QuantumDARTS: Differentiable Quantum Architecture Search for Variational Quantum Algorithms

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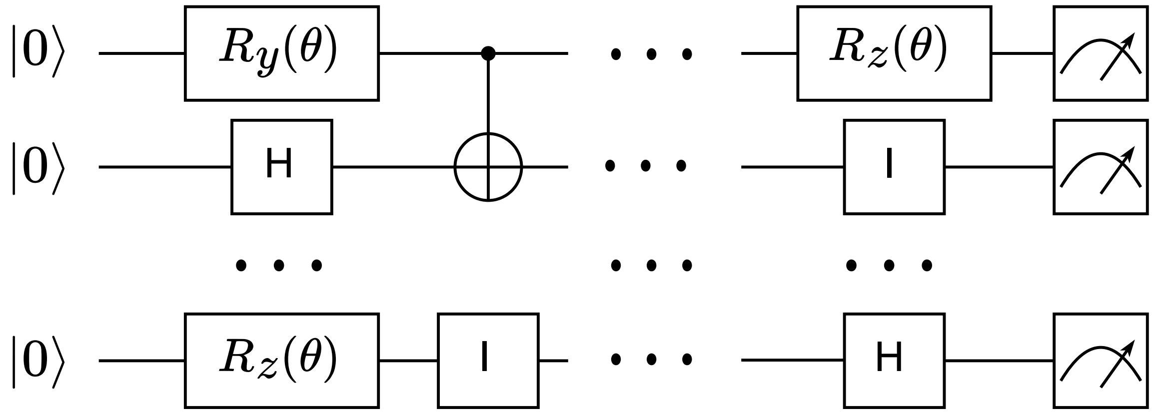
Background

- Variational Quantum Algorithms (VQA) use a classical optimizer to train a parameterized quantum circuit (PQC).



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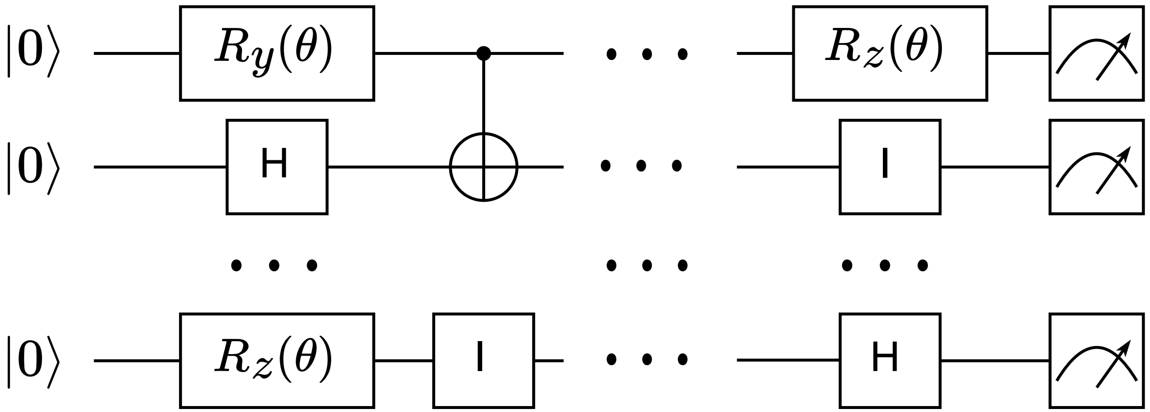

- Quantum Architecture Search (QAS)
  - Search for variational quantum eigensolver (VQE) ---- without input data
  - Search for quantum neural network (QNN) ---- with input data and ground truth

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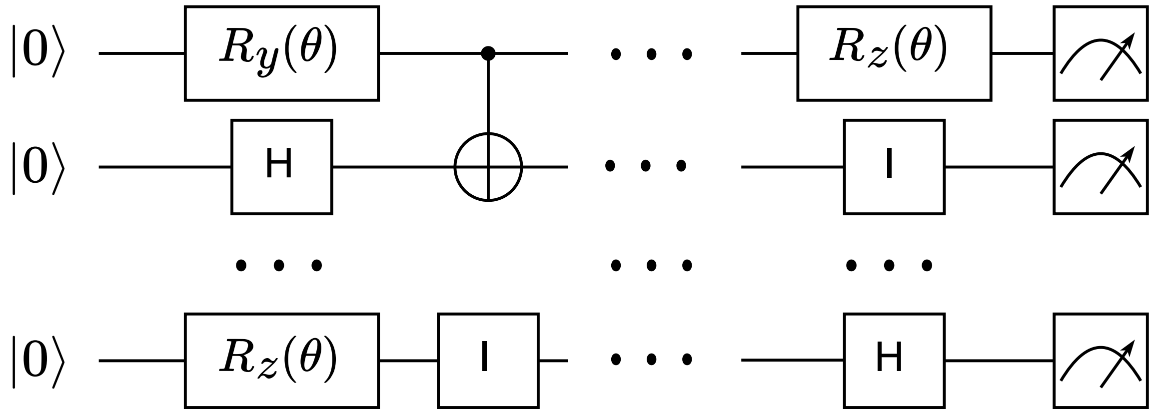

☐ Quantum Architecture Search (QAS)

- Search for variational quantum eigensolver (VQE) ---- without input data
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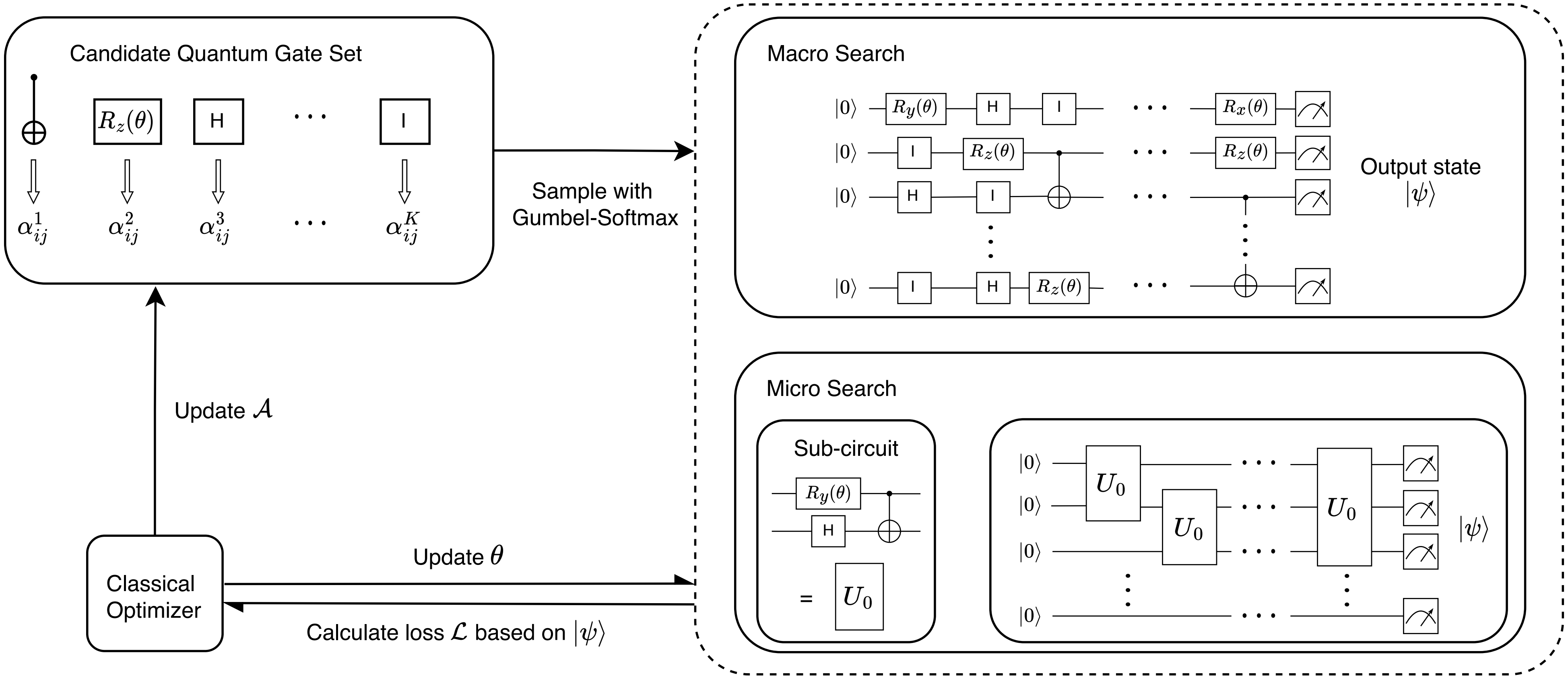
☐ Challenges

- The operation of sampling quantum circuits is not differentiable.
- The search space is too large, and comprised of both discrete and continuous space.

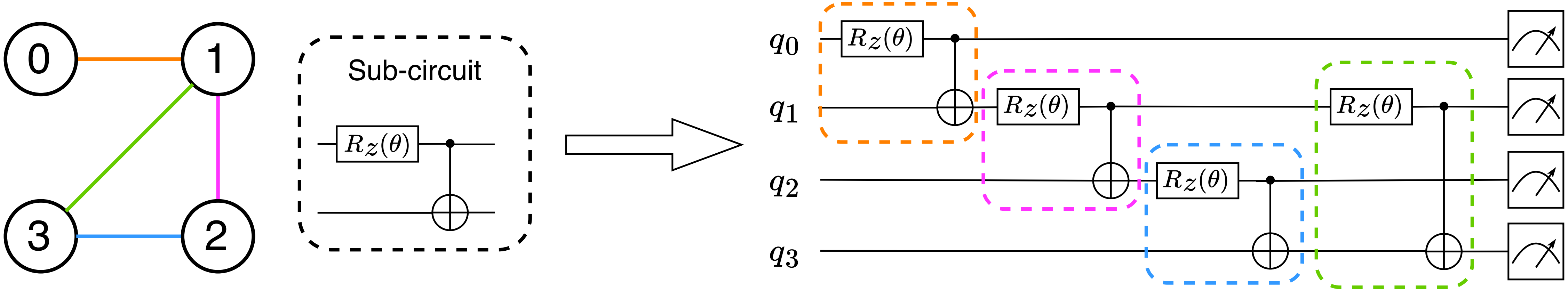
Method



- An end-to-end differentiable quantum architecture search framework prompted by the Gumbel-Softmax trick

Method

- An example of micro search for the Max-Cut problem.



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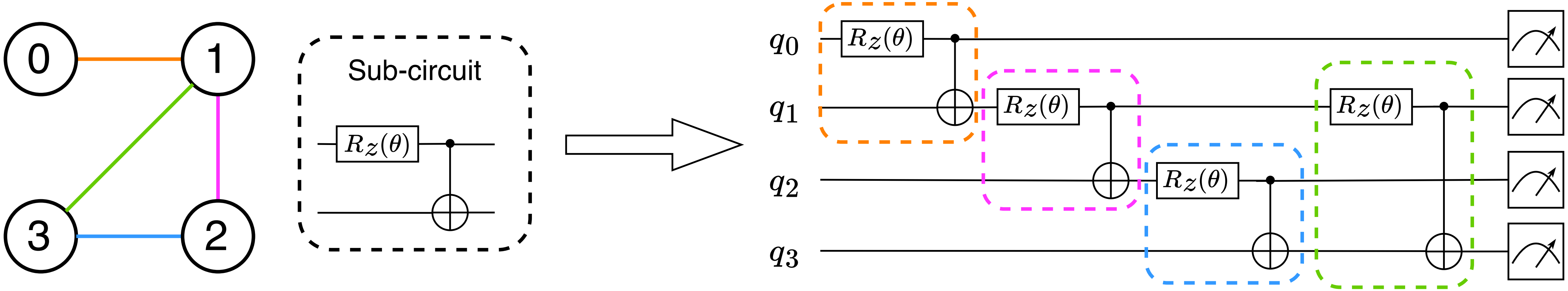
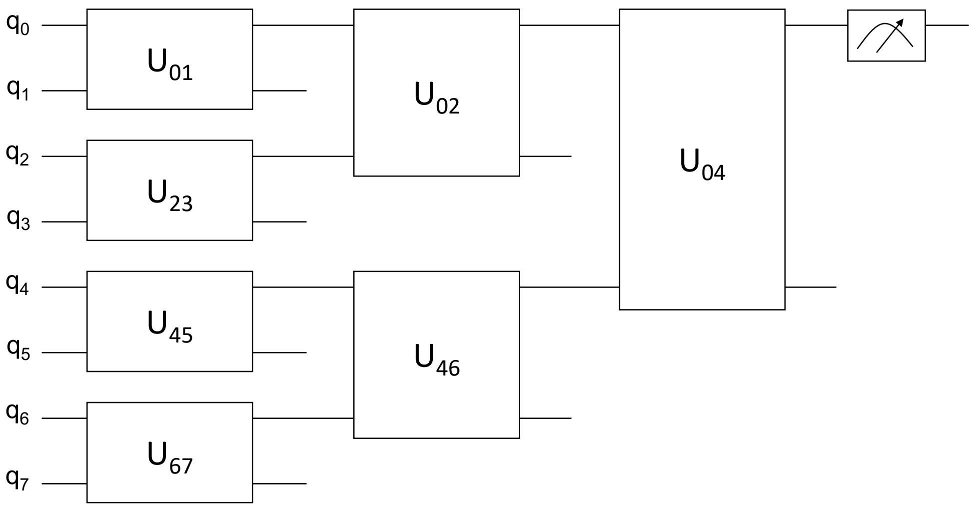
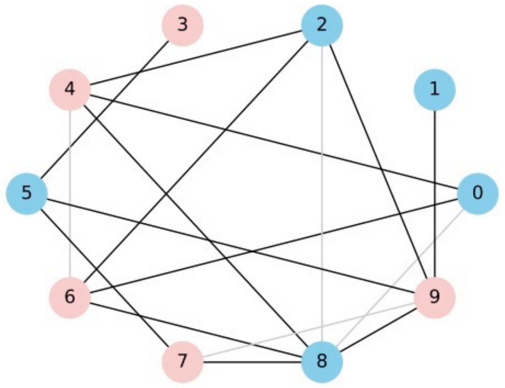


- An example of micro search for image classification.

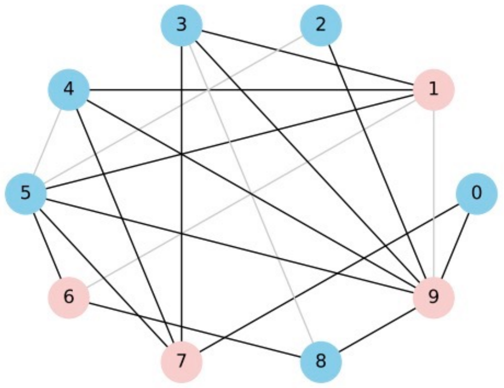


Experiments

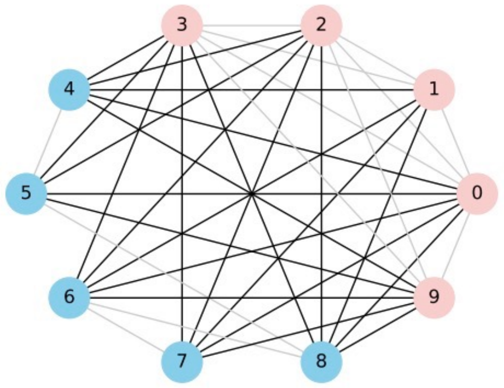
- Performance on Max-Cut (Macro Search and Micro Search)
  - Macro Search results



(a) $P_e = 0.25.$



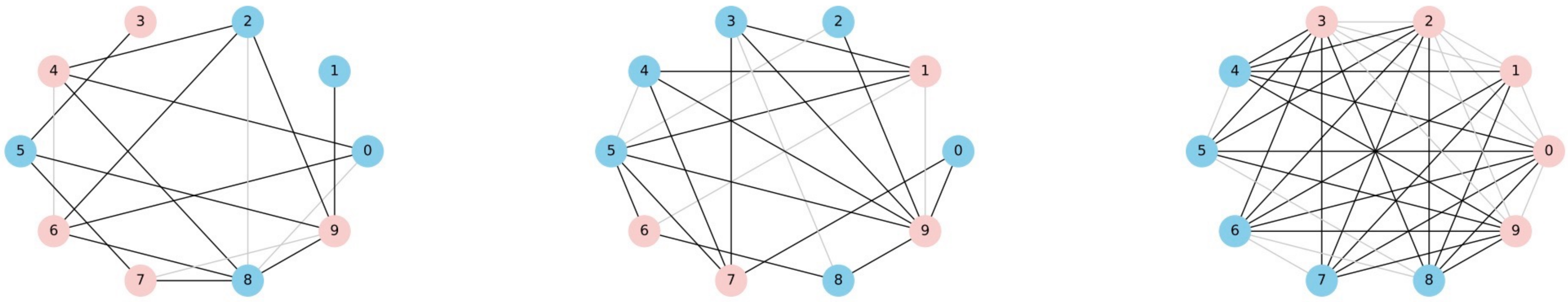
(b) $P_e = 0.50.$



(c) $P_e = 0.75.$

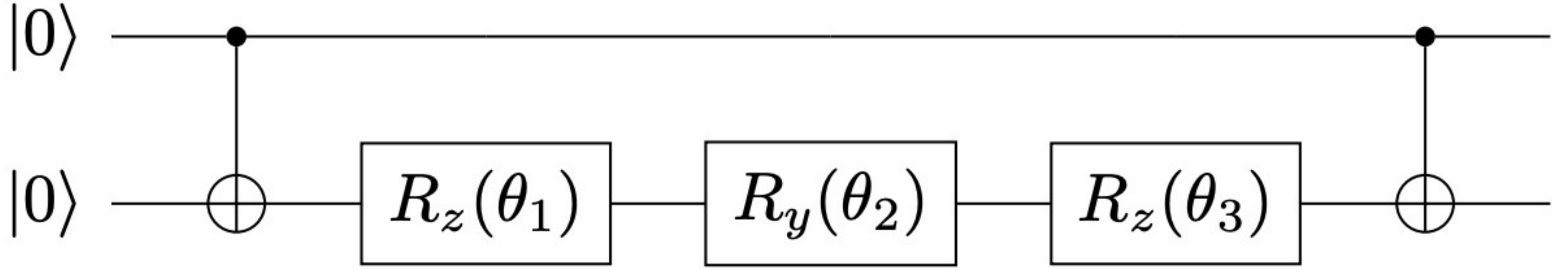
Experiments

- Performance on Max-Cut (Macro Search and Micro Search)
  - Macro Search results



(a) $P_e = 0.25$. (b) $P_e = 0.50$. (c) $P_e = 0.75$.

  - Micro Search results

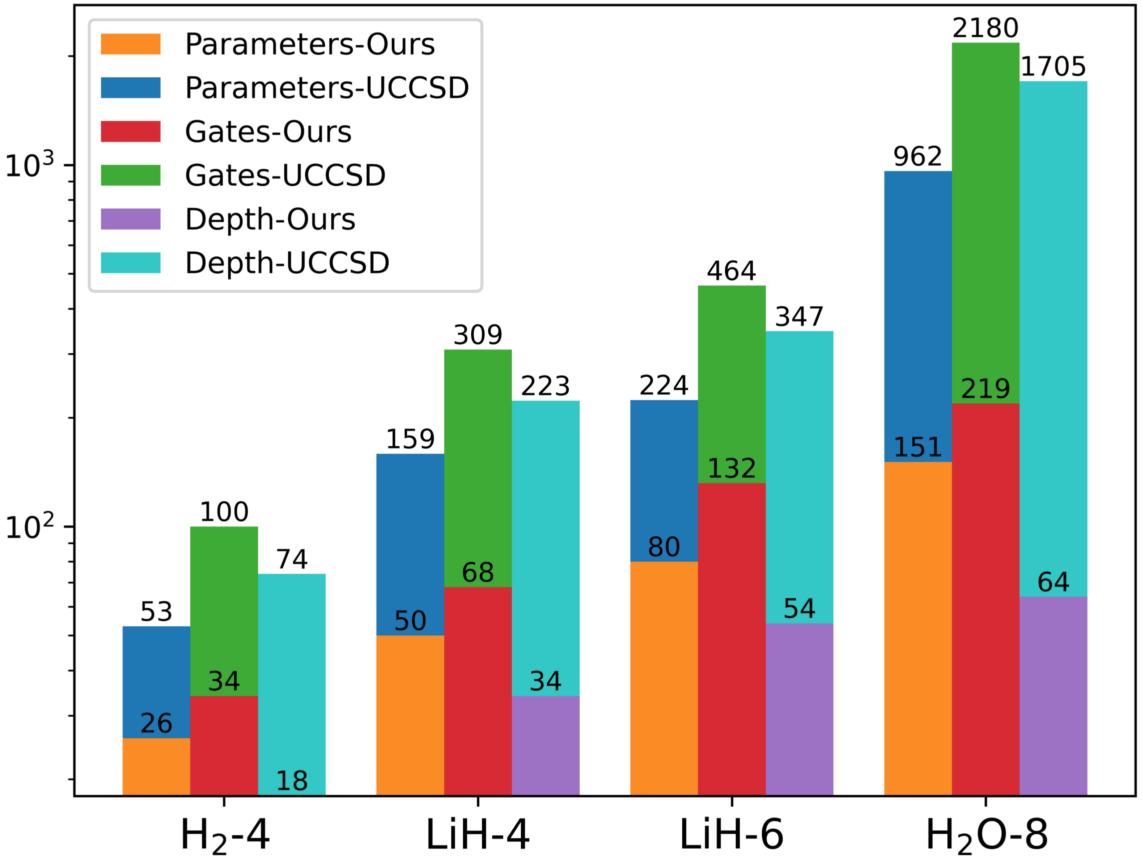


Experiments

- Performance on ground state energy estimation (Macro Search)

MODEL	H_2	LiH-4	LiH-6	H_2O-8
UCCSD	5.5×10^{-11}	4.0×10^{-5}	4.0×10^{-5}	4.0×10^{-6}
OURS	4.3×10^{-6}	1.7×10^{-4}	2.9×10^{-4}	3.1×10^{-4}
QCAS	2.2×10^{-2}	8.6×10^{-2}	7.3×10^{-2}	7.0×10^{-1}
DQAS	3.1×10^{-4}	5.3×10^{-4}	1.5×10^{-3}	5.2×10^{-1}
RS	1.9×10^{-2}	1.3×10^{-2}	6.2×10^{-3}	4.0×10^{-1}

- All the energy errors are lower than chemical accuracy.
- Energy errors are two orders of magnitude lower than those of other QAS methods in average.
- Circuit depth is about one order of magnitude lower than that of UCCSD.



Experiments

- Performance on image classification (Macro Search and Micro Search)