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TRAINING SUPPORT VECTOR REGRESSION BY QUANTUM-NEURON-BASED HOPFIELD NEURAL NET WITH NESTED LOCAL ADIABATIC EVOLUTION

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Abstract. *Adaptive support vector regression (ASVR) algorithm we introduced earlier has been employed to compute initial free parameters for support vector regression (SVR) modeling. Since a conventional quadratic programming cannot guarantee to resolve the NP-complete problem or the problem of over-fit, we herein proposed a novel approach to tune weight vector and bias of SVR model to best fit its regression instead of a quadratic one. That is, quantum-neuron-based Hopfield Neural Net adapted by nested local adiabatic evolution algorithm for structured search is applied to find the optimal or near-optimal solutions of weight vector and bias, globally, for SVR model associated with the high probability of success and a good reduction of computational complexity.*
Keywords: Support vector regression, Hopfield neural net, Nested local adiabatic evolution algorithm, Structured adiabatic quantum search

1. **Introduction.** A quantum-neuron-based (QN-based) optimization [1] applied to Hopfield Neural Net (HNN) [2] can break NP-complete problem where quantum behavior brings HNN global information to overcome the shortcoming, local minima solutions to the optimization. QN-based optimization considers a Hopfield-Neural-Net's neuron as a qubit, and a Hamiltonian for HNN is built by means of converting the synaptic weights between HNN neurons into the interactions of qubits. The dissipation-like effect of adiabatic Hamiltonian evolution [3] operated to a qubit-like neural network is associated with the computational complexity in polynomial-time rather than exponential one, which actually turns NP-problem into P-problem.

However, QN-based optimization based on traditionally adiabatic Hamiltonian evolution solved an unstructured search problem in a time of order $\sqrt{N}$ where N is the dimension of search space. In order to speedup QN-based optimization associated with quantum adiabatic algorithms [4], Cerf, Grover, and Williams showed that partitioning the unknown variables into two (or more) sets and then nesting a partial search over a reduced set of variables into a global search for solving an optimization problem yielded an average complexity of order $\sqrt{N^\alpha}$ with $\alpha < 1$ [5]. That is, a local adiabatic search over a subset of the variables built a proper initial Hamiltonian for a global adiabatic search later on, reported by Roland and Cerf [6]. In summary, nested local adiabatic evolution QN-based optimization makes it possible to *nest* the preliminary adiabatic search locally