QuantumNAS: Efficient Quantum Machine Learning System

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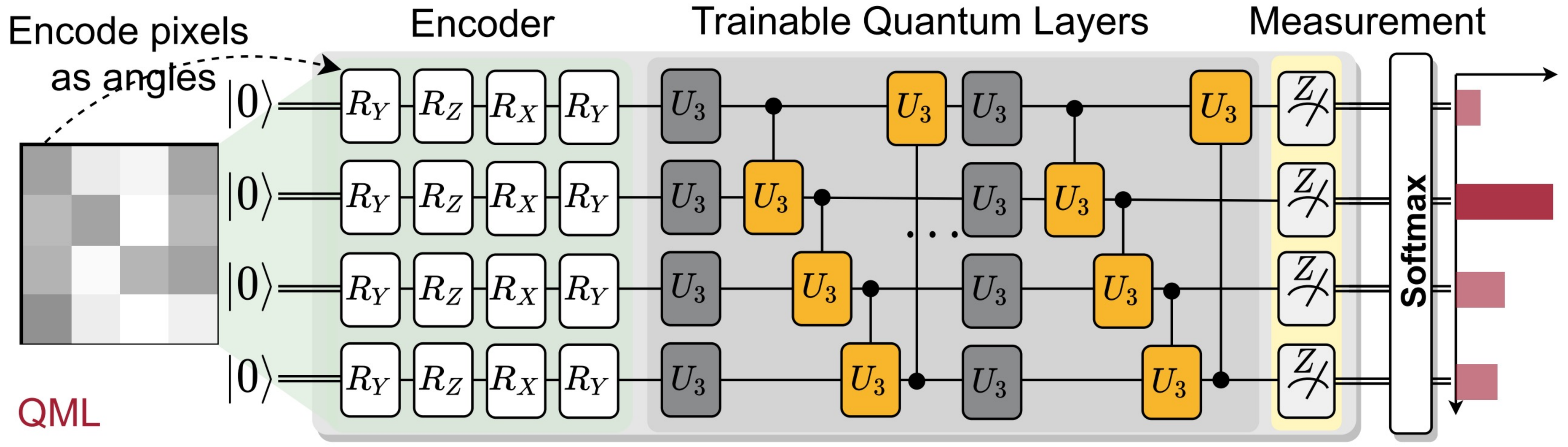
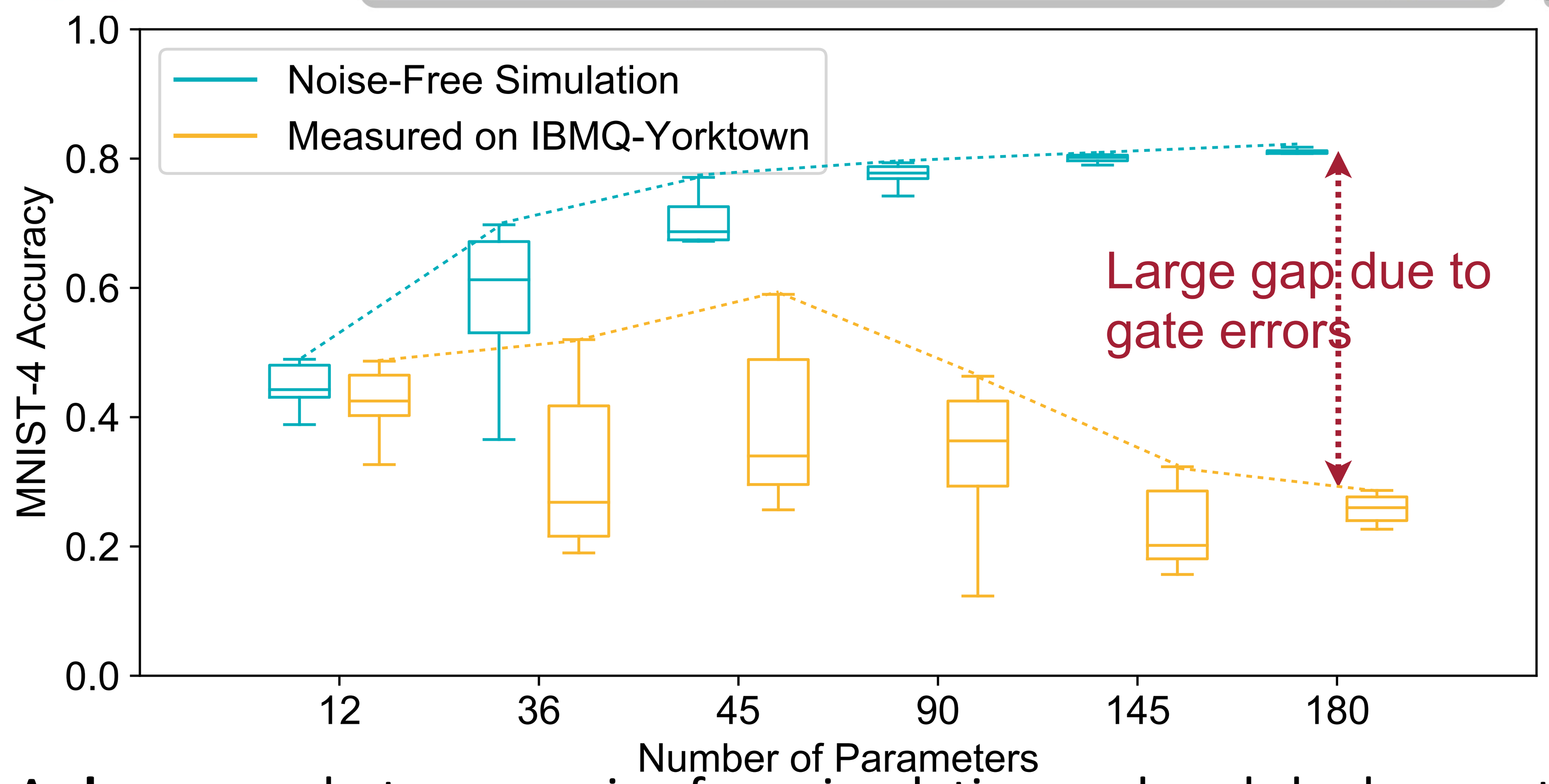
Abstract

- Quantum Computer can potentially provide **exponential speedup** on problems such as quantum machine learning and molecular dynamics
- However, the current **bottleneck is the large quantum noise** which severely degrades the reliability of computed results
- Our core contribution is a framework to search for the most noise-robust circuit and corresponding qubit mapping for parameterized quantum circuits
- Demonstrate over 95% 2-class, and 32% 10-class image classification accuracy on **real** quantum computers; more accurate eigenvalue for VQE tasks on H2, H2O, LiH, CH4, BeH2 compared with UCCSD baselines

Background and Motivation

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

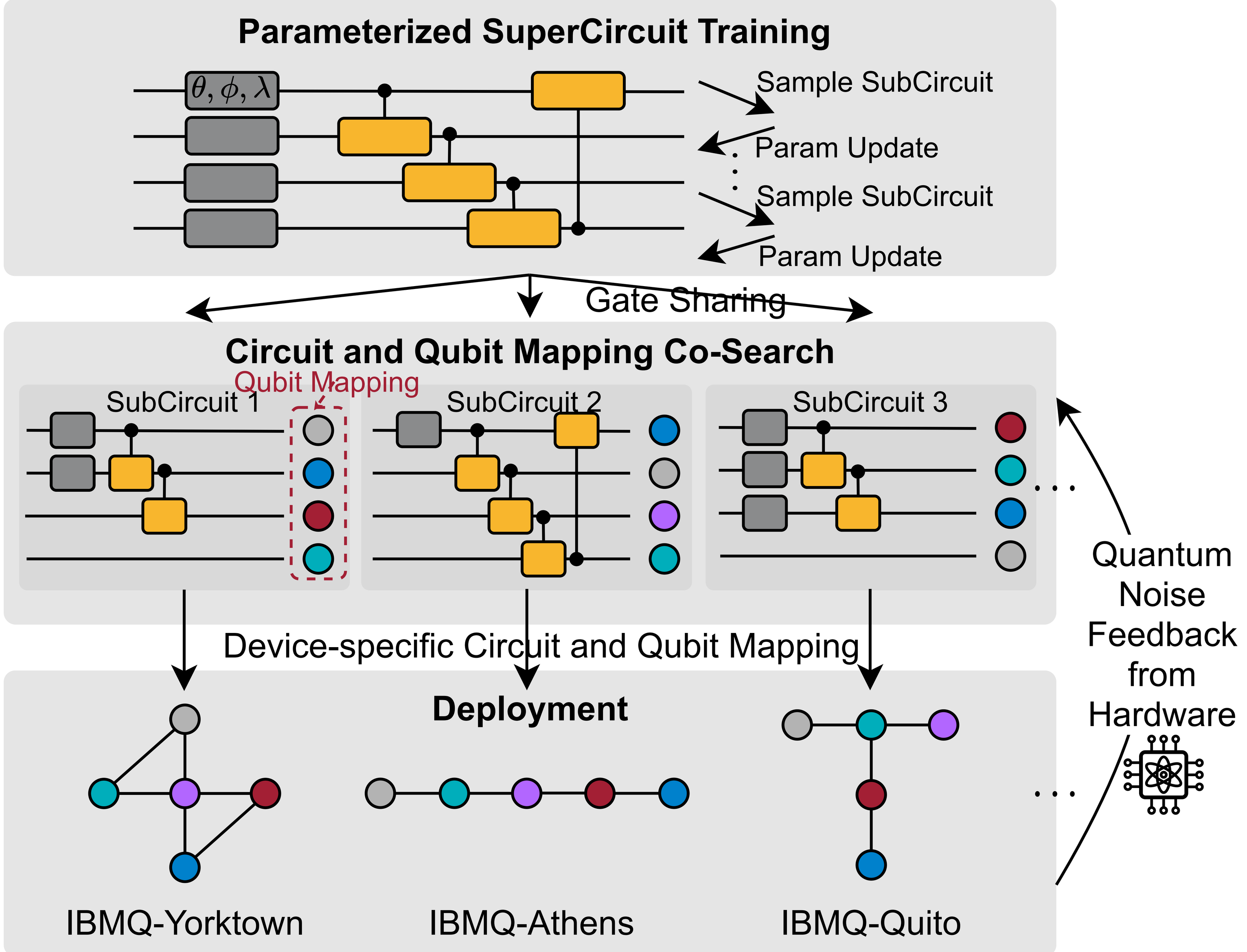




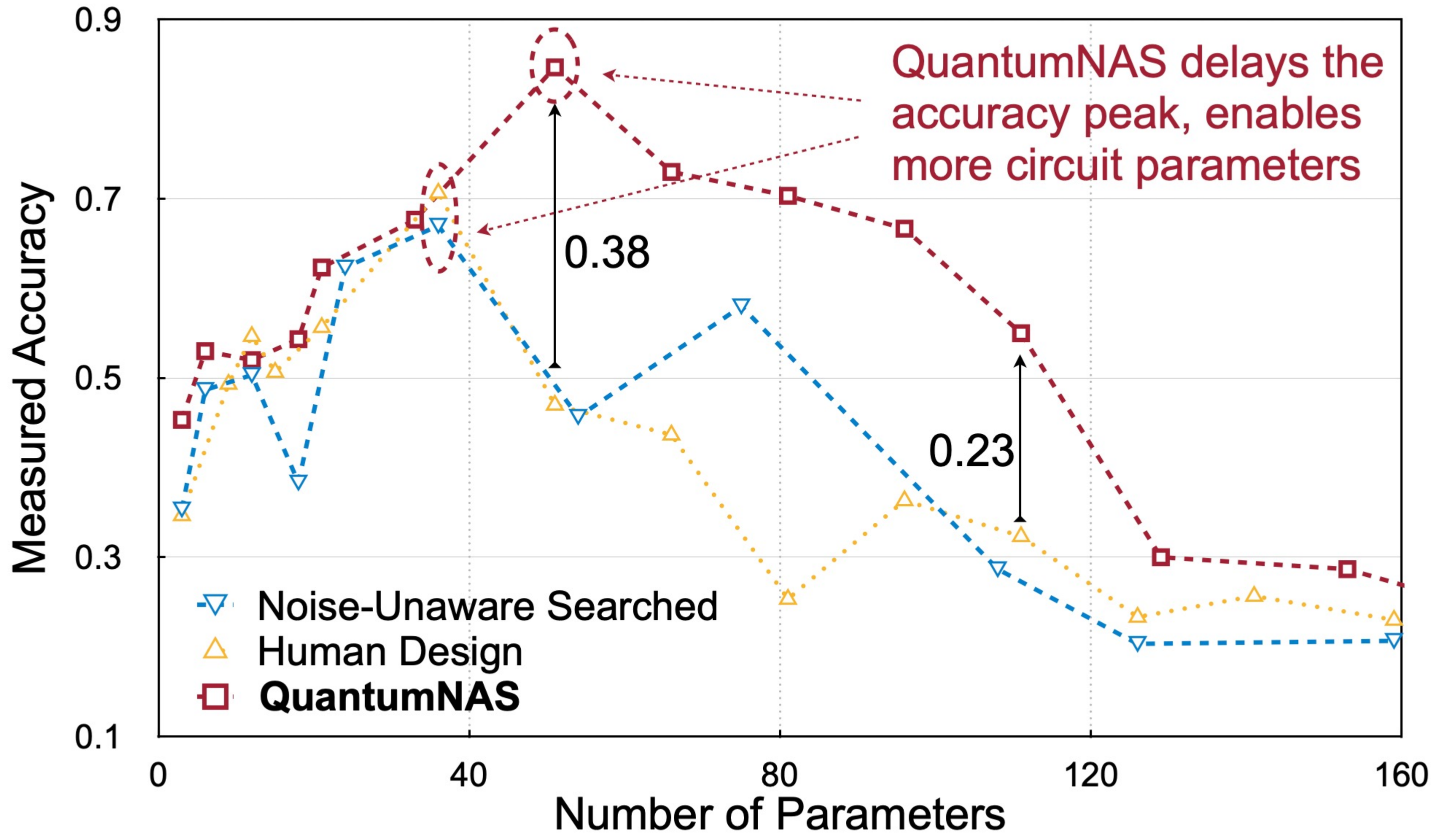
- A **large gap** between noise-free simulation and real deployment due to quantum noises (errors)
- More parameters increase the noise-free accuracy but **degrade measured accuracy**
- Quantum noises exacerbate the performance **variance**

Search for Robust Quantum Circuit & Qubit Mapping

- Step 1: Given a circuit design space, a '**SuperCircuit**' is constructed as the largest possible circuit. The parameters of it are trained by iteratively **sampling and updating a subset of parameters ('SubCircuit')**
- 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

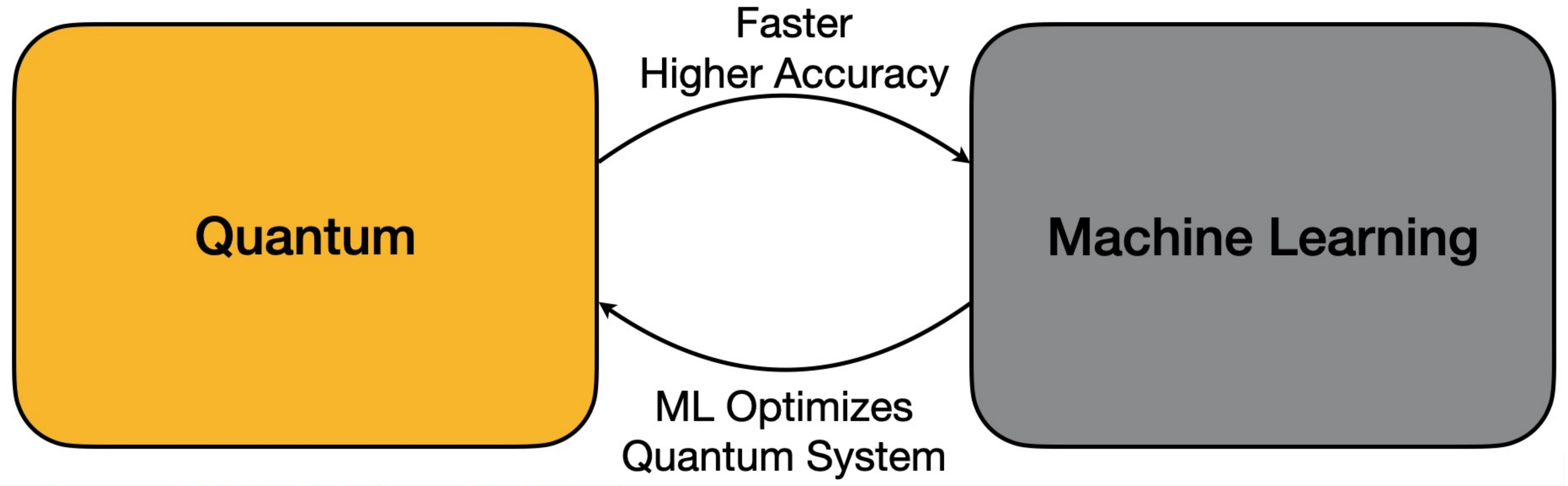


MNIST-4 Results



TorchQuantum – A library for fast Quantum+ML

- **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
- Provide tutorials, videos and example projects of QML and using ML to optimize quantum computer system problems.




```
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)
```

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***

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