

A quantum annealing approach to the Minimum Multicut problem on general graphs

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1 Introduction

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- ◇ We discuss the limitations of the current family of quantum annealing processors.

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Section 4: Mapping of the Minimum multicut to QUBO

Section 5: Embedding into the hardware

Section 6: Hardware simulation

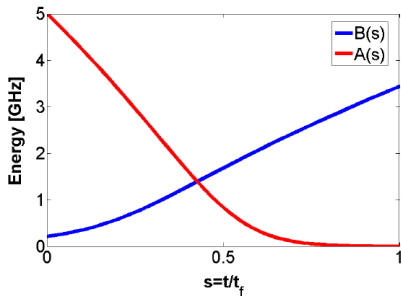
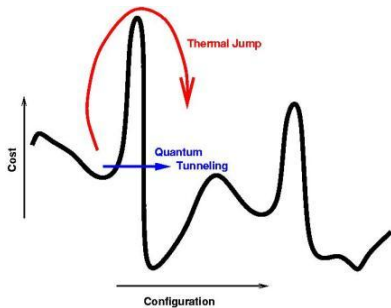
Section 7: Summary and conclusions

2 Quantum annealing

- QA annealing is used to traverse from the ground state of an initial Hamiltonian to the ground state of the final Hamiltonian. [Finnila et al., 1994] [Kodawaki-Nishimori, 1998] [Farhi et al., 2001]

$$H(\tau) = A(s)H_I + B(s)H_{\text{problem}},$$

$$H_{\text{problem}} = \sum_i^N h_i \sigma_i^z + \sum_{j>i}^N J_{ij} \sigma_i^z \sigma_j^z, \quad H_I = \sum_i \sigma_i^x$$



$$t_f = 20, \dots, 2000 \mu\text{s}$$

Adiabatic evolution

$$i \frac{d|\Psi(t)\rangle}{dt} = H(t)|\Psi(t)\rangle$$

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$$T \gg \frac{1}{\min_t \{\gamma(t)\}^2}, \quad \gamma = E_1(t) - E_0(t)$$

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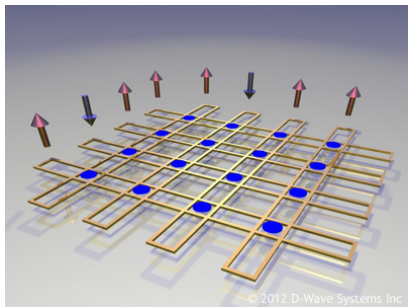
No crossing in the paths of the corresponding eigenvectors.

Linear interpolation between H_0 and H_1 : [Farhi et al., 2001]

$$H(s) = (1-s)H_0 + sH_1, \quad s = \frac{t}{T}.$$

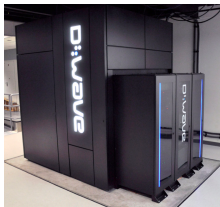
$$A(s) \sim (1-s), \quad B(s) \sim s$$

(Experimental) Quantum annealing

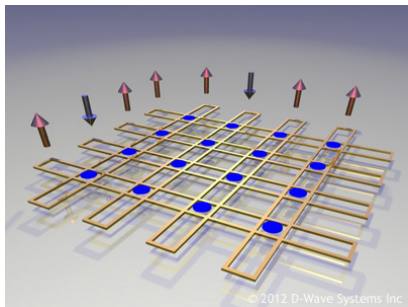


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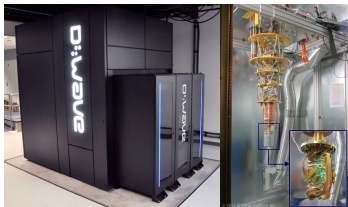


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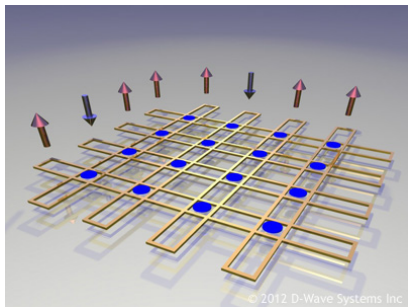


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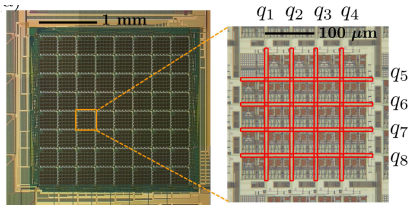
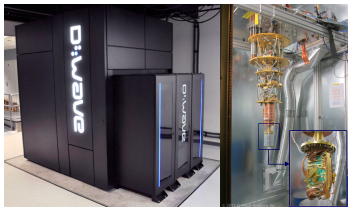


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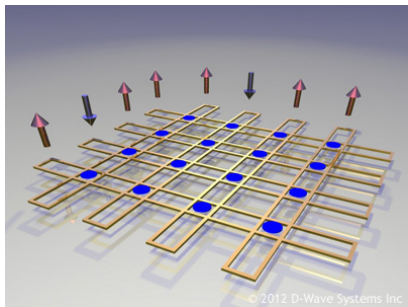


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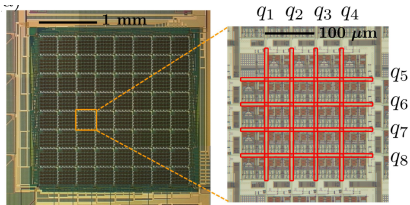
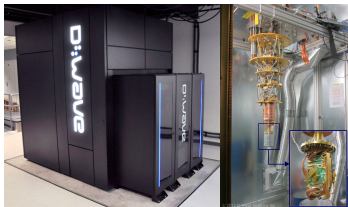


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[Lanting et al, 2014]

Adiabatic quantum optimization

- The ground state of H_p corresponds to a configuration $\mathbf{s} = (s_1, \dots, s_N) \in \{+1, -1\}^N$ of spins that minimize the following energy function

$$E(\mathbf{s}) = \sum_i^N h_i s_i + \sum_{j>i}^N J_{ij} s_i s_j.$$

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From classical objective function to quantum Hamiltonian

Find the optimal assignment

$$\mathbf{s}^* = (s_1^*, \dots, s_N^*)$$

$$E(\mathbf{s}) = \sum_i^N h_i s_i + \sum_{j>i}^N J_{ij} s_i s_j$$



Find the ground state

$$|\psi_g\rangle = |\mathbf{s}^*\rangle = |s_1^*, \dots, s_N^*\rangle$$

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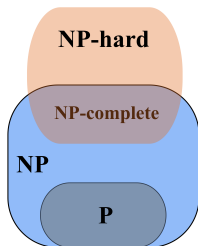
3 Combinatorial optimization

- NPO is the class of optimization problems, NP-hard are the most difficult problems in NPO

- Factor ϵ -approximation algorithms \mathcal{A} for problem Π ,

$$\forall x \in \Pi : \text{cost}_{\Pi}(x, \mathcal{A}(x)) \leq \epsilon \cdot \text{OPT}(x).$$

- $\text{APX} \subseteq \text{NPO}$ class of problems that can be approximated in polynomial time for some $\epsilon > 1$.



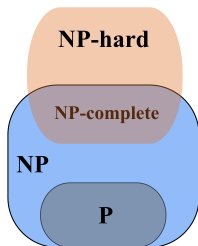
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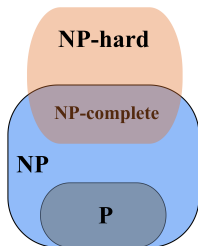
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The concept of inapproximated problems

Theorem [ALM, 1992]: There is a fixed $\epsilon > 0$ and a polynomial-time reduction τ from SAT to MAX-3SAT such that for every boolean formula I :

$$I \in \text{SAT} \Rightarrow \text{MAX-3SAT}(\tau(I)) = 1$$

$$I \notin \text{SAT} \Rightarrow \text{MAX-3SAT}(\tau(I)) < \frac{1}{1 + \epsilon}.$$

In other words, achieving an approximation ratio $1 + \epsilon$ for MAX-3SAT is NP-hard.

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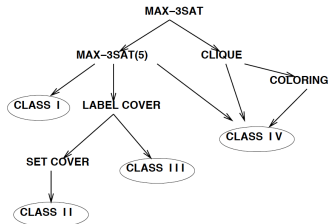
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Classification of inapproximated problems [Arora-Lund, 1996]

Class	Representative problem	Hard ratio	Best ratio
I	MAX-3SAT MULTIWAY CUTS	$1 + \epsilon$	1.2987 [AHO ⁺ 97] $3/2 - 1/ S $ [CKR98]
II	MINIMUM SETCOVER	$O(\log n)$	$1 + \ln n $ [J97]
III	NEAREST LATTICE VECTOR	$2^{n \log^{1-\gamma}}$	Not in APX [ABS ⁺ 97]
IV	MAXIMUM CLIQUE	n^ϵ	$O\left(\frac{n}{(\log n)^2}\right)$ [BH92]

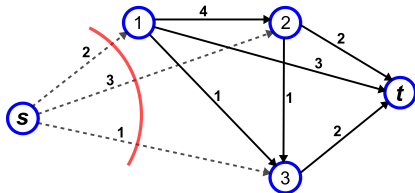


4 Mapping of the Minimum multicut to QUBO

Minimum multicut: Given a weighted graph $G = (V, E, w)$ and a set of pairs $H = \{(s_1, t_1), \dots, (s_k, t_k)\} \subset V \times V$, find a multi-cut with minimum capacity, i.e., a subset $E' \subseteq E$ such that the removal of E' from E disconnects s_i from t_i for every pair (s_i, t_i) , where the capacity of E' is given as $\sum_{e \in E'} w(e)$.

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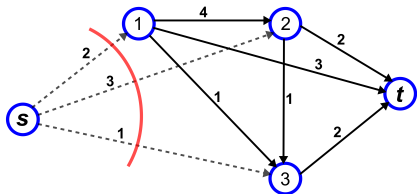
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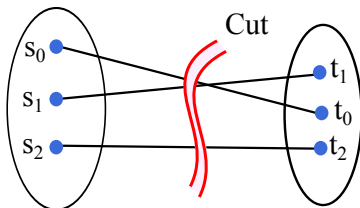
Min s - t cut

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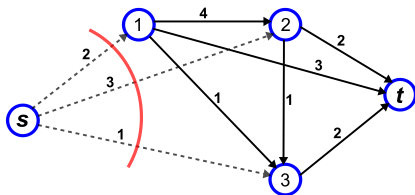
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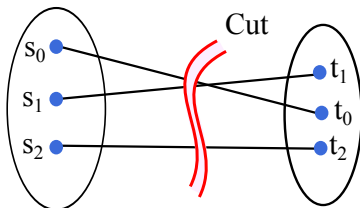
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Min s-t cut



3-multicut

- For $k = 1, 2$, it is solvable in polynomial time. [Bollobas, 79] [Seymour, 79]
- For $k \geq 3$, Minimum Multi-Cut becomes APX-hard. [Dahlhaus, 94]
- It is NP-hard even if restricted to trees of height 1. [Garg et al., 97]

QUBO formulation of Minimum multicut in trees

For each edge $e \in G$, $x_e = 1$ (in the cut), 0 (not in the cut)

$$h_G = h_{\text{weight}} + h_{\text{penalty}}$$

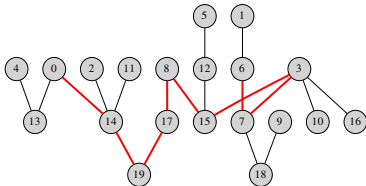
$$1. h_{\text{weight}} = \sum_{e \in G} w(e)(1 - x_e)$$

$$2. h_{\text{penalty}} = \lambda_{\text{path}} \sum_{i=1}^k \prod_{e \in p_i} x_e$$

p_i is the path from s_i to t_i ,

$$\lambda_{\text{path}} = \sum_{e \in p_i} w(e)$$

$$3. \text{deg}(h_{\text{penalty}}) = \max_i \{\text{length}(p_i)\}$$



There exists a unique path between every pair of vertices in a tree.

Reduction methods

$$f(x) = \sum_{S \subseteq [1, n]} a_S \prod_{j \in S} x_j$$

$\Downarrow \tau_r$

$$f(x) = \min_{w \in \{0, 1\}^m} g(x, w)$$

$$\deg\{g(x, w)\} \leq 2$$

w "ancilla variables"

τ_r "polynomial reduction"

- (a) Negative terms can be reduced using only one extra ancilla variable

[Freedman-Drineas, 2005]

$$-x_1 x_2 \cdots x_d = \min_{w \in \{0, 1\}} w \left((d-1) - \sum_{j=1}^d x_j \right)$$

- (b) For positive terms, only $\left\lfloor \frac{d-1}{2} \right\rfloor$ new ancilla variables are added.

$$\prod_{j=1}^d x_j = S_2 + \min_{w \in \{0, 1\}^k} B - 2AS_1$$

if $d=2k+2$,

$$\prod_{j=1}^d x_j = S_2 + \min_{w \in \{0, 1\}^k} B - 2AS_1 + w_k(S_1 - d + 1)$$

if $d=2k+1$.

See [Ishikawa, 2011].

- (c) In the penalty approach, for each occurrence of xy , a new term is added.

[Boros-Hammer, 2002]

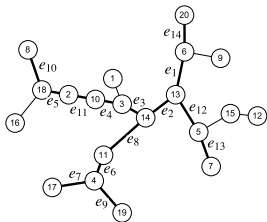
$$M(xy - 2xw - 2yw + 3w)$$

Upper bound: $M = 1 + 2 \sum_{S \subseteq [1, n]} a_S$

Ancilla variables: $O(n^2 \log \deg(f))$

Bad news: large coefficients

Example of reduction (2)



$$H = \{(6, 10), (2, 18), (11, 17), (14, 19), (8, 13), (10, 11), (3, 5), (13, 17), (7, 14), (6, 20)\}$$

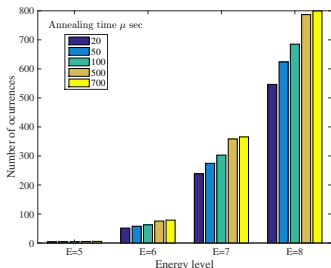
$$h_G = 14 - x_1 - x_2 - x_3 - x_4 + 9x_5 - x_6 - x_7 - x_8 - x_9 - x_{10} - x_{11} - x_{12} - x_{13} + 9x_{14} + 10x_1x_2x_3x_4 + 10x_6x_7 + 10x_6x_8x_9 + 10x_2x_3x_4x_5x_{10}x_{11} + 10x_3x_4x_8 + 10x_2x_3x_{12} + 10x_2x_6x_7x_8 + 10x_2x_{12}x_{13}$$



h_G^{qubo} : 22 logical variables, 51 physical qubits

Scalability of embedding

n	k	logical variables	
		H	H_{qubo}
20	3	10	17
30	5	14	23
45	6	22	37
100	30	75	199
100	130	97	402
100	200	99	559



Setup: $N_r = 100000$ readouts over 100 gauges.

QUBO formulation of Minimum multicut on general graphs

Given a graph $G = (V, E)$ and a set of pairs $H = \{(s_1, t_1), \dots, (s_k, t_k)\}$. The Minimum multicut problem can be logically formulated as follows:

$$\min_{C \subseteq E} |C|. \quad \bigwedge_{(s_i, t_i) \in H} \neg \text{connected}(s_i, t_i, C)$$

where

$$\text{connected}(s_i, t_i, C) \equiv \forall U \subseteq V. \varphi(s_i, t_i, C)$$

and

$$\begin{aligned} \varphi(s_i, t_i, C) \quad \equiv \quad & ((s_i \in U \wedge t_i \notin U) \rightarrow \\ & \exists x \in U. \exists y \notin U. \exists e \in E. \text{inc}(x, e) \wedge \text{inc}(y, e) \wedge e \notin C). \end{aligned}$$

To verify if a given subset $C \subseteq E$ is a cut in G that disconnect every pair (s_i, t_i) , then it is sufficient to find a subset $U \subseteq V$ such that $\neg \text{connected}(s_i, t_i, C)$ is true.

Mapping: Logical variables y_{uw} and x_v^i

- For each $\{u, w\} \in E$, $y_{uw} = 1$ (0) if $\{u, w\}$ is (not) selected for a cut.
- For each $v \in V$ and $i = 1, \dots, k$, $x_v^i = 1$ (0) if v is (not) in U where U is a subset of V .

Construction: Let f_G be defined as

$$f_G = \text{card}(y_{uw}) + \alpha \cdot \text{penalty}(x_v, y_{uw}, H)$$

where

$$\text{card}(y_{uw}) = \sum_{\{u,w\} \in E} y_{uw} \quad \text{and}$$

$$\begin{aligned} \text{penalty} &= \sum_{i=1}^k (\neg(x_{s_i}^i \oplus x_{t_i}^i)) + \sum_{\{u,w\} \in E} (x_u^i \oplus x_w^i) \oplus y_{uw} \\ &= \sum_{i=1}^k (1 - x_{s_i}^i - x_{t_i}^i + 2x_{s_i}^i x_{t_i}^i + \\ &\quad \sum_{\{u,w\} \in E} (x_u^i + x_w^i + y_{uw} - 2x_u^i x_w^i - 2x_u^i y_{uw} - \\ &\quad 2x_w^i y_{uw} + 4x_u^i x_w^i y_{uw})) \end{aligned}$$

Using the Ishikawa method we obtain

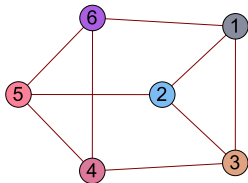
$$\begin{aligned}
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 &\quad \sum_{\{u,w\} \in E} (x_u^i + x_w^i + y_{uw} - 2x_u^i x_w^i - 2x_u^i y_{uw} - \\
 &\quad 2x_w^i y_{uw} + 4(x_u^i x_w^i + x_u^i y_{uw} + x_w^i y_{uw} + \\
 &\quad z_{uw}^i (1 - x_u^i - x_w^i - y_{uw}))) \\
 &= \sum_{i=1}^k (1 - x_{s_i}^i - x_{t_i}^i + 2x_{s_i}^i x_{t_i}^i + \\
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 &\quad 4z_{uw}^i (1 - x_u^i - x_w^i - y_{uw})))
 \end{aligned}$$

where z_{uw}^i are ancilla variables.

f_G uses $k(n + m) + m$ variables.

α is upper bounded by $\text{card}(y_{uw})$

Example of construction

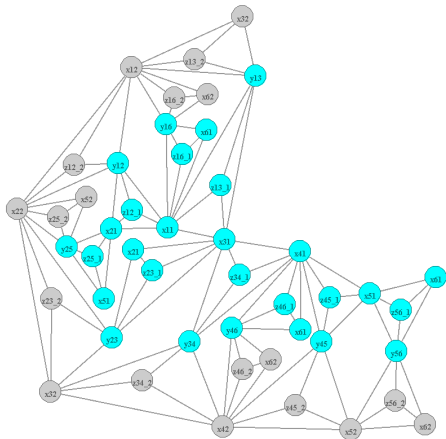


Boolean variables to represent the given problem:

$$x_1^1, x_2^1, x_3^1, x_4^1, x_5^1, x_6^1, x_1^2, x_2^2, x_3^2, \\ x_4^2, x_5^2, x_6^2, y_{12}, y_{13}, y_{16}, y_{23}, y_{25}, \\ y_{34}, y_{45}, y_{46}, y_{56}$$

Ancilla variables

$$z_{12}^1, z_{13}^1, z_{16}^1, z_{23}^1, z_{25}^1, z_{34}^1, z_{45}^1, z_{46}^1, z_{56}^1 \\ z_{12}^2, z_{13}^2, z_{16}^2, z_{23}^2, z_{25}^2, z_{34}^2, z_{45}^2, z_{46}^2, z_{56}^2$$



Logical graph of f_G^{qubo}

5 Summary and conclusions

- ◇ The programming model is problem dependent.
- ◇ Can we avoid the reduction of pseudo-Boolean functions into QUBO?
- ◇ The minimum embedding is not always the best choice.
- ◇ Approximate solutions are also useful.
- ◇ To investigate programming inapproximated problems.

Thanks for your kind attention!

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