Quantum Data Management and Quantum Machine Learning for Data Management: State-of-the-Art and Open Challenges

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Abstract. Quantum computing is an emerging technology and has yet to be exploited by industries to implement practical applications. Research has already laid the foundation for figuring out the benefits of quantum computing for these applications. In this paper, we provide a short overview of the state-of-the-art in data management issues that can be solved by quantum computers and especially by quantum machine learning approaches. Furthermore, we discuss what data management can do to support quantum computing and quantum machine learning.

Keywords: Quantum Computing · Data Management · Quantum Machine Learning · Databases

1 Introduction

There is a race going on among major quantum computer hardware developers like Google and IBM. This becomes visible when we look at Fig. 1, which shows the timeline of available and future quantum computers dependent on the number of supported qubits. The exponential growth of the number of supported qubits promise quantum applications for end-users by the end of this decade.

The performance of data management tasks is the key for efficient processing of many applications, especially those that are data-driven and large-scale. Nowadays, these applications are essential and ubiquitous, and the amount of data available and their complexity increase drastically. Thus, research to improve data management tasks is vital, even though this area is one of the most well-established ones in computer science. It is obvious that it is important to investigate the possibilities of using quantum computing to solve research and implementation challenges in data management.

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In this paper we discuss the state-of-the-art and open challenges for quantum computing approaches speeding up data management tasks, and data management systems integrating quantum computing approaches. We call the whole area quantum data management. Furthermore, we especially focus on quantum machine learning in our discussion, where machine learning tasks are partly or completely processed on quantum computers.

The remainder of this contribution is organized as follows. Section 2 provides an overview over quantum data management starting with a short discussion about quantum machine learning and its applications in Sect. 2.2. We deal with data management for quantum computing with a special focus on quantum machine learning in Sect. 2.3. Finally, we sum up and conclude in Sect. 3.

2 Quantum Data Management

In this section we discuss the state-of-the-art and open challenges of two aspects: 1) quantum computing (including quantum machine learning) for data management tasks, and 2) data management for quantum computing (including quantum machine learning).

2.1 Quantum Machine Learning

Extensive surveys [1,15,68] about quantum machine learning show that for nearly every major area of machine learning, a quantum counterpart has been proposed and discussed.

Recent scientific contributions extensively investigate the benefits of applying quantum machine learning over classical machine learning. For example, in comparison to classical support vector machines, an exponential speedup can be achieved by applying quantum support vector machines [51]. Indeed, quantum machine learning methods have the potential to learn on fewer data points than classical methods alone [12]. It is even possible to identify data sets that have a potential quantum advantage in learning tasks by looking at the properties of the data sets [39].

Applications of Quantum Machine Learning: The applications of quantum machine learning have a broad spectrum and range from natural science like chemistry and physics [55], to research in software engineering like software supply chain attacks [48], to quantum sciences itself [18] including phase classification, quantum feedback control, representation of many-body quantum states and quantum circuits optimization. In the following sections, we discuss possibilities of using quantum machine learning to support data management tasks.

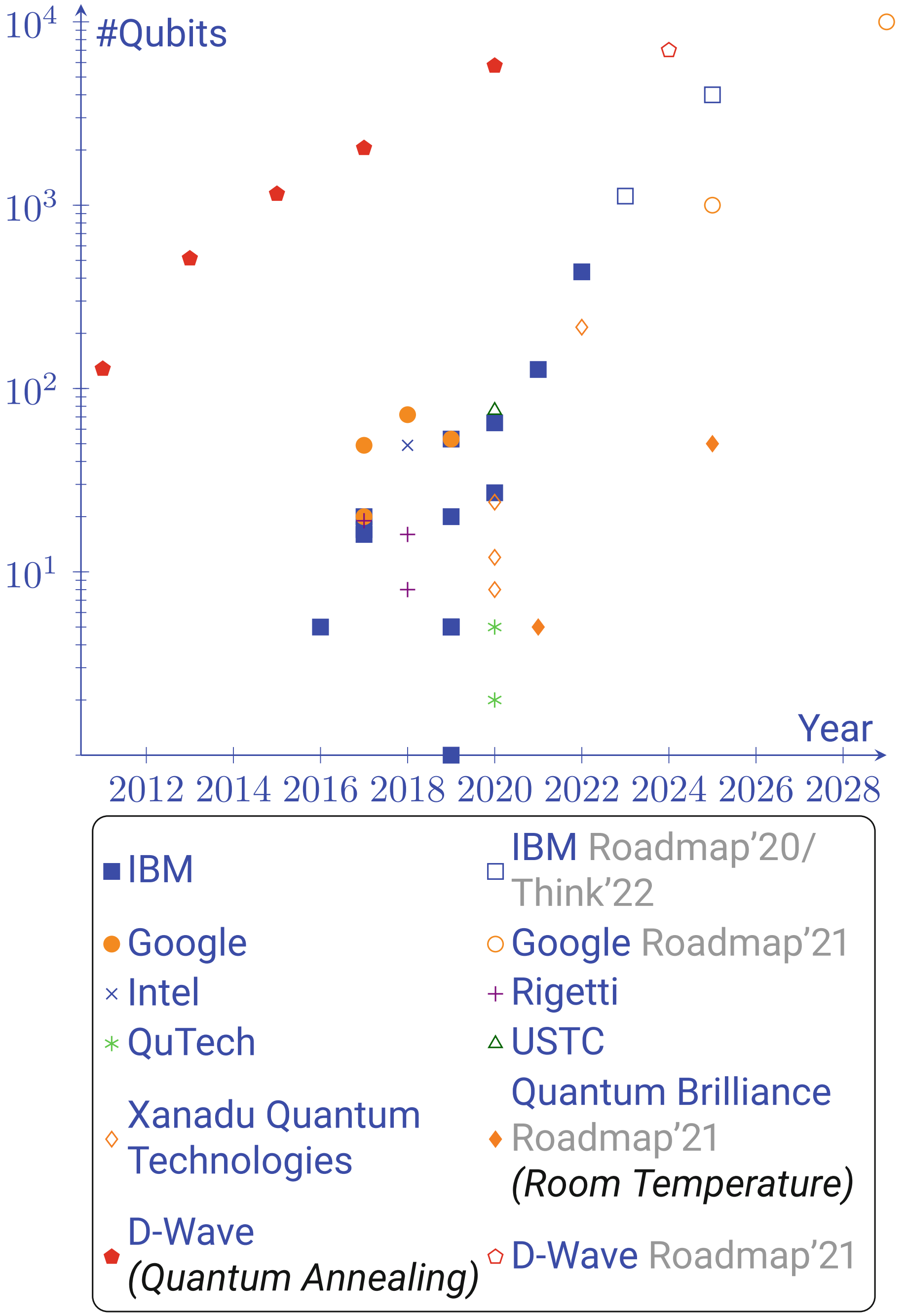

Fig. 1. Timeline and Roadmaps of Quantum Computers (Data according to https://en.wikipedia.org/wiki/List_of_quantum_processors. Roadmaps according to https://research.ibm.com/blog/ibm-quantum-roadmap, https://spectrum.ieee.org/ibm-quantum-computer, https://quantumai.google/research, https://www.dwavesys.com/media/xvjpraig/clarity-roadmap_digital_v2.pdf (all visited on 20.6.2022) and [19])

2.2 Quantum Computing for Data Management

Whenever a new technology emerges, in order to apply it to an area of one's interest, one would need to analyze the new technology and its benefits. Especially, one would want to identify which tasks in the area of interest would benefit the most from using the new technology. There are quantum counterparts[1] [2,3,5–8,14,20,22,30,34,41,45,52,54,58,62,63] of many classical algorithms for mathematical optimization problems like dynamic programming [23], exhaustive searches [22], simulated annealing, reinforcement learning [9], regression, linear programming [17], random walk [23], genetic algorithm [37], ant colony optimization [16,21] and whale optimization [49]. Some optimization algorithms like QAOA [24] and quantum annealing [42] are developed based on the capabilities and features of quantum computers restricting the input further (here to quadratic binary optimization problems) compared to their more general counterpart in the classical world (here simulated annealing).

Whenever a problem can be reduced to the application of basic mathematical optimization approaches, it can be sped up by quantum computers by replacing classical routines with their quantum computing counterparts promising quadratic speedups in many cases (see e.g. [30,52] up to polylogarithmic factors) or even exponential speedup for some approaches [54].

This straight-forward solution for applying quantum technologies in a domain of interest like data management promises predictable benefits. For example, well-studied subproblems of data management like optimizing queries use many different mathematical optimization approaches as basic routines: Dynamic programming [57], simulated annealing [40], reinforcement learning [33,47,64,66], linear programming [60], random walk [25], genetic algorithm [38] and ant colony optimization [16,21], where this list is not exhaustive. Only few scientific contributions [56,59] deal with applying quantum approaches to query optimization. There are also only few contributions dealing with quantum approaches in other related areas of data management. Another example to the problems in data management is the transaction schedule optimization problem [46]. Although this problem is not as well-studied as query optimization, there are still studies [10,11,29] applying quantum computing approaches for optimizing transaction schedules.

Hybrid multi-model multi-platform (HM3P) databases [27,28] take not only quantum computers, but also other heterogeneous hardware like many-core CPUs, GPUs, FPGAs, Internet-of-Things, and mobile environments into account. Hence, they are a generalization of the idea to integrate quantum computers into database management systems for speeding up the processing of database management tasks.

Besides this straight-forward way to apply quantum technologies in the domain of interest, one might also investigate and research on applying the concepts of a new technology in some new way to the domain of interest. For example, the authors of [53] introduce *quantum databases*, which are deferring

[1] We regard here quantum algorithms and quantum-inspired [50] algorithms as quantum counterparts, although quantum-inspired algorithm are designed to run on classical hardware, but are inspired from the quantum computing concept.

the making of choices in transactions until the state of the database must be observed by an application or user.

Quantum Machine Learning for Data Management: Investigating some subdomains of data management like query optimization, one may discover the potential use of quantum machine learning in query optimizers. In recent years, there have been many contributions [4,26,32,35,43,65,67] dealing with estimating the runtime of a query or its cardinality, which can be used by a query optimizer to choose the best query execution plan. Other approaches [13,36,47,61,66] propose to directly predict the optimal join order with the benefits of a short runtime of the query optimizer achieving good join orders. Future work includes replacing these classical machine learning approaches with quantum machine learning approaches and investigating the benefits of quantum machine learning in query optimization.

There are many more problems that have been considered to be improved by machine learning approaches [44]. For example, there have been learned tuning methods proposed for improving the tuning performance or resource utilization. For a large number of columns, tables and queries, machine learning approaches provide benefits for the recommendation of creating and maintaining indexes or materialized views in databases. Machine learning methods also predict incoming queries and workload for proactively optimizing the database. Future work might address also these and other topics for evaluating the benefits of quantum machine learning.

2.3 Data Management for Quantum Computing

We should look at not only what quantum computing can do to improve data management tasks as discussed in Sect. 2.2, but also what data management systems can provide to support quantum computing applications. We envision a database management system that offers easy access to quantum computing applications by integrating high-level functionalities for quantum computing applications into the data management system. The high-level functionalities include an extension of the language constructs of query languages to call quantum computing subroutines. The data management system should also allow for easy storing and accessing the input and output of quantum computing applications. Furthermore, the data management system should automatically choose the needed and available quantum resources as well as apply hybrid algorithms. These algorithms are tailored in a way that missing resources and support of qubits and circuit depths in quantum computers are overcome by taking over more computations by classical algorithms or simulations of quantum computing on classical hardware.

Data Management for Quantum Machine Learning: There is a trend for data management systems to offer machine learning functionalities [31]. While data management systems offer support for traditional requirements like memory management, parallelism and fault tolerance also to machine learning tasks, machine learning tasks pose additional requirements for

- scalable training, where often large-scale data sets are processed in comparison to the (often simple and efficient to perform) application/prediction phase,
- storing models and their parameters after training for their use in the application/prediction phase,
- language constructs for expressing complex machine learning tasks in a simple way while combining these language constructs with query languages, and
- automatic choosing and optimizing models and machine learning tasks.

Open challenges include the integration of quantum machine learning into data management systems and adapting the requirements and solutions to quantum machine learning and available quantum computers with an additional focus on hybrid algorithms. These algorithms combine a quantum algorithm with a classical algorithm to flexibly adapt the available system configuration of classical and quantum hardware.

3 Summary and Conclusions

In this paper, we discussed the intersection between quantum computing and data management, and reasoned that the methods developed in each discipline can be used to improve the other. Many studies, some of which we cited in this paper, show that quantum machine learning can dramatically speed up the learning process of some classical machine learning approaches. We also provided a short literature survey on quantum computing approaches to improve the processing times of some data management procedures, namely query optimization and transaction scheduling. We discussed how to embed quantum computing approaches and especially the quantum machine learning functionality into data management systems.

In our future work we aim to implement the quantum counterparts of the well-studied query optimization methods. To achieve this, we plan to analyze the quantum optimization and learning algorithms in depth and develop applicable quantum methods. Also, we aim to broaden the toolbox for transaction schedule optimization both by developing classical algorithms and by further speeding them up via quantum computing.

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