Quantum circuit architecture selection via local optimization towards quantum machine learning of chemical bond dissociation energy data

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Background

- n qubits $\rightarrow 2^n$ computational states
- quantum algorithms are operations on computational states



Background: Examples

 $|0\rangle, |1\rangle$ are orthogonal basis vectors of \mathbb{C}^2 : can consider the state

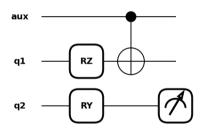
$$|\psi
angle=lpha\,|0
angle+eta|1
angle$$
 as $|\psi
angle=egin{bmatrix}lpha\eta\end{bmatrix}$

- **NOT** has matrix form $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$: maps basis $|0\rangle \to |1\rangle$, $|1\rangle \to |0\rangle$
- Hadamard is a single qubit operation that outputs a sum of both basis states

$$H=egin{bmatrix} rac{1}{\sqrt{2}} & rac{1}{\sqrt{2}} \ rac{1}{\sqrt{2}} & -rac{1}{\sqrt{2}} \end{bmatrix} \quad H|0
angle =rac{1}{\sqrt{2}}|0
angle +rac{1}{\sqrt{2}}|1
angle$$

Background

- Quantum circuit: a sequence of operations (rotations, entanglements) on quantum states
- Parametrized quantum circuit (PQC): a quantum circuit with operations depending on parameters (eg. rotation depending on θ)
- Quantum machine learning: applying a quantum circuit to a learning task. E.g. fitting a regressor via circuit implementation

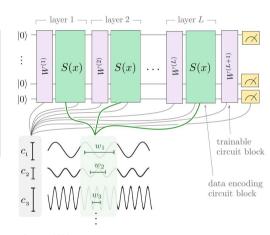


Regression PQC structure

- **1 Encoding**: data x embedded in quantum state via rotations S(x)
- **2 Param. Blocks**: embeddings S(x) entangled and rotated with parameters θ_i in block W_i
- Measurement: final state is measured

More encoding \rightarrow more Fourier terms.

$$f_{\theta}(x) = W_{L+1}S(x)W_{L}S(x)\cdots S(x)W_{1}$$

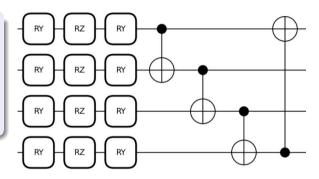


M. Schuld, 2020

How are W_i parametrized?

- follows a 'template' (ansatz) sequence of gates
- functional form f_{θ} determined by ansatz
- trainability, expressibility, generalizibility

 θ are optimized wrt. loss as in usual ML



Hardware efficient ansatz block (HWE) in a 4 qubit system.

Project Goals

- Develop framework for architecture selection in quantum regression models
- Ensure scalability, flexibility, generalization
- Apply to BSE49 chemical dataset on larger qubit system

Strategy

The gate sampling strategy is parametrized by four actions

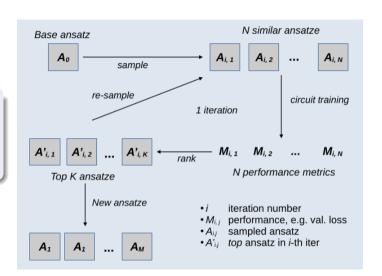
• p_{add}: addition

p_{remove}: removal

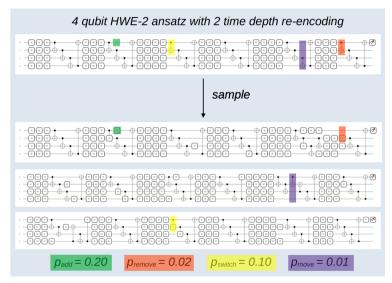
p_{switch}: gate switch

• *p_{move}*: wire change

Probabilities may be decayed during training, number of samples controlled.



4 Qubit HWE-2 sampling



Data Application

The framework is used for circuit selection in

- **4 Qubit Noisy quadratic:** $y = ||x||^2 + \epsilon, x \in (-2, 2)^4, \epsilon \sim N(0, 0.5^2)$
- **2 16 Qubit BSE49**: featurized bond separation energy dataset



Homolytic bond separation

Comparison

Local framework

- slightly modifies base ansatz
- sampling occurs locally
- flexible number of circuit executions
- iteration and algorithm level changes from base controlled
- no meta learning required
- unseen gate types in base may be incorporated

Other approaches

- aims for best global ansatz
- involves random sampling from exponential search space
- GNN-based approaches require non-sparse training data
- involves meta-learning (model on a model), incorporating lots of noise

Outlook

- local framework applicable to a general PQC task
- flexible, scalable, lots of control over computing resources
- a step towards automated circuit design for regression in quantum chemistry

Acknowledgements









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