

Optimization Strategies in Complex Systems

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Abstract

We consider a class of combinatorial optimization problems that emerge in a variety of domains among which: condensed matter physics, theory of financial risks, error correcting codes in information transmissions, molecular and protein conformation, image restoration. We show the performances of two algorithms, the “greedy” (quick decrease along the gradient) and the “reluctant” (slow decrease close to the level curves) as well as those of a “stochastic convex interpolation” of the two. Concepts like the average relaxation time and the wideness of the attraction basin are analyzed and their system size dependence illustrated.

A decision-making problem is often formulated as minimization of a function of several variables (the *cost function*) possibly subjected to some constraints. Consider, for example, the following combinatorial optimization problem ¹: “Suppose that you are organizing housing accommodations for a group of four hundred university students. Space is limited and only one hundred of the students will receive places in the dormitory. To complicate matters, the Dean has provided you with a list of pairs of incompatible students, and requested that no pair from this list appear in your final choice”. It is clear that one may check “easily” (in a polynomial time) if a proposed solution is correct; nevertheless the extensive search of the solution is extremely *hard* because the total number of possible accommodations is as large as $\binom{400}{100}$, a number which is larger of the estimated number of atoms in the universe! This is an example of a so-called NP complete problem, i.e. a problem for which no polynomial algorithm is known to find the solution. There are many instances of NP complete problems coming for very different subjects. In the classical formulation of the theory of financial risk with short-selling included, the choice of the optimal portfolio from the historical prices correlations is casted in the selection of an investment strategy among a huge number of possibilities [1]. Another example comes from the theory of error-correcting codes, where one faces the problem of reconstructing an original sequence of

¹from the *Millennium Prize Problems* list at *Clay Mathematics Institute*, <http://www.claymath.org>

bits which has been corrupted during transmission [2]. More familiar to physicists is the NP complete problem coming from the realm of condensed matter. Here particles carrying a magnetic moment (spin) is modeled by dichotomic variables $\sigma_i = \pm 1$. The interaction between different atoms is described by a function $H(J, \sigma)$ (the Hamiltonian or energy), which plays the role of the cost function, and which depends also on some randomness through the set of variables J . The optimization problem amounts to find, for a given instance of the problem specified by the variables J , the ground state configuration, i.e. the spin configuration which minimize energy.

It is our aim in this report to show how new concepts and techniques from Statistical Mechanics can be helpful in finding approximated optimal solutions to complex NP complete problems [4].

We perform a statistical analysis of energy-decreasing algorithms on a specific mean-field spin model with complex energy landscape. We specifically address the following question: in the search of low energy configurations is it convenient (and in which sense) a quick decrease along the gradient (greedy dynamics) or a slow decrease close to the level curves (reluctant dynamics)? Average time and wideness of the attraction basins are introduced for each algorithm together with a convex interpolation among the two and experimental results are presented for different system sizes. We found that while the reluctant algorithm performs better for a fixed number of trials, the two algorithms become basically equivalent for a given elapsed time due to the fact that the greedy has a shorter relaxation time which scales linearly with the system size compared to a quadratic dependence for the reluctant. A final test is also performed in a stochastic convex combination of the two algorithms: at each step the motion is greedy with probability P and reluctant with probability $1 - P$. It is found that for large N and for fixed running times a substantial improvement is obtained with a $P = 0.1$

Model and Algorithms

We consider the paradigmatic model of complex spin systems, the so-called Sherrington-Kirkpatrick model [3]. This is defined by the following Hamiltonian

$$H(J, \sigma) = -\frac{1}{2} \sum_{i,j=1}^N J_{ij} \sigma_i \sigma_j \quad (1)$$

where $\sigma_i = \pm 1$ for $i = 1, \dots, N$ are Ising spin variables and J_{ij} is an $N \times N$ symmetric matrix which specifies local interaction between them. The J_{ij} are independent identically distributed symmetric gaussian random variables ($J_{ij} = J_{ji}$, $J_{ii} = 0$) with zero mean and variance $1/N$, in order to have a sensible thermodynamic limit. Since this is a disordered model one is interested in the quenched average ground state energy. For each N this is defined as:

$$e_N^{GS} = Av \left\{ \frac{1}{N} \inf_{\sigma} H_N(J, \sigma) \right\} \quad (2)$$

where we denoted by $Av\{\cdot\}$ the average over the couplings. Analytical knowledge of this quantity is available in the thermodynamical limit $N \rightarrow \infty$ using

Parisi Ansatz for replica symmetry breaking theory: $e_{\infty}^{GS} = -0.7633$ [4], a result which has been confirmed by numerical simulations using finite size scaling, yielding $e_{\infty}^{GS} = -0.76 \pm .01$ [5].

The *greedy* and *reluctant* dynamics work as follows. The initial spin configuration at time $t = 0$ is chosen at random with uniform probability. Then, at each step t , the whole spectrum of energy change obtained by flipping one of the spin is calculated

$$\Delta E_i = \sigma_i(t) \sum_{j \neq i} J_{ij} \sigma_j(t) \quad (3)$$

The configuration is then updated at time $t + 1$ by flipping the spin which corresponds to the largest (greedy) or smallest (reluctant) energy decrease. Both the dynamics follow an energy descent trajectory till they arrive to a 1-spin-flip stable configuration, i.e. a configuration whose energy can not be decreased by a single spin-flip. These represent local minima in energy landscape at zero temperature and the ground state is one of them. Moreover, we investigate the efficiency of a stochastic convex combination of the two algorithms: with probability $0 \leq P \leq 1$ we perform a greedy move and with probability $1 - P$ the corresponding reluctant move. The deterministic dynamics are obtained at $P = 1$ (greedy) and $P = 0$ (reluctant), respectively. Intermediate values of P are stochastic dynamics where the greedy and reluctant moves are weighted by the probability P .

Computational Resources and Results

Our simulations used about 5000 hours of CPU time on the machine IBM SP3. Parallelization has been highly efficient due to the fact that we run different disorder realization and/or different initial conditions on each processor, simply averaging the results at the end of the elaboration.

First of all, we analyzed the average time τ of the dynamics for different values of P , which is easily accessible to measurements and has good self-averaging properties. This is defined as

$$\tau = \frac{1}{M} \sum_{i=1}^M t_i \quad (4)$$

where t_i , $i = 1, \dots, M$ is the time of each realization of the dynamics, measured by counting the number of “spin flip” necessary to reach a metastable configuration.. The number of trials M is an increasing function of the system size. For the largest sizes ($N = 250, 300$) we used up to 10^9 initial configurations. Results are shown in Fig. (1), together with the best numerical fits. Note the progressive increase of the slope in log-log scale from an almost linear law for greedy (bottom) $\tau(N) \sim N^{1.04}$ to an almost quadratic law for reluctant (top) $\tau(N) \sim N^{2.07}$. However, an interesting result is that for $P = 0.1$ we have still have $\tau(N) \sim N^{1.26}$, i.e. a stochastic algorithm which makes on average one greedy move (and nine reluctant moves) out of ten has a much

smaller average time than the deterministic reluctant algorithm $P = 0$. We notice that the exponents for greedy (resp. reluctant) algorithm are very close to the integers 1 (resp. 2) with an observed slow crossover between the two for intermediate P . It would be interesting to have a theoretical understanding of this phenomenon even if only at a heuristic level. We plan to return over this problem in a future work.

Next, we measured the lowest energy value found for a fixed number of initial conditions for different probabilities P . One has to choose a protocol to fix the number of initial conditions. Obviously, the larger the system size the bigger must be the number of trials. We tried different choices obtaining similar results. For the sake of space we show in Fig. (2) the results of the run where we choose N initial conditions for a system of size N . The data have been averaged on 1000 disorder realizations. We see that the smaller is the probability of making greedy moves, the lower is the energy found. The best result is obtained for $P = 0$, which corresponds to deterministic reluctant dynamics. This means that, ignoring the total amount of time and imposing constraint only on the number of initial conditions, reluctant dynamic is the most efficient in reaching low energy states, i.e. it has a larger basin of attraction.

Finally, we compared results of different probabilities in the case one considers a fixed elapsed time. As an example, we present results for an elapsed time of 100 hours of CPU on a IBM SP3 for N in the range [50, 300]. We considered again 1000 disorder realizations and assigned the same time length to each sample (6 minutes). Obviously, in this way reluctant dynamics starts from a smaller number of initial conditions than greedy, because its relaxation time is longer. In Fig. (3) we plot the values of the lowest energy state as a function of N . We can see from the data that, for a fixed elapsed time, greedy dynamics ($P = 1$) find lower energy states than reluctant ($P = 0$). Moreover, we observe that the best result is obtained for $P = 0.1$. Thus, we suggest that the more power full strategy to find low energy state using greedy and reluctant dynamic is a combination of them, where most of the steps the move is reluctant and on a small fraction of steps (say 0.1) the move is greedy.

The results of the present work is extensively presented in ref [6]. Improvements of the greedy and reluctant algorithms is presently under study (on IBM SP4), by permitting also *increase* in energy with exponential decrease in time, in the same spirit of the well-known Simulated Annealing strategies [7].

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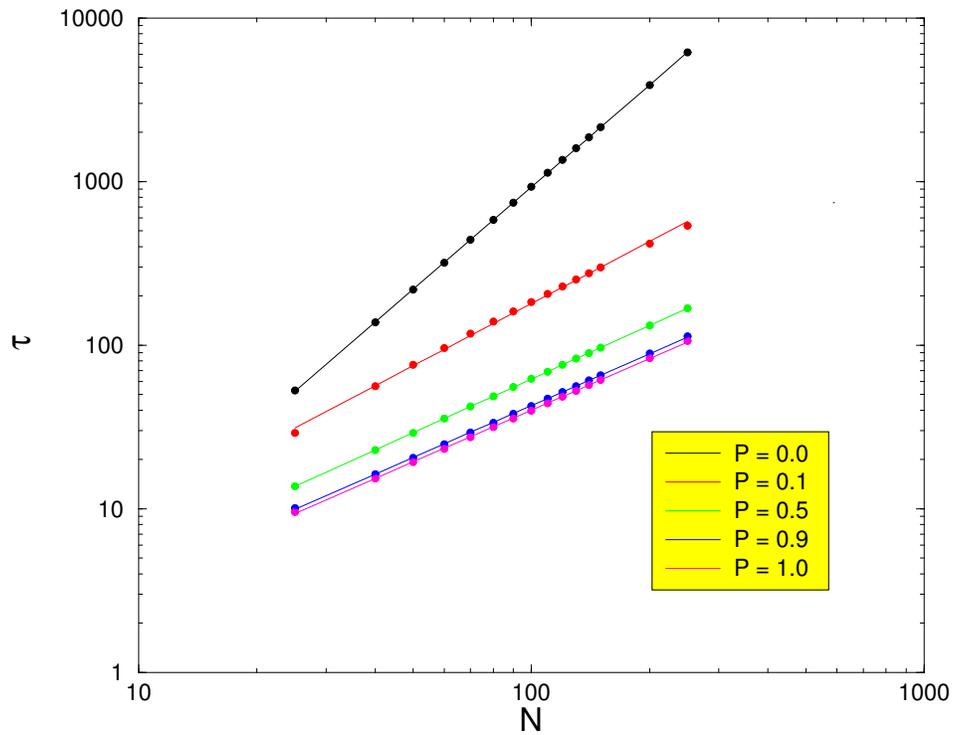


Figure 1: The average time to reach a metastable configuration for different values of P . Top to bottom: $P = 0$ (reluctant), $P = 0.1$, $P = 0.5$, $P = 0.9$, $P = 1$ (greedy). The continuous lines are the numerical fits to power law: $\tau(N) \sim N^\alpha$, with $\alpha = 2.07, 1.26, 1.08, 1.05, 1.04$ from top to bottom.

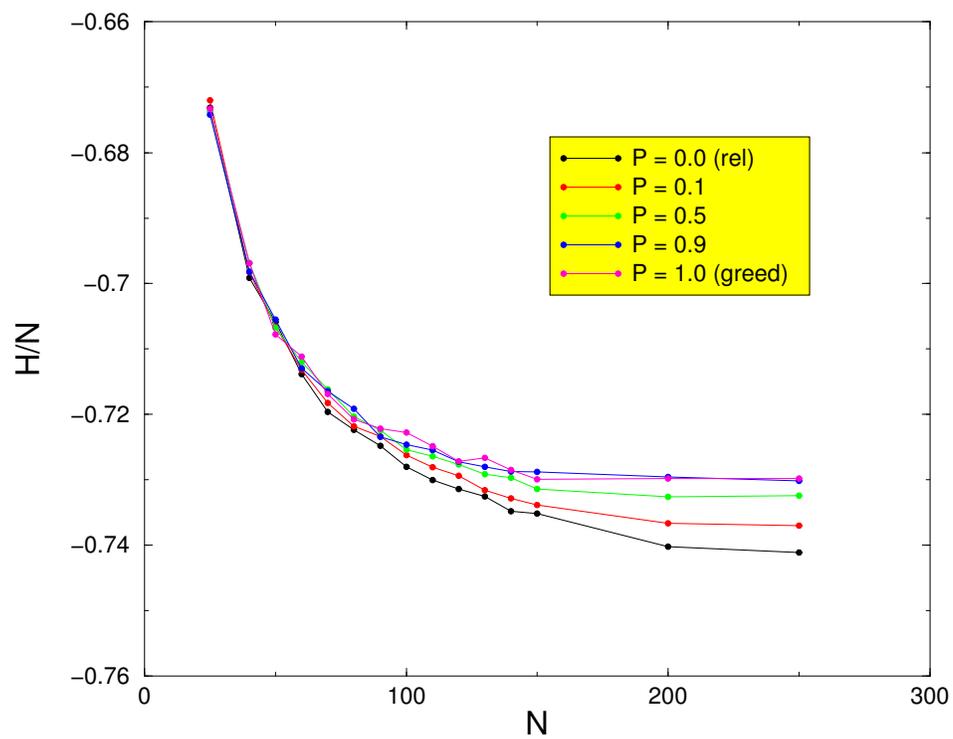


Figure 2: Lowest energy value for a fixed number of N initial conditions for different value of P . Bottom to top: $P = 0$ (reluctant), $P = 0.1$, $P = 0.5$, $P = 0.9$, $P = 1$ (greedy)

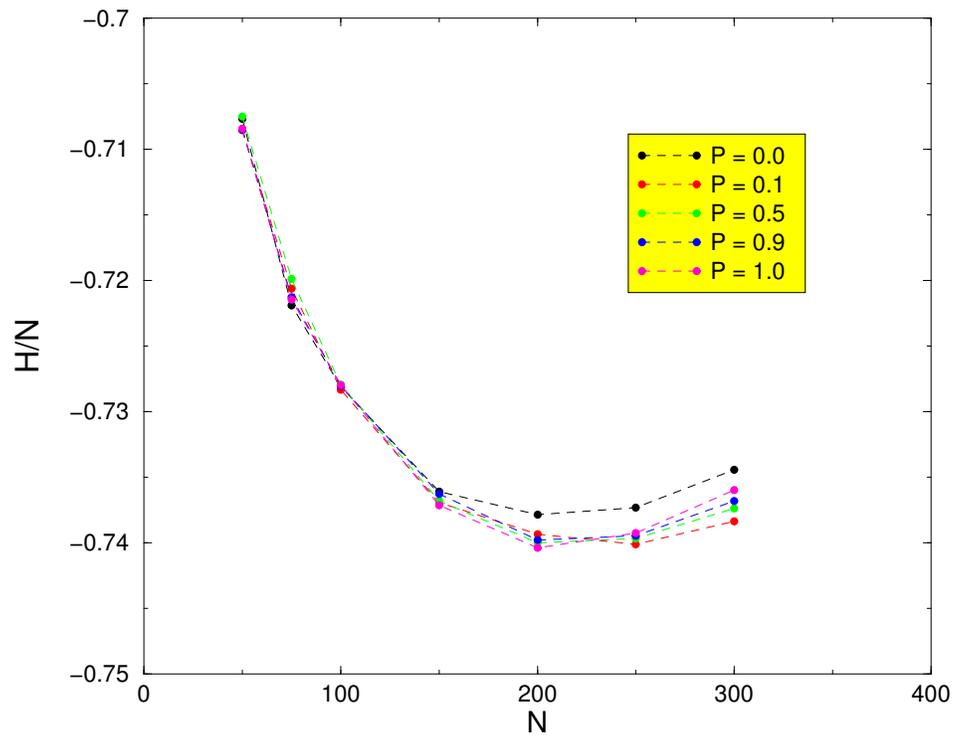


Figure 3: Lowest energy value for a fixed elapsed time of 100 hours (each run) on a IBM SP3 for different value of P (see legend)