

# Symmetries in Neural Quantum States

**Javier Rozalén Sarmiento**

**Advisor: Arnau Rios Huguet**



# The Hadronic, Nuclear and Atomic Physics Group (ε FQA)

## People



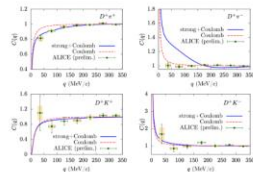
## HadNuc@UB Seminars

27 September

Juan Torres-Rincón (ICC-UB & FQA)

TROIA: T-matrix based routine for hadron femtoscopy

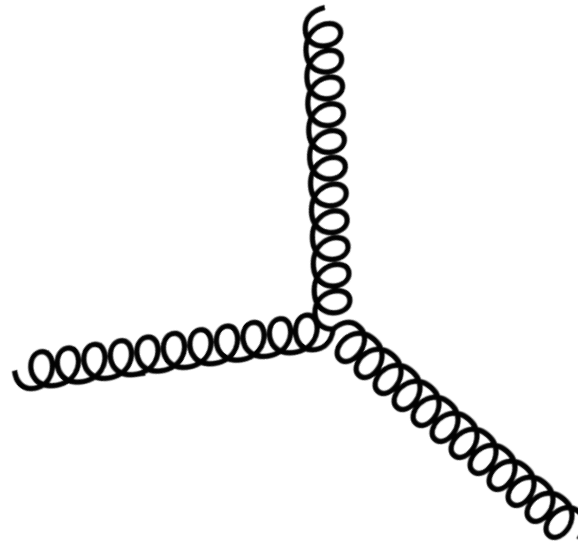
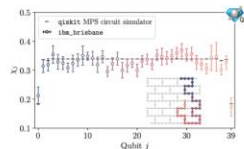
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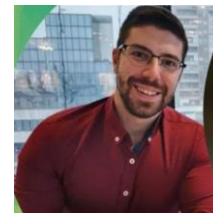
6 October

Marc Illa (University of Washington)

Lattice Quantum Electrodynamics in 1+1 Dimensions: The Vacuum on 100 Qubits



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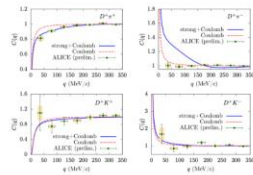
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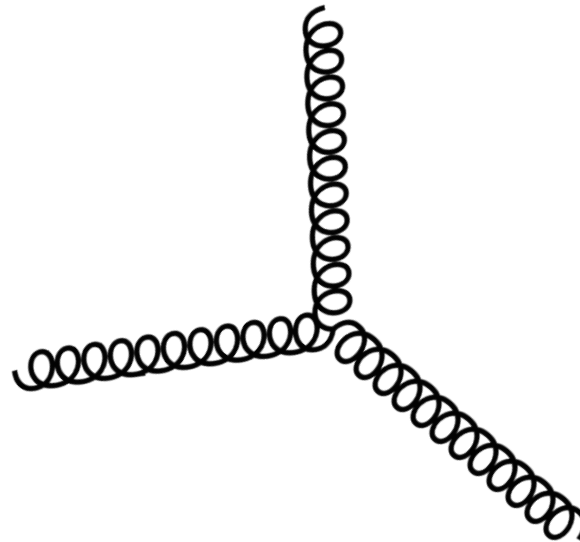
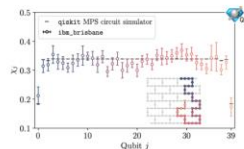
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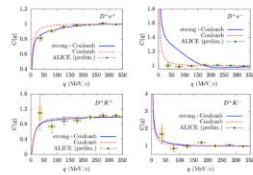
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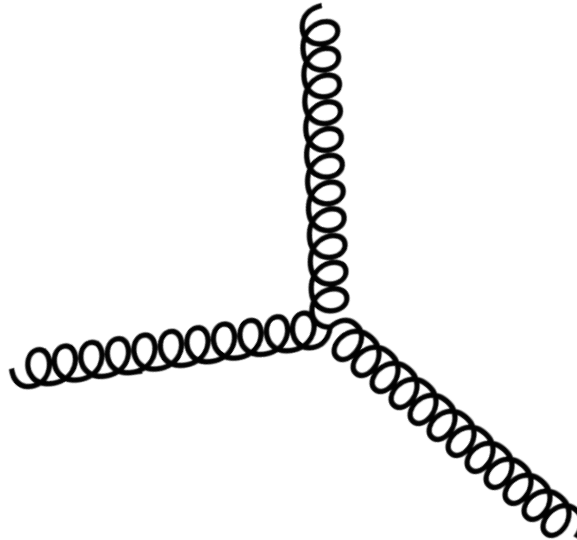
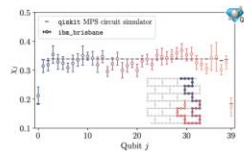
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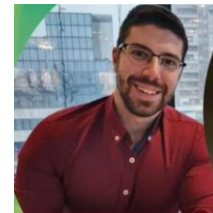
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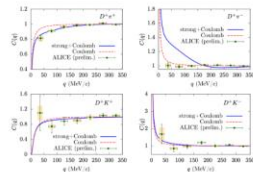
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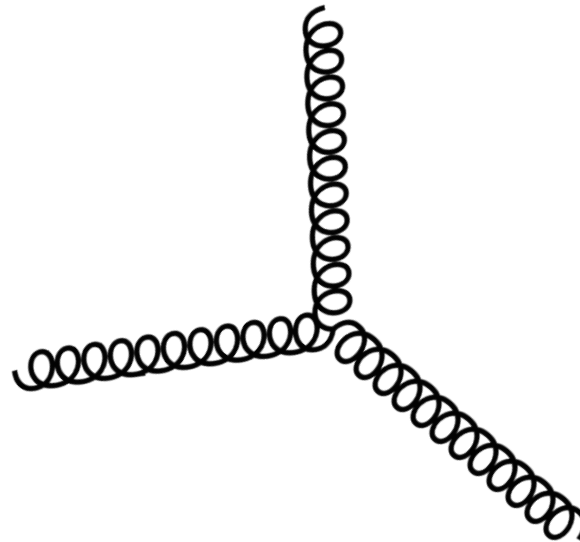
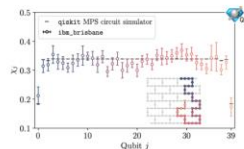
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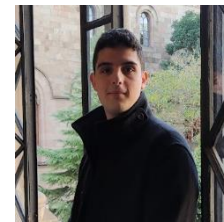
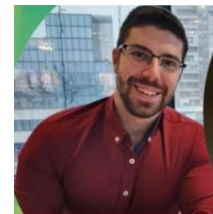
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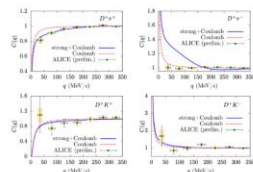
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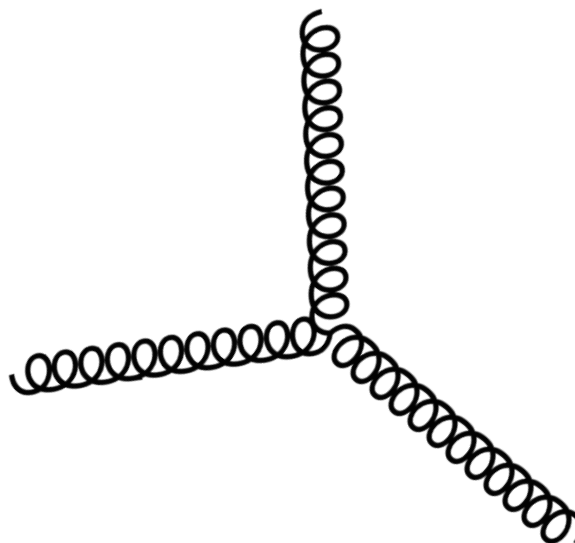
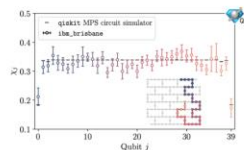
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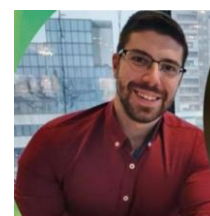
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**ICCUB has  $\approx$  80 PhDs & Postdocs (as of 2022)**

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# Nuclear Physics

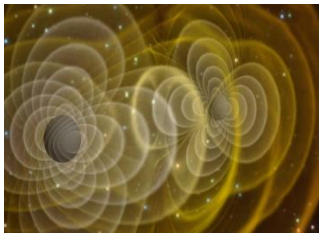


**Dark Matter** detection: baryonic DM interacts with nuclei!

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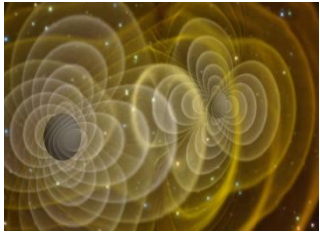
**Gravitational waves:** strong interaction determines the GW signal in NS mergers



# Nuclear Physics



**Dark Matter** detection: baryonic DM interacts with nuclei!



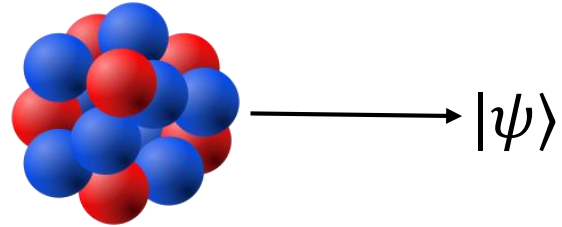
**Gravitational waves:** strong interaction determines the GW signal in NS mergers



**Nuclear structure:** static properties of nuclei

# The Quantum Many-Body Problem

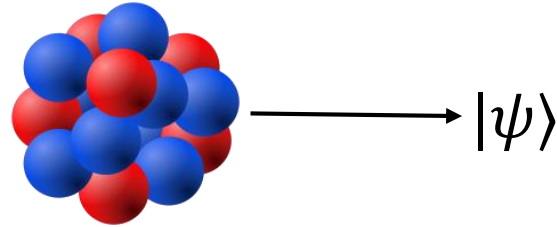
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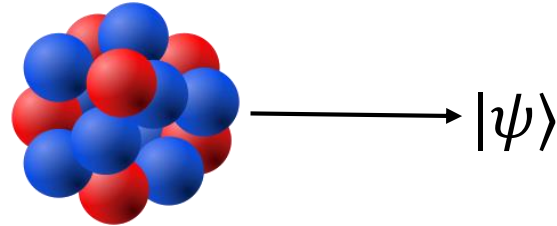
- **How?** Rayleigh-Ritz variational principle

$$\frac{\langle \psi_\theta | \hat{H} | \psi_\theta \rangle}{\langle \psi_\theta | \psi_\theta \rangle} \geq E_{GS}$$

$$|\psi_\theta\rangle = \int |p\rangle \psi_\theta(\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_N) d^{3N}p$$

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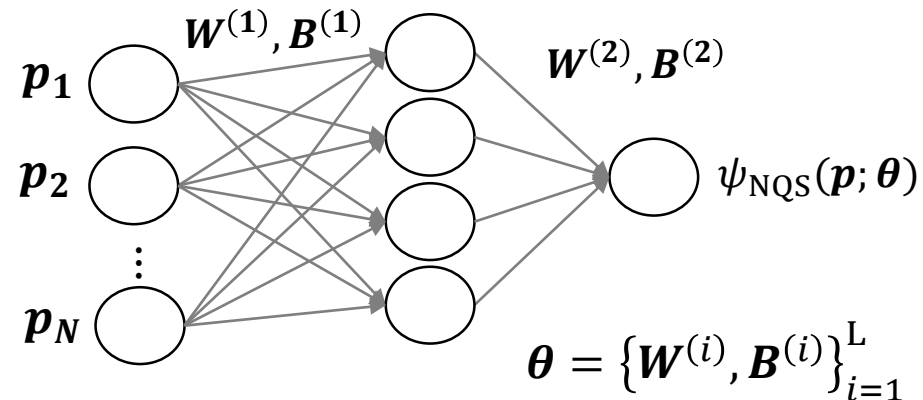


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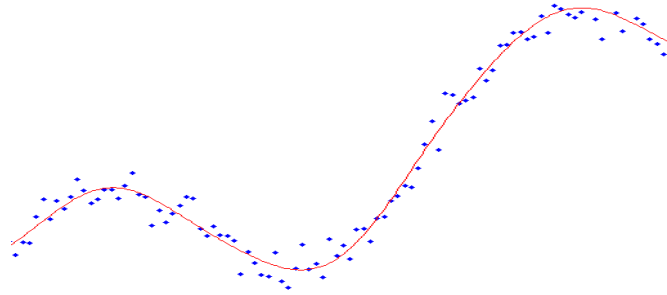
- **NQS Ansatz:**  $\psi_{NQS}(\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_N; \boldsymbol{\theta})$





# Why Neural Networks?

- **NNs have “ $\infty$  power”**: a neural network can approximate any continuous function [1], [2].



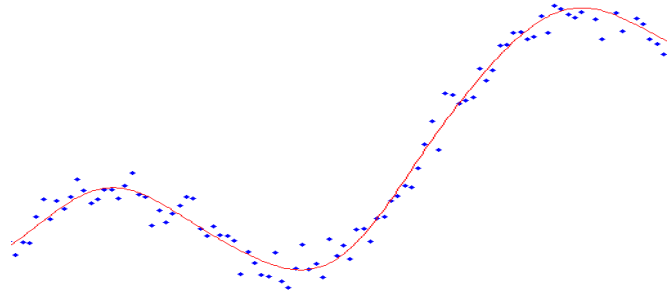
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[1] G. Cybenko, *Approximation by superpositions of a sigmoidal function*, 1989

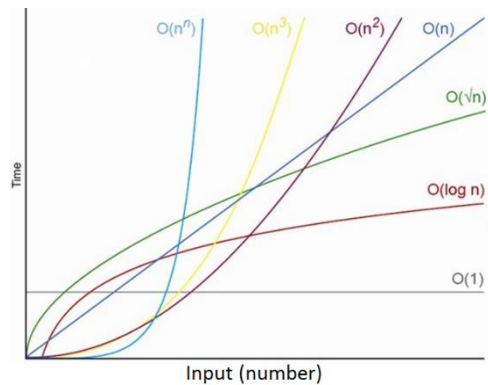
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- **Space complexity**: polynomial scaling of memory resources... possibly!



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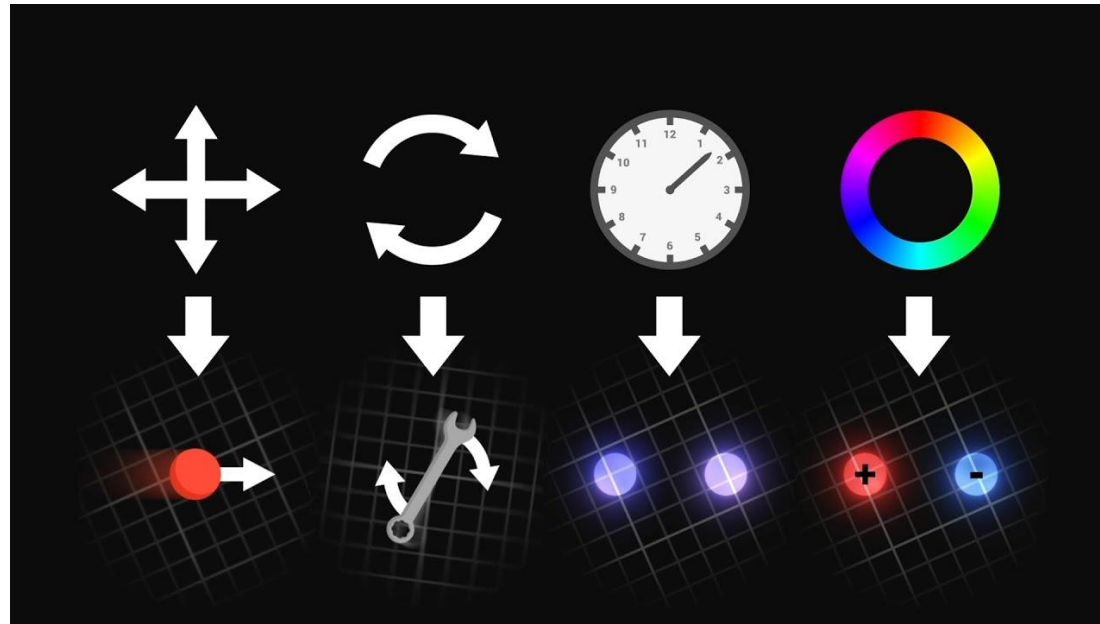
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# Physics-Inspired Neural Networks

**Encoding physics in NNs:** symmetries of  $\hat{H}$ , boundary conditions, etc.

└─→ My current work!



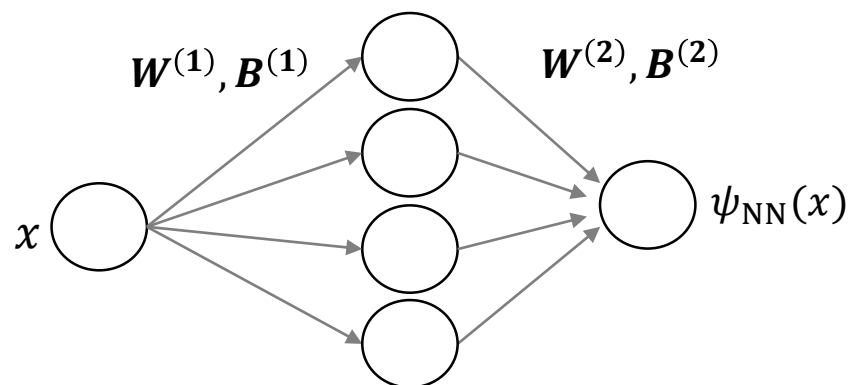
[https://www.youtube.com/watch?v=hF\\_uHfSoOGA&ab\\_channel=ScienceClicEnglish](https://www.youtube.com/watch?v=hF_uHfSoOGA&ab_channel=ScienceClicEnglish)

# Symmetries in neural networks

## 1D HO: naive approach (but good!)

$$\hat{H} = -\frac{1}{2}\nabla^2 + \frac{1}{2}m\omega^2\hat{x}^2 \rightarrow \psi(x) = \pm\psi(-x)$$

$$\psi_{\text{NQS}}(x) := \psi_{\text{NN}}(x) \pm \psi_{\text{NN}}(-x)$$



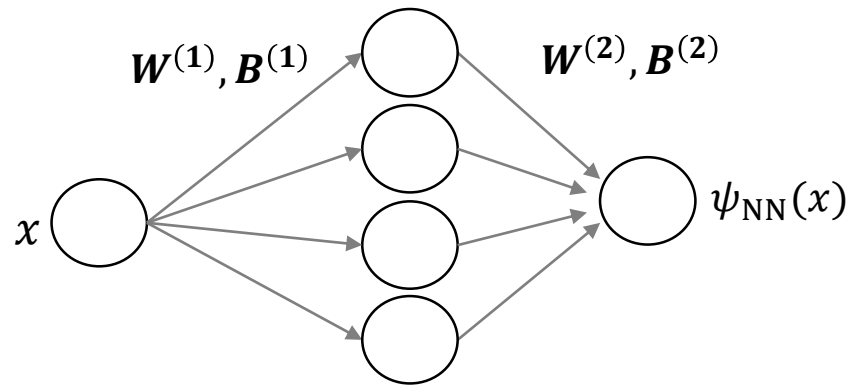


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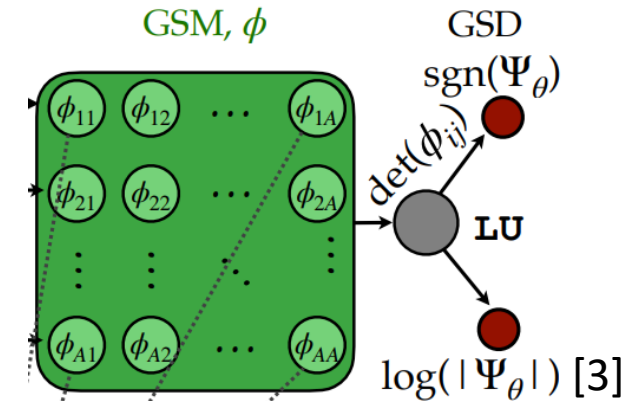


## Fermionic particle exchange: common approach

Spin-statistics theorem  $\rightarrow$

$$\psi(x_1, \dots, x_i, \dots, x_j, \dots, x_N) = \pm\psi(x_1, \dots, x_j, \dots, x_i, \dots, x_N)$$

$$\psi_{\text{NQS}}(x_1, x_2, \dots, x_N) = \varphi_{\text{EQUIV}} \circ \det \phi_{\text{GSM}}(x_1, x_2, \dots, x_N)$$

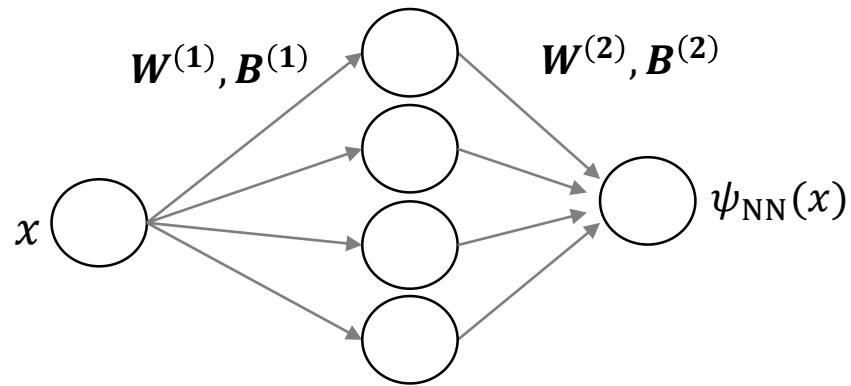


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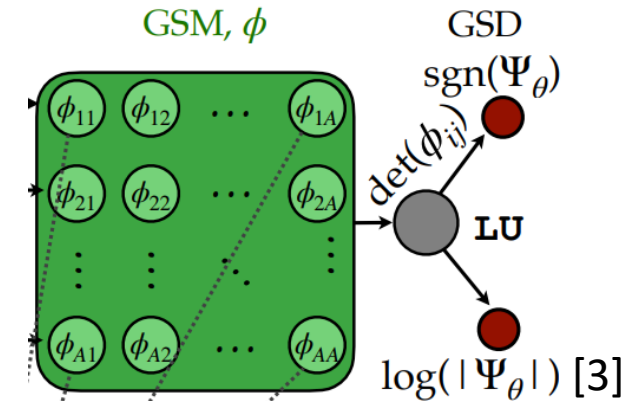
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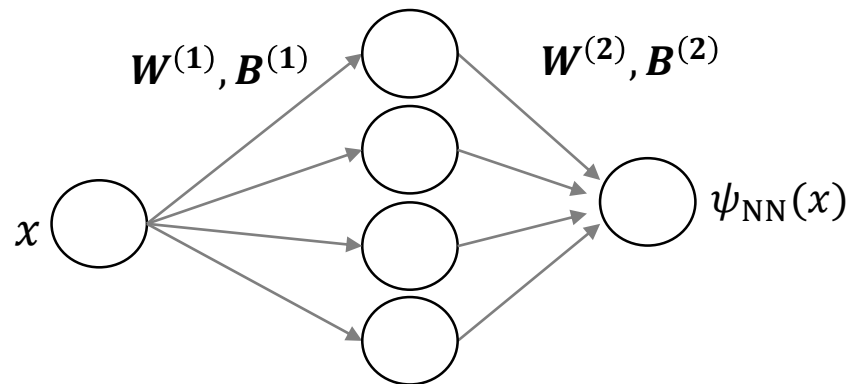


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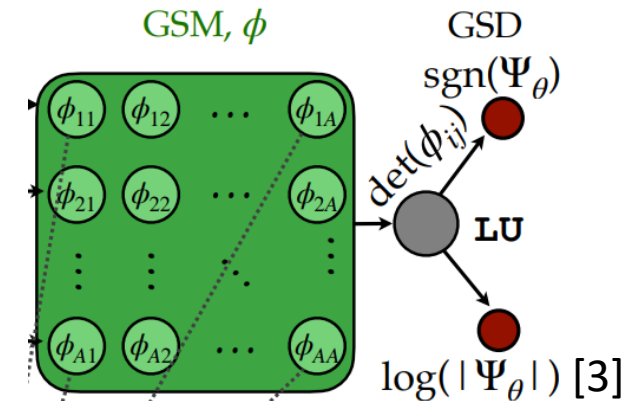
What about other symmetries (continuous groups)?

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# Convolution is all you need

$\Phi$  is **equivariant** under a group  $G$  if:

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**Group convolution  $\Leftrightarrow$  Group equivariance (2016-2018) [4, 5, 6]**

$$(f \star \chi)(g) = \sum_{u \in G} f(u^{-1}g)\chi(u)$$

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[4] T S Cohen and M Welling, *Group Convolutional Neural Networks*, [arXiv:1602.07576](https://arxiv.org/abs/1602.07576)

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**Can we re-think past networks as G-CNNs?**

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**Should we design NQs within this framework?**

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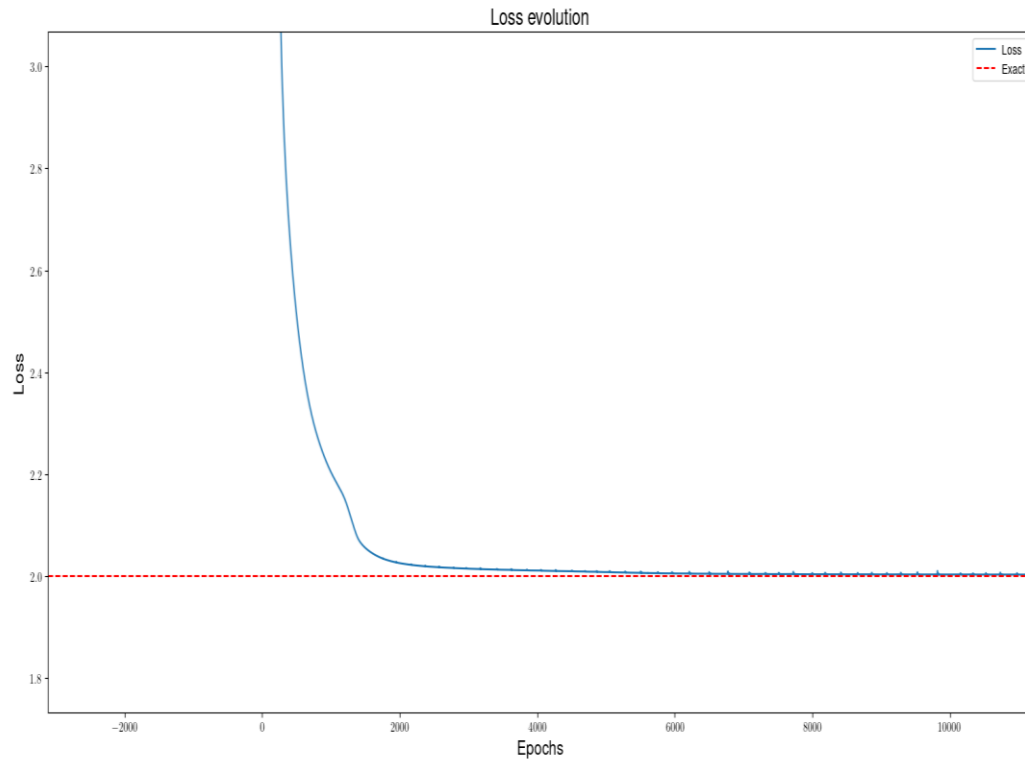
# Toy example: $G = S_N$

$N = 2$ , 1D HO

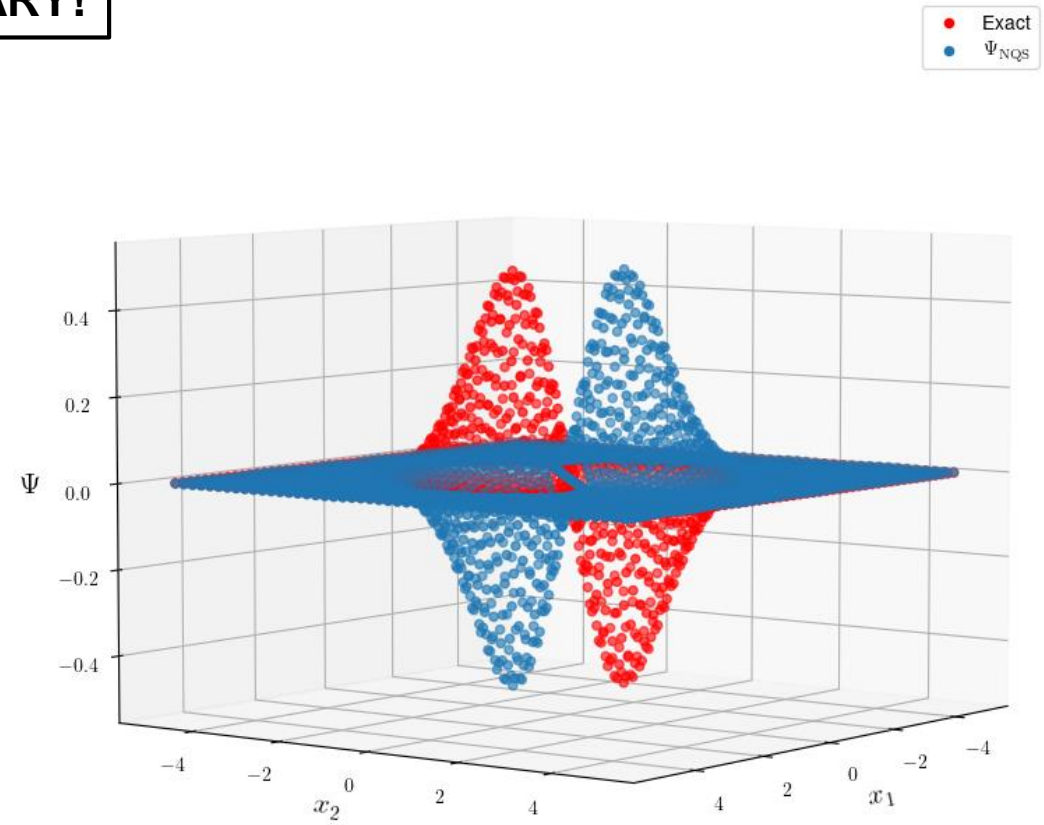
1 conv layer w/ bias  $\rightarrow$  # weights =  $k(|G| + 1 + |G|dN)$

$k = 25, |G| = 2, d = 1$

**PRELIMINARY!**



Wave function



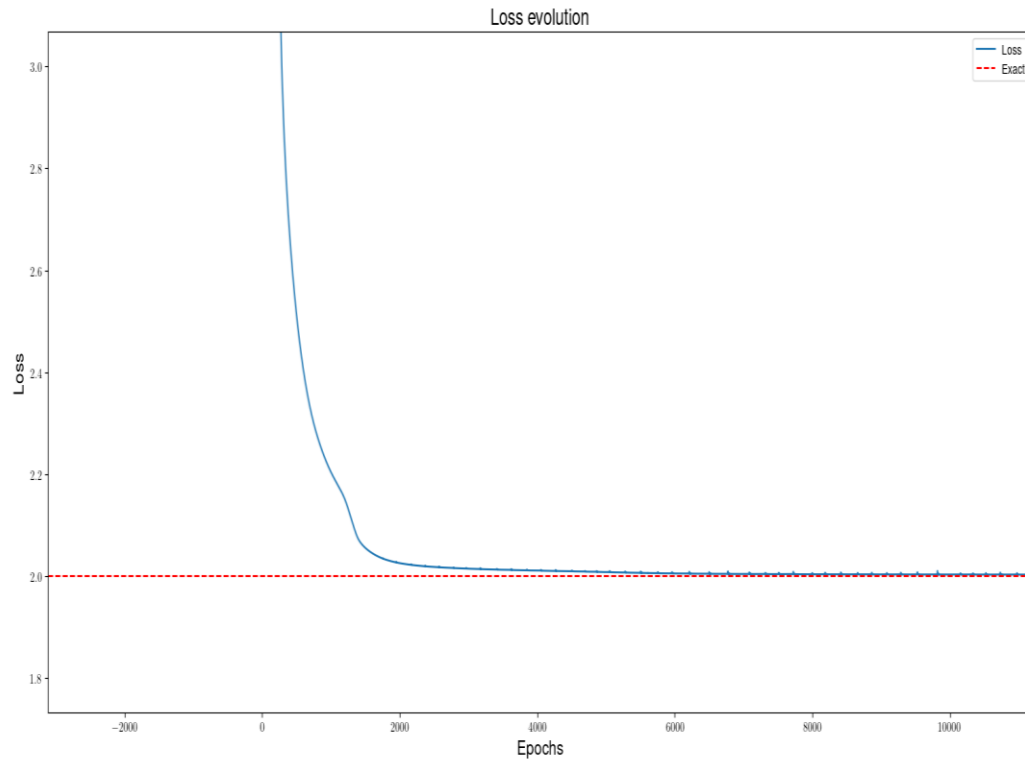
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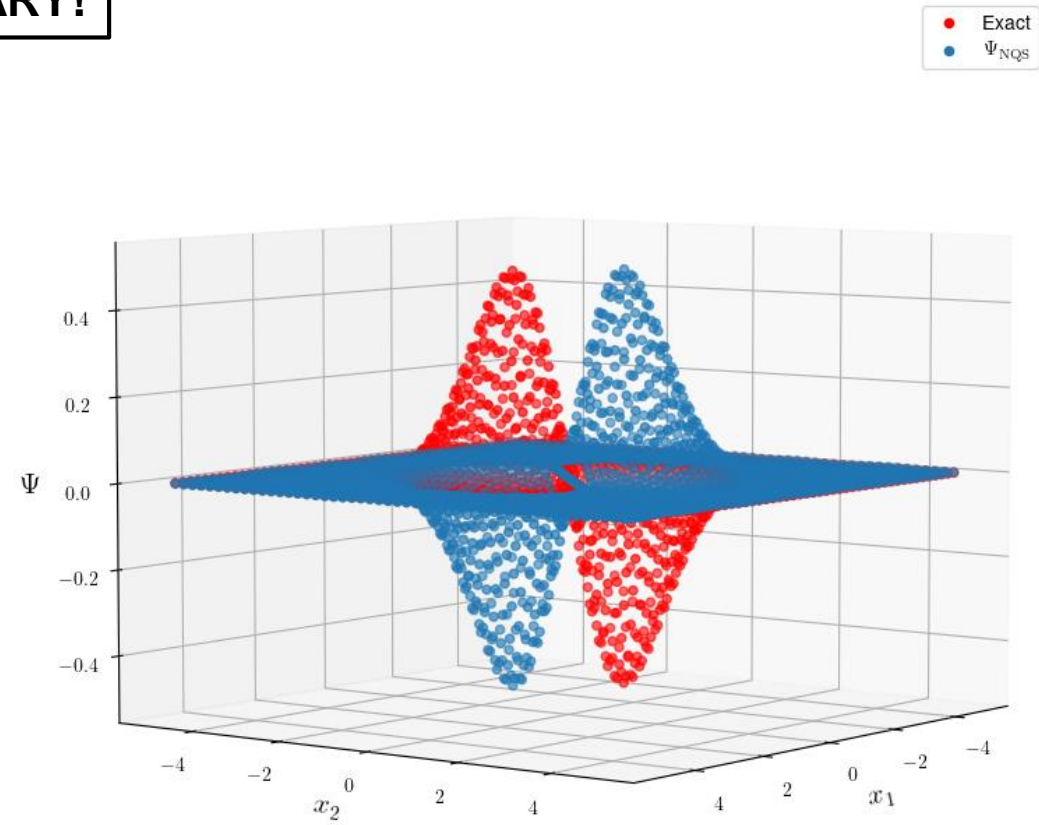
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Wave function



Memory grows factorially with  $N$  😞

# Next steps and open questions...

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- Can we compute any excited state?
- What about continuous groups (SU(N))?

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