

Local Energy Gradient Derivation

$$\begin{aligned}
\nabla_\alpha \langle E_L \rangle &= \nabla_\alpha \langle H \rangle = \nabla_\alpha \left(\frac{\int d\mathbf{R} \Psi^* \mathcal{H} \Psi}{\int d\mathbf{R} |\Psi|^2} \right) \\
&= \frac{\left(\int d\mathbf{R} |\Psi|^2 \right) \nabla_\alpha \left(\int d\mathbf{R} \Psi^* \mathcal{H} \Psi \right) - \left(\int d\mathbf{R} \Psi^* \mathcal{H} \Psi \right) \nabla_\alpha \left(\int d\mathbf{R} |\Psi|^2 \right)}{\left(\int d\mathbf{R} |\Psi|^2 \right)^2} \\
&= \frac{\int d\mathbf{R} \left[\nabla_\alpha (\Psi^*) \mathcal{H} \Psi + \Psi^* \nabla_\alpha (\mathcal{H} \Psi) \right]}{\int d\mathbf{R} |\Psi|^2} - \frac{\left(\int d\mathbf{R} \Psi^* \mathcal{H} \Psi \right) \int d\mathbf{R} \nabla_\alpha |\Psi|^2}{\left(\int d\mathbf{R} |\Psi|^2 \right)^2} \\
&= \frac{\int d\mathbf{R} |\Psi|^2 \frac{\nabla_\alpha (\Psi^*) \mathcal{H} \Psi + \Psi^* \nabla_\alpha (\mathcal{H} \Psi)}{|\Psi|^2}}{\int d\mathbf{R} |\Psi|^2} - \frac{\int d\mathbf{R} \Psi^* \mathcal{H} \Psi \int d\mathbf{R} |\Psi|^2 \frac{\nabla_\alpha |\Psi|^2}{|\Psi|^2}}{\int d\mathbf{R} |\Psi|^2 \int d\mathbf{R} |\Psi|^2} \\
&= \left\langle \frac{\nabla_\alpha (\Psi^*) \mathcal{H} \Psi + \Psi^* \nabla_\alpha (\mathcal{H} \Psi)}{|\Psi|^2} \right\rangle - \langle H \rangle \left\langle \frac{\nabla_\alpha |\Psi|^2}{|\Psi|^2} \right\rangle \\
&= \left\langle \frac{\nabla_\alpha (\Psi^*) \mathcal{H} \Psi + \nabla_\alpha (\Psi^*) \mathcal{H} \Psi}{|\Psi|^2} \right\rangle - \langle H \rangle \left\langle \frac{2|\Psi| \nabla_\alpha |\Psi|}{|\Psi|^2} \right\rangle \\
&= \left\langle \frac{2\nabla_\alpha \Psi^*}{\Psi^*} E_L \right\rangle - \langle E_L \rangle \left\langle \frac{2\nabla_\alpha |\Psi|}{|\Psi|} \right\rangle = 2 \left[\left\langle \frac{\nabla_\alpha \Psi^*}{\Psi^*} E_L \right\rangle - \langle E_L \rangle \left\langle \frac{\nabla_\alpha |\Psi|}{|\Psi|} \right\rangle \right]
\end{aligned}$$

Depending on the trial function, in particular if the trial function is proportional to an exponential, the following equivalent expression might be easier to compute.

$$\nabla_\alpha \langle E_L \rangle = 2 \left[\left\langle E_L \nabla_\alpha \ln \Psi^* \right\rangle - \langle E_L \rangle \langle \nabla_\alpha \ln |\Psi| \rangle \right]$$

Simple Gaussian trial function:

For $\Psi_T(\mathbf{R}, \alpha) = \prod_i^N g(r_i, \alpha)$ where $g(r_i, \alpha) = \exp(-\alpha r_i^2)$. We have $|\Psi_T| = \Psi_T^* = \Psi_T$ because the function is real and (strictly) positive.

$$\ln \Psi_T = \ln \left[\prod_i^N g(r_i, \alpha) \right] = \sum_i^N \ln[g(r_i, \alpha)] = \sum_i^N \ln[\exp(-\alpha r_i^2)] = -\alpha \sum_i^N r_i^2$$

$$\frac{\partial}{\partial \alpha} \ln \Psi_T = - \sum_i^N r_i^2$$

We thus have

$$\begin{aligned} \frac{\partial}{\partial \alpha} \langle E_L \rangle &= 2 \left[\left\langle - \sum_i^N r_i^2 E_L \right\rangle - \langle E_L \rangle \left\langle - \sum_i^N r_i^2 \right\rangle \right] \\ &= 2 \left[\langle E_L \rangle \left\langle \sum_i^N r_i^2 \right\rangle - \left\langle \sum_i^N r_i^2 E_L \right\rangle \right] \end{aligned}$$

Asshole trial function:

$$\Psi_T(\mathbf{R}, \alpha, \beta) = \prod_i^N g(r_i, \alpha, \beta) \prod_{j < k}^N f(r_{jk}, a) \text{ where } g(r_i, \alpha, \beta) = \exp[-\alpha(x_i^2 + y_i^2 + \beta z_i^2)]$$

$$\text{and } f(r_{jk}, a) = \begin{cases} 0 & r_{jk} \leq a \\ 1 - \frac{a}{r_{jk}} & r_{jk} > a \end{cases}$$

We again have $|\Psi_T| = \Psi_T^* = \Psi_T$ because the function is real and positive.

Using the gradient expression with fractions (as opposed to natural logs) is probably (a lot) more computationally efficient for this trial function.

$$\begin{aligned}
\frac{\partial}{\partial \alpha} \Psi_T &\propto \frac{\partial}{\partial \alpha} \prod_i^N g(\mathbf{r}_i, \alpha, \beta) \\
&= \sum_l^N \left[\frac{\partial}{\partial \alpha} g(\mathbf{r}_l, \alpha, \beta) \right] \prod_{i \neq l}^N g(\mathbf{r}_i, \alpha, \beta) = - \sum_l^N (x_l^2 + y_l^2 + \beta z_l^2) g(\mathbf{r}_l, \alpha, \beta) \prod_{i \neq l}^N g(\mathbf{r}_i, \alpha, \beta) \\
&= - \sum_l^N (x_l^2 + y_l^2 + \beta z_l^2) \prod_i^N g(\mathbf{r}_i, \alpha, \beta) = - \prod_i^N g(\mathbf{r}_i, \alpha, \beta) \sum_l^N (x_l^2 + y_l^2 + \beta z_l^2) \\
\frac{\partial}{\partial \alpha} \Psi_T &= - \prod_i^N g(\mathbf{r}_i, \alpha, \beta) \prod_{j < k}^N f(r_{jk}, a) \sum_l^N (x_l^2 + y_l^2 + \beta z_l^2) = - \Psi_T \sum_l^N (x_l^2 + y_l^2 + \beta z_l^2) \\
\frac{\partial_\alpha \Psi_T}{\Psi_T} &= - \sum_l^N (x_l^2 + y_l^2 + \beta z_l^2)
\end{aligned}$$

Similarly we have

$$\begin{aligned}
\frac{\partial}{\partial \beta} \Psi_T &\propto \sum_l^N \left[\frac{\partial}{\partial \beta} g(\mathbf{r}_l, \alpha, \beta) \right] \prod_{i \neq l}^N g(\mathbf{r}_i, \alpha, \beta) \\
&= - \sum_l^N \alpha z_l^2 g(\mathbf{r}_l, \alpha, \beta) \prod_{i \neq l}^N g(\mathbf{r}_i, \alpha, \beta) = - \prod_i^N g(\mathbf{r}_i, \alpha, \beta) \alpha \sum_l^N z_l^2 \\
\frac{\partial}{\partial \beta} \Psi_T &= - \prod_i^N g(\mathbf{r}_i, \alpha, \beta) \prod_{j < k}^N f(r_{jk}, a) \alpha \sum_l^N z_l^2 = - \Psi_T \alpha \sum_l^N z_l^2
\end{aligned}$$

$$\frac{\partial_{\beta}\Psi_T}{\Psi_T} = -\alpha^N \sum_l^N z_l^2$$

Putting everything together;

$$\frac{\partial}{\partial\alpha}\langle E_L\rangle = 2\left[\left\langle\frac{\partial_{\alpha}\Psi_T}{\Psi_T}E_L\right\rangle - \langle E_L\rangle\left\langle\frac{\partial_{\alpha}\Psi_T}{\Psi_T}\right\rangle\right]$$

$$= 2\left[\left\langle-\sum_l^N\left(x_l^2+y_l^2+\beta z_l^2\right)E_L\right\rangle - \langle E_L\rangle\left\langle-\sum_l^N\left(x_l^2+y_l^2+\beta z_l^2\right)\right\rangle\right]$$

$$= 2\left[\langle E_L\rangle\left\langle\sum_l^N\left(x_l^2+y_l^2+\beta z_l^2\right)\right\rangle - \left\langle E_L\sum_l^N\left(x_l^2+y_l^2+\beta z_l^2\right)\right\rangle\right]$$

$$\frac{\partial}{\partial\beta}\langle E_L\rangle = 2\left[\left\langle\frac{\partial_{\beta}\Psi_T}{\Psi_T}E_L\right\rangle - \langle E_L\rangle\left\langle\frac{\partial_{\beta}\Psi_T}{\Psi_T}\right\rangle\right]$$

$$= 2\left[\left\langle-\alpha^N\sum_l^N z_l^2 E_L\right\rangle - \langle E_L\rangle\left\langle-\alpha^N\sum_l^N z_l^2\right\rangle\right] = 2\alpha^N\left[\langle E_L\rangle\left\langle\sum_l^N z_l^2\right\rangle - \left\langle E_L\sum_l^N z_l^2\right\rangle\right]$$