# Classifying the Charge State of Quantum Dots by Machine Learning and Improving the Performance by Visual Explanations of the Model

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Semiconductor spin qubits are expected to be a good candidate for future qubits because of their high operation fidelity, excellent integration, and good compatibility with conventional semiconductor technology. To construct semiconductor spin qubits, tuning multiple gate electrode voltages is needed. However, this tuning by humans is time-consuming. Thus, automation for tuning is increasingly becoming a vital factor in larger-scale quantum devices. The classifier for classifying the charge state in each area of the charge stability diagram (CSD) is required for the auto-tuning.

In this study, we realize the classifier that classifies the charge state of the CSD into five states by deep convolutional neural networks (CNN). In [1], the authors prepared training data that more closely resembled real CSD by the simulation. We think even simpler data with charge transition lines can also train the classifier. This is because humans see only charge transition lines in the CSD when judging the charge state. In addition, we visualize the classifier's interest to ensure whether the classifier operates as we intend. If the classifier does not work well, we can improve the classifier's performance by analyzing the visualization.

To prepare the training data, we simulate the CSD with a constant interaction (CI) model, simplify the data by preprocess and add noise. We train the CNN model by this simple data and obtain the classifier of the charge state. We demonstrate the automatic classification of charge states in the experimental CSD. We then adapt the gradient-weighted class activation mapping (Grad-CAM) [2]. Grad-CAM can visualize the interest of the classifier and we can ensure that the classifier classifies the charge state based on the change transition lines. This is the same way as humans' judgement. Furthermore, we improve the classifier by visualizing the misclassifications region with Grad-CAM and examining the cause of the error. From the analysis, the error could be caused by the classifier mistaking noises for the charge transition line. We improve the classifier by changing the number of training data. Finally, we can get enough classifier performance for auto-tuning the spin qubits in double quantum dots (Fig.1). Specifically, the accuracy is evaluated as about 93 % [3]. This method is expected to be useful in auto-tuning the larger semiconductor spin qubits.

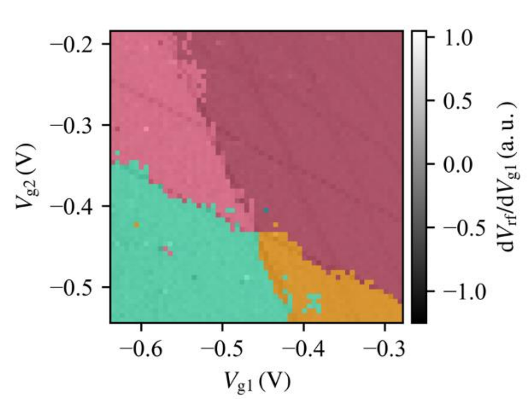


Fig.1. The charge state recognition of experimental data by the improved classifier. The color indicates the classification result.

References

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