Studies of Quantum Dots using Machine Learning



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Outline

- Motivation
- Quantum Theory
- ▶ Machine Learning
- Methods
- ▶ Results
- ► Conclusion
- ► (Code)





Motivation





Why quantum dots?

- ► Technology¹
- ► Theoretically
- ► Experimentally (2D)





Why is it challenging?

- Quantum many-body problem
- ► Fermi-Dirac statistics





How to overcome the challenges?

- ▶ Efforts..
- ▶ gh
- ▶ Our approach: Machine Learning^{2,3}





Quantum Theory





The Time-independent Schrödinger Equation

A stationary quantum mechanical system is described by

$$E_n = \frac{\int d\mathbf{R} \Psi_n^*(\mathbf{R}) \hat{\mathcal{H}} \Psi_n(\mathbf{R})}{\int d\mathbf{R} \Psi_n^*(\mathbf{R}) \Psi_n(\mathbf{R})}$$

which gives the energy of state n.





Machine Learning Theory





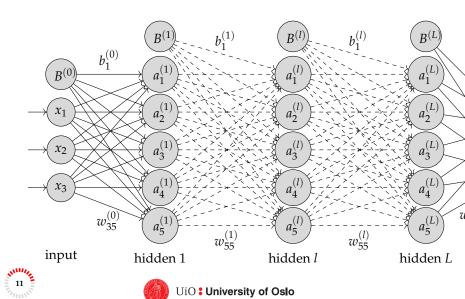
Machine Learning

Machine learning is the science of getting computers to act without being explicitly programmed.

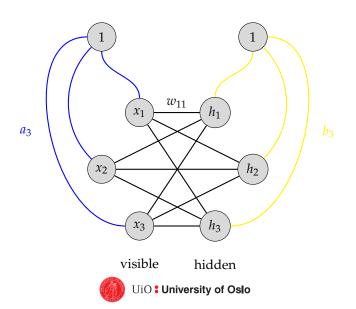




Feed-forward Neural Network



Restricted Boltzmann machines







Methods





Variational Monte Carlo (VMC)

Exploit the variational principle in order to obtain the ground state energy

$$E_{0} < E_{\text{VMC}} = \frac{\int d\mathbf{R} \Psi_{T}(\mathbf{R})^{*} \hat{\mathcal{H}} \Psi_{T}(\mathbf{R})}{\int d\mathbf{R} \Psi_{T}(\mathbf{R})^{*} \Psi_{T}(\mathbf{R})}$$

$$= \int d\mathbf{R} \underbrace{\frac{\Psi_{T}(\mathbf{R})^{*} \Psi_{T}(\mathbf{R})}{\int d\mathbf{R} \Psi_{T}(\mathbf{R})^{*} \Psi_{T}(\mathbf{R})}}_{P(\mathbf{R})} \cdot \underbrace{\frac{1}{\Psi_{T}(\mathbf{R})} \hat{\mathcal{H}} \Psi_{T}(\mathbf{R})}_{E_{L}(\mathbf{R})}$$





Monte Carlo Integration

We attempt to solve the integral by sampling from the probability density function P(r)

$$E_{VMC} = \int d\mathbf{R} E_L(\mathbf{R}) P(\mathbf{R})$$
$$\approx \frac{1}{M} \sum_{i=1}^{M} E_L(\mathbf{R}_i)$$





Trial Wave Function

$$P(\mathbf{R}) \propto \Psi_T(\mathbf{R})^* \Psi_T(\mathbf{R})$$

Use the Slater-Jastrow function as our trial wave function

$$\Psi_T(\mathbf{R}) = |\hat{D}(\mathbf{R})|J(\mathbf{R})$$

where the Slater matrix, $\hat{D}(\mathbf{R})$, contains all the single-particle functions

$$\hat{D}(\mathbf{R}) = \begin{pmatrix} \phi_1(\mathbf{r}_1) & \phi_2(\mathbf{r}_1) & \dots & \phi_N(\mathbf{r}_1) \\ \phi_1(\mathbf{r}_2) & \phi_2(\mathbf{r}_2) & \dots & \phi_N(\mathbf{r}_2) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_1(\mathbf{r}_N) & \phi_2(\mathbf{r}_N) & \dots & \phi_N(\mathbf{r}_N) \end{pmatrix}$$





Single-particle Functions

The Hermite functions,

$$\phi_n(\mathbf{r}) \propto H_n(\mathbf{r}) \exp\left(-\frac{1}{2}\alpha\omega|\mathbf{r}|^2\right),$$

are used as the single-particle functions for quantum dots in standard VMC. The Gaussian can be factorized out from the Slater determinant.

$$|\hat{D}(\boldsymbol{R};\alpha)| \propto \exp\left(-\frac{1}{2}\alpha\omega|\boldsymbol{R}|^2\right) \begin{vmatrix} H_1(\boldsymbol{r}_1) & H_2(\boldsymbol{r}_1) & \dots & H_N(\boldsymbol{r}_1) \\ H_1(\boldsymbol{r}_2) & H_2(\boldsymbol{r}_2) & \dots & H_N(\boldsymbol{r}_2) \\ \vdots & \vdots & \ddots & \vdots \\ H_1(\boldsymbol{r}_N) & H_2(\boldsymbol{r}_N) & \dots & H_N(\boldsymbol{r}_N) \end{vmatrix}$$





Restricted Boltzmann Machine

We use the marginal distribution of the visible units as the single-particle functions in the Slater determinant, and see if them can model the correlations

$$\phi_n(\mathbf{r}) \propto H_n(\mathbf{r}) P(\mathbf{r}; \mathbf{a}, \mathbf{b}, \mathbf{W})$$

where P(r) is the marginal distribution of the visible units.

$$|\hat{D}(\mathbf{r}; \mathbf{a}, \mathbf{b}, \mathbf{W})| \propto P(\mathbf{r}; \mathbf{a}, \mathbf{b}, \mathbf{W}) \begin{vmatrix} H_1(\mathbf{r}_1) & H_2(\mathbf{r}_1) & \dots & H_N(\mathbf{r}_1) \\ H_1(\mathbf{r}_2) & H_2(\mathbf{r}_2) & \dots & H_N(\mathbf{r}_2) \\ \vdots & \vdots & \ddots & \vdots \\ H_1(\mathbf{r}_N) & H_2(\mathbf{r}_N) & \dots & H_N(\mathbf{r}_N) \end{vmatrix}$$





Jastrow Factor

The Jastrow factor is added to account for the correlations Simple Jastrow factor

$$J(r; \boldsymbol{\beta}) = \exp\left(\sum_{i=1}^{N} \sum_{j>i}^{N} \beta_{ij} r_{ij}\right).$$

Padé-Jastrow factor

$$J(r;\beta) = \exp\bigg(\sum_{i=1}^{N} \sum_{j>i}^{N} \frac{a_{ij}r_{ij}}{1 + \beta r_{ij}}\bigg).$$





Results





Ground State Energy

Table: Ground state energy of two-dimensional quantum dot with N=2 electrons and frequency $\omega=1.0$.

ω	RBM	RBM+SJ	RBM+PJ	HF^{\dagger}	Exact ^{††}
1/6	0.7036(1)	0.67684(7)	0.66715(6)	0.768675	2/3
1	3.0803(2)	3.02108(5)	2.999587(5)	3.1690	3





One-body density

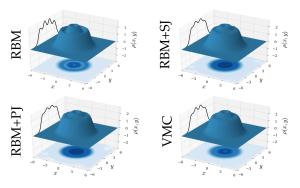
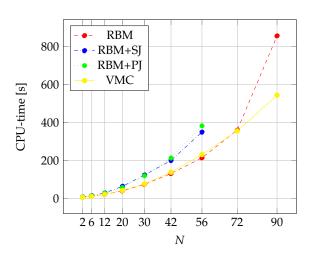


Figure: Plots of the one-body density profiles, $\rho(x,y)$, for two-dimensional quantum dots with N=20 electrons and frequency $\omega=1.0$.





Computational Cost









Conclusion





Conclusions

- ▶ RBM is able to account for most of the correlations
- ► RBM+PJ implies to give a lower ground state energy and model the correlations better than a traditional VMC
- ▶ RBM+SJ is both more expensive and less accurate than its fellow methods, and we see no reason to choose it





Future Work

- ▶ Repeat the exercise using spherical coordinates interactions are easier to model in spherical coordinates
- Check the ability of modeling the three-body correlations, considering nuclear systems
- ► Reduce the computational cost





Thank you!





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