Adiabatic Quantum Computing

Bob Lucas
USC Viterbi School of Engineering
Information Sciences Institute
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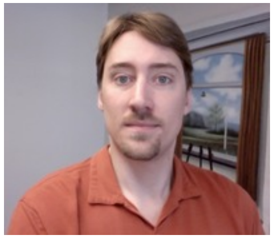
USC / ISI Colleagues


Daniel Lidar


Federico Spedalieri


Greg Ver Steeg

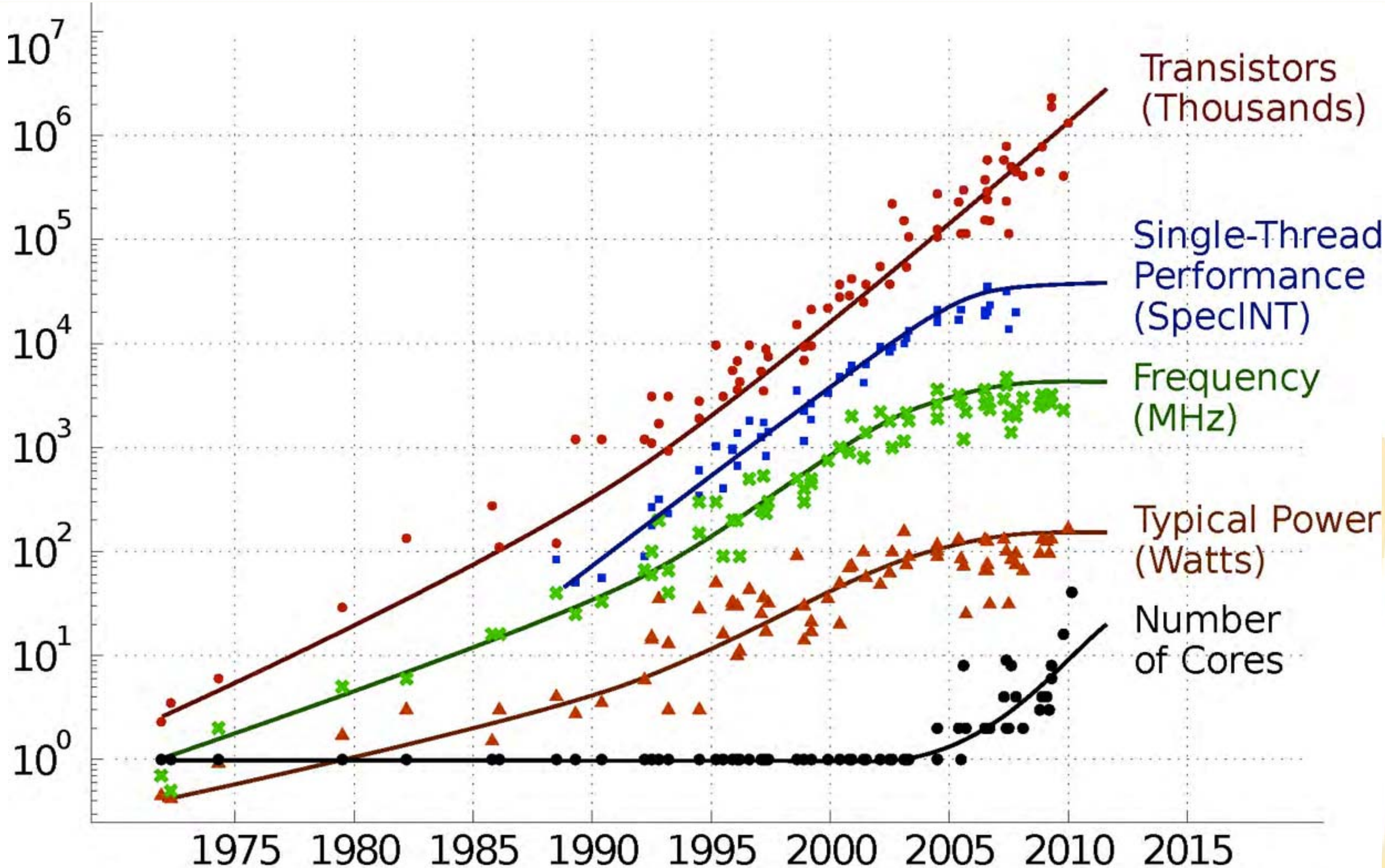

Kristen Pudenz


Sergio Boixo

Many others including:

Ben Reichardt
Edmun Jonckheere
John Damoulakis
Lorenzo Campos
Massoud Pedram
Milad Marvian
Paolo Zanardi
Stephan Haas
Susumu Takahashi
Tameem Albash
Todd Brun
Tony Levi
Dan Davenport
Greg Tallant
Peter Stanfill

The End of Dennard Scaling



Data collected by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, C. Batten

Need More Capability?

Massive Scaling - LANL/SNL Cray XE6

Application Specific Systems
D.E. Shaw Research Anton

Exploit a New Phenomenon
Adiabatic Quantum Processor
D-Wave One

A bit of perspective ...

R. Landauer

Memo to IBM

The transistor:
Nothing to worry about ...

Looking Backwards

R. Landauer

The memo was precisely right about the first transistor… but not the second transistor!

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D-Wave One
Adiabatic Quantum Optimization Device

Adiabatic Quantum Optimization

Problem: find the ground state of

$$H_{\text{Ising}} = \sum_j h_j \sigma_j^z + \sum_{(i,j)\in E} J_{ij} \sigma_i^z \sigma_j^z$$

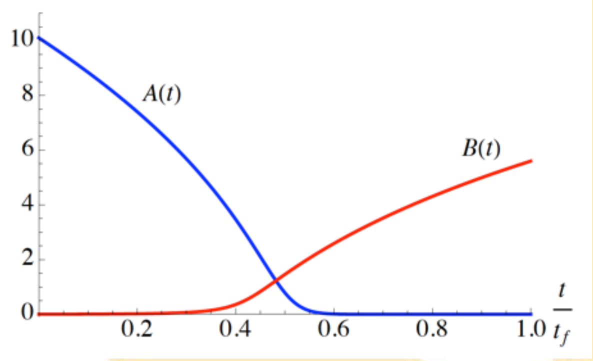
Shown by Barahona (1982) to be NP-hard in 2D, $J_{ij} = \pm,\ h_j \neq 0.$

Use adiabatic interpolation from transverse field **(Farhi et al., 2000)**

$$H(t) = A(t)\sum_j \sigma_j^x + B(t) H_{\text{Ising}}$$

$t \in [0, t_f]$

Program $\{h_i\},\{J_{ij}\}$



Graph Embedding implemented on DW-1 via Chimera graph retains NP-hardness **V. Choi (2010)**

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USC LM D-Wave One 128 Qubit (OK, 108) Chip

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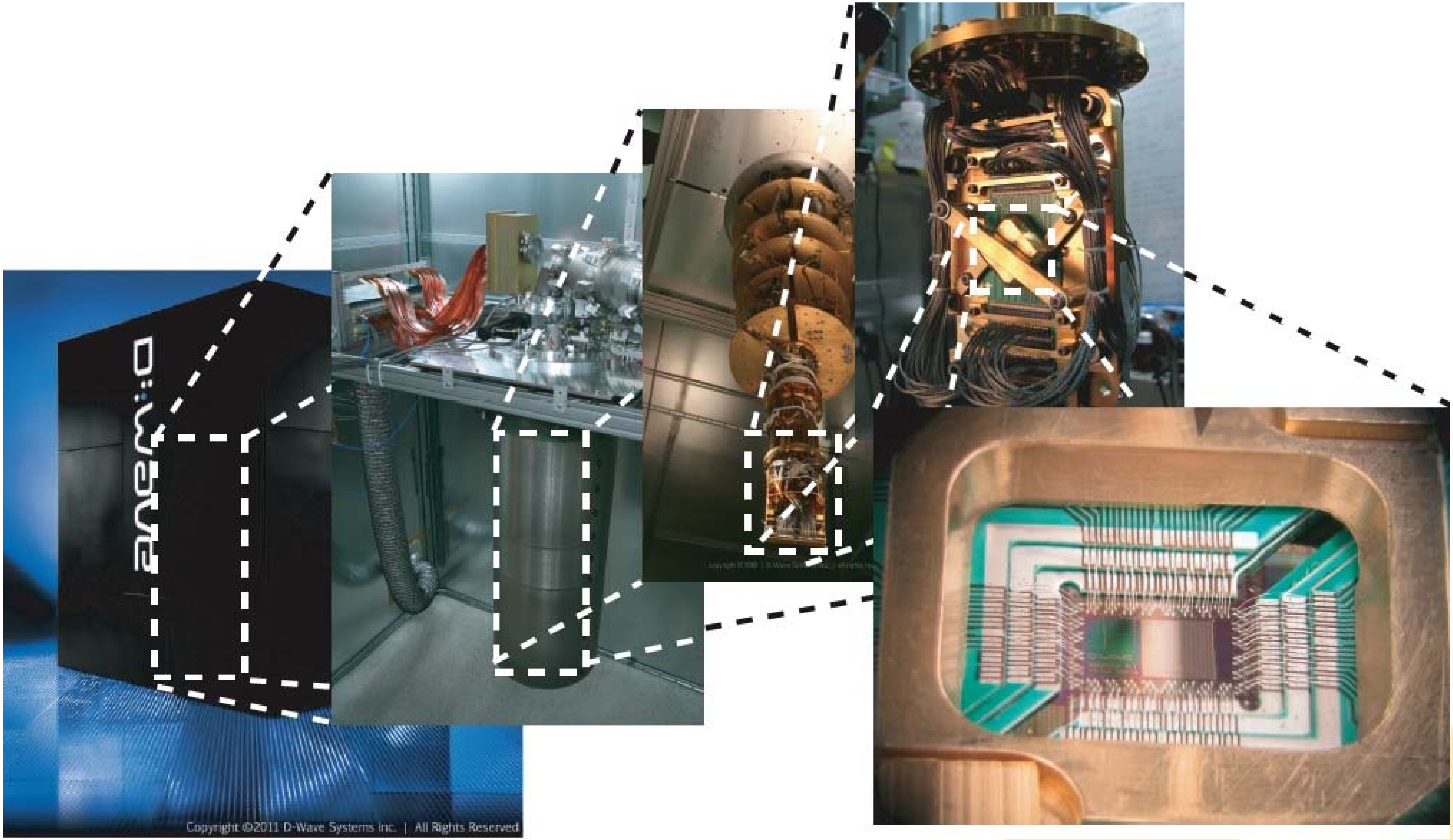
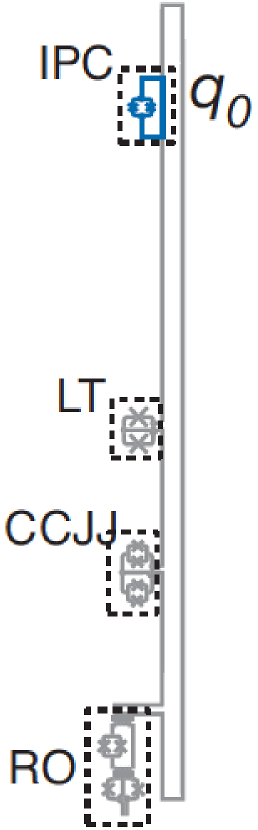
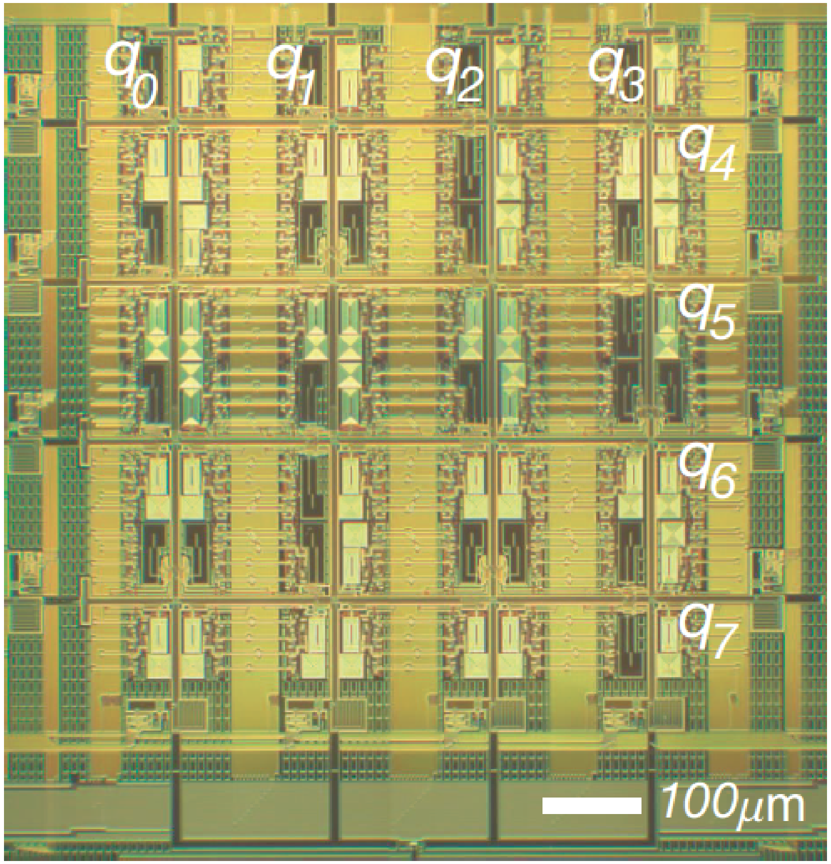


Images courtesy D-Wave

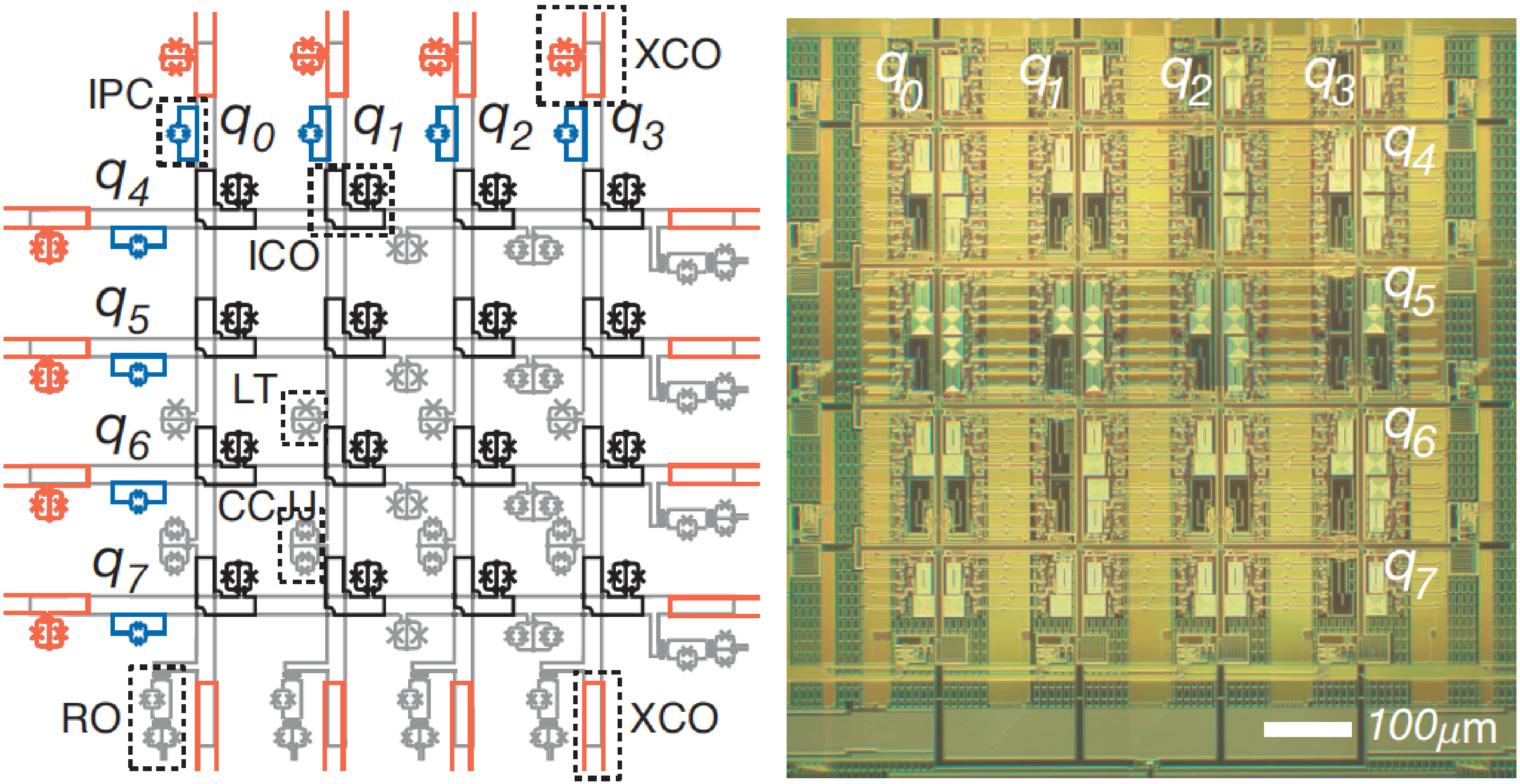
Eight Qubit Unit Cell





Images courtesy D-Wave

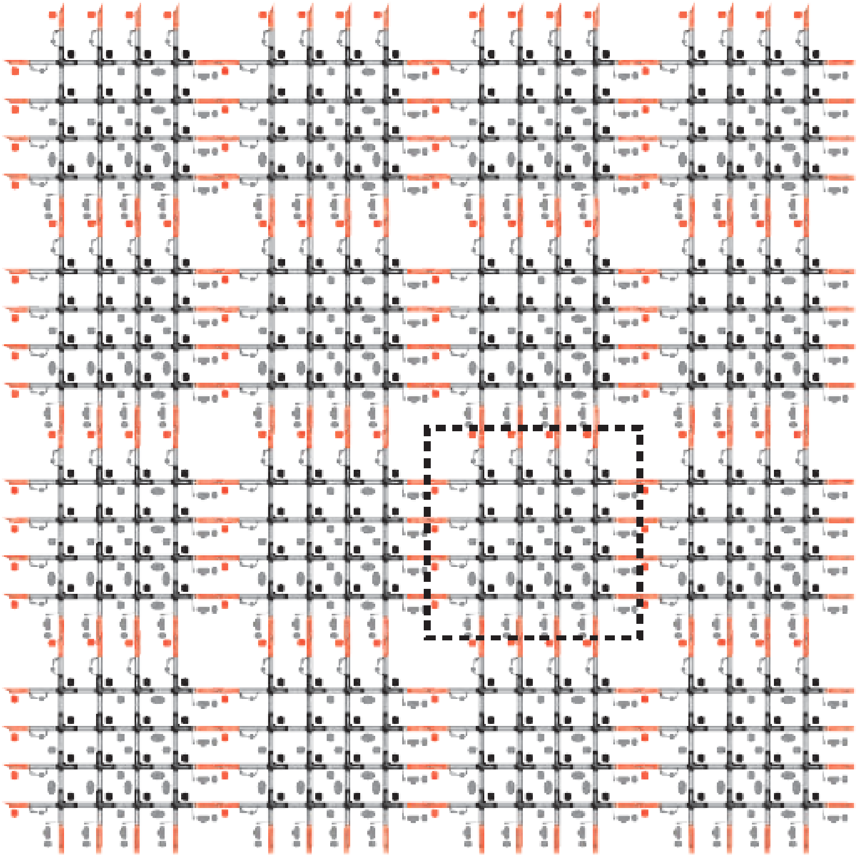
Eight Qubit Unit Cell

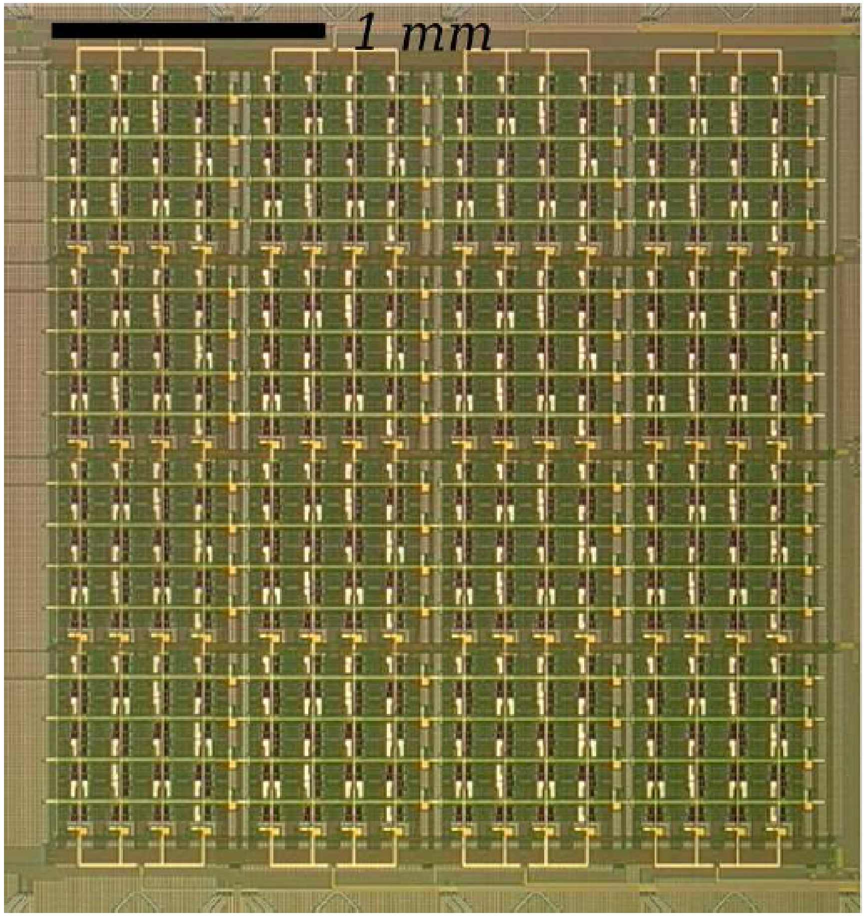


Images courtesy D-Wave

Tiling of Unit Cells

A 128-qubit chip composed of a 4×4 array of eight-qubit unit cells.





Images courtesy D-Wave

Scalable Design

Component counts

digital to analog converters → DACS
Josephson junctions → JJs

	Unit cells	Qubits	Couplers	DACS	JJs
	1	8	16	56	1 500
	4	32	72	232	6 000
Rainier →	16	128	328	968	24 000
Vesuvius → **end of 2012**	64	512	1416	3 976	96 000
	256	2048	5896	16 136	384 000

Data courtesy D-Wave

D-Wave One Processor Graph

108 functional qubits in a “Chimera graph”

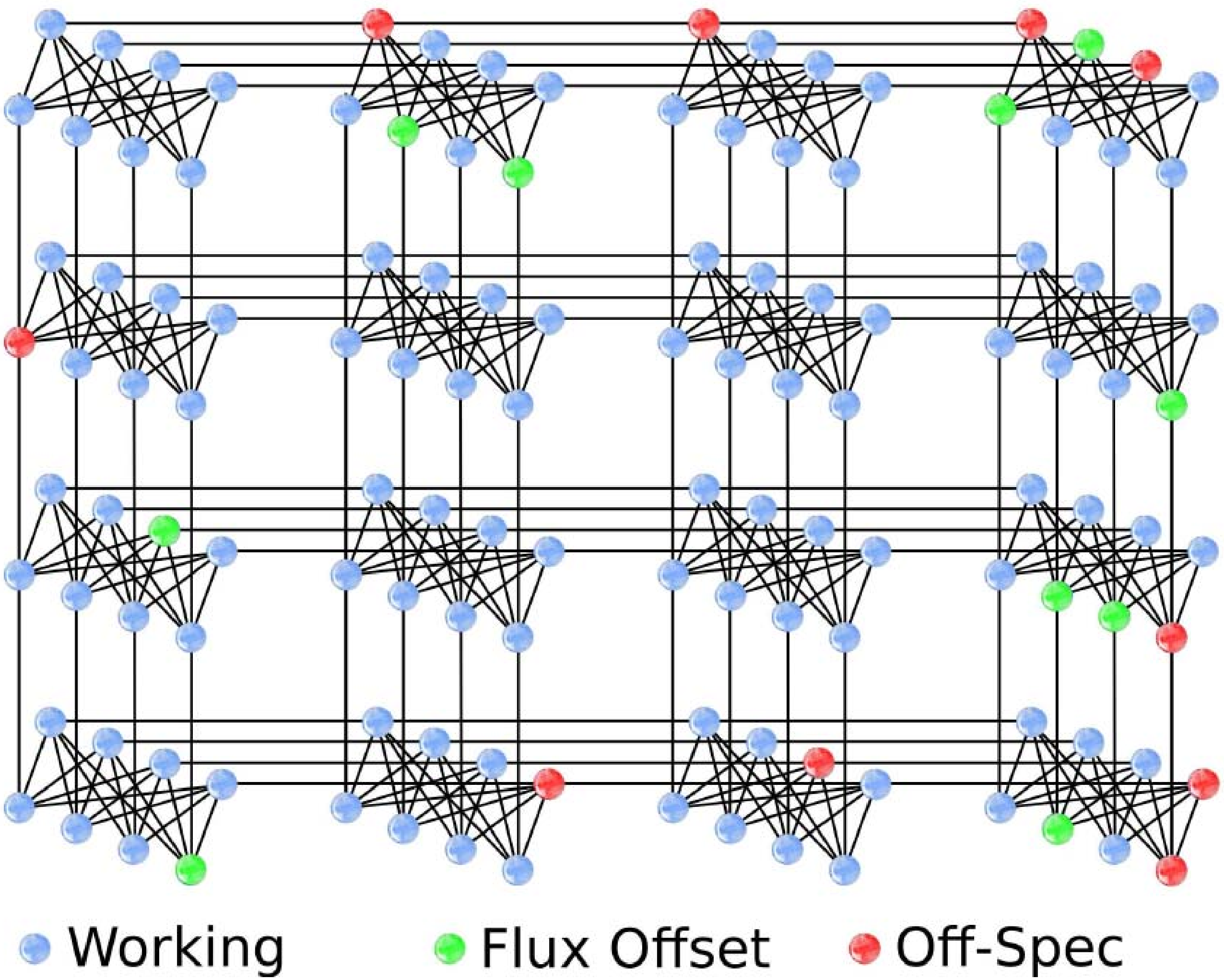


Image courtesy D-Wave

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Mapping Spin Glasses

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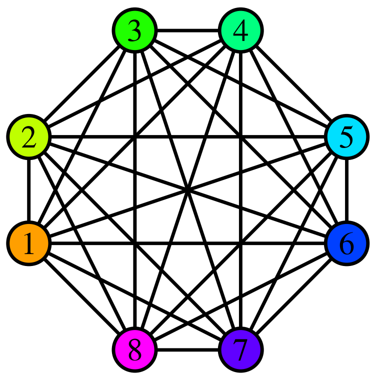
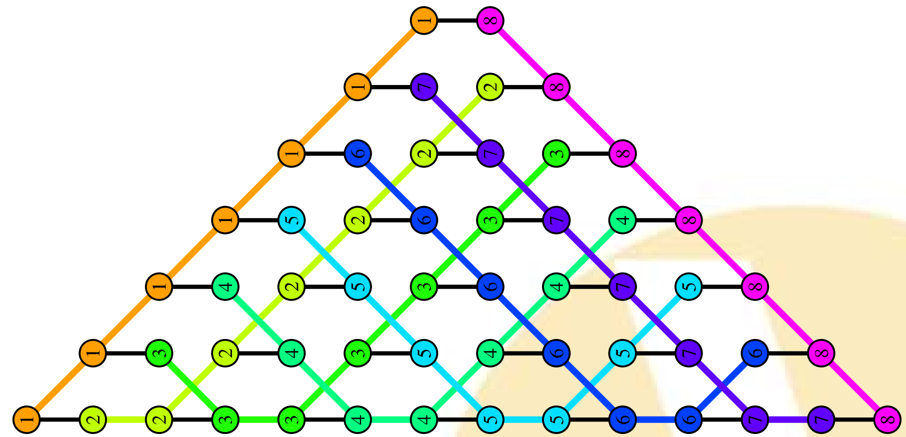
Complex graphs can be embedded into simpler graphs using strong ferromagnetic couplings (Kaminsky and Lloyd, 2002)

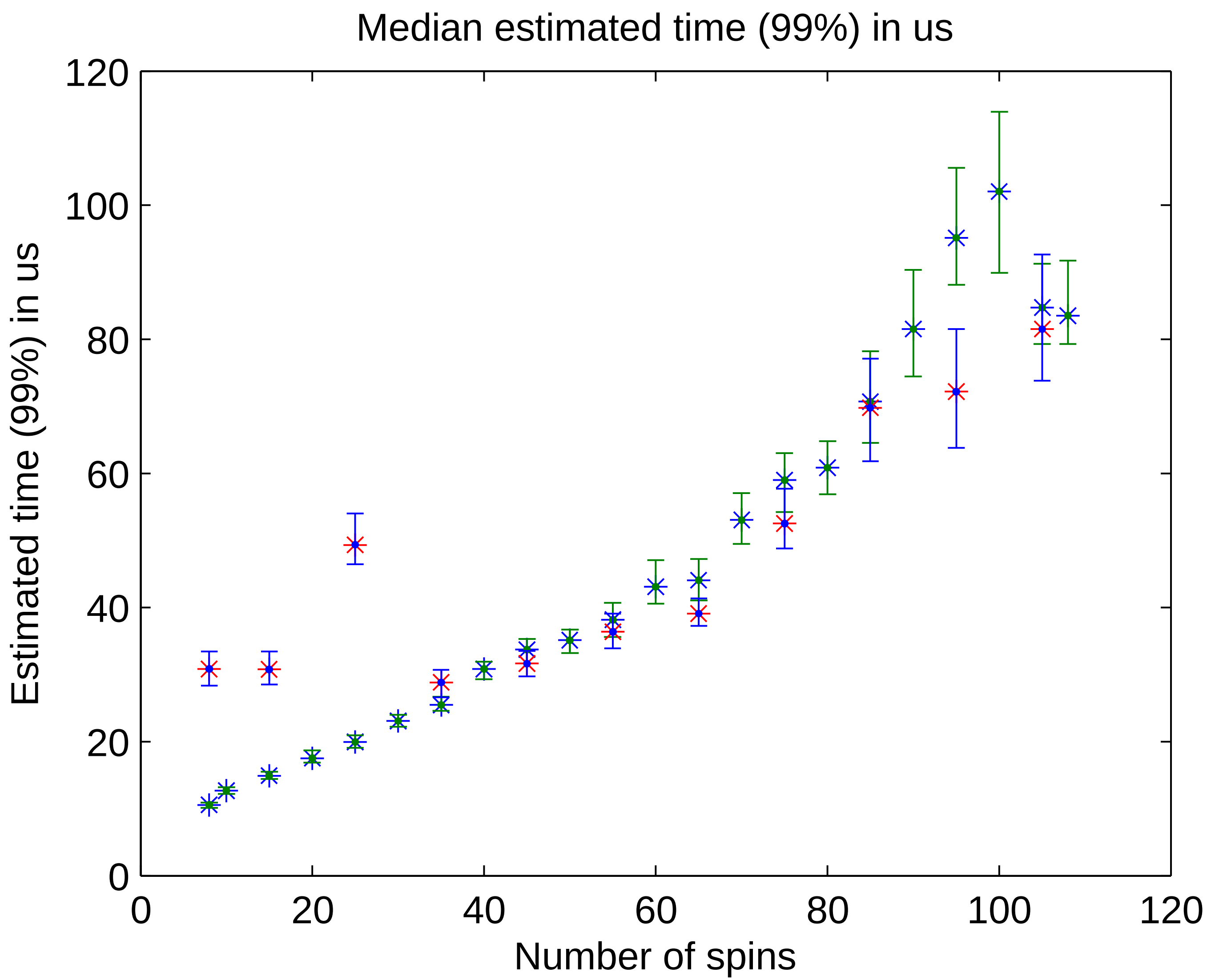




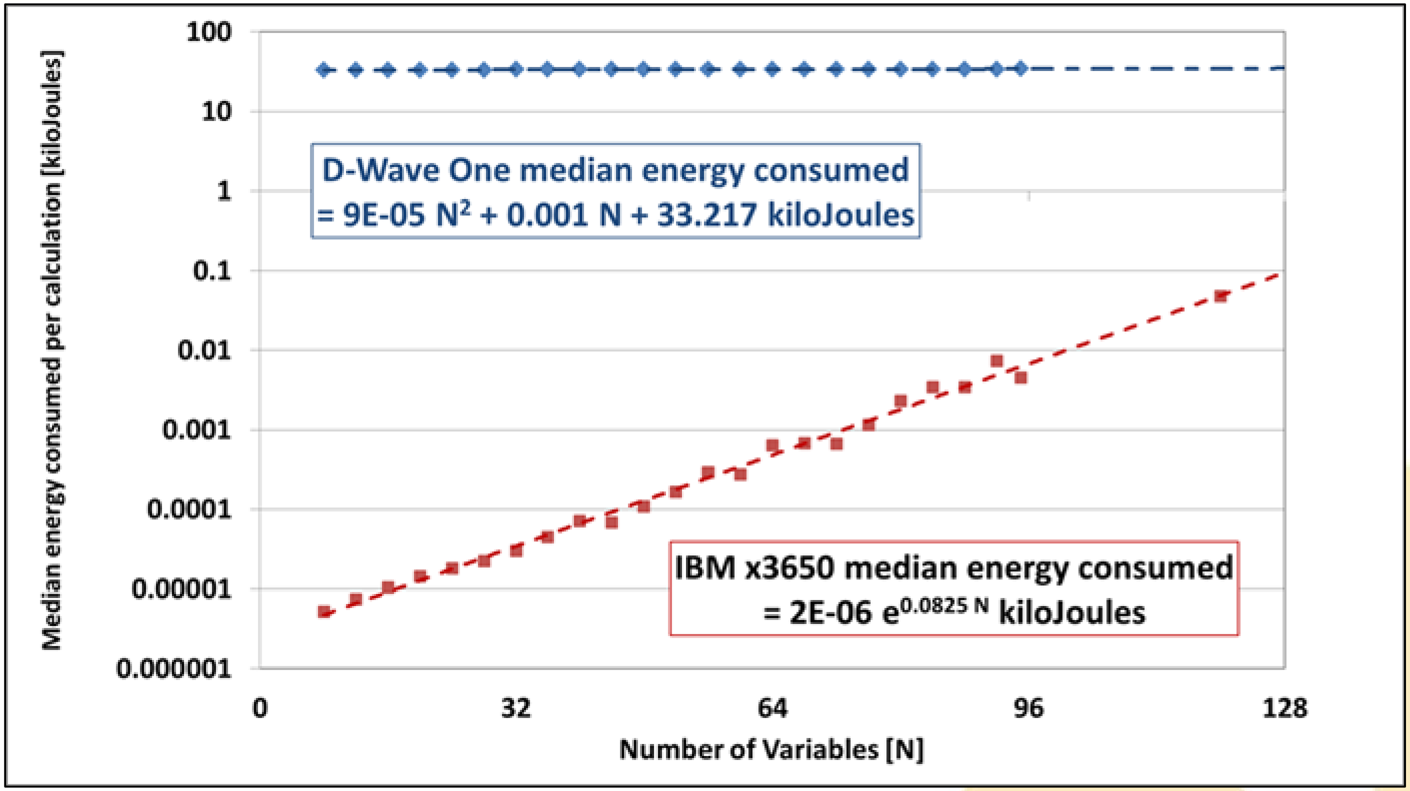
The strength of the ferromagnetic couplings grows with the degree of the embedded graph (Choi 2008)

In principle, an N-complete graph can be embedded in the geometry implemented by Dwave using N^2 vertices (Choi 2010)

Estimated Median Time to 99% Success Probability for Random 2D Spin Glasses



Energy Scaling



Energy consumption of DW-1 is dominated by refrigeration

Effectively independent of system or the problem scale

Figure courtesy D-Wave

Does it behave as an Adiabatic Quantum Machine?

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Random 2D Ising
10 – 108 qubits, 5 us annealing

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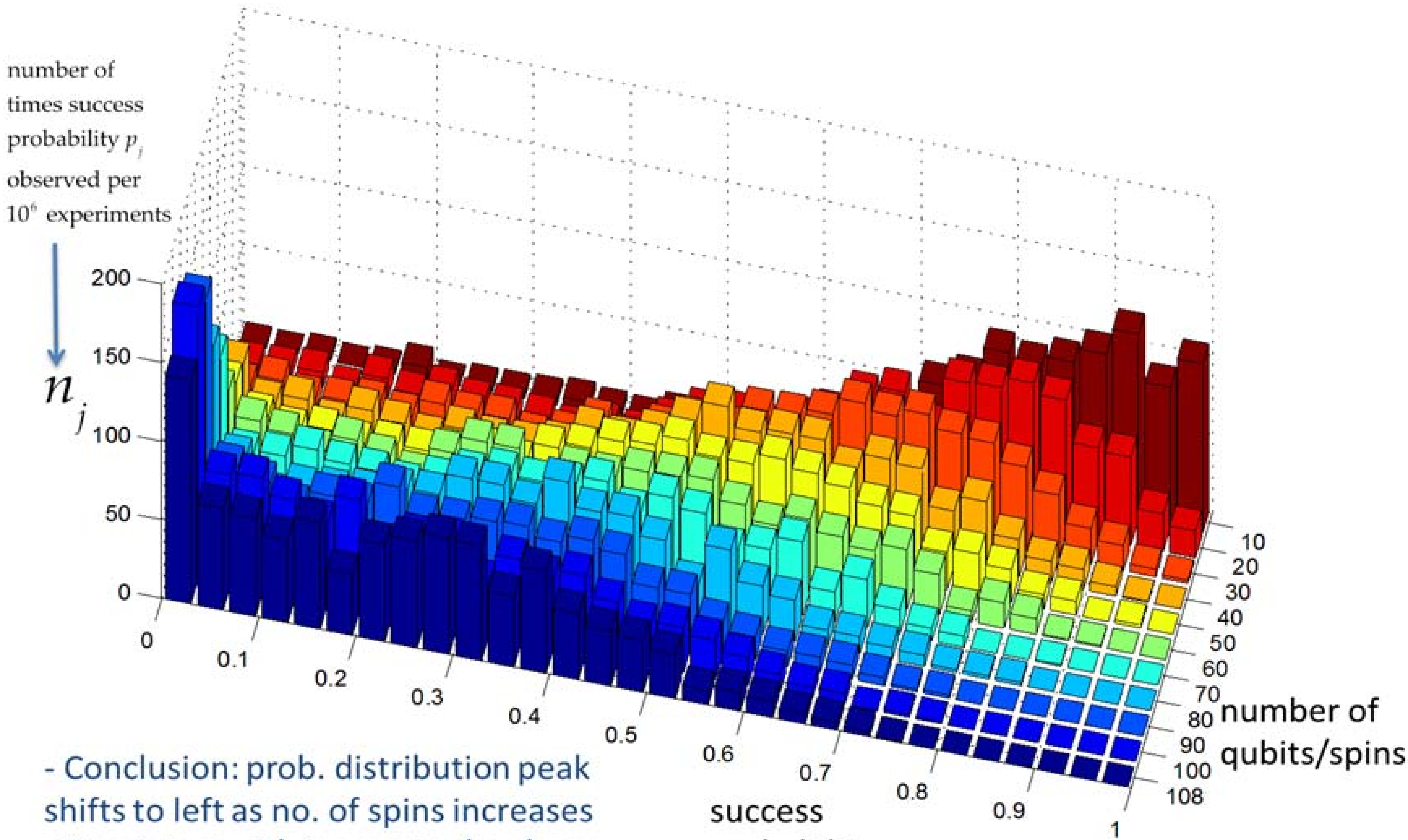
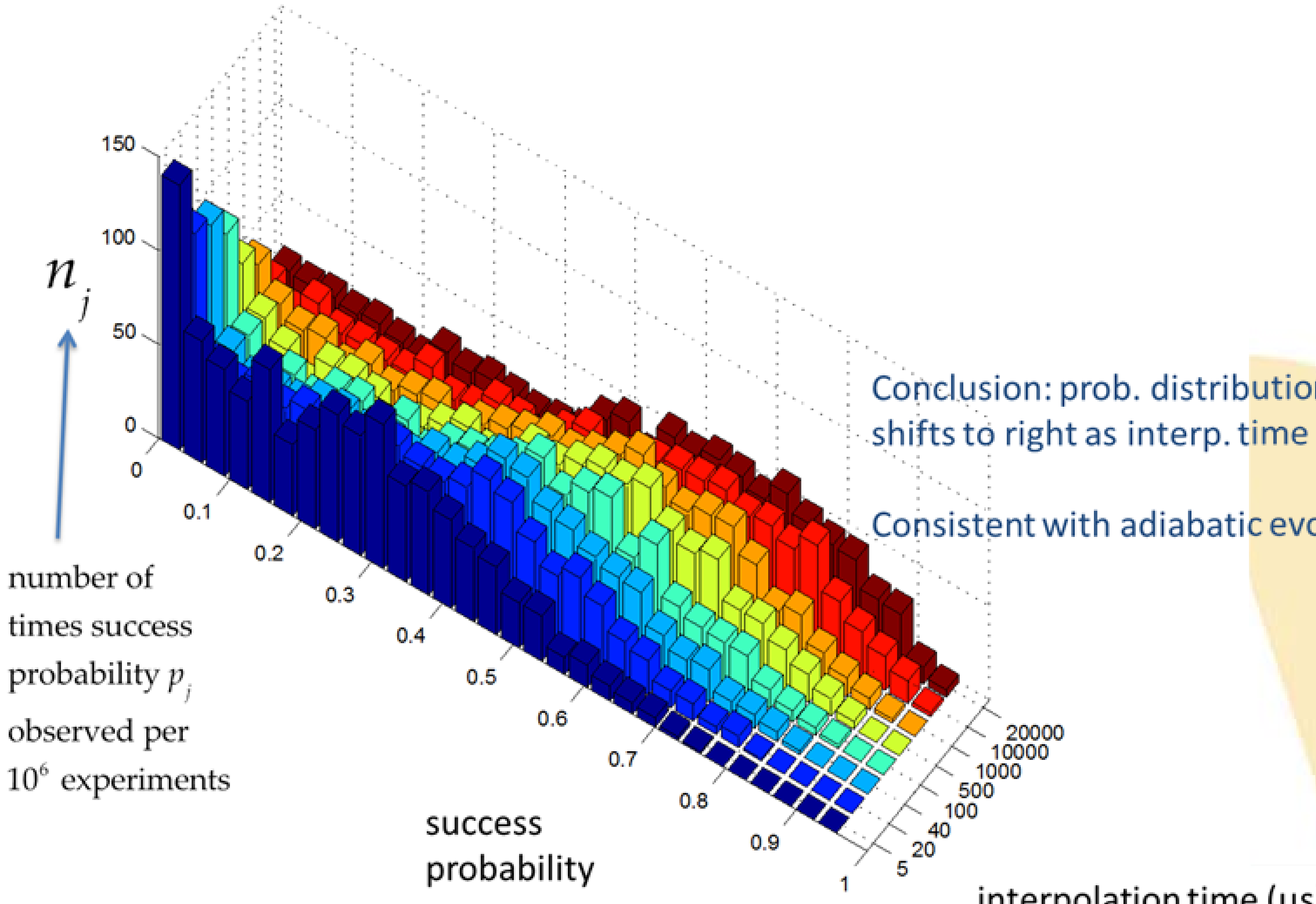


- Conclusion: prob. distribution peak shifts to left as no. of spins increases
- Consistent with increasing hardness

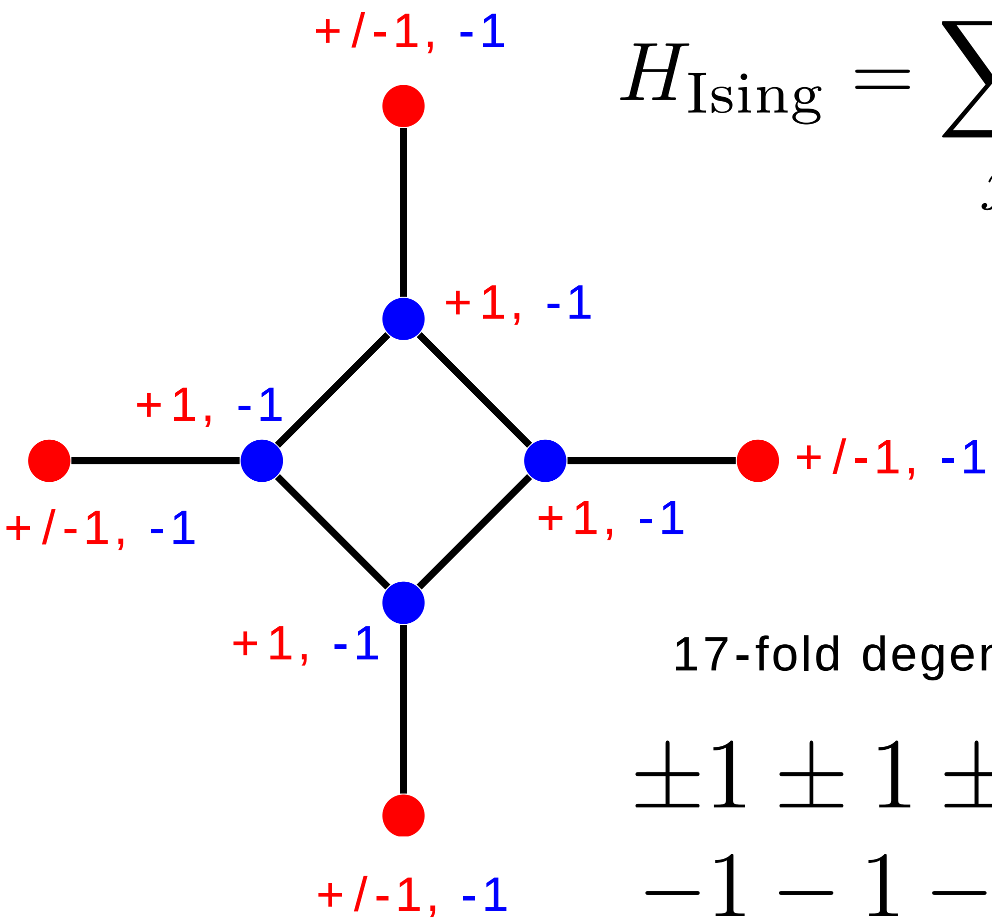
Random 2D Ising
108 qubits, 5us – 20ms



Conclusion: prob. distribution peak shifts to right as interp. time increases

Consistent with adiabatic evolution

Degenerate Ising Hamiltonian



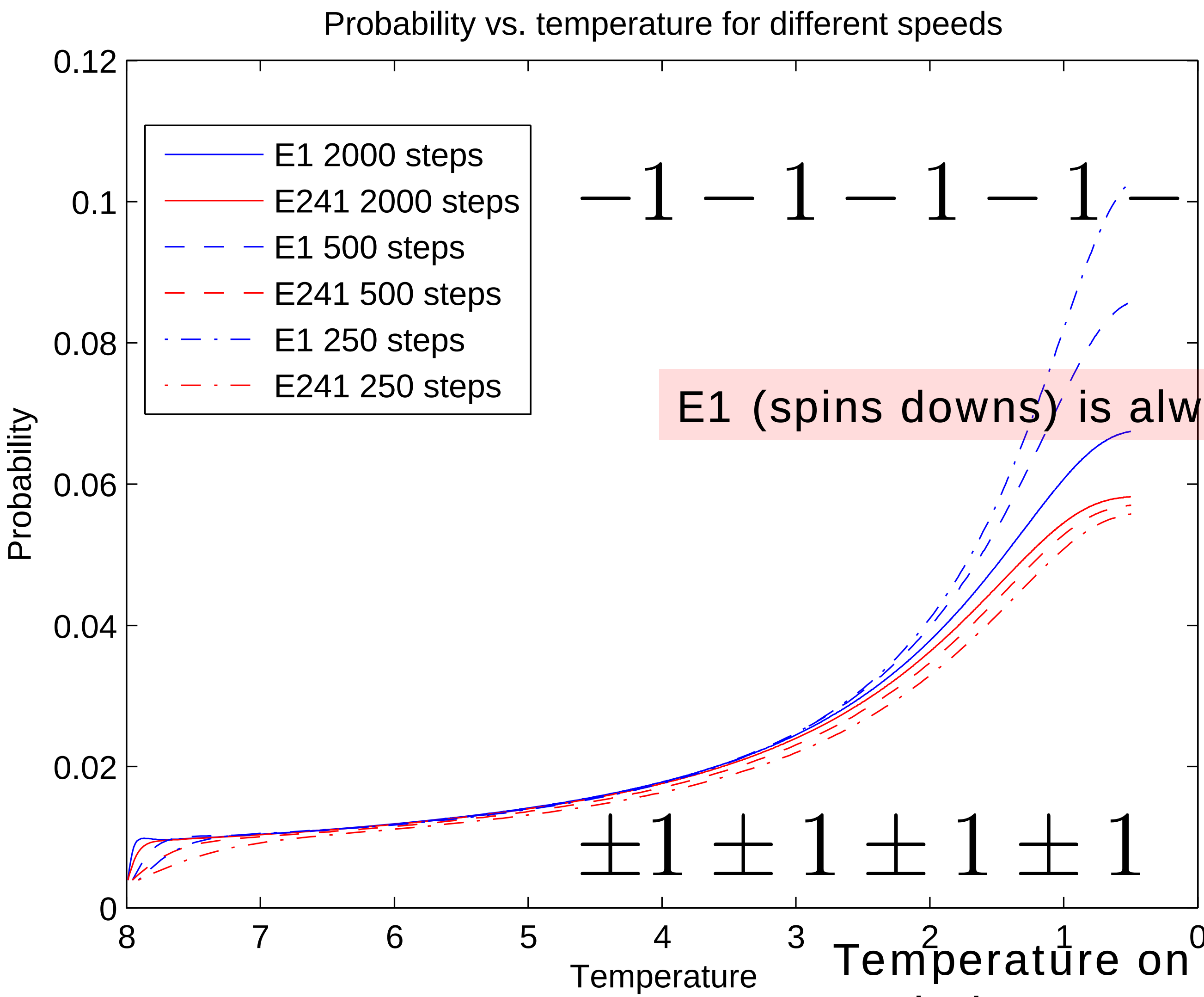
$$H_{\text{Ising}} = \sum_j h_j \sigma_j^z + \sum_{(j,k)\in E} J_{jk} \sigma_j^z \sigma_k^z$$

hj = -1, hj = 1, Jik = -1

17-fold degenerate ground space:

$$\begin{matrix} \pm 1 & \pm 1 & \pm 1 & \pm 1 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{matrix}$$

Simulated Annealing At Several Speeds



$$-1 -1 -1 -1 -1 -1 -1 -1$$

E1 (spins downs) is always more probable

$$\pm 1 \pm 1 \pm 1 \pm 1 \quad 1 \quad 1 \quad 1 \quad 1$$

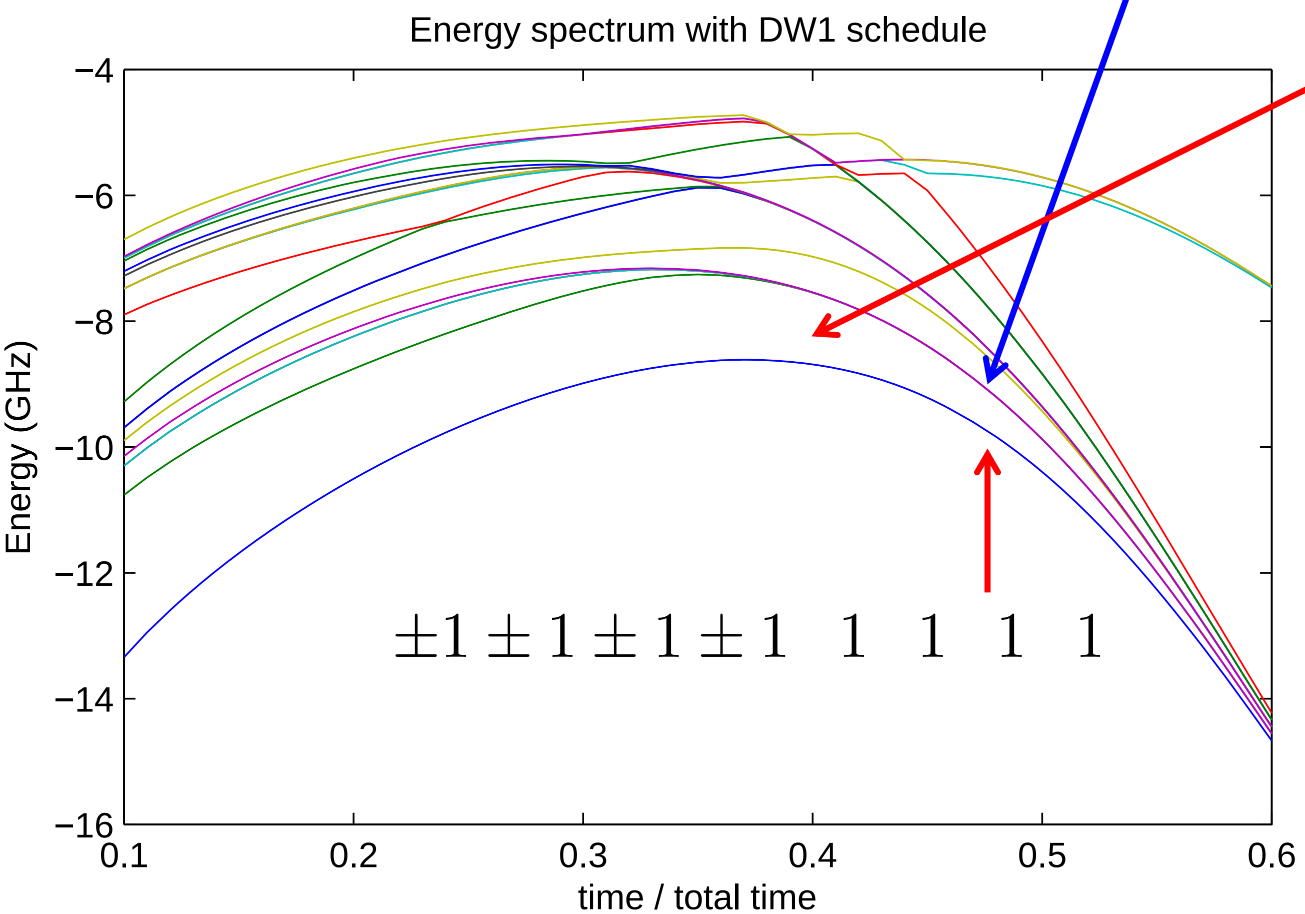
Temperature on a simple annealing evolution

DW1 Spectrum

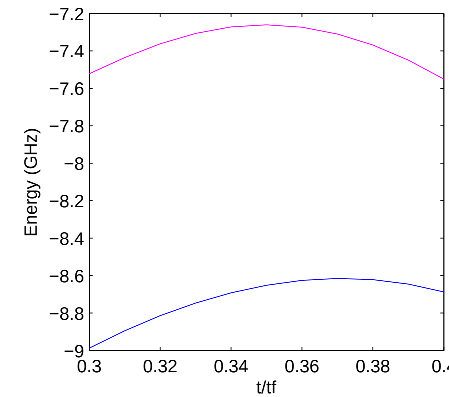
$$-1-1-1-1-1-1-1-1$$

Gap 1.35 GHz

(Temp: 0.5 GHz)



$$\pm1\pm1\pm1\pm1\quad 1\quad 1\quad 1\quad 1$$

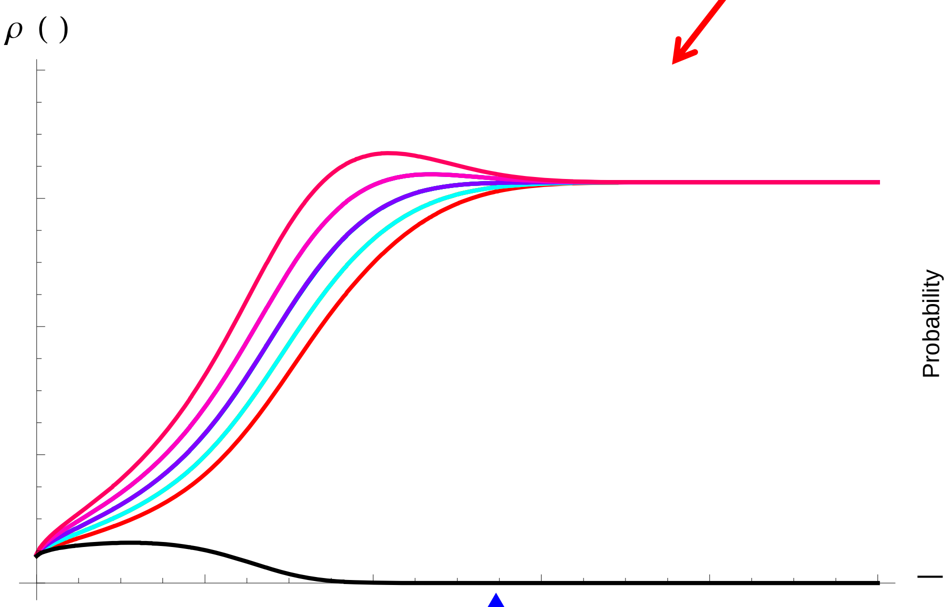


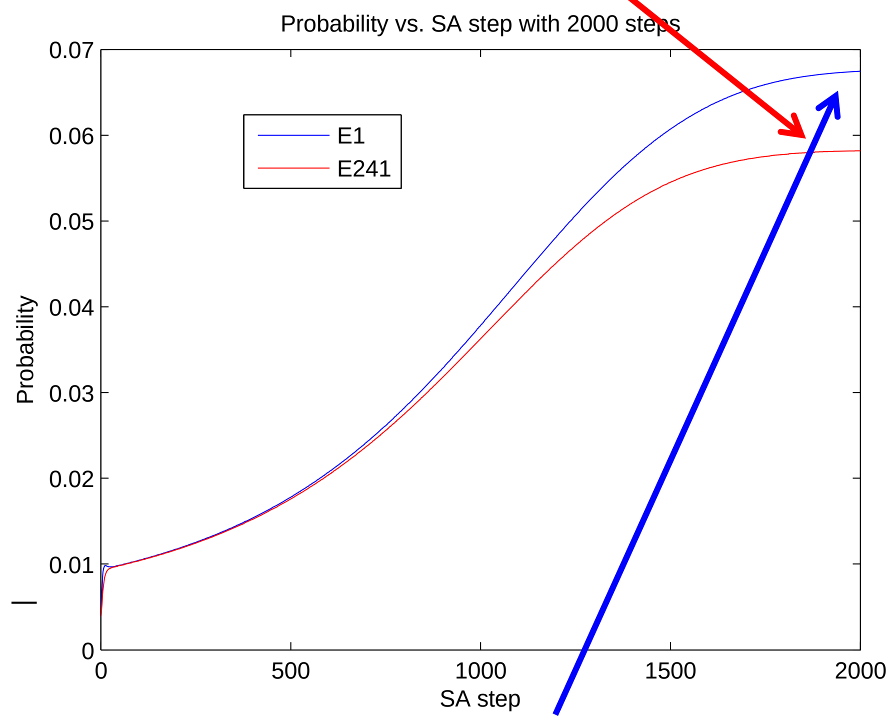
Transitions to 4^{th} order in σ^x

Small gap -> small coupling!!!

QA vs. SA

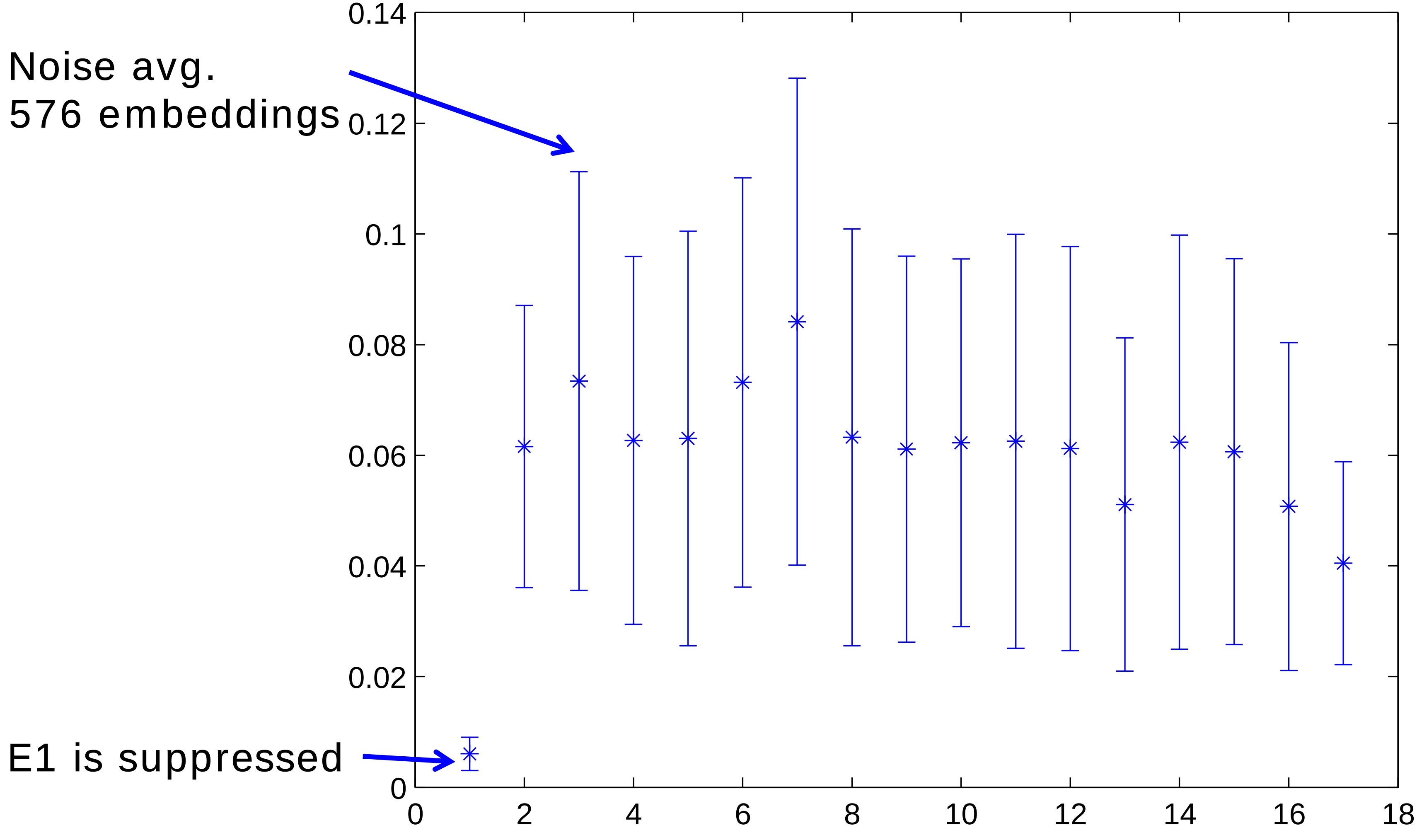
$$\pm 1 \pm 1 \pm 1 \pm 1 \quad 1 \quad 1 \quad 1 \quad 1$$





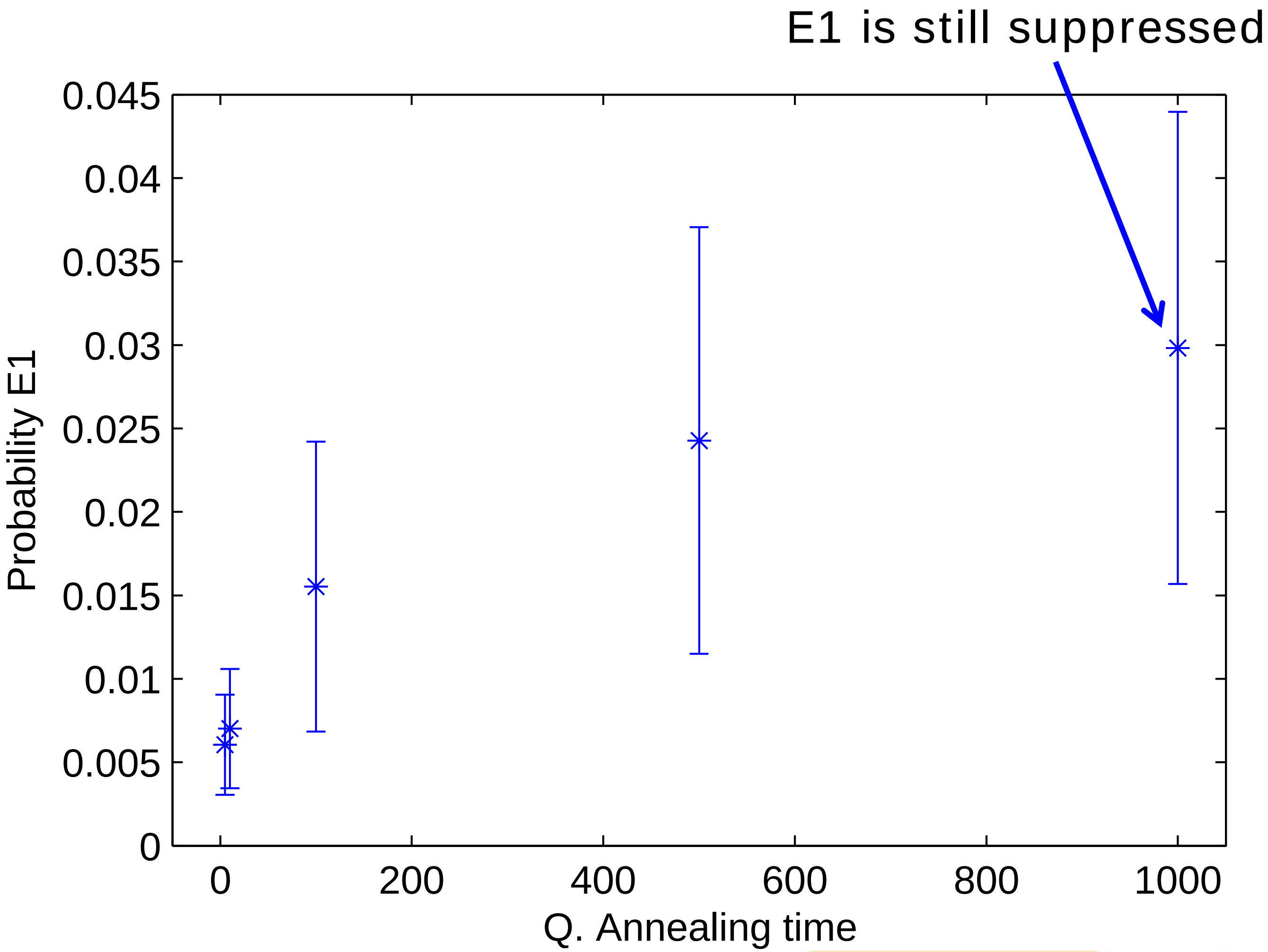
$$-1 -1 -1 -1 -1 -1 -1 -1$$

DW1 Experiments



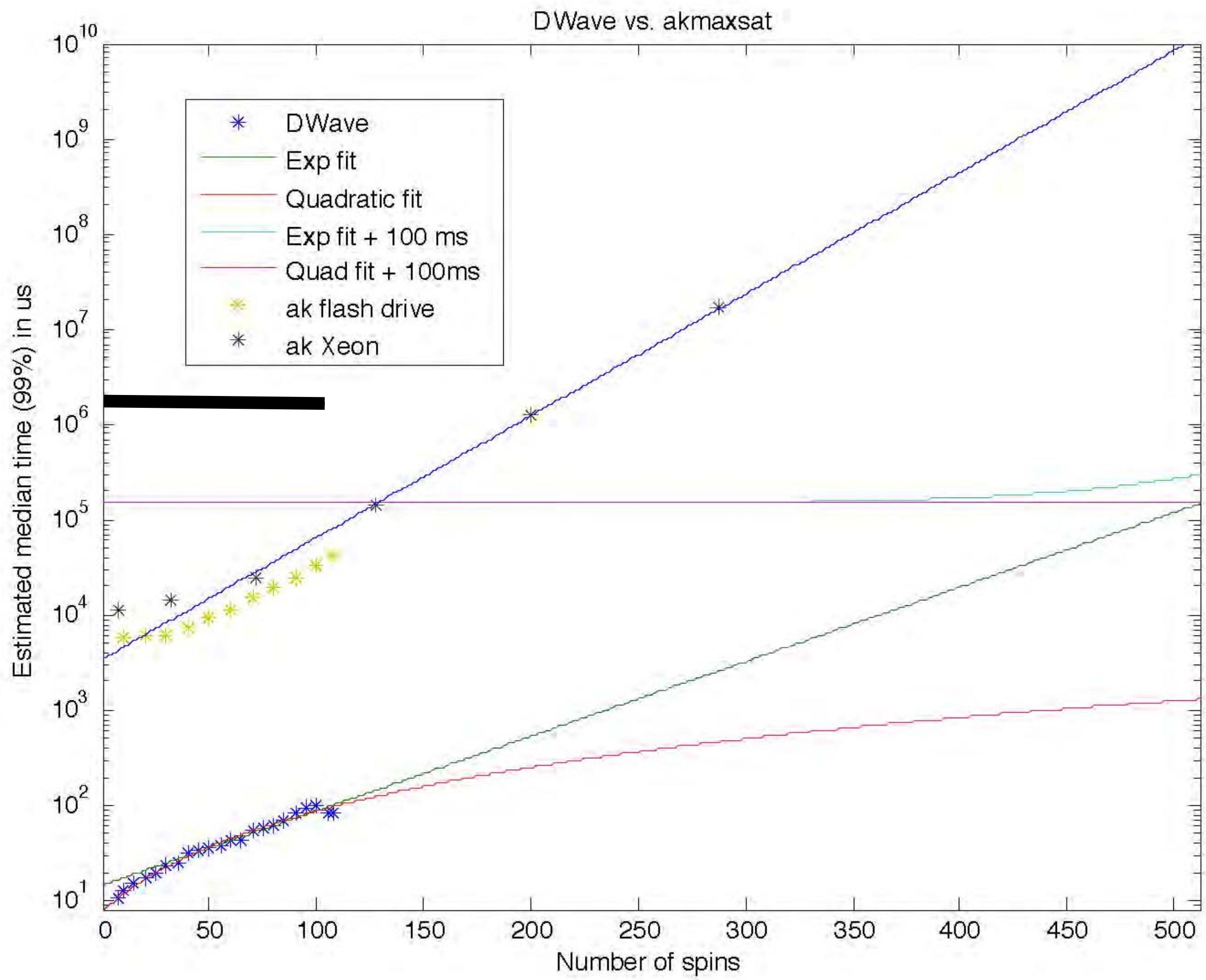
Less Suppression with Time

More time: more noise at small gap



A Few Open Questions

When Might it Out-Perform Classical Alternatives?



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How Should You Program It?

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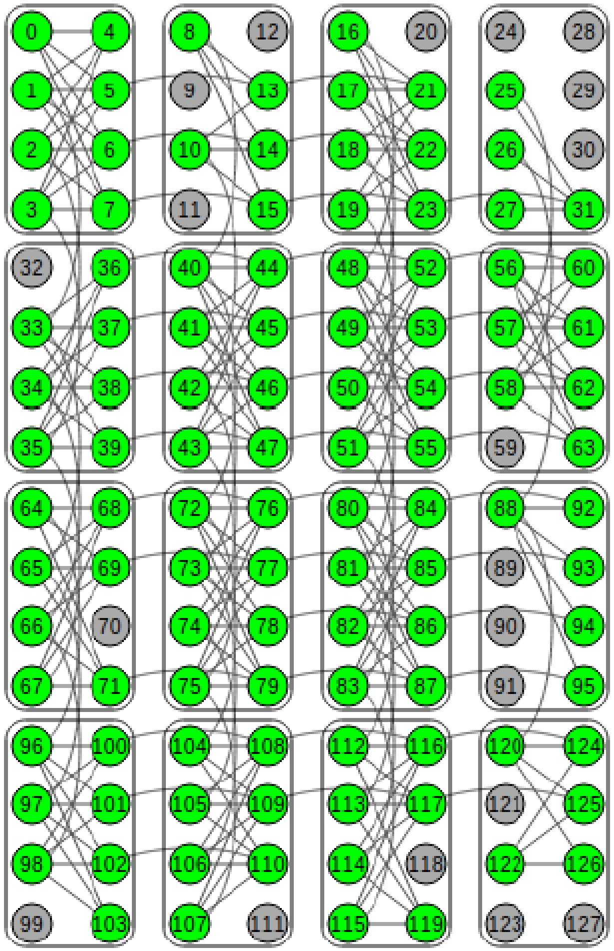
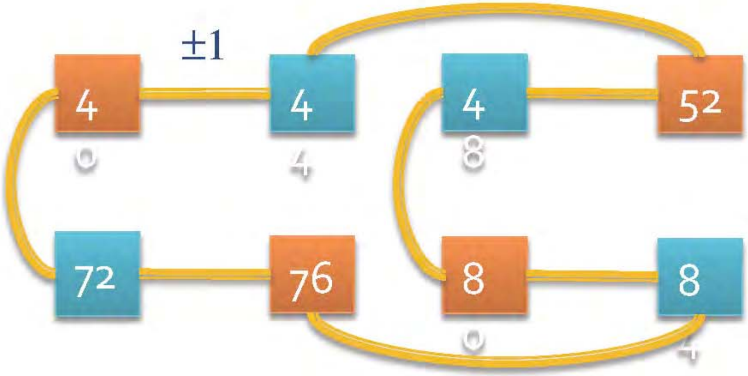
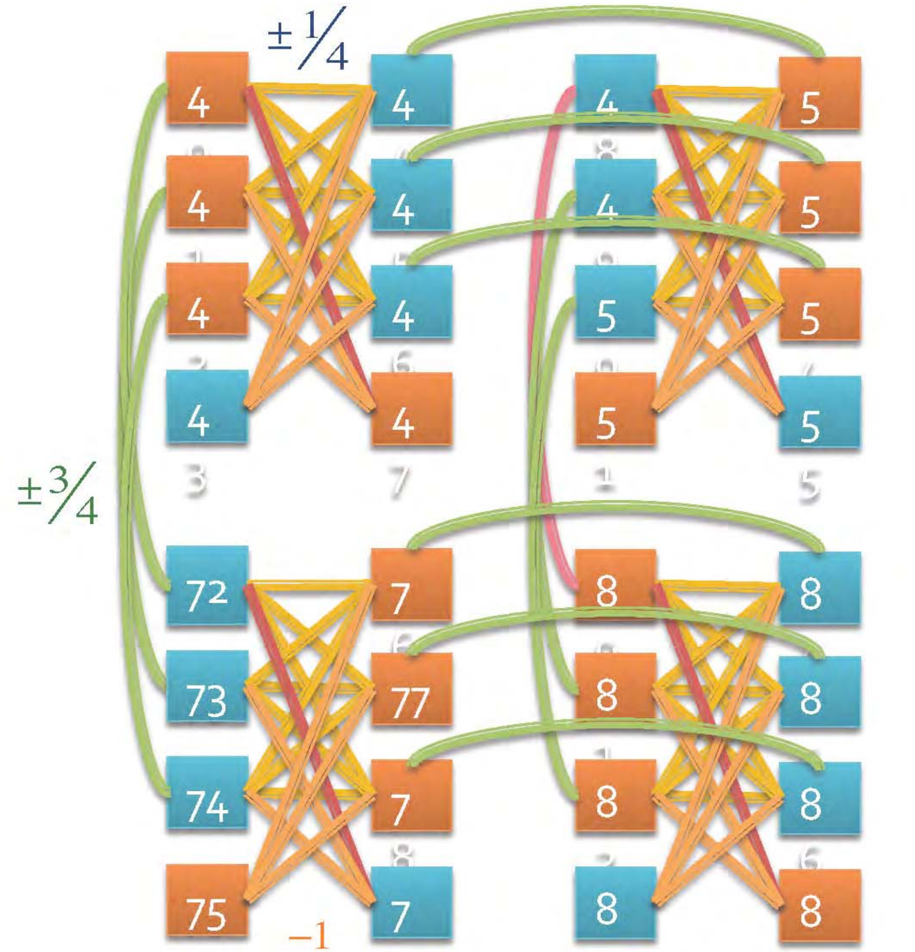
- **Enter your Hamiltonian**
  - Use a GUI and a mouse
  - Sparse matrix in Matlab
- **D-Wave Black Box tool kit**
  - Optimization abstraction
  - G. Rose, “This is not Fortran”
- **Will a general purpose language come along?**
- **Will we have domain specific abstractions?**



What About Error Correction?

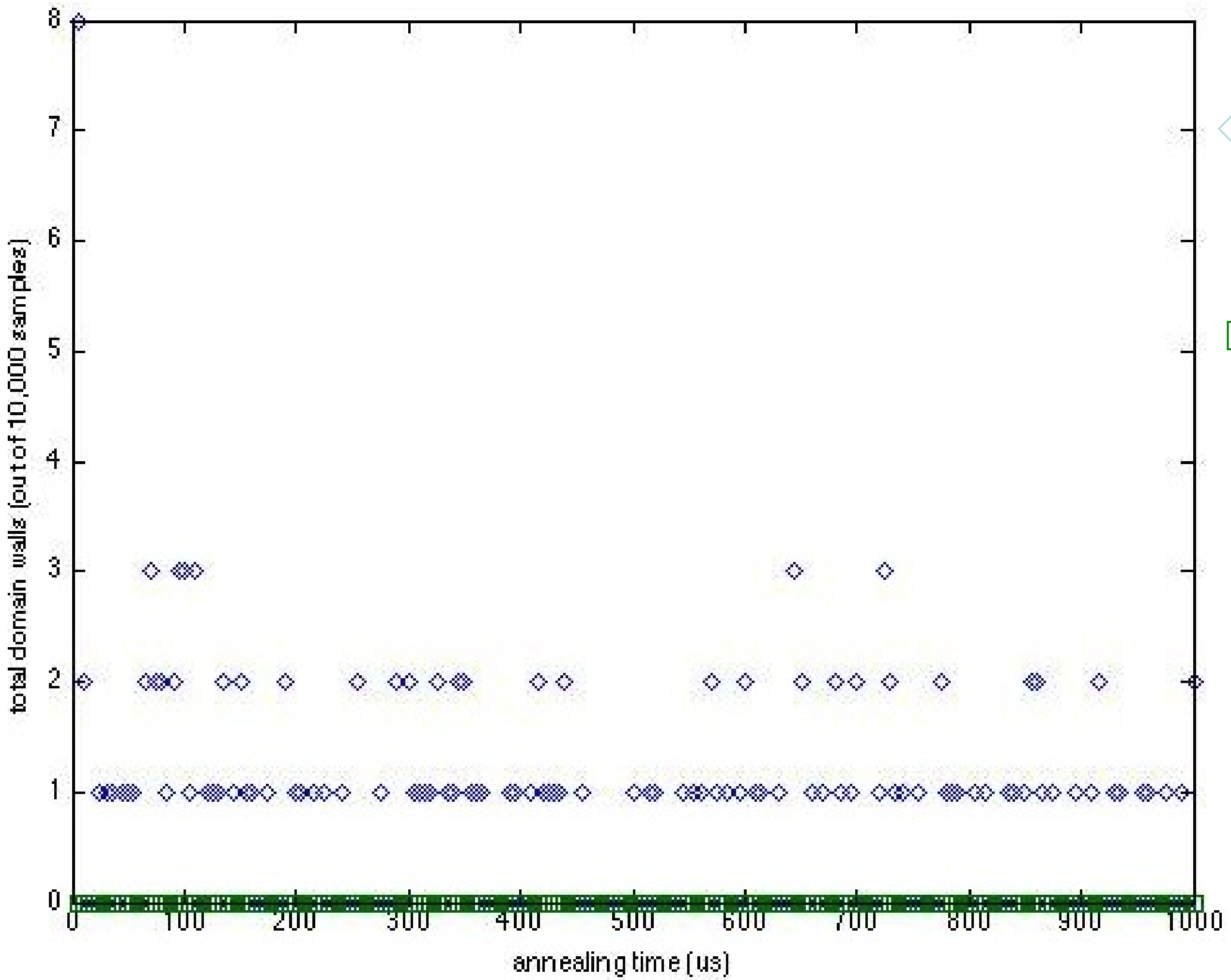


unencoded embedding



encoded embedding
bottom row ancilla qubits

Ferromagnetic chain experimental results



◇ unencoded

□ encoded

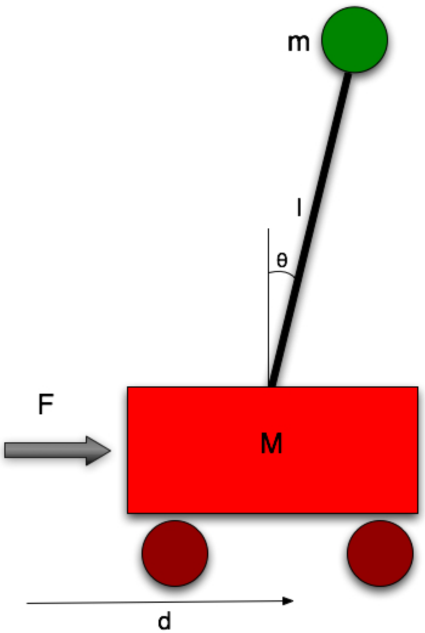
Application Research

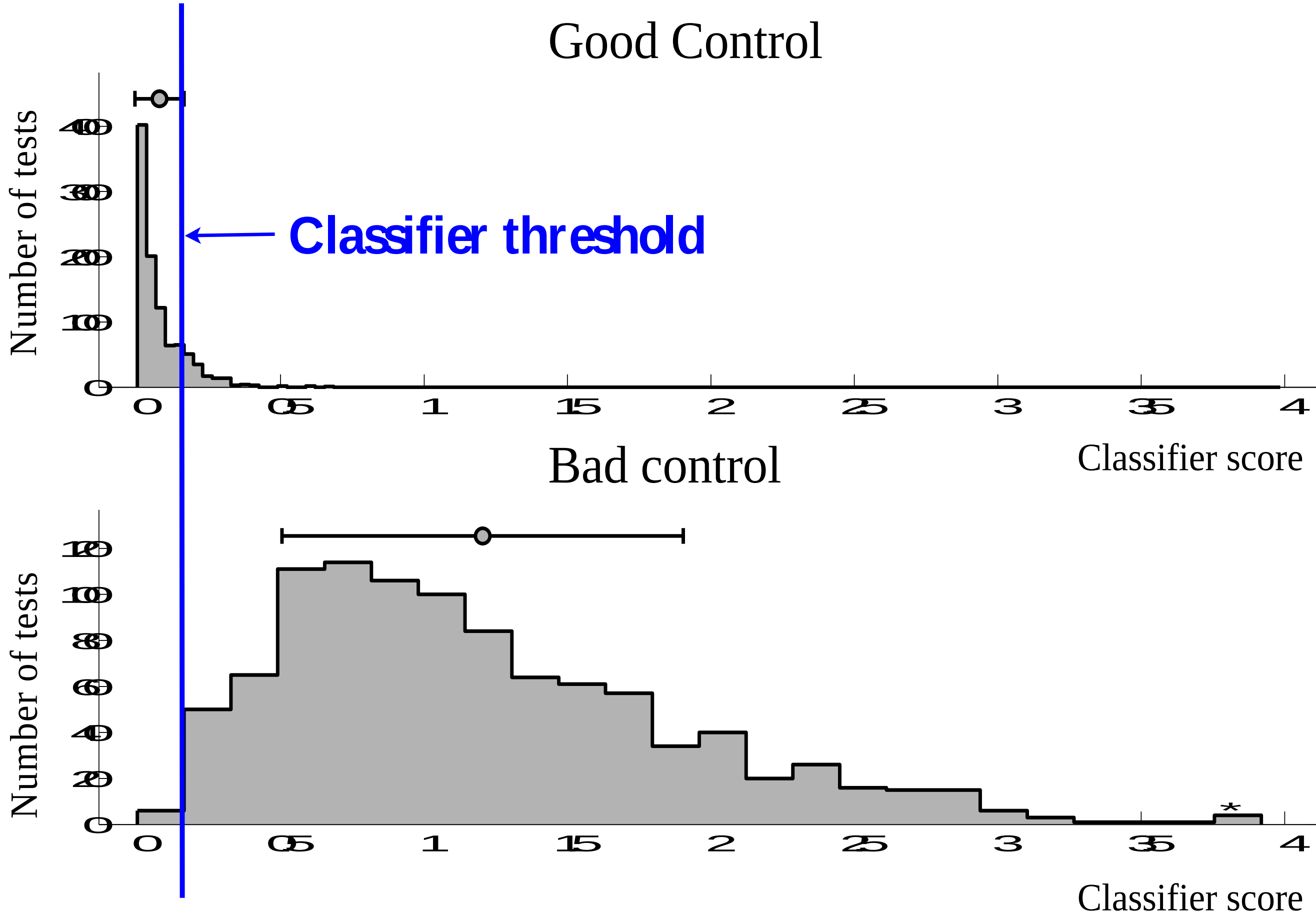
Some NP-Complete Problems and their Application

The problem addressed by quantum annealing is **NP-Complete**

Problem	Application
Traveling salesman	Logistics, vehicle routing
Minimum Steiner tree	Circuit layout, network design
Graph coloring	Scheduling, register allocation
MAX-CLIQUE	Social networks, bioinformatics
QUBO	Machine learning
Integer Linear Programming	Natural language processing
Sub-graph isomorphism	Cheminformatics, drug discovery
Job shop scheduling	Manufacturing
Motion planning	Robotics
MAX-2SAT	Artificial intelligence

Validation of Dynamical Control





- Error for good control: 4%
- Error for bad control: 3%

Work in progress.
Initial tests on DWave's processor.

Collaboration with Harvard

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Binary Classification For Organic Photovoltaics

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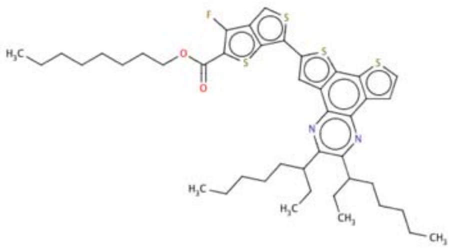
Dragon 6



MW	Amw	Me	Mp	Mi	nBP	…
0	**0**	**1**	**0**	**1**	**0**	**…**

< 0 0 1 0 1 0 … >

!

PCE ! 6.5

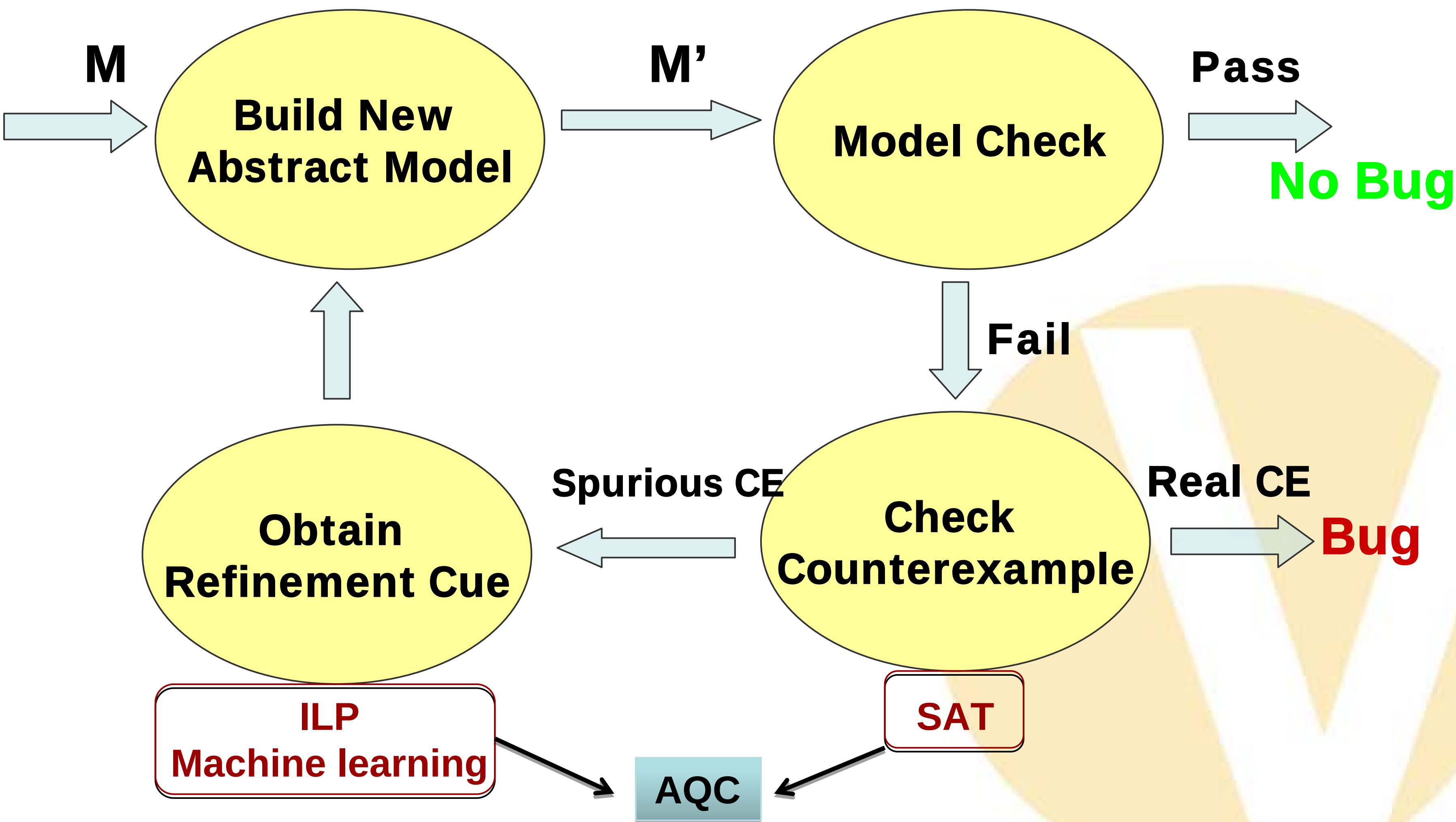
Rather than predicting numerical value for efficiency, predicts whether or not it will be over a certain threshold

Solution is a binary vector marking each descriptor as a “good predictor” or “bad predictor”

Reduces descriptor space at expense of complexity of output

Collaboration with Harvard

Counterexample-Guided Abstraction-Refinement for Model Checking



Others

Slides I couldn't pinch …

Low Density Parity Check (LDPC) Codes

Software Verification and Validation

- Machine Learning
- Collaboration with Lockheed Martin

Natural Language Processing

- Integer Linear Programming

Summary

Summary

After little over a decade, adiabatic quantum computing is moving from theory to practice.

The D-Wave architecture raises a variety of research questions:

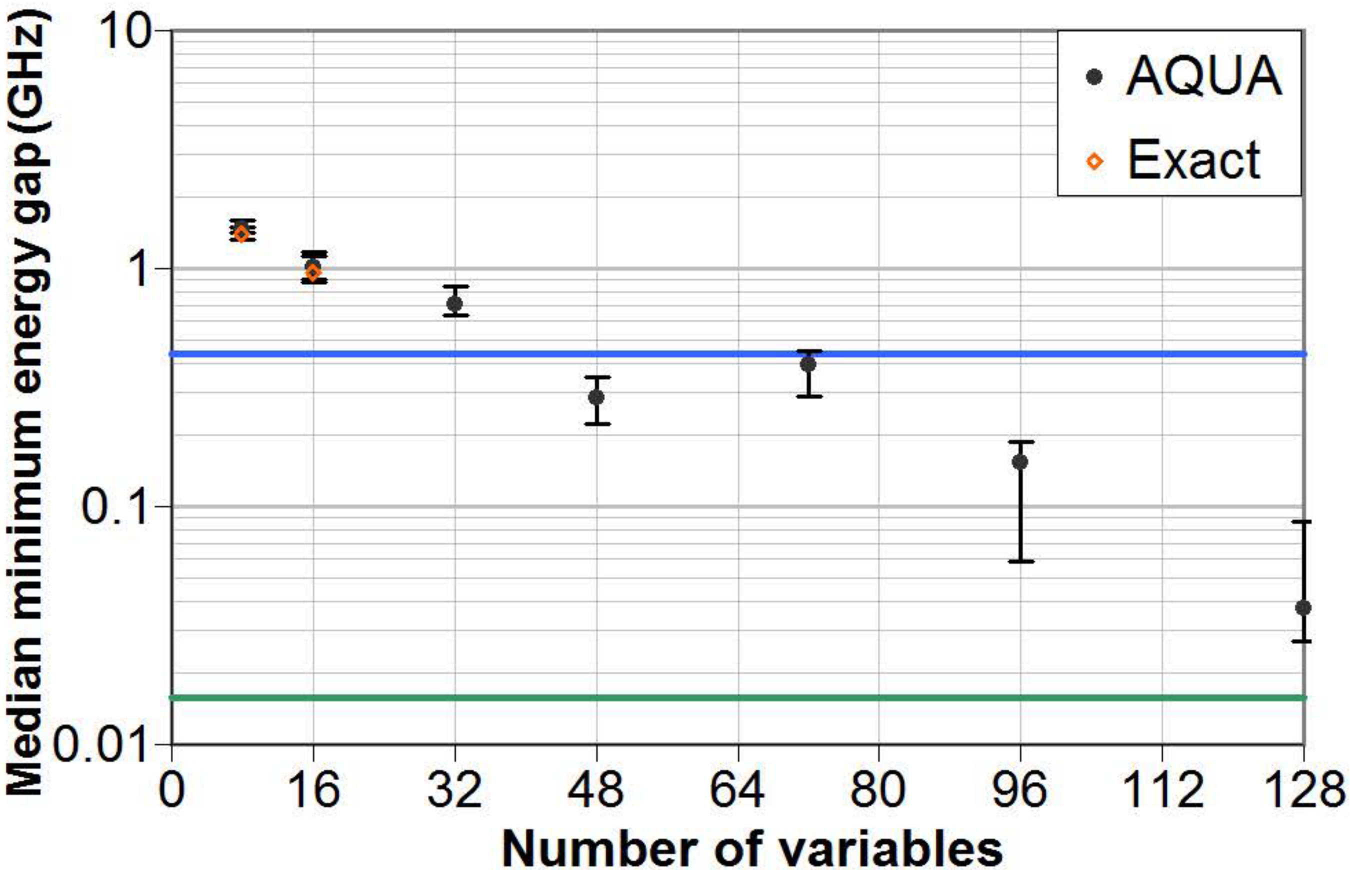
- Understanding the physics of what it does
- Developing programming abstractions
- Finding applications it can uniquely solve

USC and Lockheed Martin are jointly investigating all of the above

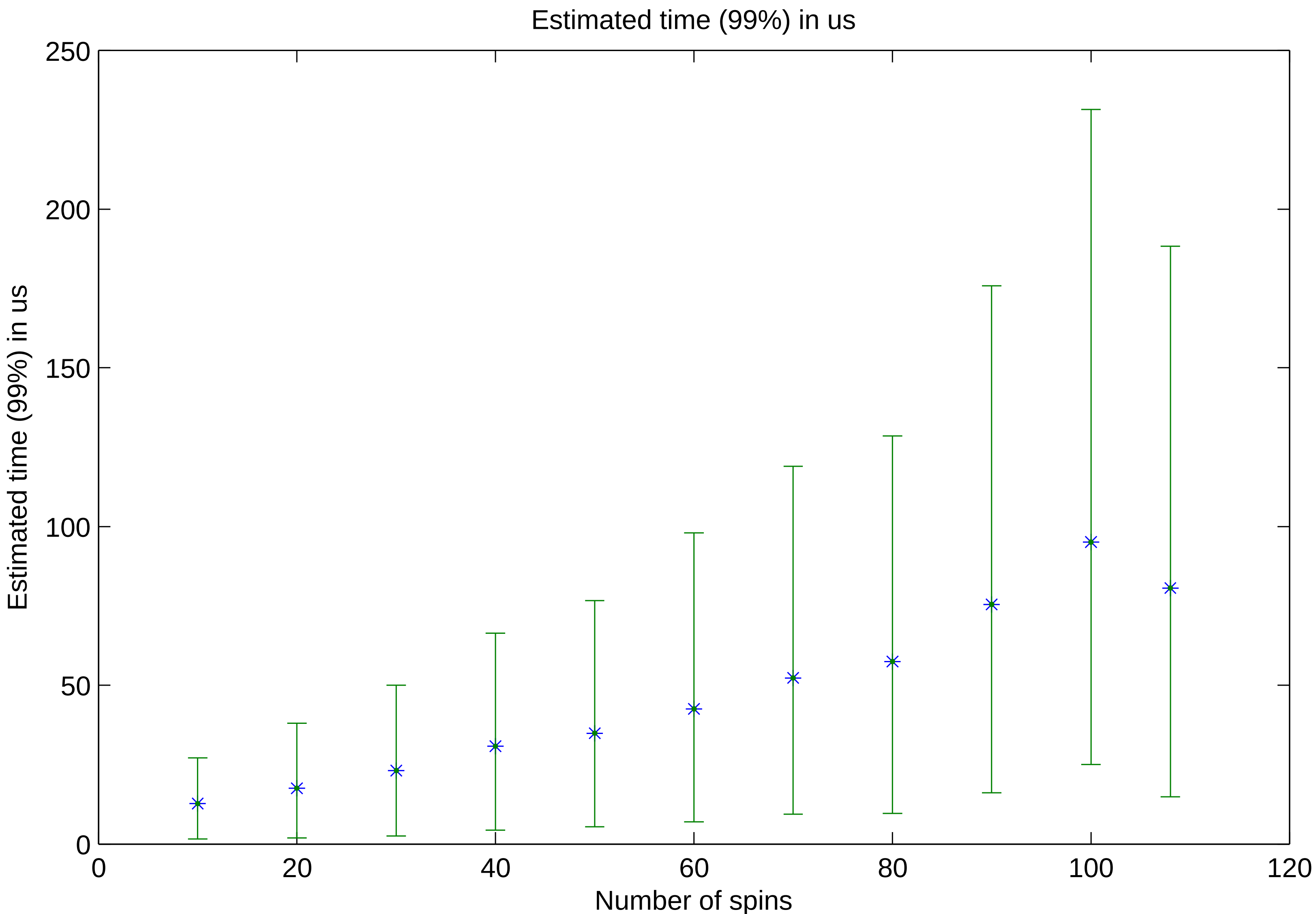
Questions?

Gaps of spin glasses

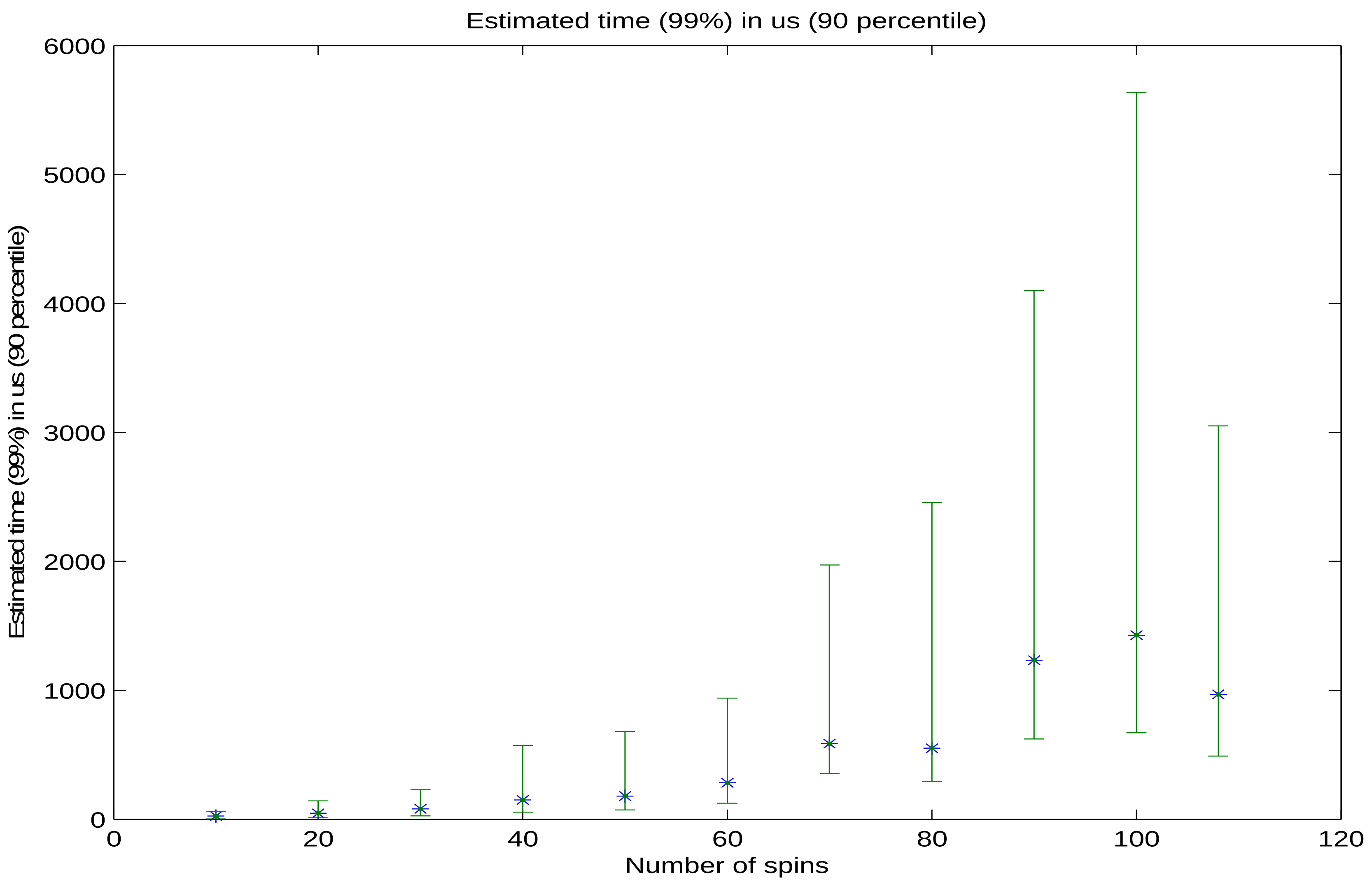
Karimi et al. 2010



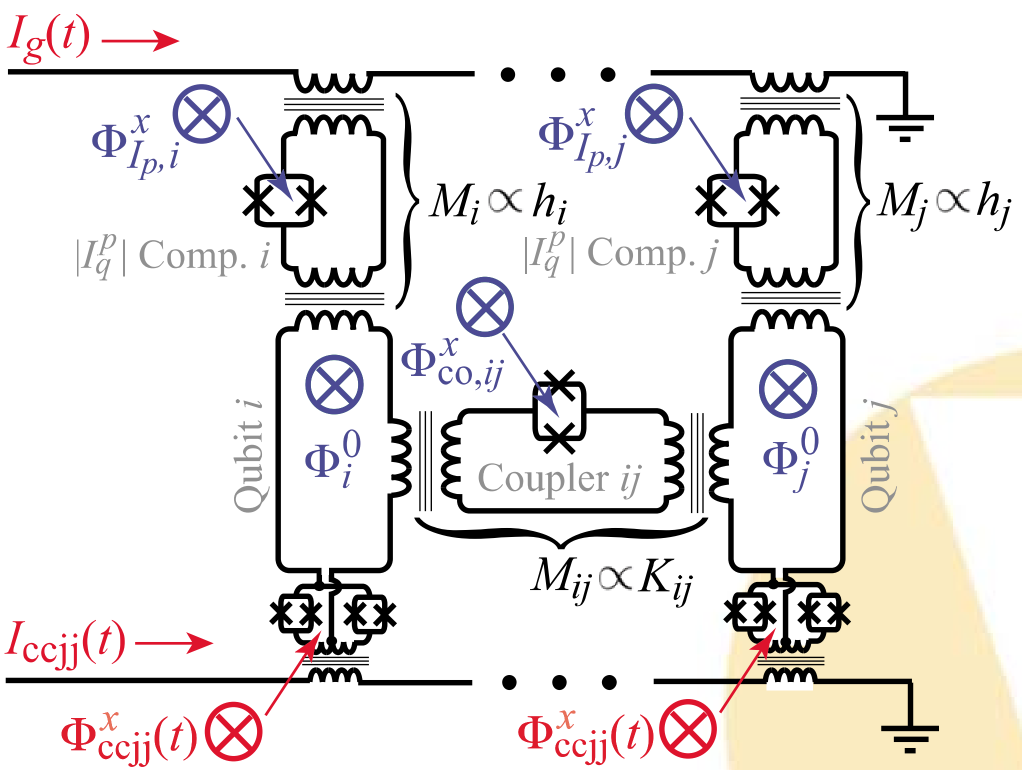
Spin Glasses
Median times vs. spins



Spin Glasses
90th percentile

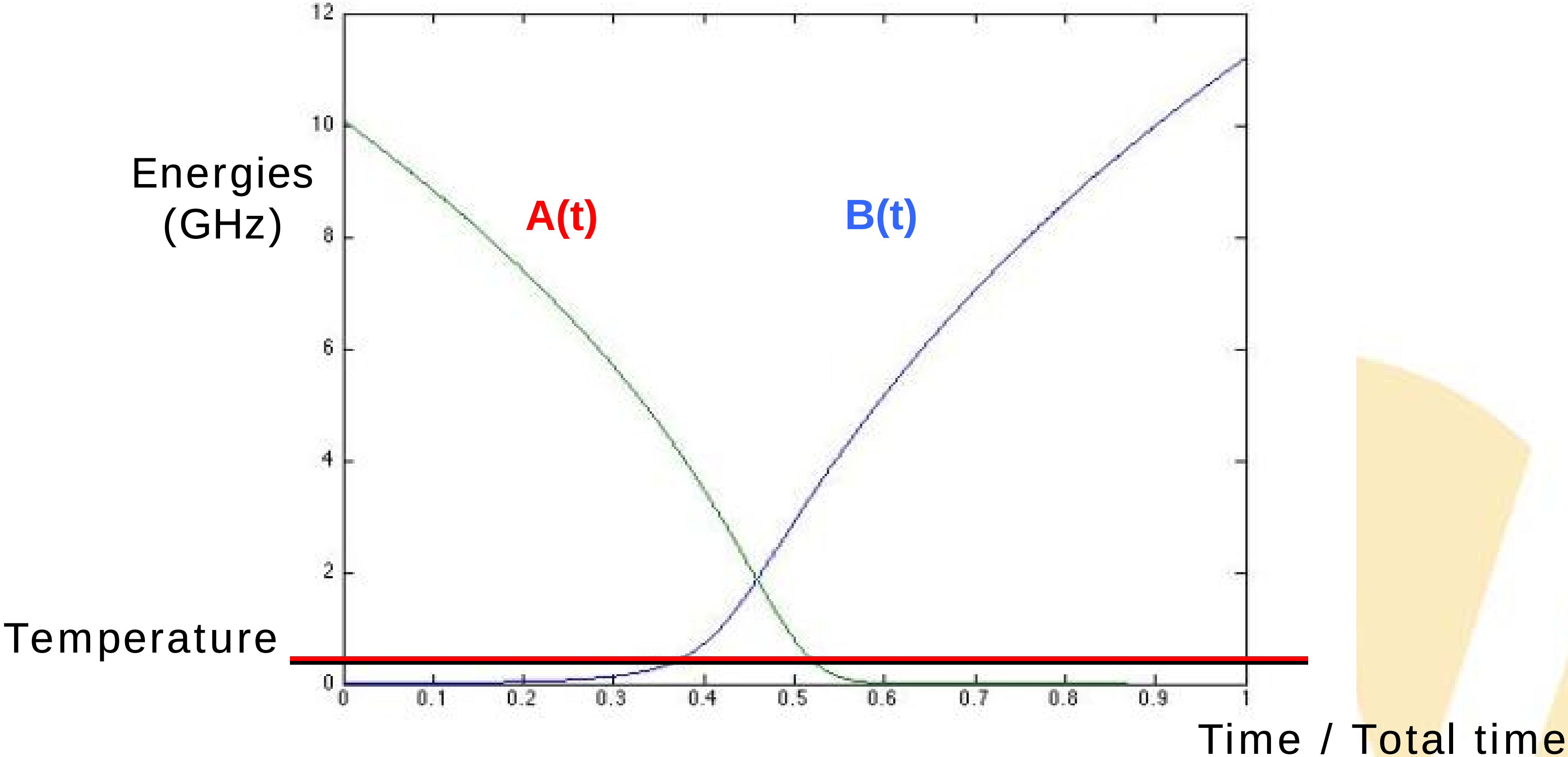


Coupled CJJ



R. Harris et. al.

Adiabatic Interpolation



$$H(t) = A(t)\sum_j \sigma_x + B(t)H_{\text{Ising}}$$

Whence the Power of Adiabatic QC?

Many optimization problems can be thought of as exploring an "energy landscape" in which the globally optimal solution corresponds to the deepest trough in this landscape

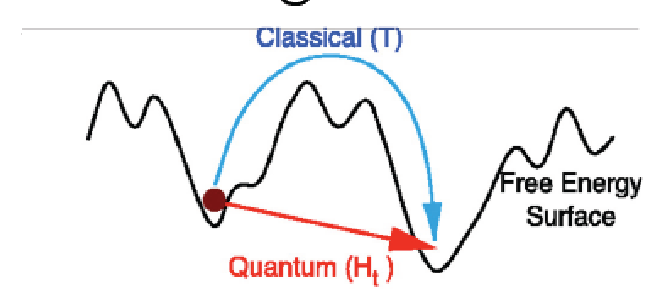
A classical, thermal annealing process is confined to move only ON this landscape; consequently, it can get stuck in local minima

A quantum annealing process (implemented in the DW-1) can tunnel THROUGH the peaks in this landscape and thereby evade entrapment in local minima & find deeper minima more quickly

Quantum adiabatic computation

as quantum annealing

Quantum adiabatic computation can tunnel between minima.



Classical Repetition Cost r

Let p_e = expt. prob. of finding GS; know $p_e > 0$ for sufficiently large t_f

Prob. of failing r consecutive times $= (1 - p_e)^r$

Prob. of succeeding at least once after r attempts $= 1 - (1 - p_e)^r$

Let p_d = desired success probability

Set $p_d = 1 - (1 - p_e)^r$

$$r = \frac{\log(1 - p_d)}{\log(1 - p_e)}$$