

# Fys4110: Project 2

Knut Halvor Helland

24. mai 2017

Sammendrag

...

## 1 Introduction

In this project I continue the study of many interacting particles in an isotropic two dimensional harmonic oscillator. In project 1 [1] I used Hartree-Fock methods to construct the Slater determinant of linear combinations of single particle non-interacting states that minimized the energy. In this project I would like to improve this estimate of the ground state by adding a Jastrow factor. Then the energy cannot be found with Hartree-Fock methods, but rather from direct integration of the Hamiltonian. I will do this using the Metropolis algorithm to pick out integration points. I will add a Jastrow factor with a free parameter, minimize the energy with respect to this parameter, and then calculate the energy of this new approximation of the ground state. In addition I will study the 2 particle case with a singly parametrized symmetric wavefunction instead of the Slater determinant.

## 2 Physical Problem

The full Hamiltonian of the problem with  $N$  particles and using atomic units is

$$H = \sum_i^N -\frac{1}{2}\nabla_i^2 + \frac{1}{2}\omega^2 r_i^2 + \sum_{i<j}^N \frac{1}{r_{ij}}, \quad (1)$$

where  $r_{ij} = |\mathbf{r}_i - \mathbf{r}_j|$ .

## 3 Trial wave functions

### 3.1 2 Particle Case

For the two particle case I will approximate the ground state with the parametrized trial wavefunction

$$\psi_T = A \exp \left( -\alpha \omega (r_1^2 + r_2^2) - \frac{r_{12}}{1 + \beta r_{12}} \right), \quad (2)$$

with  $\alpha$  and  $\beta$  as free parameters.

### 3.2 Slater case

For the many particle case we will use the non-interacting ground state Slater determinant multiplied with a Jastrow factor with one free parameter. We could use Slater determinants from linear combinations of different non-interacting single particle states as found in [1] by Hartree-Fock methods,

however this turned out to be too complicated. Instead we will compare the Hartree-Fock approach to adding a Jastrow factor to the ground state.

$$\psi_T = \text{ADet}(\psi_1 \dots \psi_N; \mathbf{r}_1 \dots \mathbf{r}_N) \prod_{i < j}^N \exp\left(-\frac{a_{ij} r_{ij}}{1 + \beta r_{ij}}\right), \quad (3)$$

where  $\psi_i$  is the non-interacting single particle state with the  $i$ th lowest energy, and  $a_{ij}$  is 1 when the particles have anti-parallel spins and  $1/3$  when parallel. Since we are talking about spin  $1/2$  electrons there are two spin configurations for each spatial configuration for the single particle states that go into the Slater determinant. However the hamiltonian is independent of spin. We can exploit this to simplify the wavefunction we use. If we let the  $N/2$  first particles be in one spin state and the next  $N/2$  in the other we may use a product of Slater determinants with only the particles in the same spin state in each:

$$\psi_T = \text{ADet}(\psi_{1\downarrow} \dots \psi_{N/2\downarrow}; \mathbf{r}_1 \dots \mathbf{r}_{N/2}) \text{Det}(\psi_{1\uparrow} \dots \psi_{N/2\uparrow}; \mathbf{r}_{N/2+1} \dots \mathbf{r}_N) \prod_{i < j}^N \exp\left(-\frac{a_{ij} r_{ij}}{1 + \beta r_{ij}}\right). \quad (4)$$

In the 2 particle case this reduces to equation 2 with  $\alpha = 1$ .

## 4 Monte-Carlo Integration

In this project I will estimate the energy of the trial wavefunctions with Monte-Carlo (MC) integration. MC integration is a method of estimating the value of integrals on the form

$$\langle F \rangle = \int F(x_1, \dots, x_N) p(x_1, \dots, x_N) \prod_{k=1}^N dx_k, \quad (5)$$

where  $p(x_1, \dots, x_N)$  is a probability density function. MC integration is then based on drawing points  $\mathbf{r}_i$  according to  $p$  and evaluating  $F$  in these points

$$F_i \equiv F(\mathbf{r}_i). \quad (6)$$

Then defining

$$\bar{F} \equiv \frac{1}{N} \sum_{i=1}^N F_i \quad (7)$$

we have that

$$\langle F \rangle = \lim_{N \rightarrow \infty} \bar{F}. \quad (8)$$

Since we cannot draw infinite points we use  $\bar{F}$  as an estimate of  $\langle F \rangle$ .

In order to estimate an integral in this way we thus need a method to draw positions according to  $p$ , a way to compute  $F_i$  and a way to estimate the error in the integration.

### 4.1 The Metropolis Algorithm

The Metropolis algorithm is an algorithm for computing expectation values for functions of many variables efficiently. It is based on semi-randomly walking through the integration space and finding the value of the function at each point. Let  $F(x_1, \dots, x_N)$  be the function we wish to find the expectation value of. Then

$$\langle F \rangle = \frac{\int F(x_1, \dots, x_N) p(x_1, \dots, x_N) \prod_{k=1}^N dx_k}{\int p(x_1, \dots, x_N) \prod_{k=1}^N dx_k}, \quad (9)$$

where  $p(x_1, \dots, x_N)$  is the (generally) non-normalized probability density function. In our case  $p$  is  $|\psi|^2$ . One advantage with this method is that it does not require explicit normalization of the probability density.

#### 4.1.1 Detailed Balance

The Metropolis algorithm may be derived by demanding that the Markov chain exhibits detailed balance. The criterion for detailed balance is

$$P(a)P(b|a) = P(b)P(a|b), \quad (10)$$

or rewritten

$$\frac{P(a)}{P(b)} = \frac{P(a|b)}{P(b|a)}. \quad (11)$$

We may split  $P(a|b) = G(a|b)A(a|b)$ , where  $G(a|b)$  is the probability of proposing a move from  $b$  to  $a$ , while  $A(a|b)$  is the probability of accepting a proposed move from  $b$  to  $a$ . The detailed balance requirement may be rewritten as

$$\frac{A(a|b)}{A(b|a)} = \frac{P(a)G(b|a)}{P(b)G(a|b)}. \quad (12)$$

Now we choose an acceptance ratio that satisfies this requirement. The Metropolis choice is to use

$$A(a|b) = \min \left( 1, \frac{P(a)G(b|a)}{P(b)G(a|b)} \right). \quad (13)$$

So the Metropolis algorithm for drawing points from a probability distribution is

1. Draw a proposed move from the proposal distribution.
2. Evaluate the acceptance ratio  $a$  from equation 13.
3. Draw a random number  $0 \leq r < 1$  from a uniform distribution.
4. If  $a > r$  accept the move. Else reject the move.
5. Save position
6. return to point 1.

#### 4.1.2 Symmetric Proposal Density

If the proposal probability  $G(a|b) = G(b|a)$  the proposal distribution is called symmetric and drops out of the acceptance ratio. Thus there is less to calculate for each loop in the algorithm. However symmetric proposal densities lead to many proposed steps being rejected, and thus to higher correlations between the points.

#### 4.1.3 Importance Sampling

If we instead choose a non-symmetric proposal distribution we may choose one to maximise the acceptance rate. If we choose a proposal distribution so that the probability of proposing a move into an area with a higher probability is higher than the probability of proposing a move into an area with a lower probability. In other words if  $P(a) > P(b)$  then  $G(a|b) > G(b|a)$ .

### 4.2 Local Energy

In quantum mechanics the probability distribution is given by  $|\psi|^2$  and the expectation value for an operator  $O$  is given by

$$\langle O \rangle = \frac{\int \psi^* O \psi \prod_i dx_i}{\int |\psi|^2 \prod_i dx_i}, \quad (14)$$

This is not exactly on the form of equation 9, but it can be rewritten in terms of local variables given by

$$O_L = \frac{1}{\psi} O \psi, \quad (15)$$

so that the expectation value is

$$\langle O \rangle = \frac{\int |\psi|^2 O_L \prod_i dx_i}{\int |\psi|^2 \prod_i dx_i}. \quad (16)$$

So the expectation value of the energy is given by

$$\langle E \rangle = \frac{\int |\psi|^2 E_L \prod_i dx_i}{\int |\psi|^2 \prod_i dx_i}, \quad (17)$$

with

$$E_L = \frac{1}{\psi} H \psi, \quad (18)$$

#### 4.2.1 2 Particle Case

In the two particle case with hamiltonean given by equation 1 and trial wavefunction by equation 2 the local energy is given by

$$E_L(\mathbf{r}_1, \mathbf{r}_2) = \left[ \frac{1}{2} (1 - \alpha) \omega (r_1^2 + r_2^2) + 2\alpha\omega \right] - \frac{a}{(1 + \beta r_{12})^2} \left[ \frac{a}{(1 + \beta r_{12})^2} + \frac{1}{r_{12}} - \frac{2\beta}{(1 + \beta r_{12})} - \alpha\omega r_{12} \right] + \frac{1}{r_{12}}, \quad (19)$$

as shown in appendix B.2.

#### 4.2.2 Slater Case

In the  $N$  particle case with hamiltonean given by equation 1 and trial wavefunction by equation 4 the local energy is given by

### 4.3 Error Estimation and Blocking

In this section I follow [2] and [4] in explaining the blocking method. Let  $\{F_i\}$  be a finite set of consecutive measurements of the quantity  $F$  on a system in equilibrium, in other words the probability distribution for the measurements is independent of time. Then as above the average of  $\{F_i\}$   $\bar{F}$  is an estimate of the true average of  $F$   $\langle F \rangle$ . An estimate of the error in this approximation is given by the standard deviation of  $\bar{F}$   $\sigma_{\bar{F}}$ . The variance in  $\bar{F}$  is given by

$$\sigma_{\bar{F}}^2 = \langle \bar{F}^2 \rangle - \langle \bar{F} \rangle^2, \quad (20)$$

expanding this we find

$$\begin{aligned} \sigma_{\bar{F}}^2 &= \left\langle \left( \frac{1}{N} \sum_{i=1}^N F_i \right)^2 \right\rangle - \left\langle \frac{1}{N} \sum_{i=1}^N F_i \right\rangle^2 \\ &= \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N (\langle F_i F_j \rangle - \langle F_i \rangle \langle F_j \rangle) \\ &= \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N \text{cov}(F_i, F_j). \end{aligned}$$

The time independence of the pdf means that the covariance should only depend on the relative distance between  $i$  and  $j$   $t \equiv |i - j|$ . So we can define  $C(t) = \text{cov}(F_i, F_j)$ . Now we can split  $\sigma_{\bar{F}}^2$  into

$$\sigma_{\bar{F}}^2 = \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N C(t(i, j)) = \frac{1}{N} \left[ C(0) + 2 \sum_{t=0}^{N-1} \left( 1 - \frac{t}{N} \right) C(t) \right] \quad (21)$$

Now the problem is that we don't know the true covariance, but we can estimate it with the sample covariance so that for example

$$C(0) = \sigma_F^2 \approx \bar{F}^2 - \bar{F}^2. \quad (22)$$

For uncorrelated data  $C(t > 0) = 0$  so the error is  $\sigma_F/\sqrt{N}$ , which is easy to estimate. With correlations things are more complicated, however the blocking method allows us to incorporate correlations into a similar calculation. If we transform the data set  $\{F_i\}$  into another set  $\{\tilde{F}_i\}$ , where

$$\tilde{F}_i = \frac{1}{B} \sum_{j=1}^B F_{(i-1)B+j}, \quad (23)$$

where  $B$  is a whole number called the block size. Call  $\tilde{F}_i$  a block. Now it is easy to estimate the block variance  $\tilde{C}(0) = \sigma_{\tilde{F}}^2$  by  $\overline{\tilde{F}^2} - \bar{\tilde{F}}^2$ , but expanding it we see that

$$\begin{aligned} \tilde{C}(0) &= \langle \tilde{F}_i^2 \rangle - \langle \tilde{F}_i \rangle^2 \\ &= \frac{1}{B^2} \sum_{a,b}^B \langle \tilde{F}_{i+a} \tilde{F}_{i+b} \rangle - \langle \tilde{F}_{i+a} \rangle \langle \tilde{F}_{i+b} \rangle \\ &= \frac{1}{B^2} \sum_{a,b}^B C(|a-b|) \\ &= \frac{1}{B} \sum_{t=0}^{B-1} C(t), \end{aligned}$$

and so

$$\frac{\tilde{C}(0)}{N/B} = \frac{1}{N} \left[ C(0) + \sum_{t=1}^{B-1} C(t) \right], \quad (24)$$

comparing with equation 21 we see that blocking has incorporated part of the error from correlations into  $\tilde{C}(0)$ , which is just as easy to estimate as  $C(0)$ . So, for an appropriate block size an improved estimate of the error is approximated by

$$\sigma_{\tilde{F}}^2 \approx \frac{B}{N} \left( \overline{\tilde{F}^2} - \bar{\tilde{F}}^2 \right). \quad (25)$$

To find the appropriate block size we may plot this estimate as a function of block size, and choose a value where this seems to flatten.

## 5 Implementation

### 5.1 Structure

### 5.2 Paralellization

## 6 Cost

## 7 Accuracy

### 7.1 Blocking

## 8 Benchmarks

### 8.1 2 Particle Case

A first test of the code is to check that when the interaction and jastrow factor are turned off and  $\alpha = 1$  the energy is 2 with variance 0.

## 9 Results

## 10 Discussion

## 11 Conclusion

### A A Note About Cofactors and Determinants

Determinants can be somewhat hard to work with, following [4] we may use cofactors to do some trickery. For a matrix  $A$  with elements  $A_{ij}$  the cofactors  $C_{ij}$  are given by  $(-1)^{i+j}M_{ij}$ , with  $M_{ij}$  being the determinant of the matrix formed by deliting the  $i$ th row and  $j$ th collumn from  $A$ . There two properties of cofactors that will be important here are

$$|A|\mathbf{1} = AC^T \Leftrightarrow |A| = \sum_j A_{ij}C_{ij}, \quad (26)$$

and thus

$$A^{-1} = \frac{1}{|A|}C^T \Leftrightarrow A_{ij}^{-1} = \frac{1}{|A|}C_{ji}, \quad (27)$$

and the fact that  $C_{ij}$  is independent of row  $i$  and collumn  $j$  of  $A$ .

### B Derivatives of the 2 particle trial wavefunction

In the course of the project we needed analytical expressions for different derivatives of the 2 particle trial wavefunction 2. I have collected the differentiations here.

#### B.1 Gradient

In order to compute the driftforce for importance sampling we needed

$$\frac{1}{\psi_T} \frac{\partial \psi_T}{\partial z},$$

where  $z_i = x_1, x_2, y_1, y_2$ . As  $\psi_T$  is an exponential

$$\begin{aligned} \frac{1}{\psi_T} \frac{\partial \psi_T}{\partial z_i} &= \frac{\partial}{\partial z_i} \left( -\frac{1}{2}\alpha\omega(r_1^2 + r_2^2) + \frac{ar_{12}}{1 + \beta r_{12}} \right) \\ &= -\alpha\omega z_i + a \left( \frac{1}{1 + \beta r_{12}} - \frac{r_{12}\beta}{(1 + \beta r_{12})^2} \right) \frac{\partial r_{12}}{\partial z_i} \\ &= -\alpha\omega z_i + \frac{a}{(1 + \beta r_{12})^2} \frac{\partial r_{12}}{\partial z_i} \\ &= -\alpha\omega z_i + \frac{a}{(1 + \beta r_{12})^2} \frac{(z_i - z_j)}{r_{12}}, \end{aligned}$$

where  $z_j$  is the coordinate of the other particle along the same dimension as  $z_i$ , so for example when  $z_i = x_2, z_j = x_1$ .

#### B.2 Laplacian

The local energy is defined as

$$E_L(\mathbf{r}_1, \mathbf{r}_2) = \frac{1}{\psi_T} H \psi_T.$$

In our case the Hamiltonian is

$$H = \sum_{i=1}^2 -\frac{1}{2}\nabla_i^2 + \frac{1}{2}\omega^2 r_i^2 + \frac{1}{r_{12}}.$$

The laplacian is

$$\sum_i \nabla^2 = \sum_i \frac{\partial^2}{\partial z_i^2},$$

where  $z_i$  is the same as above.

Again since  $\psi_T$  is an exponential we have

$$\begin{aligned} \frac{1}{\psi_T} \frac{\partial^2 \psi_T}{\partial z_i^2} &= \frac{\partial^2}{\partial z_i^2} \left( -\alpha\omega(r_1^2 + r_2^2)/2 + \frac{ar_{12}}{1 + \beta r_{12}} \right) + \left( \frac{\partial}{\partial z_i} \left( -\alpha\omega(r_1^2 + r_2^2)/2 + \frac{ar_{12}}{1 + \beta r_{12}} \right) \right)^2 \\ &= \frac{\partial}{\partial z_i} \left( -\alpha\omega z_i + \frac{a}{(1 + \beta r_{12})^2} \frac{(z_i - z_j)}{r_{12}} \right) + \left( -\alpha\omega z_i + \frac{a}{(1 + \beta r_{12})^2} \frac{(z_i - z_j)}{r_{12}} \right)^2 \\ &= -\alpha\omega + \frac{a}{(1 + \beta r_{12})^2 r_{12}} - \frac{2a\beta(z_i - z_j)^2}{(1 + \beta r_{12})^3 r_{12}^2} - \frac{a(z_i - z_j)^2}{(1 + \beta r_{12})^2 r_{12}^3} + \alpha^2 \omega^2 z_i^2 - \frac{2\alpha\omega a z_i (z_i - z_j)}{(1 + \beta r_{12})^2 r_{12}} + \frac{a^2 (z_i - z_j)^2}{(1 + \beta r_{12})^4 r_{12}^2}. \end{aligned}$$

So, because the  $\psi_T$  is symmetric under  $1 \leftrightarrow 2$  and  $x \leftrightarrow y$ :

$$\frac{1}{\psi_T} \sum_i \nabla_i^2 \psi_T = \alpha\omega(r_1^2 + r_2^2) - 4\alpha\omega + \frac{2a^2}{(1 + \beta r_{12})^4} + \frac{4a}{(1 + \beta r_{12})^2 r_{12}} - \frac{4a\beta}{(1 + \beta r_{12})^3} - \frac{2a}{(1 + \beta r_{12})^2 r_{12}} - \frac{2\alpha\omega a r_{12}}{(1 + \beta r_{12})^2}$$

and finally:

$$\frac{1}{\psi_T} \sum_i \nabla_i^2 \psi_T = \alpha\omega(r_1^2 + r_2^2) - 4\alpha\omega + \frac{2a}{(1 + \beta r_{12})^2} \left[ \frac{a}{(1 + \beta r_{12})^2} + \frac{1}{r_{12}} - \frac{2\beta}{(1 + \beta r_{12})} - \alpha\omega r_{12} \right]$$

Using this expression we have the local energy as

$$E_L(r_1, r_2) = \left[ \frac{1}{2}(1 - \alpha)\omega(r_1^2 + r_2^2) + 2\alpha\omega \right] - \frac{a}{(1 + \beta r_{12})^2} \left[ \frac{a}{(1 + \beta r_{12})^2} + \frac{1}{r_{12}} - \frac{2\beta}{(1 + \beta r_{12})} - \alpha\omega r_{12} \right] + \frac{1}{r_{12}},$$

where the second term contains the terms from the Jastrow-factor and the cross term and the third is the interaction term.

### B.3 Derivatives w.r.t $\alpha$ and $\beta$

In order to find the optimal parameters  $\alpha$  and  $\beta$  we needed the derivatives of  $\psi_T$  with respect to these.

$$\frac{1}{\psi_T} \frac{\partial \psi_T}{\partial \alpha} = -\frac{1}{2}\omega(r_1^2 + r_2^2).$$

$$\frac{1}{\psi_T} \frac{\partial \psi_T}{\partial \beta} = -\frac{ar_{12}^2}{(1 + \beta r_{12})^2}.$$

## C Derivatives of the N particle trial wavefunction

In the course of the project we needed analytical expressions for different derivatives of the N particle trial wavefunction 4. I have collected the differentiations here.

## C.1 Gradient

We note that for any coordinate  $z_i$  only one of the determinants depends on it. So

$$\frac{1}{\psi_T} \frac{\partial \psi_T}{\partial z_i} = \frac{1}{|s|} \frac{\partial |s|}{\partial z_i} + \frac{1}{J} \frac{\partial J}{\partial z_i}.$$

For the derivative of the determinant we exploit the properties noted in section A to see that

$$\frac{1}{|s|} \frac{\partial |s|}{\partial z_i} = \frac{1}{|s|} \sum_j \frac{\partial s_{ij}}{\partial z_i} C_{ij},$$

since  $C_{ij}$  is independent of  $z_i$ . Rewriting  $C_{ij} = |s| s_{ji}^{-1}$  we find

$$\frac{1}{|s|} \frac{\partial |s|}{\partial z_i} = \sum_j \frac{\partial s_{ij}}{\partial z_i} s_{ji}^{-1}.$$

From section B.1 it is clear that

$$\frac{1}{J} \frac{\partial J}{\partial z_i} = \sum_{j \neq i} \frac{a_{ij}}{(1 + \beta r_{ij})^2} \frac{(z_i - z_j)}{r_{ij}},$$

so

$$\frac{1}{\psi_T} \frac{\partial \psi_T}{\partial z_i} = \sum_j \frac{\partial s_{ij}}{\partial z_i} s_{ji}^{-1} + \sum_{j \neq i} \frac{a_{ij}}{(1 + \beta r_{ij})^2} \frac{(z_i - z_j)}{r_{ij}}.$$

## C.2 Laplacian

Writing  $\psi_T = \psi_S J$  we can write the Laplacian as

$$\frac{\nabla^2 \psi_T}{\psi_T} = \frac{\nabla^2 \psi_S}{\psi_S} + \frac{\nabla^2 J}{J} + 2 \frac{\nabla \psi_S}{\psi_S} \cdot \frac{\nabla J}{J},$$

expanding the Slater part  $\psi_S = |S|_{\downarrow} |S|_{\uparrow}$  we find

$$\frac{\nabla^2 \psi_T}{\psi_T} = \frac{\nabla^2 |S|_{\downarrow}}{|S|_{\downarrow}} + \frac{\nabla^2 |S|_{\uparrow}}{|S|_{\uparrow}} + \frac{\nabla^2 J}{J} + 2 \left( \frac{\nabla |S|_{\downarrow}}{|S|_{\downarrow}} + \frac{\nabla |S|_{\uparrow}}{|S|_{\uparrow}} \right) \cdot \frac{\nabla J}{J},$$

noting that there is no cross-term between the determinants as they depend on different coordinates. By the same arguments as above we find

$$\frac{1}{|S|} \frac{\partial^2 |S|}{\partial z_i^2} = \sum_j \frac{\partial^2 s_{ij}}{\partial z_i^2} s_{ji}^{-1},$$



which means that

$$\begin{aligned}
\frac{\nabla^2 \psi_s}{\psi_s} &= \sum_{ij} (\nabla^2 s_{ij}^\downarrow) s_{ji}^{\downarrow,-1} + (\nabla^2 s_{ij}^\uparrow) s_{ji}^{\uparrow,-1} \\
&= \sum_{ij}^{N/2} (\nabla^2 \psi_{\downarrow,j}(\mathbf{r}_i)) s_{ji}^{\downarrow,-1} + (\nabla^2 \psi_{\uparrow,j}(\mathbf{r}_i)) s_{ji}^{\uparrow,-1} \\
&= \sum_{ij}^{N/2} (\omega^2 r_i^2 - 2\epsilon_j) \psi_j(\mathbf{r}_i) s_{ji}^{\downarrow,-1} + (\omega^2 r_{i+N/2}^2 - 2\epsilon_j) \psi_j(\mathbf{r}_{i+N/2}) s_{ji}^{\uparrow,-1} \\
&= \sum_{ij}^{N/2} (\omega^2 r_i^2 - 2\epsilon_j) s_{ij}^\downarrow s_{ji}^{\downarrow,-1} + (\omega^2 r_{i+N/2}^2 - 2\epsilon_j) s_{ij}^\uparrow s_{ji}^{\uparrow,-1} \\
&= \sum_{ij}^{N/2} (\omega^2 r_i^2 - 2\epsilon_j) \delta_{ij} + (\omega^2 r_{i+N/2}^2 - 2\epsilon_j) \delta_{ij} \\
&= \sum_i^N \omega^2 r_i^2 - 4 \sum_j^{N/2} \epsilon_j.
\end{aligned}$$

For the jastrow part

$$\frac{1}{J} \frac{\partial^2 J}{\partial z_i^2} = \sum_{j \neq i} \frac{\partial^2 f_{ij}}{\partial z_i^2} + \left( \sum_{j \neq i} \frac{\partial f_{ij}}{\partial z_i} \right)^2,$$

with  $f_{ij} = a_{ij} r_{ij} / (1 + \beta r_{ij})$ , so

$$\frac{1}{J} \frac{\partial^2 J}{\partial z_i^2} = \sum_{j \neq i} \frac{a_{ij}}{(1 + \beta r_{ij})^2} \left[ \frac{1}{r_{ij}} \left( 1 - \left( \frac{(z_i - z_j)}{r_{ij}} \right)^2 \right) - \frac{2\beta}{(1 + \beta r_{ij})} \left( \frac{(z_i - z_j)}{r_{ij}} \right)^2 \right] + \left( \sum_{j \neq i} \frac{\partial f_{ij}}{\partial z_i} \right)^2,$$

and

$$\frac{\nabla_i^2 J}{J} = \sum_{j \neq i} \frac{a_{ij}}{(1 + \beta r_{ij})^2} \left[ \frac{1}{r_{ij}} - \frac{2\beta}{(1 + \beta r_{ij})} \right] + \left( \sum_{j \neq i} \frac{\partial f_{ij}}{\partial x_i} \right)^2 + \left( \sum_{j \neq i} \frac{\partial f_{ij}}{\partial y_i} \right)^2,$$

and finally

$$\frac{\nabla^2 J}{J} = 2 \sum_{j < i} \frac{a_{ij}}{(1 + \beta r_{ij})^2} \left[ \frac{1}{r_{ij}} - \frac{2\beta}{(1 + \beta r_{ij})} \right] + \sum_i \left[ \left( \sum_{j \neq i} \frac{\partial f_{ij}}{\partial x_i} \right)^2 + \left( \sum_{j \neq i} \frac{\partial f_{ij}}{\partial y_i} \right)^2 \right],$$

The cross terms become

$$2 \left( \frac{\nabla |S|_\downarrow}{|S|_\downarrow} + \frac{\nabla |S|_\uparrow}{|S|_\uparrow} \right) \cdot \frac{\nabla J}{J} = 2 \sum_i \left( \frac{1}{|s|} \frac{\partial |s|}{\partial x_i} \frac{1}{J} \frac{\partial J}{\partial x_i} + \frac{1}{|s|} \frac{\partial |s|}{\partial y_i} \frac{1}{J} \frac{\partial J}{\partial y_i} \right).$$

### C.3 Derivative w.r.t $\beta$

In order to find the optimal parameters  $\alpha$  and  $\beta$  we needed the derivatives of  $\psi_T$  with respect to these.

$$\frac{1}{\psi_T} \frac{\partial \psi_T}{\partial \beta} = - \frac{ar_{12}^2}{(1 + \beta r_{12})^2}.$$

## Referanser

[1] K. Helland "Fys4411: Project 1" available at <https://github.com/khhelland/Fys4411/blob/master/1/rapport.pdf>

- [2] H. Flyvbjerg and H.G. Petersen "Error estimates on averages of correlated data". The Journal of Chemical Physics 91, 461, 1989
- [3] E. Anisimovas and A. Matulis, "Energy spectra of few-electron quantum dots.", J. Phys.,10:601 615, 1998.
- [4] M. Hjort-Jensen, *Computational Physics: Lecture Notes Fall 2015*, found at <https://github.com/CompPhysics/ComputationalPhysics2/blob/gh-pages/doc/Literature/lectures2015.pdf> on the 31/01/17
- [5] M. Hjort-Jensen, *Computational Physics: Hartree-Fock methods and introduction to Many-body Theory* found at <http://compphysics.github.io/ComputationalPhysics2/doc/pub/basicMB/pdf/basicMB-print.pdf> on the 16/03/17
- [6] Simen Kvaal, *Lecture notes for Fys-Kjm4480: Quantum Mechanics for many-particle systems*, october 2016, not published.