About the Use of Ontologies for Fuzzy Knowledge Representation

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Abstract

This paper proposes an ontology which enables fuzzy data to be defined in order to conceptualize them and to represent another type of information. The Fuzzy Knowledge Representation Ontology described is based on the fuzzy data theoretical model, and a method for classifying both classical and fuzzy data is proposed. This ontology defines a framework for storing fuzzy information in fuzzy data types by defining them using classes, slots, and instances.

Keywords: Fuzzy Data, Metadata, DBMS Catalog, Fuzzy Knowledge Representation, Ontology, Databases, Database Modeling

1 Introduction

A Relational Database Management System (RDBMS) extension for representing fuzzy data is obviously not a new problem. The problem arises when the system is extended in order to manage other structured data (logical aspects, data mining operations and data types, etc.) [2]. The extended system increases the number of catalog relations making very complex and tedious to understand and handle.

In recent years, knowledge representation trends have been concerned with the generalization and reuse of modelled problems. An ontology is "a set of objects, concepts, and other entities about which knowledge is being expressed and of relationships that hold among them" [9]. Nowadays, ontologies are used in knowledge representation, including the representation of metadata if necessary. Because of this feature, the use of ontologies could be a good solution for the complexity problem that have just arisen with the extension of a RDBMS.

In Section 2, a brief resume of the architectures that extends the DBMS is presented. In Section 3, a Fuzzy Knowledge Representation Ontology (FKRO) is proposed as the solution to the problem presented. An example of how a relation can be represented in the ontology is then shown in Section 4. Finally, some conclusions and future lines of work are presented as result of this first approach to knowledge representation.

2 Showing the Problem

To date, there have been many proposals for representing fuzzy data in specific RDBMSs. Vila in [6] introduced GEFRED (a fuzzy data representation model) and FIRST (an architecture definition in a real RDBMS in [7]). This architecture defined new fuzzy data types and operations enabling the system to make fuzzy queries to the database using an extension of SQL called FSQL [3, 4]. An implementation for all relations in the system catalog and an example of how structures can be stored in the database are described in [7]

Some extended models have been developed using the GEFRED model mentioned above. The extended FREDDI architecture described in [1] represents logical information in the fuzzy relational model. This architecture stores rules and intensional relations, manages fuzzy information, and implements inference algorithms for making deductions. DMFIRST* architecture, based in the GEFRED* model[3, 4], incorporates another fuzzy data type that allows to define complex domains. These domains represent other types of information (e.g. XML, tables, etc.) necessary for data mining operations (such as fuzzy clustering, classification operations or fuzzy functional dependencies search) may be performed.

Using the previously described architectures, in [2] the infrastructure for a unified server was proposed. It integrates capabilities of all of these architectures and enables their functionalities to be combined. This integration would be capable of processing several types of queries in the same sentence; for example, queries about deductions with fuzzy data or deductions using the results of a data mining process. Moreover, the proposed architecture establishes a mechanism to add more implementations of new servers with different functionalities.

This proposal is very difficult to achieve, however, because of the complexity of the system and the difficulty of making this system scalable. The huge number of catalog relations, which enables the metadata to establish the structure of the information and domain constraints, also makes it more difficult to understand and to implement.

3 A Fuzzy Knowledge Representation Ontology and its Integration with Existing Infrastructure

In order to solve these problems, the unified server architecture should be isolated from a concrete DBMS representation. Our proposal is based on the fact that all architectures are integrated in a single hierarchy that generalizes the data representation. This solution will consist in an ontology that allows the integration of the existing infrastructures and the representation of the knowledge independently of the context and environment that it uses. In the following section a first prototype of an ontology for representing a part of the unified server is suggested.

An ontology for fuzzy information representation is proposed in this paper. The ontology includes knowledge about how to manage and represent uncertain and imprecise data. This representation of the ontology makes the structure of the GEFRED model easier to understand and avoids references to one specific DBMS implementation. The *Protegè* environment tool [8, 5] has been used to implement this. This ontology is a first approach for representing a relational fuzzy information knowledge ontology but its design will enable representation into other database systems (e.g. object-oriented ones).

Figure 1 shows how the system catalog is related to the ontology modeling it. The Ontology Client module carries out the same operations through the Ontology than the DBMS Clients. The connection between the ontology and the database needs an interface, the *Ontology Interface*, which establishes the communication and refreshes the data.



Figure 1: FIRST Architecture and Fuzzy Knowledge Representation Ontology Integration

The fuzzy model representation comprises two well-differentiated parts. Firstly, the ontology must define the necessary classes and slots to represent the metadata. These metadata define intermediate structures (i.e. fuzzy data types, domains, etc.) which are needed for representing the different fuzzy relations. Secondly, the ontology will be able to represent classical or fuzzy information as instances of the relations defined in the previous part.

The metadata definition in an Fuzzy RDBMS allows the system to define the structures, domains, data types, etc. described in the theoretical model. In this ontology, metadata establish how the fuzzy information will be stored. In Figure 2, the class hierarchy for representing the metadata is shown. Table 1 describes all the classes and slots that cover this part of the ontology.



Figure 2: Metadata Representation Ontology These classes allow the user to define any classic or fuzzy data relation. The relation name, attributes and domain are defined as instances The instantiation of the Taof these classes. *ble_Definition Class* begins the relation definition process. In this model, it is not necessary to specify concrete data types because the ontology enables generical classes to be defined which refer to them. Once the information structure has been defined, the classes for storing the information must be created in the hierarchy. This class generation process must be automatically developed in order to prevent user involvement. Figure 3 shows the part of the ontology which allows fuzzy information to be stored. The ontology classes and slots are described in Table 2.



Figure 3: Fuzzy Information Representation Ontology



tions defined in the ontology. There will be one subclass for each relation defined. The instantiation of one of these subclasses enables information to be stored in the ontology as if it were a database relation. This instantiation starts an instantiation process of all the classes involved in the data definition. The following example shows a relation defining process and a tuple storing.

4 An example: Fuzzy Information Description and Storing

The following FSQL sentence defines a new relation with fuzzy and classic attributes. This relation can be represented as a set of instances of the *Metadata Representation Ontology* classes. The *Table_Definition Class* instantiation begins a recursive process that will instantiate all the classes needed to define the relation. Table 3 describes all the instances which allow the *Cats* Relation to be defined.

CREATE TABLE Cat:	s (
Name	STRING,	
Behavior	FTYPE3(1)	
Age	FTYPE2 (1,1)	FLOAT
Weight	FTYPE1 (3,5)	FLOAT)

where FTYPE3(1) represents that the behavior can be represented by only one discrete value. FTYPE2(1,1) means that Age is a fuzzy data type 2 (see [7]) with margin= 1 and much = 1 (these values are described in table 1) and FLOAT represent the base type of this attribute values. The parameters of Weight have the same meaning than the Age ones.

In order to store data in the ontology, some new classes must be automatically generated once the relation in the ontology has been defined. The *Cats* relation and its attributes are now subclasses of *Fuzzy_Tables Class* and *Fuzzy_Attributes Class*, respectively, and these are represented in Figure 4 with a gray background.

The subclass *Cats* must define four new slots: *SCat_Name, SCat_Age, SCat_Weight* and *SCat_Behavior* as instances of the *Cat_Name, Cat_Age, Cat_Weight* and *Cat_Behavior* subclasses, respectively. This definition will enable data to be stored by instantiating the *Cats* Class. The relation shown in Figure 4 reflects the connection between the *Cats* relation tuples and the

Class	Description	Slots
Table	defines all the structures that enable fuzzy and	<i>Table_name</i> : relation name and <i>LColDef</i> :
$_Definition$	non-fuzzy information to be stores	set of instances of Attribute_Definition
		Class
Attribute	defines the structure attributes	Name: attribute name, Domain: instance
$_Definition$		of Definition_Domain Class
Definition	defines the data type domain. All the existing	No slots
_Domain	data types in the fuzzy model are defined in	
	this class	
Fuzzy	groups all the fuzzy data types defined in the	No slots
_Domain	ontology	
Classic	represents classical data types	Base_Type: refers to an instance of
_Domain		Base_Type Class
FD_With	defines ordered referential data types	Base_Type: refers to an instance of
_Base Type		Base_Type Class, Margin: margin of a tri-
		angular value (Approx) and Much: estab-
		lishes when two fuzzy numbers are different
F_Type1	represents the fuzzy data types 1	Slots of this class are inherited
FType2	represents the fuzzy data types 2	Slots of this class are inherited
F_Type3	represents the fuzzy data type 3	LEN: establishes the number of discrete
		values defined in the data type
Base_Type	represents generic data types. This definition	$BT_value:$ stores Any value
	avoids the use of specific data types names	
String	represents generic strings	BTValue: changes its inherited type into
		a String type
Number	represents different types of numbers	$BT_Value:$ is inherited
Float	represents a float value	BT_Value : changes into a Float type
Integer	represents an integer value	BT_Value : changes into an Integer type

 Table 1: The Metadata Representation Ontology



Figure 4: Relation between the Ontology and the Cats relation

ontology classes which allow these values to be stored. In Table 4, all the necessary instances for defining the first tuple of Figure 4 are shown.

A single name is associated to each ontology instance. This name is not always relevant in the ontology, as we can see in Table 4, but allows us to know the order in which the instances were created according to their sequence number. The information is stored in the instances of the *Base_Type* Subclasses: Float, String, etc. Labels and Discrete values must also be previously defined in the ontology.

5 Conclusions

The ontology in this paper attempts to represent fuzzy data regardless of implementations in concrete database models. Moreover, the structure of this ontology allows scalability so new data types as well as fuzzy ones can be represented. A first approach to a fuzzy information representation ontology has been proposed. This ontology is important as an intuitive tool which allows nonexpert users to define specific information (fuzzy information) without the help of an expert knowing about catalog structures in the database. Ob-

Class	Description	Slots
Fuzzy _Tables	represents the structures previously de-	Name: relation name
	fined as instances in the metadata ontology	
Fuzzy_Attributes	represents all the knowledge system at-	Contains: instance of Fuzzy_Value_Types
	tributes (fuzzy or not) and everything de-	Class
	fined in the metadata ontology as instances	
	of Attribute_Definition Class	
Fuzzy_Value	represents the values that an attribute can	No slots
_Types	store	
Type1	represents the fuzzy data type 1 values	<i>FT1_Base_Type</i> : instance of <i>Base_Type</i>
		Class
Type2	represents the fuzzy data type 2 values	No slots
Null, Unknown,	represents the values Null, Undefined and	No slots
Undefined	Unknown, respectively	
Crisp	represents a crisp value	D: instance of the Base_Type Class
Approx	represents an approximate value	x : instance of the Base_Type Class
Interval	represents an interval value	m and n : instances of the Base_Type Class.
Trapezoid	represents a trapezoidal value	alfa, beta, delta and gamma: instances of
		the Base_Type Class
Label	represents a previously defined label in the	Label_Name: instance of the Fuzzy_Labels
	Fuzzy_Labels Class	Class
Discrete	represents a previously defined discrete	DiscreteName: instance of the
	value in the <i>Fuzzy_Discrete Class</i>	Fuzzy_Discrete Class
Possibility	represents a possibility distribution with	Par: set of instances of the Discrete Class
$_Distribution$	multiple discrete values	
Classic Types	represents all the classic values	Classic_Base_Type: is an instance of
		Base_Type Class
Fuzzy_Labels	maintains a register of each defined label	Attribute: refers to the Fuzzy_Attributes
		Class, Name: label name and Type: in-
		stance of Type1 or Type2 Classes
Fuzzy_Discrete	maintains a register of each defined dis-	Attribute: refers to the Fuzzy_Attributes
	crete value	<i>Class</i> and <i>Discrete</i> : discrete value name
Fuzzy_Discrete	establishes a similarity relationship be-	Discrete1 and Discrete2: instances of the
_Relations	tween two discrete values	Fuzzy_Discrete Class and Similitude: sim-
		ilarity degree between two discrete values

 Table 2: The Fuzzy Information Representation Ontology

Table 3: M	Ietadata	Representation	Ontology	Example

Class	Instance Name	Slots
Table	Table_Cats	Table_name: Cats. LColDef: Attr_Cat_Name Instance, Attr_Cat_Age
$_Definition$		Instance, Attr_Cat_Weigh Instance, Attr_Cat_Behavior Instance
Attribute	Attr_Cat_Name	Name: Cat_Name. Domain: Name_Domain Instance
$_Definition$	Attr_Cat_Age	Name: Cat_Age. Domain: CatAge_Domain Instance
	Attr_Cat_Weigh	Name: Cat_Weigh. Domain: CatWeigh_Domain Instance
	Attr_Cat_Behavior	Name: Cat _Behaviour. Domain: CatBehaviour_Domain Instance
Classic	Name _domain	Base_Type: Reference to Class String
$_{-}Type$		
$F_{-}Type2$	CatAge_Domain,	Base_Type: Reference to Class Float and Margin: 1 and Much: 1
$F_{-}Type1$	CatWeigh_Domain	Base_Type: Reference to Class Float, Margin: 1 and Much 1
FType3	CatBehaviour	<i>LEN</i> : 1
	_Domain	

Class	Instance	Slots
	Name	
Cats	Instance15	Name: Cats.
		$SCat_Name:$ Instance24,
		$SCat_Age:$ Instance27,
		$SCat_Weigh:$ Instance31,
		SCat_Behaviour: In-
		stance34
Cat_Name	Instance24	Content: Instance25
Cat_Age	Instance27	Content: Instance28
Cat_Weigh	Instance31	Content: Instance32
Cat	Instance34	Content: Instance35
_Behaviour		
Classic	Instance25	Base_Type: Instance26
$_{-}Type$		
String	Instance26	$BT_Value: Kity$
Interval	Instance28	N: Instance29 and M: In-
$_{-}Type$		stance30
Float	Instance29	BT_Value: 2.0
Float	Instance30	BT_Value: 3.0
Type1	Instance32	FT1Base_Type: In-
		stance33
Float	Instance33	BT_Value: 2.3
Discret	Instance35	Possibility: 0.9 and Dis-
		cret_Name: Loving

Table 4: Fuzzy Information Representation On-
tology Example

viously every implementation in a concrete DBMS requires an interface able to translate the ontology elements into database language. Furthermore, this ontology acts as an interface between the users and the database system. It simplifies the way in which users creates their own fuzzy elements even if they know nothing about the database underlying the ontology.

In our future work, logical and data mining aspects will be modelled, and the integration of all data types into an unified ontology will be studied. We think that the use of knowledge representation methods are useful for representing complex structures which database model environments complicate.

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References

- I. Blanco, M. J. Martin-Bautista, O. Pons, and M. A. Vila. A mechanism for deduction in a fuzzy relational database. *International Jour*nal of Uncertainty, Fuzziness and Knowledge-Based Systems, 11:47–66, September 2003.
- [2] I. Blanco, C. Martinez-Cruz, J.M. Serrano, and M. A. Vila. A first approach to multipurpose relational database server. *Mathware, In Press*, 2005.
- [3] R. A. Carrasco, M. A. Vila, and J. Galindo. Fsql: a flexible query language for data mining. *Enterprise information systems IV*, pages 68–74, 2003.
- [4] R.A. Carrasco, J. Galindo, M.C. Aranda, J.M. Medina, and M.A. Vila. Classification in databases using a fuzzy query language. In 9th International Conference on Management of Data, COMAD'98, 1998.
- [5] Holger Knublauch. An ai tool for the real world. knowledge modeling with protègè. Technical report. http://www.javaworld.com/javaworld/jw-06-2003/jw-0620-protege.html.
- [6] J. M. Medina, O. Pons, and M. A. Vila. Gefred. a generalized model of fuzzy relational databases. *Information Sciences*, 76(1-2):87– 109, 1994.
- [7] J. M. Medina, M. A. Vila, J. C. Cubero, and O. Pons. Towards the implementation of a generalized fuzzy relational database model. *Fuzzy Sets and Systems*, 75:273–289, 1995.
- [8] Natalya F. Noy and Deborah L. McGuinness. Ontology development 101: A guide to creating your first ontology. Technical report, http://protege.stanford.edu/publications/ ontology_development/ontology101.html.
- [9] Natalya Fridman Noy and Carole D. Hafner. The state of the art in ontology design. a survey and comparative review. *The American Association for Artificial Intelligence*, pages 53–74, 1997.