Hybrid computing with quantum annealing

D-Wave Systems Inc. Visit

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Joint Quantum Centre

Durham University

NQIT Networked Quantum Information Technologies

My Background

Bachelor in Engineering Physics from Colorado School of Mines

PhD from University of Southern California in Physics

Post-doc at UCL performing remote experiments on D-Wave quantum annealers

Post-doc at Durham in hybrid quantum/classical computing

Awarded EPSRC UKRI Innovation fellowship in June 2018

Talk Structure

Overall approach: A quick overview of three projects, can discuss the ones with most interest in more detail

1. Examining Reverse Annealing
    - Initial results
    - Planned work
2. Enhancing robustness of solutions with reverse annealing
    - Experimental setup
    - Results and future experiments
3. Annealing co-processor for quantum error correction
    - Quick background
    - Implementation

Examining reverse annealing

Goals:

1. Proof-of-principle that reverse annealing searches solution space locally (mostly completed)
2. Test how well local searches find local minima and perform sampling
3. Use tests to understand algorithmic performance
4. (Secondary) Reexamine data to understand physics

Joint work with Viv Kendon, funded through EPSRC and NQIT

NQIT Networked Quantum Information Technologies

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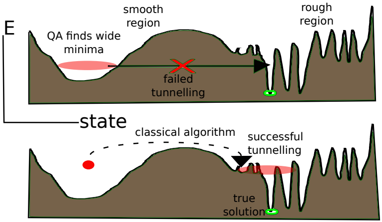
Experimental proof-of-principle

Algorithmic potential of reverse annealing comes from searching solution space locally

- Theoretical and numerical evidence it should
- But want to explicitly show that this happens *experimentally*

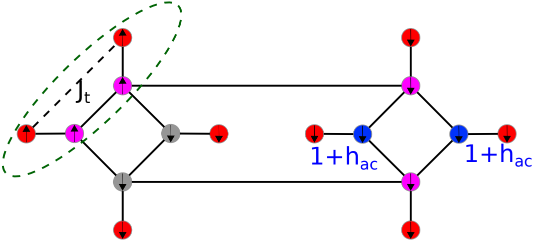


Minimum requirements for proof-of-principle:

1. False minimum which is found often by traditional annealing
2. Starting configuration near true solution but separated by energy barrier
3. Tunneling between start and true minimum when ground state is mostly in the false minimum

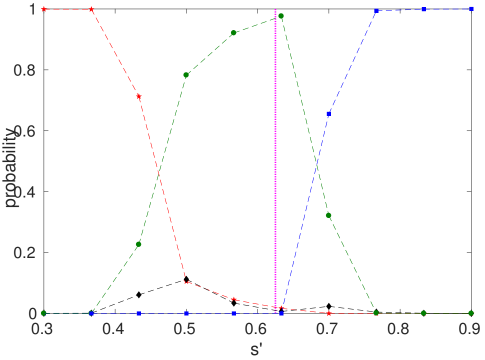
Designing proof-of-principle Experiment

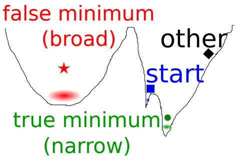
Modify Hamiltonian known to have false minimum with 'free' spins
N. G. Dickson et. al. Nature Comm. 4, 1903 (2013)



- Barrier between true GS and start state controlled by J_t
- Close avoided crossing with position tunable by h_{ac}, ground state dominated by false minimum before avoided crossing
- Start state with four circled spins flipped from ground state

Proof-of-principle results





- Magenta dashed line is position of avoided crossing
- Significant tunneling to true minimum even when global ground state is mostly in the false minimum
- Searching too far finds false minimum, not far enough and tunneling to true minimum cannot occur

What next?

More realistic chip scale problems

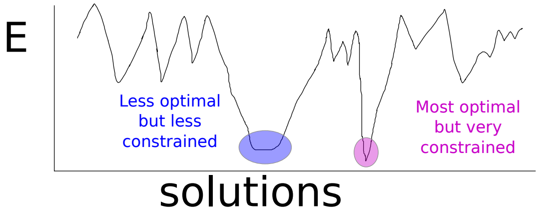
- Start known Hamming distance from solution in hard problems with known (planted) solutions
  - How far can we start and still solve the problem
  - What are the appropriate parameters to choose depending on distance
  - Potentially use planted solution problem from I. Hen et. al. Phys. Rev. A 92, 042325 (2015)
- Using seeded states for sampling
  - Want to be influenced by starting state but still search a significant portion of solution space
  - Compare to distribution from traditional QA using

Happy to discuss details after talk

Enhancing Robustness of Solutions using reverse annealing

Using quantum annealers to find solutions which are robust in the sense that they can be adjusted to a modified problem definition at little or no energy cost

- Simplest way this manifests is free spins → annealers known to find this feature
- If a good solution is already known, can we use an annealer to trade optimality for robustness?



Joint work with Simon Benjamin, funded by BP and EPSRC

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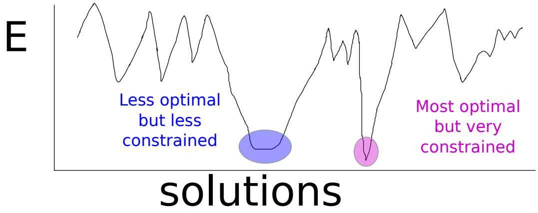
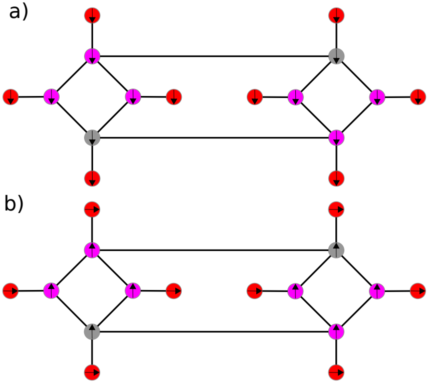
Why might we want this?

- Adjust solution if we later learn that our problem definition was slightly incorrect
- Penalty terms which are too expensive to encode on annealer could be implemented by adjustments in post-processing
  - Global non-linear constraints for instance are expensive to map
- Find 'template' solution which can be adjusted to solve many similar but not identical problems



A simple (motivational) example

Consider the same 16 qubit gadget from N. G. Dickson et. al. Nature Comm. 4, 1903 (2013) :



- a is the ground state but
- A D-Wave 2000Q with $1,280,000$ $5\mu s$ runs finds b $1,277,824$ times and a only 17 times (20 μS runtime)

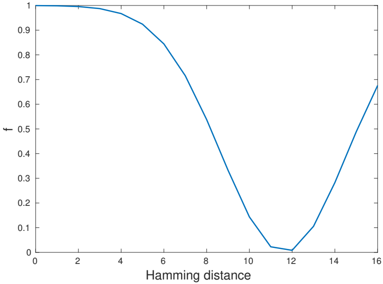
Simple test: add global penalty and do greedy search

Global penalty:

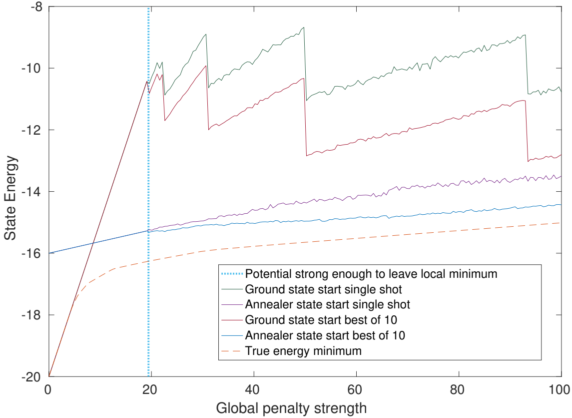
$$E(q) = E_{\mathrm{Ising}}(q) + g\, f[\mathfrak{h}(q, r)]$$

where:

- q is a bitstring representing the state
- g is the strength of the penalty
- $\mathfrak{h}$ is Hamming distance
- r is a random bitstring
- f is a single variable function:



Starting in true ground state vs. state annealer finds



The large degeneracy in the state the annealer finds allows for much more effective adjustment $\rightarrow$ higher energy but more robust

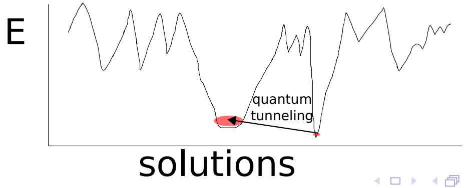
Reverse annealing to trade off optimality and robustness

Hypothetical situation:

- Already know the most optimal (planted) solution
- But we want more flexibility
- Are willing to 'pay' some optimality for a more flexible solution

Algorithm:

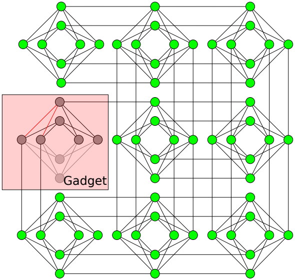
1. Start reverse annealing in planted solution
2. Search over a set range
3. Repeat many times
4. Keep most optimal solutions with a given number of gadgets 'free'



Free spin gadgets

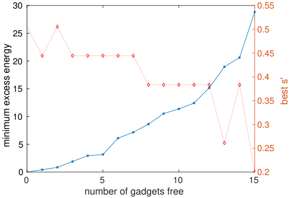
- Use planted solution method from Hen et. al. Phys. Rev. A 92, 042325 (2015) to make ‘hard’ problems with all -1 and all $+1$ ground state
- Before constructing replace some unit cells with free spin gadgets
  - All spins fixed if ‘outside’ spins agree
  - Become free if they do not (but energy unchanged)
  - Energy penalty because has to leave planted solution

Problem with planted solution (not shown)

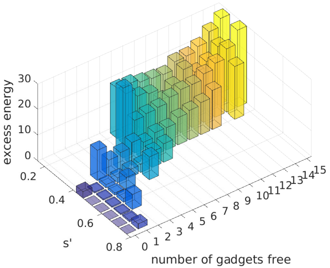


The tradeoff

What is the best excess energy we can find with a given number of gadgets free?

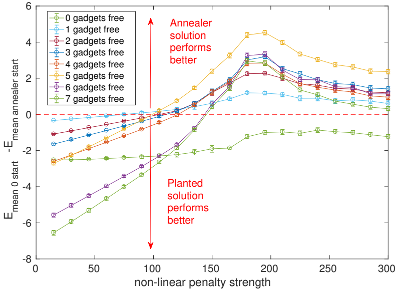


(smallest s' value taken in the event of a tie)



Putting new solutions to the test

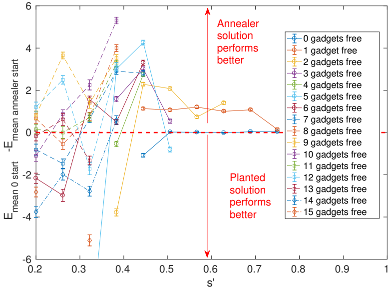
- Choose $s' = 0.4444$ dataset $\rightarrow$ contains some of the best solutions
- Choose $10,000$ different instances of non-linear penalties
- Perform greedy search in each case and compare with planted solution
- Compare for different penalty strengths



Crossover where annealer solution becomes the better choice

Comparing performance at different s' values

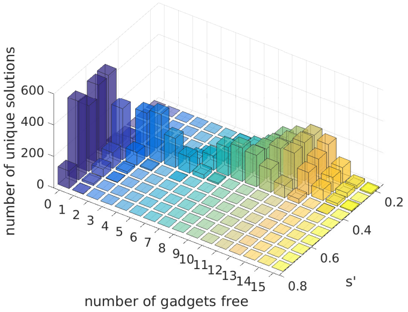
- Choose non-linear penalty strength of 195
- Examine performance of solutions found at different values of s'



- Best performance at intermediate values of s'
- Smaller values of s' better for finding solutions with smaller number of 'free' gadgets

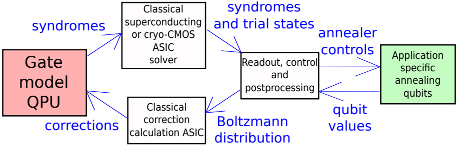
What's next?

- Sample over more problem instances
- Run test with 'no free variable' gadgets for comparison
- More data analysis



Annealing co-processor for quantum error correction

- 'Coherent parity check' (CPC) framework can map quantum error correction decoding to an Ising model for a broad class of codes
- Natural to think of co-processor architectures, gate model QC with annealer for error correction
- Effectively using an annealer as an 'accelerator' for a gate model device



Joint work with Joschka Roffe, Stefan Zohren, and Dominic Horsman, funded by EPSRC and others

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Justification for co-processor approach

Value justification

- Gate model QC will already be used for high value tasks, expensive approach to error correction is justified

Need for fast error correction

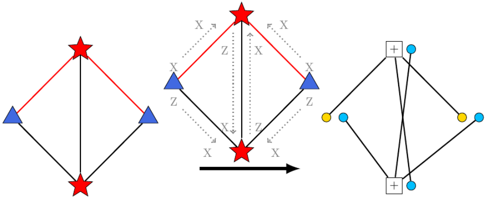
- Could produce $\approx$ 100 Gb a second of syndrome data, need a powerful processor

Room for improvement through thermal sampling

- Toric code example (see Breuckmann et. al. Quantum Info. Comput. 17, 181 (2017)):
    - Threshold achieved using standard maximum likelihood methods of $\approx 10.3\%$
    - Theoretical maximum threshold of $\approx 10.9\%$
    - Theoretical maximum based on Ising model properties $\rightarrow$ achievable in principle with thermal sampling

The coherent parity check (CPC) framework

Describe a quantum error correction code in terms of the encoding operation, graphical procedure to convert decode to classical factor graph (see arχiv:1804.07653)



Almost what we need to map QEC to an annealer

- Factor graph can be translate easily to an Ising model, however
- Y errors treated as burst errors, not naturally expressed in an Ising model
- Need a mapping which explicitly includes Y errors (bit and phase degree of freedom errored at same time)

Ising model mapping including Y errors

Mathematical procedure:

1. Add an additional parity check to represent correlations between bit and phase errors on same qubit
2. Write down Boltzmann distribution
3. Choose a finite temperature T and match probabilities to error model

Details not important for this talk, but can now map QEC decoding to an Ising model:

(Unmeasured) data qubit:

(Measured) parity check qubit:

Co-processor architectures

Fixed connectivity structure

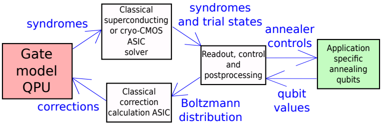
- Annealer can be constructed as an application specific integrated circuit (ASIC)
- Greatly reduce embedding costs $\rightarrow$ no need for general graph

May be constructed out of similar hardware to gate model QPU

- Both co-processors in same cryostat, greatly reduce I/O going to room temperature

Amenable to hybrid approach

- Find high probability solutions using classical methods, construct thermal sample with aid of reverse annealing



Thank You for Listening

Examining reverse annealing

- Experimental project to study the reverse annealing protocol
- Study details of local search by reverse annealing
- Already have proof-of-principle results

Enhancing robustness using reverse annealing

- A novel way to use reverse annealing
- Allows us to trade off optimality for flexibility in solutions
- Chip scale demonstrations of underlying principles

Annealing co-processor for quantum error correction

- Map QEC decoding to Ising models
- Allows quantum annealer to be used as a co-processor
- There is a strong case for annealing co-processors