Headway in Quantum domain for Machine learning towards improved Artificial Intelligence

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Abstract

A vital, transformative and impactful field on our society is levied on us by the incoming quantum computation and information technologies. The undergoing research on the interaction of fields of quantum computation with the machine learning and artificial intelligence is witnessing significant investigations. Evidently there has been a major demonstration of quantum enhancements in interactive learning tasks and the optimization of quantum experiments using Machine Learning sowing the seeds of interdisciplinary activities to improve their influence in our hugely populated data intensive digital world. The quantum mechanical world is evidently taking shapes beyond theoretical analysis with the aid of Artificial Intelligence previously uncharted. This composite review, to the best of our knowledge, makes an attempt to explore the recent headway for actuating AI and ML in the quantum domain.

Keywords: Quantum Computation; Artificial Intelligence, Machine Learning, Quantum AI, Cognitive Quantum Security

I. Introduction

Quantum information science explored since decades cover the various area including cryptography [1], computing, sensing and metrology, which are already in a mature stage of research. Though many questions have been put up for the interdisciplinary research of quantum information processes and fields of artificial intelligence and machine learning, it has got its recognition recently showing results in its interplay comparable to classical domains.

Information as a result of measurement is an answer to a question, which does not depend on physical support. Thus one wants to encode it through universal encoding, transmit it using communication, process it through computation and store it using memory. As per Claude Shannon in 1948, information depends on laws of physics. The question arises, can we quantify information, the answer to which is best described as with the measure of surprise, which is inverse to the probability of an instance/event. The Shannon's Entropy further quantifies this function H as can be seen in Eq (1)

$$\mathrm{H} = -\sum_{i=0}^{n} Pi \ln Pi \tag{1}$$

where P is the probability of occurrence of an instance/event i.

Quantum physics is abruptly generalized as the classical physics that is described in the atomic and subatomic level. In quantum mechanics particles can be predicted as microstates following principles like Superposition principle, time solution, measurement principle and combined states. Thus it is said that quantum mechanics is deterministic up and until measurement, where it turns stochastic and probabilistic [2]. Entanglement, as defined generally, within physically detached particles, implies a quantifiable effect on one another, that is having a distinct reliance on each other, is the core of applied physics. So is the relevance of humanity and uncertainty.

In this paper, review of the progress made in quantum machine learning is organized in the below sections. Section II states a brief state of the art progress in QAI. In section III a classification of AI and learning technique in quantum domain is briefed. Section IV discusses the usage of the headway in practical scenario stressing the quantum supremacy. A concluding remark is subjected finally.

II. Quantum Artificial Intelligence and Machine Learning

Artificial intelligence (AI) was defined as the ability of machines to acquire knowledge and apply it smartly in order to increase chances of success with a certain amount of accuracy to a particular task mimicking human's response. It is the capability of computer programs to find optimal solution to complex problems and aid in decision making wisely. There are apparently two viewpoints on its conception [3]: computationalism [4] and connectionism [5]. Thus this played a significant role in fragmenting the field into various specialized sub-fields for different tasks. Problem solving and planning [6] aspects of decision making are strategies used by humans for coming to best decisions which are incorporated in systems with reasoning over formal logic. This is possible through learning catching experience in machines thus deriving the most successful aspect of AI.

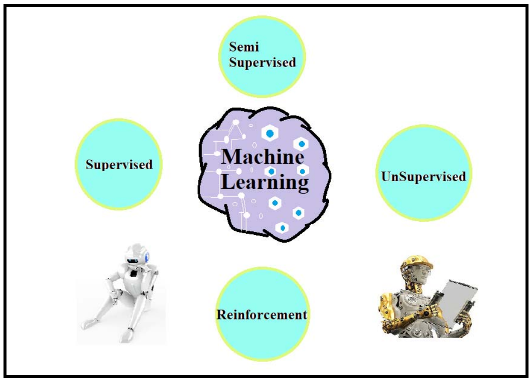

Fig. 1 Machine Learning control

Machine learning is defined as the skill of acquiring knowledge to increase accuracy irrespective of success. The computer program needs a set of data to learn of a particular task and maximize the performance of machines duly updating its self-learning capabilities with every set of new data. ML is divided as labelled supervised learning (artificial neural networks, support vector machines, etc.) to assign labels to data outside training set, and unlabelled unsupervised techniques to find natural categories of training data set [7]. Supervised learning deals with the conditional probabilistic distribution from n $P(Y = y|X = x)$ based on a certain number of samples from the joint distribution $P(X,Y)$. In unsupervised learning data points are provided to algorithms to extract features and reduce dimensionality, where task is to infer properties of the distribution $P(X = x)$, relative to a user specified guideline using techniques like principal component analysis [8].

Capacity of agents to learn while interacting with their environments is what reinforcement learning and projective simulations (PS) in Quantum Information Processing (QIP) deal with. But its applications are less explored compared to Quantum enhancements in supervised and unsupervised environments have been. A route to quantization occurs naturally through the projective simulation agents structured memory system, which learns from experience and reacts in the form of physical inputs. This memory is the Episodic and Compositional memory (ECM) network of clips which is a percept, an action or a structure over clips.

An h-matrix characterization is evaluated by the ECM network occurring in basically two modes, weights of edges and topology of the network that describes the principle behind PS agents. These real valued weights (h-values) connect the percept clips to action clips, realized by random walks in memory space. The authors in [9] presented another construction of the PS framework for re-learning using reflection mechanism through iteratively taking random walks to perform mixing process for the agent's chances of hitting desired flag with certain speed up. In all the cases, the process is deliberated governing a stochastic walk, specified by a collection of Markov chain models over the ECM.

Benchmarking these PS models and RL approaches, the authors in [10] [11] have analyzed performances and have evaluated against different models. Further these learning models are used in real time applications [12] [13] giving an edge over the random walks. Using its memories, the agents projects effectively into plausible situations, consolidating experiences in to stochastic networks. The stochastic process use quantum random walks for a quadratic speed-up.

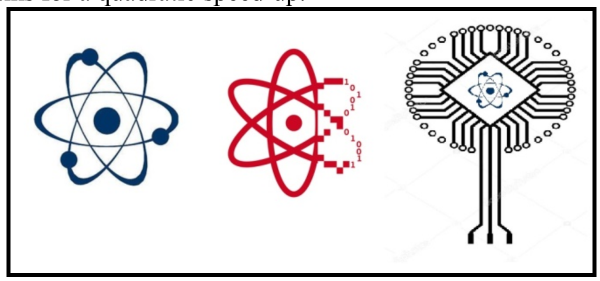

Fig. 2 Quantizing Quantum Information Processing

Without loss of generality, the quantum database is a unitary map that needs no additional memory of its own as it does not change during steps of interaction. A paradigm needs to be framed for characterizing the interactions between quantum agents and quantum environments that preserves their interactions to enhance the potential of learning through quantum enhancement. The learning agents can Grover-search the history of interactions for improved performance in the future, analogous to the speculative execution for improving performance and utilization in classical computing. In QIP this technique gives a quadratic advantage to the overall quantum enhanced agent against basic classical agent [14].

The Agent Environment paradigm are provided with unlabeled data sets and the agents respond with labels, such as supervised learning, which in general is encountered in AI settings. The quantum database access is required for the data sets in the quantum AE paradigm for solving problems in the quantum domain. The Turing test for Quantum Artificial Intelligence itself defines the environment as the testing administrator and the agent is the machine convincing the administrator [15] that it is intelligent [16], thus fitting it in the quantum AE paradigm. The components are conceptualized to form a basis for quantum enhanced intelligent agents to build a framework [17] for the Quantum AE paradigm

III. Classifying quantum AI based on Quantum ML

Being the most unexplored creations of humanity, Artificial Intelligence as one perceives today, is displaying just the tip of an iceberg, let alone the impact of quantum world on it. Research in the AI domain always seems to be outreaching its maximum, but once it gets to the edge, new opportunities tempt scientists to see the long path ahead. Replicating the behavior of humans is the parameters on which AI is being judged on its evolution. In literature AI has been classified on the basis of levels of proficiency as advanced with huge functionality and less evolved with limited performance [18].

Revolutionizing the field of AI with the impact of QML could be substantiated from reports discussed in various learning problems [19] [20] [21] [22]. The main branches as per the discussions in these reports can be classified as supervised and unsupervised learning. Learning problems from the distribution P(x,y), the conditional distribution P(y|x) assigns labels y to data x, for classifying data and training sets in supervised learning. In the second case, samples are identified in a structure to form clusters from the distribution P(x). Further classification is researched for Reinforcement Learning (RL), whereby learning is based on interaction among agents and environment, through signals termed as rewards and punishment [23].

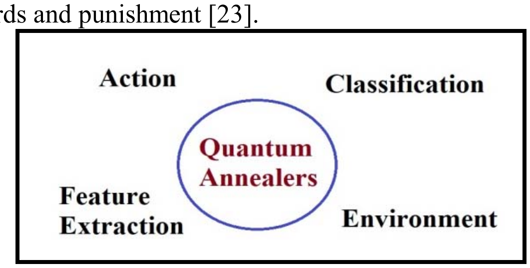

Fig. 3 Quantum AI applications

Classifying quantum AI may not be an easy task at this rudimentary stage of research, but in this section we have tried to organize them in a systematic order considering the vast literature available on its respective supporting parameters. One of the major parameters on which intelligence of a system depends in the quantum world is the available research on quantum machine learning algorithms [24]. Beginning from the various algorithms of classical ML, Linear-algebra-based QML, quantum principal component analysis, qBLAS-based optimization, deep quantum learning, etc., we have attempted to analyze different set of parameters before organizing them in a few naming categories.

The tomography context states partition of a system ρ^{X}_{Y} conditioned from a measurement perspective is reconstructed from the measurement statistics of the joint state ρ_{XY} encoded from the distribution P(x,y) [23]. Accordingly the characteristics can be considered as per the computational complexity of the learner's algorithm, depending on the volume of the training set. In this context it counts the number of copies of ρ_{XY} needed to have a desired confidence to reconstruct the states ρ^{X}_{Y}. In RL based technique the learning efficiency is given significance instead of the sample complexity. Nonetheless, to what extent these techniques will benefit (quantum) AI is a general predicament.

Quantum mechanics is all about matrix operations in high-dimensional vector spaces. HHL algorithm [25] shows the building up of such matrix transformations through which quantum computers can solve many day to day functions in time exponentially faster than their classical counterparts. The quantum PCA algorithm scales $O[(\log N)^2]$ in computational complexity and query complexity [26] which is also exponentially efficient than classical PCA. Quantum support vector machines (SVM) classify data via parameters of the hyperplane through which margins are maximized via kernel [27] functions. Beginning from usage of Grover's search algorithm for function minimization to the recent least-squares quantum SVM harnessing full power of qBLAS subroutines by accessing classical data from qRAM or quantum states, the data are processed in polynomial time log N, N being the hyperplane matrix dimension for usage in different tasks [28].

Machine Learning	**Quantum Machine Learning**		**Quantum Information Processing**
Simulated annealing	Annealing Quantum annealing		Quantum gibbs sampling
Markov chain monte-carlo	Quantum BM	Quantum topological algorithms	qBLAS
Feed forward neural net	Quantum perceptron	Quantum PCA SVM	Quantum ODE solvers
Neural Nets	NN classification	clustering data fitting	Deep Quantum Learning
	Quantum Rejection Sampling / HHL		
	Control and metrology		
Reinforcement learning	Quantum control phase estimation Hamiltonian learning		tomography

Table 1 Quantum Machine Learning Algorithms

Quantum deep learning networks are constructed using quantum annealers and programmable photonic circuits for processing quantum information tasks [29] without the necessity of a general purpose quantum computer. Commercially available devices are used to construct tunable couplings for implementation [30] of universal quantum logic. In order to learn a desire task, using the quantum Boltzmann machine, quantum coherence reduces the number of samples quadratically, using fewer access requests to train data and form quantum associative memory [31]. Moreover richer models of data can be classified using these machines which is absent in classical ML.

In order to aid in characterizing a quantum system and states using quantum computer, considering the near-term applications of QML, the task of incorporating the coherent input states is a significant technical test. Fault tolerant quantum information processing needs the alignment of supervised and controlled quantum gates with fidelity above 99.9%. In the presence of decoherence and noise Reinforcement Learning algorithms have been comparatively successful for designing circuits. A brief summary of the many algorithms discussed herein are depicted in Table 1.

IV. Quantum AI Supremacy

The battle between classical and quantum supremacy is on stage with the Quantum AI Lab announcement in a paper by Martinis group with collaboration of Google on October 2019 [32]. Google has been running its quantum processor Sycamore using 54 (53 to be accurate) transmon qubits quantum chips each made of superconducting loops for special purpose and researchers are yet to discover a quantum general purpose processor for analyzing an advantage over supremacy on a large scale, yet this feat is a breakthrough. A major difficulty in adding more qubits is in maintaining the fragile states of further qubits in an operating device.

The fault tolerant qubits implementation in a quantum processor is a rather tough problem, but a high feat has been attained. The problem of random number generation in the quantum processor is solved in terms of minutes. Initially with quantum speed up, challenges were faced to perform quantum computation in a large Hilbert space engineered with minimal errors. Next step was to analyze the statistics with the performance of a classical analogy. Using the method of cross-entropy benchmarking, to measure the bitstrings x_i, probability $P(x_i)$ and their fidelity (ɟ) Eq (2) was utilized.

$$ɟ_{XEB} = 2^n \langle P(xi) \rangle i - 1 \quad (2)$$

where n is the number of qubits. The value ranges from 0 for uniform distribution, to 1 for exponential probability distribution in error free quantum circuits.

Yet another diverse emerging field of research is the Quantum Cognition that takes aid of quantum theory to mold human brain activities including memory, judgment and reasoning [33]. There are speculations about its ethics for use cases on human emotions, but its benefits are far beyond the doubts arising in many. In research community the concerns about its widespread use among public and side effects like that of security and vulnerability runs amuck wildly [34]. Recent development of neurosciences makes an effort not only in studying mental capabilities, but also manipulating and controlling specific mental abilities, though it is not publicly criticized.

The ongoing research capability is pushing the topic from investigating technology to achieving real time bid in new ventures. The applications are immense and hitherto undiscovered, but not unforeseen. The near future will for sure not be hesitant to take slow steps in Machine Learning but giant leaps with Artificial Intelligence in propelling the cumulative efforts in Quantum realm.

V. Conclusion

Quantum hardware is the need of the hour to test and verify the vast set of algorithms for a impactful quantum Artificial Intelligent system, which can not only learn from prior experiences without the aid of memory based functionality as well as learn from the large set of data to solve future problems, but also a system that can understand human cognitive thinking. Seeing the ongoing research, it is not imperative to say that in future we may deal with artificial emotional intelligence which can discern needs, emotions, beliefs and thought process.

This paper is a bird's eye view perspective of a quantum filed technical enthusiast, with naïve knowledge of the imminent thriving applications of the QAI. Moreover, a self-evolving QAI which can interact with others and develop human emotions and potential desires of its own is not far away. The authors have attempted to summarize pertinent information in a limited amount of space.

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