

Unsupervised Learning of Phase Transitions

Seminar: Machine Learning Quantum Matter

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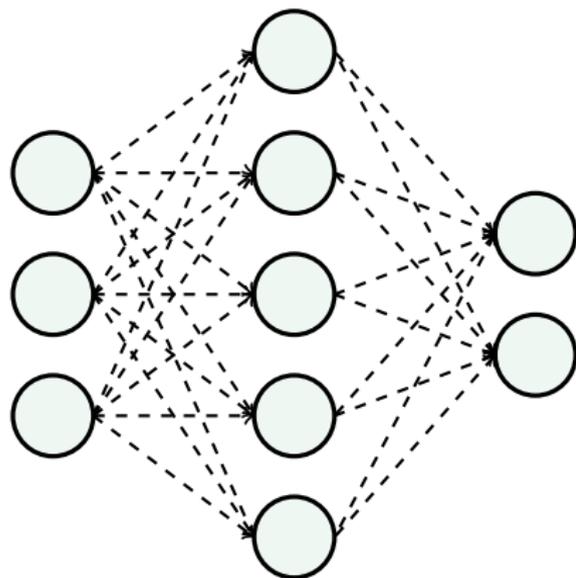
May 10, 2021,
Cologne

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- 2 Learning Phase Transitions by Confusion
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Unsupervised Compared to Supervised Methods

Supervised learning

Input Hidden layer Output



$$C \propto \sum_{\underline{x}} \|\text{Label}(\underline{x}) - \text{Output}(\underline{x})\|^2 + l_2 \|\underline{\omega}\|^2$$

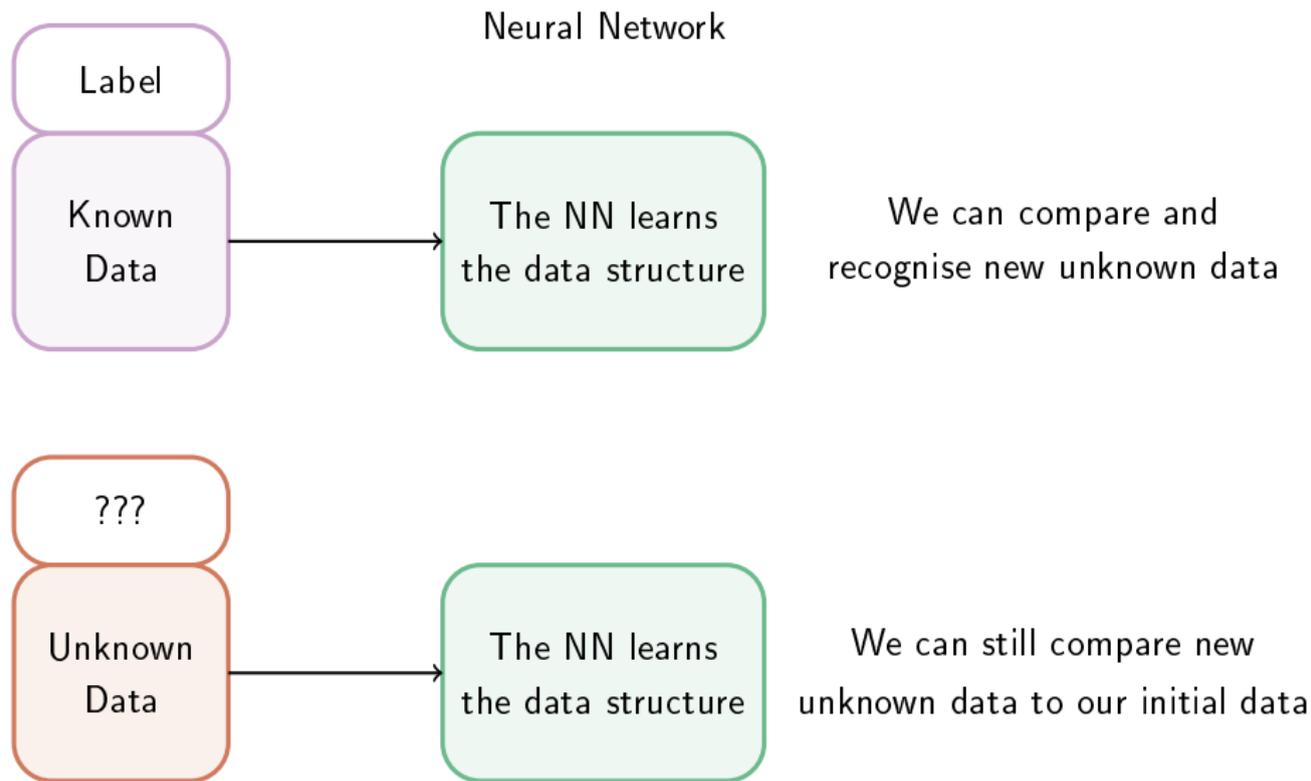
\underline{x}



Output_{*i*} ∈ (0, 1)

$$\sigma(\underline{\omega}^{(i)} \cdot \underline{x} + b_i)$$

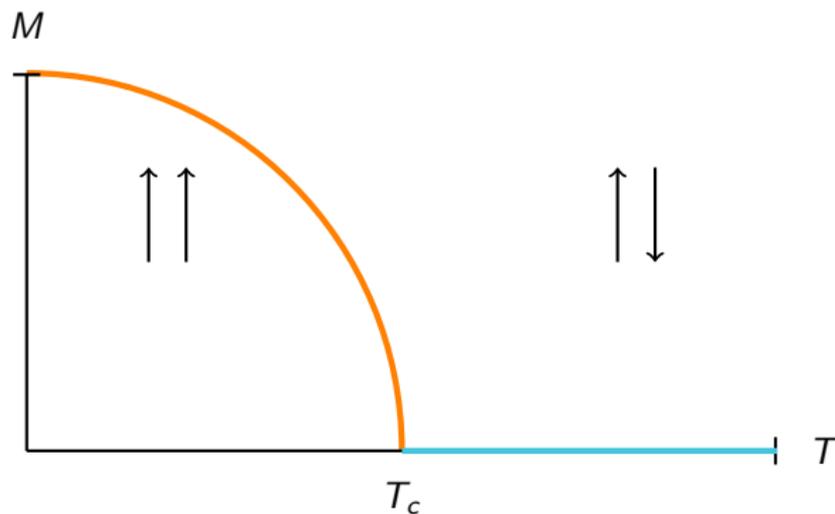
Unsupervised Compared to Supervised Methods



Learning Phase Transitions by Confusion

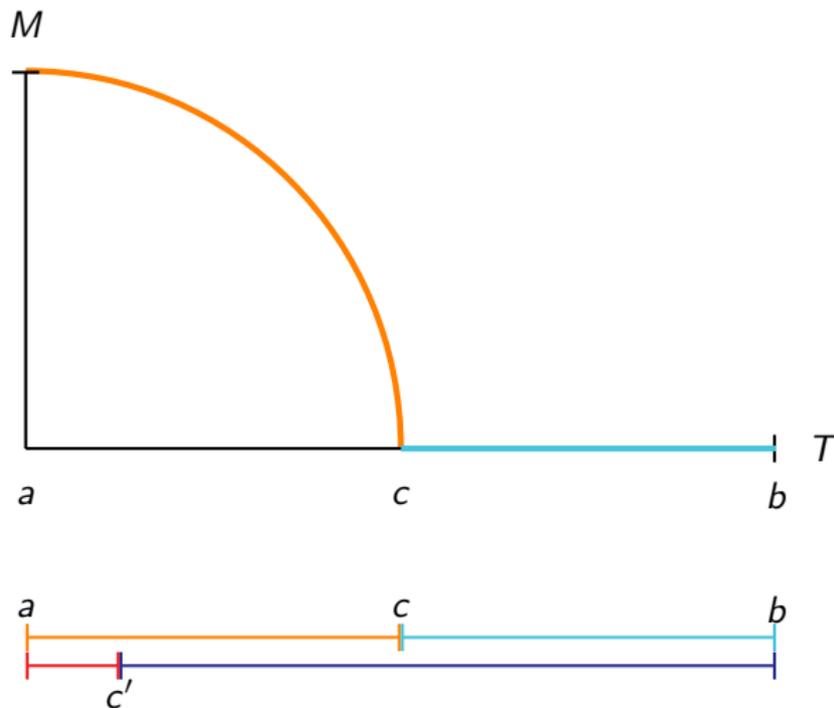
van Nieuwenburg, Evert P. L. and Liu, Ye-Hua and Huber, Sebastian D.
2017

Classical Ising model on L^2 grid

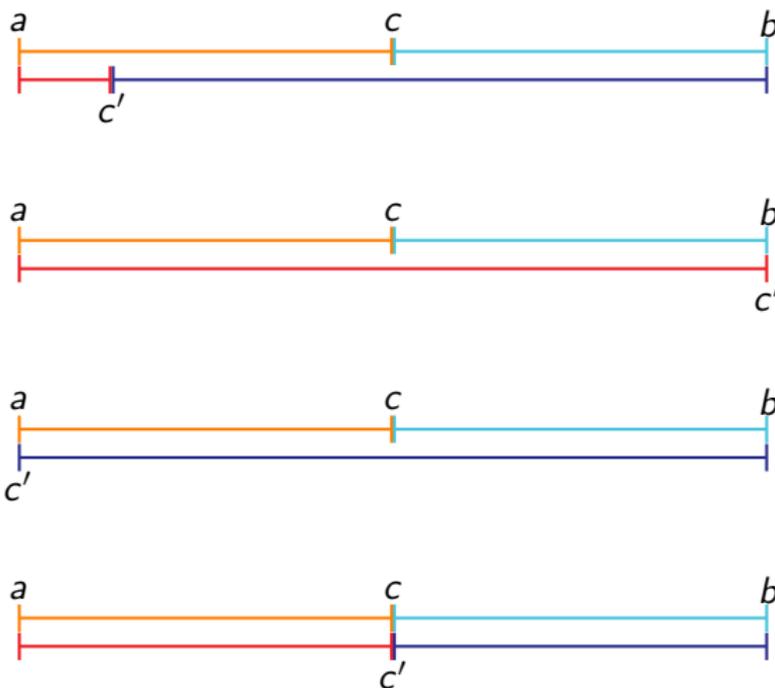


$$H = -J \sum_{\langle i,j \rangle} S_i^Z S_j^Z$$

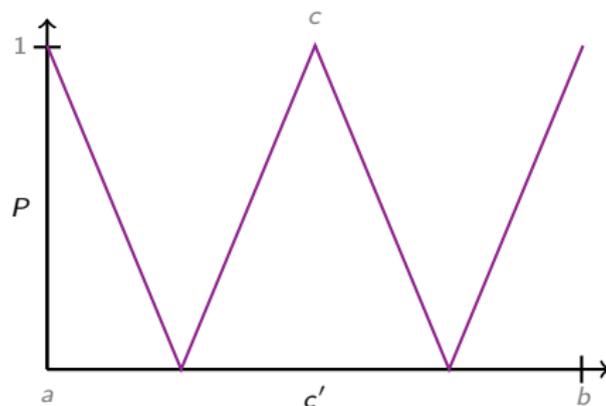
Learning Phase Transitions by Confusion



Learning Phase Transitions by Confusion

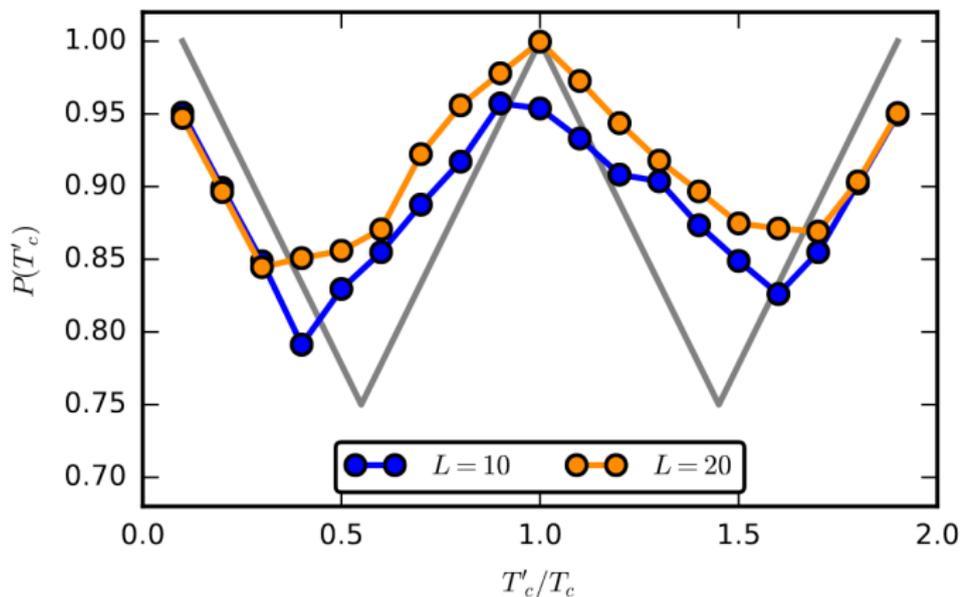


Learning Phase Transitions by Confusion

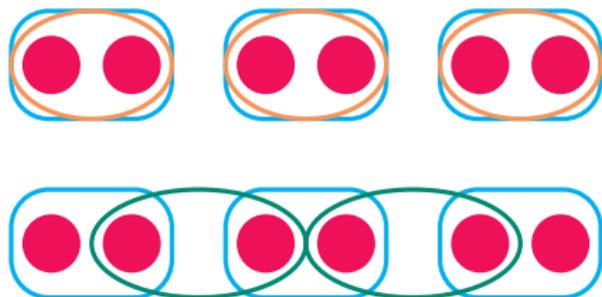


$$P(c') = \begin{cases} 1 - \frac{\min(c-c', c'-a)}{c-a}, & c' < c \\ 1 - \frac{\min(c'-c, b-c')}{b-c}, & c' > c \end{cases}$$

Classical Ising model on L^2 grid



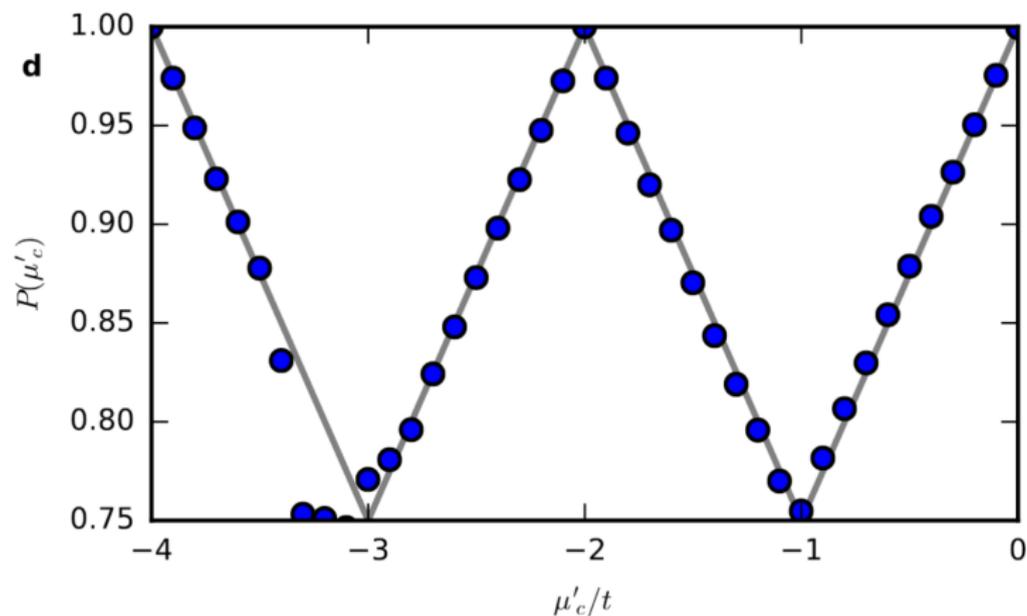
Source: van Nieuwenburg et al. [1]



$$\hat{H} = -t \sum_{i=1}^L \left(\hat{c}_{i+1}^\dagger \hat{c}_i + \hat{c}_{i+1} \hat{c}_i + h.c. \right) - \mu \sum_{i=1}^L \hat{c}_i^\dagger \hat{c}_i$$

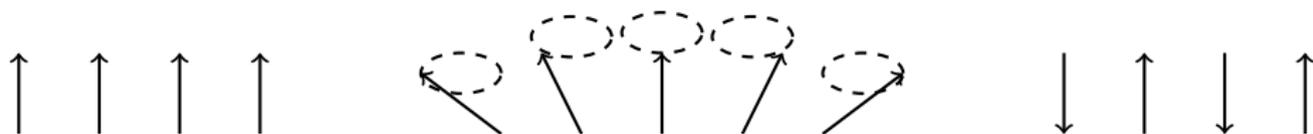
- 1 phase transition at $\mu_c = -2t$

Kitaev chain



Source: van Nieuwenburg et al. [1]

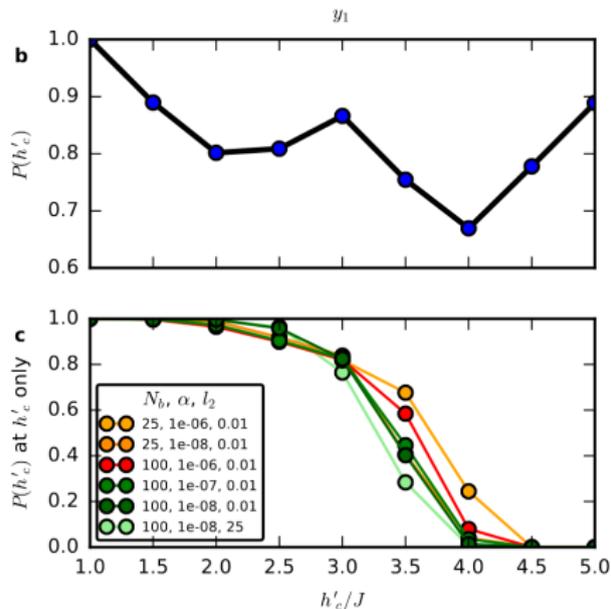
Heisenberg model



$$H = J \sum_{i=1}^L \mathbf{S}_i \cdot \mathbf{S}_{i+1} + \sum_{\alpha=x,y,z} \sum_{i=1}^L h_i^\alpha S_i^\alpha$$

- 1 phase transition at $h_c \approx 3J$

Heisenberg model



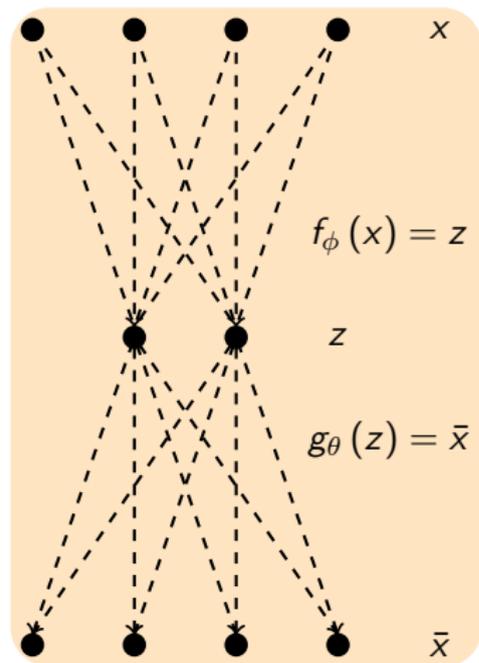
- The algorithm parameters are learning rate (α), regularization (adds $l_2 \sum |\omega|^2$ to cost the function) and batch size of training data (N_b)

Source: van Nieuwenburg et al. [1]

Unsupervised Phase Discovery with Deep Anomaly Detection

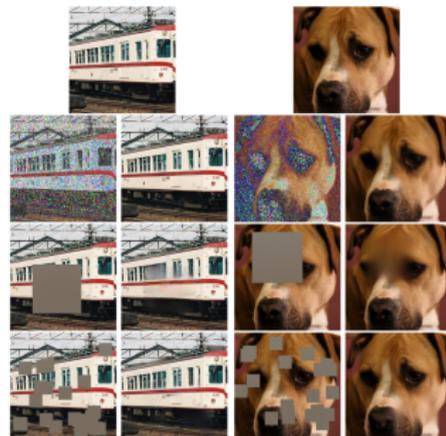
Kottmann, Korbinian and Huembeli, Patrick and Lewenstein, Maciej and Acín, Antonio
2020

Auto encoder



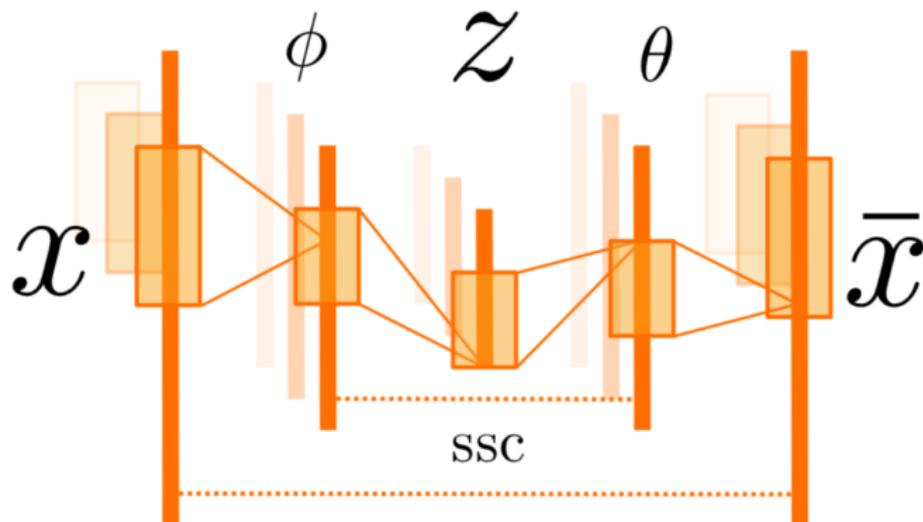
$$L(x, \bar{x}) = \frac{|x - \bar{x}|^2}{\dim(x)}$$

$$\dim(x) = \dim(\bar{x})$$



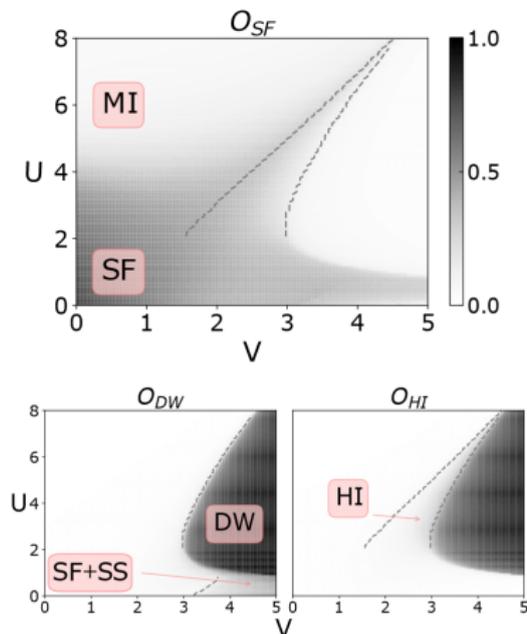
Source: Jianfeng Dong et al. [3]

Symmetric shortcut connections



Source: Kottmann et al. [2]

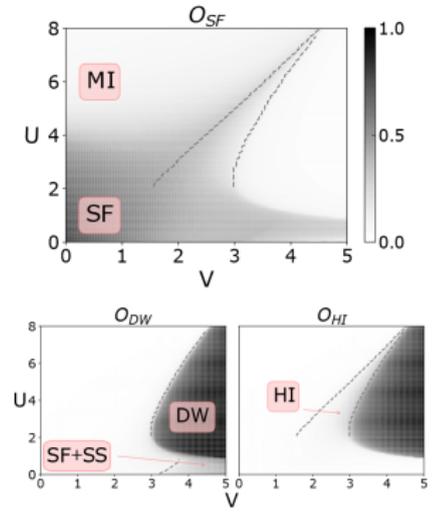
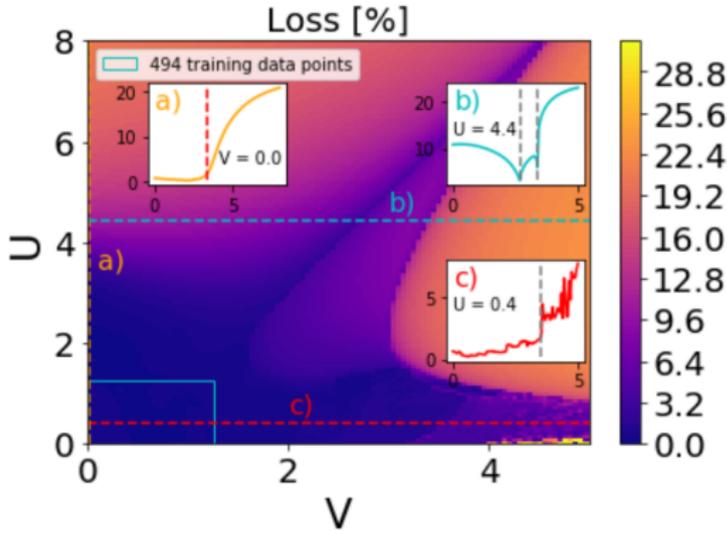
Extended Bose-Hubbard Model



$$H = -t \sum_i \left(b_i^\dagger b_{i+1} + b_{i+1}^\dagger b_i \right) + \frac{U}{2} \sum_i b_i^\dagger b_i \left(b_i^\dagger b_i - 1 \right) + V \sum_i b_i^\dagger b_i b_{i+1}^\dagger b_{i+1}$$

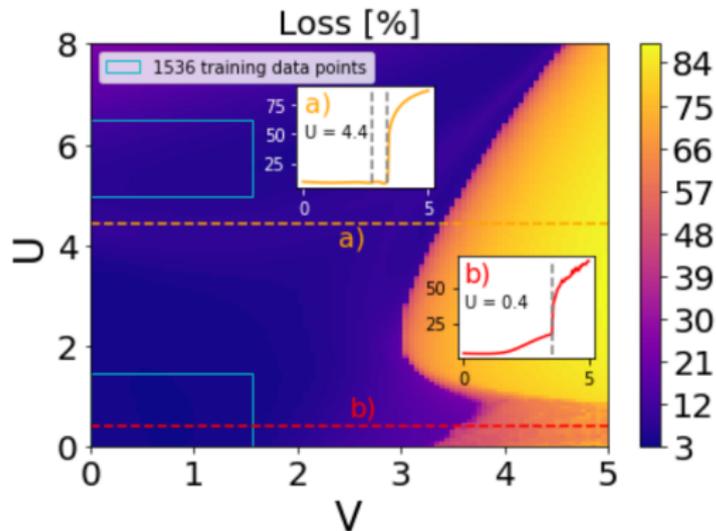
Source: Kottmann et al. [2]

Extended Bose-Hubbard Model



Source: Kottmann et al. [2]

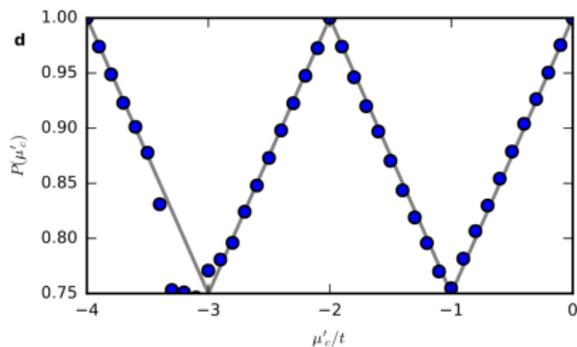
Extended Bose-Hubbard Model



Source: Kottmann et al. [2]

Summary

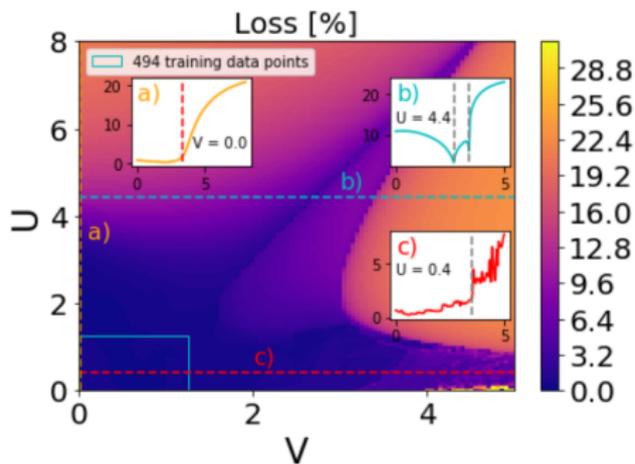
Learning Phase Transitions by Confusion



- No knowledge over phases needed
- Sampling over the dataset gives a robust tool to find transitions
- But each sample needs a training cycle and is more costly than our second method

Source: van Nieuwenburg et al. [1]

Unsupervised Phase Discovery with Deep Anomaly Detection



- One training over only a small region is sufficient
- Spans a whole phase diagram
- Runs on different kinds of input data type

Source: Kottmann et al. [2]

-  van Nieuwenburg, Evert P. L. and Liu, Ye-Hua and Huber, Sebastian D.: *Learning phase transitions by confusion*. In: *Nature Physics*. Springer Science and Business Media LLC. 2017
-  Kottmann, Korbinian and Huembeli, Patrick and Lewenstein, Maciej and Acín, Antonio: *Unsupervised Phase Discovery with Deep Anomaly Detection*. In: *Physical Review Letters*. American Physical Society (APS). 2020
-  Jianfeng Dong and Xiao-Jiao Mao and Chunhua Shen and Yu-Bin Yang: *Learning Deep Representations Using Convolutional Auto-encoders with Symmetric Skip Connections*. 2017