Classification Reasoning as a Basic Part of Machine Learning

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INTRODUCTION

We focus on the logical or symbolic supervised methods of machine learning. This mode of learning covers mining logical rules and dependencies from data: "if-then" rules, decision trees, functional, and associative dependencies. This learning is also used for extracting concept from data sets, constructing rough sets, hierarchical classification of objects, mining ontology from data, generating hypotheses, and some others (Kotsiantis, 2007). It has been proven in (Naidenova, 1996) that the tasks of mining all logical dependencies from data sets are reduced to approximation of a given classification (partitioning) on a given set of object descriptions.

The search for best approximation of a given object classification leads to a concept of good classification (diagnostic) test firstly introduced in (Naidenova & Polegaeva, 1986). A good classification test has a dual nature. On the one hand, it makes up a logical expression in the form of implication, associative or functional dependency. On the other hand, it generates the partition of a training set of objects equivalent to a given classification (partitioning) of this set or the partition that is nearest to the given classification with respect to the inclusion relation between partitions (Cosmadakis et al., 1986).

We consider two ways for giving classifications as it is shown in Figure 1: (1) by a target attribute *KL* or (2) by a value *v* of target attribute. The target attribute partitions a given set of examples into disjoint classes the number of which is equal to the number of values of this attribute. The target value of attribute partitions a given set of examples into two disjoint classes: the examples in description of which the target value appears (positive examples); all the other examples (negative examples).

We are interested in solving the following tasks:

Given attribute *KL*, to infer logical rules of the form:

$A\ B\ C \rightarrow KL$ or

$D\ S \rightarrow KL$ or

or

$A\ S\ Q\ V \rightarrow KL$

where *A, B, C, D, Q, S, V* – the names of attributes.

2. Given value *v* of attribute *KL*, to infer logical rules of the form:

if ((value of attribute *A* = "*a*") &

(value of attribute *B* = "*b*") &

……………………………………),

then (value of attribute *KL* = "*v*").

Rules of the first form are functional dependencies as they are determined in relational data base constructing. Rules of the second form are implicative dependencies as they are determined in association rule mining (Agarval et al., 2011). Left parts of rules can be considered as descriptions of given classifications or classes of objects. In our diagnostic test approach (the DTA) to logical rules mining, left parts of these rules constitute diagnostic tests.

Implicative assertions (logical rules of the first kind in our terminology) describe regular relationships connecting together objects, properties and classes of

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Figure 1. Two modes of giving the target classification

	A	B	C	KL
1	a_1	b_1	c_1	k_1
2	a_2	b_2	c_1	k_1
3	a_1	b_2	c_2	k_2
4	a_1	b_3	c_1	k_3
5	a_3	b_4	c_2	k_3

	A	B	C	D
1	a_1	b_1	c_1	h
2	a_2	b_2	c_1	v
3	a_1	b_2	c_2	v
4	a_1	b_3	c_1	f
5	a_3	b_4	c_2	v

KL
v–
v
v
v–
v

KL – the target attribute; *v* – the target value of attribute

objects. The DTA enables one to mine a whole class of implicative assertions including not only simple implication (a, b, $c \rightarrow d$), but also forbidden assertion (a, b, $c \rightarrow$ *false* (*never*), diagnostic assertion (x, $d \rightarrow a$; x, $b \rightarrow$ not a; d, $b \rightarrow$ *false*), assertion of alternatives (a or $b \rightarrow$ *true* (*always*); a, $b \rightarrow$ *false*), compatibility (a, b, $c \rightarrow VA$, where *VA* is the occurrence's frequency of rule).

In our consideration, commonsense reasoning rules (CRRs) (rules of the second kind in our terminology) are rules with the help of which implicative assertions are used, updated and inferred from instances. The deductive CRRs infer consequences from observed facts with the use of implicative assertions. Our analysis of human commonsense reasoning shows that these rules are based on well-known deductive inference rules: modus ponens: "if *A*, then *B*"; *A*; hence *B*; modus ponendo tollens: "either A or B" (A, B – alternatives); A; hence not B; modus tollendo ponens: "either *A* or *B*" (*A*, *B* – alternatives); not *A*; hence *B*; modus tollens: "if *A*, then *B*"; not *B*; hence not *A*; generating hypothesis: "if *A*, then B"; *B*; *A* is possible.

Let *X* be a set of true values of some attributes (or evidences) observed simultaneously. Let *r* be an implication, left(r) and right(r) be the left and right parts of r, respectively. Using implication: if left(r) $\subseteq X$, then X can be extended by right(r): $X \leftarrow X \cup$ right(r). It is based on modus ponens. Using forbidden assertion: let r be an implication $y \rightarrow$ not k. If left(r) $\subseteq X$, then k is the forbidden value for all extensions of X. It is based on modus ponendo tollens. Using compatibility: let r = 'a, b, $c \rightarrow k$, *VA*', where *VA* is the support of r. If left(r) $\subseteq X$, then k can be used to extend X along with the calculated value *VA* for this extension. Calculating *VA* requires a special consideration. Using compatibility is based on modus ponens. Using diagnostic rules: let r be a diagnostic rule 'X, $d \rightarrow$ a; X, $b \rightarrow$ not a', where 'X' is true, and 'a', 'not a' are some alternatives. Using diagnostic rule is based on modus ponens and modus ponendo tollens. Using rule of alternatives is based on modus tollendo ponens. Letters a, b, c, d, k are used as names of objects, classes of objects, or properties of objects.

When applied, these rules generate the reasoning, which is not demonstrative. Its goal is to extend an incomplete description X of some evidences and disproving impossible extensions. All the generated extensions must not contradict with knowledge (the first-kind rules) and an observable real situation, where the reasoning takes place. They must be intrinsically consistent (there are no prohibited values in such extensions). A more detailed discussion of the subject may be found in (Naidenova, 2010).

The inductive CRRs are the canons formulated by John Stuart Mill (1872): Method of Agreement, Method of Difference, Joint Method of Agreement and Difference, Method of Concomitant Changes, and Method of Residuum. These methods are not rules but