Monte Carlo Simulation of a Lennard Jones Fluid

CHEM 280: Foundations of Programming and Software Engineering for Molecular Science

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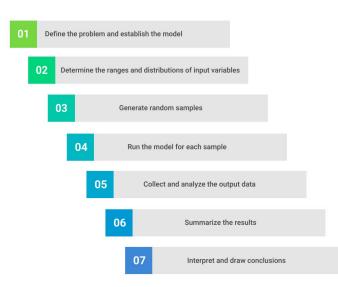
Molecular Simulations

Casey Tomlin

Monte Carlo Simulations

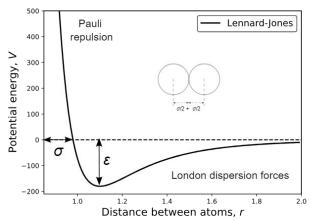
- Mathematical technique used to estimate the possible outcomes of an uncertain event
- Created by John von Neumann and Stanislaw Ulam during
 WWII
- Probe possible solutions to a problem defined with some element of randomness
 - Models a normal distribution for each variable
 - Obtains results and runs again
 - Each run uses a new set of random variables
- As more simulations are added, accuracy tends to increase

How a Monte Carlo Simulation Works

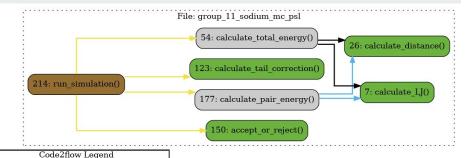


Lennard Jones Equation (12-6) $V(r) = 4arepsilon \left[\left(rac{\sigma}{r} ight)^{12} - \left(rac{\sigma}{r} ight)^{6} ight]$

- Arguably the most widely-used pair potential in molecular simulations
- Models the pairwise interaction energy of two noble gas particles
- Reduced Units:
 - \circ $\varepsilon = 1$ (depth of energy well, kJ/mol) and $\sigma = 1$ (van der Waals radius, Å)
 - o r = distance between the two particles
 - o Lennard Jones fluid possess near universal behavior with reduced units
 - Limits the range of influence of particles
- r⁻¹² term approximates the strong Pauli repulsion
- r⁻⁶ term approximates the weaker attractive forces from locally induced dipoles



Implementation to Code



Regular function
Trunk function (nothing calls this)
Leaf function (this calls nothing else)
Function call

- Utilized data from NIST (National Institutes of Standards and Technology)
 - 3D coordinates of 800 particles
- Coordinates input to several functions:
 - Distance = returns distance between coordinates
 - Total Energy = returns the Lennard Jones energy of a system of particles
 - Pairwise Energy = returns the interaction energy of a particle with its environment
- Implementing a cutoff
 - Calculating tail correction accounts for this loss
- Monte Carlo Simulation of Lennard Jones Energy
 - Pick random particle
 - Interaction energy with system (current)
 - Displace particle randomly
 - Interaction energy with system (proposed)
 - Accept or reject proposed changes to particle
 - Print results

Programming

Luis Hernandez

Python vs C++

- Advantages/Disadvantages
- Performance
- Ease of Use
- Suitability for Projects

Interpreted VS. Compiled

Interpreted

- Python, JavaScript, Ruby, Perl, and PHP
- Code is translated to machine code at run-time
- Tend to be slower due to translation at run-time
- Debugging occurs at run-time so can be easier
- Easier for beginners
- More portable since it does not provide machine code

Compiled

- C, C++, Erlang, Haskell, Rust, and Go
- Code is compiled to machine code before execution
- Tend to be faster and more efficient since the machine code has already been compiled
- Code can fail compilation if errors are present
- Better for performance and memory management

Python VS. C++

Python

- Easier to code
- Typically fewer lines of code
- Dynamically typed
- Rapid development and deployment
- Automatic memory management
- Uses
 - Web development
 - Data Analysis
 - Machine learning

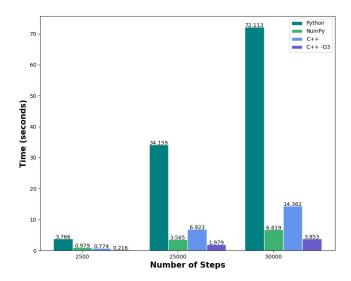
C++

- Typically more lines of code
- Variable type must be stated
- Must be compiled before execution
- Manual memory management
 - o Increased control, but error prone
- Uses
 - Game Development
 - High Performance Computing
 - Embedded Systems

Best VS. Bestest Language

Implementations Evaluated

- Python Standard Library
- NumPy
- C++
 - o Optimization flag -O0
 - o Optimization flag -O3



Best VS. Bestest Language - Programming Ease

```
import math
import random
import numpy as np

> def calculate_distance(coord1, coord2, box_length=None): ...

> def calculate_LJ(r_ij): ...

> def calculate_total_energy(coordinates, box_length, cutoff): ...

> def read_xyz(filepath): ...

> def calculate_tail_correction(n_particles, box_length, cutoff): ...

> def accept_or_reject(delta_e, beta): ...

> def calculate_pair_energy(coordinates, i_particle, box_length, cutoff): ...

# create a function called run_simulation that takes in simulation parameters and
> def run_simulation(coordinates, box_length, cutoff, reduced_temperature, num_steps
```

```
#include <iostream>
#include <cmath>
#include <random> // From random number generator
#include <chrono> // From random_number_generator for generating random seeds
#include <fstream> // From read xyz, for reading and writing files
#include <vector> // From read xyz, for std::vector
#include <utility> // From read xvz. for std::pair
// Make some types more convenient
typedef std::array<double, 3> AtomCoord; // From read xyz
typedef std::vector<AtomCoord> Coordinates; // From read xyz
std::default random engine re: // A Global! Probably shouldn't be used in real code - for Random Number Generator
std::pair<Coordinates, double> read xyz(std::string file path); // From read xyz
double calculate LJ(double r ij);
bool accept_or_reject(double delta_e, double beta);
double random double(double lower bound, double upper bound):
int random integer(int lower bound, int upper bound);
double calculate tail correction(int n particles, double box length, double cutoff);
double calculate pair energy(const Coordinates & coordinates, int i particle, double box length, double cutoff);
double calculate distance(const AtomCoord & coord1, const AtomCoord & coord2, double box length);
double calculate total energy(const Coordinates & coordinates, double box length, double cutoff):
std::pair<std::vector<double>, std::vector<double> > run simulation(Coordinates coordinates, double box length, do
```

Best VS. Bestest Language - Rewriting

- Coding .cpp from .py (PSL) was tedious, but straightforward
 - Significant boost in performance by using optimization flag -O3
- Rewriting PSL version to NumPy version was not initially straightforward
 - Once we had a better understanding of NumPy, it was much easier to program to gain significant performance improvement and complete the rewrites of the functions
 - Using NumPy:
 - Creating Arrays np.array()
 - Manipulating Arrays: np.delete(), np.concatenate(), slicing
 - Rapid Calculations
- In this case, the ease of writing and large gain in improvement using NumPy provided the most satisfaction

Best VS. Bestest Language - Conclusion

- The Bestest Language is determined by the use case
- Python programming
 - Rapid development and deployment
 - Great for beginners
 - Ease of use is more important than performance
- C++ programming
 - Use for complex deployments
 - Use when performance is most important

Software Engineering

Thomas Janas

Software Testing

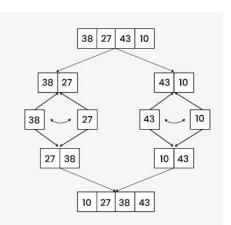
- Debugging
- Assert functions
- Printing variables
- Unit tests
 - "Sanity Checks"
 - Jupyter Notebook
 - Significant ease of producing and testing python code in real-time

Performance Improvements

- Switching from Python to NumPy or C++
- Instead of calculating the total energy for particles after a movement, we check for the differences associated with the moved particle
- Altering Python arrays in NumPy arrays for the calculate_LJ and calculate_distance functions
- Utilizing the optimization flag O-3, which optimizes the compiling to improve execution performance

Team Workflow

Divide and Conquer



Individual level

- Drafting code
- Testing
- Debugging

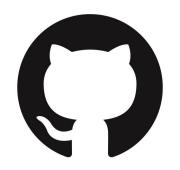
Group level

- Code review
- Task balancing
- Group brainstorming
- Git/Github code management

Benefits

- Allows for quick solutions to be developed
 - Ensures code is descriptive
 - Code is built to be understandable
 - Allows coding tasks to be transferable

Git/GitHub - Useful tools for collaboration



Likes

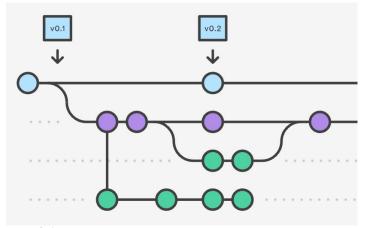
- Great online visualization for organizing files
- Provides all of the benefits of version control
- Allows teammates to pull branches and test code on their machines

Significantly helped with tracking changes and managing project

Dislikes

- Unique set of commands that are not entirely straightforward as a beginner
- Different operating systems and coding environments create frequent problems for beginners

Version Control



Definition: Method for tracking changes in code.

- Retains older code structures that was previously working
 - Allows for rollback of a current version to a previous version of code
- Allows changes to code without altering a current version that is being used by others
- Useful for managing a software project with a team
 - Delegated tasks can be tracked by users for progress
 - Any code changes which crashes a program can be directly sourced with proper management

Bibliography

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