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Sports Economic Activities Income Forecasting based on Genetic Support Vector Regression Algorithm

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Abstract: In order to solve the shortcoming of support vector regression algorithm, sports economic activities income forecasting based on genetic support vector regression algorithm is presented in this paper. As the kernel parameter, insensitive loss parameter and penalty parameter have a great influence on the forecasting performance of support vector regression algorithm, genetic algorithm is used to perform the parameters optimization of support vector regression algorithm simultaneously in this study. The experimental results show that the sports economic activities income forecasting results of genetic support vector regression model trained by the four-dimension training samples are more excellent than those of genetic support vector regression model trained by the three-dimension training samples, and the sports economic activities income forecasting ability of genetic support vector regression model trained by the four-dimension training samples is better than that of support vector regression model trained by the four-dimension training samples. Thus, genetic support vector regression algorithm has a good application prospect in sports economic activities income forecasting.

Keywords: Economic activities income, Support vector regression algorithm, The sports.

1. INTRODUCTION

Support vector regression algorithm is a non-linear kernel function-based regression method. As the kernel parameter σ, insensitive loss parameter ε and penalty parameter *C* have a great influence on the forecasting performance of support vector regression algorithm, genetic algorithm is used to perform the parameters optimization of support vector regression algorithm simultaneously in this study [1, 2]. In order to solve the shortcoming of support vector regression algorithm, sports economic activities income forecasting based on genetic support vector regression algorithm is presented in this paper. The dimension of the training samples has a great influence on the forecasting performance of genetic support vector regression algorithm. Thus, the three-dimension training samples and four-dimension training samples are used to train genetic support vector regression model respectively. It can be seen that the sports economic activities income forecasting results of genetic support vector regression model trained by the four-dimension training samples are more excellent than those of genetic support vector regression model trained by the three-dimension training samples, and the sports economic activities income forecasting ability of genetic support vector regression model trained by the four-dimension training samples is better than that of support vector regression model trained by the four-dimension training samples.

Thus, genetic support vector regression algorithm has a good application prospect in sports economic activities income forecasting [3].

2. GENETIC SUPPORT VECTOR REGRESSION ALGORITHM

Support vector regression algorithm is a non-linear kernel function-based regression method, and the model of support vector regression algorithm can be described as follows:

$$f(x) = w'\phi(x) + b \tag{1}$$

where w is the weight and b is the bias term.

The weight w and the bias b can be obtained by solving the following optimization problem:

$$\min\left[\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} L(y_i, f(x))\right] \tag{2}$$

Subject to

$$\begin{cases} y_i - \langle w, \phi(x_i)\rangle - b \le \varepsilon \\ \langle w, \phi(x_i)\rangle + b - y_i \le \varepsilon \end{cases}$$

where C is regularization parameter.

Then, the slack variables ξ_i, ξ_i^* are introduced to generate the convex optimization problem:

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$$\min\left[\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)\right] \tag{3}$$

Subject to

$$\begin{cases} y_i - \langle w, \phi(x_i)\rangle - b \le \varepsilon + \xi_i, \xi_i \ge 0 \\ \langle w, \theta(x_i)\rangle + b - y_i \le \varepsilon + \xi_i^*, \xi_i^* \ge 0 \end{cases}$$

Finally, the model of support vector regression algorithm can be written as follows:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)k(x_i, x) + b \tag{4}$$

where α_i and α_i^* with non-zero values are the support vectors, and $k(x_i, x)$ is the kernel function [4, 5].

Radial basis function (RBF) is used to create the support vector regression model, which is defined as follows:

$$k(x_i, x) = \exp\left(-\|x_i - x\|/2\sigma^2\right) \tag{5}$$

The training sample sets are established as follows:

$$X = \begin{bmatrix} b_1 & b_2 & \cdots & b_l \\ b_2 & b_3 & \cdots & b_{l+1} \\ \vdots & \vdots & & \vdots \\ b_{n-l} & b_{n-l+1} & \cdots & b_{n-1} \end{bmatrix} Y = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} \tag{6}$$

where l is the dimension of the input vector in the training sample sets.

As the kernel parameter σ, insensitive loss parameter ε and penalty parameter C have a great influence on the forecasting performance of support vector regression algorithm, genetic algorithm is used to perform the parameters optimization of support vector regression algorithm simultaneously in this study.

The operational process of genetic support vector regression algorithm can be shown in Fig. (**1**).

(1) Generate the initial population

The population is consisted of 20 chromosomes which is composed of the kernel parameter σ, insensitive loss parameter ε and penalty parameter *C*. Randomly generate initial population of chromosomes.

(2) Evaluate the fitness of each chromosome

The training subsets and the fitness function are used to evaluate the fitness value of each chromosome.

(3) Set up GA operators

The new chromosomes are generated by GA operators, and the roulette wheel is used to select and reproduce, crossover with 0.5 rate is used to exchange the genes between two chromosomes, and mutation with 0.01 rate is used to alter binary code.

(4) Judge the stopping criteria

The evolutionary process proceeds until the stopping criteria is satisfied.

3. EXPERIMENTAL RESULTS OF SPORTS ECONOMIC ACTIVITIES INCOME FORECASTING

As shown in (Fig. **2**), sports economic activities income data of China from 1991 to 2002 are applied to testify sports economic activities income forecasting ability of genetic support vector regression algorithm. The dimension of the training samples has a great influence on the forecasting

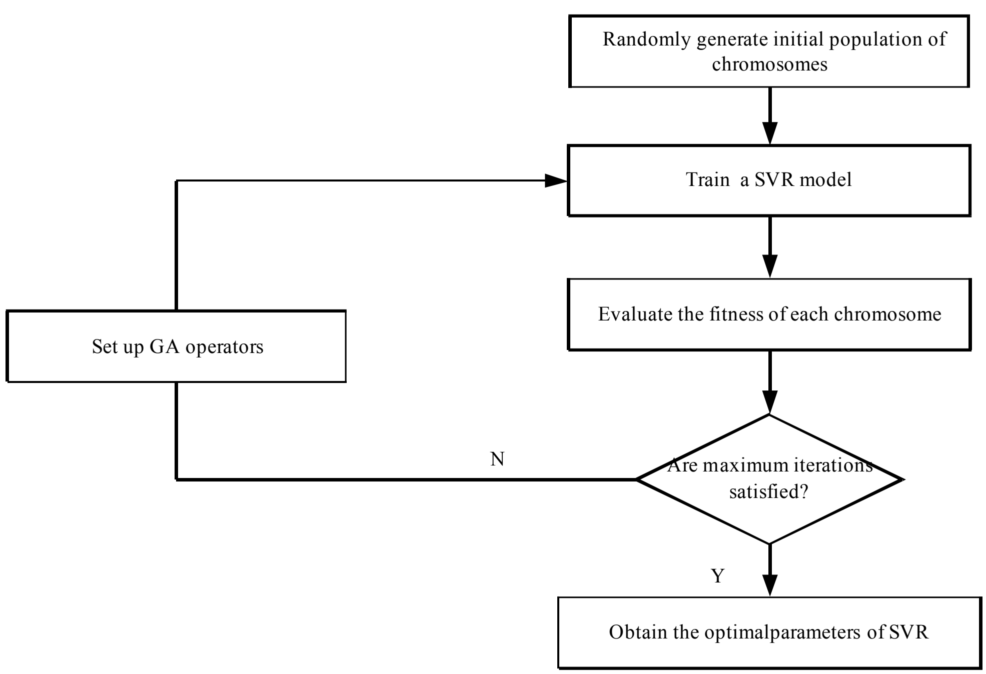

Fig. (1). The operational process of genetic support vector regression algorithm.

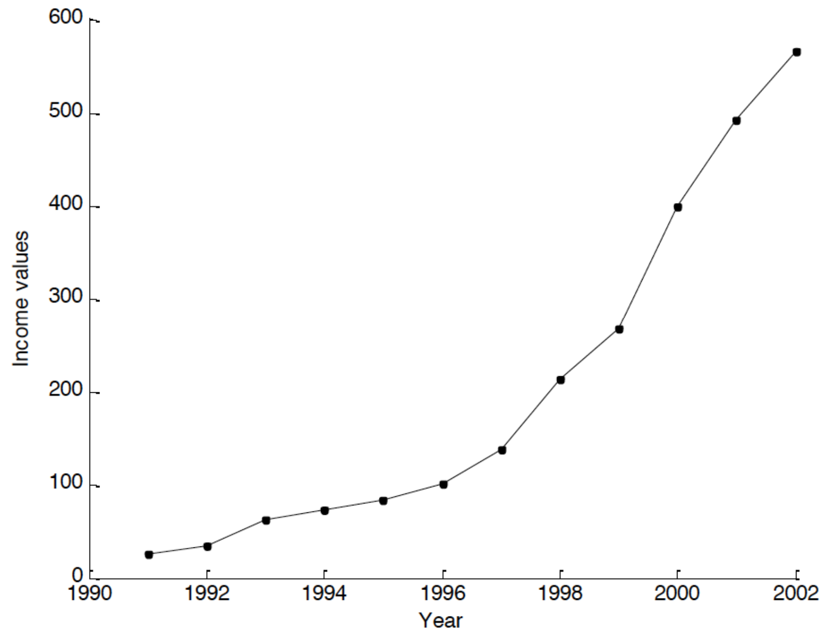

Fig. (2). Sports economic activities income data of China from 1991 to 2002.

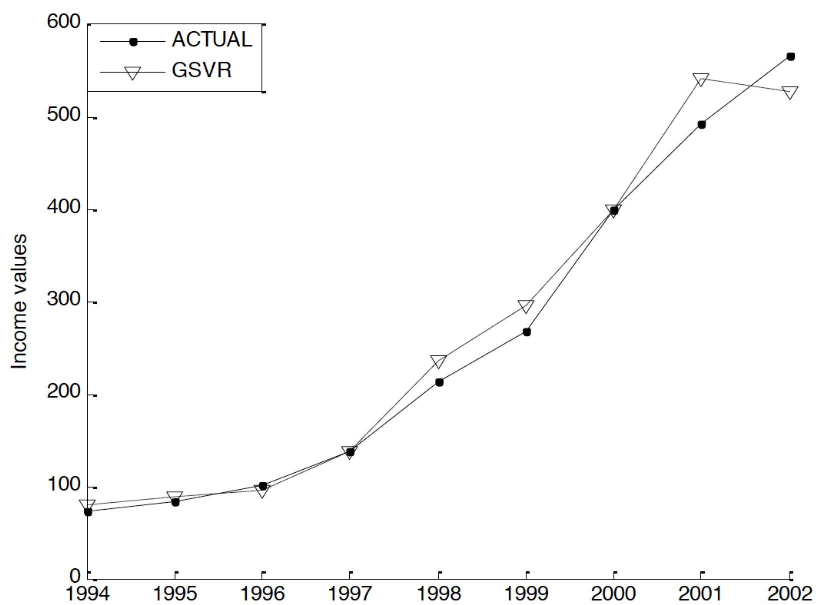

Fig. (3). The sports economic activities income forecasting results of genetic support vector regression model.

performance of genetic support vector regression algorithm. Thus, the three-dimension training samples are firstly used to train genetic support vector regression model [6-8].

The sports economic activities income forecasting results of genetic support vector regression model are shown in (Fig. **3**), and the sports economic activities income forecasting results of support vector regression model are shown in (Fig. **4**). It can be seen that the sports economic activities income forecasting ability of genetic support vector regression model trained by the three-dimension training samples is better than that of support vector regression model trained by the three-dimension training samples.

Then, the four-dimension training samples are firstly used to train support vector regression model. The sports economic activities income forecasting results of genetic support vector regression model are shown in (Fig. **5**), and the sports economic activities income forecasting results of support vector regression model are shown in (Fig. **6**). It can be seen that the sports economic activities income forecasting results of genetic support vector regression model trained by the four-dimension training samples are more excellent than those of genetic support vector regression model trained by the three-dimension training samples, and the sports economic activities income forecasting ability of genetic support vector regression

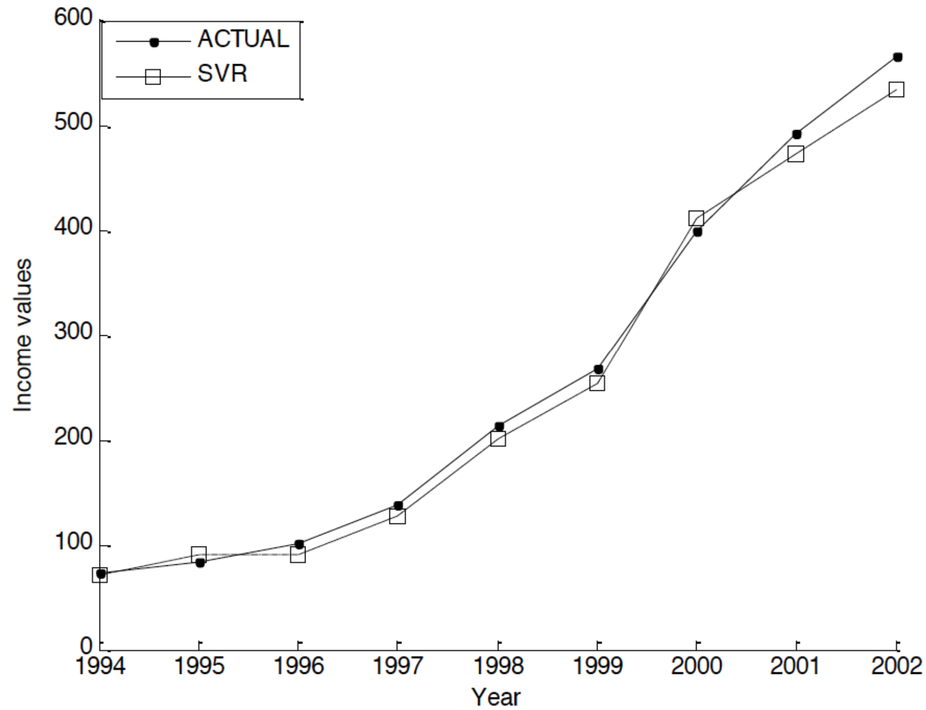

Fig. (4). The sports economic activities income forecasting results of support vector regression model.

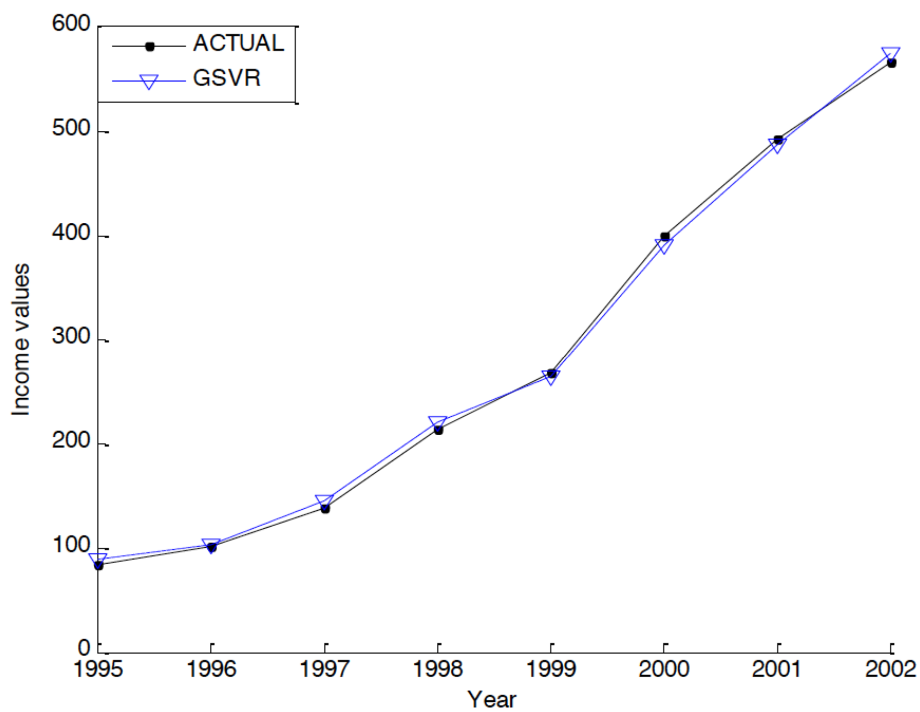

Fig. (5). The sports economic activities income forecasting results of genetic support vector regression model.

model trained by the four-dimension training samples is better than that of support vector regression model trained by the four-dimension training samples. Thus, genetic support vector regression algorithm has a good application prospect in sports economic activities income forecasting [9, 10].

CONCLUSION

In order to solve the shortcoming of support vector regression algorithm, sports economic activities income forecasting based on genetic support vector regression algorithm is presented in this paper. The experimental results

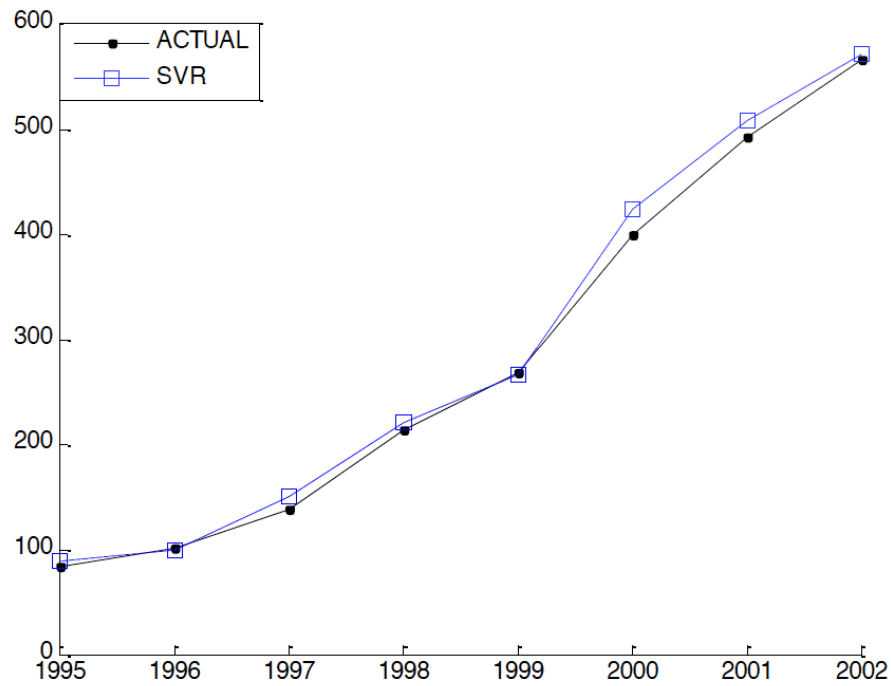

Fig. (6). The sports economic activities income forecasting results of support vector regression model.

show that the sports economic activities income forecasting results of genetic support vector regression model trained by the four-dimension training samples are more excellent than those of genetic support vector regression model trained by the three-dimension training samples, and the sports economic activities income forecasting ability of genetic support vector regression model trained by the four-dimension training samples is better than that of support vector regression model trained by the four-dimension training samples. Thus, genetic support vector regression algorithm has a good application prospect in sports economic activities income forecasting.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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