

# Detection of Phase Transition via Convolutional Neural Networks



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A. Tanaka (RIKEN AIP center)

Based on JPSJ86, 063001 (2017)

(arXiv:1609.09087 )

# Self-introduction

I am interested in machine learning with/for physics

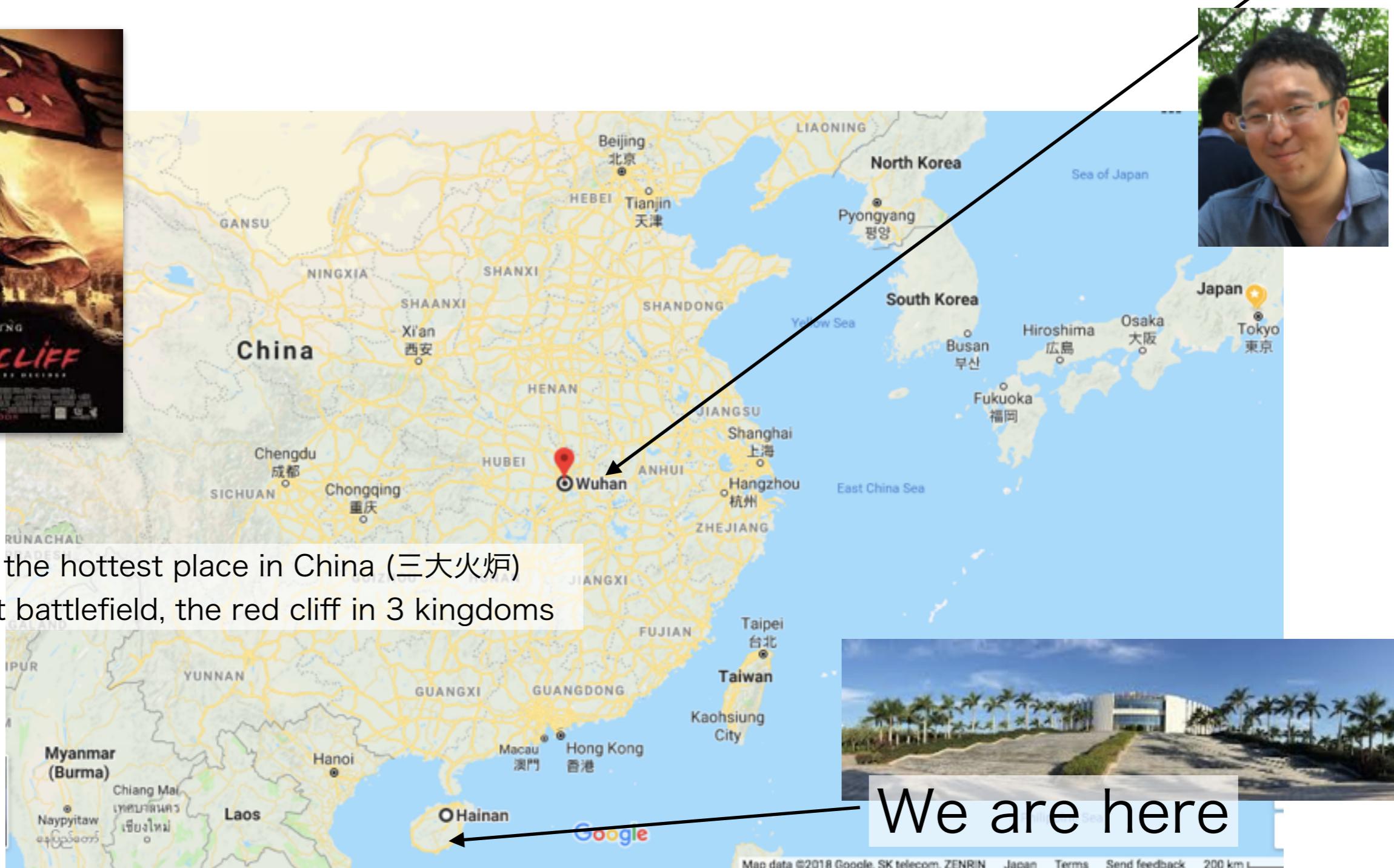
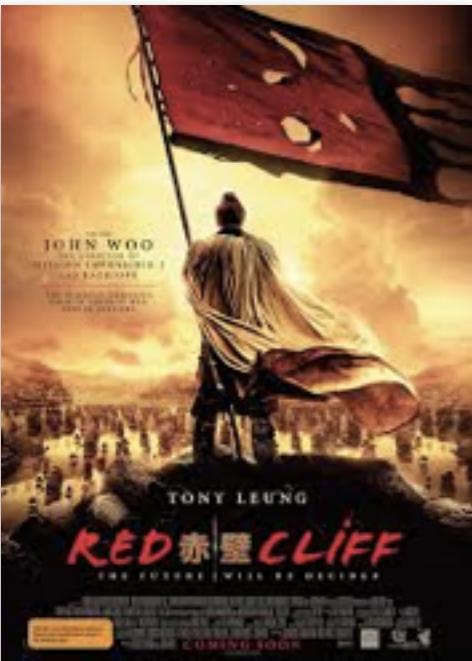
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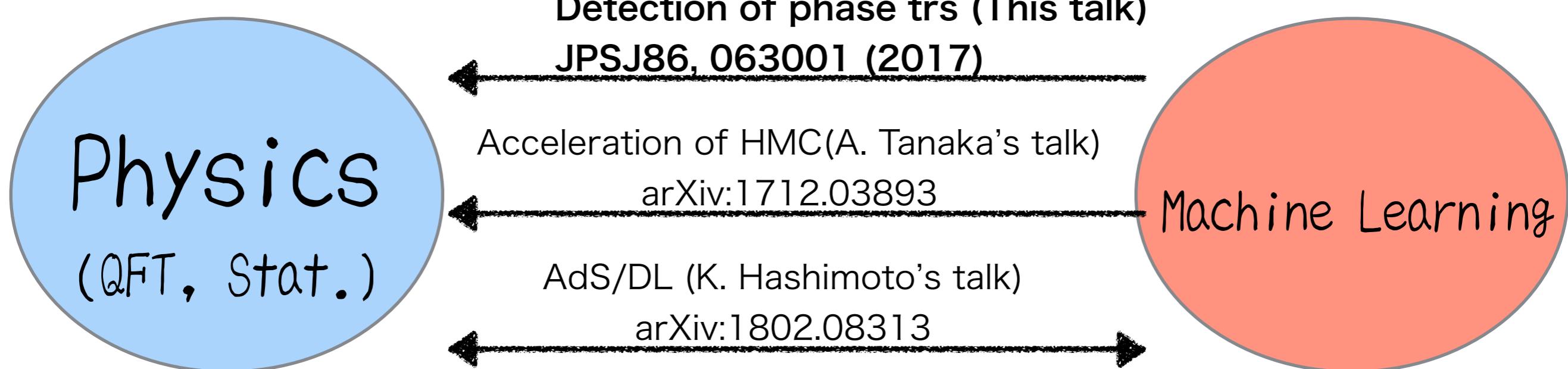
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Ph.D: Theory of high energy particle physics

Interest: Lattice gauge theory(QCD) at finite temperature,  
phase transitions, quantum entanglement

My viewpoint to ML&physics:



# Summary : Motivations and Results

Neural networks (NN) can detect the critical point

**Motivation:** NN can recognize images and configurations of spin system are similar to images.

Can NN recognize phase or phase transition?

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**Results:** CNN can detect phase transition in few % accuracy without explicit information of  $T_c$

System size	$\beta_c$ (CNN)
$8 \times 8$	0.478915
$16 \times 16$	0.448562
$32 \times 32$	0.451887

$$\beta_c^{\text{Exact}} = \frac{1}{2} \log(\sqrt{2} + 1)$$

$$\sim 0.440686$$

# **Introduction**

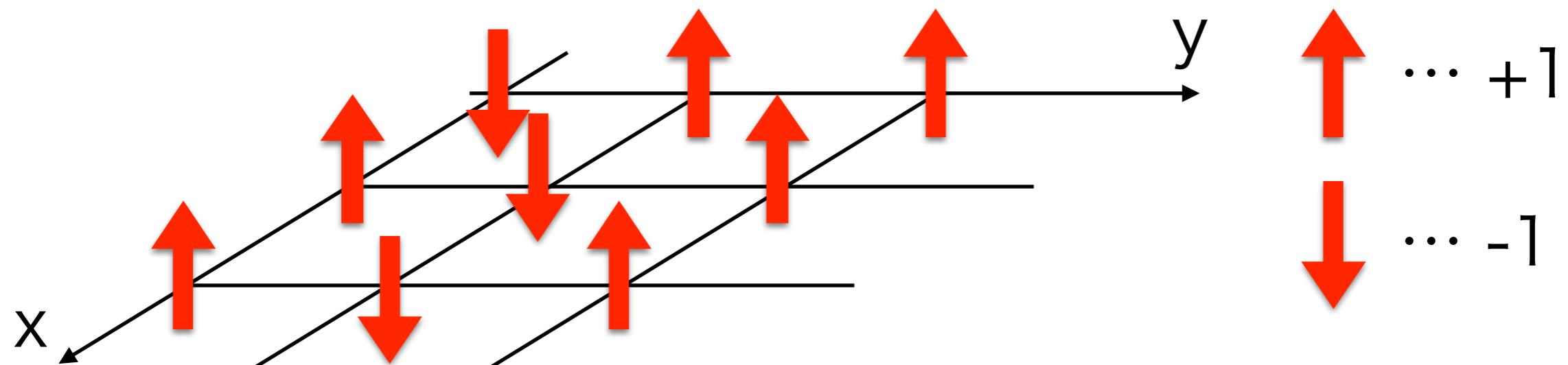
**2 dimensional Ising model**

# Ising model and phase transition(1/4)

2 dimensional ferromag. Ising model in the statistical mechanics

+1 or -1 on each point in 2 dim. lattice (grid)

Wilhelm Lenz (1920)



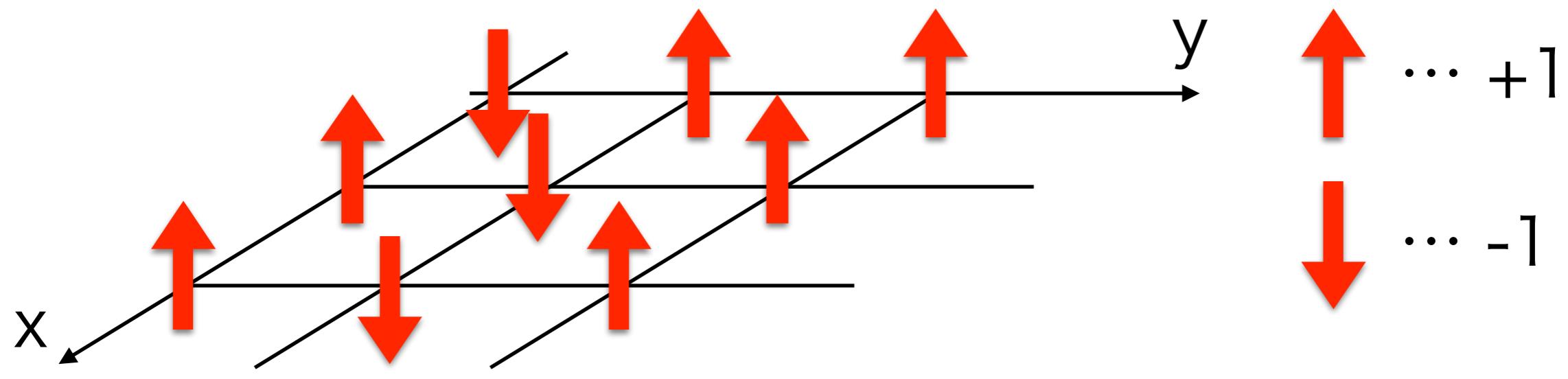
A toy model of ferro-magnetism, similar to quantum field theory (QFT) and exactly solvable  
i.e. good testing ground for new methods  
towards applications to QFT

# Ising model and phase transition(2/4)

2 dimensional Ising model in the statistical mechanics

+1 or -1 on each point in 2 dim. lattice (grid)

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$$\sigma_{x,y} = -1 \text{ or } +1,$$

$\{\sigma\}$  : a spin configuration, which is given by in a probability,

$$P[\{\sigma\}] \propto \exp [-\beta H[\{\sigma\}]] \quad \beta \propto 1/T$$

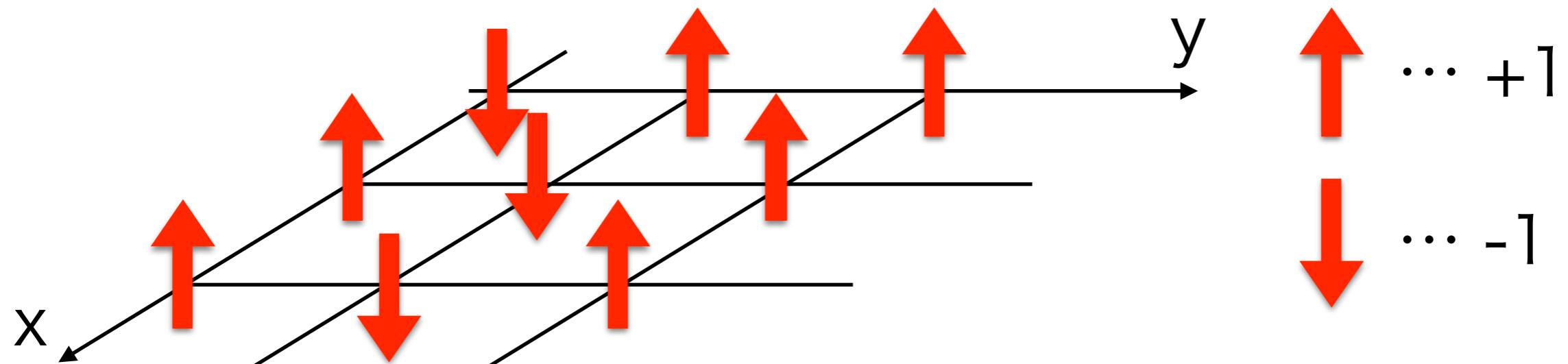
$$H = - \sum_{x,y} \sigma_{xy} (\sigma_{(x+1),y} + \sigma_{x,(y+1)}),$$

Energy function

# Ising model and phase transition(3/4)

2 dim. Ising model is the simplest model which has a phase transition

Wilhelm Lenz (1920)



The expectation value of magnetization  $\langle \sigma \rangle$  at inv. temp.  $\beta \propto 1/T$ :

$$\langle \sigma \rangle \propto \sum_{\{\sigma\}} \sum_{x,y} \sigma_{x,y} \exp [ -\beta H[\{\sigma\}] ]$$

Sum over all possible spin combinations: Difficult  
Done by Onsager(1944), Nambu(1950), ...

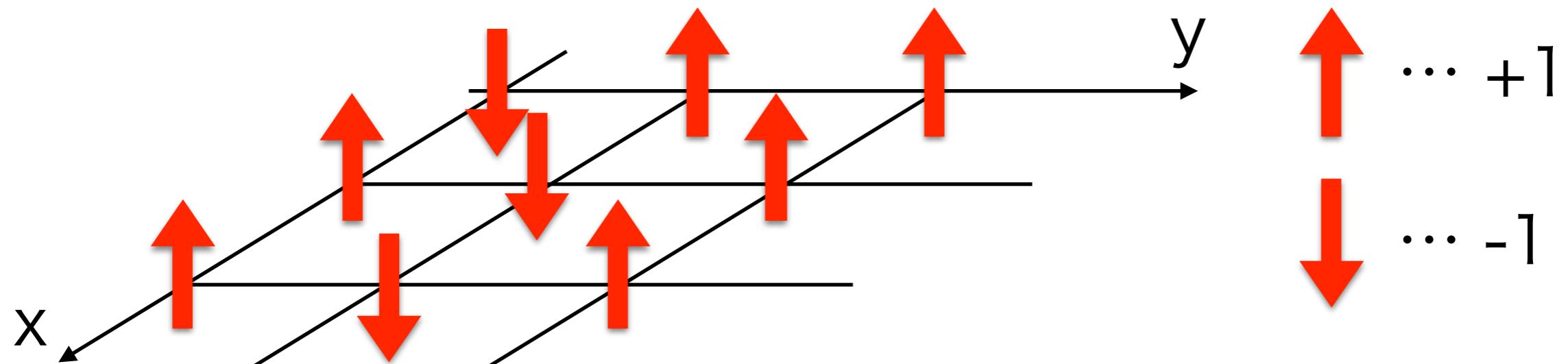
$\langle \sigma \rangle$  is zero above  $T_c$  and non-zero below  $T_c$

$$\begin{aligned} \beta_c^{\text{Exact}} &= \frac{1}{2} \log(\sqrt{2} + 1) \\ &\sim 0.440686 \end{aligned}$$

# Ising model and phase transition(4/4)

We have to choose order parameters to define phase transitions

Wilhelm Lenz (1920)



$$\langle \sigma \rangle \propto \sum_{\{\sigma\}} \sum_{x,y} \boxed{\sigma_{x,y}} \exp [ -\beta H[\{\sigma\}] ]$$

$$H = - \sum_{x,y} \sigma_{xy} (\sigma_{(x+1),y} + \sigma_{x,(y+1)}),$$

$H$  is invariant under  $\sigma \rightarrow -\sigma$  but  $\langle \sigma \rangle$  can be non-zero.

$\sigma$  is called “order parameter” (spontaneous symmetry breaking)

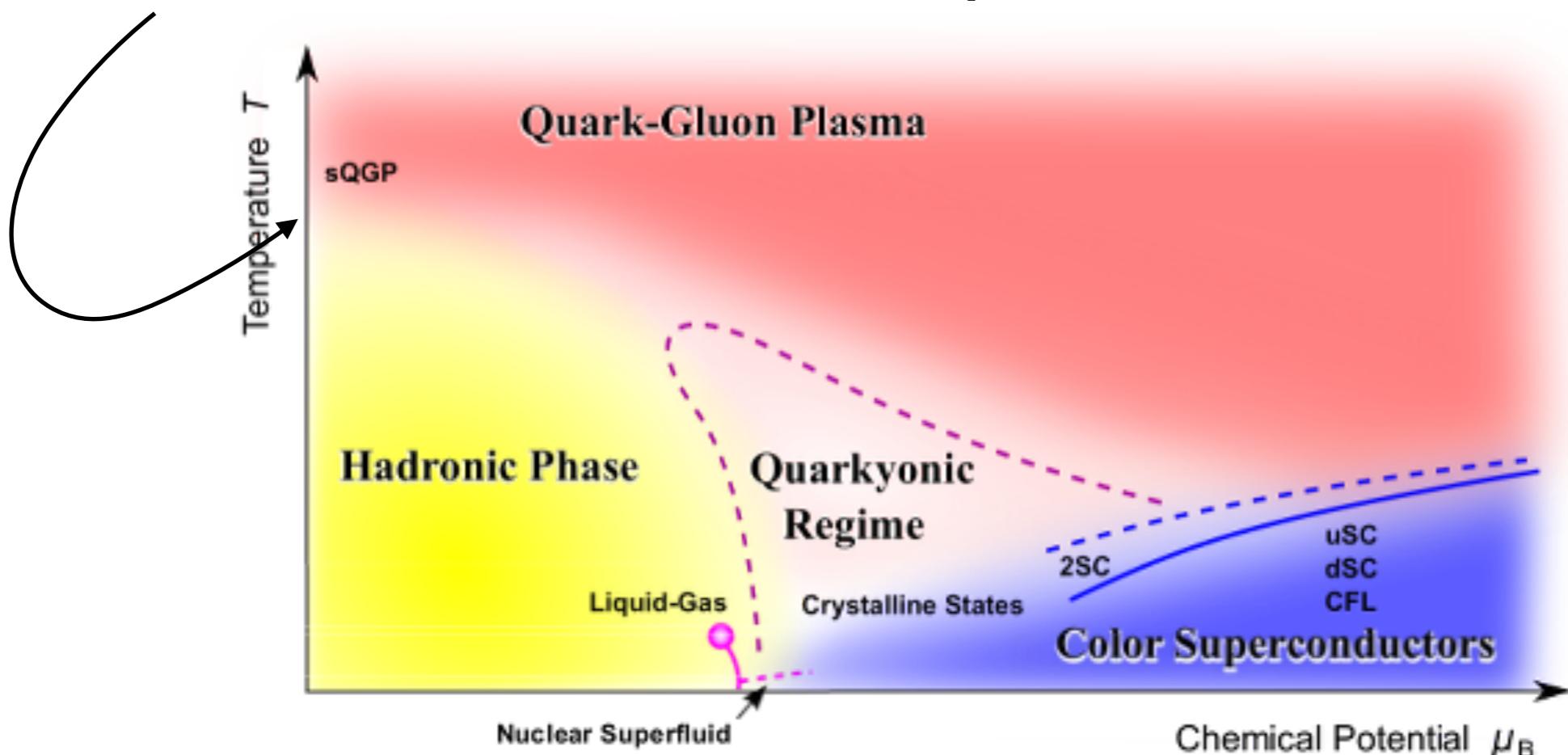
Q. To define phase transition, we need to specify order parameters.

**Without teaching order parameter, can we find phase transitions?**

# Context of this work(1/2)

Deconfinement phase transition in QCD (Quantum Chromo-Dynamics)

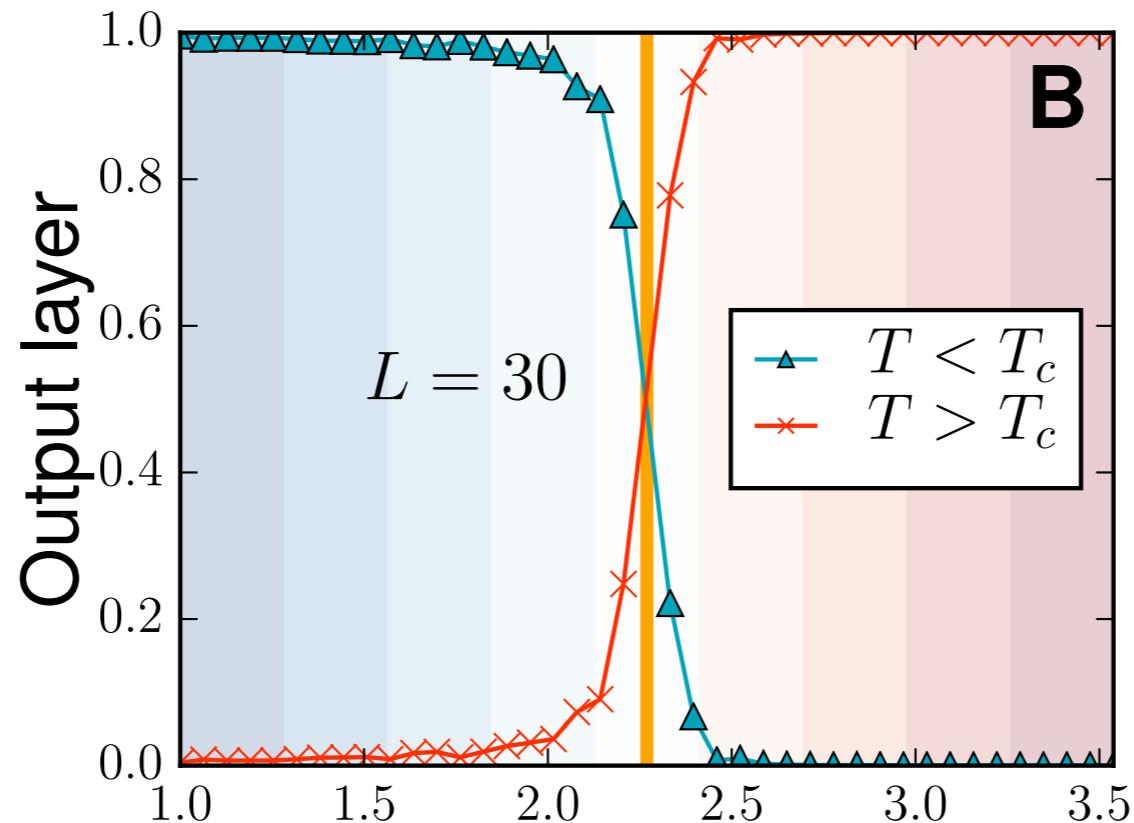
Nucleons (hadrons) dissociate to quarks/gluons above  
 $T \sim 150 \text{ MeV} \sim 10^{11} \text{ Kelvin}$  (ALICE experiment in LHC)  
= Confinement/deconfinement phase transition in QCD



If we ignore quarks, Polyakov loops give an order parameter but  
QCD phase trs. with quarks does not have clear order parameters...

# Context of this work(2/2)

## A previous work by a Perimeter group



Juan Carrasquilla and Roger G. Melko  
arXiv: 1605.01735

2D Ising model.

Input configurations, phases as labels (2 labels).

Output layer exhibits the critical temperature

Teaching the phase  $\rightarrow$  implicitly teaching  $T_c$

# Outline

✓ 1. Introduction

2. Convolutional NN

3. Our works & results

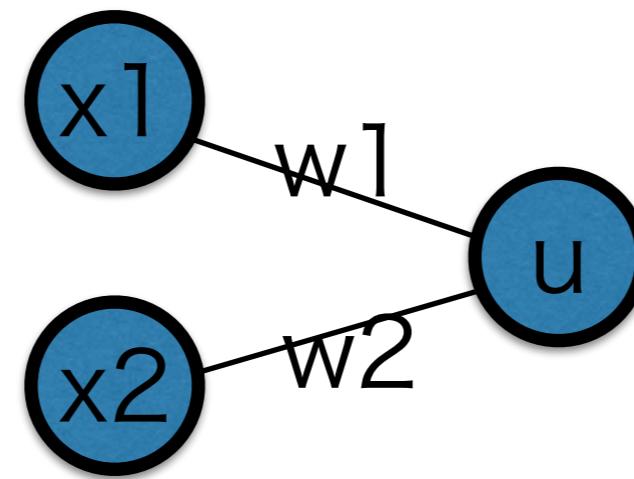
4. Summary

# **Convolutional NN**

# Neural networks

## Elements in our neural networks

$x_1, x_2$ :  
Inputs

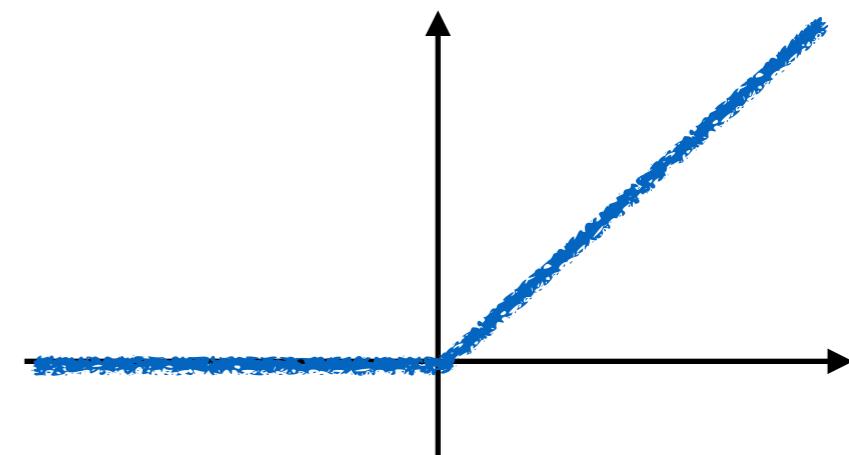


$w$ : fit parameters

$$u = \text{ReLU}(w_1x_1 + w_2x_2)$$

Bias terms can be included

$$\text{ReLU}(x) = \max(x, 0)$$

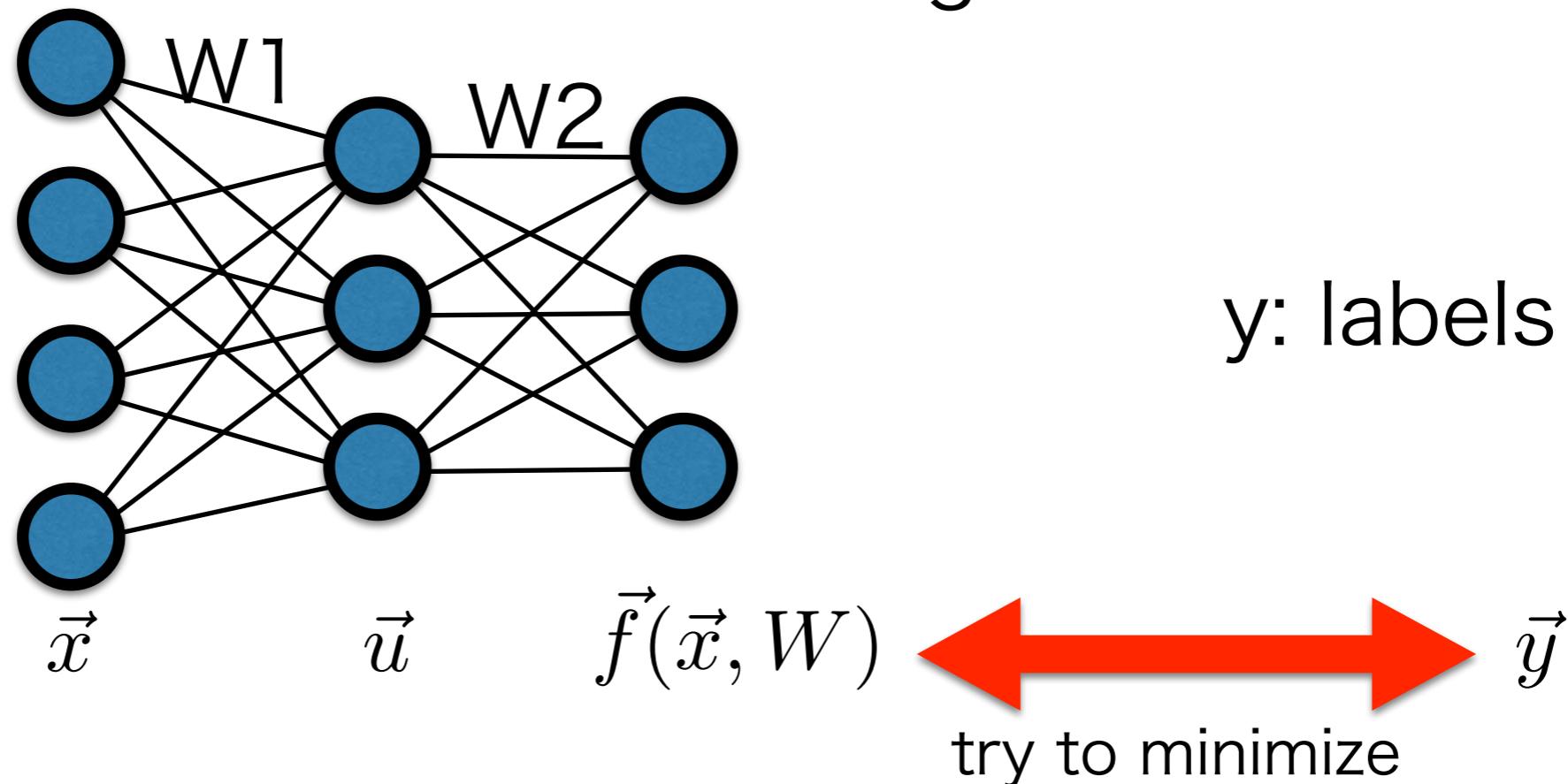


# Neural networks

## Neural networks

W: Weight matrices

x: Input



$E(\vec{f}(\vec{x}, W), \vec{y})$  : Error function, “distance” between  $f$  and  $y$

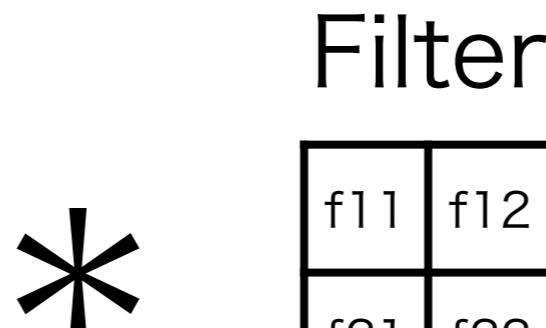
Minimizing  $E$  by tuning weight matrices  $W$  = Learning of NN

# Convolutional Neural networks

It improves image recognition

Convolution = Filtering with fitted filters  
 = special sparse weights

p <sub>11</sub>	p <sub>12</sub>	p <sub>13</sub>	p <sub>14</sub>
p <sub>21</sub>	p <sub>22</sub>	p <sub>23</sub>	p <sub>24</sub>
p <sub>31</sub>	p <sub>32</sub>	p <sub>33</sub>	p <sub>34</sub>
p <sub>41</sub>	p <sub>42</sub>	p <sub>43</sub>	p <sub>44</sub>



f also will be trained

$$f_{st} \in \mathbb{R}$$

Output:  $u_{ij} = \sum_s \sum_t f_{st} p_{i+s, j+t}$

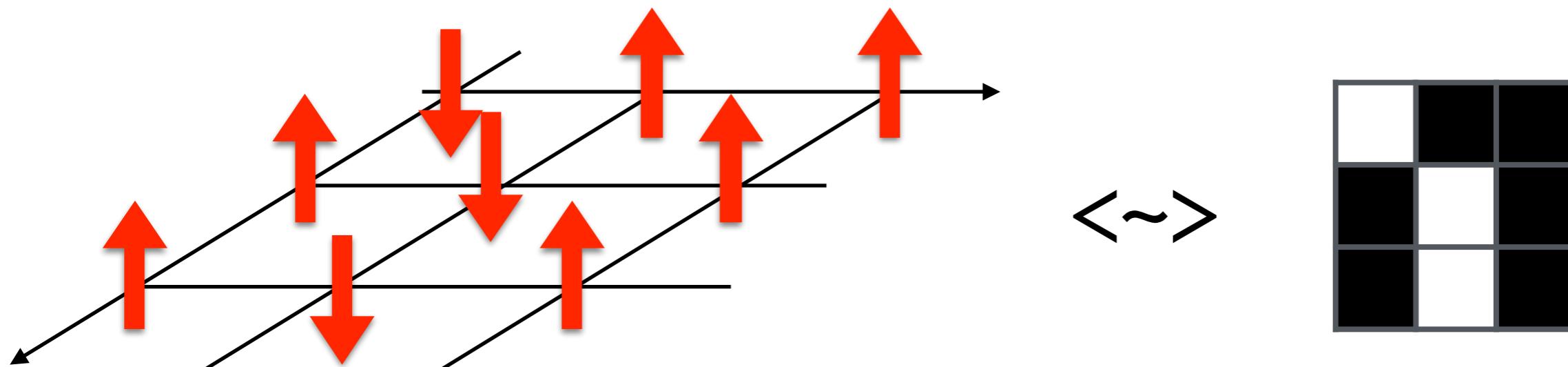
1. Essentially same as the convolution in the Fourier transformation.
2. It helps to solve image recognition problem

# **Our works & results**

# Idea of this work

## Neural networks

By employing Convolutional NN(CNN), we try to detect phase transition in the 2D Ising model.



Q. To define phase transition, we need to specify order parameters.

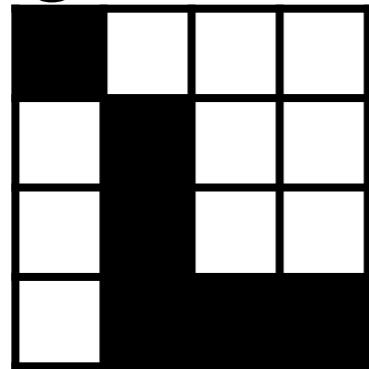
**Without teaching order parameter, can we find phase transitions?**

A. Yes (in some sense)

# Setup

## Convolutional neural net as a “thermometer”

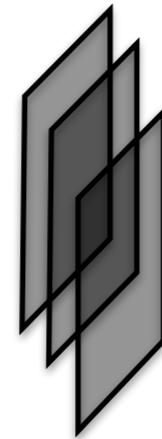
Ising conf. at  $\beta$



$10^2$  confs.  
for each  $\beta$

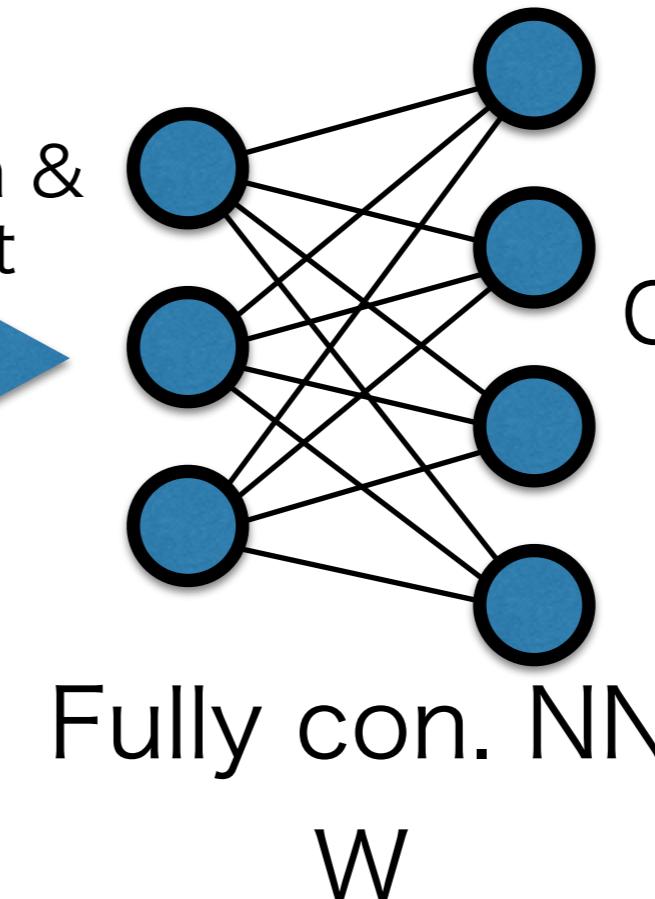
Inv.  $\beta$  is  
discretized for  
labeling  
(one-hot)

\*



Conv. w/  
3 filters

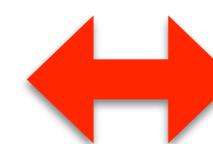
Flatten &  
Input



Fully con. NN

$W$

Output  
 $\beta$  CNN



Ans.  
 $\beta$

$$-\sum_{I=1}^N \beta_I \log \beta_I^{\text{CNN}},$$

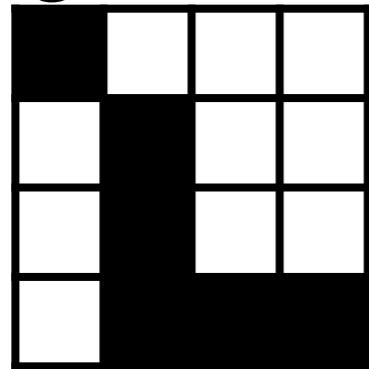
$$\vec{\beta} = \begin{cases} (1, 0, \dots, 0, 0) & \text{for } \beta < 0 \\ (0, 1, \dots, 0, 0) & \text{for } \beta \in \left[0, \frac{1}{N-2}\right) \\ \dots \\ (0, 0, \dots, 1, 0) & \text{for } \beta \in \left[\frac{N-3}{N-2}, 1\right) \\ (0, 0, \dots, 0, 1) & \text{for } 1 \leq \beta \end{cases}.$$

$0.2 < \beta < 10,$   
 $N = 100$

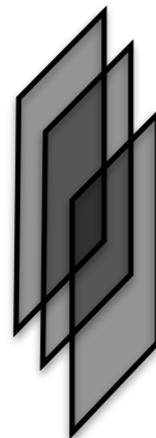
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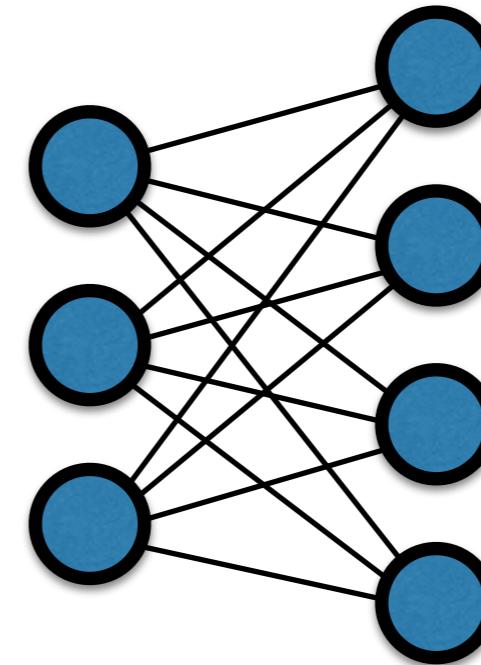
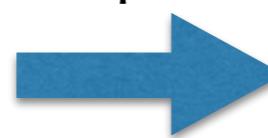
Ising conf. at  $\beta$



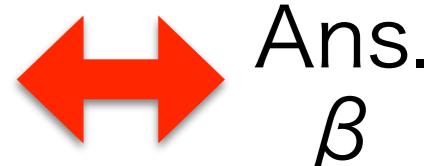
\*



Flatten &  
Input



Output  
 $\beta$  CNN



Ans.  
 $\beta$

Training process:

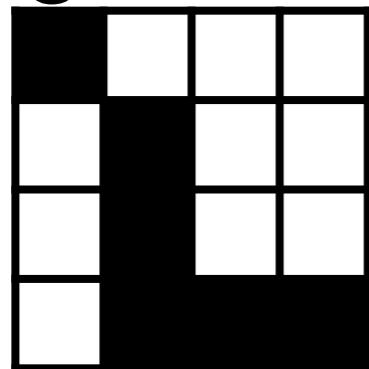
$$\beta_c^{\text{Exact}} \sim 0.440686$$

0. Configurations for  $\beta \in [0.2, 10]$  are prepared by MCMC
1. Choose one dataset for  $\beta$ , i.e. configurations( $\beta$ ) and label( $\beta$ )
2. Training with configurations with the  $\beta$
3. Back 1 and repeat for  $10^5$ .

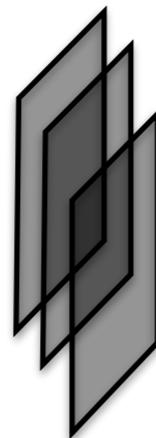
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Convolutional neural net as a “thermometer”

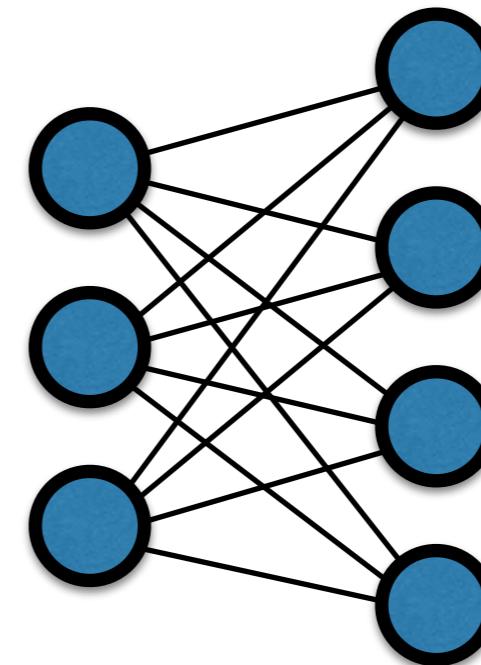
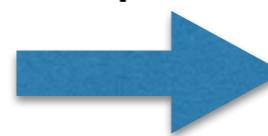
Ising conf. at  $\beta$



\*



Flatten &  
Input



Fully con. NN

**W**

Output  
 $\beta$  CNN

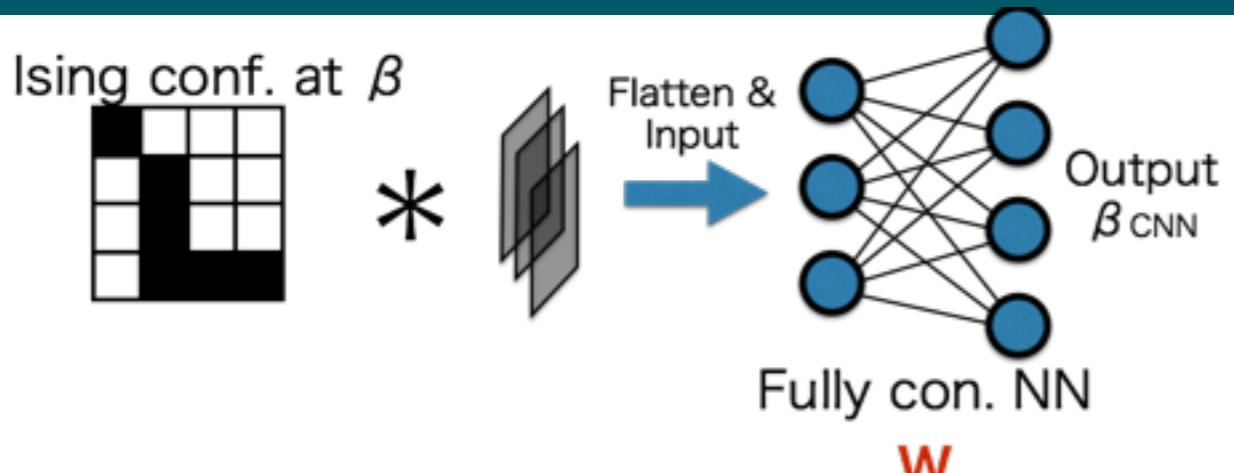
Ans.  
 $\beta$

$W$  connects “Spin configurations” to “temperature”

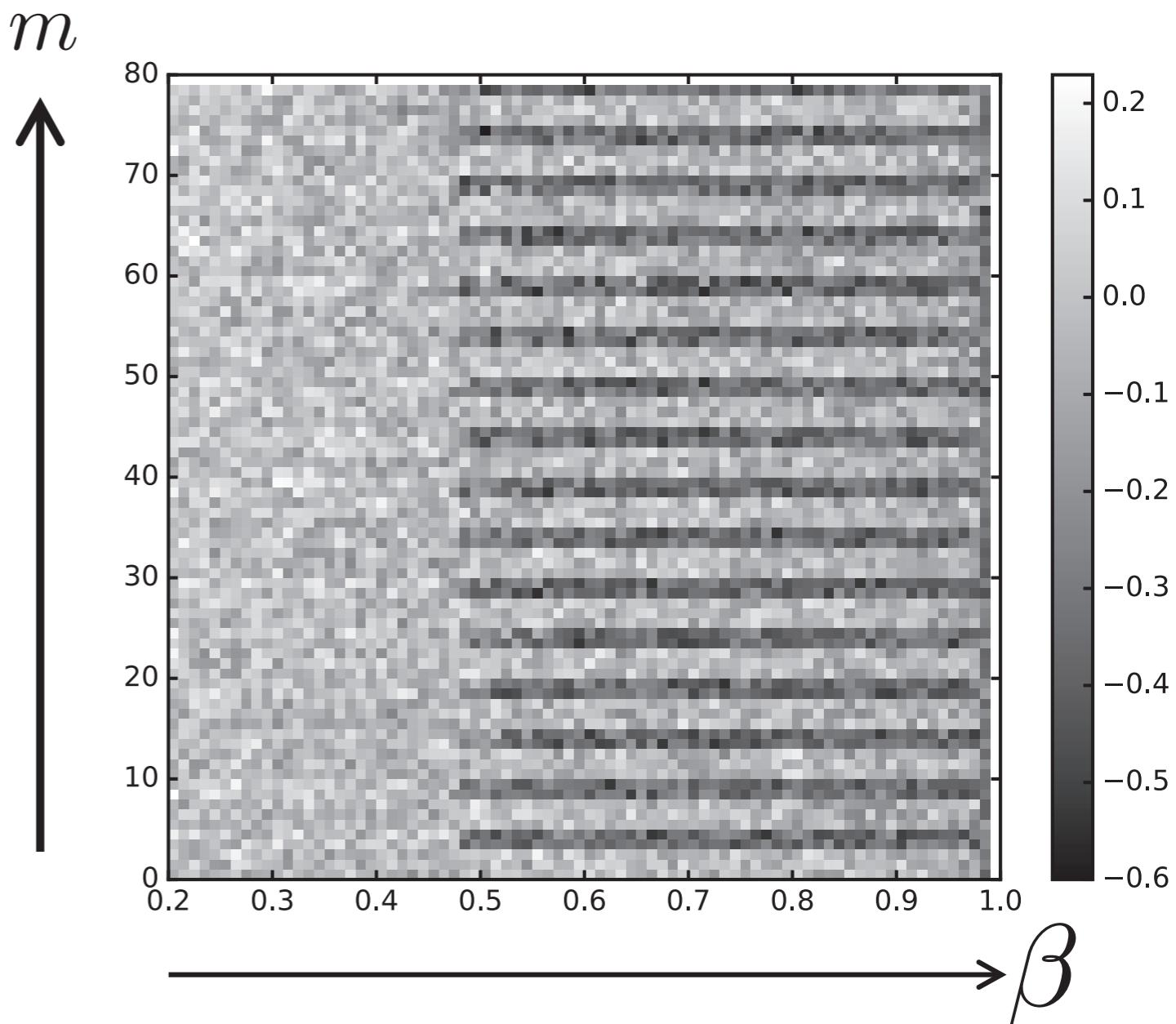
We plot **W** as a heat map after training.

# Results (CNN)

Weight  $W$  has a pattern

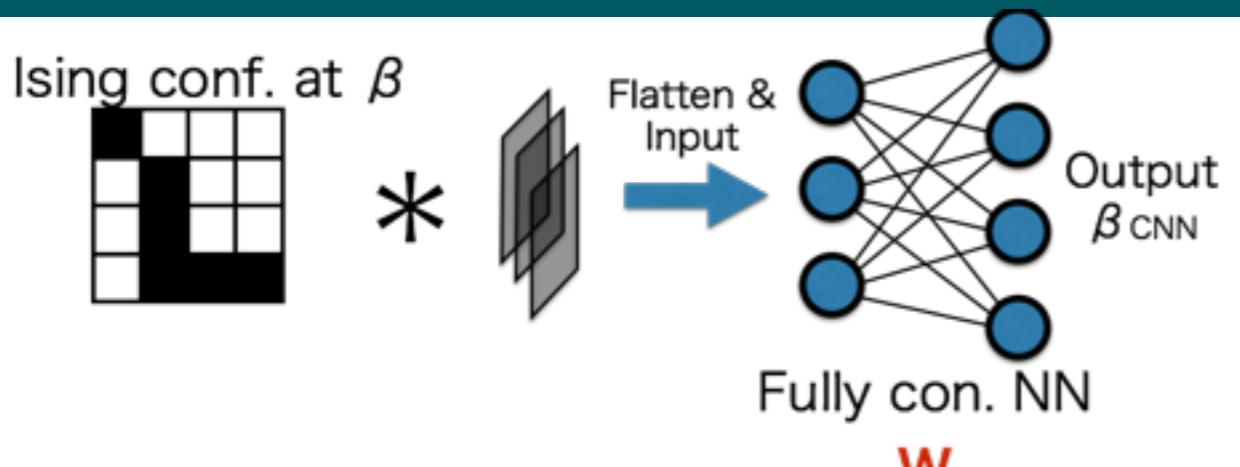


Heat map of  $W$   
(After whole training)



# Results (CNN)

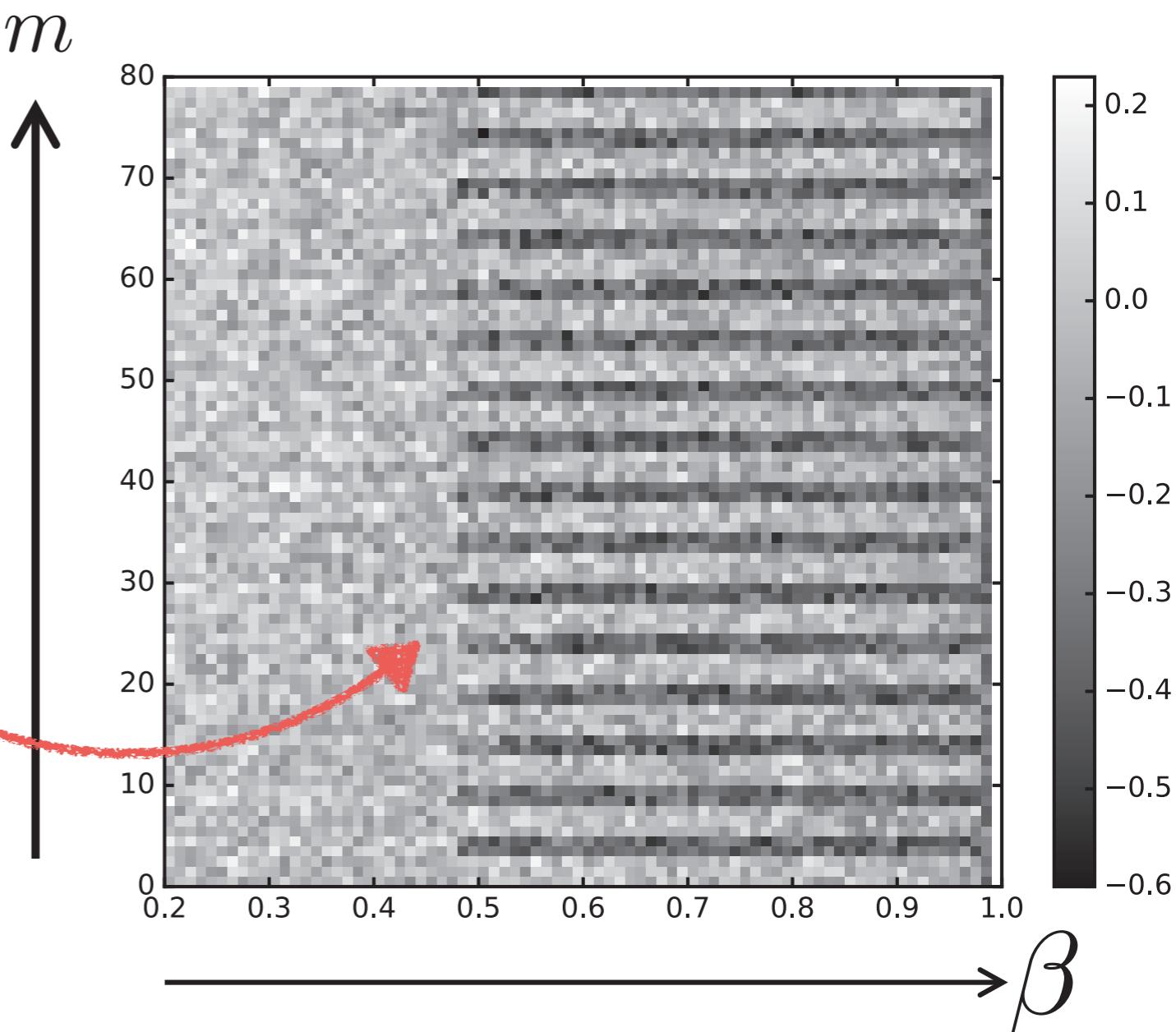
Weight W has a pattern



Heat map of **W**  
(After whole training)

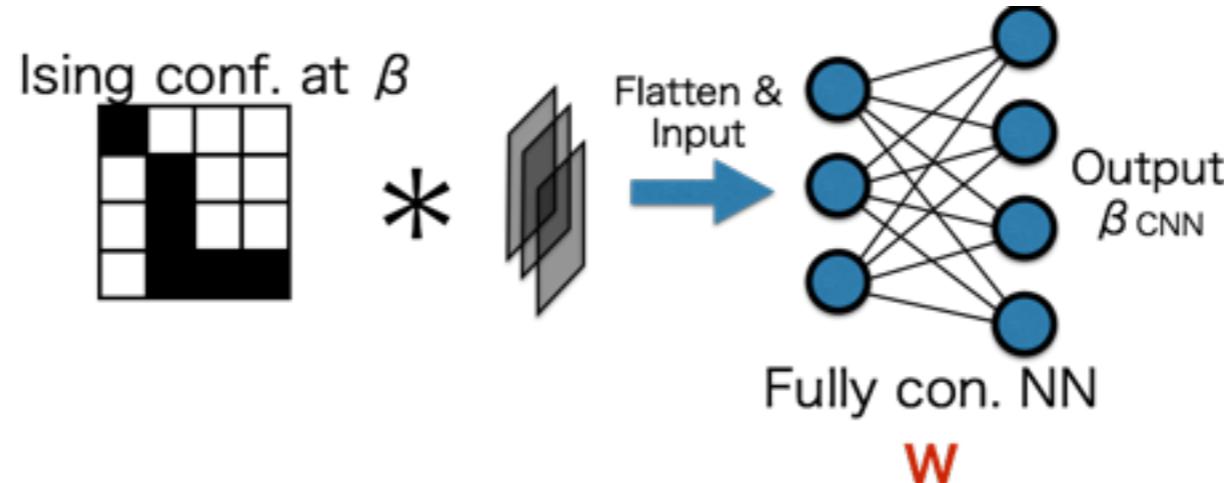
The weight matrix  
has a pattern

$$\beta_c^{\text{Exact}} = \frac{1}{2} \log(\sqrt{2} + 1) \\ \sim 0.440686$$

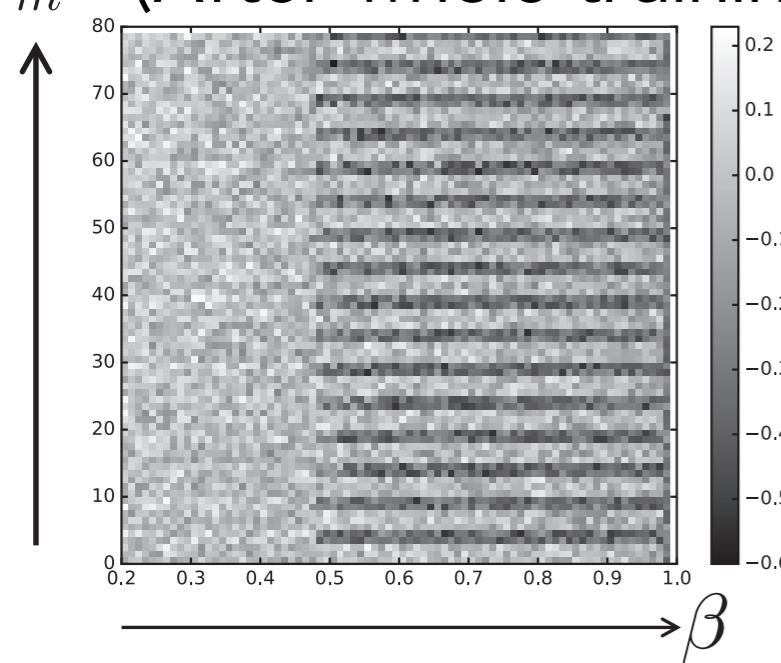


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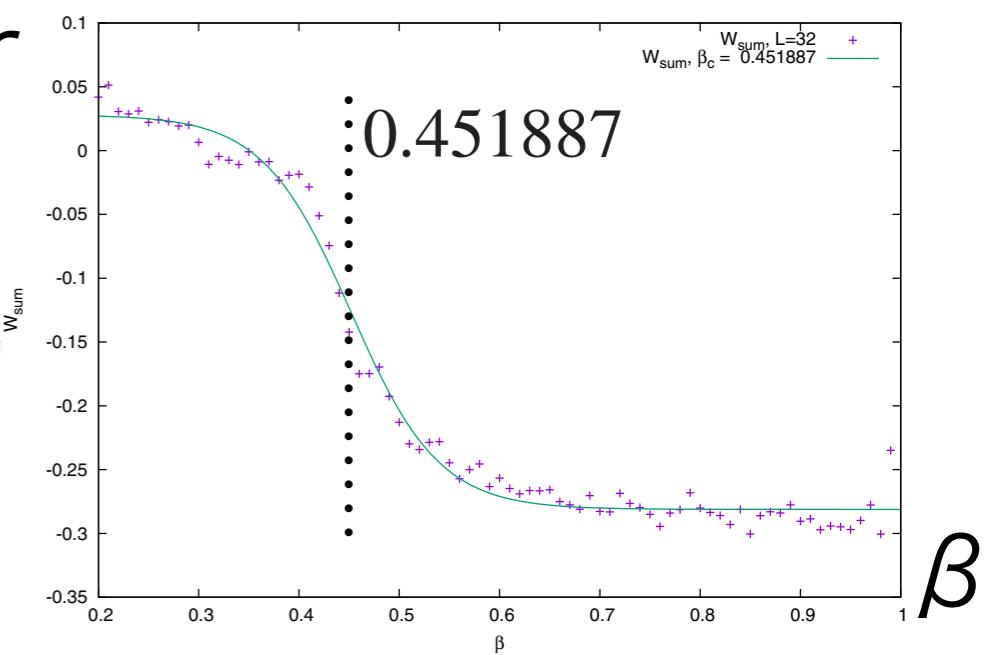
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Heat map of  $W$   
(After whole training)



Summing  $W$  over  
m direction



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$$\sim 0.440686$$

# Discussions

## W carries information of criticality?

- We do not know why W has information of criticality

System size	$\beta_c$ (CNN)
$8 \times 8$	0.478915
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- This behavior is stable for L=8, 16, 32.

- It looks like behavior of magnetization along with the temperature but there are no (explicit) reasons for such coincidence.

- Filter F seems to capture information of magnetization but FNN can capture Tc.

- On the other hand, this network is not a good thermometer

- There are still some discussions:

- Weights cannot carry information! (K-I. Aoki et al. ) Using RG

- Weights can carry information! (Iso et al.) Using RG

# Related works

## Detecting phase transitions

1. Ising models: Juan Carrasquilla and Roger G. Melko arXiv: 1605.01735
2. Transverse Ising model (**Quantum phase trs**), S. Arai et. al. JPSJ 87, 033001 (2018)
3. XY model
  1. W. Hu, R. R. P. Singh, and R. T. Scalettar, Phys. Rev. E95, 062122 (2017).
  2. S. J. Wetzel, Phys. Rev. E 96, 022140 (2017).
  3. C. Wang and H. Zhai, Phys. Rev. B 96, 144432 (2017).
  4. M. J. S. Beach, A. Golubeva, and R. G. Melko, Phys. Rev.B 97, 045207 (2018).
4. Heisenberg model
  1. I. A. Iakovlev, O. M. Sotnikov, and V. V. Mazurenko, arXiv:1803.06682
5. RG:
  1. S. Iso, S. Shiba, and S. Yokoo, Phys. Rev. E 97, 053304 (2018).
  2. K-I. Aoki et al, Learning from estimation of temperature (Only in Japanese)
6. Skyrmion, Vinit Kumar Singh, Jung Hoon Han, arXiv:1806.03749

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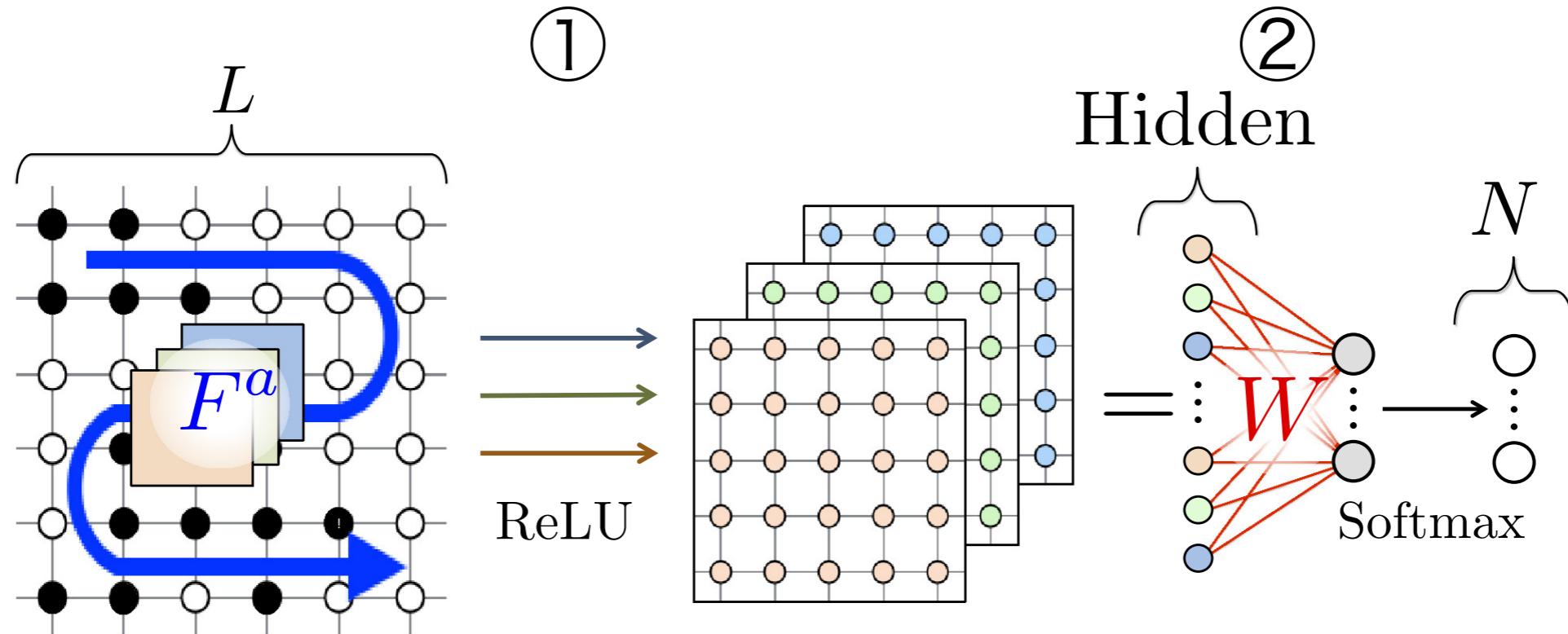
$$\beta_c^{\text{Exact}} = \frac{1}{2} \log(\sqrt{2} + 1)$$

$$\sim 0.440686$$

# Backups

# Setup (detailed)

## Our Neural networks



①  $\{\sigma_{xy}\}$

$$\xrightarrow{\text{conv}} \sum_{i,j=1}^{N_f} \sigma_{(sX+i)(sY+j)} F_{ij}^a = \Sigma_{XY}^a$$

$$\xrightarrow{\text{ReLU}} \max(0, \Sigma_{XY}^a) = u_{XY}^a$$

$$\xrightarrow{\text{flatten}} \vec{u} = [u_{11}^1, u_{11}^2, \dots, u_{11}^C, u_{21}^1, u_{21}^2, \dots, u_{21}^C, \dots] = [u_m].$$

②  $[u_m]$

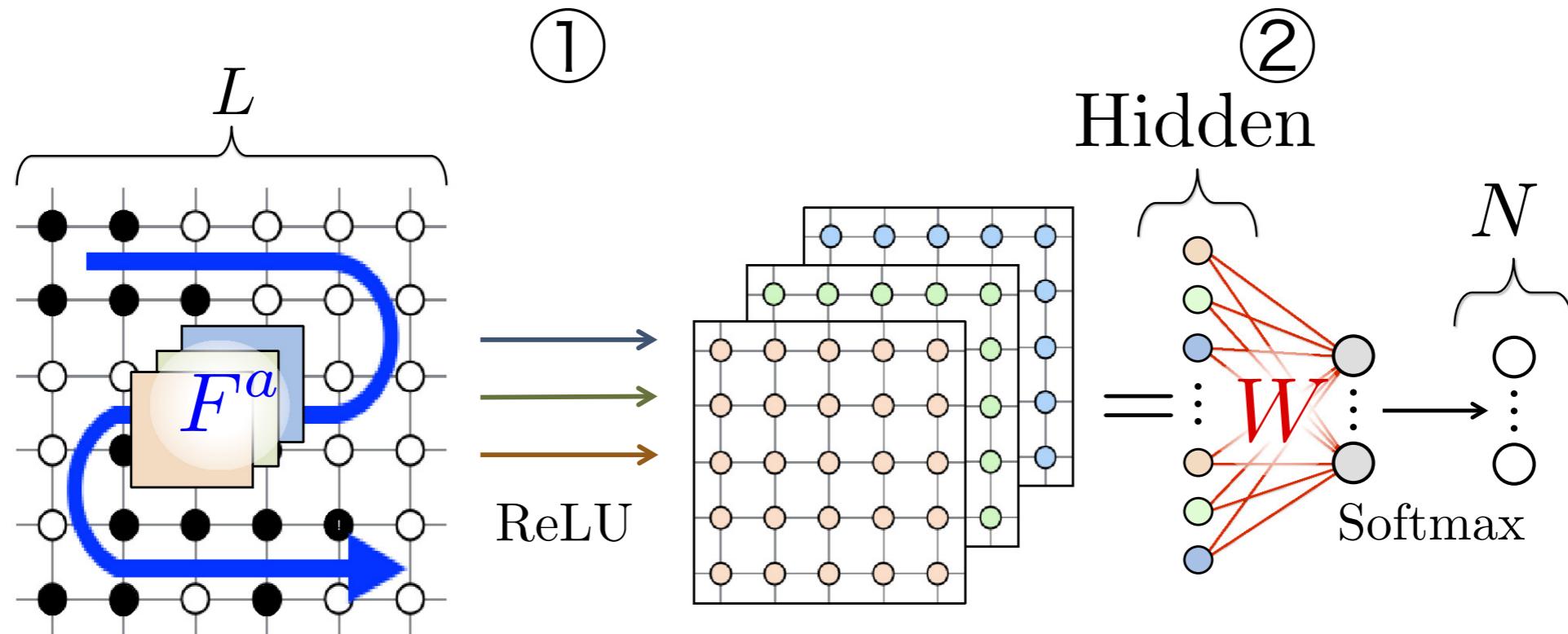
$$\xrightarrow{\text{fully-connected}} \sum_{m=1}^{L^2/s^2 \times C} W_I^m u_m = z_I$$

$$\xrightarrow{\text{Softmax}} \frac{e^{z_I}}{\sum_{J=1}^N e^{z_J}} = \beta_I^{\text{CNN}}.$$

$$C = 5, \text{ and } s = L/4 \quad N_f = 3,$$

# Setup (detailed)

## Our Neural networks

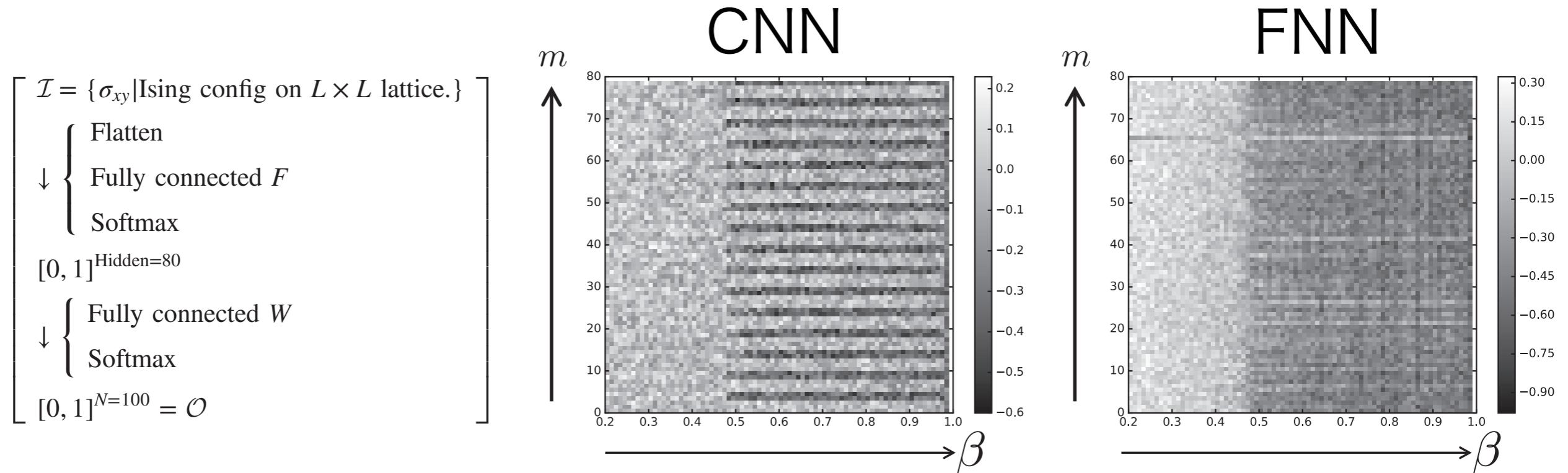


$F^a_{ij}$  in convolution,     $W_I^m$  in fully connected layer.

$$\left[ \begin{array}{c} a = 1, \dots, C \\ i, j = 1, \dots, N_f \end{array} \right] \quad \left[ \begin{array}{c} m = 1, \dots, L^2/s^2 \times C \\ I = 1, \dots, N \end{array} \right]$$

# Fully connected results

FNN gives Tc but CNN gives precise Tc

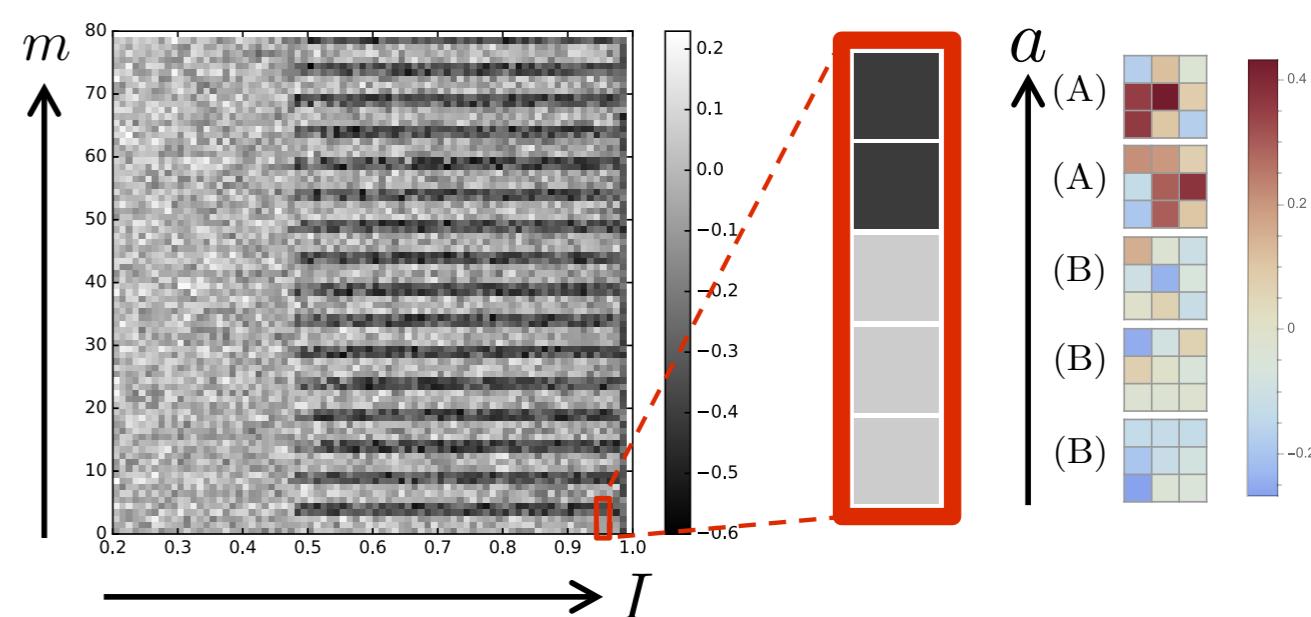
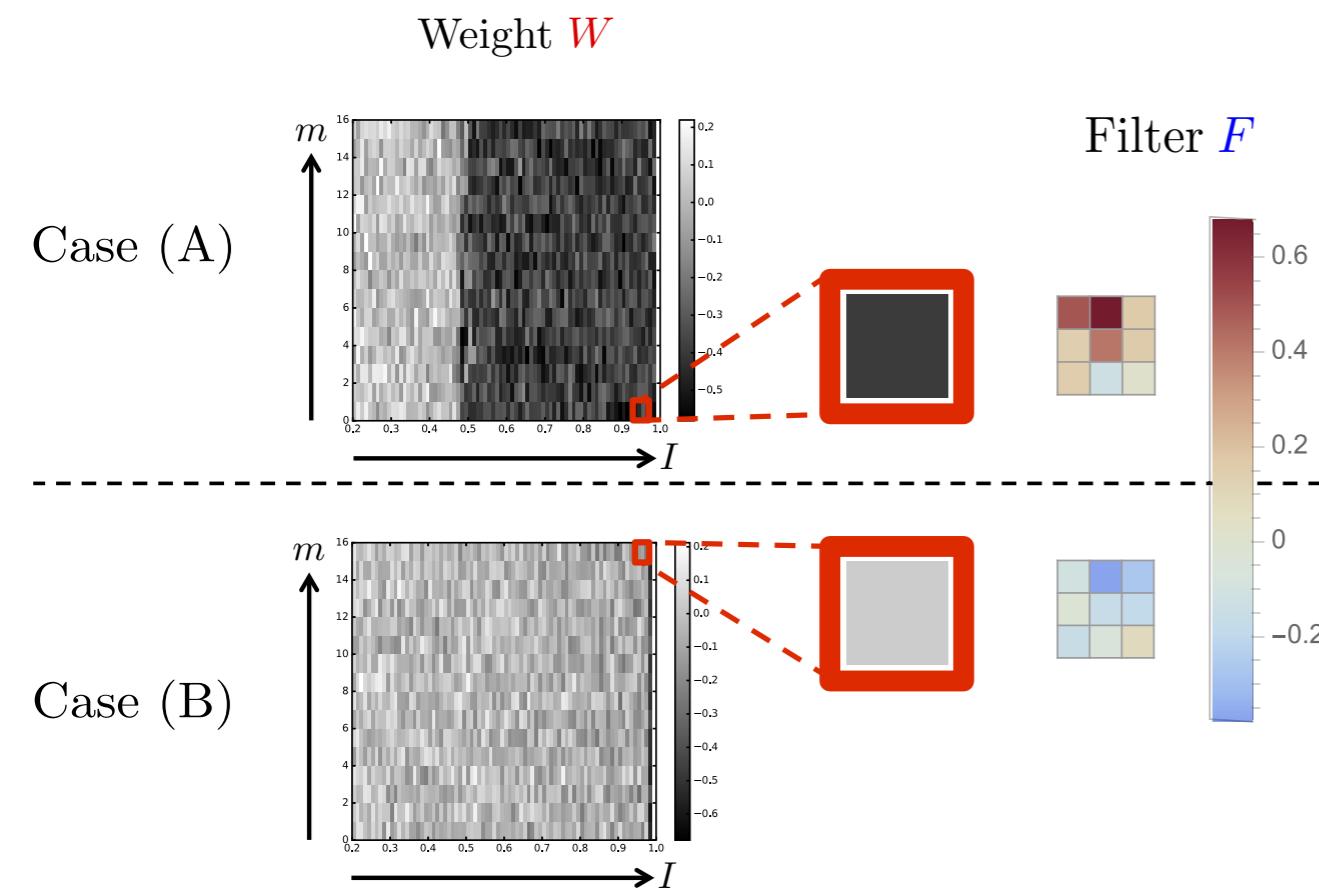


System size	$\beta_c$ (CNN)	$\beta_c$ (FC)
$8 \times 8$	0.478915	0.462494
$16 \times 16$	0.448562	0.433915
$32 \times 32$	0.451887	0.415596
$L \rightarrow \infty$		$\beta_c^{\text{Exact}} \sim 0.440686$

CNN gives better Tc

# What's the role of filters?

If filters have positive values, W in CNN has domain structure



**Fig. 4.** (Color online) Heat maps of  $W_I^m$  and  $F_{ij}^a$  with five filters.

**Fig. 3.** (Color online) Heat maps of  $W_I^m$  and  $F_{ij}$  for the CNN with one filter. In case (A), there always exist two distinct regions (black and gray). In case (B), there is no such clear decomposition.