

# PRJ501: Thesis Research

## Low temperature phases of Dipolar gas in an optical lattice

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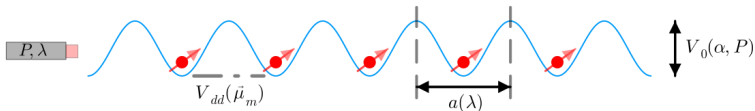
Thursday 12<sup>th</sup> January, 2023



- ① Introduction
- ② Bose Hubbard Model
- ③ Extended Bose Hubbard Model
- ④ Extra Slides

# The Experiment

Dipolar gases trapped in an optical lattice creates a highly tunable quantum simulator setup.



Such a system is also a physical realization of the Bose Hubbard Hamiltonian. This gives us a direct mapping of a theoretical toy model and an experimental setup.

# The Hamiltonian

$$H = \underbrace{-t \sum_{\langle i,j \rangle} a_i^\dagger a_j + \frac{U}{2} \sum_i n_i(n_i - 1)}_{\text{Bose Hubbard Model}} + V \sum_{\langle i,j \rangle} n_i n_j + \dots$$

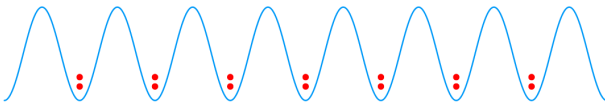
- $t$  - hopping strength
- $U$  - on-site interaction
- $V$  - nearest-neighbour interaction

What (quantum) phases can be exhibited?

- 1 Introduction
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# BHM: Expected phases

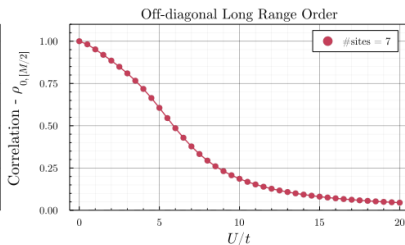
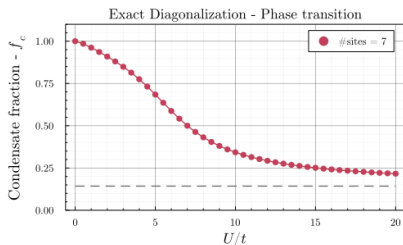
- Mott Insulator ( $U \gg t$ )  $\rightarrow |\Psi_{MI}\rangle = \bigotimes_{i=1}^M |n\rangle$



- Superfluid ( $U \ll t$ )  $\rightarrow |\Psi_{SF}\rangle = \frac{1}{N!} (\sum_{i=1}^M a_i^\dagger)^N |0\rangle$



# BHM: Exact Diagonalization (1D)

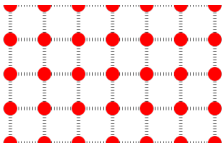


$$\text{Condensate fraction} \implies \| |a_i^\dagger a_j| \|_\infty / N \sim \mathcal{O}(1)$$

$$\text{Off-diagonal long-range order (ODLRO)} \implies \lim_{|i-j| \rightarrow \infty} \langle a_i^\dagger a_j \rangle \neq 0$$

## BHM: Mean Field Approximation

$$\hat{a}_i = \Psi_i + \delta \hat{a}_i \quad | \quad \mathcal{O}(\delta a_i^2) \approx 0$$



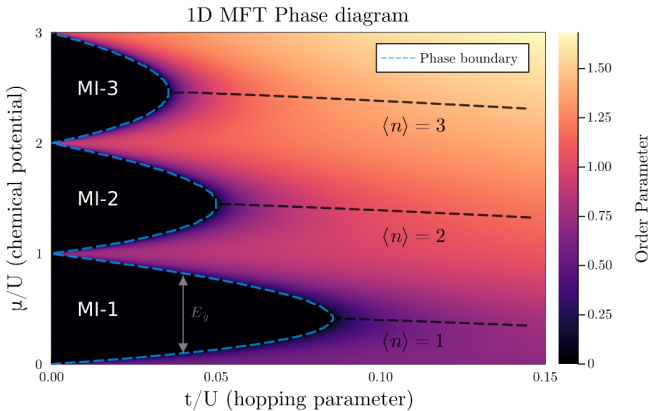
$$H = \underbrace{-t \sum_{\langle i,j \rangle} a_i^\dagger a_j + \frac{U}{2} \sum_i n_i(n_i - 1)}_{\text{coupled lattice sites}}$$



$$H\{\Psi\} = \underbrace{\sum_i -zt \cdot (\Psi^* a_i + \Psi a_i^\dagger - |\Psi|^2) + \frac{U}{2} n_i(n_i - 1)}_{\text{de-coupled lattice sites}}$$



# BHM: Mean Field Approximation, Phase Diagram



$$\text{ODLRO} \implies \lim_{|i-j| \rightarrow \infty} \langle a_i^\dagger a_j \rangle = |\Psi|^2 \neq 0 \quad (\text{S.S.B.})$$

## BHM: Mean Field Approximation, Phase Diagram, contd.

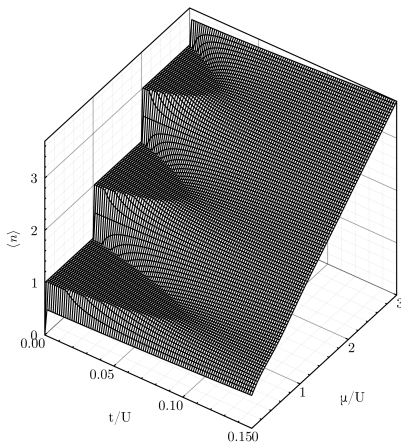
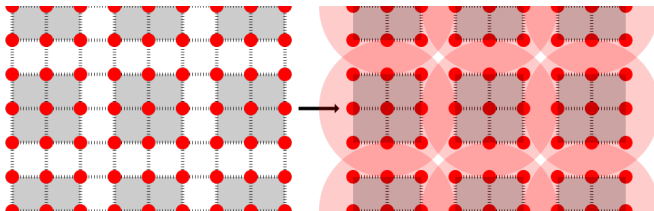


Figure 1: Average occupation number

## BHM: Cluster MFA

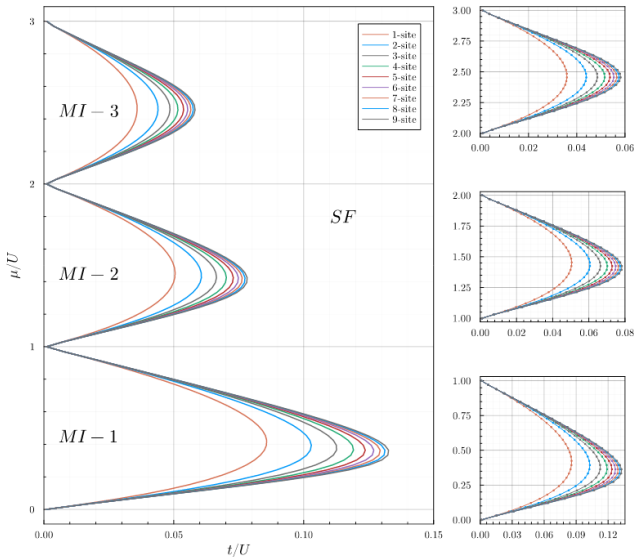


$$H = \underbrace{-t \sum_{\langle i,j \rangle} a_i^\dagger a_j + \frac{U}{2} \sum_i n_i(n_i - 1)}_{\text{coupled lattice sites}}$$

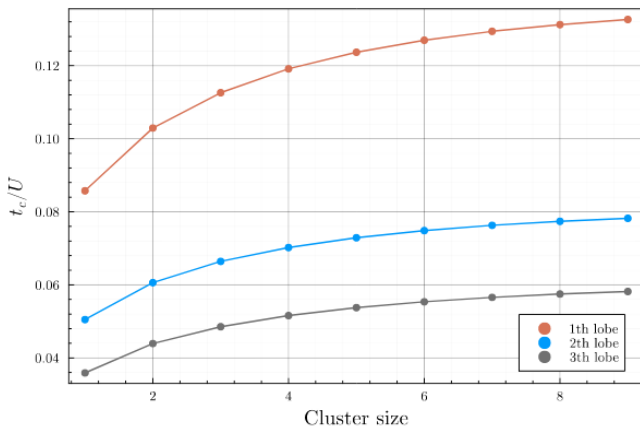
→

$$H\{\Psi_i\} = \underbrace{\sum_C H_{\text{exact}} + \sum_{C,C'} H_{\text{MFT}}\{\Psi_i\}}_{\text{de-coupled clusters of sites}}$$

# BHM: Cluster MFA, Phase Diagram



# BHM: Cluster MFA, Mott lobe critical points



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# eBHM: Expected Phases

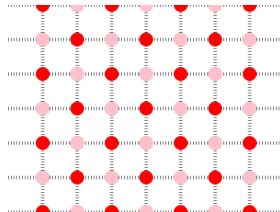
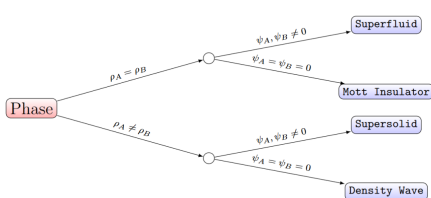
$$H = -t \sum_{\langle i,j \rangle} a_i^\dagger a_j + \frac{U}{2} \sum_i n_i(n_i - 1) + V \sum_{\langle i,j \rangle} n_i n_j$$

$V$  vs.  $U$  terms introduces density modulations in the lattice giving rise to two more phases, analogous to the BHM phases.

- Mott Insulator  $\longrightarrow$  Density Wave
- Superfluid  $\longrightarrow$  Supersolid

## eBHM: Mean Field Approximation

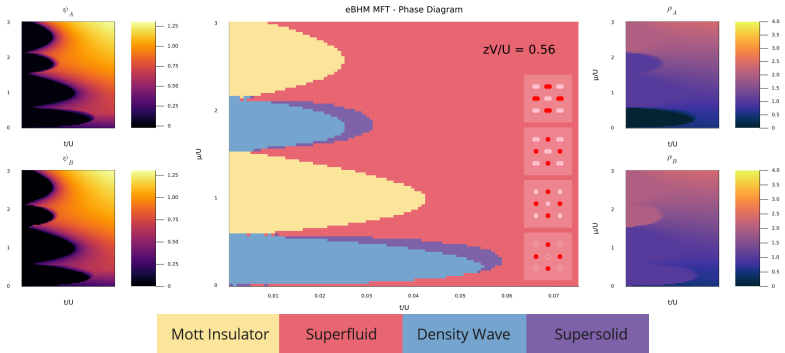
$$\hat{a}_i = \Psi_i + \delta \hat{a}_i \quad \hat{n}_i = \rho_i + \delta \hat{n}_i$$



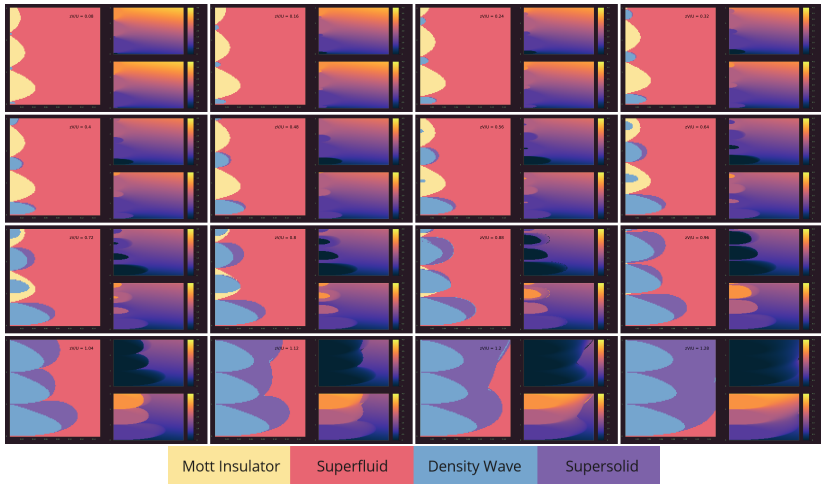
Mean-field parameters:  $\{\Psi_A, \Psi_B, \rho_A, \rho_B\}$



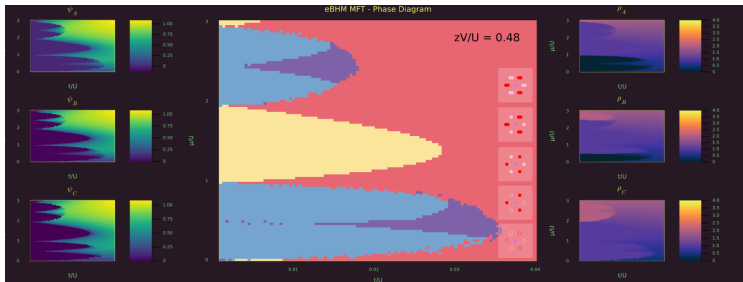
# eBHM: MFA Phase Diagram



## eBHM: MFA Phase Diagram (Left to Right, Top to Bottom)



## eBHM: MFA, Triangular Lattice



Mott Insulator

Superfluid

Density Wave

Supersolid

# Moving beyond mean field; QMC

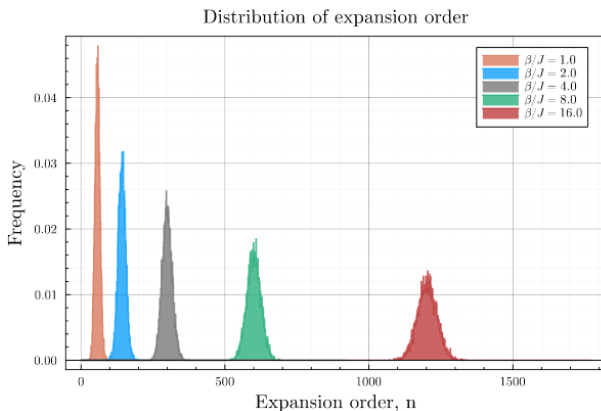
$$Z = \text{Tr}(\exp(-\beta H))$$

$$Z = \text{Tr} \left[ \sum_{n=0}^{\infty} \frac{(-\beta)^n}{n!} \cdot \left( \sum_b H_{b,1} + H_{b,2} \right)^n \right]$$

$$Z = \sum_{n=0}^{\infty} \frac{(-\beta)^n}{n!} \cdot \sum_{|\alpha\rangle} \sum_{S_n} \langle \alpha | \left( \prod_{\{b,i\} \in S_n} H_{b,i} \right) | \alpha \rangle = \sum_{C_i \in \mathcal{C}} w(C_i)$$

Define configuration of the system,  $C_i \equiv [|\alpha\rangle, S_n]$ . Sample these  $C_i \in \mathcal{C}$  ergodically to compute diagonal observables.

# Stochastic Series Expansion



We can maintain a cut-off  $n_{max}$  dynamically as the simulation progresses and introduce negligible error.

Spin-1/2 chain  $\longleftrightarrow$  Hard-core bosons

XXZ spin-1/2 model:

$$H = \frac{J_x}{2} \sum_{\langle i,j \rangle} (S_i^+ S_j^- + S_j^+ S_i^-) + J_z \sum_{\langle i,j \rangle} S_i^z S_j^z + h_z \sum_i S_i^z$$

eBHM w/ hard-core bosons:

$$H = -t \sum_{\langle i,j \rangle} (a_i^\dagger a_j + a_j^\dagger a_i) + V \sum_{\langle i,j \rangle} n_i n_j - \mu \sum_i n_i$$

Map the operators like so:

$$S_i^+ \equiv a_i^\dagger \quad S_i^z \equiv (n_i - 1/2)$$

Analogous quantities:

$$t \equiv \frac{J_x}{2} \quad V \equiv J_z \quad \mu = J_z - h_z$$



*to be continued*

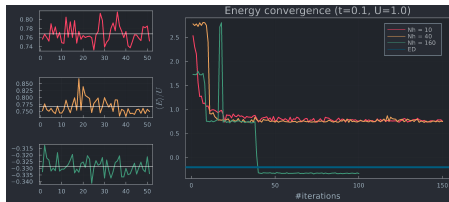
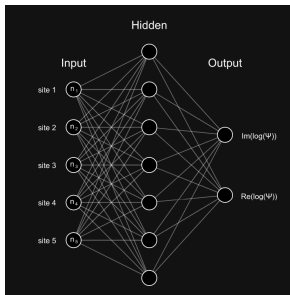


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# Supplement 0: Neural Network ansatz

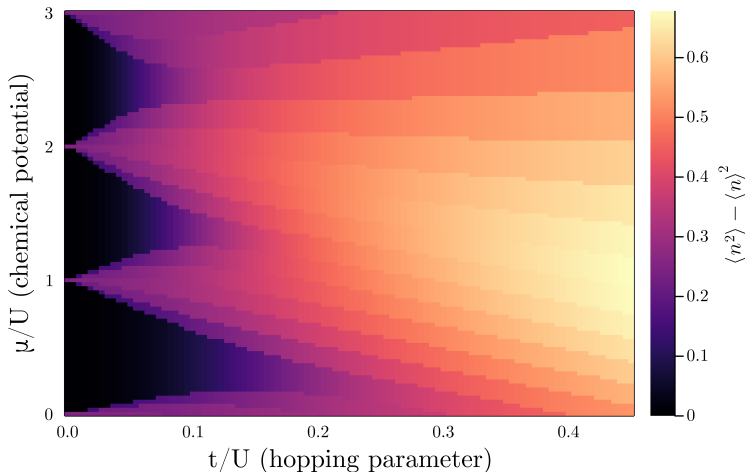
Ansatz for the wave-function:  $\Psi = \sum_n \Psi(n) |n\rangle$  such that  $\Psi(n)$  is captured by a neural network.



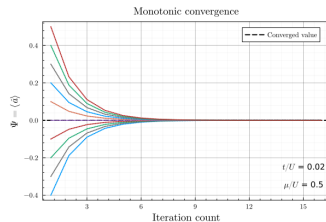
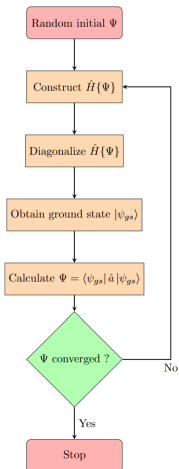
Train the network weights to minimize  $\langle \hat{H} \rangle$ .

## Supplement 1: Exact Diagonalization, Phase Diagram

## 6-site Exact Diagonalization



## Supplement 2: BHM Mean Field



## Supplement 3: eBHM Mean Field

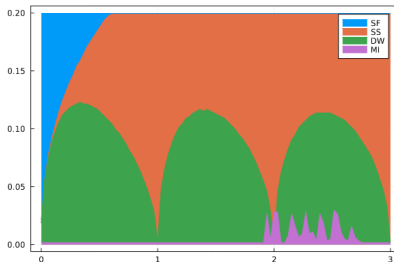
$$H_A\{\Psi_A, \Psi_B, \rho_A, \rho_B\} = -zt \cdot (\Psi_B^* a_A + \Psi_B a_A^\dagger - \Psi_A^* \Psi_B) \\ + zV \cdot (\rho_B n_A - \rho_A \rho_B) + \frac{U}{2} n_A (n_A - 1)$$

$$H_B\{\Psi_A, \Psi_B, \rho_A, \rho_B\} = -zt \cdot (\Psi_A^* a_B + \Psi_A a_B^\dagger - \Psi_B^* \Psi_A) \\ + zV \cdot (\rho_A n_B - \rho_B \rho_A) + \frac{U}{2} n_B (n_B - 1)$$

$$H\{\Psi_A, \Psi_B, \rho_A, \rho_B\} = \sum_{i \in A} H_i + \sum_{j \in B} H_j$$

## Supplement 4: Extracting Phase Boundaries

**Naive method:** Compute for a grid of parameter values and find the points where the order parameter jumps.



**Precise method:** Use a bisection algorithm. Precision scales as  $2^{-n}$  for  $n$  iterations. But very sensitive to convergence issues.

## Supplement 5: Local minima

