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A support vector regression based prediction model of affective responses for product form design

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ABSTRACT

In this paper, a state-of-the-art machine learning approach known as support vector regression (SVR) is introduced to develop a model that predicts consumers' affective responses (CARs) for product form design. First, pairwise adjectives were used to describe the CARs toward product samples. Second, the product form features (PFFs) were examined systematically and then stored them either as continuous or discrete attributes. The adjective evaluation data of consumers were gathered from questionnaires. Finally, prediction models based on different adjectives were constructed using SVR, which trained a series of PFFs and the average CAR rating of all the respondents. The real-coded genetic algorithm (RCGA) was used to determine the optimal training parameters of SVR. The predictive performance of the SVR with RCGA (SVR–RCGA) is compared to that of SVR with 5-fold cross-validation (SVR–5FCV) and a back-propagation neural network (BPNN) with 5-fold cross-validation (BPNN–5FCV). The experimental results using the data sets on mobile phones and electronic scooters show that SVR performs better than BPNN. Moreover, the RCGA for optimizing training parameters for SVR is more convenient for practical usage in product form design than the timeconsuming CV.

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1. Introduction

The basic assumption for modeling consumers' affective responses (CARs) is that there exists a cause-and-effect relationship between CARs and the product form features (PFFs); that is, specific PFFs will produce different subjective feelings (Han & Hong, 2003). Therefore, by analyzing the relationship between CARs and the PFFs in a systematic way, a prediction model can be constructed to facilitate product development. With the aid of the prediction model, an especially designed product form that targets specific consumer groups can be produced more objectively and efficiently instead of only relying on the designers' intuition and experience.

The crux to constructing such a prediction model is how to deal with the inter-attribute correlations that exist between product attributes and how to reconcile the nonlinear properties of these attributes (Park & Han, 2004; Shimizu & Jindo, 1995). There have been some attempts to define the relationship between the PFFs. The most noted research was by Kansei engineering (Nagamachi, 1995). The most adapted techniques in the product design field such as multiple regression analysis (Park & Han, 2004) and quantification theory type I (Jindo, Hirasago, & Nagamachi, 1995) depend heavily on an assumption of linearity and, therefore, cannot deal effectively with nonlinear relationships. In addition, prior to establishing a mathematical model, data simplification and variable screening is often needed to obtain better results (Han, Yun, Kim, & Kwahk, 2000). Fuzzy regression analysis (Shimizu & Jindo, 1995) and other methods suffer from the same shortcomings (Park & Han, 2004).

To deal with the nonlinearity of many-to-many mapping between variables, neural network (NN) is a good candidate for building the prediction model. A few researches have illustrated the use of NN in the product design field. For example, Hsiao and Huang (2002) demonstrated the ability of NN to deal with nonlinear relationships between the PFFs. In later research by Hsiao and Tsai (2005), NN was used as part of a hybrid framework for a product form search. However, NN suffers from a number of shortcomings. NN is considered a "black-box" necessitating numerous control parameters and it is difficult to obtain a stable solution. Another drawback of NN, which is shared by all types of black-box models, is that the data of the resulting model and its parameters are difficult to interpret. In addition, NN follows the empirical risk minimization (ERM) approach, which is commonly employed by conventional machine learning methods. In the ERM approach, a measure of the prediction error, such as the root mean square error (RMSE), pertaining to the training set outputs, is minimized. Since the ERM is based exclusively on the training set error, it does not

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guarantee that the resulting model will give a good generalization performance.

Vapnik (1995) developed a new kind of NN algorithm called support vector machine (SVM). SVM follows the principle of structural risk minimization (SRM), seeking to minimize an upper bound of the generalization error rather than minimize the training error (the principle followed by NN). SVM has been shown to provide better performance than traditional learning techniques (Burges, 1998). SVM's remarkable performance with respect to sparse and noisy data makes it a first choice in a number of real-world applications such as pattern recognition (Burges, 1998) and bioinformatics (Scholkopf, Guyon, & Wetson, 2003). SVM is also known for its elegance in solving nonlinear problems with the "kernels" technique, which automatically carries out a nonlinear mapping to a feature space. With the introduction of an ε-insensitive loss function, SVM can be extended to solve function estimation problems. This is known as support vector regression (SVR). The properties of SRM equip the SVR model with a greater potential for generalizing the input–output relationship learnt during the training process. SVR has also been shown to exhibit excellent performance which benefits from their roots in SVM (Vapnik, Golowich, & Smola, 1997).

Despite being endowed with a number of attractive properties, SVR has yet to be applied widely in the field of product design. In this paper, SVR has been introduced for the purpose of developing a model that effectively predicts CARs. The remainder of the paper is organized as follows: Section 2 gives an introduction to SVR. Section 3 presents the proposed prediction model of CAR for product form design. Section 4 demonstrates the experimental results using mobile phone and electronic scooter as examples. Section 5 presents some brief conclusions. Finally, several suggestions for future research to extend this study are described in Section 6.

2. Theoretical backgrounds

2.1. Support vector regression

In this section, a description of the basic idea and formulation of SVR are reviewed. A data set, D of l training samples are given,

$$(x_1, y_1) \ldots (x_l, y_l) \tag{1}$$

where $x_i \in R^n$ is the input data, $y_i \in R$ is the desired output value. The objective of the SVR model is to identify the regression function, $y = f(x)$, which accurately predicts an output value that corresponds to a new set of data points. The SVR begins by introducing a loss function to minimize the regression risk. Various loss functions such as the linear ε-insensitive loss function, quadratic ε-insensitive loss function and Huber loss function can be used to construct different SVR models. In this study, standard SVR with a linear ε-insensitive loss function L is used:

$$L = (f(x) - y) = \begin{cases} |f(x) - y| - \varepsilon, & |f(x) - y| \geqslant \varepsilon \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where ε is a precision parameter representing the radius of the tube located around the regression function, $f(x)$. Then, the SVR problem is regarded as the solution to

$$\text{minimize } \frac{1}{2}||w||^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \tag{3}$$

$$\text{subject to } \begin{cases} y_i - w \cdot \phi(x_i) - b_i \leqslant \epsilon + \xi_i, & \xi_i \geqslant 0 \\ w \cdot \phi(x_i) + b_i - y_i \leqslant \varepsilon + \xi_i^*, & \xi_i^* \leqslant 0 \\ i = 1, \ldots, l \end{cases} \tag{4}$$

where $\phi(x)$ is the high dimensional feature space that is nonlinearly mapped from the input space x. The constant C is a regulation parameter. ξ_i is the upper training error (ξ_i^* is lower), subject to the ε-insensitive tube:

$$|y - (w \cdot \phi(x) + b)| \leqslant \varepsilon \tag{5}$$

By introducing the Lagrange multipliers α_i^*, α_i and a kernel function K, the optimization problem in Eq. (3) can be rewritten as

$$f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x, x_i) + b, \quad 0 \leqslant \alpha_i^*, \ \ \alpha_i \leqslant C \tag{6}$$

In Eq. (6), α_i and α_i^* satisfy the equalities $\alpha_i * \alpha_i^* = 0, \alpha_i \geqslant 0$ and $\alpha_i \geqslant 0$, where $i = 1, 2, \ldots, l$ and are obtained by maximizing the dual function of Eq. (6), which has the following form:

$$\begin{aligned} \text{maximize } W(\alpha_i, \alpha_i^*) = & \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) \\ & -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) \end{aligned} \tag{7}$$

with constraints

$$\begin{aligned} & \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) \\ & 0 \leqslant \alpha_i \leqslant C, \quad i = 1, 2, \ldots, l \\ & 0 \leqslant \alpha_i^* \leqslant C, \quad i = 1, 2, \ldots, l \end{aligned} \tag{8}$$

Finally, the regression function can be obtained as

$$f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x_i, x_j) + b \tag{9}$$

The training points with corresponding α_i and α_i^* equal to zero have no influence on the regression function solution. If these points are removed from the training set, the solution obtained would be still the same (Thissen, Van Brakel, De Weijer, Melssen, & Buydens, 2003). This characteristic is known as the "sparseness" of the solution and enables the SVR model to be defined as a combination of a relatively small number of input vectors.The mapping ϕ is usually nonlinear and unknown. Instead of calculating ϕ, the kernel function K is used to compute the inner product of two vectors x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$, that is, $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$. The elegance of using the kernel function is that one can deal with feature spaces of arbitrary dimensionality without having to compute the map $\phi(x)$ explicitly. Any function satisfying Mercer's condition can be used as the kernel function. The following are three commonly used kernel functions:

$$\text{Linear}: K(x_i, x_j) = x_i \cdot x_j \tag{10}$$

$$\text{Polynomial}: K(x_i, x_j) = (1 + x_i \cdot x_j)^{\rho}, \quad \rho > 0 \tag{11}$$

$$\text{Radial basic function (RBF)}: \ K(x_i, x_j) = \exp(-||x_i - x_j||/\sigma^2) \tag{12}$$

Here, ρ and σ are adjustable kernel parameters. The kernel parameter should be carefully chosen as it implicitly defines the structure of the high dimensional feature space $\phi(x)$ and thus controls the complexity of the final solution. In addition, the performance of the SVR model is heavily dependent on the regulation parameter C, the width of the tube ε and the parameter of the chosen kernel function. From the implementation point of view, training SVR is equivalent to solving a linearly constrained quadratic programming (QP) with the number of variables twice that of the input data dimension.

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