

# Action Rule Extraction from a Decision Table: ARED

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**Abstract.** In this paper, we present an algorithm that discovers action rules from a decision table. Action rules describe possible transitions of objects from one state to another with respect to a distinguished attribute. The previous research on action rule discovery required the extraction of classification rules before constructing any action rule. The new proposed algorithm does not require pre-existing classification rules, and it uses a bottom up approach to generate action rules having minimal attribute involvement.

## 1 Introduction

In this paper, we present an algorithm that discovers action rules. An action rule is a rule extracted from a database that describes a possible transition of objects from one state to another with respect to a distinguished attribute called a decision attribute [14]. Values of some attributes, used to describe objects stored in a database, can be changed. This change can be influenced and controlled by users. For example, let us assume that a number of customers have closed their bank accounts. We construct a description of this group of customers. Then, we search for another description of a new group of customers who keep the bank accounts active. If these descriptions have a form of rules, they can be seen as actionable rules. For instance, by comparing those two descriptions, we may identify the reason for closing their accounts, and formulate an action, which if undertaken by the bank, may prevent other customers from closing their accounts. In this case, an action rule may say that, if the bank lowers the interest rate by 2 percent on credit cards for certain group of customers, it is almost guaranteed that they do not close their accounts. A similar definition, but with different notation, of an action rule was given earlier in [4]. Also, interventions introduced in [5] are conceptually similar to action rules. Action rules introduced in [14] has been further investigated in [17][13][12][18][15].

Paper [7] was probably the first attempt towards formally introducing the problem of mining action rules without pre-existing classification rules. Authors explicitly formulated it as a search problem in a support-confidence-cost framework. The proposed algorithm is similar to Apriori [1]. Their definition of an action rule allows changes on stable attributes. Changing the value of an attribute, either stable or flexible, is linked with a cost [18]. In order to rule out action rules with undesired changes on stable attributes, authors have assigned very high cost to such changes. However, that way, the

cost of action rules discovery is getting unnecessarily increased. Also, they did not take into account the dependencies between attribute values which are naturally linked with the cost of rules used either to accept or reject a rule.

Algorithm *ARED*, presented in this paper, is based on Pawlak's model of an information system  $S$  [10] and its goal is to identify certain relationships between granules defined by the indiscernibility relation on objects in  $S$ . Some of these relationships uniquely define action rules for  $S$ .

The rest of this paper is organized as follows. Section 2 describes the background and objectives of our work. The details of the algorithm *ARED* are presented in Section 3. Experimental results are shown in Section 4. Section 5 discusses possible future work and concludes the paper.

## 2 Backgrounds and Objectives

Action rules are extracted from an information system. By an information system  $S$ , we mean  $S = (X, A, V)$  where  $X$  is a nonempty finite set of objects,  $A$  is a nonempty finite set of attributes, and  $V = \bigcup\{V_a : a \in A\}$  is set of their values. For example, Table 1 presents an information system  $S$  with  $X = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$ ,  $A = \{a, b, c, d\}$ , and  $V = \{a_1, a_2, b_1, b_2, b_3, c_1, c_2, d_1, d_2, d_3\}$ .

An information system  $S = (X, A, V)$  is called a decision system (or decision table), if  $A = A_{St} \cup A_{Fl} \cup \{d\}$ , where  $d$  is a distinguished attribute set called the decision. Attributes in  $A_{St}$  are called *stable* and attributes in  $A_{Fl}$  are called *flexible*. They jointly form the set of conditional attributes. "Date of birth" is an example of a stable attribute. "Interest rate" for each customer account is an example of a flexible attribute.

In earlier works in [14][17][13][12][15], action rules are constructed from classification rules. This means that we use pre-existing classification rules or generate them using a rule discovery algorithm, such as LERS [6] or ERID [2], then, construct action rules either from certain pairs of the rules or from a single classification rule. For instance, algorithm *ARAS* [15] generates sets of terms (built from values of attributes) around classification rules and constructs action rules directly from them. In this study, we propose a different approach to achieve the following objectives:

1. Extract action rules directly from an information system without using pre-existing conditional rules.
2. Extract all distinct action rules that have minimal attribute involvement.

To meet these two goals, we first generate action rules using two attributes, and iteratively apply the technique to generate more specific action rules.

## 3 Algorithm ARED

We describe the algorithm, *ARED* (Action Rule Extraction from Decision table), by working through an example using the decision Table  $S$  shown in Table 1. We assume that the decision attribute is  $d$ , stable attributes  $A_{St} = \{a\}$ , and the flexible attributes  $A_{Fl} = \{b, c\}$ . The minimum support ( $\lambda_1$ ) and confidence ( $\lambda_2$ ) are given as 1 and 0.85.

**Table 1.** Decision Table S

	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>
$x_1$	$a_1$	$b_1$	$c_1$	$d_1$
$x_2$	$a_2$	$b_1$	$c_2$	$d_1$
$x_3$	$a_2$		$c_2$	$d_1$
$x_4$	$a_2$	$b_1$	$c_1$	$d_1$
$x_5$	$a_2$	$b_3$	$c_2$	$d_1$
$x_6$	$a_1$	$b_1$		$d_2$
$x_7$	$a_1$	$b_2$	$c_2$	$d_1$
$x_8$	$a_1$	$b_2$	$c_1$	$d_3$

For simplicity reason, we will consider decision tables with only one decision in this paper.

The first step is to find the pessimistic interpretation in  $S$  of all attribute values in  $V$ , as shown in Table 2 (for conditional attributes) and Table 3 (for decision attribute). The resulting sets are called granules. In  $S$ ,  $Dom(a) = \{a_1, a_2\}$ ,  $Dom(b) = \{b_1, b_2, b_3\}$ ,  $Dom(c) = \{c_1, c_2\}$ , and  $Dom(d) = \{d_1, d_2, d_3\}$ . The granule  $a_1^*$  associated with attribute value  $a_1$  in  $S$  (see Table 1) is the set of objects having property  $a_1$  (e.g. objects  $\{x_1, x_6, x_7, x_8\}$ ). The set of granules associated with an attribute  $a$  in  $S$  is defined as  $\{v^* : v \in V_a\}$ .

**Table 2.** Granules associated with attributes in  $a, b, c$

$$\begin{aligned}
 a_1^* &= \{x_1, x_6, x_7, x_8\} \\
 a_2^* &= \{x_2, x_3, x_4, x_5\} \\
 b_1^* &= \{x_1, x_2, x_4, x_6\} \\
 b_2^* &= \{x_7, x_8\} \\
 b_3^* &= \{x_5\} \\
 c_1^* &= \{x_1, x_4, x_8\} \\
 c_2^* &= \{x_2, x_3, x_5, x_7\}
 \end{aligned}$$

**Table 3.** Granules associated with attribute  $d$

$$\begin{aligned}
 d_1^* &= \{x_1, x_2, x_3, x_4, x_5, x_7\} \\
 d_2^* &= \{x_6\} \\
 d_3^* &= \{x_8\}
 \end{aligned}$$

Next, we define two sets,  $\tau$  and  $\delta$ , to examine possible *property transitions* between objects in  $S$ . Let  $T$  be a set of proper conjuncts built from elements in  $\cup\{V_i, i \neq d, i \in A\}$ . By proper conjunct, we mean a conjunct which contains maximum one element from each  $V_i$ .

- $\tau = T \cdot d_1$ , where  $d_1 \in V_d$ , and  $(\forall \rho_1 \in T \cdot d_1)(sup(\rho_1) \geq \lambda_1)$ .
- $\delta = T \cdot d_2$ , where  $d_2 \in V_d$ , and  $(\forall \rho_2 \in T \cdot d_2)(sup(\rho_2) \geq \lambda_1)$ .

By  $T \cdot d_i$ , we mean  $\{t \cdot d_i : t \in T\}$ ,  $i=1,2$ . The support of  $\rho_i$ ,  $sup(\rho_i)$ , is the number of objects in  $S$  supporting all attribute values listed in  $\rho_i$ ,  $i = 1, 2$ . They can be easily calculated by intersecting two granules listed in Table 2 and Table 3. For example,  $(a_1 \cdot d_2)^* = \{x_1, x_6, x_7, x_8\} \cap \{x_6\} = \{x_6\}$ . So,  $sup((a_1 \cdot d_2)^*) = 1$ .

Each set contains only terms built from one decision value and at least one value of conditional attribute. Therefore, these sets represent (1) a relationship between conditional attributes and the decision attribute, and (2) property of a set of objects. If the property transition from  $\tau$  to  $\delta$  is valid,  $\tau$  and  $\delta$  are interpreted as the *condition* and the *decision of an action rule*.

As mentioned, *ARED* attempts to discover the shortest action rules in terms of the number of attributes, then iteratively generates longer action rules. Therefore, we first construct  $\tau$  containing two elements (which is the shortest form of  $\tau$ ) by combining one attribute from Table 2 and the other from Table 3. This process aims to find the meaning in  $S$  of all terms in a conjunctive form built from values in  $V$  [16]. The concatenation functor used to build these terms is interpreted as the set-theoretical intersection.

**Table 4.** 2-element  $\tau$  and  $\delta$

$\tau$	$\delta$
$(a_1 \cdot d_1)$	$(a_1 \cdot d_1)$
$(a_1 \cdot d_2)$	$(a_1 \cdot d_2)$
$(a_1 \cdot d_3)$	$(a_1 \cdot d_3)$
$(a_2 \cdot d_1)$	$(a_2 \cdot d_1)$
$(b_1 \cdot d_1)$	$(b_1 \cdot d_1)$
$(b_1 \cdot d_2)$	$(b_1 \cdot d_2)$
$(b_2 \cdot d_1)$	$(b_2 \cdot d_1)$
$(b_2 \cdot d_3)$	$(b_2 \cdot d_3)$
$(b_3 \cdot d_1)$	$(b_3 \cdot d_1)$
$(c_1 \cdot d_1)$	$(c_1 \cdot d_1)$
$(c_1 \cdot d_3)$	$(c_1 \cdot d_3)$
$(c_2 \cdot d_1)$	$(c_2 \cdot d_1)$

**Table 5.** Action Rules

$\tau$	$\delta$	<i>sup</i>	<i>conf</i>	<i>rule</i>
$(b_1 \cdot d_2) \mapsto$	$(b_2 \cdot d_1)$	1	1	y
$(b_1 \cdot d_2) \mapsto$	$(b_2 \cdot d_3)$	1	1	y
$(b_1 \cdot d_2) \mapsto$	$(b_3 \cdot d_1)$	1	1	y
$(b_2 \cdot d_1) \mapsto$	$(b_1 \cdot d_2)$	1	1	y
$(b_2 \cdot d_3) \mapsto$	$(b_1 \cdot d_1)$	1	1	y
$(b_2 \cdot d_3) \mapsto$	$(b_1 \cdot d_2)$	1	1	y
$(b_2 \cdot d_3) \mapsto$	$(b_3 \cdot d_1)$	1	1	y
$(b_3 \cdot d_1) \mapsto$	$(b_1 \cdot d_2)$	1	1	y
$(b_3 \cdot d_1) \mapsto$	$(b_2 \cdot d_3)$	1	1	y
$(c_1 \cdot d_3) \mapsto$	$(c_2 \cdot d_1)$	1	1	y

**Table 6.** Invalid Transitions

$\tau$	$\delta$	<i>sup</i>	<i>conf</i>	<i>rule</i>
$(b_1 \cdot d_1) \mapsto$	$(b_2 \cdot d_3)$	1	0.33	n
$(c_2 \cdot d_1) \mapsto$	$(c_1 \cdot d_3)$	1	0.25	n
$(a_1 \cdot d_1)$	$(a_1 \cdot d_1)$			
$(a_1 \cdot d_2)$	$(a_1 \cdot d_2)$			
$(a_1 \cdot d_3)$	$(a_1 \cdot d_3)$			
$(a_2 \cdot d_1)$	$(a_2 \cdot d_1)$			

Clearly, it is required that  $sup(\rho_1) \geq \lambda_1 \wedge sup(\rho_2) \geq \lambda_1$  because we need to find property transitions that involve at least  $\lambda_1$  objects. Terms satisfying these criteria, related to the example in Table 1, are shown in Table 4.

Now, we construct action rules using  $\tau$  to  $\delta$  in Table 4 by evaluating the validity of their transitions. We use the following code to explain the evaluation method.

input :  $\{\tau\}, \{\delta\}$   
output : action\_rule [], gen\_τ[], gen\_δ[]

```

1: for each  $\tau_i = [t_1 \cdot d_1] \in \tau, \delta_j = [t_2 \cdot d_2] \in \delta$ 
2: if  $d_1 \neq d_2$  then
3:   if  $\exists(a(x_i) \in t_1, a(x_j) \in t_2)$ , where  $a \in A_{Fl}$  and  $a(x_i) \neq a(x_j)$  then
4:     if  $conf(\tau_i \mapsto \delta_j) \geq \lambda_2$ 
5:       action_rule [end+1] =  $\tau_i \mapsto \delta_j$ 
6:     elseif
7:       gen_τ[end+1] =  $\tau_i$ , gen_δ [end+1] =  $\delta_j$ 
8:     end if
9:   else
10:    gen_τ[end+1] =  $\tau_i$ , gen_δ [end+1] =  $\delta_j$ 
11:   end if
12: end if

```

In line 1, we read each  $\tau_i$  and  $\delta_j$  listed in Table 4. Note that an information system may or may not produce two-way action rules (e.g. if  $b$  changes from  $b_1$  to  $b_2$  then  $d$  changes from  $d_1$  to  $d_2$ , and vice versa). Therefore, we generate all pairs of elements from  $\tau$  and  $\delta$ . The condition in line 2 is clear. No action can be performed if the decision values are equal. The condition in line 3 checks if there exist different flexible attribute values between  $t_1$  and  $t_2$ , and they are from the same domain. For example,  $d_1 \neq d_2$  and  $a_1 \neq a_2$  for  $(a_1 \cdot d_2)$  and  $(a_2 \cdot d_1)$ . However,  $a$  is a stable attribute, so no action rule is constructed. If two sets do not meet this condition, we put them in two separate arrays (line 10) and use them to generate  $\tau$  and  $\delta$  for the next iteration. Last 4 rows in Table 6 are the sets in this category. The reasoning behind this strategy is simple. Clearly, there are at least  $\lambda_1$  objects supporting  $(a_1 \cdot d_2)$  and  $(a_2 \cdot d_1)$ . These sets may be concatenated with one or more flexible attribute values in later iterations, and produce action rules. An example of this case is  $(a_1 \cdot b_1 \cdot d_1) \mapsto (a_1 \cdot b_2 \cdot d_3)$  in Table 8. The condition in line 4 checks the confidence of  $\tau_i \mapsto \delta_j$ . If it is greater than or equal  $\lambda_2$ ,  $\tau_i \mapsto \delta_j$  becomes an action rule. To compute the confidence, we first find the support of  $ar = \tau \mapsto \delta$  which is defined as the minimum support of two sets.

$$sup(ar) = \min(sup(\tau), sup(\delta))$$

$\min(sup, sup)$  finds the exact number of object transitions because at least one element is different between  $\tau$  and  $\delta$ , and by definition of  $S$ , an object cannot support two different values of the same attribute. Note that we do not need to check the support of  $ar$  in line 4 because the support of  $\tau$  and  $\delta$  were checked when they were generated, and the support of the action rule is the smaller value between them. The confidence of an  $ar$  is defined as,

$$conf(ar) = \frac{sup(ar)}{sup(\tau)}$$

Two-element action rules extracted from  $S$  are shown in Table 5. For example,  $(b_1 \cdot d_2) \mapsto (b_2 \cdot d_1)$  is an action rule, and it is interpreted as, “if  $b$  changes from

**Table 7.** 3-element  $\tau$  and  $\delta$ 

$\tau$	$\delta$
$(a_2 \cdot b_1 \cdot d_1)$	$(a_1 \cdot c_2 \cdot d_3)$
$(a_2 \cdot c_3 \cdot d_1)$	$(a_1 \cdot b_2 \cdot d_3)$
$(a_1 \cdot b_1 \cdot d_1)$	$(b_2 \cdot c_2 \cdot d_3)$
$(a_1 \cdot c_3 \cdot d_1)$	
$(b_1 \cdot c_3 \cdot d_1)$	

**Table 8.** Action Rule

$\tau$	$\delta$	<i>sup conf rule</i>		
$(a_1 \cdot b_1 \cdot d_1) \mapsto$	$(a_1 \cdot b_2 \cdot d_3)$	1	1	y
$(a_1 \cdot c_3 \cdot d_1) \mapsto$	$(a_1 \cdot c_2 \cdot d_3)$	1	1	y
$(b_1 \cdot c_3 \cdot d_1) \mapsto$	$(b_2 \cdot c_2 \cdot d_3)$	1	1	y

**Table 9.** Invalid Transition

$\tau$	$\delta$	<i>sup conf rule</i>		
$(a_2 \cdot b_1 \cdot d_1) \mapsto$	$(a_1 \cdot b_2 \cdot d_3)$	1	0.50	n
$(a_2 \cdot c_3 \cdot d_1) \mapsto$	$(a_1 \cdot c_2 \cdot d_3)$	1	0.33	n

**Table 10.** 4-element  $\tau$  and  $\delta$ 

$\tau$	$\delta$
$(a_2 \cdot b_1 \cdot c_3 \cdot d_1)$	$(a_1 \cdot b_2 \cdot c_2 \cdot d_3)$

**Table 11.** Action Rule

$\tau$	$\delta$
$(a_2 \cdot b_1 \cdot c_3 \cdot d_1) \mapsto$	$(a_1 \cdot b_2 \cdot c_2 \cdot d_3)$

$b_1$  to  $b_2$ , then  $d$  changes from  $d_1$  to  $d_2$ ". Finally, if the confidence is less than  $\lambda_2$  (line 7)  $\tau_i$  and  $\delta_j$  are considered in the next iteration to generate 3-element candidate sets. In Table 6, we have two transitions having confidence of 0.33 and 0.25 that are less than 1 ( $\lambda_2$ ).

Assume that  $|t_i|$ , for any conjunct term  $t_i$ , denotes the set of all values of attributes listed in  $t_i$ . To find the action rules of length 3, we generate  $\tau$  of length 3 from  $\tau$ s in Table 6. Two terms  $\tau_1 = t_1 \cdot d_1$  and  $\tau_2 = t_2 \cdot d_2$  are concatenated if (1)  $d_1 = d_2$  (2)  $|t_1 \cup t_2| - |t_2 \cap t_1| = \{v_1 \in V_a, v_2 \in V_b\}$ , where  $a \neq b$ . The set  $\{\delta\}$  is generated from  $\delta$ s in Table 6 using the same method. That means they are generated independently. The reason that we build 3-element candidate sets separately in this way is that all pairs are considered in the initial step. Therefore, any super set of the candidate set identified as an action rule will not be considered. Table 7 shows those 3-element candidate sets. Corresponding action rule and invalid transitions are show in Tables 8 and 9 respectively.

In the next iteration, we construct  $\tau$  and  $\delta$  listed in Table 10 and build an action rule containing 4 elements as shown in Table 11. However, it is not included in the list of action rules because it's  $\tau$  and  $\delta$  are supersets of  $(b_1 \cdot c_3 \cdot d_1) \mapsto (b_2 \cdot c_2 \cdot d_3)$  in Table 8, which is a more general action rule.

The process stops because there are no sets to be combined.

## 4 Experiment

We implemented the algorithm in Matlab on a Pentium M 1.6 GHz computer running Windows XP, and tested it using a sample data set (nursery database) obtained from [8]. The data set contains information about applications for nursery schools, and used to rank them. The decision attribute has five classes (not recommend, recommend,

**Table 12.** Experiment Result

Type	Attribute Name	Description
flexible	parents (p)	Parents' occupation
stable	has_nurs (n)	Child's nursery
stable	form (o)	Form of the family
stable	children (c)	Number of children
flexible	housing (h)	Housing conditions
flexible	finance (f)	Financial standing of the family
stable	social (s)	Social conditions
flexible	health (t)	Health conditions
flexible	decision (d)	Rank

**Table 13.** Experiment Result

Experiment No.	Num. of objects	Stab. attribute	Flex. attribute	Sup	Conf	Num. of action rules	Computation time (in seconds)
1	12960	4	5	5%	85%	86	2.36
2	12960	4	5	10%	85%	53	1.07
3	12960	4	5	15%	85%	12	0.88

**Table 14.** Action Rules

condition	decision	sup	conf
$(f)convenient \rightarrow (d)notrecom$	$\mapsto (f)inconvenient \rightarrow (d)priority$	2022	0.9
$(f)convenient \rightarrow (d)notrecom$	$\mapsto (f)inconvenient \rightarrow (d)spec\_prior$	2160	1
$(f)convenient \rightarrow (d)priority$	$\mapsto (f)inconvenient \rightarrow (d)notrecom$	2160	1
$(f)convenient \rightarrow (d)priority$	$\mapsto (f)inconvenient \rightarrow (d)spec\_prior$	2188	1
$(f)inconvenient \rightarrow (d)notrecom$	$\mapsto (f)convenient \rightarrow (d)priority$	2160	1
$(f)inconvenient \rightarrow (d)priority$	$\mapsto (f)convenient \rightarrow (d)notrecom$	2022	1
$(f)inconvenient \rightarrow (d)spec\_prior$	$\mapsto (f)convenient \rightarrow (d)notrecom$	2160	1
$(f)inconvenient \rightarrow (d)spec\_prior$	$\mapsto (f)convenient \rightarrow (d)priority$	2188	1
$(t)priority \rightarrow (d)spec\_prior$	$\mapsto (t)notrecom \rightarrow (d)notrecom$	2466	1
$(t)priority \rightarrow (d)spec\_prior$	$\mapsto (t)recommended \rightarrow (d)priority$	2412	1
$(t)recommended \rightarrow (d)priority$	$\mapsto (t)notrecom \rightarrow (d)notrecom$	2412	1
$(t)recommended \rightarrow (d)priority$	$\mapsto (t)priority \rightarrow (d)spec\_prior$	2412	1

very recommend, priority, special priority). We partitioned the attributes into stable and flexible based on the description given by the provider. For example, the number of children in a family (1, 2, 3, more) is considered as a stable attribute, while financial standing of the family (convenient, inconvenient) or parents' occupation (usual, pretentious, great pretentious) are considered as flexible attributes.

Table 12 shows the attributes names, descriptions, and the partitions. All attributes are categorical in the data set. If a data set contains continuous data, one can use a discretization method (such as Rosetta [9]) to convert them to categorical data. Table 13 shows the parameters used in our experiment, the number of action rules generated, and the time required to complete the task.

Table 14 shows the action rules generated during experiment No. 3. The first action rule can be read as, if the housing standing of the family changes from *convenient* to *inconvenient*, then the decision changes from *not recommend* to *priority* with support value of 2022 and confidence of 0.9. The overall result shows that the change of rank (decision attribute) is strongly related to the changes in financial standing of the family and health conditions in experiment 3.

## 5 Conclusion and Future Work

We presented an algorithm that discovers action rules from a decision table. The proposed algorithm generates a complete set of shortest action rules without using pre-existing classification rules. During the experiment with several data sets, we noticed that the flexibility of attributes are not equal. For example, the social condition is most likely less flexible than the health condition in the data set used in our experiment, and this may have to be considered. Future work shall address this issue as well as further analysis of the algorithm with real world data sets.

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