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Torch Quantum

QuantumNAS: Noise-Adaptive Search for Robust Quantum Circuits using GPUs

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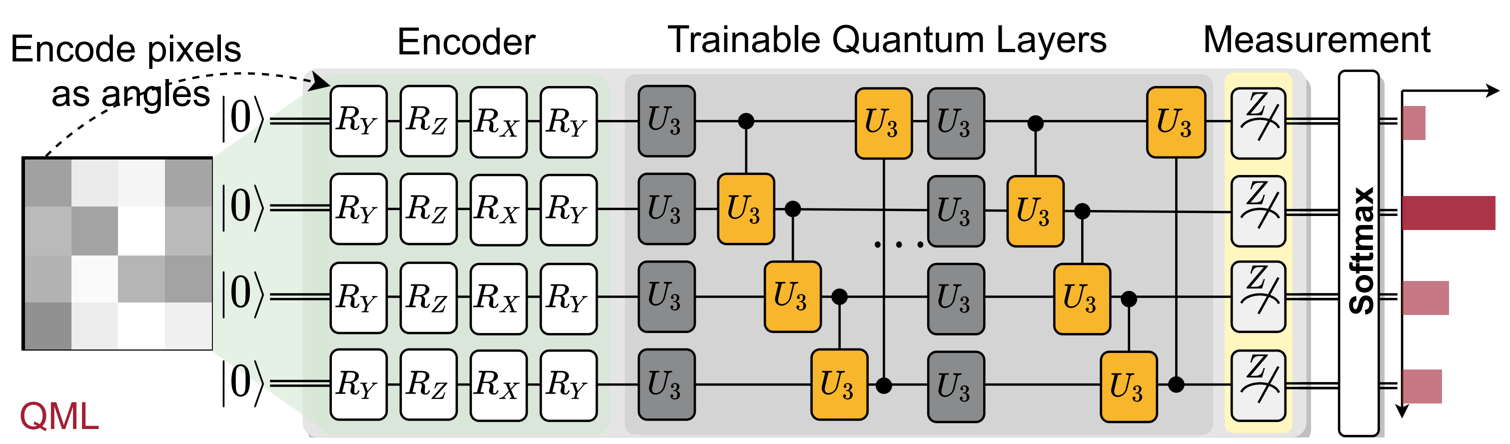
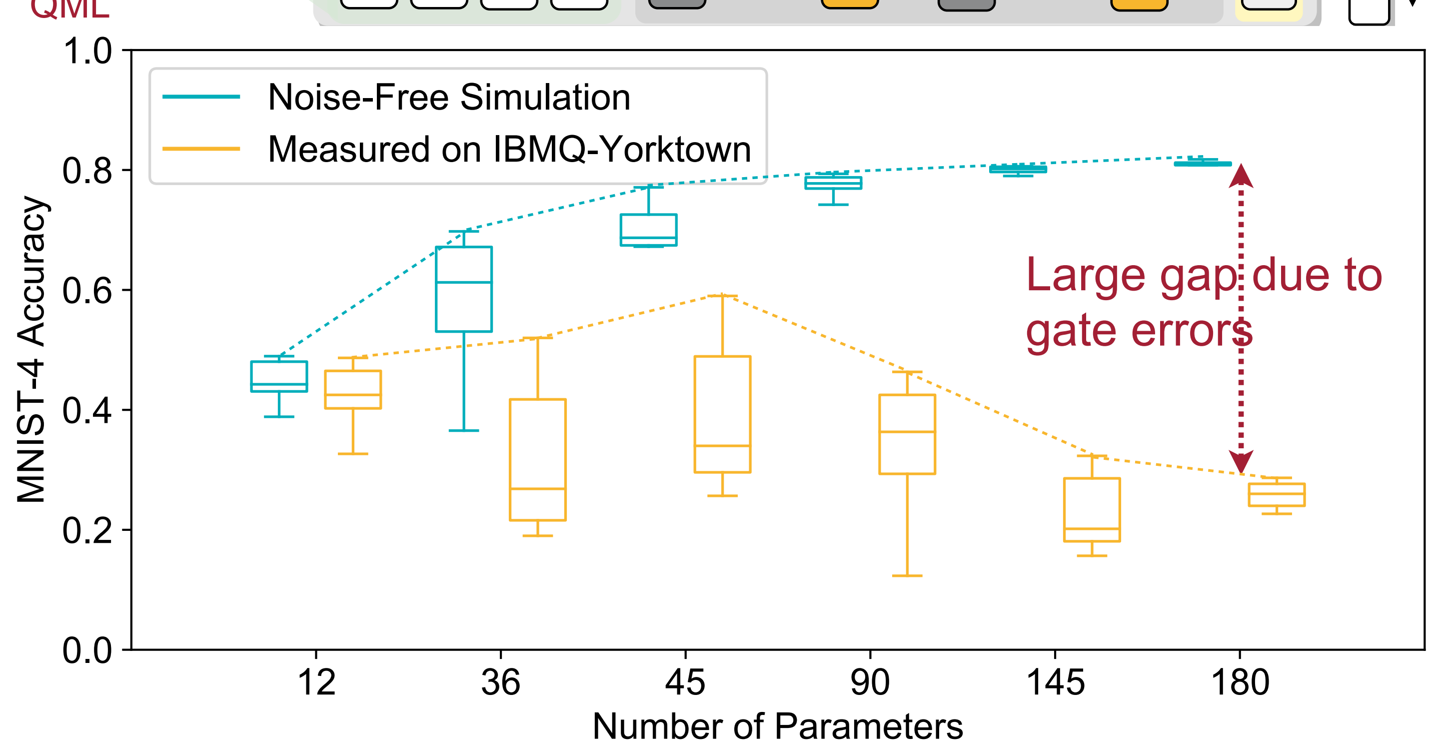
Abstract

- A framework to search for the most **noise-robust** circuit ansatz and corresponding qubit mapping for **parameterized quantum circuits**.
- **SuperCircuit** based efficient search
- Demonstrate over 95% 2-class, 85% 4-class, and 32% 10-class classification accuracy on **real** quantum computers; Achieves the lowest eigenvalue for VQE tasks on H_2, H_2O, LiH, CH_4, BeH_2 compared with UCCSD baselines
- Open-source our **TorchQuantum** library for **training Quantum Circuits using GPUs**

Background and Motivation

- Example Quantum Neural Networks architecture for **image classification**
- Contains encoder, trainable quantum layers, measurement

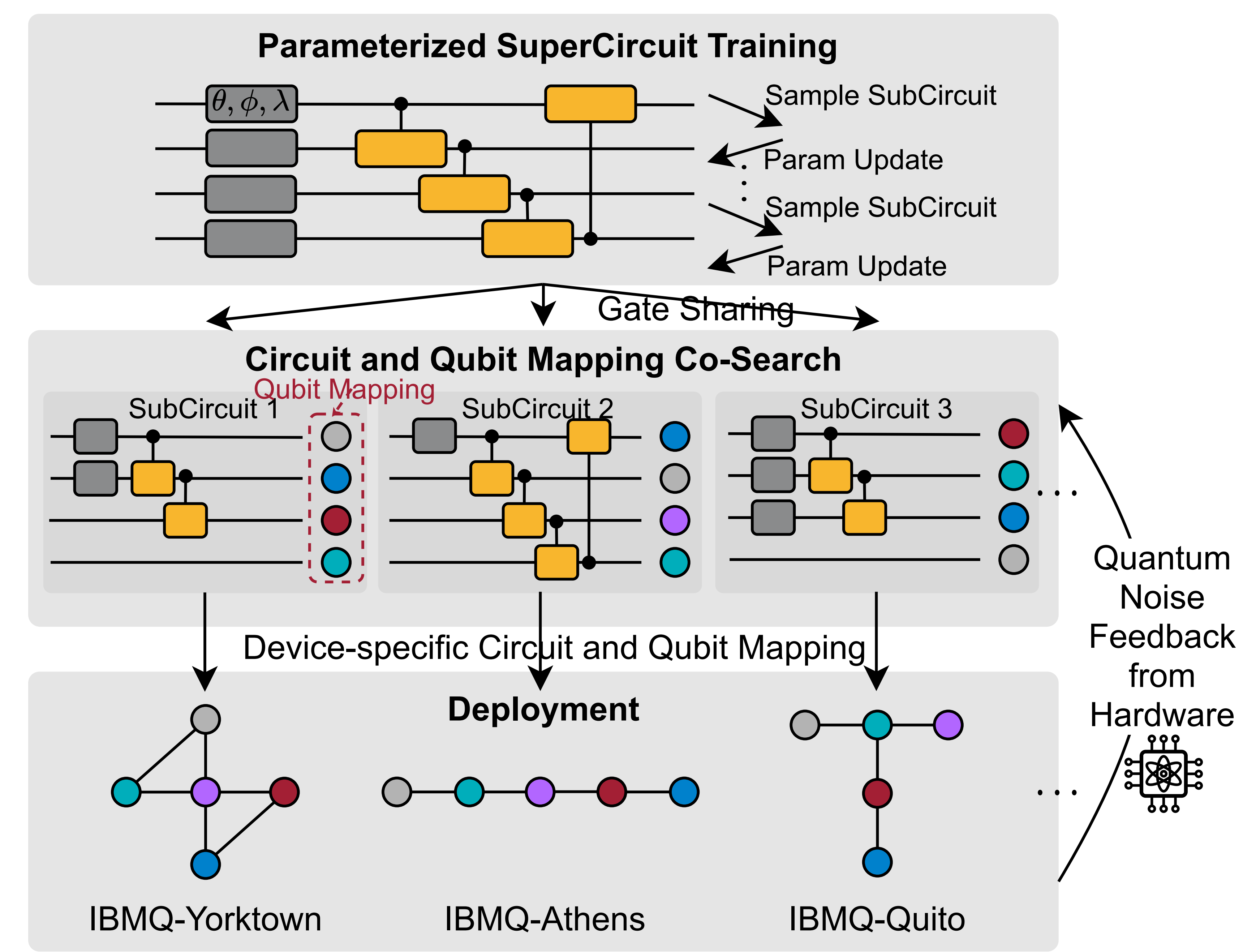




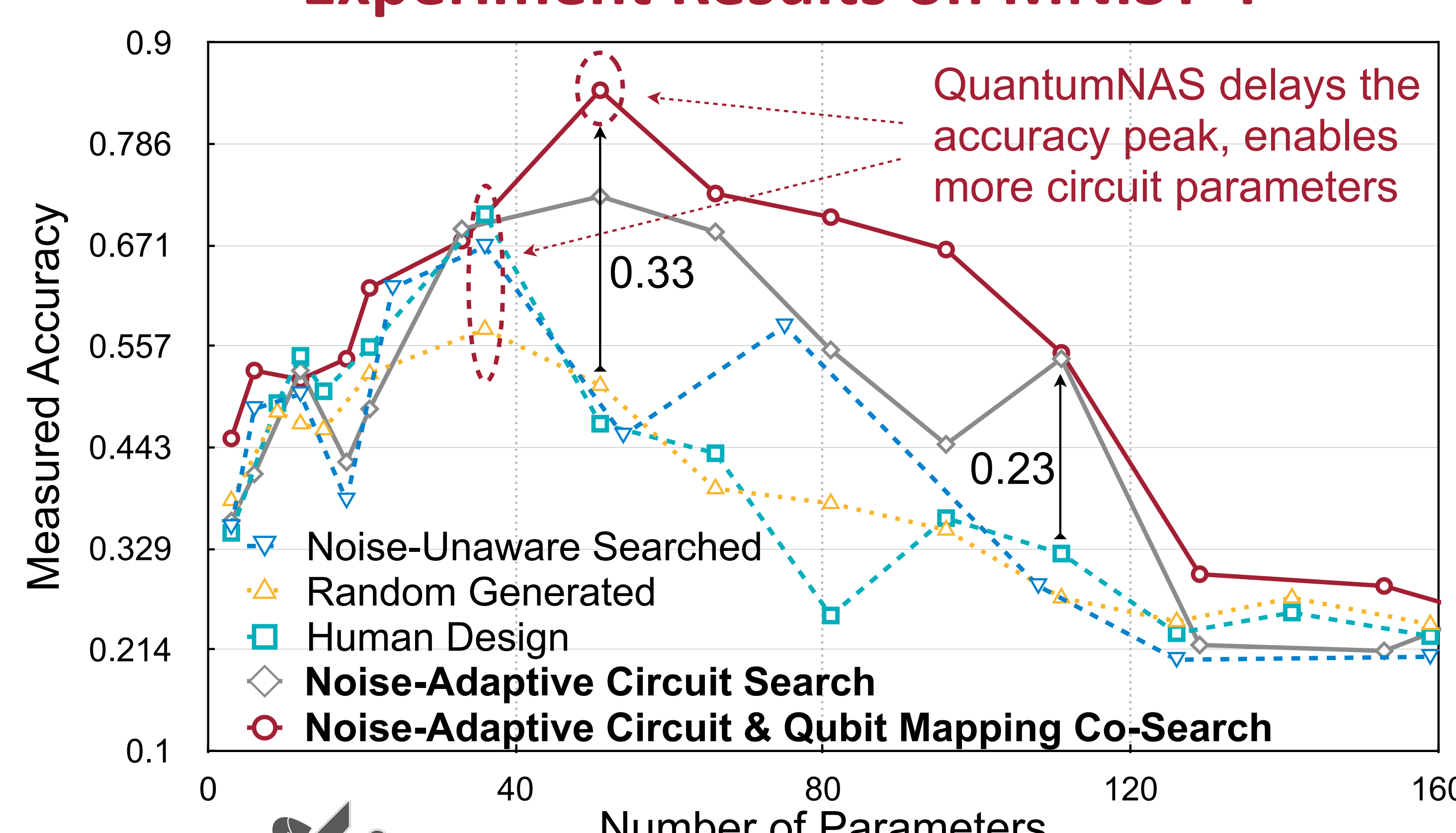
- A **large gap** between noise-free simulation and real deployment due to quantum noises (errors)
- More parameters increase the noise-free accuracy but **degrade measured accuracy**
- Quantum noises exacerbate the performance **variance**

Search for Robust Quantum Circuit and Qubit Mapping

- Step 1: Train a gate-sharing supernet named '**SuperCircuit**' to include numerous QNN architectures
- Step 2: Perform an evolutionary search **with real hardware feedback** to find the most robust model architecture and its qubit mapping
- Step 3: Train the search architecture from-scratch
- Step 4: Perform **magnitude-based fine-grained pruning** of quantum gates. Gates with small rotation angles will be removed
- Step 5: Deploy on **real** Quantum devices



Experiment Results on MNIST-4



TorchQuantum – A library for fast training of Quantum Circuits on GPUs

- **Easy construction** of parameterized quantum circuits such as Quantum Neural Networks in **PyTorch**
- Support batch mode inference and training on GPU/CPU, supports **highly-parallelized** parameter shift and back-propagation training
- Support **both static and dynamic** computation graph for easy debugging (statevector simulation & tensor network simulation)
- Support **easy deployment** on real quantum devices such as IBMQ

```
class QFCModel(nn.Module):
  def __init__(self):
    super().__init__()
    self.n_wires = 4
    self.q_device = tq.QuantumDevice(n_wires=self.n_wires)
    self.measure = tq.MeasureAll(tq.PauliZ)

    self.encoder_gates = [tqf.rx] * 4 + [tqf.ry] * 4 + \
                         [tqf.rz] * 4 + [tqf.rx] * 4
    self.rx0 = tq.RX(has_params=True, trainable=True)
    self.ry0 = tq.RY(has_params=True, trainable=True)
    self.rz0 = tq.RZ(has_params=True, trainable=True)
    self.crx0 = tq.CRX(has_params=True, trainable=True)
```

qmlsys.mit.edu

Reference

Wang, H., Ding, Y., Gu, J., Lin, Y., Pan, D. Z., Chong, F. T., & Han, S. (2021). Quantumnas: Noise-adaptive search for robust quantum circuits. ***HPCA 2022***
Wang, H., Gu, J., Ding, Y., Li, Z., Chong, F. T., Pan, D. Z., & Han, S. (2021). RoQNN: Noise-Aware Training for Robust Quantum Neural Networks. arXiv:2110.11331