



Computational Physics - Home assignment 2a

Monte Carlo simulations - Properties of the CuZn binary alloy

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Introduction

The goal of this project is to study the properties of a binary alloy. A binary alloy is a material consisting of two atoms, where (at least) one of the elements is a metal. As an example, this study uses the binary alloy consisting of N copper (Cu) and N zinc (Zn) atoms, which are arranged in a body-centered-cubic lattice (bcc).

The energy of this system depends on the arrangement of the two atom types. In the following, the atom type Cu is represented by A and the atom type Zn is represented by B . Let N_{ij} be the number of bonds between atom type i and j and E_{ij} the corresponding bond energy contribution, then

$$E = N_{AA}E_{AA} + N_{BB}E_{BB} + N_{AB}E_{AB}. \quad (1)$$

According to the assignment description, reasonable bond energies for the CuZn alloy, that are used in this project, are

$$\begin{aligned} E_{AA} &= E_{\text{CuCu}} = -436 \text{ meV}, \\ E_{BB} &= E_{\text{ZnZn}} = -113 \text{ meV}, \\ E_{AB} &= E_{\text{CuZn}} = -294 \text{ meV} [1]. \end{aligned} \quad (2)$$

Another important property of any material is the heat capacity

$$C = \frac{dE}{dT}. \quad (3)$$

To quantify the amount of order in the binary alloy, a long-range order parameter P and a short-range order parameter r are introduced.

P quantifies the separation of the atom types into the two cubic sublattices (named a and b) of the bcc lattice, where the atoms in one sublattice are in the center of the unit cells of the other sublattice and vice versa. It is defined as

$$P = 2 \frac{N_{Aa}}{N} - 1 \quad (4)$$

where N_{Aa} is the number of atoms A on sublattice a and N is the total number of A atoms in the alloy. Therefore, $P = \pm 1$ if the alloy is in perfect order, so that both sublattices contain only one type of atom. And $P = 0$ if the alloy is not ordered, but each sublattice contains equal amounts of each atom type.

r quantifies the separation of the atom types into regions and is defined as

$$r = \frac{N_{AB} - 4N}{4N}. \quad (5)$$

The total number of bonds is $8N$, so for $r = 1$ all bonds are AB -bonds, and it is basically the same as $P = \pm 1$. However, for $r \approx 0$, only half of the bonds are AB -bonds and the system is in complete disorder. Theoretically, a negative value of r is possible, but this means that the atoms clump together in large regions of one atom type and is unlikely.

The main goal of this project is to investigate the temperature dependence of these four properties using both a numerical approximation and a Monte Carlo simulation.[1]

Task 1 4/4

Objective and procedure

Instead of simulating the binary alloy, the temperature dependence of several properties are calculated numerically using the so-called *mean field approximation* (MFA). In this approximation, the thermodynamic free energy is

$$F(N, P) = E_0 - 2NP^2\Delta E + Nk_B T[-2\ln(2) + (1+P)\ln(1+P) + (1-P)\ln(1-P)] \quad (6)$$

with

$$E_0 = 2N(E_{AA} + E_{BB} + 2E_{AB}), \quad (7)$$

$$\Delta E = E_{AA} + E_{BB} - 2E_{AB}, \quad (8)$$

the number of atoms per sublattice N , the temperature T , the Boltzmann constant k_B and the long-range order parameter P . [2]

To find the thermodynamic equilibrium state at temperature T , the free energy is minimized numerically with respect to P . In a binary alloy with equal number of A and B atoms, the long-range order parameter can take values between -1 and +1. However, because the free energy is symmetric around $P = 0$, it is sufficient to only consider positive P .

Once $P(T)$ is found (in equilibrium), the total energy of the system is calculated using Eq. (1), where in the mean field approximation

$$N_{AA} = 2(1 - P^2)N, \quad (9)$$

$$N_{BB} = 2(1 - P^2)N, \quad (10)$$

$$N_{AB} = 4(1 + P^2)N. \quad (11)$$

And finally the heat capacity can be calculated using the numerical finite differences method

$$\frac{dE}{dT} \approx \frac{E(T + \Delta T) - E(T)}{\Delta T} \quad (12)$$

for a sufficiently small ΔT .

The phase transition from the β' -phase (ordered bcc-structure) to the β -phase (disordered bcc structure) occurs at the critical temperature

$$T_{c,\text{MFA}} = \frac{2\Delta E}{k_B} \quad (13)$$

in the mean field approximation of a binary alloy.[2]

Results and discussion

The numerically calculated temperature dependence of the long-range order parameter P , the energy E and the heat capacity C in the mean field approximation of the CuZn binary alloy are shown in Fig. 1. A temperature range $T \in [0 \text{ K}, 1200 \text{ K}]$ in steps of $\Delta T = 1 \text{ K}$ is chosen. To make this illustration independent of the number of atoms, each equation mentioned in the last section, which is dependent on N , is divided by N on both sides. Using Eq. (13) and the bond energies mentioned in Eq. (2) the theoretical critical temperature is

$$T_{c,\text{MFA}} = 905.15 \text{ K}. \quad (14)$$

This value corresponds very well to the plots shown in Fig. 1, where at this temperature the behavior instantly changes. However, when comparing this value to the experimentally found phase transition temperature of the CuZn binary alloy

$$T_{c,\text{exp}} = 468^\circ\text{C} = 741.15 \text{ K} [1], \quad (15)$$

it differs by over 150 K. This indicates that the mean field approximation is not very accurate in determining the temperature of the phase transition.

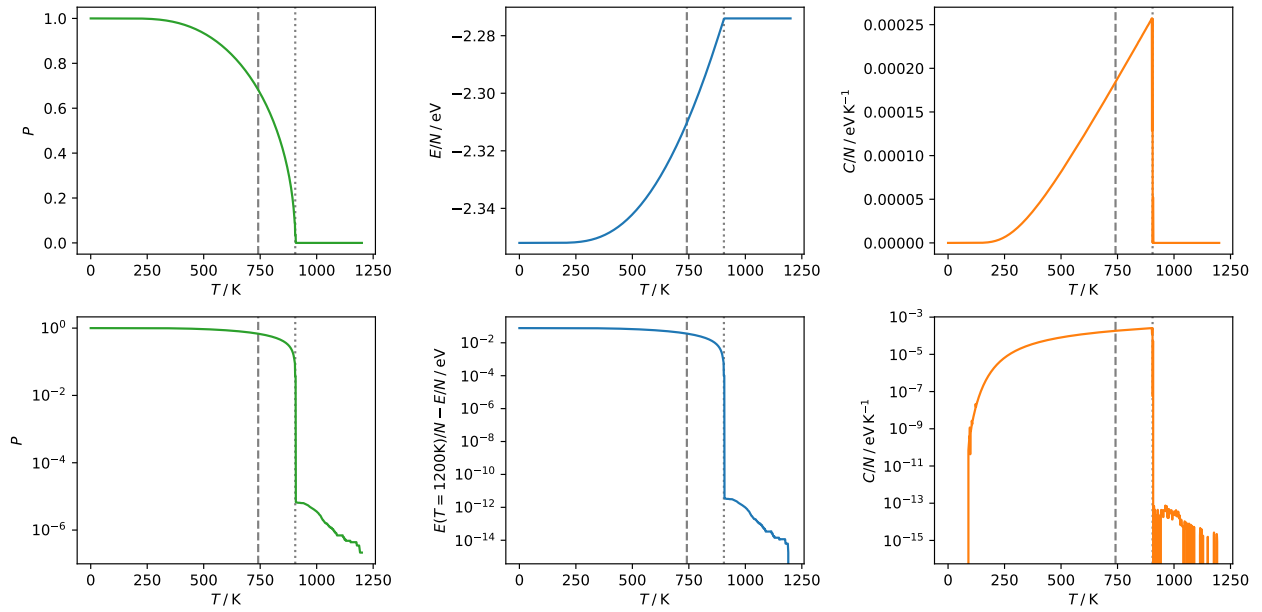


Figure 1: Temperature dependence of the long-range order parameter P , the energy E and the heat capacity C in the mean field approximation of the CuZn binary alloy. Shown are these properties per number of atoms N both on a normal and on a logarithmic scale (the difference in the energy to the last value is plotted). Also marked are the calculated critical temperature $T_{c,\text{MFA}} = 905.15 \text{ K}$ (dotted line) and the experimentally measured critical temperature $T_{c,\text{exp}} = 741.15 \text{ K}$ (dashed line).

For low temperatures, the alloy is modelled to be in almost perfect order ($P = 1$). Then P decreases with increasing temperature until at $T_{c,\text{MFA}}$ it instantly becomes 0 and stays at complete disorder for higher temperatures. The decrease in the quantities at $T > T_c$ is a result of

numerical errors and changes, when the tolerance of the minimization algorithm is decreased. $F(P)$ in Eq. (6) has the only minimum at exactly $P = 0$ for $T > T_c$. To illustrate the symmetry of $F(P)$ and the positions of its minima, it is plotted for five different temperatures in Fig. 2. The general trend is physically reasonable, however the sudden change to $P = 0$ suggests an idealized behavior in the model. The same holds for the inner energy E , where it increases with the temperature but above $T_{c,MFA}$ it suddenly stays constant. In a physical system, if the temperature increases and no other properties are changed, the inner energy must also increase. However, this model only considers the atom type arrangement and therefore the energy increase could be seen in the dynamics of the system. The heat capacity, which is the numerical derivative of the energy, shows an increase below the phase transition and also suddenly drops to 0. This might also be physically reasonable, since the dynamics of the system are not considered here.

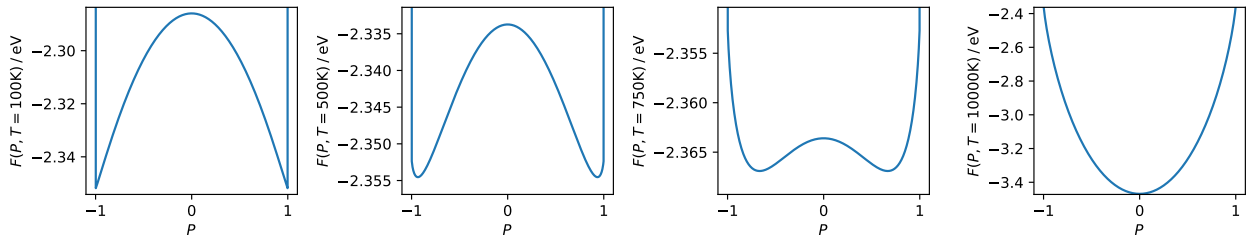


Figure 2: Dependence of the free energy F on the long-range order parameter P for five different temperatures $T = 100$ K, $T = 500$ K, $T = 750$ K and $T = 1000$ K respectively from left to right.

Task 2

Objective and procedure

In this task, a *Markov Chain Monte Carlo* (MCMC) simulation of a binary alloy is performed to determine the temperature dependence of the properties introduced in the first section (E, C, P, r). More specifically, the *Metropolis algorithm* is used to sample the microstates of the binary alloy at a given temperature. The system of interest is a bcc lattice with two atom types of equal proportions, which is visualized in Fig. 3. The movement of the lattice vertices is neglected in this study, and only the arrangement of the atom types (i.e. the nearest neighbor bonds) is considered.

Therefore, the state of the system is represented by a list of $2N$ atomic positions and the type of atom (A or B) that sits at this position. The positions $(x, y, z)^T$ are taken to be at integer multiples of the lattice constant a_0 (width of one unit cell) together with a binary variable $w = a, b$ that specifies whether the position is in sublattice a (i.e. $\vec{r} = (x, y, z)^T \cdot a_0$) or in sublattice b (i.e. $\vec{r} = (x + 1/2, y + 1/2, z + 1/2) \cdot a_0$). The number of simulated bcc unit cells in each direction is called n . This means that $x, y, z \in \{0, 1, \dots, n-1\}$ and $N = 2n^3$. To be able to count the types of nearest neighbor bonds (N_{AA}, N_{BB}, N_{AB}), a list of indices of the 8 nearest neighbors is also generated for each position. Since only a finite and potentially small number of atoms can be simulated compared to the number of atoms in a real crystal,

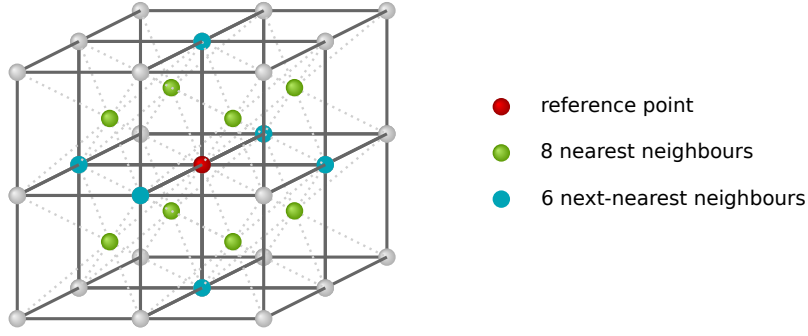


Figure 3: Illustration of a bcc lattice with the green atoms in one sublattice and all other atoms in a different sublattice. Shown are only $2 \times 2 \times 2$ unit cells. [3]

periodic boundary conditions are applied to the list of nearest neighbors. This means that, for example, an atom in sublattice b with $x = n - 1$ has nearest neighbors in sublattice a with both $x = n - 1$ and $x = 1$.

Given a specific temperature T and an initial state of the system, the microstates of the system are sampled using the Metropolis algorithm. At each simulation step, a random change in the system's state is proposed, and then the probability of the current state and the proposed state is compared to accept or decline the proposal. The new current state is used to calculate and save various instantaneous properties, which can later be used to calculate canonical ensemble averages.

The proposed change used to simulate the binary alloy is the swap of two randomly picked atoms. To increase the efficiency of this simulation without loss of generality, only swaps are proposed where both atoms are of different type. Otherwise, the proposed state would be exactly the same as the current state, because the only difference of the atoms are the atom type. Then, the number of bonds for each bond type (N_{AA}, N_{BB}, N_{AB}) are calculated for the proposed state to calculate the difference in energy

$$\Delta E = E_{\text{proposed}} - E_{\text{current}} \quad (16)$$

using Eq. (1). If $\Delta E \leq 0$, the proposed state is more likely and therefore accepted. Otherwise, the proposed state is accepted with the probability of

$$P(\text{accept proposal}) = \exp\left(-\frac{\Delta E}{k_B T}\right) [2]. \quad (17)$$

To decrease the computation time, instead of counting the bonds in each simulation step, the bond counts are updated by only evaluating how the bonds between the swapped atoms and their nearest neighbors change. It is important to also consider the special case, when the swapped atoms are nearest neighbors themselves.

Since the first steps in the Metropolis algorithm are needed to find the region of interest (thermodynamic equilibrium), each simulation must consist of a number of burn-in/equilibration steps followed by the actual production steps where physical quantities are calculated. The quantities of interest in this study are calculated in each simulation step using Eq. (1), Eq. (4)

and Eq. (5). Afterwards, the averages of these quantities are calculated per simulation (one temperature), and the heat capacity is calculated as

$$C = \frac{1}{k_B T^2} (\langle E^2 \rangle - \langle E \rangle^2) [1]. \quad (18)$$


The error estimation of the calculated average quantities needs a simulation property called *statistical inefficiency* s , which quantifies how many subsequent simulated measurements are highly correlated. The correct uncertainty (standard deviation) of the average of measured quantities $\{f_i\}$ is therefore

$$\sigma_{\langle f \rangle} = \sqrt{\frac{s}{M}} \sigma_f \quad (19)$$

where M is the number of measurements and σ_f is the standard deviation of $\{f_i\}$.

The statistical inefficiency can be estimated in several ways. The method chosen here is to set $s = k_0$, where k_0 is the lowest integer for which the autocorrelation function

$$\Phi(k) = \frac{\langle f_i \cdot f_{i+k} \rangle - \langle f \rangle^2}{\langle f^2 \rangle - \langle f \rangle^2} \quad (20)$$

is less than $\Phi_0 = \exp(-2) \approx 0.135$. Since calculating $\Phi(k)$ for all values $k \in \{1, 2, \dots, M\}$ after each simulation would take a lot of computation time, the search for k_0 is implemented in two steps. First, the value of k is steadily increased by a factor of 2 until $\Phi(k_{\text{start}} \cdot 2^i) < \Phi_0$. Then, the exact value k_0 is searched using a binary search that starts with the boundaries $k_{\text{start}} \cdot 2^{i-1}$ and $k_{\text{start}} \cdot 2^i$. This way, k_0 is found using only a few tens of $\Phi(k)$ computations instead of the up to M computations. 

A different method of calculating the statistical inefficiency is block averaging. Here, the variance of the measurable f is compared to the variance over the block averages

$$F_j = \frac{1}{M} \sum_i^B f_{i+(j-1)B} \quad (21)$$

where B is a specific block size and $j \in \{1, 2, \dots, M/B\}$. The statistical inefficiency is then estimated as

$$s = B \frac{\text{Var}[F]}{\text{Var}[f]} \quad (22)$$

and converges to the correct value for large B . [4]

All the procedures explained above are repeated for multiple temperatures, so that the temperature dependence of the mentioned quantities can be investigated. The number of needed equilibration steps is heavily reduced by simulating the system with increasing temperatures and using the last system state of the previous temperature as the initial state for the next temperature. The first initial state is chosen to be the perfectly ordered state, where all atoms A are in sublattice a and all atoms B are in sublattice b .

Results and discussion

The procedures described in the previous section are used to simulate the CuZn binary alloy using the bond energies given in Eq. (2). The simulation cell consists of $10 \times 10 \times 10$ unit cells ($\Rightarrow N = 1000$) with the previously mentioned periodic boundary conditions.

The resulting ensemble averages for several temperatures are shown in Fig. 6. These results are however discussed only later in this section. Included are the uncertainties calculated through Eq. (19). However, the uncertainties are too small to be visible and are therefore plotted separately in Fig. 7. Chosen is the temperature range between 300 K and 1000 K with a $\Delta T = 1$ K in the range between 600 K and 800 K (region of the phase transition) and a $\Delta T = 20$ K outside of this range. Each simulation is performed with $M_{eq} = 0.5 \times 10^6$ equilibration steps and $M = 4.5 \times 10^6$ production steps.

To show that M_{eq} is indeed enough to find the thermodynamic equilibrium, Fig. 4 shows the evolution of the quantities during several simulations. All quantities show a more or less constant behavior for all shown temperatures, with some degree of noise. The number of equilibration steps appears to be more than sufficient, since equilibrium is reached with a lot less steps for all temperatures. For temperatures in the region of the phase transition (700 K and 750 K), the variation/oscillation happens over much longer step intervals. Especially for $T = 750$ K (red) a large oscillation around $P = 0$ is visible. This explains the large uncertainties in the phase transition region in Fig. 7 and why $P(T)$ in Fig. 6 is oscillating around $P = 0$.

To illustrate how the statistical inefficiency is calculated, Fig. 5a shows the autocorrelation function $\Phi_E(k)$ of the energy for several temperatures. Even though the procedure used to find the first k_0 for $\Phi(k_0) < \exp(-2)$, explained at the end of the last section, does not need to calculate all $\Phi(k)$, the dashed lines show that the k_0 found is indeed the correct k_0 (at least for these five temperatures). It also shows why a simple binary search would not work, because for higher k the autocorrelation function is very noisy and becomes greater than $\exp(-2)$ again.

The autocorrelation method of calculating the statistical inefficiency should yield about the same results as the block averaging method. To verify this, the block averaging method is performed for several temperatures. This is shown in Fig. 5b together with the statistical inefficiencies calculated during the production. In theory, the statistical inefficiency should converge to the correct value for very large block sizes. Fig. 5b shows that it converges to similar values as calculated through the autocorrelation method. However, for too large block sizes, there are too few blocks to take the variance over. It could not be determined with certainty, why the block averaging for the temperatures $T = 650$ K and $T = 750$ K only converges for a relatively small B interval and drops so quickly for larger B . However, it might be because for temperatures near the phase transition, P jumps between positive and negative values and stays there for a certain number of simulation steps. In the cases, where the block averaging result differs from value during production, the production value is higher. Therefore, the statistical inefficiencies in this study are not underestimated.

The resulting statistical inefficiencies s for each temperature are shown in Fig. 5c. It turns out that the $s(E)$ and $s(r)$ are the same, which is based on the definitions Eq. (1) and Eq. (5) with the approximation that $N_{AA} \approx N_{BB}$. The statistical inefficiencies show a general decrease with temperature, except that in the phase transition region it increases a lot. This corresponds to

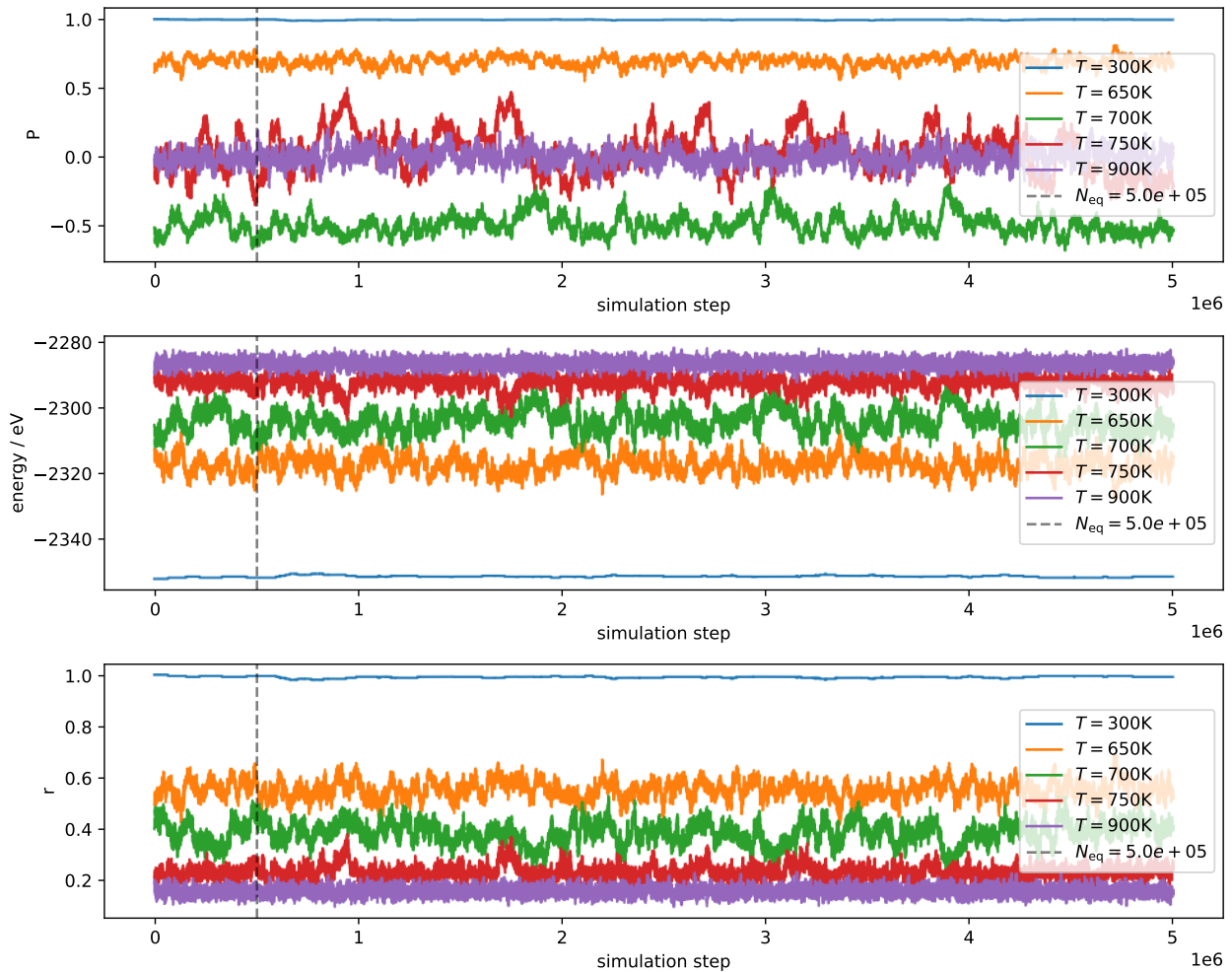


Figure 4: Evolution of the energy E , the long-range order parameter P and the short-range order parameter r in simulations of the temperatures 300 K, 650 K, 700 K, 750 K and 900 K. Shown is each tenth simulation step. The first step of the production is marked with a vertical dashed line at $M_{eq} = 0.5 \times 10^6$.

the oscillations seen in Fig. 4 and shows an instable behavior of the CuZn binary alloy during phase transition. For temperatures below the phase transition, additionally $s(P) \approx s(E)$.

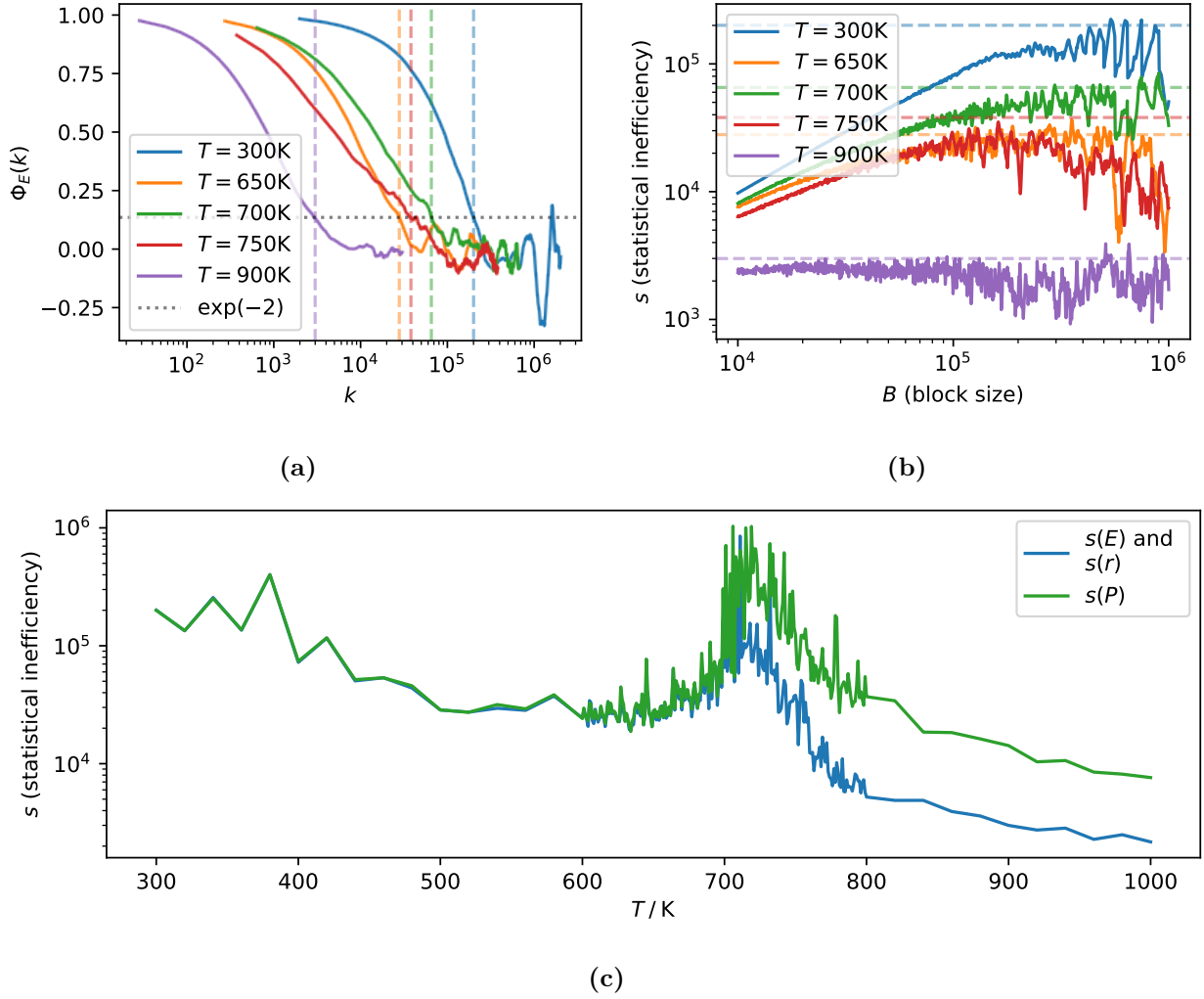


Figure 5: (a) shows a section of the autocorrelation functions for the energy of several different temperatures. The vertical dashed lines show the statistical inefficiency that is calculated during production. (b) shows the calculated statistical inefficiencies using block averaging for several block sizes and several temperatures. The horizontal dashed line show the statistical inefficiency that is calculated during production. (c) shows the statistical inefficiencies s for the quantities E , r and P that are calculated during production. Since $s(E)$ and $s(r)$ are the same, they are plotted together.

The final results of this study are shown in Fig. 6 with the uncertainties in Fig. 7. Rough comparisons to the mean field approximation in Fig. 1 show the same general trends. The energy E is increasing and flattens out after the phase transition. The heat capacity C is increasing until around 700 K and is then decreasing rapidly to almost $C = 0\text{ eV/K}$. The long-range order parameter $|P|$ is decreasing more and more until it rapidly goes to the unordered state $P \approx 0$. The short-range order parameter r shows a similar trend as P but converges much slower towards $r = 0$. In general, the values of the quantities also roughly correspond to the values in Fig. 1, when multiplying by $N = 1000$.

A major difference to the mean field approximation is that the phase transition does not happen instantly, but continuously over a temperature range of around 50 K starting at around $T = 700$ K. Additionally, the phase transition in the simulation is much closer to the experimentally found critical temperature (dashed line) than the mean field approximation critical temperature (dotted line). Since the transition happens gradually, no concrete critical temperature could be determined. That said, the critical temperature in the simulation from which point onwards $P \approx 0$ (disordered β -phase) coincides very well with the experimentally found critical temperature. It is also worth to note, that the same physical constants (Eq. (2)) are used in both models and the simulation still outperforms the mean field approximation.

The energy is monotonously increasing with temperature, which is physically reasonable. The slower flattening of the energy at high temperatures leads to higher values of C than found in the mean field approximation. The heat capacity looks very noisy in the region of the phase transition, however this is a result of the more precise sampling in this region. Although, around the turning point at $T \approx 700$ K, the variation is very large.

The same turning point can be observed in P , where the value of P suddenly oscillates between positive and negative values. As mentioned before, this oscillation also happens during one simulation, as seen in Fig. 4 for $T = 750$ K. However, the fact that P is purely positive before the phase transition is not a physical property, but a result of choosing the initial state as the $P = +1$ state. The absolute value $|P|$ shows a steady decrease (with some noise) towards $P \approx 0$ with increasing temperature. The short-range order parameter r is also steadily decreasing, but presumably reaches $r \approx 0$ only for much higher temperatures. The fact, that both order parameters start in almost complete order for low temperatures and ends in almost complete disorder for high temperatures, is also physically reasonable and shows indeed that there are the two different phases β' and β in the CuZn binary alloy.

When considering the uncertainties in Fig. 7 and the statistical inefficiencies in Fig. 5c, it becomes apparent that a lot more simulation steps would be needed to achieve precise results in the region of the phase transition. Additionally, a larger amount of simulated atoms would potentially show a more sharp phase transition and also increase the precision. Both of which could not be done in this project, due to time limitations and limitations in the available computing power.

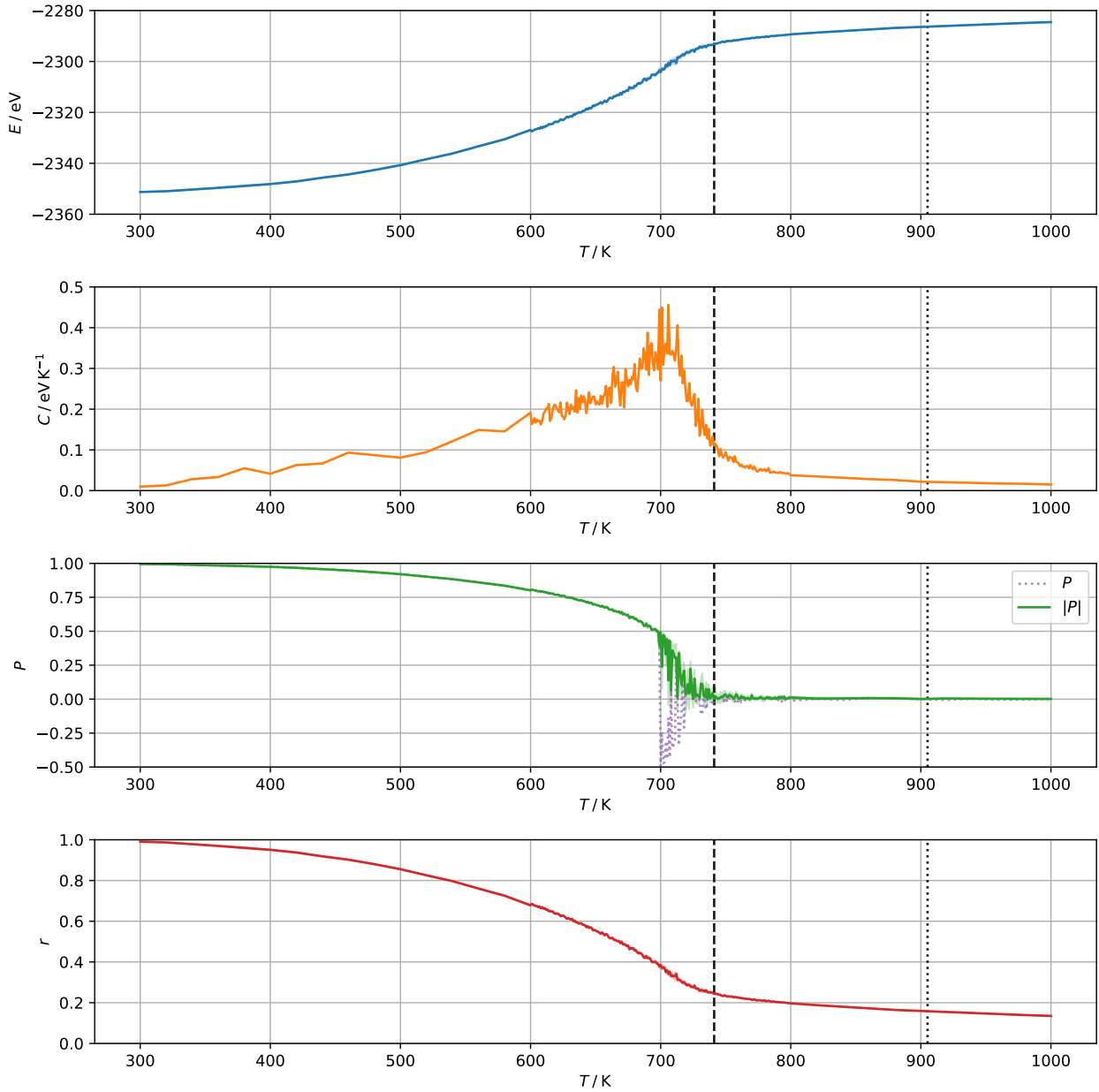


Figure 6: Temperature dependence of the energy E , the heat capacity C , the long-range order parameter P and the short-range order parameter r as the resulting canonical ensemble averages of MCMC simulations of a CuZn binary alloy. Each value (except for C) is plotted with the corresponding uncertainty. However, most uncertainties are too small to be visible and are therefore shown in Fig. 7. Both P and $|P|$ are plotted, however the error region is only plotted for $|P|$. Also marked are the mean field approximation critical temperature $T_{c,\text{MFA}} = 905.15$ K (dotted line) and the experimentally measured critical temperature $T_{c,\text{exp}} = 741.15$ K (dashed line).

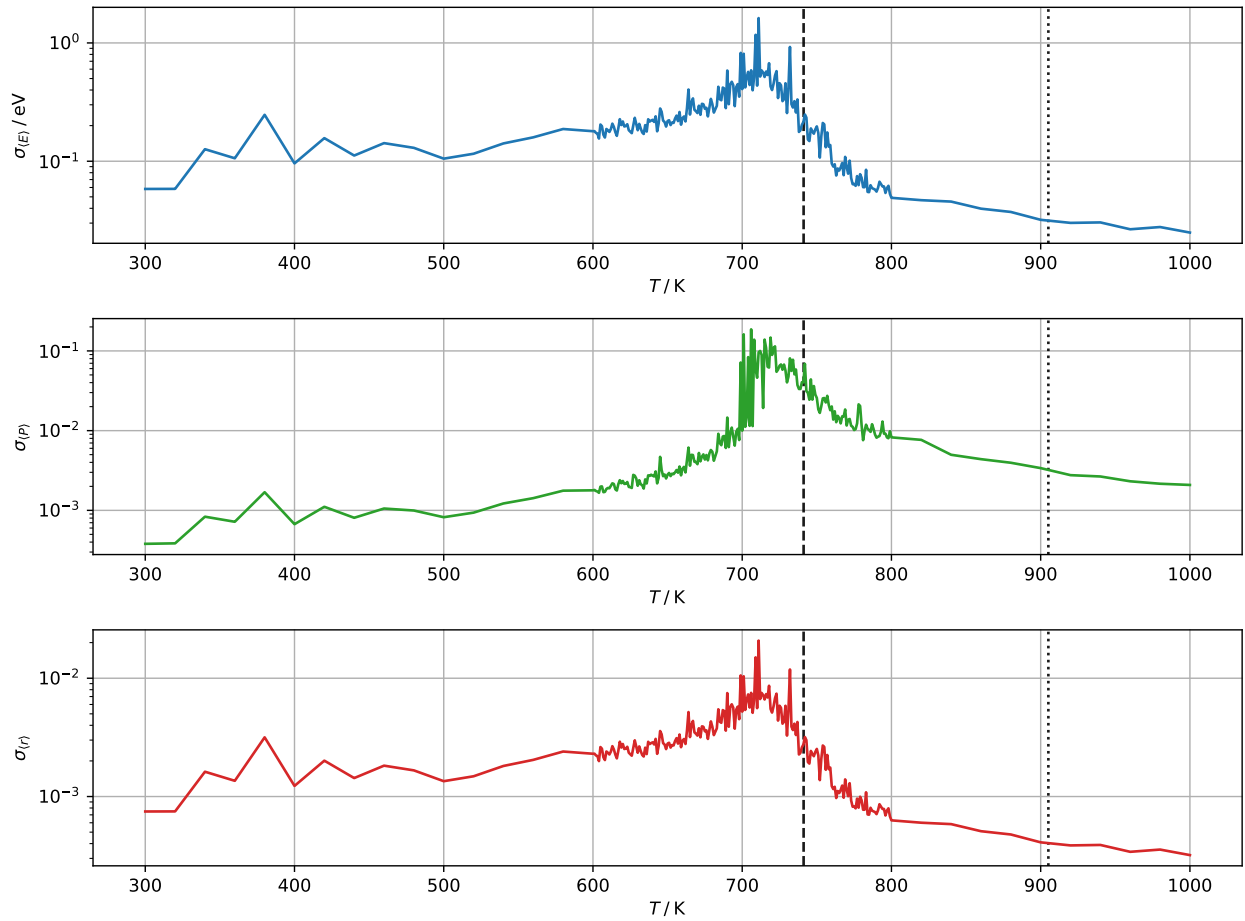


Figure 7: Uncertainties of the quantities in Fig. 6 calculated through Eq. (19).

Concluding discussion

In this study, it is shown that both the mean field approximation and a MCMC-simulation yield physically reasonable behaviors of several properties of the CuZn binary alloy. The critical temperature of the phase transition (between the ordered β' -phase and the disordered β -phase) in the mean field approximation differs by over 100 K from the experimentally found temperature. However, the phase transition found through the simulation is much closer to the experimentally found value. In the mean field approximation, the phase transition is very sharp, but the transition found through simulation is more gradual and therefore probably closer to physical reality. Overall, this study illustrates that Monte Carlo simulations of physical systems can be used to investigate their thermodynamic behavior.

References

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- [4] Göran Wahnström, Department of Physics, Chalmers, Göteborg. *Monte Carlo lecture notes*. 2019.

Source Code

Included in this appendix is all the relevant code that I wrote myself. The entire project is attached as a zip file, where also the code is included that was already provided.

Main code for all calculations/simulations: run.c

```

1  #include <stdio.h>
2  #include <math.h>
3  #include <stdlib.h>
4  #include <stdbool.h>
5  #include <gsl/gsl_rng.h>
6
7  #include "tools.h"
8  #include "lattice_tools.h"
9  #include "statistical_ineff.h"
10
11 // physical constants
12 const double k_B = 8.617333262e-5; // eV/K;
13
14 // parameters of the simulation
15 const int n_cells = 10;
16 const int N_atoms = 2*n_cells*n_cells*n_cells;
17
18 void update_bond_counts_after_swap(int N_atoms, int* atype,
19     int** nn_idx, int** pos,
20     int swap_idx_a, int swap_idx_b,
21     int* N_AA, int* N_BB, int* N_AB, int* N_Aa) {
22     int atype_a = atype[swap_idx_a]; // old atype at position a
23     int atype_b = atype[swap_idx_b]; // old atype at position b
24     if (atype_a == atype_b) {
25         // the swap introduces no change
26         return;
27     }
28
29     // update the Number of A atoms in sublattice a
30     // if position a is on a different sublattice than position b, N_Aa can change
31     if (pos[swap_idx_a][3] != pos[swap_idx_b][3]) {
32         if (pos[swap_idx_a][3] == 0) {
33             // position a is on sublattice a
34             if (atype_a == 0) {
35                 (*N_AA)--;
36             } else {
37                 (*N_Aa)++;
38             }
39         } else {
40             // position b is on sublattice a
41             if (atype_b == 0) {
42                 (*N_AA)--;
43             } else {
44                 (*N_Aa)++;
45             }
46         }
47     }
48
49     // update bonds at position a
50     for (int j=0; j<8; j++) {
51         int atype_nn = atype[nn_idx[swap_idx_a][j]];
52
53         // if the nn of a is b then the change is already accounted for
54         if (nn_idx[swap_idx_a][j] == swap_idx_b) {
55             continue;
56         }
57     }

```

```

58     // subtract old bond and add new bond
59     if (atype_a == 0 && atype_nn == 0) {
60         (*N_AA)--;
61         (*N_AB)++;
62     } else if (atype_a == 1 && atype_nn == 1) {
63         (*N_BB)--;
64         (*N_AB)++;
65     } else if (atype_a == 0 && atype_nn == 1) {
66         (*N_AB)--;
67         (*N_BB)++;
68     } else if (atype_a == 1 && atype_nn == 0) {
69         (*N_AB)--;
70         (*N_AA)++;
71     }
72 }
73
74 // update bonds at position b
75 for (int j=0; j<8; j++) {
76     int atype_nn = atype[nn_idx[swap_idx_b][j]];
77
78     // if the nn of b is a then the change is already accounted for
79     if (nn_idx[swap_idx_b][j] == swap_idx_a) {
80         continue;
81     }
82
83     // subtract old bond and add new bond
84     if (atype_b == 0 && atype_nn == 0) {
85         (*N_AA)--;
86         (*N_AB)++;
87     } else if (atype_b == 1 && atype_nn == 1) {
88         (*N_BB)--;
89         (*N_AB)++;
90     } else if (atype_b == 0 && atype_nn == 1) {
91         (*N_AB)--;
92         (*N_BB)++;
93     } else if (atype_b == 1 && atype_nn == 0) {
94         (*N_AB)--;
95         (*N_AA)++;
96     }
97 }
98 }
99
100 void metropolis_algorithm(int N_atoms, int n_steps, double T,
101                          int* atype, int** pos, int** nn_idx, gsl_rng* rng,
102                          double* E_out, double* P_out, double* r_out) {
103     int N_AA, N_BB, N_AB, N_Aa=0;
104     count_bonds(N_atoms, atype, nn_idx, &N_AA, &N_BB, &N_AB);
105     // count A atoms on a sublattice
106     for (int i=0; i<N_atoms; i++) {
107         if (atype[i] == 0 && pos[i][3] == 0) {
108             N_Aa++;
109         }
110     }
111
112     double E_curr = calc_energy(N_AA, N_BB, N_AB);
113     print_progress(0,0,n_steps-1,true);
114     // calc the energy of the current configuration
115     for (int i_step=0; i_step<n_steps; i_step++) {
116         // make trial change by swapping two atoms
117         // choose which atoms to swap
118         int swap_idx_a = gsl_rng_uniform_int(rng, N_atoms);
119         int swap_idx_b = gsl_rng_uniform_int(rng, N_atoms);
120         while (swap_idx_a == swap_idx_b || atype[swap_idx_a] == atype[swap_idx_b]) {
121             swap_idx_b = gsl_rng_uniform_int(rng, N_atoms);
122         }
123
124         // save the current bond counts if the trial change is not accepted
125         int N_AA_trial = N_AA;
126         int N_BB_trial = N_BB;
127         int N_AB_trial = N_AB;
128         int N_Aa_trial = N_Aa;

```



```

129
130 // check if the swap should be accepted as the new configuration
131 update_bond_counts_after_swap(N_atoms, atype, nn_idx, pos,
132                               swap_idx_a, swap_idx_b,
133                               &N_AA_trial, &N_BB_trial, &N_AB_trial, &N_Aa_trial);
134 double E_trial = calc_energy(N_AA_trial, N_BB_trial, N_AB_trial);
135 double DeltaE = E_trial - E_curr;
136 //DeltaE = E_curr - E_trial;
137 bool accept = (DeltaE <= 0);
138 if (!accept) {
139     accept = gsl_rng_uniform(rng) <= exp(-DeltaE/(k_B*T));
140 }
141
142 if (accept) {
143     E_curr = E_trial;
144     // perform the swap
145     int temp_atype = atype[swap_idx_a];
146     atype[swap_idx_a] = atype[swap_idx_b];
147     atype[swap_idx_b] = temp_atype;
148     // update the counts
149     N_AA = N_AA_trial;
150     N_BB = N_BB_trial;
151     N_AB = N_AB_trial;
152     N_Aa = N_Aa_trial;
153 }
154
155 //if (T>600 && i_step>8e6) {
156 //    printf("N_AA = %i, N_BB = %i, N_AB = %i, N_Aa = %i, E = %f\n", N_AA, N_BB, N_AB, N_Aa, ←
157 //    E_curr);
158 //}
159
160 if (4*N_atoms != N_AA+N_BB+N_AB || N_AA<0 || N_BB<0 || N_AB<0) {
161     printf("\nERROR: bonds calculated wrong: N_AA = %i, N_BB = %i, N_AB = %i\n", N_AA, ←
162           N_BB, N_AB);
163     exit(1);
164 }
165
166 // calculate various instantaneous quantities
167 // save the quantities somehow
168 E_out[i_step] = E_curr;
169 P_out[i_step] = calc_P(N_atoms, N_Aa);
170 r_out[i_step] = calc_r(N_atoms, N_AB);
171
172 print_progress(i_step, 0, n_steps-1, false);
173 }
174 }
175
176 void perform_simulation(double T, int n_eq_steps, int n_steps,
177                       int* atype, int** pos, int** nn_idx, int idx_by_pos[n_cells][n_cells][←
178                       n_cells][2],
179                       bool save_steps, char* save_steps_file_path, gsl_rng* rng, int n_skip_saves,
180                       double* E_avg, double* P_avg, double* r_avg, double* C,
181                       double* E_std, double* P_std, double* r_std,
182                       int* s_E, int* s_P, int* s_r) {
183
184     // Monte Carlo Simulation, Metropolis Algorithm
185     int n_tot_steps = n_eq_steps+n_steps;
186     double* E = (double*)malloc(n_tot_steps*sizeof(double));
187     double* P = (double*)malloc(n_tot_steps*sizeof(double));
188     double* r = (double*)malloc(n_tot_steps*sizeof(double));
189
190     metropolis_algorithm(N_atoms, n_tot_steps, T, atype, pos, nn_idx, rng, E, P, r);
191
192     // calculate the average quantities (without the equilibration steps)
193     *E_avg = average(E+n_eq_steps, n_steps);
194     *P_avg = average(P+n_eq_steps, n_steps);
195     *r_avg = average(r+n_eq_steps, n_steps);
196     *E_std = standard_deviation(E+n_eq_steps, n_steps);
197     *P_std = standard_deviation(P+n_eq_steps, n_steps);
198     *r_std = standard_deviation(r+n_eq_steps, n_steps);
199

```

```

197 // calculate the heat capacity:  $C = 1/k_B T * (\langle E^2 \rangle - \langle E \rangle^2)$ 
198 double* E_squared = (double*)malloc(n_steps*sizeof(double));
199 elementwise_multiplication(E_squared, E+n_eq_steps, E+n_eq_steps, n_steps);
200 double E_squared_avg = average(E_squared, n_steps);
201 *C = (E_squared_avg - (*E_avg)*(E_avg))/(k_B*T*T);
202
203
204 // calculate the statistical inefficiency
205
206 printf("Calculate statistical inefficiencies...\n");
207 print_progress(0,0,3,true);
208 *s_E = calc_s_corr(E+n_eq_steps, n_steps);
209 print_progress(1,0,3,false);
210 *s_P = calc_s_corr(P+n_eq_steps, n_steps);
211 print_progress(2,0,3,false);
212 *s_r = calc_s_corr(r+n_eq_steps, n_steps);
213 print_progress(3,0,3,false);
214
215
216 // save a few simulations with E(t),P(t),...
217 if (save_steps) {
218     int n_save_steps = n_tot_steps / n_skip_saves;
219     printf("Save %i steps from %i for T = %.4f K ...\n", n_save_steps, n_tot_steps, T);
220     // write it to a file
221     FILE* file = fopen(save_steps_file_path, "w");
222     fprintf(file, "# {\\"T[K]\": %.2f, \\"n_eq_steps\": %i, \\"n_steps\": %i, \\"n_skip_saves\": %i,\n", T, n_eq_steps, n_steps, n_skip_saves);
223     fprintf(file, "# \\"P\": %.10f, \\"E[eV]\": %.10f, \\"C[eV/K]\": %.10f, \\"r\": %.10f}\n", *P_avg, *E_avg, *C, *r_avg);
224     fprintf(file, "# i_step, E[eV], P, r\n");
225     for (int i_step=0; i_step<n_eq_steps+n_steps; i_step+=n_skip_saves) {
226         fprintf(file, "%i, %.10e, %.10e, %.10e\n", i_step, E[i_step], P[i_step], r[i_step]);
227     }
228     fclose(file);
229
230     // calculate the correlation function
231     printf("Calculate and save the correlation function...\n");
232     int k_min = (*s_E)/100;
233     int k_max = (*s_E)*10;
234     int k_step = (*s_E)/100;
235     int n_k = (k_max-k_min)/k_step + 1;
236     int* k = (int*)malloc(n_k*sizeof(int));
237     double* Phi = (double*)malloc(n_k*sizeof(double));
238     for (int i=0; i<n_k; i++) {
239         k[i] = k_min + i*k_step;
240     }
241     calc_all_corr_func(E+n_eq_steps, n_steps, k, Phi, n_k);
242
243     // save the file to data/corr_simulations/
244     save_steps_file_path[5] = 'c';
245     save_steps_file_path[6] = 'o';
246     save_steps_file_path[7] = 'r';
247     save_steps_file_path[8] = 'r';
248     file = fopen(save_steps_file_path, "w");
249     fprintf(file, "# {\\"s_E\": %i, \\"T[K]\": %.2f}\n", *s_E, T);
250     fprintf(file, "# k, Phi(E,k)\n");
251     for (int i=0; i<n_k; i++) {
252         fprintf(file, "%i, %.10f\n", k[i], Phi[i]);
253     }
254     fclose(file);
255     free(k);
256     free(Phi);
257
258     // calculate the block average statistical inefficiencies
259     printf("Calculate and save the block averaging...\n");
260     int n_B = 1000;
261     int B_min = 1e4;
262     int B_max = 1e6;
263     double logB_min = log10(B_min);
264     double logB_max = log10(B_max);
265     double dlogB = (logB_max-logB_min)/(n_B-1);

```

```

266     int* B = (int*)malloc(n_B*sizeof(int));
267     double* s = (double*)malloc(n_B*sizeof(double));
268     print_progress(0,0,n_B,true);
269     for (int j=0; j<n_B; j++) {
270         B[j] = (int)pow(10.,logB_min + j*dlogB);
271         s[j] = calc_s_block_avg(E+n_eq_steps, (*E_std)*(*E_std), B[j], n_steps);
272         print_progress(j+1,0,n_B,false);
273     }
274
275     // write the block average statistical inefficiencies to a file
276     // to data/blok_simulations/
277     save_steps_file_path[5] = 'b';
278     save_steps_file_path[6] = 'l';
279     save_steps_file_path[7] = 'o';
280     save_steps_file_path[8] = 'k';
281     file = fopen(save_steps_file_path, "w");
282     fprintf(file, "# {\\"s_E\\": %i, \\"T[K]\\": %.2f}\\n", *s_E, T);
283     fprintf(file, "# B, s_E\\n");
284     for (int i=0; i<n_B; i++) {
285         fprintf(file, "%i, %.10f\\n",B[i], s[i]);
286     }
287     free(B);
288     free(s);
289     fclose(file);
290 }
291
292 // tidy up
293 free(E);
294 free(E_squared);
295 free(P);
296 free(r);
297 }
298
299 int
300 run(
301     int argc,
302     char *argv[]
303 )
304 {
305     // Write your code here
306     // This makes it possible to test
307     // 100% of you code
308     gsl_rng* rng = init_rng(42);
309
310     int n_eq_steps = 0.5e6;
311     int n_steps = 4.5e6;
312     int n_skip_saves = 10;
313
314     // make 3 sections of temperature, where around the critical temperature it more dense
315     int T_0 = 300;
316     int T_1 = 600;
317     int T_2 = 800;
318     int T_3 = 1000;
319     // delta T steps in the sections
320     int dT01 = 20;
321     int dT12 = 1;
322     int dT23 = 20;
323     // number of T steps in each section
324     int n_T01 = (T_1-T_0)/dT01;
325     int n_T12 = (T_2-T_1)/dT12;
326     int n_T23 = (T_3-T_2)/dT23 + 1; // plus the last one
327     int n_T = n_T01 + n_T12 + n_T23;
328
329     int T_saves[] = {300, 650, 700, 750, 900};
330     int n_T_saves = sizeof(T_saves)/sizeof(T_saves[0]);
331
332     double* T = (double*)malloc(n_T*sizeof(double));
333     double temp_T = T_0;
334     for (int i=0; i<n_T; i++) {
335         T[i] = temp_T;
336         if (T_0 <= temp_T && temp_T < T_1) {

```

```

337     temp_T += dT01;
338 } else if (T_1 <= temp_T && temp_T < T_2) {
339     temp_T += dT12;
340 } else if (T_2 <= temp_T && temp_T < T_3) {
341     temp_T += dT23;
342 }
343 }
344
345 double* E = (double*)malloc(n_T*sizeof(double));
346 double* P = (double*)malloc(n_T*sizeof(double));
347 double* r = (double*)malloc(n_T*sizeof(double));
348 double* C = (double*)malloc(n_T*sizeof(double));
349 double* E_std = (double*)malloc(n_T*sizeof(double));
350 double* P_std = (double*)malloc(n_T*sizeof(double));
351 double* r_std = (double*)malloc(n_T*sizeof(double));
352 int* s_E = (int*)malloc(n_T*sizeof(int));
353 int* s_P = (int*)malloc(n_T*sizeof(int));
354 int* s_r = (int*)malloc(n_T*sizeof(int));
355
356
357 // init the lattice completely ordered
358 int* atype = (int*)malloc(N_atoms*sizeof(int));
359 int** pos = create_2D_int_array(N_atoms, 4);
360 int** nn_idx = create_2D_int_array(N_atoms, 8);
361 int idx_by_pos[n_cells][n_cells][n_cells][2];
362 construct_bcc_binary_alloy(n_cells, atype, pos, nn_idx, idx_by_pos);
363
364 // perform the simulations
365 for (int i=0; i<n_T; i++) {
366     bool save = false;
367     char save_step_file_path[100];
368     // check if this step should be saved
369     for (int j=0; j<n_T_saves; j++) {
370         if (T_saves[j] == T[i]) {
371             save = true;
372             sprintf(save_step_file_path, "data/full_simulations/H2a_simsteps_%0*i_T%.0fK.csv",
373                     ((int)log10(n_T))+1, i, T[i]);
374             break;
375         }
376     }
377     perform_simulation(T[i], n_eq_steps, n_steps,
378                       atype, pos, nn_idx, idx_by_pos,
379                       save, save_step_file_path, rng, n_skip_saves,
380                       E+i, P+i, r+i, C+i,
381                       E_std+i, P_std+i, r_std+i,
382                       s_E+i, s_P+i, s_r+i);
383     printf("%i/%i done. (T = %.2f K)\n", i+1, n_T, T[i]);
384 }
385
386 // save the results
387 FILE* file = fopen("data/H2a.csv", "w");
388 fprintf(file, "# {"n_eq_steps\\": %i, \"n_steps\\": %i}\\n", n_eq_steps, n_steps);
389 fprintf(file, "# T[K], E[eV], E_std[eV], s_E, P, P_std, s_P, r, r_std, s_r, C[eV/K]\\n");
390 for (int i=0; i<n_T; i++) {
391     fprintf(file, "%.5f, %.10f, %.10f, %i, %.10f, %.10f, %i, %.10f, %.10f, %i, %.10f\\n",
392             T[i],
393             E[i], E_std[i], s_E[i],
394             P[i], P_std[i], s_P[i],
395             r[i], r_std[i], s_r[i],
396             C[i]);
397 }
398 fclose(file);
399
400 // tidy up
401 free(T);
402 free(E);
403 free(P);
404 free(r);
405 free(C);
406 free(E_std);
407 free(P_std);
408 free(r_std);
409 free(s_E);
410 free(s_P);
411 free(s_r);

```

```

407     free(r_std);
408     free(s_E);
409     free(s_P);
410     free(s_r);
411     gsl_rng_free(rng);
412     free(atype);
413     destroy_2D_int_array(pos);
414     destroy_2D_int_array(nn_idxxs);
415     return 0;
416 }

```

Functions for calculations and initialization of the lattice:

lattice_tools.c

```

1  #include <stdio.h>
2  #include <stdlib.h>
3
4  // parameters of the simulation
5  const double E_AA = -436e-3; // eV E_CuCu
6  const double E_BB = -113e-3; // eV E_ZnZn
7  const double E_AB = -294e-3; // eV E_CuZn
8
9  /*
10 * Constructs the arrays that describe a binary alloy with perfect ordering
11 * @n_cells - number of unit cells per direction -> N_atoms = 2*n_cells^3
12 * @atype - array of shape (N_atoms,) to be filled with the atom type
13 * @pos - array of shape (N_atoms,4) to be filled with the atom coordinates (x,y,z,w)
14 * x,y,z determine the unit cell and w=0,1 determines if its at the corner or the center
15 * @nn_idxxs - array of shape (N_atoms,8) to be filled with the indices of the nearest neighbors
16 * @idx_by_pos - array of shape (n_cells, n_cells, n_cells, 2) to be filled
17 * with the index of a specific position (x,y,z,w)
18 */
19 void construct_bcc_binary_alloy(int n_cells, int* atype, int** pos,
20                                int** nn_idxxs, int idx_by_pos[n_cells][n_cells][n_cells][2]) {
21     int N_atoms = 2*n_cells*n_cells*n_cells;
22
23     int i = 0;
24
25     // construct the lattice
26     for (int x=0; x<n_cells; x++) {
27         for (int y=0; y<n_cells; y++) {
28             for (int z=0; z<n_cells; z++) {
29                 for (int w=0; w<2; w++) {
30                     // w==0 -> corner atom
31                     // w==1 -> center atom
32                     atype[i] = w;
33                     pos[i][0] = x;
34                     pos[i][1] = y;
35                     pos[i][2] = z;
36                     pos[i][3] = w;
37                     idx_by_pos[x][y][z][w] = i;
38                     i++;
39                 }
40             }
41         }
42     }
43
44     // assign the nearest neighbors
45     // loop over all lattice positions
46     for (int x=0; x<n_cells; x++) {
47         for (int y=0; y<n_cells; y++) {
48             for (int z=0; z<n_cells; z++) {
49                 for (int w=0; w<2; w++) {
50                     i = idx_by_pos[x][y][z][w];

```

```

51     int j = 0;
52
53     // the nearest neighbors have opposite w
54     // the positions differ by (-1 or 0) if w==0 or by (0 or 1) if w==1
55     // loop over all 8 nearest neighbors
56     for (int dx=w-1; dx<=w; dx++) {
57     for (int dy=w-1; dy<=w; dy++) {
58     for (int dz=w-1; dz<=w; dz++) {
59         // position of this particular nearest neighbor
60         int x_nn = x+dx;
61         int y_nn = y+dy;
62         int z_nn = z+dz;
63         int w_nn;
64         if (w==0) w_nn = 1;
65         if (w==1) w_nn = 0;
66         // periodic boundary conditions:
67         if (x_nn==n_cells-1) x_nn = 0;
68         if (y_nn==n_cells-1) y_nn = 0;
69         if (z_nn==n_cells-1) z_nn = 0;
70         if (x_nn==n_cells) x_nn = 0;
71         if (y_nn==n_cells) y_nn = 0;
72         if (z_nn==n_cells) z_nn = 0;
73         nn_idxes[i][j] = idx_by_pos[x_nn][y_nn][z_nn][w_nn];
74         // sanity check:
75         if (nn_idxes[i][j] >= N_atoms || nn_idxes[i][j]<0) {
76             printf("ERROR: nn_idxes[%i][%i] = %i even though N_atoms = %i\n",i,j,nn_idxes[i][j],
77                    N_atoms);
78             exit(1);
79         }
80         j++;
81     }
82 }
83 }
84 }
85 }
86 }
87 }
88
89
90
91 void count_bonds(int N_atoms, int* atype, int** nn_idxes,
92                 int* N_AA, int* N_BB, int* N_AB) {
93     // count the types of nearest neighbor pairs
94     (*N_AA) = 0;
95     (*N_BB) = 0;
96     (*N_AB) = 0;
97
98     for (int i=0; i<N_atoms; i++) {
99         int atype_a = atype[i];
100         for (int j=0; j<8; j++) {
101             int atype_b = atype[nn_idxes[i][j]];
102             if (atype_a == 0 && atype_b == 0) {
103                 (*N_AA)++;
104             } else if (atype_a == 1 && atype_b == 1) {
105                 (*N_BB)++;
106             } else {
107                 (*N_AB)++;
108             }
109         }
110     }
111     // but now we counted each bond twice
112     if ((*N_AA)%2 == 1 || (*N_BB)%2 == 1 || (*N_AB)%2 == 1) {
113         perror("ERROR: number of pairs should be even");
114         exit(1);
115     }
116     (*N_AA) /= 2;
117     (*N_BB) /= 2;
118     (*N_AB) /= 2;
119 }
120

```

```

121 double calc_energy(int N_AA, int N_BB, int N_AB) {
122     return N_AA*E_AA + N_BB*E_BB + N_AB*E_AB;
123 }
124
125 double calc_P(int N_atoms, int N_Aa) {
126     // long-range order parameter P
127     int N_A = N_atoms/2;
128     return 2.*((double)N_Aa)/N_A - 1.;
129 }
130
131 double calc_r(int N_atoms, int N_AB) {
132     // short-range order parameter r
133     int N = N_atoms/2;
134     return (N_AB-4.*N)/(4.*N);
135 }

```

Functions for calculations of the statistical inefficiency: statistical_ineff.c

```

1  #include <stdio.h>
2  #include <math.h>
3  #include "tools.h"
4
5  #include "statistical_ineff.h"
6
7  double calc_corr_func(double* f, double f2_mean, double f_mean2, int k, int n_f) {
8      // f2_mean = <f^2> and f_mean2 = <f>^2
9      // calculate <f_{i+k}*f_i> (each product is saved in ff)
10     int n_ff = n_f - k;
11     double *ff = (double*)malloc(n_f*sizeof(double));
12     elementwise_multiplication(ff, f+k, f, n_ff);
13     double ff_mean = average(ff, n_ff);
14     free(ff);
15
16     return (ff_mean - f_mean2)/(f2_mean - f_mean2);
17 }
18
19 void calc_all_corr_func(double* f, int n_f, int* k, double* Phi, int n_k) {
20     // calculate corr func for all given k
21
22     // first shift f
23     double f_mean = average(f, n_f);
24     double* f_shifted = (double*)malloc(n_f*sizeof(double));
25     for (int i=0; i<n_f; i++) {
26         f_shifted[i] = f[i] - f_mean;
27     }
28     // calculate <f^2> and <f>^2
29     double* f_squared = (double*)malloc(n_f*sizeof(double));
30     elementwise_multiplication(f_squared, f_shifted, f_shifted, n_f);
31     double f2_mean = average(f_squared, n_f);
32     double f_mean2 = 0;
33     free(f_squared);
34
35     print_progress(0,0,n_k,true);
36     for (int i=0; i<n_k; i++) {
37         Phi[i] = calc_corr_func(f_shifted, f2_mean, f_mean2, k[i], n_f);
38         print_progress(i+1,0,n_k,false);
39     }
40
41     free(f_shifted);
42 }
43
44 double calc_s_corr(double* f, int n_f) {
45     // calculate the statistical inefficiency through the correlation function

```

```

46 // use binary search to find the k so that the correlation function is at exp(-2)
47
48 // first shift f
49 double f_mean = average(f, n_f);
50 double* f_shifted = (double*)malloc(n_f*sizeof(double));
51 for (int i=0; i<n_f; i++) {
52     f_shifted[i] = f[i] - f_mean;
53 }
54 // calculate <f^2> and <f>^2
55 double* f_squared = (double*)malloc(n_f*sizeof(double));
56 elementwise_multiplication(f_squared, f_shifted, f_shifted, n_f);
57 double f2_mean = average(f_squared, n_f);
58 double f_mean2 = 0;
59 free(f_squared);
60
61 // do binary search to find k0
62 // for which phi(k0) is just below exp(-2)
63 // and phi(k0-1) is just above exp(-2)
64 // assumption: phi(k<k0)>= exp(-2) and phi(k>k0)< exp(-2)
65 // (hopefully true)
66 double Phi_wanted = exp(-2);
67
68 // start with a rough search going for higher values until its lower
69 double rough_step_scaler = 2.0;
70 double temp_k = 1;
71 double temp_Phi = calc_corr_func(f_shifted, f2_mean, f_mean2, (int)(temp_k), n_f);
72 int n_steps_rough = 1;
73 while (temp_Phi > Phi_wanted && (temp_k*rough_step_scaler) < n_f) {
74     temp_k *= rough_step_scaler;
75     temp_Phi = calc_corr_func(f_shifted, f2_mean, f_mean2, (int)(temp_k), n_f);
76     n_steps_rough++;
77 }
78 int k_low = (int)(temp_k/rough_step_scaler);
79 int k_high = (int)temp_k;
80 double Phi_k_low = calc_corr_func(f_shifted, f2_mean, f_mean2, k_low, n_f);
81 double Phi_k_high = temp_Phi;
82 int n_steps_binary = 1;
83 while (k_high-k_low > 1) {
84     if (Phi_k_low < Phi_wanted || Phi_k_high >= Phi_wanted) {
85         // assumption probably does not hold
86         // Phi_wanted is not in the range k_low, k_high anymore
87         printf("ERROR: Binary search failed. (Phi_wanted = %.5f)\n", Phi_wanted);
88         printf("ERROR: k_low = %i, Phi_k_low = %.5f\n", k_low, Phi_k_low);
89         printf("ERROR: k_high = %i, Phi_k_high = %.5f\n", k_high, Phi_k_high);
90         exit(1);
91     }
92     int k_mid = (k_high+k_low)/2;
93     double Phi_k_mid = calc_corr_func(f_shifted, f2_mean, f_mean2, k_mid, n_f);
94     if (Phi_k_mid >= Phi_wanted) {
95         k_low = k_mid;
96         Phi_k_low = Phi_k_mid;
97     } else {
98         k_high = k_mid;
99         Phi_k_high = Phi_k_mid;
100     }
101     //printf("k_low = %i; k_high = %i ; Phi_k_low = %f; Phi_k_high = %f\n",k_low,k_high,↵
102     Phi_k_low,Phi_k_high);
103     n_steps_binary++;
104 }
105 // check if Phi wanted is still in the found range
106 if (Phi_k_low < Phi_wanted || Phi_k_high >= Phi_wanted) {
107     // assumption probably does not hold
108     // Phi_wanted is not in the range k_low, k_high anymore
109     printf("ERROR: Binary search found the wrong range. (Phi_wanted = %.5f)\n", Phi_wanted);
110     printf("ERROR: k_low = %i, Phi_k_low = %.5f\n", k_low, Phi_k_low);
111     printf("ERROR: k_high = %i, Phi_k_high = %.5f\n", k_high, Phi_k_high);
112     exit(1);
113 }
114 //printf("n_steps_rough = %i; n_steps_binary_search = %i; s_corr = %i\n", n_steps_rough, ↵
115     n_steps_binary, k_high);

```



```
115     free(f_shifted);
116     return k_high;
117 }
118
119
120 double calc_s_block_avg(double* f, double f_variance, int B, int n_f) {
121     int n_F = n_f/B;
122     // the last block might not be full
123     //if (n_f%B!=0) {
124     //    n_F++;
125     //}
126     double* F = (double*)malloc(n_F*sizeof(double));
127     for (int i=0; i<n_F; i++) {
128         F[i] = average(f+i*B, B);
129     }
130     double F_variance = standard_deviation(F, n_F);
131     F_variance *= f_variance;
132     free(F);
133     return B*(F_variance/f_variance);
134 }
```

Utility functions for C: tools.c

```
1  #include <stdio.h>
2  #include <stdlib.h>
3  #include <stdbool.h>
4  #include <math.h>
5  #include <gsl/gsl_rng.h>
6
7  #include "tools.h"
8
9  void constant_multiplication(double* res,
10                             double* v1,
11                             double a1,
12                             unsigned int len)
13  {
14      for(int i=0;i<len;i++){
15          res[i] = a1*v1[i];
16      }
17  }
18
19  void
20  elementwise_addition(
21      double *res,
22      double *v1,
23      double *v2,
24      unsigned int len
25  )
26  {
27      for(int i=0;i<len;i++){
28          res[i] = v1[i] + v2[i];
29      }
30  }
31
32  void
33  elementwise_multiplication(
34      double *res,
35      double *v1,
36      double *v2,
37      unsigned int len
38  )
39  {
40      for(int i=0;i<len;i++){
41          res[i] = v1[i] * v2[i];
42      }
```

```

43 }
44
45 double
46 dot_product(
47     double *v1,
48     double *v2,
49     unsigned int len
50 )
51 {
52     double res = 0;
53     for(int i=0;i<len;i++){
54         res += v1[i] * v2[i];
55     }
56     return res;
57 }
58
59 double**
60 create_2D_array(
61     unsigned int nrows,
62     unsigned int ncols
63 )
64 {
65     // allocate 1D array of doubles containing the whole matrix
66     double* linear_array = (double*)malloc(nrows*ncols*sizeof(double));
67     // allocate 1D array of pointers to doubles containing the pointers to each row starting ↵
68     // point
69     double** array = (double**)malloc(nrows*sizeof(double*));
70     // let each row pointer point to the correct address
71     for(int row=0;row<nrows;row++){
72         array[row] = linear_array + row*ncols;
73     }
74     return array;
75 }
76
77 void
78 destroy_2D_array(
79     double **array
80 )
81 {
82     // free the linear_array
83     free(array[0]);
84     // free the pointers array
85     free(array);
86 }
87
88 int**
89 create_2D_int_array(
90     unsigned int nrows,
91     unsigned int ncols
92 )
93 {
94     // allocate 1D array of doubles containing the whole matrix
95     int* linear_array = (int*)malloc(nrows*ncols*sizeof(int));
96     // allocate 1D array of pointers to doubles containing the pointers to each row starting ↵
97     // point
98     int** array = (int**)malloc(nrows*sizeof(int*));
99     // let each row pointer point to the correct address
100     for(int row=0;row<nrows;row++){
101         array[row] = linear_array + row*ncols;
102     }
103     return array;
104 }
105
106 void
107 destroy_2D_int_array(
108     int **array
109 )
110 {
111     // free the linear_array
112     free(array[0]);
113     // free the pointers array

```

```

112     free(array);
113 }
114
115 void
116 matrix_multiplication(
117     double **result,
118     double **m1,
119     double **m2,
120     unsigned int m,
121     unsigned int n
122 )
123 {
124     // https://en.wikipedia.org/wiki/Computational_complexity_of_matrix_multiplication#↔
125     // Schoolbook_algorithm
126     for(int i=0; i<n; i++){
127         for(int j=0; j<n; j++){
128             // calculate matrix element in row i, col j
129             result[i][j] = 0;
130             for(int k=0; k<m; k++){
131                 result[i][j] += m1[i][k] * m2[k][j];
132             }
133         }
134     }
135
136 double
137 vector_norm(
138     double *v1,
139     unsigned int len
140 )
141 {
142     return sqrt(dot_product(v1, v1, len));
143 }
144
145
146 void
147 normalize_vector(
148     double *v1,
149     unsigned int len
150 )
151 {
152     double norm = vector_norm(v1, len);
153     constant_multiplication(v1, v1, 1./norm, len);
154 }
155
156 double
157 average(
158     double *v1,
159     unsigned int len
160 )
161 {
162     double res = 0;
163     for(int i=0; i<len; i++){
164         res += v1[i];
165     }
166     return res/len;
167 }
168
169
170 double
171 standard_deviation(
172     double *v1,
173     unsigned int len
174 )
175 {
176     /* https://numpy.org/doc/stable/reference/generated/numpy.std.html
177     * The standard deviation is the square root of the average of the squared deviations from ↔
178     * the mean,
179     * i.e., std = sqrt(mean(x)), where x = abs(a - a.mean())**2.
180     * std(v1) = sqrt(sum(v1 - v1_mean)^2 / len(v1)) */
181     double mean = average(v1, len);

```

```

181     double res = 0;
182     for(int i=0;i<len;i++){
183         res += (v1[i] - mean)*(v1[i] - mean);
184     }
185     return sqrt(res/len);
186 }
187
188 double
189 distance_between_vectors(
190     double *v1,
191     double *v2,
192     unsigned int len
193 )
194 {
195     // dist(v1,v2) = |v1 - v2|
196     double res = 0;
197     for(int i=0;i<len;i++){
198         res += (v1[i] - v2[i])*(v1[i] - v2[i]);
199     }
200     return sqrt(res);
201 }
202
203
204
205 void print_vector(double* vec, int length){
206     printf("[");
207     for(int i=0; i < length; i++){
208         printf("%.2f, ", vec[i]);
209     }
210     printf("\b\b]\n");
211 }
212 void print_vector_int(int* vec, int length){
213     printf("[");
214     for(int i=0; i < length; i++){
215         printf("%i, ", vec[i]);
216     }
217     printf("\b\b]\n");
218 }
219
220 void fprintf_vector(FILE* file, double* vec, int length){
221     for(int i=0; i < length; i++){
222         fprintf(file, "%.6f", vec[i]);
223         if(i<length-1) fprintf(file, ", ");
224     }
225     fprintf(file, "\n");
226 }
227
228 void print_matrix(double** mat, int n, int m){
229     printf("[");
230     for(int i=0; i < n; i++){
231         printf("[");
232         for(int j=0; j < m; j++){
233             printf("%.2f, ", mat[i][j]);
234         }
235         printf("\b\b],");
236         if(i<n-1) printf("\n");
237     }
238     printf("\b\b]\n");
239 }
240
241 void print_matrix_int(int** mat, int n, int m){
242     printf("[");
243     for(int i=0; i < n; i++){
244         printf("[");
245         for(int j=0; j < m; j++){
246             printf("%i, ", mat[i][j]);
247         }
248         printf("\b\b],");
249         if(i<n-1) printf("\n");
250     }
251     printf("\b\b]\n");

```

```

252 }
253 void print_matrix_stack(int n, int m, double mat[][m]){
254     printf("[");
255     for(int i=0; i < n; i++){
256         printf("[");
257         for(int j=0; j < m; j++){
258             printf("%.2f, ", mat[i][j]);
259         }
260         printf("\b\b],");
261         if(i<n-1) printf("\n");
262     }
263     printf("\b]\n");
264 }
265
266 void fprintf_matrix(FILE* file, double** mat, int n, int m){
267     // write matrix to a file
268     for(int i=0; i < n; i++){
269         for(int j=0; j < m; j++){
270             fprintf(file, "%.6f", mat[i][j]);
271             if(j<m-1) fprintf(file, ", ");
272             else fprintf(file, "\n");
273         }
274     }
275 }
276
277 void init_matrix_stack(int n, int m, double mat[n][m], double value){
278     for(int i=0; i<n; i++){
279         for(int j=0; j<m; j++){
280             mat[i][j] = value;
281         }
282     }
283 }
284
285 gsl_rng* init_rng(int seed){
286     // seed = 0 means the seed is random
287     // set up the random number generator from GSL
288     gsl_rng_env_setup();
289     const gsl_rng_type* T = gsl_rng_default;
290     gsl_rng* rng = gsl_rng_alloc(T);
291     if(seed != 0){
292         gsl_rng_set(rng, seed);
293     }
294
295     return rng;
296 }
297
298 void print_progress(double current_value, double min_value, double max_value, bool start_new) {
299     // shows the progress, but only at each round percentage, so that it does not slow down the ↵
300     // computation
301     static int percent;
302     if (start_new) {
303         percent = -1;
304     }
305     int curr_percent = (int)(100*(current_value-min_value)/(max_value-min_value));
306     if (curr_percent != percent) {
307         percent = curr_percent;
308         printf("\33[2K\r%i %% (%.0f / %.0f)", percent, current_value, max_value);
309         if(percent >= 100) {
310             printf("\n");
311         }
312         fflush(stdout);
313     }
314 }

```

Plotting of task 1: task1.py

```

1  # %%
2  import numpy as np
3  import matplotlib.pyplot as plt
4  from scipy.optimize import minimize
5  from tqdm.auto import tqdm
6
7  E_AA = -436e-3 # eV
8  E_BB = -113e-3 # eV
9  E_AB = -294e-3 # eV
10
11 k_B = 8.617333262e-5 # eV/K
12
13 N = 100000
14
15 E_0_per_N = 2*(E_AA+E_BB+2*E_AB)
16 dE = E_AA + E_BB - 2*E_AB
17
18 T_c = 2*dE/k_B
19 T_c_exp = 468 + 273.15
20
21 print(f"T_c(mfa) = {T_c:.2f} K ; T_c(exp) = {T_c_exp:.2f} K")
22
23 T = np.linspace(0,1200,1200) # K
24 #T = np.linspace(906,1200,1000) # K
25
26 def F_per_N(P,T):
27     if P==1 or P==-1:
28         return - 2*k_B*T*np.log(2)
29     return E_0_per_N - 2*P**2*dE - 2*k_B*T*np.log(2) + k_B*T*((1+P)*np.log(1+P)+(1-P)*np.log(1-P))
30
31 P_0 = 0.5
32 P = []
33 for T_i in tqdm(T):
34     P_0 = minimize(F_per_N, P_0, args=T_i, bounds=((0,1),), tol=1e-10).x[0]
35     P.append(P_0)
36 P = np.array(P)
37
38 N_AA_per_N = 2*(1-P**2)
39 N_BB_per_N = 2*(1-P**2)
40 N_AB_per_N = 4*(1+P**2)
41
42 E_per_N = N_AA_per_N*E_AA + N_BB_per_N*E_BB + N_AB_per_N*E_AB
43 E_MFA_per_N = E_0_per_N - 2*P**2*dE
44
45 C_per_N = np.gradient(E_per_N, T)
46
47 fig, axs = plt.subplots(2,3, figsize=(12,6))
48
49 #fig.suptitle(f"$T_c = {T_c:.3f} \, \mathrm{{K}}$")
50
51 plt.sca(axs[0][0])
52 plt.axvline(T_c, linestyle=":", color="k", alpha=0.5)
53 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.5)
54 plt.plot(T,P, color="C2")
55 plt.xlabel(r"$T \, /\, \mathrm{{K}}$")
56 plt.ylabel(r"$P$")
57
58 plt.sca(axs[0][1])
59 plt.axvline(T_c, linestyle=":", color="k", alpha=0.5)
60 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.5)
61 plt.plot(T,E_per_N, color="C0")
62 #plt.plot(T,E_MFA_per_N)
63 plt.xlabel(r"$T \, /\, \mathrm{{K}}$")
64 plt.ylabel(r"$E/N \, /\, \mathrm{{eV}}$")
65
66 plt.sca(axs[0][2])
67 plt.axvline(T_c, linestyle=":", color="k", alpha=0.5)
68 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.5)
69 plt.plot(T,C_per_N, color="C1")

```

```

70 plt.xlabel(r"$T \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{K}$")
71 plt.ylabel(r"$C/N \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{eV} \text{ , } K^{-1}$")
72
73 # log scale plots below
74 plt.sca(axes[1][0])
75 plt.axvline(T_c, linestyle=":", color="k", alpha=0.5)
76 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.5)
77 plt.plot(T,P, color="C2")
78 plt.yscale("log")
79 plt.xlabel(r"$T \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{K}$")
80 plt.ylabel(r"$P$")
81
82 plt.sca(axes[1][1])
83 plt.axvline(T_c, linestyle=":", color="k", alpha=0.5)
84 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.5)
85 plt.plot(T,E_per_N[-1]-E_per_N, color="C0")
86 plt.yscale("log")
87 #plt.plot(T,E_MFA_per_N)
88 plt.xlabel(r"$T \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{K}$")
89 plt.ylabel(rf"$E(T=\{T[-1]:.0f\}\mathrm{{K}})/N - E/N \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{eV}$")
90
91 plt.sca(axes[1][2])
92 plt.axvline(T_c, linestyle=":", color="k", alpha=0.5)
93 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.5)
94 plt.plot(T,C_per_N, color="C1")
95 plt.yscale("log")
96 plt.xlabel(r"$T \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{K}$")
97 plt.ylabel(r"$C/N \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{eV} \text{ , } K^{-1}$")
98
99 plt.tight_layout()
100 plt.savefig("plots/task1.pdf")
101
102
103
104 # plot 3 different F(P) to visualize the minimization of F
105
106 def F_per_N(P,T):
107     res = np.zeros_like(P)
108     mask = (P==1)|(P==-1)
109     res[mask] = - 2*k_B*T*np.log(2)
110     P = P[~mask]
111     res[~mask] = E_0_per_N - 2*P**2*dE - 2*k_B*T*np.log(2) + k_B*T*((1+P)*np.log(1+P)+(1-P)*np.log(1-P))
112     return res
113
114 Ts = [100,500,750,10000] # K
115
116 P_lin = np.linspace(-1,1,1000)
117
118 fig, axes = plt.subplots(1,len(Ts),figsize=(len(Ts)*3,2.5))
119 for i,T_i in enumerate(Ts):
120     F_ = F_per_N(P_lin, T_i)
121     plt.sca(axes[i])
122     plt.plot(P_lin, F_per_N(P_lin, T_i))
123     plt.ylim(np.min(F_[F_<-1.5])*1.001, np.max(F_[F_<-1.5])*0.999)
124     plt.xlabel(r"$P$")
125     plt.ylabel(rf"$F(P, T=\{T_i:.0f\}\mathrm{{K}}) \text{ : } \backslash \text{ : } \backslash \text{ : } \mathrm{eV}$")
126
127 plt.tight_layout()
128 plt.savefig("plots/task1_F.pdf")

```

Plotting of task 2: task2.py

```

1 # %%
2 import numpy as np

```

```

3 import matplotlib.pyplot as plt
4 from pathlib import Path
5 import json
6
7
8 # plot the results
9 print(f"Plot final results...")
10 T, E, E_std, s_E, P, P_std, s_P, r, r_std, s_r, C = np.genfromtxt("data/H2a.csv", delimiter=",", ↵
    unpack=True)
11
12 # get header metadata
13 with open("data/H2a.csv", "r") as file:
14     metadata_str = "".join([file.readline() for i in range(1)])
15     metadata_str = metadata_str.replace("# ", "")
16     metadata = json.loads(metadata_str)
17
18 n_eq_steps = metadata["n_eq_steps"]
19 n_steps = metadata["n_steps"]
20
21 # calculate T_c
22 k_B = 8.617333262e-5 # eV/K
23 E_AA = -436e-3 # eV
24 E_BB = -113e-3 # eV
25 E_AB = -294e-3 # eV
26 dE = E_AA + E_BB - 2*E_AB
27 T_c = 2*dE/k_B
28 T_c_exp = 468 + 273.15
29
30 E_err = np.sqrt(s_E*E_std**2/n_steps)
31 P_err = np.sqrt(s_P*P_std**2/n_steps)
32 r_err = np.sqrt(s_r*r_std**2/n_steps)
33
34 fig, axs = plt.subplots(4,1, figsize=(10,10))
35
36 #fig.suptitle(f"$T_{{c,task1}} = {T_c:.3f} \, \mathrm{{K}}$, $N_{{\mathrm{{eq}}}} = {n_eq_steps:.1e}$↵
    , $N = {n_steps:.1e}$")
37
38
39 plt.sca(axs[0])
40 plt.axvline(T_c, linestyle=":", color="k", alpha=0.9)
41 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.9)
42 plt.fill_between(T, E-E_err, E+E_err, color="C0", alpha=0.3)
43 plt.plot(T,E, color="C0")
44 plt.ylim(-2360,-2280)
45 plt.xlabel(r"$T \, /\, \mathrm{{K}}$")
46 plt.ylabel(r"$E \, /\, \mathrm{{eV}}$")
47 plt.grid()
48
49 plt.sca(axs[1])
50 plt.axvline(T_c, linestyle=":", color="k", alpha=0.9)
51 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.9)
52 plt.plot(T,C, color="C1")
53 plt.ylim(0,0.5)
54 plt.xlabel(r"$T \, /\, \mathrm{{K}}$")
55 plt.ylabel(r"$C \, /\, \mathrm{{eV}} \, , \, K^{-1}$")
56 plt.grid()
57
58 plt.sca(axs[2])
59 plt.axvline(T_c, linestyle=":", color="k", alpha=0.9)
60 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.9)
61 plt.fill_between(T, np.abs(P)-P_err, np.abs(P)+P_err, color="C2", alpha=0.3)
62 plt.plot(T,P, color="C4", linestyle=":", alpha=0.8, label="$P$")
63 plt.plot(T,np.abs(P), color="C2", label="$|P|$")
64 plt.ylim(-0.5,1)
65 plt.xlabel(r"$T \, /\, \mathrm{{K}}$")
66 plt.ylabel(r"$P$")
67 plt.grid()
68 plt.legend()
69
70 plt.sca(axs[3])
71 plt.axvline(T_c, linestyle=":", color="k", alpha=0.9)

```



```

72 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.9)
73 plt.fill_between(T, r-r_err, r+r_err, color="C3", alpha=0.3)
74 plt.plot(T,r, color="C3")
75 plt.ylim(0,1)
76 plt.xlabel(r"$T \text{ \textbackslash:/\textbackslash: \mathrm{K}}$")
77 plt.ylabel(r"$r$")
78 plt.grid()
79
80 plt.tight_layout()
81 plt.savefig("plots/task2.pdf")
82
83 # plot the uncertainties
84 fig, axs = plt.subplots(3,1, figsize=(10,7.5))
85
86 plt.sca(axs[0])
87 plt.axvline(T_c, linestyle=":", color="k", alpha=0.9)
88 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.9)
89 plt.plot(T,E_err, color="C0")
90 plt.yscale("log")
91 plt.xlabel(r"$T \text{ \textbackslash:/\textbackslash: \mathrm{K}}$")
92 plt.ylabel(r"$\sigma_{\textbackslash\langle \textbackslashrangle E \textbackslash\textbackslash: \mathrm{eV}}$")
93 plt.grid()
94
95 plt.sca(axs[1])
96 plt.axvline(T_c, linestyle=":", color="k", alpha=0.9)
97 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.9)
98 plt.plot(T,P_err, color="C2")
99 plt.yscale("log")
100 plt.xlabel(r"$T \text{ \textbackslash:/\textbackslash: \mathrm{K}}$")
101 plt.ylabel(r"$\sigma_{\textbackslash\langle \textbackslashrangle P \textbackslash\textbackslash: \mathrm{eV}}$")
102 plt.grid()
103
104 plt.sca(axs[2])
105 plt.axvline(T_c, linestyle=":", color="k", alpha=0.9)
106 plt.axvline(T_c_exp, linestyle="--", color="k", alpha=0.9)
107 plt.plot(T,r_err, color="C3")
108 plt.yscale("log")
109 plt.xlabel(r"$T \text{ \textbackslash:/\textbackslash: \mathrm{K}}$")
110 plt.ylabel(r"$\sigma_{\textbackslash\langle \textbackslashrangle r \textbackslash\textbackslash: \mathrm{eV}}$")
111 plt.grid()
112
113 plt.tight_layout()
114 plt.savefig("plots/task2_uncertainties.pdf")
115
116
117 # plot the statistical inefficiency
118 plt.figure(figsize=(8,3))
119 plt.plot(T,s_E, "C0", label="$s(E)$ and $n(s(r))$")
120 plt.plot(T,s_P, "C2", label="$s(P)$")
121 #plt.plot(T,s_r, "C3", linestyle=":", label="$s(r)$")
122 plt.yscale("log")
123 plt.xlabel(r"$T \text{ \textbackslash:/\textbackslash: \mathrm{K}}$")
124 plt.ylabel(r"$s$ (statistical inefficiency)")
125 plt.legend()
126 plt.tight_layout()
127 plt.savefig("plots/H2a_stat_ineff.pdf")
128
129
130 # Plot a few full simulations
131 full_simulations_dir = Path("data/full_simulations/")
132 fig, axs = plt.subplots(3,1, figsize=(10,8))
133
134 #fig.suptitle(f"$T = \{T:2f\} \text{ \textbackslash:/\textbackslash: \mathrm{K}}$, $N_{\textbackslash\mathrm{eq}} = \{n_{\textbackslash\mathrm{eq\_steps}:.1e}\}$, $n\langle P \rangle = \{P_{\textbackslash\mathrm{avg}:.4f}\} \text{ \textbackslash\mathrm{eV}}$, $E = \{E_{\textbackslash\mathrm{avg}:.4f}\} \text{ \textbackslash\mathrm{eV}}$, $C = \{C:.4f\} \text{ \textbackslash\mathrm{eV/K}}$")
135 #fig.suptitle(f"$T = \{T:2f\} \text{ \textbackslash:/\textbackslash: \mathrm{K}}$, $N_{\textbackslash\mathrm{eq}} = \{n_{\textbackslash\mathrm{eq\_steps}:.1e}\}$, $n\langle P \rangle = \{P_{\textbackslash\mathrm{avg}:.4f}\} \text{ \textbackslash\mathrm{eV}}$, $E = \{E_{\textbackslash\mathrm{avg}:.4f}\} \text{ \textbackslash\mathrm{eV}}$, $C = \{C:.4f\} \text{ \textbackslash\mathrm{eV/K}}$")
136
137 for full_simulation_file in full_simulations_dir.iterdir():
138     # get header metadata
139     with open(full_simulation_file, "r") as file:
140         metadata_str = "".join([file.readline() for i in range(2)])
141         metadata_str = metadata_str.replace("# ", "")
142         metadata = json.loads(metadata_str)

```

```

141     T = metadata["T[K]"]
142     n_eq_steps = metadata["n_eq_steps"]
143
144     E_avg = metadata["E[eV]"]
145     P_avg = metadata["P"]
146     r_avg = metadata["r"]
147     C = metadata["C[eV/K]"]
148
149     print(f"Plot full simulation T={T:.0f} K ...")
150
151     i_step, E, P, r = np.genfromtxt(full_simulation_file, delimiter=",", unpack=True)
152
153     plt.sca(axes[0])
154     plt.plot(i_step, P, label=f"$T = {T:.0f} \mathrm{{K}}$", rasterized=True)
155
156     plt.sca(axes[1])
157     plt.plot(i_step, E, label=f"$T = {T:.0f} \mathrm{{K}}$", rasterized=True)
158
159     plt.sca(axes[2])
160     plt.plot(i_step, r, label=f"$T = {T:.0f} \mathrm{{K}}$", rasterized=True)
161
162     plt.sca(axes[0])
163     plt.axvline(n_eq_steps, linestyle="--", color="k", alpha=0.5, label=rf"$N_{\mathrm{{eq}}} = \{\leftrightarrow n\_eq\_steps:.1e\}$")
164     plt.xlabel("simulation step")
165     plt.ylabel("P")
166     plt.legend(loc="center right")
167
168     plt.sca(axes[1])
169     plt.axvline(n_eq_steps, linestyle="--", color="k", alpha=0.5, label=rf"$N_{\mathrm{{eq}}} = \{\leftrightarrow n\_eq\_steps:.1e\}$")
170     plt.xlabel("simulation step")
171     plt.ylabel("energy / eV")
172     plt.legend(loc="center right")
173
174     plt.sca(axes[2])
175     plt.axvline(n_eq_steps, linestyle="--", color="k", alpha=0.5, label=rf"$N_{\mathrm{{eq}}} = \{\leftrightarrow n\_eq\_steps:.1e\}$")
176     plt.xlabel("simulation step")
177     plt.ylabel("r")
178     plt.legend(loc="center right")
179
180     plt.tight_layout()
181     plt.savefig(f"plots/H2a_simsteps.pdf")
182
183     # Plot a few full simulation correlation functions
184     corr_simulations_dir = Path("data/corr_simulations/")
185     plt.figure(figsize=(4,3))
186
187     for i, corr_simulation_file in enumerate(corr_simulations_dir.iterdir()):
188         # get header metadata
189         with open(corr_simulation_file, "r") as file:
190             metadata_str = "".join([file.readline() for i in range(1)])
191             metadata_str = metadata_str.replace("# ", "")
192             metadata = json.loads(metadata_str)
193
194             T = metadata["T[K]"]
195             s_E = metadata["s_E"]
196
197             print(f"Plot correlation function T={T:.0f} K ...")
198
199             k, Phi = np.genfromtxt(corr_simulation_file, delimiter=",", unpack=True)
200
201             plt.plot(k, Phi, color=f"C{i}", label=f"$T = {T:.0f} \mathrm{{K}}$", rasterized=True)
202             plt.axvline(s_E, linestyle="--", color=f"C{i}", alpha=0.5)
203
204             plt.axhline(np.exp(-2), linestyle=":", color="k", alpha=0.5, label=f"$\exp(-2)$")
205             plt.xscale("log")

```

```

209 plt.yscale("log")
210 plt.xlabel("$k$")
211 plt.ylabel(r"$\Phi_E(k)$")
212 plt.legend(loc="lower left")
213
214 plt.tight_layout()
215 plt.savefig(f"plots/H2a_corr_func.pdf")
216
217
218
219
220 # Plot a few simulation block averages
221 blok_simulations_dir = Path("data/blok_simulations/")
222 plt.figure(figsize=(4,3))
223
224 for i,blok_simulation_file in enumerate(blok_simulations_dir.iterdir()):
225     # get header metadata
226     with open(blok_simulation_file, "r") as file:
227         metadata_str = "".join([file.readline() for i in range(1)])
228         metadata_str = metadata_str.replace("# ", "")
229         metadata = json.loads(metadata_str)
230
231         T = metadata["T[K]"]
232         s_E = metadata["s_E"]
233
234         print(f"Plot block averaging T={T:.0f} K ...")
235
236         B, s = np.genfromtxt(blok_simulation_file, delimiter=",", unpack=True)
237
238         plt.plot(B, s, color=f"C{i}", label=f"$T = {T:.0f} \mathrm{{K}}$")
239         plt.axhline(s_E, linestyle="--", color=f"C{i}", alpha=0.5)
240
241 plt.xscale("log")
242 plt.yscale("log")
243 plt.xlabel("$B$ (block size)")
244 plt.ylabel(r"$s$ (statistical inefficiency)")
245 plt.legend(loc="upper left")
246
247 plt.tight_layout()
248 plt.savefig(f"plots/H2a_block_avg.pdf")
249
250 # %%

```