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Fuzzy data mining and management of interpretable and subjective information

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Abstract

Fuzzy set theory offers an important contribution to data mining leading to fuzzy data mining. It enables the management of interpretable and subjective information in both input and output of the data mining process. In this paper, we discuss the notion of interpretability in fuzzy data mining and we present some references on the management of emotions as a particular kind of subjective information.

Keywords: Fuzzy data mining; Interpretable systems; Subjective information; Emotions

Introduction

Since its introduction by Lotfi Zadeh fifty years ago, fuzzy set theory has been fruitfully used in many domains. Data mining is one of the important fields of application, introduced in the 1990s as a particular step in knowledge discovery from database (KDD): "*The data-mining component of KDD currently relies heavily on known techniques from machine learning, pattern recognition, and statistics to find patterns from data in the data-mining step of the KDD process*" [1]. Early after the appearance of data mining, several works have proposed the use of fuzzy set theory to this domain.

The contributions of fuzzy sets in data mining are various: increasing the interpretability, enhancing the robustness of the process and managing unclear information, in particular subjective and emotional information. Both are provided by the introduction of fuzzy set theory to build up *fuzzy data mining*, offering to that process the capacity to mine complex information difficult to treat in a classic environment, considering the particular case of emotions.

Interpretability is the focus of this paper and it is discussed hereafter. Robustness of the process enables it to produce similar results when facing only small changes in the data (for instance, in the presence of noise). Robustness of fuzzy systems has been extensively studied and is well-known even in non-machine learning domains.

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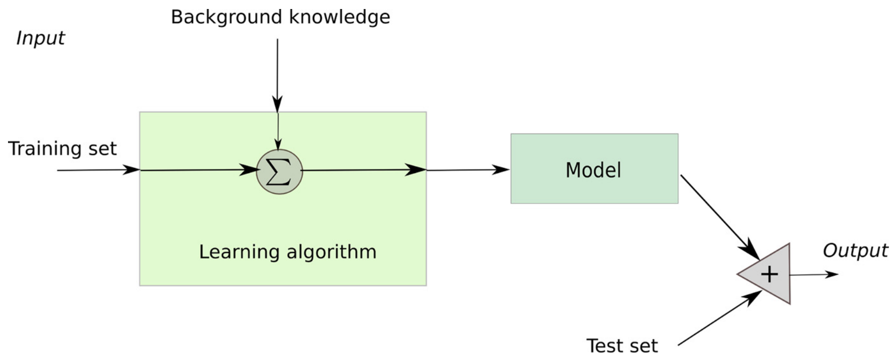

Fig. 1. Machine learning: from data to model.

Section 1 presents fuzzy data mining. In Section 2, interpretability in fuzzy data mining is discussed. In Section 3, the particular case of handling subjective information, such as emotions, is studied. Lastly, a conclusion and some future works are presented.

1. Fuzzy data mining

This section presents fuzzy data mining giving basic recalls on data mining and its links to machine learning. Then, various uses of fuzzy sets in data mining are presented.

Data mining refers to a global process that is composed of several steps (data pre-processing, learning, analyses, selection,...) [1]. Data mining and machine learning are two intertwined domains in the sense that data mining usually includes a machine learning algorithm as a step. In the literature, "data mining" can also refer to "the machine learning step of a data mining process". Here, data mining and machine learning differ mainly in the sense that each of them has a particular *aim*. In [2,3] the following difference is highlighted: "*Machine learning main aim is leaded by performances in predictive perspective, whereas data mining is related to understandability of discovered patterns*".

Machine learning aims to set up a *model* from a set of *data* providing some *background knowledge*. Data compose the training set available either to build up the model, or to tune it. If available, background knowledge is provided by an expert of the domain or is related to domain expertise. In this process, the model can be viewed as a new knowledge that is produced from the learning, it can be of various forms: e.g. mathematical function, neural network, rule base, patterns, association rules,...

Fig. 1 illustrates the links between these elements. It should be noted that the model can be included as a part of the learning algorithm if the algorithm is a way to tune it rather than to build it up completely (for instance, neural networks are tuned, and decision trees are constructed). In this figure, one possible use of the model is represented: the model can be exploited to provide an output for any forthcoming data (i.e. data that can be different from those present in the training set) composing the so-called test set. The test set, in a more general sense, can be associated with practical use cases of the model in practical situations.

Given that machine learning algorithms are highly reliable,[1] the choice of an algorithm to be used in data mining is made thanks to the interpretability of the model it builds.

Data mining is a process that is based on the use of a machine learning algorithm in a given application task. One main difference is that the constructed model is afterwards used not only to classify new cases, but also to provide an additional knowledge. Data mining is also concerned with accuracy of the obtained model in order to offer its validation or an evaluation of its performances [1]. In this case, models with a *good* accuracy rather than the *highest* one can be sufficient as the main aim is to obtain understandable knowledge on the data.

Fuzzy data mining is an extension of data mining where fuzzy set modelling is introduced. Various kinds of fuzzy data mining can be highlighted, depending on the application or the problem that has to be dealt with. The main

[1] Reliability in terms of *accuracy* refers to the efficiency of the model when applied to cases not belonging to the training set. The more accurate, the more usable the model for any forthcoming data and thus the more reliable it is.

question that can be pointed out is *what does "fuzzy" mean in fuzzy data mining?* To answer this question, components of the data mining process are studied in depth in the following.

1.1. Input data and knowledge

Input of the machine learning step (see Fig. 1) is composed of data and background knowledge. Data are usually provided as a training set from which the learning algorithm extracts relations or correlations, and infers the model. Knowledge is composed of (background) information that helps the learning algorithm to handle training sets or to speed it up.

In fuzzy data mining, fuzziness can appear at two levels:

- Data are fuzzy. When the data are fuzzy sets (or type-2 fuzzy sets, intuitionistic fuzzy sets, or other kinds of uncertain sets), the learning algorithm must handle fuzzy sets. This leads either to an extension of the formal parameters of the algorithm to enable it to handle fuzzy sets (for instance, [4]), or to create new algorithms that are built from fuzzy set theory (for instance, [5] or [6]).
- Knowledge is fuzzy. For instance, fuzzy sets can be provided to represent numerical data, rather than being built up from numerical values in a pre-processing step (for instance, [7] or [8]). The knowledge can also be uncertain or a belief distribution to bring additional information on the data. In this case, each datum can be weighted with a probability, a belief, or any uncertainty degree.

Usually, fuzzy data mining works refer to numerical data from which fuzzy sets are deduced. These fuzzy sets can be built up by means of either a learning algorithm [9] or by means of an optimisation procedure used to tune the parameters of a fuzzy partition [10].

It should be noted that unlike in classic data mining, up to now in fuzzy data mining, there is no popular benchmarks composed of fuzzy data sets to compare algorithms. Thus, they are usually compared by means of classic benchmarks, sometimes after an artificial fuzzification process of the numerical data. Unfortunately, such a kind of comparison is useful in particular to compare the accuracy of models rather than their interpretability. Approaches can be proposed in order to balance accuracy and interpretability in fuzzy modelling [11].

1.2. The model

The model is produced by the learning algorithm at the end of the training step. The model is made of underlying relations existing in the training set and that have been highlighted by the machine learning algorithm.

Examples of models in machine learning include: decision trees, association rules, prototypes, support vector machines, clustering algorithms... Depending on the algorithm, the model can be a set of rules or more complex mathematical functions.

Many classic machine learning algorithms have been extended to fuzzy cases (see [12–16] for a non-exhaustive list of references). Extending a classic algorithm to build up a fuzzy learning algorithm is an interesting task. Many papers have been published in the case of fuzzy decision trees [17–20,4,21], and in fuzzy rule base construction [5,22,23]. The challenge in such a case is to propose an algorithm that can both handle fuzzy input and still satisfy the main properties of the classical algorithm.

Classic algorithms have also been extended to handle complex data, for instance beliefs [24] or intuitionistic fuzzy sets [25].

1.3. The output knowledge

The output may have two forms. On the one hand, the model itself can be the output of the data mining process. In this case, the aim is to have a characterisation of the data as a summary by means of the model. For instance, the learning algorithm can produce a set of rules, a set of groups, or a decision tree.

On the other hand, the output results of the use of the model with other data (the test data). Examples of results can be a class (the model is used to classify test data), a membership (the model produces a membership to a cluster or a category), a belief, or it can also have a more complex form (for instance, in case-based reasoning).

In fuzzy data mining, for instance when the model is a (fuzzy) rule base, it can either be used "as it is" to provide some information on the links between variables describing the data, or it can be used to infer a decision, a membership degree, or a belief for any forthcoming (test) data.

2. Fuzzy data mining and interpretable information

The gain in interpretability obtained by means of a fuzzy data mining algorithm rather than a (classic) data mining one is complex to evaluate. In fact, the evaluation of the interpretability level depends on the step of the data mining process in which fuzzification occurs. From the presentation of fuzzy data mining shown in the previous section, interpretability can be highlighted at several steps of the process.

Interpretability can be viewed considering two kinds of persons (or users): the *operator* and the *end user*. The operator is concerned with the building of the data mining process and has to set several parameters of this process: selecting the machine learning algorithm, preparing the data, ... The end user is concerned with the produced model and its use in the real-world application domain.

These two users can have usually different kinds of knowledge and abilities (for instance, the operator is commonly a computer scientist, and the end user is usually a physician or an application-domain expert,...). Thus, the interpretability is usually considered in the end user's point of view.

2.1. Interpretability of the model

It is the main kind of interpretability that is searched for in many fuzzy data mining applications. As stated in [10], "*a fuzzy solution is not only judged for its accuracy, but also – if not especially – for its simplicity and readability*". There exist many measures of interpretability. To evaluate the interpretability, [26] proposed two categories of measures: complexity-based interpretability and semantic-based interpretability.

The interpretability of the model is concerned with its structure (for instance, a decision tree, a set of rules, a mathematical function, ...), its readability (e.g. its complexity in size) and its intuitive coherence (e.g. the semantic validity of involved variable).

Indeed, the interpretability of a fuzzy model is usually done thanks to the use of linguistic terms to express the model and the relations it highlights. For instance, to illustrate that point, let a (classic) rule defined as "*if the price is greater than 13.75 euros then the book is hard-cover*". Such a rule can be highlighted from a training set composed of books in a book store by means of a machine learning algorithm that can also infer automatically the boundaries for prices. In a same way, an equivalent fuzzy rule can be "*if the price is high then the book is hard-cover*". Here, the term "high" is a label associated with a corresponding fuzzy set deduced from the training set. The interpretability in this case can be considered as better than in the previous rules: the term which is used is semantically convenient for any person and it can also be understood for any person even if the "euros" is not her/his national currency. Of course, we talked here of the interpretability according to the end user. We can remark that according to the operator, the interpretability is also related to the knowledge of fuzzy set theory that enables her/him to understand the numerical values underlying a fuzzy term.

Usually, classic means to evaluate this interpretability are based on its complexity: the number of (fuzzy) rules the model is composed of, the number of variables in each rule, the use of *meaningful* fuzzy sets [10,26]. However, the interpretability of the structure of the model that should be understood clearly by the end user can lead to the choice of a specific algorithm. For instance, decision trees or rules are basic knowledge in many domains and are thus highly interpretable for any kind of end users.

Nowadays, many works focus on enhancing the interpretability of models inferred by fuzzy data mining. Usually, it is related to the use of fuzzy rules as a representation of the model, for instance fuzzy decision trees [27] or fuzzy association rules [28]. For instance, in the Medical domain, the proposal of a fuzzy representation for numerical variables representing patients can greatly increase the understandability of the links between the description of patients and their classes [29,30].

It should also be noted that the interpretability of the model is somehow related to the way it is used (e.g. the "internal" process to produce an output by means of the model).

2.2. Interpretability of the output

However, interpretability should also be associated with the output of the model when used for test data. The result produced by the model should be understandable as it is often proposed to end users not specialist in computer science (e.g. in fuzzy set theory, in machine learning, in statistics,...). In this case, it is important to provide an output that can be semantically explained, and to refer to classic expression of knowledge in the involved domain. Moreover, it should also refer to intuitive knowledge as "membership to a class", easily understandable even by a user unaware of fuzzy modelling.

For instance, in breast cancer detection, detected micro-calcification patterns in mammography can be described by means of linguistic terms as "round" or "not round" associated with a fuzzy representation [7]. The output can also be the recognition of fuzzy categories (for instance, emotions as discussed in Section 3), or the association of belief degrees to classes [24].

In this kind of interpretability, even classic data mining algorithms can be concerned as it is easy to provide them with a post-processing step in which the output of the model is fuzzified to offer linguistic labels to the user.

2.3. Interpretability of the algorithm

A last level in which the interpretability can be important is the learning algorithm itself. We consider here the interpretability with regard to the end user as it is often crucial for the operator to explain to him/her *how* the model has been built from the data set.

In this case, the understandability of the algorithm should be focused on. This kind of interpretability has been heavily taken into account in classic data mining. For instance, according to end users, the understandability of the decision tree-based learning algorithm can be considered as higher than the one of the SVM algorithm. Indeed, this last algorithm requests more specific mathematical notions (matrix, vector, hyper-plane, model optimisation, ...) than those involved in the previous one.

On this topic, few works have been proposed in the fuzzy data mining community. The interpretability of the algorithm involves the understandability of its validity and the proof of the appropriateness of the learning mechanisms it is based on. The validity is defined here as the way the algorithm fits the theoretical process of construction of the model that have been thought about.

For instance, in classic machine learning, the decision tree algorithm validity is based on the use of information theory that provides strong and rigorous explanations about its proceeding. In a similar way, to provide a better understandability of the fuzzy decision tree construction algorithm, in [31,32] a study has been conducted to propose strong justifications of the extension of the classical algorithm of construction of decision trees to the algorithm adapted to construct fuzzy decision trees.

This kind of interpretability and formal proofs of the validity of the "fuzzy" algorithm are thus crucial to better explain to end users how the algorithm proceeds.

3. Fuzzy data mining and management of emotions

Fuzzy data mining is among the most active fields of research where fuzzy set-based knowledge representations are fruitful. Many of its domains are still extensively studied and we will focus on two promising aspects where much developments remain to be done and, in addition, interpretability and subjectivity handling are important.

Among the main domains where fuzzy data mining can prove to be useful, we would like to end this paper by pointing out a domain still to explore, with a very promising variety of applications to real-world problems, challenging because of its cognitive components and its inherent subjectivity. This very active domain is called affective computing or emotional computing and it corresponds to the production of virtual emotions and to the recognition and analysis of natural emotions or psychological states in digital supports, for instance in web open sources containing images, videos or textual documents. It is clear that a fuzzy knowledge representation could efficiently contribute more than in the present state of the art to such tasks, because of its capacity to handle imprecise and subjective data, as well as its interactions with natural language.

The production of virtual emotions and the recognition of natural emotions have been a challenge for several years in the emerging framework of affective computing. Fuzzy modelling has been used to express the graduality of emotions, often associated with learning processes. These processes provide a general behaviour of systems associating subjective factors such as emotions or psychological states with objective information which can be extracted from digital images, videos or sounds as well as elements of man–machine interactions. We will review successively the production of virtual emotions and the recognition of natural emotions.

3.1. Production of virtual emotions

The production of virtual emotions is considered in the design of avatars, intelligent agents or characters for video games or cartoons. It corresponds to the reproduction of characteristics of human emotions on artefacts and it requests subtle indicators of emotions on virtual faces and gestures. Fuzzy modelling helps to capture the subtlety of emotions, for instance by means of a fuzzy rule-based system, [33,34] or fuzzy similarities [35].

In [36], a model of emotions for artificial agents able to communicate with humans is proposed, using fuzzy inference rules to determine the levels of emotional factors causing emotions of various intensity. A learning mechanism is used to diversify behaviours associated with a given emotional state.

A more sophisticated modelling is available in [37] on the basis of psychological models of emotions, with the aim of providing a way to improve the interactions between an intelligent agent and its environment. The proposed Fuzzy Logic Adaptive Model of Emotions (FLAME) uses fuzzy logic to take into account the intensity of emotions and a smooth transition between emotional states by means of fuzzy rules capturing relationships between events, emotions and behaviours. It contains a learning component managing perceptions and associations between events and emotions.

3.2. Recognition of natural emotions

The recognition of natural emotions in human agents deals with the extraction of emotions from texts or images, as well as the analysis of videos or the processing of biological signals to recognise human emotions or human agent mental state. Such recognition is involved in a number of application domains, mainly through data mining techniques.

In the context of interactions between man and machine, adaptive systems can react to their user's emotions if emotions are correctly identified. It is for instance the case when web usage logs are mined and analysed through fuzzy association rules or fuzzy temporal patterns [38] to take into account consumers behavioural and emotional cues.

Many others aspects of man–machine interactions remain to explore with the help of fuzzy modelling, in particular to identify emotional or psychological states from data provided by various types of sensors, such as biological sensors or cameras, with critical applications in a medical environment or to help ageing or disabled people. Other real world applications concern product quality evaluation. The utilisation of eye-tracking exploitation, user recording followed by video mining or mining in sensor outputs have not enough been approached by means of fuzzy set-based representations It is the case, for instance when emotions are identified to evaluate the quality of video-games or to contribute to their design, even though such applications have already been tackled [39].

Relations between digital textual documents and emotions they evoke have already been investigated [40], but the domain is complex. Applications of opinion mining, sentiment analysis or e-reputation to business intelligence, intelligent relations with customers or automatic email answering are a fertile field where the flexibility of fuzzy models can bring solutions which have not yet been studied.

Detecting emotions aroused by images is also an important subject, with obvious applications in image retrieval, for instance to find solutions to a request such as "I look for a merry image", coping with the lack of clear emotional annotations for most images. Some links between emotions and colours have been studied with the help of a fuzzy knowledge representation [41]. Utilisation of links between emotions and shapes of objects detected on images are also used in industrial design in a very promising approach [42]. The identification of emotions in music has also been tackled through fuzzy classification, either directly from the sound [43] or on the basis of song texts [40]. The utilisation of fuzzy modelling in these environments has not yet been achieved and would reinforce the capacity of the system to cope with the complexity of emotions.

4. Conclusion

In this paper, we presented contributions of fuzzy data mining to improve interpretability. It can be shown that interpretability occurs at various steps of the fuzzy data mining process. It thus takes several forms and should be particularly considered at the level it is concerned with.

Moreover, some references on the management of emotions as a particular kind of subjective information were presented to highlight some present and future application domains in which fuzzy data mining can propose new perspectives of research.

In conclusion, the interpretability of the output is an important way to sing the praises of fuzzy data mining in application domains. This kind of interpretability can be very attractive for non-(fuzzy) scientist users looking for tools to handle their data.

However, in fuzzy data mining, much work still remains to be done.

Firstly, the interpretability of the model should be focused on. It is important to select a set of measures in order to be able to evaluate and compare models. Moreover, this kind of measures should enable us to position fuzzy data mining with respect to data mining and to better highlight the advantages of fuzziness in these aspects.

Secondly, the interpretability of the algorithm is a main point to consider further. It is crucial and fundamental to prove that a fuzzy extension of a classic algorithm or a newborn fuzzy algorithm should be used in fuzzy data mining. Such a proof is the unique way to convince data mining and machine learning communities that fuzzy algorithms are not "rule of thumbs" based algorithms but deeply justified algorithms.

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