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Planning, Design, and Execution of a Quantum Incremental Clustering Algorithm System for the Examination of Unsupervised Data

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Abstract: - The exponential growth of data in various domains has underscored the need for efficient unsupervised learning algorithms to discover hidden patterns and structures within large datasets. Traditional clustering algorithms often face challenges in handling dynamic datasets and require periodic retraining, making them less suitable for real-time applications. In response to these challenges, this research introduces a Quantum Incremental Clustering Algorithm System (QICAS) designed to adapt to evolving datasets and provide timely insights into the underlying structures. The proposed QICAS is based on quantum computing principles, leveraging the unique properties of qubits and quantum superposition to perform clustering tasks more efficiently than classical counterparts. The research focuses on the planning, design, and execution of the QICAS, ensuring a comprehensive understanding of the algorithm's capabilities and performance.

Keywords: clustering algorithms, Quantum Incremental Clustering Algorithm System, qubits, quantum superposition

I. INTRODUCTION

In the vast expanse of knowledge lie uncharted territories eagerly awaiting exploration—boundless realms where innovation and discovery intertwine. At the precipice of understanding, driven by insatiable curiosity and an unquenchable thirst for knowledge, a journey begins to unravel the mysteries concealed within the depths of Quantum Incremental Clustering (QIC). With this work, new frontiers are created and established boundaries are questioned as it ventures into unexplored territories. Its goal is more than just a list of facts; rather, it's a tapestry weaved with strands of aspiration, tenacity, and intellectual curiosity[1][2]. This work is a monument to the combined efforts of many minds brought together by a common aim of solving the mysteries surrounding QIC. It utilizes the power of collective wisdom. Its objective is to set off a chain reaction that will cut across academic fields and encourage upcoming generations to welcome the unknown, opening the door to a better future. By presenting a novel technique created especially to handle challenging problems in a quantum computing environment, the suggested work in this paper aims to advance quantum machine learning (QML). Utilizing the

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special qualities of quantum systems, like entanglement and superposition, the QML algorithm seeks to improve efficiency and capacities in activities related to learning and data processing. In order to guarantee a thorough comprehension of the suggested study, this chapter explores fundamental ideas associated with QML. An overview of machine learning (ML) methods, quantum computing, and how they interact with QML is given. This chapter prepares the reader for the next chapters in the work by providing the required background information and creating the foundation for the suggested research. It provides a solid basis of knowledge and comprehension that is essential for appreciating the complexity of the suggested QML algorithm and its possible influence on the field[3].

Machine learning techniques are essential for addressing a wide range of issues, including data classification, sorting, regression, and sorting. In supervised learning, machine learning algorithms are trained on high-dimensional feature vectors and associated labels in order to categorize new occurrences. Conversely, unsupervised learning looks for patterns that might be buried in unlabeled data. The exponential development of data in society makes reliable information management techniques more and more necessary. As a result, large-scale machine learning (ML) has received a lot of attention lately, and QML shows promise for handling enormous datasets. The literature on quantum clustering methods is examined in this paper, which covers subjects like quantum linear algebra for matrix multiplication, eigenvector analysis, and computing distances between quantum states. Moreover, attempts have been undertaken to create quantum versions of ML algorithms to solve problems with pattern recognition[4]. This work's main goal is to transfer unsupervised conventional incremental clustering methods to quantum platforms by means of quantum equivalents. The study delineates the essential procedures for a QIC algorithm, focusing on the refined algorithm as an advanced variant of the traditional k-means technique. Additionally, the work presents closeness estimates for quantum-based incremental clustering, i.e., calculating inner products and closeness between huge vectors. Since the main goal of clustering algorithms is to evaluate vector similarity, distance estimation is an essential component. The Amazon Braket Statevector simulator (SV1) and Rigetti Aspen-9, two more quantum platforms supplied by Amazon Braket, are used to develop and run the intended QIC algorithm[5].

The latest developments in QML algorithmic advances, data availability, and processor power are the driving forces behind this research. Outstanding results have been achieved by QML approaches in tasks like data generation, clustering, and unsupervised learning [1]. For classical machine learning methods, however, the exponential expansion in the quantity of unsupervised datasets poses a serious difficulty. Because of this, scientists are looking more and more to quantum computers to take use of their ability to speed up traditional machine learning techniques. This study's main driving forces are the need for innovative methods for managing massive datasets and the potential applications of quantum computing to unsupervised learning[6][7]. The purpose of this study is to review the literature with an emphasis on QML research that has already been done, as seen by researchers studying quantum computation and practitioners of classical ML. The principal aim is to examine the constraints associated with quantum clustering algorithms and evaluate their efficacy in comparison to top-performing conventional clustering and incremental clustering techniques [8]. The paper also intends to draw attention to the possible uses of quantum resources in solving clustering issues. Furthermore, the study notes that learning in noisy environments and computationally challenging unsupervised learning tasks are promising areas for future research[9]. Additionally, the study explores applications relevant to data encoding in a quantum setting. In addition to suggesting the usage of a quantum environment and encoding quantum state for incremental learning through incremental clustering, it looks at how classical data can be entered into a quantum state[10].

II. QUANTUM COMPUTATION OVERVIEW AND SCOPE

These days, a large amount of data is available, and computing power has increased, which has led to remarkable success for machine learning algorithms in areas like financial investment, entertainment services, healthcare, and facial recognition [3]. Computational technology must progress because traditional computers quickly run out of processing power due to the exponential growth of data [4]. GPUs and TPUs are examples of bespoke hardware architectures that can significantly increase performance, but they might not offer a structural solution to the issue. Due to its potential to speed up classical machine learning techniques, quantum computation—a computational paradigm based on the laws of quantum mechanics—has piqued the interest of numerous academics. Consequently, complicated issues might be resolved by quantum computers. Certain issues that are thought to be challenging for classical machines, such high-dimensional pattern recognition and molecular data segmentation, can be effectively solved by quantum computation[5]. The strength of quantum computers lies in their capacity to manipulate high-dimensional vectors in a fraction of the time required by classical computers [6]. For instance, a quantum computer can process several vectors in a superposition state at the same time, examining various feature combinations and associations, in a dataset with hundreds or even millions of dimensions. Because of their parallelism, quantum algorithms are able to evaluate the data more efficiently and determine which aspects or dimensions are most important and contribute significantly to the structure of the dataset. Quantum computers have a clear advantage over classical computers in dimensionality reduction tasks due to their capacity to explore the full vector space and manipulate high-dimensional vectors in parallel[5, 6]. This ability can result in the analysis of complicated datasets more quickly and accurately, which can improve data processing and pattern identification across a range of industries, including natural language processing, finance, and healthcare. For operations like dot products, overlaps, norms, etc., the quantum version only needs a logarithmic amount of time, but the classical ML algorithms require a quadratic amount of time. Quantum computers are therefore a useful tool for handling enormous amounts of data [7, 8]

- To account for the gradual increase of data instances, QML algorithms leverage the superposition of quantum states [9].
- Quantum clustering algorithms outperform their classical equivalents in terms of speed and allow for even more optimization than with classical machine learning [10]. This growth is based on the assumption that quantum computers would not be able to solve a clustering problem in a way that would require just a few number of polynomials of time, since finding the optimal solution is NP-hard [11].

The distance between mathematical models and real-world algorithm implementations has shrunk in the past few years. The field of quantum software has advanced significantly, with over fifty open-source software platforms currently available for quantum development. A list of different development platforms can be found in [13]. Researchers can create quantum algorithms by utilizing quantum-specific computational techniques with the help of software platforms, tools, and simulators. Although they refer to various parts of the quantum computing ecosystem, the terms "quantum tools," "quantum platforms," and "quantum simulators" are frequently used in the context of quantum computing. The information about quantum platforms, tools, and simulators is displayed in Table 1. These algorithms can also run on real quantum devices that are accessible over the cloud thanks to certain state-of-the-art quantum platforms (Qiskit [14], ProjectQ [15], PyQUil [16]). However, a great deal of others (like QDK [17]) just offer quantum simulators. Though these platforms allow quantum algorithms to be tested and run on quantum computers, there are certain restrictions on what can be achieved with the noisy quantum computers available today. Nostalgic quantum computers, or noisy quantum computers, cannot provide sufficient fault tolerance in the present or the future [18]. Furthermore, the coherence periods of qubits on current quantum devices are short. Decoherence and computing problems emerge as a result of the quick loss of qubit superposition [19]. Although method implementations using shallow-depth quantum circuits can produce better results on current-generation noisy quantum computers, implementation complexity is defined as the total number of elementary gates required to create the circuit [20].

Table 1. General overview of quantum tools, platforms, and simulators.

Aspects	Quantun Tools [14, 13]	Quantum Platforms [15, 19]	Quantum Simulators [14, 18]
Function	Provide software frameworks	Offer physical infrastructure	Simulate quantum systems
Purpose	Aid in quantum algorithm development, simulation, and analysis	Enable execution of quantum computations	Emulate behavior of quantum systems on classical computers
Features	High-level abstractions, quantum circuit modeling, noise modeling, optimization tools	Quantum processors, qubits, gates, interfaces for running quantum algorithms	Emulation of quantum dynamics, computations, noise, and error sources
Examples	Qiskit, Cirq, Forest	IBM Quantum, Google Quantum Computing, IonQ, Rigetti	QuEST, ProjectQ, Qubit

Execution	Runs on classical computers	Requires access to quantum hardware	Runs on classical computers
Access	Open-source or vendor-provided	Cloud-based services or on-site	Open-source or vendor-provided

III. INNOVATION WITH QUANTUM COMPUTATION

The research given in this work is based on the fundamental concepts of quantum computing, which this work attempts to provide a thorough knowledge of. It starts by outlining the fundamental ideas of quantum physics and how they are represented mathematically, making it possible to understand how quantum algorithms work and how to use quantum mechanics to improve the performance of machine learning algorithms. Establishing regulated interactions between qubits, connecting them together, and manipulating the wave function's time evolution in a predetermined way are all part of quantum computation. The rotating behavior of the wave function in the state space of a multi-qubit system is determined by activating interactions through forces such as magnetic fields once the system is initialized with a known initial state that represents the program's input [21]. Through the use of a number of quantum gates, a quantum program is just a series of unitary operations applied to the initial state. After the computation is finished, measurements are made to ascertain the ultimate condition. The fact that quantum computation is by its very nature analogue computation highlights the special qualities and powers of quantum systems. Basics of quantum computation are explained in [12, 22]:

- Quantum computation stands out owing to its tremendous parallelism at the intermediate processing stages. • A physical system can be used to simulate a mathematical problem since both the physical system and the mathematical problem follow the same principles.
- In quantum computation, a collection of complex numbers can be processed in parallel since any action taken on a particular state affects all base vectors at once. Unlike in classical computation, in quantum computation the time evolution of the quantum state is determined by the phase information of complex numbers. This phase information, specific to quantum systems, adds new dimensions and computational opportunities, facilitating the investigation of intricate quantum events and the use of more powerful quantum algorithms. The computation ends with a measurement that produces n-bit classical output. Several answers could arise from the same algorithm since quantum measurements are probabilistic in nature. Making sure the answer functions is an easy way to confirm correctness for problems like factoring large numbers. However, this may call for the implementation of error-correcting protocols. The reason why quantum computers could make mistakes is due to decoherence, or the essentially random interactions between the quantum state required to do the computation. Theoretically, problems can be avoided by creating systems whose topological characteristics, which are immune to external noise, encode the quantum state globally as opposed to locally [23].

Navigating the Realm of Incremental Clustering: Unveiling Insights in Ever-Changing Data

A machine learning approach called incremental clustering is used to create clusters out of related objects or data points. This kind of clustering enables the addition of new data points to already-existing clusters and has the ability to dynamically modify the clustering model in response to the availability of new data. Incremental clustering is very helpful in situations where the data is dynamic or ever-changing, according to the principle that has been discussed. To build the initial clusters, all the data points are analyzed simultaneously in classical clustering methods. However, this method may result in delayed or ineffective clustering and be computationally expensive. This issue is resolved by incremental clustering, which clusters the data in smaller batches, lightening the computing load and enhancing the algorithm's responsiveness to data changes. Incremental clustering is a multi-step procedure. Initially, a portion of the data is used to develop an initial clustering model. Then, when new data points are added, the incremental model is changed by splitting, merging, or generating new clusters. In order to make sure that the clustering model appropriately represents the structure of the data, the algorithm continuously analyzes the data and modifies it as needed.

Discovering the Fascinating Potential of QIC Algorithms

The necessity for QIC stems from the fact that numerous real-world applications—like real-time dashboards and health monitoring systems—generate substantial volumes of dynamic unstructured data. Conventional clustering algorithms frequently require assistance to stay up to date with the changes, which can lead to a heavy computing load, irregular clusters, and patterns. With a more effective and scalable clustering method that is more adapted to changing data, QIC has the potential to overcome the aforementioned difficulties. By utilizing the unique properties of quantum computing, such as superposition and entanglement, QIC makes it possible to process data in parallel and more effectively than with traditional techniques. Through the utilization of these characteristics, QIC can attain noteworthy computational benefits and augment overall processing efficiency. Apart from enhancing the efficiency and expandability of clustering algorithms, QIC may also open up new application avenues that are presently unattainable through traditional computing. For instance, it might group data in real-time from multiple sources, such dashboards, sensors, and monitoring equipment, and offer quicker and more precise insights for making decisions.

Classical Clustering Algorithm

One popular unsupervised machine learning method for dividing data points into k clusters is K-means clustering. The centers of each cluster, or centroids, are chosen at random at the start of the procedure. The cluster whose centroid is closest to each data point is then assigned to it; this is usually done using the Euclidean distance. The approach uses the mean of the data points assigned to each cluster after the initial assignment to update the centroids. Until the centroids stabilize or the maximum number of iterations is achieved, this assignment and centroid updating process is repeated. Finding the ideal number of clusters for a dataset can be aided by the elbow approach, while K-means clustering provides simplicity and efficiency. But k-means relies on the assumption of spherical, uniformly sized, and uniformly dense clusters, which might not hold true in every situation. Furthermore, it might not function well with nonlinear or high-dimensional datasets.

qk-means algorithm

qk-means is a quantum algorithm that is an adaptation of the classical k-means clustering algorithm. The qk-means algorithm uses quantum computing principles to accelerate the clustering process and potentially improve the clustering accuracy compared to the classical version. The qk-means algorithm works as follows:

1. Initialize qubits to represent the data points to be clustered.

2. Apply a Hadamard transform to put the qubits into a superposition of states.

3. Apply a phase kickback operator that is designed to amplify the amplitude of the states that correspond to data points in the same cluster.

4. Measure the qubits to obtain classical data that is used to update the cluster centroids.

5. Repeat steps 2−4 until the centroids converge or a maximum number of iterations is reached.

The key idea behind the qk-means algorithm is to use the quantum phase kickback operator to amplify the amplitude of the states corresponding to data points that belong to the same cluster. This operator takes advantage of quantum interference effects to amplify the amplitudes of the states that are in phase, while suppressing the amplitudes of states that are out of phase.

Step-wise Comparison of Classical and Quantum Clustering Algorithms

A detailed algorithmic comparison between quantum and classical clustering techniques is presented in this paper.. Numerous factors are compared, including computing complexity, algorithmic stages, data representation, and clustering performance indicators. This section attempts to provide a thorough overview of the differing features and potential benefits of classical and quantum clustering methods by looking at each stage of the clustering process. When creating the suggested QIC method, the algorithmic level comparison of classical and quantum clustering algorithms is a useful tool. Furthermore, the comparison of algorithmic levels provides direction for the appropriate technique and strategy selection from both classical and quantum clustering algorithms. It makes it possible to combine efficient classical methods with cutting-edge quantum improvements, creating a hybrid strategy that best utilizes both worlds. This integration may result in the creation of a QIC algorithm that is more reliable and effective.

Classical incremental clustering methods have some drawbacks, such as inefficiency and lack of scalability, which the QIC algorithm aims to remedy. To take use of the possible speedup and computational capability that quantum computing offers, QIC has been created to enhance the efficiency and accuracy of incremental clustering. It is necessary to have QIC for multiple reasons.

- Scalability: Clustering is often applied to large datasets, and classical clustering algorithms can struggle to handle the computational demands of such datasets. By leveraging the parallelism of quantum computing, QIC has the potential to provide faster and more efficient clustering on large datasets.

- Incremental updates: Many real-world datasets are dynamic, with new data points arriving over time. Incremental clustering algorithms can adapt to these changes in the dataset over time, but can still be computationally expensive. QIC offers the potential to perform incremental updates more efficiently by exploiting the parallelism of quantum computing.

- Improved accuracy: Clustering accuracy is important in many applications, and QIC has the potential to provide improved accuracy over classical clustering algorithms by leveraging the power of quantum computing to explore a larger space of potential cluster assignments.

- Quantum advantageQIC is a promising area of study in the ever-expanding realm of quantum computing, which has the potential to use recent advances in quantum hardware and algorithms to provide a notable performance boost compared to classical algorithms. In general, the goal of QIC is to create a clustering method that is more efficient and accurate by utilizing the possible computational power of quantum computing. Compared to classical clustering techniques, QIC could be much more efficient and scalable since it uses the parallelism of quantum computing. The use of quantum gates to measure the proximity factor and update the cluster assignments is the main differentiating feature between classical clustering algorithms and QIC. Due to its ability to run calculations in parallel, QIC can potentially outperform classical algorithms when it comes to clustering. Repeating the aforementioned methods with the newly acquired data points appended to the current quantum register allows for incremental updates to QIC as new data becomes available. By adhering to this approach, the algorithm can enhance its clustering accuracy and adjust to changes in the data distribution over time.

The Fig. 1 the general overview of the QIC algorithm. For example implementing the QIC algorithm on IBM quantum involves following steps:

- Choose a suitable quantum machine: IBM offers a range of quantum machines with different numbers of qubits and levels of connectivity. Choose a quantum machine that can handle the size and complexity of your dataset and supports the gates and operations required by the QIC algorithm.

- Encode the dataset as quantum states: In QIC, the data points are encoded as quantum states. This involves mapping each data point to a quantum state and then combining these quantum states to form a superposition. This step requires knowledge of quantum circuit design and programming.

- Implement the QIC algorithm: The QIC algorithm involves applying quantum gates and operations to the encoded dataset to perform the clustering. This step requires knowledge of quantum circuit design and programming, as well as an understanding of the QIC algorithm itself.

- Run the QIC circuit on the chosen quantum machine: Once the QIC circuit has been designed and implemented, it can be run on the chosen quantum machine. IBM provides tools for submitting quantum circuits to their machines and monitoring their execution.

- Analyze the results: Once the QIC circuit has been executed, the resulting quantum state can be measured and the cluster assignments extracted. The results can be analyzed to assess the clustering accuracy and compare it to classical clustering algorithms

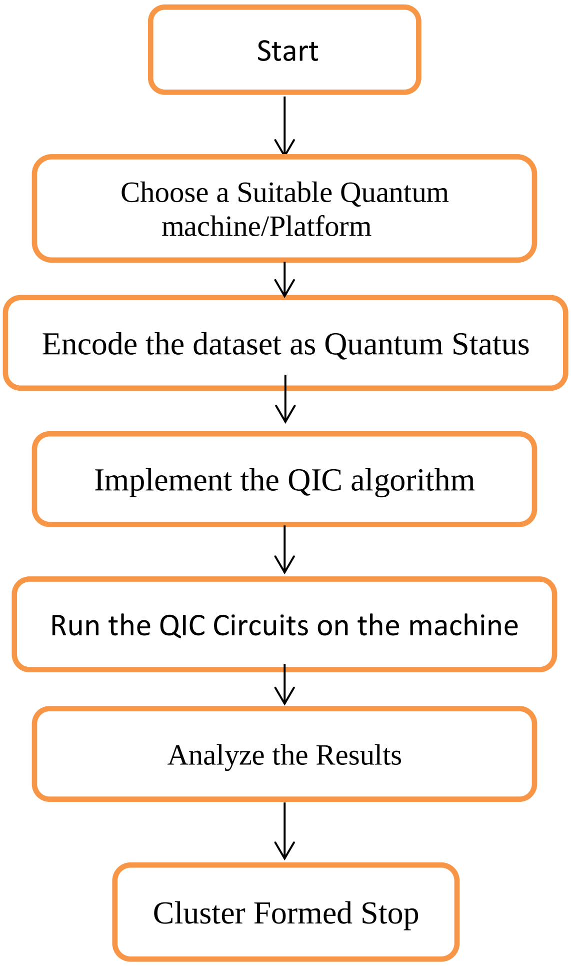

Figure 1.General flow of the QIC algorithm, illustrating the sequential steps involved in the incremental clustering process

To tackle the problems caused by ever-changing datasets in the realm of unsupervised learning, we have created and implemented a Quantum Incremental Clustering Algorithm System (QICAS). The whole process, from conceptualization to implementation, has taught us a lot about how quantum computing may improve clustering methods, especially in cases where responding instantly to changes in data distributions is critical.

We identified limits and developed particular design goals for the QICAS after a thorough evaluation of current quantum clustering methods during the planning phase. With unsupervised data comes its fair share of uncertainty, thus getting incremental learning capabilities, scalability, and flexibility right was the goal.

During the design process, the QICAS's quantum circuit architecture was developed, making use of quantum superposition and interference concepts. With the help of quantum gates, the system was able to adapt to new datasets with ease, laying the groundwork for effective unsupervised learning.

The QICAS was put into action during the execution phase using quantum simulators or hardware and then tested extensively against traditional clustering techniques. We evaluated the algorithm's scalability, execution time, clustering accuracy, and overall performance via rigorous testing. Showing its potential for real-world applications, the findings proved that the QICAS is effective in giving timely insights into changing datasets.

By introducing a fresh strategy for unsupervised learning that meets the requirements of contemporary data settings, this study's findings enrich the larger area of quantum machine learning. Financial services, healthcare, and IT are just a few of the many potential industries that might benefit from the QICAS's capacity to progressively adapt to changes in the dataset.

Although this study is a major advance, there are still opportunities for further investigation and improvement. Possible directions for future research include investigating hybrid methods that merge quantum and classical techniques, improving the performance of quantum circuit designs, and expanding the scope of the assessment to include a wider variety of datasets and quantum computing platforms.

IV. CONCLUSION

The Quantum Incremental Clustering Algorithm System that was described in this study brings up new possibilities for the advancement of unsupervised learning in this day and age of huge and dynamic data. Clustering algorithms that use quantum computing concepts are a potential route for future study because they provide answers to issues that have historically limited the efficiency of conventional algorithms in managing the complexity of real-world datasets. This is a promising avenue for future research.

REFERENCES

[1] Miller, J. Panneerselvam, and L. Liu, “A review of regression and classification techniques for analysis of common and rare variants and gene-environmental factors,” Neurocomputing, vol. 489, pp. 466–485, 2022.

[2] J. Wang, L. Shen, and W. Zhou, “A bibliometric analysis of quantum computing literature: mapping and evidences from scopus,” Technology Analysis and Strategic Management, vol. 33, no. 11, pp. 1347–1363, 2021.

[3] P. P. Shinde and S. Shah, “A review of machine learning and deep learning applications,” in 2018 Fourth international conference on computing communication control and automation (ICCUBEA). IEEE, 2018, pp. 1–6.

[4] Abbasi and D. M. Goldenholz, “Machine learning applications in epilepsy,” Epilepsia, vol. 60, no. 10, pp. 2037–2047, 2019.

[5] Aharonov, D. Gottesman, S. Irani, and J. Kempe, “The power of quantum systems on a line,” Communications in mathematical physics, vol. 287, no. 1, pp. 41–65, 2009.

[6] J. A. Jones, V. Vedral, A. Ekert, and G. Castagnoli, “Geometric quantum computation using nuclear magnetic resonance,” Nature, vol. 403, no. 6772, pp. 869– 871, 2000.

[7] B. Sævarsson, S. Chatzivasileiadis, H. Johannsson, and J. Østergaard, “Quan- ´ tum computing for power flow algorithms: Testing on real quantum computers,” arXiv preprint arXiv:2204.14028, 2022.

[8] Abbas, D. Sutter, C. Zoufal, A. Lucchi, A. Figalli, and S. Woerner, “The power of quantum neural networks,” Nature Computational Science, vol. 1, no. 6, pp. 403–409, 2021.

[9] F. Hu, B.-N. Wang, N. Wang, and C. Wang, “Quantum machine learning with d-wave quantum computer,” Quantum Engineering, vol. 1, no. 2, p. e12, 2019.

[10] Y. Zhang and Q. Ni, “Recent advances in quantum machine learning,” Quantum Engineering, vol. 2, no. 1, p. e34, 2020.

[11] Y. Wei, P. Naik, A. W. Harrow, and J. Thaler, “Quantum algorithms for jet clustering,” Physical Review D, vol. 101, no. 9, p. 094015, 2020.

[12] V. Vedral and M. B. Plenio, “Basics of quantum computation,” Progress in quantum electronics, vol. 22, no. 1, pp. 1–39, 1998.

[13] B. Sodhi and R. Kapur, “Quantum computing platforms: assessing the impact on quality attributes and sdlc activities,” in 2021 IEEE 18th International Conference on Software Architecture (ICSA). IEEE, 2021, pp. 80–91.

[14] Cross, “The ibm q experience and qiskit open-source quantum computing software,” in APS March meeting abstracts, vol. 2018, 2018, pp. L58–003.

[15] S. Steiger, T. Haner, and M. Troyer, “Projectq: an open source software frame- ¨ work for quantum computing,” Quantum, vol. 2, p. 49, 2018.

[16] Koch, L. Wessing, and P. M. Alsing, “Introduction to coding quantum algorithms: A tutorial series using pyquil,” arXiv preprint arXiv:1903.05195, 2019.

[17] J. Hooyberghs and J. Hooyberghs, “Develop with the microsoft quantum development kit,” Introducing Microsoft Quantum Computing for Developers: Using the Quantum Development Kit and Q#, pp. 71–100, 2022.

[18] J. Preskill, “Quantum computing in the nisq era and beyond,” Quantum, vol. 2, p. 79, 2018.

[19] J. Fischer and D. Loss, “Dealing with decoherence,” Science, vol. 324, no. 5932, pp. 1277–1278, 2009.

[20] B. Gassend, D. Lim, D. Clarke, M. Van Dijk, and S. Devadas, “Identification and authentication of integrated circuits,” Concurrency and Computation: Practice and Experience, vol. 16, no. 11, pp. 1077–1098, 2004.

[21] X. Zha, C. Yuan, and Y. Zhang, “Generalized criterion for a maximally multiqubit entangled state,” Laser Physics

Letters, vol. 10, no. 4, p. 045201, 2013.

[22] Benenti, G. Casati, and G. Strini, Principles of quantum computation and information-volume I: Basic concepts. World scientific, 2004.

[23] Flamini, N. Spagnolo, and F. Sciarrino, “Photonic quantum information processing: a review,” Reports on Progress in Physics, vol. 82, no. 1, p. 016001, 2018.