Title: Recurrent neural networks for Rydberg atom arrays

Speakers: Mohamed Hibat Allah

Collection/Series: Special Seminars

Subject: Other

Date: May 02, 2025 - 9:30 AM

URL: https://pirsa.org/25040058

Abstract:

Rydberg atom arrays have emerged as powerful quantum simulators, capable of preparing strongly correlated phases of matter that are potentially challenging to access with classical computational methods. A major focus has been on realizing these arrays on frustrated geometries, aiming to stabilize exotic many-body states like spin liquids. In this talk, I will show how two-dimensional recurrent neural network (RNN) wave functions can be used to study the ground states of Rydberg atom arrays on the kagome lattice. For Hamiltonians previously investigated in this geometry, I will demonstrate that the RNN finds no evidence for exotic spin liquid phases or emergent glassiness. In particular, I will argue that signals of glassy behavior, such as a nonzero Edwards-Anderson order parameter seen in quantum Monte Carlo (QMC) studies, may arise from artifacts related to long autocorrelation times. These results highlight the potential of language model-inspired approaches, like RNNs, for advancing the study of frustrated quantum systems and Rydberg atom physics more broadly.

arXiv paper: https://arxiv.org/pdf/2405.20384

UNIVERSITY OF WATERLOO

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Recurrent Neural Networks (RNNs) for Rydberg atom arrays

Mohamed Hibat-Allah

May 2nd, 2025

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Simulating quantum systems with classical computers?

Wave function:

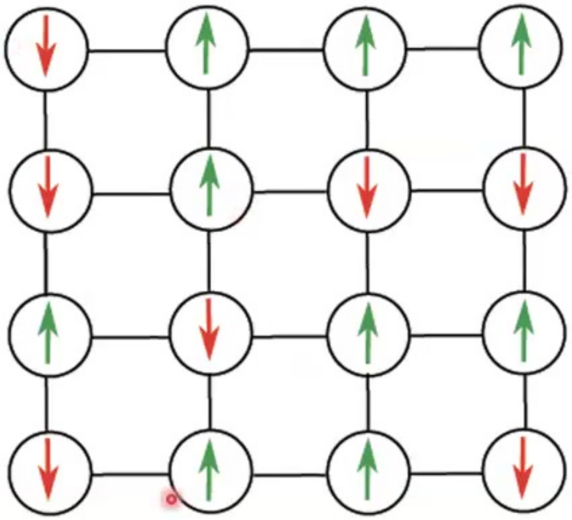
$$\Psi = (\Psi_1, \Psi_2, ..., \Psi_{2^N}) \in \mathbb{C}^{2^N}$$

The module squared of the wave function defines a probability distribution:

$$|\Psi_1|^2 + |\Psi_2|^2 + ... + |\Psi_{2^N}|^2 = 1$$

For N = 266:

$$\mathbf{2^{266}} \approx \mathbf{10^{80}} \sim \text{number of atoms in our known universe}$$



Lattice of spins

Simulating quantum systems with classical computers?

Simulating Physics with Computers

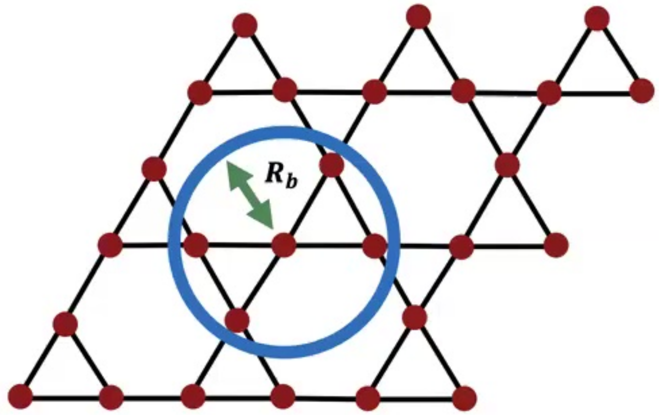
Richard P. Feynman

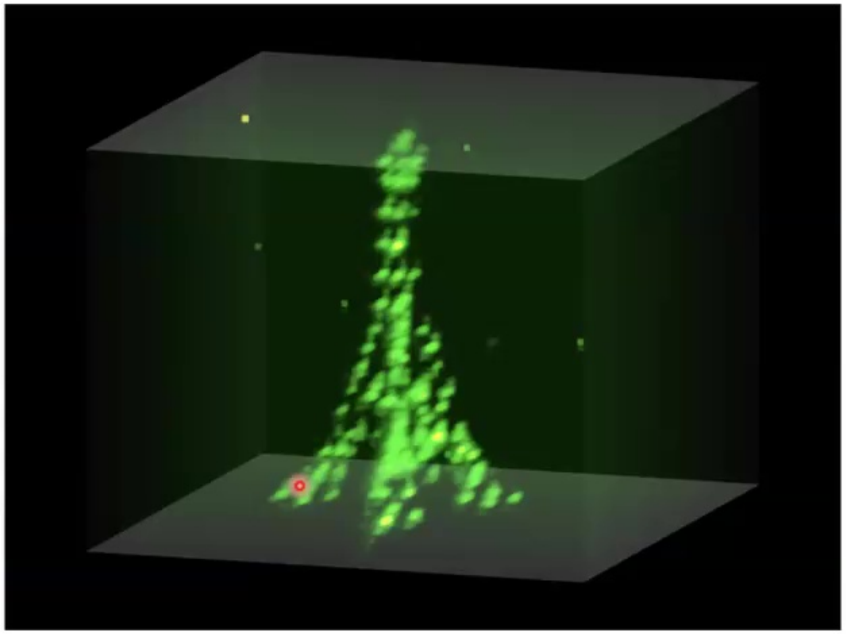
Department of Physics, California Institute of Technology, Pasadena, California 91107

Received May 7, 1981

"...if you want to make a simulation of nature, you'd better make it quantum mechanical,..."

Quantum Simulator: Rydberg atom arrays



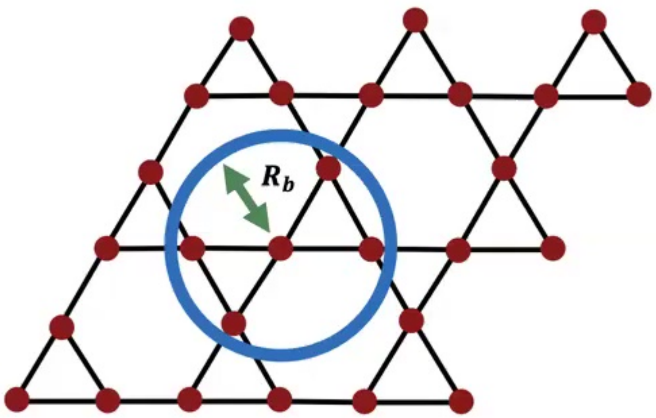


Credit: Thierry Lahaye/CNRS, 2018

Programmable quantum simulator:

- **Artificially simulate phases of matter in the lab.**
- **Realizable in the lab by manipulating Rydberg atoms.**
- **Can be implemented on different geometries with tunable parameters.**

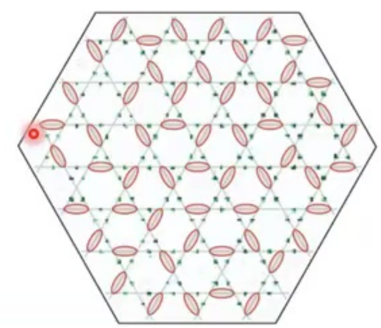
Rydberg atom arrays



TOPOLOGICAL MATTER

Probing topological spin liquids on a programmable quantum simulator

G. Semeghini[1], H. Levine[1], A. Keesling[1,2], S. Ebadi[1], T. T. Wang[1], D. Bluvstein[1], R. Verresen[1], H. Pichler[3,4], M. Kalinowski[1], R. Samajdar[1], A. Omran[1,2], S. Sachdev[1,5], A. Vishwanath[1*], M. Greiner[1*], V. Vuletić[6*], M. D. Lukin[1*]



Programmable quantum simulator:

- **Artificially simulate phases of matter in the lab.**
- **Realizable in the lab by manipulating Rydberg atoms.**
- **Can be implemented on different geometries with tunable parameters.**

Realization of "Topological order" in Rydberg atom arrays (2021)

Goal of this talk

Showcase that we can use Recurrent Neural Networks (RNNs) to understand the physics of Rydberg atoms arrays on Kagome lattice

Goal of this talk

Density Matrix Renormalization Group: Spin liquid phase (topological order).

R. Samajdar et al., PNAS 2021.

↓

Quantum Monte Carlo: Spin glass phase.

Z. Yan et al., PRL 2023.

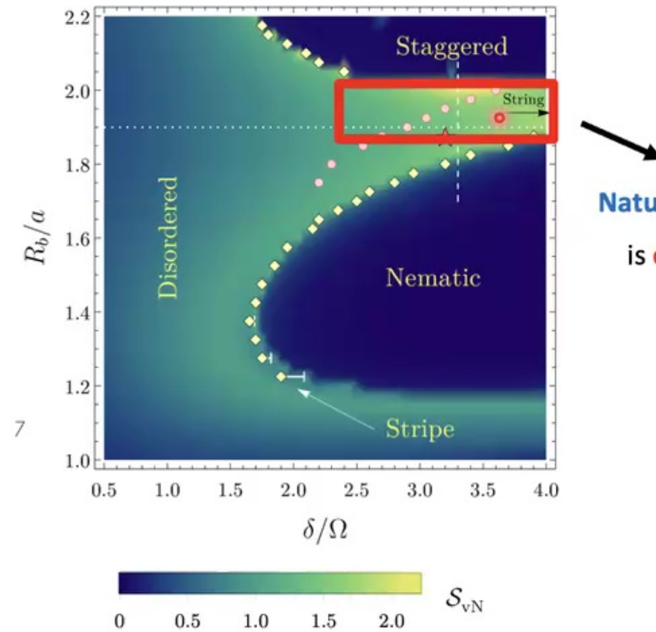
↓

2D Recurrent Neural Networks (RNNs): Paramagnetic phase.

Quantum Monte Carlo (fine-tuned simulations): Paramagnetic phase.

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

> Very promising example where RNNs offer a powerful complementary numerical method in quantum matter.



Nature of the phase is controversial

Rydberg atoms arrays on Kagome Lattice

R. Samajdar et al., PNAS 2021.

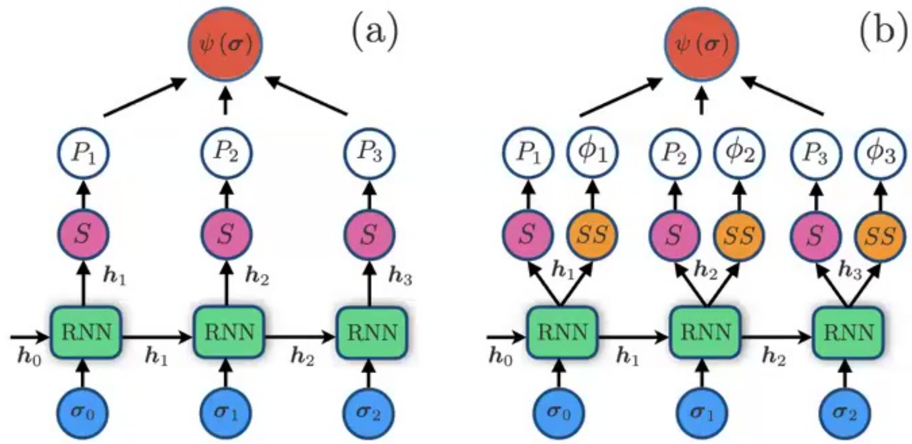
Outline

I. Recurrent Neural network (RNN) wave functions

II. Variational annealing with RNNs.

III. Investigating topological order with RNNs.

IV. RNNs for Rydberg atoms arrays on Kagome Lattice.



I. Recurrent Neural Network Wave Functions

M.H, M. Ganahl, L. Hayward, R. Melko, J. Carrasquilla, Recurrent Neural Network Wave Functions, Physical Review Research, Jun 2020.

M.H, R. Melko, J. Carrasquilla, Supplementing RNN wave functions with symmetry and annealing to improve accuracy, ML for Physical Sciences Workshop, NeurIPS, Dec 2021.

M.H, R. Melko, J. Carrasquilla, Investigating topological order using Recurrent Neural Networks, Physical Reviews B, Aug 2023.

Ground state problem

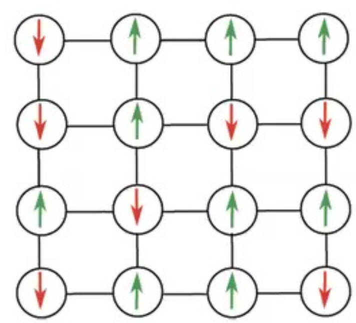
$$H\Psi_G = E_G \Psi_G$$

Hamiltonian
(matrix with size $2^N \times 2^N$)

Ground State Wave function
(complex-valued vector with size 2^N)

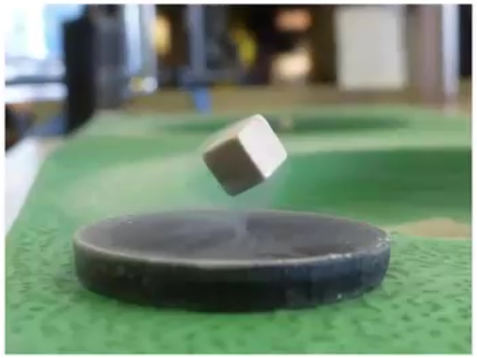
The lowest energy of the system
(Lowest eigenvalue)

Interactions are fully described by the Hamiltonian : H

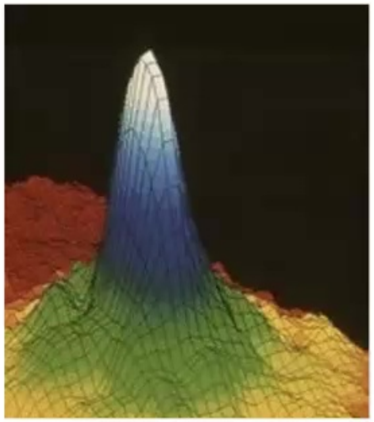


Why do we need ground states?

- To understand quantum phenomena (superconductivity, Bose-Einstein condensate,...).



Credit: Phys.org



Credit: © SPL

Exact diagonalization

$$\mathbf{H} = \underbrace{\begin{pmatrix} * & \cdots & * \\ \vdots & \ddots & \vdots \\ * & \cdots & * \end{pmatrix}}_{2^N \times 2^N} \xrightarrow{\text{Diagonalize}} \begin{pmatrix} \color{red}{E_G} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & * \end{pmatrix}$$

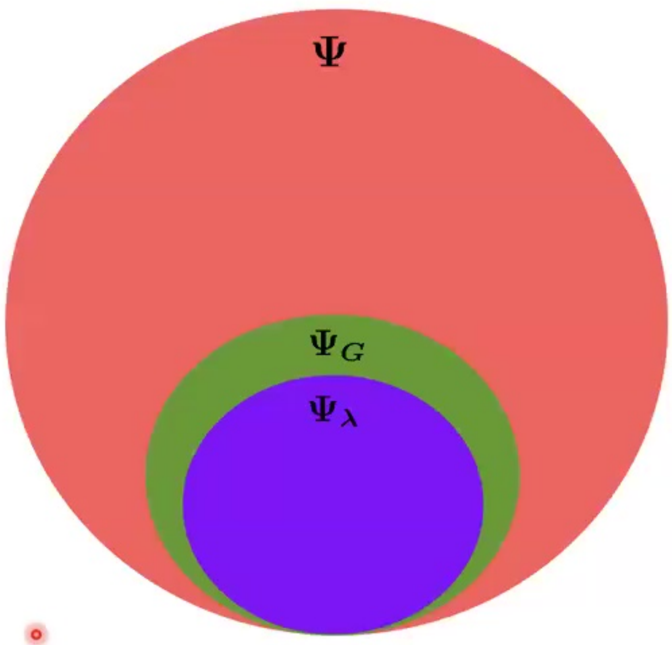
Exact diagonalization

$$\mathbf{H} = \underbrace{\begin{pmatrix} * & \cdots & * \\ \vdots & \ddots & \vdots \\ * & \cdots & * \end{pmatrix}}_{2^N \times 2^N} \xrightarrow{\textbf{Diagonalize}} \begin{pmatrix} E_G & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & * \end{pmatrix}$$

- Computational complexity of diagonalization: $\sim \mathcal{O}(2^{cN})$

- **Example:** 2^{110} **FLOPS** is about **3 times the age of the known universe** on **a modern GPU** (**10^{15} FLOPS per second**)

Variational Principle



$$H\boldsymbol{\Psi_G} = E_G\boldsymbol{\Psi_G}$$

↓

$$E_G = \min_{||\boldsymbol{\Psi}||_2=1} \boldsymbol{\Psi}^\dagger H \boldsymbol{\Psi}$$

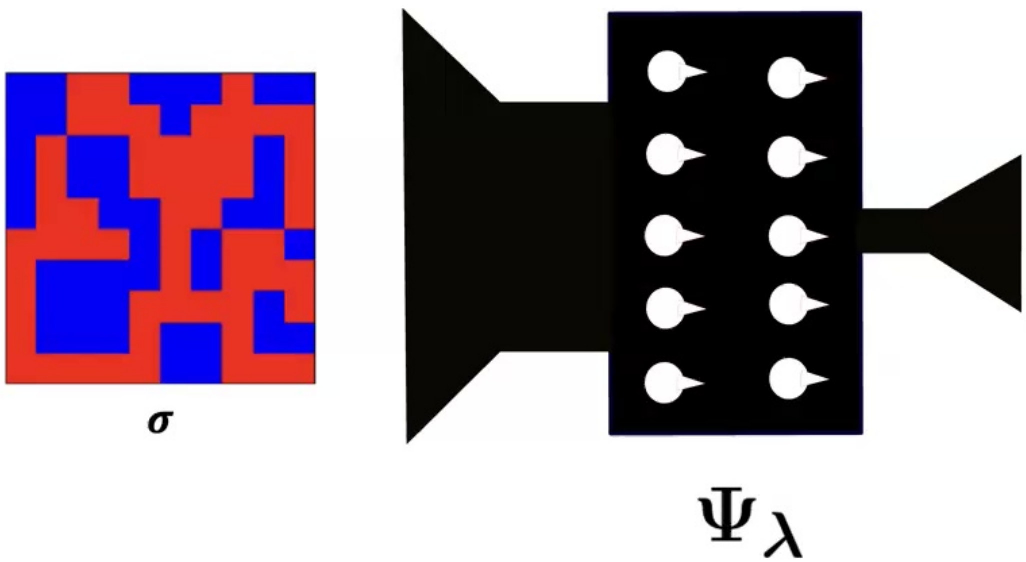
↓

$$E_G \lessapprox \min_{\boldsymbol{\lambda}} \boxed{\boldsymbol{\Psi_\lambda}^\dagger H \boldsymbol{\Psi_\lambda}}$$

Ψ_λ needs to be expressive enough!

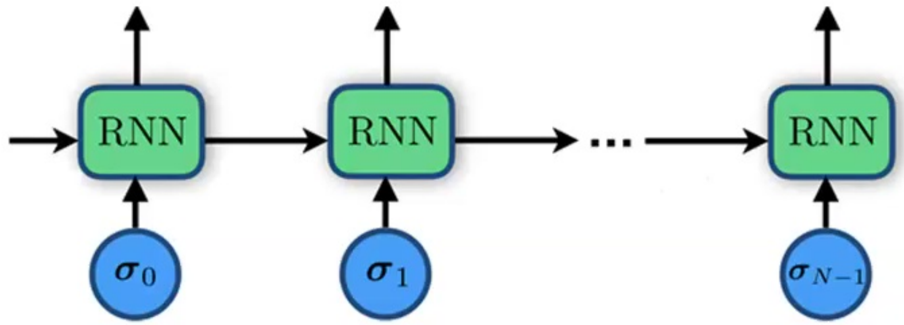
Variational energy
=
Cost function

Neural network quantum states



Carleo and Troyer, Science, 2017

Recurrent Neural Networks (RNNs)



An RNN is a Universal Turing Machine approximator: can be seen as a general-purpose computer that can perform any classical computation.

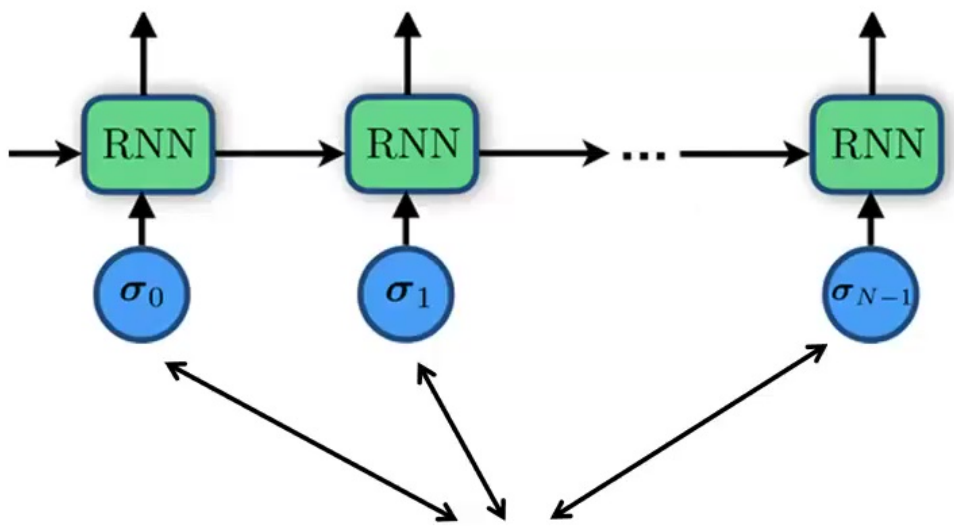
Very powerful at generating sequential data:

- Speech recognition, machine translation,...

Siegelmann and Sontag, ACM, 1982

Chung and Siegelmann, NeurIPS 2021

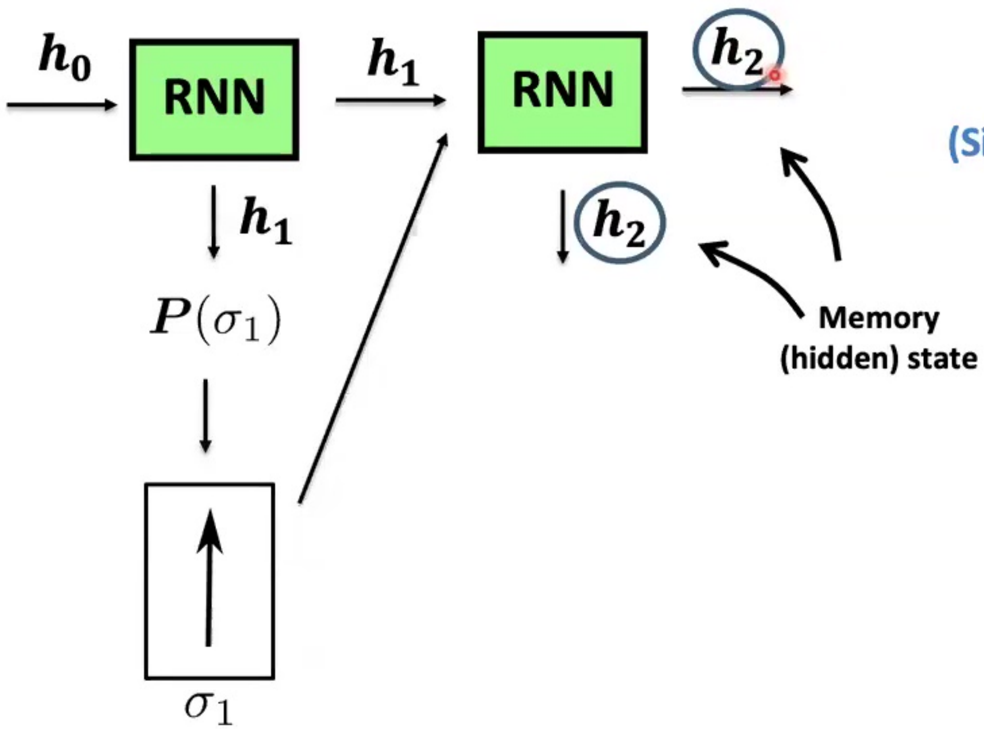
RNNs can be used in many-body Physics



"Spins", "occupation number" or "excitation" instead of "Words"

"Artificial intelligence for advanced functional materials: Exploring current and future directions", Journal of Physics: Materials, 2025

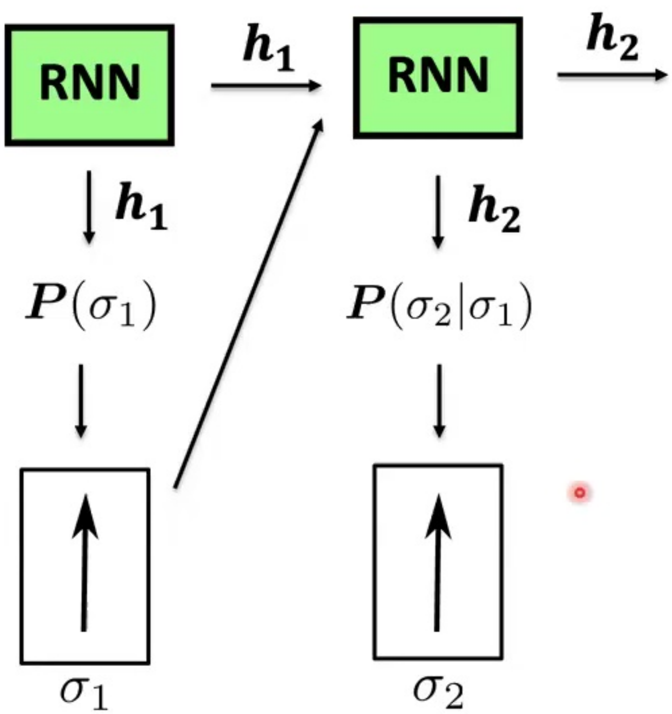
Autoregressive sampling



(Simplest) Recursion relation:

$$\boldsymbol{h}_n = f(W[\boldsymbol{h}_{n-1}; \boldsymbol{\sigma}_{n-1}] + \boldsymbol{b})$$

Autoregressive sampling



(Simplest) Recursion relation:

$$\boldsymbol{h}_n = f(W[\boldsymbol{h}_{n-1}; \boldsymbol{\sigma}_{n-1}] + \boldsymbol{b})$$

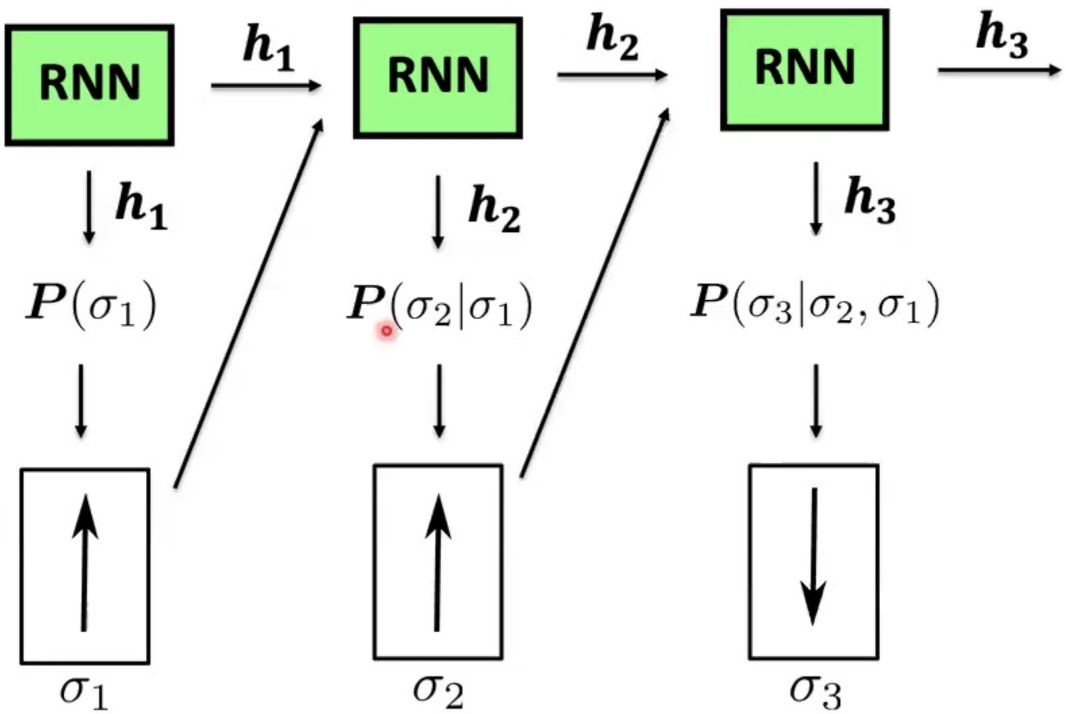
Conditional probability:

$$\boldsymbol{P}(\sigma_i|\sigma_{<i}) = \text{Softmax}(U\boldsymbol{h}_n + \boldsymbol{c}) \cdot \boldsymbol{\sigma}_n$$

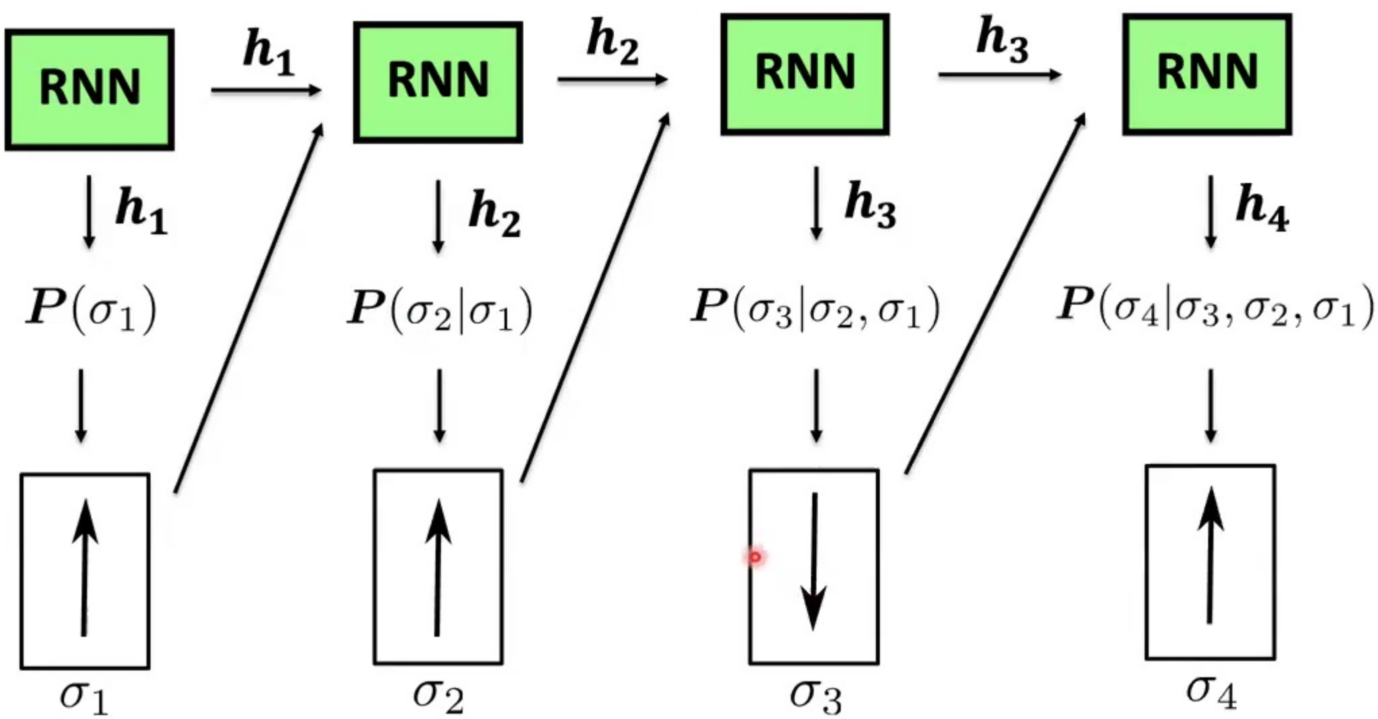
$\boldsymbol{W}, \boldsymbol{U}, \boldsymbol{b}$ and $\boldsymbol{c}$ are the parameters of the RNN.

In this work, we use gated recurrent units (GRUs).

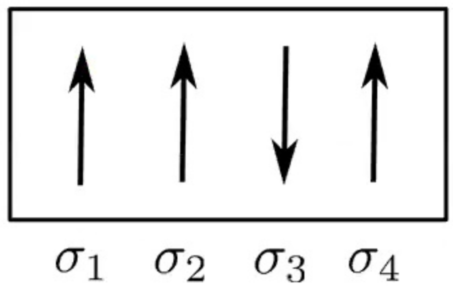
Autoregressive sampling



Autoregressive sampling



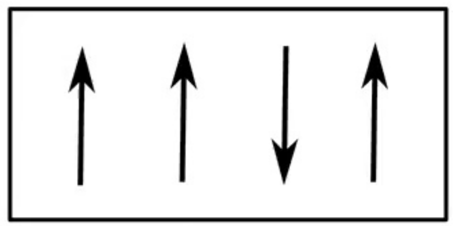
RNN wave functions



$$|\Psi_{\mathbf{RNN}}(\sigma_1, \sigma_2, \sigma_3, \sigma_4)|^2 = \boldsymbol{P}(\sigma_1)\boldsymbol{P}(\sigma_2|\sigma_1)\boldsymbol{P}(\sigma_3|\sigma_2, \sigma_1)\boldsymbol{P}(\sigma_4|\sigma_3, \sigma_2, \sigma_1)$$

M.H, M. Ganahl, L. Hayward, R. Melko, J. Carrasquilla, Recurrent Neural Network Wave Functions, PRReasearch, 2020.

Autoregressive sampling



$\sigma_1 \quad \sigma_2 \quad \sigma_3 \quad \sigma_4$

$$|\Psi_{\mathbf{RNN}}(\sigma_1, \sigma_2, \sigma_3, \sigma_4)|^2 = \boldsymbol{P}(\sigma_1)\boldsymbol{P}(\sigma_2|\sigma_1)\boldsymbol{P}(\sigma_3|\sigma_2, \sigma_1)\boldsymbol{P}(\sigma_4|\sigma_3, \sigma_2, \sigma_1)$$

The samples are independents and can be generated in parallel $\{\boldsymbol{\sigma}^{(j)}\}_{i=1}^{N_s}$

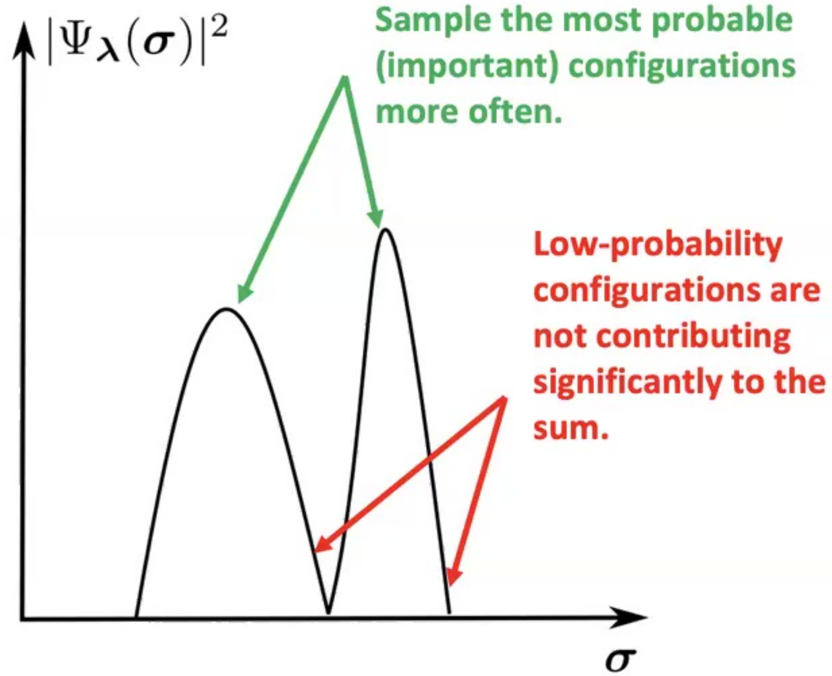
Importance Sampling (Variational Monte Carlo)

$$E_{\boldsymbol{\lambda}} = \boldsymbol{\Psi}_{\boldsymbol{\lambda}}{}^{\dagger} H \boldsymbol{\Psi}_{\boldsymbol{\lambda}}$$

$$= \sum_{\boldsymbol{\sigma}} |\Psi_{\boldsymbol{\lambda}}(\boldsymbol{\sigma})|^2 E_{\text{loc}}(\boldsymbol{\sigma})$$

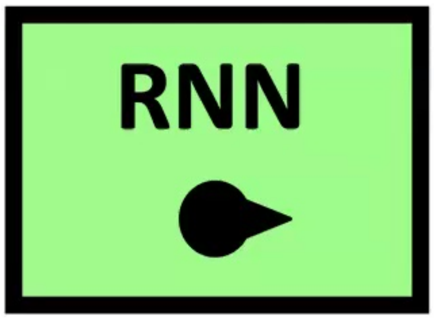
$$\approx \frac{1}{N_s} \sum_{\boldsymbol{\sigma} \sim |\Psi_{\boldsymbol{\lambda}}(\boldsymbol{\sigma})|^2} E_{\text{loc}}(\boldsymbol{\sigma})$$

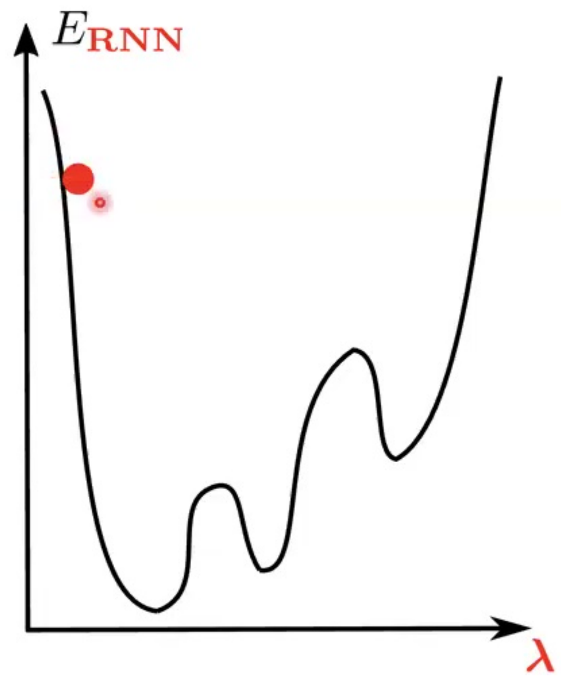
No need for training data.
The data comes from the model itself!



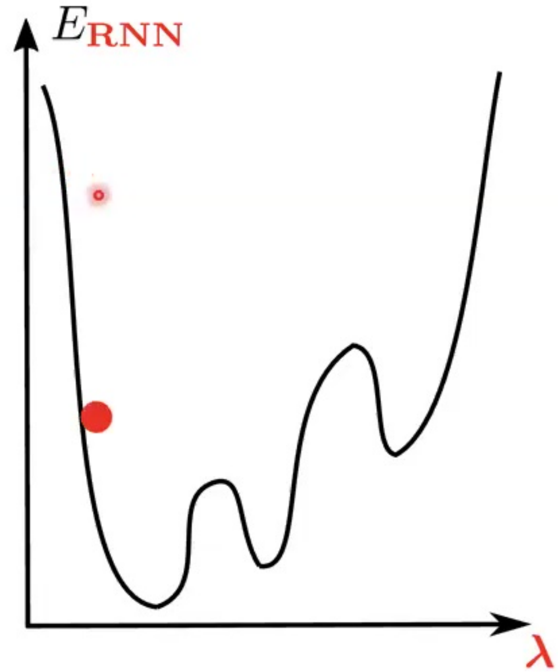
Becca and Sorella, Quantum Monte Carlo Approaches for Correlated Systems, Cambridge, 2017.

RNN wave functions optimization

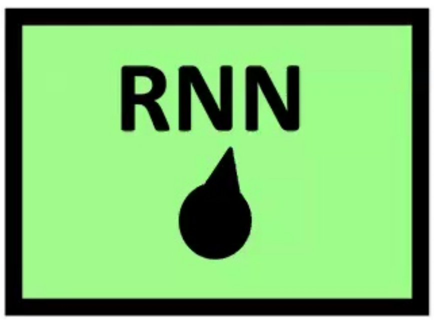


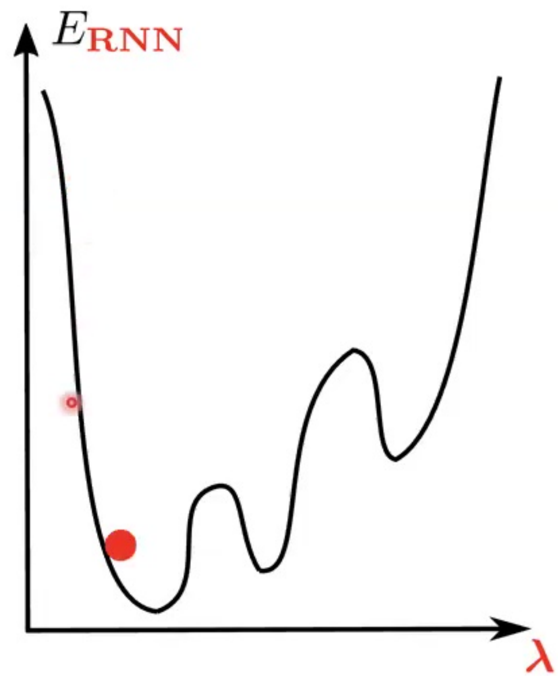


RNN wave functions optimization



RNN wave functions optimization



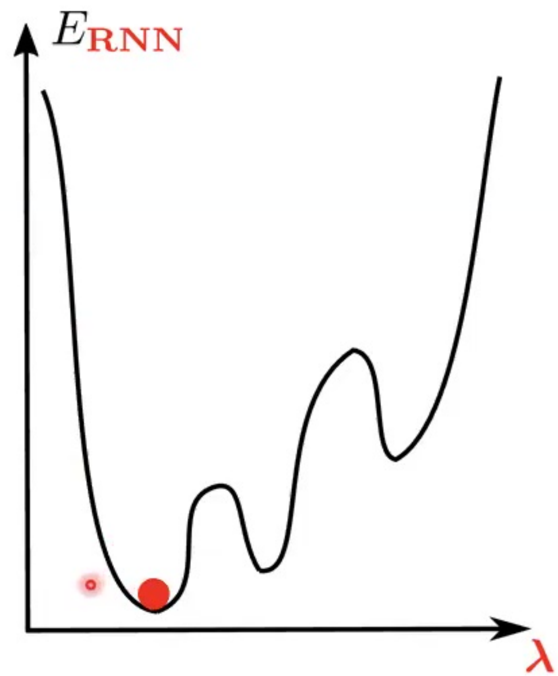


RNN wave functions optimization

M.H, M. Ganahl, L. Hayward, R. Melko, J. Carrasquilla,

Recurrent Neural Network Wave Functions,

PRReasearch, 2020.



An approximation of the ground state is found!

$$\Psi_{\mathrm{RNN}} \approx \Psi_G$$

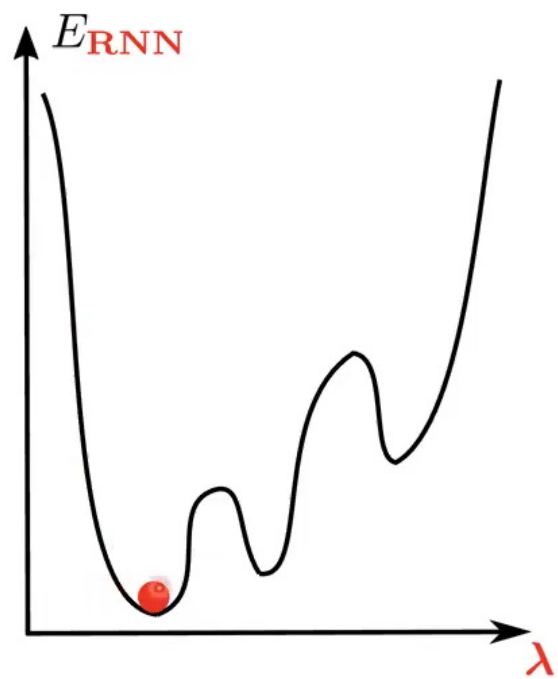
$$E_{\mathrm{RNN}} \approx E_G$$

RNN wave functions optimization

M.H, M. Ganahl, L. Hayward, R. Melko, J. Carrasquilla,

Recurrent Neural Network Wave Functions,

PRReasearch, 2020.

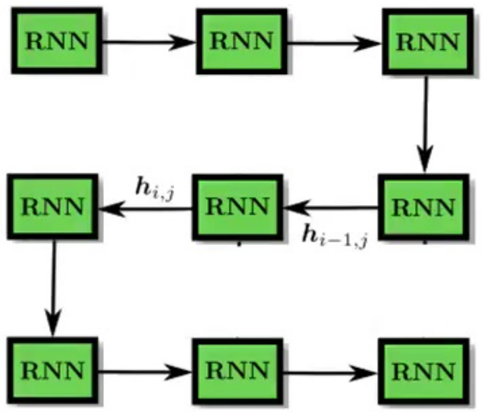


An approximation of the ground state is found!

$$\Psi_{\mathrm{RNN}} \approx \Psi_G$$

$$E_{\mathrm{RNN}} \approx E_G$$

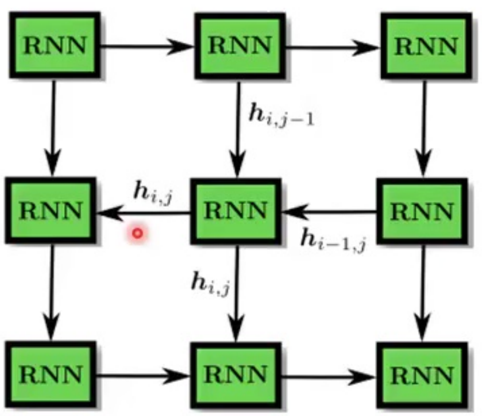
1D recurrent neural networks



1D recursion relation:

$$\boldsymbol{h}_n = f(W[\boldsymbol{h}_{n-1}; \boldsymbol{\sigma}_{n-1}] + \boldsymbol{b})$$

2D recurrent neural networks



M.H, M. Ganahl, L. Hayward, R. Melko, J. Carrasquilla, RNN Wave functions, PRReasearch, 2020.

A. Grave et al., Multi-dimensional recurrent neural networks, 2007.

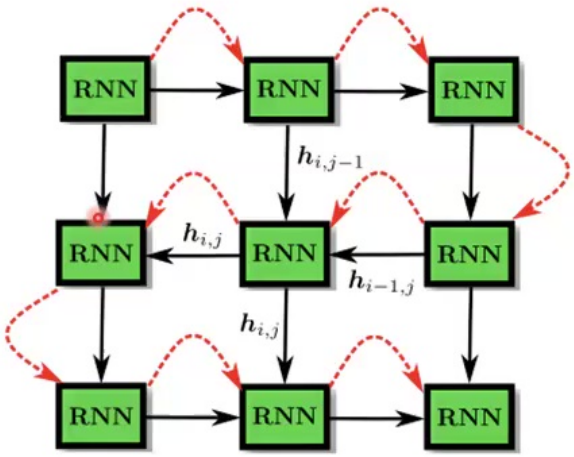
1D recursion relation:

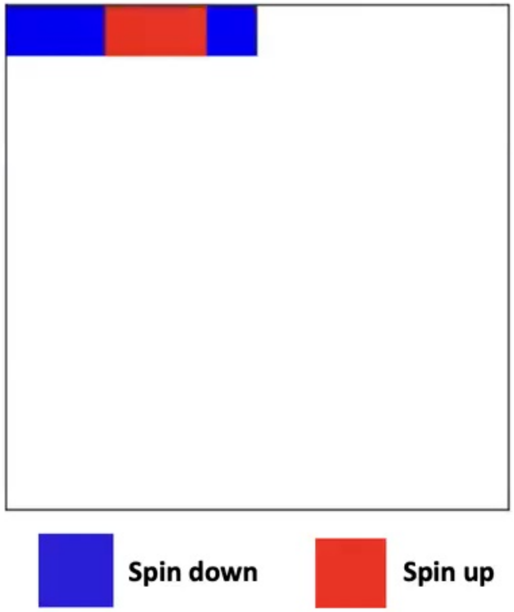
$$\boldsymbol{h}_n = f(W[\boldsymbol{h}_{n-1}; \boldsymbol{\sigma}_{n-1}] + \boldsymbol{b})$$

2D recursion relation:

$$\boldsymbol{h}_{i,j} = f\Big(W^{(h)}[\boldsymbol{h}_{i-1,j}; \boldsymbol{\sigma}_{i-1,j}] + W^{(v)}[\boldsymbol{h}_{i,j-1}; \boldsymbol{\sigma}_{i,j-1}] + \boldsymbol{b}\Big)$$

Zigzag Autoregressive Sampling

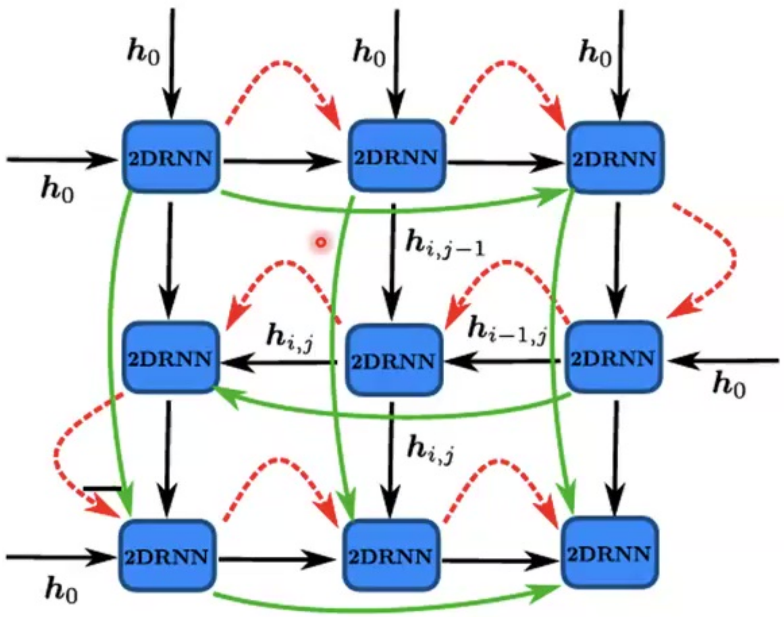




M.H, M. Ganahl, L. Hayward, R. Melko, J. Carrasquilla, RNN Wave functions, PRReasearch, 2020.

A. Grave et al., Multi-dimensional recurrent neural networks, 2007.

2D periodic recurrent neural networks

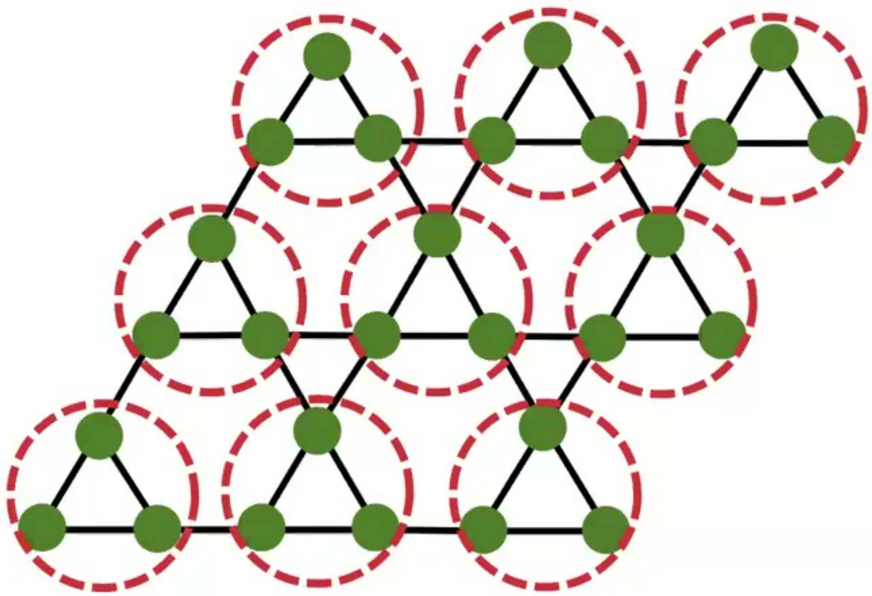


$$h_{i,j} = f\Big(W[\text{Neighbours}(h_{i,j}); \text{Neighbours}(\sigma_{i,j})] + b\Big)$$

M.H, R. Melko, J. Carrasquilla, Physical Reviews B, (2023)

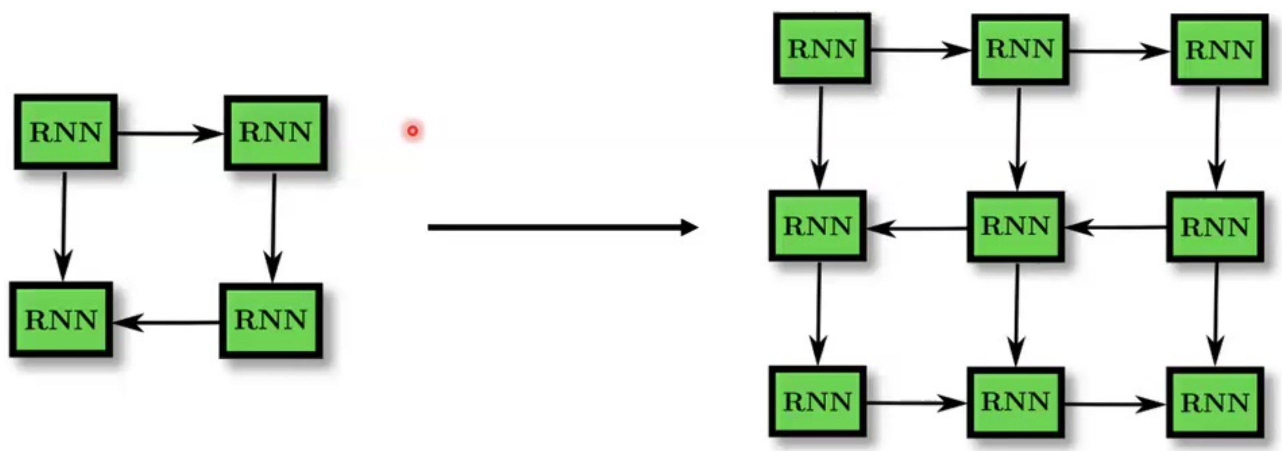
D. Luo et al, Physical Review Research 5, 013216 (2023)

Kagome to Square mapping



M.H, R. Melko, J. Carrasquilla, Physical Reviews B, (2023)

Iterative retraining of RNNs



C. Roth, arXiv:2003.06228, 2020

M.H, R. Melko, J. Carrasquilla, NeurIPS, 2021

M.H, R. Melko, J. Carrasquilla, Physical Reviews B, 2023

S. Moss, R. Wiersema, M.H, J. Carrasquilla, R. Melko, arXiv:2502.17144, 2025

Heating

Slow Cooling

Strong Metal

Credit: FUJITSU Digital Annealer

II. Variational annealing with RNNs

M.H, E. Inack, R. Wiersema, R. Melko, J. Carrasquilla, Variational Neural Annealing, Nature Machine Intelligence, Oct 2021.

Variational Annealing with RNNs

$$\mathbf{F}_{\mathrm{RNN}}(\mathbf{T}) = \left\langle \hat{\mathbf{H}} \right\rangle_{\mathrm{RNN}} - \mathbf{T}\mathbf{S}_{\mathrm{RNN}}$$

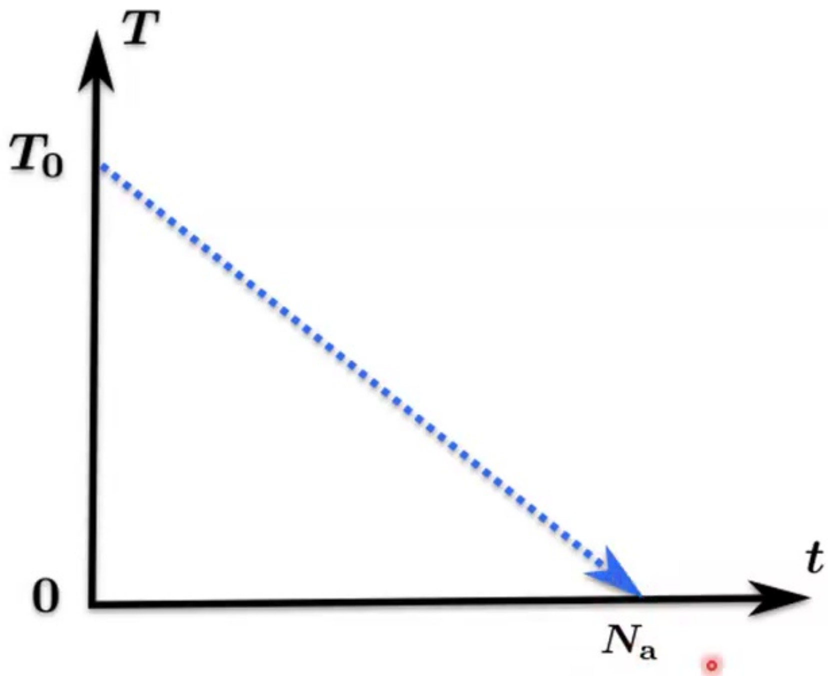
"Free energy" = Cost function

Shannon entropy term (thermal-like fluctuations)

C. Roth, arXiv:2003.06228, 2020

M.H, E. Inack, R. Wiersema, R. Melko, J. Carrasquilla, Nature Machine Intelligence, Oct 2021

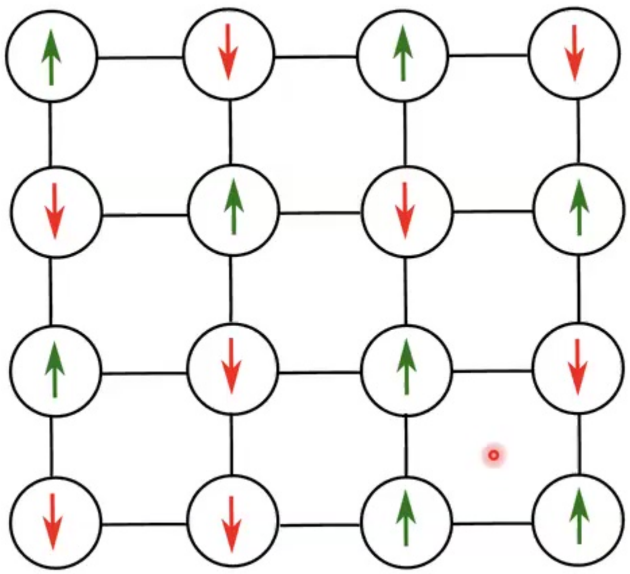
Annealing schedule



$$\mathbf{F}_{\mathrm{RNN}}(\mathbf{T}) = \left\langle \hat{\mathbf{H}} \right\rangle_{\mathrm{RNN}} - \mathbf{T}\mathbf{S}_{\mathrm{RNN}}$$

M.H, E. Inack, R. Wiersema, R. Melko, J. Carrasquilla, Nature Machine Intelligence, Oct 2021.

Example: Spin Ising glass in 2D



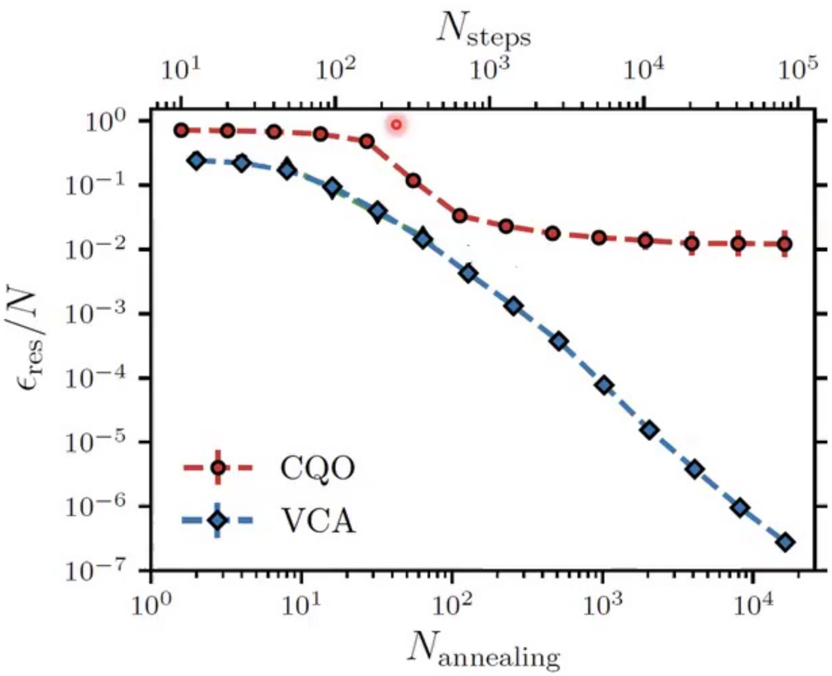
Edwards-Anderson model:

$$H_{\mathrm{EA}} = \sum_{\langle i,j \rangle} J_{ij} \sigma_i \sigma_j$$

The couplings are drawn from **random uniform** distribution in the range **[-1,1)**

M.H, E. Inack, R. Wiersema, R. Melko, J. Carrasquilla, Nature Machine Intelligence, Oct 2021.

Example: Spin Ising glass in 2D (N = 10x10 spins)



Edwards-Anderson model:

$$H_{\mathbf{EA}} = \sum_{\langle i,j \rangle} J_{ij}\sigma_i\sigma_j$$

Classical-Quantum Optimization (CQO)

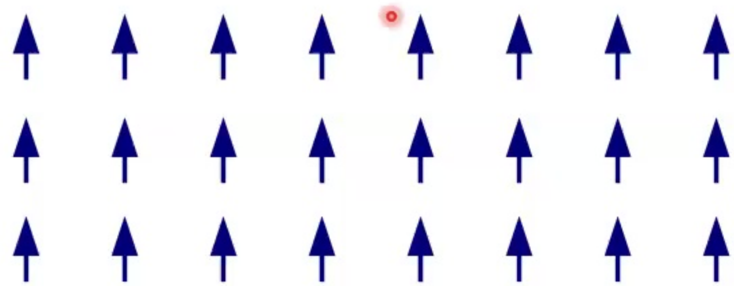
- $\mathbf{T = 0, B_x = 0}$

Variational Classical Annealing (VCA)

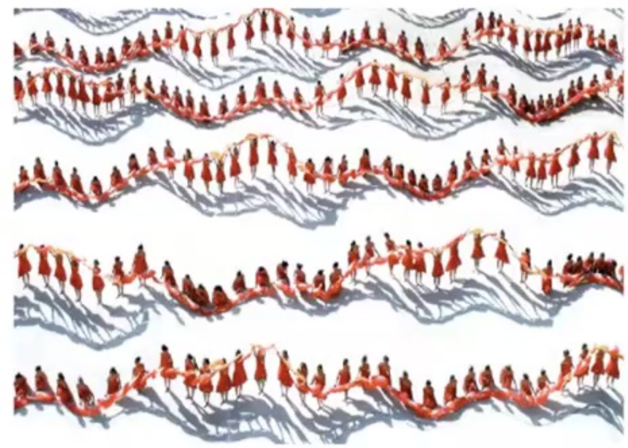
- $\mathbf{T(t) = T_0(1 - t/N_{annealing})}$

M.H, E. Inack, R. Wiersema, R. Melko, J. Carrasquilla, Nature Machine Intelligence, Oct 2021.

III. Investigating topological order with RNNs



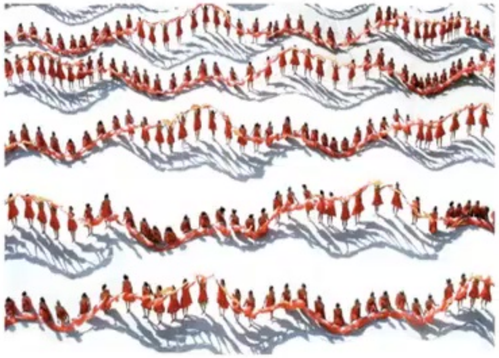
Ferromagnet (non topological – local)
(credit: Michael Schmidt)



Spin liquid (topological – nonlocal)
(credit: Xiao-Gang Wen)

Topological order

- Zero-temperature phase of quantum matter.
    - Quantum Hall Effect.
    - Fault-tolerant quantum computation.



Spin liquid (credit: Xiao-Gang Wen)

- Can be characterized using 'Topological entanglement entropy'.

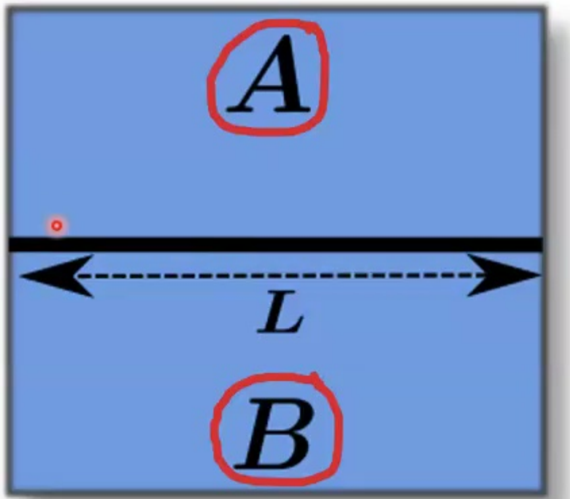
Topological entanglement entropy

$$S_2(A) = -\log(\mathrm{Tr}(\rho_A^2))$$

Second Renyi entropy can be computed using RNN wave functions with the Swap trick.

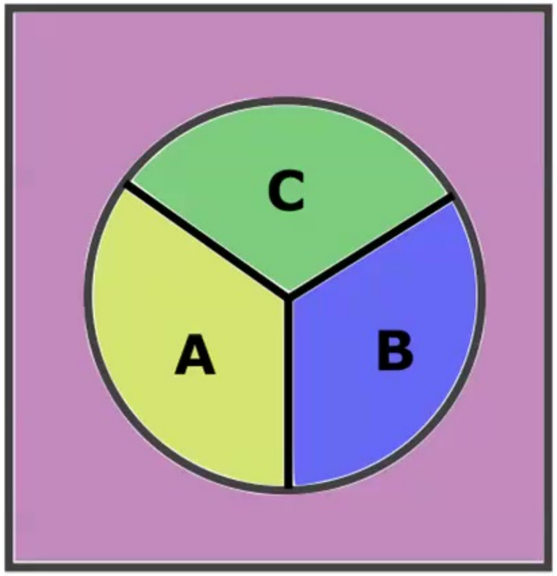
M.H, M. Ganahl, L. Hayward, R. Melko, J. Carrasquilla, PRRResearch, 2020.

$$S_2(A) = aL - \gamma + \mathcal{O}(L^{-1})$$



Kitaev-Preskill construction

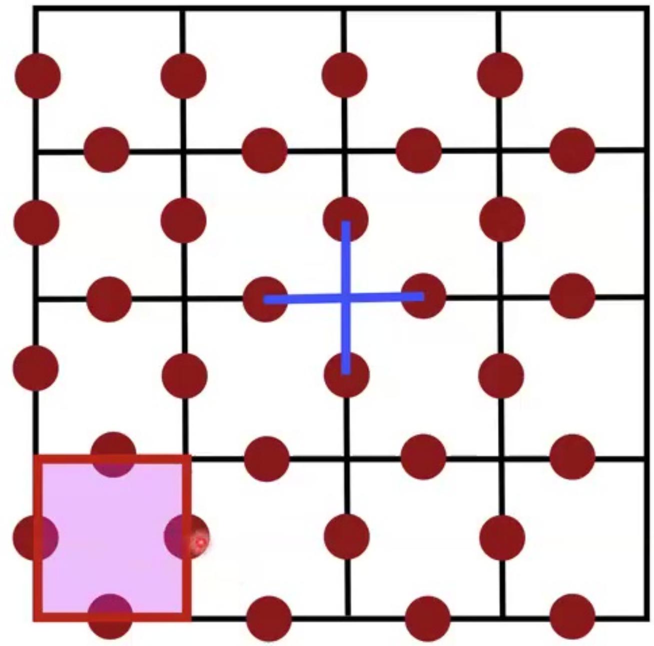
$$\gamma = -S_A - S_B - S_C$$
$$+S_{AB} + S_{AC} + S_{BC}$$
$$-S_{ABC}$$



Kitaev, Preskill, 2005

2D Toric Code

$$\hat{H} = -\sum_p \Pi_{i\in p}\hat{\sigma}_i^z - \sum_v \Pi_{i\in v}\hat{\sigma}_i^x$$



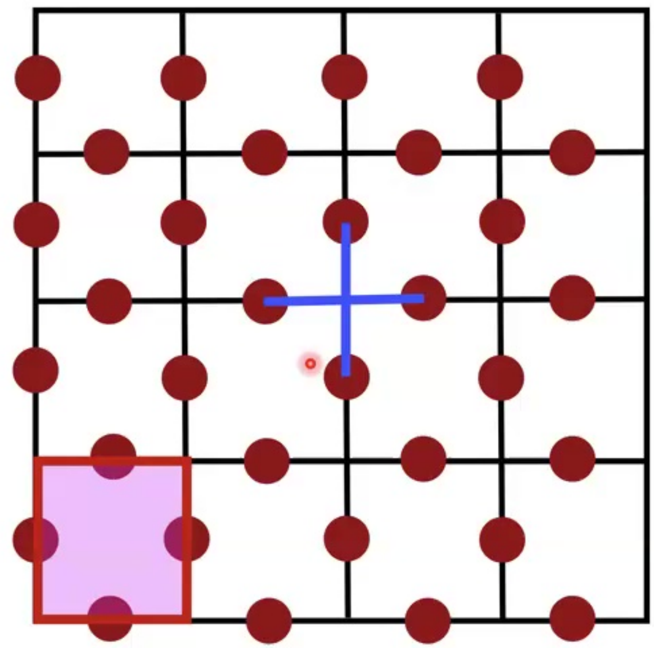
M.H, R. Melko, J. Carrasquilla, Physical Review B, Aug 2023

2D Toric Code

$$\hat{H} = -\sum_{p} \Pi_{i \in p} \hat{\sigma}_i^z - \sum_{v} \Pi_{i \in v} \hat{\sigma}_i^x$$

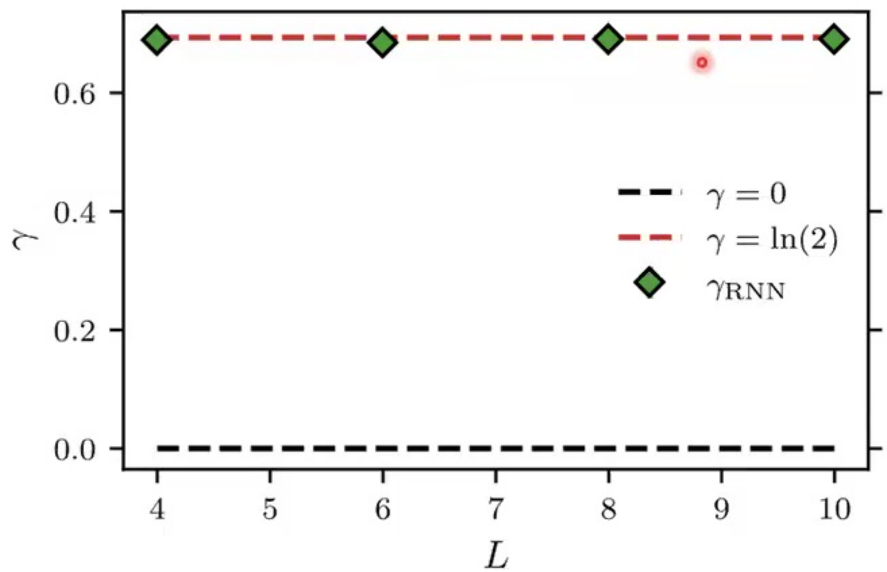
$$\gamma = \ln(2)$$

Z_2 topological order



M.H, R. Melko, J. Carrasquilla, Physical Review B, Aug 2023

2D Toric Code



TEE computed using Kitaev-Preskill construction

M.H, R. Melko, J. Carrasquilla, Physical Review B, Aug 2023

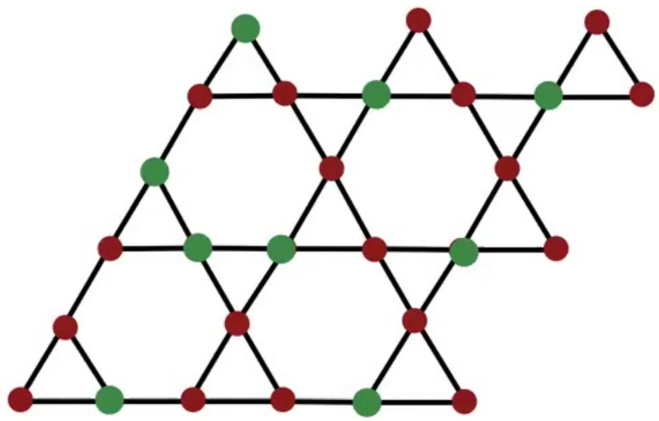
IV. RNN wave functions for Rydberg atoms on Kagome Lattice

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Rydberg atom arrays

$$\hat{H} = \boxed{\sum_{i=1}^{N} \frac{\Omega}{2}\Big(|g\rangle_i \langle r| + |r\rangle_i \langle g| \Big)} - \delta \sum_{i=1}^{N} |r\rangle_i \langle r| + \frac{1}{2}\sum_{(i,j)} V(||\boldsymbol{x}_i - \boldsymbol{x}_j||)\, |r\rangle_i \langle r| \otimes |r\rangle_j \langle r| .$$

Rabi Oscillation for each atom:

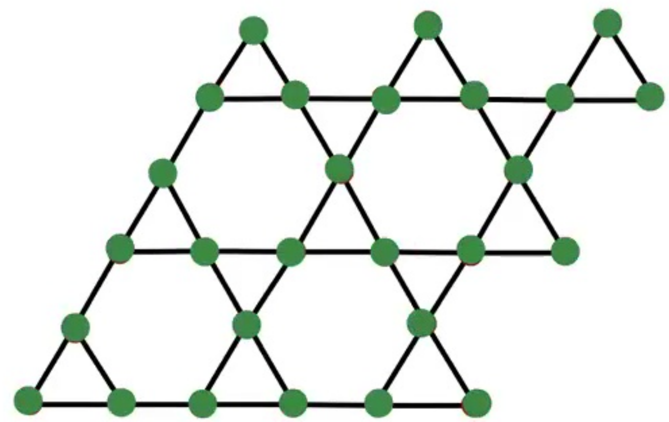


Rydberg atom arrays

$$\hat{H} = \sum_{i=1}^{N} \frac{\Omega}{2} \Big(|g\rangle_i \langle r| + |r\rangle_i \langle g| \Big) \boxed{- \delta \sum_{i=1}^{N} |r\rangle_i \langle r|}$$
$$+ \frac{1}{2} \sum_{(i,j)} V(||\boldsymbol{x}_i - \boldsymbol{x}_j||) \, |r\rangle_i \langle r| \otimes |r\rangle_j \langle r| \, .$$

Laser detuning: δ

Encourage all Rydberg atoms to be in the excited state level $|r\rangle$



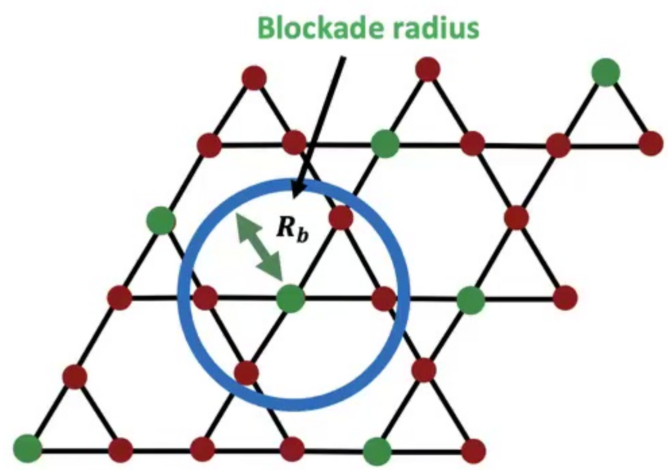
Rydberg atom arrays

$$\hat{H} = \sum_{i=1}^{N} \frac{\Omega}{2}\Big(|g\rangle_i \langle r| + |r\rangle_i \langle g| \Big) - \delta \sum_{i=1}^{N} |r\rangle_i \langle r|$$
$$+ \frac{1}{2} \sum_{(i,j)} V(||\boldsymbol{x}_i - \boldsymbol{x}_j||)\, |r\rangle_i \langle r| \otimes |r\rangle_j \langle r| .$$

Van-der-Waals interaction:

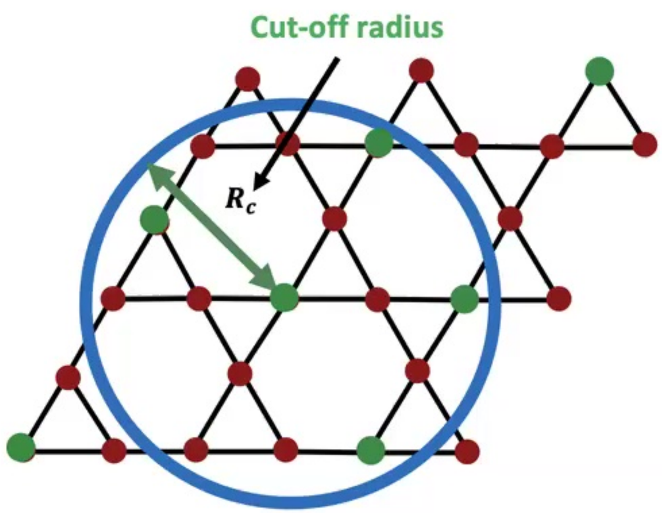
$$V(R) = \Omega \frac{R_b^6}{R^6}$$

A penalty for two atoms within the blockade radius R_b to be both excited.



Rydberg atom arrays

$$\hat{H} = \sum_{i=1}^{N} \frac{\Omega}{2}\Big(|g\rangle_i \langle r| + |r\rangle_i \langle g| \Big) - \delta \sum_{i=1}^{N} |r\rangle_i \langle r|$$
$$+ \frac{1}{2} \sum_{(i,j)} V(||\boldsymbol{x}_i - \boldsymbol{x}_j||) \, |r\rangle_i \langle r| \otimes |r\rangle_j \langle r| \, .$$

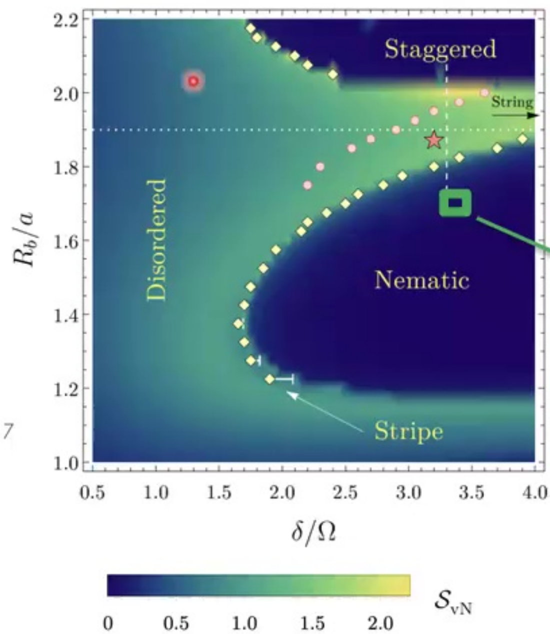


Cut-off radius

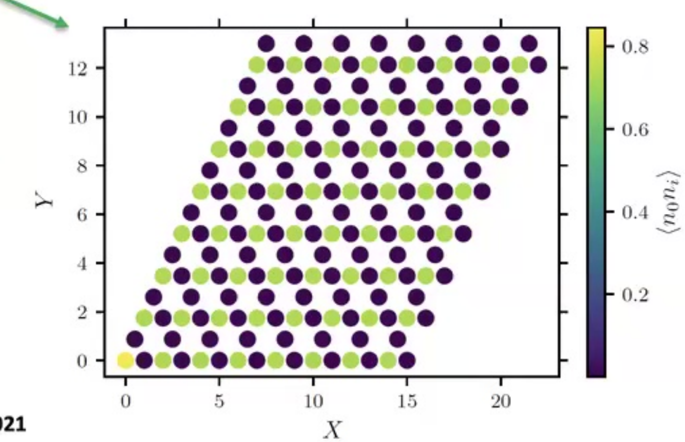
For $R > R_c$, interactions are set to zero.

$$V(R) = \Omega \frac{R_b^6}{R^6}$$

Rydberg atom arrays on Kagome Lattice



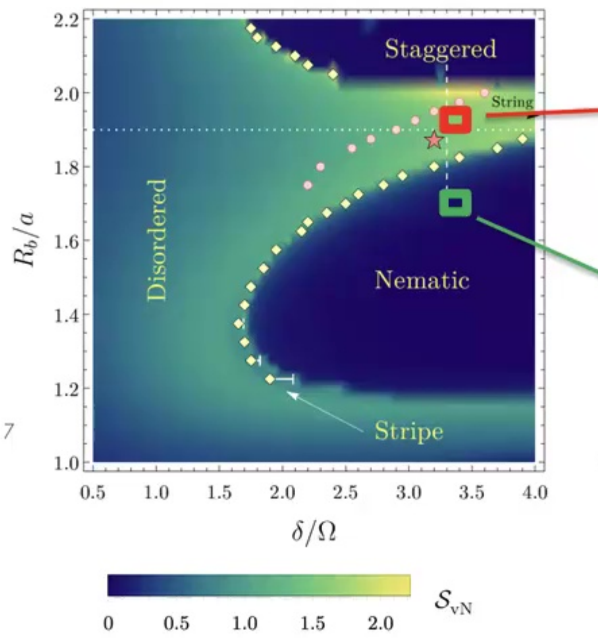
R. Samajdar et al., PNAS 2021



$R_b = 1.7, \ \delta = 3.3$

Nematic phase

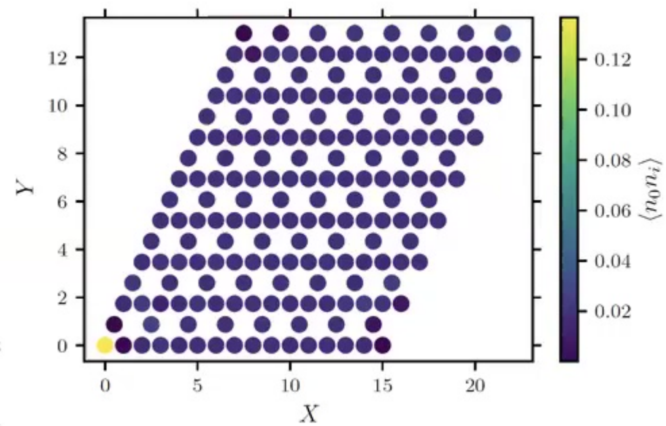
Rydberg atom arrays on Kagome Lattice

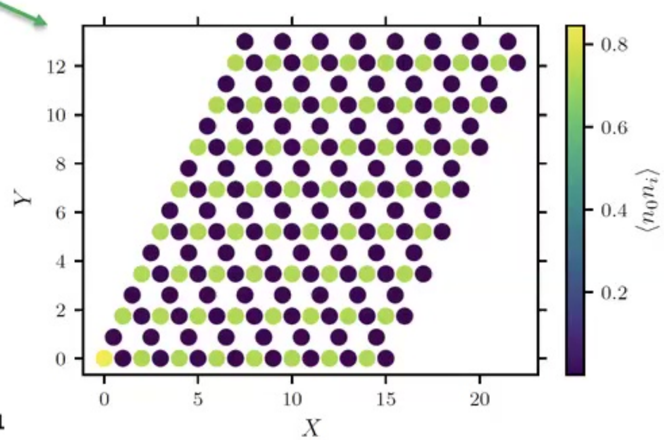


R. Samajdar et al., PNAS 2021

$R_b = 1.95, \ \delta = 3.3$

Spin liquid, spin glass, or paramagnetic (disordered) phase?



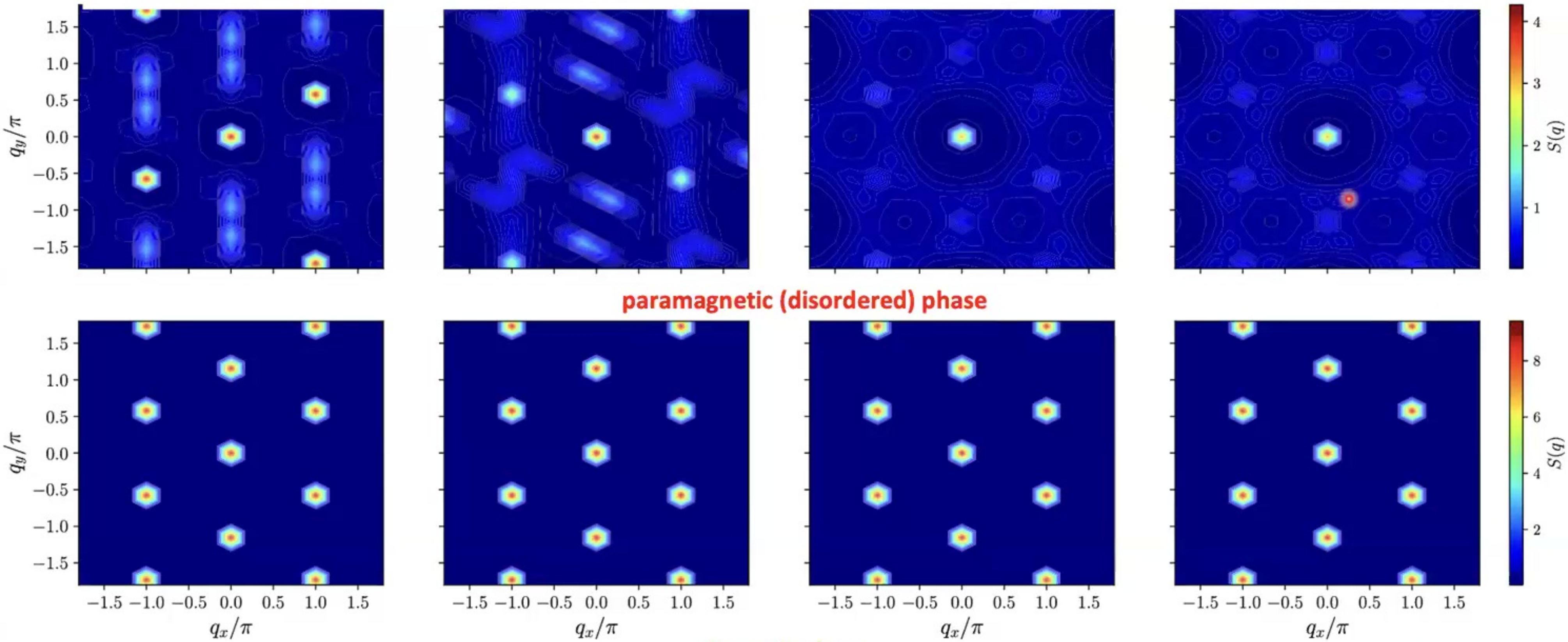


$R_b = 1.7, \ \delta = 3.3$

Nematic phase

More annealing steps

$N_a = 0$ → $N_a \gg 1$



paramagnetic (disordered) phase

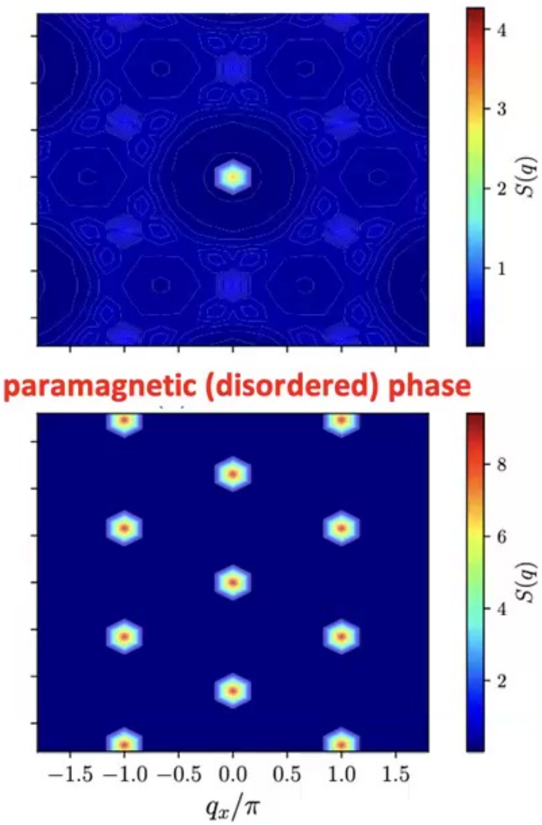
Nematic phase

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

$N_a \gg 1$

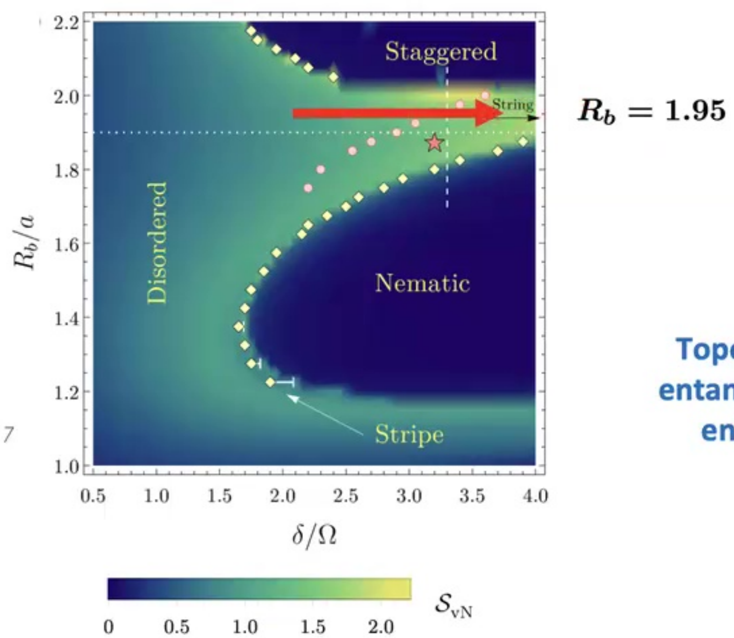
Difficult optimization landscape: **annealing is helpful to escape excited states (local minima)** **and converge close to the ground state.**

Easy optimization landscape: **annealing is not needed**

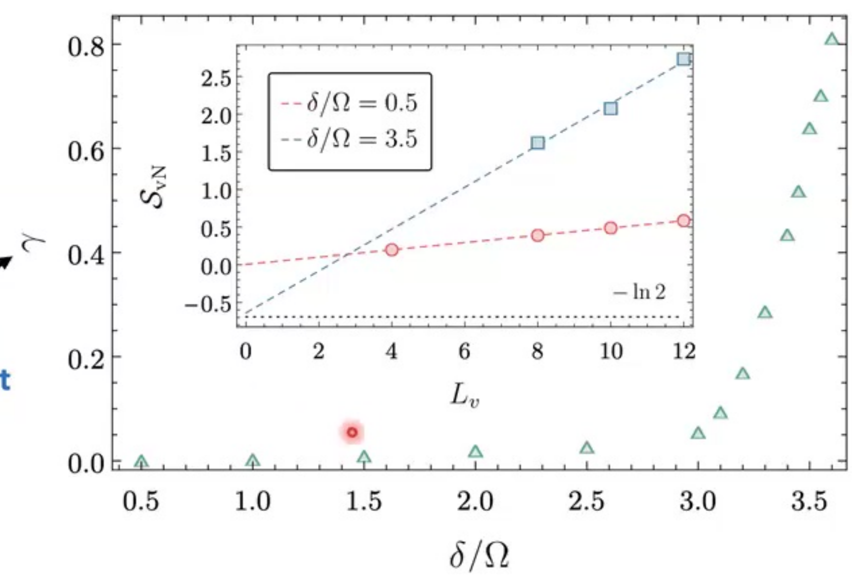


Nematic phase

DMRG prediction of topological order

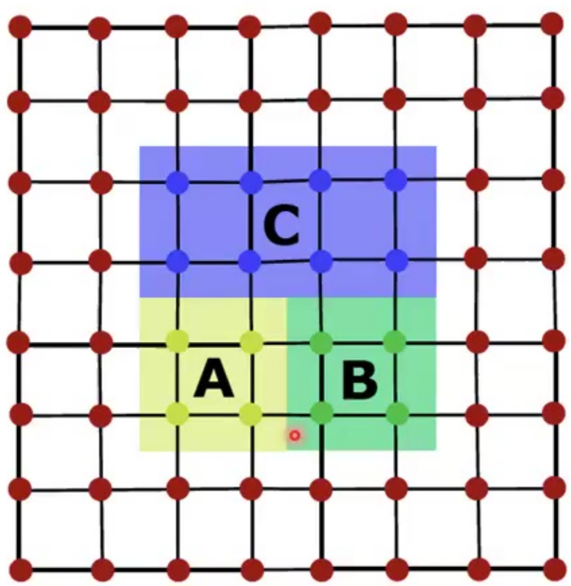


Topological entanglement entropy



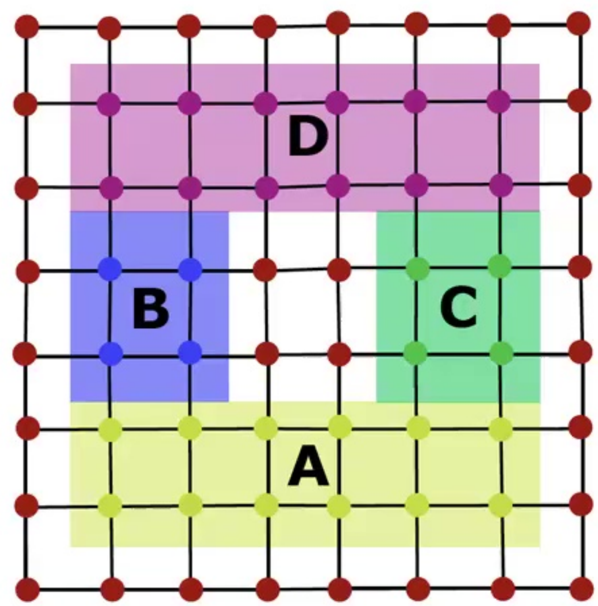
Samajdar et al., PNAS, 2021

TEE constructions



Kitaev-Preskill (KP) construction

Kitaev, Preskill, 2005

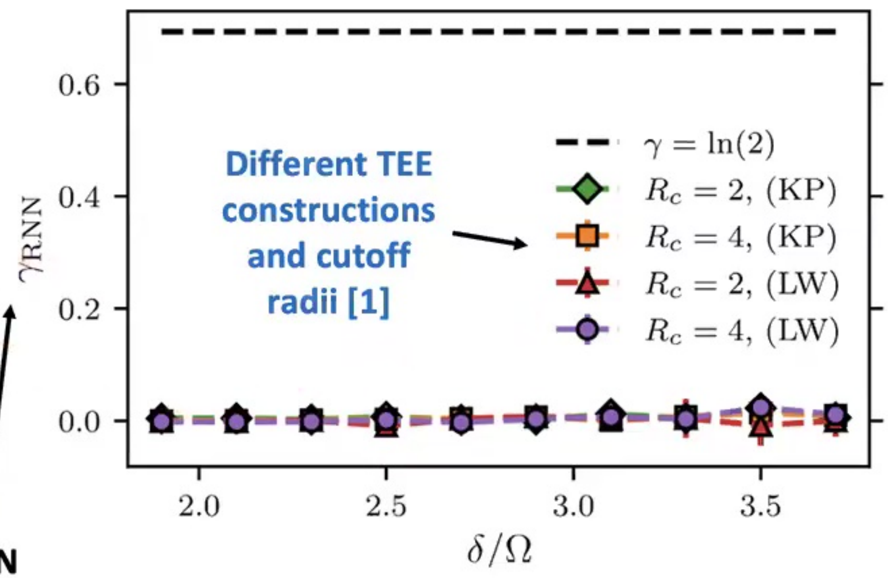


Levin-Wen (LW) construction

Levin, Wen, 2006

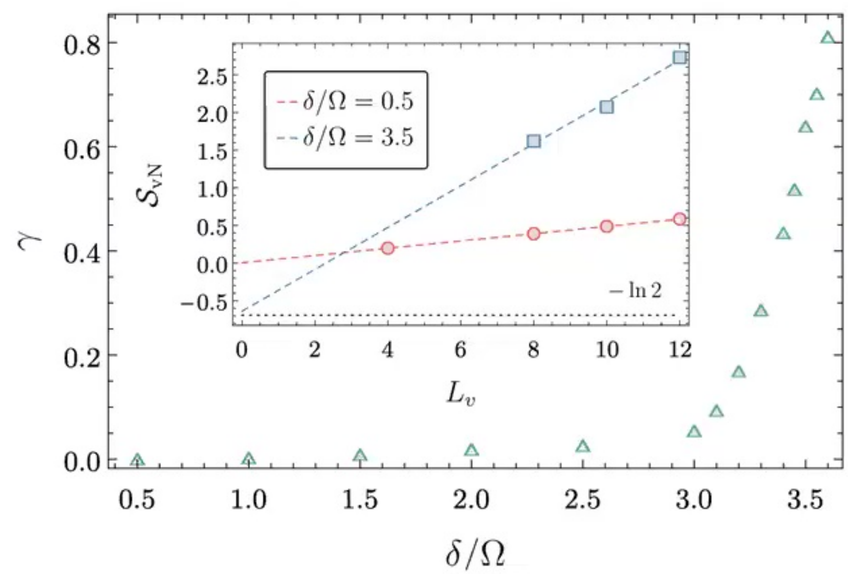
[1] M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Absence of **topological order**



RNN topological entanglement entropy

Our RNN results
(8x8x3 on fully periodic boundary conditions)
(same conclusion for 10x10x3 and 12x12x3)

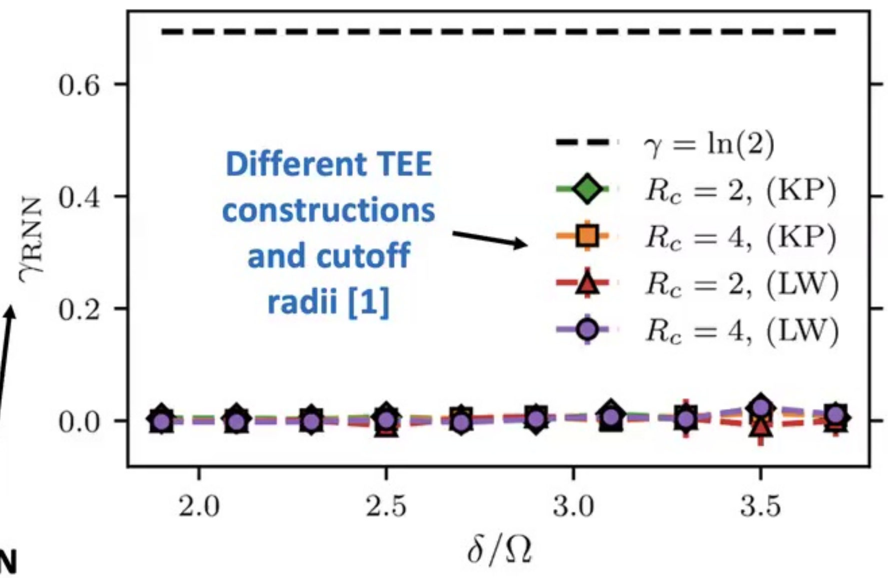


DMRG results
(on cylinders)

Samajdar et al., PNAS, 2021

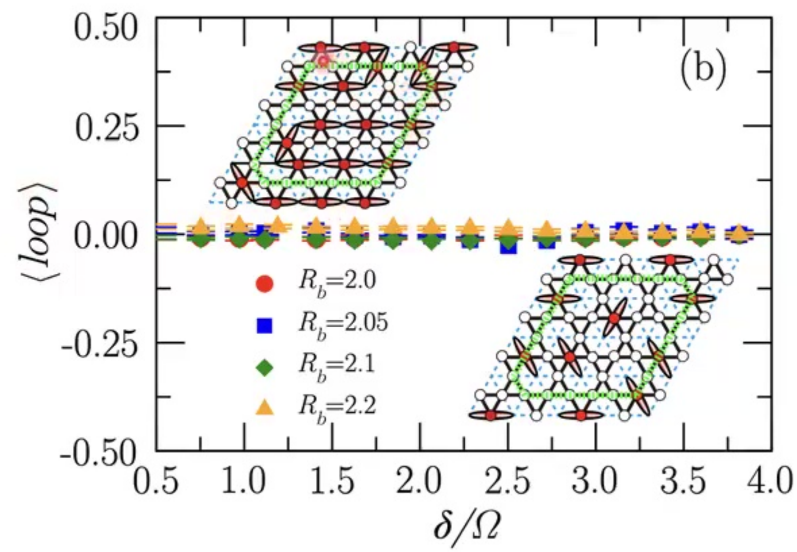
[1] M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Absence of topological order



RNN topological entanglement entropy

Our RNN results
(8x8x3 on fully periodic boundary conditions)
(same conclusion for 10x10x3 and 12x12x3)



Quantum Monte Carlo (QMC) results
(fully periodic boundary conditions)

Yan et al, PRL, 130, 206501, 2023.

Spin-glass order?

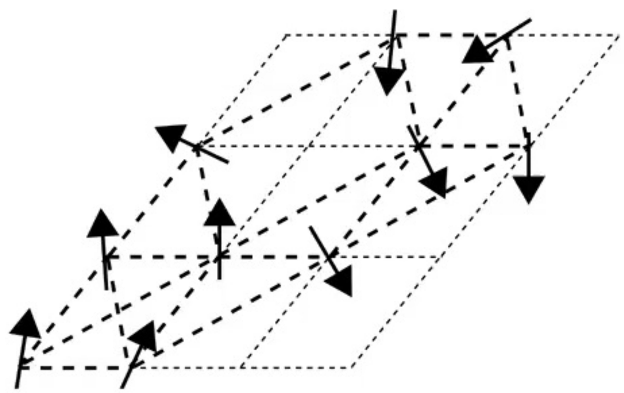
Edwards-Anderson order parameter:

$$q_{\text{EA}} = \frac{\sum_{i=1}^{N} \langle n_i - \rho \rangle^2}{N\rho(1-\rho)}$$

Average density

Close to 1: **spin glass order.**

Close to zero: **no spin glass order.**



Credit: Zureks, Wikipedia

Spin-glass order?

Edwards-Anderson order parameter:

$$q_{\mathrm{EA}} = \frac{\sum_{i=1}^{N} \langle n_i - \rho \rangle^2}{N\rho(1-\rho)}$$

Average density

Close to 1: **spin glass order.**

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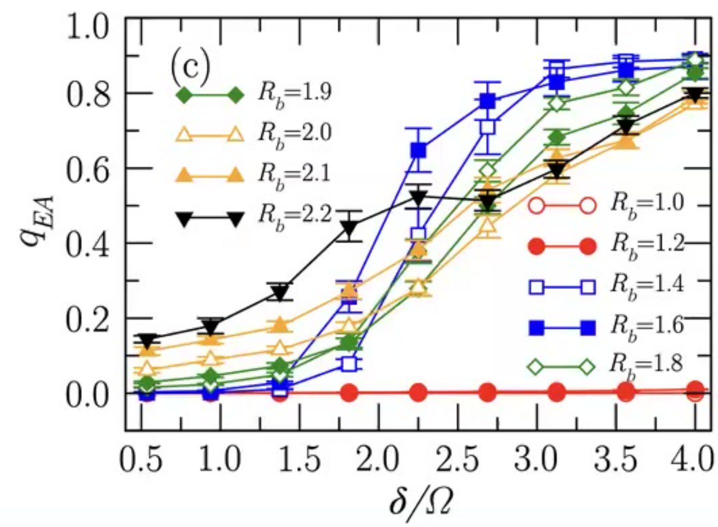


Quantum Monte Carlo (QMC) results

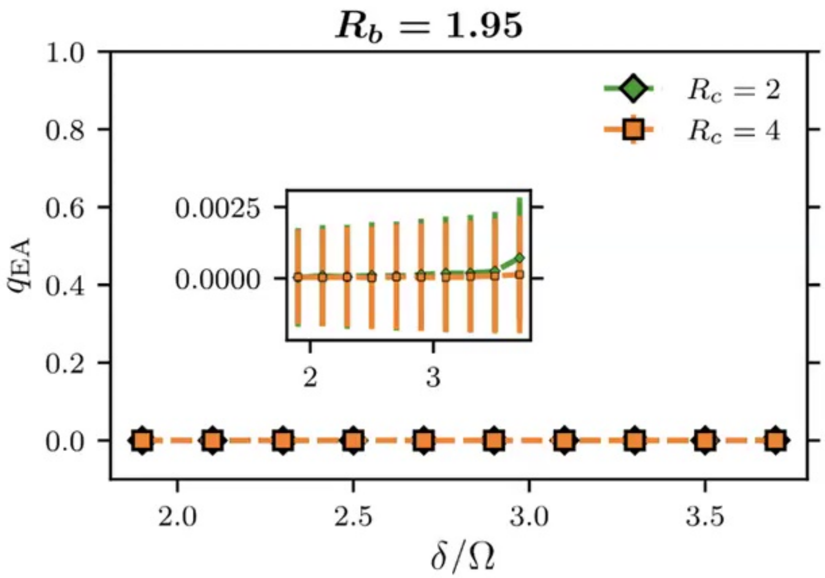
Yan et al, PRL, 130, 206501, 2023.

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

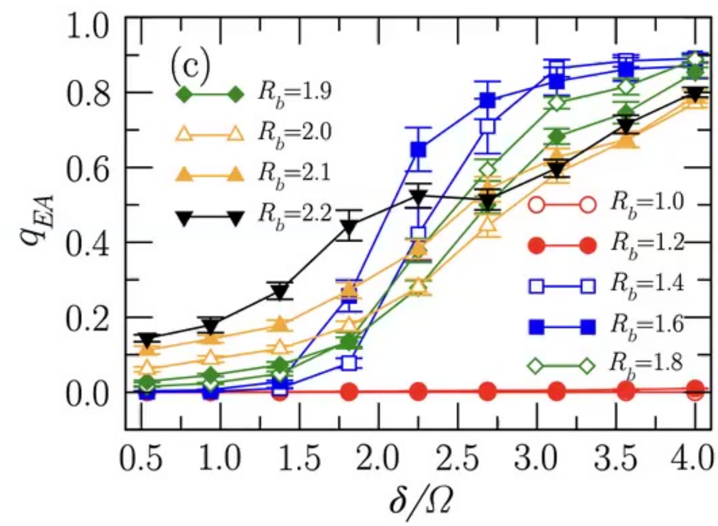
Edwards-Anderson order parameter

$$q_{\mathrm{EA}} = \frac{\sum_{i=1}^{N} \langle n_i - \rho \rangle^2}{N\rho(1-\rho)}$$

Absence of spin-glass order



Our RNN results (8x8x3)
(perfect sampling: no autocorrelation)



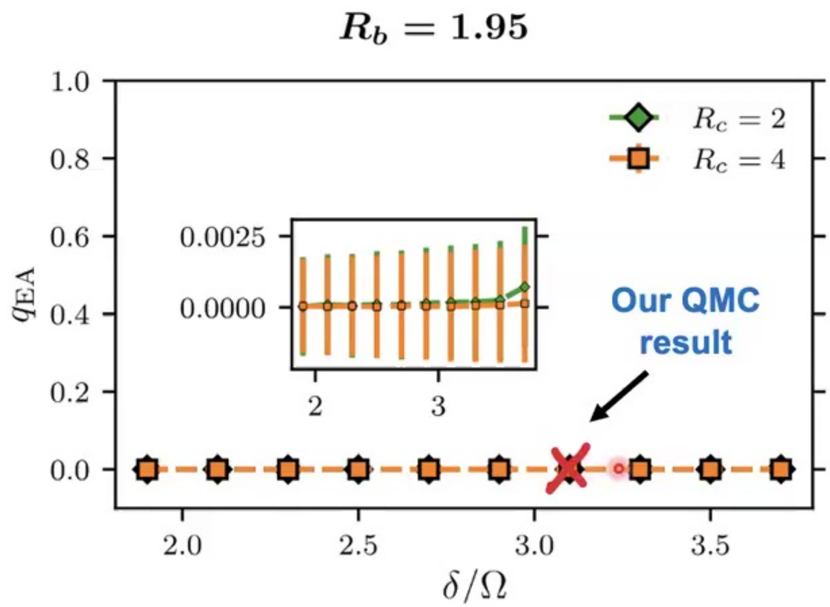
Quantum Monte Carlo (QMC) results
(approximate sampling in practice: autocorrelation)

Yan et al, PRL, 130, 206501, 2023.

Absence of spin-glass order in our QMC calculations

We run **QMC** for a longer time compared to **Ref. [1]**

$$q_{\mathrm{EA}}^{\mathrm{QMC}} = 0.0000018(5) \text{ for } R_b = 1.95, \delta = 3.3$$



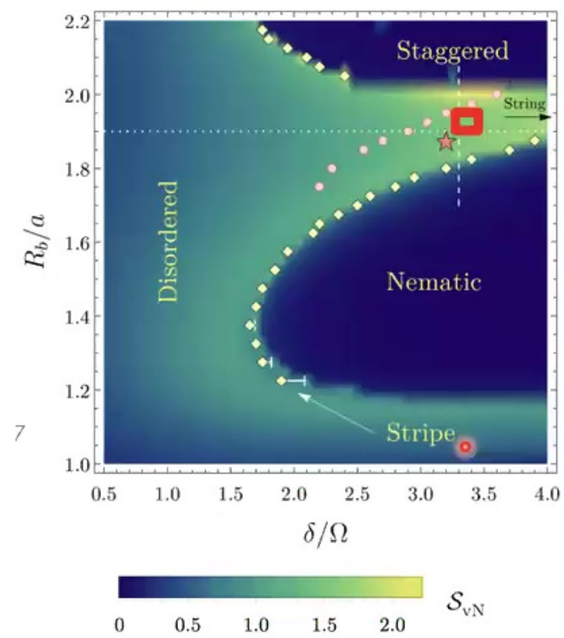
Our RNN results

[1] Yan et al, PRL, 130, 206501, 2023.

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Final conclusion!

Both **RNNs** and **QMC** predict a **trivial paramagnetic (disordered) phase**



M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Samajdar et al., PNAS, 2021

Time comparison: RNNs vs QMC

L	RNN: P100	RNN: A100	QMC (CPU)
6	26.567 h	**3.460 h**	48.751 h
8	4.074 h	**1.537 h**	70.422 h

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Takeaways

1. Our RNN variational calculations suggest the absence of topological and spin-glass orders in Rydberg atoms arrays on Kagome Lattice (backed up by QMC).

2. RNN wave functions and language-model based quantum states offer a powerful complementary numerical method in quantum matter.

Acknowledgments

Juan Carrasquilla

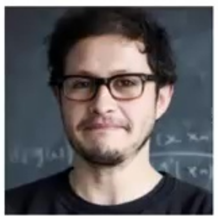
Roger Melko

Giacomo Torlai

Ejaaz Merali

M.H, E. Merali, G. Torlai, R. Melko, J. Carrasquilla, arXiv: 2405.20384

Thank you for your attention!


Juan Carrasquilla


Roger Melko


Lauren Hayward


Estelle Inack


Roeland Wiersema


Martin Ganahl


Shoummo Khandoker


Jawaril Abedin


Schuyler Moss


Giacomo Torlai


Ejaaz Merali

Non-weight sharing

	2DRNN-NWS ($R_c = 2$)	2DRNN ($R_c = 2$)
E/N	-0.59447(2)	-0.59666(2)
q_{EA}	0.001416(6)	0.000205(1)
γ_{RNN}	-0.006(6)	-0.003(20)

Table V. A table comparing the 2DRNN results with weight sharing with the 2DRNN with no-weight sharing (2DRNN-NWS). Here use the system size $N = 8 \times 8 \times 3$ and $R_b = 1.95, \delta = 3.3$ for the comparison.

Variational Annealing with RNNs

$$\mathbf{F}_{\mathrm{RNN}}(\mathbf{T}) = \left\langle \hat{\mathbf{H}} \right\rangle_{\mathrm{RNN}} - \mathbf{T}\mathbf{S}_{\mathrm{RNN}}$$

Free energy = Cost function

Expectation values over RNN distribution P_{RNN}

Shannon entropy:

$$S_{\mathrm{RNN}} = -\sum_{\sigma} P_{\mathrm{RNN}}(\sigma)\log(P_{\mathrm{RNN}}(\sigma)) = \langle -\log(P_{\mathrm{RNN}}(\sigma))\rangle_{\mathrm{RNN}}$$

M.H, E. Inack, R. Wiersema, R. Melko, J. Carrasquilla, Variational Neural Annealing, Nature Machine Intelligence, Oct 2021.