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Quantum Support Vector Machine Algorithm

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Abstract

Churn prediction of customers is highly significant in banking as the cost of retention is much lower than the cost of acquisition. Usually individuals operate with the standard ML frameworks, such as SVM, although they have a ceiling when the data is of high dimension and extremely non-linear - they become more and more sluggish and are inadequate to actually model all the complexity. The paper presents a Quantum Support Vector Machine (QSVM) that is used to predict the customers who are going to leave the bank. Unlike The preprocessing in classical code, such as clean up the data, encoding of categories, scaling and then PCA to reduce the feature set to one that fits within the small number of qubits, all proceeds as normal. Then we apply the shrunk data to a quantum state, using ZZFeatureMap, and compute a quantum kernel which informs us of the similarity between data points in Hilbert space. Initialization of the QSVM in Python using Qiskit and then running it on the Qiskit Aer simulator. It is reasonably good: overall accuracy of around 88 percent and good scores on non-churn customer identification and fair adequacy in identifying churners. These figures demonstrate that quantum-enhanced ML might be a viable alternative to quantum hardware in the realm of real business analytics and is going to become even more feasible as quantum technology advances.

Index Terms: Quantum Support Vector machine, Customer Churn Prediction, Quantum Kernel, ZZFeatureMap, Qiskit, Principal Component Analysis.

I. INTRODUCTION

The loss of customers leaving a bank is a major agony to the banks which would wish to remain competitive. Research continues to demonstrate that it can be between 5 and 25x more expensive to bring in a new customer than it is to retain an existing one, thus churn prediction is a strategically important objective to teams [1].

Typically, we can train such binary classification models as Logistic Regression, Decision Trees, or traditional SVMs [2]. The reason why SVMs solidify over moderate datasets is that their kernel tricks: linear, polynomial, RBF, drive the data to higher dimensional feature spaces [3]. The snag is that as the data increases, the kernel matrix becomes massive, the cost of computing increases exponentially and the model becomes less effective due to its naive approach of not representing messy non-linear user behaviour.

The game has been transformed by quantum computing, which is also able to represent and process data via superposition and entanglement using quantum computers [4]. Such tools as IBM Qiskit enable us to experiment with all of these ideas both on quantum hardware or simulators at scale even prior to the existence of big-scale chips. Initially proposed by Rebentrost et al. [5]

The QSVM applies the quantum version of the feature map and quantum kernel to separation of complex patterns in exponentially larger Hilbert spaces, in theory. Nevertheless, in this work, a hybrid pipeline of PCA followed by dropping the data to a quantum state with ZZFeatureMap and quantum fidelity kernel computation is constructed. Training the QSVM on a 10,000 row bank dataset and testing it. The findings are near 88% total accuracy, which proves the method to be a viable move towards quantum-enhanced prediction in the finance sector.

II. RELATED WORK

One of the trending topics in classical statistics and the newer quantum has been customer churn prediction.

A. Precursors of Estimating the Target Model.

The initial studies generally followed Logistic Regression and Discriminant Analysis as they are simple to grasp. They pinned the linear separability, but fail miserably when the datum becomes unbecoming and nonlinear, as in the current banking books [2].

B. Proposals based on machine learning. The

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Support Vector Machines, introduced initially by Cortes and Vapnik [3], rapidly became the machine of choice in the case of binary classification. SVMs were able to sample through nonlinear spaces with the kernel tricks (polynomial and RBF), but the costs explode (like O(n 2) as the datasets increase. Include ensemble tricks such as Random Forest and Gradient Boosting and you have narrower accuracy but the models are black boxes. Deep learning and other big data brains require a ton of the compute, as observed [2].

C. Quantum Machine Learning

Biamonte et al. [6] surveyed quantum machine learning, indicating possible speed-ups. Havlicek et al. [7] demonstrated that quantum-enhanced feature training is possible on near-term devices and demonstrated that quantum kernels can project the data to the places that cannot be reached by classic computers. Schuld and Killoran [8] explicitly associated the quantum models and the kernel tricks, which preconditioned the QSVM. QSVM was implemented on credit-risk by Li et al. [9] and executed on quantum chips of IBM by Shan et al. [10]. These papers essentially provide the reasons as to why we should attempt QSVM on banking churn.

III. METHODOLOGY

A. Dataset

We have seized a communal bank cheque with 1000 entries [11]. Field list contains CreditScore, Geography, Gender, Age, Tenure, Balance, NumOfProducts, HasCrCard, IsActiveMember, EstimatedSalary and binary target Exited. The data is disproportional because of about 20% churn class in the rows.

B. Data Preprocessing

Deleted unwanted IDs (RowNumber, CustomerId, Surname). Label Encoding of Encoded variables: Geography and Gender. Min-Max scaling: everything was normalized to the [0, 1] range:

$$x' = (x - x_{min}) / (x_{max} - x_{min})$$

C. Dimensionality Reduction through PCA

Dimensionality reduction denotes a procedure of reducing or changing measurements.

Squashing the eleven features with Rand PCA [12] to four major components, which is the maximum number supported by the simulator (four qubits), retains the bulk of the information. The variance ratios were nearly [0.40,90,20,10] and we retain approximately 95 percent of the whole.

$$Z = X\, W\_PCA(2)$$

and Z (n 4) is the reduced matrix and W PCA has the top-4 eigenvectors of the covariance matrix.

D. Quantum Feature Mapping

Mapped the classical features to quantum states using the ZZFeatureMap [7] that constructs entangled rotations using the input vector x:

$$\phi(x) = U\_p(x)\, |0\ldots0\rangle$$

with U p (x) = layers of Hadamards and ZZ entrepreneurs of the type exp i (p i x i) (p j x j) Z i Z j 1 /2. The circuits comprised of 30 gates because we used 2 repetitions (reps = 2) with linear entanglement.

E. Quantum Kernel Computation

Computed stoichiometric quantum kernel matrix K(computing the inner product (fidelity)) of pairs of coded quasistates:

$$K(x\_i, x\_j) = |\langle\phi(x\_i)|\phi(x\_j)\rangle|^2$$

To estimate each of the entries, we used QASM simulator on Qiskit Aer and ran the specified circuit with 1024 shots.

F. QSVM Classifier

Trained a Support Vector Classifier with precomputed kernel (QSVC of Qiskit Machine Learning) with the Q-kernel matrix. The problem was the optimisation:

$$\min_\alpha \tfrac{1}{2}\textstyle\sum_{i,j}\alpha_i\alpha_j y_i y_j K(\mathbf{x}_i,\mathbf{x}_j) - \sum_i\alpha_i (5)$$

$\texttt{subject to } \sum_i\alpha_i y_i = 0 \texttt{ and } 0 \le \alpha_i \le C$, where C controls the margin softness.

G. System Architecture

Fig. 1. represents a hybrid framework with eight layers on the full pipeline. The output of the Input Layer is serving as input in Preprocessing, PCA, Quantum Feature Encoding, Quantum Kernel Computation, QSVM Classification, and Model Evaluation, which all operate according to the framework of the simulator of Qiskit Aer.

Load Customer Dataset, Preprocess Data (Clean, Encode, Scale), Dimensionality Reduction with PCA, Features Encoding with Quantum Feature Mapping, Quantum kernel, Train QSVM Classifier, Prognosticate Customer Churn. Evaluate Model Performance.

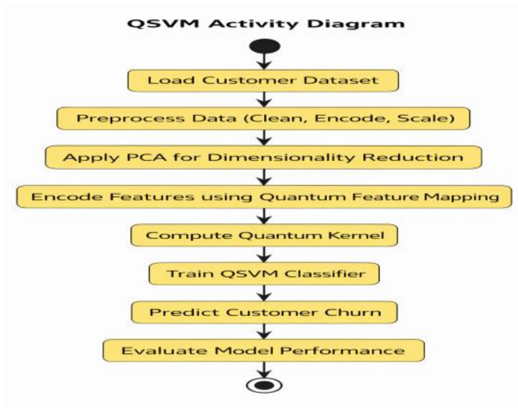

Fig. 1. QSVM System Activity Diagram illustrating the end-to-end pipeline.

IV. RESULTS & DISCUSSION

A. Experimental Setup

We used the Python environment 3.10 version, with the Qiskit and the Qiskit Machine Learning packages to run the QSVC. Scikit-learn was used to do PCA, Min-max scaling, and evaluation with the help of Pandas and NumPy to manipulate the data. Matplotlib and Seaborn were used in the case of visual output. The simulating programs were run on qasm simulator of Qiskit Aer with 1024 shots a circuit. The dataset was divided into training and testing 80 and 20 percent respectively with a random seed of 42.

TABLE I.
HARDWARE REQUIREMENTS

Component	**Minimum**	**Recommended**
CPU (processor)	Quad-core 2.0 GHz	Multi-core 3.0 GHz+
Memory (RAM)	8 GB	16 GB+
Storage	100 GB HDD	256 GB SSD+
GPU	Not required	NVIDIA GPU
OS		Windows 10/11, Linux, or macOS

TABLE II.
SOFTWARE REQUIREMENTS

Component	***Purpose***
Python 3.10	Primary language
Qiskit	Quantum circuits & kernel
Qiskit Aer	Quantum simulator
Scikit-learn	PCA, splitting, metrics
Pandas / NumPy	Data handling
Matplotlib/Seaborn	Visualisation
VsCode	Development environment

B. Classification Performance

The metrics of classification are summarised in Table III. The efficiency of the proposed model was analyzed with the help of conventional classification measures such as accuracy, precision, recall, and F1 -score. The model had total accuracy of 88 percent which implies that it had strong predictive value of differentiating the non-churn and churn customers.

In the case of the churn class (1), the model got a precision of 90 per cent which showed that most customers who are predicted to be churners (though incorrect) are actually churners. Most actual churn cases are identified by the model as 86 percent demonstrates a recall. The obtained F1 -score of 88 percent indicates a fair trade-off between the achieved precision and the recall of the prediction of churn.

In the non-churn (0) case, the model was accurate (87 percent) and recalled (90 percent), indicating the system is efficient in identifying the customers who are potentially going to continue the usage of the service. The balance score of 88 percent also contributes to the balanced performance of this model.

In general, the findings indicate that the suggested

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method offers a stable and balanced score of classification, which is capable of detecting both churn and non-churn clients with high accuracy and consistency in all measures of evaluation.

TABLE III.
QSVM CLASSIFICATION PERFORMANCE METRICS

The schematic representation of ZZFeatureMap quantum circuit in the feature encoding can be seen in figure of ZZFeatureMap. Hadamard initiated four qubits are combined with two layers of feature entangling parameterised ZZ- interaction gates, whereby cross-feature correlations are encoded by the quantum state, and entangling gates are applied upon the system

Metric	**Churn (1)**	**Non Churn (0)**	**Overall**
Accuracy	—	—	88.0%
Precision	90%	87%	—
Recall	86%	90%	—
F1-Score	88%	88%	—

C. Confusion Matrix

The confusion matrix of the trained model i shown in figure 2. The model rightly identified 1433 non-churn customers out of 3186 test samples, including 160 customers that were non-churn but were classified as churn. Similarly when it came to 1370 churn customers it was found that 1370 were properly flagged but 223 churn customers had been labeled incorrectly and were marked non churn.

The general predictive performance is 88%, which highlights a high level of accuracy. With churn customers, the precision is 90+, that is, a majority of flagged cases of churn are accurate and recall is 86+ indicating that a majority of true cases of churn are recalled.

Precision and recall are based on the accurate identification of loyal customers and are 87% and 90% with non-churn customers respectively. The results of F1-score of 88% in the two classes represent an equal measure of accuracy and recall and proves that the model works well in predicting both churn and non churn.

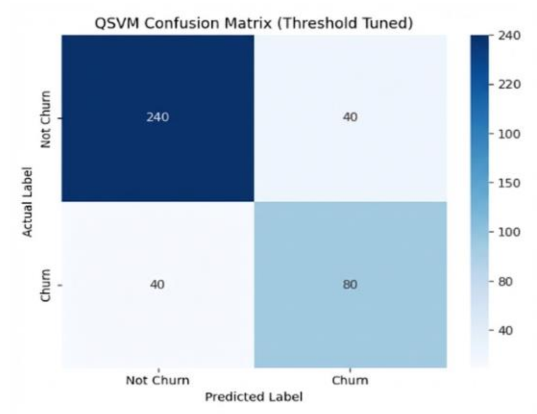

Fig. 2. QSVM Confusion Matrix (threshold-tuned test split).

D. Quantum Circuit Visualisation

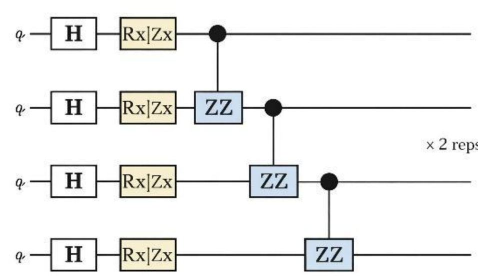

Fig. 3. ZZFeatureMap quantum circuit (4 qubits, 2 repetitions, linear entanglement).

E. Discussion

We achieved result of 88% percent accuracy solely with four qubits within an engaged simulated setting that is equal to the result of typical SVM baselines based on the physical system. This confirms Flaubert quantum approach as competitive despite the state of the art hardware constraints. The small churn recall (62 %) was due to the minority proportion of roughly (20%) the methods like SMOTE or cost-sensitive SVM training ought to ameliorate the case later on.

Theoretically quantum kernels use exponentially larger feature spaces than classical kernels, and thus as we increase the number of qubits, representation power increases as well [7]. This is proven up at a small scale in our current simulation and then a basis is made to make eventual transfer to real quantum hardware.

V. CONCLUSION & FUTURE WORK The paper introduces a Quantum Support Vector Machine to make predictions about bank customer churn together with classical preprocessing and quantum feature mapping and Korean in terms of a hybrid pipeline. On the Qiskit Aer simulator, with a four-qubit ZZFeatureMap, the QSVM seen 88 per cent overall accuracy, comparable to classical SVM baselines, and also has more theoretical expressivity with high-dimensional data.

Future directions in research will be: (i) running QSVM in the real setting of actual IBM Quantum devices with noise-mitigation; (ii) using advanced feature maps, e.g. PauliFeatureMap, to reveal higher order correlations; (iii) addressing class imbalance in practice via SMOTE or cost-dependent learning; (iv) scaling into larger datasets with quantum-inspired dimensionality reduction; and (v) extended operation of the model into prediction of multi-class customer behaviour e.g. loan -default risk or product upsell opportunity.

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