

A Hybrid Quantum-Classical Workflow for Hyperparameter Optimization of Neural Networks

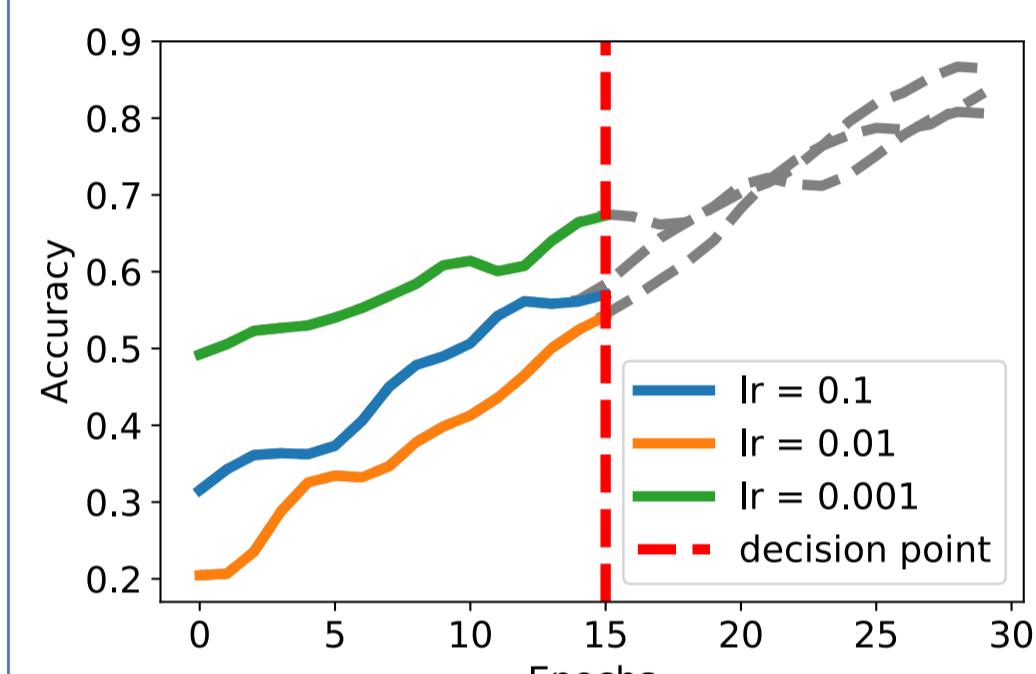
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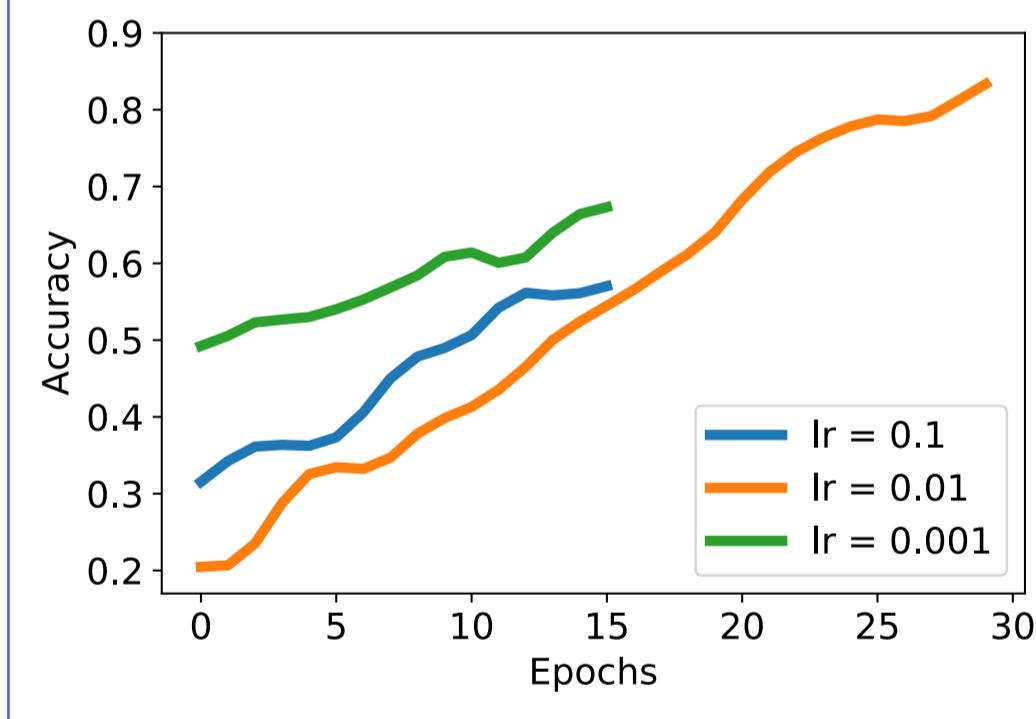


1. PROBLEM DEFINITION

- HPO requires significant computational resources
- Run trials on classical GPUs
- Early stopping of bad trials with Quantum Annealer (QA) by Quantum Support Vector Regression (Q-SVR) learning curve extrapolation



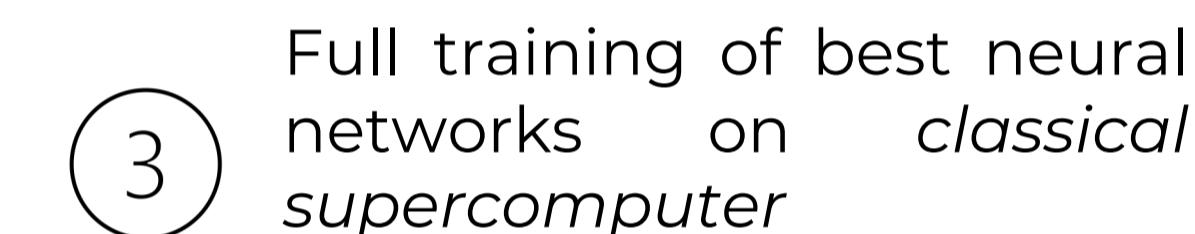
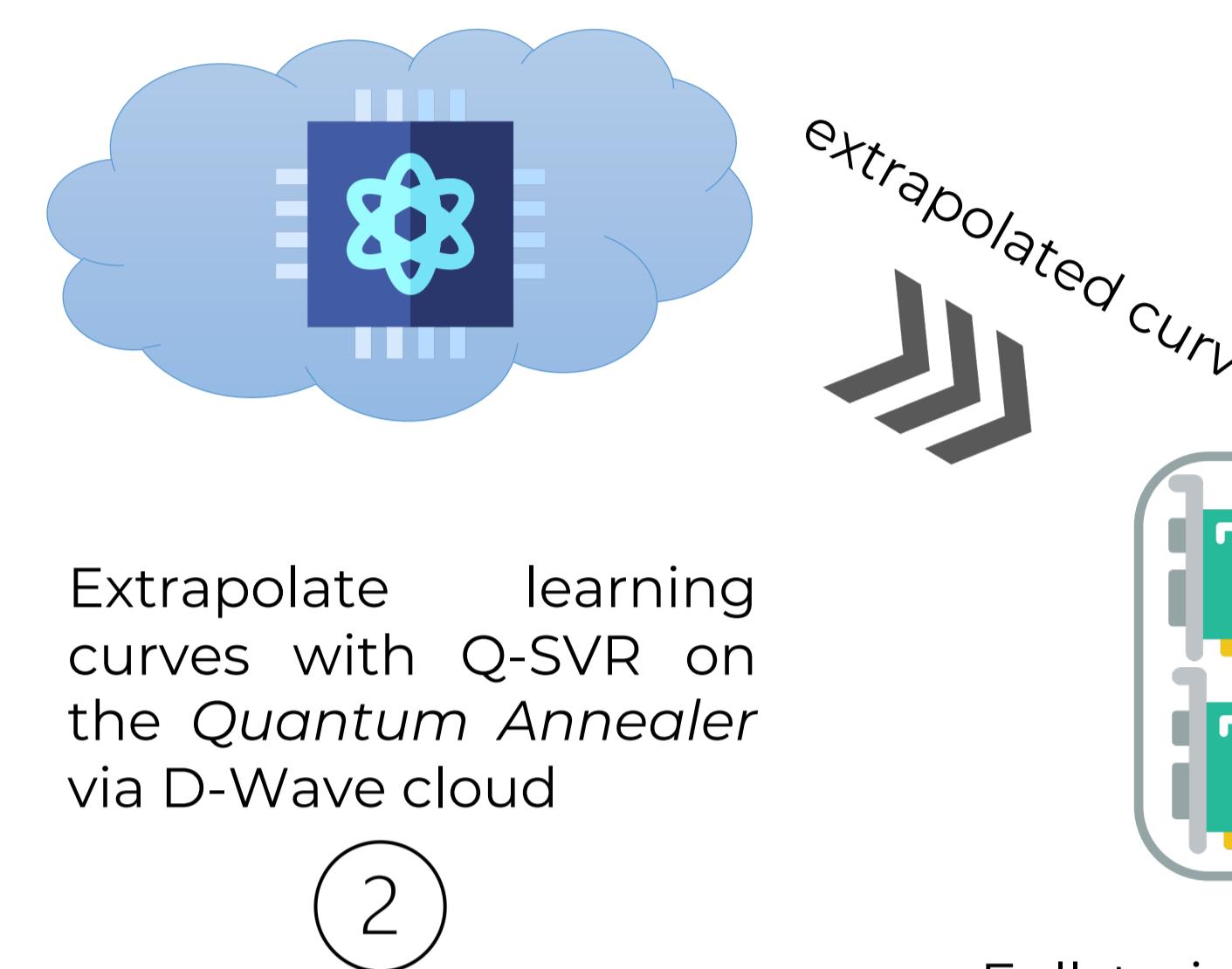
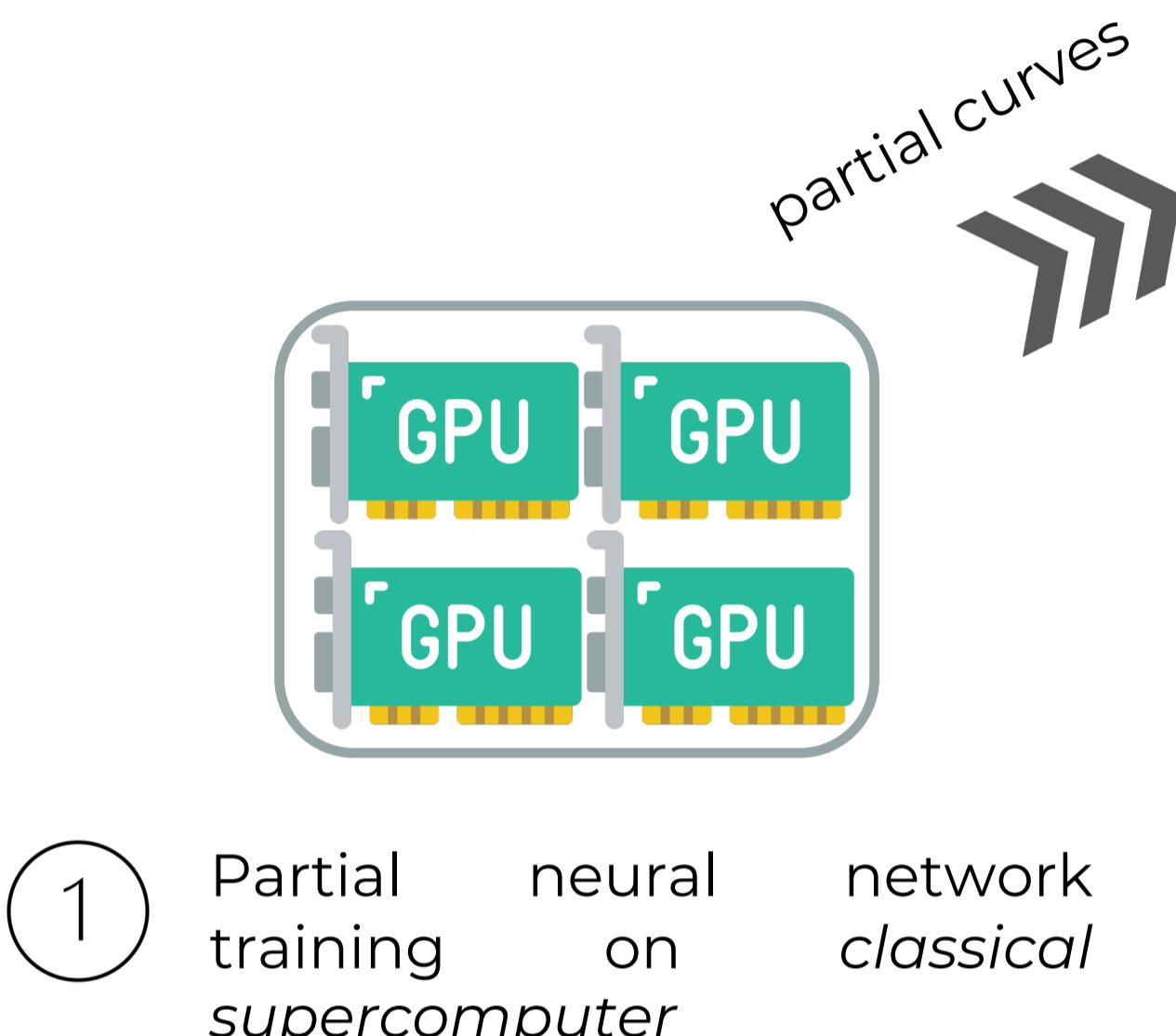
Good vs. bad trial?



Only continue good trials!

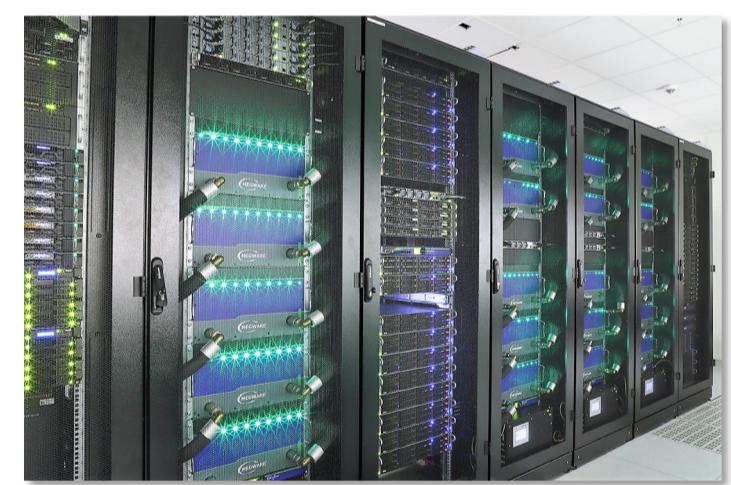
3. WORKFLOW

Three step workflow

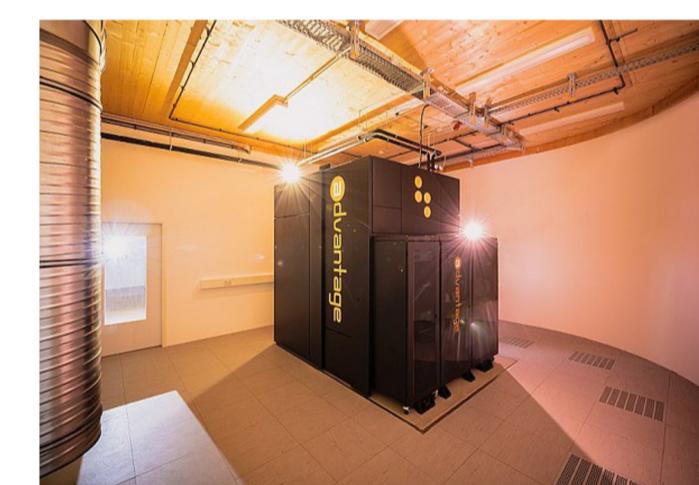


Systems

DEEP-EST-ESB



JUPSI



Hyperparameter Search Space

Convolutional neural network trained on cifar-10

Parameter	Range
Layers	[2, 3, 4]
Filters	[16, 32, 48, 64]
Batch size	[64, 128, 256, 512]
Learning rate	Log[1e-4, 1]
Momentum	Log[1e-4, 0.9]

2. THEORETICAL BACKGROUND

Performance Prediction:

- Regression on learning curve of a neural network can accurately predict final performance [Baker et al. 2018]

Quantum Support Vector Regression:

- QA solves quadratic unconstrained binary optimization (QUBO) problems: $E = \sum_{i \leq j} a_i Q_{ij} a_j, \quad a_{i,j} \in \{0, 1\}$
- Reformulate Classical Support Vector Regression (C-SVR) into QUBO form [Pasetto et al. 2022]:

$$L(\alpha, \hat{\alpha}) = \frac{1}{2} \sum_{n=0}^{N-1} \sum_{m=0}^{N-1} (\alpha_n - \hat{\alpha}_n)(\alpha_m - \hat{\alpha}_m) k(\mathbf{x}_n, \mathbf{x}_m) - \epsilon \sum_{n=0}^{N-1} (\alpha_n + \hat{\alpha}_n) + \sum_{n=0}^{N-1} (\alpha_n - \hat{\alpha}_n) y_n$$

Kernel function Error margin

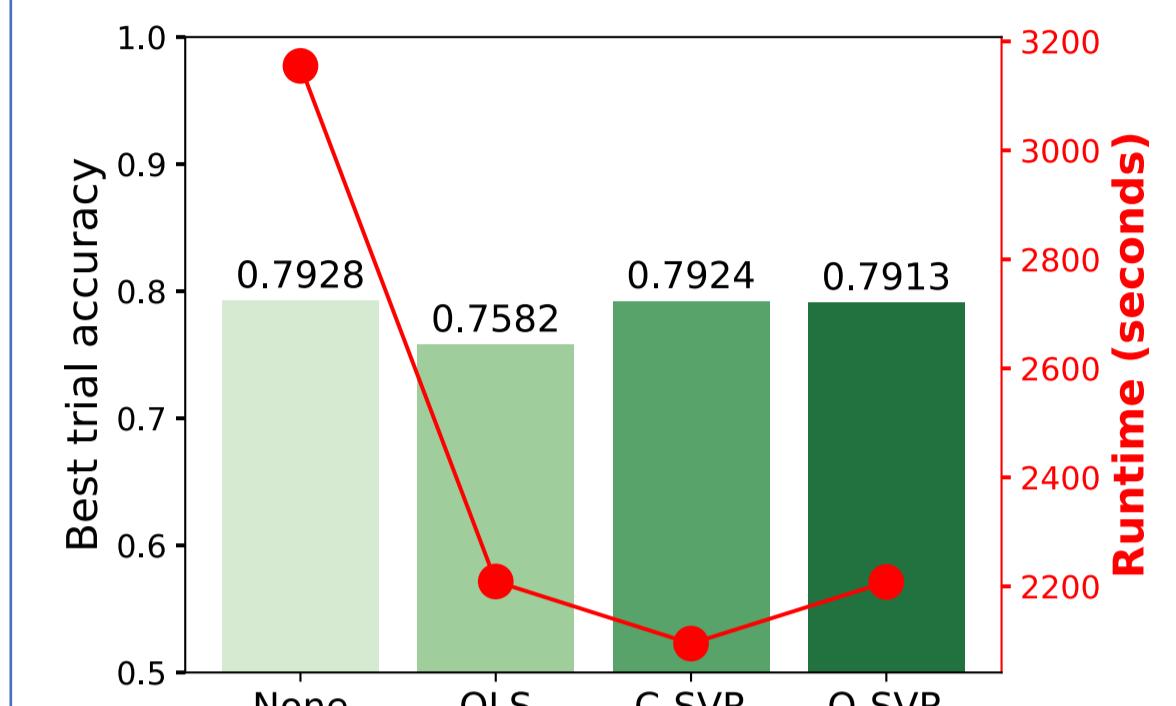
Number of qubits → $K-1$

$$\alpha_n = \sum_{k=0}^{K-1} B^{k-P} a_{Kn+k}$$

Encoding basis

$$\hat{\alpha}_n = \sum_{k=0}^{K-1} B^{k-P} a_{K(N+n)+k}$$

4. RESULTS



- 100 trials with different early stopping methods
- No early stopping: longest runtime but highest accuracy
- Q-SVR: 30% shorter runtime while comparable accuracy

Why Quantum Support Vector Regression?

- C-SVR complexity $O(n^2) - O(n^3)$
- Q-SVR complexity does not increase with problem size
- Quantum speedup possible in the future

5. CONCLUSION

- Neural network training on classical machine
- Performance prediction on quantum machine
- Save 30% compute resources

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- Images taken from: https://www.fz-juelich.de/en/as/sc/systems/prototype-systems/deep_system and <https://www.fz-juelich.de/en/as/sc/systems/quantum-computing/uniq-facility/uniq/d-wave-advantage-system-jupsi>
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