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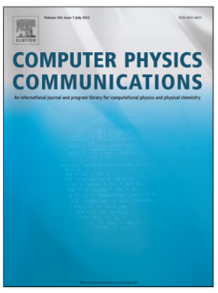

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Dynamic Greedy Algorithms for the Edwards-Anderson Model

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Abstract

To provide a novel tool for the investigation of the energy landscape of the Edwards-Anderson spin-glass model we introduce an algorithm that allows an efficient execution of a greedy optimization based on data from a previously performed optimization for a similar configuration. As an application we show how the technique can be used to perform higher-order greedy optimizations and simulated annealing searches with improved performance.

1. Introduction

For several decades spin glasses [1] have been the subject of scientific inquiry and until today they belong to the most challenging models in computational physics. While analytic results have been derived for meanfield models [2, 3], it is still strongly debated whether non-meanfield systems behave similarly. Due to the rough energy landscape basic Markov-chain Monte Carlo methods are not useful and even advanced methods like replica exchange [4] or flat-histogram techniques like multicanonical sampling [5, 6] or the Wang-Landau method [7] equilibrate or converge very slowly.

One major goal is the exploration of the properties of the ground state, i.e., the spin configuration(s) with the lowest energy and therefore the state of the system at zero temperature. To tackle this problem numerous algorithms have been proposed. While for the two-dimensional case approaches from graph theory achieve polynomial complexity, it is believed that for higher dimensions exponentially growing run times cannot be overcome. Usually heuristic methods like simulated annealing [8] or approximations [9] are applied.

Recently, the introduction of quantum annealing machines (d-wave) has sparked renewed interest in the subject [10]. These devices are supposed to exploit quantum effects in order to find solutions to problems that are similar to the optimization problem in spin glasses. Current efforts are focused on evaluating to which extent quantum effects play a role and on identifying classes of problems for which an increase in performance in comparison to classical methods becomes apparent. This is tested by comparing the performance for problems specifically chosen according to the characteristics of their energy landscape.

Our work is inspired by the so-called basin-hopping algorithm [11] which was introduced by Wales and Doye in 1997 in order to find the ground states of many-body systems.

The paper is structured as follows. We start by discussing the model in section 2 and the basic greedy algorithm in section 3. Then, we introduce the concept of a dynamical greedy algorithm, determine which data is required by such a technique and show two ways of its implementation. In section 5 we discuss some simple applications: higher-order greedy algorithms and simulated annealing in the reduced energy landscape. We finish in section 6 with some concluding remarks.

2. Edwards-Anderson model

We consider the Edwards-Anderson spin-glass model [12] defined by the Hamiltonian

$$\mathcal{H} = -\sum_{\langle ij \rangle} J_{ij} s_i s_j, \tag{1}$$

where $s \in \{-1, 1\}$ are Ising spins on a regular lattice and the interactions between adjacent spins J are randomly chosen, usually from a bimodal,

$$p_{\mathrm{bm}}(J) = \frac{\delta(J-1) + \delta(J+1)}{2}, \tag{2}$$

or normal Gaussian,

$$p_{\mathrm{Gauss}}(J) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{J^2}{2}\right), \tag{3}$$

distribution. We define the energy of a spin s_k as the sum of all terms to which it contributes

$$e_k = -\sum_{\langle ij \rangle} J_{ij} s_i s_j (\delta_{ik} + \delta_{jk}), \tag{4}$$

with the consequence that

$$\mathcal{H} = \frac{1}{2} \sum_k e_k, \tag{5}$$

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