Information Intelligent Acquisition Generated by Matrix Reasoning of Inverse P-Set

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Abstract. More and more attention has been paid to the intelligent acquisition of information in the field of data mining in big data, Internet of things and so on. Unlike popular methods such as machine learning, this paper attempts to propose a matrix reasoning method for intelligent information acquisition from the perspective of set theory. The inverse packet set (P-set) is a new set model with dynamic features. In the inverse P-set, the attribute α_i of the element x_i satisfies the expansion or contraction paradigm for attribute extraction. Based on the concept of inverse P-set, this paper presents some new concepts as α^F-information equivalence class, $\alpha^{\overline{F}}$-information equivalence class, and $(\alpha^F, \alpha^{\overline{F}})$-information equivalence class. Then, this paper gives some theorems as internal inverse P-augmented matrix inference, outer inverse P-augmented matrix inference, and inverse P-augmented matrix inference, which are generated by the above information equivalence class. At last, this paper gives the application of intelligent acquisition of information.

Keywords: Inverse P-set · Matrix inference · Information equivalence class · Intelligent acquisition algorithm

1 Introduction

Information widely exists in real life, and becomes more and more [17]. Sometimes there is "redundancy" in the data. Although machine learning method has been widely used and achieved in information intelligent acquisition [4,13], the research on the mathematical logic of information intelligent acquisition is still relatively small. More "intelligent" information acquisition methods are urgently needed to find target information or "useful" information from massive data [1,5].

Generally, data are stored in various documents in the form of "records" with multiple attributes, such as databases, data warehouses, etc. [2]. Attributes are very important in distinguishing each record and determining the number of

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elements in the dataset, the set which has dynamic characteristics in the process of adding or reducing attributes to them. The inverse P-Set [10] is one of the theories and methods to describe this dynamic feature.

The inverse packet set (P-set) [16,20] is a new set model obtained by introducing dynamic features. The function in the function space represents a kind of law, and the function space F represents a set of laws to be selected by decision makers. Function space F is very important for the construction of inverse P-sets, which is related to specific goals, such as data mining, information hiding, knowledge reasoning, etc. Applying function space to inverse P-Set can enlarge the application scope of inverse P-Set and provide better choice for decision makers.

A propositional formula is called conjunctive normal form if and only if it has the form: $A_1 \wedge A_2 \wedge \cdots \wedge A_n$, $A_1, A_2, \cdots, A_n$ are called sub normal form, which are all disjunctive forms of propositional arguments or their negations. A propositional formula is called disjunctive normal form, if and only if it has the form: $A_1 \vee A_2 \vee \cdots \vee A_n$, $A_1, A_2, \cdots, A_n$ are called a sub normal form, which are all conjunctions of propositional arguments or their negation. Any conjunctive normal form can be transformed into a disjunctive normal form through calculus.

Taking knowledge mining as an example, Knowledge (x) and its attribute set α appear in pairs or knowledge (x) has attribute set α; conversely, attribute set α corresponds to knowledge (x). This conclusion comes from a popular example: $X = \{x_i\}$ $(i = 1, 2, 3)$ is a set of toy, $\alpha = \{\alpha_j\}$ $(j = 1, 2, 3)$ is its attribute set, such as, $\alpha_1 = Red$, $\alpha_2 = Blue$, $\alpha_3 = Green$. conversely, the attribute α_j satisfies: $\alpha_i = \alpha_1 \vee \alpha_2 \vee \alpha_3 = \bigvee_{t=1}^{3} \alpha_t$. If toy x_4 with purple color is added into X, then $\alpha_i = \bigvee_{t=1}^{4} \alpha_t$. From this popular example, we get two facts: (I) Supplementing element x_i in (x) is equivalent to add attribute in attribute set α of (x) or supplementing element x_i in (x) is equivalent to expansion of disjunctive normal form of attribute α_i of element x_i. (II) Deleting element x_i from (x) is equivalent to deleting attributes, which is equivalent to contraction of disjunctive normal form of attribute α_i of element x_i. This popular example is the factual basis of this paper.

Some new analyses are given in this paper: (a) the logic features of the inverse P-augmented matrix which are the base of this paper are given; (b) the equivalence class is generated by inverse P-aggregate; (c) the theorems of matrix inference are presented as the methods for obtaining the information equivalence class; (d) the simple application of intelligence is shown in this paper. All the results given in this paper are very new.

2 Literature Review

Inverse P-sets are firstly put forward by the authors of [10] and has been studied in the field of information [6] and image processing [15].

In terms of information fusion, the authors of [7] gave the structures, the separations, and the equivalence class characteristics of P-sets by through the reasoning discovery is presented by the author of [12]; moreover, the application of intelligent fusion is presented by through P-information fusion[8].

In terms of information hiding, the information hiding generated by inverse P-intelligent fusion are put forward in [11]. On the other hand, the restoration of information hiding is analyzed in [18].

In terms of information mining, the attributes of the elements in inverse P-sets satisfy disjunctive characteristics [3]. Using the structure, the intelligent mining under the condition of disjunctive attribute expanded were presented in [9]. In addition, the intelligent mining-discovery of complete information with satisfying internal inverse P-reasoning and/or complete information condition was also put forward by [19]. Moreover, some applications of the information with expanded characteristic of the disjunctive attribute was analyzed by [20].

In terms of information reasoning, on the basis of inverse P-reasoning, the theorem of inverse P-reasoning was given by [14]. Later, The geometric characteristics of inverse P-reasoning have been given [15]. Moreover, unknown information search by using inverse P-reasoning have been given [16].

Compared with the previous literature, this paper proposes the concept inverse P-Set, and proves several theorems of the logical characteristics of information equivalence class. Based on the information equivalence class, this paper presents several theorems of matrix reasoning and information intelligent acquisition algorithm. These research contents are all new.

3 The Information Equivalence Class

For set $X = \{x_1, x_2, \cdots, x_q\} \subset U$ and its attribute $\alpha = \{\alpha_1, \alpha_2, \cdots, \alpha_q\} \subset V$, the following set pair $(\overline{X}^F, \overline{X}^{\overline{F}})$ is called as inverse P-set [10], where, $\overline{X}^F = X \cup X^+$, $\overline{X}^{\overline{F}} = X - X^-$. There are two special set $X^+ = \{u_i | u_i \in U, u_i \overline{\in} X, f(u_i) = x'_i \in X, f \in F\}$ and $X^- = \{x_i | x_i \in X, \overline{f}(x_i) = u_i \overline{\in} X, \overline{f} \in \overline{F}\}$. For the attribute set, they satisfy $\alpha^F = \alpha \bigcup \{f(\beta_i) = \alpha'_i \in \alpha, f \in F\}$ and $\alpha^{\overline{F}} = \alpha - \{\overline{f}(\alpha_i) = \beta_i \overline{\in} \alpha, \overline{f} \in \overline{F}\}$. F and $\overline{F}$ mean math function. Obviously, $\alpha_1^F \subseteq \alpha_2^F \subseteq \cdots \subseteq \alpha_{n-1}^F \subseteq \alpha_n^F$, $\alpha_n^{\overline{F}} \subseteq \alpha_{n-1}^{\overline{F}} \subseteq \cdots \subseteq \alpha_2^{\overline{F}} \subseteq \alpha_1^{\overline{F}}$, so $\overline{X}_1^F \subseteq \overline{X}_2^F \subseteq \cdots \subseteq \overline{X}_{n-1}^F \subseteq \overline{X}_n^F$ and $\overline{X}_n^{\overline{F}} \subseteq \overline{X}_{n-1}^{\overline{F}} \subseteq \cdots \subseteq \overline{X}_2^{\overline{F}} \subseteq \overline{X}_1^{\overline{F}}$. A matrix pair $(\overline{A}^F, \overline{A}^{\overline{F}})$ is defined as inverse P-augmented matrix [20] generated by $(\overline{X}^F, \overline{X}^{\overline{F}})$.

Definition 1. *For the inverse P-information $((\overline{x})^F, (\overline{x})^{\overline{F}})$, $[[\overline{x}]^F, [\overline{x}]^{\overline{F}}]$ is called as the $(\alpha^F, \alpha^{\overline{F}})$-information equivalence class, in which $(\alpha^F, \alpha^{\overline{F}})$ is its attribute set. For the inverse P-information family $\{((\overline{x})_i^F, (\overline{x})_j^{\overline{F}}) | i \in I, j \in J\}$, $\{[[\overline{x}]_i^F, [\overline{x}]_j^{\overline{F}}] | i \in I, j \in J\}$ is referred to as the $(\alpha_i^F, \alpha_j^{\overline{F}})$-information equivalent class family, in which $\{(\alpha_i^F, \alpha_j^{\overline{F}}) | i \in I, j \in J\}$ is their attribute set family.*

From the above definition, we get the following propositions.

Proposition 1. *$((\overline{x})^F, (\overline{x})^{\overline{F}})$ and $(\alpha^F, \alpha^{\overline{F}})$ are equivalence. The former is the inverse P-information, and the later is the information equivalence class.*

Proof. Given information (x) and its attribute α, let α be the relationship R between $(x) \times (x)$, $R = \alpha$. It is easy to get the followings:

1. $\forall x_i \in (x)$, x_i has a relationship R with x_i, or $x_i R x_i$, which satisfies reflexivity.
2. $\forall x_i, x_j \in (x)$, x_i has a relationship R with x_j, x_j has a relationship R with x_i or $x_i R x_j \Rightarrow x_j R x_i$, which satisfies symmetry.
3. $\forall x_i, x_j, x_k \in (x)$, $x_i R x_j, x_j R x_k \Rightarrow x_i R x_k$, which satisfies transitivity.

From Items 1–3, we get that the information (x) is an equivalence class; similarly, $[[\overline{x}]^F, [\overline{x}]^{\overline{F}}]$ is also an equivalence class. thus, Proposition 1 is proved.

Proposition 2. *$\{((\overline{x})_i^F, (\overline{x})_j^{\overline{F}}) | i \in I, j \in J\}$ and (α_i^F, α_j^F) are two equivalent concepts. The former are the The inverse P-information family. The later are the information equivalence class family.*

Similarly, The Propositions 2 could be proofed, so we omit it.

Theorem 1. *(The theorem of attribute disjunctive normal form for α-information equivalence class $[x]$) For the α-information equivalence class $[x]$, the attribute α_i satisfies*

$$\alpha_i = \bigvee_{t=1}^{q} \alpha_t \tag{1}$$

Proof. Given information (x) and its attribute set α, from the concepts of inverse P-set, we get that, for $\forall x_i \in (x)$, the attribute $\alpha_i = \alpha_1 \vee \alpha_2 \vee \cdots \vee \alpha_q = \vee_{t=1}^{q} \alpha_t$, thus we get Eq. (1).

Theorem 2. *(The expansion theorem of attribute disjunctive normal form) If the attribute α_i of information element $x_i \in [\overline{x}]^F$ satisfies the expansion of attribute disjunctive normal form, then the attribute α_i of x_i satisfies*

$$\alpha_i = (\bigvee_{t=1}^{q} \alpha_t) \bigvee_{t=q+1}^{\lambda} \alpha_t \tag{2}$$

Proof. Given information (x) and its attribute set α, the attribute α_i of $\forall x_i \in [x]$ satisfies $\alpha_i = \alpha_1 \vee \alpha_2 \vee \cdots \vee \alpha_q = \vee_{t=1}^{q} \alpha_t$. By using Eqs. (1) in Sect. 3, $(\overline{x})^F = \{x_1, x_2, \cdots, x_q, x_{q+1}, \cdots, x_\lambda\}$, $\alpha^F = \{\alpha_1, \alpha_2, \cdots, \alpha_q, \alpha_{q+1}, \cdots, \alpha_\lambda\}$ is the attribute set of $(\overline{x})^F$, the attribute α_i of $\forall x_i \in (\overline{x})^F$ satisfies that $\alpha_i = (\alpha_1 \vee \alpha_2 \vee \cdots \vee \alpha_q) \vee \alpha_{q+1} \vee \cdots \vee \alpha_\lambda = (\vee_{t=1}^{q} \alpha_t) \vee_{t=Q+1}^{\lambda} \alpha_t$. From Definition, we get that $[\overline{x}]^F = (\overline{x})^F$. Obviously, the attributes α_i of $\forall x_i \in [\overline{x}]^F$ satisfy $\alpha_i = (\alpha_1 \vee \alpha_2 \vee \cdots \vee \alpha_q) \vee \alpha_{q+1}\ Vee \cdots \vee \alpha_\lambda = (\vee_{t=1}^{q} \alpha_t) \vee_{t=q+1}^{\lambda} \alpha_t$, thus we get Eq. (2).

Theorem 3. *(The contraction theorem of attribute disjunctive normal form) If $\alpha^{\overline{F}}$ is the attribute set of $\alpha^{\overline{F}}$-information equivalence class, then the attribute α_i of x_i satisfies*

$$\alpha_i = (\bigvee_{t=1}^{q} \alpha_t) - \bigvee_{t=p+1}^{q} \alpha_t \tag{3}$$

Similarly, the proof of Theorem 3 is easy, so it is omitted. By using Theorems 1–3, we directly get Theorem 4,

Theorem 4. *(The expansion and contraction theorem of disjunctive normal form) IF the* $(\alpha^F, \alpha^{\overline{F}})$*-information equivalence class satisfy expansion and contraction, then the attributes satisfy*

$$(\alpha_i, \alpha_j) = ((\vee_{t=1}^{q}\alpha_t) \vee_{t=q+1}^{\lambda} \alpha_t, (\vee_{t=1}^{q}\alpha_t) - \vee_{t=p+1}^{q}\alpha_t) \tag{4}$$

In Eq. (4), $\alpha_i = (\vee_{t=1}^{q}\alpha_t) \vee_{t=q+1}^{\lambda} \alpha_t$, $\alpha_j = (\vee_{t=1}^{q}\alpha_t) - \vee_{t=p+1}^{q}\alpha_t$.

By using the preparatory concepts and the information equivalence class concepts in Sect. 3, we give the intelligent acquisition algorithm for information equivalence classes in Sect. 4.

4 Intelligent Acquisition Algorithm for Information Equivalence Classes

Definition 2. *For* $\overline{A}_k^F$ *and* $\overline{A}_{k+1}^F$*, if the attribute set* α_k^F *and* α_{k+1}^F *satisfy the following*

$$if \quad \overline{A}_k^F \Rightarrow \overline{A}_{k+1}^F, \quad then \quad \alpha_k^F \Rightarrow \alpha_{k+1}^F \tag{5}$$

Then, Eq. (5) is called as internal inverse P-matrix inference.

In Eq. (5), $\overline{A}_k^F \Rightarrow \overline{A}_{k+1}^F$ represents $\overline{A}_k^F \subseteq \overline{A}_{k+1}^F$ and $\alpha_k^F \Rightarrow \alpha_{k+1}^F$ represents $\alpha_k^F \subseteq \alpha_{k+1}^F$.

Definition 3. *For the outer inverse P-matrix* $\overline{A}_k^{\overline{F}}$ *and* $\overline{A}_{k+1}^{\overline{F}}$*, if the attribute set* $\alpha_k^{\overline{F}}$ *and* $\alpha_{k+1}^{\overline{F}}$ *satisfy the following*

$$if \quad \overline{A}_{k+1}^{\overline{F}} \Rightarrow \overline{A}_k^{\overline{F}}, \quad then \quad \alpha_{k+1}^{\overline{F}} \Rightarrow \alpha_k^{\overline{F}} \tag{6}$$

then, Eq. (6) is called as outer inverse P-matrix inference.

Definition 4. *For the inverse P-matrix* $(\overline{A}_k^F, \overline{A}_{k+1}^{\overline{F}})$ *and* $(\overline{A}_{k+1}^F, \overline{A}_k^{\overline{F}})$*, if the attribute set* $(\alpha_k^F, \alpha_{k+1}^{\overline{F}})$ *and* $(\alpha_{k+1}^F, \alpha_k^{\overline{F}})$ *satisfy the following*

$$if \quad (\overline{A}_k^F, \overline{A}_{k+1}^{\overline{F}}) \Rightarrow (\overline{A}_{k+1}^F, \overline{A}_k^{\overline{F}}), \quad then \quad (\alpha_k^F, \alpha_{k+1}^{\overline{F}}) \Rightarrow (\alpha_{k+1}^F, \alpha_k^{\overline{F}}) \tag{7}$$

then, Eq. (7) is called as inverse P-matrix inference.

In Eq. (7), $(\alpha_k^F, \alpha_{k+1}^{\overline{F}}) \Rightarrow (\alpha_{k+1}^F, \alpha_k^{\overline{F}})$ represents $\alpha_k^F \Rightarrow \alpha_{k+1}^F$ and $\alpha_{k+1}^{\overline{F}} \Rightarrow \alpha_k^{\overline{F}}$.

By using Definitions 2–4, we get Theorem 5.

Theorem 5. *(The intelligent acquisition theorem for α^F-information equivalence class) If the internal inverse P-matrix $\overline{A}_k^F$ and $\overline{A}_{k+1}^F$, α_k^F-information equivalence class $[x]_k^F$ and $[\overline{x}]_{k+1}^F$ satisfy*

$$if \quad \overline{A}_k^F \Rightarrow \overline{A}_{k+1}^F, \quad then \quad [\overline{x}]_k^F \Rightarrow [\overline{x}]_{k+1}^F, \tag{8}$$

then $[\overline{x}]_{k+1}^F$ is intelligently acquired from the outer of $[\overline{x}]_k^F$.

Proof. From the preliminary concepts in Sect. 3, we get that $\overline{A}_k^F$ and $\overline{A}_{k+1}^F$ are generated by the inverse P-sets $\overline{X}_k^F$ and $\overline{X}_{k+1}^F$, respectively. $\overline{A}_k^F$ and $\overline{A}_{k+1}^F$ satisfy $\overline{A}_k^F \Rightarrow \overline{A}_{k+1}^F$; $[\overline{x}]_k^F$ and $[\overline{x}]_{k+1}^F$ are the α^F- information equivalence class generated by $\overline{X}_k^F$ and $\overline{X}_{k+1}^F$, respectively; and $[\overline{x}]_k^F = \overline{X}_k^F$, $[\overline{x}]_{k+1}^F = \overline{X}_{k+1}^F$ or $\overline{X}_k^F \subseteq \overline{X}_{k+1}^F$. Obviously, under the condition of the internal inverse P-matrix reasoning $\overline{A}_k^F \Rightarrow \overline{A}_{k+1}^F$, we get that $[\overline{x}]_k^F \subseteq [\overline{x}]_{k+1}^F$, that is, $[\overline{x}]_{k+1}^F$ is intelligently acquired from the outer of $[\overline{x}]_k^F$, so we get Theorem 5.

Theorem 6. *($\alpha^{\overline{F}}$-information equivalence class intelligent acquisition theorem) If the outer inverse P-matrix $\overline{A}_{k+1}^{\overline{F}}$, $\overline{A}_k^{\overline{F}}$, and $\alpha^{\overline{F}}$-information equivalence class satisfy*

$$if \quad \overline{A}_{k+1}^{\overline{F}} \Rightarrow \overline{A}_k^{\overline{F}}, \quad then \quad [x]_{k+1}^{\overline{F}} \Rightarrow [x]_k^{\overline{F}}, \tag{9}$$

then $[x]_{k+1}^{\overline{F}}$ is intelligently acquired from the internal of $[x]_k^{\overline{F}}$.

The proof of Theorem 6 is similar to that of Theorem 5, thus it is omitted. Theorem 7 in the following are directly obtained from Theorems 5 and 6.

Theorem 7. *($(\alpha^F, \alpha^{\overline{F}})$-information equivalence class intelligent acquisition theorem) If the inverse P-matrix $(\overline{A}_k^F, \overline{A}_{k+1}^{\overline{F}})$ and $(\overline{A}_{k+1}^F, \overline{A}_k^{\overline{F}})$, and $(\alpha^F, \alpha^{\overline{F}})$-information equivalence class satisfy*

$$if \quad (\overline{A}_k^F, \overline{A}_{k+1}^{\overline{F}}) \Rightarrow (\overline{A}_{k+1}^F, \overline{A}_k^{\overline{F}}), \quad then \quad [[\overline{x}]_k^F, [\overline{x}]_{k+1}^{\overline{F}}] \Rightarrow [[\overline{x}]_{k+1}^F, [\overline{x}]_k^{\overline{F}}], \tag{10}$$

then $[\overline{x}]_{k+1}^F$ is intelligently acquired from the outer of $[\overline{x}]_k^F$, and, at the same time, $[\overline{x}]_{k+1}^{\overline{F}}$ is intelligently acquired from the inner of $[\overline{x}]_k^{\overline{F}}$. $[\overline{x}]_{k+1}^F$ and $[\overline{x}]_{k+1}^{\overline{F}}$ compose $(\alpha^F, \alpha^{\overline{F}})$-information equivalence class $[[\overline{x}]_{k+1}^F, [\overline{x}]_{k+1}^{\overline{F}}]$.

By using Definitions 2–4 and Theorem 5–7, we get the following algorithm. The algorithm is shown in Fig. 1.

Special Note: The intelligent acquisition algorithm of $\alpha_k^{\overline{F}}$-information equivalence class $[\overline{x}]_k^{\overline{F}}$ in Fig. 1 is a part of the intelligent acquisition algorithm of information equivalence class. The intelligent acquisition algorithm of α_k^F-information equivalence class $[\overline{x}]_k^F$ is omitted in Fig. 1. The intelligent acquisition algorithm of α_k^F-information equivalence class $[\overline{x}]_k^F$ is similar to Fig. 1.

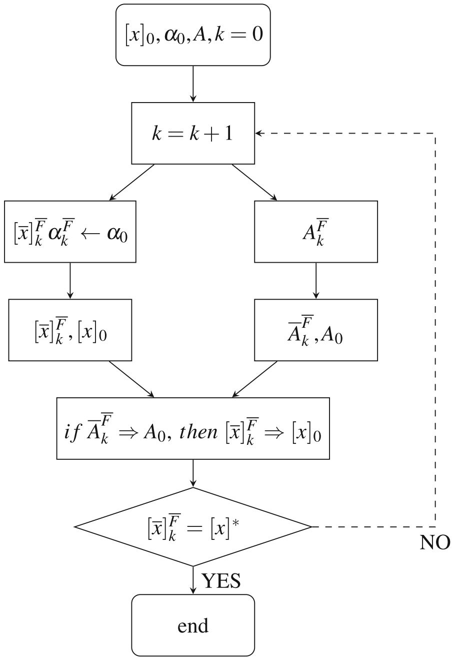

Fig. 1. Flow chart of intelligent acquisition algorithm of information equivalence class.

There are four steps in the process of intelligent acquisition algorithm of information equivalence class.

Step 1. Given the original information $(x)_0 = \{x_1, x_2, \cdots, x_q\}$, $[x]_0$ is the α-information equivalence class generated by $(x)_0$, $[x]_0 = (x)_0$; $\alpha = \{\alpha_1, \alpha_2, \cdots, \alpha_q\}$ is an attribute set of $[x]_0$, and A_0 is a matrix of information values generated by $[x]_0$; A_0 is A in Sect. 3.

Step 2. Delete several attributes α_i from α_0, α_0 generates $\alpha_k^{\overline{F}}$, $\alpha_k^{\overline{F}} \subseteq \alpha_0$; $[x]_0$ generates outer inverse P-information $(\overline{x})_k^{\overline{F}}$, $(\overline{x})_k^{\overline{F}} \subseteq (x)_0$; $[\overline{x}]_k^{\overline{F}}$ is the $\alpha_k^{\overline{F}}$-information equivalent class generated by $(\overline{x})_k^{\overline{F}}$, $[\overline{x}]_k^{\overline{F}} = (\overline{x})_k^{\overline{F}}$; from $[\overline{x}]_k^{\overline{F}}$, $[x]_0$ and $\overline{A}_k^{\overline{F}}$, A_0 in Step 1 constitutes an outer inverse P-matrix inference: $if\ \overline{A}_k^{\overline{F}} \Rightarrow A_0, then [\overline{x}]_k^{\overline{F}} \Rightarrow [x]_0$.

Step 3. Compare the $[\overline{x}]_k^{\overline{F}}$ obtained by intelligent acquisition in Step 2 with the standard $[x]^*$, if $[\overline{x}]_k^{\overline{F}} = [x]^*$, then the intelligent acquisition process of $[\overline{x}]_k^{\overline{F}}$ ends.

Step 4. If $[\overline{x}]_k^{\overline{F}} \neq [x]^*$, the process of intelligent acquisition continues. Delete several attributes α_j from $\alpha_k^{\overline{F}}$, $\alpha_k^{\overline{F}}$ generates $\alpha_{k+1}^{\overline{F}}$, $\alpha_{k+1}^{\overline{F}} \subseteq \alpha_k^{\overline{F}}$; $[\overline{x}]_k^{\overline{F}}$ generates outer inverse P-information $(\overline{x})_{k+1}^{\overline{F}}$; $[\overline{x}]_{k+1}^{\overline{F}}$ generate outer inverse P-matrix $\overline{A}_{k+1}^{\overline{F}}$. From $\overline{A}_{k+1}^{\overline{F}}$, the $\overline{A}_k^{\overline{F}}$ in Step 2 constitutes the outer inverse P-matrix inference:

if $\overline{A}_{k+1}^{\overline{F}} \Rightarrow \overline{A}_{k}^{\overline{F}}$, then $[\overline{x}]_{k+1}^{\overline{F}} \Rightarrow [\overline{x}]_{k}^{\overline{F}}$; go to Step 3. This is the cyclic process in the intelligent acquisition algorithm.

5 Application

The simple application example in this section comes from the commodity trading system, and the application examples are easily understood. w_1, w_2, w_3, w_4, w_5, and w_6 are Chinese companies in Shandong province which produce different textiles. $x_1 \sim x_6$ are six textiles. If $w_i \neq w_j$, then $x_i \neq x_j$, $i, j = 1, 2, \cdots 6$; x_1–x_6 constitute the information $(x)_0$.

$$(x)_0 = \{x_i | i = 1 \sim 6\}, \alpha_0 = \{\alpha_i | i = 1 \sim 6\} \tag{11}$$

Obviously, the attribute α_i satisfies $\alpha_i = \vee \alpha_i$.

From Definition 1, we get that $[x]_0 = (x)_0$. y_j is the profit during January–April 2018 of $x_j \in [x]_0$: the vector y_j is constituted by $y_{1,j}, y_{2,j}, y_{3,j}, y_{4,j}$, the information value matrix A_0 is generated by $[x]_o$, in which y_j is the column.

$$A_0 = \begin{pmatrix} 0.82 & 0.65 & 0.58 & 0.59 & 0.66 & 0.70 \\ 0.64 & 0.69 & 0.62 & 0.77 & 0.94 & 0.78 \\ 0.71 & 0.75 & 0.88 & 0.83 & 0.59 & 0.89 \\ 0.80 & 0.87 & 0.63 & 0.90 & 0.70 & 0.95 \end{pmatrix} \tag{12}$$

Here, for the sake of trade secrets, the value of each column of A_0 in Eq. (12) obtained by transforming the real profit value using the technical method. The value obtained by the technical method transformation does not affect the analysis of the application example.

In August 2018, the textiles x_3 and x_5 produced by the companies W_3 and W_5, respectively, were saturated in the market, thus companies W_3 and W_5 were closed. x_3 and x_5 in $(x)_0$ are deleted to generate $(\overline{x})^{\overline{F}} \subset (x)_0$.

$$(\overline{x})^{\overline{F}} = \{x_1, x_2, x_4, x_6\} \tag{13}$$

α_3 and α_5 are deleted from α in Eq. (11), thus α generates $\alpha^{\overline{F}}$

$$\alpha^{\overline{F}} = \alpha - \{\alpha_3, \alpha_5\} = \{\alpha_1, \alpha_2, \alpha_4, \alpha_6\} \tag{14}$$

Delete the third column and the fifth column from A_0 in Eq. (12), A_0 generates $\overline{A}^{\overline{F}}$, $\overline{A}^{\overline{F}} \subset A_0$

$$\overline{A}^{\overline{F}} = \begin{pmatrix} 0.82 & 0.65 & 0.59 & 0.70 \\ 0.64 & 0.69 & 0.77 & 0.78 \\ 0.71 & 0.75 & 0.83 & 0.89 \\ 0.80 & 0.87 & 0.90 & 0.95 \end{pmatrix} \tag{15}$$

The attribute α_i satisfies $\alpha_i = (\vee \alpha_i) - \alpha_3 \vee \alpha_5 = \alpha_1 \vee \alpha_2 \vee \alpha_4 \vee \alpha_6$. Equations (12), (15), (13), and (11) constitute the outer inverse P-matrix inference (shown in Eq. (6)), or, if $\overline{A}^{\overline{F}} \Rightarrow A_0$, then $[\overline{x}]^{\overline{F}} \Rightarrow [x]_0$.

We conducted a four-month survey and inquired about the user on the sales market of textiles x_3 and x_5. The results were the same as those given in the example.

Due to the limitation of the length of the paper, we use technical means to simplify the application examples without affecting the interpretation of the research content. We will show more complex application examples in further research.

6 Discussions and Conclusions

This article is inspired by the literature [1,5]. Given set X and its attribute set α, α generates α^F by adding some attributes into α, $\alpha \subseteq \alpha^F$; X generates $\overline{X}^F$, then $X \subseteq \overline{X}^F$. if deleting the attribute in α, α generates $\alpha^{\overline{F}}$, $\alpha^{\overline{F}} \subseteq \alpha$; X generates $\overline{X}^{\overline{F}} \subseteq X$. Then inverse P-set $(\overline{X}^F, \overline{X}^{\overline{F}})$ is obtained. By using the inference condition $A \Longrightarrow \overline{A}^F$, the inner inverse P-information $(\overline{x})^F$ is found intelligently from outer of (x), $(x) \subseteq (\overline{x})^F$. By using outer inverse P-matrix inference conditions: $\overline{A}^{\overline{F}} \Rightarrow A$, the outer inverse P-information $(\overline{x})^{\overline{F}}$ is found intelligently from the inner of (x), $(\overline{x})^{\overline{F}} \subseteq (x)$.

The new methods and new theories about the dynamic intelligent retrieval of information are presented in this paper. There is a fact: on a train, passenger $x_1, x_2, \cdots, x_n$ constitutes passenger information $(x) = \{x_1, x_2, \cdots, x_n\}$, each traveler $x_i \in (x)$ has attributes α_i, $\alpha_i=$ tickets; We get that if $\forall x_i, x_j \in (x)$, $x_i \neq x_j$, then $\alpha_i \neq \alpha_j$, $\alpha_i, \alpha_j \in \alpha$, or if $\forall x_i, x_j \in (x)$, $x_i = x_j$, then $\alpha_i = \alpha_j$, $\alpha_i, \alpha_j \in \alpha$.

Inverse P-sets include not only all kinds of elements, but also the attributes of elements. They are in pairs. In prediction or reasoning, elements and their attributes cooperate, interact, and influence each other to complete tasks together.

Inverse P-Set theory can be used to study the characteristics of dynamic information law. It is very different from other traditional methods, such as clustering, regression analysis, and so on. They are two different theoretical methods.

The theorems, propositions, and methods proposed in this paper are mainly applied to the discrete system composed of many elements. The research results of this paper are more applied to the analysis of the relationship between elements and systems, but less to the analysis of the relationship between elements.

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