Exponentially-Biased Ground-State Sampling of Quantum Annealing Machines with Transverse-Field Driving Hamiltonians

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What is fair sampling?

Definition (fair sampling):
- The ability of an algorithm to find all solutions of a degenerate problem with equal probability when run in repetition mode.

Why is it important?
- In some contexts (SAT-Filter, #SAT, machine learning, …) finding a good variety of solutions is more important than finding a single solution quickly.

Optimize benchmarking:
- Standard test: Find the ground-state energy fast and reliably.
- Stringent test: Find all minimizing configurations equiprobably.
Previous studies on transverse field QA [1]

Transverse field QA is biased ...

\[ H_D = - \sum_i S_i^x \]

Previous studies on transverse field QA [1]

Non-stoquastic $H_D$ mitigates the problem!

The D-Wave 2X quantum annealer

- Unavoidable noise
- Non-zero temperature

\[ H_D = - \sum_i \hat{\sigma}_i^x \]

Superconducting qubit chip

~1000 working qubits
Experimental analysis using DW2X device [1]

- Random couplings from **Sidon set** ($J_{ij} = \pm 5, \pm 6, \pm 7$ on Chimera of $c \times c$ unit cells)
- Limit the study to instances with **well controlled degeneracy** ($\# gs = 3 \cdot 2^k$)
- No **trivial** degeneracy
- 100 gauges x {10k, 100k} readouts
- $T_{\text{ann}} = 5\mu, 20\mu, 200\mu$

**DW2X is exponentially biased!**

Classical algorithms sample more homogeneously

Experimental analysis using DW2X device [1]

Could the bias be a consequence of the intrinsic noise of the DW2x?

No.
The bias is unchanged by rescaling the energy

- Energy of the target problem rescaled by a factor $\varepsilon$
- Intrinsic noise rescaled by a factor $1/\varepsilon$

Adding **extra noise does not change** the bias.

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Classical algorithms are marginally affected by the noise

The bias persists up to the 20th excited state!

Different of the sampling respect to the flat distribution (larger is worse)

Implications & Future directions

The bias can limit the use of QA for sampling

- Applications like SAT-Filter and machine learning may not be suitable for QA without mitigating the sampling problem

How to mitigate the sampling problem?

- Explore different driver Hamiltonians (e.g. non-stoquastic)

How to understand the bias problem better?

- Theoretical understanding of the role of the driver Hamiltonian in sampling
- Theoretical exploration of the implication of many-body localization
Thanks for the attention!

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Quantum Enhanced Optimization
Experimental analysis using DW2X device [1]

Adiabatic Quantum Optimization (AQO)

\[ H = (1 - s)H_d + sH_p \]

Initial "driver" Hamiltonian

Target Problem
Adiabatic Quantum Optimization (AQO)

\[
H = (1 - s)H_d + sH_p
\]
Adiabatic Quantum Optimization (AQO)

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Adiabatic Quantum Optimization (AQO)

\[ H = (1 - s)H_d + sH_p \]

\[ T \sim \frac{1}{g^2} \]
Adiabatic Quantum Optimization (AQO)

\[ H = (1 - s)H_d + sH_p \]