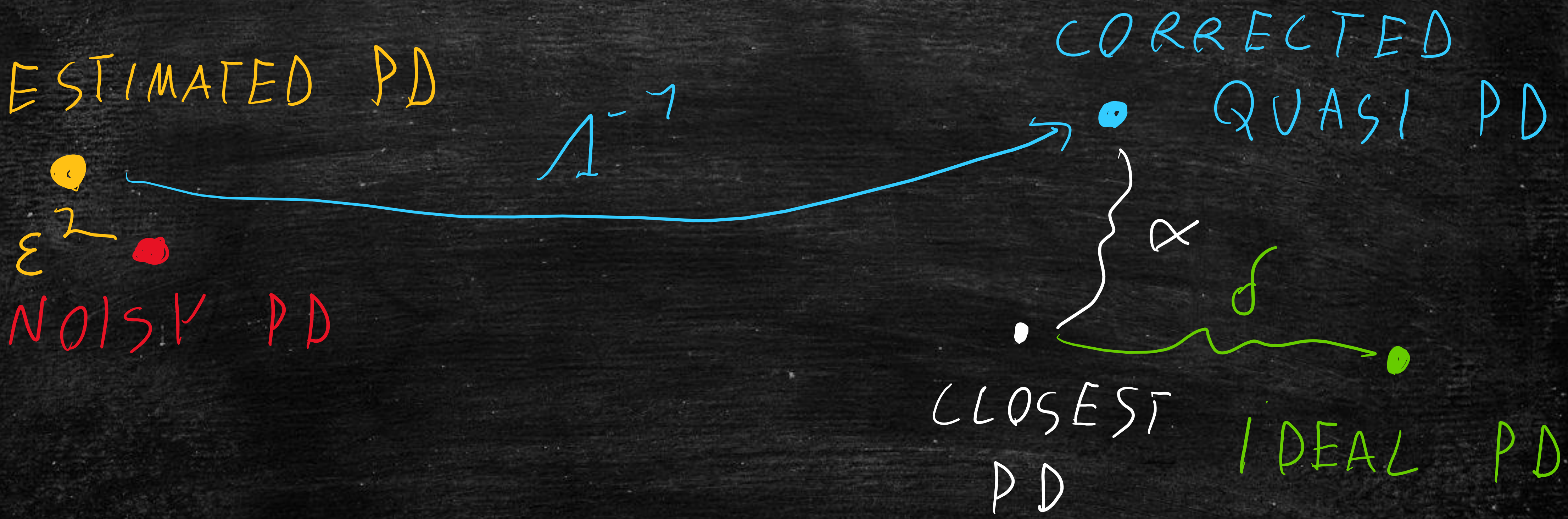


Illustration of statistical errors



$$\delta \leq \|\Lambda^{-1}\|_{1\to 1} \cdot \varepsilon + \alpha$$

Effects of coherent errors

$$\underbrace{\vec{M}}_{\text{NOISY MEAUSEREMENT}} = \underbrace{\Lambda \vec{P}}_{\text{CLASSICAL NOISE}} + \underbrace{\vec{\Delta}}_{\text{COHERENT NOISE}}$$

$$\delta \leq \| \Lambda^{-1} \|_{1 \to 1} D_{op}(M, \Lambda \vec{P})$$

Effects of coherent and statistical errors

$$\delta \leq \|\Lambda^{-1}\|_{1\to 1}\Big(\underbrace{D_{op}(M, \Lambda\vec{P})}_{\text{COHERENT ERRORS}} + \underbrace{\varepsilon}_{\text{STATISTICAL ERRORS}}\Big) + \alpha$$

What can go wrong?

- Presented error mitigation method is not perfect because:
  - noise is not completely classical,
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What can go wrong?

- Presented error mitigation method is not perfect because:
  - noise is not completely classical,
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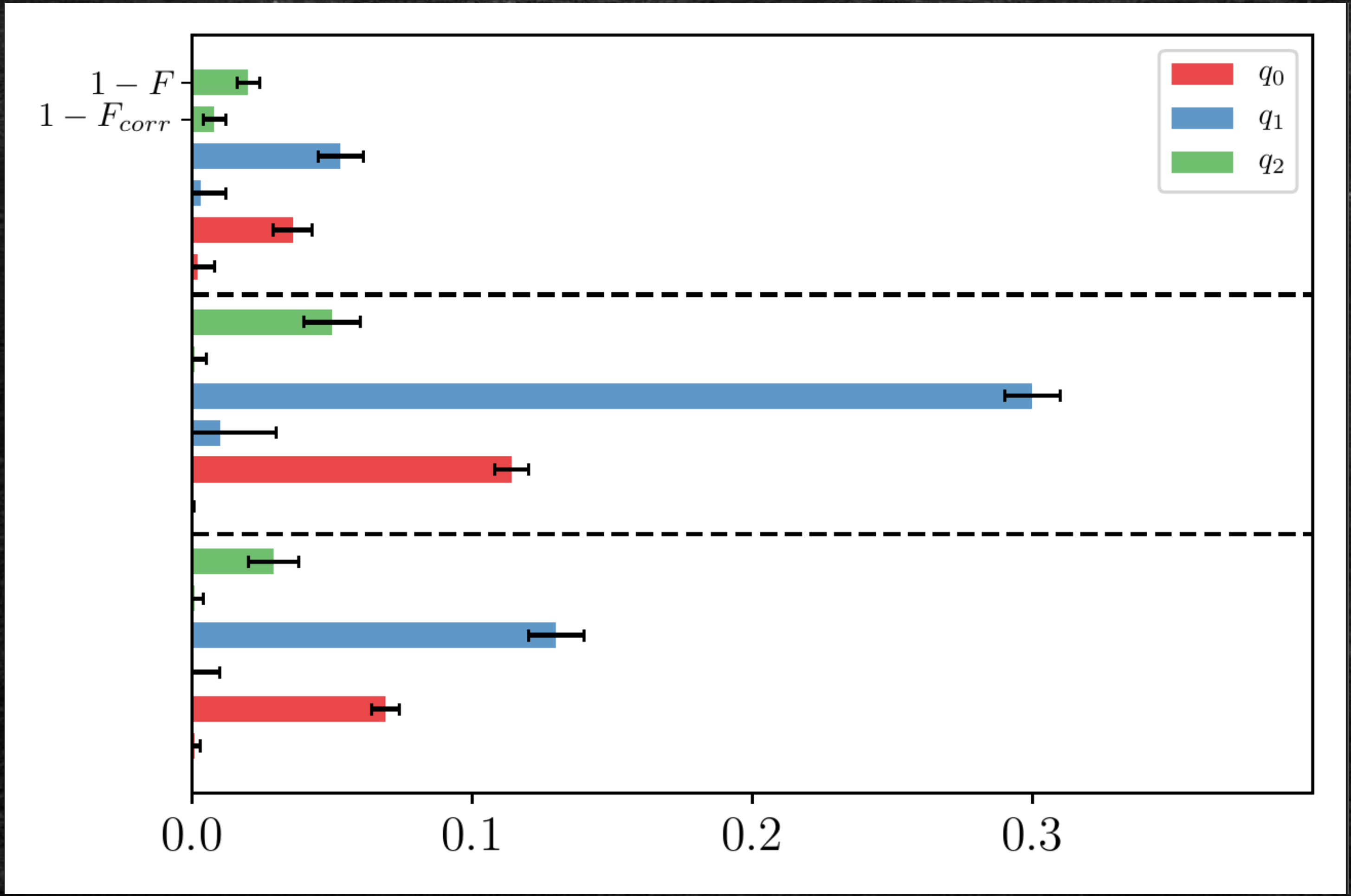
- So does this actually work?

Error-mitigation – experiments on 1 qubit

- Single-qubit quantum state tomography.
- Figure of merit: infidelity.

$$\underbrace{1 - F}_{\text{INFIDELITY WITHOUT MITIGATION}} \qquad \underbrace{1 - F_{\text{CORR}}}_{\text{INFIDELITY WITH MITIGATION}}$$

Error-mitigation – experiments on 1 qubit

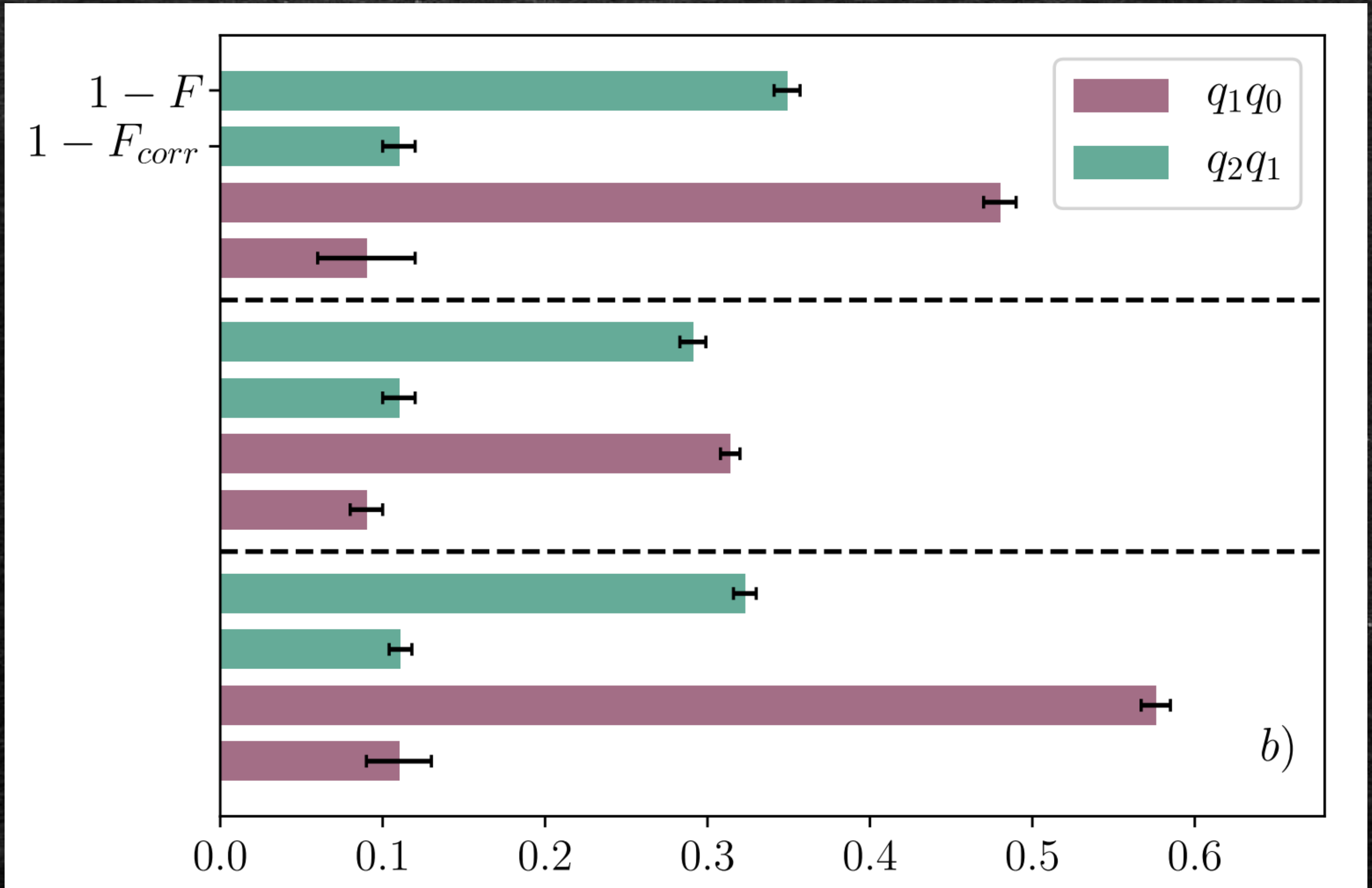


Error-mitigation – experiments on 2 qubits

- Two-qubit quantum state tomography.
- Figure of merit: infidelity.

$$\underbrace{1 - F}_{\text{INFIDELITY WITHOUT MITIGATION}} \qquad \underbrace{1 - F_{CORR}}_{\text{INFIDELITY WITH MITIGATION}}$$

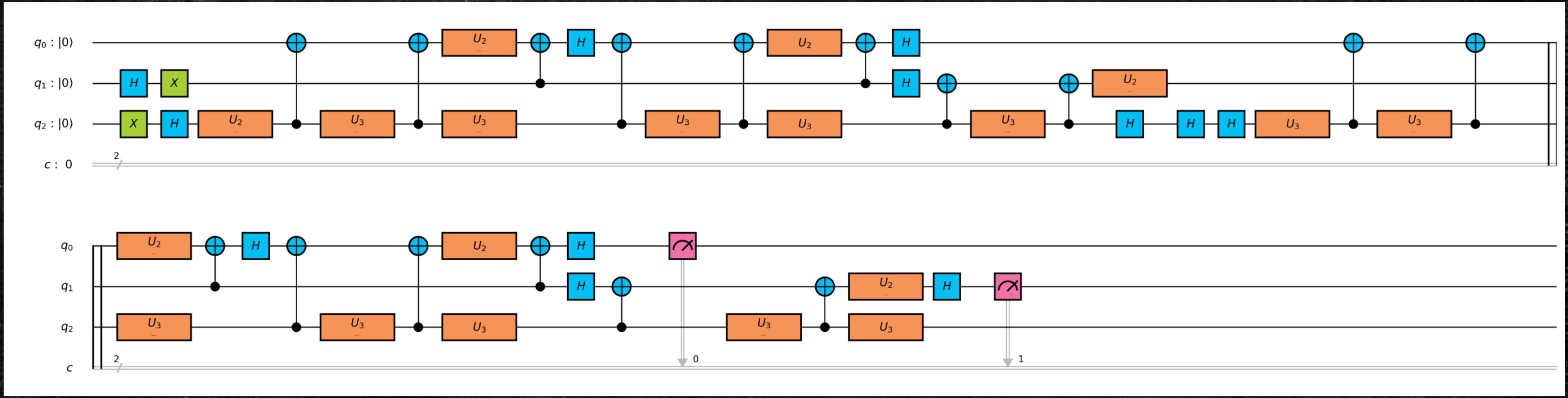
Error-mitigation – experiments on 2 qubits



Error-mitigation – experiments on 2 qubits

- Two-qubit quantum algorithms: Grover's and Bernstein–Vazirani.
- Figure of merit: probability of success.

Error-mitigation – experiments on 2 qubits



Error-mitigation – experiments on 5 qubits

UNCORRELATED NOISE MODEL

CORRELATED

Algorithm	Standard	Corr ($1q \otimes 1q$)	Corr ($2q$)
Grover's	0.58 ± 0.01	0.70 ± 0.02	0.79 ± 0.02
BV	0.55 ± 0.02	0.63 ± 0.02	0.61 ± 0.02

Error-mitigation – experiments on 5 qubits

- Implementation of five-qubit probability distributions.
- Figure of merit: Total-Variation Distance from perfect distribution.

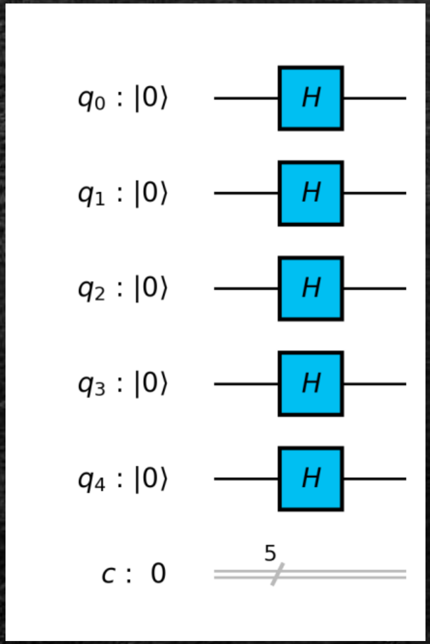
$$\mathrm{TVD}(\vec{p}, \vec{q}) = \frac{1}{2}\sum_i |p_i - q_i|$$

IDEAL DISTRIBUTION

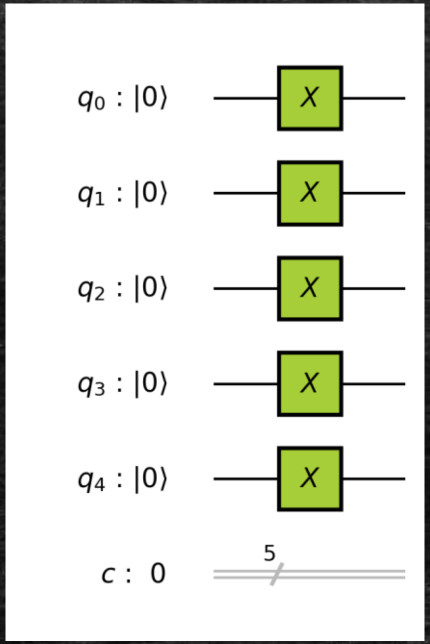
ESTIMATED DISTRIBUTION

Error-mitigation – experiments on 5 qubits

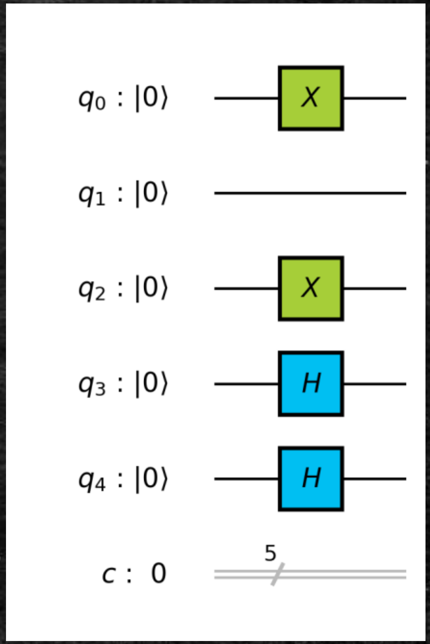
Error-mitigation – experiments on 5 qubits



„UNIFORM"



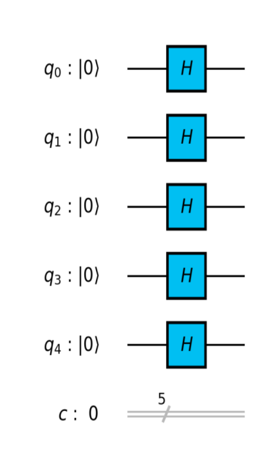
„NOT"



„MIXED"

Error-mitigation – experiments on 5 qubits

UNCORRELATED NOISE MODEL



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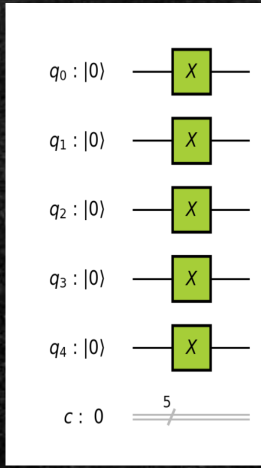
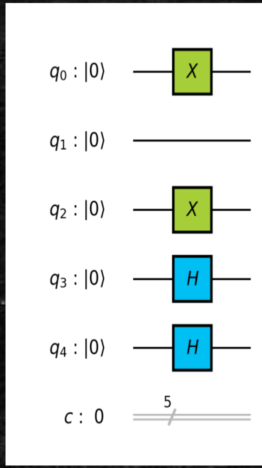


„NOT"

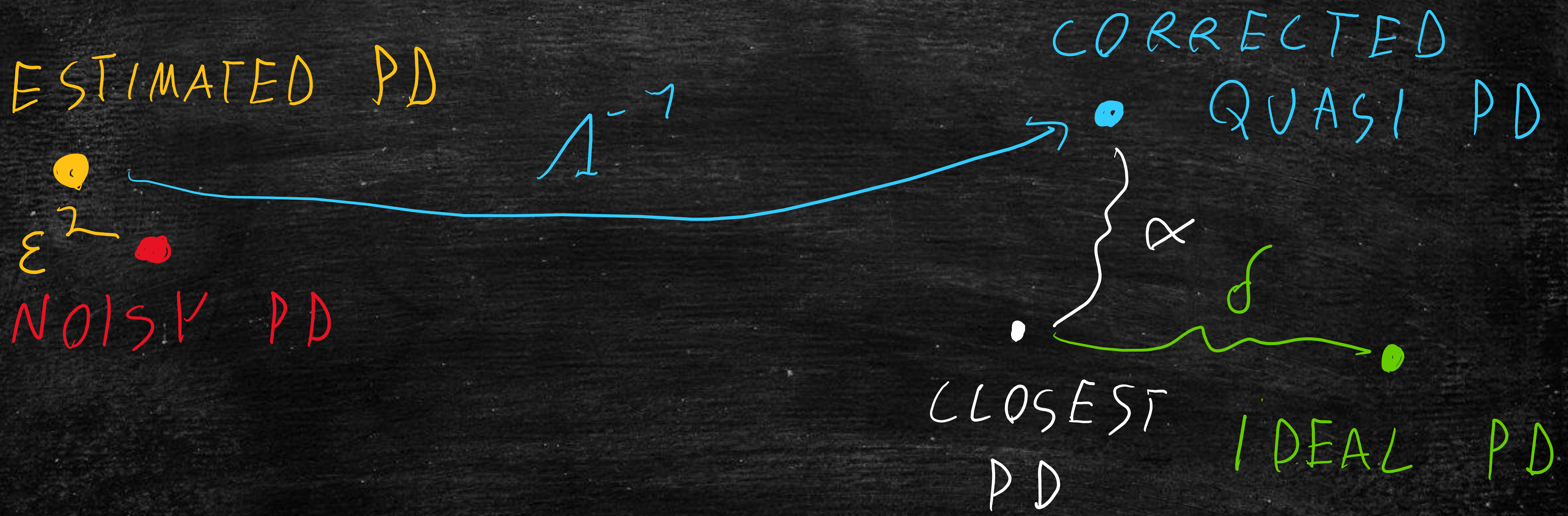


„MIXED"

Name	Standard	Corrected	α
Uniform	0.110 ± 0.006	0.100 ± 0.007	0
NOT	0.66 ± 0.02	0 ± 0	0.36 ± 0.09
Mixed	0.196 ± 0.006	0.031 ± 0.008	0.019 ± 0.005

Name	Corrected	α
Uniform	$\pm$	
NOT	$\pm$	$\pm$
Mixed	$\pm$	$\pm$

Illustration of statistical errors



$$\delta \leq \alpha + \|\Lambda^{-1}\|_{1\to 1} \cdot \varepsilon$$

Error-mitigation – experiments on 5 qubits

UNCORRELATED NOISE MODEL

Name	Standard	Corrected	α
Uniform	0.110 ± 0.006	0.100 ± 0.007	0
NOT	0.66 ± 0.02	0 ± 0	0.36 ± 0.09
Mixed	0.196 ± 0.006	0.031 ± 0.008	0.019 ± 0.005

Name	Corrected	α
Uniform	$\pm$	
NOT	$\pm$	$\pm$
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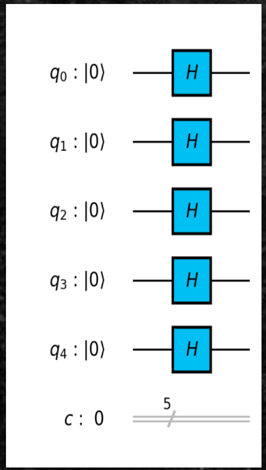
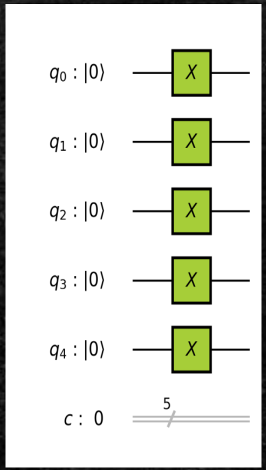
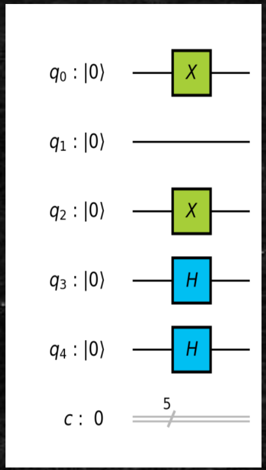


"UNIFORM"



"NOT"



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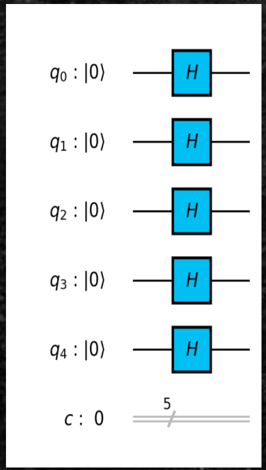

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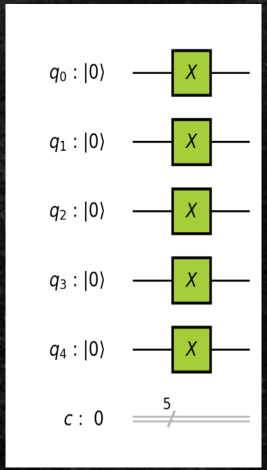

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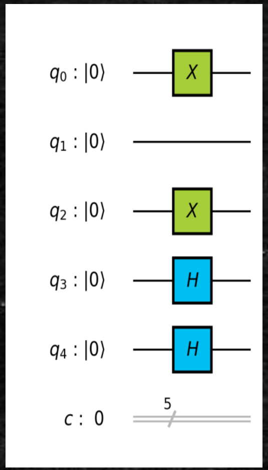


„MIXED"

Name	Corrected	α
Uniform	0.03 ± 0.02	0
NOT	0.004 ± 0.023	0.04 ± 0.04
Mixed	0.022 ± 0.007	0.023 ± 0.007

CORRELATED (1 PAIR)

Outline of presentation

Measurement noise + mitigation

~~PART I – on small systems~~

PART II – on big systems

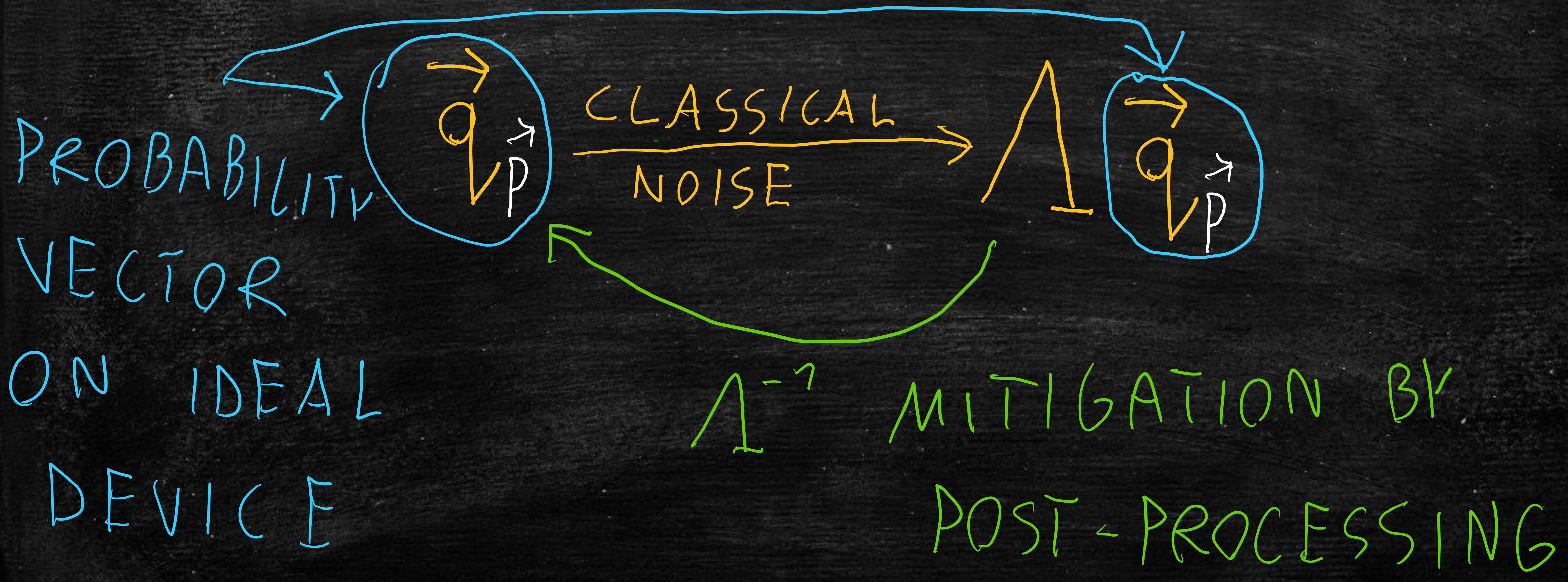
Outline of PART I

Measurement noise + mitigation on big systems

1. Problems with noise description + solution.
2. Problems with noise mitigation + “solution”.

Mitigation of classical noise

- On the level of probability vectors:



Problems with noise characterization

- Problem: Requires reconstruction of generic noise matrix.

$$\Lambda \in \mathbb{R}^{2^n \times 2^n}$$

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$\Rightarrow$ EXPONENTIAL

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EXPONENTIAL

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Quantum Detector Tomography complexity

- Number of states we need to prepare is in general equal to 4^N.

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- ... we can restrict ourselves to reconstruction of only diagonal elements of noisy measurement operatos...

1q classical noise

$$|0\rangle \xrightarrow{\text{MEASURE}} \text{"0"} \xrightarrow{\text{RELABEL}} \begin{cases} q(0|0) \to \text{"0"} \\ q(1|0) \to \text{"1"} \end{cases}$$

$$\Lambda = \begin{pmatrix} q(0|0) & \\ q(1|0) & \end{pmatrix}$$

1q classical noise

$$|1\rangle \xrightarrow{\text{MEASURE}} \text{"1"} \xrightarrow{\text{RELABEL}}$$

$q(0|1)$: "0"

$q(1|1)$: "1"

$$\Lambda = \begin{pmatrix} q(0|0) & q(0|1) \\ q(1|0) & q(1|1) \end{pmatrix}$$

2q noise-matrix characterization via DDT

$$\mathbb{1} \quad \mathbb{1} \longrightarrow \Lambda_{x_1 x_2 | 00}$$

$$\mathbb{1} \quad X \longrightarrow \Lambda_{x_1 x_2 | 01}$$

$$X \quad \mathbb{1} \longrightarrow \Lambda_{x_1 x_2 | 10}$$

$$X \quad X \longrightarrow \Lambda_{x_1 x_2 | 11}$$

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- ... we can restrict ourselves to reconstruction of only diagonal elements of noisy measurement operatos...

- ... which anyway gives 2^N circuits using DDT.

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- Problem: Requires reconstruction of generic noise matrix.

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→ EXPONENTIAL

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3. SAMPLING COMPLEXITY

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EXPONENTIAL

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EXPONENTIAL

- Solution:
  Real noise is unlikely to be generic –
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Simple solution

- Think about the simplest model – uncorrelated noise:

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(too) Simple solution

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- Unfortunately, it is not very accurate[1]!

[1] Quantum 4, 257, FBM, Z. Zimborás, M. Oszmaniec (2020).

Slightly less simple solution

- Model correlations locally, but do not be too naive.

Multi-qubit noise model

Multi-qubit noise model - illustration

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$C_C = \{Q_1\}$

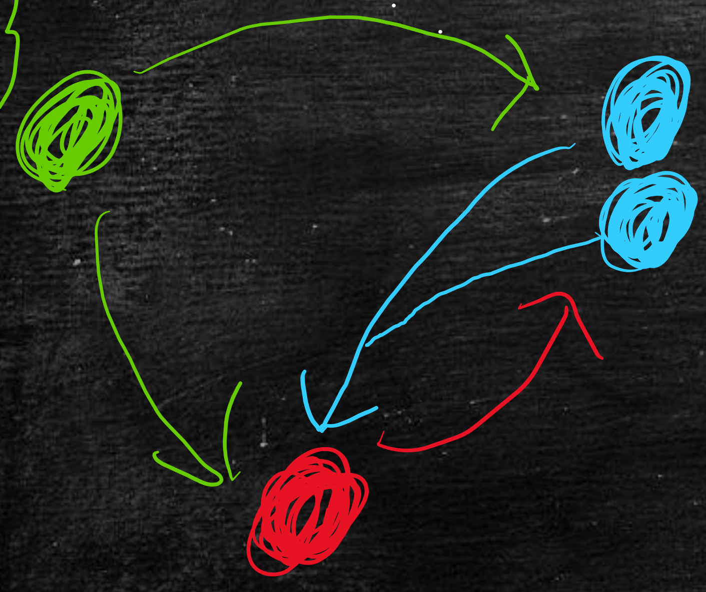
$C_A = \{Q_3, Q_4\}$

- Strongly correlated qubits are grouped into clusters. Each cluster has corresponding noise matrix.

$C_B = \{Q_2\}$

Multi-qubit noise model - illustration

$C_C = \{Q_1\}$



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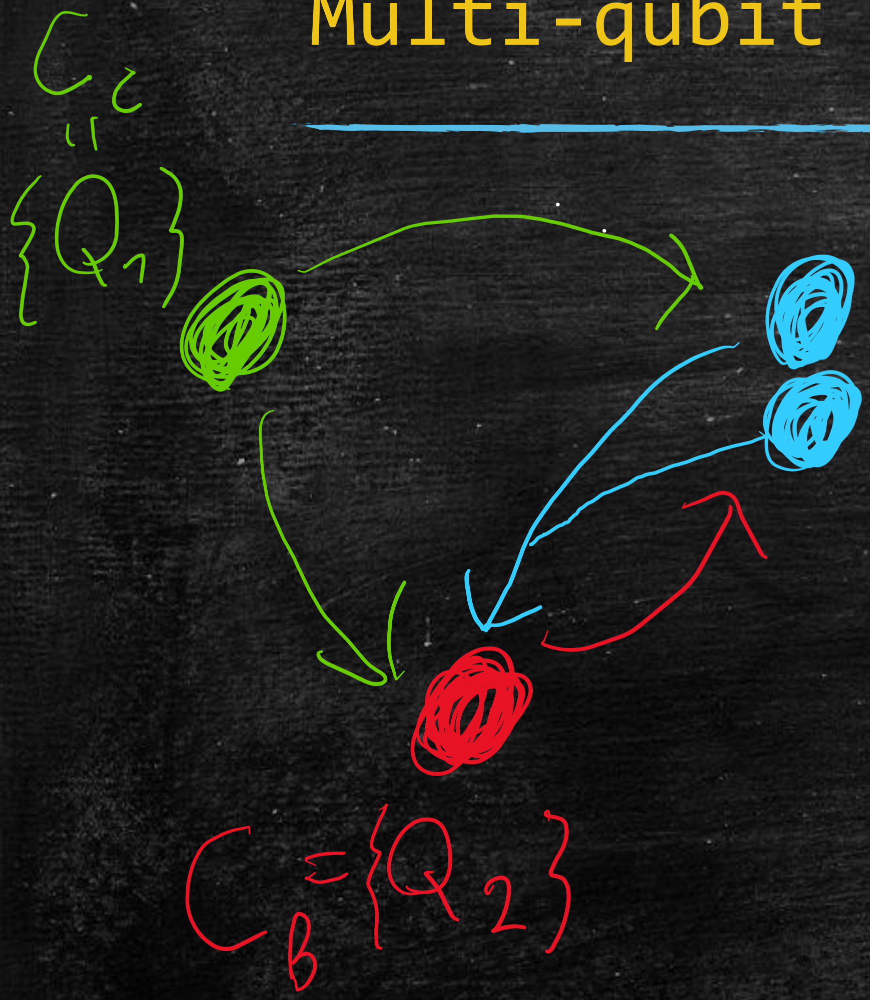
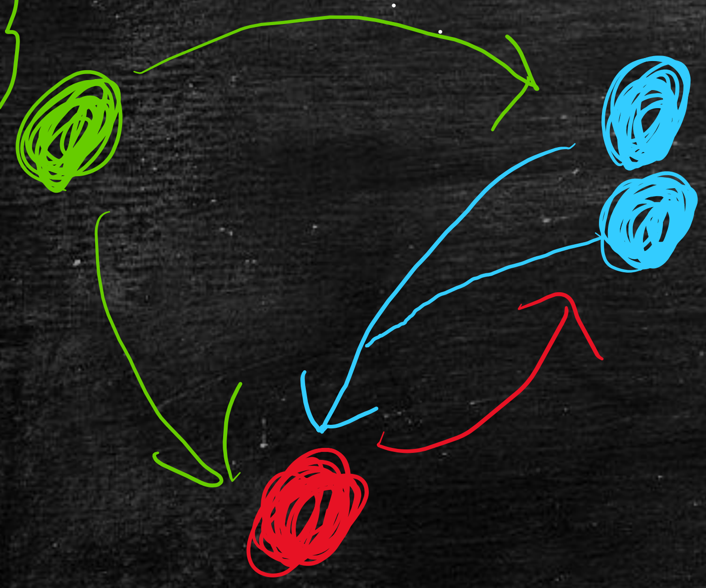


$C_A = \{Q_3, Q_4\}$

- Strongly correlated qubits are grouped into clusters. Each cluster has corresponding noise matrix.
- The noise matrix in each cluster depends on the state of the neighbors just before measurement.
- Characterization of clusters and neighbors can be cheap (if they are not too big).

Multi-qubit noise model - construction

$C_C = \{Q_1\}$



$C_A = \{Q_3, Q_4\}$

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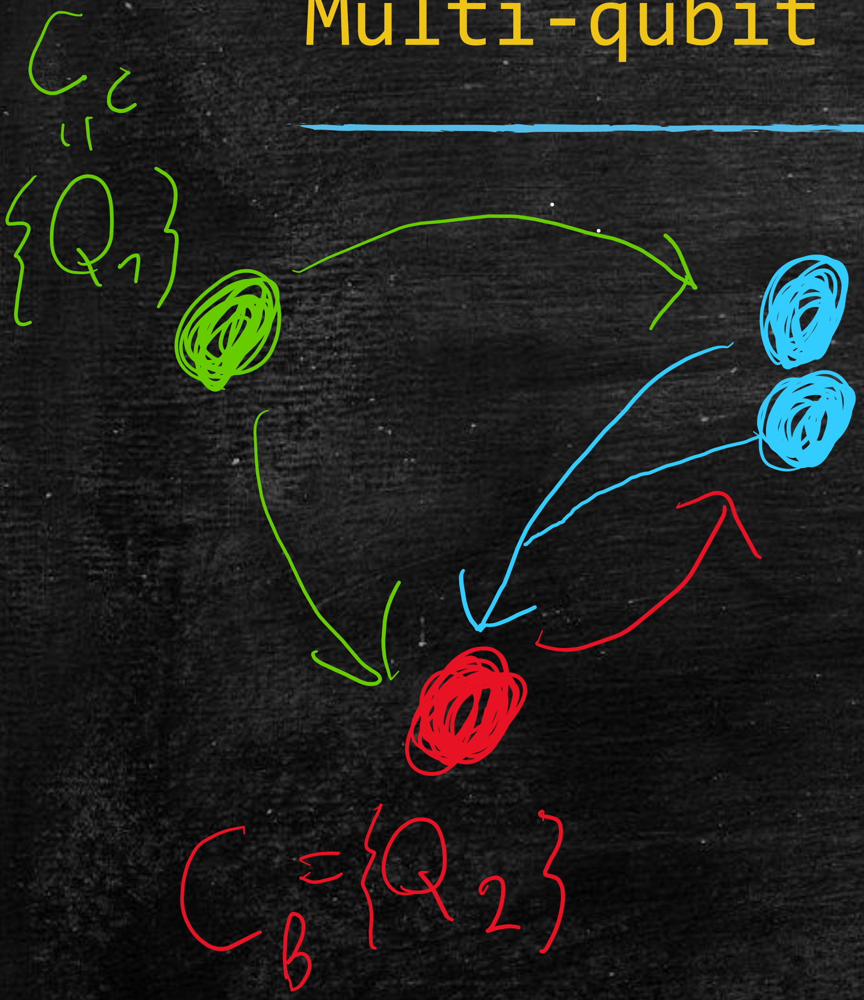
$$\mathbb{1}\, X_1 X_2 Y_3 X_4 \mid Y_1 Y_2 Y_3 Y_4 =$$

Multi-qubit noise model - construction



$$C_A = \{Q_3, Q_4\}$$

$$\Lambda_{X_1 X_2 Y_3 X_4 \mid Y_1 Y_2 Y_3 Y_4} = \Lambda^{Y_1 Y_2}_{X_3 X_4 \mid Y_3 Y_4} \cdot \Lambda^{Y_1 Y_3 Y_4}_{X_2 \mid Y_2} \cdot \Lambda_{X_1 \mid Y_1}$$

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$$\Lambda_{X_1 \ldots X_N | Y_1 \ldots Y_N} = \prod_{C_X} \Lambda_{\mathbf{X}_{C_X} | \mathbf{Y}_{C_X}}^{\mathbf{Y}_{\mathcal{N}(C_X)}}$$

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Multi-qubit noise characterization

- Method of efficiently characterizing readout noise:
  - Perform parallel noise characterization using generalized Quantum Overlapping Tomography[1] – Diagonal Detector Overlapping Tomography.

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- Separate DDTs on pairs of qubits require ~N^2 circuits…

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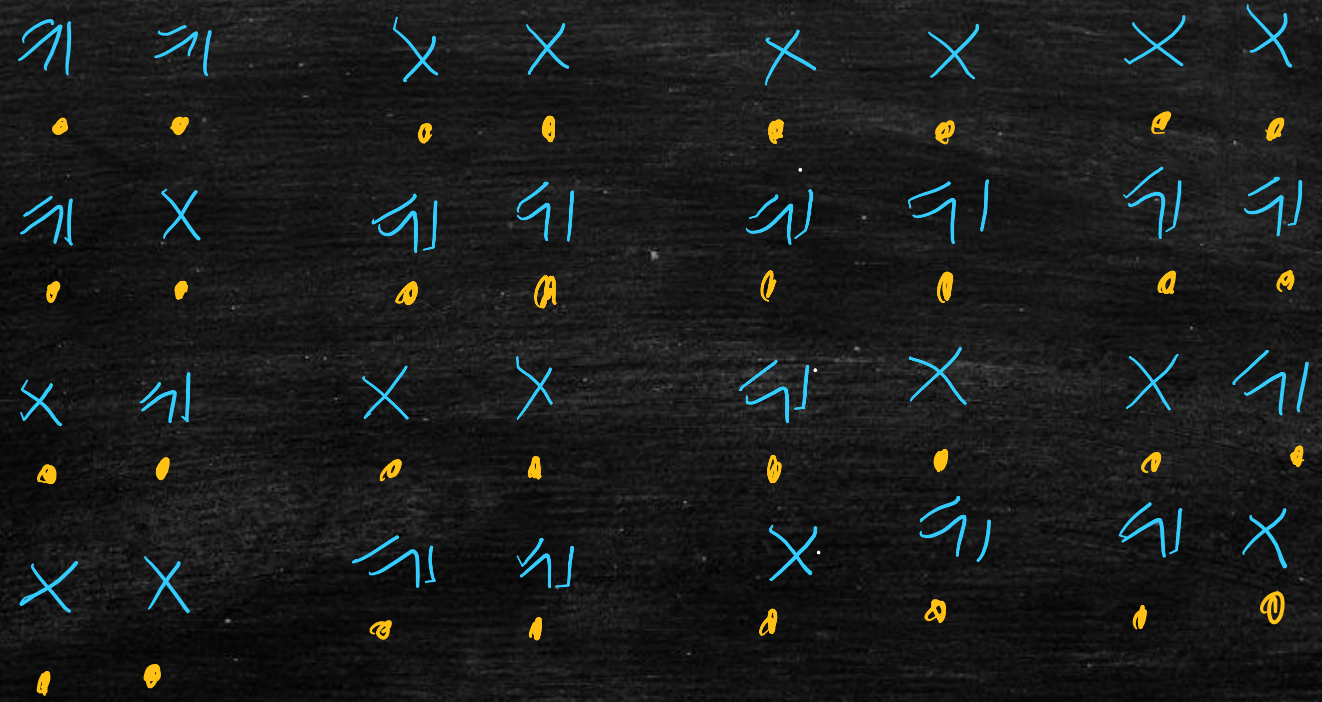
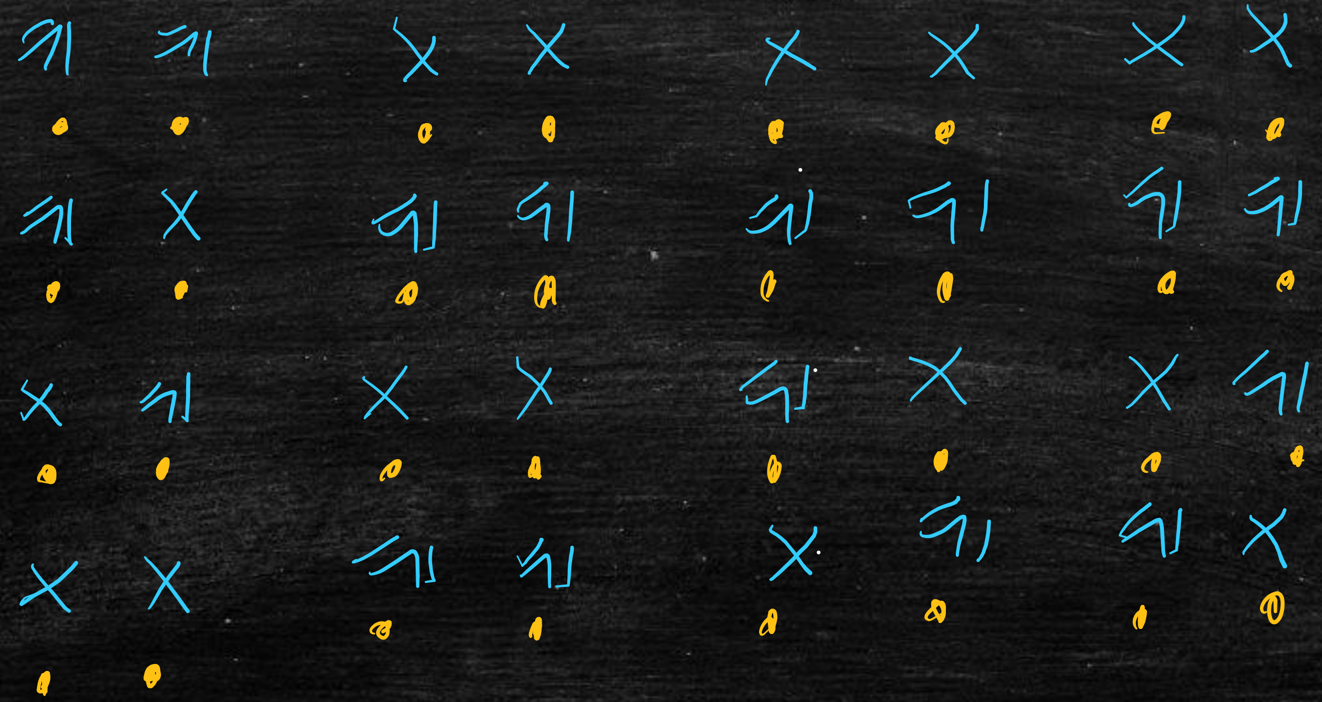


Detector Overlapping Tomography – main idea

- Separate DDTs on pairs of qubits require ~N² circuits…
- … but if you make it paralel… DDOT uses ~log(N) exp(K) circuits.



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- Relevant example: for 15 qubits, reconstruction of noise matrices on all fives of qubits requires $2^5\binom{15}{5} \sim 100{,}000$ circuits.
- Overlapping tomography allows to do so using ~350 circuits.

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  - Construct a noise model.

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Experimental results – IBM, 15 qubits

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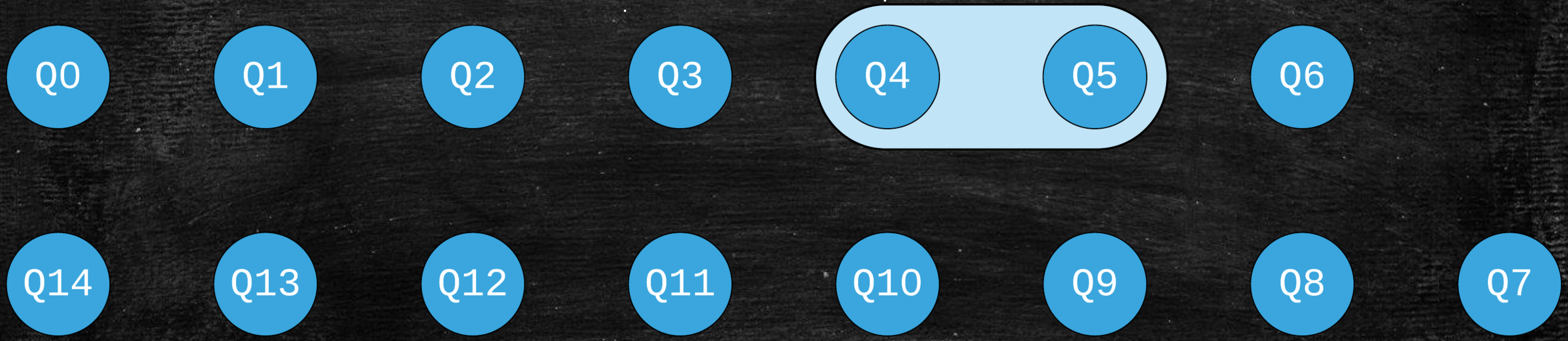
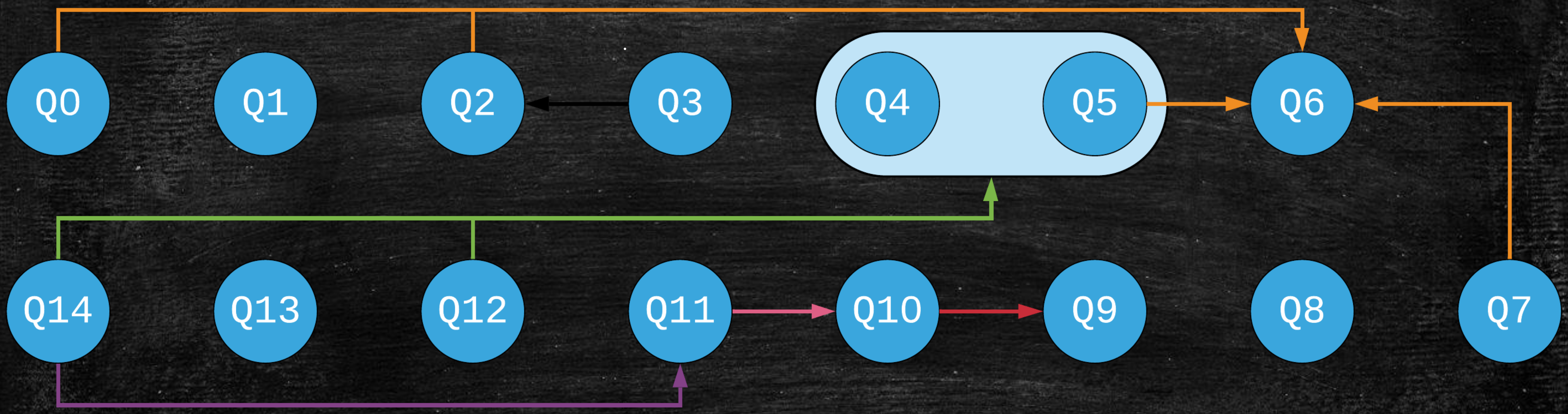


Experimental results – IBM, 15 qubits (clusters and neighbours)



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See other works on this:

- arXiv:2001.09980
  M.R. Geller, M. Sun (Jan 2020)
- arXiv:2001.09980
  K. E. Hamilton, T. Kharazi, T. Morris, A. J. McCaskey, R. S. Bennink, R.C. Pooser (Jun 2020)
- arXiv:2006.14044
  S. Bravyi, S. Sheldon, A. Kandala, D.C. Mckay, J. M. Gambetta (Jun 2020)

Problems with noise-mitigation

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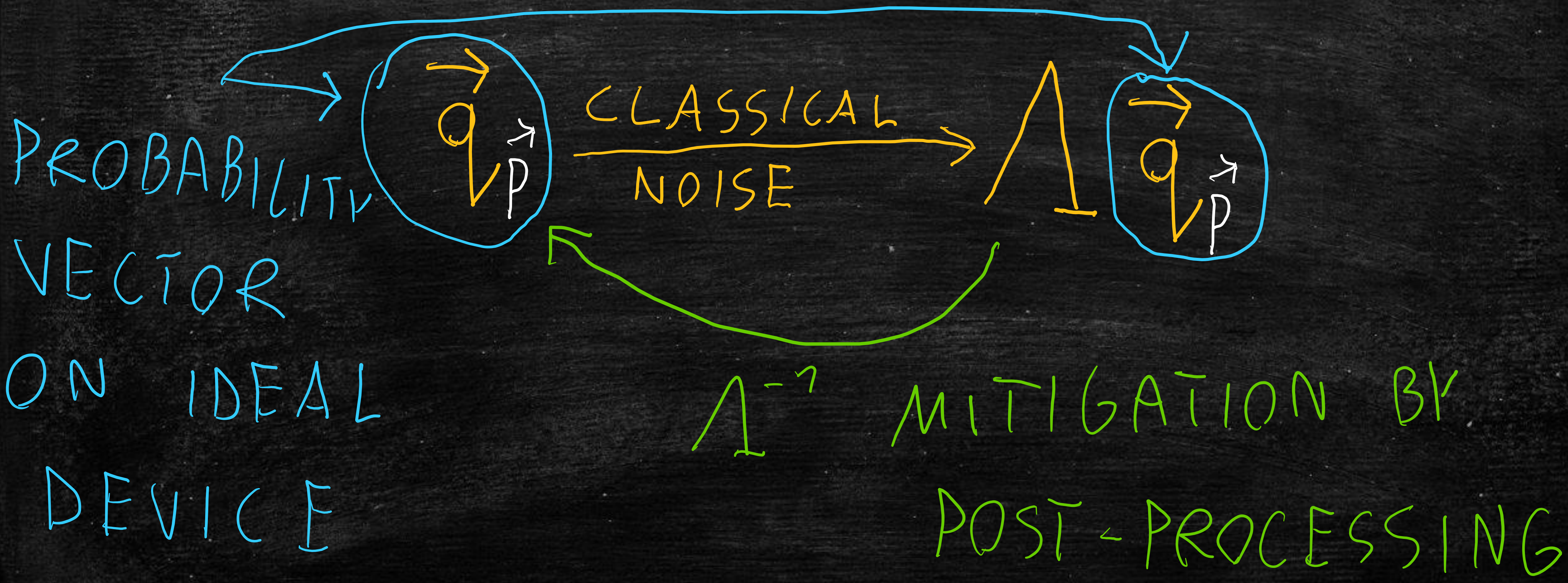
- Problem:
  Requires post-processing of exponentially big noise matrix and exponentially big probability vectors.

Mitigation of classical noise

- On the level of probability vectors:



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- "Solution" :

Focus on problems which are feasible.

Feasible problems

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$$H = \sum_K H_K = \sum_i \sigma_i \sigma_{i+1} h_{i,i+1}$$

Noise-mitigation on marginals

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- Take global noise with local clusters and neighbors:

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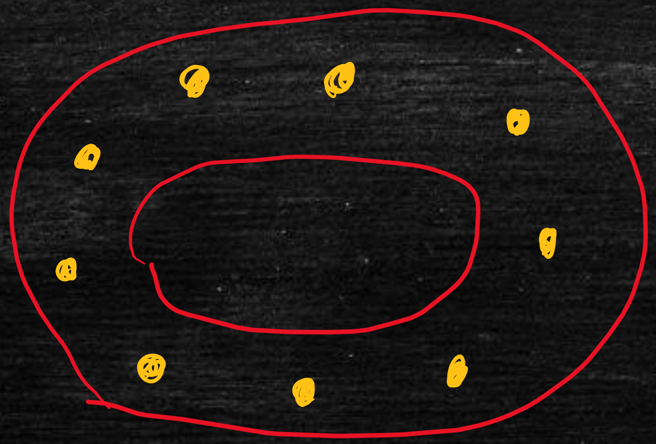

Noise-mitigation on marginals

- Check how it affects marginal distributions:

$$\tilde{\Lambda}^{\mathcal{K}}_{\mathbf{X}_{\mathbf{C}^{\mathcal{K}}}|\mathbf{X}_{\mathbf{C}^{\mathcal{K}}}} = \sum_{\mathbf{Y}_{\mathcal{N}^{\mathcal{K}}}} p\left(\mathbf{Y}_{\mathcal{N}^{\mathcal{K}}}|\mathbf{Y}_{C^{\mathcal{K}}}\right) \prod_{C_\chi = C_1}^{C_{\mathcal{K}}} \Lambda^{\mathbf{Y}_{\mathcal{N}_{C_\chi}}}_{\mathbf{X}_{C_\chi}|\mathbf{Y}_{C_\chi}}$$

$\mathcal{K}$

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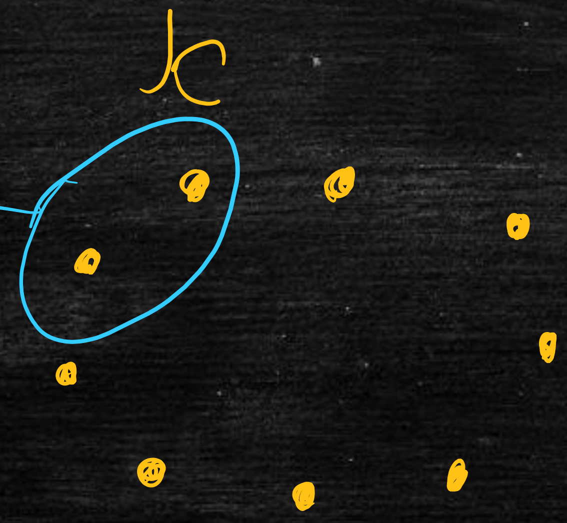
NOISE MATRIX ON MARGINAL



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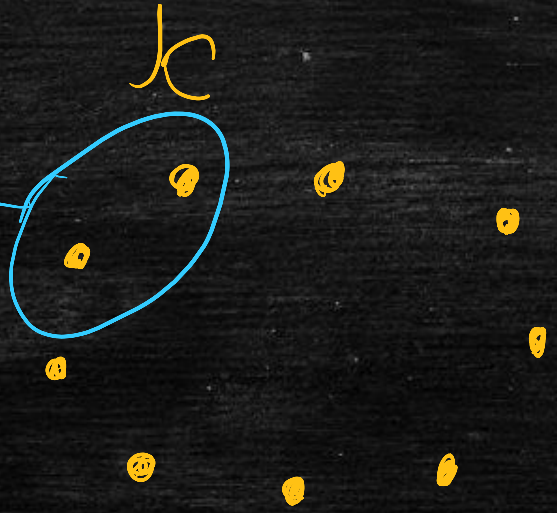
NOISE MATRIX ON MARGINAL



SMALL MATRICES WE GOT FROM CHARACTERIZATION

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NOISE MATRIX ON MARGINAL

PERFECT CONDITIONAL DISTRIBUTION

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NOISE MATRIX ON MARGINAL

PERFECT CONDITIONAL DISTRIBUTION (UNKNOWN)

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PERFECT CONDITIONAL DISTRIBUTION

(UNKNOWN)

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PERFECT CONDITIONAL DISTRIBUTION

(UNKNOWN)

PUT HERE UNIFORM

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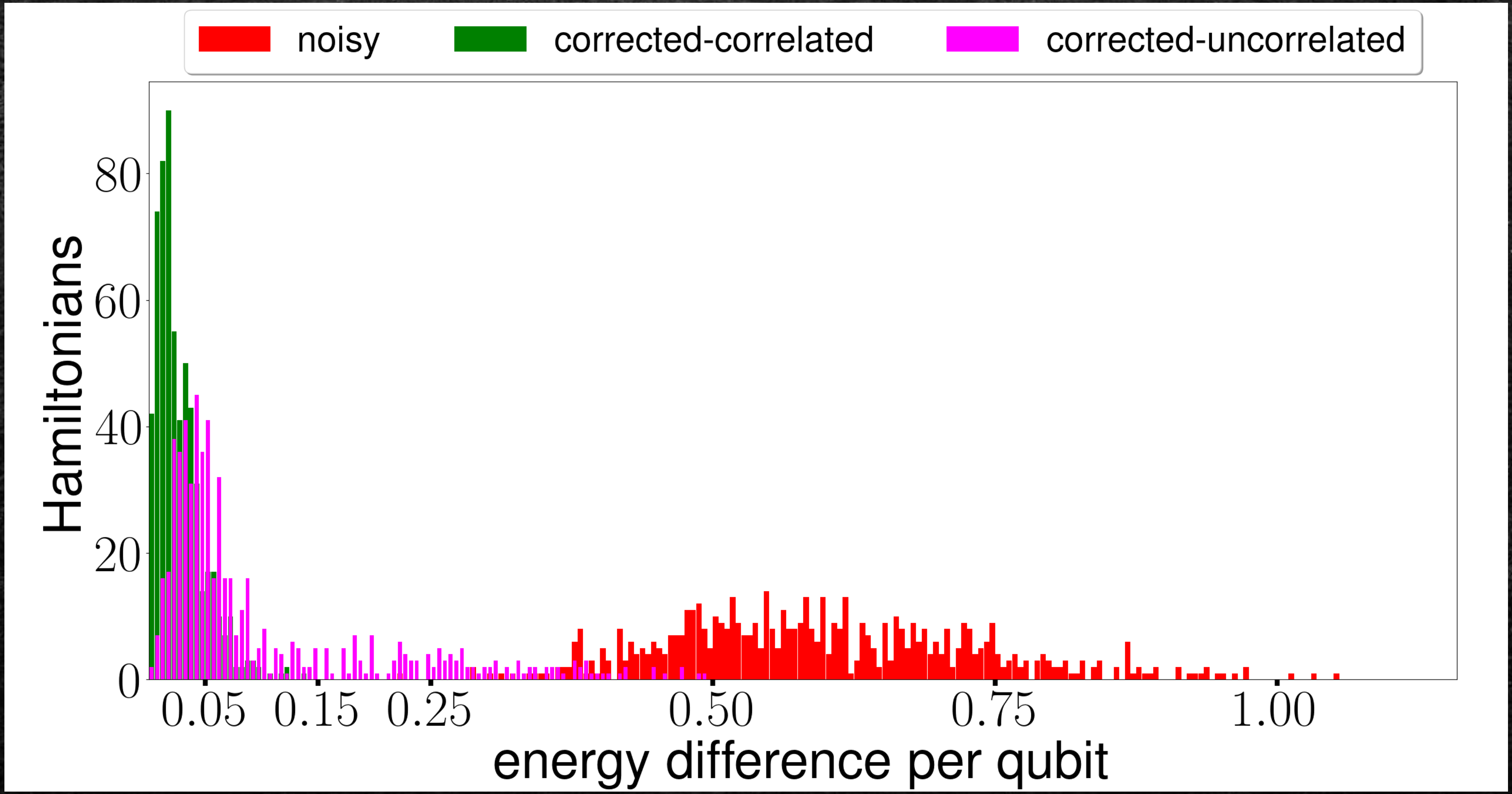
- We did it for 600 Hamiltonians encoding random MAX 2SAT (clause density 4) instances and fully connected random 2-local Hamiltonians on IBM's 15Q Melbourne device.

Experimental results – IBM, 15 qubits (MAX 2SAT)



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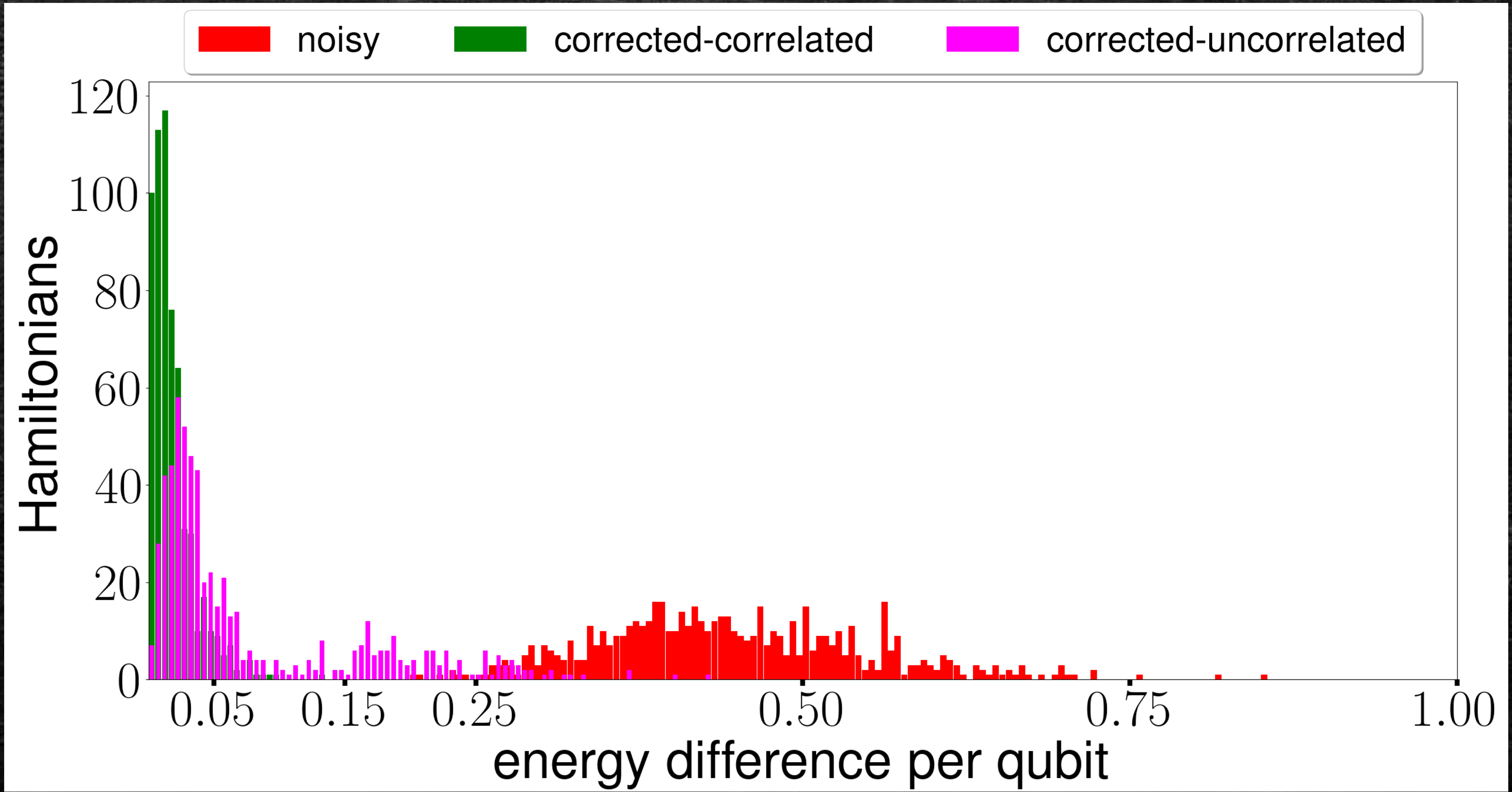

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QUANTUM 4 257
(2020)

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SOON ON ARXIV!

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THANK YOU!

Additional slides

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- Successful noise-mitigation in experiments on 15 qubits.
- Effects of approximate mitigation and statistical errors.
- Effects of realistic readout noise on Quantum Approximate Optimization Algorithm.
- Statistical analysis of estimation of energy of local Hamiltonians.

SOON ON ARXIV!

- Check out our GitHub repository: github.com/fbm2718/QREM