P2IO meeting

Quantum machine learning for nuclear and particle, experimental and theoretical physics

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in collab with
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From one to two projects

Quantum machine learning for
nuclear and particle, experimental and theoretical physics

From one to two projects

Quantum machine learning for experimental particle physics

in collaboration with F. Magniette & M. Papin (LLR)

1st part

From one to two projects

Quantum machine learning for theoretical nuclear physics

in collaboration with D. Lacroix & G. Hupin (IJCLab)

2^{nd} part

QML for experimental particle physics

Quantum versus classical: comparative study & software development in collaboration with F. Magniette, M. Papin (LLR)

1) Classical neural networks: broadly used, heuristic [1] & formal [2][3] understanding
2) Quantum neural networks: nascent technology, limited resources, leverage ClNN knowledge

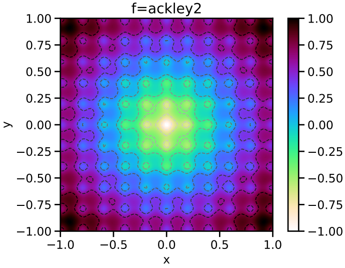
Quantum computing $\supset$ classical computing

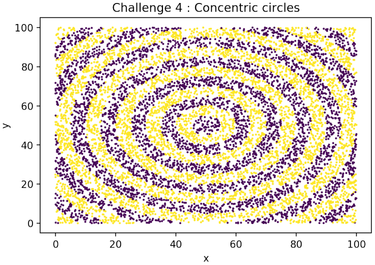
- perfs at same resources? • resources for same perfs? • which models?

Project: thorough comparison ClNN/QNN to (i) assess performances, (ii) gauge if realistic applications possible in real devices

QML for experimental particle physics

- ✓ developer of `mosaic`, a "toolbox" code for benchmarking classical and quantum AI models on several relevant test cases (from simple regression/classification tasks to PID in calorimeters)
  - ✓ several quantum and classical neural networks available
  - ✓ several classes of data available (regression, classification, realistic)





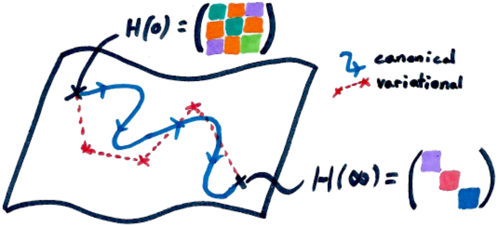
QML for experimental particle physics

- ✓ developer of `mosaic`, a "toolbox" code for benchmarking classical and quantum AI models on several relevant test cases (from simple regression/classification tasks to PID in calorimeters)
  - ✓ several quantum and classical neural networks available
  - ✓ several classes of data available (regression, classification, realistic)
  - ✓ easy to implement new ones
- ✓ first large-scale run performed
- 🕒 run on real devices scheduled
- 🕒 papers planned:
  - `mosaic` to be published (classical part in ANR OGCID, classical+quantum: post-doc project, `mosaicqc`)
  - comparative study on easy-to-interpret data
  - realistic study on calorimeter data

QML for theoretical many-body physics

Quantum computing and machine learning for many-body problems in collaboration with D. Lacroix, G. Hupin (IJCLab)

- solving small MB problems on QC [1][2][3]: ansatzes + optimisation techniques
- Similarity renormalisation group (SRG): unitary transformation as a flow equation



$$H(s) = U^\dagger(s) H(0) U(s)$$

$$\leftrightarrow \frac{\mathrm{d}H(s)}{\mathrm{d}s} = \left[H(s), U^\dagger(s) \frac{\mathrm{d}U(s)}{\mathrm{d}s} \right]$$

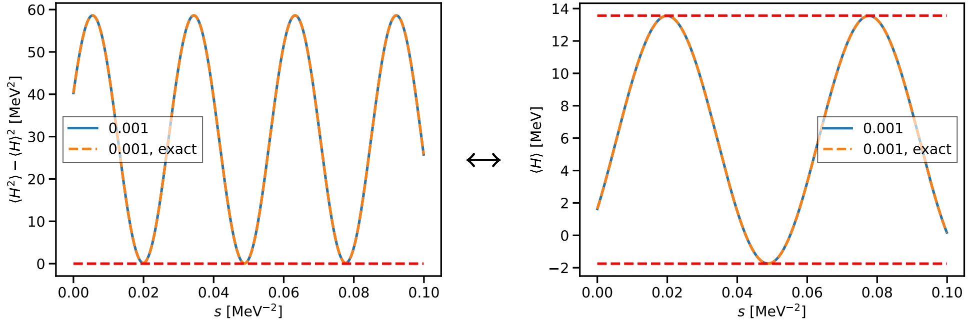
- straightforward classically, not at all on a QC (need $H(s)$)
- flow eq. naturally conserves the symmetries of the Hamiltonian
- on QC, naturally unitary (not eigenvalue drift)

QML for theoretical many-body physics

Schematic model: deuteron nucleus [1], $\not{\pi}$EFT Hamiltonian mapped on 2 or 3 qubits

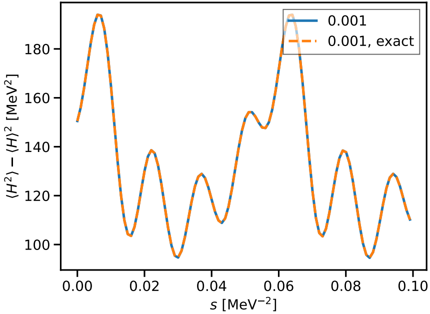
$$H_2 = \frac{e_0}{2}(I_0 - Z_0) + \frac{e_1}{2}(I_1 - Z_1) + \frac{v_{01}}{2}(X_0X_1 + Y_0Y_1)$$

✓ meaningful & easy to measure metric: $\sigma^2(H(s)) = \langle\psi|H^2(s)|\psi\rangle - \langle\psi|H(s)|\psi\rangle^2$



QML for theoretical many-body physics

✓ work fine if not mixing orthogonal subspaces
✗ else, $\sigma^2 \neq 0$ & need multiple steps



- proposing a variational method to work around:

$$U(s) \to U(s,n) = \prod_{k=1}^{n} \mathcal{U}_k(\vec{\theta}_k)$$

with $\vec{\theta}_k$ from $\dfrac{\partial \sigma^2(H(s,k))}{\partial \vec{\theta}_k} = 0$

- recover eigenstates by measurements

⌚ variational construction using machine learning
⌚ towards realistic Hilbert spaces

Thank you for your attention!