Entanglement Detection as a Positive and Unlabeled Learning Problem

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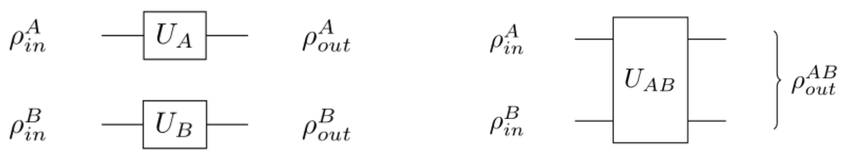
Abstract

Entanglement detection, the task of verifying quantum entanglement, is an important problem in quantum information processing, and various approaches have been proposed to solve it for several decades. Especially in recent years, many experimental researches have been applied to the task using classical computers, such as machine learning. While such methods have achieved high accuracy in entanglement detection, it is reasonable to keep the number of entangled states used for training as small as possible under the assumption that the problem of entanglement detection is being tackled. In this study, we propose a machine learning method for entanglement detection based on PU learning (positive and unlabeled learning), one of the classical machine learning frameworks, that does not use data from negative (entangled) states.

Keywords: Entanglement detection, Positive and unlabeled learning, Binary classification, Semi-supervised learning

1 Introduction

Quantum entanglement plays an important role in quantum information processing. Its use in areas such as quantum teleportation, quantum computation algorithms, and quantum cryptography, has been studied to find quantum applications that are not feasible with classical computers. Quantum states are generally controlled by quantum circuits, and verifying the generation of entanglement during the execution of quantum circuits is an important issue for verifying the operation of algorithms. The problem of determining whether a given quantum state is an entangled state is known as entanglement detection and has been studied for some time (Gühne and Tóth, 2009). PPT criterion (Peres-Horodeci criterion) is one of the most famous criteria to determine whether a quantum state is entangled. This is a powerful analytical tool for entanglement detection but there are strong constraints on the applicable system. For this reason, many experimental researches that use classical computers such as machine learning, have been taken in recent years. In general, classification problem in machine learning assumes that data of both separable and entangled states are available, but in the entanglement detection problem, it is generally difficult to prepare the entangled state. As a solution to the difficulty of data generation, learning method using a GAN (Generative Adversarial Network) that does not use entangled states has been proposed (Chen et al, 2021). Here, we have proposed a method for the entanglement detection problem using both separable and unlabeled states (quantum states that are either separable or not entangled), following the PU learning framework (positive and unlabeled learning), which is one of the classical machine learning frameworks. We propose an approach to the entanglement detection problem using both separable and unlabeled states (Figure 1).



(a) process to make separable state

(b) process to make unlabeled state

Fig. 1: Generation processes of separable and unlabeled state. Preparing entangled data is difficult in the point of verifying so we focus on using separable and unlabeled states for entanglement detection

2 Methods

We provide a PU learning method using spy, which is one of the labeling methods in PU learning. This method uses spy to estimate some of the unlabeled states as negative and then uses these negative data with the original positive data to obtain classification boundaries with a semi-supervised learning method. In spy method we divide positive samples in train dataset into two set, positive and spy, which are really positive but they are treated those as unlabeled($\boldsymbol{x}_1$ and $\boldsymbol{x}_3$ in Table 1). Then, from the dataset including spy, we predict the probability of how likely each data point is labeled from the dataset including spy. The minimum value of the predicted labeled probability in the spy dataset p_{min}(0.55 in Table 1) is used as the threshold value, and the datum whose labeled probability is predicted to be less than p_{min} is treated as unlabeled datum. Now that the dataset has data labeled with positive and negative, we can use this data to determine the classification boundary using semi-supervised learning model.

Table 1: Spy method application for Positive and Unlabeled training set example

Data	labeled?	Pr(labeled|$\boldsymbol{x}$)	spy?	output label
$\boldsymbol{x}_1$	✓	0.7	✓	separable
$\boldsymbol{x}_2$	✓	0.4		separable
$\boldsymbol{x}_3$	✓	0.55	✓	separable
$\boldsymbol{x}_4$		0.6		unlabeled
$\boldsymbol{x}_5$		0.3		negative

3 Preliminary results

As preliminary experiments, we applied the PU learning method to a simple 2 qubit system to check its classification performance (Table 2). As training data, we used 30,000 separable states and 30,000 randomly generated states (unlabeled states), for a total of 60,000 states. We choiced Gaussian kernel with $\gamma = 10$ for one class SVM (ν-SVM) and (two class) SVM. For hyperparameter ν of one class SVM, we set $\nu = 0.5$ for separable only data and $\nu = 0.01$ for separable and unlabeled data.

Table 2: Experimental results

Method	Accuracy	F1 score
One class SVM(Separable only)	0.6363	0.7304
One class SVM(Separable+Unlabeled)	0.8115	0.8003
spy(Naive Bayes)+SVM	0.5004	0.6668
spy(Naive Bayes)+Naive Bayes	0.5723	0.6922
spy(Multivariate Normal)+SVM	0.5646	0.6966
spy(Multivariate Normal)+Naive Bayes	0.6258	0.7165

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