

Machine Learning, artificial intelligence and quantum science at the university of Oslo; research and education

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Basic activities, Overview of our main activities

- ▶ Machine Learning applied to classical and quantum mechanical systems and analysis of physics experiments
- ▶ Quantum Engineering
- ▶ Quantum algorithms
- ▶ Quantum Machine Learning

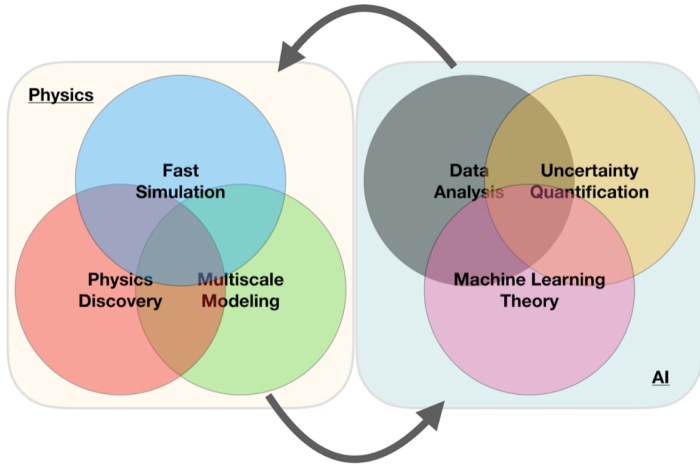
Quantum Science at CCSE@UiO

During the last five to six years we have started a large scientific activity on Quantum Computing and Machine Learning at the Center for Computing in Science Education (CCSE), with four PhD students hired since October 2019 and several master of Science students (six second year students as of now). This activity spans from the development of quantum-mechanical many-particle theories for studying systems of interest for making quantum computers, via the development of machine learning and quantum algorithms for solving classical and quantum mechanical problems to exploring quantum machine learning algorithms.

More activities

1. Center of Materials Science UiO, Lasse Vines (Expt) Andrej Kuznetsov(Expt), David Rivas Gongora (Expt) and Marianne Bathen
2. Gemini center on Quantum Computing (SINTEF-UiO-NTNU)
3. Analysis of experiments in subatomic physics
4. OsloMet and Simula Research lab
5. Machine learning and computational neuroscience
6. and probably many I have forgotten....please excuse me

A simple perspective on the interface between ML and Physics

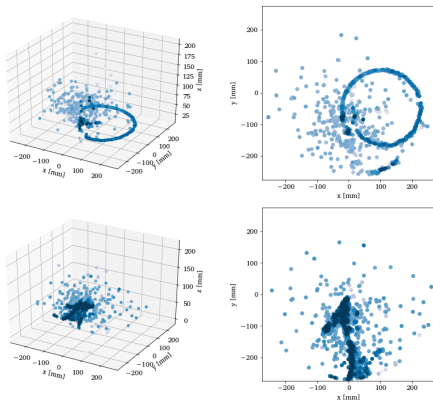


Selected references

- ▶ Mehta et al. and Physics Reports (2019).
- ▶ Machine Learning and the Physical Sciences by Carleo et al
- ▶ Artificial Intelligence and Machine Learning in Nuclear Physics, Amber Boehnlein et al., Reviews Modern of Physics 94, 031003 (2022)
- ▶ Dilute neutron star matter from neural-network quantum states by Fore et al, Physical Review Research 5, 033062 (2023)
- ▶ Neural-network quantum states for ultra-cold Fermi gases, Jane Kim et al, Nature Physics, in press
- ▶ Message-Passing Neural Quantum States for the Homogeneous Electron Gas, Gabriel Pescia, Jane Kim et al. arXiv.2305.07240,
- ▶ Efficient solutions of fermionic systems using artificial neural networks, Nordhagen et al, Frontiers in Physics 11, 2023

Argon-46 by Solli et al., NIMA 1010, 165461 (2021)

Representations of two events from the Argon-46 experiment. Each row is one event in two projections, where the color intensity of each point indicates higher charge values recorded by the detector. The bottom row illustrates a carbon event with a large fraction of noise, while the top row shows a proton event almost free of noise.



Quantum Monte Carlo and deep learning

Given a hamiltonian H and a trial wave function Ψ_T , the variational principle states that the expectation value of $\langle H \rangle$, defined through

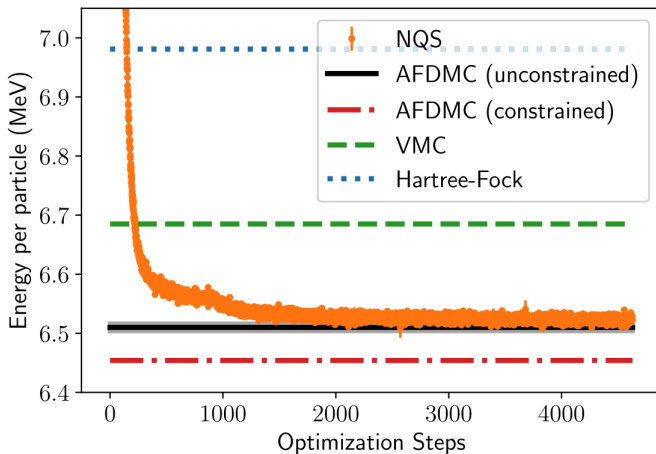
$$\langle E \rangle = \frac{\int d\mathbf{R} \Psi_T^*(\mathbf{R}) H(\mathbf{R}) \Psi_T(\mathbf{R})}{\int d\mathbf{R} \Psi_T^*(\mathbf{R}) \Psi_T(\mathbf{R})},$$

is an upper bound to the ground state energy E_0 of the hamiltonian H , that is

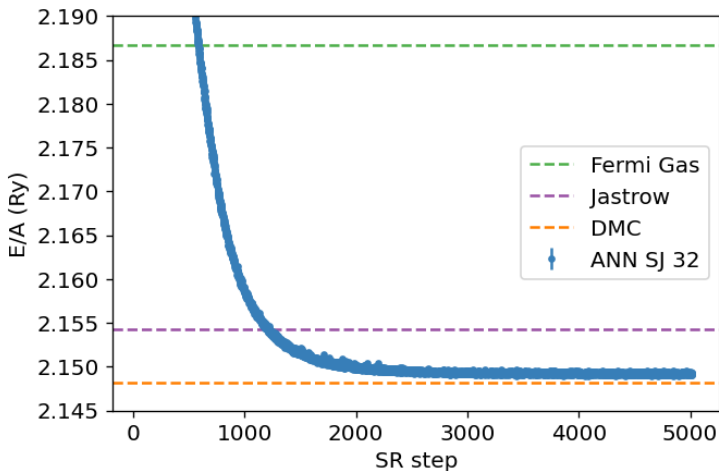
$$E_0 \leq \langle E \rangle.$$

In general, the integrals involved in the calculation of various expectation values are multi-dimensional ones. Traditional integration methods such as the Gauss-Legendre will not be adequate for say the computation of the energy of a many-body system. **Basic philosophy: Let a neural network find the optimal wave function**

Dilute neutron star matter from neural-network quantum states by Fore et al, Physical Review Research 5, 033062 (2023) at density $\rho = 0.04 \text{ fm}^{-3}$



The electron gas in three dimensions with $N = 14$ electrons (Wigner-Seitz radius $r_s = 2$ a.u.), Gabriel Pescia, Jane Kim et al. arXiv.2305.07240,



References, Quantum Computing

Machine Learning and Quantum Computing hold great promise in tackling the ever increasing dimensionalities. A hot new field is **Quantum Machine Learning**, see for example the recent textbook by [Maria Schuld](#) and [Francesco Petruccione](#).

1. Master of Science thesis of [Stian Bilek](#), **Quantum Computing: Many-Body Methods and Machine Learning**, August 2020, PhD student at UiO
2. Master of Science thesis of [Heine Åbø](#), **Quantum Computing and Many-Particle Problems**, June 2020, now at OsloMet
3. Master of Science thesis of Kristian Wold, **Parameterized Quantum Circuits for Machine Learning**, September 2021, now at OsloMet
4. [Marianne Etzelmüller Bathen's PhD](#), December 2020

Quantum Engineering

Quantum Computing requirements

1. be scalable
2. have qubits that can be entangled
3. have reliable initializations protocols to a standard state
4. have a set of universal quantum gates to control the quantum evolution
5. have a coherence time much longer than the gate operation time
6. have a reliable read-out mechanism for measuring the qubit states
7. and many more

Candidate systems

1. Superconducting Josephon junctions
2. Single photons
3. Trapped ions and atoms
4. Nuclear Magnetic Resonance
5. Quantum dots, expt at MSU
6. Point Defects in semiconductors, experiments at UiO, center for Materials Science
7. more

Overview and Motivation

How to use many-body theory to design quantum circuits (Quantum engineering)

1. Many-body methods like F(ull)C(onfiguration)I(nteraction) theory with
 - ▶ Adaptive basis sets (see for example [Sigmundson et al arXiv:2111.09638](#))
 - ▶ Time dependence
 - ▶ Optimization of experimental parameters
 - ▶ Feedback from experiment
2. Finding optimal parameters for tuning of entanglement
3. Numerical experiments to mimick real systems, using many-body methods to develop **quantum twins** ([inspiration from work by Herschel Rabitz et al on Control of quantum phenomena, see New Journal of Physics 12 \(2010\) 075008](#))!

Recent work

We have developed theoretical tools for generating motional entanglement between two (and more) electrons trapped above the surface of superfluid helium. In this proposed scheme these electronic charge qubits are laterally confined via electrostatic gates to create an anharmonic trapping potential. When the system is cooled to sufficiently low temperature these in-plane charge qubit states are quantized and circuit quantum electrodynamic methods can be used to control and readout single qubit operations. We work now on Perspectives for quantum simulations with quantum dots systems.

Electrons (quantum dots) on superfluid helium

Electrons on **superfluid helium** represent a promising platform for investigating strongly-coupled qubits.

Therefore a systematic investigation of the controlled generation of entanglement between two trapped electrons under the influence of coherent microwave driving pulses, taking into account the effects of the Coulomb interaction between electrons, is of significant importance for quantum information processing using trapped electrons.

1. Time-Dependent full configuration interaction theory
2. Time-dependent Coupled-Cluster theory
3. Designing quantum circuits

Where we are now

1. Adding time-dependent studies of two electrons in two wells in one and two dimensions
2. Studies of the time-evolution of entangled states (now two electrons only)
3. Use theory to find optimal experimental setup
4. Expect two-electron system realized experimentally in approx 1 year, great potential for studies of quantum simulations

Plans

1. Add two and three-dimensions in order to simulate in a more realistic way such many-body systems.
2. Develop time-dependent FCI code, useful up to approximately 10 particles with **effective** (and effective Hilbert space) Hamiltonians in two and three dimensions
3. Develop codes for studies of entanglement as function of time
4. Do tomography and extract density matrices and compare with experiment.
5. Study the feasibility of various setups for quantum simulations of specific Hamiltonians such as the Lipkin model
6. For larger many-body systems, study for example time-dependent CC theory

Courses, theory path

1. FYS4150 Computational Physics I, Fall semester, 10 ECTS
2. FYS-STK4155 Applied Data Analysis and Machine Learning, 10 ECTS
3. FYS4110 Modern Quantum Mechanics, Fall semester, 10 ECTS
4. FYS4480 Many-body Physics, Fall semester, 10 ECTS
5. FYS5419 Quantum Computing and Quantum Machine Learning, Spring semester, 10 ECTS
6. FYS5429 Advanced Machine Learning for the Physical Sciences, Spring Semester, 10 ECTS
7. FYS4411 Computational Physics II, Quantum Mechanics, Spring semester, 10 ECTS
8. MAT3420 Quantum Computing, Spring semester, 10 ECTS
9. MAT4430 Quantum Information Theory, Spring semester, 10 ECTS