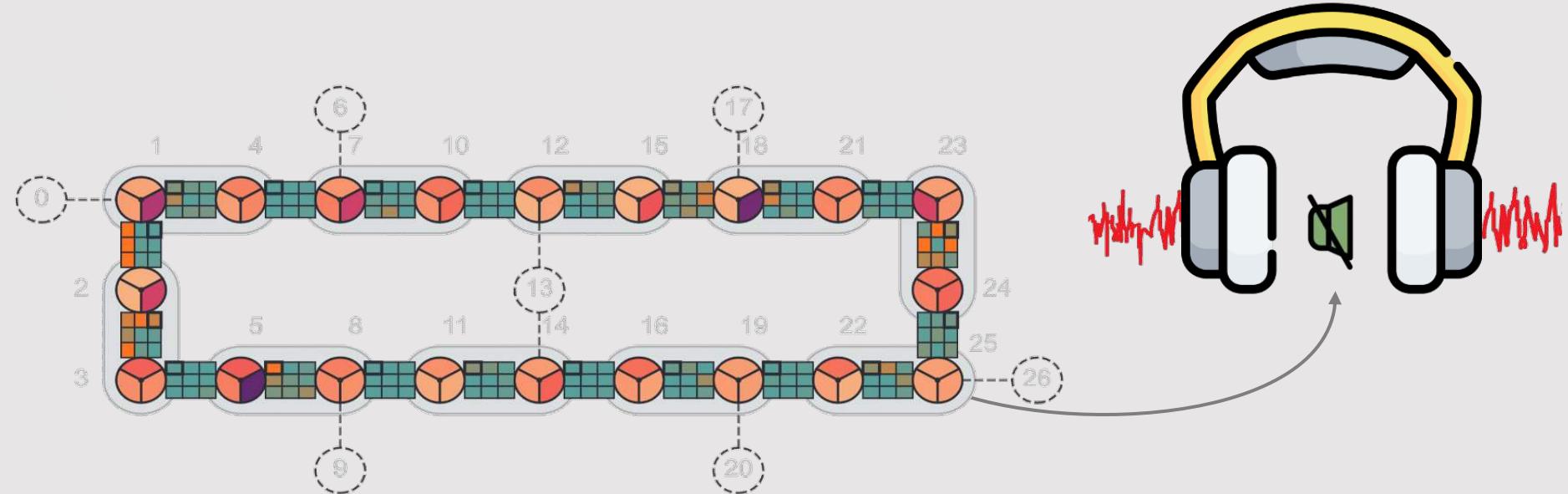


To learn and cancel quantum noise

IBM Quantum

Probabilistic error cancellation with sparse Pauli-Lindblad models on noisy quantum processors



Zlatko K. Minev

Ewout van den Berg, Zlatko K. Minev, Abhinav Kandala, Kristan Temme
arXiv:2201.09866 (2022)



Acknowledgements: broader IBM Quantum team



@zlatko_minev



zlatko-minev.com

Biggest challenge?

Reply in comment chat box

Biggest challenge?



Zlatko Minev @zlatko_minev

What is the biggest challenge to quantum computing today?

(Reply in thread)

98 31 176 

Biggest challenge?

Noise
(Errors)

hardware
development

decoherence

loss

stability

error correction
overheads

scalability

engineering

need CS/EE
talent

material
quality

heat

algo
development

modularization

gravity

hype

expectations

Biggest challenge

Noise
(Errors)



Cancel quantum noise



High-level message

Learn

accurate, efficient, scalable



Cancel

noise with noise,
practical



Cost

more noise more cost



Outline



Idea

Probabilistic error cancelation (PEC) idea

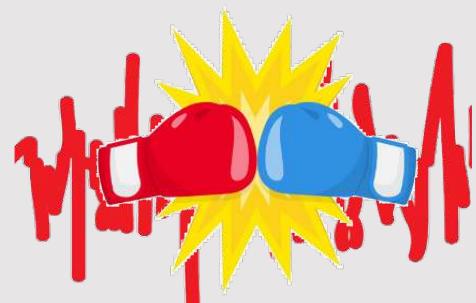
Why not possible at scale until now?



Learn

Challenge

Sparse Pauli-Lindblad model in experiment



Cancel (realization)

Mitigation in practice with Ising

Cost

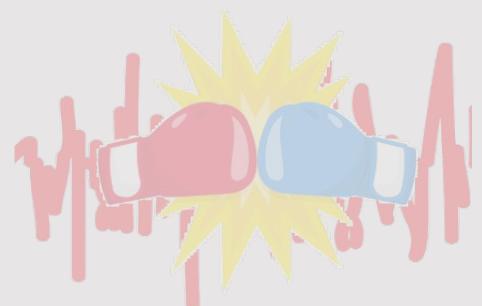
Outline



Idea

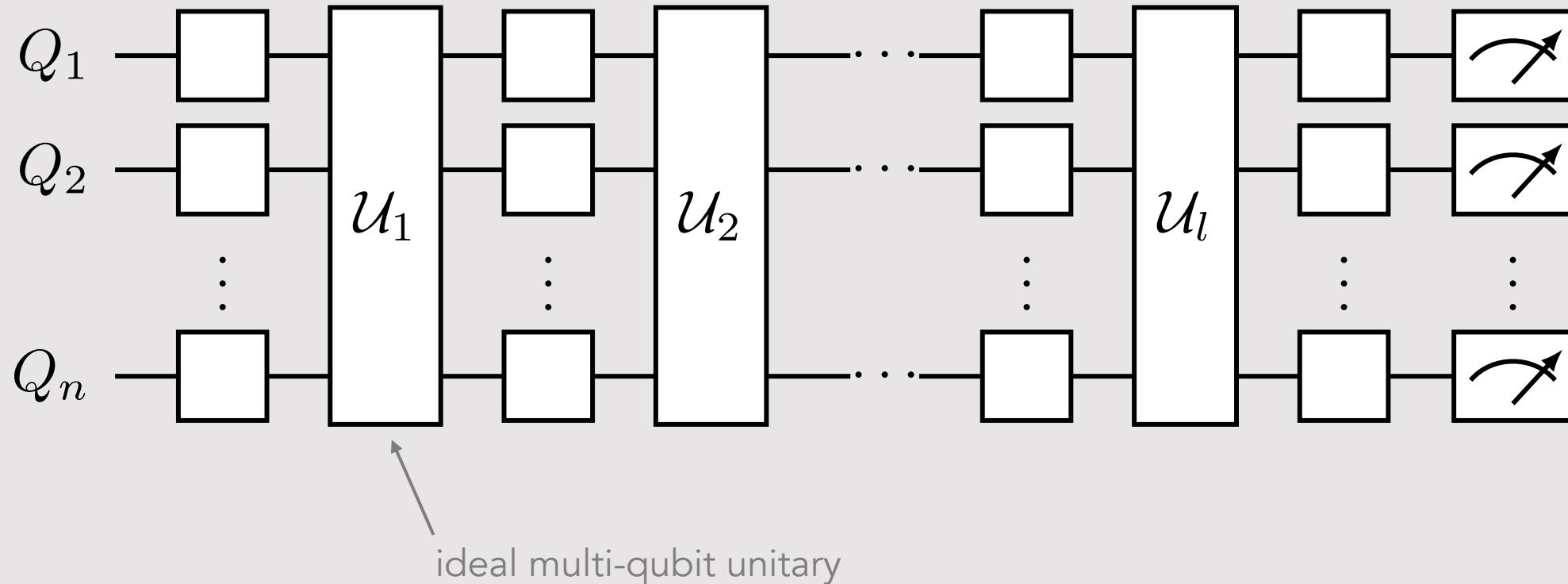


Learn



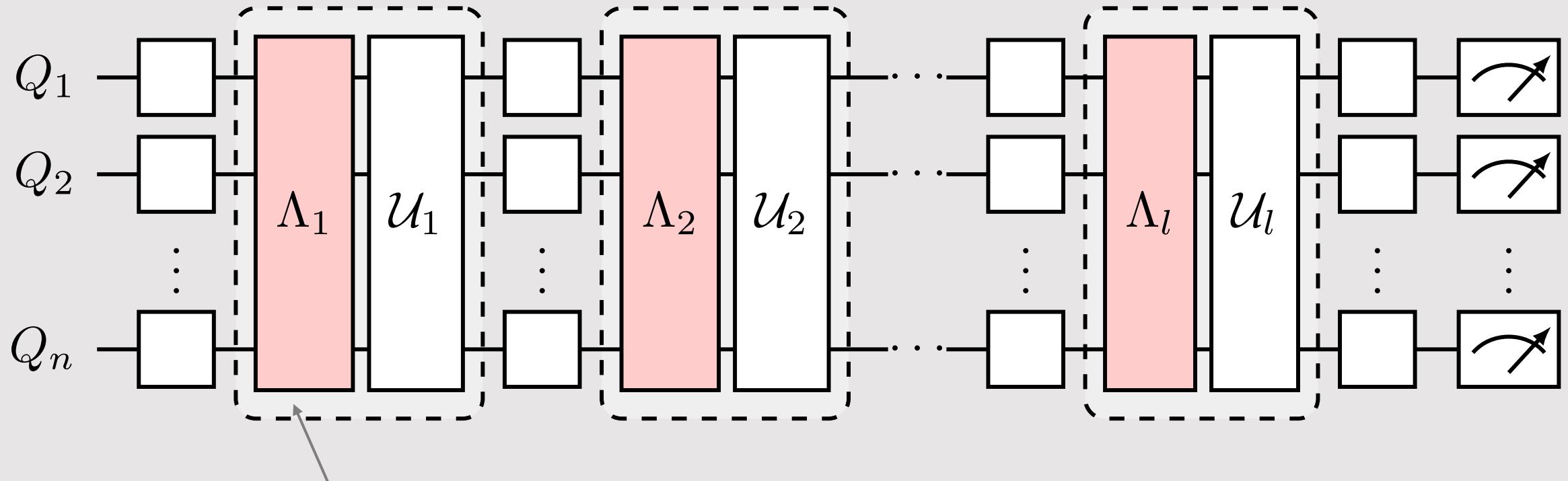
Cancel
(realization)

Ideal (noise-free) quantum circuit



A circuit can be decomposed into a layer construction
Example: Trotterization of Ising model simulation

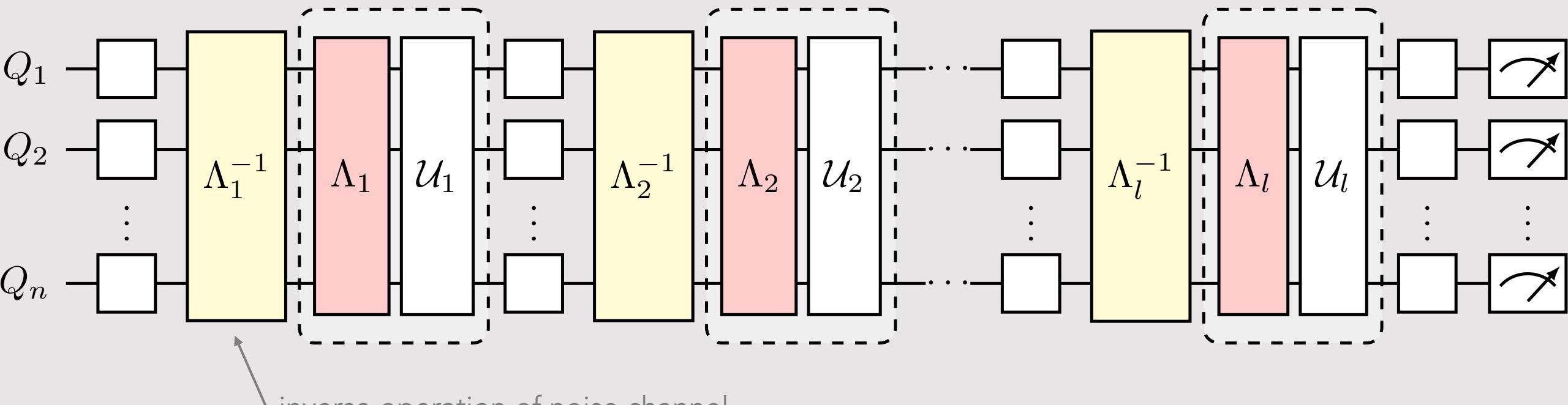
Real (noisy) quantum circuit



multi-qubit noise channel
inseparable from gate

completely positive and trace preserving (CPTP)
representable by a $4^n \times 4^n$ matrix

Why not invert noise?

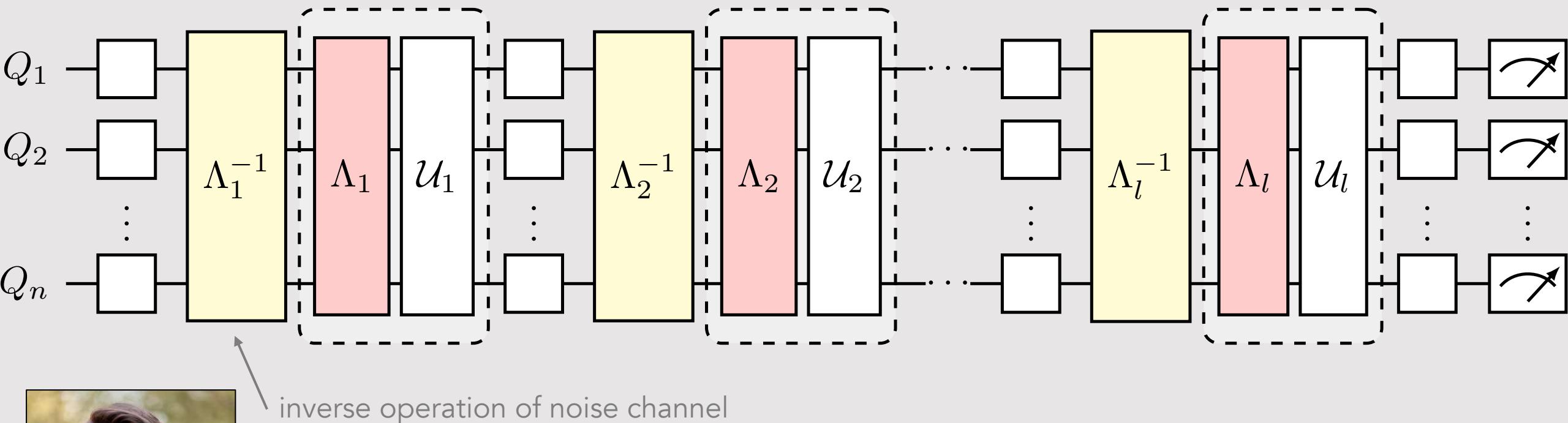


Not possible?

inverse operation of noise channel
unphysical
would need to know lost information due to noise
non CPTP map
has negative eigenvalues

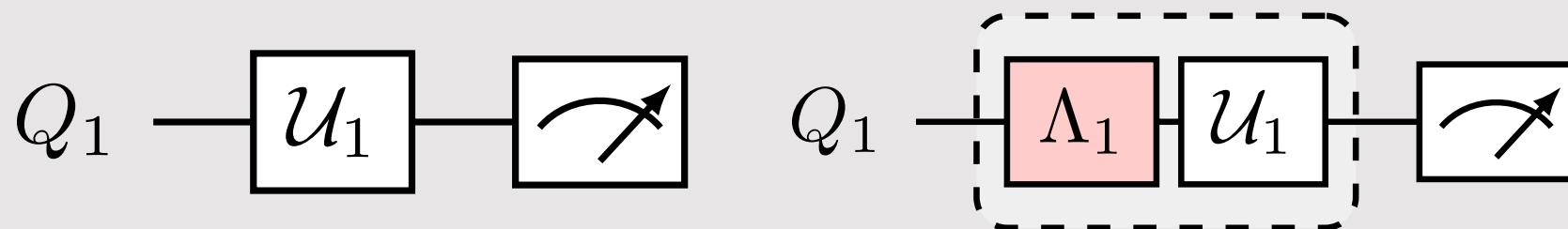
...

Probabilistic error cancellation

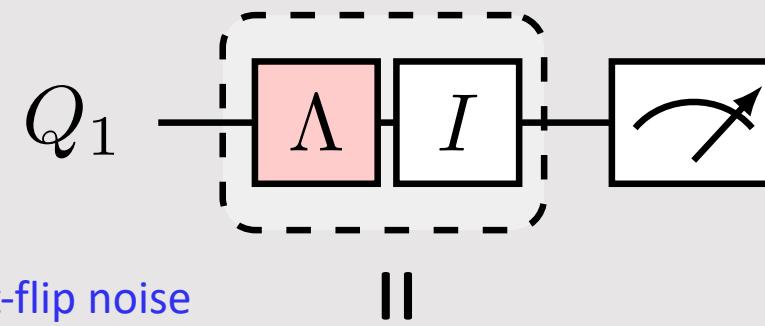
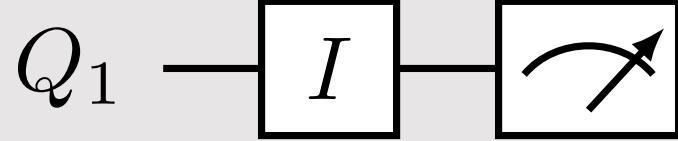


K. Temme, S. Bravyi, J. M. Gambetta,
Physical Review Letters 119, 180509 (2017)

Toy model

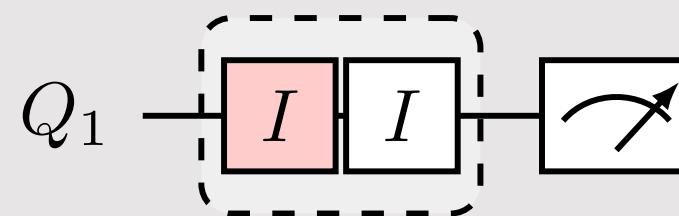
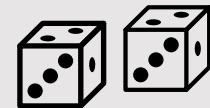


Toy model: noise unraveling into quantum trajectories

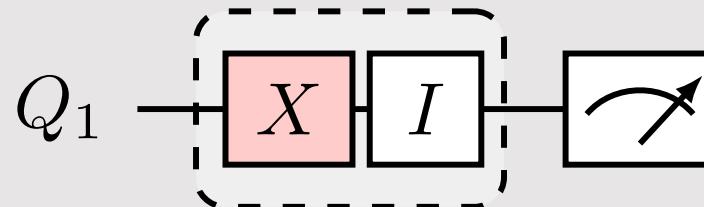


unraveling
(quantum trajectories)

probability $1-p$

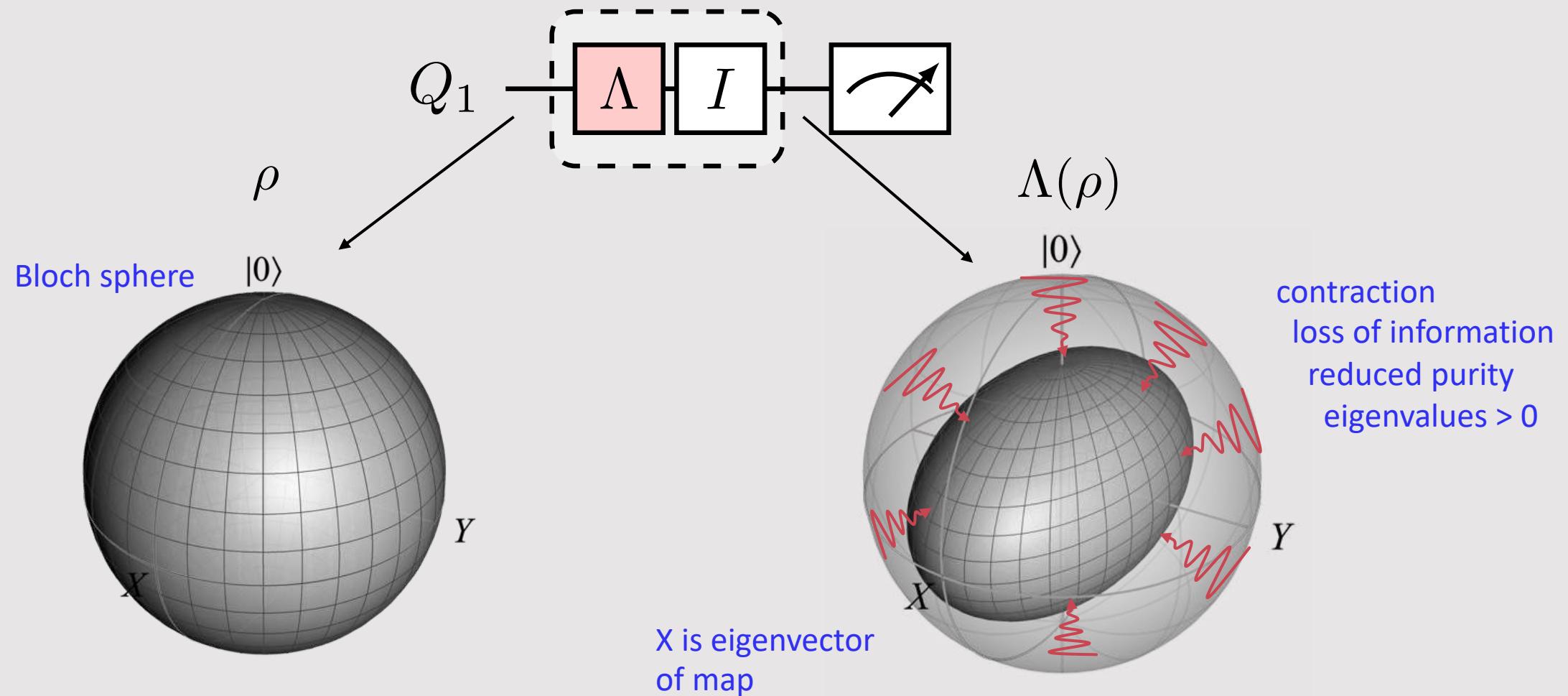


probability p

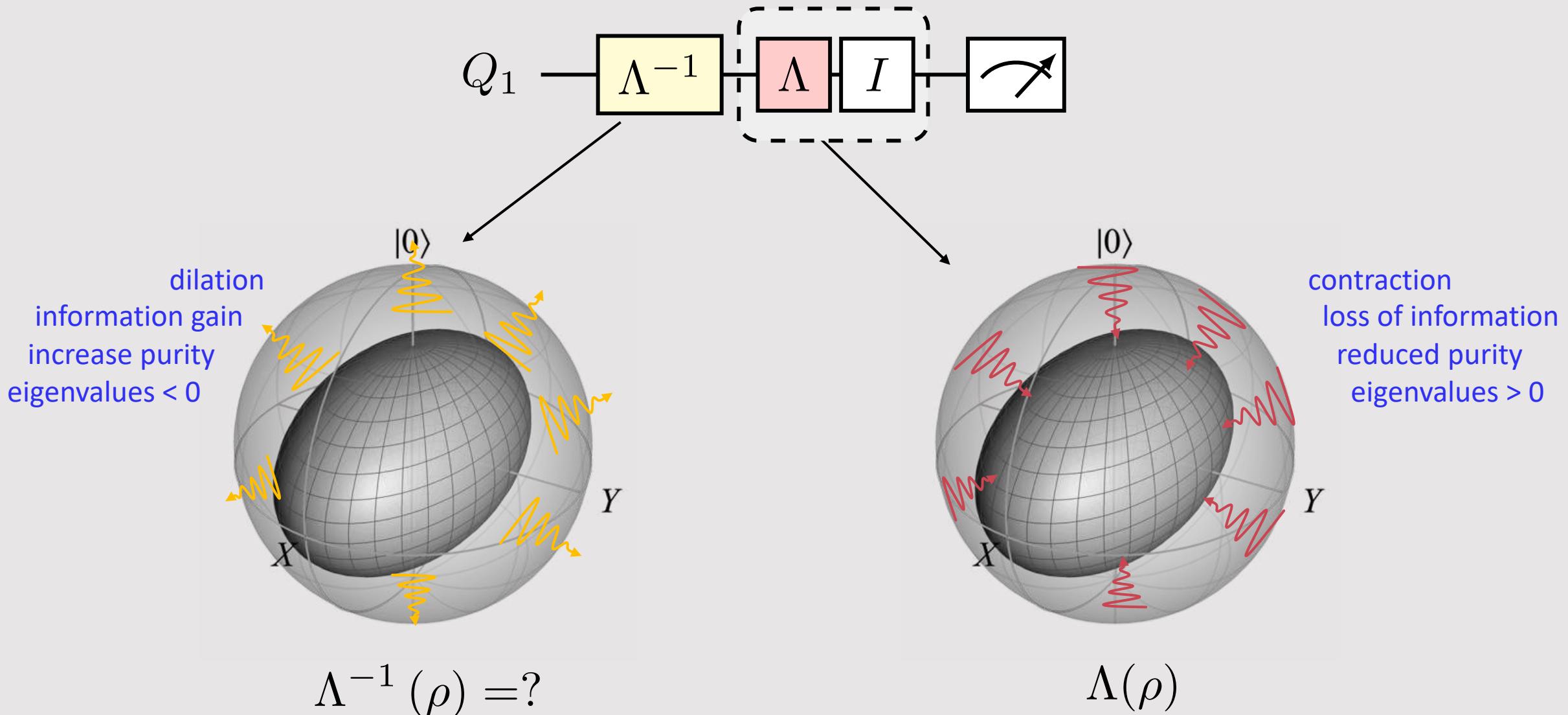


$$\Lambda(\rho) = (1 - p)I\rho I + pX\rho X$$

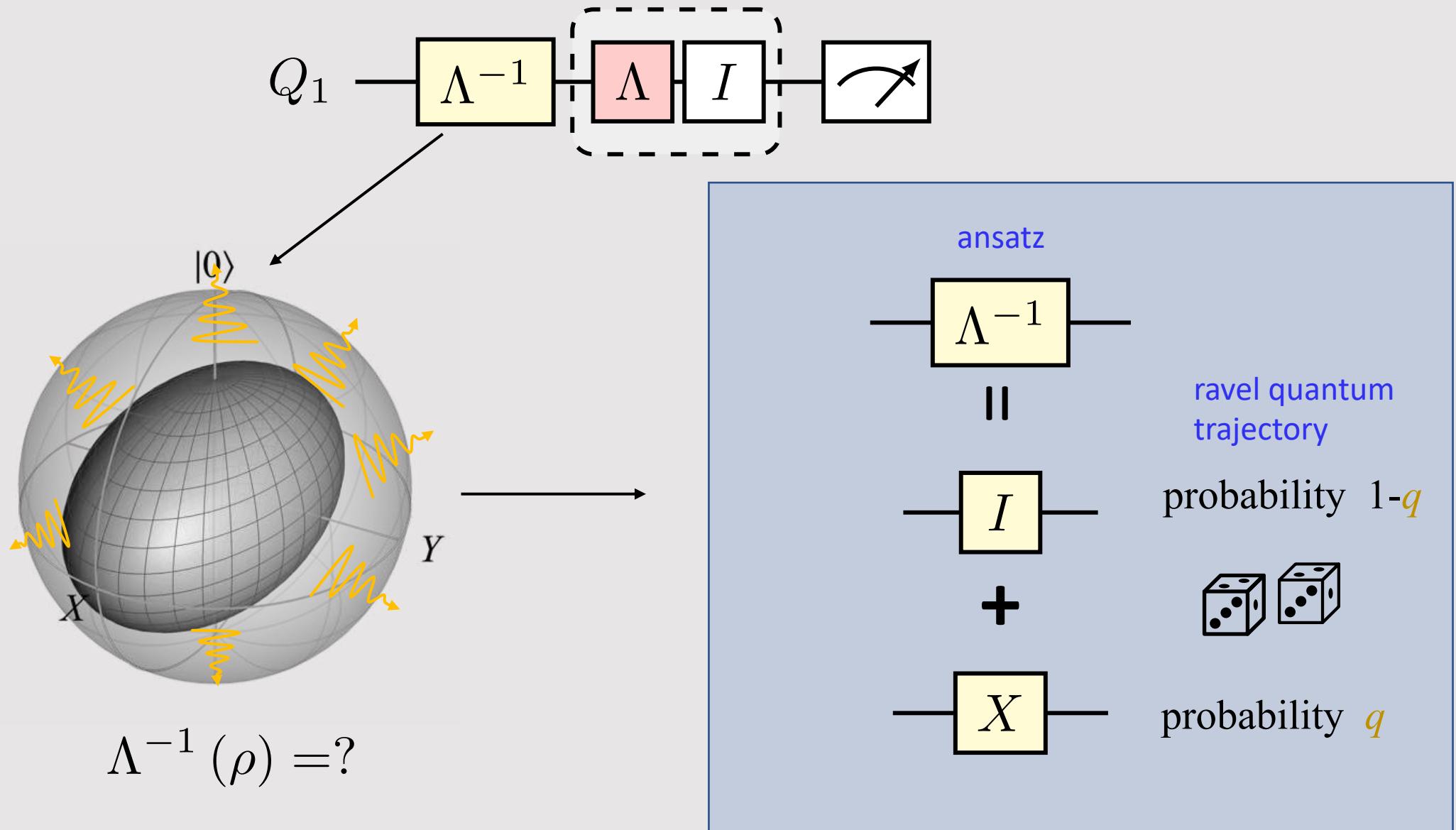
Toy model: noise unraveling into quantum trajectories



Inverse of noise map is not physical



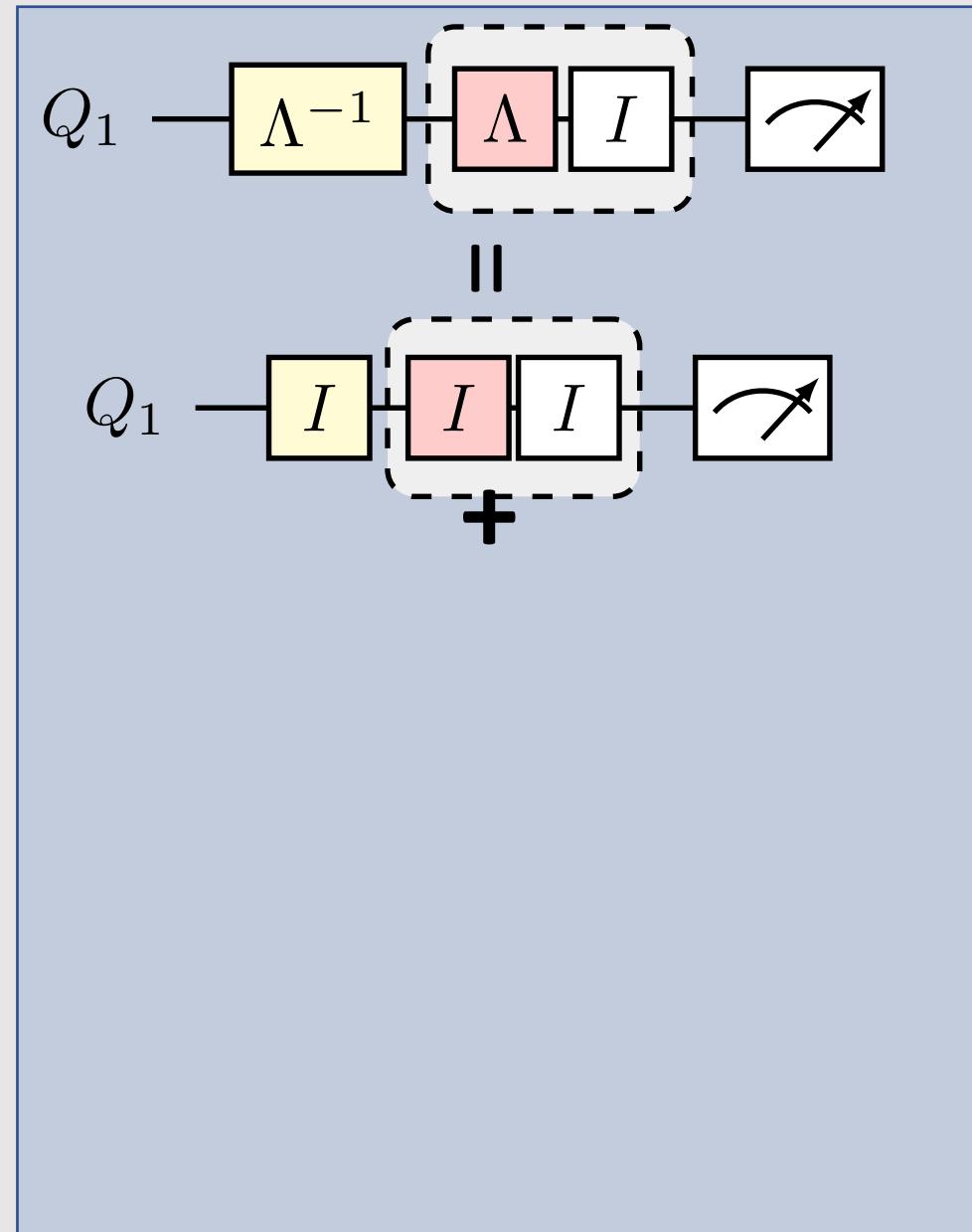
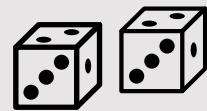
Inverse of noise map is not physical



Raveling quantum trajectories to undo noise

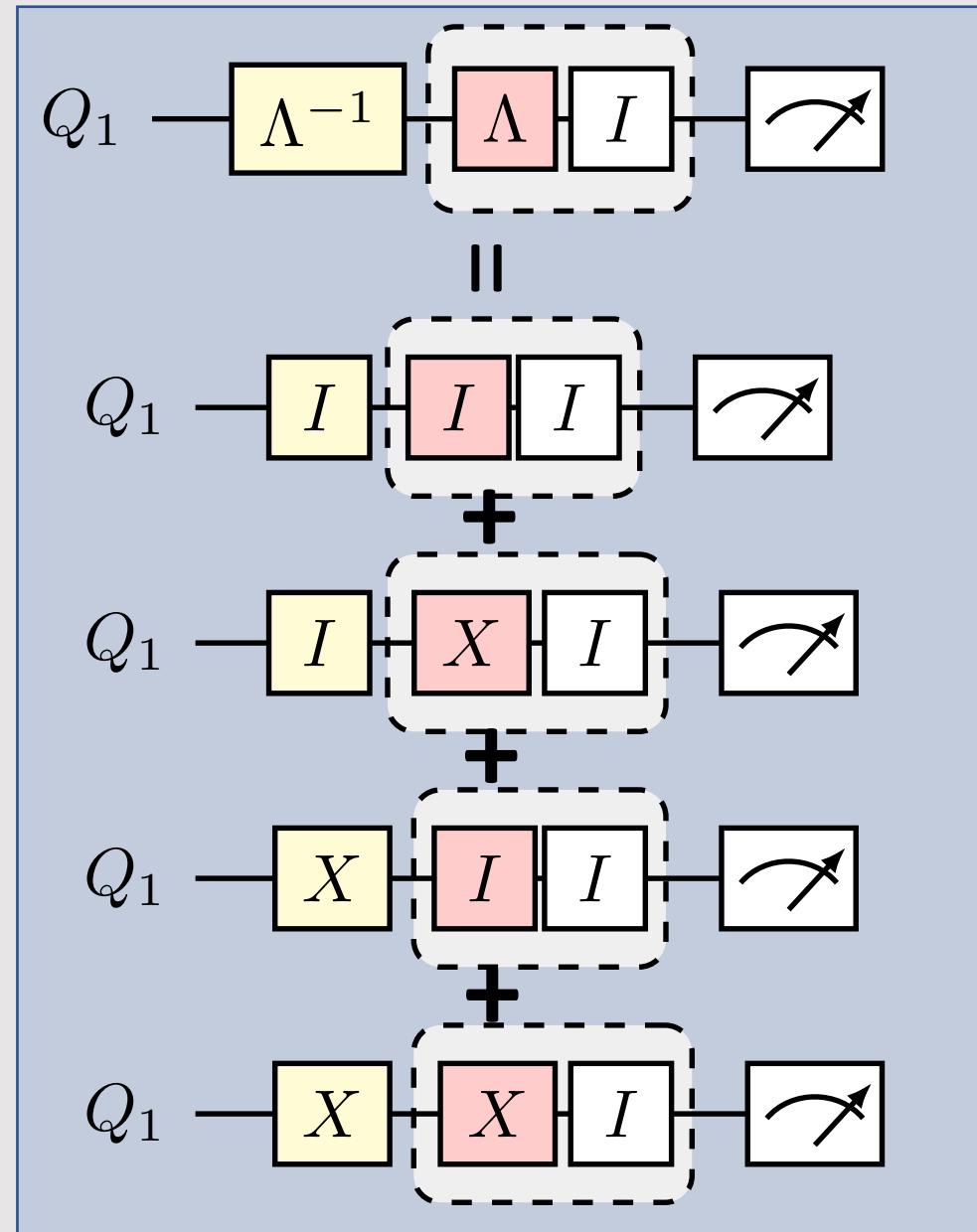
No error!

probability
 $(1-q)(1-p)$



Raveling quantum trajectories to undo noise

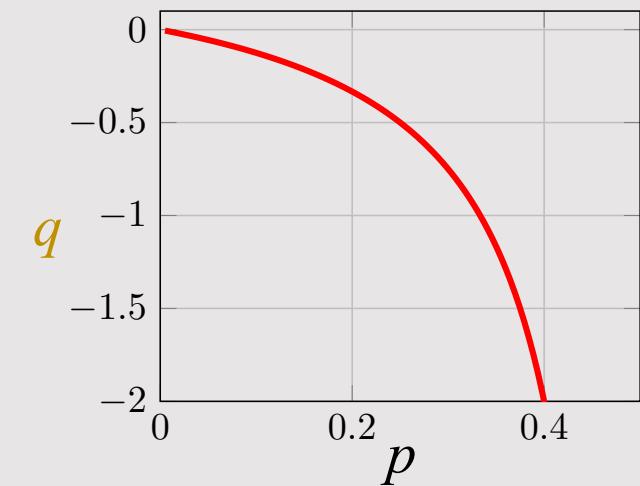
No error!	probability $(1-q)(1-p)$	probability $(1-q)p$
ERROR!		
ERROR!		
Error canceled!	$q p$	



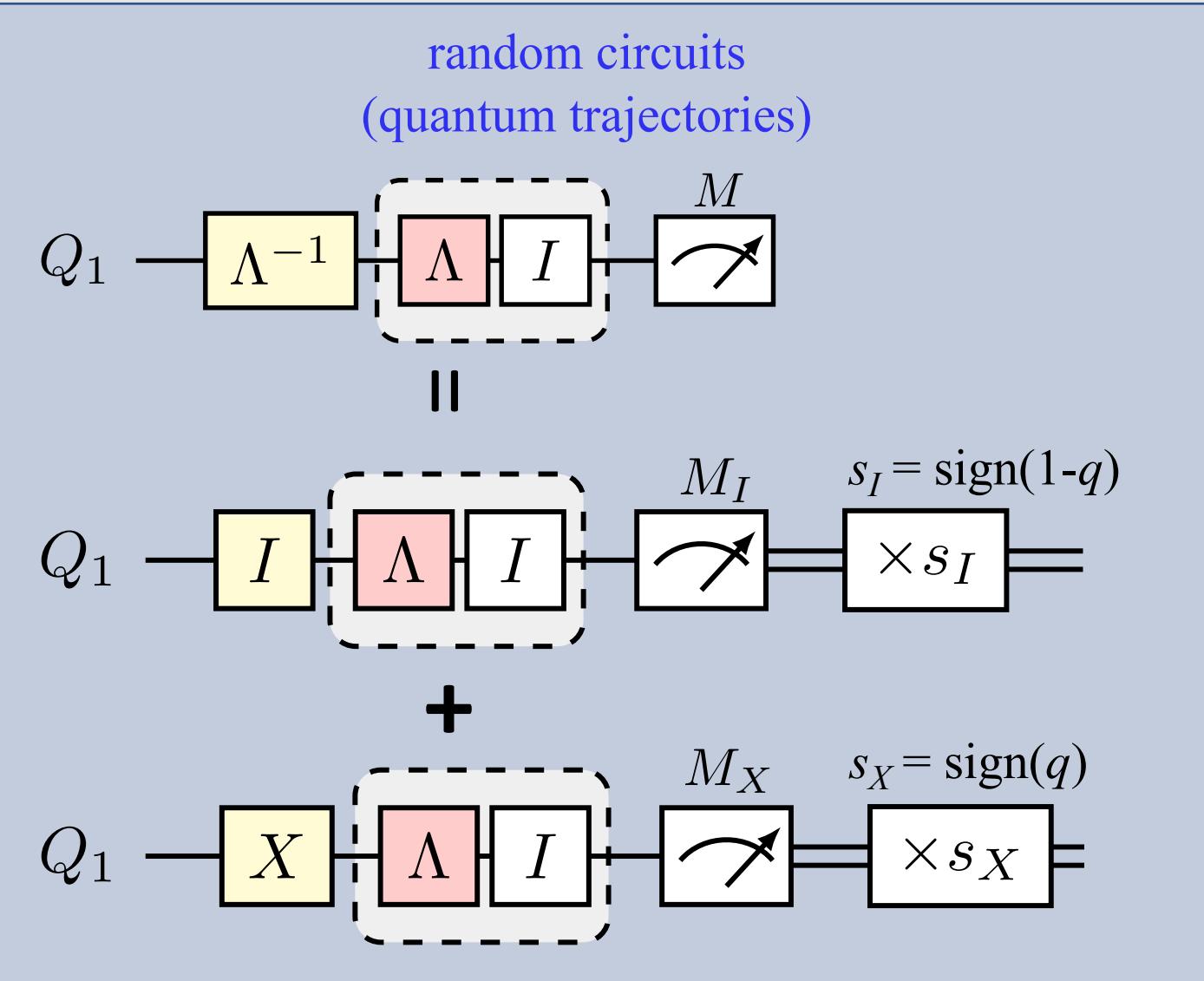
Solution to noise free!

$$q = \frac{-p}{1 - 2p}$$

Sign & scale:
quasi-probability

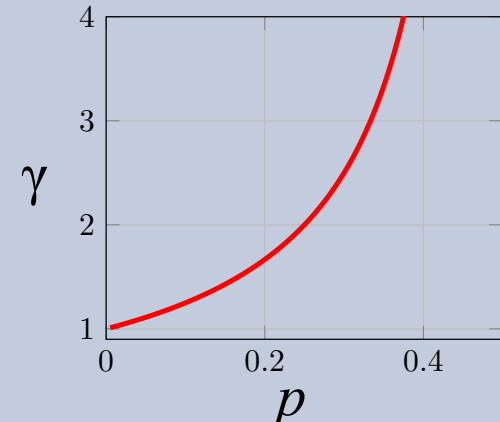


How to implement?



sampling overhead

$$\gamma = |1-q| + |q|$$



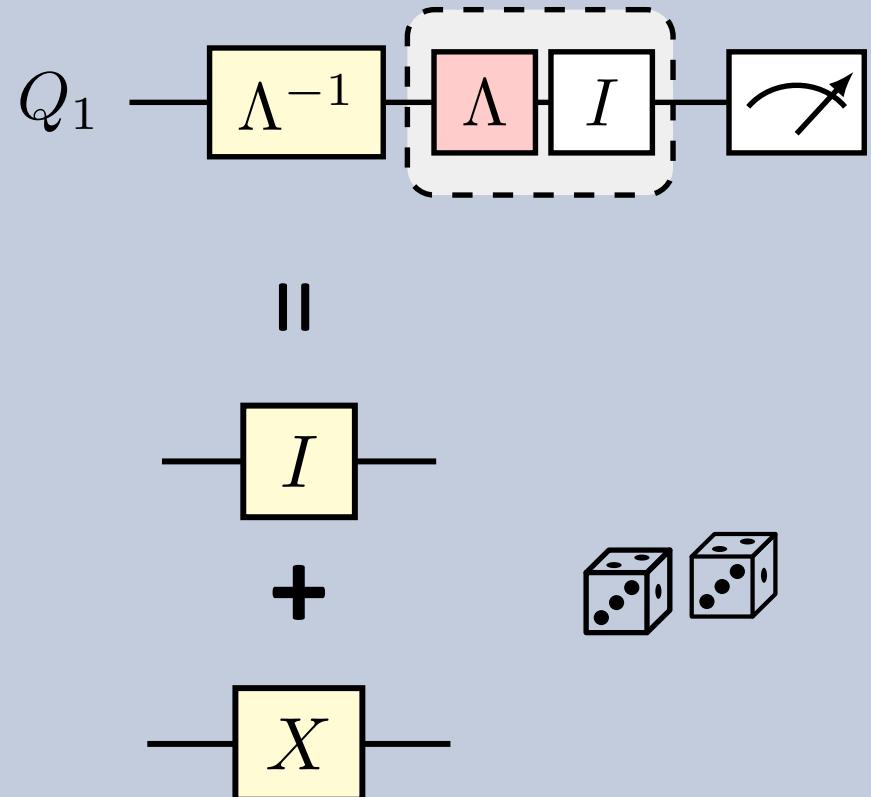
mitigated expectation

$$\langle M \rangle = \gamma(s_I P_I M_I + s_X P_X M_X)$$

Gain: bias-free estimate!

Cost: variance

Cancelling noise with noise



Cancelling noise with noise: Drunkard's classical random walk analogy



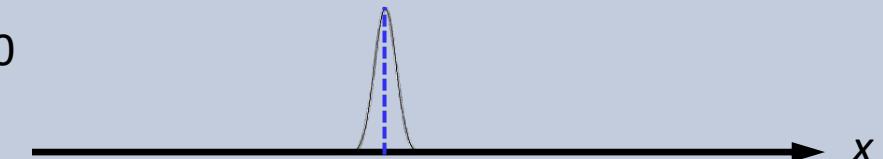
$P(1 \text{ step left}) = \frac{1}{2} - p$

$P(1 \text{ step right}) = \frac{1}{2} + p$

Random step

Distribution of random walk

$t = 0$



$t > 0$



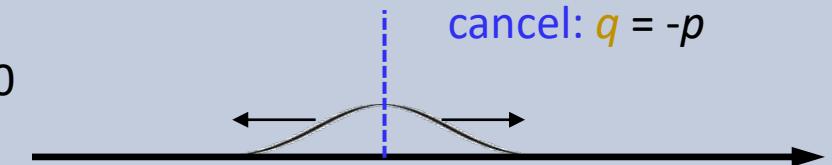
add 2nd random process
wind blows

$P(1 \text{ step left}) = \frac{1}{2} + q$

$P(1 \text{ step right}) = \frac{1}{2} - q$

Distribution of random walk with wind

$t > 0$



Gain: bias-free estimate!
Cost: variance

Putting them all on the same footing: David Sutter chat

$$\overbrace{\mathcal{E}(\cdot)}^{\text{want to do}} = \sum_i a_i \underbrace{F_i(\cdot)}_{\substack{\text{operation} \\ \text{we can do}}} \quad \text{CPTP}$$

Q P D

$\mathcal{E}(\cdot)$

want to do

EIR

operation we can do

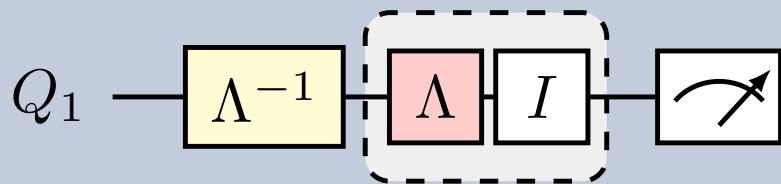
$$\overbrace{1 \leq N := \sum_i |a_i|}^{\text{Overhead}}$$

- ① PEC, $\mathcal{E}(\cdot)$ unitary, $F_i(\cdot)$ noisy op.
 - ② class. sim. alg., $\mathcal{E}(\cdot)$ unitary, $F_i(\cdot)$ Clifford
 - ③ Gate cutting
 - ④ Wire cutting
- $\mathcal{E}(\cdot)$ nonlocal gate (two-qubit) $F_i(\cdot)$ local
- fixed $F_i(\cdot)$
- Benyamin - Tennen - Gemp -
- $O(\frac{2T}{N})$, $T = \#\mathcal{T}$

Nice, but why hasn't worked so far?

Challenges

Small scale



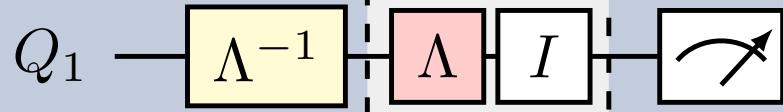
Critically hinges on knowing the full noise near perfectly

Despite the method's theoretical appeal (1-10), practical challenges have limited its demonstration to the one and two-qubit level (2, 3)

1. S. Endo, S. C. Benjamin, Y. Li, Physical Review X 8, 031027 (2018).
2. C. Song, et al., Science Advances 5, arXiv:2109.04457(2019).
3. S. Zhang, et al., Nature Communications 11, 587 (2020).
4. C. Piveteau, D. Sutter, S. Woerner, arXiv:2101.09290 (2021).
5. S. Endo, et al., J. Physi Soc. of Japan 90, 032001 (2021).
6. C. Piveteau, et al., arXiv:2103.04915 (2021).
7. R. Takagi, Phys. Rev. Research 3, 033178 (2021).
8. R. Takagi, S. Endo, S. Minagawa, M. Gu, arXiv:2109.04457 (2021).
9. Y. Guo, S. Yang, arXiv preprint arXiv:2201.00752 (2022).
10. ...

Nice, but why hasn't worked so far? Challenges

Small scale



2 qubits

10 qubits

50 qubits

noise param values $10^{-2} - 10^{-5}$

additive error sampling cost ($>10^2 - 10^{10}$)

255 parameters

10^{12} parameters

10^{60} parameters

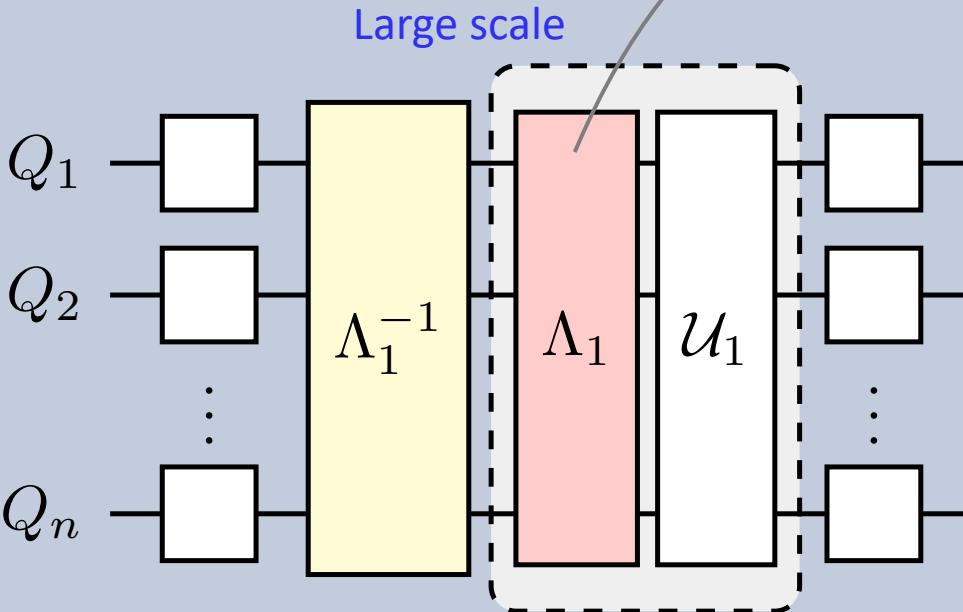
Challenges

learning complexity

- efficient
- scalable
- accurate
- compact, tractable representation

noise in full device

- cross-talk
- correlated errors
- parallel gates



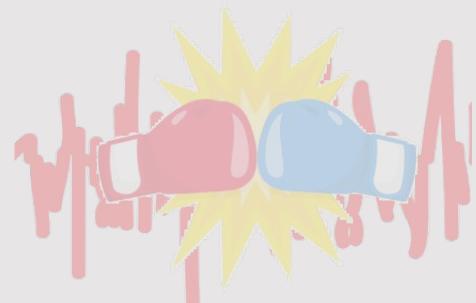
Outline



Idea

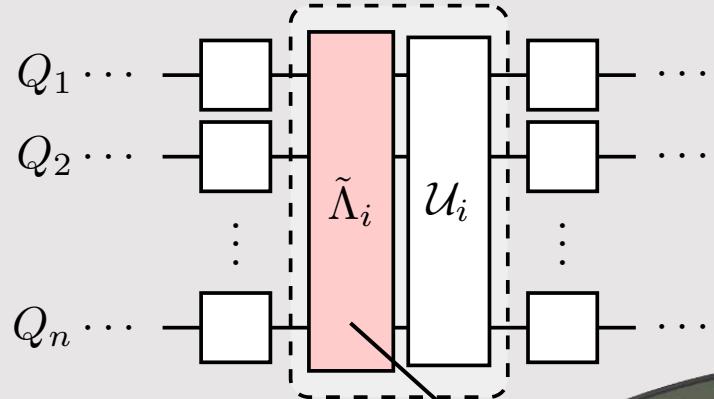


Learn

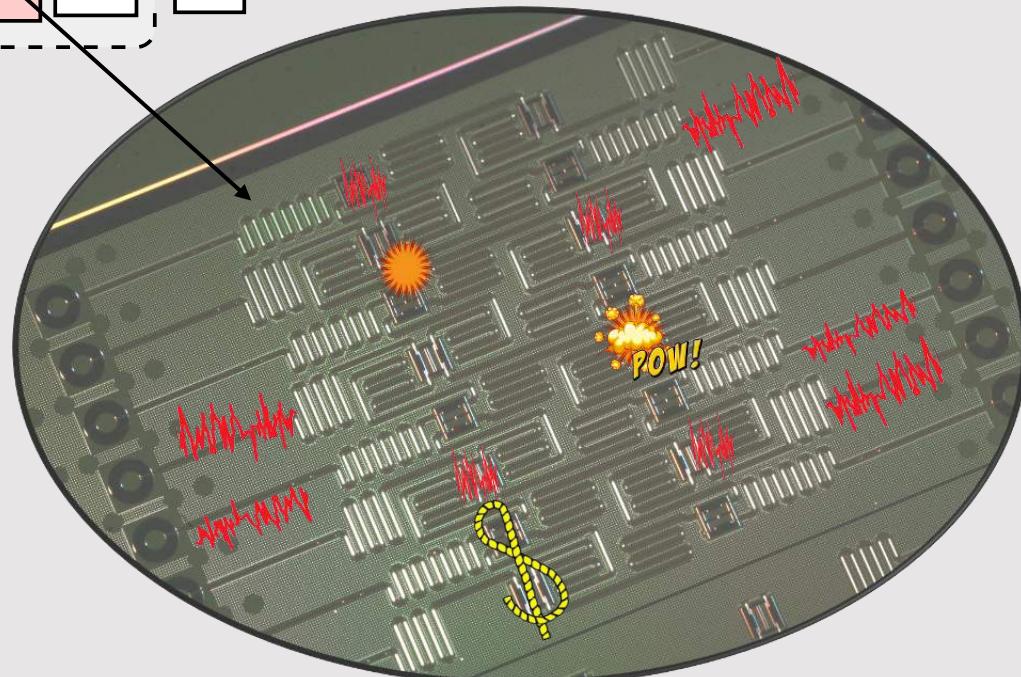


Cancel
(realization)

Is it possible to learn the noise with accuracy, efficiency, and scalability?

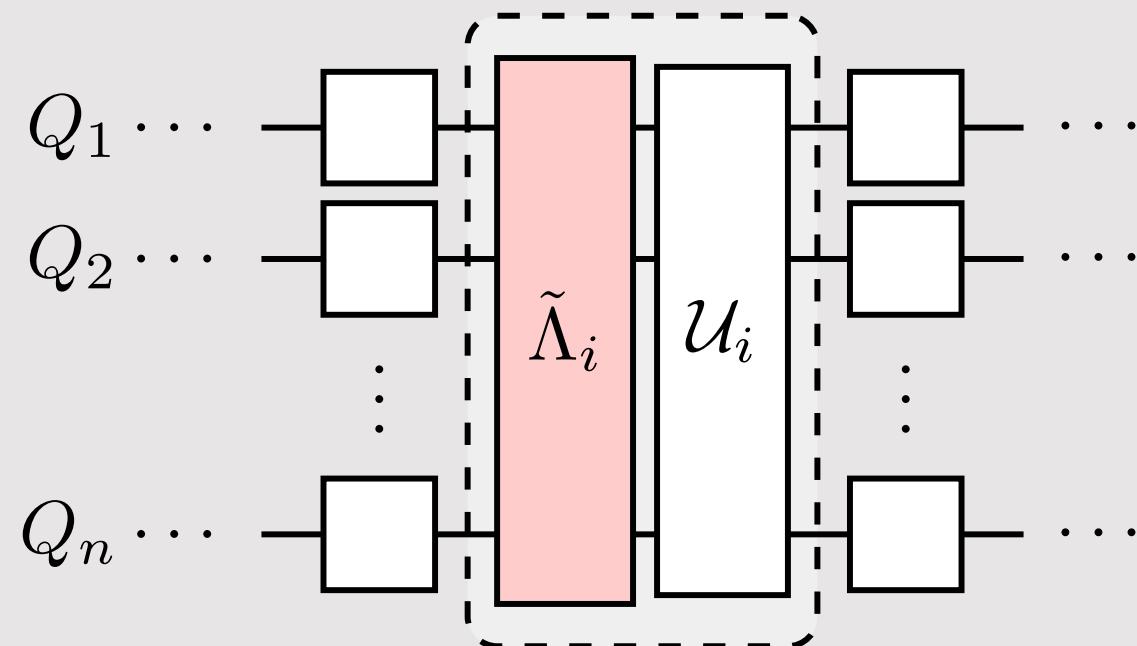


Energy relaxation T_1
Dephasing T_2
Coherent errors ZZ
Classical crosstalk
Quantum crosstalk
State preparation error
Measurement correlated errors
...



Control errors
Photon shot noise
1/f charge noise
1/f flux noise
Nonequilibrium quasiparticles
Leakage
Cosmic rays
...

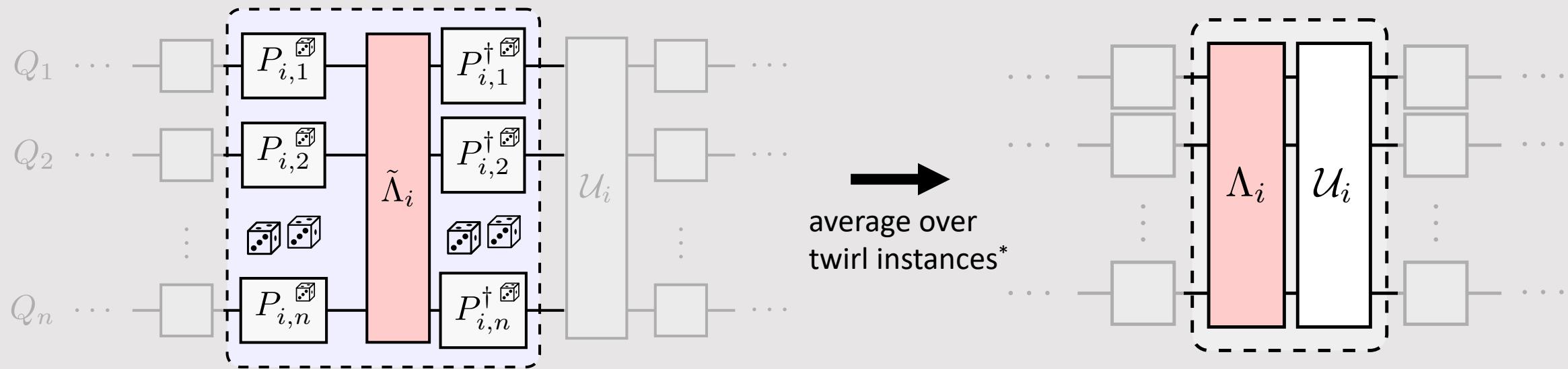
Step 1: Simplify the noise



noise that includes cross-talk errors, etc.
characterized by some $4^n \times 4^n$ matrix

Step 1: Simplify the noise: twirl

twirl reduces to noise $4^n \times 4^n$ matrix to diagonal one with 4^n entries in Pauli basis



Twirling references

1. C. H. Bennett, et al., Phys. Rev. Lett. 76, 722 (1996).
2. E. Knill, arXiv:0404104 (2004).
3. O. Kern, G. Alber, D. L. Shepelyansky, EPJ D 32, 153 (2005).
4. M. R. Geller, Z. Zhou, Physical Review A 88, 012314 (2013).
5. J. J. Wallman, J. Emerson, Physical Review A 94, 052325 (2016)
6. Hashim *et al.*, Phys. Rev. X 11, 041039 (2021)
7. Z. Minev et al., Qiskit Global Summer School Lecture Notes (in prep; see zlatko-minev.com/blog for update) (2022)
8. ...

Stochastic Pauli channel

$$\Lambda_i(\rho) = \sum_{a=0}^{4^n - 1} c_{ia} P_a \rho P_a^\dagger$$

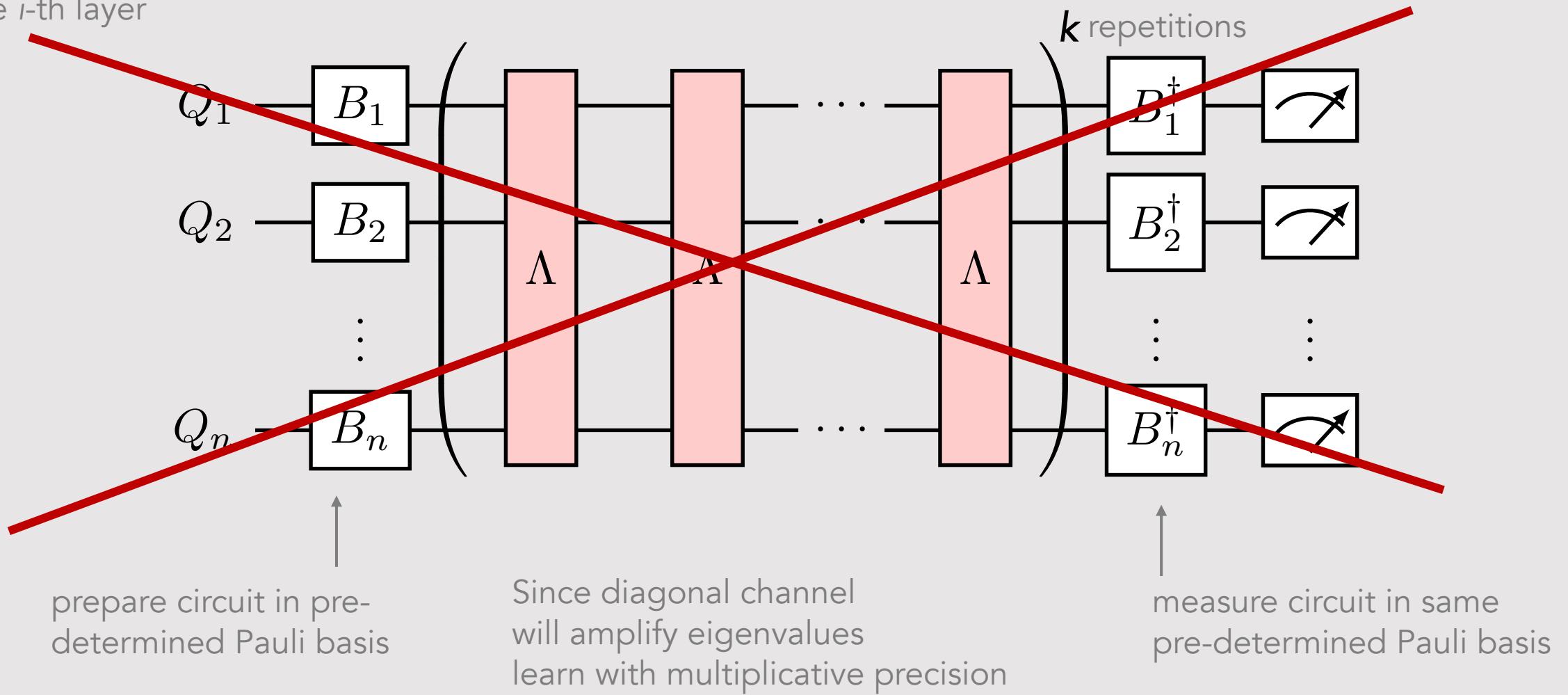
$$\Lambda(P_a) = f_a P_a$$

eigenvecs are Paulis

* some sub-Clifford twirl group (use Paulis)

Step 2 wish: amplify noise

for the i -th layer



Akin to:

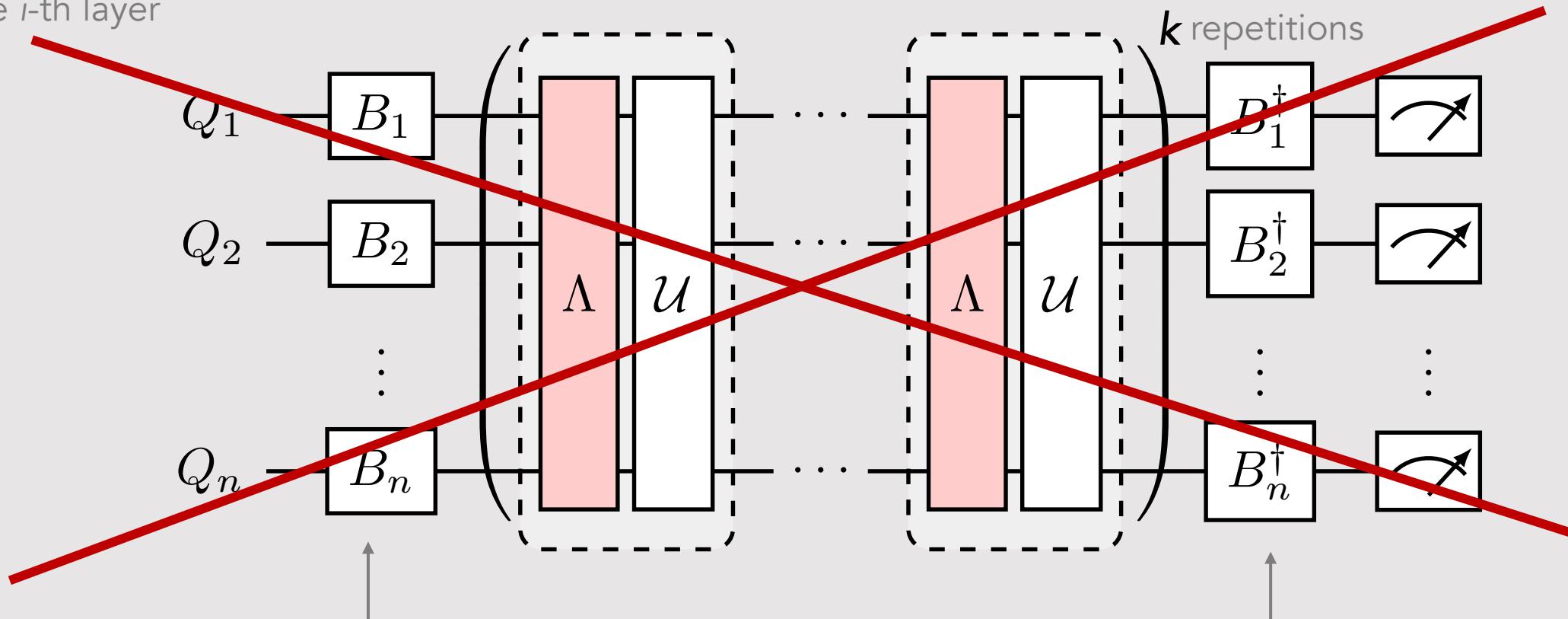
RB, Cycle RB, K-body noise reconstruction, ...

S.T. Flammia and J.J. Wallman ACM Trans QC 1, 3 (2020), ...

For something of a review of protocols, see Helsen, et al., *A general framework for randomized benchmarking* (arXiv:2010.07974)

Step 2 wish: amplify noise with gates?

for the i -th layer



prepare circuit in pre-determined Pauli basis

Since diagonal channel will amplify eigenvalues learn with multiplicative precision

measure circuit in same pre-determined Pauli basis

Akin to:

RB, Cycle RB, K-body noise reconstruction, ...

S.T. Flammia and J.J. Wallman ACM Trans QC 1, 3 (2020), ...

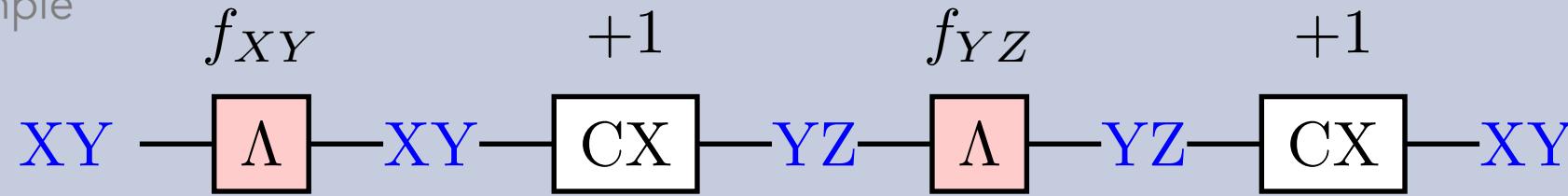
Erhard *et al.*, arXiv:1902.08543; Ferracin *et al.*, arXiv:2201.10672, ...

For something of a review of protocols, see Helsen, *et al.*, arXiv:2010.07974

Let's see how the amplification works with gates: no-go theorem

$$\Lambda(P_a) = f_a P_a$$

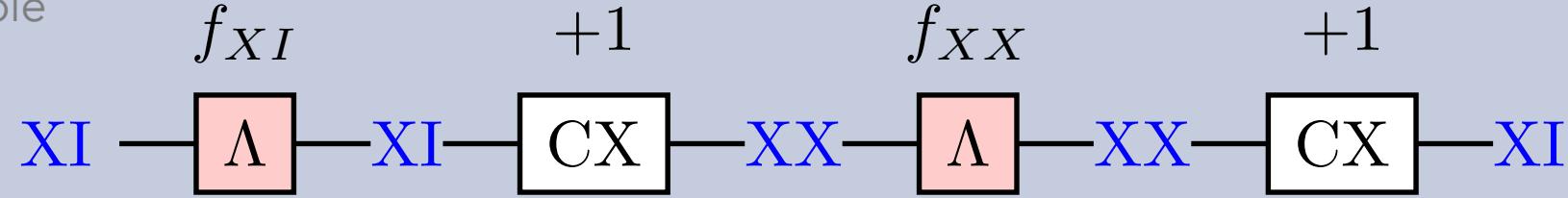
2Q example



action of CX here can be undo by SQ gates

$f_{XY} f_{YZ} XY$

2Q example

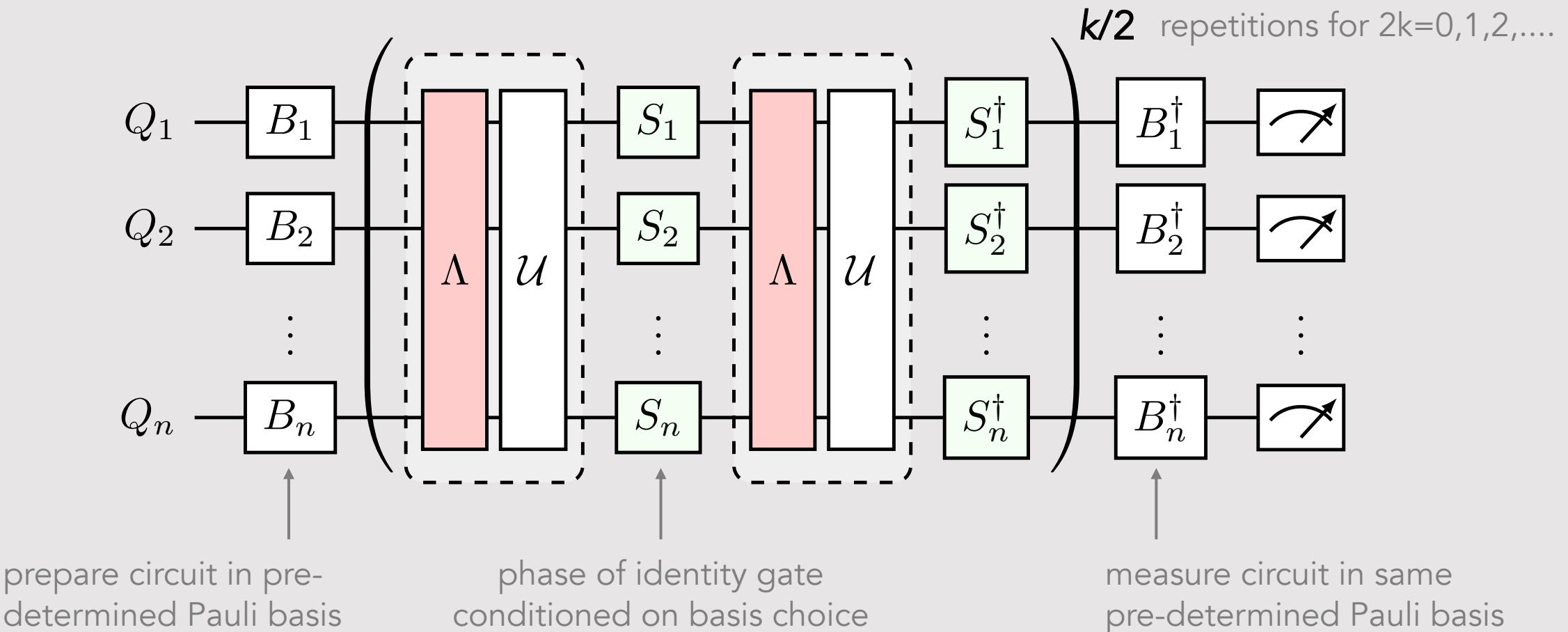


action of CX here can not be undone by SQ gates

$f_{XI} f_{XX} XI$

fundamental degeneracy – can not undo some non-local – need entangling operation

Step 2: Amplify & learn noise per layer



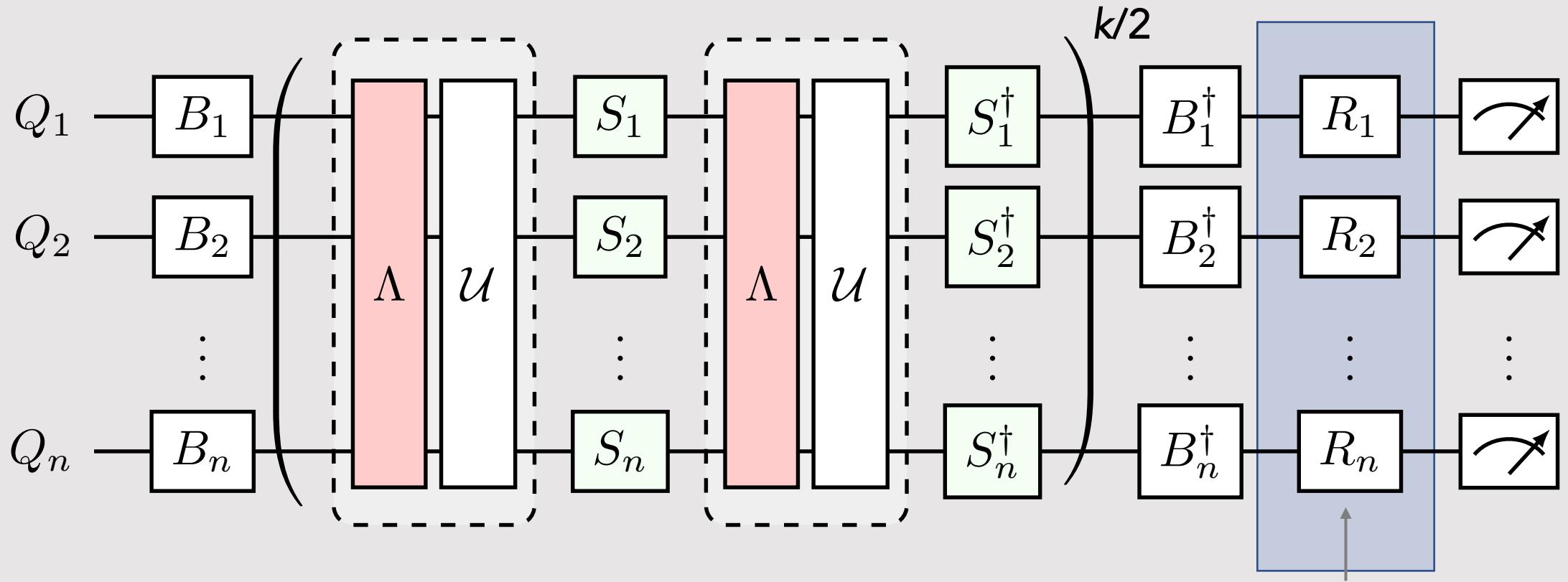
Akin to:

RB, Cycle RB, K-body noise reconstruction, ...

S.T. Flammia and J.J. Wallman ACM Trans QC 1, 3 (2020), ...

Erhard *et al.*, arXiv:1902.08543; Ferracin *et al.*, arXiv:2201.10672, ...

Step 3: Twirl readout-error mitigation



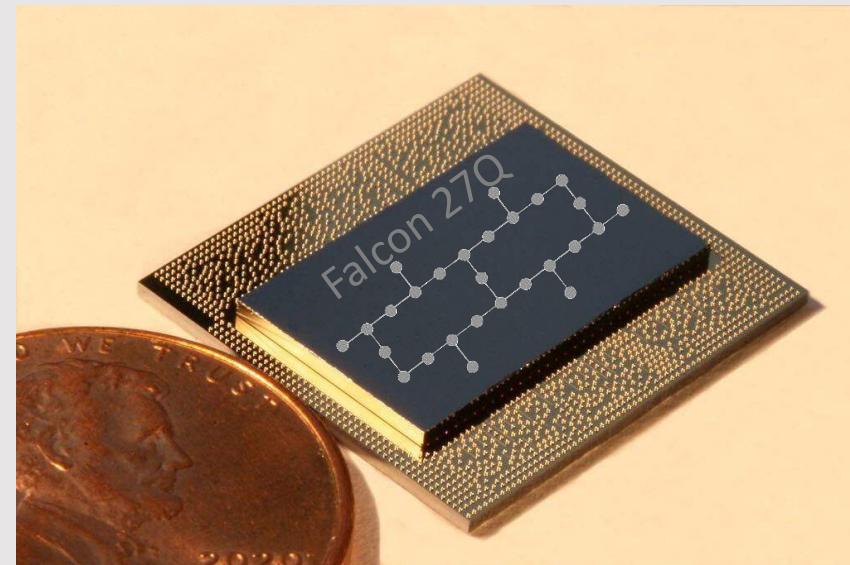
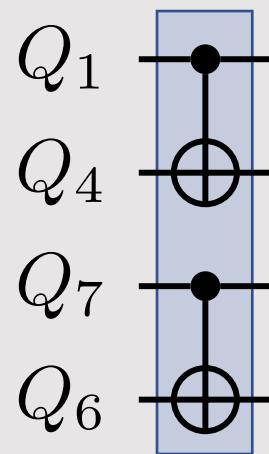
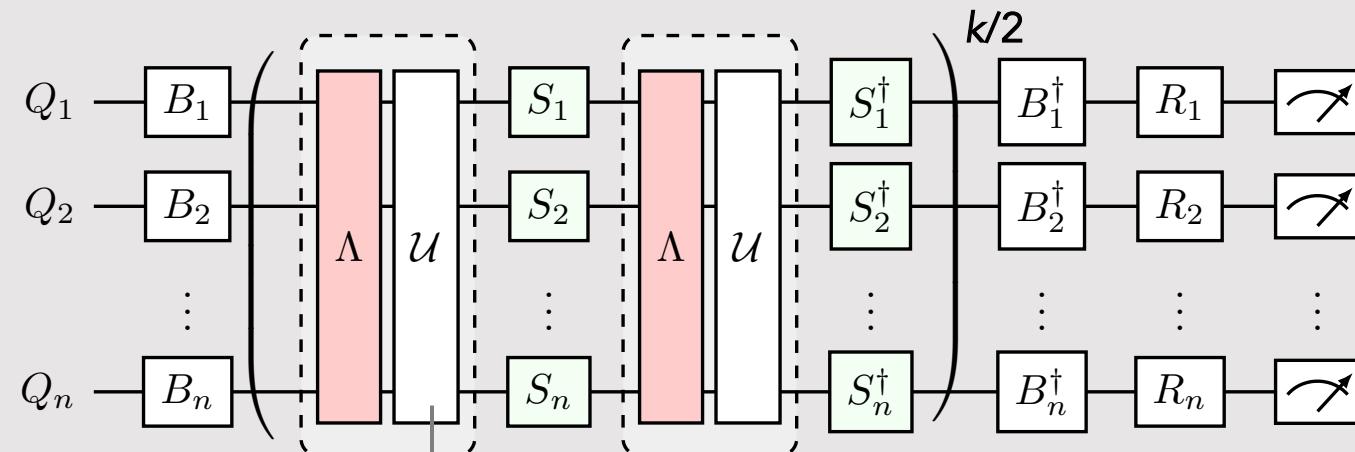
twirl readout to do readout
error mitigation in-situ*

* Model-free readout-error mitigation for quantum expectation values

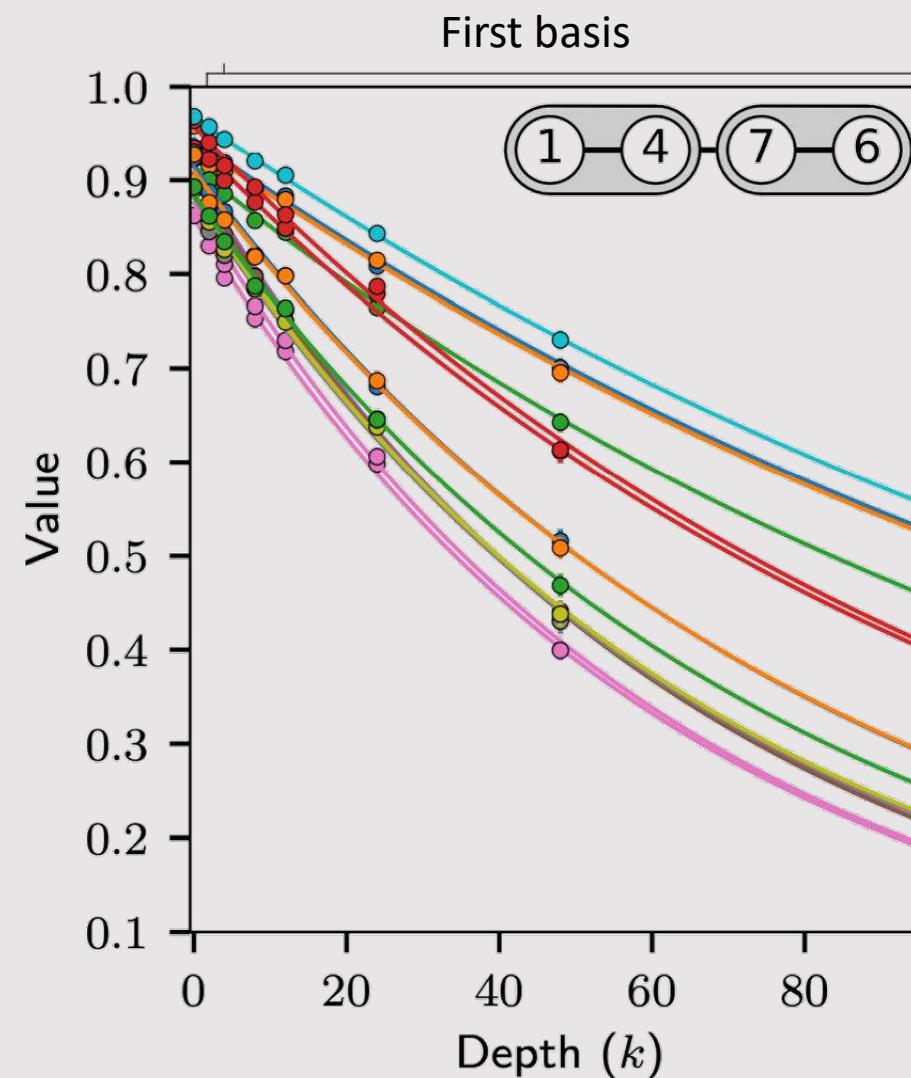
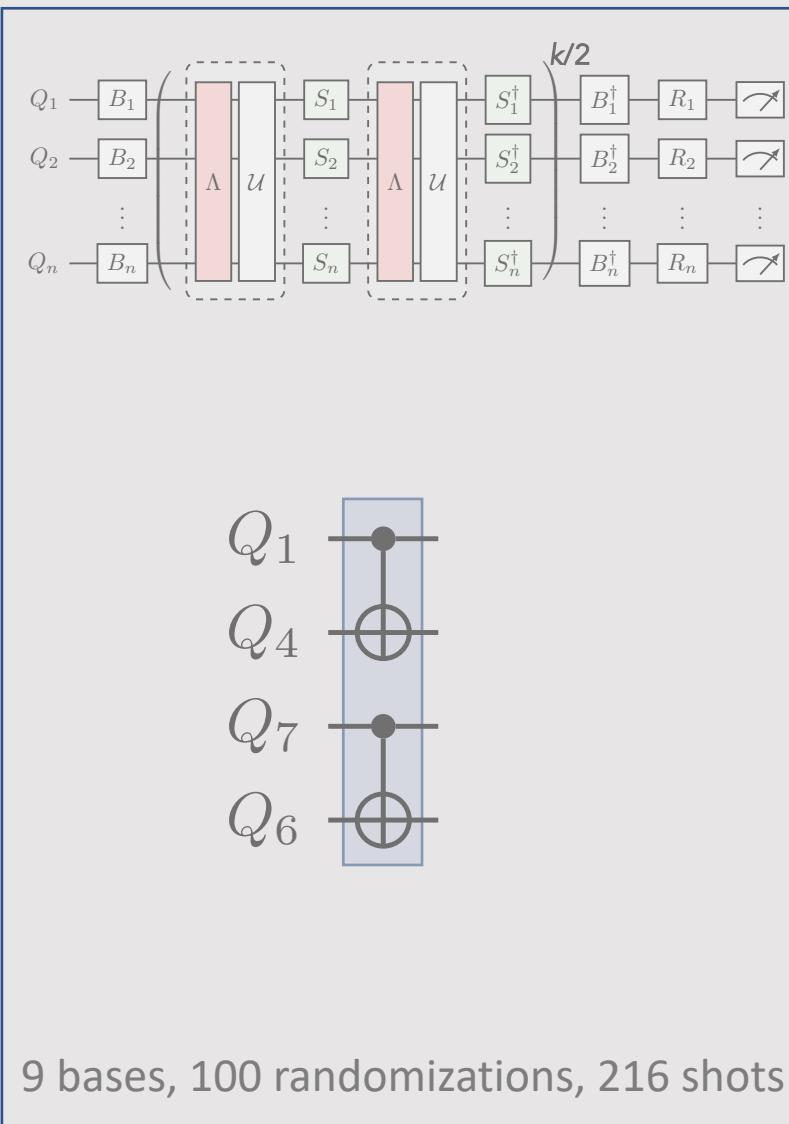
Ewout van den Berg, Zlatko K. Minev, and Kristan Temme

Phys. Rev. A 105, 032620 (2022)

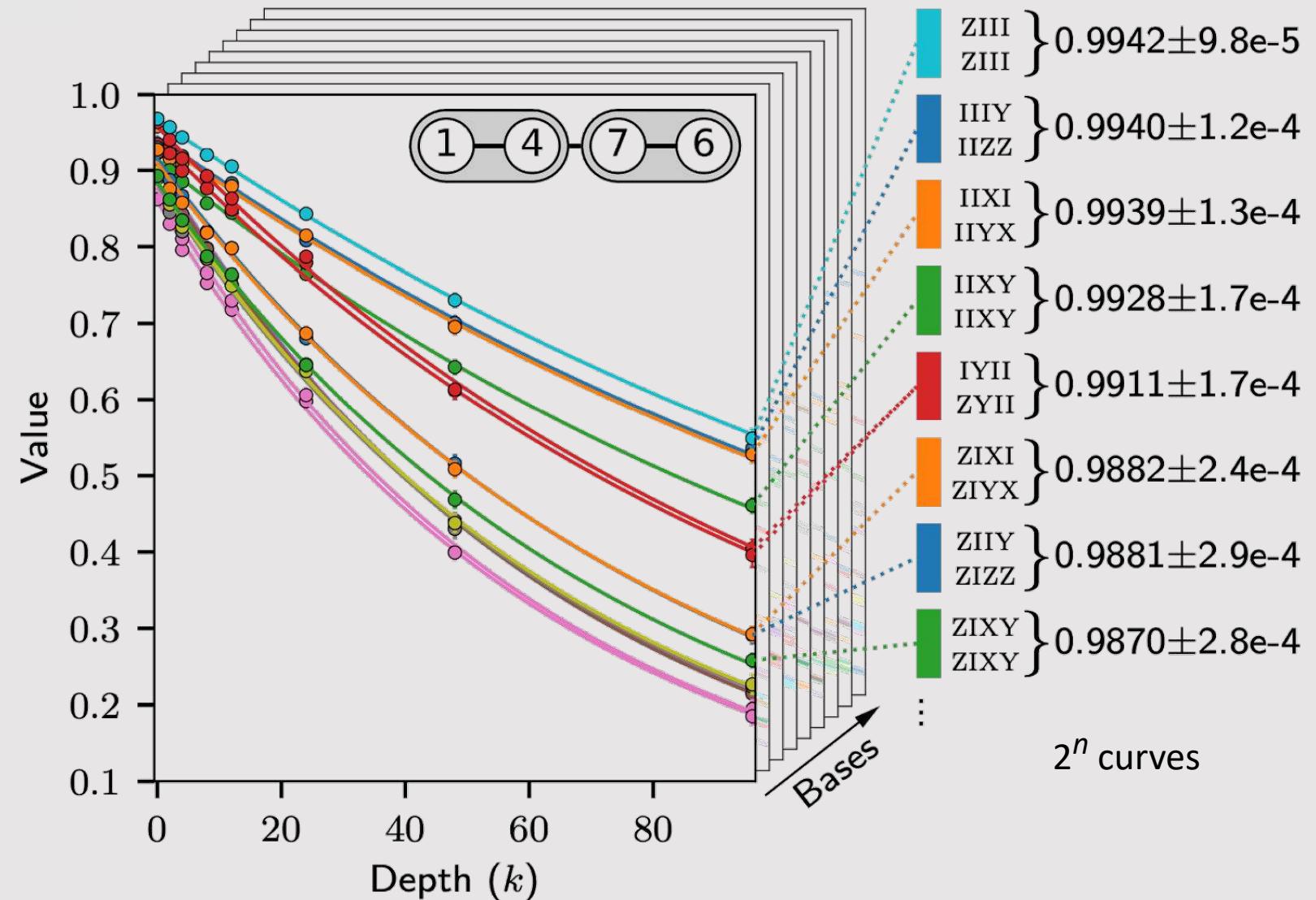
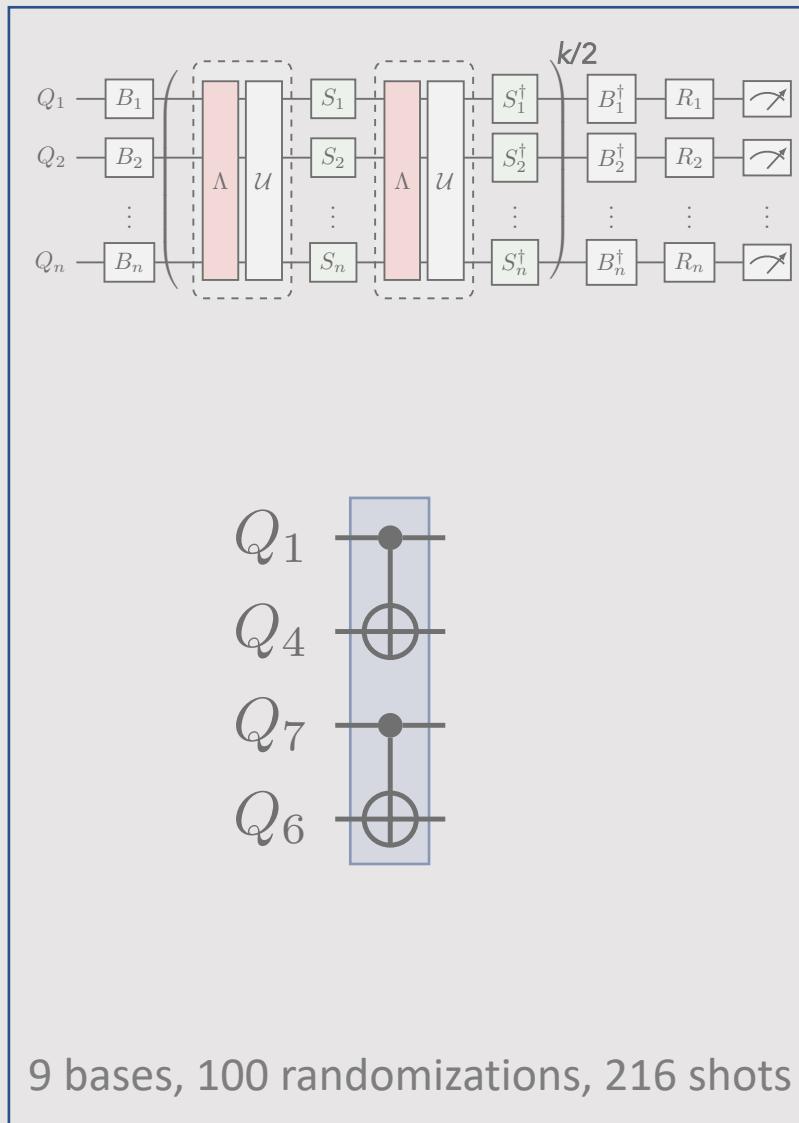
Experiment



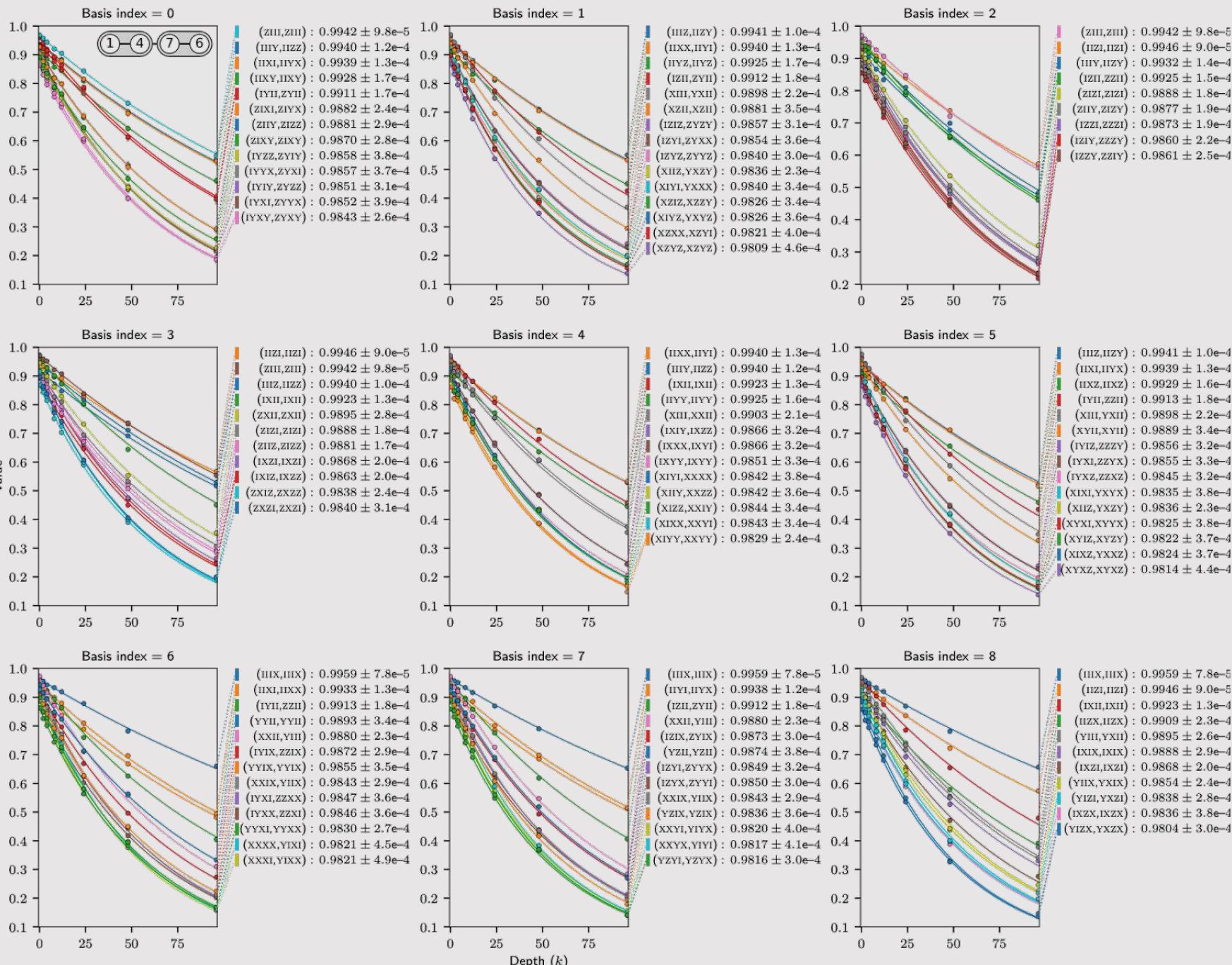
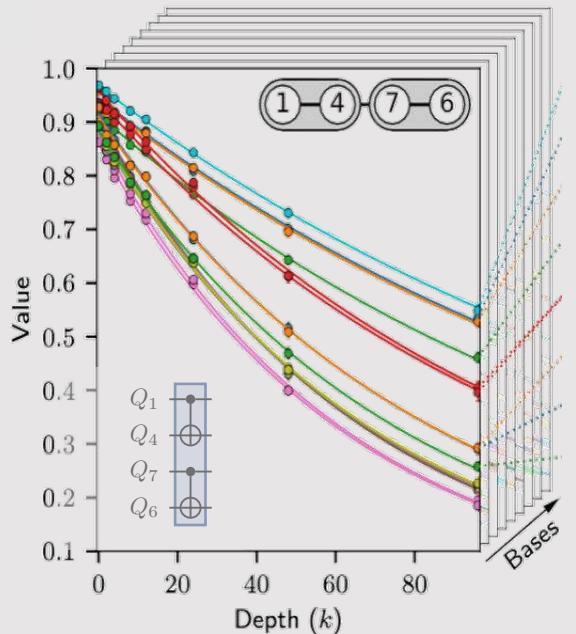
Learning the noise: raw data



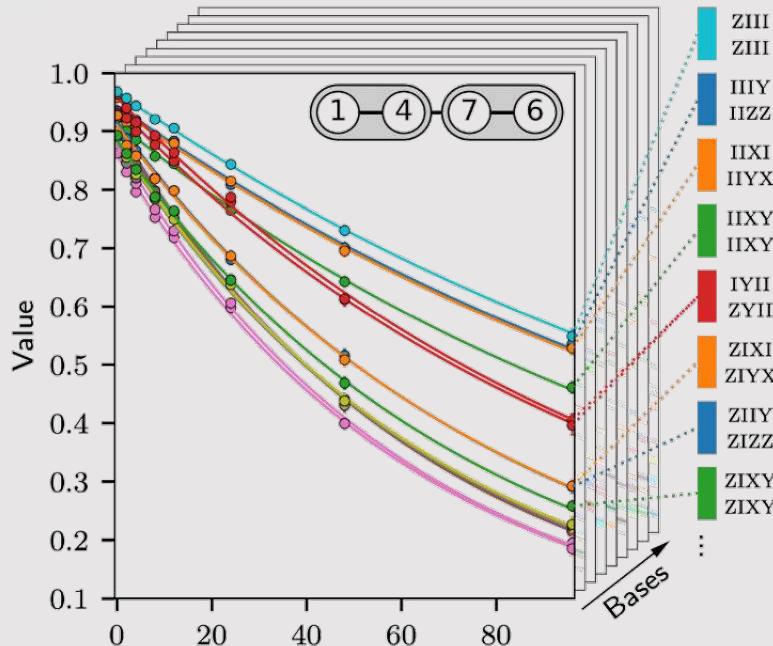
Learning the noise: raw data



Raw data



Sparse Pauli-Lindblad model



$$\Lambda(\rho) = \sum_{a=0}^{4^n - 1} c_a P_a \rho P_a^\dagger$$

$$\Lambda(\rho) = \exp[\mathcal{L}](\rho)$$

$$\mathcal{L}(\rho) = \sum_{k \in \mathcal{K}} \lambda_k (P_k \rho P_k - \rho)$$

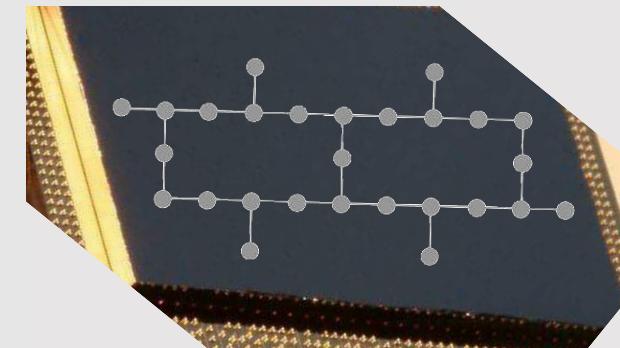


Highlight: Ewout van den Berg

Magic

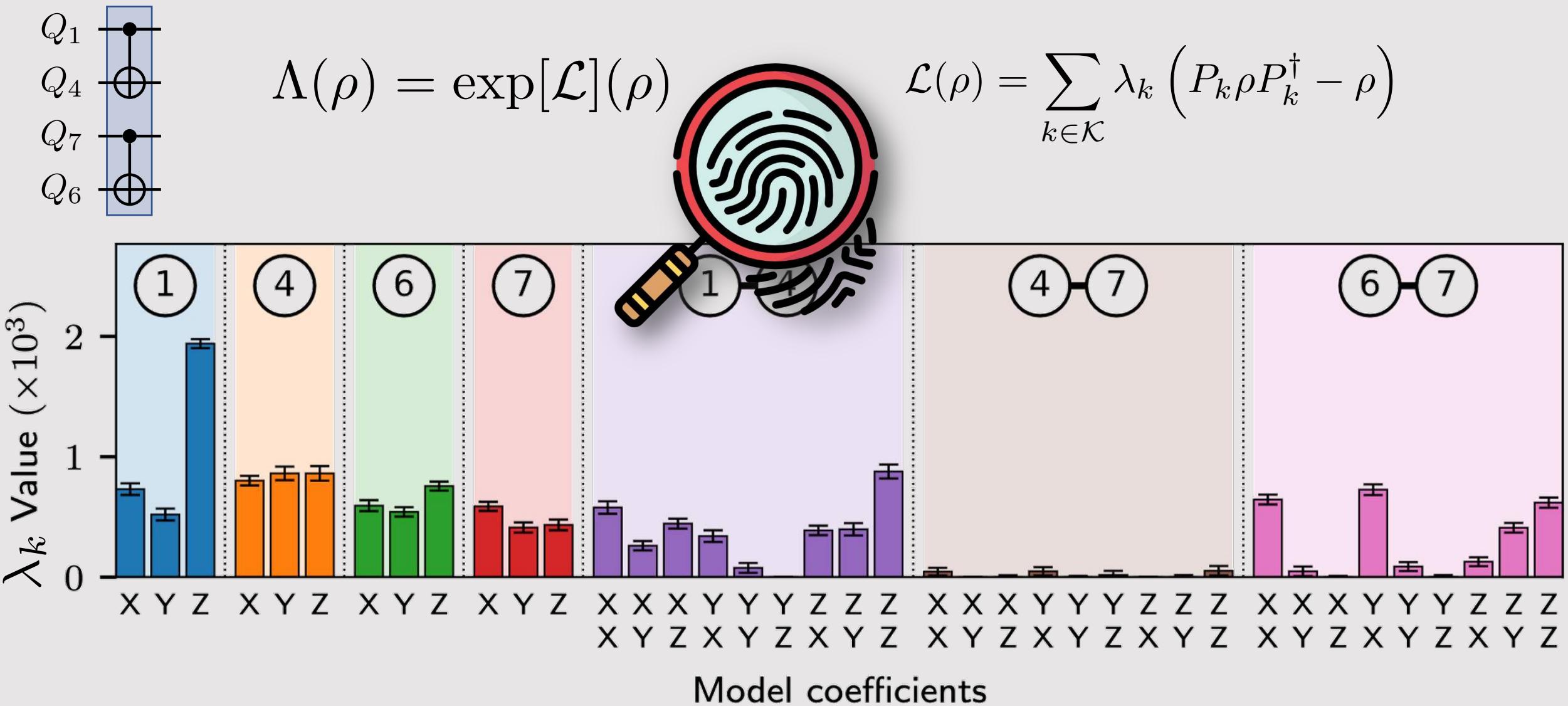


icon: Eucalyp

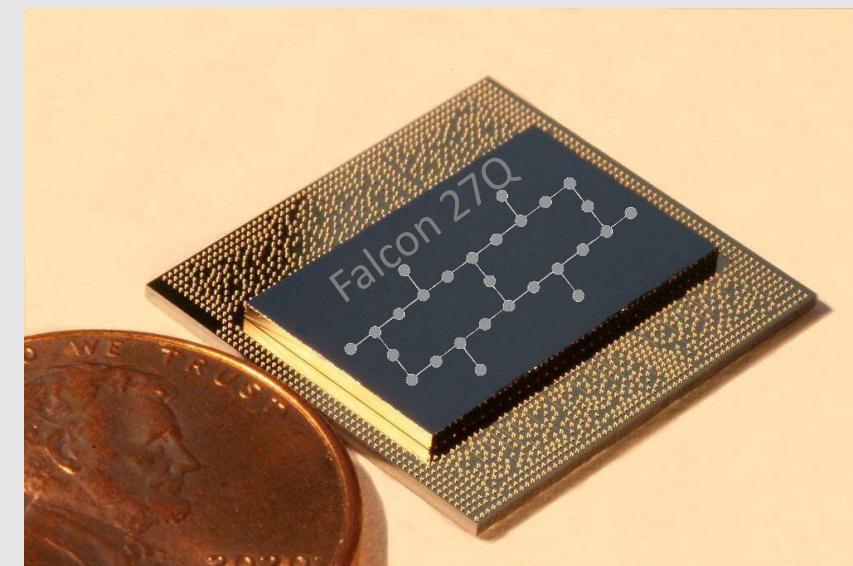
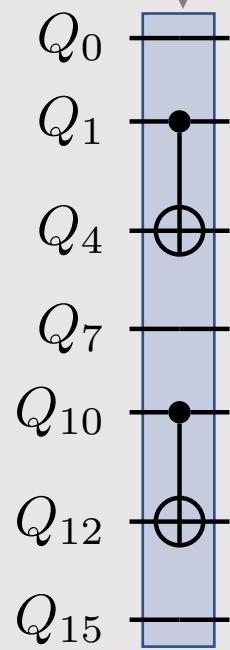
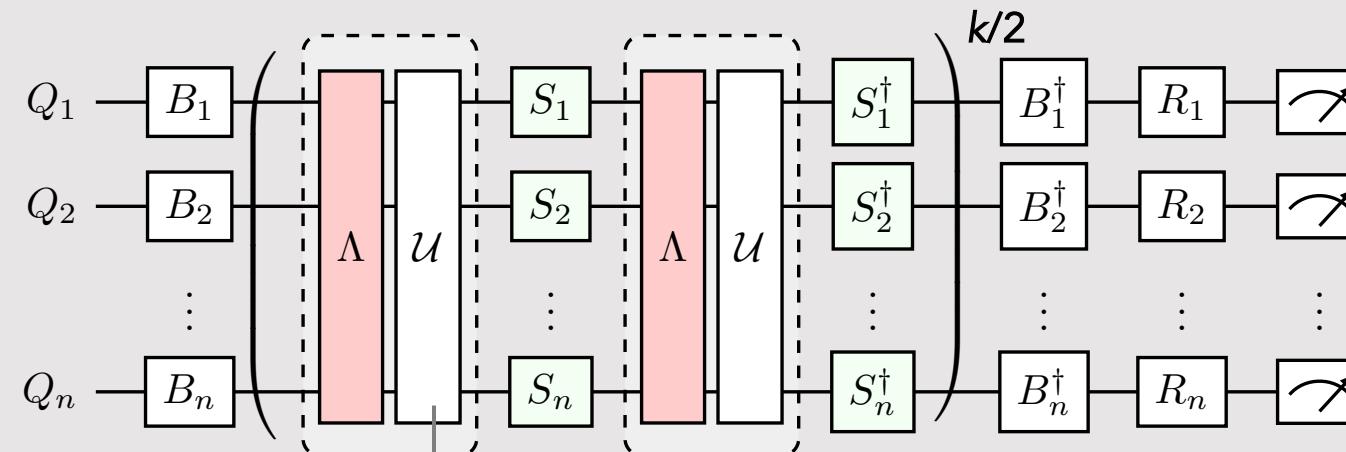


Zlatko Minev, IBM Quantum (40)

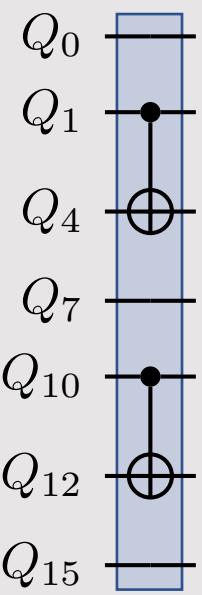
Fingerprint of the noise: sparse Lindblad tomogram



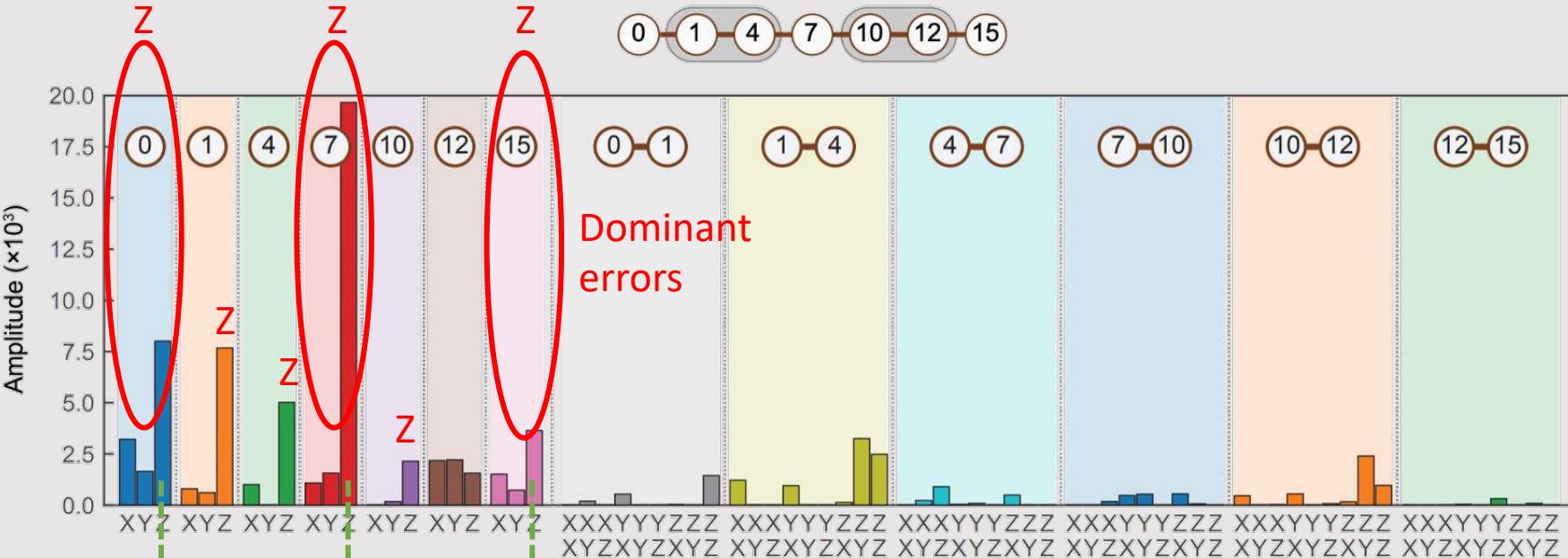
Experiment on a larger, mixed layer



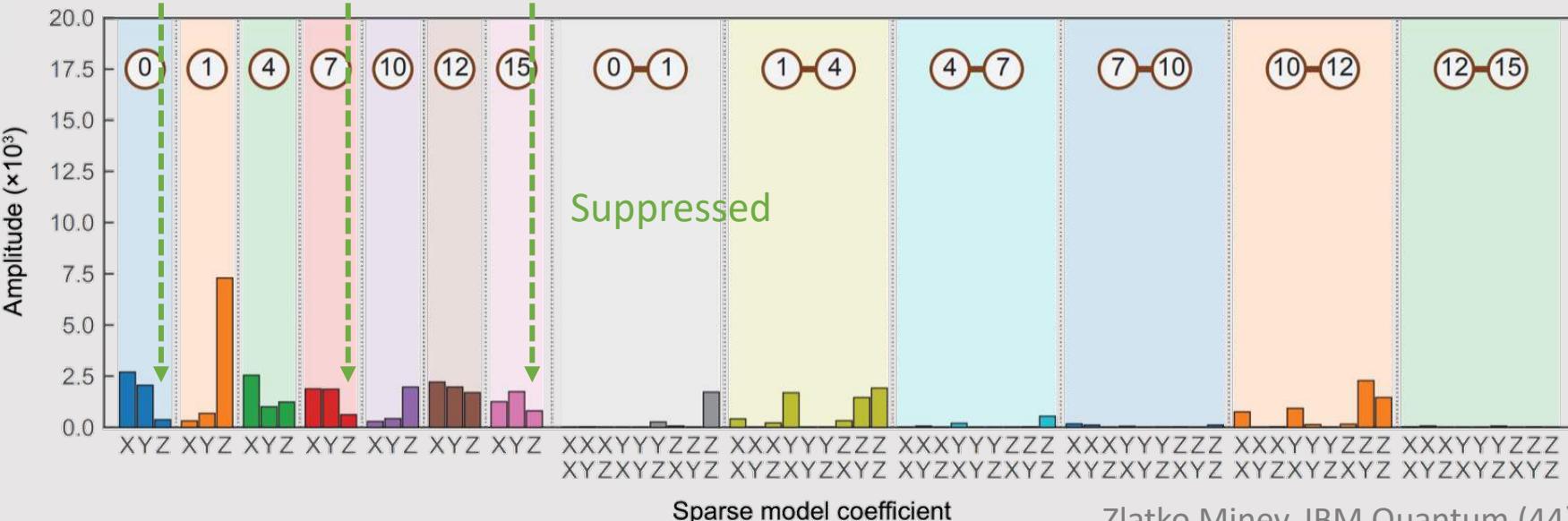
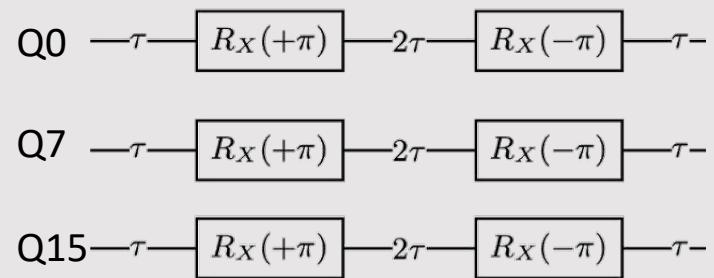
Diagnosing errors with the Lindblad tomogram



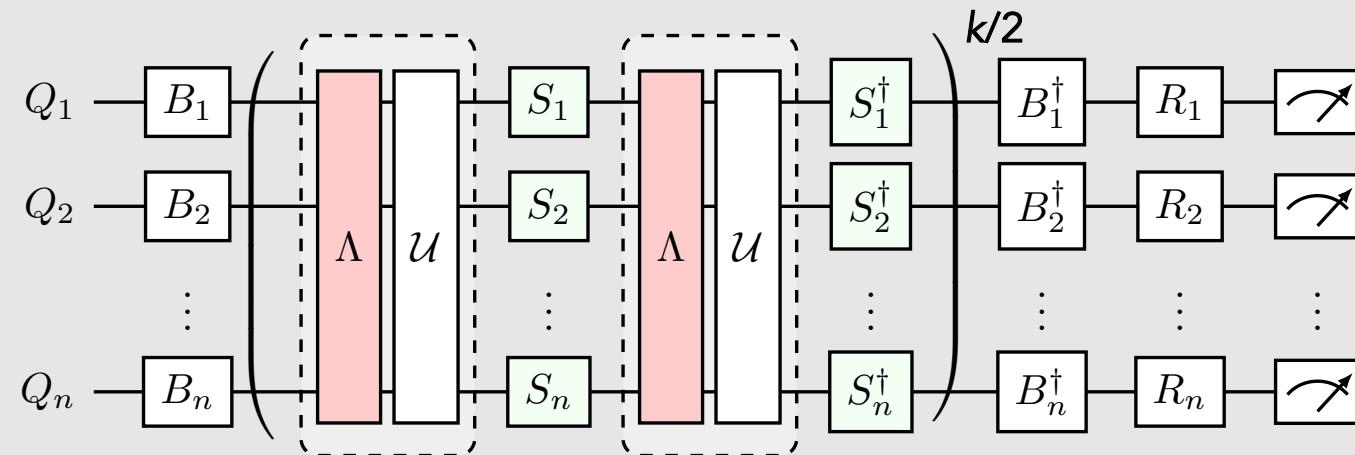
**Without
dynamical
decoupling
(DD)**



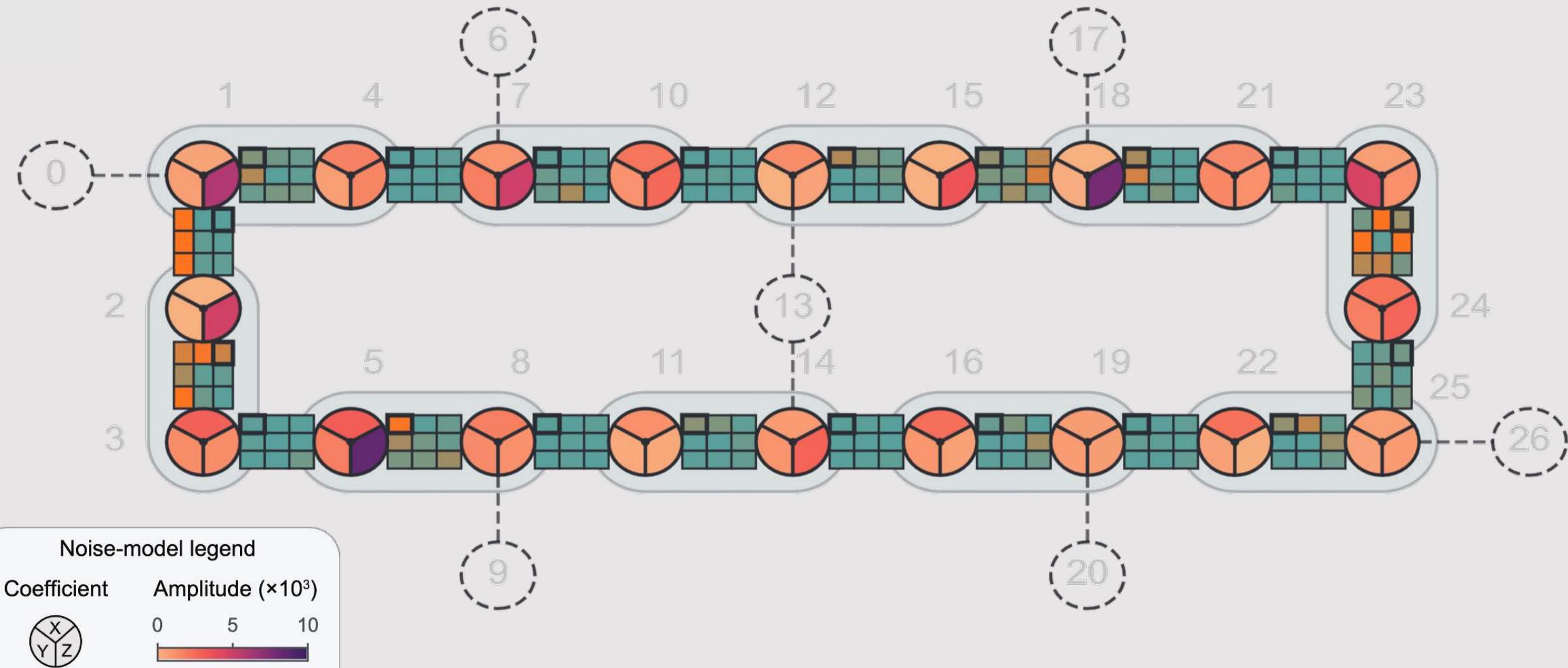
With DD on idle qubits



Experiment on a 20Q layer



20 qubit layer tomogram



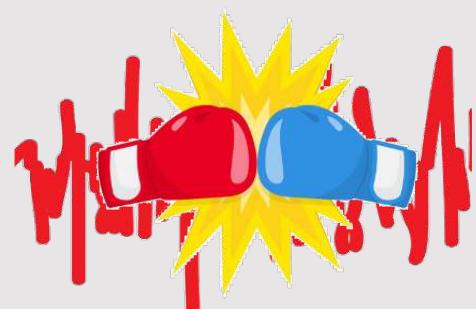
Outline



Idea



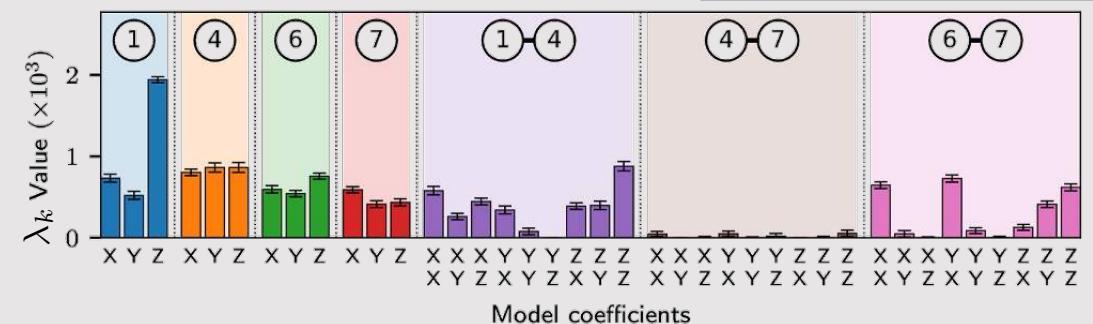
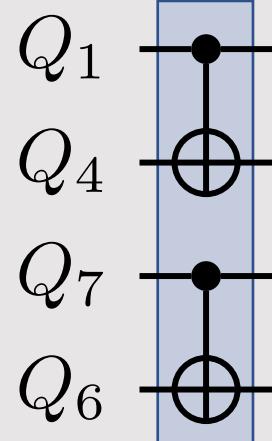
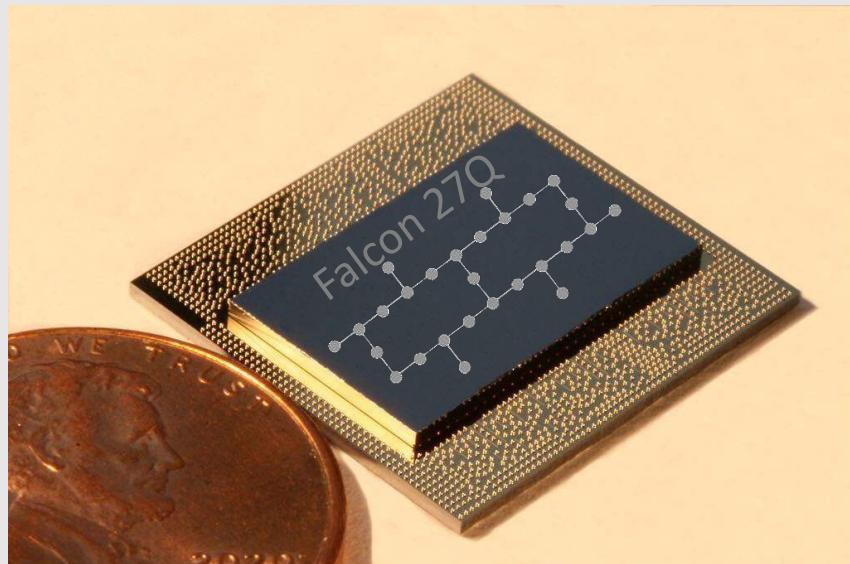
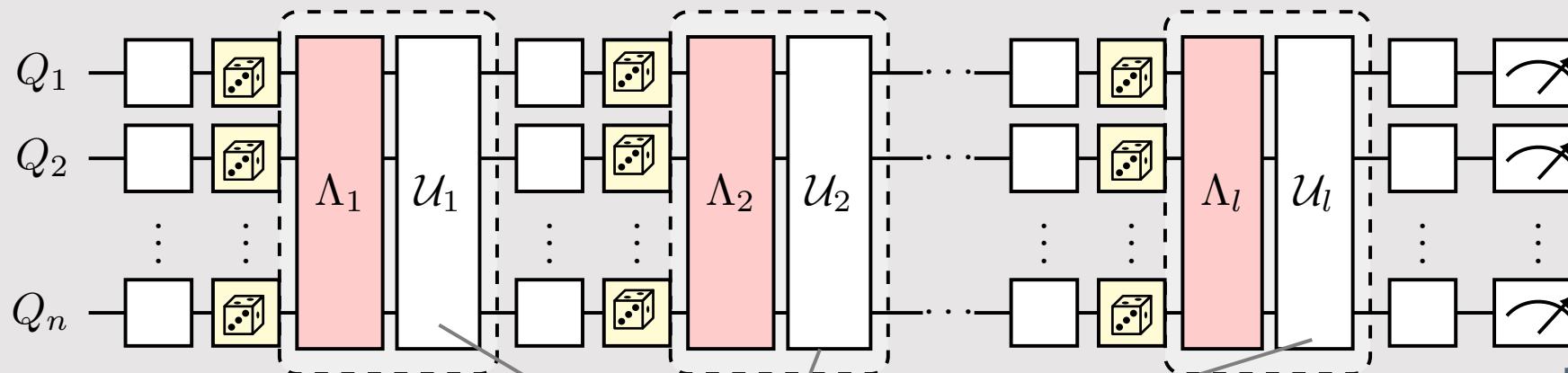
Learn



Cancel
(realization)

PEC mitigation:
inverting noise to
obtain expectation
values

Simple example: mitigation of repeated cNOT



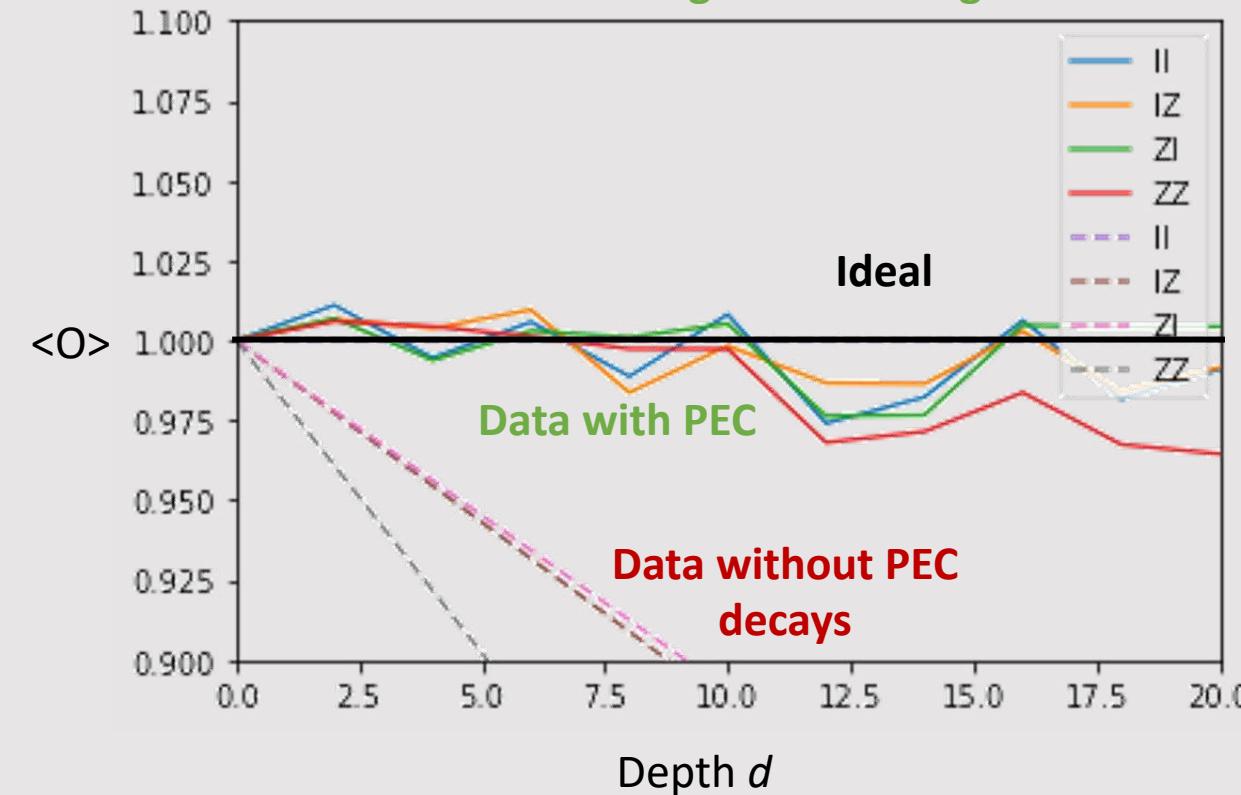
$$\text{CNOT}^{2n} = I$$

$$\langle II \rangle = \langle IZ \rangle = 1$$

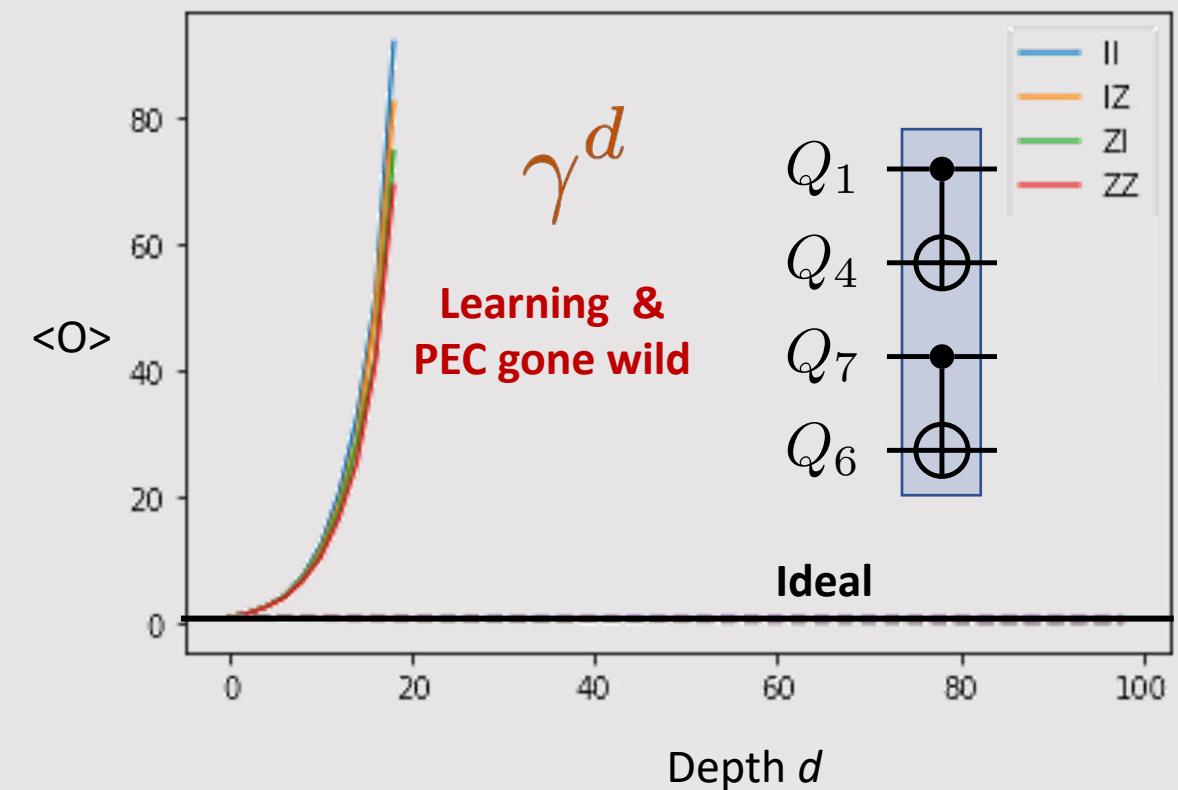
$$\langle ZI \rangle = \langle ZZ \rangle = 1$$

Simple example: mitigation of repeated cNOT

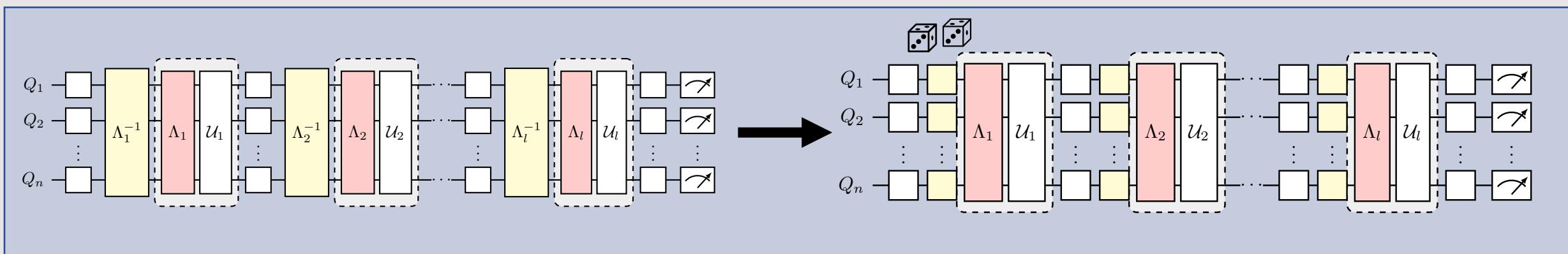
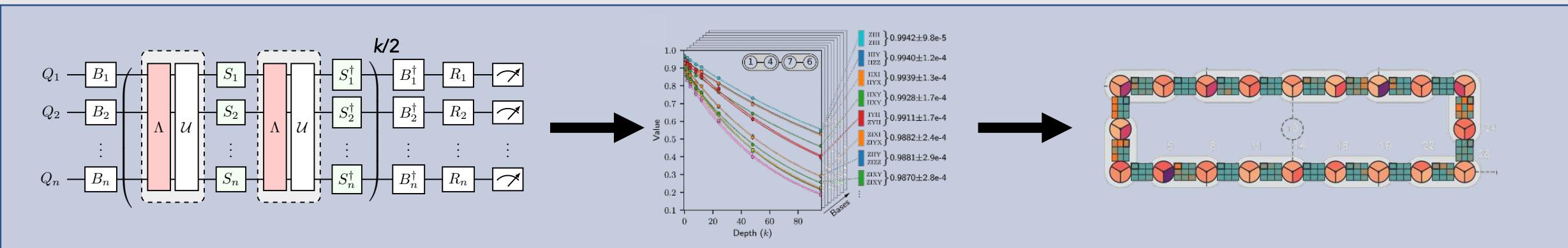
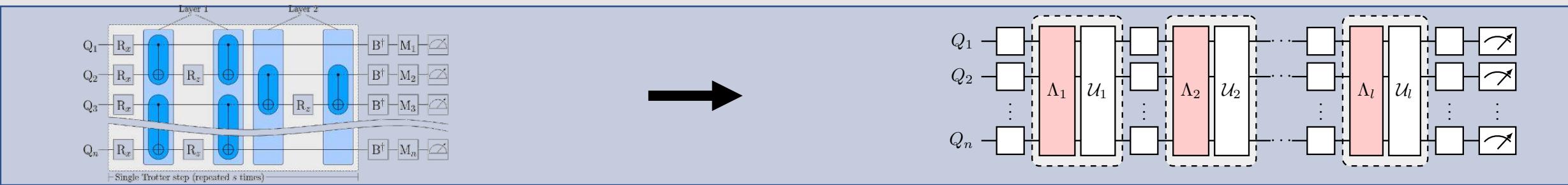
Correct learning used to mitigate



Using wrong data set to mitigate



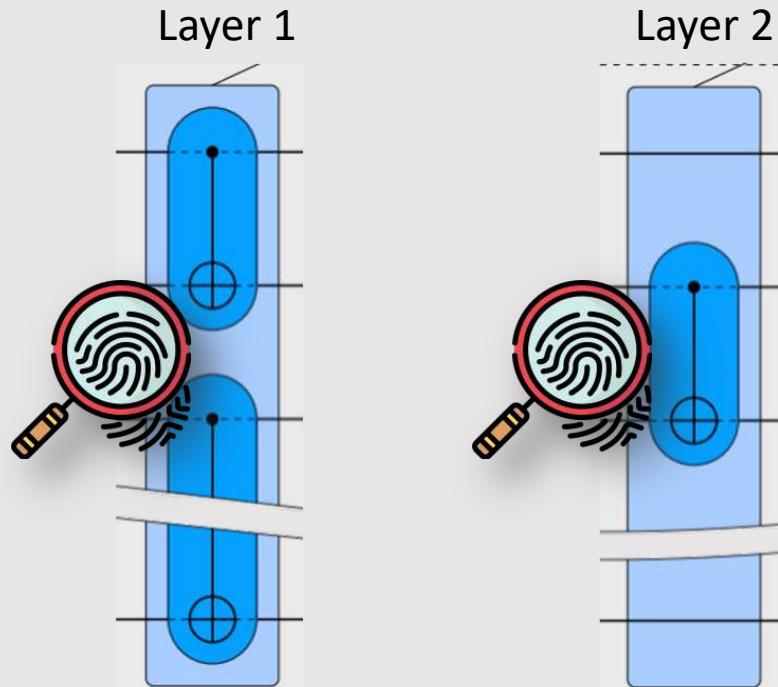
Protocol overview



Ising model Trotterized time evolution



$$\vec{M} := \sum_n (\langle X \rangle_n, \langle Y \rangle_n, \langle Z \rangle_n) / N$$



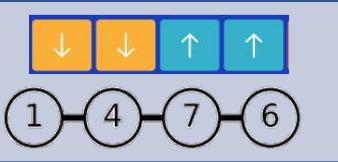
Observables for $N = 4$ (then 10)

XIII	YIII	ZIII
IXII	IYII	IZII
IIXI	IIYI	IIZI
IIIX	IIIY	IIIZ

$h = 1, J = 0.15, \delta t = 1/4$

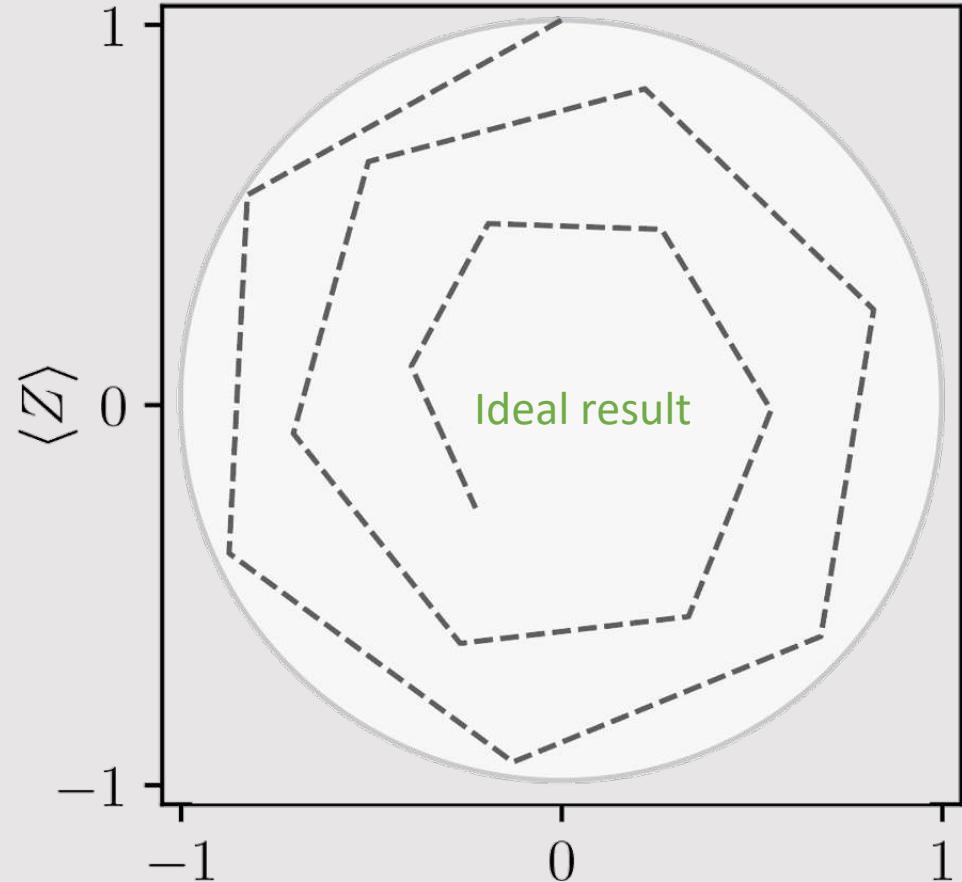
$$\gamma_1 = 1.0309 \pm 8.40 \cdot 10^{-5} \quad \gamma_2 = 1.0384 \pm 2.20 \cdot 10^{-4}$$

Ideal Ising model evolution

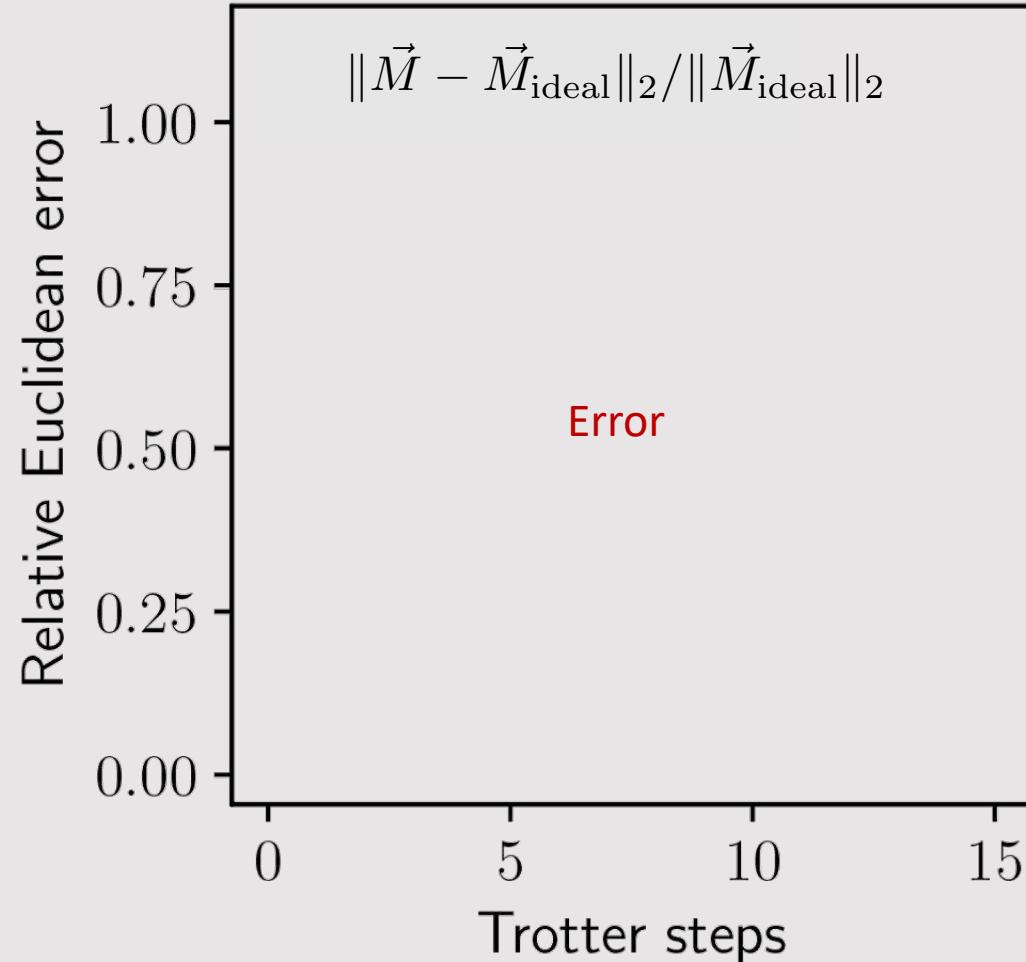


----- Ideal

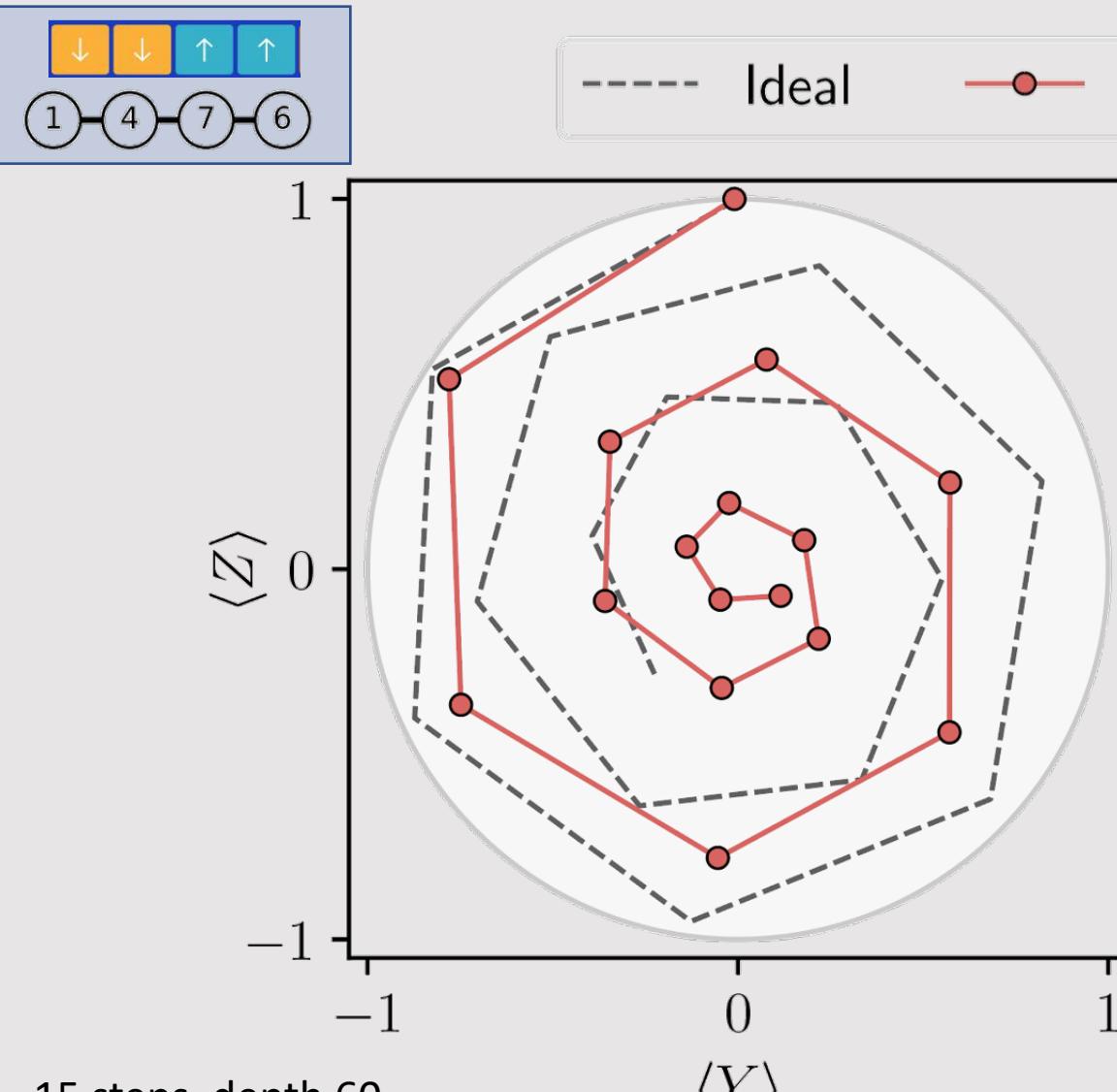
$$\vec{M} := \sum_n (\langle X \rangle_n, \langle Y \rangle_n, \langle Z \rangle_n) / N$$



$$h = 1, J = -0.15, \delta t = 1/4$$

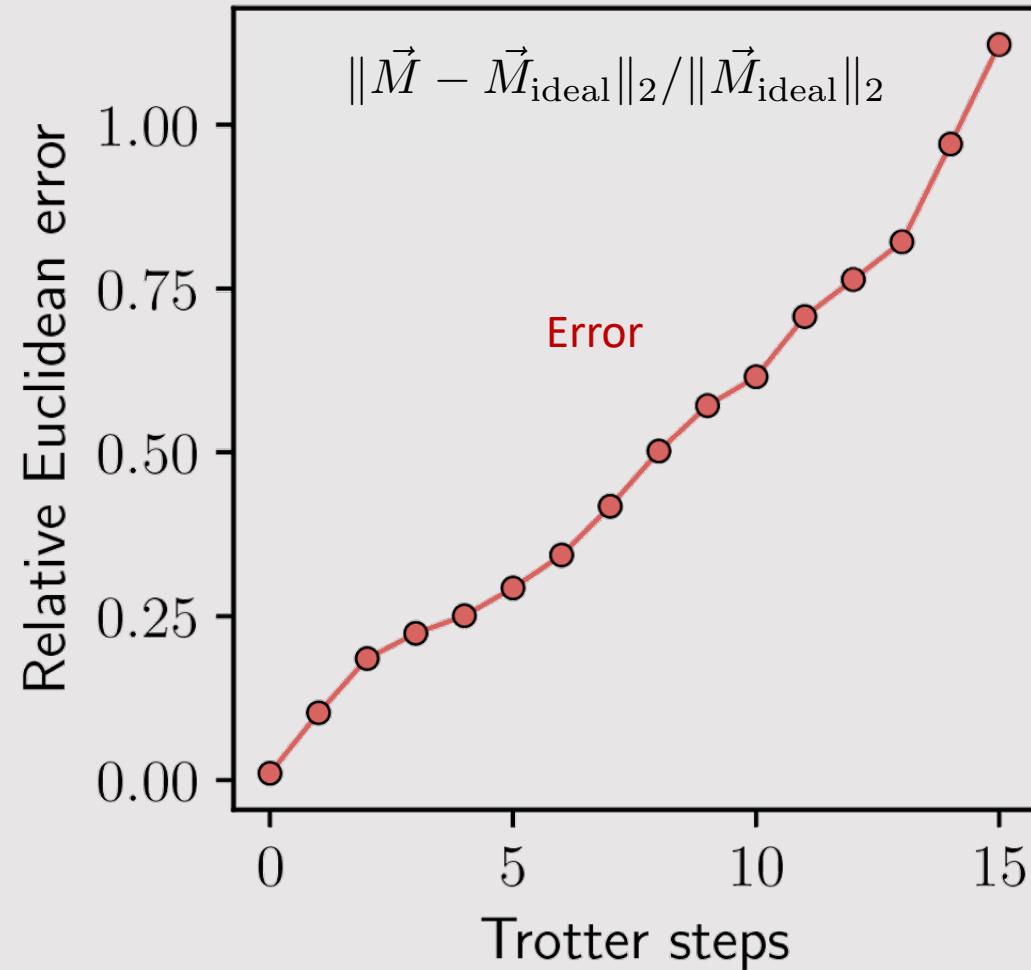


Without PEC: but with DD & twirl readout mitigation

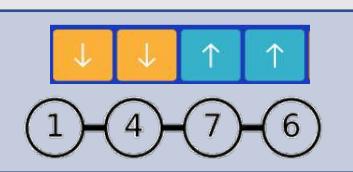


$$h = 1, J = -0.15, \delta t = 1/4$$

----- Ideal —●— without PEC

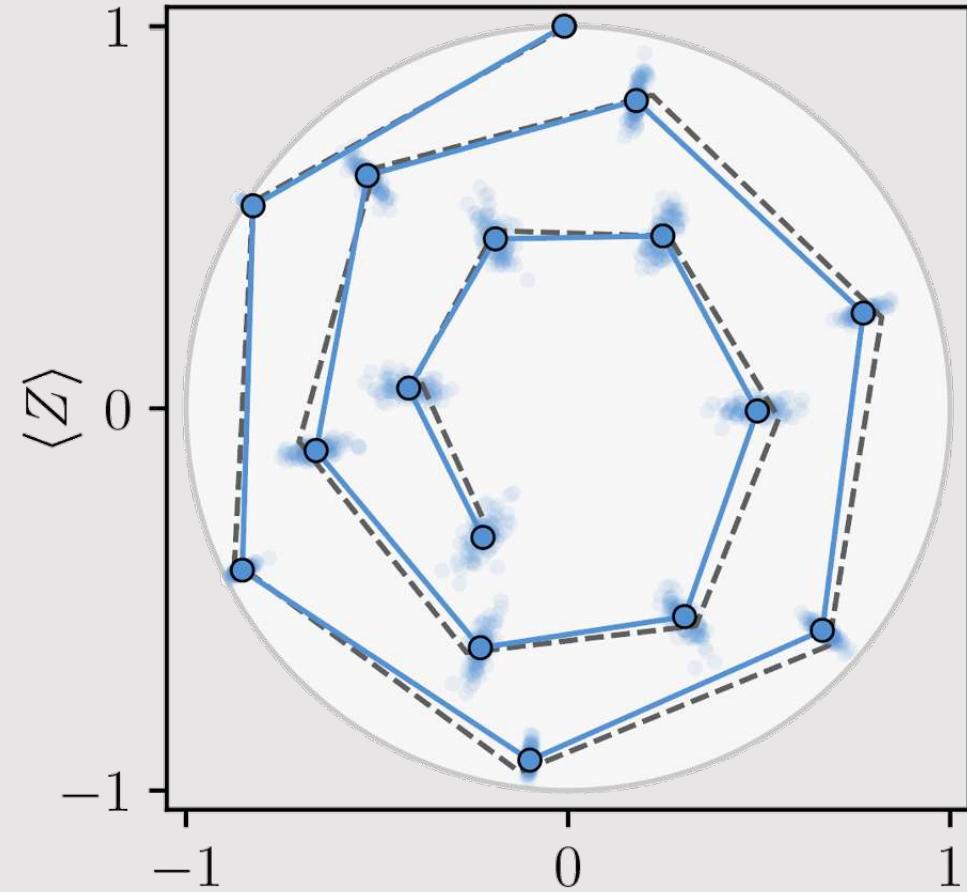


With PEC



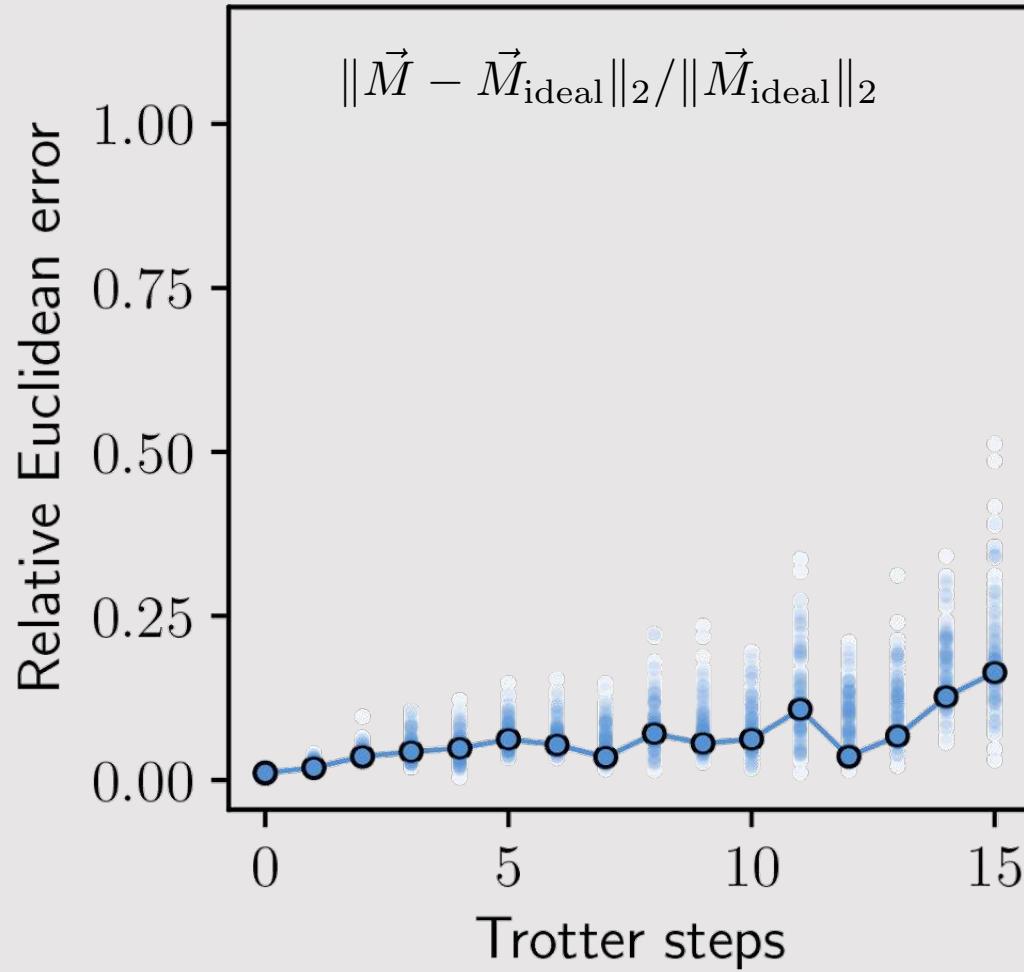
----- Ideal

—●— with PEC

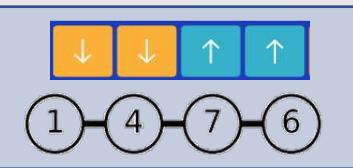


15 steps, depth 60

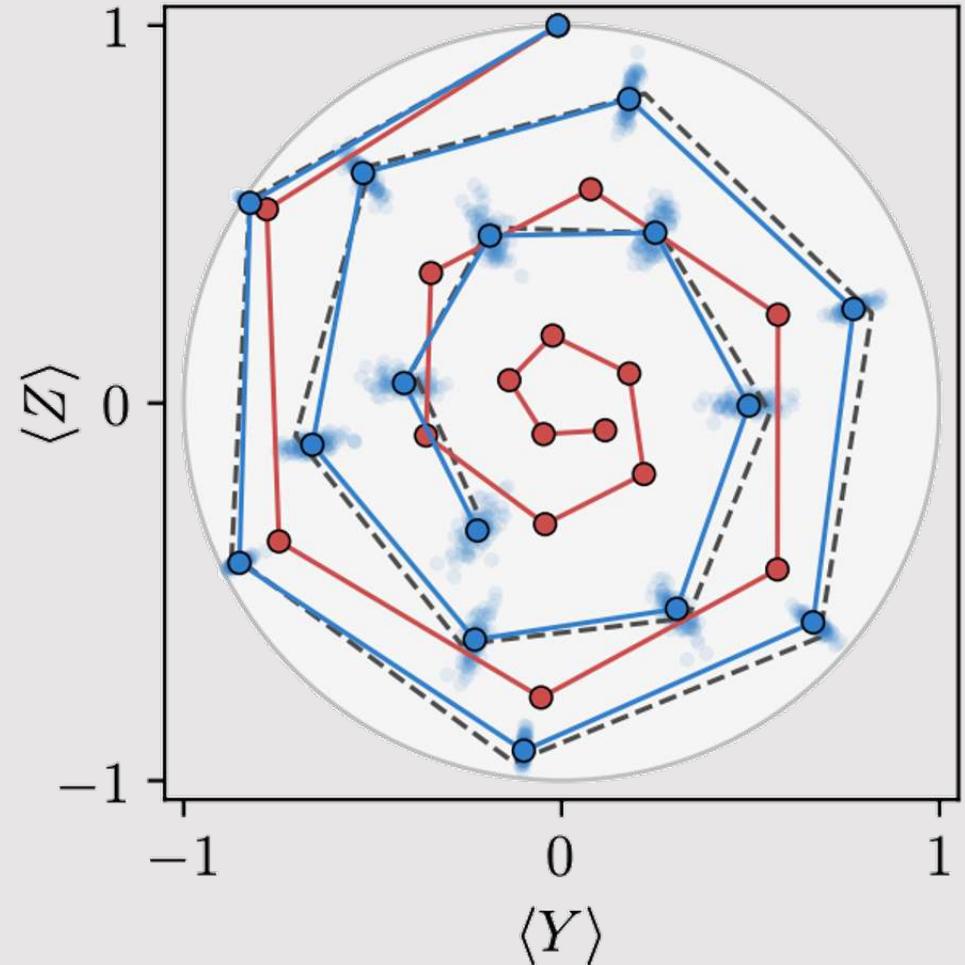
$h = 1, J = -0.15, \delta t = 1/4$



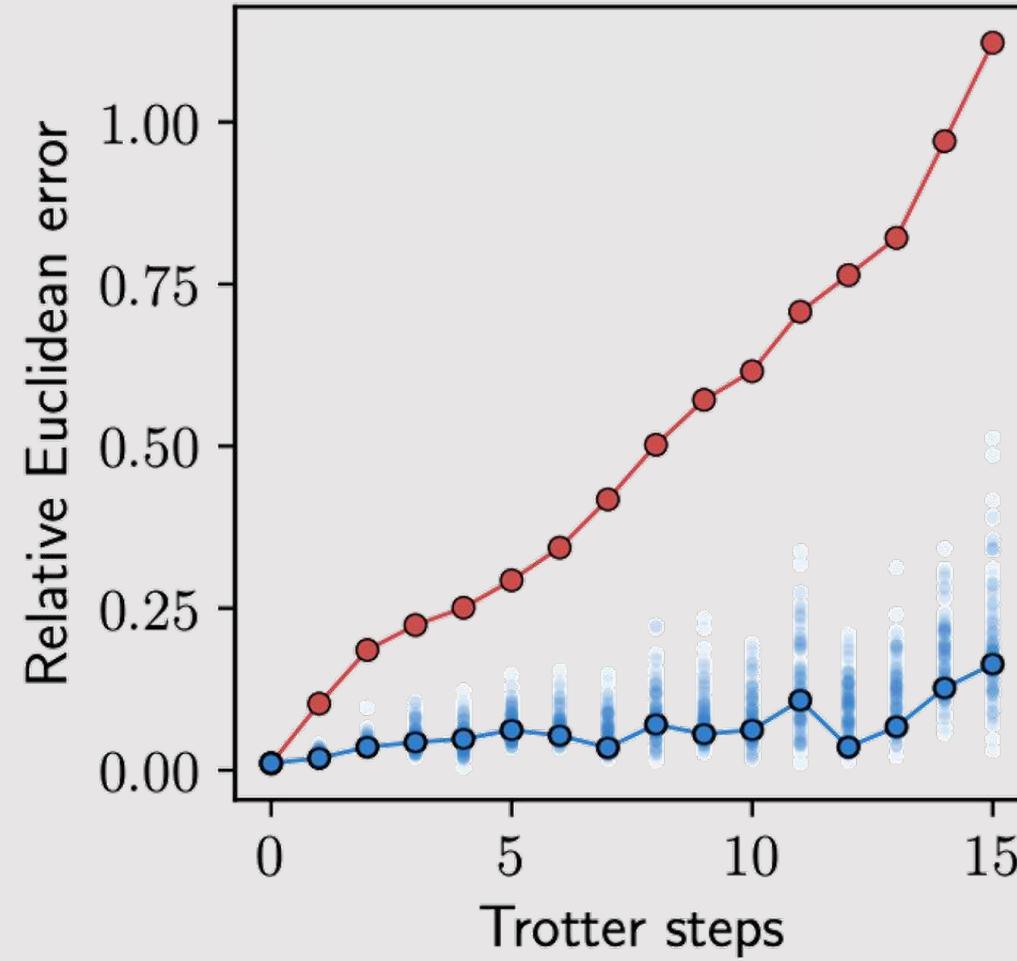
With vs. without PEC



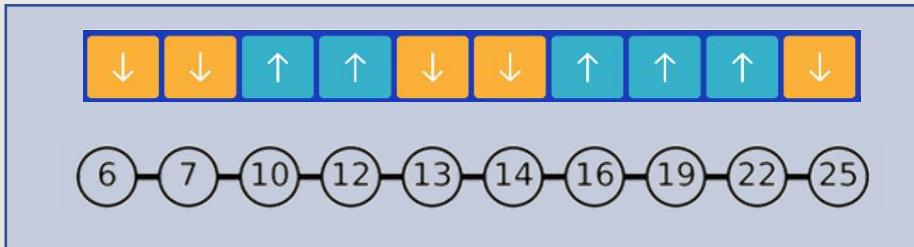
----- Ideal ● without PEC ●—● with PEC



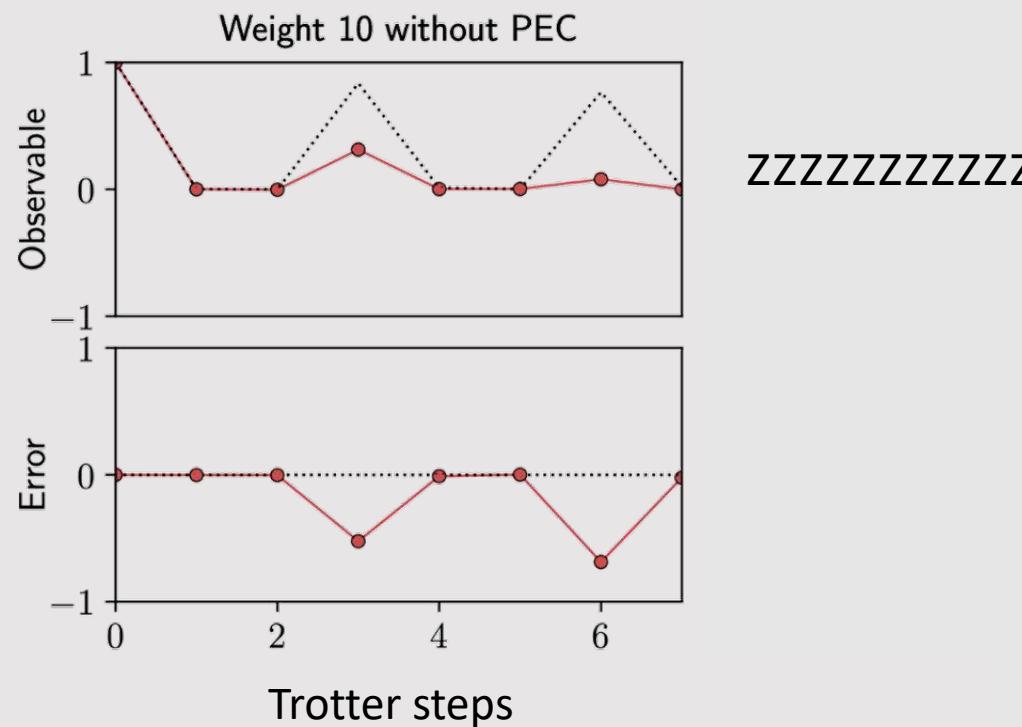
$$h = 1, J = -0.15, \delta t = 1/4$$



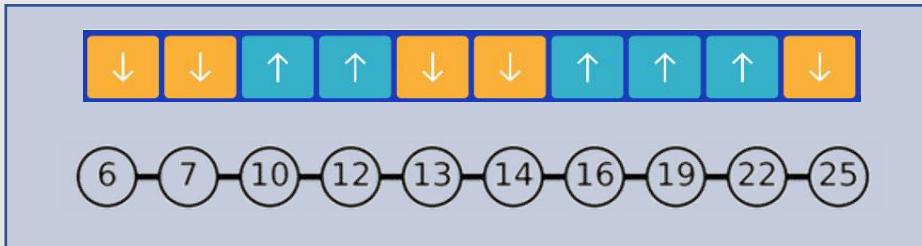
With vs without PEC: 10 qubit high-weight observables



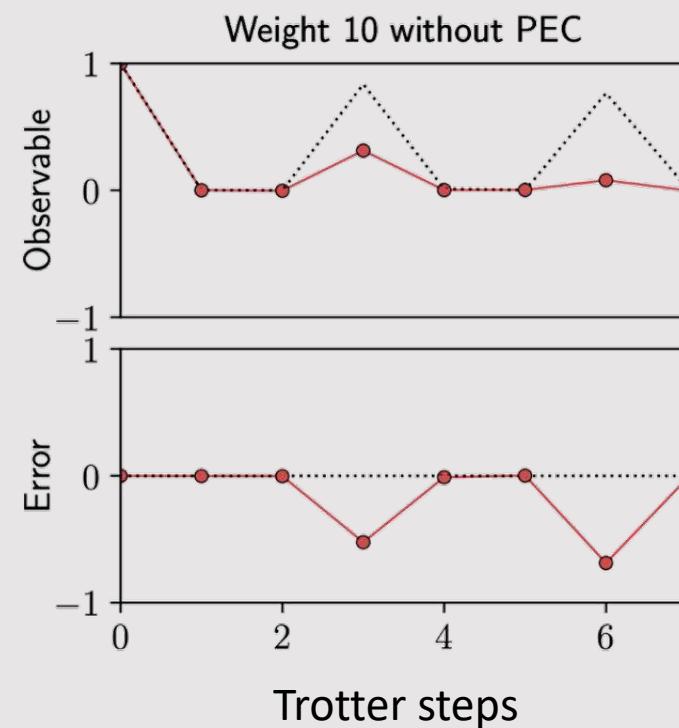
----- Ideal
—●— without PEC
—●— with PEC



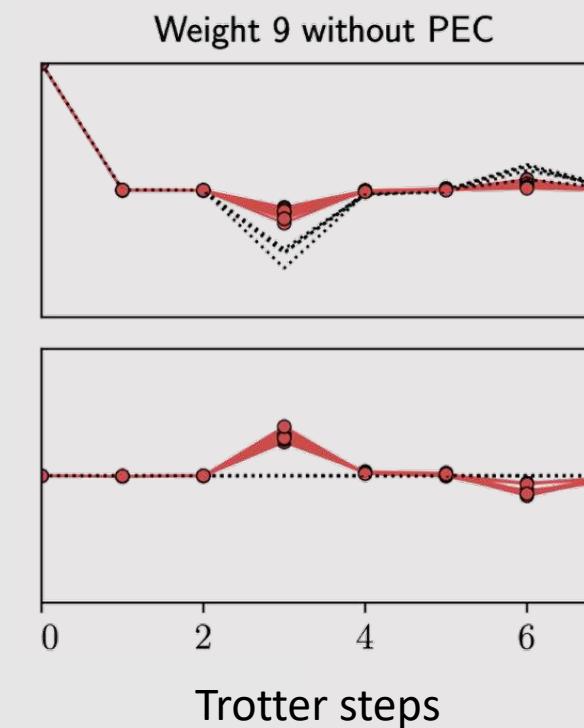
With vs without PEC: 10 qubit high-weight observables



----- Ideal -●- without PEC -●- with PEC

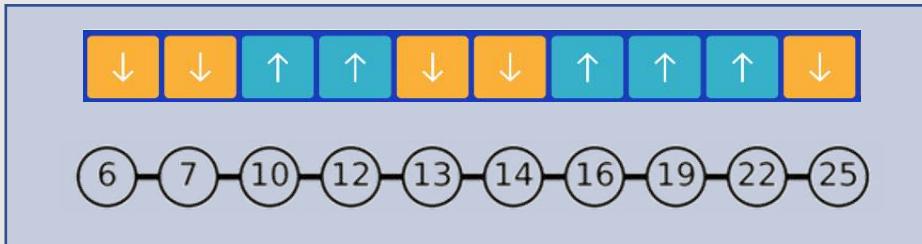


ZZZZZZZZZZZZ

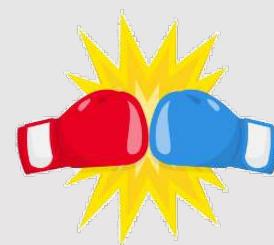
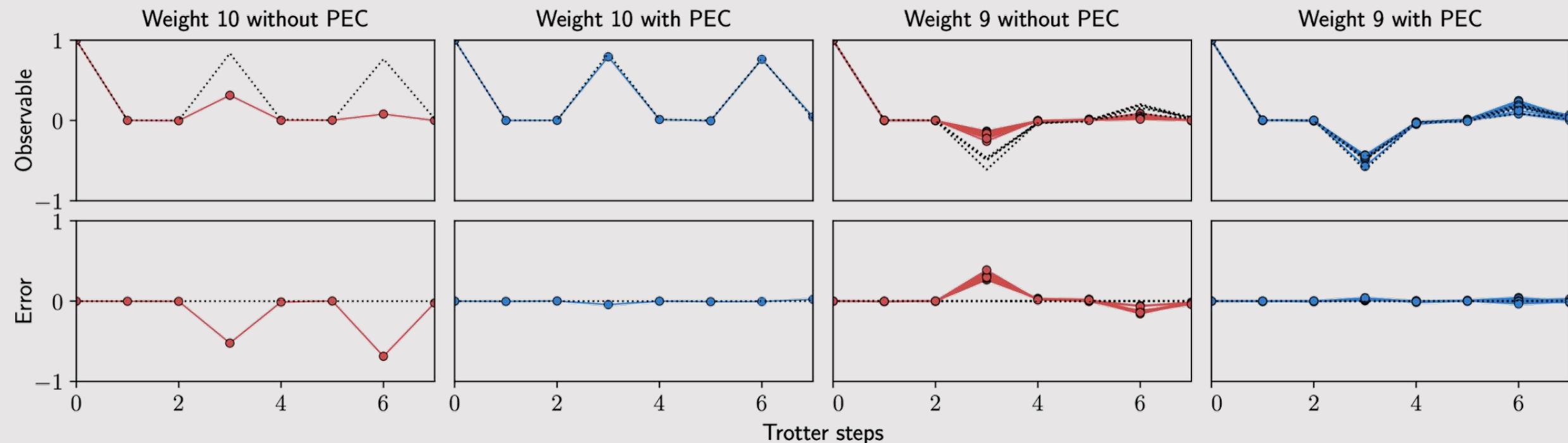


IZZZZZZZZZZZ
ZIZZZZZZZZZZ
ZZIIZZZZZZZZ
...
ZZZZZZZZZZZI

With vs without PEC: 10 qubit high-weight observables

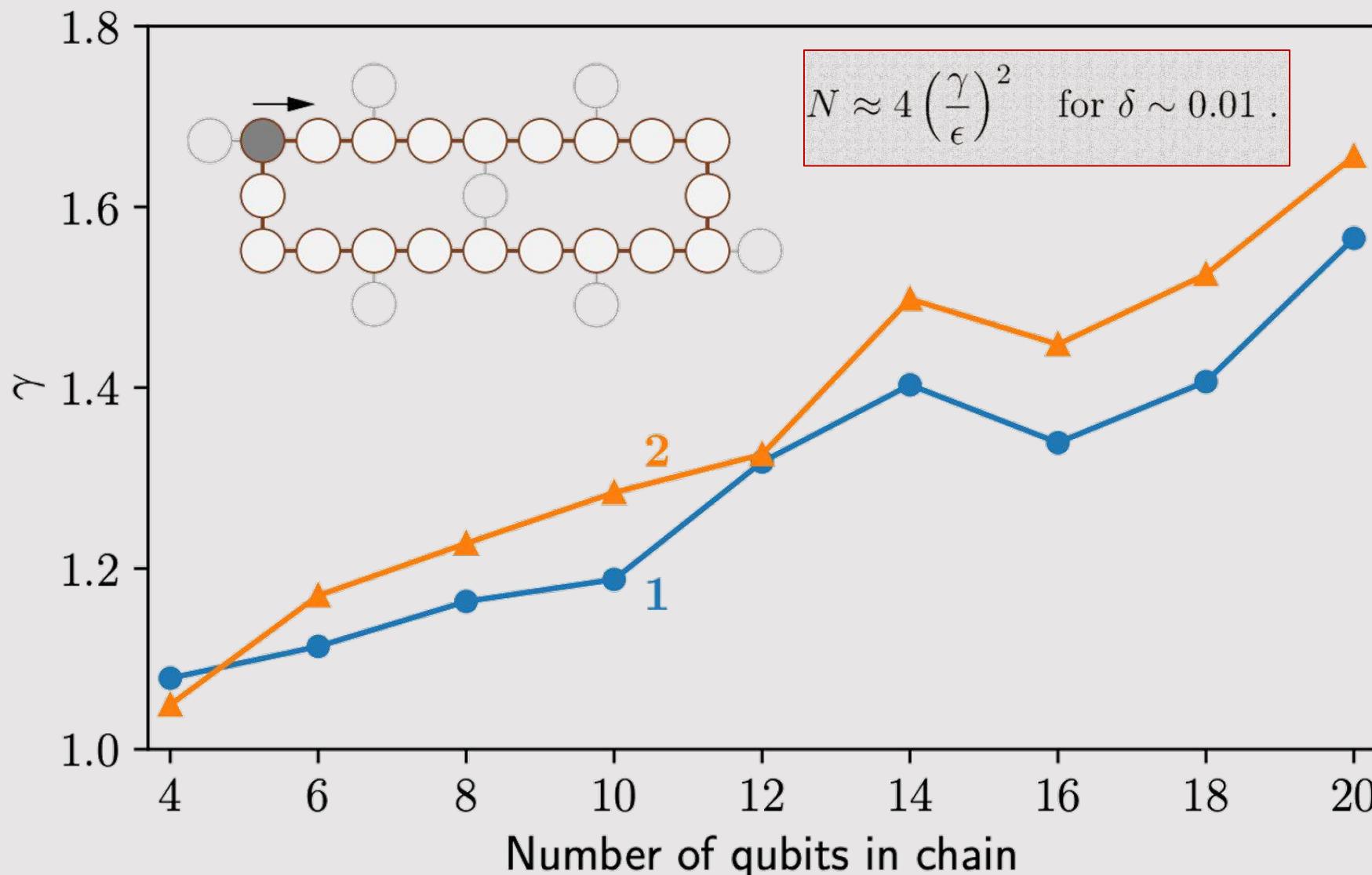


----- Ideal -●- without PEC -●- with PEC

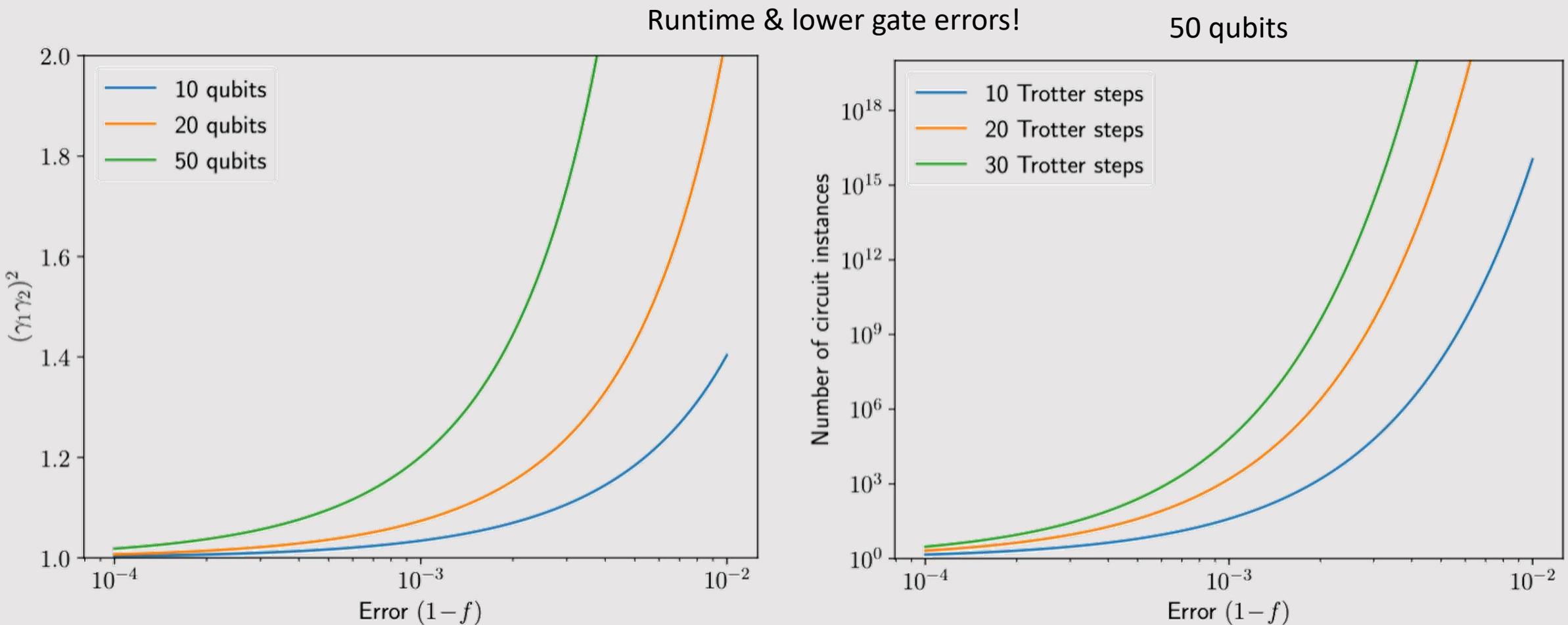


Error budget and scaling

Mitigation sampling overhead



Outlook



Path to quantum computing

Noise-free estimators can be obtained from noisy quantum computers TODAY, at a runtime cost that is exponential in number of qubits n and circuit depth d

$$\text{Runtime} = (1/\delta) \times d \times (\gamma)^{n^*d} \text{ seconds}$$

d is the depth of the quantum circuit

δ is a measure of how many circuit layer operations that can be done per second (increase by pushing **speed**)

γ is a measure of the collective quantum noise (increasing **quality** brings it closer to 1)

n is the number of operational qubits (increase by pushing **scale**)

Thank you!

Lindbladian learning is accurate, efficient, and scalable

Powerful characterization and benchmarking tool

Enable the study and mitigation of noise in quantum
processors at a new scale

Ewout van den Berg, Zlatko K. Minev, Abhinav Kandala, Kristan Temme
[arXiv:2201.09866 \(2022\)](https://arxiv.org/abs/2201.09866)

Thanks to discussion with many folks on the
broader IBM team.



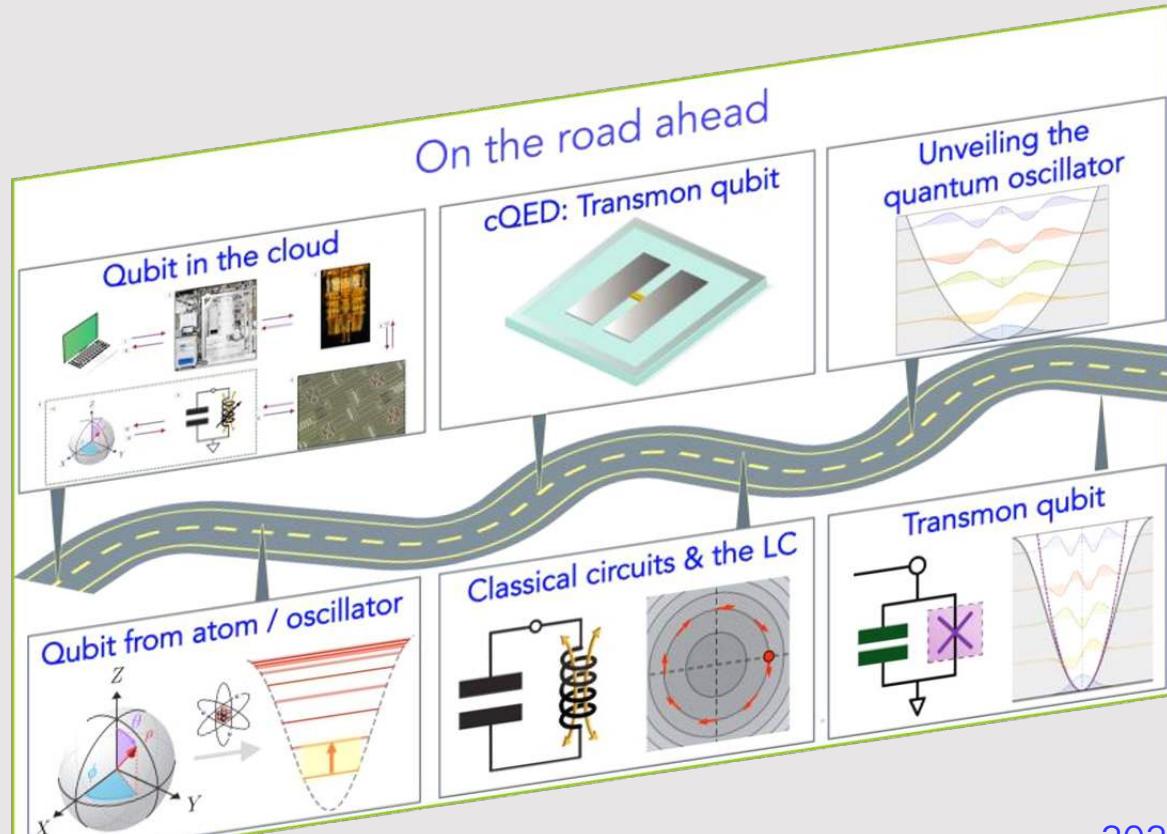
@zlatko_minev



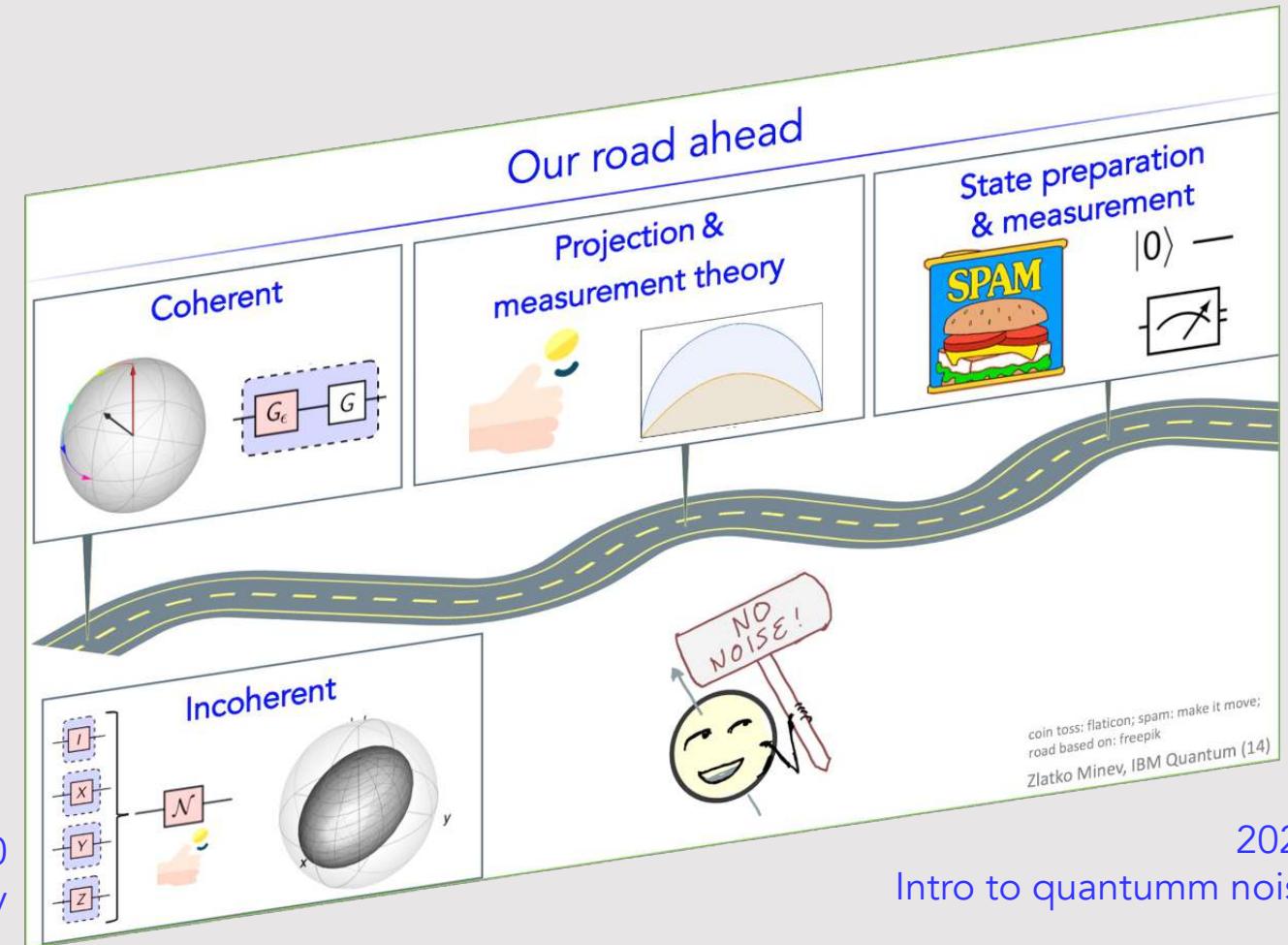
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Global Summer Schools QGSS

On the road ahead



Our road ahead



2022 coming up soon!

Tech Note T23: Probabilistic error cancellation: paper notes

Summary for key notation of *Probabilistic error cancellation with sparse Pauli-Lindblad models on noisy quantum processors* [Ref. van den Berg et al. (2020)]

Symbol	Description	Value
Circuit constants & indices		
n	number of qubits in circuit	$n = 1, 2, 3, \dots$
l	number of layers in circuit	$l = 1, 2, 3, \dots$
i	layer index within circuit	$i = 1, \dots, l$
Pauli-Lindblad model inputs		
k	model coefficient index, corresponds to a Pauli	$k = 1, 2, 3, \dots$ or equiv. n -qubit Pauli string
b	fidelity vector indices	$b = 1, 2, \dots$ or equiv. n -qubit Pauli string
\mathcal{K}	set of Pauli fidelity support indices for the sparse model \mathcal{L} of Λ . Small set	$k \in \mathcal{K}$
\mathcal{B}	set of benchmark Paulis (Pauli fidelity support indices of Λ). Can be all of them, big set	$b \in \mathcal{B}$
N	number of error-mitigated circuit instances	$N = 1, 2, 3, \dots$
Pauli-Lindblad model variables		
γ	sampling overhead	$\gamma \geq 1$, $\gamma = \exp(\sum_{k \in \mathcal{K}} 2\lambda_k)$
$\gamma_i, \gamma(l)$	sampling overhead for the i -th layer and a total of l layers	$\gamma(l) = \prod_{i=1}^l \gamma_i$
λ_k	k -th model coefficient	$\lambda_k \geq 0$
w_k	noise model weight in Λ factoring	$w_k := \frac{1}{2}(1 + e^{-2\lambda_k})$
f_b	Pauli Λ fidelity of b -th Pauli index	$f_b := \frac{1}{2^n} \text{Tr}(P_b^\dagger \Lambda(P_b))$
f	vector of Pauli fidelities of Λ	$f = \{f_b\}_{b \in \mathcal{B}}$
\hat{f}	fidelity estimates for a set of	
$M(\mathcal{B}, \mathcal{K})$	binary matrix with entries $M_{b,k} = \langle b, k \rangle_{sp}$ where the symplectic product is 0 if the Paulis commute and 1 if they do not	$\log(f) = -2M(\mathcal{B}, \mathcal{K})\lambda$ (element-wise log) (used to fit with $\lambda \geq 0$)
Quantum operators and superoperators		
P_k	Pauli operator, indexed by k	$P_k \in \{I, X, Y, Z\}^{\otimes n}$
$U, \mathcal{U}, \tilde{\mathcal{U}}$	unitary ideal gate; tilde: noisy i -th layer unitary	
Λ, Λ_i	noise channel	$\Lambda(\rho) = \exp[\mathcal{L}](\rho) = \prod_{k \in \mathcal{K}} (w_k \cdot + (1 - w_k)P_k \cdot P_k^\dagger) \rho$
Λ^{-1}	inverse noise map	$\Lambda^{-1}(\rho) = \exp[-\mathcal{L}](\rho) = \prod_{k \in \mathcal{K}} (w_k \cdot - (1 - w_k)P_k \cdot P_k^\dagger) \rho$
$\mathcal{L}(\rho)$	Lindblad generator	$\mathcal{L}(\rho) = \sum_{k \in \mathcal{K}} \lambda_k (P_k \rho P_k - \rho)$
$\langle \hat{A}_N \rangle$	average error mitigated estimate of $\langle \hat{A} \rangle$ for some operator \hat{A} using N circuit instances	

23.1 Common questions

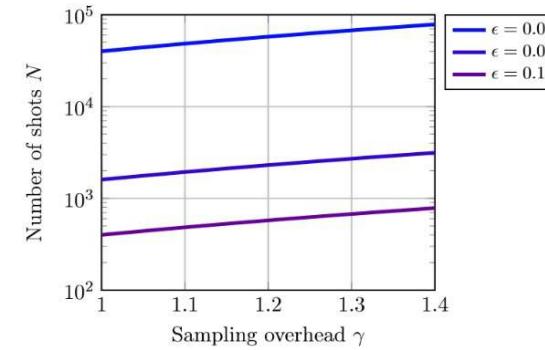
How many random circuits to run? For a maximum error bound ϵ between the the ideal and mitigated expectation values $|\langle \hat{A} \rangle_{\text{ideal}} - \langle \hat{A}_N \rangle| \leq \epsilon$ satisfied with a probability $1 - \delta$ (assuming a weak enough noise, $C^{lr} \approx 1$), we can solve for the number of error-mitigated, random circuit instances N in van den Berg et al. (2020)

$$\epsilon = \gamma \frac{\sqrt{2 \log(2/\delta)}}{\sqrt{N}},$$

$$\therefore N = 2 \log(2/\delta) \left(\frac{\gamma}{\epsilon}\right)^2,$$

$$N \approx 4 \left(\frac{\gamma}{\epsilon}\right)^2 \text{ for } \delta \sim 0.01.$$

For probability $\delta = 2\%$, $\log(2/\delta) = 2$, a small overhead; for $\delta = 0.01$, it is 2.3, and for $\delta = 0.001$, it is 3.3.



Bibliography

E. van den Berg, Z. K. Minev, and K. Temme, arXiv (2020), ISSN 23318422, 2012.09738, URL <http://arxiv.org/abs/2012.09738>.
Nature Physics **16**, 233 (2020), ISSN 1745-2473, URL <https://doi.org/10.1038/s41567-020-0847-3>.

Caveat emptor These pages are a work in progress, inevitably imperfect, incomplete, and surely enriched with typos and unannounced inaccuracies. Sources credited in Bibliography to the best of my ability, though certain omissions certainly remain.

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Paper and talk notation summary:
<https://www.zlatko-minev.com/blog/pec-notation>