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Diversity of quantum optimizations for training adaptive support vector regression and its prediction applications

Bao Rong Chang [a,*], Hsiu Fen Tsai [b,1], Chung-Ping Young [c,2]

[a] Department of Computer Science and Information Engineering, National Taitung University, Taiwan, 684 Chunghua Road, Sec. 1, Taitung 950, Taiwan
[b] Department of International Business Shu-Te University, 59, Hun Shang Road, Yen Chao, Kaohsiung County 824, Taiwan
[c] Department of Computer Science and Information Engineering, National Cheng Kung University, Taiwan1, University Road, Tainan 701, Taiwan

Abstract

Three kinds of quantum optimizations are introduced in this paper as follows: quantum minimization (QM), neuromorphic quantum-based optimization (NQO), and logarithmic search with quantum existence testing (LSQET). In order to compare their optimization ability for training adaptive support vector regression, the performance evaluation is accomplished in the basis of forecasting the complex time series through two real world experiments. The model used for this complex time series prediction comprises both BPNN-Weighted Grey-C3LSP (BWGC) and nonlinear generalized autoregressive conditional heteroscedasticity (NGARCH) that is tuned perfectly by quantum-optimized adaptive support vector regression. Finally, according to the predictive accuracy of time series forecast and the cost of the computational complexity, the concluding remark will be made to illustrate and discuss these quantum optimizations.

Keywords: Quantum minimization; Neuromorphic quantum-based optimization; Logarithmic search with quantum existence testing; Adaptive support vector regression; Nonlinear generalized autoregressive conditional heteroscedasticity

1. Introduction

Many computing and engineering problems can be tracked back to an optimization process which aims to find the extreme value (minimum or maximum point) of a so-called cost function or a database. From a quantum computing point view Grover algorithm (Grover, 1996) has been viewed as the most promising candidate. Unfortunately Grover-based solutions are efficient only in term of expected number of database quires. In order to tackle this main drawback we decide to introduce three algorithms to solve the problem of finding the extreme values. First, three kinds of quantum optimizations are introduced in the following consecutive Sections 2–4, that is quantum minimization (QM) (Chang & Tsai, 2006), neuromorphic quantum-based optimization (NQO) (Tank & Hopfield, 1986), and logarithmic search with quantum existence testing (LSQET) (Imre & Balazs, 2005), respectively. Next, in order to compare their ability of optimization among three quantum approaches, the performance evaluation for every quantum approach is implemented by the following two stages. Applying every quantum approach to optimizing adaptive support vector regression (Chang, 2005) is done at the initial stage and denoted as QOASVR. Subsequently, this trained support vector regression is exploited to adapting a complex model that comprises both BPNN-Weight Grey-C3LSP (BWGC) and nonlinear generalized autoregressive conditional heteroscedasticity (NGARCH) and is denoted as BWGC/NGARCH (Chang, Tsai, Chen, & Chen, 2006). Thus, combining two above-mentioned

* Corresponding author. Tel.: +886 89 318855x6205; fax: +886 89 350214.
E-mail addresses: brchang@nttu.edu.tw (B.R. Chang), soenfen@mail.stu.edu.tw (H.F. Tsai), cpyoung@mail.ncku.edu.tw (C.-P. Young).
[1] Tel.: +886 7 6158000x3315; fax: +886 7 6158001.
[2] Tel.: +886 6 2757575x62533; fax: +886 6 2747076.

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abbreviations, that are both QOASVR and BWGC/NGARCH, one can express the whole structure proposed in this paper to QOASVR-BWGC/NGARCH. Finally, forecasting the complex time series through two real world experiments is implemented. According to the predictive accuracy of time series forecast and the cost of the computational complexity, the concluding remark will be made to illustrate and discuss these quantum optimizations.

2. Quantum minimization

Quantum-based minimization that makes optimization task work out associated with probability of success at least 1/2 within an unsorted database is realized by quantum minimum searching algorithm (Durr & Hoyer, 2005). A quantum exponential searching algorithm (Boyer, Brassard, Hoyer, & Tapp, 1998) is called by quantum minimum searching algorithm to be as a subroutine to serve a fast database searching engine.

2.1. Quantum exponential searching algorithm

As reported in (Boyer et al., 1998) where the searching problem is to find the index i such that $T[i] = x$, we are ready to describe the algorithm for finding a solution when the number t of solutions is known. For simplicity, we assume at first that $1 \leqslant t \leqslant 3N/4$.

Step 1: Initialize $k = 1$ and set $\rho = 6/5$. (Any value of ρ strictly between 1 and 4/3 would do.)
Step 2: Choose j uniformly at random among the nonnegative integers small than k.
Step 3: Apply j iterations of Grover's algorithm (Grover, 1996) starting from initial state $|\Psi_0\rangle = \sum_i \frac{1}{\sqrt{N}}|i\rangle$.
Step 4: Observe the register: let i be the outcome.
Step 5: If $T[i] = x$, the problem is solved: exit.
Step 6: Otherwise, set k to $\min(\rho k, \sqrt{N})$ and go back to step 2.

2.2. Quantum minimum searching algorithm

We second give the minimum searching algorithm (Durr & Hoyer, 2005) in which the minimum searching problem is to find the index i such that $T[i]$ is minimum where $T[0, \ldots, N-1]$ is to be an unsorted table of N items, each holding a value from an ordered set.

Step 1: Choose threshold index $0 \leqslant i \leqslant N-1$ uniformly at random.
Step 2: Repeat the following (2a, 2b, and 2c) and interrupt it when the total running time is more than $22.5\sqrt{N} + 1.4\lg^2 N$. Then go to stage 3.
  (a) Initialize the memory as $\sum_j \frac{1}{\sqrt{N}}|j\rangle|i\rangle$. Mark every item j for which $T[j] < T[i]$.
  (b) Apply the quantum exponential searching algorithm of (Boyer et al., 1998).
  (c) Observe the first register: let i' be the outcome. If $T[i'] < T[i]$, then set threshold index i to i'.
Step 3: Return i

This process is repeated until the probability that the threshold index selects the minimum is sufficiently large. In other words, the maximum cost for search process is $22.5\sqrt{N} + 1.4\lg^2 N$ iterations consumed in the quantum minimization.

3. Neuromorphic quantum-based optimimization

The synaptic weights w_{ijkl} are given in a Hopfield network (Tank & Hopfield, 1986).

$$E_{\mathrm{HN}} = -\frac{1}{2}\sum_{ij}\sum_{kl} w_{ijkl} o_{ij} o_{kl} - \sum_{ij} h_{ij} o_{ij}, \tag{1}$$

where h_{ij} is the external bias for a neuron. The synaptic weights are obtained as

$$\begin{aligned} w_{ijkl} = {} & -2a\delta_{j,l}(1-\delta_{i,k}) - 2b\delta_{i,k}(1-\delta_{j,l}) \\ & - 2c\delta_{i+j,k+l}(1-\delta_{i,k}) - 2d\delta_{i-j,k-l}(1-\delta_{i,k}), \end{aligned} \tag{2}$$

where δ_{ij} is the Kronecker delta. Let us consider that each qubit corresponds to each neuron of a Hopfield network. The state vector $|\psi\rangle$ of the whole system is given by the product of all qubit states.

The time evolution of the system is given by the following chr̈odinger equation.

$$|\psi(t+1)\rangle = U(1)|\psi(t)\rangle = \mathrm{e}^{-\frac{\mathrm{i}H(t)}{\hbar}}|\psi(t)\rangle. \tag{3}$$

Here, the operator is given by the Pad'e approximation (Golub & Loan, 1996).

The quantum computation algorithm utilizing adiabatic Hamiltonian evolution has been proposed by Farhi et al. (2001). Adiabatic Hamiltonian evolution is given as

$$H(t) = \left(1 - \frac{t}{T}\right)H_{\mathrm{I}} + \frac{t}{T}H_{\mathrm{F}}, \tag{4}$$

where H_{I} and are the initial and final Hamiltonians, respectively. We assume that the quantum system starts at $t = 0$ in the ground state of, so that all possible candidates are set in the initial state $|\psi(0)\rangle$. T denotes the period in which the Hamiltonian evolves and the quantum state changes, and we can control the speed of such changes to be suitable for finding the optimal solution among all candidates set in $|\psi(0)\rangle$. If a sufficiently large T is chosen, the evolution becomes adiabatic. The adiabatic theorem says that the quantum state will remain close to each ground state (Messiah, 1999). Therefore, the optimal solution can be found as the final state $|\psi(T)\rangle$. However, successful operation is not guaranteed in the case that there exists any degeneracy in energy levels or any energy crossing during the evolution (Messiah, 1999). The initial Hamiltonian H_{I} is chosen so that its ground state is given by the superposition of all states as

$$|\psi(0)\rangle = \frac{1}{\sqrt{2^n}}\sum_{i=0}^{2^n-1}|i\rangle, \tag{5}$$