Reflective Visualization of the Agreement Quality in Mediation

Yoshiharu Maeno[1], Katsumi Nitta[2], and Yukio Ohsawa[3]

[1] Social Design Group, Bunkyo-ku, Tokyo 112-0011, Japan
maeno.yoshiharu@socialdesigngroup.com
[2] Tokyo Institute of Technology, Yokohama-shi, Kanagawa 226-8502, Japan
[3] The University of Tokyo, Bunkyo-ku, Tokyo 113-8563, Japan

Abstract. Training for mediators is a complex issue. It is generally effective for trainees to reflect on their past thinking, speaking, and acting. We present a text processing method which aids mediation trainees in reflecting on how they reached an agreement from their dialogue. The method is an improved variant of the Data Crystallization algorithm, which visualizes the inter-topic associations which foreshadow the intentional or unintentional subsequent development of topics far apart in time. We demonstrate how the dialogues which differ in the agreement quality affects the topological characteristics of the associations.

1 Introduction and Background

Resolving a conflict between parties having opposing opinions is an important social requirement. Mediation is a form of alternative dispute resolution, which refers to a rather private and confidential extrajudicial process. Mediation aims at assisting disputants in reaching an agreement on a disputed matter. Companies often hire mediators in an attempt to resolve a dispute with workers' unions. Mediation is different from arbitration where an arbitrator imposes a solution on the disputants. Rather, a mediator uses appropriate skills to improve the dialogue between the disputants and find solution.

Information technologies are applied to assist mediators and disputants in reaching a good agreement. For example, software agents are used in many related works in analyzing and aiding the mediation process. A software agent [1] is a piece of software that acts on behalf of a user. An intelligent software agent is capable of adapting to the environment by choosing problem solving rules, and of learning by trial and error, or by generalizing the given examples. The software agent analyzes the mediation and aids mediators or disputants in making decisions. Case based reasoning is a powerful technique for the software agents. This technique is the process of solving new problems based on the solutions of similar past problems. The process formalizes four steps: retrieving the relevant cases from a knowledge base, reusing the retrieved case to a new problem, revising the retrieved solution to a new situation, and retaining the new problem and its solution to the knowledge base.

K. Nakakoji, Y. Murakami, and E. McCready (Eds.): JSAI-isAI, LNAI 6284, pp. 33–44, 2010.

Besides, logic programming and ontology are frequently used as techniques to implement the case based reasoning. Logic programming [16] is the use of logic as a language for declarative and procedural representation. Prolog remains one of the most commonly used logic programming languages today. It has been applied to the fields of theorem proving, expert systems, games, automated answering systems, and ontology. Building ontology is an essential task in analyzing the knowledge base. Ontology refers to a formal representation of a shared conceptualization of a particular domain. It includes a set of individuals which are the basic objects, classes which are the collections of things, attributes which describe the aspects of the individuals and classes, and relations in which the individuals and classes can be related to one another.

On the other hand, education and training for mediator trainees (improvement of mediator trainees' human skills) become a complex issue because the mediator's skills range widely from the ability to remain neutral, the ability to move the disputants from the impasse points, to the ability to evaluate the strength and weakness of the disputants correctly. Appropriate means are, therefore, necessary to education and training. The idea of reflection can be a clue in the situation when we need to improve a skill which can not be defined clearly and taught by trainers.

Reflection in cognitive science [17] and computer-mediated communication [20] means the ability to recognize and understand oneself, discover something unexpected, and create something new [7], [19], [18]. *Particularly, visualization of the past utterances, decision-making, and actions is one of the most practical tools to aid the trainees in reflection.* Reflective visualization and verbalization are proven effective in helping a person become aware of his or her unconscious preferences [9], [6]. We expect that such reflective visualization is also promising in education and training for mediation trainees. Utterances are relevant and convenient information records for the trainees to reflect on. They are essential inputs to negotiation log analysis [13] and online agent based negotiation assistant systems [21], [22]. Similarly, mediators and disputants can reflect on the quality of the agreement they made by looking back the way how the dispute was resolved in a dialogue.

In this paper, we explore a text processing method for reflective visualization and apply it to a mediation case. It is an improved variant of the Data Crystallization algorithm [15] in which a graph-structured diagram evolves to explore unknown structures with the introduction of dummy variables. The Data Crystallization algorithm has also been studied in [10], [11], and [14]. The method derives temporal topic clusters and inter-topic associations from the recorded utterance texts, and draws the clusters and associations on a graph-structured diagram. *The inter-topic associations foreshadow the intentional or unintentional subsequent development of topics far apart in time.* Two dialogue examples in mediating a dispute on cancelling a purchase transaction at an online auction site demonstrate how the difference between the agreement quality affects the topological characteristics of the associations.

2 Method

2.1 Dialogue

The dialogue $\boldsymbol{d}$ is a time sequence of the recorded utterance texts u_t from a mediator and disputants. It is represented by eq.(1) formally. The subscript t means the time when the utterance is observed. We do not use the absolute time from the beginning of mediation. Instead, the i-th utterance from the beginning is associated with an integer time $t = i$ approximately. In eq.(1), T is the number of utterances in mediation.

$$\boldsymbol{d} = (u_0, \ldots, u_t, \ldots, u_{T-1}). \tag{1}$$

A recorded utterance text is a set of words w_i which appear in the sentences in an utterance. It is in the form of eq.(2). The number of words in an utterance text u_t is $|u_t|$.

$$u_t = \{w_i\} \ (0 \leq i < |u_t|). \tag{2}$$

The utterances are analyzed morphologically while assembling a dialogue. Morphology is the identification, analysis and description of structure of words. Verbs are changed into un-conjugated forms. Nouns are changed into un-inflected forms. Besides, irrelevant words are deleted. They are articles, prepositions, pronouns, and conjunctions. Periods are not words. For example, the first utterance of a mediator, *Thank you for agreeing in attempting to solve the dispute by mediation. Are you ready for starting mediation?*, becomes $u_0 = \{$agree, attempt, be, dispute, mediation, solve, start, thank, ready$\}$. A word may appear in many utterance texts. On the other hand, a word which appears multiple times in an utterance appears only once in the set of words in eq.(2).

2.2 Graphical Diagram

A graph-structured diagram [15], [9] is employed here to represent the dialog $\boldsymbol{d}$ visually. Two characteristic structures are extracted from the time sequence pattern of word appearance in $\boldsymbol{d}$. The first structure is a temporal topic cluster. It is a group of words whose time sequence pattern of appearance is similar. The cluster is drawn as a sub-graph including nodes representing words and links representing strong similarity between words. The second structure is an inter-topic association. The ability to extract the inter-topic association is the strength of our proposed method described in 2.3 and 2.4. The inter-topic association corresponds to an utterance which can be a trigger to move from a temporal topic cluster to another. It does not necessarily mean a temporally adjacent relationship between 2 clusters. Rather, it may foreshadow the intentional or unintentional subsequent development of topics indicated by clusters which are far apart in time. The inter-topic association is drawn as a set of links between multiple temporal topic clusters. The set of links has a label pointing to a trigger utterance.

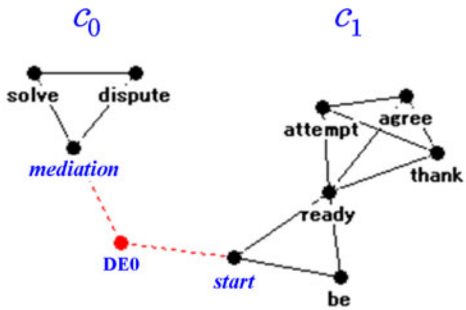

Fig. 1. Example of a graph-structured diagram which visualizes temporal topic clusters (c_0 and c_1), and inter-topic associations (DE0) found in the recorded utterance texts in a dialog. The nodes *mediation* and *start* are gateway words of the clusters.

Fig. 1 shows an example of a graph-structured diagram which represents temporal topic clusters and inter-topic associations in the recorded utterance texts in a dialog. The cluster c_0 includes 3 words and c_1 includes 6 words. The association is a link between c_0 and c_1 which is labeled as DE0 pointing to u_0. The gateway word is the word in a cluster to which the link representing an inter-topic association is connected.

The gateway word has strong associations with the words in other clusters as well as the words in the cluster to which it belongs. It is interpreted as a trigger (or a switch) which plays a role to ignite the subsequent development from a cluster to another. For example, the word *mediation* is the gateway word to c_0 for DE0 (u_0).

2.3 Temporal Topic Cluster

Every word w_i which appears in $\boldsymbol{d}$ is classified into temporal topic clusters. The number of clusters C is a granularity parameter which can be adjusted so that visualization can assist mediation trainees in reflecting their dialogues most effectively. As the granularity becomes finer, C increases, that is, the number of words in a cluster decreases and the time difference between neighbor clusters decreases. As the granularity becomes coarser, C decreases and the time difference increases. At the beginning of reflection, if the trainees want to grasp the rough sketch of the subsequent development of topics, coarser granularity visualization may be appropriate. Large number of clusters is not necessary for this purpose. After that, if they want to detail the subsequent development between the topics of particular interests, finer granularity visualization may be appropriate.

At first, a simple measure is introduced to characterize the time sequence pattern of word appearance. The characteristic time of a word is defined by eq.(3). It is the average of the time when a word appears.

$$a(w_i) = \frac{\sum_{t=0}^{T-1} tB(w_i \in u_t)}{\sum_{t=0}^{T-1} B(w_i \in u_t)}. \tag{3}$$

The function $B(s)$ is define by eq.(4).

$$B(s) = \begin{cases} 1 & \text{if the statement } s \text{ is true} \\ 0 & \text{otherwise (false)} \end{cases} . \tag{4}$$

The similarity between 2 words is defined by eq.(5). The function min is included to avoid divergence of the similarity when the characteristic time is very close. Two words appear closely in time if the similarity is large. Eq.(5) measures the degree of similarity in temporal appearance pattern while the Jaccard coefficient used in text analysis [8] measures the degree of co-occurrence.

$$I(w_i, w_j) = \min(\frac{1}{|a(w_i) - a(w_j)|}, 1). \tag{5}$$

Then, a clustering algorithm for discrete objects is applied for given C. The k-medoids algorithm is a simple example [5]. A medoid is an object that is the closest to the center of gravity in a cluster. Its principle is similar to that of the k-means algorithm [4] for continuous numerical variables where the center of gravity is updated repeatedly according to the expectation-maximization method [3]. The distance between words is evaluated by the similarity in eq.(5). Initially, the words are classified into clusters at random in the k-medoids algorithm. The cluster into which a word w_j is classified is denoted by $c(w_j)$. It is given by eq.(6).

$$c(w_j) = \text{random interger} \in [0, C-1]. \tag{6}$$

The medoid $w_{\text{med}}(c_k)$ of a cluster c_k is also assigned at random. It is given by eq.(7).

$$w_{\text{med}}(c_k) = \text{random word} \in c_k \ (0 \leq k < C). \tag{7}$$

The clusters into which words are classified and the medoids are updated repeatedly. The cluster into which a word is classified is updated according to eq.(8). The operator arg in eq.(8) means that $c(w_j)$ is the cluster which gives the largest $I(w_{\text{med}}(c_k), w_j)$. of all the clusters.

$$c(w_j) = \arg \max_{c_k} I(w_{\text{med}}(c_k), w_j). \tag{8}$$

The medoid is updated according to eq.(9). The operator arg in eq.(9) means that the medoid is the word w_j classified into c_k, which maximizes $M(c_k, w_j)$.

$$w_{\text{med}}(c_k) = \arg \max_{w_j \in c_k} M(c_k, w_j) \ (0 \leq k < C). \tag{9}$$

The quantity $M(c_k, w_j)$ in eq.(9) is given by eq.(10). The operator $\wedge$ means logical AND.

$$M(c_k, w_j) = \sum_{w_l \in c_k \wedge w_l \neq w_j} I(w_l, w_j). \tag{10}$$

After the medoids are determined, the clusters into which words are classified are updated according to eq.(8) again. Eq.(8), (9), and (10) are calculated repeatedly until their value converges. The characteristic time of a cluster is defined by eq.(11). The time when a topic cluster c_k appears is evaluated by the time when its medoid word appear approximately.

$$a(c_k) = a(w_{\mathrm{med}}(c_k)) \tag{11}$$

2.4 Inter-topic Association

After extracting temporal topic clusters, every utterance is next assigned a score which measures the degree of being an inter-topic association [15], [10], [9]. The score $s(u_t)$ of the utterance u_t is calculated by eq.(12).

$$s(u_t) = \max_{w_i \in u_t} \sum_{c_k} \max_{w_j \in c_k \wedge w_j \neq w_i} I(w_i, w_j). \tag{12}$$

The utterances which are assigned large value of the score are extracted to draw on a diagram. The utterance which has the l-th largest score is given by eq.(13).

$$U(\boldsymbol{d}, l) = \arg \max_{u_i \neq U(\boldsymbol{d},m) \text{ for } \forall m<l} s(u_i). \tag{13}$$

A gateway word of a cluster is selected when $U(\boldsymbol{d}, l)$ is drawn as a link between clusters on a graph. It is given by eq.(14). The operator arg means that the gateway word $w_{\mathrm{gtw}}(l, c_k)$ of a cluster c_k for the utterance of the l-th largest score is the word $w_j \in c_k$ which maximizes $I(w_i, w_j)$.

$$w_{\mathrm{gtw}}(l, c_k) = \arg_{w_j \in c_k} \max_{w_i \in U(\boldsymbol{d},l)} I(w_i, w_j). \tag{14}$$

A set of links are drawn between the gateway words $\{w_{\mathrm{gtw}}(1, c_k)\}$ $(0 \leq k < C)$ for the utterance assigned the largest value of the score $(u_t = U(\boldsymbol{d}, 1))$ on a diagram. The label DEt indicating u_t is attached to the links. Similarly, a set of links are drawn between the gateway words $\{w_{\mathrm{gtw}}(l, c_k)\}$ $(0 \leq k < C)$ for the utterance assigned the l-th largest value of the score $(u_t = U(\boldsymbol{d}, l))$.

3 Extended Example

3.1 Mediation Case

The method described in 2 is applied to dialogues recorded in a mediation training program. The disputed matter in the program is on a purchase transaction at an online auction site. Two groups of three mediation trainees played mediator and disputant roles. Their utterances until the dispute is resolved were recorded and assembled into two dialogues.

Disputed Matter. The disputed matter is on cancelling a purchase transaction between two persons (seller disputant and buyer disputant) at an online auction site. A seller disputant offered a car muffler for bid at the auction site. The seller disputant provided bidders with photographs of the muffler and showed them its condition and vendor information. A buyer disputant won the bid 7 days later. The buyer disputant paid for 20,000 yens two days later, and the seller disputant sent the muffler to the buyer disputant. The transaction at the auction site completed.

The disputed matter consists of many sub-matters. After two and half months, the buyer disputant asked the seller disputant whether the muffler is made of stainless steel or aluminum-plated steel. The seller disputant answered that the muffler is made of aluminum-plated steel as the photographs at the auction site had indicated. But, all the mufflers found at the muffler vender's web catalogue were made of stainless steel at the time of bidding. A muffler made of stainless steel is expensive, but excellent in quality. The muffler vender's hallmark can not be found on the muffler which the seller disputant sent to the buyer disputant. The muffler vender used to place the vender's hallmark on the products at the time of bidding. The buyer disputant became disappointed at this. The buyer disputant requested that the purchase transaction be cancelled and the paid money be returned. The seller disputant rejected the buyer disputant's request. The buyer disputant assigned a low rating score to the seller disputant at the auction site. The seller disputant did similarly in return. These low rating scores had the effect of making them untrustworthy at the auction site.

Resolution. The buyer disputant asked the seller disputant to attempt to resolve their dispute by mediation. The seller disputant agreed. With the aid of a mediator, the disputants talked about the undisclosed facts on each side in both of the two dialogues.

The seller disputant had bought the muffler at the same auction site before. The seller disputant was not aware that the muffler vender did not supply mufflers made of aluminum-plated steel at the time of bidding. The seller disputant investigated the muffler after the buyer requested cancellation. The seller disputant found that it was a custom-made muffler from the vendor. The seller disputant was embarrassed by the low rating score, which harmed the seller disputant's business reputation. The seller disputant could not agree on the request that the paid money be returned because the seller disputant happened to have little money at the time of mediation. Instead, the seller disputant had a number of mufflers, which might be used to make an agreement. The buyer disputant had not tried to check the quality of the sent muffler for a long time. The buyer disputant had trouble with a car because of the insufficient quality of the sent muffler, and wanted to settle the trouble by all means.

Finally, they reached an agreement although the buyer disputant's original request on returning the paid money did not survive the mediation. In the two dialogues, however, the two groups of the trainees reached different agreements. In dialogue 1, the agreement was to substitute the muffler for one made of stainless steel which the seller disputant possesses and delete both of the low rating scores at the online auction site. In dialogue 2, the agreement was to substitute the disputed muffler for one that cost 70 % as much. They discussed about the low rating scores at the online auction site but did not make an agreement about them.

In both dialogues, the mediators succeeded in assisting the disputants in reaching an agreement on a disputed matter. The mediator in dialogue 2, however, failed to make an agreement on the disputed sub-matter of the low rating scores. It was not beneficial to both of the disputants. The agreement in dialogue 1 looks better than that in dialogue 2 in that it incorporates beneficial compromises on most of the disputed sub-matters. How is this intuitive interpretation of the agreement quality visualized in terms of the difference between the diagrams? It is demonstrated next.

3.2 Visualization

Figure 2 shows the diagram drawn by the method from the dialogue 1. The number of temporal topic clusters is $C = 12$. They are placed clockwise from c_0 to c_{11}. The black nodes in the clusters are labeled with Japanese words which they represent. The inter-topic associations found within the whole $0 \leq t < T(= 54)$ utterances are labeled by the red nodes DEt. The number of the associations which have a non-zero score $s(u_t) > 0$ and are drawn on a diagram is 24 ($t = 0, \cdots, 23$). Figure 3 shows the diagram drawn by the method from the dialogue 2. The number of temporal topic clusters is $C = 12$. They are placed clockwise from c_0 to c_{11}. The black nodes in the clusters are labeled with Japanese words which they represent. The inter-topic associations found within the whole

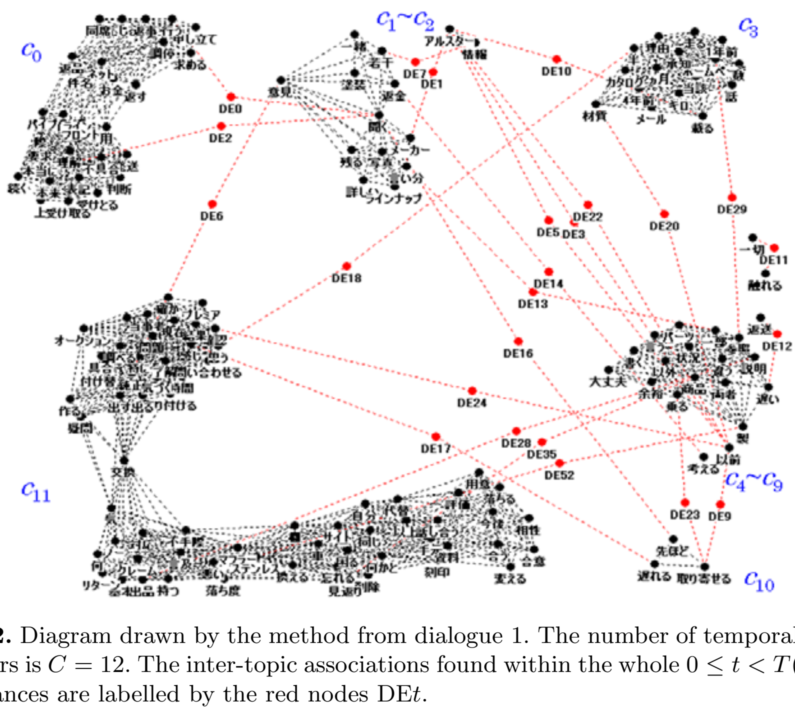

Fig. 2. Diagram drawn by the method from dialogue 1. The number of temporal topic clusters is $C = 12$. The inter-topic associations found within the whole $0 \leq t < T(= 54)$ utterances are labelled by the red nodes DEt.

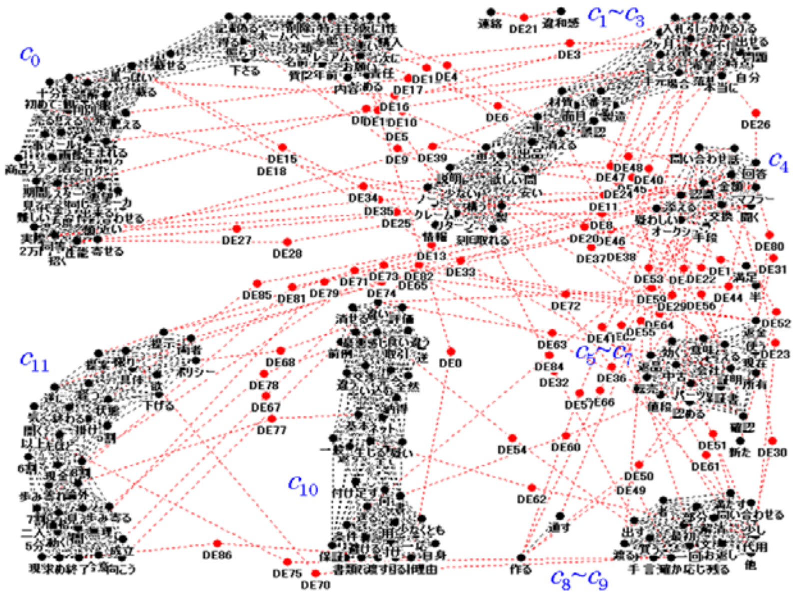

Fig. 3. Diagram drawn by the method from dialogue 2. The number of temporal topic clusters is $C = 12$. The inter-topic associations found within the whole $0 \leq t < T(= 87)$ utterances are labelled by the red nodes DEt.

$0 \leq t < T(= 87)$ utterances are labeled by the red nodes DEt. The number of the associations which have a non-zero score $s(u_t) > 0$ and are drawn on a diagram is 81 ($t = 0, \cdots, 80$).

There are inter-topic associations between most of the clusters in Figure 2 while there are few inter-topic associations between the early-stage clusters (c_0 to c_4) and the late-stage clusters (c_5 to c_{11}). To analyze quantitatively, let us count the number of the inter-topic associations between individual clusters and the concluding cluster c_{11}. The concluding cluster at the end of the mediation summarizes the content of the agreement. Table 1 shows the result.

Table 1. Number of the inter-topic associations between individual clusters and the concluding cluster c_{11}

	c_0	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
Dialogue 1	0	1	0	1	0	0	0	2	0	1	0
Dialogue 2	0	0	0	0	6	0	4	0	2	0	5

The Gini coefficient can be calculated from Table 1. The Gini coefficient is a measure of statistical dispersion. It is commonly used in economics as a measure of inequality of income or wealth. The Gini coefficient can range from 0 to 1. A small Gini coefficient indicates a more equal distribution while a large Gini coefficient indicates more unequal distribution. The value of 0 corresponds to perfect equality. The value of 1 corresponds to perfect inequality. The Gini coefficient is 0.56 for the dialogue 1 and 0.65 for the dialogue 2. The inter-relationship between the temporal clusters in dialogue 2 suffers from more inequality. The concluding cluster in dialogue 2 is less related to the sub-matters in the early-stage clusters than that in dialogue 1. This may result in the defect in the agreement quality of the dialogue 2.

This result demonstrates that the agreement quality and the visual structure of the diagrams may be dependent. This implication is relevant because the diagrams provide the mediation trainees with a clue to assess the agreement quality. The number of the associations between the concluding cluster and the early-stage clusters is of particular interest. A list of the problems posed in the dispute and the preliminary opinions on them from the disputants are usually presented in the early-stage clusters. The agreement in the concluding clusters is supposed to solve all the problems in a successful mediation. For this reason, very weak inter-relationship between the early-stage clusters and the concluding clusters can be a sign of bad agreement quality. The method can be an effective means in education and training to visualize such inequality and present it to mediator trainees for reflection on how they reached an agreement and how good or bad the way they discussed and decided was.

4 Discussion

The agreement which the disputant reached in mediation is often different from the best solution from the viewpoints of many similar past mediation cases. It is, therefore, more important to understand the intention in the agreement toward which the disputants are reaching (and possibly foresee and adjust it) than to know the best solution of the disputed matter. Our study focuses on the reflective visualization of mediators' human skills, rather than the information technology based mediation assistance. Analyzing the subsequent development of topics in the dialogue is essential for this purpose. The utterances are noisy and fluctuating information, which are not suitable for machines to understand by means of the knowledge base and ontology (above mentioned purely computational information technologies). Rather, a human-computer interacting process is potentially advantageous in combining text processing methods with experts' opinion and trainees' reflection through visual interfaces. The method in this paper emphasizes the practical usefulness of visualization in strengthening the mediation trainees' intuitive understanding of the vast amount of texts in the dialogue.

Although the topology of the inter-topic associations is a big clue to understand the dialogue, the graph-structured diagrams such as Figure 2 and Figure 3 may be difficult to interpret for those who are not familiar with such mathematical constructs Instead, short easy-to-understand text-based summary information on the quality of the agreement and other characteristics of the utterances is convenient to the trainees. Furthermore, a single digit, score for a mediator and disputants, may be simple but very useful information. With such information, trainees' reflection on their utterances with the aid of the information would remain very relevant and essential to improve the skills of the trainees. The score needs to include a clue to reflect on how and why the disputants have reached better or worse agreements in the dialogue.

The method is more suitable to analyze the Internet based text records than real time face-to-face conversations. This is mainly because speech recognition is not a mature technology. Negotiation between two parties through on-line chats [2] is an attractive field of application. For this purpose, the method needs to be improved to analyze streaming data (accumulating records of utterances) rather than a database (a complete dataset from the beginning to the end of the dialogue). The graph-structured diagrams will have to be updated utterance by utterance. A big change in the diagram during a single utterance affects badly the understanding of a mediator and disputants. They are likely to be confused. Gradual but noticeable change in the diagram would aid the trainees in understanding the effect of an utterance on the subsequent development of topics. Such visualization techniques are within the scope for future works.

5 Conclusion

Training for mediators is a complex issue. We present a text processing method which is a promising tool to address such an issue. The method aids mediation trainees in reflecting on how they reached an agreement from their dialogue. The strength of the method is the ability to visualize the inter-topic associations which foreshadow the intentional or unintentional subsequent development of topics indicated by temporal topics clusters far apart in time. The method is applied to a mediation case where a dispute between a seller and a buyer at an online auction site is resolved. The result demonstrates that the agreement quality and the visual structure of the diagrams which our method outputs may be dependent.

This implication is relevant because the diagrams may provide the mediation trainees with a clue to access the agreement quality from the associations between the concluding cluster and the early-stage clusters. With this in mind, in the future, we may be able to design an effective computer-aided training tool which visualizes mediation trainees' dialogue in real time, aids them in reflecting on how they are making a discussion and how they are reaching an agreement, and strengthens their ability to foresee the conclusion to which they are approaching and set it in the right direction.

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