Actions Ontology System for Action Rules Discovery in Mammographic Mass Data

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Abstract - *Actionable knowledge is a golden nugget within the data mining research field. Action rules describe possible transitions of objects in an information system - from one state to another more desirable state, with respect to a distinguished attribute. In this paper we propose an improved method for generating action rules by incorporating an additional ontology layer on top of the information system. It contains nodes of higher-level actions knowledge, which are linked with individual terms at the lower levels. The system shows the likely changes within classification attributes, with respect to a decision attribute of our interest. We experiment with Mammographic Mass DataSet in attempts to re-classify tumors from malignant to benign. In addition to medical domain, application areas include financial, and industrial domain.*

Keywords: Action rules, Ontology, Mammography

1 Introduction

An action rule is a rule extracted from a decision system that describes a possible transition of objects from one state to another with respect to a distinguished attribute called a decision attribute [13]. We assume that attributes used to describe objects in a decision system are partitioned into stable and flexible. Values of flexible attributes can be changed. This change can be influenced and controlled by users. Action rules mining initially was based on comparing profiles of two groups of targeted objects - those that are desirable and those that are undesirable [13]. An action rule was defined as a term $[(\omega) \wedge (\alpha \rightarrow \beta)] \Rightarrow (\varphi \rightarrow \psi)$, where ω is a conjunction of fixed condition features shared by both groups, $(\alpha \rightarrow \beta)$ represents proposed changes in values of flexible features, and $(\varphi \rightarrow \psi)$ is a desired effect of the action. The discovered knowledge provides an insight of how values of some attributes need to be changed so the undesirable objects can be shifted to a desirable group. How to identify an *action* which triggers the desired changes of flexible attributes and which is not described by values of attributes listed in the decision system is a difficult problem. In this paper, we propose locating such *actions* in an ontology [3] layer. We therefore call this layer - *actions ontology*.

Clearly, there has to be a link between the *actions* and the changes they trigger within the values of flexible attributes in the decision system. Such link can be provided either by an ontology [3] or by a mapping/linking *actions* with changes of attributes values used in the decision system. For example, one would like to find a way to improve his or her salary from a low-income to a high-income. Another example in business area is when an owner would like to improve his or her company's profits by going from a high-cost, low-income business to a low-cost, high-income business. Action rules tell us what changes within flexible attributes are needed to achieve that goal.

2 Previous work

Action rules have been introduced in [13] and investigated further in [16], [14], [10], [17], [15], [4], and [9]. Paper [6] was probably the first attempt towards formally introducing the problem of mining action rules without pre-existing classification rules. Authors explicitly formulate it as a search problem in a support-confidence-cost framework. The proposed algorithm has some similarity with 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 [17]. In order to rule out action rules with undesired changes on attributes, authors designate very high cost to such changes. However, in this way, the cost of action rules discovery is getting unnecessarily increased. Also, they did not take into account the correlations between attribute values which are naturally linked with the cost of rules used either to accept or reject a rule. Algorithm ARED, presented in [7], is based on Pawlak's model of an information system S [8]. The goal was to identify certain relationships between granules defined by the indiscernibility relation on its objects. Some of these relationships uniquely define action rules for S. Paper [11] presents a strategy for discovering action rules directly from the decision system. Action rules are built from atomic expressions following a strategy similar to ERID [2]. Paper [18] introduced the notion of *action* as a domain- independent way to model the domain knowledge. Given a data set about actionable features and a utility measure, a pattern is actionable if it summarizes a population that can be acted upon towards a more promising population observed with a higher utility. Algorithms for mining actionable patterns (changes within flexible attributes) take into account only numerical attributes. The distinguished (decision) attribute is called utility. Each *action Ai* triggers changes of attribute values described by terms [a ↓], [b ↑], and [c (don't know)]. They are represented as an influence matrix built by an expert. While previous approaches used only features - mined directly from the decision system, authors in [18] define actions as its foreign concepts. Influence matrix shows the link between actions and changes of attribute values and the same shows correlations between some attributes, i.e. if [a ↓], then [b ↑]. In this paper, we propose an additional ontology layer, which contains the link between actions and changes of attribute values. Clearly, expert does not know correlations between classification attributes and the decision attribute. Such correlations can be described as action rules and they have to be discovered from the decision system. Authors in [18] did not take into consideration stable attributes and their classification attributes are only numerical. In this paper, for simplicity reason, we use only symbolic attributes. Numerical attributes, if any, are discretized before action rules are discovered.

3 Information systems and actions

In this section we introduce the notion of an information system and actions.

By an information system [8] we mean a triple $S = (X, At, V)$, where:

1. X is a nonempty, finite set of objects
2. At is a nonempty, finite set of attributes, i.e. $a : U \rightarrow V_a$, where V_a is called the domain of a
3. $V = \cup\{ V_a: a \in A \}$.

For example, Table 1 shows an information system S with a set of objects $X = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$, set of attributes $At = \{a, b, c, d\}$, and a set of their values $V = \{a_1, a_2, b_1, b_2, b_3, c_1, c_2, d_1, d_2, d_3\}$.

TABLE I
INFORMATION SYSTEM S

	a	b	c	d
	a_1	b_1	c_1	d_1
x_1	a_2	b_1	c_2	d_1
x_2	a_2	b_2	c_2	d_1
x_3	a_2	b_1	c_1	d_1
x_4	a_2	b_3	c_2	d_1
x_5	a_1	b_1	c_2	d_2
x_6	a_1	b_2	c_2	d_1
x_7	a_1	b_2	c_1	d_3

An information system $S = (X, At, V)$ is called a decision system, if one of the attributes in At is distinguished and called the decision. The remaining attributes in $\underline{At}$ are classification attributes. Additionally, we assume that $At = A_{St} \cup A_{Fl} \cup \{d\}$, where attributes in A_{St} are called *stable* and in A_{Fl} *flexible*. Attribute d is the decision attribute. "Date of birth" is an example of a stable attribute. "Interest rate" for each customer account is an example of a flexible attribute.

By *actions* associated with S we mean higher level concepts modeling certain generalizations of actions introduced in [18]. *Actions*, when executed, can influence or trigger changes in values of some flexible attributes in S. They are specified by expert. To give an example, let us assume that classification attributes in S describe teaching evaluations at some school and the decision attribute represents their overall score. *Explain difficult concepts effectively*, *Speaks English fluently*, *Stimulate student interest in the course*, *Provide sufficient feedback* are examples of classification attributes. Then, examples of *actions* associated with S will be: *Change the content of the course*, *Change the textbook of the course*, *Post all material on the Web*. Clearly, any of these three *actions* will not influence the attribute *Speaks English fluently* and therefore its values will remain unchanged. It should be mentioned here that an expert knowledge concerning *actions* involves only classification attributes. Now, if some of these attributes are correlated with the decision attribute, then the change of their values will cascade to the decision through the correlation. The goal of action rule discovery is to identify possibly all such correlations.

4 Action rules

In earlier works in [13], [16], [14], [10], and [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 [5] or ERID [2], then, construct action rules either from certain pairs of these 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 [12] authors present a strategy for extracting action rules directly from a decision system and without using pre-existing classification rules.

Let $S = (X, At, V)$ be an information system, where $V = \cup \{V_a : a \in At\}$. First, we recall the notion of an atomic action set [11]. By an *atomic action set* we mean an expression $(a, a_1 \rightarrow a_2)$, where a is an attribute and a_1 , $a_2 \in V_a$. If $a_1 = a_2$, then a is called stable on a_1. Instead of $(a, a_1 \rightarrow a_2)$, we often write (a, a_1) for any $a_1 \in V_a$.

By *Action Sets* [11] we mean a smallest collection of sets such that:

1. If t is atomic action set, then t is an action set.
2. If t_1, t_2 are action sets, then $t_1 \wedge t_2$ is a candidate action set.
3. If t is a candidate action set and for any two atomic action sets $(a, a_1 \rightarrow a_2)$, $(b, b_1 \rightarrow b_2)$ contained in t we have $a \neq b$, then t is an action set .

By the domain of an action set t, denoted by $Dom(t)$, we mean the set of all attribute names listed in t. For instance, assume that $\{(a, a_2), (b, b_1 \rightarrow b_2)\}$, $\{(a, a_2), (b, b_2 \rightarrow b_1)\}$ are two collections of atomic action sets associated with *actions* A_1, A_2. It means that both A_1, A_2 can influence attributes *a*, *b* but attribute *a* in both cases has to remain stable. The corresponding action sets are: $(a, a_2) \wedge (b, b_1 \rightarrow b_2)$, $(a, a_2) \wedge (b, b_2 \rightarrow b_1)$.

Consider several *actions*, denoted $A_1, A_2, \ldots, A_n$. An *action* can influence the values of classification attributes in *At*. We assume here that $At - \{d\} = At_1 \cup At_2 \cup \ldots \cup At_m$. The influence of these *actions* on classification attributes in *At* is specified by the *actions ontology*.

By an *action rule* we mean any expression r = $[t_1 \Rightarrow t_2]$, where t_1 and t_2 are action sets. Additionally, we assume that $Dom(t_1) \cup Dom(t_2) \in At$ and $Dom(t_1) \cap Dom(t_2) = \emptyset$. The domain of action rule *r* is defined as $Dom(t_1) \cup Dom(t_2)$.

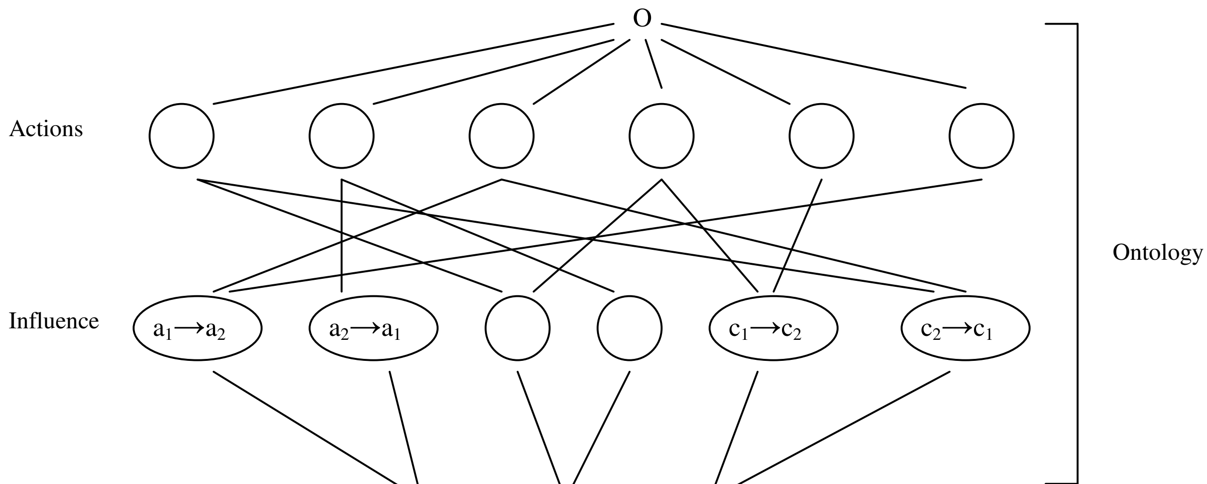
Now, we give an example of action rules assuming that the information system *S* is represented by Table 1. *a*, *c*, *d* are flexible attributes and *b* is stable. Expressions (a, a_2), (b, b_2), $(c, c_1 \rightarrow c_2)$, $(d, d_1 \rightarrow d_2)$ are examples of *atomic action sets*. Expression $(c, c_1 \rightarrow c_2)$ means that the value of attribute *c* is changed from c_1 to c_2 . Expression (a, a_2) means that the value a_2 of attribute *a* remains unchanged. Expression $r = [[(a, a_2) \wedge (c, c_1 \rightarrow c_2)]) \Rightarrow (d, d_1 \rightarrow d_2)]$ is an example of an *action rule*. The rule says that if value a_2 remains unchanged and value *c* changes from c_1 to c_1 , then it is expected that the value *d* will change from d_1 to d_2. We recall that *d* is the distinguished (decision) attribute, which the user is interested in. The domain *Dom(r)* of action rule *r* is equal to *{a, c, d}*.

We extract candidate *action rules* by using algorithm ARD[11].

5 Action rules discovery through actions ontology

An *ontology* [3], which is a system of fundamental concepts, that is, a system of background knowledge of any knowledge base, explicates the conceptualization of the target world and provides us with a solid foundation on which we can build sharable knowledge bases for wider usability than that of a conventional knowledge base. From knowledge-based systems point of view, it is defined as “a theory(system) of concepts/ vocabulary used as building blocks of an information processing system” by Mizoguchi [3]. Ontologies are agreements about shared conceptualizations. A very simple case would be a type hierarchy, specifying classes and their subsumption relationships.

Actions ontology associated with *S* is used to identify which candidate action rules, extracted by the algorithm *ARD*, are valid with respect to our *actions* and hidden correlations between classification attributes and the decision attribute.



	a	*b*	*c*	*d*
x_1	a_1	b_1	c_1	d_1
x_2	a_2	b_1	c_2	d_1
x_3	a_2	b_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	c_2	d_2
x_7	a_1	b_2	c_2	d_1
x_8	a_1	b_2	c_1	d_3

Information System (from Table 1)

Fig. 1. *Ontology Based Information System.*

Assume that: $S = \{X, At \cup \{d\}, V\}$ is an information system; $At - \{d\} = a \cup b \cup \ldots \cup z$; $\{A_1, A_2, \ldots, A_n\}$ are *actions* associated with S; $O\{[A_1, A_2, \ldots, A_n, [I_{i,j} : 1 \leq i \leq n, 1 \leq j \leq m]\}$ is the *ontology*, where $I_{i,j}$ is the influence of these *actions* on S; and, $r = [(a, a_1 \rightarrow a_2) \wedge (b, b_1 \rightarrow b_2) \wedge \ldots \wedge (z, z_1 \rightarrow z_2)] \Rightarrow (d, d_1 \rightarrow d_2)$ is a candidate *action rule* extracted from S . We assume that $At_{[i,j]}(A_i) = I_{i,j}$, where value $I_{i,j}$ is either an atomic action set, or *NULL* (undefined). By ontology based information system, we mean a couple consisting of: the information system S, and the *ontology* O. The ontology contains the *actions*, and the influence $I_{i,j}$ they have on S.

We say that r is valid in S with respect to action A_i , if the following condition holds:

$$\text{if } [At_{[i,j]}(A_i) \text{ is defined}]$$
$$\text{then } (At_{[i,j]}, At_{[i,j]} \rightarrow At_{[i,k]}) = (At_{[i,j]}, I_{i,j})$$

We say that r is valid with respect to actions ontology O , if there is i, $1 \leq n$, such that r is valid in S with respect to at least one *action* A_i specified in O .

To give an example, assume that S is an information system represented by Table 1 and $\{A_1, A_2, \ldots, A_n\}$ is the set of actions assigned to S with an ontology O shown in Figure 1. Assume two candidate action rules have been constructed by the algorithm *ARD*.

$$r_1 = [(b, b) \wedge (c, c_1 \rightarrow c_2)] \Rightarrow (d, d_1 \rightarrow d_2) \quad \text{and}$$
$$r_2 = [(a, a_2 \rightarrow a_1)] \Rightarrow (d, d_1 \rightarrow d_2).$$

r_1 is valid in S with respect to A_4 and A_5. However, we cannot say that r_2 is valid in S with respect to A_2 since b_2 is not listed in the classification part of r_2.

Assume that S is an information system with actions ontology O. Any candidate action rule extracted from S, which is valid in the ontology based information system is called *action rule*. In this way, the process of action rules discovery is simplified to checking the validity of candidate action rules.

6 Experiment

We conduct an experiment with a Mammographic Mass DataSet, donated by Prof. Dr. Rüdiger Schulz-Wendtland, Institute of Radiology, Gynaecological Radiology, University Erlangen-Nuremberg, Erlangen, Germany [19].

Mammography is the most effective method for breast cancer screening available today. This data set is used to predict the severity (benign or malignant) of a mammographic mass lesion from BI-RADS attributes and the patient's age. It contains a BI-RADS assessment, the patient's age and three BI-RADS attributes together with the ground truth (the severity field) for 516 benign and 445 malignant masses that have been identified on full field digital mammograms collected at the Institute of Radiology of the University Erlangen-Nuremberg between 2003 and 2006. Each instance has an associated BI-RADS assessment ranging from 1 (definitely benign) to 5 (highly suggestive of malignancy) assigned in a double-review process by physicians. Assuming that all cases with BI-RADS assessments greater or equal to a given value (varying from 1 to 5), are malignant and the other cases are benign.

The dataset contains 961 instances, and has 6 attributes (1 goal field, 1 non-predictive, 4 predictive attributes). The attributes are:

1. BI-RADS assessment: 1 to 5 (ordinal)
2. Age: patient's age in years (integer)
3. Shape: mass shape: round=1 oval=2 lobular=3 irregular=4 (nominal)
4. Margin: mass margin: circumscribed=1 microlobulated=2 obscured=3 ill-defined=4 spiculated=5 (nominal)
5. Density: mass density high=1 iso=2 low=3 fat-containing=4 (ordinal)
6. Severity: benign=0 or malignant=1 (binominal)

Class Distribution: benign: 516; malignant: 445;

We extract *action rules* on the Mammographic Mass DataSet. We designate as *flexible* – attributes: 3. Shape; 4. Margin; and 5. Density; assuming that we have control over changing the values of these lesion properties. In other words, we have certain treatment or drugs available to be able to alter them. We designate as *stable* – attribute 2. Age; because we are unable to change the age of a patient. We designate attribute 6. Severity - as our *decision* (class) attribute. In this way, the *action rules* we extract suggest changes in flexible attributes, in order to re-classify a mammographic mass lesion from class: malignant to class: benign.

By using algorithm ARD[11], we obtain 64 *action rules*. We list several below:

Action Rules:
```
=============== Margin ===============
r1  (5->1) => (1->0) sup=114 conf= 74.19
=============== &Margin&Shape =================
r2 (5->1)(4->2) => (1->0) sup= 93 conf= 74.35
=============== &Margin&Shape =================
r3 (4->1)(4->2) => (1->0) sup= 149 conf= 70.11
=============== &Margin&Shape =================
r4 (5->1)(4->1) => (1->0) sup= 93 conf= 72.90
=============== &Margin&Density ===============
r5 (5->1)(3->3) => (1->0) sup= 106 conf= 73.94
=============== &Shape&Margin ==================
r6 (4->2)(5->1) => (1->0) sup= 93 conf= 74.35
=============== &Shape&Margin ==================
r7 (4->1)(5->1) => (1->0) sup= 93 conf= 72.90
=============== &Shape&Margin ==================
r8 (4->2)(5->1) => (1->0) sup= 93 conf= 74.35
=============== &Shape&Margin ==================
r9 (4->1)(5->1) => (1->0) sup= 93 conf= 72.90
===============&Margin&Shape&Density=============
r10 (5->1)(4->2)(3->3) =>(1->0) sup= 89 conf= 71.62
```

To clarify, let us consider for example, *action rule 2* above. By *r2* = Margin(5->1) & Shape(4->2) => Class(1->0) sup= 93 conf= 74.35 we mean that: IF Margin is changed from value 5 (spiculated) to -> value 1 (circumscribed) AND Shape is changed from 4 (irregular) to -> 2 (oval) THEN class of tumor (severity) is changed from 1(malignant) to -> 0 (benign). The support of this *action rule* is = 93 instances in the dataset, and our confidence in this rule is = 74%.

Based on the rest of the *action rules* we discovered, the following are desirable influences $I_{i,j}$ we would like to have on objects in the system *S*:

I_1 : A change in the margin from spiculated to circumscribed
I_2 : A change in the margin from spiculated to circumscribed AND a change in shape from irregular to oval
I_3 : A change in the margin from spiculated to circumscribed AND a change in shape from irregular to round
I_4 : A change in the margin from ill-defined to microlobulated AND a change in shape from irregular to oval
I_5 : A change the shape from irregular to oval AND a change in the margin from ill-defined to circumscribed

The *actions* we are willing or able to undertake, in order to trigger these desired influences on the tumors (objects) are defined or specified by experts; assuming that we have control over changing the values of these lesion properties. For example, action A_1 may involve *administering certain treatment*; action A_2 may be to *take particular drug*.
These actions, along with the changes they trigger within the flexible (classification) attributes are included in an Ontology Layer placed on top of the DataSet, resulting in an intelligent Mammographic Mass Information System.

7 Conclusions

We have introduced an ontology based information system, which is a couple consisting of: the information system *S*, and the *ontology O*. The ontology contains the *actions*, and the influence $I_{i,j}$ they have on *S*. Actions ontology is used as a postprocessing tool in action rules discovery. The influence $I_{i,j}$ shows the correlations among classification attributes triggered off by *actions*. If the candidate action rules are not in agreement with the *actions*, then they are not classified as *action rules*. However, if the actions ontology does not show all the interactions between classification attributes, then still some of the resulting action rules may fail when tested on real data. We have applied the proposed system to a Mammographic Mass DataSet. We discoverd 64 action rules, and associated actions suggesting ways to re-classify tumors from class: malignant to class:benign. The proposed system can be applied with other medical datasets, such as: diabetes or heart disease; as well as financial, and industrial data.

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