International Journal of Computational Intelligence Systems, Vol. 7, Supplement 2 (July 2014), 85-92

Demand forecasting procedure for short life-cycle products with an actual food processing enterprise

Rie Gaku *

Graduate School of Business Administration, Momoyama Gakuin University
Osaka, 594-1198, Japan
E-mail: r-gaku@andrew.ac.jp

Received 6 January 2014

Accepted 16 March 2014

Abstract

A procedure of demand forecasting using data mining techniques is proposed to forecast the sales amount of new short life-cycle products for an actual food processing enterprise. The enterprise annually produces 100~150 kinds of new items with short life-cycle between one week and three months to supply 260 convenience stores in the region of jurisdiction. Based on the previous delivery data in the first selling week, sales amount in the second, and the third selling weeks can be forecasted for their new products. Especially, some effective association rules about hot items and cold items are obtained by using data mining technologies for new short life-cycle products.

Keywords: Demand Forecasting, Data Mining, Short Life-cycle, Convenience store.

1. Introduction

In recent years, the retailing environment is undergoing a significant change. Since the 1980s, accordingly consumption patterns take on a diversified tendency, the life-cycle of products put on the market is gradually shortening. In particular, for manufacturing enterprises whose new product life cycle is relatively short, when products are put on the market, the demand forecasting approach is a key to accelerate marketing activities in order to achieve a sustainable competitive advantage on management. Against this background, this study is focused on finding a procedure to forecast new commodity market demand based on their actual sales database, which describes the purchasing behavior of the customers at the early stages when products are put on the market.

The subject of this study is a food manufacturing enterprise, located the central Japan, as a box lunch plant. The enterprise produces the box lunch for convenience chain stores within its jurisdiction of Tokai region, providing 140 thousand boxes of three meals a day for about 260 stores per day. The life-cycle of new products by this plant is so short that 70 percent of the new product box lunch is annually developed and produced, and the selling cycle is no more than 3 month. The research shows that to maintain efficient production, advanced information techniques for the analysis of marketing demand should be developed to transform available sales data into knowledge and into effective production action. Especially for this food manufacturing enterprise, it is critical to develop an advanced procedure to analyze the new product demand trend with a relatively short life-cycle.

Based on the above mentioned issue, in order to promote even more efficient production activities, especially to minimize raw materials wasting toward the end of the production cycle, a procedure with data

* 1-1-Manabino, Izumi, Osaka 594-1198, JAPAN.

mining technique is proposed in this study to analyze the demand trends for those very short life-cycle new products, based on the actual delivery data at the initial stage of the sales.

2. Recent representative studies on marketing analysis using data mining techniques

Data mining is one of business intelligence methodologies that are concerned with the customer oriented marketing. Table 1 shows the pioneering studies concerned with applying data mining techniques to various case studies related to marketing analysis.

Data mining is a process to find useful business association or marketing sales rules from a large amount of data collected and stored to facilitate the decision-making process. This study adopts two methods to forecast demand trends of new short life-cycle products, called *Neural Netw*ork and *Decision Tree*[1].

Neural network is a computer simulated mathematical model that resembles the visible functional portion of the cerebral cortex. In this study, a hierarchical neural network model receives as input the actual sales data of the new short life-cycle products during the first selling week so as to forecast the sales amount for the second and the third selling weeks.

On the other hand, the decision tree technique is one of the most intuitive and divisive hierarchical methods, which can provide explicit rules for classification. It is also used to investigate the relationship between the objective variable and the multiple input variables from a large volume of marking database. In this study, the relationship between the sales data during the first selling week and the sales amount for the second and the third selling weeks could be found by using the CART techniques.

The preview in Table 1. shows that the studies concerned with marketing analysis of new products or delicatessen products using varied methods. However, there are no studies regarded as an empirical study for new products whose life-cycle span is only between one week and three months. In this study, a procedure of demand forecasting using data mining techniques is proposed to forecast demand trends for short life-cycle products.

3. Characterization of shortened life-cycle products in this study and proposed demand forecasting procedure

3.1. *Characterization of products in this study*

To select a specific demand forecasting method of products which are served to convenience stores, especially, in this study, the characteristics of the products should be fully considered. This study focuses on new short life-cycle delicatessen products sold in the convenience chain stores. These products in this study bear the following characteristics:

Table 1. Studies concerned with marketing analysis.

Segment	Contents	Studies
Concurrent analysis	Concurrent sales analysis for specific products or constituencies, etc.	Aggarval and Yu (2002)[2], Brijs et al. (2004)[3], Jukic and Nestorov(2006)[4]
Products analysis	Demand forecasting and time series purchasing analysis, etc.	Roger and Blair (1980)[5], Au, Chan and Yao (2003)[6], Manish and Jharkharia (2011)[7], Dennis, Spruit, and Waal (2014)[8], Jongsu, Lee and Lee (2012)[9]
Areas analysis	Store characteristics analysis and shopping centrescustomer knowledge, etc.	Dennis, Marsland and Cockett (2001)[10]
Campaign analysis	Customer segment selecting and campaign effect evaluation, etc.	Changchien, Lee and Hsu (2004)[11], Kim and Moon (2006)[12], Wu et al. (2005)[13]
Customers analysis	Customer classification, good customers analysis and Activation Member analysis, etc.	Brijs et al. (2004)[14], Jukic and Nestorov (2006)[15]

(i) Shortened life-cycle between one week and three months

Demand amount variation from the first selling day on sale is shown in Figure 1. Sales topped on the first selling day, plummeted in the following week, and then slowly decreased until the end of the sales period. Figure 2 shows the representative part of the product life spans. Apart from regular well-sold items and seasonal items, the average life span on sale of these products is 48 days, and over 90 percentage of product life spans stay within three months. Therefore, when sufficient sales data is gathered and analyzed, it is time for new products to be withdrawn from a market or it is about to be soon.

(ii) Multi-products environment

There are over 200 box lunch new products are released into the market from this food processing enterprise each year. Once new products are launched on the market, the competitive relation structure among products will become more and more complicated.

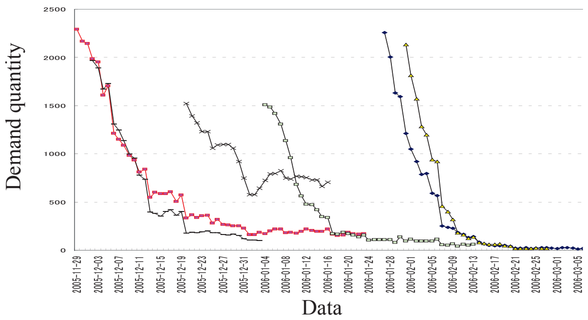


Fig. 1. Demand amount variation from sales release.

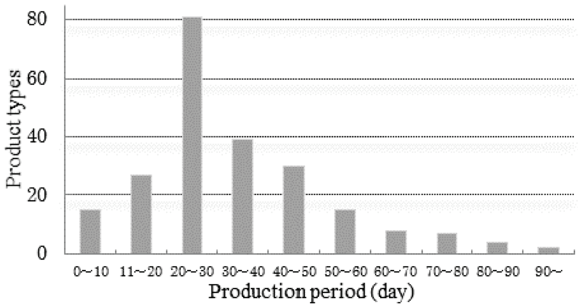


Fig. 2. Life-cycle spans of the products.

3.2. *Proposed demand forecasting procedure for shortened life-cycle products*

The procedure of demand forecasting using data mining techniques proposed in this study is shown in Figure 3.

[Step 1] Definition of the objective variables and the explanatory variables

[Step 2] Formatting the datasets for learning and verification mechanism

[Step 3] Neural network model generation for the learning mechanism

[Step 4] Model validation using the dataset for the verification mechanism

[Step 5] Evaluation of forecasting results

[Step 6] Classification by decision tree to extract the marketing sales association rules.

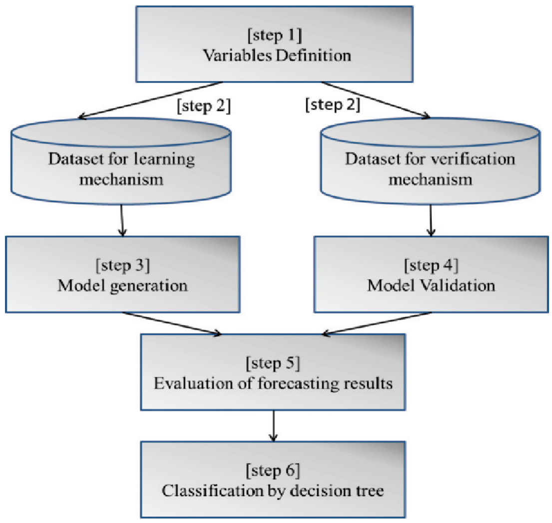


Fig. 3. Procedure of demand forecasting.

4. Applications

In accordance with the above mentioned procedure, in this section, an actual example is described based on the procedure mentioned to forecast the demand trend of new shortened life-cycle products. The data related to the 228 items of shortened life-cycle products is provided by an actual food processing manufacturer in Japan. These data used in this study are:

(i) Product types: Box lunch new products sold in the bellow period for 228 sorts.

(ii) Production period: About 2 years and 3 months.

(iii) Data items: Date of order, delivery date, product ID, product name, total quantity and category.

4.1. *Definition of objective variables and explanatory variables*

The objective variable in this study is defined as “the sales amount for the second and the third selling week” according to step 1 in Figure 3 mentioned above. The correlation coefficient between the objective variables and all of the possible categories of each explanatory variable which are the sales amount during the first selling week is shown as Table 2. It can be drawn from this table that the correlation coefficient has a tendency which increases along with the number of days on sale. Likewise, seen from the comparison of both two days sales data, it indicates that the correlation coefficient of the sales amount in the sixth and seventh day is relatively bigger than the first two days.

4.2. *Formatting the datasets for learning and verification mechanism*

Follow the step 2, a random sample of 46 sorts of products are extracted from 228 sorts using as the verification dataset, and then the rest 182 sorts are used as learning dataset. Keep the two dataset in respective file. The learning dataset is applied to generate a forecasting model called “learning process”, and the verification dataset is used to evaluate the model generated called “verifying process”. The details of the learning process are showed as Figure 4.

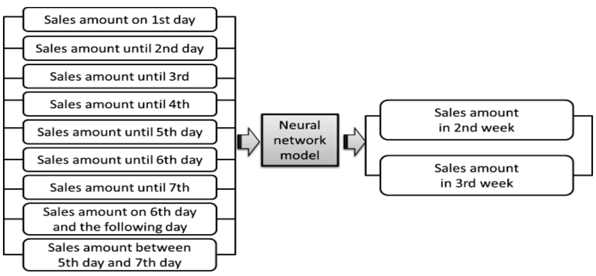


Fig. 4. Detail of learning process.

4.3. *Neural network model generation for the learning mechanism*

Table 3 shows a part of result of the learning process in Step 3. The neural network[16] can compare the calculated output value with the expected actual value, and calculate the error functions as shown in Table 4. Here, when it comes to linear correlation, the difference between the value forecasted and the actual value (0.965, 0.938) will become extremely minimal.

Table 3. Result of the learning process.

	Sales amount in 2nd week	Sales amount in 3rd week
Estimated accuracy	95.286	92.226
Input layers	8 neurals	8 neurals
Hidden layers	7 neurals	2 neurals
Output layers	1 neurals	1 neurals
Ralative inportance of Sales amount on 6th day and the following day	0.803761	0.846731

Table 4. Accuracy analysis on the basis of learning data.

	Sales amount in 2nd week	Sales amount in 3rd week
Minimum error	-3,235	-3,983
Maximum error	2,292	3,322
Mean error	-319.206	-371.138
Average mean error	821.618	982.421
Std. deviation	995.696	1,210.095
Linear correlation	0.965	0.938
Frequency	182	182

4.4. *Verification Process*

For cross validation, an accuracy analysis is made by using verification data in Step 4. Figure 5 shows a representative part of the results obtained from the verification process.

Table 2. Correlation coefficient between the sales amounts in the second, third selling week and the number of days on sale.

		Sales amount until 1st day following its release	Sales amount until 2nd day following its release	Sales amount until 3rd day following its release	Sales amount until 4th day following its release	Sales amount until 5th day following its release	Sales amount until 6th day following its release	Sales amount until 7th day following its release	Sales amount on 6th day and the following day	Sales amount between 5th day and 7th day
Sales amount in 2nd week	Pearson's correlation coefficient	.431(**)	.544(**)	.646(**)	.718(**)	.772(**)	.807(**)	.838(**)	.938(**)	.929(**)
	Sig. (2-tailed)	3.72E-11	5.75E-18	8.81E-27	2.16E-35	7.69E-44	1.11E-50	4.46E-58	5.99E-100	1.06E-93
	N	215	215	215	215	215	215	215	215	215
Sales amount in 3rd week	Pearson's correlation coefficient	.320(**)	.427(**)	.534(**)	.611(**)	.665(**)	.700(**)	.734(**)	.853(**)	.840(**)
	Sig. (2-tailed)	3.05E-06	1.83E-10	1.82E-16	3.17E-22	2.28E-27	2.15E-31	1.00E-35	7.08E-59	2.04E-55
	N	204	204	204	204	204	204	204	204	204

**. Correlation is significant at the 0.01 level (2-tailed).

For an example, taking "sweet and sour pork" shown as item No. 62, the sales amount forecasted in the second selling week is 4323, while the actual value is 4381. Afterwards, the value forecasted in 3th selling week is 3291, while the actual value is 3187. The result of accuracy analysis obtained by using verification data indicates that the linear correlation is 0.969 and 0.946. Follow Step 5, the forecasting model generated from the result of the accuracy analysis shows a high precision accuracy, shown as Table 5. The charts in Figure 6 and Figure 7 show the relationship between the demand amount forecasted and the actual data obtained by using learning data and verification data. These figures show that there is a decrease in the number of new products from the launch to the third selling week.

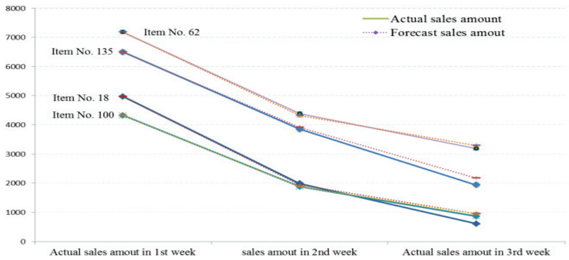
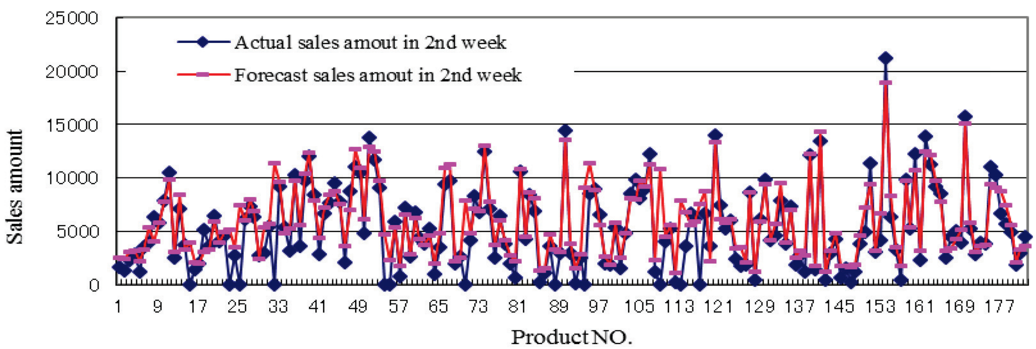


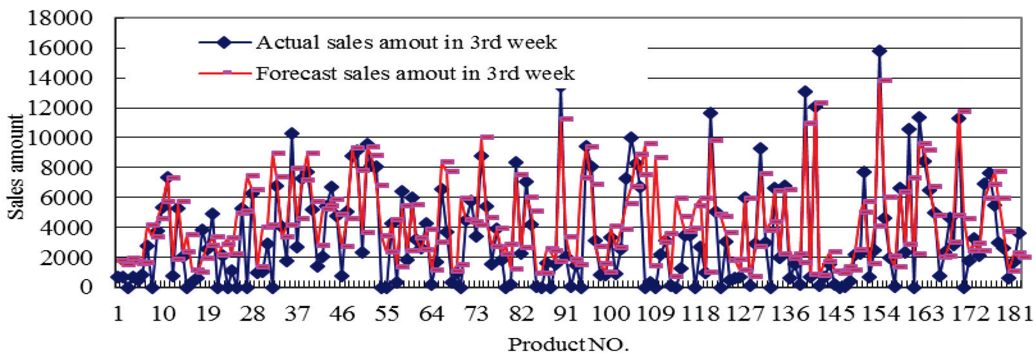
Fig. 5. Forecasting results using verification data.

Table. 5. Accuracy analysis of the verification process.

	Sales amount in 2nd week	Sales amount in 3rd week
Minimum error	−2,767	−2,409
Maximum error	3,635	4,107
Mean error	−133.311	−153.711
Average mean error	1,014.511	1,389.933
Std. deviation	1,320.957	1,735.244
Linear correlation	0.969	0.946
Frequency	46	46

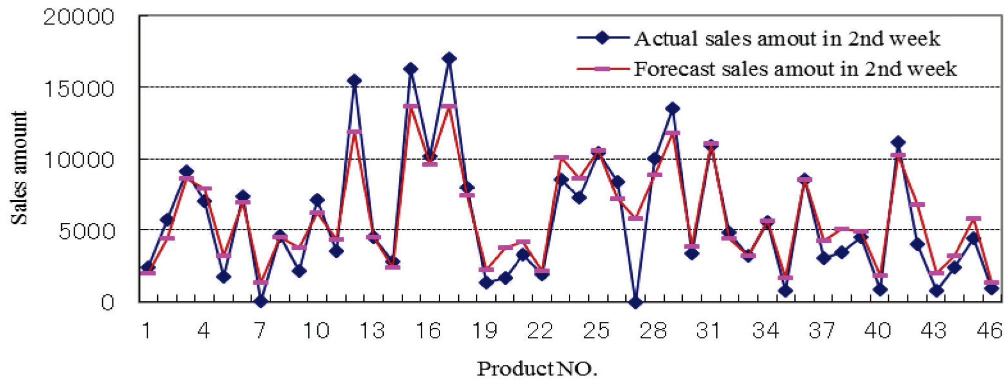


(a) The second selling week.

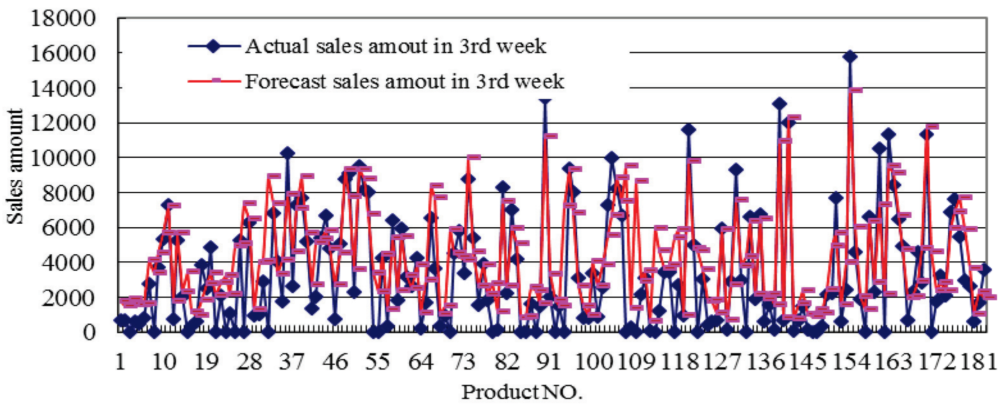


(b) The third selling week.

Fig. 6. Forecasting result using learning data.



(c) The second selling week.



(d) The third selling week.

Fig. 7. Forecasting result using verification data.

4.5. *Extracting the sales association rules*

The CART (Classification And Regression Tree)[17] is one of the most effective decision trees. According to Step 6, the CART is used to extract the sales association rules. The construction of this tree consists of the input nodes and the terminal nodes as shown in Figure 8. The set of rules for all the terminal nodes forms the classification model as shown in Figure 9. With these rules, we can forecast the demand trends of new products for the second selling week that whether the item would be the favorable commodity and which one would be unfavorable. For example, in case of the second selling week, the total number (n) of items to be provided is 182, which accounts for one hundred percent of the total items, and the average forecasted sales amount in the second selling week is 6028.956. Furthermore, according to the rules, the sales amount in the sixth and the seventh days is the most import input variable to forecast the demand trends in the second selling week or later.

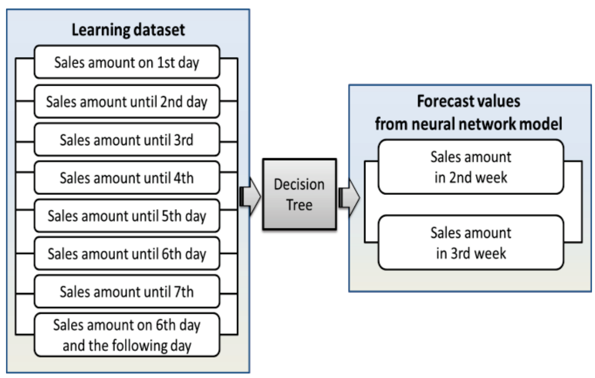


Fig. 8. Construction of decision tree.

For example, if the total demand quantity in the sixth and seventh day is more than 2673, the sales amount forecasted in the second selling week should be 9477.549, which account for 39.011 percent of the total items. Otherwise, it can be seen that when the actual delivery data in the first selling week is used to forecast the demand trends in the second or the third selling week, the floor level of the hot items for the second selling week is much the same with that for the third selling week, and the floor level of the favorable items in the second selling week is almost similar with that of the third selling week.

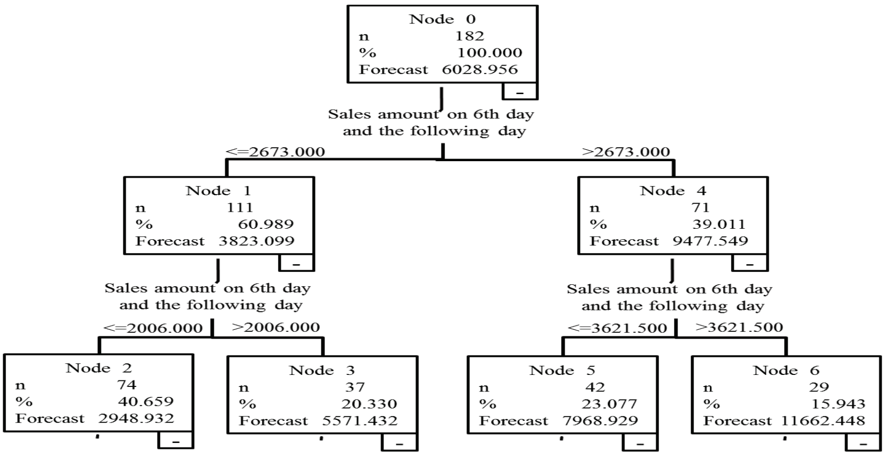
The main sales association rules extracted for the second selling week are:

(i) New product whose sales amount in the sixth and the seventh days totaled over 2673 should continually maintain its "favorable sales condition" in the second selling week.

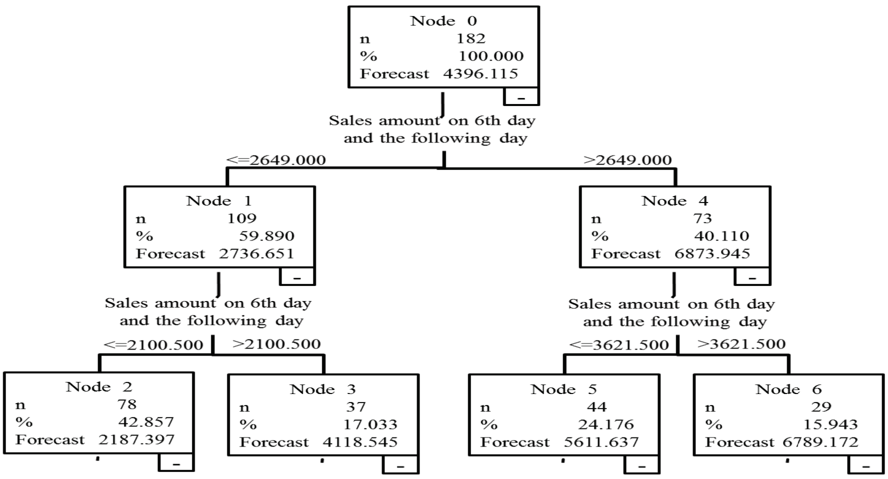
(ii) New product whose sales amount in the sixth and the seventh days totaled over 3621 should continually maintain its "extremely hot sales condition" in the second selling week.

(iii) New product whose sales amount in the sixth and the seventh days totaled below 2673 should keep its "unfavorable sales condition" in the second selling week.

(iv) New product whose sales amount in the sixth and the seventh days totaled below 2006 should keep its "poor sales condition" in the second selling week.



(a) Decision tree for the second week



(b) Decision tree for the third selling week
Fig. 9. Split produced by CART

5. Conclusion

In this study, a procedure making use of data mining techniques is proposed to forecast demand trends of new short life-cycle products. The procedure proposed is applied for an actual food processing enterprise. Based on the actual delivery data of the first selling week, the sales amount and the demand trends in the second and the third selling weeks can be precisely forecasted. Furthermore, the sales association rules are extracted to forecast the demand trends that whether a new product would be favorable or not in the second and the third selling weeks through the sales data of the first selling week.

This study is developed based on the research result[18] of the collaboration project between industry and academia. As a future research, the proposed procedure should be applied to other short life-cycle products to verify its efficacy. I would like to devote myself into research on data mining methodologies for decision making to analyze and understand new customer behaviors.

Acknowledgements

The author wishes to express sincere gratitude to FamilyMart Company, Ltd. and Fast food Nagoya Company, Ltd. for their cooperation in completing this research. This research is supported by Grant-in-Aid for Young Scientists (B) of Japan Society for the Promotion of Science (JSPS) (Grant Number: 23730347).

References

1. J. A. B. Michael and S. L. Gordon, “Data mining techniques: for marketing, sales, and customer relationship management, 2nd edition” (Chapter 4 and 5), (Wiley publishing, Inc., New Jersey, 2004).
2. C. C. Aggarval and P. S. Yu, Finding localized associations in market basket data, *IEEE Transactions on Knowledge and Data Engineering* **14**(2002) 51–62.
3. T. Brijs, G. Swinnen, K. Vanhoof, and G. Wets, Building an association rules framework to improve product assortment decisions, *Data mining and knowledge discovery* **8**(1) (2004) 7-23.
4. N. Jukic, and S. Nestorov, Comprehensive data warehouse exploration with qualified association-rule mining, *Decision Support Systems* **42**(2006) 859–878.
5. A. M. Roger, and L. Blair, The application of discriminant analysis to the prediction of sales forecast uncertainty in new product situations, *Journal of the Operational Research Society* **31**(1) (1980)71-77.
6. W. H. Au, K. C. C. Chan, and X. Yao, A novel evolutionary data mining algorithm with applications to churn prediction, *IEEE Transactions on Evolutionary Computation* **7** (2003) 532–545.
7. S. Manish and S. Jharkharia, ARIMA models to forecast demand in fresh supply chains, *International Journal of Operational Research* **11**(1) (2011) 1-18.
8. M. Dennis, M. Spruit, and P. D. Waal, Improving short-term demand forecasting for short-lifecycle consumer products with data mining techniques, *Decision Analytics* **1**(1) (2014) 1-17.
9. L. Jongsu, C. Lee, and K. S. Lee, Forecasting demand for a newly introduced product using reservation price data and Bayesian updating, *Technological Forecasting and Social Change* **79**(7) (2012) 1280-1291.
10. C. Dennis, D. Marsland, and T. Cockett, Data mining for shopping centrescustomer knowledge management framework, *Journal of Knowledge Management* **5**(2001) 368–374.
11. S. W. Changchien, C. F. Lee, and Y. J. Hsu, On-line personalized sales promotion in electronic commerce, *Expert Systems with Applications* **27**(2004) 35–52.
12. Y. H. Kim, and B. R. Moon, Multicampaign assignment problem, *IEEE Transactions on Knowledge and Data Engineering* **18**(2006) 405–414.
13. C. H. Wu, S. C. Kao, Y. Y. Su, and C. C. Wu, Targeting customers via discovery knowledge for the insurance industry, *Expert Systems with Applications* **29**(2005) 291–299.
14. T. Brijs, G. Swinnen, K. Vanhoof, and G. Wets, Building an association rules framework to improve product assortment decisions, *Data mining and knowledge discovery* **8**(1) (2004) 7-23.
15. N. Jukic, and S. Nestorov, Comprehensive data warehouse exploration with qualified association-rule mining, *Decision Support Systems* **42**(2006) 859–878.
16. T. Stephane, “Data mining and statistics for decision making” (a John Wiley and Sons, Ltd., ISBN: 978-0-470-68829-8, 2011) 217-234.
17. V. Carlo, “Business intelligence: data mining and optimization for decision making” (a John Wiley and Sons, Ltd., ISBN: 978-470-51139-8, 2009) 221-275.
18. Y. LIU, A study on demand forecast for new products of convenience stores in the region of Jurisdiction, Journal of information and management 29(1) (2008) 63-7.