

Operator Size Dynamics:

Theory & Applications

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Outline

1. Introduction:

Why operator size? Relation to various topics

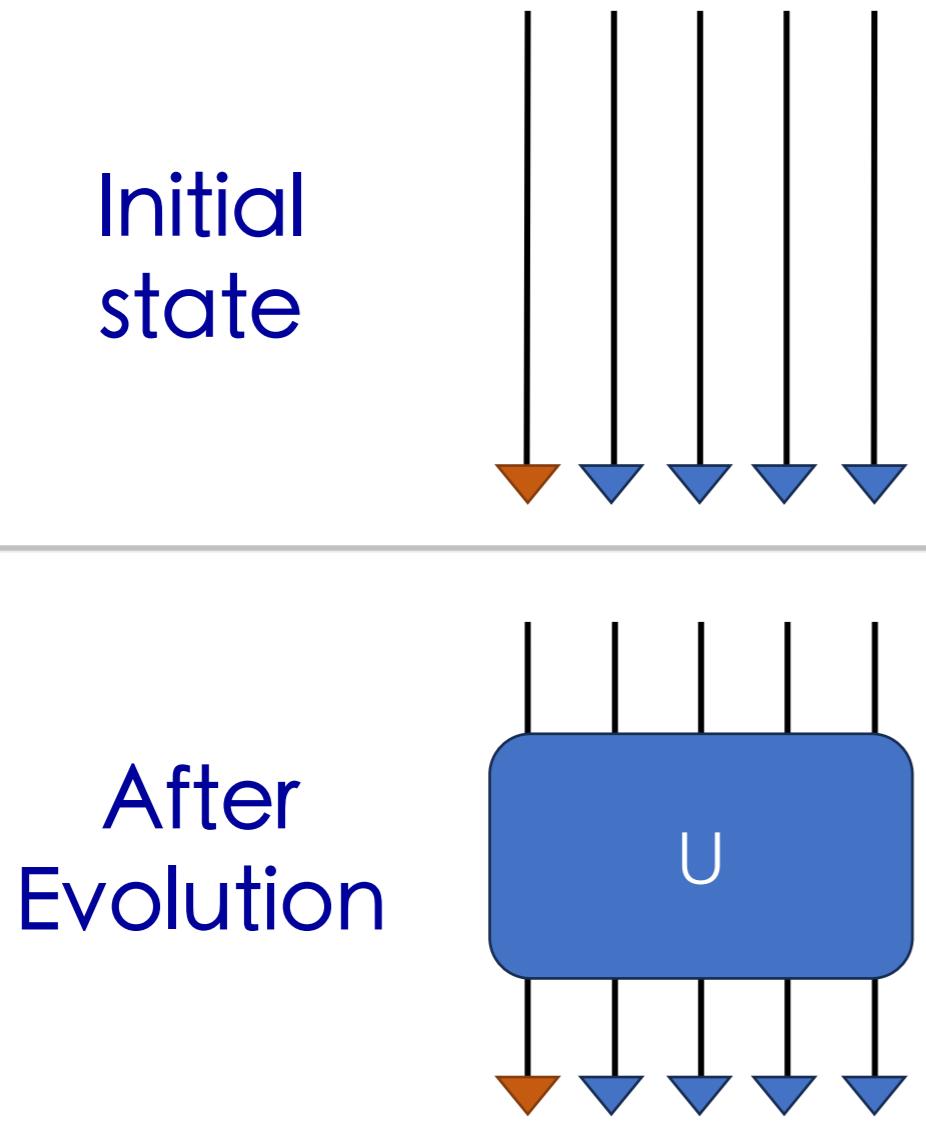
2. Theoretical Analysis

Closed / Open systems with all-to-all interactions

3. Application in Shadow Tomography

Information Scrambling

- Quantum information **never** disappears.



$$|\psi_0\rangle = |\psi\rangle \otimes |0\rangle \otimes |0\rangle \dots$$

Manipulate $|\psi\rangle$: $\{\sigma_1^x, \sigma_1^y, \sigma_1^z\}$

$$|\psi_t\rangle = U|\psi_0\rangle$$

Manipulate $|\psi\rangle$:

$$\{U\sigma_1^x U^\dagger, U\sigma_1^y U^\dagger, U\sigma_1^z U^\dagger\}$$

Becomes complex

Operator Size Distribution

- The scrambling can be quantified by size

$$\sigma_1^x(t) = \sum_n \sum_{\{i_1, \dots, i_n\}} \sum_{\{\alpha_1, \dots, \alpha_n\}} C_{i_1 \dots i_n}^{\alpha_1, \dots, \alpha_n} \sigma_{i_1}^{\alpha_1} \sigma_{i_2}^{\alpha_2} \dots \sigma_{i_n}^{\alpha_n}.$$

- The size of a basis $\sigma_{i_1}^{\alpha_1} \sigma_{i_2}^{\alpha_2} \dots \sigma_{i_n}^{\alpha_n}$ is n .
- The size distribution of $\sigma_1^x(t)$ is

$$P(n, t) = \sum_{\{i_1, \dots, i_n\}} \sum_{\{\alpha_1, \dots, \alpha_n\}} |C_{i_1 \dots i_n}^{\alpha_1, \dots, \alpha_n}|^2 \geq 0.$$

- Normalization: $\sum_n P(n, t) = 1$.

A classical
distribution

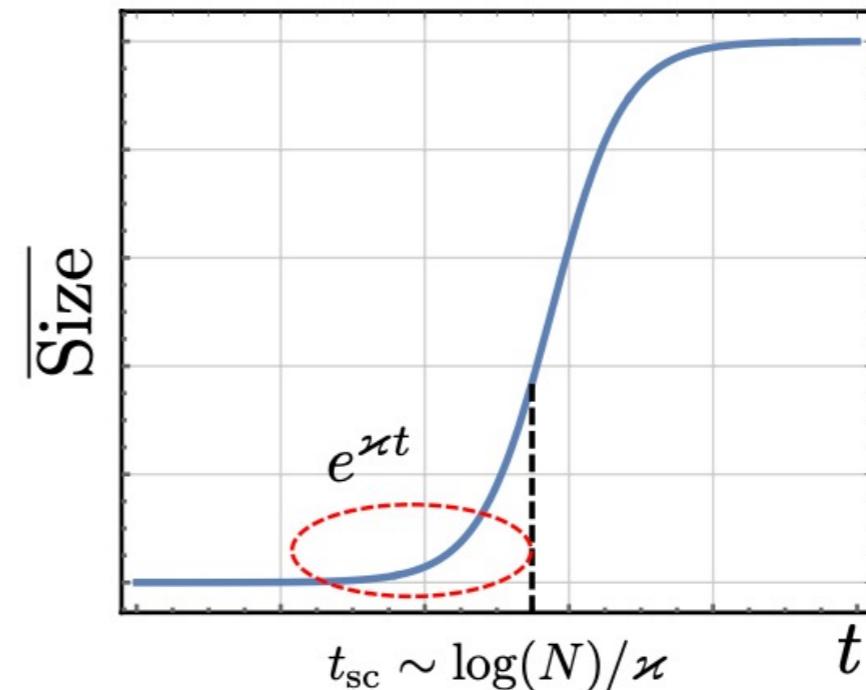
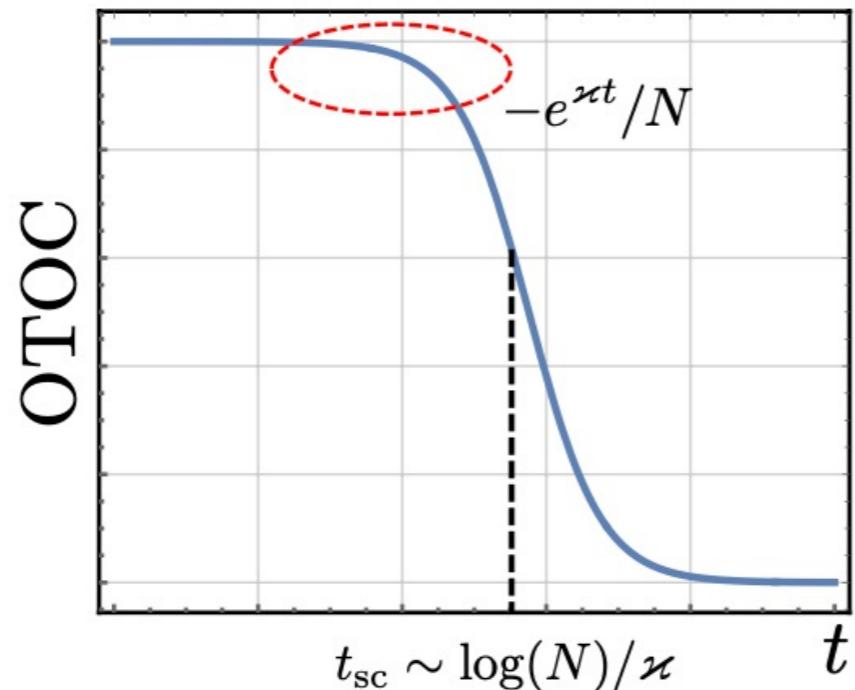
D. A. Roberts, D. Stanford, and L. Susskind, JHEP 2015, 51 (2015).

Moments and OTOC

- The **average size** is the first moment

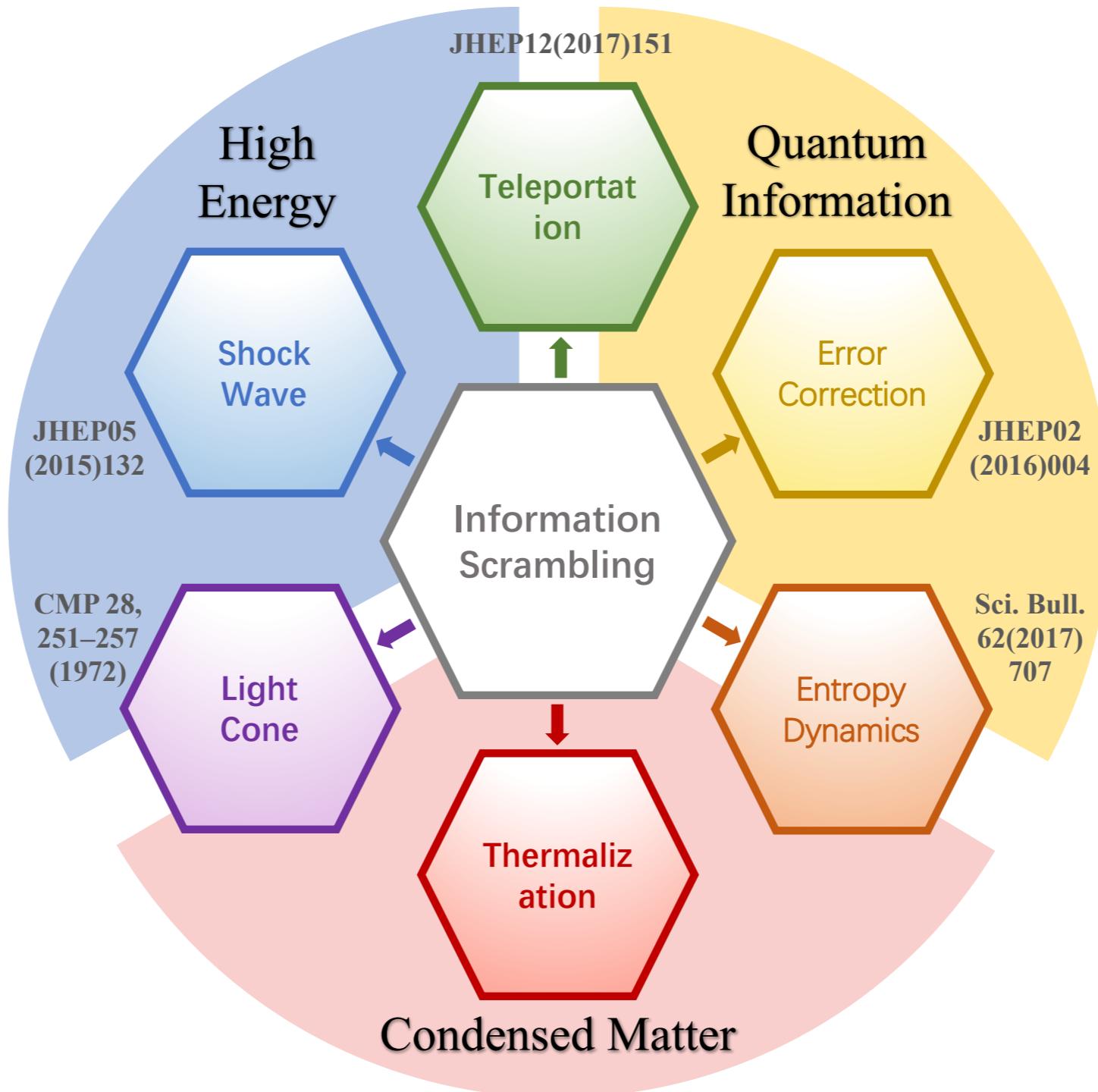
$$\sum_n n P(n, t) = \frac{3N}{4} - \frac{1}{4} \sum_{i,\alpha} \langle \sigma_1^x(t) \sigma_i^\alpha \sigma_1^x(t) \sigma_i^\alpha \rangle.$$

OTOC



- Higher Moments: $\overline{n^k} = \sum_n n^k P(n, t)$.

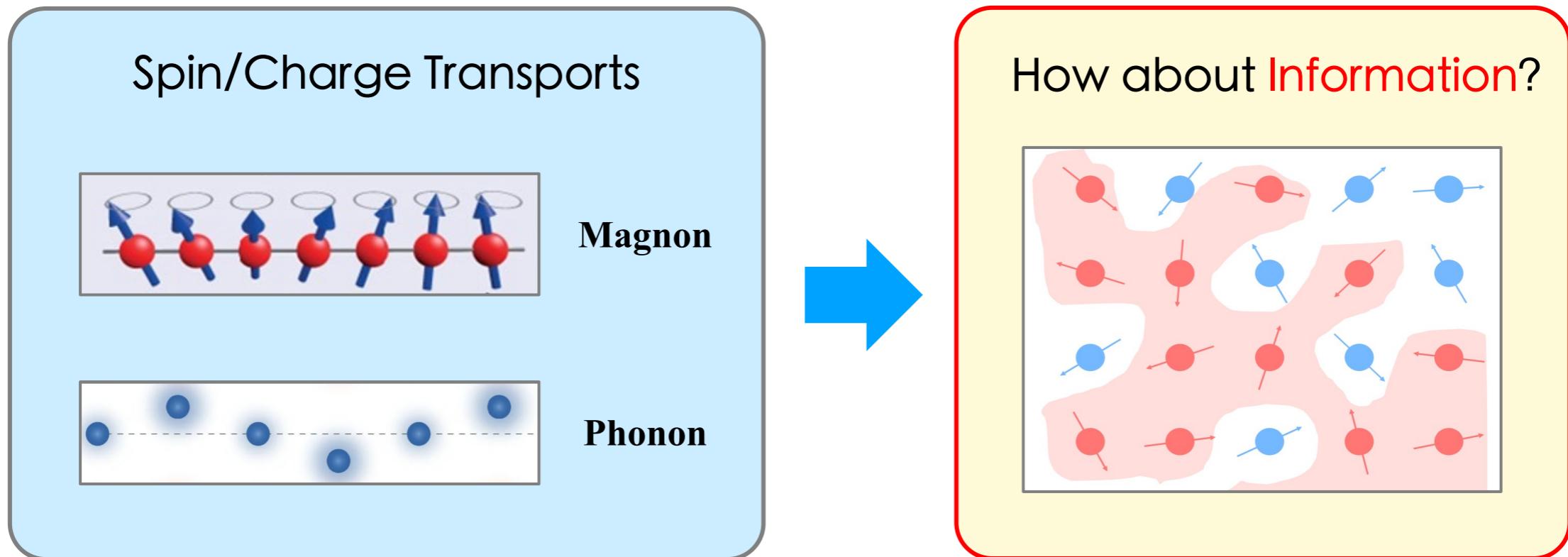
Interplay Between CMP, HEP, and QI



Theoretical Analysis in Many-body Systems

Transports in Many-body Systems

- Collective modes are important in transports.



- Look for the dominant mode for $\sum_{i,\alpha} \langle \sigma_1^x(t) \sigma_i^\alpha \sigma_1^x(t) \sigma_i^\alpha \rangle$.

Sachdev-Ye-Kitaev Model

- The SYK model

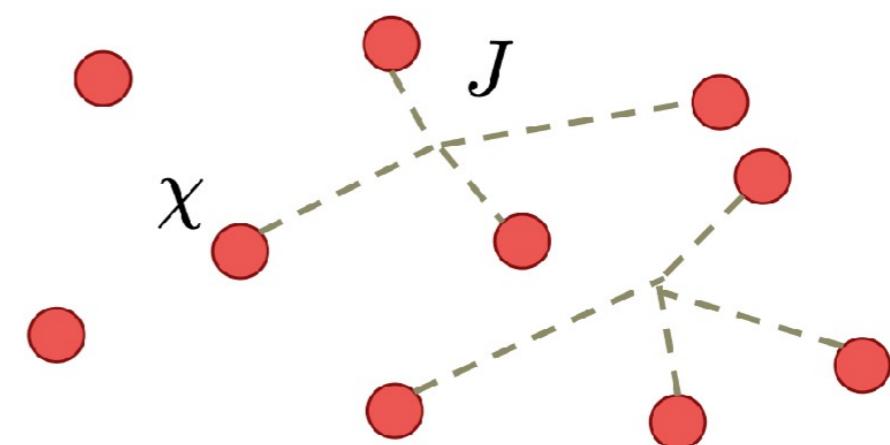
$$H_{\text{SYK}} = \sum_{1 \leq i_1 < i_2 < \dots < i_q \leq N} J_{i_1 i_2 \dots i_q} \chi_{i_1} \chi_{i_2} \dots \chi_{i_q},$$

The random variables

$$\overline{J_{i_1 i_2 \dots i_q}} = 0, \quad \overline{J_{i_1 i_2 \dots i_q}^2} = \frac{(q-1)! J^2}{N^{q-1}} = \frac{(q-1)! 2^{q-1} \mathcal{J}^2}{q N^{q-1}}.$$

Self-energy are **melons**:

$$\Sigma(\tau) = \text{---} \circ \text{---} = J^2 G^{q-1}(\tau)$$



S. Sachdev and J. Ye, PRL 70, 3339 (1993); Kitaev talk @2015.

OTOC Ladder Diagram

- The early-time OTOC are **ladders**

$$\text{OTOC}_c = \frac{\text{---}}{\text{---}} + \frac{\text{---}}{\text{---}} + \frac{\text{---}}{\text{---}} + \frac{\text{---}}{\text{---}} + \dots,$$

$$= \begin{array}{ccccc} & 1 & & 3 & \\ & \backslash & & / & \\ & \text{---} & \text{---} & \text{---} & \\ & / & & \backslash & \\ & \text{---} & & \text{---} & \\ & 2 & & 4 & \end{array} = \left(-\frac{e^{\nu t}}{Nc} \right) \Upsilon^{\text{R},1}(t_{12}) \Upsilon^{\text{A},1}(t_{34}).$$

- Only valid at

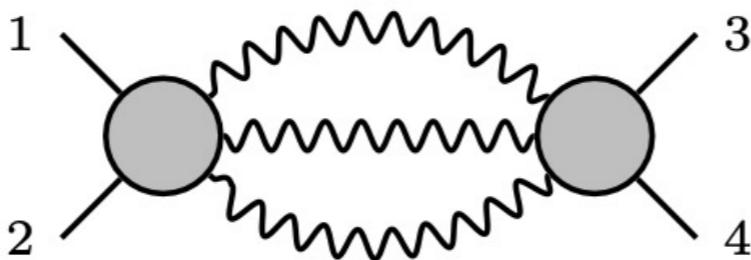
$$t \ll \ln N \quad (\text{Early-time limit})$$

S. Sachdev and J. Ye, PRL 70, 3339 (1993); Kitaev talk @2015.

Scramblon Effective Theory

- Scrambling are dominated by **scramblons**

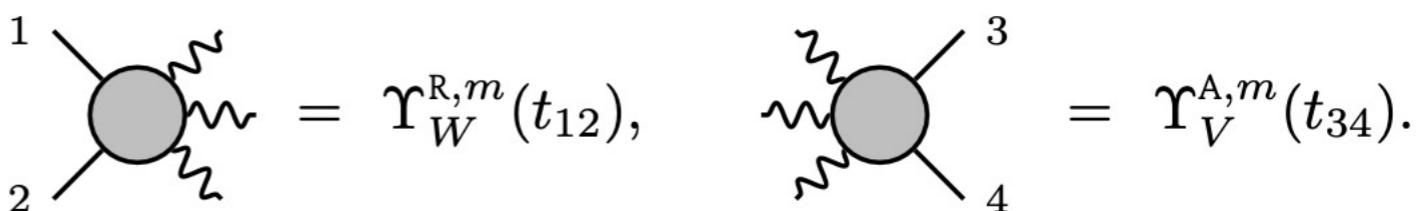
$$\langle W^\dagger(t_1)V^\dagger(t_3)W(t_2)V(t_4) \rangle =$$


$$= \sum_{m=0}^{\infty} \frac{(-\lambda)^m}{m!} \Upsilon_W^{R,m}(t_{12}) \Upsilon_V^{A,m}(t_{34}).$$

Propagator

$$\text{wavy line} = \lambda = \frac{e^{\nu \frac{t_1+t_2-t_3-t_4}{2}}}{C}$$

Scattering amplitude


$$\text{Diagram 1} = \Upsilon_W^{R,m}(t_{12}), \quad \text{Diagram 2} = \Upsilon_V^{A,m}(t_{34}).$$

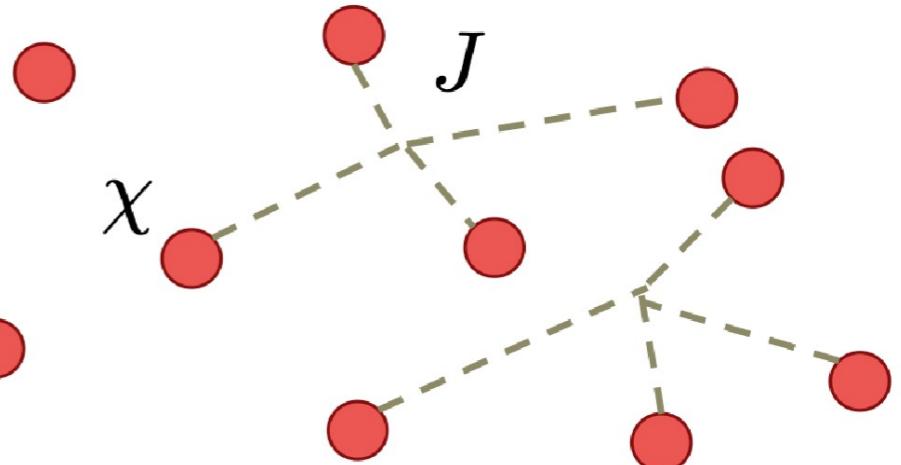
D. Stanford, Z. Yang, S. Yao, JHEP 2022, 200 (2022); Y. Gu, A. Kitaev, and PZ[†], JHEP 2022, 133 (2022).

The Brownian SYK Model

- The SYK is easier when **Brownian**

$$H_{\text{BSYK}} = \sum_{1 \leq i_1 < i_2 < \dots < i_q \leq N} J_{i_1 i_2 \dots i_q}(t) \chi_{i_1} \chi_{i_2} \dots \chi_{i_q},$$

Time-dependent



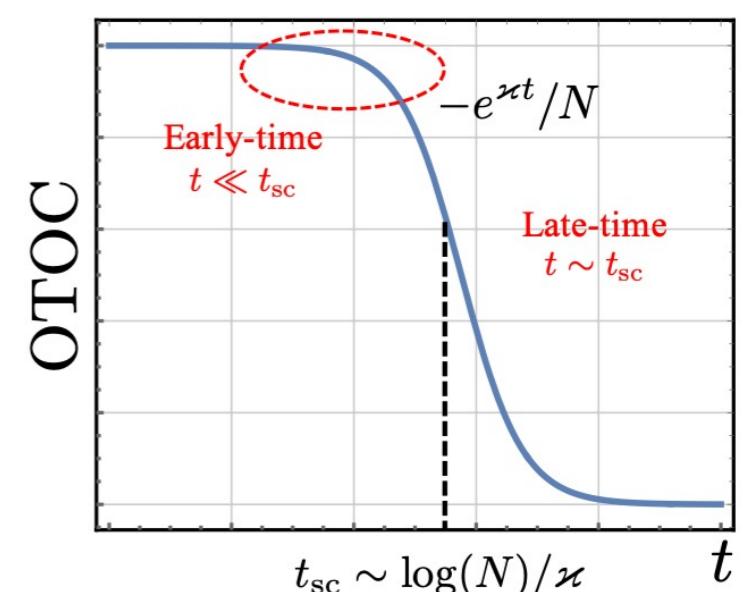
- All** scattering amplitudes are known:

$$f(x, t) = \sum_n \frac{(-x)^n}{n!} \Upsilon^n(t) = \left(\frac{1}{e^{\nu|t_{12}|/2} + x} \right)^{2\Delta},$$

- Result:**

$$\text{OTOC}(\{t_i\}) = \frac{1}{\lambda^{2\Delta}} U \left(2\Delta, 1, \frac{e^{\nu|t_{12}|/2} e^{\nu|t_{34}|/2}}{\lambda} \right)$$

$$2\Delta = 1/(q - 2)$$

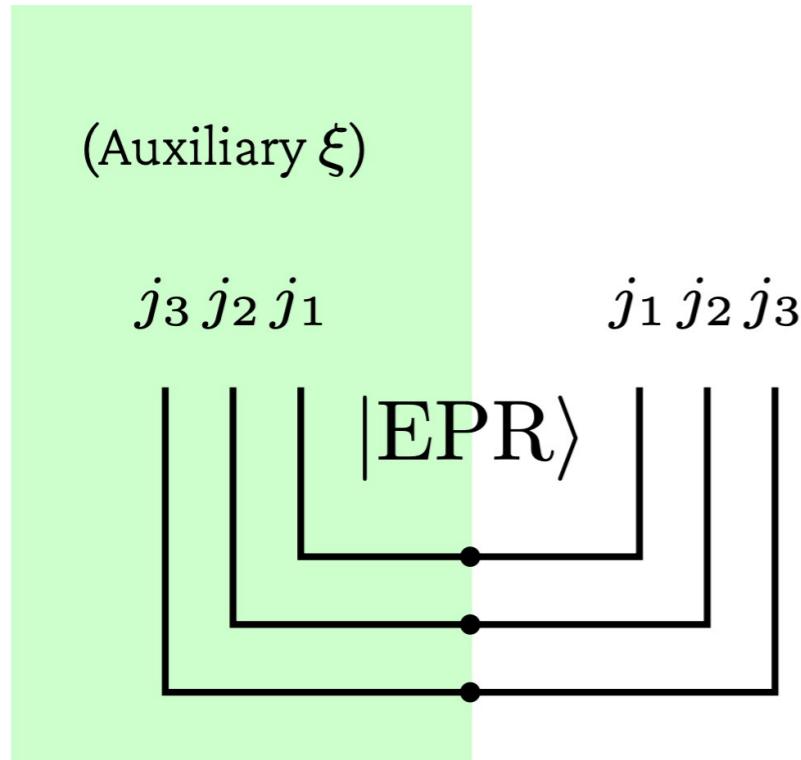


Y. Gu, A. Kitaev, and PZ[†], JHEP 2022,133 (2022).

Size Distribution & Total Spin

- Theoretical Trick: **states** are easier than **operators**!

operator-state mapping: $O \rightarrow |O\rangle = (O \otimes I)|\text{EPR}\rangle$



1. Introduce auxiliary spin system τ_i^α

2. Prepare σ_i and τ_i in singlets

$$|\text{EPR}\rangle_i = |s\rangle_i = (|01\rangle - |10\rangle)/\sqrt{2}$$

3. Since $\sigma_i^\alpha |s\rangle_i = |t\rangle_i$

$$P(n, t) = \langle O(t) | \delta_{n, \sum s_{tot,j}^2} | O(t) \rangle$$

Z. Liu and PZ[†], PRL 132, 060201 (2024).

→ Exp. protocol

Relation between Early-time & Late-time

- Using the scramblon effective theory:

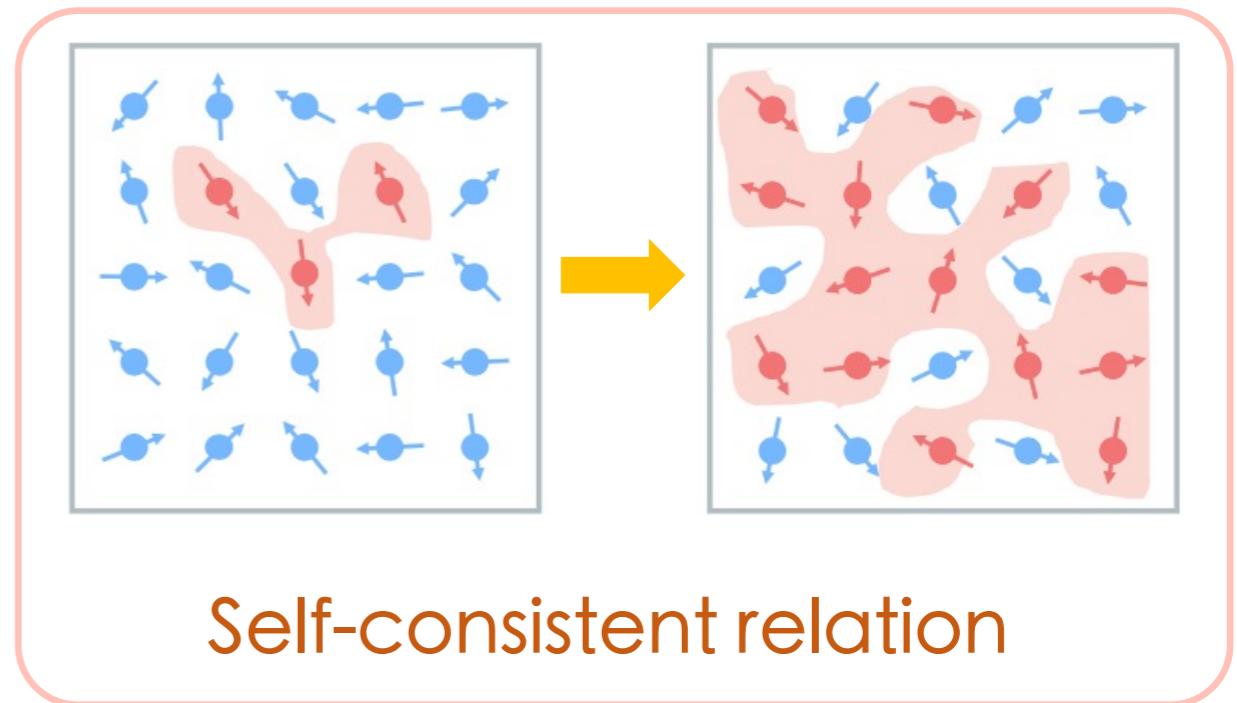
$$\mathcal{P}(s, t) = \textcolor{red}{N} P(sN, t) = \int_0^\infty dy \bar{h}(y) \delta(s - s_{\text{sc}}(1 - \bar{f}(\lambda y)))$$

with $f(x) = \sum_m (-x)^m \Upsilon^m / m!$, $f(x) = \int dy e^{-xy} h(y)$

Early-time limit $\lambda \ll 1$

$$\bar{\mathcal{P}}(s, t) = (s_{\text{sc}} \lambda \bar{\Upsilon}^1)^{-1} \bar{h}\left(s (s_{\text{sc}} \lambda \bar{\Upsilon}^1)^{-1}\right)$$

$h(y)$ contains the **Full** information!



Z. Liu and **PZ[†]**, PRL 132, 060201 (2024).

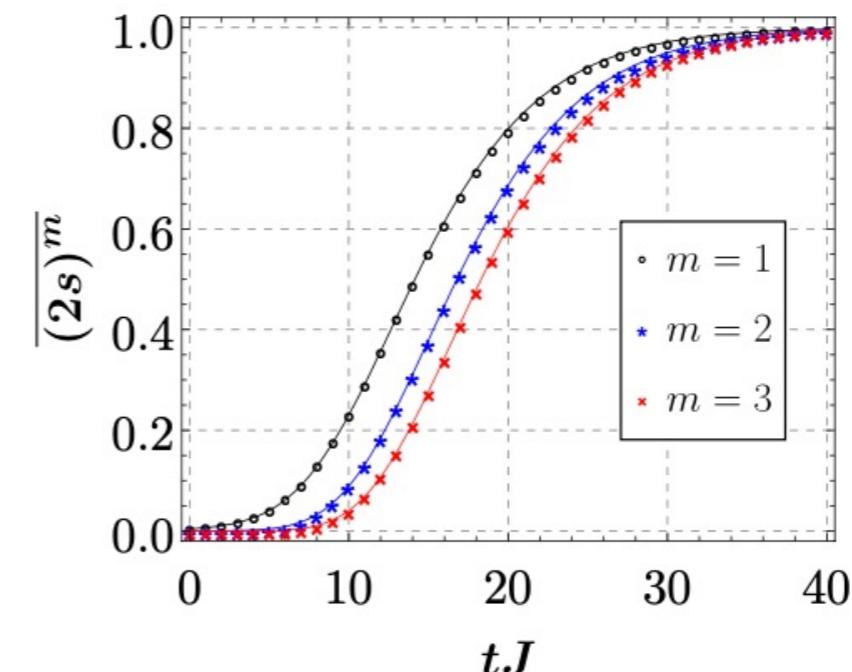
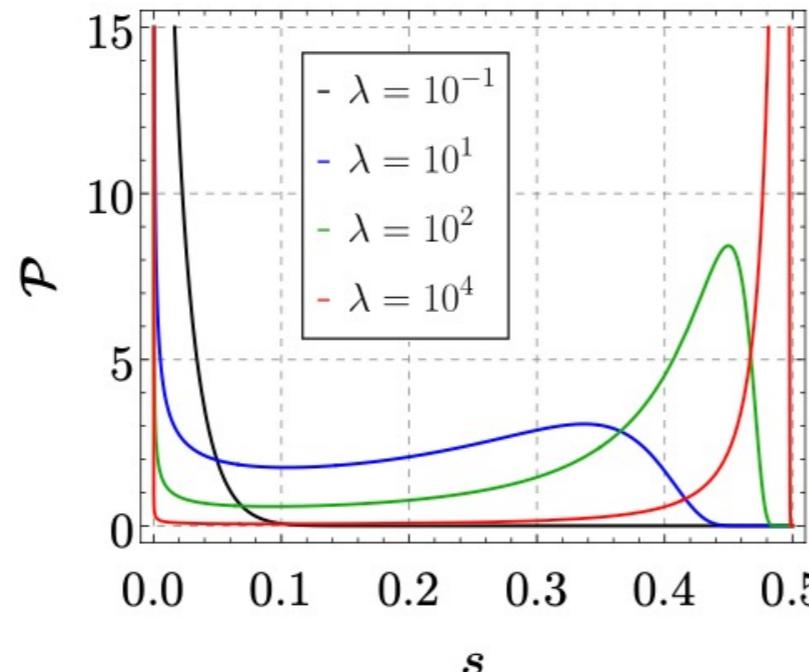
Late-time Size Distribution

- In the long-time limit, assuming $f(\infty) = 0$:

$$\mathcal{P}(s, \infty) = \delta(s - s_{\text{sat}}), \quad \text{"Maximally Scrambled" } \delta s \sim N^{-1/2} \rightarrow 0.$$

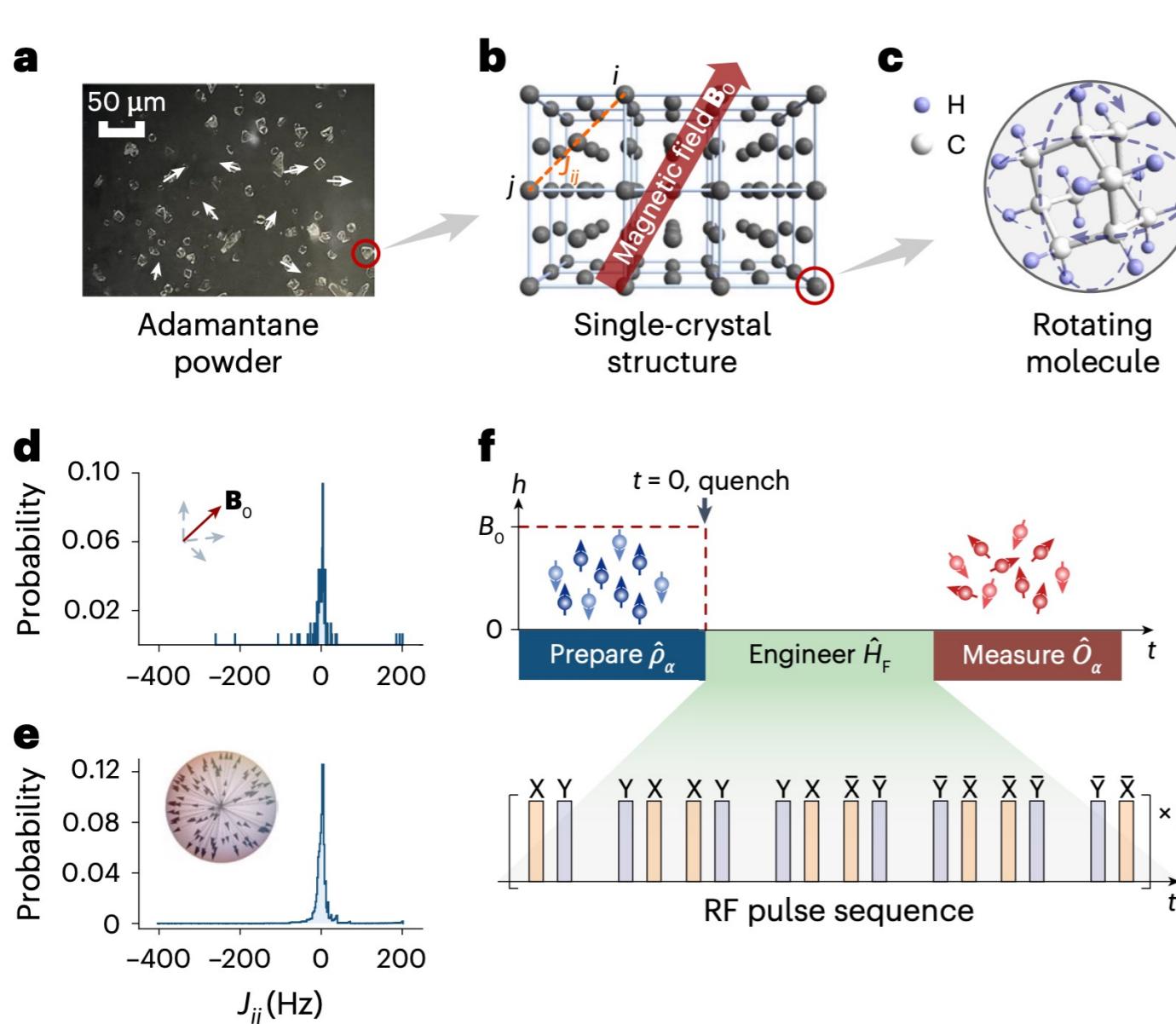
Example: Brownian SYK

$$\mathcal{P}(s, t) = \frac{2p^{2\Delta-1}e^{-p}}{\lambda\Gamma(2\Delta+1)(1-2s)^{\frac{2\Delta+1}{2\Delta}}}, \quad p = \frac{(1-2s)^{-\frac{1}{2\Delta}} - 1}{\lambda},$$



Z. Liu and PZ[†], PRL 132, 060201 (2024).

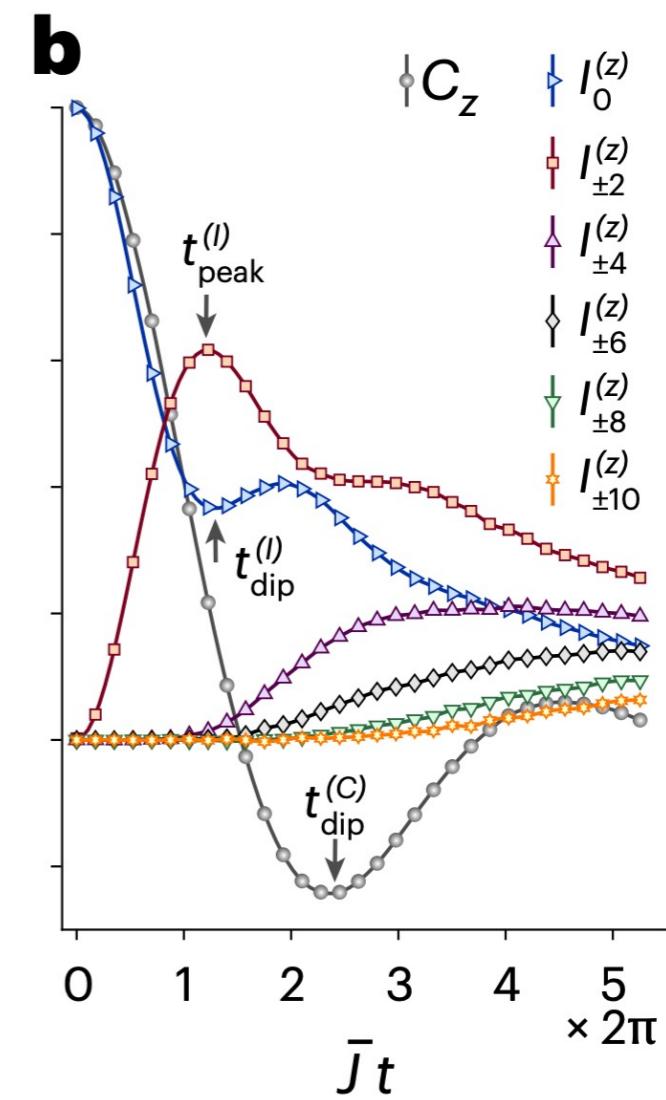
Experimental Progress



Verify scramblon theory?

$$F(\phi, t) = \frac{1}{c_0} \text{Tr}[e^{-i\hat{O}_\alpha\phi} \hat{O}_\alpha(t) e^{i\hat{O}_\alpha\phi} \hat{O}_\alpha(t)]$$

Fourier Transform $\rightarrow I_m$

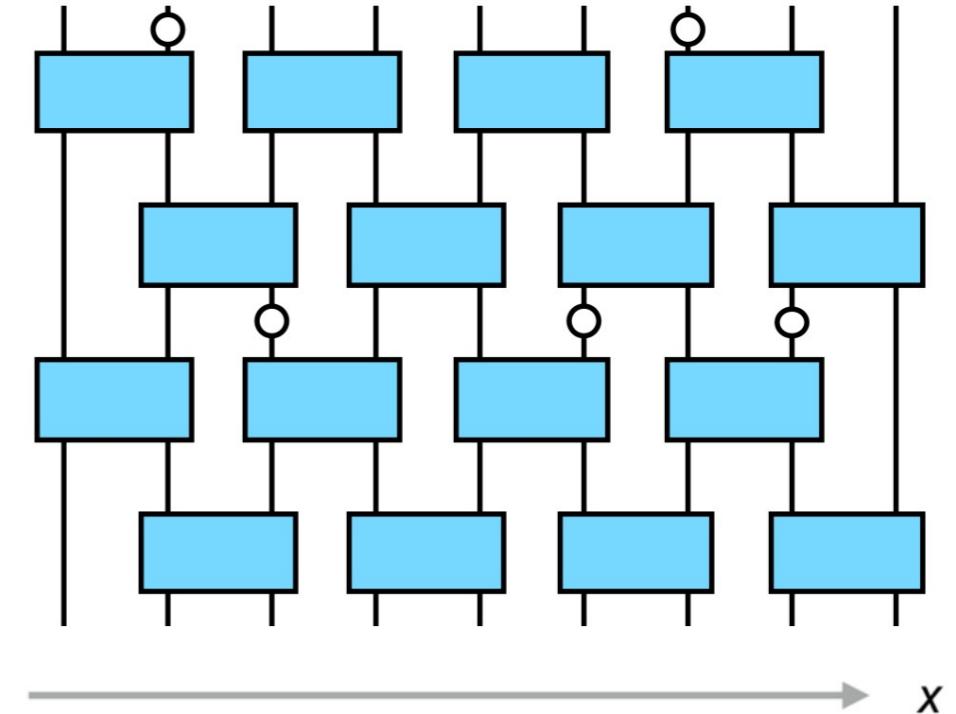
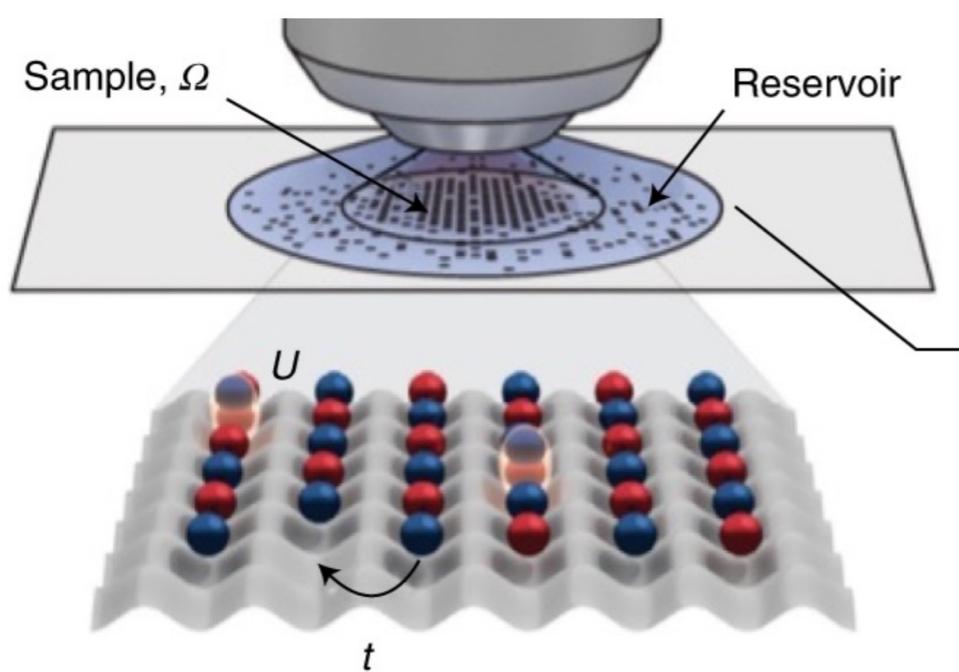


Collaboration with Hui Zhai and Xinhua Peng's groups, Nature Physics (2024)

From Closed to Open

Why open systems?

- **Experimentally**, any realistic system is open.
- **Theoretically**, Novel dynamical phases.



Operator Size in Open Systems

- We **define** size in open systems by only count system operator

$$\text{size} \left(\sigma_{i_1}^{\alpha_1} \sigma_{i_2}^{\alpha_2} \dots \sigma_{i_n}^{\alpha_n} O_B \right) = n$$

- An expansion of operator evolution:

$$\sigma_1^x(t) = \sum_n \sum_{\{i_1, \dots, i_n\}} \sum_{\{\alpha_1, \dots, \alpha_n\}} C_{i_1 \dots i_n}^{\alpha_1, \dots, \alpha_n} \sigma_{i_1}^{\alpha_1} \sigma_{i_2}^{\alpha_2} \dots \sigma_{i_n}^{\alpha_n} O_{B, \{i, \alpha\}}.$$

$$P(n, t) = \sum_{\{i_1, \dots, i_n\}} \sum_{\{\alpha_1, \dots, \alpha_n\}} \left| C_{i_1 \dots i_n}^{\alpha_1, \dots, \alpha_n} \right|^2 \langle O_{B, \{i, \alpha\}}^2 \rangle.$$

PZ and Z. Yu, PRL 130, 250401 (2023); Also see N. Y. Yao et al, P. Nandy et al ...

Scrambling Transition

- Competition:

A. System interaction

$$i [J\sigma_i\sigma_j, \sigma_1] \sim \sigma_1\sigma_j$$

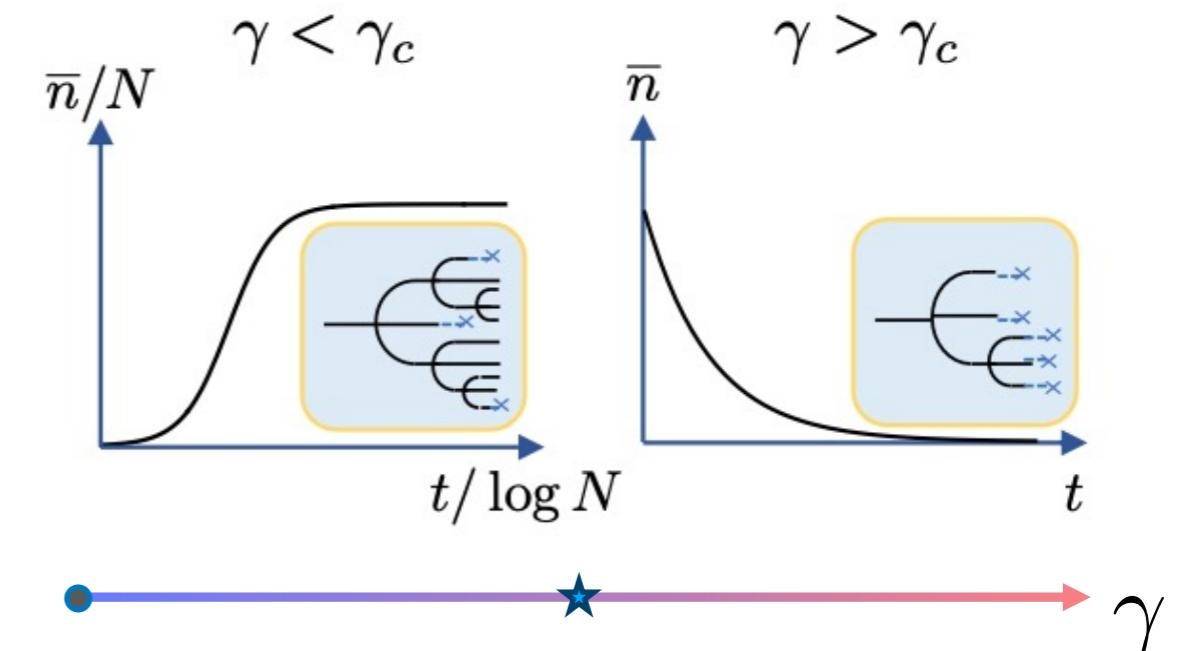
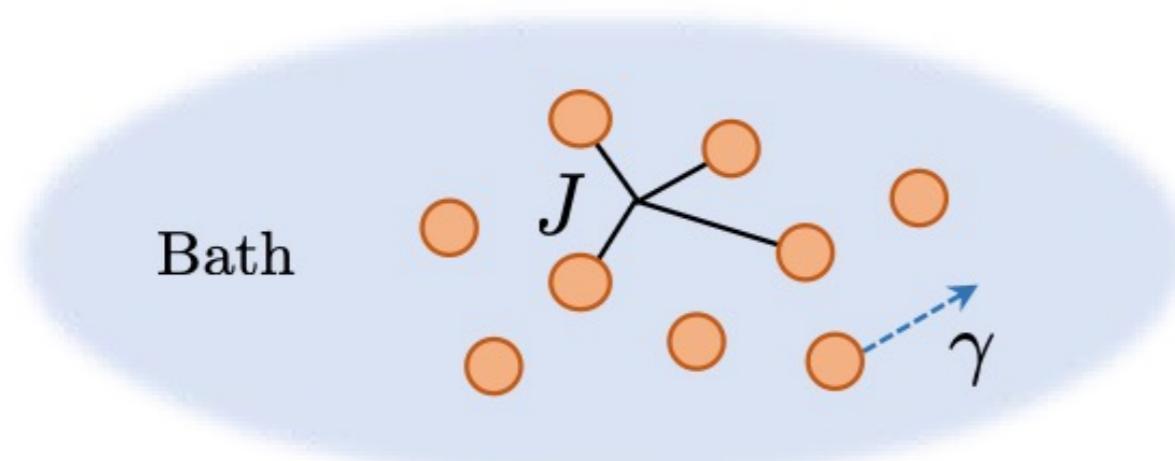


B. System-both coupling

$$\text{SWAP}_{1B} \sigma_1 \text{ SWAP}_{1B} \sim \sigma_B$$



- There is a **scrambling** transition



PZ and Z. Yu, PRL 130, 250401 (2023), E. Altman, et. al , PRL 131, 220404 (2023)

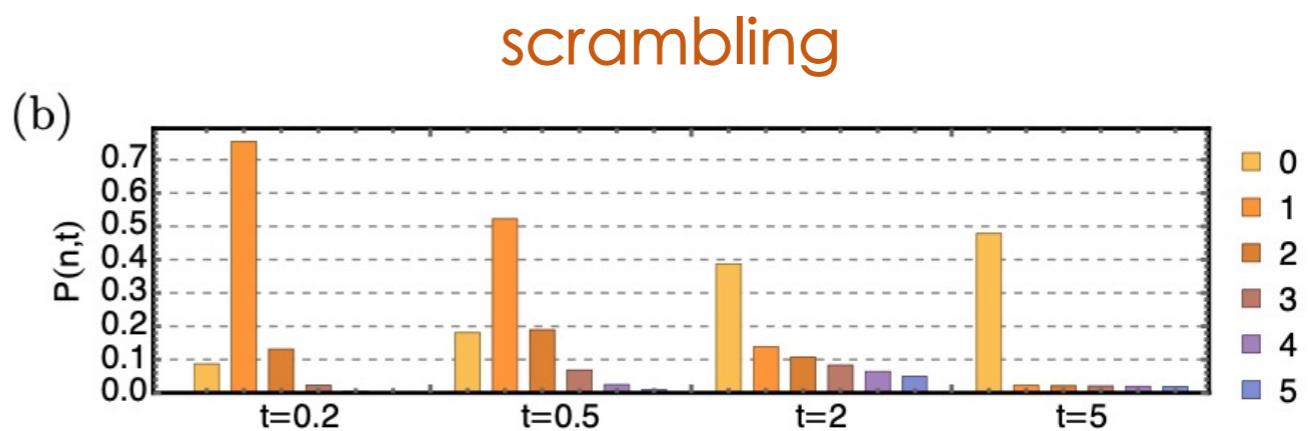
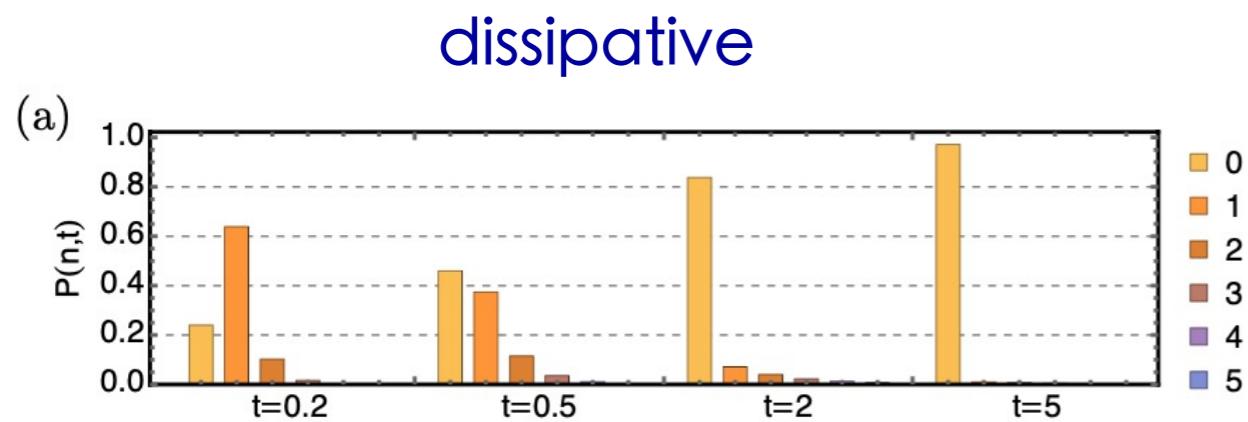
SYK Solvable Model

- The transition can be verified in

$$H(t) = \sum_{i_1 < \dots < i_q} i^{\frac{q}{2}} J_{\{i_p\}}(t) \chi_{i_1} \chi_{i_2} \dots \chi_{i_q} + \sum_{j,a} i V_{ja}(t) \chi_j \psi_a$$

System fermion χ , bath fermion ψ

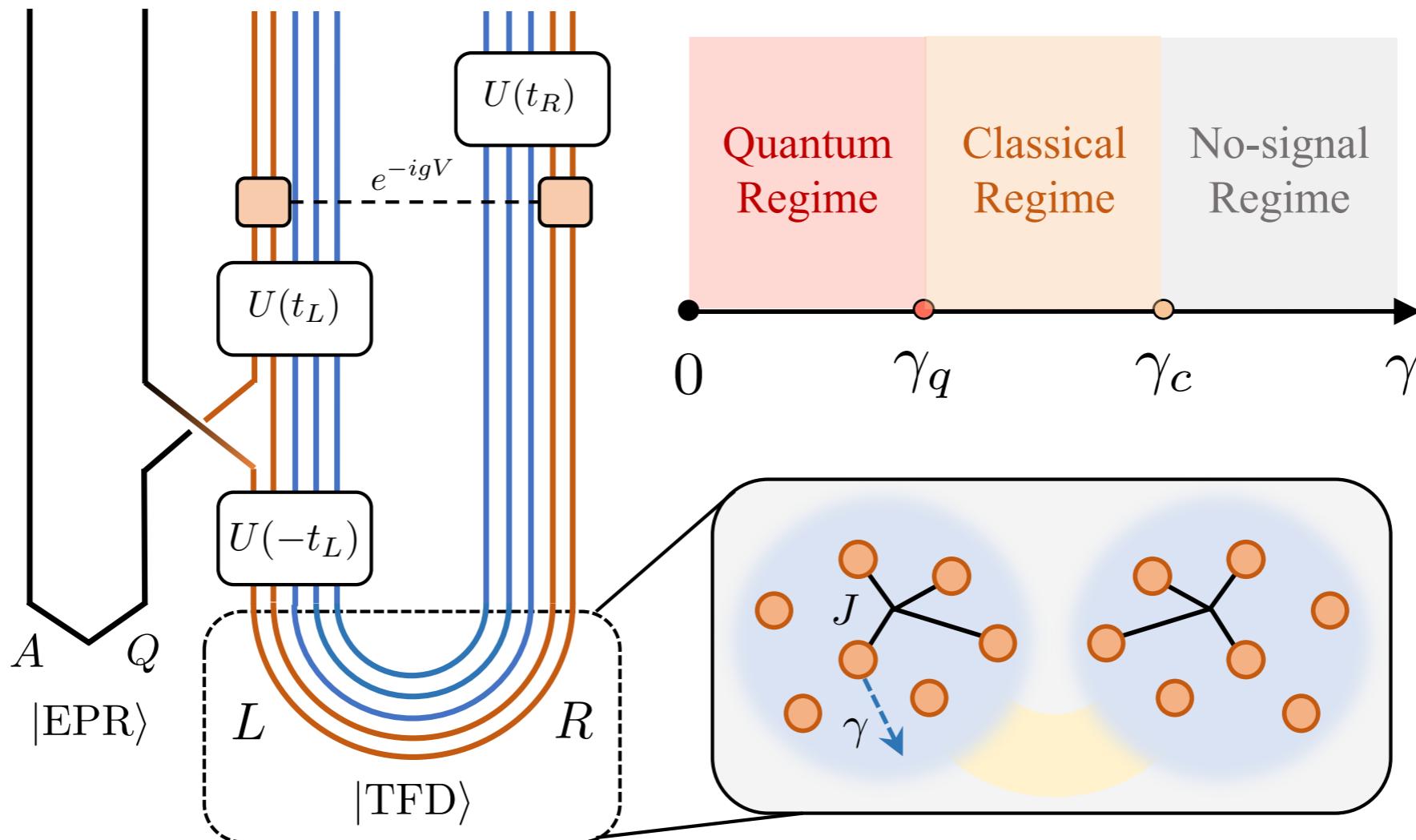
- Scrambling transition occurs at $V/J = 1$



PZ and Z. Yu, PRL 130, 250401 (2023).

Scrambling & Teleportation

- The scrambling **transition** is a **teleportation** transition

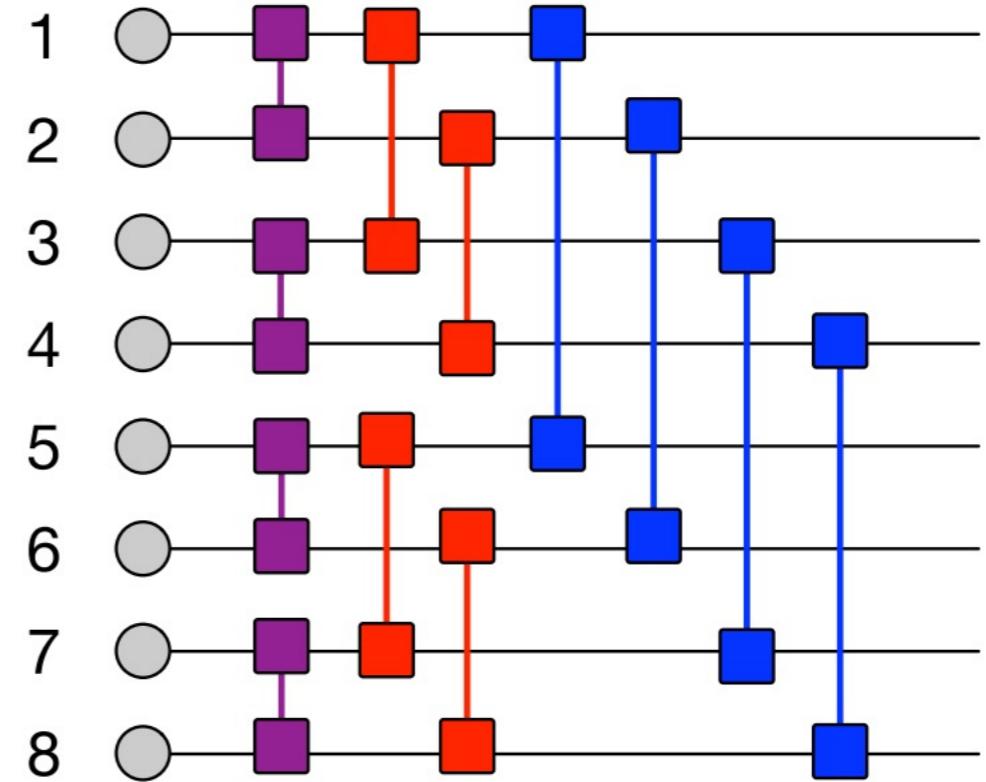
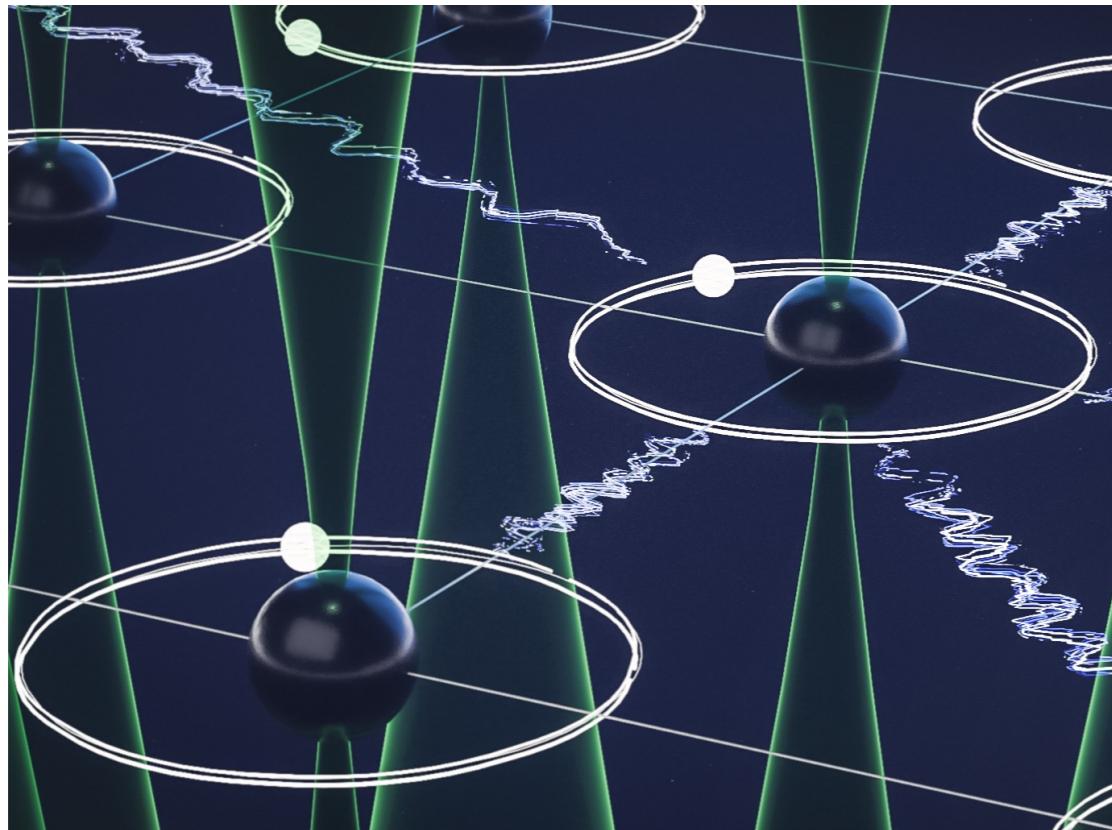


S. Zhou, PZ[†] and Z. Yu[†], arXiv:2406.02277.

Applications in Shadow Tomography

New Quantum Platforms

- Rydberg atom array in optical tweezers.



No Hamiltonian, No symmetry, No locality.

Observables

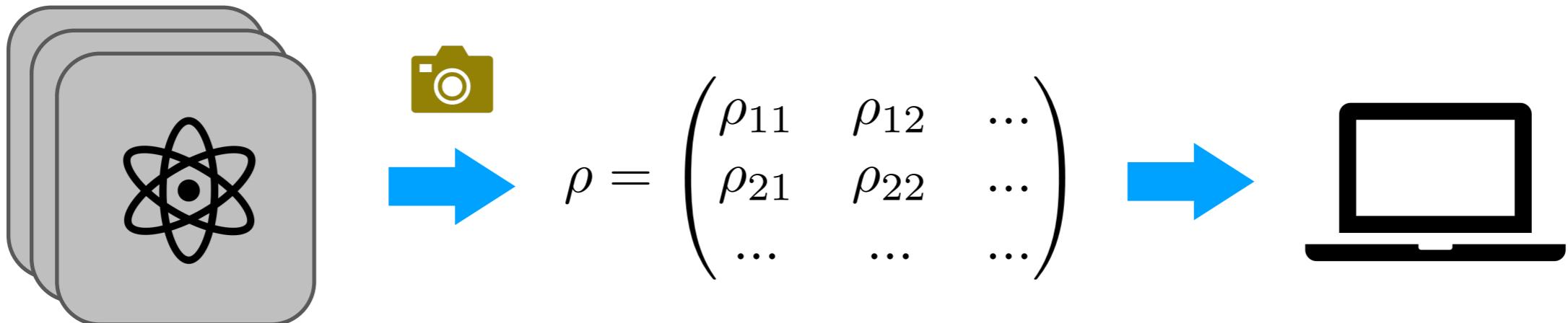


Quantum Information

Quantum State Tomography

- How to storage a **generic** quantum state?

Naïve answer: store the full density matrix:



Pauli basis:

$$\rho = \sum_{P_i \in \{I, X, Y, Z\}} c_{\{P_i\}} P_1 P_2 \dots P_N / 2^N$$
$$c_{\{P_i\}} = \text{tr} (\rho P_1 P_2 \dots P_N)$$

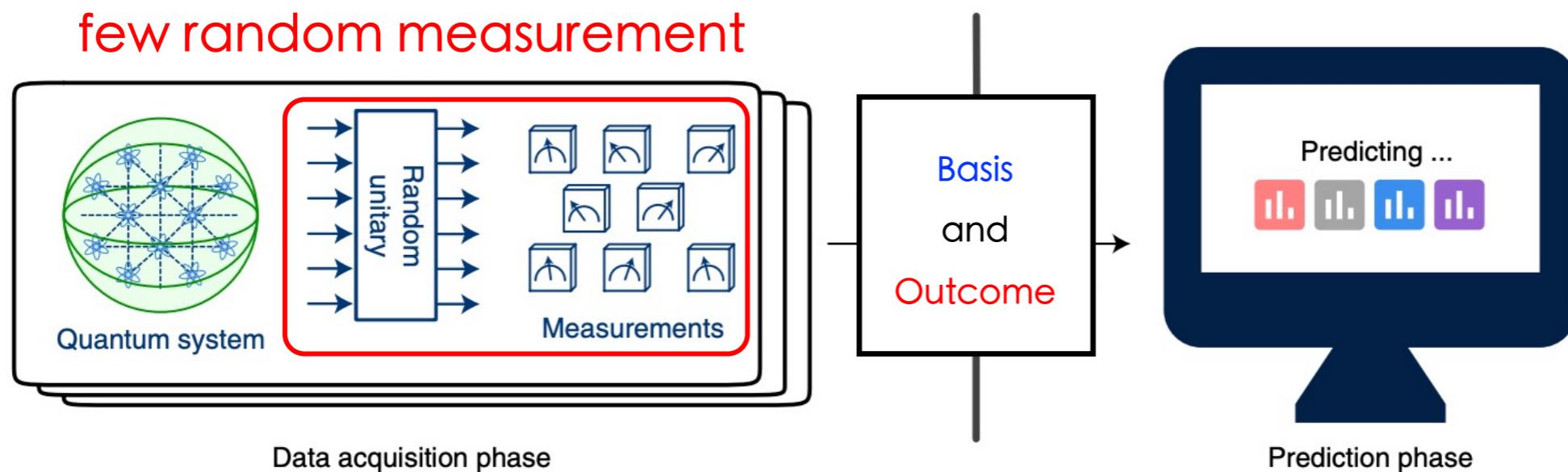
4^N elements!

$$N = 384, \quad 4^N \approx 10^{115}$$

Requires 10^3 TB to store!

Classical Shadow Tomography

- Only certain properties are of interests:
 - ✓ Local Observable ✓ Entropy ✓ Fidelity
 - $\text{tr}(\rho P)$ $\text{tr}(\rho^2)$ $\langle \psi | \rho | \psi \rangle$
- Shadow Tomography with Randomness

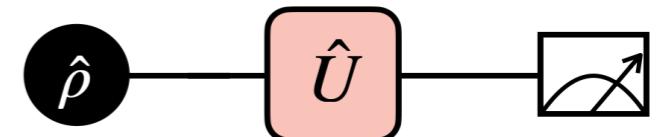


[1]. H.-Y. Huang, R. Kueng, and J. Preskill, Nature Physics volume 16, p1050–1057 (2020).

A Single-qubit Example

$$\rho = I/2 + (c_X X + c_Y Y + c_Z Z)/2$$

- The shadow tomography protocol:

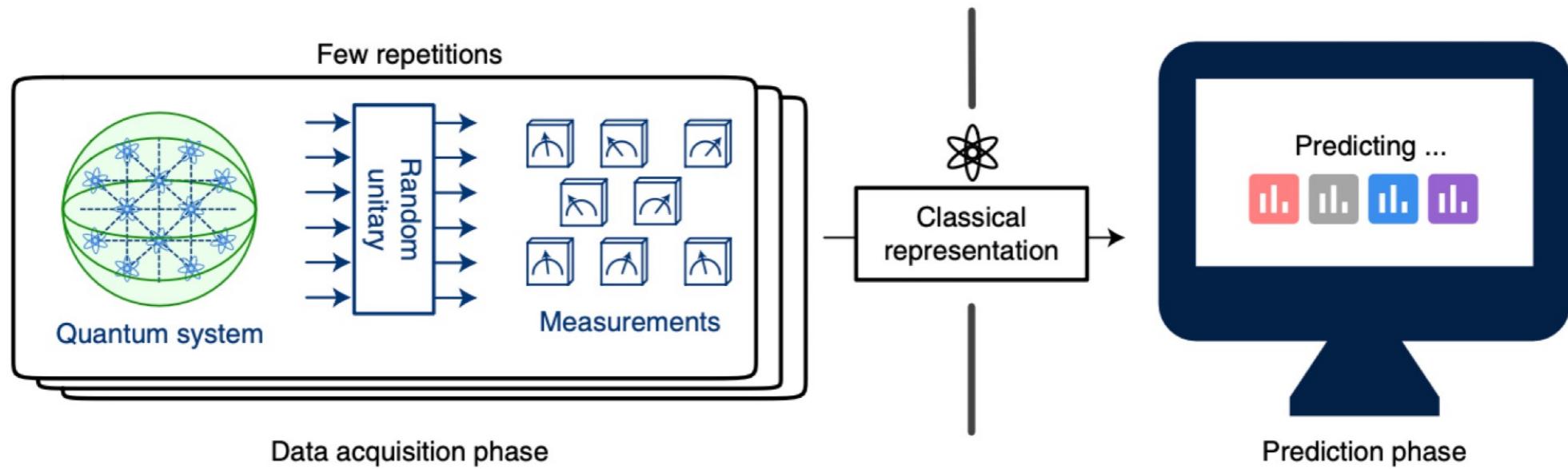


= Randomly measure in x/y/z direction:

Direction	Outcome $ o\rangle$ (Shadow)	Probability	Partial Average	Full Average
x	$ +x\rangle$	$(1 + c_X)/2$	$(I + c_X X)/2$	$\bar{\sigma} = I/2 + (c_X X + c_Y Y + c_Z Z)/6$
	$ -x\rangle$	$(1 - c_X)/2$		
y	$ +y\rangle$	$(1 + c_Y)/2$	$(I + c_Y Y)/2$	
	$ -y\rangle$	$(1 - c_Y)/2$		
z	$ +z\rangle$	$(1 + c_Z)/2$	$(I + c_Z Z)/2$	
	$ -z\rangle$	$(1 - c_Z)/2$		

Quantum Experiment Data collection

General Strategy



Random unitary $U \in \mathcal{E}(U)$

$$\rho \rightarrow U\rho U^\dagger \rightarrow |z^a\rangle\langle z^a|$$

Classical snapshot

$$|o^a\rangle = U^\dagger |z^a\rangle, \quad p^a = \langle o^a | \rho | o^a \rangle$$

Measurement channel

$$\bar{\sigma} = \mathcal{M}[\rho]$$

Rebalance $\rho = \mathcal{M}^{-1}[\bar{\sigma}]$

Make prediction

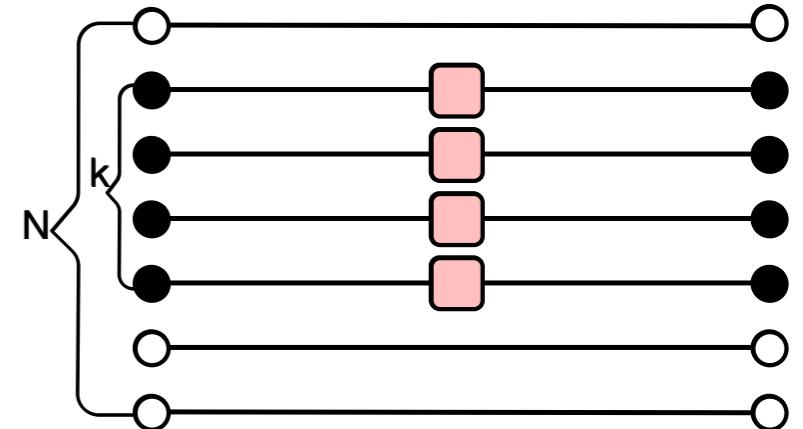
$$\langle P \rangle = \text{tr} (P \mathcal{M}^{-1}[\bar{\sigma}])$$

Sample Complexity

- How many **samples** are needed?

1. Random **single-qubit** rotations

$$U = u_1 u_2 \dots u_N$$



Example: Pauli observable $P = X_3 Y_4 Z_5$ (size $k = 3$)

➤ Each sample measures $P_3 P_4 P_5$ with $P_i \in \{X, Y, Z\}$.

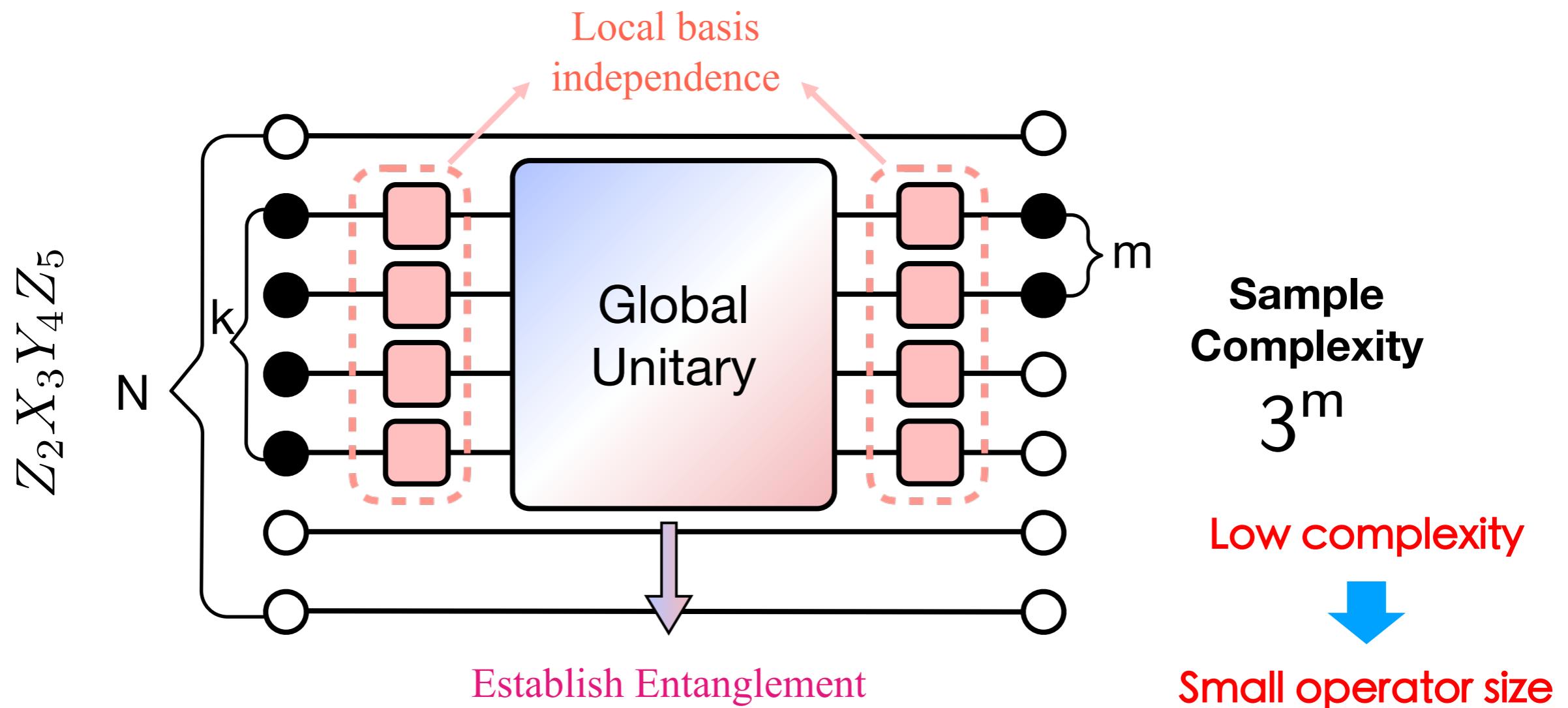
➡ Sample complexity $\sim 3^k$

Independent of N !

Sample Complexity

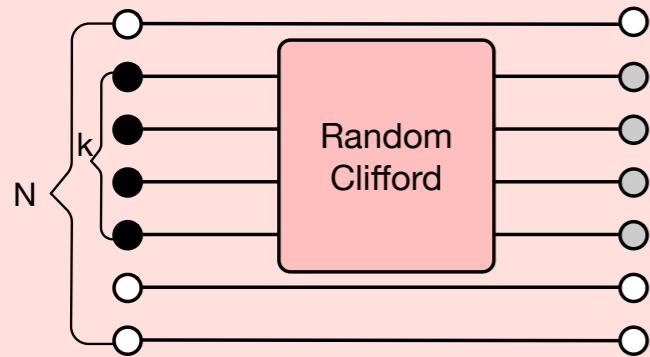
- How many **samples** are needed?

2. Adding Clifford **entanglement** unitary



Barrier for Sample Complexity?

Nature Physics 16, p1050 (2020).



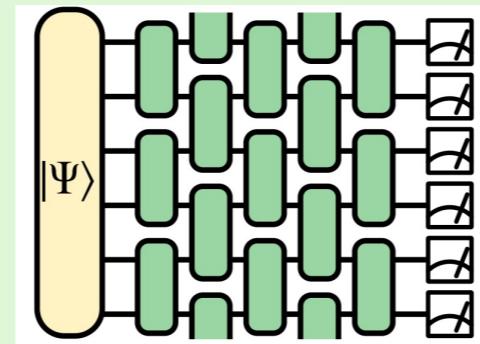
k -qubit Clifford unitary

$\pi(m)$ is **binomial**,

with $\|O\|_{sh} = 2^k + 1$

with Prior Knowledge

PRR 5, 023027 (2023); PRL 130, 230403 (2023), and others

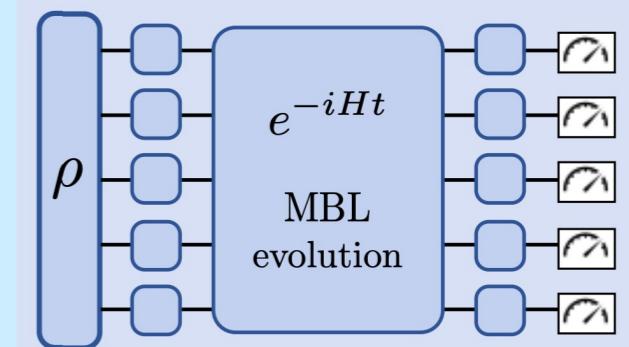


Shallow circuits with
circuit depth $d \sim \ln k$

has $\|O\|_{sh} > 2^k$

no Prior Knowledge

Collaboration with Tian-Gang
Zhou, Quantum 8, 1467 (2024)



Hamiltonian dynamics
with MBL systems

has $\|O\|_{sh} \sim 2.25^k$

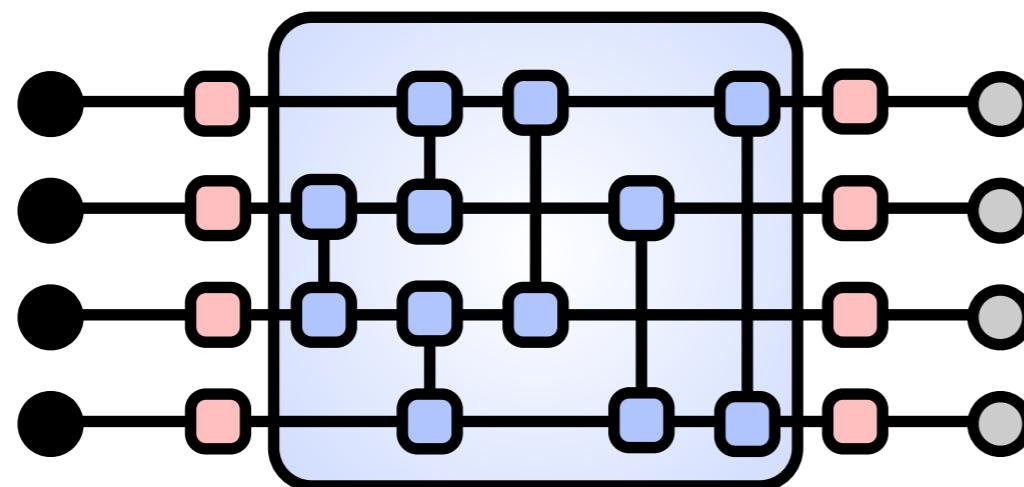
no Prior Knowledge

Easier for simulation

- Can the sample complexity be lower than 2^k ?

Contractive Unitary

- Main result: the target-driven design of a unitary operation that rapidly contract operator size:



$$U_{ct} = \prod_{i < j} U_{ij}^{ZZ},$$

$$U_{ij}^{ZZ} = \exp\left(-\frac{i\pi}{4} Z_i Z_j\right)$$

Best two-qubit gate

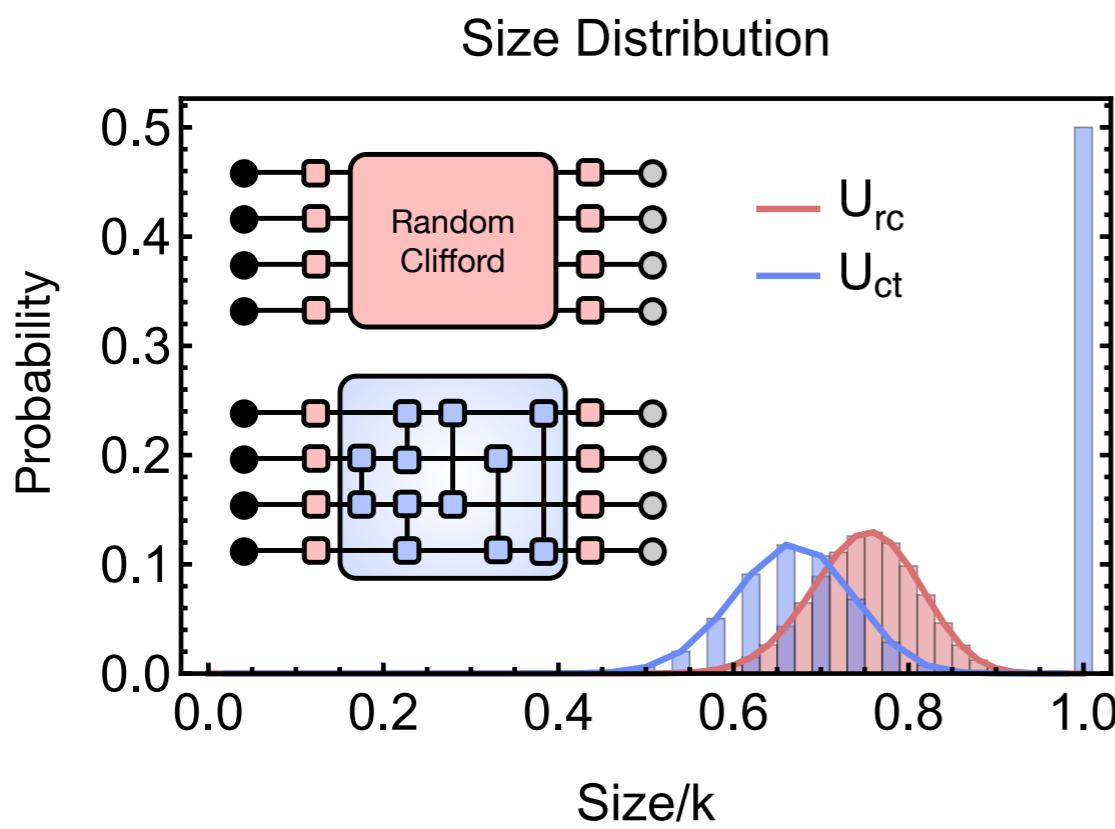
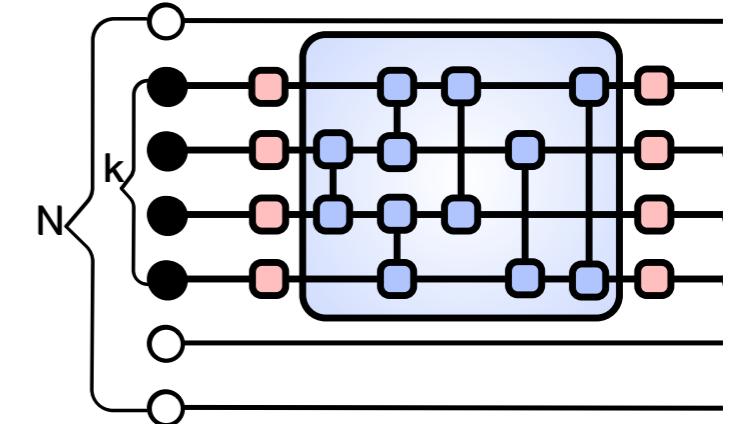
	Information of the precise location of \hat{O}	Contractive Unitary	Random Clifford	Shallow Circuit
Known		1.8^k	2^k	$> 2^k$
Unknown		$k \times 1.8^k$	$k \times 2^k$	

Y. Wu, C. Wang, J. Yao, H. Zhai, Y.-Z. You, and P. Zhang[†], 2412.01850.

Contractive Unitary Protocol

- This leads to the size at the output:

$$m = \text{Size} \left(\hat{U}_{\text{ct}} \hat{O} \hat{U}_{\text{ct}}^\dagger \right) = \begin{cases} N_{XY} & \text{if } N_{XY} \in \text{odd}, \\ k & \text{if } N_{XY} \in \text{even}. \end{cases}$$



$$\begin{aligned} w(\hat{O})_{\text{ct}} &= \sum_m \frac{\pi_{\text{ct}}(m)}{3^m} \\ &= \sum_{N_{XY} \in \text{even}} \binom{k}{N_{XY}} \frac{2^{N_{XY}}}{3^k} \frac{1}{3^k} \xrightarrow{\sim} \frac{1}{2} \frac{1}{3^k} \\ &+ \sum_{N_{XY} \in \text{odd}} \binom{k}{N_{XY}} \frac{2^{N_{XY}}}{3^k} \frac{1}{3^{N_{XY}}} \xrightarrow{\sim} \frac{1}{2} \left(\frac{5}{9}\right)^k \end{aligned}$$

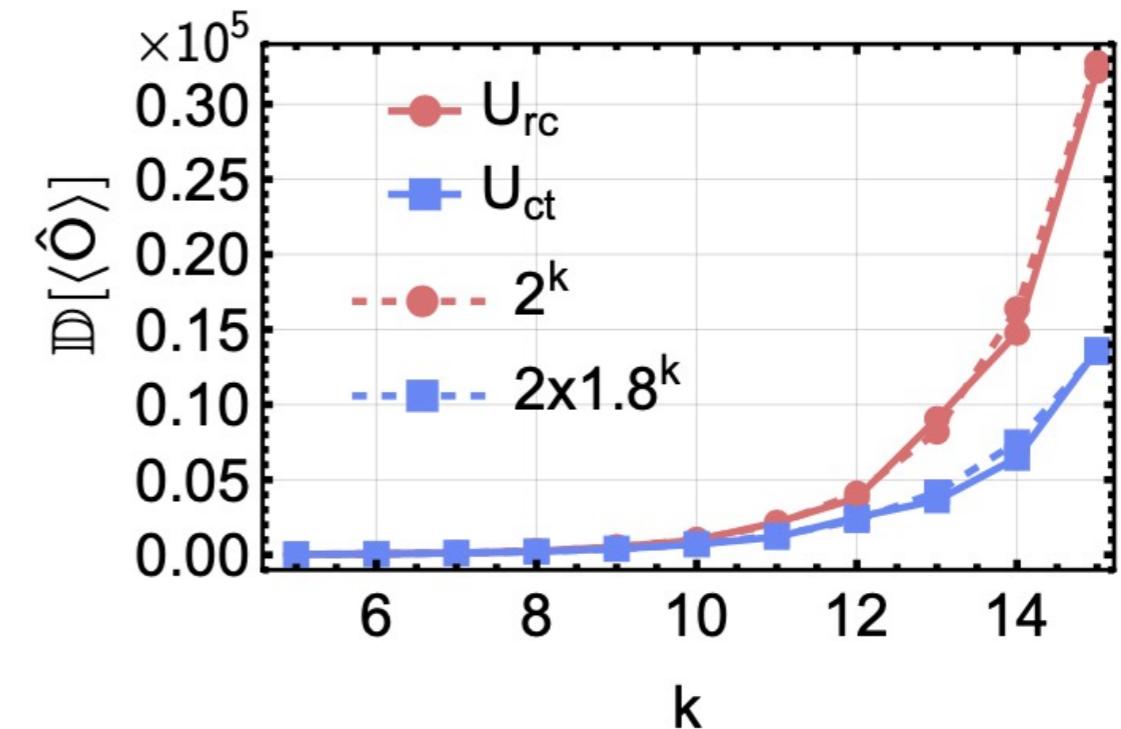
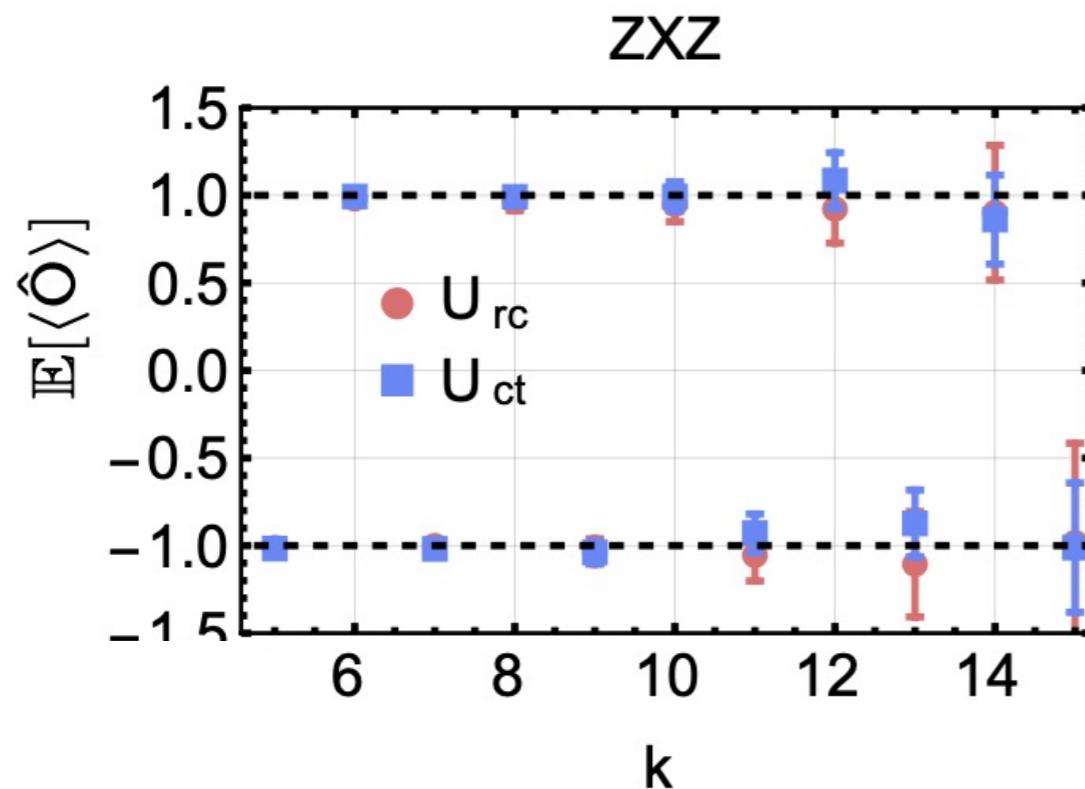
$$\|\hat{O}\|_{\text{ct}}^2 \sim 2 \times 1 \cdot 8^k < \|\hat{O}\|_{\text{rc}}^2 = 2^k + 1$$

Numerical Demonstration

- 1D cluster states (PBC)

$$S = \{Z_i X_{i+1} Z_{i+2}\}$$

Observable $O = Z_1 Y_2 X_3 \dots X_{k-2} Y_{k-1} Z_k \quad \langle O \rangle = (-1)^k$



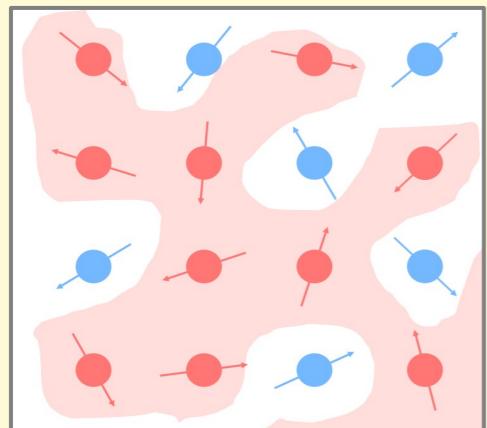
Take Home Message

Summary

Information Scrambling

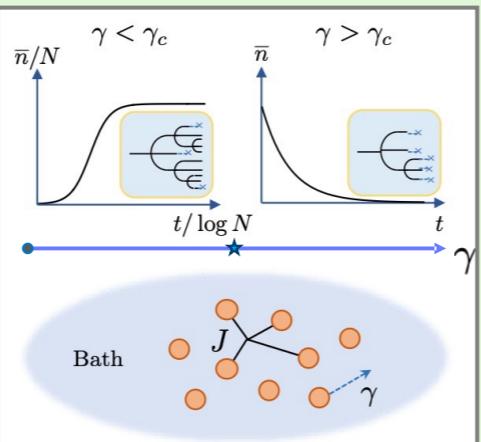
Fundamental Theory

Scramblon Theory



PRL 2024, JHEP 2022

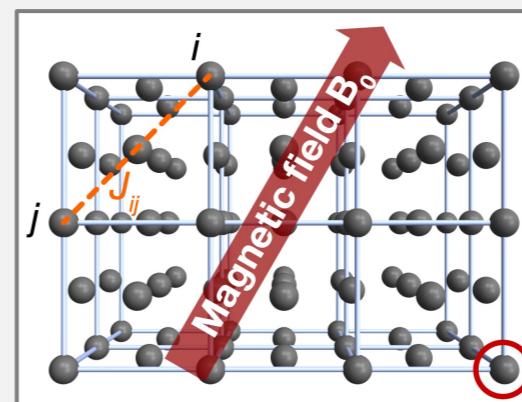
Scrambling Transition



PRL 2023, AAPPS 2024

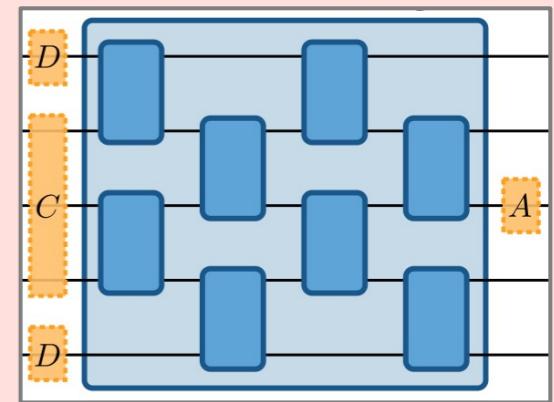
Verification & Application

NMR Dynamics



Nature Physics 2024

Quantum Algorithm



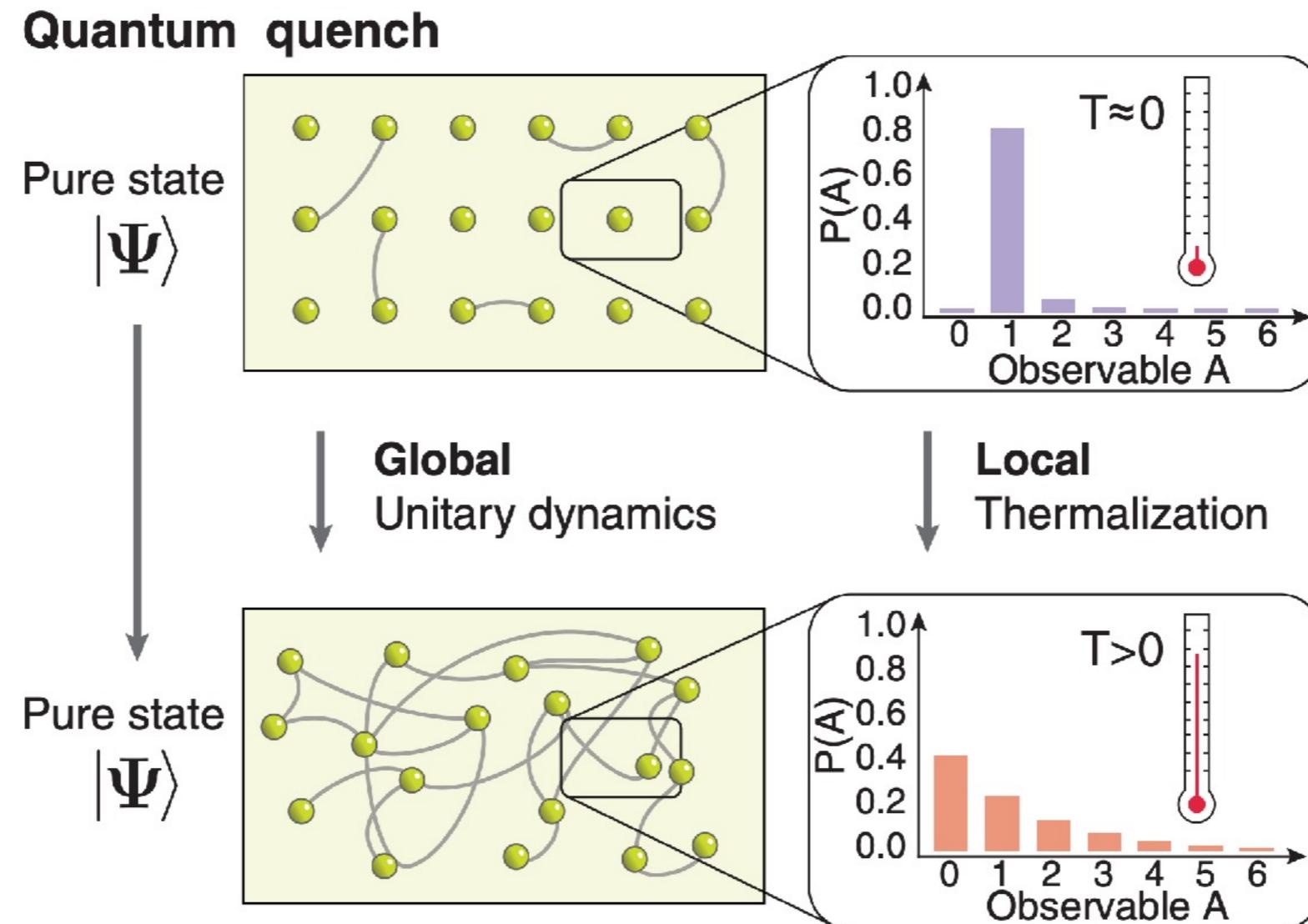
PRL 2024, PRL 2020



Thanks for you attention!

Scrambling & Thermalization

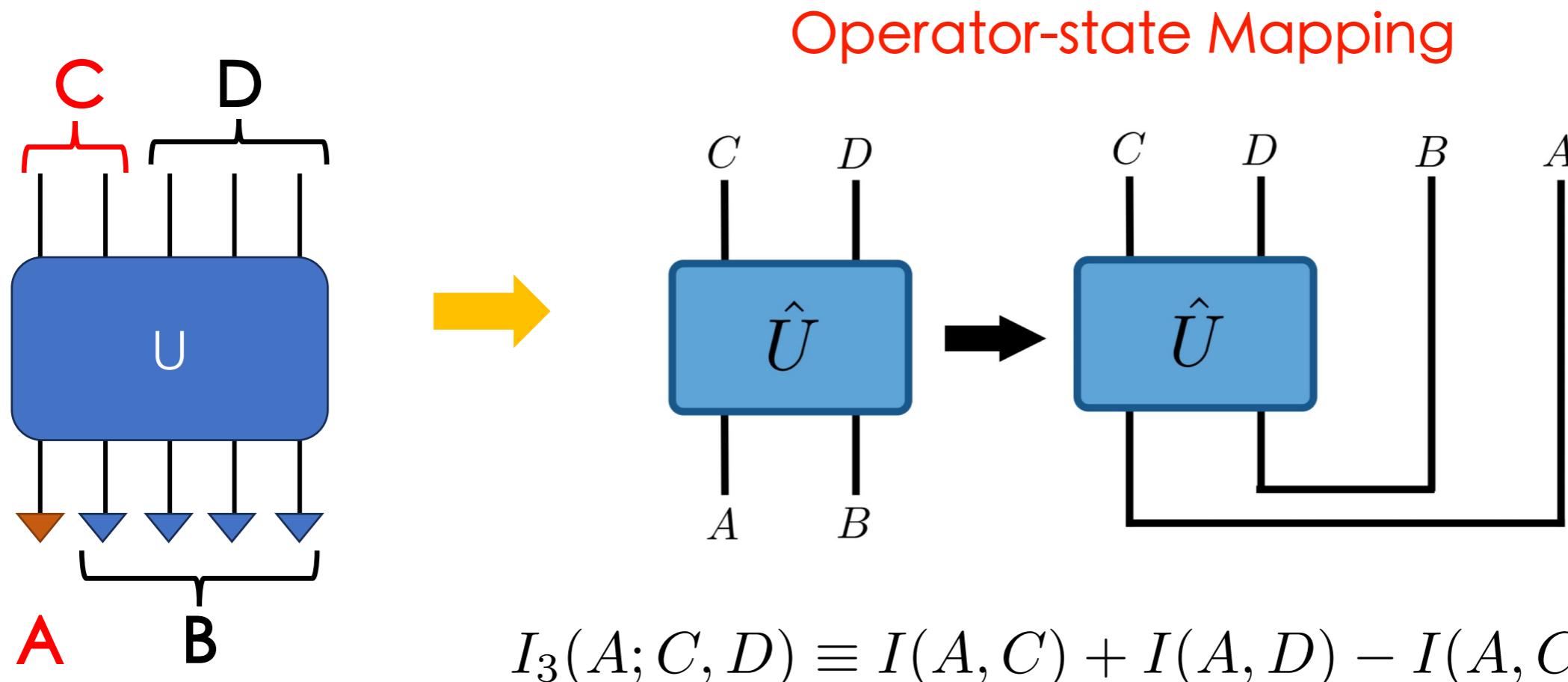
- Closed quantum systems **thermalize!**



A. M. Kaufman et.al. Science, 353, 6301 (2016).

Scrambling & Entropy

- The scrambling is also described by **tripartite information**:



- Haar random unitary

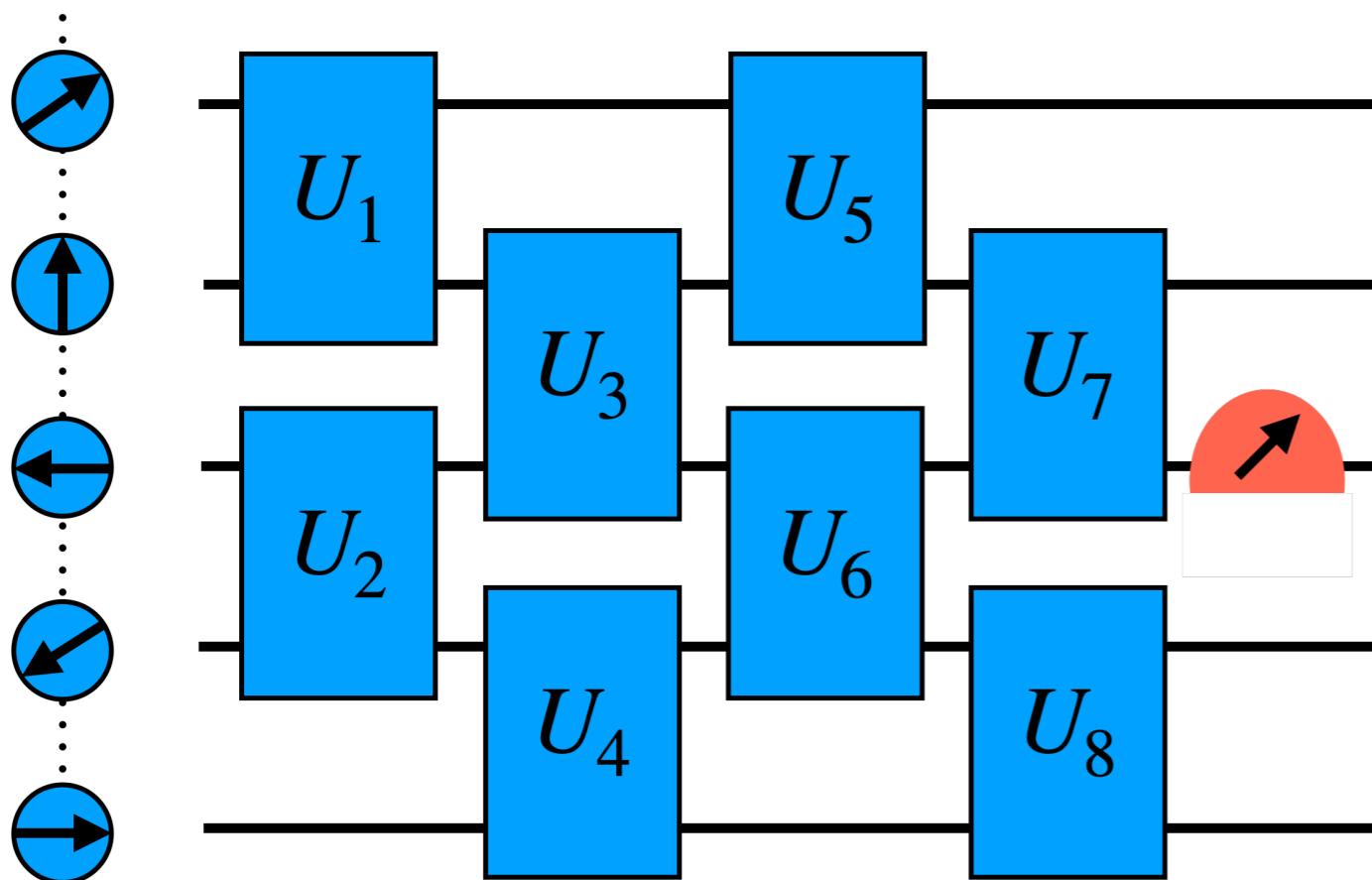
$$I_3(A; C, D) = -2|A|$$

Related to
OTOC/Size

P. Hosur, X.-L. Qi, D. A. Roberts, B. Yoshida, JHEP 2016, 4 (2016).

Quantum Neural Network

- QNN is a **parametrized quantum circuit**:



Other architectures?

$$M_z = \sum \langle \sigma_i^z \rangle / N$$

Output is:

$$\langle G | \prod_i U_i^\dagger \sigma_3^x \prod_i U_i | G \rangle$$

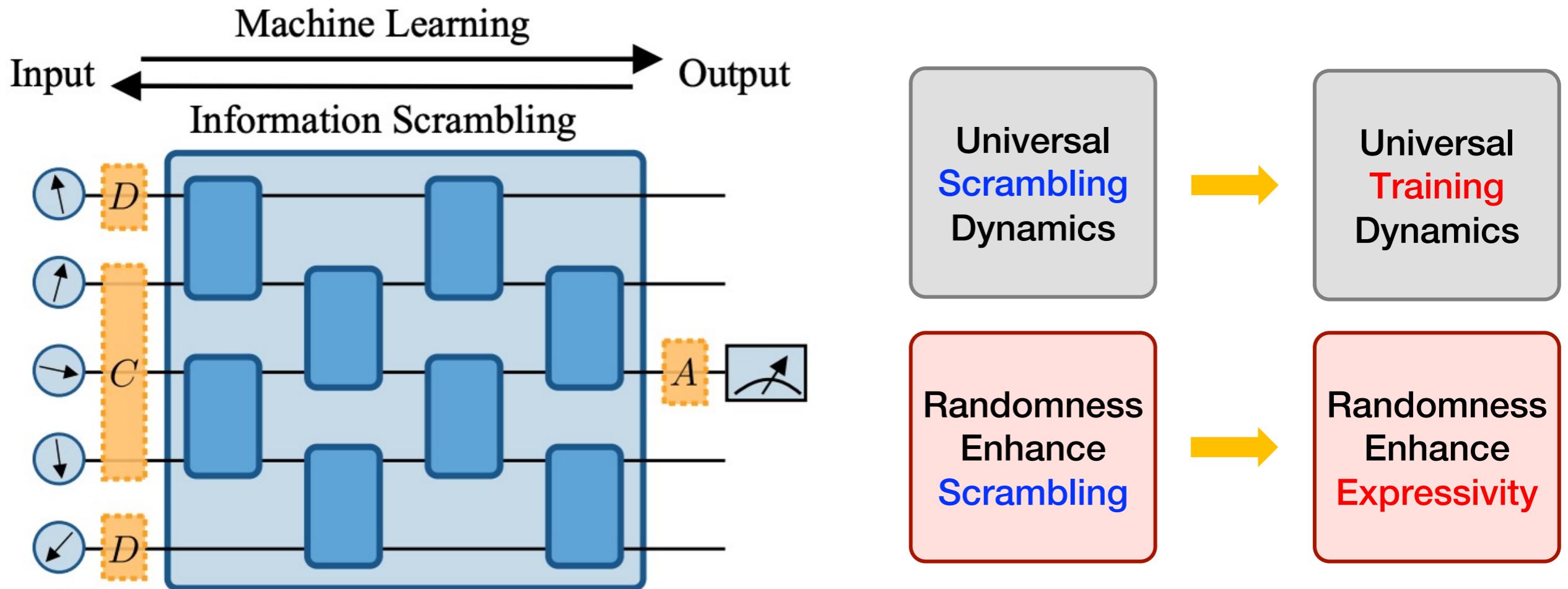
$$U_i = U_i(w_i^j)$$

fitting parameters

$$L = \sum_{\alpha} \left| \langle G^\alpha | \prod_i U_i^\dagger \sigma_3^x \prod_i U_i | G^\alpha \rangle - M_z^\alpha \right|$$

QNN and Information Scrambling

- Learning is the reverse of scrambling:



Y. Wu, J. Yao, PZ^\dagger , and X. Li[†], PRL 132, 010602 (2024).

H. Shen, PZ , Y.-Z. You, and H. Zhai, PRL 124, 200504 (2020).