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Efficient Unconnected Pattern Learning for Machine Learning-Based Techniques to Variational the quantum Classifier

S Sundeep kumar[1],
Mocharla Ramesh babu[2]
P VEERANNA[3]
Chilakabathula swathi[4]
[1](Asst. prof,
Dept of CSE
Sree Dattha Institute of Engineering and Science))
[2](Assignment professor
Dept of CSE
CMR Technical campus
rameshbabu.it@cmrtc.ac.in
Kandlakoya(v),medchel (m), Malkangiri (d), Hyderabad)
[3](Asst prof,
Dept of CSE
Sri indu college of engineering and technology(Autonomous
Rangareddy District, Auditorium - Sri Indu Main Block Rd, Sheriguda, Telangana 501510)
[4](Asst. prof
Dept of EEE
Sri indu college of engineering and technology(Autonomous
Rangareddy District, Auditorium - Sri Indu Main Block Rd, Sheriguda, Telangana 501510)

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Abstract:

This Is A Lot Of Buzz Recent To The Use Of Quantum-Enhanced Technologies For Addressing Various Machine-Learning Tasks. For Supervised Learning, Variational Techniques Which Utilize Classical Capacities Of Inefficient Quantum Machines With The Aid Of Classic Computing Techniques Are Widely Used. Among These Techniques, Variational Atomic Classification (Vqc) Offers An Eventual Quantum Advantage In That It Makes Use Of Quantum-Enhanced Characteristics That Are Challenging To Compute Using Conventional Methods. The Mapping Of Traditional Face Appeal Into A Quantum-Enhanced Appearance Space Influences Its Performance. Although Multiple Quantum-Mapping Methods Have Been Proposed Thus Far, There Has Been Limited Discourse Over Appropriate Mapping Of Discrete Features, Including Zip Code, Age Group, And Others, Which Can Frequently Important For Classifying Relevant Datasets. We First Present The Efficient Mappings Of Such Discrete Features Into Just A Couple Of Qubits For Vqc Using Quantum Random-Access Coding (Qrac). We Outline Numerous Methods Of Encoding And Show Their Strengths And Limitations In Algebraic Simulations. We Showed Experimentally That Qrac Might Help By Decreasing The Parameters Of Vqc And Speeding Up The Mapping Process Using Fewer Qubits. Using Both Simulators And Sincere Quantum Devices, We Conducted Experiments On Real-World Datasets To Verify The Efficacy Of The Qrac In Vqc.

Keywords — supervised instruction, variational quantum computations, quantitative device learning, quantum random-access code (QRAC), and discrete features.

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I.INTRODUCTION

Research on utilizing quantum computing for machine learning applications, like as grouping, degradation, and anomaly detection, has surged due to improvements in quantum[1] computing technology. The variational methods which are additionally frequently employed in optimization are the core of many quantum-enhanced machine learning methods especially those for classification. It has been suggested that these methods may use either noisy quantum devices and classical computing devices to gain a quantum advantage. The variational quantum classifier (VQC) direct approach and the quantum kernel estimation indirect approach are the two categories into whose the quantum-improved techniques can be separated Under certain computational complexity arguments, each of the methods are, in the end, for mapping real-valued features into quantum-enhanced feature space, which mapping is thought to be hard to compute by any classical computational device However, the majority of mapping algorithms serve real-valued mark vectors; there lack many for binary and discrete features. However, the power of quantum bits is constrained, even if quantum feature space can be linked to analog features of quantum bits that have capacity to store chronic values. For example, the Holevo[2] bound restricts that n if the information is to be recovered with certainty. The Holevo bound confines the quantity of information that n qubits can store to n bits, and nothing more. Due to the Nayak bound, whose restricts the amount information that can be retrieved from m qubits in order to recover any one out of n bits (for n ≥ m), the limit even holds in the probabilistic instance. In particular, to recover any one out of n bits with certainty, one still needs n qubits. If constant errors allowable upon retrieving any one of the bits, however a linear saving is attainable; However, in that case, quantum-enhanced coding adds no further benefit. In real-world datasets, classification models generally utilize binary features, such yes/no responses to questions, in addition to (discrete) grouping details, as zip code, age, and ethnic group, that is naturally represented with bitstrings. Before the discrete features can be efficiently used in machine learning models that depend upon the continuity of their inputs, they has to be encoded into continuous admit appearance. For such purposes, many encodings have been proposed, the most often used becoming one-hot encoding[3]. It is widely acknowledged that the encodings may significantly influence how well the learning models work (for extra details, see Section II). It is not simple to map such binary and discrete features into quantum-enhanced feature space, because as of this writing,

This article's remaining sections are organized as follow. In Section II, we review pertinent studies focusing on feature mapping strategies. After that, we look to the QRAC[4] in Part IV and the VQC in Chapter III-B. More specifically, Section IV-B explains the proposed technique for merging QRACs into VQCs, and Section IV-C explores the connection to functional QRACs, which can be thought of as binary classification with binary inputs. In Section V, we give arguments regarding the potential and constraints of QRACs for supervised learning along with a geometric instance of encoding binary features using QRACs in several forms. In Section VI, we present empirical comparisons of the recommended technique to traditional VQC on some of the benchmark datasets[5].

II.ASSOCIATED EFFORT

Discrete feature datasets which are structured are widely available. Categorical or qualitative data are phrases utilized for describing the distinct features. These are significant features that have an essential effect on prediction models' performance. In specific learning models, like decision trees, discrete features can be utilized simply; nevertheless, in the majority of applications of neural-network models, discrete features have to be translated into continuous features first. In fact, it has been noted that whilst neural-network models are prevalent for handling unstructured datasets, tree-based models[6] tend to be more frequently selected by winning teams in machine learning rivalries when dealing with structured datasets that contain categorical features, as pointed out in.

It's essential for understanding how to employ categorical features in neural network models with continuous inputs. For the purpose of for uniformity within the training phase and output stability following small input changes within the prediction phase, features have to stay similar. Many traditional techniques exist for translating discrete values to numerical values because easy replacement of categorical qualities with integers fails to operate well in neural network models. In addition, they come under multiple names, including (dense) encodings, (distributed) representations , and (entity) embeddings .

The Mapping Techniques Can Be Categorized Into Three Groups: Determined, Algorithmic, And Automated, According To The Level Of Complexity[7] . The Techniques Most Commonly Employed Are Determined Ones And Which Include Hash Encoding, Ordinal Encoding, And One-Hot Encoding. The Indoctrination Of The Categorical Values Based On Certain Simple Regulations Or Lookup Tables Has Been Rectified Through The Techniques In This Category.

One-Hot Encoding, For Example, Utilises Bit Strings Of Length D That Have A Single 1 And A Single 0 To Represent D Distinct Class Values, Such As 100, 010, And 001 When D = 3. They Are Commonly Employed, And Popular Machine Learning Libraries As Scikit-Learn Give Their Implementation. Combining Kernel Techniques With Quantum-Enhanced Support Vector Machine (SVM)[8] On Near-Term Quantum Devices Centers Upon The Embedding Of Classical Data Into The Large Hilbert Space Of Quantum Devices,. Nevertheless, As Soon As We Understand, These Are No Quantum Approaches Available For Handling Categorical Features. This May Happen Because They Can Be Encoded Using The Previously Presented Traditional Methods Before Using Them In The Quantum Subprograms. For Classification And Other Machine Learning[9] Difficulties, Regular Neural Networks And Quantum Models Have Been Merged At Particular Recent Suggested Tackles.

Combining Kernel Techniques With Quantum-Enhanced Support Vector Machine (SVM) On Near-Term Quantum Devices Centers Upon The Embedding Of Classical Data Into The Large Hilbert Space Of Quantum Devices. Nevertheless, As Soon As We Understand, These Are No Quantum Approaches Available For Handling Categorical Features. This May Happen Because They Can Be Encoded Using The Previously Presented Traditional Methods Before Using Them In The Quantum Subprograms. For Classification And Other Machine Learning Difficulties, Regular Neural Networks And Quantum Models Have Been Merged At Particular Recent Suggested Tackles.

III.VARIATIONAL QUANTUM CLASSIFIER

Here, we present a brief overview of the VQC framework, notably for binary organizations problems, in which a two-valued quantum measurement generates two labels. Bear mindful that, as indicated, we can extend the classifier for multiclass organization. The n-class classification, for examples, occurs in by determining the overlap among its final state and n maximally orthogonal target states, each of that corresponding to a label. Since many measurements are used to figure out the goals state, this can be thought of as the QRAC de-coding process.

A. CLASSICAL SVM

Assume that we are given the training dataset S = {(x1, y1), (x2, y 2) ,..., (xm ,S ym)S}, where xi ∈ Rd and yi ∈{−1, 1}. The goal of learning a binary classifier from S is to construct a function f (x) so that f (xi)yi > 0 ∀i.

{−1, 1}. The goal of learning a binary classifier from *S* is to construct a function *f* (***x***) so that $f(\boldsymbol{x}_i)y_i > 0$ ∀*i*. The simplest form of such function is a linear classifier *f* (***x***) = $\boldsymbol{w}^T \boldsymbol{x} + b$, where $\boldsymbol{w} \in \mathbb{R}^d$ and $b \in \mathbb{R}$. *S* is called linearly sep.

B. CLASSICAL SVM

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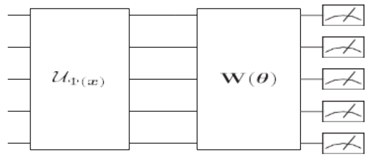
The function f (x) is then given by the mean of g with the bias b f (x) = (Φ(x) .W†(θ) g W(θ . Φ(x))+ b. (1)

The predicted label is then given by the sign of f (x). The hyperplane (w, b) is now parameterized by θ. The ith el-ement of w(θ) is wi(θ) = tr(W†(θ)gW(θ)Pi), where Pi is a diagonal matrix whose elements are all zeros except the (i, i) element, which is one. Also the ith element of Φ(x) is Φi(x) = (Φ(x)|Pi|Φ(x)).

Learning the best θ can be obtained by minimizing the cost function formulated as empirical risk R(θ) or binary cross entropy H (θ) with regards to the training data S. These cost functions to be minimized are

A.QUANTUM-ENHANCED VARIATIONAL CLASSIFIER

VQC relies on techniques for finding the best hyperplane (w, b) that linearly separates the embedded data. First, the data x ∈Rd are mapped to a (pure) quantum state by the feature map circuit UΦ(x) that realizes Φ(x). This means that,conditioned on the data x, we apply the circuit UΦ(x) to the n-qubit all-zero state|0n)to obtain the quantum state| Φ(x)). A short-depth quantum circuit W(θ) is then applied to the quantum state, where θ is the vector composed of parameters that will be learned from the training data. Finding the circuit W(θ) is akin to finding the separating hyperplane (w, b) in the soft-



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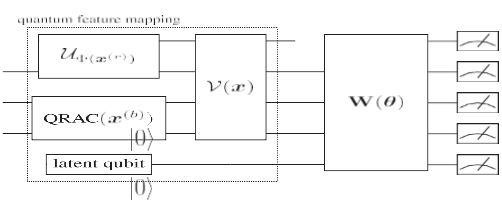
E. NONLINEAR EMBEDDING

There are many classical methods[10] for nonlinear embedding of data x : Φ(x)∈Rn for n > d, such as the polynomial kernel, which is also popular for natural language process- ing . In this case, the two-dimensional data (x1, x2) is embedded into√a three-dimensional one (z1 , z2 , z3) such that z1 = x2, z2 = 2x1x2, and z3 = x2. On the other hand, in the quantum-enhanced SVM,

$$U_{\Phi(x)} = \exp\left(i \sum_{S\subseteq[n]} \varphi_S(x) \prod_{k\in S} Z_k\right) \quad (4)$$

where the coefficients φS(x) ∈ R are fixed to encode the data x. For example, for n= d = 2 qubits, φi(x) = xi and φ1,2(x) =(π −x1)(π −x2) were used in . The classifi- cation performance greatly depends on these functions,

[63]. In general, UΦ(x) can be any diagonal unitary that is effi- ciently realizable with short-depth quantum circuits. In total, one needs at least n≥d qubits to construct such quantum- enhanced feature map, i.e., the number of qubits is at least the dimension of the feature vector of the datasets.qubits in VQC[11]. When the inputs are binaries, the classification can be regarded as evaluating Boolean functions, which coincides with the functional QRAC (or f -QRAC). We discuss the relation of our proposal with f -QRAC, which will0:85)-QRAC. (b) (3, 1, 0:78)-QRAC



the embedding of data to the n-qubit feature space is performed by applying the uni- tary UΦ(x) = UΦ(x)H⊗nUΦ(x)H⊗n, where H is the Hadamard gate, and UΦ(x) denotes a diagonal gate in the Pauli-Z basis as follows:

. Each bitstring is mapped on the surface of the sphere. The distance between two quantum states is proportional to the Hamming distance of their corresponding bitstrings. (a) (2, 1,

FIG. 1. Quantum circuit for VQC+QRAC for encoding discrete features. The additional gate (Vx) may be included for entangling the quantum states for continuous variables and discrete variables. Also, latent qubits may be included to extend the dimension of the Hilbert space.

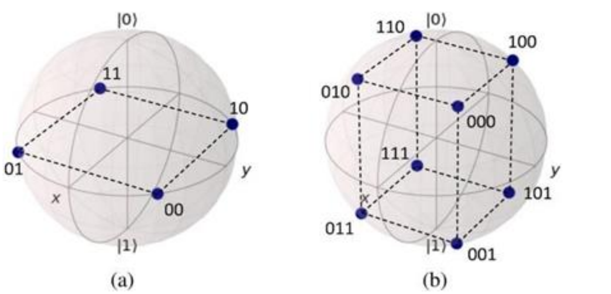


FIG. 2. Quantum circuit for VQC without QRAC, which consists of fixed quantum feature mapping ΦU(x) and the separator W(θ) trained with the variational method.

circuit W(θ) followed by the computational basis measure- ment. In the following, we refer to the VQC with QRAC as simply VQC+QRAC, as shown in Fig. 2. Also, we show the schematic of

VQC without QRAC in Fig. 3, which will be compared to VQC+QRAC in the next section

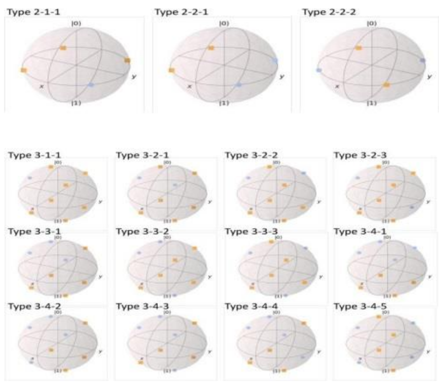


FIG. 3. All possible configurations of (2, 1)-QRAC and (3, 1)-QRAC. Type a- b-c represents the pattern number c of (a, 1)-QRAC with b blue points and 2a − b orange points. (a) Case of (2, 1)-QRAC. (b) Case of (3, 1)-QRAC.

higher dimension. There are at least three means to add dimensionality. First, by adding latent qubits, as suggested in [45], which are qubits initialized to some fixed quan- tum states, as shown in Fig. 2. Second, by using multiple copies of QRACs for encoding the same discrete features, as will be seen in Section VI-B1, which is similar to using copies encoding suggested in [39]. Third, we may use higher dimensional QRACs, such as (3,2,0.91)-QRAC shown in [24], for mapping eight points into two-qubit Hilbert space. We ran experiments comparing the effectiveness of these three methods and obtained the train loss curves for type 3-4-5, as shown in Fig. 6. We confirmed that all methods overcome the limitation of the QRAC; in particular, the use of higher dimensional QRACs seems to be the most effective. In fact, two-qubit VQC+QRAC[12] with the copies of (3,1)-QRAC and (3,2)-QRAC can completely separate the data points of

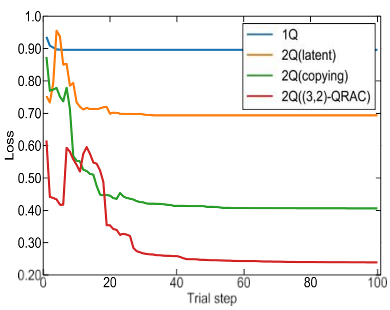
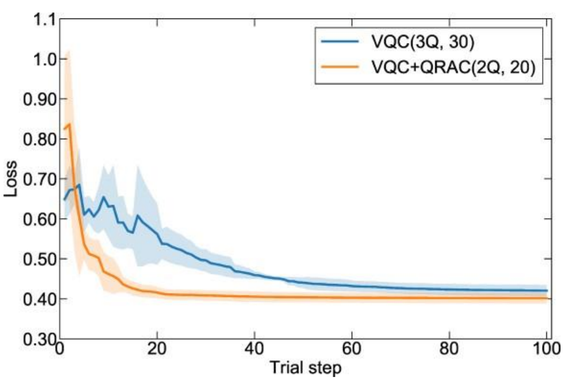


FIG. 4. Loss curves of four types of VQC+QRAC on type 3-4-5 over iterations. 1Q is one-qubit VQC+QRAC with (3,1)-QRAC. 2Q (latent), 2Q (copying), and 2Q ((3,2)-QRAC) represent two-qubit VQC+QRAC with latent qubits, the copies of (3,1)-QRAC, and (3,2)-QRAC, respectively

type 3-4-5. We also confirmed that by adding dimension to the inseparable types of Fig. 5, there are many cases where all points can then be shattered.

A. VQC WITH TWO-QUBIT QRAC

The aforementioned discussion shows that while still achiev- ing a constant-factor saving, (3,2)-QRAC can be more pow- erful than the one-qubit QRAC at the expense of one more qubit used. In addition, multiqubit QRACs are therefore im- portant in order to encode more discrete features with better efficiency. Unfortunately, a general method for construct- ing multiqubit QRACs beyond concatenation of one-qubit QRACs is not known, and so far only two-qubit QRACs, de- noted as (n, 2, p)-QRACs, were studied in the literature [23], [24], [58].For the first scenario, we turned real-valued features, such as oldpeak, into binary features by partitioning them with their median values, and applied the one-hot encoding method for discrete features, such as cp and thal. We then took the three most imperative features based on their importance estimated by a random forest classifier. The selected three features are chest pain type cp(0), number of major vessels colored by fluoroscopy ca(0), and thallium heart scan thal(2). Here, for example, the discrete feature cp was transformed into the



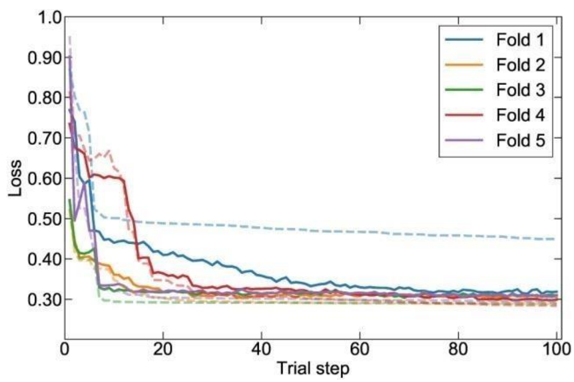


FIG.5. Training loss of VQC with 3 qubits and 30 parameters (blue) and VQC+QRAC with 2 qubits and 20 parameters (orange), on the HD dataset. The solid line is the mean of the loss values, and the shading represents their standard deviation over five-fold cross-validation.

and false if not. The VQC used three qubits for mapping the aforementioned features, whereas the VQC+QRAC can encode them with a single (3, 1)-QRAC. Nevertheless, we used two (3,1)-QRACs for VQC+QRAC to encode the same 3-b features in order to increase the dimension of the Hilbert space[13]. Thus, the VQC+QRAC used two qubits for mapping the aforementioned features. This is the technique proposed in Section V-A.

After our work was published, there have been other evidences of the high efficiency of QRAC- based quantum classifiers on other datasets. Those demonstrate the generality of our proposal. Also, even when an ideal fault-tolerant quantum computer emerges, the pro- posed scheme still has a clear merit in that, compared to quantum classifiers without QRAC, a shorter circuit is eas- ier to train, which hopefully may realize better classifi- cation performance. This practical advantage was in fact observed in the numerical simulation demonstrated in this article.

As described in Section IV-A, originally, QRAC is a theory providing a solid quantum advantage over the classical one, in the problem for probabilistically extracting (1 b) informa- tion by appropriately synthesize quantum measurement. Although in this article, we only utilize the encoding part of this QRAC theory, we will further combine the proba- bilistic information-extraction aspect of QRAC to extend the proposed method so that it could have a certain quantum advantage in the machine learning context. Additionally, an- alyzing the robustness of the proposed system itself and its tolerance to the noise is left for future work.

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(n, m)-QRAC or (n, m)- f -QRAC with, e.g., m = n/2 will work, as indicated by the demonstration given in Sections V-B and V-C. Note that the size of the example problems considered in this article is very small, and thus the barren plateau issue is not clearly observed. We will study large- size problems to prove the genuine advantage of our QRAC- based method as a variational quantum circuit having both the trainability and the expressibility

V.CONCLUSION

This article proposed the QRAC-based quantum classifier for a given dataset having discrete features. The main improvement of the scheme is to provide the mean for brainwashing an input bitstring to a quantum state with less number of quantum bits: more precisely, the QRAC theory guarantees that we can encode a bitstring of length n into log(n)/2 qubits and recover any one out of n bits with probability bigger than 1/2. This results in a shorter circuit for education the organization

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