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Week-ahead Price Forecasting of Computer Accessories Based on BP and SVM

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Abstract: Computer market becomes more sophisticated and price forecasting is gaining importance for market participants to adjust their market behavior. In the past, price forecasting of computer market is mainly concentrated in the forecasting of the computer itself such as desktops, laptops and so on. Whereas a contrast resolution is proposed to deal with this issue that forecasts price trends of computer market through price forecasting of main computer accessories which can make the forecasting window in advance. Two classic model, Back Propagation (BP) neural network and Support Vector Machine (SVM), are introduced to implement the week-ahead price forecasting of computer accessories. The simulation results show that SVM model is better than BP neural network model for its higher forecasting accuracy. Under the same forecasting conditions, the Relative Errors of SVM model is 1.87% lower than that of BP NN model and the mean absolute errors of SVM model is 17.91% lower than that of BP NN model. Therefore, price forecasting for computer accessories based on SVM is valuable and feasible for computer market which can provide richer and more accurate analysis information of price trends for market participants in advance, with a high reference value.

Key words: Price forecasting, BP neural network, SVM, computer accessories

INTRODUCTION

Price forecasting is an important financial issue for investors and consumers and is currently receiving considerable attention from both researchers and practitioners. However, the inherent characteristics of prices, namely, high volatility and complexity, make forecasting a challenging endeavor. In the past, various approaches have been proposed to deal with this issue (Chang and Fan, 2008; Chen *et al*., 2012; Gonzalez *et al*., 2012; Gradojevic and Gencay, 2011; Ilic *et al*., 2011; Motamedi *et al*., 2012) and various fields have been introduced these approaches into practical price forecasting (Catalao *et al*., 2011; Lei and Shahidehpour, 2010; Lira *et al*., 2009; Pindoriya *et al*., 2008; Rotering and Ilic, 2011; Xu *et al*., 2009).

In the field of computer market, previous researches on price forecasting are mainly focused on the computer itself such as desktops, laptops, tablet PCs and so on. In contrast, a new resolution is proposed in this study that forecasts price trends of computer market through price forecasting of main computer accessories weekly. Two classic models, Back Propagation (BP) neural network and Support Vector Machine, are utilized to realize this new resolution. The feasibility and effectiveness of these two models are evaluated through experiments which run on the simulation software MATLAB. Three categories of computer accessories (CPU, memory and hard disk) and dozens of products are selected as experimental subjects whose price are all extracted from the Website (http://www.jd.com) every day from October 2012 to December 2012 based on the Web-extracting method.

The forecast accuracy of these two models is evaluated by comparing the actual price with the forecasted price and the relative errors and the mean absolute errors (MAE) are calculated according to different products and models, respectively and compared with each other to identify which model is superior with a high accuracy and to reveal whether this new resolution is feasible and valuable for price forecasting of computer market and helpful for market participants.

NOTATIONS AND MODELS

Notations: Some definitions used in this study are given as follows:

- Single errors of predicted value:

$$e_t = Y_t - \hat{Y}_t, \quad t = 1, 2, \cdots, n \tag{1}$$

- Relative errors of single predicted value:

$$\tilde{e}_t = \frac{e_t}{Y_t} = \frac{Y_t - \hat{Y}_t}{Y_t}, \quad t = 1, 2, \cdots, n \tag{2}$$

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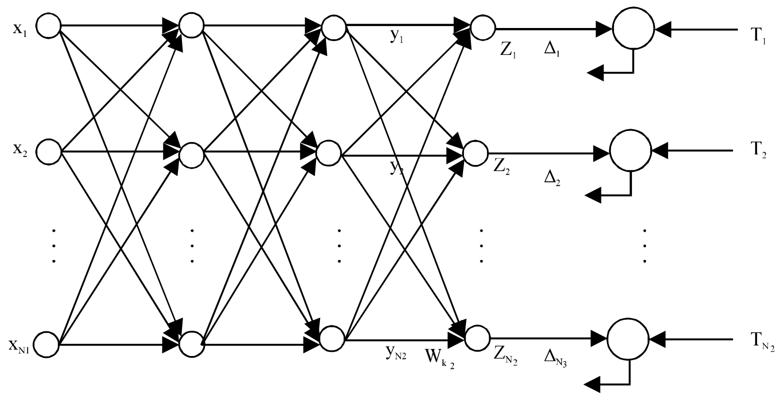

Fig. 1: BP NN architecture and its inter-neural

- Mean Absolute Errors (MAE):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| = \frac{1}{n}\sum_{t=1}^{n}|Y_t - \hat{Y}_t| \quad (3)$$

BP neural network model: The BP NN is the network that can establish relationships between layers orderly from inputs to outputs. It has an input layer, an output layer and some hidden layers. It is an error back propagation error learning process of back-propagation algorithm consists of two processes of the information forward propagation and error back-propagation. Through the hidden layer, depend on the weight error of the output layer, the error gradient descent back-propagation to the hidden layer and input layer and so on. The BP NN's architecture shows as in Fig. 1.

BP NN always uses activation function show as follows:

- Linear transfer function:

$$f(x) = x \quad (4)$$

The function string is "purelin":

- Logarithmic sigmoid transfer function:

$$f(x) = \frac{1}{1+e^{-x}} \quad (0 < f(x) < 1) \quad (5)$$

The function string is "logsig"

- Hyperbolic tangent sigmoid transfer function:

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \quad (-1 < f(x) < 1) \quad (6)$$

The function string is "tagsig".

The mail training functions for the BP NN show as follows:

- **Traingd:** It is a Batch gradient descent training function. Along with the negative gradient direction of the network performance parameters adjust the network weights and thresholds
- **Traingdm:** It is a momentum batch gradient descent function. A batch feed-forward neural network training methods, not only has a faster convergence, but also the introduction of a momentum term, effective way to avoid the local minimum problem in the network training
- **Trainrp:** It is a resilient BP algorithm. Used to eliminate the impact of the value of the gradient mode network training, improve the training speed
- **Trainlm:** It is a Levenberg-Marquardt algorithm. The fastest convergence rate for medium-sized BP NN is the default algorithm to avoid the direct calculation of its matrix, thereby reducing the amount of training in computing, but requires a large amount of memory
- **Traincgb:** It is a Plwell-Beale algorithm. By the orthogonality of the gradient before and after the judge decided to adjust the direction of the weights and thresholds on back to the negative gradient direction
- **Trainscg:** It is a proportion of conjugate gradient algorithm. Modulus value of the trust region algorithm and conjugate gradient algorithm to combine, reduce the time used to adjust the direction the search network

SVM model: SVM is a supervised learning model with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. SVMs arose from statistical learning theory. Based on the structural

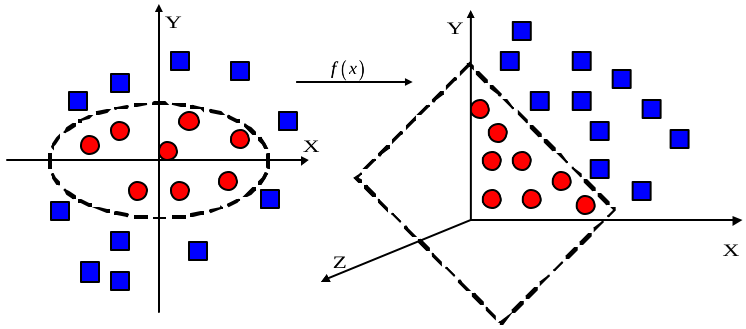

Fig. 2: Mapping from the two-dimensional space to the three-dimensional space

risk minimization principle, it makes the actual learning risk to a minimum by selecting proper discriminant function which defines the support vector spaces. And the classifier constructed by this way can maximize the interval between two categories. Therefore SVM has a higher classification accuracy rate.

If the sample is given like $(x_1, y_1),\ldots, (x_l, y_l)$, $x \in R^n$ then it cannot find the linear classification hyperplane in the sample space. Thus it needs to adopt a non-linear mapping ϕ which maps samples to a higher dimensional space where the linear classification hyperplane could be found. As can be seen from the Fig. 2 samples are nonlinear and inseparable in the two-dimensional space but linear and separable after mapped to the three-dimensional space.

When the training set by mapping projected onto the high-dimensional feature space, its dimension may be infinite. So it is unrealistic to calculate the inner product in a high-dimensional space. In order to overcome the computational difficulties caused by too high dimension Boser *et al*. introduced the kernel function which is interpreted as the inner product in a Hilbert space. Therefore in a high-dimensional feature space the corresponding kernel function is used to calculate the inner product. Then the non-linear support vector machine is transferred into the optimization issue of Eq. 7:

$$\begin{cases} \min \quad \phi(w) = \frac{1}{2}(\omega\cdot\omega) + C\sum_{i=1}^{l}\xi_i \\ \text{s.t.} \quad y_i\left(\left(w\cdot\phi(x_i)\right)+b\right) \geq 1-\xi_i, \quad \xi_i \geq 0, i=1,\cdots,l \end{cases} \tag{7}$$

The corresponding dual form is shown as Eq. 8. Choosing a different kernel function can produce different support vector machines:

$$\begin{cases} \max \quad L(\alpha) = \sum_{j=1}^{l}\alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) \\ \text{s.t.} \quad 0 \leq \alpha_i \leq C, \quad \sum_{j=1}^{l} y_i\alpha_i = 0, \quad i = 1, 2, \cdots, l \end{cases} \tag{8}$$

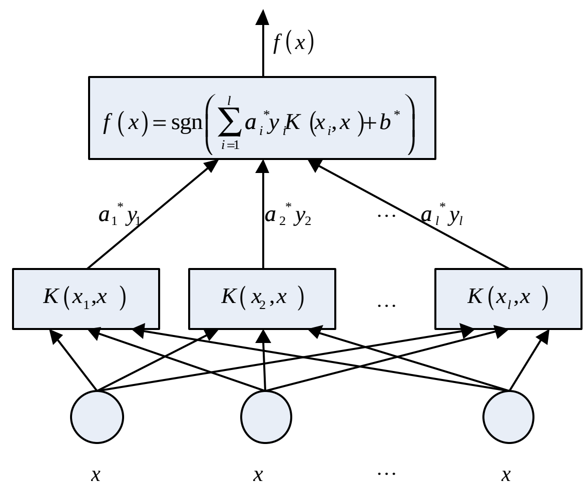

Fig. 3: SVM structure

Assuming $\alpha^* = (\alpha^*_1, \alpha^*_2,\ldots, \alpha^*_l)^T$ is the solution of Eq. 8, then:

$$w^* = \sum_{i=1}^{l}\alpha_i^* y_i \phi(x_i)$$

The optimal classification function is Eq. 9 and the SVM structure is shown in Fig. 3:

$$f(x) = \text{sgn}\left(\sum_{i=1}^{l}\alpha_i^* y_i K(x_i, x) + b^*\right) \tag{9}$$

Kernel functions commonly used in SVM classifier is shown as follows:

- Linear kernel function:

$$K(x, x_i) = xx_i \tag{10}$$

- Polynomial kernel function:

$$K(x, x_i) = (xx_i+1)^d \tag{11}$$

- RBF kernel function:

$$K(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{12}$$

- Sigmoid kernel function:

$$K(x, x_i) = \tanh(k(x, x_i) + \theta) \tag{13}$$

EXPERIMENTS PREPARATIONS

The experimental data contains three types of computer accessories, CPU, memory and hard disk (Table 1). The weekly price of products are extracted from the Website (http://www.jd.com) by the Web-extracting method and calculated based on the daily price gained from October 2012 to December 2012 (Fig. 4).

The BP neural network and SVM model are applied to do experiments using the simulation software MATLAB. Furthermore, the experiment achievement also builds on the our previous research foundation (Zhou *et al*., 2011; Zhu *et al*., 2010, 2011a, b, c, 2012a, b, c).

EXPERIMENTAL RESULTS

Week-ahead forecast price for each product: Comparisons between the week-ahead forecast price and the actual weekly price of each product based on the BP Neural Network model and A SVM model are shown from Fig. 5-9, respectively.

Errors of the week-ahead forecast price for each product: The relative errors and MAE of the week-ahead forecast price based on BP Neural Network model and A SVM model are calculated according to different products and listed, respectively in Table 2 and 3.

Table 1: Extracted products of computer accessories

Type	Product
CPU	Corei3 2100
CPU	Corei3 2200
CPU	Corei7 2600
CPU	Corei7 2600K
Memory	KingstonDDR3 2G
Memory	KingstonDDR3 4G
Hard disk	Seagate1TB Barracuda32M
Hard disk	Seagate1TB Barracuda64M
Hard disk	MomentusXT500G
Hard disk	Pipeline500G

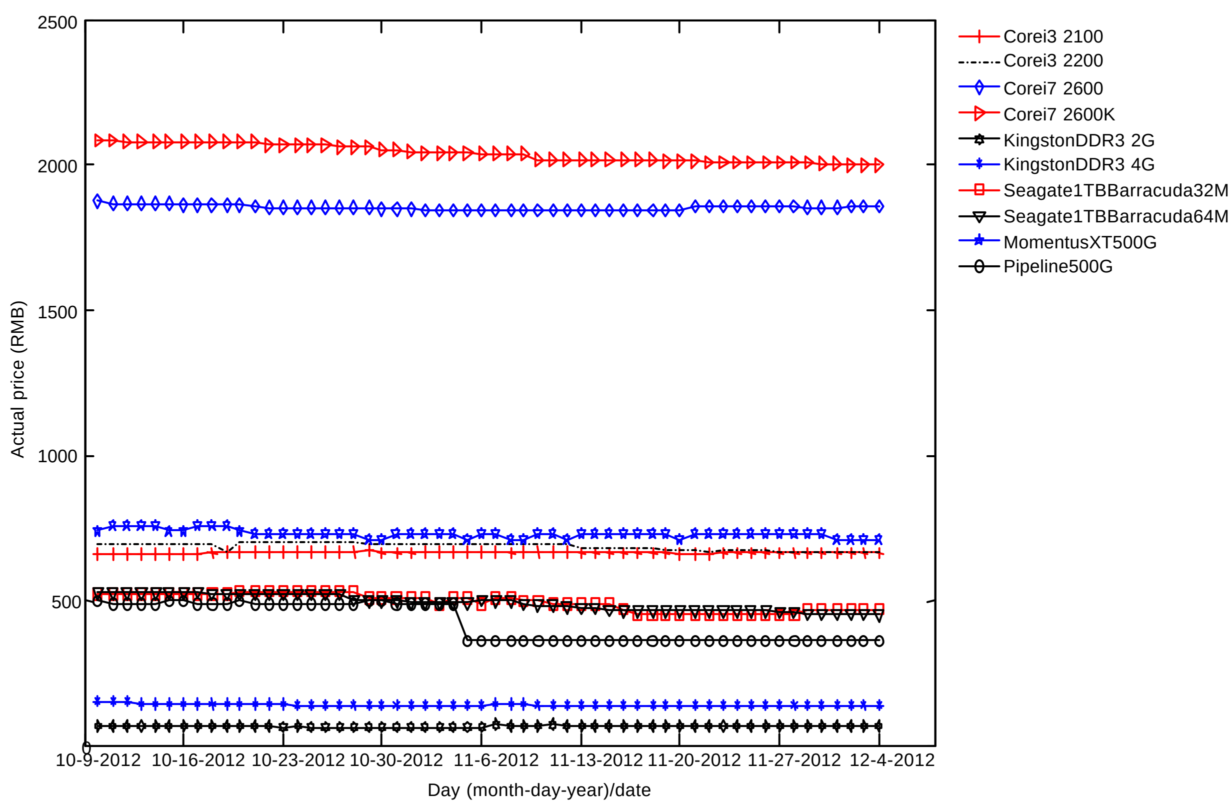

Fig. 4: Weekly prices of computer accessories extracted from web page

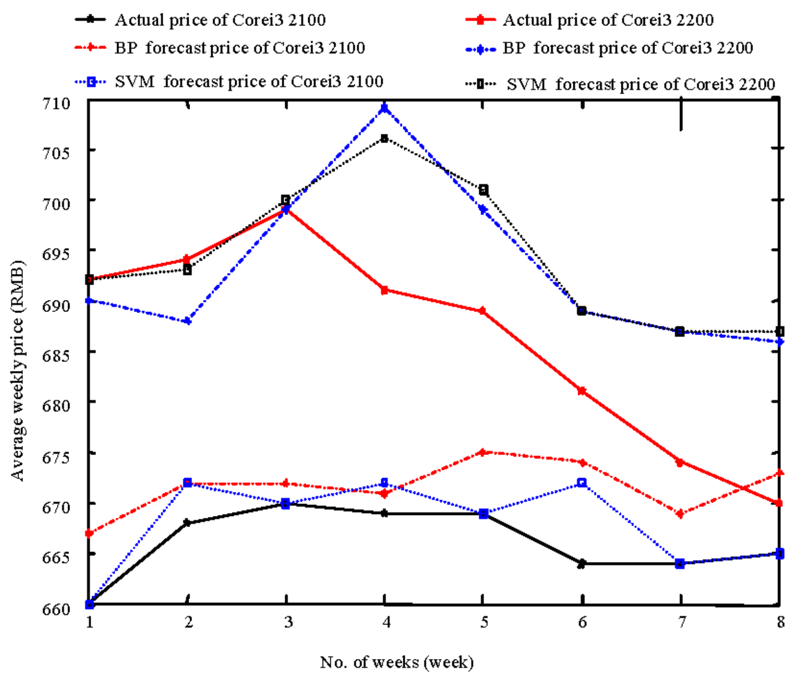

Fig. 5: Week-ahead forecast price of Corei3 2100 and Corei3 2200

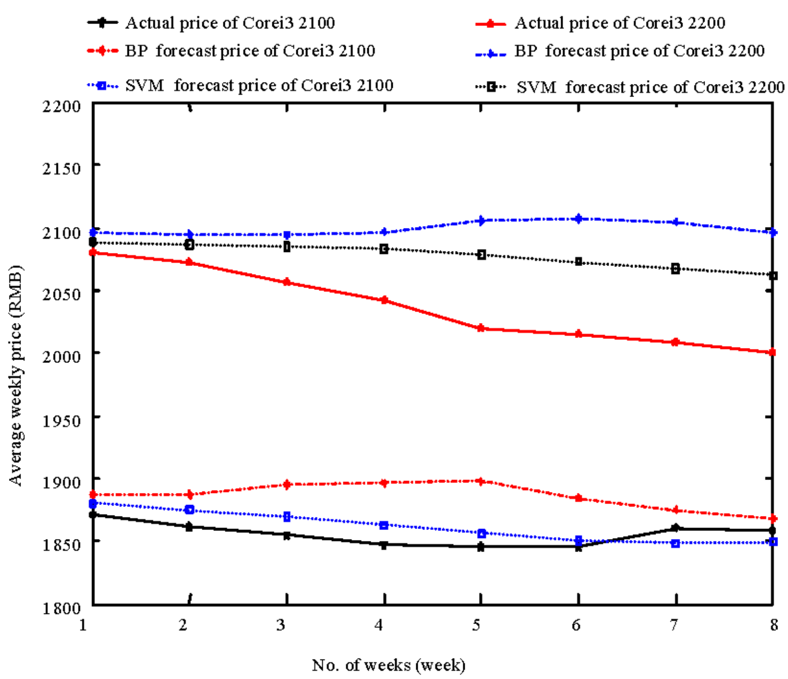

Fig. 6: Week-ahead forecast price of Corei7 2600 and Corei7 2600K

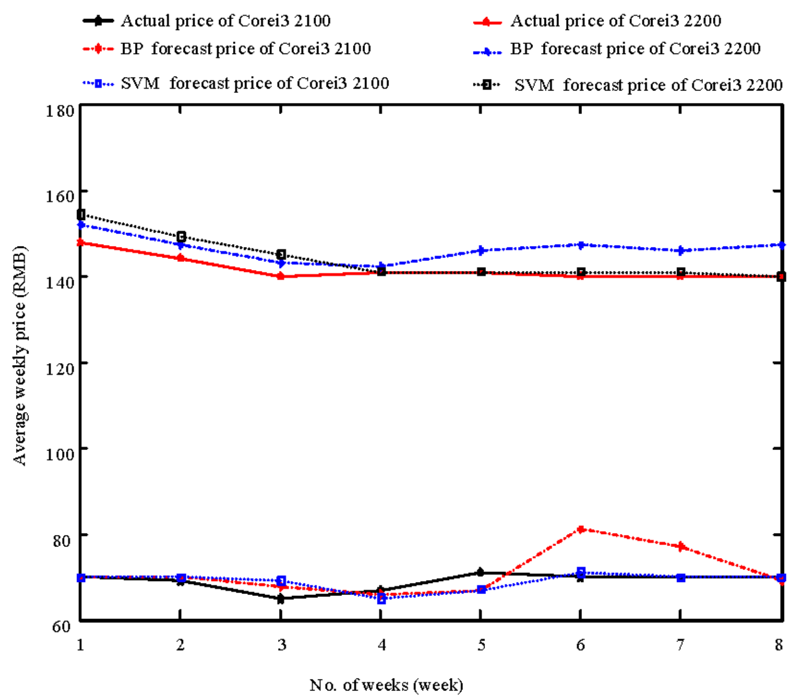

Fig. 7: Week-ahead forecast price of KingstonDDR3 2G and KingstonDDR3 4G

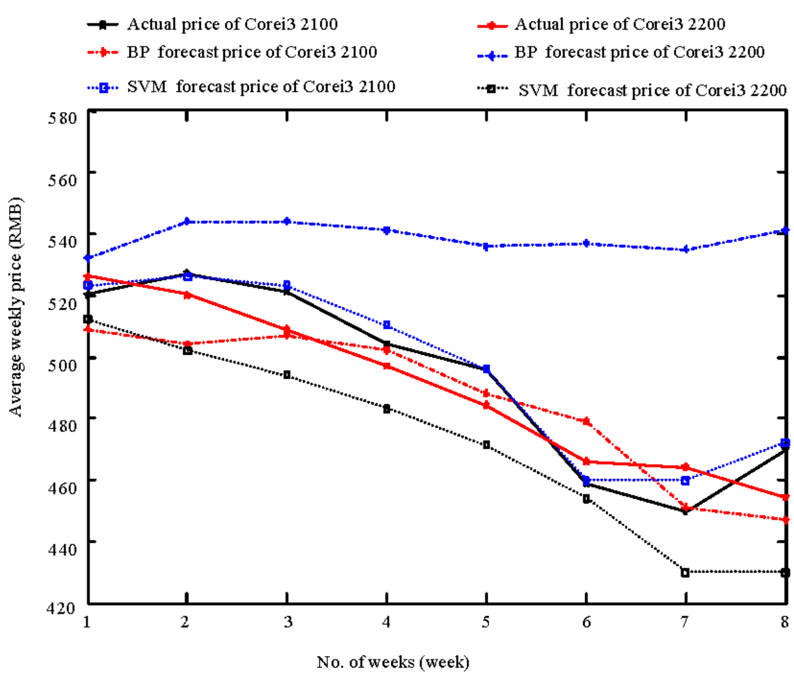

Fig. 8: Week-ahead forecast price of Seagate1TB Barracuda32M and Seagate1TB Barracuda 64 M

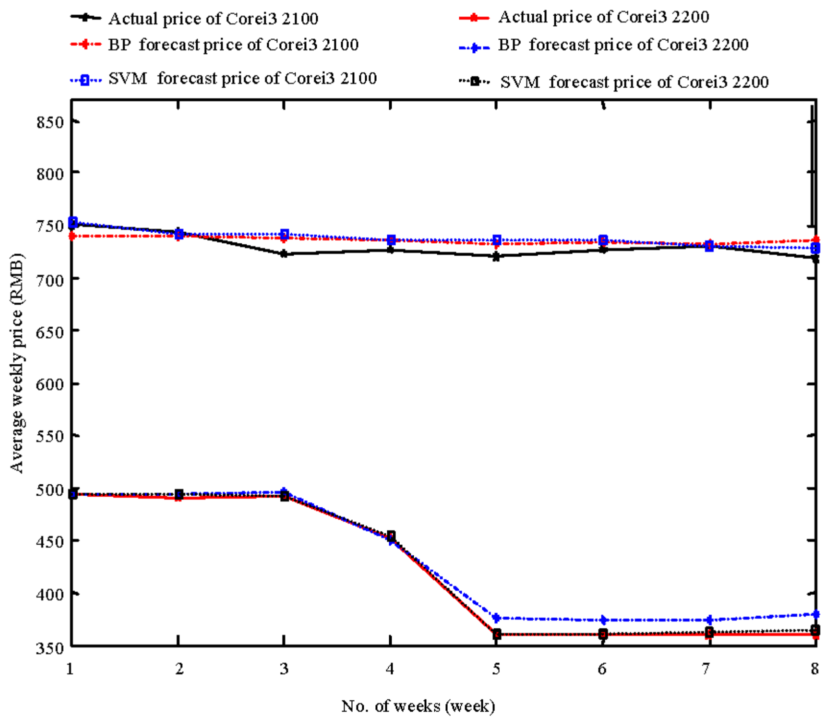

Fig. 9: Week-ahead forecast price of MomentusXT00G and Pipeline500G

Table 2: Relative errors of each product

	Relative errors	
Product	BPNN	SVM
Corei3 2100	0.008492	0.002979
Corei3 2200	0.010483	0.011977
Corei7 2600	0.016516	0.003241
Corei7 2600K	0.030779	0.020178
KingstonDDR3 2G	0.031762	0.000593
KingstonDDR3 4G	0.032216	0.015270
Seagate1TB Barracuda32M	-0.01424	0.005875
Seagate1TB Barracuda64M	0.102639	0.037070
MomentusXT500G	0.008467	0.010629
Pipeline500G	0.021569	0.003422

Table 3: MAE of each product

	MAE	
Product	BPNN	SVM
Corei3 2100	6.000	2.000
Corei3 2200	8.875	8.375
Corei7 2600	31.000	11.250
Corei7 2600K	62.000	41.000
KingstonDDR3 2G	3.375	1.500
KingstonDDR3 4G	5.000	2.000
Seagate1TB Barracuda32M	12.875	3.000
Seagate1TB Barracuda64M	49.000	18.125
MomentusXT500G	9.750	8.250
Pipeline500G	8.375	1.500

Experimental results analysis: From the experimental results the following conclusions can be drawn. It can be seen from the Fig. 7 and 9 that a BP NN model and a SVM model both have good prediction results. Meanwhile, differences of forecasting effect between them are not so obvious. However, in the figure 5, 6 and 8, the curve of week-ahead forecast prices deviates obviously from the curve of actual prices at some points. Comparing these two models when there is a certain bias between the actual price and the forecast price, it can clearly see that their forecasting performance varies widely and basically the SVM model is more effective.

Seen from Table 2 and 3, the Relative Errors and MAE of a SVM model is far less than that of a BP NN model in most cases. For example, the Relative Errors of forecast price for KingstonDDR3 2G based on BP NN model is about 52 times higher than that based on a SVM model. Another example, the MAE of forecast price for PipeLine500G based on a BP NN model is about 5.58 times as high as that based on VSM model. After a comprehensive analysis of Table 2 and 3, it can be found that a SVM model is a better resolution for price forecasting, though it still has some defects in terms of forecast accuracy.

CONCLUSION

The BP NN model and VSM model are evaluated through lots of experiments in order to identify their accuracy and practicality and certify which one is more suitable for week-ahead price forecasting. The statistical results can indicate that SVM model is a better way since its forecasting performance is much higher than that obtained through BP NN model. Under the same forecasting conditions, the Relative Errors of SVM model is 1.87% lower than that of BP NN model and the mean absolute errors of SVM model is 17.91% lower than that of BP NN model. Though SVM model has a higher accuracy of price forecasting it still has some problems or defects which need a further study or more future work to resolve, such as how to reduce the time cost on training. In a word, price forecasting for computer accessories based on SVM is valuable and feasible since it can not only ensure a high forecasting accuracy but also make the forecasting window in advance. Furthermore, it is helpful as it can help market participants to evaluate the risks associated with price volatility and determine their investment or consumption strategy.

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