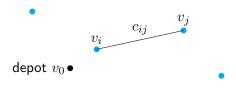
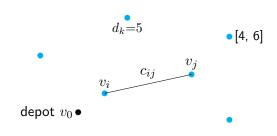
# Seminar: Advanced Topics in Quantum Computing

On efficient encodings for QAOA solutions to vehicle routing problems

Eben Jowie Haezer

November 29, 2023









https://www.freepik.com/free-photos-vectors/airport-night/4 https://pictures.reuters.com/

3

#### Adiabatic computation

A physical system remains in its instantaneous eigenstate if a given perturbation is acting on it slowly enough and if there is a gap between the eigenvalue and the rest of the Hamiltonian's spectrum. [1]

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$$H(t) = \left(1 - \frac{t}{T}\right) \cdot H_0 + \frac{t}{T} \cdot H_p$$

## Adiabatic approximation

$$e^{A+B} = \lim_{n \to \infty} \left( e^{\frac{A}{n}} \cdot e^{\frac{B}{n}} \right)^n$$

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$$\forall A, B \in \mathbb{C}^{m \times m}. \ e^{A+B} = \lim_{n \to \infty} \left( e^{\frac{A}{n}} \cdot e^{\frac{B}{n}} \right)^n$$

$$([A, B] = 0 \implies e^{A+B} = e^A e^B)$$

## Adiabatic approximation

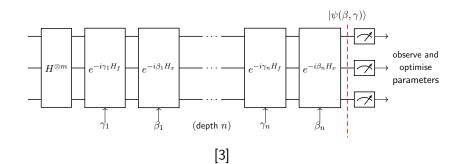
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$$\left( [A,B] = 0 \implies e^{A+B} = e^A e^B \right)$$

$$|\psi(\beta,\gamma)\rangle = \prod_{k} e^{-i\beta_i H_x} e^{-i\gamma_i H_f} |+\rangle^{\otimes m}$$

#### **QAOA**

$$|\psi(\beta,\gamma)\rangle = \prod_k e^{-i\beta_i H_x} e^{-i\gamma_i H_f} |+\rangle^{\otimes m}$$



QUBO

## QUBO quadratic unconstrained binary optimisation

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$$|x^*\rangle = \underset{|x\rangle \in \{0,1\}^n}{\operatorname{argmin}} \langle x|Q|x\rangle$$

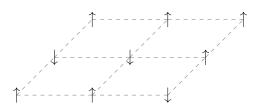
## QUBO quadratic unconstrained binary optimisation

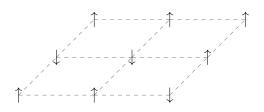
$$|x^*\rangle = \underset{|x\rangle \in \{0,1\}^n}{\operatorname{argmin}} \langle x|Q|x\rangle$$

where  $Q \in \mathbb{R}^{n \times n}$ .

$$f_Q(x) = \langle x|Q|x\rangle = \sum_{i=1}^n \sum_{j=i}^n Q_{ij}x_ix_j$$

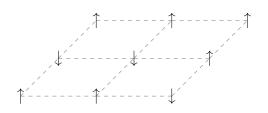
Problem	QUBO formulation		
Number Partitioning (NP)	Glover et al.2		
Maximum Cut (MC)	Glover et al.2		
Minimum Vertex Cover (MVC)	Glover et al.:		
Set Packing (SP)	Glover et al.:		
Set Partitioning (SPP)	Glover et al.2		
faxinum 2-SAT (M2SAT)	Glover et al.:	k-densest Common Sub-Graph Isomorphism	Huang et al.32
Daximum 3-SAT (M3SAT)	Dinner et al s	Community Detection	Negre et al.33
iranh Coloring (GC)	Glover et al.	Nurse Scheduling problem	Ikeda et al.34
Seneral 0/1 Programming (G01P)	Glover et al.	Aircraft Loading Optimization	Pilon et al.15
undratic Assignment (OA)	Glover et al.:	PageRank	Garnerone et al.16
usdratic Assignment (QA)	Glover et al.:	Ransey numbers	Gaitan et al. 27
	Lucasi	Generalized Ramsey numbers	Ranjbar et al. H
Graph Partitioning Decisional Clique Problem	Lucas	Transaction Settlement	Braine et al. 29
		Sensor placement problem in water distribution	on Speziali et al. o
Maximum Clique Problem	Chapuis:9	networks	
Sinary Integer Linear Programming	Lucasi	Fault Detection and Diagnosis of Graph-Based Systems	Perdomo-Ortiz et al.41
Exact Cover	Lucast	Bounded-Depth Steiner Trees	Liu et al.42
ISAT	Lucas	Graph Matching with Permutation Matrix Constraints	Benkner et al.43
Maximal Independent Set	Djidjev et al.:	Gaussian Process Variance Reduction	Bottarelli et al.44
Minimal Maximal Matching	Lucasi	Quantum Permutation Synchronization	Birdal et al.«
Set Cover	Lucast	Unit Commitment Problem	Ajagekar et al.«
Cnapsack with Integer Weights	Lucast	Heat Exchanger Network Synthesis	Ajagekar et al.«
lique Cover	Lucas7	Garden Optimization Problem	Calaza et al. 0
Tob Sequencing Problem	Lucas	Two-Dimensional Cutting Stock Problem	Arai et al. «
Hamiltonian Cycles Problem	Lucas	Labelled Maximum Weighted Common Subgraph	Hernandez et al.«
tinimal Spanning Tree	Lucas	Maximum Weighted Co-k-plex	Hernandez et al.«
Steiner Trees	Lucas	Molecular Similarity based on Graphs	Hernandez et al. (*)
Directed Feedback Vertex Set	Lucasi		Palmer et al Phillipson
Indirected Feedback Vertex Set	Lucas	Portfolio Optimization (Modern Portfolio Theory)	al. 11
eedback Edge Set	Lucas	Weighted Maximum Cut	Pelofske et al.53
Traveling Salesman (TSP)	Lucas	Weighted Maximum Clique	Pelofske et al 33
	Papalitsas et al., Salehi et	Satellite Scheduling	Stollenwerk et al.54
Traveling Salesman with Time Windows (TSPTW)	al er	Refinery Scheduling	Ossorio-Castillo et al. 55
Frach Isomorphism	Calude et al.4	Job Shop Scheduling	Yenturelli et al.
yraph Isomorphism Subgraph Isomorphism	Calude et al.4	Extended Job Shop Scheduling with Autonomous Grou	
Subgraph Isomorphism Induced Subgraph	Calude et al.	Yehicles	deitz et al.73
		Parallel Flexible Job Shop Scheduling	Denkena et al.57
Capacitated Vehicle Routing (CVRP)	Irie et al.5, Feld et al.5 Harikrishnakumar et al.6	Bin Packing with Integer Weights	Lodewijks: (alternative: ref)
tulti-Depot Capacitated Vehicle Routing (MDCVRP)		Number Partitioning with m sets	Lodevi iksti
1 norm	Yokota et al.	Graph Partitioning with m sets	Lodewi iks 11
r-Medolds	Bauckhage1 et al. 10	Subsect Sum Problem	Lodewi iks 11
Contact Map Overlap Problem	Oliveira et al. !!	Numerical Three-Dimensional Matching	Lodewi iks 11
Minimum Multicut Problem	Cruz-Santos et al.12	Social Workers Problem	Adelomou et al. 22
Sroadcast Time Problem	Calude et al.13	EV-Bus Charging Scheduling Problem	Yu et al. si
faximum Common Subgraph Isomorphism	Huang et al.14	Vehicle Routing Problem	Borowski et al.so
Densest k-subgraph	Calude et al.15	Robot Path Planning	Finizar et al. 0
ongest Path Problem	McCollum et al.16	Scheduling on Undirected Hamiltonian Paths	Rieffel et al.
Airport Gateway Assignment	Stollenwerk et al.18	Market Graph Clustering	Hong et al.ss
inear regression	Date et al.17	Market Graph Clustering Balanced k-Means Clustering	Arthur et al. 55
Support Vector Machine	Date et al.17	Distance-based Clustering in general	Matsumoto et al se
-means clustering	Date et al.17	Credit Scoring and Classification	Milne et al.
Eigencentrality	Prosper et al. :	Credit Scoring and Classification  Dynamic Portfolio Dotimization	Muzel et al.()
Container Assignment Problem	Phillipson et al.21	Dynamic Portfolio Optimization Railway Dispatching and Conflict Management	
colorable subgraph problem	Rodolfo et al.22	Hailway Dispatching and Conflict Managemen Ontimization	<sup>10</sup> Domino et al.70
Souting and Wavelength Assignment with Protection	Ovlum et al.33	Workflow Application Scheduling	Tomasiewicz et al. 11
ircraft Loading Optimization	Giovanni et al.24	Mirrored Double Round-robin Tournament	Kuramata et al.72
ircraft Loading Optimization inear least squares / system of linear equations	Alinkya et al.35	Mirrored Double Round-robin Tournament Transaction Scheduling	Ruramata et al.72 Bittner et al.74
inear least squares / system of linear equations raffic flow Optimization	Neukart et al.35	Transaction Scheduling Transformation Estimation	Golvanik et al.75
	Neukart et al.20 Tolsa et al.27		
Permutation Synchronization		Point Set Registration	Golyanik et al.25
tax-Flow Problem	Krauss et al.20	Maximum Cardinality Matching	Vert et al.26
Metwork Shortest Path Problem	Krauss et al.29	Multi-car Paint Shop Optimization	Yarkoni et al. 17
Structural Isomer Search Problem	Terry et al. 10	Binary Paint Shop Problem	Streif et al.78





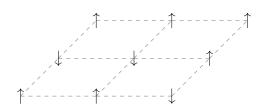
$$H = -\sum_{\langle i | j \rangle} J_{ij} \sigma_i^z \sigma_j^z - \mu \sum_i h_i^z \sigma_i^z - \mu \sum_i h_i^x \sigma_i^x$$

Eq. Ref. [7] [5]



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$$\sigma \mapsto 2x - 1, \ x \in \{0, 1\}$$

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$$\Delta = \sum_{b=0}^{\lceil \log_2 1 + m \rceil - 1} 2^b \ a_b^r, \ a_b^r \in \{0, 1\}$$

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#### consider:

- number of customer nodes
- number of time steps required
- routes / vehicles

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$$n_c \in \mathcal{O}(\|V\|^3)$$

#### Two phase procedure

$$H_p = H_c + p_1 H_{\mathsf{once}} + p_2 H_{\mathsf{step}} + p_3 H_{\mathsf{cap}}$$

 $n_c$ : number of classical binary variables

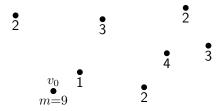
#### consider:

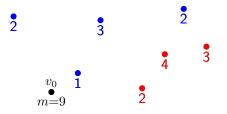
- number of customer nodes
- number of time steps required
- routes / vehicles

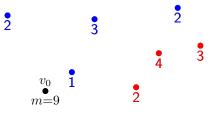
$$n_c \in \mathcal{O}(\|V\|^3)$$

divide and conquer [8] [9]

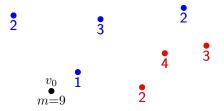
- clustering phase
- routing phase



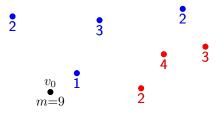




subject to constraints:

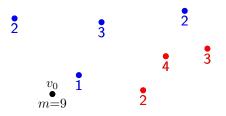


subject to constraints: once, cap



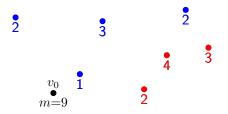
subject to constraints: once, cap

additional constraint: cluster



subject to constraints: once, cap

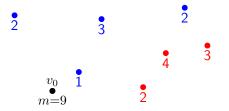
additional constraint: cluster The cumulative edge cost  $c_{ij}$  between all pairs of nodes (i,j) within a cluster should be minimal.

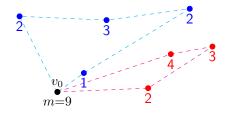


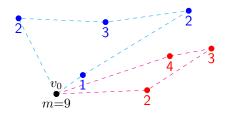
subject to constraints: once, cap

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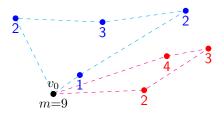
$$H_{\text{cluster}} = \sum_r \sum_{i,\ j} c_{ij}\ x_i^r\ x_j^r$$
 where  $x_i^r = \sum_t x_{i,t}^k$ 







subject to constraints: once, step, edge costs



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$$H_{\rm tsp} = q_1 H_{\rm once} + q_2 H_{\rm step} + q_3 H_c$$

$$\left. \begin{array}{ccc} - & \cdots & - \\ - & \cdots & - \\ - & \cdots & - \end{array} \right\} |\psi\rangle$$

$$|\psi\rangle = \sum_{z \in \{0,1\}^n} \beta_z |z\rangle$$

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$$|z\rangle$$
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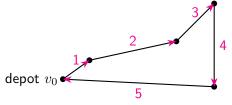
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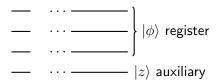
depot  $v_0 ullet$ 

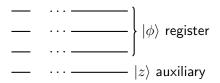
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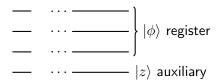
#### $|z\rangle$ corresponds to





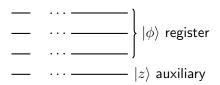


register width  $n_r$ , aux width  $n_a$ ,  $n_q = n_r + n_a$ 



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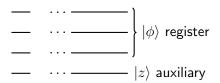
$$|\psi(\theta)\rangle = \sum_{i=1}^{n_c} \beta_i(a_i|0\rangle + b_i|1\rangle) |\phi_i\rangle$$



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$$n_q = 1 + \log_2 n_c$$

let 
$$n_c = 4$$
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# Solution probability

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Born rule: 
$$\Pr(x_i = 1) = \|\langle 1|z_i \rangle\|^2 = \|b_i\|^2$$

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$$E x_i x_j = ||b_i||^2 ||b_j||^2$$

$$cov(x_i, x_j) = E x_i x_j - E x_i E x_j$$

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$$= 0$$





## Tradeoffs



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$$|\psi(\theta)\rangle = \sum_{i=1}^{n_c} \beta_i(a_i|0\rangle + b_i|1\rangle) |\phi_i\rangle$$

## **Tradeoffs**

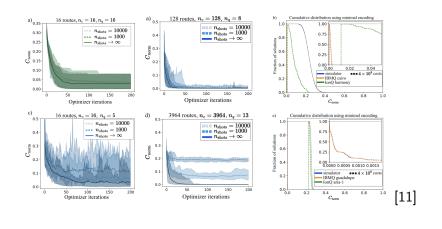


$$|\psi(\theta)\rangle = \sum_{i=1}^{n_c} \beta_i (a_i|0\rangle + b_i|1\rangle) |\phi_i\rangle$$

example:

$$|\psi^*\rangle = \frac{1}{2}(|1\rangle|00\rangle + |1\rangle|01\rangle + |1\rangle|10\rangle + |0\rangle|11\rangle)$$

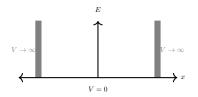
## Experimental results



Thank you for your attention.

github.com/ge42faz/qsem-23w

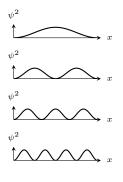
### Adiabatic computation



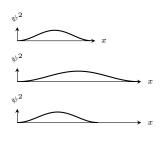
$$i\hbar \frac{\partial}{\partial t} \psi(x,t) = \frac{-\hbar^2}{2m} \frac{\partial}{\partial x^2} \psi(x,t) + V(x) \psi(x,t)$$

 $\psi(x,t)=e^{-i\omega t}(A\sin kx+B\sin kx)$  for x within the box.

### Adiabatic computation



$$H|\psi\rangle = E|\psi\rangle$$
 
$$E_k = \hbar\omega_k = \frac{n^2\pi^2}{L^2}\frac{\hbar^2}{2m}$$



$$H(t) = \left(1 - \frac{t}{T}\right) \cdot H_0 + \frac{t}{T} \cdot H_p$$
$$0 \le t \le 1, \ T \in \mathcal{O}(\frac{1}{g^2})$$
$$[H_0, H_p] \ne 0$$

$$\mathbf{B} = \frac{\mu_0}{4\pi} \left( \frac{3\mathbf{r}(\mathbf{m} \cdot \mathbf{r})}{r^5} - \frac{\mathbf{m}}{r^3} \right)$$

$$H = -\sum_{\langle i j \rangle} J_{ij} \sigma_i \sigma_j + \mu \sum_i h_i \sigma_i$$

$$\mu = \frac{-e}{2m_e}L$$

 $J_{ij} > 0$  ferromagnetic,  $J_{ij} < 0$  antiferromagnetic.

#### Cost function

$$C_{\mathsf{cpl}}(\theta) = \langle H \rangle = \langle \psi(\theta) | H | \psi(\theta) \rangle$$

$$C_{\min}(\theta) = \sum_{i \neq j}^{n_c} Q_{ij} ||b_i||^2 ||b_j||^2 + \sum_{i=1}^{n_c} Q_{ii} ||b_i||^2$$
$$= \sum_{i \neq j}^{n_c} Q_{ij} \frac{\langle P_i^1 \rangle}{\langle P_i \rangle} \frac{\langle P_j^1 \rangle}{\langle P_j \rangle} + \sum_{i=1}^{n_c} Q_{ii} \frac{\langle P_i^1 \rangle}{P_i}$$

expressed as projectors  $P_i = |\phi_i\rangle\langle\phi_i|$  and  $P_i^1 = |1\rangle\langle1|\otimes P_i$ .

$$\overline{C} = \frac{C(\theta) - C^*}{\Delta C}$$

# Backup slides QAOA

$$|\psi(\beta,\gamma)\rangle =$$

$$|\psi(\beta,\gamma)\rangle = e^{-i\gamma_i H_f} |+\rangle^{\otimes m}$$

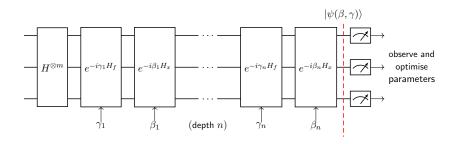
$$- H^{\otimes m} e^{-i\gamma_1 H_f}$$

$$|\psi(\beta,\gamma)\rangle = e^{-i\beta_i H_x} e^{-i\gamma_i H_f} |+\rangle^{\otimes m}$$

$$- H^{\otimes m} | e^{-i\gamma_1 H_f} | e^{-i\beta_1 H_x} |$$

$$|\psi(\beta,\gamma)\rangle = \prod_k e^{-i\beta_i H_x} e^{-i\gamma_i H_f} \ |+\rangle^{\otimes m}$$
 
$$-\prod_{H^{\otimes m}} e^{-i\gamma_1 H_f} - e^{-i\beta_1 H_x} - \cdots - e^{-i\gamma_n H_f} - e^{-i\beta_n H_x}$$
 
$$(\text{depth } n)$$

$$|\psi(\beta,\gamma)\rangle = \prod_k e^{-i\beta_i H_x} e^{-i\gamma_i H_f} \ |+\rangle^{\otimes m}$$



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