

# An Optical Reservoir Computing Design based on Two-Dimensional Quantum Walk

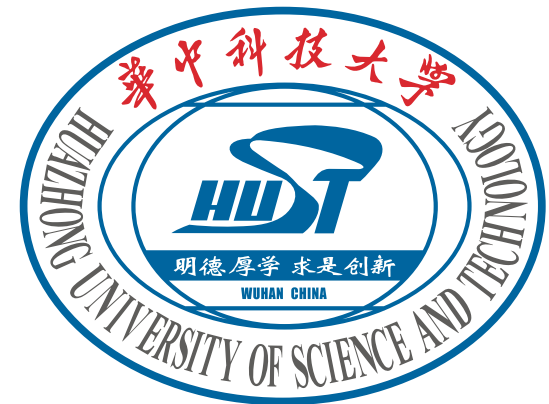
Yushu Wang, Yuheng Ding, Yang Chen, Yangcan Long, Ming Tang, Chao Wang\*

*Huazhong University of Science and Technology, Wuhan, China.*

*Email: wys\_anicy@hust.edu.cn*

*\*chao\_wang\_me@hust.edu.cn*

*Nov.7 2025*



# Outline

---

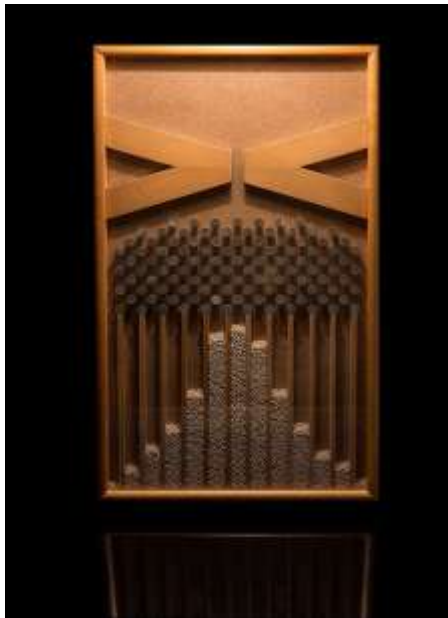
- **Preface: Quantum Walks, Entanglement and Interference**
- Introduction: Reservoir Computing & Extreme Learning Machine
- Method: Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)
  - Architecture and Simulations
  - Evaluation Results
- Conclusions and Perspectives

# Quantum Walks

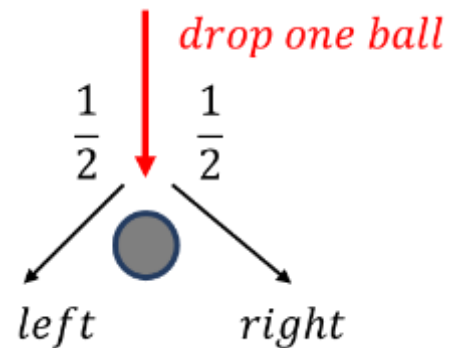
## Questions ahead

- **Why** Quantum?
- **How** to Introduce Quantum Benefits into Computational Architectures?
- **What** Kind of Quantum Properties Shall We Exploit?

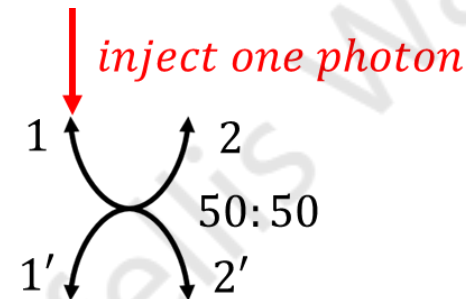
## Classical Random Walk



Galton Board

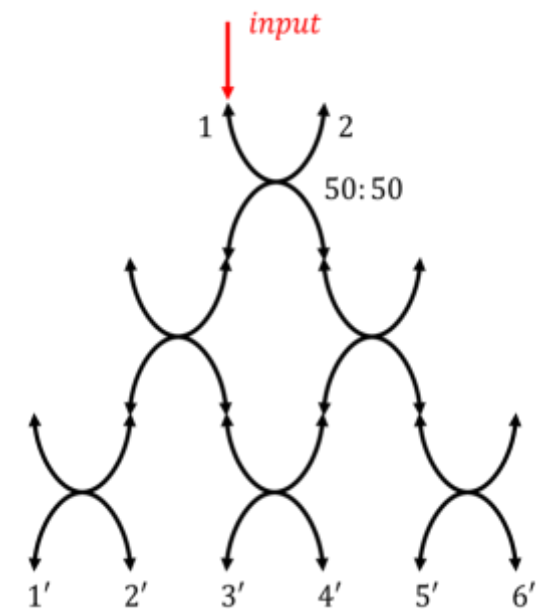


- spatial
- fixed possibility
- discrete



- can walk in **different dimension & quantities**
- **adjustable** possibility
- **discrete/continuous** walks
- **quantum entanglement & interference**

## Quantum Walk



Splitter Array

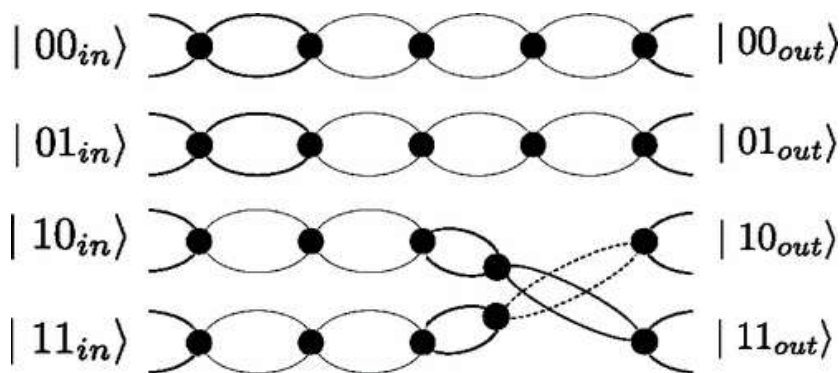
# Quantum Walks

## Questions ahead

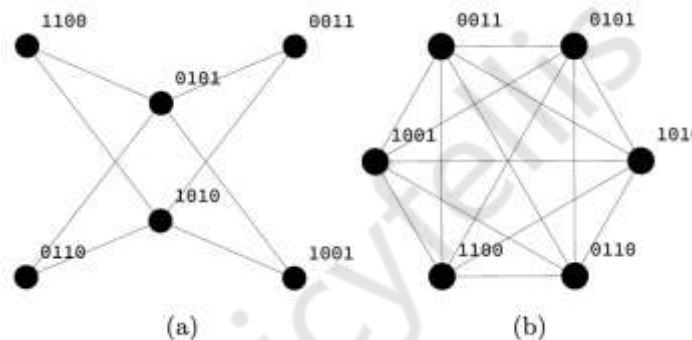
- **Why** Quantum?
- **How** to Introduce Quantum Benefits into Computational Architectures?
- **What** Kind of Quantum Properties Shall We Exploit?

## Quantum Walk (QW): Powerful and Convenient Physical Platform for **Quantum Algorithms**

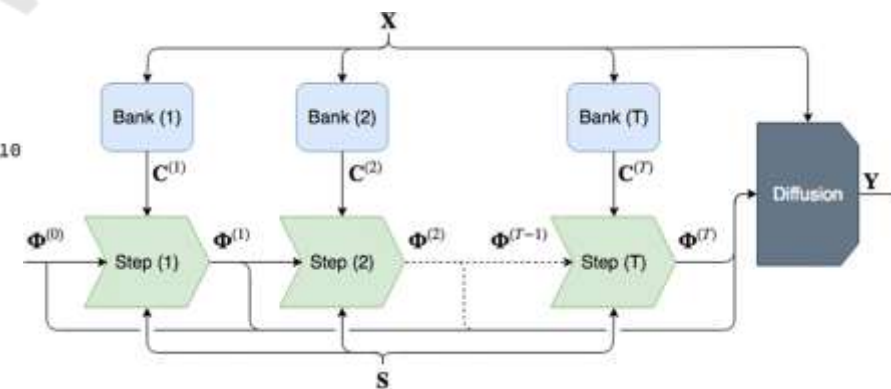
### I. Multiple **quantum computing algorithms** realized through Quantum Walks



[1] universal quantum computation



[2] combinatorial optimization algorithms



[3] machine learning

[1] N. B. Lovett, et al., Universal quantum computation using the discrete-time quantum walk, Phys. Rev. A, vol. 81, p. 042330, Apr. 2010.

[2] S. Marsh, et al., Combinatorial optimization via highly efficient quantum walks, Phys. Rev. Res., vol. 2, p. 023302, June 2020.

[3] S. Dernbach, et al., Quantum walk neural networks with feature dependent coins, Applied Network Science, vol. 4, no. 1, p. 76, Sept. 2019.

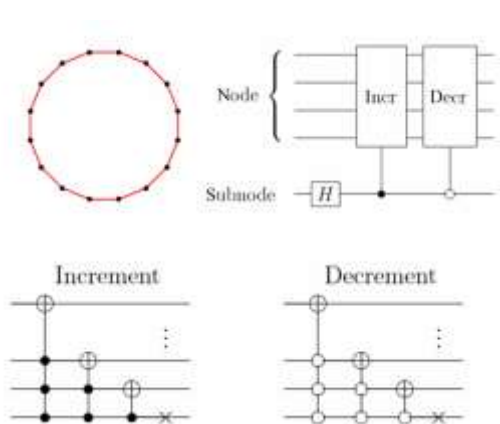
# Quantum Walks

## Questions ahead

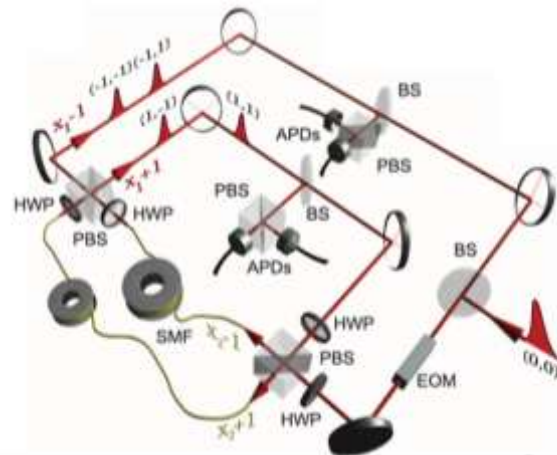
- **Why** Quantum?
- **How** to Introduce Quantum Benefits into Computational Architectures?
- **What** Kind of Quantum Properties Shall We Exploit?

## Quantum Walk (QW): Powerful and Convenient **Physical Platform** for Quantum Algorithms

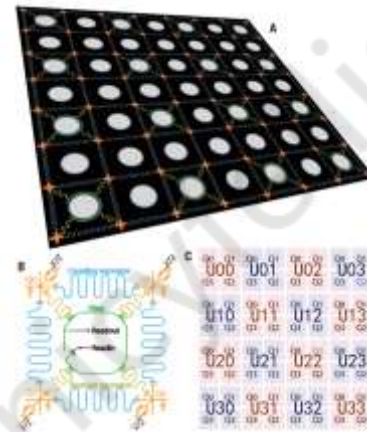
### II. Discrete & Continuous QWs of different dimensions implemented on various **physical systems**



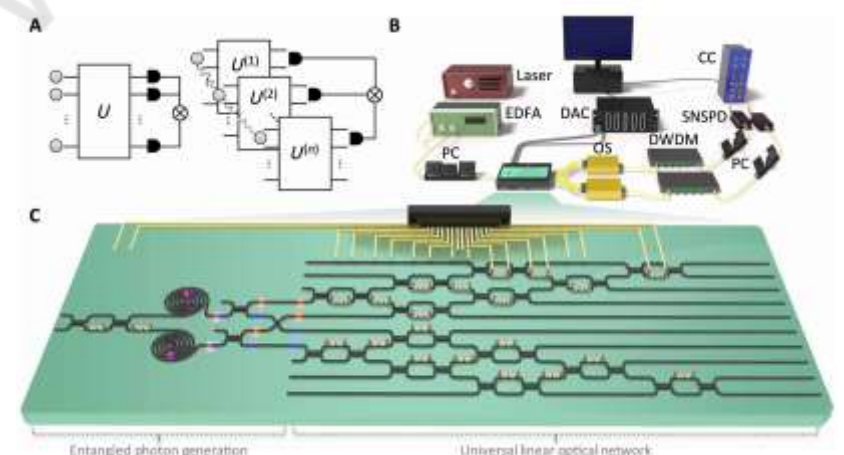
[4] quantum circuit



[5] laser optics



[6] superconducting material



[7] integrated photonics

[4] Douglas BL, et al., Efficient quantum circuit implementation of quantum walks. *Phys Rev A*. 2009;79(5):Article 052335.

[5] A. Schreiber, et al., A 2D Quantum Walk Simulation of Two-Particle Dynamics, *Science*, vol. 336, no. 6077, pp. 55–58, 2012.

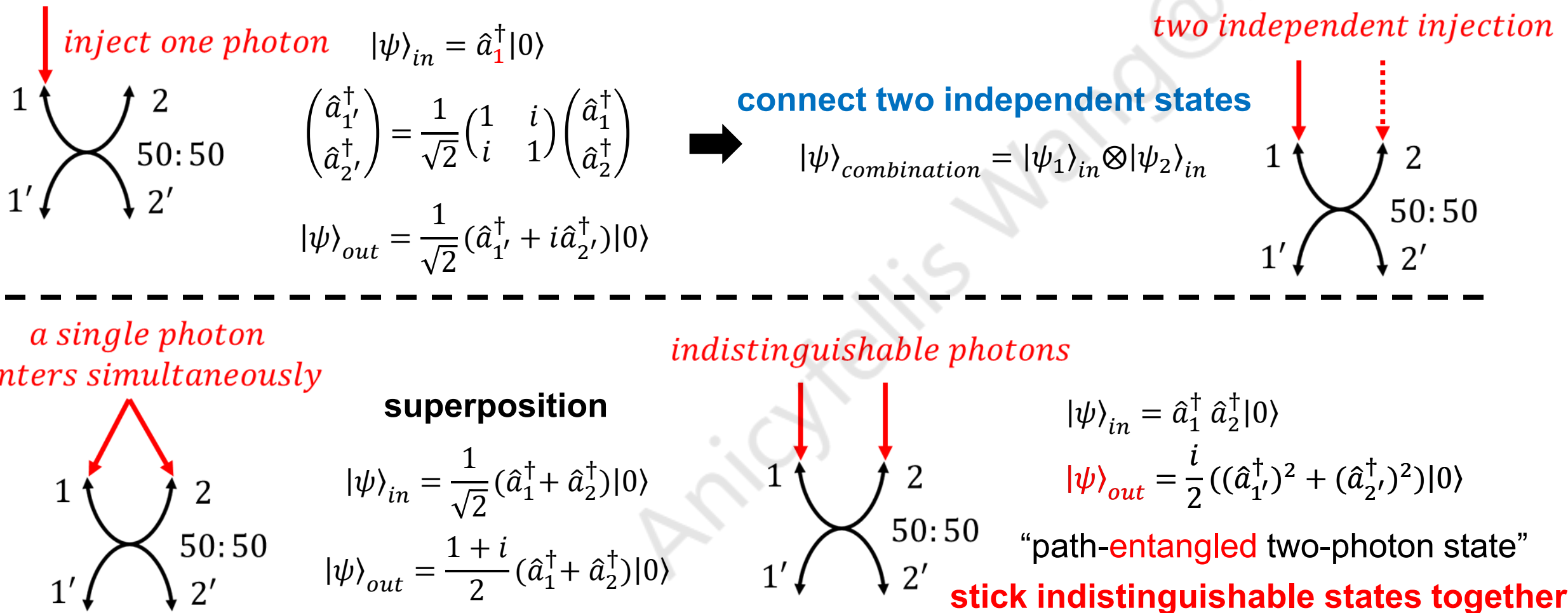
[6] Gong M, et al., Quantum walks on a programmable two-dimensional 62-qubit superconducting processor. *Science*. 2021;372(6545):948–952.

[7] Qiang X, et al., Implementing graph-theoretic quantum algorithms on a silicon photonic quantum walk processor. *Sci Adv*. 2021;7(9):Article eabb8375.

# Classical Random Walk & Quantum Walk

Toy example: Galton Board-like random walk and its quantum version

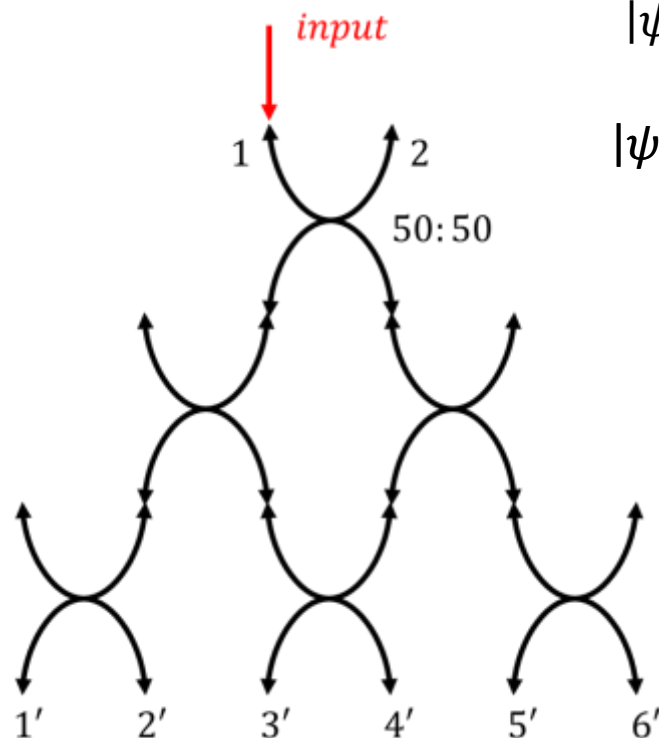
A. 2-indistinguishable photons injected **when entanglement emerges**





# Classical Random Walk & Quantum Walk

## B. 3-step Galton Board-like walk **when quantum interference emerges**



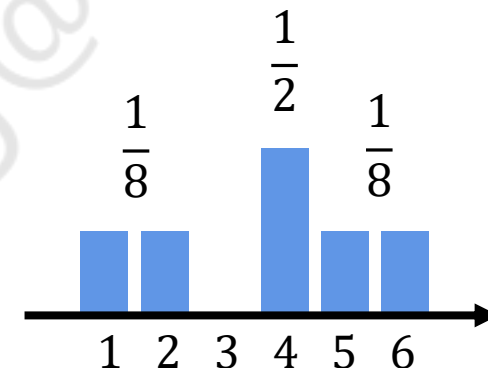
**Photons**

$$|\psi\rangle_{in} = \hat{a}_1^\dagger |0\rangle$$

**Destructive interference**

$$\begin{aligned} |\psi\rangle_{out} &= \frac{1}{2\sqrt{2}} (-\hat{a}_1^\dagger + i\hat{a}_2^\dagger + \hat{a}_3^\dagger - \hat{a}_3^\dagger + 2i\hat{a}_4^\dagger - \hat{a}_5^\dagger - i\hat{a}_6^\dagger) |0\rangle \\ &= \frac{1}{2\sqrt{2}} (-\hat{a}_1^\dagger + i\hat{a}_2^\dagger + 2i\hat{a}_4^\dagger - \hat{a}_5^\dagger - i\hat{a}_6^\dagger) |0\rangle \end{aligned}$$

**Average Photon Number**



**To avoid interference:**

Introduce random phase noise  $\theta_1$  &  $\theta_2$  in each step

$$\begin{pmatrix} \hat{a}_{1'}^\dagger \\ \hat{a}_{2'}^\dagger \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & i \\ i & 1 \end{pmatrix} \begin{pmatrix} \hat{a}_1^\dagger e^{i\theta_1} \\ \hat{a}_2^\dagger e^{i\theta_2} \end{pmatrix}$$

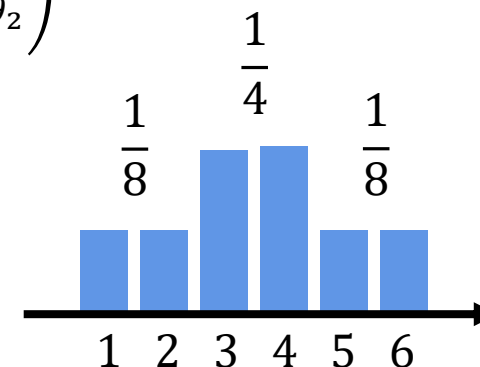
Classical

**Balls**

$$P(k') = \binom{k}{3} \left(\frac{1}{2}\right)^{k+1} \quad (k \in \mathbb{N})$$

**Binomial distribution**

**Probability**



# Outline

---

- Preface: Quantum Walks, Entanglement and Interference
- **Introduction: Reservoir Computing & Extreme Learning Machine**
- Method: Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)
  - Architecture and Simulations
  - Evaluation Results
- Conclusions and Perspectives

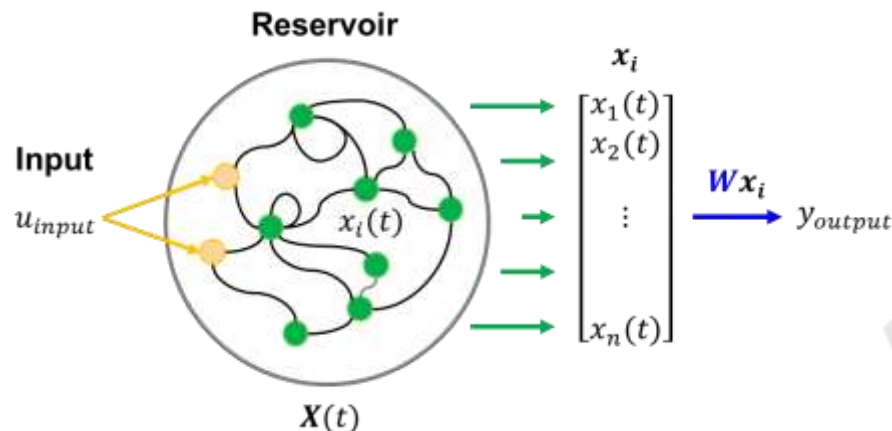


# Reservoir Computing & Extreme Learning Machine

- **Given:** Training Input signal  $u_{train}(t)$ , target output  $y_{train}(t)$
- **Target:** **a filter  $\mathcal{F}$ :** input  $u_{train}(t)$ , generates an output signal  $\hat{y}_{train}(t) \rightarrow$  target  $y_{train}(t)$
- **Approach**
  - Step1: Prepare reservoir  $X(t)$ , observable variables  $x_i(t)$
  - Step2: Drive reservoir by input  $u_{train}(t)$ , get the internal variables  $x_i^{train}(t)$
  - Step3: Find a readout vector  $W$ :  $W x_i^{train}(t) = \hat{y}_{train}(t) \sim y_{train}(t)$

## Reservoir Computing (RC)

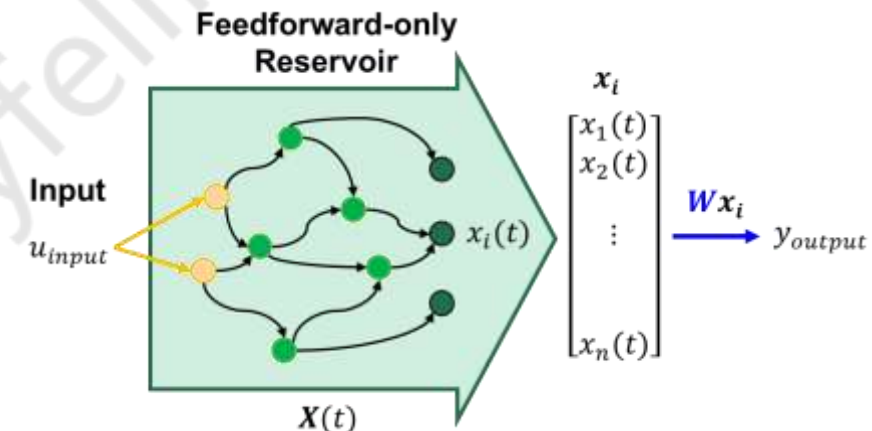
**Interconnected** nodes with nonlinearity



$\ni$

## Extreme Learning Machine (ELM)

**Forward-propagation only**

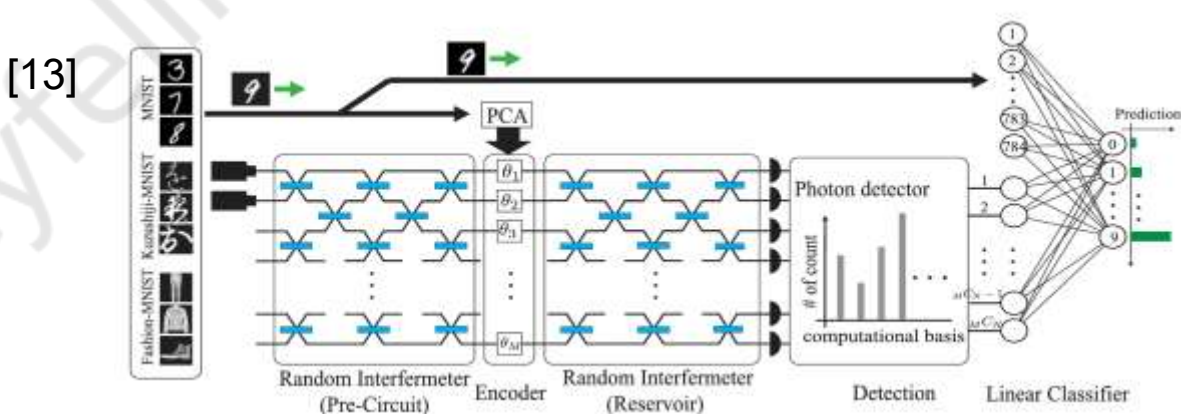
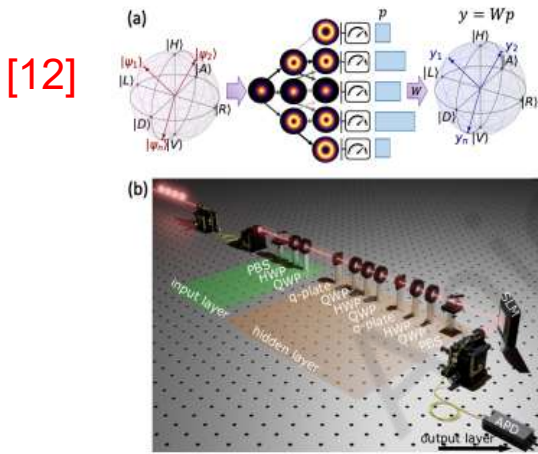
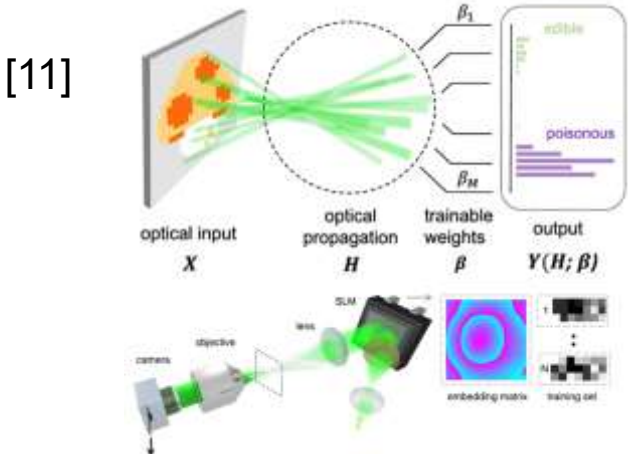


[9] Ingo Fischer, et al., *Reservoir Computing Theory, Physical Implementations, and Applications Book*, 2021.

[10] Gauthier. et al. Next generation reservoir computing. *Nat Commun* **12**, 5564, 2021.

# Existing Works & Limitations

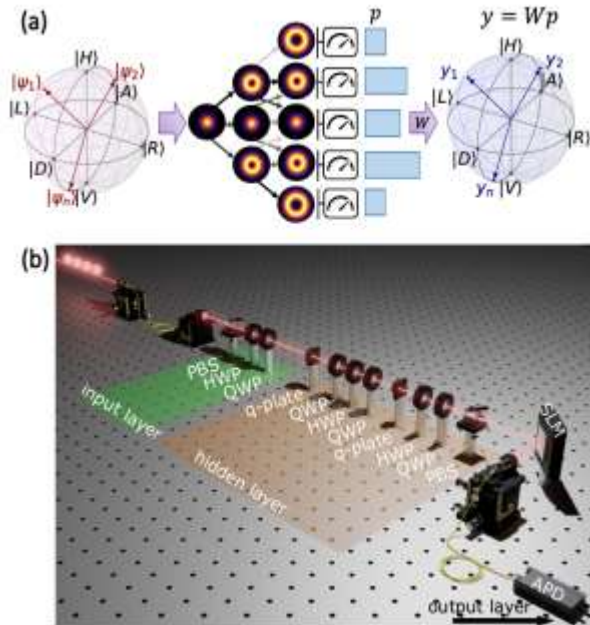
Comparison		[11] PELM	[12] QELM <span style="color: red;">→</span> <span style="color: red;">empirical platform</span>	[13] Boson Sampler ELM
Reservoir Dynamics		Classical: Coherent wave propagation in free space	Discrete quantum walk on bulk optics	Photons propagate through interferometer matrices
Reservoir Size	Input channels	28×28 (for MNIST)	2	28×28 (for MNIST)
	Output channels	~4000 even more	5	$\frac{M!}{(N!(M - N)!)} \quad (N \sim 2; M \sim 40)$
Application Example		Classification/Regression (Abalone & MNIST)	Estimating expectation values of the Pauli matrices	Classification (MNIST & k-MNIST)



[11] Davide Pierangeli, et al., Photonic extreme learning machine by free-space optical propagation, Photon. Res. 9, 1446-1454, 2021  
[12] A. Suprano, et al., Experimental Property Reconstruction in a Photonic Quantum Extreme Learning Machine, Phys. Rev. Lett., vol. 132, p. 160802, 2024.  
[13] A. Sakurai, et al., Quantum optical reservoir computing powered by boson sampling, Optica Quantum, vol. 3, pp. 238–245, 05 2025.

# Existing Works & Limitations

## [12] QW-based ELM (QELM)



### Limitations

- **Weak quantum features**
- One-dimensional quantum walk can be exactly mapped onto EM wave phenomena [14]
- **Weak nonlinearity & simple intrinsic dynamic**
- Nonlinearity comes from encoding layer & detection process, QW does not introduce nonlinearity [15]
- **Bulk optical components**

### Counterplay

- **Multi-dimensional QW**
- **Interference** between different possibility distribution (coin DOFs) emerges
- **Entangled States in QW**
- **Entanglement** stick states in different dimensions together, enhancing **interconnected dynamics**
- **Potentially compatibility with integrated quantum optics**

**Limited  
Quantum Benefits,  
Application Scenarios  
and Cascade Ability!!**

[14] A. Peruzzo et al., Quantum walks of correlated photons, *Science*, vol. 329, no. 5998, pp. 1500–1503, 2010, doi: 10.1126/science.1193515.

[15] L. Innocenti et al., Potential and limitations of quantum extreme learning machines, *Communications Physics*, vol. 6, no. 1, pp. 118, May 2023, doi: 10.1038/s42005-023-01233-w.

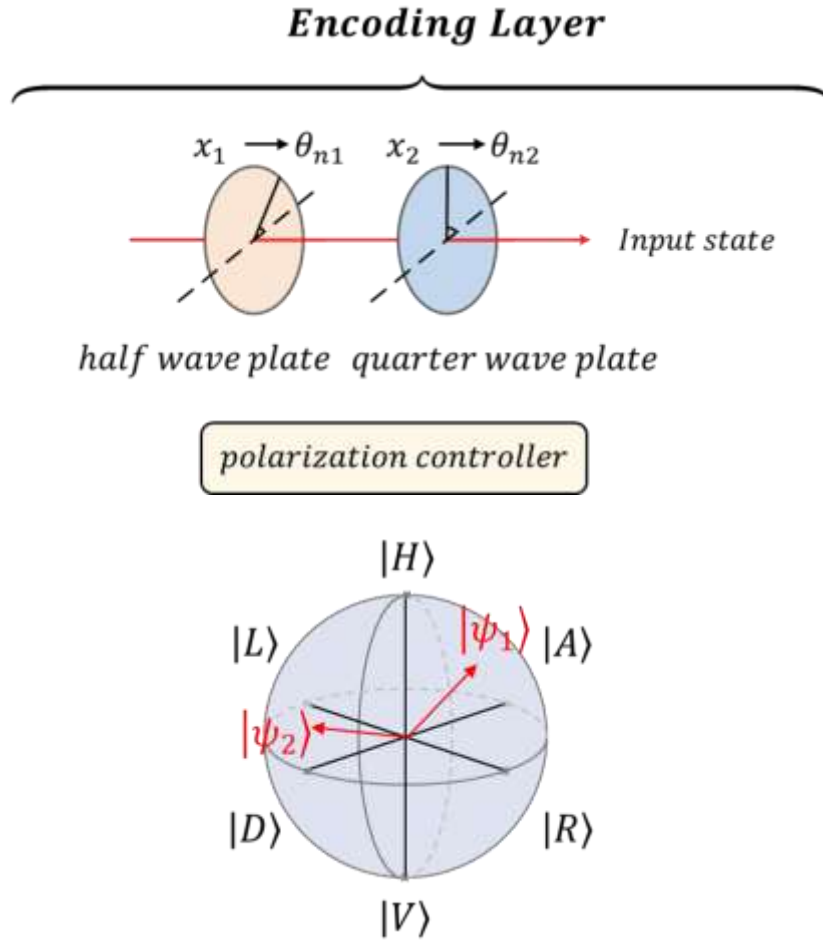
# Outline

---

- Preface: Quantum Walks, Entanglement and Interference
- Introduction: Reservoir Computing & Extreme Learning Machine
- **Method: Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)**
  - **Architecture and Simulations**
  - **Evaluation Results**
- Conclusions and Perspectives

# Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)

## I: Encoding Layer encodes data to polarization states



- Input data:  $x_1$  &  $x_2$
- Normalize:  $x_{max} \rightarrow \pi$ ; coefficient  $m = \frac{\pi}{x_{max}}$
- Linear mapping:  $\theta_1 = mx_1, \theta_2 = mx_2$

Polarization state:

$$|\psi\rangle_{in} = G_{QWP} G_{HWP} \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

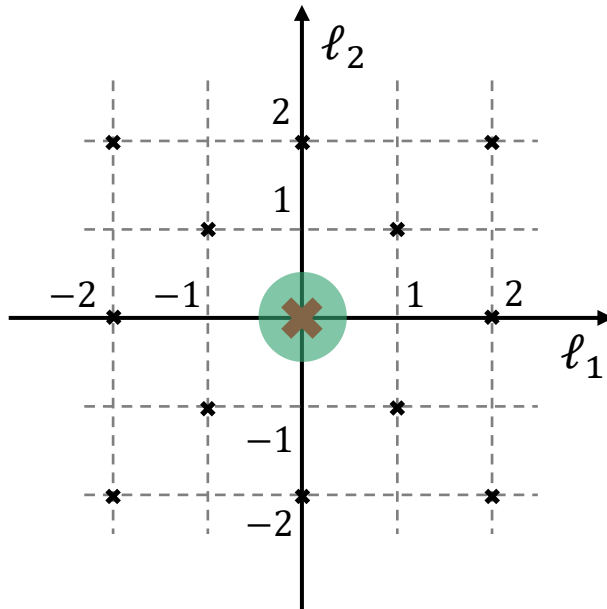
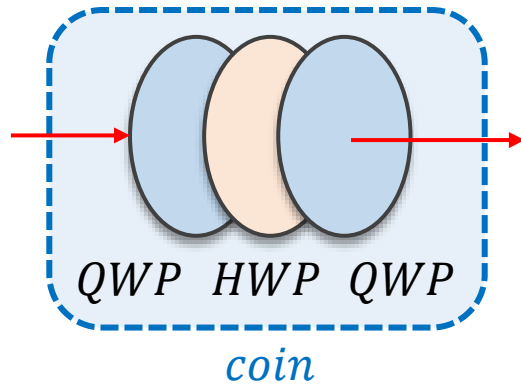
$$G_{Waveplate} = \begin{pmatrix} \cos\theta & \sin\theta \\ \sin\theta & -\cos\theta \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & \exp(i\delta) \end{pmatrix} \begin{pmatrix} \cos\theta & \sin\theta \\ \sin\theta & -\cos\theta \end{pmatrix}$$

Two dimensional QW: connect two state by tensor product

$$|\psi\rangle_{input} = |\psi\rangle_{in} \otimes |\psi\rangle_{in}$$

# Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)

II: **Reservoir Layer** performs 2-step **quantum walks with entanglement**



- **Entangle two dimensions:** entanglement matrices

$$\hat{C}_{total} = (\hat{C}_1 \otimes \hat{C}_2) \hat{C}_{entangle}$$

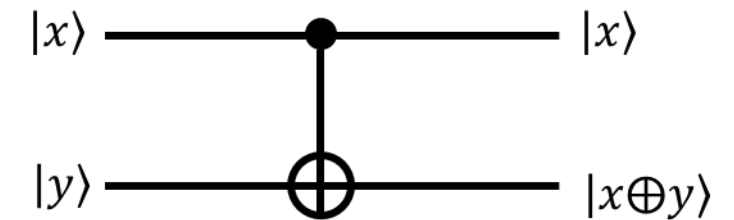
- Prepare two-dimensional **Coins**: polarization manipulation

$$\hat{C} = G_{QWP} G_{HWP} G_{QWP} = \begin{pmatrix} e^{-i(\zeta-\phi)} \cos \eta & e^{i(\zeta+\phi)} \sin \eta \\ -e^{-i(\zeta+\phi)} \sin \eta & e^{i(\zeta-\phi)} \cos \eta \end{pmatrix} \quad (\eta = \zeta + \phi - 2\theta)$$

$$\hat{C}_{com} = \hat{C}_1 \otimes \hat{C}_2$$

$$\hat{C}_{CNOT} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

$$\hat{C}_{upper\_triangle} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

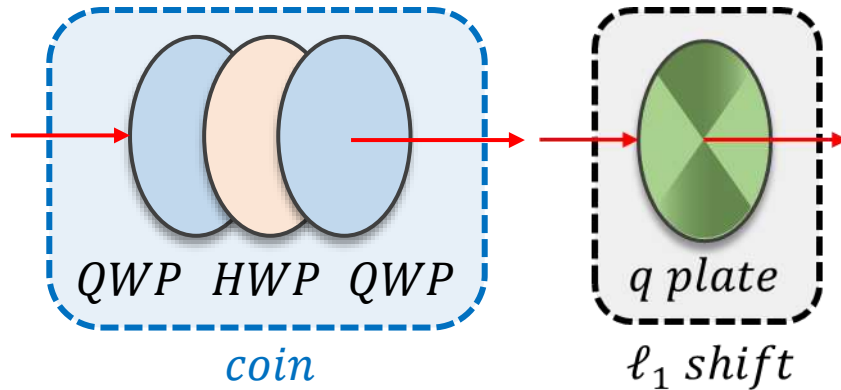


A typical two-qubit CNOT gate



# Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)

II: **Reservoir Layer** performs 2-step **quantum walks with entanglement**

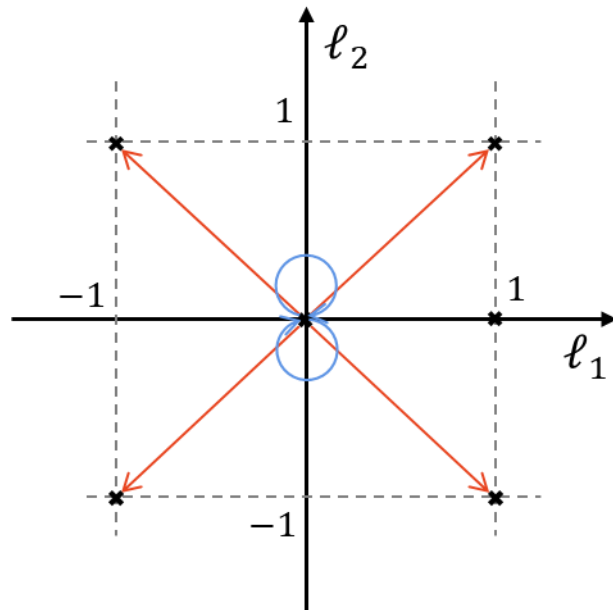


- Shifts: Walk and interfere in OAM space**

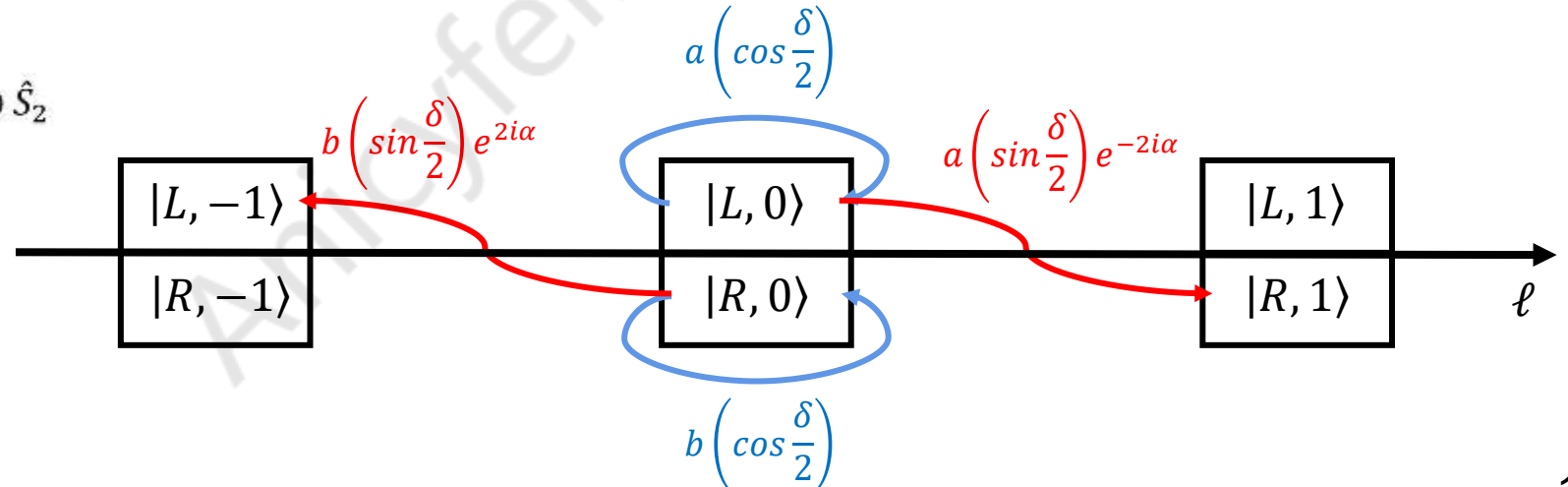
$$\hat{S} = \sum_{\ell} \left\{ \cos \frac{\delta}{2} (|L, \ell\rangle \langle L, \ell| + |R, \ell\rangle \langle R, \ell|) + \sin \frac{\delta}{2} (e^{2i\alpha} |L, \ell\rangle \langle R, \ell+1| + e^{-2i\alpha} |R, \ell\rangle \langle L, \ell-1|) \right\}$$

- Polarization states** determine the walking possibilities (average photon number) to different **OAM states**

$$|\psi\rangle_{in} = a|L\rangle + b|R\rangle \text{ (at OAM value } \ell_1 = 0\text{)}$$



$$\hat{S}_{total} = \hat{S}_1 \otimes \hat{S}_2$$

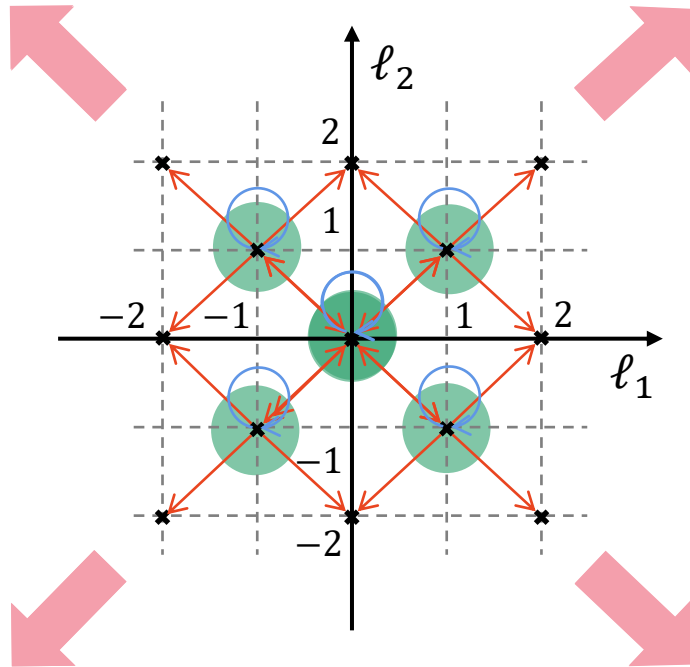




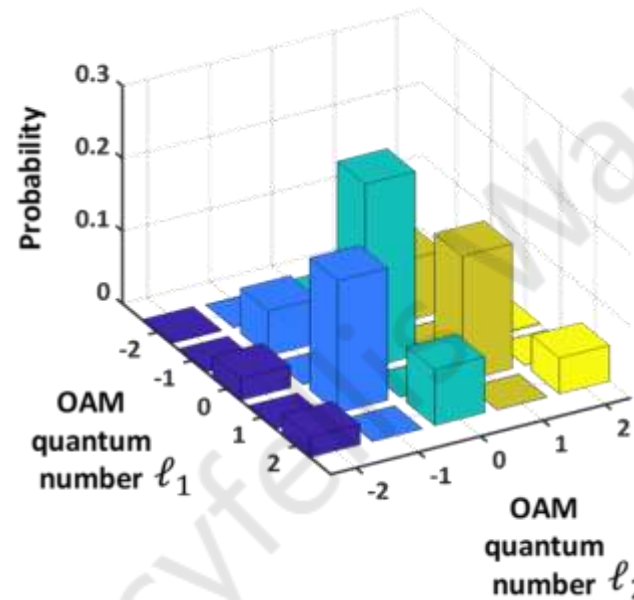
# Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)

Multi-step: Coin operators & Shift operators act alternately

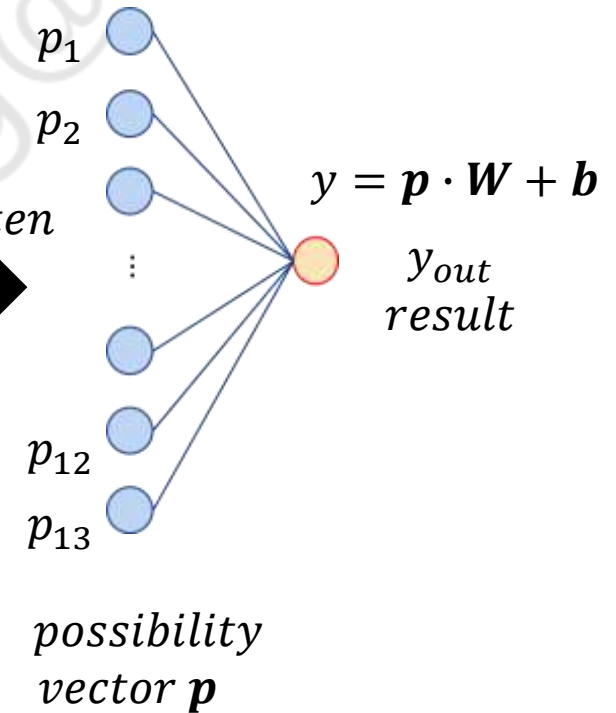
$$\hat{S}'_{total} \hat{C}'_{total} \hat{S}_{total} \hat{C}_{total} |\psi\rangle_{input}$$



III: **Output Layer optimizes weights and generates the final result**



Flatten



● : where entanglement and interference join the game

Optimize weight vector  $W$  conveniently with **damped least square** (also called Levenberg-Marquardt algorithm)

# Evaluation Results

## I: Function fitting task

- **Training dataset:** points sampled from original functions, with interval of 0.002
- **Models:** To keep weight vector sizes in output layer the same (13 parameters)
  - 2D-QWRC: 2-step 2D quantum walk
  - 2D-QWRC with entanglement: 2-step 2D quantum walk with CNOT entangle matrices
  - QELM: 6-step 1D quantum walk
- **Objective/Evaluation Function:** MSE between original functions and predicted functions

## Original functions

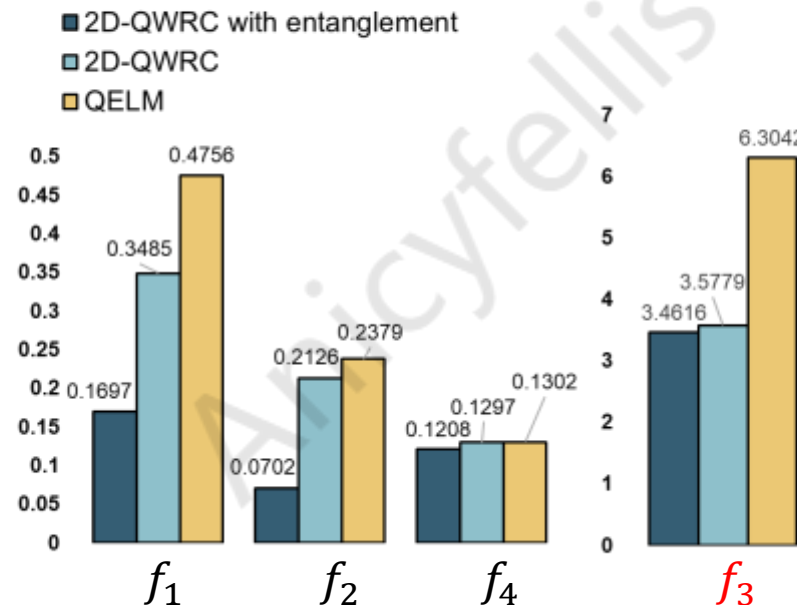
$$f_1 = \frac{\sin \pi x}{\pi x} e^{-x} + 0.01\xi \quad (-3 < x < 0)$$

$$f_2 = \sin \pi x + 0.01\xi \quad (0 < x < 3)$$

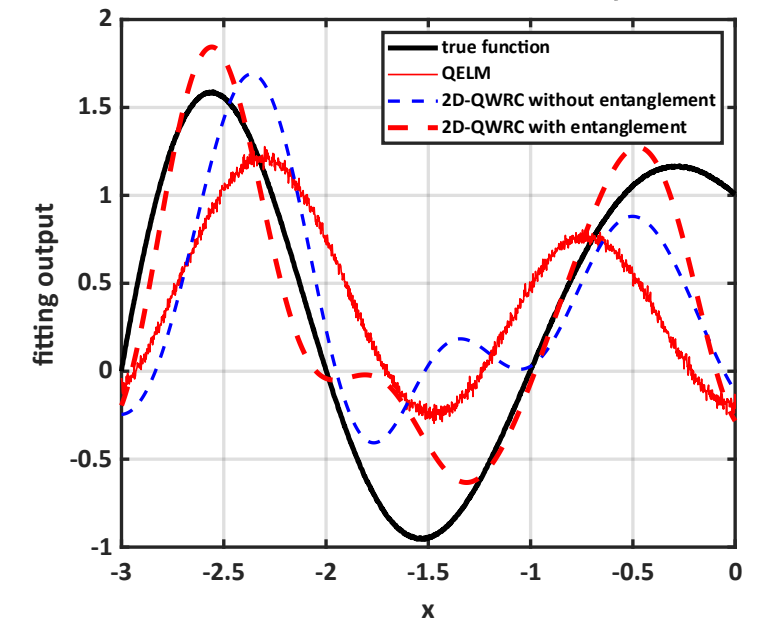
$$f_3 = e^x + 0.01\xi \quad (0 < x < 3)$$

$$f_4 = \begin{cases} 0 & (-2 < x \leq 0) \\ 1 & (0 < x < 2) \end{cases}$$

## Evaluation results: MSE



## Fitting results of $f_1$



# Evaluation Results

## I: Function fitting task

### Original functions

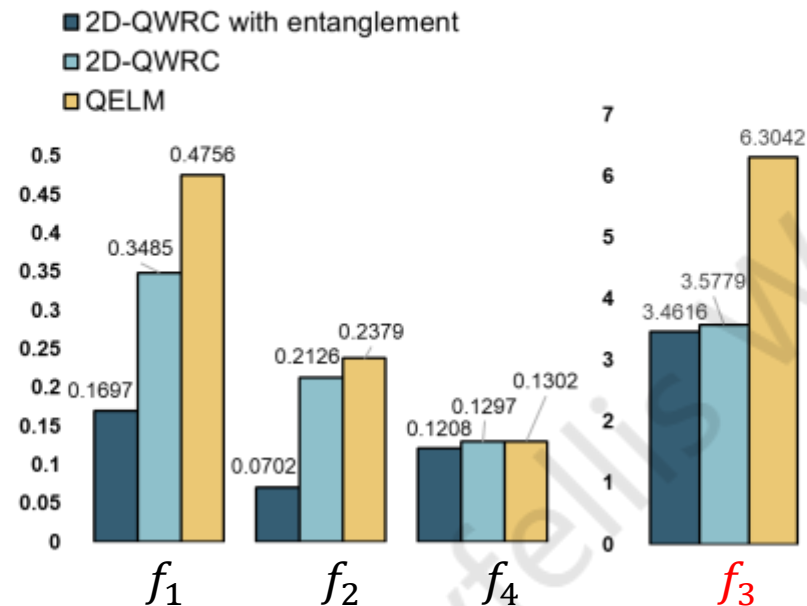
$$f_1 = \frac{\sin \pi x}{\pi x} e^{-x} + 0.01\xi \quad (-3 < x < 0)$$

$$f_2 = \sin \pi x + 0.01\xi \quad (0 < x < 3)$$

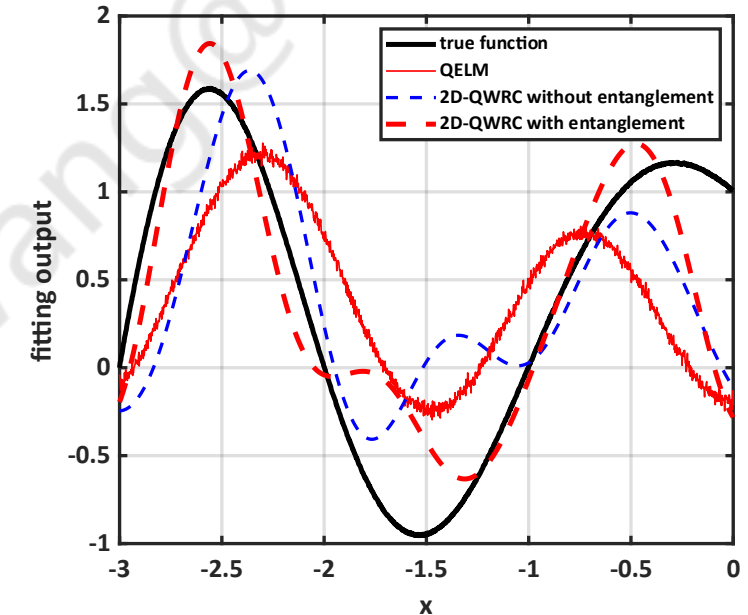
$$f_3 = e^x + 0.01\xi \quad (0 < x < 3)$$

$$f_4 = \begin{cases} 0 & (-2 < x \leq 0) \\ 1 & (0 < x < 2) \end{cases}$$

### Evaluation results: MSE



### Fitting results of $f_1$



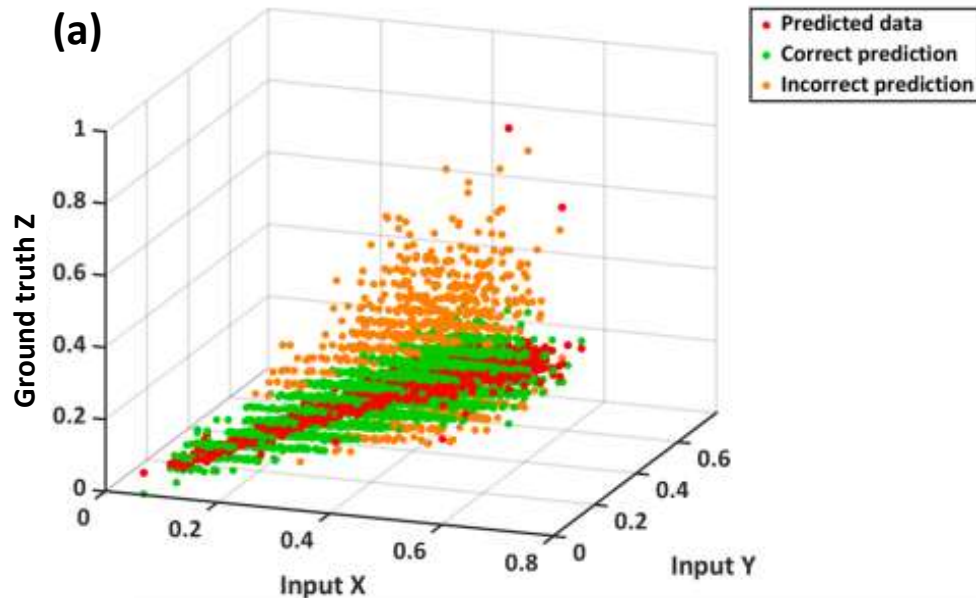
- Obvious and universal high-dimensional QW benefits
- Obvious and universal entanglement benefits
- Weak when fitting non-periodic functions ← encoding method

# Evaluation Results

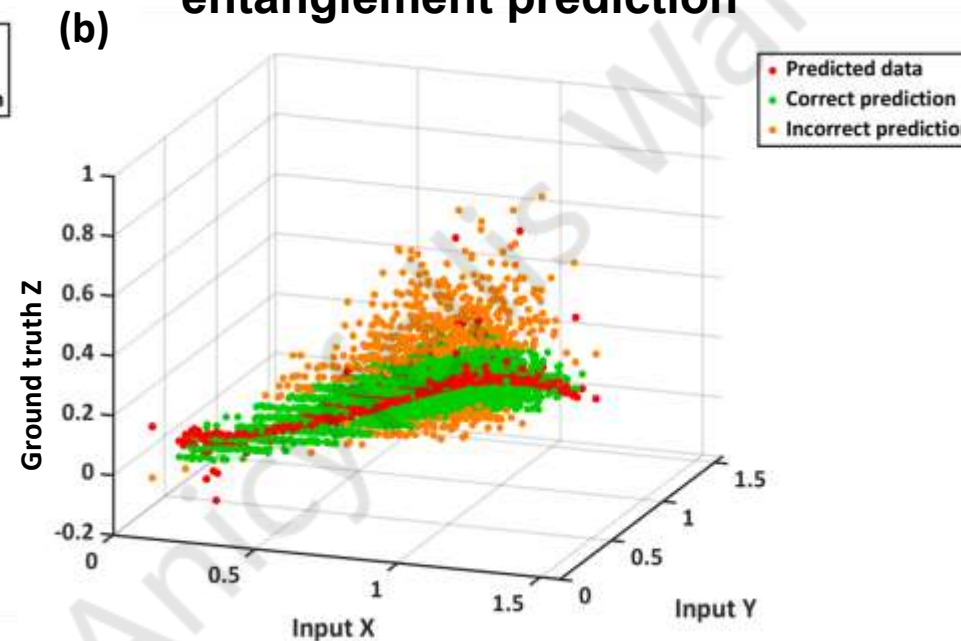
## II: Abalone dataset prediction task

- **Training dataset:** Abalone dataset on lengths & diameters, to predict the number of rings of abalone
- **Models:** as stated formerly
- **Objective/Evaluation Function:** Accuracy, allowed error to be 0.1

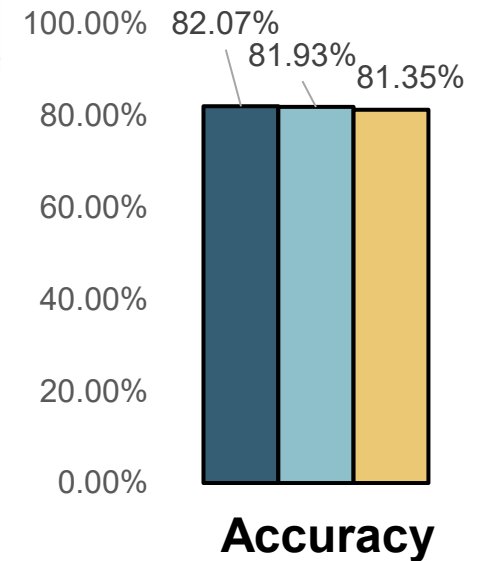
QELM prediction



2D QWRC without entanglement prediction



■ 2D-QWRC with entanglement  
■ 2D-QWRC without entanglement  
■ QELM



- Prediction accuracy: potential in universal machine learning tasks
- No entanglement benefits! No high-dimensional benefits!

# Outline

---

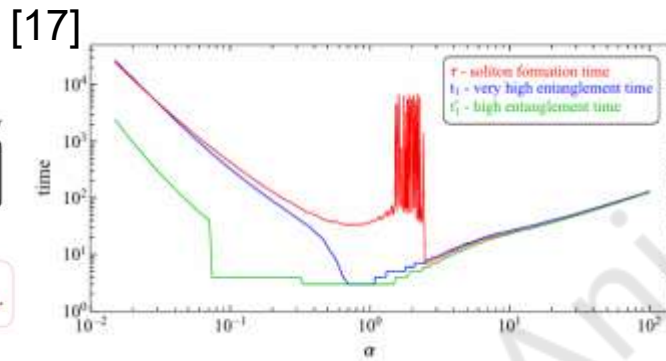
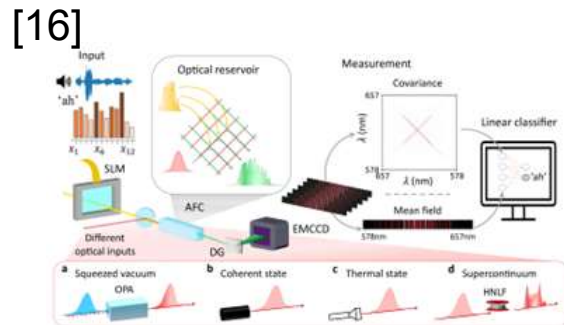
- Preface: Quantum Walks, Entanglement and Interference
- Introduction: Reservoir Computing & Extreme Learning Machine
- Method: Two-Dimensional Quantum Walk Reservoir Computing (2D-QWRC)
  - Architecture and Simulations
  - Evaluation Results
- **Conclusions and Perspectives**

# Conclusions & Perspectives

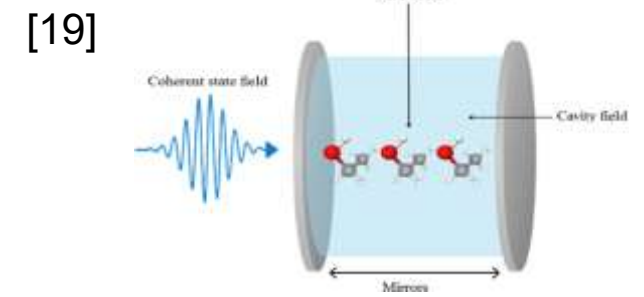
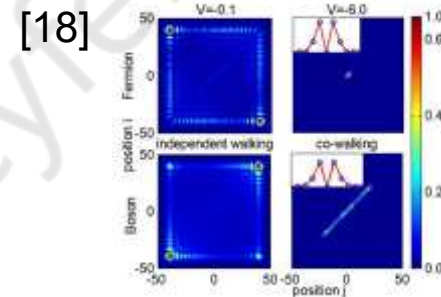
- Presents an optical **two-dimensional quantum walk reservoir computing** model, possessing **quantum interference & entanglement**
  - Demonstrates a 64.32% accuracy improvement over the QELM model in **nonlinear function approximation tasks**. Validated the **effectiveness in general machine learning tasks** of the 2D-QWRC through the abalone age prediction task, with accuracy of 82%
- 

## Towards Quantum Optical Intelligence

### a) Intrinsic Quantum Properties of Photons Squeeze light, Entanglement, and Correlated photons



### b) Atomic, Molecular & Optics (AMO) level Compactness and Compatibility Nanophotonics, Light-matter interactions, and Complex dynamic systems



[16] Valeria Cimini, et al., (2024). Large-scale quantum reservoir computing using a Gaussian Boson Sampler. *arXiv preprint arXiv:2505.13695v1*

[17] Bauer, J.H., et al.. Entanglement entropy in a certain nonlinear discrete quantum walk model. *Quantum Inf Process* **23**, 118, 2024.

[18] X. Cai, et al., Multiparticle Quantum Walks and Fisher Information in One-Dimensional Lattices, *Phys. Rev. Lett.*, vol. 127, p. 100406, Sept. 2021.

[19] D. M. Welakuh, et al., Cavity-Mediated Molecular Entanglement and Generation of Non-classical States of Light, *The Journal of Physical Chemistry A*, vol. 128, no. 4, pp. 799–806, Feb. 2024.

# References

---

- [1] N. B. Lovett, et al., Universal quantum computation using the discrete-time quantum walk, *Phys. Rev. A*, vol. 81, p. 042330, Apr. 2010.
- [2] S. Marsh, et al., Combinatorial optimization via highly efficient quantum walks, *Phys. Rev. Res.*, vol. 2, p. 023302, June 2020.
- [3] S. Dernbach, et al., Quantum walk neural networks with feature dependent coins, *Applied Network Science*, vol. 4, no. 1, p. 76, Sept. 2019.
- [4] Douglas BL, et al., Efficient quantum circuit implementation of quantum walks. *Phys Rev A*.2009;79(5):Article 052335.
- [5] A. Schreiber, et al., A 2D Quantum Walk Simulation of Two-Particle Dynamics, *Science*, vol. 336, no. 6077, pp. 55–58, 2012.
- [6] Gong M, et al., Quantum walks on a programmable two-dimensional 62-qubit superconducting processor. *Science*. 2021;372(6545):948–952.
- [7] Qiang X, et al., Implementing graph-theoretic quantum algorithms on a silicon photonic quantum walk processor. *Sci Adv*. 2021;7(9):Article eabb8375.
- [8] Markus Gräfe, et al., 2020 *J. Phys. B: At. Mol. Opt. Phys.* **53** 073001.
- [9] Ingo Fischer, et al., *Reservoir Computing Theory, Physical Implementations, and Applications Book*, 2021.
- [10] Gauthier. et al. Next generation reservoir computing. *Nat Commun* **12**, 5564, 2021.
- [11] Davide Pierangeli, et al., Photonic extreme learning machine by free-space optical propagation, *Photon. Res.* 9, 1446-1454, 2021
- [12] A. Suprano, et al., Experimental Property Reconstruction in a Photonic Quantum Extreme Learning Machine, *Phys. Rev. Lett.*, vol. 132, p. 160802, 2024.
- [13] A. Sakurai, et al., Quantum optical reservoir computing powered by boson sampling, *Optica Quantum*, vol. 3, pp. 238–245, 05 2025.
- [14] A. Peruzzo et al., Quantum walks of correlated photons, *Science*, vol. 329, no. 5998, pp. 1500–1503, 2010, doi: 10.1126/science.1193515.
- [15] L. Innocenti et al., Potential and limitations of quantum extreme learning machines, *Communications Physics*, vol. 6, no. 1, pp. 118, May 2023, doi: 10.1038/s42005-023-01233-w.
- [16] Valeria Cimini, et al., (2024). Large-scale quantum reservoir computing using a Gaussian Boson Sampler. arXiv preprint arXiv:2505.13695v1
- [17] Bauer, J.H., et al.. Entanglement entropy in a certain nonlinear discrete quantum walk model. *Quantum Inf Process* **23**, 118, 2024.
- [18] X. Cai, et al., Multiparticle Quantum Walks and Fisher Information in One-Dimensional Lattices, *Phys. Rev. Lett.*, vol. 127, p. 100406, Sept. 2021.
- [19] D. M. Welakuh, et al., Cavity-Mediated Molecular Entanglement and Generation of Non-classical States of Light, *The Journal of Physical Chemistry A*, vol. 128, no. 4, pp. 799–806, Feb. 2024.



**Thanks for listening!**

