

Variational Quantum Demodulation for Coherent Optical Multi-Dimensional QAM

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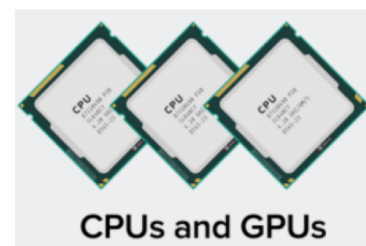
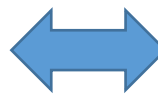
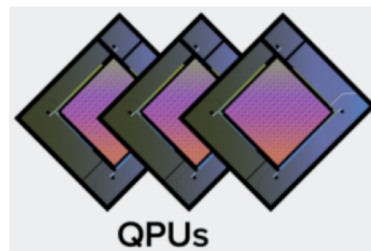
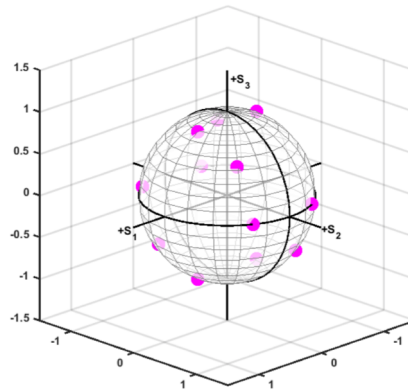
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Outline

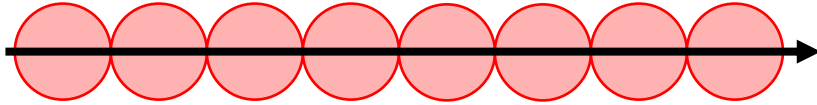
- High-dimensional modulation (HDM)
- Quantum technology trend
 - Quantum approximate optimization algorithm (QAOA)
- QAOA hybrid quantum-classical demodulation
- Simulation and real quantum processor results



High-Dimensional Modulation (HDM)

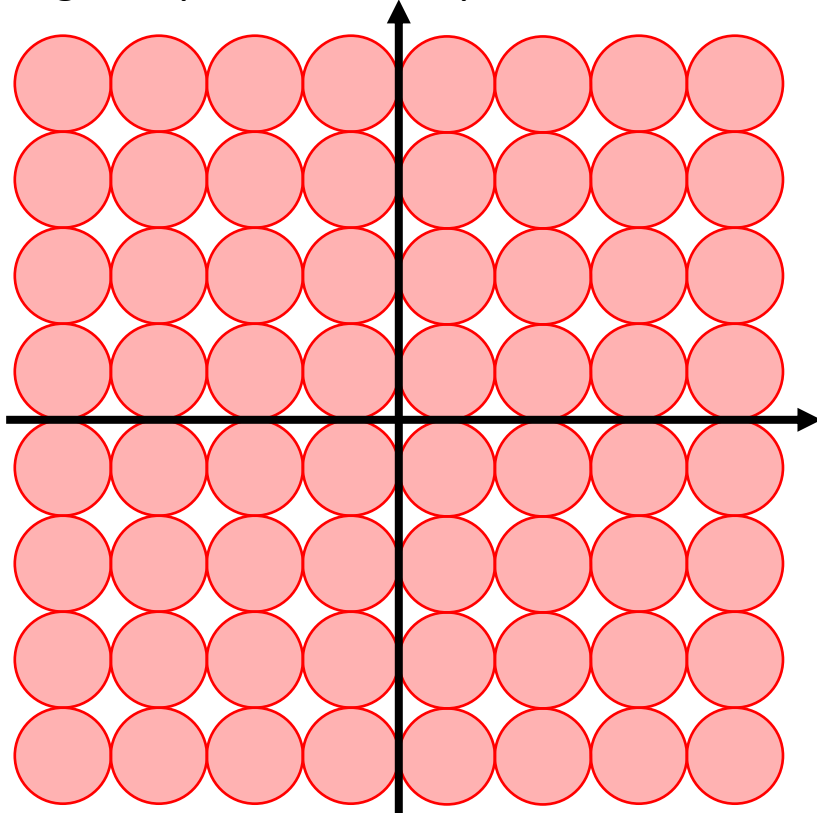
Regular lattice in 1-D:

Regular pulse-amplitude modulation (PAM)

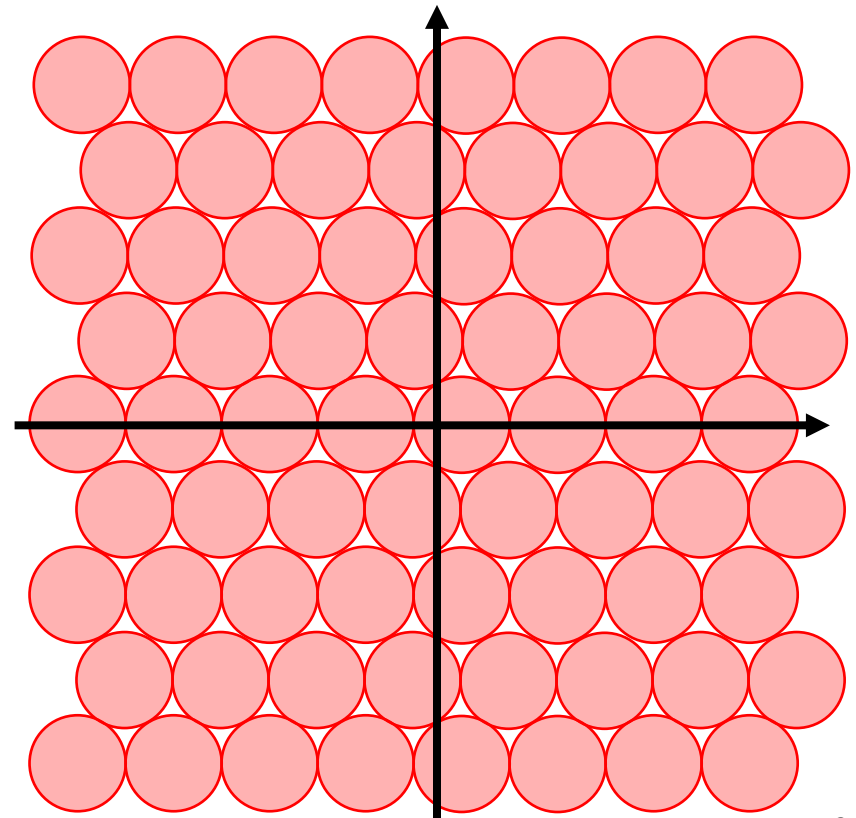


Lattice in 2-D:

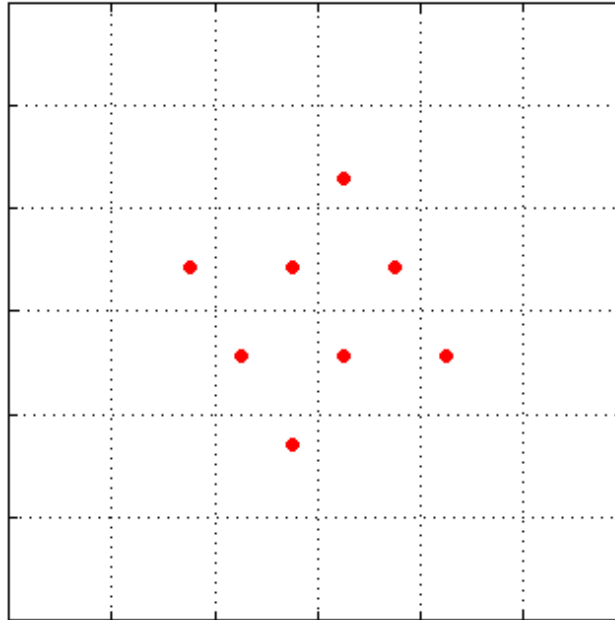
Regular quadrature-amplitude modulation (QAM)



Optimally packed lattice in 2-D:
Hexagonal lattice: max 0.8dB gain



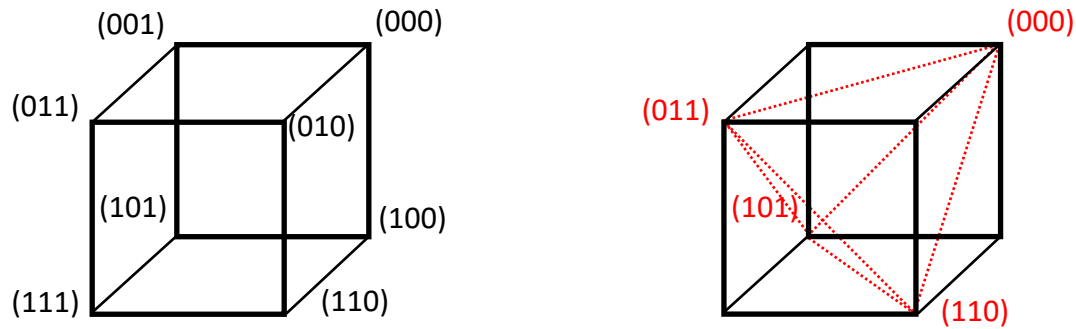
Spherical Cutting of Lattices



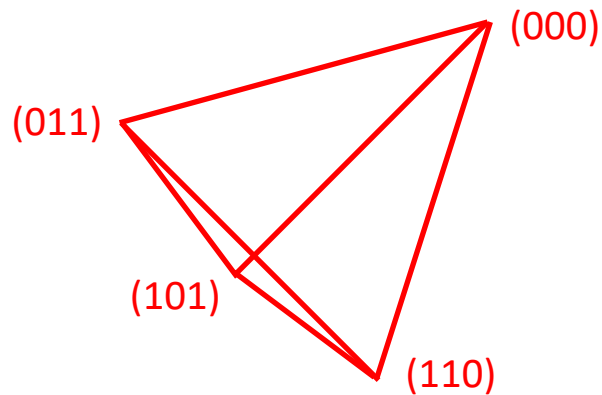
- Start with lattice in N-dimensions
- Select 2^p neighboring points
- Optimize selection
- Remove mean
- Labeling?

Block-Coded HDM

- Selecting a good subset of non-adjacent points from a Gray-coded hypercube



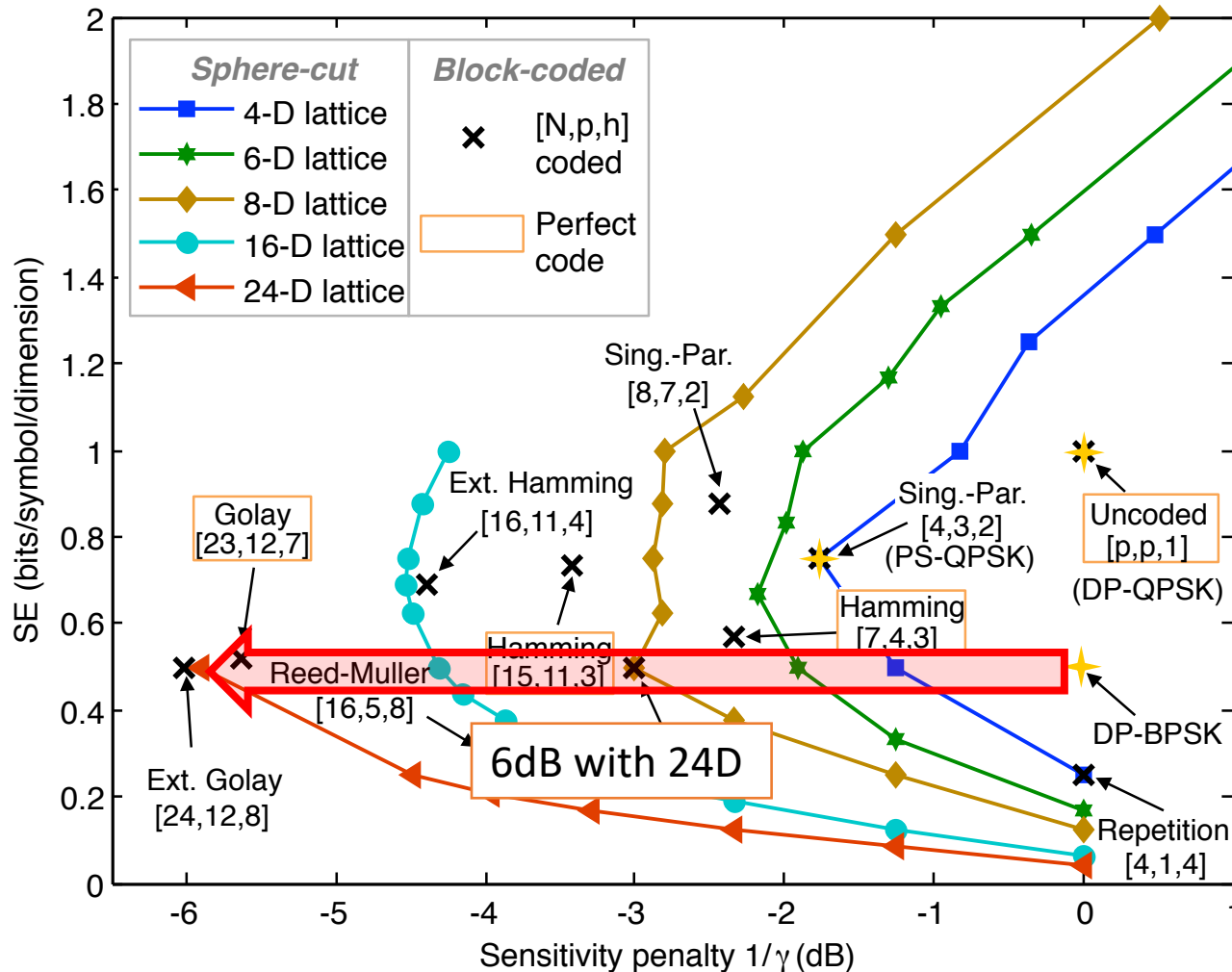
- Codewords define the set of points that are selected; e.g., [3,2,2] single-parity-check (SPC) code



- Labeling optimization is not required

Packing Gain of High-Dimensional Modulation

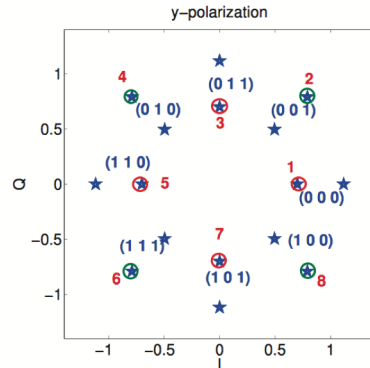
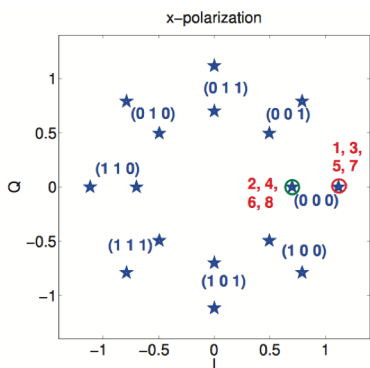
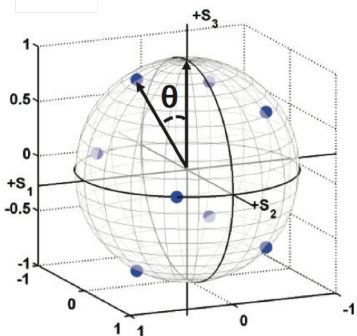
- Increasing dimensionality provides higher power efficiency: $\gamma = d_{min}^2/(4\epsilon_b)$



Nonlinearity-Mitigating HDM

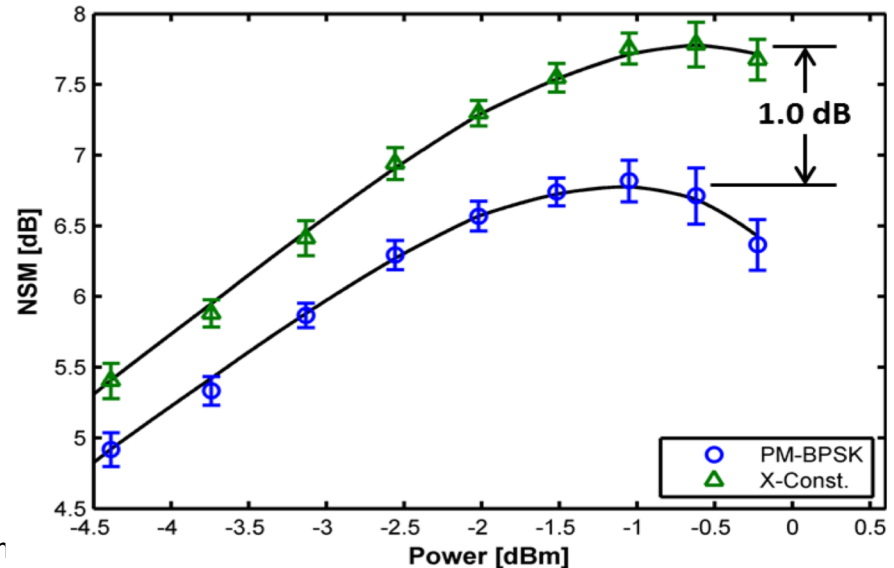
- Some HDM can further mitigate nonlinear interference (NLI)
 - 4-dimensional constant-modulus modulation (4D-2A8PSK) [Kojima et al., ECOC14]
 - 8-dimensional Grassmann modulation [Koike-Akino et al., SPPCom15]
 - 8-dimensional X-constellation [Shiner et al., OpEx14]

Constant modulus



Zero degree of polarization (DOP)

Binary Value	0000	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111
Slot A x-pol	-1-i	-1-i	-1-i	-1-i	-1+i	-1+i	-1+i	-1+i	1-i	1-i	1-i	1-i	1+i	1+i	1+i	1+i
Slot A y-pol	1+i	-1+i	1-i	-1-i	-1-i	1-i	-1+i	1+i	-1-i	1-i	-1+i	1+i	1+i	-1+i	1-i	-1-i
$S_A=(S_1, S_2, S_3)$	(0,-4,0)	(0,0,-4)	(0,0,4)	(0,4,0)	(0,0,4)	(0,-4,0)	(0,4,0)	(0,0,-4)	(0,0,-4)	(0,4,0)	(0,-4,0)	(0,0,4)	(0,4,0)	(0,0,4)	(0,-4,0)	(0,-4,0)
Slot B x-pol	1+i	-1+i	1-i	-1-i	1+i	-1+i	1-i	-1-i	1+i	-1+i	1-i	-1-i	1+i	-1+i	1-i	-1-i
Slot B y-pol	1+i	-1-i	-1-i	1+i	1-i	-1+i	-1+i	1-i	-1+i	1-i	1-i	-1+i	-1-i	1+i	1+i	-1-i
$S_B=(S_1, S_2, S_3)$	(0,4,0)	(0,0,4)	(0,0,-4)	(0,-4,0)	(0,0,-4)	(0,4,0)	(0,-4,0)	(0,0,4)	(0,0,4)	(0,-4,0)	(0,4,0)	(0,0,-4)	(0,-4,0)	(0,0,-4)	(0,0,4)	(0,4,0)
DOP $ S_A+S_B $	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

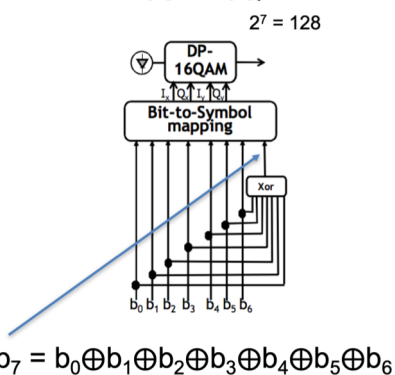


HDM Demodulation

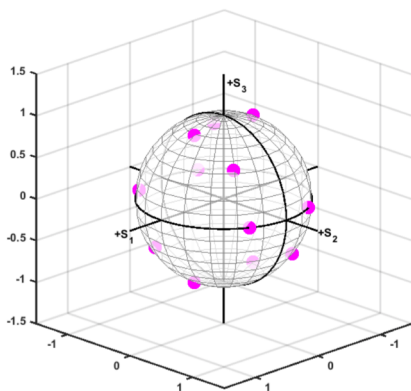
- In exchange of higher packing gain, HDM can increase the demodulation complexity for higher dimensions
- Log-likelihood ratio (LLR) calculation is not straightforward in general to feed into soft-decision decoders
- Simplified LLR calculation based on min-sum belief propagation over algebraic constrains
- We propose **quantum processing unit (QPU)**-based demodulator

128SP-16QAM

$2^7 = 128$

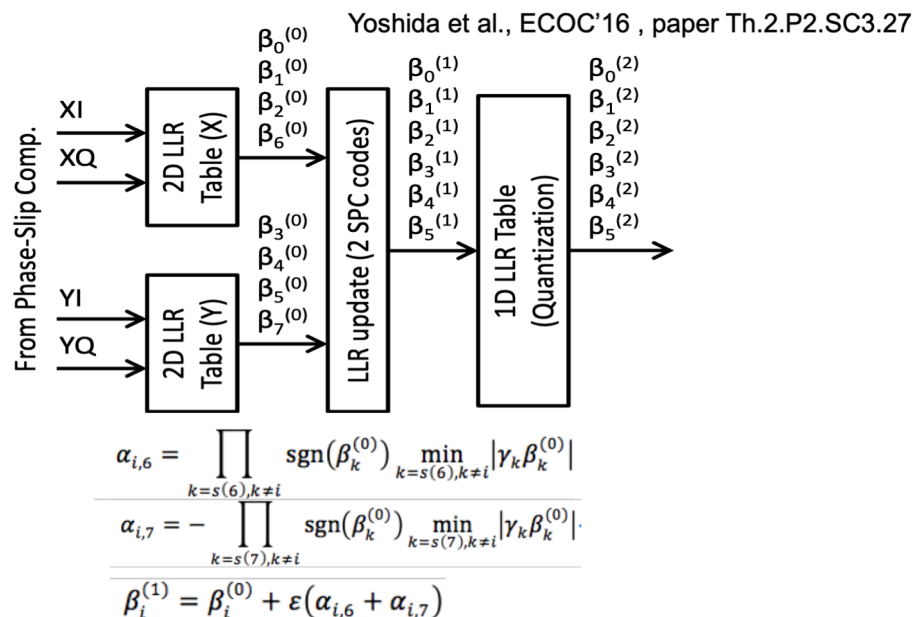


Renaudier et al., ECOC'12, We.1.C.5



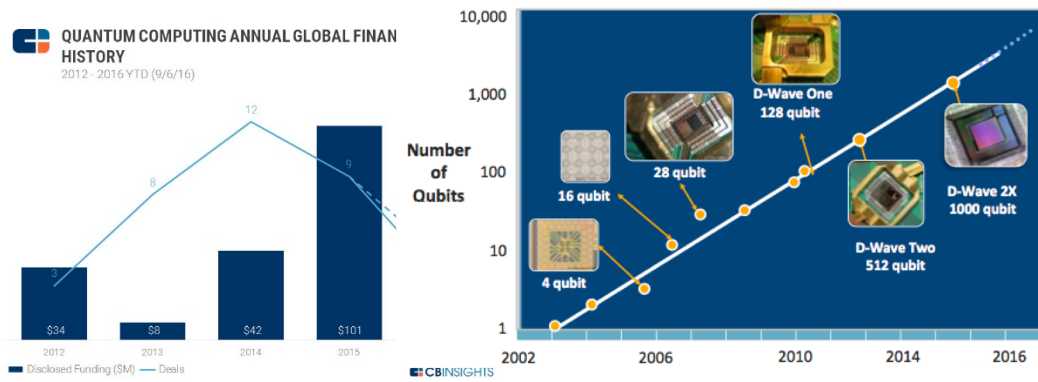
$$\begin{aligned} B[5] &= B[0] \oplus B[1] \oplus B[2], \\ B[6] &= B[2] \oplus B[3] \oplus B[4]. \\ B[7] &= \overline{B[6]}. \end{aligned}$$

Kojima et al. JLT 17



Quantum Computing

- Morgan Stanley: Quantum tech can drive **4th industrial revolution**
- Escalating government funds: National Quantum Initiative **\$1.2B**
- Quantum chip providers: **IBM, Google, Microsoft, Honeywell, Intel, Nokia, AirBus, IONQ, rigetti**



Free libraries to evaluate quantum computing on realistic simulators or real devices



Post-2014 Trend: Variational Quantum Principle

- Hybrid use of quantum measurement and classical optimization
 - VQE: Variational Quantum Eigensolver (2014)
 - QAOA: Quantum Approximate Optimization Algorithm (2014)
 - VQF: Variational Quantum Factoring (2018)



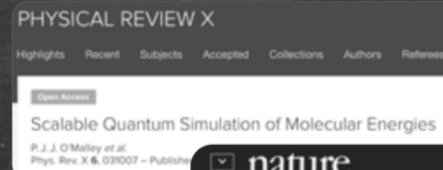
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Article | OPEN | Published: 23 July 2014

A variational eigenvalue solver on a photonic quantum processor

Alberto Peruzzo, Jarrod McClean, Peter Shadbolt, Man-Hong Yung, Xiao-Qi Zhou, Peter J. Love, Alán Aspuru-Guzik & Jeremy L. O'Brien

Nature Communications 5, Article number: 4213 (2014) | Download Citation



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P. J. J. O'Malley et al.
Phys. Rev. X 6, 031007 – Published 14 July 2016



nature International journal of science

Letter | Published: 13 September 2017

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PHYSICAL REVIEW X

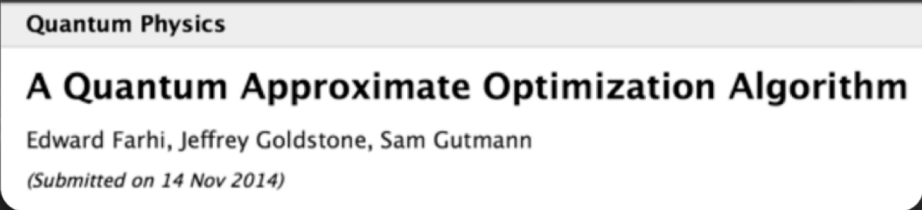
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Cornelius Hempel, Christine Maier, Jonathan Romero, Jarrod McClean, Thomas Monz, Hong Shen, Peter Jurio, Ben P. Lanyon, Peter Love, Ryan Babbush, Alan Aspuru-Guzik, Robert Blatt, and Christian F. Roos
Phys. Rev. X 8, 031022 – Published 24 July 2018

arXiv.org > quant-ph > arXiv:1411.4028



Quantum Physics

A Quantum Approximate Optimization Algorithm

Edward Farhi, Jeffrey Goldstone, Sam Gutmann

(Submitted on 14 Nov 2014)



arXiv.org > quant-ph > arXiv:1712.05771

Quantum Physics

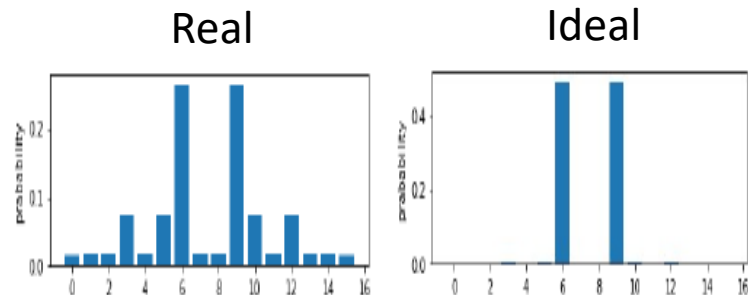
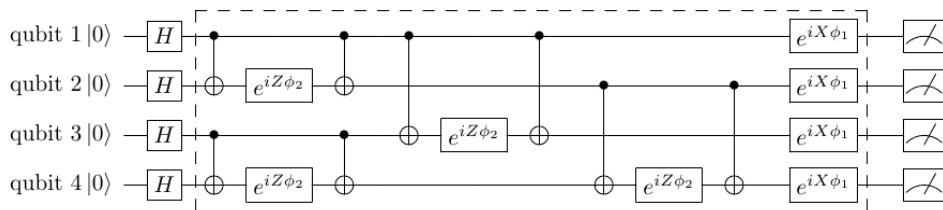
Unsupervised Machine Learning on a Hybrid Quantum Computer

J. S. Otterbach, R. Manenti, N. Alidoust, A. Bestwick, M. Block, B. Bloom, S. Caldwell, N. Didier, E. Schuyler Fried, S. Hong, P. Karalekas, C. B. Osborn, A. Papageorge, E. C. Peterson, G. Prawiroatmodjo, N. Rubin, Colm A. Ryan, D. Scarabelli, M. Scheer, E. A. Sete, P. Sivarajah, Robert S. Smith, A. Staley, N. Tezak, W. J. Zeng, A. Hudson, Blake R. Johnson, M. Reagor, M. P. da Silva, C. Rigetti

(Submitted on 23 Dec 2017)

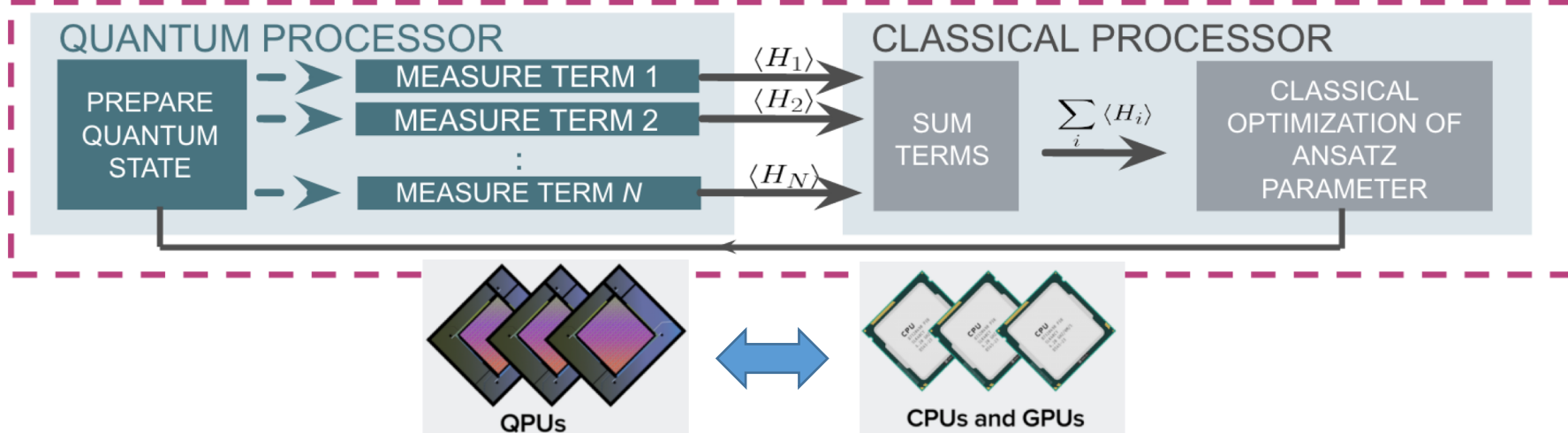
Variational Quantum Algorithms for NISQ

- Current quantum processors are noisy and coherence-limited: quantum gates are imperfect



- For noisy intermediate-scale quantum (**NISQ**) devices, variational hybrid quantum-classical algorithms may be a viable driver for quantum supremacy due to shallow gates and noise resilience

V.Q.E. QUANTUM-CLASSICAL HYBRID ALGORITHM



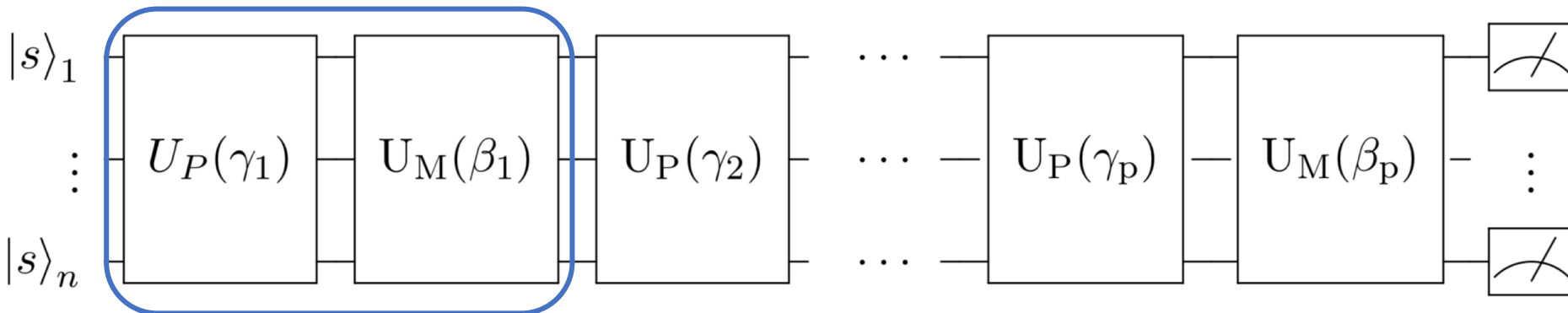
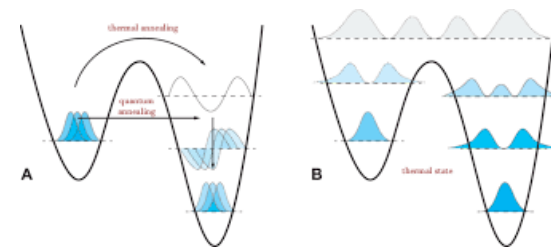
QAOA: Quantum Approximate Optimization Alg.

- Alternating cost Hamiltonian and mixer Hamiltonian like annealing
- Convergence theorem to eigenstate for infinite-level QAOA
 - Infinite Suzuki-Trotter decomposition with adiabatic annealing
- Classical optimization of variational angle parameters given quantum measurement
- Theoretical analysis showed better accuracy than classical counterparts; e.g. MaxCut, MaxSat, MaxClique

$$\lim_{p \rightarrow \infty} F_p^* = \max_{\mathbf{z}} C(\mathbf{z})$$

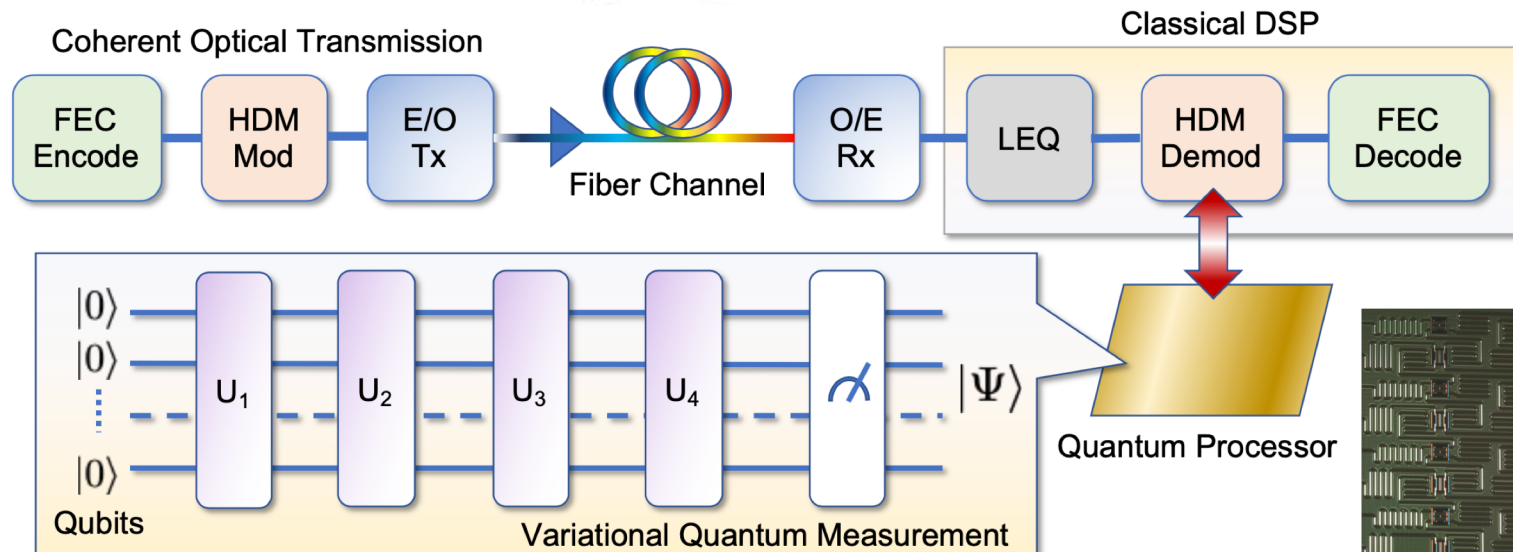
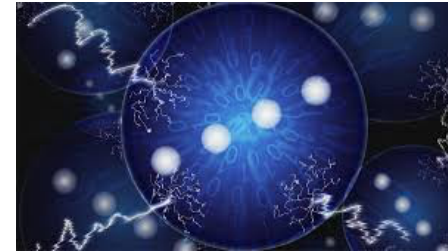
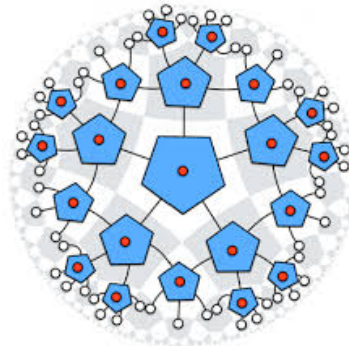
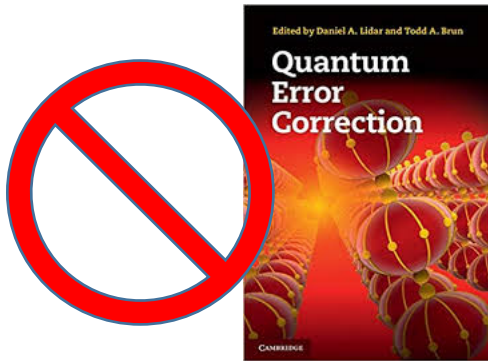
A Quantum Approximate Optimization Algorithm

Edward Farhi and Jeffrey Goldstone
*Center for Theoretical Physics
 Massachusetts Institute of Technology*



Quantum Application to Optical DSP

- This talk is **not** “Quantum Error Correction Codes (QECC)” nor “Quantum Communications”
- We want to offload classical demodulation computation on CPU towards QPU



Classical Channel Decoding

- Hamming codes, Reed-Muller codes, Golay codes, convolutional codes, turbo codes, low-density parity-check (LDPC) codes, polar codes, ...
- Suppose linear binary codes with generator matrix $\mathbf{G} \in \mathbb{F}_2^{k \times n}$

Redundancy: Parity

[01011100101011] \rightarrow [01011100101011 00100101110111011]

$$\mathbf{u} \in \mathbb{F}_2^k$$

$$\mathbf{x} = \mathbf{u}\mathbf{G}$$

$$\mathbf{x} \in \mathbb{F}_2^n$$

- Communication channel exhibits noise

$$\mathbf{y} = \mathbf{x} + \mathbf{w}$$

$$\mathbf{w} \in \mathbb{R}^n$$

- Maximum-likelihood (ML) decoding for symmetric channels:

$$\arg \min_{\mathbf{u}} d_H(\mathbf{y}|\mathbf{x}) = \arg \max_{\mathbf{u}} \sum_{\nu=1}^n (1 - 2y_{\nu})(1 - 2x_{\nu})$$

NP-hard 2^k search for maximum correlation

QAOA Channel Decoding

- Convert ML decoding problem into Ising Hamiltonian model [Koike-Akino ISIT19]

$$\arg \min_{\mathbf{u}} d_H(\mathbf{y}|\mathbf{x}) = \arg \max_{\mathbf{u}} \sum_{\nu=1}^n (1 - 2y_{\nu})(1 - 2x_{\nu})$$

$$\mathbf{x} = \mathbf{u}\mathbf{G}$$

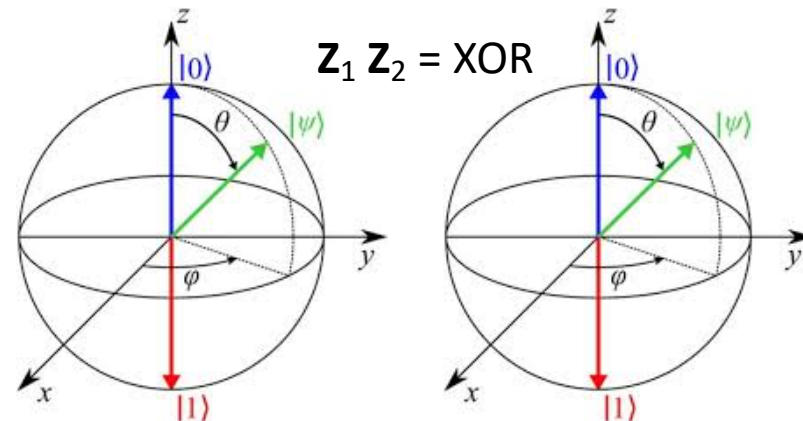
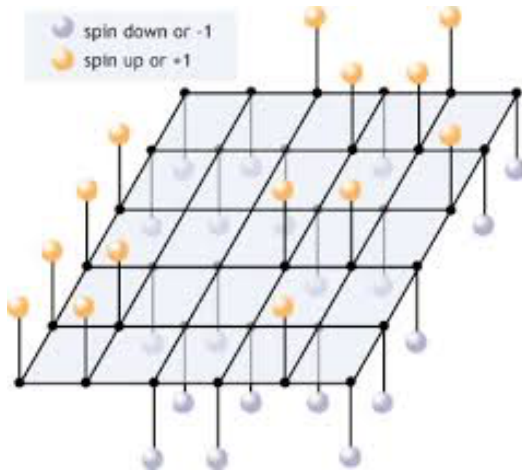
k-bit search: 2^k



k-qubit parallel operation

$$C = \sum_{\nu=1}^n C_{\nu} = \sum_{\nu=1}^n (1 - 2y_{\nu}) \prod_{\kappa \in \mathcal{I}_{\nu}^c} \mathbf{Z}_{\kappa}$$

Pauli-Z

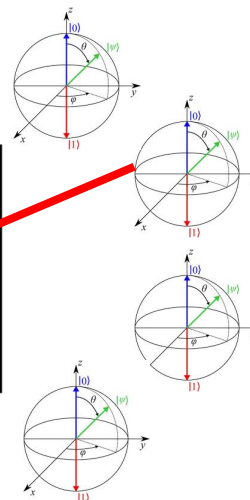


Example: Hamming Code Hamiltonian

- [7, 4]-Hamming code with minimum distance 3, corrects 1 bit error
- Generator matrix:

$$G = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Degree: $[1, 1, 1, 1, 3, 3, 3]$



$$C = r_1 \mathbf{Z}_1 + r_2 \mathbf{Z}_2 + r_3 \mathbf{Z}_3 + r_4 \mathbf{Z}_4$$

Degree-1

$$+ r_5 \mathbf{Z}_1 \mathbf{Z}_2 \mathbf{Z}_4 + r_6 \mathbf{Z}_1 \mathbf{Z}_3 \mathbf{Z}_4 + r_7 \mathbf{Z}_2 \mathbf{Z}_3 \mathbf{Z}_4$$

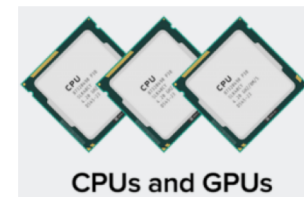
Degree-3

c.f.) MaxCut Hamiltonian is regular degree-2

QAOA Channel Decoding

- CPU:

- Given generator matrix G and received signal y
- Construct cost Hamiltonian with variational angles
- Quantum shots on QPU to obtain quasi-ML decision
- Re-optimize angles if necessary and re-shot

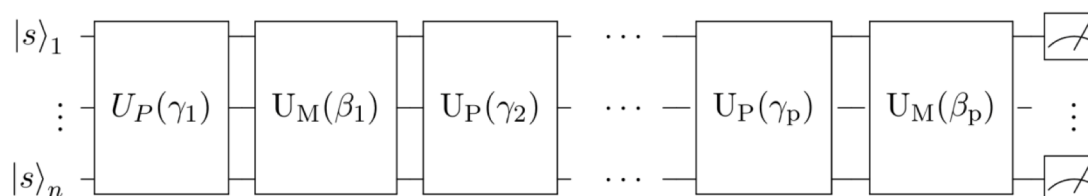
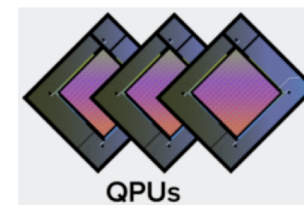


$$G = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix} \quad C = r_1 Z_1 + r_2 Z_2 + r_3 Z_3 + r_4 Z_4 \\ + r_5 Z_1 Z_2 Z_4 + r_6 Z_1 Z_3 Z_4 + r_7 Z_2 Z_3 Z_4$$



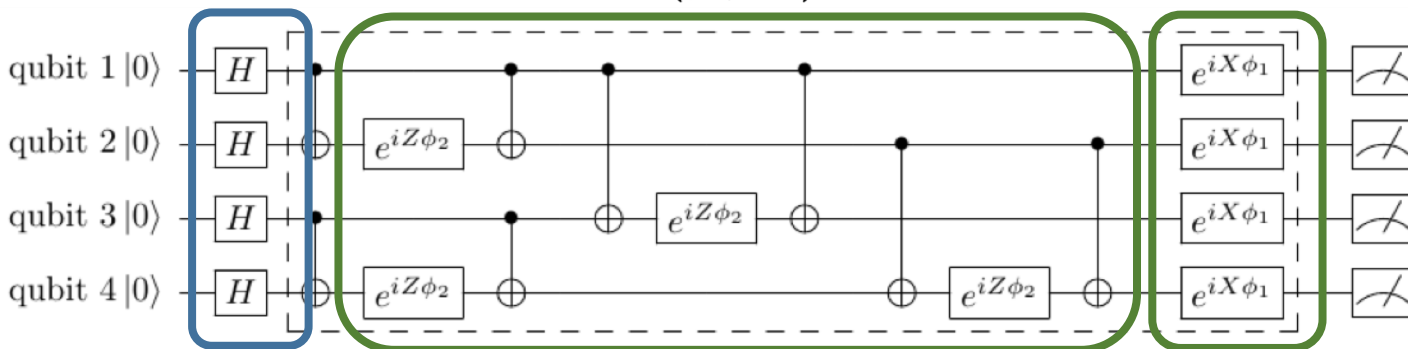
- QPU: QAOA

- Initialize quantum state: $|+\rangle$ with Hadamard gates
- Apply gamma angle rotation with cost Hamiltonian C
- Apply beta angle rotation with mixer Hamiltonian B
- Cascade p -times for level- p QAOA
- Measure

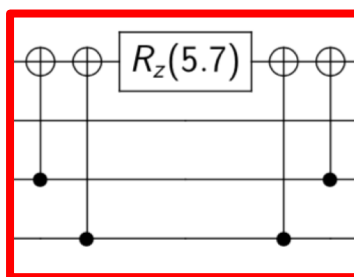


Quantum Circuits for QAOA Decoding

- State preparation: Hadamard H
- Mixer Hamiltonian operation: $\exp(j\beta\mathbf{B})$
- Cost Hamiltonian operation: $\exp(j\gamma\mathbf{C})$

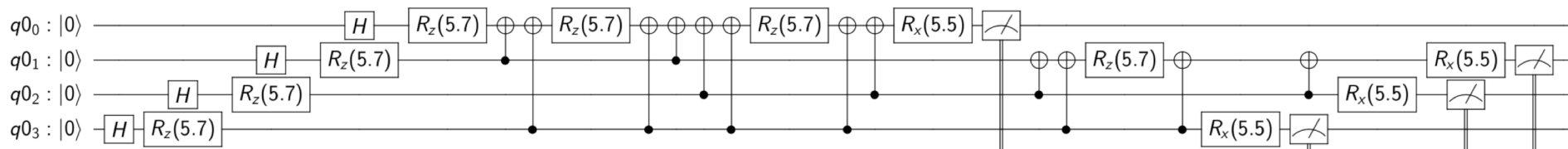


Degree- d XOR: $2(d-1)$ CNOT



$\times p$

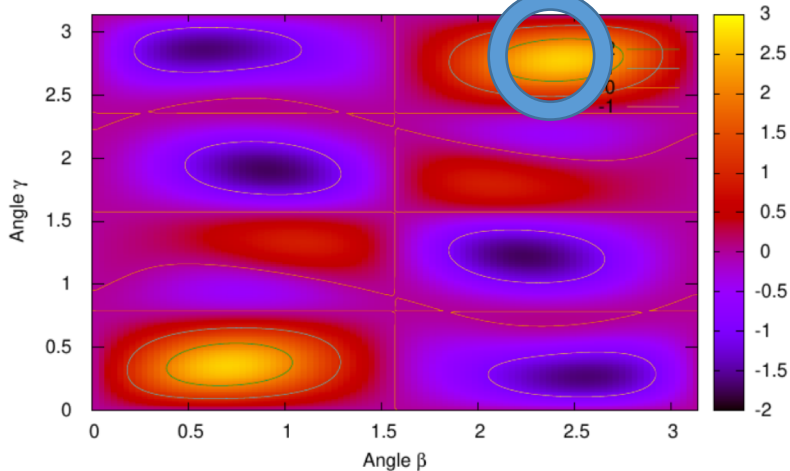
Hamming code QAOA decoder



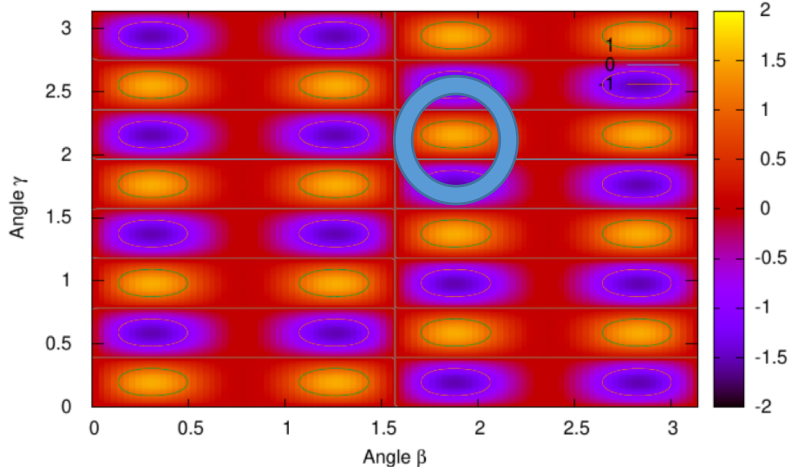
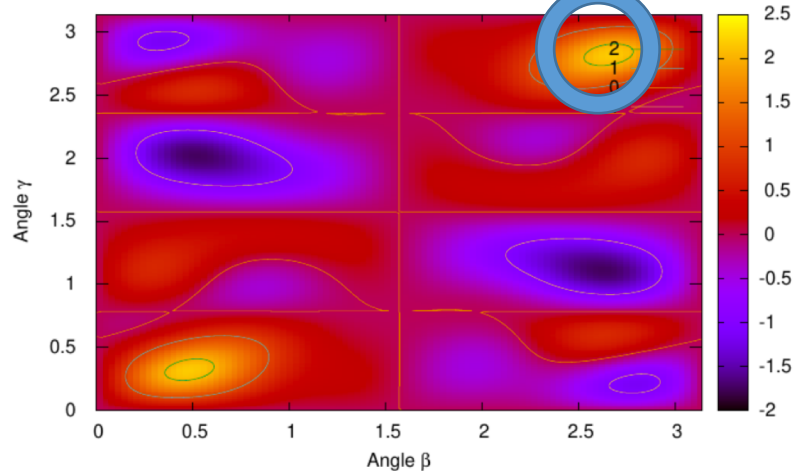
Variational Angle Optimization for HDM

- We can obtain optimal variational angles through VQE
- Landscape of cost expectation (quantum eigenvalue)

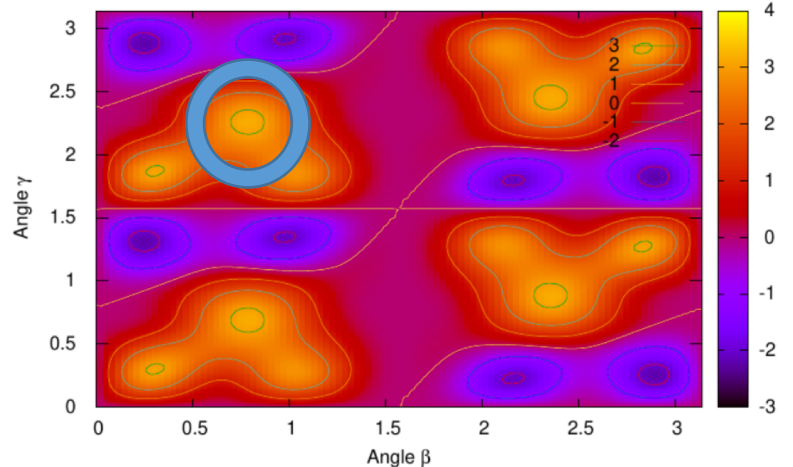
4D HDM



6D HDM



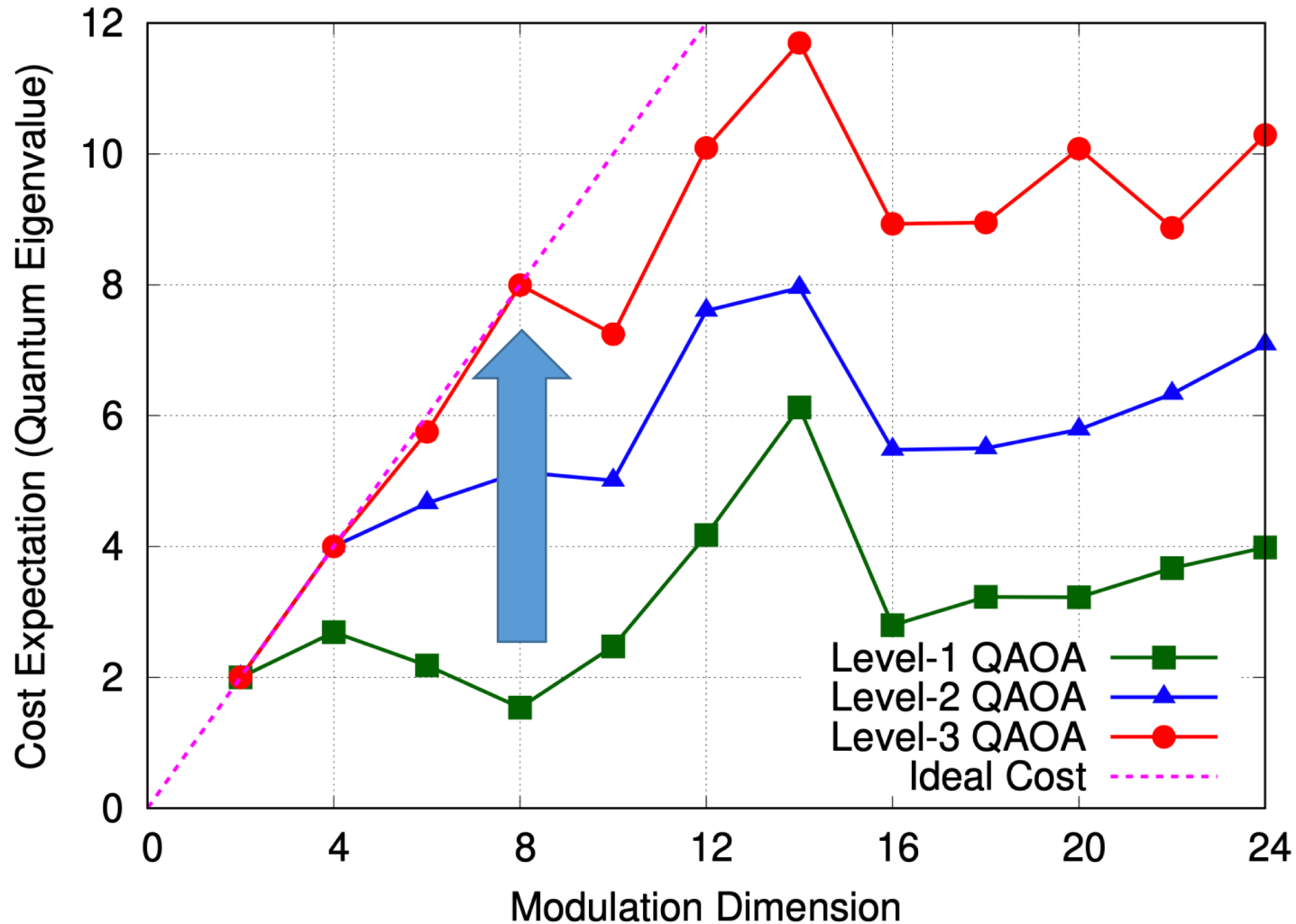
8D HDM



12D HDM

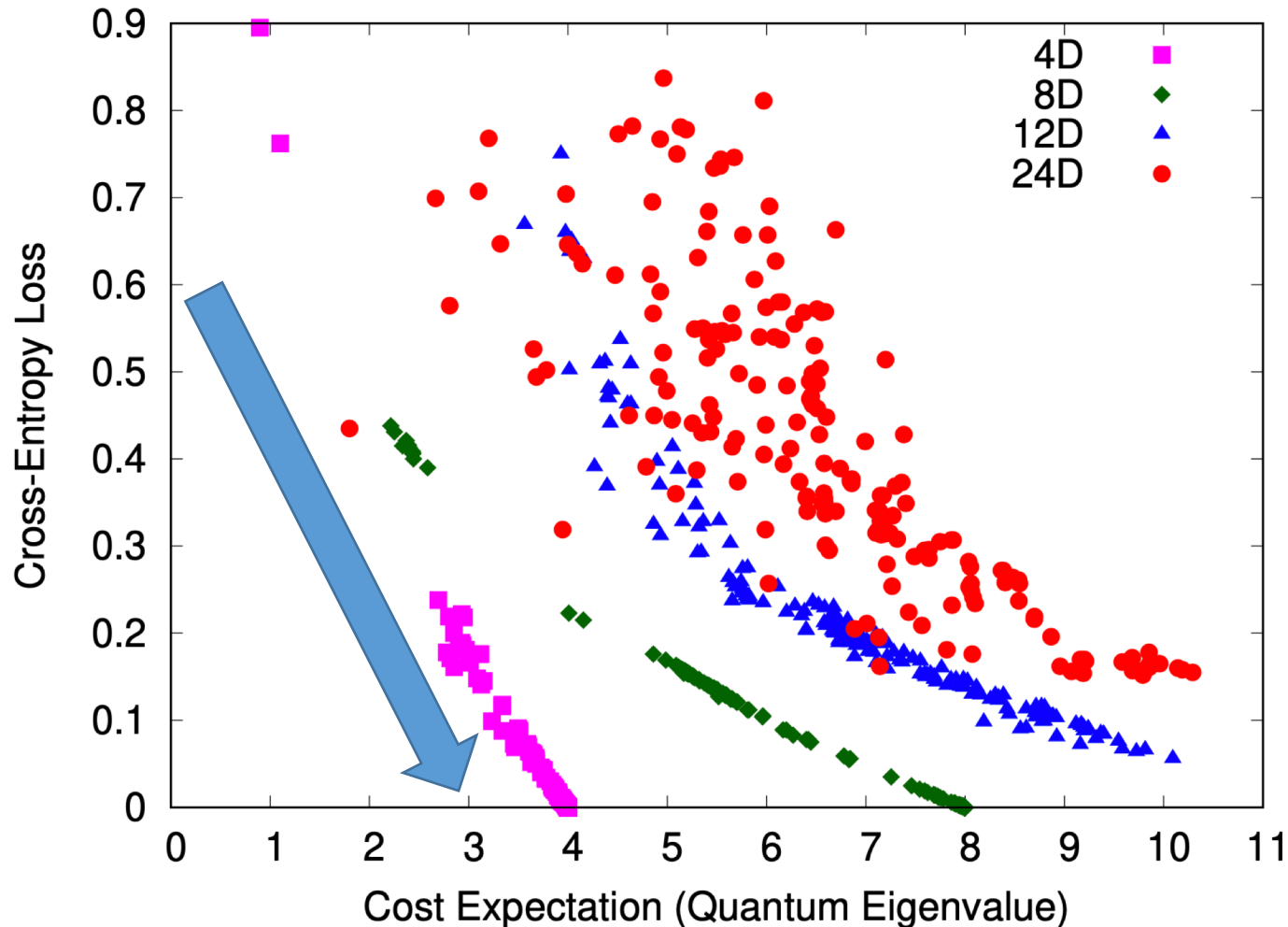
High-Level QAOA Gain

- Using higher-level QAOA, quantum eigenvalue can approach ideal quantum eigenvalue



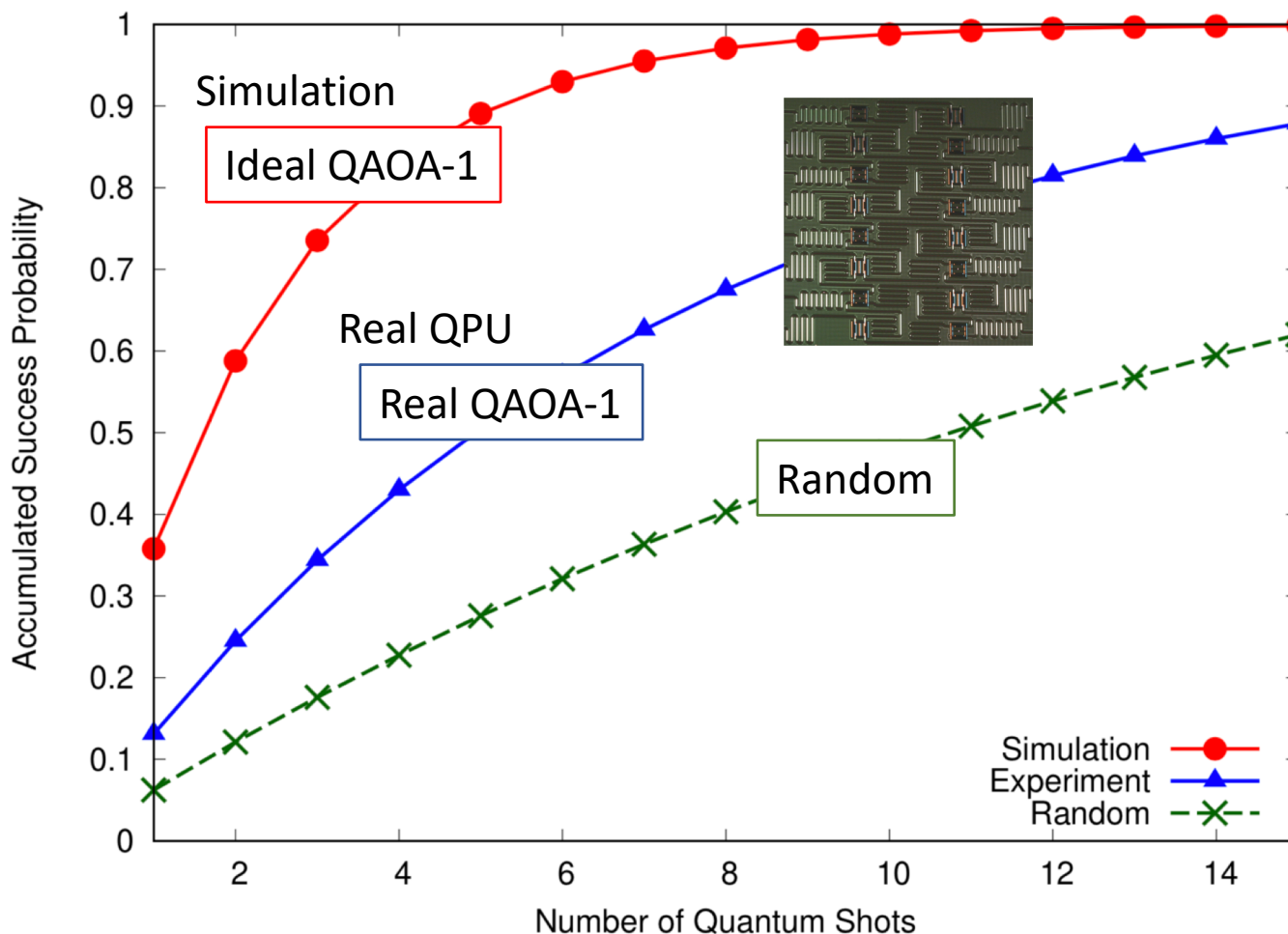
Quantum Eigenvalue and Cross Entropy

- Higher cost expectation (quantum eigenvalue) leads to smaller cross entropy loss, i.e., higher generalized mutual information (GMI)



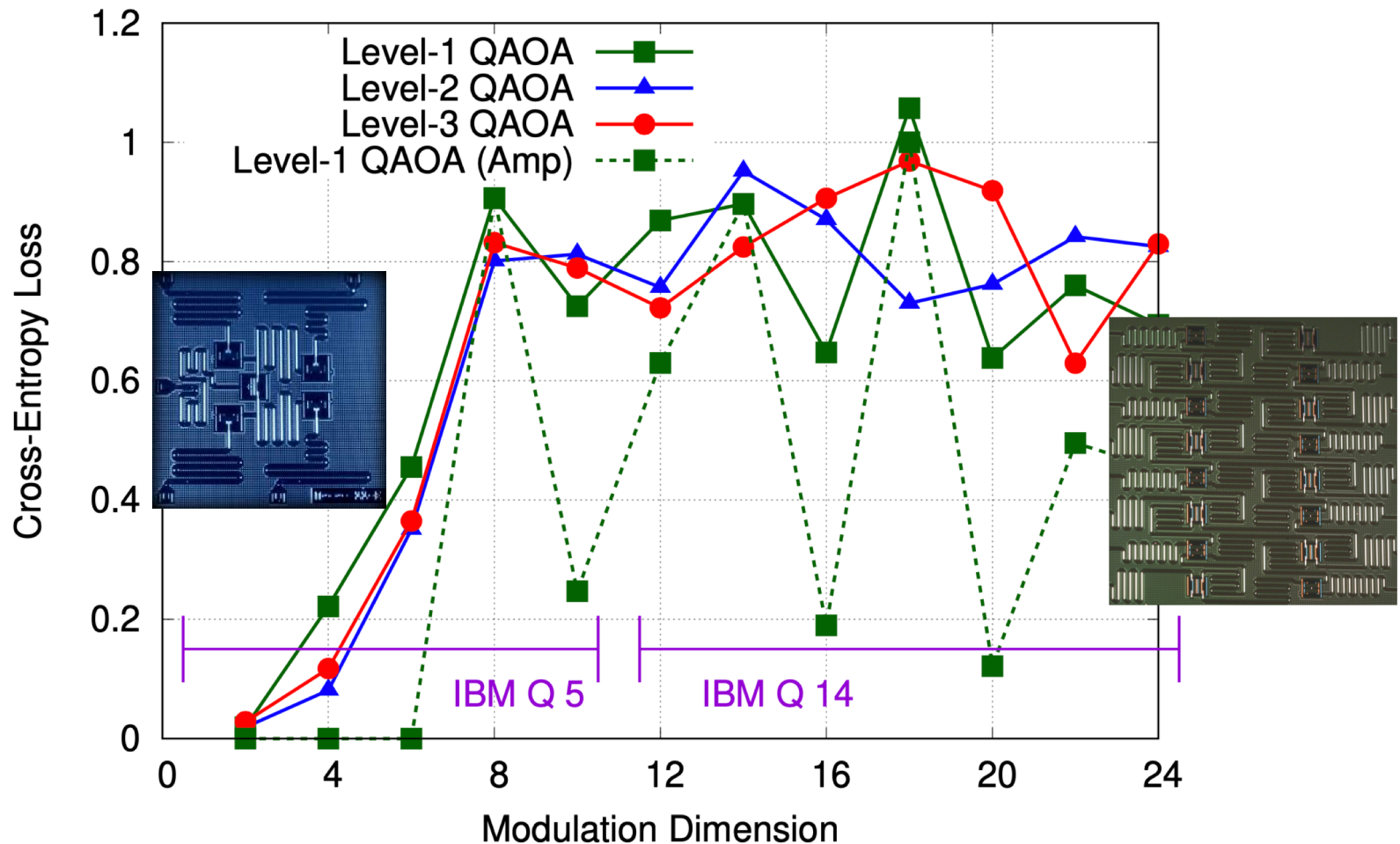
Performance on Simulated CPU and Real QPU

- ML decision success probability can be improved by taking multiple measurements of QPU shots



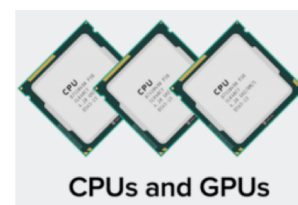
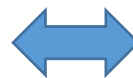
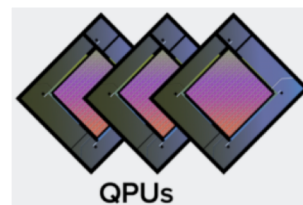
Real QPU Performance of HDM Demodulation

- Due to quantum errors, higher-level QAOA had no significant gain in real QPUs
- To optimize angles under decoherence scenarios
- Wavefunction amplification helps improving the performance



Conclusions

- We investigated HDM demodulation using quantum processor
- We introduced variational hybrid quantum-classical algorithms for HDM demodulation
 - QAOA demodulation was demonstrated to approach ML performance
 - Higher-level QAOA achieves better performance
- We also showed feasibility on real quantum processor
 - Quantum decoherence degraded performance
 - Parameter finetuning is required on real QPU
- To the best of our knowledge, this is the first proof-of-concept paper investigating variational quantum algorithms for HDM demodulation
 - Further rigorous analysis and improvement to follow
 - Developing quantum-ready DSP algorithms may be important for future quantum era



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