

Unsupervised learning universal critical behavior via the intrinsic dimension

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International Centre
for Theoretical Physics

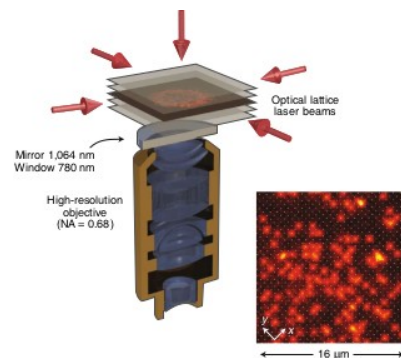


Large data sets

Handwriting



Physical data sets [Many-body physics]



Large [high-dimensional]
data sets



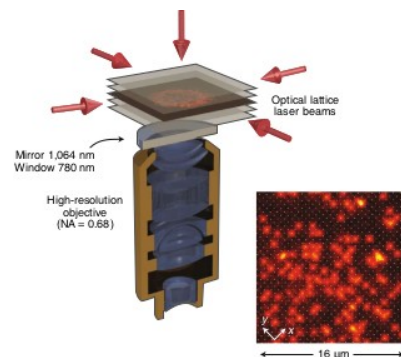
Extract information
[Characterize **phases of matter** and **their transitions**]

Handwriting



0	0	0	1	0	1	1	0
0	1	1	1	0	1	0	1
0	1	0	0	1	0	0	1
...							
0	0	0	0	1	0	1	1

Physical data sets
[Many-body physics]

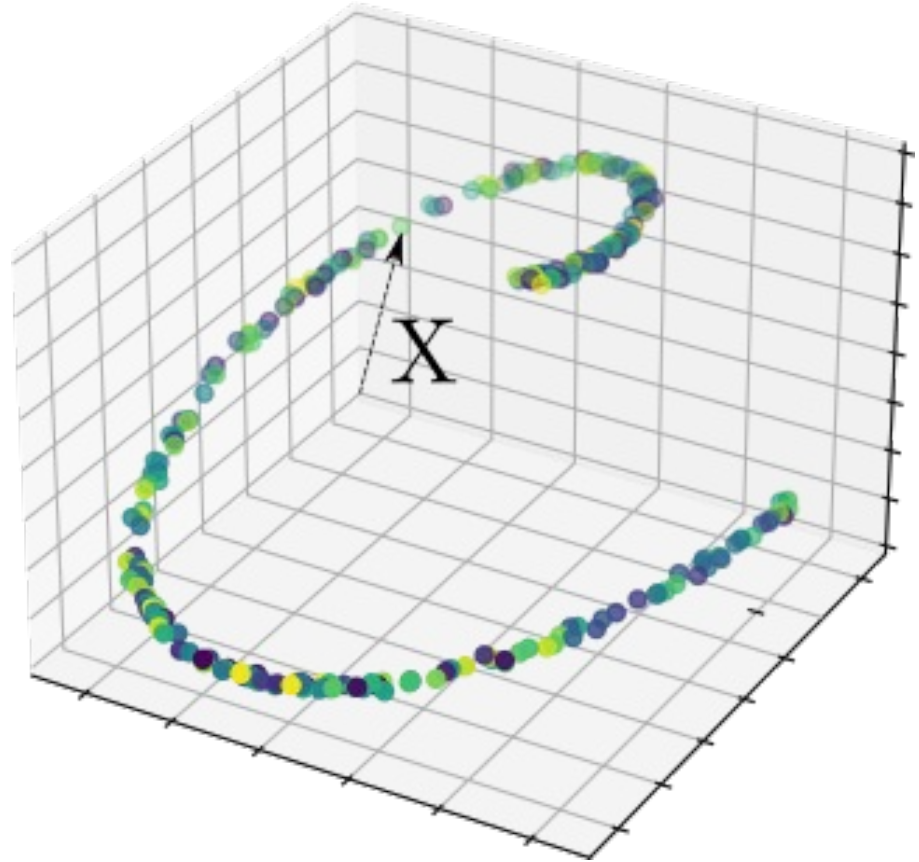


Intrinsic dimension (ID)

Data set lies in a manifold
whose ID is lower than the
number of coordinates

$$\vec{X} = (x_1, x_2, x_3)$$

$$\text{ID} = 1$$

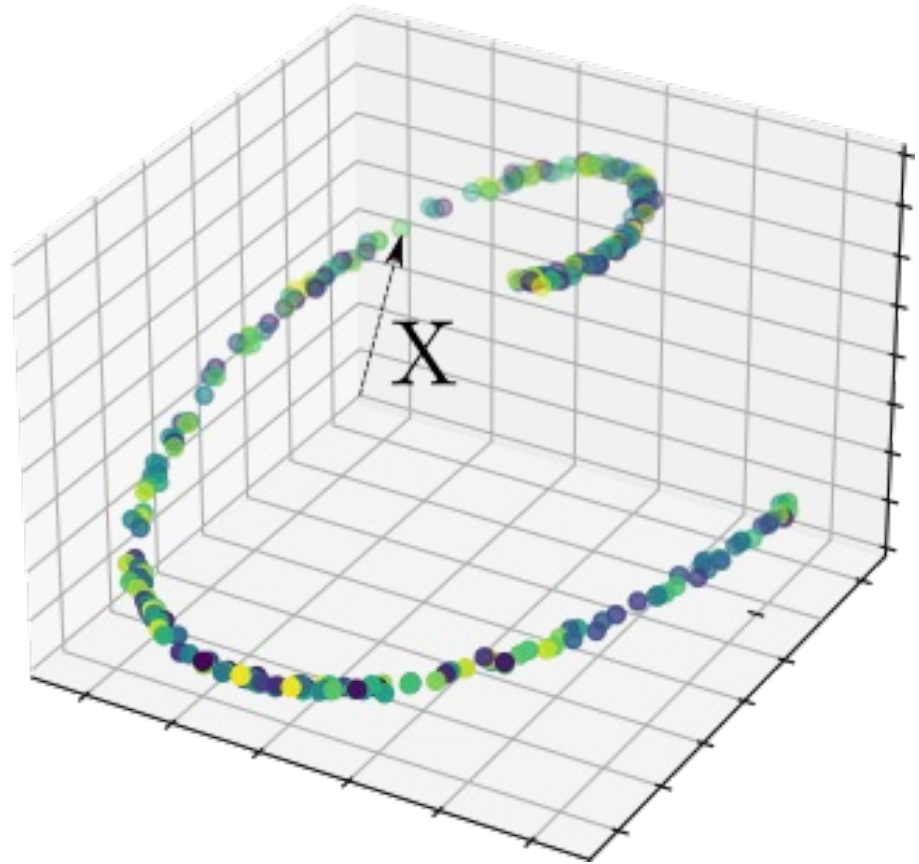


Intrinsic dimension (ID)

Data set lies in a manifold whose ID is lower than the number of coordinates

$$\vec{X} = (x_1, x_2, x_3)$$

$$\text{ID} = 1$$



Physical data sets ?

Partition-function data sets

$$\beta = \frac{1}{k_B T}$$

$$Z = \sum_{\vec{X}} e^{-\beta E(\vec{X})}$$

$$\vec{X} = (x_1, x_2, \dots, x_{N_s})$$

Partition-function data sets

$$\beta = \frac{1}{k_B T}$$

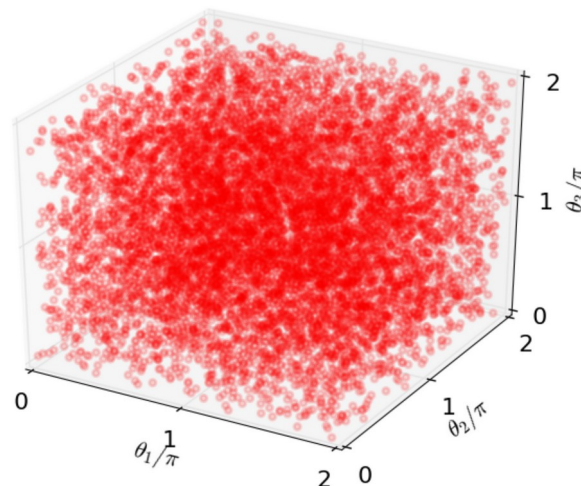
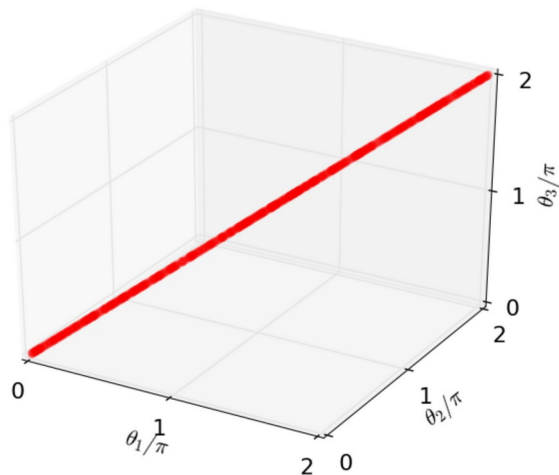
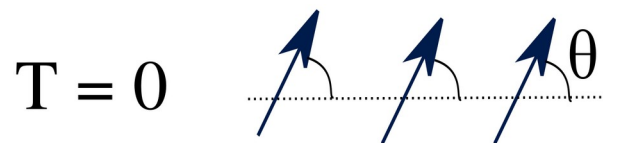
$$Z = \sum_{\vec{X}} e^{-\beta E(\vec{X})}$$

$$\vec{X} = (x_1, x_2, \dots, x_{N_s})$$

Set of points in a high-dimensional space

Partition-function data sets

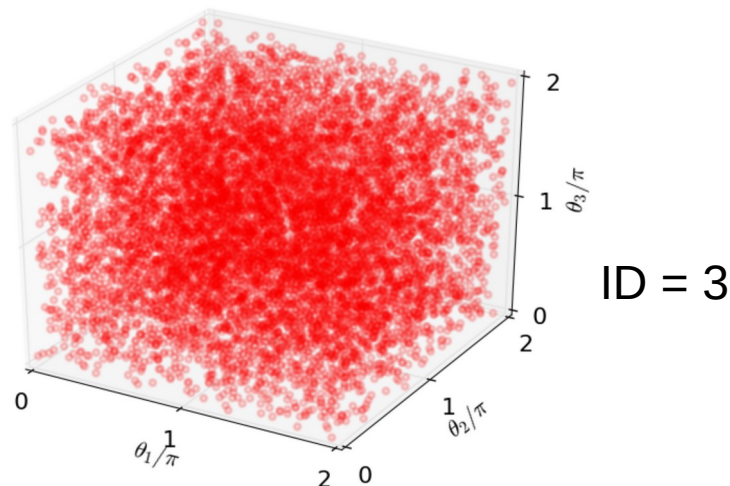
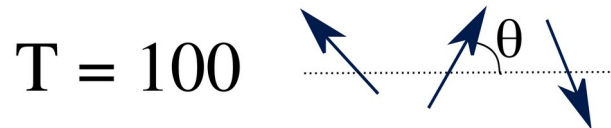
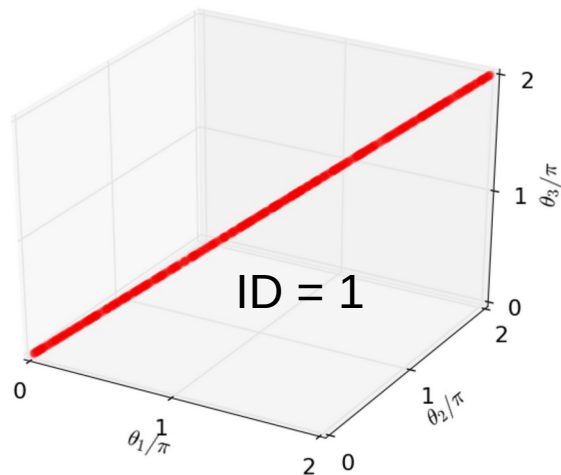
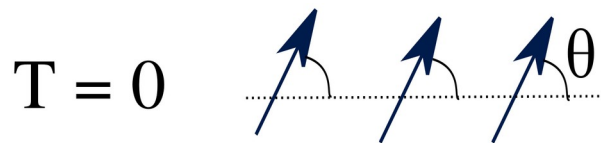
3-spin XY model



Partition-function data sets

3-spin XY model

$$Z = \sum_{\vec{X}} e^{-\beta E(\vec{X})}$$

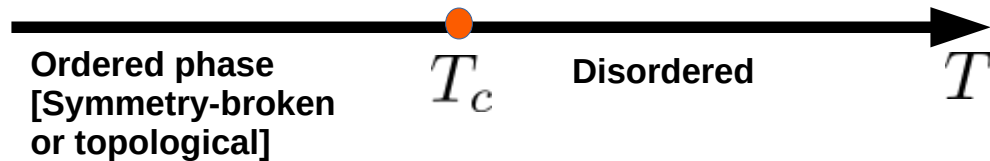


$$E(\{\vec{\theta}\}) = -J \sum_{\langle i,j \rangle} \cos(\theta_i - \theta_j)$$

$$\vec{\theta} = (\theta_1, \theta_2, \theta_3)$$

$$Z = \sum_{\vec{X}} e^{-\beta E(\vec{X})}$$

0	0	0	1	0	1	1	0
0	1	1	1	0	1	0	1
0	1	0	0	1	0	0	1
...							
0	0	0	0	1	0	1	1



ID of data sets emerging
in the vicinity of **phase
transitions**



Phase transition in
configuration space?

Extract information of the
system from raw data -
universal properties?

Outline

→ Machine learning phases of matter and phases transitions
[Many-body physics]

→ How to estimate the intrinsic dimension (ID)

→ ID and phase transitions

Machine learning → raw physical data sets

Characterize **phases of matter** and **their transitions**

→ Which physical quantity to measure?

Topological transitions, thermal-MBL transitions, ...

→ Detect the important degrees of freedom of a system

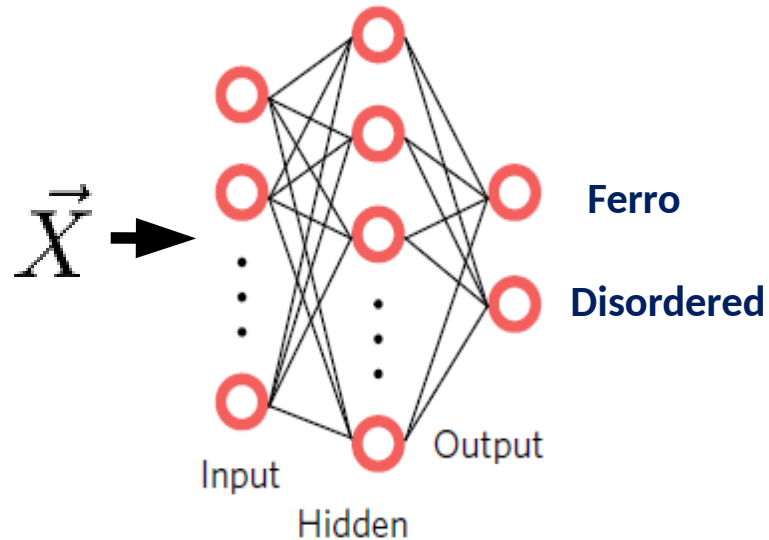
Supervised ML: Labeled configurations

Machine learning phases of matter

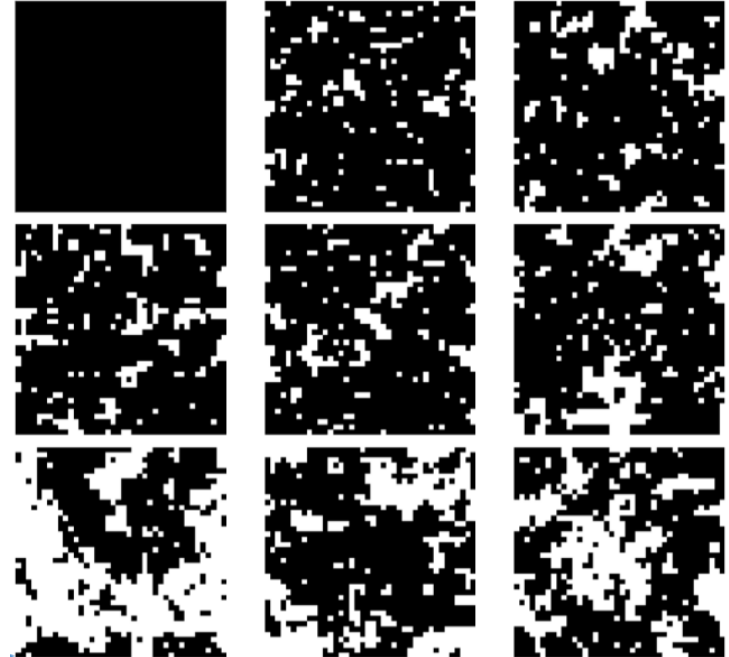
Juan Carrasquilla^{1*} and Roger G. Melko^{1,2}



(2017)



2D-Ising configurations

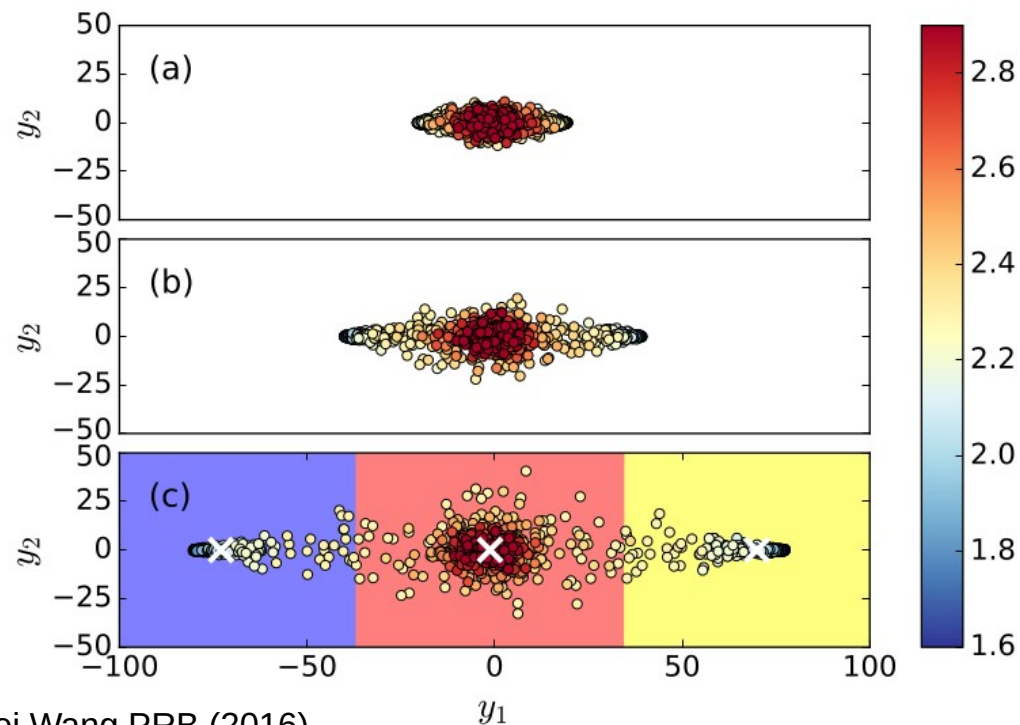


Unsupervised ML: Unlabeled configurations

Dimension reduction

0	0	0	1	0	1	1	0
0	1	1	1	0	1	0	1
0	1	0	0	1	0	0	1
...							
0	0	0	0	1	0	1	1

2D Ising model



Principal component analysis (PCA)

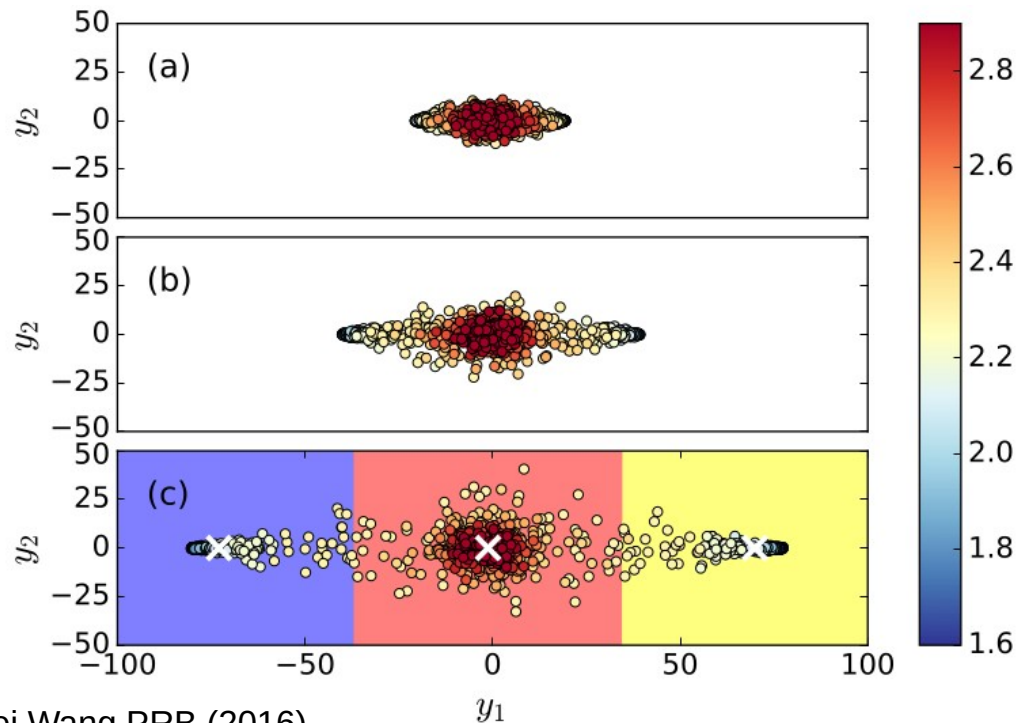
Unsupervised ML: Unlabeled configurations

Dimension reduction

0	0	0	1	0	1	1	0
0	1	1	1	0	1	0	1
0	1	0	0	1	0	0	1
...							
0	0	0	0	1	0	1	1

→ **X**

2D Ising model



Principal component analysis (PCA)
→ Linear transformation

$$\mathbf{X}^T \mathbf{X} \mathbf{w}_n = \lambda_n \mathbf{w}_n$$

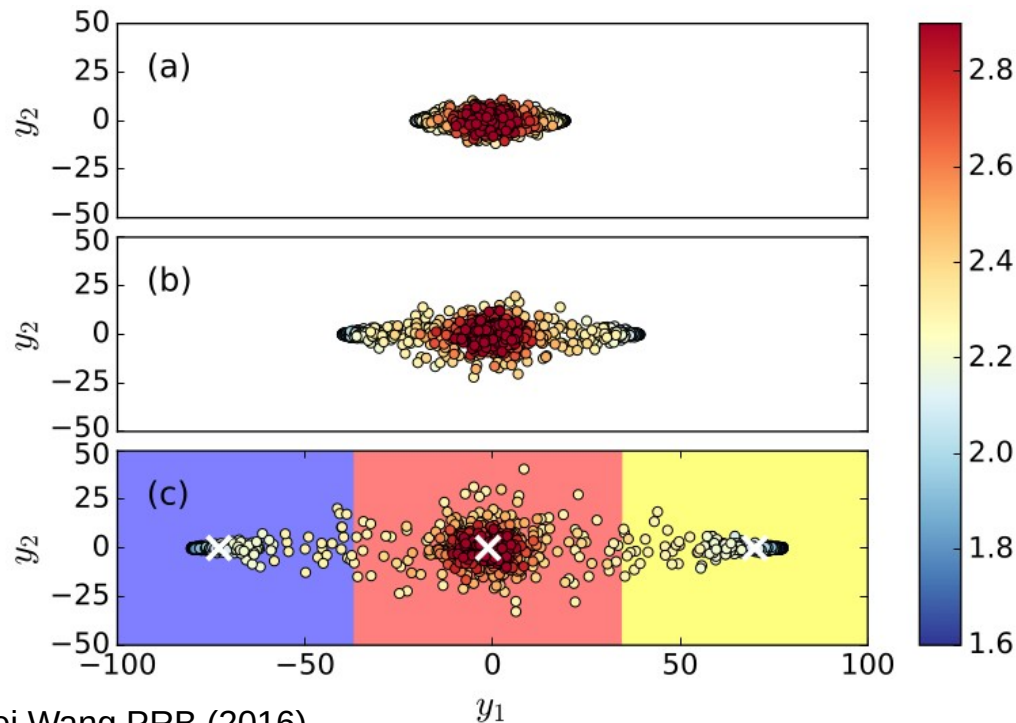
Unsupervised ML: Unlabeled configurations

Dimension reduction

0	0	0	1	0	1	1	0
0	1	1	1	0	1	0	1
0	1	0	0	1	0	0	1
...							
0	0	0	0	1	0	1	1

→ **X**

2D Ising model



Principal component analysis (PCA)
→ Linear transformation

$$\mathbf{X}^T \mathbf{X} \mathbf{w}_n = \lambda_n \mathbf{w}_n$$

More complicated transitions
(e.g., topological transitions, ...)
are not described by PCA

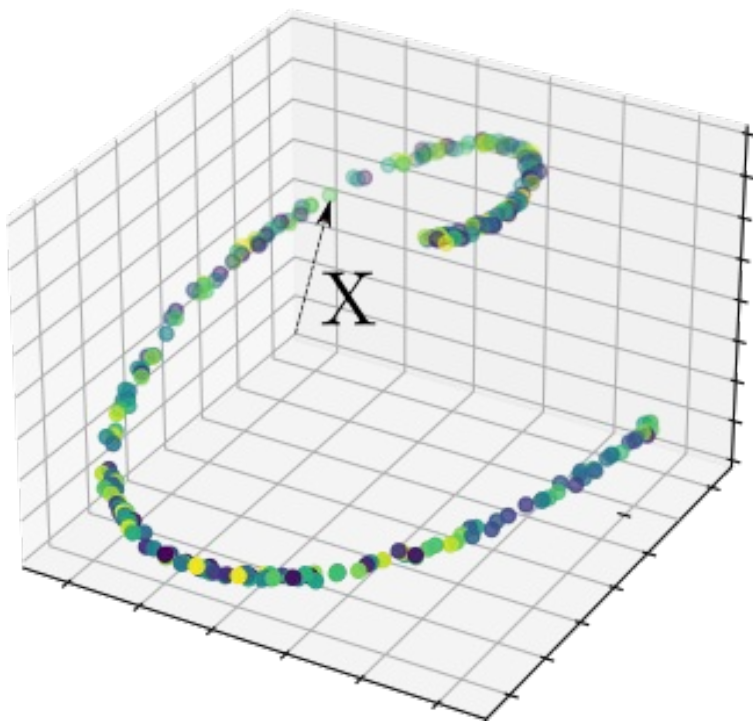
Intrinsic dimension (ID)

(I) How to estimate the ID?

(II) ID and phase transitions [classical and quantum]

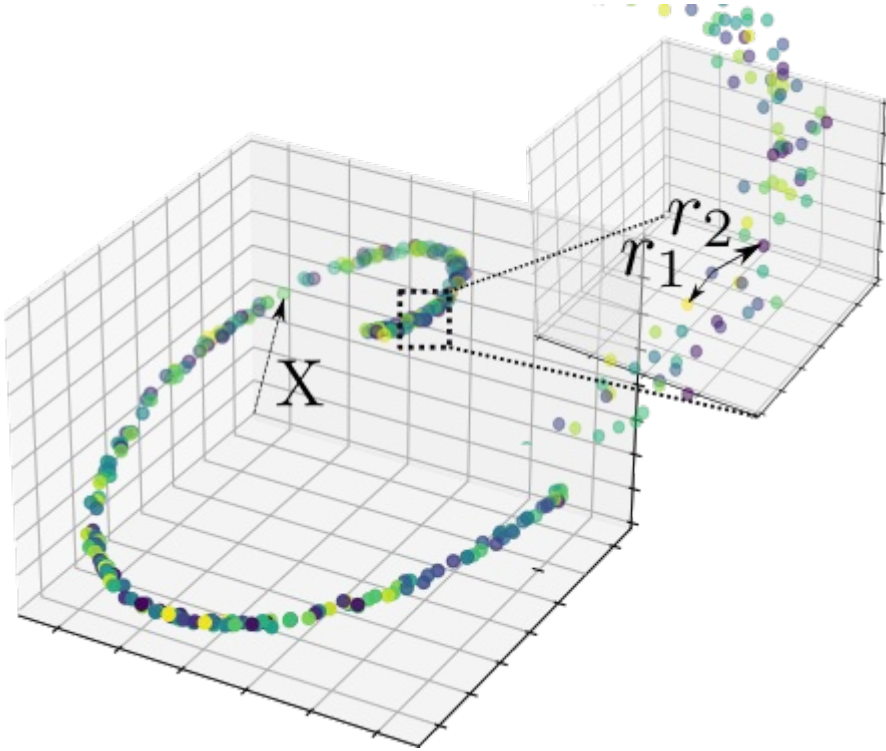
How to estimate the ID?

Different approaches: projection (e.g., **PCA**), fractal, **nearest-neighbors (NN)**

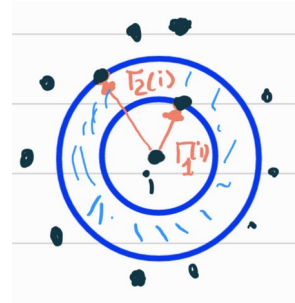


How to estimate the ID?

nearest-neighbors (NN) method
→ geometrical approach



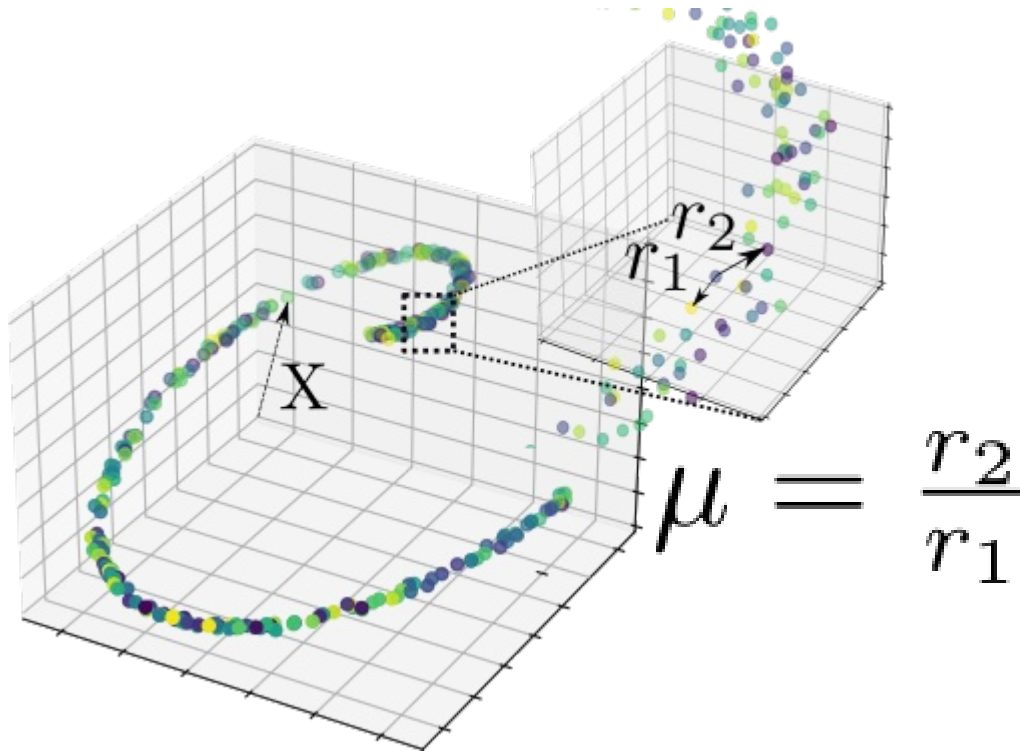
Statistics of NN distances
[e.g., Euclidian, Hamming, etc]



$$v(i) \sim (r_2(i)^{I_d} - r_1(i)^{I_d})$$

How to estimate the ID?

Nearest neighbors(NN)-based estimator [**TWO-NN** method]

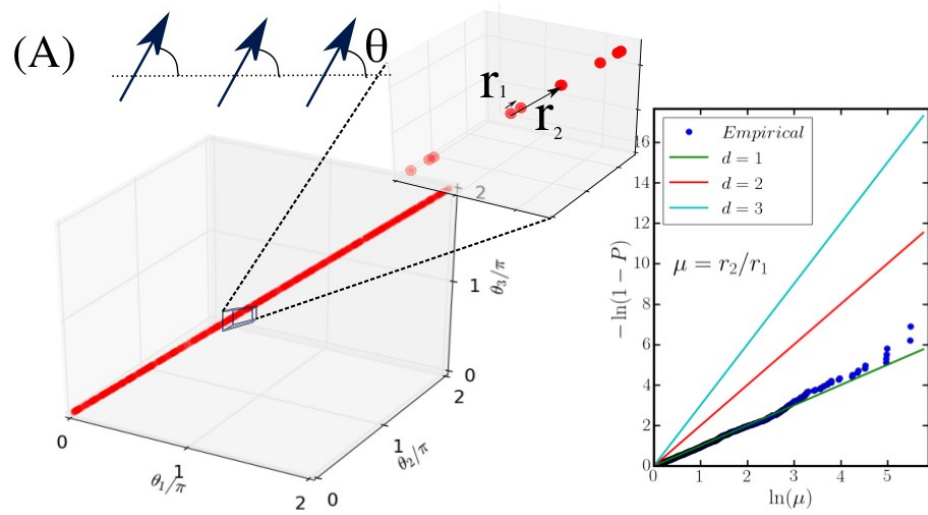


Probability distribution function

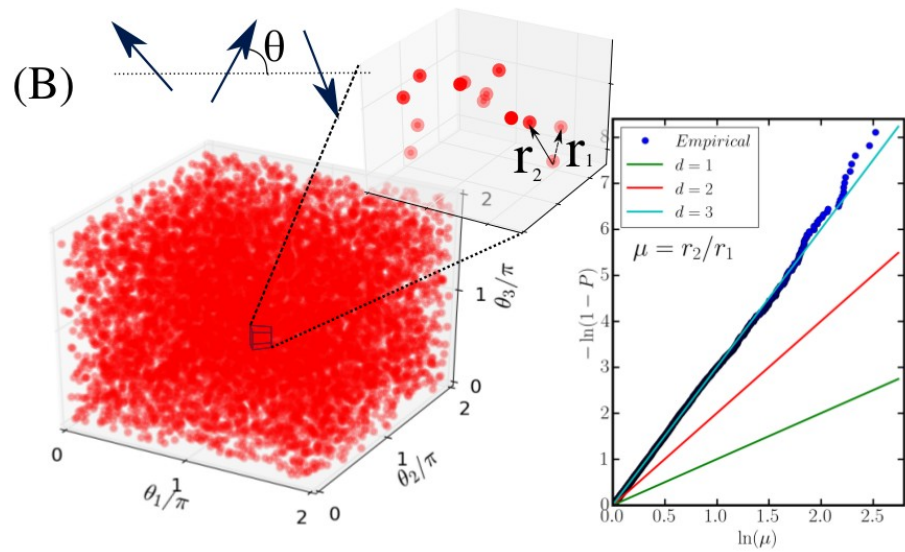
$$f(\mu) = I_d \mu^{-1-I_d}$$

Elena Facco et. al. Scientific Reports (2017)

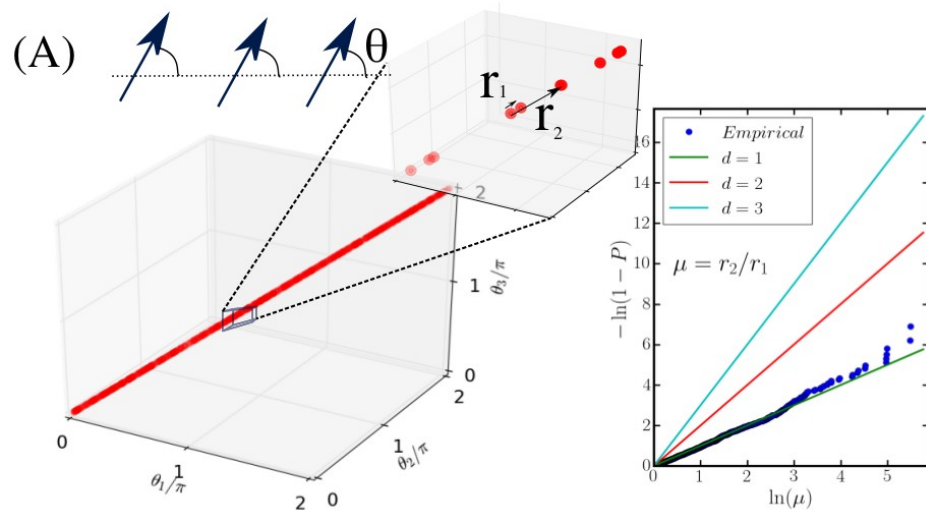
Assumption: data set is
locally uniform in density



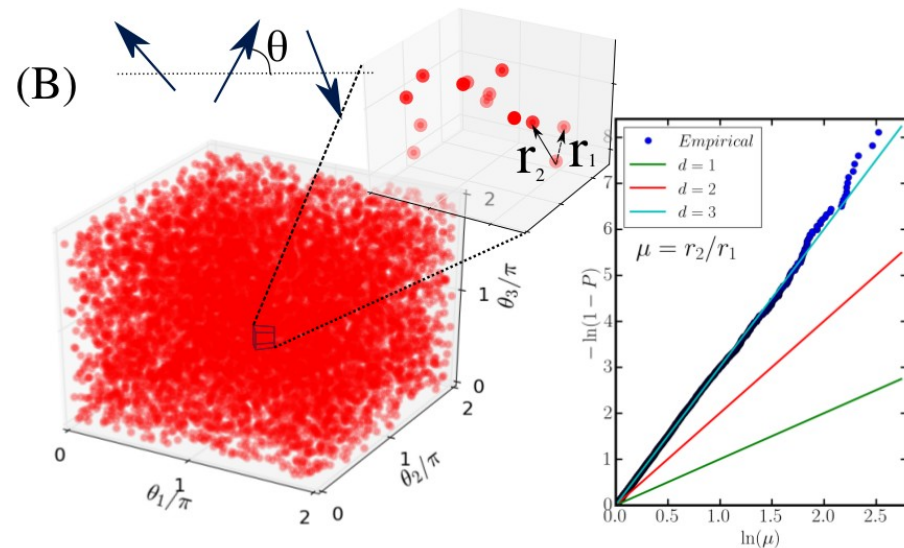
$$I_d \approx 1$$



$$I_d \approx N_s$$



$$I_d \approx 1$$



$$I_d \approx N_s$$

ID (TWO-NN)

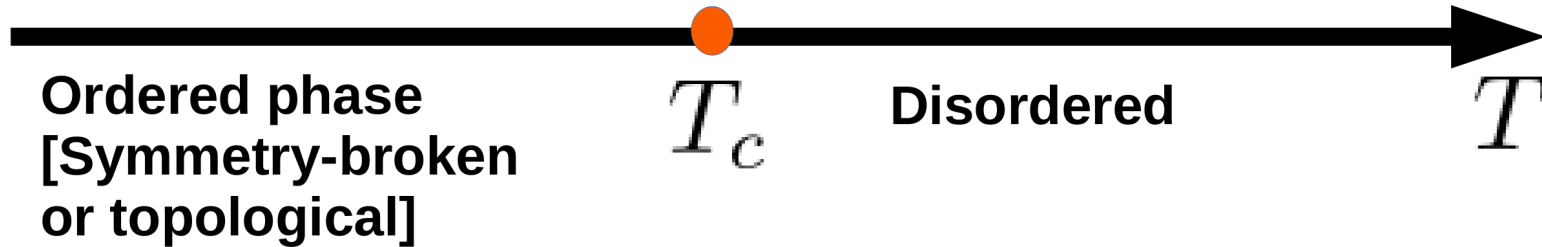
→ Local feature of configuration space

→ Depends on the typical value of distances [scale-dependent quantity]

$N_r \rightarrow$ Number of points in the data set

ID of partition-function data sets

→ Vicinity of phase transitions (Classical and Quantum)



ID of partition-function data sets

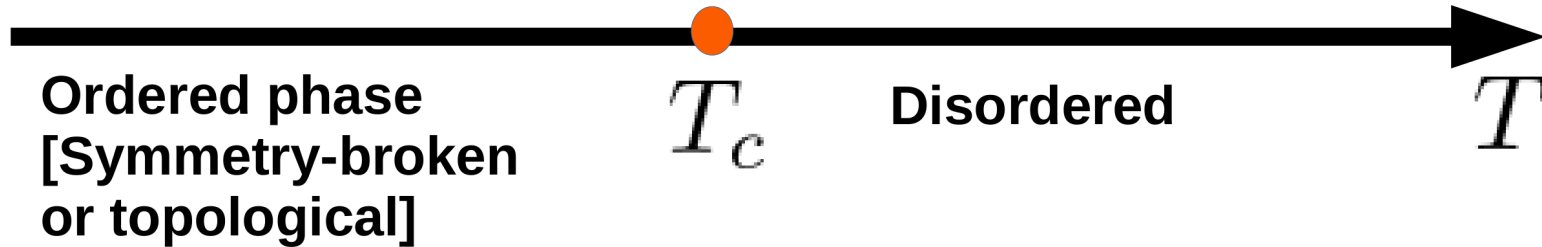
→ Vicinity of phase transitions (Classical and Quantum)

(1) Second-order PT

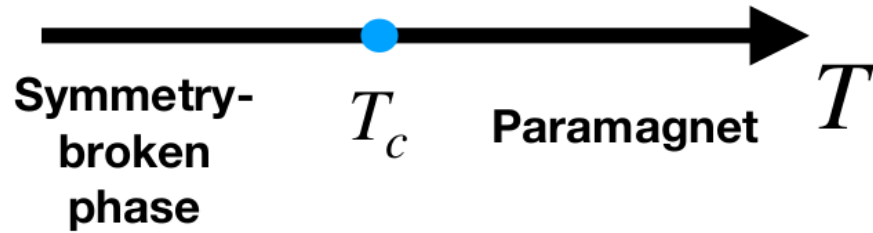
(2) Berezinskii-Kosterlitz-Thouless (BKT)

(3) First-order PT

Data sets generated by Monte Carlo simulations



1. Second-order phase transition

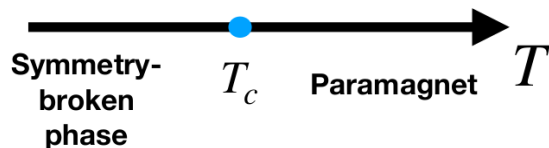


$$\xi \sim (T - T_c)^{-\nu}$$

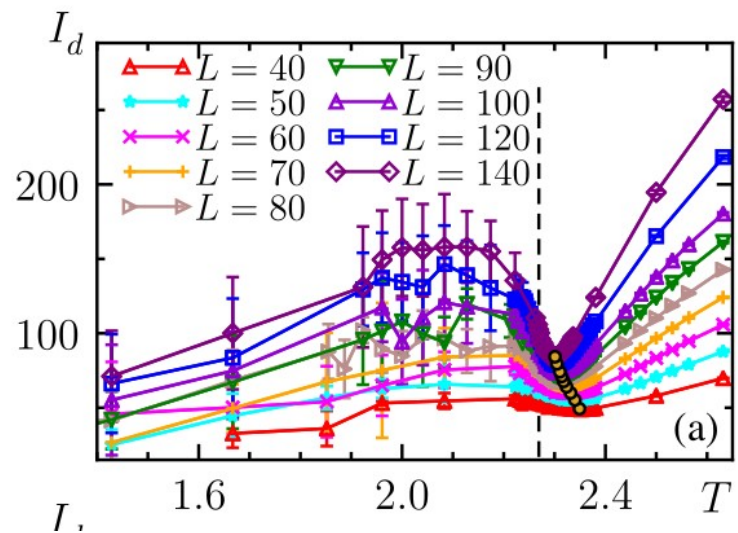
Finite size scaling

$$Q(t, L) = L^\sigma f(\xi / L)$$

2D Ising model

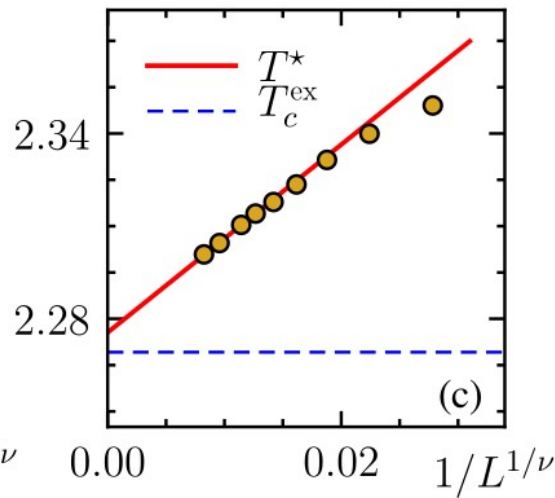
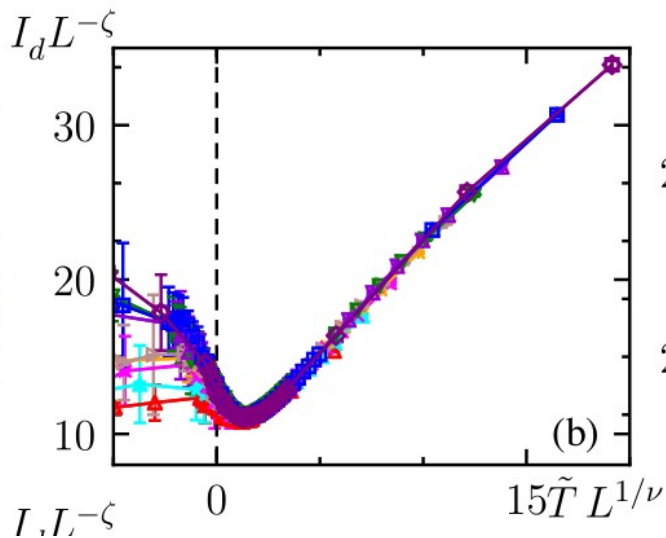
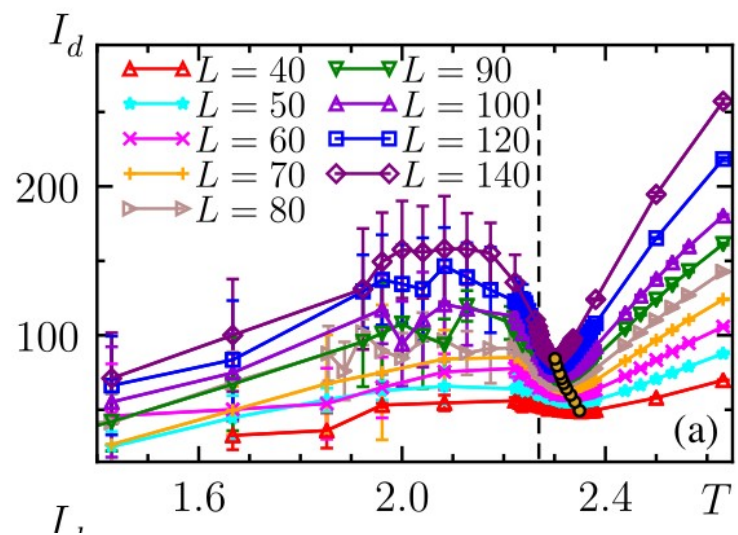
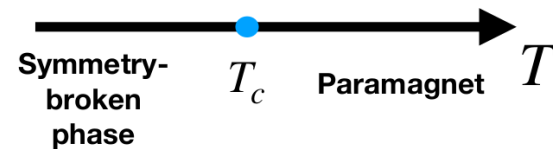


$$E_\sigma = -J \sum_{\langle ij \rangle} \sigma_i \sigma_j$$



I_d exhibit a local minimum at T^*

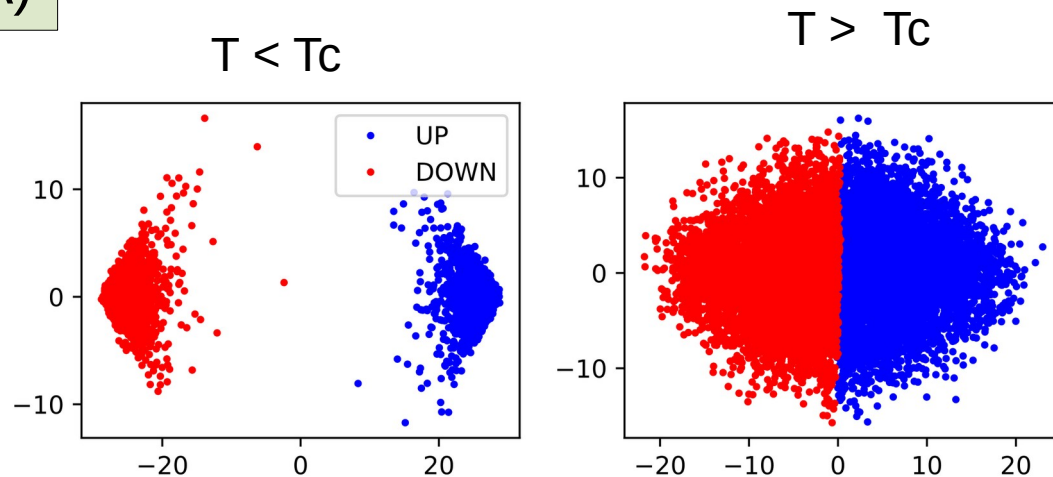
2D Ising model



$$T_c = 2.283(2), \quad \nu = 1.02(2),$$

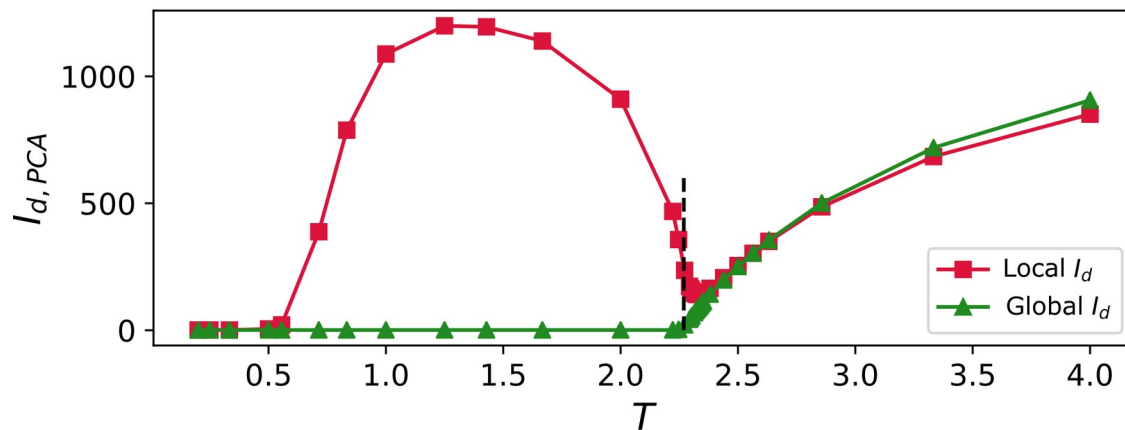
Principal component analysis (PCA)

Projection of the Ising data set in the two leading PC



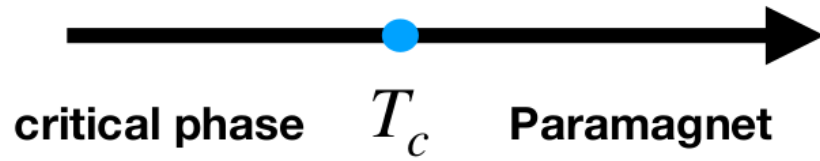
ID obtained with PCA

$$\sum_{n=1}^{I_{d,PCA}} \tilde{\lambda}_n \approx f,$$



2. BKT phase transition

$$E(\{\vec{\theta}\}) = -J \sum_{\langle i,j \rangle} \cos(\theta_i - \theta_j)$$



$$\xi \sim \exp\left(\frac{a}{\sqrt{T - T_c}}\right)$$

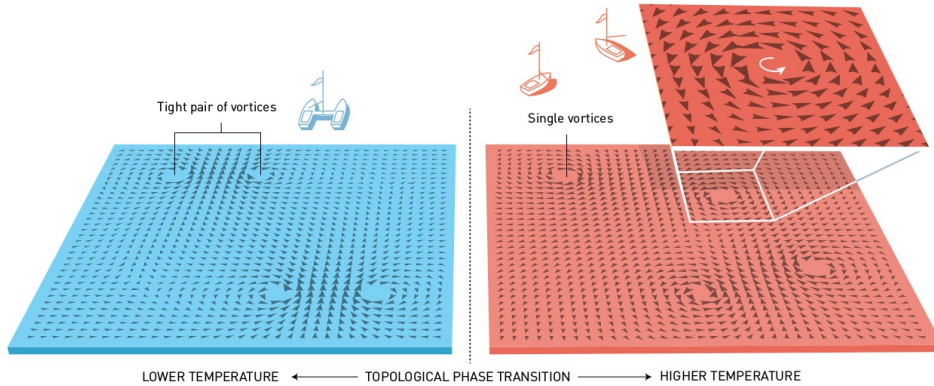
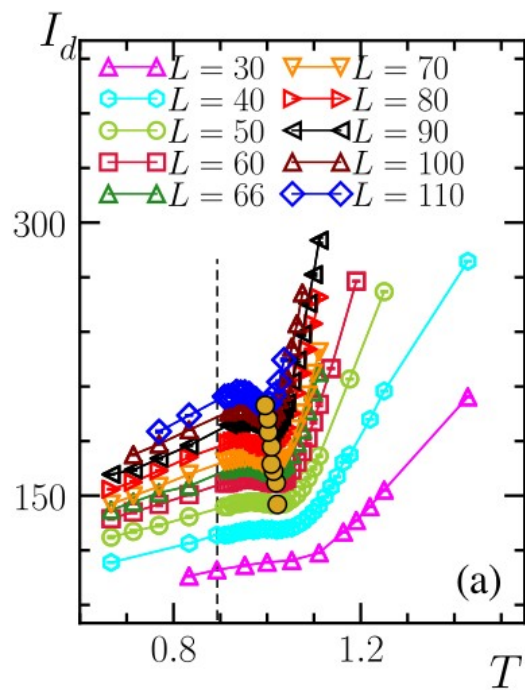
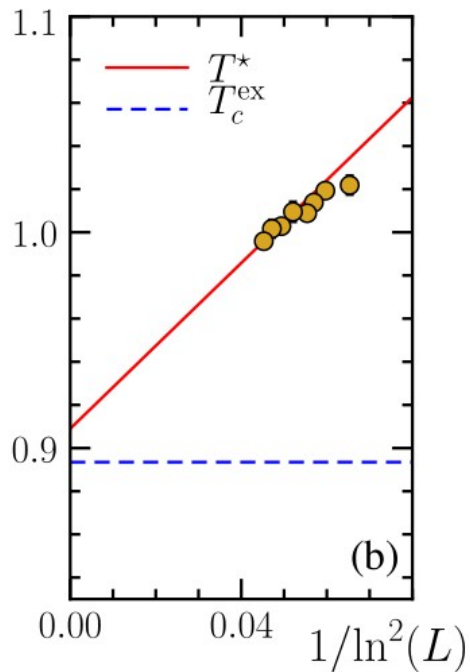


Illustration: ©Johan Jarnestad/The Royal Swedish Academy of Sciences

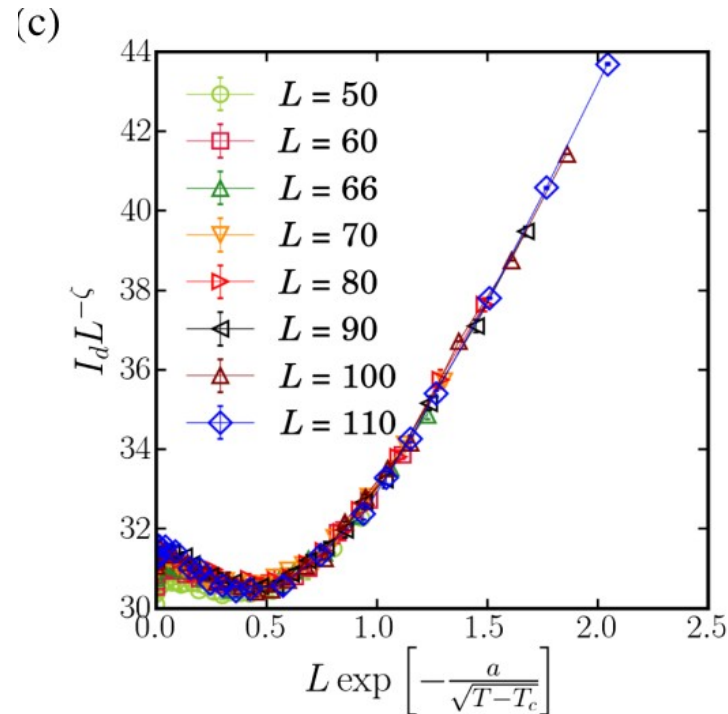
2D XY model



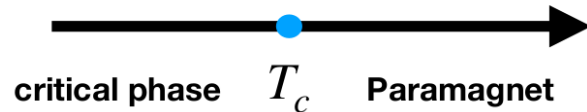
I_d exhibit a **local minimum at T^***



Finite size scaling

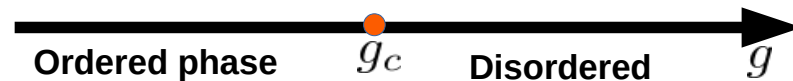
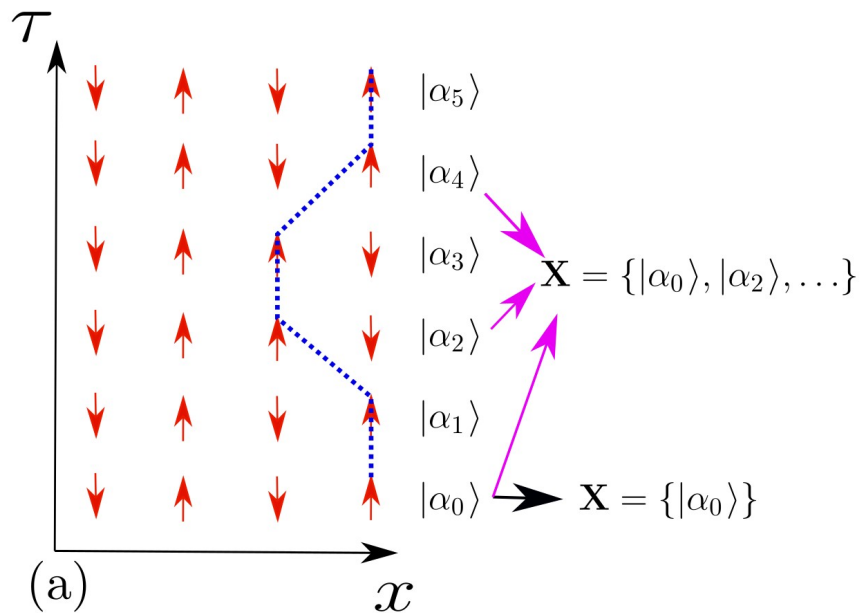


$$\xi \sim \exp \left(\frac{a}{\sqrt{T-T_c}} \right)$$



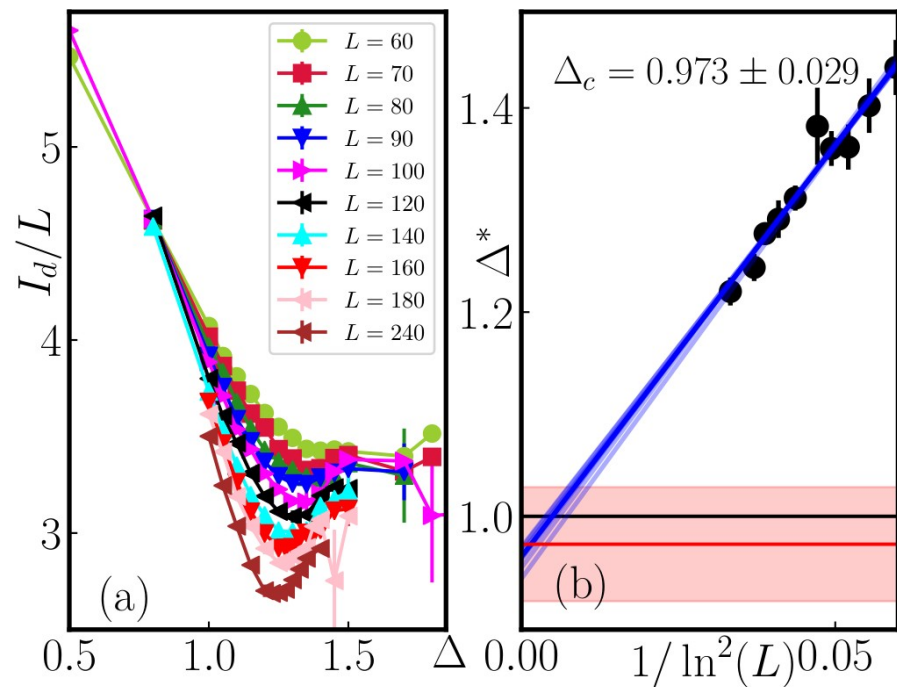
Quantum phase transitions

$$Z = \sum_{\alpha} \langle \alpha | e^{-\beta \hat{H}} | \alpha \rangle$$

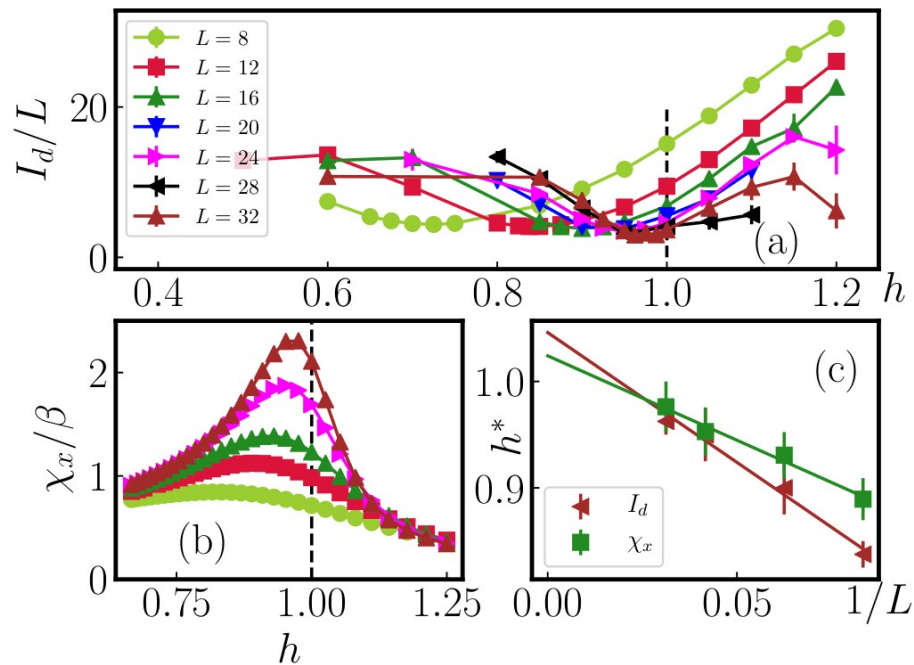


Quantum models

1d XXZ model
BKT transition



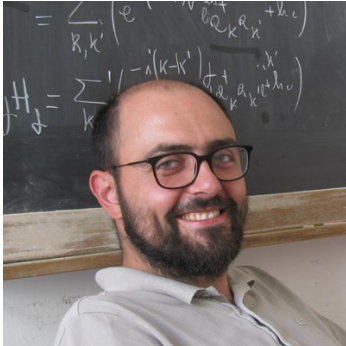
1d Quantum Ising model
Sec. order transition



Conclusion

Generic features of raw quantum data sets [e.g., Id] exhibit scaling behavior in the vicinity of quantum critical points
→ Unsupervised learning quantum phase transitions

Thank you!



Marcello Dalmonte (ICTP/SISSA)



Xhek Turkeshi (ICTP/SISSA)



Alex Rodriguez (ICTP)



Adriano Angelone
(LPTMC, Sorbonne Université)



Rosario Fazio (ICTP)

PRX 11, 011040 (2021)

PRX Quantum 2, 030332 (2021)

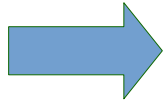
Supplemental material

Why the ID exhibit universal scaling behavior?

Distances are related with many-body correlation functions

$$r(\vec{\theta}^i, \vec{\theta}^j) = \sqrt{2 \sum_{k=1}^{N_s} (1 - \vec{S}_k^i \vec{S}_k^j)}.$$

$$\begin{array}{l} S_k^i = \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow \\ S_k^j = \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow \end{array} \quad \boxed{S_k^i \cdot S_k^j \equiv S_0 \cdot S_k}$$



$$I_d \sim -\frac{1}{\ln(r_2^*/r_1^*)}$$

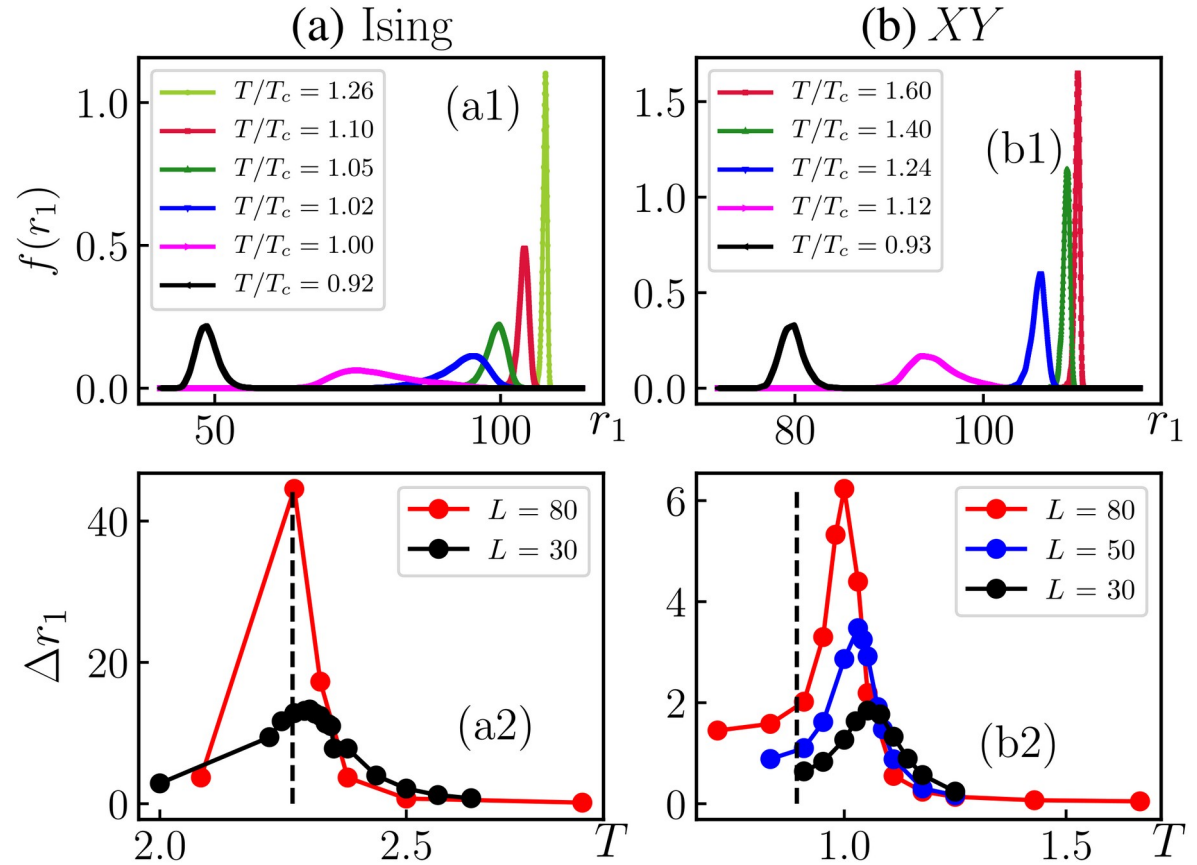
Statistics of first nearest-neighbor distances

Phase transitions



Change of scale in
configuration space

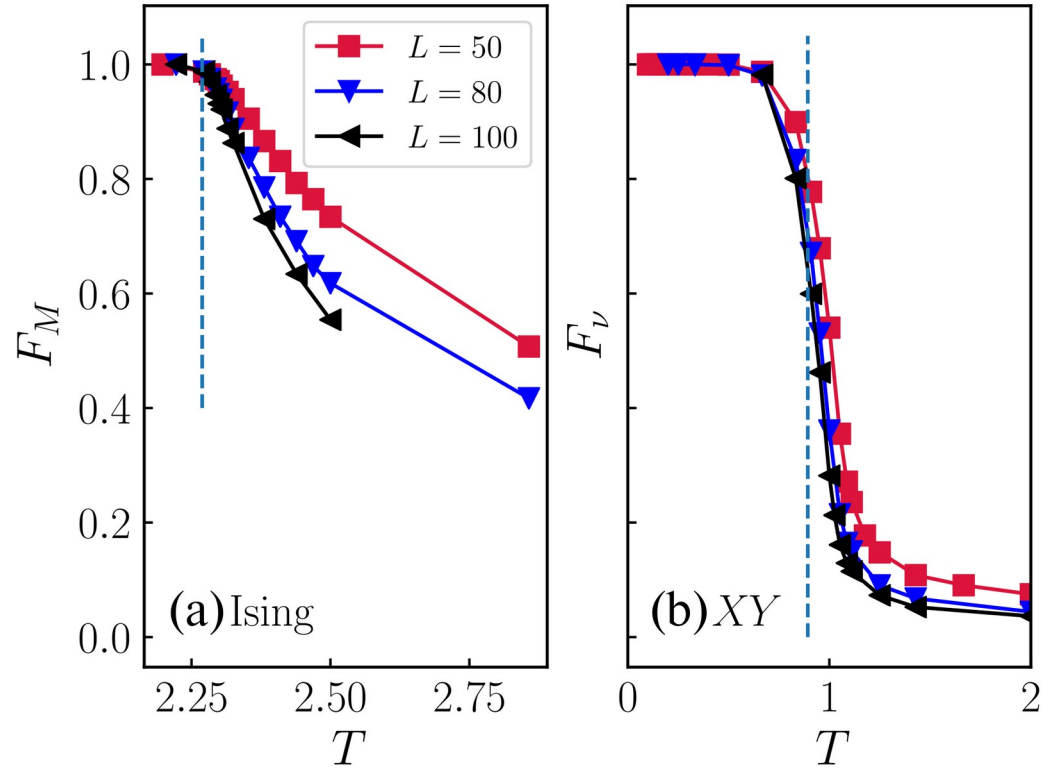
Structural transition in
Configuration space



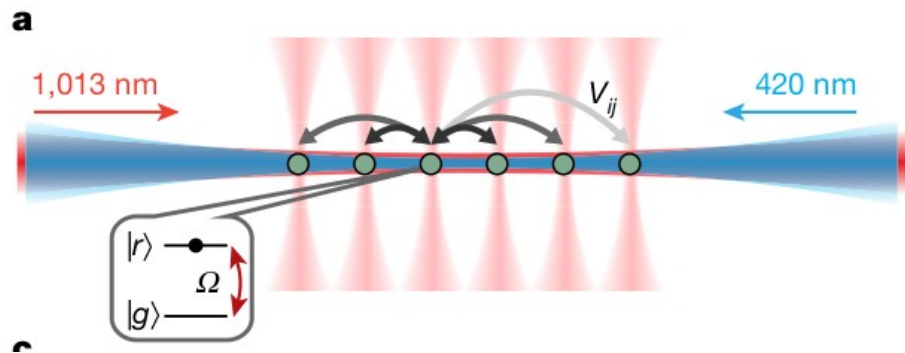
Connectivity between neighboring points in configuration space

$F_M \rightarrow$ fraction of points in the data set
whose first two neighbors have same
magnetization sign

$F_{nu} \rightarrow$ fraction of points in the data set
whose first two neighbors have same
winding number



(1) Rydberg atom arrays



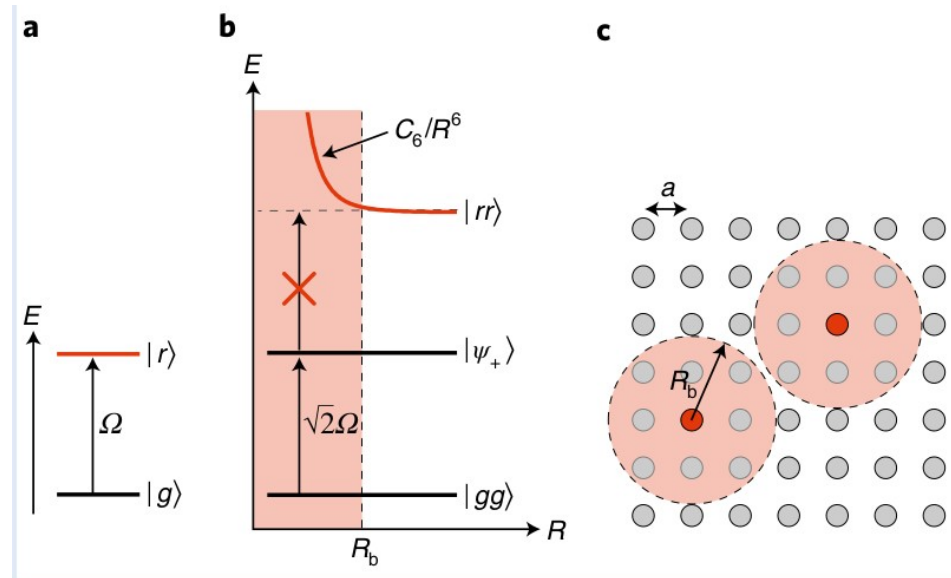
Hard-core bosons (FSS model)

$$\frac{H}{\hbar} = \frac{\Omega(t)}{2} \sum_i \sigma_i^x - \Delta(t) \sum_i n_i + \sum_{i < j} V_{ij} n_i n_j$$



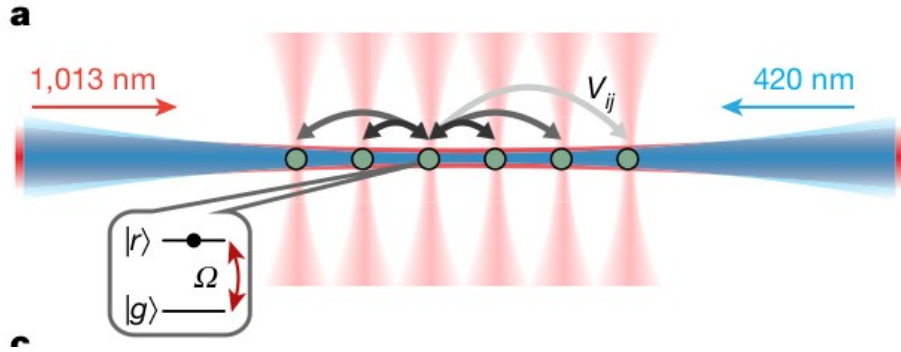
PXP model

$$H = \frac{1}{2} \sum_i (\Omega P \sigma_i^x P - \delta \sigma_i^z)$$



Rydberg blockade
→ constraint

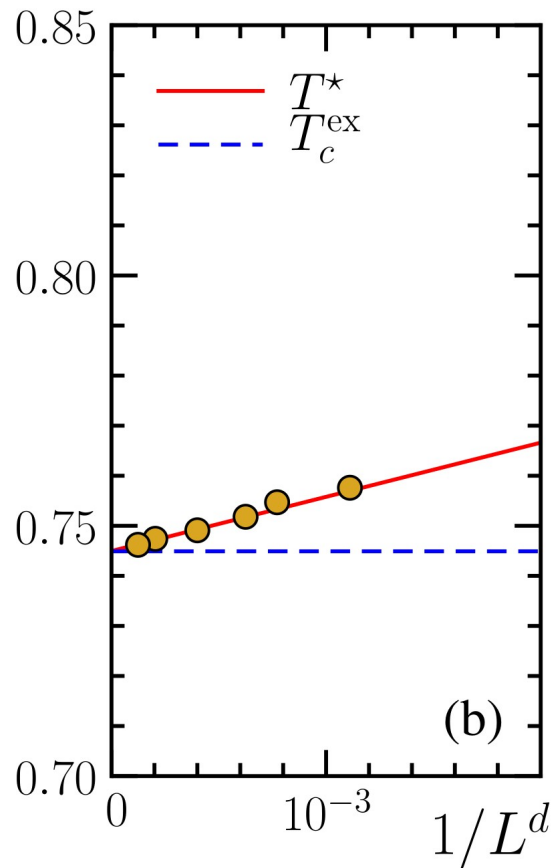
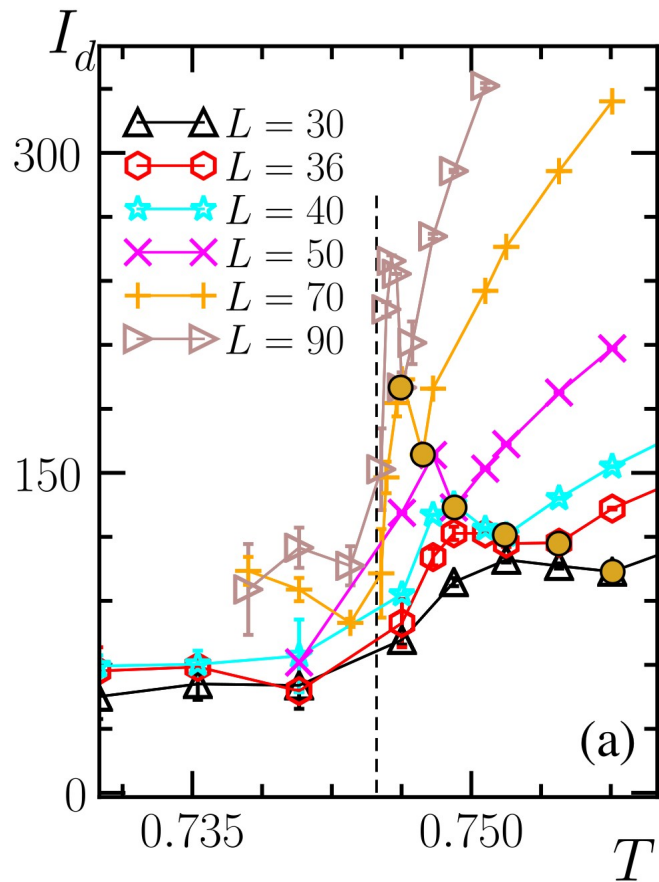
(1) Rydberg atom arrays

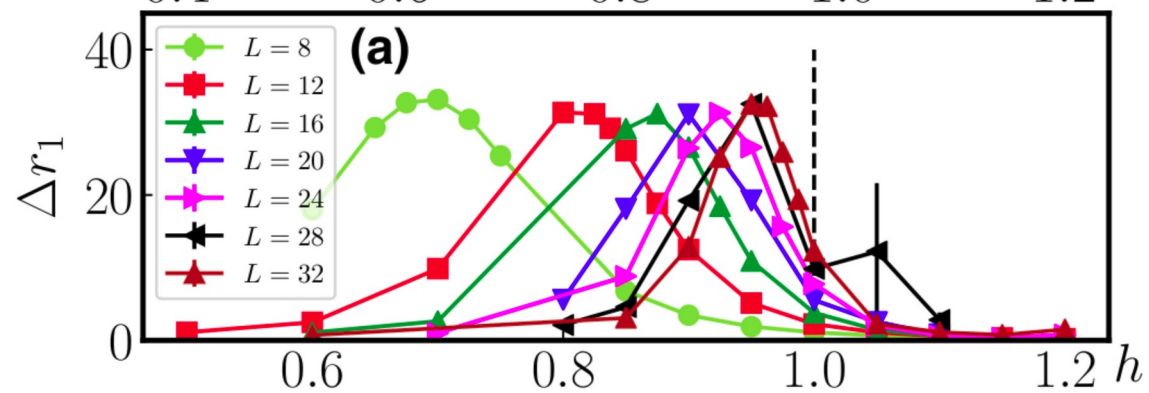
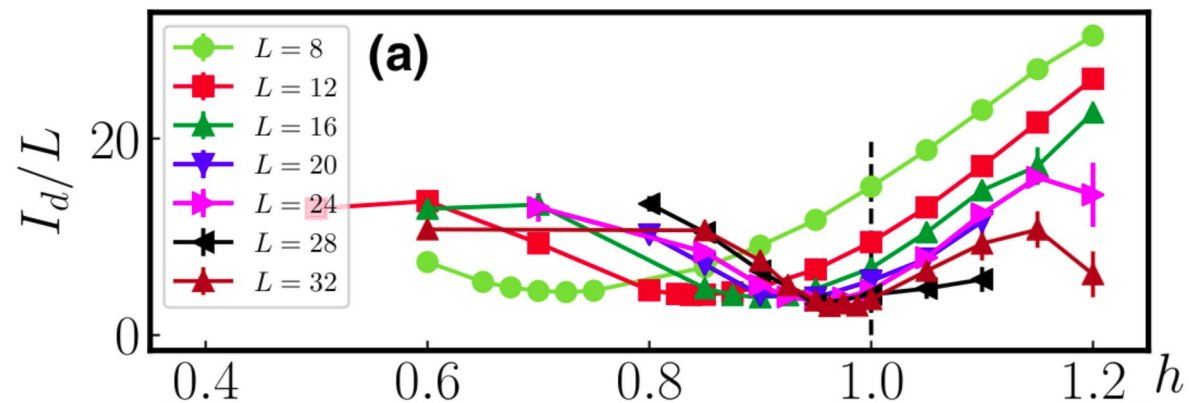


Hard-core bosons (FSS model)

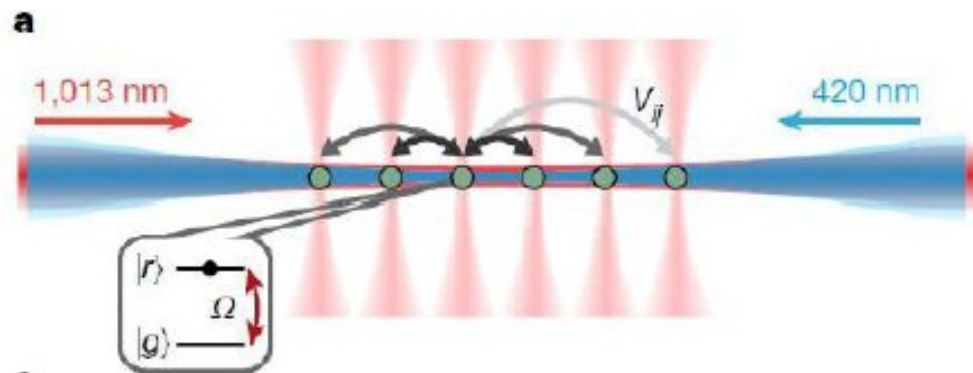
$$\frac{H}{\hbar} = \frac{\Omega(t)}{2} \sum_i \sigma_i^x - \Delta(t) \sum_i n_i + \sum_{i < j} V_{ij} n_i n_j$$

3. First-order phase transition

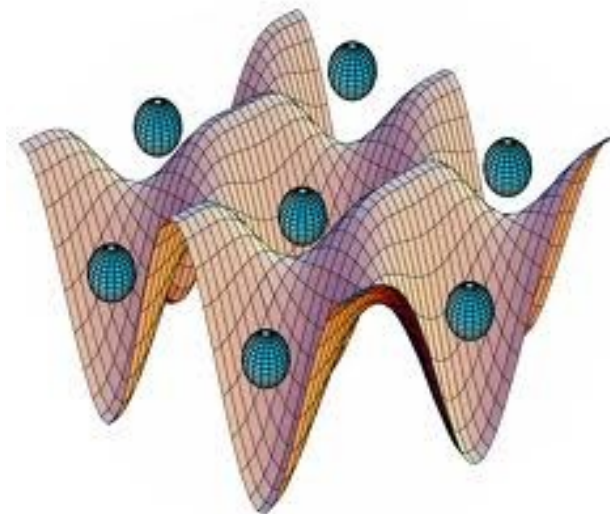




Synthetic quantum systems



Rydberg atoms in optical tweezers



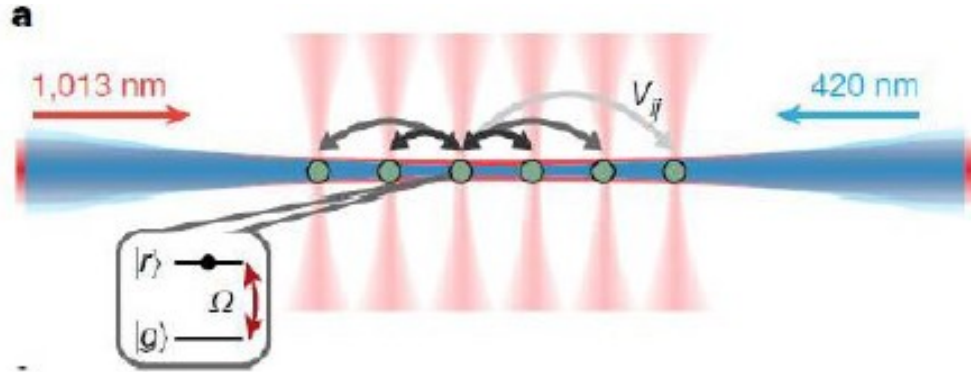
Fermions in optical lattices

Strongly correlated quantum systems

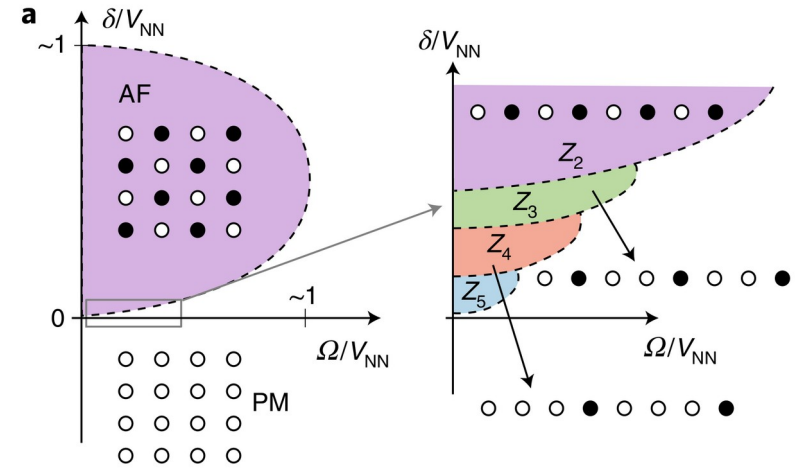
Synthetic quantum systems



Quantum simulators



Rydberg atoms in optical tweezers
[Ising-like Hamiltonians]

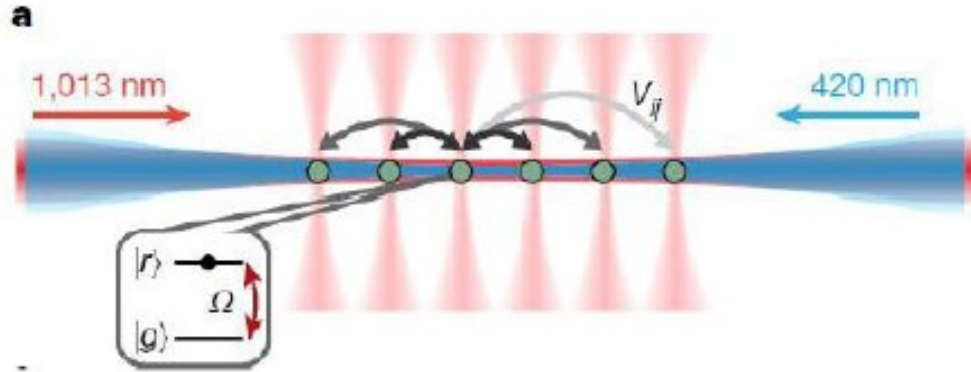


- Quantum many-body phases and phase transitions
- Coherent dynamics

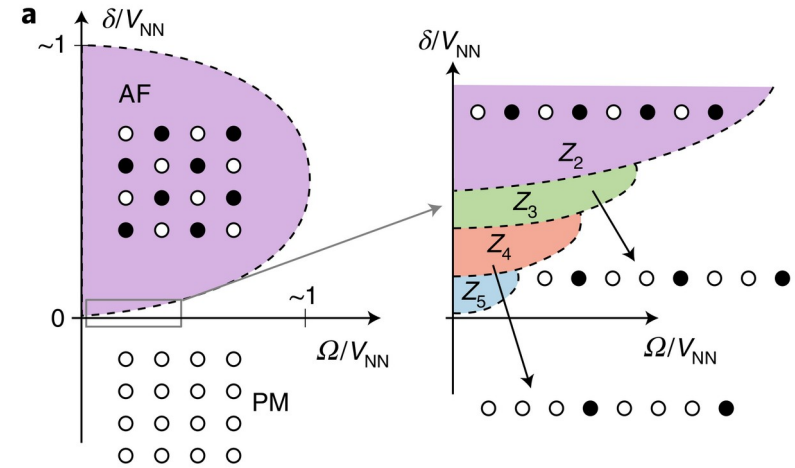
Synthetic quantum systems



Quantum simulators



Rydberg atoms in optical tweezers
[Ising-like Hamiltonians]



- Tunability
- Probe **local properties** and quantum correlations [**Entanglement**]

Quantum correlations



Entanglement

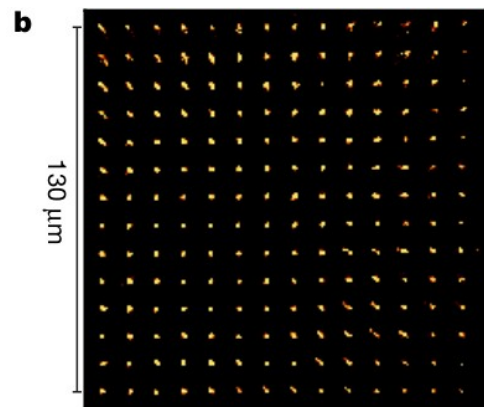
Probing Rényi entanglement entropy via randomized measurements

Science 2019

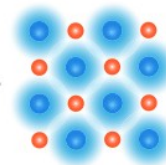
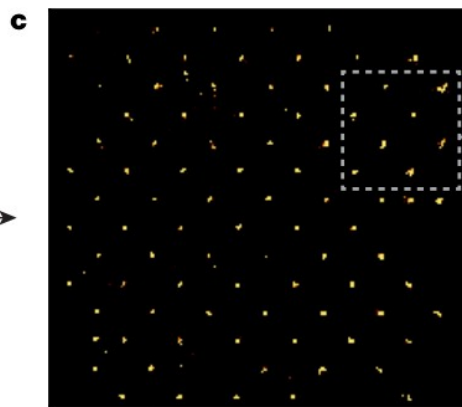
Tiff Brydges^{1,2*}, Andreas Elben^{1,2*}, Petar Jurcevic^{1,2}, Benoît Vermersch^{1,2},
Christine Maier^{1,2}, Ben P. Lanyon^{1,2}, Peter Zoller^{1,2}, Rainer Blatt^{1,2}, Christian F. Roos^{1,2†}

Quantum simulation of 2D antiferromagnets with hundreds of Rydberg atoms

Pascal Scholl et. al. Nature (2021)



$H_{\text{Ryd}}(t)$



Probe MB quantum phases and transitions



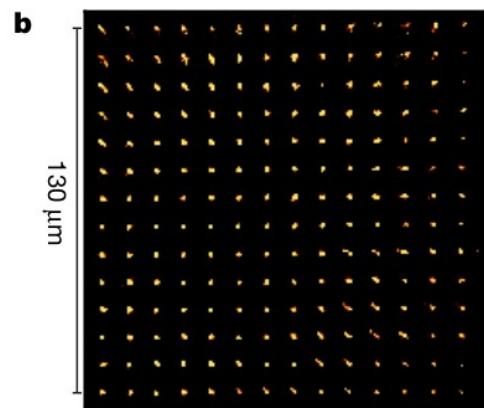
Measure wave function snap shots

Quantum phases of matter on a 256-atom programmable quantum simulator

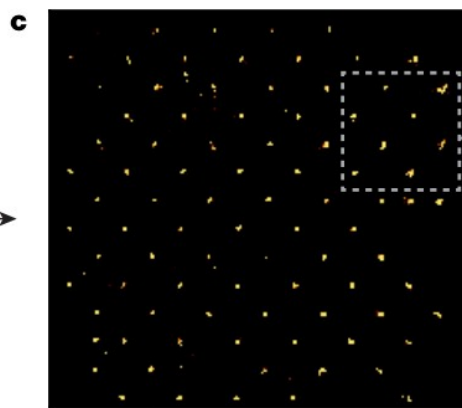
Sepehr Ebadi et. al. Nature (2021)

Quantum simulation of 2D antiferromagnets with hundreds of Rydberg atoms

Pascal Scholl et. al. Nature (2021)



$H_{\text{Ryd}}(t)$



Probe MB quantum phases and transitions



Measure wave function snap shots

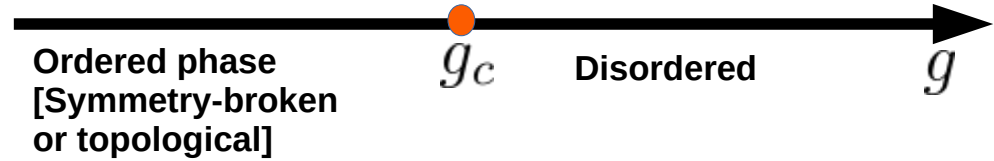
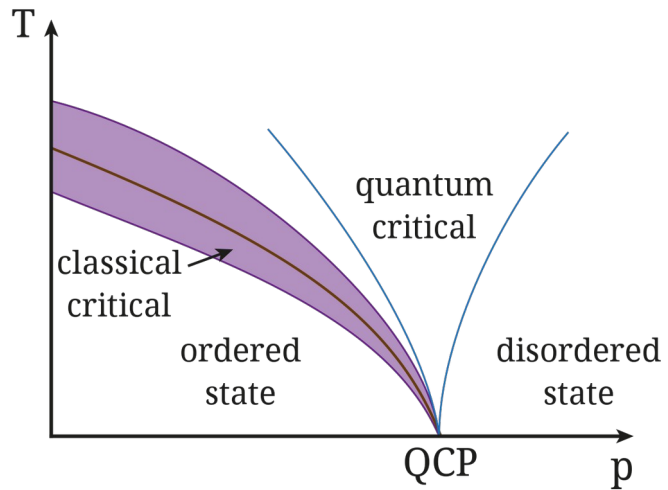
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0	1	1	1	0	1	0	1
0	1	0	0	1	0	0	1
...							
0	0	0	0	1	0	1	1

Quantum phases of matter on a 256-atom programmable quantum simulator

Sepehr Ebadi et. al. Nature (2021)

New tools to characterize quantum correlations in many-body systems?

Quantum phase transitions

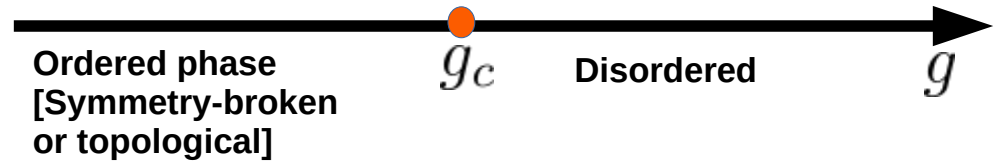


- Quantum spin models
- 1d quantum Ising model
 - 1d XXZ model
 - 2d Heisenberg bilayer model

Quantum phase transitions

Defining quantum data sets

$$Z = \sum_{\alpha} \langle \alpha | e^{-\beta \hat{H}} | \alpha \rangle$$



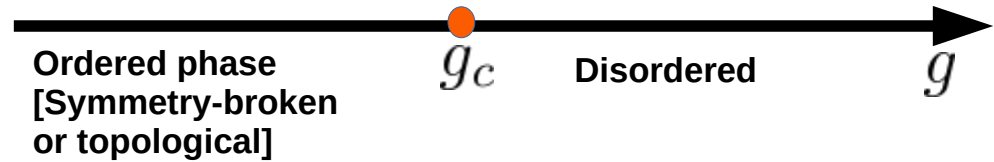
Quantum phase transitions

Defining quantum data sets

$$Z = \sum_{\alpha} \langle \alpha | e^{-\beta \hat{H}} | \alpha \rangle$$

Quantum-to-classical mapping
→ path-integral

$$Z = \sum_{\alpha_0} \sum_{\alpha_1} \cdots \sum_{\alpha_{L-1}} \langle \alpha_0 | e^{-\Delta\tau H} | \alpha_{L-1} \rangle \cdots \langle \alpha_2 | e^{-\Delta\tau H} | \alpha_1 \rangle \langle \alpha_1 | e^{-\Delta\tau H} | \alpha_0 \rangle$$



Quantum models

1d Quantum Ising model Sec. order transition

$$Z = \sum_{\alpha} \langle \alpha | e^{-\beta \hat{H}} | \alpha \rangle$$

