Title: Machine learning meets quantum physics

Speakers: Dong-Ling Deng

Collection: Machine Learning for Quantum Design

Date: July 08, 2019 - 2:00 PM

URL: http://pirsa.org/19070020

Abstract: Recently, machine learning has attracted tremendous interest across different communities. In this talk, I will briefly introduce some new progresses in the emergent field of quantum machine learning ---an interdisciplinary field that explores the interactions between quantum physics and machine learning. On the one hand, I will talk about a couple of quantum algorithms that promise an exponential speed-up for machine learning tasks. On the other hand, I will show how ideas and techniques from machine learning can help solve challenging problems in the quantum domain.

Machine learning meets quantum physics

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

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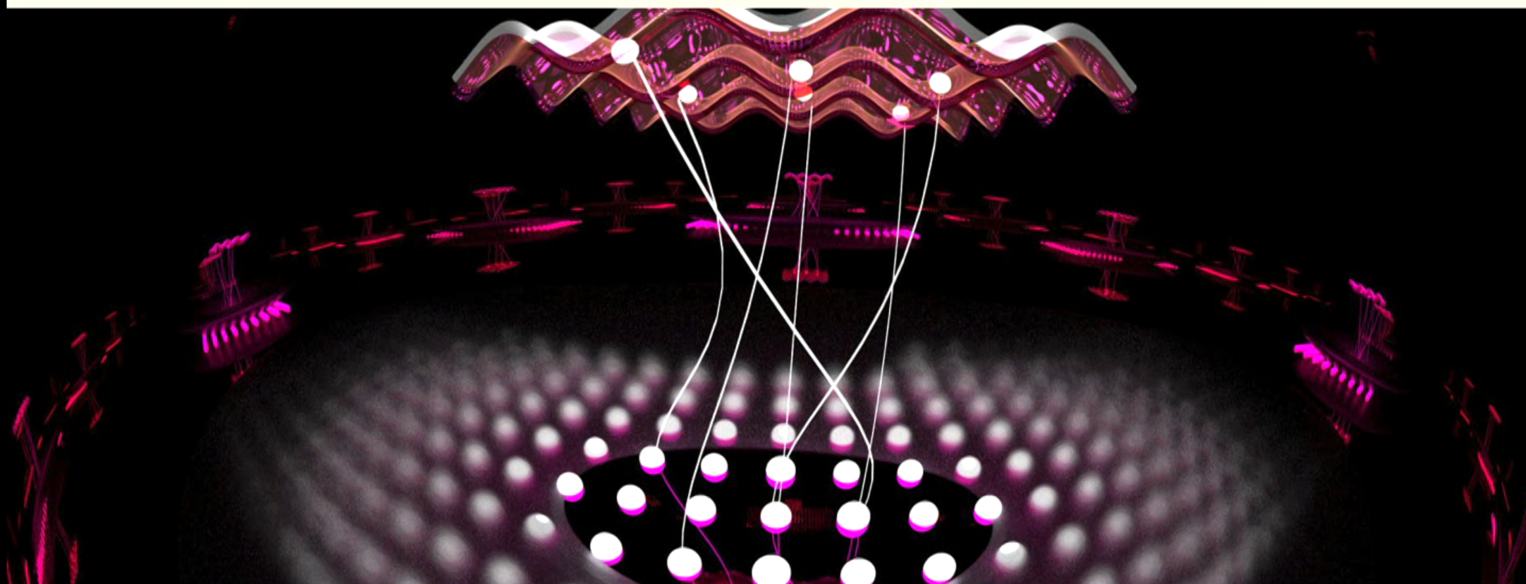
Center for Quantum Information



Machine Learning for Quantum Design, Perimeter Institute，07/09/2019

*Some images shown found online


ERIMETER

What is artificial intelligence (AI)?

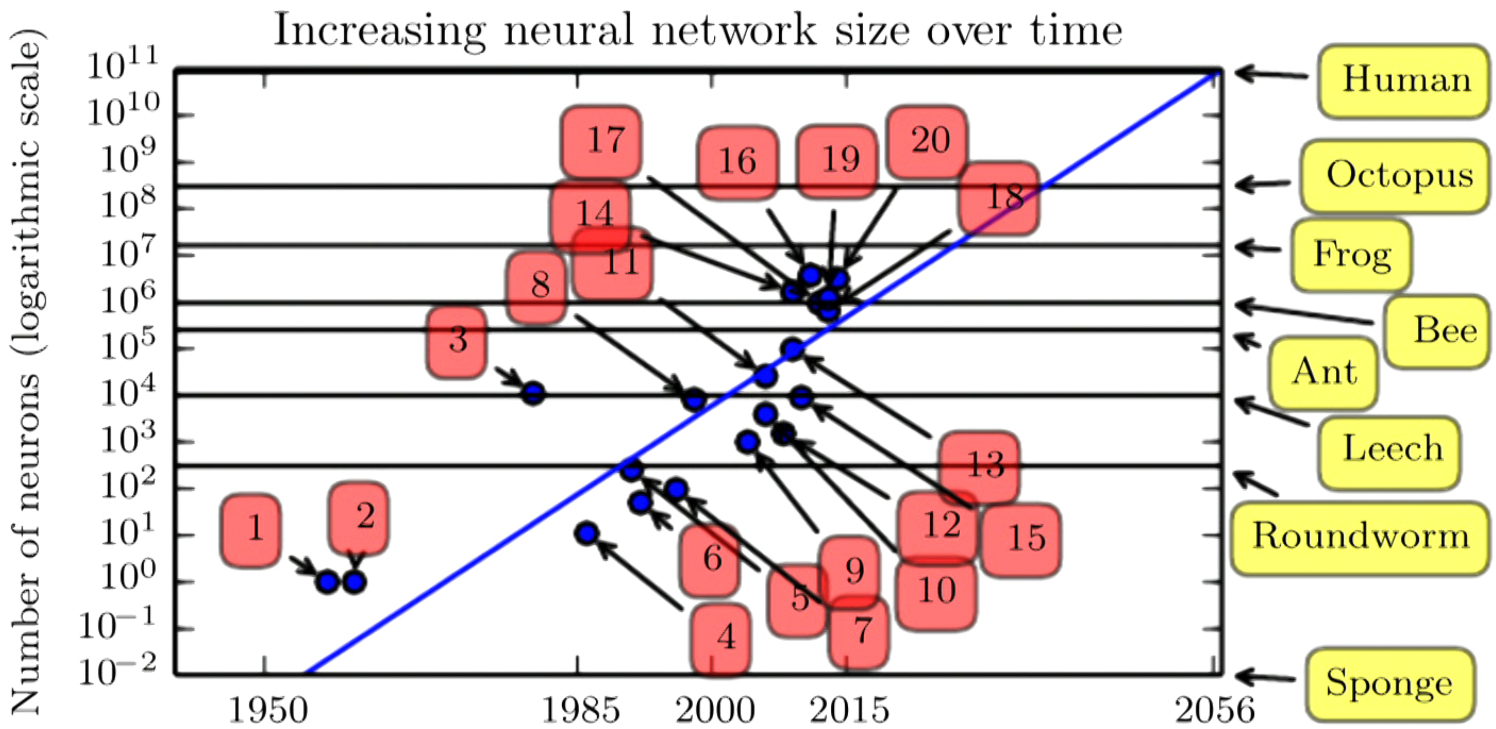
Definition: *intelligence demonstrated by machines*

Three categories:

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

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

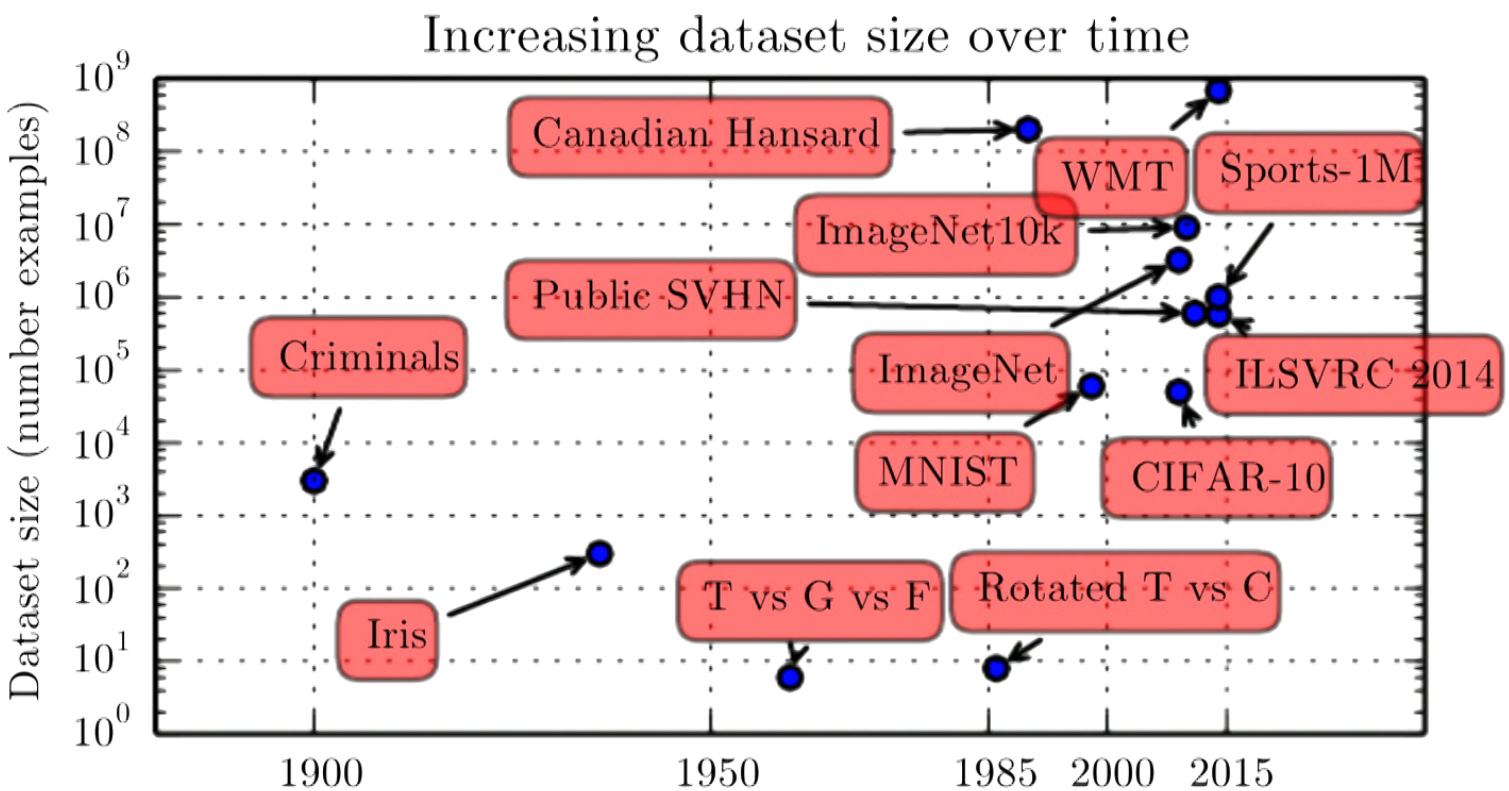
Moore's law in machine learning



1. Perceptron (Rosenblatt, 1958)
4. Early back-propagation network (Rumelhart et al, 1986)
6. Multilayer perceptron for speech recognition (Bengio et al, 1991)
8. LeNet-5 (LeCun et al, 1998)
10. Deep belief network (Hinton et al, 2006)
20. GoogLeNet (Szegedy et al, 2014)

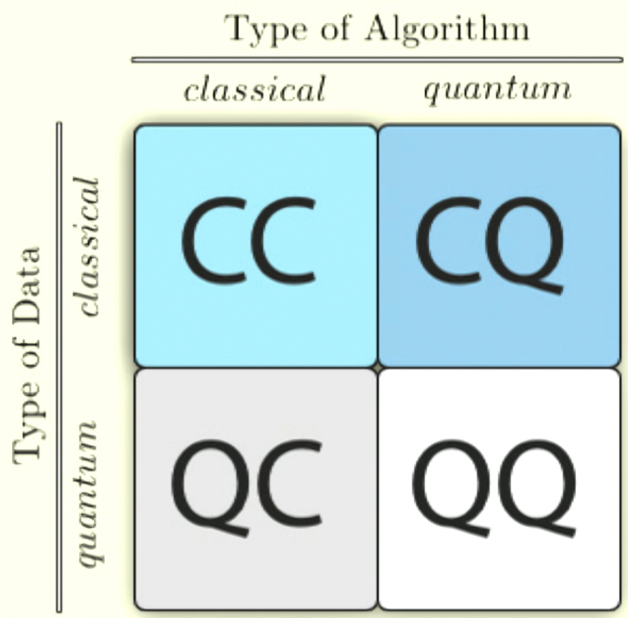
Goodfellow, Bengio, & Courville, Deep learning, MIT press

Big data era

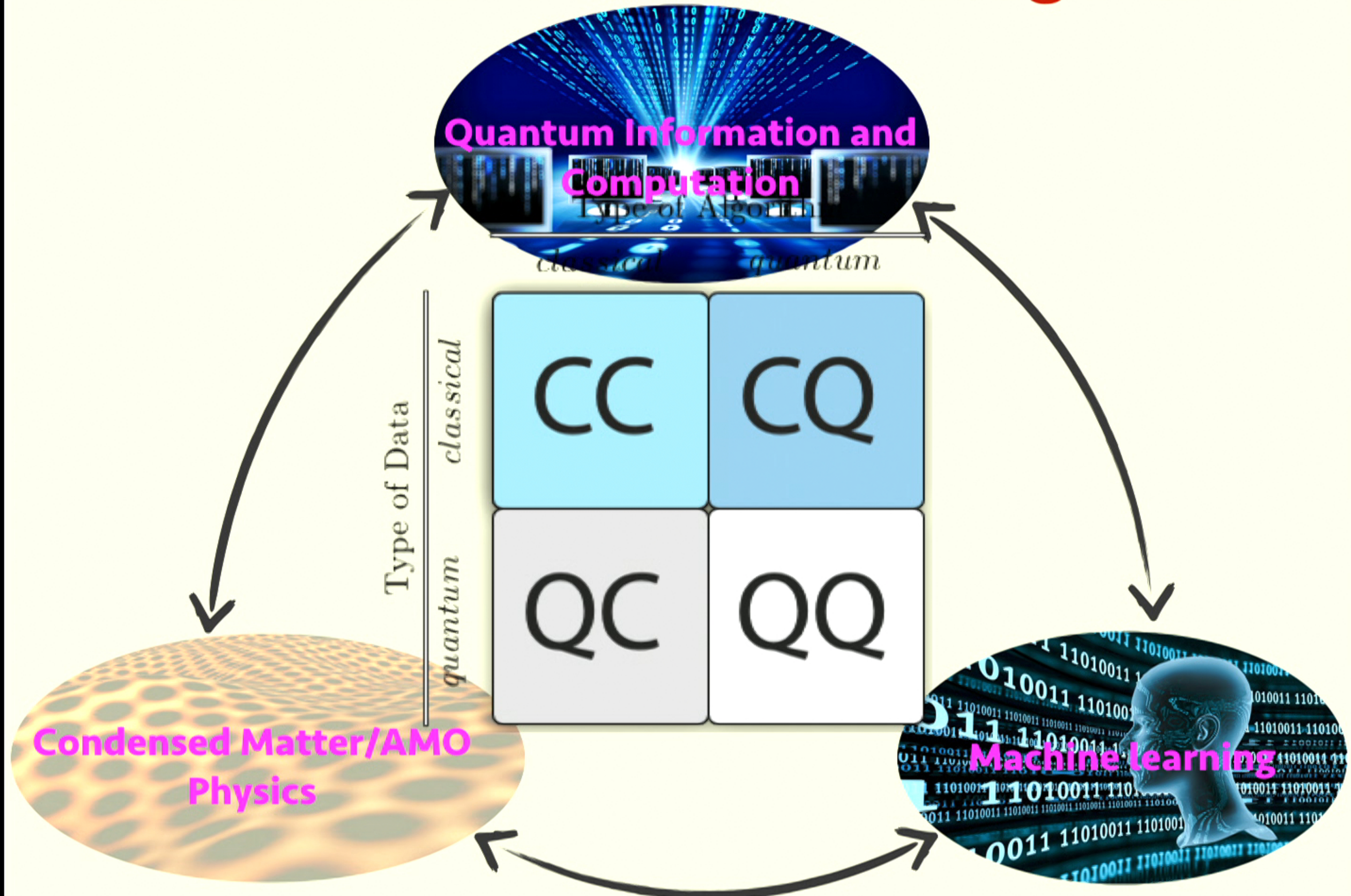


Goodfellow, Bengio, & Courville, Deep learning, MIT press

Quantum Artificial Intelligence



Quantum Artificial Intelligence



Outline for the rest of the talk

- **Quantum enhanced machine learning**
  1. *HHL algorithm*
  2. *Quantum generative model (QGM)*
  3. *Quantum generative adversarial network (QGAN)*
- **Machine learning in quantum physics**
  1. *Restricted Boltzmann machine (RBM)*
  2. *RBM representation, entanglement, non-locality*
  3. *Machine learning phases of matter*
  4. *Machine learning topological phases*
- **Summary**

Quantum enhanced machine learning

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**

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

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

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

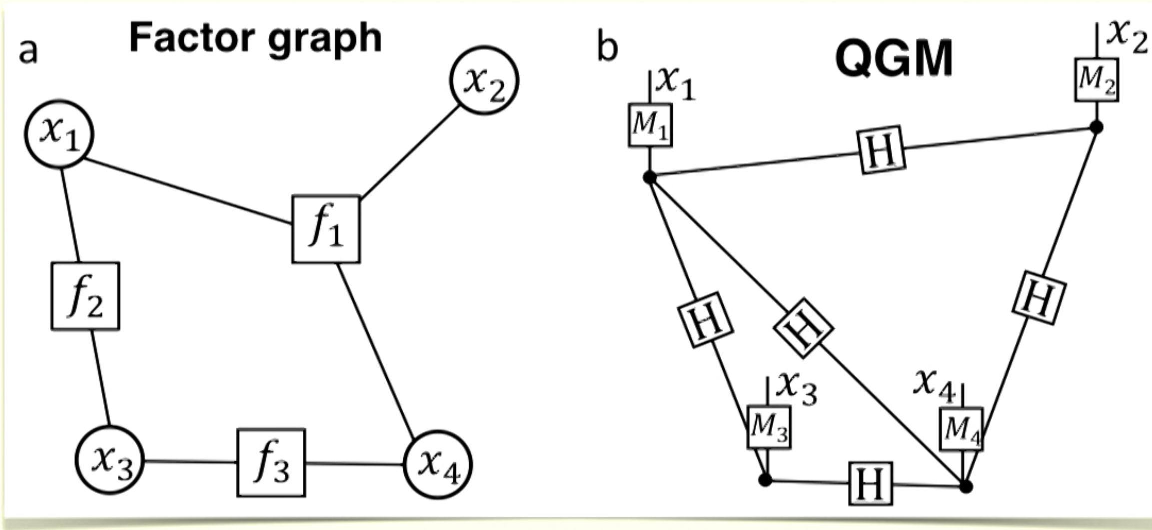
Caveats:

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

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

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

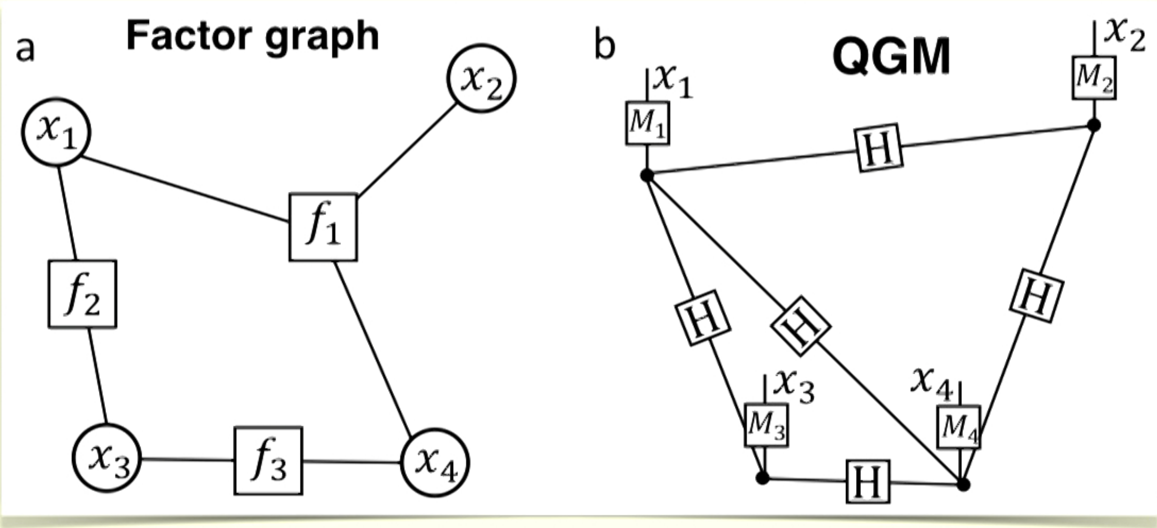
Quantum generative model (QGM)



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

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

Quantum generative model (QGM)



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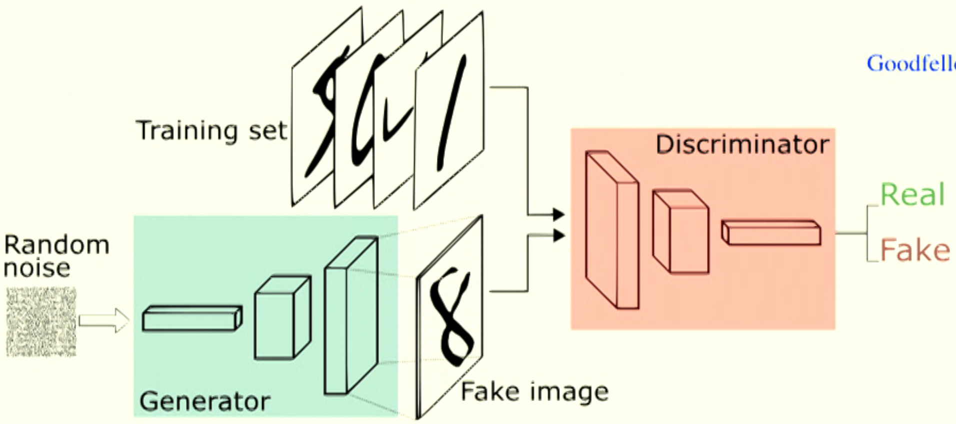
Advantages:

- *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)



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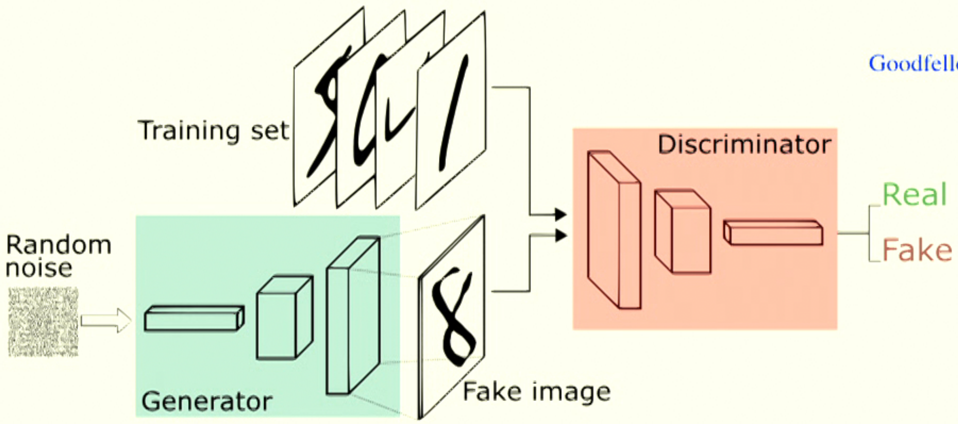
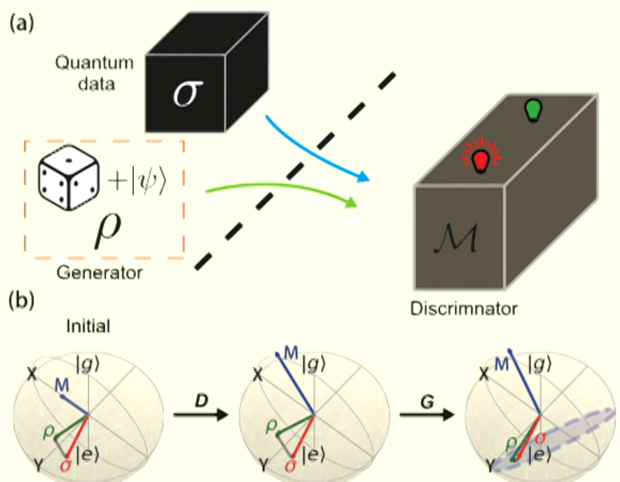


Goodfellow *et al*, ANIPS, pp. 2672-2680, (2014)



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

Dallaire-Demers and Killoran, arXiv: 1804.08641

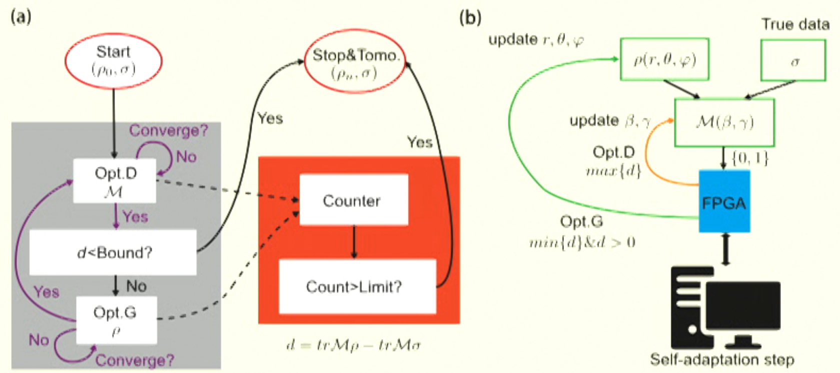
Benedetti et al, arXiv: 1806.00468

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

Zeng et al, arXiv: 1808.03425

Quantum generative adversarial network (QGAN)

Exp. setup



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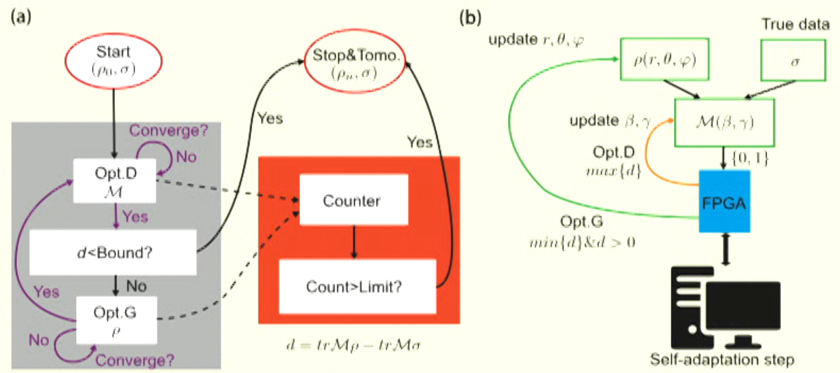
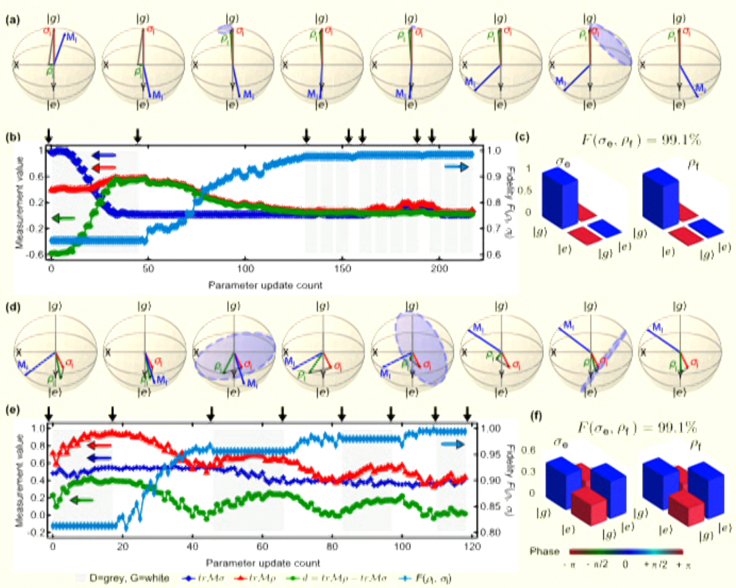


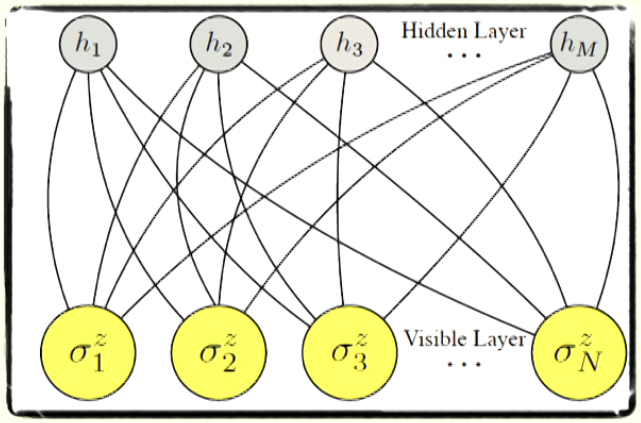


- Converge well
- Noise robust
- Carry over to NISQ devices
- *Learning quantum data!*

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

Machine learning in quantum physics

RBM representation of quantum states



Allow complex parameters and regard the probability as the

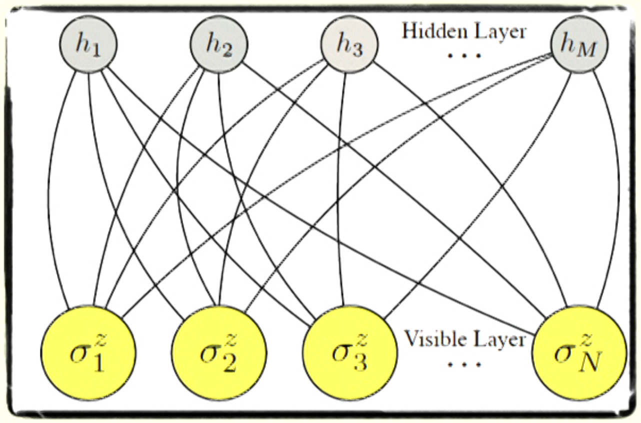
$$\Psi_M(\mathcal{S};\mathcal{W}) = \sum_{\{h_k\}} e^{\sum_j a_j \sigma_j^z + \sum_k b_k h_k + \sum_{kj} W_{kj} h_k \sigma_j^z}$$

The actual quantum state:

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

G. Carleo and M. Troyer, Science **355**, 602 (2017)

RBM representation of quantum states



Examples for quantum models:

Transverse field Ising:

$$\mathcal{H}_{\mathrm{TFI}} = -h \sum_i \sigma_i^x - \sum_{\langle i,j \rangle} \sigma_i^z \sigma_j^z$$

Anti-Ferro Heisenberg:

$$\mathcal{H}_{\mathrm{AFH}} = \sum_{\langle i,j \rangle} \sigma_i^x \sigma_j^x + \sigma_i^y \sigma_j^y + \sigma_i^z \sigma_j^z$$

Allow complex parameters and regard the probability as the

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

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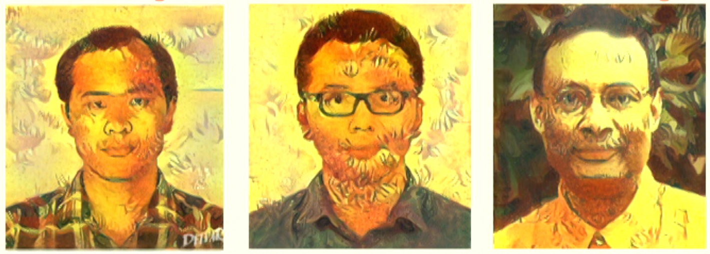
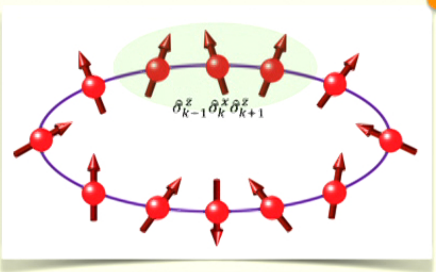
G. Carleo and M. Troyer, Science **355**, 602 (2017)

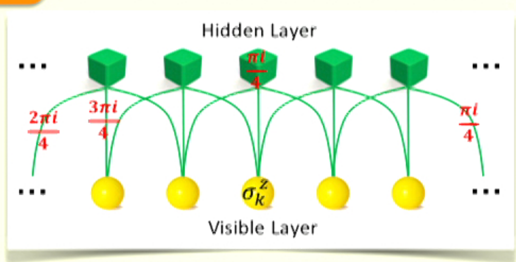
Exact RBM representation of topological states



DLD, X.-P. Li, S. Das Sarma, PRB, 96, 195145(2017)

1D SPT Hamiltonian： $\boxed{H_{spt} = -\sum_{k=1}^{N} \hat{\sigma}_{k-1}^{z}\hat{\sigma}_{k}^{x}\hat{\sigma}_{k+1}^{z}}$





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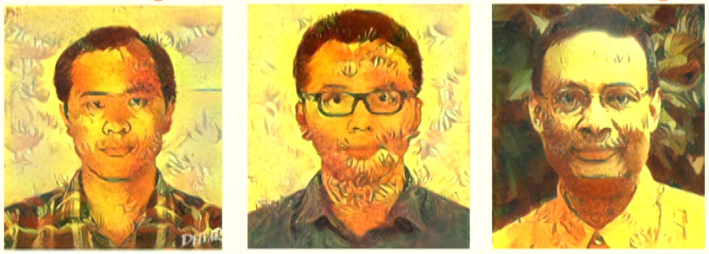

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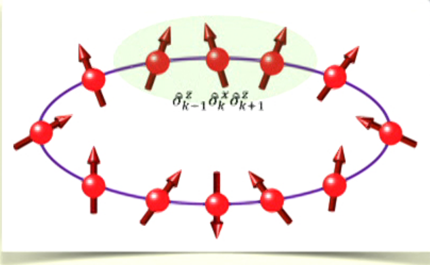
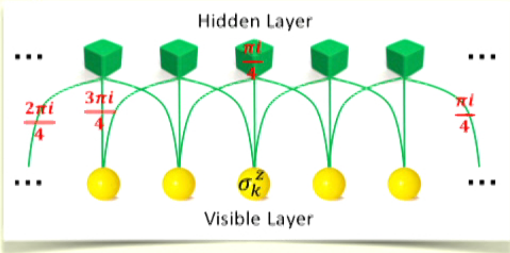
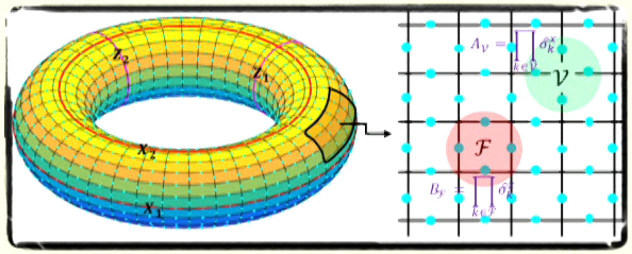
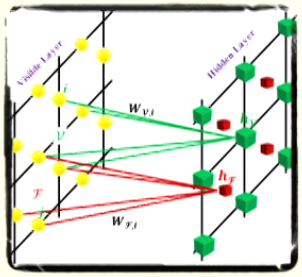




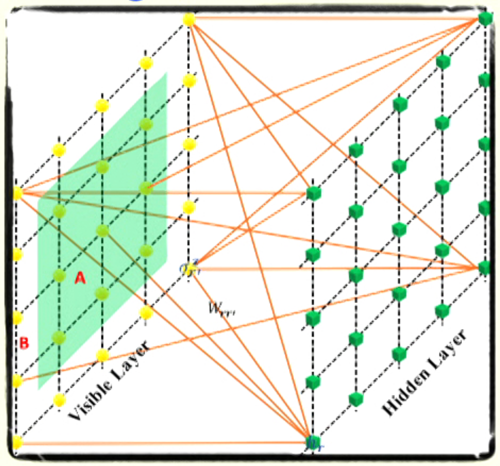
2D toric-code Hamiltonian: $H_{tor} = -\sum_{\mathcal{V}\in\mathbb{T}^2} A_{\mathcal{V}} - \sum_{\mathcal{F}\in\mathbb{T}^2} B_{\mathcal{F}}$





Quantum entanglement in neural network states

Entanglement area law for short-range RBMs:



The α-th order Renyi entropy:

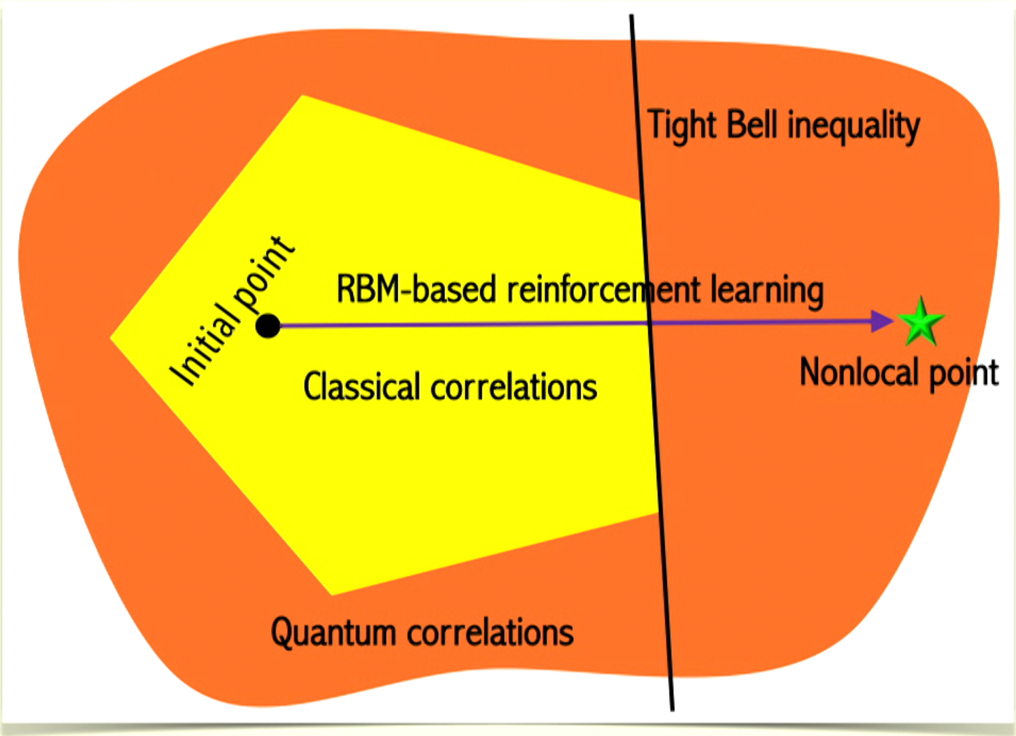
$$S_\alpha^A \equiv \frac{1}{1-\alpha}\log[\mathrm{Tr}(\rho_A^\alpha)]$$

Theorem 1: All short-range RBM states satisfy an area law:

$$S_\alpha^A \leq 2\mathcal{S}(A)\mathcal{R}\log 2, \quad \forall\alpha$$

DLD, Xiaopeng Li, S. Das Sarma, PRX, 7, 021021 (2017)

Machine Learning Detection of Bell nonlocality



DLD, PRL, 120, 240402 (2018)

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)
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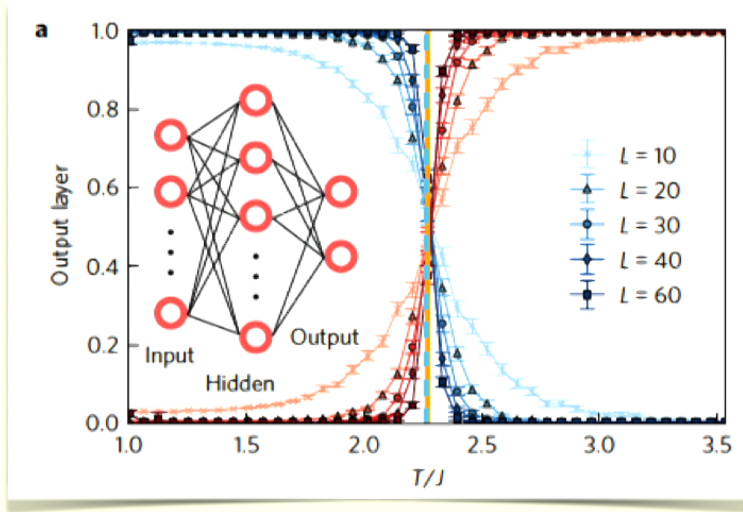

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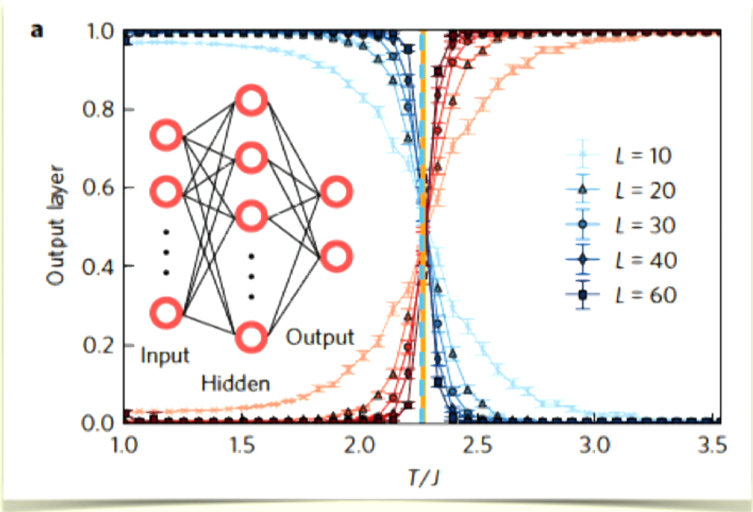

Unsupervised learning:

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)
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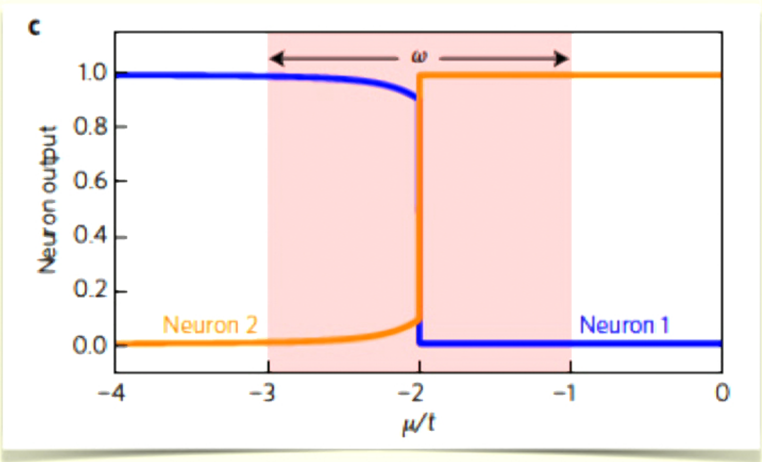
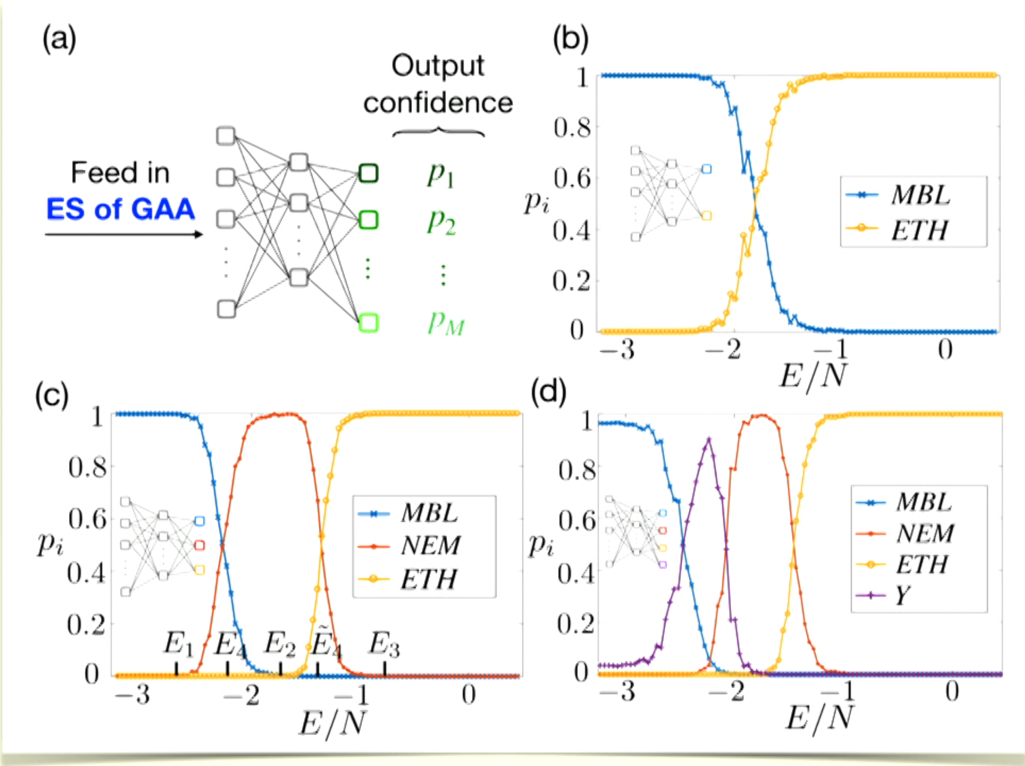


Machine learning nonergodic metals

The GAA model: $H = \sum_{j=1}^{L}\left(-t(c_j^\dagger c_{j+1} + H.c.) + 2\lambda\frac{\cos(2\pi q j+\phi)}{1-\alpha\cos(2\pi q j + \phi)}n_j + V n_{j+1}n_j\right)$



- *High confidence*
- *Single diagnostic: entanglement spectra*

Hsu, Li, **DLD**, & Das Sarma, PRL,121,245701 (2018)

Machine Learning Topological Phases

Model: **3D chiral TI** $H = \sum_{\mathbf{k} \in \mathrm{BZ}} \Psi^\dagger_{\mathbf{k}} \mathcal{H}_{\mathbf{k}} \Psi_{\mathbf{k}}$

$$\mathcal{H}_{\mathbf{k}} = \begin{pmatrix} 0 & q_1(\mathbf{k}) - i q_2(\mathbf{k}) & 0 \\ q_1(\mathbf{k}) + i q_2(\mathbf{k}) & 0 & q_3(\mathbf{k}) + i q_0(\mathbf{k}) \\ 0 & q_3(\mathbf{k}) - i q_0(\mathbf{k}) & 0 \end{pmatrix}$$

Wang, **DLD**, & Duan, PRL 113, 033002 (2014)

Machine Learning Topological Phases

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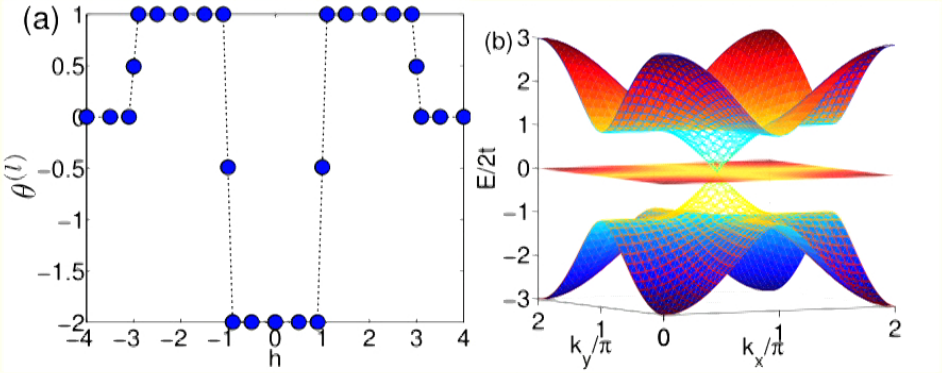
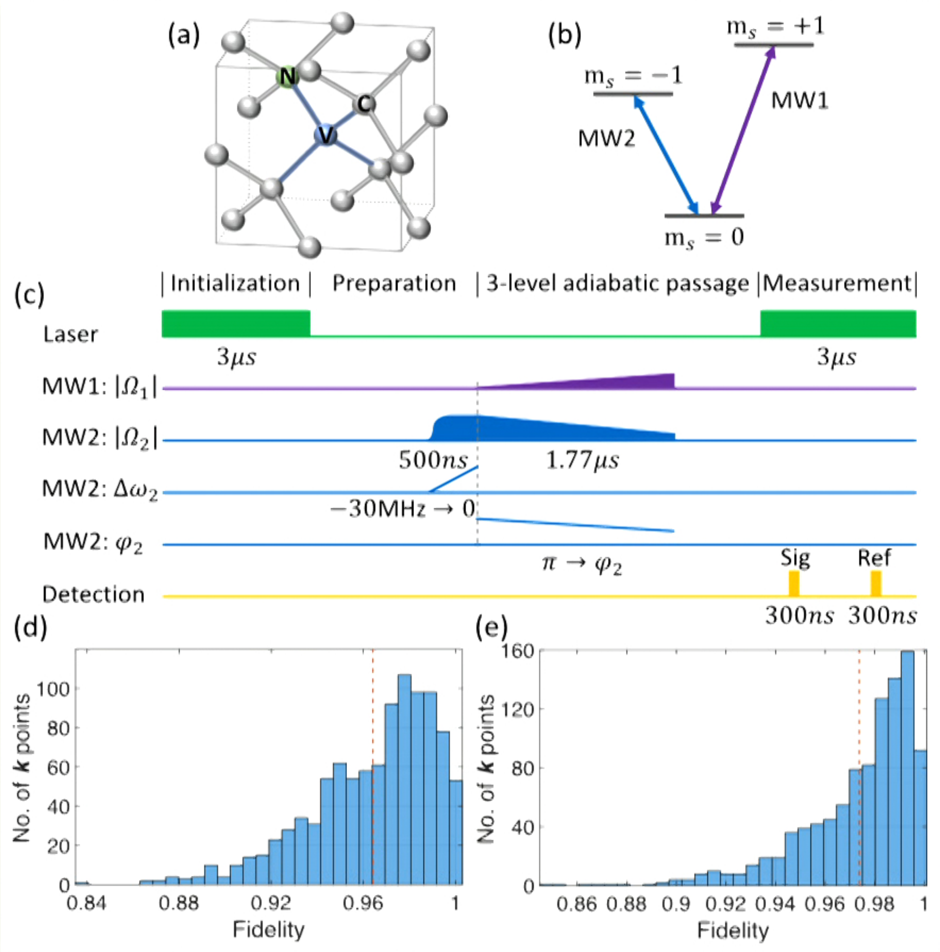
Topological index: $\theta^{(\lambda)} = \frac{1}{4\pi} \int_{\mathrm{BZ}} \epsilon^{\mu\nu\tau} A_{\mu}^{(\lambda)} \partial_{k^{\nu}} A_{\tau}^{(\lambda)} \, d^3k$



Wang, **DLD**, & Duan, PRL 113, 033002 (2014)

Solid-state Quantum Simulator



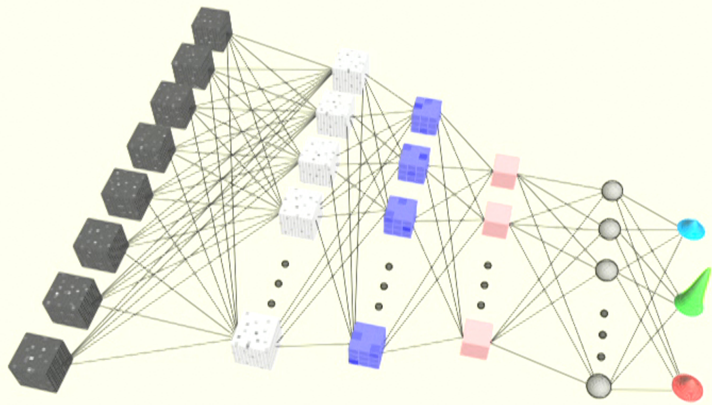
Main idea:

- NV center
- Adiabatic passage
- Tomography

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

Learning topological invariant

Neural network

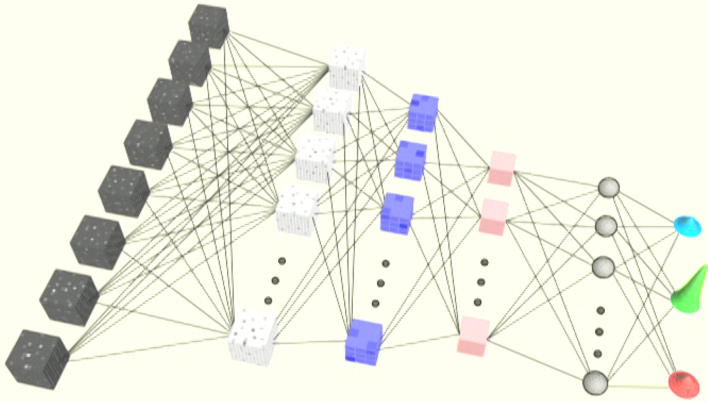


- Use CNN
- Training data numerically generated
- Input data: measured state density

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

Learning topological invariant

Neural network



- Use CNN
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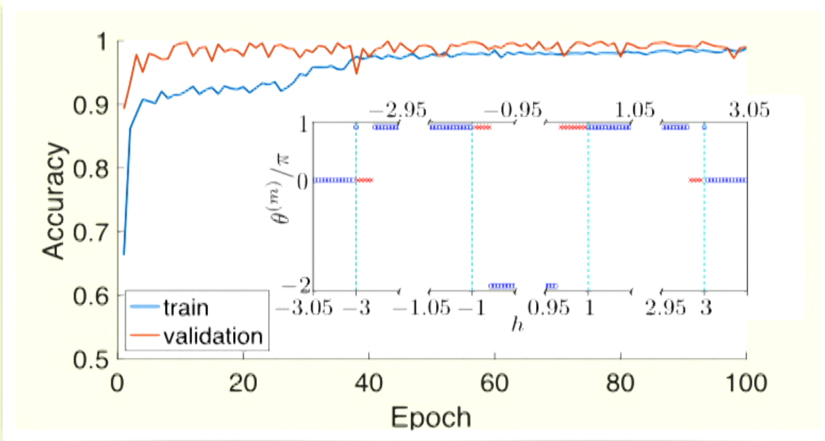
Benchmark

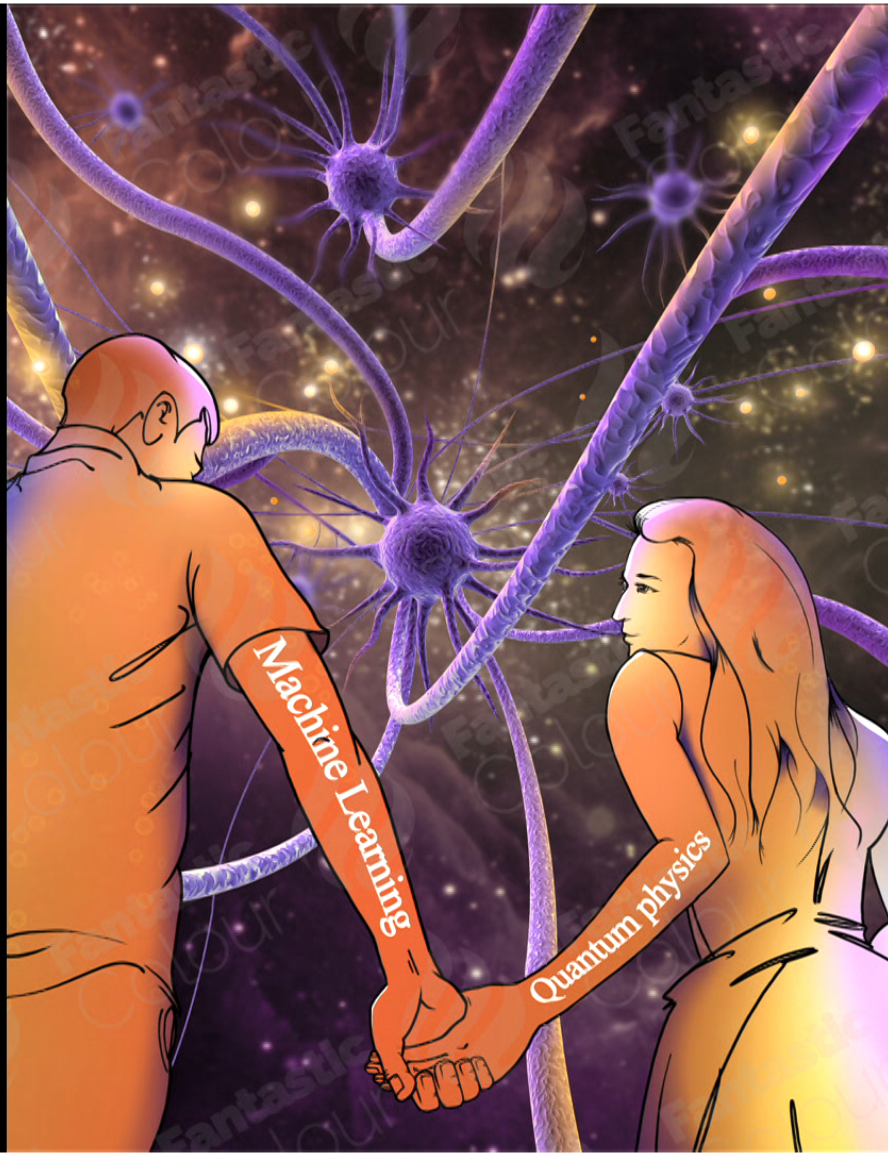


Lian, Wang, ……, **DLD***, & Duan*, PRL, 122, 210503 (2019)

Open positions: 1~2 Ph.D. and 1~2 postdocs

Why Tsinghua?

- One of the top universities, international
- Beautiful campus—former imperial gardens of the Qing Dynasty
- Competitive fellowship/scholarship/Salary
- For postdocs: "Shuimu Scholar", 58000 C$/year+rent-subsidized apartment+other benefits



MACHINE LEARNING *meets* QUANTUM PHYSICS

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

Thank you!