

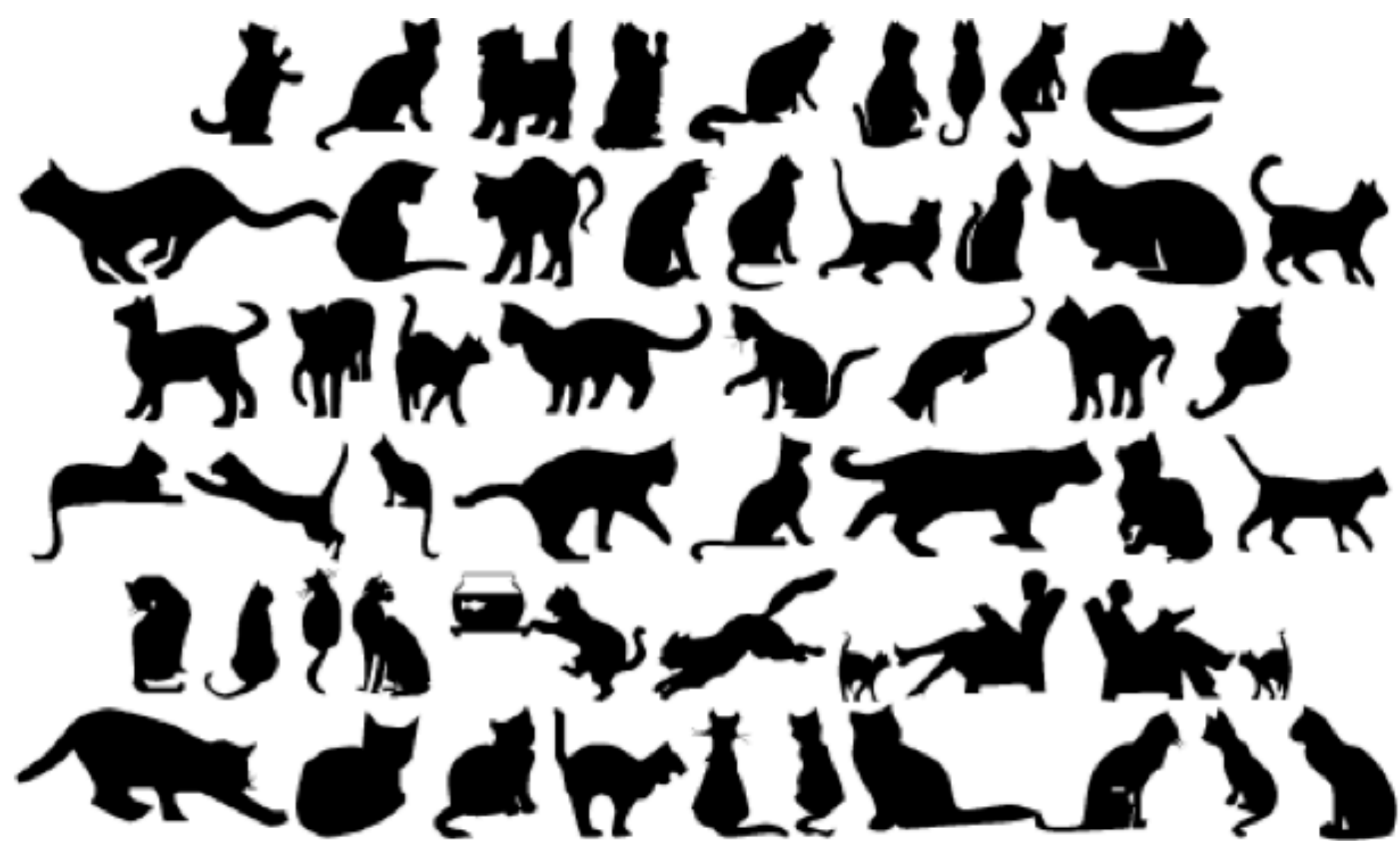
# Artificial Intelligence and Quantum Physics

Lei Wang (王磊)

Institute of Physics, CAS

<https://wangleiphy.github.io>

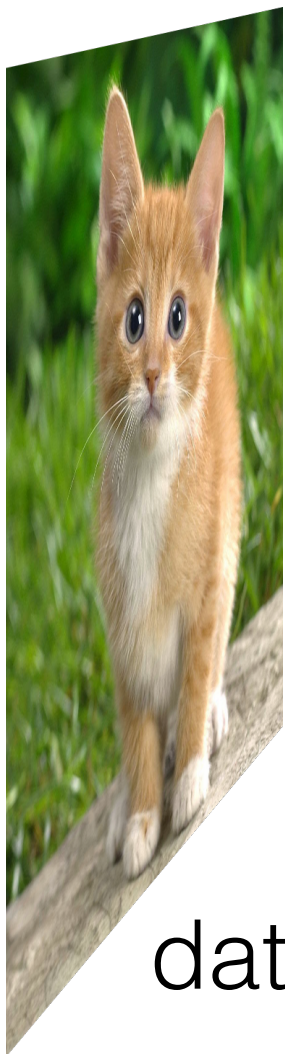
*What is common of AI and  
quantum physics researches ?*



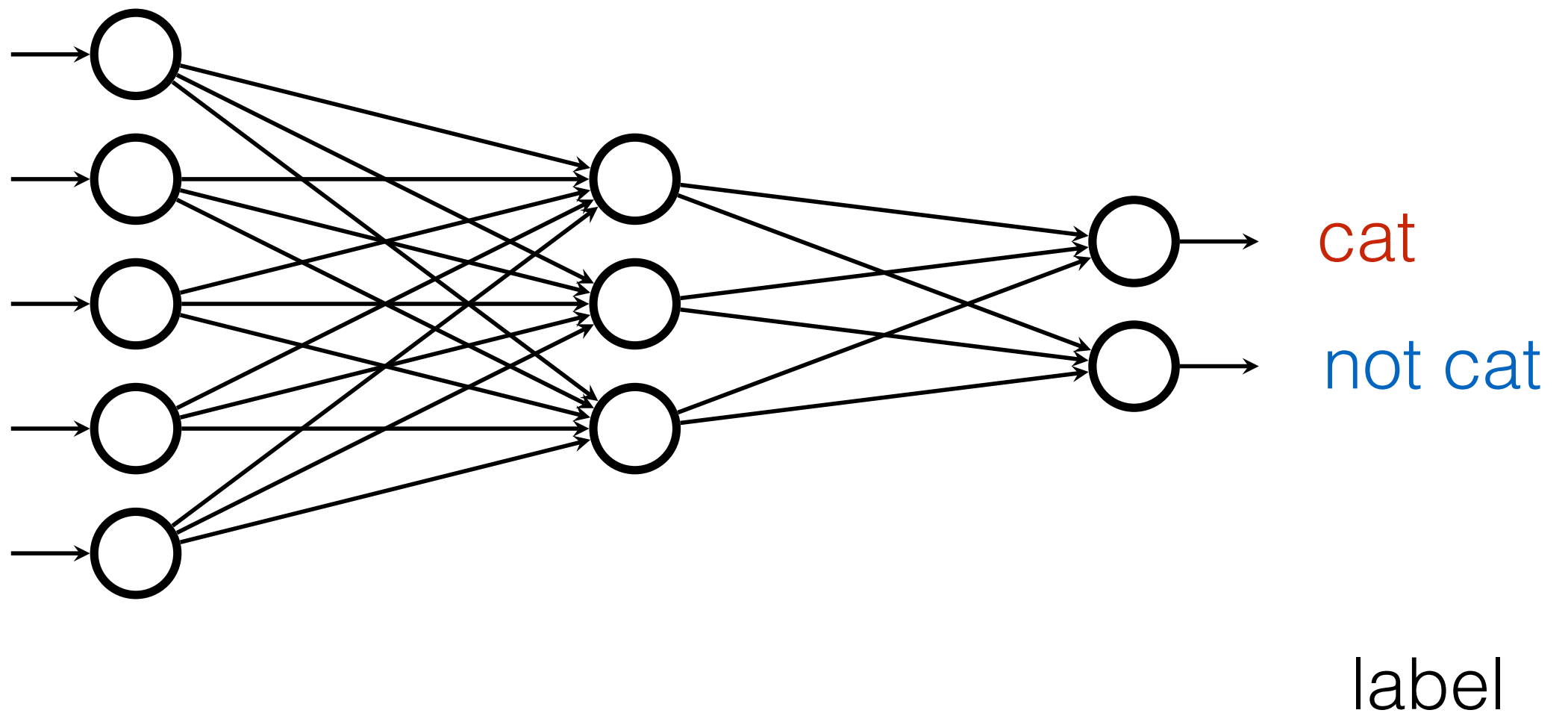
*We both love cats!*

$$\frac{1}{\sqrt{2}}|\text{cat}\rangle + \frac{1}{\sqrt{2}}|\text{cat}\rangle$$

# How to recognize a cat ?

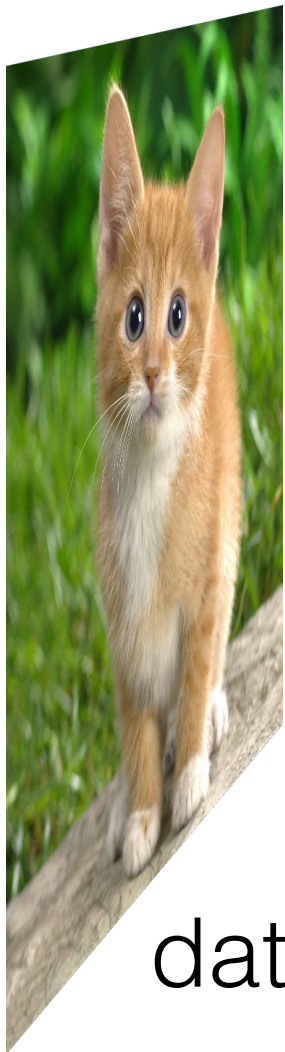


data

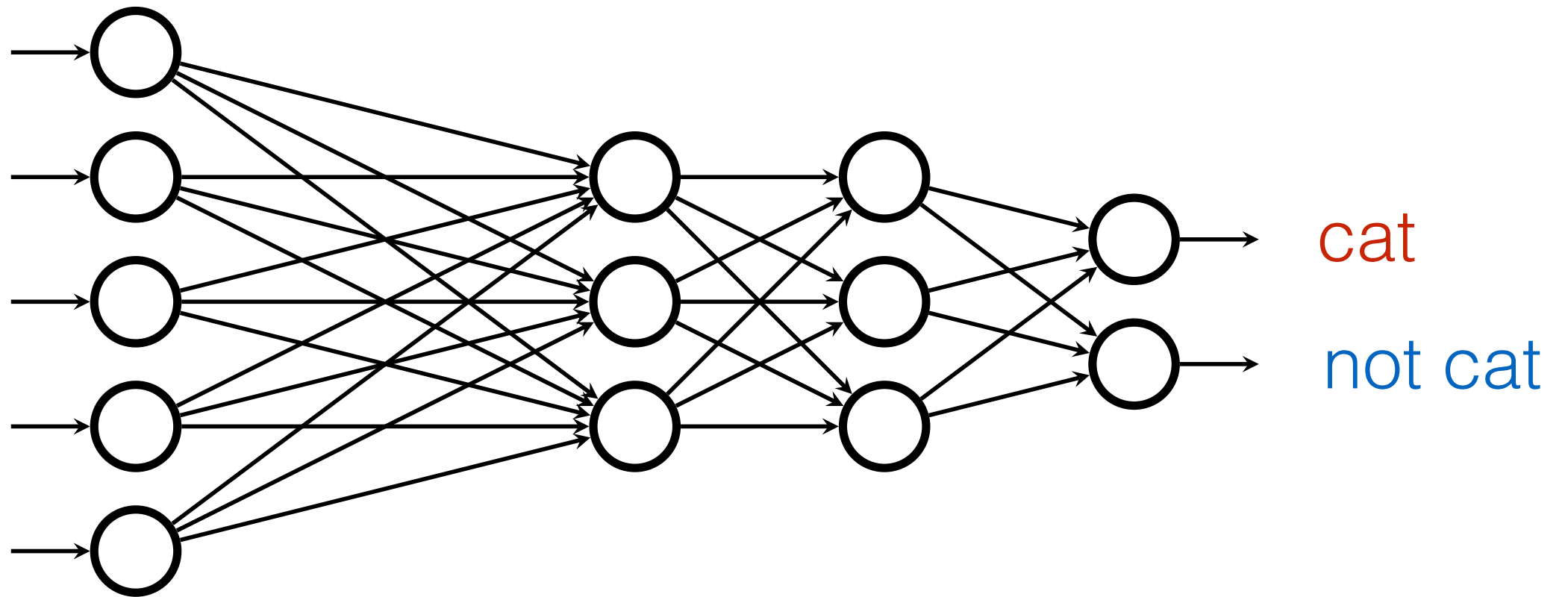




# How to recognize a cat ?



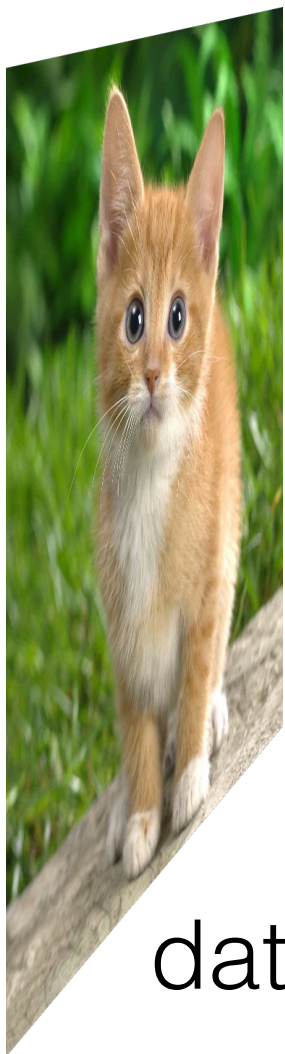
data



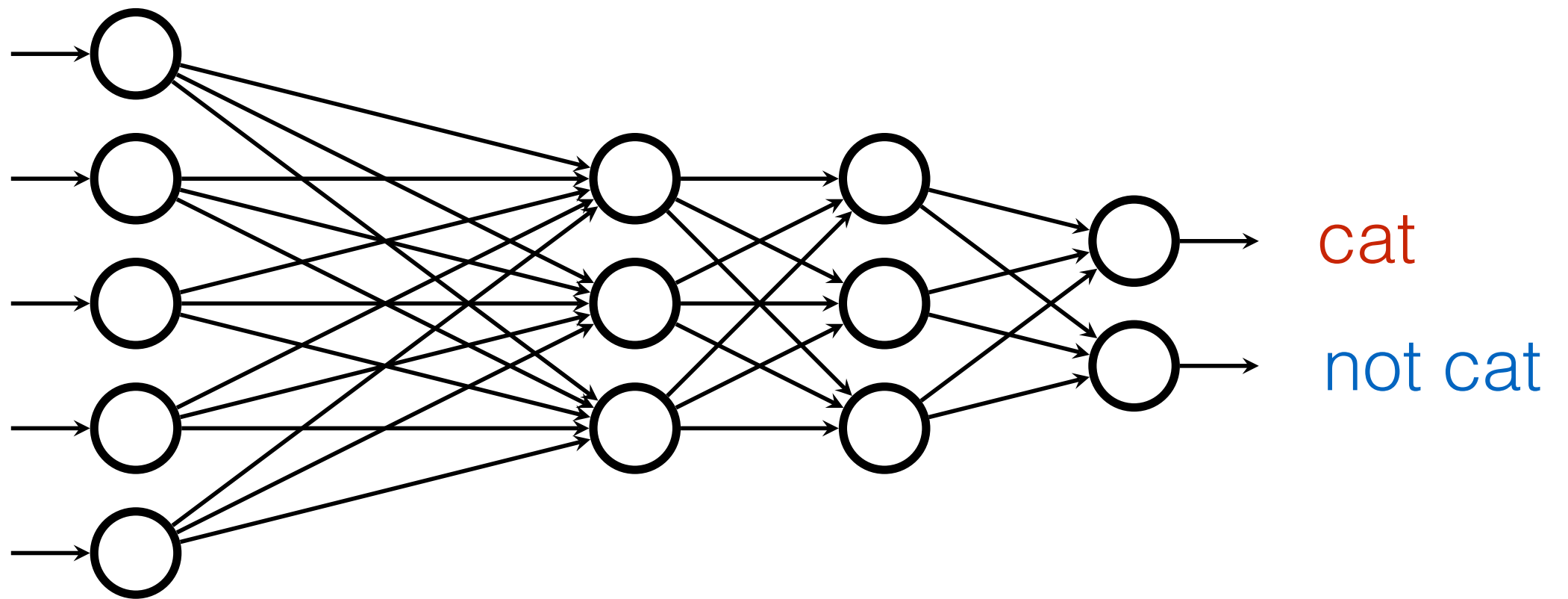
Depth appears to be important!

label

# How to recognize a cat ?



data

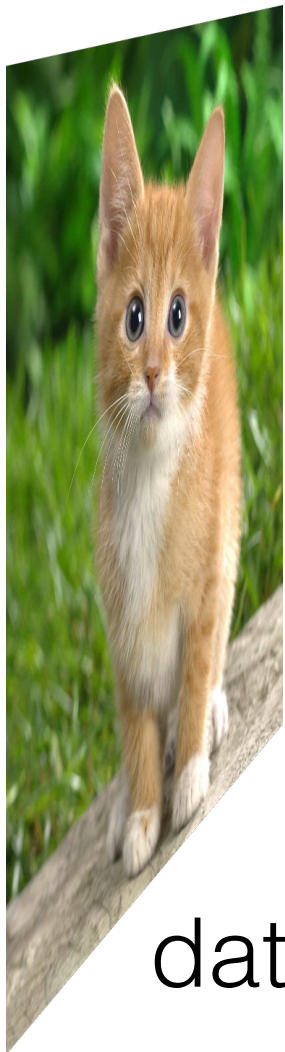


Depth appears to be important!

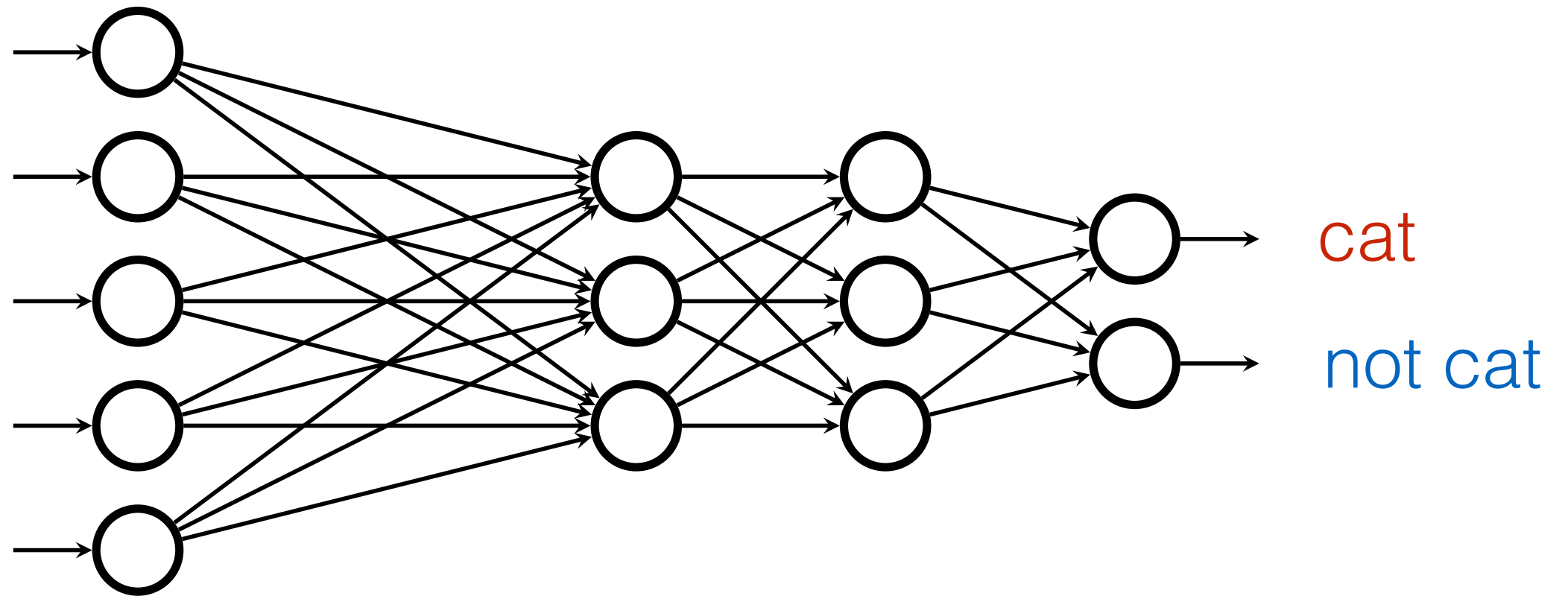
label

**Q: Why does deep learning work?**

# How to recognize a cat ?



data



Depth appears to be important!

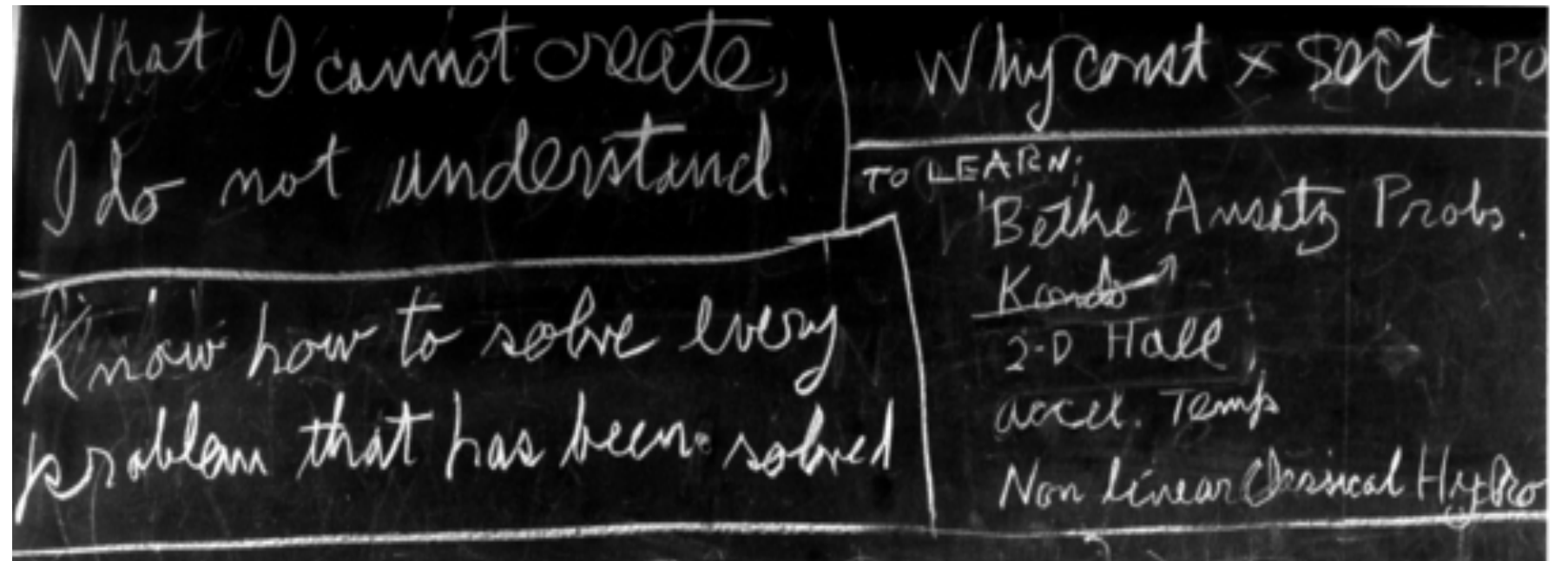
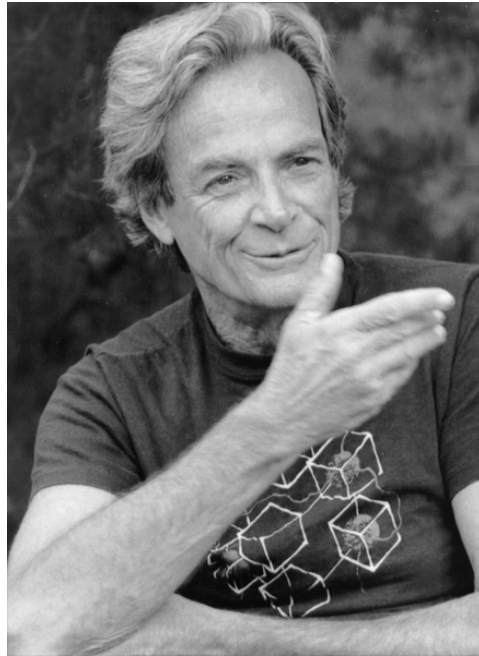
label

**Q: Why does deep learning work?**

**A: Law of physics: symmetry, locality, compositionality, renormalization group, and quantum entanglement.**

Deep learning is more than  
function fitting

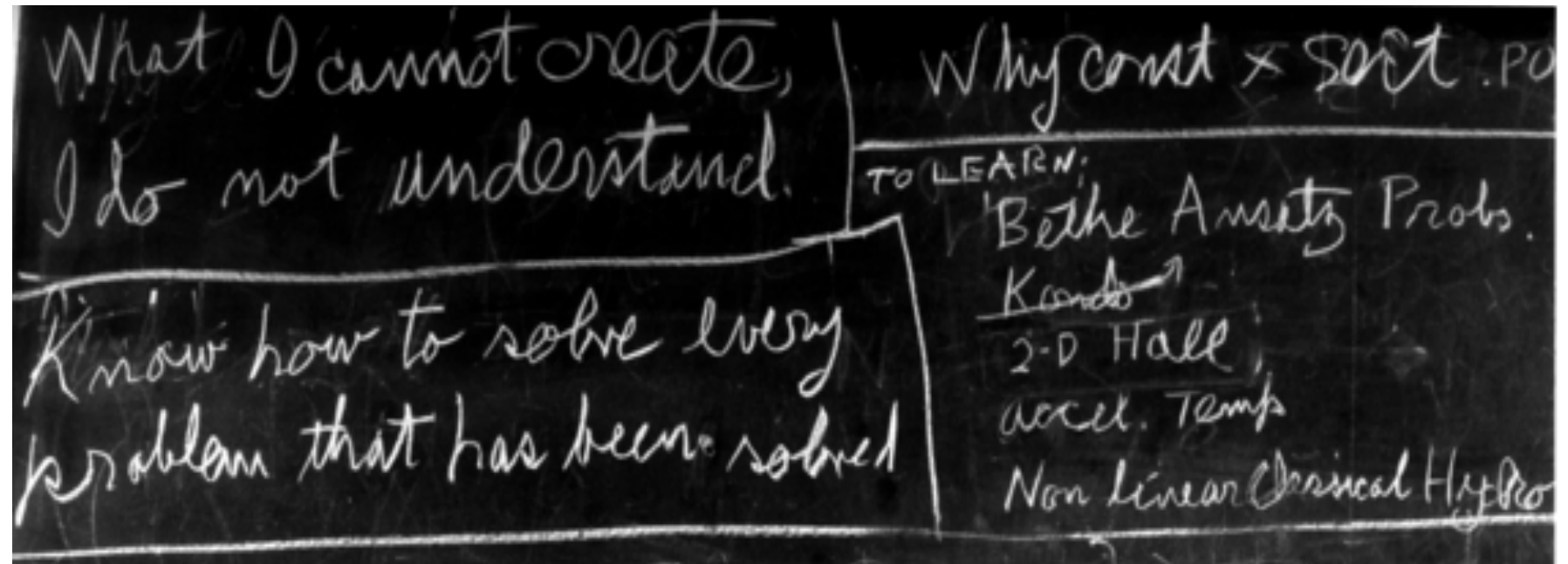
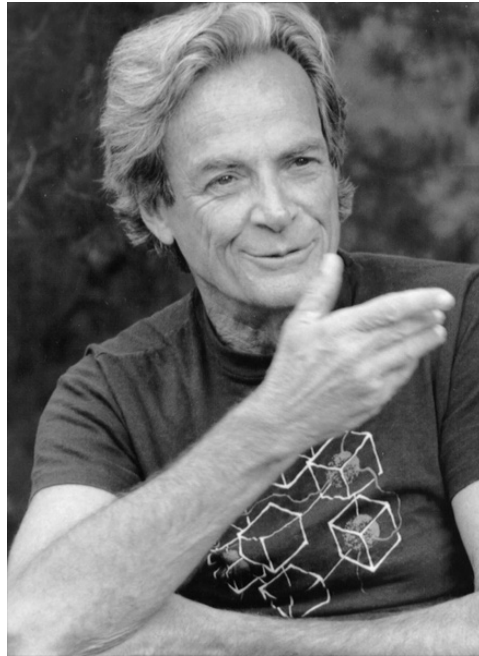
# Deep learning is more than function fitting



“What I can not create, I do not understand”



# Deep learning is more than function fitting



## Progress in Brain Research

Volume 165, 2007, Pages 535–547

Computational Neuroscience: Theoretical Insights into Brain Function

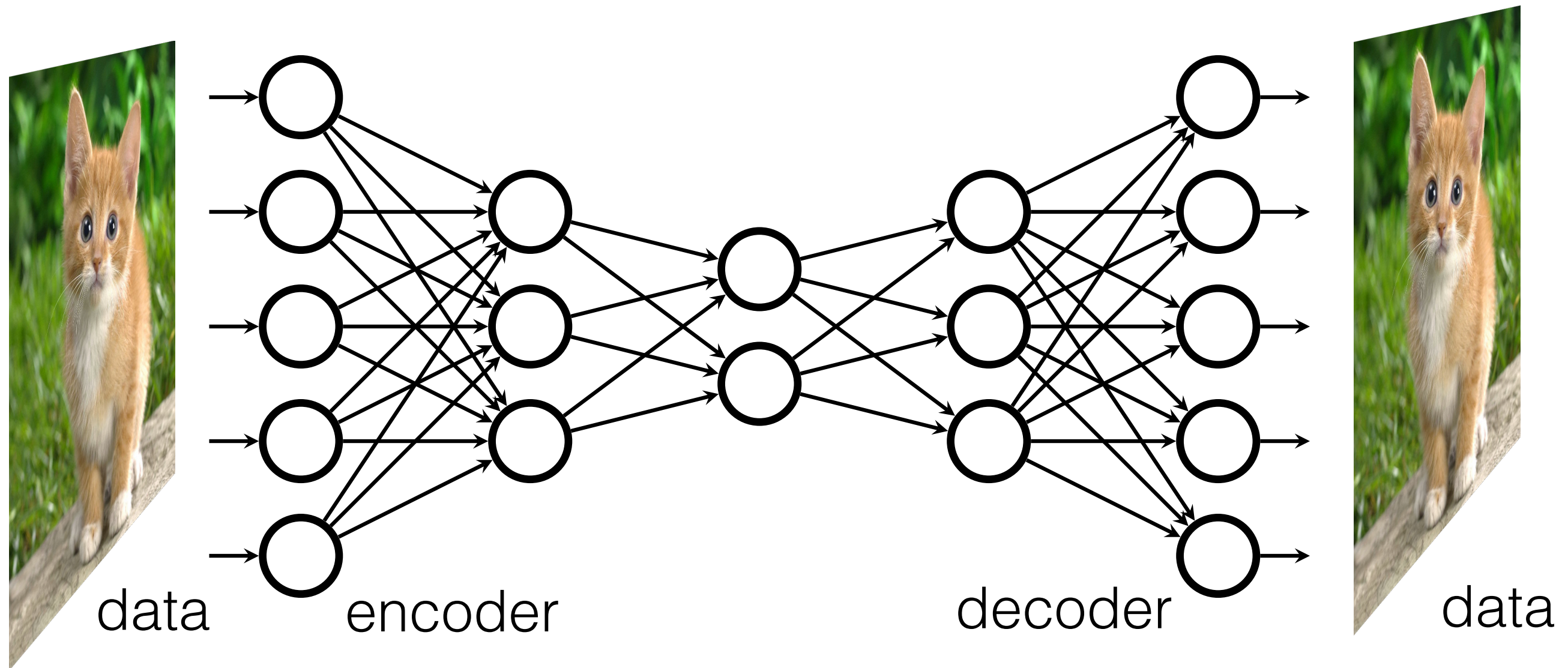


To recognize shapes, first learn to generate images

Geoffrey E. Hinton  

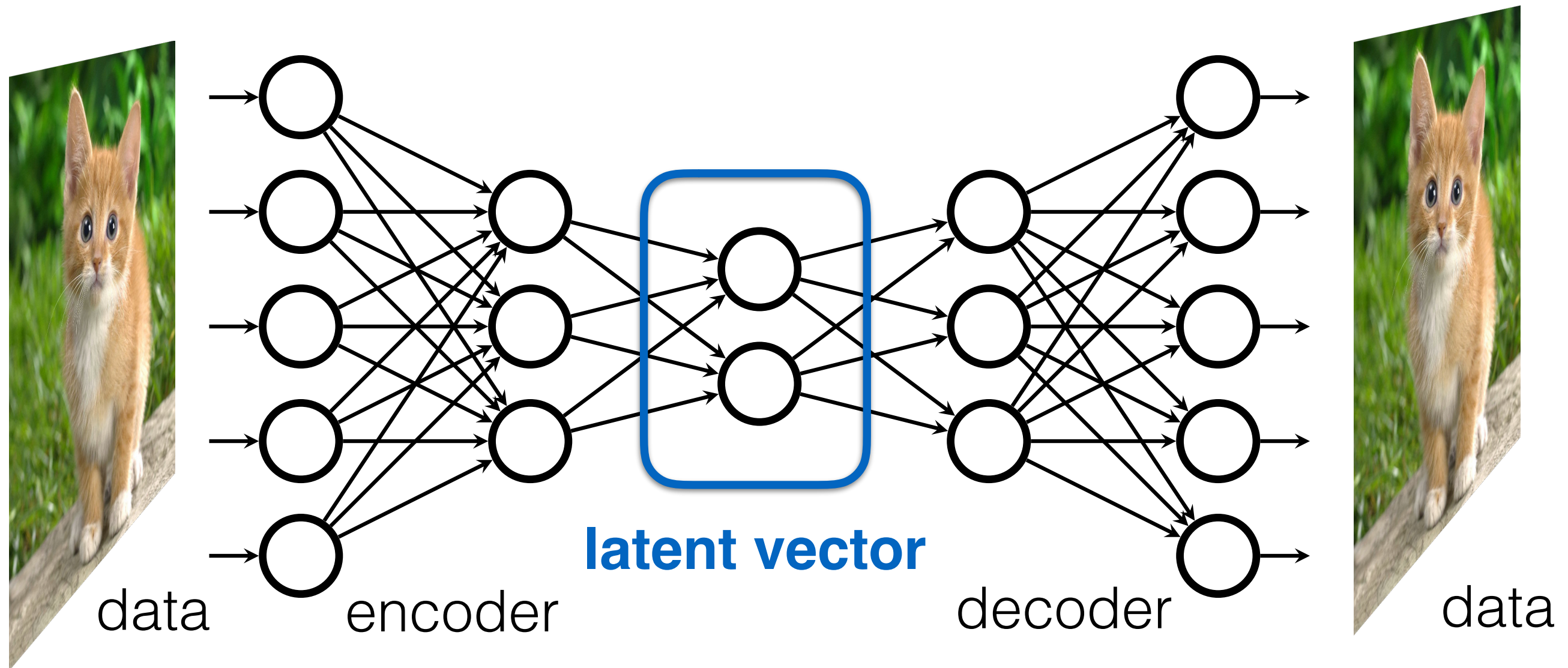
Department of Computer Science, University of Toronto, 10 Kings College Road, Toronto, M5S 3G4  
Canada

# Generative Learning



"Auto-Encoding Variational Bayes", Kingma and Welling, 1312.6114

# Generative Learning



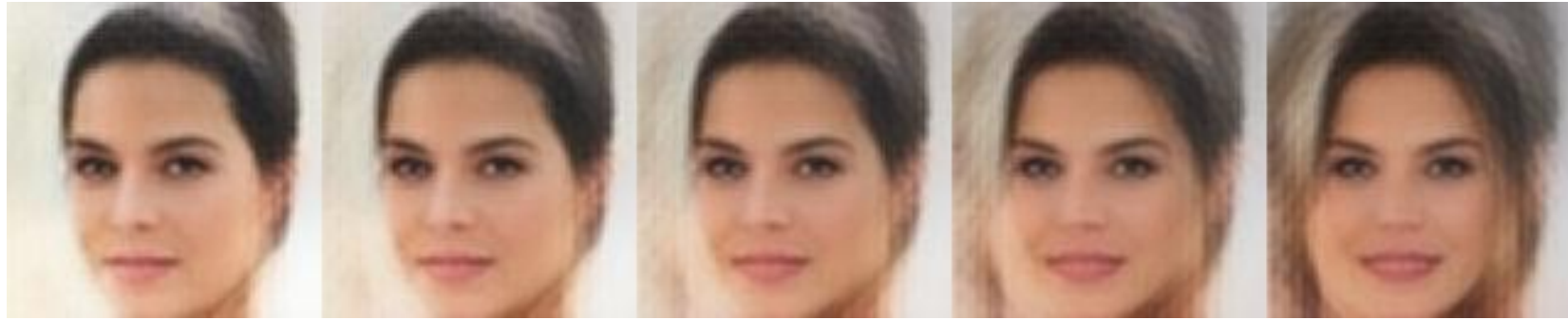
"Auto-Encoding Variational Bayes", Kingma and Welling, 1312.6114



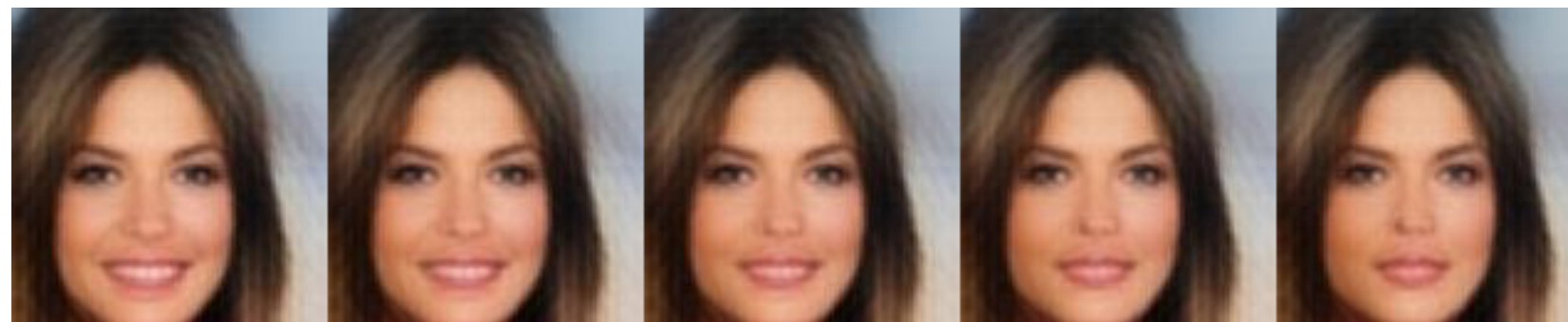


Interpolate  
between faces

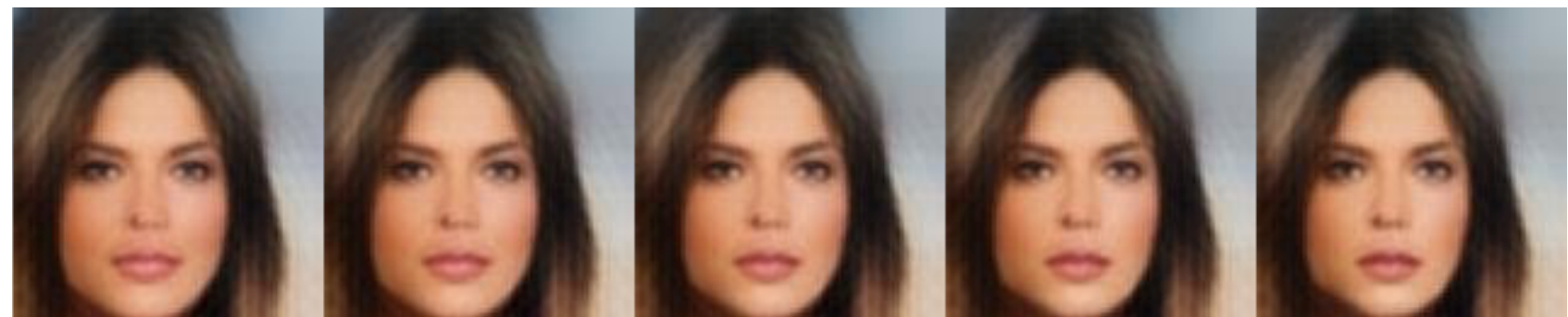




Interpolate  
between faces



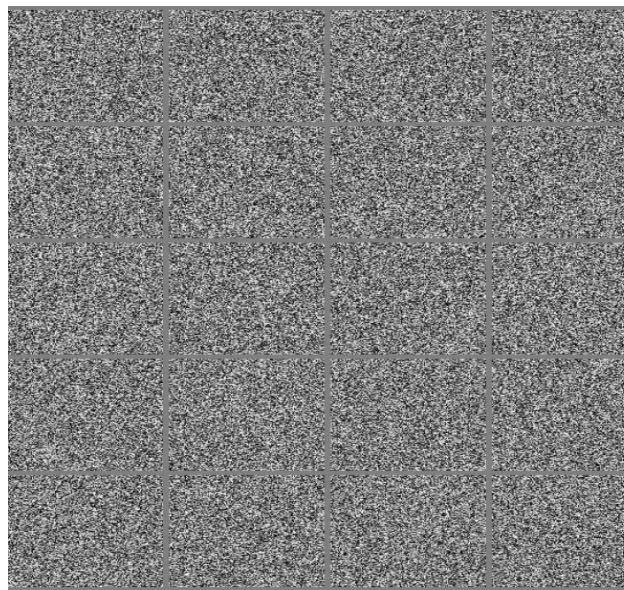
Subtract  
Smiling vector



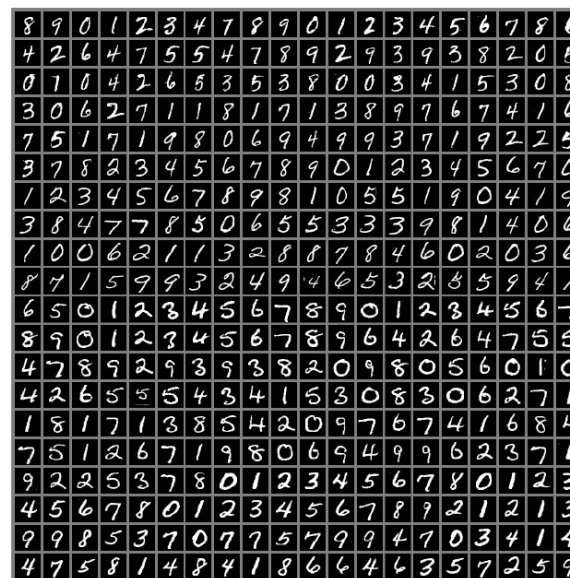
# Probabilistic Generative Modeling

$$p(\mathbf{x})$$

How to **express, learn, and sample from** a probability distribution of enormous size ?



“random” images



“natural” images





# Probabilistic Modeling

## DEEP LEARNING

Ian Goodfellow, Yoshua Bengio,  
and Aaron Courville

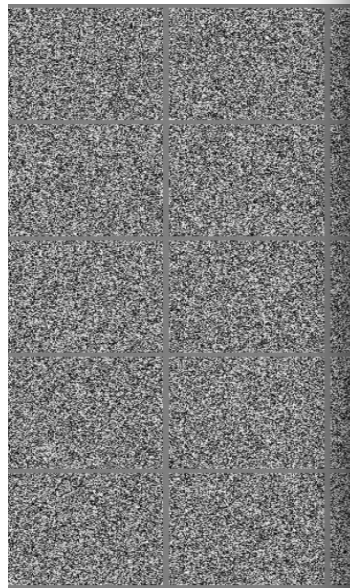
How to  
probab

from a  
size ?

Page 159

***“... the images encountered in  
AI applications occupy a  
negligible proportion of  
the volume of image space.”***

“random”

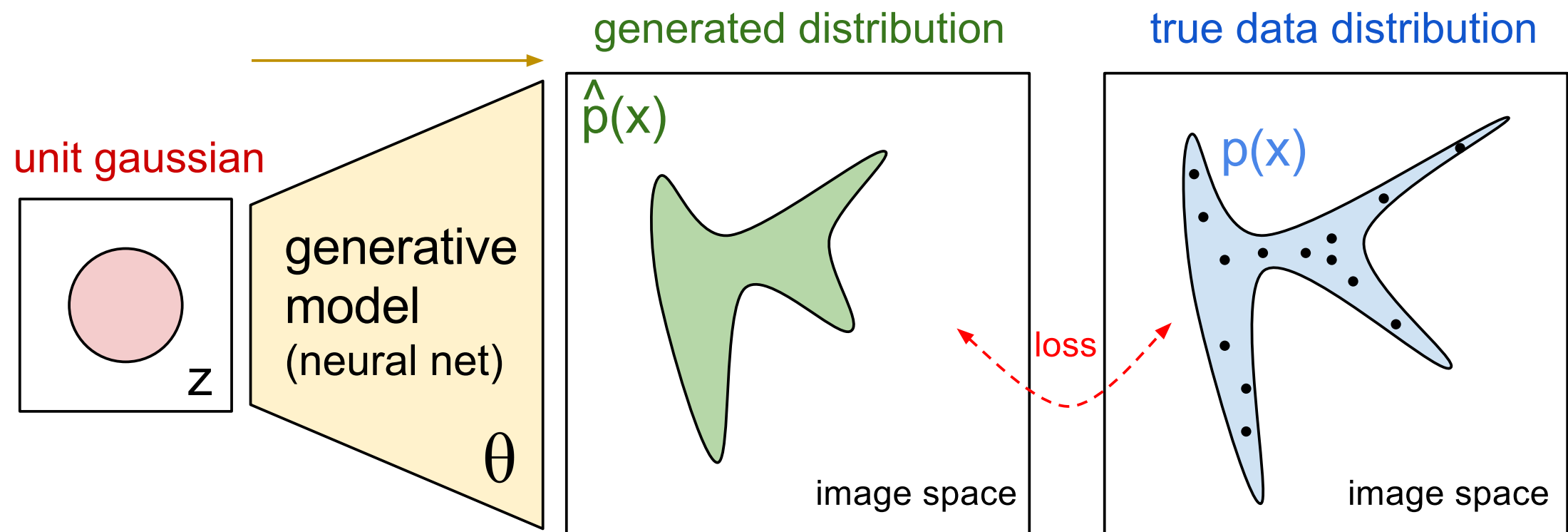




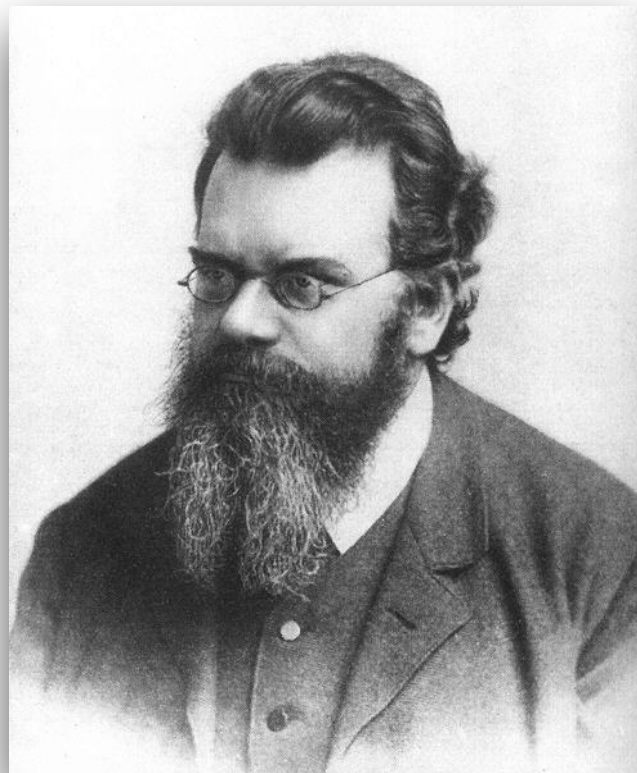
# Probabilistic Generative Modeling

$$p(\mathbf{x})$$

How to **express, learn, and sample from** a probability distribution of enormous size ?



# Generative Modeling and Physics



Boltzmann Machines

$$p(\mathbf{x}) = \frac{e^{-E(\mathbf{x})}}{\mathcal{Z}}$$

**statistical physics**

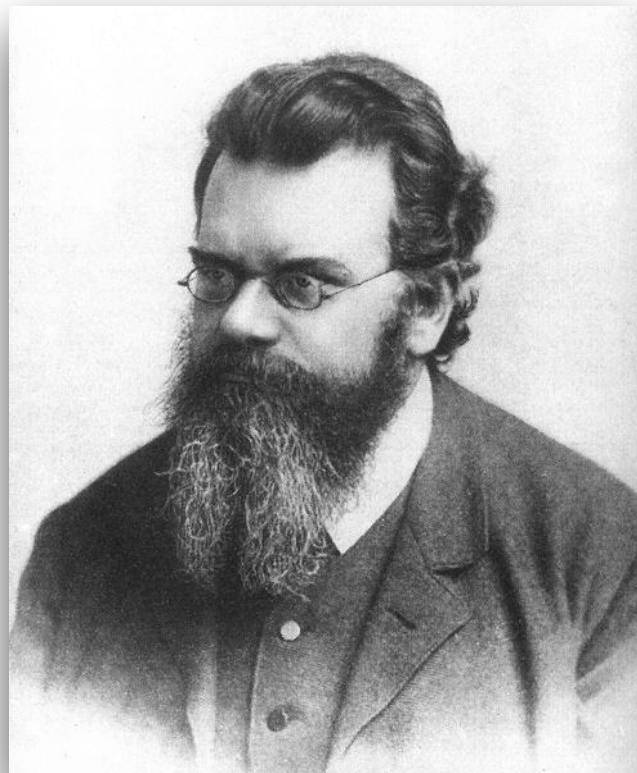


“Born” Machines

$$p(\mathbf{x}) = \frac{|\Psi(\mathbf{x})|^2}{\mathcal{N}}$$

**quantum physics**

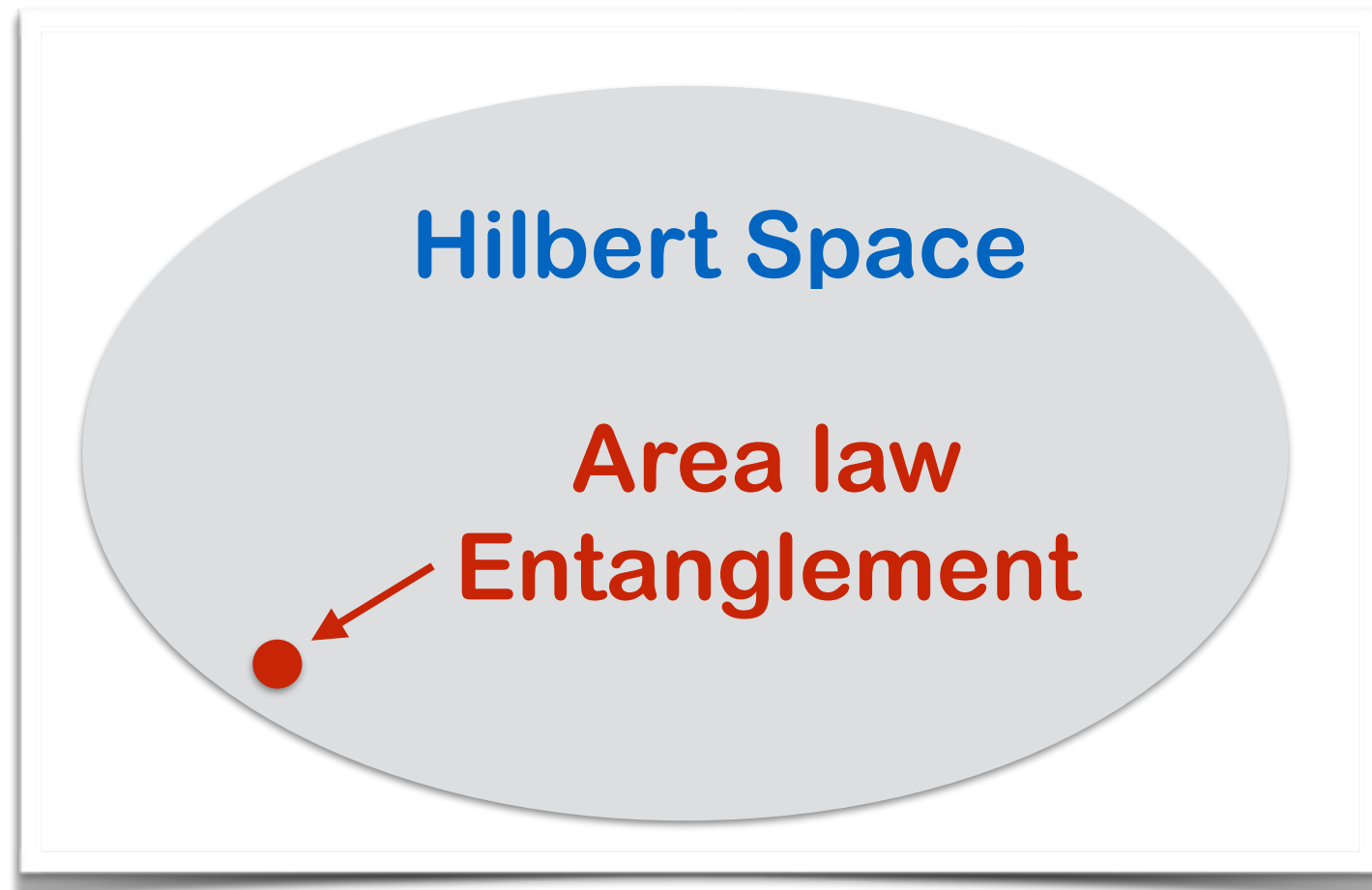
# Generative Modeling and Physics



Boltzmann Machines

$$p(\mathbf{x}) = \frac{e^{-E(\mathbf{x})}}{\mathcal{Z}}$$

**statistical physics**

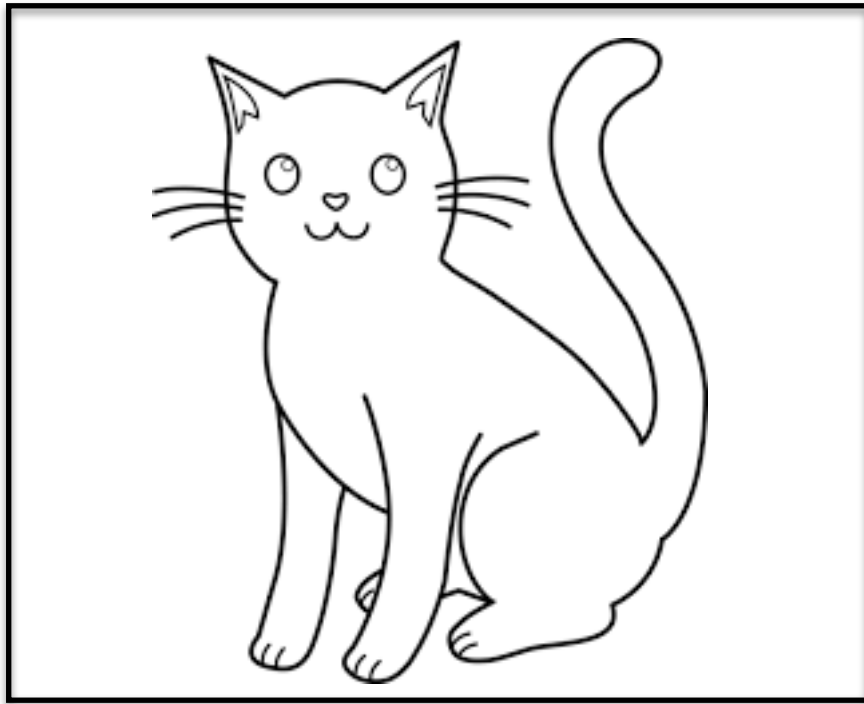


“Born” Machines

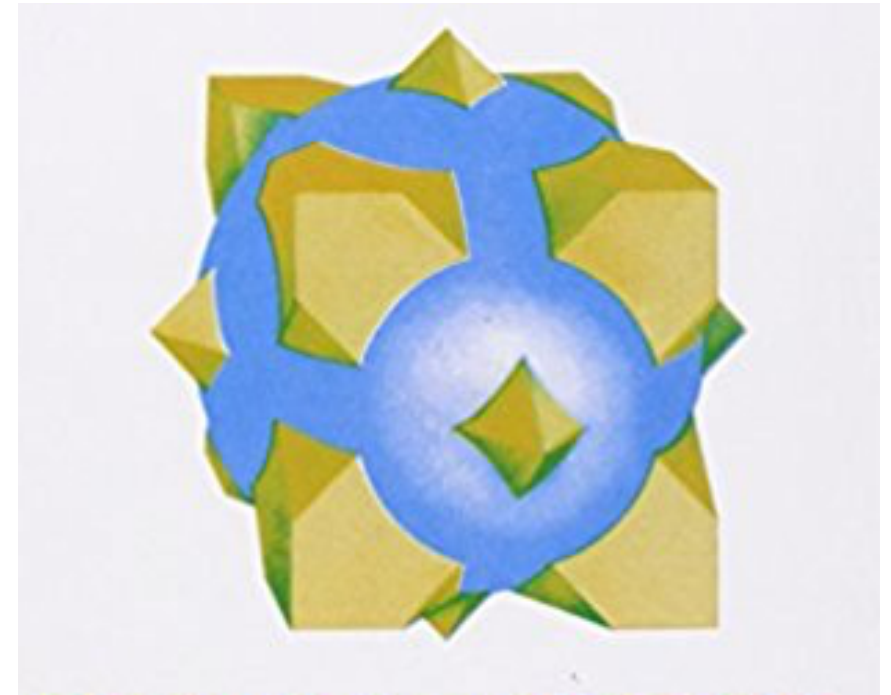
$$p(\mathbf{x}) = \frac{|\Psi(\mathbf{x})|^2}{\mathcal{N}}$$

**quantum physics**

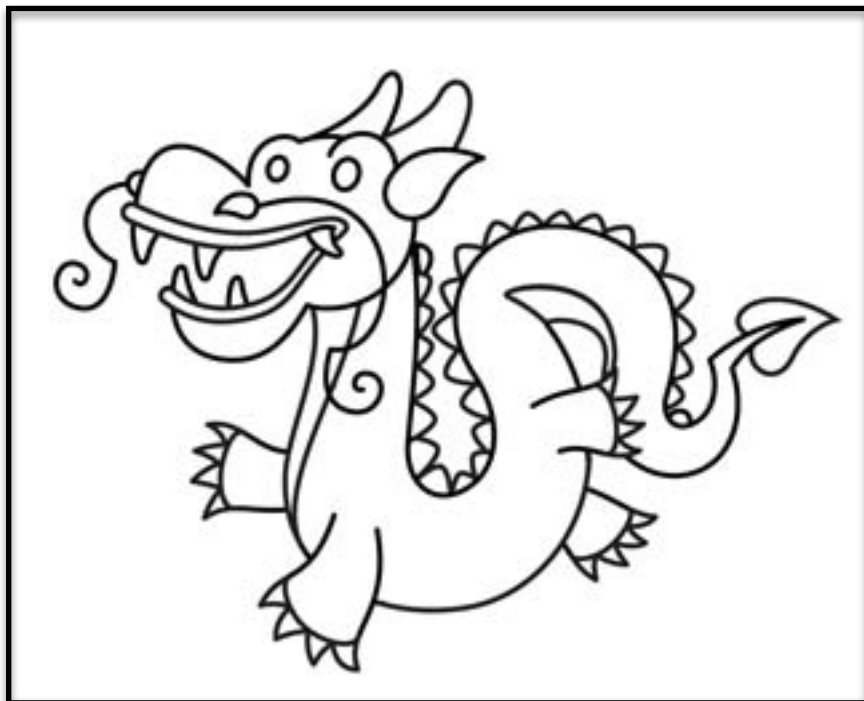
# Image space versus Hilbert space



~



“ordinary” metal



~

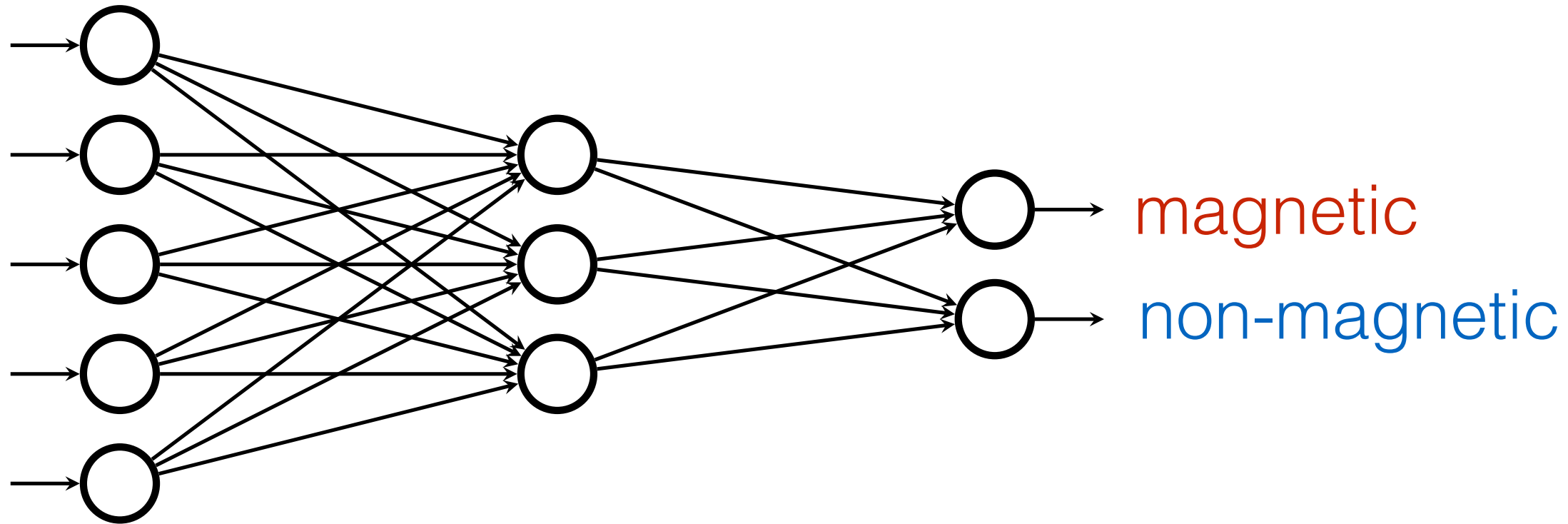
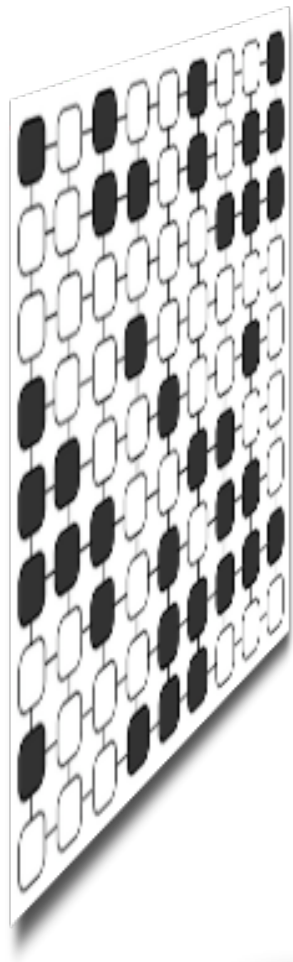


“exotic” superconductors



# Quantum “Phase” Recognition

Microscopic  
Configurations



**Classify quantum states of matter**

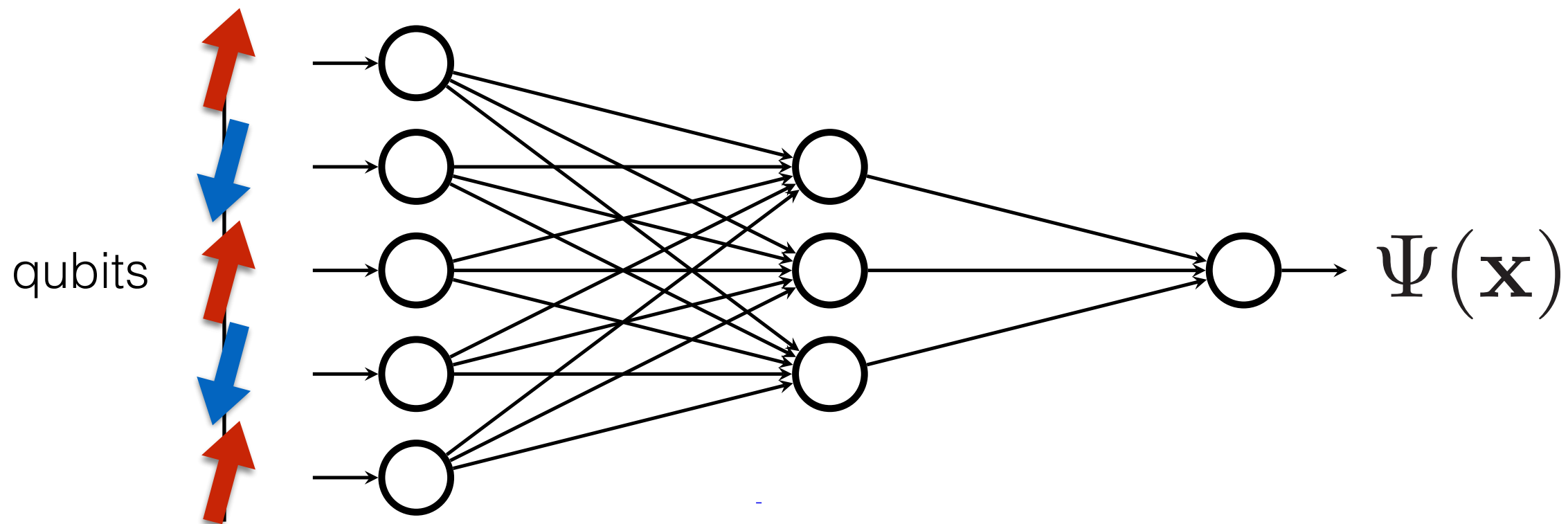
Carrasquilla, Melko, Nat. Phys. 2017

Nieuwenburg, Liu, Huber, Nat. Phys. 2017

LW, PRB 2016,

and many others

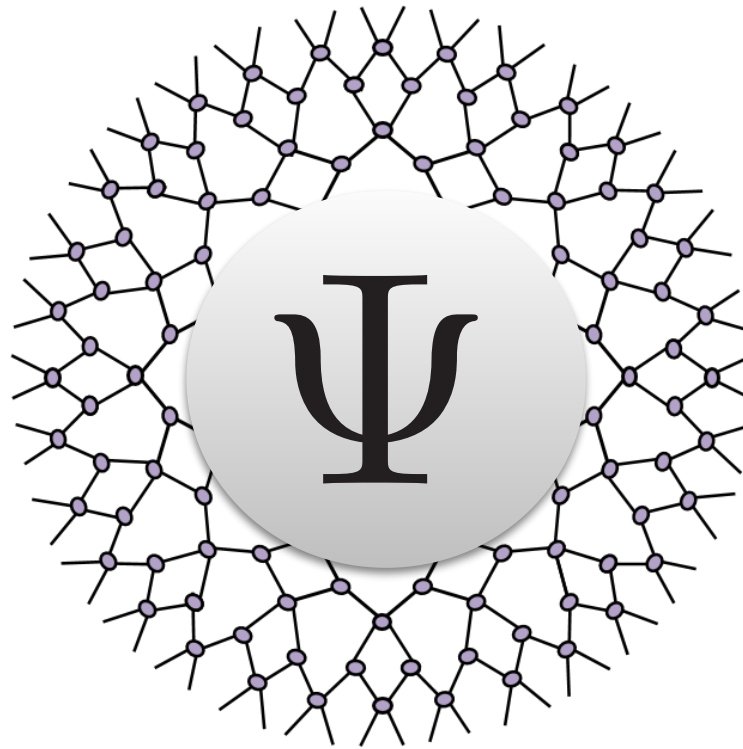
# Boltzmann machines as a wavefunction



- Train the network with variational principle
- Feature discovery and abstraction power of deep hierarchical structure

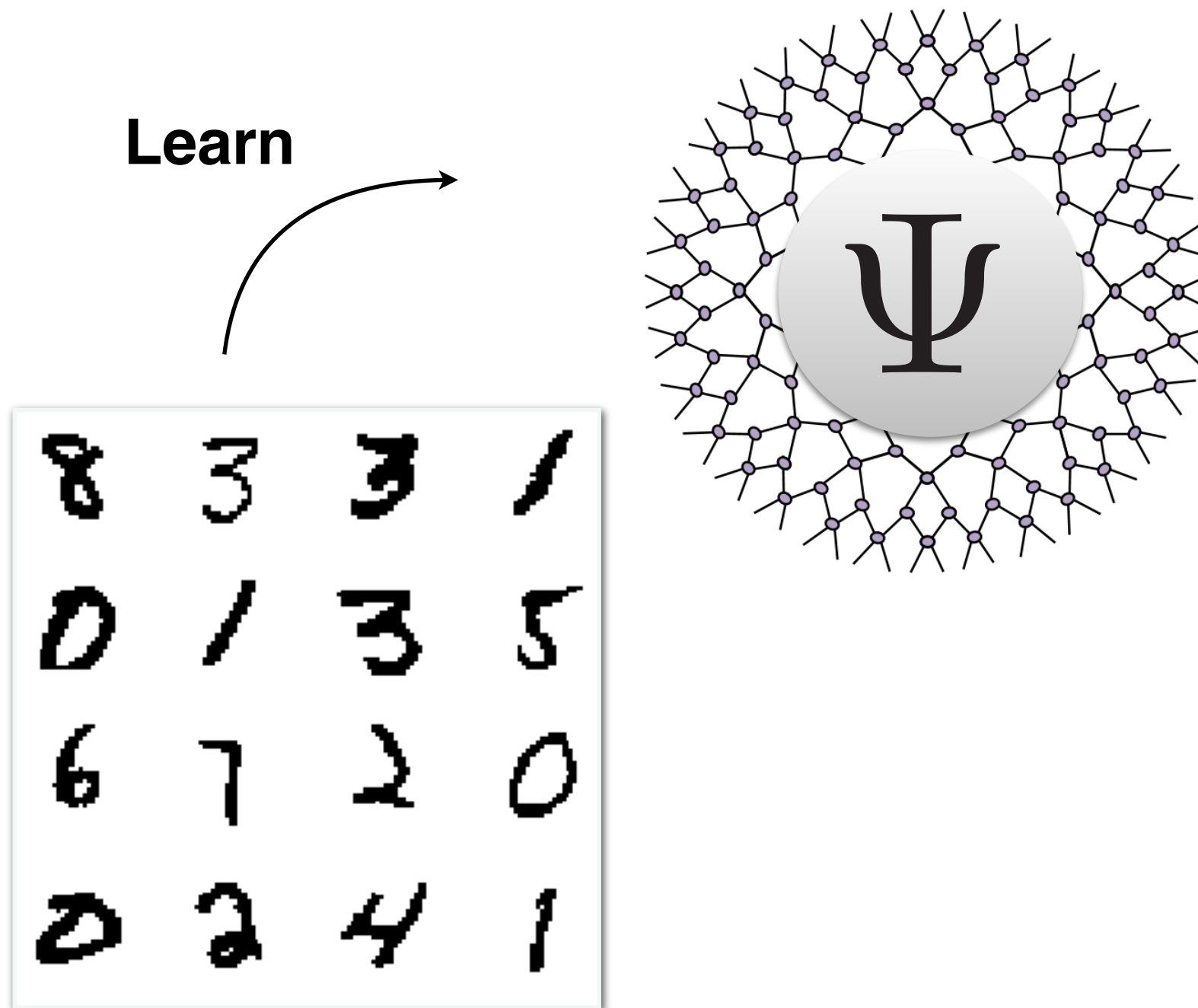
**“Teach a neural network quantum physics”**

# Quantum inspired generative modeling

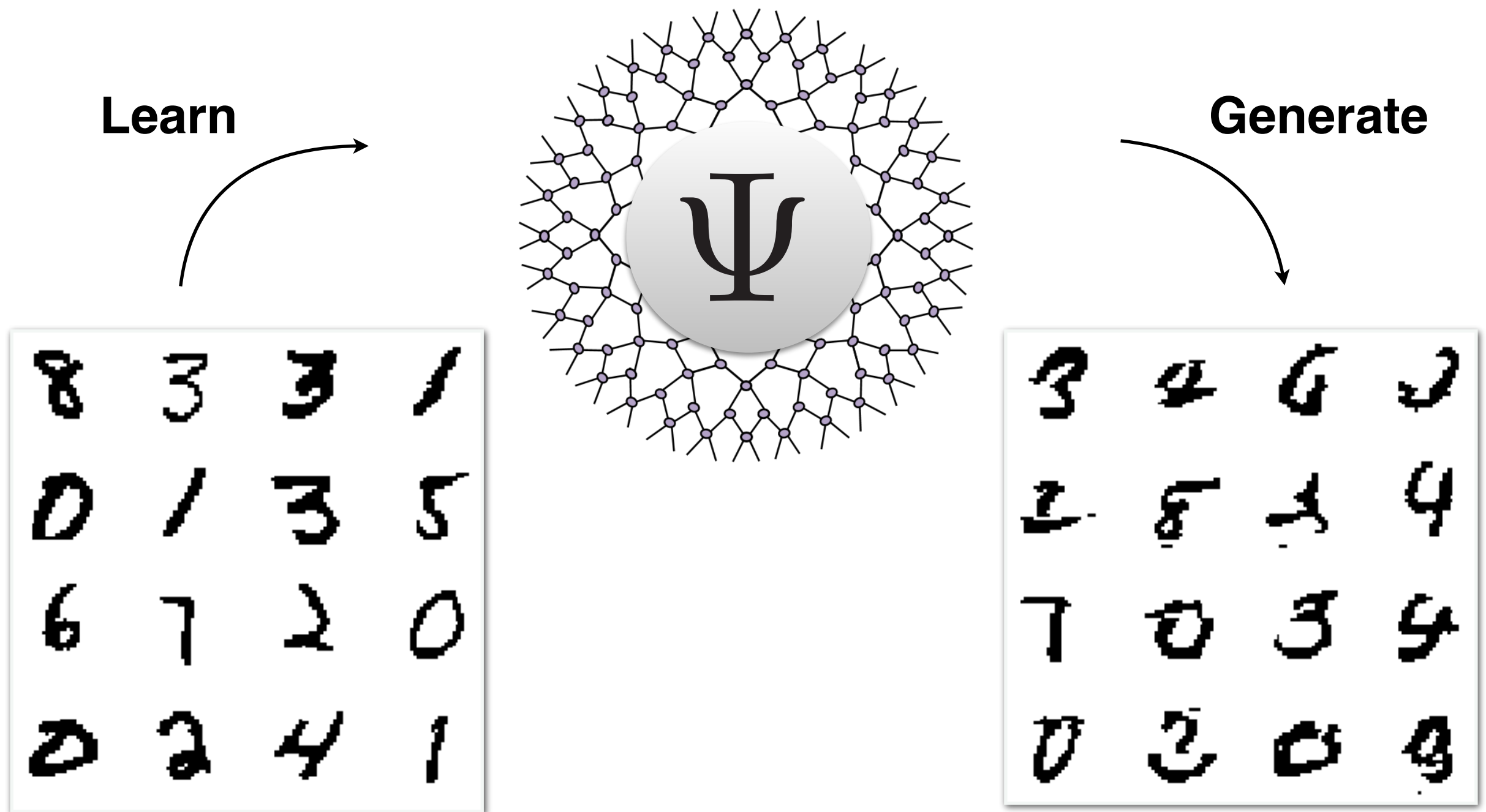


Han, Wang, LW, Zhang, arXiv 2017 cf. Stoudenmire and Schwab, NIPS 2016

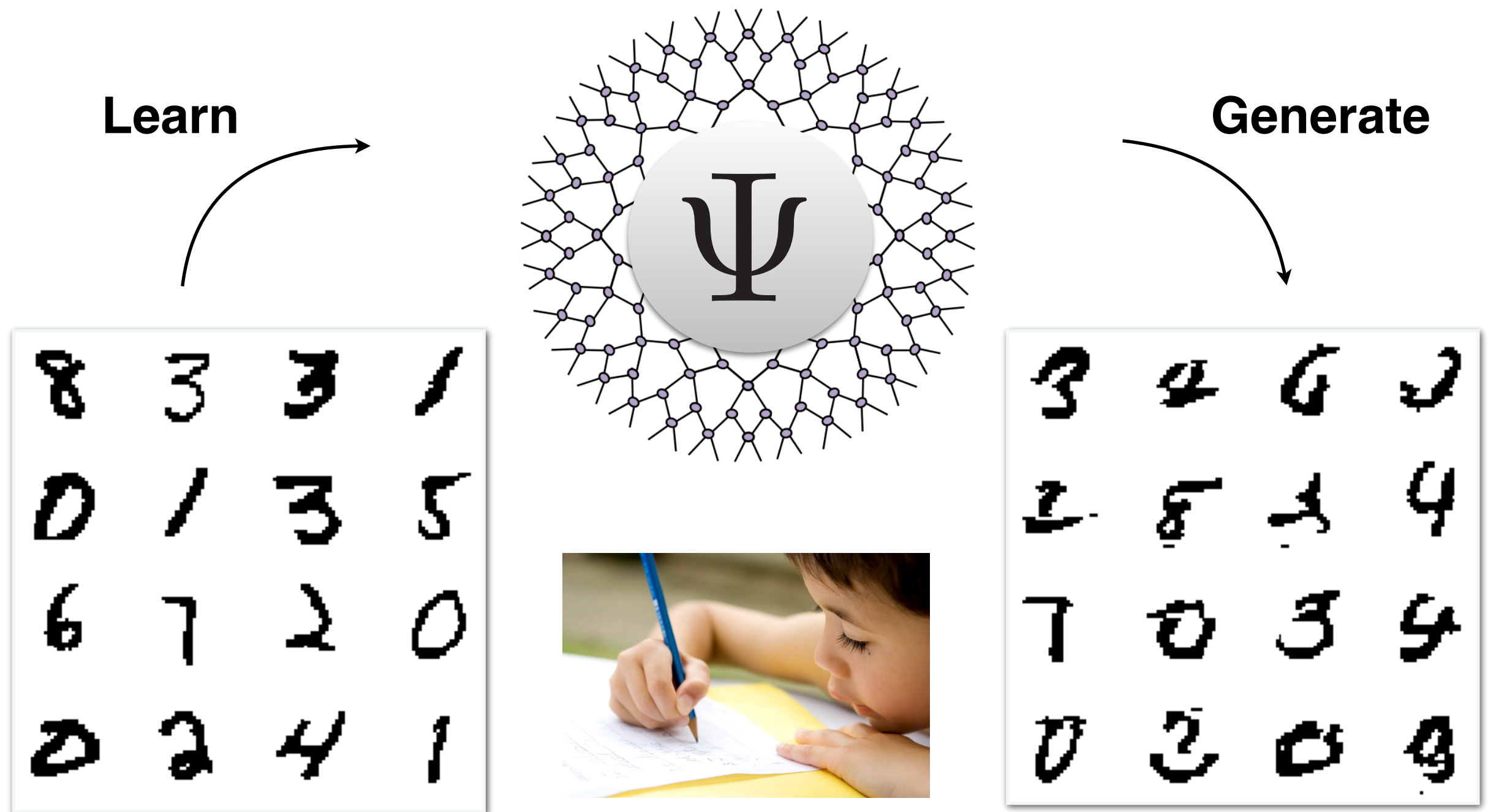
# Quantum inspired generative modeling



# Quantum inspired generative modeling



# Quantum inspired generative modeling

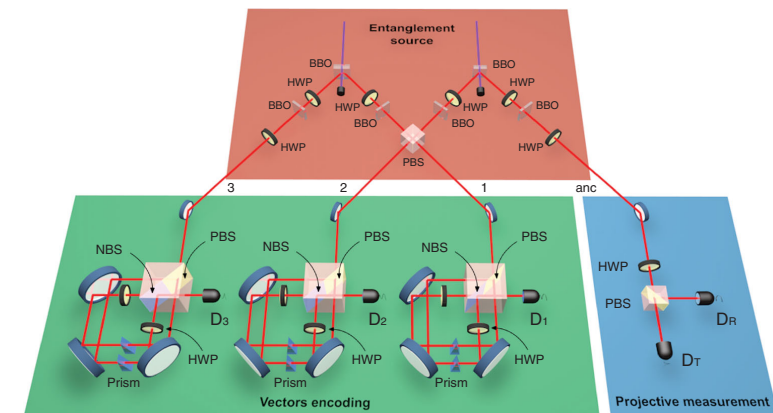


**“Teach a quantum state to write digits”**

Han, Wang, LW, Zhang, arXiv 2017 cf. Stoudenmire and Schwab, NIPS 2016

# Quantum Machine Learning

- Search
- Sampling
- Clustering
- Optimization
- Linear system solver
- Support vector machines
- Principal component analysis



Cai et al, PRL **114**, 110504 (2015)

	$^{13}\text{C}$	$F_1$	$F_2$	$F_3$
$^{13}\text{C}$	15479.9Hz			
$F_1$	-297.7Hz	-33130.1Hz		
$F_2$	-275.7Hz	64.6Hz	-42681.4Hz	
$F_3$	39.1Hz	51.5Hz	-129.0Hz	-56443.5Hz
$T_2^*$	1.22s	0.66s	0.63s	0.61s
$T_2$	7.9s	4.4s	6.8s	4.8s

Li et al, PRL **114**, 140504 (2015)

few qubits demo

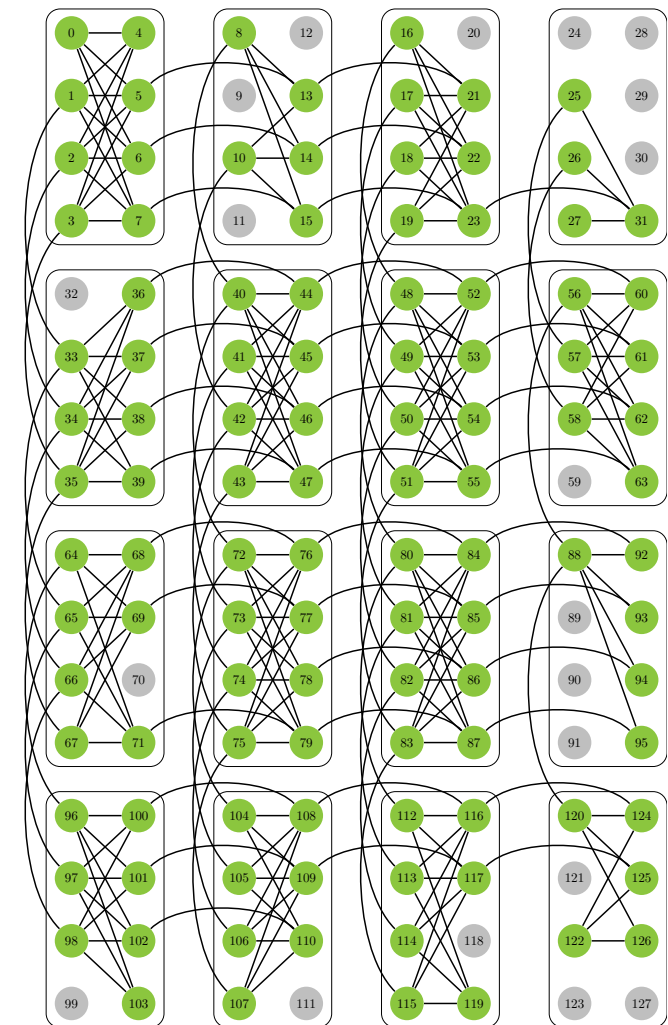
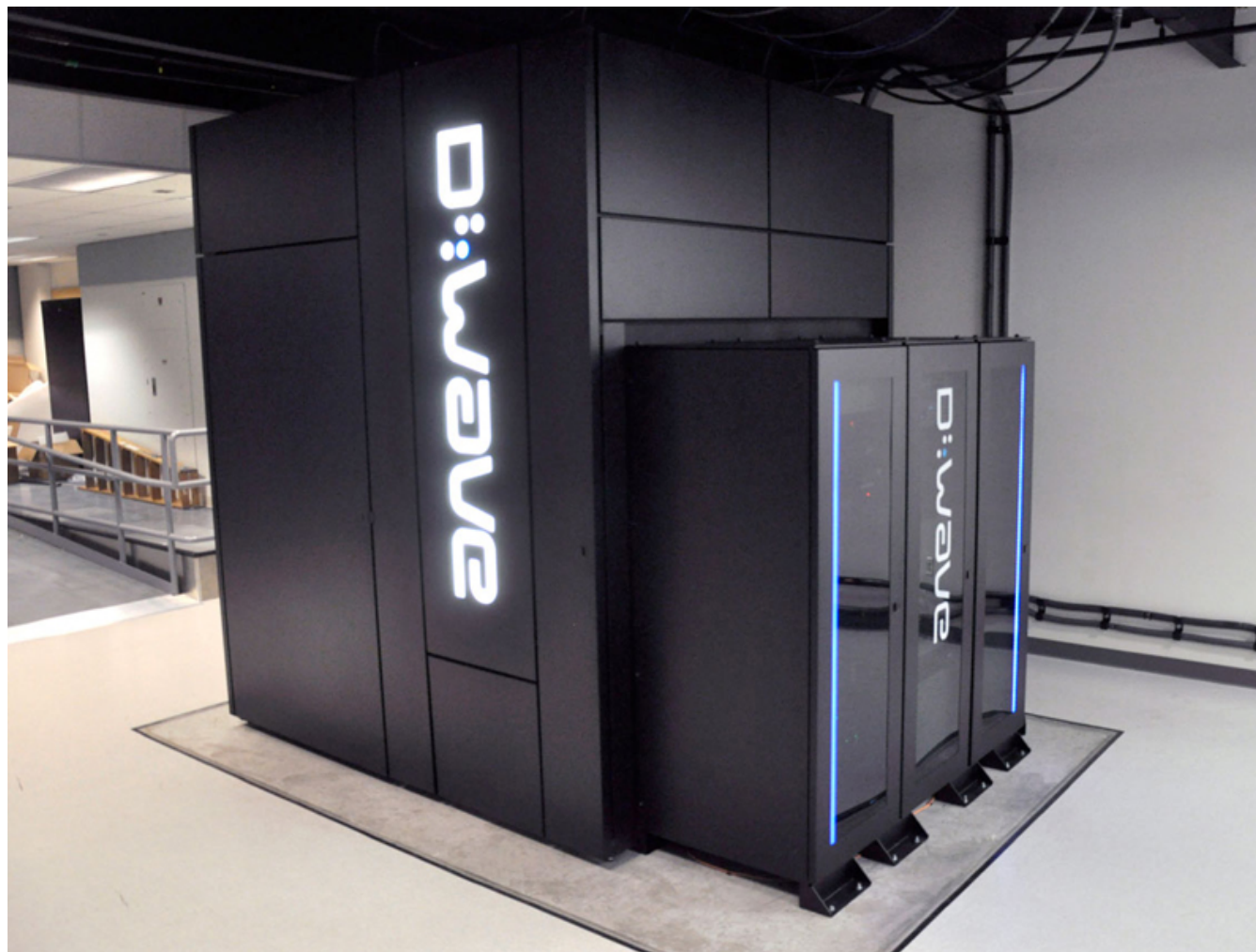
**“Use a quantum computer to speed up  
ML subroutines”**

Review “Quantum machine learning”, Biamonte et al, Nature 2017



# Quantum Boltzmann Machines

\$15 million “analog quantum device”



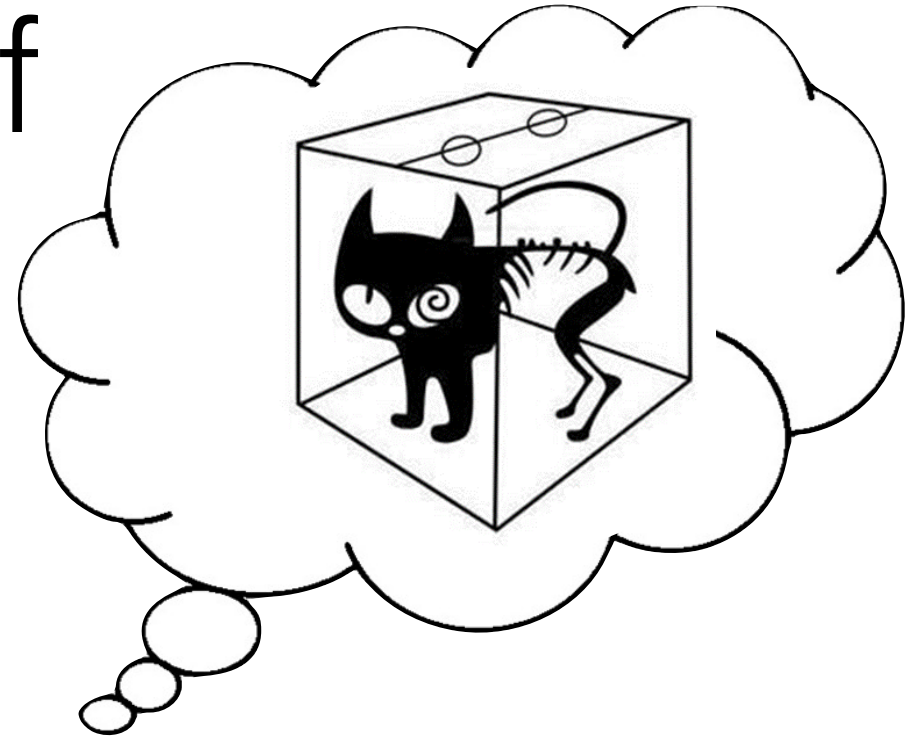
~2000  
“qubits”

**Is there any advantage of this quantum architecture?**

Amin et al, 1601.02036   Perdomo-Ortiz et al, 1708.09757



Do Androids dream of  
Schrödinger's cat ?



**Thank you!**