



# A Brief Introduction to Quantum Annealing

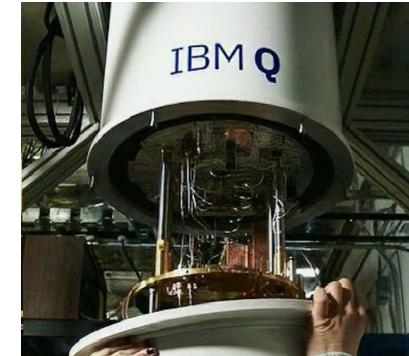
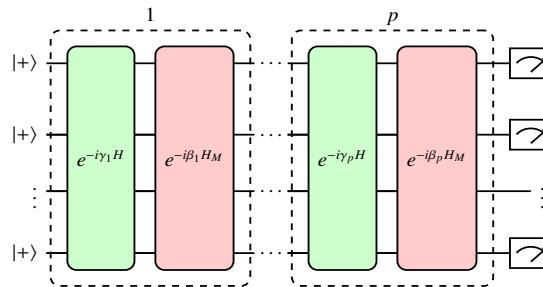
Zachary Morrell

May 28, 2024

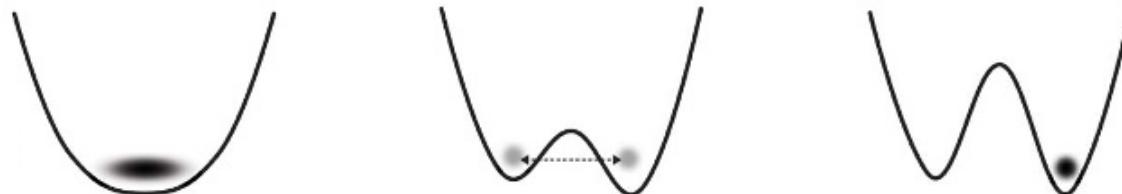
LA-UR-24-25016

# Optimization With Quantum Computers?

## Gate Based: Variational Methods



## Analog: Quantum Annealing



# Why Analog?

It's fast!\*



Gate Based



Analog

# What is Quantum Annealing?

Minimize the eigenvalue of a “target” function

$$H = A(s)H_{\text{initial}} + B(s)H_{\text{target}}$$

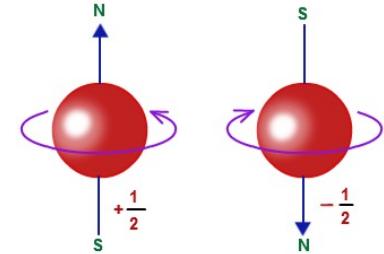
Target is often the Ising Model

$$H_{\text{target}} = \sum_i h_i \sigma_i + \sum_{i < j} J_{ij} \sigma_i \sigma_j \text{ where } \sigma_i \in \{-1, 1\}$$

 Classical

# Why The Ising Model?

Directly realizable by some quantum systems



Quadratic Unconstrained Binary Optimization (QUBO)

**QUBO**

$$\min : \sum_{i,j \in \mathcal{E}} c_{ij} x_i x_j + \sum_{i \in \mathcal{N}} c_i x_i$$

s.t.

$$x_i \in \{0, 1\} \quad \forall i \in \mathcal{N}$$

**Ising Model**

$$\min : \sum_{i \in \mathcal{N}} c_i \sigma_i + \sum_{i,j \in \mathcal{E}} c_{ij} \sigma_i \sigma_j$$

$$\text{s.t.: } \sigma_i \in \{-1, 1\} \quad \forall i \in \mathcal{N}$$

$$\sigma_i = 2x_i - 1$$

$$x_i = \frac{\sigma_i + 1}{2}$$

# What Kind of Problems Can I Encode?

Many Common Problems of Interest!\*

Number Partitioning

Graph Partitioning

Cliques

Binary Integer Linear Programming

Exact Cover

Set Packing

Vertex Cover

3SAT

Minimal Maximal Matching

Set Cover

Integer Knapsack

Graph Coloring

Clique Cover

Job Sequencing

Hamiltonian Paths/Cycles

Minimal Spanning Tree

Steiner Trees

Directed Feedback Vertex Set

Feedback Edge Set

Graph Isomorphism

And more...

<https://www.frontiersin.org/articles/10.3389/fphy.2014.00005/full>

\*With polynomial overhead in a lot of cases

# How Do I Encode My Problem?

$$\sigma^z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

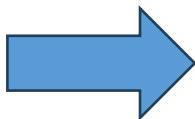
$$|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\sigma^z |0\rangle = |0\rangle$$

$$|1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\sigma^z |1\rangle = -|1\rangle$$

$$\begin{aligned} |1\rangle &\leftrightarrow -1 \leftrightarrow |\downarrow\rangle \\ |0\rangle &\leftrightarrow +1 \leftrightarrow |\uparrow\rangle \end{aligned}$$



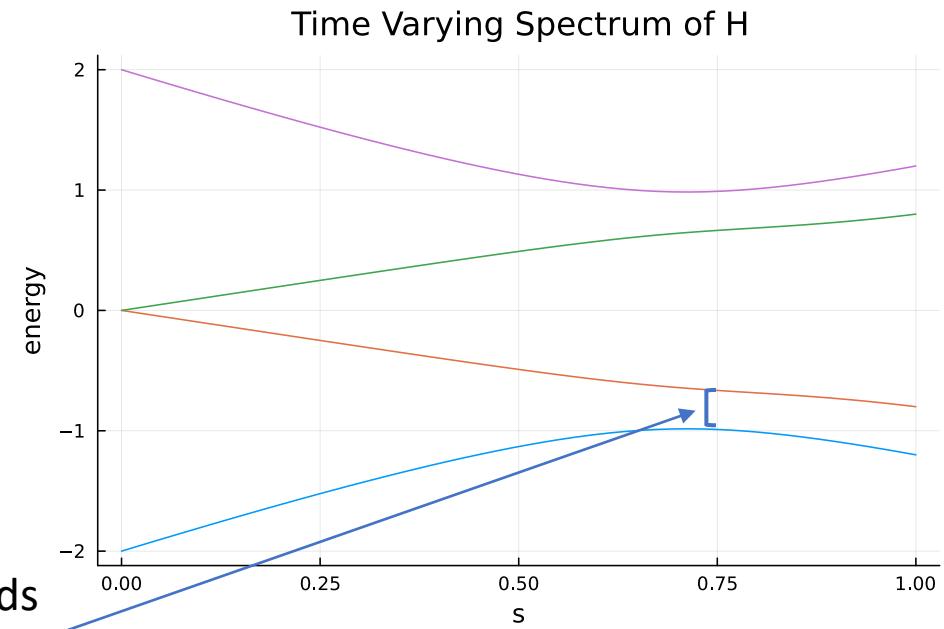
$$H_{\text{target}} = \sum_i h_i \sigma_i^z + \sum_{i < j} J_{ij} \sigma_i^z \sigma_j^z$$

# How Do I Solve My Problem?

Slowly change from  $H_{\text{initial}}$  to  $H_{\text{target}}$

**Adiabatic Theorem:** If you start in a minimal eigenvector of your initial Hamiltonian and change your system slowly enough, you will finish in the minimal eigenvector of your target Hamiltonian!

Time depends  
on this gap



# What Should I Start With?

Start with easy initial problem

$$H_{\text{initial}} = - \sum_i \sigma_i^x$$

Known minimal eigenvector

$$|\psi_0\rangle = \bigotimes_i |+\rangle_i \quad \text{where} \quad |+\rangle = \frac{1}{\sqrt{2}} (|0\rangle + |1\rangle)$$

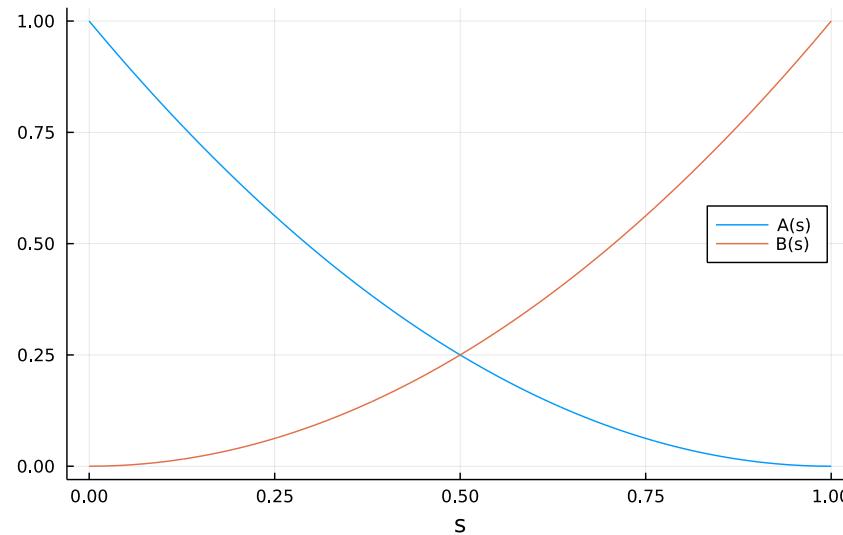
# How Should I Interpolate?

Subject to annealing schedules  $A(s)$  and  $B(s)$

Required that  $|A(0)| \gg |B(0)|$  and  $|A(1)| \ll |B(1)|$

$$s = \frac{t}{t_{\text{total}}}$$

$$t \in [0, t_{\text{total}}]$$

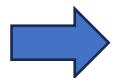


# Bringing It All Together

$$H(s) = -A(s) \sum_i \sigma_i^x + B(s) \left( \sum_i h_i \sigma_i^z + \sum_{i < j} J_{ij} \sigma_i^z \sigma_j^z \right)$$

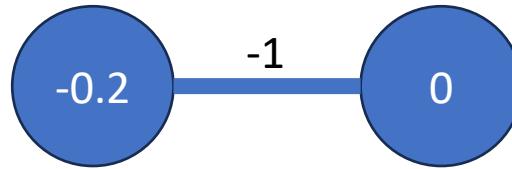
# Example

$$\begin{aligned} \min : & -0.2\sigma_1 - \sigma_1\sigma_2 \\ \text{s.t. } & \sigma_1, \sigma_2 \in \{-1, 1\} \end{aligned}$$

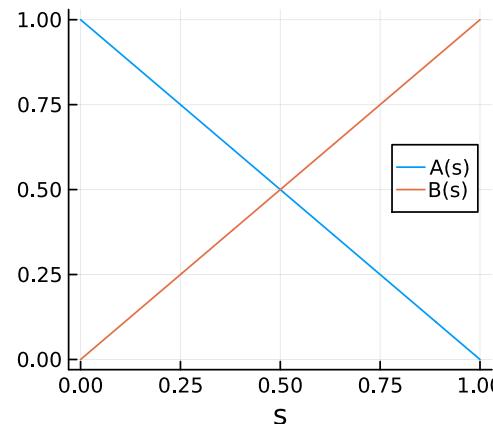


$$H(s) = (1-s)(-\sigma_1^x - \sigma_2^x) + s(-0.2\sigma_1^z - \sigma_1^z\sigma_2^z)$$

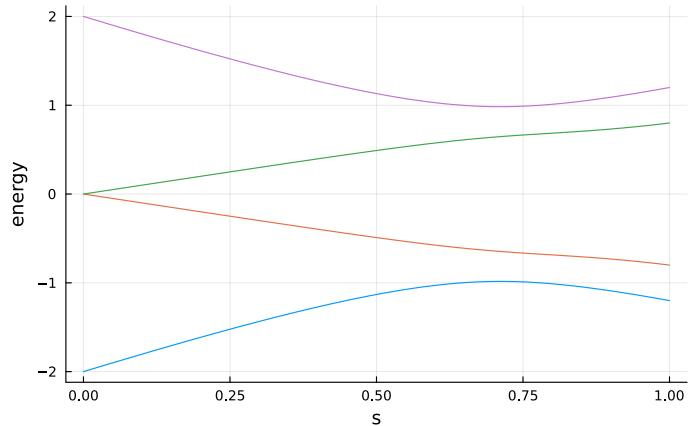
label	$\sigma_1$	$\sigma_2$	$f(\sigma)$
$ \uparrow\uparrow\rangle$	1	1	-1.2
$ \uparrow\downarrow\rangle$	-1	1	1.2
$ \downarrow\uparrow\rangle$	1	-1	0.8
$ \downarrow\downarrow\rangle$	-1	-1	-0.8



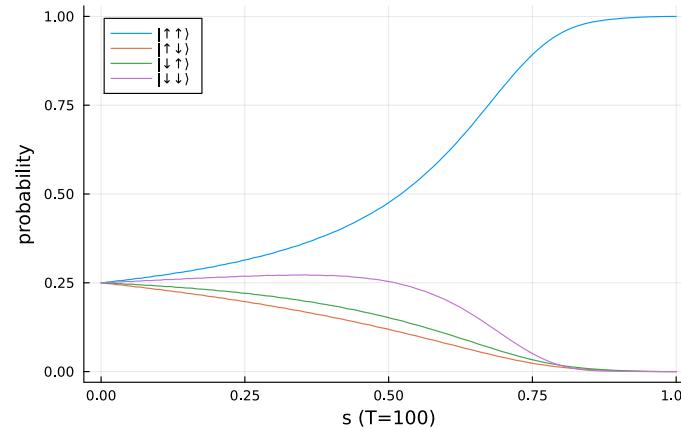
Annealing Schedule



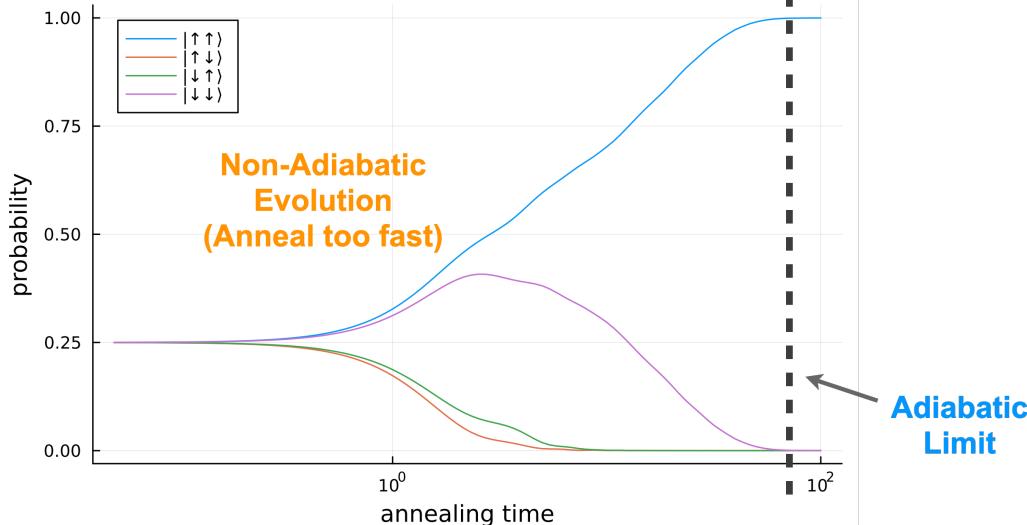
Time Varying Spectrum of H



Spin State Trajectories

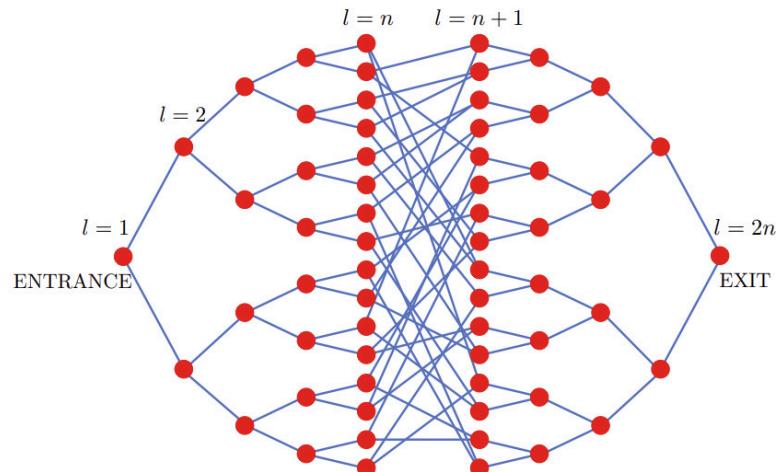


Time Varying State Probabilities

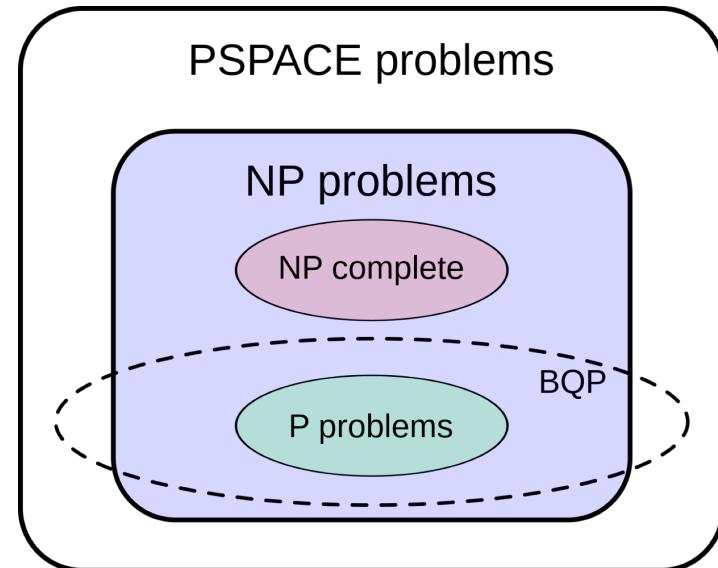


# Can I solve NP Hard Problems?

Not generally in polynomial time



<https://arxiv.org/abs/1202.6257>



<https://en.wikipedia.org/wiki/BQP>

# Hardware Vendors



200 Qubits



| QuEra >  
256 Qubits



D-Wave  
5500 Qubits



# Hardware Considerations

Qubit Count

Qubit Type

Connectivity

Native Hamiltonian

Energy Scale

Programable Annealing Schedules

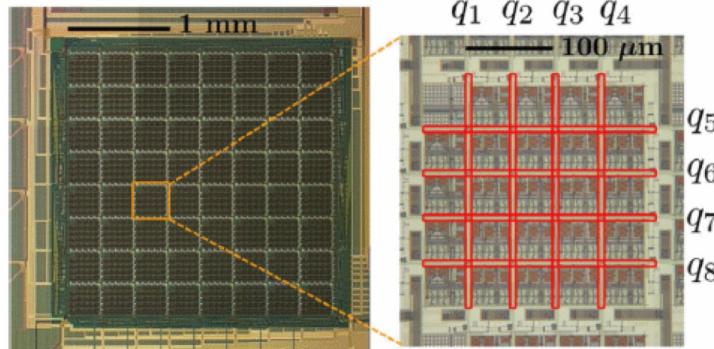
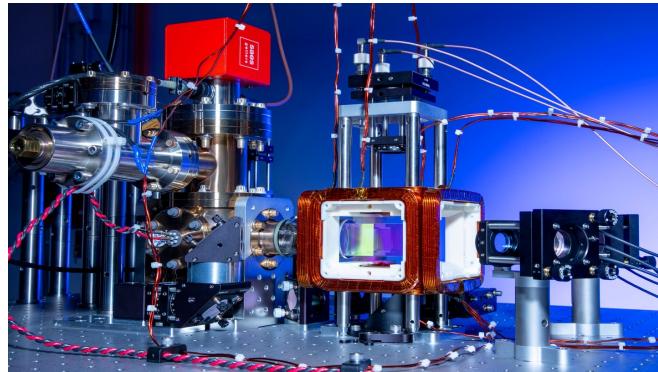
Noise Sources

Coherence Times

Alternative Modes of Operation

Shot Rate

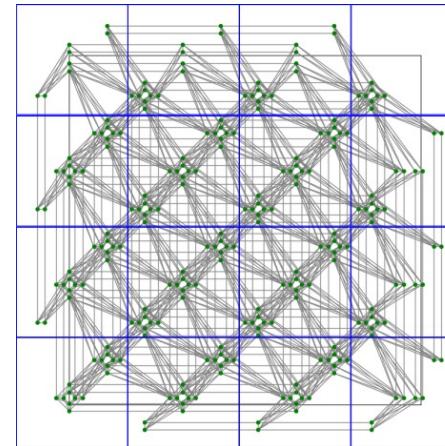
The list goes on...



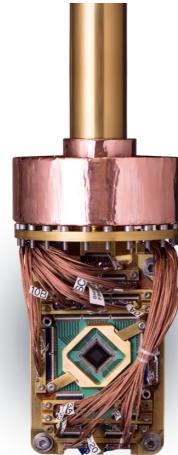
# Superconducting Architecture

- Approach used by D-Wave
- Higher energy scale = Faster
- Low coherence times
- Highly connected
- Higher qubit counts
- More programmable couplers
- Less programmable annealing schedules

D-Wave



[https://docs.dwavesys.com/docs/latest/c\\_gs\\_4.html#zephyr-graph](https://docs.dwavesys.com/docs/latest/c_gs_4.html#zephyr-graph)



# Optimization Achievements of Superconducting Annealers

## Minimizing Spin Glasses

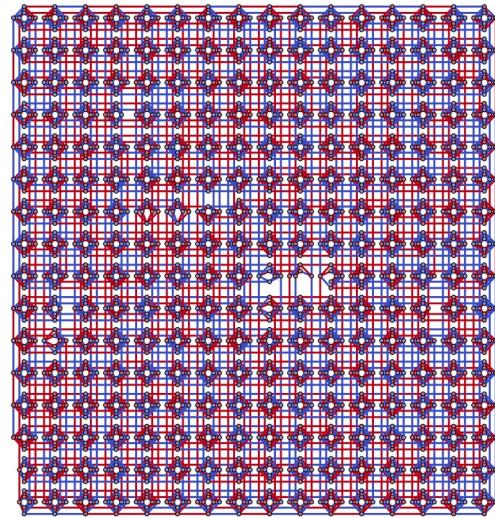
5,627 Qubits

40,279 Couplers (quadratic terms)

P16 Sparsity Pattern

$$\min : \sum_{i \in \mathcal{N}} c_i \sigma_i + \sum_{i,j \in \mathcal{E}} c_{ij} \sigma_i \sigma_j$$

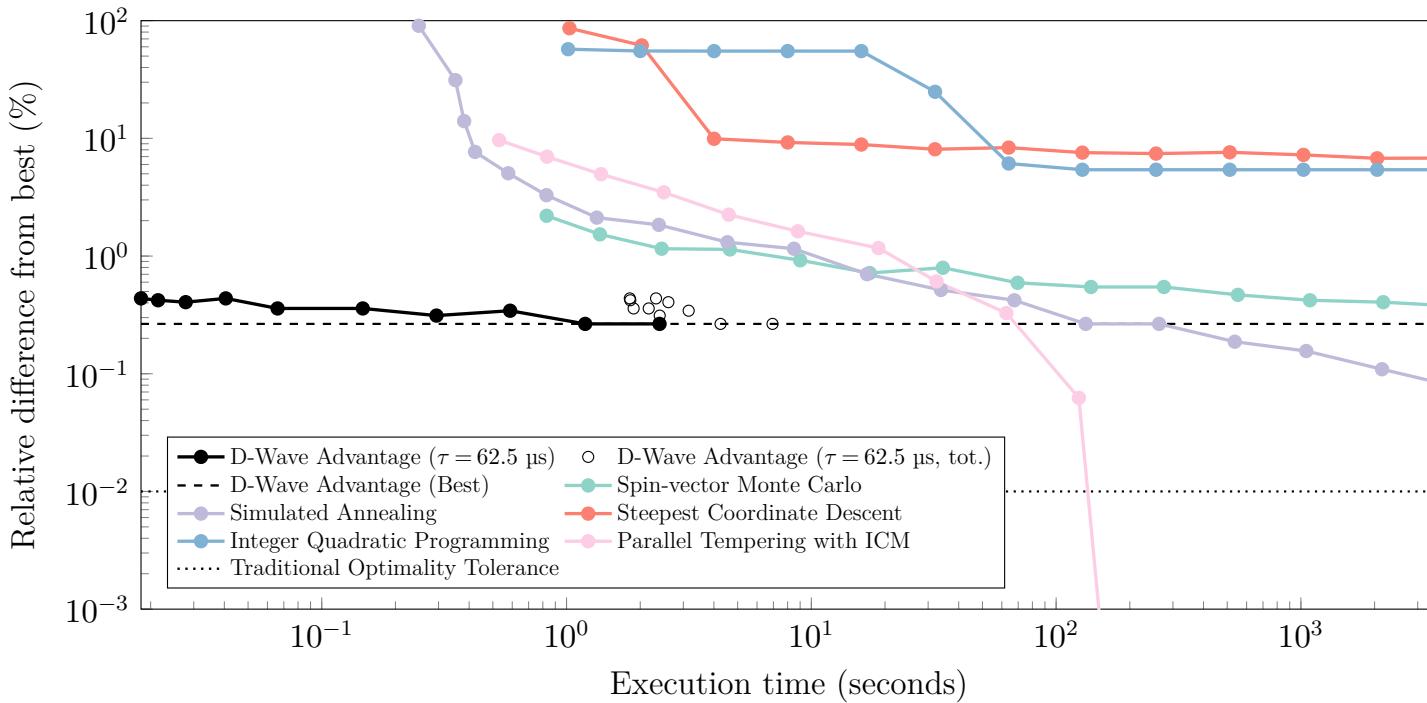
$$\text{s.t.: } \sigma_i \in \{-1, 1\} \quad \forall i \in \mathcal{N}$$



$$P(c_i = 0) = 0.15, P(c_i = -1) = 0.85, P(c_i = 1) = 0, \forall i \in \mathcal{N}$$

$$P(c_{ij} = 0) = 0.35, P(c_{ij} = -1) = 0.10, P(c_{ij} = 1) = 0.55, \forall (i, j) \in \mathcal{P}_{16}$$

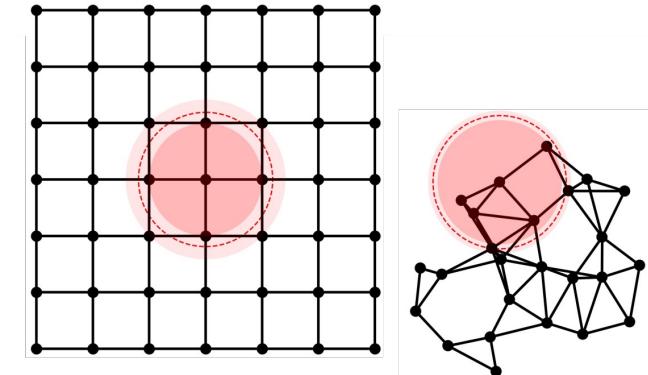
# Optimization Achievements of Superconducting Annealers



<https://arxiv.org/abs/2210.04291>

# Neutral Atom Architecture

- Approach used by QuEra and Pasqal
- Lower Energy Scale = Slower
- High coherence times
- Spatially Connected
- Lower Qubit Counts
- Less programmable couplers
- More programmable annealing schedules



<https://queracomputing.github.io/Bloqade.jl/stable/tutorials/1.blockade/main/>

# Optimization Achievements of Neutral Atom Annealers

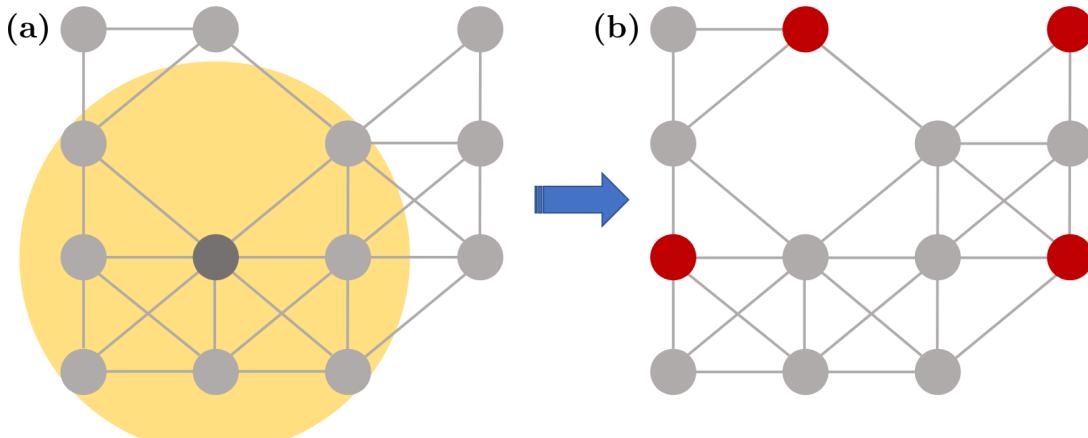
## MIS on Unit Disk Graphs

289 Qubits, 894 Couplers, 80% filled King's Graph

$$\begin{aligned} \max \quad & \sum_i x_i \\ \text{s.t.} \quad & x_i + x_j \leq 1 \quad \forall (i, j) \in \mathcal{E} \\ & x_i \in \{0, 1\} \quad i = 1, \dots, N \end{aligned}$$

$\downarrow$

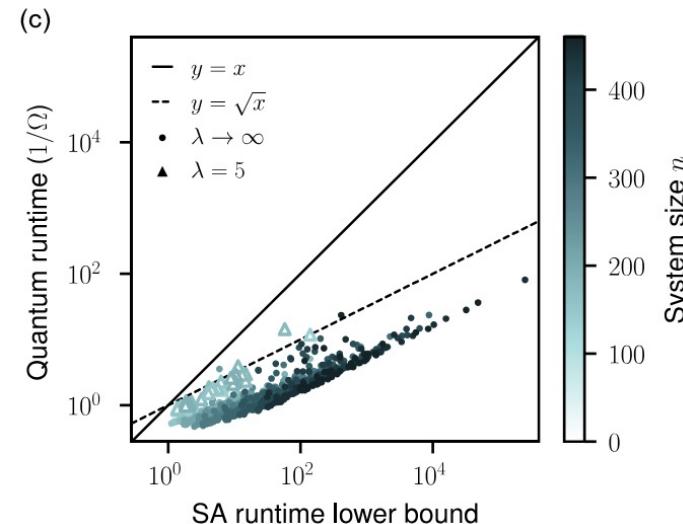
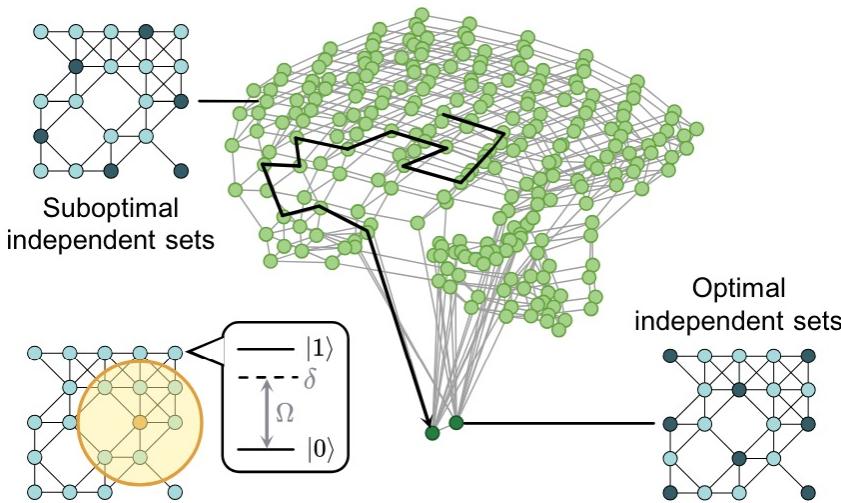
$$H_{\text{MIS}} = - \sum_i \sigma_i^z + P \sum_{(i,j) \in \mathcal{E}} \sigma_i^z \sigma_j^z$$



<https://arxiv.org/pdf/2307.09442>

# Optimization Achievements of Neutral Atom Annealers

\*Only compares against Markov Chain based methods



<https://arxiv.org/abs/2306.13123>  
<https://arxiv.org/pdf/2307.09442>

# Why Didn't My Favorite Problem Perform Well?

## Several Possible Reasons

- Logical Chains
- Biased Hardware
- Penalty Terms
- Too Much Structure
- Too Few Qubits

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You need to walk  
before you can run,  
but that leaves a lot of  
research opportunity

# So What Should I Use?

No clear answer!

Classical optimizers are really good

Hybrid algorithms?

Superconducting annealers are probably  
more mature quantum optimizers for now

# Further Reading

Comprehensive Review Article of Quantum Annealing

- <https://journals.aps.org/rmp/abstract/10.1103/RevModPhys.90.015002>

D-Wave Quantum Supremacy Demonstration (Quantum Dynamics)

- <https://arxiv.org/abs/2403.00910>

Neutral Atom MIS Scaling Studies

- <https://www.science.org/doi/full/10.1126/science.abo6587>
- <https://arxiv.org/abs/2307.09442>

Speedup over single threaded classical computing on a toy problem using D-Wave

- <https://arxiv.org/abs/2210.04291>

Comparison of Analog and Gate Based Hardware for simulating Ising Model dynamics

- <https://arxiv.org/abs/2402.17667>