Quadratic Monte Carlo to Understand Jupiter's Interior Structure and the Origin of Saturn's Ring



B. Militzer, W. B. Hubbard, J. Wisdom, R. Dbouk, UC Berkeley U Arizona MIT MIT F. Nimo, B. Downey, R. French UCSC UCSC Wellesley

Big Questions that my Group Helps Address

- 1. How did our solar system form?
- 2. What are giant planets made of?
- 3. How do material behave at high pressure?

Outline

- 1. Juno mission and Jupiter's **Dilute Core**
- 2. How did Saturn become the
 - Lord of the Rings?
- Quadratic Monte Carlo a generalpurpose sampling method

1. Juno Mission and Dilute Core

2. How did Saturn become the Lord of the Rings?

What is so Unusual About Planet Saturn?



3. Quadratic Monte Carlo Method







Affine Invariance MCMC by Goodman & Weare



Our Quadratic Monte Carlo Method Explained at http://militzer.berkeley.edu/QMC

```
// Set up nWalkers different states of type S
Array1 <S> s = SetUpNStates(nWalkers);
for(int iBlock=0; i<nBlocks; iBlock++) {</pre>
                                                 // loop over blocks
   for(int iStep=0; i<nStepsPerBlock; iStep++) { // loop over steps</pre>
      for(int i=0; i<nWalkers; i++) {</pre>
                                                 // try moving every walker once per step
         int j,k;
         SelectTwoOtherWalkersAtRandom(i,j,k);
         const double tj = -1.0;
         const double tk = +1.0;
         const double ti = SampleT(a); // sample t space
         const double tNew = SampleT(a); // sample t space one more time
         const double wi = LagrangeInterpolation(tNew,ti,tj,tk);

    New lines

         const double wj = LagrangeInterpolation(tNew,tj,tk,ti);
         const double wk = LagrangeInterpolation(tNew,tk,ti,tj);
         S sNew = s[0]; // Create new state by coping over an existing one.
         for(int d=0; d<nDim; d++) {</pre>
            sNew[d] = wi*s[i][d] + wj*s[j][d]+ wk*s[k][d]; // set nDim parameters of new state
         }
                                             // check if state sNew is valid before calling Evaluate()
         if (sNew.Valid()) {
            sNew.Evaluate();
                                             // Sets the energy sNew.y which defines the state's probability = exp(-y/temp)
            double dy = <u>sNew.y</u> - <u>s[i].y</u>; // difference in energy between new and old state
            double prob = pow(fabs(wi),nDim) * exp(-dy/temp); // Note |wi|^nDim and Boltzmann factors
            bool accept = (prob>Random());
                                             \checkmark Random() returns a single random number between 0 and 1.
                                                   Prefactor requires discussion
            if (accept) {
               for(int d=0; d<nDim; d++) {</pre>
                  s[i][d] = sNew[d]; // copy over state sNew
               }
               s[i].y = sNew.y;
                                     // copy also its energy
         }
      } // look over all walkers
      ComputeDifferentEnsembleAverages(s);
        // end of loop over steps
   PrintEndOfBlockStatement();
        // end of loop over blocks
PrintEndOfRunStatement();
```

Sampling Details and Prefactors

Affine moves, type 1	Affine moves, type 2	Quadratic moves
$ec{r_i'} = ec{r_j} + \lambda (ec{r_i} - ec{r_j})$	$ec{r}_i'=ec{r}_j+\lambda(ec{r}_i-ec{r}_j)$	$ec{r_i'} = w_i ec{r_i} + w_j ec{r_j} + w_k ec{r_k}$
$egin{aligned} T_1(\lambda) &= rac{1}{\lambda} T_1(rac{1}{\lambda}) \ T_1(\lambda) \propto rac{1}{\sqrt{\lambda}} ext{ if } \lambda \in \left[rac{1}{ ext{a}}, ext{a} ight] \end{aligned}$	$T_2(\lambda) = \frac{a}{a^2 - 1} = \text{const}$	$w_i = L(t'_i; t_i, t_j, t_k), \ w_j = L(t'_i; t_j, t_k, t_i), \ w_k = L(t'_i; t_k, t_i, t_j), \ L(x; x_0, x_1, x_2) \equiv rac{x - x_1}{x_0 - x_1} rac{x - x_2}{x_0 - x_2}$
$\alpha = N - 1$	$\alpha=N-2$	t_i and t'_i from the same distribution $\mathcal{P}(t)$
$A(\vec{r_i} ightarrow \vec{r'_i}) = \min$	$\left[1,rac{\pi(ec{r_i'})}{\pi(ec{r_i})}\lambda^lpha ight]$	$A(\vec{r_i} ightarrow \vec{r'_i}) = \min\left[1, rac{\pi(\vec{r'_i})}{\pi(\vec{r_i})} w_i ^N ight]$
		BM, Astrophys. J. 953 (2023) 111

In Our Derivation of Prefactors, we follow Green and Mira

Regular detailed balance between two states $\pi(\vec{r})P(\vec{r} \rightarrow \vec{r'}) = \pi(\vec{r'})P(\vec{r} \rightarrow \vec{r'})$

Green & Mira (2001) who formulated a generatized condition

$$\int \pi(d\vec{r}) P(\vec{r} \to d\vec{r'}) = \int \pi(d\vec{r'}) P(\vec{r'} \to d\vec{r'})$$

The notation $\int \pi(d\vec{r})$ refers to the integral,

$$\int \dots \pi(d\vec{r}) \equiv \int \dots p(\vec{r}) d\vec{r}$$
 ,

Green & Mira (2001) showed that the acceptance probability for a move from \vec{r} to $\vec{r'}$ is given by,

$$A(\vec{r} \to \vec{r'}) = \min\left\{1, \frac{\pi(\vec{r'})T'(\vec{\lambda}')}{\pi(\vec{r'})T(\vec{\lambda})} \left| \frac{\partial(\vec{r'}, \vec{\lambda}')}{\partial(\vec{r}, \vec{\lambda})} \right|\right\} \quad , \tag{A4}$$

Jacobian determinant for the transformation from $(\vec{r}, \vec{\lambda})$ to $(\vec{r'}, \vec{\lambda'})$

In Our Derivation of Prefactors, we follow Green and Mira

$$\frac{\partial \lambda_1'}{\partial \lambda_1} = 0 \quad , \quad \frac{\partial \lambda_2'}{\partial \lambda_2} = 0 \quad , \quad \frac{\partial \lambda_1'}{\partial \lambda_2} = 1 \quad \text{and} \quad \frac{\partial \lambda_2'}{\partial \lambda_1} = 1$$

The Jacobian becomes a (N+2, N+2) matrix:

$$J = \frac{\partial(\vec{r}'_i, \lambda'_1, \lambda'_2)}{\partial(\vec{r}_i, \lambda_1, \lambda_2)} = \begin{pmatrix} \frac{\partial r'_{ib}}{\partial r_{ia}} = w_i \delta_{ab} & \frac{\partial r'_{ib}}{\partial \lambda_1} & \frac{\partial r'_{ib}}{\partial \lambda_2} \\ \frac{\partial \lambda'_1}{\partial r_{ia}} = \frac{\partial \lambda_2}{\partial r_{ia}} & \frac{\partial \lambda'_1}{\partial \lambda_1} = 0 & \frac{\partial \lambda'_1}{\partial \lambda_2} = 1 \\ \frac{\partial \lambda_2}{\partial r_{ia}} = \frac{\partial \lambda_1}{\partial r_{ia}} & \frac{\partial \lambda'_2}{\partial \lambda_1} = 1 & \frac{\partial \lambda'_2}{\partial \lambda_2} = 0 \end{pmatrix} \quad ,$$

and its determinant is given by a sum over permutations, σ_k ,

$$|J| = \sum_{\sigma_1 \cdots \sigma_N} \prod_{k=1}^N \frac{\partial r'_{i,\sigma_k}}{\partial \lambda_2} \frac{\partial \lambda_2}{\partial r_{i,k}} + \prod_{k=1}^N \frac{\partial r'_{i,\sigma_k}}{\partial \lambda_1} \frac{\partial \lambda_1}{\partial r_{i,k}} - \prod_{k=1}^N w_i \delta_{k,\sigma_k} = \sum_{\sigma_1 \cdots \sigma_N} \prod_{k=1}^N w_i \delta_{k,\sigma_k} = w_i^N$$

Our Quadratic Monte Carlo is more Efficient Than The Affine Invariant Sampler (emcee) that Moves Linearly



Our Test Case: A Ring Potential



Two Performance Criteria: Autocorrelation & Travel Time



Comparison: QMC vs Affine Invariant Method



Comparison: QMC vs Affine Invariance Method



Our Modified Walk moves



Our Modified Walk moves: Just Add a Scaling Factor

We follow Goodman & Weare (2010) in computing the average location all walkers in the subset,

$$\langle ec{r}
angle = rac{1}{N_S} \sum_{j \in S} ec{r}_j$$

but we then modify their formula for computing the step size, W, by introducing a scaling factor a:

$$W = a \sum_{j \in S} Z_j \left(\vec{r_j} - \langle \vec{r} \rangle
ight)$$

 Z_i are univariate standard normal random numbers. By setting a = 1, one obtains the original walk moves,

Modified "walk" moves also perform very well.



Dilute core model T_{1bar}=166.1 K but EOS change by -3%

Dilute core model T_{1bar}=170 K

Our five-layer refence model with a dilute core T_{1bar}=166.1 K











How does a 3% density reduction change Z₁?



Conclusions for MC Methods

- Quadratic Monte Carlo a generalpurpose sampling method
- We recommend using a modest number of walkers only, between 2×D and 3×D
- We modified the walk moves by adding a scaling factor. There is no universal scaling factor that works for all applications.