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Building granular fuzzy decision support systems

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ABSTRACT

In various scenarios of fuzzy decision-making we encounter a collection of sources of knowledge – local models describing decision pursuits undertaken by individual decision-makers. These sources have to be agreed upon. The reconciliation mechanisms are present quite vividly in any collective pursuit including distributed modeling, time series characterization and classification. There is an interesting and practically pertinent task of reconciling decisions coming from the decision models and construct a decision of a holistic character. In this study, we introduce a concept of a *granular* fuzzy decision built on a basis of decisions formed by individual decision models. Here the term "granular" pertains to a wealth of possible realizations of such decision thus giving rise to fuzzy fuzzy (namely, fuzzy^2), interval-valued, probabilistic-fuzzy and rough-fuzzy representations of information granules. Information granularity plays a pivotal role in reconciling differences among existing decisions, quantifying their diversity and associating it with the overall fuzzy decision. We exploit a principle of justifiable granularity to develop and articulate a granular fuzzy decision of a holistic nature. Along with the passive way of forming the granular fuzzy decisions, we introduce an active form of design in which established is a feedback loop using which on a basis of the holistic view adjusted are the individual decisions. Detailed optimization schemes are discussed along with compelling examples of forming type-2 and type-3 fuzzy sets.

1. Introduction

Quite often one encounters modeling scenarios where a number of *local* sources of knowledge become available and need to be used *en block* in further processing to arrive at a holistic, global view of the phenomenon under discussion. The evident diversity of these sources has to be taken into account when constructing piece knowledge of a *global* nature. For instance, considering that the local sources are descriptors of some decision-making processes realized by humans (and in this way exhibiting a quite local character confined to a single individual), we are interested in retaining and quantifying the diversity of the local sources of knowledge when arriving at the model formed at the higher level of abstraction when dealing with group decision making. Each decision-maker comes with a local model of decision – by ranking possible decision actions. A collective (group) decision-making naturally gives rise to some ranking agreeable by the group with an indication as to the diversity of the preferences and opinions being expressed within the group. Likewise the effect of hesitancy resulting because of the diversity in the points of view has to be captured. One can refer here to the recent developments in the area of group decision-making [1,5,8] including approaches involving linguistic preferences [7,10], intuitionistic fuzzy sets [4,25] and type 2 fuzzy sets [12].

A similar effect is observed when fusing classifiers. In this situation, each classifier is regarded as a local source of knowledge being reflective of the realization of some local views at the classification problem (classification data). Taking these classifiers altogether we are offered an interesting alternative of carrying out classification results at the global, more general level. The classifiers may produce different results. They have to be reconciled by invoking some mechanisms of consensus building [14,15,22,24,26]. The final outcome should be reflective of the existing diversity offering an important overview of the classification pursuits completed so far and, if necessary, produce some guidelines as to the enhancements of the local sources of knowledge (say, classifiers or predictors of time series).

It is instructive to highlight the main features of the problems we are interested in this study. It is also beneficial to identify some structural commonalities, functional resemblance and highlight the essential motivating factors behind the emergence of aggregation of individual, local results. Now we look at several representative categories of problems.

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1.1. Decision-making

While there is a genuine plethora of models of fuzzy decision-making, a generic architecture is concerned with a web of linkages from a collection of objectives (goals and constraints), say **x** where dim(**x**) = n to the collection (vector) of decisions (alternatives) **y**, dim(**y**) = m. Both **x** and **y** are treated as fuzzy sets defined in the corresponding finite spaces of objectives and alternatives where a given coordinate describes a level of satisfaction of the objective or the alternative. The mapping from the space of objectives to the space of alternatives could be described as a family of logical relationships. In group decision making we have a collection of decision-makers who typically produce different decisions. Consensus building is aimed at the reduction of differences [11]. The reconciliation of the individual decisions leads to a high level, abstract construct whose role is twofold: to raise awareness about the diversity of individual findings and to quantify the variety of opinions expressed. Fuzzy sets of type-2 serve as a sound and intuitively convincing vehicle to address these two points identified above. In particular, AHP comes with interesting mechanisms supporting a formation of consensus in presence of a group of decision-makers [21] along with a quantification of the levels of consensus achieved [19]. In the consensus building used are advanced optimization techniques such as e.g., PSO [13].

1.2. Pattern recognition

The problems of pattern recognition can be conveniently cast in the similar setting as presented above. A family of classifiers typically working with on different feature spaces is often considered. The results of classification, once combined, are described not by single numbers (degree of belongingness to a certain class) but by more abstract and representative entities such as, e.g., intervals of membership degrees.

1.3. Time series description, classification and prediction

This class of problems, see Fig. 1, is concerned with a representation of time series (commonly a variety of alternatives is considered formed in different feature spaces). Each model of time series (say, a predictor or a classifier) used in concert with other models contributes to the results of classification or prediction [6]. The inevitable diversity of the models (resulting because of a plethora of representation schemes as well as models of classification or prediction) leads to the reconciliations of pieces of knowledge/points of view, which at the end strongly support an emergence of the concepts and algorithmic setting of granular time series.

In all the categories of applications, we see that information granularity and information granules play an important role by elevating an aggregate model to the higher level of abstraction and delivering a quantification of the diversity of results being formed at the level of the individual constructs.

The paper is organized in the following way. The exposure of the material is structured in a bottom up manner. We start with a presentation of the logic-oriented decision-making model by stressing the role of the logic-driven backbone of the models. In Section 3, we discuss a general way of forming information granules (intervals and fuzzy sets, in particular) in the presence of some experimental evidence. In the sequel, Section 4 is devoted to the fundamental schemes of passive and active aggregation schemes where we emphasize the role of emerging information granules of type 2 by stressing that these forms of granules are quite intuitive and highly advantageous in the quantification of the diversity of local models. In the passive mode we also discuss on how to adjust the local models involved in the reconciliation process. In Section 5, we discuss how fuzzy sets of higher type arise when forming hierarchies of processing of increasing depth.

In the study, we adhere to the standard notation used in fuzzy sets. Boldface letters are used to denote fuzzy sets regarded as mappings from a finite space (universe of discourse) to [0,1]. Fuzzy relations are shown in capital letters. Capital boldface letters are mostly reserved to fuzzy sets of higher type (however the meaning of the symbol in this case depends on the context in which it is being used). Square brackets used in the descriptors, say $R[ii]$, $\mathbf{x}[ii]$, etc. are used to emphasize the corresponding local construct, say a local model.

2. Logic-oriented decision-making model

We introduce a logic relationship as a certain logic expression coming in a conjunctive or disjunctive format [9]. The iith logic descriptors involving "n" input variables (objectives) and "m" output variables (alternatives) coming in a calibrated conjunctive form read as follows

$$\begin{aligned} y_1[ii] &= (r_{11}[ii] \text{ or } x_1) \text{ and } (r_{12}[ii] \text{ or } x_2) \text{ and } \ldots \text{ and } (r_{1n}[ii] \text{ or } x_n) \\ &\ldots \\ y_j[ii] &= (r_{j1}[ii] \text{ or } x_1) \text{ and } (r_{j2}[ii] \text{ or } x_2) \text{ and } \ldots \text{ and } (r_{jn}[ii] \text{ or } x_n) \\ &\ldots \\ y_m[ii] &= (r_{m1}[ii] \text{ or } x_1) \text{ and } (r_{m2}[ii] \text{ or } x_2) \text{ and } \ldots \text{ and } (r_{mn}[ii] \text{ or } x_n) \end{aligned} \quad (1)$$

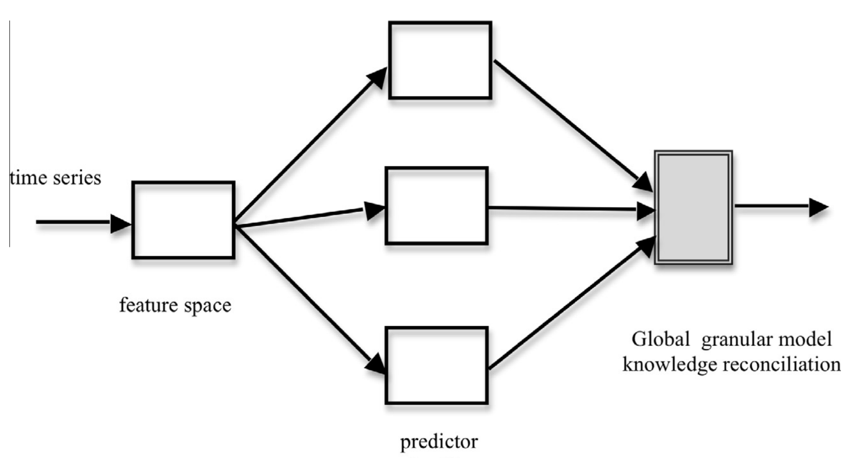

Fig. 1. Knowledge reconciliation in classification/prediction of time series.