

HPCA 2025 Tutorial

Topic 2. QuCT: A Framework for Analyzing Quantum Circuit by Extracting Contextual and Topological Features







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https://janusq.github.io/HPCA_2025_Tutorial/

Outline of Presentation





Background and challenges

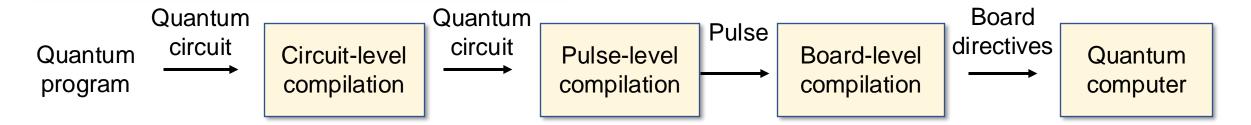
- QuCT overview
- Upstream model: Circuit feature extraction
- Downstream model 1: Circuit fidelity prediction
- Downstream model 2: Unitary decomposition

Background





Compilation of a quantum program



Circuit-level compilation:

Input: quantum circuit
 Output: Quantum circuit that satisfies the constraints

Pulse-level compilation:

Input: quantum circuit
 Output: Pulses received by qubits

Board-level compilation:

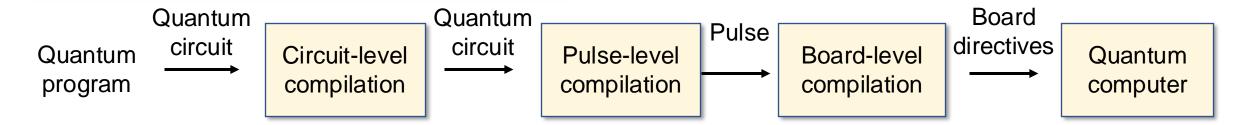
Input: pulses
 Output: Board directives

Background

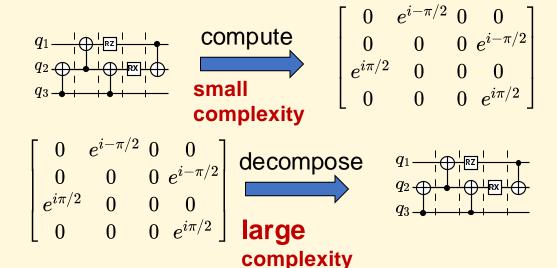




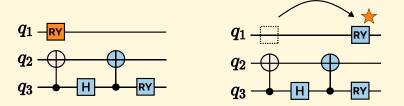
Key passes of quantum circuit compilation



Pass 1: Unitary decomposition



Pass 2: Fidelity prediction and optimization



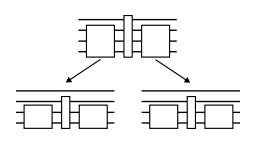
Optimize the noise while keeping the equivalence of circuits

Challenges of Unitary Decomposition





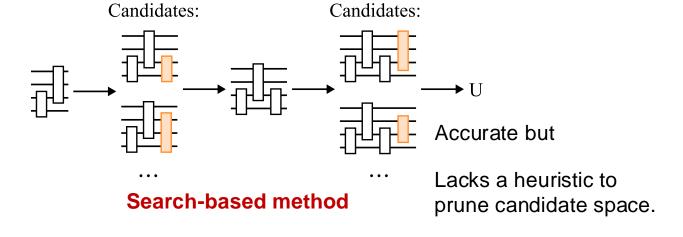
Unitary decomposition



Template-based method

Fast but

Leads to numerous redundant gates



Category	Template-based		Search-based	
Method	CCD [1]	QSD [2]	QFAST [3]	Squander [4]
Time	3.6 s	2.1 s	511.2 h	426.2 h
#Gate	3,592	3,817	806	887
	O(4 ^N) #Gate		O(4N) Time	

5-qubit unitary decomposition

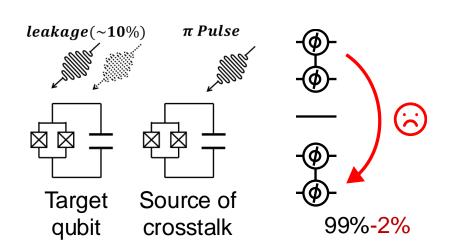
- [1] R. Iten, et al. PRA. 2016
- [2] V. Shende, et al. ASP-DAC. 2005
- [3] E. Younis, et al. QCE. 2021.
- [4] P. Rakyta, et al. Quantum, 2022

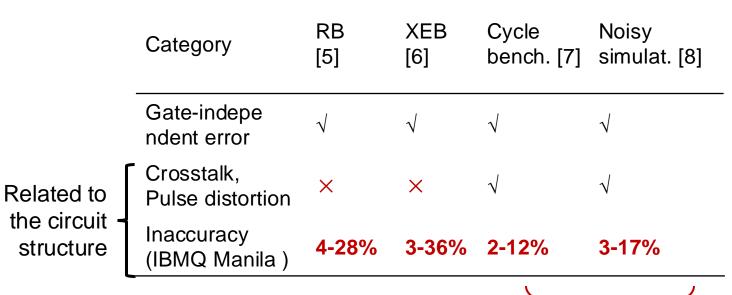
Challenges





Fidelity prediction





Fidelity prediction

Not one-shot

- [5] E. Knill, et al. D. PRA. 2008.
- [6] F. Arute, et al. Nature. 2019
- [7] A. Erhard, et al. Nature communications. 2019
- [8] Isakov, et al ArXiv. 2021.

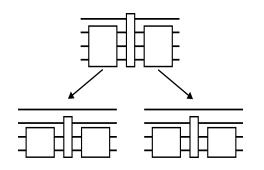
Current Compilation Methods





Unitary decomposition

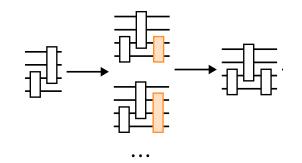
Template-based method



Fast by not accurate:

10-qubit unitary -> 20,000 gate

Search-based method



Accurate but slow:

10-qubit unitary-> one year

Fidelity prediction

Method	Independ ent noise	Depende nt noise	Inaccuracy
RB	$\sqrt{}$	×	4-28% Fast by inaccurate:
XEB	$\sqrt{}$	×	3-36% cannot model dependent noise
СВ	$\sqrt{}$	\checkmark	2-12% Accurate but slow:
Noisy Simulat.	√	$\sqrt{}$	require repeated executions

They face a trade-off between the efficiency and accuracy

Outline of Presentation





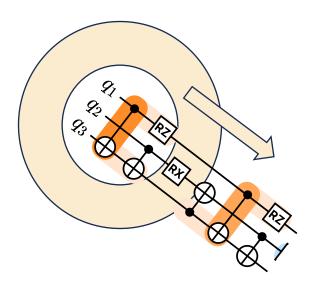
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Origin of the name



Computerized Tomography

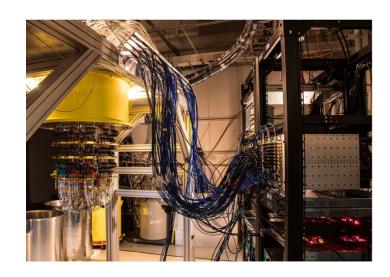


Analyzing Quantum Circuit by Contextual and Topological Features

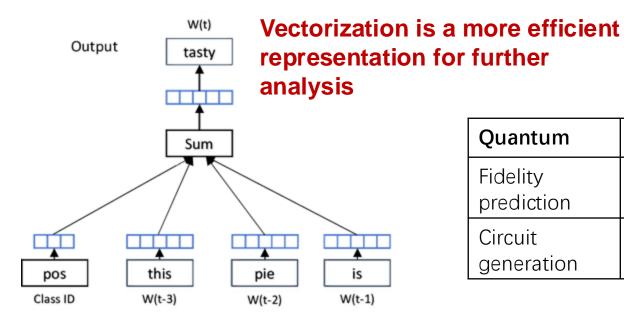
QuCT Insight



Solution: Implement circuit topology and context-aware gate vectorization



Quantum circuits are implemented via pulses. There are interactions between wirings of qubits.



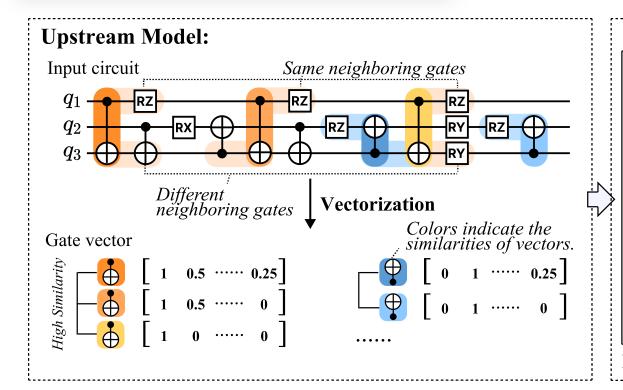
extraction Context is common in natural language processing (NLP) and classical program analysis

Quantum	NLP	
Fidelity	grammar	
prediction	analysis	
Circuit	Test	
generation	generation	

Quantum program analysis and NLP have similar tasks



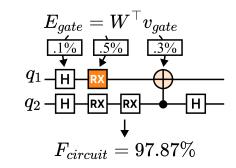
Each model is one-shot generated



Downstream Model:

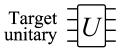
Circuit Fidelity Prediction

a) Circuit fidelity prediction



b) Compilation- and calibration-level optimizations

Unitary Decomposition



 $\downarrow U2V model$

Vectors serve as search candidates

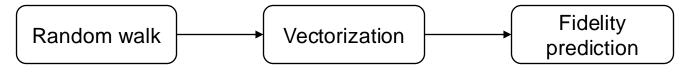
$$v_1 = [...] v_2 = [...]$$

$$\downarrow Reconstruct$$





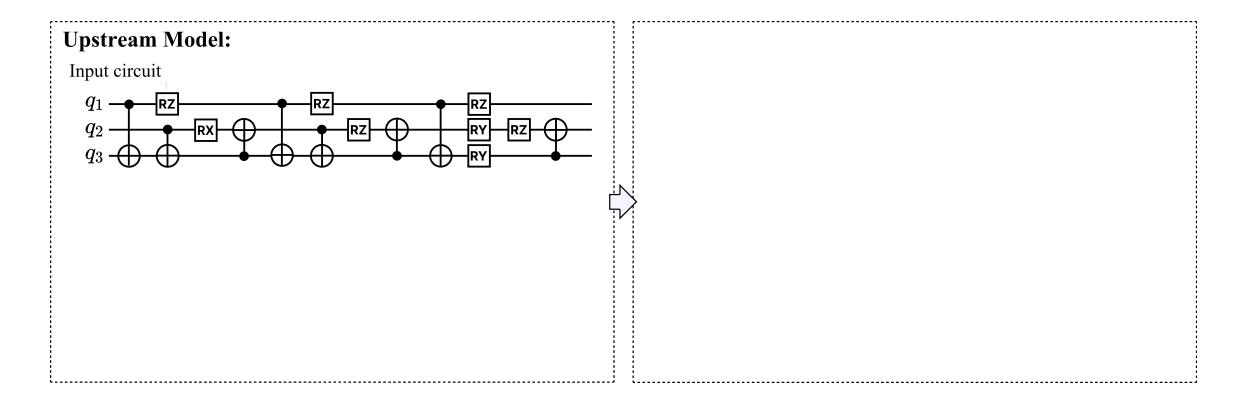
More tasks: gate cancellation, bug detection ···



or

Unitary decomposition

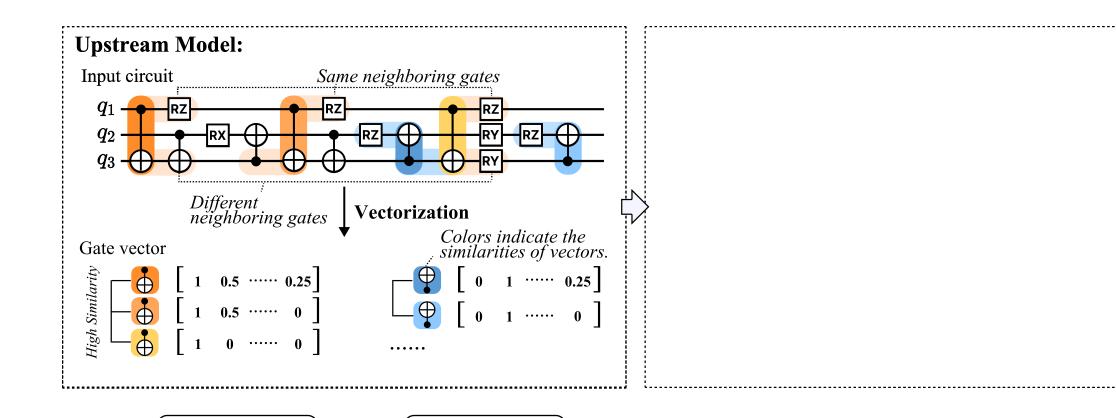




Random walk

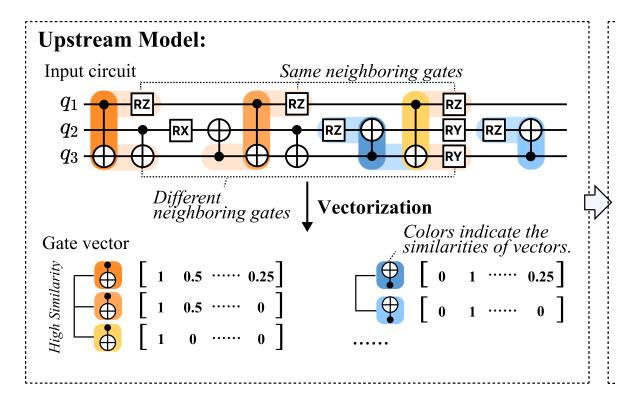
Random walk





Vectorization

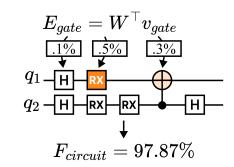




Downstream Model:

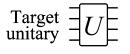
Circuit Fidelity Prediction

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Unitary Decomposition



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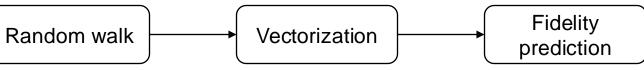
$$v_1 = [...] v_2 = [...]$$

$$\downarrow Reconstruct$$





More tasks: gate cancellation, bug detection ···



or

Unitary decomposition

Outline of Presentation

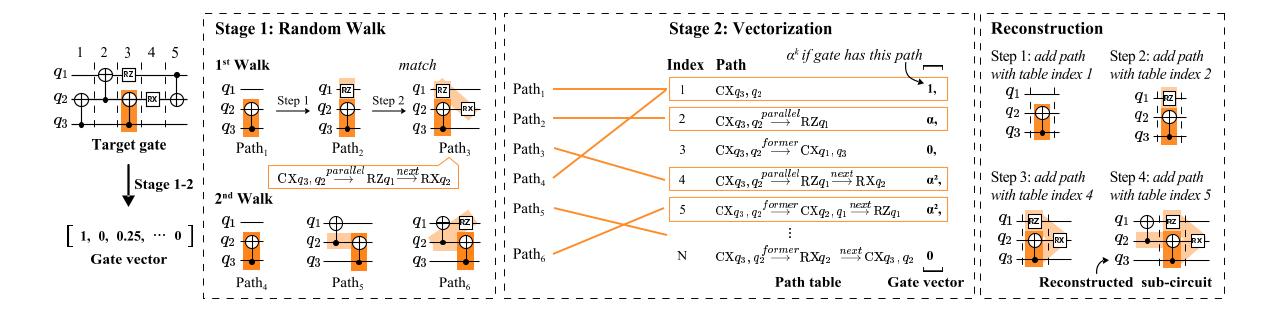




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- Experiment





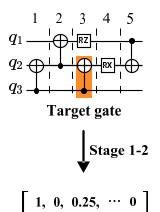






Two-step vectorization flow

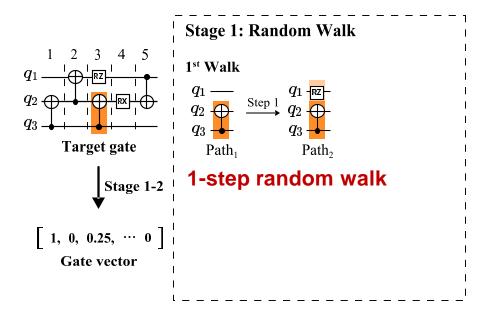
For each gate



Gate vector



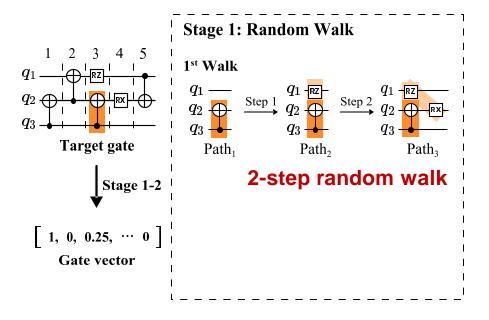




Step 1: Extract features as paths.



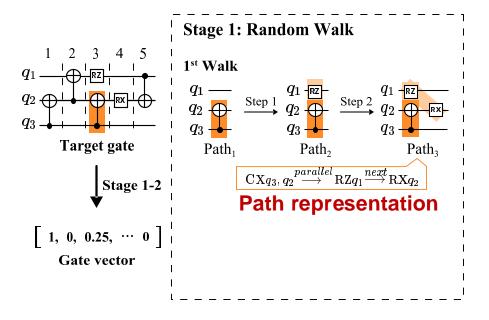




Step 1: Extract features as paths.



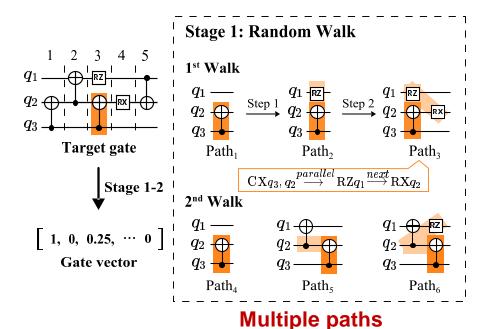




Step 1: Extract features as paths.





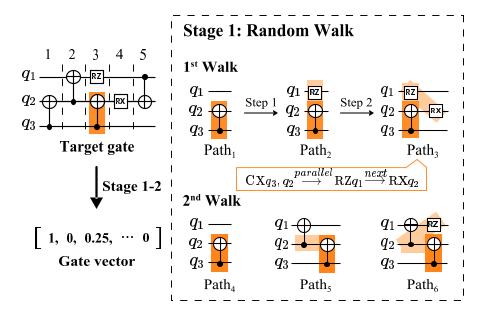


Step 1: Extract features as paths.





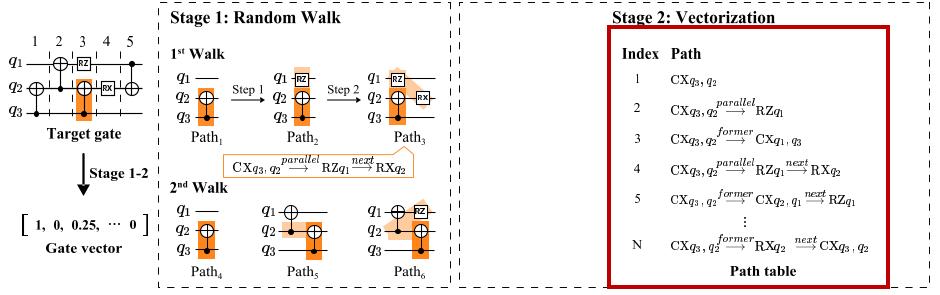
Two-step vectorization flow







Two-step vectorization flow

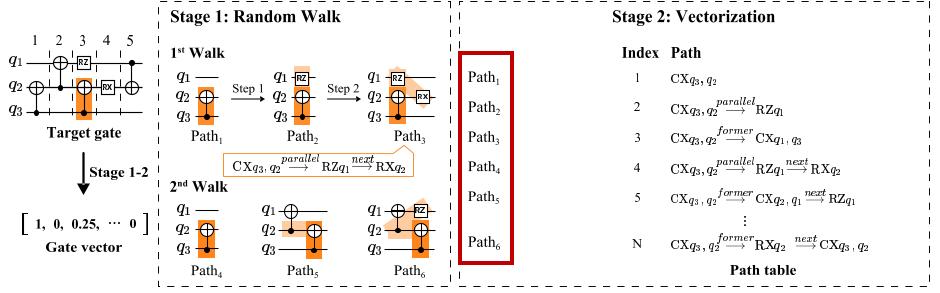


Pre-generated





Two-step vectorization flow



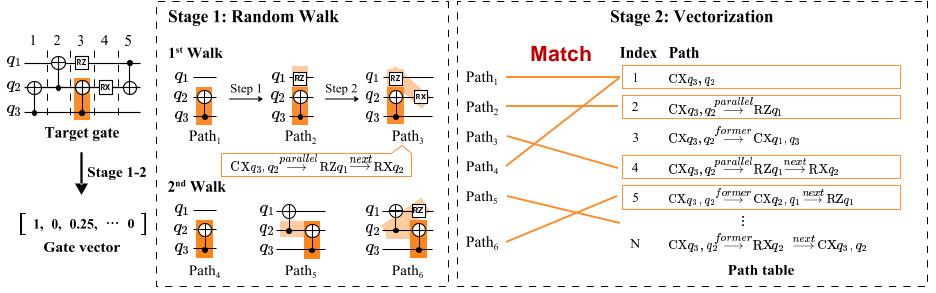
From random walk

Pre-generated





Two-step vectorization flow



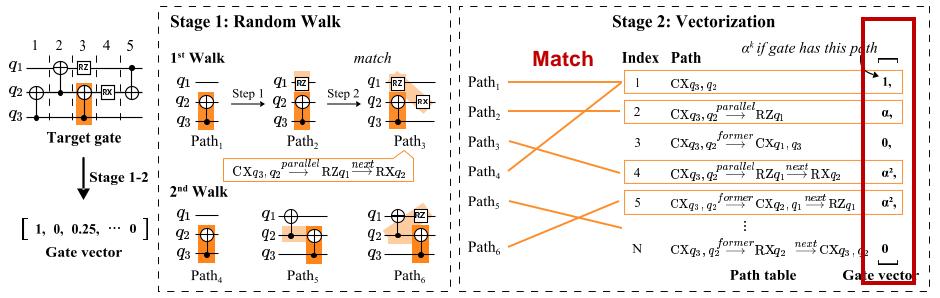
From random walk

Pre-generated





Two-step vectorization flow



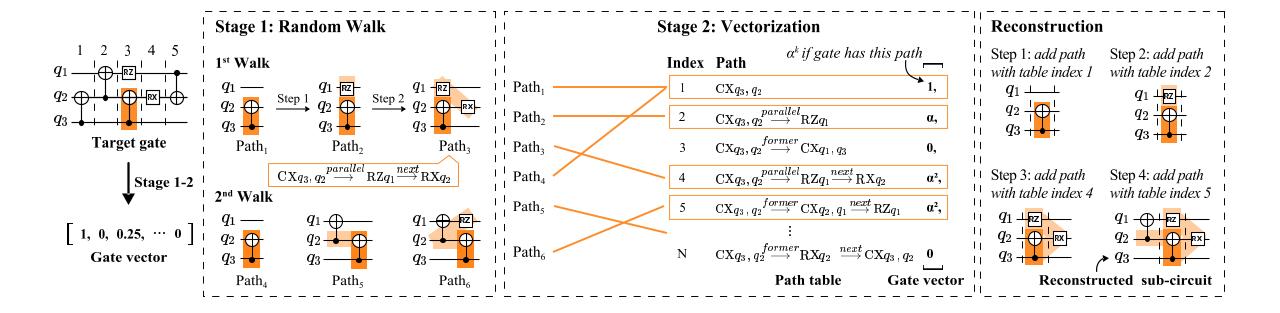
From random walk

Pre-generated





Two-step vectorization flow



Reconstruct circuit.

API to Construct Upstream Model





File:

- JanusQ/examples/ipynb/2_1_vectorization.ipynb
- https://janusq.github.io/tutorials/demo/2_1_vectorization

```
from janusq.analysis.vectorization import RandomwalkModel
                      from janusq.objects.backend import GridBackend
                      from janusq.objects.random_circuit import random_circuits
                      # define the information of the quantum device
define backend
                      n_qubits = 6
                       backend = GridBackend(2, 3)
                      # generate a dataset including varous random circuits
generate fidelity
                      circuit_dataset = random_circuits(backend, n_circuits=100, n_gate_list=[30, 50, 100],
                      two_qubit_prob_list=[.4], reverse=True)
                      # apply random work to consturct the vectorization model with a path table
                      n_{steps}, n_{walks} = 1, 100
construct model
                      up_model = RandomwalkModel(n_steps = n_steps, n_walks = n_walks, backend = backend,
  using random
                      decay= 0.5, circuits = circuit dataset)
           walk
                      up_model.train(circuit_dataset, multi_process=False)
```

Outline of Presentation





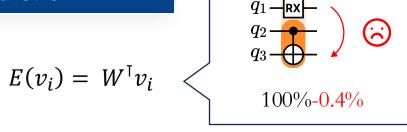
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Downstream Model 1: Circuit Fidelity Prediction



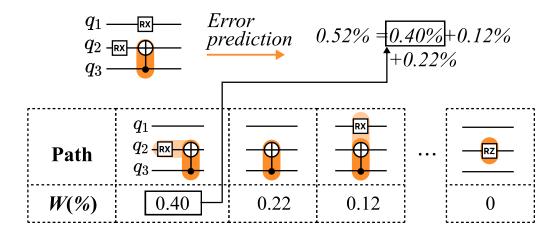


Gate error prediction



Model dependent error

 v_i : gate vector. W: weight vector obtained via training.



Downstream Model 1: Circuit Fidelity Prediction





Gate error prediction

$$E(v_i) = W^{\mathsf{T}} v_i$$

 v_i : gate vector. W: weight vector obtained via training.

Circuit fidelity prediction

$$F_{circuit} = \prod_{g_i \in G} (1 - E(v_i)) \prod_{q \in Q} MF_q$$

G: gate set, Q: qubit set, MF_q : measurement fidelity

The probability that all gates are correct.

Downstream Model 1: Circuit Fidelity Prediction





Gate error prediction

$$E(v_i) = W^{\mathsf{T}} v_i$$

 v_i : gate vector. W: weight vector obtained via training.

Circuit fidelity prediction

$$F_{circuit} = \prod_{g_i \in G} (1 - E(v_i)) \prod_{q \in Q} MF_q$$

G: gate set, Q: qubit set, MF_q : measurement fidelity

Training process of weight vector W:

Obtain fidelity dataset (circuit, $F_{ground-truth}$) ..., $F_{ground-truth}$: ground-truth circuit fidelity on the target quantum device.

$$\min_{W} |F_{circuit} - F_{ground-truth}|$$

Minimize the distance between the prediction and ground-truth fidelity.

API to Construct Fidelity Prediction Model





File:

- JanusQ/examples/ipynb/2_2_fidelity_prediction_simulator.ipynb
- https://janusq.github.io/tutorials/demo/2_2_fidelity_prediction_simulator

```
from janusq.objects.backend import FullyConnectedBackend from janusq.analysis.fidelity_prediction import FidelityModel

circuits, fidelities = real_qc_5bit backend = FullyConnectedBackend(5) up_model = RandomwalkModel(n_steps = 1, n_walks = 10, backend = backend, circuits = circuits)

construct fidelity { fidelity_model = FidelityModel(up_model) fidelity_model.train((circuits, fidelities), multi_process = False)

predict the fidelity of the given circuit { circuit = random_circuit(backend, n_gates = 100, two_qubit_prob = 0.5) fidelity_model.predict_circuit_fidelity(circuit)
```

from janusq.dataset import real qc 5bit

Outline of Presentation





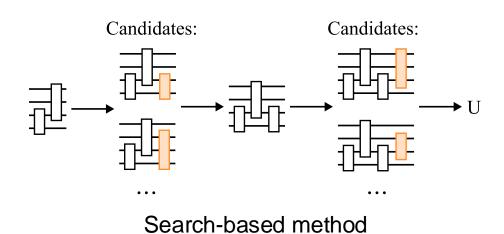
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Downstream Model 2: Unitary Decomposition





Improve the current search-based method



Category	Template-based		Search-based	
Method	CCD [1]	QSD [2]	QFAST [3]	Squander [4]
Time	3.6 s	2.1 s	511.2 h	426.2 h
#Gate	3,592	3,817	806	887

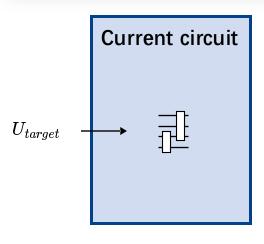
5-qubit unitary decomposition

Downstream Model 2: Unitary Decomposition





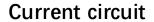
QFAST workflow



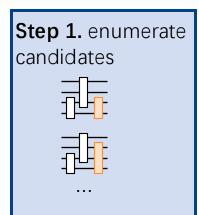




QFAST workflow







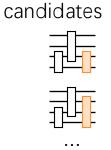


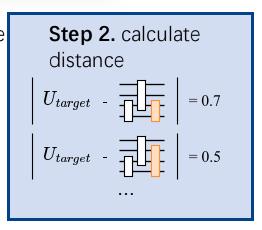


QFAST workflow

Current circuit Step 1. enumerate

 $U_{target} \longrightarrow$







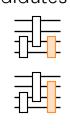


QFAST workflow

Current circuit

Step 1. enumerate candidates





Step 2. calculate distance

Step 3. pick best candidate







QFAST workflow

Current circuit

Step 1. enumerate candidates





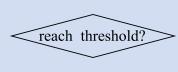
e **Step 2.** calculate distance

$$U_{target}$$
 - $= 0$.

te **Step 3.** pick best candidate



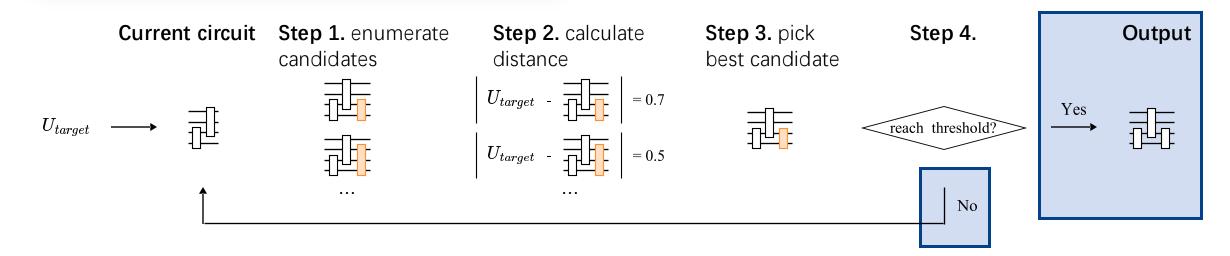
Step 4.







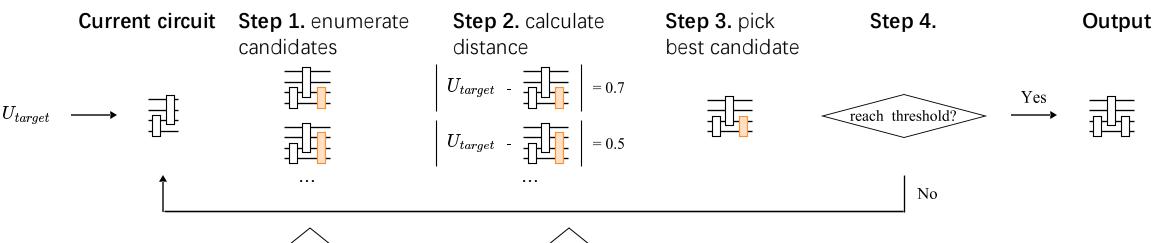
QFAST workflow

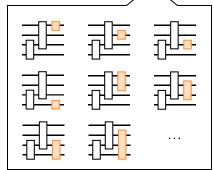




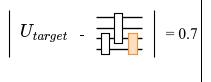


QFAST workflow





248 candidates for 8 qubits



high computation cost

60s/candidate

thousands of iterations take more than 6 months





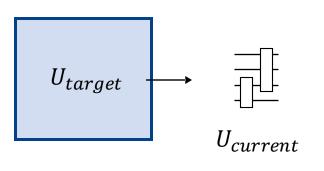
QuCT workflow

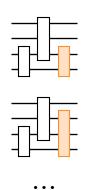


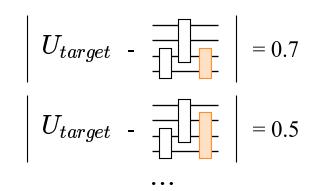
Step 1. enumerate candidates

Step 2. calculate distance







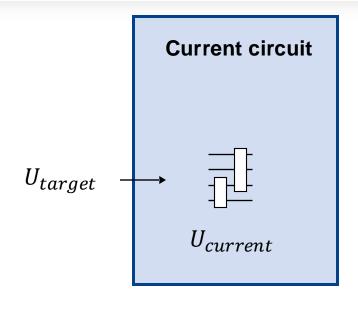


Candidates and should equal $U_{target}U_{current}^{-1}$

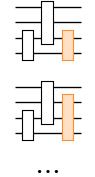




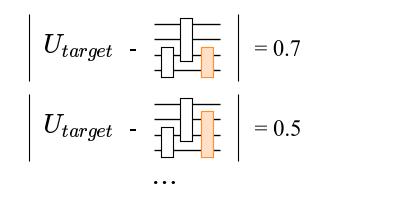
QuCT workflow



Step 1. enumerate candidates



Step 2. calculate distance



Candidates and should equal
$$U_{target}U_{current}^{-1}$$

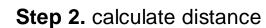




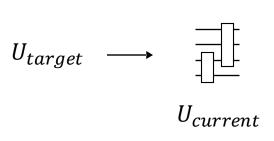
QuCT workflow

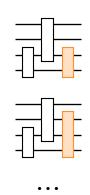


Step 1. enumerate candidates









Candidates and should equal $U_{target}U_{current}^{-1}$





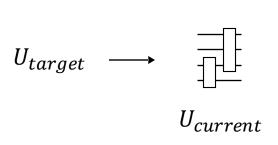
QuCT workflow

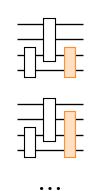


Step 1. enumerate candidates

Step 2. calculate distance

...





$$igg| U_{target} - igg| = 0.7$$
 $igg| U_{target} - igg| = 0.5$

Candidates and should equal $U_{target}U_{current}^{-1}$

Instead of exhaustive search, QuCT only try the candidates that have high probability of equaling $U_{target}U_{current}^{-1}$





QuCT workflow

$$U_{target}U_{current}^{-1}$$

↓ U2V model

Gate vectors serve as search candidates

$$v_1 = [...]$$
 $v_2 = [...]$

Reconstruct





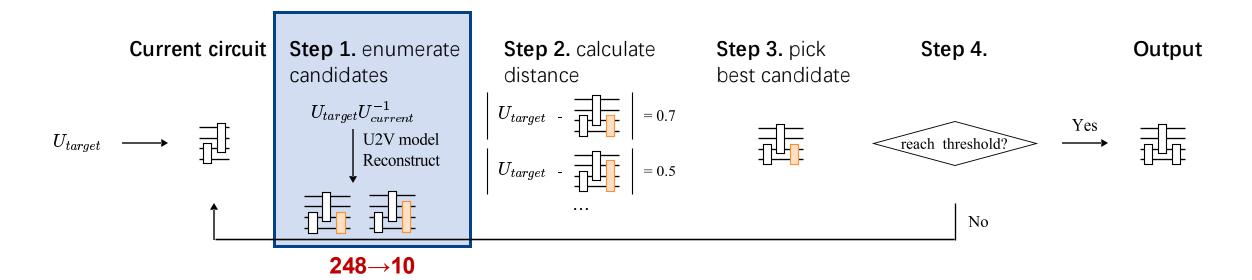
U2V model: a random forest model, trained by the pre-generated decomposition results.

Use gate vectors to construct good candidates.





QuCT workflow



Comparison to the template-based method: template-based approach has smaller design space, as it can only selects candidates from a limited-size template library.

 $1.8 \times$ speedup and $1.6 \times$ gate reduction compared to the template-based method.

API to Construct Unitary Decomposition Model





File:

- JanusQ/examples/ipynb/2_5_unitary_decomposition.ipynb
- https://janusq.github.io/tutorials/demo/2_5_unitary_decomposition

```
from giskit.guantum info import random unitary
                          from janusq.objects.backend import FullyConnectedBackend
                          from janusq.analysis.unitary decompostion import U2VModel
                          from janusq.analysis.unitary decompostion import decompose
                          backend = FullyConnectedBackend(n_qubits=5)
       construct the
      decomposition
                          dataset = random_circuits(backend = backend, n_circuits=50, n_gate_list=[30, 50, 100],
             dataset
                          two_qubit_prob_list=[.4], reverse=True)
                          up_model = RandomwalkModel(n_step, 4 ** n_step, backend, directions=('parallel', 'next'))
                          u2v_model = U2VModel(up_model)
    construct unitary
decomposition model
                          data = u2v_model.construct_data(dataset, multi_process=False)
                          u2v_model.train(data, n_qubits)
                          unitary = random_unitary(2**n_qubits).data
apply decomposition
                          decompose(unitary, allowed_dist = 0.01, backend = backend, u2v_model = u2v_model,
   to random unitary
                          multi_process = True)
```

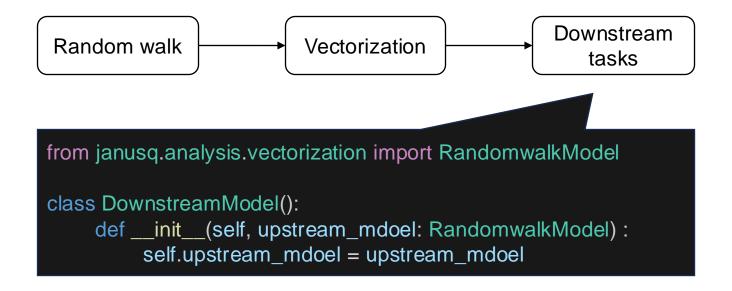
Extending QuCT To More Downstream Tasks





File:

- JanusQ/examples/ipynb/2_6_extend_framework_bug_identification.ipynb
- https://janusq.github.io/tutorials/demo/2_6_extend_framework_bug_identification



Downstream task implementation

Extending QuCT To More Downstream Tasks



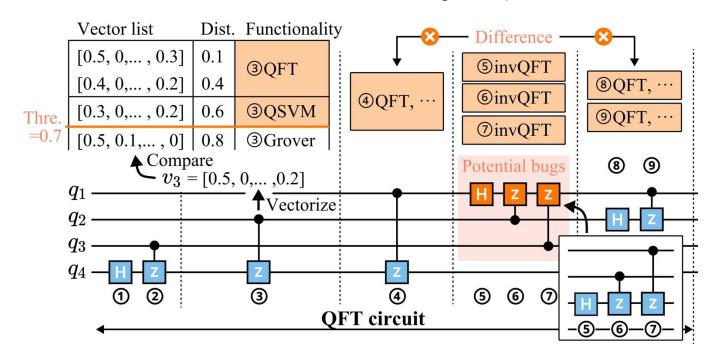


File:

- JanusQ/examples/ipynb/2_6_extend_framework_bug_identification.ipynb
- https://janusq.github.io/tutorials/demo/2_6_extend_framework_bug_identification

For example: Bug Identification

- 1. Identify the possible functionality
- 2. Identify the abnormal functionality (different from neighbors)

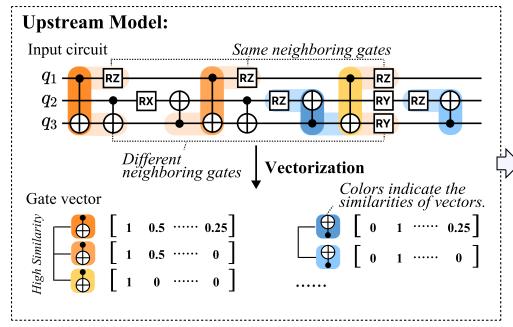


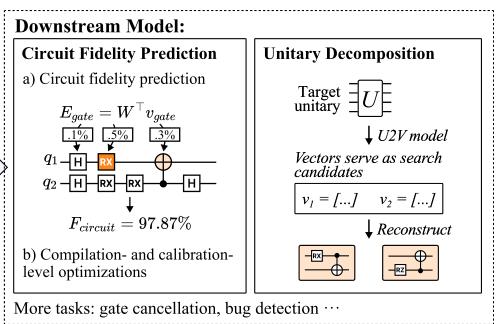
Conclusion





- Random walk-based method to extract contextual and topological circuit feature.
- Accurate circuit fidelity prediction via modeling gate interactions.
- Fast unitary decomposition via pruning candidate space.







Thanks for listening

QuCT: A Framework for Analyzing Quantum Circuit by Extracting Contextual and Topological Features

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