



Program-Synthesis-Driven Autodesign of Universal Unitary Operators

AI智能体赋能核物理研究研讨会

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2026.07.04 上海



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PART 01

Matrix Decomposition



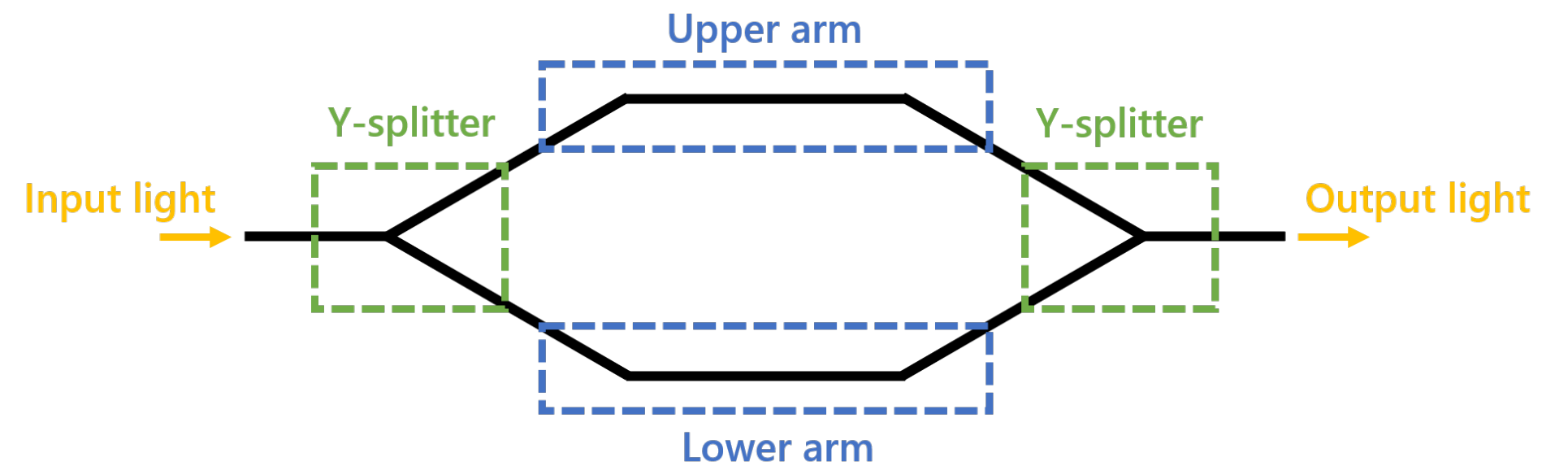
Optical Computing Needs Compact Circuits

Why optical computing?

- Fast matrix operations
- Natural parallelism
- Quantum-compatible hardware

Main bottleneck

- Large unitary matrices need many MZIs
- More MZIs mean more physical cost

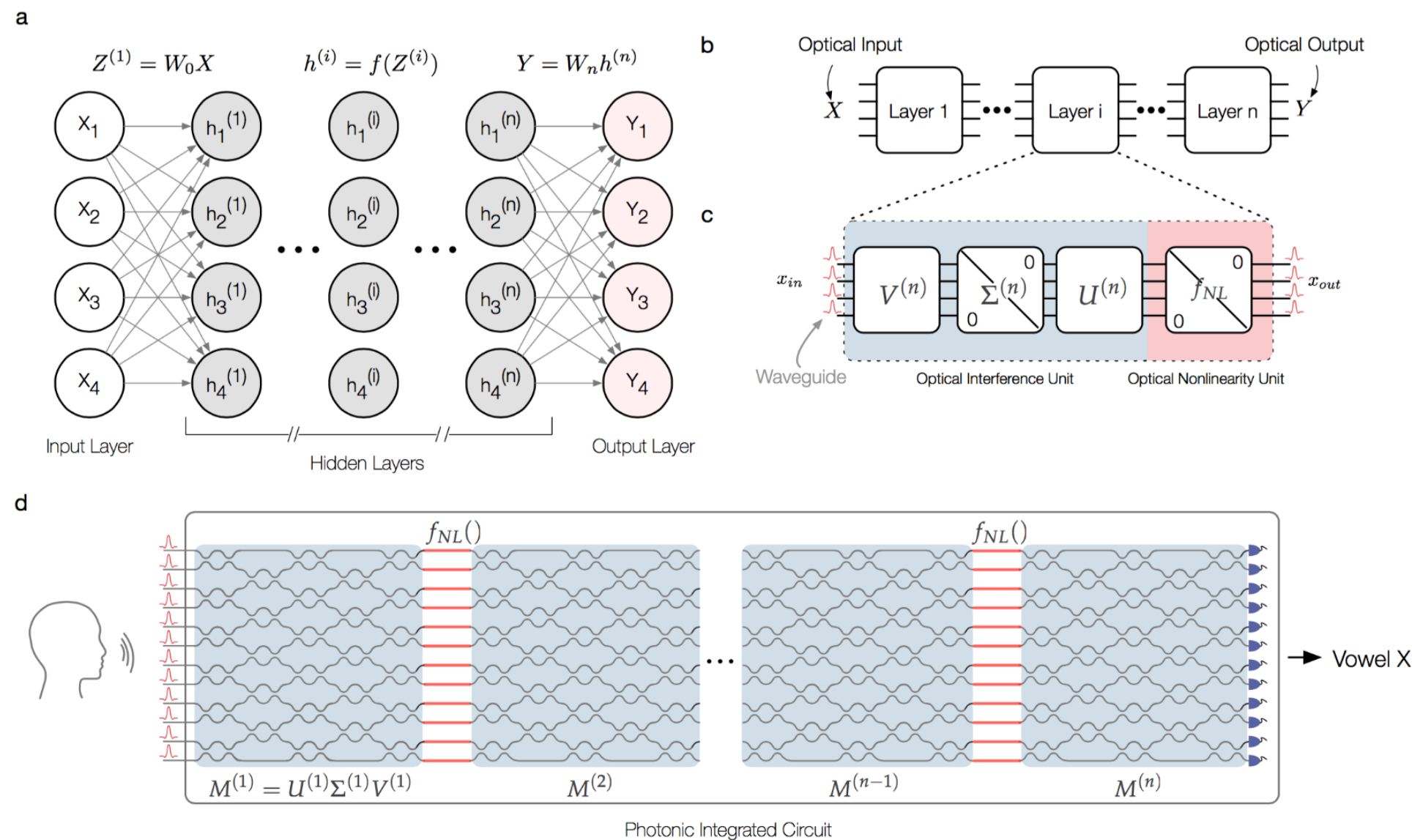


Mach-Zehnder Interferometer

fewer MZIs → smaller chips, lower optical loss, easier calibration



Optical Neural Networks (ONN)



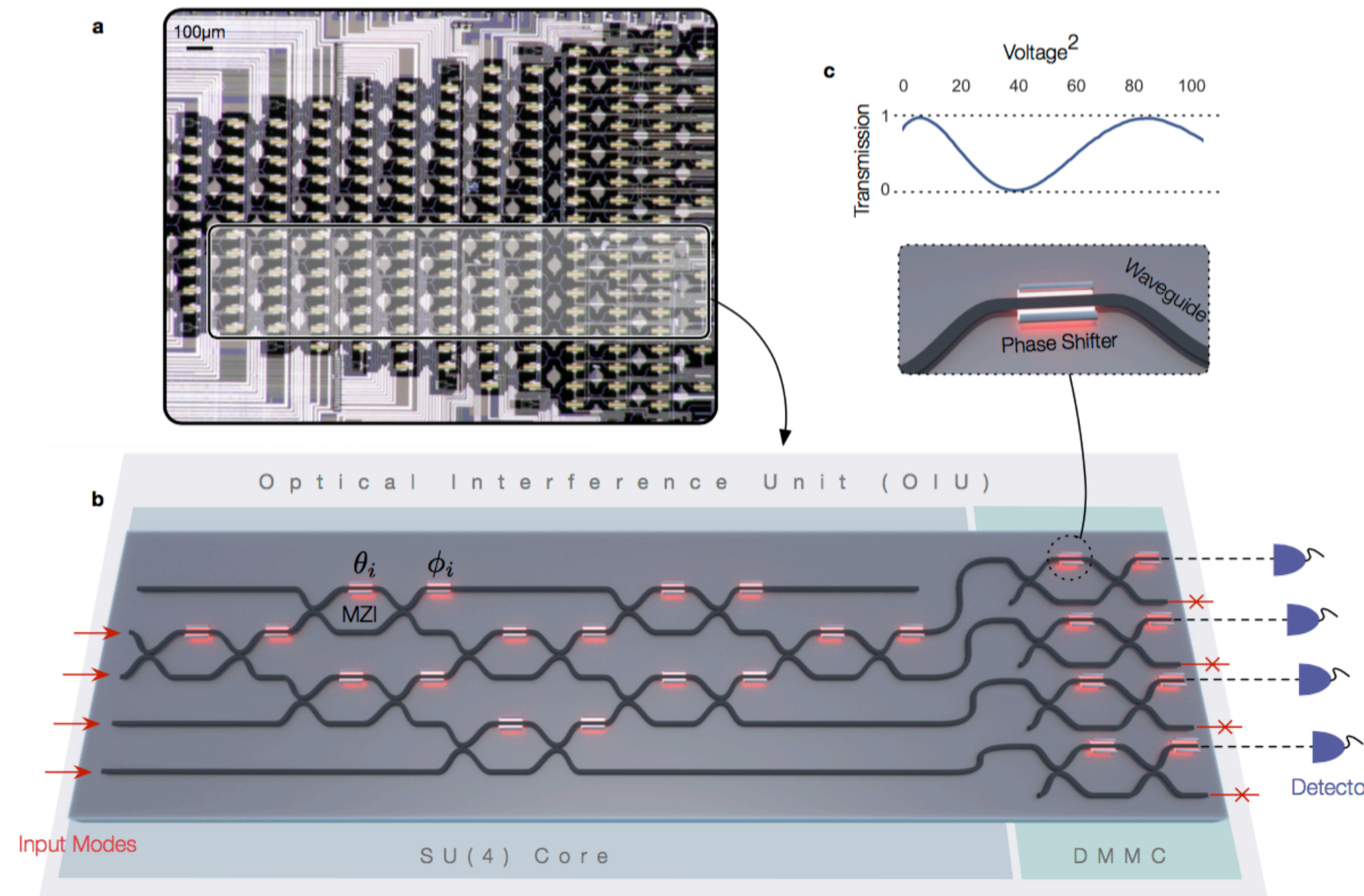
Reck's Theorem (1994)

Any arbitrary unitary matrix can be decomposed into a network of Mach-Zehnder Interferometers (MZIs).

Reck, Michael, et al. *Physical Review Letters* 73.1 (1994): 58–61.



Previous Work



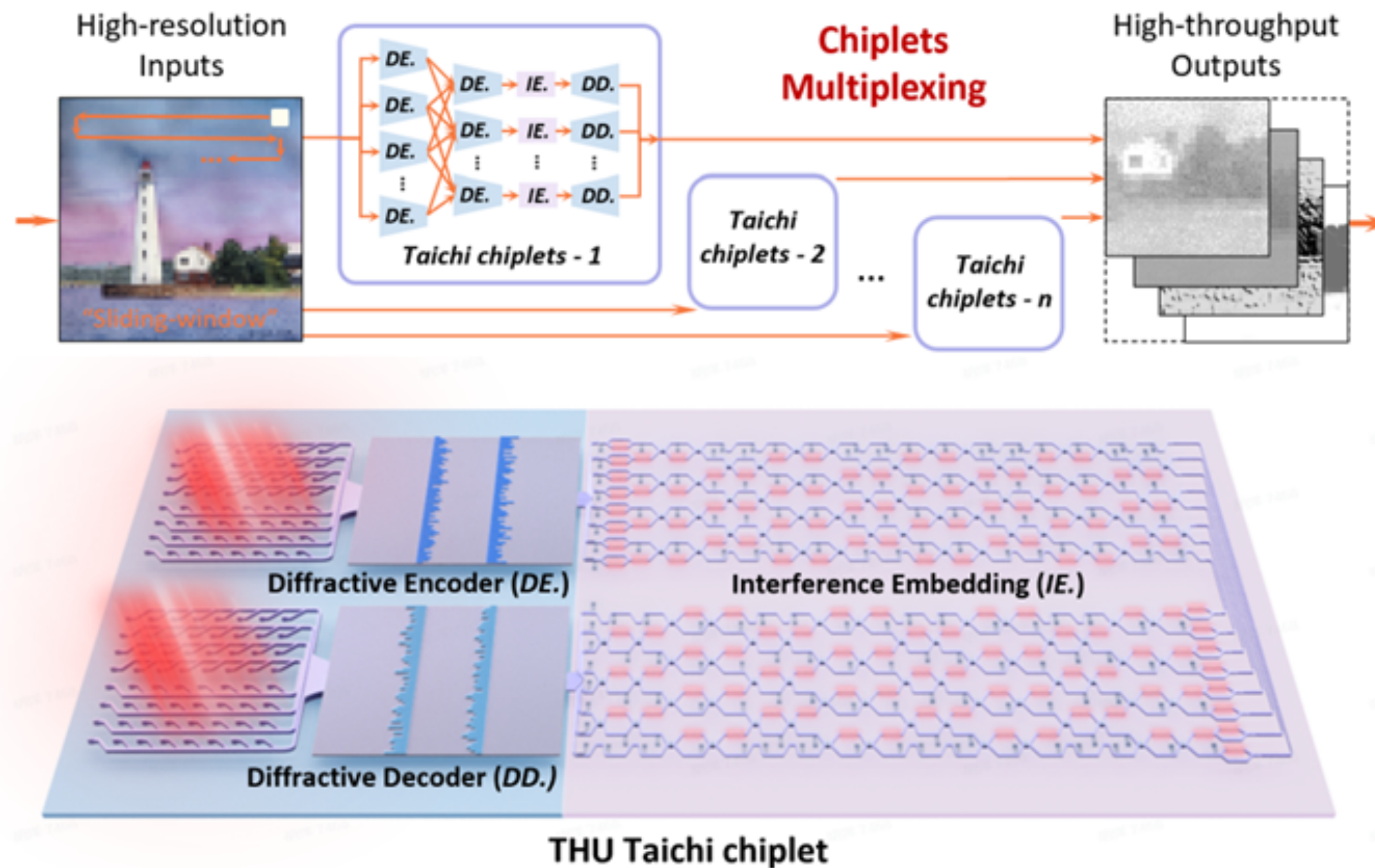
Deep learning with coherent nanophotonic circuits

A 56-MZI nanophotonic processor uses coherent optical interference to perform matrix multiplication for ONN inference.

Shen, Yichen, et al. *Nature Photonics* 11.7 (2017): 441–446.



Previous Work



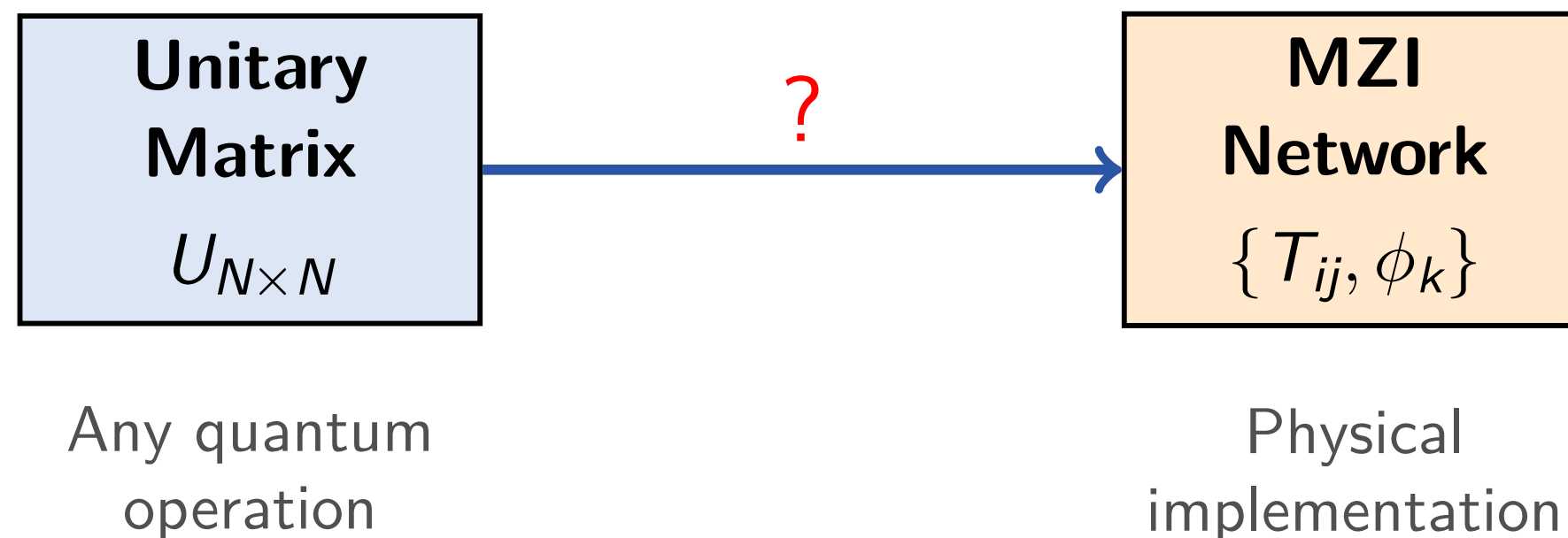
**Large-scale photonic
chiplet Taichi
empowers
160-TOPS/W artificial
general intelligence**

Taichi combines diffractive encoding and interference processing to scale photonic AI from a small mesh to a distributed chiplet system.

Xu, Ziyi, et al. *Science* 384.6692 (2024): 202–209.



Matrix Decomposition: Core Challenge



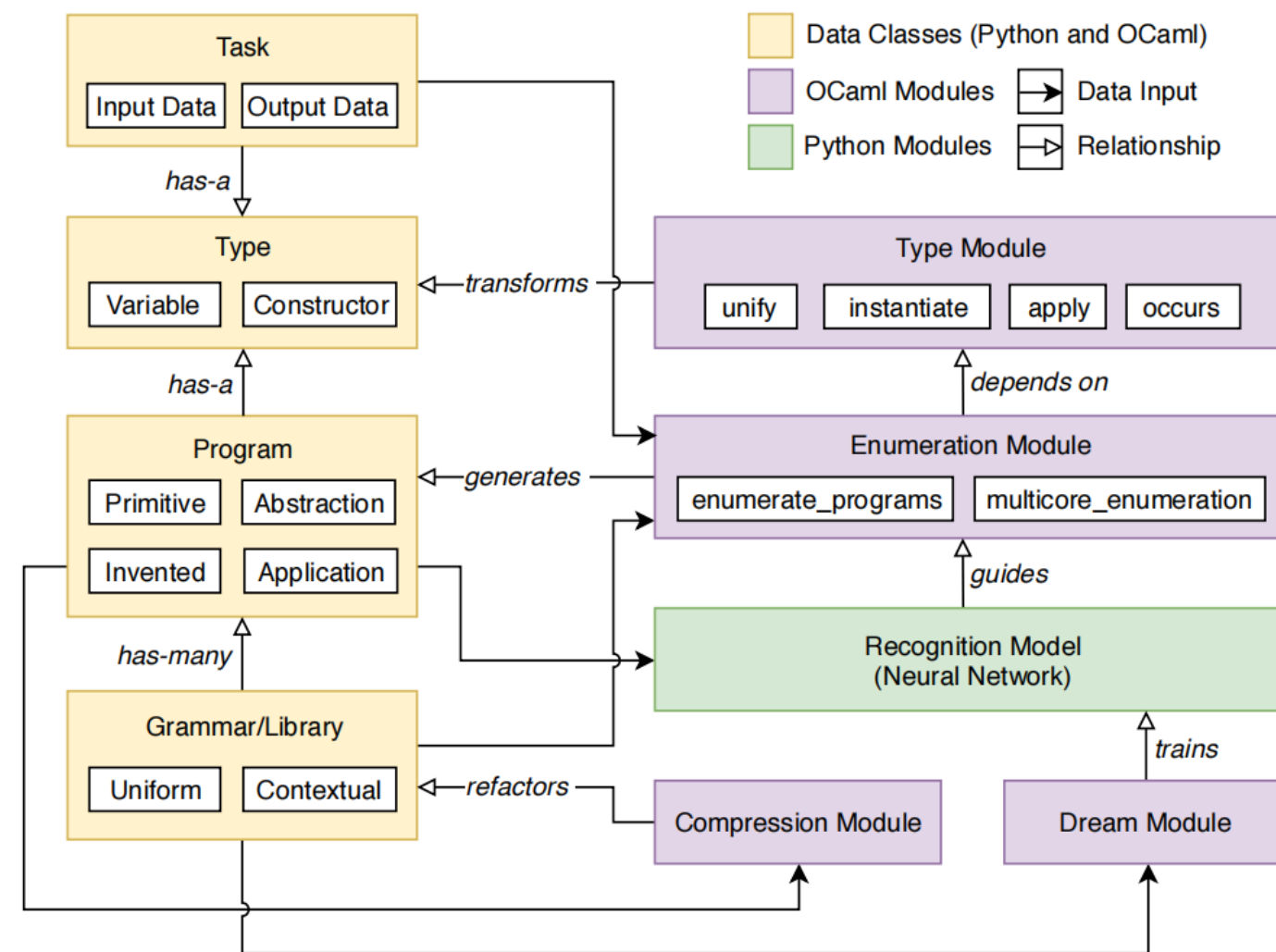
Classical universal schemes:

- Reck / Clements give fixed patterns
- Designed for worst-case dense unitaries
- Hard to exploit sparse or structured matrices

$$G_{tij} = \begin{bmatrix} 1 & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 1 & 0 & 0 & \dots & 0 \\ 0 & \dots & 0 & e^{-i\theta} \cos \omega & e^{-i\theta} \sin \omega & \dots & 0 \\ 0 & \dots & 0 & -\sin \omega & \cos \omega & \dots & 0 \\ 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 0 & 0 & \dots & 1 \end{bmatrix}$$



Our Approach: Program Synthesis



DreamCoder Framework

Wake-Sleep Learning:

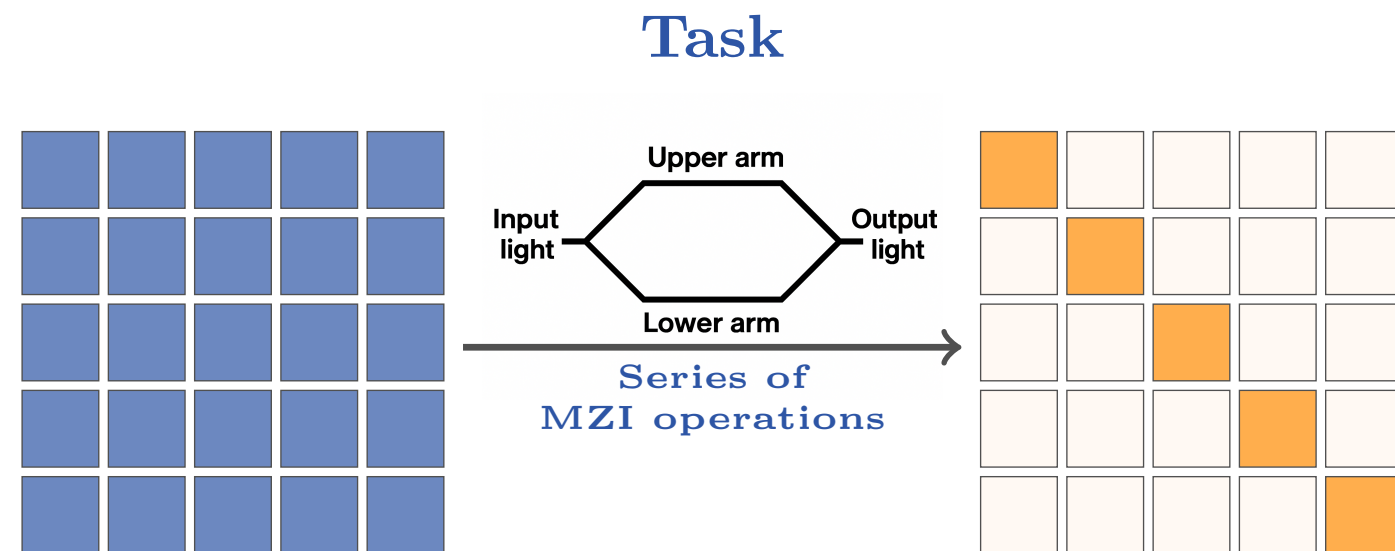
- Wake: search for valid MZI programs
- Sleep: identify recurring sub-sequences
- Abstract: add them as reusable primitives

What it learns:

1. How to decompose general unitaries
2. How to scale rules to larger matrices
3. How to use structure to save MZIs

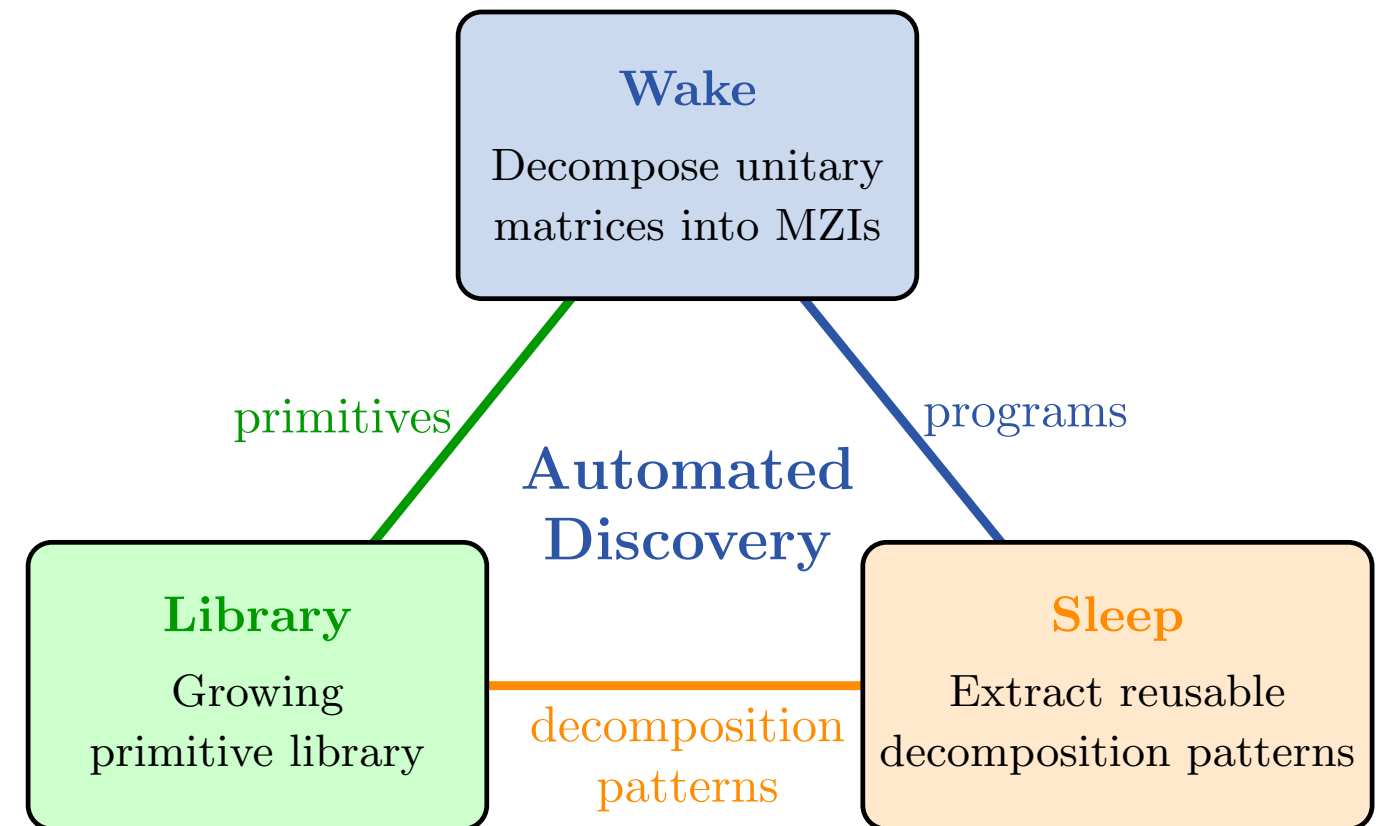


Program Synthesis: Task and Discovery Loop



Unitary → diagonal
through a sequence of MZI operations

search programs → extract patterns → grow the MZI library



Wake–sleep learning
successful programs become reusable
primitives



Task Formulation

Input-Output Examples

$$T = \{(U_k, D_k)\}_{k=1}^N$$

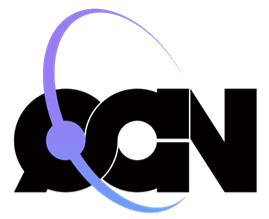
- U_k : Random unitary matrix
- D_k : Diagonal target
- Find program p : $p(U_k) \approx D_k$

Independent Learning:

- No classical hints
- Discover from scratch
- Find new elimination orders

Curriculum Learning:

- Start from easier subtasks
- Grow reusable library
- Scale to deeper programs



MZI Primitive Operations

Primitive Library:

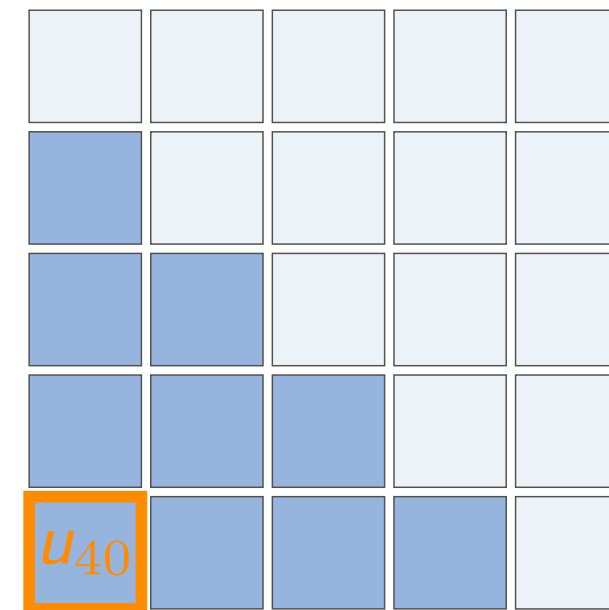
For $N \times N$ matrix:

$$\{t_{ij}, f_{ij}\}$$

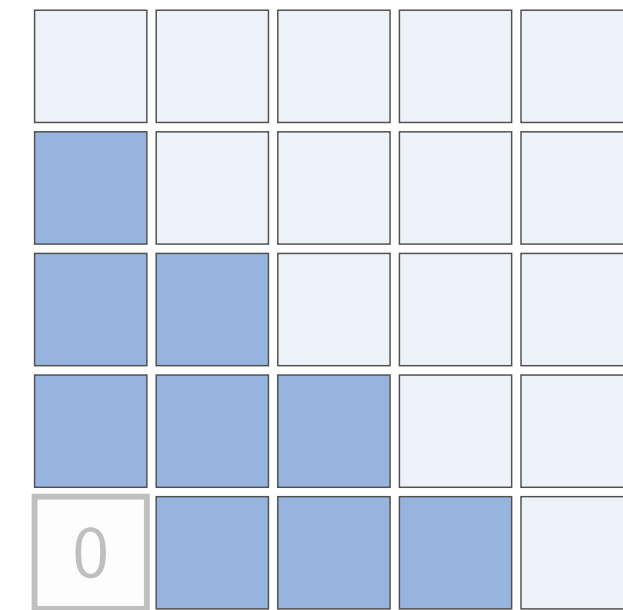
where $i > j$

$$M_t = \begin{pmatrix} e^{-i\theta} \cos \omega & e^{-i\theta} \sin \omega \\ -\sin \omega & \cos \omega \end{pmatrix}$$

$$M_f = \begin{pmatrix} e^{i\theta} \cos \omega & -\sin \omega \\ e^{i\theta} \sin \omega & \cos \omega \end{pmatrix}$$



nullify
→





Independent Learning: 5×5 Matrices

Configuration:

- Step 0 task
- No curriculum
- 9 iterations

Best Program:

- $f_{40}, t_{41}, t_{42}, t_{43}$
- t_{30}, t_{31}, t_{32}
- t_{20}, t_{21}, t_{10}

10 operations = optimal

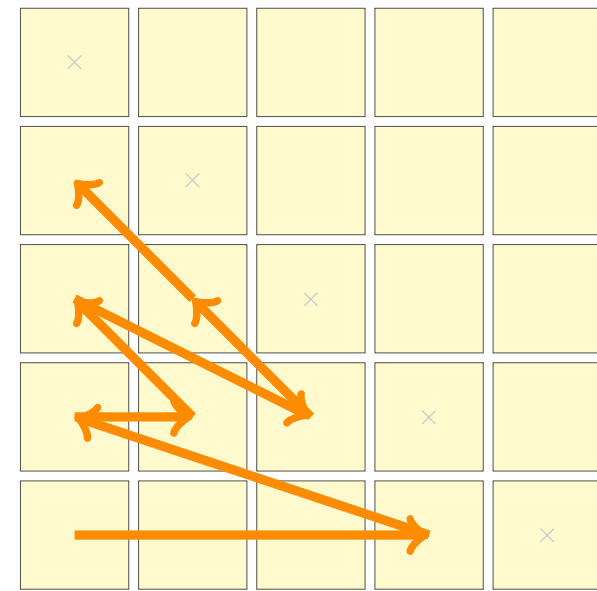
10				
8	9			
5	6	7		
1	2	3	4	

Bottom-up elimination

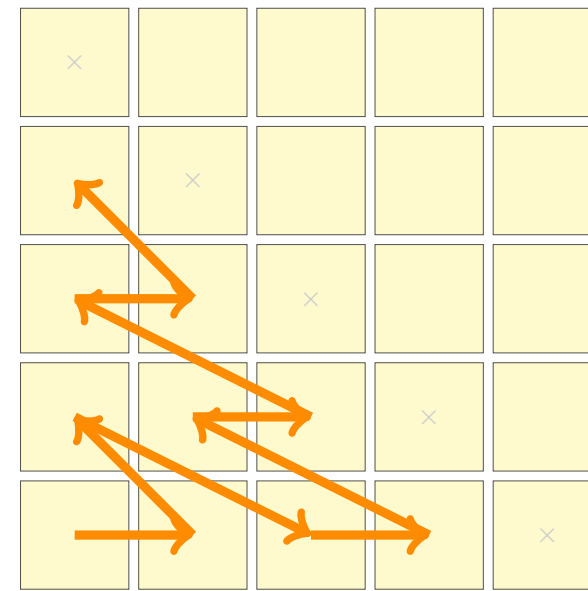
System learned systematic elimination!



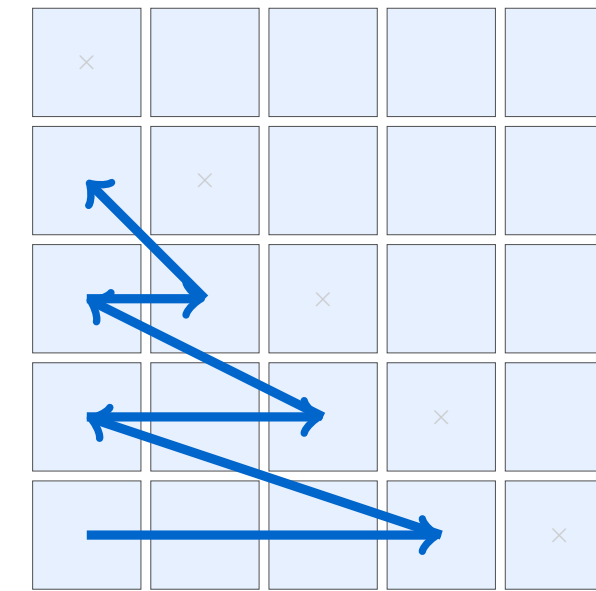
Discovered Patterns: Beyond Reck and Clements



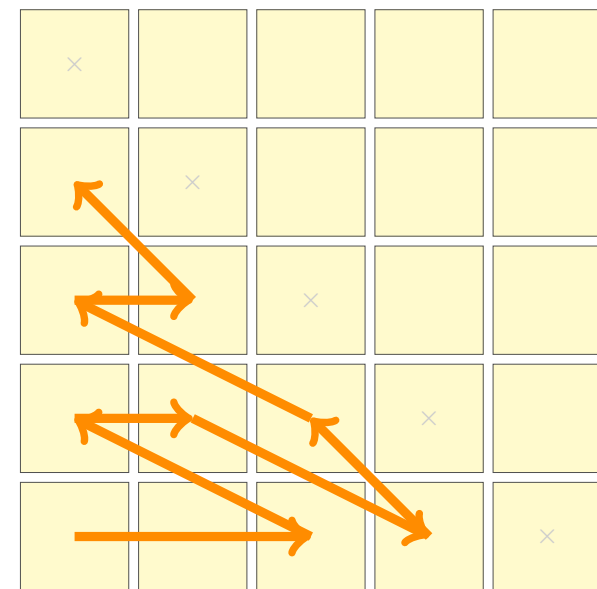
Pattern 1



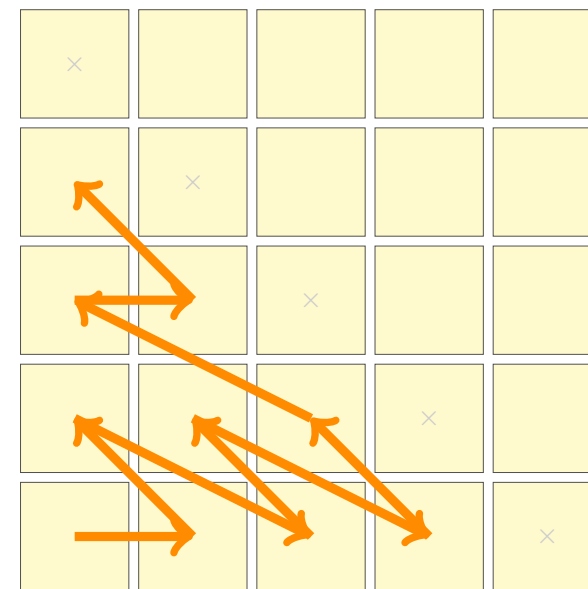
Pattern 2



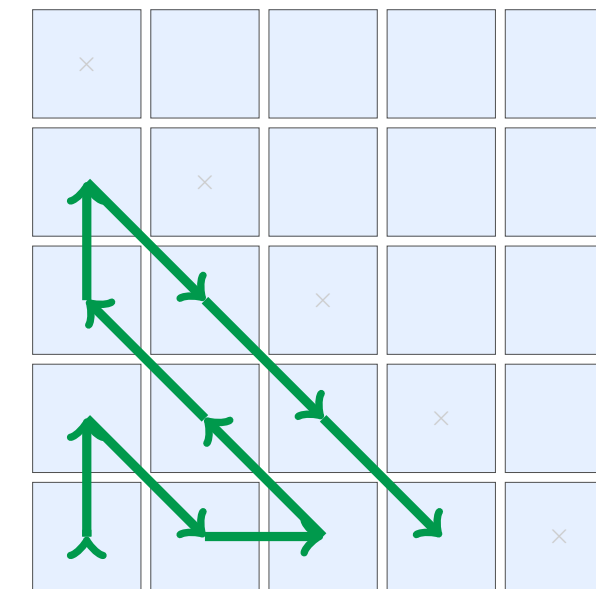
Reck



Pattern 3



Pattern 4



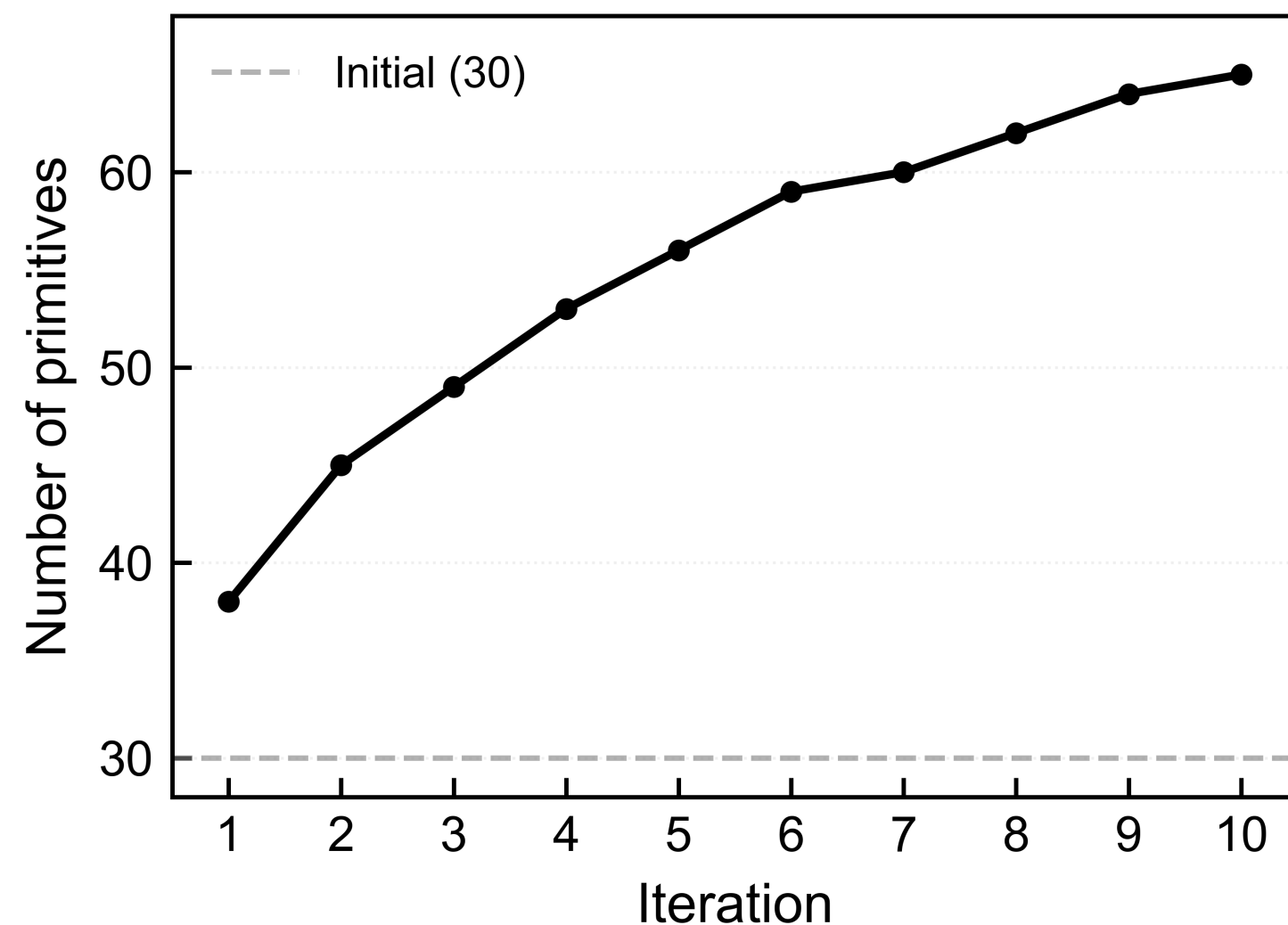
Clements

AI-discovered optimal orders
beyond classical Reck/Clements meshes



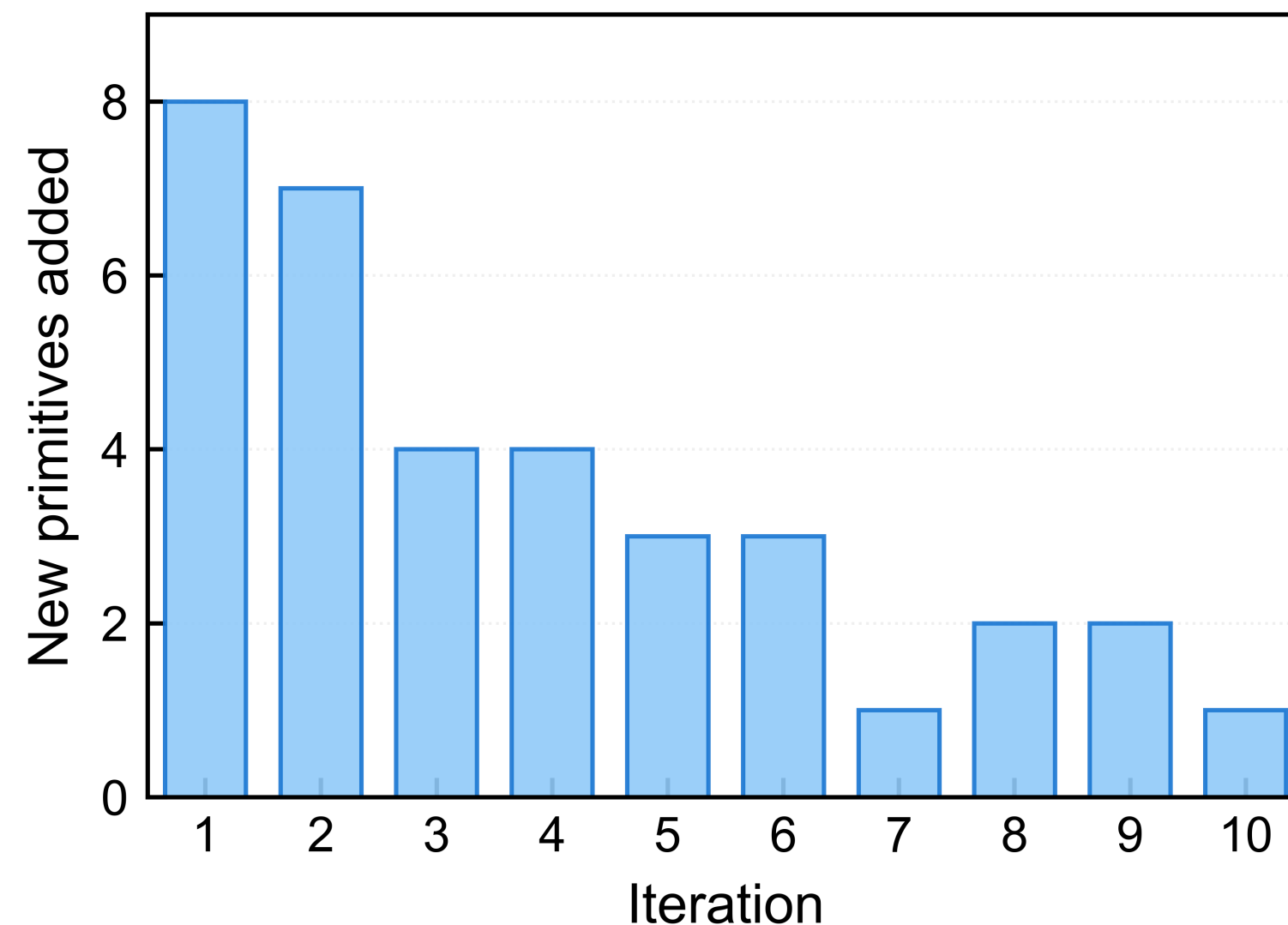
Curriculum Learning: 6×6 Matrices

Library Growth:



Start: 30 primitives
End: 65 primitives

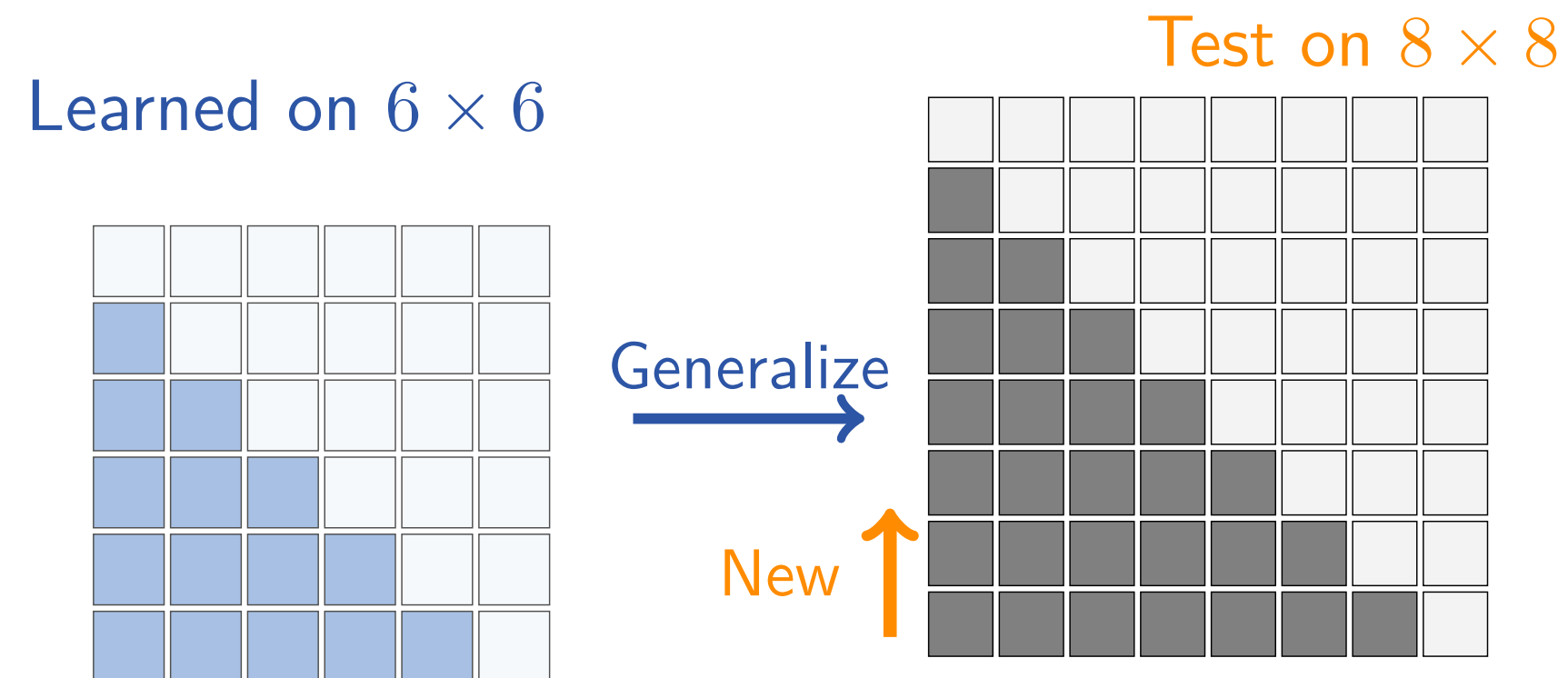
Delta per Iteration:



- Early: rapid growth
- Later: stabilization

In production, PRL

Learned Pattern: Bottom-to-top, left-to-right



✓ Verification passed! Off-diagonal residual scale $\sim 10^{-16}$

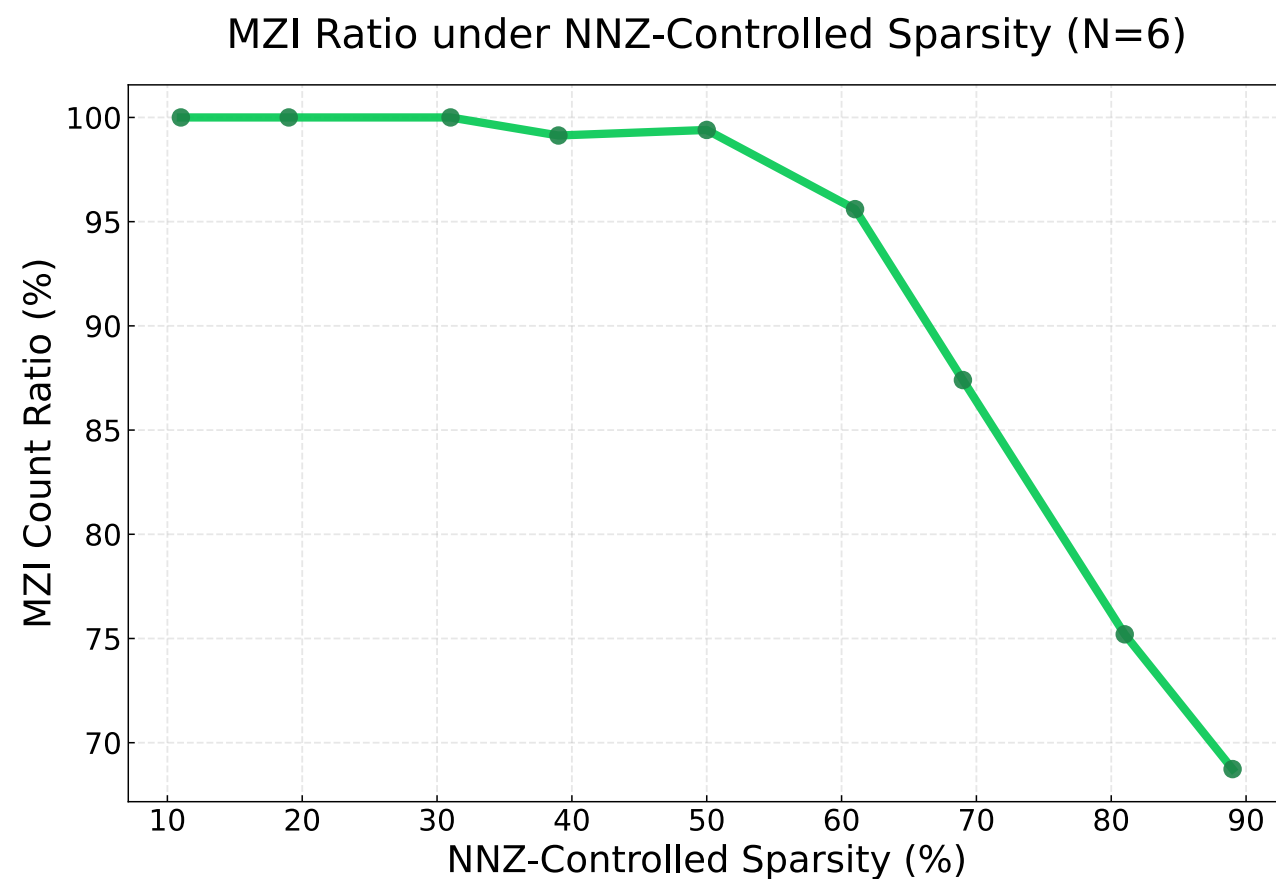


Sparse Matrix Families

In production, PRL

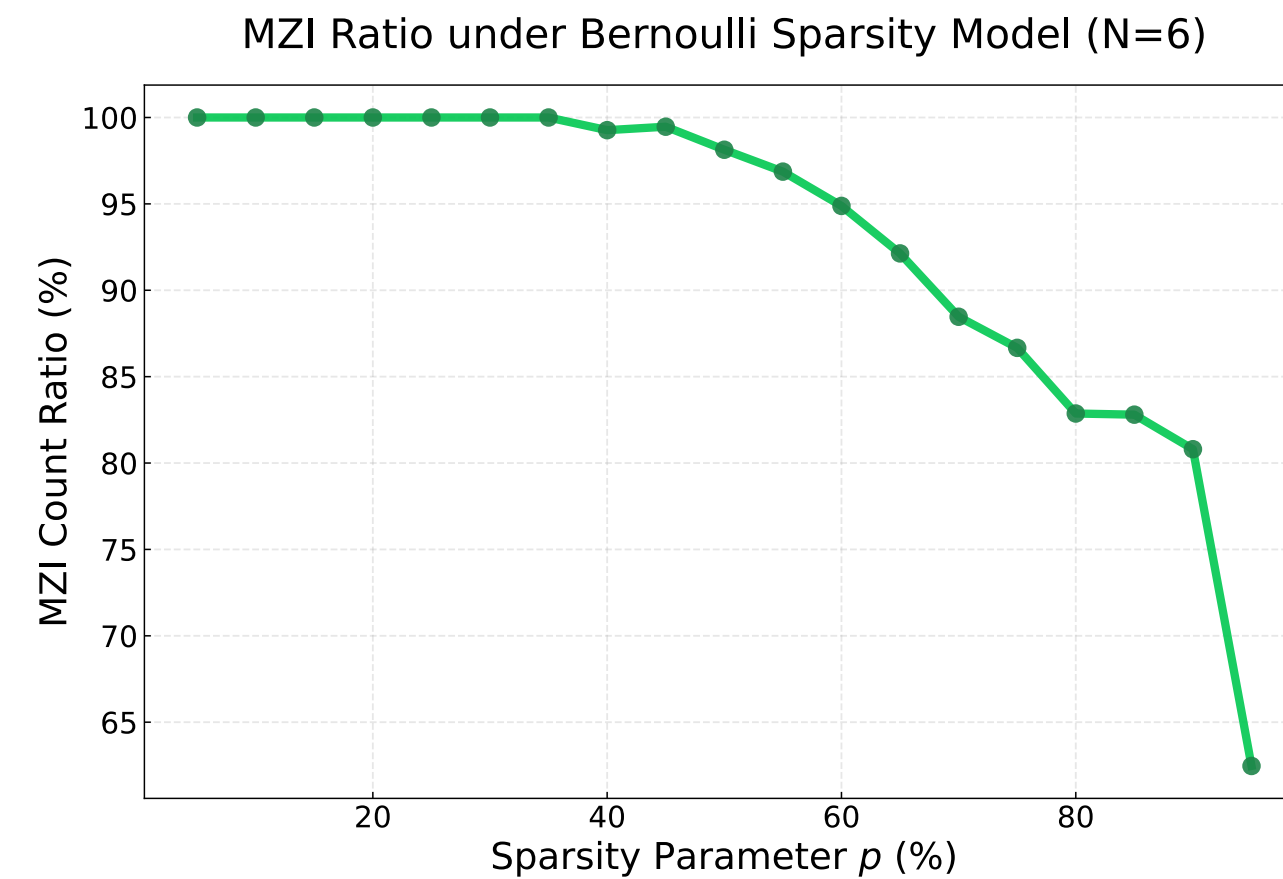
Sparse structure reduces required MZI operations.

NNZ-Controlled Sparsity



31% fewer MZIs

Bernoulli Sparsity



38% fewer MZIs

Both sparse families are verified by execution and show reduced MZI counts at high sparsity.

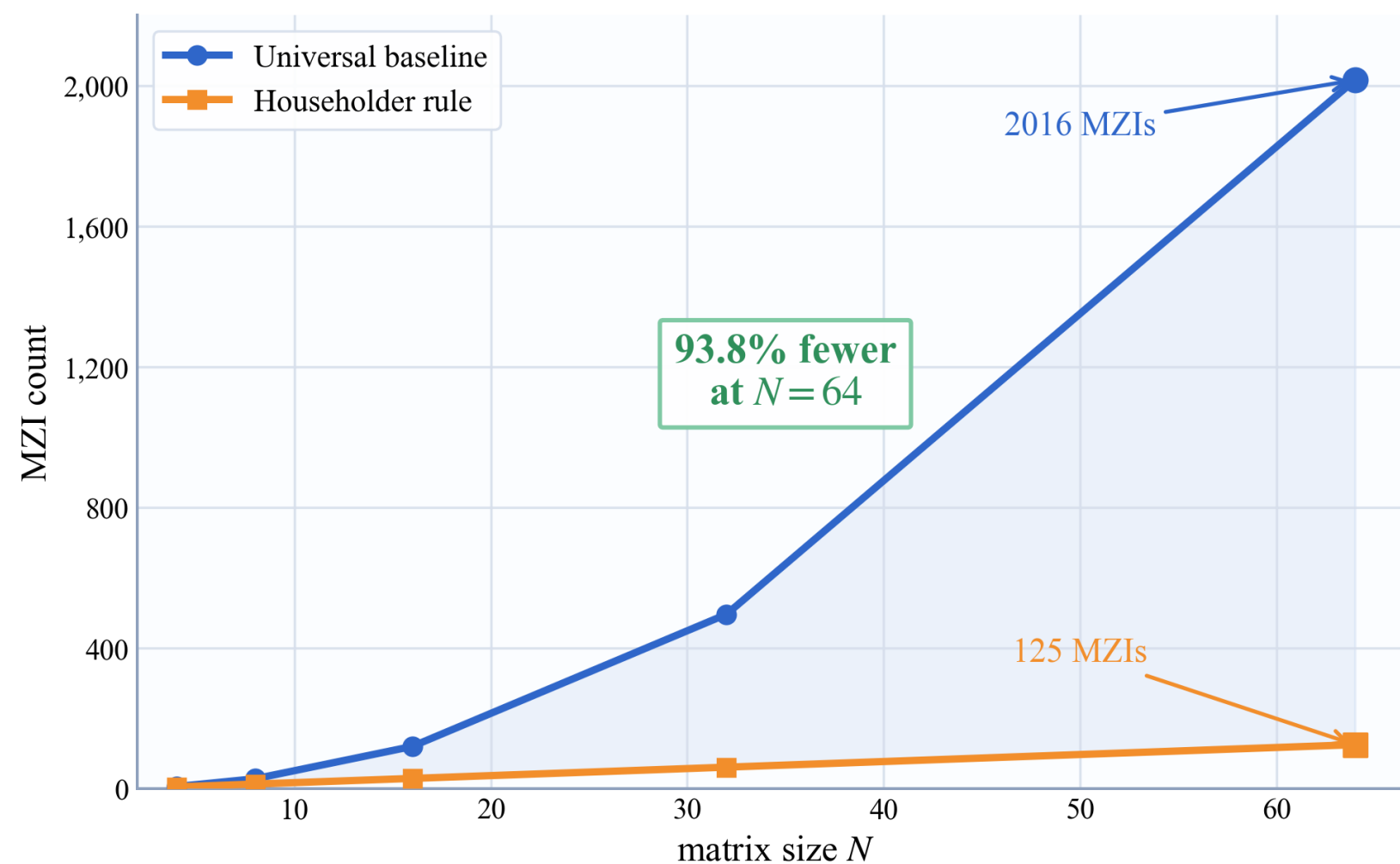


Structured Optimization: Householder Family

In production, PRL

Example: Householder reflector family

$$H = I - 2vv^H$$



Discovered structure-aware rule

$$2N - 3$$

MZIs for Householder

At $N = 64$

93.8%
fewer MZIs than dense
universal decomposition

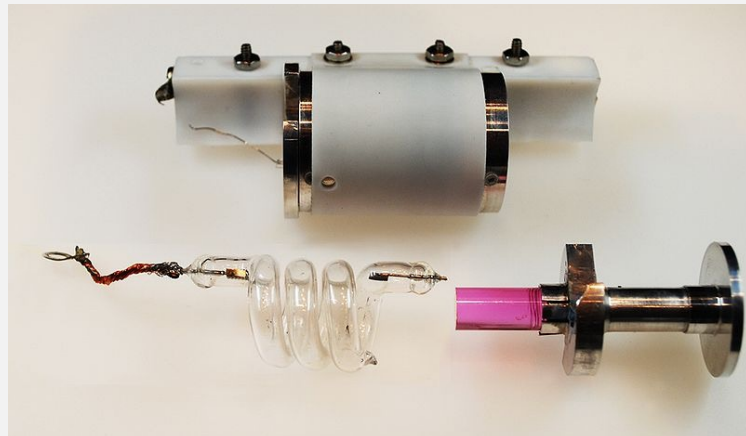
PART 02

Spectral Deconvolution

Quantum Control of Nuclei

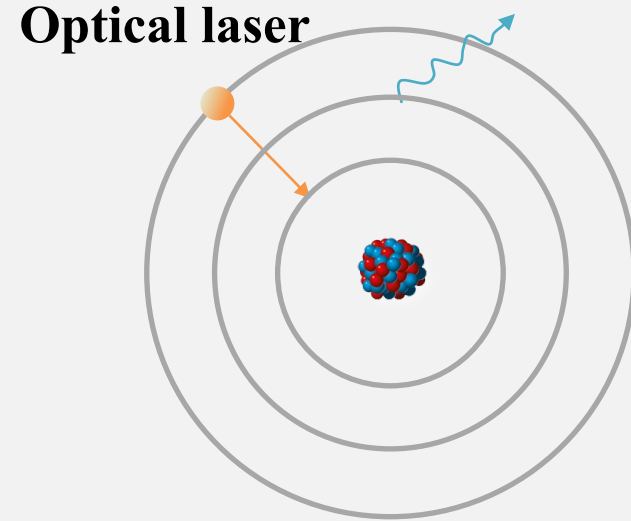
From optical-electron systems to x-ray nuclei systems

The first quantum revolution



1960s, the first laser

Optical laser



Optical laser

+

Electron

Quantum metrology

Quantum simulation

Quantum computing

Quantum communication

The second quantum revolution

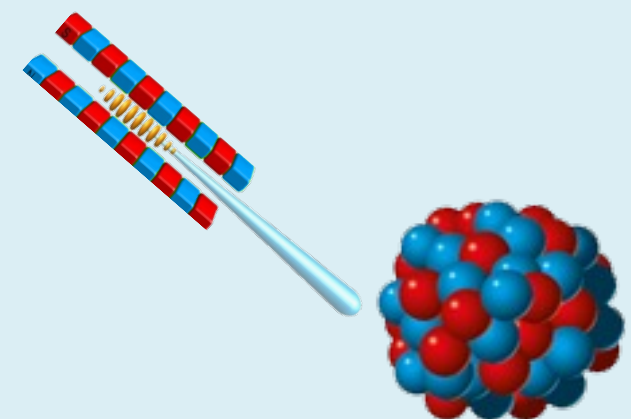


51-bit quantum simulator
Lukin's group



X-ray sources in Shanghai

X-ray



Excitation of nuclei

X-ray sources

+

Nuclei

Why x-ray?

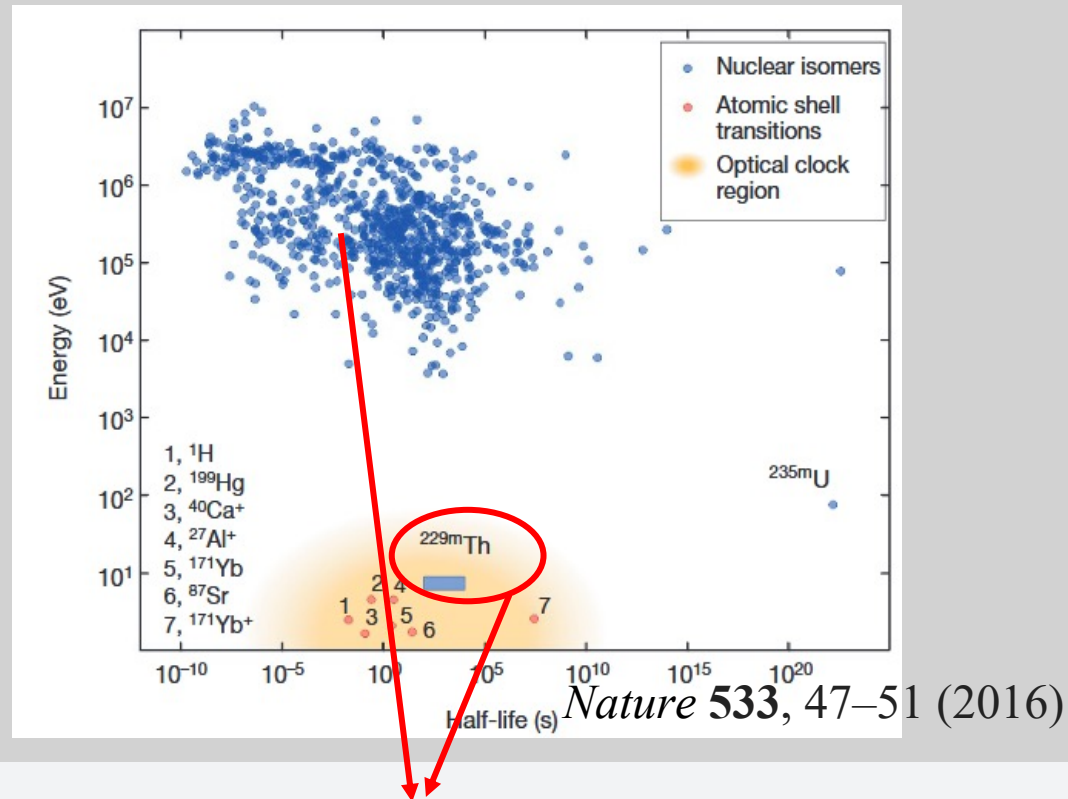
- ✓ More robust
- ✓ Better detection efficiency
- ✓ Better focus

Why nuclei?

- ✓ High-quality transitions
- ✓ Isomer to store energy
- ✓ Room-temperature experiment

Quantum Control of Nuclei

Next-generation quantum technologies ?



Nuclear clocks hold promise as next-generation high-precision metrological tools

Nuclear Clock Candidates:

^{229}Th (VUV) and ^{45}Sc (X-ray)

Article

Resonant X-ray excitation of the nuclear clock isomer ^{45}Sc

<https://doi.org/10.1038/s41586-023-06491-w>

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Check for updates

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Nature, 622, 471(2023)

Direct Laser Excitation of ^{229}Th (PTB & JILA, 2024)



Quantum control of nuclei (QCN) using novel X-ray sources

Novel X-ray sources + Nuclei = New quantum technologies/devices ?

- ① Quantum Information:
Room-temperature X-
ray nuclear simulators?



Quantum Simulator Concept

- ② Navigation & Timing:
More precise nuclear
clocks?



Nuclear Clock Concept

- ③ Energy & Aerospace:
High energy-density
nuclear batteries?



Nuclear Battery Concept

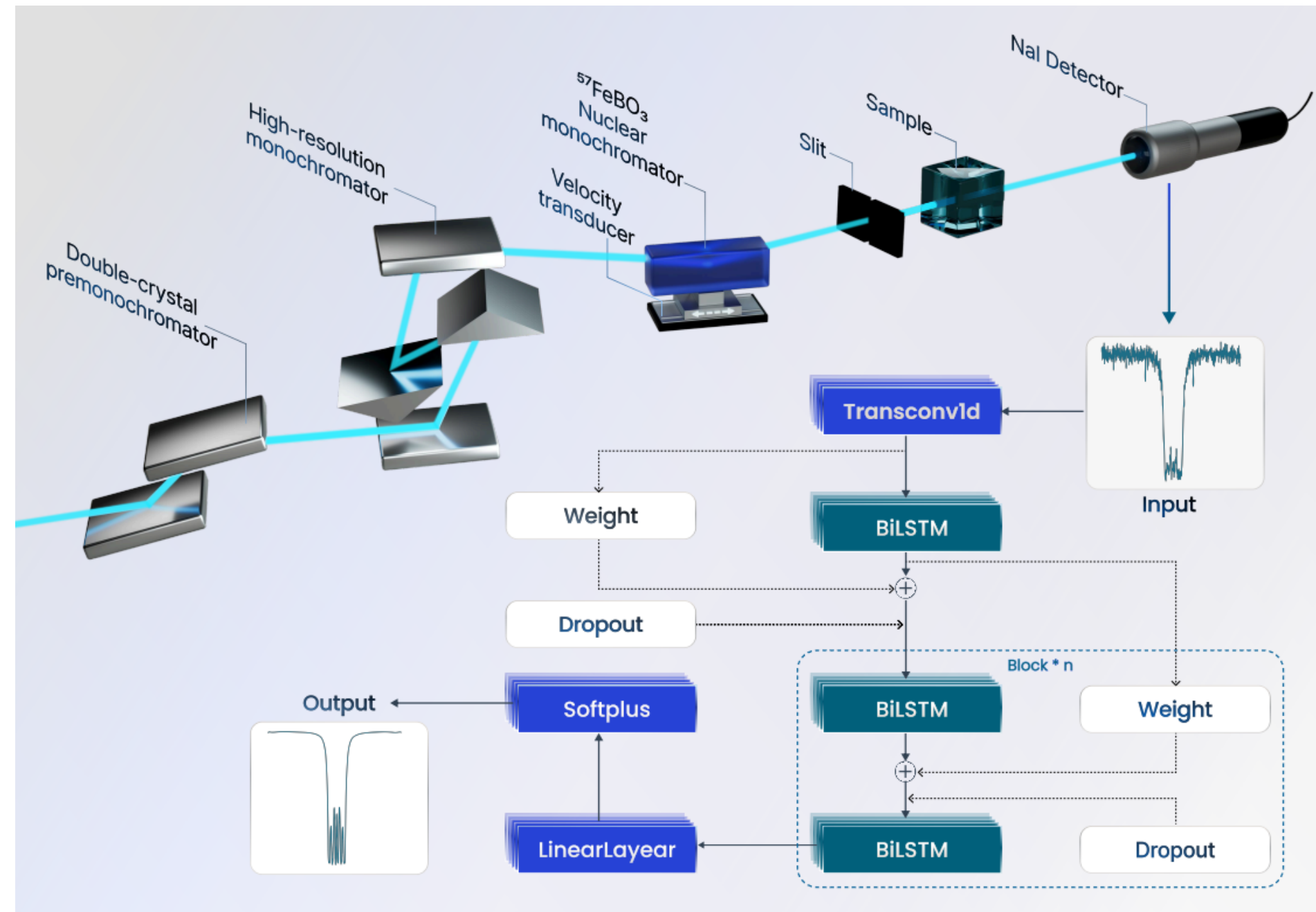
- ④ Fundamental Science:
Dark matter detection
with X-ray nuclei?



Dark Matter Concept



AI-Based Deconvolution: Key Advantages



1. Break trade-off broader linewidth $\rightarrow$ higher intensity

2. Resolution-adaptive reliable across different SMS linewidths

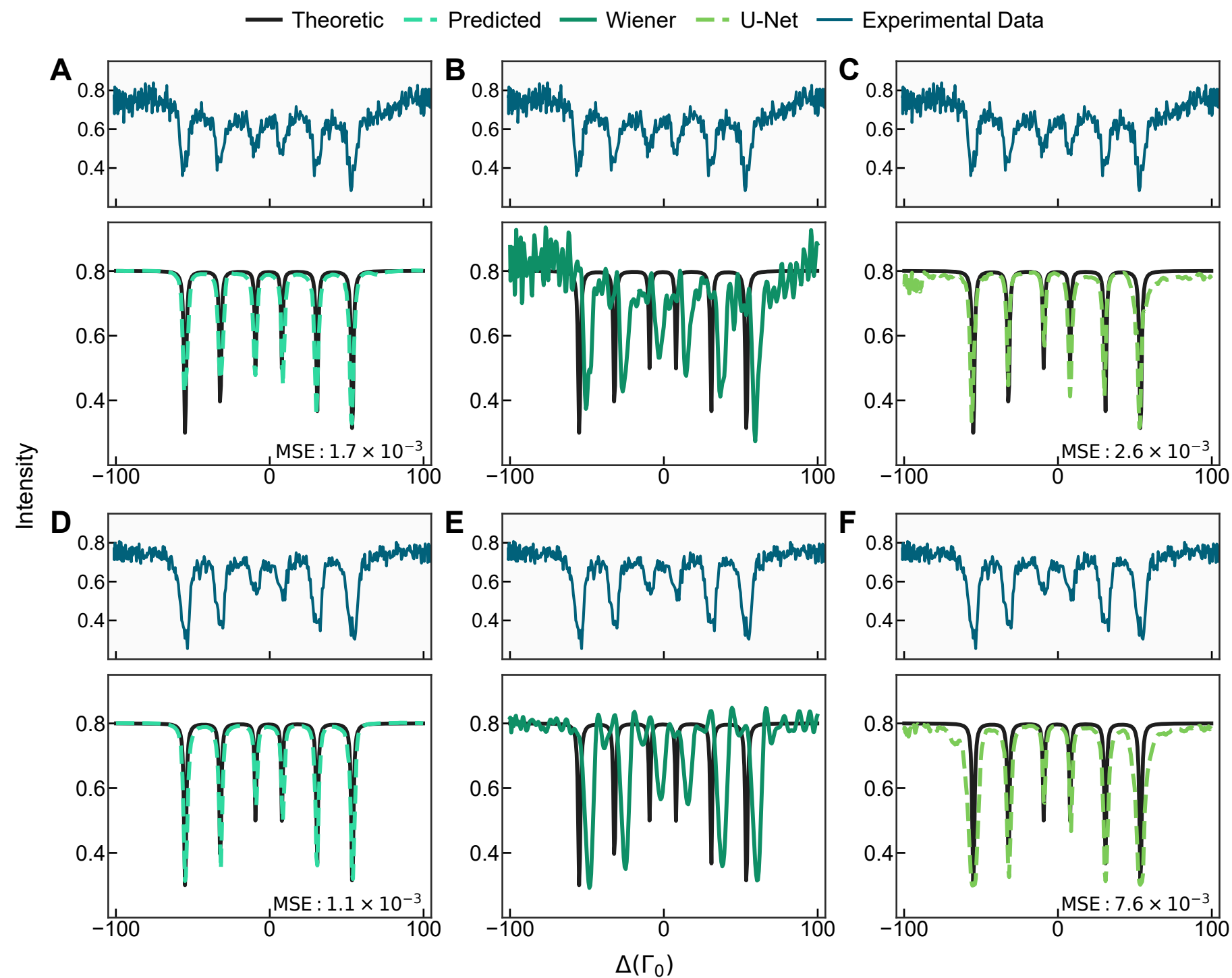
3. Noise-robust trained with mixed noise statistics

Architecture:

TransConv1d $\rightarrow$ BiLSTM $\rightarrow$ weighted residuals



Deconvolution Results: Experimental Validation

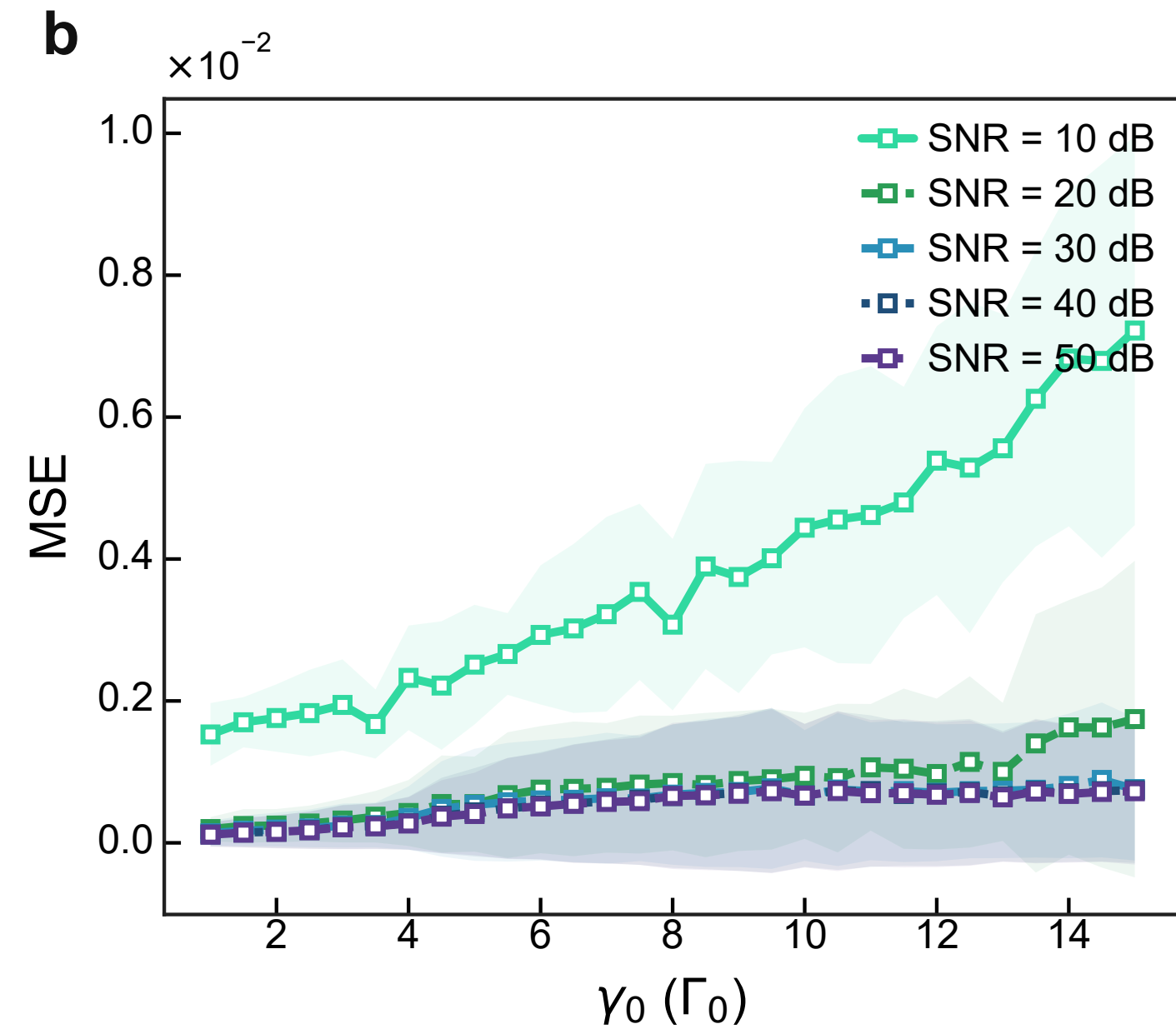
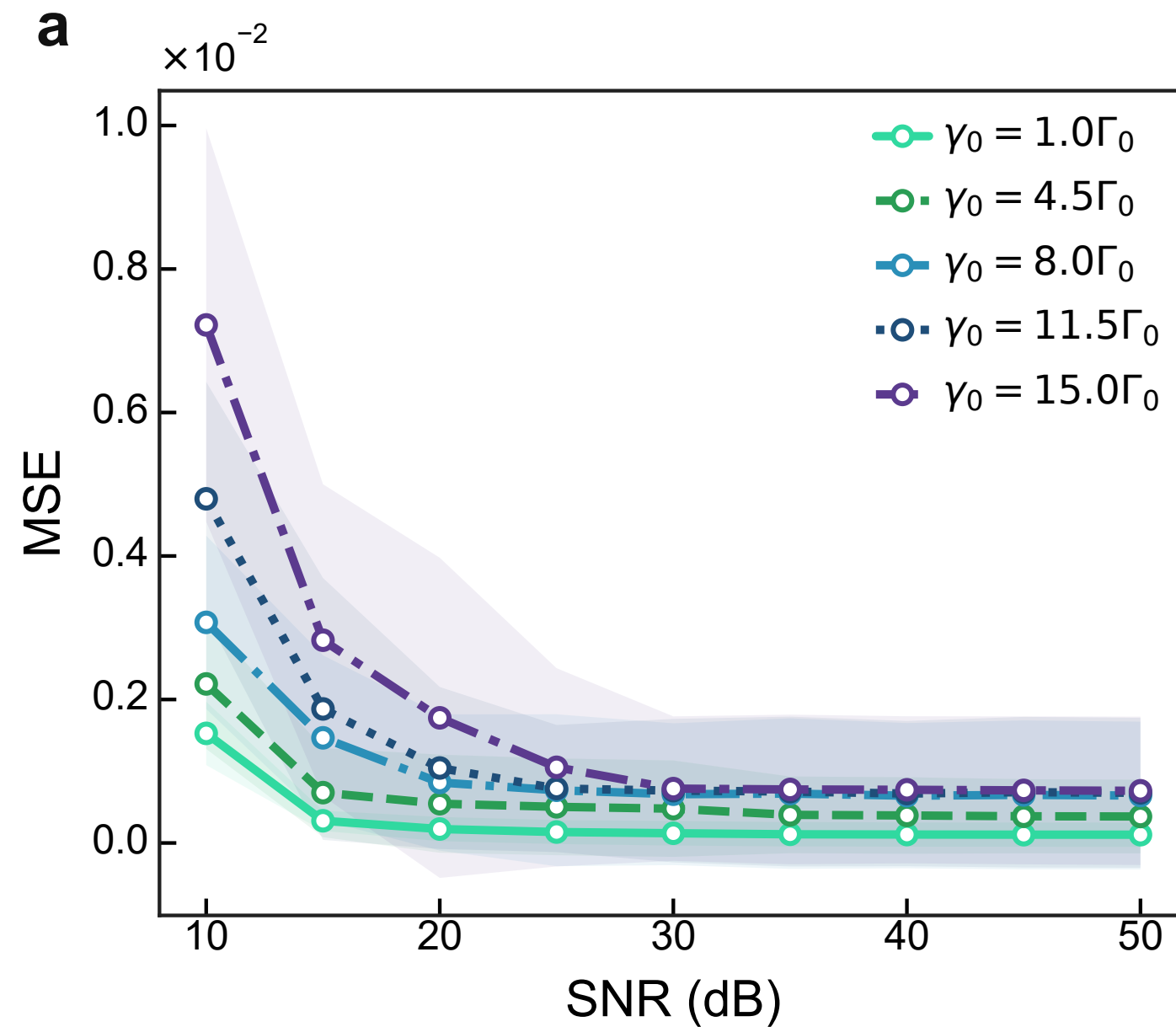


Key Results

- **Sharper recovery:** recovers sharp spectra from noisy data by deconvolution
- **Better baselines:** closer to theory than Wiener and U-Net
- **Resolution-adaptive:** works under reduced SMS resolution
- **Higher throughput:** up to **17-fold** count rate



Deconvolution: Error Analysis

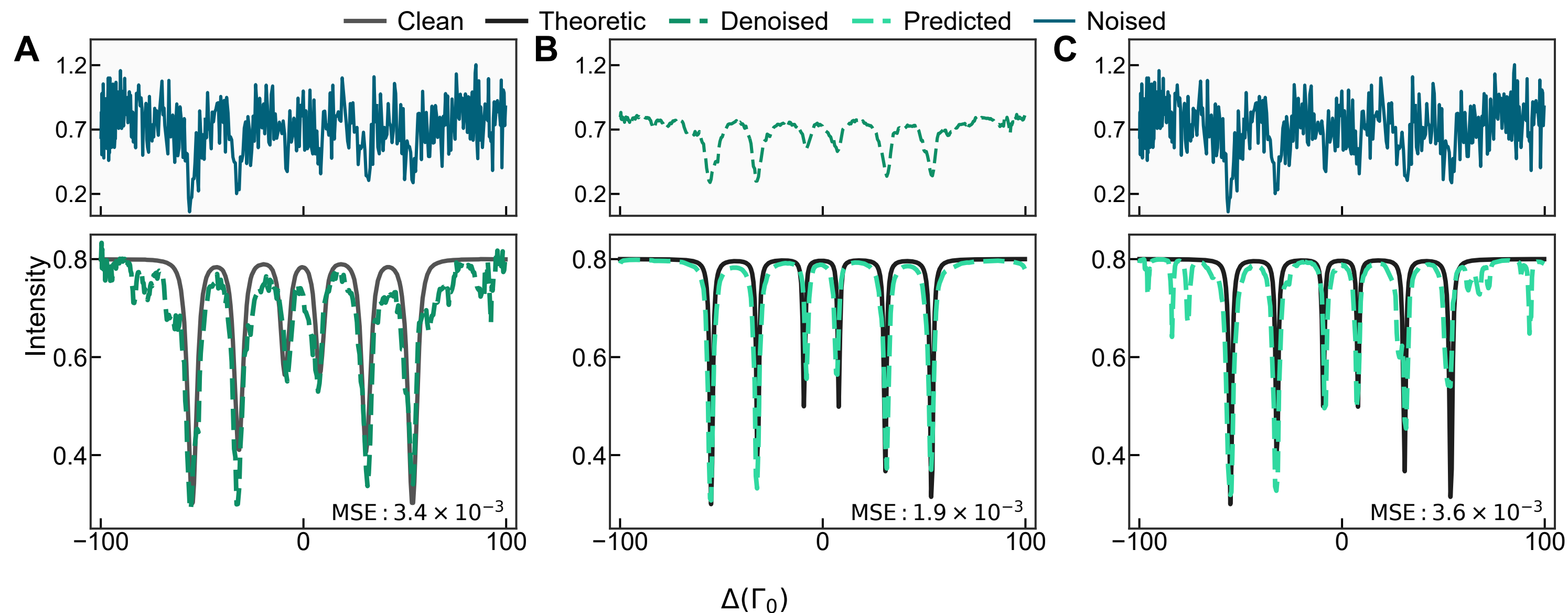


The error stays low across different noise levels and linewidths.



Deconvolution: Low-SNR Extension

Under review



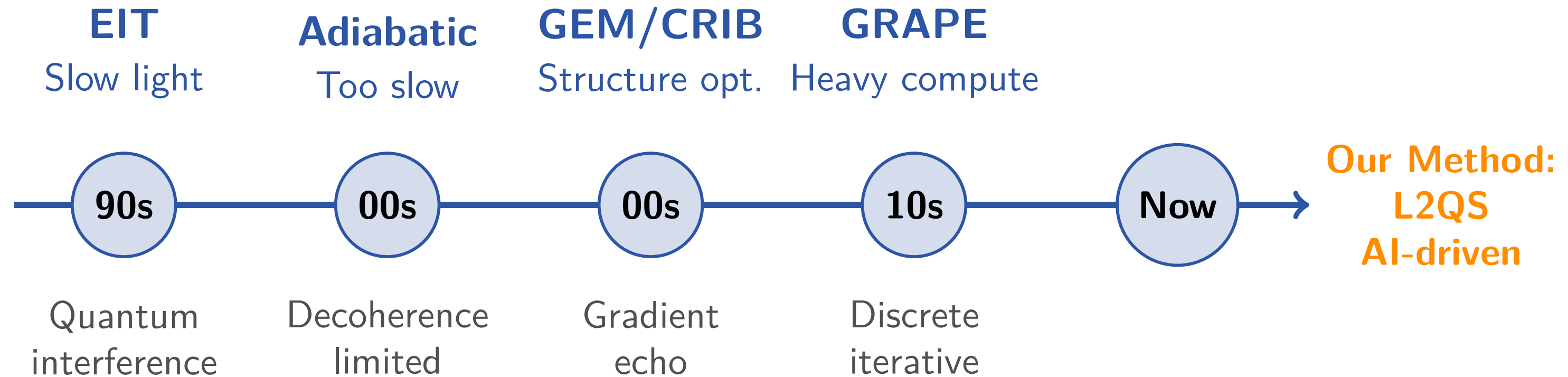
Denoising helps recover the fine structure even in the low-SNR case.

PART 03

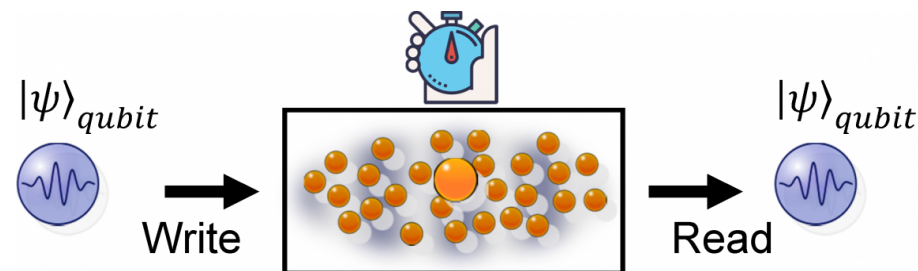
Quantum Storage



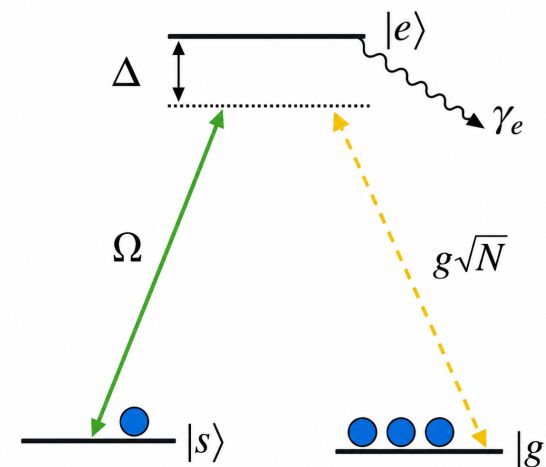
Evolution of Quantum Memory: From Manual to AI-Driven



Quantum Storage



System



Storage strategy

Manual physical intuition

↓
AI-automated discovery



L2QS Results: Recovering the Theoretical Limit

Near-Adiabatic Benchmark

Storage Efficiency Bound

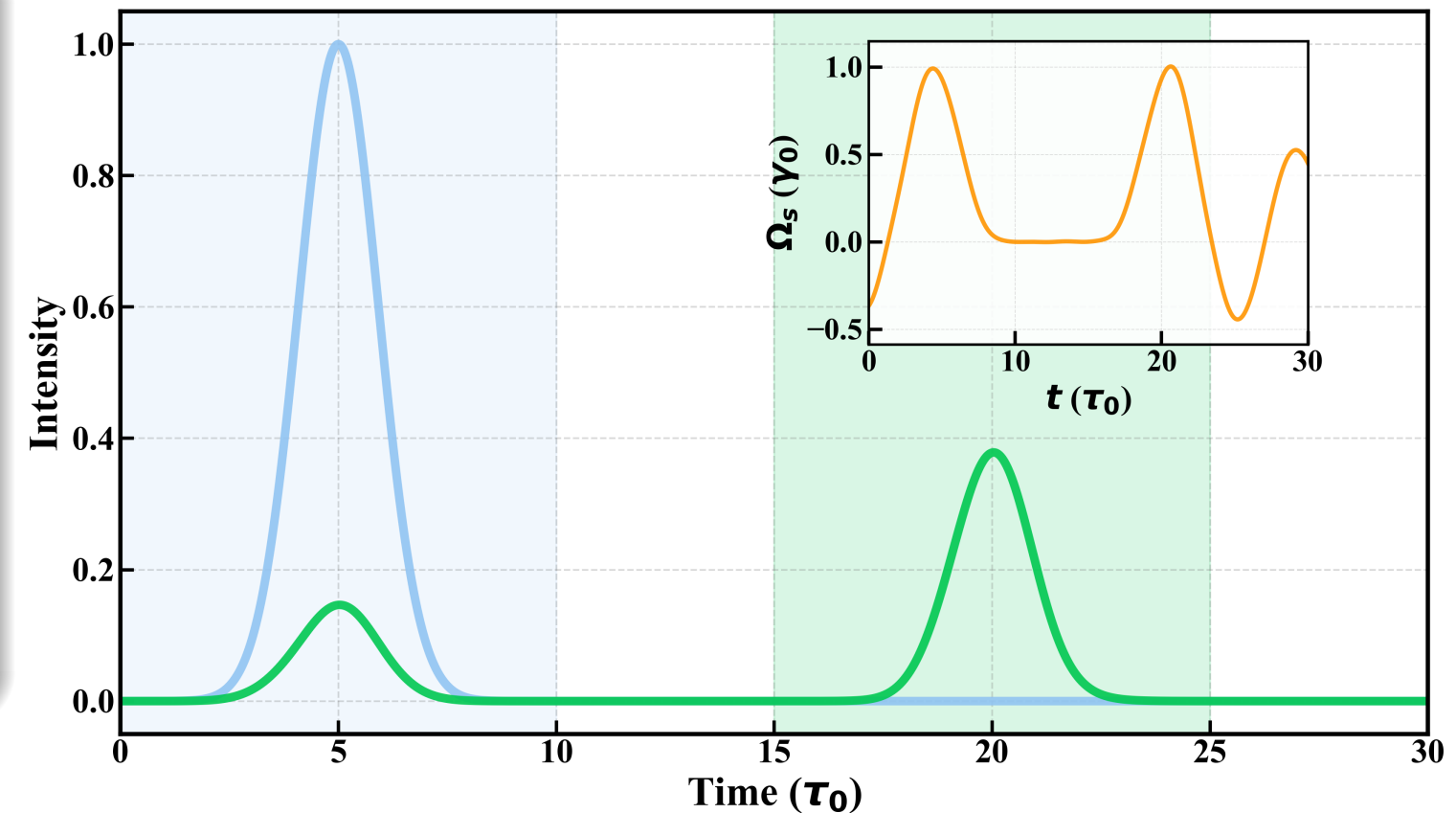
$$\eta_{\max} = \left(\frac{C}{1+C} \right)^2$$

$$C = 1.6, \quad T = 10\tau_0$$

$$\eta_{\max} \approx \mathbf{0.3787}$$

L2QS Results

- **Efficiency:** $\eta \approx 0.3780$
- **Fidelity:** $F > 0.99$
- **Benchmark:** near the known adiabatic optimum



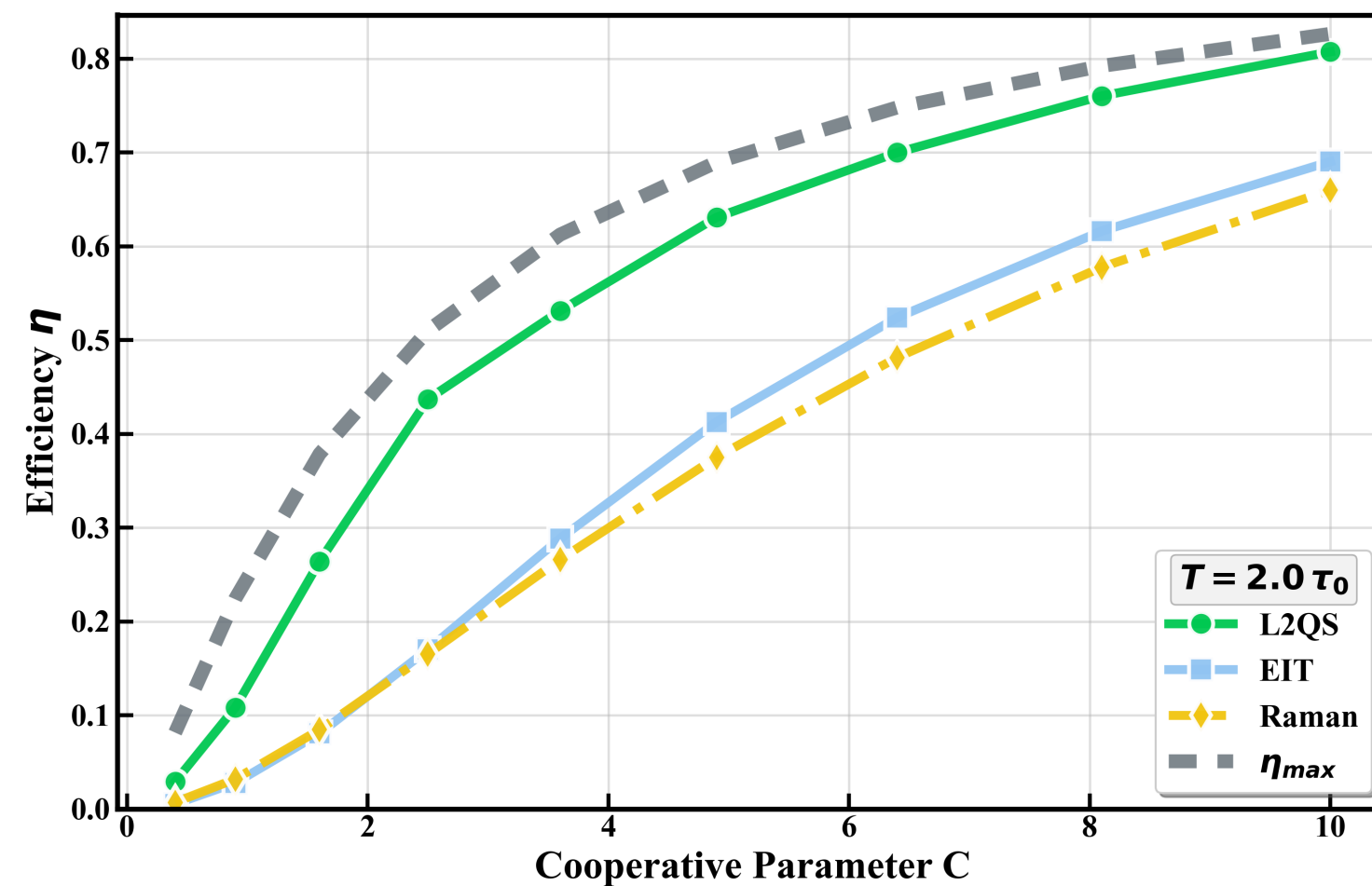
near-bound efficiency while
maintaining high fidelity



L2QS Beyond the Adiabatic Regime

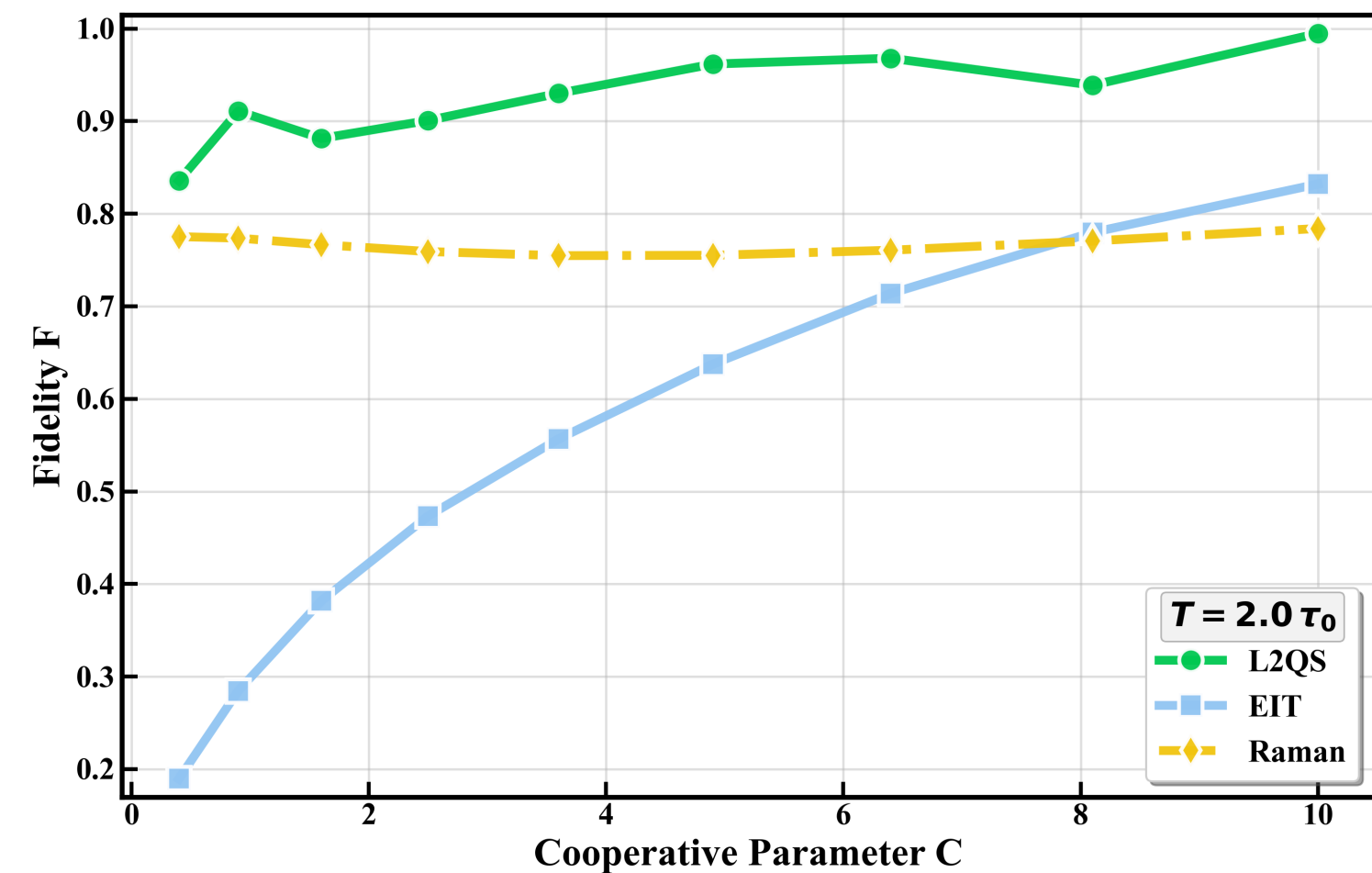
Efficiency, $T = 2\tau_0$

Efficiency: protocols vs theoretical bound



Fidelity, $T = 2\tau_0$

Fidelity comparison among different protocols



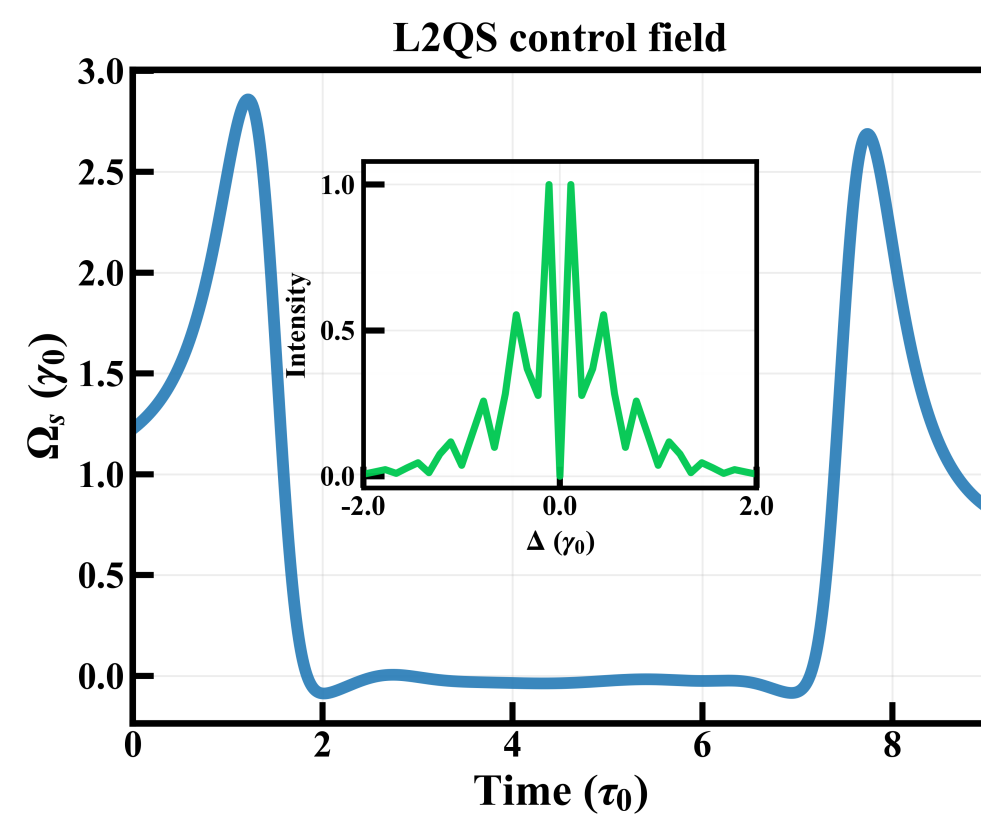
short-pulse regime: higher efficiency without losing fidelity



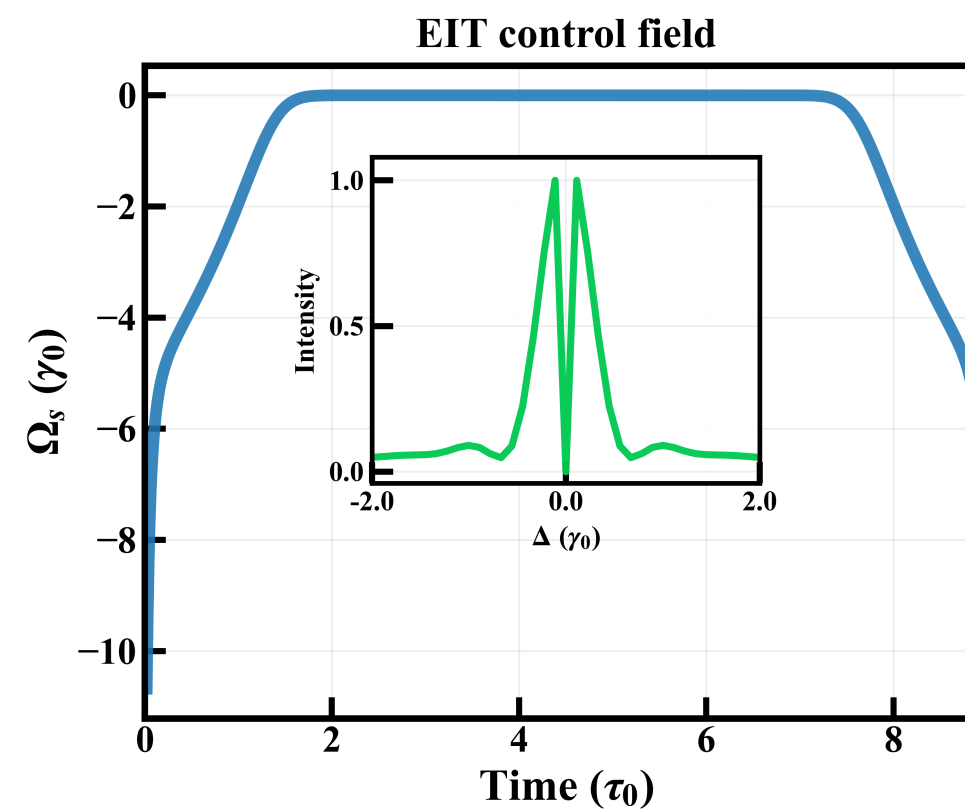
What the Network Learns

Under review

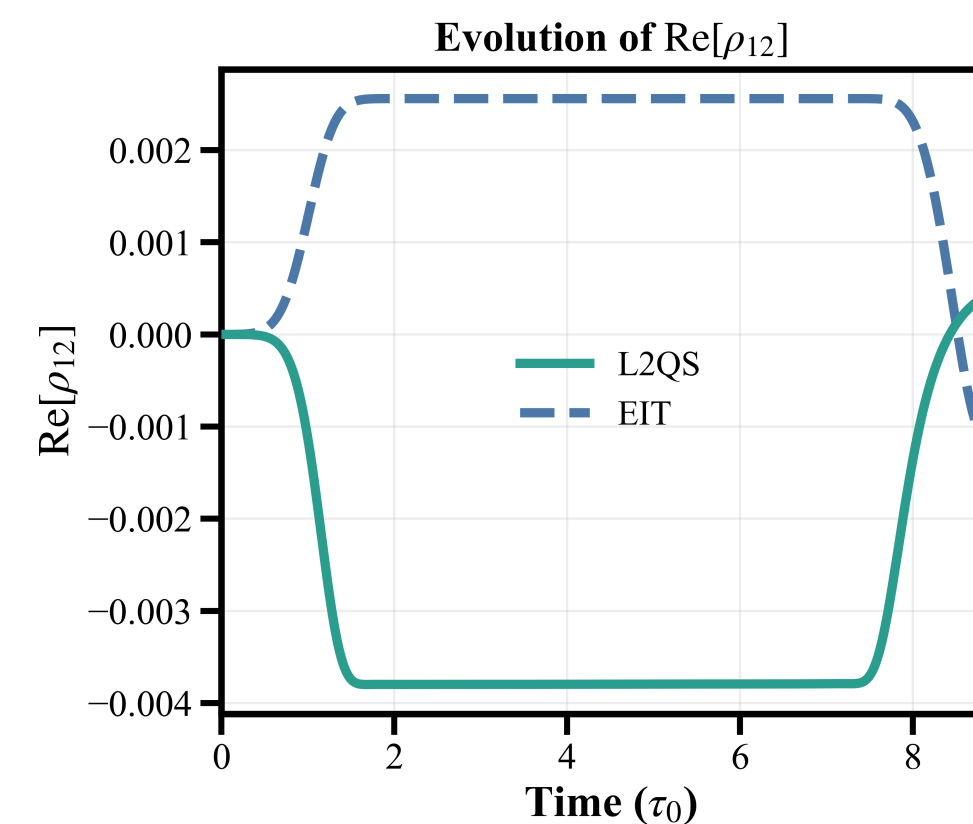
L2QS control



EIT control



Spin-wave coherence



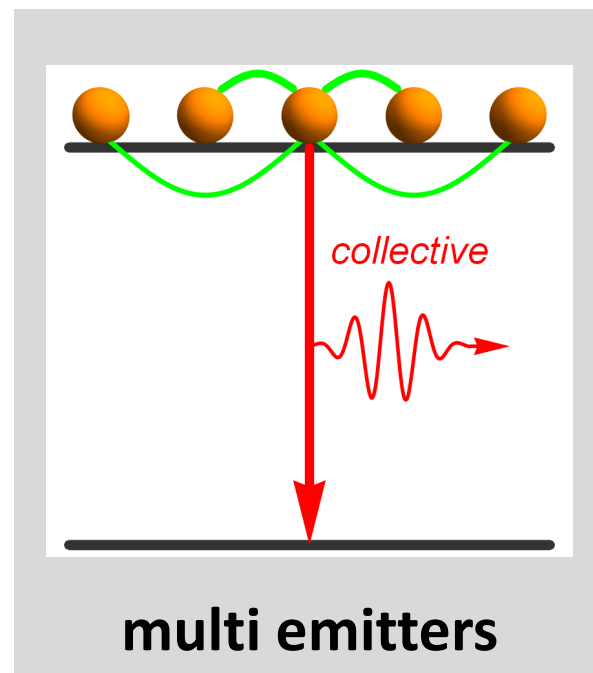
multi-frequency control improves field–spin-wave conversion

PART 04

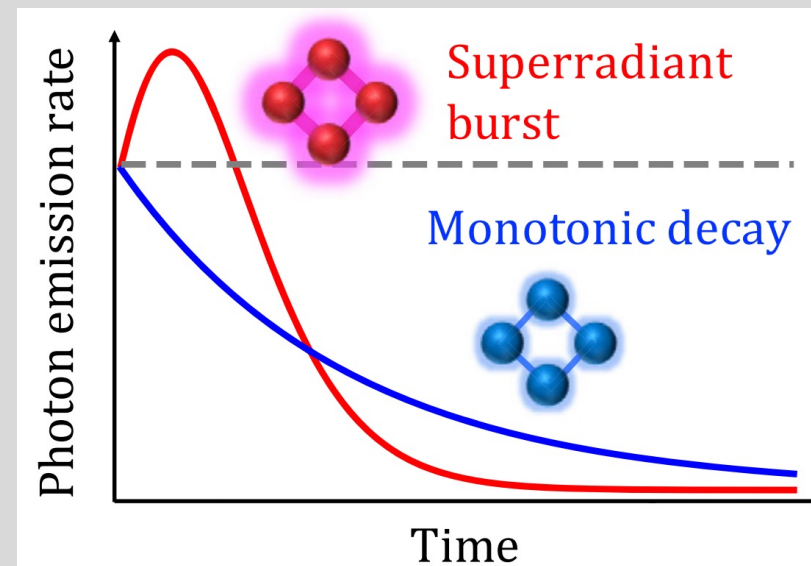
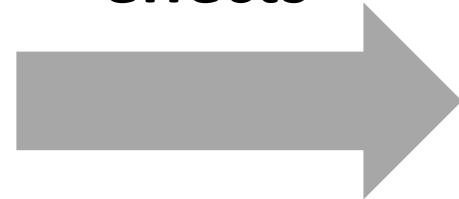
Feature-embedded VMC

OCN Many-body dynamics of nuclei

Superradiance burst



Collective
effects

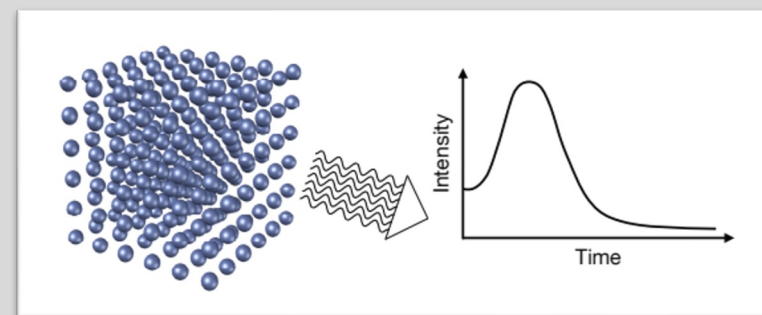


Superradiant burst

Application:
Quantum communication
Quantum sensing
Quantum engine
Ultrabright LED

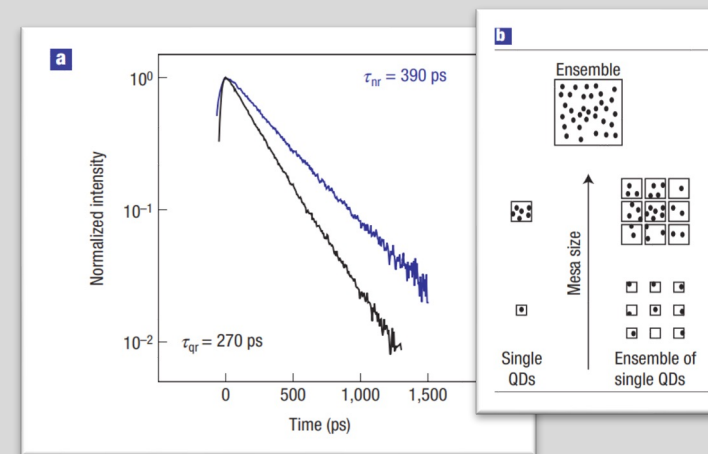
...

Atomic array:



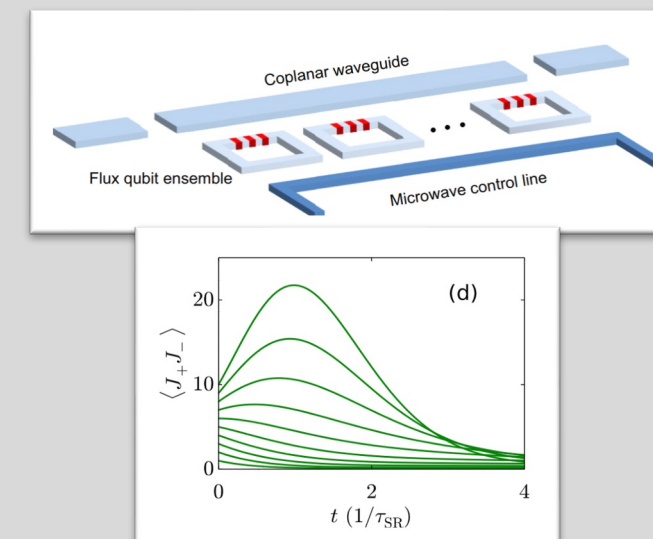
Nat. Commun., 13, 2285 (2022)

Quantum dots:



Phys. Rev. Lett., 130, 213605 (2023)

Superconduct qubits:



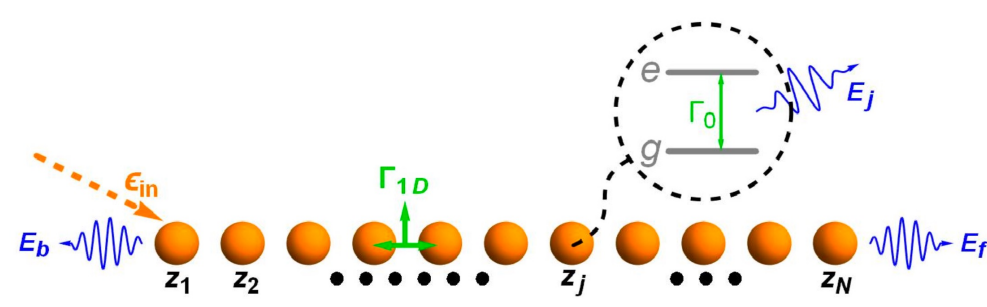
Phys. Rev. Lett., 124, 013601 (2020)

Nuclei?

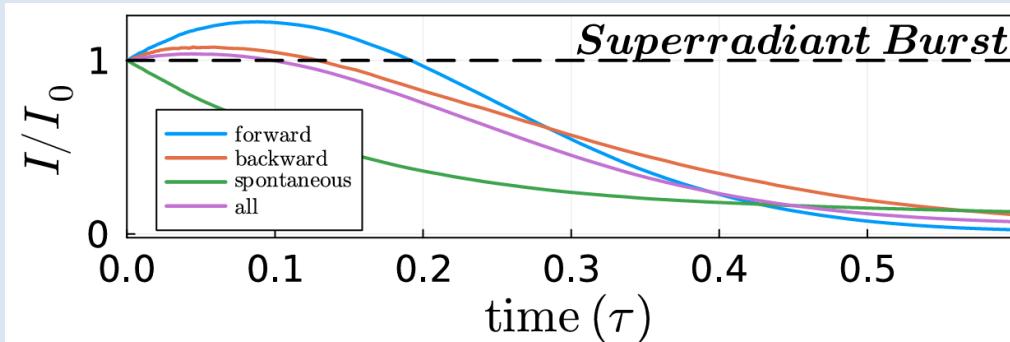
Many-body dynamics of nuclei

X-ray Superradiance burst with cooperative nuclei

Characteristics and criterion of burst



Model of nuclei chain

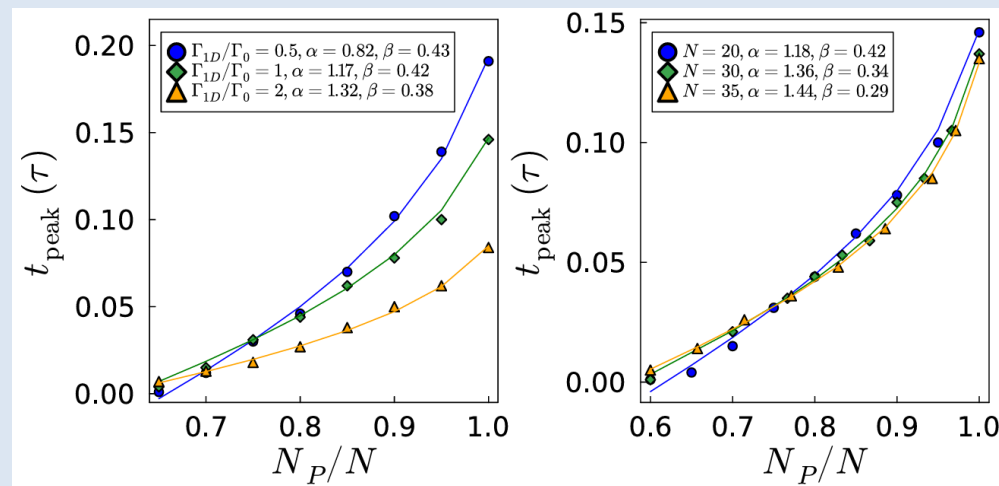


Burst of nuclei

$$N_P > \frac{1}{2}N + \frac{1}{2} + \frac{N(N-1)}{N^2 - 2N + \left(\frac{\sin N k_0 a}{\sin k_0 a}\right)^2} \left(1 + \frac{\Gamma_0}{\Gamma_{1D}}\right)$$

Criterion for burst

Nonlinearity of the time to reach burst peak



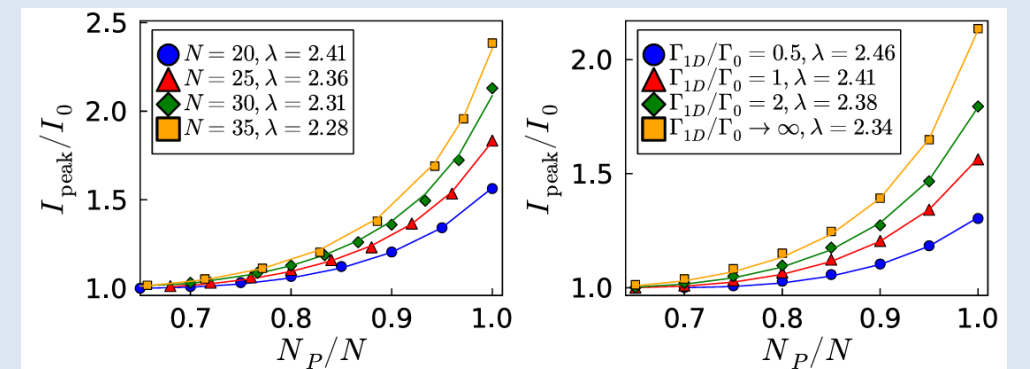
Relationship between t_{peak} and excitation number

$$t_{\text{peak}} = \frac{\alpha}{(N+1)\Gamma_{1D}} \ln \frac{N_P}{N - N_P + 1} - \frac{\beta}{(N+1)\Gamma_{1D}}$$

Analytical equation

Logarithmic nonlinearity!

Nonlinearity of the value of burst peak



Relationship between I_{peak}/I_0 and excitation number

$$\tilde{I}_{\text{peak}} = \frac{1}{1 - 4 \left(\frac{N_P - N_{P0}}{N} \right)^\lambda}$$

Analytical equation

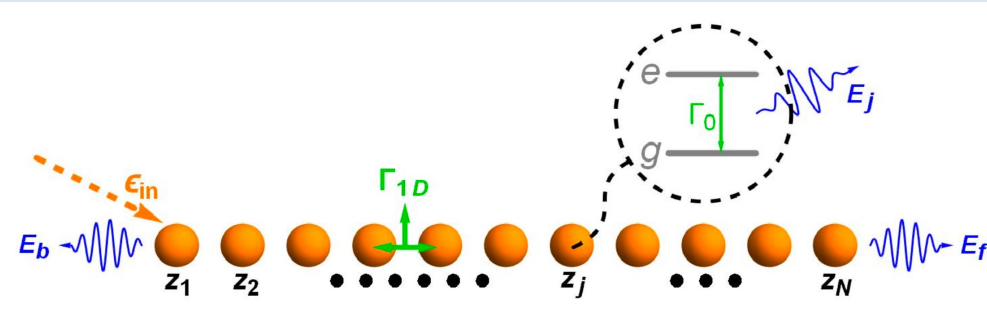
Rational nonlinearity!

Many-body dynamics of nuclei

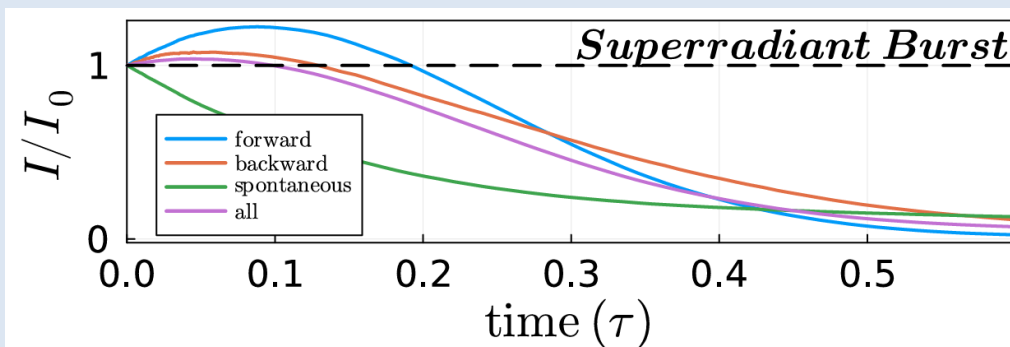
X-ray Superradiance burst with cooperative nuclei

How to calculate the steady-state solution?

Characteristics and criterion of burst



Model of nuclei chain

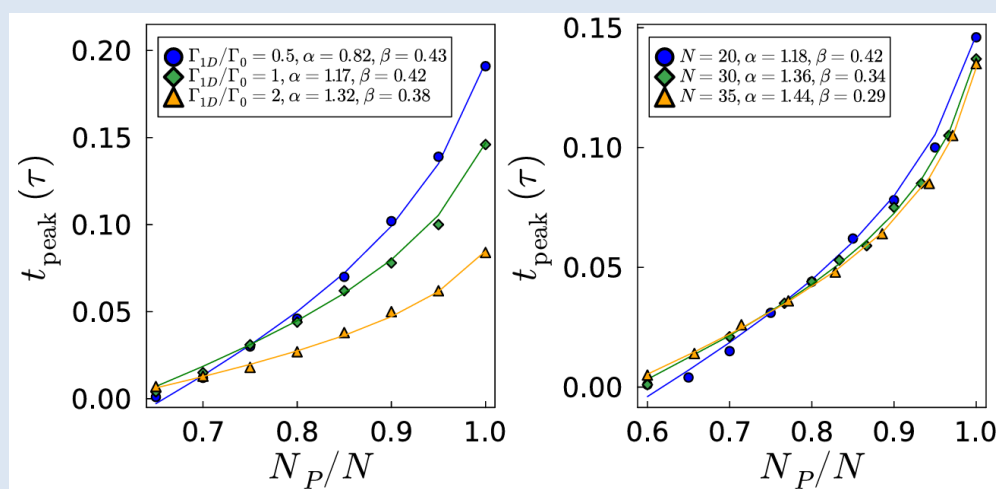


Burst of nuclei

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Criterion for burst

Nonlinearity of the time to reach burst peak



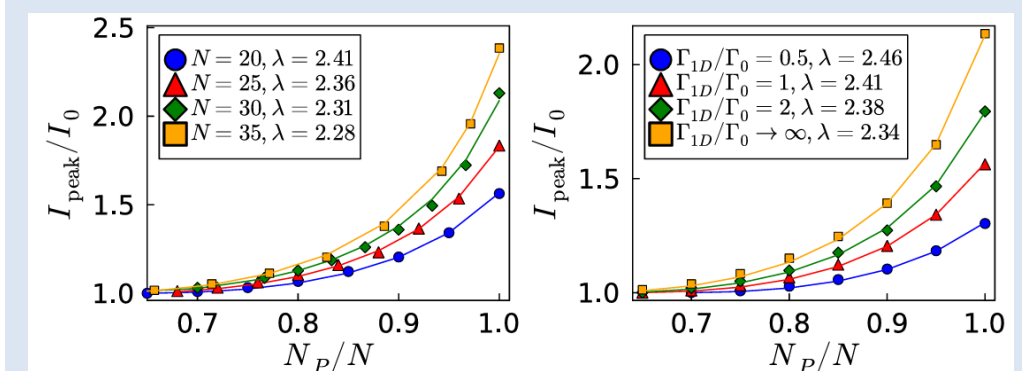
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Analytical equation

Logarithmic nonlinearity!

Nonlinearity of the value of burst peak



Relationship between I_{peak}/I_0 and excitation number

$$\tilde{I}_{\text{peak}} = \frac{1}{1 - 4 \left(\frac{N_P - N_{P0}}{N} \right)^\lambda}$$

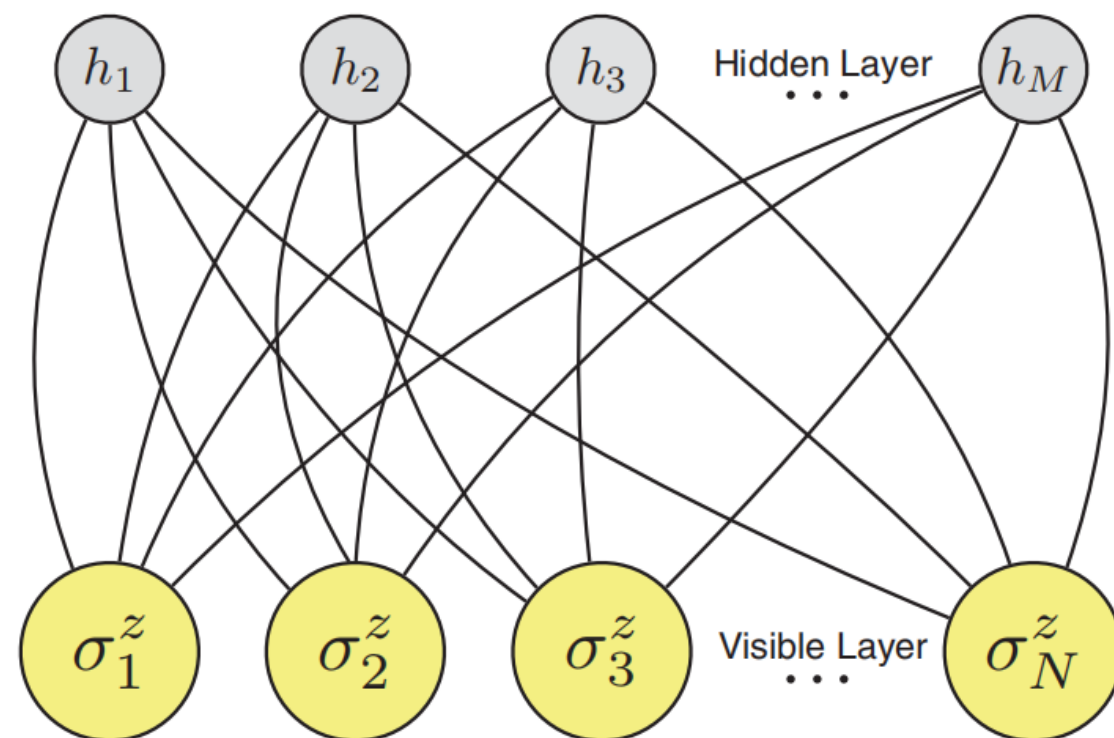
Analytical equation

Rational nonlinearity!



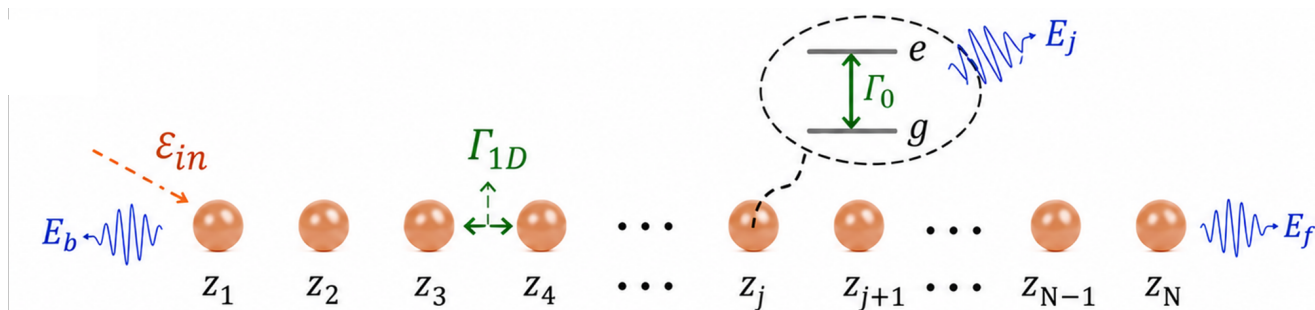
Feature-Embedded VMC: Background and Method

RBM wavefunction ansatz

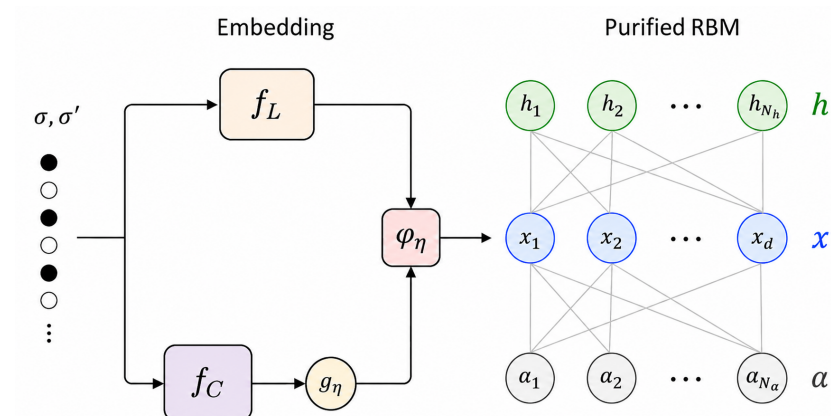


Solving the quantum many-body problem with artificial neural networks

Waveguide-mediated collective dissipation



Liouvillian-adapted feature embedding



embedded input

$$\varphi_{\eta}(n) = [f_L(n), \lambda_G g_{\eta}(n) s(n)]$$

Carleo, Giuseppe, and Matthias Troyer. *Science* 355.6325 (2017): 602–606.



Feature-Embedded VMC: Many-Body Liouvillian Model

Open-system equation

$$\dot{\rho} = \mathcal{L}[\rho]$$

$$\mathcal{L}[\rho] = -i[H, \rho] + \sum_{\mu} \left(L_{\mu} \rho L_{\mu}^{\dagger} - \frac{1}{2} \{ L_{\mu}^{\dagger} L_{\mu}, \rho \} \right)$$

Liouvillian split

$$\mathcal{L} = \mathcal{L}_0 + \mathcal{L}_{\text{in}}$$

$$\mathcal{L}_0[\rho] = -i[H_0, \rho] + \mathcal{D}[L_f]\rho + \mathcal{D}[L_b]\rho + \sum_{j=1}^N \mathcal{D}[L_j]\rho$$

$$\mathcal{D}[L]\rho = L\rho L^{\dagger} - \frac{1}{2} \{ L^{\dagger} L, \rho \}$$

Waveguide-emitter terms

$$H_0 = \sum_{j=1}^N \Delta_j \sigma_j^{ee} + \frac{\Gamma_{1D}}{2} \sum_{j,l} \sin(k_0 |z_j - z_l|) \sigma_j^{eg} \sigma_l^{ge}$$

$$H_{\text{in}} = \sum_{j=1}^N \sqrt{\frac{\Gamma_{1D}}{2}} \epsilon_{\text{in}} \left(e^{-ik_0 z_j} \sigma_j^{ge} + e^{ik_0 z_j} \sigma_j^{eg} \right)$$

$$L_f = i\sqrt{\frac{\Gamma_{1D}}{2}} \sum_{j=1}^N e^{-ik_0 z_j} \sigma_j^{ge}, \quad L_b = i\sqrt{\frac{\Gamma_{1D}}{2}} \sum_{j=1}^N e^{ik_0 z_j} \sigma_j^{ge}$$

$$L_j = i\sqrt{\Gamma_0} \sigma_j^{ge}, \quad \mathcal{L}_{\text{in}}[\rho] = -i[H_{\text{in}}, \rho]$$

$$\mathcal{L}[\rho_{\text{ss}}] = 0$$



Feature-Embedded VMC: Results

Under review

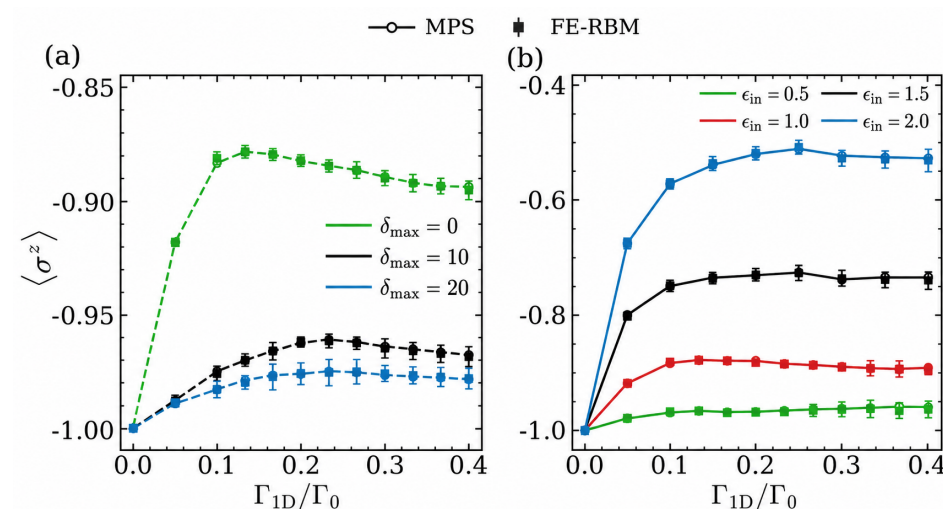
Results: MPS benchmark and FE-RBM stability

MPS match

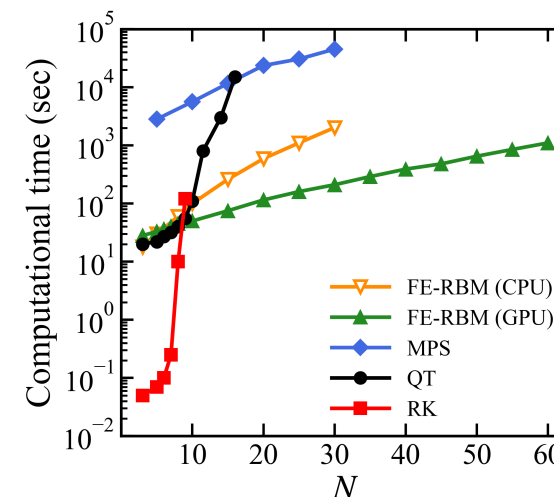
stable scans

fast computation

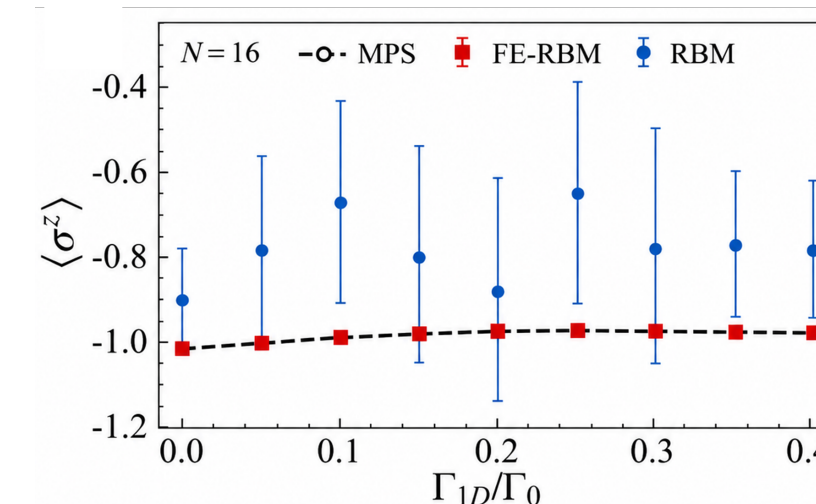
large-scale simulation



scan disorder / drive
MPS-level accuracy

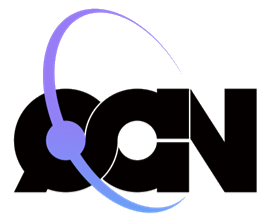


benchmark runtime
faster, larger scale



compare FE-RBM / RBM
more stable

$\langle \sigma^z \rangle$ vs. Γ_{1D}/Γ_0



Summary

One thread: ML for data processing, physics modeling, and algorithm discovery.

PART 01

Matrix Decomposition

Algorithm discovery

AI finds compact MZI programs for unitary matrices.

PART 02

Spectral Deconvolution

Data processing

AI recovers sharp spectra from noisy data by deconvolution.

PART 03

Quantum Storage

Strategy discovery

AI optimizes control pulses from the physics objective.

PART 04

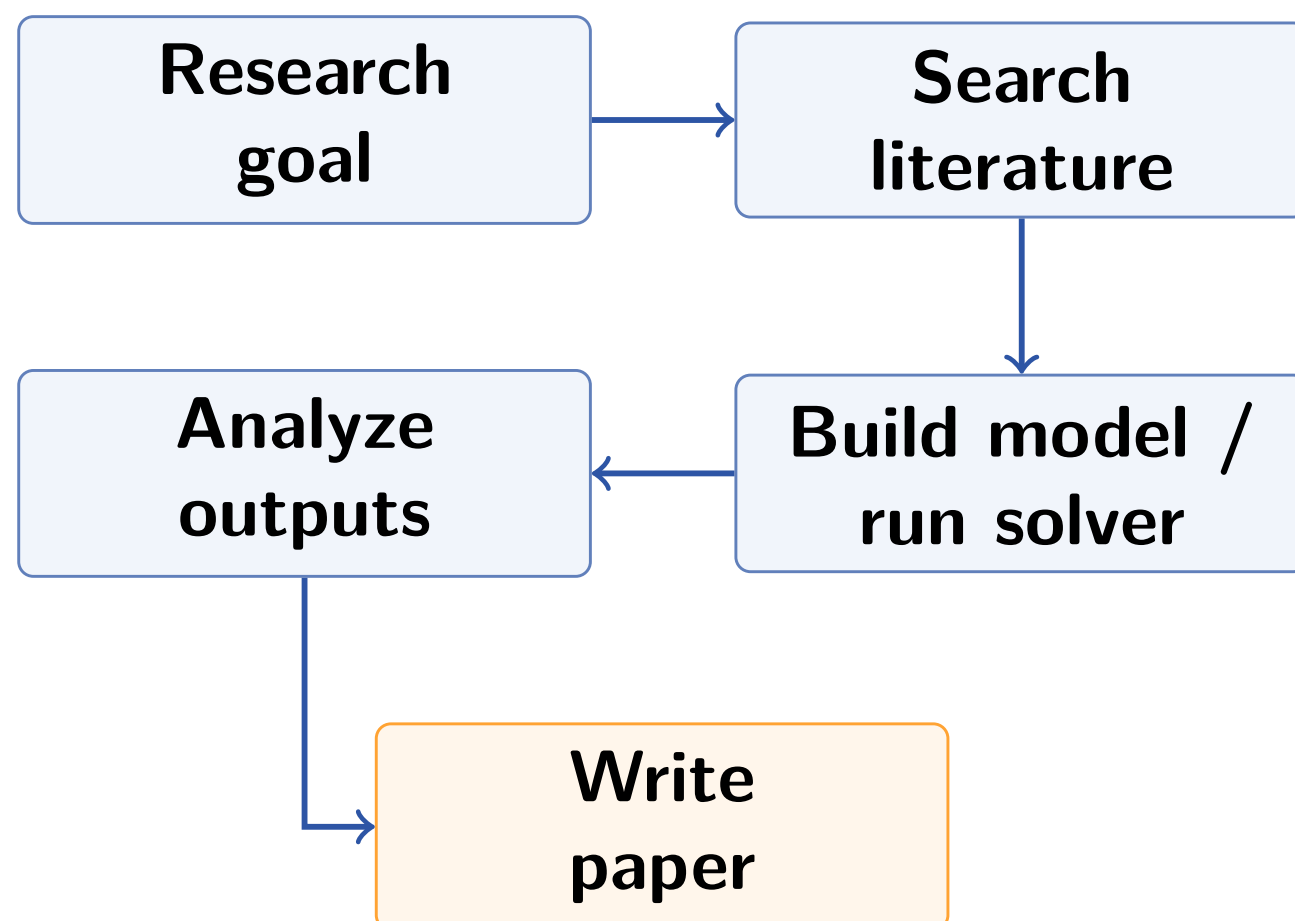
Feature-embedded VMC

Many-body simulation

Feature embedding stabilizes open-system VMC.



Outlook: Closed-Loop Research Agents



Next step

- From single ML models to a research loop
- Agent reads papers, runs tools, and checks outputs
- Human verifies key decisions and final claims

For quantum physics

Connect theory models, numerical solvers, and data analysis in one research workflow.



Thank You



Thank You



马余刚院士



孔祥进
青年研究员



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