46. Extracting Patterns Using Information Granules: A Brief Introduction

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The paper realizes a step in developing a foundation for approximate reasoning from experimental data to conclusions in natural language. Granule decomposition strategies based on background knowledge are outlined.

46.1 Introduction

Information granulation belongs to a collection of intensively studied topics in soft computing (see, e.g., [46.19], [46.20], [46.21]). One of the recently emerging approaches to deal with information granulation is based on information granule calculi (see, e.g., [46.10], [46.12], [46.15], [46.13])developed on the basis of the rough set [46.6] and rough mereological approaches (see, e.g., [46.9], [46.10], [46.12]). The development of such calculi is important for making progress in many areas like object identification by autonomous systems (see, e.g., [46.1], [46.18]), web mining (see, e.g., [46.4]), approximate reasoning based on information granules (see, e.g., [46.15], [46.7]) or spatial reasoning (see, e.g., [46.2], [46.8]). In particular, reasoning methods using background knowledge as well as knowledge extracted from experimental data (e.g., sensor measurements) represented by concept approximations [46.1] are important for making progress in such areas.

Schemes of approximate reasoning (AR-schemes, for short) are derived from parameterized productions [46.11], [46.13]. The productions, specifying properties of operations on information granules, are assumed to be extracted from experimental data and background knowledge. The problem of AR-schemes deriving is closely related to perception (see, e.g., [46.21]). In the paper we outline some methods for decompostion of information granules.

46.2 Granule Decomposition

In this section, we discuss briefly a granule decomposition problem. This is one of the basic problems in synthesis of approximate schemes of reasoning

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from experimental data. We restrict our considerations to the case of information granule decomposition supported by background knowledge. Some other decomposition methods are presented in [46.9], [46.5].

Assume that a knowledge base consists of a fact expressing that if two objects belong to concepts C_1 and C_2, then the object constructed out of them by means of a given operation f belongs to the concept C provided that the two objects satisfy some constraints. However, we can only approximate these concepts on the basis of available data. Using a (generalized) rough set approach [46.14] one can assume that an inclusion measure v_p for $p \in [0, 1]$ is given making it possible to estimate the degree of inclusion of data patterns Pat, Pat_1, and Pat_2 from languages L, L_1, and L_2 in the concepts C, C_1, and C_2, respectively. Patterns included to a satisfactory degree p in a concept are classified as belonging to its lower approximation while those included to a degree less than a preset threshold $q \leq p$ are classified as belonging to its complement. Information granule decomposition supported by background knowledge is accomplished by searching for patterns Pat of *high* quality (e.g., supported by a large number of objects) and included in a satisfactory degree in the target concept C. These patterns are obtained by performing a given operation f on some input patterns Pat_1 and Pat_2 (from languages L_1 and L_2, respectively) sufficiently included in C_1 and C_2, respectively.

One can develop a searching method for such patterns Pat based on tuning of inclusion degrees p_1, p_2 of input patterns Pat_1, Pat_2 in C_1, C_2, respectively, to obtain patterns Pat (constructed from Pat_1, Pat_1 by means of a given operation f) included in C in a satisfactory degree p and of acceptable quality (e.g., supported by the number of objects larger than a given threshold).

Assume degrees p_1, p_2 are given. There are two basic steps of searching procedures for relevant pairs of patterns (Pat_1, Pat_2) : (i) searching in languages L_1 and L_2 for sets of patterns included in degree at least p_1 and p_2 in concepts C_1 and C_2, respectively, (ii) selecting from sets of patterns generated in step (i) satisfactory pairs of patterns.

We would like to add some general remarks on the above steps.

One can see that our method is based on a decomposition of degree p into degrees p_1 and p_2 under some constraints. In Step 2, we search for a relevant constraint relation R between patterns. By $Sem(Pat)$ we denote the meaning of Pat in, e.g., a given information system. The goal is to extract the following approximate rule of reasoning:

if

$R(Sem(Pat_1), Sem(Pat_2)) \wedge \nu_{p_1}(Sem(Pat_1), C_1) \wedge \nu_{p_2}(Sem(Pat_2), C_2)$

then

$\nu_p(f(Sem(Pat_1) \times Sem(Pat_2)), C) \wedge Quality_t(f(Sem(Pat_1) \times Sem(Pat_2)))$

where p is a given inclusion degree, t - a threshold of pattern quality measure $Quality_t$, f- operation on objects (patterns), Pat- target pattern, C, C_1, C_2-given concepts, R, p_1, p_2 are expected to be extracted from data and (Pat_1, Pat_2) is satisfying R (in the case we consider R is represented by a finite set of pattern pairs).

One can also consider soft constraint relations R_r where $r \in [0,1]$ is a degree of truth to which the constraint relation holds.

Two sets P_1, P_2 are returned as the result of the first step. They consist of pairs (*pattern*, *degree*) where *pattern* is included in C_1, C_2, respectively in degree at least *degree*.

These two sets are used to learn the relevant relation R. We outline two methods.

The first method is based on an experimental decision table (U, A, d) [46.6] where U is a set of pairs of discovered patterns in the first step; $A = \{deg_1, deg_2\}$ consists of two attributes such that $deg_i((Pat_1, Pat_2))$ is equal to the degree to which Pat_i is at least included in C_i for $i = 1, 2$; the decision d has value p to which the granule composed by means of operation f from (Pat_1, Pat_2) is at least included in C. From this decision table the decision rules of a special form are induced: **if** $deg_1 \geq p_1 \wedge deg_2 \geq p_2$ **then** $d \geq p$ where (p_1, p_2) is a minimal degree pair such that if $p_1' \geq p_1$ and $p_2' \geq p_2$ then the decision rule obtained from the above rule by replacing p_1', p_2' instead of p_1, p_2, respectively, is also true in the considered decision table.

A version of such a method has been proposed in [46.9]. The relation R consists of the set of all pairs (Pat_1, Pat_2) of patterns with components included in C_1, C_2, respectively in degrees $p_1' \geq p_1$, $p_2' \geq p_2$ where p_1, p_2 appear on the left hand side of some of the generated decision rules.

The second method is based on another experimental decision table (U, A, d) where objects are triplets $(x, y, f(x, y))$ composed out of objects x, y and the result of f on arguments x, y; attributes from A describe features of arguments of objects and the decision d is equal to the degree to which the elementary granule corresponding to the description of $f(x, y)$ by means of attributes is at least included in C. This table is extended by adding new features being characteristic functions a_{Pat_i} of patterns Pat_i discovered in the first step. Next the attributes from A are deleted and from the resulting decision table the decision rules of a special form are induced: **if** $a_{Pat_1} = 1 \wedge a_{Pat_2} = 1$ **then** $d \geq p$ where if Pat_1, Pat_2 are included in C_1, C_2, in degree at least p_1, p_2, respectively and Pat_1', Pat_2' are included in C_1, C_2 in degree $p_1' \geq p_1$ and $p_2' \geq p_2$, respectively then a decision rule obtained from the above rule by replacing Pat_1', Pat_2' instead of Pat_1, Pat_2 is also true in the considered decision system. The decision rules describe constraints specifying the constraint relation R. Certainly, in searching procedures one should also consider constraints for the pattern quality.

The searching methods discussed in this section return local granule decomposition schemes. These local schemes can be composed using techniques discussed in [46.10]. The received schemes of granule construction (which can be also treated as approximate reasoning schemes) have also the following stability (robustness) property: if the input granules are sufficiently close to input concepts then the output granule is sufficiently included in the target concept provided this property is preserved locally [46.10].

Conclusions

We have discussed methods for decompostion of information granules as a way to extract from data productions used to derive AR-schemes. Searching for relevant patterns for information granule decomposition can be based on methods for tuning parameters of rough set approximations of fuzzy cuts or concepts defined by differences between cuts [46.13], [46.16], i.e., by using so called rough-fuzzy granules. In this case, pattern languages consist of parameterized expressions describing the rough set approximations of *parts* of fuzzy concepts being fuzzy cuts or differences between cuts. Hence, an interesting research direction related to the development of new hybrid rough-fuzzy methods arises aiming at developing algorithmic methods for rough set approximations of such parts of fuzzy sets relevant for information granule decomposition.

In our further study we plan to implement the proposed strategies and test them on mentioned above real life data. This will recquire: (i) to develop ontologies for considered applications, (ii) further development of methods for extracting productions from data on the basis of decomposition, and (iii) synthesis methdos for AR-schemes from productions. These methods will make it possible to reason by means of sensor measurements *along* inference schemes over ontologies (i.e., inference schemes over some standards) by means of attached to them AR-schemes discovered from backround knowledge (including ontologies) and experimental data.

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