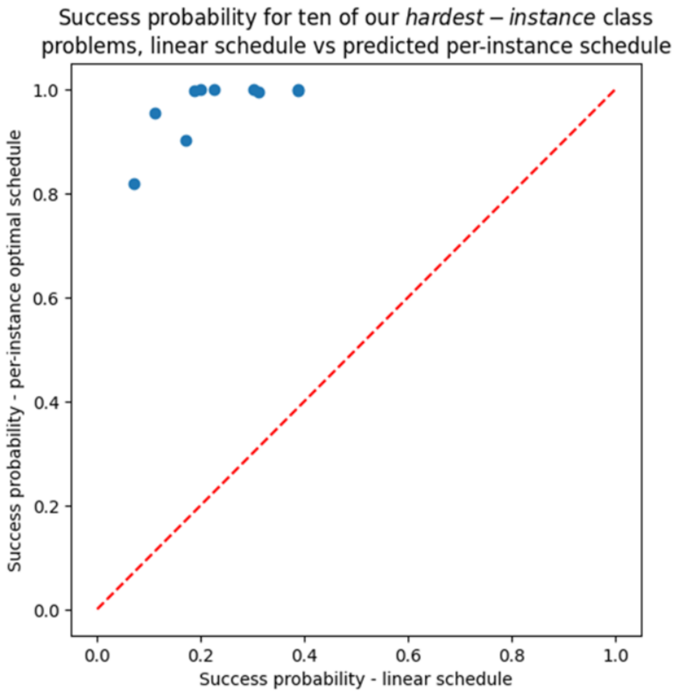
Improving Quantum Annealing Success Rate with Machine Learning

Víctor Martín-Mayor[1], Gabriel Álvarez[1], **Emilio Pomares**[1]

[1]Universidad Complutense De Madrid, Madrid, Spain

Solving NP-complete problems is one of the most prominent challenges in computer science, with applications in fields such as optimization, logistics, and cryptography. Spin glasses, models for disordered systems with extremely rugged energy landscapes, are often regarded as an arena to explore computationally feasible ways to address these hard problems. One promising approach to solving spin-glass problems is quantum annealing (QA), which leverages quantum fluctuations to escape the numerous local minima in the complex energy landscape of spin glasses and find the lowest-energy configuration without brute-force search. QA is attractive compared to classical methods such as simulated annealing (SA), because the system can tunnel quantum mechanically through high, narrow barriers.

However, the success rate of QA is highly sensitive to the annealing schedule used during the process, since it influences whether the evolution remains adiabatic. Furthermore, generic schedules do not make the best use of the available annealing time, and greater performance can be achieved by following instance-specific schedules. Determining such schedules is computationally challenging because they depend on spectral properties that are extracted by diagonalization of the system's Hamiltonian. Finding such instance-specific schedules in a computationally efficient way could be critical. The superior performance of these per-instance schedules with respect to the standard schedule has been validated via the numerical integration of the time-dependent Schrödinger equation. However, current quantum hardware limitations on implementing such schedules need to be considered in order to carry these methods over to actual QA hardware.



In this work we explore a sixteen-qubit problem with Ising-type couplings. Using a considerable amount of initial computational resources, we produced a hardness-balanced sample dataset which we exploited to find machine-learning-based efficient estimators.

We present our efforts to find machine-learning-based methods and results for efficiently estimating such instance-specific optimal schedules that will hopefully improve the overall success rate of the annealing process. Our results also allow us to efficiently find additional extremely hard samples, by leveraging our trained models as predictors of a sample's hardness, and only performing diagonalization on candidate samples, which can be very useful for further research.

We also consider the possibility of using transfer learning to extend the method to problems where the binary spins are connected by Ising-type couplings restricted to m discrete levels between 1 and +1, effectively forming a pseudo-continuum of interaction strengths.

References:

[1] King, A.D., Raymond, J., Lanting, T. et al. Quantum critical dynamics in a 5,000-qubit programmable spin glass. Nature 617, 61–66 (2023). https://doi.org/10.1038/s41586-023-05867-2