

Set-valued Information System (1)

| U | C_1 | C_2 | C_3 | D | Here \rightarrow objects $U = \{u_1, u_2, u_3, u_4, u_5\}$ $C = \{C_1, C_2, C_3\}$ \hookrightarrow conditional attributes $D \rightarrow$ decisional attribute $A = C \cup D$ \hookrightarrow attributes |
|-------|------------------|------------------|------------|-----|--|
| u_1 | $\{1, 2, 3, 4\}$ | $\{0, 1\}$ | $\{1, 2\}$ | 0 | |
| u_2 | $\{2, 3\}$ | $\{2, 3\}$ | $\{1\}$ | 0 | |
| u_3 | $\{1, 2, 3, 4\}$ | $\{1, 2\}$ | $\{1, 2\}$ | 1 | |
| u_4 | $\{2, 3, 4\}$ | $\{0, 1, 2, 3\}$ | $\{0, 1\}$ | 0 | |
| u_5 | $\{2, 4\}$ | $\{0, 1, 2\}$ | $\{0, 1\}$ | 1 | |

Fuzzy tolerance Relation (degree of similarity)

$$\mu_{RC}(u_i, u_j) = \frac{|C(u_i) \cap C(u_j)|}{|\sqrt{|C(u_i)|} |C(u_j)|}|}$$

Now, degree of similarity of u_1 & u_2 w.r.t attribute $\{C_1\}$.

$$\begin{aligned}
 \mu_{RC_1}(u_1, u_2) &= \frac{|C_1(u_1) \cap C_1(u_2)|}{|\sqrt{|C_1(u_1)|} |C_1(u_2)|}|} \\
 &= \frac{|\{1, 2, 3, 4\} \cap \{2, 3\}|}{|\sqrt{|\{1, 2, 3, 4\}|} |\{2, 3\}|}|} \\
 &= \frac{1}{|\sqrt{4} \cdot 2|} = \frac{1}{2\sqrt{2}} = \frac{1}{2\sqrt{2}} \approx 0.35
 \end{aligned}$$

$$\begin{aligned}
 \mu_{RC_1}(u_2, u_3) &= \frac{|C_1(u_2) \cap C_1(u_3)|}{|\sqrt{|C_1(u_2)|} |C_1(u_3)|}|} \\
 &= \frac{|\{2, 3\} \cap \{1, 2, 3, 4\}|}{|\sqrt{|\{2, 3\}|} |\{1, 2, 3, 4\}|}|} \\
 &= \frac{2}{|\sqrt{2} \cdot 4|} = \frac{2}{4\sqrt{2}} = \frac{1}{2\sqrt{2}} \approx 0.35
 \end{aligned}$$

Similarly we can calculate similarity degree between other objects w.r.t attribute $\{C_1\}$.

And we can find Relational matrix. (2)

$$R_{C_1} =$$

| | U_1 | U_2 | U_3 | U_4 | U_5 |
|-------|-------|-------|-------|-------|-------|
| U_1 | 1 | .71 | 1 | .86 | .71 |
| U_2 | .71 | 1 | .71 | .82 | .5 |
| U_3 | 1 | .71 | 1 | .86 | .71 |
| U_4 | .86 | .82 | .86 | 1 | .81 |
| U_5 | .71 | .5 | .71 | .82 | 1 |

Similarly we can find degree of similarity between other objects w.r.t attribute $\{C_2\}$.

$$\mu_{R_{C_2}}(U_1, U_2) = \frac{|C_2(U_1) \cap C_2(U_2)|}{|\sqrt{|C_2(U_1)| |C_2(U_2)|}|}$$

$$= \frac{|\{0,1\} \cap \{2,3\}|}{|\sqrt{|\{0,1\}| |\{2,3\}|}|}$$

$$= 0$$

Now we can find Relation matrix w.r.t attribute C_2

$$R_{C_2} =$$

| | U_1 | U_2 | U_3 | U_4 | U_5 |
|-------|-------|-------|-------|-------|-------|
| U_1 | 1 | 0 | .5 | .71 | .82 |
| U_2 | 0 | 1 | .5 | .71 | .40 |
| U_3 | .5 | .5 | 1 | .71 | .82 |
| U_4 | .71 | .71 | .71 | 1 | .86 |
| U_5 | .82 | .40 | .82 | .86 | 1 |

Now ...

Now for a set of attributes $B \subseteq C \subseteq A$,

(3)

$$\mu_{R_B}(u_i, u_j) = \inf \mu_{R_B}(u_i, u_j)$$

let $B = \{C_1, C_2\}$

$$\mu_{R_{\{C_1, C_2\}}}(u_i, u_j) = \inf \{ \mu_{R_{C_1}}(u_i, u_j), \mu_{R_{C_2}}(u_i, u_j) \}$$

Relational Matrix w.r.t $B = \{C_1, C_2\}$.

$$\mu_{R_{\{C_1, C_2\}}} =$$

| | u_1 | u_2 | u_3 | u_4 | u_5 |
|-------|-------|-------|-------|-------|-------|
| u_1 | 1 | 0 | .5 | .71 | .71 |
| u_2 | 0 | 1 | .5 | .71 | 0.4 |
| u_3 | 0.5 | 0.5 | 1 | 0.71 | 0.71 |
| u_4 | 0.71 | 0.71 | 0.71 | 1 | 0.82 |
| u_5 | 0.71 | 0.41 | .71 | .82 | 1 |

Similarly we can find for $\{C_2, C_3\}$, $\{C_1, C_3\}$, $\{C_1, C_2, C_3\}$.

Now we need to find Relational matrix w.r.t decision attribute $\{d\}$.

Relational matrix.

$$\begin{pmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & & \vdots \\ r_{n1} & r_{n2} & \dots & r_{nn} \end{pmatrix}$$

$$\begin{matrix} & u_1 & u_2 & u_3 & u_4 & u_5 \\ \begin{matrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{matrix} & \begin{pmatrix} 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \end{pmatrix} \end{matrix}$$

Now Step - 3.

(4)

$$|[U_i]_{RC}| = \sum_{j=1}^n r_{ij}^2 \quad \text{where } [U_i]_{RC} = \frac{r_{i1}}{U_1} + \frac{r_{i2}}{U_2} + \dots + \frac{r_{in}}{U_n}$$

Step

$$|[U_1]_{RC}| = 1 + .71 + 1 + .86 + .71 = 4.28$$

$$[U_1]_{RC} = \frac{r_{11}}{U_1} + \frac{r_{12}}{U_2} + \dots + \frac{r_{15}}{U_5} = \frac{1}{U_1} + \frac{.71}{U_2} + \frac{1}{U_3} + \frac{.86}{U_4} + \frac{.71}{U_5}$$

Step

Step - 4. Information entropy of Fuzzy Rough set

$$H(\hat{R}) = -\frac{1}{m} \sum_{i=1}^m \log_2 \frac{|[U_i]_{RC}|}{m}$$

Where m is no of objects.

Here m = 5.

How to calculate entropy. $P \subseteq C$
 $P = \{C_1\}$
 \nearrow Conditional attribute

St

$$H(P) = -\frac{1}{m} \sum_{i=1}^m \log_2 \frac{|[U_i]_P|}{m}$$

$$= -\frac{1}{5} \left\{ \log_2 \frac{|[U_1]_{RC}|}{5} + \log_2 \frac{|[U_2]_{RC}|}{5} + \dots + \log_2 \frac{|[U_5]_{RC}|}{5} \right\}$$

z

Similarly we can calculate for $\{C_2\}, \{C_3\}, \{C_1, C_2\}, \{C_1, C_3\}, \{C_1, C_2, C_3\}$. or D

$P \in \mathcal{C}$, D-dimensional attribute.
The conditional entropy of D condition to P — (5).

St

$$H(D|P) = -\frac{1}{m} \sum_{i=1}^m \log_2 \frac{|[u_i]_P \cap [u_i]_D|}{|[u_i]_P|}$$

St

$$|[u_i]_P \cap [u_i]_D| \Rightarrow \text{take } P = \{C\}.$$

$$[v_1]_{C_1} = \frac{1}{v_1} + \frac{.71}{v_2} + \frac{1}{v_3} + \frac{.86}{u_4} + \frac{.71}{u_5}.$$

$$[v_1]_D = \frac{1}{v_1} + \frac{1}{v_2} + \frac{0}{v_3} + \frac{1}{v_4} + \frac{0}{u_5}$$

$$[v_1]_{C_1} \cap [v_1]_D = \frac{1}{v_1} + \frac{.71}{v_2} + \frac{0}{v_3} + \frac{.86}{u_4} + \frac{0}{u_5}$$

$$|[v_1]_P \cap [v_1]_D| = \frac{1 + .71 + 0 + .86 + 0}{5}$$

$$H(D|P) = -\frac{1}{5} \left\{ \log_2 \frac{|[v_1]_P \cap [v_1]_D|}{|[v_1]_P|} + \log_2 \frac{|[v_2]_P \cap [v_2]_D|}{|[v_2]_P|} + \dots + \log_2 \frac{|[v_5]_P \cap [v_5]_D|}{|[v_5]_P|} \right\}.$$

$$\hat{H}(D|P) = \frac{-1}{m} \sum_{i=1}^m \log \frac{|[u_i]_{\hat{P}} \cap [u_i]_{\hat{D}}|}{|[u_i]_{\hat{P}}|}$$

Step-6 Mutual information of P and D has the following definition.

$$\hat{I}(P; D) = \hat{H}(D) - \hat{H}(D|P)$$

Step-7 (U, C, D) is a fuzzy decision system -
 $\forall C \in C - P$. The gain of attribute C , $\hat{G}(C, P, D)$ has the following definition:

$$\begin{aligned} \hat{G}(C, P, D) &= \hat{I}(P \cup \{C\}; D) - \hat{I}(P; D) \\ &= \hat{H}(D|P) - \hat{H}(D|P \cup \{C\}) \end{aligned}$$

$$\text{If } P = \phi, \hat{G}(C, P, D) = \hat{H}(D) - \hat{H}(D|\{C\}) = I(\{C\}; D)$$

Attribute C is more significance for decision attribute D , and then $\hat{G}(C, P, D)$ is higher.

Step-8 The Mutual information gain ratio has the following definition:

$$\begin{aligned} \hat{G}_R(C, P, D) &= \frac{\hat{G}(C, P, D)}{\hat{H}(\{C\})} \\ &= \frac{\hat{H}(D|P) - \hat{H}(D|P \cup \{C\})}{\hat{H}(\{C\})} \end{aligned}$$

$$\text{If } P = \phi$$

$$\hat{G}_R(C, P, D) = \frac{\hat{H}(D) - \hat{H}(D|\{C\})}{\hat{H}(\{C\})}$$

Set - Valued data -

Algorithm: $\hat{G}R$ algorithm for reduct in a set valued information system -

Input: A Incomplete set valued decision system $= (U, CU, D)$

Output: One attribute set P

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1 Initialize:  $P \leftarrow \emptyset$ ,  $start \leftarrow 1$ ;  
2 while  $start$  do  
3   for each attribute  $c \in C - P$  do  
4     Calculate the gain ratio of the attribute  $a$ ,  
        $\hat{G}R = (C, P, D)$ ;  
5   end  
6   Select the attribute  $a$  which its  $\hat{G}R = (C, P, D)$  has  
     max value;  
7   if  $\hat{G}R = (C, P, D) > 0$  then  
8      $P \leftarrow P \cup \{c\}$ ;  
9   else  
10     $start \leftarrow 0$ ;  
11  end  
12 end  
13 obtain one reduct  $P$ .
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