Many others including:

Ben Reichardt  
Edmyn 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

Transistors (Thousands)

Single-Thread Performance (SpecINT)

Frequency (MHz)

Typical Power (Watts)

Number of Cores

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

Massive Scaling - LANL/SNL Cray XE6

Exploit a New Phenomenon
Adiabatic Quantum Processor
D-Wave One

Application Specific Systems
D.E. Shaw Research Anton
Memo to IBM

The transistor: Nothing to worry about ...

R. Landauer
The memo was precisely right about the first transistor... but not the second transistor!

R. Landauer
D-Wave One
Adiabatic Quantum Optimization Device
Problem: find the ground state of

\[ H_{\text{Ising}} = \sum_j h_j \sigma^z_j + \sum_{(i,j) \in E} J_{ij} \sigma^z_i \sigma^z_j \]

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)

\[ H(t) = A(t) \sum_j \sigma^x_j + B(t) H_{\text{Ising}} \]

\[ t \in [0, t_f] \]

Program \( \{ h_i \}, \{ J_{ij} \} \)

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

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

Images courtesy D-Wave
Eight Qubit Unit Cell

Images courtesy D-Wave
Eight Qubit Unit Cell

Images courtesy D-Wave
A 128-qubit chip composed of a $4 \times 4$ array of eight-qubit unit cells.

Images courtesy D-Wave
## Component counts

| Unit cells | Qubits | Couplers | DACS | JJs   |
|------------|--------|----------|------|-------|
| 1          | 8      | 16       | 56   | 1500  |
| 4          | 32     | 72       | 232  | 6000  |
| 16         | 128    | 328      | 968  | 24000 |
| 64         | 512    | 1416     | 3976 | 96000 |
| 256        | 2048   | 5896     | 16136| 384000|

Rainier end of 2012

Vesuvius

Data courtesy D-Wave
D-Wave One Processor Graph

108 functional qubits in a “Chimera graph”

Image courtesy D-Wave
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 N² vertices (Choi 2010)
Estimated Median Time to 99% Success Probability for Random 2D Spin Glasses

Median estimated time (99%) in us

Number of spins

Estimated time (99%) in us
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?
Random 2D Ising
10 – 108 qubits, 5 us annealing

- 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

number of times success probability $p_i$ observed per $10^6$ experiments

success probability

interpolation time (μs)
Degenerate Ising Hamiltonian

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

\[ h_j = -1, \quad h_j = 1, \quad J_{jk} = -1 \]

17-fold degenerate ground space:

\[ \pm 1 \pm 1 \pm 1 \pm 1 \ 1 \ 1 \ 1 \ 1 \]
\[ -1 -1 -1 -1 -1 -1 -1 -1 -1 \]
Simulated Annealing
At Several Speeds

Probability vs. temperature for different speeds

E1 (spins downs) is always more probable
Energy spectrum with DW1 schedule

Gap 1.35 GHz
(Temp: 0.5 GHz)

Transitions to 4\textsuperscript{th} order in $\sigma^x$

Small gap $\rightarrow$ small coupling!!!
QA vs. SA

\[ \pm 1 \pm 1 \pm 1 \pm 1 \ 1 \ 1 \ 1 \ 1 \]

\[ -1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 - 1 \]

Probability vs. SA step with 2000 steps

E1
E241
Noise avg.
576 embeddings

E1 is suppressed
Less Suppression with Time

More time: more noise at small gap

E1 is still suppressed
A Few Open Questions
When Might it Out-Perform Classical Alternatives?
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
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                          |
Good control

Bad control

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

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

Collaboration with Harvard
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

M → Build New Abstract Model → M' → Model Check

M' → Obtain Refinement Cue → Check Counterexample

Model Check → Pass, No Bug

Fail

Spurious CE

Real CE, Bug

ILP Machine learning

SAT

AQC
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
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

The diagram shows the median minimum energy gap (GHz) as a function of the number of variables. The graph compares the AQUA and Exact methods, with error bars indicating the variability of the data.
Spin Glasses
Median times vs. spins

Estimated time (99%) in us

Number of spins vs. Estimated time (99%) in us
Spin Glasses
90th percentile

Estimated time (99%) in us (90 percentile)

Number of spins

Estimated time (99%) in us (90 percentile)
Coupled CJJ

\[ I_g(t) \]

\[ |I_g^p| \text{ Comp. } i \]

\[ M_i \propto h_i \]

\[ M_j \propto h_j \]

\[ \Phi_{I_p,i}^x \]

\[ \Phi_{I_p,j}^x \]

\[ \Phi_{cij}^x \]

\[ \Phi_{ccij}^x \]

\[ \Phi_{cij}^x \]

\[ \Phi_{ccij}^x \]

\[ \text{Qubit } i \]

\[ \text{Coupler } ij \]

\[ \text{Qubit } j \]

R. Harris et. al.
Adiabatic Interpolation

\[ H(t) = A(t) \sum_j \sigma_x + B(t)H_{\text{Ising}} \]
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.
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 $p_d = 1 - (1 - p_e)^r$

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