

FYS4411 - Computational Physics II

Project 2

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- Github repository containing programs and results:
<https://github.com/evenmn/FYS4411/tree/master/Project%202>

Abstract

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1 Introduction

2 Theory

2.1 Presentation of potential

In this project, we simulate a system of P electrons trapped in a harmonic oscillator potential, with a Hamiltonian given by

$$\hat{H} = \sum_{i=1}^P \left(-\frac{1}{2} \nabla_i^2 + \frac{1}{2} \omega^2 r_i^2 \right) + \sum_{i < j} \frac{1}{r_{ij}} \quad (1)$$

where ω is the harmonic oscillator potential and $r_i = \sqrt{x_i^2 + y_i^2}$ is the position of electron i . The term $\frac{1}{r_{ij}}$ is the interacting term, where $r_{ij} = |r_i - r_j|$ is the distance between a given pair of interacting electrons. Natural units have been used, such that $\hbar = c = m_e = e = 1$.

2.2 Solving with machine learning

Usually, when solving a system of particles as the one described in the previous system, we would need an ansatz for the wave function, where we use our physical intuition to create the form of a wave function with different variational parameters, and then let it be up to the computer to find the optimal parameters through a minimization method. However, this method is only as good as the physical intuition; if the form of the wave function is unrealistic, the results will be the same, and there is no guarantee that we have actually found a ground state energy.

This challenge can be solved by using machine learning.

2.2.1 Restricted Boltzmann Machines

2.3 Energy calculation

2.4 Onebody density

2.5 Scaling

2.6 Error estimation

3 Method

3.1 Variational Monte Carlo

3.2 Metropolis Algorithm

3.2.1 Brute force

3.2.2 Importance sampling

3.2.3 Gibbs sampling

3.3 Minimalization method

3.3.1 Gradient decent

4 Code

4.1 Structure

4.2 Implementation

5 Results

6 Discussion

7 Conclusion

8 Appendix A

9 References

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