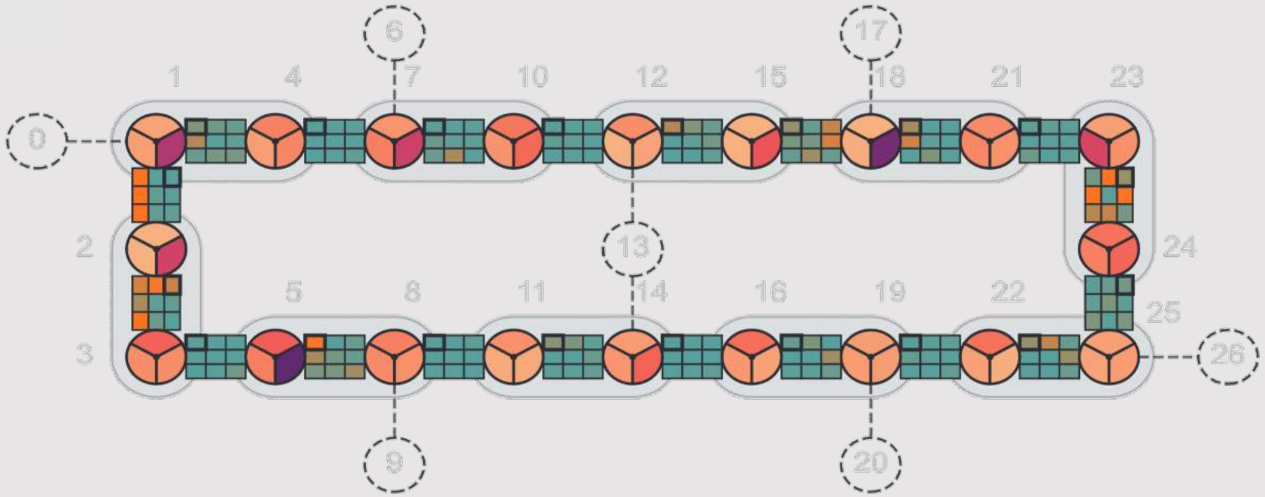
To learn and cancel quantum noise

IBM **Quantum**

Got Slides?

SCAN ME

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

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Biggest challenge?

Please do share

hardware development

decoherence

loss

stability

heat

algo development

error correction overheads

Noise (Errors)

high error rates

scalability

Biggest challenge?

engineering

modularization

importance of N in NISQ

hype

need CS/EE talent

material quality

gravity

expectations

Biggest challenge

Noise
(Errors)



How to deal with noise?

How to deal with errors due to noise?

Monitor
Error occurs
Error detect

Quantum error correction

Shor, PRA (1995), ...

Monitor
Error anticipated
Tell signal detected

Catch and reverse

Minev, Nature (2019), ...

No monitor
Error occurs
Error undetected

Error mitigation

... subject of today

Cancel quantum noise

Icon: Flaticon

High-level message

Learn
accurate, efficient, scalable

Cancel
noise with noise, practical

Cost
more noise more cost

Icon: Flaticon

Outline

Idea

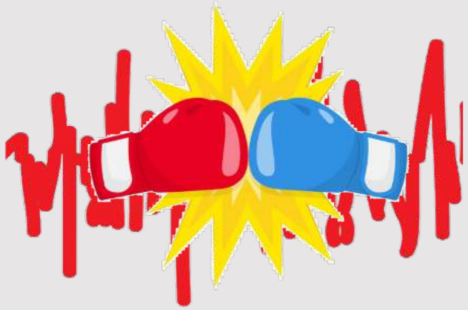
Probabilistic error cancelation (PEC) idea

Why not possible at scale until now?

Learn

Challenge

Sparse Pauli-Lindblad model in experiment



Cancel (realization)

Mitigation in practice with Ising

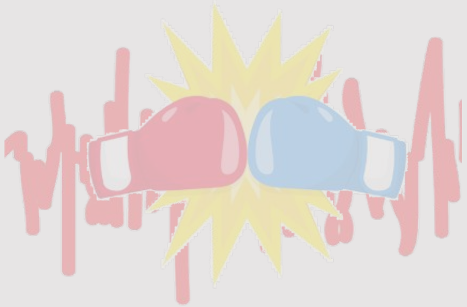
Cost

Icon: Flaticon

Outline

Idea

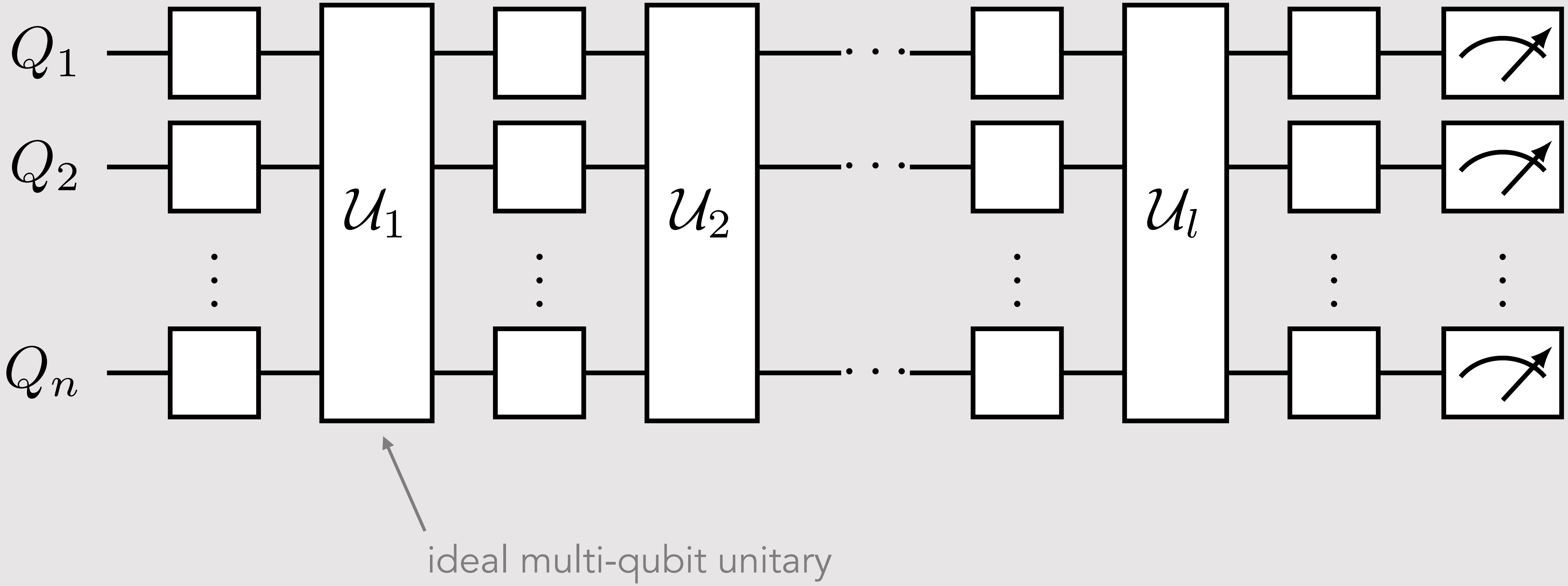
Learn



Cancel
(realization)

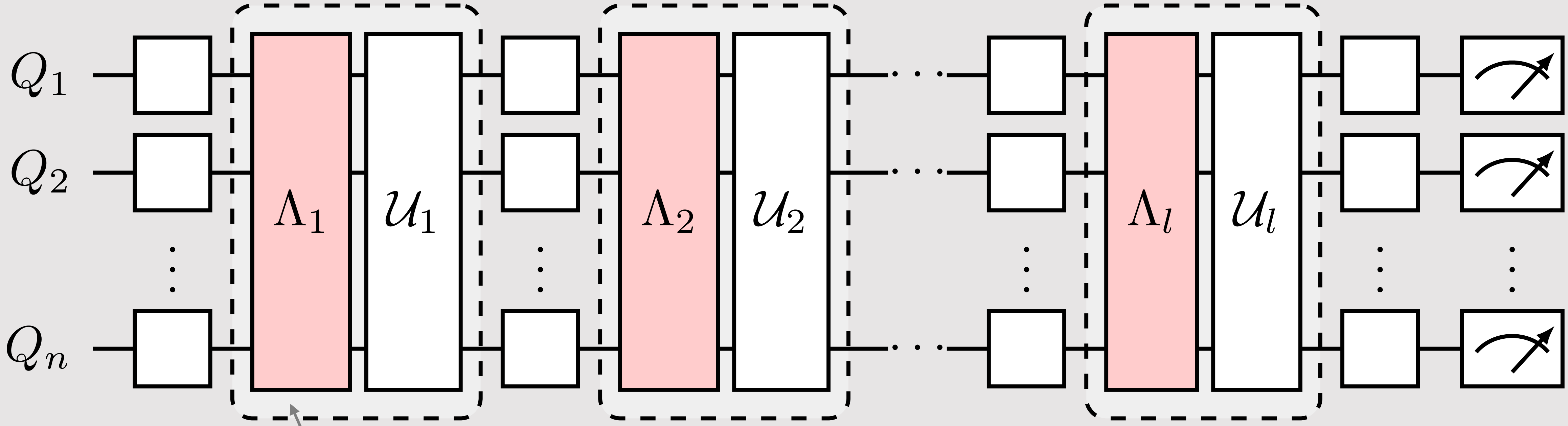
Icon: Flaticon

Ideal (noise-free) quantum circuit



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

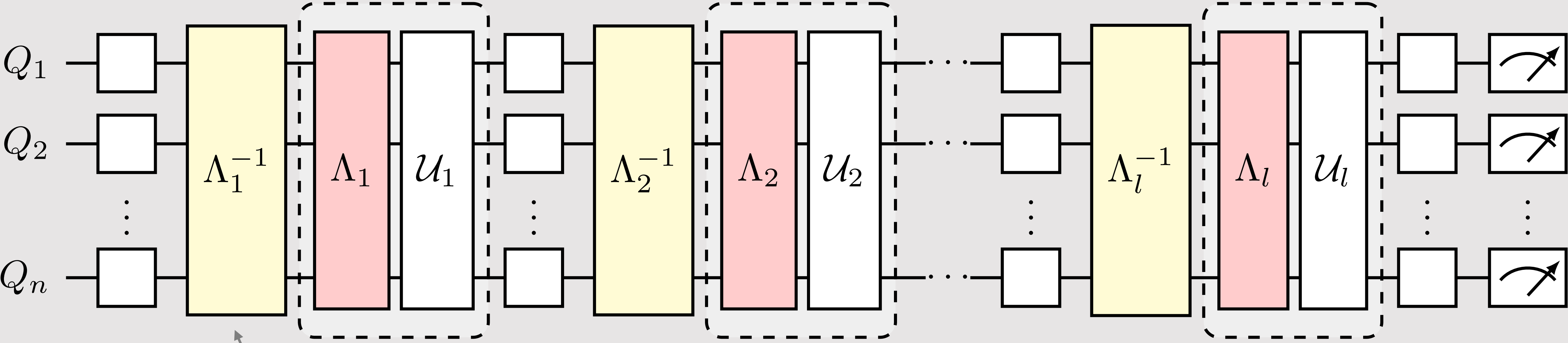
Real (noisy) quantum circuit



multi-qubit noise channel
inseparable from gate

completely positive and trace preserving (CPTP)
representable by a 4^n x 4^n matrix

Why not invert noise?

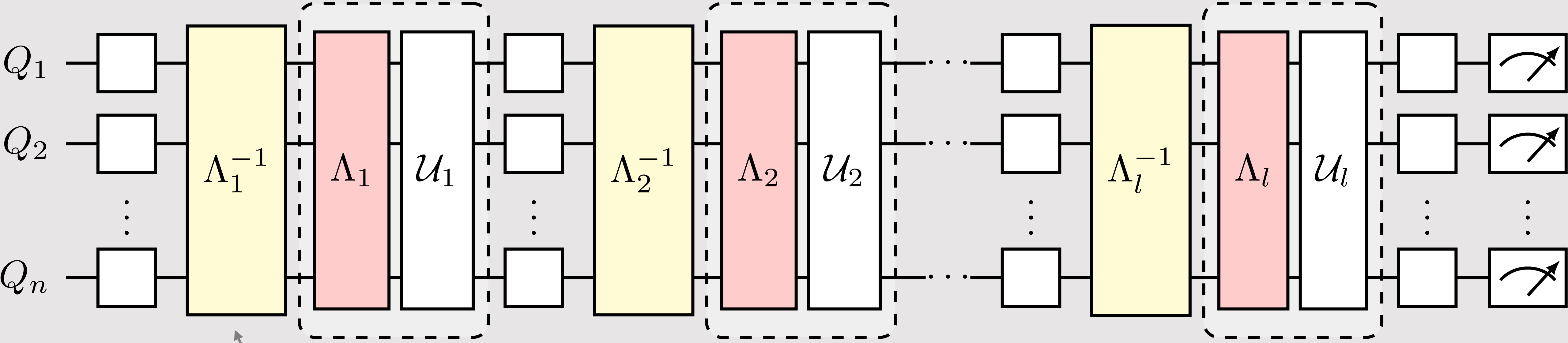


inverse operation of noise channel

Not possible?

unphysical
would need to know lost information due to noise
non CPTP map
has negative eigenvalues
...

Probabilistic error cancelation

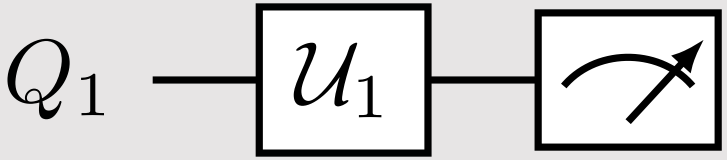


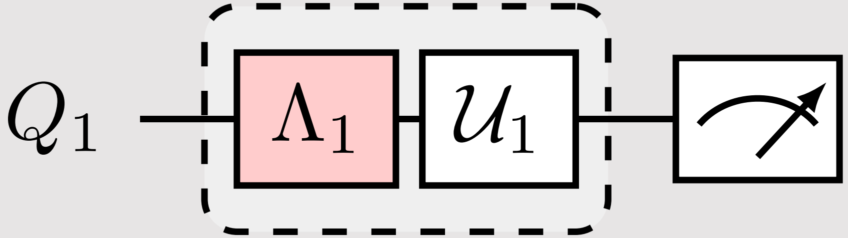
inverse operation of noise channel
implement on average

K. Temme, S. Bravyi, and J. M. Gambetta
PRL 119, 180509 (2017)

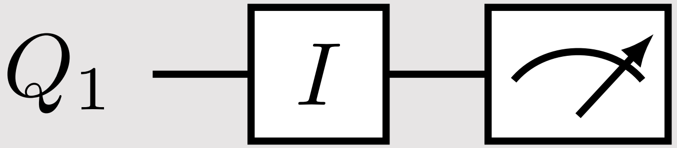
See also S. Endo, S. Benjamin, and Y. Li
Phys. Rev. X 8, 031027 (2018)

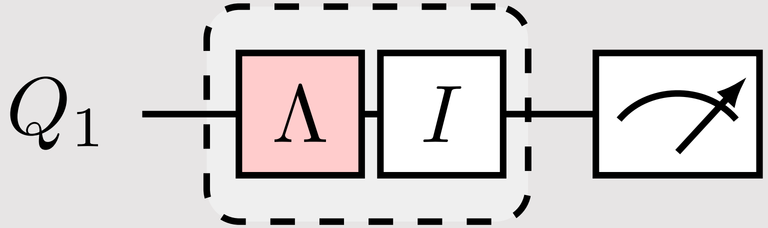
Toy model





Toy model: noise unraveling into quantum trajectories



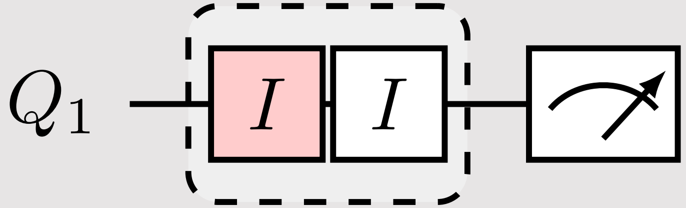


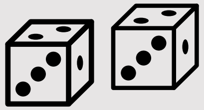
bit-flip noise

=

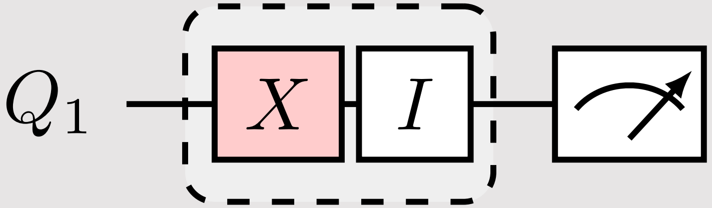
unraveling
(quantum trajectories)

probability 1-p



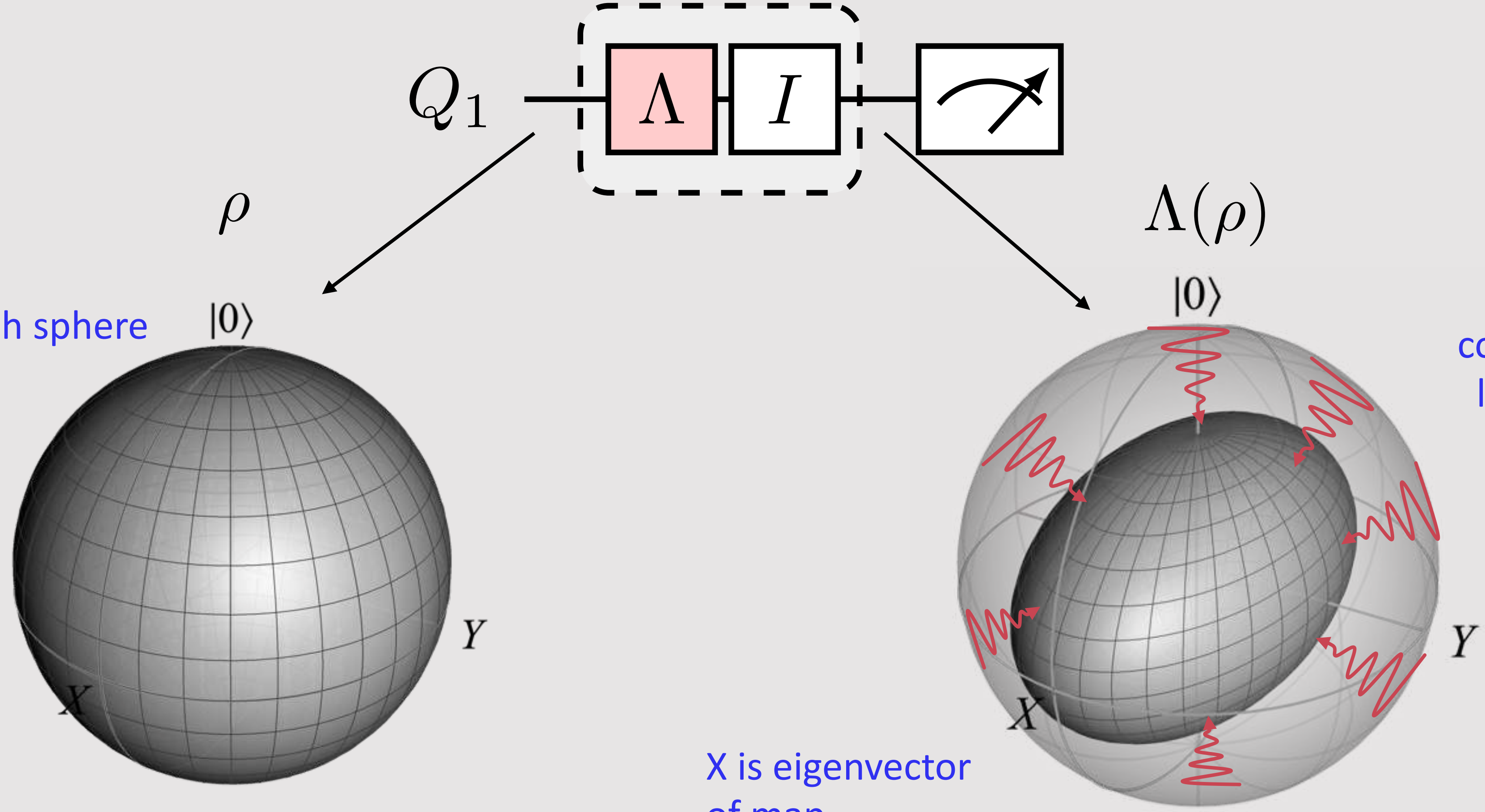


probability p



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

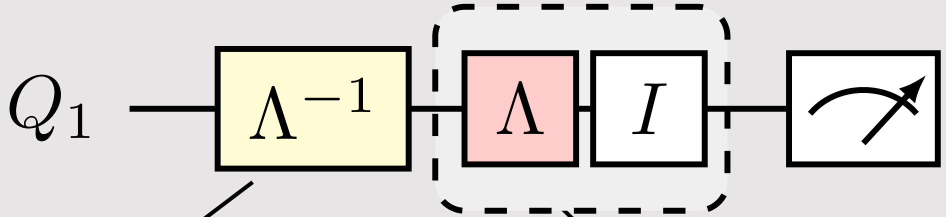
Toy model: noise unraveling into quantum trajectories

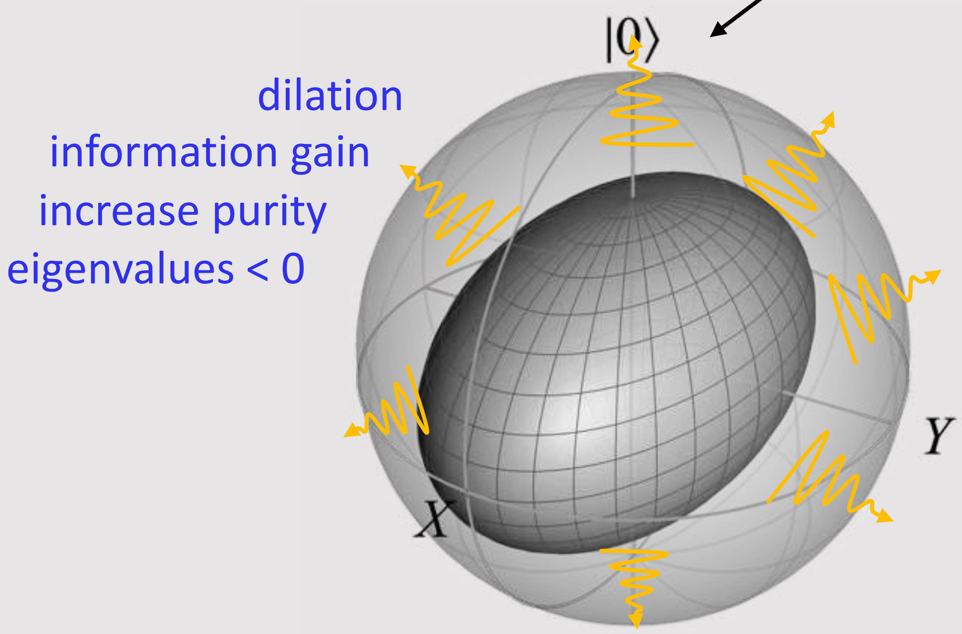


contraction
loss of information
reduced purity
eigenvalues > 0

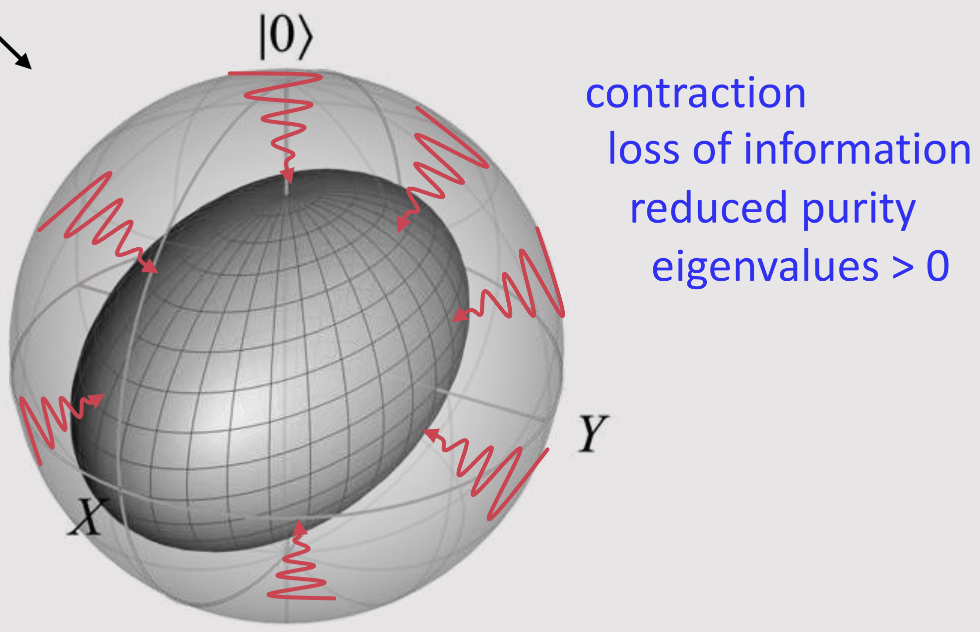
X is eigenvector
of map

Inverse of noise map is not physical



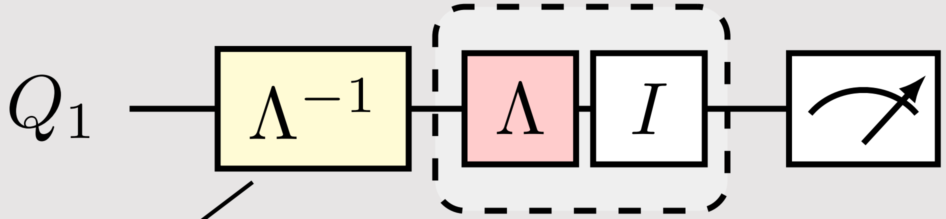


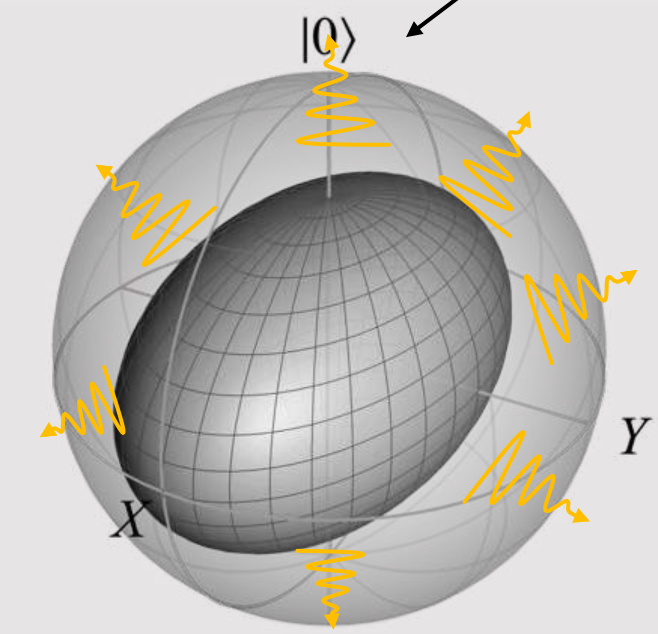
$\Lambda^{-1}(\rho) = ?$



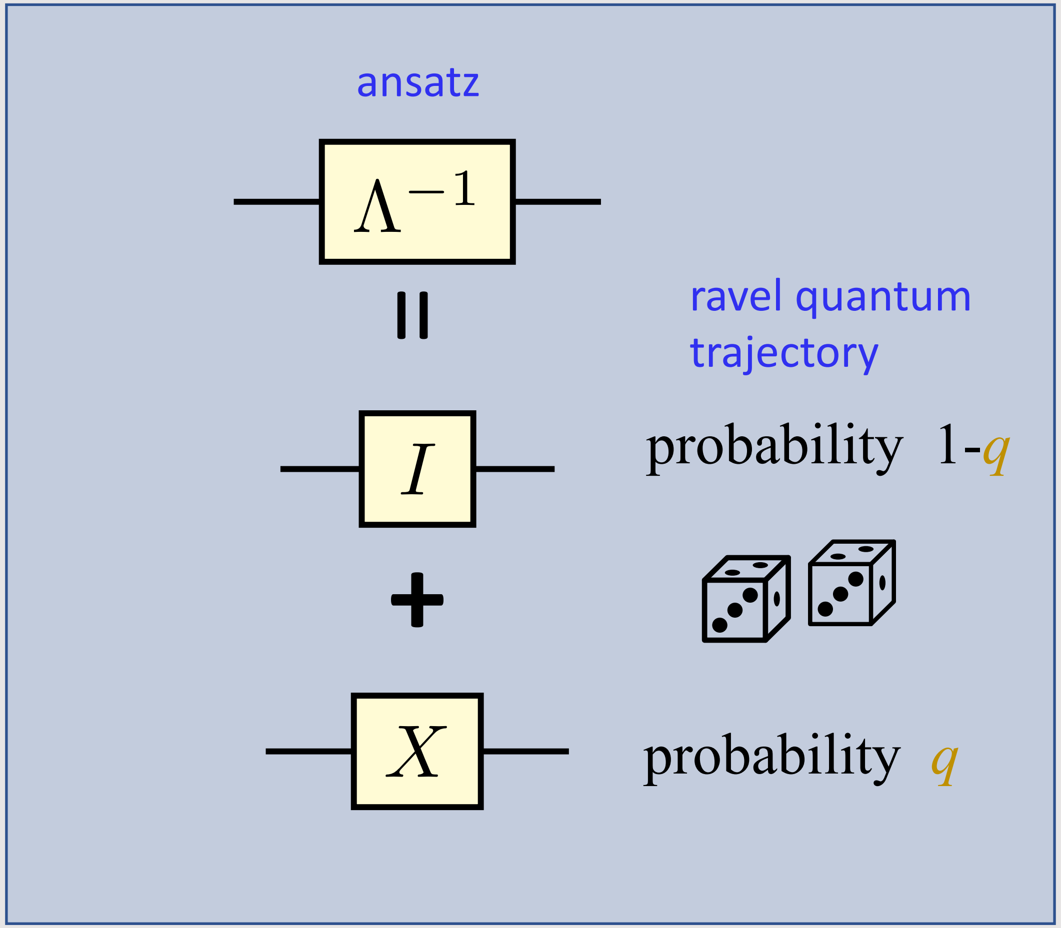
$\Lambda(\rho)$

Inverse of noise map is not physical





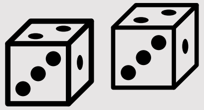
$$\Lambda^{-1}(\rho) = ?$$

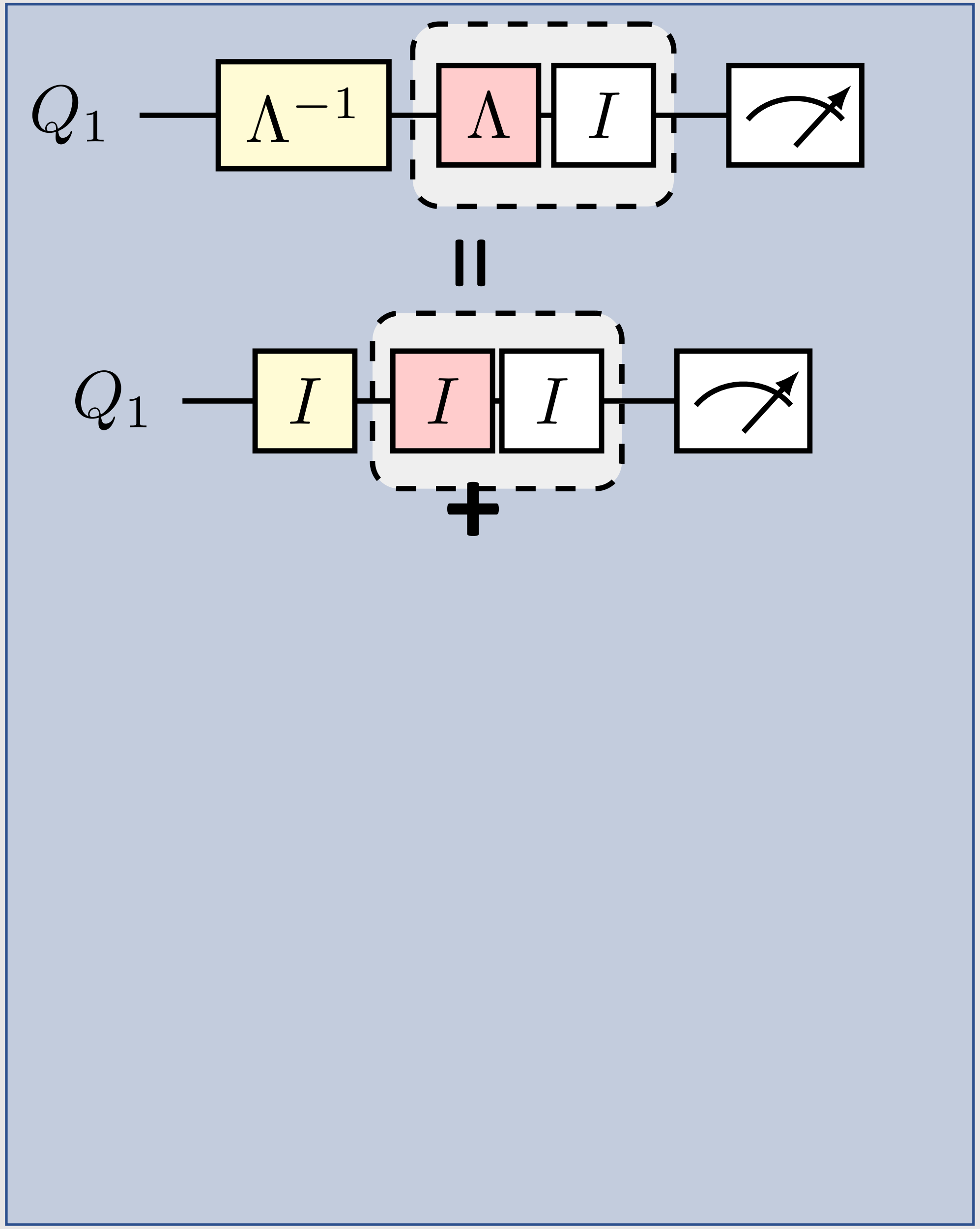


Raveling quantum trajectories to undo noise

probability

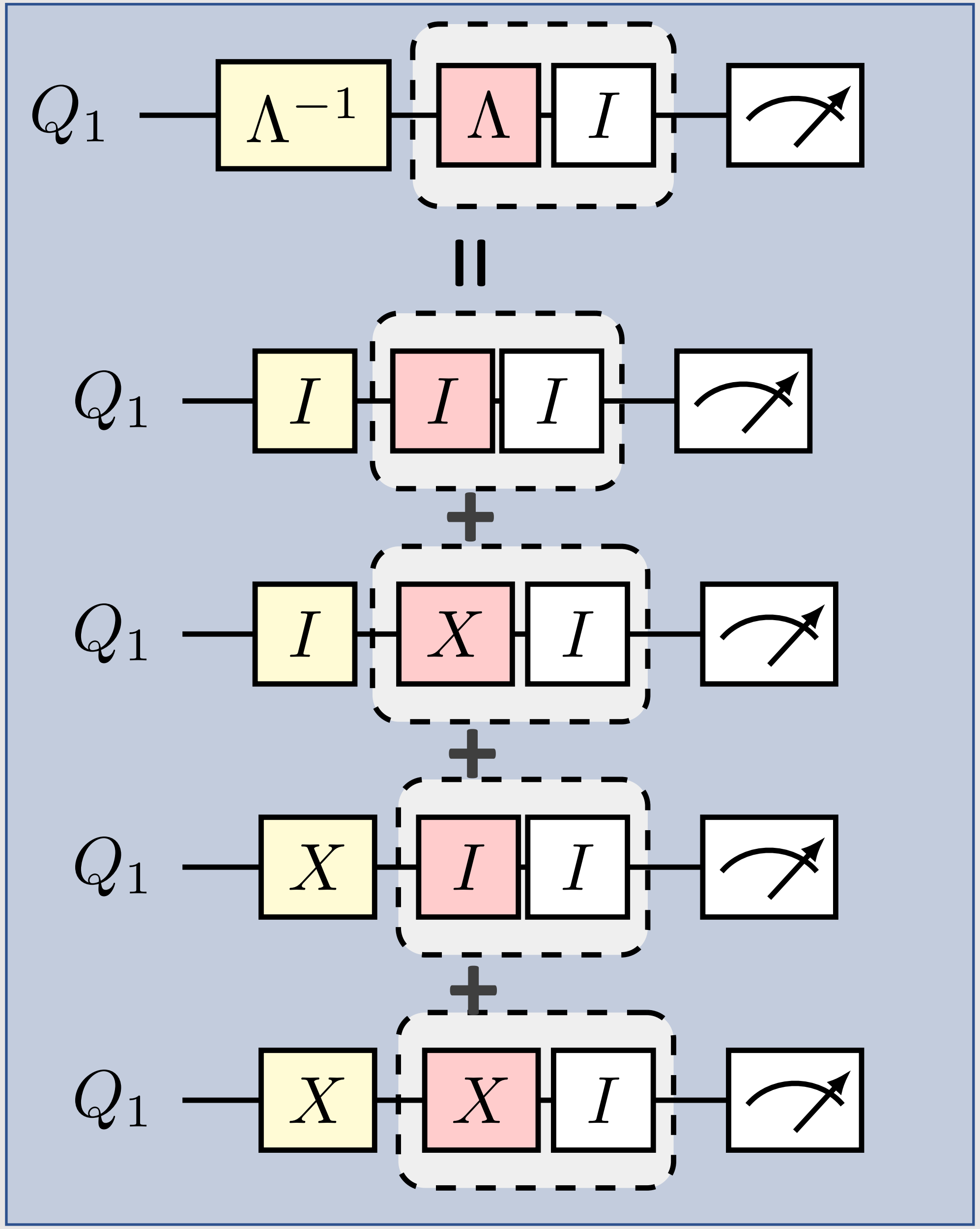
No error $(1\text{-}q)\ (1\text{-}p)$





Raveling quantum trajectories to undo noise

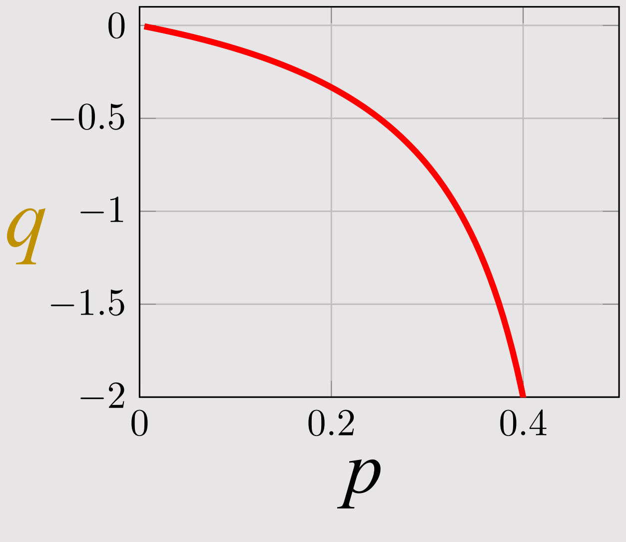
	probability
No error	(1-q) (1-p)
ERROR!	(1-q) p
ERROR!	q (1-p)
Error CANCELED!	q p



Solution to noise free!

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

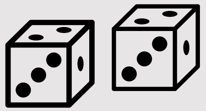
Sign & scale:
quasi-probability



How to implement?

probability

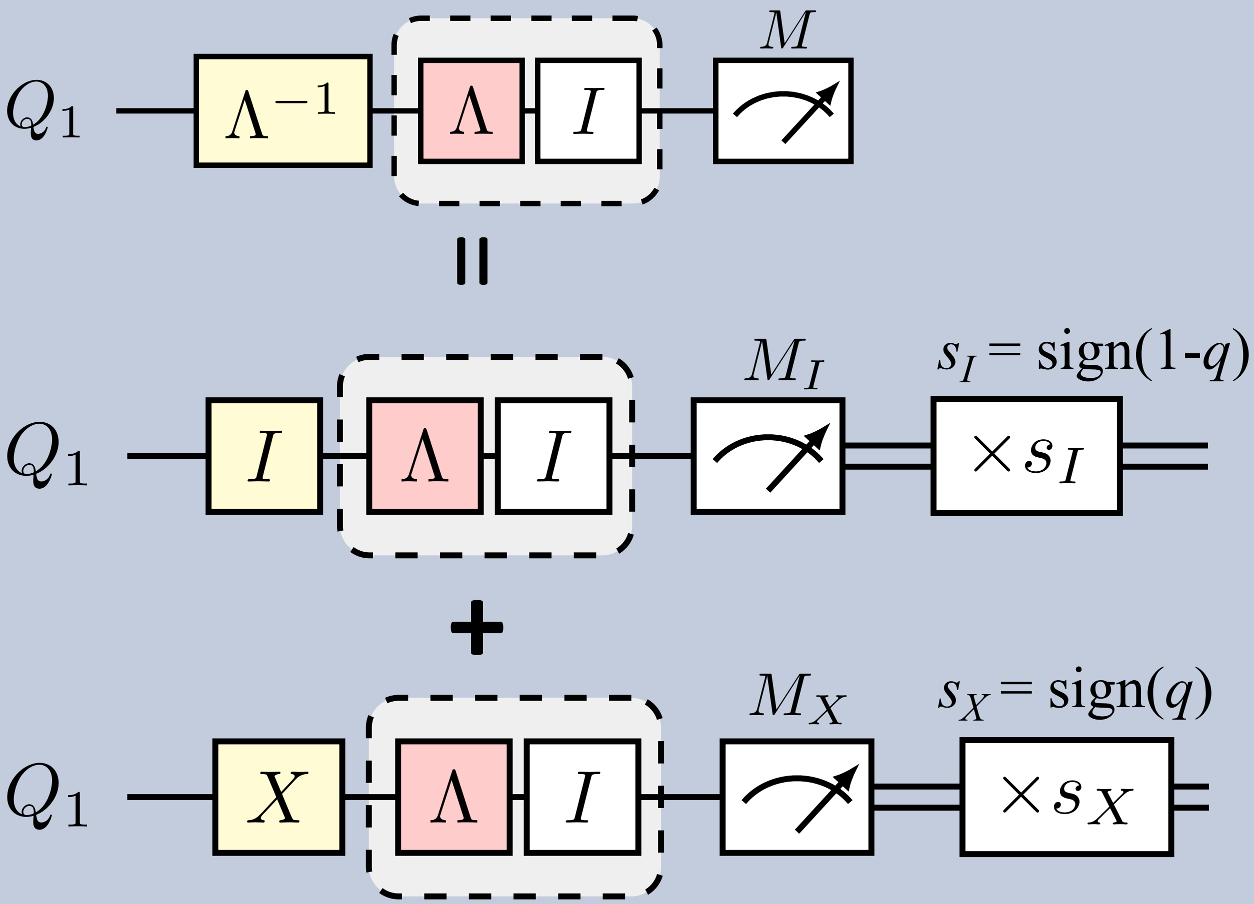
$P_I = |1\text{-}q|/\gamma$



$P_X = |q|/\gamma$

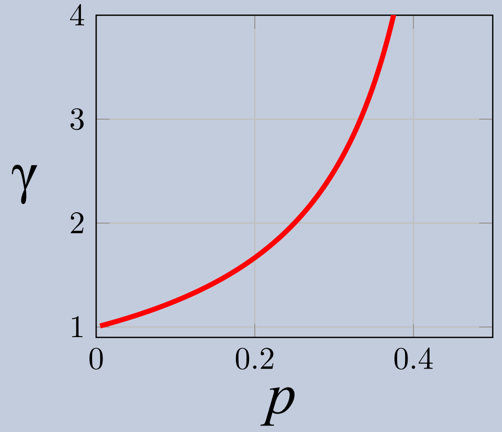
$P_I + P_X = 1$

random circuits
(quantum trajectories)



sampling overhead

$\gamma = |1\text{-}q| + |q|$



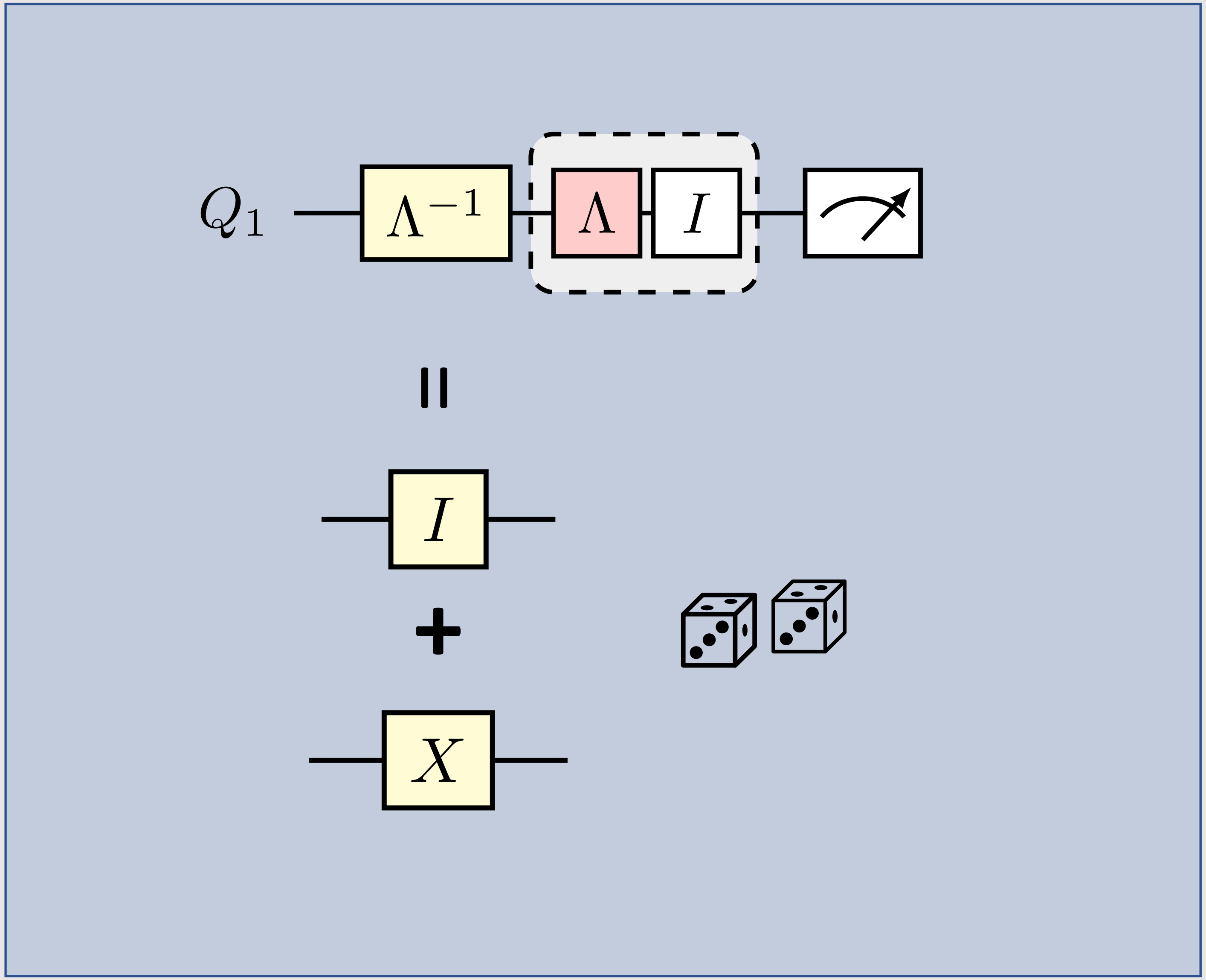
mitigated expectation

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

Gain: Bias-free estimate!

Cost: Variance

Canceling noise with noise

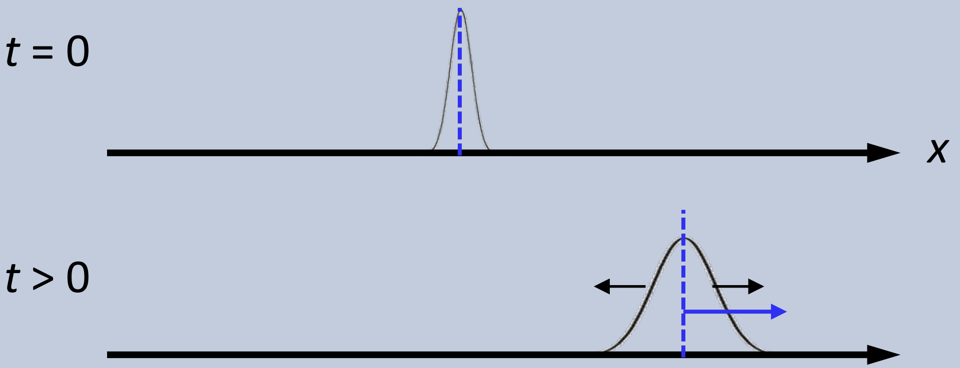


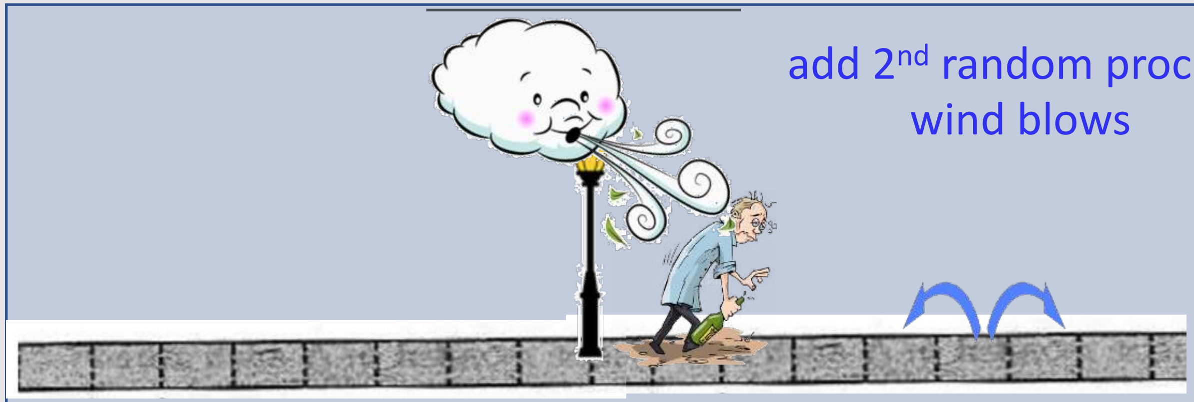
Canceling noise with noise: Drunkard's classical random walk analogy

P(1 step left) = ½-p

P(1 step right) = ½+p

Distribution of random walk

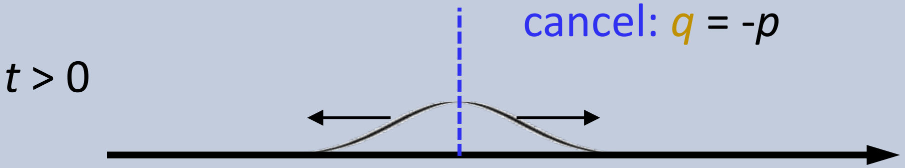




P(1 step left) = ½+q

P(1 step right) = ½-q

Distribution of random walk with wind



Gain: Bias-free estimate!

Cost: Variance

Image: A. Brand

Generalizing: Raveling trajectories with quasiprobabilities

Channel we *want* to implement

CPTP operation we *can* implement

$$\mathcal{C}(\cdot) = \sum_i a_i \mathcal{F}_i(\cdot)$$

Real coefficients, turn into quasi-probability

Putting the following techniques all on the same footing

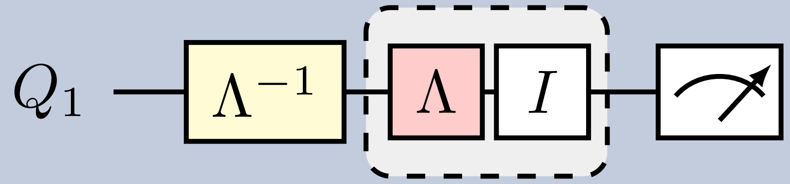
Technique	**Channel** $\mathbb{C}$
Prob. error cancelation (PEC)	noise inverse
Cricut cutting (knitting) of gates	non-local gate
Cricut cutting of wires	large unitary
Classical sim. algorithms (QP)	unitary

Discussions with David Sutter

PEC: Nice, but why hasn't worked so far for experiments?

Practical challenges

Small scale

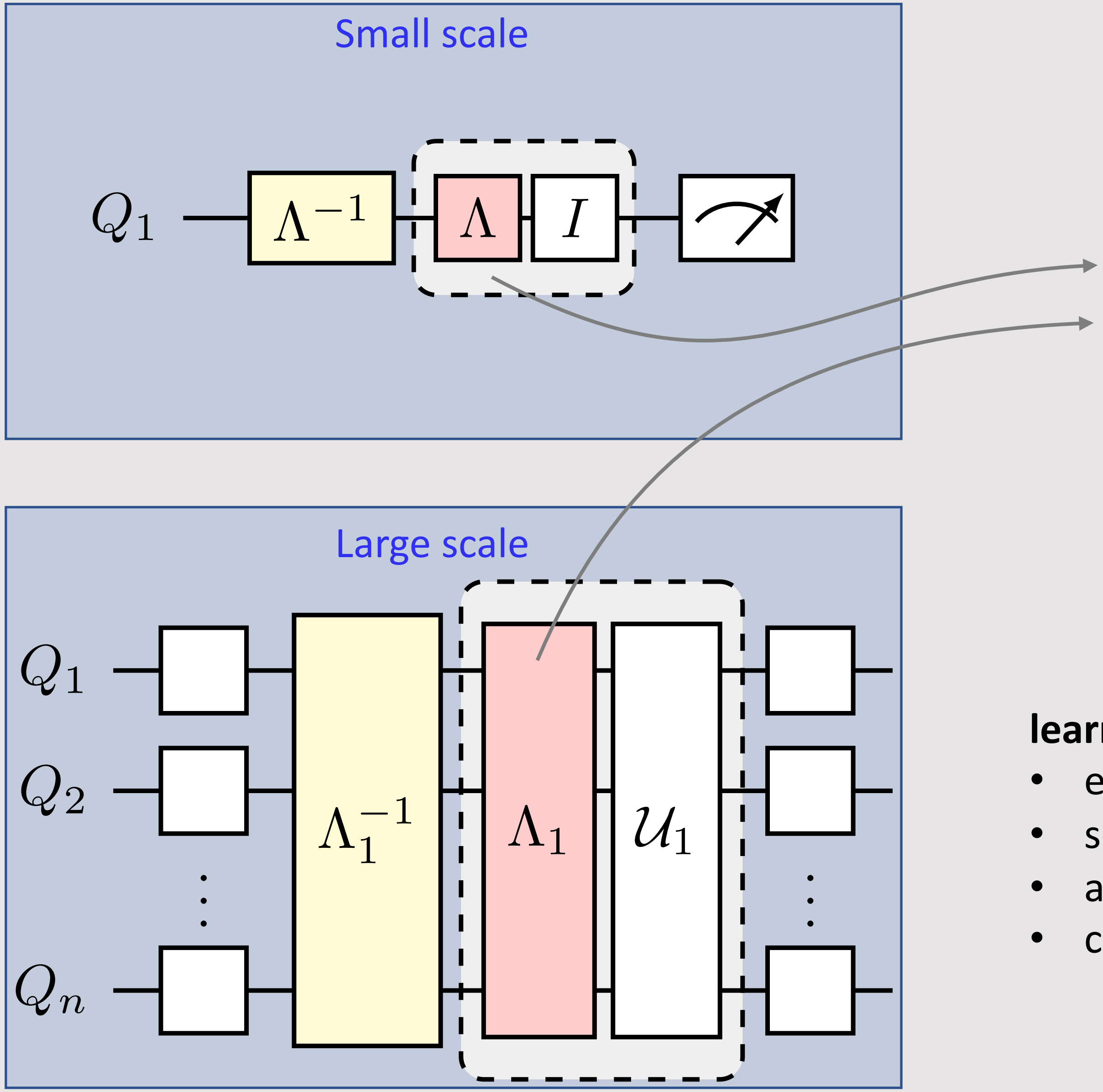


Critically hinges on knowing the full noise near perfectly

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. . . .

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



2 qubits	255 parameters
10 qubits	10^{12} parameters
50 qubits	10^{60} parameters

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

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

Challenges

learning complexity

- efficient
- scalable
- accurate
- compact, tractable representation

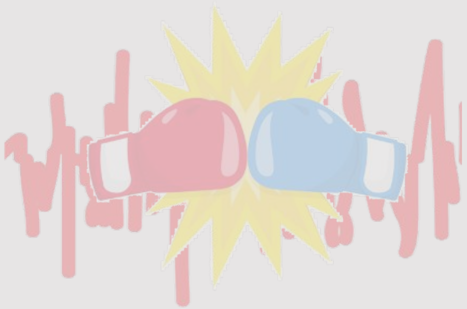
noise in full device

- cross-talk
- correlated errors
- parallel gates

Outline

Idea

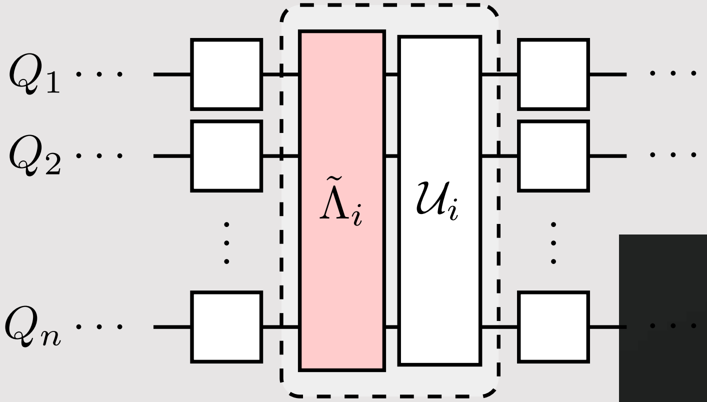
Learn



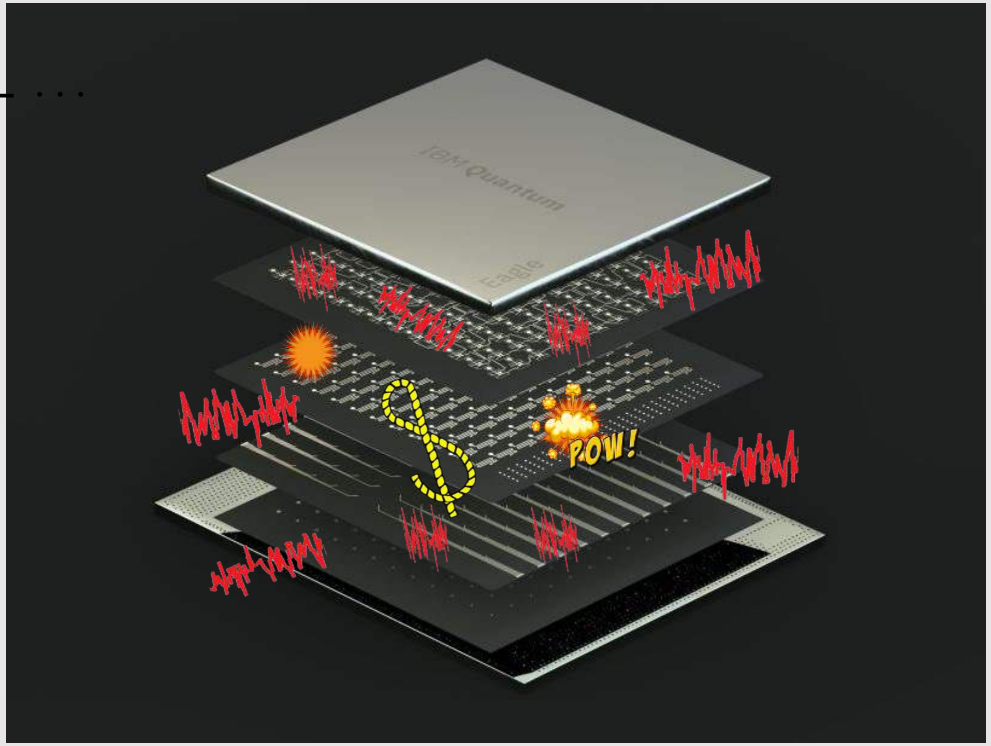
Cancel
(realization)

Icon: Flaticon

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

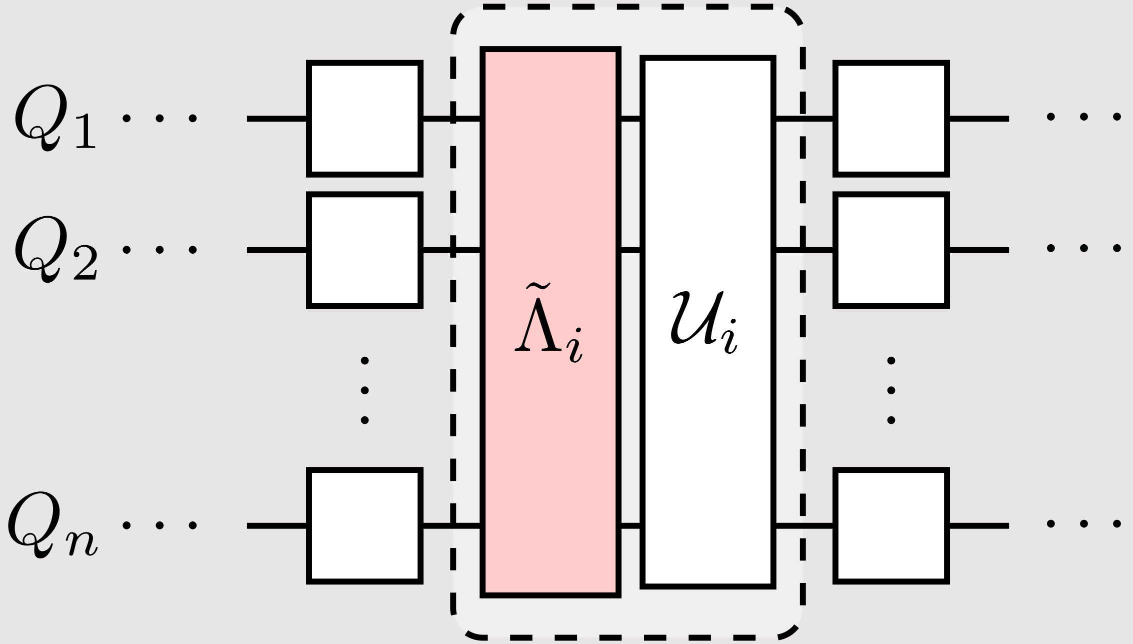


Energy relaxation T_1
Dephasing T_2
Coherent errors ZZ
Classical crosstalk
Quantum crosstalk
State preparation error
Measurement correlated errors
…



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

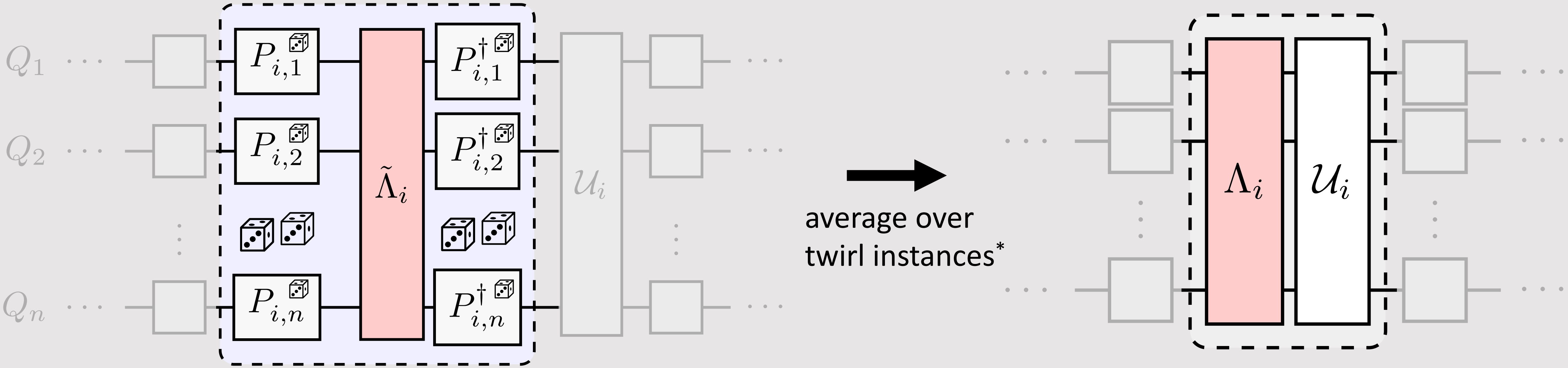
Step 1: Simplify the noise



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

Step 1: Simplify the noise: twirl

twirl reduces to noise 4^n x 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. Tutorial: zlatko-minev.com/blog/twirling (2022)
8. ...

Tutorial

SCAN ME

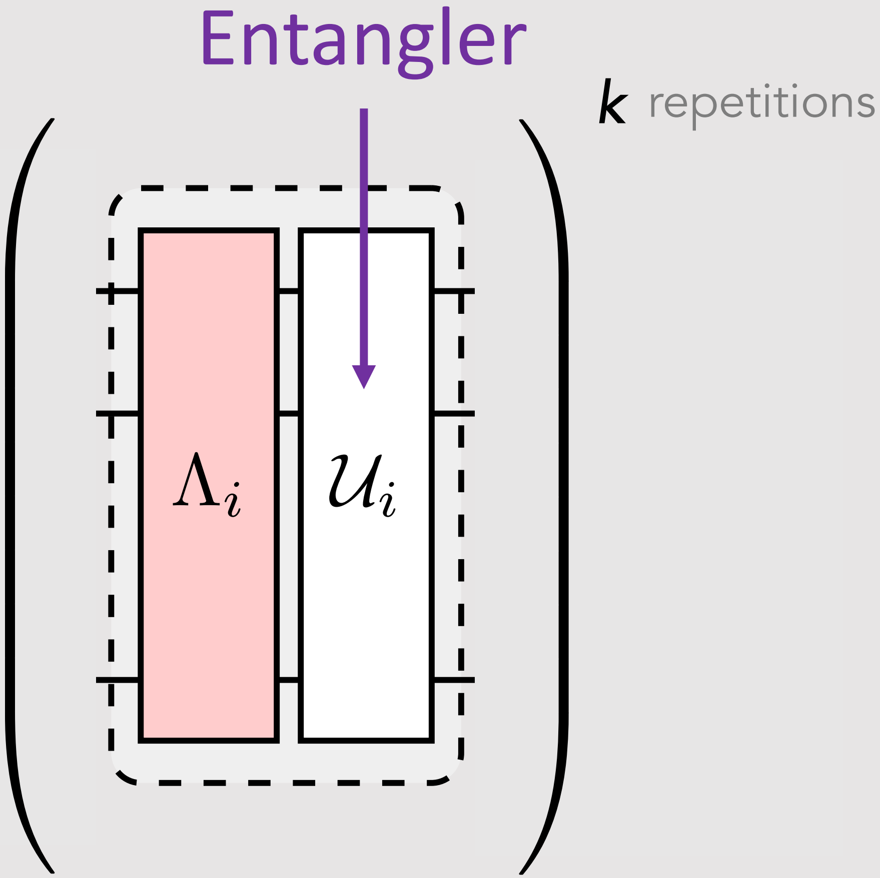
Stochastic Pauli channel

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

$$\Lambda(P_a) = f_a P_a$$ eigenvecs are Paulis

* some sub-Clifford twirl group (use Paulis)

Step 2: Ideally, amplify the noise and learn

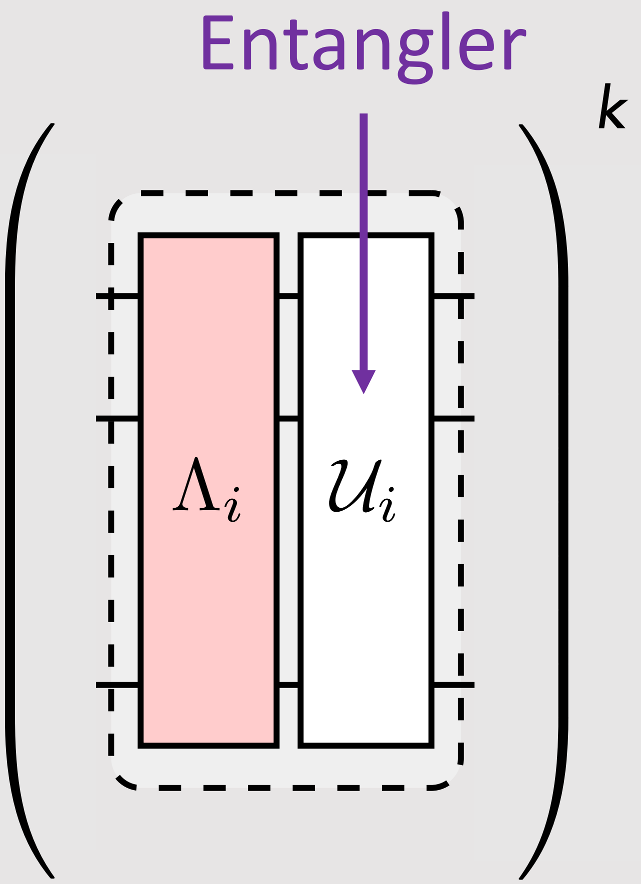


Ideally wish

$$\cancel{\Lambda_i^k\left(P_a\right) = f_{ia}^k P_a}$$

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

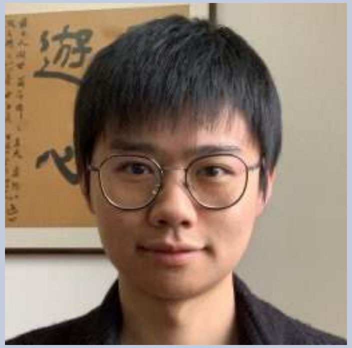
Step 2: Ideally, amplify the noise and learn



Ideally wish

$$\cancel{\Lambda_i^k(P_a) = f_{ia}^k P_a}$$

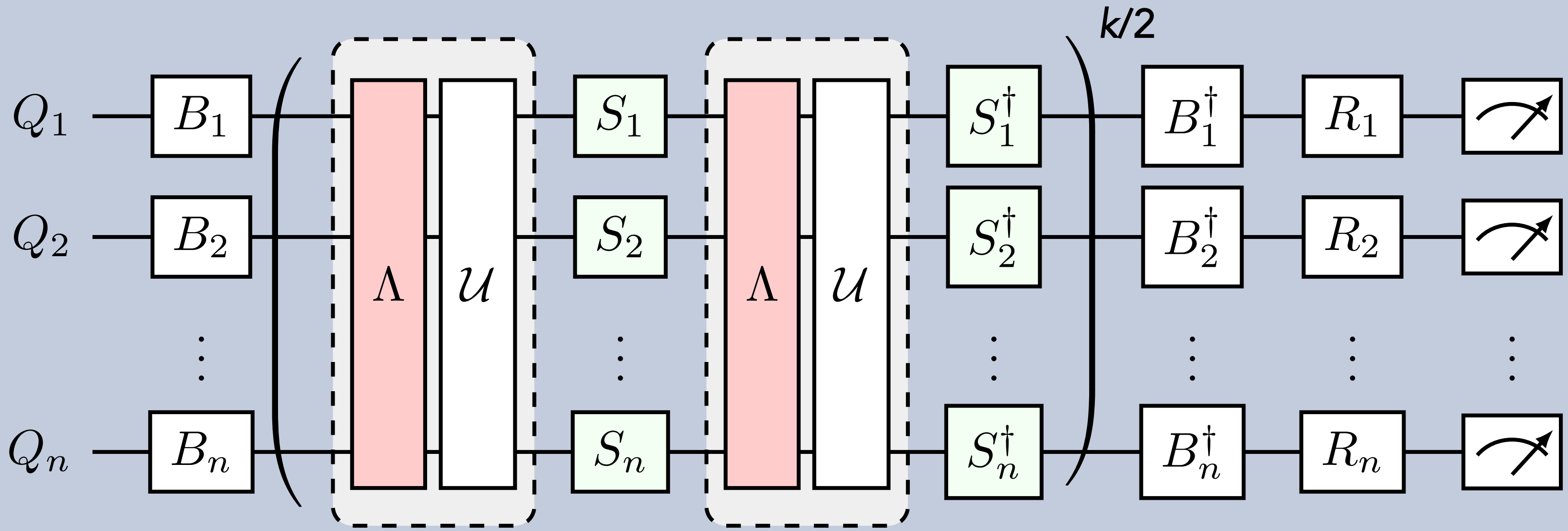
Fundamental no-go theorem on learning



For general and in-depth
Senrui Chen, Y. Liu, M. Otten, A. Seif, B. Fefferman, L. Jiang
arXiv:2206.06362 (2022)
or supplement of our paper for qubit version and work by
S. Flammia, S Benjamin, and teams.

Solution: Custom protocol + weak assumption

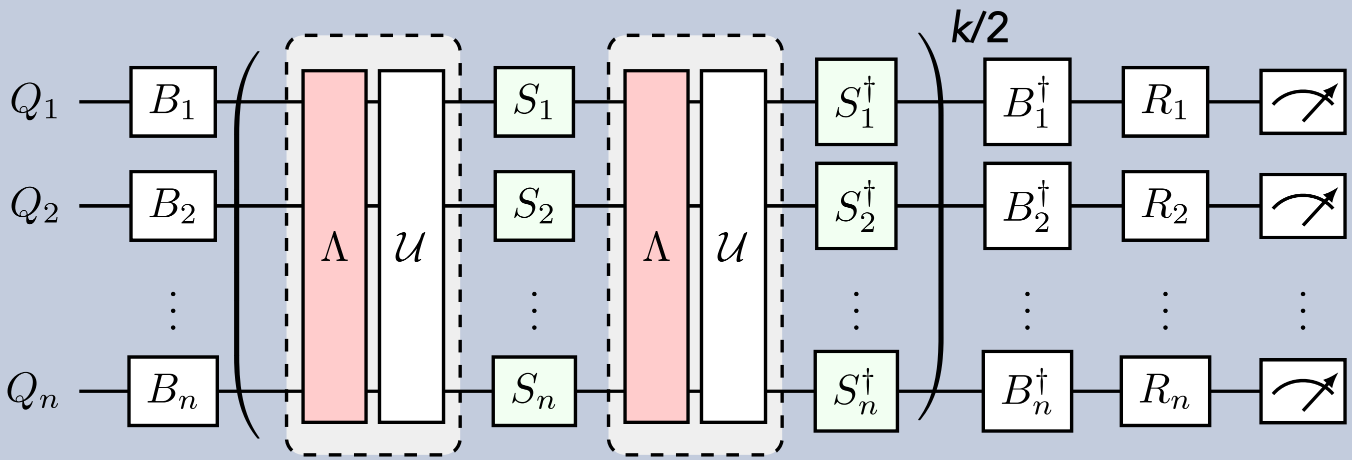
Learning circuits akin to cycle RB

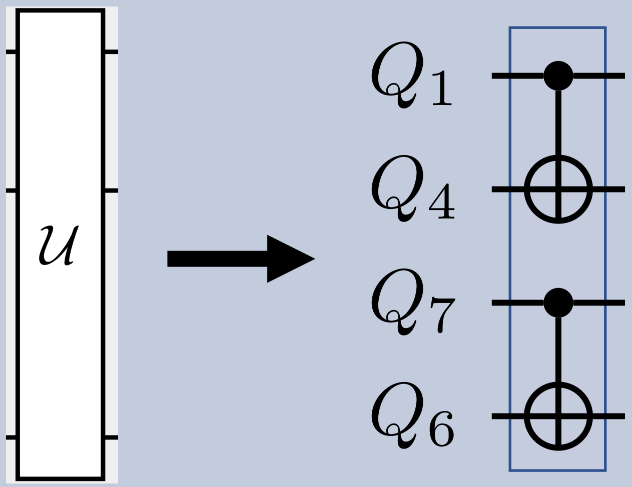


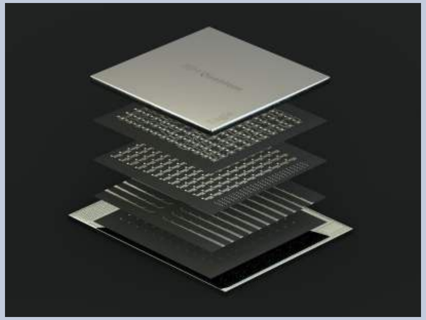
(ask me in questions for how it works)

In a simple experiment?

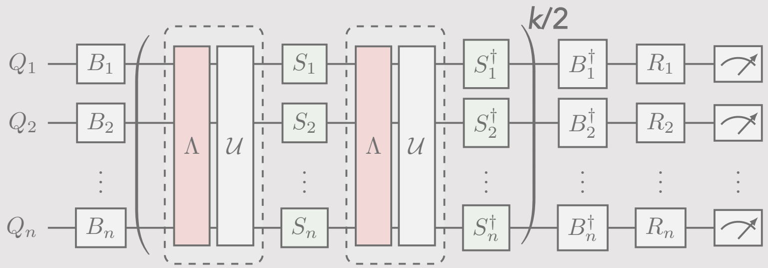
Learning circuits

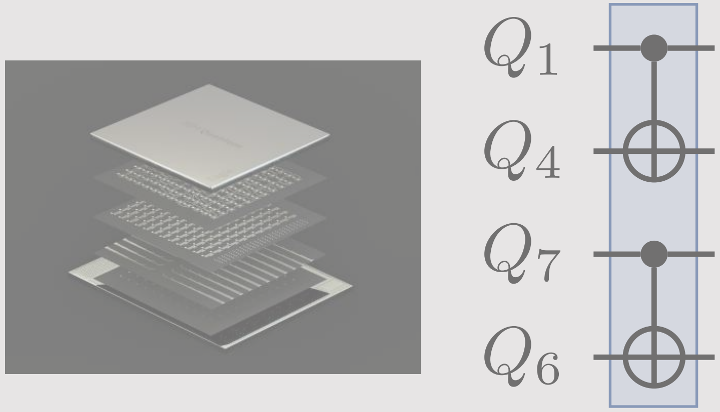




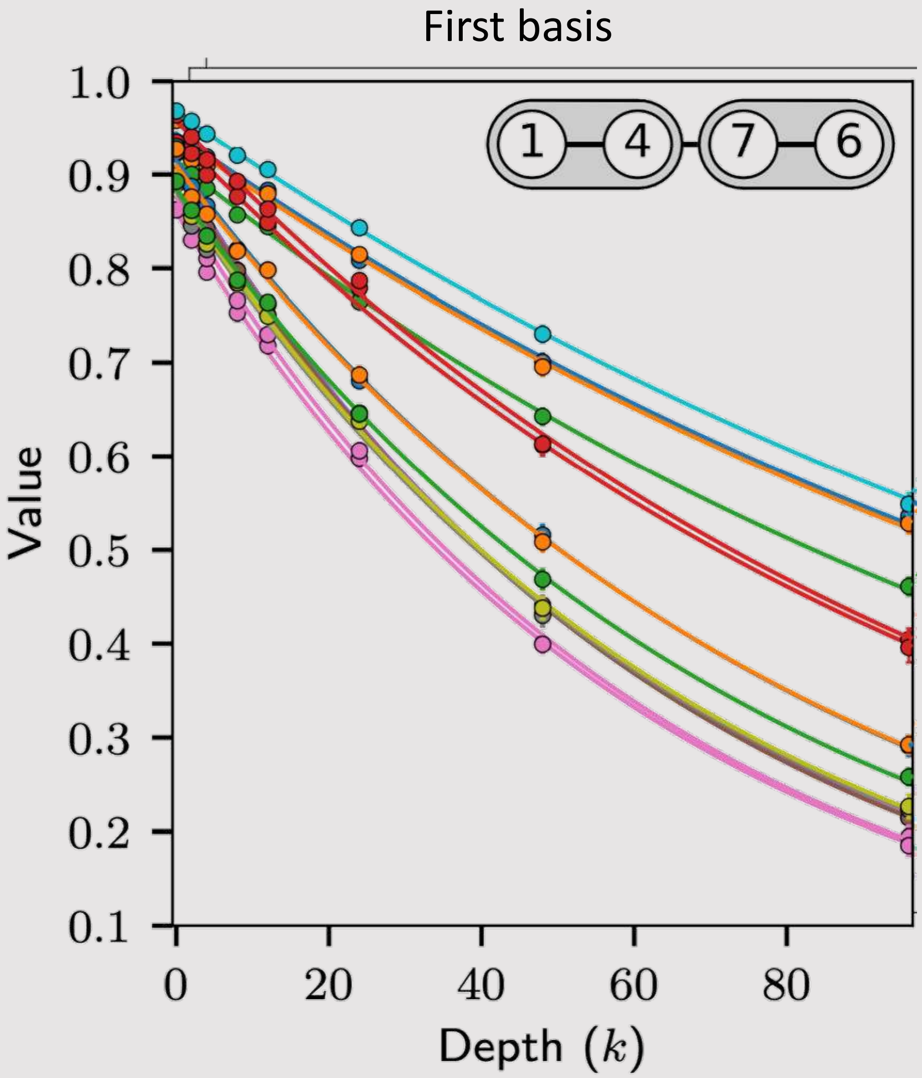


Learning the noise: raw data

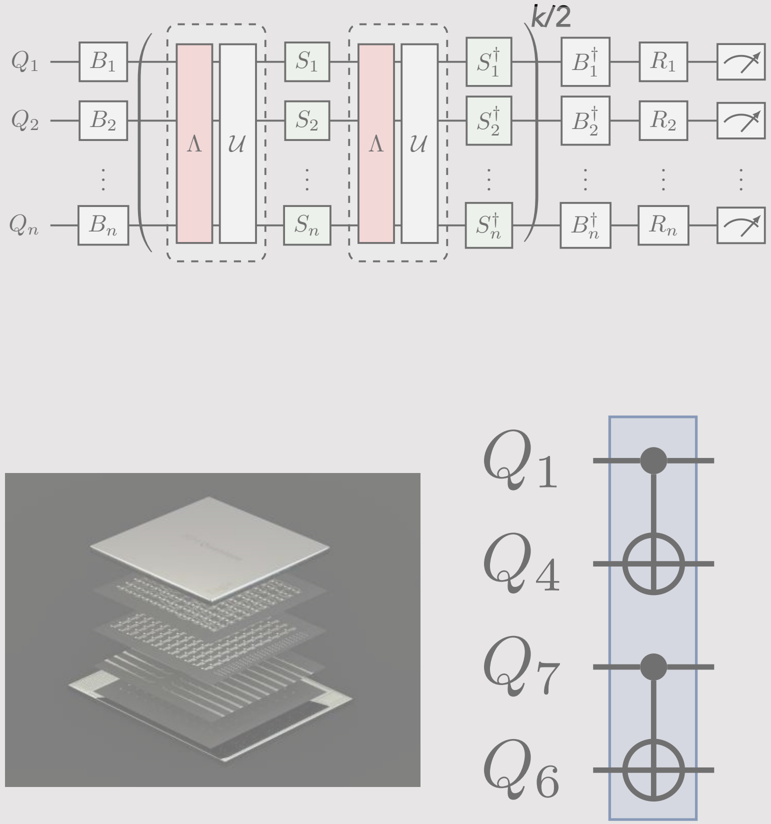




9 bases, 100 randomizations, 216 shots



Learning the noise: raw data



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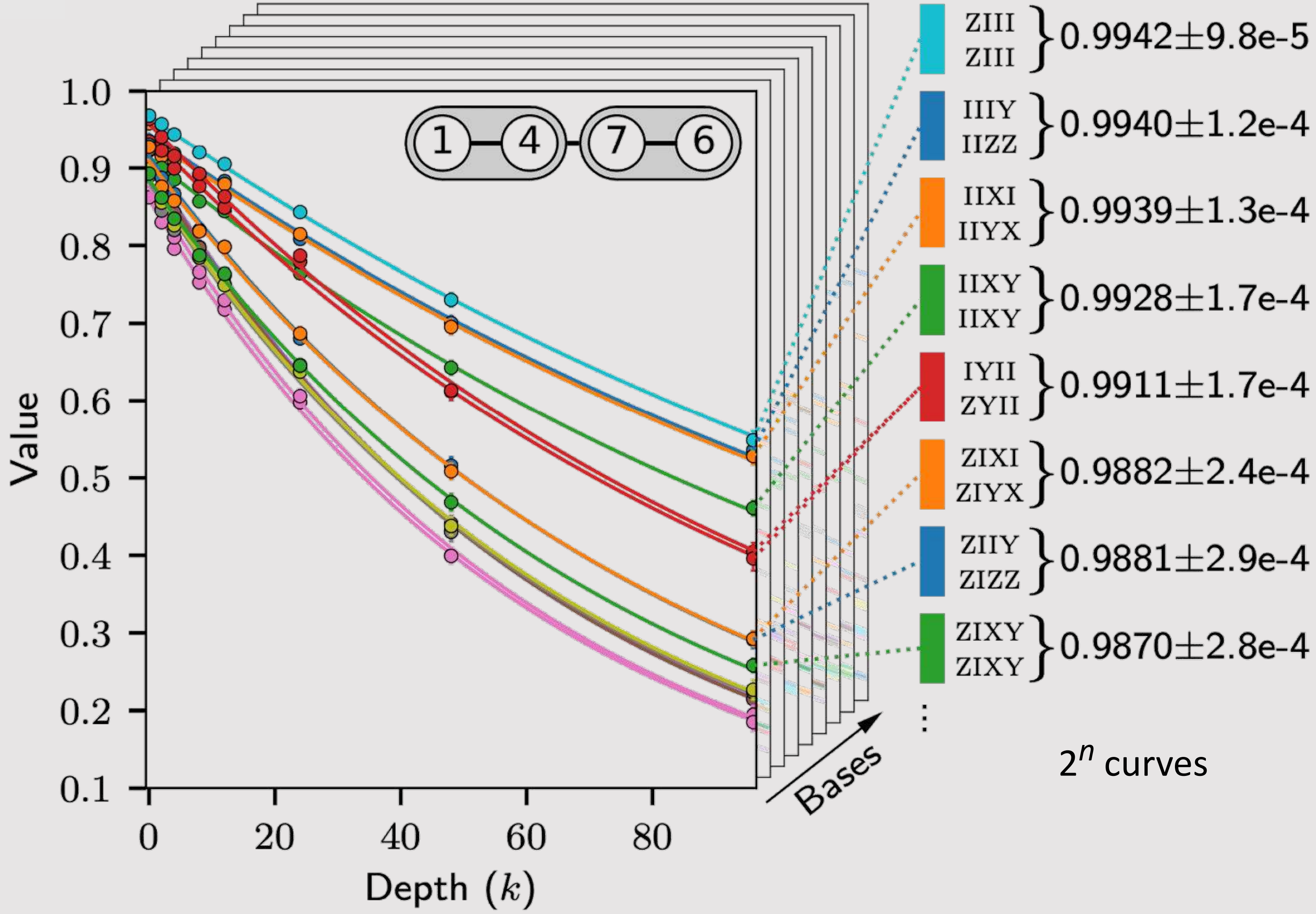
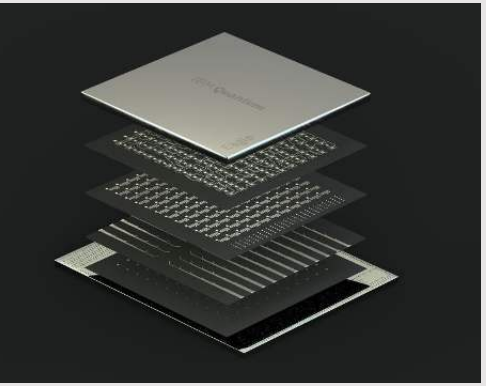
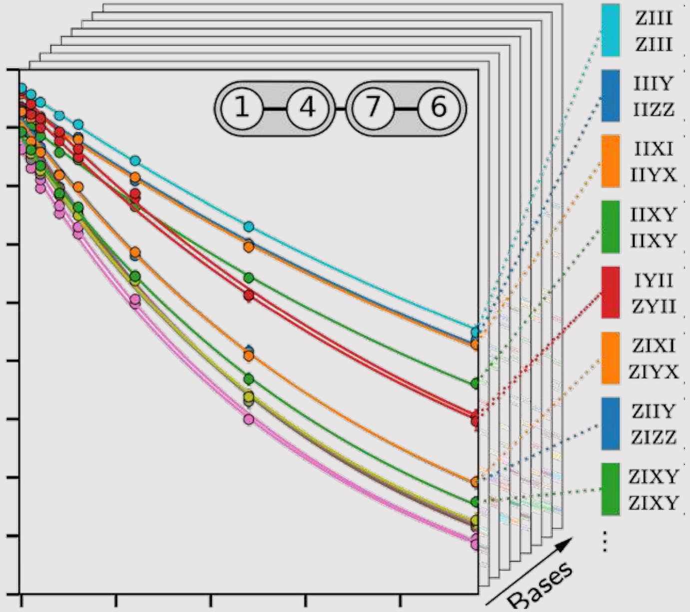


Reconstructing quantum channel from measurement data

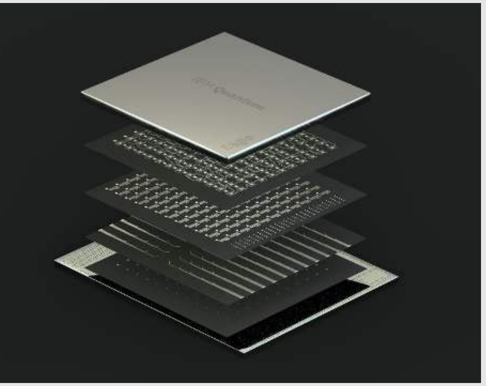


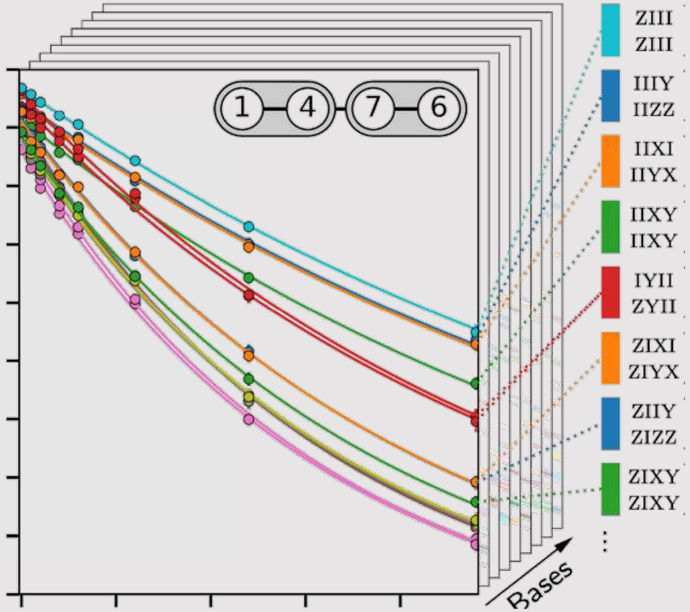


$$\Lambda(\rho) = \sum_{a=0}^{4^n-1} \boxed{c_a} P_a \rho P_a^\dagger$$

Still 4^n

Sparse Pauli-Lindblad model

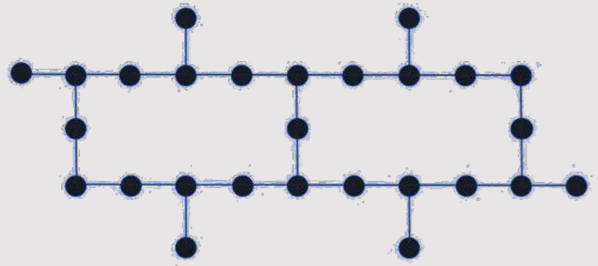




$$\Lambda(\rho) = \sum_{a=0}^{4^n-1} \boxed{c_a} P_a \rho P_a^\dagger$$

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

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

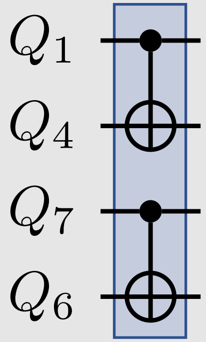


Highlight: Ewout van den Berg

Magic

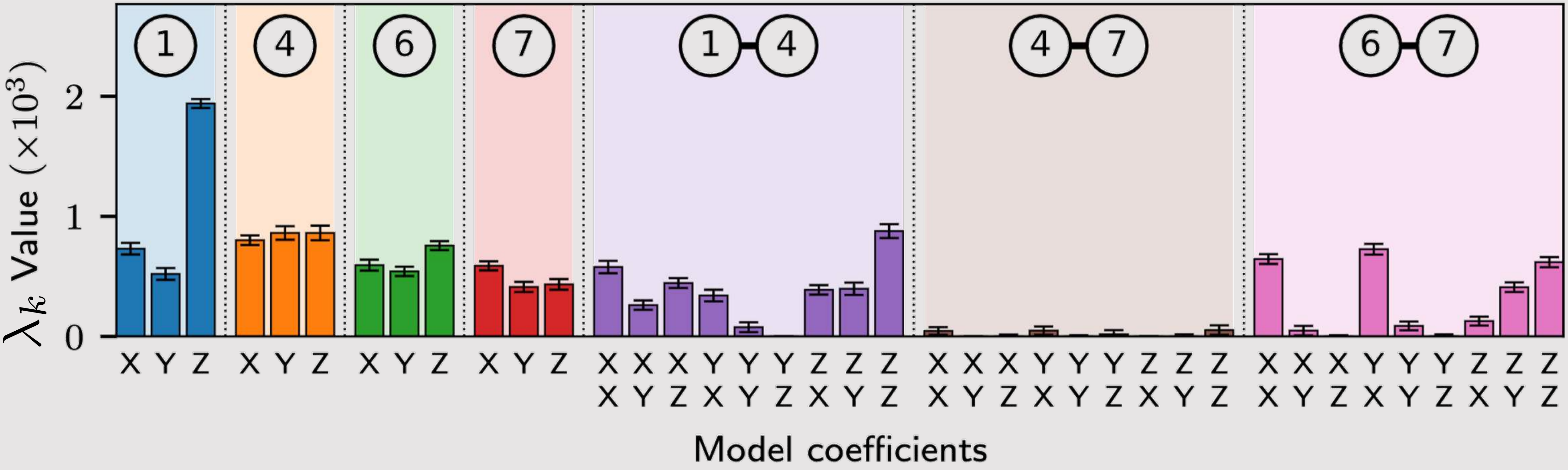
icon: Eucalyp

See *Peter Zoller* talk tomorrow for Hamiltonian learning

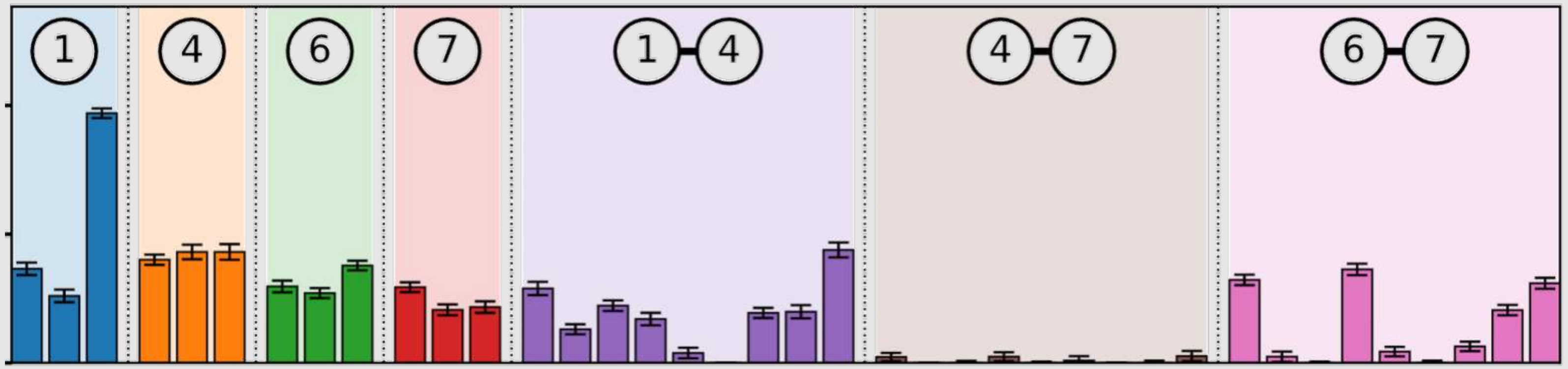


Sparse Lindblad tomogram

$$\mathcal{L}(\rho) = \sum_{k \in \mathcal{K}} \boxed{\lambda_k} \left(P_k \rho P_k^\dagger - \rho \right)$$



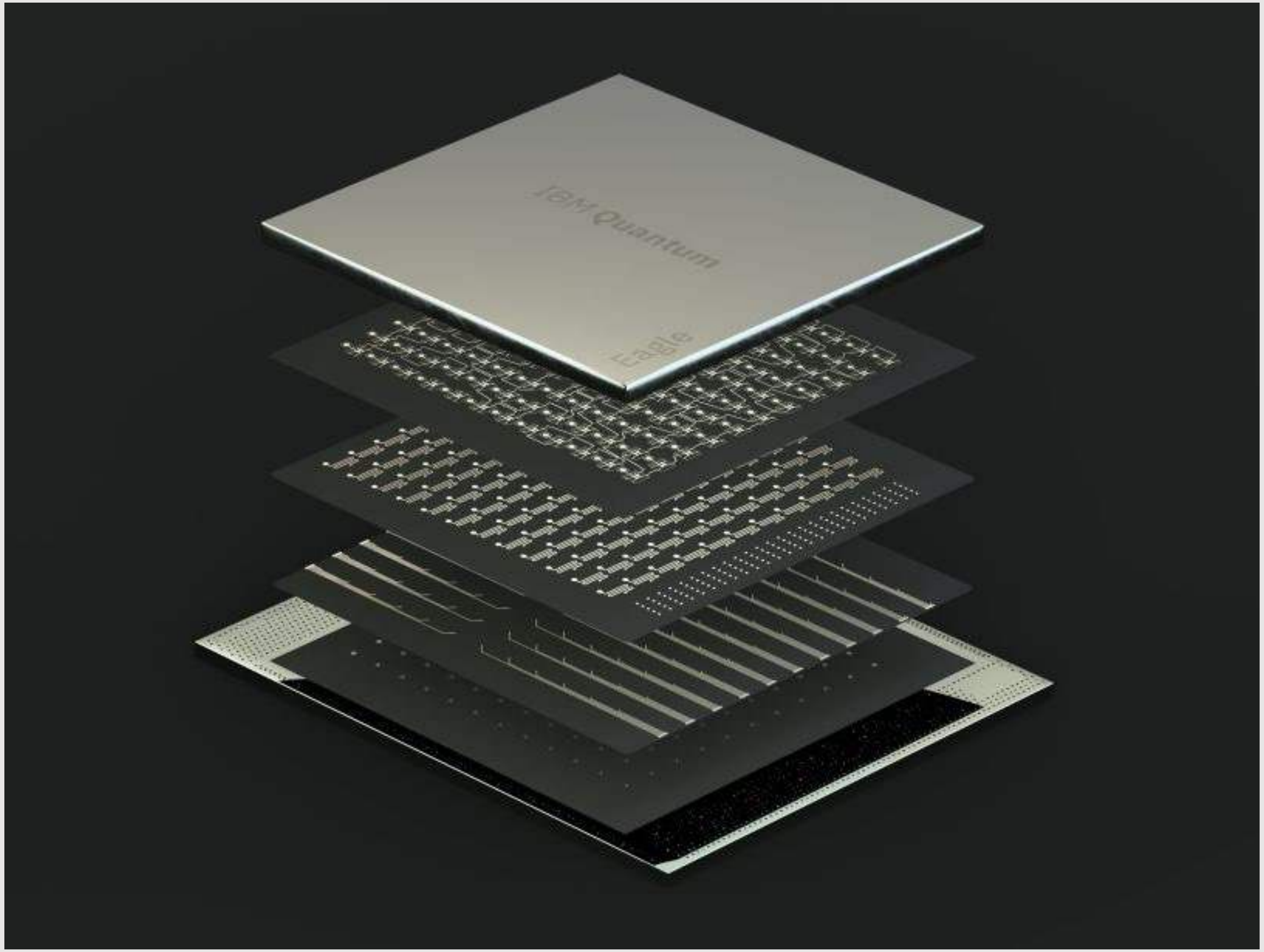
Fingerprint



Application: Device inspection/optimization

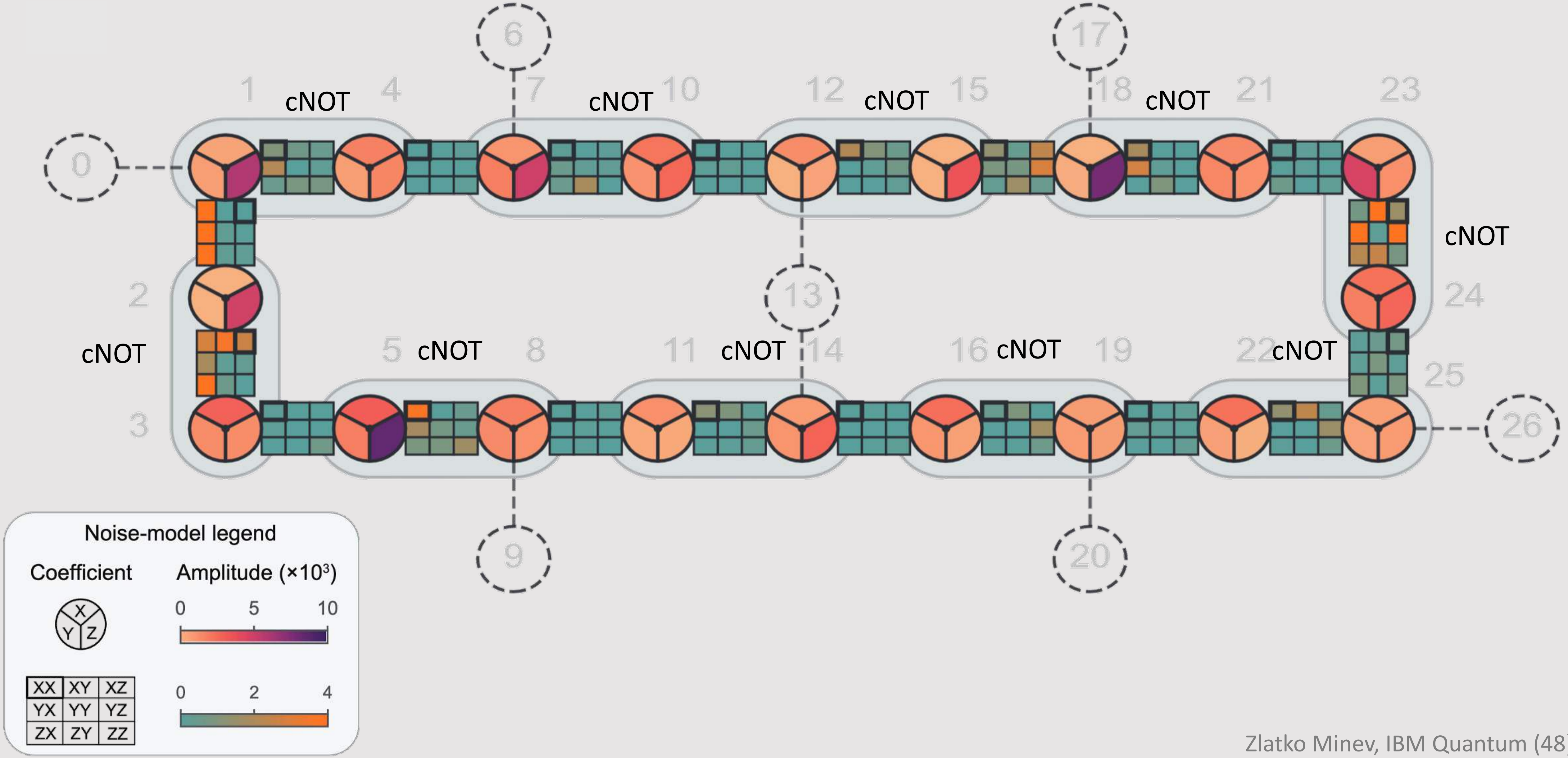
- Ask me about dynamical decoupling (DD) application

Learning noise across large device?



Fingerprint image: freepik

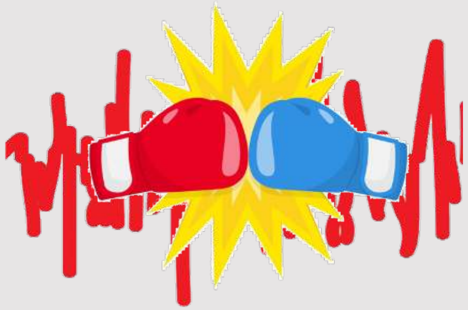
Noise tomogram for 20Q Ising-ring Trotter layer



Outline

Idea

Learn



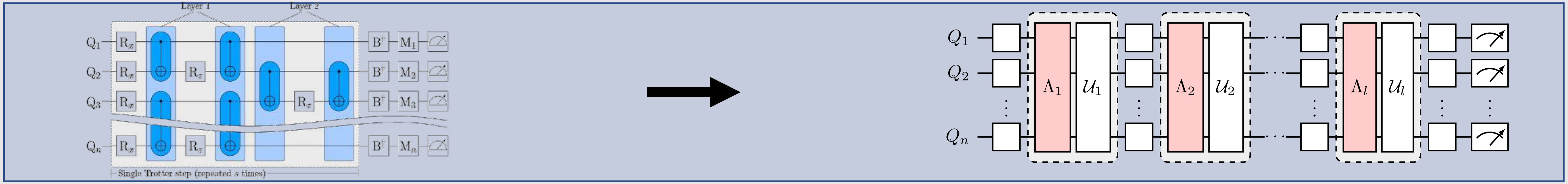
Cancel

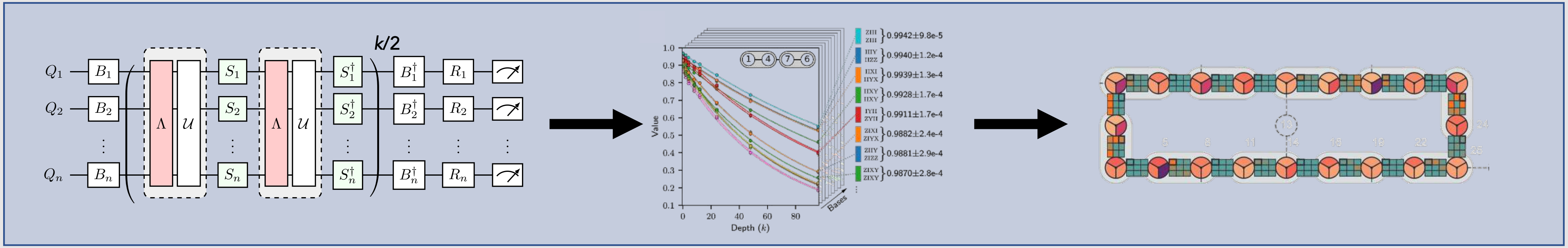
(realization)

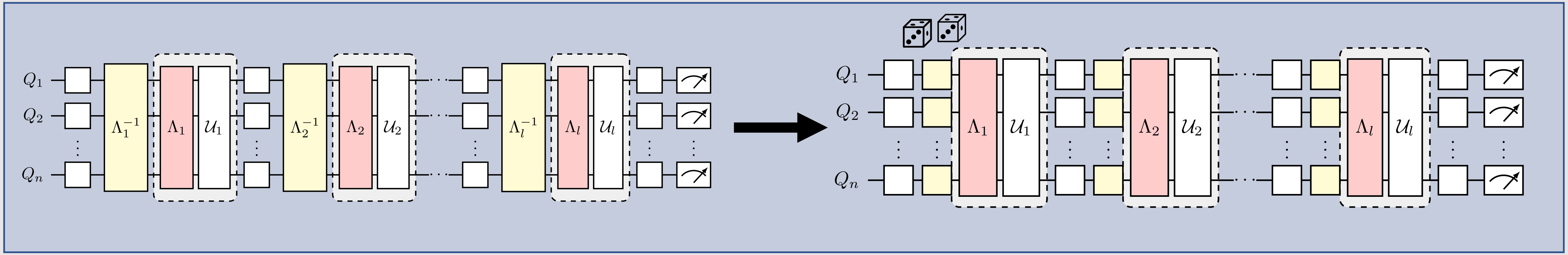
PEC mitigation:

inverting noise to obtain expectation values

Protocol overview







PEC + Simulating transverse-field Ising model time evolution

$$H = -J\sum_j Z_j Z_{j+1} + h\sum_j X_j$$

Study global magnetization

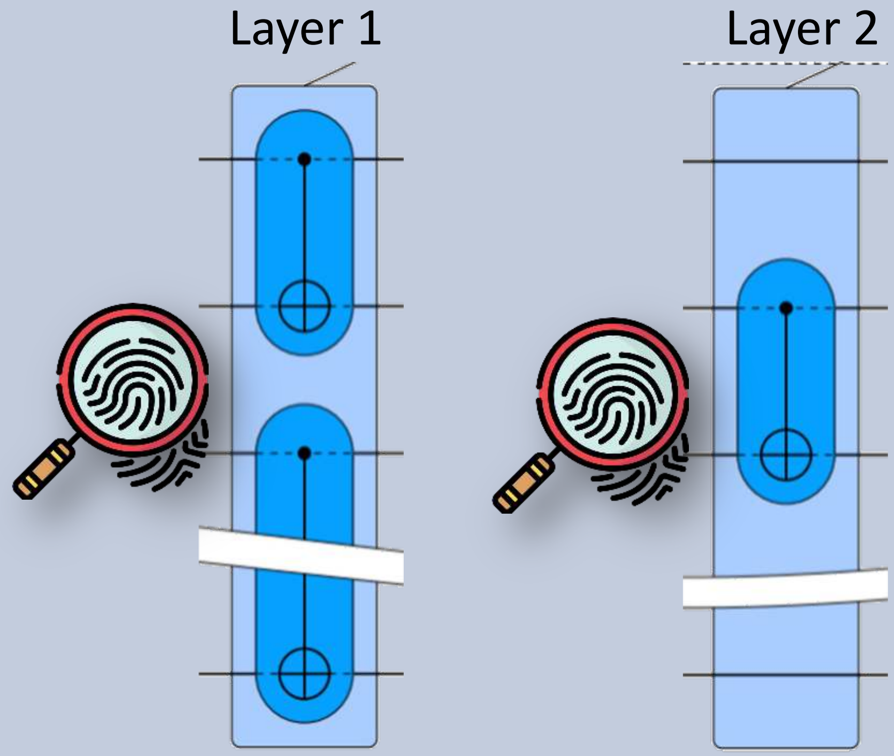
$$\vec{M} := \sum_n \left(\langle X\rangle_n, \langle Y\rangle_n, \langle Z\rangle_n\right)/N$$

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

Top image: Samuel Velasco/Quanta Magazine

Trotterized time evolution

Evolution Trotter layers



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

Observables

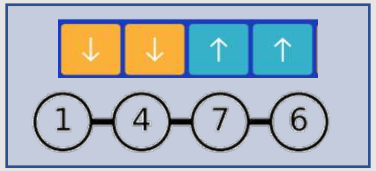
$$\vec{M} := \sum_n \left(\langle X \rangle_n , \langle Y \rangle_n , \langle Z \rangle_n \right) / N$$

Example: Observables for *N* = 4

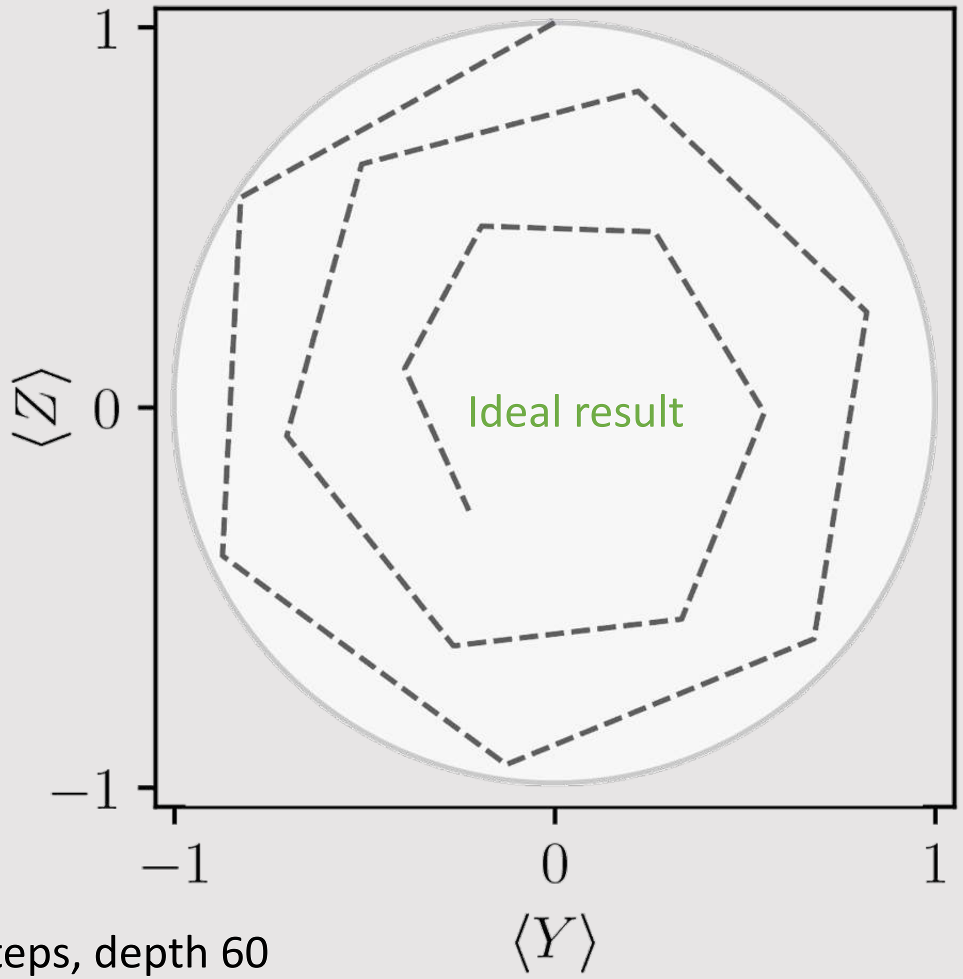
XIII	YIII	ZIII
IXII	IYII	IZII
IIXI	IIYI	IIZI
IIIX	IIIY	IIIZ

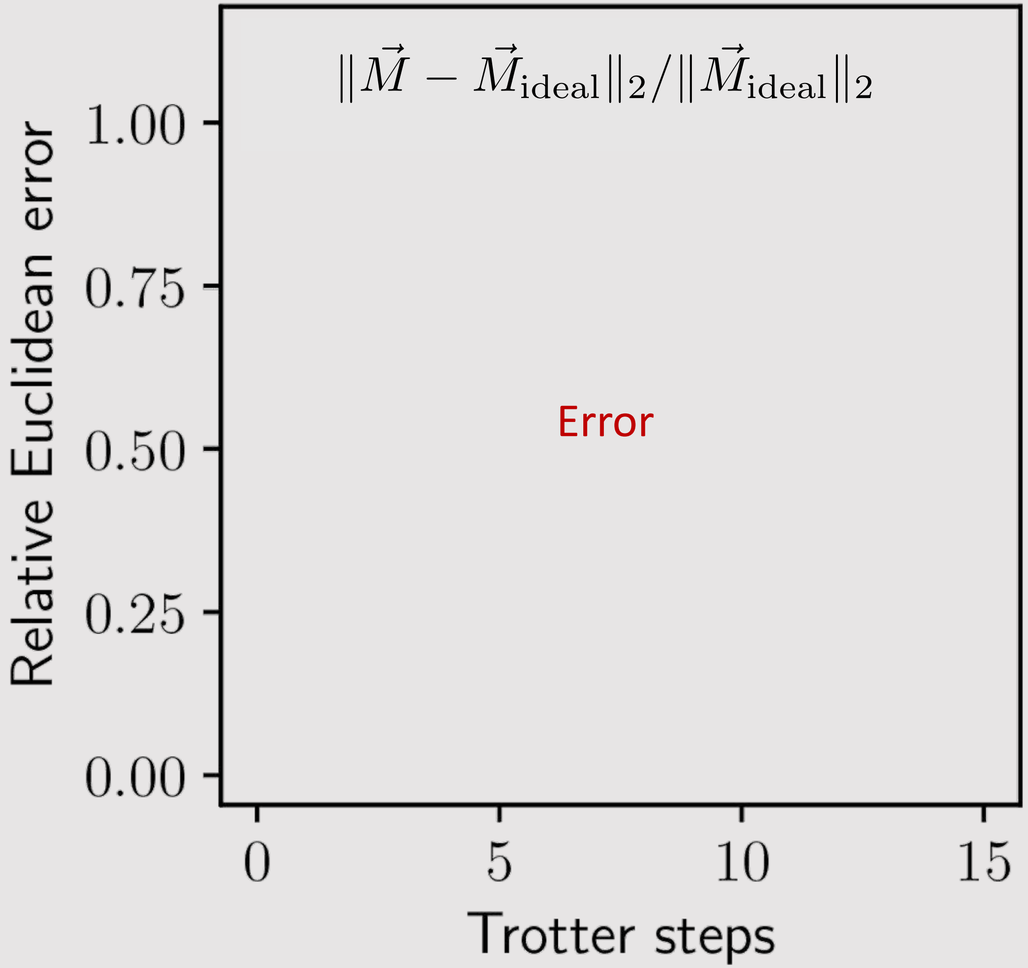
Top image: Samuel Velasco/Quanta Magazine

Ideal Ising model evolution



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

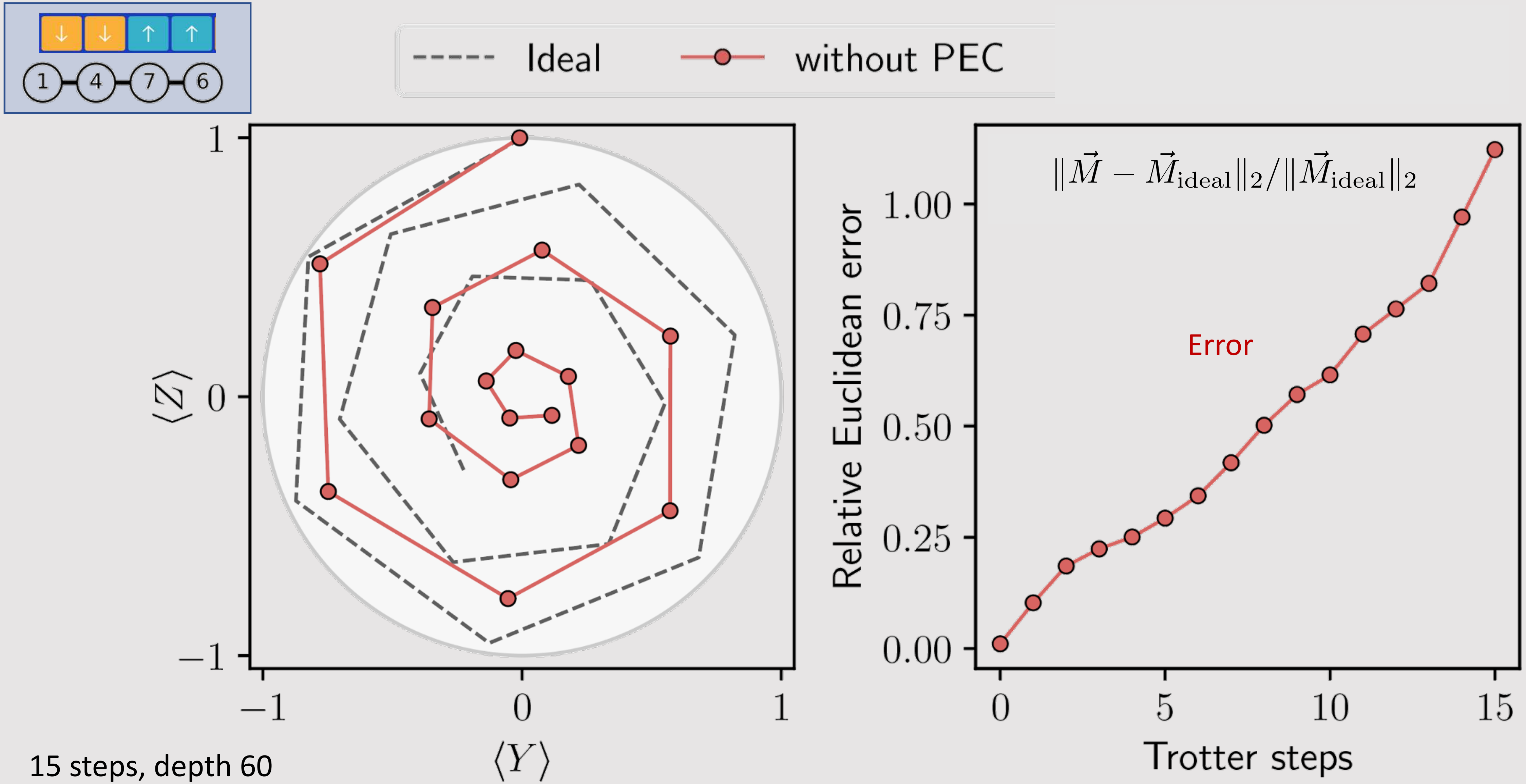




4Q, 15 steps, depth 60

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

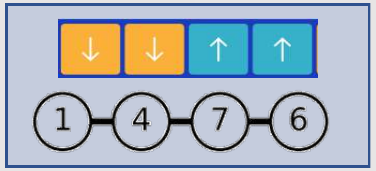
Without PEC: but with DD & twirl readout mitigation

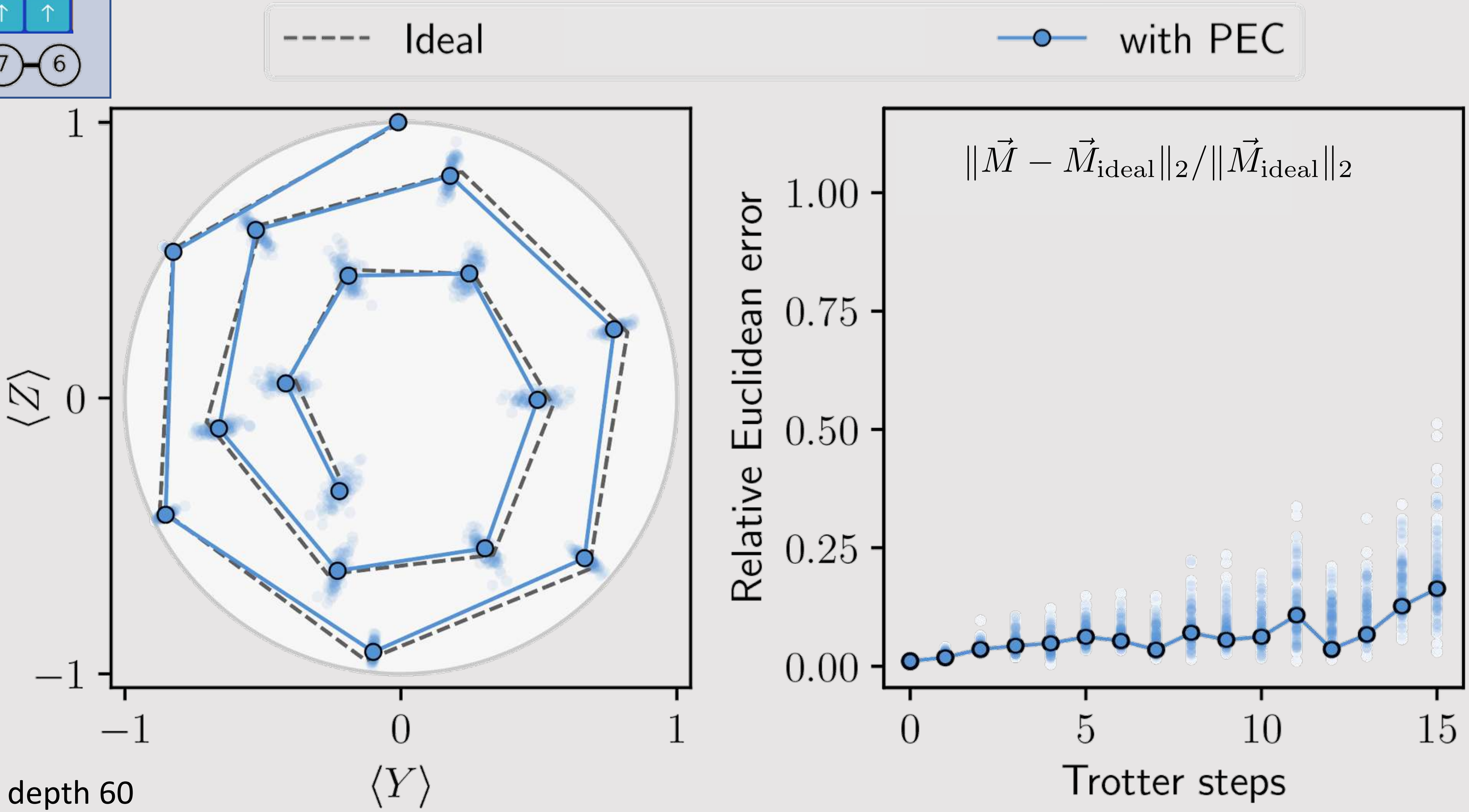


15 steps, depth 60

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

With PEC

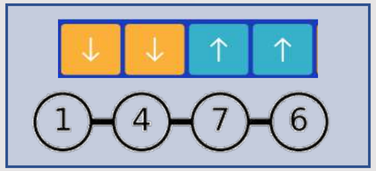


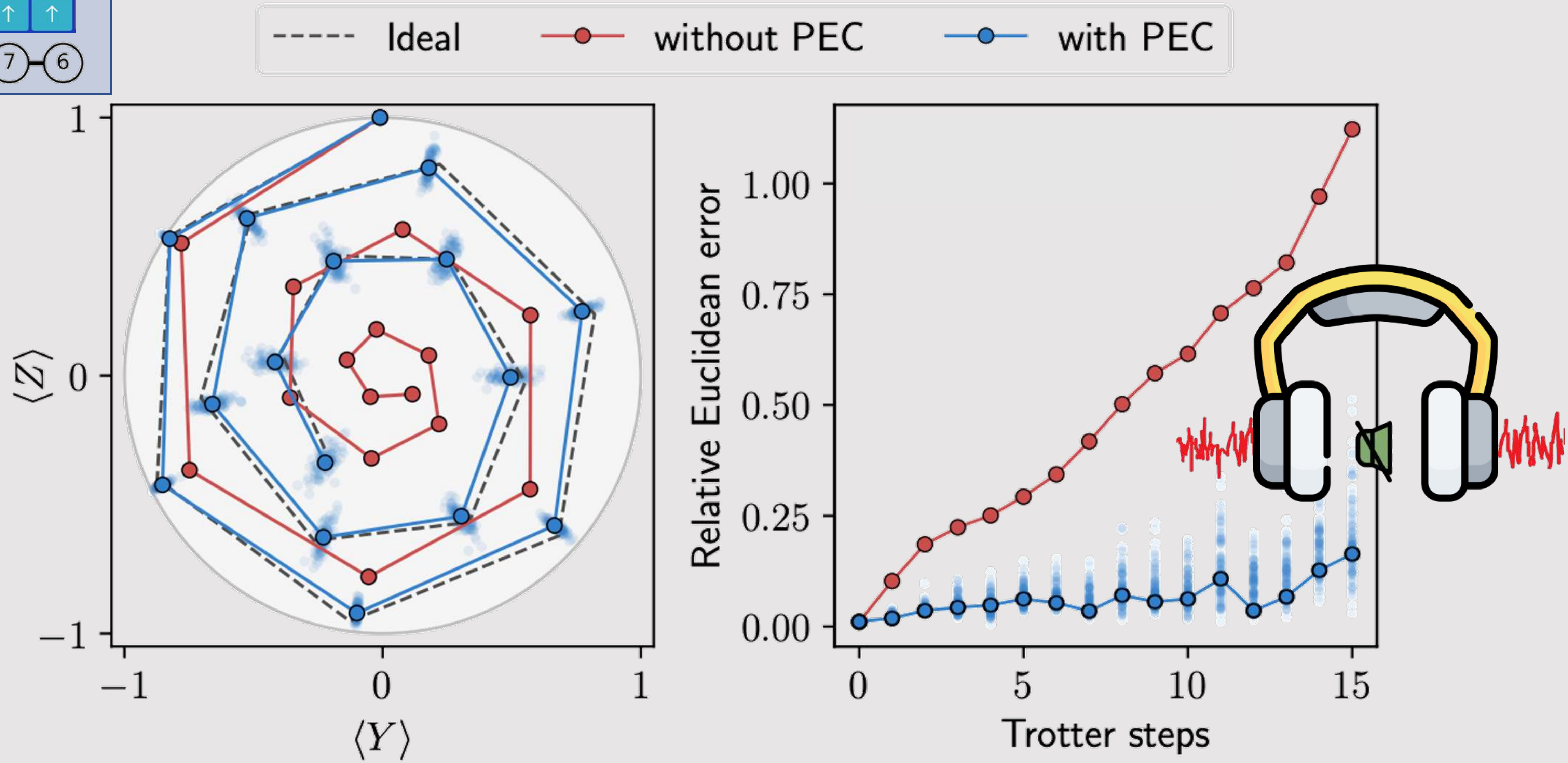


15 steps, depth 60

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

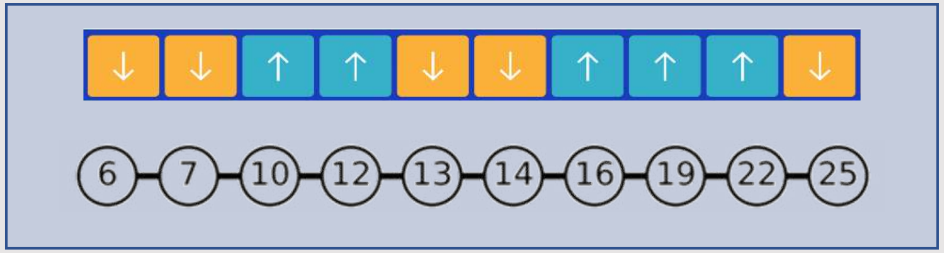
With vs. without PEC

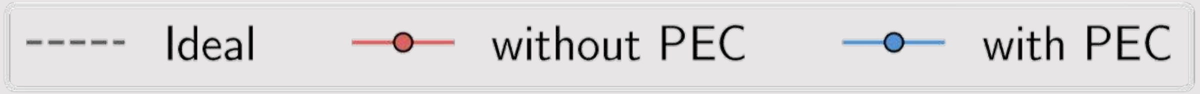


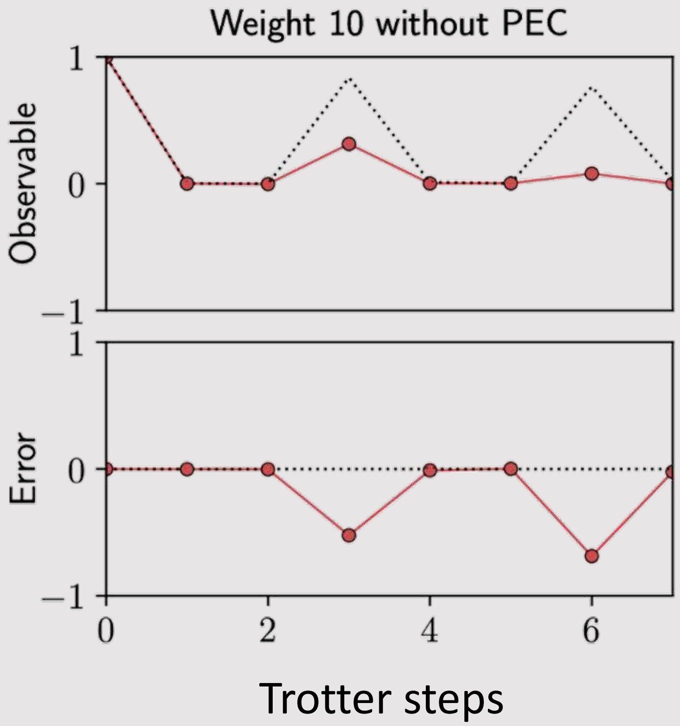


$h = 1, J = -0.15, \delta t = 1/4$

With vs without PEC: 10 qubit high-weight observables



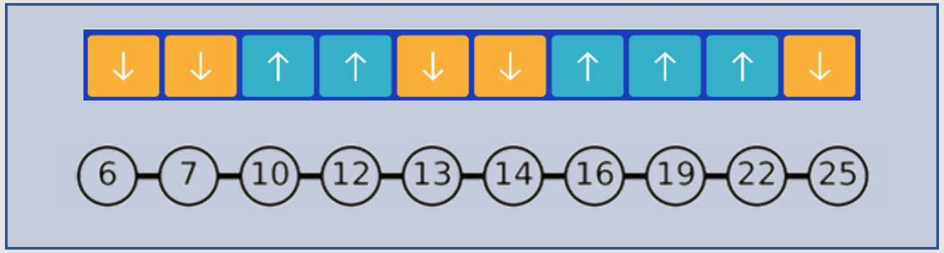


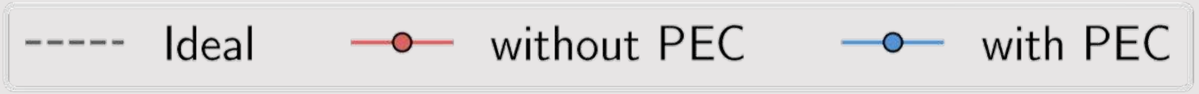


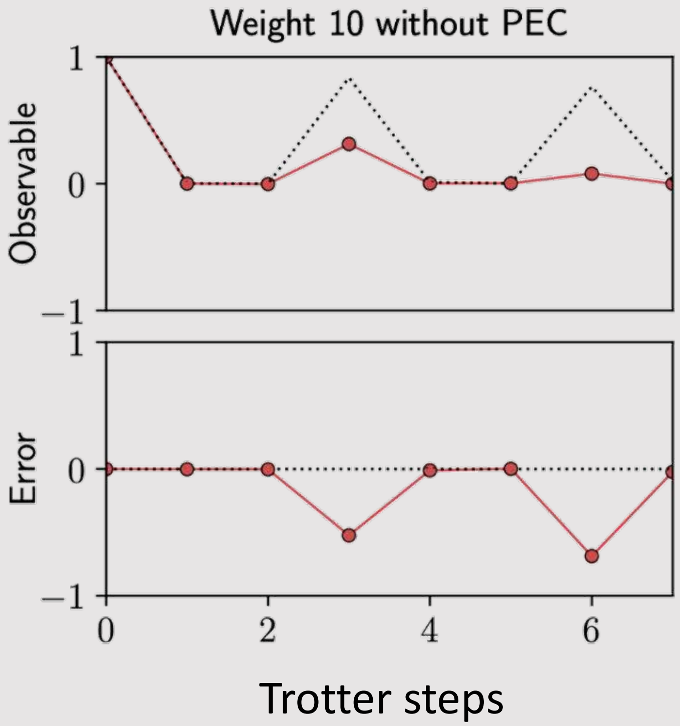
ZZZZZZZZZZ

$h = 1, J = -0.5236, \delta t = 1/4$

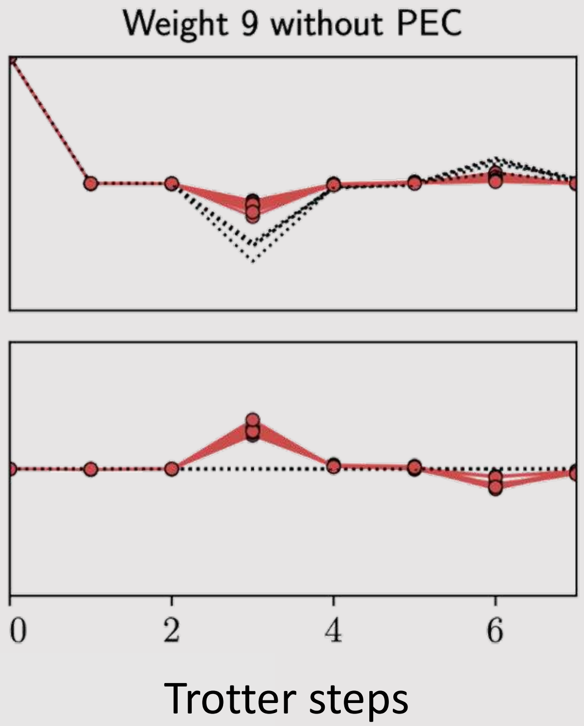
With vs without PEC: 10 qubit high-weight observables







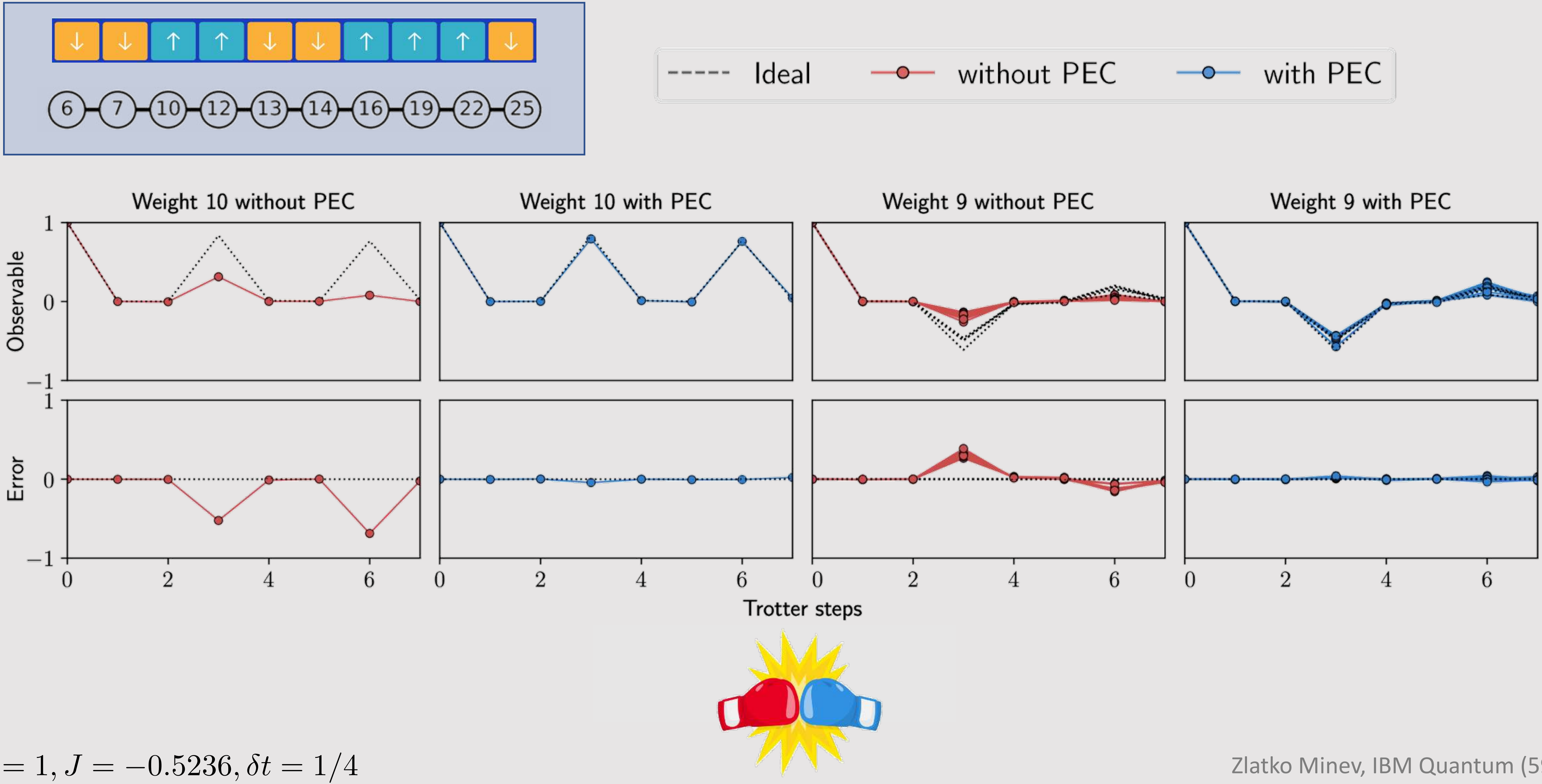
ZZZZZZZZZZ



IZZZZZZZZZ
ZIZZZZZZZZ
ZZIZZZZZZZ
...
ZZZZZZZZZI

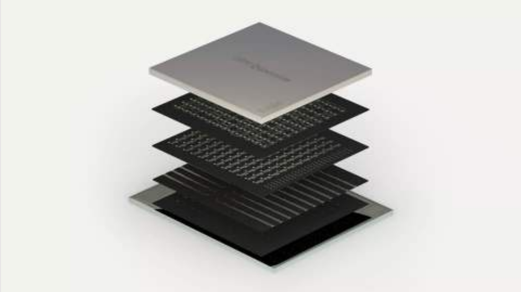
$h = 1, J = -0.5236, \delta t = 1/4$

With vs without PEC: 10 qubit high-weight observables



$h = 1, J = -0.5236, \delta t = 1/4$

Scaling and error budget

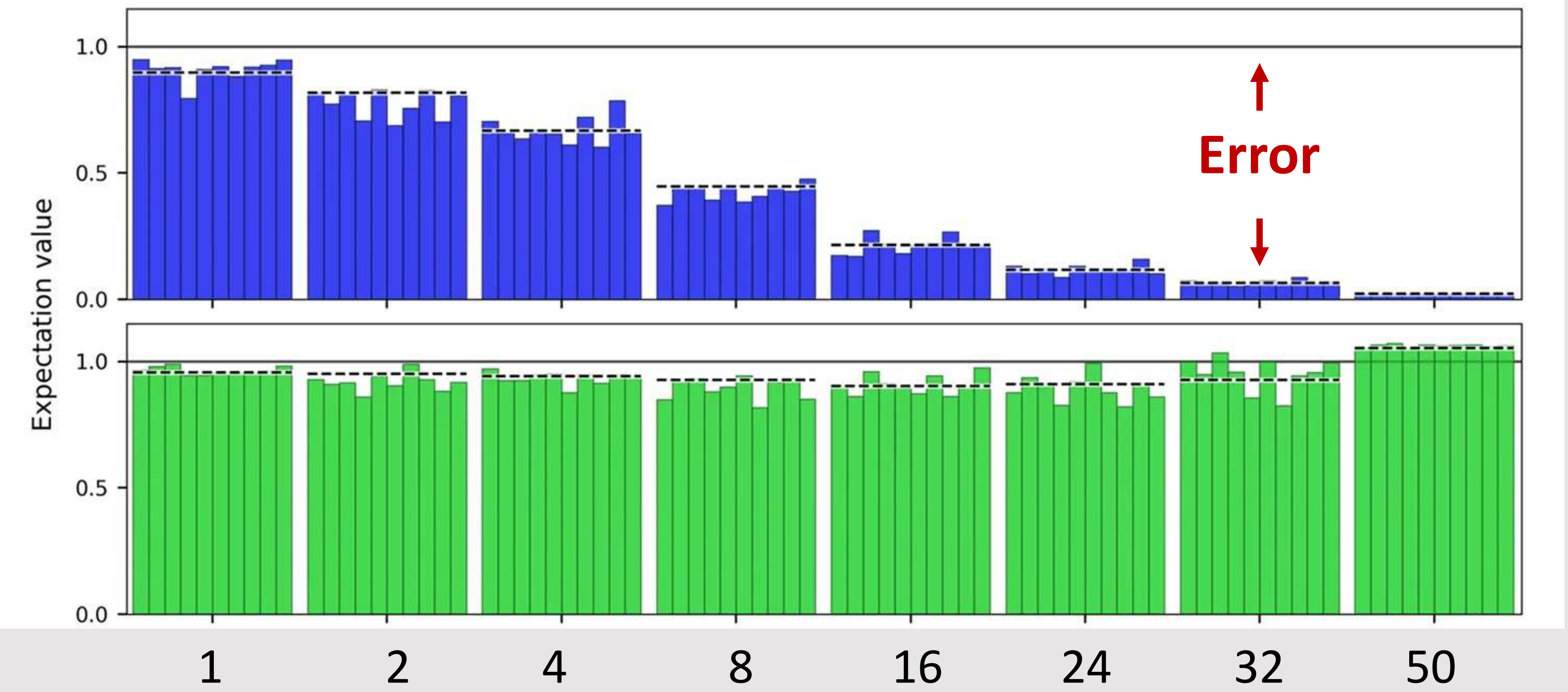


50 qubits

Z stabilizers of increasing weight

Without PEC

With PEC

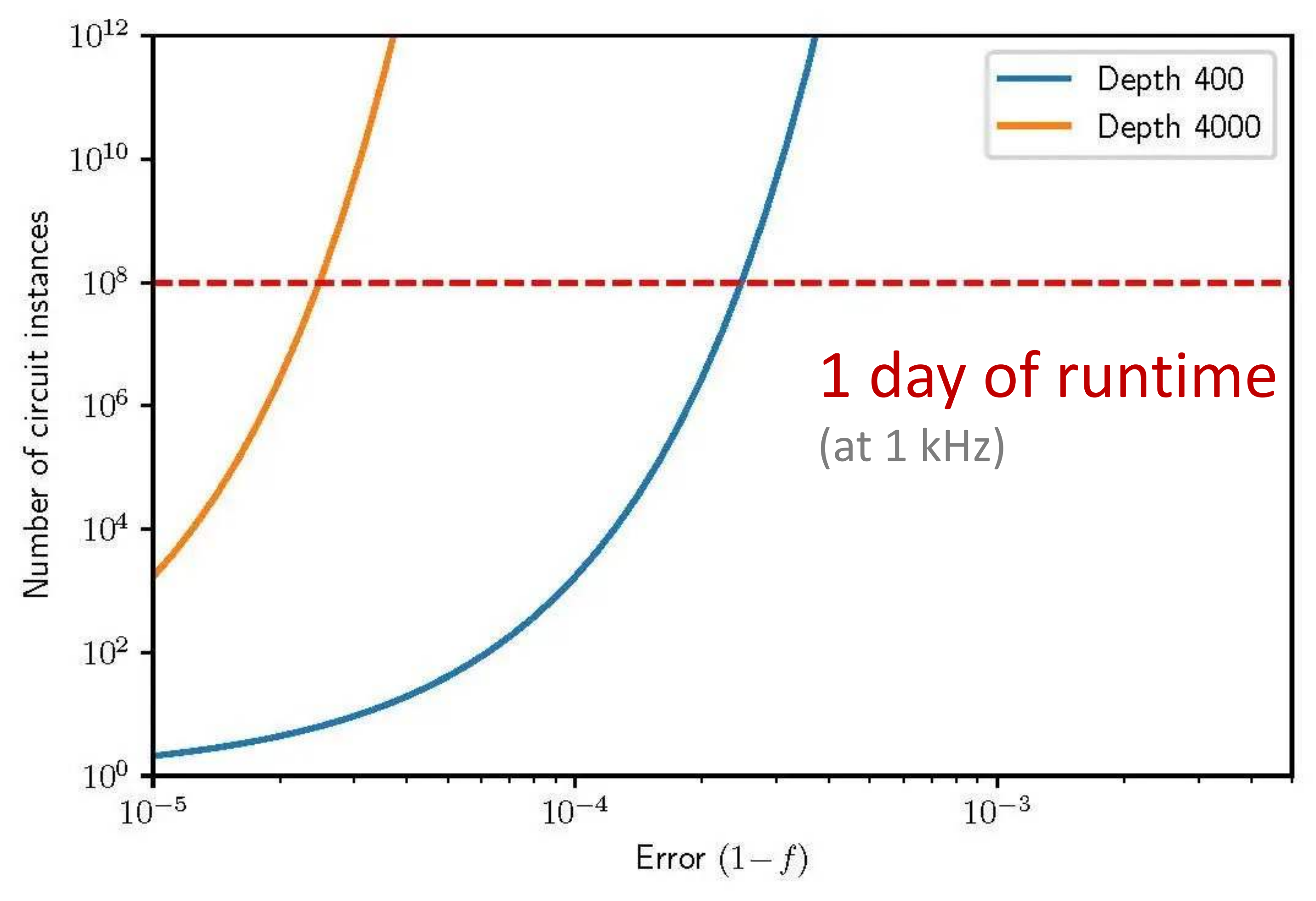


50Q, 2 layers of cNOT gates
(preliminary data)

See research.ibm.com/blog/gammabar-for-quantum-advantage

Path to 100+ qubits?

Estimating PEC overhead for Trotter circuits comprising 100 qubits



See also on speed: A. Wack, et al., Quality, speed, and scale: three key attributes to measure the performance of near-term quantum computers (2021).

Q: Is it useful to build a quantum computer with a few percent error?

- John Martinis

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*

$$\text{Runtime} = \beta\, d\ (\bar{\gamma})^{n\,d}\ \text{seconds}$$

d is the depth of the quantum circuit

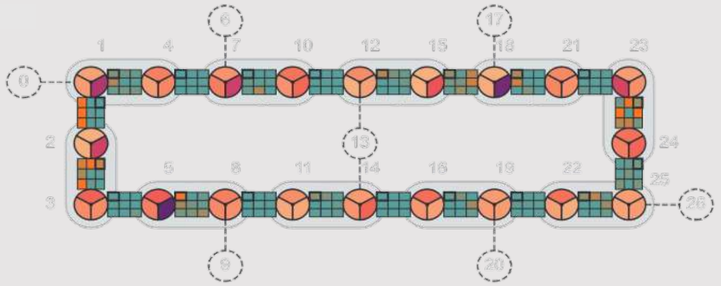
β is a measure of the time per circuit layer operation (CLOPS)
(increase by pushing speed)

$\bar{\gamma}$ 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)

IBM **Quantum**

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

Got Slides?

SCAN ME

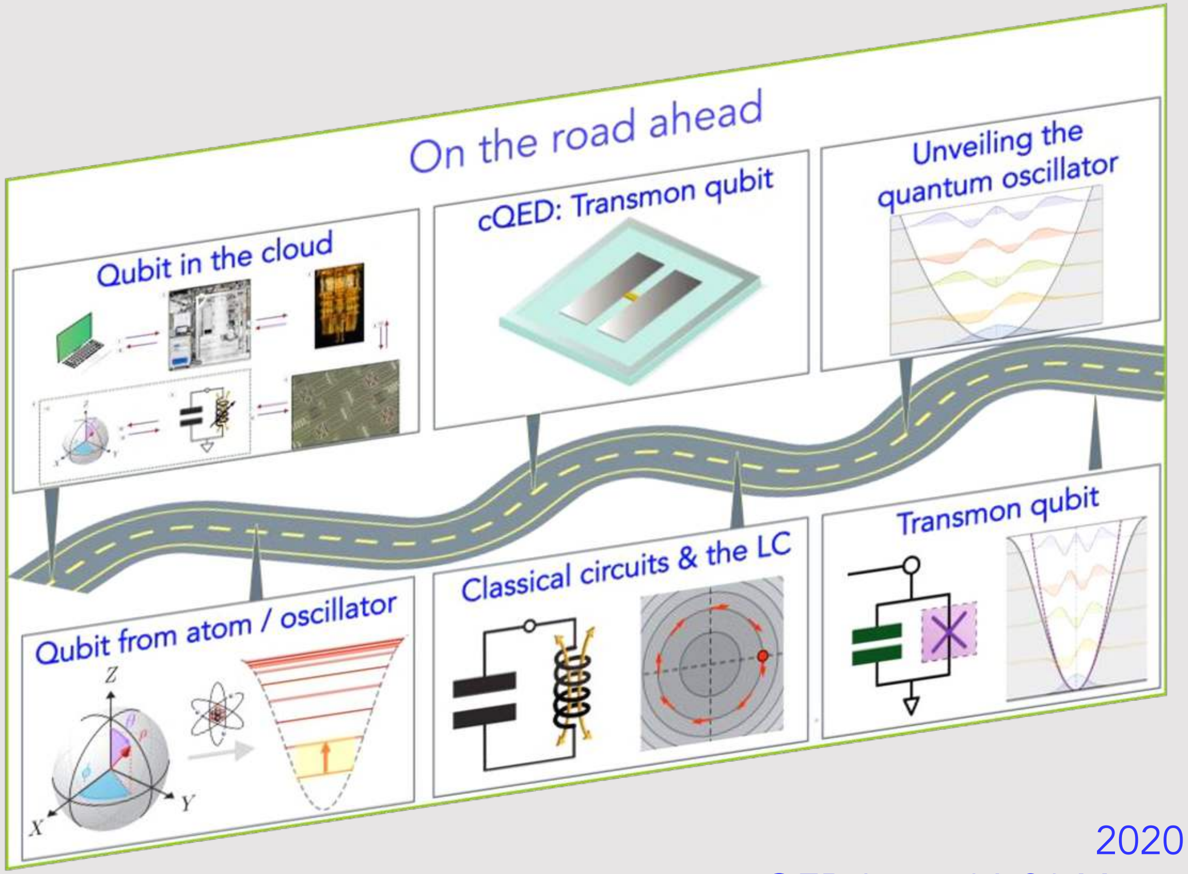
Ewout van den Berg, Zlatko K. Minev, Abhinav Kandala, Kristan Temme
arXiv:2201.09866 (2022)

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

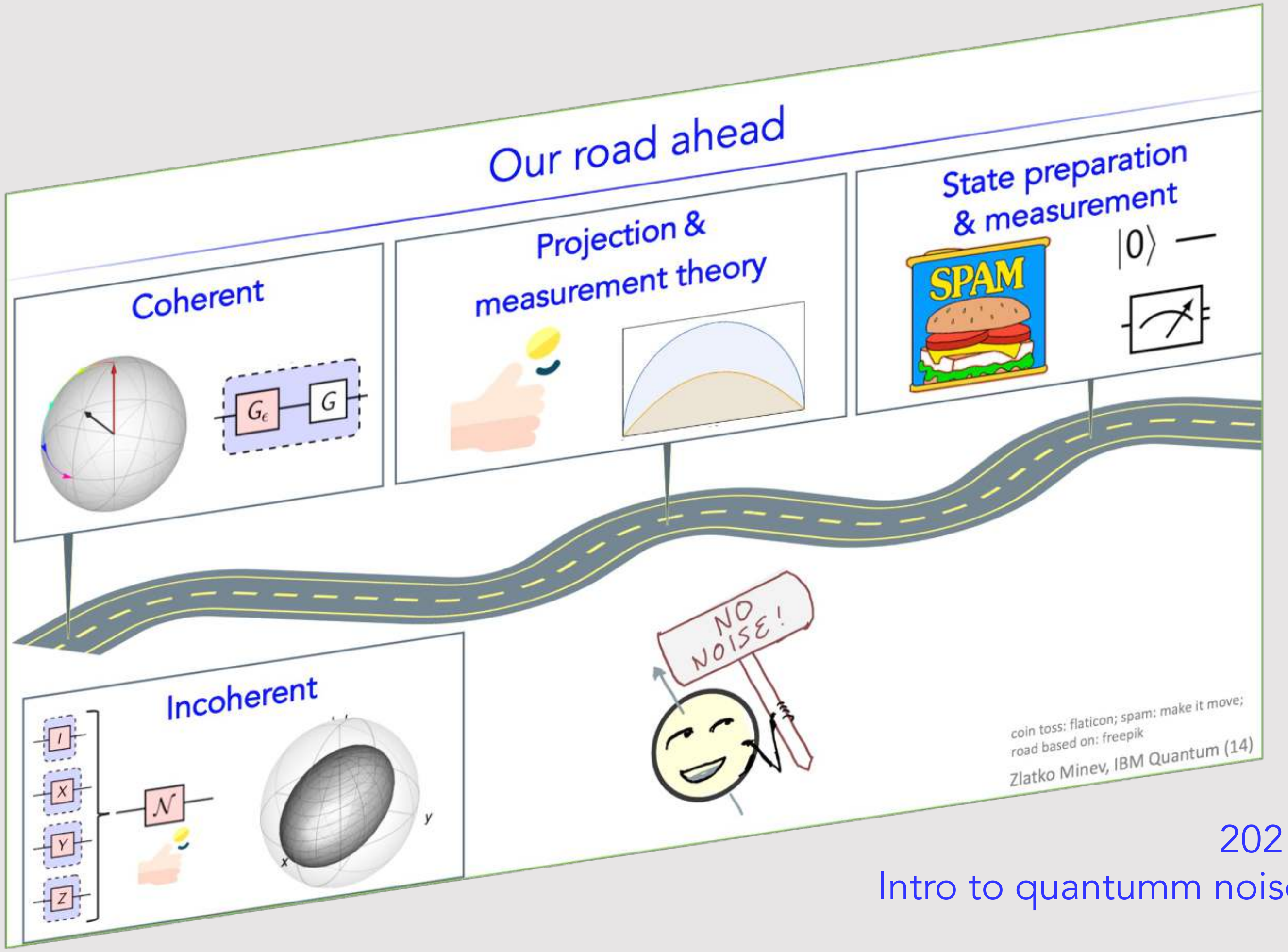
@zlatko_minev

zlatko-minev.com

Global Summer Schools QGSS



2020
cQED Lecs. 16-21 Minev



2021
Intro to quantumm noise

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)]

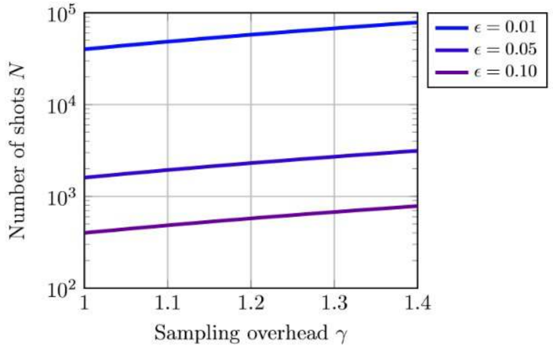
Symbol	Description	Value
	Circuit constants & indices	
n	number of qubits in circuit	$n = 1, 2, 3, \ldots$
l	number of layers in circuit	$l = 1, 2, 3, \ldots$
i	layer index within circuit	$i = 1, \ldots, l$
	Pauli-Lindblad model inputs	
k	model coefficient index, corresponds to a Pauli	$k = 1, 2, 3, \ldots$ or equiv. n-qubit Pauli string
b	fidelity vector indices	$b = 1, 2, \ldots$ 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	$N = 1, 2, 3, \ldots$
	Pauli-Lindblad model variables	
γ	sampling overhead	$\gamma \geq 1$, $\gamma = \exp\left(\sum_{k\in\mathcal{K}} 2\lambda_k\right)$
$\gamma_i, \gamma(l)$	sampling overhead for the i-th layer and a total of l layers	$\gamma(l) = \Pi_{i=1}^{l}\gamma_i$
λ_k	k-th model coefficient	$\lambda_k \geq 0$
w_k	noise model weight in Λ factoring	$w_k := \frac{1}{2}\left(1 + e^{-2\lambda_k}\right)$
f_b	Pauli Λ fidelity of b-th Pauli index	$f_b := \frac{1}{2^n}\operatorname{Tr}\left(P_b^\dagger \Lambda(P_b)\right)$
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 is 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	$P_k \in \{I, X, Y, Z\}^{\otimes n}$
$U, \mathcal{U}, \tilde{\mathcal{U}}_i$	unitary ideal gate; tilde: noisy i-th layer unitary	
Λ, Λ_i	noise channel	$\Lambda(\rho) = \exp[\mathcal{L}](\rho) = \Pi_{k\in\mathcal{K}}\left(w_k \cdot +(1-w_k)P_k \cdot P_k^\dagger\right)\rho$
Λ^{-1}	inverse noise map	$\Lambda^{-1}(\rho) = \exp[-\mathcal{L}](\rho) = \gamma\Pi_{k\in\mathcal{K}}\left(w_k \cdot -(1-w_k)P_k \cdot P_k^\dagger\right)\rho$
$\mathcal{L}(\rho)$	Lindblad generator	$\mathcal{L}(\rho) = \sum_{k\in\mathcal{K}}\lambda_k\left(P_k\rho P_k - \rho\right)$
$\langle \hat{A}_N \rangle$	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 $\left|\langle\hat{A}\rangle_{\text{ideal}} - \langle\hat{A}_N\rangle\right| \leq \epsilon$ satisfied with a probability $1-\delta$ (assuming a weak enough noise, $C^{l\tau} \approx 1$), we can solve for the number of error-mitigated, random circuit instances N in van den Berg et al. (2020)

$$\epsilon = \gamma\frac{\sqrt{2\log(2/\delta)}}{\sqrt{N}},$$
$$\therefore \quad N = 2\log(2/\delta)\left(\frac{\gamma}{\epsilon}\right)^2,$$
$$N \approx 4\left(\frac{\gamma}{\epsilon}\right)^2 \quad \text{for } \delta \sim 0.01\,.$$

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.



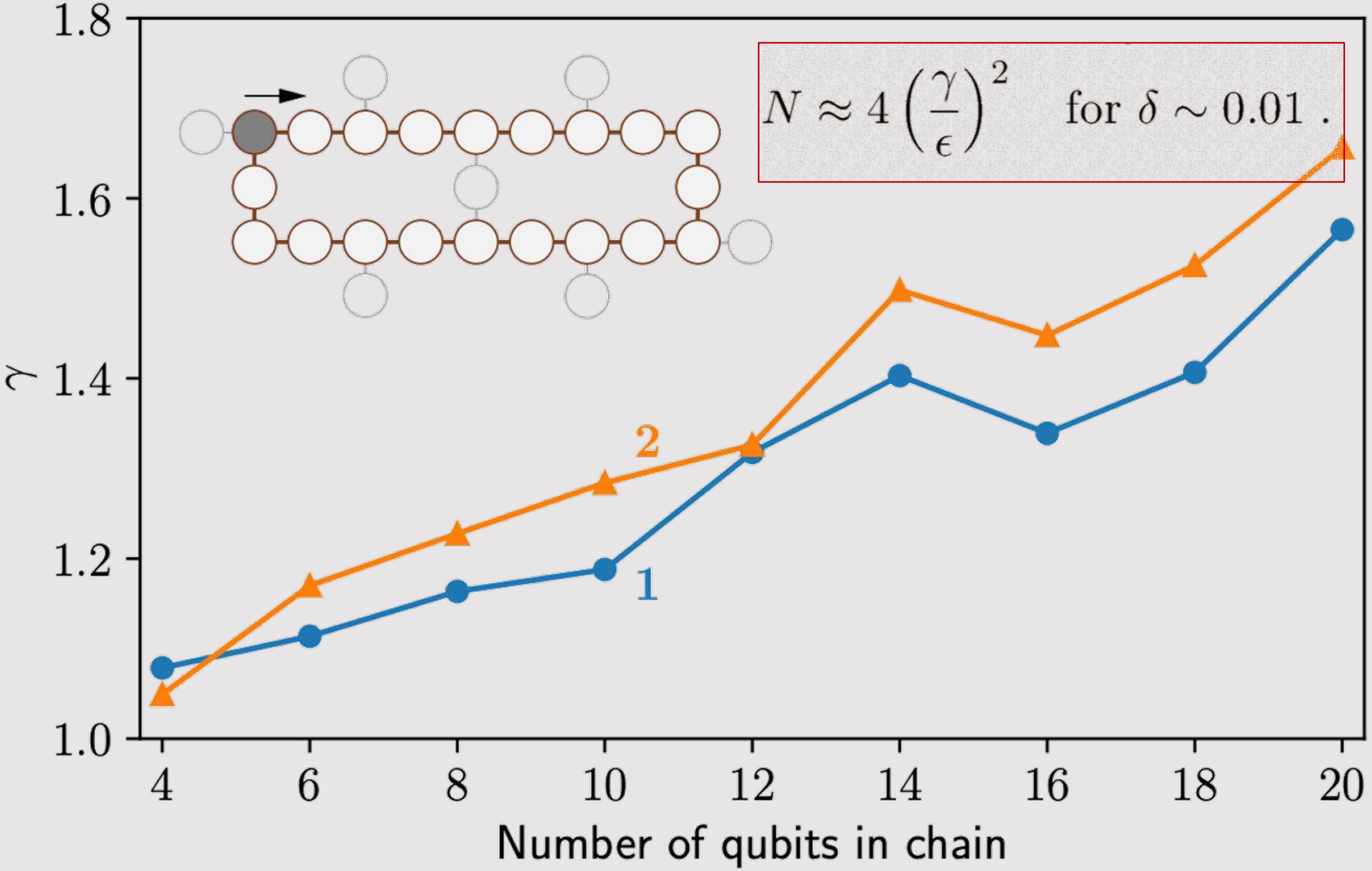
Bibliography

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/s41567-020-0847-3http://www.nature.com/articles/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.

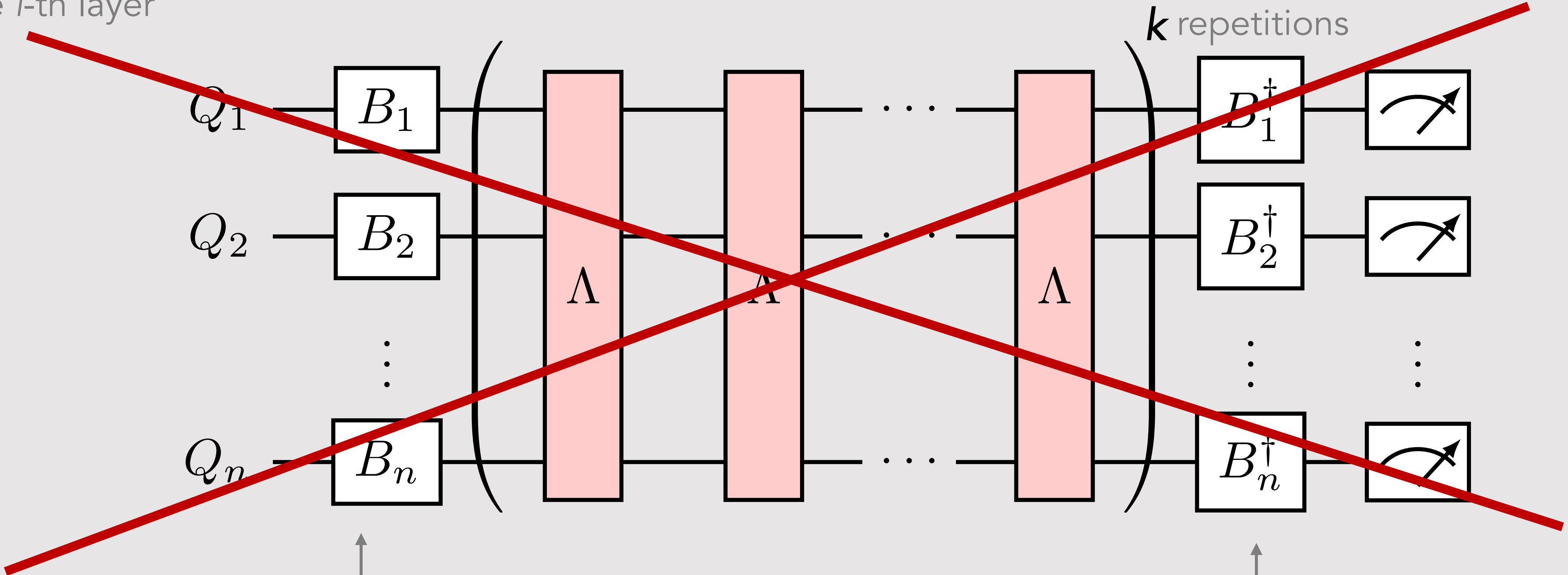
Paper and talk notation summary: https://www.zlatko-minev.com/blog/pec-notation

Mitigation sampling overhead



Step 2 wish: amplify noise

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

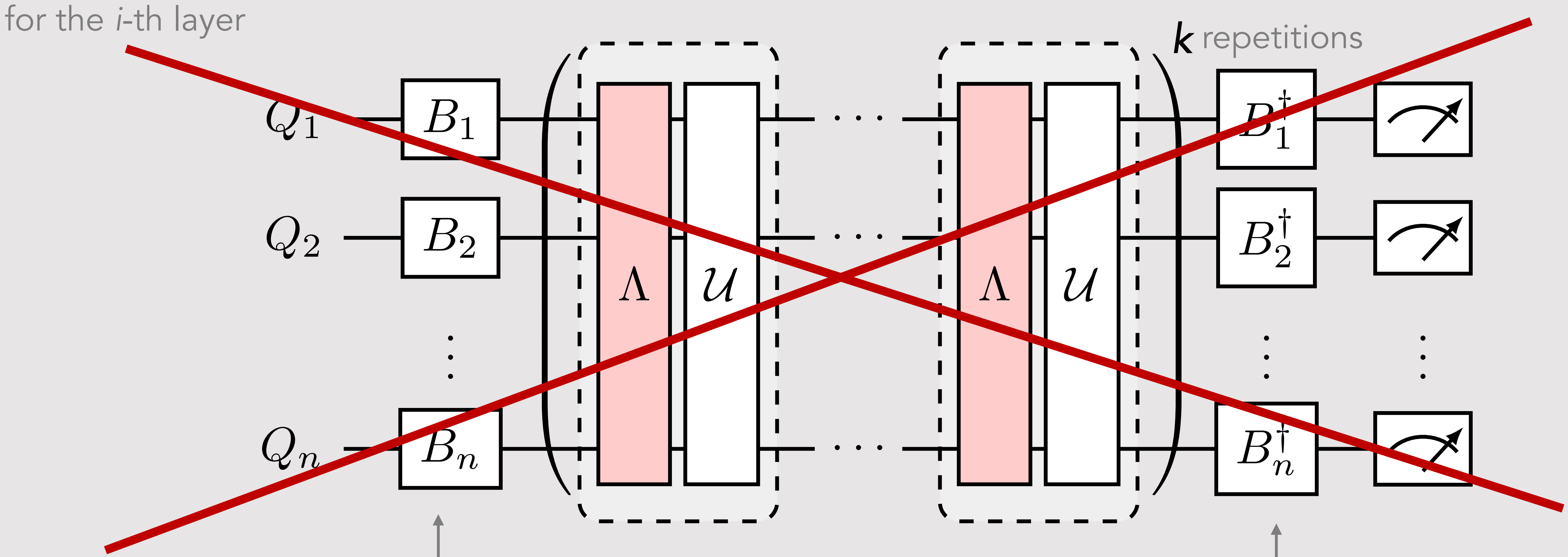
Akin to:

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

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

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?



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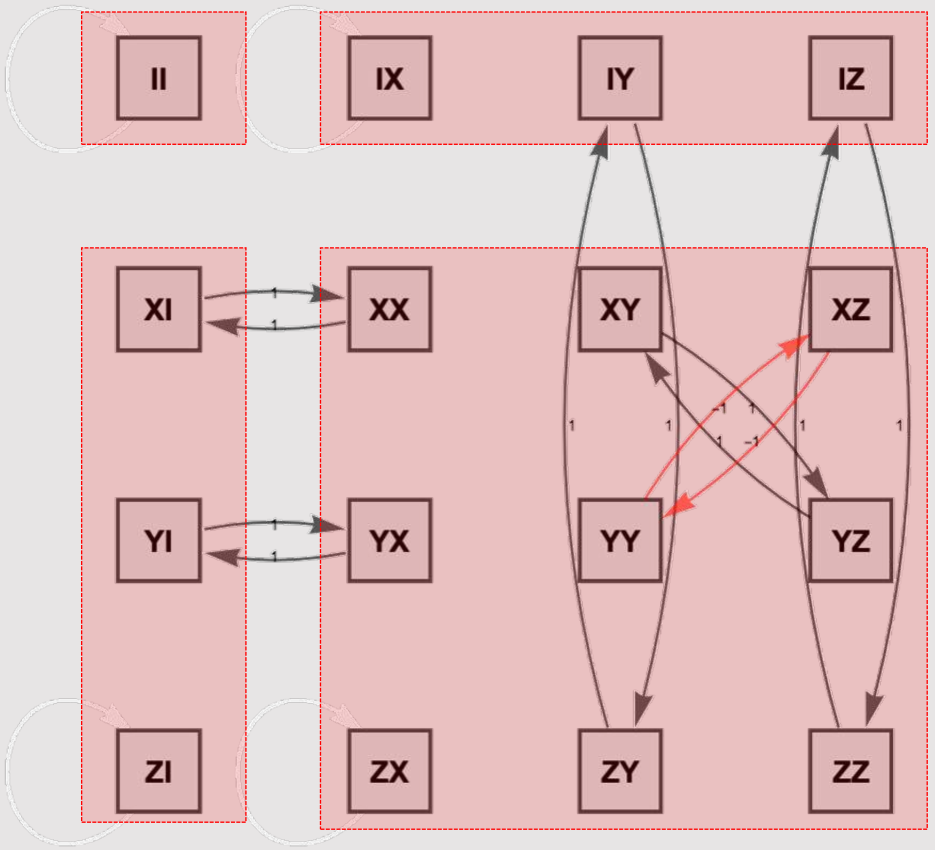
Erhard *et al.*, arXiv:1902.08543; Ferracin *et al.*, arXiv:2201.10672, …

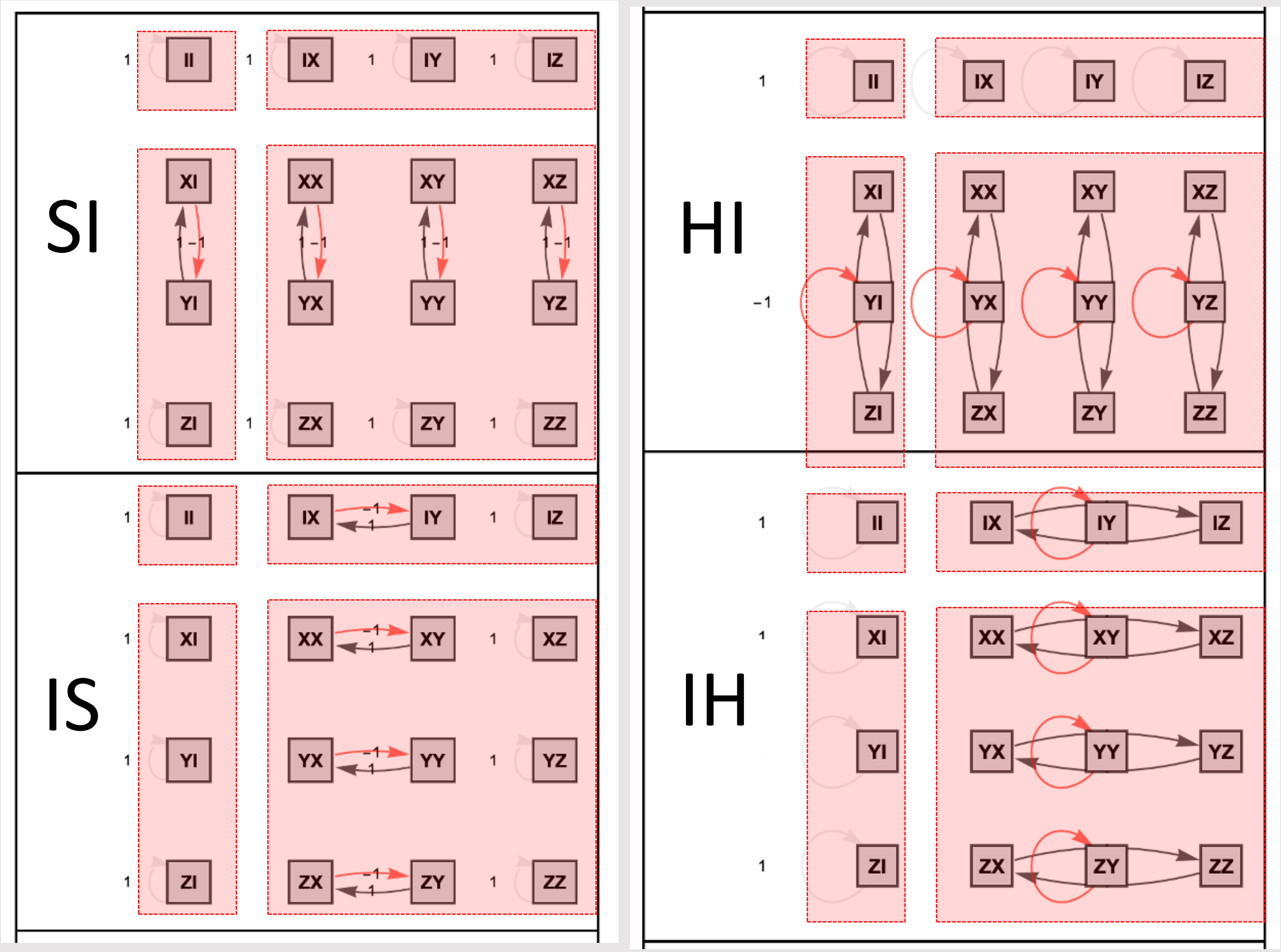
For something of a review of protocols, see Helsen, *et al.*, arXiv:2010.07974

How to gates move state Paulis around?

cNOT



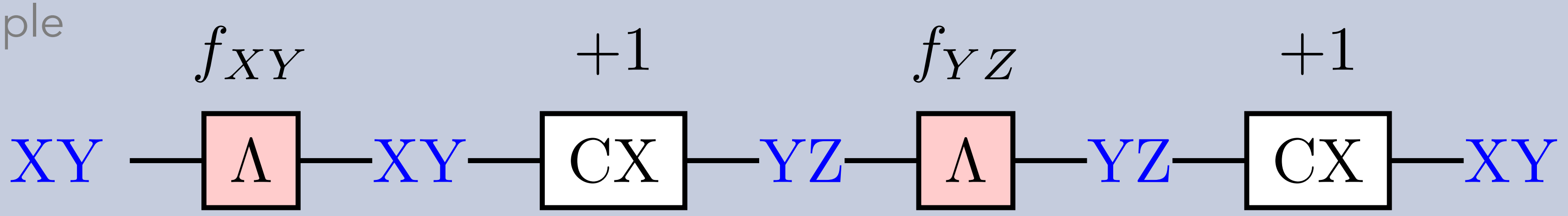
Example single qubit gates



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

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

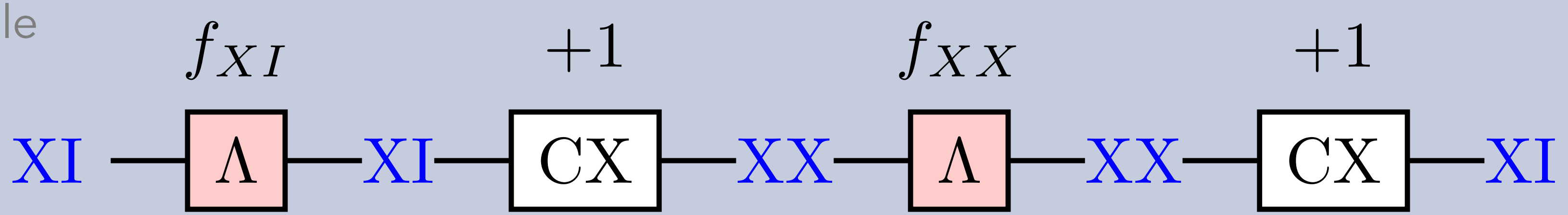
2Q example



action of CX here can be undo by SQ gates

$f_{XY} f_{YZ} XY$

2Q example

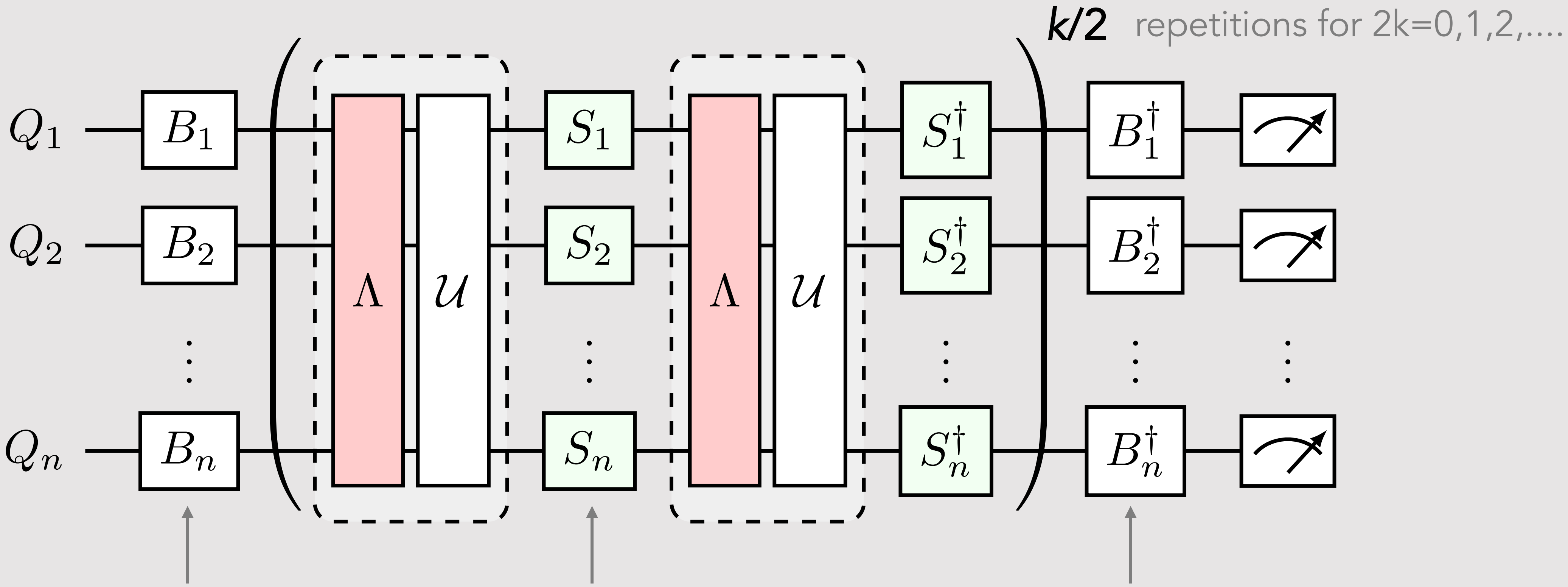


action of CX here can **not** be undone by SQ gates

$f_{XI} f_{XX} XI$

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

Step 2: Amplify & learn noise per layer



prepare circuit in pre-determined Pauli basis

phase of identity gate conditioned on basis choice

measure circuit in same pre-determined Pauli basis

Akin to:

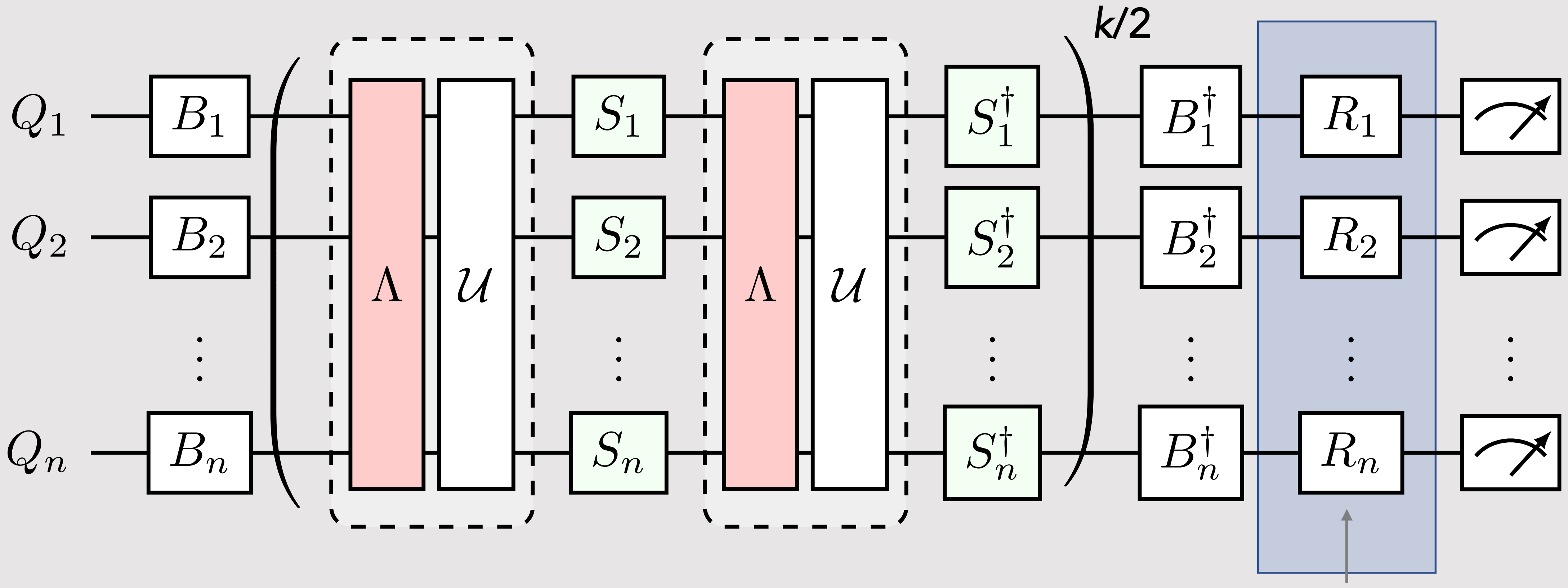
RB, Cycle RB, K-body noise reconstruction, ...

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, ...

...

Step 3: Twirl readout-error mitigation

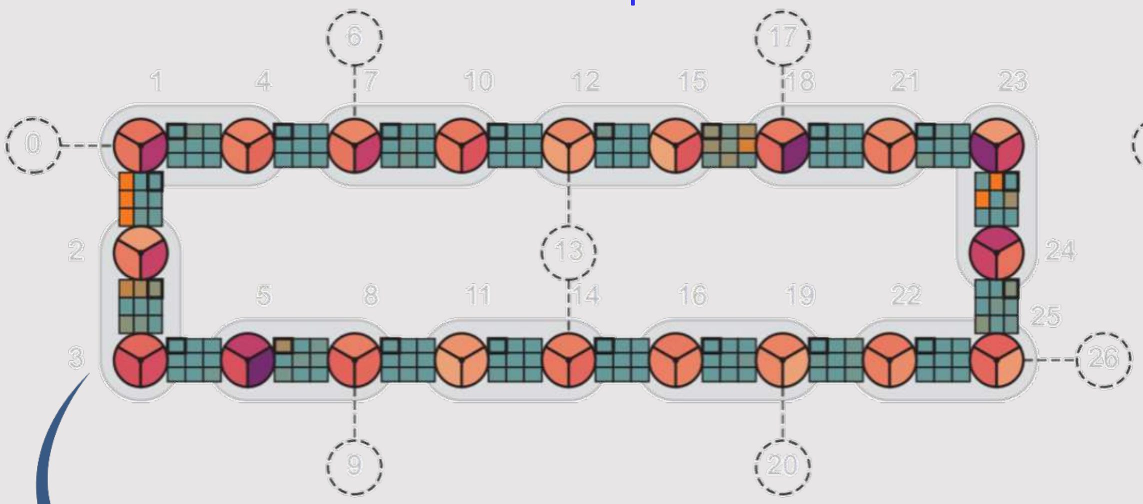


twirl readout to do readout error mitigation in-situ*

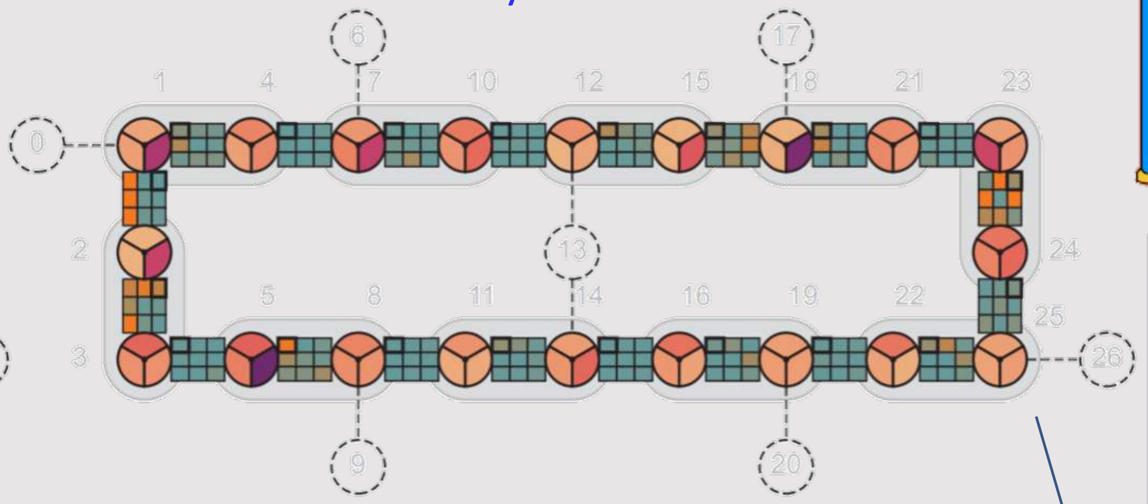
* Model-free readout-error mitigation for quantum expectation values
Ewout van den Berg, Zlatko K. Minev, and Kristan Temme
Phys. Rev. A 105, 032620 (2022)

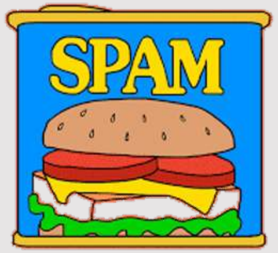
Complete (SPAM-sensitive) vs symmetry (SPAM-free) learning

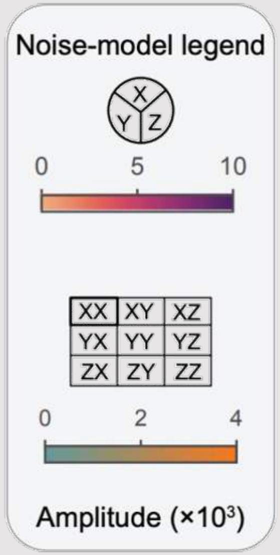
Unit-depth

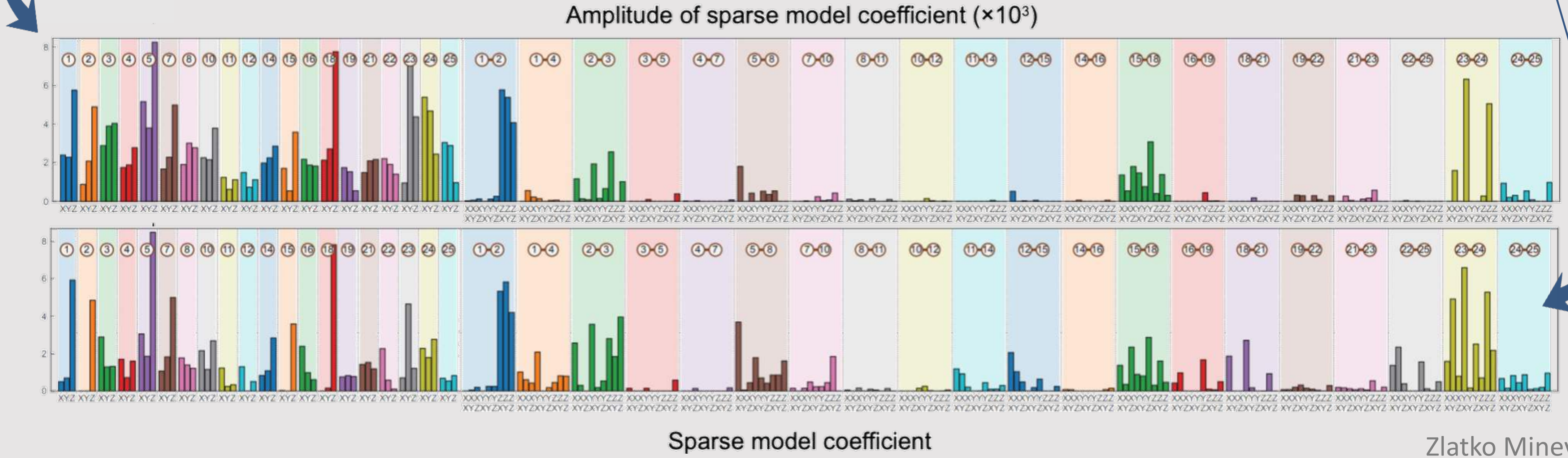


Symmetric



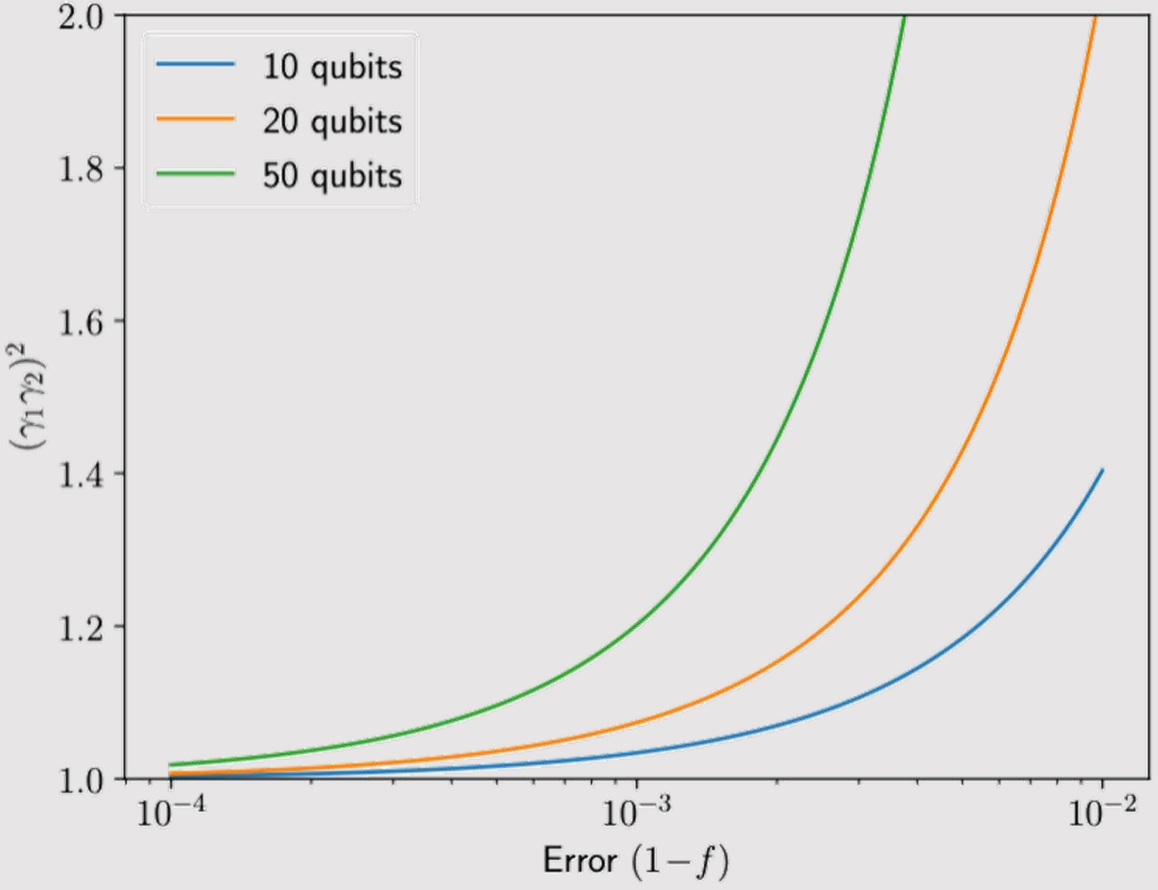




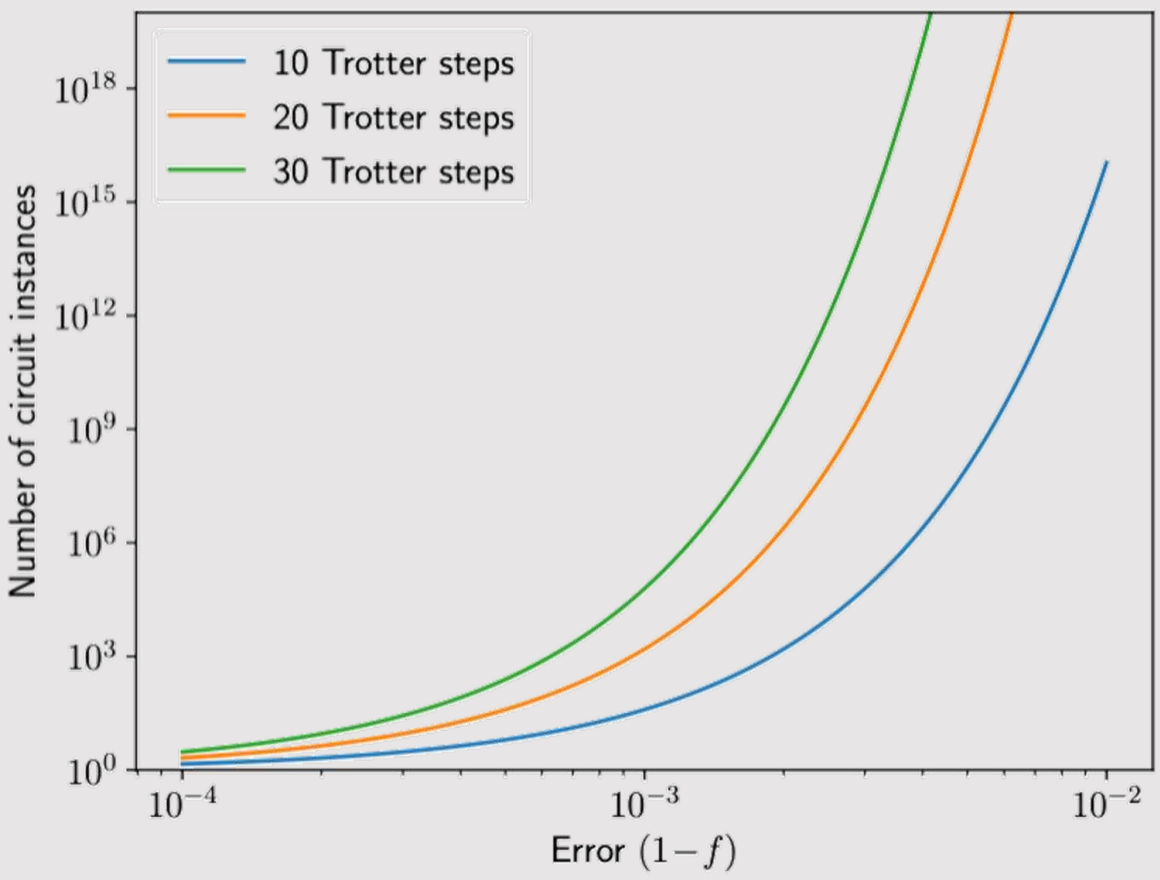


Outlook

Runtime & lower gate errors!



50 qubits



CLOPS: A. Wack, et al., Quality, speed, and scale: three key attributes to measure the performance of near-term quantum computers (2021).

Bit-string probability distributions

From 2^n Pauli expectation values to 2^n bitstring probabilities
Walsh-Hadamard (WH) transform

p(00…00)	WH	p(II…II)
p(00…01)	⇄	p(II..IZ)
p(00…10)		p(II…ZI)
…	WH^{-1}	…
p(11…11)		p(ZZ…ZZ)

Example for 2 qubits

	00	01	10	11
II	1	1	1	1
IZ	1	−1	1	−1
ZI	1	1	−1	−1
ZZ	1	−1	−1	1