Quantum Similarity Testing with Convolutional Neural Networks

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Learning Quantum State Similarity

- When the full knowledge of two quantum states are known, we can calculate the quantum fidelity or trace distance to measure their distance.
- However, in practical situation, what we ultimately have is just measurement data obtained from different measurements over two quantum states.
- The task is then to determine whether two given data sets have been generated from the same state or not.

Learning Human Face Similarity

1 Schroff, F et al. Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE conference on computer vision and pattern recognition.*

Representation Learning Matters

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StateNet: Mapping from Measurement Data to Compact Representations

- Inspired by the success of $FaceNet¹$ in the task of face recognition, StateNet adopts the similar architecture which is composed of a deep representation network denoted by f_{ξ} and a L_2 normalization layer.
- StateNet embeds the measurement data into a low-dimensional feature space. The low-dimensional state representations are then used by the network to decide whether the two measurement data sets belong to the same state.

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Training: Triplet Loss

- In order to train our neural network, we adopt a loss function called Triplet Loss.
- The Triplet Loss minimizes the distance between two state representations corresponding to two sets of measurement data, both of which belong to the same quantum state. Meanwhile, it maximizes the distance between two state representations corresponding to two sets of measurement data belonging to different quantum states.

Numerical Experiment: States in Oscillators

- We consider quantum states encoded in an oscillator, i.e. continuous-variable states as a testbed for our neural network model.
- Continuous-variable quantum state ρ is characterized by its Wigner function $W_{\rho}(\cdot)$ on phase space.
- Suppose that Alice (Bob) can estimate the Wigner function at a finite number of points, chosen at random from a square grid over the phase space. After a finite set of measurement runs, Alice (Bob) obtains a two-dimensional data image, where some pixels are missing and the value at each of the existing pixels is an estimate of the Wigner function at the associated phase-space point.

Numerical Experiment: States in Oscillators

- We train StateNet using simulated measurement data from ideal cat states as well as noisy cat states with a fixed amount of thermal noise.
- After the training is concluded, we test the performance of StateNet in distinguishing between pairs of noisy cat states degraded by photon loss.
- For each pair of noisy states, we make the reference state ρ close to its noiseless counterpart, with fidelity 99%. We allow the untrusted state σ to be generally noisier.

Numerical Experiment: High-dimensional Quantum States

Wigner function Wigner function 1.5 0.6 15 0.4 1.0 10 0.5 0.2 5 0.0 0.0 0 -5 -0.2 -0.5 -10 -1.0 -0.4 -15 -0.6 $-1.0 - 0.5 0.0$ 1.0 -1.5 0.5 1.5 $-15 - 10$ 15 10

- We focus on a small area of the whole phase space to perform the similarity testing.
- We illustrate the performances of StateNet for the comparison of two noisy cat states with amplitudes $\alpha \in [15, 16]$ (corresponding to an average number of photons between 225 and 256).

Cross-platform Similarity Testing

- We consider a scenario where Alice performs displaced parity measurements on state ρ , while Bob performs homodyne measurements on state σ .
- We jointly train two neural networks, so that their measurement data from these two different types of measurements are mapped into a single representation space.

Data-driven State Representations Can Do More

• Quantum State Learning:

Yan Zhu, Ya-Dong Wu, et al. "Flexible learning of quantum states with generative query neural networks." *Nature Communications 13, no. 1 (2022): 6222.*

• Quantum Process Learning:

Yan Zhu, Ya-Dong Wu, et al. "Predictive Modelling of Quantum Process with Neural Networks." *arXiv:2308.08815 (2023).*

• Learning and Discovering Quantum Properties:

Ya-Dong Wu, Yan Zhu, et al. "Learning and Discovering Quantum Properties with Multi-Task Neural Networks." *arXiv:2310.11807 (2023).*

• Explainable State Representations

• …

• Beyond the Characterization: Optimization/Generation

THANK YOU!

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