

Learning ground states of gauge theories with neural networks

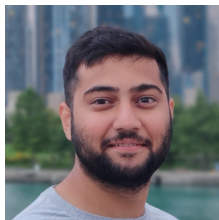
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Many-body quantum systems

Many-body quantum mechanics describes systems with many interacting quantum degrees of freedom

- Spin chains (exactly solvable / integrable models)
- Topological phases of matter (quantum Hall / topological order)
- Fundamental physics (EM / QCD)

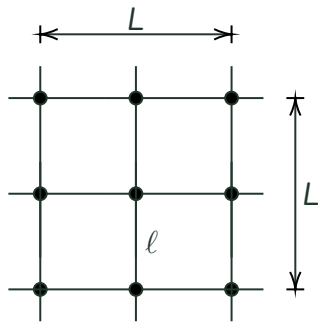
Wavefunction Ψ gives complete description of quantum system

- How do we find the **ground-state wavefunction** Ψ_0 ?
- What if system has **gauge symmetry**?

\mathbb{Z}_N lattice gauge theory in $(2 + 1)d$

QM description of QFT

- Space discretised as $L \times L$ lattice
- Gauge field degrees of freedom live on **links** between lattice sites



Clock Q and **shift** P operators satisfy a \mathbb{Z}_N algebra

$$P^N = Q^N = \mathbf{1}, \quad P^\dagger Q P = e^{2\pi i/N} Q.$$

States on link l labelled by

$$|q\rangle_\ell, \quad q \in \{0, \dots, N-1\}$$

Clock associates a \mathbb{Z}_N **phase** to a link

$$Q|q\rangle = e^{2\pi i q/N} |q\rangle, \quad P|q\rangle = |q-1\rangle$$

\mathbb{Z}_N lattice gauge theory in $(2 + 1)d$

Physics determined by **Hamiltonian** H with

$$H = \frac{g^2}{2} \sum_{\ell} [1 - P_{\ell}] + \frac{1}{2g^2} \sum_{\ell_i \in \square} [1 - Q_{\ell_1}^{\dagger} Q_{\ell_2}^{\dagger} Q_{\ell_3} Q_{\ell_4}] + \text{h.c.}$$

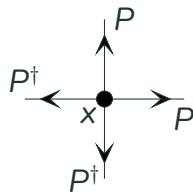
Coupling g encodes **interaction strength**

Gauge transformations generated by product of P operators around a lattice site

$$\Theta_x = P_{x,\hat{x}} P_{x,\hat{y}} P_{x-\hat{x},\hat{x}}^{\dagger} P_{x-\hat{y},\hat{y}}^{\dagger}.$$

Local symmetry: $[\Theta_x, H] = 0$

- Physical states must be **gauge invariant**



Gauge-equivariant data

A **configuration** of the gauge field is given by a set of link phases

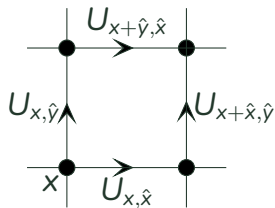
$$\mathcal{U} = \{U_{x,\mu}\} \in \mathbb{C}^{2L^2}$$

A **wavefunction** Ψ maps a configuration \mathcal{U} to a complex number

$$\Psi: \mathbb{C}^{2L^2} \rightarrow \mathbb{C}, \quad \mathcal{U} \mapsto \Psi(\mathcal{U}),$$

where $\Psi(T_\theta \mathcal{U}) = \Psi(\mathcal{U})$ is a **gauge-invariant function**

$U_{x,\mu}$ transform **non-locally** – equivariant data: products of **phases around closed loops** of all shapes and sizes



An optimisation problem

We seek the ground-state wavefunction Ψ_0 – minimises **energy** $E[\Psi] = \langle \Psi | H | \Psi \rangle$

$$\Psi_0 = \operatorname{argmin} E[\Psi]$$

High-dimensional optimisation problem for Ψ_0

- Minimum energy $E_0 = E[\Psi_0]$ **unknown**
- **Exponentially large** state space: $\dim \mathcal{H} = N^{2L^2}$
- Gauge invariance – highly non-trivial **constraint**

Want large class of gauge-invariant trial functions for Ψ

Neural quantum states

Neural quantum states

[Carleo, Troyer '16] introduced a new kind of variational ansatz for Ψ : **neural quantum state** (NQS)

- Wavefunction Ψ_θ represented by **neural network** with hidden layers
- Parameters θ of network adjusted by stochastic **gradient descent** to minimise energy $E[\Psi_\theta]$

At end of training, neural network gives approximate ground-state wavefunction

We need a **gauge-invariant neural network**!

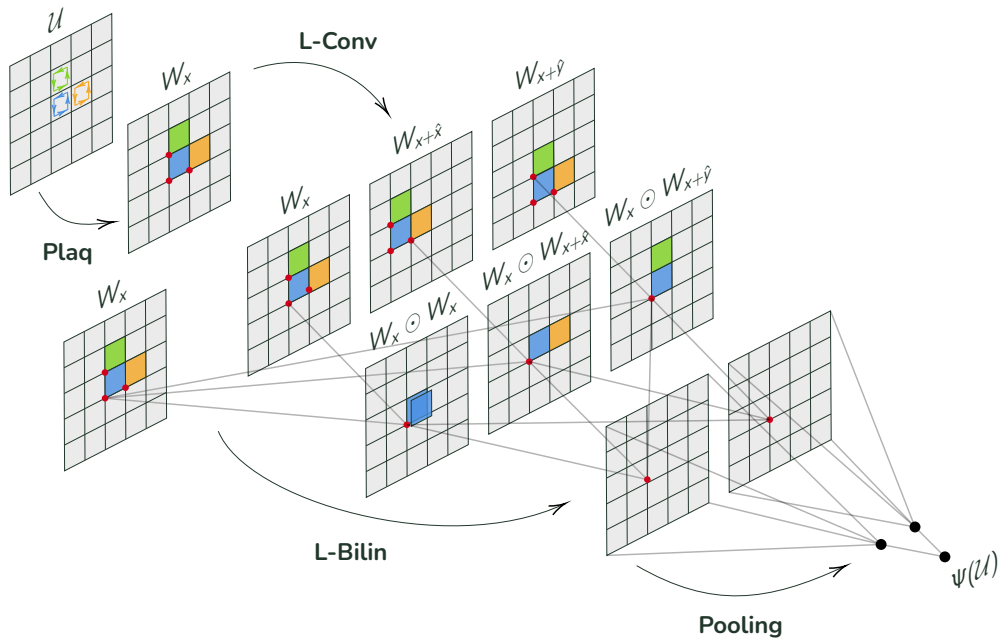
Lattice gauge-equivariant convolutional neural networks (LGE-CNNs) introduced by [Favoni et al. '20] for supervised learning

- Can approximate arbitrary gauge invariant or equivariant functions of a lattice system
- Automatically translation and rotation invariant

Implemented using NetKet 3 [Vicentini et al. '21] and JAX/Flax

(See also [Luo et al. '22] for \mathbb{Z}_N , [Luo et al. '22] for $U(1)$, [Spriggs et al. '25] for $SU(2)$)

LGE-CNN architecture



Gauge-invariant trial functions

Deep LGE-CNNs can construct all possible closed loops [Favoni et al. '20] – network constructs a trial function

$$\Psi_{\theta}(\mathcal{U}) \sim \exp \left[\sum_{\text{Lattice}} f_{\theta}(\text{closed loops}) \right]$$

where f_{θ} is a **non-linear gauge-invariant function** of closed loops of all sizes and shapes

- **Finite network width** \rightarrow network keeps only those loops that contribute significantly to ground state

Training minimises $E[\Psi_{\theta}]$ over θ via stochastic gradient descent

Test bed: \mathbb{Z}_2 lattice gauge theory

Ground-state energy

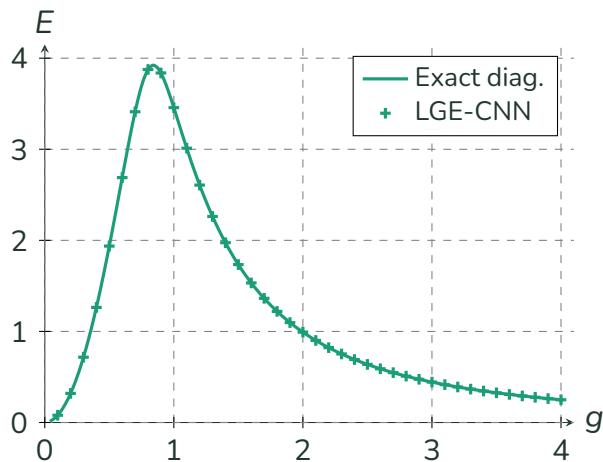


Figure 1: Ground-state energy on a 2×2 lattice as a function of interaction strength g compared with results from exact diagonalisation.

Ground-state energy

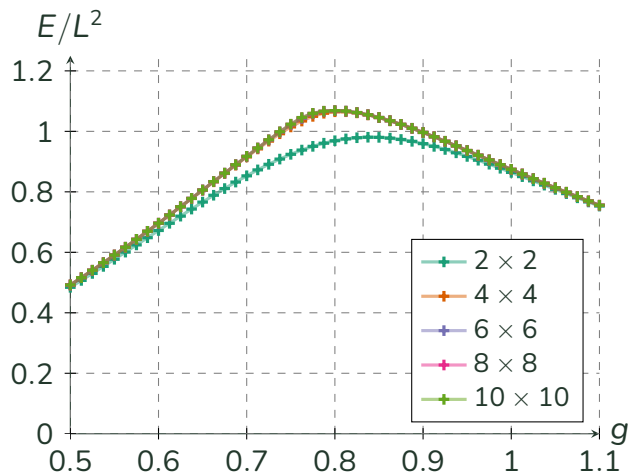


Figure 2: Ground-state energy for varying lattice sizes as a function of interaction strength g .

Phase transition

Energy alone is not that interesting – wavefunction encodes much more!

For \mathbb{Z}_2 , clock / shift are usual **Pauli operators**: $Q \equiv \sigma_z$ and $P \equiv \sigma_x$

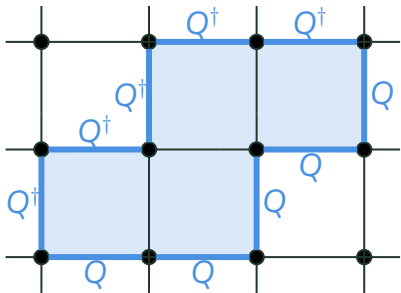
- Gauge theory dual to quantum Ising spin model [Wegner '71]
- In universality class of **Ising CFT3** [Wilson, Fisher '72]

As g varies, expect **phase transition** from deconfined to confined phase (ordered to disordered) – can we see this?

Detecting a phase transition

Wilson loop of Q operators along directed closed path Γ on lattice

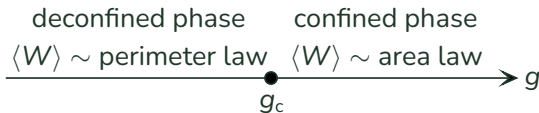
$$W_\Gamma = \prod_\Gamma Q$$



Phase detected by decay of $\langle W_\Gamma \rangle$
[Wegner '71; Kogut '79]

Deconfined phase: decays with **perimeter** P_Γ of loop

Confined phase: decays with **area** A_Γ of loop



Order parameter

Expectation value takes the form

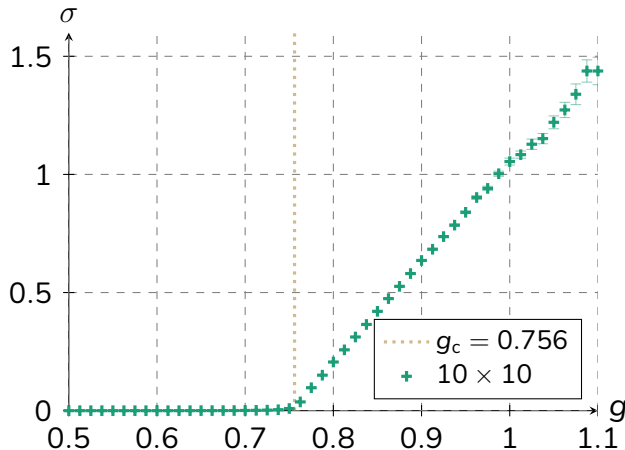
$$\langle W_\Gamma \rangle \sim \exp(-\kappa P_\Gamma - \sigma A_\Gamma),$$

where **string tension** σ acts as order parameter

- Use trained NQSs to extract σ as function of g

Signals **phase transition** at

$$g_c = 0.756$$



Critical exponents

Finite-size scaling and curve collapse determine **critical coupling** g_c , and correlation length and magnetisation **critical exponents** ν and β

NQS for \mathbb{Z}_2 gauge theory: [AA et al. '24]

$$g_c = 0.7546(8), \quad \nu = 0.630(3), \quad \beta = 0.326(4)$$

Previous results from spin models / CFT: [Blöte, Deng '02; Kos et al. '16; Simmons-Duffin '17]

$$g_c = 0.757051, \quad \nu = 0.629971, \quad \beta = 0.326419$$

Conclusions

Neural networks are powerful tools for solving high-dimensional optimisation problems

- Gauge-equivariant networks extend this to **local gauge symmetries**
- Salient **gauge-equivariant features** constructed “on the fly”

Provide accurate approximation of ground state for lattice gauge theories – can be used to probe **phase transitions**, **critical exponents**, and more

Future directions

Extension to finite groups A_N / D_N [Kitaev '03], $SU(N)$ Yang–Mills [Spriggs et al. '25]

- Network architecture remains the same

Inspiration for mathematics?

- Optimisation over functions on quotient spaces by local symmetry groups commonly needs invariant basis functions or explicit gauge choice – often **impractical**
- Gauge-equivariant neural networks might provide a new approach for **constrained variational problems** in geometry / mathematical physics

Extra

Curve collapse

Near phase transition, **finite-size scaling** predicts a specific scaling with lattice size L

- Observables are functions of renormalised coupling $\tilde{g} = L^{1/\nu}(g - g_c)/g_c$

e.g. 't Hooft string **disorder parameter** should scale as

$$\langle T \rangle = L^{-2\beta/\nu} t(\tilde{g})$$

where ν and β are correlation length and magnetisation **critical exponents**

“Curve collapse”: plot of $L^{2\beta/\nu} \langle T \rangle$ vs \tilde{g} should be **independent of L**

- Extract g_c , β and ν by minimising distance between curves

Curve collapse for $\langle T \rangle$

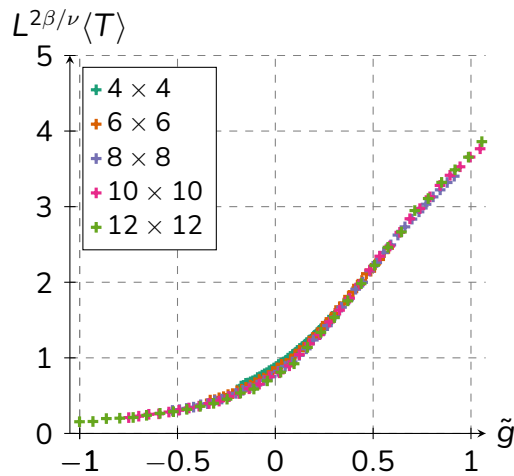
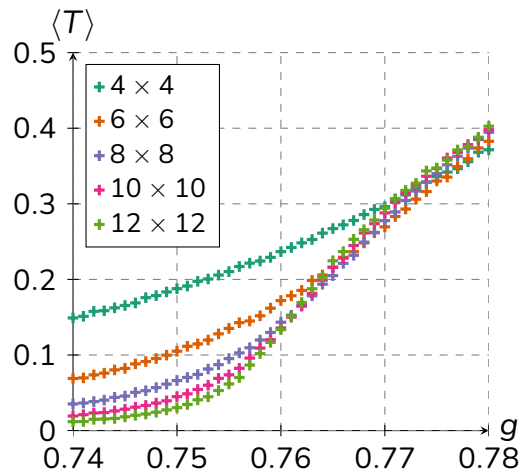


Figure 3: Curve collapse for 't Hooft string disorder parameter $T = \prod_{\tilde{f}} P$.

What do we learn?

What can we learn from the trained network?

As $g \rightarrow \infty$, network parameters show loop phases not used at all

- $\Psi(\mathcal{U}) = \text{constant}$

As $g \rightarrow 0$, 1×1 loops used, but larger loops not constructed

- $\Psi(\mathcal{U})$ non-zero on trivial flux configurations, $W_x = 1$

Near **phase transition**, loops of all shapes and sizes constructed

- Scale invariance \rightarrow conformal field theory

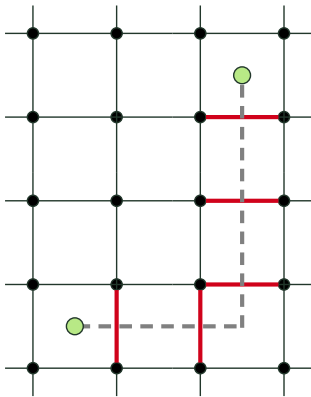
Identifying the critical coupling

Ordered phase	Disordered phase
$g < g_c$	$g > g_c$
$\langle W \rangle \sim$ perimeter law	$\langle W \rangle \sim$ area law
$\langle T \rangle \sim$ exp. decay with distance	$\langle T \rangle \sim$ constant
electric flux lines condensed	mag. monopoles condensed
$\mathbb{Z}_2^{(1)}$ broken	$\mathbb{Z}_2^{(1)}$ preserved
“deconfined”	“confined”

[Rayhaun, Williamson '23]

Cleaner to look at decay of 't Hooft string

Disorder parameter



't Hooft string of P operators, $T = \prod_{\tilde{\Gamma}} P$, along open path $\tilde{\Gamma}$ between two points on *dual* lattice

- $\langle T \rangle$ independent of path due to Gauss' law
- In deconfined phase, creates a pair of quasi-particles (magnetic monopoles) – $\langle T \rangle$ decays exponentially with distance
- In confined phase, $\langle T \rangle$ independent of distance – “monopoles condensed”

Disorder parameter

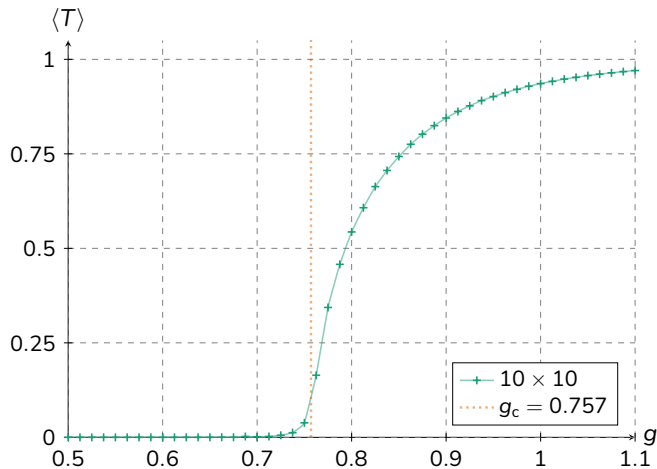
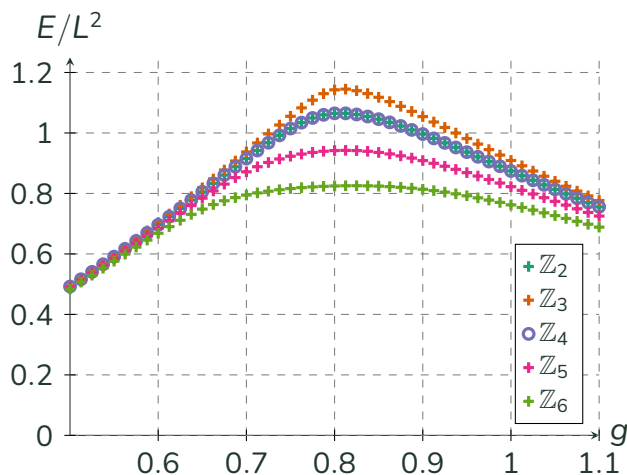


Figure 4: Lattice average of the 't Hooft string operator near the critical point for $L = 10$. Distance $L/2 = 5$ between ends of 't Hooft string.

\mathbb{Z}_N energies

Ground-state energy for \mathbb{Z}_N theories on a 4×4 lattice

The \mathbb{Z}_4 theory splits into two decoupled \mathbb{Z}_2 theories for every value of the coupling
[Grosse et al. '81]



Stochastic reconfiguration

Stochastic gradient descent with a non-trivial weight-space metric, c.f. **imaginary time evolution** [Sorella et al. '07]

$$(1 - \epsilon H)|\Psi\rangle \approx e^{-\epsilon H}|\Psi\rangle = e^{-\epsilon H} \sum_{i=0} c_i |i\rangle = e^{-\epsilon E_0} c_0 |0\rangle + e^{-\epsilon E_1} c_1 |1\rangle + \dots$$

- Iterating this will project a trial wavefunction onto the ground state

Construct a weight update rule so that the updated state is $(1 - \epsilon H)|\Psi\rangle$

$$\theta_\alpha \mapsto \theta_\alpha - \eta (S^{-1})_{\alpha\beta} R_\beta$$

where

$$O_\alpha |\psi\rangle = \partial_\alpha |\psi\rangle, \quad R_\alpha = \langle O_\alpha^\dagger H \rangle - \langle O_\alpha^\dagger \rangle \langle H \rangle, \quad S_{\alpha\beta} = \langle O_\alpha^\dagger O_\beta \rangle - \langle O_\alpha^\dagger \rangle \langle O_\beta \rangle$$

Calculating expectation values

Given a state $|\Psi\rangle$, one can estimate $E[\Psi] = \langle H \rangle$ via

$$\langle H \rangle = \langle \Psi | H | \Psi \rangle = \mathbb{E}_{\mathcal{U} \sim p(\mathcal{U})} [E_{\text{loc}}(\mathcal{U})],$$

where $\mathbb{E}_{\mathcal{U} \sim p(\mathcal{U})}$ takes the expectation value over \mathcal{U} , with \mathcal{U} chosen according to the PDF $p(\mathcal{U}) = |\Psi(\mathcal{U})|^2$, and the “local energy” is

$$E_{\text{loc}}(\mathcal{U}) = \sum_{\mathcal{U}'} \langle \mathcal{U} | H | \mathcal{U}' \rangle \frac{\Psi(\mathcal{U}')}{\Psi(\mathcal{U})}.$$