

“Data mining investigation of BKT transitions”

Samuele Pedrielli – 29/09/2023 - Nicosia, Cyprus.



AQTIVATE

CONTEXT

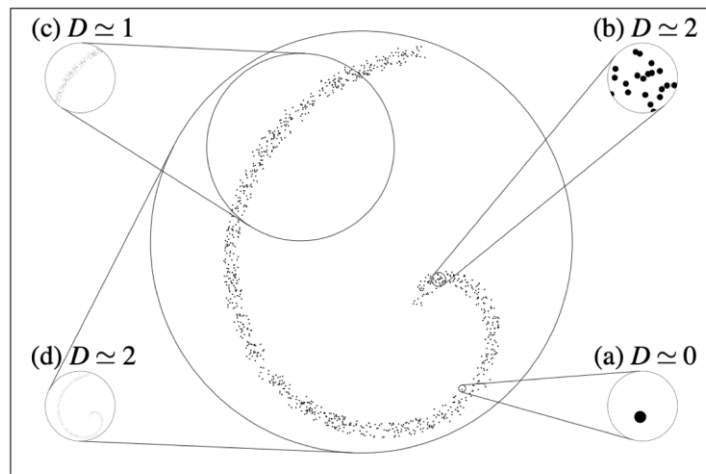
- Using data science tools to study physics problems ^[1,2]
 - Can these methods improve our understanding?
 - What are their (dis)advantages w.r.t. traditional methods (MC)?
- Young research field still in its testing phase
 - Are these techniques able to **reproduce known results**?
 - Which tools are best suited to study a given problem?

[1] P. Mehta et al., Rep. Prog. Phys., 2019

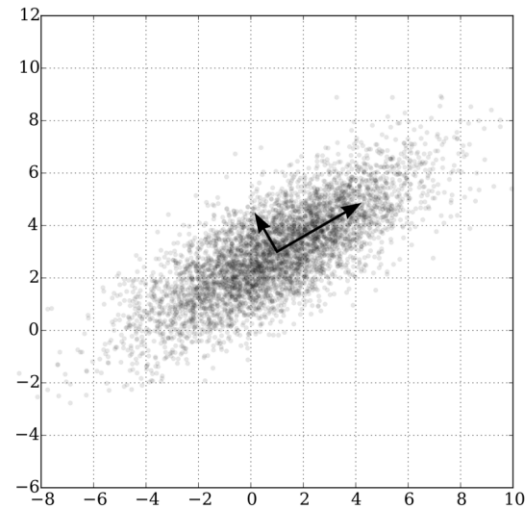
[2] G. Carleo et al., Rev. Mod. Phys., 2019

CONTEXT

In recent works [3,4], promising results were obtained in the context of **phase transitions**.



Adapted from K. Balázs., NIPS (2002).



Adapted from https://en.wikipedia.org/wiki/Principal_component_analysis

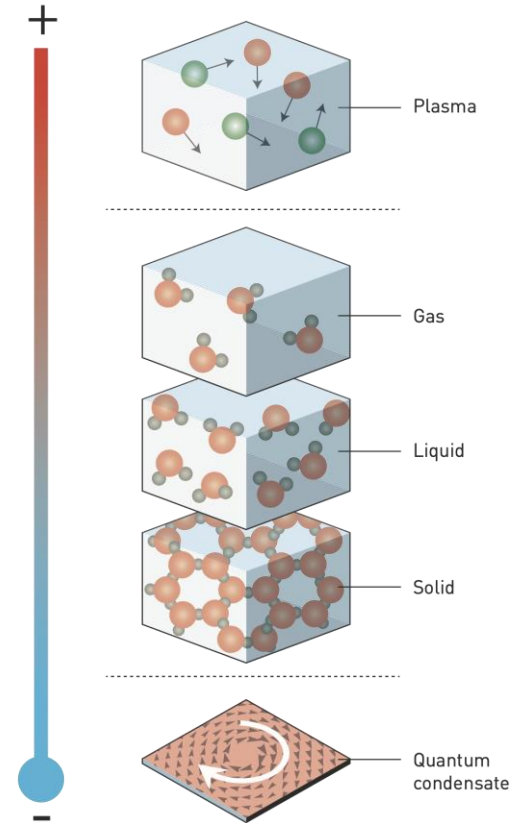


Illustration: © Johan Jarnestad/The Royal Swedish Academy of Sciences

Adapted from <https://www.nobelprize.org/prizes/physics/2016/press-release/>

We focus on **Berezinskii-Kosterlitz-Thouless** [5,6] transitions.

[3] C. Wang et al., Phys. Rev. B, 2017

[4] T. Mendes-Santos et al., Phys. Rev. X, 2021

[5] V. L. Berezinskii, Sov. J. of Exp. and Th. Phys., 1971

[6] J. M. Kosterlitz, D. J. Thouless, J. Phys. C, 1973

OUTLINE

PHASE TRANSITIONS

- Landau-Ginzburg-Wilson paradigm
- BKT transitions
 - XY model
 - 6-clock model

MONTE CARLO SIMULATIONS

- Generating configurations
- Evaluating critical temperatures

DATA MINING

- Intrinsic dimension
 - Application to XY model
 - Application to 6-clock model
- Principal Component Analysis
 - PCA entropy
 - Application to XY model
 - Application to 6-clock model

PHASE TRANSITIONS

PHASE TRANSITIONS

THE LANDAU-GINZBURG-WILSON PARADIGM

- Theoretical framework to describe standard phase transitions
- Based on the notion of **spontaneous symmetry breaking**
 - *The ground state does not possess the full symmetry of the Hamiltonian*
- Does not explain all possible phase transitions

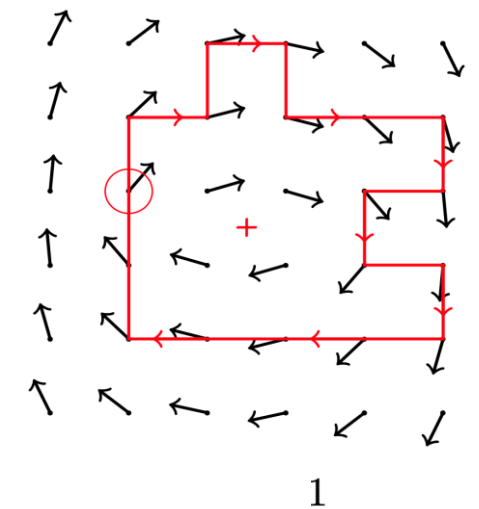
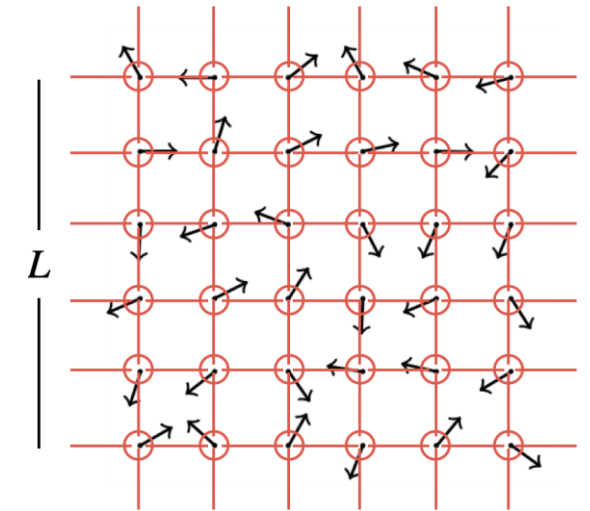
BKT TRANSITIONS

- Phase transitions that are ***not*** the result of s.s.b.
- **Mermin-Wagner-Hohenberg Theorem**
Continuous symmetries cannot be spontaneously broken at finite temperature in systems of dimensionality $D \leq 2$ for sufficiently short-ranged interactions

BKT TRANSITIONS

XY MODEL

- Prototypical example
 - $D = 2$
 - $U(1)$ global symmetry
 - Nearest neighbour interaction
- *Different* kind of transition driven by **topological defects**
 - $T < T^{BKT}$ - vortices are bound in pairs (QLRO)
 - $T > T^{BKT}$ - vortices unbind and proliferate (DIS)



BKT TRANSITIONS

6-CLOCK MODEL

- Same Hamiltonian as XY, now 6 discrete spins $\phi = 2\pi q/6, q = 0, \dots, 5$
 - $D = 2$
 - Z_6 global symmetry
 - Nearest neighbour interaction
- MWH Theorem *does not* apply, but 2 BKTs nevertheless



GOALS

- Understand if we can use **PCA Entropy** to obtain the critical points of
 - XY model
 - 6C model
- If so, obtain estimates of the critical points with
 - PCA Entropy
 - **Intrinsic dimension**and compare them to those obtained with Monte Carlo techniques.
- Compare PCA Entropy and Intrinsic dimension with each other.

MONTE CARLO SIMULATIONS

MONTE CARLO SIMULATIONS

GENERATING CONFIGURATIONS

Monte Carlo simulation - numerical technique that simulates the thermal evolution of a system

- Start from a configuration $\{\sigma\}_{i=1}^N$
- Propose a new configuration $\{\bar{\sigma}\}_{i=1}^N$
- Decide whether to transform $\{\sigma\}_{i=1}^N$ into $\{\bar{\sigma}\}_{i=1}^N$

At each MC step, a *new configuration* of the system is generated and **averages of observables** can be computed from it

MONTE CARLO SIMULATIONS

EVALUATING CRITICAL TEMPERATURES

- Find T^* at a given L from observables^[8]
- Finite size scaling^[9]: $T^* - T^{BKT} \sim \ln^{-2}(L)$

System	Average
XY: (L=24,32,64)	0.910(5) ← T_{MC}^{BKT}
6C: (L=24,48,64,80)	0.91(1) ← $T_{MC,2}^{BKT}$

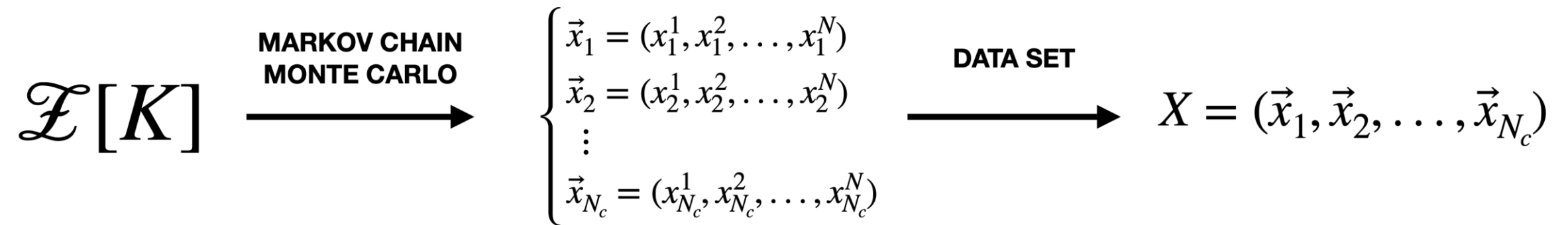
[8] D. R. Nelson, J. M. Kosterlitz, Phys. Rev. Lett., 1977.

[9] A. W. Sandvik, AIP Conf. Proc., 2010.

DATA MINING

DATA MINING

- How do we get the **data set** associated with a physical system?
 - Experimental measurements
 - Output configurations of Monte Carlo simulations



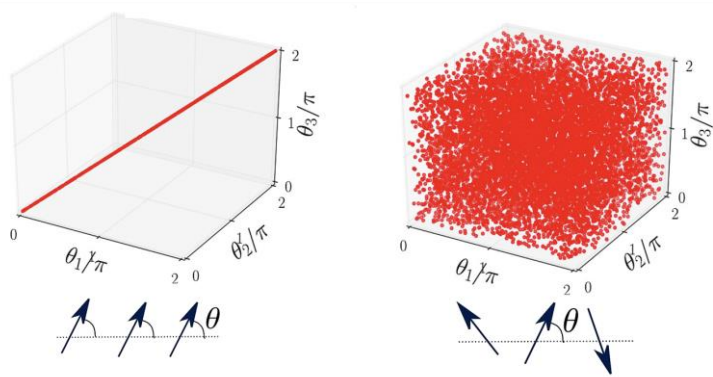
- Once the data set is at hand, we apply our data mining techniques
- The power of the approach resides in its **agnostic** spirit

DATA MINING

INTRINSIC DIMENSION

Minimum number of variables that describe a data set \mathbf{X} embedded in an ND space

Example: 3 sites XY model

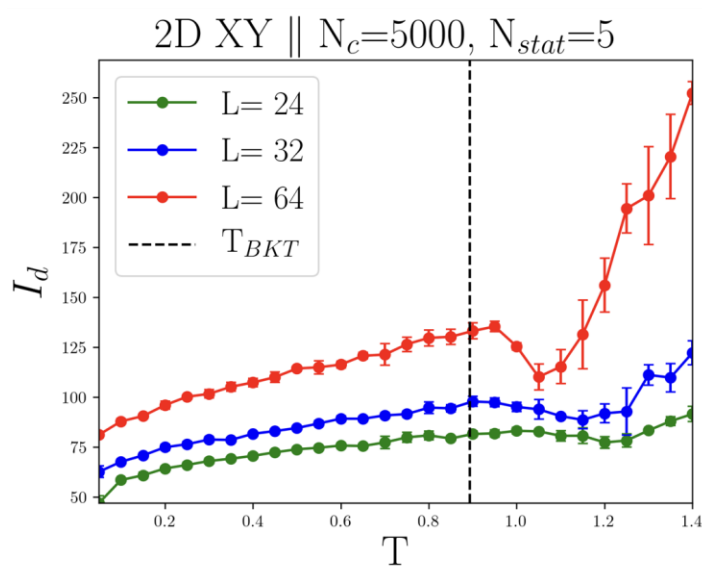


- $T = 0$) spins aligned configurations live on a line: $I_d = 1$
- $T = \infty$) random spins configurations fill the space: $I_d = N = 3$
- I_d able to distinguish different phases

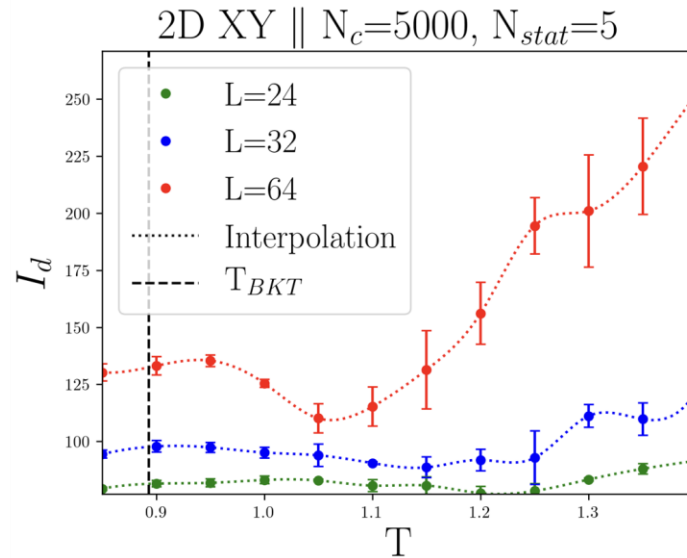
- How do we compute it? *Two nearest neighbour method*
- What happens at intermediate temperatures?
- Can we identify a signal that scales properly? Can we find T^{BKT} from it?

INTRINSIC DIMENSION

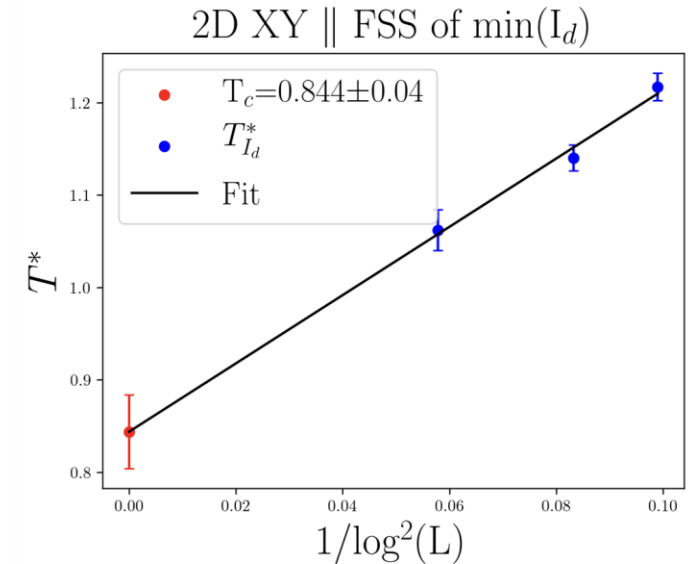
APPLICATION TO XY MODEL



- I_d displays a minimum
- Does it scale as expected?



- Interpolation of the data to determine T^*

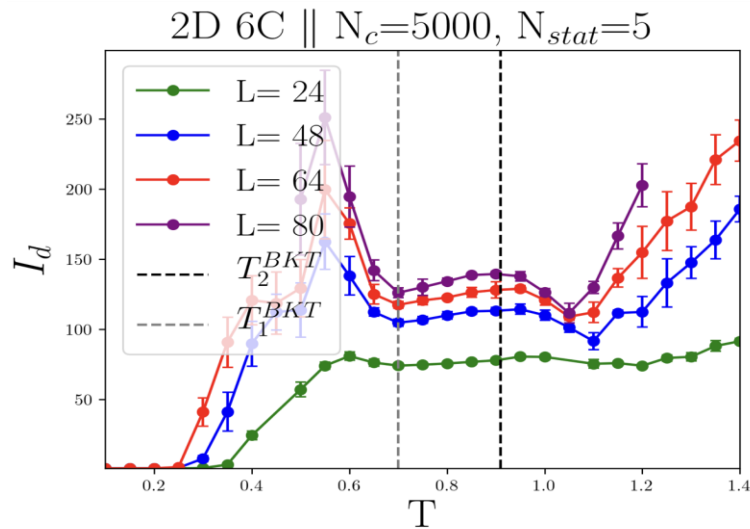


- Plot T^* against $\ln^{-2}(L)$
- Scaling is satisfied

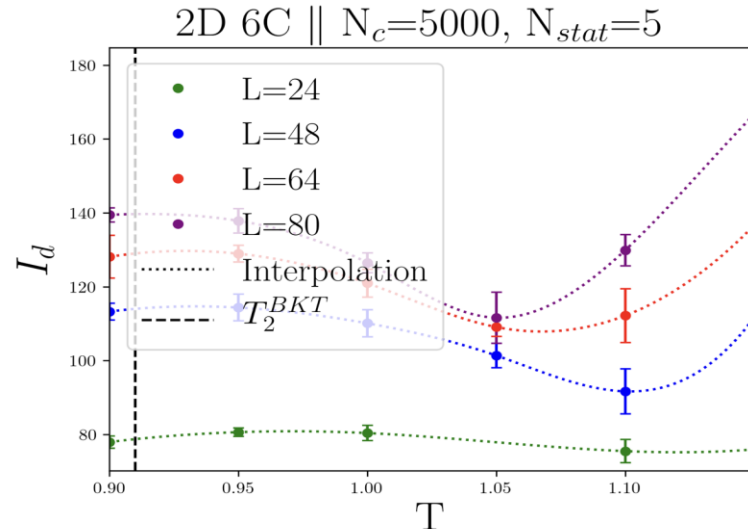
Result: $T_{I_d}^{BKT} = 0.84(4)$, 3% away from agreeing with T_{MC}^{BKT}

INTRINSIC DIMENSION

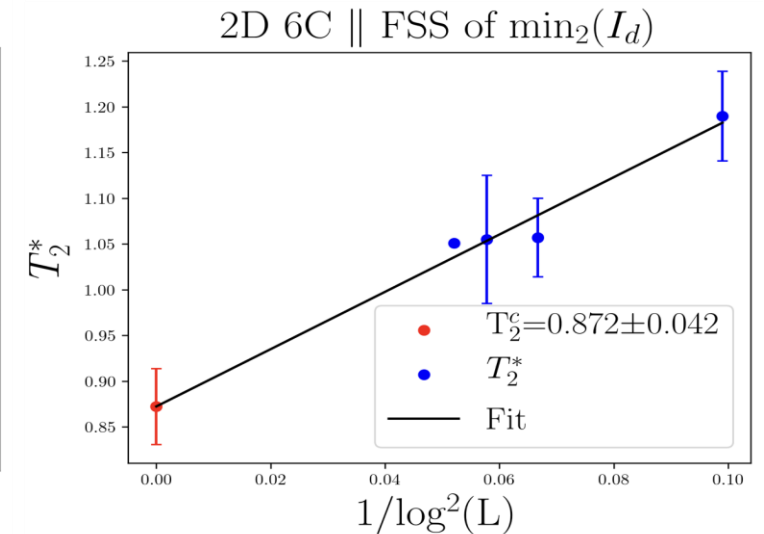
APPLICATION TO 6-CLOCK



- I_d displays two minima
- Do they scale as expected?



- Interpolation of the data to determine T_2^*



- Plot T^* against $\ln^{-2}(L)$
- Scaling is satisfied

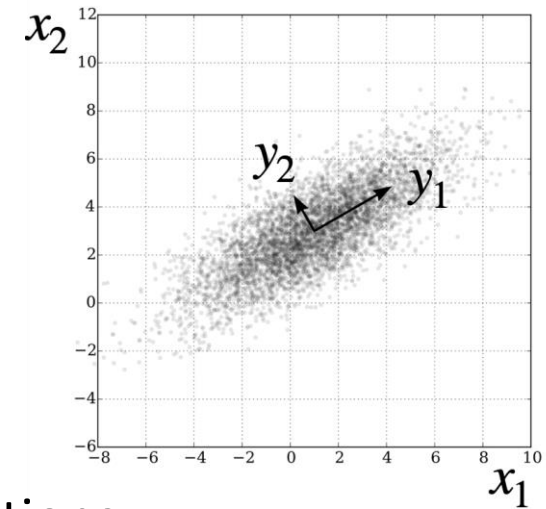
$T_{I_d,2}^{BKT} = 0.87(4)$, agrees with T_{MC}^{BKT} ; $T_{I_d,1}^{BKT} = 0.87(4)$, agrees with $T_1^{BKT} = 0.6901(4)^{[10]}$

DATA MINING

PRINCIPAL COMPONENT ANALYSIS

Dimensionality reduction technique based on a linear transformation of the data set

- **Idea:** relevant information in the directions of maximum variance
- **Figure:** we want to reduce the dimensionality from 2 to 1
 - Linear transformation $(x_1, x_2) \rightarrow (y_1, y_2)$ eigenvectors of $C(\mathbf{X})$
 - Discard eigenvectors with lower eigenvalues (y_2)
- **General case:** $C(\mathbf{X})$ has N eigenvectors: systematic way of eliminating directions
 - Set a threshold for the **fidelity**: $[0,1] \ni F \equiv Tr[C(\mathbf{Y})]/Tr[C(\mathbf{X})]$
 - Keep all eigenvalues in decreasing order until the threshold is met



PRINCIPAL COMPONENT ANALYSIS

PCA ENTROPY

- Problems with PCA
 - Arbitrary threshold
 - By only looking at eigenvalues/vectors is not possible to get T_{PCA}^{BKT} [4]
- Define a new quantity using **all** the eigenvalues

$$S_{PCA} := \frac{1}{\ln R} \sum_{i=1}^R \tilde{\lambda}_i \ln \tilde{\lambda}_i,$$

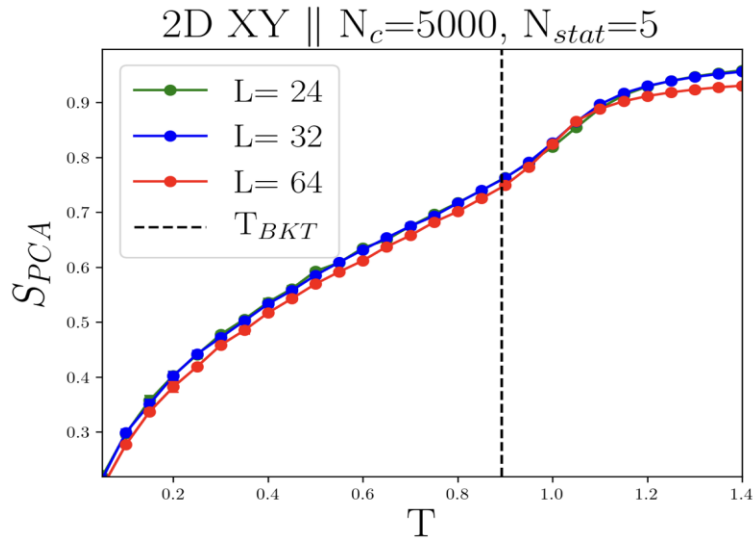
$$\tilde{\lambda}_i = \lambda_i^2 / \sum_j \lambda_j$$

$S_{PCA} = 0$ at $T = 0$ and $S_{PCA} = 1$ at $T = \infty$

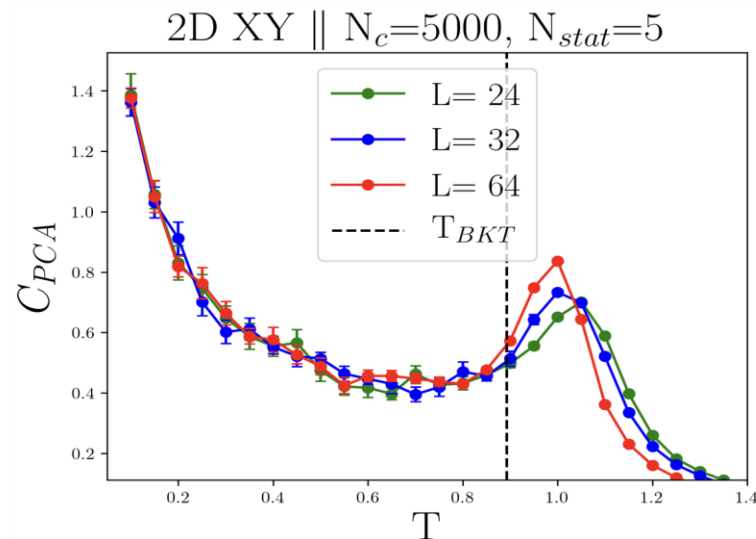
$\tilde{\lambda}_i$ are now positive and sum up to 1, like probabilities: S_{PCA} is an entropy.

PCA ENTROPY

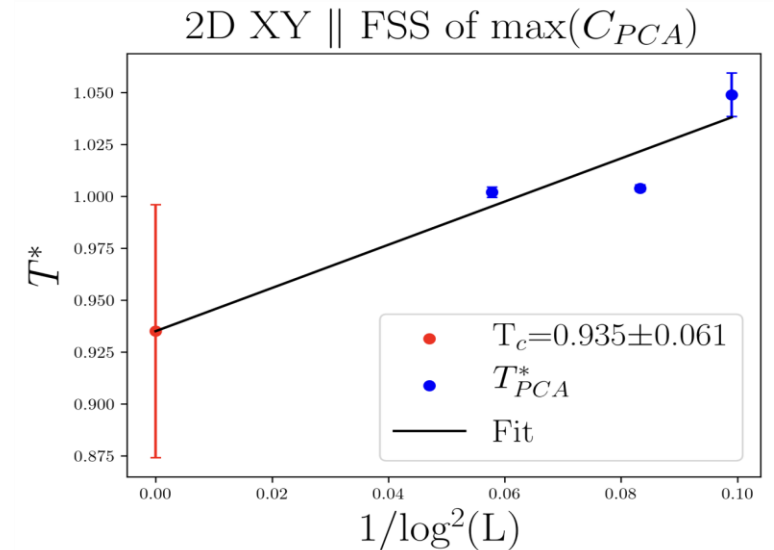
APPLICATION TO XY MODEL



- Agrees with interpretation
- Shows a kink close to T^{BKT}



- Derivative has a maximum
- Does it scale properly?

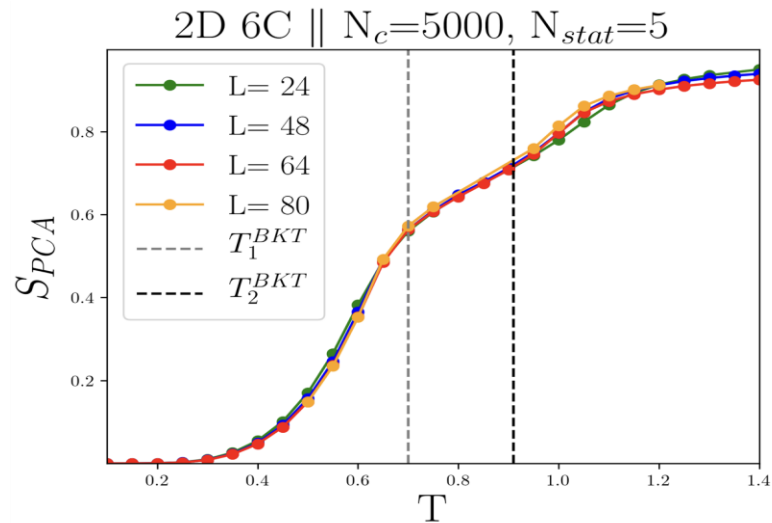


- Small error bars
- The fit gives $T_{PCA}^{BKT} = 0.93(6)$

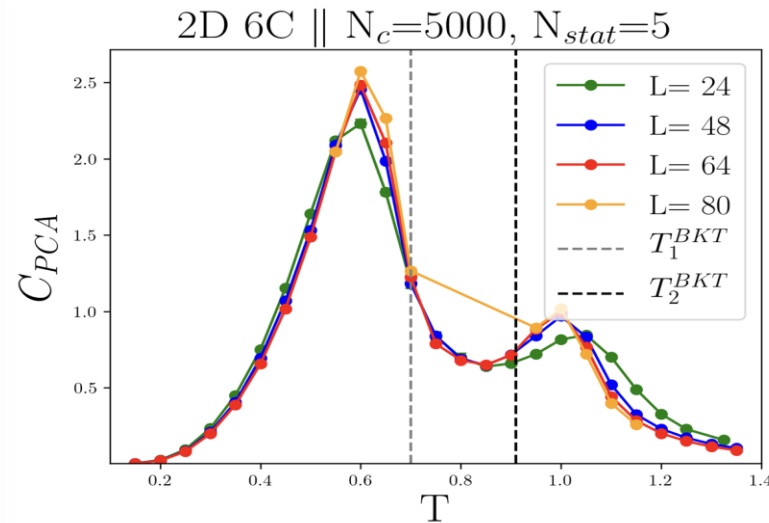
This result is in agreement with T_{MC}^{BKT}

PCA ENTROPY

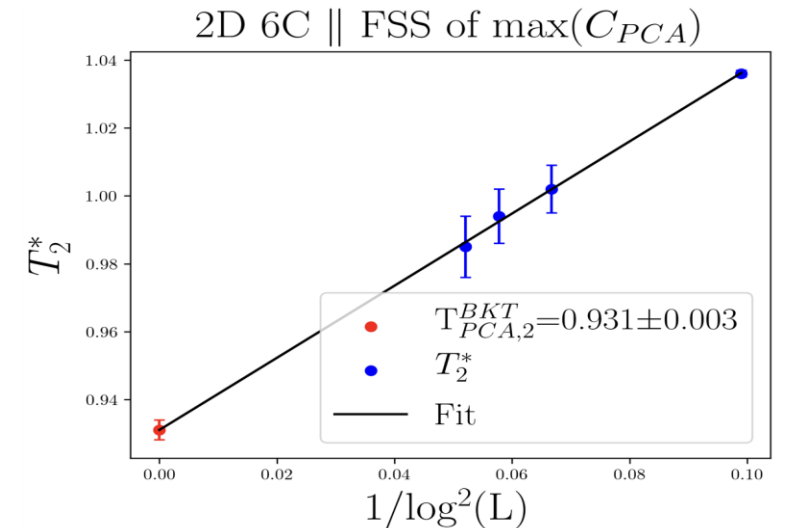
APPLICATION TO XY MODEL



- Fast growth in LRO
- Kink close to T_2^{BKT}



- Two maxima
- Biggest signal at T_1^{BKT}



- Scaling is satisfied
- Fit gives $T_{PCA,2}^{BKT} = 0.93(3)$

$T_{PCA,2}^{BKT}$ agrees with T_{MC}^{BKT} , while $T_{PCA,1}^{BKT} = 0.627(2)$ does not for a 9%

PCA ENTROPY

SUMMARY OF THE RESULTS

- PCA entropy compatible results with Monte Carlo methods in both models for the estimation of T^{BKT} for QLRO→DIS
 - T_1^{BKT} does not give satisfying results
 - Looking at bigger system sizes
 - More sophisticated techniques for evaluating the error on T^*
- I_d does not give compatible results with T_{MC}^{BKT} in the XY model, but this is due to limited system sizes, as supported by other works [4]
- Results obtained with I_d and S_{PCA} are not always compatible, furthermore
 - I_d seems to work better for LRO→QLRO
 - S_{PCA} seems to work better for QLRO→DIS

THANK YOU