

QMCPACK: Enabling Breakthrough QMC Simulations at Leadership Computing Facilities

Presented at

**Accelerating Computational
Science Symposium 2012**

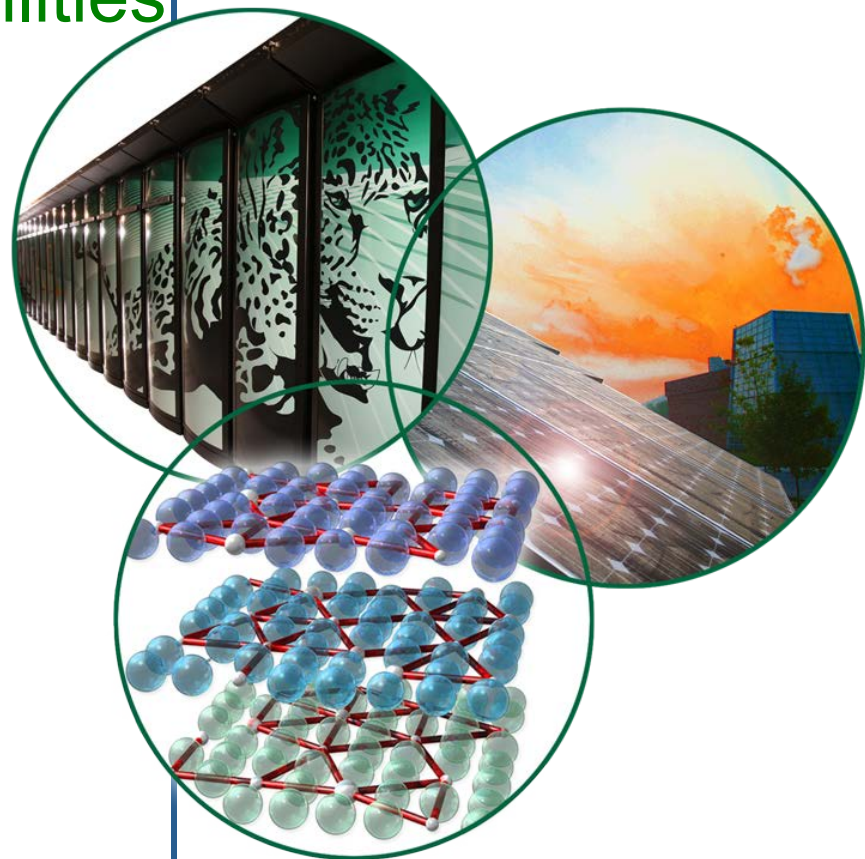
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Acknowledgements

QMCPACK developers

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- others

<http://qmcpack.cmscc.org>

QMC Endstation

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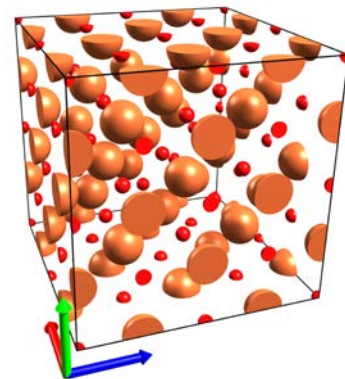
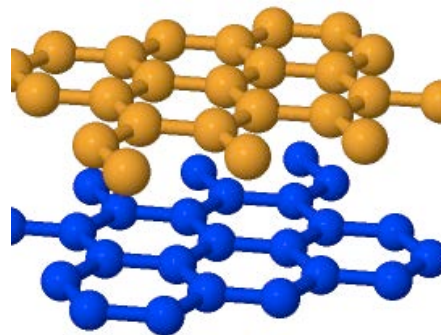
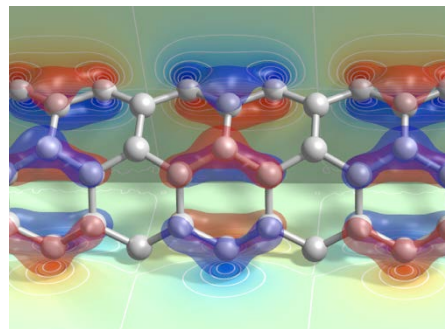
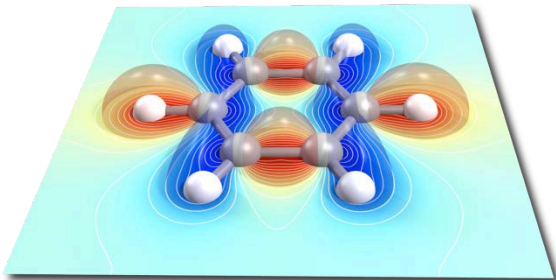
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QMC advantages: accuracy and scalability

- Applicable to a wide range of problems
 - Any boundary conditions: molecular and solid-state systems
 - Dimensionality: 1D, 2D, and 3D
 - Representation: atomistic to model Hamiltonians
- Scale with a few powers in system size: $O(N^3)$ - $O(N^4)$
 - Routine calculations of 100s-1000s electrons
- Ample opportunities of parallelism

QMC has enabled **accurate, many-body** predictions of electronic structures of **atoms, molecules to solids; molecular solids to highly correlated metals**



Basics of QMC for ES

For N -electron system

$$\{\mathbf{R}\} = (\mathbf{r}_1, \dots, \mathbf{r}_N)$$

Many-body
Hamiltonian

$$\hat{H} = \sum_i \frac{1}{2m_e} \nabla^2 + \frac{1}{2} \sum_{i \neq j} \frac{e^2}{|\mathbf{r}_i - \mathbf{r}_j|} + \sum_i V_{ext}(\mathbf{r}_i)$$

Many-body trial wavefunction $\Psi_T(\mathbf{R})$

$$E_T = \frac{\int d^{3N} \mathbf{R} \Psi_T^*(\mathbf{R}) \hat{H} \Psi_T(\mathbf{R})}{\int d^{3N} \mathbf{R} |\Psi_T(\mathbf{R})|^2}, \quad E_T \geq E_0$$



QMC

$$\langle E_T \rangle = \frac{\sum_i^M w(\mathbf{R}_i) E_L(\mathbf{R}_i)}{\sum_i^M w(\mathbf{R}_i)}, \quad E_L = \frac{\hat{H} \Psi_T(\mathbf{R})}{\Psi_T(\mathbf{R})}$$

Efficiency of QMC

- QMC employs sampling to obtain

$$\langle E_T \rangle = \frac{\sum_i^M w(\mathbf{R}_i) E_L(\mathbf{R}_i)}{\sum_i^M w(\mathbf{R}_i)}, \quad E_L = \frac{\hat{H}\Psi_T(\mathbf{R})}{\Psi_T(\mathbf{R})}$$

with an error bar $\delta = \frac{\sigma}{\sqrt{M}}$, $\sigma^2 = \langle E_T^2 \rangle - \langle E_T \rangle^2$ variance

- Efficiency of QMC simulations is high, when
 - Variance is small: $\sigma \rightarrow 0$ as $\Psi_T \rightarrow \Psi$ (zero-variance)

Physical insights & improved optimization

- M/τ , the rate of MC sample generation is high

Parallelism, compact form of Ψ_T & optimized kernels

Accelerating QMC

- Better Ψ_T

Accelerating QMC

- **Better** $\Psi_T = e^{J_1 + J_2 + \dots} \sum_k^M C_k D_k^\uparrow(\phi) D_k^\downarrow(\phi)$
 $N = N^\uparrow + N^\downarrow$

Correlation (Jastrow)

$$J_1 = \sum_i^N \sum_I^{N_{ions}} u_1(|\mathbf{r}_i - \mathbf{r}_I|)$$

$$J_2 = \sum_{i \neq j}^N u_2(|\mathbf{r}_i - \mathbf{r}_j|)$$

Anti-symmetric function
(Pauli principle)

$$D_k^\sigma = \begin{vmatrix} \phi_1(\mathbf{r}_1) & \cdots & \phi_1(\mathbf{r}_{N^\sigma}) \\ \vdots & \vdots & \vdots \\ \phi_{N^\sigma}(\mathbf{r}_1) & \cdots & \phi_{N^\sigma}(\mathbf{r}_{N^\sigma}) \end{vmatrix}$$

Single-particle orbitals $l = N_b$

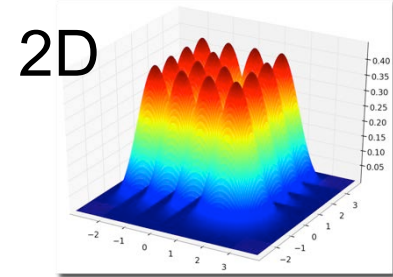
$$\phi_i = \sum_l c_l^i \Phi_l$$

Basis sets: molecular orbitals,
plane-wave, grid-based orbitals ...

Accelerating QMC

- Better Ψ_T

- Improved algorithms



$$[1] \quad \phi_i = \sum_{l=1}^{l=N_b} c_l^i \Phi_l$$

$$[2] \quad \sum_i^{M \rightarrow \infty} C_i D_i^\uparrow D_i^\downarrow$$

[3] Optimization of Ψ_T

[1] einspline library, Esler, <http://einspline.svn.sourceforge.net/>

[2] Clark *et al.*, JCP **135** 244105 (2011); Morales *et. al.* (2012)

[3] Umrigar, *et. al.*, PRL **98**,110201 (2007)

Accelerating QMC

- Better Ψ_T
- Improved algorithms
- Faster computers
- Bigger computers

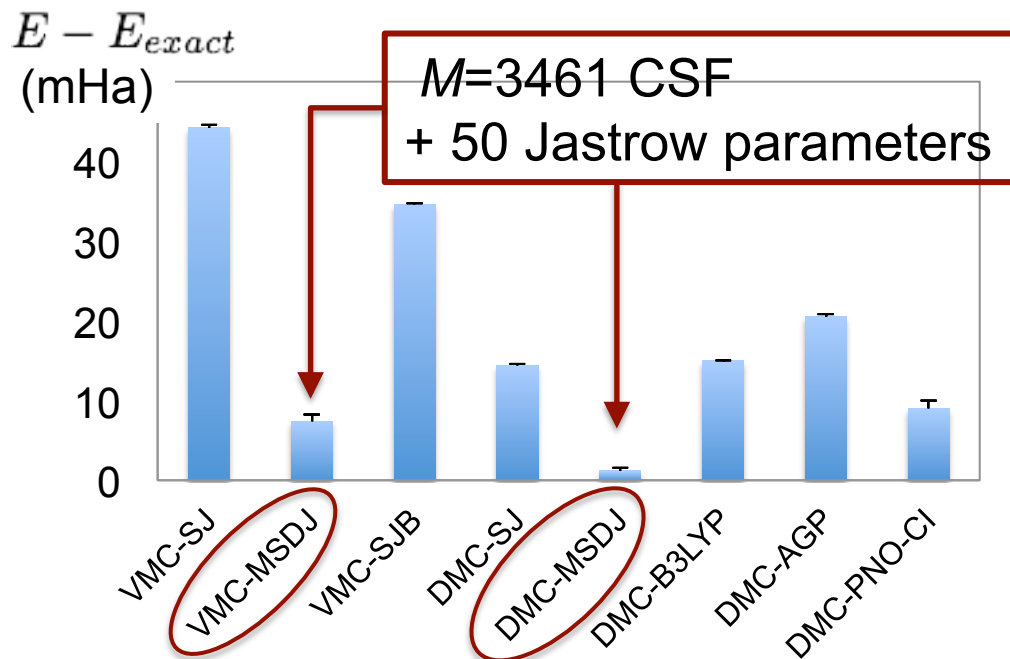
Increase the QMC efficiency
Minimize time-to-solution
(wall-clock time) to reach a
target error bar

More science

State-of-art QMC

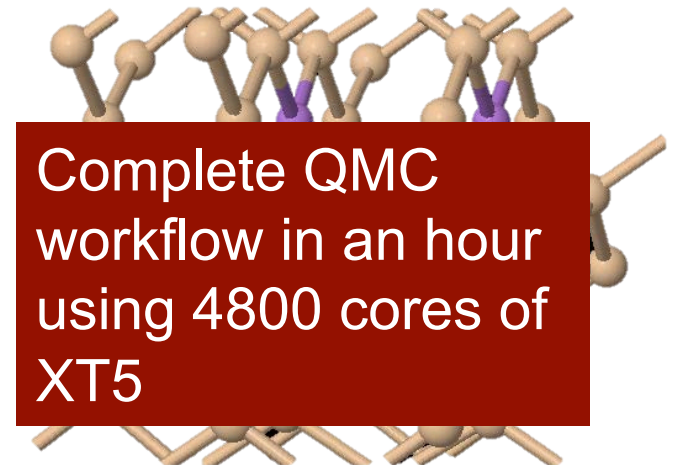
- Fast algorithm for multi-determinant evaluation
- Improved energy minimization in VMC
- QMCPACK: efficient and scalable QMC for large clusters of multi-core and GPUs

Energy of H₂O

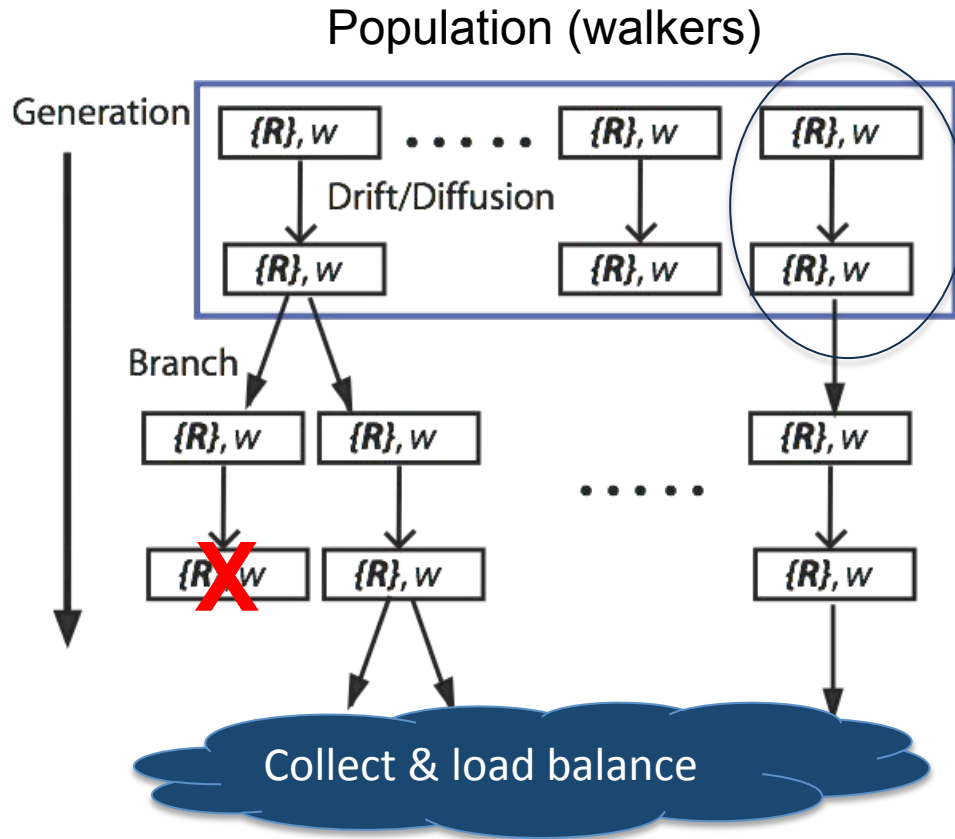


Formation energy of a defect in bulk Si (64 atoms)

$$E_f = 3.07 (11) \text{ eV}$$



DMC: computational view



Make a move

$$\mathbf{R}' = \mathbf{R} + \tau \nabla \ln \Psi_T(\mathbf{R}) + \chi$$

Random

"Quantum Force"

Accept/reject a move

$$\frac{|\Psi_T(\mathbf{R}')|^2}{|\Psi_T(\mathbf{R})|^2} \frac{G_d(\mathbf{R} \rightarrow \mathbf{R}'; \tau)}{G_d(\mathbf{R}' \rightarrow \mathbf{R}; \tau)}$$

Branch with the weight

$$\exp^{-\tau[(E_L(\mathbf{R}) + E_L(\mathbf{R}'))/2 - \tilde{E}_T]}$$

- **Computationally Intensive:** Quantum Force, Ratio, Local Energy
- Communication light
- Ample parallel opportunities : configurations, k-point, walkers

QMC on GPUs: Why & How

- Major performance limiting factors for QMC
 - Random access
 - Memory bandwidth
 - Mostly BLAS I/II operations
- GPUs provide higher bandwidth & FLOPS/s than conventional CPUs : acceleration possible
- But, how to exploit GPUs' power? Need
 - Keep GPUs busy
 - Minimize/hide cost of data transfer between CPUs & GPUs
 - Expose fine-grained parallelisms

QMC on GPU

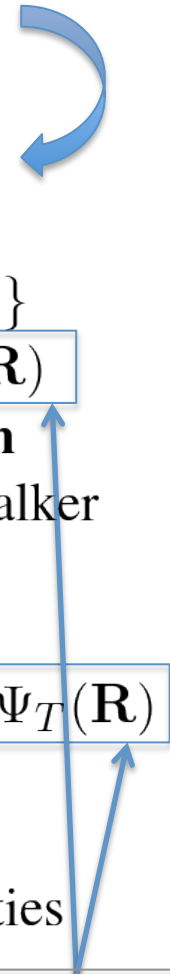
```
for walker = 1 ...  $N_w$  do  
  let  $\mathbf{R} = \{\mathbf{r}_1 \dots \mathbf{r}_N\}$   
  for particle  $i = 1 \dots N$  do  
    set  $\mathbf{r}'_i = \mathbf{r}_i + \delta$   
    let  $\mathbf{R}' = \{\mathbf{r}_1 \dots \mathbf{r}'_i \dots \mathbf{r}_N\}$   
    ratio  $\rho = \Psi_T(\mathbf{R}') / \Psi_T(\mathbf{R})$   
    if  $\mathbf{r} \rightarrow \mathbf{r}'$  is accepted then  
      update the state of a walker  
    end if  
  end for{particle}  
  Compute  $E_L = \hat{H} \Psi_T(\mathbf{R}) / \Psi_T(\mathbf{R})$   
end for{walker}  
Reweight and branch walkers  
Update  $E_T$  and collect properties
```

Loops

- Restructure the algorithm and data structure to expose & exploit parallelisms
multiple walkers per kernels

QMC on GPU

```
for walker = 1 ...  $N_w$  do  
  let  $\mathbf{R} = \{\mathbf{r}_1 \dots \mathbf{r}_N\}$   
  for particle  $i = 1 \dots N$  do  
    set  $\mathbf{r}'_i = \mathbf{r}_i + \delta$   
    let  $\mathbf{R}' = \{\mathbf{r}_1 \dots \mathbf{r}'_i \dots \mathbf{r}_N\}$   
    ratio  $\rho = \Psi_T(\mathbf{R}') / \Psi_T(\mathbf{R})$   
    if  $\mathbf{r} \rightarrow \mathbf{r}'$  is accepted then  
      update the state of a walker  
    end if  
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  Compute  $E_L = \hat{H} \Psi_T(\mathbf{R}) / \Psi_T(\mathbf{R})$   
end for{walker}  
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```



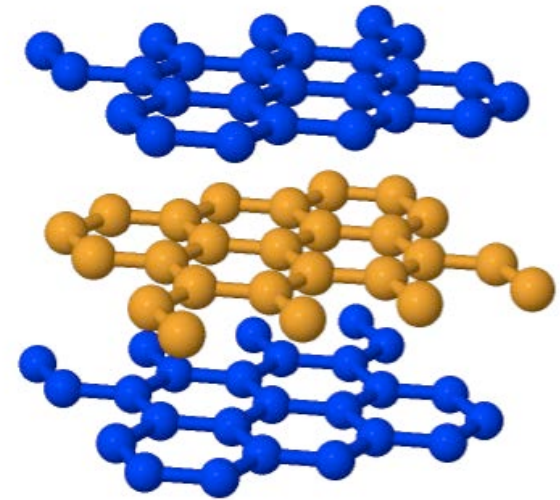
Loops

- Restructure the algorithm and data structure to expose & exploit parallelisms
multiple walkers per kernels
- Mixed precision sufficient for the target accuracy
- Higher-level implementation intact
- MPI for load balancing & reductions : sustain high parallel efficiency

Graphite Benchmark Problem

- DMC simulations of graphite
 - $N=256$ electrons (4x4x1, 64 carbons)
- **Efficiency = # of MC samples / sec**
 - Reflects node performance
- Walkers distributed over MPI
 - CPU: 4 MPI and 8 threads per node; each thread works on different walkers
 - GPU: 1 MPI per GPU; work on all the walkers concurrently

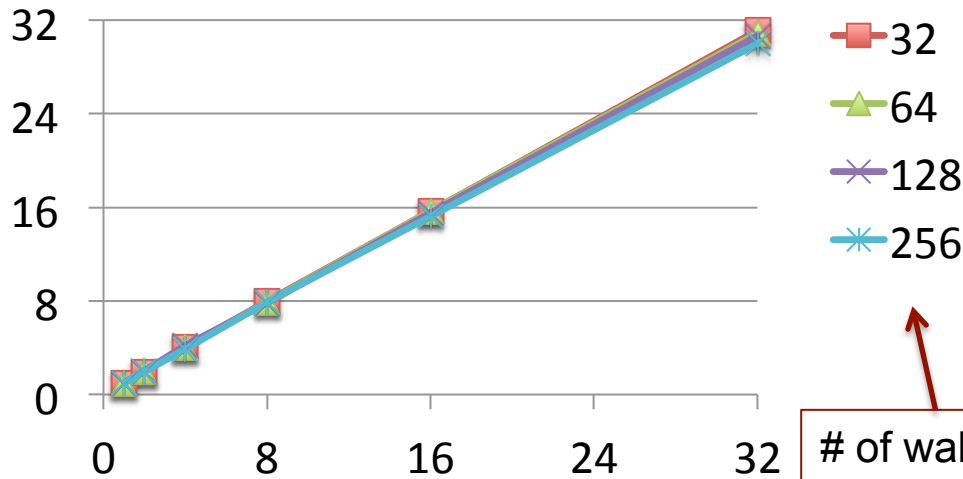
Graphite
using 24x24x4 k points



- Weak-scaling: fixed samples (works) per node per MC step
- Strong-scaling: fixed total samples per MC step
- Parallel efficiency of weak-scaling has to be perfect, unless the target samples are set to too low (unrealistic) or system problems (MPI,...)
- Node-to-node comparison of XK6 w or wo GPUs & XE6

Performance on Titandev@OLCF

Parallel efficiency of XK6 w GPU

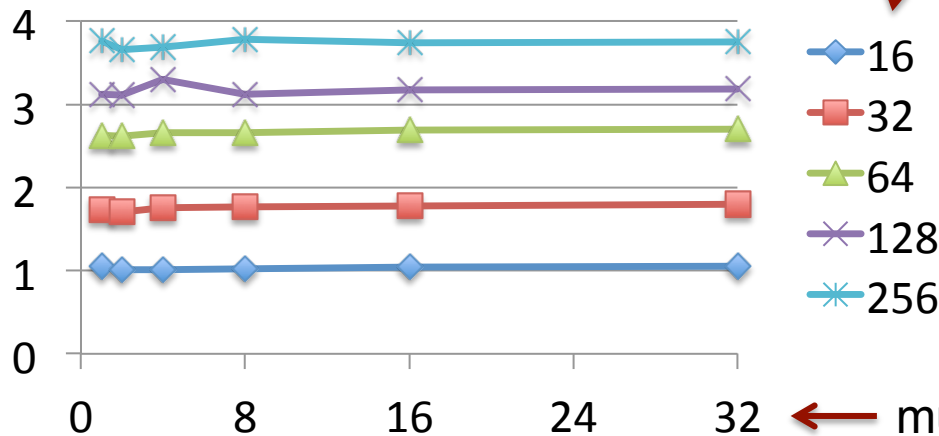


- Fix # of walkers per node = “average” work per node
- Time-to-solution decreases with increasing MPI nodes: **strong scaling in science**

- GPU Speedup compared to 4-walker per core runs on Titan

of walkers per GPU

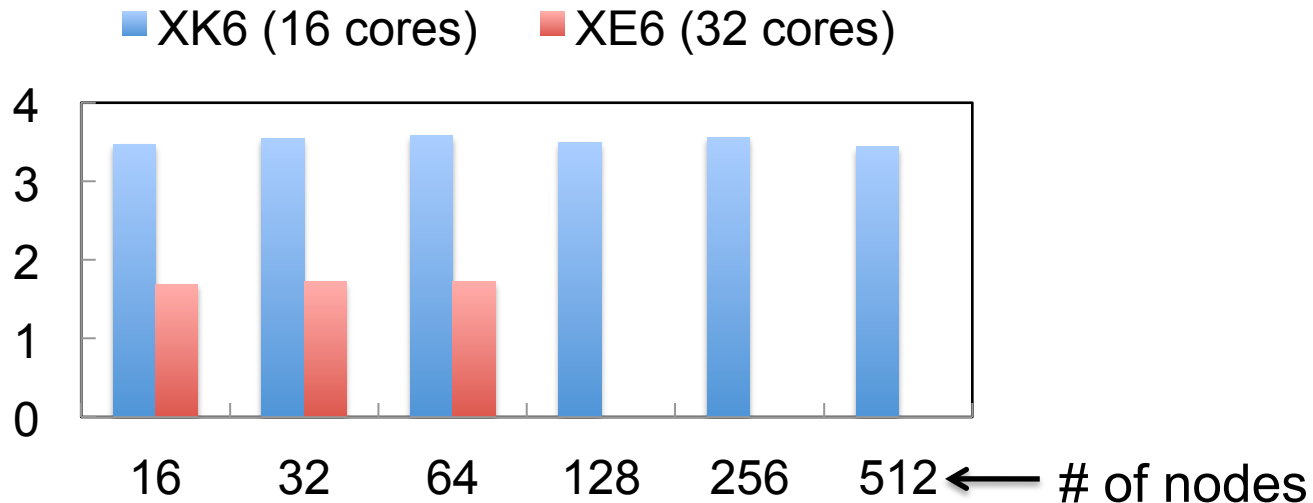
Speedup of GPU (node-to-node)



← multiples of 16 nodes

Comparisons of XK6 and XE6*

Speedup on XK6g over XK6c & XE6

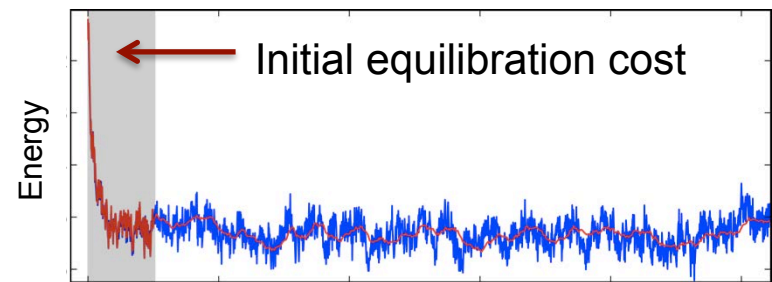
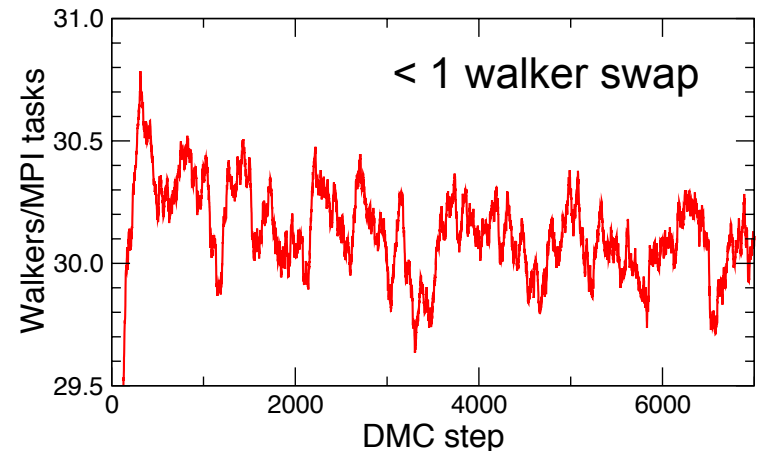
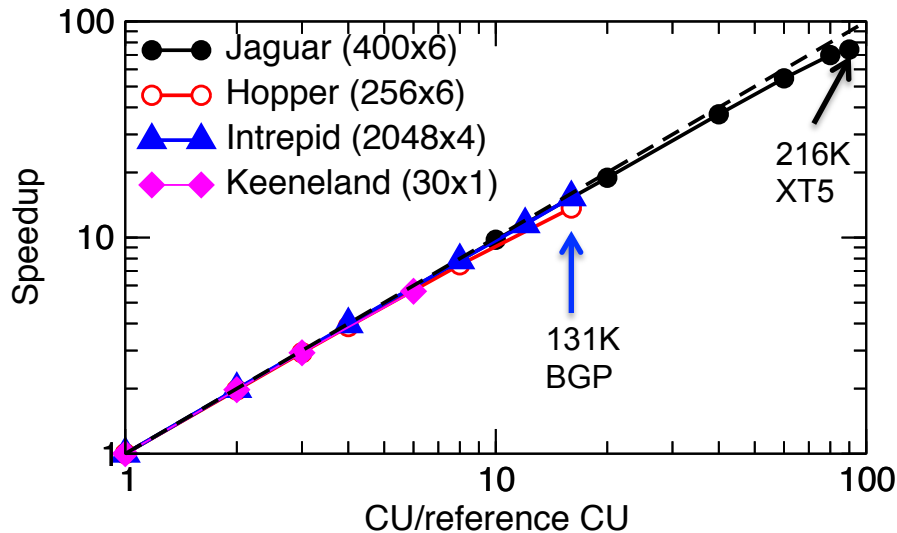


- The number of walkers per node is fixed at 128
[XK6g] 128 per GPU [XK6c] 8 per core [XE6] 4 per core
- CPU in double precision, GPU in mixed precision
- XK6g: optimal throughput with large systems, many walkers
- XK6c & XE6, insensitive to the number of walkers

*Titan/Titandev @OLCF and Monte Rosa @CSCS

Parallel Performance

- DMC scaling is almost perfect , $> 90\%$ efficiency
 - Limited by collectives for $E_T, N_p^w - \langle N^w \rangle$
- 1 MPI to 1 GPU or NUMA mapping
 - Large average number of walkers per MPI task, thus small fluctuations : easy to balance walkers per node



- (MPI x OpenMP) for the reference Compute Unit
- Keeneland@NICS, Fermi (3 cards per node)
- Strong scaling on CPUs; weak scaling on GPUs

Status Update on XK6

- Obtained the speedup as expected by the bandwidth and peak FLOPS of GPUs

More Accurate Answers, Faster Breakthrough QMC Simulations

- Works in progress
 - Maximize utilizations : asynchronous, non-blocking operations*
 - Launch several kernels in parallel
 - Fast atomics to communicate between blocks
 - Facilitated by newer GPUs and CUDA
 - Utilize CPU as well: potentially > 25% gains on XK6
 - Enable larger systems to be simulated: Use GPU peer-to-peer to allow distribution of read-only orbital dataset between GPUs on same node

*Cliff Woolley & Chris Cameron, NVIDIA

QMC on 10-100 PF

Better QMC simulations with more resources

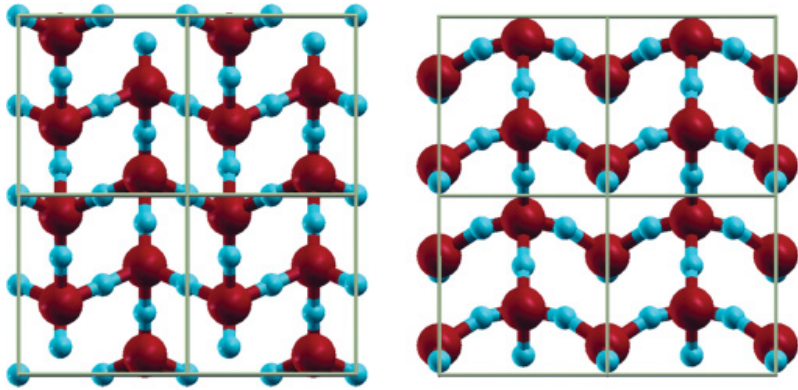
- Increase fidelity of QMC simulations: better Ψ_T
- Beyond ground-state simulations: excited states, finite temperatures
- Accelerate discovery

Materials Genome Initiative*

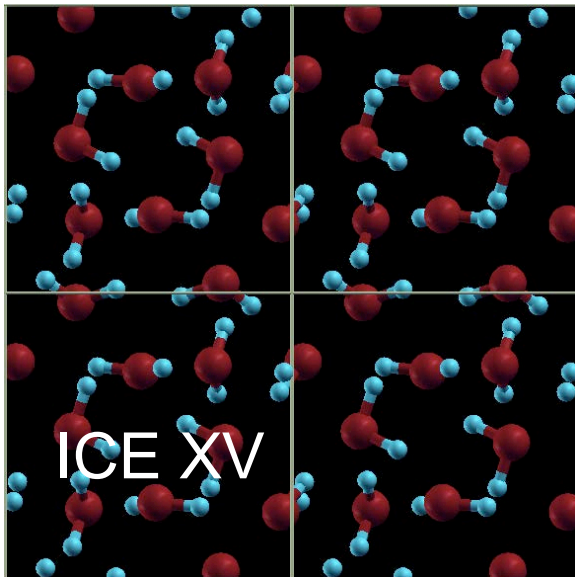
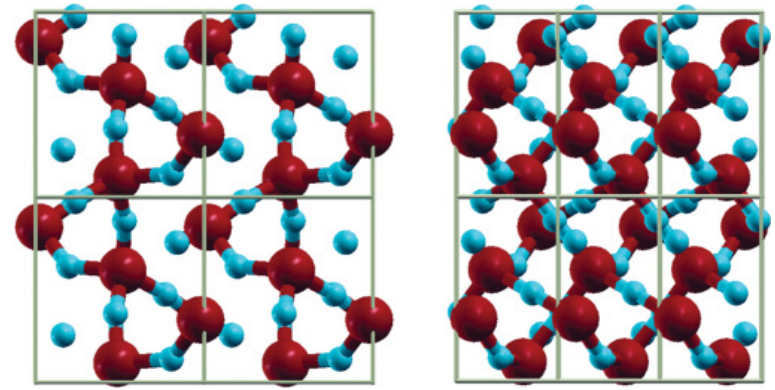
In the same way that the Human Genome Project accelerated a range of biological sciences by identifying and deciphering the basic building blocks of the human genetic code, the **Materials Genome Initiative** will **speed our understanding of the fundamentals of material science**, providing a wealth of practical information that entrepreneurs and innovators will be able to use to develop new products and processes.

High-pressure Phases of H₂O*

(a) 1 TPa

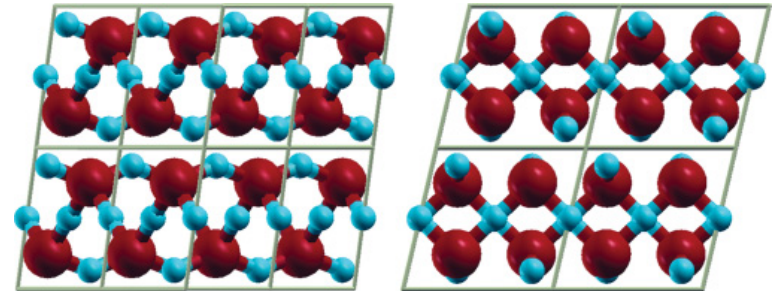


(b) 1.4 TPa



ICE XV:Salzmann et al, PRL (2009)

(c) 5 TPa



*Figures by J. M. McMahon,
Phys. Rev. B **84**, 220104(R) (2011)

Challenges

- New methods and algorithms

E.g., current algorithms and data structure on GPUs are not ideal for the fast algorithm for massive multi-determinant expansions

$$\sum_i^{M \rightarrow \infty} C_i D_i^\uparrow D_i^\downarrow \longleftarrow \text{10-100 times more expensive than } M=1$$

- New bottlenecks: e.g., general eigen-value solvers, I/O
- Deeper memory, communication and algorithmic hierarchy
- Mixed precisions: single to quad
- Exploit increase node performance & parallelism

Programming models and software environments for productivity: need portable and efficient solutions on multiple platforms, now and future

Conclusions

- QMC has kept up with the HPC evolution and will continue improving predictive powers in physics, materials and chemistry
 - ✓ Clusters of multi- and many-core SMP
 - ✓ Clusters of GPU
 - 😓 Clusters of hybrid
 - 😱 What is next
- More to be done improve science productivity
 - Reduce impacts of application-level, software and hardware faults: Algorithms for robust and fault-tolerant simulations
 - Faster off-node communication and I/O

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- ORNL-LDRD (DOE-BES/ASCR)

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 - Oak Ridge Leadership Computing Facility (OLCF)
 - Argonne Leadership Computing Facility (ALCF)
- NSF Teragrid facilities at NCSA, NICS, PSC and TACC
- National Energy Research Scientific Computing Center (NERSC)