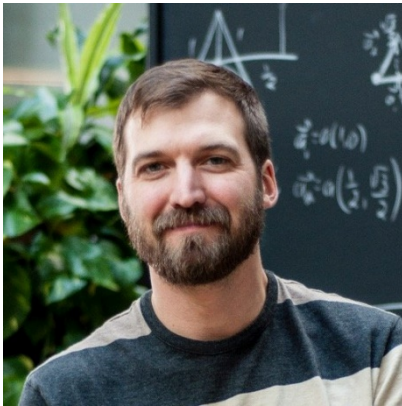


Quantum Loop Topography for Machine Learning

- on topological phases, phase transitions, and beyond

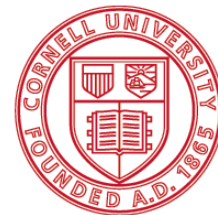
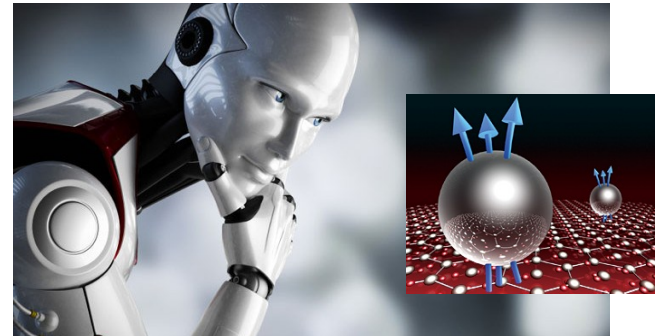
Yi Zhang (Frank)
Cornell University



Roger G. Melko



Eun-Ah Kim



Cornell University



Aug. 31, 2017 @ KITP

Plain language version

- I. Machine learning quantum systems made possible



Plain language version

- 1. Machine learning quantum systems made possible



- 2. Phase identification made reliable via machine learning
– study from the system, by the system, for the system

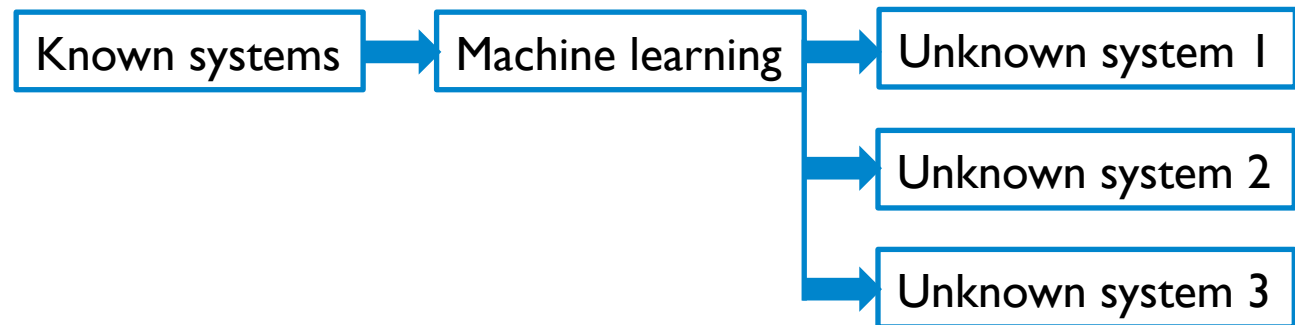


Plain language version

- 1. Machine learning quantum systems made possible



- 2. Phase identification made reliable via machine learning
– study from the system, by the system, for the system


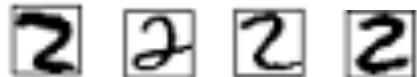



- 3. How it changes the game and is indeed not an overkill
– a topological phase diagram in minutes



I. Machine learning

Learning by examples

#1:  ...
#2:  ...
#3:  ...
...

1. learning









Training set



2. Application

504192

Neural network for image recognition

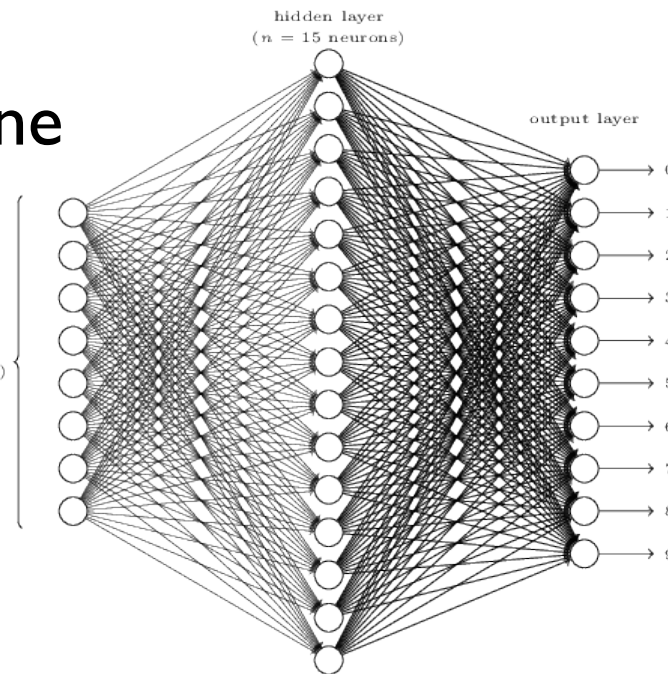
#1:     ...
#2:     ...
#3:     ...
...

Training set

I. Machine learning



input layer
(784 neurons)



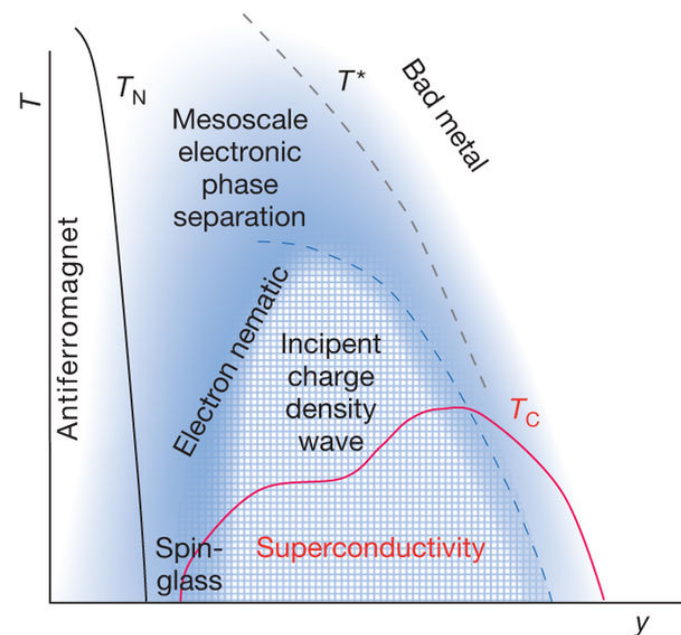
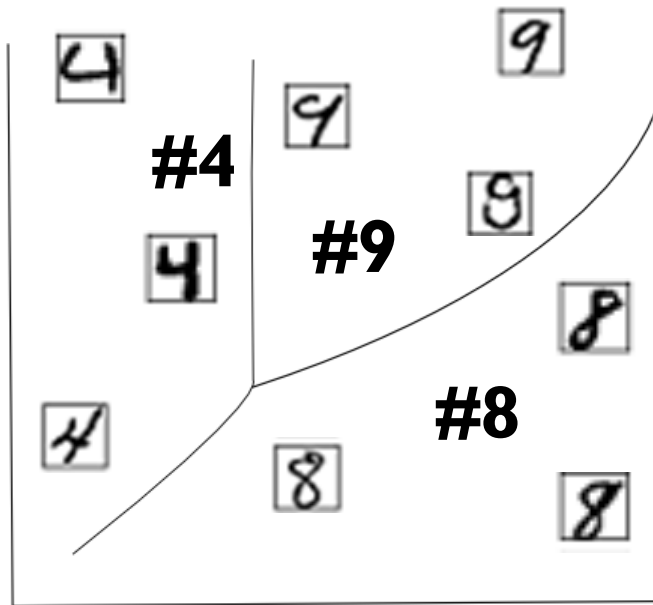
Optimal weights and biases



504192

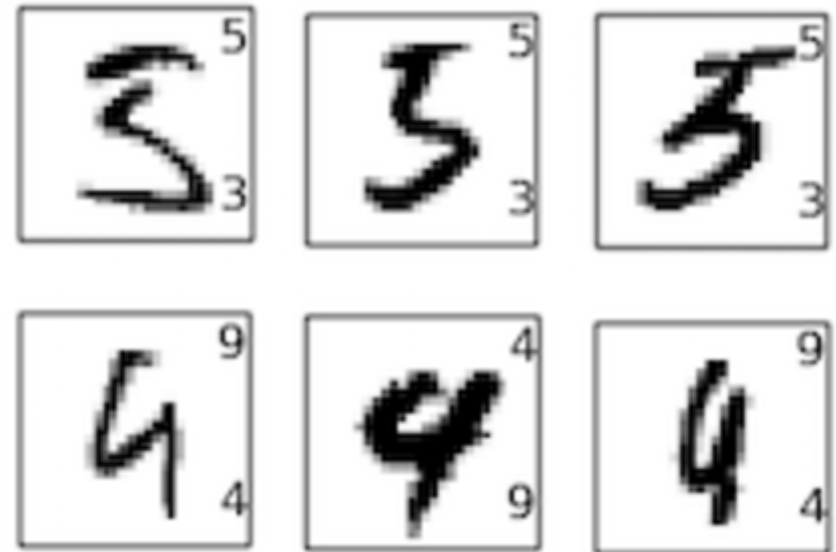
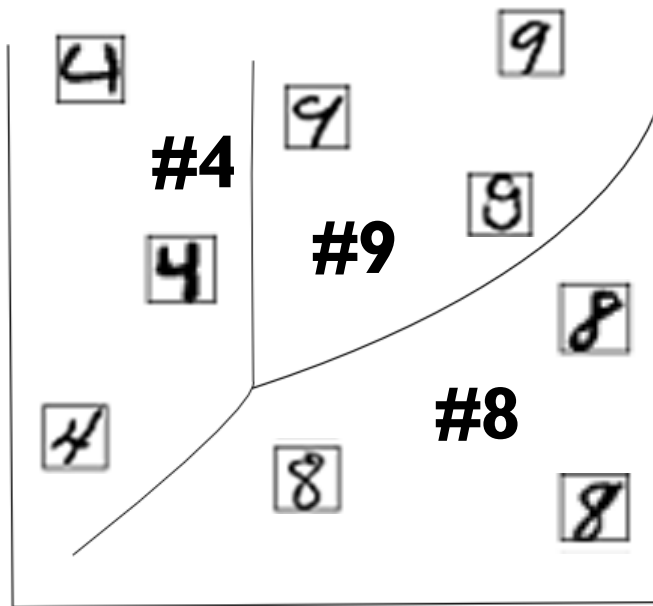
2. Application

Machine learning as phase classification



Eduardo Fradkin & Steven A. Kivelson,
Nature Physics **8**, 864–866 (2012).

Machine learning as phase classification



Coexisting 'phases'

Machine learning in Condensed Matter Physics

- **Machine learning phases of matter and phase transitions (for phase diagrams)**
- Boltzmann machine as neural network states
- Algorithmic development, e.g. cluster update in Monte Carlo calculations, spectrum analysis, etc.
- Material, dynamics and molecule simulations
- Many more ...

Machine learning phases of matter

- **Machine learning phases of matter and phase transitions (for phase diagrams)**

- What do we use as data?

- How do we process it?



- What information is relevant?

Total info

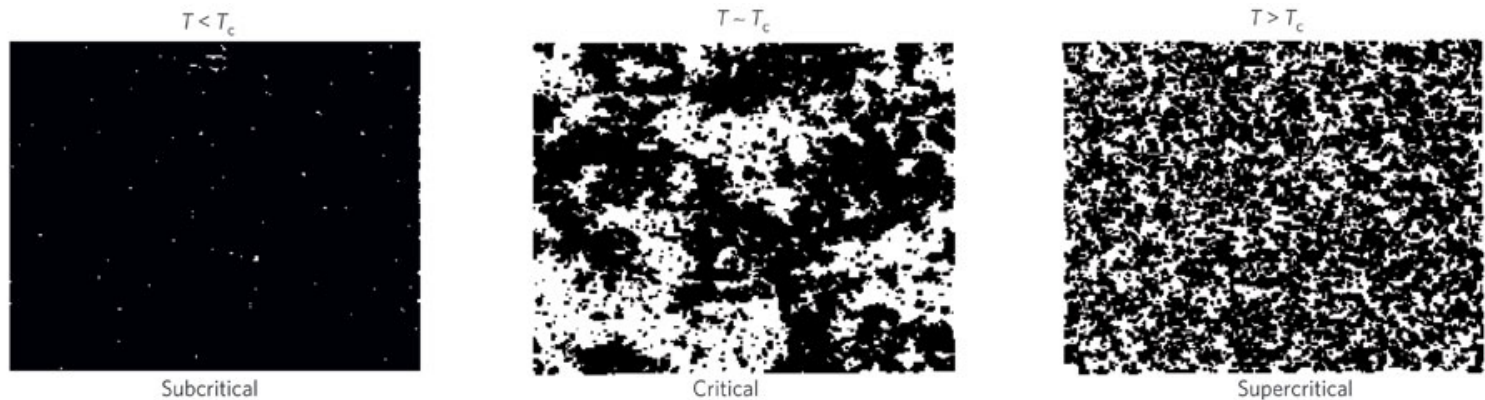
● Relevant info



Machine learning phases of matter

- **Machine learning phases of matter and phase transitions (for phase diagrams)**
- What do we use as data?
 - Snapshots of the order parameter field

J. Carrasquilla and R. G. Melko (2016)



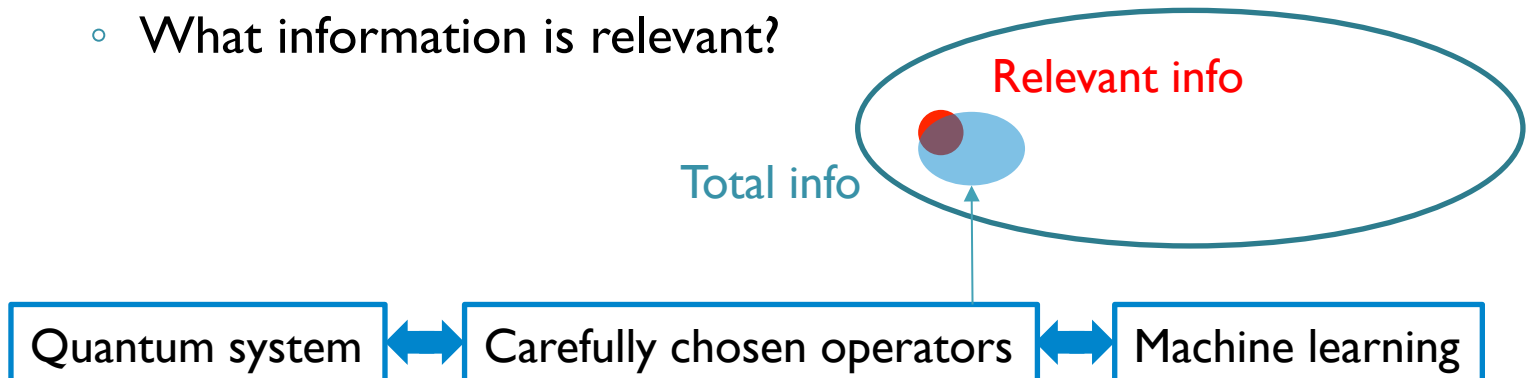
Machine learning phases of matter

- **Machine learning phases of matter and phase transitions (for phase diagrams)**
- What do we use as data?

- How do we process it?



- What information is relevant?





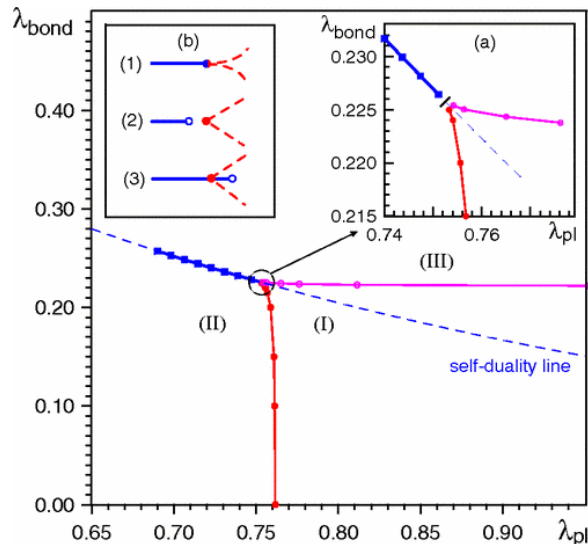
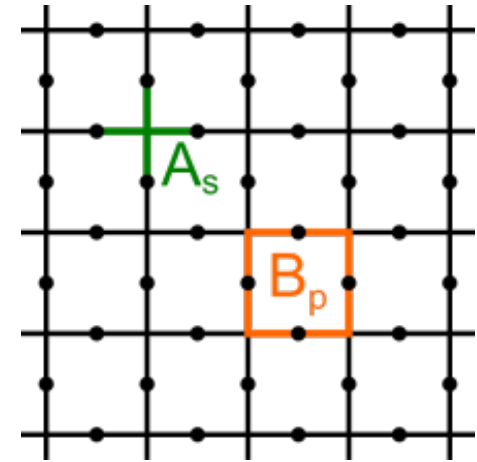
II.A physical problem

A model for Z_2 quantum spin liquid

Kitaev's toric code in magnetic field

$$H_{2D} = -J_x \sum_s A_s - J_z \sum_p B_p - h_x \sum_j \sigma_j^x - h_z \sum_j \sigma_j^z$$

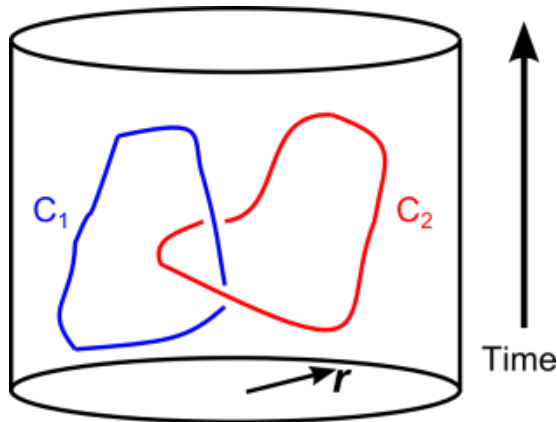
$$A_s = \prod_{j \in s} \sigma_j^x \quad \text{and} \quad B_p = \prod_{j \in p} \sigma_j^z$$



Equivalent Z_2 gauge Higgs model on a 3D cubic lattice

$$\beta H_{3D} = -\lambda_b \sum_j S_j - \lambda_p \sum_p \prod_{j \in p} S_j$$

Topological quantum field theory for the Z_2 quantum spin liquid



Ideal TQFT:

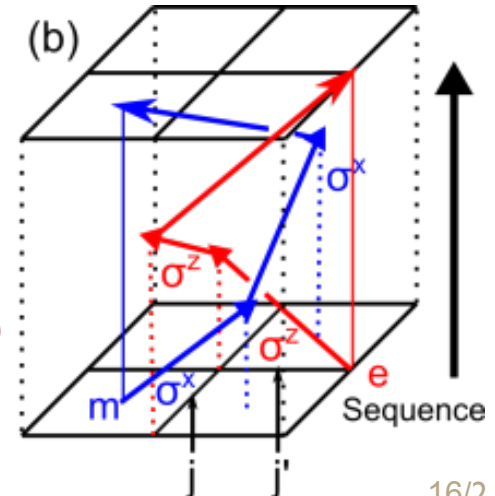
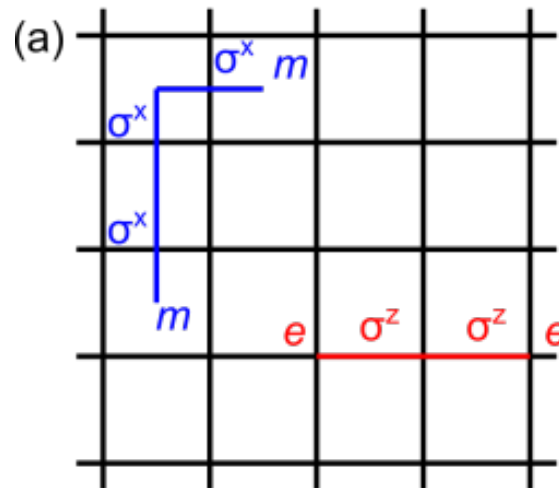
$$\mathcal{L}_{CS} = \frac{K_{IJ}}{4\pi} \epsilon^{\mu\nu\lambda} a_\mu^I \partial_\nu a_\lambda^J - a_\mu^I j_I^\mu \quad K = \begin{pmatrix} 0 & 2 \\ 2 & 0 \end{pmatrix}$$

$$\mathcal{P}W_{C_1}^I W_{C_2}^J = e^{2\pi i K_{IJ}^{-1} L(C_1, C_2)}$$

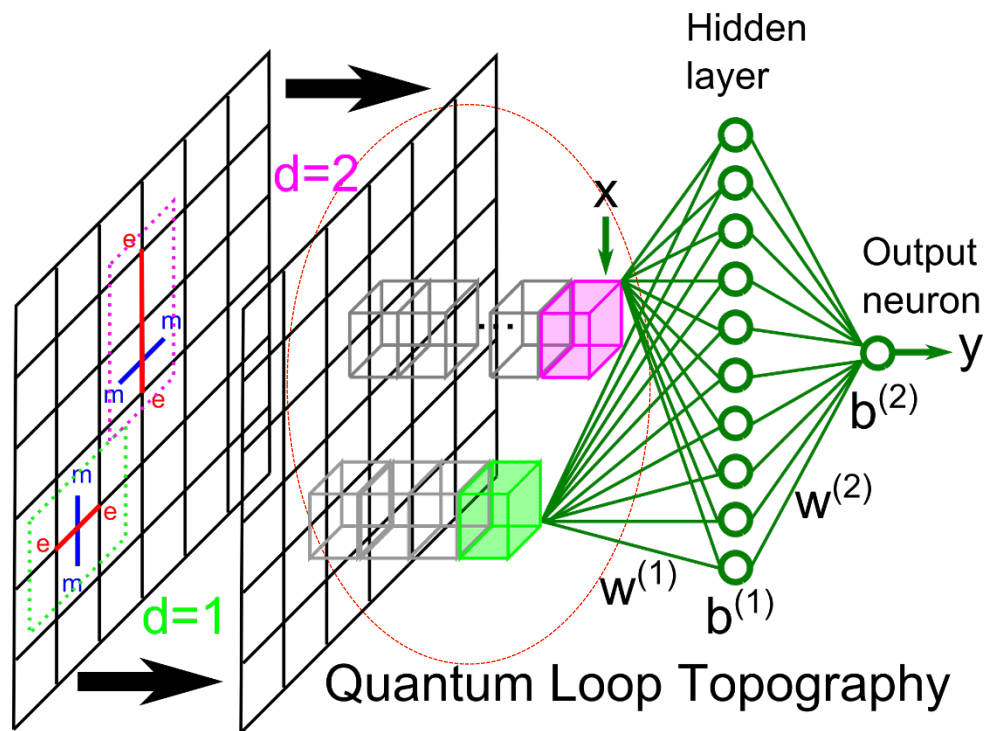
$$W_C^I \equiv \mathcal{P} \exp \left(i \oint_C a_l^I dl \right)$$

Reality in a lattice Hamiltonian:

- Discrete lattice
- Finite correlation length
- Cut off, fluctuation and uncertainty in measurement



III.A love story



PRL **118**, 216401 (2017)

Selected for a **Viewpoint** in *Physics*
 PHYSICAL REVIEW LETTERS

week ending
 26 MAY 2017

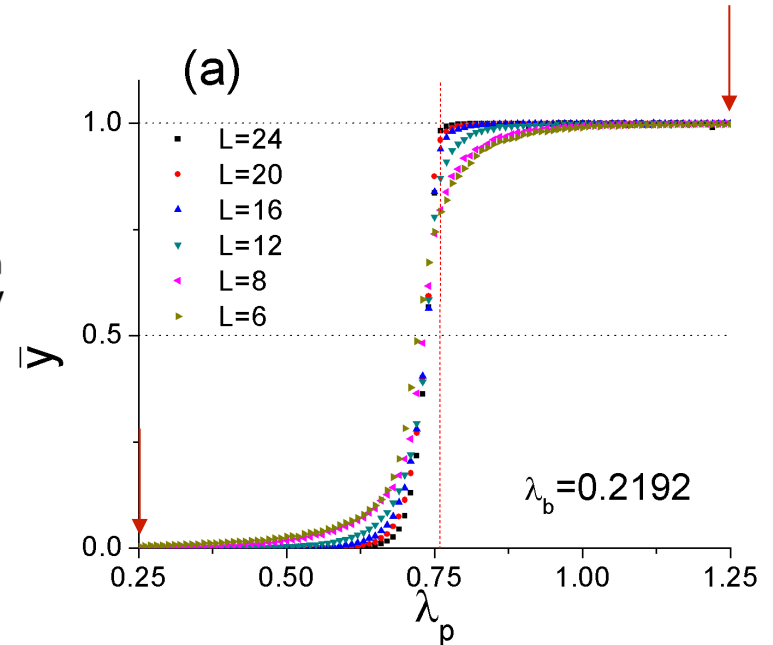
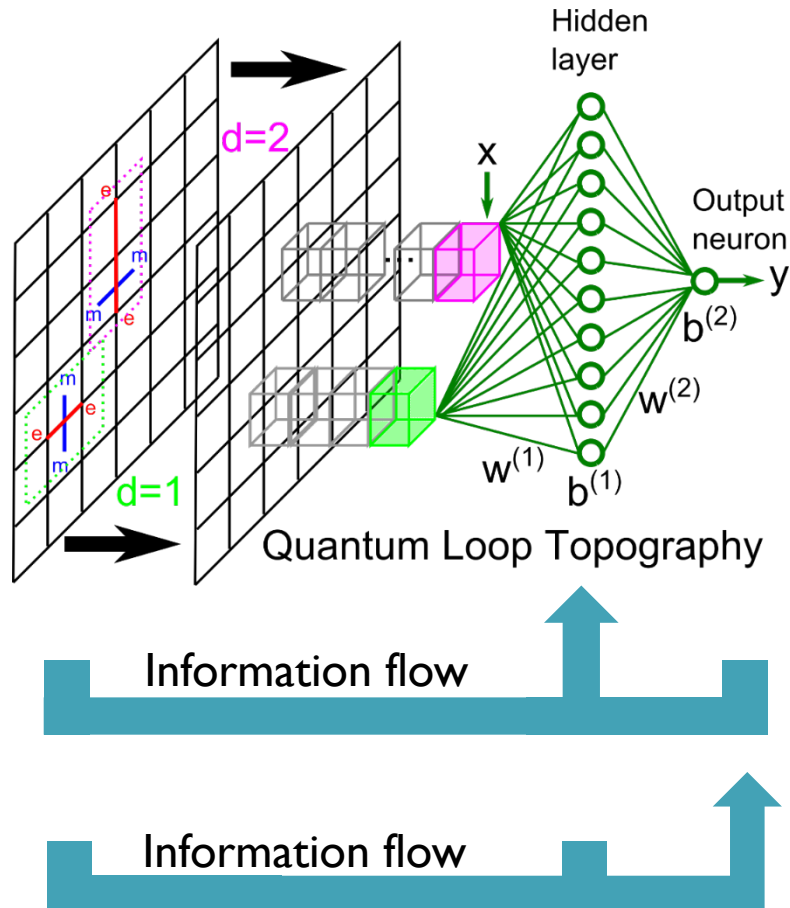


Quantum Loop Topography for Machine Learning

Yi Zhang* and Eun-Ah Kim†

Department of Physics, Cornell University, Ithaca, New York 14853, USA
 and Kavli Institute for Theoretical Physics, University of California, Santa Barbara, California 93106, USA

Machine learning Z_2 quantum spin liquid

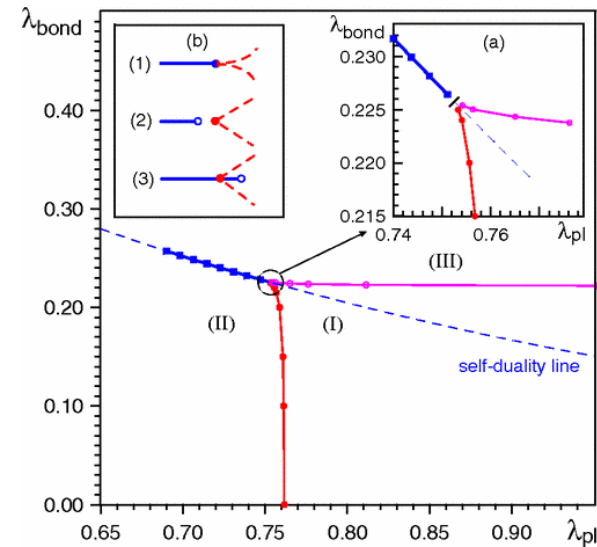
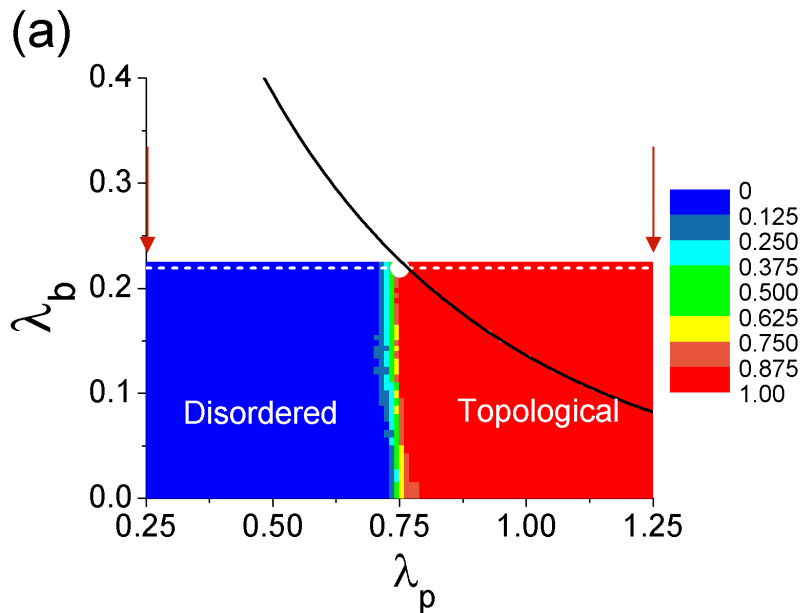


I. Training

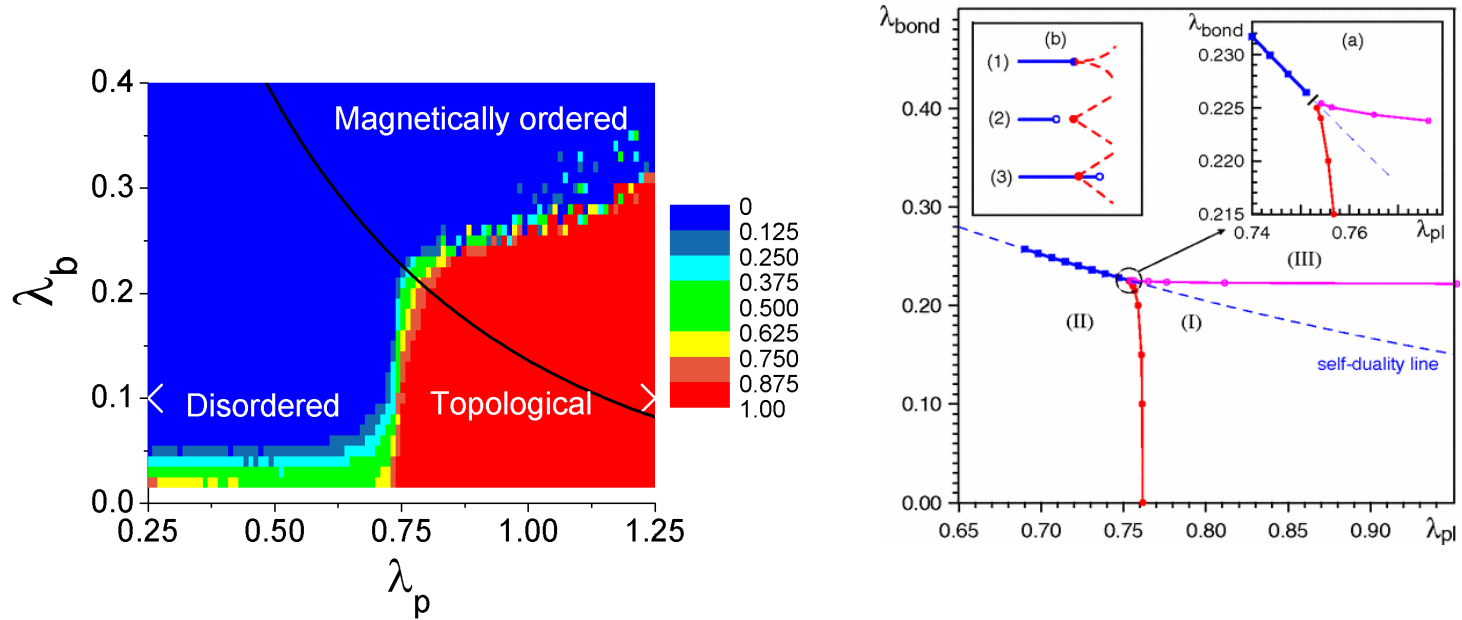
I. Training

2. Interpolating

Machine learning Z_2 quantum spin liquid



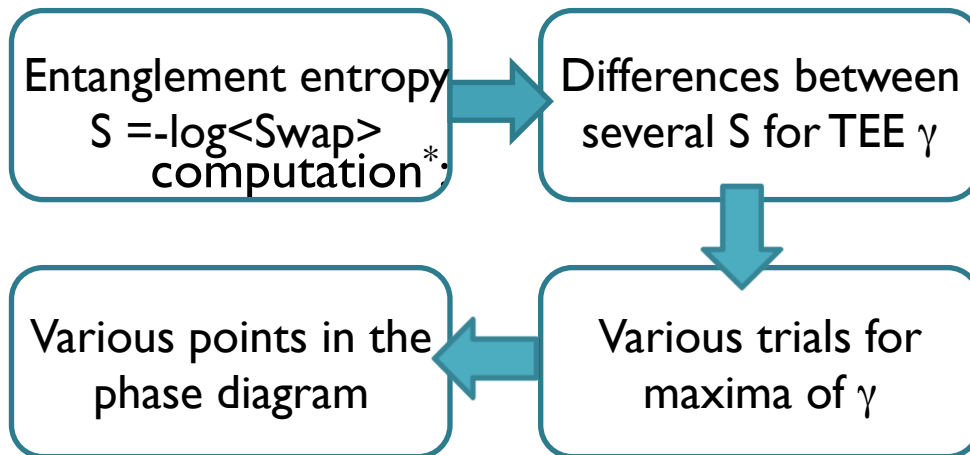
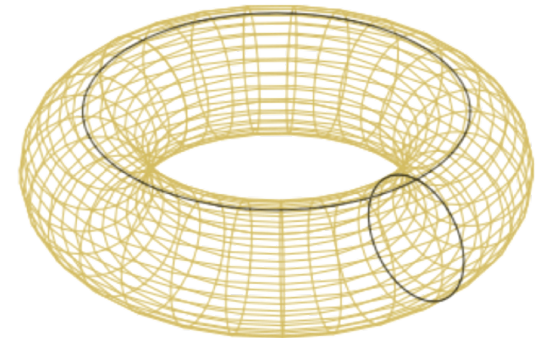
Machine learning Z_2 quantum spin liquid



Efficiency: one training for the entire multi-parameter phase diagram

Calculations take days, if not years

- We can resort to critical scaling, or long-range behavior
- E.g. minimum entropy states, but
 - Constraints
 - All degenerate ground states
 - Nontrivial manifold
 - Cost



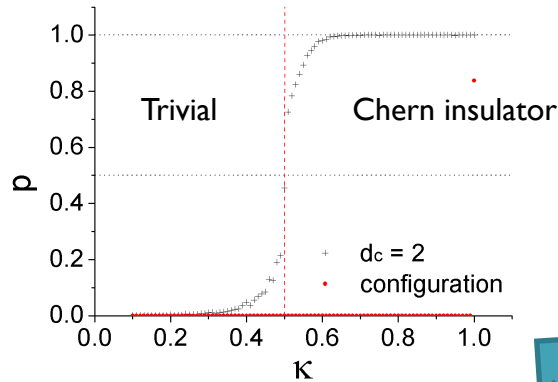
Parallel MC

$105 \text{ CPU mins} \times 100 \times 100 / 2$
 56 CPUs

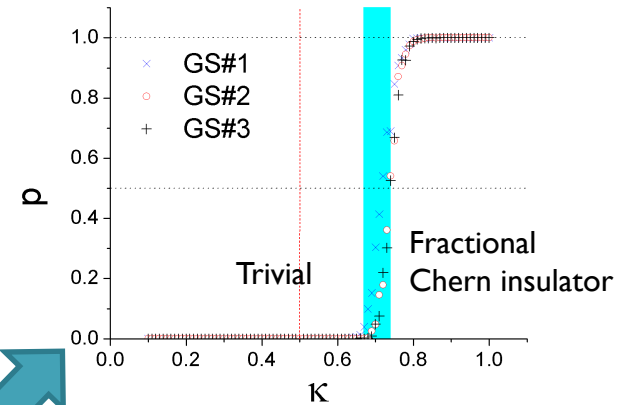
= 7.5 years...

* Assuming 100 trials for maxima and 100 parameters in phase space

Not years, not days, just minutes

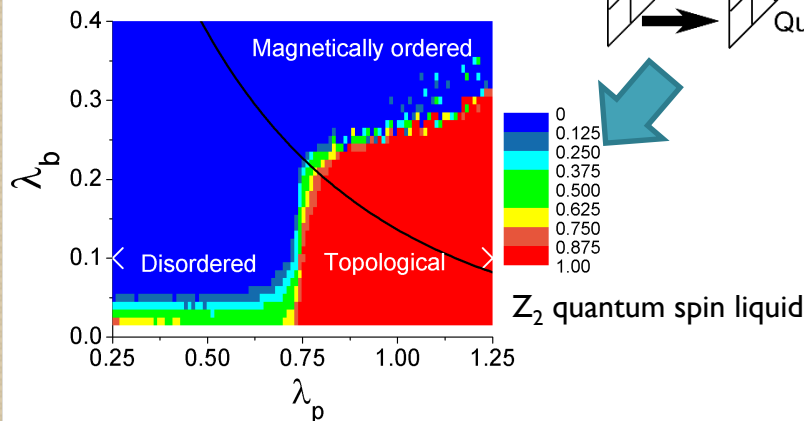


YZ, Eun-Ah Kim(2016)

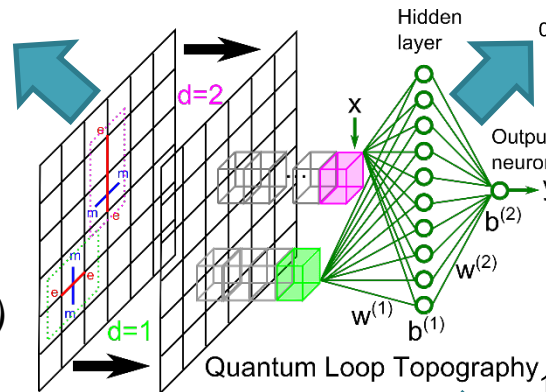


YZ, Eun-Ah Kim(2016)

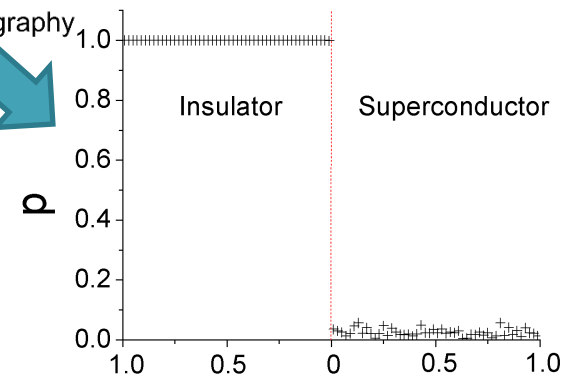
YZ, R. G. Melko, Eun-Ah Kim(2017)



Z_2 quantum spin liquid



Quantum Loop Topography



In preparation

Summary

- Quantum Loop Topography as a bridge between the physical systems and machine learning technology
- Machine learning as a novel approach for physical problems, such as the phase diagram with Z_2 quantum spin liquid
- Advantages:
 - Accuracy
 - Efficiency
 - Versatility
- The story is just beginning...

