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Sales Forecast of Dual-Channel Supply Chain based on Improved Bass and SVM Model

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Abstract: As the increasingly fierce competition, more and more manufacturers have started to sell products through online channels apart from traditional retail channel. Meanwhile, increased competition has significantly shortened the product life cycle, which makes sales forecast meaningful. Taking lack of historical record into account, the sales forecast model based on historical sales data based on Bass model as well as the improved Bass model by consideration of service and purchase factors are firstly discussed. And then, based on analysis of above model, a multi-factors sales forecast model based on SVM (Support Vector Machine) for short-life cycle product in dual-channel is creatively proposed, which integrates multi-factors, such as the improved Bass model predictive value, seasonal index, number of customers, credit value in practice. Finally, through simulation analysis, it is found that SVM-based multi-factor model is able to improve sales forecast of short life-cycle products in dual-channel supply chain system.

Keywords: Dual-channel, Bass, SVM, sales forecast, short life-cycle.

1 Introduction

With the rapid development of e-commerce, a significant number of enterprises are using online stores as a direct distribution channel in addition to their traditional retail channels. When enterprises expand their business through dual-channel, it is inevitable for supply chain parities to face market demand uncertainties. To better plan their resources, they have to precisely evaluate market demand and forecast their sales. Therefore, how to precisely forecast the market demand from different channels has been one of research hotspots in recent years. Apart from pricing, Kumar argued that the motivation to open direct channel service level factor should be considered. Furthermore the retail price is largely affected by online wholesale price [1]. Kurata proposed price rebate strategy based on channel coexistence and brand competition [2]. Cai explored price discount strategy under Stackelberg and Nash game equilibrium [3]. Xujin quantified the bullwhip effect for a simple two-stage supply chain and demonstrated that centralizing demand information can significantly reduce the increase in variability [4]. Cai GS considers a supply chain model with a manufacturer and multiple symmetric retailers [5]. Meanwhile, the life-cycle of products such as fashion electronic products or trend-setting clothing has become much shorter with improved of consumer demand level, increased competition and technological advances. Therefore, dual-channel supply chain of short life-cycle product has been given more attention. As to hybrid supply chain of short life-cycle selling product, Haiyang analyzed inventory policy of manufacturer and retailer and he reported on how demand uncertainty affects optimal inventory policy [6]. Yina and Junxue Xu reported a dual-channel of the short selling season product supply chain inventory transshipment with the constraint of production capacity [7]. In their study they analyzed the ordering decisions in the case of non-cooperative and transshipment strategy as well as decisions when demand is normally distributed.

On the other hand, there exist some of products with short selling season, such as fashion goods, toys, high-tech products, which need to produce or order before the season. They are susceptible to uncertainty demand risk and that is the reason why manufacturers of short life-cycle products prefer dual-channel supply chain so as to response to the changing demand as quickly as possible. Thus, a scientific and effective forecast for the demand of dual-channel supply chain of short selling season products has become extremely important. There

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are several methods to evaluate and forecast the demand. None of them can guarantee 100% yields of the demand data. However, accuracy and confidence level enable to be improved by using more than one method. Some researchers have employed several classical statistical methods such as exponential smoothing, time series method to forecast demand and make sales plan [8].

Actually, traditional forecast methods are often used to identify the regularity of historical data change over a certain period, and are also adopted as a basis to predict market demand for the products. However, the impact of lack of historical data on forecast process has always been neglected. Some scholars have taken into account of characteristics of the short life-cycle products and applied the Bass and improved Bass model family into their research. However, diffusion models are hard to include all of characteristics of the market and lack of differential treatment on retail channel and online channel. One of the most accurate methods used today is Support Vector Machine (SVM) This method has been developed to solve the dataset with small sample, nonlinear and high latitudes of the limitation and improved generalization ability. In this paper, SVM statistical learning, structural risk minimization principle and the VC dimension are mainly focused. The linearly constrained quadratic programming problem has been considered on the first training session, which is to achieve global optimization [9]. Nevertheless, it has to be emphasized that only a small amount of data is more suitable for sales forecast of products when SVM model is employed.

In this paper, sales historical data is considered as a single impact factor. After brief explanation of short selling season product forecast based on Bass model, an improved Bass model by considering service-purchase intention factor is conducted. The influence factors of short selling season products in dual-channel sales not only include price, season, promotion, industry status and historical sales data but also the type of the channel. Therefore, the inputs of SVM model include correction values of improved Bass model as well as other market factors]. Finally, through simulation, we are able to prove the effect of sales forecast of short selling season products in dual-channel supply chain.

The two-stage supply chain system of a short selling season products with a single manufacturer and multiple retailers has been considered in this study. The manufacturer operates through two channels; one channel is the traditional retail one where he sells the products to the retailers, while for the other one, the manufacturer own online shop and sells the products directly to the end-customers.

2 Sales forecast based on improved Bass model

2.1 Sales forecast with past Sales based on Bass model

Past sales records can be used for future sales forecast. The longer term past sales record used the more accurate for forecast. However, it is difficult to obtain long-term past sales data for the short life-cycle products due to its short-life season of sales. Therefore, we consider the market as a continuous diffusion and penetration process. In this case, the dealers firstly attract a small part of consumers with a certain sense of innovation through product promotion or trials [10]. Actually, realistic diffusion process involves a large number of factors and the relationships among them. The scenario can be built through Bass diffusion model. In this section we use Bass model to explore the short life-cycle product sales forecast problem based on single factor, which is the sales record.

Based on Bass theory, the relevant definition and notation are described as follows. f(t) is the time density function of purchasers, indicating the likelihood of purchase at time t; F(t) is the cumulative ratio of the purchasers at time t accounting for all purchasers; p defined by p (0,1) is the coefficient of innovation group, suggesting the role of external factors on how they affects the process of dissemination of the product attributes such as price; q defined by q (0,1) is the coefficient of imitation group, which indicates the publicity effect of experienced users on potential users. The potential users require a long-term experience which later will enable them to explore certain features of the product. Potential purchases are denoted m; N(t) indicates the cumulative purchase at time t; n(t) represents the non-cumulative purchase at time t; X(i) is the product demand. p, q and m can be estimated by using Bass model. According to the principle of the Bass model, the sales forecast model of a short-life selling season products can be described as follow:

$$X(i)=m[\frac{p-pe^{-(p+q)t_i}}{p+qe^{-(p+q)t_i}}-\frac{p-pe^{-(p+q)t_{i-1}}}{p+qe^{-(p+q)t_{i-1}}}]+\mu_i \quad (1)$$

where (t_{i-1},t_i) indicates the product sales in a certain interval.

Based on the above described equation, we put the past sales records of the two channels as the training groups and set the initial values. And then, Bass model is used to determine the fitting parameter values. The algorithm is as follows where x(i) is for initial value, xdata for cycle index and y for historical sales data:

$$\text{Fun} = \text{inline}('x(1)\times(x(2)\times(x(2)+x(3)\hat{}2\times\exp(-x(2)\times xdata -x(3)\times xdata))./(x(2)+x(3)\times\exp(-x(2)\times xdata -x(3)\times xdata)).\hat{}2','x','xdata') \quad (2)$$

Therefore, we are able to obtain each phase of market sales through using fitting function which can approximately reflect the market demand. The innovation and imitation coefficient of the two channels are different, so the two channels can be distinguished from each other. Although the model enables to find a solution to the problem, it is still difficult to accurately or comprehensively reflect the demand of short selling season products by considering only one single factor which is short-term historical sales record.

2.2 Sales forecast with service-purchase intention based on improved Bass model

Past sales records can be used for future sales forecast. The longer term past sales record used the more accurate for forecast. However, it is difficult to obtain long-term past sales data for the short life-cycle products due to its short-life season of sales. Therefore, we consider the market as a continuous diffusion and penetration process. In this case, the dealers firstly attract a small part of consumers with a certain sense of innovation through product promotion or trials [10]. Actually, realistic diffusion process involves a large number of factors and the relationships among them. The scenario can be built through Bass diffusion model. In this section we use Bass model to explore the short life-cycle product sales forecast problem based on single factor, which is the sales record.

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$$X(i) = m[\frac{p - pe^{-(p+q)t_i}}{p + qe^{-(p+q)t_i}} - \frac{p - pe^{-(p+q)t_{i-1}}}{p + qe^{-(p+q)t_{i-1}}}] + \mu_i \quad (3)$$

where (t_{i-1},t_i) indicates the product sales in a certain interval.

Based on the above described equation, we put the past sales records of the two channels as the training groups and set the initial values. And then, Bass model is used to determine the fitting parameter values. The algorithm is as follows where x(i) is for initial value, xdata for cycle index and y for historical sales data:

$$\text{Fun} = \text{inline}('x(1) \times (x(2) \times (x(2) + x(3)^\wedge 2 \times \exp(-x(2) \times xdata -x(3) \times xdata))./(x(2) + x(3) \times \exp(-x(2) \times xdata -x(3) \times xdata)).^\wedge 2','x','xdata') \quad (4)$$

Therefore, we are able to obtain each phase of market sales through using fitting function which can approximately reflect the market demand. The innovation and imitation coefficient of the two channels are different, so the two channels can be distinguished from each other. Although the model enables to find a solution to the problem, it is still difficult to accurately or comprehensively reflect the demand of short selling season products by considering only one single factor which is short-term historical sales record.

2.3 Sales forecast with service-purchase intention based on improved Bass model

In this section, a relatively ideal solution that forecast is on the basis of sales records is proposed. In reality, sales forecast is affected by many factors, no matter which situations, service quality of the seller and the buyer's purchase intention cannot be replaced. To this end, the two factors are set to be adjusted, which is able to make dual-channel sales forecast more reliable.

It is supposed that$\overline{n(t)}$indicates the purchase amount at time t and $\overline{N(t)}$ represents the cumulative purchase amount at time t.

$$\overline{n(t)} = \frac{d\overline{N(t)}}{dt} = \beta n(t) + \beta \cdot \gamma N(t) \quad (5)$$

In formula (5), β denotes service impact factor describing the extent of customers' satisfaction; λ represents rate repeat purchase describes how much the customers would like to continue to buy the products. Supposing β>0, λ>0, the formula is as follows:

$$\overline{n(t)} = m\{\beta[\frac{p(p+q)^2 e^{-(p+q)t}}{(p+qe^{-(p+q)t})^2}] - \beta\gamma[\frac{p-pe^{-(p+q)t}}{p+qe^{-(p+q)t}}]\} \quad (6)$$

Cumulative purchase amount $\overline{N(t)}$:

$$\overline{N(t)} = \beta N(t) + \int_0^t \beta\gamma N(t)dt \quad (7)$$

$$\overline{N(t)} = m\{\beta[\frac{p-pe^{-(p+q)t}}{p+qe^{-(p+q)t}}] - \frac{\beta\gamma}{q}[\ln\frac{p+qe^{-(p+q)t}}{e^{-(p+q)t}} - pt - \ln(p+q)]\}$$

For the nonlinear model, we use nonlinear least squares method to estimate the parameters. Sales volume between t_{i-1} and t_i is as follows:

$$X(i) = \overline{N(t_i)} - \overline{N(t_{i-1})} + \mu_i$$

$$= m\{\beta[\frac{p-pe^{-(p+q)t_i}}{p+qe^{-(p+q)t_i}}] + \frac{\beta\gamma}{q}\ln[\frac{p+qe^{-(p+q)t_i}}{e^{-(p+q)t_i}}] - \frac{\beta\gamma}{q}pt_i\}$$
$$-m\{\beta[\frac{p-pe^{-(p+q)t_{i-1}}}{p+qe^{-(p+q)t_{i-1}}}] + \frac{\beta\gamma}{q}\ln[\frac{p+qe^{-(p+q)t_{i-1}}}{e^{-(p+q)t_{i-1}}}] - \frac{\beta\gamma}{q}pt_{i-1}\} + \mu_i \tag{8}$$

where μ indicates the sales at time t, $\overline{\mathrm{N}(\mathrm{t_i})} - \overline{\mathrm{N}(\mathrm{t_{i-1}})}$ deducts the sales at that time, so X(i) is used to make up.

X(i), which is derived from the model is able to tell the difference retail channel and online channel. In detail, the two channels can be distinguished by specific historical data. Compared with the Bass model mentioned in the section 2.1, the improved model includes not only the seller's service level but also buyer's willingness to buy the product. Taking all the major factors mentioned above into account, forecast reliability can be enhanced.

3 Sales forecast with multiple-factor based on

SVM model

There still exist some limitations in the model when we base on only historical sales records. Nevertheless, some breakthroughs have been made in improved service-purchase intention model. No matter whether it is the previous model or the improved one, it is hard to get a comprehensive and precise distinction between the two channels. This would happen due to ignoring the unique features of channels.

Therefore, we need to further consider sales forecast for the short life-cycle products in dual-channel under a number of influencing factors. Multiple factors here refer to factors which may affect the market demand; meanwhile different channel is impacted by different factor. As for the retail channel, the demand is mainly affected by the price of the product, seasonal index, promotional index, industry situation, the scale of the store and historical sales. As for online channel, the scale of the store is replaced by credit index while other factors remain unchanged. A model which enables to reflect the characteristics of the different channels in forecast needs to be built. Due to the fact that SVM enables us to make effective analysis of small sample and multiple input factors, we introduce and put the factors and predictive sales values derived by improved Bass model as input vectors when building SVM forecast model.

3.1 *Analysis of input factors of the model*

To reflect comprehensively, the model takes advantage of not only the correction values in improved Bass model but also considering the selling price, seasonal index, promotion index and other influencing factors of the market. Demand of the products is mainly determined by the following relevant factors. Retail channel and online channel are respectively are expressed as follows:

$$X(t) = S(t) + M(t) + L(t) + P(t) + Y(t) + [changedB(t)]$$

$$X(t) = S(t) + M(t) + L(t) + P(t) + N(t) + [changedB(t)]$$

where X(t) represents the sales forecast values of the products; S(t) denotes seasonal index; M(t)represents industry situation; L(t)represents promotional efforts; P(t)represents price of the product; Y(t) denotes customers' trust towards online shopping; and N(t), the number of customers in the store at time t; changed(t) represents sales value obtained by improved Bass model.

3.2 *Pretreatment of input vector*

Firstly, we need to calculate sales forecast value by using improved Bass model where x(i) represents initial value, x data for cycle index and y data for revised sales data. The algorithm is as follows:

$$\begin{aligned}&ydata\\&= (x(5)_\bullet \times ((x(2) - x(2) \times \exp(-x(2) \times xdata - x(3) \times xdata))_\bullet/(x(2)+\\&x(3) \times \exp(-x(2) \times xdata - x(3) \times xdata))) + x(4) \times x(5) \times \log((x(2) + x(3)\times\\&\exp(-x(2) \times xdata - x(3) \times xdata))_\bullet/\exp(-x(2) \times xdata - x(3) \times xdata))/\\&x(3) - x(4) \times x(5) \times x(2) \times xdata/x(3)) \times x(1) - (x(5)_\bullet \times ((x(2) - x(2)\times\\&\exp(-x(2) \times (xdata-1) - x(3) \times (xdata-1)))_\bullet/(x(2) + x(3) \times \exp(-x(2)\times\\&(xdata-1) - x(3) \times (xdata-1)))_\bullet/\exp(-x(2) \times (xdata-1) - x(3) \times (xdata-\\&1)))/x(3) - x(4) \times x(5) \times x(2) \times (xdata-1)/x(3)) \times x(1)\end{aligned} \tag{9}$$

3.3 *Pretreatment of the sample and normalization*

To avoid singular data i.e. large demand fluctuations in the model, the data need to be normalized. To speed up the convergence of the algorithm, we are able to use formula (10) to achieve normalization process [12].

$$\bar{x_i} = \frac{x_i - x_{i\min}}{x_{i\max} - x_{i\min}}(i = 1, \ldots, m) \tag{10}$$

3.4 *Sales forecast model based on Support Vector Machine*

Based on the basic idea of ??SVM regression, through a nonlinear mapping$\emptyset$, sample dataset $(\mathrm{x_i}, \mathrm{y_i}), \mathrm{x_i} \in \mathrm{R^n}, \mathrm{y_i} \in \mathrm{R}$, $\mathrm{i} = 1, \ldots, \mathrm{l}$ are mapped to high-latitude feature space F and achieved to linear regression [13].

$$f(x) = (\alpha^T \emptyset(x)) + b, \emptyset : R^n \to F, \alpha \in F \tag{11}$$

The SVM regression can be expressed as a constraint optimization problem. The objective function of quadratic programming is given as:

$$\min \frac{1}{2}[\alpha^T, (\alpha^*)^T]Q\begin{bmatrix}\alpha\\ \alpha^*\end{bmatrix} + P\begin{bmatrix}\alpha\\ \alpha^*\end{bmatrix} \tag{12}$$

$$s.t.R^T \begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix} = 0, 0 \le \alpha_i, \alpha_i^* \le C(i = 1, \dots, m) \quad (13)$$

α is weight vector, αŁF, Q and P is vector group, which is defined as:

$$Q = \begin{bmatrix} K & -K \\ -K & K \end{bmatrix}, K_{ij} = K(x_i, x_j) = Exp(\frac{-\|x_i - x_j\|^2}{\sigma^2}) \quad (14)$$

where $K(x_i, x_j)$ is kernel function.

$$P = [\varepsilon E^T + Y^T, \varepsilon E^T - Y^T] \quad (15)$$

where ε represents insensitive loss coefficient; E is a unit column vector of $|X|$; $R = [r_i]$ is unit column vector of $|X2|$ and $Y = (y_1, y_2, \dots, y_l)^T$. $r_i = 1$ when $i = 1, 2, \dots, l$; $r_i = -1$ when $i = l+1, l+2, \dots, 2l$.
Besides, $x_i(i = 1, 2, \dots, l)$denotes the i-th input of training sample while $y_i(i = 1, 2, \dots, l)$ is the i-th output of training sample. From the above equations, an optimal solution to a_i and $a_i^*(i = 1, 2, \dots, l)$ can be obtained through Matlab2010: $\overline{\alpha} = (\overline{\alpha_1}, \overline{\alpha_1}^*, \dots, \overline{\alpha_l}, \overline{\alpha_l}^*)$

Substituting them into the formula (6), the regression decision function of SVM can be obtained:

$$f(x) = \sum_{i=1}^{l} (\bar{\alpha}_i, \bar{\alpha}_i^*) K(x, x_i) + \bar{b} \quad (16)$$

where $\bar{b}$ represents intercept of linear function.

3.5 *Determination of optimal parameters*

The method of selecting optimal parameters in SVM is to find out the smallest penalty parameter of the highest validation classification accuracy c and reciprocal of the number of the attributes in the input data g, and then take the values within certain rang. For a given set of c and g, according to K-CV method, the group of c and g would be selected.

$$y = \overset{\Lambda}{y}(y_{\max} - y_{\min}) + y_{\min} \quad (17)$$

From the above prediction process, the fitted values ??of improved Bass model, history values ??and other market characteristics are substituted into the model as the dataset of input vector. Optimal parameters and demand predictive values are determined through simulation.

4 Numerical calculations

Supposing the manufacturer sells electronic products through dual-channel supply chain, which are traditional and online shopping channels, the indexes of each phase

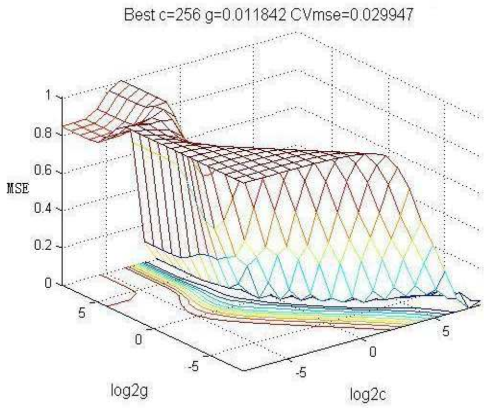

Fig. 1: SVR parameters selection results of retail channel (3D map)

of sales and influencing factors of retail channel and online channel are shown in Table 1 and Table 2:

By simulation of an improved Bass model described earlier, historical record of past 14 months of both channels and fitted sales values are shown in Table 4 and Table 5:

We get the influencing factors shown in Table 1 and the sales data of retail channel in improved Bass model presented in Table 4 as input vector and the data are composed through SVM toolbox. Through simulation, we select a group of (c, g) which satisfies the minimum penalty parameter c of the highest validation classification accuracy. Thereafter we substitute the optimal parameters obtained into SVM model and put the training set of data into the SVM model. By substituting the training data to be predicted into SVM model, we obtain the comparison results and relative error between actual sales and forecast sales of following 3 months. Figure 1 shows the angle of 3D which is the results of optimal parameters for the retail channel. Figure 2 describes the fitting sales data of retail channel for the previous 14 months. Figure 3 depicts the sales forecast data of retail channel in the previous 14 months.

Similarly, we put influencing factors (Table 2) and sales data of online channel in and improved Bass model presented in Table 5 as the input of SVM model and compose the program through SVM toolbox. The main difference here is that for the sales forecast of retail channel, the number of customers in the store needs to be considered, while the credit index caused by the payment of security will be concentrated in online channel forecast. Finally, by substituting the training data into SVM model, parameters selection of online can be achieved, which is described in Figure 4. Similarly, we can get the fitting sales data of online channel for the previous 14 months, which is shown in Figure 5, Figure 6

Table 1: The indexes of retail sales

Month	Price	Seasonal index	Promotional index	Industry index	Numbers customers in the store	Sales
1	287	0.08	1	0.96	3460	23
2	491	0.28	1	0.95	2995	41
3	432	0.50	0.9	0.82	2675	67
4	459	0.05	0.8	0.75	2623	64
5	496	0.37	0.8	0.75	2106	67
6	453	0.25	1	0.72	2735	86
7	468	0.21	1	0.74	3150	76
8	430	0.36	0.5	0.77	3026	93
9	421	0.60	0.4	0.68	2405	79
10	488	0.22	0.3	0.64	2809	85
11	228	0.36	0.2	0.66	2902	85
12	222	0.09	0.2	0.61	2561	51
13	296	0.21	0.1	0.56	2282	48
14	247	0.52	0.2	0.58	1941	31

Table 2: The indexes of online sales

Month	Price	Seasonal index	Promotional index	Industry index	Credit index	Sales
1	287	0.25	1	0.96	0.87	151
2	491	0.32	1	0.95	0.86	536
3	432	0.06	0.9	0.82	0.83	1330
4	459	0.08	0.8	0.75	0.76	1370
5	496	0.37	0.8	0.75	0.76	1606
6	453	0.18	1	0.72	0.73	2454
7	468	0.58	1	0.74	0.75	2373
8	430	0.10	0.5	0.77	0.78	2409
9	421	0.54	0.4	0.68	0.69	1487
10	488	0.58	0.3	0.64	0.65	1105
11	228	0.22	0.2	0.66	0.67	1350
12	222	0.42	0.2	0.61	0.62	1170
13	296	0.36	0.1	0.56	0.57	539
14	247	0.00	0.2	0.58	0.59	128

Table 3: Actual sales to be predicted of retail channel and online channel

Month			
	15	16	17
Actual sales of retail channel	26	13	9
Actual sales of online channel	148	82	53

Table 4: Fitting sales of retail channel

Month							
	1	2	3	4	5	6	7
Actual sales of retail channel	43.5	56.9	71.7	86.4	99.0	107.5	110.2
	8	9	10	11	12	13	14
Actual sales of retail channel	107.0	98.8	87.6	75.3	63.6	53.4	45.0

Table 5: Fitting sales of online channel

Month							
	1	2	3	4	5	6	7
Actual sales of online channel	397.3	659.6	1026	1464.8	1869.5	2086.3	2024.2
	8	9	10	11	12	13	14
Actual sales of online channel	1737.7	1370.6	1040.9	795.7	632.4	530.3	468.9

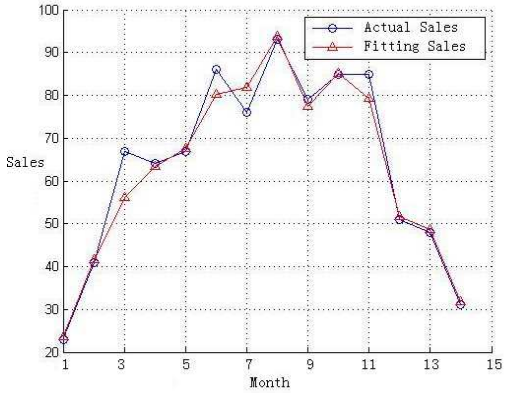

Fig. 2: Fitting sales data of retail channel for the previous 14 months

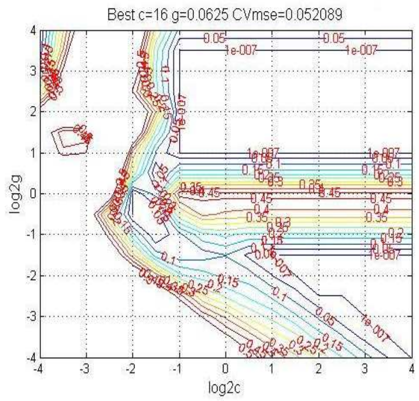

Fig. 4: SVR Parameters selection results of online channel (contour map)

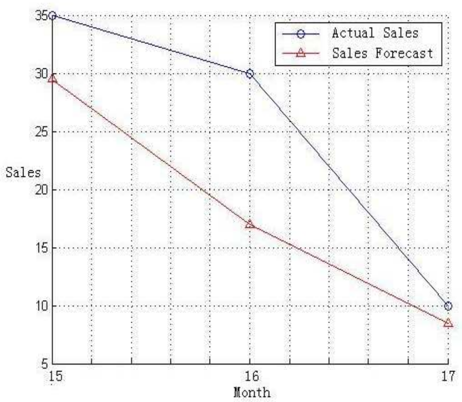

Fig. 3: Sales forecast data of retail channel based on SVM

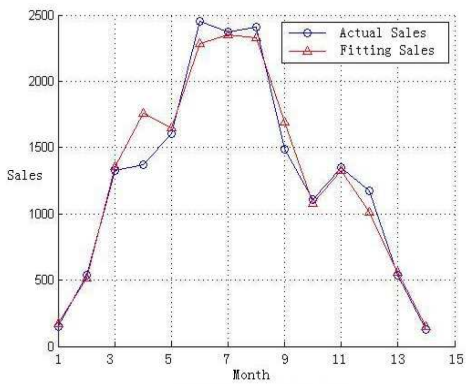

Fig. 5: Fitting sales data of online channel for the previous 14 months

depict the sales forecast data of online channel and relative error of sales data of online channel, respectively.

Table 6 and Table 7 demonstrate the actual sales and forecast sales in the next 3 months by using improved Bass model and SVM model. Table 8 compares the indicator RMSE, namely regression root mean square or fitting standard deviation in the regression system. From the tables, we can see that no matter which channel it is, the RMSE obtained by SVM model is smaller than that obtained by improved Bass model. Therefore, taking into account the number of input factors, we can find that SVM sales forecast model is able to provide supply chain parties more accurate and objective prediction.

According to the definition of dual-channel described above, no matter whether is a traditional retail channel or online channel, the short selling season products comes from the manufacturer and ultimately flow to the end-customers. Obviously, the sales forecast for the whole

Table 6: Comparison between actual sales and forecast sales of retail channel from the 15th to the 17th month

Month	15	16	17
Actual sales	40	35	30
Improved Bass forecast sales	34.5512	30.0246	29.6160
SVM forecast sales	36.6103	33.5650	27.2505

Table 7: Comparison between actual sales and forecast sales of online channel from the 15th to the 17th month

Month	15	16	17
Actual sales	542	542	487
Improved Bass forecast sales	634.8265	604.0543	586.3053
SVM forecast sales	488.7873	455.1177	440.0680

Table 8: Comparison of forecast effect of retail channel and online channel

Indicator	Improved Bass retail channel	SVM retail channel	Indicator	Improved Bass online channel	SVM online channel
RMSE	4.7441	1.5315	RMSE	92.2739	32.0484

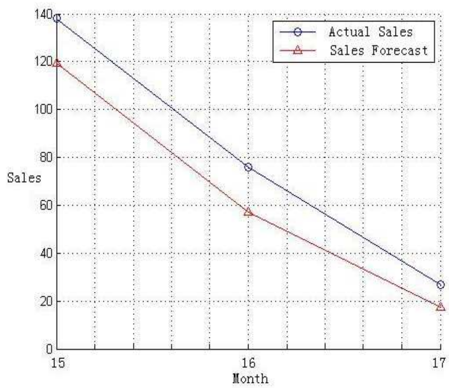

Fig. 6: Sales forecast data of online channel based on SVM

market comprises two parts, namely forecast sales from retail channel and online channel. Actually, however, for more than one retail stores, it is necessary to consider the number of retail outlets when calculating the total sales forecast. For simplicity, we assume that in a certain area each store's historical sales data are broadly similar, so we get the sales of retail channel, sales of online channel and total sales under different number of retailers, which is shown in Figure 7.

Obviously, the scale of retailers exerts an impact on the entire market demand, which causes change of sales plan. The figures indicated above reflect the features of dual-channel structure and pave a way for further study on coordination and optimization processes.

5 Conclusions

The sales forecast of short life-cycle products for the parties in dual-channel supply chain system is a complicated problem. Thus, we have to consider not only the features of the short life-cycle products but also the sales of the two channels. In this paper, on the basis of the existing findings, sales forecast method for short life-cycle product of dual-channel supply chain based on SVM has been put forward. The introduction of input vectors (sales effort, seasonal index, number of customers in the store, and the price) in the improved Bass model, we choose different training samples to build SVM model. Through analysis and simulation, major indicators such as fitting data, RMSE have been compared. The results indicate that SVM model enables to provide the supply chain parties better demand prediction. However, due to short selling season of the product and market uncertainty, it is necessary to further explore a way of dynamic tracking, which will help the manufacture and retailer to absorb and update data, improve self-adaption, prediction flexibility consequently as well as enhance corporate decision-making validity.

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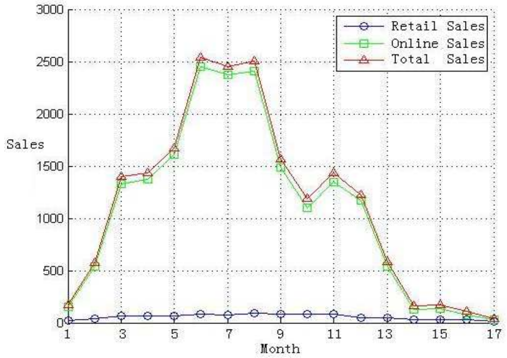
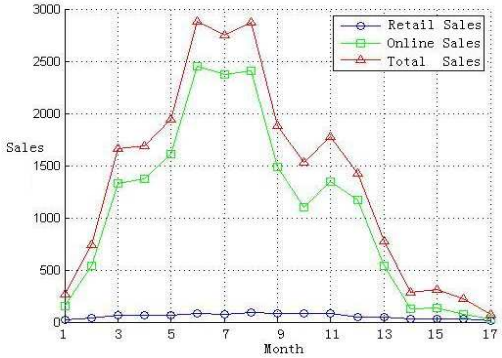
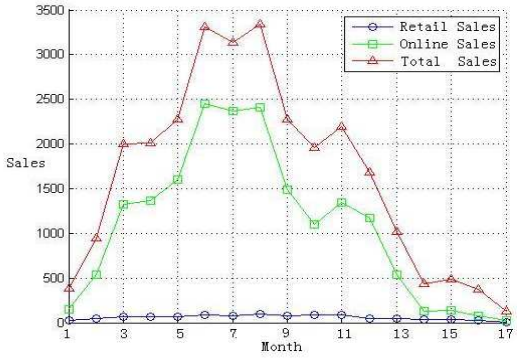


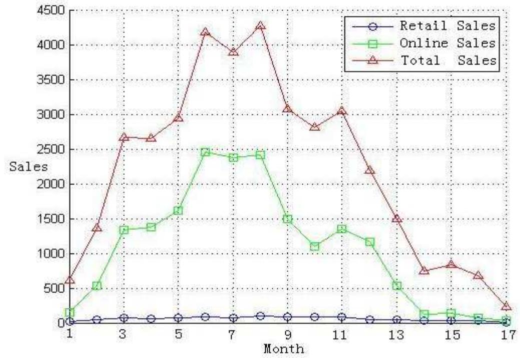
(N=1)



(N=5)



(N=10)



(N=20)

Fig. 7: Sales of retail channel, sales of online channel and total sales under different number of retailers.

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