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The Price Forecasting of Military Aircraft Based on SVR

Jifeng Tong[1], Jiaxing Du[1], Ping Chen[2], Jianguang Yuan[2], Zhan Huan[2]

[1]The Ministry of Science Research, Academy of Armored Force Engineering, Beijing, China
[2]Institute of Nonlinear Science, Academy of Armored Force Engineering, Beijing, China
Email: dhtl2004@163.com, qingpingguo_135@163.com

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Abstract

The difficulty of the prediction of military aircraft purchase price lies in the small sample data, and the sample data have the complicated non-linear characteristics. By analyzing the influence of parameters of aircraft purchase price, SVR is proposed to predict the aircraft purchasing price model, and uses the model to predict the aircraft purchase price. The calculation results show that the prediction of the purchase price to establish military aircraft model has higher prediction accuracy.

Keywords

Military Aircraft, SVR, The Purchase Price

1. Introduction

With the increasing requirement of modern warfare, military aircrafts are increasingly using high technology, new processes and new materials, leading to a sharp rise in the development and production costs, the purchase price is also rising, and the contradiction between lack of defense expenditure is becoming increasingly acute, which makes the prediction of purchase price becoming more and more important. Prediction of military aircraft purchase price has become an important content of military aircraft. But with the development of science and technology, it makes the system performance and complexity of modern military aircraft constantly increasing. There are many factors to influence the aircraft purchase prices, and it also put forward higher requirements for the military aircraft procurement price prediction models. It needs to study more to put forward more accurately forecast model of the proposed military aircraft purchase price

Statistical learning theory (SLT) is a machine learning rule of a specialized research in small samples under the theory established by Vapnik. Support vector machine (SVM) is developed on the basis of this theory into a new classification and regression tools. Support vector regression is mainly including ε-SVR presented by Vapnik and ν-SVR proposed by Schlkopf [1] [2]. ε-SVR control algorithm is hoping to achieve precision by predeterminedε, and ν-SVR to minimizeε, so as to ensure that the algorithm can achieve the highest precision. Support vector machine to improve the generalization ability through the structural risk minimization principle, solves the small sample, non-linear, high dimension, local minimum and so on, it has been widely used in [3]-[6]. Aiming at the existing problems of the characteristics of few sample data and support vector regression prediction of military aircraft purchase price, we provide a method to predict the military aircraft purchase price

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based on SVR.

2. The Basic Principle of ν-SVR Support Vector Regression

A training set

$$T=\{(x_1,y_2),\cdots(x_l,y_l)\}\in(X\times Y)^l,$$

among them $x_i\in X=R^n, y_i\in Y=R, i=1,2,\cdots,l$, which uses the nonlinear mapping of $\varphi(x)$ the input vector x is mapped to the feature space, and then linear regression in high dimensional feature space, construct the regression function

$$f(x)=\omega^T\cdot\varphi(x)+b \tag{1}$$

Among them ω and b respectively denote the weight vector and bias. The introduction of slack variables $\xi^{(*)}=(\xi_1,\xi_1^*,\cdots,\xi_l,\xi_l^*)^T$ and the penalty parameter C, and to construct the two times planning original problem:

$$\begin{aligned}&\min_{\omega\in R^n,\xi^{(*)}\in R^{2l},b\in R}\frac{1}{2}\|\omega\|^2+C\cdot(\nu\varepsilon+\frac{1}{l}\sum_{i=1}^{l}(\xi_i+\xi_i^*))\\ &s.t.\quad(\omega^Tx_i+b)-y_i\le\varepsilon+\xi_i,\quad i=1,2,\cdots,l\\ &y_i-(\omega^Tx_i+b)\le\varepsilon+\xi_i^*,\quad i=1,2,\cdots,l\\ &\varepsilon,\xi_i,\xi_i^*\ge0,\quad i=1,2,\cdots,l\end{aligned}\tag{2}$$

Type (2) for the dual problem:

$$\begin{aligned}&\min_{\alpha^{(*)}\in R^{2l}}\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i^*-\alpha_i)(\alpha_j^*-\alpha_j)K(x_i,x_j)-y_i\sum_{i=1}^{l}(\alpha_i^*-\alpha_i)\\ &s.t.\quad\sum_{i=1}^{l}(\alpha_i^*-\alpha_i)=0\\ &0\le\alpha_i^*,\alpha_i\le\frac{C}{l}, i=1,2,\cdots,l\\ &\sum_{i=1}^{l}(\alpha_i^*-\alpha_i)\le C\cdot\nu\end{aligned}\tag{3}$$

α,α^* is the Lagrange multiplier, $K(x_i,x_j)$ as a satisfying Mercer condition symmetric kernel function, kernel function are commonly used polynomial kernel function (Polynomial), radial basis function (RBF), Sigmoid kernel function etc.

ν-SVR algorithm steps:

1) A training set

$$T=\{(x_1,y_2),\cdots(x_l,y_l)\}\in(X\times Y)^l,$$

The

$$x_i\in X=R^n, y_i\in Y=R, i=1,2,\cdots,l$$

2) Select the appropriate positive ν, C, and kernel function $K(x,x')$.

3) Constructing and solving the optimization problem (3), to obtain the optimal solution

$$\bar\alpha=(\bar\alpha_1,\bar\alpha_1^*,\cdots,\bar\alpha_l,\bar\alpha_l^*)^T$$

4) To construct the decision-making function

$$f(x)=\sum_{i=1}^{l}(\bar\alpha_i^*-\bar\alpha_i)K(x_i,x)+\bar b$$

The choice is located in the open interval in $\bar{\alpha}_j$ or $\bar{\alpha}_k^*$.
Order:

$$\bar{b} = \frac{1}{2}[y_i + y_k - (\sum_{i=1}^{l}(\bar{\alpha}_i^* - \bar{\alpha}_i)K(x_i, x_j) + \sum_{i=1}^{l}(\bar{\alpha}_i^* - \bar{\alpha}_i)K(x_i, x_k)$$

3. Military Aircraft Price Prediction

Now, military turbofan transporter purchase price prediction model is established to analysis as an example. A lot of parameters to describe the performance of turbofan transporter, then we take 8 typical examples of feature parameters, which include: the flat maximum take-off weight is x_1, fuselage length is x_2, the height of the plan is x_3, take off distance is x_4, the voyage rang with full oil is x_5, the optimal height of oil fly speed is x_6, aircraft empty weight is x_7 and maximum fuel load is x_8. The price indicated by y, the benchmark price for the year 2004.

The 9 type of turbofan transporter sample performance parameters and purchasing prices listed in **Table 1**. In order to carry out the error analysis and prediction test of the model, we select the 8 sub sample table as training samples, I models for testing samples.

We take the maximum take-off weight, body length, and maximum height of the plane, the take-off distance, full range, the optimal height of oil fly speed, aircraft empty weight and maximum fuel capacity as the input parameters, we take the price as output, kernel function takes the radial basis kernel function (RBF)

$$K(x, x') = \exp(-\gamma \|x - x'\|^2),$$

Among them, $\gamma = 0.5$, the penalty coefficient $C = 1$, $\nu = 0.5$, $\varepsilon = 0.001$, we establish ν-SVR model, Comparison between the measured value and fitted value as shown in **Table 2**. As can be seen, SVR model to fit the average value of relative error is only 5.37%, the coefficient of determination is $R^2 = 0.99$, and the fitting effect is good.

To predict the price of I transport plane by this model, get the forecasting results as shown in **Table 3**.

Table 1. Performance parameters and acquisition costs of transporters samples.

Type	x_1/kg	x_2/m	x_3/m	x_4/m	x_5/km	x_6/m·s^{-1}	x_7/kg	x_8/kg	x_9/Million Yuan
A	13494	23.500	8.43	867	4262	425.0	425.0	5683	6666.70
B	6849	14.390	4.57	987	3701	746.0	746.0	2640	3624.30
C	9979	16.900	5.12	1581	4679	874.0	874.0	3350	6569.90
D	5670	13.340	4.57	536	3641	536.0	536.0	1653	5586.23
E	63503	39.750	9.30	1859	6764	925.0	925.0	21273	27768.80
F	22000	29.870	6.75	1200	2870	907.0	907.0	5500	17575.20
G	21500	27.170	7.65	1050	2000	580.0	580.0	5000	18137.60
H	70310	29.790	11.66	1091	7876	602.0	602.0	36300	50476.00
I	21000	24.615	7.30	1300	3100	819.2	819.2	6000	14250.00

Table 2. Comparison between the measured value and fitted value of transport price.

Type	The observation values	The fitted values	The relative error
A	6666.7	7140.14	7.10
B	3624.3	4072.22	12.36
C	6569.9	7017.82	6.82
D	5586.23	6075.55	8.76
E	27768.8	27292.88	-1.71
F	17575.2	18057.98	2.75
G	18137.6	17671.77	-2.57
H	50476	50013.42	-0.92

Table 3. The prediction price results of transport plane.

type	The measured value	The fitted values	The relative error
I	14250.00	14173.95	−0.53

The practical results show: SVR has stronger generalization ability in the case of limited samples, SVR has certain universality, it can be used as a suitable method and it should be popularized.

4. Conclusion

A small sample of multivariate data is a difficult problem to predict the military aircraft in the purchase price, and support vector regression is a new statistical learning model by the principle of structural risk minimization instead of empirical risk minimization principle, and it has perfect theory basis. Based on the analysis of the price data, using support vector regression theory, we establish the model of aircraft purchase price. From the example above we can see that, the method of support vector machine have a better calculation accuracy, and stronger generalization ability in dealing with nonlinear problems.

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