Recent advances in quantum artificial intelligence

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Mathematical Picture Language Seminar， Harvard University， 02/21/2023

*Some images shown found online

What is artificial intelligence (AI)?

Definition: *intelligence demonstrated by machines (knowledge representation, automated reasoning, natural language processing, computer vision, robotics, machine learning, ……)*

Three categories:

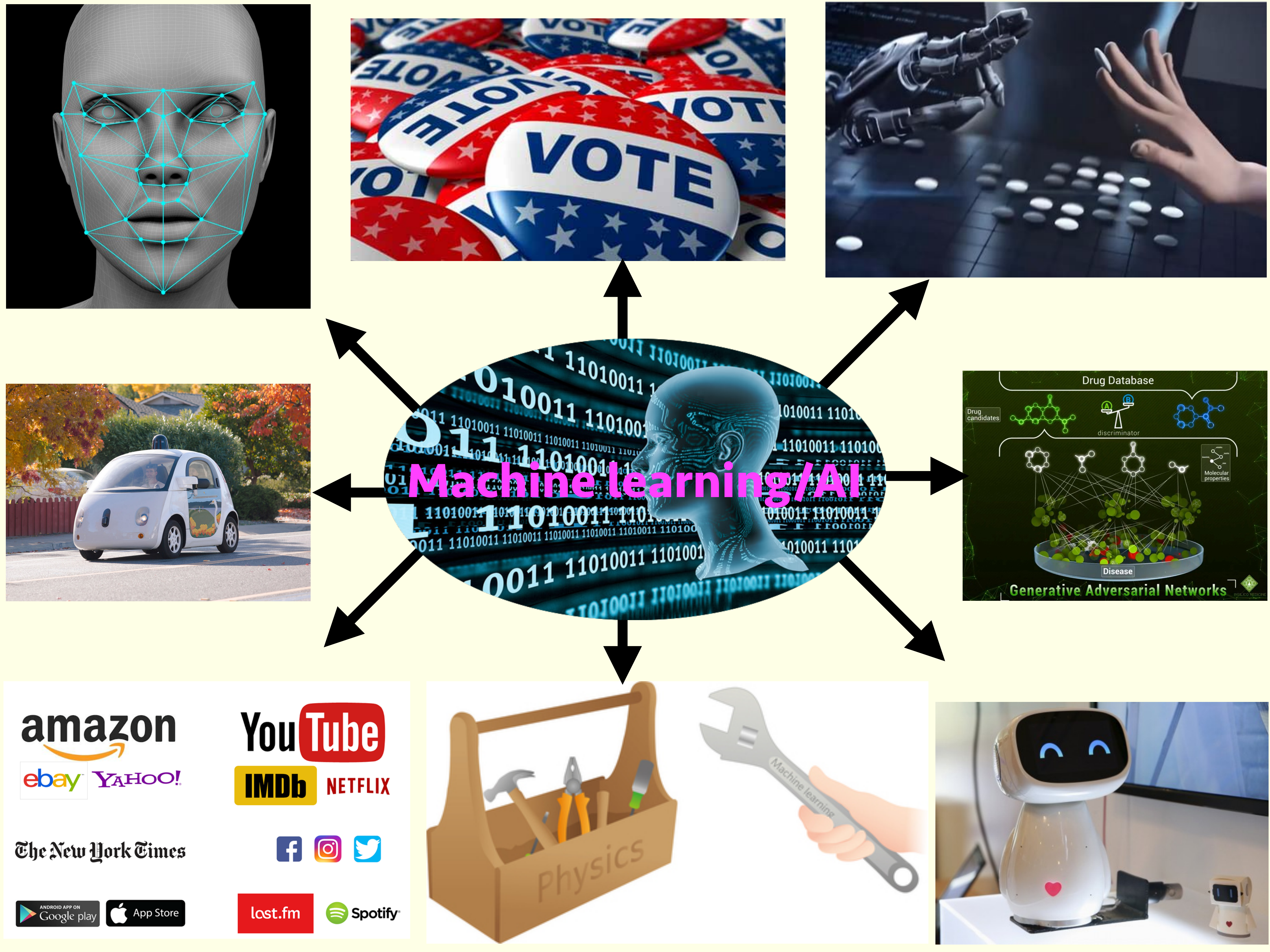
- **Weak AI:** *focused on one narrow task (Deep blue, AlphaGo)*
- **Strong AI:** *with consciousness, sentience, and mind; human level*
- **Super Strong AI:** *Stronger than human in every field*

Three key factors: *Big data, new algorithms, hardware (TPU)*

Basic methods: *machine learning and deep learning*

- **Geoffrey Hinton**: *BP algorithm, Boltzmann machine*
- **Yann LeCun:** *CNN, Pattern recognition*
- **Yoshua Bengio:** *GAN, neural language models*
- **Schmidhuber:** *RNN, LSTM, Speech recognition*
- **Goodfellow:** *GAN*
- ……

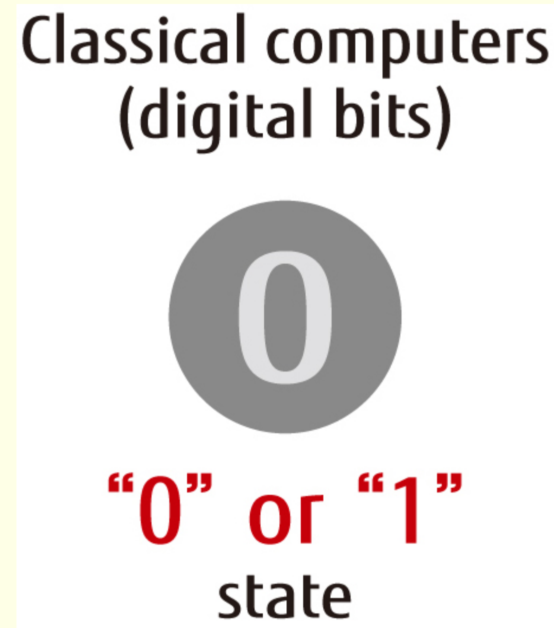
Ref: Russell & Norvig, "Artificial intelligence, a modern approach", third edition


VOTE
Machine learning/AI
Drug Database
Drug candidates
discriminator
Molecular properties
Disease
Generative Adversarial Networks
amazon
ebay
YAHOO!
YouTube
IMDb
NETFLIX
The New York Times
ANDROID APP ON Google play
App Store
last.fm
Spotify
Physics
Machine learning

What is quantum computing?

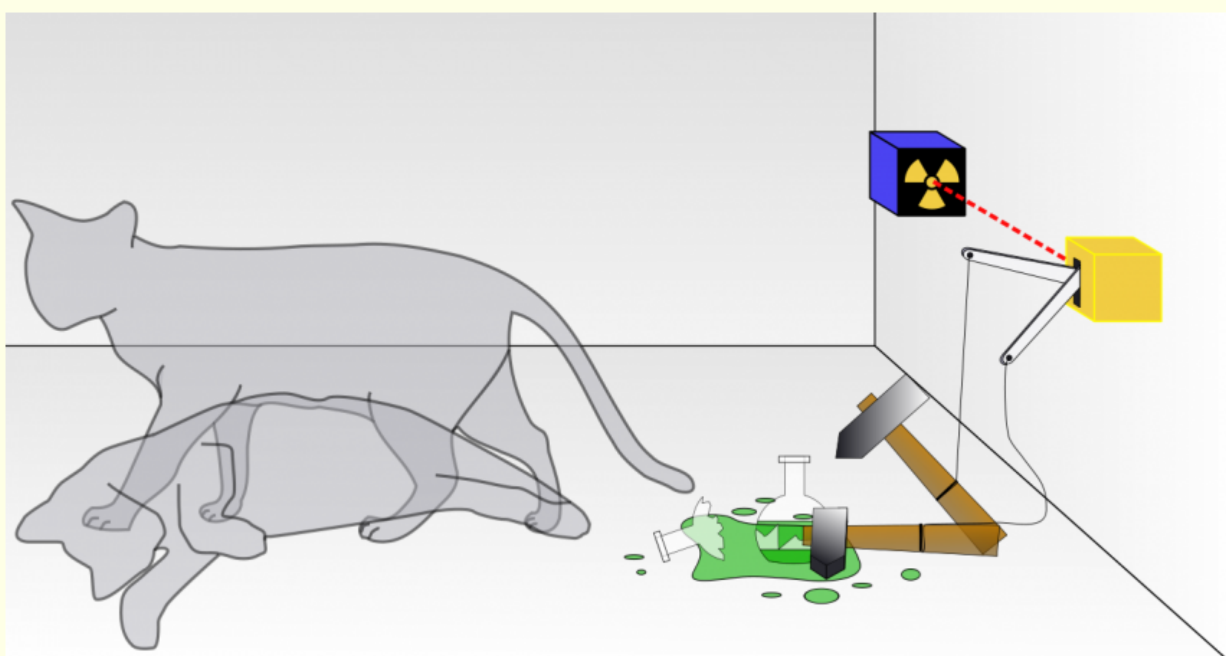
《淮南子·说林篇》曰：“杨子见逵路而哭之，为其可以南可以北

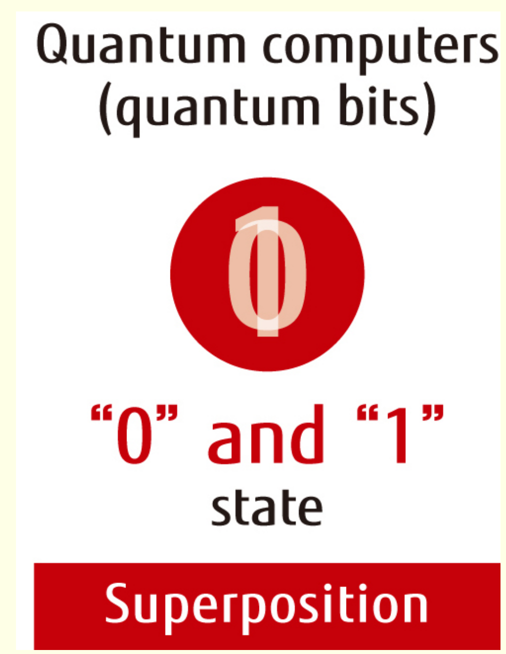
(Yangzi wept upon seeing roads with multiple crossings, as they could lead south or north)；



n bits can store one of the 2^n numbers at any time

Quantum superposition: Schrödinger's cat

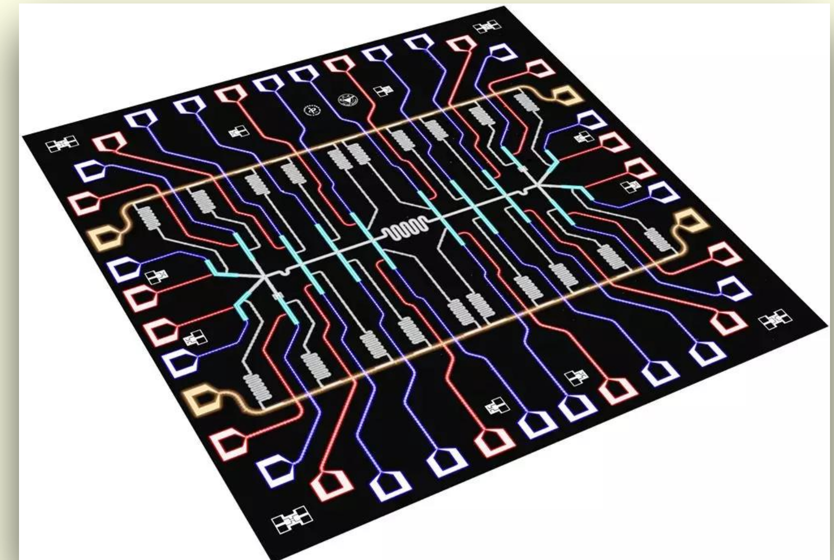




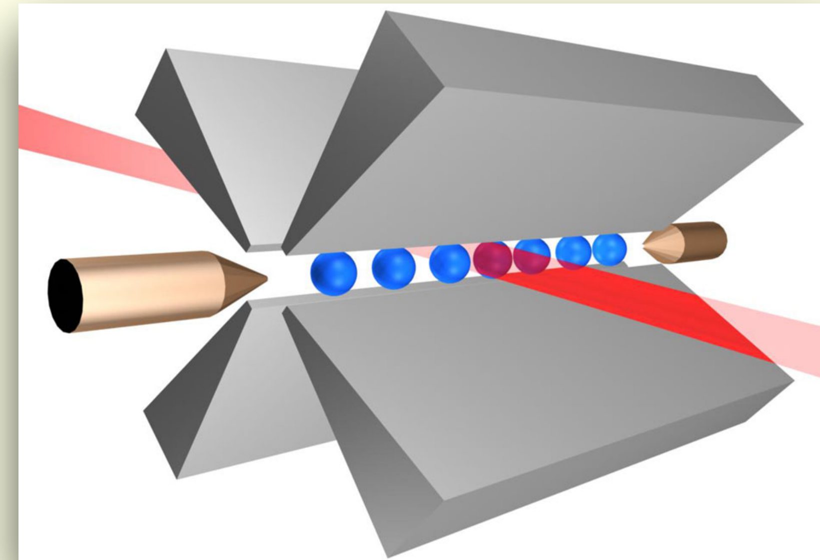
n qubits can store all the 2^n numbers at once

Advantages: exponential storage, exponential speedup

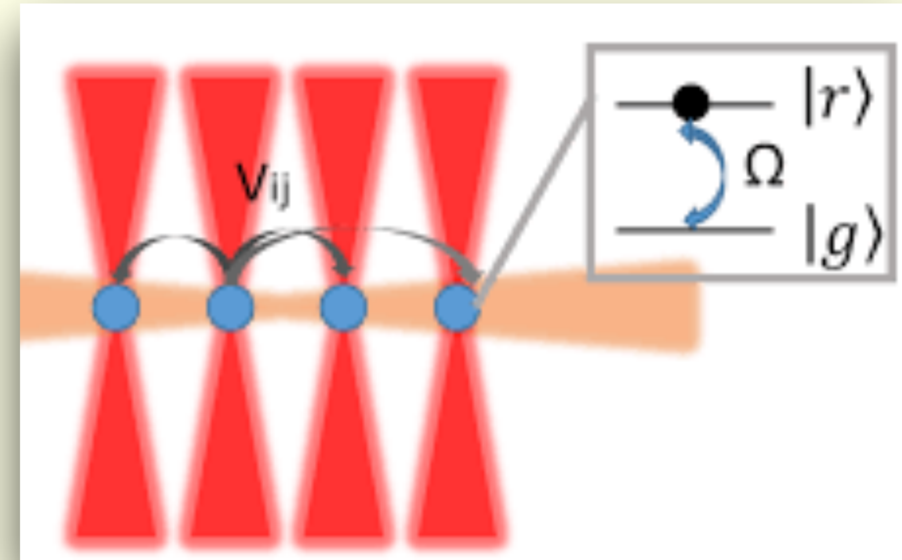
Candidates for Quantum Computers



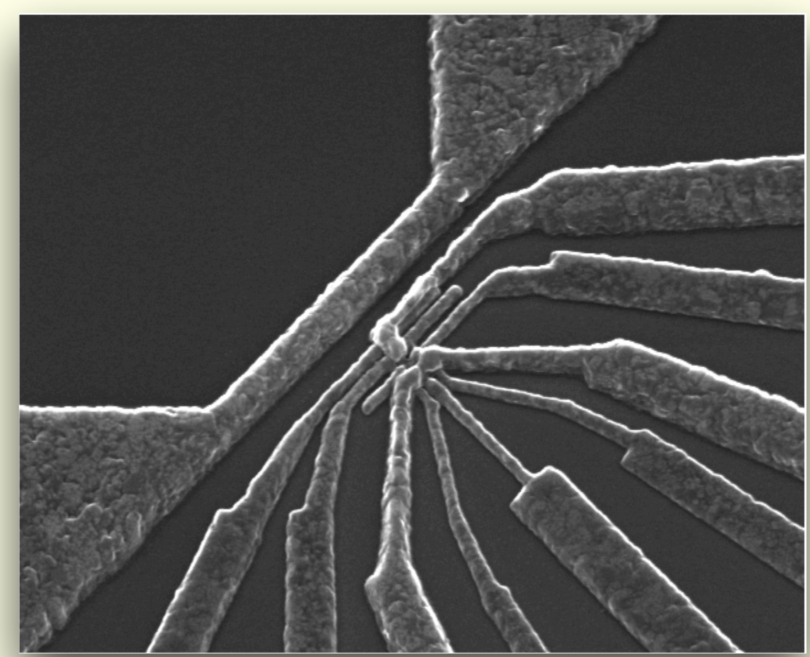
Superconducting qubits



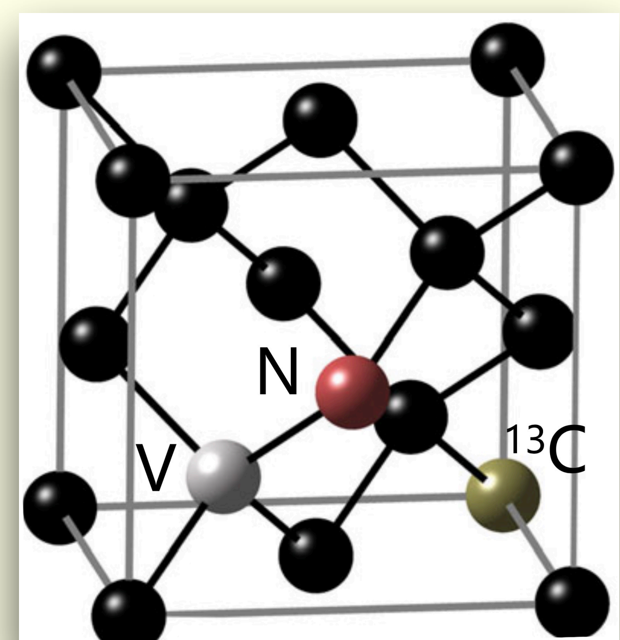
Trapped ions



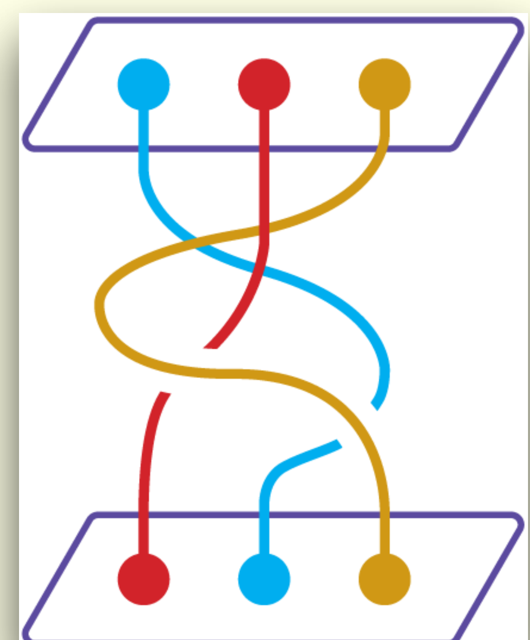
Ryderg atoms



Quantum dots



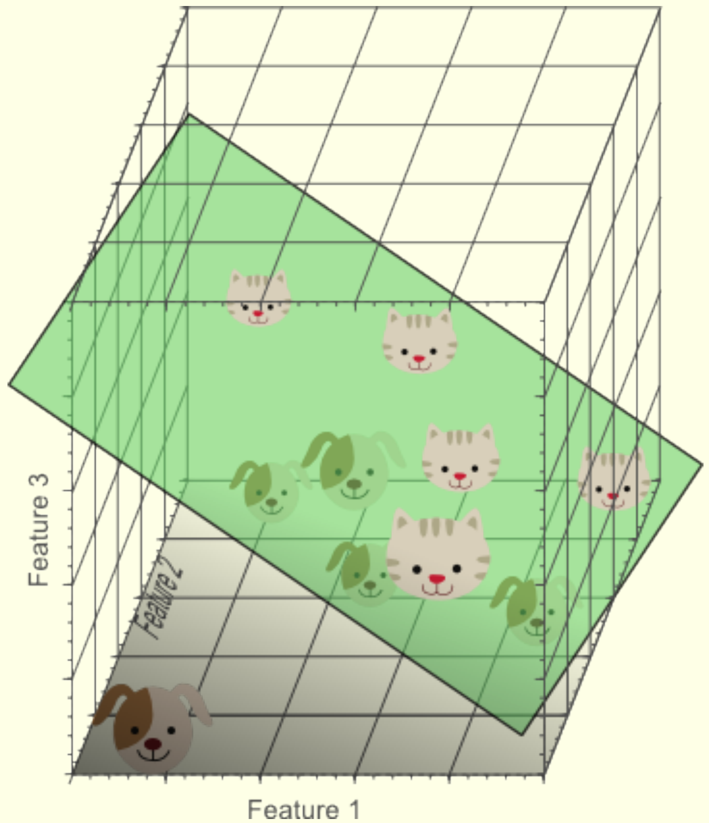
NV centers

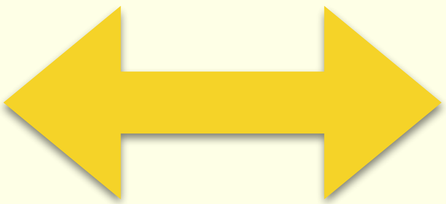


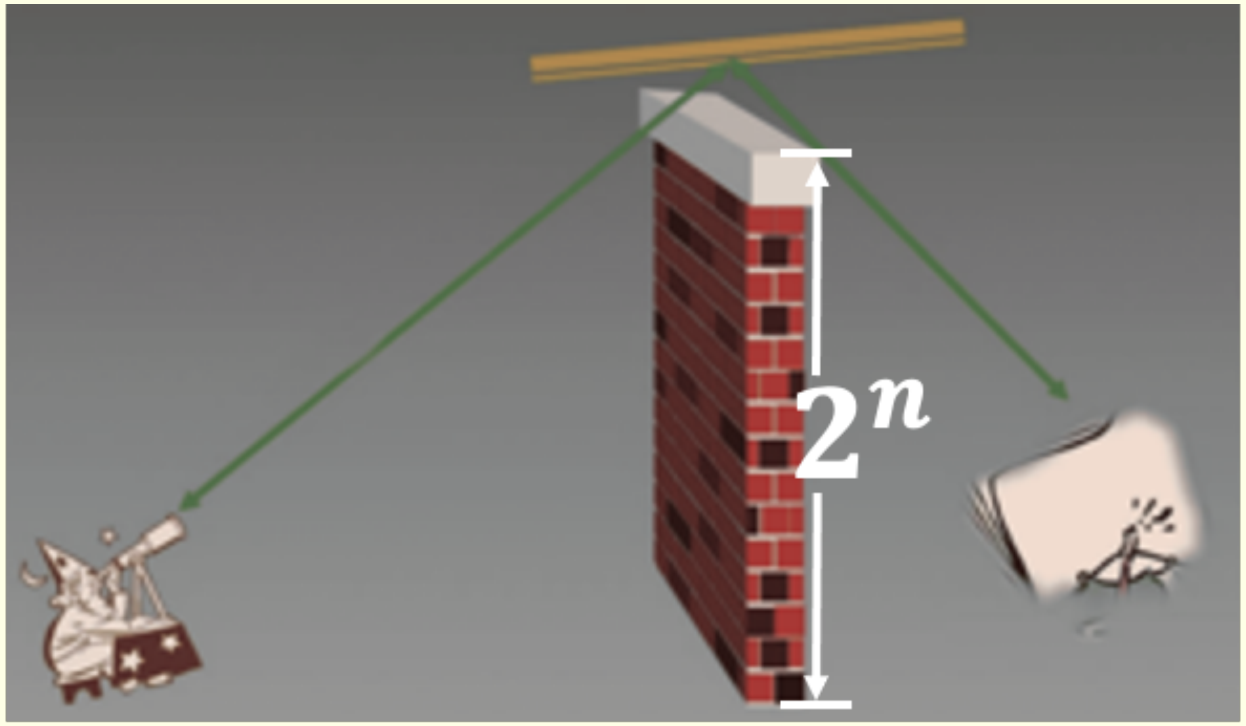
Topological qubits

. . . . . .

Quantum Artificial Intelligence







Curse of dimensionality:
data samples needed grows exponentially with the number of features (Richard Bellman)

Exponential Wall:
the Hilbert space is exponentially large (Walter Kohn)

Quantum AI { Quantum enhanced AI; AI for quantum physics }

Quantum Artificial Intelligence

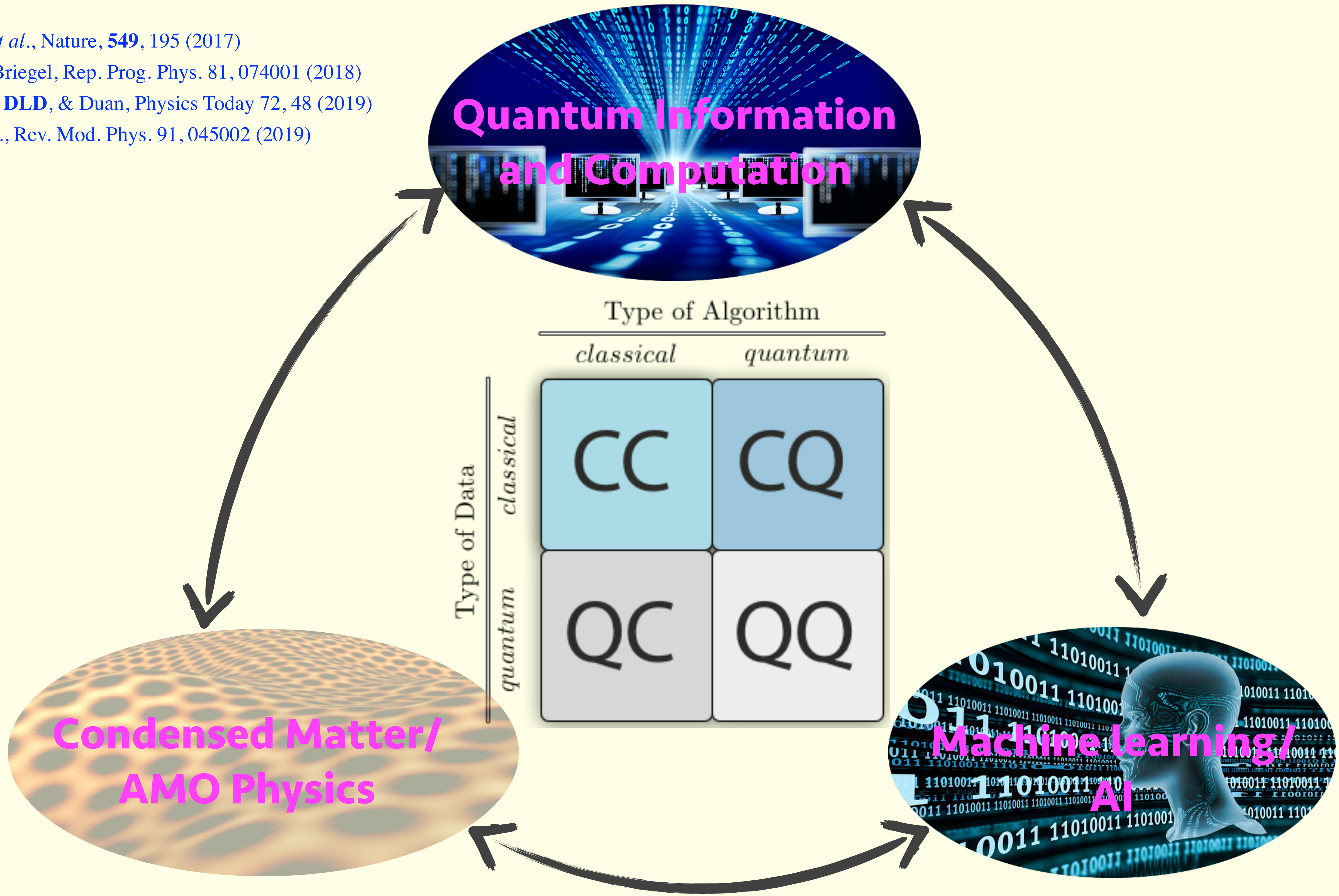
Biamonte *et al*., Nature, **549**, 195 (2017)

Dunjko & Briegel, Rep. Prog. Phys. 81, 074001 (2018)

Das Sarma, **DLD**, & Duan, Physics Today 72, 48 (2019)

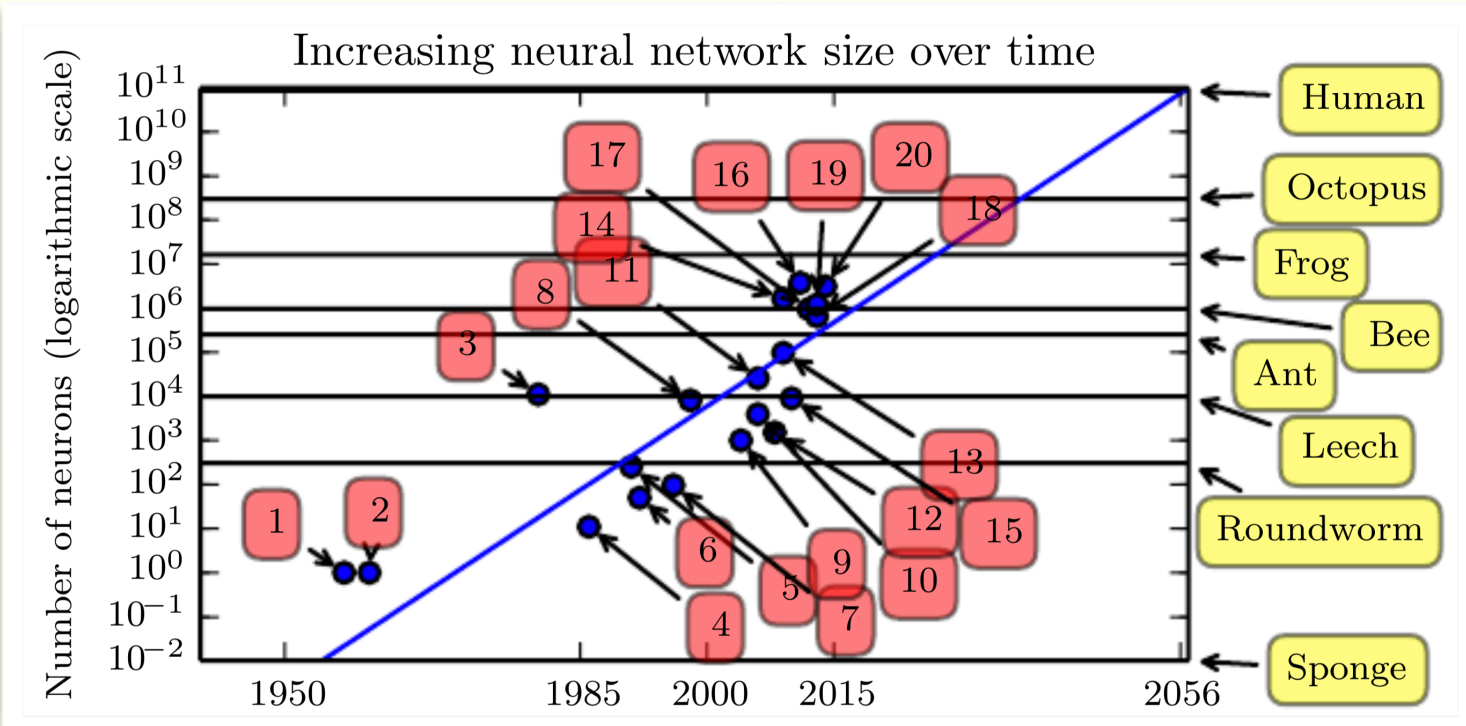
Carleo et al., Rev. Mod. Phys. 91, 045002 (2019)

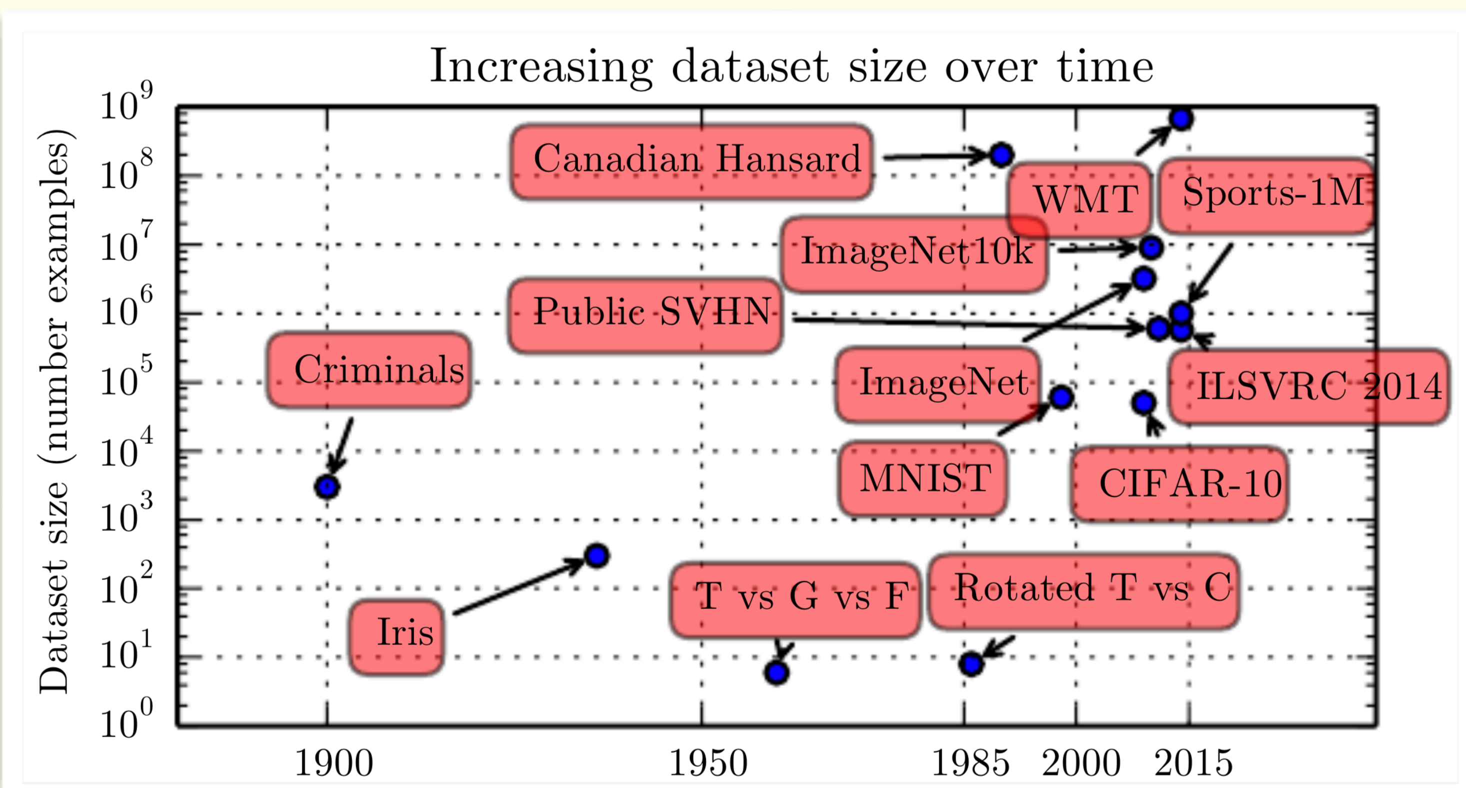
……



Why Quantum AI? classical AI perspective

Moore's law in machine learning





Goodfellow, Bengio, & Courville, Deep learning, MIT press

arXiv.org > cs > arXiv:2005.14165

OpenAI

Computer Science > Computation and Language

[Submitted on 28 May 2020 (v1), last revised 5 Jun 2020 (this version, v3)]

Language Models are Few-Shot Learners

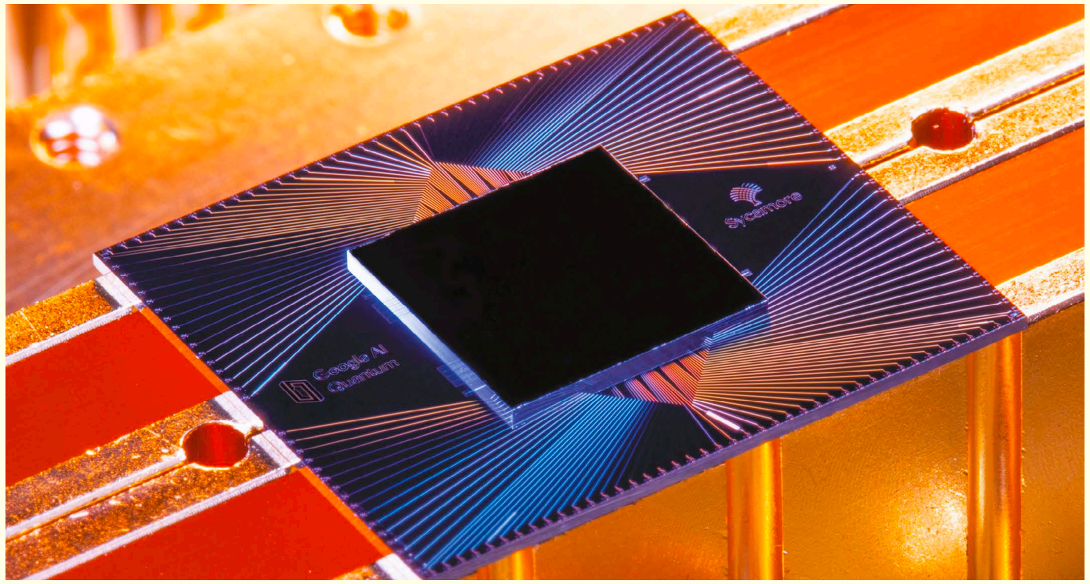
- **# of parameters: 175B**
- **Data set: 45TB**
- **Training cost: 12M $**

Motivations:

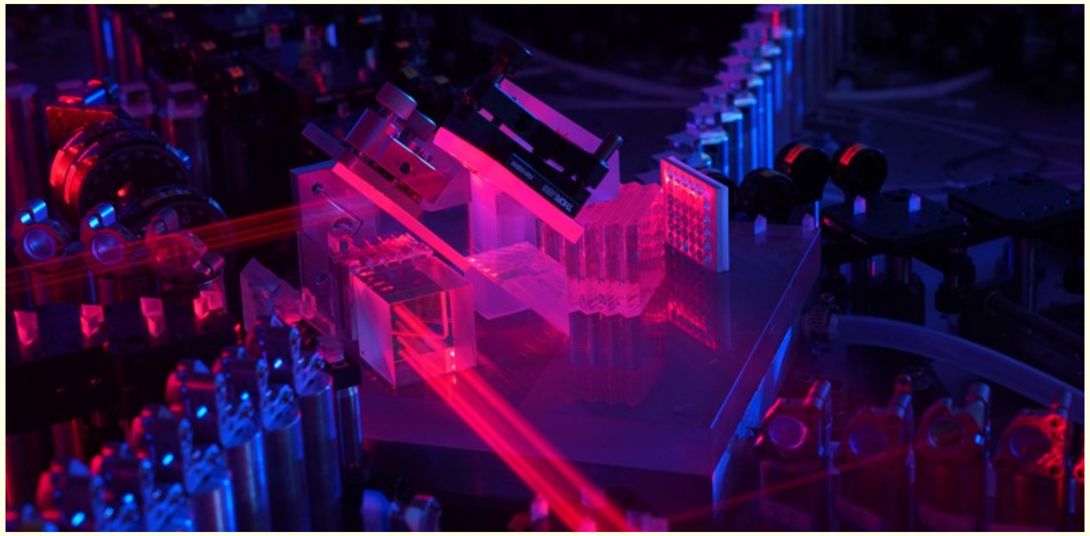
- **To enhance AI performance**
- **To understand AI better**
- **To save cost**
- **To build strong AI? (Science: Can quantum artificial intelligence imitate the human brain?)**
- **……**

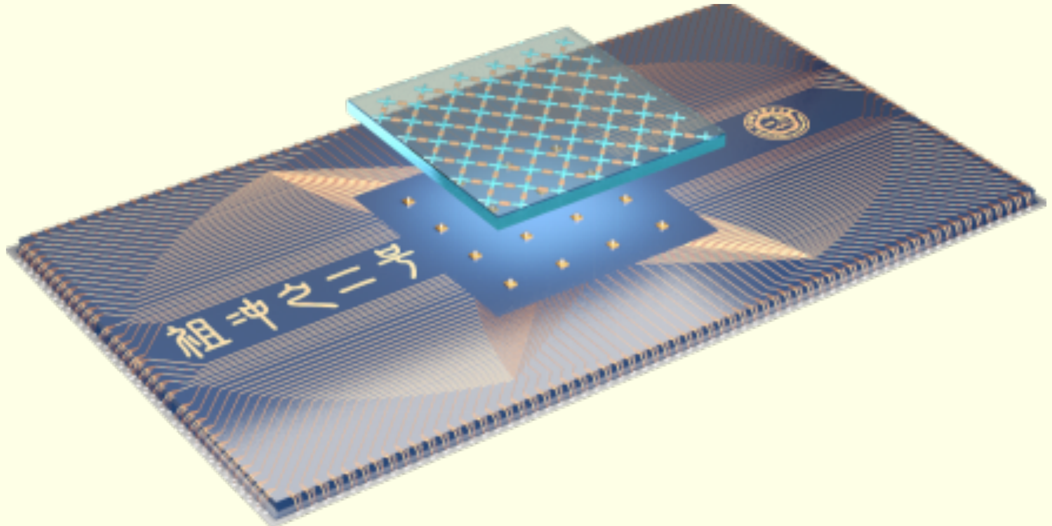
Why Quantum AI? quantum perspective

Google's quantum advantage

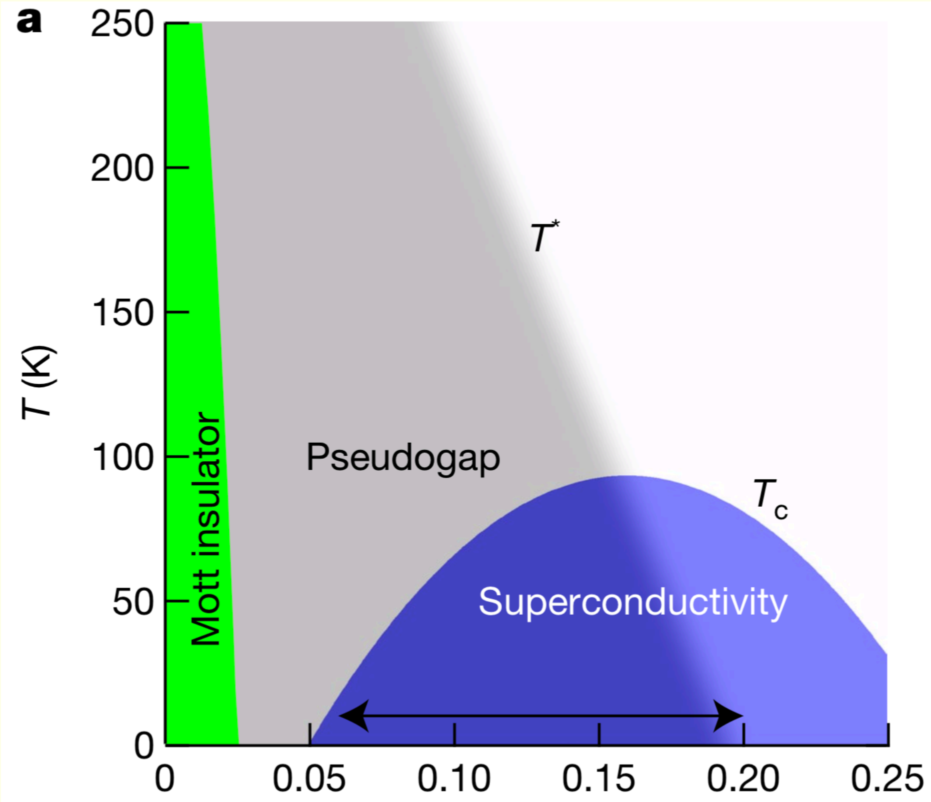


USTC's quantum advantage





Learning phases of matter



Zhang et al, Nature 570, 484 (2019)

- **Practical applications in the NISQ era**
- **Learn new phases of matter**
- **Solve quantum many-body problems**
- **Quantum big data is at the horizon**
- **Quantum learning supremacy**
- **……**

Outline

- **Quantum enhanced machine learning/AI**
  1. *HHL algorithm, quantum generative models*
  2. *Quantum neural networks/classifiers*
  3. *Quantum adversarial machine learning*
  4. *Secure quantum distributed learning*
- **Machine learning in quantum physics**
  1. *Machine learning phases of matter*
  2. *Neural-network states approaches*
  3. *Quantum compiling with machine learning*
  4. *Topological time crystals*
- **Future challenges**

Quantum enhanced machine learning/AI

Harrow-Hassidim-Lloyd (HHL) algorithm

Target: solve approximately: A**x**=**b**

Basic ideas:

- **Encoding the vectors as quantum states:** $\mathbf{x} \rightarrow |\mathbf{x}\rangle, \ \mathbf{b} \rightarrow |\mathbf{b}\rangle$
- **Phase estimation under A**

Exponential speed up? $O(\log^2 N)$ VS $O(N \log N)$

Caveats:

- **qRAM**
- **A be well-conditioned**
- $|\mathbf{x}\rangle$ NOT $\mathbf{x}$

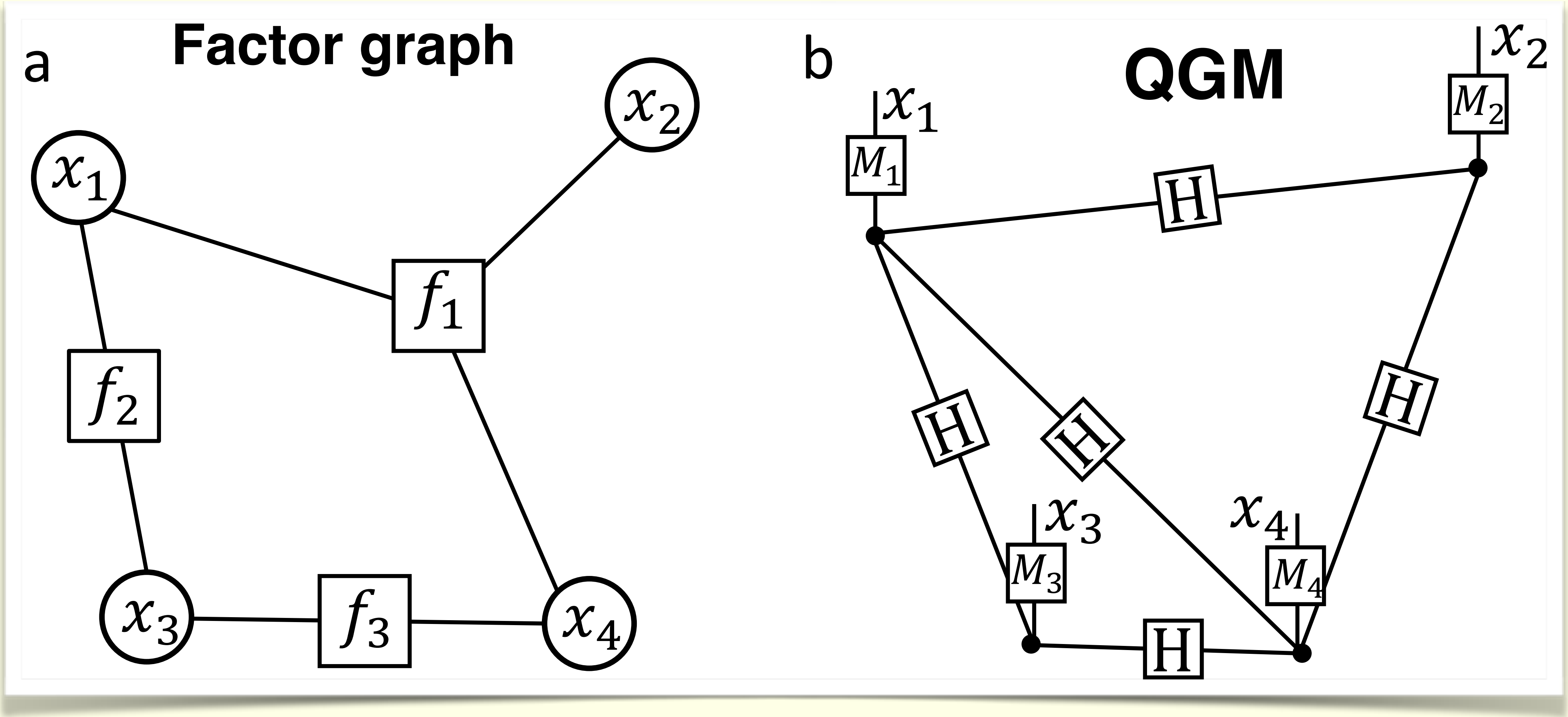
Algorithms using HHL as subroutine:

- **Bayesian inference:**
- **Least-squares fitting:**
- **Quantum PCA:**
- **Quantum SVM:**

Harrow, Hassidim, and Lloyd, PRL, 103,150502 (2009)

Biamonte *et al*., Nature, **549**, 195 (2017)

Quantum generative model (QGM)



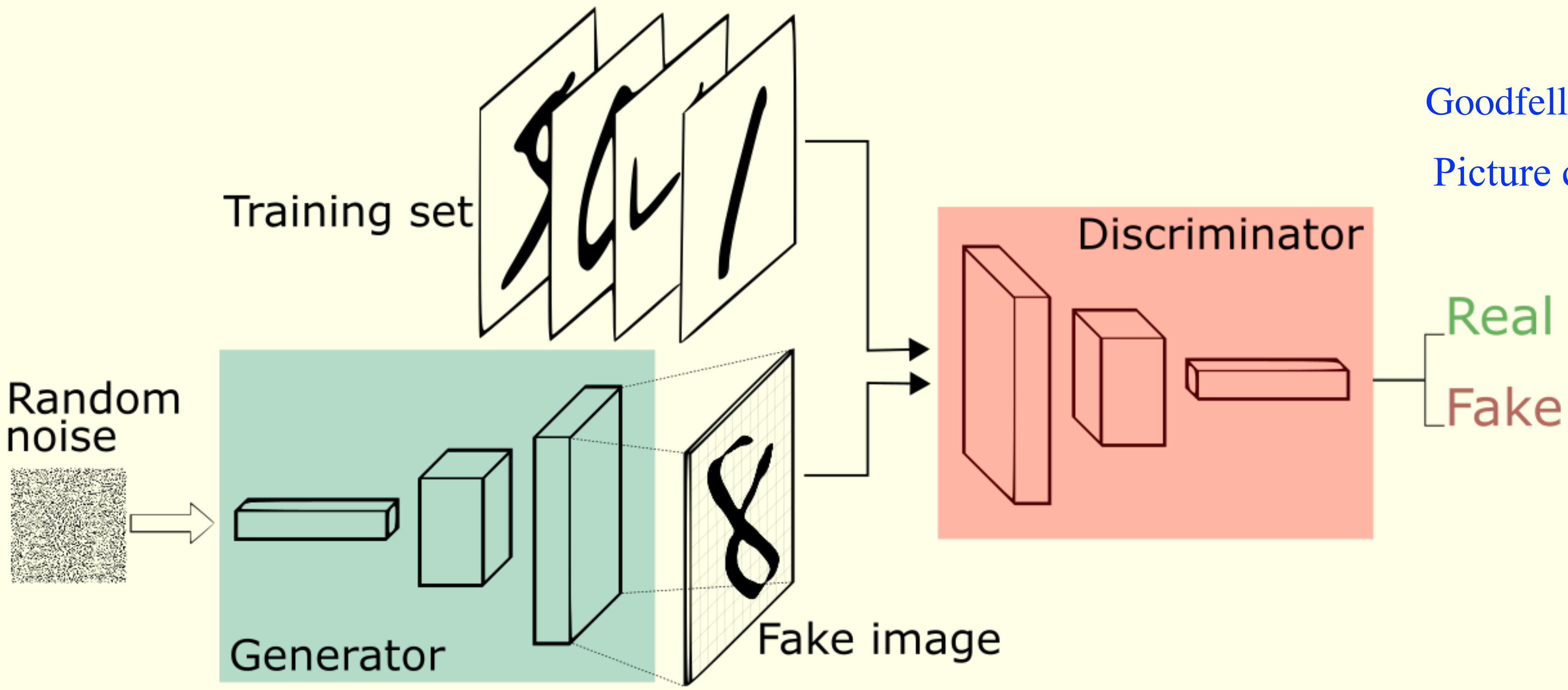
$P(x_1, x_2, x_3, x_4) \propto f_1(x_1, x_2, x_4) f_2(x_1, x_3) f_3(x_3, x_4)$ $\quad$ $|Q\rangle = M_1 \otimes M_2 \otimes M_3 \otimes M_4 |G\rangle$

Advantages:

- *Exponential representation power*
- *Exponential speed up*
- *Exponential Inference*

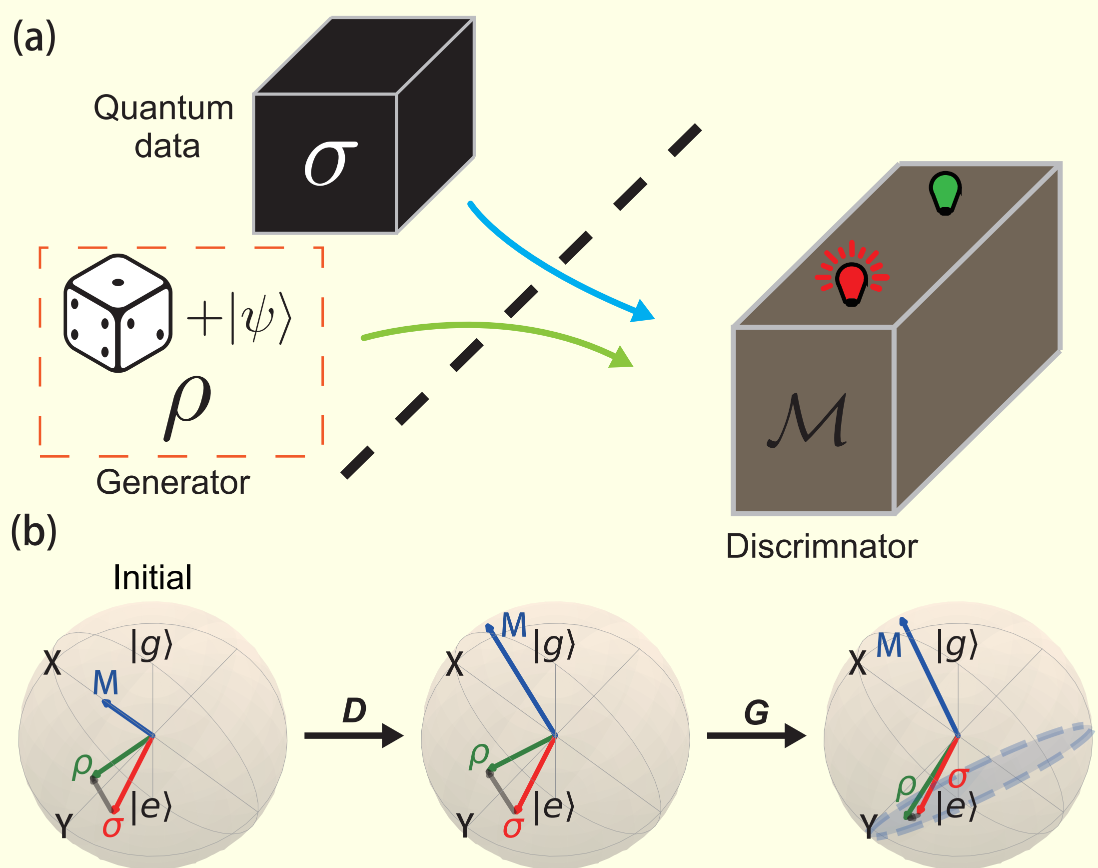
Gao, Zhang, and Duan, Science Advances, 4, 12 (2018)

Quantum generative adversarial network (QGAN)



Goodfellow *et al*, ANIPS, pp. 2672-2680, (2014)

Picture credit: Thalles Silva



Lloyd and Weedbrook, PRL, 121, 040502 (2018)

Dallaire-Demers and Killoran, arXiv: 1804.08641

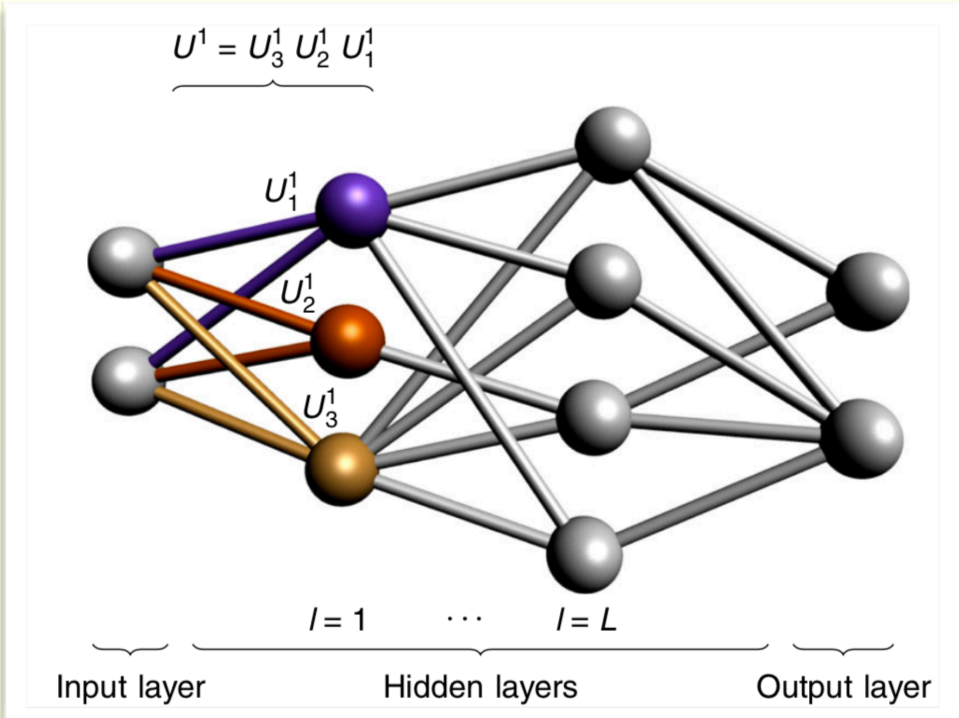
Benedetti et al, arXiv: 1806.00468

Hu, …, **DLD***, Zou*, and Sun*, Sci. Adv. **5**, eaav2761 (2019)

Zeng,…, **DLD*,** Wang, Tian, and Fan*, npj Quant. Info. 7, 165 (2021)

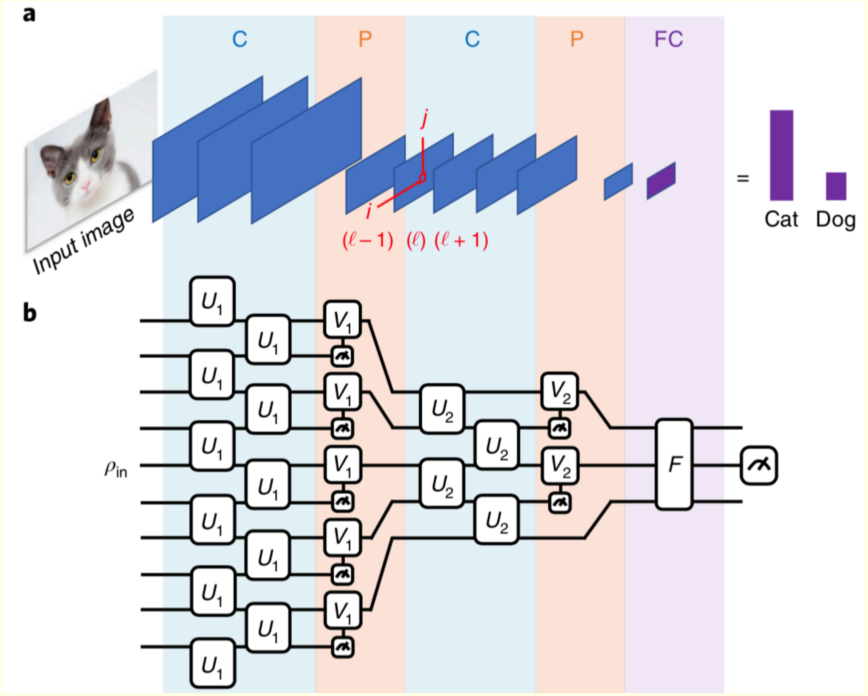
Quantum neural networks/classifiers

Quantum FFNN



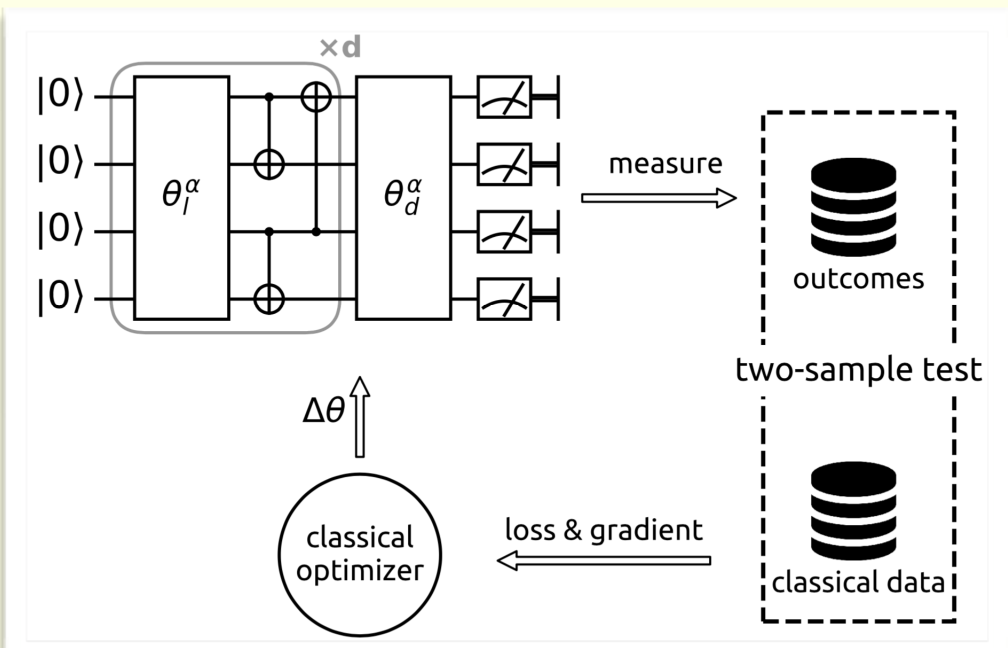
Beer et al, Nat.Comm. 11, 808 (2020)

Quantum CNN



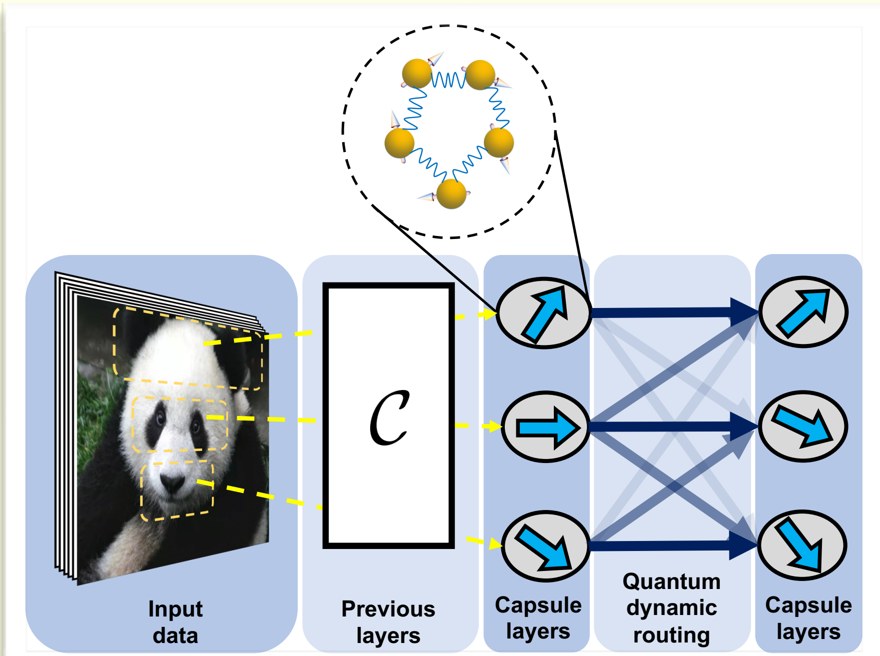
Cong, Choi, & Lukin, Nat.Phys. 15, 1273 (2019)

Quantum circuit Born machine



Liu & Wang, PRA 98, 062324 (2018)

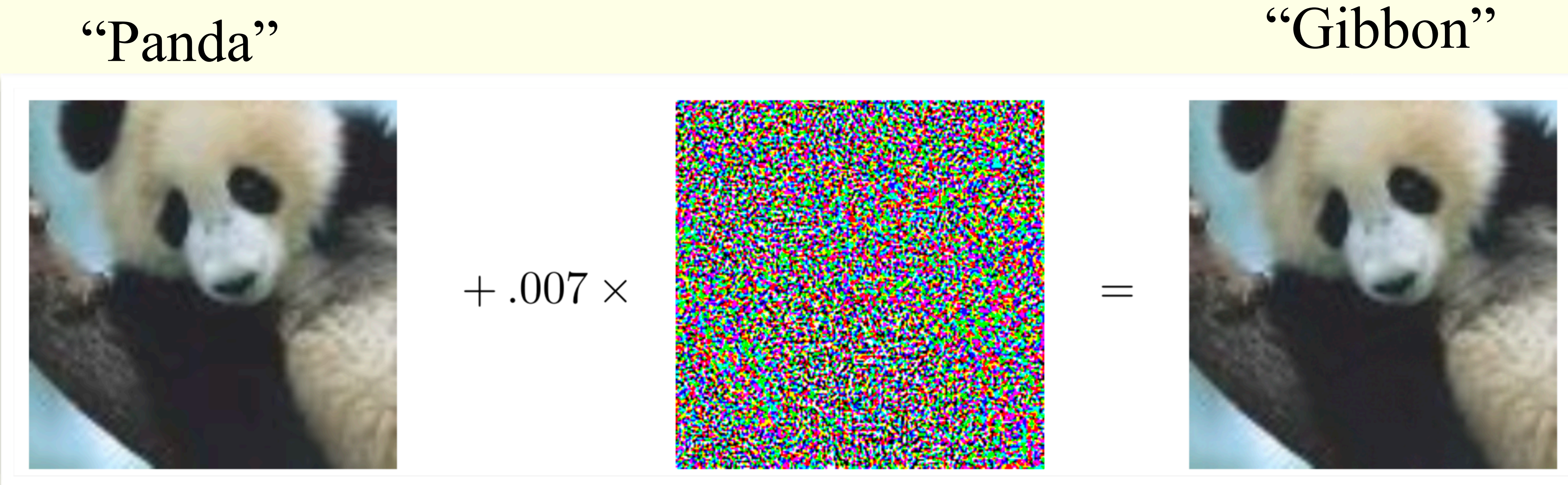
Quantum capsule networks



Liu, Shen, Li, Duan, and **DLD** Quant. Sci. Technol. 8, 015016 (2023)

Li & **DLD**, Sci. China-Phys. Mech. Astron. 65, 220301 (2022)

Introduction to Adversarial Machine Learning



Szegedy *et al*., 2014

Making a pig fly!

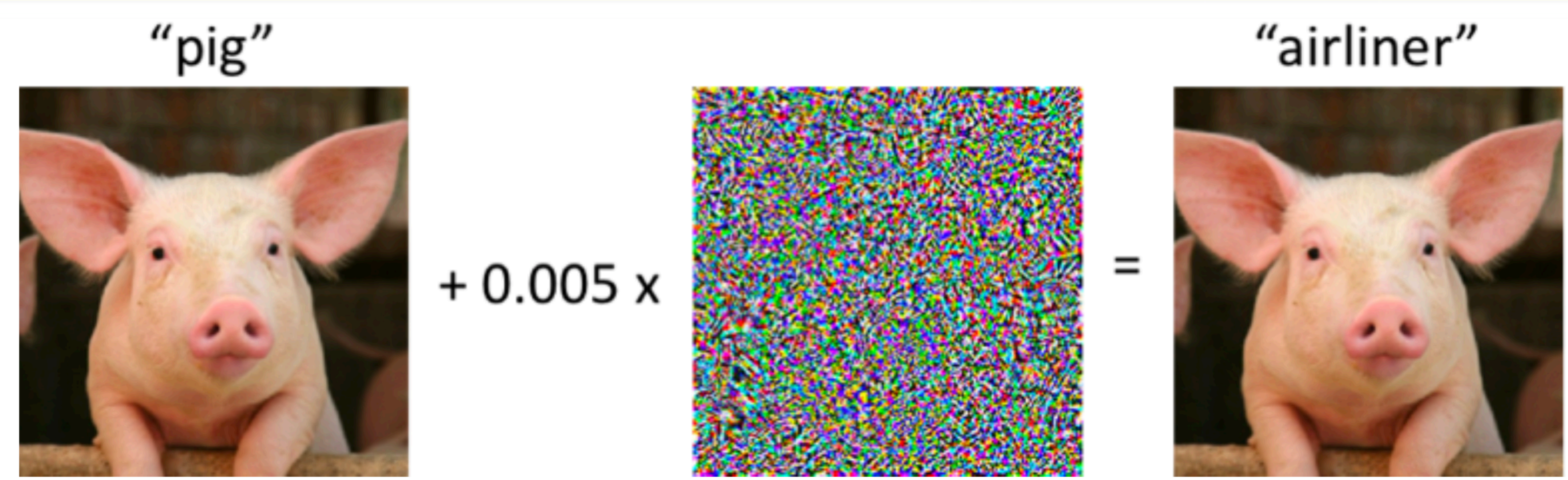
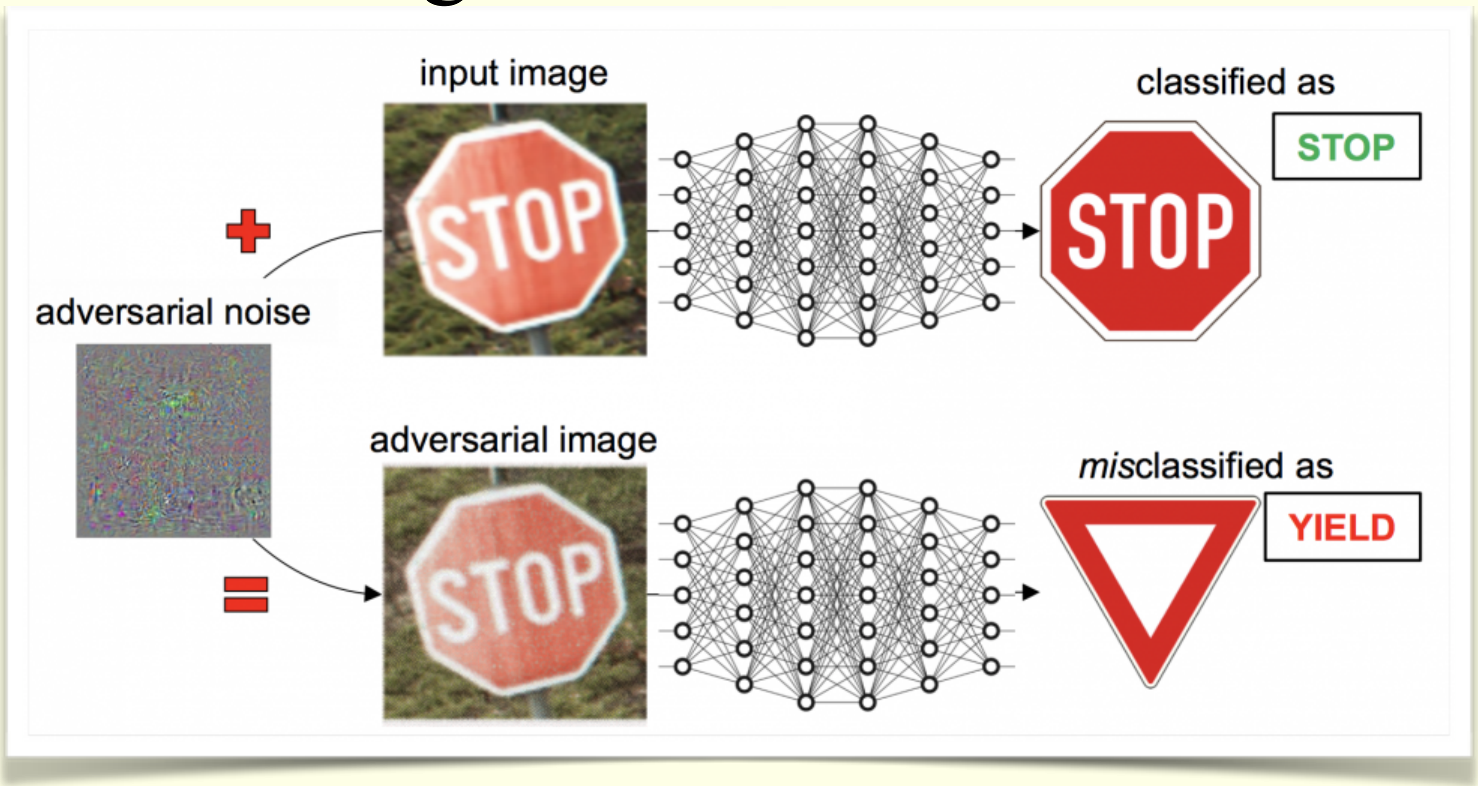


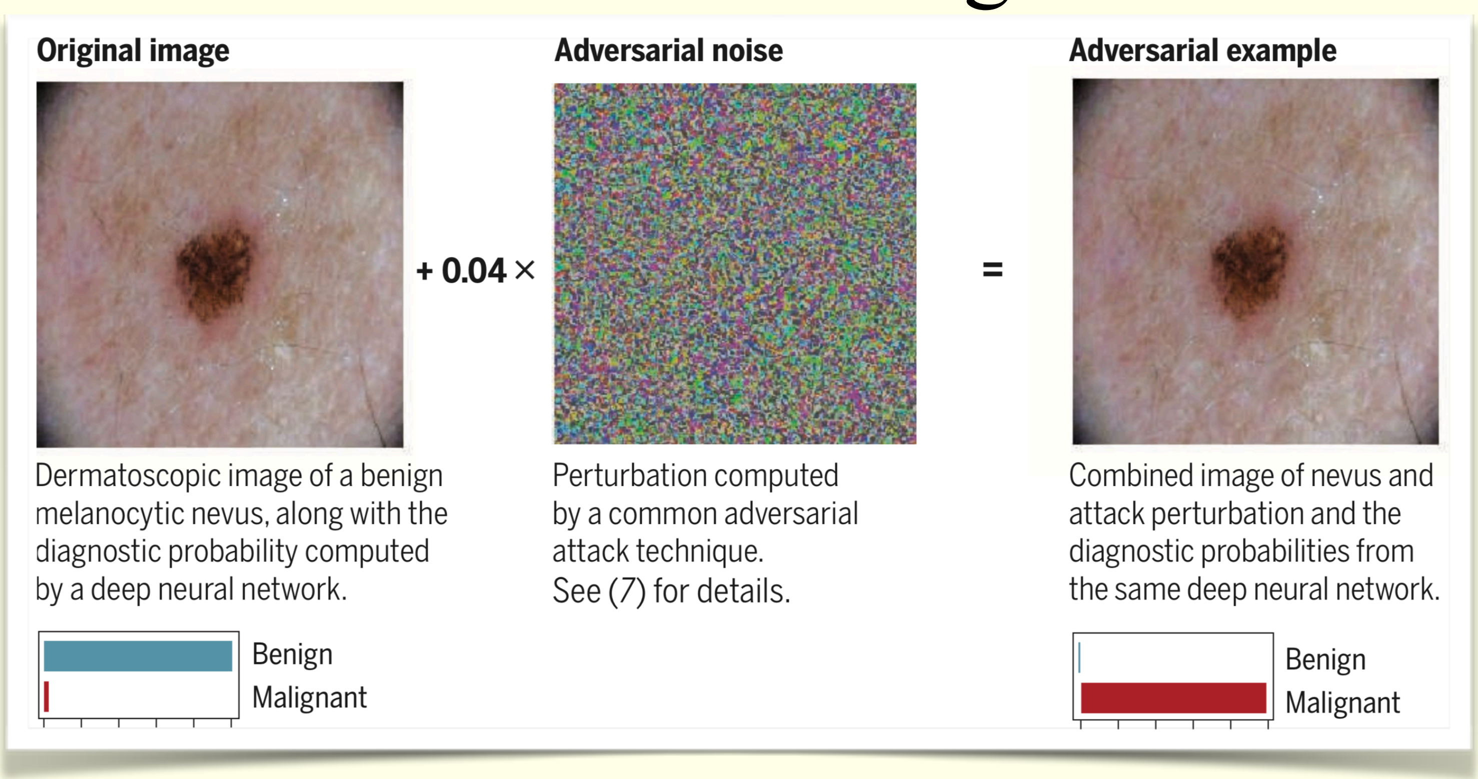
Figure from Madry et al.

Introduction to Adversarial Machine Learning

Self-driving cars



Medical machine learning



Finlayson et al., Science, 363, 1287 (2019)

Essential ideas

Consider supervised learning:

$$\mathcal{D}_n = \{(\mathbf{x}^{(1)}, y^{(1)}), \cdots, (\mathbf{x}^{(n)}, y^{(n)})\}$$

Training:

$$\min_{\theta} \frac{1}{n} \sum_{i=1}^{n} L(h(\mathbf{x}^{(i)}; \theta), y^{(i)})$$

To obtain adversarial examples:

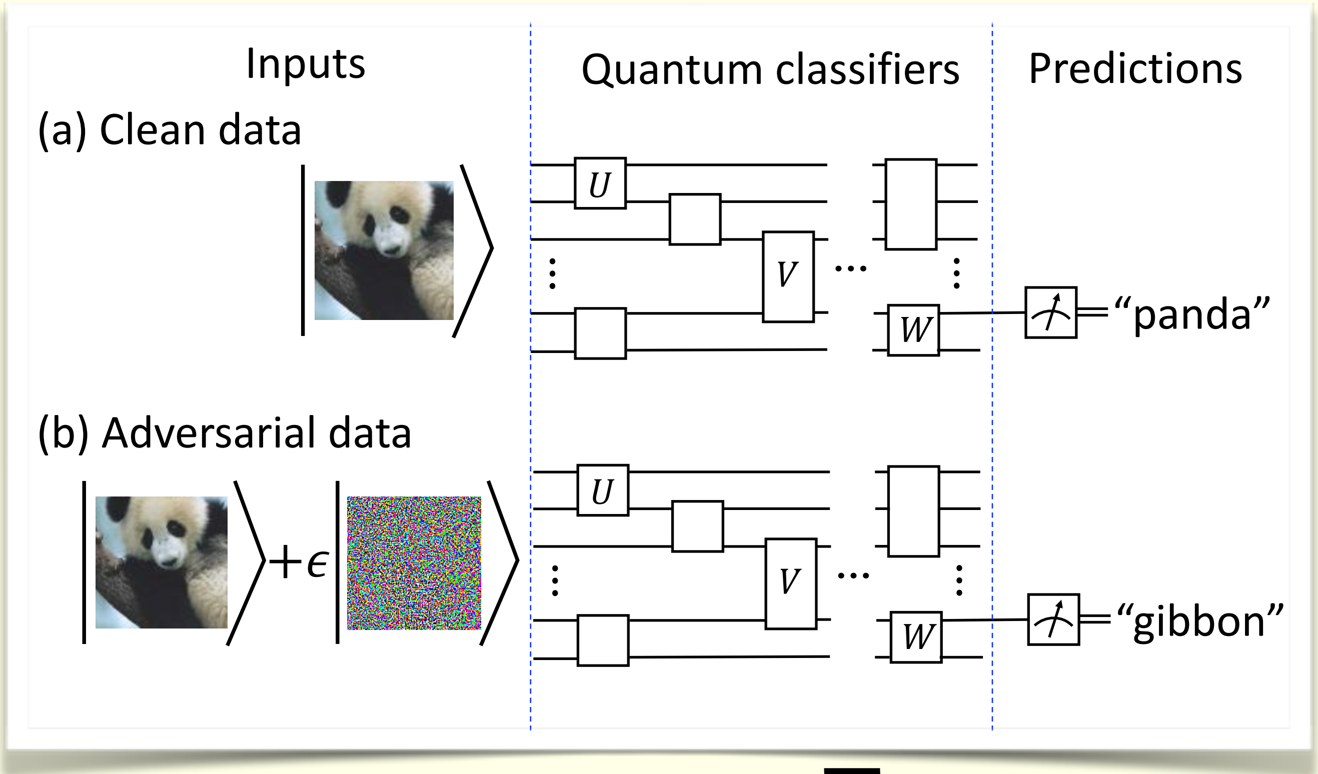
$$\max_{\delta \in \Delta} L(h(\mathbf{x}^{(i)} + \delta; \theta), y^{(i)})$$

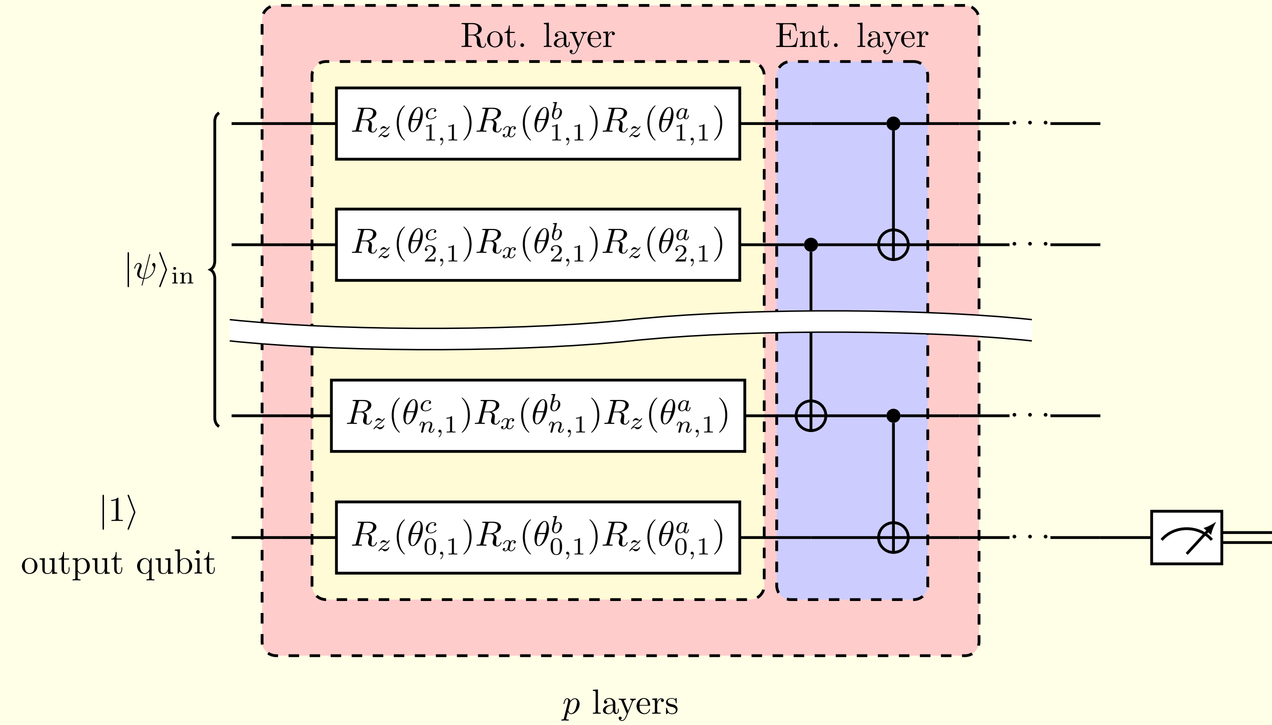
Algorithms:

- **Differential evolution algorithm**
- **Fast gradient sign method**
- **Momentum iterative method**
- **Projected gradient descent**
- **……**

Biggio and Roli, Pattern Recognition, 84, 317 (2018)

Vulnerability of Quantum Classifiers





Untargeted attack: Maximizing the loss

$$U_\delta \equiv \text{argmax}_{U_\delta \in \Delta} L(h(U_\delta |\psi\rangle_{\text{in}}; \Theta^*), \mathbf{a})$$

Targeted attack: Minimizing the loss

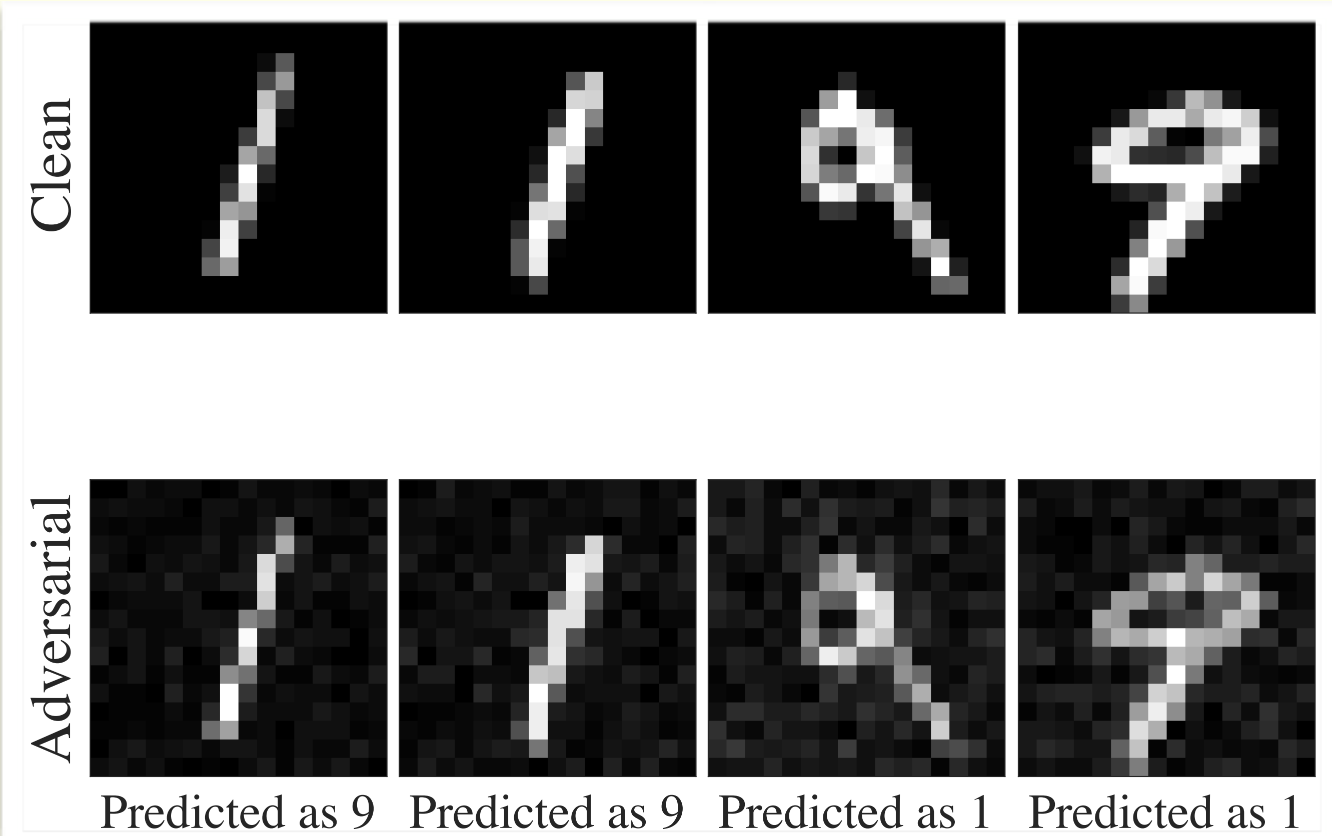
$$U_\delta^{(\text{t})} \equiv \text{argmin}_{U_\delta^{(\text{t})} \in \Delta} L(h(U_\delta^{(\text{t})} |\psi\rangle_{\text{in}}; \Theta^*), \mathbf{a}^{(\text{t})})$$

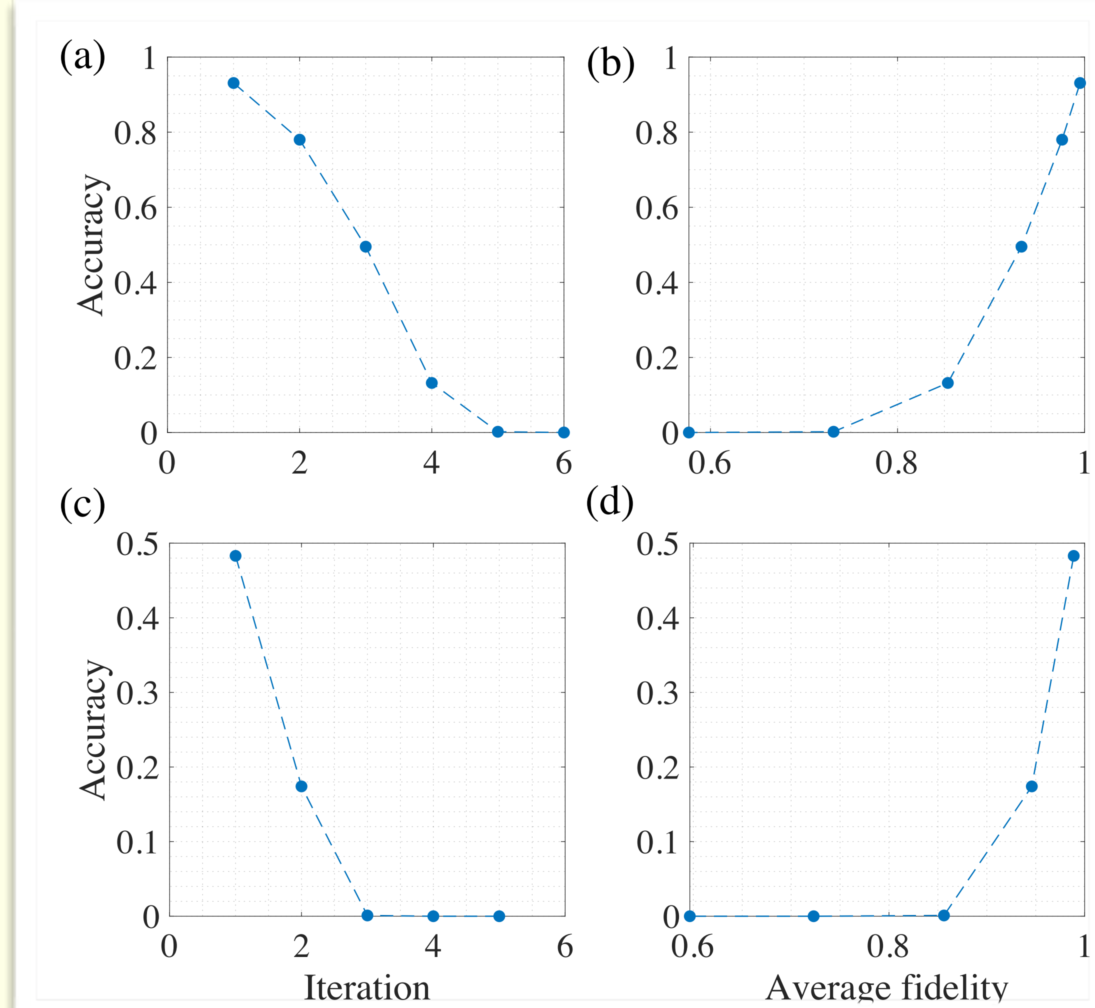
Lu, Duan, and **DLD**, PR Research 2, 033212 (2020)

Vulnerability of Quantum Classifiers

Quantum adversarial learning images: MNIST

Untargeted attack





	Attacks	$\bar{F}$	Accuracy
two-class	BIM (3 , 0.1)	0.923	15.6%
	FGSM (1, 0.03)	0.901	00.0%
four-class	BIM (3 , 0.1)	0.943	23.7%
	FGSM (1, 0.05)	0.528	00.0%

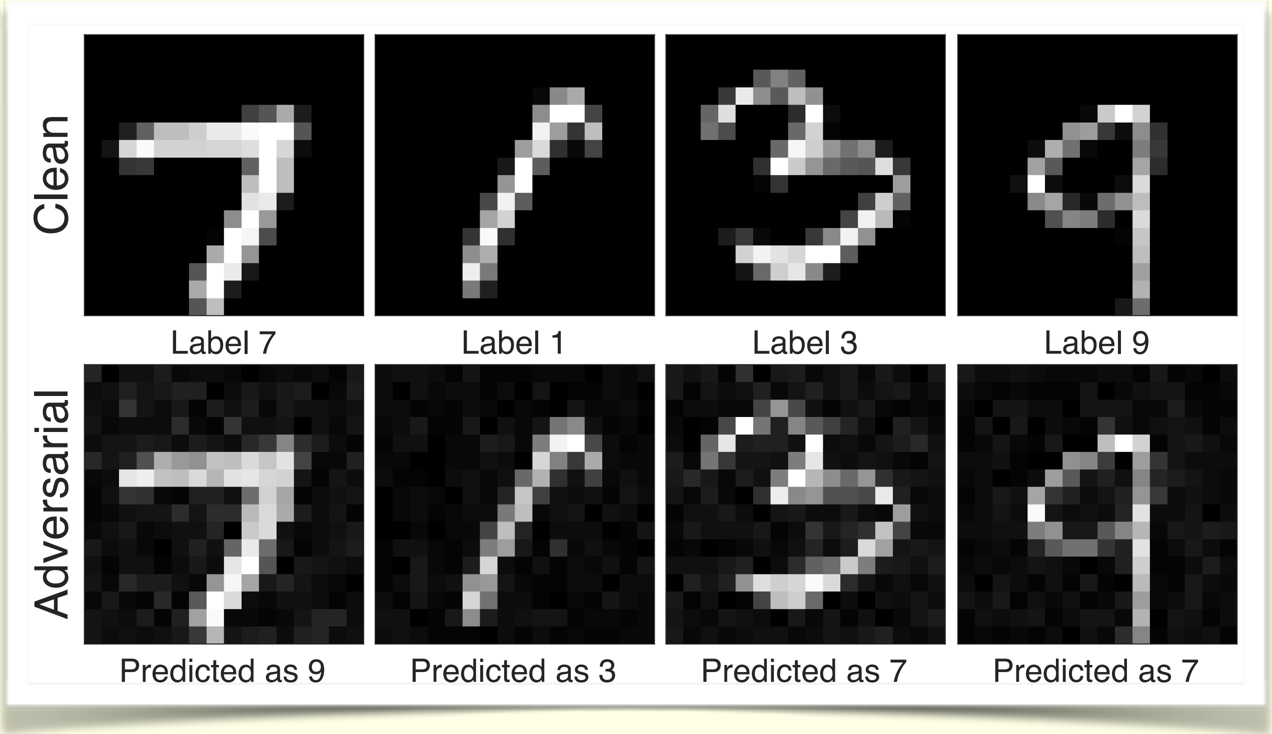
- Amplitude encoding
- Tiny perturbations
- Generality

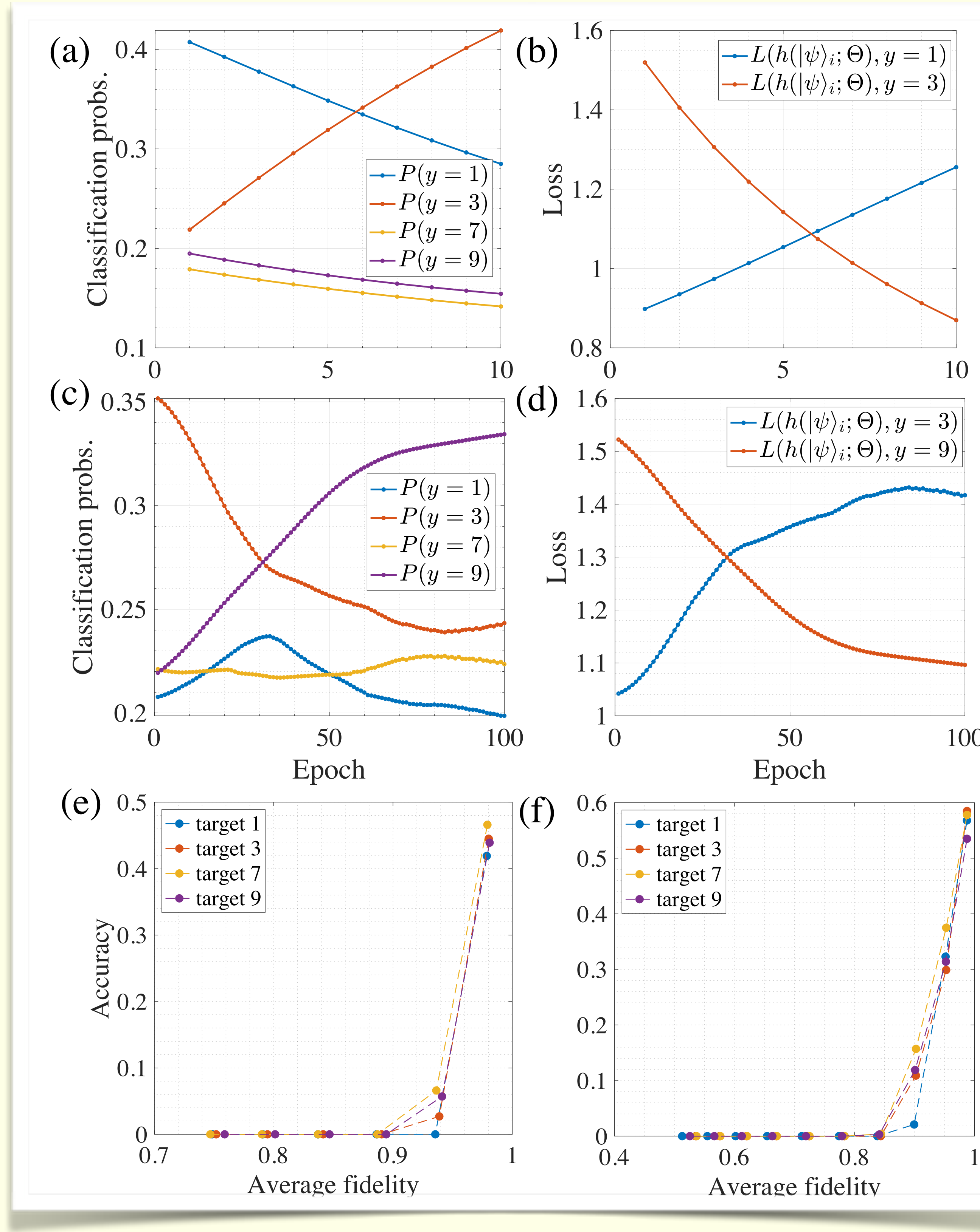
Lu, Duan, and **DLD**, PR Research 2, 033212 (2020)

Vulnerability of Quantum Classifiers

Quantum adversarial learning images: MNIST

Targeted attack





- All to one targeted label
- Tiny perturbations
- Generality

Lu, Duan, and **DLD**, PR Research 2, 033212 (2020)

Vulnerability of Quantum Classifiers

Quantum adversarial learning images: MNIST

Black-box attack: Use classical NN to generate adversarial examples for quantum classifiers

Model A: CNN	Model B: FNN
Conv(64,8,8)+ReLu	FC(512)+ReLu
Conv(128,4,4)+ReLu	Dropout(0.1)
Conv(128,2,2)+ReLu	FC(53)+ReLu
Flatten	Dropout(0.1)
FC(4)+Softmax	FC(4)+Softmax

Two classical models

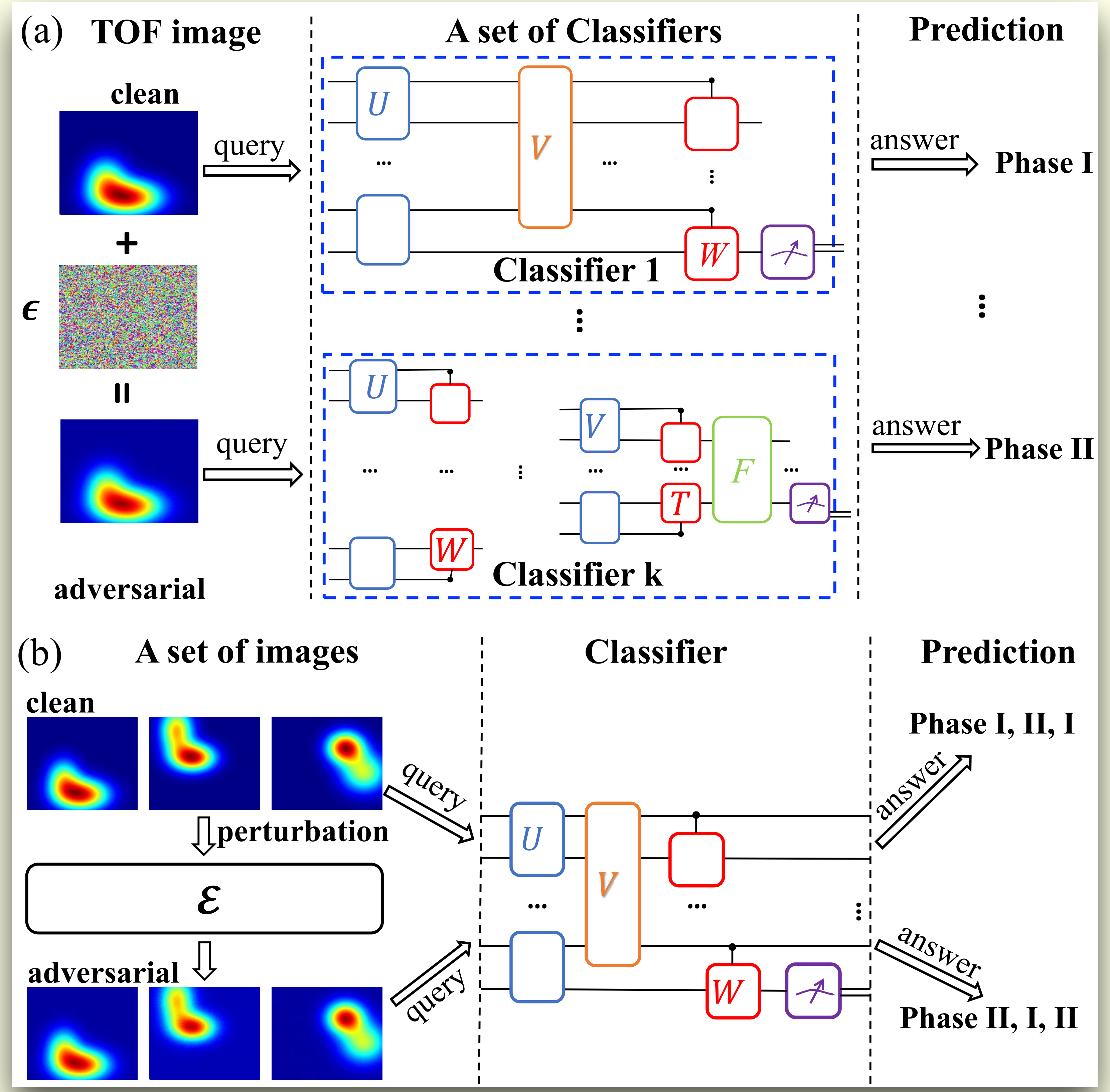
Attacks \ Accuracy		α_C^{adv}	$\alpha_C - \alpha_C^{\mathrm{adv}}$	α_Q^{adv}	$\alpha_Q - \alpha_Q^{\mathrm{adv}}$
CNN	BIM (50, 0.01)	0.07%	98.2%	66.4%	25.6%
	FGSM (1, 0.3)	0.6%	98.3%	51.6%	40.4%
	MIM (10, 0.06)	0.7%	98.2%	62.3%	29.7%
FNN	BIM (50, 0.01)	0.6%	99.3%	68.1%	23.9%
	FGSM (1, 0.3)	1.0%	98.9%	56.8%	35.2%
	MIM (10, 0.06)	0.8%	99.1%	59.9%	32.1%

Performances

- No prior knowledge
- Classically generated
- Transferability

Lu, Duan, and **DLD**, PR Research 2, 033212 (2020)

Universal Adversarial Examples and Perturbations for Quantum Classifiers



Gong, and **DLD**, Nat. Sci. Rev. 9, nwab130 (2021)

Universal Adversarial Examples and Perturbations for Quantum Classifiers

Two interesting theorems:

Theorem 1. Consider a set of k quantum classifiers $\mathcal{C}_i$, $i = 1, \ldots, k$ and let $\mu(\mathcal{E})_{\min}$ be the minimum risk among $\mu(\mathcal{E}_i)$. Suppose $\rho \in SU(d)$ and a perturbation $\rho \to \rho'$ occurs with $D_{\mathrm{HS}}(\rho, \rho') \leq \epsilon$, then we can ensure that the universal adversarial risk is bounded below by R_0 if

$$\epsilon^2 \geq \frac{4}{d} \ln \left[\frac{2k}{\mu(\mathcal{E})_{\min}(1 - R_0)} \right].$$

Basic idea of the proof

- *Concentration of measure phenomenon*
- *De Morgan's laws*

Gong, and **DLD**, Nat. Sci. Rev. 9, nwab130 (2021)

Universal Adversarial Examples and Perturbations for Quantum Classifiers

Two interesting theorems:

Theorem 2. For an adversarial perturbation with unitary operator $\hat{\epsilon}$ and n samples $\rho_1, ..., \rho_n$ chosen from $\mathcal{H}$ according to the Haar measure, the performance of the quantum classifier $\mathcal{C}$ with $\hat{\epsilon}(\rho_1), ..., \hat{\epsilon}(\rho_n)$ as input samples is bounded by:

$$|R_E - \mu(\mathcal{E})| \leq \sqrt{\frac{1}{2n} \ln\left(\frac{2}{\delta}\right)} \tag{3}$$

with probability at least $1 - \delta$ $(0 < \delta < 1)$. Here R_E is the empirical error rate defined as the ratio of the misclassified samples and $\mu(\mathcal{E})$ is the risk for $\mathcal{C}$. In addition, the expectation of the risk over all ground truth t and training set $\mathcal{S}_N$ is bounded below by:

$$\mathbb{E}_t[\mathbb{E}_{\mathcal{S}_N}[\mu(\mathcal{E})]] \geq 1 - \frac{d'}{d(d+1)}(N^2 + d + 1), \tag{4}$$

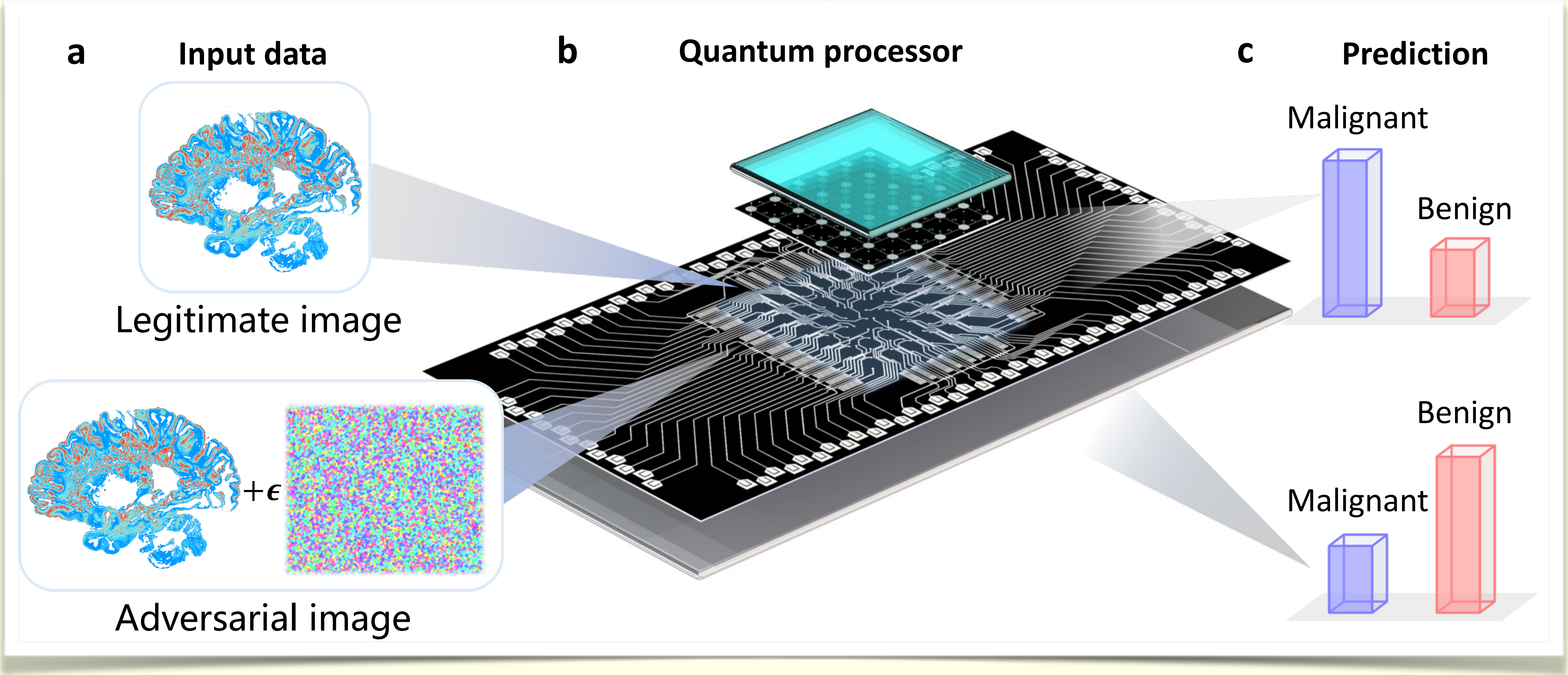
where $d = \dim(\mathcal{H})$ is the dimension of the input data and $d' = |S|$ is the number of output labels.

Basic idea of the proof

- *Hoeffding's inequality*
- *Quantum no free lunch theorem*

Gong, and **DLD**, Nat. Sci. Rev. 9, nwab130 (2021)

Experimental Quantum Adversarial Machine Learning



Experimental platform

- *Flip-chip superconducting quantum processor with 36 transmon qubits*
- *Average simultaneous single- and two-qubit gate fidelities above 99.94% and 99.4%,respectively*
- *Average life time above 150 μs*

Remark: The first experimental demonstration of quantum adversarial learning!

Ren,…, Song*, **DLD***, Wang*, Nat. Comp. Sci., 2, 711 (2022).

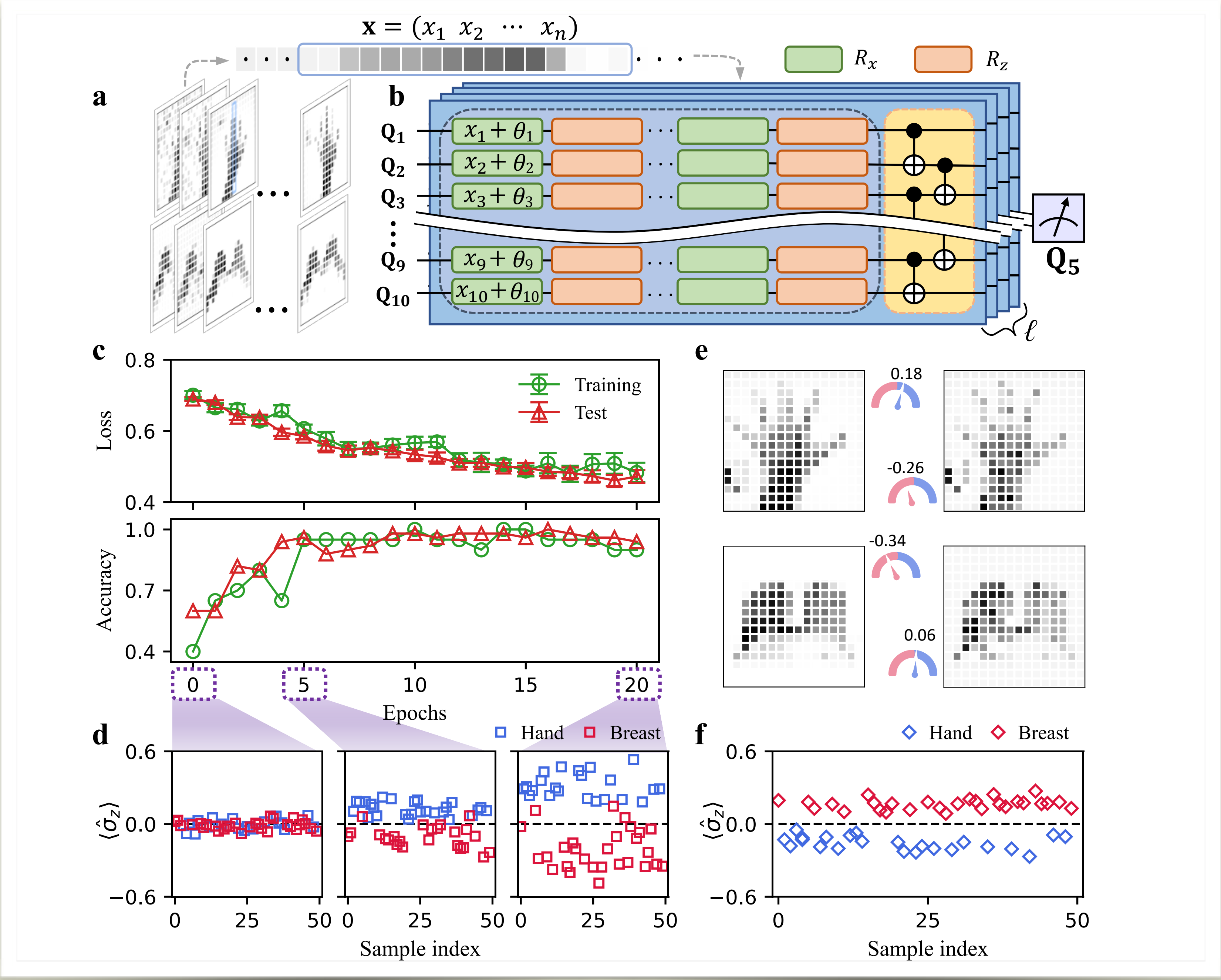
Quantum Adversarial Learning of Medical Data

Framework and setup

- *Medical hand-breast MRI data*
- *Interleaved block-encoding*

Remarks:

- *256-dimensional images*
- *Large-scale classifier*
- *High classification accuracy*
- *Misclassify all adversarial samples*

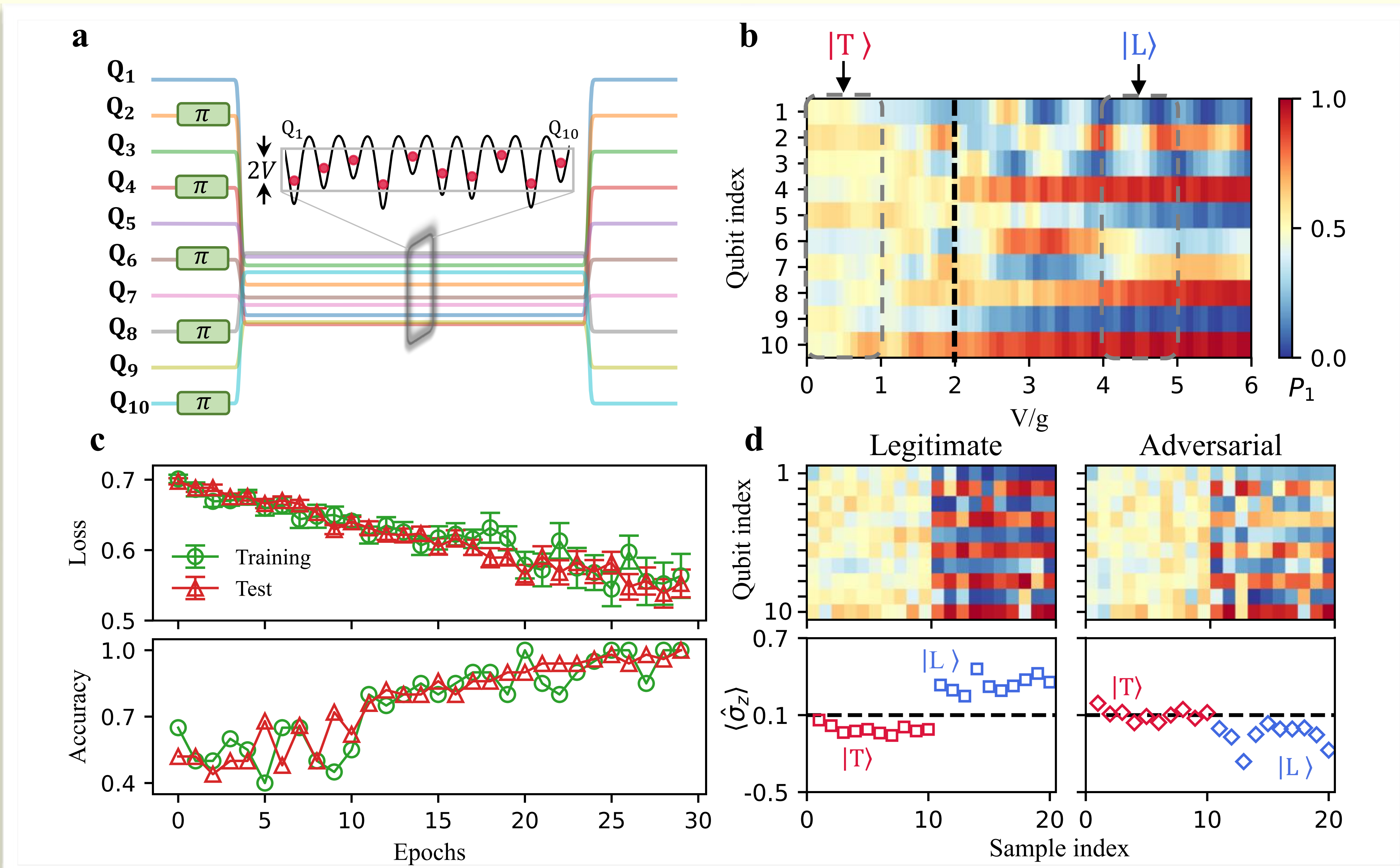


Adversarial examples for quantum data

Hamiltonian: $H/\hbar = -\frac{g}{2}\sum_k (\hat{\sigma}_k^x \hat{\sigma}_{k+1}^x + \hat{\sigma}_k^y \hat{\sigma}_{k+1}^y) - \sum_k \frac{V_k}{2}\hat{\sigma}_k^z,\ V_k = V\cos(2\pi\alpha k + \phi)$

Phase transition: Thermal (V>1) VS Localized (V<1)

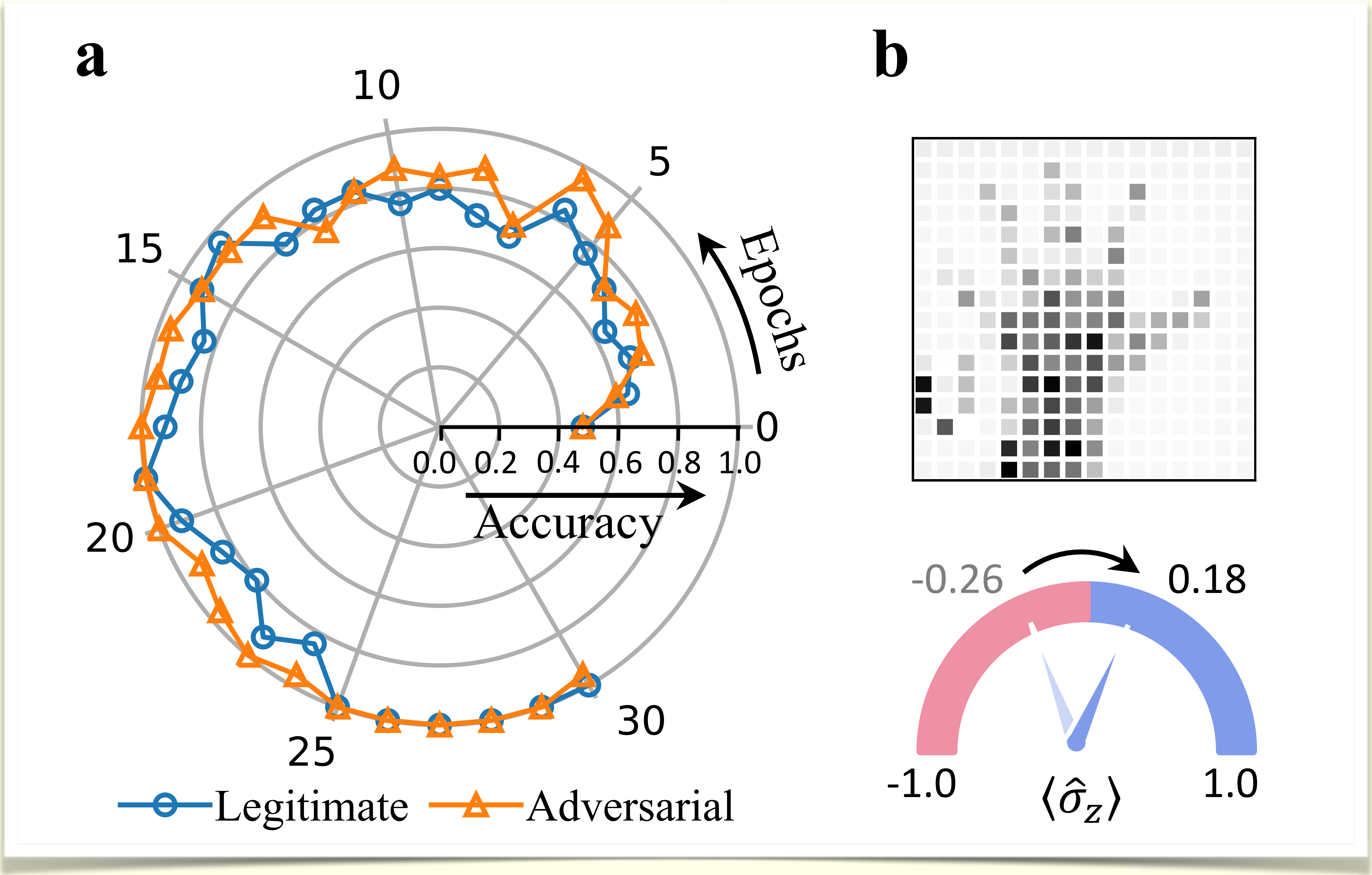
Task: classification of quantum states (thermal or localized)



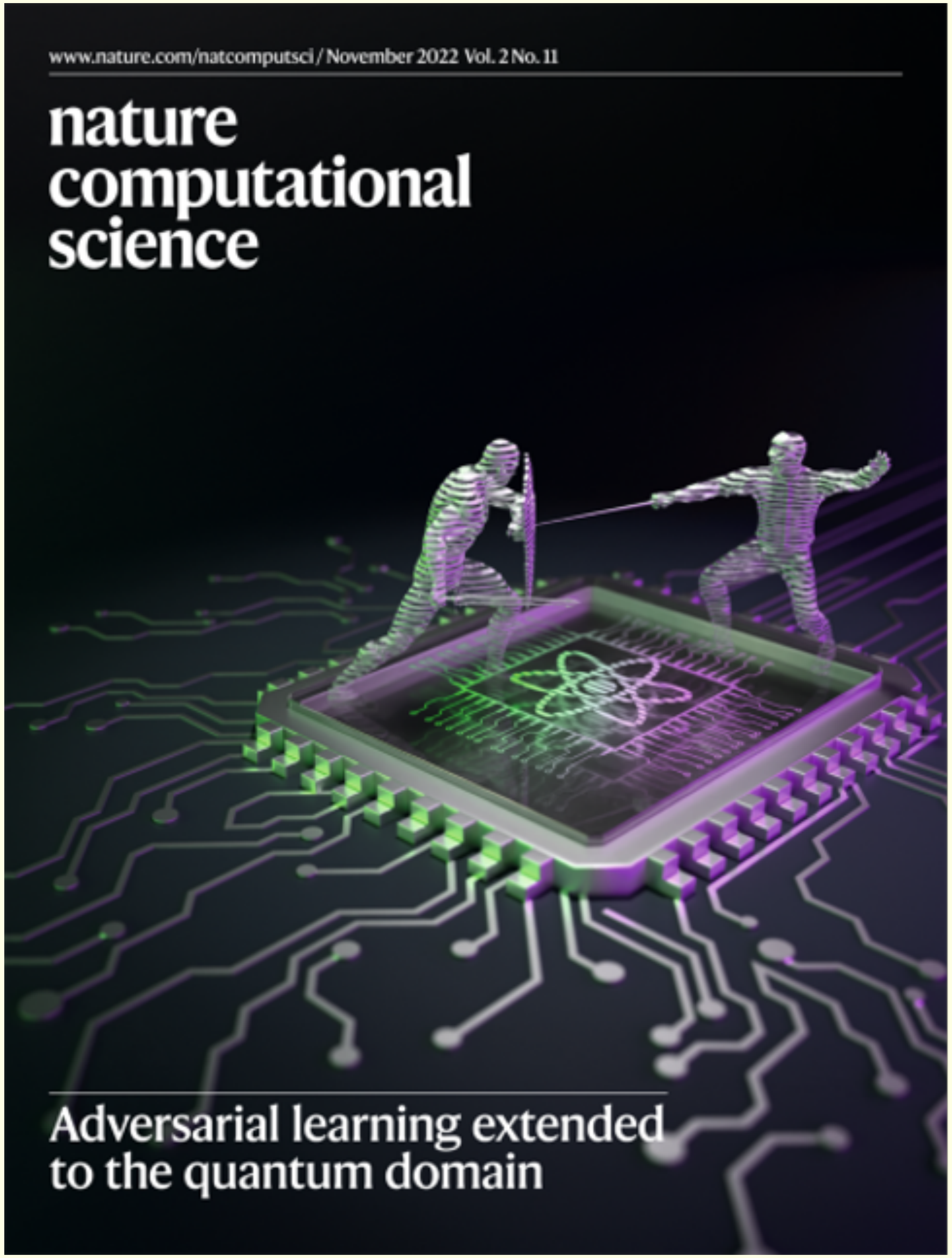
Ren,…, Song*, **DLD***, Wang*, Nat. Comp. Sci., 2, 711 (2022).

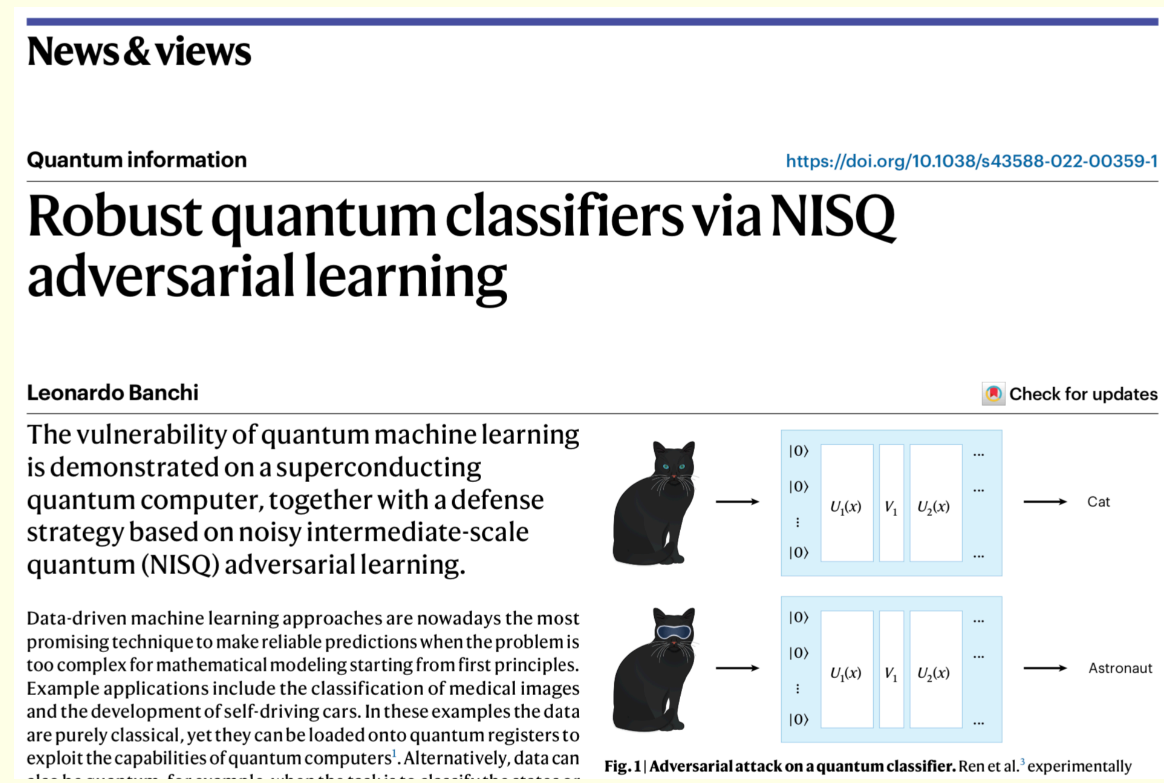
A defense strategy: Adversarial training

Essential idea: Retrain the quantum classifier with numerically generated adversarial examples



Experimental Quantum Adversarial Machine Learning





News & views

Quantum information

https://doi.org/10.1038/s43588-022-00359-1

Robust quantum classifiers via NISQ adversarial learning

Leonardo Banchi

Check for updates

The vulnerability of quantum machine learning is demonstrated on a superconducting quantum computer, together with a defense strategy based on noisy intermediate-scale quantum (NISQ) adversarial learning.

Data-driven machine learning approaches are nowadays the most promising technique to make reliable predictions when the problem is too complex for mathematical modeling starting from first principles. Example applications include the classification of medical images and the development of self-driving cars. In these examples the data are purely classical, yet they can be loaded onto quantum registers to exploit the capabilities of quantum computers[1]. Alternatively, data can

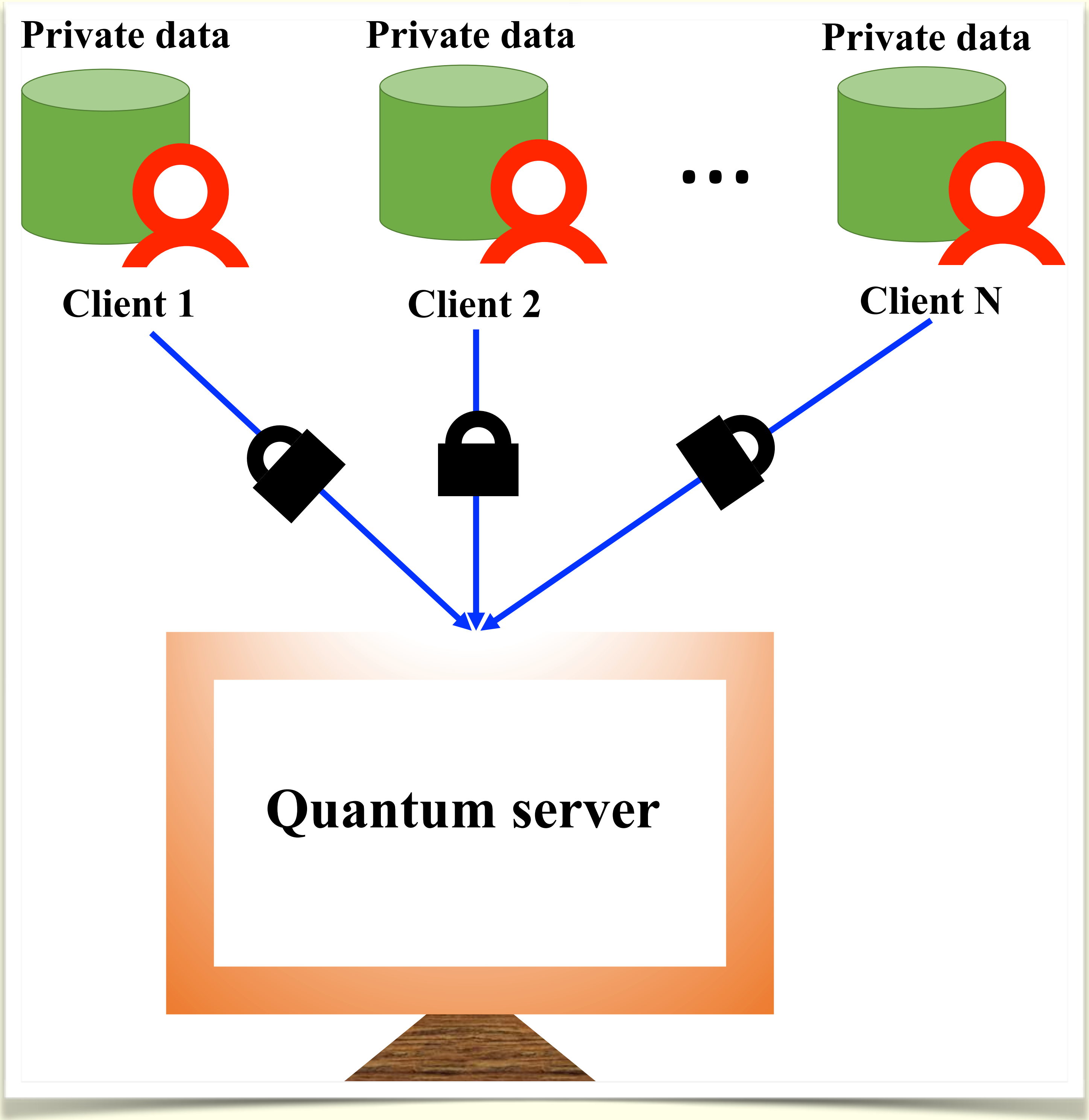
Fig. 1 | Adversarial attack on a quantum classifier. Ren et al.[3] experimentally

Ren,…, Song*, **DLD***, Wang*, Nat. Comp. Sci., 2, 711 (2022).

Vulnerability of Quantum Classifiers

Security matters: vulnerability of quantum learning demands extra care!

Quantum Federated Learning Through Blind Quantum Computing

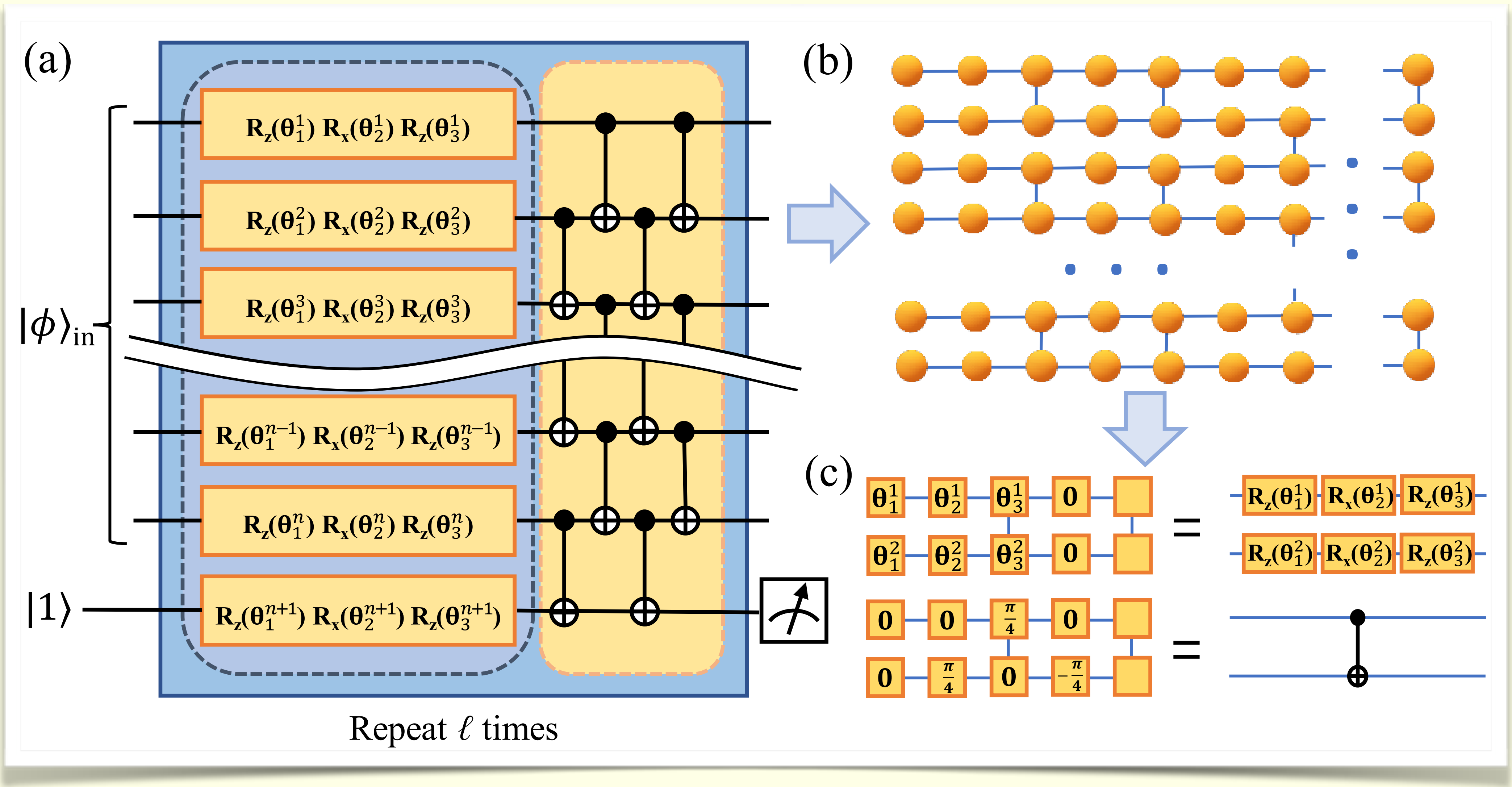


Advantages:

- Unconditional security for the single client case
- Secure under the gradient attack after the incorporation of differential privacy
- Apply to quantum data

W. K. Li, S. R. Lu, and **DLD** Sci. China-Phys. Mech. Astron. 64, 100312 (2021)

Quantum Federated Learning Through Blind Quantum Computing



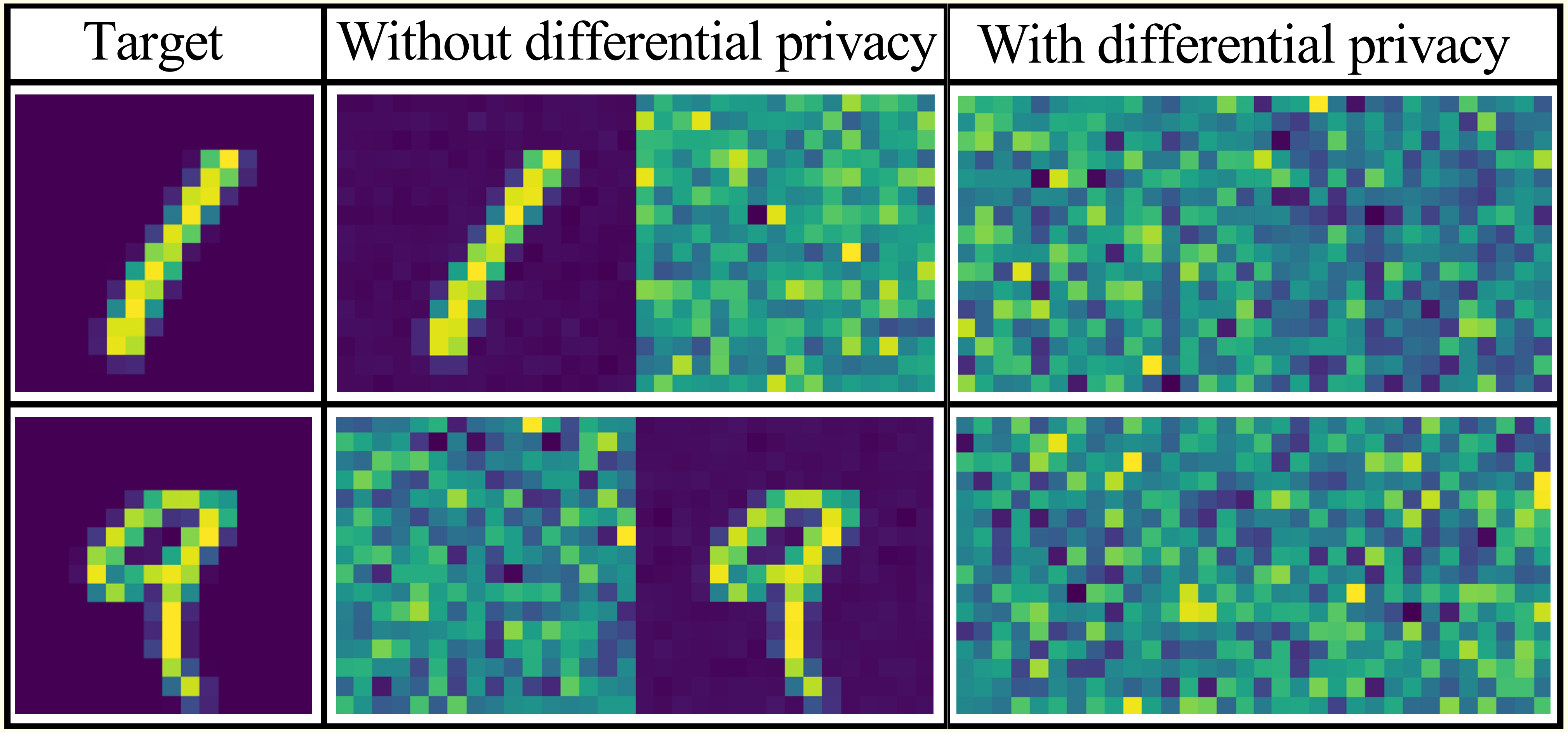
Basic idea

- *Variational quantum classifiers*
- *Blind quantum computing protocol*

W. K. Li, S. R. Lu, and **DLD** Sci. China-Phys. Mech. Astron. 64, 100312 (2021)

Warning: Gradient attack!

The publicly shared gradients may reveal the private information about the data sample!

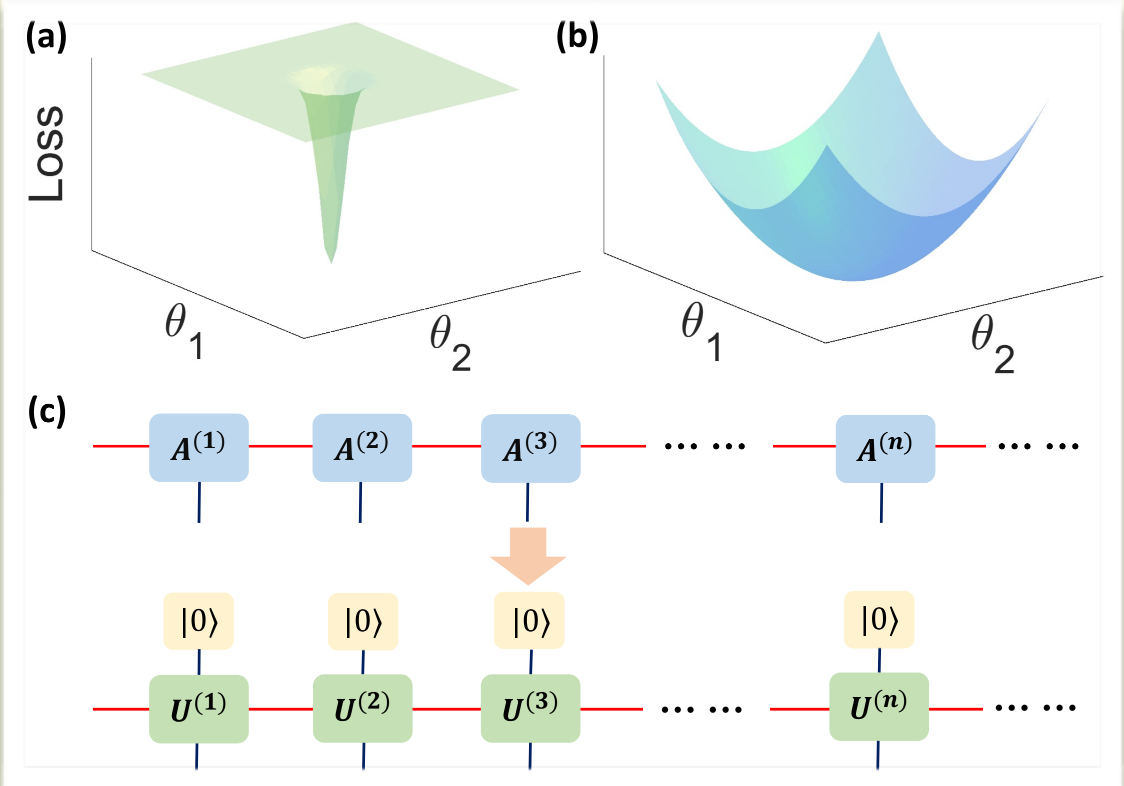


Solution: use differential privacy

Add appropriate noise such as Laplace or Gaussian noise to these gradients before publicly announcing them

W. K. Li, S. R. Lu, and **DLD** Sci. China-Phys. Mech. Astron. 64, 100312 (2021)

Presence and Absence of Barren Plateaus in Tensor-network Based Machine Learning



Liu, Yu, Duan, and **DLD**, PRL 129, 270501 (2022)

- *Barren plateaus exist for global loss*
- *Barren plateaus do not exist for local loss defined by system-size independent observables*

Jaffe group at Harvard:

Theorem 1 *If $\mathrm{Tr}_d\{O\}^2$ and $||O||_\infty^2$ grow slower than exponential in n, then for large n and fixed m, the variance of $\partial_i^{(k)}C$ with respect to $\boldsymbol{\theta}$ satisfies*

$$\mathrm{Var}_{\boldsymbol{\theta}}[\partial_i^{(k)}C] \leq \epsilon(O)\mathcal{O}\left(\frac{P(D,d)}{Q(D,d)}\right), \qquad (2.5)$$

where $\epsilon(O) \equiv \left|\left|O - \mathrm{Tr}\{O\}\frac{I_d}{d}\right|\right|_{\mathrm{HS}}^2$. The functions $P(D,d)$ and $Q(D,d)$ are polynomials of D and d. Moreover, there exists a partial derivative $\partial_i^{(k)}$ such that Ineq. (2.5) becomes an equality.

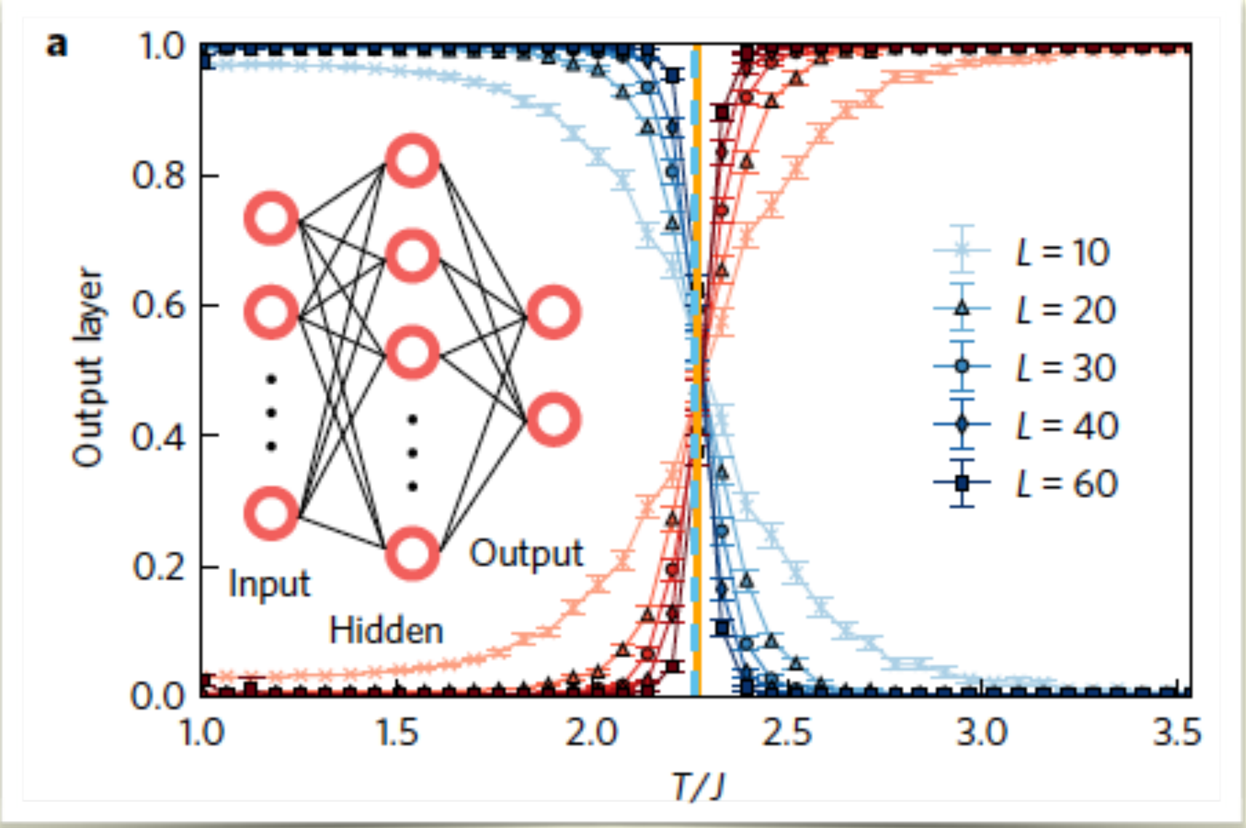
Garcia, Zhao, Bu, and Jaffe, JHEP, 90 (2023)

Machine learning in quantum physics

Machine learning phases of matter

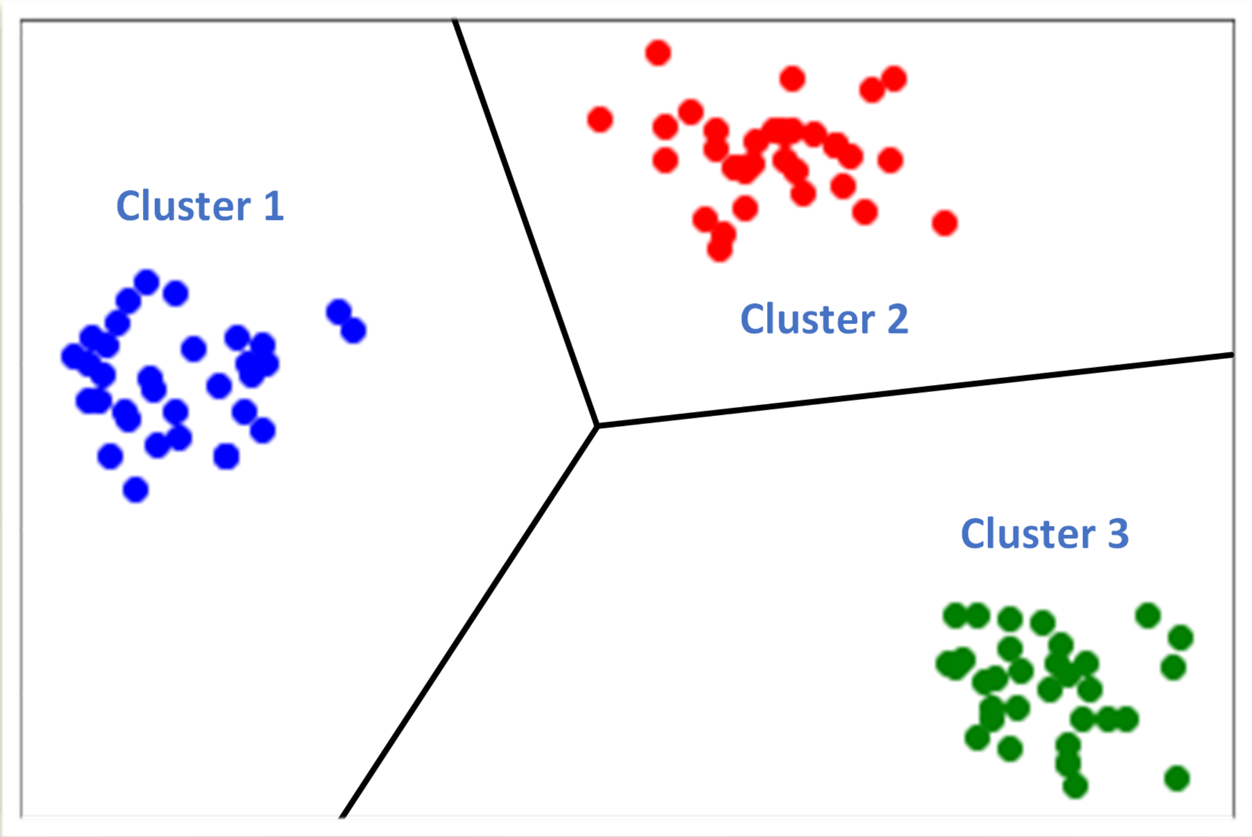
Supervised learning:

Carrasquilla & Melko, Nat. Phys. 13, 431 (2017)
Ch'ng, Carrasquilla, Melko, & Khatami, PRX, 7, 031038
Zhang & Kim, PRL, 118, 216401 (2017)
Zhang, Shen, & Zhai, PRL, 120,066401 (2018)
Lian, …, **DLD**, and Duan, PRL, 122, 210503(2019)
……



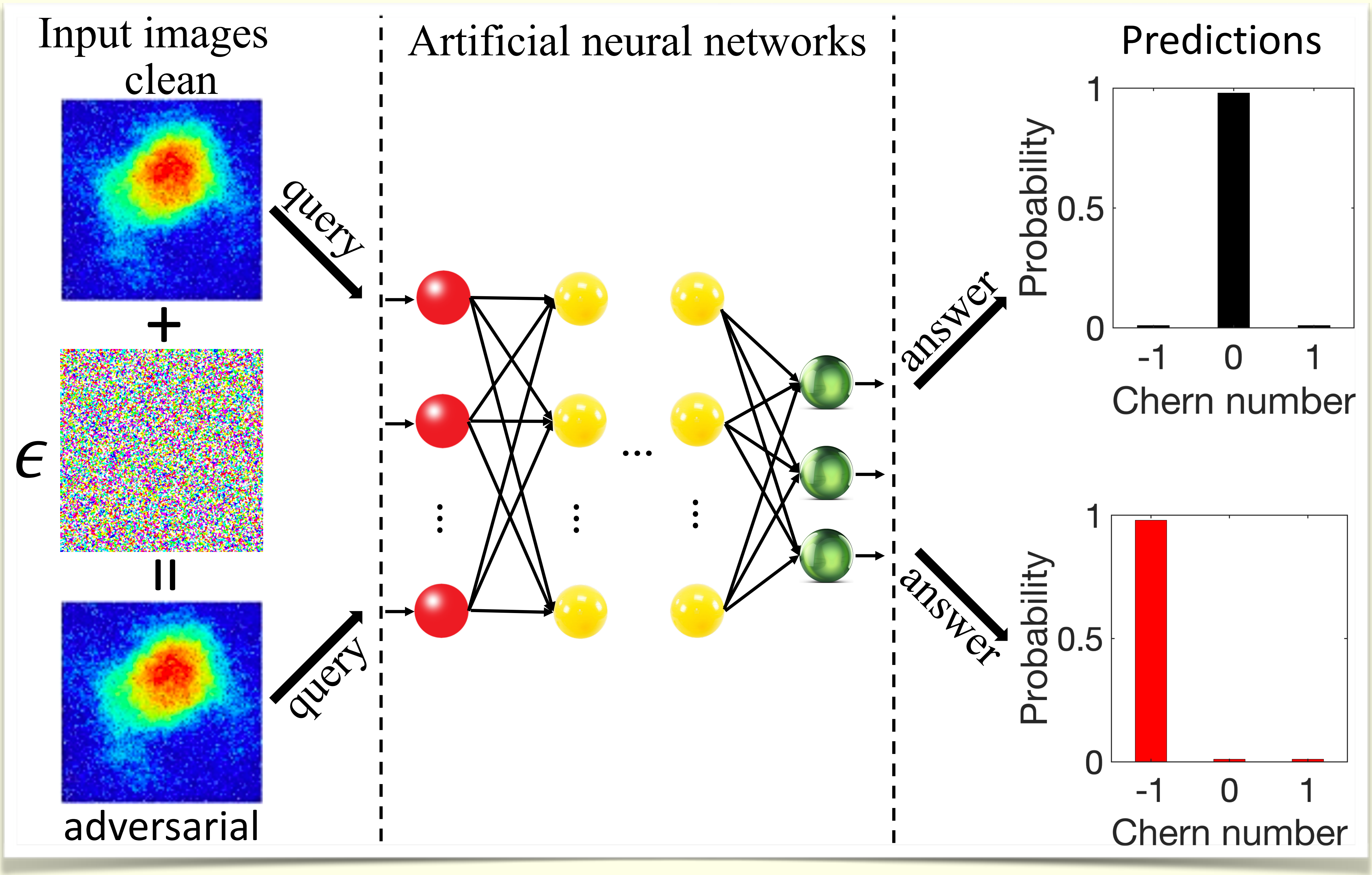
Unsupervised learning:

Nieuwenburg, Liu, & Huber, Nat. Phys. 13, 435 (2017)
L. Wang, PRB, 94, 195105 (2016)
Wetzel, PRE, 96,022140 (2017)
Hu, Singh, & Scalettar, PRE, 95, 062122 (2017)
Broecker, Assaad, & Trebst, arXiv:1707.00663
Hsu, Li, **DLD**, & Das Sarma, PRL, 121,245701 (2018)
Yu & **DLD**, PRL 126, 240402 (2021)
……



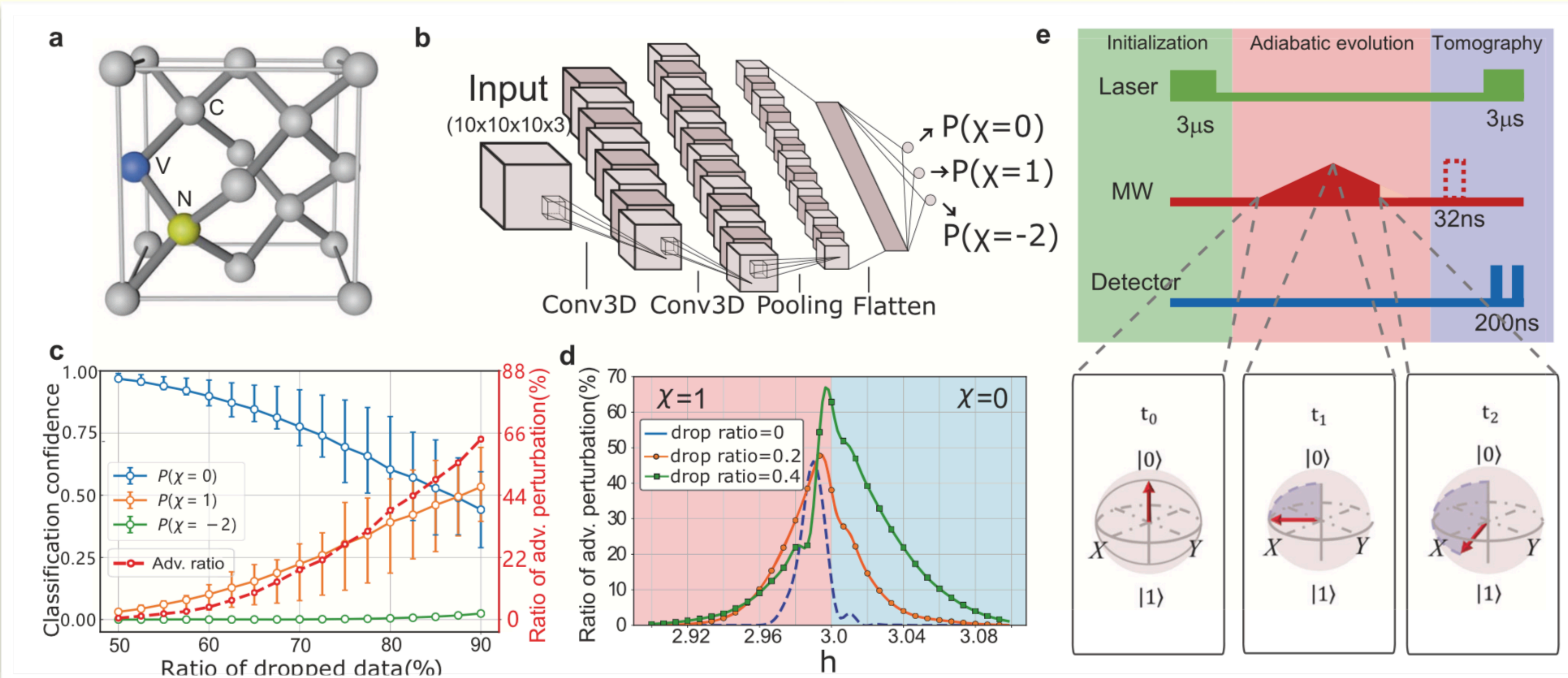
Vulnerability of Machine Learning Phases of Matter

Basic idea:



Jiang, Lu, and **DLD**, arXiv: 1910.13453v1

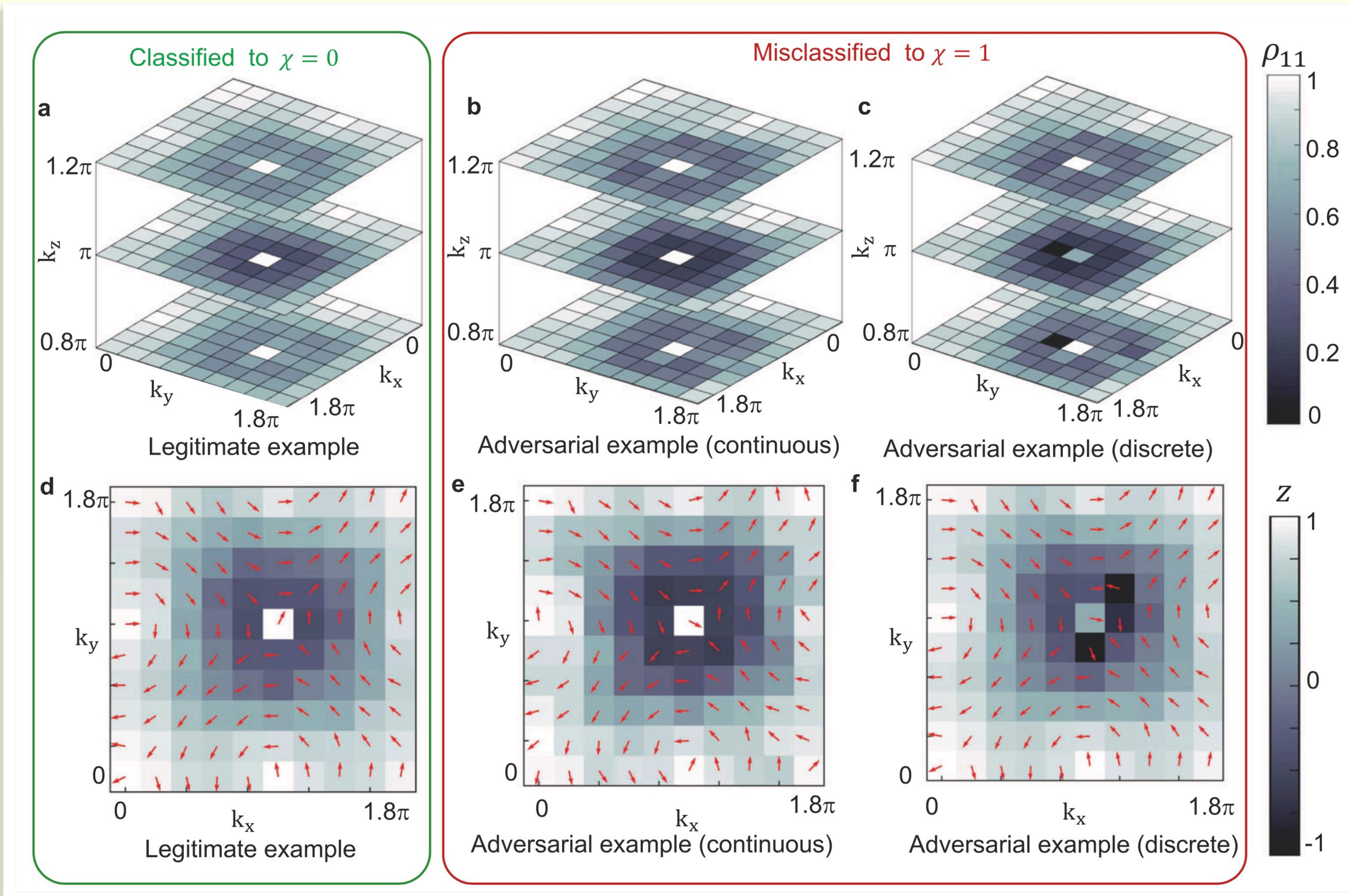
Experimental demonstration of adversarial examples in learning topological phases



Lian, … , **DLD***, and Duan*, PRL 122,210503, (2019)

Zhang, … , **DLD***, and Duan*, Nat. Commu. 13,4993, (2022)

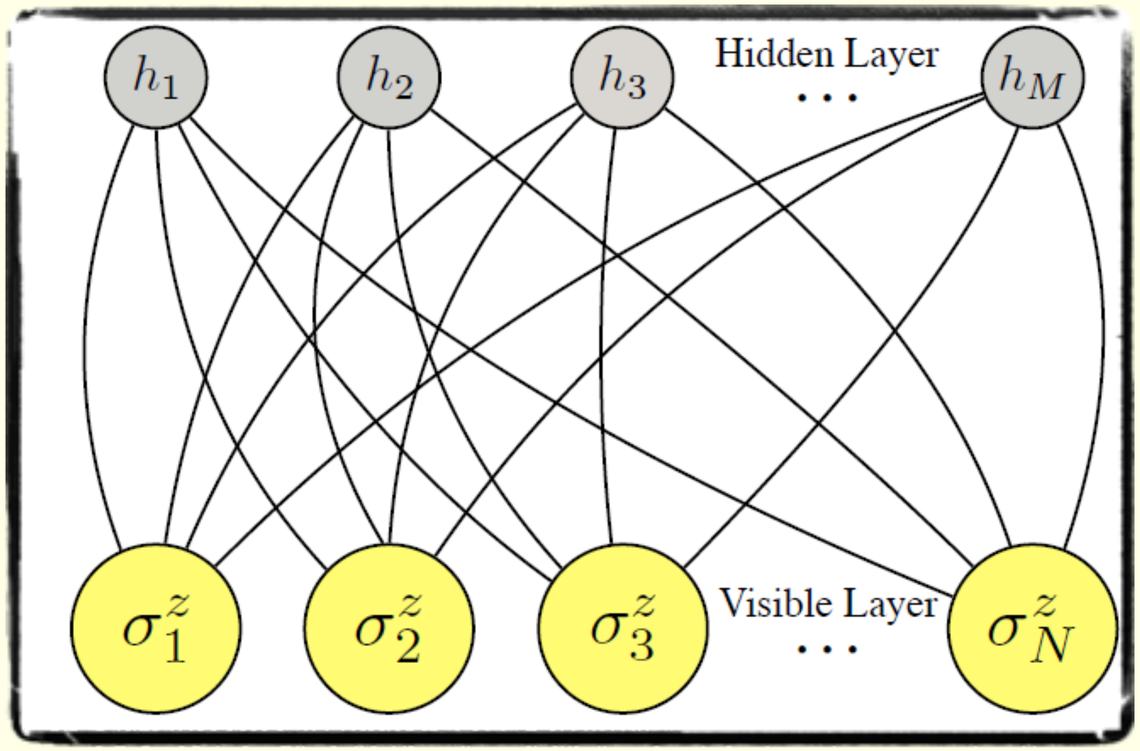
Experimental demonstration of adversarial examples in learning topological phases



Zhang, … , **DLD***, and Duan, Nat. Commu. 13,4993, (2022)

RBM representation of quantum states

Carleo & Troyer, Science, 355, 602 (2017)



$$|\Phi\rangle = \sum_{\mathcal{S}} \Psi_M(\mathcal{S}, \mathcal{W})|\mathcal{S}\rangle$$

$$\Psi_M(\mathcal{S}; \mathcal{W}) = \sum_{\{h_k\}} e^{\sum_j a_j \sigma_j^z + \sum_k b_k h_k + \sum_{kj} W_{kj} h_k \sigma_j^z}$$

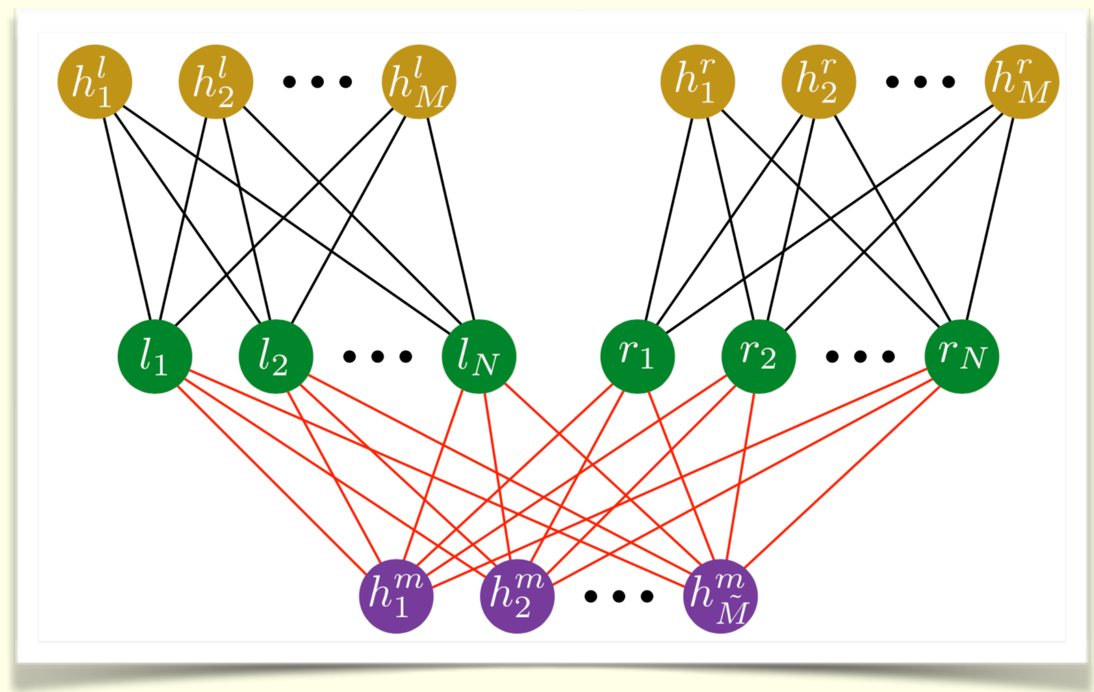
- *Massive entanglement*
- *Long-rang interactions*
- *High dimensions*

DLD, Li, and S. Das Sarma, **PRX**, 7, 021021 (2017)
Jia, Wei, Wu, Guo, and Guo, NJP 22, 053022 (2020)
……

Solve the ground states and dynamics:

$$H_{MHS} = \sum_{j<k}^{N} \frac{1}{d_{jk}^2}(-\sigma_i^x \sigma_j^x - \sigma_i^y \sigma_j^y + \sigma_i^z \sigma_j^z)$$

Open quantum systems



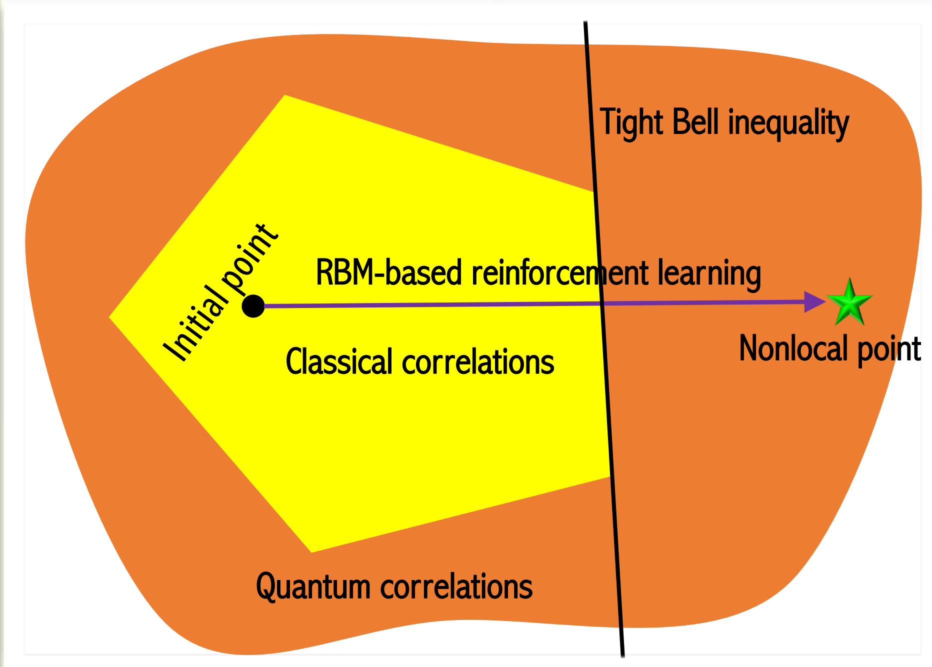
Solving the quantum master equation:

$$\dot{\rho} \equiv \mathcal{L}\rho = -i[H, \rho] + \sum_j \frac{\gamma_j}{2}[2L_j \rho L_j^\dagger - \{L_j^\dagger L_j, \rho\}]$$

Hartmann and Carleo, PRL 122, 250502 (2019)
Vicentini et al, PRL 122, 250503 (2019)
Nagy and Savona, PRL 122, 250501 (2019)
Yoshioka and Hamazaki, PRB 99, 214306 (2019)
Yuan,Wang,Wang, and **DLD**, PRL 126,160401 (2021)

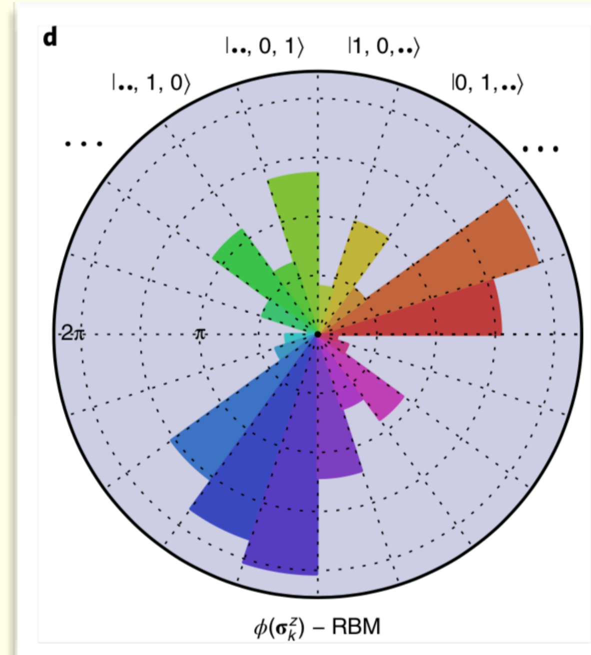
Other applications

Detecting quantum nonlocality



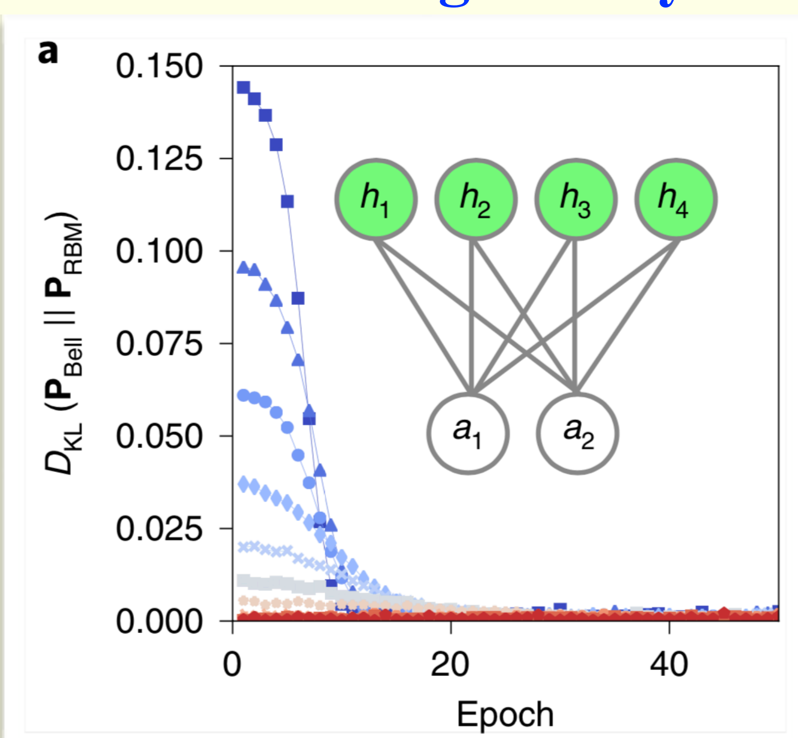
DLD, PRL, 120, 240402 (2018)

Quantum tomography



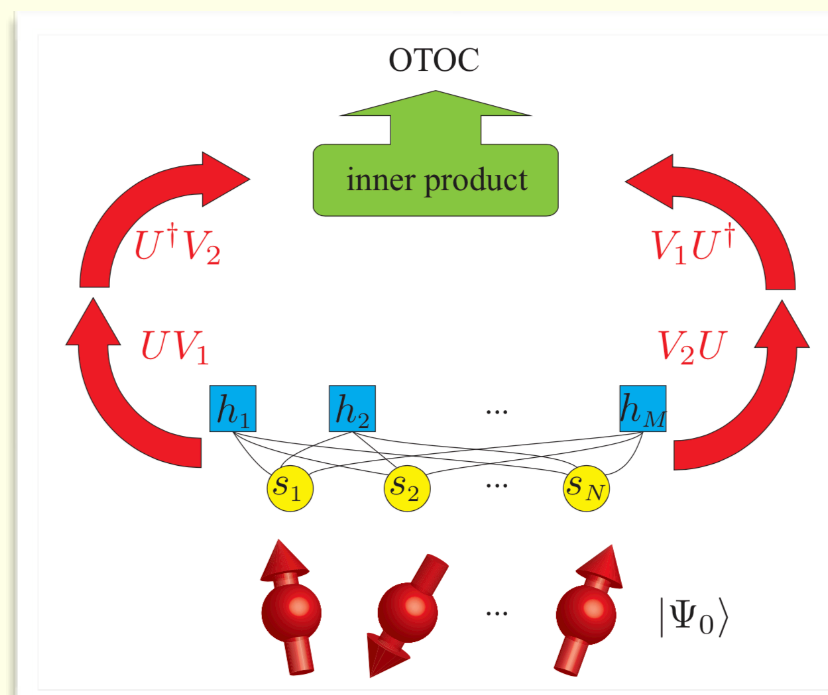
Torlai et al, Nat. Phys. 14, 447 (2018)

Reconstructing density states



Carrasquilla et al, Nat. Mach. Intell. 1, 155 (20189)

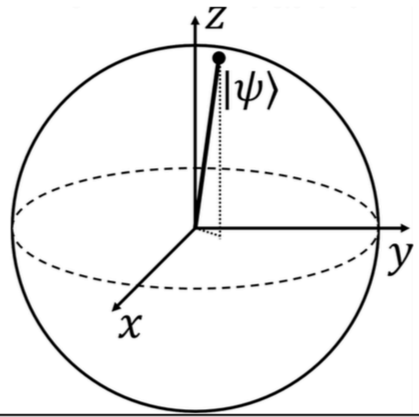
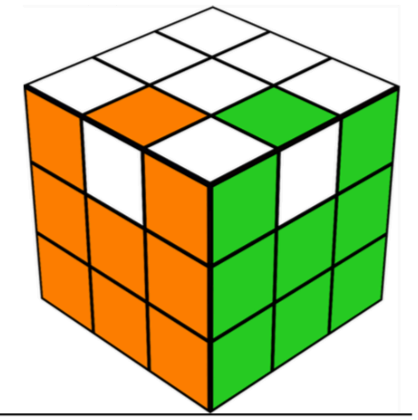
Computing OTOCs



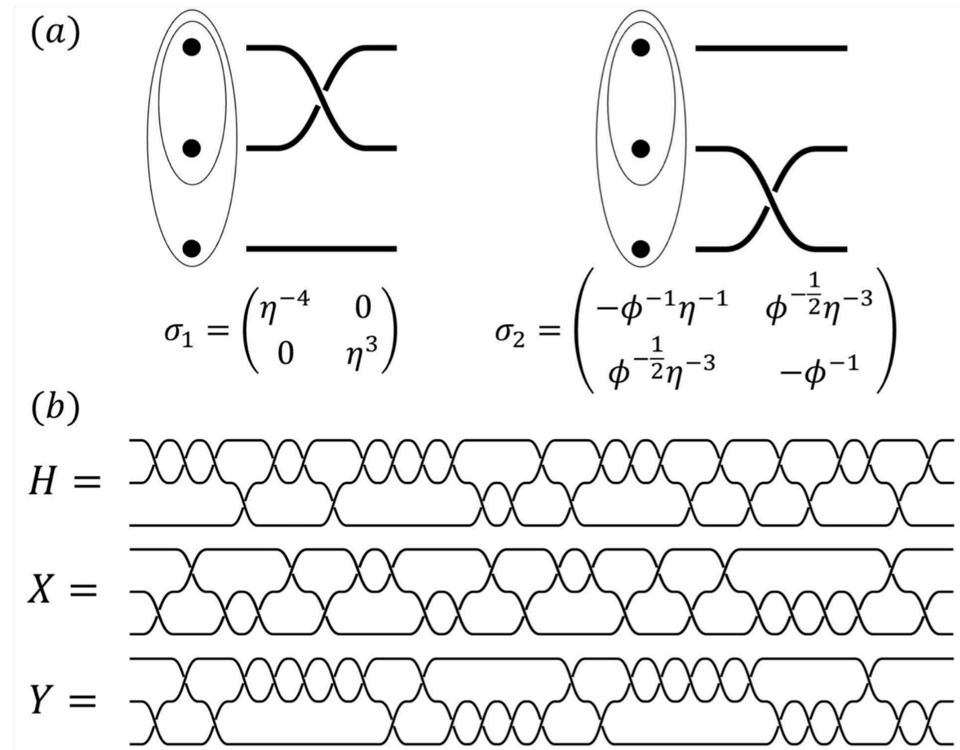
Wu, Duan, and **DLD**, PRB 101, 214308 (2020)

Quantum compiling with reinforcement learning

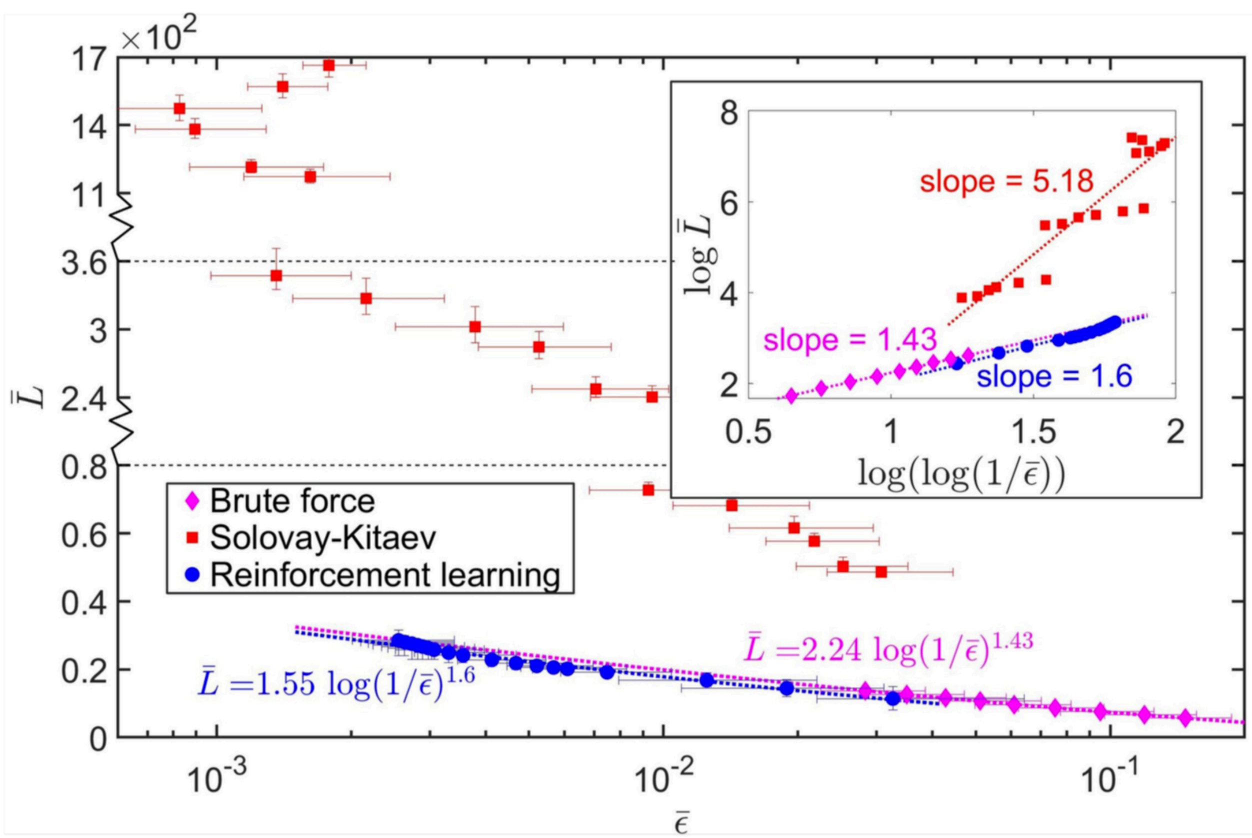
Key idea

System		
Initial state	The unitary to be approximated	The scrambled cube
Target state	The identity matrix	The solved cube
Basic move	A gate from the universal set	Rotation of one face

Example: braiding Fibonacci anyons



Performance benchmark



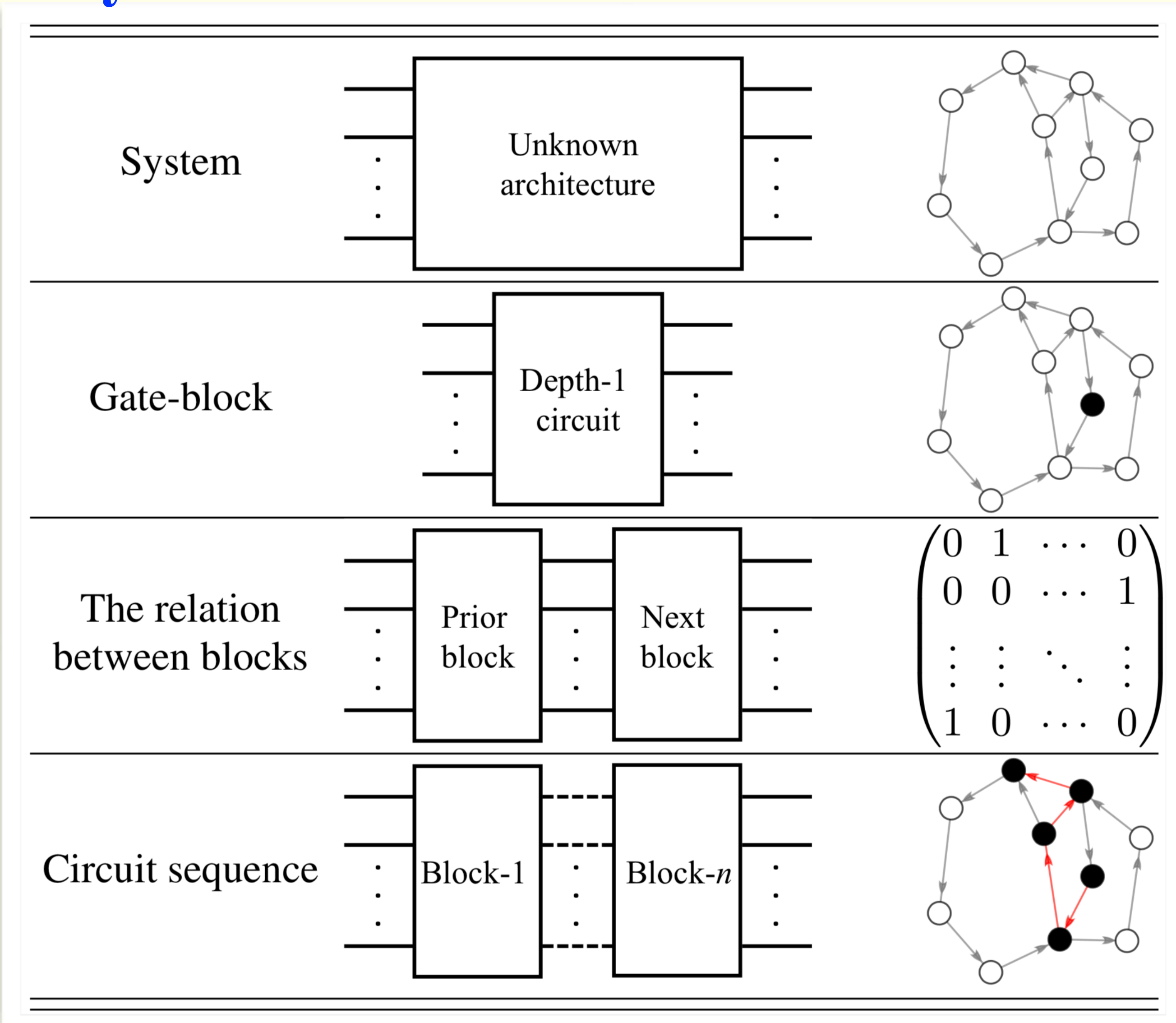
Advantages:

- ☑ Generic applicability
- ☑ No use of ancillary qubits
- ☑ Low time complexity
- ☑ Generate near-optimal gate sequence
- ☑ Easy to minimize the use of high-cost gates

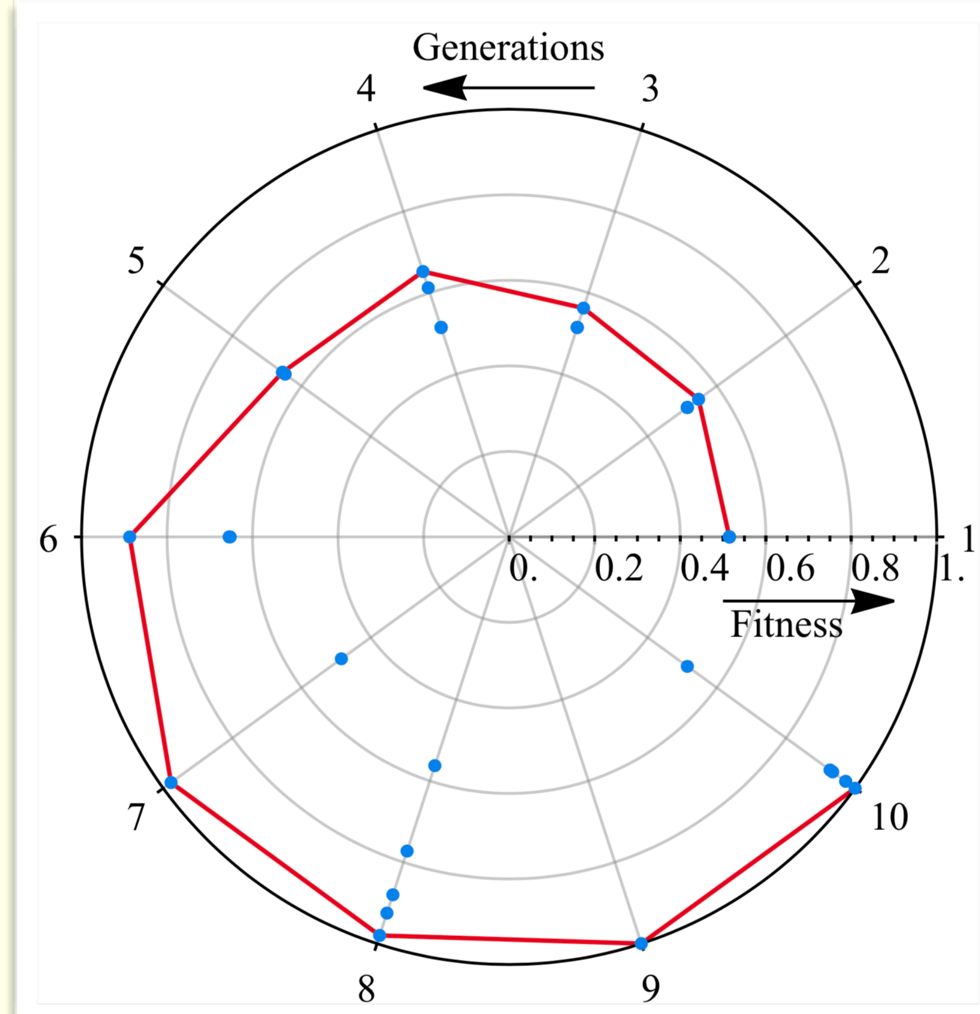
Zhang, Zheng, Zhang, & **DLD**, PRL 125,170501 (2020)

Markovian Quantum Neuroevolution for Machine Learning

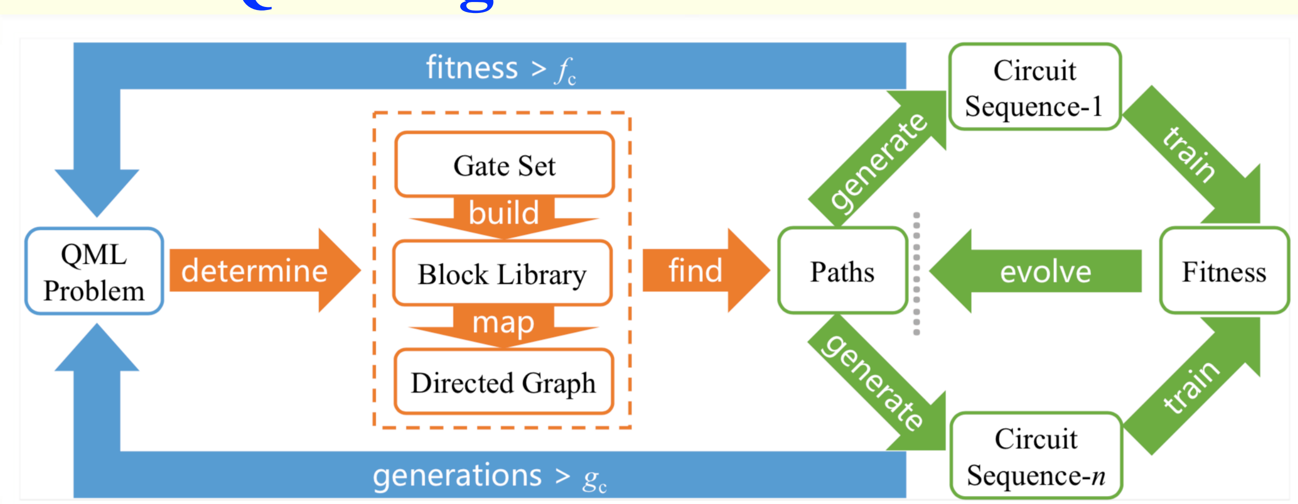
Key idea



Performance benchmark



The MQNE algorithm

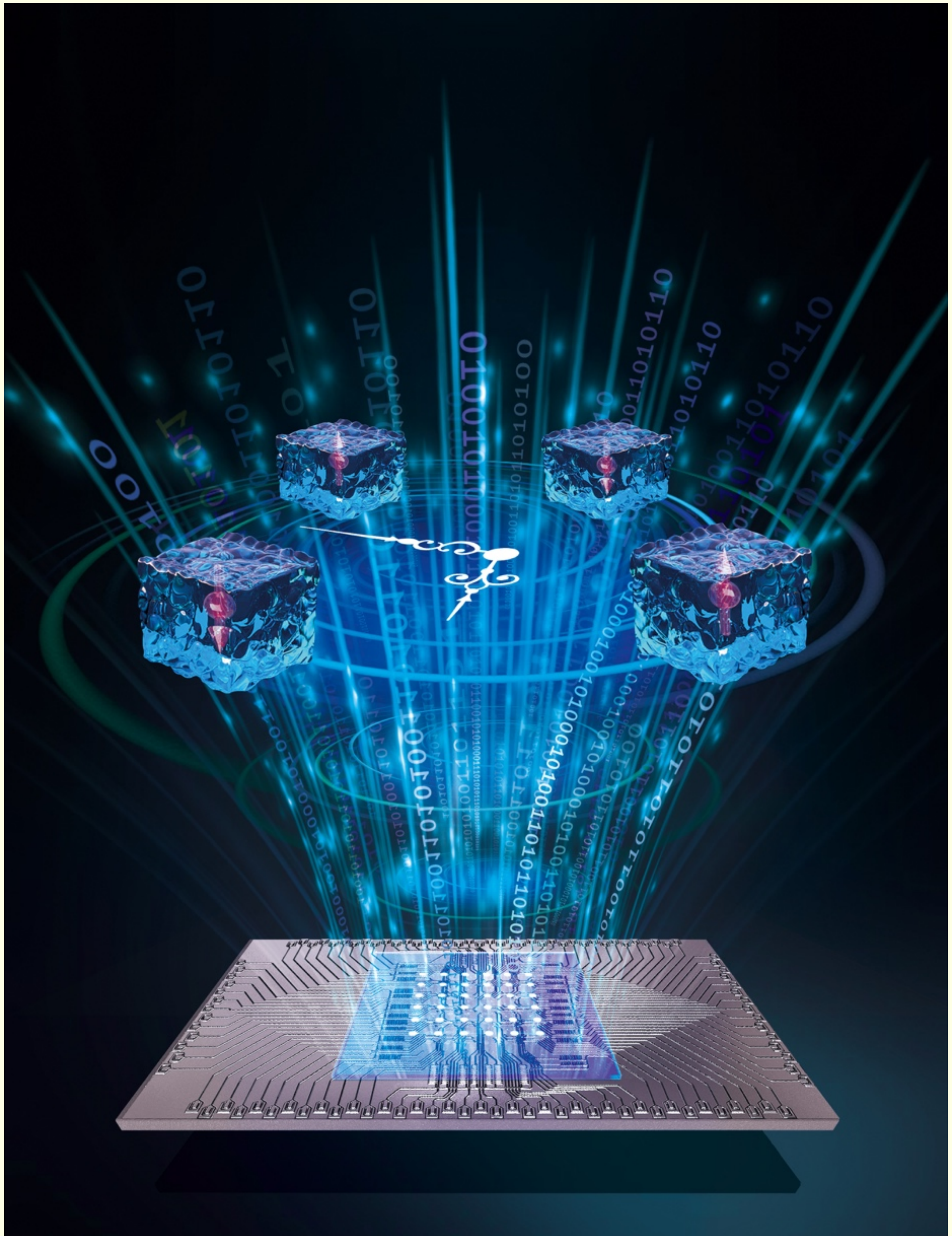


Advantages:

- Generic applicability
- Bottom-up approach
- Generate near-optimal circuit structure
- Use quantum circuits for training

Lu, Shen, & **DLD**, PR Applied **16,** 044039 (2021)

Digital quantum simulation of topological time crystals



Breaking discrete time translational symmetry only at the boundary, but not in the bulk!

Floquet Hamiltonian:

$$H(t) = \begin{cases} H_1, & \text{for } 0 \leq t < T', \\ H_2, & \text{for } T' \leq t < T \end{cases}$$

$$H_1 \equiv \left(\frac{\pi}{2} - \delta\right) \sum_k \hat{\sigma}_k^x$$

$$H_2 \equiv -\sum_k \left[J_k \hat{\sigma}_{k-1}^z \hat{\sigma}_k^x \hat{\sigma}_{k+1}^z + V_k \hat{\sigma}_k^x \hat{\sigma}_{k+1}^x + h_k \hat{\sigma}_k^x\right]$$

- *MQNE algorithm*
- *Quantum digital simulation*

Zhang,…, Wang*, **DLD***, & Wang, Nature 607, 468 (2022)

Floquet time crystals

Ordinary crystals:

Spontaneous breaking of
space translational symmetry

Time crystals:

Spontaneous breaking of
time translational symmetry

First proposed by
Frank Wilczek

Wilczek, Phys. Rev. Lett. 109, 160401 (2012).

The no-go theorem:

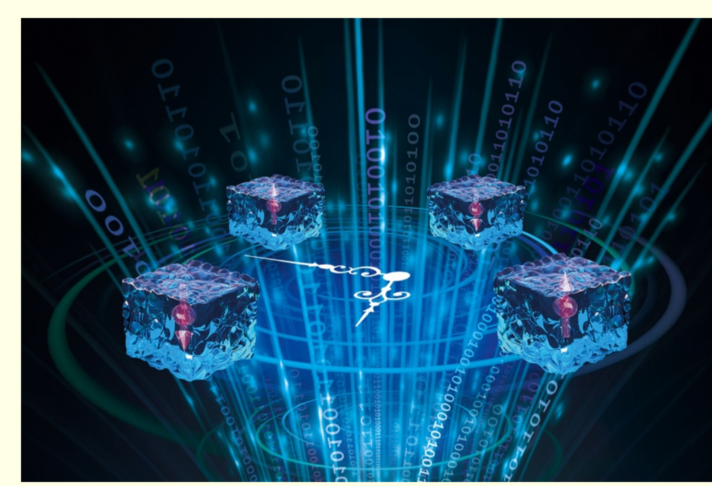
Ruling out time crystal for ground states
or thermal Gibbs states

Watanabe & Oshikawa. Phys. Rev. Lett. 114, 251603 (2015).

Floquet time crystals

Breaking discrete time translational symmetry

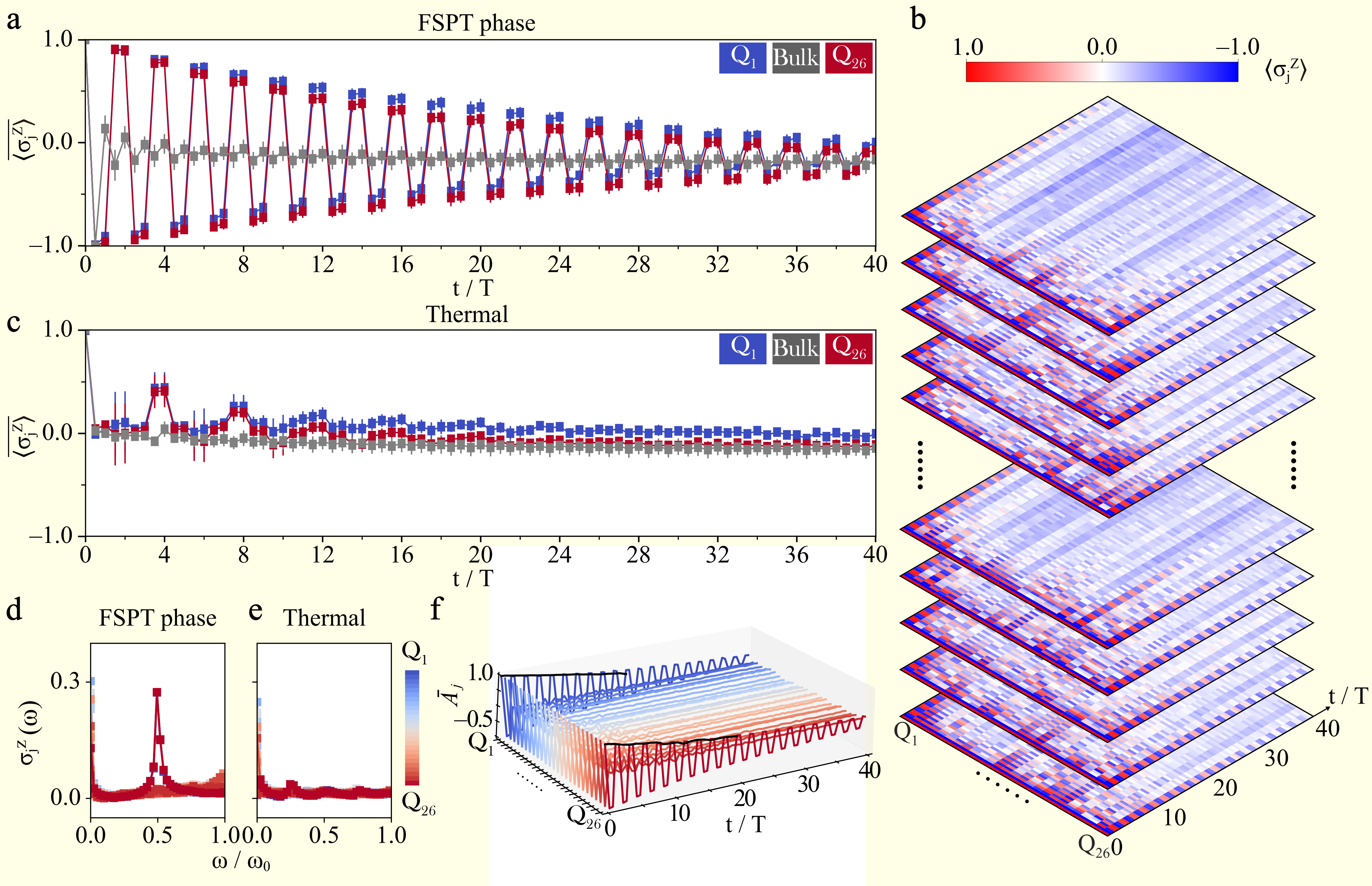
Zhang et al., Nature 543, 217 (2017); Choi et al., Nature 543, 221 (2017); …



Topological time crystals

Zhang,…, Wang*, **DLD***, & Wang, Nature 607, 468 (2022)
Dumitrescu et al., Nature 607, 463 (2022)

Experimental observation of topological time crystals



- 20 random realizations for $N = 26$; 40 cycles (around 240 layers)
- breaking the discrete time translational symmetry only at the boundaries
- Robustness
- General applicability

Future challenges

Challenge 1: Quantum automated theorem proving (first order quantum logic and quantum tree search……)

- Fitting,"First-order logic and automated theorem proving", Springer, Second edition
- **Unpublished work**
- Liu et al, CAV 2019, Computer Aided Verification, pp 187-207
- Ying, Model checking, arXiv:2104.11359 (2021)

Challenge 2: Build the quantum learning theory

- Ciliberto et al, Proc. R. Soc. A 474, 20170551 (2017)
- Arunachalam and Wolf, arXiv:1701.06806
- Dunjko and Briegel, Rep. Prog. Phys. 81, 074001 (2018)

Challenge 3: What is the essential quantum resource that enables advantages in quantum learning?

- Chitambar and Gour, Rev. Mod. Phys. 91, 025001 (2019)
- Howard et al, Nature, 510, 351 (2014)
- Gao et al, arXiv: 2101.08354v1 (2021)

Challenge 4: Quantum learning supremacy, theory and experiment, how to verify?

- Arute et al, Nature 574, 505 (2019)
- Harrow and Montanaro, Nature, 549, 203 (2017)
- Barak, Chou, and Gao, arXiv: 2005.02421v1

Challenge 5: Understanding deep learning from the physics perspective

- Lin, Tegmark, and Rolnick, J. Stat. Phys. 168, 1223 (2017); symmetry, locality, etc.
- Mehta and Schwab, arXiv: 1410.3831; Renormalization group understanding
- Hughes et al, Sci. Adv. 5, eaay6946, (2019); RNN as wave physics

Challenge 6: More efficient ways to transfer classical data to quantum states

- Giovannetti and Lloyd, PRL 100, 160501 (2008)
- Zoufal, Lucchi, and Woerner, npj Quantum Inf. 5, 103 (2019)

Challenge 7: Find a AI problem that shows unambitious complexity separation between quantum and classical algorithms

- Bravyi, Gosset, and Konig, Science 362, 303 (2018);
- Watts et al, STOC 2019;

Challenge 8: The role of noise?

- Gao and Duan, arXiv: 1810.03176v1; classical simulations of noisy quantum computing
- Du et al, arXiv: 2003.09416; used for defense
- Wang et al, arXiv: 2007.14384v1; Noise-induced barren plateaus

Challenge 9: Quantum language processing

- Wiebe et al, arXiv: 1902.05162; Fock-space representation
- Meichanetzidis et al, arXiv: 2005.04147; running on NISQ devices
- Coecke, arXiv: 1904.03478; relate to category theory
- Gao et al, arXiv: 2101.08354v1; Hidden Markov models

Challenge 10: How to measure quantum intelligence?

- Chollet, arXiv:1911.01547v2; On the measure of intelligence
- Hernandez-Orallo and Dowe, Artificial Intelligence 174, 1508 (2010);
- Schaul et al, arXiv: 1109.1314v1

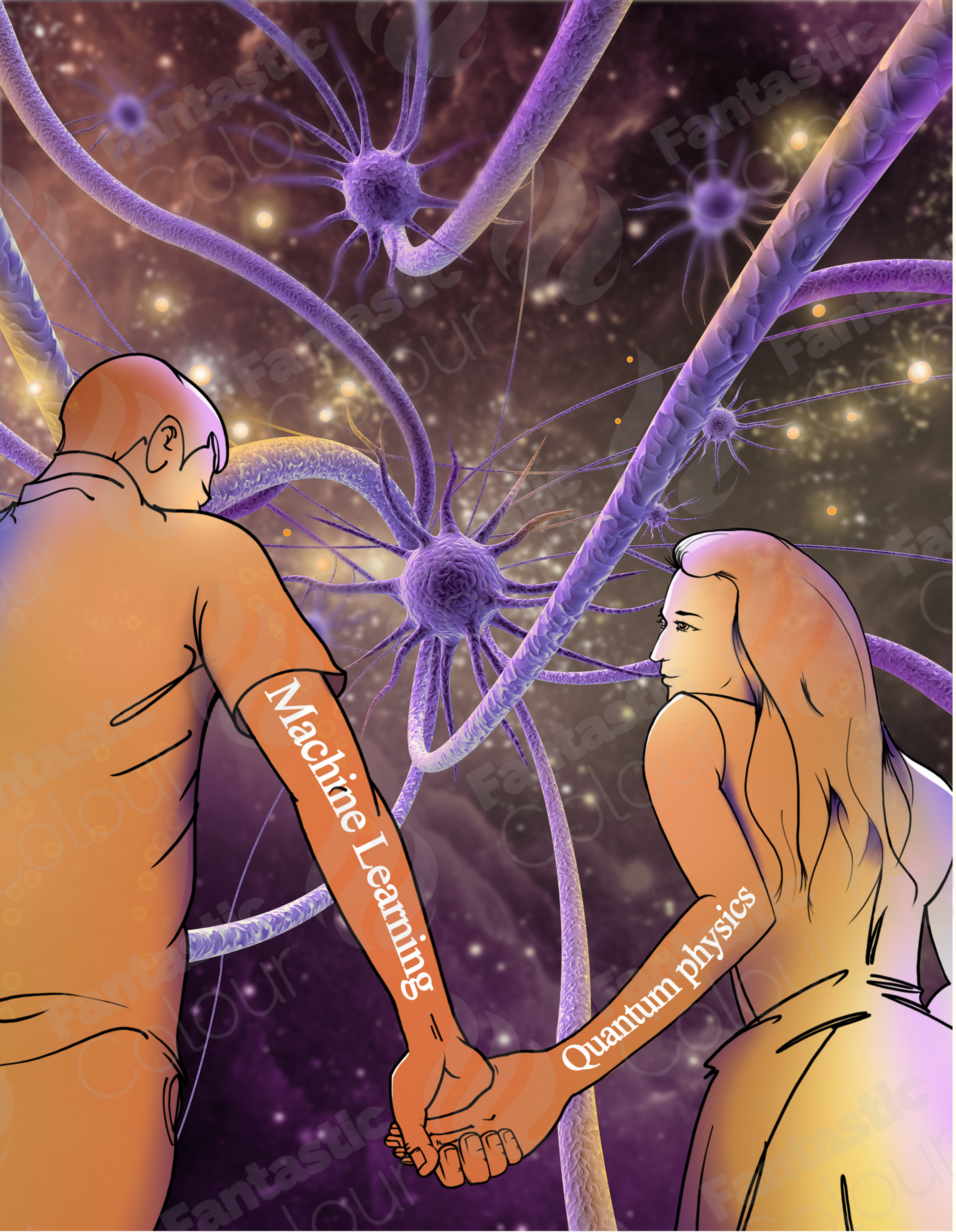
The current status

It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness.

—Charles Dickens

So is true for quantum AI.

—Dongling Deng



MACHINE LEARNING *meets* QUANTUM PHYSICS

[Physics Today, **72**, 48 (2019)]

Thank you!