

Renormalization

Chapter 5

Wednesday 8 May

Before we start:

This week and next week:

L1

Quiz: Tuesday May 21 at 11h + lecture

L2

Guest Lecture

Greg Stephens, Theoretical Biophysics

Monday 27 May: Preparation

Exam:

Issue about schedule of the exam?

Except for *Machine learning for physicists*

Questions: Information about the last quiz?

Scale Invariance and Universality

Chapter 5

Plan: **Lecture 1:** Emergent behaviors in the simple example of random walks:
scale-invariance and universality

Lecture 2: Renormalization (next Thursday)

Tutorial: Random walks + (optional) renormalization

Renormalization

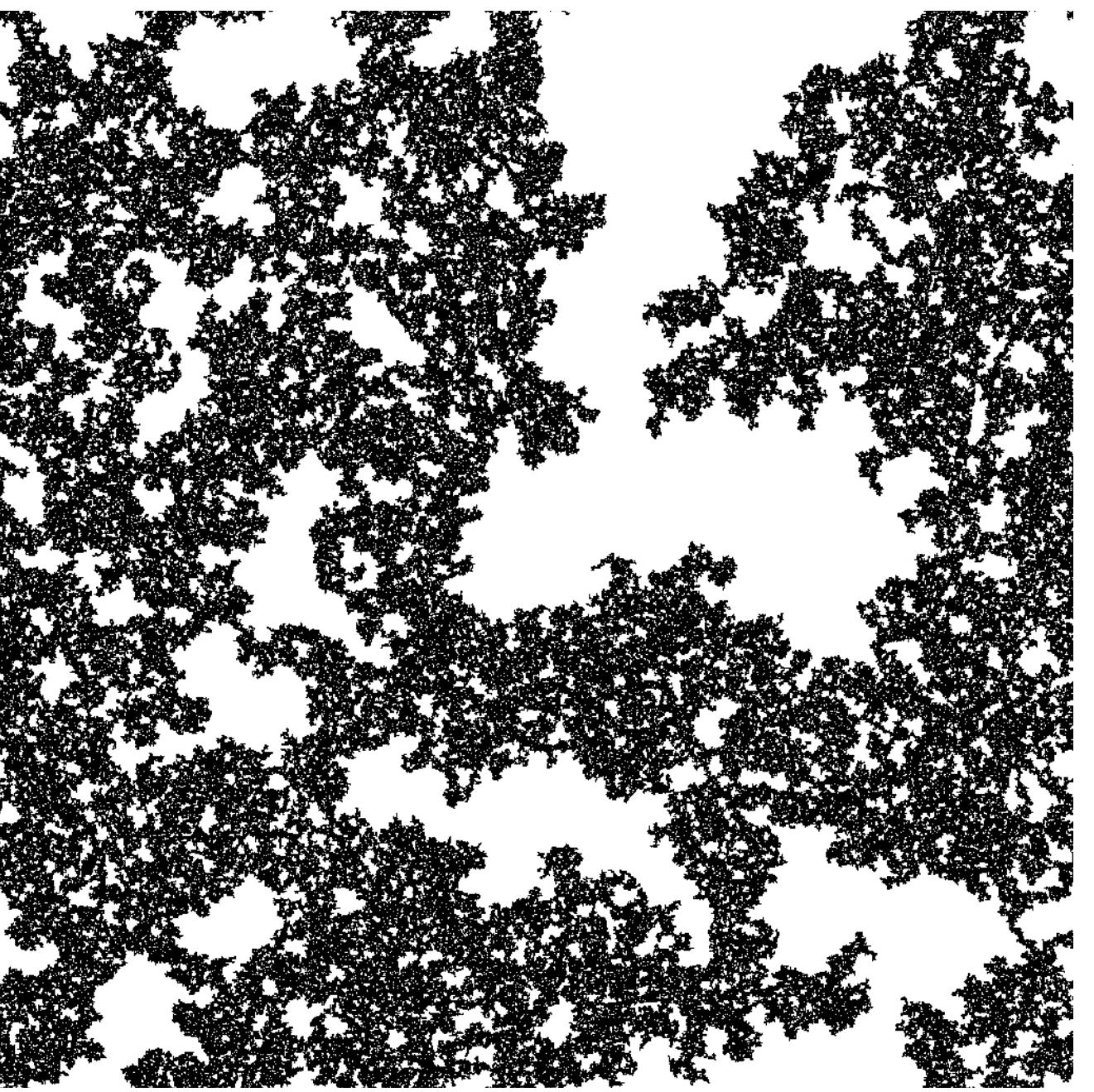
Chapter 5. L2

- Plan:**
- 1) Introduction: Scale-invariance and idea of real-space renormalisation
 - 2) Renormalisation in the 1D Ising model
 - 3) Renormalisation in data

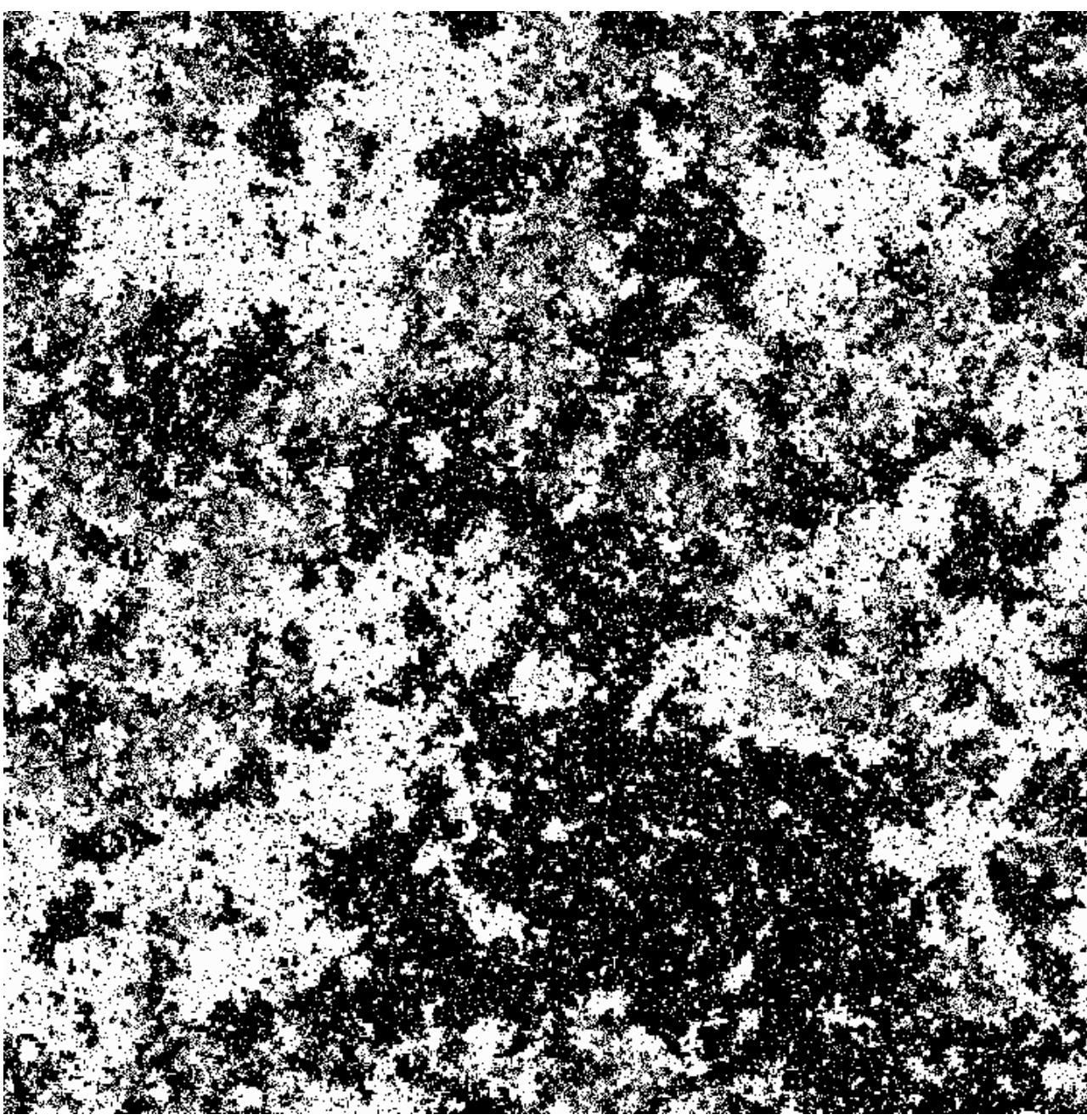
Introduction

Can you recall what is the meaning of **scale invariance**?

Properties of Critical phenomena: Scale Invariance



Bond percolation
at $p = p_c = 0.5$



Ising model
at $T = T_c \sim 2.269$

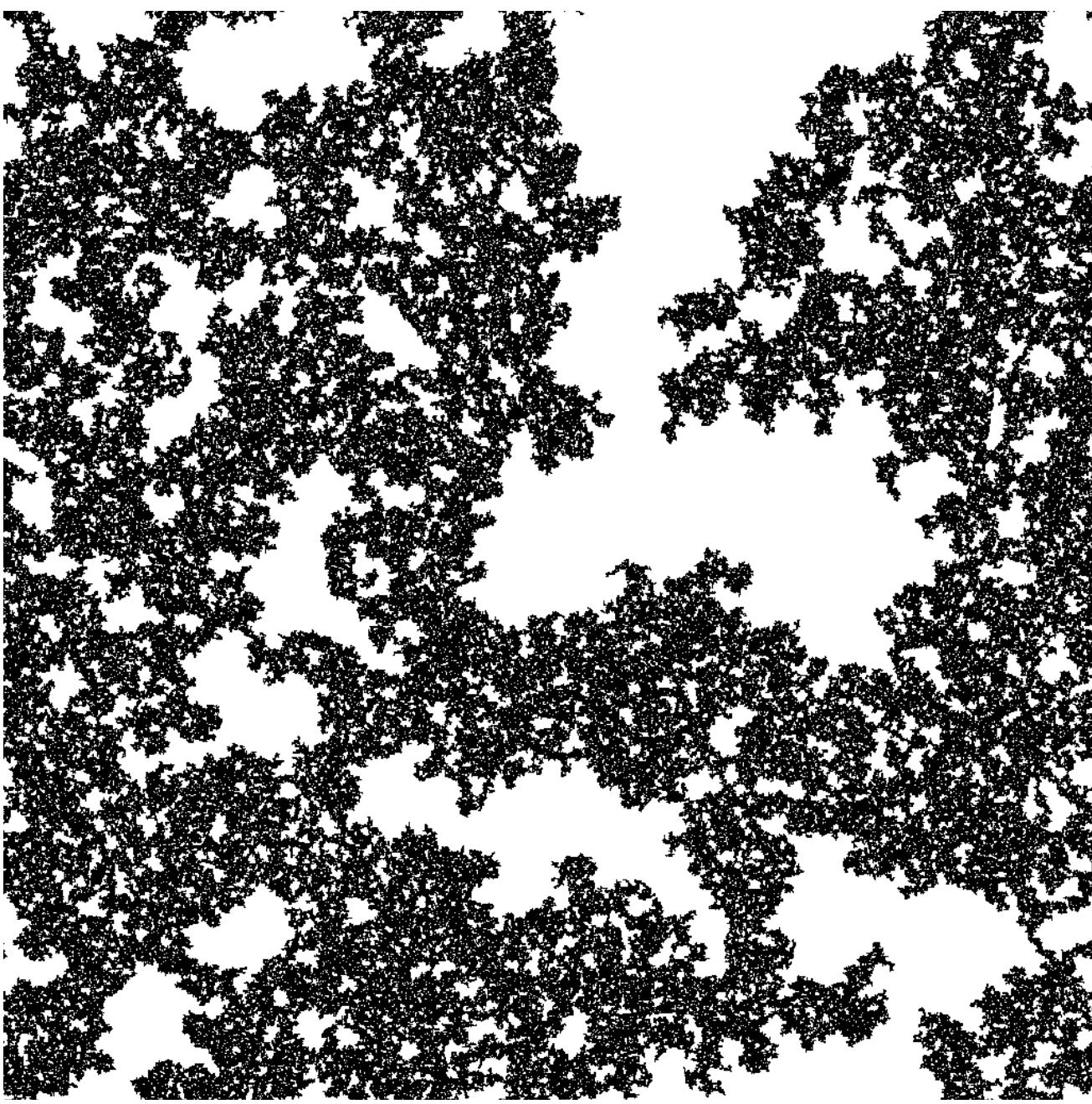
Close to criticality:

Diverging correlation length —> percolating cluster
Cluster of all sizes

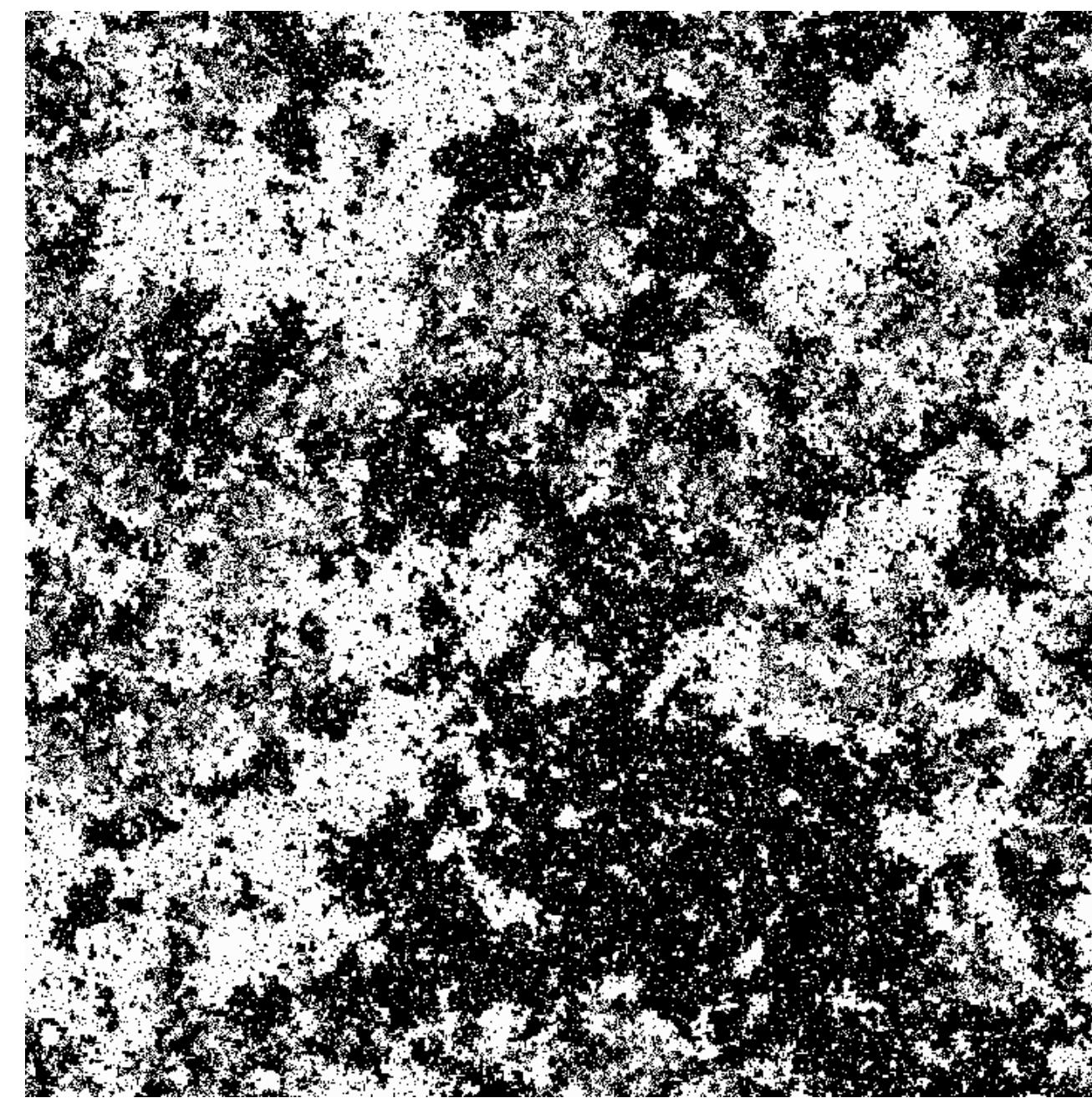
Diverging correlation length
Fluctuation of the magnetization at all scales

Scale invariance: the system “looks the same” at all scales (i.e. when zooming in)

Properties of Critical phenomena: Scale Invariance



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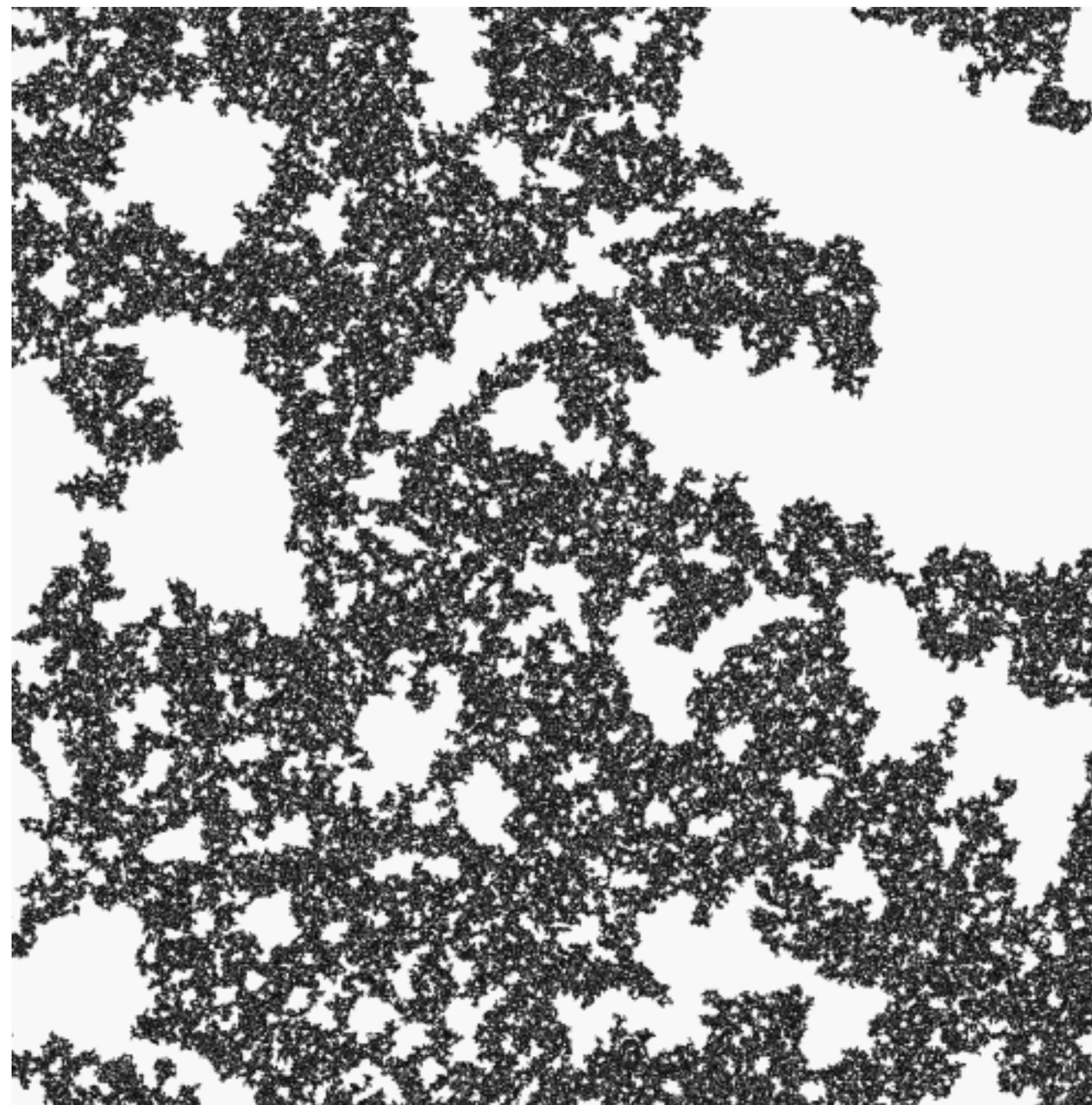
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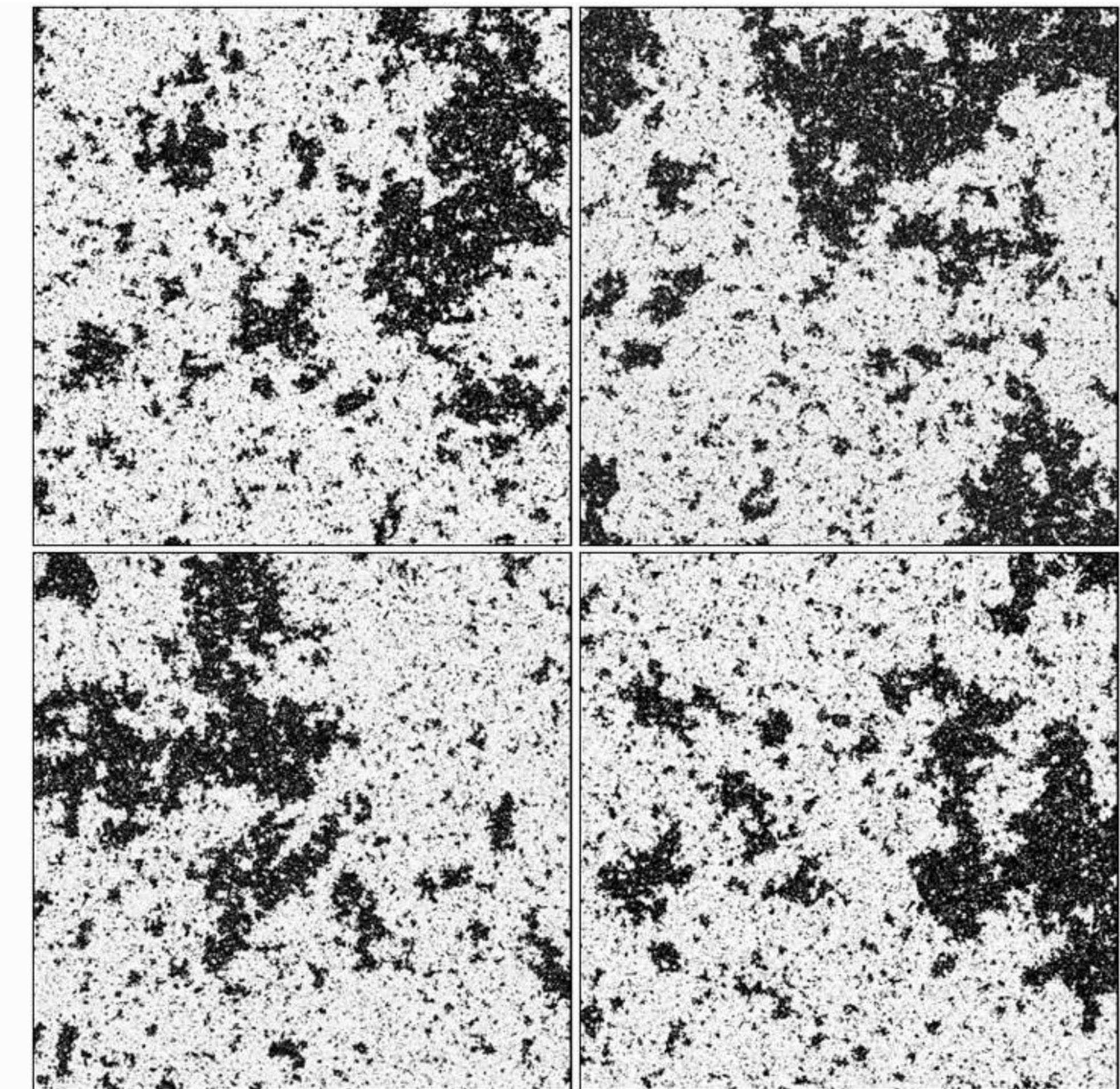
Diverging correlation length
Fluctuation of the magnetization at all scales

Scale invariance: the system “looks the same” at all scales (i.e. when zooming in)

Scale invariance: the system remains unchanged (in a statistical sense) by coarse-graining operation.



Scale invariance of critical percolating cluster



Scale invariance in the critical Ising Model

Renormalization Group

Theory of Complex Systems

Niki Stratikopoulou

University of Amsterdam



22 May 2023

Idea of RG

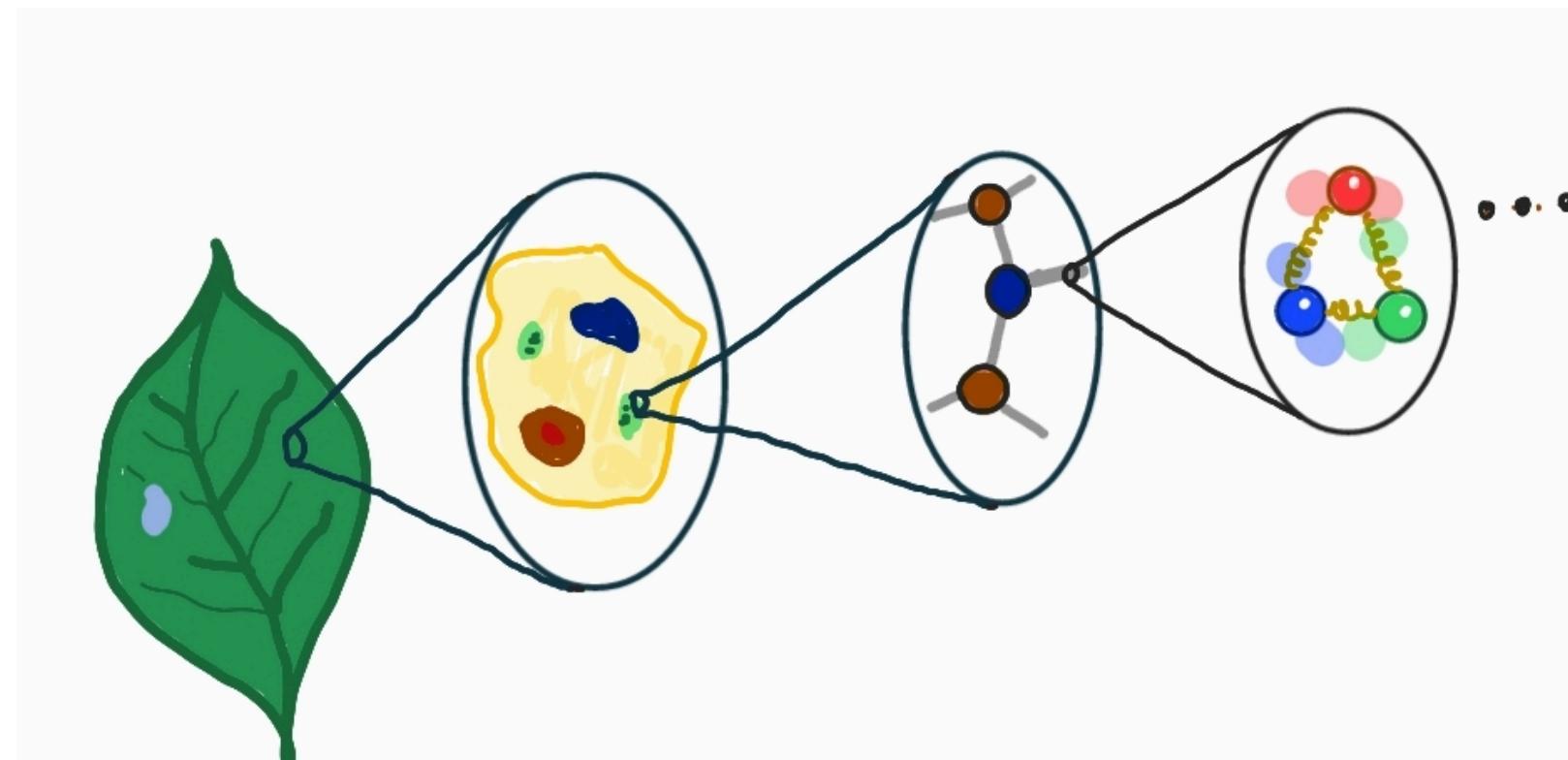
Main obstacle to understanding critical phenomena:

Fluctuations over **all scales** $a < x < \xi = \infty$ must be taken into account.

Can we simplify, by coarse-graining/integrating some of them?

Can we zoom out until smallest fluctuations disappear?

How does a system behave under **change of scales** ?



Idea of RG

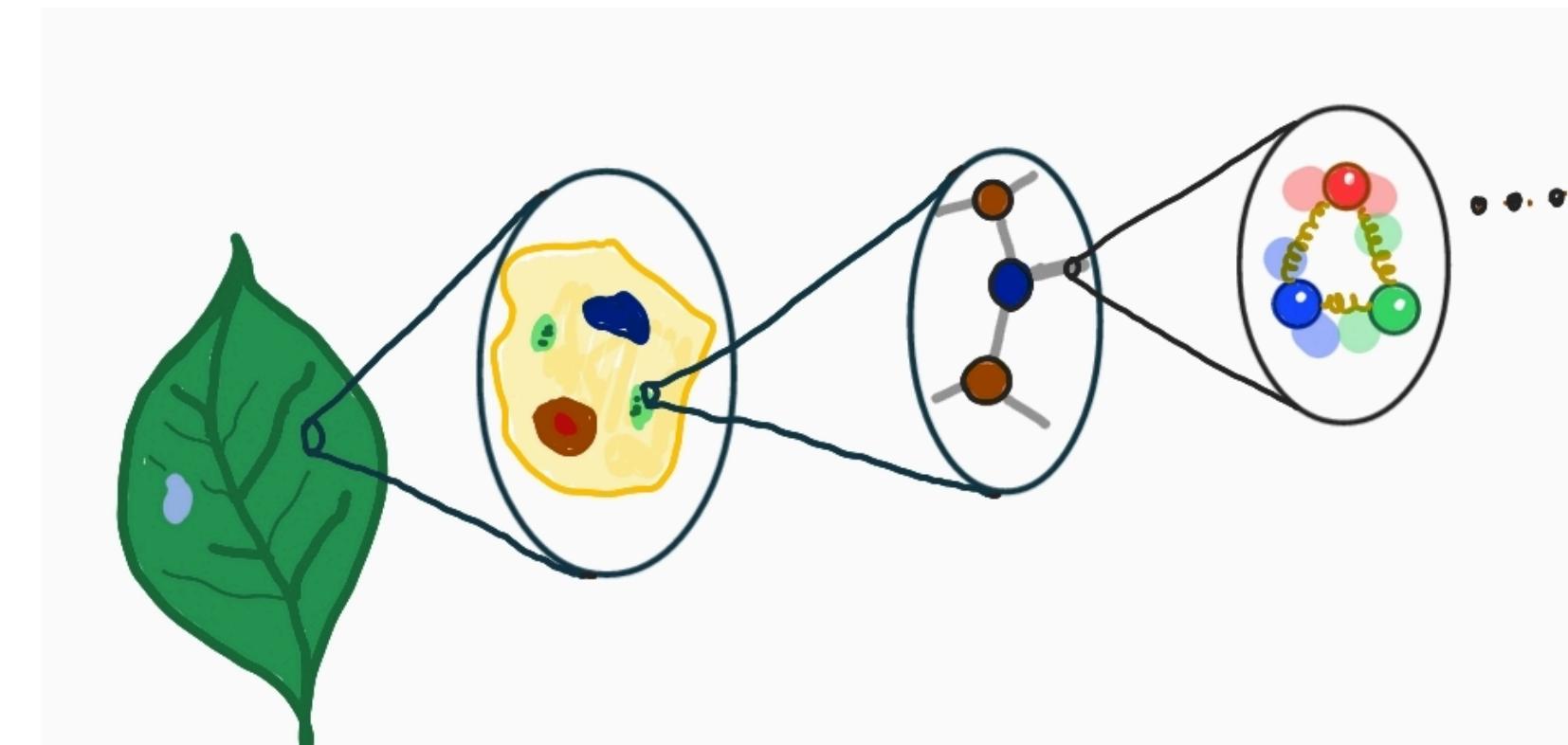
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The interactions change...

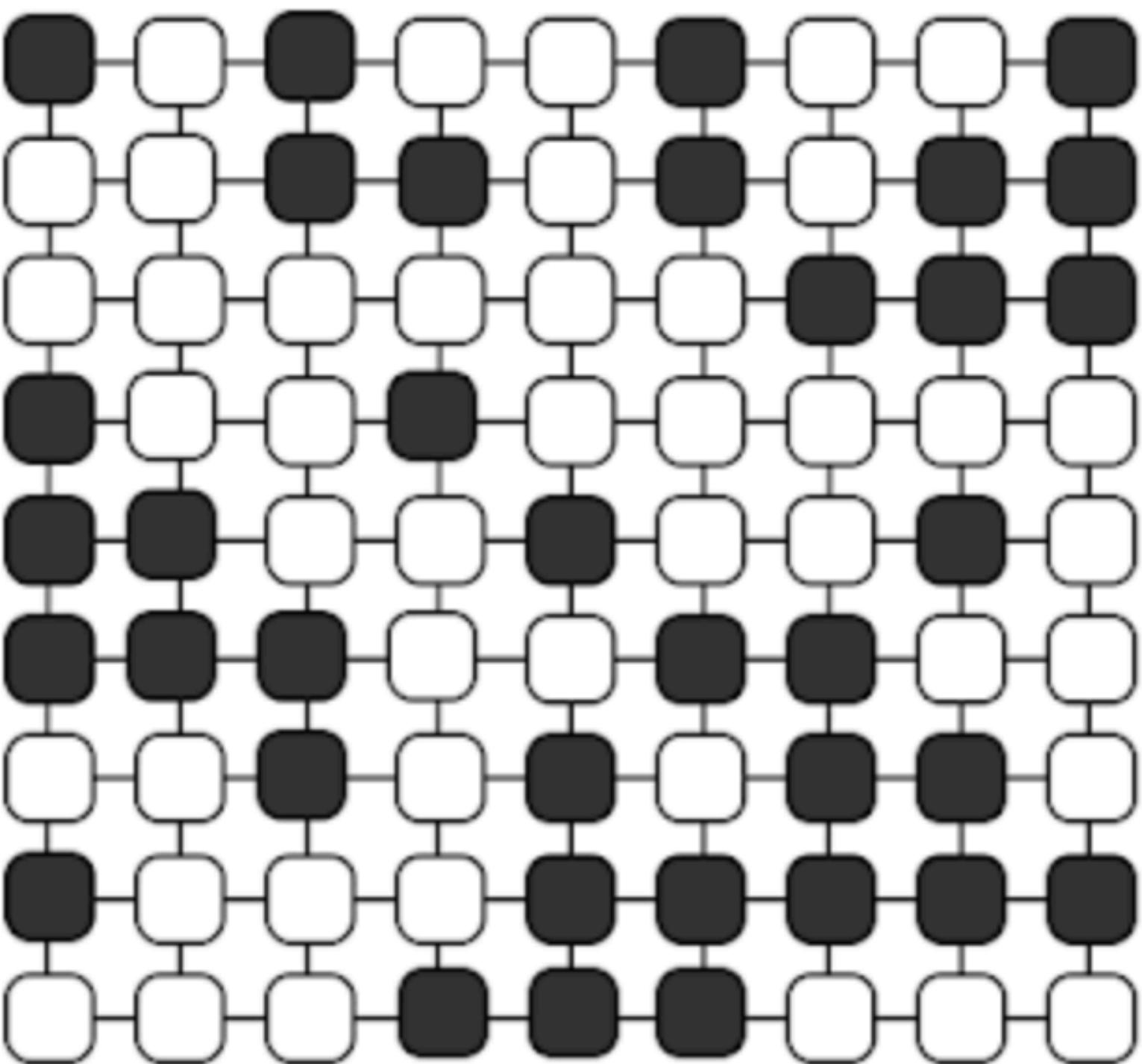
As we zoom out,
not all the details of fluctuations are important
we could remove them by integrating over them

If the physics is the same on all length scales,

then we should be able to rescale the system,
to cast it on a different length scale, and get back the original system.

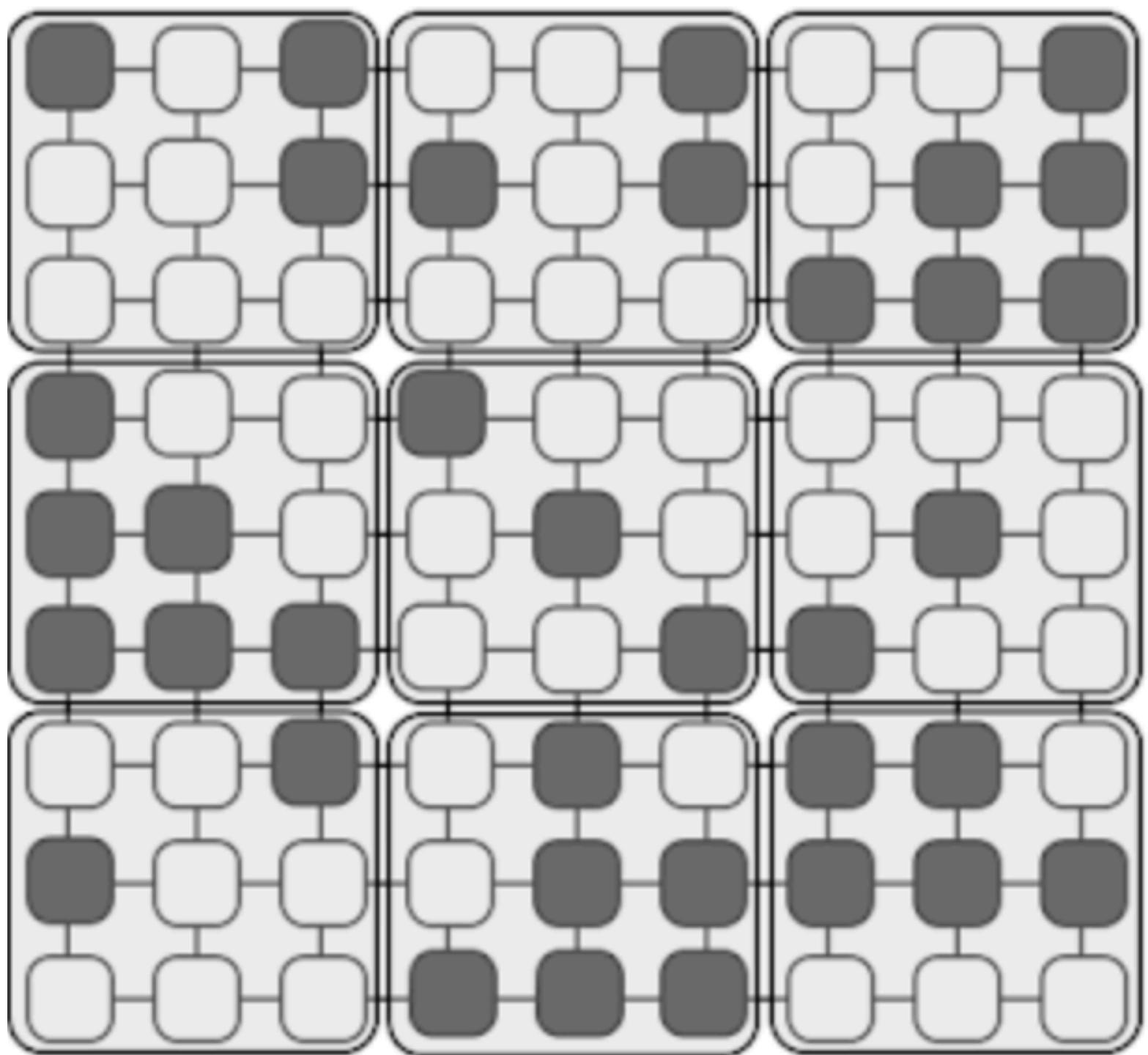
Idea of RG

Example: Take an Ising model configuration



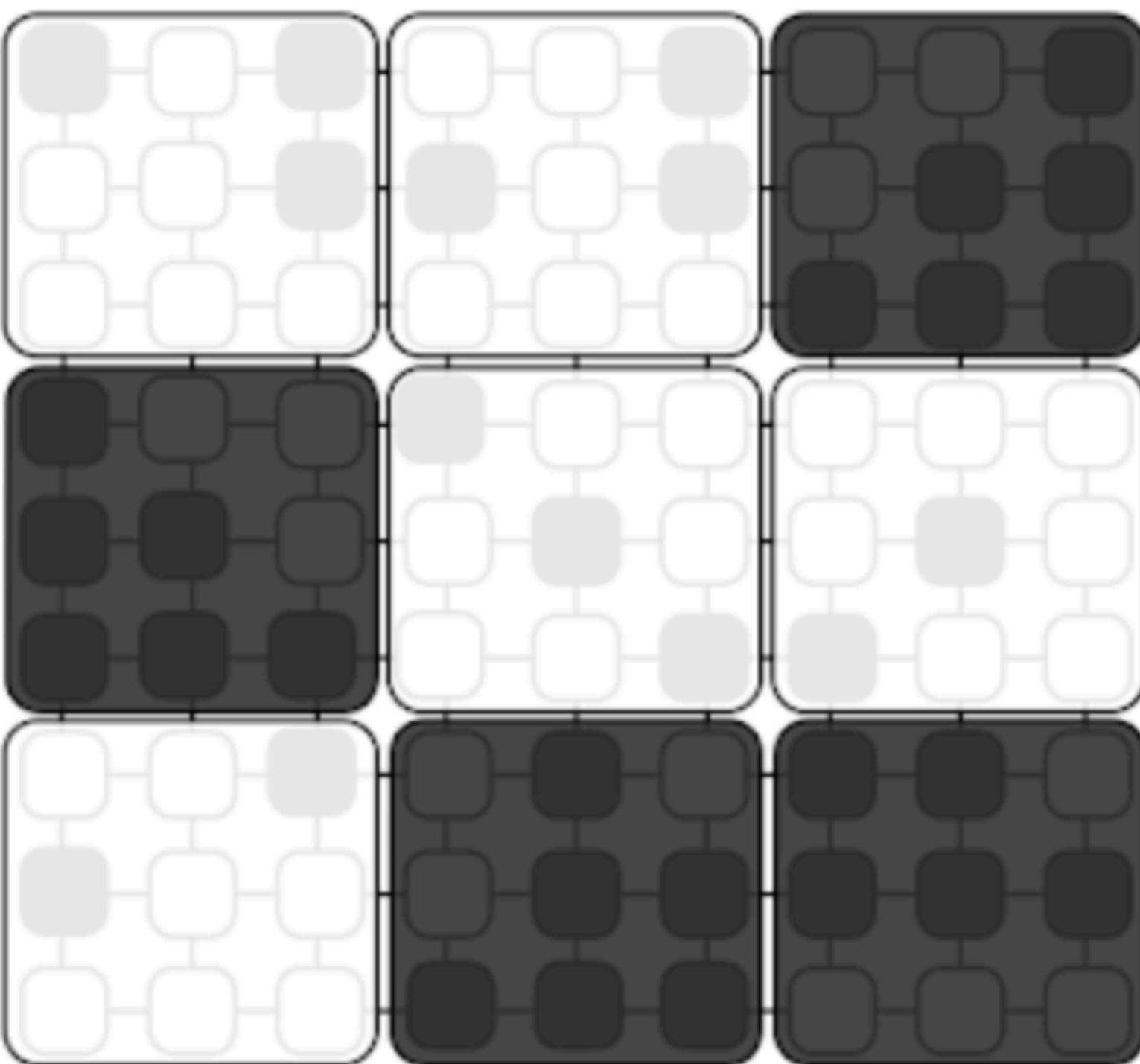
Idea of RG

Example: group neighboring variable by block



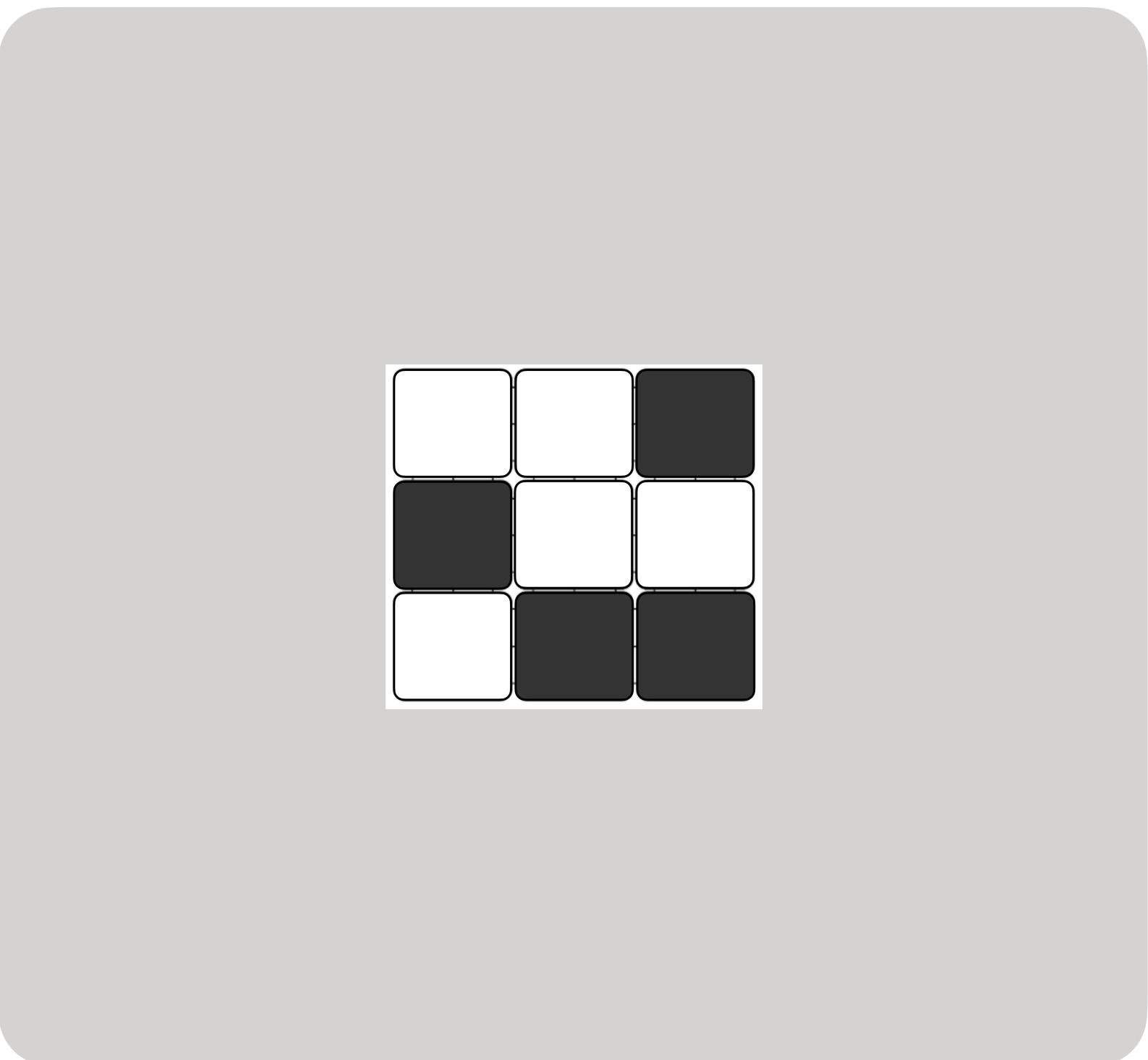
Idea of RG

Example: apply a majority rule



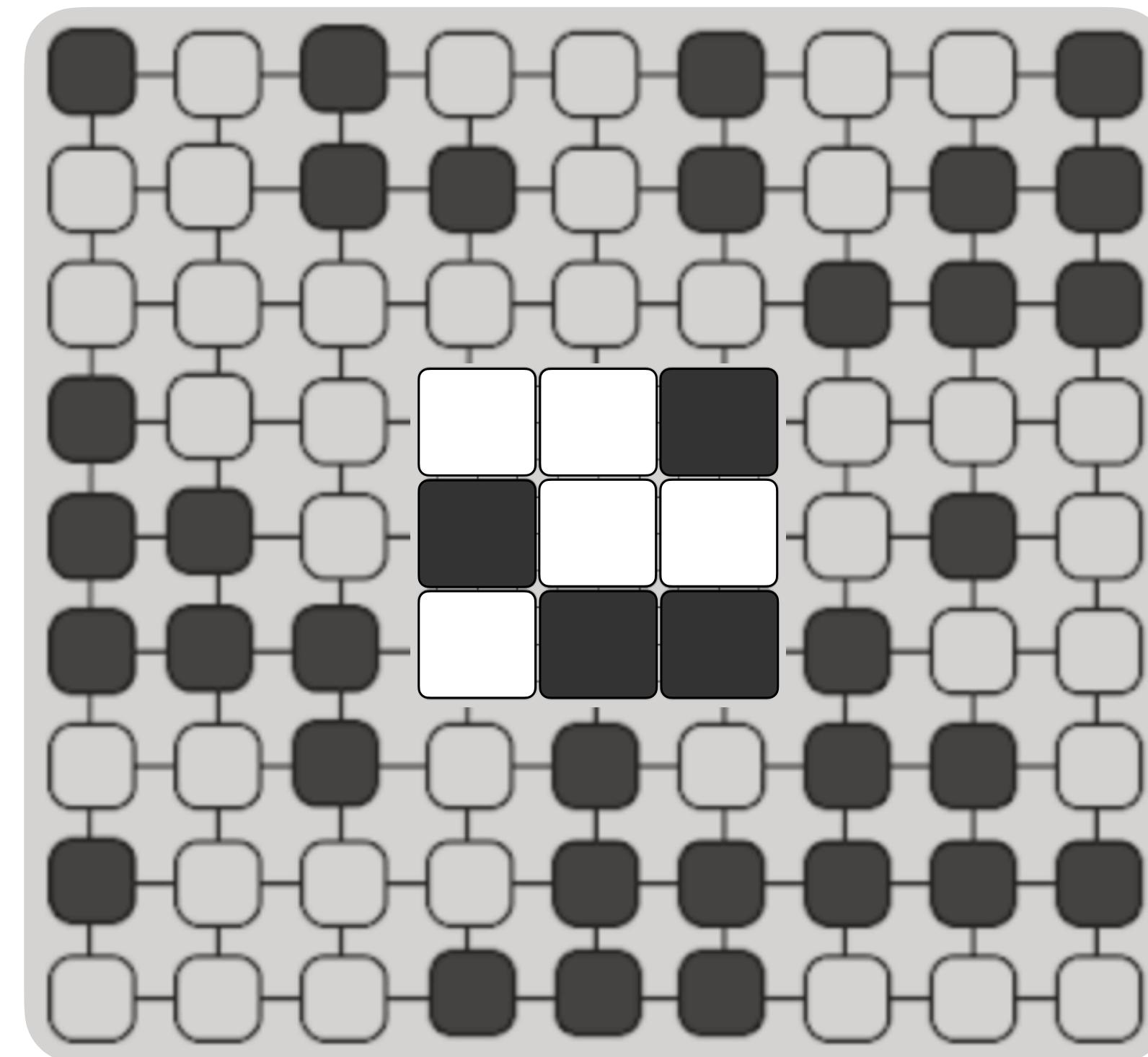
Idea of RG

Example: rescale (zoom out)



Idea of RG

Example: rescale (zoom out)

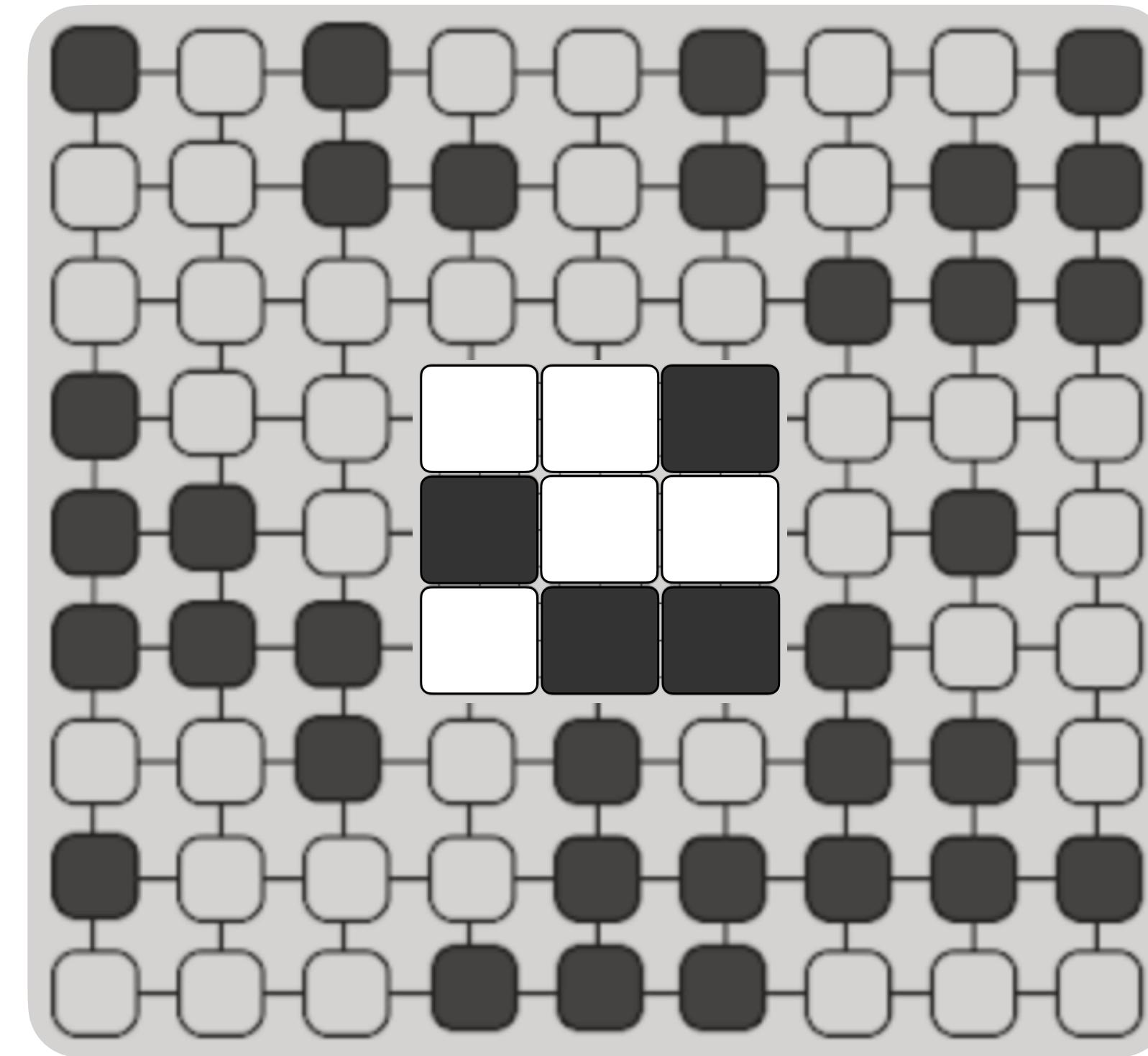


Could this still be modeled by the same Ising model?

(Assume we do this procedure for many states for instance, to have a new ensemble distribution)

Idea of RG

Example: rescale (zoom out)

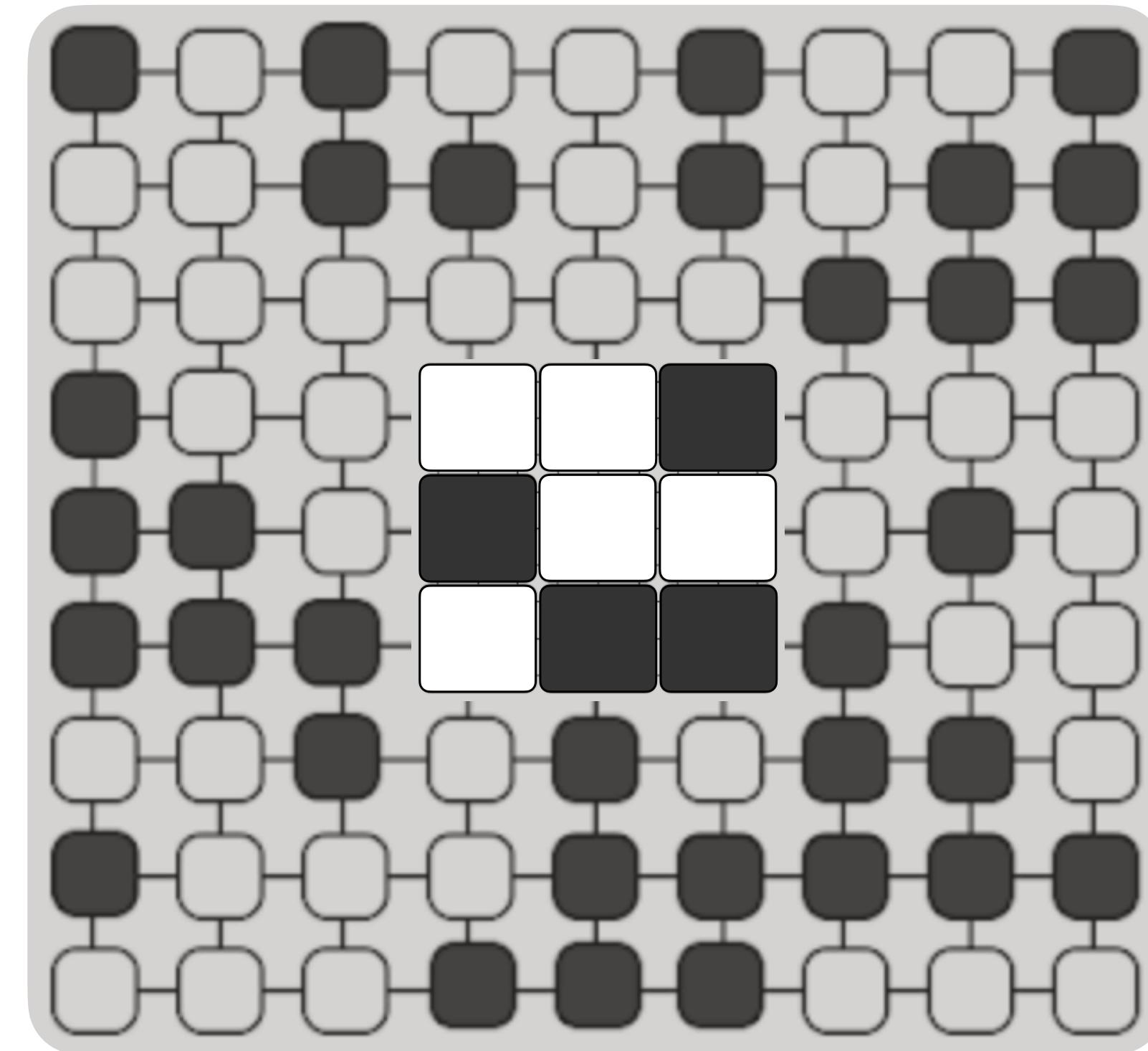


Could this still be modeled by the same Ising model? (Assume we do this procedure for many states for instance, to have a new ensemble distribution)

If so, how would the coupling change compared to the original model?

Idea of RG

Example: rescale (zoom out)

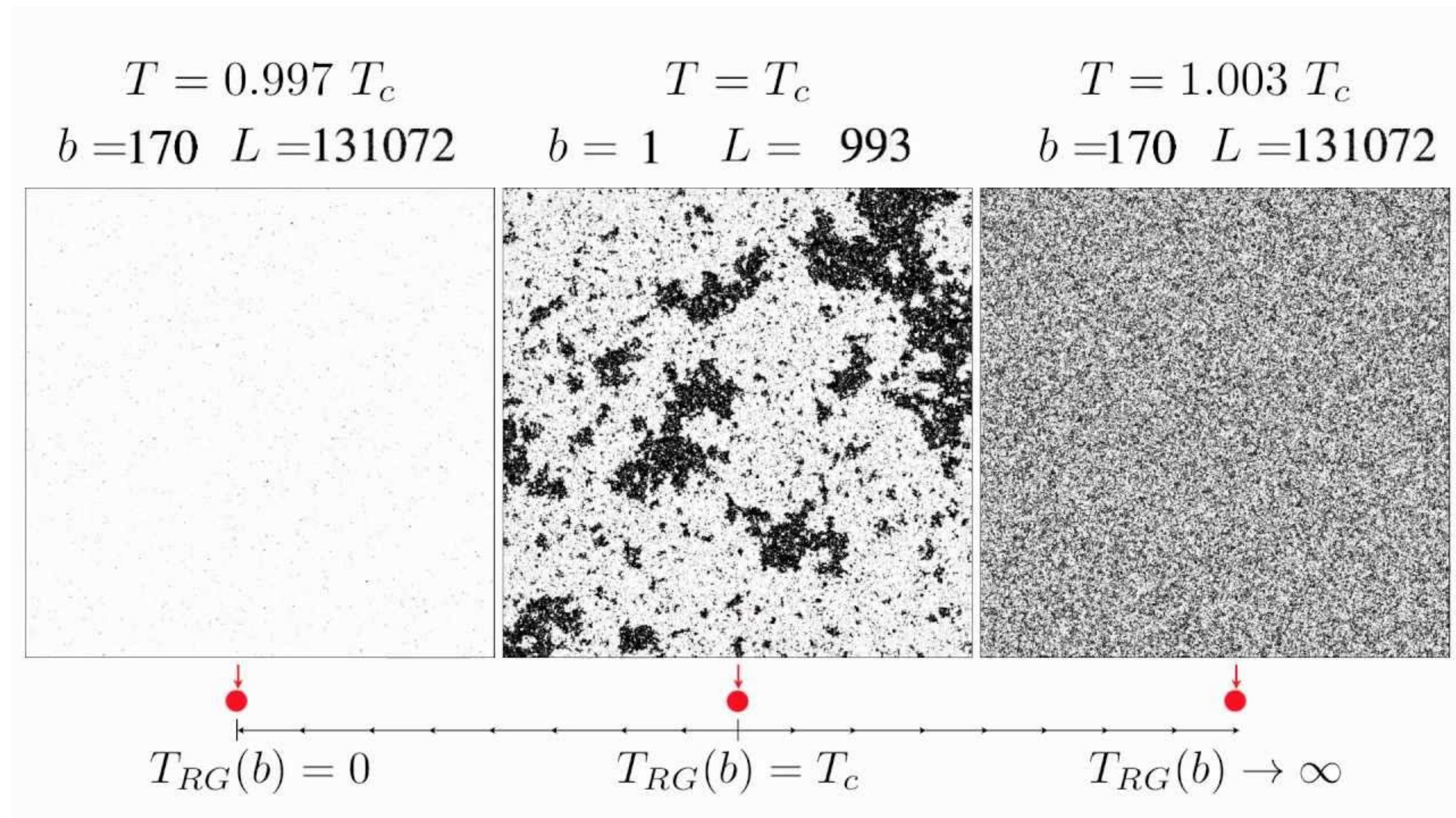


Could this still be modeled by the same Ising model? (Assume we do this procedure for many states for instance, to have a new ensemble distribution)

If so, how would the coupling change compared to the original model?

At which temperature would this new system be?

Idea of RG



Renormalization Group (RG): a formal method that allows systematic investigation of the changes of a physical system as viewed at different scales

Idea of RG

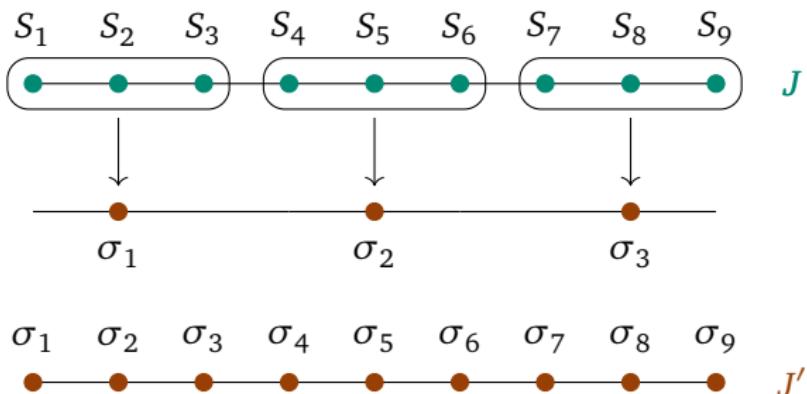
Renormalization Group (RG): a formal method that allows systematic investigation of the changes of a physical system as viewed at different scales

Renormalization 1D Ising

RG transformations

Kadanoff's block spin RG

1. Divide lattice into blocks of size b (b spins).
2. Replace each block of sites by a single site (1 Big spin).
3. Rescale all lengths by the factor b , to restore the original lattice spacing.
4. Repeat.



RG transformations

There are many choices of RG transformations → different coarse graining procedures / RG schemes.

E.g.

1. Kadanoff's Block spin:

$$\sigma_k^{(n+1)} = \sigma_j^{(n)}, \quad j \in \mathcal{B}_k$$

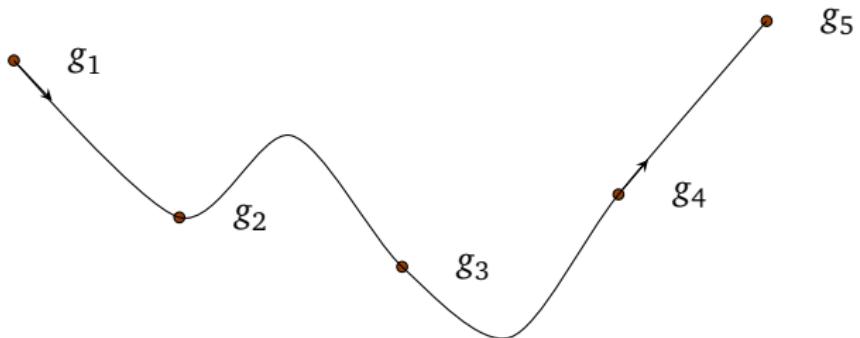
2. Majority rule

$$\sigma_k^{(n+1)} = A^{(n)} \sum_{i \in \mathcal{B}_k} \sigma_i^{(n)}$$

Fixing one, in each step we generate an *effective Hamiltonian* $H^{(n+1)}(\{\sigma_i^{(n+1)}\}, g_k^{(n+1)})$ describing the system of the block spins, with new **effective couplings** g_k .

No inverse transformation...

Flow of couplings



Fixed points can occur.

At criticality $\xi = \infty$

$$\xi \rightarrow \frac{\xi}{b} \rightarrow \frac{\xi}{b^2} \rightarrow \dots \rightarrow \frac{\xi}{b^n} = \infty .$$

System will still look critical!

RG for the 1d Ising model

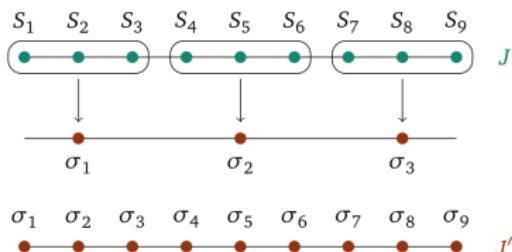
$$H(s_i; J) = J \sum_i s_i s_{i+1} \quad \text{where} \quad J \leftarrow J/(k_B T)$$

Each pair of spins has the Boltzmann weight

$$W(s_i, s_{i+1}; t) = e^{J s_i s_{i+1}} = \cosh J (1 + t s_i s_{i+1}) \quad [\text{cf. tutorial}],$$

where $t := \tanh(J)$

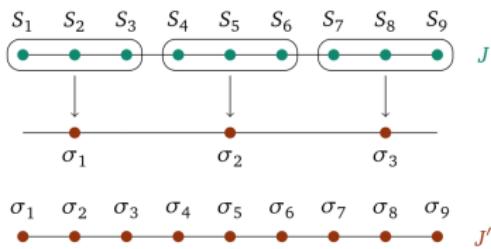
Divide into blocks of 3 spins &
keep spin at center:



RG for the 1d Ising model

1st RG step

Consider two neighboring blocks;
fix spins at center $\sigma_1 \equiv S_2$, $\sigma_2 \equiv S_5$
and sum over intermediate spins
 S_3, S_4 . Boltzmann factor:



$$\sum_{S_3, S_4} e^{JS_1S_3} e^{JS_3S_4} e^{JS_4\sigma_2} = (\cosh J)^3 (1 + t\sigma_1 S_3) (1 + tS_3 S_4) (1 + tS_4 \sigma_2)$$
$$= 2^2 (\cosh J)^3 (1 + t^3 \sigma_1 \sigma_2)$$

RG for the 1d Ising spin

Reflect:

Initial Boltzmann factor: $W(s_i, s_{i+1}; t) = \cosh J(1 + ts_i s_{i+1})$

After 1st RG step: $W(\sigma_i, \sigma_j; t) \sim \cosh^3(J)(1 + t^3 \sigma_i \sigma_j)$

Equivalent if we define

$$\begin{aligned} t' &\equiv \tanh J' = t^3 \equiv (\tanh J)^3 \\ \Leftrightarrow J' &= \tanh^{-1}[(\tanh J)^3] \end{aligned}$$

New *effective* Hamiltonian:

$$H(\sigma_i; J') = \underbrace{A(J)}_{\text{from mult. factors}} - J' \sum_i \sigma_i \sigma_{i+1}$$

+ a **recursion relation** for couplings.

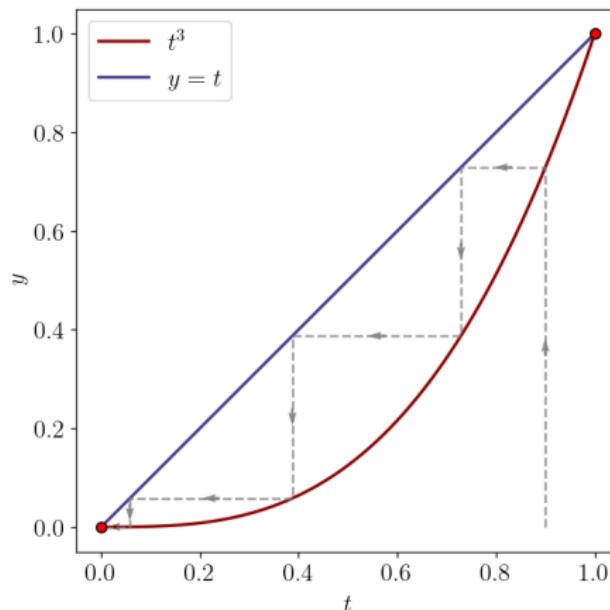
RG for the 1d Ising model

Fixed points

Plot recursion relation

$$t' = t^3.$$

At fixed points: $t' = t$.



RG for the 1d Ising model

Fixed points

- $t = 1$ unstable f.p.
- $t = 0$ stable f.p.

Approaching $t \equiv \tanh J = 0 \Leftrightarrow J = 0$,
corresponds to approaching the high temperature phase ($J \leftarrow J/(k_B T)$).



1d Ising model is always in its disordered phase
(non-interacting spins).



self-similar with $\xi = 0$ (trivial RG f.p.)

∅ phase transition in the 1d case.

RG for $d = 1$ Ising model

Generalize recursion relation

Sum over (integrate out) $k-1$ consecutive spins.

$$\sum_{S_1, \dots, S_{k-1}} e^{J(S_0S_1 + \dots + S_{k-1}S_k)} \sim \cosh^k(J)(1 + t^k S_0 S_k).$$

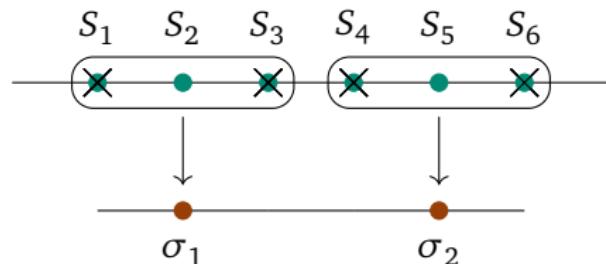
Middle terms, with spins that we sum over, cancel out, like in the case of the two intermediate spins \implies only boundary spins survive (and identity), with coefficient $t^{\text{len(summed spins)}+1}$

$$t' \equiv \tanh(J') = t^k = \tanh^k(J).$$

RG for $d = 1$ Ising model

Heuristics

For the $1d$ case:



at $T \rightarrow 0 \Leftrightarrow J \rightarrow \infty$, spins almost aligned in same state

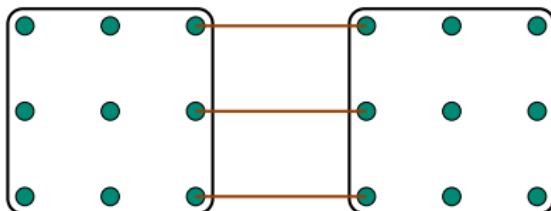
$$J' \simeq J \underbrace{\langle s_3 \rangle_{\sigma_1=1} \langle s_4 \rangle_{\sigma_2=1}}_{\text{boundary spins we integrate over}}.$$

The interaction between adjacent blocks is mediated by their boundary spins.

$$|\langle s_i \rangle| \leq 1 \text{ (max at } T = 0 \text{)} \Rightarrow J' < J.$$

RG for Ising in $d > 1$

In $d > 1$,



$$J' \simeq b^{d-1} J, \quad \text{for } J \rightarrow \infty, b \text{ the block size} .$$

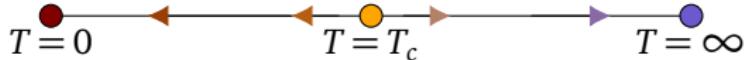
So for $d > 1$, $J' > J \Rightarrow$ the low-T f.p. is now **attractive**.

At high-T the system has to be in a paramagnetic phase \Rightarrow high-T f.p. must also be stable.

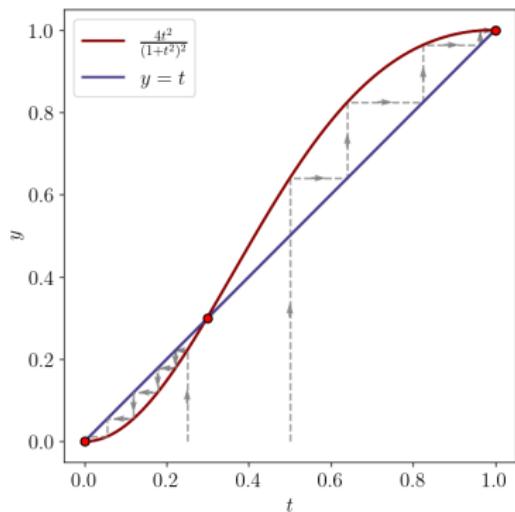


There must be a **phase transition**.

RG for Ising in $d > 1$



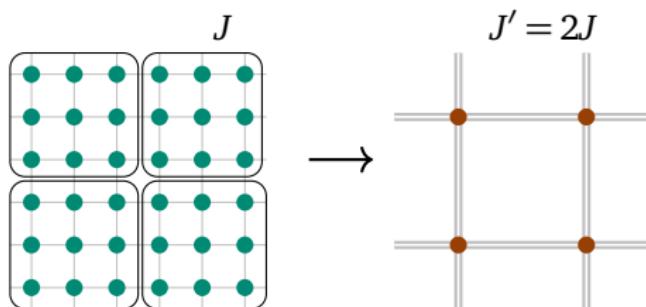
Cobweb plot from analytic recursion relation:



[link to video](#)

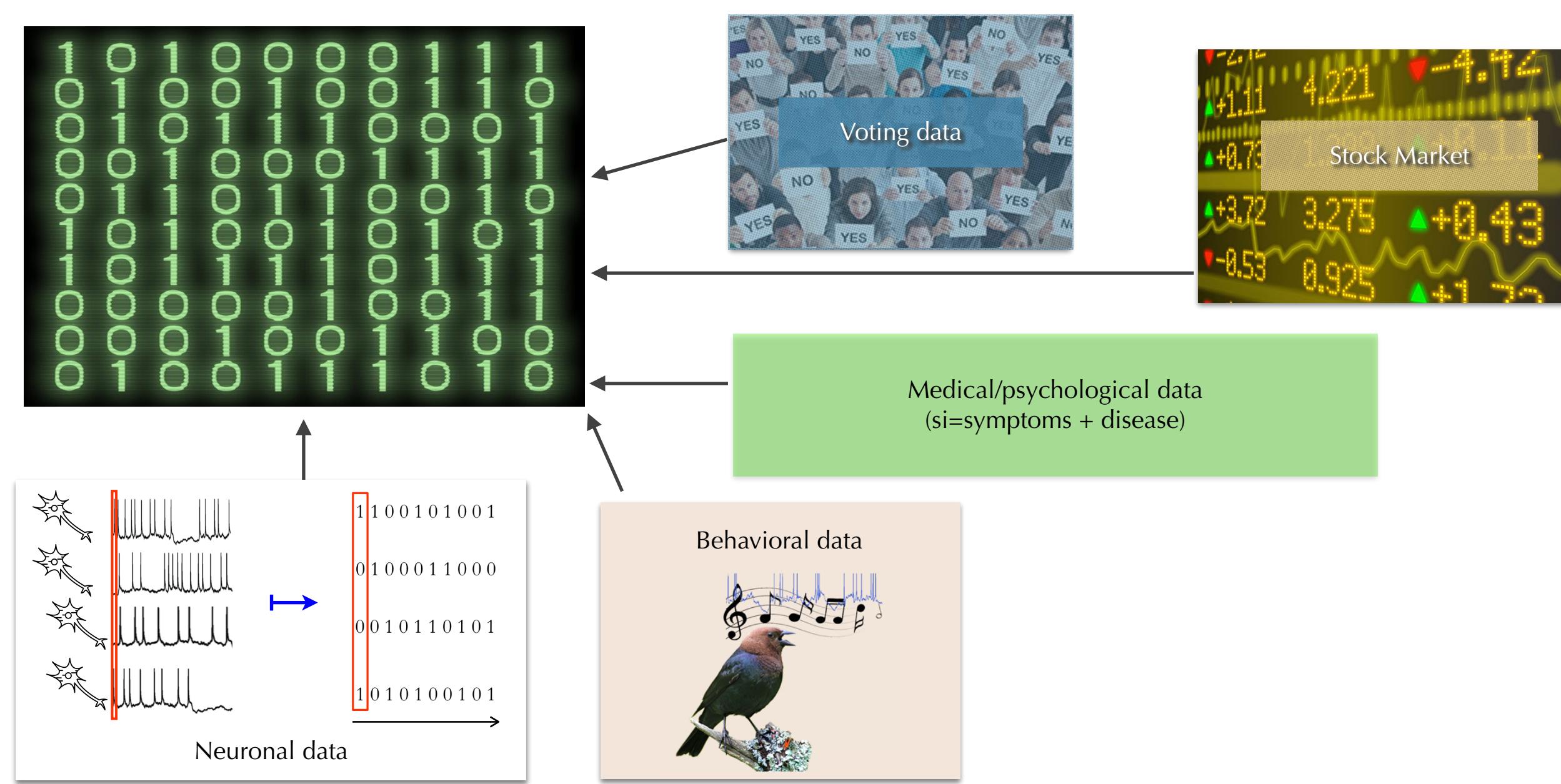
RG for 2d Ising model

One possible RG scheme



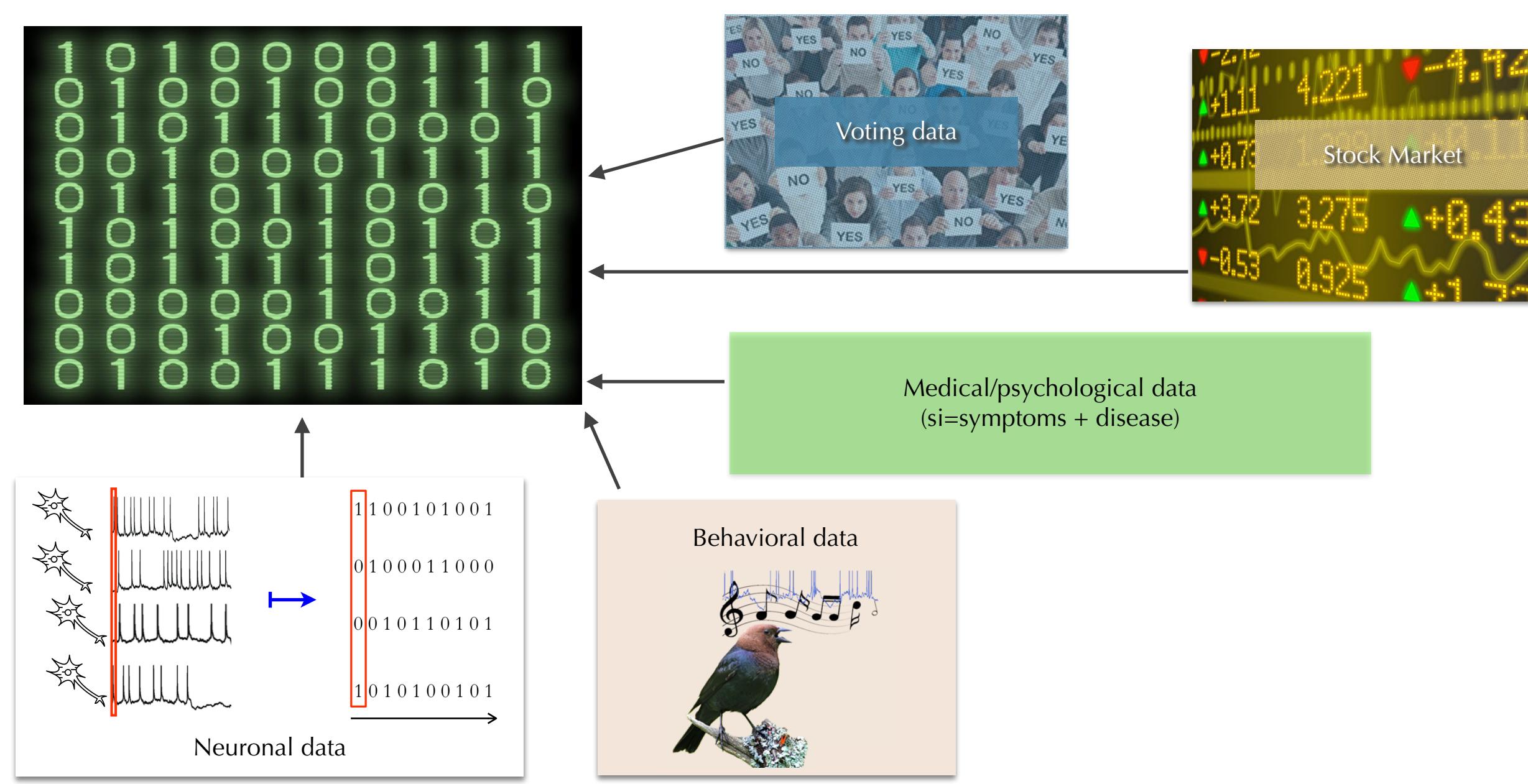
$$t' \equiv \tanh(J') = \tanh^2(2J).$$

Use $\tanh(2x) = \frac{2\tanh(x)}{1+\tanh^2(x)}$ \rightarrow recursion relation \rightarrow Cobweb plot.



Application to real data?

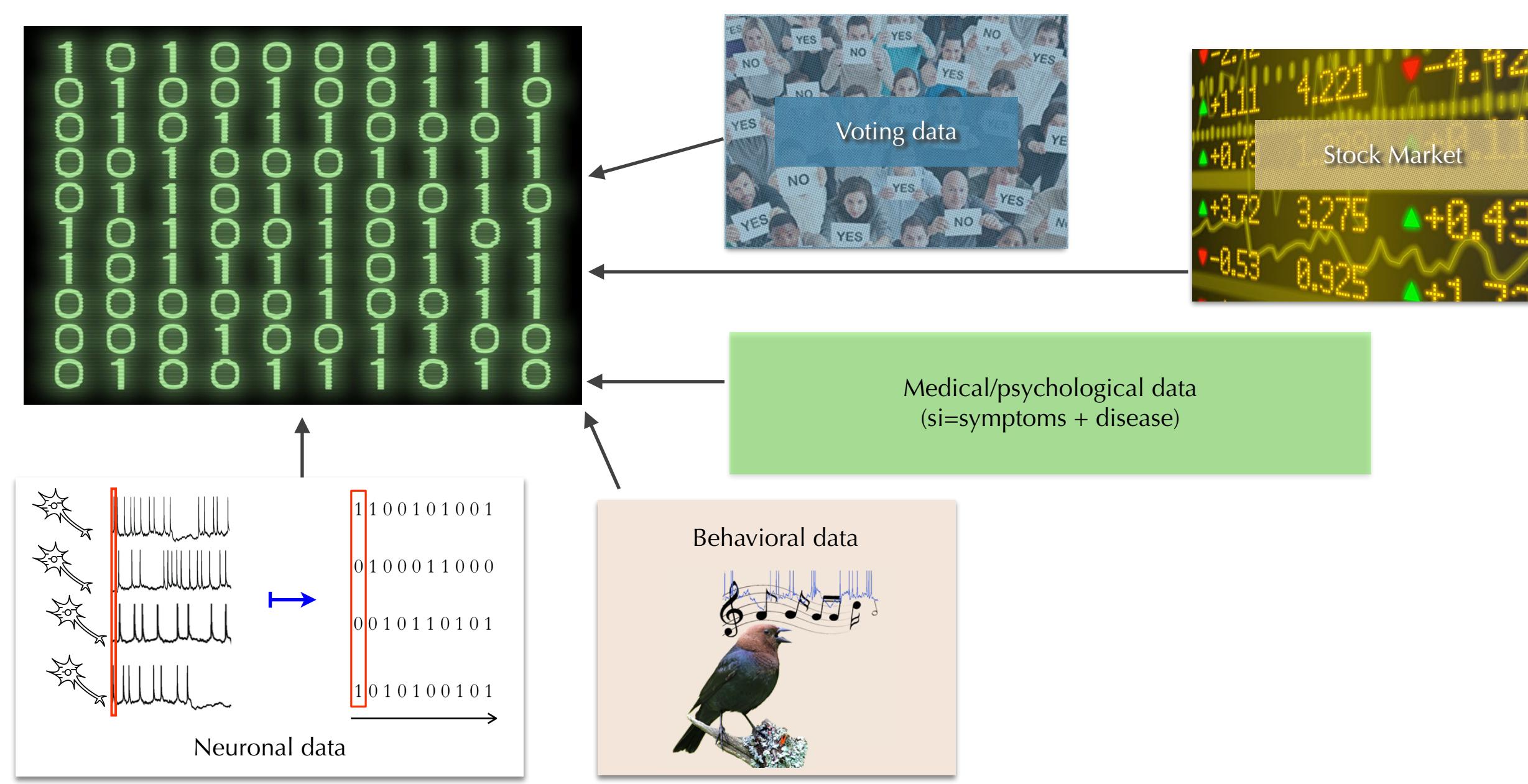
Any issue?



Application to real data?

Issue: There's no notion of locality; we don't have any notion of locality!

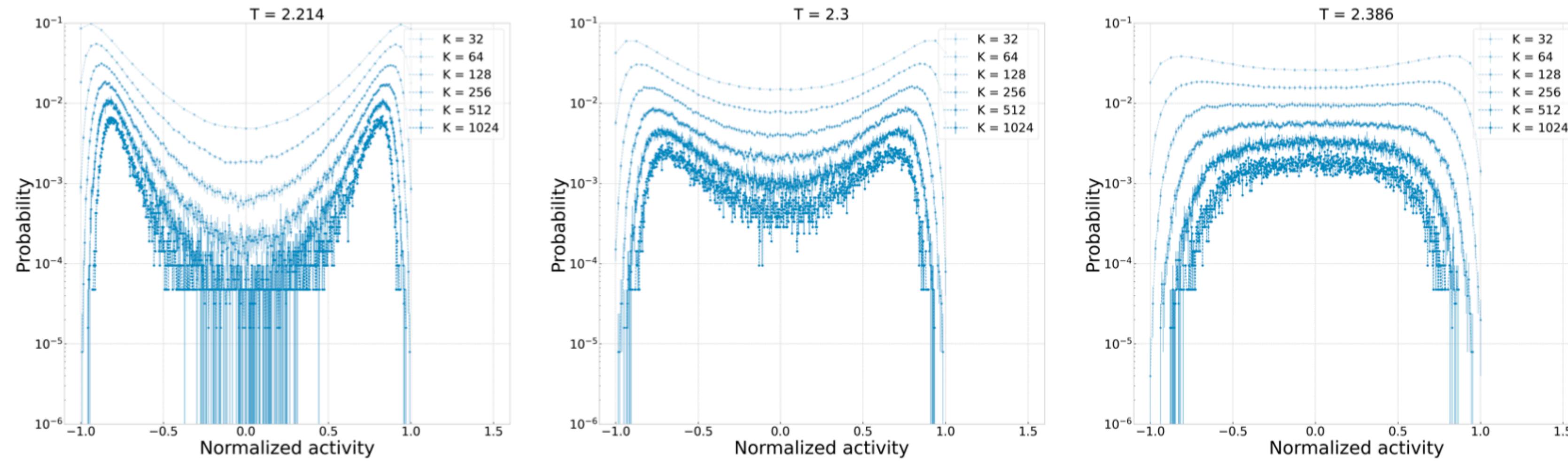
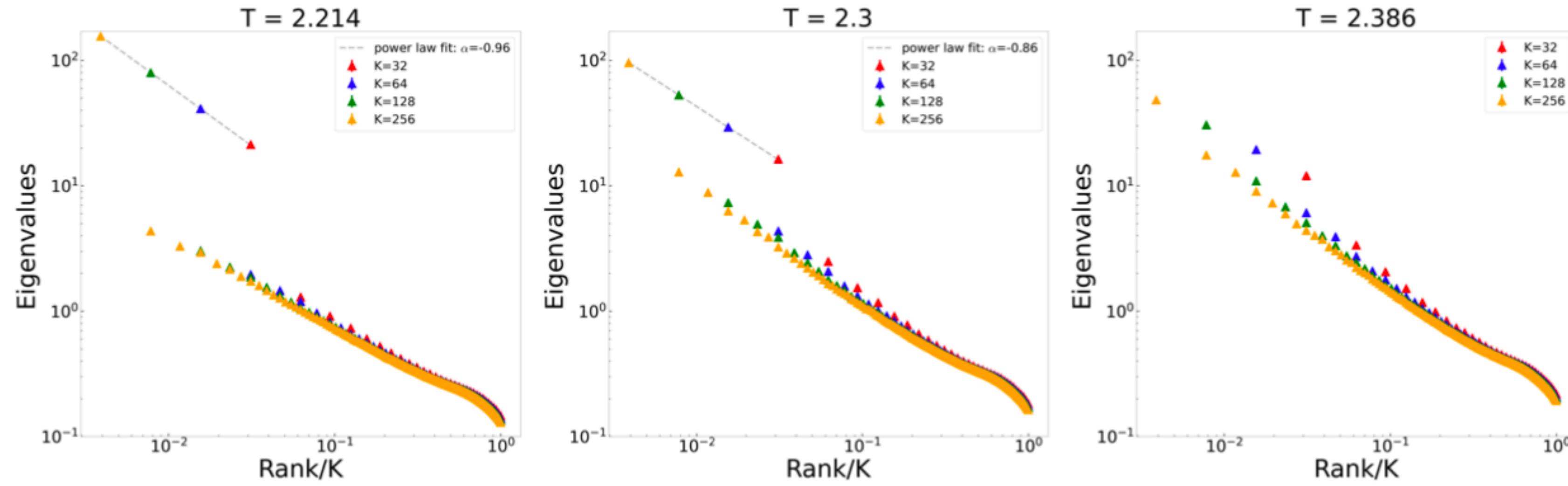
we need a way to define locality....



Application to real data?

Issue: There's no notion of locality; we don't have any notion of locality!

Idea: We will coarse-grain variables that are the most correlated.



T < T_c

T = T_c

T > T_c

Application to real data?

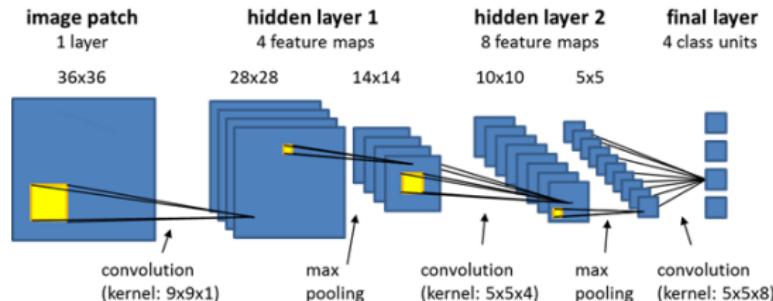
Any issue?

Applications

ML

Convolutions

- How CNNs learn to extract the important features from data?
- Iterative **coarse-graining** scheme; each new layer of NN learns increasingly abstract higher-level features.

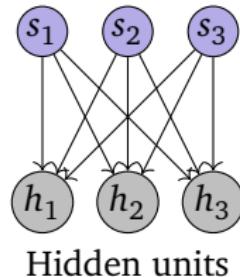


Applications

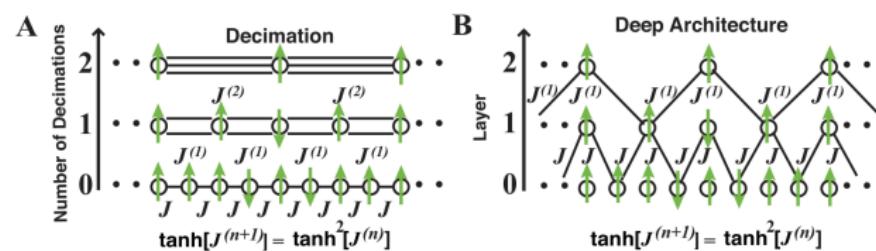
ML

Restricted Boltzmann Machines (RBM)

Visible units



[Mehta, Schwab, 2014]



A: 1d RG procedure

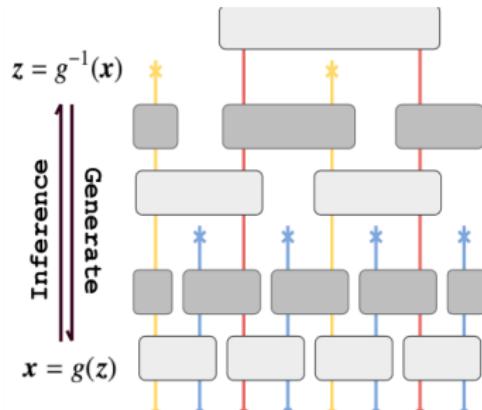
B: DNN architecture with weights J^n between $(n+1)$ and n -th hidden layer

Applications

ML

RG inspired architectures

Stacking bijections to form a reversible transformation of a probability density.



[Li,Wang, 2018]

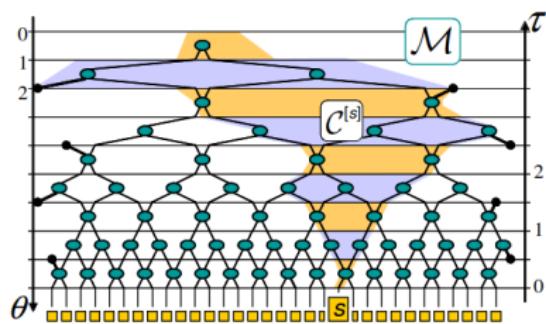
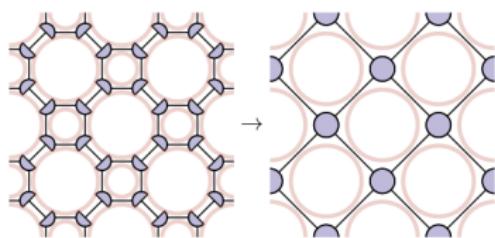
Alternation between
disentangler blocks and
decimator blocks.

disentangler blocks : Reduce correlation between inputs.
decimator blocks : Pass only subset of outputs to next layer.
Crosses → irrelevant latent variables.

Applications

Tensor Networks

(transform quantum states instead of probability densities)



Multi-Scale Entanglement Renormalization Ansatz (MERA)

[Vidal, 2006]