28. Toward Intelligent Systems: Calculi of Information Granules

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We present an approach based on calculi of information granules as a basis for approximate reasoning in intelligent systems. Approximate reasoning schemes are defined by means of information granule construction schemes satisfying some robustness constraints. In distributed environments such schemes are extended to rough neural networks. Problems of learning in rough neural networks from experimental data and background knowledge are discussed. The approach is based on rough mereology.

28.1 Introduction

Computing with Words (CWW) (see, e.g., [28.38], [28.39], [28.40]) is one among a collection of recently emerging computing paradigms. The goal of this new research direction is to build foundations for future intelligent computers and information systems performing computations on words from natural language representing concepts rather than on numbers.

Information granulation belongs to intensively studied topics in soft computing (see, e.g., [28.38], [28.39], [28.40]). One of the recently emerging approaches to deal with information granulation is based on information granule calculi (see, e.g., [28.24], [28.33]). The development of such calculi is important for making progress in many areas like object identification by autonomous systems (see, e.g., [28.3], [28.36]), web mining (see, e.g., [28.8]), spatial reasoning (see, e.g., [28.4]) or sensor fusion (see, e.g., [28.2], [28.16], [28.19]).

One way to achieve CWW is through Granular Computing (GC). The main concepts of GC are related to information granulation and in particular to information granules [28.24].

Any approach to information granulation should make it possible to define complex information granules (e.g., in spatial and temporal reasoning, one should be able to determine if the situation on the road (see Fig. 28.1) is safe on the basis of sensor measurements or to classify situations in complex games, like soccer [28.35]). These complex information granules consitute a form of information fusion. Any calculus of complex information granules should permit to (i) deal with vagueness of information granules, (ii) develop strategies of inducing multi-layered schemes of complex granule construction, (iii) derive robust (stable) information granule construction schemes with respect to deviations of granules from which they are constructed, and (iv)

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develop adaptive strategies for reconstruction of induced schemes of complex information granule synthesis.

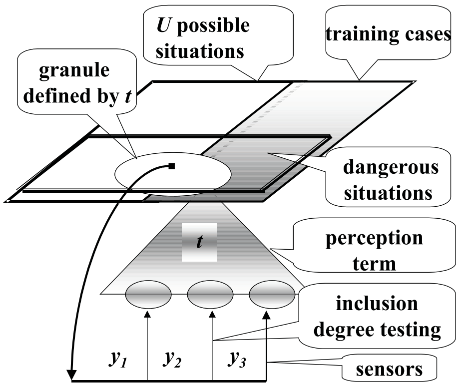

Fig. 28.1. Classification of situations

To deal with vagueness, one can adopt fuzzy set theory [28.37] or rough set theory [28.15] either separately or in combination [28.13]. The second requirement is related to the problem of understanding of reasoning from measurements to perception (see, e.g., [28.40]) and to concept approximation learning in layered learning [28.35] as well as to fusion of information from different sources (see, e.g., [28.38], [28.39], [28.40]). The importance of searching for Approximate Reasoning Schemes (AR-schemes, for short) as schemes of new information granule construction, is stressed in rough mereology (see, e.g., [28.20], [28.21], [28.21], [28.22], [28.26], [28.27]). In general, this leads to hierarchical schemes of new information granule construction. This process is closely related to ideas of co-operation, negotiations and conflict resolution in multi-agent systems [28.7]. Among important topics studied in relation to AR-schemes are methods for specifying operations on information granules; in particular, for their construction from data and background knowledge, and methods for inducing these hierarchical schemes of information granule construction. One of the possible approaches is to learn such schemes using evolutionary strategies [28.10]. Robustness of the scheme means that any scheme produces rather a higher order information granule that is a clump (e.g., a set) of close information granules rather than a single information granule. Such a clump is constructed by means of the scheme from the Cartesian product of input clumps (e.g., clusters) satisfying some constraints. The input clumps are defined by deviations (up to acceptable degrees) of input information granules.

It is worthwhile to mention that modeling complex phenomena requires to use complex information granules representing local models (perceived by local agents) which next should be fused. This process involves the negotiations between agents [28.7] to resolve contradictions and conflicts in local modeling. This kind of modeling will become more and more important in solving complex real-life problems which we are unable to model using traditional analytical approaches. If the latter approaches can be applied to modeling of such problems they lead to exact models . However, the necessary assumptions used to build them in case of complex real-life problems are often causing the resulting solutions to be *too far* from reality to be accepted as solutions of such problems.

Let us also observe, using multi-agent terminology, that local agents perform operations on information granules from granule sets that are *understandable* by them. Hence, granules submitted as arguments by other agents should be approximated by means of properly tuned approximation spaces creating interfaces between agents. The process of tuning of the approximation space [28.32], [28.27] parameters in AR-schemes corresponds to the tuning of weights in neural networks. The methods for inducing of AR-schemes transforming information granules into information granules studied using rough set (see, e.g., [28.15], [28.9]) and rough mereological methods in hybridization with other soft computing approaches create a core for Rough Neurocomputing (RNC) (see, e.g., [28.14], [28.27]). In RNC, computations are performed on information granules.

Another important problem concerns relationships between information granules and words (linguistic terms) in a natural language and also a possibility to use induced AR-schemes as schemes matching up to a satisfactory degree reasoning schemes in natural language. Further research in this direction will create strong links between RNC and CWW. The results of such research will be of great importance for many applications (e.g., web mining problems, Fig. 28.2).

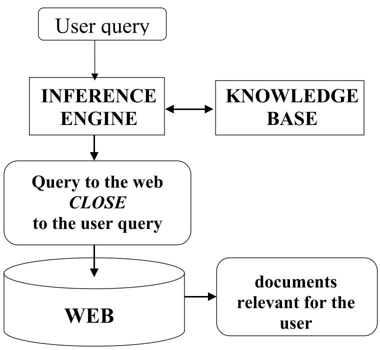

Fig. 28.2. Web mining

RNC is attempting to define information granules using rough sets [28.15], [28.9] and rough mereology (see, e.g., [28.21], [28.21], [28.22], [28.26], [28.27]) introduced to deal with vague concepts in hybridization with other soft computing methods like neural networks [28.29], fuzzy sets [28.13], [28.37], [28.39] and evolutionary programming [28.14], [28.10]. The methods based on the above mentioned approaches can be used for constructing of more complex information granules by means of schemes analogous to neural networks.

We outline a rough neurocomputing model as a basis for granular computing.

28.2 *AR*-Schemes

AR-schemes are the basic constructs used in RNC. We assume each agent ag from a given collection Ag of agents [28.7] is equipped with a system of information granules $S(ag)$ specifying information granules the agent ag is perceiving and the inclusion (or closeness) relations to a degree used by ag to measure the degree of inclusion (or closenees) between information granules. A formal definition of information granule system the reader can find, e.g., in [28.31]. Using such system $S(ag)$ the agent ag creates a representation for all components of $S(ag)$. The details of such representation the reader can find, e.g., in [28.22], [28.24]. From such representations agents are able to extract local schemes of approximate reasoning called productions. Algorithmic methods for extracting such productions from data are discussed in [28.21], [28.30], [28.34], [28.17], [28.18]. The left hand side of each production is (in the simplest case) of the form $(st_1(ag), (\epsilon_1^{(1)}, \cdot, \epsilon_r^{(1)}), \cdot, (st_k(ag), (\epsilon_1^{(k)}, \cdot, \epsilon_r^{(k)})$ and the right hand side is of the form $(st(ag), (\epsilon_1, \cdot, \epsilon_r)$ for some positive integers k, r.

Such production represents an information about an operation o which can be performed by the agent ag. In the production k denotes the arity of operation. The operation o represented by the production is transforming standard (prototype) input information granules $st_1(ag), \cdots, st_k(ag)$ into the standard (prototype) information granule $st(ag)$. Moreover, if input information granules $g_1, \cdots, g_k$ are close to $st_1(ag), \cdots, st_k(ag)$ to degrees $\epsilon_j^{(1)}, \cdot, \epsilon_j^{(k)}$ then the result of the operation o on information granules $g_1, \cdots, g_k$ is close to the standard $st(ag)$ to a degree at least ϵ_j where $1 \leq j \leq k$. Standard (prototype) granules can be interpreted in different ways. In particular they can correspond to concept names in natural language.

The described above productions are basic components of reasoning system over an agent set Ag. An important property of such productions is that they are expected to be discovered from available experimental data and background knowledge. Let us also observe that the degree structure is not necessarily restricted to reals from the interval $[0, 1]$. The inclusion degrees can have a structure of complex information granules used to represent the degree of inclusion. It is worthwhile to mention that the productions can also be interpreted as a constructive description of some operations on fuzzy sets. The methods for such constructive description are based on rough sets and Boolean reasoning (see, e.g., [28.9], [28.15]).

AR-schemes can be treated as derivations obtained by using productions from different agents. The relevant derivations defining AR-schemes are satisfying so called robustness (or stability) condition. It means that at any node of derivation the inclusion (or closeness) degree of constructed granule to the prototype (standard) granule is higher than required by the production to which the result should be sent. This makes it possible to obtain a sufficient robustness condition for the whole derivations. For details the reader is referred to, e.g., [28.22], [28.24], [28.25], [28.26]. In case where standards are interpreted as concept names in natural language and there is given a reasoning scheme in natural language over the standard concepts the corresponding AR-scheme represents a cluster of reasoning (constructions) approximately following (by mens of other information granule systems) the reasoning in natural language.

28.3 Rough Neural Networks

We extend AR-schemes for synthesis of complex objects (or granules) developed in [28.24] and [28.22] by adding one important component. As a result we obtain granule construction schemes that can be treated as a generalization of neural network models. The main idea is that granules sent by one agent to another are not, in general, exactly understandable by the receiving agent. This is because these agents are using different languages and usually does not exist any translation (from the sender language to the receiver language) preserving exactly semantical meaning of formulas. Hence, it is necessary to construct interfaces that will make it possible to understand received granules approximately. These interfaces can be, in the simplest case, constructed on the basis of information exchanged by agents and stored in the form of decision data tables. From such tables the approximations of concepts can be constructed using rough set approach [28.33]. In general, it is a complex process because a high quality approximation of concepts can be often obtained only in dialog (involving nagotiations, conflict resolutions and cooperation) among agents. In this process the approximation can be constructed gradually when dialog is progressing. In our model we assume that for any n-ary operation $o(ag)$ of an agent ag there are approximation spaces $AS_1(o(ag), in), ..., AS_n(o(ag), in)$ which will filter (approximate) the granules received by the agent for performing the operation $o(ag)$. In turn, the granule sent by the agent after performing the operation is filtered (approximated) by the approximation space $AS(o(ag), out)$. These approximation spaces are parameterized. The parameters are used to optimize the size of neighborhoods in these spaces as well as the inclusion relation [28.26]. A granule approximation quality is taken as the optimization criterion. Approximation spaces attached to any operation of ag correspond to neuron weights in neural networks whereas the operation performed by the agent ag on information granules corresponds to the operation realized on vectors of real numbers by the neuron. The generalized scheme of agents is returning a granule in response to input information granules. It can be for example a cluster of elementary granules. Hence, our schemes realize much more general computations than neural networks operating on vectors of real numbers.

We call extended schemes for complex object construction *rough neural networks* (for complex object construction). The problem of deriving such schemes is closely related to perception (see, e.g., [28.1], [28.40]). The stability of such networks corresponds to the resistance to noise of classical neural networks.

Let us observe that in our approach the deductive systems are substituted by productions systems of agents linked by approximation spaces, communication strategies and mechanism of derivation of AR-schemes. This revision of classical logical notions seems to be important for solving complex problems in distributed environments.

28.4 Decomposition of Information Granules

Information granule decomposition methods are important components of methods for inducing of AR-schemes from data and background knowledge. Such methods are used to extract from data, local decomposition schemes called produtions [28.25]. The AR-schemes are constructed by means of productions. The decomposition methods are based on searching for the parts of information granules that can be used to construct relevant higher level patterns matching up to a satisfactory degree the target granule.

One can distinguish two kinds of parts (represented, e.g., by sub-formulas or sub-terms) of AR-schemes. Parts of the first type are represented by expressions from a language, called the *domestic* language L_d, that has known semantics (consider, for example, semantics defined in a given information system [28.15]). Parts of the second type of AR-scheme are from a language, called *foreign* language L_f (e.g., natural language), that has semantics definable only in an approximate way (e.g., by means of patterns extracted using rough, fuzzy, rough–fuzzy or other approaches). For example, the parts of the second kind of scheme can be interpreted as soft properties of sensor measurements [28.3].

For a given expression e, representing a given scheme that consists of subexpressions from L_f first it is necessary to search for relevant approximations in L_d of the foreign parts from L_f and next to derive global patterns from the whole expression after replacing the foreign parts by their approximations. This can be a multilevel process, i.e., we are facing problems of discovered pattern propagation through several domestic-foreign layers.

Productions from which AR-schemes are built can be induced from data and background knowledge by pattern extraction strategies. Let us consider some of such strategies. The first one makes it possible to search for relevant approximations of parts using the rough set approach. This means that each part from L_f can be replaced by its lower or upper approximation with respect to a set B of attributes. The approximation is constructed on the basis of relevant data table [28.15], [28.9]. With the second strategy parts from L_f are partitioned into a number of sub-parts corresponding to cuts (or the set theoretical differences between cuts) of fuzzy sets representing vague concepts and each sub-part is approximated by means of rough set methods. The third strategy is based on searching for patterns sufficiently included in foreign parts. In all cases, the extracted approximations replace foreign parts in the scheme and candidates for global patterns are derived from the scheme obtained after the replacement. Searching for relevant global patterns is a complex task because many parameters should be tuned, e.g., the set of relevant features used in approximation, relevant approximation operators, the number and distribution of objects from the universe of objects among different cuts and so on. One can use evolutionary techniques [28.10] in searching for (semi-) optimal patterns in the decomposition.

It has been shown that the decomposition strategies can be based on the developed rough set methods for decision rules generation and Boolean reasoning [28.21], [28.12], [28.17], [28.33]. In particular, methods for decomposition based on background knowledge can be developed [28.30], [28.18].

Conclusions. We have discussed a methodology for synthesis of AR-schemes and rough neural networks. For more details the reader is referred to [28.21], [28.22], [28.23], [28.24], [28.26], [28.27], [28.32], [28.33], [28.34].

We enclose a list of research directions related to the synthesis and analysis of AR-schemes and rough neural networks.

1. *Developing foundations for information granule systems.* Certainly, still more work is needed to develop solid foundations for synthesis and analysis of information granule systems. In particular, methods for construction of hierarchical information granule systems, and methods for representation of such systems should be developed.
2. *Algorithmic methods for inducing parameterized productions.* Some methods have already been reported such as discovery of rough mereological connectives from data (see, e.g., [28.21]) or methods based on decomposition (see, e.g., [28.22], [28.30], [28.34], [28.17]). However, these are only initial steps toward algorithmic methods for inducing of parameterized productions from data. One interesting problem is to determine how such productions can be extracted from data and background knowledge. A method in this direction has been proposed in [28.3].
3. *Algorithmic methods for synthesis of AR-schemes.* It was observed (see, e.g., [28.22], [28.27]) that problems of negotiations and conflict resolutions are of great importance for synthesis of AR-schemes. The problem arises, e.g., when we are searching in a given set of agents for a granule sufficiently included or close to a given one. These agents, often working with different systems of information granules, can derive different gra-

nules and their fusion will be necessary to obtain the relevant output granule. In the fusion process, the negotiations and conflict resolutions are necessary. Much more work should be done in this direction by using the existing results on negotiations and conflict resolution. In particular, Boolean reasoning methods seem to be promising ([28.22]) for solving such problems. Another problem is related to the size of production sets. These sets can be of large size and it is important to develop learning methods for extracting *small* candidate production sets in the process of extension of temporary derivations out of huge production sets. For solving this kind o problems methods for clustering of productions should be developed to reduce the size of production sets. Moreover, dialog and cooperation strategies between agents can help to reduce the search space in the process of AR-scheme construction from productions.

4. *Algorithmic methods for learning in rough neural networks.* A basic problem in rough neural networks is related to selecting relevant approximation spaces and to parameter tuning. One can also look up to what extent the existing methods for classical neural methods can be used for learning in rough neural networks. However, it seems that new approach and methods for learning of rough neural networks should be developed to deal with real-life applications. In particular, it is due to the fact that high quality approximations of concepts can be often obtained only through dialog and negotiations processes among agents in which gradually the concept approximation is constructed. Hence, for rough neural networks learning methods based on dialog, negotiations and conflict resolutions should be developed. In some cases, one can use directly rough set and Boolean reasoning methods (see, e.g., [28.33]). However, more advanced cases need new methods. In particular, hybrid methods based on rough and fuzzy approaches can bring new results [28.13].
5. *Fusion methods in rough neural neurons.* A basic problem in rough neurons is fusion of the inputs (information) derived from information granules. This fusion makes it possible to contribute to the construction of new granules. In the case where the granule constructed by a rough neuron consists of characteristic signal values made by relevant sensors, a step in the direction of solving the fusion problem can be found in [28.19], [28.6].

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