## Parallel Coordinate Descent Methods for Full Configuration Interaction

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#### Problem: Searching for Ground-State

 The ground-state of a chemical system given by the many-body time-independent Schrödinger Equation

$$\hat{H}|\mathbf{\Phi_0}\rangle = E_0|\mathbf{\Phi_0}\rangle,$$

where  $|\Phi_0\rangle = \Phi_0(r_1, \dots, r_{n_{\mathrm{elec}}}), r_i \in \mathbb{R}^3$ .

• Under Born-Oppenheimer approximation, the Hamiltonian operator with  $n_{\text{nuc}}$  nuclei and  $n_{\text{elec}}$  electrons is

$$\hat{H} = -\frac{1}{2} \sum_{i=1}^{n_{\text{elec}}} \nabla_i^2 + \sum_{i=1}^{n_{\text{elec}}} V_{\text{ext}}(r_i; \{R_I\}_{I=1}^{n_{\text{nuc}}}) + \sum_{i < j}^{n_{\text{elec}}} \frac{1}{\|r_i - r_j\|}.$$



#### FCI Numerical Discretization

Schrödinger equation can be transformed to FCI eigenvalue problem

$$H\mathbf{c} = E_0\mathbf{c}, \quad H \in \mathbb{R}^{N_{\mathsf{FCI}} \times N_{\mathsf{FCI}}}, \quad \mathbf{c} \in \mathbb{R}^{N_{\mathsf{FCI}}},$$

but ...

Table: Different Molecule Systems and Storage cost

Molecule	Basis	Electrons	Spin–Orbitals	Dimension	Memory
H <sub>2</sub> O	cc-pVDZ	10	48	$\sim 10^8$	$\sim 1\;GB$
$N_2$	cc-pVDZ	14	56	$\sim 10^{11}$	$\sim 1~TB$
$N_2$	cc-p $VTZ$	14	120	$\sim 10^{16}$	$\sim 100~\text{PB}$
$Cr_2$	Ahlrichs	48	84	$\sim 10^{22}$	-

#### Why is FCI so Huge?

- Electrons fill orbitals: one-electron spin-orbitals  $\{\chi_p\}_{p=1}^{n_{\text{orb}}}$  from Hartree–Fock procedure.
- Each configuration is a Slater determinant (or, anti-symmetrized tensor products):

$$|D_i\rangle = |\chi_{p_1}\chi_{p_2}\cdots\chi_{p_n}\rangle,$$

with  $n = n_{\text{elec}}$  and  $1 \le p_1 < p_2 < \cdots < p_n \le n_{\text{orb}}$ .

- FCI variational space dimension:  $N_{\text{FCI}} = \binom{n_{\text{orb}}}{n_{\text{elec}}}$ . Combinatorial explosion!
- Traditional methods fail due to dimensionality.



#### Hamiltonian Matrix

Entry:  $H_{ij} = \langle D_i | \hat{H} | D_j \rangle$ , not guaranteed to be non-negative.

- Symmetric.  $H_{ij} = H_{ji}$ .
- Sparse. For off-diagonals  $|D_i\rangle \neq |D_j\rangle$ ,
  - If  $|D_i\rangle = a_r^{\dagger} a_p |D_j\rangle$ ,  $H_{ij} = \langle r|\hat{h}|p\rangle + \sum_k \langle rk||pk\rangle$ .
  - If  $|D_i\rangle = a_r^{\dagger} a_s^{\dagger} a_p a_q |D_j\rangle$ ,  $H_{ij} = \langle rs||pq\rangle$ .
  - Otherwise,  $H_{ij} = 0$ .

Consequence: H has  $O(n_{\text{elec}}^2 n_{\text{orb}}^2)$  entries per row.

- Ground-state eigenvalue  $E_0 < 0$ .
- Ground-state eigenvector **c** sparse in the sense of truncation.



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#### **Existing Methods**

- Selected CI: Pick the important configurations.
  - Adaptive space growth based on energy estimates.
  - Good for weakly correlated systems, cuts down cost with little accuracy loss.
- DMRG: Tensor compression.
  - Wavefunction as matrix product state (MPS), compact storage.
  - Works best when entanglement is low (e.g., 1D-like systems).
- FCIQMC: Stochastic sampling in configuration space.
  - Monte Carlo walkers project onto the ground state.
  - Saves memory, but noisy; needs enough walkers to stabilize.



## Coordinate Descent FCI (CDFCI)<sup>1</sup>

# Coordinate gradient descent method

- Minimizes computational costs by avoiding operations with the entire Hamiltonian matrix.
- In each iteration, only one coordinate of the optimizing vector is updated.
- Computation for updating involves only one column of the Hamiltonian matrix.

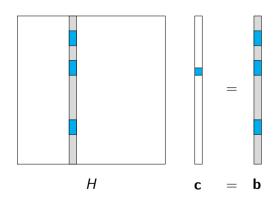


Figure: Update for one coordinate.

<sup>&</sup>lt;sup>1</sup>Z. Wang, Y. Li, J. Lu, J. Chem. Theory Comput., 2019.

## Solving Leading Eigenvalue Problem

Consider the unconstrained minimization problem

$$\min_{\mathbf{c} \in \mathbb{R}^{N_{\mathsf{FCI}}}} f(\mathbf{c}) = \min_{\mathbf{c}} \|H + \mathbf{c}\mathbf{c}^{\mathsf{T}}\|_F^2.$$

- Gradient  $\nabla f(\mathbf{c}) = 4H\mathbf{c} + 4(\mathbf{c}^{\mathsf{T}}\mathbf{c})\mathbf{c}$ .
- Hessian  $\nabla^2 f(c) = 4H + 8\mathbf{c}\mathbf{c}^\mathsf{T} + 4(\mathbf{c}^\mathsf{T}\mathbf{c})I$ .
- Non-convex problem, with unbounded Lipschitz constant.
- Stationary points:  $0, \pm \sqrt{-\lambda_1} \mathbf{v}_1, \dots, \pm \sqrt{-\lambda_m} \mathbf{v}_m \ (\dots < \lambda_m < 0 < \lambda_{m+1} < \dots)$ .
- Only two local minimizers  $\pm \sqrt{-\lambda_1} \mathbf{v}_1$  (which are also global minimizers), the others are all strict saddle points.
- Ensures convergence to the ground state  $\pm \mathbf{c}$ , given a good starting point (e.g., Hartree–Fock ground state).



#### **CDFCI** Framework

Initialize  $\mathbf{c}^{(0)}$ ,  $\mathbf{b}^{(0)} = H\mathbf{c}^{(0)}$ . For iteration  $\ell = 1, 2, \dots$ 

- Select coordinate  $i^{(\ell)} = \arg\max_{i} |\nabla_{i} f(\mathbf{c}^{(\ell-1)})|$ .
- ② Find stepsize by exact line search  $\alpha^{(\ell)} = \arg\min_{\alpha} f(\mathbf{c}^{(\ell-1)} + \alpha \mathbf{e}_{i(\ell)}).$
- **3** Update  $\mathbf{c}^{(\ell)} = \mathbf{c}^{(\ell-1)} + \alpha^{(\ell)} \mathbf{e}_{i^{(\ell)}}$ ,  $\mathbf{b}^{(\ell)} = \mathbf{b}^{(\ell-1)} + \alpha^{(\ell)} H_{:i^{(\ell)}}$ .

Remark: Gradient

$$\nabla f(\mathbf{c}) = 4H\mathbf{c} + 4\mathbf{c}^{\mathsf{T}}\mathbf{c}\mathbf{c} = 4\mathbf{b} + 4\mathbf{c}^{\mathsf{T}}\mathbf{c}\mathbf{c}.$$

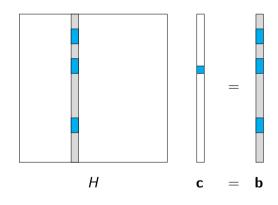


Figure: Update for one coordinate.



#### CDFCI Framework - for Two Coordinates?

Initialize  $\mathbf{c}^{(0)}$ ,  $\mathbf{b}^{(0)} = H\mathbf{c}^{(0)}$ . For iteration  $\ell = 1, 2, \dots$ 

- $\begin{aligned} & \textbf{Select coordinate} \\ & i^{(\ell)} = \arg\max_{i} |\nabla_{i} f(\mathbf{c}^{(\ell-1)})|, \\ & j^{(\ell)} = \arg\max_{j \neq j^{(\ell)}} |\nabla_{j} f(\mathbf{c}^{(\ell-1)})|. \end{aligned}$
- ② Find stepsize  $\alpha^{(\ell)} = \arg\min_{\alpha} f(\mathbf{c}^{(\ell-1)} + \alpha \mathbf{e}_{i^{(\ell)}}),$  $\beta^{(\ell)} = \arg\min_{\beta} f(\mathbf{c}^{(\ell-1)} + \beta \mathbf{e}_{i^{(\ell)}}).$
- Update  $\mathbf{c}^{(\ell)} = \mathbf{c}^{(\ell-1)} + \alpha^{(\ell)} \mathbf{e}_{i(\ell)} + \beta^{(\ell)} \mathbf{e}_{j(\ell)},$   $\mathbf{b}^{(\ell)} = \mathbf{b}^{(\ell-1)} + \alpha^{(\ell)} H_{\cdot,i(\ell)} + \beta^{(\ell)} H_{\cdot,i(\ell)}.$

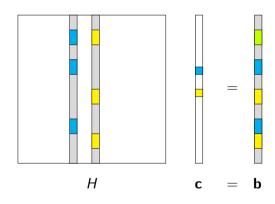


Figure: Update for two coordinates.



#### CDFCI Framework - Exact Line Search?

Initialize  $\mathbf{c}^{(0)}$ ,  $\mathbf{b}^{(0)} = H\mathbf{c}^{(0)}$ . For iteration  $\ell = 1, 2, \dots$ 

- $\begin{array}{l} \bullet \quad \text{Select coordinate} \\ i^{(\ell)} = \arg\max_{i} |\nabla_{i} f(\mathbf{c}^{(\ell-1)})|, \\ j^{(\ell)} = \arg\max_{i \neq i^{(\ell)}} |\nabla_{i} f(\mathbf{c}^{(\ell-1)})|. \end{array}$
- ② Find stepsize  $\alpha^{(\ell)}, \beta^{(\ell)} = \arg\min_{\alpha,\beta} f(\mathbf{c}^{(\ell-1)} + \alpha \mathbf{e}_{i^{(\ell)}} + \beta \mathbf{e}_{i^{(\ell)}}).$
- $\begin{aligned} & \textbf{Outsol} \\ & \mathbf{c}^{(\ell)} = \mathbf{c}^{(\ell-1)} + \alpha^{(\ell)} \mathbf{e}_{i^{(\ell)}} + \beta^{(\ell)} \mathbf{e}_{j^{(\ell)}}, \\ & \mathbf{b}^{(\ell)} = \mathbf{b}^{(\ell-1)} + \alpha^{(\ell)} H_{::i^{(\ell)}} + \beta^{(\ell)} H_{::i^{(\ell)}}. \end{aligned}$

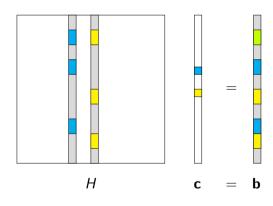


Figure: Update for two coordinates.



#### Add a Scalar $\gamma$ for Exact Line Search

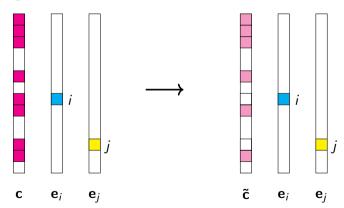
Modify the minimization problem from  $\min_{\alpha,\beta} f(\mathbf{c} + \alpha \mathbf{e}_i + \beta \mathbf{e}_j)$  to

$$\min_{\boldsymbol{\gamma}, \alpha, \beta} f(\boldsymbol{\gamma} \mathbf{c} + \alpha \mathbf{e}_i + \beta \mathbf{e}_j) = f(\begin{bmatrix} \mathbf{c} & \mathbf{e}_i & \mathbf{e}_j \end{bmatrix} \begin{bmatrix} \boldsymbol{\gamma} \\ \alpha \\ \beta \end{bmatrix}) \\
= \begin{bmatrix} H + \begin{bmatrix} \mathbf{c} & \mathbf{e}_i & \mathbf{e}_j \end{bmatrix} \begin{bmatrix} \boldsymbol{\gamma} \\ \alpha \\ \beta \end{bmatrix} \begin{bmatrix} \boldsymbol{\gamma} & \alpha & \beta \end{bmatrix} \begin{bmatrix} \mathbf{c}^T \\ \mathbf{e}_i^T \\ \mathbf{e}_i^T \end{bmatrix} \begin{bmatrix} \boldsymbol{\gamma} \\ \boldsymbol{\epsilon}_i^T \end{bmatrix}$$



#### Matrix Orthogonalization

Construct  $\begin{bmatrix} \tilde{\mathbf{c}} & \mathbf{e}_i & \mathbf{e}_j \end{bmatrix}$ , where  $\|\tilde{\mathbf{c}}\|_2 = 1$ ,  $(\tilde{\mathbf{c}}, \mathbf{e}_i) = 0$ ,  $(\tilde{\mathbf{c}}, \mathbf{e}_j) = 0$ .





#### Add $\gamma$ and $\tilde{\mathbf{c}}$ for Exact Line Search

Modify the minimization problem from  $\min_{\alpha,\beta} f(\mathbf{c} + \alpha \mathbf{e}_i + \beta \mathbf{e}_i)$  to

$$\min_{\boldsymbol{\gamma}, \boldsymbol{\alpha}, \boldsymbol{\beta}} f(\boldsymbol{\gamma} \tilde{\mathbf{c}} + \alpha \mathbf{e}_{i} + \beta \mathbf{e}_{j}) = f(\begin{bmatrix} \tilde{\mathbf{c}} & \mathbf{e}_{i} & \mathbf{e}_{j} \end{bmatrix} \begin{bmatrix} \boldsymbol{\gamma} \\ \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{bmatrix}) \\
= \| H + \begin{bmatrix} \tilde{\mathbf{c}} & \mathbf{e}_{i} & \mathbf{e}_{j} \end{bmatrix} \begin{bmatrix} \boldsymbol{\gamma} \\ \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{bmatrix} [\boldsymbol{\gamma} \quad \boldsymbol{\alpha} \quad \boldsymbol{\beta}] \begin{bmatrix} \tilde{\mathbf{c}}^{\mathsf{T}} \\ \mathbf{e}_{i}^{\mathsf{T}} \\ \mathbf{e}_{j}^{\mathsf{T}} \end{bmatrix} \|_{F}^{2} \\
= \| \begin{bmatrix} \tilde{\mathbf{c}}^{\mathsf{T}} \\ \mathbf{e}_{i}^{\mathsf{T}} \\ \mathbf{e}_{j}^{\mathsf{T}} \end{bmatrix} H \begin{bmatrix} \tilde{\mathbf{c}} & \mathbf{e}_{i} & \mathbf{e}_{j} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\gamma} \\ \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{bmatrix} [\boldsymbol{\gamma} \quad \boldsymbol{\alpha} \quad \boldsymbol{\beta}] \|_{F}^{2} + \text{constant.} \\
\in \mathbb{R}^{3 \times 3}$$

#### Extension to Multi Coordinate Descent FCI

- Select a set of coordinates  $I = \{i_1, \dots, i_k\}, 1 \le i_j \le N_{FCI}$  based on gradient  $\nabla f(\mathbf{c}) = 4H\mathbf{c} + 4\mathbf{c}^{\mathsf{T}}\mathbf{c}\mathbf{c}$ .
- Denote  $\mathcal{E}_I = [e_{i_1}, \dots, e_{i_k}] \in \mathbb{R}^{N_{\mathsf{FCI}} \times k}$
- The update is given by

$$\mathbf{c} \leftarrow \gamma \mathbf{c} + \mathcal{E}_I \mathbf{a}$$
.

• The values of  $\gamma$  and **a** are given by the eigenvector of

$$\begin{bmatrix} \mathbf{\tilde{c}}^\mathsf{T} \\ \mathcal{E}_I^\mathsf{T} \end{bmatrix} H \begin{bmatrix} \mathbf{\tilde{c}} & \mathcal{E}_I \end{bmatrix} \in \mathbb{R}^{(k+1)\times(k+1)}$$

corresponding to the minimal eigenvalue  $\lambda_{\min}$ , which is the current energy estimate.



## Compression Strategy

• Compression occurs when updating  $\mathbf{b} = H\mathbf{c}$ :

$$\mathbf{b} \leftarrow \gamma \mathbf{b} + H \mathcal{E}_I \mathbf{a},$$

$$b_i \leftarrow \gamma b_i + \sum_{j \in I} H_{ij} a_j.$$

- Update  $H_{ij}a_j$  is discarded if  $\mathbf{c}_i = 0$  and  $|H_{ij}a_j| < \tau$ .
- Not affecting eigenvalue estimator

$$\mathsf{RQ}(\mathbf{c}) = \frac{\mathbf{c}^\mathsf{T} H \mathbf{c}}{\mathbf{c}^\mathsf{T} \mathbf{c}} = \frac{\mathbf{c}^\mathsf{T} \mathbf{b}}{\mathbf{c}^\mathsf{T} \mathbf{c}}.$$

ullet Tolerance au balances between memory-cost and accuracy.



#### Parallel Implementation Details

- Shared memory parallelism based on OpenMP.
- Sparse vectors c and b = Hc are stored in a concurrent hash table<sup>2</sup> that supports parallel read/write.
- Two levels of parallelism: row-wise and column-wise.

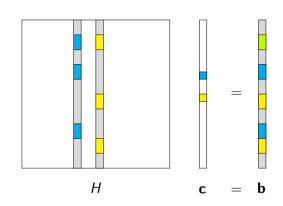
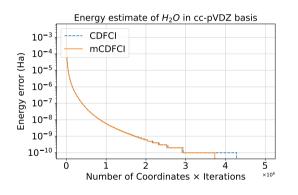


Figure: Update for two coordinates.



<sup>&</sup>lt;sup>2</sup>https://github.com/efficient/libcuckoo

## Overall Speedup: H<sub>2</sub>O/cc-pVDZ



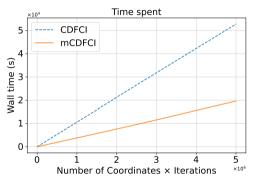
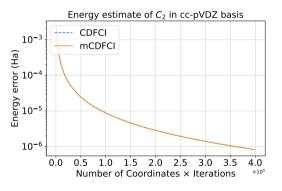


Figure: Speedup of mCDFCI compared with CDFCI, both in 64 threads and k = 64.



## Overall Speedup: $C_2/cc-pVDZ$



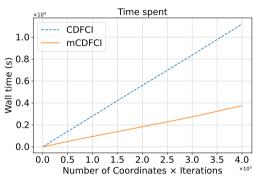


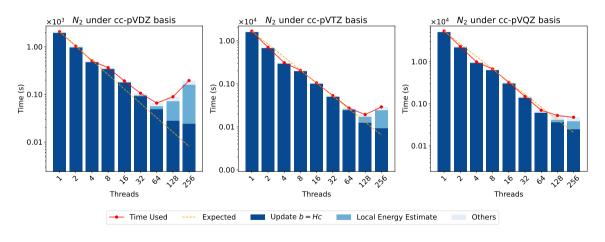
Figure: Speedup of mCDFCI compared with CDFCI, both in 128 threads and k = 128.

## Compare with Other FCI Methods

Algorithm	Parameter	Absolute Error	Mem(GB)	Time(s)	mCD Time(s)	FCI Ratio
SHCI	$\varepsilon_1 = 1.0 \times 10^{-4}$	$1.5 \times 10^{-3}$	16.1	3.3	14.0	0.23×
	$arepsilon_1 = 5.0  imes 10^{-5} \ arepsilon_1 = 1.0  imes 10^{-5}$	$\begin{array}{c c} 7.6 \times 10^{-4} \\ 1.1 \times 10^{-4} \end{array}$	17.5 32.6	7.3 53.9	23.7 113.2	0.31  imes 0.48  imes
	$arepsilon_1 = 5.0  imes 10^{-6}$	$4.6 \times 10^{-5}$	54.2	126.0	219.4	0.57×
	$arepsilon_1 = 1.0  imes 10^{-6}$	$4.7 \times 10^{-6}$	238.1	845.0	954.1	0.89×
DMRG	max M = 500	$6.9 \times 10^{-4}$	0.2	106.9	23.7	$4.52\times$
	max M = 1000	$1.5 \times 10^{-4}$	8.0	345.2	92.7	$3.72 \times$
	$\max M = 2000$	$1.9 \times 10^{-5}$	3.1	1130.1	394.9	$2.86 \times$
	$ma \times M = 4000$	$2.1 \times 10^{-6}$	11.5	3848.3	1549.2	2.48×
iS-FCIQMC	m = 10000	$7.4 \pm 1.6  imes 10^{-4}$	0.076	19.3	23.7	$0.81 \times$
	m = 50000	$6.4 \pm 0.6  imes 10^{-4}$	0.077	59.8	26.9	$2.22 \times$
	m = 100000	$1.8 \pm 0.4  imes 10^{-4}$	0.077	118.0	78.6	$1.50 \times$
	m = 500000	$2.3 \pm 0.2 \times 10^{-4}$	0.080	459.9	64.5	$7.13 \times$
	m = 1000000	$5.4 \pm 1.2  imes 10^{-5}$	0.083	872.4	196.5	$4.44 \times$

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## Scalability

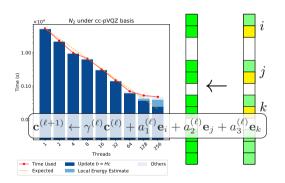




#### Summary

#### The proposed method mCDFCI

- performs configuration selection using coordinate descent and exact line search.
- visits important determinants efficiently.
- captures the significant part of FCI space for ground state approximation.





## Thanks for Your Attention!

Contact: yuejiazhang21@m.fudan.edu.cn

Preprint: https://arxiv.org/abs/2411.07565