Quantum Neural Networks - Our brain as a quantum computer?

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Abstract. Neuroscience and quantum physics have a central feature in common: both disciplines study objects that largely remain a mystery to scientists. While a century after the discovery of quantum theory, physicists still struggle to interpret their quantum objects' counterintuitive behaviour, biologists are not even close to understanding the mechanisms underlying the remarkable performance of our brain. The research field of quantum neural networks (QNNs) combines both 'mysteries' by investigating how established models of neural networks can be formulated in the language of quantum theory. Far away from the rather esoteric discourses of a 'quantum brain', QNN models first and foremost aim at developing efficient algorithms to run on future realisations of quantum computers. QNNs thereby promise to provide a substantial speed-up or increased memory capacity relative to classical neural networks. However, beyond questions of powerful computing technology, a success in the yet relatively small field of QNN research could give a first hint that our brain makes use of quantum mechanics to master its incredible tasks. In that sense, QNN research can be seen as a subfield of the 'dawn' of quantum biology which evaluates the question of how nature employs quantum effects in macroscopic (i.e. hot and dense) environments to optimise its processes.

1. Introduction

One of the most important scientific questions yet to answer is the problem of how the 'hardware' of our brain leads to its functioning in terms of thoughts, memory and consciousness. Some voices claim that an important ingredient of an explanation of 'how the mind emerges from matter' is quantum mechanics. On the more populist side, the discourse seems to be fuelled by the fascination of merging two scientific mysteries, namely the counterintuitive behaviour of the microscopic world and the black-box our most important organ still appears to be.[1] But also more established physicists argue in favour of a brain based on quantum mechanics as a potential avenue of solving the open problem of computation in the brain works. The most well-known is Sir Roger Penrose who, in collaboration with the anaesthesiologist Stuart Hameroff, located quantum computing in the microtubules or cytoskeleton of neural cells [1]. Another approach is the quantum brain model by Ricciardi and Umezawa [2] and further developed by Pessa and Vitiello [3] in which the states of neural networks are understood as collective modes using the formalism of Quantum Field Theory. The nonlocal properties of both quantum waves

[1] Popular science debates on a 'quantum brain' lead to journals of controversial scientific scope such as *QuantumNeurology*.

and consciousness gave rise to notions of a 'quantum consciousness' [4, 5]. However, solving the mind-matter problem through quantum physics is highly controversial [6, 7, 8].

Another meeting point between neuroscience and quantum physics are quantum neural networks (in short, QNNs). Conventional neural networks are simplified mathematical or computational models of the neural setup of our brain. QNNs are then models or devices that integrate quantum computing and neural networks as two promising paradigms of information processing in order to improve classical neural networks. Besides their potential computational power, QNNs contribute important arguments towards the debate on the role of quantum physics in the brain. If it can be shown that neural computation (which is widely assumed to be the basic mechanism of how the brain works) is dramatically improved by introducing quantum effects, we could further investigate if on a biological level, quantum neural computing can be observed. It turns out that QNN research feeds the arguments against quantum brain models: neural networks, characterised by nonlinear neural activation functions, and quantum systems based on a probabilistic description of linear operations, show very distinct mathematical structures. However, apart from their questionable biological explanation power, QNNs constitute an exciting research topic from a computational perspective. Increasing the performance of classical neural networks would have a significant effect on applications of machine learning and would extend the potential field in which future quantum computers could be useful.

This brief contribution intends to introduce into the theoretical foundations of QNNs (Section 2) and QNN research (Section 3) in order to reflect on the question if these have the potential to serve as realistic models of the brain. It comes to the conclusion that we have to see QNNs rather from a computational than a biological perspective, and that the challenges in merging quantum physics and neuroscience rather point towards the fact that quantum brain models are not that easy to derive (Section 4).

2. Information processing with neurons and quantum objects

To understand the basics of how neurons process information, we have to look at how they feed signals into one another through synaptic connections. Neurons are tube-like cells that transmit so called action potentials. An action potential is a localised depolarisation of the equilibrium membrane potential of usually $-70mV$ traveling along the neuron[2]. A neuron transmitting an action potential is called 'active' or 'firing' as opposed to a 'resting' neuron.

Each of the approximately 10^{11} neurons in our brain has 1 to 10^4 synaptic connections to other neurons, making up for a total number of 10^{14} synapses [9]. When an action potential reaches a (chemical) synapse, neurotransmitters are released into synaptic cleft and open up ion channels in the membrane of the subsequent or post-synaptic neuron, so that a post-synaptic potential is created. In simple words, neurons produce signals in other neurons that depend on the synaptic strength with which they are connected. If all these incoming signals to a neuron exceed a certain threshold, the neuron produces an action potential and becomes active.

This synaptic activation mechanism can be translated into a simple mathematical model called *perceptron* and first introduced in [10]. It is based on binary neurons proposed by [11] in the 1940s. In a perceptron setup, N input neurons $x_1, ..., x_N$ with values of either 0 (resting) or 1 (active) feed into a neuron y with threshold θ_y, and the strength of the synaptic connections between x_i and y is simulated by a weight w_{iy}. Neuron y is activated (represented by setting it to 1) if the input signal from $x_1, ..., x_N$ multiplied by their respective weights exceeds the

[2] The resting potential of the membranes of neural cells is kept up by the relative ion concentration inside and outside the membrane permeable through voltage-guided ion channels.

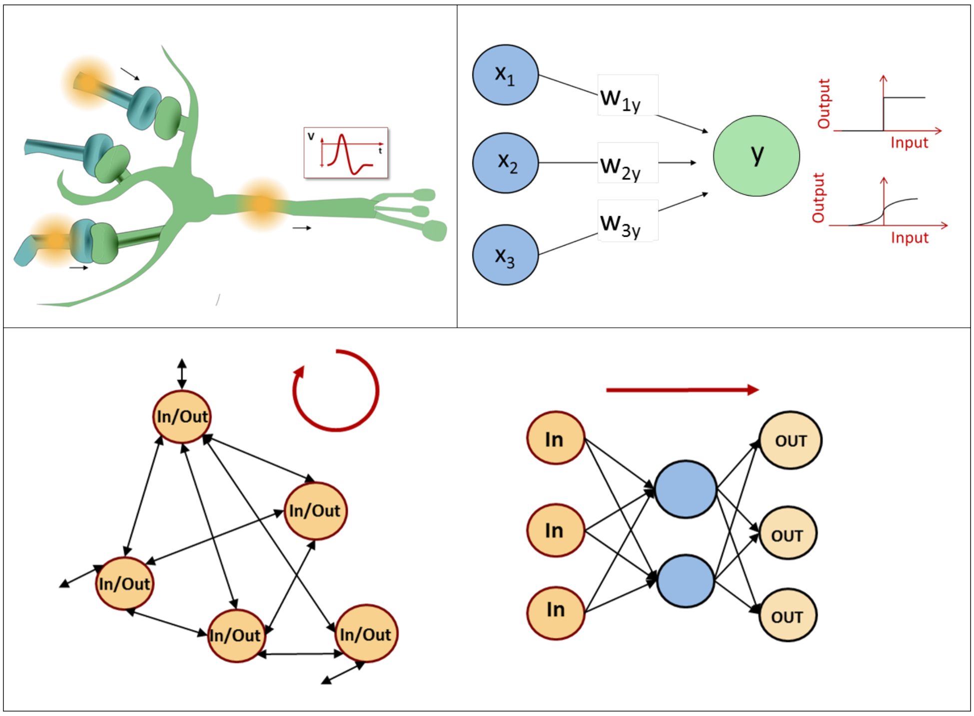

Figure 1. (Colour online) Neural computing derived from biological synapses. Top left: A neuron fires action potentials if the combined signals from neurons feeding into it through synaptic connections lead to an above threshold post-synaptic signal. Top right: Synaptic connections can be mathematically modelled by perceptrons with binary neurons $x_{1,2,3}$ connected to output neuron y through the connections weighted by $w_{1y,2y,3y}$ and a step or sigmoid activation function. Bottom: In neural networks, neurons are either recurrently connected (recurrent neural network on the left) or structured in subsequent layers (feed-forward neural network on the right).

threshold. The mathematical formulation is the activation or updating function

$$y = \begin{cases} 1, & \text{if } \sum_{i=1}^{N} w_{iy} x_i \geq \theta_y, \\ 0, & \text{else.} \end{cases}$$

This binary perceptron is often replaced by continuous versions, for example by choosing $x_i, y \in [-1, 1]$ and $y = \mathrm{sgm}(\sum_{i=1}^{N} w_{iy} x_i + \theta_y)$, where sgm denotes the sigmoid function.
A neural network is a set of interconnected neurons whose dynamics are defined by the activation mechanism. After setting neurons to an initial value, they are successively updated in a given sequence and the output of the neural network can be read out of the final state of the neurons. In recurrent neural networks, all neurons take part in this process until the network states converges to a stable point, while in feed-forward neural networks the information processing goes through layers and the output is read out at a final set of neurons [12]. Neural networks are consequently like computers that convert an input signal into an output signal, and their success is based on the fact that through adjusting the weights, neural networks can learn a input-output mapping just as our brain does.

If we want to design a quantum neural network derived from biological foundations, we need to find a way to introduce quantum effects in the perceptron updating mechanism. What do we mean by quantum effects? Quantum theory is a mathematical framework used by physicists to describe the behaviour of very small particles under isolated conditions. The physical laws on small scales are thereby very different from Newton's classical mechanics. Our description of atoms, electrons or photons for example assigns a wavefunction to a particle, that can be modelled by a vector with the notation $|\psi\rangle$ in a special vector space called Hilbert space. The wavefunction contains information on the probability of the particle to be in a certain state (e.g. position, momentum or energy). The central fact is that this probabilistic description does not correspond to our lack of knowledge on the system, but derives from the fact that the particle is in general in a so called superposition of different states, sometimes referred to as being in 'all states at the same time'. The interaction with a macroscopic environment such as a measurement then picks one of these states with the given probability and 'collapses' the particle superposition (which is why we could never observe quantum effects directly on our macroscopic scales).

This remarkable property of the microscopic world can be exploited for information processing, for example through a quantum system that encodes binary information like a computer, but is able to 'do calculations' on a superposition of all possible bit strings at the same time, and consequently retrieves a result by measuring the system. It is not easy to invent algorithms on such a quantum computer, but since two decades a number of powerful quantum routines are known to outperform classical computers, and many scientists think that it is only a question of time until quantum computers will become reality. The art of developing a quantum neural network which draws on neural computing is to use insights from quantum information theory in order to improve the performance of neural networks. We will briefly sketch the scope and results of QNN research before we discuss the central question of this article, namely what QNNs can tell us about the feasibility of a quantum brain.

3. Quantum neural network research

The development of a quantum neural network first and foremost aims at improving the computational efficiency of neural networks through the introduction of quantum effects. Neural networks are powerful devices with important application in tasks of machine learning [13, 14, 12], but they can be very costly in terms of computational resources. This is where the quantum speed-up is supposed to help.

The basic idea of introducing quantum properties into classical NNs is to replace the McCulloch-Pitts neuron $x = \{0, 1\}$ by a qubit $|x\rangle$ of the two-dimensional Hilbert space $\mathcal{H}^2$ with basis $\{|0\rangle, |1\rangle\}$. The state of a network with N neurons thus becomes a quantum product state of the 2^N-dimensional Hilbert space

$$|\psi\rangle = |x_1\rangle \otimes |x_2\rangle \otimes \ldots \otimes |x_N\rangle = |x_1 x_2 \ldots x_N\rangle \quad \in \quad \mathcal{H}^{2^N} = \underbrace{\mathcal{H}^2 \otimes \ldots \otimes \mathcal{H}^2}_{\text{Ntimes}}.$$

Apart from the 'qubit neuron' (or 'quron'), proposals for QNN models vary strongly in their proximity to the basic idea of neural networks. Some try to directly translate the activation mechanism into quantum mechanics [15, 16], a task which is nontrivial because of the structural differences between the mathematical formalism of quantum computing and neural computing. In a more liberal approach, researchers introduce a hypothetical quantum evolution that corresponds to the nonlinear function, the so called dissipative operator D [17], but they fail to find a possibility to create such an operator. Others implement a quantum neural network through interacting quantum dots [18], a task that requires advanced technologies in controlling the interaction strengths, especially if the systems are scaled up from mere proof-of-principal examples.

An important approach is also the development of a quantum associative memory (QAM) which attempts to simulate the functioning of a neural network without considering the neuroscientific basics [19, 20]. In our previous research, we followed this idea and used so called stochastic quantum walks in order to impose dynamics on an abstract quantum system that reproduces the basic features of an associative memory [21]. Quantum walks are equivalents to classical random walks which describe a stochastic process in which a walker jumps between nodes of a graph with predefined probabilities. We were able to show that a specific quantum version of these processes together with a certain construction of the underlying graph can lead the walker from a node representing an intial firing state of a neural network to a node representing the desired output. The quantum nature of the walk thereby led to a slight speed-up in a specific parameter range.

Altogether, QNN research is still in its infancy and a successful QNN model based on biological foundations is still outstanding. However, the efforts are part of the new emerging field of quantum machine learning, and might gain more importance if one day quantum computers are accessible for real applications.

4. Conclusion: Is the brain a quantum computer?

As mentioned above, it is difficult to combine quantum theory and neural computing. Neural networks rely on nonlinear activation functions, which in the case of the threshold function works as a switch to activate a neuron through an incoming signal. On the other hand, quantum theory is a probabilistic description and formulated through linear transformations of amplitudes that carry information on the probability of measuring a certain state. Even if we could understand neurons as quantum objects, neural quantum computing seems to fail with this incompatibility. As formulated in [17], we would require a dissipative quantum operator D that imitates the threshold activation function, but up to today there are no proposals known to the authors of how such a transformation could look like. Other ideas that translate neural networks into quantum mechanics while preserving the biologically observed activation mechanism fail to incorporate compatible (unitary) process of learning [15].

The difficulty in creating a powerful quantum version of neural computation supports arguments against simple notions of our brain to be a 'quantum computer' (as it was previously framed in a *Nature* contribution [22]). This adds to other important points made regarding the possibility of observing quantum effects in biological systems like the brain. First, the brain is a 'hot and messy' sphere of high temperatures and high particle densities. These properties destroy quantum coherence thereby rendering quantum effects irrelevant on observable timescales. Tegmark in fact estimated the decoherence time for collisions between the roughly 10^6 ions involved in the process of generating an action potential at a membrane site to be $\tau = 10^{-20}s$ [8]. Since this time scale is much smaller than the $10^{-3}s$ of a firing event in fast neurons, he concludes that "the computations in the brain appear to be of a classical rather than quantum nature," [8, 12, italics left away]. Litt et al. add that the brain also lacks a mechanism for the complex task of quantum error correction [23]. Second, from what we know today, information processing in the brain is executed through the above described transmission of action potentials along neurons and their connections [24]. To explain how the brain performs quantum computing based on neuroscientific insights, we would have to introduce the entire (macroscopic) neuron as a quasi-particle and its complex firing process as a quantum state. This seems to be far away from quantum objects studied up to today.

As a conclusion, we can summarize that the challenge to express the neural updating function within the framework of quantum theory might be taken as an additional argument against the hypothesis that our brain is a quantum computer, adding towards the decoherence concerns put forward by various authors. Despite this fact, QNNs provide an exciting research field focusing on the potential of quantum computing to increase the performance of neural networks. These attempts are not confined to approaches preserving biological features of neural computing but can use the entire toolbox of quantum computing to develop a powerful QNN model that is applicable for central machine learning tasks.

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