Quantum-Assisted Machine Learning in Near-Term Quantum Devices -- Part 2b: QA-based QML

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ZAPATA

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QUANTUM ENHANCED OPTIMIZATION

Quantum Languages Designs and Implementation, Sept 28, 2019

Quantum annealing capabilities

2) As a physical device to sample from Boltzmann-like distributions:

$$\boxed{P_{Boltzman} \propto exp[-\xi(s_1, \ldots, s_N)/T_{eff}]} \longrightarrow \langle v_i h_j \rangle_{p(\mathbf{h},\mathbf{v})}$$

Computationally bottleneck

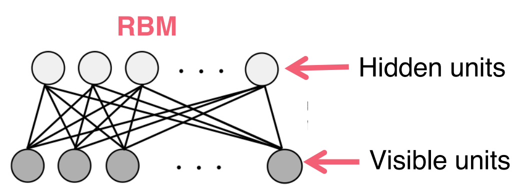
Early work:
Bian et al. 2010. The Ising model: teaching an old problem new tricks.

Follow-up work:
Raymond et al. Global warming: Temperature estimation in annealers. Frontiers in ICT, 3, 23 (2016).

Our work: Benedetti et al. PRA 94, 022308 (2016)

- We provide a robust algorithm to estimate the effective temperature of problem instances in quantum annealers.
- Algorithm uses the same samples that will be used for the estimation of the gradient

Widely used in **generative unsupervised** learning

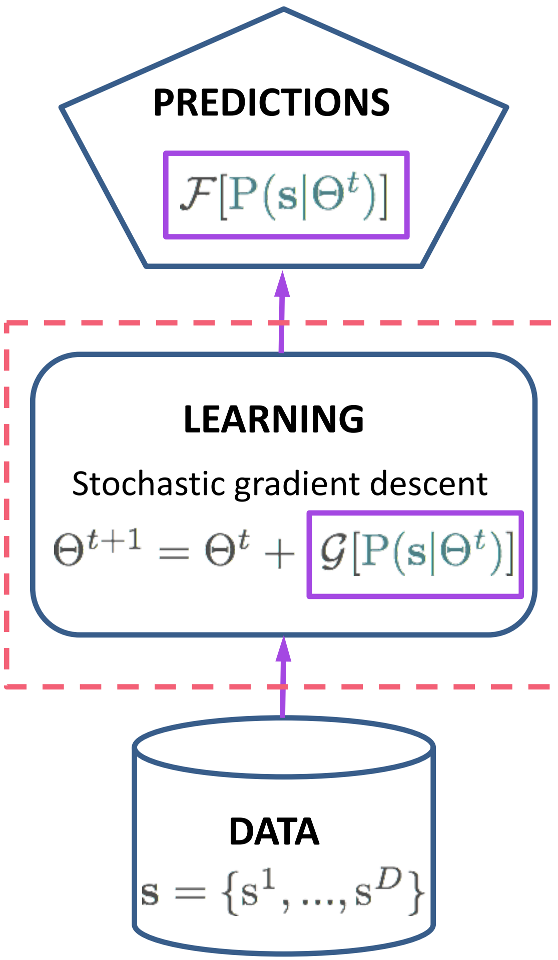


Potential applications:

- *machine leaning (e.g., training of deep-learning networks)*

A near-term approach for quantum-enhanced machine learning

Insight 2: Focus on hybrid quantum-classical approaches.
Cope with hardware constrains and available quantum resources



Challenges solved:

1. Perdomo-Ortiz, et al. **Opportunities and Challenges** in Quantum-Assisted Machine Learning in Near-term Quantum Computers. *Quantum Sci. Tecnol. 3, 030502 (2018)*.

2. Benedetti, et al. **Estimation of effective temperatures** in quantum annealers for sampling applications: A case study with possible applications in deep learning. *Phys. Rev. A 94, 022308 (2016).*

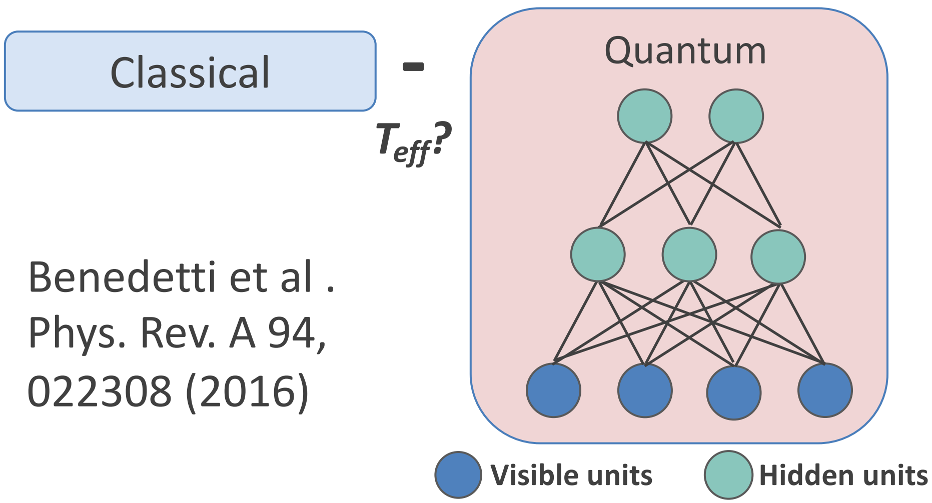
A near-term approach for quantum-enhanced machine learning

Challenges of the hybrid approach:

- Need to solve classical-quantum model mismatch

Training Method: Stochastic gradient ascent

$$\sum_{\mathbf{v} \in D} \frac{\partial \ln \mathcal{L}(\theta|\mathbf{v})}{\partial J_{ij}} \propto \boxed{\langle v_i u_j \rangle_{\text{data}}} - \boxed{\langle v_i u_j \rangle_{\text{model}}}$$



Benedetti et al . Phys. Rev. A 94, 022308 (2016)

No significant progress in 2010-2015 for generative modeling and QA sampling.

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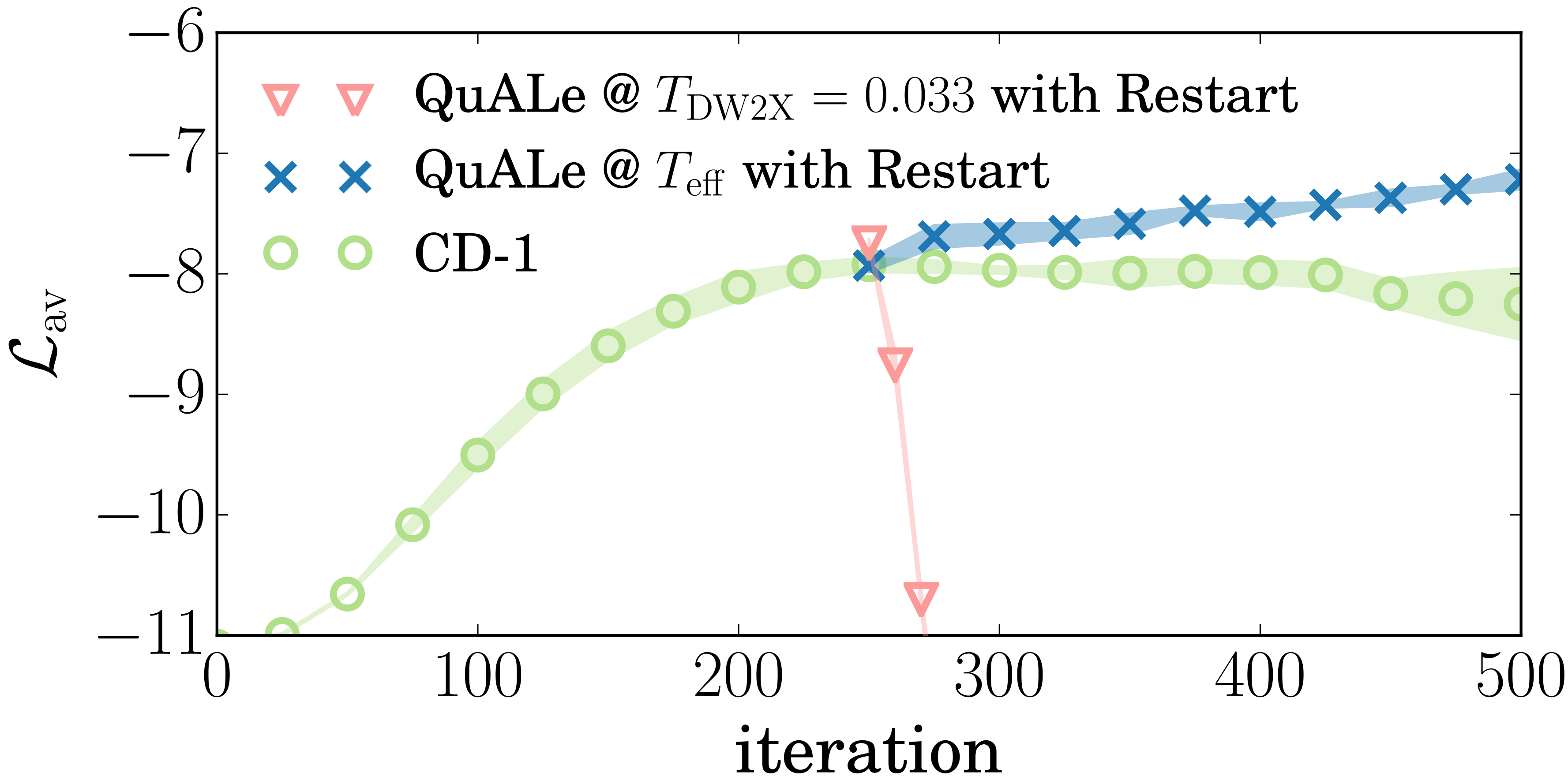
Resolving model mismatch allows for restarting from classical preprocessing



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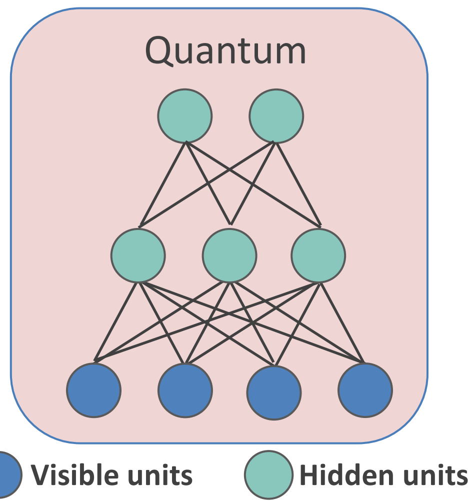
Classical - T_{eff}?



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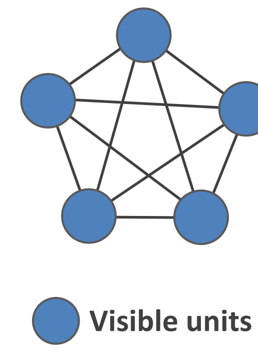
- Robustness to noise, intrinsic control errors, and to deviations from sampling model (e.g., Boltzmann)

Fully visible models



- *Curse of limited connectivity* – parameter setting

Benedetti et al. PRX 7, 041052 (2017)

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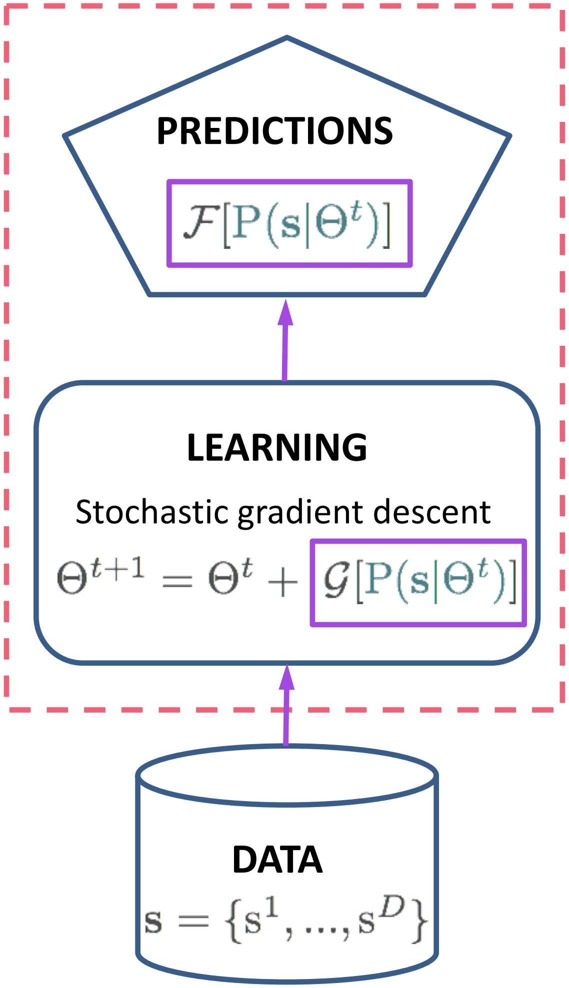

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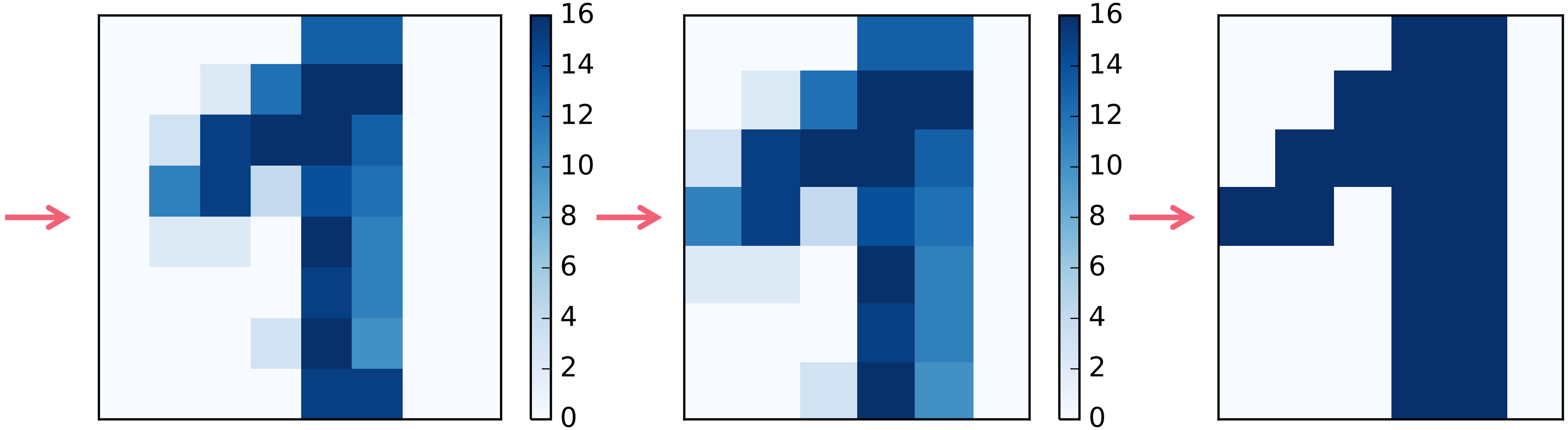
Quantum-assisted unsupervised learning on digits

<u>OptDigits Datasets</u>

32x32



8x8

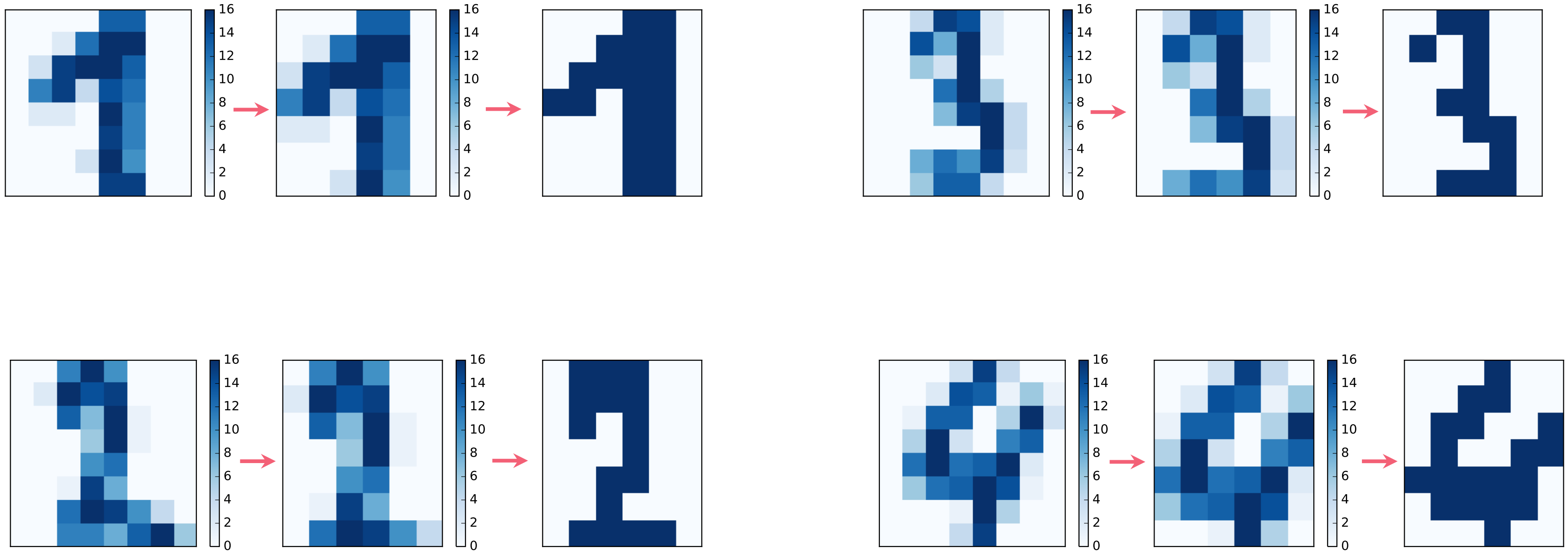
7x6

7x6, binarized

Dataset: Optical Recognition of Handwritten Digits (OptDigits)

Quantum-assisted unsupervised learning on digits

OptDigits Datasets



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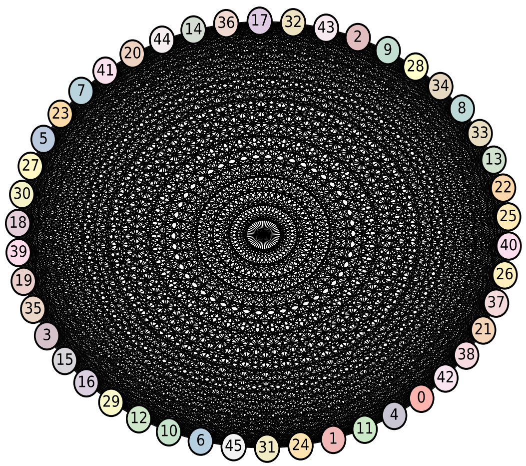
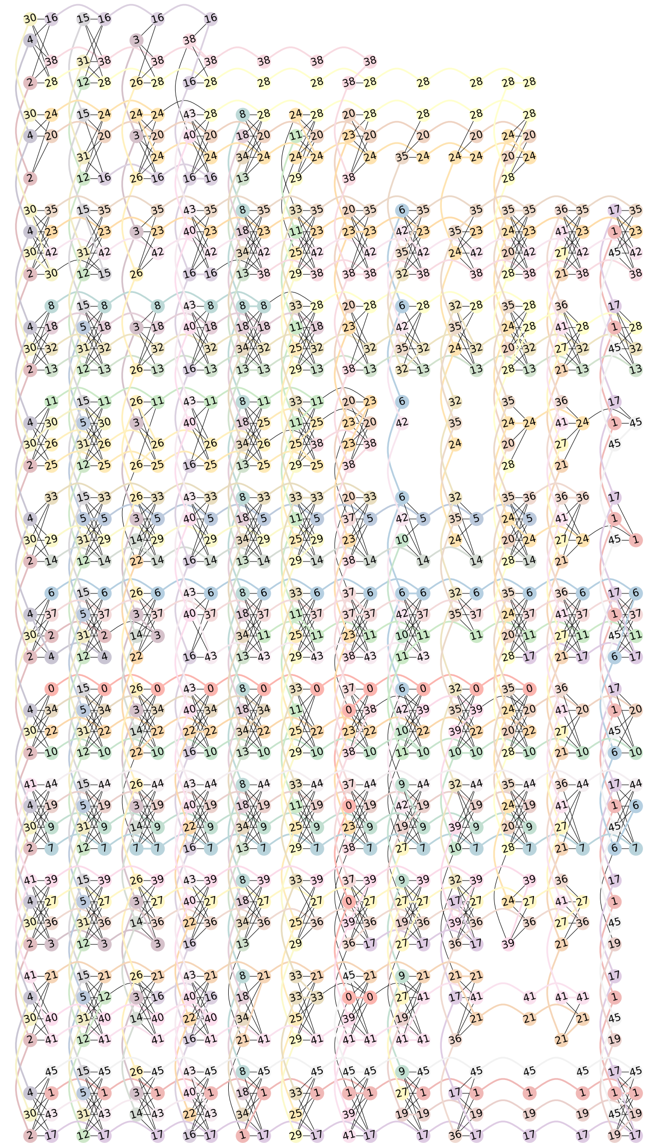
Overcoming the curse of limited connectivity in hardware.

46 fully-connected logical (visible) variables





940 physical qubits

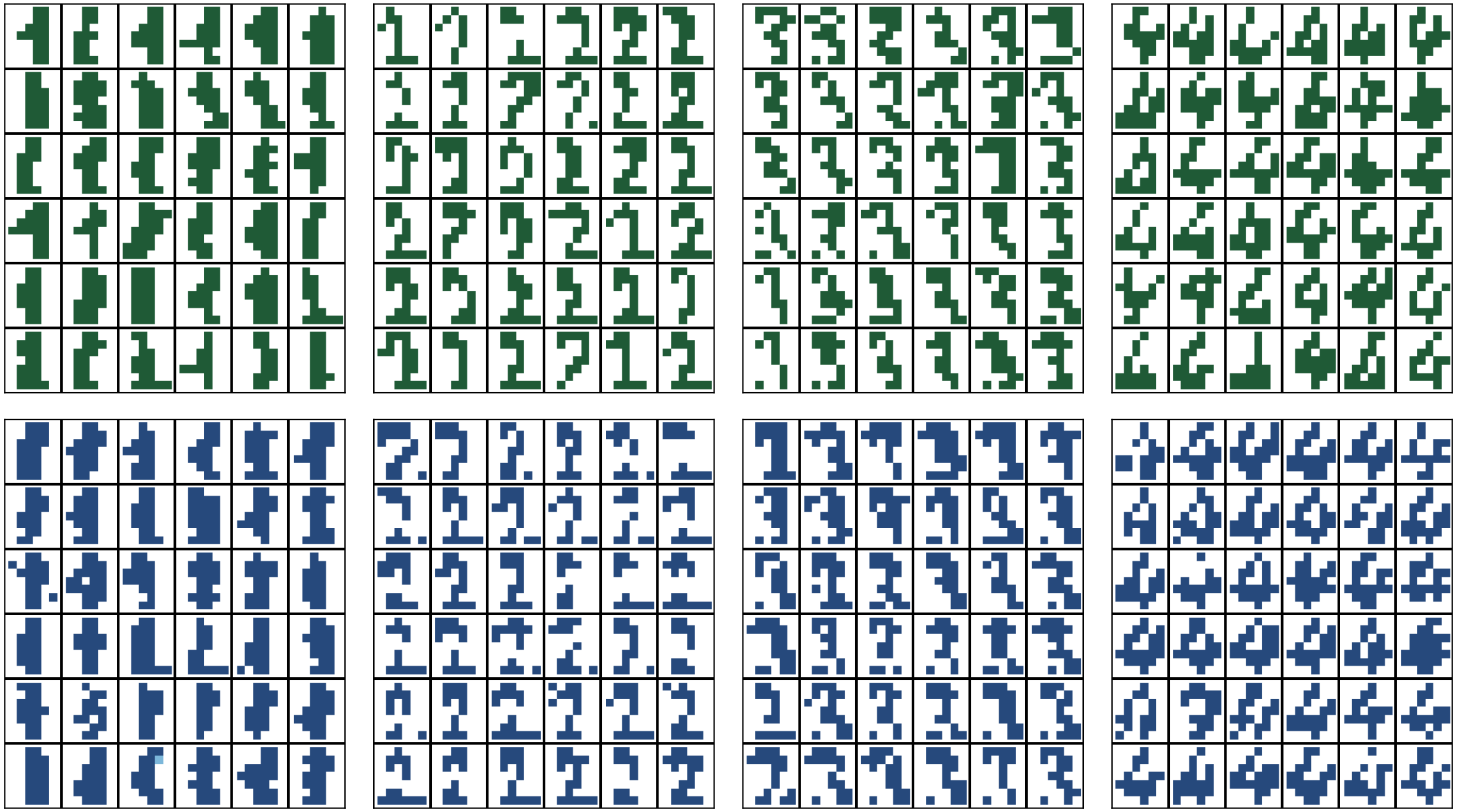
42 for pixels + 4 to one-hot encode the class (only digits 1-4)

- Are the results from this training on 940 qubit experiment meaningful?
- Is the model capable of generating digits?

Benedetti, et al. Quantum-assisted learning of **hardware-embedded** probabilistic graphical models. **PRX 7, 041052 (2017)**

Quantum-assisted unsupervised learning on digits

Human or (quantum) machine? (Turing test)



Dataset: Optical Recognition of Handwritten Digits (OptDigits)

Results from experiments using 940 qubits, without post-processing.
The hardware-embedded model represents a 46 node fully connected graph.

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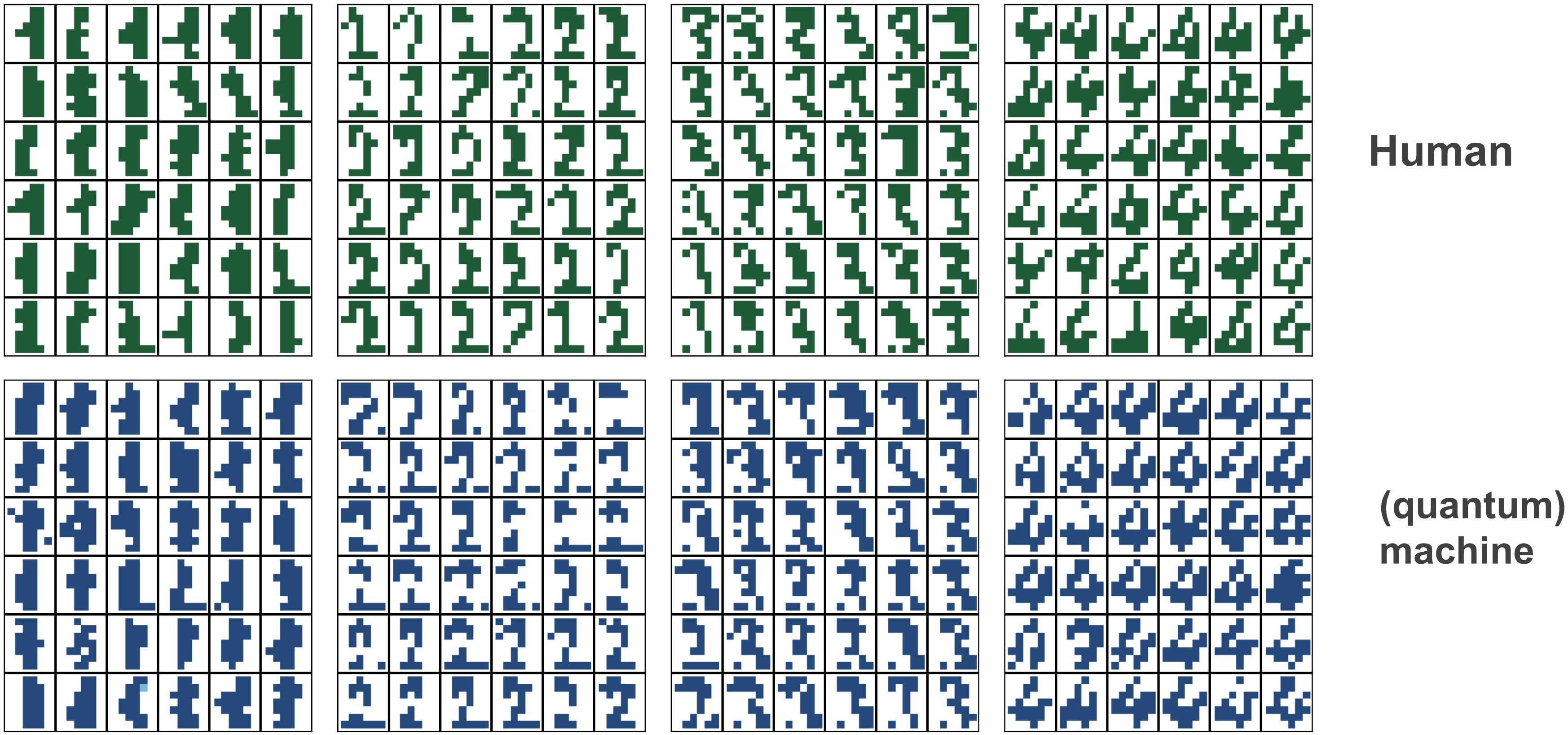

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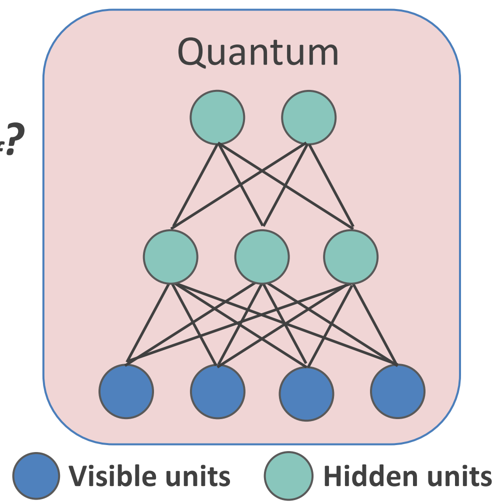

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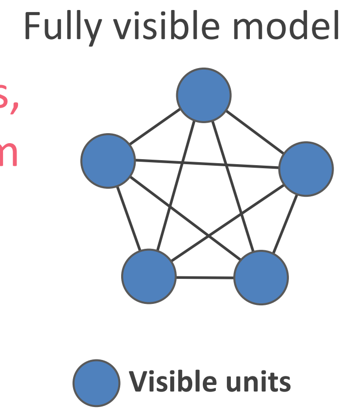
No progress in five years since QA sampling was proposed as a promising appplication.

- Robustness to noise, intrinsic control errors, and to deviations from sampling model (e.g., Boltzmann)



- *Curse of limited connectivity* – parameter setting

Benedetti et al. arXiv:1609.02542

How about large complex datasets with continuous variables?
All previous fail to do that (fully quantum and hybrid here)

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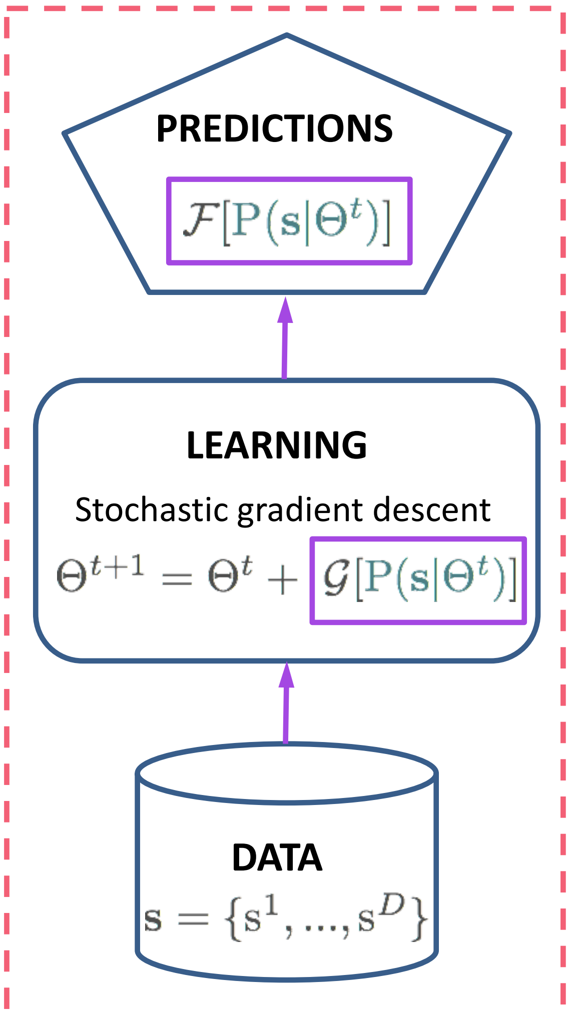

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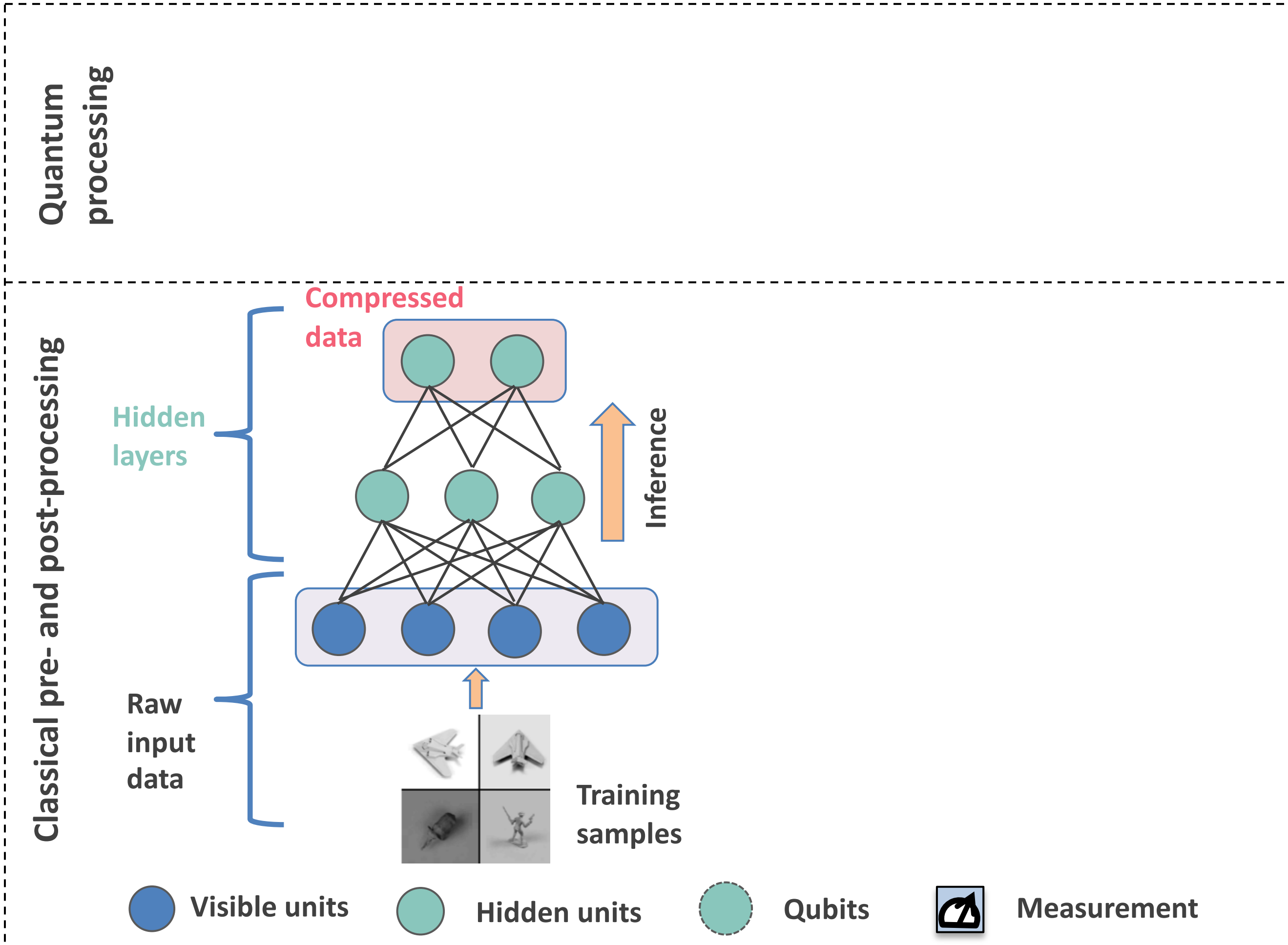
4. Benedetti, et al. Quantum-assisted Helmholtz machines: A quantum-classical deep learning framework for **industrial datasets in near-term devices**. *<u>Quantum Sci. Technol</u>. 3, 034007 (2018).*

Perspective on quantum-enhanced machine learning

- **New hybrid proposal that works directly on a low-dimensional representation of the data.**



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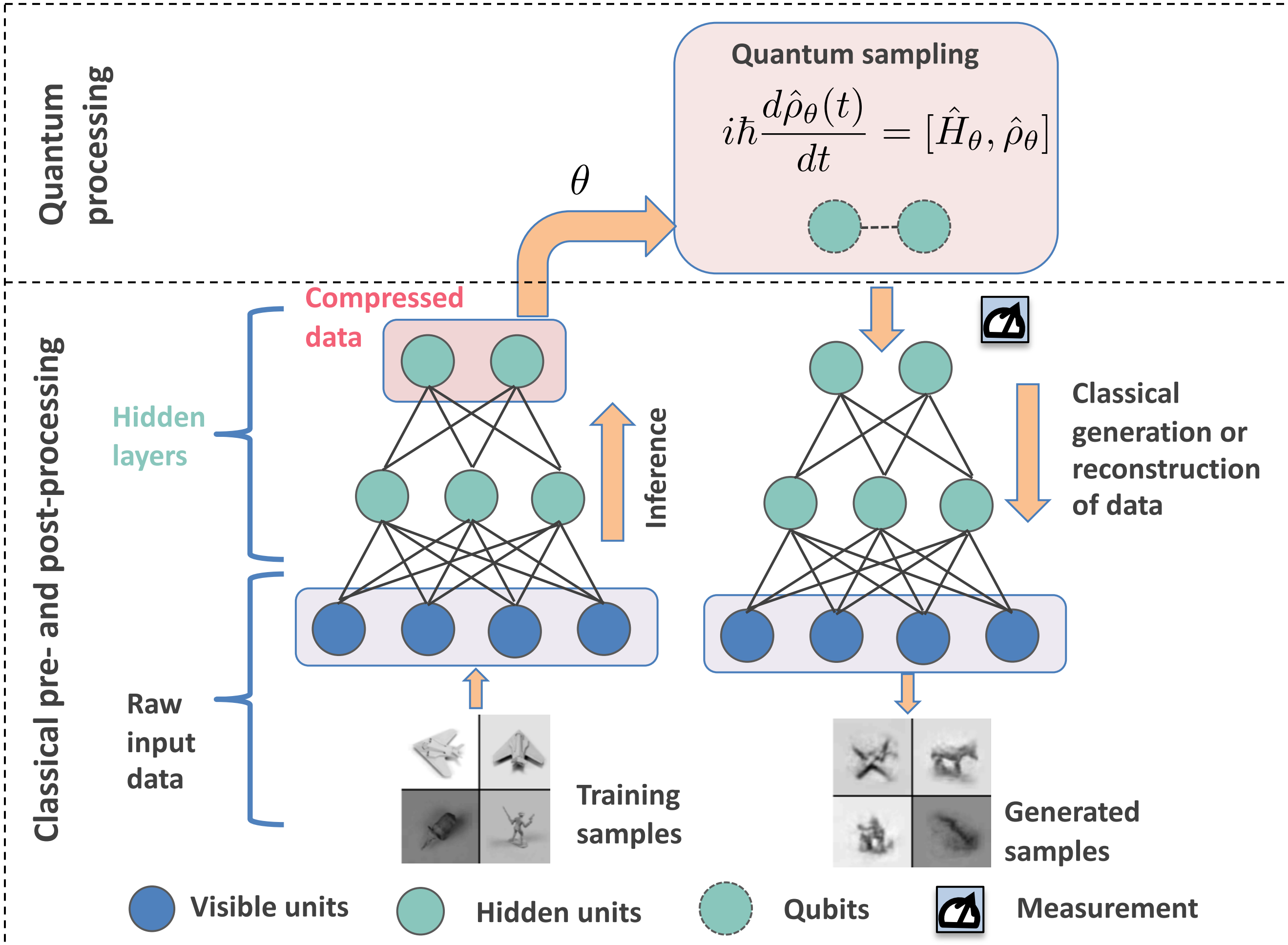

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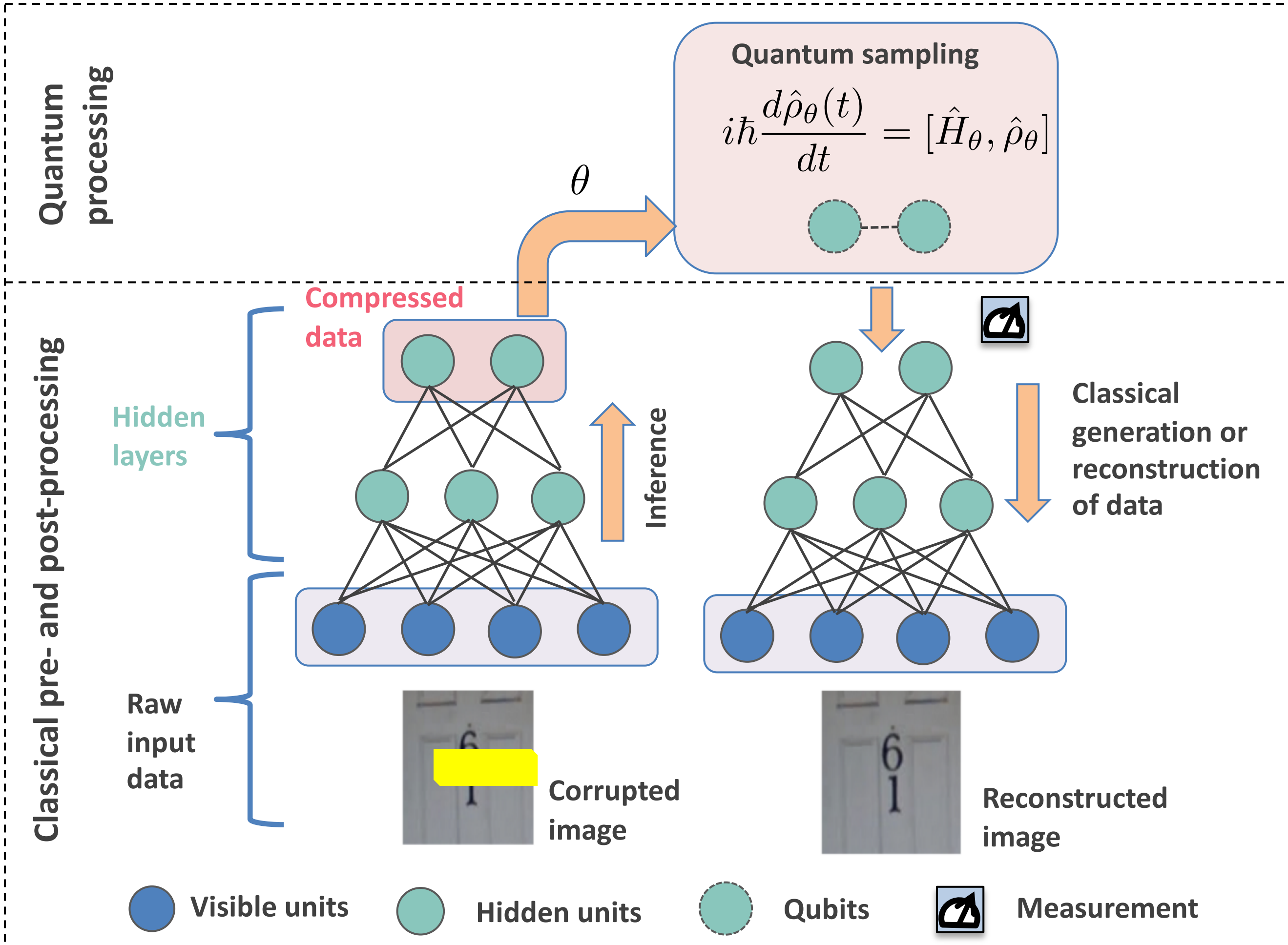

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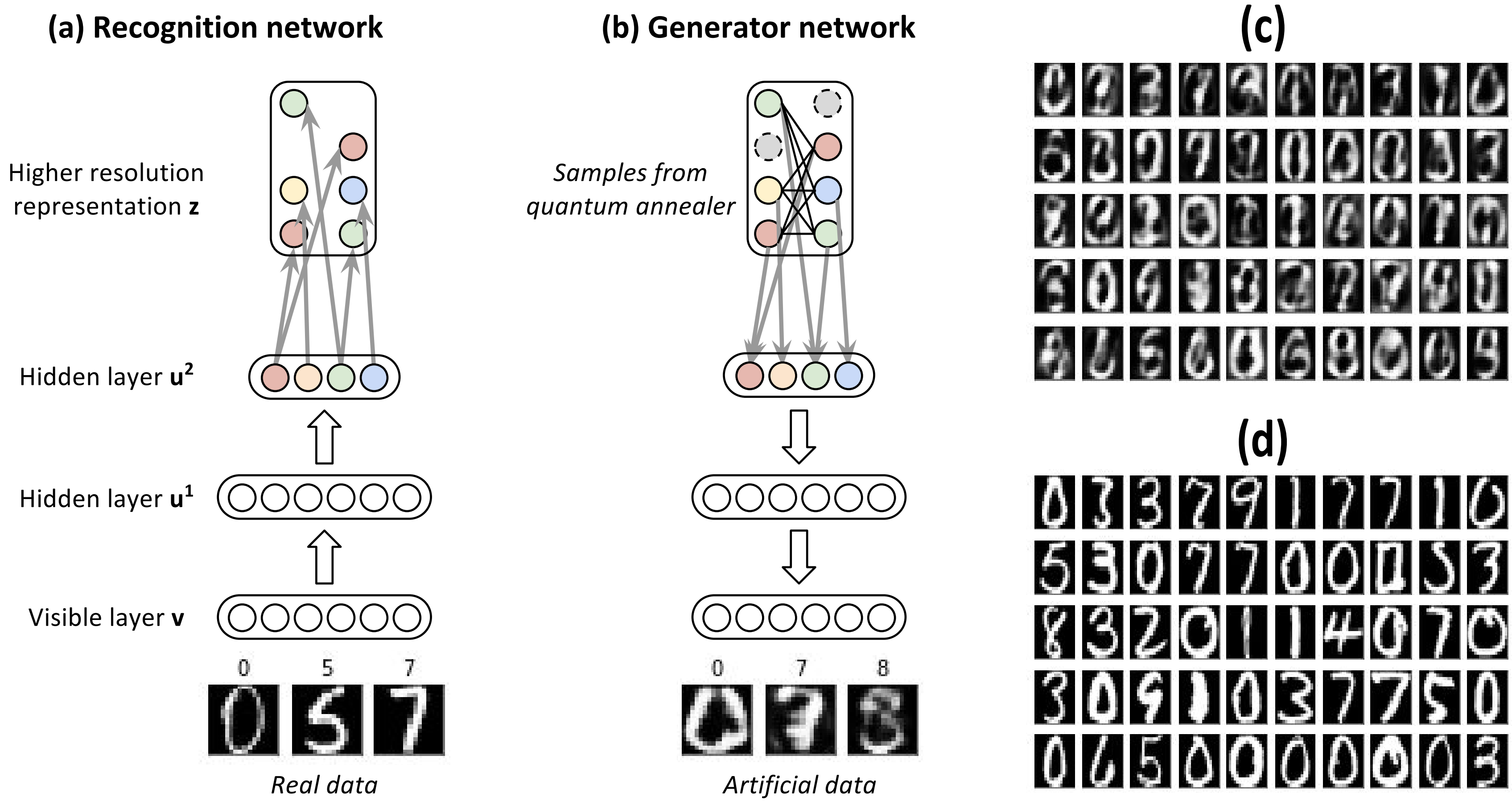
Experimental implementation of the QAHM



Experiments using 1644 qubits (no further postprocessing!)

Max. CL = 43

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Acknowledgments

Institutions/ Funding

Office of the Director of National Intelligence
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Theory collaborators

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