Zc(3900) observation at BESIII with QSVM method

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Abstract. In recent years, quantum computing shows significant potentials in many areas. In this proceeding, we revisit the observation of the Zc(3900) resonance with quantum machine learning techniques, specifically quantum support vector machine (QSVM). Meanwhile, the outcomes are compared with classical support vector machine (SVM) method. With the IBM Qiskit toolkit, the QSVM method achieves a competitive signal and background classification accuracy compared to classical methods. This study emphasizes the potential of quantum machine learning in high-energy physics research, and it reveals the feasibility of applying quantum computing in future physics data analysis.

1 Introduction

The Beijing Spectrometer (BESIII) is a detector for hadron and tau-charm physics studies. It is located at the Beijing Electron Positron Collider (BEPCII), which runs at center-of-mass energy 2.0-5.0 GeV. Zc(3900) [1] was firstly discovered by BESIII collaboration in 2013. This exotic resonance is considered to be a tetra-quark state, which scientists have been looking for a long time.

In recent years, the quantum computing technology has evolved rapidly and shows attractive prospects. Meanwhile, the potential ability of Quantum Machine Learning (QML) has been proved in many areas. Considering the significant increase in data volume in future high-energy physics experiments and the evolution of quantum computing technology, revisiting the study of the Zc(3900) resonance through the application of quantum machine learning (QML) represents a promising avenue to explore its potential utilization in experimental high energy physics.

2 Quantum Support Vector Machine

The Quantum Support Vector Machine [2] (QSVM) is a quantum variant of the classical Support Vector Machine (SVM) algorithm. The key distinction between QSVM and classical SVM lies in the utilization of a quantum kernel function [3]. While classical SVM employs a kernel function to map input data into a higher-dimensional space for improved separability, QSVM [4] replaces it with a quantum circuit that performs a quantum computation on the input data. This enables QSVM to handle large datasets more efficiently than classical SVM.

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Theoretical studies have demonstrated that QSVM can effectively address specific classification problems that are computationally challenging for classical computers. However, this proceeding is based on the IBM Qiskit [5] quantum simulator rather than any real quantum hardware.

3 Features and Datasets for QSVM

In this study, we revisit the Zc(3900) resonance from the following process:

\[ e^+ e^- \rightarrow Zc(3900) \pi^\pm \]
\[ Zc(3900) \rightarrow J/\psi \pi^\pm \]
\[ J/\psi \rightarrow e^+ e^- \text{ or } J/\psi \rightarrow \mu^+ \mu^- \]

The final state where the signal is observed consists of four charged tracks, including two charged \( \pi \) and a pair of leptons.

3.1 Features used in QSVM

From the process mentioned above, the energy, momentum, and mutual angle information of the four charged tracks are selected as the features in the QML model. Since there may be fake photons in the experimental data, the number and maximum energy of neutral particles are also taken as features. Therefore, a maximum of 28 data features are provided for the quantum machine learning model in this work.

3.2 Datasets for QSVM

3.2.1 Signal dataset

The signal dataset is generated by the BESIII Offline Software System (BOSS) [6]. The specific information of signal Monte Carlo (MC) [7] is summarized in Table 1. The phase space (PHSP) is generated according to the phase space distribution of the final particles calculated theoretically. And the \( J/\psi \rightarrow e^+ e^- \) and \( J/\psi \rightarrow \mu^+ \mu^- \) processes are generated separately.

<table>
<thead>
<tr>
<th>process</th>
<th>angular distribution function</th>
<th>decay branching ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>( e^+ e^- \rightarrow Zc(3900) \pi^\pm )</td>
<td>PHSP</td>
<td>1</td>
</tr>
<tr>
<td>( Zc(3900) \rightarrow J/\psi \pi^\pm )</td>
<td>PHSP</td>
<td>0.5 each</td>
</tr>
<tr>
<td>( J/\psi \rightarrow e^+ e^- )</td>
<td>PHSP</td>
<td>–</td>
</tr>
<tr>
<td>( J/\psi \rightarrow \mu^+ \mu^- )</td>
<td>PHSP</td>
<td>–</td>
</tr>
</tbody>
</table>

3.2.2 Background dataset

The inclusive MC data is originally used as the background for the QSVM training. Since the background in MC is not fit very well to the real data, it is unable to give a good training result. Therefore, we randomly chose events from the real data as the final background.
3.2.3 Dataset preparation

Due to the limitation of the SVM method, only the events with a similar topological structure can be used in the training. So that, a pre-selection is applied to prepare the dataset. 4 charged tracks with a net charge of 0 is required, and:

- the distance between the vertex of each charged track and the collision point in the beam direction is less than 10 cm, and in the direction perpendicular to the beam direction is less than 1 cm;
- the charged track must be within the effective detection volume of the detector, i.e. the cosine value of its pole angle satisfies $|\cos \theta| < 0.93$, with pole angle $\theta$ which is the angle between the charged track and the direction of the beam.

This pre-processing is applied on both the signal and background data. Moreover, in order to suppress the detector effects and get a better signal distribution, we repeat the procedure of traditional analysis methods to the charged tracks for the signal dataset. During model tuning, we utilize a confusion matrix to evaluate the test set and minimize false positives, thereby improving prediction accuracy. Finally, we apply the optimized model to the 4.26 GeV data from the BESIII detector to identify the signal events, enabling the reconstruction of the invariant mass of the Zc(3900).

4 Performance

The traditional SVM model is trained with all the 28 features on a dataset consisting of 120,000 events. We employed a Gaussian kernel function to map the data to a higher-dimensional space, enabling linear discrimination. The SVM successfully identified signals, which were then utilized to reconstruct the invariant mass of the Zc(3900). Initially, we utilize all pre-selected features and achieve a satisfactory result after model tuning. Figure 1 illustrates the reconstructed invariant mass plot of the Zc(3900) identified by the SVM.

![Figure 1. The Zc(3900) mass distribution from SVM method](image-url)

Throughout our research, we discovered that removing any feature or reducing the size of the training set led to a decrease in the SVM model’s ability to accurately identify the Zc(3900). This emphasizes the significance of feature selection and the size of the training set in achieving reliable outcomes.

In the investigation of QSVM, we employ the same pre-selected features as in SVM at the beginning. But after tuning and optimization, only 13 features are kept, including the energy, momentum, and opening angle of the four most significant charged tracks, as well as...
the maximum energy carried by the neutral particle. The four opening angles are defined as the angles between the four charged tracks with the highest momenta, ordered from largest to smallest.

To construct a simulated quantum circuit, we utilize the IBM Qiskit toolkit. This allows us to efficiently simulate the behavior of a quantum computer, which is crucial for the successful implementation of QSVM. In this study, we employ the built-in ZZFeatureMap in Qiskit to map the data features to a higher-dimensional Hilbert space within the quantum kernel function. We introduce linear entanglement to the circuit and encode all features twice. In the final optimization, we find that a training dataset with 1000 events is sufficient to train the QSVM model and achieve a favorable result, as shown in figure 2.

![Figure 2. The Zc(3900) mass distribution from QSVM method](image)

The application of the trained QSVM model yielded excellent results. By utilizing qiskit’s ZZFeatureMap, we effectively mapped the data features to a higher-dimensional space, which played a crucial role in achieving accurate outcomes in QSVM.

5 Summary

In this proceeding, we revisit the observation of Zc(3900) at BESIII with the QSVM method, and achieve a competitive result. Notably, QSVM performs well enough on a smaller training dataset with less features compared to the traditional SVM model. We have seen the potential capability of QSVM in physics data analysis. Quantum computing may play an important role in the future in high energy physics field.

References