Detection and evaluation of abnormal user behavior based on quantum generation adversarial network

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Quantum computing holds tremendous potential for processing high-dimensional data, capitalizing on the unique capabilities of superposition and parallelism within quantum states. As we navigate the noisy intermediate-scale quantum (NISQ) era, the exploration of quantum computing applications has emerged as a compelling frontier. One area of particular interest within the realm of cyberspace security is Behavior Detection and Evaluation (BDE). Notably, the detection and evaluation of internal abnormal behaviors pose significant challenges, given their infrequent occurrence or even their concealed nature amidst vast volumes of normal data. In this paper, we introduce a novel quantum behavior detection and evaluation algorithm (QBDE) tailored for internal user analysis. The QBDE algorithm comprises a Quantum Generative Adversarial Network (QGAN) in conjunction with a classical neural network for detection and evaluation tasks. The QGAN is built upon a hybrid architecture, encompassing a Quantum Generator (GQ) and a Classical Discriminator (DC). GQ, designed as a parameterized quantum circuit (PQC), collaborates with DC, a classical neural network, to collectively enhance the analysis process. To address the challenge of imbalanced positive and negative samples, GQ is employed to generate negative samples. Both GQ and DC are optimized through gradient descent techniques. Through extensive simulation tests and quantitative analyses, we substantiate the effectiveness of the QBDE algorithm in detecting and evaluating internal user abnormal behaviors. Our work not only introduces a novel approach to abnormal behavior detection and evaluation but also pioneers a new application scenario for quantum algorithms. This paradigm shift underscores the promising prospects of quantum computing in tackling complex cybersecurity challenges.

I. INTRODUCTION

Quantum computing exploits the quantum parallelism, entanglement, coherence and other properties arising from the superposition of quantum states, and has shown amazing capabilities in processing some computational tasks [1–3]. However, current quantum computers are kinds of noisy intermediate-scale quantum (NISQ) computers [4], which have a limited number of qubits and work with noise within a limited coherence time. Exploring possible applications in quantum computing has become an emerging topic in the context of NISQ.

Anomalies are deviations from established patterns within data, and they do not adhere to the predefined norms, as defined by Chandola et al. [5]. Anomaly detection presents a formidable challenge and has gained paramount importance across numerous research domains, including finance, networking, and health diagnostics. Within the realm of network activities, behaviors encompass all actions performed by users, such as login activities, app usage, website visits, and more. The network’s vulnerability to abnormal behaviors, often stemming from the malicious activities of internal users, poses a significant threat to information systems. The intimate knowledge of the system possessed by these users makes the detection of such anomalies particularly challenging.

A noteworthy hurdle in the identification of abnormal behaviors among internal users lies in the pronounced imbalance between negative and positive samples. In this field, numerous exceptional works have emerged, many of which revolve around training models to capture user behaviors and subsequently assessing whether these behaviors fall within the spectrum of normalcy or exhibit malicious intent [6–9]. Conversely, quantum algorithms have begun to find applications in anomaly detection within the realm of physics, notably in scenarios involving quantum data, such as quantum states [10] and topological phases [11]. A recent breakthrough by Chai et al. [12] showcased the detection of anomalies within audio samples using a three-qubit quantum spin processor embedded in a diamond.

The Generative Adversarial Networks (GAN) was introduced by Goodfellow et al. in 2014 [13]. GAN comprises two deep neural networks, namely the generator (G) and the discriminator (D). Through adversarial training of G and D, GAN has the ability to generate synthetic data that closely mimics real data. GAN has demonstrated remarkable success in modeling complex and high-dimensional distributions of real-world
data [14]. More recently, GAN has found applications in the field of anomaly detection. In 2017, Schlegl et al. proposed AnoGAN (Anomaly GAN), a technique that leverages adversarial training to model normal behavior and calculate anomaly scores for the detection of anomalies [15]. Numerous enhanced GAN-based methods for anomaly detection have emerged, including EGBAD (Efficient GAN-Based Anomaly Detection) [16] and f-AnoGAN (Fast Unsupervised Anomaly Detection with GAN) [17]. In 2022, Xia et al. provided a comprehensive review addressing the prominent challenges faced in GAN-based anomaly detection. They also proposed several promising research directions for prediction and analysis in this domain [18].

In 2018, Dallaire-Demers et al. introduced Quantum Generative Adversarial Networks (QGAN) [19], expanding the domain of Generative Adversarial Networks (GAN) into the quantum realm. They employed Parameterized Quantum Circuits (PQC) [20] to construct generative adversarial networks and compute gradients, demonstrating the successful training of QGANs. Lloyd et al. [21] further highlighted that QGANs may exhibit an exponential advantage over their classical counterparts, particularly in scenarios involving high-dimensional data samples. Considering the quantum nature of one or more components, including the generator, discriminator, or data, a diverse array of QGAN algorithm frameworks has emerged [22–25]. In 2021, Herr et al. introduced Variational Quantum-Classical Hybrid Wasserstein GANs (WGANs) [26], specifically tailored for anomaly detection within the credit card industry.

To leverage the capabilities of Quantum Generative Adversarial Networks (QGAN) in addressing the challenge of detecting abnormal behaviors among internal users, we propose a variational QGAN, designed using a quantum-classical hybrid architecture within the context of Behavior Detection and Evaluation (BDE). For simplicity and convenience, we refer to this comprehensive algorithm as QBDE, which stands for “QGAN for Abnormal Behavior Detection and Evaluation based on Internal User Behaviors.” We establish the feasibility and effectiveness of QBDE through a series of simulation experiments conducted using the CERT-R5.2 insider threat test dataset [27]. These experiments are executed within the quantum machine learning framework known as PennyLane [28].

The paper is structured as follows. Sec.II is a preliminary about the main processes of GAN and BDE. Sec.III presents our QBDE in detail, including the integration of QGAN and BDE by using parameterized quantum circuits and classical neural networks. In Sec.IV, we present the implementation of the QBDE with the insider threat test dataset CERN-R5.2. Finally, a summary and future works are discussed in Sec.V.

![FIG. 1. (Color online) The structure of GAN.](image-url)
FIG. 2. (Color online) The process of abnormal behavior detection and evaluation.

By training the discriminator $D$ against the generator $G$, the ability of $G$ to generate realistic samples is constantly improved, and $D$ is also improved in correctly identifying real and generated samples. In the ideal case, when the game reaches Nash Equilibrium, the distribution of the data generated by the generator fits that of the real data.

Quantum generative adversarial network (QGAN) is a generalized version of classical GAN using quantum properties. For the generator, discriminator and data, it is considered as a QGAN if one or more of them is quantum. In current NISQ, a large number of QGANs adopt the quantum-classical hybrid architecture that just $G$ or $D$ is quantum. For the quantum part, they usually apply PQCs to construct the quantum circuit of $G$ or $D$. We will introduce our QBDE as the specific case in Sec.III.

B. The abnormal behavior detection and evaluation based on user behaviors

The process of abnormal behavior detection and evaluation is shown in FIG. 2, which generally includes the following processes (More details see Ref.[7, 14]). It can be divided into three parts: preprocessing, behavior modeling, detection and evaluation.

Preprocessing. First, the original user datasets are selected from different multiple files. Then, behavior features are extracted. Considering the features are varied for different users, the data needs to be divided into separate datasets for each user. Further, the features are normalized into feature vectors.

Behavior modeling. A user behavior model is necessary to evaluate users’ behaviors. Ref.[7] proposed a user behaviors model training based on normal behavior sequence with GAN. During the training stage, the reconstruction is carried out in the output to minimize the reconstruction error [29]. In the test stage, samples including normal or abnormal are fed to the network. For the unknown abnormal data, the network will produce a high reconstruction error. Thus, the unknown user behavior is correctly judged.

Behavior detection and evaluation (BDE). To detect abnormal behaviors, test data is fed into the trained normal behavior model. Then, the threat degree of the detected threatening behavior is evaluated by a behavior detection and evaluation (BDE) network. In order to evaluate the security of a user’s behavior, the behavior score $d(x)$ and the abnormal threshold $T h_d$ are required.

For the testing data $x$ and the generated data $G(z)$, let $R_d$ and $R_n$ be the reconstruction errors before and after passing through the network of BDE. We have

$$R_d = \|x - G(z)\|_1,$$

and

$$R_n = \|f_n(x) - f_n(G(z))\|_1,$$

where $f_n(\cdot)$ represents the function of the BDE network, $\|\alpha\|_1$ is the $l_1$ norm of $\alpha$.

The behavior score $d(x)$ is defined as

$$d(x) = (1 - \lambda)R_d + \lambda R_n,$$

where $\lambda$ represents the weight.

The abnormal threshold depends on the specific task. During the detection stage, a behavior $X_t(x)$ can be classified as either ‘Normal’ or ‘Abnormal’ based on the behavior score $d(x)$ and the threshold $T h_d$ as

$$X_t(x) = \begin{cases} \text{Normal,} & d(x) \leq T h_d, x \in D_{test}, \\ \text{Abnormal,} & d(x) > T h_d, x \in D_{test}. \end{cases}$$

The main purpose of abnormal detection and evaluation is to analyze the threat level of user behavior, so as to defend and protect the networks and systems. The evaluation function $f(d(x))$ and the threat threshold $T h_f$ of the abnormal user behavior are used to achieve the above aim. Then, an abnormal behavior is divided into two threat levels, Low_thread and High_thread, according to $f(d(x))$ and $T h_f$ in the following way

$$f(d(x)) = \begin{cases} \text{Low_thread,} & d(x) \leq T h_f, \\ \text{High_thread,} & d(x) > T h_f. \end{cases}$$

Low_thread indicates no malicious behavior or a lower frequency abnormal operations, while High_thread indicates malicious behavior or higher frequent abnormal operations.

III. USER ABNORMAL BEHAVIOR DETECTION AND EVALUATION BASED ON QGAN

Due to the data generation ability of GAN and the superiority of quantum-classical hybrid architecture, we propose a quantum BDE algorithm, QBDE. The QBDE detects and evaluates user abnormal behavior based on a quantum generative adversarial network (QGAN). The framework of QBDE is shown in Fig.3. Similar to the classical abnormal behavior detection and evaluation model, it includes three modules: data preprocessing, the construction of the normal user behavior model (NUBM), and the behavior detection and evaluation (BDE). Specifically, the construction of NUBM is implemented by QGAN, which consists a quantum Generator $G_Q$ and a classical Discriminator $D_C$. Hence, our focus will be on the QGAN applied in the NUBM stage as well as the BDE in the following subsections.
FIG. 3. (Color online) The framework of QBDE. Here, $G_Q$, $D_C$, UNBM are the quantum Generator, the classical Discriminator and the user normal behavior model, respectively.

A. Quantum generative adversarial network for constructing user behavior model

In the anomaly detection, the samples of abnormal behavior are generally lesser than the normal samples. Especially, for the internal abnormal behaviors, it occurs much less often and are even covered by a large amount of normal data. In other words, the proportion of positive and negative samples is extremely imbalanced. Therefore, we select the normal user behaviors to form the training set, apply QGAN to generate negative samples, and then train the network to implement the construction of NUBM. Considering the limited resources of current quantum systems, the QGAN in the QBDE adopts a hybrid quantum-classical architecture, where the generator is a PQC and the discriminator is a classical neural network.

1. Quantum Generator

The quantum generator $G_Q$ of QBDE adopts PQC architecture [20], which consists of a series of single parameterized quantum gates and controlled quantum gates. Considering that the data for detecting anomaly user behavior is discrete, the special PQC architecture in $G_Q$ of QBDE is shown in Fig.4(a), which is proposed in Ref. [30]. Each layer is composed of a series of single rotation Pauli-Y gates $R_Y(\theta_{i,j})$ and entangled gates $U_e$, where $\theta_{i,j}$ represents the rotation angle of the $i$th qubit in layer $j$, and $U_e$ is composed of multiple controlled gates $Z$ as shown in Fig.4(b). The rotation gates and entangled gates are executed alternately. Assume the system consists of $n$ qubits, and let $K$ denote the depth of a quantum circuit. The $G_Q$ is trained to convert a given input state $|\psi_{in}\rangle$ into the output state

$$ |g_{\theta}\rangle = G_\theta |\psi_{in}\rangle = \sum_{j=0}^{2^n-1} \sqrt{p'_\theta} |j\rangle, \quad (9) $$

where $p'_\theta$ is the probability of state $|j\rangle$, $G_\theta$ represents the parameterized quantum circuit for $G_Q$ with the parameter $\theta$. To be specific, the input state is $|\psi_{in}\rangle = R_Y(\theta^0)|0...00\rangle$, and the $G_\theta$ can be expressed as

$$ G_\theta = R_Y(\theta^K)U_e...R_Y(\theta^2)U_eR_Y(\theta^1)U_e, \quad (10) $$

where $R_Y(\theta^j) = R_Y(\theta^{1,j}) \otimes R_Y(\theta^{2,j}) \otimes ... \otimes R_Y(\theta^n,j)$ is the rotation Pauli-Y gates in the $j$-th layer.

2. Classical Discriminator

The power of $G_Q$ is limited due to the restricted number of qubits and circuit depth in current quantum systems. Under this circumstance, it is not suitable to choose a complex network in the discriminator, so as to ensure that the $D_C$ does not overwhelm the $G_Q$ [30]. Therefore, we employ a fully connected neural network as the classical discriminator $D_C$ of QBDE, as depicted in Fig. 5. The structure of $D_C$ consists of two hidden layers composed of fully connected neurons and one neuron output layer.

FIG. 4. (Color online) The structure of $G_Q$ and its entangled gate.

FIG. 5. (Color online) The network of the classical Discriminator $D_C$. 

$$ R_Y(\theta^0)|0...00\rangle, \text{ and the } G_{\theta} \text{ can be expressed as} $$

$$ G_{\theta} = R_Y(\theta^K)U_e...R_Y(\theta^2)U_eR_Y(\theta^1)U_e, \quad (10) $$

where $R_Y(\theta^j) = R_Y(\theta^{1,j}) \otimes R_Y(\theta^{2,j}) \otimes ... \otimes R_Y(\theta^n,j)$ is the rotation Pauli-Y gates in the $j$-th layer.
The anomaly behavior detection and evaluation model (BDE) utilizes a two-classes convolutional neural network, as shown in Fig. 6. This network comprises composed of two convolution layers, two maximum pooling layers and the final output layer. The output layer consists of only one neuron with the Sigmoid activation function.

In order to validate the effectiveness of the designed algorithm, we evaluate the accuracy of the classification of the tested behaviors and the loss of BDE. The accuracy is expressed as

\[
\text{Accuracy} = \frac{TP + TP}{TP + TN + FP + FN},
\]

where TP, TN represent the ratio of true positive (negative) samples, and FP, FN are the ratio of false positive (negative) samples predicted wrong by the network.

The BDE network is optimized by minimizing its cost function, which is represented by the cross entropy loss:

\[
J(w, b) = -\frac{1}{m} \sum_{i=1}^{m} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]
\]

where \(y_i\) is the real label and \(\hat{y}_i\) is the output value of \(x_i\), respectively. Here, \(\hat{y}_i = \omega x_i + b\) is determined by the BDE network with parameters \(\omega\) and \(b\).

Since the training set only contains normal samples, we take the maximum reconstruction error of all training data as the abnormal threshold \(Th_d\), i.e.

\[
Th_d = \max(d(x_1), d(x_2), ..., d(x_i)), x_i \in D_{train}.
\]

In general, when the user takes malicious behavior or performs many abnormal operations, the behavior score \(d(x)\) is more than twice of \(Th_d\). Therefore, we take the threat threshold

\[
Th_f = 2Th_d.
\]

### IV. EXPERIMENTS AND RESULT ANALYSIS

#### A. Experimental environment and data

The experiments were performed in Win10 with 1T, the Intel i5 – 9500 processor and 16G memory. The programming platforms and software used included Python 3.8.12, PyCharm Community 2020.3, the machine learning library TensorFlow and PennyLane.

The data is from the well-known insider threat test data set CERT-IT R5.2 [27]. It includes the simulated attack behaviors such as system destruction, information theft and internal fraud carried by malicious internal users, as well as a large amount of normal behavior data. It consists of multiple files, which contain various log data of employee behaviors in the organization. Data files are processed in parallel according to user names.

| File Name  | Description about the data | Features                          |
|------------|----------------------------|-----------------------------------|
| login.csv  | System login record        | login.on, loginoff.on, login.out, loginoff.out, weekend |
| http.csv   | Http access record         | http.on, http.out                 |
| device.csv | Mobile Device usage record | connect.on, disconnect.on, connect.out, disconnect.out, size |
| email.csv  | Sending and receiving of mails | send.on, send.out                     |
| file.csv   | File operation record      | file.on, file.off                  |

TABLE I. Files and features of the selected data
Then, for each individual user, behavior data is collected by day as features. Here, we select the data from 5 specific files and extract 16 behavior features as shown in Table I. In the features column, ‘on’, ‘out’ represent the records that occurred during the working time and out of working time, respectively.

For user behaviors, some values of features are much larger than others. Hence, we normalize the values of features to $[0, 1]$ in the following way

$$x'_{i,j} = \frac{x_{i,j} - \min(x_j)}{\max(x_j) - \min(x_j)}, \quad x_{i,j} \in [1, 16],$$  \hspace{1cm} (17)

where $x_{i,j}$ is the value of the row $i$ (the $i$th day) and column $j$ (the $j$th feature) in any matrix $X$ within the dataset, and $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum of the $j$-th feature, respectively.

For the input of $G_Q$, we only need 4 qubits for 16 features of user behaviors, and initialize them with $|0000\rangle$ at first. The input state $|\psi_{in}\rangle$ will be initialized by adjusting $R_Y(\theta_{i,0})$ of quantum rotation gate $R_Y(\theta_{i,0})$ as

$$|\psi_{in}\rangle = R_Y(\theta_{i,0}) |0000\rangle, \quad i \in [1, 4].$$  \hspace{1cm} (18)

where $i$ is the $i$th qubit.

**B. Algorithm Implementation of QBDE**

Based on the theory of QBDE we proposed in the previous Sec.III, the overall procedure of QBED is summarized with pseudo-code in Algorithm 1. The input includes the data set $D$ selected from CERT-IT R5.2 [27] and the quantum state $|0000\rangle$. The QBED is first implemented by QGAN which is trained by PennyLane with the gradient descent, then a new behavior is detected and evaluated by BDE.

![FIG. 7. (Color online) The cross_entropy vs. the epoch for different layers in QGAN.](image)

![FIG. 8. (Color online) The losses of $G_Q$ and $D_C$ vs. the epoch for different layers in QGAN.](image)

**Algorithm 1: QGAN for user behavior detection and evaluation, QBDE**

**Input:** Data set $D$, the initial quantum state $|0000\rangle$.

**Output:** Normal, Low threat, High threat.

1. Preprocess the original user data set, normalize the data into a feature vector, and divide them into $D_{train}$ and $D_{test}$.
2. Training QGAN with PennyLane:
3. for training iterations do
   - Prepare the initial quantum state $|\psi_{in}\rangle$ by adjusting $R_Y(\theta)$.
   - Generate $\{g'_l\}$ using PQC, and obtain $\{g_l\}$ by measurement.
   - Sample $\{x'_l\}$ from $D_{train}$.
4. end
5. Fed the generating data and training sets into the NUBM and train it with cost function $J(\omega, b)$.
6. Detection and evaluation:
7. Calculate the behavior score $d(x)$, and compare it with $Th_d$:
8. if $d(x) < Th_d$ then
   - Normal
9. else if $Th_d < d(x) < Th_f$ then
   - Low threat
10. else
   - High threat
11. end
12. end

![Algorithm 1](image)
G in its training process. In the case of QGAN, where G abnormal behaviors that happen on that day. for different layers in QGAN. The red dots represent the real 
FIG. 9. (Color online) The scores of threat d(x) vs. the days 
for different layers in QGAN. The red dots represent the real 
abnormal behaviors that happen on that day.

c. Experimental results and analysis

1. QBDE with different layers of PQC

The depth of the neural network plays a crucial role 
in its training process. In the case of QGAN, where GQ 
adopts the PQC architecture, the performance of GQ is 
influenced by the depth (i.e. the number of layers) of 
PQC. Considering that the depth is limited in NISQ, we 
investigate the performance of GQ with different layers 
K = 2, 4, 6, 8. In terms of the average cross-entropy and 
the loss functions, the performance of QGAN is shown in 
Fig.7 and Fig.8.

The observation in Fig. 7 reveals that with an in-
creasing number of epochs, the cross entropy of 
GQ decreases quickly at first, and then slows down after a 
certain epoch, indicating that the optimization of GQ tends 
to converge. The convergence is inadequate for K = 2, 4, 
but highly satisfactory for K = 6, 8. Moreover, it is clear 
that the cross-entropy of GQ decreases more rapidly as 
the number of layers K increases. In other words, deeper 
depths result in faster and superior convergence of GQ.

In Fig. 8, the loss LG increases first and then de-
creases rapidly. On the contrary, the loss LD initially decreases and then increases. Eventually, both LG and 
LD converge to similar values and remain relatively con-
stant with the epoch, indicating that means the samples 
generated by GQ are already equivalent to the real sam-
ples. Additionally, the more layers there are, the faster 
LG and LD tend to converge.

The results of the detection, in terms of the behavioral 
score d(x) of the test data, are depicted in Fig. 9. The 
days of abnormal behaviors occurring in the real world 
were marked with red dots. We can observe that with 
different layers of QGAN, the abnormal behaviors have 
been successfully detected and evaluated with the behav-
iors scores. It is noted that several normal behaviors have 
higher scores than the Thd which may be classified as ab-
normal. Anyhow, the accuracy of the QBDE is 98.28%.

2. QBDE for different users

Now, we consider three different users. User1 has 300 
days of data, with 200 days are used for training and 100 
days for testing; User2 has 160 days of data, with 100 
days for training and 60 days for testing; User3 has 175 
days of data, with 100 days for training and 75 days for 
testing. Here, the number of layers of PQC in QGAN 
is K = 8. The losses of the GQ and DC are depicted in 
Fig.10, while the behavior scores d(x) of test data are 
illustrated in Fig.11. From these figures, we can observe 
that LG and LD tend to have the similar values for differ-
ent users, respectively. Meanwhile, almost all behaviors 
can be successfully detected and evaluated. For these 
three users, we obtain the accuracies of the QBDEs are 
97.98%, 98.28%, 97.30%.

Based on the above discussions, we can conclude that 
QBDE with QGAN can efficiently generate fake samples 
to construct the normal user behavior model, which can 
be further applied for the internal user abnormal behav-
ior detection and evaluation.

V. CONCLUSION

In this paper, we introduced QBDE, a Quantum Gen-
erative Adversarial Network founded upon a quantum-
classical hybrid architecture. QBDE was developed to 
address the challenge of detecting and evaluating abnor-
mal behaviors among internal users. The quantum gen-
erator within QBDE played a pivotal role in generating 
negative samples, effectively mitigating the imbalance is-
ssue between positive and negative samples—a common 
challenge when dealing with limited abnormal behavior 
data. Furthermore, both the quantum generator and 
classical discriminator were optimized using the Penny-
Lane framework. Our experiments demonstrated the fea-
sibility and efficacy of QBDE when applied to the CERT-
R5.2 insider threat test dataset. However, there remains 
ample room for improvement. The current QBDE imple-
mentation utilizes a limited number of qubits and shallow 
Parameterized Quantum Circuits (PQC), which con-
strains the potential of GQ. Additionally, these limita-
tions extend to the utilization of advanced and complex 
networks for DC. This designed algorithm not only paves 
the way for new applications in quantum artificial intel-
ligence but also introduces a novel approach to abnormal 
behavior detection. In light of this, there exist numerous 
avenues for future research in exploring further applications for quantum algorithms.
FIG. 10. (Color online) The losses of $G_Q$ and $D_C$ vs. the epoch for different users.

FIG. 11. (Color online) The score of threat $d(x)$ vs. the days for different users. The red dots represent the real abnormal behaviors happen in that day.

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