Pattern Classification of Value Creative Consensus Building Process in Case of Multiple-choice

Yuri HAMADA*, Tatsuya MARUYAMA** and Hiroko SHOJI*

* Chuo University, 1-13-27 Kasuga, Bunkyo-ku, Tokyo 112-8551, Japan
** Graduate School of Chuo University, 1-13-27 Kasuga, Bunkyo-ku, Tokyo 112-8551, Japan

Abstract: The authors have been conducting research on value-creating communication. It is a process where people embody and clarify their own values and form new values through communication. The authors have observed and modeled consensus building process that has few choice as an example of value-creating communication. Next, the authors observed and modeled consensus building process in case of multiple-choices and compared the process based on quantity of choices. The authors have observed one group that they created the conception through communication and one group that they reached the consensus in terms of a viewpoint. Then, in this paper, the authors classified consensus building process into patterns from two viewpoints. Moreover, the authors classified six cases in case of multiple-choice into patterns and discuss the characteristics. As a result, it was suggested that the time to reach agreement varies depending on the pattern.

Keywords: Consensus building, Communication, Bayesian network

1. INTRODUCTION

The authors have been conducting research on value-creating communication. We refer to the case where people embody and clarify their own values and form new values through communication as “value-creating communication”. Value created by value-creating communication refers to the internal value formed within the mind of each individual, not specific objects or services. The importance of value-creating communication has been stated. Fuji pointed out the limit of determining a solution rationally using an optimization method in consensus building because each individual’s preference is not consistent enough [1]. Kuwako argued the importance of Kansei communication in consensus building through observation of field communication [2]. Kuwako stated not only the opinions of participants but also the history of reasons for opinions are important. As described above, participants do not make solutions rationally in consensus building, but they share each opinions and history of it and make a solution that each person can convince each other through value-creating communication. However, there was no study that analyze value creative consensus building process in detail and evaluate it quantitatively.

Therefore, we proposed a method to model value creative communication processes using quantitative methods [4]. The authors observed and analyzed consensus building processes in the case that has few options [3, 4]. We also analyzed the consensus building process in case of multiple-choice and compared it with case that has few choices [5, 6]. In this paper, we classify the consensus building processes into patterns. Furthermore, we classify six cases in case of multiple-choice into pattern and discuss the characteristics. It is possible to expect a proposal of support method for various agreement formation patterns by classifying the consensus building process.

2. RELATED STUDIES

There is an abundance of extant research on consensus building. When people make decisions, especially at business sites, it is generally thought that rational choices will be made.

There is a voting theory as one methodology of consensus building. Researchers have discussed various ways of voting. In the old days, researches on models of candidate choice in political issues have also been conducted [7, 8].

A hierarchical analysis method (AHP) proposed by T. L. Saaty is often used as a method to reasonably determine a solution. AHP inputs the importance of the evaluation criteria and calculates from the answers, thereby making decision support [9]. Many researchers apply AHP to group as group decision support [10, 11]. Some studies try to promote consensus building by visualizing consensus building process. Ono et al. and colleagues are conducting research aimed at realizing a system that visualizes and organizes the process of discussion assuming policy decision [12].

In this way, many researches on consensus building seek to rationally determine solutions by visualizing
mathematical methods and processes, focusing on efficient consensus building. However, human decision making is very ambiguous and it cannot be said that it is necessarily rationally selected. This also points out Fujii [1]. Fujii points out the limit of optimization method in consensus building. Optimization is to reasonably determine the solution so that the degree of satisfaction of people is high as average. Fujii cited as not having enough consistency for each person’s preference as its problem. Representative research on inconsistency of preference is an empirical study related to “framing effect” [13]. Framing effect is a phenomenon that decision making is totally different depending on expression and situation even with the same option. Kuwako [2] is conducting field communication observations on social consensus formation. In consensus building, not only the opinions of participants but also the history of reasons for opinions are important. And it is important that setting of the place considering the sensitivity of participants. In view of the above, it is considered that participants do not decide solutions reasonably in consensus building, but they share their opinions and their history by communicating, while deriving a solution that each person can convince. As stated above, it is thought that participants do not rationally decide solutions, they create solutions that is convinced by each other while sharing their opinions and their history. In this way, although the importance of the value creative consensus building process was pointed out and have observed, there was no research to quantitatively evaluate it. Therefore, the authors proposed a method for modeling value creative consensus building process using mathematical method [3].

Here we briefly introduce the previous research on the observation and analysis of the consensus building process that we conducted. For details, see [3-6]. First, the authors observed and analyzed the consensus building process for the case that has few choices. As a result, members who had a negative impression on the decided candidate were given a new viewpoint and changed the preference by sharing the concept: good for everyone. Therefore, in order to show the structure of the process before and after the appearance of the conception, we modeled the consensus building process using Bayesian network. As a result of analysis using the constructed model, we clearly showed the transition of the members’ consciousness. Next, we observed and analyzed the consensus building process in case of multiple-choices [5,6]. In our previous research, we introduced a case that participants created conception and formed a consensus well in case of multiple-choice. Moreover, we compared the structure with case that has a few choices [5]. Next, the authors analyzed a case that participants did not created a conception in case of multiple-choice, and compared it with case that participants created the conception [6]. In this paper, we introduce analysis two cases in multiple-choice in detail. Furthermore, we classify consensus building process into patterns and classify six cases into the patterns.

3. OBSERVATION

3.1 Observation Method

In this study, the theme of discussion is “going to a training camp to get a driving license in summer” and determine a site of training camp where all the member stay. The Subjects were five college students belonging to the same laboratory and made discussion in six laboratories. There are thirty-five choices, and a table that is created by referring to brochures. A table has such as location information, features or selling points of the site of training camp. We surveyed personal preferences by preliminary questionnaire. The scene of the discussion was recorded with a video camera, and the analysis target is the text data that the voice data was converted into.

3.2 Case Study

In this paper, we briefly introduce the flow of the consensus building for two groups. As a result of group A’s preliminary questionnaire, the preferences of the five members were different. In group A, members gave a candidate which each of them thought best, and shared it with reasons. In the process of comparing of choices, they narrowed choices according to viewpoints of “wireless LAN” and “to limit the expense to 230,000 yen”. Further, they created the conception of “to have quality free time” and decided the school that has places to play and convenience stores, hot springs nearby according to the conception. This group was finally decided as a different school from the school that five members thought the best at first. This group took 35 minutes and 10 second to reach agreement.

As a result of group A’s preliminary questionnaire, the preferences of the five members were also different. In group B, members gave a candidate which each of them thought best, and stated features of candidate. In the process of discussion, all the members reached consensus to put emphasis on viewpoint of “low cost” and three candidates was narrowed. They eventually decided the school that matched viewpoints of “wireless LAN” and “a lot of surrounding facilities”. Finally, this group was also decided as a different school from the school that five members thought the best at first. This group took 16 minutes and 20 second to reach agreement.
4. ANALYSIS BY BAYESIAN NETWORK

4.1 Bayesian network

The Bayesian network features the ability to predict the likelihood and possibility of the occurrence of an uncertain event by representing the causal structure as a network and then performing probabilistic reasoning [14]. The Bayesian network is a network-like probabilistic model defined by three variables: random variable, conditional dependency between random variables, and conditional probability. According to Motomura [14], the Bayesian network uses random variables as nodes and represents dependency relationships between variables as effective links. For example, the conditional dependency between random variables \( X_i, X_j \) is denoted by \( X_i \rightarrow X_j \), and the node in front of the arrow (\( X_i \) in this case) is called a child node, and the node after the arrow (\( X_j \) in this case) is called the parent node. When there are multiple parent nodes, let \( P_r(X) \) be a set of parent nodes of child node \( X \). The dependence between \( X \) and \( P_r(X) \) is quantitatively represented by the following conditional probability.

\[
P(X | P_r(X))
\]

Furthermore, considering each of the individual random variables as child nodes in the same way, the joint probability distribution of all the random variables is represented by the following equation.

\[
P(X_1, \ldots, X_n) = P(X_1 | P_1(X_1)) \cdot P(X_2 | P_2(X_2)) \cdots P(X_n | P_n(X_n))
\]

A probabilistic dependency between these variables can be modeled by a Bayesian network constructed by linking each child node and its parent node. The probability distribution of all variables is obtained by calculating the previous joint probability distribution.

In this study, we use BayoLink [15] to construct a Bayesian network. BayoLink is a Bayesian network construction support system implemented by Java developed by Motomura et al. [16-18]. In this study, “Reason” for “Choice” is a factor, while “Evaluation” is the result. We make a Bayesian network analysis by representing the remarks in the consensus building process as a causal structure.

4.2 Classification method of remarks

In order to classify the “Reason” into several nodes, we use the KJ method. As a result, it could be classified into nine categories: “Conception”, “Cost”, “Place”, “Meal”, “Life”, “Entertainment”, “Sports”, “Tourism/Nature” and “Others.” Table 1 shows the classification method. Therefore, a network was constructed using “Conception”, “Cost”, “Place”, “Meal”, “Life”, “Entertainment”, “Sports”, “Tourism/Nature”, “Others”, “Choice”, “Evaluation” as nodes (Figure 1). The state of “—Reason”— is “A” if it is described for each item, and “None” if not described. The state of “Choice” is the school’s number that has a range from 1 to 35. “Evaluation” status is “Positive” or “Negative”. One sentence is one remark and the item of “Reason” necessarily selects “A” or “None”. However, since BayoLink has a function to complement missing values using a neural network [15], “Choice” and “Evaluation” do not necessarily need to select a state and there may be a blank. A part of the data used for the analysis is shown in Table 2. The first line represents nodes of model. For example, the number 1 in Table 2 is a classification of remarks that “⑫ is expensive.”, “Choice” is “⑫”, “Evaluation” is “Negative”, “Cost” is “A”, and the other nodes are “None”.

| Table 1: Classification method of remarks |
|------------------------------------------|
| Class | Remarks including intention, grounds |
|------|-------------------------------------|
| Cost | Remarks on expenses of a driving school, usage fee of surrounding facilities |
| Place | Remarks on place of a driving school |
| Meal | Remarks on meal of a driving school |
| Life | Remarks on life such as hot spring, wireless LAN etc. |
| Entertainment | Remarks on entertainment such as movie theater, Karaoke etc. |
| Sports | Remarks on sports such as tennis, football, bouldering etc. |
| Tourism/Nature | Remarks on tourism or nature such as castle, botanical garden, sea etc. |
| Others | Remarks on others such as a pickup bus, hospital etc. |

![Bayesian network model diagram]

**Figure 1**: Bayesian network model

| Table 2: Data used for analysis |
|-------------------------------|
| No. | Choice | Evaluation | Conception | Cost | Place | Meal | Life | Entertainment | Sports | Tourism/Nature | Others |
|-----|--------|------------|------------|------|------|------|------|---------------|-------|----------------|--------|
| 1   | 12     | Negative   | None       | A    | None | None | None | None          | None  | None           | None   |
| 2   |        | None       | None       | A    | None | None | None | None          | None  | None           | None   |
| 3   |        | None       | None       | A    | None | None | None | None          | None  | None           | None   |
| 4   | 5      | Positive   | None       | A    | None | None | None | None          | None  | None           | None   |
| 5   | 5      | None       | None       | None | A    | None | None | None          | None  | None           | None   |
| 6   | 5      | None       | None       | None | A    | None | None | None          | None  | None           | None   |
4.3 Sensitivity analysis

Sensitivity analysis was performed using the constructed Bayesian network model. Sensitivity analysis is a method of quantitatively calculating the influence of each factor in a model where an event is generated from a plurality of factors. BayoLink has a sensitivity analysis tool, which can infer with the specified explanatory variable and search for explanatory variables with a large influence on the objective variable. Therefore, we clarify by sensitivity analysis the “Reason” that greatly influences when “Evaluation” of “Choice”.

We made an analysis with “Evaluation” as an objective variable and “Conception”, “Cost”, “Place”, “Meal”, “Life”, “Entertainment”, “Sports”, “Tourism/Nature” and “Others” as explanatory variables. In the sensitivity analysis, we made several pairs of values from explanatory variables and input them into the model to infer.

Here, it is possible to specify the upper limit of the number of input values to the model, but in this study the maximum number of combinations is set to 2. This is because “Conception” does not appear alone but often appears together with other items.

In Chapter 2, it stated that group A created the conception by other member’s remark that “we want to have quality free time.” It also stated that group B reach consensus in terms of the view point that “low cost” by other member’s remark that “the school where the cost is cheap is good.” Therefore, we analyze separately for the first half and the second half of these remarks.

The results of the sensitivity analysis in group A are shown in Tables 3 and 4. “Probability value” in Tables 3-6 denotes the probability value (posterior probability) of the objective variable under the condition that the value of the explanatory variable is input. This indicates the probability of “Evaluation” becoming “Positive” when a value of a specific explanatory variable is input. “Difference in probability” denotes the difference between the prior and posterior probabilities for the objective variable. “Lift value” represents the ratio of the probability (certain posterior probability) of occurrence of a certain state when observation is input and the probability (prior probability) of occurrence of that condition irrespective of the condition.

That is, the higher the lift value, the greater the influence of the selected “Reason” set on “Evaluation”. In addition, the prior probability value of group A at which the evaluation of the first half becomes positive (Table 3) is 0.731, negative (Table 4) is 0.339, at which the evaluation of the second half becomes positive (Table 5) is 0.485, negative (Table 6) is 0.284. The prior probability value of group B at which the evaluation of the first half becomes positive (Table 7) is 0.730, negative (Table 8) is 0.339, at which the evaluation of the second half becomes positive (Table 9) is 0.716, negative (Table 10) is 0.516.

In group A, Table 3 and Table 4 shows that they emphasize “Place” in terms of positive viewpoint and “Cost” in terms of negative viewpoint in the first half. However, Table 5 shows they emphasize “Life” and “Sports” in the second half in terms of positive viewpoint. In addition, Table 6 shows that they emphasize “Entertainment” in terms of negative viewpoint and there is also the combination of “Conception” and “Entertainment.” This result indicates

| Table 3: Sensitivity analysis result (Group A/ First/ Positive) |
|---|---|---|---|---|---|---|---|---|---|
| No. | Concept | Cost | Place | Meal | Life | Entertain | Sports | Tourism | Nature | Others | Probability value | Difference in probability | Lift value |
| 1 | A | None | 0.767 | 0.036 | 0.092 |
| 2 | None | A | 0.764 | 0.024 | 0.026 |
| 3 | A | None | 0.763 | 0.032 | 0.084 |
| 4 | A | None | 0.760 | 0.030 | 0.041 |
| 5 | A | None | 0.759 | 0.029 | 0.046 |
| 6 | A | None | 0.759 | 0.029 | 0.039 |
| 7 | A | None | 0.759 | 0.029 | 0.039 |
| 8 | None | A | 0.759 | 0.029 | 0.039 |
| 9 | None | A | 0.759 | 0.029 | 0.038 |
| 10 | None | A | 0.757 | 0.027 | 0.037 |
| 11 | None | A | 0.756 | 0.028 | 0.038 |
| 12 | None | A | 0.754 | 0.023 | 0.032 |

| Table 5: Sensitivity analysis result (Group A/ Second/ Positive) |
|---|---|---|---|---|---|---|---|---|---|
| No. | Concept | Cost | Place | Meal | Life | Entertain | Sports | Tourism | Nature | Others | Probability value | Difference in probability | Lift value |
| 1 | A | None | 0.528 | 0.043 | 0.096 |
| 2 | None | A | 0.525 | 0.048 | 0.103 |
| 3 | A | None | 0.521 | 0.036 | 0.075 |
| 4 | None | A | 0.517 | 0.033 | 0.067 |
| 5 | None | A | 0.516 | 0.032 | 0.066 |
| 6 | None | A | 0.515 | 0.031 | 0.064 |
| 7 | None | A | 0.515 | 0.030 | 0.063 |
| 8 | None | A | 0.514 | 0.030 | 0.063 |
| 9 | None | A | 0.513 | 0.028 | 0.059 |
| 10 | None | A | 0.511 | 0.026 | 0.054 |
| 11 | None | A | 0.510 | 0.026 | 0.053 |
| 12 | None | A | 0.506 | 0.024 | 0.053 |

| Table 6: Sensitivity analysis result (Group A/ Second/ Negative) |
|---|---|---|---|---|---|---|---|---|---|
| No. | Concept | Cost | Place | Meal | Life | Entertain | Sports | Tourism | Nature | Others | Probability value | Difference in probability | Lift value |
| 1 | A | None | 0.574 | 0.050 | 0.113 |
| 2 | None | A | 0.569 | 0.053 | 0.103 |
| 3 | None | A | 0.566 | 0.050 | 0.098 |
| 4 | None | A | 0.565 | 0.048 | 0.095 |
| 5 | None | A | 0.565 | 0.048 | 0.095 |
| 6 | None | A | 0.564 | 0.048 | 0.094 |
| 7 | None | A | 0.564 | 0.048 | 0.094 |
| 8 | None | A | 0.563 | 0.048 | 0.092 |
| 9 | None | A | 0.563 | 0.048 | 0.092 |
| 10 | A | None | 0.557 | 0.041 | 0.079 |
| 11 | A | None | 0.556 | 0.041 | 0.079 |
| 12 | A | None | 0.556 | 0.041 | 0.079 |
that the conception has created through communication, and what to put emphasis on has changed according to the conception in group A.

Next, the results of the sensitivity analysis in group B are shown in Tables 7-10. Table 7 and Table 8 show that they emphasize “Place” and “Cost” in terms of positive viewpoint and in the first half. However, Table 9 and Table 10 shows they emphasize “Life” in terms of negative viewpoint in the second half. This result shows that what to put emphasis on has changed without the conception.

Thus, we visualized the change of the process structure using Bayesian network model (Figure 2, Figure 3) . This figure clearly shows the difference in structural change between the two groups.

Table 7: Sensitivity analysis result (Group B/ First/ Positive)

| No. | Conception | Cost | Place | Meal | Life | Enter | Nature | Sports | Tourism | Others | Probability value | Difference in probability | Lift value |
|-----|------------|------|-------|------|------|-------|--------|--------|---------|---------|------------------|--------------------------|-----------|
| 1   | A          | None | None  | None | None | None  | None   | None   | None    | None    | 0.676           | 0.015                     | 1.022      |
| 2   | A          | None | None  | None | None | None  | None   | None   | None    | None    | 0.675           | 0.014                     | 1.021      |
| 3   | None       | A    | None  | None | None | None  | None   | None   | None    | None    | 0.675           | 0.014                     | 1.020      |
| 4   | None       | A    | None  | None | None | None  | None   | None   | None    | None    | 0.675           | 0.014                     | 1.020      |
| 5   | None       | A    | None  | None | None | None  | None   | None   | None    | None    | 0.674           | 0.013                     | 1.020      |
| 6   | A          | None | None  | None | None | None  | None   | None   | None    | None    | 0.674           | 0.013                     | 1.020      |
| 7   | A          | None | None  | None | None | None  | None   | None   | None    | None    | 0.674           | 0.013                     | 1.020      |
| 8   | A          | None | None  | None | None | None  | None   | None   | None    | None    | 0.674           | 0.013                     | 1.020      |
| 9   | None       | A    | None  | None | None | None  | None   | None   | None    | None    | 0.673           | 0.012                     | 1.018      |
| 10  | None       | A    | None  | None | None | None  | None   | None   | None    | None    | 0.673           | 0.012                     | 1.018      |
| 11  | A          | None | None  | None | None | None  | None   | None   | None    | None    | 0.670           | 0.009                     | 1.014      |
| 12  | A          | None | None  | None | None | None  | None   | None   | None    | None    | 0.670           | 0.009                     | 1.013      |

Table 9: Sensitivity analysis result (Group B/ Second/ Positive)

| No. | Conception | Cost | Place | Meal | Life | Enter | Nature | Sports | Tourism | Others | Probability value | Difference in probability | Lift value |
|-----|------------|------|-------|------|------|-------|--------|--------|---------|---------|------------------|--------------------------|-----------|
| 1   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.736           | 0.020                     | 1.029      |
| 2   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.736           | 0.020                     | 1.029      |
| 3   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.736           | 0.020                     | 1.029      |
| 4   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.736           | 0.020                     | 1.029      |
| 5   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.736           | 0.020                     | 1.029      |
| 6   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.736           | 0.020                     | 1.029      |
| 7   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.734           | 0.019                     | 1.026      |
| 8   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.734           | 0.019                     | 1.026      |
| 9   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.734           | 0.019                     | 1.026      |
| 10  | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.734           | 0.019                     | 1.026      |
| 11  | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.733           | 0.018                     | 1.025      |
| 12  | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.732           | 0.018                     | 1.024      |

Table 10: Sensitivity analysis result (Group B/ Second/ Negative)

| No. | Conception | Cost | Place | Meal | Life | Enter | Nature | Sports | Tourism | Others | Probability value | Difference in probability | Lift value |
|-----|------------|------|-------|------|------|-------|--------|--------|---------|---------|------------------|--------------------------|-----------|
| 1   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.988           | 0.113                     | 1.015      |
| 2   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.988           | 0.113                     | 1.015      |
| 3   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.988           | 0.113                     | 1.015      |
| 4   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.988           | 0.113                     | 1.015      |
| 5   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.988           | 0.113                     | 1.015      |
| 6   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.988           | 0.113                     | 1.015      |
| 7   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.988           | 0.113                     | 1.015      |
| 8   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.989           | 0.114                     | 1.019      |
| 9   | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.989           | 0.114                     | 1.019      |
| 10  | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.989           | 0.114                     | 1.019      |
| 11  | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.989           | 0.114                     | 1.019      |
| 12  | None       | None | None  | None | None | None  | None   | None   | None    | None    | 0.989           | 0.114                     | 1.019      |

Figure 2: Structure change of Bayesian network model (Group A)

Figure 3: Structure change of Bayesian network model (Group B)
5. PATTERN CLASSIFICATION OF THE CONSENSUS BUILDING PROCESS

As a result of observation six consensus building processes, it is suggested that the consensus building processes are classified into patterns from two viewpoints.

The first is the structure change of consensus building process model. As shown in Figure 2, Group A created conception in the course of communication, and changed the emphasizing viewpoint according to the conception. As shown in Figure 3, Group B did not create the conception, the emphasizing viewpoint has changed. Of the six groups, there were three patterns (I) and three patterns (II).

The second is about the transition of consensus building process. A comparison of visualized processes is shown in Figure 4. The vertical axis is a candidate, and the horizontal axis is a time series. Remarks including positive reasons are black, remarks including negative reasons are gray. Section A is the stage that they share reasons selected for the candidate that the subject thinks the best, Section B is the stage that they narrow down candidates from the choices for negative reasons, and Section C is the stage that they determine the candidate for positive reasons. As shown in the previous study, Section B and Section C are common in cases of few choices and in cases of multiple-choice, Section A is a feature seen in case of multiple-choice. In this paper, we classify cases of multiple-choice into Pattern (i) and Pattern (ii). The flow of Section B and Section C is the same after Section A in both cases. However, Pattern (i) has more choices to talk after Section A, Pattern (ii) has not increased choices to discuss after Section A. In this way, in the case of multiple-choice, there are two patterns: Pattern (i) is that they narrow down candidate from all choices, and Pattern (ii) is that they narrow down candidate from choices listed by members. Of the six groups, there were four patterns (i) and two patterns (ii). For groups classified as pattern (i), the number of choices to be discussed is small, even in the case of multiple-choice.

Table 11 summarizes the above results. According to Table 11, it is suggested there is no relationship between the structural change of the model and the transition of the process. However, when looking at the average time in each pattern, pattern (I) is longer than pattern (II) in structure change of the model. In many cases, the pattern (II) tends to be agreed smoothly from a viewpoint that emphasizes, and the pattern (I) tend to create the conception when the viewpoint of emphasis is not clearly defined. Therefore, the pattern (II) is thought to shorten the time to reach consensus. Regarding the transition of the process, the pattern (i) is longer than the pattern (ii). This is because pattern (i) has the large number of choices to be compared, so it is considered that the time to reach agreement will be longer. Despite being a pattern (i), group E has a short time. This group is presumed to have carried out the discussion smoothly because there were many members that has similar emphasizing viewpoints at the preliminary questionnaire.

Thus, we classified the consensus building process into patterns and discussed the time to reach agreement in this chapter. However, the number of cases observed in this study is small, and it is necessary to compare more cases. In addition, this time we classified them from the above two perspectives and considered using the average time to agreement, however from now on, it is necessary to classify by other viewpoints and consider using other indexes as well.
6. CONCLUSION

We modeled consensus building process in case of multiple-choice using Bayesian network. We showed the structure and characteristics of consensus building process in case of multiple-choice by quantitative analysis using the model. There are two groups: one is that created conception, and the other is that reached the consensus in terms of a viewpoint. We explained the characteristics of two groups and visualized the structure change of Bayesian network model of each groups.

In addition, we classified consensus building process into patterns from two viewpoints and classify six cases into the patterns. As a result, it turned out that the pattern to narrow down candidate from all the options and the pattern to create the conception tended to have a long time to reach agreement. In this way, we proposed one method for pattern classification of consensus building and feature extraction.

From now on, we would like to gather more cases and improve the accuracy of pattern classification. Furthermore, we need to classify patterns by various viewpoints and extract features using new indices.

REFERENCES

1. Fujii, S.; Examination on the problem of consensus building. Operations Research as a Management Science Research, 48(11), pp.795-801, 2003. (in Japanese)
2. Kuwako, T.; Consensus building and Kansei in communications, The Journal of the Institute of Electronics, Information, and Communication Engineers, 92(11), pp.967-969, 2009. (in Japanese)
3. Hamada, Y., and Shoji, H.; A study on the feature analysis of the success pattern of consensus building processes, Transactions of Japan Society of Kansei Engineering, 16(1), pp.43-50, 2017. (in Japanese)
4. Hamada, Y., and Shoji, H.; How to model value-creating communication: consensus building process as an example, Proceedings of 3rd International Symposium on Affective Science and Engineering, Japan Society of Kansei Engineering, 2017.
5. Hamada, Y., and Shoji, H.; Characteristics of Consensus building process model in case of multiple-choice, Transactions of Japan Society of Kansei Engineering, 17(3), pp.357-364, 2018. (in Japanese)
6. Hamada, Y., Maruyama, T., and Shoji, H.; Characteristics of modeling of value creative consensus building process in case of multiple-choice, Proceedings of 4th International Symposium on Affective Science and Engineering, 2018.
7. Lazarsfeld, P. F., Bernard, R. B., and Gaudet, H.; The people’s choice: how the voter makes up his mind in a presidential campaign, 2nd ed., Columbia University Press, 1948.
8. Bernard, R. B., Lazarsfeld, P. F., and McPhee, W. N.; Voting: a study of opinion formation in a presidential campaign, University of Chicago Press, 1954.
9. Saaty, T. L.; The analytic hierarchy process, McGraw-Hill, 1981.
10. Koshiba, H., Kato, N., and Kunifugi, S.; Proposal of communication support function for group decision making, Journal of Information Processing, 49(1), pp.96-104, 2008. (in Japanese)
11. Matsuo, T., and Ito, T.; A group integration support system based on buyers’ multiple attribute preferences in substitute goods group buying, The Transactions of the Institute of Electronics, Information and Communication Engineers. D-I, 86(10), pp.762-772, 2003. (in Japanese)
12. Onoe, N., Ishibashi, N., and Yoshida, N.; An implementation of a social consensus system by forming the wisdom of crowds from independent idea, IEICE Technical Report, 114(101), pp.7-9, 2014. (in Japanese)
13. Tversky, A., and Kahneman, D.; The framing of decisions and the psychology of choice, Science, 211, pp.453-458, 1981.
14. Motomura, Y., and Iwasaki, H.; Bayesian network technology – user and customer modeling and inference of uncertainty –, Tokyo Denki University Press, 2006.
15. NTT DATA Mathematical Systems HP: https://www.msi.co.jp/bayolink/ (accessed 2019.03.29).
16. Motomura, Y.; BAYONET: Bayesian network on neural network, Foundation of Real-World Intelligence, pp.28-37, CSLI california, 2002.
17. Motomura, Y.; Bayesian network software, Journal of the Japanese Society for Artificial Intelligence, 17(5), pp.559-565, 2002. (in Japanese)
18. Motomura, Y.; Bayesian network software “BayoNet”, Journal of the Society of Instrument and Control Engineers, 42(8), pp.693-694,2003. (in Japanese)
Yuri HAMADA (Member)
Yuri Hamada received B.S., M.S. and Ph.D. degrees in Engineering from Chuo University, Japan, in 2008, 2010, and 2017, respectively. Since 2018, she is currently an Assistant Professor in Industrial and Systems Engineering at Chuo University. Her research interests fall in modeling of communication processes and analysis of decision making processes. She is a member of Japan Society of Kansei Engineering, Japanese Cognitive Science Society.

Tatsuya MARUYAMA (Non-member)
Tatsuya Maruyama received B.S. and M.S. degrees in Engineering from Chuo University, Japan, in 2016, 2018, respectively.

Hiroko SHOJI (Member)
Hiroko Shoji received B.S., M.S. and Ph.D. degrees in Engineering from the University of Tokyo, Japan, in 1989, 1991, and 2002, respectively. She has been an Associate Professor since 2004, and she is currently a Professor since 2011 in Industrial and Systems Engineering at Chuo University, Japan. Her research interests include understanding and support of process of thinking including ambiguity, construction of dynamic sensibility model and engineering application. She is currently president of Japan Society of Kansei Engineering. She is also a member of Information Processing Society of Japan, the Japanese Society for Artificial Intelligence, Japanese Cognitive Science Society.