Quantum device measurement and tuning using machine learning

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Device fabrication:  Machine learning:
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(University of Basel)
Quantum devices

Gate electrodes

$V_{\text{bias}}$

Google

NQIT, Oxford

Measurement and tuning

1 qubit (4 gates)

4 × 10^{12} points

127 years

How to automate the measurement and tuning of quantum devices?
The AI revolution

Big data
Massive computer power
Powerful algorithms
Automated tuning

Machine learning algorithm measuring and tuning a device in real time


<table>
<thead>
<tr>
<th>Device measurements</th>
<th>Device tuning</th>
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<tbody>
<tr>
<td><img src="image1" alt="Device measurements" /></td>
<td><img src="image2" alt="Device tuning" /></td>
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</table>
Device measurements

Device tuning
Deep learning

Image recognition

a cat

Deep generative models
Deep learning

\[ y = f_1 \left( f_2 \left( f_3 (...) \right) \right) \]

where \( f_i(x) = \max (W_i x + b_i, 0) \)
Image recognition and deep generative models

1.2 M training images

Error rates on visual recognition (%)

Sources: ImageNet; Stanford Vision Lab


These are not real people

Jun-Yan Zhu*, Taesung Park*, Phillip Isola, and Alexei A. Efros, ICCV 2017
Reconstructions

Gate voltage

Bias voltage

[Image of a color-coded matrix and three triangular patterns]
Deep generative model

Encoder \{\theta\} \rightarrow \text{Subsample} \rightarrow \text{Decoder} \{\phi\} \rightarrow \text{Discriminator} \{\gamma\}

Loss 1 (\theta) \rightarrow \text{Loss 2 (\theta,\phi)}

Y_{128x128} \rightarrow \text{Encoder } \{\theta\} \rightarrow \text{P(Z)} \rightarrow \text{Decoder } \{\phi\} \rightarrow \hat{Y}_{128x128}
Deep generative model

Training

Encoder \{\theta\} \rightarrow Z \rightarrow \text{Difference} \rightarrow \text{Latent} \rightarrow \text{Decoder} \{\phi\} \rightarrow Y_0

Training examples \rightarrow \text{Subsample} \rightarrow \text{Reconstructions}
Deep generative model

Reconstructions

\[ Y_0 : \]
8x8

Prob Distr. of z

Reconstructions

\[ m=1 \quad \cdots \quad m=M \]
Information theoretic models
Information gain map

[Image of a diagram showing current vs. gate voltage and information gain map with markers X1 and X2]
Machine learning for quantum device measurement

Initial scan

Reconstructions

Predicted information gain

Next measurement
Machine learning for quantum device measurement

Measurement

Acquisition map

Bias voltage

Gate voltage
Machine learning for quantum device measurement

$r(n) = \frac{\text{unmeasured current gradient}}{\text{total current gradient}}$
Machine learning for quantum device measurement

Gate voltage 1

Gate voltage 2

Measurement

Acquisition map
Machine learning for quantum device measurement

Gate voltage 1

Gate voltage 2

arXiv:1810.10042
GitHub: CVAE_for_QE
Device tuning

Device measurements

Bayesian learning

Quantum device

Latent variables

Data

(a)

V_1 V_2 V_3 V_4 V_5

(b)

(i) (ii)

Control voltages

Bayesian optimisation
Machine learning for quantum device tuning

Score function
\[ f(V_{\text{gate1}}, V_{\text{gate2}}) \]
Bayesian optimisation
Machine learning for quantum device tuning

Tall and sharp peaks!
Machine learning for quantum device tuning

Virtual gate voltage (mV)

Current (pA)

Virtual gate voltage (mV)

Score

Samples

Current (pA)

Virtual gate voltage (mV)

Sample score

Best score
Machine learning for quantum device tuning

Bias triangles!

Score: 8.2  8.3  9.8  10.6  12.7
Reinforcement learning for finer tuning

Deep Mind (2015)
Reinforcement learning for finer tuning
Summary

- Efficient quantum dot measurements using machine learning
- Efficient quantum dot tuning using machine learning

Perspectives:

- Characterise and tune large quantum dot circuits
- Apply our findings to different qubit realisations
Thank you