Entangled Neural Networks from Multi-fold Universes to Biology

Stephane H. Maes[1]

December 25, 2020

Abstract:

In a multi-fold universe, gravity emerges from Entanglement through the multi-fold mechanisms. As a result, gravity-like effects appear in between entangled particles, that they be real or virtual. Long range, massless gravity results from entanglement of massless virtual particles. Entanglement of massive virtual particles leads to massive gravity contributions at very smalls scales. Multi-folds mechanisms also result into a spacetime that is discrete, with a random walk fractal structure and non-commutative geometry that is Lorentz invariant and where spacetime nodes and particles can be modeled with microscopic black holes. All these recover General relativity at large scales, and semi-classical model remain valid till smaller scale than usually expected. Gravity can therefore be added to the Standard Model. This can contribute to resolving several open issues with the Standard Model without new Physics other than gravity. These considerations hints at a even stronger relationship between gravity and the Standard Model.

Recently a controversial series of papers ended up proposing the possibility that the universe be a neural network. It is the result of observing that, with an irreversible thermodynamics model of the learning process of the neural network (NN), it might appear possible to model quantum and classical physics, to observe the emergence of a General Relativistic spacetime with gravity, and plausibly to construct a generalized holographic principle beyond the AdS/CFT correspondence conjecture. The approach has been received with some skepticism.

In this paper, we revisit the notion of NN in relationship to multi-fold universes, and illustrate how the multi-fold mechanism can be implemented with grafted NN. Relying on progress in biology and medicine, we argue that not only just NN can emulate NN universe, but also that it can provide new tools for AI, and new approaches to NNs, shallow or deep. It validates our multi-fold models and offer models for biological neurological models.

____

1. Introduction

The new preprint [1] proposes contributions to several open problems in physics like the reconciliation of General Relativity (GR) with Quantum Physics, explaining the origin of gravity proposed as emerging from quantum (EPR-Einstein Podolsky Rosen) entanglement between particles, detailing contributions to dark matter, and dark energy, and explaining other Standard Model mysteries without requiring New Physics beyond the Standard Model, other than the addition of gravity to the Standard Model Lagrangian. All this is achieved in a multi-fold universe that may well model our real universe.

With the proposed model of [1], spacetime and Physics are modeled from Planck scales to quantum and macroscopic scales, and semi classical approaches appear valid till very small scales. In [1], it is argued that spacetime is discrete, with a random walk-based fractal structure, fractional and noncommutative at, and above Planck scales (with a 2-D behavior and Lorentz invariance preserved by random walks till the early moments of the universe). Spacetime results from past random walks of particles. Spacetime locations and particles can be

[1] shmaes.physics@gmail.com

Cite as: Stephane H Maes, (2020), "Entangled Neural Networks from Multi-fold Universes to Biology", https://shmaesphysics.wordpress.com/2020/12/31/entangled-neural-networks-from-multi-fold-universes-to-biology/, December 25, 2020.

modeled as microscopic black holes (Schwarzschild for photons and spacetime coordinates, and metrics between Reisner Nordstrom [2] and Kerr Newman [3] for massive and possibly charged particles – the latter being possibly extremal). Although surprising, [1] recovers results consistent with others like [4], while also being able to justify the initial assumptions of black holes from the gravity or entanglement model in a multi-fold universe. The resulting gravity model recovers General Relativity at larger scale, as a 4-D process, with massless gravity, but also with massive gravity components at very small scale, that contribute to make gravity significant at these scales. Semi-classical models also turn out to work well till way smaller scales that usually expected.

In previous papers, we analyzed how works, that proposed to model Physics in the universe as a neural network (NN) [5,6,7], relate to multi-fold universes when entanglement is added [8,9]. In this paper, we discuss how the multi-fold mechanisms, and grafted NN are indeed QNN, and conversely. Interestingly, NN, which can represent any AI algorithm, can also model QNN. QNN are postulated to relate to deeper properties of the human mind, including possible consciousness [10,11]. The analogies between these different domains can be the basis for new NN-based algorithms.

2. Entangled Neurons and the Mind

As discussed in [10], it has been proposed that consciousness and other mind features are related to entanglement in the brain. Although the initial mechanisms proposed by Penrose [12,13] did not (yet) pan out [14], new models suggest that entanglement indeed exist in the brain [11].

According to [15], Phosphorus has the right spin properties to be both a QuBit and an entanglement transporter (that can carry an entangled state from a region of, say a chain, to another, e.g. from the beginning of a chain to the end of that chain) with long enough coherent times to support transport. And we know that macroscopic systems and large molecules or objects can be entangled [1,15,16]. So, with this, the arguments of Penrose or other considerations, we can expect that it is possible to entangle (non-local) neurons.

Plausibility of the proposal of [15], and the role of entanglement in the mind and consciousness can be deducted from the results of [18], where Lithium is seen impacting differently the treatment of bipolar disorder when using different isotopes (a sign that the impact comes from nuclear properties like spin rather than the electronics, i.e., chemical properties). Considering that Phosphorus entanglement properties comes from its nuclear spin 1/2, Lithium can substitute for Calcium in the associated molecules with Phosphorus and impact the entanglement. The fact that it impacts bipolarity, seems to validate the proposal.

In this paper, based on the reasoning above, we assume the following:

- Neuron entanglement are the key properties of the human brain, including consciousness, ability to reason, imagine and “decide”, as well as to learn, or best act, on data never encountered and learned before.
- NNs implementing non-local neuron entanglement, can implement these behavior with the right optimization algorithms.

We keep also in mind that any function, classification, or ML/AI algorithm can be modeled and implemented by NNs [19-21].

3. Multi-fold NNs

Based on [1,8,9]: entanglement takes place under a mode where Quantum Physics dominates. According to [5], wavefunction and mechanisms from the Schrödinger equation, governs the parameters of the NN weights, and biases, when close to equilibrium. As quantum mechanics dominates, entanglement can take place among spacetime regions with significant wavefunction contributions [22]. When that is the case, the neurons dominantly associated to these regions, are entangled: their weights and biases are correlated, as are the states of the hidden layer: the emergent spacetime.

Both aspects (GR governed spacetime, and Quantum behaviors underlying the weights and biases) coexist as we are close to equilibrium (and learning has taken place). However entanglement requires that the states be represented as Bell states, which, in quantum computing, means applying Hadamard gates on the quantum circuits [23]. That step is not included in the [5] model, that was not focused on modeling entanglement [8,9].

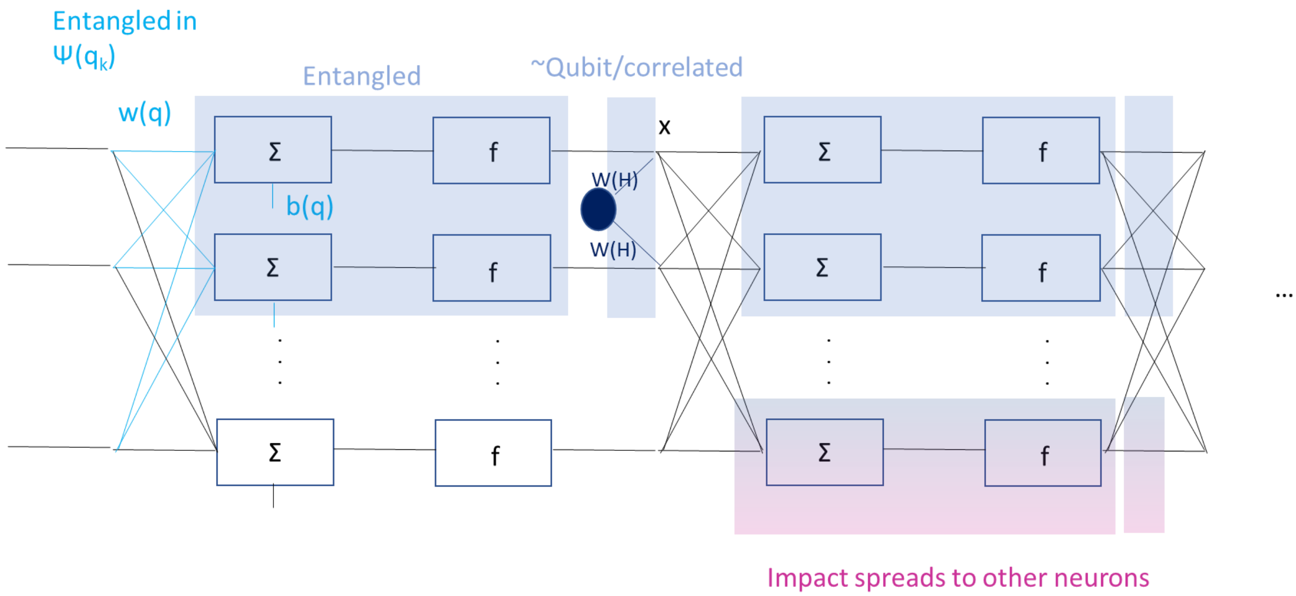

Figure 1: Multi-fold Grafted NN to emulate entanglement. W(H) refers to the weights of extra layer described in [24].

Per [24,25], such H gate is emulated in NN, e.g. Boltzmann restricted Machines (BRM), by adding hidden layers (nodes) [24,25]. These can be the multi-folds activated by entanglement (and in 7D), as discussed in [8,9]. These are the additional grafted NN between entangled spacetime points as shown on figure 1. Their effects mixes and correlates entangled states, and that propagates to all the subsequent neurons and states at the next clock click; something shown in [25] to well approximate the Hadamard gate effects (figure 1b in [25]).

These NNs are the ones we mentioned but did not detailed in [8,9]. The presence of the Grafted NN create gravity modifications in the spacetime of x(t) (per [5]).

4. New NNs: Grafted Multi-fold NN

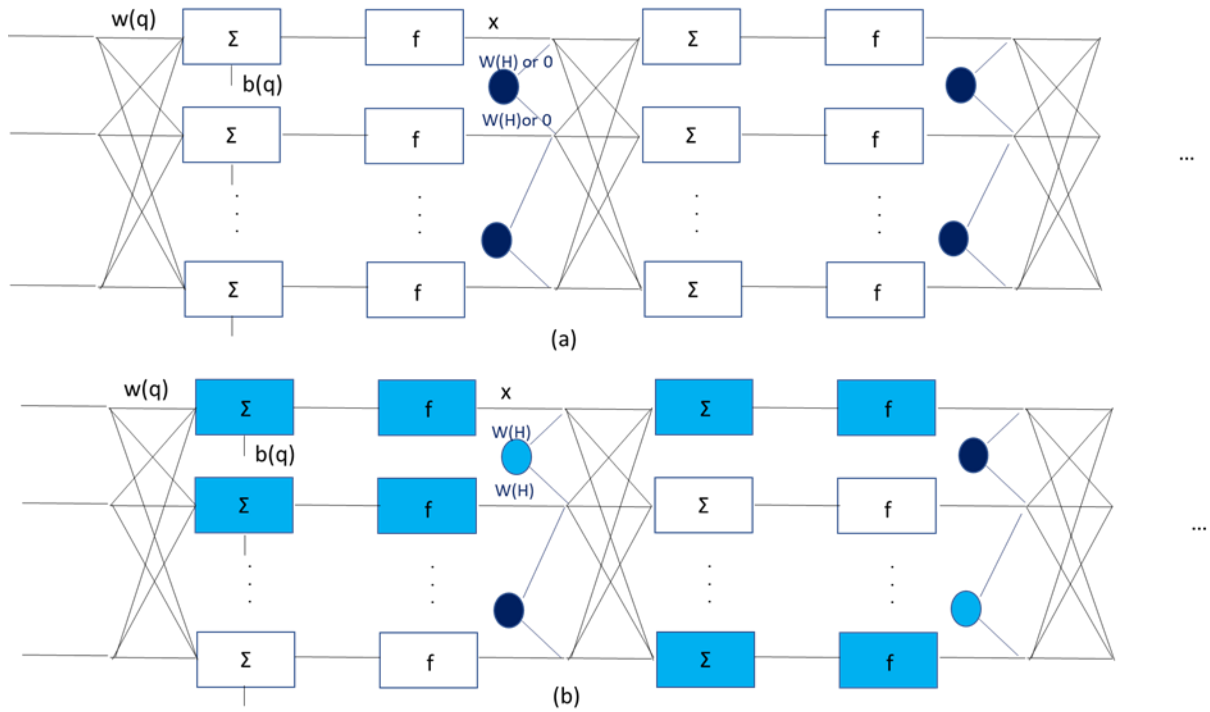

Figure 2 – (a) Grafted multi-fold NN: optimization includes deciding node pairs to entangle by emulation. When entangled, multi-folds appear and Hadamard emulation weights are set. (b) Entangled pairs may then continue to be entangled, be disentangled or propagate (entanglement propagation to a neighbor). This propagation strategy can just be an option: another approach can just consider any possible pair for entanglement at every step.

Following the model of section 3, and the considerations of section 2, we propose to consider the following new NN types for AI and deep learning: Non quantum grafted NN where, at each time click, pairs of nodes can be considered for entanglement, and the corresponding weights and biases are correlated, and Hadamard layers are added to emulate the behavior.

Whatever are the cost/loss functions to optimize, and the optimization algorithm, now each node pair (neighbor) can be considered for "entanglement", or QNN circuit behaviors, if it better optimizes the target function that with the two NN branches, business as usual. Then entangled pairs are next considered for disentanglement, maintaining entanglement or moving it to a neighbor node (e.g. as if the nodes correspond to particles that are moving away). The optimization algorithm where the evolution of the weights and biases purportedly entangled evolve in a correlated manner (e.g. roughly the same increase, or decrease, say in percentage).

It is illustrated in Figure 2. Note that it is different from more conventional hybrid NN where layers are either conventional or QNNs [26].

Doing so fully emulates a multi-fold universe, and adds entanglement to NN, copying biological behavior as discussed in section 2.

Entanglement (emulation) is expected to improve learning (more accurate and with less training data) [27]. It also allows exploring different (many) options in parallel which accounts for better learning and decision capabilities. From a learning angle, the entanglement, or its emulation, reduces the entropy of the encoder (and therefore the mutual information between visible and hidden layers) and increases the mutual entropy between the hidden layer of the decoder and the output (e.g. classification) as in [28], following Information Theory's coding theorems [31]. We believe it also is the basis for adding efficient decision-making features to NN based AI beyond just decision trees types of approaches. Exploring and combining options is also expected to provide new abilities to act on new data, or situations/contexts. Implementing and validating such proposals is for future work.

5. Dimensions of the Mind

[29] presents some results that suggest that the brain works in 7+ dimensions. This is something also hinted by the 7D induction model for a multi-fold universe [30]. We may also come back to this in the future.

6. Conclusions

The paper proposes new NNs: multi-fold graft NNs, and how they can be implemented and trained or used. The approach further validates and complements the analyses in [8,9].

Future work is warranted to study and validate Grafted multi-fold NNs, both in AI, and in the context of modeling neurological models of biological neurons as well as models of the human mind including consciousness, decision making, bipolarity and other related aspects, on the road to quantum supremacy for AI.

____

References:

[1]: Stephane H. Maes, (2020), "Quantum Gravity Emergence from Entanglement in a Multi-Fold Universe", viXra:2006.0088v1, https://vixra.org/pdf/2006.0088v1.pdf (June 9, 2020).

[2]: https://en.wikipedia.org/wiki/Reissner%E2%80%93Nordstr%C3%B6m_metric

[3]: https://en.wikipedia.org/wiki/Kerr-Newman_metric

[4]: Burinskii, Alexander, (2008), “The Dirac-Kerr-Newman electron”, arXiv:0507109v4

[5]: Vitaly Vanchurin, (2018), " The world as a neural network", arXiv:2008.01540v1

[6]: Vitaly Vanchurin, (2018), “Covariant Information Theory and Emergent Gravity”, arXiv:1707.05004v4

[7]: Vitaly Vanchurin, (2020), “Towards a theory of machine learning”, arXiv:2004.09280v3

[8]: Stephane H Maes, (2020), “Implicit Multi-Fold Mechanisms in a Neural Network Model of the Universe”, viXra:2012.0191v1, https://shmaesphysics.wordpress.com/2020/09/12/implicit-multi-fold-mechanisms-in-a-neural-network-model-of-the-universe/, September 12, 2020.

[9]: Stephane H Maes, (2020), “Interpretation of “Neural Network as the World””, viXra:2012.0197v1, https://shmaesphysics.wordpress.com/2020/09/14/interpretation-of-neural-network-as-the-world/, September 14, 2020.

[10]: Philip Ball, (2017), " Nobody understands what consciousness is or how it works. Nobody understands quantum mechanics either. Could that be more than coincidence?", http://www.bbc.com/earth/story/20170215-the-strange-link-between-the-human-mind-and-quantum-physics. Retrieved on November 28, 2020.

[11]: Matthew P.A. Fisher (2015), Quantum cognition: The possibility of processing with nuclear spins in the brain, Annals of Physics, Volume 362.

[12]: Penrose, R. (1989). "The emperor's new mind: Concerning computers, minds, and the laws of physics", Oxford University Press.

[13]: Penrose, R. (1994). "Shadows of the mind: A search for the missing science of consciousness", Oxford University Press.

[14]: Max Tegmark, (1999), "Importance of quantum decoherence in brain processes", Importance of quantum decoherence in brain processes.

[15]: C Marletto, D M Coles, T Farrow and V Vedral, (2018), "Entanglement between living bacteria and quantized light witnessed by Rabi splitting", Journal of Physics Communications, Volume 2, Number 10.

[16]: C. F. Ockeloen-Korppi, E. Damskagg, J.-M. Pirkkalainen, A. A. Clerk, F. Massel, M. J. Woolley, M. A. Sillanpaa, (2017), "Entangled massive mechanical oscillators", arXiv:1711.01640v1.

[17] : Yaakov Y. Fein et al. (2019), “Quantum superposition of molecules beyond 25 kDa”, Nature Physics.

[18]: Severus, E., Taylor, M.J., Sauer, C. et al., (2014), "Lithium for prevention of mood episodes in bipolar disorders: systematic review and meta-analysis. Int J Bipolar Disord", 2, 15.

[19]: Wikipedia, "Kolmogorov–Arnold representation theorem" https://en.wikipedia.org/wiki/Kolmogorov%E2%80%93Arnold_representation_theorem, Retrieved on September 14, 2020.

[20]: Wikipedia, "Universal approximation theorem", https://en.wikipedia.org/wiki/Universal_approximation_theorem, Retrieved on September 14, 2020.

[21]: Andre Ye, (2020), "Every Machine Learning Algorithm Can Be Represented as a Neural Network", https://towardsdatascience.com/every-machine-learning-algorithm-can-be-represented-as-a-neural-network-82dcdfb627e3. Retrieved on December 19, 2020

[22]: Stephane H Maes, (2020), “The W-type Multi-Fold Hypothesis and Quantum Physics Interpretation of wave Functions and QFT”, viXra:2207.0118v1, https://shmaesphysics.wordpress.com/2020/12/24/the-w-type-multi-fold-hypothesis-and-quantum-physics-interpretation-of-wave-functions-and-qft/, December 20, 2020.

[23]: Michael A. Nielsen, Isaac L. Chuang, (2011), "Quantum computation and quantum information", Cambridge University press.

[24]: Gao, X. & Duan, L.-M. (2017) "Efficient representation of quantum many-body states with deep neural networks". Nature Communications 8, 662

[25]: Bjarni Jónsson, Bela Bauer, Giuseppe Carleo, (2018), "Neural-network states for the classical simulation of quantum computing", arXiv:1808.05232v1

[26]: Qiskit, "Hybrid quantum-classical Neural Networks with PyTorch and Qiskit ", https://qiskit.org/textbook/ch-machine-learning/machine-learning-qiskit-pytorch.html. Retrieved on December 19, 2020.

[27]: Tohru Nitta, (2009), "Complex-Valued Neural Networks: Utilizing High-Dimensional Parameters", Information Science Reference

[28]: Mukul Malik, (2018), "Information Theory of Neural Networks, Opening the Black Box …. Somewhat", https://towardsdatascience.com/information-theory-of-neural-networks-ad4053f8e177. Retrieved on December 19, 2020.

[29]: Paul Ratner, (2017), "The human brain builds structures in 11 dimensions, discover scientists", https://bigthink.com/paul-ratner/our-brains-think-in-11-dimensions-discover-scientists. Retrieved on December 27, 2020.

[30]: Stephane H Maes, (2020), "Tracking Down The Standard Model With Gravity In Multi-Fold Universes", viXra:2011.0208v1, https://shmaesphysics.wordpress.com/2020/08/30/tracking-down-the-standard-model-with-gravity-in-multi-fold-universes/, August 20, 2020.

[31]: Parthasarathy, K. R, (2013), "Coding Theorems of Classical and Quantum Information Theory", Hindustan Book Agency