Action rules and meta-actions

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1 Abstract

An action rule is a rule which can be extracted from a decision system S and it describes a possible transition of objects from one decision class to another. Formally, it is defined as a term $[(\omega) \wedge (\alpha \rightarrow \beta)] \Rightarrow (\phi \rightarrow \psi)$, where ω is the header of the rule which is a conjunction of fixed classification feature, called stable features, $(\alpha \rightarrow \beta)$ represents proposed changes in values of flexible features, and $(\phi \rightarrow \psi)$ is a desired effect of the action. The discovered knowledge provides an insight of how values of some attributes need to be changed in S so the undesirable objects can be shifted to a desirable group. The notion of a cost of action rule will be introduced.

By meta-actions associated with S we mean higher level concepts representing actions. Meta-actions, when executed, are expected to trigger changes in values of some attributes in S. In medical domain, taking a drug is a classical example of a meta-action. For instance, Lamivudine is used for treatment of chronic hepatitis B. It improves the seroconversion of e-antigen positive hepatitis B and also improves histology staging of the liver but at the same time it can cause a number of other symptoms. This is why doctors order certain lab tests to check patient's response to that drug.

The influence matrix is used to describe the relationship between meta-actions and the expected changes within classification attributes. It should be mentioned that expert knowledge concerning meta-actions involves only classification attributes. Now, if some of these attributes are correlated with the decision attribute, then any change in their values will cascade to the decision attribute through this correlation. One of the goals of action rule discovery is to identify all correlations between classification attributes and the decision attribute.

To reduce the number of values for numerical attributes in S we use a classical method based either on entropy or Gini index resulting in a hierarchical discretization. Classification attributes are partitioned into stable and flexible. Before we use any flexible attribute in the process of a decision tree construction, all stable attributes have to be used first. This way the decision table is split into a number of decision subtables leading to them from the root of the tree by uniquely defined pathes built from stable attributes. Each path defines a header in all action rules extracted from the corresponding subtable. Initial testing shows that the action rules built that way are more compact (have larger intervals) than action rules built with prior discretization of the decision table done for instance by Rough Sets Exploration System.