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A New Algorithm to Improve Efficiency of Resource Scheduling in Clouding Computing Based on Extended Support Vector Machine

Quan Gan and Jun-Hui Zheng*

College of computer science and technology, PINGDINGSHAN University, Pingdingshan Henan, China 467000
spring.gump@163.com

Abstract

A high effective scheduling in cloud computing environment is significant to guarantee quality of cloud service. In this paper, Weighted Least Squares Support Vector Machine (WLS-SVM) is introduced to reflect finished time and cost of assignments in cloud computing and can obtain robust estimates for regression through the limited observation. There is a simple and efficient approach to model parameters selection. Some significant parameters of support vector machine are defined to further improve convergence performance of algorithm. Moreover, high effective scheduling will be acquired and service cost may be generated in cloud computing environment. Through the simulation experiment, the validity of the proposed model is demonstrated. The results show that the method has more superior performance than other methods like Least Squares Support Vector Machine (LS-SVM).

Keywords: *support vector machine (SVM), classification, cloud computing, resource scheduling*

1. Introduction

Cloud computing is rapidly becoming the dominant computing paradigm of today's highly technologically dependent society and a distributed computing paradigm that enables access to virtualized resources including computers, networks, storage, development platforms or applications [1-2]. With the support of important industry stakeholders like Google, Amazon or Microsoft, cloud computing is being widely adopted in different domains. Johns et al. considered that the use of cloud-based technologies has been a key trend in the technology-enhanced domain that enables access to online services anywhere and promises scalability, enhanced availability and cost savings [3]. Jose et al. surveyed that the state of the art on the use and research of cloud computing in education which selected 112 works [4].

Resource scheduling is a fundamental issue in cloud computing [5]. Efficient task scheduling in the cloud will reduce the task completion time so that efficient services can be provided to the users. From the literature review, the resource scheduling methods of reducing energy consumption and improving resource utilization in cloud computing data, and economics-based resource management models were discussed. Meanwhile, cloud computing resource scheduling model of minimizing energy consumption and minimizing number of servers was proposed [6]. Ding et al. developed energy efficient scheduling of virtual machines in cloud with deadline constraint. The simulation results showed that our proposed scheduling algorithm achieves over 20% reduction of energy and 8% increase of processing capacity in the best cases [7]. Lakra and Yadav proposed a multi-objective task ssheduling algorithm formappingtasks to a Vms (virtual machine) in order to improve the throughput of the datacenter and reduce the cost without violating the SLA (Service Level

Jun-Hui Zheng is the corresponding author.

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Agreement) for an application in cloud SaaS environment [8].

Many methods have been developed to solve resource scheduling in cloud computing environment [9-10]. Support Vector Machine (SVM), as a useful method, has been widely used in this problem. Based on principal of structural risk minimization, SVM can be applied to address some problems such as high dimension, small sample and local minimum. SVM requires special input data format and high-speed computers due to long calculation time. One important point is to decide the type of the kernel function and determine the optimum parameter values of this function [11-13]. Wang (2010) have implemented SVR and ANN to 30-min mean wind speed data and chaotic approach for preparation of input data and relative root-mean squared error (RRMSE) for SVR has been found smaller than ANN [14].

Least Squares Support Vector Machine (LS-SVM) is a new extension of SVM. In this method, equality constraint can be used instead of inequality constraint of SVM. That is, quadratic programming problem is transformed into linear equation problem to decrease the complexity of computing, increase the speed of solving solution and improve capacity of resisting disturbance [15]. Liu and Tan (2014) introduced LS-SVM method to predict the distribution of defects before and after scheme optimization using aggregated defect data, outage duration, maintenance operation defect detection rate, etc [16].

Weighted Least Squares Support Vector Machine (WLS-SVM) can provide different weight vector according to the different importance of samples to improve learning precision of model [17]. WLS-SVM, as a machine learning algorithm, compared with LS-SVM, keeps the estimate more robust and precise by assigning "weights" to the training samples. In this paper, WLS-SVM is introduced to reflect finished time and cost of assignments in cloud computing and can obtain robust estimates for regression through the limited observation. There is a simple and efficient approach to model parameters selection. Some significant parameters of support vector machine are defined to further improve convergence performance of algorithm. Moreover, high effective scheduling will be acquired and service cost may be reduced in cloud computing environment. Through the simulation experiment, the validity of the proposed model is demonstrated. The results show that the method has more superior performance than other methods like Least Squares Support Vector Machine (LS-SVM).

The rest of this paper is organized as follows. In Section 2, some basic concepts of cloud resource scheduling are introduced. Section 3 introduces the model of SVM. Based on LS-SVM and WLS-SVM, Section 4 constructs the proposed model in this paper. A simulation experiment is developed to verify the validity of the proposed model and results are further analyzed in Section 5. Section 6 concludes this paper.

2. Cloud Resource Scheduling

Cloud technology connects a network of virtualized computers that are dynamically provisioned as computing resources, based on negotiated agreements between service providers and users. It delivers information technology resources in diverse forms of service, and the explosion of Cloud services on the Internet brings new challenges in Cloud service discovery and selection. To address these challenges, a range of studies has been carried out to develop advanced techniques that will assist service users to choose appropriate services.

2.1 Scheduling Model

The model of resource scheduling in cloud computing environment can be described by an element set including n consumers and m resources as follows:

$$M = (U, V, F),$$

where U is a consumer set including n consumers; V is a virtual machine resource set including m virtual machine; F is a object function of cloud resource scheduling and optimization; θ is scheduling and optimization algorithm where intelligence algorithm always be used. Only the situation with one consumer who carries out assignments is considered in this paper and several consumers can repeat to carry out assignments [15-17].

Then, the characteristics of scheduling model are demonstrated in the following:

(1) In virtual machine resource set $V = \{v_1, v_2, ..., v_m\}$, each virtual machine is divided according to the number of core, the size of internal storage, and the space of disc. Suppose $v_i = \{\lambda_i, \mu_i, \varphi_i\}$ $i = 1, 2, ..., m$, where i denotes the number of virtual machine and λ_i, μ_i, φ_i denote the number of core, the size of internal storage, and the space of disc respectively.

(2) Meta task set $T = \{t_1, t_2, ..., t_n\}$ denotes n dependent meta task of a consumer.

(3) Task time matrix $S_{n\times m} = (s_{ij})$ $(i = 1, 2, ...n; j = 1, 2, ...m)$ is proposed where s_{ij} denotes the implementing time of task i on resource j. The values of task time matrix are based on performance of assigned virtual machine.

(4) Resource scheduling matrix $E_n = (e_{ij})$ $(i = 1, 2, ...n)$ is developed to denote implementing task i of resource e_i. If E_n=[3 2 2 4 1] denotes implementing task 1 of number 3 virtual machine, implementing task 2 of number 2 virtual machine,…, implementing task 5 of number 1 virtual machine.

(5) Resource using matrix $X_{n\times m} = (x_{je_i})$ $(j = 1, 2, ...n)$ is demonstrated satisfying $e_i \in E_n, x_{je_i} = 1$ and others equal to 0. The generation of $X_{n\times m}$ is based on resource scheduling matrix. Here, x_{je_i} denotes virtual machine e_i is used by task j.

Therefore, as the features of resource scheduling model mentioned above, three hypothesizes are provided in the following:

Hypothesis 1. The performance of virtual machine can satisfy the requirement of each task.

Hypothesis 2. A task can be assigned a virtual machine [8-9].

Hypothesis 3. All tasks can be assigned absolutely [8-9].

Completion time of task in virtual machine vj can be obtained from task time matrix and resource using matrix:

$$T_j = \max_{1\le i\le n}\{s_{ij}, x_{je_i}\} \ (i = 1, 2, ...n; j = 1, 2, ...m). \tag{1}$$

Therefore, the total completion time of implementing task in m virtual machines can be obtained

$$\text{Makespan} = \sum_{j=1}^{m} \max_{1\le i\le n}\{s_{ij}, x_{je_i}\} \ (i = 1, 2, ...n; j = 1, 2, ...m). \tag{2}$$

2.2 Cost of Cloud Service

In cloud computing environment, service provider is concerned with not only completion time of tasks offered by consumer but also the cost of cloud service. Service model Pay-as-you-go of cloud computing requires that service provider quantifies the charge of service used by consumers. In this paper, virtual machine of cloud resource is considered as scheduling unit and task requirement of consumer is assigned and scheduled according to virtual machine instance. Completion time of consumer's task in virtual machine will be different with respect to different configuration of virtual machine. Thus, a good scheduling algorithm is required to reduce the cost of cloud service of service provider and further increase the benefit of service provider. Based on pricing model of virtual machined in Google Compute Engine, the cost p_j in the per unit time of virtual machine of cloud service provider is defined as

$$P_j = p_{i1}\times\alpha_i + p_{i2}\times\beta_i + p_{i3}\times\gamma_i\,, \tag{3}$$

where p_{i1}, p_{i2}, p_{i3} are the cost of unit core, memory and disc space, respectively [9]. Then, unit time of each virtual machine is obtained by

$$P = \{p_1, p_2, ..., p_m\} \tag{4}$$

With respect to a task of consumer, the cost v_j of virtual machine offered by cloud service provider can be defined as follows

$$P_j = \left(p_{i1}\times\alpha_i + p_{i2}\times\beta_i + p_{i3}\times\gamma_i\right)\times\max_{1\le i\le n}\left\{s_{ij}, x_{je_i}\right\} = p_j\times\max_{1\le i\le n}\left\{s_{ij}, x_{je_i}\right\} \tag{5}$$

Here, Eq. (5) is obtained by multiplying Eq. (3) with Eq. (2). Thus, with respect to a task of consumer, the total cost of cloud service provider is

$$P = \sum_{j=1}^{m} p_j\times\max_{1\le i\le n}\left\{s_{ij}, x_{je_i}\right\} \tag{6}$$

Obviously, Eq. (6) is deduced from Eqs. (2) and (5). Therefore, the objective function can be created as min P.

3. The Basic Concepts of SVM

Based on VC dimension theory of statistical learning and structural risk minimization, Vapnik et al. proposed support vector machine as a new general learning method. Through using finite sample information, SVM can search an optimal compromise between complexity and learning capability of model to obtain better predictive ability and solve some practical problems such as small sample, non-linearity, high dimension and partial minimal point. Here, SVM only need to determine insensitive coefficient, penalty factor and core parameter where the modelling is simpler than BP network. It has been a research focus in machine learning and successfully applied in classification and regression.

Support vector machine regression has two types including linear regression and non-linear regression. For linear regression, linear regression function is developed as follows:

$$f(x) = \omega x + b\,. \tag{7}$$

Assume training sample set D_n consist of n samples $(x_i, y_i)(i=1,2,...,n)$, where $x_i \in X$, $y_i \in R$ are the best assessments. In order to guarantee flat of Eq. (1), we need to find a smallest w. Therefore, universal number of minimized Euclidean space is introduced and some technologies such as duality principle and lagrangian multiplier method are applied to find smallest w. Here, a regression function is obtained as follows:

$$f(x) = \sum_{i=1}^{n}\left(a_i - a_i^*\right)\left(x_i\cdot x\right) + b\,. \tag{8}$$

The basic ideal of non-linear support vector machine regression is demonstrated in the following. Firstly, data can be mapped into high dimensional feature space by a non-linear mapping. Secondly, linear regression can be implemented in this space. Therefore, the linear regression in the high dimensional feature space can correspond to non-linear regression in the low dimensional input space, which can be achieved through core function $k\left(x_i, x_j\right) = \Phi(x_i)\Phi\left(x_j\right)$. Thus, the following equation can be acqui

$$\begin{cases} \max -\dfrac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(a_i^* - a_i\right)\left(a_j^* - a_j\right)k\left(x_i, x_j\right) - \varepsilon\sum_{i=1}^{n}\left(a_i^* + a_i\right) + \sum_{i=1}^{n} y_i\left(a_i^* - a_i\right) \\ s.t. \sum_{i=1}^{n} a_i^* = \sum_{i=1}^{n} a_i, \\ a_i^*, a_i \in [0, \mathrm{C}], i = 1, 2, ..., n \end{cases} \tag{9}$$

where constant C >0 is named penalty factor. If C is big, fitness bias has bigger penalty. ε is biggest bias that regression can be allowed. Then, regression function can be demonstrated as follows:

$$f(x)=\sum_{i=1}^{n}\left(a_i-a_i^*\right)k\left(x_i,x\right)+b \tag{10}$$

Parameter b can be obtained from the following equation.

$$b=\begin{cases} y_l-\sum_{i=1}^{n}\left(a_i^*-a_i\right)k\left(x_i,x_l\right)+\varepsilon, if a_l\in[0,\mathrm{C}] \\ y_l-\sum_{i=1}^{n}\left(a_i^*-a_i\right)k\left(x_i,x_l\right)-\varepsilon, if a_i^*\in[0,\mathrm{C}] \end{cases} \tag{11}$$

The common core function includes the following types:

(1) polynomial core function, $k\left(x_i,x\right)=\left(xx_i+1\right)^d$;

(2)Gauss core function, $k\left(x_i,x\right)=\exp\left(-\frac{\left\|x-x_i\right\|^2}{2\sigma^2}\right)$;

and (3) Sigmoid core function, $k\left(x_i,x\right)=\tanh\left(v<x,x_i>c\right)$.

4 The Modeling of WLS-SVR

In 1999, Suykens proposed a new type of SVM, called Least Squares Support Vector Machines (LS-SVM), which has a faster training time, a less uncertain training result and is more suitable for on-line data analysis. LS-SVM has been broadly used in fuzzy recognition, model optimization, and prediction [18-19]. LS-SVM maps the input data into a high dimensional feature space and constructs a linear regression function. A brief introduction is demonstrated in the following.

Consider a classification or regression problem with training samples $\left\{x_i,y_i\right\}_{i=1}^{l}$ where x_i is an input sample vector and y_i is the corresponding target. Then, a support vector regression model can be formulated as

$$f(x)=w^T\phi\left(x\right)+b\,. \tag{12}$$

$\phi\left(\cdot\right):R^l\rightarrow R^n$ is a nonlinear mapping function which maps the input data from R^l into a high-dimensional feature space R^n, $w\in R^n$, $b\in R$, respectively, are the coefficients in high-dimensional feature space and the bias. The model based on LS-SVM results from solving a constraint-based optimization problem.

$$\min_{w,b,\xi}\frac{1}{2}w^Tw+C\frac{1}{2}\sum_{i=1}^{l}\zeta_i^2 \tag{13}$$

s.t. $y_i=w^T\phi\left(x_i\right)+b+\zeta_i\left(i=1,...,l\right)$, (14)

where $C>0$ denotes the regularization parameter, ζ_i denotes the difference between the output y_i and $f\left(x_i\right)$. Using standard techniques, the Lagrangian for (13) is

$$L=\frac{1}{2}\omega^T\omega+\frac{1}{2}C\sum_{i=1}^{N}\xi_i^2-\sum_{i=1}^{N}\alpha_i\left[\phi(x_i)\omega+b+\xi_i-y_i\right] \tag{15}$$

where α_i are Lagrangian multipliers.

The Karush-Kuhn-Tucher (KKT) conditions are

$$\begin{cases} w = -\sum_{i=1}^{N} \alpha_i \phi(x_i) = 0 \\ \sum_{i=1}^{N} \alpha_i y_i = 0 \\ \alpha_i = \frac{C\xi_i}{N} \\ w \cdot \phi(x_i) + b + \xi_i - y_i = 0 \end{cases} \tag{16}$$

However, there is a drawback in LS-SVM. Sparsity is not considered in this algorithm and the number of support vector is bigger. So, WLS-SVM is introduced to address this problem by using weight vector v_i.

In WLS-SVM, models (13) and (14) are transformed into the following models.

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \frac{1}{2} \sum_{i=1}^{l} v_i \zeta_i^2 \tag{17}$$

s.t. $y_i = w^T \phi(x_i) + b + \zeta_i \; (i = 1, ..., l)$, (18)

where $C > 0$ denotes the regularization parameter, ζ_i denotes the difference between the output y_i and $f(x_i)$.

The equation (15) is transformed into

$$L(\omega, b, \xi_i, \alpha_i, v_i) = \frac{1}{2}\omega^T \omega + \frac{1}{2} C \sum_{i=1}^{N} v_i \xi_i^2 - \sum_{i=1}^{N} \alpha_i \left[\phi(x_i)\omega + b + \xi_i - y_i \right] \circ \tag{19}$$

The Karush-Kuhn-Tucher (KKT) conditions in EQ (16) are transformed into

$$\begin{cases} \frac{\partial L}{\partial \omega} = \omega - \sum_{i=1}^{N} \alpha_i \phi(x_i) = 0 \\ \frac{\partial L}{\partial b} = \sum_{i=1}^{N} \alpha_i = 0 \\ \frac{\partial L}{\partial \xi_i} = \alpha_i - \frac{C\upsilon_i \xi_i}{N} = 0 \\ \frac{\partial L}{\partial \alpha_i} = \omega \cdot \phi(x_i) + b + \xi_i - y_i = 0 \end{cases} \tag{20}$$

In the numerical solution proposed by Suykens et al., KKT conditions are reduced to a linear system as follows:

$$\begin{bmatrix} 0 & E^T \\ E & \Omega + V_C \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{21}$$

where E is weight variable and

$$\begin{cases} V_C = diag\left\{ \frac{1}{C\upsilon_1}, ..., \frac{1}{C\upsilon_N} \right\} \\ \alpha = [\alpha_1, \alpha_2, ..., \alpha_N]^T \\ y = [y_1, y_2, ..., y_N]^T \end{cases}$$

(22)

Meanwhile, E is an identity matrix $N \times 1$ that all elements equal to 1 and Ω is $N \times N$ *Hessian* matrix. According to Mercer's condition, kernel functions that satisfy the following condition can be selected:

$$\Omega_{ij} = \phi(x_i)^T \phi(x_j) = K(x_i, x_j). \tag{23}$$

Therefore, the regression function model of WLS-SVR can be obtained that

$$f(x) = \sum_{i=1}^{N} \alpha_i K(x_i, x_j) + b \tag{24}$$

The common kernel function includes linear kernel, polynomial kernel, radial basis kernel and so on. Because radial basis kernel has better generalization ability, it is applied in this paper as follows.

$$K(x_i, x_j) = \phi(x_i)\phi(x_j) = \exp(-\|x_i - x_j\| / 2\delta^2) \tag{25}$$

where penalty coefficient C and kernel width δ are two important parameters of $WLS-SVR$.

By introducing weight vector $\upsilon_i (i = 1,..., N)$, $WLS-SVR$ can modifies bias vector ξ (non-Guass distribution), which can make its distribution close to Guass distribution to obtain robust of algorithm.

The way to obtain $\upsilon_i (i = 1,..., N)$ is showed in the following:

$$\upsilon_i = \begin{cases} 1 & if \quad |\xi_i / \hat{s}| \le c_1 \\ \dfrac{c_2 - |\xi_i / \hat{s}|}{c_2 - c_1} & if \quad c_1 \le |\xi_i / \hat{s}| \le c_2 \le \\ 10^{-4} & otherwise \end{cases} \tag{26}$$

$$\hat{s} = 1.483 MAD(\xi), \tag{27}$$

where bias $\xi_i = \alpha_i / C$ can be acquired by $WLS-SVR$. Here, $\hat{s}$ is used to measure the gap between the distribution of bias vector e and Guass distribution. MAD is the middle value of bias absolute value. In general, $c_1 = 2.5$ and $c_2 = 3$.

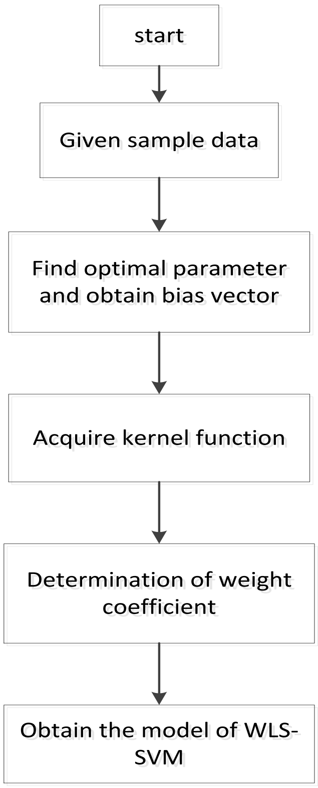

Figure 1. The Procedure of the Algorithm

5. Simulation Experiment

In this paper, Matlab 2009a is applied as the imitative experiment platform to achieve the comparison of resource scheduling performance with the different number of resources between LS-SVM and WLS-SVM. The average result is determined by repeating 10 experiments showed in Figure 2.

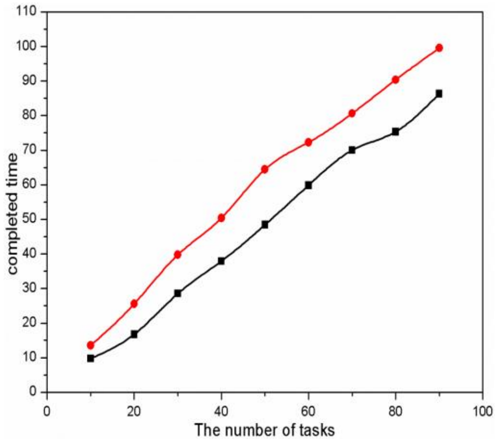

Figure 2. Comparison of Average Completion Time between Two Algorithms under the Different Number of Tasks

From Figure 2, with the gradual increasing of the number of tasks, average completion time of task becomes gradually increasing. It reflects that the algorithm in the proposed method is more flexible and valuable. The function is a key factor to the results, which is decided by some important parameters: the width of kernel function, the regularization parameter, and the size of training samples. So, it is rooted to determine the parameters.

6. Conclusion

Clouds are next-generation data-storage and computing systems with virtualization as the core, enabling technology to interconnect and manage distributed computers where resources are dynamically provisioned on demand as a personalized inventory to meet a specific service-level agreement. Least Squares Support Vector Machine (LS-SVM) is a new extension of SVM. In this method, equality constraint can be used instead of inequality constraint of SVM. That is, quadratic programming problem is transformed into linear equation problem to decrease the complexity of computing, increase the speed of solving solution and improve capacity of resisting disturbance. Weighted Least Squares Support Vector Machine (WLS-SVM) can provide different weight vector according to the different importance of samples to improve learning precision of model. In this paper, WLS-SVM is introduced to reflect finished time and cost of assignments in cloud computing. Some significant parameters of support vector machine are defined again to strengthen mutual learning capability and sorting ability, which can also further improve convergence performance of algorithm. Moreover, high effective scheduling will be acquired and service cost may be reduced in cloud computing environment. Through the simulation experiment, the validity of the proposed model is demonstrated.

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