Performance Tuning for D-Wave Quantum Processors

QUBITS 2018

Catherine McGeoch

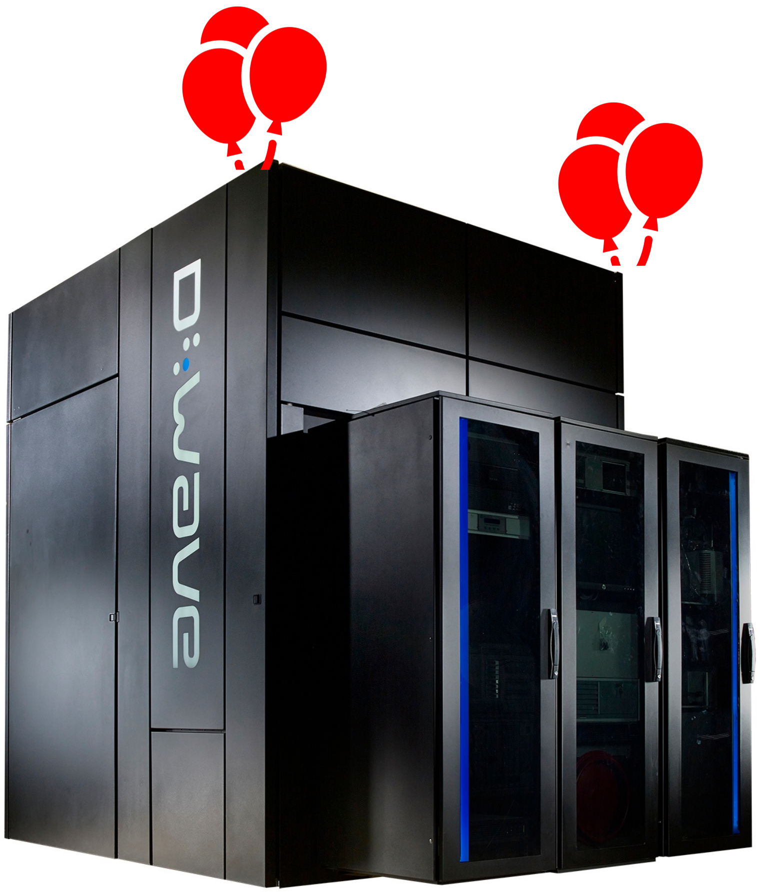
Congratulations!

You've tried your application on a D-Wave processor: it works!

Next step: Best practices in quantum performance tuning.

Outline:

- Repurposing classical tuning strategies.
- Survey of QA techniques, tools, and utilities for achieving improved performance.



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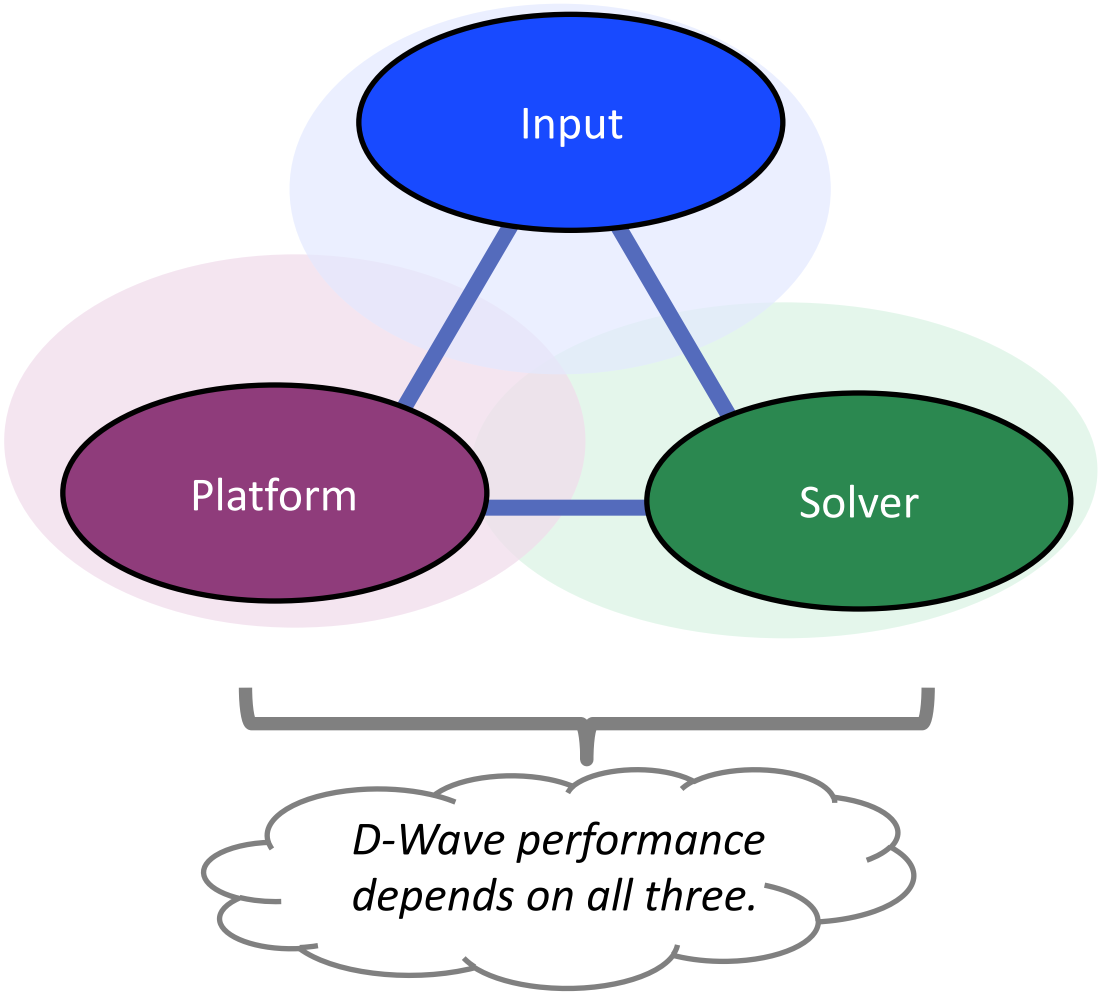
Computational Performance Modeling

Classical performance tuning: change the solver, change the platform, or change the input.

Performance models guide your decisions about what works when.

Quantum Annealing:

- Same three strategies apply.
- Models are very new, relatively primitive.
- Models are based on empirical results not theorems.
- Distinction between solver and platform is fuzzier.

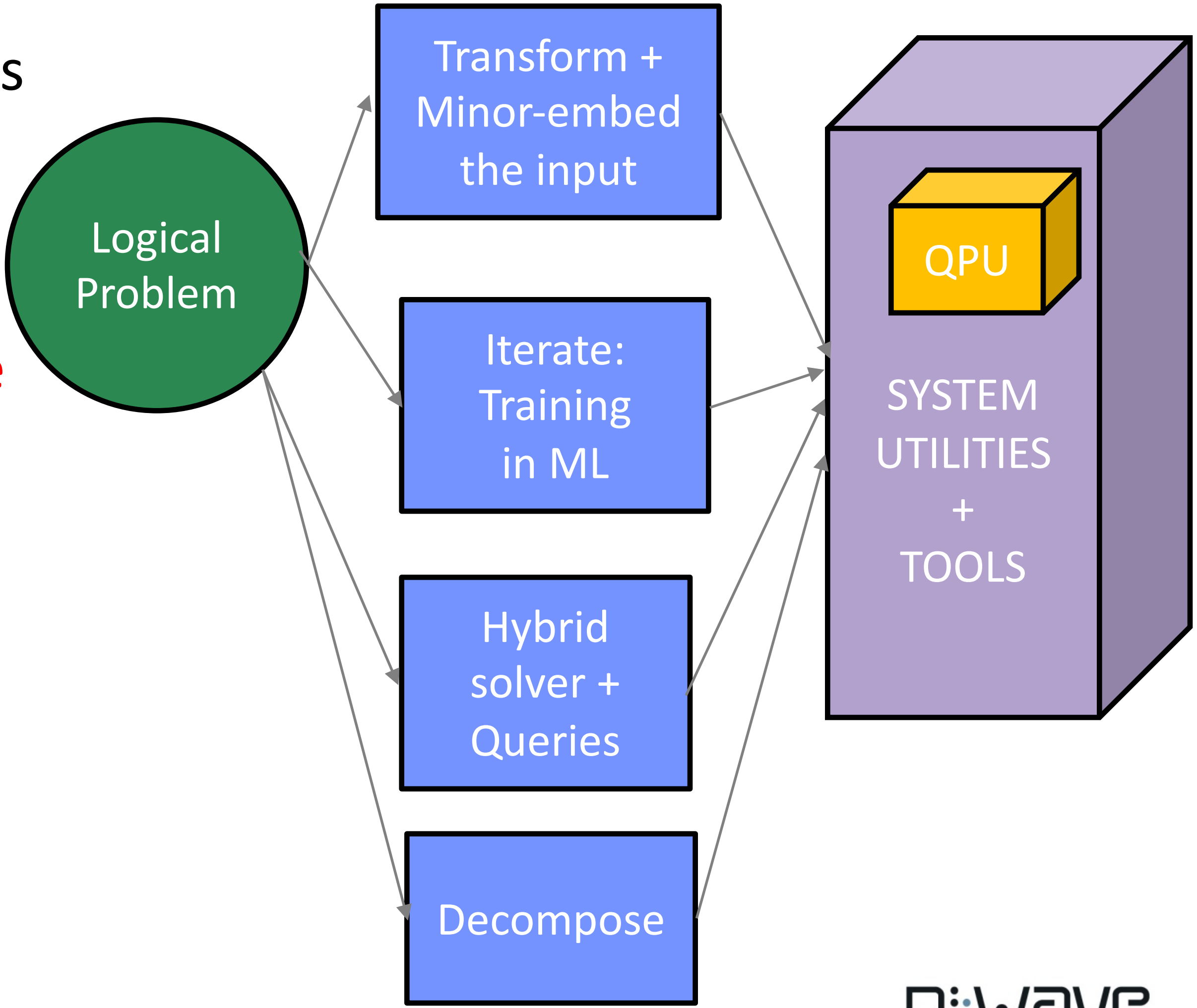


Scope of this Talk

Core operation: One input instance, *R* solutions sampled from a hidden distribution.

How to improve the chances that your sample contains a ground state.

1. Preprocessing
2. During the anneal
3. Postprocessing



Preprocessing: Change the *Presentation* of the Input

The answer is the same but the computation is easier.

Classical examples:

- Randomize inputs to avoid worst-case.
- Routing in massive road maps: Add fake roads make common queries fast.
- CPLEX: linearize a quadratic problem.

- Quantum Annealing:
  - *Sparse problem transformation.*
  - *Better embeddings.*
  - *Gap – aware problem transformation.*
  - *Better chains.*

Bigger problems are better problems.

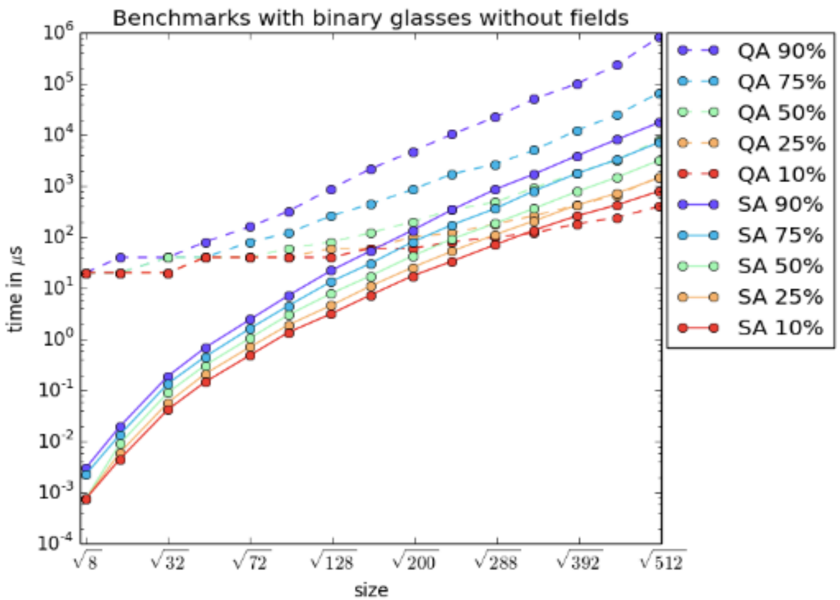
Improve probability of seeing ground states.

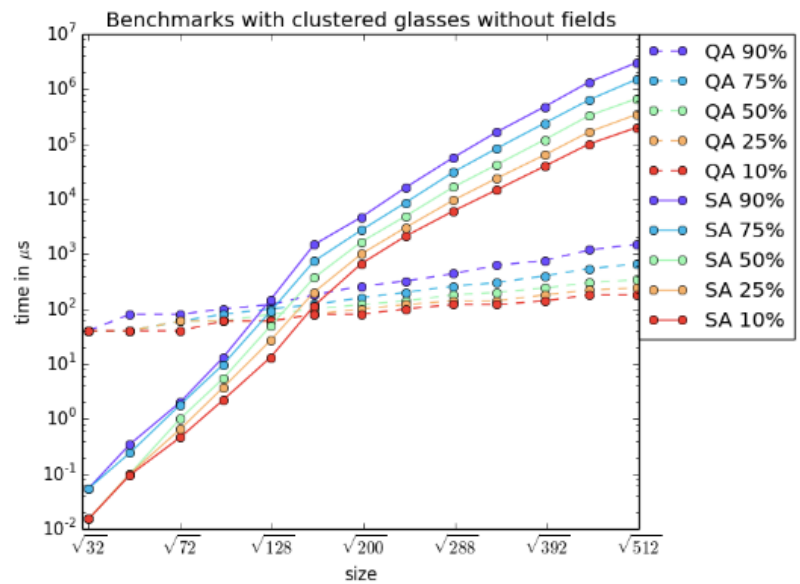
Why Bigger Problems are Better Problems

On some inputs QA is faster than classical, on others it is not.

QA never wins on the smallest problems, due to lower bounds on computation times.

The best place to find quantum advantage on fix-sized hardware is by maximizing variables per chip → minimizing qubits per variable.





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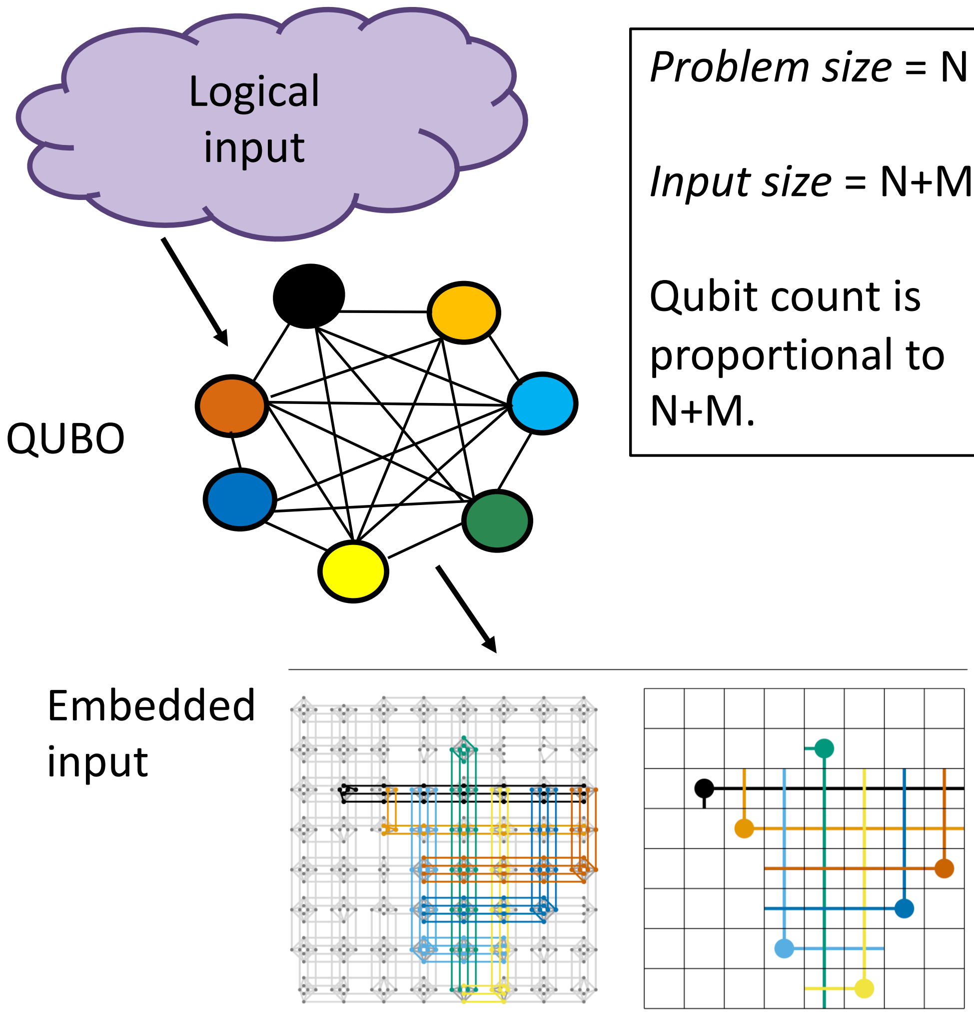
Packing Bigger Problems onto the Hardware

Goals: Minimize qubits per logical variable = maximize logcial variables per qubit.

Tactics:

- Variable reduction strategies.
- Error mitigation strategies.
- Better embeddings.



Problem size = N

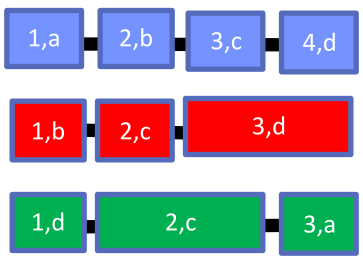
Input size = N+M

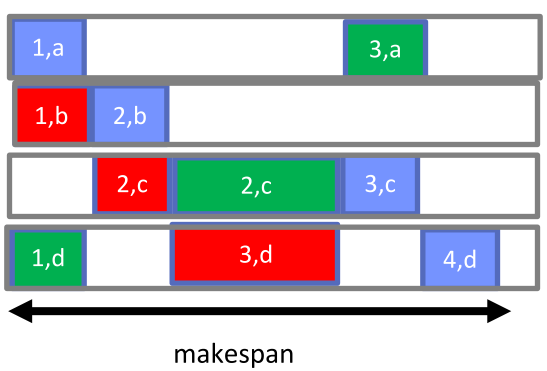
Qubit count is proportional to N+M.

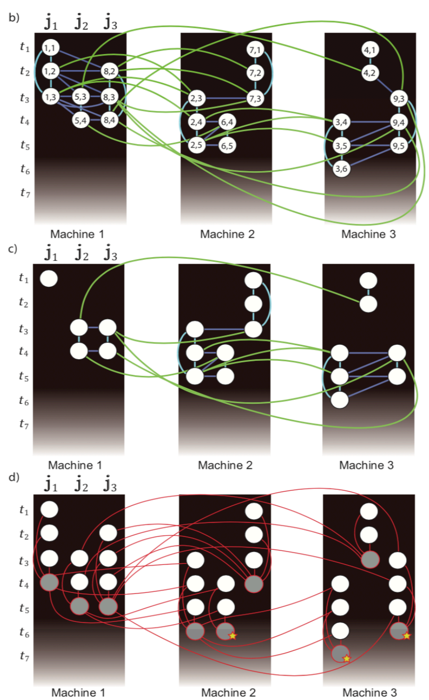
Variable Reduction Strategies

Quantum Annealing Implementation of Job-Shop Scheduling

Davide Venturelli[1,2], Dominic J.J. Marchand[3], Galo Rojo[3]
[1] *Quantum Artificial Intelligence Laboratory (QuAIL), NASA Ames*
[2] *U.S.R.A. Research Institute for Advanced Computer Science (RIACS)*
[3] *1QB Information Technologies, Vancouver, BC, Canada*







Integer outputs must be mapped to binary outputs.

Three gnarly constraints.

Variable reduction strategies:

- Remove impossible start and finish times.
- ``Window shaving'' removes more infeasible assignments.
- Simplify (approximate) the objective function.

Can solve 7x7 inputs on a 512-qubit D-Wave Two.

Preprocessing: Error Mitigation Strategies

Error models for quantum annealers.

Network transmission errors: flipped bits are fatal.

Coping Strategies:

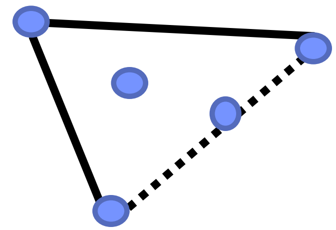
- Probabilistic error models.
- Checksums
- Error correction codes

$$r = 10/3$$
$$A = \pi r^2$$

Precision errors: may not be fatal, depending on problem tolerance.

Coping Strategies:

- Numerical analysis.
- Flags & exceptions.
- Extended–precision software.



Computational geometry errors: sometimes fatal, sometimes not.

Coping Strategies:

- Random perturbations
- Robust primitives
- Self-checking algorithms

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Simple Error Model for QA

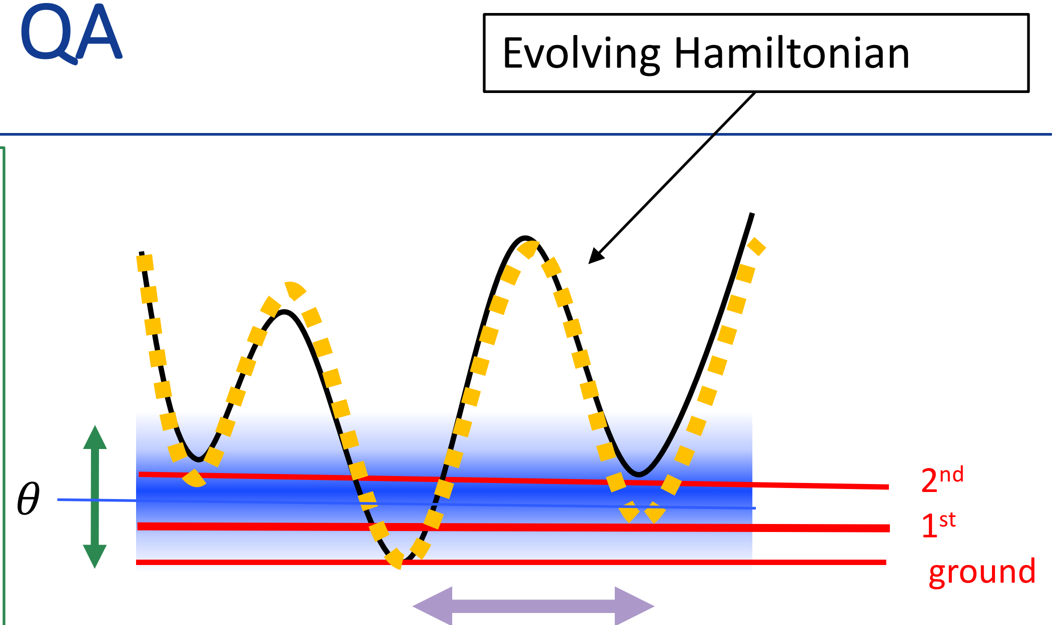
Inputs (h,J) are perturbed by Gaussian errors, slightly altering the solution landscape.

Samples from a Boltzmann-like distribution centered at $\theta > 0$.

Creates a band near ground state where sampled solutions come from.

Measure solution quality by:

- Hamming distance to ground state.
- Energy distance to ground state.
- Rank distance to ground state.



Goal: Aim for fewer excited states in the band, which compete with ground states.

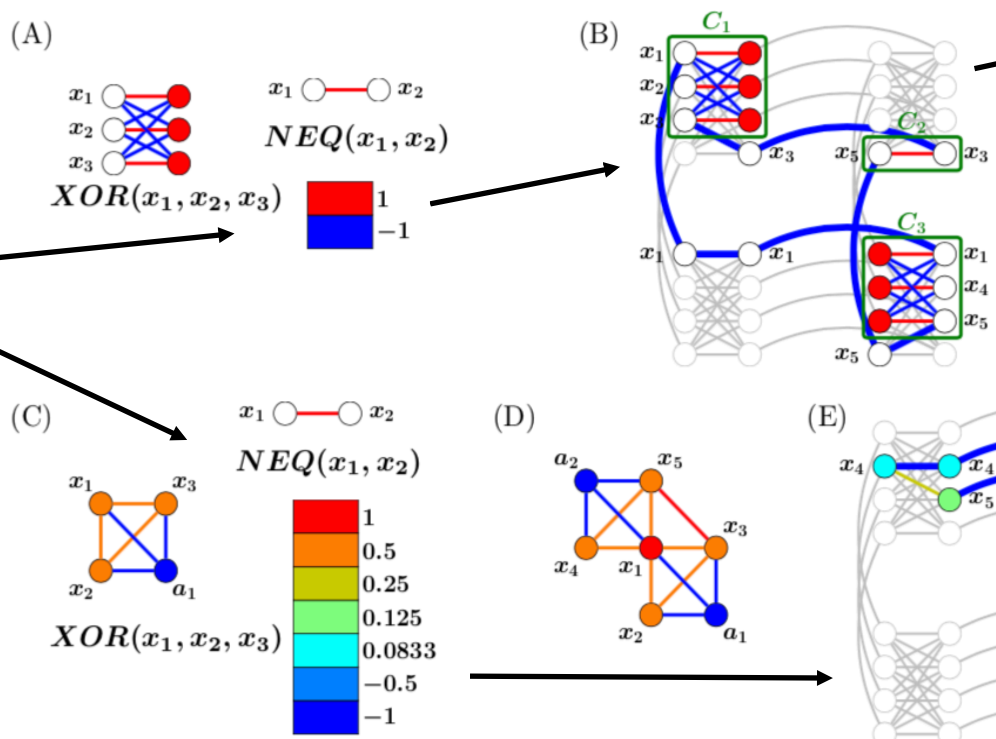
Strategies:

- Gap control in the Hamiltonian
- Chain weights and problem scale
- Error control codes (extra qubits).

Gap Control in the Problem Hamiltonian

Fewer *distinct h, J* values can create bigger gaps near ground state.

Big gaps good
Small gaps bad



19 qubits

14 qubits

Different ways to transform boolean constraints to Ising model.

Some use more qubits but produce better energy gaps.

Mapping constrained optimization problems to quantum annealing with application to fault diagnosis

Z. Bian[1], F. Chudak[1], R. Israel[1], B. Lackey[2], W. G. Macready[1], and A. Roy[1]
[1]D-Wave Systems, Burnaby, BC, Canada
[2]Joint Institute for Quantum Information and Computer Science, University of Maryland, College Park, MD, USA

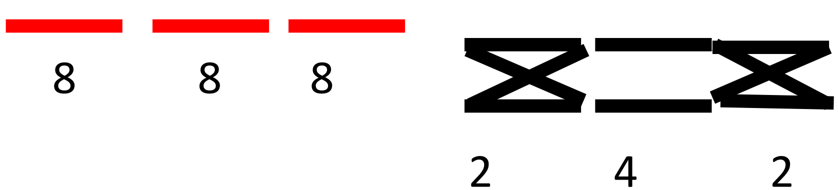
Embeddings and Chain Strength: J_{chain}

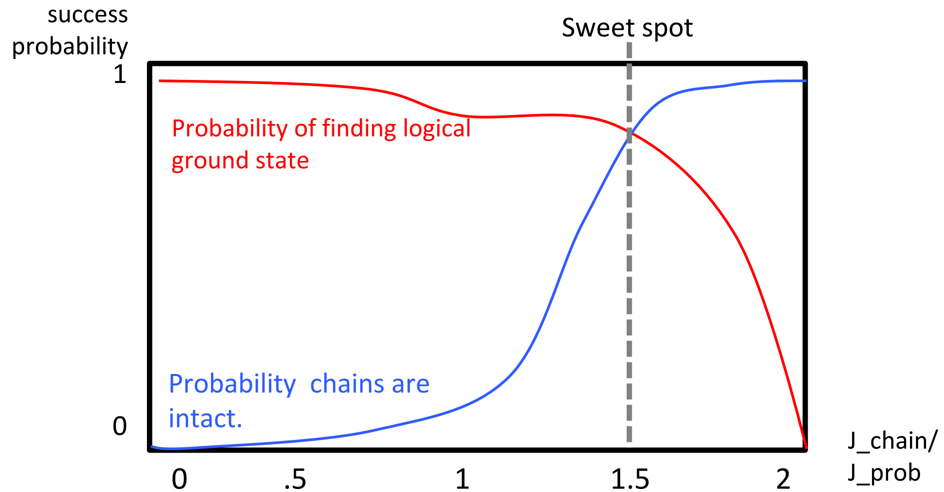
Weak chains break. Strong chains compress the problem scale:

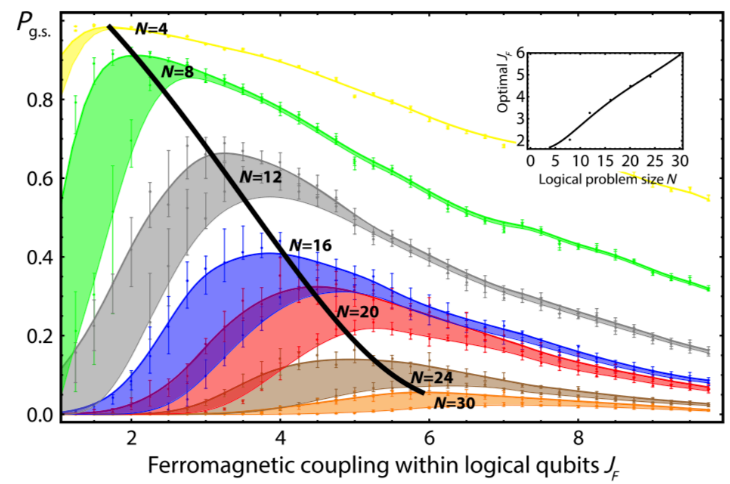
- Find the sweet spot.

Aim for embeddings with:

- Shorter chains
- Balanced chains (all the same length).
- Fortified chains (more chains, less weight):







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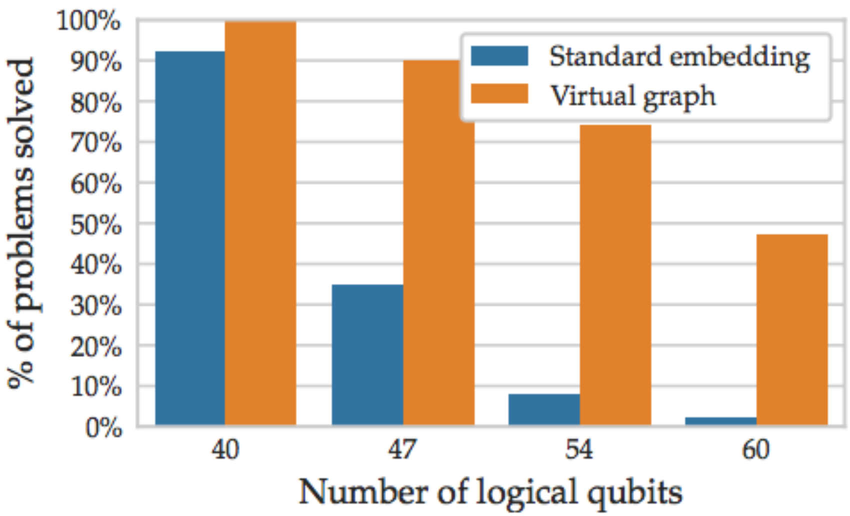
Virtual Graphs

New feature supports stronger chains with less problem compression.

Extended J range allows to specify coupler weights with bigger energy scale compared to fields:

$$h, J_{\text{problem}} : \quad [-1, +1]$$
$$J_{chain} : \quad [-2, +1]$$

May need to add **flux_biases** to qubit weights to offset biases due to strong negative weights on incident couplings. This is a straightforward calculation.



Improves success rates on inputs that require both long (strong) chains and high-precision problem weights.

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Preprocessing Resources and Tools

SAPI

- **find_embedding**. Find an embedding of a general graph.
- **fix_variables**. Find variables that can be pre-optimized and removed from the input.
- **reduce_degree.** Transform *f(a,b,c,d)* to a function with pairwise terms.
- **make_quadratic**. Transform a function expressed as a truth-table to QUBO.
- **New solver parameters for virtual graphs.**

https://github.com/dwavesystems

- **dwavebinarycsp.** Map binary-valued constraint satisfaction problems to QUBO.
- **qbsolv.** Solves a large QUBO by splitting into pieces solved by a D-Wave system or tabu search.
- **minorminer.** A heuristic tool for minor embedding.
- **penaltymodel.** Utilities and interfaces for specifying constraints as penalty models.
- **dwave_networkx**. An extension of NetworkX for users of D-Wave systems.
- **dwave_embedding_utilities**. Mapping between source and target graph models.
- **chimera-embedding**. Collected algorithms to generate native embeddings.

Tuning via Preprocessing: Examples and Advice

Practical Integer-to-Binary Mapping for Quantum Annealers

Sahar Karimi · Pooya Ronagh

Algorithm engineering for a quantum annealing platform

Andrew D. King*[1] and Catherine C. McGeoch[1,2]

Enhancing Quantum Annealing Performance for the Molecular Similarity Problem

By Maritza Hernandez & Maliheh Aramon

Optimizing Adiabatic Quantum Program Compilation using a Graph-Theoretic Framework

Timothy D. Goodrich · Blair D. Sullivan · Travis S. Humble

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Virtual Graphs for High-Performance Embedded Topologies

WHITEPAPER

Quantum Optimization of Fully Connected Spin Glasses

Davide Venturelli,[1,2,*] Salvatore Mandrà,[1,3] Sergey Knysh,[1,4] Bryan O'Gorman,[1] Rupak Biswas,[1] and Vadim Smelyanskiy[5]

Nested quantum annealing correction

Walter Vinci[1,2,3], Tameem Albash[2,3,4] and Daniel A Lidar[1,2,3,5]

Error-corrected quantum annealing with hundreds of qubits

Kristen L. Pudenz, Tameem Albash & Daniel A. Lidar

Nature Communications **5**, Article number: 3243 (2014) | Download Citation

Reducing Binary Quadratic Forms for More Scalable Quantum Annealing

Georg Hahn, Imperial College, London, UK — Hristo Djidjev (PI), Los Alamos National Laboratory

Mapping discrete optimization problems to sparse Ising models

Aidan Roy

Joint work with
Bill Macready (lead), Zhengbing Bian, Jun Cai, Fabian Chudak, Patrick Hagerty, Robert Israel, Andrew King, Brad Lackey

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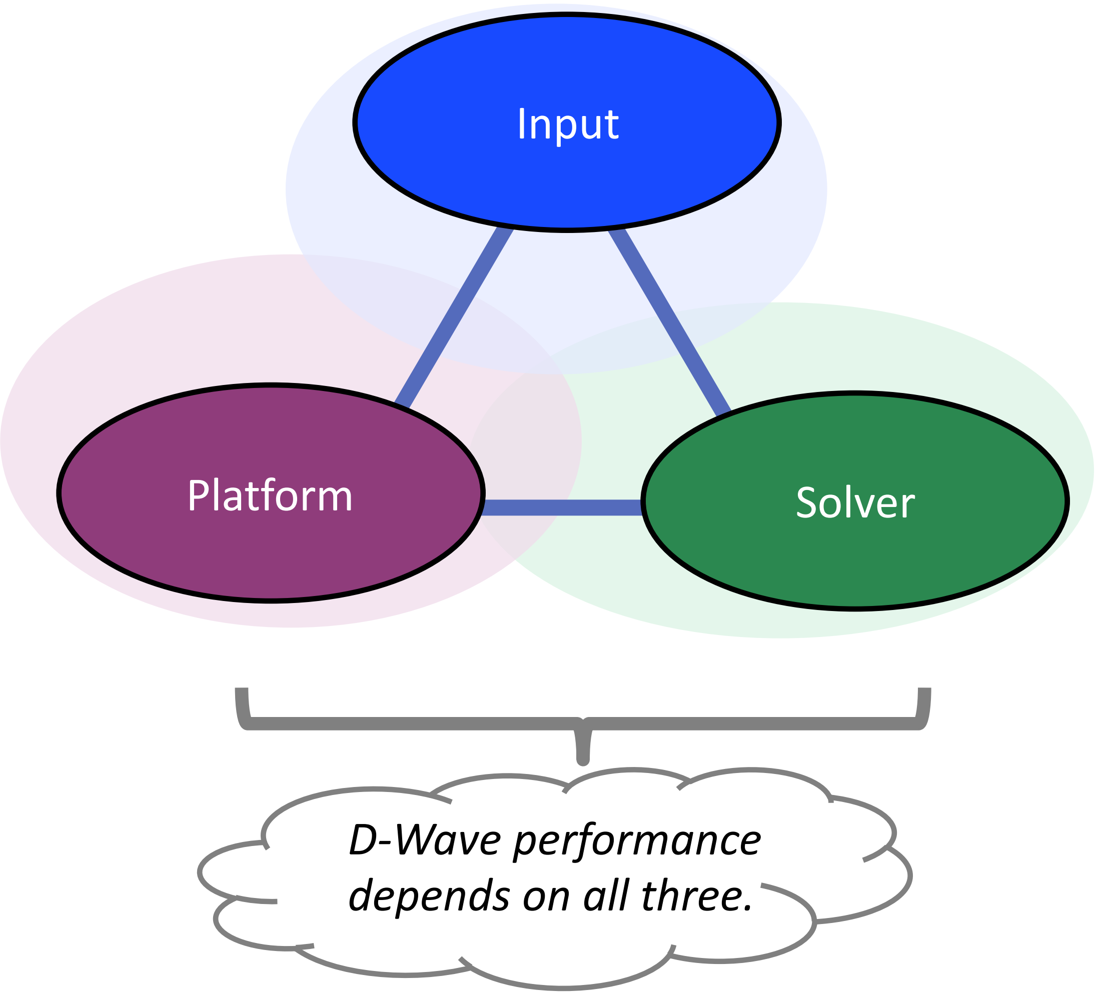
Computational Performance Modeling

Classical performance tuning: **change the solver**, change the platform, or change the input.

Associate *platform* with properties that can be changed by D-Wave engineers. (Not addressed today.)

Associate *solver* with properties that can be changed by the user.

Next: How to tune solver parameters for better results.



Change the Solver

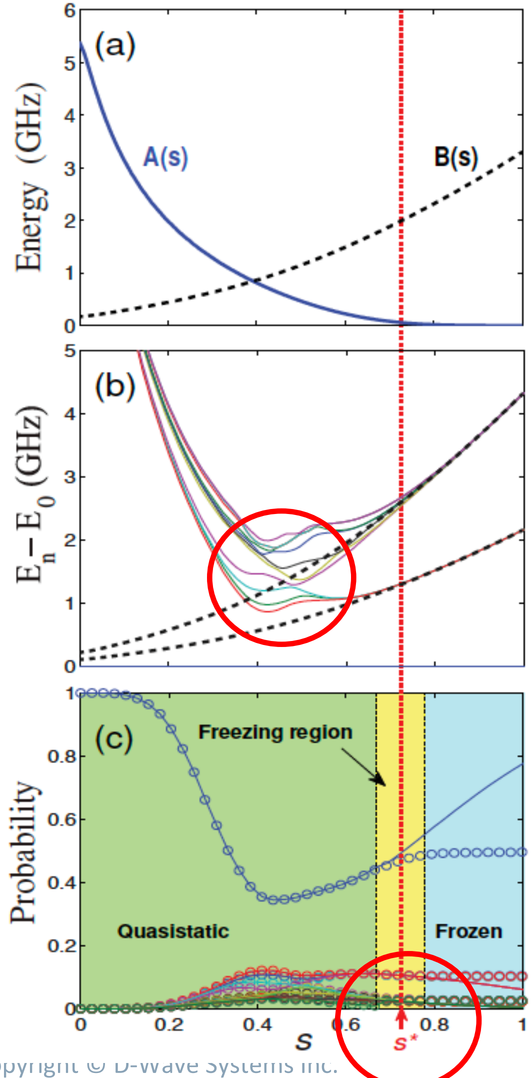
Classical solver tuning strategies:

- **Algorithm**: Simulated Annealing vs Greedy
- **Algorithm tuning**: Change the step size, anneal path, stopping rule …
- **Code tuning**: Remove tail recursion, unroll loops, …

Quantum solver tuning strategies:

- Modify the anneal path
- Invoke system tools surrounding the QPU

Simple Model for Anneal Path Tuning



Transition is controlled by path parameters *A(s), B(s)* and anneal time T_{ann}.

System can move to excited (superposition) states when *energy gap is small* and *anneal is too fast.*

System dynamics slow down near the end of the anneal. Freezout means tunneling has stopped.

Goal: Try to keep the system in low-energy (superposition) states as it evolves.

Strategies:

- Find the anneal-time sweet spot.
- Slow the anneal near small gaps; or shift gaps in time.
    - Pause and Ramp
    - Annealing Offsets
    - Reverse anneal

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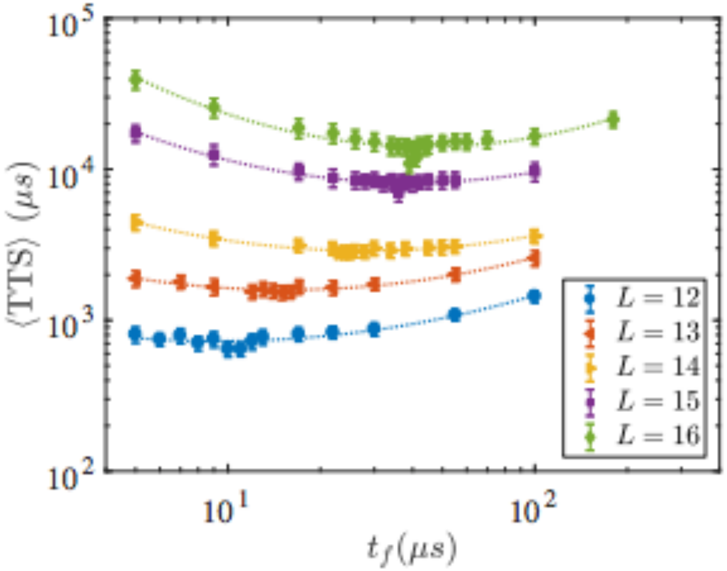
Finding the Optimal Anneal Time T*

$$1\mu s \leq T_{ann} \leq 2000\mu s$$

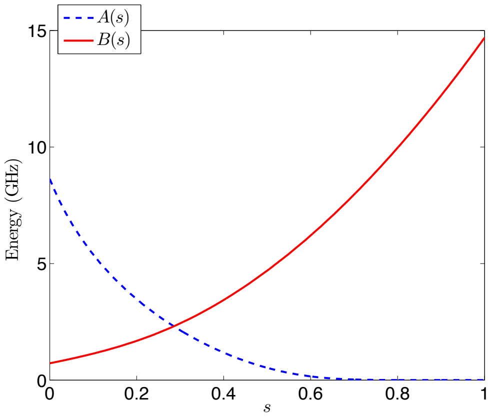
- T* may be outside this range.
- T* depends on the problem Hamiltonian.
- T* depends on the metric and may not be monotonic in T_{ann}.
- Freezeout location s* increases logarithmically with T_{ann}, happens relatively earlier in the process.

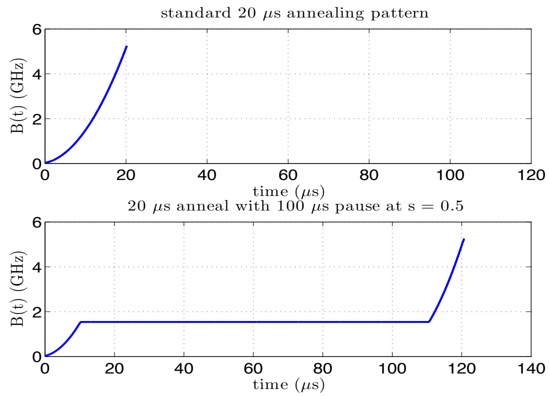


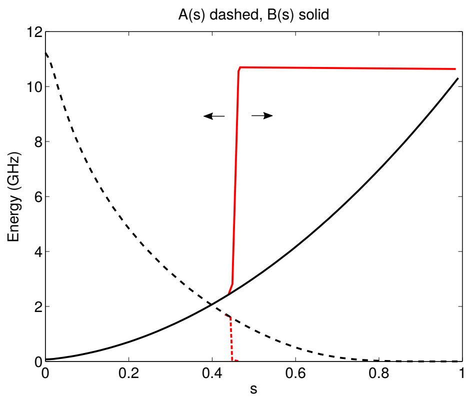
Expect longer anneal times for larger problems.

Image source: Albash&Lidar, Demonstration of scaling advantage for a quantum annealer over simulated annealing.

Pause and Ramp



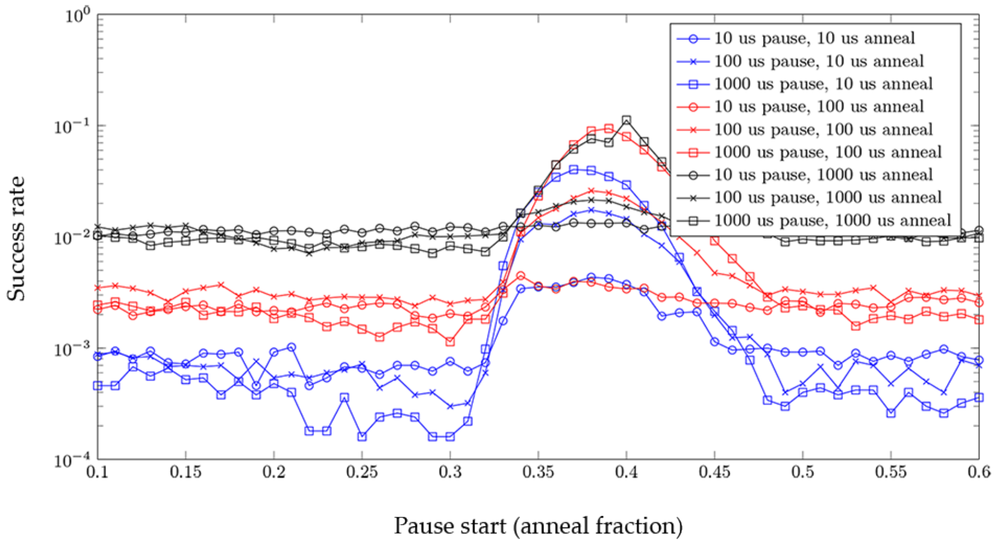




Pause: Specify a location and duration to hold A(s), B(s) fixed. Can improve success probabilities.

Try a pause near $0.25 \leq s \leq 0.5$

Ramp: Specify location for fast quench. *Good for examining quantum distributions mid-anneal.*



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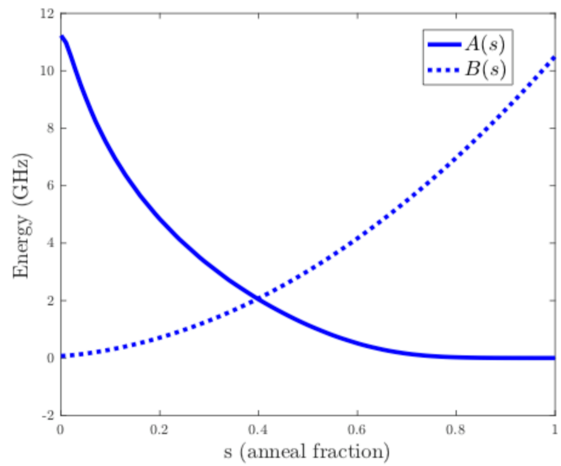
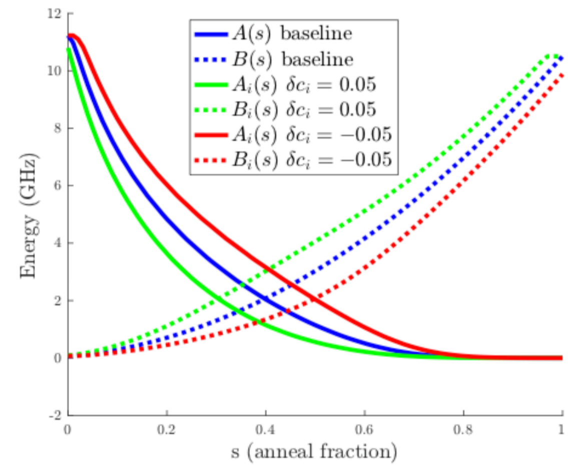
Anneal Offsets

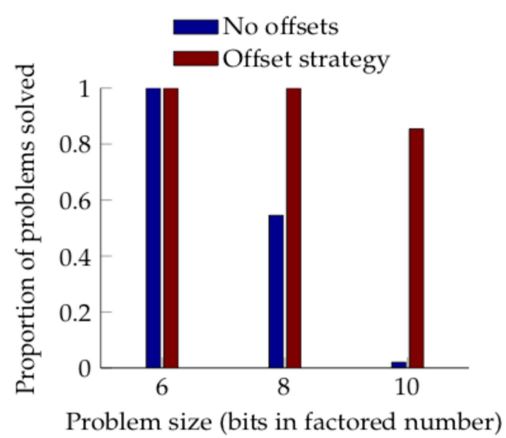
Apply small offsets to the anneal paths of *individual qubits.*

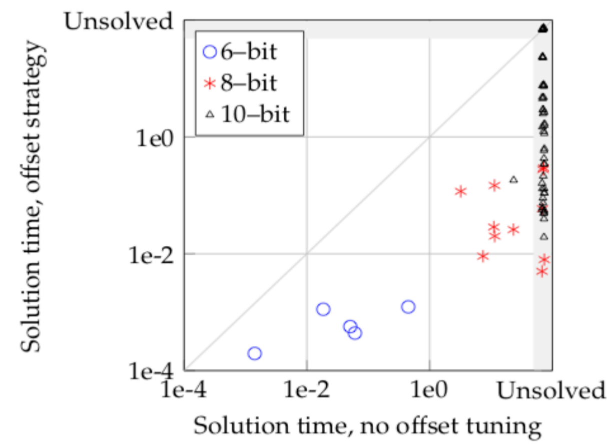
- Long chains freeze out earlier than short chains.
- Use offsets to synchronize qubits in different-length chains.
- Offsets can be calculated as a function of chain length.





Huge improvement in solving factoring problems.



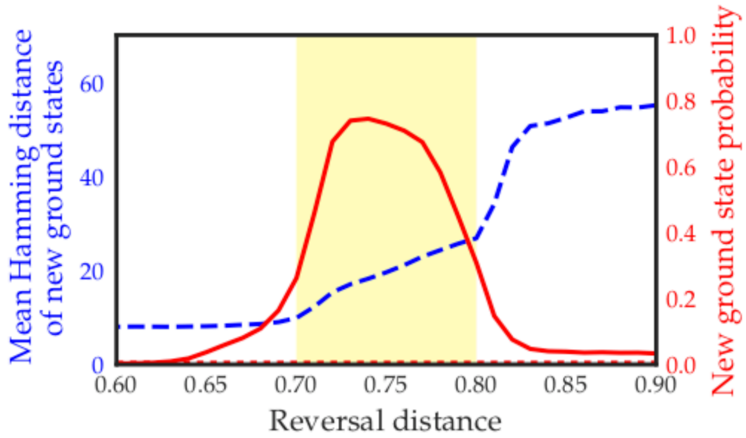


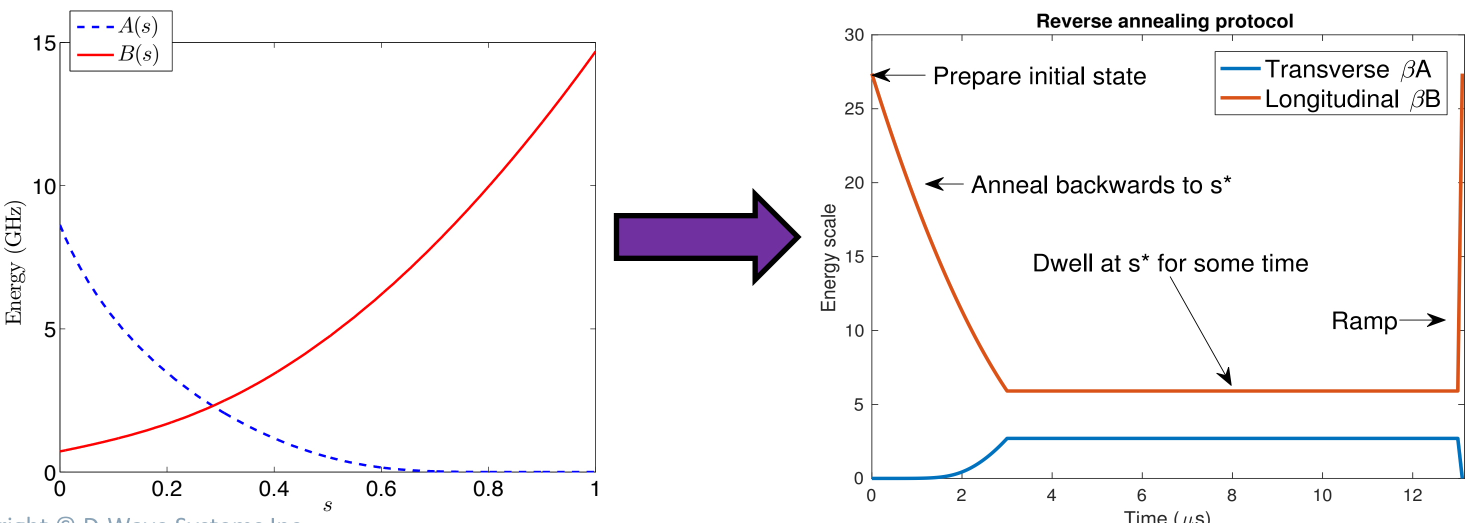
Reverse Anneal

A ``warm start'' from a specified initial state, with a local search near that state.

Use pause and ramp to control how local the search is.

Great for improving diversity in ground state sampling applications.   Much more study is needed.





Where to Find Out More

- Andriyash et al., Boosting integer factoring performance via quantum annealing offsets. D-Wave Technical Report 14-1002A-B, 2016.
- Lanting et al., Experimental demonstration of perturbative anticrossing mitigation using non-uniform driver Hamiltonians, Phys. Rev. A 96 042322, 2017.
- ---, Reverse quantum annealing for local refinement of solutions. D-Wave White Paper 14-1018A-A, 2017.
- Ohkuwa et al., Reverse annealing for the fully connected p-spin model, Phys. Rev. A 98, 022134, 2018.
- King et al., Observation of topological phenomena in a programmable lattice of 1,800 qubits, *Nature* 560, 456-460*, 2018.*

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Tuning the Solver

Solver parameters for tuning anneal paths

- annealing_time
- anneal_offsets
- anneal_schedule (pause & ramp for forward & reverse anneal)
- initial_state, reinitialize_state (for reverse anneal)
- reverse_anneal (boolean)

Other parameters and system utilities

- Spin reversal transforms!!!
- Thermalization delays
- Virtual full yield (VFY)
- Postprocessing for optimization or for sampling

Any Questions? Thanks for your Attention!

Call for Submissions

***Algorithms* special issue on ``Quantum Optimization Theory, Algorithms, and Applications'' Deadline December 31, 2018.**

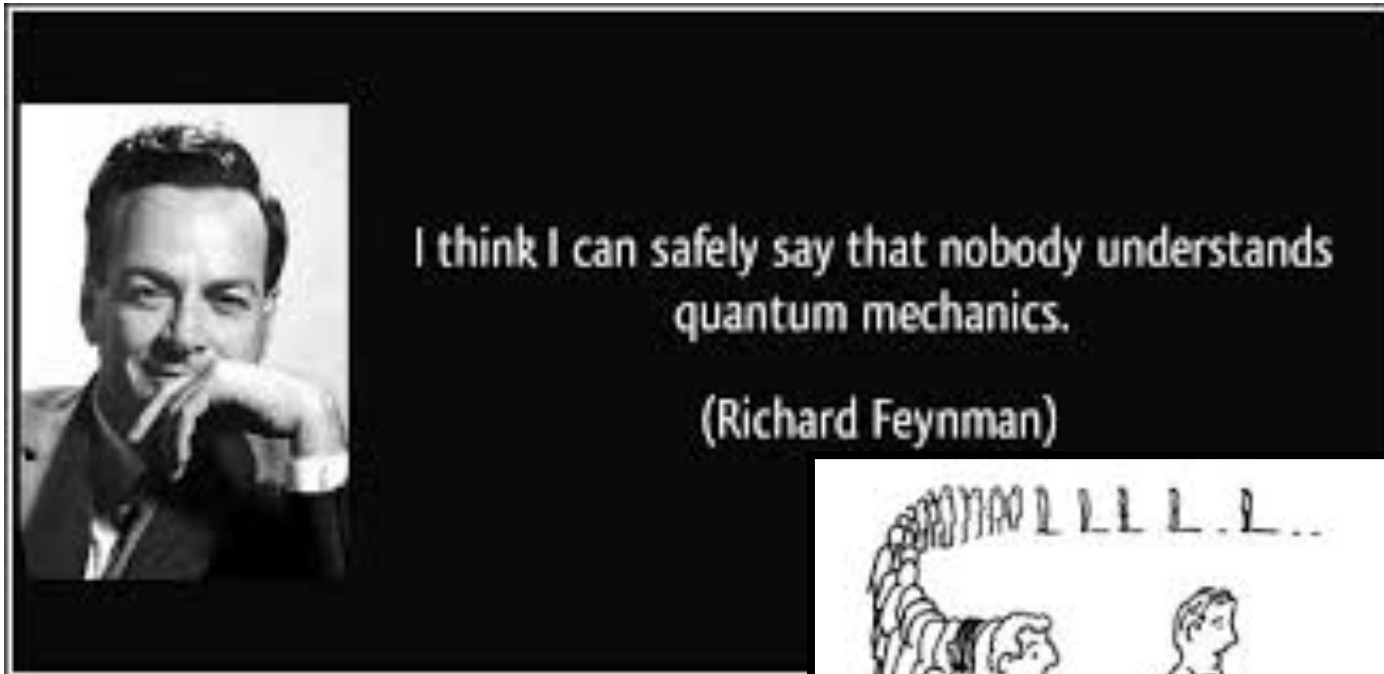
Papers related with the theory of quantum optimization and applications are welcomed. Special interest will be given to global optimization, but any other quantum optimization algorithm will fit this Special Issue. Applications of quantum optimization in machine learning and big data are also welcome.

Quantum computation provides tools to solve two broad classes of optimization problems: Semi-definite programming (SDP) and constraint satisfaction problems (CSPs). For example, in 2016, a quantum algorithm for SDP was developed that is quadratically faster in the number of constraints and variables. SDP finds a number of applications in machine learning. The quantum approximate optimization algorithm and the quantum adiabatic algorithm are known for CSPs. New problems related with machine learning require more efficient optimization algorithms to handle big data.

Prof. Theodore B. Trafalis
Guest Editor

[CCM has inquired: The guest editor is willing to consider empirical work for this special issue.]

Error Model for Anneal Path Tuning



Current models are still fairly weak:

- Limited to very small systems
- Assume closed system
- Can't say much about what works when