Finite-size corrections in spin glasses and combinatorial optimization problems

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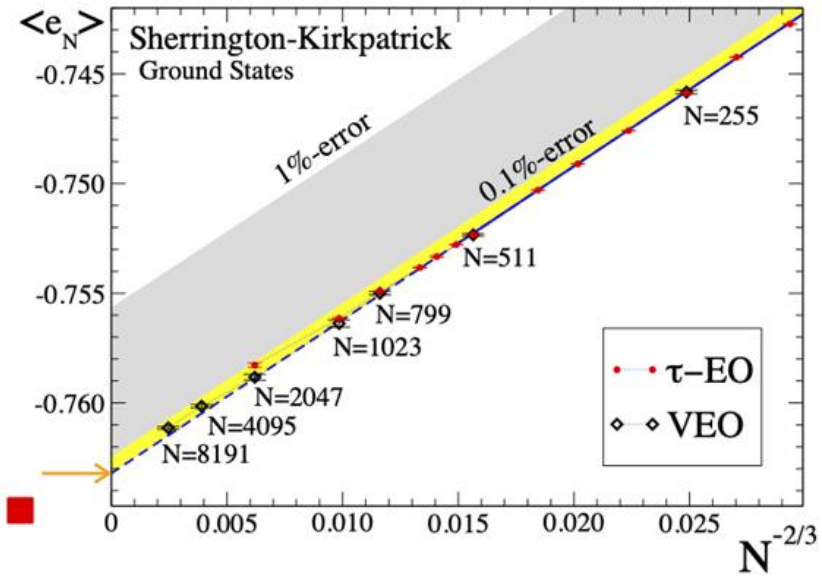
Finite-size corrections (FSC) in statistical physics are often seen as a nuisance in inevitably limited simulations that struggle to reach the (physically desirable) thermodynamic limit. For spin glasses, in particular, theoretical results (like, from replica theory) are still mostly out of reach and provide little guidance to interpret FSC. However, much insight can be gained about the nature of the physical system under investigation using FSC constructively. We will demonstrate the use of FSC in various applications to study ground states and low energy excitations in finite and infinite-dimensional spin glasses (ie, the Edwards-Anderson lattice spin glass and the mean-field Sherrington-Kirkpatrick model) as well as to assess to quality of heuristics for NP-hard combinatorial optimization problems, such as quadratic unconstraint binary optimization (QUBO) or MAX-CUT. FSC may have exponents that vary with system parameters in interesting ways [1]. Simple scaling arguments relate FSC to the energetics of domain wall excitations that characterize the stability of the glassy ordered phase [2,3]. An extrapolation plot provides a powerful means to reveal the qualities and inadequacies of recently proposed optimization heuristics based on customized hardware or the latest AI techniques for learning [4,5,6].



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