Exercise class 1

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General information

First part:

- Discussion of the previous exercise
- Additional information about the new exercise

Second part:

- You work on the tasks
- You can ask questions

General information

- Default programming language: Julia
- You are free to use your favorite language
- Hand-in is voluntary

The procedure for handing in your results (if you want to do so) is:

- 1. Create a new directory named in the format exXX_lastname_firstname (XX is the corresponding exercise sheet number).
- 2. Copy the solution files into this directory. The files should be formatted in a readable way. Make sure that you include both the *source code* (e.g. *.jl) as well as a *scientific report* in pdf-format that includes a list of used parameters, the plots you produced (with these parameters) and additional comments/explanations.
- 3. Zip the directory and send it to holstm@phys.ethz.ch.

Hand-ins that do not follow this guidline will not be accepted! Please do not hand in files that do not need to be corrected!

It solves the tradeoff: fast coding vs. fast execution

- Code like in python
- Execution nearly as fast as C

Installing Julia

https://julialang.org



Julia in a Nutshell

Julia is fast!

Julia was designed from the beginning for high performance. Julia programs compile to efficient native code for multiple platforms via LLVM.

General

Julia uses multiple dispatch as a paradigm, making it easy to express many object-oriented and functional programming patterns. It provides asynchronous I/O, debugging, logging, profiling, a package manager, and more.

Dynamic

Julia is dynamically-typed, feels like a scripting language, and has good support for interactive use.

Easy to use

Julia has high level syntax, making it an accessible language for programmers from any background or experience level. Browse the Julia microbenchmarks to get a feel for the language.

Optionally typed

Julia has a rich language of descriptive datatypes, and type declarations can be used to clarify and solidify programs.

Open source

Julia is provided under the MIT license, free for everyone to use. All source code is publicly viewable on GitHub.

Installing Julia

Download Julia

If you like Julia, please consider starring us on GitHub and spreading the word!

We provide several ways for you to run Julia:

- In the terminal using the built-in Julia command line using the binaries provided below.
- Using Docker images from Docker Hub maintained by the Docker Community.
- JuliaPro by Julia Computing includes Julia and the Juno IDE, along with access to a curated set of packages for plotting, optimization, machine learning, databases and much more (requires registration).

Please see platform specific instructions for further installation instructions and if you have trouble installing Julia. If the provided download files do not work for you, please file an issue in the Julia project. Different OSes and architectures have varying tiers of support, and are listed at the bottom of this page.

Current stable release: v1.3.1 (Dec 30, 2019)

Checksums for this release are available in both MD5 and SHA256 formats.

Windows (.exe) [heip]	32-bit		64-bit	
macOS 10.8+ (.dmg) [help]			64-bit	
Generic Linux Binaries for x86 [help]	32-bit (GPG)		84-bit (GPG)	
Generic Linux Binaries for ARM [help]	32-bit (ARMv7-a hard float) (GPG)		84-bit (AArch64) (GPG)	
Generic FreeBSD Binaries for x86 [help]			84-bit (GPG)	
Source	Tarball (GPG)	Tarball with dependencies (GPG) GitHub		GitHub

Run Julia

• In console:

julia code... exit()

- julia myscript.jl
- Juno, Jupiter,...

Installing packages

Install package:

julia> using Pkg; Pkg.add("myPkg")

Include package:

julia> using myPkg

julia> import myPkg

julia> myPkg.function(x)

Plotting





Arrays

Empty:a = []Zeros:zeros(3)Ones:ones(3,2)Column[1, 2, 3]vector:vector:

Row [1 2 3] vector:

a[1] index counting starts from 1!a[from:step:to]a[from:to]

Arrays

N-dimensional array:

•
$$A = [[1, 2, 3,] [4, 5, 6]]$$
 A[row, col
• $A = [1 4; 2 5; 3 6]$ A[4] → 4

Array of arrays:

$$\mathsf{B} = [[1, 2, 3,], [4, 5, 6]] \qquad \qquad \mathsf{B}[2][3]$$

Functions: exp.(A)

Array

Example

```
2 a = [i+j for i=1:2, j=1:3] # construct array
3
4 N_row, N_col = size(a)
5
6 # transpose a
7 a_T = zeros(Int, N_col, N_row) # integer array
8 for i = 1:N_col, j = 1:N_row # for loop
9 a_T[i,j] = a[j,i]
10 end
```

Functions

- f(x, y) = 2x + y
- function f(x, y)
 2x + y
 end

function f(x, y) return 2x + y end

Functions which manipulate input:

function g!(x)x[2] = 2end

Exercise 1. Ising model

Goal: We start by simulating the 3D Ising model using the Metropolis-based single-spin flip Monte Carlo method. For those who attended last semester's lecture it is (to some degree) a revision.

Write a program for a Monte Carlo simulation to solve the three-dimensional Ising model with periodic boundary conditions. Implement the *single-spin flip* Metropolis algorithm for sampling. As you will have to reuse this code for upcoming exercise sheets, it might be worth to make sure that it is well-structured!

Task 1: Measure and plot the energy E, the magnetization M, the magnetic susceptibility χ and the heat capacity C_V at different temperatures T.

Task 2: Determine the critical temperature T_c .

Hint: You should obtain $T_c \simeq 4.51$.

Task 3: Study how your results depend on the system size.

Hint: Start with small systems to reduce the computation time.

Task 4 (OPTIONAL): Save computation time by avoiding unnecessary reevaluations of the exponential function. To achieve this, use an array to store the possible spin-flip acceptance probabilities.

Task 5 (OPTIONAL): Plot the time dependence of M for a temperature $T < T_c$.

Hint: For small systems you should be able to observe sign-flips in M.

3D Ising model

- Hamiltonian: $H = -J\sum_{\langle i,j \rangle} \sigma_i \sigma_j - H\sum_i \sigma_i$ • Mean of observable: $\langle O \rangle = \sum_x O(x) \frac{1}{Z} e^{-\beta H(x)}$
- Relevant observables at zero magnetic field:

Energy	$\langle H \rangle$
Magnetization	$\left\langle \frac{1}{N} \sum_{i} \sigma_{i} \right\rangle$
Susceptibility	$\beta(\langle M^2\rangle-\langle M\rangle^2)$
Heat capacity	$\beta^2(\langle E^2\rangle-\langle E\rangle^2)$

Rather than computing the observables over the exponentially large phase space, we sample them on statistically relevant configurations

- Choose randomly a new configuration in phase space
- Accept or reject the new configuration, depending on the strategy
- 3. Compute physical quantities
- 4. Repeat

Metropolis algorithm

- Propose new configuration: $\sigma_i \rightarrow -\sigma_i$ Probability = 1/N
- Accept new configuration with probability $\min\left(1, \exp\left(-\beta(E_{new} - E_{old})\right)\right)$





Implementation

- Start with any spin configuration (e.g. random)
- Perform MC-steps until the system is thermalized Sampling:
- Calculate observables and keep them for sampling
- Do subsweep to obtain a new uncorrelated configuration (again calculate the observables)
- Repeat

Post processing

Calculate mean and fluctuations

Repeat for different temperature and system size

- Julia is column major
- Calculate energy and magnetization for

new configuration locally

1 1 1 1 1 1 1 1 1 1 1 1 1 1<mark>-1</mark> 1 1 1 1 1 1 1 1 1 1 1 1 1 1

 Use a lookup table for the the Metropolis acceptance probabilities