

QMCPACK Training Program

Argonne National Laboratory

July 15, 2014

Quantum Monte Carlo Methods

Wave-function Optimization

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Outline

- Basics
- Cost Functions
- Optimization Algorithms
 - Algorithms
 - Estimators
- QMCPACK specifics

VMC Review

VMC: Calculate matrix elements with a given wave-function using MC integration

Energy

$$E_V[\Psi_T, \{a_i\}] = \frac{\langle \Psi_T | \hat{H} | \Psi_T \rangle}{\langle \Psi_T | \Psi_T \rangle} = \frac{\int d\vec{r} \Psi_T^* \hat{H} \Psi_T}{\int d\vec{r} \Psi_T^* \Psi_T} = \int d\vec{r} \pi(\vec{r}) E_L(\vec{r})$$

Variance

$$\sigma^2 = \frac{\langle \Psi_T | (\hat{H} - E_V)^2 | \Psi_T \rangle}{\langle \Psi_T | \Psi_T \rangle} = \langle \hat{H}^2 \rangle - E_V^2$$

**VMC
Distribution**

$$\pi(\vec{r}) = \frac{|\Psi_T(\vec{r})|^2}{\int d\vec{r}' |\Psi_T|^2}$$

**Local
Energy**

$$E_L(\vec{r}) = \frac{\langle \vec{r} | \hat{H} | \Psi_T \rangle}{\langle \vec{r} | \Psi_T \rangle}$$

- Variational Principle: Rigorous upper bound to the energy (= only for exact wfn)

$$E_V[\Psi_T] \geq E_{exact}$$

- Zero-Variance Principle: (Only!!!) Exact solution has zero variance

$$E_V \xrightarrow{\sigma^2 \rightarrow 0} E_{exact}$$

Wave-function Optimization

- Wave-function optimization used to be a complicated and time consuming task. Recent developments led to robust and efficient methods, e.g. linear method.
- QMC can use complicated wave-functions!
 - Include terms which depend on inter-electron distances, three-body terms, etc.
 - Very hard in deterministic methods, leads to high-dimensional integrals!
- Typical strategy:
 - Add variational freedom to the trial wave-function.
 - Optimize with VMC.
 - If result is not accurate enough, increase flexibility of your trial wave-function.

Type of variational parameters

Standard wave-function form: $\Psi_T(\vec{r}) = A(\vec{r})e^{J(\vec{r})}$

Anti-symmetric term

- Typically a linear combination of Slater Determinants of single particle orbitals
- Anti-symmetric under particle exchange
- Variational parameters can include:
 - Linear coefficients
 - Parameters in the single particle orbitals
 - Parameters in the basis set
 - gaussian exponents

Multi-Particle Correlation

- Best known as the Jastrow
- Symmetric under particle exchange
 - Does not affect the nodes!
 - In principle, only affects efficiency in DMC! (Very important nonetheless)

$$J(\vec{r}) = \sum_i u^{e-I}(\vec{r}_i) + \sum_{i>j} u^{e-e}(\vec{r}_i, \vec{r}_j) + \dots$$

- Many forms of variational parameters!

More on trial wave-functions tomorrow!

Cost Functions – What to optimize?

- 2 main alternatives: **Energy** and **variance** minimization
 - For a given wave-function form, both conditions can lead to different wave-functions.
 - Parameters that lead to energy minimum do not lead to variance minimum.
 - Energy minimization is typically preferred, but it is more challenging.
 - Variance minimization is usually faster and more stable.
 - Other conditions can be used, e.g. maximize overlap with exact wave-function, minimize mean absolute difference of local energy, etc.
- Most codes (including QMCPACK) can optimize a mixture of energy and variance.

$$Cost = \alpha E + \beta \sigma^2$$

Optimization Methods

Gradient and hessian of the cost function

$$g_i^t = \left(\frac{\partial C(\vec{a})}{\partial a_i} \right) \bigg|_{\vec{a}=\vec{a}_t} \quad \left| \quad h_{ij}(\vec{a}_t) = \left(\frac{\partial^2 C(\vec{a})}{\partial a_i \partial a_j} \right) \bigg|_{\vec{a}=\vec{a}_t}$$

Derivatives of the wave-function

$$\Psi_i(\vec{a}) = \left(\frac{\partial \Psi(\vec{a})}{\partial a_i} \right) \bigg|_{\vec{a}=\vec{a}_t} \quad \left| \quad \Psi_{ij}(\vec{a}) = \left(\frac{\partial^2 \Psi(\vec{a})}{\partial a_i \partial a_j} \right) \bigg|_{\vec{a}=\vec{a}_t}$$

Steepest Descents

$$\vec{a}^{t+1} = \vec{a}^t - \gamma \vec{g}^t$$

- Will converge to the minimum, but slowly.
- Different type of parameters vary on very different length scales
 - linear parameters in the determinant expansion vs parameters in the exponent
- Small values of γ are typically required for smooth convergence.
- No need for Hessians!

Optimization Methods

Newton's Method

$$C(\vec{a}) = C(\vec{a}_0) + \vec{g}^t \cdot \Delta\vec{a} + \frac{1}{2} \Delta\vec{a} \cdot \vec{h} \cdot \Delta\vec{a}$$

$$\vec{a}^{t+1} = \vec{a}^t - \vec{h} \cdot \vec{g}^t$$

- Efficient method, typically requires less iterations than SD.
- Needs second derivatives!
 - These can be hard to implement, many potential cross terms!

Linear Method

1. Expand the wave-function to first order around the current set of parameters

$$\bar{\Psi}_{lin}(\vec{a}) = \Psi_0 + \sum_{i=1}^{N_{opt}} \Delta a_i \bar{\Psi}_i$$

Orthogonalized Derivatives

$$\bar{\Psi}(\vec{a}) = \frac{\Psi(\vec{a})}{\sqrt{\langle \Psi(\vec{a}) | \Psi(\vec{a}) \rangle}}$$

$$\bar{\Psi}_i = \left(\frac{\partial \bar{\Psi}(\vec{a})}{\partial a_i} \right) \bigg|_{\vec{a}=\vec{a}_0} = \Psi_i - \langle \Psi_0 | \Psi_i \rangle \Psi_0 = \Psi_i - S_{0,i} \Psi_0$$

2. Minimization of the linear energy leads to a generalized eigenvalue problem:

$$\min E_{lin}(\vec{a}) = \min \frac{\langle \bar{\Psi}_{min}(\vec{a}) | \hat{H} | \bar{\Psi}_{min}(\vec{a}) \rangle}{\langle \bar{\Psi}_{min}(\vec{a}) | \bar{\Psi}_{min}(\vec{a}) \rangle}$$

$$\bar{H} \cdot \Delta \vec{a} = E_{lin} \bar{S} \cdot \Delta \vec{a}$$

$$\left. \begin{aligned} \bar{H}_{i,j} &= \langle \bar{\Psi}_i | \hat{H} | \bar{\Psi}_j \rangle \\ \bar{S}_{i,j} &= \langle \bar{\Psi}_i | \bar{\Psi}_j \rangle \end{aligned} \right\} \begin{array}{l} \text{Hamiltonian and overlap matrix} \\ \text{over } N_{opt}+1 \text{ basis functions } \{ \Psi_0, \bar{\Psi}_1, \dots, \bar{\Psi}_{N_{opt}} \} \end{array}$$

Gradients and Hessian of the VMC Energy

$$\frac{dE}{da_i} = \frac{d}{da_i} \left[\frac{\int d\vec{R} \pi(\vec{R}) E_L(\vec{R})}{\int d\vec{R} \pi(\vec{R})} \right] = 2 \left\langle \frac{\Psi_i}{\Psi} (E_L - \langle E_L \rangle) \right\rangle$$

$$\begin{aligned} \frac{d^2 E}{da_i da_j} = & 2 \left\langle \left(\frac{\Psi_{ij}}{\Psi} - \frac{\Psi_i}{\Psi} \frac{\Psi_j}{\Psi} \right) (E_L - \langle E_L \rangle) \right\rangle + 4 \left\langle \left(\frac{\Psi_i}{\Psi} - \left\langle \frac{\Psi_i}{\Psi} \right\rangle \right) \left(\frac{\Psi_j}{\Psi} - \left\langle \frac{\Psi_j}{\Psi} \right\rangle \right) (E_L - \langle E_L \rangle) \right\rangle \\ & + \left\langle \frac{\Psi_i}{\Psi} (E_{L,j} - \langle E_{L,j} \rangle) + \frac{\Psi_j}{\Psi} (E_{L,i} - \langle E_{L,i} \rangle) \right\rangle \end{aligned}$$

Gradient of the
local energy

$$E_{L,i}(\vec{R}) = \frac{\partial E_L(\vec{R})}{\partial a_i}$$

Notice that $\langle E_{L,i}(\vec{R}) \rangle = 0$

All quantities necessary to construct the hessian and gradients can be easily calculated from a standard VMC calculation.

Hamiltonian and Overlap Matrices

$$\begin{array}{l|l} \bar{S}_{00} = 1 & \bar{S}_{i,j} = \left\langle \frac{\Psi_i}{\Psi} \frac{\Psi_j}{\Psi} \right\rangle - \left\langle \frac{\Psi_i}{\Psi} \right\rangle \left\langle \frac{\Psi_j}{\Psi} \right\rangle \\ \bar{S}_{i0} = \bar{S}_{0j} = 0 & \end{array}$$

$\bar{H}_{0,0} = \langle E_L \rangle$	$\bar{H}_{0,j} = \left\langle \frac{\Psi_j}{\Psi} (E_L - \langle E_L \rangle) \right\rangle + \langle E_{L,j} \rangle$
$\bar{H}_{i,0} = \left\langle \frac{\Psi_i}{\Psi} (E_L - \langle E_L \rangle) \right\rangle$	$\begin{aligned} \bar{H}_{i,j} = & \left\langle \frac{\Psi_i}{\Psi} \frac{\Psi_j}{\Psi} E_L \right\rangle - \left\langle \frac{\Psi_i}{\Psi} \right\rangle \left\langle \frac{\Psi_j}{\Psi} E_L \right\rangle - \left\langle \frac{\Psi_j}{\Psi} \right\rangle \left\langle \frac{\Psi_i}{\Psi} E_L \right\rangle \\ & + \left\langle \frac{\Psi_i}{\Psi} \right\rangle \left\langle \frac{\Psi_j}{\Psi} \right\rangle \langle E_L \rangle - \left\langle \frac{\Psi_i}{\Psi} (E_{L,j} - \langle E_{L,j} \rangle) \right\rangle \end{aligned}$

Non-symmetric H matrix leads to lower variance!

Solving 1-D Minimization Problem

- Due to the strong non-linearity of many parameter types, it is usually necessary to perform a 1-D minimization along the direction produced by the previous methods. Some options:
 - Use a fixed (and small) time-step.
 - Leads to very slow convergence.
 - Evaluate the cost function at various points along the chosen direction and fit a polynomial
 - Cost function can be evaluated with a short VMC calculation, with correlated sampling or using reweighting.
 - Perform a direct line-minimization using reweighting.
 - Careful with wave-function overlap (reweighting efficiency) when parameters get far.
- C. Umrigar, et al. suggest various rescaling procedures to obtain reasonable step lengths, thus avoiding the line minimization step.
 - C. Umrigar, et al., “*Alleviation of the Fermion-Sign Problem by Optimization of Many-Body Wave Functions*” PRL 98, 110201 (2007).

Reweighting

Monte Carlo Integration

$$Q = \int f(x) g(x) dx = \frac{1}{N} \sum_i f(x_i) + O\left[\sqrt{\frac{\sigma_f^2}{N}}\right]$$

The points in the set $\{x_i\}$ are distributed according to $g(x)$.

What happens when we want to perform the integral with respect to a different distribution $g'(x)$, but we already have a set of points sampled from $g(x)$.
Can we estimate the new integral using the old set? **YES, use reweighting!!!**

$$Q' = \int f(x) g'(x) dx = \int \left[f(x) \frac{g'(x)}{g(x)} \right] g(x) dx = \frac{1}{N} \sum_i \left[f(x_i) \frac{g'(x_i)}{g(x_i)} \right] + O\left[\sqrt{\frac{\sigma_{f \frac{g'}{g}}^2}{N}}\right]$$

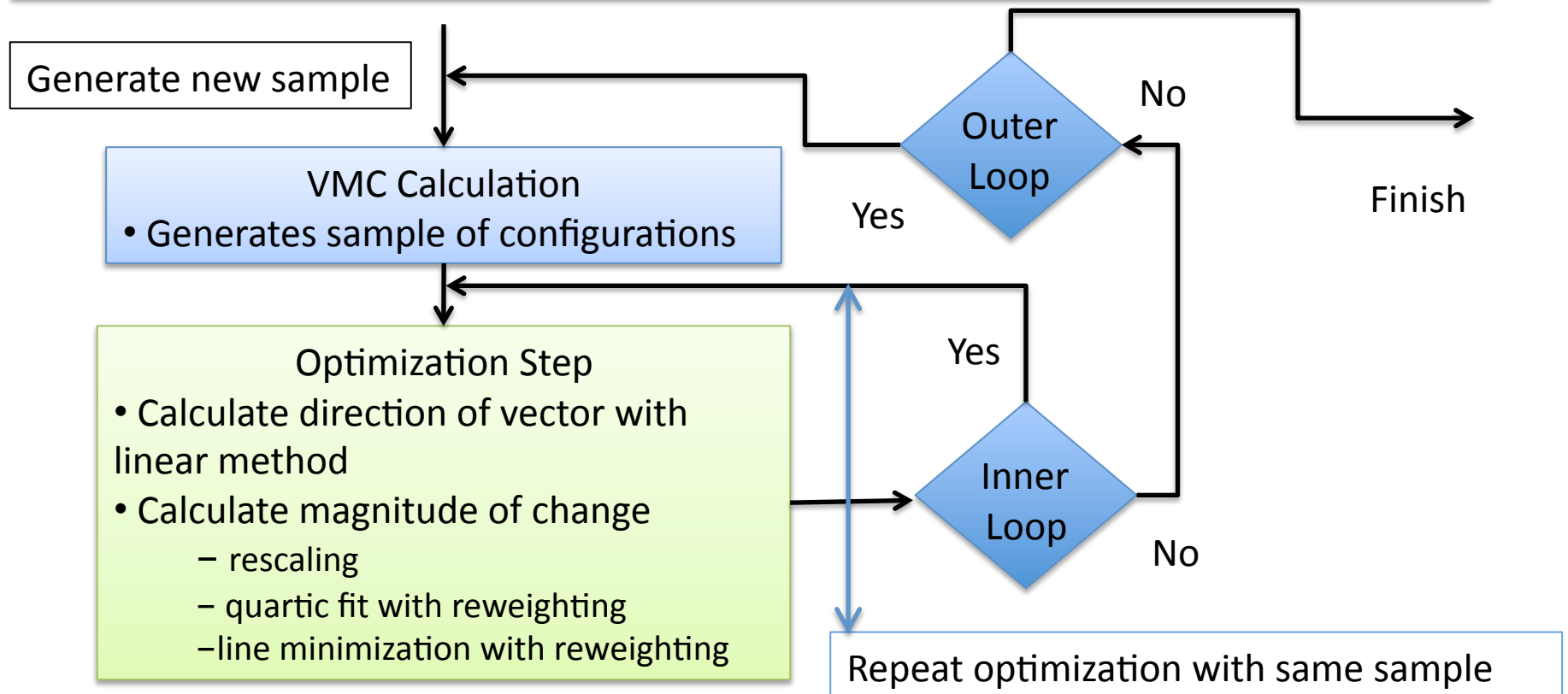
The efficiency of the procedure will depend on how close g and g' are.

Effective number of samples: $\frac{N_{eff}}{N} = \frac{\langle w \rangle^2}{\langle w^2 \rangle}$, where $w(x) = \frac{g'(x)}{g(x)}$

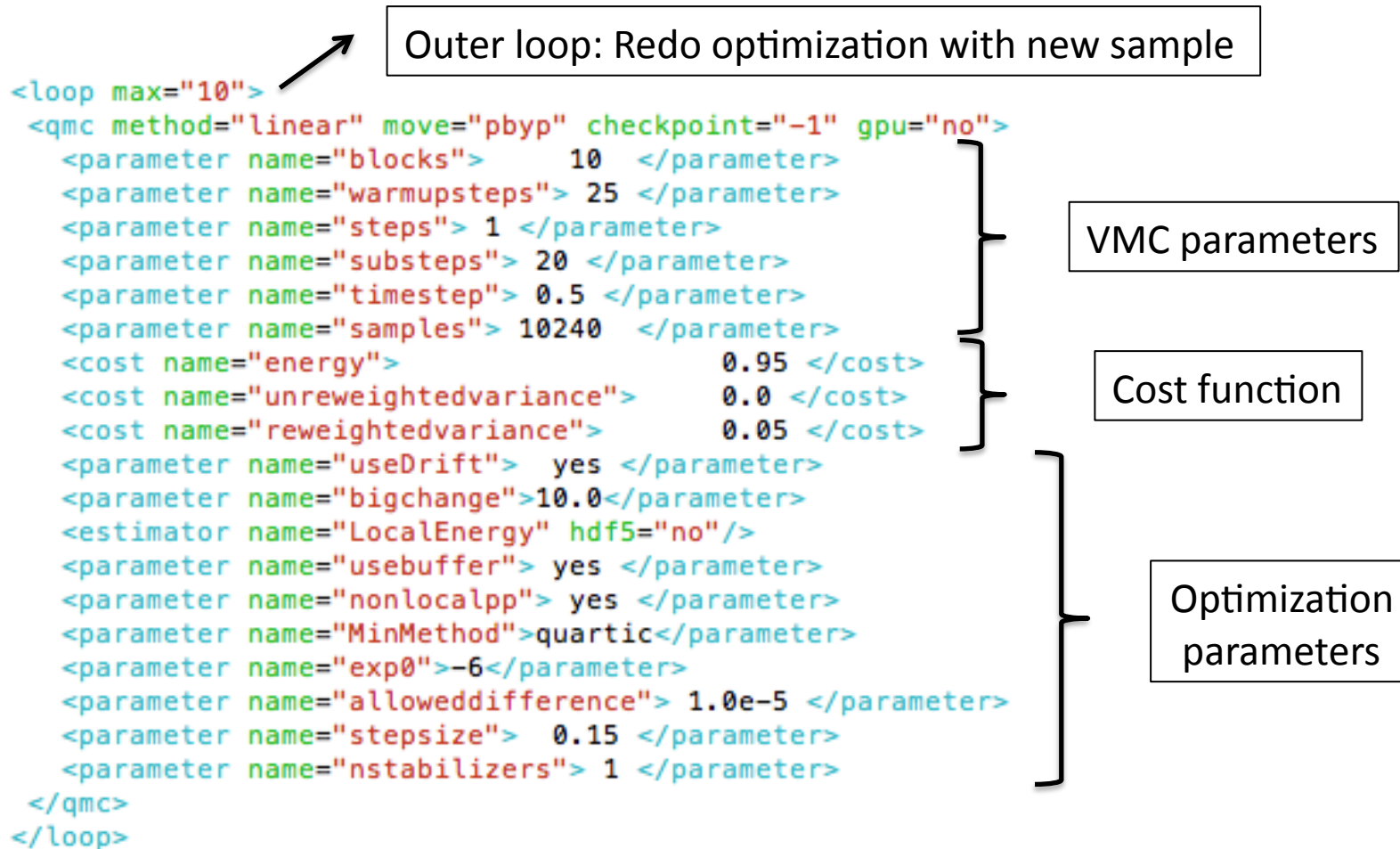
QMCPACK Specifics - I

The linear method is the recommended optimization algorithm in QMCPACK.

- Robust: Can handle all type of parameters efficiently.
- Fast and simple: Only first derivatives of the wave-function and local energy are needed.



QMCPACK Specifics – Sample XML Block



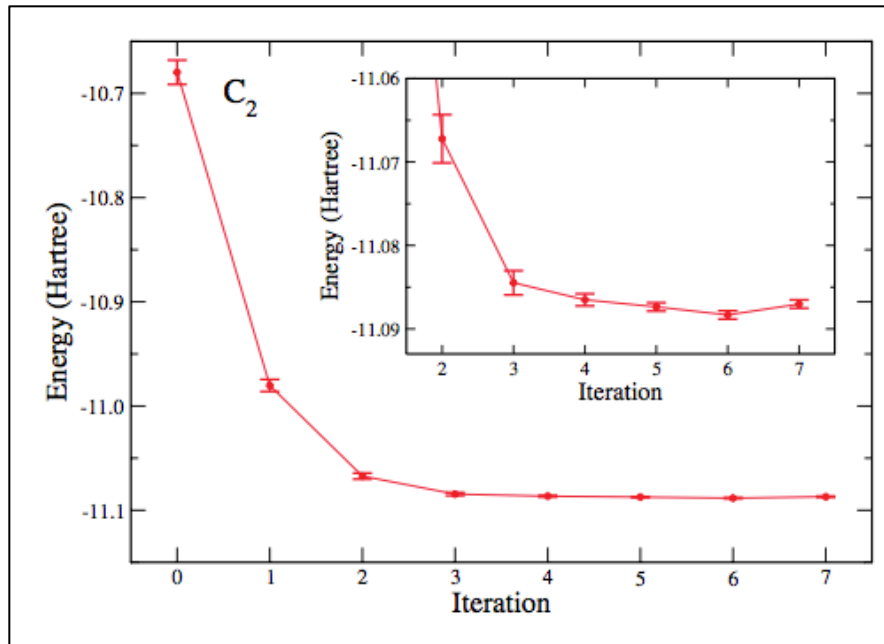
QMCPACK Specifics

- Important parameters:
 - ***bigchange***: (default 50.0) largest parameter change allowed
 - ***usebuffer***: (default “no”) Save useful information during VMC
 - ***nonlocalpp***: (default “no”) Include non-local energy on 1-D min
 - ***MinMethod***: (default “quartic”) Method to calculate magnitude of parameter change
 - quartic: fit quartic polynomial to 4 values of the cost function obtained using reweighting along chosen direction
 - linemin: direct line minimization using reweighting
 - rescale: no 1-D minimization. Uses Umrigar’s suggestions.
 - ***stepsize***: (default 0.25) step size in either quartic or linemin methods.
 - ***allowedifference***: (default 1e-4) Allowed increased in energy
 - ***exp0***: (default -16.0) Initial value for stabilizer (shift to diagonal of H)
 - Actual value of stabilizer is 10^{exp0}
 - nstabilizers***: (default 3) Number of stabilizers to try
 - ***stabilizaterScale***: (default 2.0) Increase in value of exp0 between iterations.
 - ***max_its***: (default 1) number of inner loops with same sample

QMCPACK Specifics

- Important parameters:
 - ***minwalkers***: (default 0.3) minimum value allowed for the ratio of effective samples to actual number of walkers in a reweighting step. The optimization will stop if the effective number of walkers in any reweighting calculation drops below this value. Last set of acceptable parameters are kept.
 - **maxWeight**: (default 1e6) Maximum weight allowed in reweighting. Any weight above this value will be reset to this value.
- Recommendations:
 - Set ***samples*** to equal to $(\text{\#threads}) * \text{\textit{blocks}}$.
 - Set ***steps*** to 1. Use ***substeps*** to control correlation between samples.
 - For cases where equilibration is slow, increase both ***substeps*** and **warmupsteps**.
 - For hard cases (e.g. simultaneous optimization of long MSD and 3-Body J), set ***exp0*** to 0 and do a single inner iteration (***max_its***=1) per sample of configurations.

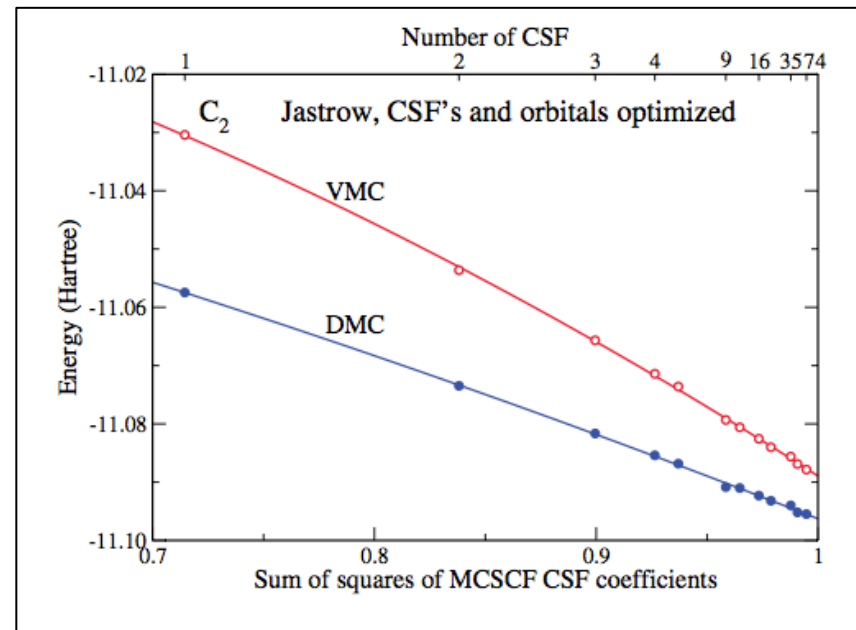
Examples from literature



- Convergence to mHa accuracy with less than 10 iterations
- Can recover energy in large MSD expansions!

Simultaneous optimization of Jastrow, CSF and orbital parameters.

- Robust and automatic
- Little need for human intervention



Important References

- X. Lin, et al., "*Optimization of quantum Monte Carlo wave functions using analytical energy derivatives*", J. Chem. Phys. **112**, 2650 (2000).
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- S. Sorella, "Wave function optimization in the variational Monte Carlo method", PRB **71**, 241103 (R) (2005).
- A. Scemama, et al., "*Simple and efficient approach to the optimization of correlated wave functions*", J. Chem. Phys. **73**, 241101 (R) (2006).
- J. Toulouse and C. Umrigar, "*Optimization of quantum Monte Carlo wave functions by energy minimization*", J. Chem. Phys. **126**, 084102 (2007).
- C. Umrigar, et al., "*Alleviation of the Fermion-Sign Problem by Optimization of Many-Body Wave Functions*" PRL **98**, 110201 (2007).
- J. Toulouse and C. Umrigar, "*Full optimization of Slater-Jastrow wavefunctions with application to the first-row atoms and homonuclear dimers*", J. Chem. Phys. **128**, 174101 (2008).