2024 IEEE Mediterranean and Middle-East Geoscience and Remote Sensing Symposium (M2GARSS) | 979-8-3503-5858-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/M2GARSS57310.2024.10537558

A TAXONOMY OF RELATIONSHIPS BETWEEN INFORMATION PROCESSING, MACHINE LEARNING AND QUANTUM PHYSICS: QUANTUM-INSPIRED, QUANTUM-ASSISTED, QUANTUM-TARGETED AND RELATED APPROACHES

Yannick Deville[1], *Leonardo Tomazeli Duarte*[2], *Alain Deville*[3]

[1] Université de Toulouse, UPS, CNRS, CNES, OMP, IRAP (Institut de Recherche en Astrophysique et Planétologie), F-31400, Toulouse, France
[2] Universidade Estaudal de Campinas, Faculdade de Ciências Aplicadas (FCA), Limeira-SP, Brasil
[3] Aix-Marseille Université, CNRS, IM2NP UMR 7334, F-13397, Marseille, France

ABSTRACT

In this paper, we provide an overview of the connections that were developed, during the current second quantum revolution, between information processing (IP) and machine learning (ML) in the classical (i.e. non-quantum) framework on the one hand, and several aspects of quantum physics on the other hand, namely properties involved in quantum theory and practical implementations leading to quantum computers. Moreover, we propose a taxonomy of the new fields resulting from these connections, both at the general level of IP methods and at the more specific level of data-driven, i.e. ML, methods. We thus consider quantum-inspired (or quantum-like), quantum-assisted (or quantum-enhanced), quantum-executed and quantum-targeted IP and ML methods.

Index Terms— quantum-inspired information processing / machine learning, quantum-assisted information processing / machine learning, quantum-targeted information processing / machine learning, quantum computer, remote sensing (Earth observation) applications

1. DEFINITION OF THE TOPIC OF THIS PAPER

Whereas the first quantum revolution was focused on quantum physics itself, the second quantum revolution [1, 2] is especially exploring the connections between quantum physics and information processing, in particular inspired by Feynman's seminal work [3] (see also e.g. [4, 5] for comments about early works from Feynman, Benioff and Deutsch). These connections include several aspects, especially depending whether one focuses on (i) using theoretical quantum physics concepts to extend general-purpose classical (i.e. non-quantum) processing methods, (ii) using quantum hardware to achieve higher computing speed than classical general-purpose processing systems, or (iii) manufacturing quantum hardware and using classical (i.e., again, non-quantum, but possibly original) processing methods in this framework.

We therefore stress that the quantum part of such hybrid, i.e. "classical plus quantum", configurations may be (i) either only a means of the considered investigation, when this investigation is dedicated to general-purpose information processing, or (ii) the main target of this investigation, when the latter investigation is dedicated to the development of a given quantum system and it uses specific information processing methods to this end.

Moreover, in any of the above-mentioned cases, a processing method may either perform a predefined data transform or may first learn (from training data) the transform to be eventually used. The latter configuration corresponds to a so-called machine learning[1] approach, or data-driven approach.

The articles published so far most often focus on only one specific problem within one of the above-defined classes, or they only address one of these classes. The present paper therefore mainly aims at providing a taxonomy of these quite different classes of problems. Moreover, not only do we highlight the terminology that was already introduced for part of these problems in the literature, but we also extend it so as to cover all considered situations. Part of the cited papers deal with remote sensing, in the sense "Earth observation". The considered types of quantum methods are likely to become of high importance in this application field, due to the large amount of data to be manipulated in these applications, as discussed e.g. in [6, 7].

The classes of problems suggested above are successively explored in Section 2, moving from configurations that have a weak emphasis on quantum hardware to those that put a strong emphasis on it.

[1] We here employ the term "machine learning" in its usual sense, that is, focusing on the considered *algorithms*, whose main feature is their above-mentioned ability to learn the transform they perform, from training data. In the classical framework, the physical system, i.e. "*machine*", on which these algorithms are implemented (and which thus learns how to behave) is usually a standard computer, although more specific hardware such as robots may also be considered.

2. A TAXONOMY OF INVESTIGATIONS THAT INCLUDE CLASSICAL AND QUANTUM ASPECTS

2.1. Quantum-inspired (or quantum-like) information processing and machine learning

The first class of approaches to be considered is based on taking advantage of quantum theory, that is, of properties met in quantum physics, so as to derive new processing methods to be executed on classical, i.e. non-quantum[2], computers. This type of approaches is therefore referred to as "quantum-inspired information processing" (QIIP). In particular, this includes "quantum-inspired machine learning" (QIML) methods. As briefly stated above, the term "machine learning" typically refers to processing methods that first use a set of data points in order to learn a function (that maps a given type of input data onto another type of output data) and that then apply that learned function to new data. That makes them able to perform such general-purpose processing tasks as classification or regression. For a more detailed discussion of these tasks and of the connections between classical and quantum machine learning, the reader may e.g. refer to [8]. In the classical framework, classification methods have been used to identify the nature of a wide variety of "objects", such as handwritten characters [8], materials that form the surface of Earth, phonemes that compose speech, structures in medical images. Besides, quantum approaches for classification in Earth observation problems are reported e.g. in [6, 7].

The above type of approach is also referred to as "quantum-like learning" (meaning "quantum-like machine learning" or QLML ; QLIP could be defined accordingly) in [9], where it is stated: *"Machine learning has a lot to adopt from quantum mechanics, and this statement is not restricted to actual quantum computing implementations of learning algorithms. Applying principles from quantum mechanics to design algorithms for classical computers is also a successful field of inquiry. We refer to these methods as quantum-like learning."* Typical applications of QIML are then also provided in [9].

Another type of generic information processing tasks is referred to as (global) optimization, including both continuous and discrete optimization: see e.g. the survey of quantum-inspired metaheurisitics in [10]. For decades, some optimization methods have been developed by taking advantage of *classical* physics properties. This e.g. gave rise to simulated annealing methods [11]. This type of idea is now being applied to *quantum* physics properties, e.g. using the tunnel effect [12, 13]. This especially yields quantum annealing methods, that are discussed in more detail in [14] (see also e.g. [13, 15, 5]). If only using the considered properties, derived from quantum physics *theory*, and implementing the resulting algorithms on a system that only uses classical computation, one obtains a quantum-inspired approach that may be referred to as a quantum annealing simulator or emulator. By the way, the term "simulator" should be used with care in discussions about "quantum computing" in general, because the term "quantum simulation" is also used with a much more specific meaning (say, simulating molecules), as discussed in more detail in Section 2.2. Beyond the above quantum annealing simulators, quantum annealing is often used with associated quantum hardware means, thus leading to the quantum-assisted approach described in Section 2.2.

A general-purpose open source software environment is available for QIML, with extensions for quantum-assisted approaches. It is called TensorFlow Quantum and it is claimed to allow one *"to simulate [quantum processing units] while designing, training, and testing hybrid quantum-classical models, and eventually run the quantum portions of these models on actual quantum processors as they come online"* [16]. It was e.g. used for an application to Earth observation in [6], to perform classification with a quantum-classical convolutional neural network.

2.2. Quantum-assisted (or quantum-enhanced) information processing and machine learning

The second considered type of approaches also aims at defining processing systems on which one can execute general-purpose algorithms, such as the above-mentioned ones. However, unlike in the first type of approaches, the second type exploits quantum hardware to run these algorithms. A major motivation for this approach is to improve computing speed. This is based on the fact that quantum computing has been shown to potentially yield huge gains in computing speed for some processing tasks, as compared with classical computing (see e.g. [4]). As suggested above, this includes quantum annealing methods [5], especially because the D-Wave company manufactures hardware quantum processing units based on quantum annealing. For an overview of these quantum computers, the reader may refer to [15].

More generally speaking, various processing tasks emerged because they have to be performed in newly introduced quantum-inspired processing methods. In such methods, it is natural not only to exploit quantum physical properties to obtain algorithms that operate according to new rules, but also to implement these algorithms (at least partly) on quantum

[2] The terminology "classical computer" and "quantum computer" refers to the final use that is made of the considered computer. Classical and quantum computers are thus quite different in the sense that classical digital computers essentially perform data manipulation by using numbers represented in base 2, hence as series of 0 and 1, whereas quantum computers manipulate quantum states, hence with associated quantum properties that have no counterpart in the classical world.

However, now consider the intimate operation of the above-mentioned "classical computers", i.e. at the level of the transistors currently used to implement such computers. At that intimate level, the opposition between classical and quantum computers is not so strong as it is in their above-mentioned final use, because the behavior of the transistors used as the elementary building blocks of classical computers is governed by the rules of quantum physics. This intimate feature is disregarded hereafter, when using the terms "classical computer" and "quantum computer": only their final use is considered.

hardware processing means. This not only yields a quantum-inspired method, but also a so-called “quantum-assisted information processing” (QAIP) method. The latter terminology comes from the fact that various methods will not be fully implemented on quantum hardware means but only partly, i.e. these methods will be assisted by quantum hardware. Using quantum hardware is more attractive only for some of the processing subtasks to be performed in a given application, because only these subtasks can exploit quantum properties and hence yield the above-mentioned speed improvement. The above approaches include machine learning methods, that may be called “quantum-assisted machine learning” (QAML) methods. QAIP methods are sometimes also referred to as “quantum-enhanced information processing” (QEnIP) methods, thus including “quantum-enhanced machine learning” (QEnML) methods [17].

Some applications correspond to the limit case of this QAIP framework, when one aims at implementing *all* the considered application on quantum hardware means. If one would like to distinguish this limit case from the overall QAIP framework, we here propose to call this case “quantum-executed information processing”, or QExIP, because processing is then completely executed on quantum hardware. This then includes the limit case of “quantum-executed machine learning”, or QExML, methods.

The above discussion especially applies to investigations currently performed to create quantum versions of artificial neural networks. For instance, [18] ultimately aims at implemeting neural networks on systems based on quantum optics, e.g. with inputs composed of single photon Fock states (but the preliminary results reported in [18] itself were obtained by means of numerical simulations running on a classical computer, thus restricting that investigation to QIML at this stage).

Another major type of problems, where quantum computing is important for handling processing tasks that are untractable with classical computers, is so-called “quantum simulation” in the following sense: simulating the behaviour of, e.g., a given molecule (i.e. finding the dynamics of its time evolution), by accordingly tuning the Hamiltonian of an actual physical quantum system that has a different nature as compared with the molecule of interest [13, 17, 19]. This approach is therefore a QAIP (or even QExIP) approach from the point of view of its use of an actual physical quantum system for performing computations (and we will reconsider the same problem from the point of view of the molecule of interest in Section 2.3).

Beyond the above somewhat focused examples, it should be stressed that QAIP approaches are also attractive for various general-purpose processing tasks that were already of interest before the second quantum revolution took place. This includes factoring integers [4] (which is of major importance for cryptography [4]) or solving high-dimensional sets of linear equations (see e.g. [13] for comments about the Harrow, Hasidim and Lloyd, or HHL, algorithm). Again, the motivation for revisiting these processing tasks with quantum approaches is that the latter approaches potentially make it possible to perform these tasks at a much higher speed than with classical computers.

2.3. Quantum-targeted information processing and machine learning

The third type of investigations considered in this paper also involves a physical quantum “system” but, unlike in the approaches of Section 2.2, this system is here not considered as a means (for executing an algorithm, which is then the topic of interest) but as the main topic of the investigation. In other words, this investigation is then targeted at the considered quantum system, and we consider the case when this investigation includes information processing, or more specifically a machine learning method. We therefore propose to call this type of approaches “quantum-targeted information processing” (QTIP), including “quantum-targeted machine learning” (QTML) approaches. More precisely, the tasks to be performed for the considered quantum system typically consist of characterizing its behavior or expanding that system for improving its performance. It is for performing these tasks that information processing or machine learning is used in these investigations.

A major type of information processing task that belongs to this QTIP/QTML framework is quantum process tomography, that may be defined as follows. A wide class of quantum computer architectures consists of quantum gates, that are interconnected so as to achieve the desired overall processing function. Each such gate is thus selected so as to perform a specific subfunction when designing the considered quantum computer. However, the gates that are actually implemented yield some discrepancies with respect to their desired behavior. Their actual behavior should therefore be experimentally characterized. Various algorithms have been developed to this end. They constitute the quantum form of so-called system identification algorithms [20] and they are often referred to as quantum process tomography (QPT), as proposed in [21]. They have complementary features as compared with those of various methods of Sections 2.1 and 2.2: (i) they are dedicated to the specific QPT task required for analyzing the operation of the quantum computer itself, as opposed to a final general-purpose application task such as classification, (ii) they are executed on classical processing means (although they aim at analyzing quantum properties). They not only belong to the general field of information processing but also to the subfield of machine learning, in the sense that they are strongly based on using data to learn a function, that is, the input/output transform of the considered quantum gate. More precisely, in their usual version, these algorithms derive that transform from the known values imposed on the input of the gate and from the associated values measured at its output, somewhat like in the generic regression task. This is the supervised (or non-blind) version of QPT algorithms (see e.g. [20, 22, 23]). Besides, more advanced versions were introduced in [24] and then developed in [25, 26]. They are based on unsupervised (or blind) learning, i.e. they do not require one to know the values taken by the input of the gate, but e.g. only some of its statistical properties. They thus have the advantage of not requesting the cumbersome repeated and accurate preparation of fixed input quantum states, that are required in supervised methods.

A related class of methods, but now aiming at expanding the capabilities of quantum computers, consists of (especially blind) quantum source separation methods. They were introduced in [27] and then e.g. developed in [28, 29, 30, 8] (see other references in [8]). These algorithms aim at restoring quantum states after they have been altered. They may thus be of interest for improving quantum memories [8].

Finally, the quantum simulation problem defined in Section 2.2 here deserves additional comments, because it involves two parts: the molecule of interest and the other type of physical quantum system, used to analyze the behavior of that molecule. This two-part configuration therefore not only involves the QAIP aspect presented in Section 2.2 (because of the computations performed on the other type of physical quantum system) but also QTIP: when focusing on the molecule, that molecule is the quantum system of interest, and its behavior is analyzed by some processing means (namely the other type of physical quantum system).

3. DISCUSSION AND CONCLUSION

In this paper, we provided an overview of the connections that were developed, during the current second quantum revolution, between information processing and machine learning in the classical (i.e. non-quantum) framework on the one hand, and several aspects of quantum physics on the other hand, namely properties involved in quantum theory and practical implementations leading to quantum computers. Moreover, we proposed a taxonomy of the new fields resulting from these connections.

All these domains are e.g. starting to impact the field of remote sensing (i.e. Earth observation), because quantum-inspired approaches will e.g. yield new classification algorithms for performing thematic mapping, quantum-assisted approaches will be required to process huge amounts of data in a reasonable time frame on quantum computers, and quantum-targeted approaches will first be used to guarantee the operation of these quantum computers. Various applications of quantum-inspired and quantum-assisted approaches to remote sensing were already reported in the literature and some of them were cited above in this paper.

We hope that this overview may help newcomers in the second quantum revolution find their way and select their fields of interest, e.g. depending whether they mainly aim at taking advantage of quantum-inspired and quantum-assisted approaches to expand their information processing capabilities, e.g. for remote sensing applications, or whether they want to enter the field of quantum-targeted methods and expand it, thanks to their expertise in designing new processing methods that they previously applied to the classical framework.

4. REFERENCES

[1] J. P. Dowling and G. J. Milburn, "Quantum technology: the second quantum revolution," *Phil. Trans. R. Soc. Lond. A*, vol. 361, pp. 1655–1674, 2003.

[2] A. Aspect, *Photonic quantum technologies: science and applications*, chapter 2: The second quantum revolution: from basic concepts to quantum technologies, Wiley, M. Benyoucef (Ed.), Online Library, 2023.

[3] R. P. Feynman, *Feynman lectures on computation*, Westview (edited by T. Hey and R. W. Allen), 1999.

[4] P. W. Shor, "Algorithms for quantum computation: Discrete logarithms and factoring," in *35th Annual Symposium on Foundations of Computer Science*, Santa Fe, New Mexico, Nov. (20-22) 1994, pp. 124–134.

[5] T. Albash and D. A. Lidar, "Adiabatic quantum computation," *Reviews of Modern Physics*, vol. 90, no. January-March, pp. 015002 (1–64), 2018.

[6] F. Fan, Y. Shi, and X. X. Zhu, "Earth observation data classification with quantum-classical convolutional neural network," in *2022 IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2022)*, Kuala Lumpur, Malaysia, July (17-22) 2022, pp. 191–194.

[7] S. Y. Chang, B. Le Saux, S. Vallecorsa, and M. Grossi, "Quantum convolutional circuits for earth observation image classification," in *2022 IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2022)*, Kuala Lumpur, Malaysia, July (17-22) 2022, pp. 4907–4910.

[8] Y. Deville and A. Deville, "New single-preparation methods for unsupervised quantum machine learning problems," *IEEE Transactions on Quantum Engineering*, vol. 2, no. Article Sequence Number: 3104224, DOI: 10.1109/TQE.2021.3121797, pp. 1–24, 2021.

[9] P. Wittek, *Quantum Machine Learning. What Quantum Computing Means to Data Mining*, Academic Press / Elsevier, San Diego (USA) / Amsterdam (The Netherlands), 2014.

[10] S. Hakemi, M. Houshmand, E. KheirKhah, and S. A. Hosseini, "A review of recent advances in quantum–inspired metaheuristics," *Evolutionary Intelligence*, vol. https://doi.org/10.1007/s12065-022-00783-2, 2022.

[11] J. J. Schneider and S. Kirkpatrick, *Stochastic optimization*, Springer, Berlin, 2006.

[12] E. P. DeBenedictis, "A future with quantum machine learning," *Computer*, vol. 51, no. 2, pp. 68–71, Feb. 2018.

[13] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," *Nature*, vol. 549, no. 14 Sept., pp. 195–202, 2017.

[14] L. T. Duarte and Y. Deville, "Quantum-assisted methods for data analysis by means of quantum adiabatic computing," in *submitted to the Mediterranean and Middle-East Geoscience and Remote Sensing Symposium 2024 (M2GARSS 2024)*, Oran, Algeria, April (15-17) 2024.

[15] C. C. McGeoch, R. Harris, S. P. Reinhardt, and P. I. Bunyk, "Practical annealing-based quantum computing," *Computer*, vol. 52, no. June, pp. 38–46, 2019.

[16] M. Broughton, G. Verdon, T. McCourt, A. J. Martinez, J. H. Yoo, S. V. Isakov, P. Massey, R. Halavati, M. Y. Niu, A. Zlokapa, E. Peters, O. Lockwood, A. Skolik, S. Jerbi, V. Dunjko, M. Leib, M. Streif, D. Von Dollen, H. Chen, S. Cao, R. Wiersema, H.-Y. Huang, J. R. McClean, R. Babbush, S. Boixo, D. Bacon, A. K. Ho, H. Neven, and M. Mohseni, "Tensorflow quantum: A software framework for quantum machine learning," *arXiv:2003.02989v2*, 26 Aug 2021.

[17] S. D. Sarma, D.-L. Deng, and L.-M. Duan, "Machine learning meets quantum physics," *Physics Today*, vol. 72, no. 3, pp. 48–54, March 2019.

[18] G. R. Steinbrecher, J. P. Olson, D. Englund, and J. Carolan, "Quantum optical neural networks," *Nature Partner Journals Quantum Information*, vol. 5, pp. 1–9 (paper no. 60), 2019.

[19] K. Bourzac, "4 tough chemistry problems that quantum computers will solve [news]," *IEEE Spectrum*, vol. 54, no. 11 (November), pp. 7–9, 2017.

[20] M. A. Nielsen and I. L. Chuang, *Quantum computation and quantum information*, Cambridge University Press, Cambridge, UK, 2000.

[21] I. L. Chuang and M. A. Nielsen, "Prescription for experimental determination of the dynamics of a quantum black box," *Journal of Modern Optics*, vol. 44, no. 11-12, pp. 2455–2467, 1997.

[22] C. H. Baldwin, A. Kalev, and I. Deutsch, "Quantum process tomography of unitary and near-unitary maps," *Physical Review A*, vol. 90, pp. 012110–1 to 012110–10, 2014.

[23] A. Shukla and T. S. Mahesh, "Single-scan quantum process tomography," *Physical Review A*, vol. 90, pp. 052301–1 to 052301–6, 2014.

[24] Y. Deville and A. Deville, "From blind quantum source separation to blind quantum process tomography," in *Proceedings of the 12th International Conference on Latent Variable Analysis and Signal Separation (LVA/ICA 2015)*, Liberec, Czech Republic, Springer International Publishing Switzerland, LNCS 9237, Aug. 25-28 2015, pp. 184–192.

[25] Y. Deville and A. Deville, "The blind version of quantum process tomography: operating with unknown input values," in *Proceedings of the 20th World Congress of the International Federation of Automatic Control (IFAC 2017)*, Toulouse, France, July 9-14 2017, pp. 12228–12234.

[26] Y. Deville and A. Deville, "Quantum process tomography with unknown single-preparation input states: Concepts and application to the qubit pair with internal exchange coupling," *Physical Review A*, vol. 101, no. 4, pp. 042332–1 to 042332–18, April 2020.

[27] Y. Deville and A. Deville, "Blind separation of quantum states: estimating two qubits from an isotropic Heisenberg spin coupling model," in *Proceedings of the 7th International Conference on Independent Component Analysis and Signal Separation (ICA 2007), ISSN 0302-9743, Springer-Verlag, vol. LNCS 4666. Erratum: replace two terms* $E\{r_i\}E\{q_i\}$ *in (33) of [27] by* $E\{r_i q_i\}$, *since* q_i *depends on* r_i., London, UK, Sept. 9-12 2007, pp. 706–713.

[28] Y. Deville and A. Deville, "Classical-processing and quantum-processing signal separation methods for qubit uncoupling," *Quantum Information Processing*, vol. 11, no. 6, pp. 1311–1347, 2012.

[29] Y. Deville and A. Deville, *Blind Source Separation: Advances in Theory, Algorithms and Applications*, chapter 1. Quantum-source independent component analysis and related statistical blind qubit uncoupling methods, pp. 3–37, Springer, G. R. Naik and W. Wang Eds, Berlin, Germany, 2014.

[30] Y. Deville and A. Deville, "Blind quantum source separation: quantum-processing qubit uncoupling systems based on disentanglement," *Digital Signal Processing*, vol. 67, pp. 30–51, August 2017.