Quantum Machine Learning

Giuseppe D'Ambruoso

Politecnico di Bari

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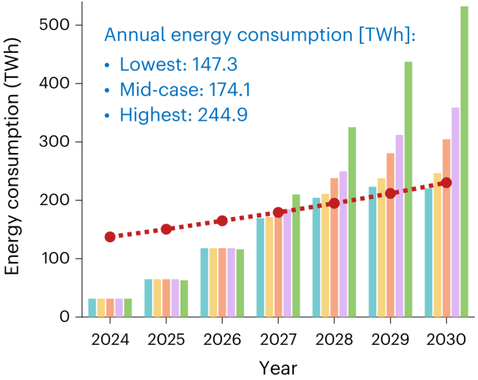
Classical ML algorithms are very resource demanding

Model	Parameters	Training Tokens
GPT-3	175B	300B
MT-NLG 530B	530B	270B
LaMDA	137B	168B
Chinchilla	70B	1.4T
PaLM	540B	780B
Falcon-180B	180B	3.5T
LLaMA	65B	1.4T
LLaMA-2	70B	2T

Parameter counts and training token sizes for major large language models.

Hoffmann, J. et al. (2022). arXiv:2203.15556

Classical ML algorithms are very resource demanding



Projected energy consumption of the installed AI servers from 2024 to 2030

Xiao et al., Nature Sustainability, 2025

We have to to relax the need for training data and trainable parameters.

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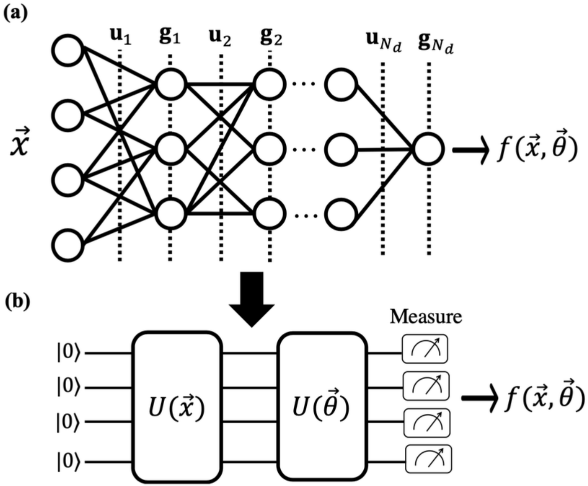
In my PhD project, we are trying to relax through equivariant quantum neural networks.

Classical vs quantum neural networks



Basic structure of classical (a) and quantum (b) neural networks

Key aspects of quantum neural networks

- Highly customizable architecture.
- The classical data encoding $U(x)$ can be chosen according to hardware needs.
- The number of qubits is limited by the technology of our time.
- Easy integratability in classical ML pipelines for a sub-routine processes makes them already suitable for current quantum devices.

As physicists, we have a thing for symmetries!

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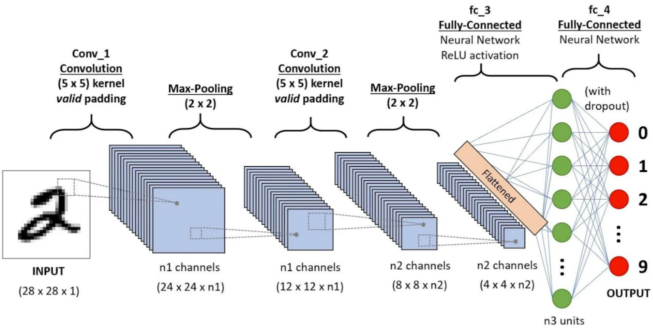
How can we take advantage from symmetries when designing a machine learning (ML) model?

Group-invariant ML models

$$\boxed{f(x,\boldsymbol{\theta}) = f(V_g(x),\boldsymbol{\theta}) \quad \forall x \in \mathcal{X}, g \in \mathcal{G}, \boldsymbol{\theta} \in \mathbb{R}^n}$$

where V_g represents the transformation g of a given symmetry group $\mathcal{G}$ in the input space $\mathcal{X}$.

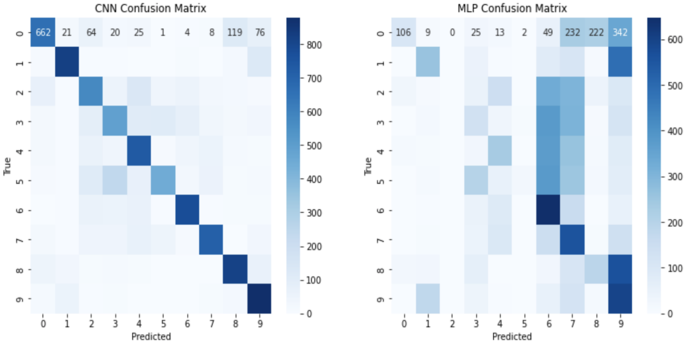
Group-invariance in classical neural networks: CNNs



CNNs are O(2)-invariant

LeCun et al., 2025, *Proceedings of the IEEE*

The effect of group-invariance in classical neural networks



Equivariance in classical NNs leads to improved generalization

Joel et al., 2025, *International Journal of Applied Mathematics*

Group-invariance in quantum neural networks

Equivariant embedding $U(x)$

$$U(V_g(x)) = R(g)U(x)R(g)^\dagger$$

$$+$$

Equivariant quantum circuit $\tilde{U}(\boldsymbol{\theta})$

$$R(g)\tilde{U}(\boldsymbol{\theta})\rho(x)\tilde{U}(\boldsymbol{\theta})^\dagger R(g)^\dagger = \tilde{U}(\boldsymbol{\theta})R(g)\rho(x)R(g)^\dagger \tilde{U}(\boldsymbol{\theta})^\dagger$$

$$+$$

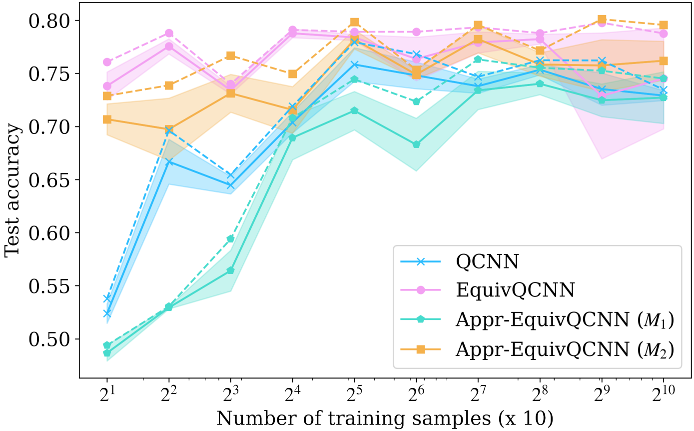
Invariant observables O

$$[O, R(g)] = 0$$

$$=$$

Invariant QML model w.r.t. the unitary representation R of $\mathcal{G}$

The effect of group-invariance in quantum neural networks

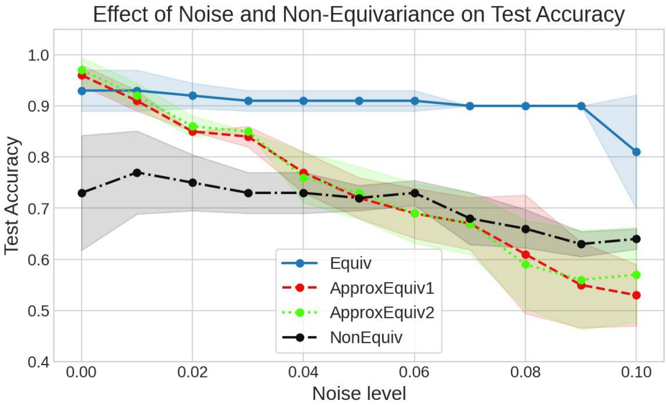


Group-invariance in quantum NNs leads to improved generalization for small sizes of the training set

S. Y. Chang et al. (2023), IEEE QCE

- How does noise affect the performance of group-invariant QNNs?
- Can the results obtained so far be extended to many-qubit QNNs?
- Are group-invariant QNNs useful in real-world image classification tasks?

First results



Group-invariance allows for improved noise resilience

Thank you for your attention!