About Summarization in Large Fuzzy Databases

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***Abstract*—Moved by the need increased for modeling of the fuzzy data, the success of the systems of exact generation of summary of data, we propose in this paper a new approach of generation of summary from fuzzy data called "Fuzzy-SaintEtiQ". This approach is an extension of the SaintEtiQ model to support the fuzzy data. We prove that our approach presents the following optimizations: 1) the minimization of the expert risk, 2) the construction of a more detailed and more precise summaries hierarchy, and 3) the co-operation with the user by giving him fuzzy summaries in different hierarchical levels.**

Keywords-Fuzzy DB; Fuzzy SQL; FCM; FCA; Concept Summary.

I. INTRODUCTION

In the field of the Databases (DB), volumes of the data reached today make necessary a better exploitation of the data.

Several solutions have been proposed to solve this problem and to contribute in database summarization. However, to support massive data evolutionary, formal approaches have been proposed to surround this problem [1][2][3][4].

Several methods of DB summarization have been proposed such as statistical approaches, classification and conceptual classification. Among these data summarization methods, one of the most close to our research tasks, we distinguish the system SaintEtiQ [1] that is inspired primarily by the approach of conceptual classification. This system makes it possible to generate a hierarchy of summaries allowing to cover parts of the database. In [5], we proposed a new system for optimizing the SaintEtiq summarization system. This approach is based on the combination of fuzzy logic, fuzzy clustering and Formal Concept Analysis (FCA).

Moreover, with the evolution of the data processing, the need of modeled fuzzy data has become a necessity for the user [6]. Indeed, in the real world, we are confronted more and more with the situation where applications need to manage fuzzy data and to make profit their users from flexible querying. We speak, then, about flexible querying and Fuzzy Databases (FDB) [6][7][8].

In this paper, we propose an extension of the SaintEtiQ summarization model for modeling fuzzy data. We prove that our approach presents some optimizations: 1) the minimization of the expert risk, 2) the construction of a more detailed and more precise summaries hierarchy, and 3) the co-operation with the user by giving him fuzzy summaries in different levels from the hierarchy. This approach is based on the combination of fuzzy logic, fuzzy clustering and Formal Concept Analysis. For the classification of these fuzzy data, we propose a new algorithm, called Fuzzy FCM. Fuzzy-FCM is an extension of FCM algorithm in order to support fuzzy data.

The rest of this paper is organized as follows: Section 2 presents an overview of some summarization model and the basic concepts of Fuzzy Databases. Section 3 presents an example of fuzzy data. Section 4 presents problems and limits of the existing summarization approach. Section 5 presents our proposed Fuzzy-SaintEtiq system. Section 6 presents a comparison between our summary model Fuzzy-SaintEtiq and others models. We finish this paper with a conclusion and a presentation of some future works.

II. BASIC CONCEPTS

In this section, we present an overview of some summarization model and the basic concepts of Fuzzy Databases.

A. *Overview of the SaintEtiQ summarization model*

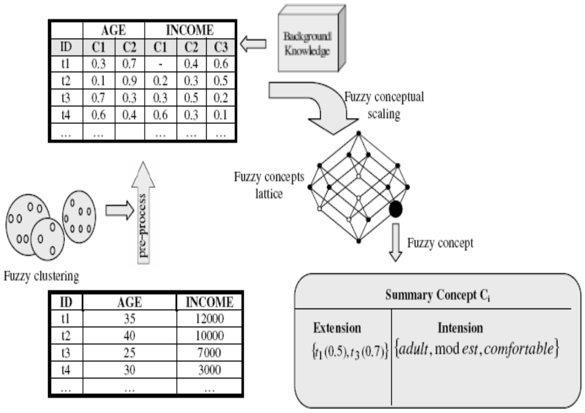
The SaintEtiQ model [1] aims at apprehending the information from a DB in a synthetic manner. This is done through linguistic summaries structured is a hierarchy. The model offers different granularities, i.e., levels of abstraction, over the data. The system architecture and the steps necessary to build a hierarchy are described below. With SaintEtiQ model, the summarization process can be divided into three major steps:

- **A Translation step**: this step allows the system to rewrite DB records in order to be processed by the mining algorithm. This translation step gives birth to candidate records, which are different representations of a single DB record, according to some background knowledge. Background knowledge's are fuzzy partitions defined over attribute domains. Each class of a partition is also labeled with a linguistic descriptor provided by the user or a domain expert. For instance, the fuzzy label young could belongs to a partition built over the domain of the attribute AGE.

- **A data mining step**: it considers the candidate records one at a time, and performs a scalable machine learning algorithm to extract knowledge. Obviously, the intensive use of background knowledge, which supports the translation step, avoids finding surprising knowledge nuggets.
- **A post processing step**: SaintEtiQ model tries to define summaries at different level of granularity. The post-processing step consists in organizing the extracted summaries into a hierarchy, such that the most general summary is placed at the root of the tree, and the most specific summaries are the leaves.

B. Overview of FCA-based Summary

In [5], we proposed to extend the SaintEtiQ summarization model [1] by introducing some optimization processes including: i) minimization of the expert risks domain, ii) building of the summary hierarchy from DB records, and iii) cooperation with the user by giving him summaries in different hierarchy levels. With our model, the summarization process can be divided into two major phases as shown on Figure 1.



	AGE		INCOME		
ID	C1	C2	C1	C2	C3
t1	0.3	0.7	-	0.4	0.6
t2	0.1	0.9	0.2	0.3	0.5
t3	0.7	0.3	0.3	0.5	0.2
t4	0.6	0.4	0.6	0.3	0.1
…	…		…	…	…

ID	AGE	INCOME
t1	35	12000
t2	40	10000
t3	25	7000
t4	30	3000
…	…	…

Figure 1. The Overall process of proposed FCA-based summary model [5].

C. Fuzzy Databases

In this section, we present the basic concepts of Fuzzy Databases.

A Fuzzy Databases (FDB) is an extension of the relational DB. This extension introduces fuzzy predicates under shapes of linguistic expressions that, at the time of a flexible querying, permits to have a range of answers (each one with a membership degree) in order to offer to the user all intermediate variations between the completely satisfactory answers and those completely dissatisfactory [8].

The FDB models are considered in a very simple shape and consist in adding a degree, usually in the interval [0,1], to every tuple.

It allows maintaining the homogeneity of the data in DB. The main models are those of Prade-Testemale[9], Umano-Fukami[10], Buckles-Petry[11], Zemankova-Kaendel[12] and GEFRED of Medina et al. [13].

This last model constitutes an eclectic synthesis of the various models published so far with the aim of dealing with the problem of representation and treatment of fuzzy information by using relational DB.

D. The GEFRED Model

The GEFRED model (GEneralised model Fuzzy heart Relational Database) has been proposed in 1994 by Medina et al. [13]. One of the major advantages of this model is that it consists of a general abstraction that allows for the use of various approaches, regardless of how different they might look. In fact, it is based on the generalized fuzzy domain and the generalized fuzzy relation, which include respectively classic domains and classic relations.

In order to model fuzzy attributes we distinguish between two classes of fuzzy attributes: Fuzzy attributes whose fuzzy values are fuzzy sets and fuzzy attributes whose values are fuzzy degrees [6][14].

Fuzzy Sets as Fuzzy Values: These fuzzy attributes may be classified in four data types. This classification is performed by considering the type of referential or underlying domain. In all of them the values Unknown, Undefined, and Null are included:

- **Fuzzy Attributes Type 1 (FTYPE1)**: These are attributes with “precise data”, classic or crisp (traditional, with no imprecision). However, they can have linguistic labels defined over them, which allow us to make the query conditions for these attributes more flexible.
- **Fuzzy Attributes Type 2 (FTYPE2)**: These attributes admit both crisp and fuzzy data, in the form of possibility distributions over an underlying ordered domain (fuzzy sets). It is an extension of the FTYPE1 that does, now, allow the storage of imprecise information.
- **Fuzzy Attributes Type 3 (FTYPE3)**: They are attributes over “data of discreet non-ordered dominion with analogy”. In these attributes some labels are defined (“blond”, “red”, “brown”, etc.) that are scalars with a similarity (or proximity) relationship defined over them, so that this relationship indicates to what extent each pair of labels be similar to each other.
- **Fuzzy Attributes Type 4 (FTYPE4)**: These attributes are defined in the same way as FTYPE3 attributes without the necessity of a similarity relationship to exist between the labels.

Fuzzy Degrees as Fuzzy Values: The domain of these degrees can be found in the interval [0,1], although other values are also permitted, such as a possibility distribution (usually over this unit interval) [13][14]. The meaning of these degrees is varied and depends on their use. The most important possible meanings of the degrees used by some authors are: Fulfillment degree, Uncertainty degree, possibility degree and Importance degree.

E. The FSQL language

The Fuzzy SQL (FSQL) language is an authentic extension of SQL language to model fuzzy queries. It means that all the valid statements in SQL are also valid in FSQL [13][14].

III. Example of Fuzzy Data

In this example, we want to model an employee described by the following information: his *Id* (identifier), his name, his surname, his address, his *Age*, his *Salary*, and his productivity. Attributes *Age*, *Salary* and *Productivity* are described as follows:

- The attribute *Age***,** presented in Figure 2, has the linguistic labels *Young*, *Adult* and *Old*, defined on the trapezoidal possibility distributions as following: *Young(18, 22, 30, 35), Adult(25, 32, 45, 50), Old(50, 55, 62, 70).* An approximate value has a margin of 5. The minimal value to consider two values of this attribute as completely different is of 10.

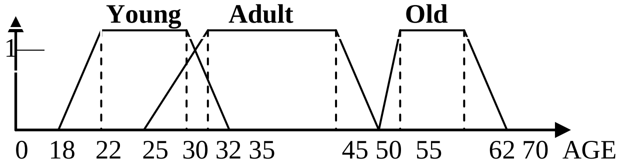


Figure 2. Definition of labels on Age attribute.

- The attribute salary, presented in Figure 3, has the linguistic labels *Low*, *Medium* and *High*, defined on the trapezoidal possibility distributions as following: *Low(50,80,120,180), Medium(150,300,400,550), High(400, 600,800,1000)*. An approximate value has a margin of 10 and the minimal value to consider two values of this attribute as completely different is of 50.

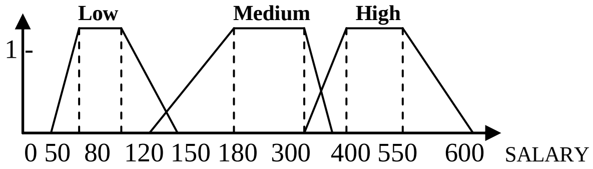


Figure 3. Definition of salary labels.

- The attribute *productivity*, presented in Table I, has the linguistic labels *Bad*, *Regular* and *Good*. In this situation, the data are not quantifiable, but present resemblances in their values. For example, the value *Regular* of the attribute "productivity" resembles to the value *Good* with a degree equal to 0.7.

TABLE I. Relations Of Similarity For The Values Of The Productivity Attribute

Similarity degree	**BAD**	**REGULAR**	**GOOD**
BAD	1	0.3	0.2
REGULAR	0.3	1	0.7
GOOD	0.2	0.7	1

While applying the rules of Medina et al., we can say that the *age* attribute is FTYPE2 (5, 10) type, the attribute *salary* is FTYPE1 (10, 50) type and the attribute *productivity* is FTYPE3 (1) type.

An abstract representation of the schema of relation EMPLOYE will be as follows: (ID, NAME, SURNAME, ADDRESS, *AGE*, *SALARY*, *PRODUCTIVITY*). This description in FSQL script is presented in the Figure 4.

```
CREATE TABLE EMPLOYEE (
ID# VARCHAR(4) NOT NULL,
NAME VARCHAR(20) NOT NULL,
SURNAME VARCHAR(20) NOT NULL,
ADDRESS VARCHAR(40) NOT NULL,
AGE FTYPE2(5,10) NUMBER(3) DEFAULT UNKNOWN
NOT NULL,
SALARY FTYPE1(10,50) NUMBER(7) NOT NULL,
PRODUCTIVITY FTYPE3(1) NOT NULL,
PRIMARY KEY (ID#));
```

Figure 4. FSQL script.

A. Problems and Motivation

We present in the following table a synthesis of the existing summarization techniques.

As Table II depicts, these approaches are applicable only to simple data sets; they do not allow treating fuzzy data, describe with FSQL language, like linguistic labels (string), interval, and approximate values.

In this paper, we propose to define a new approach of summarization allowing treating as well the simple data set or the fuzzy data described with FSQL language.

TABLE II. COMPARATIVE STUDY OF SOME SUMMARIZATION TECHNIQUES

	Understandable	**Sampling**	**Data Nature**	**Huge data**	**Ratio with the original data**	**hierarchical levels**	**Reliability**	**Subject depending**	**Fuzzy DB**
Statistical Model	comprehensible	No	Numeric/ Nominal	No	Lost	No	High	Yes	No
Classification	No	Yes	Numeric	No	Kept	No	Low	No	No
Conceptual classification	Partially	Yes	Numeric	No	Kept	No	Means	No	No
SaintEtiQ	Yes	Yes	Numeric/ Nominal	Yes	Kept	Partially	Means	No	No
FCA-based Summary	Yes	Yes	Numeric	Yes	Kept	Yes	High	No	No

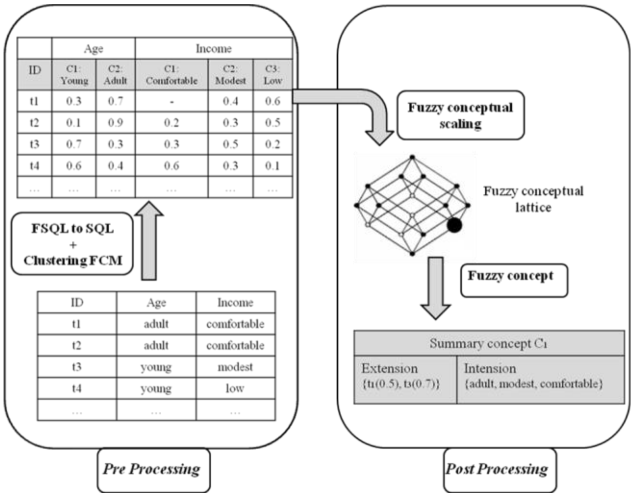
IV. MODEL DESCRIPTION

In this section, we present the architecture of the summarization model, the principal of summaries generation and the formal summary description.

A. *System architecture*

Our summary model takes the database records and provides knowledge.

Figure 5 gives the system architecture. The summarization act considered like a process of knowledge discovery from database, in the sense that it is organized according to two following principal steps.



	Age		Income		
ID	C1: Young	C2: Adult	C1: Comfortable	C2: Modest	C3: Low
t1	0.3	0.7	-	0.4	0.6
t2	0.1	0.9	0.2	0.3	0.5
t3	0.7	0.3	0.3	0.5	0.2
t4	0.6	0.4	0.6	0.3	0.1
...	...	...	...	...	...

ID	Age	Income
t1	adult	comfortable
t2	adult	comfortable
t3	young	modest
t4	young	low
...	...	...

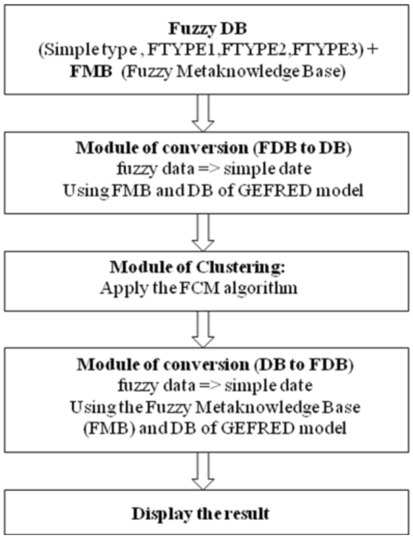
Summary concept C1	
Extension {t1(0.5), t3(0.7)}	Intension {adult, modest, comfortable}

Figure 5. The Overall process of Fuzzy-SaintEtiq.

1) *The preprocessing step*

This step organizes the database records in homogeneous clusters having common properties. This step gives a certain number of clusters for each attribute. Each tuple has values in the interval [0..1] representing these membership degrees according the formed clusters. Linguistic labels, which are fuzzy partitions, will be assigned on attribute's domain.

For the classification on these fuzzy data, we propose a new algorithm, called Fuzzy FCM. Fuzzy-FCM is an extension of FCM algorithm in order to support different types of data represented by GEFRED model. Figure 6 shows the different steps of this algorithm.



Fuzzy DB
(Simple type , FTYPE1,FTYPE2,FTYPE3) +
FMB (Fuzzy Metaknowledge Base)
Module of conversion (FDB to DB)
fuzzy data => simple date
Using FMB and DB of GEFRED model
Module of Clustering:
Apply the FCM algorithm
Module of conversion (DB to FDB)
fuzzy data => simple date
Using the Fuzzy Metaknowledge Base
(FMB) and DB of GEFRED model
Display the result

Figure 6. Principe of Fuzzy-FCM algorithm.

The Fuzzy-FCM algorithm allows the user to select attributes according to which he wants to carry out classification. This treatment gives a refined intermediate matrix only formed of the codes of the selected attributes.

Once the selection achieved, the FCM algorithm is applied on the refined table to get a matrix of adherence and a cut is exercised on this matrix of adherence to purify it by eliminating all values lower to the cut.

The main idea of the algorithm is to define an intermediate matrix to model fuzzy data. For this, we define the function $\mathscr{F}$ which permits the construction of this matrix. $\mathscr{F}$ is defined as follows:

Definition 1: Let E be the set of linguistic labels and C the set of numbers.

We define $\mathcal{F}$ as a function which for all e belonging to E, makes correspond a code c belonging to C the set of correspondence codes:

$$\mathcal{F} : \quad E \longrightarrow C$$
$$e \longrightarrow c = \text{Number of Attribute.Threshold}$$

Since the attributes of the type FTYPE1 do not authorize to store fuzzy values they undergo the same treatment as the simple data and thereafter the function $\mathcal{F}$ = id.

For the attributes of the type FTYPE 2 and FTYPE 3, the function $\mathcal{F}$ makes correspond to each linguistic label a code of the form NumberAttribut.Threshold.

We define the Threshold as being the minimal value to be able to consider two values as completely different.

Example: Let us consider the relational DB table Personal, represented in Table III, described by Id, Age, and Experience.

The attribute Age has the linguistic labels definite on the following trapezoidal distributions possibility : Young (18,22,30,35), Adult (25, 32,45,50), Old(50,55,62,70). The minimal value to consider two values of this attribute as completely different is 10.

The attribute Experience has the linguistic labels: Small(2,3,5,6), Good(5,7,10,12), Sufficient(7, 8,15,20), Large(12,15,50,50). These values depend on the numbers of years worked by an employee. The minimal value to consider two completely different Experiences is 5.

TABLE III. PERSONAL DB TABLE

Id	Age	Experience
001	Young	Good
002	Old	Small
003	Adult	Sufficient
004	Young	Large

While applying the rules of Medina et al., we can say that the AGE attributes and Experience attribute is FTYPE2. Thus, the correspondence table is presented by Table IV.

TABLE IV. TABLE OF CORRESPONDANCE

Id	Age	Experience
001	1.1	2.15
002	1.3	2.10
003	1.2	2.20
004	1.1	2.25

For the first attribute Age of this table, the choice of the number 1 translated the number of the attribute on which one works. Here, the Age attribute is the attribute number 1 and thereafter codes corresponding to the linguistic labels start all with 1. The minimal value to consider two values of this attribute as completely different is 10; we fix a step then = 10 in the choice of codes. For the second attribute experience, the choice of the number 2 translated the number of the attribute on which one works. Here, the attribute Experience is the attribute number 2 and thereafter codes corresponding to the linguistic labels start all with 2. The minimal value to consider two values of this attribute as completely different is 5; we fix a step then = 5 in the choice of codes. Moreover, the choice of these codes concord with the semantics of labels.

For example, the small label is nearer "semantically" to the good label than of the big label, thus we chose the codes according to this logic "of ascending order".

2) The post treatment step

This step takes into account the result of the fuzzy clustering on each attribute, visualizes by using the fuzzy concepts lattices. Then, it imbricates them in a fuzzy nested lattice.

Finally, it generalizes them in a fuzzy lattice associating all records in a simple and hierarchical structure. Each lattice node is a fuzzy concept which represents a concept summary.

This structure defines summaries at various hierarchical levels.

This step consists in organizing the summaries within a hierarchy such that the most general concept summary is placed at the root of the fuzzy lattice, and the most specific concept's summaries are the leaves.

This summary model corresponds to prototypical approaches since the intention of a concept summary present for each attribute the various possible values in the form of a fuzzy descriptors and the representativeness of these descriptors within the specified concept summary.

This model will be described formally in subsection C.

B. Principal of summaries generation

The summary model presented here is based on the fuzzy subsets theory with each one of its steps.

1) Generating attribute's clusters

For the generation of the clusters for each attribute, we carry out a fuzzy clustering while benefiting from fuzzy logic. This operation makes it possible to generate, for each attribute, a set of membership degrees. Each cluster of a partition is labeled by linguistic descriptor provided by a domain expert.

For example, the fuzzy label young belongs to a partition built on the domain of attribute AGE.

2) Building the summary hierarchy

After the generation of the clusters of each attribute, data are ready to be summarized. This operation is based on the fuzzy lattices notion.

This very simple sorting procedure gives us for each many-valued attribute the distribution of the objects in the line diagram of the chosen fuzzy scale. Usually, we are interested in the interaction between two or more fuzzy many-valued attributes. This interaction can be visualized using the so-called fuzzy nested line diagrams. It is used for visualizing larger fuzzy concept lattices, and combining fuzzy conceptual scales on-line.

Example: Table V presents the results of fuzzy clustering applied to AGE and INCOME attributes. For INCOME attribute, fuzzy clustering generates three clusters

(C1,C2 and C3). For AGE attribute, two clusters have been generated (C4 and C5).

TABLE V. FUZZY CONCEPTUAL SCALES FOR AGE AND INCOME ATTRIBUTES.

	Age		Income		
	C4	*C5*	*C1*	*C2*	*C3*
t1	0.5	0.4	0.4	0.5	0.5
t2	0.6	-	-	-	0.6
t3	-	-	-	0.7	-
t4	0.4	0.5	0.5	-	0.8
t5	0.4	0.4	0.4	0.6	-
t6	0.3	-	-	0.5	0.5

The minimal value (resp. maximal) of each cluster corresponds on the lower (resp. higher) interval terminal of the values of this last. Each cluster of a partition is labeled with a linguistic descriptor provided by the user or a domain expert.

For instance, the fuzzy labels young and adult could belong to a partition built over the domain of the attribute AGE.

Also, the fuzzy labels miserable, modest and comfortable could belong to a partition built over the domain of the attribute INCOME. So, the table VI can be rewrite as follows:

TABLE VI. FUZZY CONCEPTUAL SCALES FOR AGE AND INCOME ATTRIBUTES.

	Age		Income		
	Young ***C4***	***Adult*** ***C5***	***Miserable*** ***C1***	***Modest*** ***C2***	***Comfortable*** ***C3***
t1	0.5	0.4	0.4	0.5	0.5
t2	0.6	-	-	-	0.6
t3	-	-	-	0.7	-
t4	0.4	0.5	0.5	-	0.8
t5	0.4	0.4	0.4	0.6	-
t6	0.3	-	-	0.5	0.5

The corresponding summary hierarchy is illustrated in Figure 7.

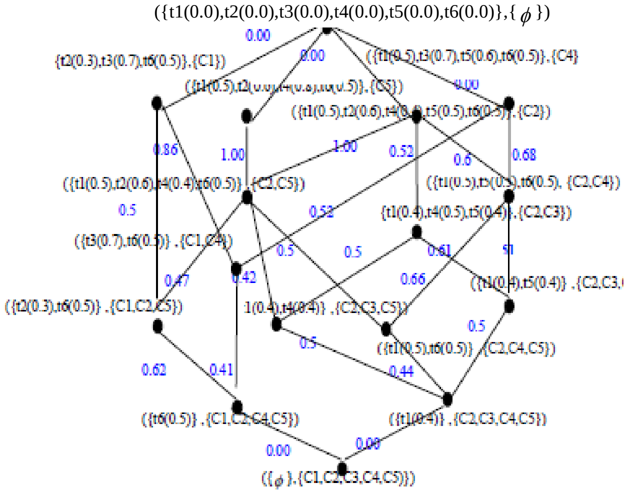

({t1(0.0),t2(0.0),t3(0.0),t4(0.0),t5(0.0),t6(0.0)},{ ϕ })
0.00
{t2(0.3),t3(0.7),t6(0.5)},{C1})
0.00
({t1(0.5),t3(0.7),t5(0.6),t6(0.5)},{C4}
({t1(0.5),t2(0.6),t4(0.4),t6(0.5)},{C5})
0.00
({t1(0.5),t2(0.6),t4(0.4),t5(0.5),t6(0.5)},{C2})
0.86
1.00
1.00
0.52
0.6
0.68
({t1(0.5),t2(0.6),t4(0.4)t6(0.5)},{C2,C5})
({t1(0.5),t5(0.5),t6(0.5), {C2,C4})
0.5
0.52
{t1(0.4),t4(0.5),t5(0.4)},{C2,C3})
({t3(0.7),t6(0.5)} ,{C1,C4})
0.5
0.5
0.61
51
0.47
0.42
0.66
({t1(0.4),t5(0.4)} ,{C2,C3,
({t2(0.3),t6(0.5)} ,{C1,C2,C5})
1(0.4),t4(0.4)} ,{C2,C3,C5})
0.5
0.5
({t1(0.5),t6(0.5)} ,{C2,C4,C5})
0.62
0.41
0.44
({t6(0.5)} ,{C1,C2,C4,C5})
({t1(0.4)} ,{C2,C3,C4,C5})
0.00
0.00
({ ϕ },{C1,C2,C3,C4,C5})

Figure 7. A summary Hierarchy.

C. *Formal representation of summaries*

As shown in Figure 7, each concept summary can be viewed like an n-uplet of a relation R^* whose diagram is the same one as the origin relation R to summarize. Each concept summary z of the set of concept' s summary Z is thus a description of a set of n-uplets of R, which jointly form his extension and which is noted by R_Z.

Definition 2. Concept summary: A concept summary is a couple $z = (R_Z, I_Z)$ in which R_Z is the subset of database records involved into the summarization, the extent, whereas the summarized description I_Z of these database records is the intent.

Each concept summary $z = (R_Z, I_Z)$ provides a synthetic view of a part of the database.

Thus, the root contains the summary of all the candidate records, whereas leaves represent only one combination of fuzzy linguistic labels over all the attributes.

Example: *z=({t1(0.5),t5(0.5),t6(0.5), {modest, young})*

Definition 3. Abstraction level: An abstraction level is an abstraction level is regarded as a level in the summary hierarchy generated.

Definition 4. Level: A level L of a summary hierarchy is a set of concept's summary z_k verifying the following property: the majors and the minors of z_k are at the same distance d .

Definition 5. Majors/Minors: Let $(E, \leq_E)$ be an ordered set and S a subset of E. Major's elements (successors) and Minor's elements (predecessors) of S are defined by:

$$\text{Majors}(S) = \{x \in E \wedge \forall y \in S, y \leq_E x\}$$
$$\text{Minors}(S) = \{x \in E \wedge \forall y \in S, x \leq_E y\}$$

Considering the summary hierarchy in Figure 7, we can generate the following levels with the corresponding summaries:

Level 0 { z1=({t1(0.0),t2(0.0),t3(0.0),t4(0.0),t5(0.0),t6(0.0)},{ ϕ })

Level 1 {
z21= {t2(0.3),t3(0.7),t6(0.5)},{miserable})
z22= t1(0.5),t2(0.6),t4(0.8),t6(0.5)},{adult})
z23= ({t1(0.5),t2(0.6),t4(0.4),t5(0.5),t6(0.5)}, {modest})
z24= ({t1(0.5),t3(0.7),t5(0.6),t6(0.5)},{young})

Level 2 {
z31= ({t1(0.5),t2(0.6),t4(0.4),t6(0.5)},{modest, adult})
z32= ({t1(0.5),t5(0.5),t6(0.5)},{modest, young})
z33= {t1(0.4),t4(0.5),t5(0.4)},{modest, comfortable})
z34= ({t3(0.7),t6(0.5)} ,{miserable, young})

Level 3 {
z41= ({t1(0.4),t5(0.4)},{modest,comfortable, young})
z42= ({t1(0.4),t4(0.4)},{modest,comfortable, adult})
z43= ({t2(0.3),t6(0.5)},{miserable, modest,adult})
z44= ({t1(0.5),t6(0.5)} ,{modest, young, adult})

Level 4 {
z51= ({t6(0.5)},{miserable, modest, young, adult})
z52= ({t1(0.4)},{modest,comfortable,young, adult})

Level 5 { z61= ({ ϕ },{miserable,modest,comfortable, young,adult})

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Levels 0 and 5 are both the root and leaves concept summary.

A concept summary is defined in an extensional manner with a collection of candidate records $R_z = \{t_1, t_2, ..., t_N\}$.

Each t_i is associated to one primitive database records, i.e., an element of R .

Denote by $card(R_z) = \sum_{t \in R_z} w(t)$ the representativity of the concept summary z according to the primary database R . $|R_z|$ the number of candidate records in R_z .

D. About complexity

The space complexity, whatever the number of database records, is thus reduced to a constant value, i.e., about O(1). This characteristic is fundamental in the treatment of the large database in knowledge discovery. Temporal complexity includes the following costs:

- Construction of the attribute’s clusters.
- Building the fuzzy lattice.

For cluster’s construction, the complexity of fuzzy clustering algorithms is about O(NC^2), where N corresponds to database table records number and C is the maximum number of clusters.

For fuzzy lattice construction, temporal complexity of lattice construction algorithm is about O(N^2) .

V. Comparative study

In recent years, several methods of DB summarization have been proposed such as statistical approaches, classification and conceptual classification. Unfortunately, all these techniques cannot be applied to the large Fuzzy DB.

In this paper, we have proposed a new approach to linguistic summarization for fuzzy databases, called fuzzy-SaintEtiq. This approach is an extension of the SaintEtiQ model to support the fuzzy data.

Based on a hierarchical conceptual clustering algorithm, SaintEtiQ model builds a summary hierarchy from DB records. However, for building hierarchy, this model passes by a three steps which, after their study, each one can be optimized while keeping its hierarchical aspect.

- For the first step, the pre-processing, we have considered a fuzzy clustering allowing generating a membership matrix associating the DB records to generated clusters by means the membership degrees. In this context we have proposed an extension of FCM algorithm, called Fuzzy-FCM, in order to support different types of data represented by GEFRED model.
  This is a form of optimization as much in DB navigation as minimization of the domain expert risks.
- The second and the third steps have been associated together in order to generate the summary hierarchy. So, we have proposed to use fuzzy FCA in order to generate fuzzy hierarchy.
  This step presents an optimization form in building summaries. On the one hand, it cooperates with the user by giving him summaries in different hierarchy levels. In the other hand, it allows the calculation of different measures from possible evaluations.

Table VII gives a comparison between our summary model Fuzzy-SaintEtiq and the other models.

TABLE VII. Comparative study of some summarization techniques

	Understandable	**Sampling**	**Data Nature**	**Huge data**	**Ratio with the original data**	**hierarchical levels**	**Reliability**	**Subject depending**	**Fuzzy DB**
Statistical Model	comprehensible	No	Numeric/ Nominal	No	Lost	No	High	Yes	No
Classification	No	Yes	Numeric	No	Kept	No	Low	No	No
Conceptual classification	Partially	Yes	Numeric	No	Kept	No	Means	No	No
SaintEtiQ	Yes	Yes	Numeric/ Nominal	Yes	Kept	Partially	Means	No	No
FCA-based Summary	Yes	Yes	Numeric	Yes	Kept	Yes	High	No	No
Fuzzy_SaintEtiq	Yes	Yes	Numeric	Yes	Kept	Yes	High	No	Yes

VI. CONCLUSION

With the increasing size of databases, the extraction of data summaries becomes more and more useful, thus, several methods of DB summarization have been proposed.

Unfortunately, all these techniques cannot be applied to the Fuzzy DB. In this paper, we proposed a new approach to linguistic summarization for fuzzy DB, called fuzzy-SaintEtiq. This approach is an extension of the SaintEtiQ model to support the fuzzy data represented by GEFRED model. Although this solution is based on the fuzzy model GEFRED, it can be applied to other fuzzy models.

To validate our approach, we currently plan to develop this approach with JAVA language.

As futures perspectives of this work, we mention essentially 1) to test our approach on the large fuzzy data set and 2) to describe a new approach for Knowledge Discovery in Fuzzy Databases (KDFDB) described with FSQL language. While basing on the summary hierarchy, generated by fuzzy-SaintEtiq, we proceed to discover the Knowledge in a hierarchical way. Thus, according to the degree of detail required by the user, this approach proposes a level of knowledge and different views of this knowledge.

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