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Intuitionistic Fuzzy Hybrid Data Mining-MAGDM Approach Using Correlated Aggregation for Solving Complex Decision Problems

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Abstract

This paper addresses Multiple Attribute Group Decision Making (MAGDM) problems where attribute values are represented as Intuitionistic Fuzzy Sets (IFSs). A novel decision-making framework is developed by integrating the Choquet integral operator with Intuitionistic Fuzzy Ordered Weighted Averaging (IFOWA) operators, effectively capturing both the importance and ordered influence of attributes under uncertainty. A distinguishing feature of this work is the fusion of Data Mining techniques into the MAGDM model, enabling the identification and elimination of irrelevant or redundant attributes. This integration significantly enhances the model's efficiency and decision quality by reducing complexity and focusing on the most impactful variables. The synergy between intuitionistic fuzzy logic and data mining provides a more intelligent and scalable decision-support system. The effectiveness and practicality of the proposed approach are demonstrated through a comprehensive numerical illustration.

Keywords: MAGDM, Intuitionistic Fuzzy sets, Data mining, Choquet integral operator.

1 | Introduction

Multiple Attribute Group Decision Making (MAGDM) is the process of selecting the best alternatives. In this competitive world, an organization can exist when the correct and appropriate decisions are made. Therefore, correct decisions help in the successful operation of a business with the help of fuzzy sets. Atanassov [1], [2] introduced the concept of Intuitionistic Fuzzy Set (IFS) characterized by a membership function and a non-membership function, which is a generalization of the concept of fuzzy set [3]. Data mining applications with statistical methods are inevitable in today's decision-making problems. A novel

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technique of mining trapezoidal intuitionistic fuzzy correlation rules for eigenvalue MAGDM Problems [4] was proposed. The correlation coefficient of IFSs was proposed in [5], which also plays a vital role in data mining in the form of identifying close relationships between fuzzy itemsets. Many aggregation operators that direct the decision-making process are found in [4], [6–8]. Some induced correlated aggregating operators with intuitionistic fuzzy information and their application to MAGDM were proposed in [6]. Recently, Zhang and Ma [9], Zhang et al. [10] proposed chaotic MAGDM problem solving in different domains. This paper aims to investigate the multiple attribute decision-making problems for evaluating the teaching effectiveness of the higher colleges and universities based on the IFECG operator with intuitionistic fuzzy information, and also to apply some data mining techniques for the reduction of the number of alternatives in the decision environment.

2 | Preliminaries

In this section, some basic definitions and IFECG operators are presented.

Definition 1. An IFS A in X is given by and $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle / x \in X\}$ where $\mu_A: X \to [0,1]$ and $\nu_A: X \to [0,1]$, with the condition $0 \le \mu_A(x) + \nu_A(x) \le 1$, for all $x \in X$. The numbers $\mu_A(x)$ and $\nu_A(x)$ represent, respectively, the membership degree and non-membership degree of the element x to the set A.

Definition 2. Let $\tilde{a} = (\mu, \nu)$ be an intuitionistic fuzzy number, a score function S of an intuitionistic fuzzy value can be represented as follows: $S(\tilde{a}) = \mu - \nu, S(\tilde{a}) \in [-1,1]$.

Definition 3. Let $\tilde{a} = (\mu, \nu)$ be an intuitionistic fuzzy number, an accuracy function H of an intuitionistic fuzzy value can be represented as follows: $H(\tilde{a}) = \mu + \nu$, $H(\tilde{a}) \in [0,1]$. To evaluate the degree of accuracy of the intuitionistic fuzzy value $\tilde{a} = (\mu, \nu)$, where $H(\tilde{a}) \in [0,1]$. The larger the value of $H(\tilde{a})$, the more the degree of accuracy of the intuitionistic fuzzy value $\tilde{a}$.

Definition 4. Let $\tilde{a} = \left(\mu_j, \nu_j\right)$ $(j = 1,2,\dots,n)$ be a collection of intuitionistic fuzzy values on Q, and μ be a fuzzy measure on Q, the intuitionistic fuzzy Einstein correlated geometric(IFECG) operator of $\tilde{a}_j$ with respect to μ is defined by

$$\mathrm{IFECG}_\mu(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \left(\tilde{a}_{\sigma(1)}\right)^{\left(\mu(A_{(1)})-\mu(A_{(2)})\right)} \otimes \left(\tilde{a}_{\sigma(2)}\right)^{\left(\mu(A_{(2)})-\mu(A_{(3)})\right)} \otimes \dots \otimes \left(\tilde{a}_{\sigma(n)}\right)^{\left(\mu(A_{(n)})-\mu(A_{(n+1)})\right)} = \bigotimes_{j=1}^{n} \left(\tilde{a}_{\sigma(j)}\right)^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)}$$

$$= \left(\frac{2\prod_{j=1}^{n}\mu_{\sigma(ij)}^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)}}{\prod_{j=1}^{n}\left(2-\mu_{\sigma(ij)}\right)^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)} + \prod_{j=1}^{n}\mu_{\sigma(ij)}^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)}}, \frac{\prod_{j=1}^{n}\left(1+v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)} - \prod_{j=1}^{n}\left(1-v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)}}{\prod_{j=1}^{n}\left(1+v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)} + \prod_{j=1}^{n}\left(1-v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)})-\mu(A_{(j+1)})\right)}} \right), \quad (1)$$

Where $\left(\sigma(1), \sigma(2), \dots, \sigma(n)\right)$ is a permutation of $(1,2,\dots,n)$, such that $\tilde{a}_{\sigma(j-1)} \le \tilde{a}_{\sigma(j)}$ for all $j = 2,\dots,n$, $A_{(i)} = \left((i),\dots,(n)\right)$, $A_{(n+1)} = \phi$.

It can be easily proved that the IFECG operator has the following properties.

Theorem 1. (Idempotency) If all $\tilde{a}_j (j = 1,2,\dots,n)$ are equal,i.e.$\tilde{a}_j = \tilde{a}$ for all j, then $\mathrm{IFECG}_w(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \tilde{a}$.

Theorem 2. (Boundedness) Let $\tilde{a}_j (j = 1,2,\dots,n)$ be a collection of IFVNs, and let $\tilde{a}^- = \widetilde{\min}\, a_j$, $\tilde{a}^+ = \widetilde{\max}\, a_j$ Then $\tilde{a}^- \le \mathrm{IFECG}_w(\tilde{a}_1 \tilde{a}_2, \dots, \tilde{a}_n) \le \tilde{a}^+$.

Theorem 3. (Monotonicity) Let $\tilde{a}_j (j = 1,2,\dots,n)$ and $\tilde{a}'_j (j = 1,2,\dots,n)$ be two set of IFVNs, if $\tilde{a}_j \le \tilde{a}_j'$, for all j, then $\mathrm{IFECG}_w(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) \le \mathrm{IFECG}_w\left(\tilde{a}_1', \tilde{a}_2', \dots, \tilde{a}_n'\right)$.

Theorem 4. (commutativity) Let $\tilde{a}_j(j = 1,2,\ldots,n)$and $\tilde{a}'_j(j = 1,2,\ldots,n)$ be two set of IFVNs, then $IFECG_w(\tilde{a}_1, \tilde{a}_2,\ldots,\tilde{a}_n) = IFECG_w(\tilde{a}_1', \tilde{a}_2',\ldots,\tilde{a}_n')$, where $\tilde{a}'_j(j = 1,2,\ldots,n)$ is any permutation of $\tilde{a}_j(j = 1,2,\ldots,n)$.

3 | Algorithm For Solving the MAGDM Problem

The following assumptions or notations are used to represent the MADM problems for evaluating the teaching effectiveness of the higher colleges and universities based on the IFECG operator with intuitionistic fuzzy information. Let $A = \{A_1, A_2,\ldots,A_m\}$ be a discrete set of alternatives, $G = \{G_1, G_2,\ldots,G_n\}$ be a set of attributes. The information about attribute weights is completely known. Let $\omega = \{\omega_1, \omega_2,\ldots,\omega_n\}$ be the weight vector of attributes, where $\omega_j \geq 0, j = 1,2\ldots,n$. Suppose that $\tilde{R} = (\tilde{r}_{ij})_{m\times n} = (\mu_{ij}, \nu_{ij})_{m\times n}$ is the intuitionistic fuzzy decision matrix, where μ_{ij} indicates the degree of the alternative A_i satisfies the attribute G_j given by the decision maker, ν_{ij} indicates the degree of the alternative A_i doesn't satisfy the attribute G_j given by the decision maker,

$$\mu_{ij} \subset [0,1], \nu_{ij} \subset [0,1], \mu_{ij} + \nu_{ij} \leq 1, i = 1,2,\ldots,m, j = 1,2,\ldots,n.$$

In the following, we apply the IFECG operator to multiple attribute decision making (MADM) problems for evaluating the teaching effectiveness of the higher colleges and universities based on the IFECG operator with intuitionistic fuzzy information.

Step 1. Determine the fuzzy measure of the attribute of $G_j(j = 1,2,\ldots,n)$ and attribute sets of G. There are a few methods for the determination of the fuzzy measure. For example, linear methods, quadratic methods, heuristic-based methods, genetic algorithms, and so on are available in the literature.

Step 2. Utilize the IFCGM operator

$$\tilde{r}_i = IFECG(\tilde{r}_{i1}, \tilde{r}_{i2},\ldots,\tilde{r}_{in}) = (\tilde{r}_{\sigma(i1)})^{(\mu(G_{(1)})-\mu(G_{(2)}))} \otimes (\tilde{r}_{\sigma(i2)})^{(\mu(G_{(2)})-\mu(G_{(3)}))} \otimes\ldots\otimes (\tilde{r}_{\sigma(in)})^{(\mu(G_{(n)})-\mu(G_{(n+1)}))} = \bigotimes_{j=1}^{n} (\tilde{r}_{(ij)})^{(\mu(G_{(j)})-\mu(G_{(j+1)}))},$$

to derive the overall preference values $\tilde{r}_i(i = 1,2,\ldots,m)$ of the alternative A_i.

Step 3. Calculate the scores $S(\tilde{r}_i)(i = 1,2,\ldots,m)$ of the collective overall intuitionistic fuzzy preference values $\tilde{r}_i(i = 1,2,\ldots,m)$ to rank all the alternatives $A_i(i = 1,2,\ldots,m)$ and then to select the best one (s).

Step 4. Rank all the enterprises $A_i(i = 1,2,\ldots,m)$ and select the best one (s) in accordance with $S(\tilde{r}_i)$ and $H(\tilde{r}_i)(i = 1,2,\ldots,m)$.

Step 5. The fuzzy support fsupp $(\tilde{r}_i)$, of each trapezoidal IFS item is computed.

Let $L_1 = \{\tilde{r}_p/\tilde{r}_p \in F, fsupp(\tilde{r}_p) \geq s_{\tilde{r}}\}$ be the set of frequent fuzzy item sets whose size is equal to 1.

Let $C_2 = \{(F_A, F_B)\}$ be the set of all combinations of two elements belonging to L_1, where $F_A, F_B \in L_1, F_A \neq F_B$. That is, $C_2 = \{(F_A, F_B)\}$ is generated by L_1 joint with L_1. Since F_A, F_B are the elements of L_1, the size of each element of C_2 is 2.

For each element of C_2, (F_A, F_B), the fuzzy support, fsupp $\{(F_A, F_B)\}$ is computed by using the comparison of the hesitation degree of each intuitionistic fuzzy information, and then the trapezoidal intuitionistic fuzzy correlation coefficient between F_A, F_B , $K(F_A, F_B)$ is computed from equation (11). Calculate the median value $K_{MED}(F_A, F_B)$ of all the correlation coefficients $K(F_A, F_B)$ and consider all the $K(F_A, F_B) > K_{MED}(F_A, F_B)$ for the next level.

For each element, whose fuzzy support is greater than or equal to $s_{\tilde{r}}$ and the maximum fuzzy correlation coefficients with their correlation coefficient $K(F_A, F_B) > K_{MED}(F_A, F_B)$ of C_2, will be an element of L_2.

Hence, L_2 is the set of the frequent combinations of two fuzzy itemsets, and the size of each element is 2. Next, each C_k, $k \geq 3$, is generated by L_{k-1} joint with L_{k-1}. Assume that (F_W, F_X) and (F_Y, F_Z) are two elements of L_{k-1}, where $F_X = F_Y$. If the size of the combination $(F_X, \{F_W, F_Z\})$ is k, and (F_W, F_Z) is also a frequent combination of 2-fuzzy itemsets, then the combination $(F_X, \{F_W, F_Z\})$ is an element with size k of C_k. For each element of C_k, its fuzzy support and fuzzy correlation coefficient are still used to find the elements of L_k.

When each L_k, $k \geq 2$, is obtained, for each element of L_k, (F_G, F_H), the 2-candidate fuzzy correlation rules can be generated. At this level, the itemsets with the highest correlation coefficient can be selected or ranked, which can be considered as interesting fuzzy correlation rules. The loop will stop when the next C_{k+1} cannot be generated.

4 | Numerical Example

To demonstrate the approach suggested in this work, a numerical example is provided in this section. Let's say a school wants to assess how well physical education is taught. Four potential physical education teachers are on a panel from whom to choose. To evaluate the four potential physical education teachers, the school chooses five attributes: G1 is the assessment of the students; G2 is the assessment of peers; G3 is the assessment of the experts; and G4 is the assessment of the leadership. As indicated in the following matrix, the decision maker is to assess the five potential teachers utilizing intuitionistic fuzzy information under the four aforementioned criteria.

$$A = \begin{bmatrix} (0.3,0.4) & (0.4,0.6) & (0.8,0.1) & (0.6,0.3) \\ (0.7,0.1) & (0.5,0.3) & (0.6,0.2) & (0.4,0.3) \\ (0.3,0.6) & (0.3,0.4) & (0.5,0.4) & (0.6,0.3) \\ (0.7,0.2) & (0.4,0.5) & (0.6,0.3) & (0.7,0.3) \\ (0.5,0.3) & (0.9,0.1) & (0.6,0.3) & (0.5,0.4) \end{bmatrix}.$$

Then, we utilize the approach developed to evaluate the teaching effectiveness of the higher colleges and universities.

Step 1. Suppose the fuzzy measure of the attribute of $G_j (j = 1,2,3,4)$ and attribute sets of G as follows:

$$\mu(G_1) = 0.30, \mu(G_2) = 0.20, \mu(G_3) = 0.35, \mu(G_4) = 0.25, \mu(G_1, G_2) = 0.50,$$
$$\mu(G_1, G_3) = 0.65, \mu(G_1, G_4) = 0.70, \mu(G_2, G_3) = 0.65, \mu(G_2, G_4) = 0.60,$$
$$\mu(G_3, G_4) = 0.50, \mu(G_1, G_2, G_3) = 0.80, \mu(G_1, G_2, G_4) = 0.85,$$
$$\mu(G_1, G_3, G_4) = 0.85, \mu(G_2, G_3, G_4) = 0.78, \mu(G_1, G_2, G_3, G_4) = 1.00.$$

Step 2. Utilize the decision information given in matrix $\tilde{R}$, and the IFECG operator, we obtain the overall preference values $\tilde{r}_i$of the teaching effectiveness of the five teachers $A_i (i = 1,2,\ldots,5)$.

$$\tilde{r}_i = \left(\frac{2\prod_{j=1}^{n} \mu_{\sigma(ij)}^{\left(\mu(A_{(j)}) - \mu(A_{(j+1)})\right)}}{\prod_{j=1}^{n} \left(2 - \mu_{\sigma(ij)}\right)^{\left(\mu(A_{(j)}) - \mu(A_{(j+1)})\right)} + \prod_{j=1}^{n} \mu_{\sigma(ij)}^{\left(\mu(A_{(j)}) - \mu(A_{(j+1)})\right)}}, \frac{\prod_{j=1}^{n} \left(1 + v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)}) - \mu(A_{(j+1)})\right)} - \prod_{j=1}^{n} \left(1 - v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)}) - \mu(A_{(j+1)})\right)}}{\prod_{j=1}^{n} \left(1 + v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)}) - \mu(A_{(j+1)})\right)} + \prod_{j=1}^{n} \left(1 - v_{\sigma(ij)}\right)^{\left(\mu(A_{(j)}) - \mu(A_{(j+1)})\right)}} \right).$$

For i=1,

$$\tilde{r}_1 = \Bigg(\frac{2(0.3)^{0.30} \times (0.4)^{0.20} \times (0.8)^{0.30} \times (0.6)^{0.20}}{(2-0.3)^{0.30} \times (2-0.4)^{0.20} \times (2-0.8)^{0.30} \times (2-0.6)^{0.20} + (0.3)^{0.30} \times (0.4)^{0.20} \times (0.8)^{0.30} \times (0.6)^{0.20}},$$
$$\frac{(1+0.4)^{0.30} \times (1+0.6)^{0.20} \times (1+0.1)^{0.30} \times (1+0.3)^{0.20} - (1-0.4)^{0.30} \times (1-0.6)^{0.20} \times (1-0.1)^{0.30} \times (1-0.3)^{0.20}}{(1+0.4)^{0.30} \times (1+0.6)^{0.20} \times (1+0.1)^{0.30} \times (1+0.3)^{0.20} + (1-0.4)^{0.30} \times (1-0.6)^{0.20} \times (1-0.1)^{0.30} \times (1-0.3)^{0.20}} \Bigg) \tilde{r}_1 =$$
$$(0.5039, 0.344).$$

For i=2,

$$\tilde{r}_2 = \left(\frac{2(0.7)^{0.30}\times(0.5)^{0.20}\times(0.6)^{0.30}\times(0.4)^{0.20}}{(2-0.7)^{0.30}\times(2-0.5)^{0.20}\times(2-0.6)^{0.30}\times(2-0.4)^{0.20}+(0.7)^{0.30}\times(0.5)^{0.20}\times(0.6)^{0.30}\times(0.4)^{0.20}}, \frac{(1+0.1)^{0.30}\times(1+0.3)^{0.20}\times(1+0.2)^{0.30}\times(1+0.3)^{0.20}-(1-0.1)^{0.30}\times(1-0.3)^{0.20}\times(1-0.2)^{0.30}\times(1-0.3)^{0.20}}{(1+0.1)^{0.30}\times(1+0.3)^{0.20}\times(1+0.2)^{0.30}\times(1+0.3)^{0.20}+(1-0.1)^{0.30}\times(1-0.3)^{0.20}\times(1-0.2)^{0.30}\times(1-0.3)^{0.20}}\right) \tilde{r}_2 = (0.5630, 0.2115).$$

For i=3,

$$\tilde{r}_3 = \left(\frac{2(0.7)^{0.30}\times(0.5)^{0.20}\times(0.6)^{0.30}\times(0.4)^{0.20}}{(2-0.7)^{0.30}\times(2-0.5)^{0.20}\times(2-0.6)^{0.30}\times(2-0.4)^{0.20}+(0.7)^{0.30}\times(0.5)^{0.20}\times(0.6)^{0.30}\times(0.4)^{0.20}}, \frac{(1+0.1)^{0.30}\times(1+0.3)^{0.20}\times(1+0.2)^{0.30}\times(1+0.3)^{0.20}-(1-0.1)^{0.30}\times(1-0.3)^{0.20}\times(1-0.2)^{0.30}\times(1-0.3)^{0.20}}{(1+0.1)^{0.30}\times(1+0.3)^{0.20}\times(1+0.2)^{0.30}\times(1+0.3)^{0.20}+(1-0.1)^{0.30}\times(1-0.3)^{0.20}\times(1-0.2)^{0.30}\times(1-0.3)^{0.20}}\right) \tilde{r}_3 = (0.3895, 0.4476).$$

For i=4,

$$\tilde{r}_4 = \left(\frac{2(0.7)^{0.30}\times(0.4)^{0.20}\times(0.6)^{0.30}\times(0.7)^{0.20}}{(2-0.7)^{0.30}\times(2-0.4)^{0.20}\times(2-0.6)^{0.30}\times(2-0.7)^{0.20}+(0.7)^{0.30}\times(0.4)^{0.20}\times(0.6)^{0.30}\times(0.7)^{0.20}}, \frac{(1+0.2)^{0.30}\times(1+0.5)^{0.20}\times(1+0.3)^{0.30}\times(1+0.3)^{0.20}-(1-0.2)^{0.30}\times(1-0.5)^{0.20}\times(1-0.3)^{0.30}\times(1-0.3)^{0.20}}{(1+0.2)^{0.30}\times(1+0.5)^{0.20}\times(1+0.3)^{0.30}\times(1+0.3)^{0.20}+(1-0.2)^{0.30}\times(1-0.5)^{0.20}\times(1-0.3)^{0.30}\times(1-0.3)^{0.20}}\right) \tilde{r}_4 = (0.6027, 0.3144).$$

For i=5,

$$\tilde{r}_5 = \left(\frac{2(0.5)^{0.30}\times(0.9)^{0.20}\times(0.6)^{0.30}\times(0.5)^{0.20}}{(2-0.5)^{0.30}\times(2-0.9)^{0.20}\times(2-0.6)^{0.30}\times(2-0.5)^{0.20}+(0.5)^{0.30}\times(0.9)^{0.20}\times(0.6)^{0.30}\times(0.5)^{0.20}}, \frac{(1+0.3)^{0.30}\times(1+0.1)^{0.20}\times(1+0.3)^{0.30}\times(1+0.4)^{0.20}-(1-0.3)^{0.30}\times(1-0.1)^{0.20}\times(1-0.3)^{0.30}\times(1-0.4)^{0.20}}{(1+0.3)^{0.30}\times(1+0.1)^{0.20}\times(1+0.3)^{0.30}\times(1+0.4)^{0.20}+(1-0.3)^{0.30}\times(1-0.1)^{0.20}\times(1-0.3)^{0.30}\times(1-0.4)^{0.20}}\right) \tilde{r}_5 = (0.3540, 0.2513).$$

Step 3. Calculate the scores $S(\tilde{r}_i)(i = 1,2,3,4,5)$ of the overall intuitionistic fuzzy preference values $\tilde{r}_i(i = 1,2,3,4,5)$.

$$S(\tilde{r}_1) = 0.1599, S(\tilde{r}_2) = 0.3515, S(\tilde{r}_3) = -0.0581, S(\tilde{r}_4) = 0.2883, S(\tilde{r}_5) = 0.2817.$$

Step 4. Rank all the teaching effectiveness of the five teachers $A_i(i = 1,2,3,4,5)$ in accordance with the scores $S(\tilde{r}_i)(i = 1,2,3,4,5)$ of the overall intuitionistic fuzzy preference values $\tilde{r}_i(i = 1,2,3,4,5)$:$A_2 \succ A_4 \succ A_5 \succ A_1 \succ A_3$, and thus the most desirable teaching effectiveness of the five teachers is A_2.

Step 5: Using the above data mining algorithm, we can reduce the number of decision variables as follows $A_2 \succ A_4 \succ A_5$. $A_1$and A_3 are eliminated from the system of the decision-making process.

5 | Conclusion

In this work, we have investigated the MAGDM problems based on ordered weighted averaging operators and evaluated the teaching effectiveness of the higher colleges and universities based on the intuitionistic fuzzy correlate geometric (IFECG) operator with intuitionistic fuzzy information. We utilize the IFECG operator to aggregate the intuitionistic fuzzy information corresponding to each alternative and get the overall value of the alternatives, then rank the teaching effectiveness of the higher colleges and universities based on the IFECG operators and select the most desirable one (s) according to the score function and accuracy function. We have also used a data mining algorithm to reduce the number of variables in the decision process. Finally, an illustrative example is given.

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