A QFT Approach to Data Streaming in Natural and Artificial Neural Networks

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During the last twenty years a lot of research has be done for the development of probabilistic machine learning algorithms, especially in the field of the *artificial neural networks* (ANN) for dealing with the problem of *data streaming* classification and, more generally for the*real time* information extraction/manipulation/analysisfrom (infinite) data streams.For instance, sensor networks, healthcare monitoring, social networks, financial markets, … are among the main sources of data streams, often arriving at high speed and always requiring a real-time analysis, before all for individuating *long-range and higher order correlations*among data, which are continuously *changing over time*.Indeed, the standard statistical machine learning algorithms in ANN models starting from their progenitor, the so-called *backpropagation* (BP)algorithm–based on the presence of the "sigmoid function"acting on the activation function of the neurons of the hidden layers of the net for detecting higher order correlations in the data, and the *gradient descent*(GD) stochastic algorithm for the (supervised) neuron weight refresh–are developed for *static*also huge bases of data ("big data"). Then, they are systematically inadequate and unadaptable for the analysis of data streaming, i.e., of *dynamic* bases of data characterized by sudden changes in the correlation length among the variables (phase transitions), and then by the unpredictable variation of the number of the signifying degrees of freedom of the probability distributions. From the computational standpoint, this means the *infinitary* character of the data streaming problem, whose solution is in principle unreachable by a TM, either classical or quantum (QTM).Indeed, for dealing with the data streaming infinitarychallenge, the exponential increasing of the computational speed derived by the usage of quantum machine learning algorithms is not very helpful, either using "quantum gates" (QTM), or using "quantum annealing" (*quantum Boltzmann Machine* (QBM)),both objects of an intensive research during the last years. In the case of ANNs, the improvement given by the*Boltzmann-Machine*(BM) learning algorithm to GD is that BM uses "thermal fluctuations" for jumping out of the local minima of the cost function (*simulated annealing*),so to avoid the main limitation of the GD algorithm in machine learning.In this framework, the advantage of *quantum annealing*in a QBM is that it uses the "quantum vacuum fluctuations" instead of thermal fluctuations of the classical annealing for bringing the system out of swallow (local) minima, by using the "quantum tunnelling" effect. This outperforms the thermal annealing, especially where the energy (cost) landscape consists of high but thin barriers surrounding shallow local minima. However, despite the improvement that, at least in some specific cases, QBM can give for finding the absolute minimum size/length/cost/distance among a large even though *finite* set of possible solutions, the problem of data streaming remains because in this case this finitary supposition does not hold. Like the analogy with the coarse-graining problem in statistical physics emphasizes very well, the search for the global minimum of the energy function makes sense *after* the system performed a phase transition. That is, physically, after that a sudden change in the correlation length among variables, generally under the action of an *external field*, determined a new way by which they are aggregated for defining the signifying number of the degrees of freedom N characterizing the system statistics after the transition.In other terms, the infinitary challenge implicit in the data streamingis related with *phase transitions*so that, from the QFT standpoint, this is the same phenomenon of the infinite number of degrees of freedom of the Haag Theorem, characterizing the quantum superposition inQFT systems in *far from equilibrium conditions*. This requires the extension of the QFT formalism to dissipative systems, inaugurated by the pioneering works of N. Bogoliubov and H. Umezawa. The Bogoliubov transform, indeed, allows to map between different phases of the bosons and the fermions quantum fields, making the dissipative QFT – differently from QM and from QFT in theirstandard (Hamiltonian)interpretation for closed system – able to calculate over *phase transitions.*Indeed, inspired by the modeling of natural brains as many-body systems, the QFT dissipative formalism has been used to model ANNs[1, 2]. The mathematical formalism of QFT requires that for *open* (dissipative) systems, like the brain which is in a permanent "trade" or "dialog" with its environment, the degrees of freedom of the system (the brain), say A, need to be "doubled" by introducing the degrees of freedom $\tilde{A}$ describing the environment, according to the coalgebraic scheme: $A \to A \times \tilde{A}$. Indeed, Hopf coproducts (sums) are generally used in quantum physics to calculate the *total energy* of a superposition quantum state. In the case of a dissipative system, the coproducts represent the total energy of a *balanced state* between the system and its thermal bath. In this case, because the two terms of the coproduct are not mutually interchangeable like in the case of closed systems(where the sum concerns the energy of two superposed particles), we are led to consider the *non-commutative q-deformed* Hopf bialgebras, out of which the*Bogoliubov transformations* involving the $A, \tilde{A}$ modes are derived, and where the *q*-deformation parameter is a thermal parameter strictly related with the Bogoliubov transform[3]. These transformations induce *phase transitions*, i.e., transitions through physically distinct spaces of the states describing different dynamical regimes in which the system can sit. The brain is thus continuously undergoing phase transitions (*criticalities*) under the action of the inputs from the environment ($\tilde{A}$ modes). The brain activity is therefore the result of a continual balancing of fluxes of energy (in all its forms) exchanged with the environment. The balancing is controlled by the minimization of the free energy at each step of time evolution. Since fluxes "in" for the brain (*A* modes) are fluxes "out" for the environment ($\tilde{A}$ modes), and vice-versa, the $\tilde{A}$ modes are the *time-reversed images* of the *A* modes (Wigner distribution), they represent the *Double* of the system. In such a way, by the doubling of the algebras – and then of the state spaces, and finally of the Hilbert spaces – the Hamiltonian canonical (closed) representation of a dynamic system can be recovered also in the case of a dissipative system, by inserting in the Hamiltonian the degrees of freedom of the environment (thermal bath).From the theoretical computer science (TCS) standpoint, this means that the system satisfies the notion of a particular type of automaton, the*Labelled State Transition Machine* (LTM). I.e., the so-called *infinite-state* LTM, coalgebraically interpreted and used in TCS for modelling *infinite streams of data*[2, 4]. Indeed, the doubling of the degrees of freedom (DDF) $\{A, \tilde{A}\}$ just illustrated and characterizing a dissipative QFT system acts as a *dynamic* selection criterion of admissible because balanced states (minimum of the free energy). Effectively, it acts as a mechanism of "phase locking" between the data flow (environment) and the system dynamics. Moreover, each system-environment entangled (doubled) state is *univocally* characterized by a *dynamically generated code*$\mathcal{N}$, or *dynamic labelling* (memory addresses). In our model, indeed, an input triggers the *spontaneous breakdown of the symmetry* (SBS) of the system dynamical equations. As a result of SBS, massless modes, called Nambu-Goldstone (NG) modes, are dynamically generated. The NG-bosons are quanta of *long-range correlations* among the system elementary components and their *coherent condensation value* $\mathcal{N}$ in the system ground state (the least energy state or vacuum state $|0\rangle$, that in our dissipative case is a *balanced,* or 0-sum energy state with $T > 0$) describes the recording of the information carried by that input, *indexed univocally (labeled) in* $\mathcal{N}$. *Coherence* denotes that the long-range correlations are not destructively interfering in the system ground state[2]. The memory state turns out to be, therefore, a *squeezed coherent state*:$|0(\theta)\rangle_{\mathcal{N}} = \sum_j w_j(\theta)\, |w_j\rangle_{\mathcal{N}}$, to which Glauber information entropy Q directly applies, with $|w_j\rangle$ denoting states of A and $\tilde{A}$ pairs, θ is the time- and temperature-dependent Bogoliubov transformation parameter. $|0(\theta)\rangle_{\mathcal{N}}$is, therefore, *a time-dependent ground state* at finite temperature$T > 0$; it is an entangled state of the modes A and$\tilde{A}$, which provides the mathematical description of the *unavoidable* interdependence between the brain and its environment. Coherence and entanglement imply that quantities relative to the *A* modes depend on corresponding ones of the $\tilde{A}$ modes.To conclude, the natural implementation of such a quantum computational architecture for data streaming machine learning based on the DDF principle is by an optical ANN using the tools of *optical interferometry,* just as in the applications discussed in [3]. The fully programmable architecture of this optical chip allows indeed "to depict" over coherent light waves how many interference figures as we like, and overall to maintain stable in time their *phase coherences,* so to allow the implementation of quantum computing architectures (either quantum gates or squeezed coherent states) working at *room temperature.* In our application for data streaming analysis, the DDF principle can be applied in a recursive way, by using the *mutual information* as a measure of *phase distance,* like an optimization tool for minimizing the input-output mismatch. In this architecture, indeed, the input of the net is not on the initial conditions of the net dynamics, like in the ANN architecture based on statistical mechanics, but on the boundary conditions (thermal bath) of the system, so to implement the architecture of a net in unsupervised learning, as required by the data streaming challenge.

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