Super Attribute Representative for Decision Attribute Selection

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Abstract. Soft set theory proposed by Molodstov is a general mathematic tool for dealing with uncertainties. Recently, several algorithms had been proposed for decision making using soft set theory. However, these algorithms still concern on a Boolean-valued information system. In this paper, Support Attribute Representative (SAR), a soft set based technique for decision making in categorical-valued information system is proposed. The proposed technique has been tested on two datasets. The results of this research will provide useful information for decision makers to handle categorical datasets.

Keywords: Information system; Data mining; Soft set theory; Decision attributes selections.

1 Introduction

In today's fast moving world, decision making is a very critical issues. Good decision making is aiding by the good information. Unfortunately, some information is uncertain. Handling uncertain data is very important because in reality, there are lots real life problems in which still involve uncertain data, for example in field of engineering, medical, social, medical sciences and etc [1]. There are several theories, such as probabilities theories, theory of fuzzy set, theory of rough set and etc, which can be considered as the mathematical tools for dealing with uncertainties.

The theory of soft set proposed by Molodtsov [2] 1999 as a new way for managing uncertain data. Molodtsov pointed out that one of the main advantages of soft set theory is that it is free from the inadequacy of the parameterization tools, unlike in the theories mentioned above. The soft set theory uses parameterization sets, as its main vehicles for problem solving, which makes it very convenient and easy to apply in practice. Therefore, many applications based on soft set theory have already been demonstrated by Molodtsov [2], such as the smoothness of functions, game theory, operations research, Riemann integration, Perron integration, probability theory, and

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measurement theory. Presently, great progresses of study on soft set theory have been made. Maji *et al.* [3] firstly introduced some definitions of the related operations on soft sets. Ali *et al.* [4] took into account some errors of former studies and put forward some new operations on soft sets. As for practical applications of soft set theory, great progress has been achieved. Maji *et al.* [1] employed soft sets to solve the decision-making problem. Roy and Maji [5] presented a novel method of object recognition from an imprecise multi-observer data to deal with decision making based on fuzzy soft sets, which was revised by Kong *et al.* [6]. Feng *et al.* [7] showed an adjustable approach to fuzzy soft set based decision making by means of level soft sets. It is worthwhile to mention that some effort has been done to such issues concerning reduction of soft sets. Chen *et al.* [8] pointed out that the conclusion of soft set reduction offered in [1] was incorrect, and then present a new notion of parameterization reduction in soft sets in comparison with the definition to the related concept of attributes reduction in rough set theory. The concept of normal parameter reduction is introduced in [9], which overcome the problem of suboptimal choice and added parameter set of soft sets. An algorithm for normal parameter reduction is also presented in [9]. However, these soft set-based algorithms still concern on a Boolean-valued information system.

In this paper, Support Attribute Representative (SAR), a soft set based technique for decision making in categorical-valued information system is proposed. The proposed technique has been tested on two datasets. The results of this research will provide useful information for decision makers to handle categorical datasets.

The rest of the paper is organized as follows. Section 2 described the soft set theory. In section 3, the proposed technique is describe. An experiment and analysis is described in section 4. Finally, conclusion of this work described in section 5.

2 Soft Set Theory

An *information system* as in is a 4-tuple (quadruple) $S = (U, A, V, f)$, where $U = \{u_1, u_2, u_3, \cdots, u_{|U|}\}$ is a non-empty finite set of objects, $A = \{a_1, a_2, a_3, \cdots, a_{|A|}\}$ is a non-empty finite set of attributes, $V = \bigcup_{a \in A} V_a$, V_a is the domain (value set) of attribute a, $f : U \times A \to V$ is an information function such that $f(u,a) \in V_a$, for every $(u,a) \in U \times A$, called information (knowledge) function. An information system can be intuitively expressed in terms of an information table (see Table 1).

Table 1. An information system

U	a_1	$\cdots$	a_k	$\cdots$	$a_{\|A\|}$
u_1	$f(u_1, a_1)$	$\cdots$	$f(u_1, a_k)$	$\cdots$	$f(u_1, a_{\|A\|})$
u_2	$f(u_2, a_1)$	$\cdots$	$f(u_2, a_k)$	$\cdots$	$f(u_2, a_{\|A\|})$
u_3	$f(u_3, a_1)$	$\cdots$	$f(u_3, a_k)$	$\cdots$	$f(u_3, a_{\|A\|})$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
$u_{\|U\|}$	$f(u_{\|U\|}, a_1)$	$\cdots$	$f(u_{\|U\|}, a_k)$	$\cdots$	$f(u_{\|U\|}, a_{\|A\|})$

In many applications, there is an outcome of classification that is known. This a posteriori knowledge is expressed by one (or more) distinguished attribute called decision attribute; the process is known as supervised learning. An information system of this kind is called a decision system. A *decision system* is an information system of the form $D = (U, A \cup \{d\}, V, f)$, where $d \notin A$ is the decision attribute.

Throughout this section U refers to an initial universe, E is a set of parameters, $P(U)$ is the power set of U and $A \subseteq E$.

Definition 1. (See [2].) *A pair (F, A) is called a soft set over U, where F is a mapping given by*

$$F : A \to P(U).$$

In other words, a soft set over U is a parameterized family of subsets of the universe U. For $\varepsilon \in A$, $F(\varepsilon)$ may be considered as the set of ε-elements of the soft set (F, A) or as the set of ε-approximate elements of the soft set. Clearly, a soft set is not a (crisp) set.

As an illustration, let consider a soft set which describes the 'attractiveness of programming language' that Mr. X is considering to use. Let assume that there are ten programming languages in the universe U that are under consideration by Mr. X such that $U = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}\}$, and is a set of decision parameter where $E = \{e_1, e_2, e_3, e_4, e_5, e_6, e_7\}$. Every $e \in E$ representing an element of attractiveness such that e_1 representing an element of 'system', e_2 representing an element of 'education', e_3 representing an element of 'web', e_4 representing an element of 'procedural', e_5 representing an element of 'object oriented', e_6 representing an element of 'reflective' and e_7 representing an element of 'functional'. Consider the mapping $F : E \to P(U)$ given by "programming language (.)", where (.) is to be filled in by one of parameters $e \in E$. Suppose that $F(e_1) = \{p_1, p_3, p_4, p_{10}\}$, $F(e_2) = \{p_2, p_7, p_8\}$, $F(e_3) = \{p_5, p_8, p_9\}$, $F(e_4) = \{p_1, p_2, p_3, p_4, p_7\}$, $F(e_5) = \{p_1, p_4, p_5, p_6, p_7, p_8, p_9\}$, $F(e_6) = \{p_5, p_8, p_9\}$ and $F(e_7) = \{p_5, p_8, p_9\}$. As for example, $F(e_1)$ means system programming languages, whose functional value is the set $\{p_1, p_3, p_4, p_{10}\}$. Thus we can view the soft set (F, E) as a collection of approximations as illustrated below:

$$(F, E) = \left\{ \begin{array}{l} e_1 = \{p_1, p_3, p_4, p_{10}\} \\ e_2 = \{p_2, p_7, p_8\} \\ e_3 = \{p_5, p_8, p_9\} \\ e_4 = \{p_1, p_2, p_3, p_4, p_7\} \\ e_5 = \{p_1, p_4, p_5, p_6, p_7, p_8, p_9\} \\ e_6 = \{p_5, p_8, p_9\} \\ e_7 = \{p_5, p_8, p_9\} \end{array} \right\}$$

Proposition 1. *If (F,E) is a soft set over the universe U, then (F,E) is a Boolean-valued information system $S = (U, A, V_{\{0,1\}}, f)$*

Proof. Let (F,E) be a soft set over the universe U, we define a mapping $F=\{f_1,f_2,..,f_n\}$ where

$$f_i : U \to V_i \qquad and \qquad f_i(x)=\begin{cases}1, & x\in F(e_i)\\ 0, & x\notin F(e_i)\end{cases}, for \quad 1\le x\le |A|$$

Hence, if $A=E,\ V=\bigcup_{e_i\in A} V_{e_i}$ where $V_{e_i}=\{0,1\}$ then the soft set (F,E) can be considered as a Boolean-valued information system $S=(U,A,V_{\{0,1\}},f)$. Therefore, a soft set (F,E) can be represented in the form of binary table. As can be seen in the Table 2, '1' denote the presence of the described parameters, while '0' mean the parameter is not part of the description of the programming languages attractiveness.

Table 2. Tabular representation of a soft set (F,E)

(F,E)	e_1	e_2	e_3	e_4	e_5	e_6	e_7
p_1	1	0	0	1	1	0	0
p_2	0	1	0	1	0	0	0
p_3	1	0	0	1	0	0	0
p_4	1	0	0	1	1	0	0
p_5	0	0	1	0	1	1	1
p_6	0	0	0	0	1	0	0
p_7	0	1	0	1	1	0	0
p_8	0	1	1	0	1	1	1
p_9	0	0	1	0	1	1	1
p_{10}	1	0	0	0	1	0	0

For multi-valued information system, it needs to convert into *multi-soft sets* [10]. It is based on the notion of a decomposition of a multi-valued information system. Let $S=(U,A,V,f)$ be a multi-valued information system and $S^i=(U,a_i,V_{ai},f)$, $i=1,2,\cdots,|A|$ be the $|A|$ binary-valued information systems. From Proposition 1, we have

$$S=(U,A,V,f)=\begin{cases}S^1=(U,a_1,V_{\{0,1\}},f) & \Leftrightarrow (F,a_1)\\ S^2=(U,a_2,V_{\{0,1\}},f) & \Leftrightarrow (F,a_2)\\ \quad\vdots & \quad\vdots \quad \vdots\\ S^{|A|}=(U,a_{|A|},V_{\{0,1\}},f) & \Leftrightarrow (F,a_{|A|})\end{cases}$$
$$=\left((F,a_1),(F,a_2),\cdots,(F,a_{|A|})\right)$$

We define $(F,E)=\left((F,a_1),(F,a_2),\cdots,(F,a_{|A|})\right)$ as a multi-soft set over universe U representing a multi-valued information system $S=(U,A,V,f)$.

Example 1. We consider the following data to illustrate the concept of multi-soft sets.

Table 3. Multi-value information system

Object	Volume	Material	Location
1	High	Hard	Pacific
2	High	Hard	Midwest
3	High	Medium	East Coast
4	High	Soft	Northern
5	Low	Soft	Pacific
6	Low	Medium	Midwest

The Dataset consist of three categorical-valued attributes so-called Volume, Material and Location. Attribute Volume only has two categories i.e. High and low. Attribute Material has 3 categories i.e. Hard, Medium and Soft. Meanwhile, attribute Location contains four categories i.e. Pacific, Midwest, East-Coast and Northern. The multi-soft sets representing the above information system is as follow.

$$(F,E)=\left\{\begin{array}{l}(F,Volume_{High})=\{1,2,3,4\}\\(F,Volume_{Low})=\{5,6\}\\(F,Material_{Hard})=\{1,2\}\\(F,Material_{Medium})=\{3,6\}\\(F,Material_{Soft})=\{4,5\}\\(F,Location_{Pacific})=\{1,5\}\\(F,Location_{Midwest})=\{2,6\}\\(F,Location_{East-coast})=\{3\}\\(F,Location_{Northern})=\{4\}\end{array}\right\}$$

3 Super Attribute Representative (SAR)

Throughout this section a pair (F,A) refers to multi-soft sets of universe U representing a categorical-valued information system $S=(U,A,V,f)$.

Definition 2 (Support). *Let* (F,A) *is a multi-soft set over the universe* U, *where* $(F,a_i)..(F,a_{|A|})\subseteq(F,A)$, *and* $(F,a_{i_1})..(F,a_{|a_i|})\subseteq(F,a_i)$. *The support of* (F,a_{i_j}) *by* (F,a_{i_k}) *denoted by* $Sup_{(F,a_{i_k})}(F,a_{i_j})$ *is defined as*

$$Sup_{(F,a_{i_k})}(F,a_{i_j})=\frac{\left|(F,a_{i_j})\cap(F,a_{i_k})\right|}{\left|(F,a_{i_j})\cup(F,a_{i_k})\right|},\forall(F,a_{i_j})\in(F,A);1\le i\le|A|;1\le j,k\le|a_i|$$

Definition 3 (Total Support). *The summation of all support for* (F,a_{j_k}) *denoted by* $TSup(F,a_{j_k})$ *is defined as*

$$TSup\left(F, a_{j_k}\right) = \sum^{|A|} Sup_{\left(F, a_{m_n}\right)}\left(F, a_{j_k}\right), \quad \forall\left(F, a_{j_k}\right) \in (F, A), 1 \le n \le |A|; 1 \le n \le |a_m|$$

Definition 4 (Attribute Representation). *The soft set in* (F, A) *that have maximum total support in their domain is known as attribute representative denoted by* $\mathrm{Rep}(A_i)$ *is defined as*

$$\mathrm{Rep}(A_i) = Max\left(TSup(\left(F, a_{i_1}\right), .., TSup\left(F, a_{i_{|A_i|}}\right)\right)$$

Definition 5 (Super Attribute Representative). *Attribute Representative with maximum value is known as Super Attribute Representative* (SAR), *defined as*

$$SAR = \begin{cases} Max\left(Mode\left(\mathrm{Re}\,p(A_i), .., \mathrm{Re}\,p\left(A_{|A|}\right)\right)\right), & Multiple \quad Occurences \\ Max\left(\mathrm{Re}\,p(A_i), .., \mathrm{Re}\,p\left(A_{|A|}\right)\right), & No \quad Multiple \quad Occurence \end{cases}$$

Next, the SAR algorithm is presented as follows.

```
Algorithm SAR
Input: Categorical-valued Dataset
Output: Decision Attribute
Begin
 1. Calculate Support and Total Support
      For i = all categories
         For j=all categories
             Intersection=Sum(And(Data(:,i),Data(:,j))
             Union = Sum(Or(Data(:,i),Data(:,j)
             Support i=Intersection / Union
             Total Support I += Support i
         End
      End

 2. Determine Representative of Domain Ai
    Size(R)=[row,column]
    For i=1:row
      If Mode([Ai])
         Rep(Ai)=Large([Ai])
      else
       Rep(Ai)=large([Ai])
      End

 3. Determine SAR of Domain A
     If mode(Rep())
      SAR=SAR(Rep())
     Else
        SAR = Large(Rep())
      end
```

Fig. 1. Algorithm SAR for Selecting Decision Attribute

3.1 Computational Complexity

Suppose that in an information system U, there are n objects, m attributes and l numbers of distinct values of each attribute. Process to determining an elementary set of all attributes needs nm. The computation of calculating the support of all subsets of U having different value of a_i is $n^2 l$. Meanwhile, by taking the worst-case, the process to determining the SAR is 1. Therefore, the computational complexity of SAR techniques is polynomial $O(n^2 l + nm + 1)$.

3.2 Example

In this section, an example of SAR implementation will be presented. Information system in Table 3 will be used as an input. All steps in this example are as the algorithm in Figure 1. Support for each soft set is computed using Definition 2. For example, all supports of $(F, Volume_{High})$ are calculated as follows.

a. Support by $(F, Volume_{High})$

$$Sup_{(F,Volume_{High})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{1,2,3,4\}|}{|\{1,2,3,4\} \cup \{1,2,3,4\}|} = \frac{4}{4} = 1$$

b. Support by $(F, Volume_{Low})$

$$Sup_{(F,Volume_{Low})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{5,6\}|}{|\{1,2,3,4\} \cup \{5,6\}|} = \frac{0}{6} = 0$$

c. Support by $(F, Material_{Hard})$

$$Sup_{(F,Material_{Hard})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{1,2\}|}{|\{1,2,3,4\} \cup \{1,2\}|} = \frac{2}{4} = 0.5$$

d. Support by $(F, Material_{Medium})$

$$Sup_{(F,Material_{Medium})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{3,6\}|}{|\{1,2,3,4\} \cup \{3,6\}|} = \frac{1}{5} = 0.2$$

e. Support by $(F, Material_{Soft})$

$$Sup_{(F,Material_{Soft})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{4,5\}|}{|\{1,2,3,4\} \cup \{4,5\}|} = \frac{1}{5} = 0.2$$

f. Support by $(F, Location_{Pacific})$

$$Sup_{(F,Location_{Pacific})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{1,5\}|}{|\{1,2,3,4\} \cup \{1,5\}|} = \frac{1}{5} = 0.2$$

g. Support by $(F, Location_{Midwest})$

$$Sup_{(F,Location_{Midwest})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{2,6\}|}{|\{1,2,3,4\} \cup \{2,6\}|} = \frac{1}{5} = 0.2$$

h. Support by $(F, Location_{East-coast})$

$$Sup_{(F, Location_{East-coast})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{3\}|}{|\{1,2,3,4\} \cup \{3\}|} = \frac{1}{4} = 0.25$$

i. Support by $(F, Location_{Northern})$

$$Sup_{(F, Location_{Northern})}(F, Volume_{High}) = \frac{|\{1,2,3,4\} \cap \{4\}|}{|\{1,2,3,4\} \cup \{4\}|} = \frac{1}{4} = 0.25$$

Based on the support given by each soft set, total support is computed using Definition 3. Therefore, the total support for $(F, Volume_{High})$ is given as

$$TSup(Volume_{High}) = 1 + 0 + 0.5 + 0.2 + 0.2 + 0.2 + 0.2 + 0.25 + 0.25$$

Table 4. Total support summary

Soft Set	Total Support
$(F, Volume_{High})$	2.8000
$(F, Volume_{Low})$	2.3333
$(F, Material_{Hard})$	2.1667
$(F, Material_{Medium})$	2.3667
$(F, Material_{Soft})$	2.3667
$(F, Location_{Pacific})$	2.2000
$(F, Location_{Midwest})$	2.2000
$(F, Location_{East-coast})$	1.7500
$(F, Location_{Northern})$	1.7500

Representative selection for each $(F, A_i) \in (F, A)$ is made using the formula in Definition 4. For example, representative for soft set $(F, Volume)$ is determined as follows

$$\mathrm{Re}\, p(F, Volume) = Max(TSup(F, Volume_{High}), TSup(F, Volume_{Low}))$$

It is clear that $(F, Volume_{High}) = 2.800$ is the representative for $(F, Volume)$ compared to $(F, Volume_{Low}) = 2.3333$. As shown in Table 4, $(F, Material)$ have two sub soft set with equal maximum value, one soft-set will be selected randomly as representative. The same step is repeated for soft-set $(F, Location)$. Thus, representatives with their value of total support for all soft set (F, A) are as follows.

$$\mathrm{Re}\,p(F,Volume) = (F,Volume_{High}) = 2.8000$$
$$\mathrm{Re}\,p(F,Material) = (F,Material_{Medium}) = 2.3667$$
$$\mathrm{Re}\,p(F,Location) = (F,Location_{Pacific}) = 2.200$$

Finally, super attribute representative will be determined based on Definition 5. For the above case, the decision choice will be made based on second option, since there is no repeat occurrence in representative values. Therefore, in this example, attribute Volume is selected as a decision attribute.

4 Experimental Resuts

Two simple small datasets from previous research [11] have been selected. Those dataset are Credit Card Promotion **(CCP)** and Modified Animal **(MA)**. The experiment is been done using Matlab R2008a on i5 Intel CPU with 3GB Memory. Preprocessing has been done earlier using Java.

4.1 Experiment 1 - Credit Card Promotion Dataset

The dataset as shown in Table 5, contains 10 objects with 5 categorical-value attributes, i.e. Magazine Promotion (MP), Watch Promotion (WP), Life Insurance Promotion (LIP), Credit Card Insurance (CCI) and Sex. Each attributes in the dataset contains two categories.

Table 5. Credit Card Promotion Dataset

Object	MP	WP	LIP	CCI	SEX
1	Yes	No	No	No	Male
2	Yes	Yes	Yes	No	Female
3	No	No	No	No	Male
4	Yes	Yes	Yes	Yes	Male
5	Yes	No	Yes	No	Female
6	No	No	No	No	Female
7	Yes	No	Yes	Yes	Male
8	No	Yes	No	No	Male
9	Yes	No	No	No	Male
10	Yes	Yes	Yes	No	Female

Table 6. Value of Attribute Representative of CCP Dataset

Soft Set	Value
(F,MP)	4.3389
(F,WP)	3.9722
(F,LIP)	3.8587
(F,CCI)	4.5889
(F,SEX)	4.0071

In SAR, as in Table 6, it is shown that CCI has the highest and directly selected as the decision attribute.

4.2 Experiment 2 - Modified Animal Dataset

A modified animal dataset is shown in Table 7. There are nine animals with nine attributes of categorical value namely Hair, Teeth, Eye, Feather, Feet, Eat, Milk, Fly and Swim. Six attributes namely Hair, Eye, Feather, Milk, Fly and swim have two values. One attribute namely Teeth has three values and two attributes namely Feet and Eat have four categorical values.

Table 7. Modified Animal Dataset

Animal	**Hair**	**Teeth**	**Eye**	**Feather**	**Feet**	**Eat**	**Milk**	**Fly**	**Swim**
Tiger	Y	Pointed	Forward	N	Claw	Meat	Y	N	Y
Cheetah	Y	Pointed	Forward	N	Claw	Meat	Y	N	Y
Giraffe	Y	Blunt	Side	N	Hoof	Grass	Y	N	N
Zebra	Y	Blunt	Side	N	Hoof	Grass	Y	N	N
Ostrich	N	N	Side	Y	Claw	Grain	N	N	N
Penguin	N	N	Side	Y	Web	Fish	N	N	Y
Albatros	N	N	Side	Y	Claw	Grain	N	Y	Y
Eagle	N	N	Forward	Y	Claw	Meat	N	Y	N
Viper	N	Pointed	Forward	N	N	Meat	N	N	N

Table 8. Value of Attribute Representative of MA Dataset

Soft Set	**Total Support Value**
(F,Hair)	7.8190
(F,Teeth)	7.0270
(F,Eye)	7.2738
(F,Feather)	7.3286
(F,Feet)	2.7762
(F,Eat)	3.4429
(F,Milk)	7.8190
(F,Fly)	8.2341
(F,Swim)	7.0548

As in Table 8, since there exist multi occurrence of attribute representative values, thus the first option in Definition 5 is used. Using this technique, decision can be made faster.

5 Conclusion

In this paper, Support Attribute Representative (SAR), a soft set based technique for decision making in categorical-valued information system has been proposed. In this technique, comparisons at the attribute level is firstly made before representative for each attributes and finally compared to each other. Using this technique, the execution time on selecting a decision can be reduced. The results of this research will provide useful information for decision makers to handle categorical-valued information system. Additionally, for future research, implementation and analysis of SAR using scalable dataset (high number of records, high number of attributes and high number of categories) will be carried out.

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