# ALGORITHMIC PERSPECTIVE ON STRONGLY CORRELATED SYSTEMS 

Last Time: Your first QMC code.
But... we made assumptions that everything was positive.

Q: What do we do when these assumptions are not correct.

Guess a wave-function, compute it's properties.
Once we have a wave-function, we need to 'simply' compute the following integrals.

$$
\begin{aligned}
E & =\frac{\int\left|\Psi\left(r_{1}, r_{2}, . . r_{n}\right)\right|^{2} \frac{[H \Psi](R)}{\Psi(R)} d R}{\int\left|\Psi\left(r_{1}, r_{2}, . . r_{n}\right)\right|^{2} d R} \\
O & =\frac{\int\left|\Psi\left(r_{1}, r_{2}, . . r_{n}\right)\right|^{2} O(R)}{\int\left|\Psi\left(r_{1}, r_{2}, . . r_{n}\right)\right|^{2} d R}
\end{aligned}
$$

We want to compute some property and we have the vector or function.

$$
\langle O\rangle=\int \frac{|\Psi(R)|^{2} O(R) d R}{|\Psi(R)|^{2} d R}
$$

How do we do it?

## Integrate by grid



8 bars


91 bars

L points per dimension - grid cube size $h=1 / L$
error: $h^{2}$ for trapezoid rule
time: $L^{D}$
time for fixed error: $\epsilon^{-D / 2}$

Even if we have the function (vector) this is not helpful.

## (Improved) Integration by Grid

Trapezoid Rule: $\epsilon \sim f^{(2)}(x) h^{2}$
Simpson's Rule: $\epsilon \sim f^{(4)}(x) h^{4}$
... Rule: $\epsilon \sim f^{(\alpha)}(x) h^{\alpha}$

Total Time: $T \sim \epsilon^{-D / \alpha}$

Instead of doing integration exactly, we should use Monte Carlo!


Probability: $|\Psi(R)|^{2}$

## Stochastic Integration

Sample x with probability $p(x)$ to compute $\frac{\int p(x) f(x) d x}{\int p(x) d x}$
$p(x)$ need not be normalized
time for fixed error: $\epsilon^{-2}$

10 times the error bar (one decimal point) => 100 times the work

But still wins for D>4 (trapezoid rule)

$$
D>2 \alpha \text { (generally) }
$$

(We're hiding a variance)

## The Best of the 20th Century: Editors Name Top 10 Algorithms

1946: John von Neumann, Stan Ulam, and Nick Metropolis, all at the Los Alamos Scientific Laboratory, cook up the Metropolis algorithm, also known as the Monte Carlo method.

Equation of State Calculations by Fast Computing Machines
Nicholas Metropolis, Arianna W. Rosenbluth, Marsilall n. Rosenbluth, and Augusta h. Teller, Les Alamas Scientific Laboratory, Los Alamos, Nevo Mexico

AND
Edward Teller,* Depariment of Physics, University of Chicago, Chicago, Illinois
(Received March 6, 1953)


#### Abstract

A general method, suitable for fast computing machines, for investigating such properties as equations of state for substances consisting of interacting individual molecules is described. The method consists of a modified Monte Cario integration over configuration space. Results for the two-dimensional rigid-sphere system have been obtained on the Los Alamos MANIAC and are presented here. These results are compared to the free volume equation of state and to a four-term virial coefficient expansion.


## I. INTRODUCTION

THE purpose of this paper is to describe a general method, suitable for fast electronic computing machines, of calculating the properties of any substance which may be considered as composed of interacting individual molecules. Classical statistics is assumed, only two-body forces are considered, and the potential field of a molecule is assumed spherically symmetric. These are the usual assumptions made in theories of liquids. Subject to the above assumptions, the method in not restricted to any range of temperature or density. This paper will also present results of a preliminary twodimensional calculation for the rigid-sphere system. Work on the two-dimensional case with a LennardJones potential is in progress and will be reported in a later paper. Also, the problem in three dimensions is being investigated.

[^0]II. THE GENERAL METHOD FOR AN ARBITRARY POTENTIAL BETWEEN THE PARTICLES

In order to reduce the problem to a feasible size for numerical work, we can, of course, consider only a finite number of particles. This number $N$ may be as high as several hundred. Our system consists of a squaret containing $N$ particles. In order to minimize the surface effects we suppose the complete substance to be periodic, consisting of many such squares, each square containing $N$ particles in the same configuration. Thus we define $\boldsymbol{d}_{A B}$, the minimum distance between particles $A$ and $B$, as the shortest distance between $A$ and any of the particles $B$, of which there is one in each of the squares which comprise the complete substance. If we have a potential which falls off rapidly with distance, there will be at most one of the distances $A B$ which can make a substantial contribution; hence we need consider only the minimum distance $d_{A B}$.
$\dagger$ We will use the two-dimensional nomenclature here since it is easier to visualize. The extension to three dimensions is obvious.

## A simple goal: sample a probability distribution $\pi(R)$

Markov Chain A graph with (directed) edges and probability to move between them.


Q: Suppose I walk around this graph.
After 1000 steps, what is the probability I am on a red node?

After 5000 steps, what is the probability I am on a red node?

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Q: Suppose I walk around this graph.


After 1000 steps, what is the probability I am on a red node?

After 5000 steps, what is the probability I am on a red node?
$\pi(2)=\pi(1) P[1 \rightarrow 2]+\pi(2) P[2 \rightarrow 2]$
$\pi(1)=\pi(1) P[1 \rightarrow 1]+\pi(2) P[2 \rightarrow 1]$

Stationary State: Marbles in = Marbles out

$$
\begin{aligned}
& \pi(2)=\pi(1) P[1 \rightarrow 2]+\pi(2) P[2 \rightarrow 2] \\
& \pi(1)=\pi(1) P[1 \rightarrow 1]+\pi(2) P[2 \rightarrow 1] \\
& \pi_{j}=\sum_{i} P_{j i} \pi_{i}
\end{aligned}
$$

Q: Is their a fixed point?

Q: How many fixed points?

Q: Do you approach a fixed point?

$$
\begin{aligned}
& \pi(2)=\pi(1) P[1 \rightarrow 2]+\pi(2) P[2 \rightarrow 2] \\
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$$

Q: Is their a fixed point?

Q: How many fixed points?

Q: Do you approach a fixed point?

This is matrix multiplication

Consider the eigenvectors of $P$

$$
v P=\epsilon v P
$$

Suppose you are in an eigenvector of $\mathbf{P}$ with $|\epsilon|<1$

Suppose instead you are in an eigenvector of $\mathbf{P}$ with $|\epsilon|=1$

How many of those can there be?

Suppose you start somewhere else?

$$
\begin{aligned}
& \pi(2)=\pi(1) P[1 \rightarrow 2]+\pi(2) P[2 \rightarrow 2] \\
& \pi(1)=\pi(1) P[1 \rightarrow 1]+\pi(2) P[2 \rightarrow 1] \\
& \pi_{j}=\sum_{i} P_{j i} \pi_{i}
\end{aligned}
$$

## This is matrix multiplication



Q: Is their a fixed point?
yes
Q: How many fixed points?
1 (usually)

Q: Do you approach a fixed point? yes

Q: What's going on with molecular dynamics?

Q: What about if I only walk right?

## Eigenvalues

$$
\begin{aligned}
P^{n} v & =P^{n}\left[\alpha_{0} v_{0}+\alpha_{1} v_{1}+\alpha_{2} v_{2}+\ldots\right] \\
& =\left[\epsilon_{0}^{n} \alpha_{0} v_{0}+\epsilon_{1}^{n} \alpha_{1} v_{1}+\epsilon_{2}^{n} \alpha_{2} v_{2}+\ldots\right]
\end{aligned}
$$

(WLOG, order by size of eigenvalues)
If $v$ is a probability distribution:
No term can go negative.
The state has to stay normalized
If vo has negative terms in it, eventually that term will dominate and go negative.
If it has all positive terms and $\left|\epsilon_{0}\right|>1$ eventually it will not be normalized

## Eigenvalues

$$
\begin{aligned}
P^{n} v & =P^{n}\left[\alpha_{0} v_{0}+\alpha_{1} v_{1}+\alpha_{2} v_{2}+\ldots\right] \\
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\end{aligned}
$$

(WLOG, order by size of eigenvalues)
If $v$ is a probability distribution:
No term can go negative.
The state has to stay normalized
|f $\left|\epsilon_{0}\right|<1$ eventually the state will be 0 and not normalized

## Eigenvalues

$$
\begin{aligned}
P^{n} v & =P^{n}\left[\alpha_{0} v_{0}+\alpha_{1} v_{1}+\alpha_{2} v_{2}+\ldots\right] \\
& =\left[\epsilon_{0}^{n} \alpha_{0} v_{0}+\epsilon_{1}^{n} \alpha_{1} v_{1}+\epsilon_{2}^{n} \alpha_{2} v_{2}+\ldots\right]
\end{aligned}
$$

(WLOG, order by size of eigenvalues)
If $v$ is a probability distribution:
No term can go negative.
The state has to stay normalized

If $\epsilon_{0} \neq 1$ you have a limit cycle. Choose uniform superposition over cycle.

## Eigenvalues

$$
\begin{aligned}
P^{n} v & =P^{n}\left[\alpha_{0} v_{0}+\alpha_{1} v_{1}+\alpha_{2} v_{2}+\ldots\right] \\
& =\left[\epsilon_{0}^{n} \alpha_{0} v_{0}+\epsilon_{1}^{n} \alpha_{1} v_{1}+\epsilon_{2}^{n} \alpha_{2} v_{2}+\ldots\right]
\end{aligned}
$$

(WLOG, order by size of eigenvalues)
If $v$ is a probability distribution:
No term can go negative.
The state has to stay normalized

Suppose there are two stationary states...

Q: How do we set up a Markov chain with a particular distribution?

A: Metropolis

Q: Why does this work?

## Metropolis

## Starting at node i

Pick a node $\mathbf{j}$ with probability $\mathrm{T}(\mathrm{i}, \mathrm{j})$
Move to j with probability

$$
\min \left(1, \frac{\pi(j)}{\pi(i)} \frac{T(j \rightarrow i)}{T(i \rightarrow j)}\right)
$$

Q: How do we set up a Markov chain with a particular distribution?

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## Metropolis

## Starting at node i

Pick a node $\mathbf{j}$ with probability $\mathbf{T}(\mathbf{i}, \mathrm{j})$
Move to j with probability

$$
\min \left(1, \frac{\pi(j)}{\pi(i)} \frac{T(j \rightarrow i)}{T(i \rightarrow j)}\right)
$$

Q: Why does this work?

$$
\begin{aligned}
& P(i \rightarrow j)=T(i \rightarrow j) \min \left(1, \frac{\pi(j)}{\pi(i)} \frac{T(j \rightarrow i)}{T(i \rightarrow j)}\right) \\
& P(j \rightarrow i)=T(j \rightarrow i) \min \left(1, \frac{\pi(i)}{\pi(j)} \frac{T(i \rightarrow j)}{T(j \rightarrow i)}\right)
\end{aligned}
$$

## Examples:

* Uniform hopping on a line
* Uniform hopping on a hypercube
* Greater probability on one node
* Moving right more then left (how about always moving left?)
* Metropolis with a barrier (how to fix?)


## Some intuition...

$\pi[1]=0.25 \quad \pi[2]=0.25$

$$
T[2 \rightarrow 1]=0.1 \quad T[3 \rightarrow 2]=0.1
$$

$$
T[4 \rightarrow 3]=0.1
$$

$T[1 \rightarrow 2]=0.9$
$T[2 \rightarrow 3]=0.9$
$T[3 \rightarrow 4]=0.9$

Q: Why doesn't it flow away?
Q: What's the probability to go right?

$$
\begin{aligned}
& P(1 \rightarrow 2)=T(1 \rightarrow 2) \min \left(1, \frac{\pi(2)}{\pi(1)} \frac{T(2 \rightarrow 1)}{T(1 \rightarrow 2)}\right) \\
& P(1 \rightarrow 2)=0.9 \min \left(1,1 \frac{0.1}{0.9}\right)=0.1 \\
& P(2 \rightarrow 1)=T(2 \rightarrow 1) \min \left(1, \frac{\pi(1)}{\pi(2)} \frac{T(1 \rightarrow 2)}{T(2 \rightarrow 1)}\right) \\
& P(2 \rightarrow 1)=0.1 \min \left(1,1.0 \frac{0.9}{0.1}\right)=0.1
\end{aligned}
$$

A comment about mixing times...

The variational principle

$$
\begin{aligned}
& E\left[\Psi\left(r_{1}, r_{2}, \ldots r_{n}\right)\right] \geq E_{0} \\
& E\left[\Psi_{0}\left(r_{1}, r_{2}, \ldots r_{n}\right)\right]=E_{0}
\end{aligned}
$$

Let's just guess the ground state.

More refined: Let's guess many states and assume the one with the lowest energy is the best guess.

## Important steps:

1. How to compute energy?
2. What wave-functions?
3. How to optimize?

## Variational Monte Carlo



> Measure: $$
\frac{H \Psi(R)}{\Psi(R)}
$$


[^0]:    - Now at the Radiation Laboratory of the University of California, Livermore, California.

