REDUCTION GENERATION WITH DISTANCE MEASURE IN SET VALUED ORDERED DECISION TABLES

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ABSTRACT. An effective pattern of decision making is proved to be with the assistance of ordered decision tables. Manipulating the multi valued information is aided with set valued ordered decision model. The studies in establishing reduction of the conditional attributes based on the amount of information carried by the individual attribute still could not cope up with the consistency of the original information system. The distance measure was proposed and significance measure was established between objects with dominance classes. The distance coefficient between the objects treated under different sets of available circumstances and the decision values forms the basis of achieving the reduction of the system with highest significance which also matches with the stability of targeted set valued ordered decision table. A heuristic algorithm was presented to explain the process and the algorithm was demonstrated by using sample data in attaining the valuable redacts.

1. INTRODUCTION

Rough set theory encourages the data interpretation with the existing mass of invalidated data and achieves at the decision for the future related circumstances. The theory can identify the redundant and data in negative regions of our proposed study and reduce the data dimensions and settle on with the idea

in the simple format. The useful information thus extracted creates the path for relevant knowledge compilation and classification. The ordering of data finds much attention in revealing the relationship between objects in stronger basis. The worse and better class of data in ordered decision tables helps to build the much more confident decisions. The equivalence classes in classical rough sets were replaced by effective pattern of upward and downward dominance relation in Dominance based rough set model. Set valued dominance based model is designed in such a way that the dominance classes are defined to meet the multiple values of the attributes for the objects in the universe. The strength of the Set valued ordered decision model lies in its nature of defining dominance objects with the aid of multiple valued criterions. The objects that satisfy condition as well as decision parameters finds inclusion in lower approximation where as the objects that obey either possibilities acquire membership in upper approximation set.

Huge data are to be monitored and required ideas has to be grasped and analyzed for the useful interpretation of information. Knowledge was considered as the valuable part of data while observation and investigation of records [1]. The complicated continuous data is considered easy to access if it was simplified. Fuzzy rough sets are used to discretize the condition attributes and assign a degree to decision variable through which the identification of optimum mixture of glass materials [2]. The incomplete decision tables are studied [3] and an algorithm was proposed for attribute reduction. The conditional attributes with better significance are annexed to the redact set and the decision rules are framed with minimal set of condition attributes in incomplete decision tables [4]. Each individual object in the universe is associated with a weight along with membership degree and the measures of selected features are presented [5]. The possibility of application of rough set in real world problems are presented in detail and basic ideas was clearly explained [6]. Bayesian decision procedure combined with regression analysis is introduced [7] for extraction of constructive information and achieving the decision using the three framed paths.

The intrinsic worth [8] of the Dominance rough set model than that of standard rough set model was studied and tried to frame the decision rules with Dominance rough set model. The evidence theory in which the mass of the dominance class was made use to identify the useful attributes and obtaining

the belief reduction [9]. Both dominance and non dominance properties of the object are studied [10] in which the various classes are analyzed to obtain the inter class reduction in Dominance oriented rough set model. Studies [11] evaluated the qualities of different classes in ordered classes for the emergency communication. Procedure for individual analyses of the appended data was proposed [12] with the validity of the method. The inner and outer significance of attributes in compacted decision system is to find three types of reduction with positive region and two other entropies [13]. Boolean reasoning techniques and dominance indiscernibility model is used for reduction construction and rule optimization in inconsistent set valued ordered decision model [14]. The ordered decision tables are used to identify the decision set of rules and further the rules are validated with different measures under the knowledge of conditions and decisions. Various designs possible in ordered decision tables are discussed in detail [15]. A new method [16] was proposed to estimate the distance between the attribute values and the feature selection was performed in set valued decision tables. The distance based measure combined with set valued dominance approach rough set model was studied through this paper to simplify the data and extract all possible reductions and faster convergence to decision progress.

Our work is planned as per the following structure. Some fundamental ideas of Dominance based set valued decision tables and its properties are presented in section 2. The proposed reduction induced by distance between the dominance classes under condition and decision preferences of the set valued ordered decision table was constructed in section 3. In section 4 the technique was used for sample data and the valuable features are extracted. Conclusion part of the paper is discussed in section 5.

2. Dominance set valued decision model and Jaccard Distance

2.1. **Dominance set valued decision model.** Consider the decision model $S = < U,\ CD,\ SV,\ f >$. Here the nonempty finite universe is denoted by U; The finite set of condition along with the decision variable is CD; the domain of attributes is $SV = \bigcup_{a \in CD} V_a$, V_a is the value set of each attribute $a \in CD$. The function $f : U \times CD \to SV$, defined as $f(u_x, a) \in SV$ for every $u_x \in U,\ a \in CD$.

If an attribute 'a' in CD has more than one value in V_a for some the objects in U, then S is set valued information system.

For the subset $A \subseteq CD$ and $(u_x, u_y) \in U \times U$, the set valued dominance relation can be specified by the expression [15].

$$\delta_A^+ = \{(u_x, u_y) \in U \times U / \min f(u_x, a) \geq \max f(u_y, a), \ \forall a \in A\}.$$

It was understood that if $(u_x, u_y) \in \delta_A^+$, then u_x dominate u_y or u_x is observed to have better values than u_y for all the attributes in A. The set valued dominance function is reflexive and transitive.

$$\delta_A^+(u_x) = \{u_y \in U / \max f(u_y, a) \geq \min f(u_x, a), \ \forall a \in A\},$$
$$\delta_A^-(u_x) = \{u_y \in U / \min f(u_y, a) \leq \max f(u_x, a), \ \forall a \in A\}.$$

If $\delta_Q^+(x) = \delta_P^+(x)$ and $\delta_Q^-(x) = \delta_P^-(x)$, then we can realize that

$$f(u_x, a) = f(u_y, a) \ \forall a \in Q, \ (u_x, u_y) \in U \times U \text{ and } P \subseteq Q \subseteq CD.$$

Let $S = < U, \ CD, \ SV, f >$ be the set valued ordered decision table, $A \subseteq CD$, $d = \{d_1, d_2, \cdots, d_n\}$ are the choices initiated by the decision attribute d, the lower and upper approximations of $d_i^+ = \{u_x \in U / f(u_x, d) \geq d_i\}$ with respect to the dominance relation δ_A^+ are defined as

$$\underline{\delta_A^+(d_i^+)} = \{u_x \in U / \delta_A^+(u_x) \subseteq d_i^+\} \text{ and } \overline{\delta_A^+(d_i^+)} = \bigcup_{u_x \in \ d_i^+} \delta_A^+(u_x).$$

2.2. Jaccard distance.
The Jaccard distance between the sets $M, N \subseteq U$ can be characterized as

$$JD(M, N) = 1 - \frac{|M \cap N|}{|M \cup N|}.$$

3. DISTANCE BASED REDUCT IN ORDERED SET VALUED DECISION TABLE

3.1. Consistency measure.
The consistency of the decision in the decision table $SD = (U, CD, SV, f)$ can be measured by the coefficient

$$\psi_C^+(u_x) = \frac{|\delta_{C \cup d}^+(u_x)|}{|\delta_C^+(u_x)|} \text{ for any } u_x \in U.$$

The set valued dominance decision table is considered to be consistent if $\psi_C^+(u_x) = 1$ and inconsistent if $\psi_C^+(u_x) \neq 1$ for any $u_x \in U$.

Definition 3.1. *The set* $A \subset C$ *is the reduct of the set valued decision table* $SD = (U, CD, SV, f)$, *if*

(i) $\psi_A^+(u_x) = \psi_C^+(u_x)$ *for any* $u_x \in U$ *and*

(ii) $\psi_P^+(u_x) \neq \psi_C^+(u_x)$ *for any* $P \subset A$.

3.2. **Distance in set valued ordered decision table.** Consider the set valued decision table $SD = (U, CD, SV, f)$:

$$M = \{u_y \in U / u_y \in \delta_C^+(u_x)\} \text{ and } N = \{u_x \in M / u_x \in \delta_d^+(x)\} .$$

Based on Jaccard distance, the distance between the Dominance set M and its decision performance in U with in condition attribute set C can be considered as the average of the distance calculated for its partition in U.

$$(3.1) \qquad L_M(C, d) = 1 - \frac{1}{|U|} \sum_{\substack{M_i \in U/\delta_c^+ \\ N_i \in U/\delta_{C \cup d}^+}} \frac{|M_i \cap N_i|}{|M_i \cup N_i|}.$$

Equation (3.1) is same as defining

$$(3.2) \qquad L_M(C, d) = 1 - \frac{1}{|U|} \sum_{u_i \in \cup} \frac{|\delta_c^+(u_i) \cap \delta_{C \cup d}^+(u_i)|}{|\delta_c^+(u_i) \cap \delta_{C \cup d}^+(u_i)|}.$$

Since $\delta_C^+(u_i) \supseteq \delta_{C \cup d}^+(u_i)$, for any $u_i \in U$ the equations (3.1) and (3.2) can be simplified as

$$L_M(C, d) = 1 - \frac{1}{|U|} \sum_{\substack{M \in U/\delta_C^+ \\ N_i \in U/\delta_{C \cup d}^+}} \frac{|N_i|}{|M_i|} \text{ and } L_M(C, d) = 1 - \frac{1}{|U|} \sum_{u_i \in U} \frac{|\delta_{C \cup d}^+(u_i)|}{|\delta_C^+(u_i)|} .$$

Proposition 3.1. *For the set valued decision table* $SD = (U, CD, SV, f)$, *the distance between the universe and the partition induced by* $P \subset C$ *is*

1. $L_M(U, P) = 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\delta_P^+(u_i)|}{|U|} \right)$
2. *The minimal distance* $L_M(U, P)$ *is zero.*
3. *The maximal distance* $L_M(U, P)$ *is* $1 - \frac{1}{|U|}$.

Proof. 1.

$$L_M(U, P) = 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|U \cap \delta_P^+(u_i)|}{|U \cup \delta_P^+(u_i)|} \right) \text{ for any } u_i \in U$$

$$= 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\delta_P^+(u_i)|}{|U|} \right)$$

2. The distance is minimum when $\delta_P^+(u_i)$ equal to the universe U and the minimum distance is given to be

$$1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\delta_P^+(u_i)|}{|U|} \right) = 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \frac{|U|}{|U|} = 0 .$$

3. The distance is maximum when $\delta_P^+(x_i) = \{x_i\}$ for all $x_i \in U$ and the maximal distance

$$1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(|\frac{\delta_P^+(u_i)|}{|U|} \right) = 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\{u_i\}|}{|U|} \right)$$

$$= 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{1}{|U|} \right) = 1 - \frac{1}{|U|}.$$

$\square$

Proposition 3.2. *Let $SD = (U, CD, SV, f)$ be the set valued ordered decision table and let P and Q are the subsets of the condition attribute C such that $P \subset Q$. Then*

$$L_M(P, d) \geq L_M(Q, d) \text{ and } L_M(P, d) \geq L_M(Q, d) \text{ iff } \psi_P^+(u_x) = \psi_Q^+(u_x).$$

Proof. We know that $\delta_Q^+(u_x) = \bigcap \delta_q^+(u_x)$ for all $q \in Q$ and $u_x \in U$. Since $P \subset Q$, we conclude that $\delta_Q^+(u_x) \subseteq \delta_P^+(u_x)$ and $\delta_{Q \cup \{d\}}^+(u_x) \subseteq \delta_{P \cup \{d\}}^+(u_x)$ so that

$$|\delta_Q^+(u_x)| \leq |\delta_P^+(u_x)|, \ |\delta_{Q \cup \{d\}}^+(u_x)| \leq |\delta_{P \cup \{d\}}^+(u_x)|, \ |\delta_{Q \cup \{d\}}^+(u_x)| \leq |\delta_Q^+(u_x)|$$

and also $|\delta_{P \cup \{d\}}^+(u_x)| \leq |\delta_P^+(u_x)|$. We also notice that for the consistent set valued ordered decision tables the degree of convergence of $\delta_Q^+(u_x) \to \delta_{Q \cup \{d\}}^+(u_x)$ is more than the degree of convergence of $\delta_P^+(u_x) \to \delta_{P \cup \{d\}}^+(u_x)$ for $P \subseteq Q$ $\frac{|\delta_{Q \cup d}^+(u_x)|}{|\delta_Q^+(u_x)|} \geq \frac{|\delta_{P \cup d}^+(u_x)|}{|\delta_P^+(u_x)|}$ and hence

$$1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\delta_{Q \cup d}^+(u_i)|}{|\delta_Q^+(u_i)|} \right) \leq 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\delta_{P \cup d}^+(u_i)|}{|\delta_P^+(u_i)|} \right) .$$

So that $L_M(Q, d) \leq L_M(P, d)$ is proved

$$L_M(P, d) = L_M(Q, d) \quad \Leftrightarrow 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\delta_{P \cup d}^+(u_i)|}{|\delta_P^+(u_i)|} \right) = 1 - \frac{1}{|U|} \sum_{i=1}^{|U|} \left(\frac{|\delta_{Q \cup d}^+(u_i)|}{|\delta_Q^+(u_i)|} \right).$$
$$\Leftrightarrow \psi_P^+(u_x) = \psi_Q^+(u_x)$$

$\square$

Proposition 3.3. *Let $SD = (U, CD, SV, f)$ be the set valued ordered decision table and let P and Q are the subsets of the condition attribute C such that $P \subset C$. Then we have the following assumptions*

1. *$L_M(P, d)$ achieves its maximum value $\dfrac{1}{|U|}$ when $\psi_P^+(u_x) = \dfrac{1}{|\delta_P^+(u_x)|}$.*
2. *$L_M(P, d)$ achieves its minimum value 0 when $\psi_P^+(u_x) = 1$.*

Proof. 1. $L_M(P, d)$ is maximum when $\dfrac{|\delta_{P \cup d}^+(u_x)|}{|\delta_P^+(u_x)|}$ is minimum for all $u_x \in U$ and is achieved when $|\delta_{P \cup d}^+(u_i)| = 1$ for all $u_i \in U$ which means $\psi_P^+(u_x) = \dfrac{1}{|\delta_P^+(u_x)|}$.

2. $L_M(P, d)$ is minimum when $\dfrac{|\delta_{P \cup d}^+(u_i)|}{|\delta_P^+(u_i)|}$ is maximum for all $u_i \in U$ and is achieved when $|\delta_{P \cup d}^+(u_i)| = |\delta_P^+(u_i)|$ for all $u_i \in U$ and hence $\psi_P^+(u_x) = 1$.

$\square$

Definition 3.2. *The set $R \subset C$ is the reduct of the set valued decision table $SD = (U, CD, SV, f)$ if*

(i) *$L_M(RED, d) = L_M(C, d)$*
(ii) *$L_M(RED - \{a\}, d) \neq L_X(RED, d)$ for any $\{a\}$ belong to the condition attribute set C.*

Definition 3.3. *For the dominance set valued decision table $SD = (U, CD, SV, f)$, if $P \subset C$ and $c \in C - P$*

(3.3) $$SIGN_P^{\geq}(c) = L_M(P, d) - L_M(P \cup \{c\}, d).$$

Algorithm 3.1. *An algorithm to find the possible dominance based distance reduct in the set valued decision table was constructed for the ordered decision table.*

Algorithm 1. Distance based set valued reduct

Input: Set valued Decision Table 'SD', Decision Attributes 'd', Condition Attributes '$C = c_1, c_2, \cdots, c_n$'.	
Output: Reduct generation	

1   IR$=\varphi$, $S = 0$

2   Estimate $L_M(IR, d)$ and $L_M(C, d)$

3   Begin

4   For $L_M(IR, d) \neq L_M(C, d)$ then

5   Measure $L_M(IR \cup \{c_i\}, d)$ and $SIGN_R^{\geq}(c_i)$
     over the decision attribute for all $c_i \in C - IR$

6   If $SIGN_R^{\geq}(c_i) \geq S$, then $SIGN_R^{\geq}(c_i) = S$ and $c_R = c_i$

7   End for

8   IR$=\{IR \cup \{c_R\}\}$

9   Estimate $L_X(IR, d)$

10   End

11   Begin

12   For Decision Table 'SD' with Condition Attributes set
     $IR \subseteq C$ and Decision Attribute 'd'.

13   Estimate $L_X(IR - \{c_i\}, d)$

14   If $L_M(IR, d) = L_M(IR - \{c_i\}, d)$ then $IR = IR - \{c_i\}$

15   End

16   Reduct $=IR$

17   End

4. FEATURE SELECTION IN SAMPLE SET VALUED ORDERED DECISION TABLE

Sample set valued ordered decision table.

U	c_1	c_2	c_3	c_4	c_5	d
u_1	$\{1\}$	$\{2\}$	$\{1\}$	$\{1,2\}$	$\{1,2\}$	1
u_2	$\{1\}$	$\{2\}$	$\{1,2\}$	$\{1\}$	$\{1\}$	2
u_3	$\{1\}$	$\{2\}$	$\{1\}$	$\{1,2\}$	$\{1,2\}$	2
u_4	$\{1\}$	$\{1,2\}$	$\{1\}$	$\{1\}$	$\{1\}$	1
u_5	$\{1,2\}$	$\{2\}$	$\{2\}$	$\{1\}$	$\{1,2\}$	3
u_6	$\{2\}$	$\{1\}$	$\{1,2\}$	$\{2\}$	$\{1\}$	1
u_7	$\{1\}$	$\{1,2\}$	$\{1,2\}$	$\{1\}$	$\{2\}$	1

We calculate the set valued upward dominance classes for all the objects in U on the basis of the conditional attributes in $C = c_1, c_2, c_3, c_4, c_5$ as follows:

$$\delta_c^+(u_1) = \{u_1\}, \ \delta_c^+(u_2) = \{u_2, u_5\}, \ \delta_c^+(u_3) = \{u_3, u_6\}, \ \delta_c^+(u_4) = \{u_1, u_4, u_5\}$$

$\delta_c^+(u_5) = \{u_5\}$, $\delta_c^+(u_6) = \{u_6\}$ and $\delta_c^+(u_7) = \{u_7\}$. We also have $\delta_{c \cup d}^+(u_1) = \{u_1\}$, $\delta_{c \cup d}^+(u_2) = \{u_2, u_5\}$ $\delta_{c \cup d}^+(u_3) = \{u_3\}$, $\delta_{c \cup d}^+(u_4) = \{u_1, u_4, u_5\}$, $\delta_{c \cup d}^+(u_5) = \{u_5\}$, $\delta_{c \cup d}^+(u_6) = \{u_6\}$ and $\delta_{c \cup d}^+(u_7) = \{u_7\}$. The calculated distance between the conditional attribute set C and the decision attribute d can be presented as

$$L_M(C, d) = 1 - \frac{1}{|U|} \sum_{\substack{M_i \in U/\delta_c^+ \\ N_i \in U/\delta_{C \cup d}^+}} \frac{|N_i|}{|M_i|} = \frac{1}{14}$$ initially we assume the reduct set IR

as the null set φ. Proceeding the calculations as above for the reduct set R, the upward dominance classes for each element of U in R is found to be

$$\delta_{IR}^+(u_1) = \delta_{IR}^+(u_2) = \delta_{IR}^+(u_3) = \delta_{IR}^+(u_4) = \delta_{IR}^+(u_5) = \delta_{IR}^+(u_6) = \delta_{IR}^+(u_7)$$
$$= \{u_1, u_2, u_3, u_4, u_5, u_6, u_7\}$$
$$\delta_{IR \cup d}^+(u_1) = \delta_{IR \cup d}^+(u_4) = \delta_{IR \cup d}^+(u_6) = \delta_{IR \cup d}^+(u_7) = \{u_1, u_2, u_3, u_4, u_5, u_6, u_7\}$$
$$\delta_{IR \cup d}^+(u_2) = \delta_{IR \cup d}^+(u_3) = \{u_2, u_3, u_5\} \text{ and } \delta_{IR \cup d}^+(u_5) = \{u_5\}$$
Hence $L_M(IR, d) = \frac{2}{7}$.

We notice here that $\dfrac{|\delta_{C \cup d}^+(u_i)|}{|\delta_C^+(u_i)|} \geq \dfrac{|\delta_{IR \cup d}^+(u_i)|}{|\delta_{IR}^+(u_i)|}$ $\forall u_i \in U$. As $L_M(IR, d) \neq L_M(C, d)$, we continue the loop in search of the best reduct. We have to include an attribute in C to the reduct R which has the greater significance. We have the similar calculations for the attribute $IR \cup \{c_1\} \subset C$ which gives $L_M(IR \cup \{c_1\}, d) = \frac{73}{294}$ and adding other conditional attributes one at a time $L_M(IR \cup \{c_2\}, d) = \frac{11}{49}$, $L_M(IR \cup \{c_3\}, d) = \frac{4}{49}$, $L_M(IR \cup \{c_4\}, d) = \frac{27}{98}$ and $L_M(IR \cup \{c_5\}, d) = \frac{23}{98}$ and their significance as in (3.3) was given by

$$SIGN_{IR}^{\geq}(c_1) = L_M(IR, d) - L_M(IR \cup \{c_1\}, d) = \frac{2}{7} - \frac{73}{294} = \frac{11}{294}$$
$$SIGN_{IR}^{\geq}(c_2) = L_M(IR, d) - L_M(IR \cup \{c_2\}, d) = \frac{2}{7} - \frac{11}{49} = \frac{3}{49}$$
$$SIGN_{IR}^{\geq}(c_3) = L_M(IR, d) - L_M(IR \cup \{c_3\}, d) = \frac{2}{7} - \frac{4}{49} = \frac{10}{49}$$
$$SIGN_{IR}^{\geq}(c_5) = L_M(IR, d) - L_M(IR \cup \{c_5\}, d) = \frac{2}{7} - \frac{11}{49} = \frac{3}{49}.$$

We notice that the attribute set $IR \cup \{c_3\} = \{c_3\}$ has the maximum significance and to be included into the reduct set so that now $IR = \{c_3\}$. Also note that $L_M(IR, d) \neq L_M(C, d)$ and continue the step 5 of the algorithm 1.

$$SIGN_{IR}^{\geq}(c_1) = L_M(IR, d) - L_M(IR \cup \{c_1\}, d) = \frac{4}{49} - \frac{1}{14} = \frac{1}{98}$$

$$SIGN_{IR}^{\geq}(c_2) = L_M(IR, d) - L_M(IR \cup \{c_2\}, d) = \frac{4}{49} - \frac{4}{49} = 0$$

$$SIGN_{IR}^{\geq}(c_4) = L_M(IR, d) - L_M(IR \cup \{c_4\}, d) = \frac{4}{49} - \frac{1}{14} = \frac{1}{98}$$

$$SIGN_{IR}^{\geq}(c_5) = L_M(IR, d) - L_M(IR \cup \{c_5\}, d) = \frac{4}{49} - \frac{4}{49} = 0 \,.$$

The attributes c_1 and c_4 has the same maximum significance and thus included in the reduct set. Now, $IR = IR \cup \{c_1, c_4\} = \{c_1, c_3, c_4\}$ and $L_M(IR, d) = \frac{1}{14} = L_M(C, d)$. Also $L_M(IR - \{c_1\}, d) = L_M(IR - \{c_4\}, d) = \frac{1}{14}$ and $L_M(IR - \{c_3\}, d) = \frac{3}{14} \neq L_M(C, d)$. Hence we conclude $R_1 = \{c_3, c_4\}$ and $R_2 = \{c_1, c_3\}$ are both reduction sets of our set valued ordered decision system.

5. CONCLUSION

In practical world we see the data for some fragment of condition attributes is many valued and there is a need for set valued decision tables. The ordering property of the objects related to the attribute values helps the reasoning process of the decision and also converges to the clear ideas in relatively minimum expected time. We had taken a set valued ordered decision table and constructed a distance between the object set based on the attribute values and tried a methodology to find the most featured attribute for the inclusion in the reduct set. We have explained the procedure with the help of sample data set and concluded that all the possible reducts can be extracted from the data with the simplified method in comparably minimum time interval.

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