A Study on Type Classification of Employees and Sales Support Analysis Based on Similarity of Sales-purchase Bayesian Network Structure

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***Abstract*—Since services contain human factors of service providers and receivers, the quality and the value of services are essentially difficult to define, especially because of the two service characteristics of 'heterogeneity' and 'simultaneity'. On the other hand, because there are many opportunities to provide services that are suitable for individual customer in job categories where employees directly serve customers, providing services that make use of know-how of individual employees and companies is considered to be important. However, studies which propose the optimal service method in cases featuring heterogeneity and predict its effect are unsatisfactory, despite the fact that heterogeneity of employees and customers is found to exist. The aim of this paper is to propose a sales support analysis method which can suggest reinforcement on which product or service sales is effective, by comparing the sales characteristics of the employee's type and the current state of each employee's sales behavior, and considering employees' sales abilities. We constructed each employee's sales-purchase Bayesian network model based on nationwide sales data, and proposed employees' classification method by their sales style. Then, we calculated the conditional purchase probability of each product by stochastic reasoning, based on the constructed Bayesian network model for each type and individual employees, and proposed a sales support analysis method that enables each employee to focus on products that have not yet improved the purchase probability as recommended products, based on the comparison between the characteristics of each type's purchase probability and that of each employee of that type.**

***Index Terms*—employee classification, heterogeneity, sales-purchase Bayesian network, product recommendation**

I. Introduction

In response to the increase in the share contributed by service areas in the economy, the concept of service science, management, and engineering have been proposed; observing service data using scientific method, management method, and engineering method is required to improve the quality and productivity of real services.

Since service contains human factors of the service providers and receivers, the quality and value of service are difficult to define, especially because of the two service characteristics (Motomura (2011)[1]). The first is 'heterogeneity', which depends both on service providers' ability and the service receivers' circumstance, and causes a different evaluation of the same service by different receivers. The other is the 'simultaneity' of production and consumption, which leads to interactions between employees and customers.

On the other hand, there are many opportunities to provide services that are suitable for individual customers. This is true for jobs such as automobile sales dealers or individual cram school teachers, where employees directly serve customers, unlike the jobs in other service categories. Hence, if it is possible to provide services that make use of know-how of individual employees and companies for improving customers' usage value, it can potentially lead to more purchasing by the customer, which improves company's profits.

In a previous study considering customer heterogeneity in service science, some researchers have proposed recommendation methods for products and services by using stochastic reasoning of Bayesian networks. In a travel plan suggestion service, Huang and Bian (2009)[2] proposed a method of modelling travel preferences for recommending travel attractions, based on Bayesian network, according to customer attributes and personality, customer type based on travel preferences, and motivation against travel.

Ishigaki, Takenaka, and Motomura (2011)[3] analyzed customer lifestyle characteristics, purchased product features, and customer purchasing status, by constructing a consumer behavior model using a Bayesian network with big sales data based on customer behavior and customer questionnaire data.

Ramasubbu, Mithas and Mrishnan (2008)[4], discussing the support service for a software system, divides customers into two types—new and repeat—. Pointing out the importance of managing the interaction between customers and employees, they propose customer satisfaction modelling considering the interaction between the customer types and employees' technical and behavioral skills.

In Floh, Zauner, Koller, and Rusch (2014)[5], customer loyalty is modeled based on a customer questionnaire on service by latent class regression in two different service industries—wireless communication and financial services. They show that there are customer segments with characteristics common to two service

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areas, and the importance of appropriate segmentation in order to target customers, regardless of the service area, is pointed out.

Haraga, Tsubaki, and Suzuki (2014)[6] propose time-series expansion of a system that analyzes the service effect by each customer type from the viewpoint of customer needs, tastes and purchasing behavior, based on data from a customer questionnaire.

On the other hand, as in previous studies aiming at improving the service effect by considering the heterogeneity of employees, in Tsubaki (2016)[7], time-series sales-purchase Bayesian networks are constructed and analyzed according to the abilities of employees.

Furthermore, in Miyamoto and Tsubaki (2016)[8], a sales support method is proposed for employees, by classifying customers on the basis of their values and needs, and employees according to their aptitude and abilities, constructing sales-purchase Bayesian networks linking questionnaire data and sales behavior data for a combination of the type of customer and employee.

Employee's characteristics that affect employee turnover in call centers are analyzed using latent class analysis in Das, Nandialath, and Mohan (2013)[9].

Isobe, Tabuchi, and Tsubaki (2015)[10] examine the different sales style of each employee, by constructing each employee's sales-purchase Bayesian network using customer's questionnaire data surveying the values and communication with employees, etcetera, and the purchasing behavior data of customers handled by each employee. However, it was able to compare sales-purchase Bayesian networks for only five employees of one branch office.

However, studies which propose the optimal service method to analyze heterogeneity and predict its effect are unsatisfactory, despite the existence of heterogeneity of employees and customers in the prevailing environment.

In this research, we propose a sales support analysis method which can show the reinforcement by which product sales is effective, by constructing a sales-purchase Bayesian network model for each employee in company A based on nationwide sales data; classifying them by their sales style; and comparing the sales characteristics of each style and the current state of each employee's sales behavior.

II. Analyzing Data and Stratification by Number of Sales Product Categories

A. Analyzing Data

We analyze big sales data from all 458 branch offices of company A. An overview of the data is given in Table I.

TABLE I. The Overview of the Sales Data of the All Branch Offices

Data	Sales results of company A.
Term	1st, April, 2014 to 31st, March, 2015.
Number of branches	458 (all branches)
Target	16,461 employees who take charge of domestic product sales.
The number of product categories	31 (e.g., Floor wiper, Air filter, etc.)

B. Stratification by Number of Sales Product Categories

In this section, employees are stratified by the number of sales product categories they handle because there are thought to be differences in sales ability depending on the number of product categories that employees are selling.

Based on this stratification, in the next section, we construct sales-purchase Bayesian networks for each employee's sales product categories and classify employees by their Bayesian networks' structure that shows the employee's selling style. In this section, the result of the stratification by number of sales product categories is shown in Tables II and III. Table II gives the distribution of employees by strata and Table III shows the average of number of customers handled, purchase amount per customer visit, employee's age, number of years since the customer first purchased an item, and employee's years of service. Fig. 1 shows the scatterplot matrix.

TABLE II. Number of Employees by each Number of Sales Product Categories

Number of sales product categories	Number of employees	Number of sales product categories	Number of employees
0	0	12	659
1	1669	13	730
2	989	14	743
3	2564	15	844
4	1456	16	813
5	950	17	639
6	706	18	480
7	592	19	232
8	581	20	97
9	584	21	26
10	558	22	2
11	544	23	3
		Total	16461

TABLE III. Average Values by each Number of Sales Product Categories

Number of sales product categories	Average value				
	Number of customers handled	Customer purchase amount per visit (in yen)	Age	Number of years since the customer first purchased	Employee's years of service
1	2.9	2038.3	57.6	8.7	5.8
2	4.4	3162.8	56.4	9.4	6.1
3	6.2	4987.0	55.7	9.2	5.7
4	7.6	4463.0	55.1	9.4	5.8
5	12.5	7042.1	55.3	9.7	6.3
6	17.9	8661.8	54.2	10.9	7.1
7	25.1	10269.4	55.3	11.2	7.2
8	33.7	10865.2	54.0	11.8	7.5
9	38.8	11018.1	53.1	11.9	7.2
10	50.8	11842.8	52.6	11.7	7.2
11	57.8	12226.9	53.2	12.0	6.7
12	65.6	13136.5	52.2	12.0	7.2
13	79.1	13439.2	53.0	12.3	7.3
14	92.0	13923.9	52.4	12.4	7.6
15	107.0	14314.2	53.1	12.1	7.3
16	126.3	14515.4	53.2	12.1	7.4
17	144.2	15077.0	54.4	12.4	7.7
18	157.7	15798.7	54.3	12.8	8.3
19	170.9	15407.9	55.6	12.5	7.3
20	196.2	17284.4	56.1	12.6	7.8
21	188.4	16720.9	58.9	14.0	8.5

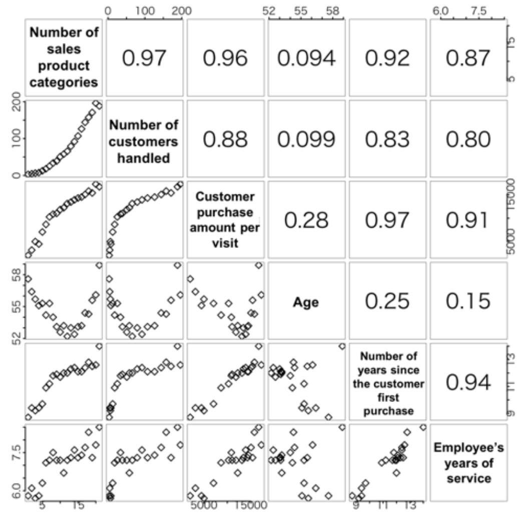


Figure 1. Scatter plot matrix of sales and purchasing features.

According to Table II, there are many employees with 5 or fewer sales product categories, whereas employees with more than 19 product categories of sales products are very few. Therefore, considering the characteristics of employees with each number of sales products categories, as shown in TABLE III, the number of sales products categories may be positively correlated with the number of customers handled, purchase amount per customer visit, customer contracted years, and employee's years of service, as shown in Fig 1. It is seen that while the number of product categories sold is small when the employee has fewer years of service, the average value of total product categories sold, the number of customers handled, and the customer purchase amount per visit increase with the increase in employee tenure.

III. Type Classification and Comparison of Employee's Sales-purchase Bayesian Network Structure

A. *Type Classification Based on each Employee's Sales-purchase Bayesian Network on each Number of Sales Product Categories*

de Jongh and Druzdzel (2009)[11] analyzed the similarity of Bayesian networks, which is one of the stochastic graphical models, and validated the qualitative evaluation method of model similarity by comparing the existence and direction of edges appearing in the network structure.

In this section, sales-purchase Bayesian networks are constructed for each employee (see employee A's model shown in Fig. 3 (a) as an example), stratified according to the number of sales product categories handled, and the employees are classified into types by the similarity of their Bayesian network structure.

Let $\boldsymbol{X} = \{X_i | i = 1, \dots, p\}$ be the set of nodes in a Bayesian network model M. Bayesian networks with many common edges are considered to be similar. To compare the consistency of Bayesian network models, define $E_{i,j}^{M}$, the directed edge of model M from node X_i to node X_j, in formula (1).

$$E_{i,j}^{M} = \begin{cases} 1 & (X_i \ to \ X_j \ edge \ exists.) \\ 0 & (X_i \ to \ X_j \ edge \ does \ not \ exist.) \end{cases} \qquad (1)$$

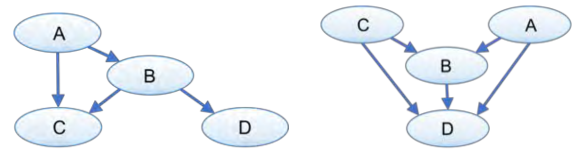
Using $E_{i,j}^{M}$, the structure of Bayesian network model M can be described as $p(p\text{-}1)$ dimensions row vector (formula(2)). Since Bayesian network is a directed graphical model, the vector has both $E_{i,j}^{M}$ and $E_{j,i}^{M}$; then, if model M_1 and M_2 have the same edge between X_i and X_j, either $E_{i,j}^{M_1} = E_{i,j}^{M_2} = 1$ $(E_{j,i}^{M_1} = E_{j,i}^{M_2} = 0)$ or $E_{j,i}^{M_1} = E_{j,i}^{M_2} = 1 (E_{i,j}^{M_1} = E_{i,j}^{M_2} = 0)$ is true and the vector coincides on the part.

$$S_M = \left[E_{1,2}^{M}\ E_{1,3}^{M} \dots E_{1,p}^{M}\ E_{2,1}^{M} \dots E_{p\text{-}2,p}^{M}\ E_{p\text{-}1,p}^{M}\right] \qquad (2)$$

Let $d(M_1, M_2)$ be squared Euclidean distance between model M_1 and M_2, defined in formula (3).

$$d(M_1, M_2) = \left(\sqrt{\sum_{i \neq j}\left(E_{i,j}^{M_1}\text{-}E_{i,j}^{M_2}\right)^2}\right)^2 = \sum_{i \neq j}\left(E_{i,j}^{M_1}\text{-}E_{i,j}^{M_2}\right)^2 \qquad (3)$$

After constructing the sales Bayesian networks for each employee, we classify the employees' sales-purchase Bayesian networks using clustering analysis with Ward method, based on the distance (formula (3)).



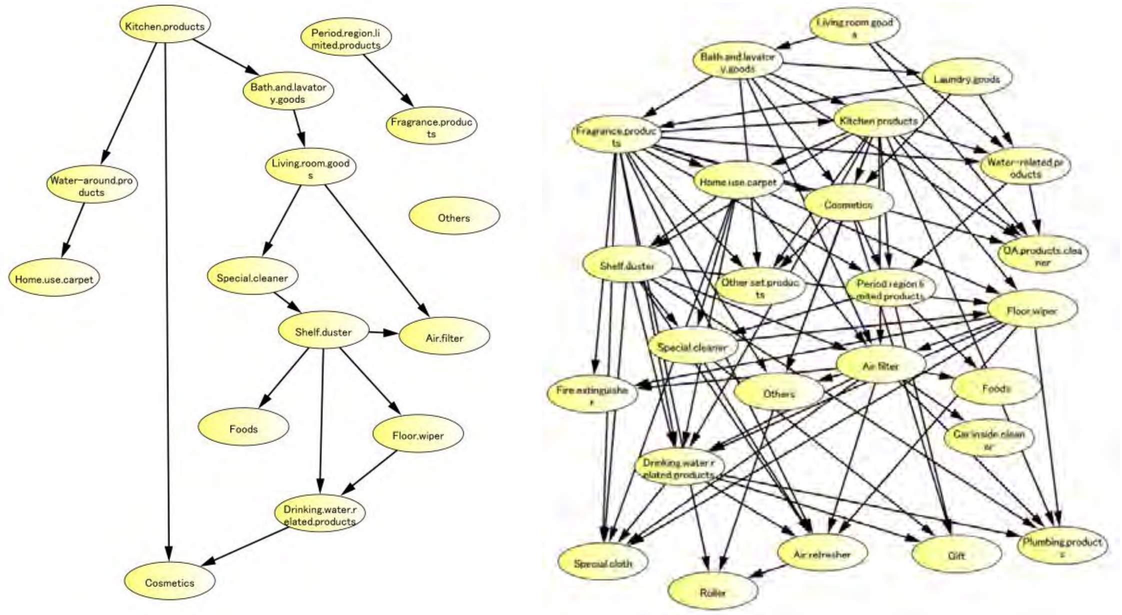
(a) Bayesian network model M_1. (b) Bayesian network model M_2.

Figure 2. Similarity of Bayesian networks' structure.

Considering the models M_1 and M_2 shown in Fig 2, the representation vectors of the network structure $S_M = [E_{A,B}\ E_{A,C}\ E_{A,D}\ E_{B,A}\ E_{B,C}\ E_{B,D}\ E_{C,A}\ E_{C,B}\ E_{C,D}\ E_{D,A}\ E_{D,B}\ E_{D,C}]$ are $S_{M_1} = [1\ 1\ 0\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0]$ for model M_1 and $S_{M_2} = [1\ 0\ 1\ 0\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0]$, for model M_2, respectively.

In this paper, we show the results of the analysis for the employees who handle 15 sales product categories. After that, the characteristics of the different number of product categories are compared in section III.B. For employee's sales-purchase Bayesian network structures for the different number of sales product categories handled, we show the result of clustering with Ward's method, and calculate the existence rate of each edge. We examine the characteristics of each type, considering the edges that indicate an existence ratio over 20%, 40 %, and 60%, colored in yellow, orange, and red, respectively. Table IV shows the existence rate of each specific edge for each type in the case of the 15 sales product categories.

Fig. 3 (a) shows the sales-purchase Bayesian network models of employee A who belongs to the type 1 and Fig. 3 (b) shows the sales-purchase Bayesian network model of type 1.



(a)Employee A's model. (b)Type 1's model.

Figure 3. Sales-purchase Bayesian network model of 15 sales product categories employees.

TABLE IV. EXISTENCE RATE OF EACH EDGE (15 SALES PRODUCT TYPES)

	Edge							
from	Air filter	Air filter	Floor wiper	Floor wiper	Floor wiper	Floor wiper	Floor wiper	Water-related products
to	Shelf duster	Floor wiper	Drinking water related products	Air filter	Special cleaner	Shelf duster	Carpet	Living room goods
Type1 (N=216)	38.43%	25.93%	29.63%	29.63%	84.26%	64.35%	22.22%	17.59%
Type2 (N=164)	12.80%	88.41%	22.56%	1.83%	79.27%	1.22%	10.98%	26.83%
Type3 (N=183)	18.03%	19.13%	21.86%	27.32%	16.94%	29.51%	13.66%	20.22%
Type4 (N=173)	15.61%	69.94%	1.73%	10.98%	84.39%	6.94%	18.50%	21.39%
Type5 (N=108)	14.81%	69.44%	17.59%	2.78%	24.07%	3.70%	19.44%	13.89%

	Edge							
from	Water-related products	Special cleaner	Special cleaner	Drinking water related products	Drinking water related products	Kitchen products	Kitchen products	Kitchen products
to	Bath and lavatory goods	Shelf duster	Floor wiper	Shelf duster	Floor wiper	Air filter	Period- or region-limited products	Fragrance products
Type1 (N=216)	14.81%	12.04%	4.63%	30.56%	23.15%	13.89%	22.22%	11.57%
Type2 (N=164)	27.44%	4.88%	3.05%	8.54%	34.15%	18.29%	13.41%	25.00%
Type3 (N=183)	11.48%	27.87%	44.26%	9.84%	18.03%	14.75%	17.49%	14.21%
Type4 (N=173)	18.50%	4.62%	3.47%	21.39%	82.08%	9.83%	24.86%	17.34%
Type5 (N=108)	6.48%	12.96%	12.04%	7.41%	29.63%	24.07%	16.67%	16.67%

	Edge								
from	Kitchen products	Kitchen products	Shelf duster	Shelf duster	Shelf duster	Shelf duster	Bath and lavatory goods	Bath and lavatory goods	Living room goods
to	Living room goods	Bath and lavatory goods	Drinking water-related products	Special cleaner	Bath and lavatory goods	Floor wiper	Kitchen products	Living room goods	Kitchen products
Type1 (N=216)	20.83%	29.63%	12.50%	51.85%	6.02%	8.33%	17.13%	15.28%	12.96%
Type2 (N=164)	20.73%	17.68%	27.44%	54.27%	8.54%	86.59%	21.34%	6.71%	9.76%
Type3 (N=183)	10.93%	26.23%	10.93%	29.51%	7.65%	20.77%	16.94%	14.21%	10.38%
Type4 (N=173)	23.12%	34.10%	6.36%	64.74%	6.94%	68.21%	13.29%	15.03%	16.18%
Type5 (N=108)	12.96%	48.15%	7.41%	39.81%	20.37%	74.07%	5.56%	24.07%	20.37%

TABLE V. CONSIDERATION OF SALES BASED ON EXISTENCE RATE (15 SALES PRODUCT CATEGORIES)

Sales structure type	Features
Type 1	This type has the feature that the employees sell Shelf duster, Special cleaner and Carpet relating with Floor wiper, besides Special cleaner with Shelf duster, since the edges from Floor wiper to Special cleaner, Shelf duster and Carpet indicate high existence rate. The edge from Shelf duster to Special cleaner indicates relatively high rate. The employees also sell Air filter and Drinking water-related products, and Kitchen products relating with Period- or region-limited products, Fragrance products, Living room goods, and Bath and lavatory goods.
Type 2	This type has the feature that the employees sell Floor wiper, Special cleaner and Drinking water-related products relating with Air filter and Shelf duster, Living room goods and Bath and lavatory goods relating with Water-related products, and Fragrance products relating with Kitchen products, since the edges from Air filter and Shelf duster to Floor wiper, and Floor wiper and Shelf duster to Special cleaner indicate high existence rate. The edges from Drinking water-related products to Living room goods and Bath and lavatory goods, and the edges from Kitchen products to Fragrance products and Living room goods indicate a moderate existence rate.
Type 3	This type has no particular feature in terms of purchase combination since there are no edges with an existence rate indicates of over 60%; however, the edge from Special cleaner to Floor wiper indicate moderate value.
Type 4	This type has the feature that the employees sell Floor wiper relating with Shelf duster, Air filter and Drinking water-related products, and Special cleaner relating with Shelf duster, since the edges from Shelf duster to Floor wiper and Special cleaner, from Air filter and Drinking water-related products to Floor wiper, and from Shelf duster to Floor wiper indicate a high existence rate. The employees also sell Period- or region-limited products, Living room goods and Bath and lavatory goods relating with Kitchen products, and Living room goods relating with Water-related products.
Type 5	This type has the feature that the employees sell Floor wiper and Special cleaner relating with Air filter and Shelf duster, and sell the combination of Kitchen products, Bath and lavatory goods and Living room goods since the edges from Air filter and Shelf duster to Floor wiper, and also to Special cleaner, indicate high existence rate. The edges from Air filter, Bath and lavatory goods and from Bath and lavatory goods to Living room good, and from Living room goods to Kitchen products also indicate a relatively high existence rate.

B. *Type Comparison Among Each Number of Sales Product Categories*

We examine the sales features of purchasing product categories as the number of sales product categories increases in order to compare the derived type features in III.A, for not only those who handle 10 and 15 product categories, but the entire range of sales product categories, by summarizing the derived type features in Table VI.

From Table VI, we see that the types that have employees selling products relating with Floor wiper exist in many number of sales product categories of employees. Additionally, since the types that employees sell relating with Shelf duster, Special cleaner, Air filter, Drinking water-related products, Kitchen products, Carpet, Period- or region-limited products and Bath and lavatory goods are derived according to increase of the number of sales product categories, it is found that suggesting a sales plan involving these products after considering employees' present number of sales product categories will help in a further increase in customers' purchasing.

IV. PROPOSAL OF RECOMMENDED PRODUCTS BY COMPARING BAYESIAN NETWORK STOCHASTIC REASONING RESULT BETWEEN EACH EMPLOYEE AND SALES STRUCTURE TYPE

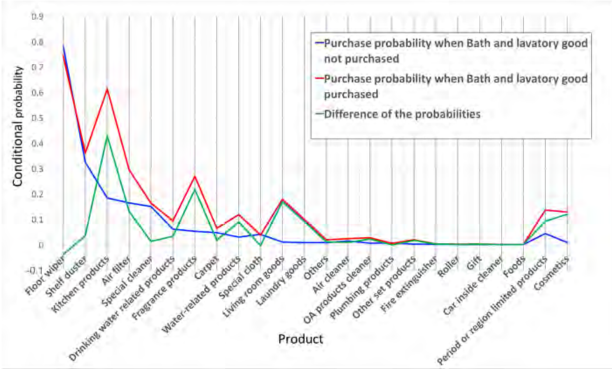
In section II, employees are stratified according to the number of sales product categories, and in section III, type classification is performed for each number of sales product categories, and features of each type and the differences between each different number of sales product categories are shown. In this chapter, by comparing the result of purchasing stochastic reasoning of the sales structure type classified in section II with the results of purchasing stochastic reasoning of each employee belonging to the sales structure type, we propose and examine a sales support method concerning which product should be on sale for employees to generate further sales.

In this study, we focus on the difference between the current sales style of each employee and the sales style of the sales structure type to which the employee belongs, as a method of proposing the products that need to be sold. We hypothesise that an employee's new sales action plan, based on the features of the type to which the employee belongs, may improve the purchasing probabilities of products that the employee has not enough been able to sell till now. The employee would also be able to push a set of recommended products, which have recommendation priority assigned to them.

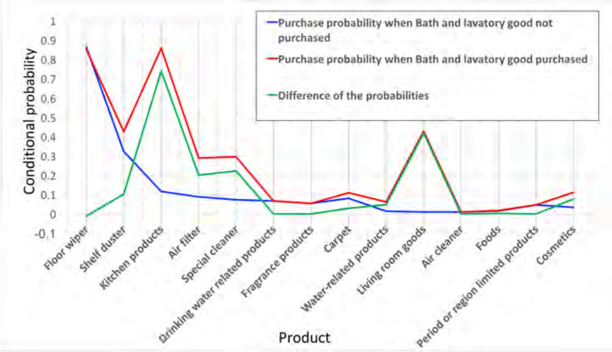
In the sales-purchase Bayesian network model of the type 1 of 15 sales product categories (Fig. 3 (b)), it is shown that Bath and lavatory goods are conditionally dependent on many products since the node has many child nodes. Therefore, considering all the employees in type 1 of 15 sales product categories and taking one of them, employee A, as an example, the conditional purchasing probability of other products conditioned by non-purchase of Bath and lavatory goods is represented by the blue line; the conditional purchasing probability of other products conditioned by purchase of Bath and lavatory goods is represented by red line; and the green line represents the difference of two conditional probabilities. Each probability value of type 1 and employee A is also shown in Fig. 4 (a) and Fig. 4 (b), respectively.

TABLE VI. TYPE FEATURES FOR DIFFERENT NUMBER OF TOTAL SALES PRODUCT CATEGORIES

	Sales related products													
	Floor wiper	Shelf duster	Kitchen products	Drinking water related products	Air filter	Special cleaner	Carpet	Period or region limited products	Bath and lavatory goods	Fragrance products	Water-around products	Living room goods	Cosmetics	Laundry goods
2 product categories	Type2 Type3													
3 product categories	Type1 Type3	Type4												
4 product categories	Type1 Type3 Type4				Type4	Type3 Type4								
5 product categories	Type1 Type2 Type3 Type4 Type5	Type3 Type4 Type5				Type4 Type5								
6 product categories	Type1 Type2 Type5	Type1 Type2 Type3 Type4 Type5		Type2	Type4 Type5	Type2 Type5								
7 product categories	Type1 Type2 Type3 Type5	Type1 Type4 Type5	Type1	Type4	Type1 Type4 Type5	Type2 Type4								
8 product categories	Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type2	Type3	Type1 Type2 Type3									
9 product categories	Type1 Type2 Type4 Type6	Type1 Type3 Type4 Type5	Type2 Type4	Type3 Type5	Type1 Type3 Type6									
10 product categories	Type3 Type4 Type5 Type6	Type1 Type3 Type4 Type5 Type6	Type4 Type6	Type3	Type1 Type3 Type5 Type6	Type2 Type4 Type6	Type3 Type4	Type4						
11 product categories	Type1 Type2 Type3 Type4	Type1 Type2 Type4	Type1 Type3 Type4	Type2 Type4	Type1 Type3 Type4				Type3					
12 product categories	Type2 Type3	Type1 Type2 Type3	Type2 Type3	Type1 Type3	Type1 Type2 Type3				Type1					
13 product categories	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type3	Type1 Type2 Type4	Type1 Type4	Type2 Type3 Type4			Type1 Type4					
14 product categories	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type2 Type4 Type5	Type2 Type3 Type4 Type5	Type1 Type3			Type1 Type2	Type4	Type1 Type4			
15 product categories	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type4 Type5	Type1 Type2 Type4 Type5	Type3			Type2 Type4		Type2 Type3 Type4	Type4		
16 product categories	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type4	Type1 Type2 Type4	Type1 Type3			Type4		Type1			
17 product categories	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type2 Type3 Type4	Type4	Type2		Type1 Type2 Type3		Type1 Type2 Type3 Type4	Type4		
18 product categories	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type1 Type2 Type3 Type4 Type5	Type1 Type2	Type4		Type1 Type3 Type4 Type5	Type1 Type5	Type1 Type2 Type3 Type4 Type5			
19 product categories	Type1 Type2	Type1 Type2	Type1 Type2	Type1 Type2	Type1 Type2	Type1 Type2	Type1		Type1 Type2		Type1 Type2	Type2		
20 product categories	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type2 Type3 Type4	Type1 Type3 Type4	Type3 Type4	Type1 Type4	Type1 Type2 Type3 Type4	Type1 Type3 Type4	Type2 Type3 Type4	Type1 Type3 Type4	Type1 Type3 Type4	Type3 Type4



(a)Sales structure type 1.



(b)Employee A.

Figure 4. Conditional purchase probabilities of other products on condition of Bath and lavatory goods (sales structure type 1 and employee A).

First, from the entire tendency of the sales structure type 1, to which employee A belongs, when Bath and lavatory goods are purchased, the conditional probability of Kitchen products, Fragrance products, Living room goods, Cosmetics and Period- or region-limited products increase about 42.9％, 21.7％, 16.9％, 12.0％, and 9.2％, respectively, compared with the conditional probability when Bath and lavatory goods are not purchased.

On the other hand, in the sales-purchase Bayesian network model of employee A, the conditional probability of purchasing Kitchen products conditioning purchasing Bath and lavatory goods is about 74.1% higher than the conditional probability when not purchasing Bath and lavatory goods. In addition, the conditional probabilities of Living room goods, Special cleaner, and Air filter also improved by about 41.8%, 22.2% and 20.1%, respectively. Therefore, it is considered that employee A is selling these products relating to Bath and lavatory goods.

However, although employee A is in charge of selling Fragrance products, Cosmetics, and Period- or region-limited products, it can be seen from Fig. 4 (b) that employee A could not have sold them in association with Bath and lavatory goods. Then, since the employee of type 1, to which employee A belongs, tend to sell these products relating with Bath and lavatory goods, it is suggested to employee A that he or she should recommend these products when Bath and lavatory goods are purchased.

In this section, we explained the suggestion of recommended products should be sold, taking as an example the assumption of buying Bath and lavatory goods. In the proposed sales support analysis method, we also calculate probabilities for other products and then suggest the recommended products, along with a list of customers corresponding to them.

V. CONCLUSION

In this study, we constructed sales-purchase Bayesian network models with each employee's sales result data in all branch offices of company A, and proposed a type classification method and sales support analysis method by comparing sales types features and each employee's present status, which suggests the product which is effective for selling to a particular customer.

In section II, we stratified the employees according to the number of sales product categories and the features were examined. It is shown that employees have differences in their sales ability depending on the number of sale product categories they handle.

In section III, we proposed and examined a method of classifying employees based on the similarity of the sales-purchase Bayesian network structure for each employee. We then performed type classification according to the number of sales product categories and compared characteristics of types to examine the sales behavior for each number of sales product categories. In addition, by comparing the features of the sales structure types due to the difference in the number of sales product categories, it was found that as the number of the categories increased, trends about the kind of products sold together could be discerned.

In section IV, taking as an example the features of the type 1 and one employee of the type, we calculated the conditional purchase probability of each product based on the constructed Bayesian network model. Then we proposed a sales support analysis method that enables each employee to focus on products with low purchase probability, as recommended products after the comparison between the characteristics of the type, the purchase probability, and each individual employee's purchase probability.

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