Information Sciences 328 (2016) 418–434

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Creating knowledge databases for storing and sharing people knowledge automatically using group decision making and fuzzy ontologies

J.A. Morente-Molinera [a,*], I.J. Pérez [b], M.R. Ureña [a], E. Herrera-Viedma [a]

[a] Department of Computer Science and Artificial Intelligence, University of Granada, Granada, Spain
[b] Department of Computer Sciences and Engineering, University of Cádiz, Cádiz, Spain

ARTICLE INFO

Article history:
Received 22 January 2015
Revised 16 June 2015
Accepted 31 August 2015
Available online 9 September 2015

Keywords:
Fuzzy linguistic modeling
Group decision making
Computing with words
Multi-granular linguistic information
Fuzzy ontology

ABSTRACT

Over the last decade, the Internet has undergone a profound change. Thanks to Web 2.0 technologies, the Internet has become a platform where everybody can participate and provide their own personal information and experiences. Ontologies were designed in an effort to sort and categorize all sorts of information. In this paper, an automatized method for retrieving the subjective Internet users information and creating ontologies is described. Thanks to this method, it is possible to automatically create knowledge databases using the common knowledge of a large amount of people. Using these databases, anybody can consult and benefit from the retrieved information. Group decision making methods are used to extract users information and fuzzy ontologies are employed to store the collected knowledge.

1. Introduction

Originally, the Internet was designed as a means of consulting. Only a few recognized experts were able to provide information while the rest of the people, who could afford to access it, were only allowed to carry out consulting tasks. Therefore, the Internet was designed for minorities and the information available, as compared to what is available nowadays, was quite limited. Nowadays, the situation has changed dramatically. Thanks to Web 2.0 [5,53], the Internet has become a place where users can connect and share large amounts of information. Therefore, Internet users have become providing and consuming information entities. This situation has made information more accessible and available than ever. Nevertheless, in most cases, the information available is badly structured and, therefore, of little use for users. Users just cannot manage all the available amount of information by themselves. In order to deal with this problem, fields like Big Data [39,46,49,51], for extracting conclusions from the data, semantic web [1,9,21,36,47], for sorting it, and intelligent systems [28,38,54], to use the information for different purposes, have arisen.

Ontologies [6,29,43] are tools that provide a way of sorting, classifying and describing large amounts of information. Knowledge databases created using ontologies are easy to manage and allow users to search for information and extract conclusions. Because our system needs to work with conceptual information provided by users, imprecision must be dealt with. For this reason, fuzzy ontologies [17] will be used. Crisp ontologies allow each element to be described or not, {0, 1}, by each concept in the

* Corresponding author. Tel.: +34 958241773.
E-mail addresses: jamoren@decsai.ugr.es (J.A. Morente-Molinera), ignaciojavier.perez@uca.es (I.J. Pérez), raquel@decsai.ugr.es (M.R. Ureña), viedma@decsai.ugr.es (E. Herrera-Viedma).

http://dx.doi.org/10.1016/j.ins.2015.08.051

ontology. On the contrary, fuzzy ontologies associate each element to each concept using a particular degree in the interval [0, 1]. This way, elements can be associated to different concepts. For example, when referring to a person's height, if John measures 1.78 m, it can be stated in a fuzzy ontology that John has a medium height of 0.7 degree and a high height of 0.3 degree. In a crisp ontology, those measures can be represented as a medium height of 1 and a high height of 0 or vice versa. Therefore, it is easy to see that a fuzzy ontology has a more flexible representation capability than a crisp one.

Retrieving information from Internet users is a quite complicated task. Especially, when subjective information is being dealt with. The provided data must be analyzed and verified. In order to carry out this task, Group Decision Making (GDM) methods [16,58,59] can be used. They allow a set of Internet users to provide information, carry out debates and make a final choice. If this approach is used, the final information outcome is not an outlier opinion from a unique user but a consensus opinion totally guaranteed by a majority of users that have dealt with the matter. Consequently, the obtained information can be considered reliable.

As previously mentioned, the information under consideration was provided by humans. Consequently, it is quite important to provide users with tools that will assist them in providing information. The easier the method of providing information, the more reliable the obtained data will be. For this reason, multi-granular linguistic information [33,50,52] is used in this paper. As a result, Internet users can express themselves using words instead of numbers, i.e. they will be able to express themselves as they are more used to doing so. Moreover, users will be able to select the linguistic term set (LTS) that they want to use to express themselves. This way, if the users want to be very concrete about the provided information, they can use a LTS with a high granularity, otherwise they can select an LTS with a lower granularity.

In this paper, the design of an automatic process for creating knowledge databases using people's common knowledge about a certain issue is being presented. GDM methods are used in order to obtain information totally guaranteed by the majority of users. In order to ease the way in which Internet users provide their opinions, multi-granular linguistic information is used. Finally, the trusted information is automatically stored in a fuzzy ontology where other users can benefit from the obtained knowledge and therefore reach conclusions.

Thanks to the automatic method designed, users can share their subjective knowledge about a certain topic and allow other people to take advantage of it. Retrieved information is sorted in a fuzzy ontology allowing a complete exploitation of the available data. Subjective information provided by human beings is difficult to deal with due to the fact that it is difficult to measure and validate. Thanks to our system, a tool for dealing with this type of information is presented. Moreover, the information used is validated and made objective because it is ratified by the majority of users in the GDM process. In such a way, stored information is no longer an individual person's opinion. It is actually the opinion of a majority, information worthy of being used and taken into account.

In Section 2, some concepts that are required to understand the designed process are presented. In Section 3, the current state of the art on ontologies and decision making applications is presented. In Section 4, the designed process structure is described. In Section 5, an example is given. In Section 6, we make a comparison between the state of the art and our own proposal by analyzing its advantages and drawbacks. Finally, some conclusions are offered.

2. Preliminaries

In order to make this paper as self-contained as possible, this section will introduce concepts and methods to be referred to throughout this paper. In 2.1, we explain how GDM methods work. In Section 2.2, how to deal with multi-granular linguistic information is shown. In 2.3, fuzzy ontologies are described.

2.1. Group decision making

Group Decision Making has been a well-studied field since its first appearance in the 80's [10] until today [15,27,55,68,69]. It has been used satisfactorily in fields such as operations research [70,79], politics [37,62], social psychology [23,42], artificial intelligence [14,18] and soft computing [56,57].

A group decision making problem is formally defined as follows. Let $E = \{e_1, \ldots, e_n\}$ be a set of experts and $X = \{x_1, \ldots, x_m\}$ a set of alternatives. A GDM problem tries to sort X using the preferences values P^k, $\forall k \in [1, n]$, provided by the experts. Generally, GDM processes are carried out following these steps:

1. **Providing preferences**: Experts provide their preferences for the set of alternatives. Thus, in this paper, the next three methods could be used:
   - *Utility functions:* Consist of providing a score value to each of the alternatives. Generally it is considered as a set $U^k = \{u_1^k, \ldots, u_m^k\}$ where $u_\cdot^k \in [0, 1]$ and k is a specific expert.
   - *Preference orderings:* Experts are asked to sort the alternatives according to their preferences. Formally, each expert provides a set $O^k = \{o^k(1), \ldots, o^k(m)\}$ where $o^k(\cdot)$ is a permutation function over the indexes $\{1, \ldots, m\}$.
   - *Preference relations:* Experts provide a pairwise comparison of all the possible pairs of alternatives. Formally, a fuzzy preference relation is a matrix $P \subset X \times X$ where each value is defined by a membership function $\mu_{pk} : X \times X \to [0, 1]$. $\mu_{pk}(x_i, x_j) = p_{ij}^k$ indicates the preferences of x_i over x_j.

   One disadvantage of utility functions is that they do not allow experts to establish relations among the alternatives, information is only based on absolute scoring. Preference orderings establish relations among the alternatives but, information about the quantity of preference among the different alternatives is not collected. Also, when a large amount of alternatives are being dealt with, it can become difficult for the experts to sort them. Preference relations allow a pairwise comparison of the alternatives that can be further analyzed. Therefore, they allow the use of consistency measures in order to determine if the experts are being coherent or not [22]. Furthermore, they can be easily used by experts independently of the number of the alternatives. Transformation functions that allow us to convert any preference ordering values and utility function values into preference relation values are presented:

- To convert preference orderings into preference relations the following expression is used:

$$p_{ij}^k = f^1\left(o_i^k, o_j^k\right) = \left(\frac{1}{2}\left(1 + \frac{\left(o_j^k\right) - \left(o_i^k\right)}{m-1}\right)\right) \tag{1}$$

  Example. Let $\{2, 1, 3\}$ be a preference ordering associated with the alternatives set $\{x_1, x_2, x_3\}$ assessed by the expert e_k. The preference relation associated values are computed as follows:

$$p_{12}^k = \left(\frac{1}{2}\left(1 + \frac{1-2}{2}\right)\right) = 0.25$$
$$p_{13}^k = \left(\frac{1}{2}\left(1 + \frac{3-2}{2}\right)\right) = 0.75$$
$$\ldots$$
$$p_{32}^k = \left(\frac{1}{2}\left(1 + \frac{1-3}{2}\right)\right) = 0$$

  After calculating p values, the following matrix is obtained:

$$P^k = \begin{pmatrix} - & 0.25 & 0.75 \\ 0.75 & - & 1 \\ 0.25 & 0 & - \end{pmatrix}$$

  These results are expressed using the interval [0,1].

- To transform utility functions into preference relations the next expression is employed:

$$p_{ij}^k = f^2(u_i^k, u_j^k) = \left(\frac{\left(u_i^k\right)^2}{\left(u_i^k\right)^2 + \left(u_j^k\right)^2}\right) \tag{2}$$

  Example. Let $\{x_1, x_2, x_3\}$ be a set of alternatives whose associated utility function values are $\{5, 3, 1\}$ assessed by the expert e_k from the [1,5] interval. The preference relation associated values are calculated one by one as follows:

$$p_{12}^k = \frac{5^2}{5^2 + 3^2} = 0.73$$
$$p_{21}^k = \frac{3^2}{3^2 + 5^2} = 0.26$$
$$\ldots$$
$$p_{32}^k = \frac{1^2}{1^2 + 3^2} = 0.1$$

  The preference relation matrix obtained after the transformation process is shown below:

$$P^k = \begin{pmatrix} - & 0.73 & 0.96 \\ 0.26 & - & 0.9 \\ 0.03 & 0.1 & - \end{pmatrix}$$

  As in the previous example, results are expressed using the interval [0,1].

2. **Aggregation step**: Once experts have provided their preferences, they are all aggregated into a collective value that represents the overall opinion of all the experts. Aggregation operators such as *OWA* [71,74] or the mean operator can be used. Also, if linguistic information is being dealt with, *LOWA* operator can be used [32].
3. **Selection step**: Using the collective matrix, selection operators are used in order to carry out the alternatives ranking. Guided dominance degree (GDD) and Guided non-dominance degree (GNDD) operators [32] can be used for this purpose. Consensus measures [3] can be used to determine if another GDM round should be carried out or if the obtained results should be considered final.

An outline of this process can be seen in Fig. 1.

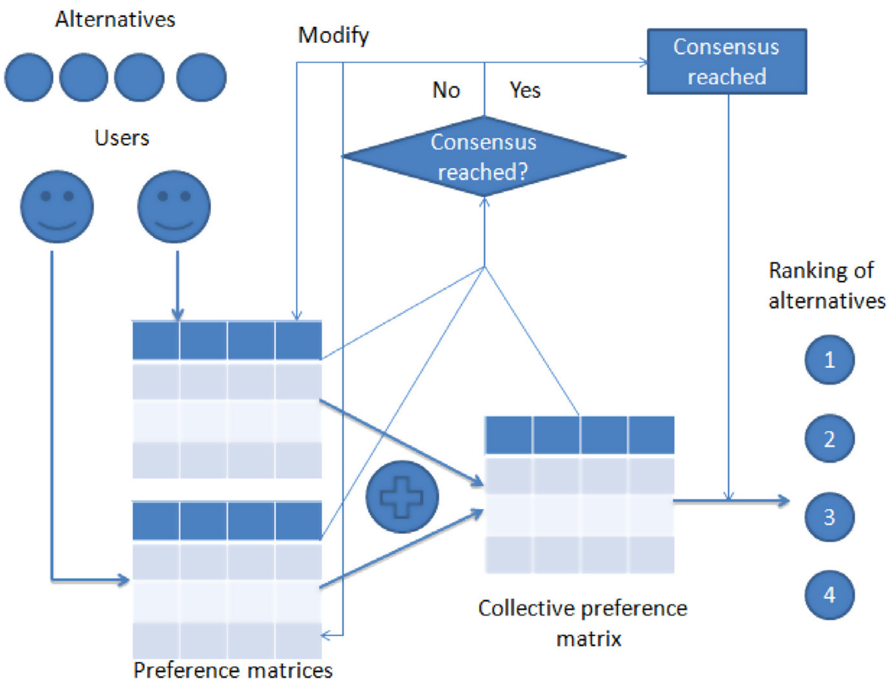

Fig. 1. Group decision making process scheme.

2.2. Multi-granular linguistic information

Dealing with a computational system can become difficult for human beings. This is because computers can only understand numbers while humans are more used to dealing with words and concepts. Misunderstandings often occur because concepts are imprecise while numbers are precise.

Linguistic Modeling employs the linguistic variable concept defined by Zadeh [76–78] and tries to reduce the communication gap between humans and computers. A linguistic variable is a *variable whose values are not numbers but words in a natural or artificial language*. Formally, a linguistic value X is a 5-tuple $\langle L, T(L), U, S, M\rangle$ where L is the name of the variable, $T(L)$ is a finite set of labels, U is the universe of discourse, S is the syntactic rule that generates terms in $T(L)$ and M is a syntactic rule that associates, with each linguistic label X, its meaning $M(X)$ where $M(X)$ denotes a fuzzy subset of U. It should be noted that a fuzzy subset $M(X)$ of U is defined by its membership function $\mu_{M(X)}: U \to [0, 1]$ where $\mu_{M(X)}(z)$ is called the degree of membership of element z in a fuzzy set $M(X)$ for each $z \in U$ [75].

For example, for the following linguistic variable:

$$Height = \{Very\_Low, Low, Medium, High, Very\_High\}$$

the linguistic variable tuple is defined as follows:

- L is *Height*.
- $T(L)$ is the set $\{Very\_Low, Low, Medium, High, Very\_High\}$.
- Universe of discourse, U, is the interval where the labels are defined, that is, [0,1].
- The syntactic rule, S, indicates that, for generating a new label, first, one of the labels from the set $\{Low, Medium, High\}$ are selected. Optionally, if *Low* or *High* labels were selected, the word *Very* can be added before them.
- Finally, M(X) can be defined as,

$$M(Very\_Low) = (0, 0, 0.25)$$
$$M(Low) = (0, 0.25, 0.5)$$
$$M(Medium) = (0.25, 0.5, 0.75)$$
$$M(High) = (0.25, 0.75, 1)$$
$$M(Very\_High) = (0.75, 1, 1)$$

where the tuple (a, b, c) presents a triangular fuzzy set. In such a way, $[a, c]$ is the fuzzy set support and b is the core.

The most commonly used linguistic modeling approach is the ordinal fuzzy linguistic one [32,73]. In it, the mathematical background associated with the labels is made based on the linguistic labels order within the LTS, that is, using their indexes.

When using linguistic modeling, each defined LTS must have a fixed granularity. When dealing with several human beings at the same time, this can cause problems. When an expert wants to provide precise information, he/she needs a LTS with a high granularity value. On the contrary, if he/she is not able to be very precise about a certain matter, the expert will prefer an LTS with a low granularity value in order to avoid getting lost among all the possible labels. When several experts are participating in the same GDM process, their knowledge and preferences about how to express themselves vary. It is not possible to select a granularity value that perfectly fits all of them. In order to solve this issue, multi-granularity linguistic information can be used. As a result, experts can choose the LTS that better fits their necessities and use it to provide their preference values. Multi-granular fuzzy linguistic modelings transform the provided information and express it using the same LTS labels allowing the computational system to work with the heterogeneous information [60,66].

A typical GDM process that works using multi-granular linguistic information follows these steps:

1. **Providing preferences step:** Experts provide their preferences using the LTS that better fit their necessities.
2. **Information standardization:** All the provided information is transformed into labels from a single LTS. This set is called the Basic LTS (BLTS).
3. **Aggregation and selection step:** After all the information is unified, the computational system can work properly with the provided information.

In this paper, the multi-granular linguistic information method that will be used is the one presented in [35]. In it, linguistic hierarchies (LHs) and 2-tuple linguistic information [34] are used.

LHs consist of a set of levels where each level represents a different granularity LTS. Each level is denoted as $l(t, n(t))$ where t indicates the level of the hierarchy and $n(t)$ the hierarchy LTS granularity value. The highest the level, the higher granularity value the assigned LTS has. Consequently, an LH is represented as the union of all its t levels as follows:

$$LH = \bigcup_t l(t, n(t)) \tag{3}$$

A linguistic 2-tuple is defined as a tuple (s, α) where s is a linguistic label and $\alpha \in [-0.5, 0.5)$ is called the symbolic translation. If β is considered as the aggregation result of the indexes of labels that are part of the same LTS and $i = round(\beta)$, then the symbolic translation is calculated as $\alpha = \beta - i$. This way, α indicates the distance from the obtained numerical aggregation value to the closest label in the LTS. It is possible to convert any aggregated numerical β to the form (s, α) using the following operator:

$$\begin{aligned} &\Delta : [0, g] \rightarrow S \times [-0.5, 0.5) \\ &\Delta(\beta) = (s_i, \alpha)\ with \begin{cases} s_i & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-0.5, 0.5) \end{cases} \end{aligned} \tag{4}$$

Any (s, α) can be expressed numerically as follows:

$$\begin{aligned} &\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g] \\ &\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \end{aligned} \tag{5}$$

Using LHs and 2-tuple representation information, the following multi-granular transformation function is defined below:

$$\begin{aligned} &TF_t^{t'} : l(t, n(t)) \rightarrow l(t', n(t')) \\ &TF_t^{t'}\left(s_i^{n(t)}, \alpha^{n(t)}\right) = \Delta\left(\frac{\Delta^{-1}\left(s_i^{n(t)}, \alpha^{n(t)}\right) \cdot (n(t') - 1)}{n(t) - 1}\right) \end{aligned} \tag{6}$$

Therefore, labels from each level t can be transformed into labels that belong to the LTS from the level t'.

2.3. Fuzzy ontologies

Due to the collaborative aspect of the knowledge collection process, in order to structure and manage all the information, we could use a simple folksonomy [67]. However, although we do not need to organize the knowledge hierarchically, we need more functionality than that provided by a folksonomy:

- Folksonomies are created directly by people. Users do their own tagging and the collection of their keywords becomes a useful source of data in the aggregate [30]. In our model, users only give values to the alternatives-criteria relations and the knowledge structure is not designed by them (see Section 2.1).
- Folksonomies do not have the necessary representation capability to hold the information generated by our system. In a folksonomy, tags are not related and have no associated semantics [67]. In our system, it is necessary to establish alternative-criteria relations by using a previously defined semantic (see Section 2.2).

Therefore, we consider the necessity of an ontology in order to support (structure and manage) the obtained knowledge.

By definition, an ontology is a mean that stores information in a sorted way and allows us to analyze the information and extract conclusions. In an ontology the following elements can be found [47]:

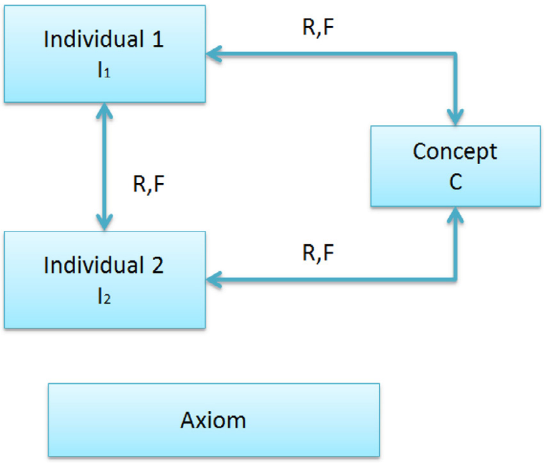

Fig. 2. Fuzzy ontology scheme.

- **Individuals:** Represent some entities that can be described.
- **Concepts:** They are perceptions used to describe the elements that conform the ontology. Each individual is described by a set of concepts.
- **Relations:** They establish relationships among the individuals and between individuals and concepts. They are used to indicate the concepts that are fulfilled by each individual.
- **Axioms:** Establish rules that must always be fulfilled.

Ontologies have traditionally been based on description logics (DL), which are not suitable for dealing with imprecise information [44]. A possible solution to this issue is to use fuzzy ontologies. Bobillo [11] describes a fuzzy ontology as follows: "A fuzzy ontology is simply an ontology which uses fuzzy logic to provide a natural representation of imprecise and vague knowledge and eases reasoning over it". Fuzzy ontologies represent the information using linguistic modeling as exposed in [76–78]. Thus, each piece of information is a word that has a fuzzy set [75] associated to it. To carry out operations using this kind of information, the mathematical environment associated to fuzzy sets can be used [72]. Also, it is possible to deal with words using a symbolic representation approach [32].

There are several ways of defining fuzzy ontologies. One of the most commonly used is described below:

A fuzzy ontology [7,17] is a quintuple $O_F = \{I, C, R, F, A\}$ where I is a set of individuals, C is a set of concepts, R is a the set of relations, F is a set of fuzzy relations and A is the set of axioms. An scheme of a fuzzy ontology can be seen in Fig. 2.

The new introduced element, F, allows the creation of fuzzy relations. These relations allow individuals to be related to concepts or other individuals to a certain degree. In crisp ontologies, each individual is related or not to each concept or individual, that is, $\{0, 1\}$. In fuzzy ontologies, individuals can establish relations in a fuzzy way, using a membership function [75]. Normally, the interval $[0, 1]$ is chosen.

Nowadays, fuzzy ontology are widely used by researchers. For instance, Jiang et al. [40] used modular fuzzy ontologies for change management purposes, and Bobillo and Straccia [13] extended their *fuzzyDL* software [12] with features for handling fuzzy integrals.

When a user wants to carry out a query on the fuzzy ontology, the following steps are followed:

1. **Query providing**: The expert provides the query that indicates the information that he/she wants to obtain from the ontology.
2. **Ontology searching**: The ontology reasoner analyses each ontology individual in order to determine if it fulfils the query. A previously determined threshold is used. In such a way, if the individual surpasses it, it is considered as a desired entity, otherwise, the individual is discarded. The system designer can choose the fuzzy ontology reasoner that better fits his/her necessities. For testing purposes in this paper, we have decided to make the fuzzy ontology queries using the maximal satisfiability degree of a fuzzy concept implemented in the FuzzyDL package by Bobillo [12].
3. **Results presentation**: A ranking of individuals that fulfil the requirements imposed by the users, is produced using their similarity to the query.

A graphical scheme of this process can be seen in Fig. 3.

Example. Imagine that the following ontology with the following characteristics is defined:

- **Individuals**: The individuals set is conformed with a set of 200 different smartphones.
- **Concepts**: Screen size, capacity and microprocessor are taken into account. Their values are all specified using the LTS $S = \{Low, Medium, High\}$.
- **Fuzzy relationships**: Each individual is related to each concept. Individuals are not related to each other.

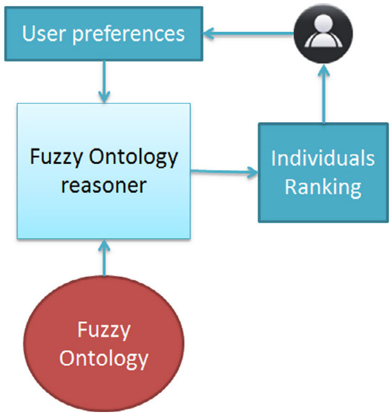

Fig. 3. Fuzzy ontology query process.

The process in which a user can select the smartphone that better fulfils his/her needs is described below:

1. The user provides the characteristics of his/her ideal smartphone. For example, a user can specify that he/she wants a smartphone with a *High* screen size, a *Medium* capacity and a *High* velocity microprocessor.
2. Similarity measures between each ontology individual and the user preferences are calculated.
3. Smartphones are sorted using the similarity measure. The ranking is presented to the user.

3. State of the art

As we have stated in Section 2.3, ontologies are widely used by researchers. In this section, we describe the current state of the art on ontologies based applications in order to summarize the recent advances in the field.

Papers conforming with the state of the art are classified in the following categories:

- **Case based reasoning systems**: Case base reasoning systems try to find solutions to certain problems based on previous experience. Ontologies can be used in order to store and manage the related information. In [8], a review on case based reasoning systems is carried out. Furthermore, recent trends are also shown. Ten different areas are identified in the field. In [4], fuzzy ontologies are used to build a case based reasoning system for emergency response services. This system uses ontologies to describe the case structure, define the case query vocabulary and facilitate similarity assessment linking the query terminology and the case base terminology.
- **Recommendation systems**: Recommendation systems is a field whose importance has increased exponentially since the appearance of Web 2.0 technologies. Recent recommendation systems have made a wide use of ontologies in order to help them classify the information dealt with. For instance, in [20], a recommendation system based on domain ontology for selecting the most adequate anti-diabetic drugs for a certain patient is presented. In this system, the ontology is used to store the knowledge base provided by a hospital specialist in the Taichung Health Department. First, the system builds an ontology using the drugs' nature attributes, the type of dispensing, side effects and patients' symptoms. Afterwards, Semantic Web Rule Language and Java Expert System Shell are used to design potential prescriptions for the diabetic patients. In [48], a novel model for representing users trust in recommender systems is described. Ontologies are employed to characterize the users' profiles that are used to generate recommendations. In [19], a library recommendation system that uses big data techniques like MapReduce and ontologies is presented. In this system, ontologies are employed for assigning keywords of interest to the users.
- **Database content management**: In this category, papers referring to the content management of an ontology are presented. Finding new ways of dealing with the information stored inside the ontology is an extremely important task in order to make the most of the advantages that ontologies offer us. In [31], a mechanism to define ontologies that is compatible with a large amount of representation systems is presented. A system called Ontolingua that is able to carry out translations from an standard form into different representations is presented. In [45], the authors focus on solving the problem of how to store the information that is contained in a fuzzy ontology. They propose the use of fuzzy databases and provide a thorough explanation of how to carry out this process. In [80], an automatic formal approach for constructing fuzzy ontologies using existing fuzzy object-oriented databases is proposed. This way, ontology builders can save time when they are building an ontology. In [65], the authors focus on reviewing methods for calculating the information content of an ontology concept, that is, the degree of generality/concreteness. Afterwards, they propose several improvements to this method in order to enhance the process. In [41], authors deal with the mapping problem. When trying to join different ontologies, it is necessary to compare them in order to establish similarities among the different concepts and point out possible incompatibilities. Therefore, ontologies mapping algorithms must be able to resolve these terminological and conceptual incompatibilities. In this paper, the authors present a method that is less time consuming than those who are currently available.

- **Applied ontologies**: In this category, applications that benefit of the use of ontologies are included. In [56], a Group Decision Making algorithm that benefits from fuzzy ontologies is presented. Possible alternatives that the users can choose from are stored in the ontology. This way, ontology queries can be used to reduce the high number of alternatives available in a feasible set. In [61] a Diabetes Mellitus Ontology for diagnosing and managing patients with diabetes is developed and validated. Thanks to ontologies, an automated purposeful extraction and assessment of the Electronic Health Records data is carried out. In [26], fuzzy ontologies are used to build a human behavior recognition system. The purpose of this system is to recognize what a certain person is doing in order to act accordingly. In [63], a new biomedical research ontology called Bio-Zen Plus is developed. The main advantage of this ontology is that is the first capable of working in an optimized way on the Semantic Web. In [64], an ontology and an automated reasoning methodology designed to deal with pharmacogenomic information is developed. The authors try to provide a concise formalism to represent the stored knowledge, find errors and lack of definitions, assign alleles and phenotypes to patients, assist patients with an appropriate support and find inconsistencies in treatment guidelines. Finally, in [2], a type-2 fuzzy ontology whose purpose is to aid in the identification of maritime obstacles is developed. Thanks to this ontology, it is possible to obtain accurate information about collision risk during real-time marine operations.

We have observed that a research gap exists between ontologies and GDM scenarios that our proposal may be able to fill. It is described in detail in Section 4.

4. A novel automatic method for creating knowledge databases for sharing people knowledge

In this section, the method designed is described. It creates automatic knowledge databases using information from Internet users. In such a way, information can be stored in an organized way and completely exploited. In order to create this user knowledge ontology, these steps are followed:

- **Individuals and concepts definition**: Each designed fuzzy ontology is related to a certain topic. Therefore, first, it is necessary to identify the individuals and concepts that are related with the topic that is being dealt with and the relations among the different elements that the fuzzy ontology is comprised of. From now on, it is considered that every individual is related to every concept. Also, it is assumed that individuals are not related. In the case that one of these two statements is false, the exposed method is still valid but the designer must deal with possible inconsistencies and introduce small modifications to the process. This issue will be further discussed in Section 6.
- **Ranking process**: GDM processes are used in order for Internet users to be able to define the values of the relations between each individual and concept.
- **Fuzzy ontology creation process**: Once the relation values between each individual and concept are defined, the fuzzy ontology is created by gathering the information.
- **Fuzzy ontology consulting process**: The steps described in Section 2.3 are followed so that Internet users can retrieve information. A graphical representation of the process can be seen in Fig. 3.

In Fig. 4, a graphical representation of the overall process is shown. In Section 4.1 the ranking creation process is described in detail. In Section 4.2, the fuzzy ontology creation process is detailed. In Section 4.3, the fuzzy ontology consulting process is described.

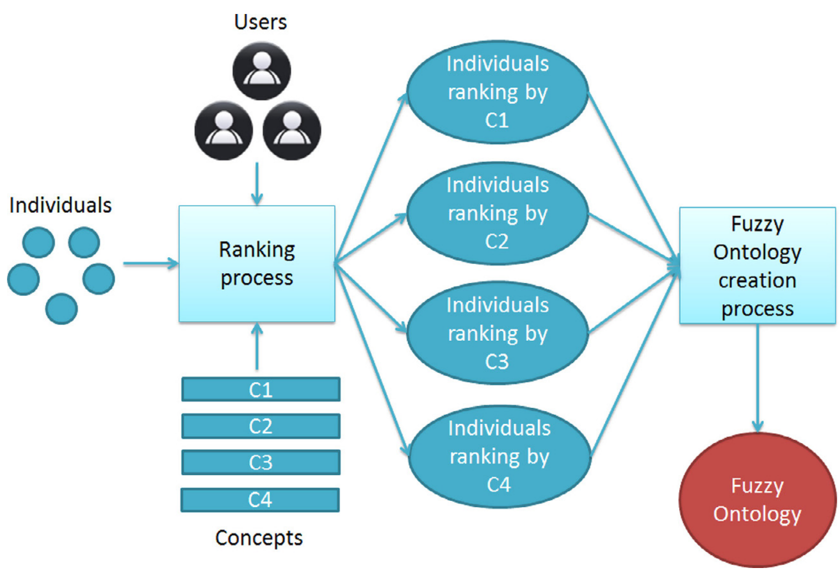

Fig. 4. Fuzzy ontology creation process scheme using GDM.

4.1. Ranking process

After defining the fuzzy ontology concepts and individuals, it is necessary to define the individual-concept relations. In order to accomplish this task, several GDM processes are carried out, one per each concept available. Elements of each of them are defined as follows:

- **Alternatives**: Each individual is considered as an alternative.
- **Experts**: Experts are compounded of the set of users that want to, or that are allowed to, participate. In order to retrieve Internet users' common knowledge, every Internet user that knows about the problem being dealt with should be allowed to participate.

Let $C = \{c_1, \ldots, c_l\}$ be the set of concepts, $D = \{d_1, \ldots, d_k\}$ the set of individuals and $E = \{e_1, \ldots, e_n\}$ the set of experts, the ranking process is performed as follows:

1. l GDM processes are created, one for each element in C. Each element in D is an alternative.
2. Each GDM process is carried out separately. Their purpose is to create a ranking with the alternatives set. Alternatives for each GDM process, GDM_i, must be sorted according to the following criteria: *the more the alternative fulfils the concept c_i the better ranking value it gets*.
3. For each GDM_i, experts express their preferences using their preferred LTS and representation method. Experts can express their preferences using three different preference providing representations: utility values, preference orderings and preference relations. For computations, preference relations are used.
4. Using fuzzy multi-granular linguistic methods and transformation expressions, the information is homogenized and expressed using preference relations and labels from the same LTS. All the used transformation functions are described in Section 2.1.
5. The uniformed information is aggregated into a single collective preference matrix. This matrix represents the overall opinion of all the experts that participate in GDM_i. Mean operator is used for the calculation as follows:
$$C_i = \phi(P_{ij}^h), i = \{1, \ldots, l\}, j = \{1, \ldots, k\}, h = \{1, \ldots, n\} \tag{7}$$
6. For each GDM process, the mean of the selection operators GDD and GNDD ranking values is calculated using the collective preference matrix. GDD and GNDD operators are calculated as follows:
$$GDD_i = \phi\left(c_{i1}, c_{i2}, \ldots, c_{i(i-1)}, c_{i(i+1)}, \ldots, c_{in}\right) \tag{8}$$
$$GNDD_i = \phi\left(c_{1i}^s, c_{2i}^s, \ldots, c_{(i-1)i}^s, c_{(i+1)i}^s, \ldots, c_{ni}^s\right) \tag{9}$$
where
$$c_{ji}^s = \max\{c_{ji} - c_{ij}, 1\}$$
Therefore, the final ranking values are calculated as follows:
$$RV = (GDD_i + GNDD_i)/2, \forall i \in [0, m] \tag{10}$$
Finally, alternatives are sorted according to their RV.
7. Once all the alternatives are sorted for each concept, a set of rankings $R = \{r_1, \ldots, r_l\}$ is obtained, a different set for each concept. Using this ranking set, the fuzzy ontology is created as shown using the guidelines given in Section 4.2.

A diagram representation of the described process can be seen in Fig. 5.

4.2. Fuzzy ontology creation process

Once the ranking set R has been calculated in the previous step, its information is used in order to build a fuzzy ontology. As a result, the knowledge that has been provided by the users is stored in a organized way. Also, other Internet users can access and benefit from it. It should be taken into account that the more users the GDM processes hold, the more reliable the collected information is. This is due to the fact that the obtained conclusions are ratified by more people.

The fuzzy ontology creation process follows these steps:

1. **Ranking LTS association**: A LTS $S = \{s_1, \ldots, s_k\}$ containing the same number of labels as individuals in the fuzzy ontology is defined. The label indicating the highest value is assigned to the first individual in the ranking, the second highest value to the second position in the ranking and so on. For example, if a set of four individuals is ranked as $R_i = \{d_3, d_2, d_1, d_4\}$ for the concept i, then the LTS $S = \{s_1, s_2, s_3, s_4\}$ is defined. Fuzzy ontology results for concept c_i is exposed in Table 1. This way, the more an individual fulfils each concept, the higher index value its associated label has.
2. **Fuzzy ontology structure construction**: After applying the ranking LTS association to all the concepts in the fuzzy ontology, the information is gathered and the fuzzy ontology constructed. It must be noted that, because the number of individuals is the same in each GDM process, the same LTS is used for all the concepts in the ontology. It should also be taken into account that in cases where a lot of individuals are available, the LTS used has an extremely high and unmanageable granularity value. Therefore, it cannot be used by experts for consulting tasks. For solving this issue, multi-granularity linguistic approaches can be used. In Section 4.3, this issue will be further discussed.

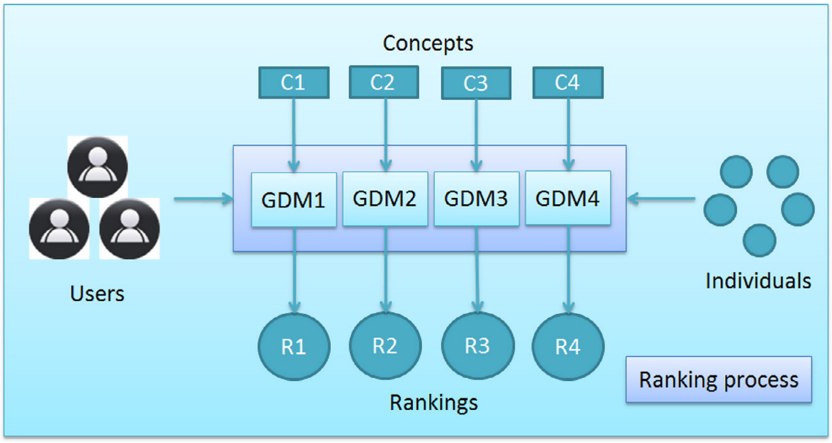

Fig. 5. Ranking process scheme.

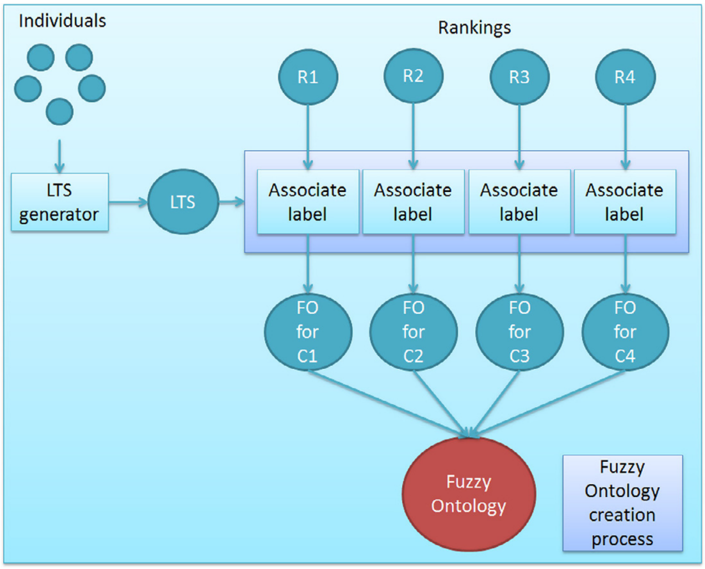

Fig. 6. Fuzzy ontology creation process scheme.

Table 1
Fuzzy ontology for concept c_i of the example.

Individual	c_i
d_1	s_3
d_2	s_2
d_3	s_1
d_4	s_4

A graphical representation of this process can be seen in Fig. 6.

4.3. Fuzzy ontology consulting process

After building the fuzzy ontology using the users knowledge, each consultant wanting to retrieve information from it can do so. For this task, these steps are followed:

1. **LTS selection**: As stated in the previous section, for representing individuals in the fuzzy ontology, a LTS whose granularity is the number of individuals has been used. Usually, number of individuals is quite high making the LTS unaffordable for user use. In order to solve this issue, users are allowed to express themselves using the LTS that better fits their necessities. The LTS labels used will be expressed into the fuzzy ontology labels using a multi-granular fuzzy linguistic method.

2. **Query providing**: After selecting an appropriate LTS, the user formulates his/her query. The query is constituted of a set of concepts and their desired value. Users do not have to specify values for all the concepts available in the ontology, only for those that he/she is interested in.
3. **Query uniforming**: Labels from the query provided by the user must be transformed into labels from the fuzzy ontology in order to carry out comparisons. For this purpose, a multi-granular fuzzy linguistic method is used. Its transformation function is showed in expression (6).
4. **Fuzzy ontology reasoning**: Once that the query is expressed using the LTS used by the fuzzy ontology, a ranking of the individuals is carried out. First, similarity values between the query and each of the individuals are calculated. Next, individuals are sorted using the similarity values obtained.
5. **Fuzzy ontology results providing**: The top values of the obtained ranking from the previous step are shown to the user. They are the choices that are closer to what the user is looking for.

5. Illustrative example

In this section, examples of a fuzzy ontology creation and consulting process are shown. A company, such as Filmaffinity, is interested in building a movie fuzzy ontology using the opinions of their users. In such a way, it can be consulted by users in order to find films that correspond to their interests. The company want to classify 20 different movies, $D = \{d_1, \ldots, d_{20}\}$ using the seven following concepts, $C = \{c_1, \ldots, c_7\}$:

1. **Action**: Measures the amount of action in the film.
2. **Humor**: Takes into account if the film is comical.
3. **Drama**: Refers to whether the film storyline is sad and touching.
4. **Mystery**: Mystery films get high label values in this concept.
5. **Argument**: Quality of the movie storyline is measured.
6. **Overall opinion**: Refers to the overall opinion of the users of an specific movie.
7. **Actors performance**: Measures the actors' performance quality in the film.

It should be noted that this is a brief movie fuzzy ontology example. Other concepts like science fiction or horror could be added. Creating a functional movie fuzzy ontology is out of the scope of this article.

Because seven concepts need to be measured using users' opinion, seven different GDM processes must be performed. For example, for the action concept, users are asked to sort the films according to the level of action on them. Because a large amount of individuals are available, it is difficult for experts to carry out a pairwise comparison of all of them. To overcome this issue, two possible paths can be followed:

1. To use a GDM method that is able to deal with these type of situations.
2. Using another preference representation method like utility values.

In this example, a GDM method that allows the participation of a large amount of experts and a high number of alternatives is followed. This method allows users to provide information only about the movies that they prefer. In such a way, a user chooses for themselves how many pairwise comparisons they wish to make. Because participation from a large number of users is expected, enough information to carry out a reliable GDM process will be collected. This example focuses on preferences provided by a set of three experts: $E = \{e_1, e_2, e_3\}$. e_1 uses preference relations and the linguistic label set S_1, e_2 uses utility function values and the linguistic label set S^2 and e_3 uses preference relations and the linguistic label set S^2. Linguistic label sets S^1 and S^2 are defined below:

$$S^1 = \left\{s^1_1, \ldots, s^1_5\right\}$$
$$S^2 = \{s^2_1, \ldots s^2_9\}$$

All three experts have decided to provide information about the set of movies $\{d_1, d_2, d_3, d_4\}$. Preferences provided are shown below:

$$P_1 = \begin{pmatrix} - & s^1_3 & s^1_1 & s^1_2 \\ s^1_5 & - & s^1_4 & s^1_5 \\ s^1_1 & s^1_3 & - & s^1_2 \\ s^1_2 & s^1_3 & s^1_3 & - \end{pmatrix}$$
$$P_2 = \left(s^2_6,\ s^2_9,\ s^2_1,\ s^2_3\right)$$
$$P_3 = \begin{pmatrix} - & s^2_5 & s^2_2 & s^2_3 \\ s^2_9 & - & s^2_8 & s^2_9 \\ s^2_2 & s^2_3 & - & s^2_1 \\ s^2_3 & s^2_5 & s^2_4 & - \end{pmatrix}$$

Table 2
Ranking results for the first four alternatives.

Alternative	GDD	GNDD	Mean	Linguistic
d_1	4.33	7.66	6	s^2_6
d_2	8.44	9	8.72	$(s^2_9, -0.22)$
d_3	2	4.98	3.5	$(s^2_3, 0.5)$
d_4	4.11	6.55	5.33	$(s^2_5, 0.33)$

In order to carry out the GDM process, preferences must be unified. Preference relations and S^2 are the preference representation method and the LTS that will be used for computations. Therefore, P_1 labels must be expressed using labels from S^2 and the utility function vector P_2 must be expressed using preference relations.

After applying the multi-granular transformation function shown in (6), the following preference relation is obtained for e_1:

$$P_1 = \begin{pmatrix} - & s^2_5 & s^2_1 & s^2_3 \\ s^2_9 & - & s^2_7 & s^2_9 \\ s^2_1 & s^2_5 & - & s^2_3 \\ s^2_3 & s^2_5 & s^2_5 & - \end{pmatrix}$$

After applying the expression (2) over P_2, the following preference relation is obtained for e_2:

$$P_2 = \begin{pmatrix} - & s^2_3 & s^2_9 & s^2_8 \\ s^2_7 & - & s^2_9 & s^2_9 \\ s^2_1 & s^2_1 & - & s^2_1 \\ s^2_2 & s^2_1 & s^2_9 & - \end{pmatrix}$$

For the sake of clarity, α values have been omitted from the labels. It is important to note that some precision has been lost in this simplification process.

After unifying the information, preferences are aggregated into a single collective matrix value. The collective matrix is not built at once using all the recollected preference values. On the contrary, collective matrix is in constant update with every new preference entry. After aggregating the three preference matrices provided by the experts $\{e_1, e_2, e_3\}$, the following collective matrix is obtained:

$$C = \begin{pmatrix} - & 4.33 & 4 & 4.66 & - & \dots & - \\ 8.33 & - & 8 & 9 & - & \dots & - \\ 1.33 & 3 & - & 1.66 & - & \dots & - \\ 2.66 & 3.66 & 6 & - & - & \dots & - \\ - & - & - & - & - & \dots & - \\ \dots & \dots & \dots & \dots & \dots & \dots & - \\ - & - & - & - & - & - & - \end{pmatrix}$$

where C has a row and column count value of 20. Because only three experts have participated in the process and they have introduced values for the same alternatives, the rest of the collective matrix values referring to other alternatives remains empty. The collective matrix is filled using numbers based on the labels from the used BLTS indexes. Because the collective matrix is only used for computational purposes, there is no need to use labels to enhance comprehension.

In order to obtain the final ranking, the mean between the GDD and GNDD operators resulting values can be used. If only the first 4 films were taken into account, the ranking would be as follows:

$$R = \{d_2, d_1, d_4, d_3\} \tag{11}$$

GDD and GNDD results for the first four alternatives can be seen in Table 2.

After carrying out the seven GDM processes over the 20 individuals with all the experts, the ranking set $R = \{R_1, \dots, R_7\}$ is obtained. An LTS with a granularity value of 20, $S^3 = \{s^3_1, \dots, s^3_{20}\}$, is chosen for the fuzzy ontology creation. For each concept, each label from the LTS is assigned to each individual according to their position in the ranking. In Table 3, a table representing the final fuzzy ontology obtained is shown.

Once the fuzzy ontology is created, users can formulate queries and extract knowledge from it. Imagine that a user wants to use the fuzzy ontology with only the 5 movies shown in Table 4. He/She wants to select a film that has a good story line and a lot of action. Although the fuzzy ontology uses the LTS $S^4 = \{s^4_1, \dots, s^4_5\}$ that has a granularity value of 5, the user wants to use the LTS $S^5 = \{s^5_1, s^5_2, s^5_3\}$ whose granularity value is 3 in order to perform the query. Therefore, the user formulates the following query:

$$Q = \left\{s^5_3 \cdot c_1, s^5_3 \cdot c_5\right\} \tag{12}$$

First, labels expressed using the LTS S^5 must be expressed in terms of S^4. Once the multi-granular linguistic transformation process has been carried out, the expert query is expressed as follows:

Table 3
Fuzzy ontology of 20 elements.

Individual	c_1	c_2	c_3	c_4	c_5	c_6	c_7
d_1	s^3_8	s^3_8	s^3_6	s^3_{19}	s^3_2	s^3_{20}	s^3_3
d_2	s^3_{10}	s^3_4	s^3_3	s^3_8	s^3_5	s^3_{17}	s^3_8
d_3	s^3_{16}	s^3_{19}	s^3_{18}	s^3_9	s^3_3	s^3_{10}	s^3_1
d_4	s^3_{19}	s^3_2	s^3_5	s^3_{12}	s^3_9	s^3_5	s^3_{13}
...	...	...	...	...	...	...	...
d_{20}	s^3_1	s^3_5	s^3_{13}	s^3_4	s^3_{12}	s^3_4	s^3_7

Table 4
Fuzzy ontology of 5 elements.

Individual	c_1	c_2	c_3	c_4	c_5	c_6	c_7
d_1	s^4_5	s^4_4	s^4_5	s^4_3	s^4_5	s^4_1	s^4_2
d_2	s^4_1	s^4_3	s^4_4	s^4_4	s^4_4	s^4_2	s^4_3
d_3	s^4_2	s^4_1	s^4_1	s^4_5	s^4_3	s^4_3	s^4_4
d_4	s^4_4	s^4_2	s^4_2	s^4_2	s^4_2	s^4_5	s^4_1
d_5	s^4_3	s^4_5	s^4_3	s^4_1	s^4_1	s^4_4	s^4_5

Table 5
Similarity values calculation.

Individual	Operations	Similarity value
d_1	$5 - (\|5 - 5\| + \|5 - 5\|)/2$	5
d_2	$5 - (\|1 - 5\| + \|4 - 5\|)/2$	2.5
d_3	$5 - (\|2 - 5\| + \|3 - 5\|)/2$	2.5
d_4	$5 - (\|4 - 5\| + \|2 - 5\|)/2$	2
d_5	$5 - (\|3 - 5\| + \|1 - 5\|)/2$	3

$$Q = \left\{ s^4_5 \cdot c_1, s^4_5 \cdot c_5 \right\} \tag{13}$$

After that, similarity between every individual in the fuzzy ontology and the query is calculated. Indexes of the labels are used. Results and calculations can be seen in Table 5. Values are expressed in the interval [1, 5]. Finally, the following ranking is presented to the user: $\{d_1, d_5, \{d_2, d_3\}, d_4\}$. Consequently, d_1 is the film that better fulfils the guidelines suggested by the user.

6. Discussion

In this article, an automatized method to retrieve and store user knowledge in an organized way has been proposed. First, information is retrieved using a GDM process. This way, the stored information is not given by an individual user. Instead, each piece of information is supported by the users majority. Next, retrieved information is stored using a fuzzy ontology. Fuzzy ontologies allow information to be stored in a organized way and provide a mathematical environment that let users perform queries over the stored data.

The presented method has the following advantages:

- **The process is automatized**: One of the most important advantages of this method is that it is automatized. Therefore, it can be easily implemented on a computer that can carry out all the required steps by itself. Consequently, a computational system can create fuzzy ontologies using the users information without any direct human intervention.
- **Allows information sharing**: The designed system allows Internet users to classify and share their own knowledge. Therefore, our system retrieves users' information and stores it in a fuzzy ontology. Afterwards, carrying out fuzzy ontology queries, any user can benefit from this knowledge.
- **The retrieved information is organized**: Because fuzzy ontologies are used, the retrieved user information is dealt with in an organized way. Good organization makes it easier for users to access the required information. Also, information utility and interpretation are increased.
- **Information is trustworthy**: The employed GDM processes allow users to provide the information that the fuzzy ontology needs. The final ranking obtained is made taking into account the opinion of all the users that wanted to participate in the process. Therefore, the obtained rankings are ratified by the majority of the users. This fact is quite important since it proves that the information stored in the fuzzy ontology is, indeed, knowledge that is held by an important majority of users and not only by a single outlier.
- **Easy to implement**: The defined process uses mainly GDM methods and fuzzy ontologies. They are quite well known tools whose implementation is available through the Internet and the research literature. Therefore, the defined method is quite easy to implement.

- **Can be used on mobile phones**: It is important to note that this method is quite easy to implement on smartphones that use Android or IOS using the available implementation frameworks. This way, users can retrieve and provide information to the system independently of time and location.
- **User-friendly interface**: Because the designed method requires active user participation, it is important to ease human–computer communications. For this purpose, linguistic modeling and multi-granular fuzzy linguistic methods have been used. Thanks to them, the user is able to express himself/herself using words instead of numbers. This way, they can communicate with the system using the means that they are used to employing when communicating with other humans. Multi-granular fuzzy linguistic methods allow users to select the precision of the information that they want to provide. This way, if they do not know much about the topic at hand, they can select a low precision granularity and provide more imprecise information. On the contrary, if they are quite fond of the topic, they can provide accurate results selecting a LTS with a high amount of labels.

Depending on the defined background and the nature of the information, this method can present several issues. Several possible problems and ways to overcome them are listed below:

- **Individual and concept dependencies**: It was previously stated that all the individuals were independent. Also, it has been assumed that all the individuals are related to all the concepts. In the case of the existence of individual-to-individual relations, it would be necessary for users to provide information about them. Also, the final fuzzy ontology designed should be analyzed and, in the case that inconsistencies are found, they should be fixed. We believe that the best way to fix inconsistencies is to present, to the same users that have provided the fuzzy ontology information, all the possible ways to solve the inconsistency and allow them to choose one. For example, imagine that a fuzzy ontology has two individuals, *John* and *Anthony*, and they are related by the relations, *son of* and *father of*. It is easy to see that a scenario where *Anthony is the father of John* and, at the same time, *Anthony is the child of John* is inconsistent. Therefore, in order to solve this issue, users are asked to elucidate whether *Antonio* is the father or the child. Afterwards, the fuzzy ontology is fixed according to the results. Because the fuzzy ontology is expected to be fulfilled with users knowledge, allowing the users decide is the most reliable way. In the case that there are individuals that are not related to some of the concepts, the solution is quite easy since the only thing that should be done is to include, in each concept related GDM process, only those individuals that are related to the concept.
- **Dealing with non-ordinal concepts**: In the described process, it has been assumed that all the concepts can be represented using ordinal values. Nevertheless, there are concepts that, because of their semantic nature, cannot be dealt with this way. For example, in the case of smartphones, a concept indicating the mobile phone brand cannot be dealt with using an ordinal LTS. This is because this concept is composed of a set of elements, for example, {*Nokia*, *Sony Ericsson*, *Samsung*, *Apple*} that cannot be sorted using their indexes. In this case, the better approach is to ask the users to select one value for each of the individuals. This way, the most voted value is the one assigned to the relation.
- **Information updating**: One possible disadvantage of the described method is that once that the fuzzy ontology is created, it remains static and no new individual information can be added without having to rebuild the entire fuzzy ontology. Because the individual-concept relations are built using the individuals ordering, the rebuilding process cannot be avoided unless another preference representation method is used. For instance, the use of utility values in the GDM process allows individuals to be dealt with individually. This way, when a new individual is aggregated, users just have to rate it and, afterwards, it is introduced in the ontology. The use of utility values has the disadvantage of making users manage a high granularity LTS if a large amount of individuals is dealt with and a certain level of precision wants to be maintained. It should be noted that users are not used to dealing with high granularity LTSs. Thus, the human–computer communication degree decreases. In conclusion, the use of utility values is recommended in cases where the fuzzy ontology must carry out daily or hourly updates. On the contrary, if only time to time updating is needed, the use of preference relations and rebuilding the fuzzy ontology is recommended. In the case of adding a new concept, the task does not produce any inconveniences. A GDM process is carried out for the newly added concept and the new information is added to the fuzzy ontology.
- **Dealing with objective information**: The described process has assumed that all the information contained in the fuzzy ontology is subjective and, therefore, the relation values depend on people' opinion. Nevertheless, there are situations where these values are well known and, thus, there is no need to carry out any GDM processes to assign them. In these cases, the corresponding values can be filled by the fuzzy ontology manager using a reliable corpus that contains the required information. This way, the number of GDM processes can be reduced and dedicated only to filling in information about the concepts that refer to subjective information.

In Table 6, a brief summary of the discussed issues and their solutions are shown.

In Section 3, state of the art of ontologies and applications are revised. As it can be seen, ontologies have been widely used in many fields for a variety of purposes. Nevertheless, in most cases, ontologies are built manually using information retrieved from experts. Because this can be a long and difficult process, it is necessary to create automatized methods that are able to ease these procedures. In [61,64,80], automatized procedures are introduced. For instance, in [61], an automatized procedure to extract information from a specific database is proposed. Moreover, [80] proposes an automatic approach for building ontologies using databases. Also, in [64], some of the reasoning methodologies are automatized. Nevertheless, all of these processes need a database of some previously stored information. In our designed method, the ontology relation values information is directly extracted from users, no intermediate database is needed. Therefore, ontology builders only define the Group Decision Making environment while users fill all the information. Due to the way that the information is retrieved, it is stored and ratified by

Table 6
Possible design issues and their solutions.

Issue	Solution
Concepts and individuals dependencies	Analyze the fuzzy ontology and carry out GDM processes to solve inconsistencies.
Non-ordinal concepts	Assign, for each individual, the value that is most voted by the users.
Constant updating information demands	Build the fuzzy ontology using utility values.
Objective information	Use a corpus instead of asking the users.

a large amount of users. Therefore, the extraction process defined also carries out some validation among the received data. Consequently, the designed method is highly recommended when ontology builders want to build a new ontology from scratch and using users knowledge. Methods like [80], can be of more use when a proper database containing all the needed information is available.

7. Conclusions and future works

With the appearance of Web 2.0, users can share and consume high amounts of information. It is common for the provided information stored on the Internet to be disorganized making it difficult to dealt with. In order to make the most of this information and not miss any data, it is important to carry out organization processes over it. In this paper, an automatic process whose purpose is to extract users subjective knowledge and represent it in a fuzzy ontology has been described. As a result, the inherent users knowledge can be stored in an organized way and easily consulted by other users that are in need of that information. Each created fuzzy ontology will organize the available data on a certain topic. Therefore, the user can select the fuzzy ontology referring to the topic he/she is interested in and retrieve the desired information.

In order to collect the required data, GDM processes are used. As a result, the retrieved information is ensured to have been ratified by a majority of users and not only by an unique outlier person. Therefore, in order to take into account a piece of information, it is necessary for an important set of users to share the same point of view. The use of methods that ratify the quality and validity of the information is critical in order to ensure a sufficient information correctness degree.

In order to store the retrieved information in a organized way, fuzzy ontologies have been used. Fuzzy ontologies are adaptable and versatile tools that allow information to be stored in an organized way. Thanks to them, users can formulate queries in order to retrieve the required information and extract conclusions.

Because human–computer communication is a critical aspect of the designed method, fuzzy multi-granular linguistic methods and linguistic modeling have been used in order to reduce the communication gap as possible. Consequently, users can provide the information using words and computers are able to carry out the required computations interpreting that information. Reducing the human–computer communication gap allows users to improve accurateness on the provided information and, therefore, the quality of the stored information is increased.

Nowadays, there is a large amount of fuzzy ontologies in the literature that deal with several kinds of information. Nevertheless, it is still unclear how to deal with the implicit and subjective information of people's opinions and how to store and share it. In this paper, a novel method that tries to solve this issue has been developed.

In conclusion, the designed method is easy to implement and can adapt itself to multiple situations. As a result, it is possible to create organized fuzzy ontologies totally prepared for users to consult them and benefit from the stored knowledge. The main novelty of the presented process is that our system allows users to benefit from other users' knowledge. Moreover, it is able to extract and store, in an explicit way, subjective and implicit common people knowledge. Thanks to GDM processes, the extracted information is assured to have been ratified by an important percentage of people.

Finally, it is worth noting that, in real world GDM problems, alternatives and opinions are too much and often an ontology might not exist for a specific topic. Thus, it is needed to extract not only individuals, but also ontology concepts by exploiting automatic fuzzy ontology extraction approaches. Therefore, the inclusion of the approach presented by Maio et al. [24,25] in the current GDM scenario could be an interesting future work and a way to go one step further in the knowledge extraction and management problem.

Acknowledgments

This paper has been developed with the financing of FEDER funds in TIN2013-40658-P and Andalusian Excellence Project TIC-5991.

References

[1] A. Abello, O. Romero, T. Bach Pedersen, R. Berlanga, V. Nebot, M.J. Aramburu, A. Simitsis, Using semantic web technologies for exploratory OLAP: a survey, IEEE Trans. Knowl. Data Eng. 27 (2) (2015) 571–588.
[2] F. Ali, E.K. Kim, Y.-G. Kim, Type-2 fuzzy ontology-based semantic knowledge for collision avoidance of autonomous underwater vehicles, Inf. Sci. 295 (2015) 441–464.
[3] S. Alonso, I.J. Pérez, F.J. Cabrerizo, E. Herrera-Viedma, A linguistic consensus model for web 2.0 communities, Appl. Soft Comput. 13 (1) (2013) 149–157.
[4] K. Amailef, J. Lu, Ontology-supported case-based reasoning approach for intelligent m-government emergency response services, Decis. Support Syst. 55 (1) (2013) 79–97.

[5] S.J. Andriole, Business Impact of Web 2.0 Technologies, Communications of the ACM 53 (12) (2010) 67–79.
[6] R. Arp, B. Smith, A.D. Spear, Building ontologies with basic formal ontology, Mit Press, 2015.
[7] F. Baader, D. Calvanese, D. McGuinness, D. Nardi, P. Patel-Schneider, The Description Logic Handbook: Theory, Implementation and Applications, Cambridge University Press, 2003.
[8] S. Begum, M.U. Ahmed, P. Funk, N. Xiong, M. Folke, Case-based reasoning systems in the health sciences: a survey of recent trends and developments, IEEE Trans. Syst., Man, Cybern., Part C: Appl. Rev. 41 (4) (2011) 421–434.
[9] T. Berners-Lee, J. Hendler, O. Lassila, The Semantic Web, Science American Magazine May 17 (2001).
[10] J.-M. Blin, M.A. Satterthwaite, Individual decisions and group decisions: The fundamental differences, J. Pub. Econ. 10 (2) (1978) 247–267.
[11] F. Bobillo, Managing Vagueness in Ontologies, University of Granada, Spain, 2008 Ph.D. thesis.
[12] F. Bobillo, U. Straccia, Fuzzydl: an expressive fuzzy description logic reasoner., FUZZ-IEEE (2008) 923–930.
[13] F. Bobillo, U. Straccia, Aggregation operators for fuzzy ontologies, Appl. Soft Comput. 13 (0) (2013) 3816–3830.
[14] F.J. Cabrerizo, S. Alonso, E. Herrera-Viedma, A consensus model for group decision making problems with unbalanced fuzzy linguistic information, Int. J. Inf. Technol. Decis. Mak. 8 (01) (2009) 109–131.
[15] F.J. Cabrerizo, E. Herrera-Viedma, W. Pedrycz, A method based on PSO and granular computing of linguistic information to solve group decision making problems defined in heterogeneous contexts, Eur. J. Operat. Res. 230 (2013) 624–633.
[16] F.J. Cabrerizo, J.M. Moreno, I.J. Pérez, E. Herrera-Viedma, Analyzing consensus approaches in fuzzy group decision making: advantages and drawbacks, Soft Comput. 14 (5) (2010) 451–463.
[17] S. Calegari, D. Ciucci, Fuzzy ontology, fuzzy description logics and fuzzy-owl, Appl. Fuzzy Sets Theory 4578 (2007) 118–126.
[18] J. Chai, J.N. Liu, E.W. Ngai, Application of decision-making techniques in supplier selection: a systematic review of literature, Expert Syst. Appl. 40 (10) (2013) 3872–3885.
[19] L.-C. Chen, P.-J. Kuo, I.-E. Liao, Ontology-based library recommender system using mapeduce, Clust. Comput. 18 (2014) 1–9.
[20] R.-C. Chen, Y.-H. Huang, C.-T. Bau, S.-M. Chen, A recommendation system based on domain ontology and SWRL for anti-diabetic drugs selection, Expert Syst. Appl. 39 (4) (2012) 3995–4006.
[21] J. Cheng, C. Liu, M. Zhou, Q. Zeng, A. Yla-Jaaski, Automatic composition of semantic web services based on fuzzy predicate petri nets, IEEE Trans. Autom. Sci. Eng. 12 (2) (2015) 680–689.
[22] F. Chiclana, E. Herrera-Viedma, S. Alonso, F. Herrera, Cardinal consistency of reciprocal preference relations: a characterization of multiplicative transitivity, IEEE Trans. Fuzzy Syst. 17 (1) (2009) 14–23.
[23] J.D. Creswell, J.K. Bursley, A.B. Satpute, Neural reactivation links unconscious thought to decision-making performance, Soc. Cogn. Affect. Neurosci. 8 (8) (2013) 863–869.
[24] C. De Maio, G. Fenza, M. Gaeta, V. Loia, F. Orciuoli, S. Senatore, Rss-based e-learning recommendations exploiting fuzzy FCA for knowledge modeling, Appl. Soft Comput. 12 (1) (2012) 113–124.
[25] C. De Maio, G. Fenza, V. Loia, S. Senatore, Hierarchical web resources retrieval by exploiting fuzzy formal concept analysis, Inf. Process. Manag. 48 (3) (2012) 399–418.
[26] N. Díaz-Rodríguez, M.P. Cuéllar, J. Lilius, M.D. Calvo-Flores, A fuzzy ontology for semantic modelling and recognition of human behaviour, Knowl.-Based Syst. 66 (2014) 46–60.
[27] Y. Dong, E. Herrera-Viedma, Consistency-driven automatic methodology to set interval numerical scales of 2-tuple linguistic term sets and its use in the linguistic gdm with preference relation, IEEE Trans.Cybern. 45 (4) (2015) 780–792.
[28] D.J. Dubois, H. Prade, R.R. Yager, Readings in Fuzzy Sets for Intelligent Systems, Morgan Kaufmann, 2014.
[29] D. Fensel, Ontologies, Springer, 2001.
[30] T. Gruber, Ontology of folksonomy: a mash-up of apples and oranges, Int. J. Semant. Web Inf. Syst. 3 (1) (2007) 1–11.
[31] T.R. Gruber, A translation approach to portable ontology specifications, Knowl. Acquis. 5 (2) (1993) 199–220.
[32] F. Herrera, S. Alonso, F. Chiclana, E. Herrera-Viedma, Computing with words in decision making: foundations, trends and prospects, Fuzzy Optim.d Decis. Mak. 8 (4) (2009) 337–364.
[33] F. Herrera, E. Herrera-Viedma, L. Martínez, A fusion approach for managing multi-granularity linguistic term sets in decision making, Fuzzy Sets Syst. 114 (1) (2000) 43–58.
[34] F. Herrera, L. Martínez, A 2-tuple fuzzy linguistic representation model for computing with words, IEEE Trans. Fuzzy Syst. 8 (6) (2000) 746–752.
[35] F. Herrera, L. Martínez, A model based on linguistic 2-tuples for dealing with multigranular hierarchical linguistic contexts in multi-expert decision-making, IEEE Trans. Syst., Man, Cybern., Part B: Cybern. 31 (2) (2001) 227–234.
[36] P. Hitzler, F. van Harmelen, A reasonable semantic web, Semant. Web 1 (1) (2010) 39–44.
[37] M. Hosli, A. Kreppel, B. Plechanovová, A. Verdun, Introduction: decision-making in the european union before and after the lisbon treaty, West Eur. Politics 36 (6) (2013) 1121–1127.
[38] J. de Jesús Rubio, J.H. Pérez-Cruz, Evolving intelligent system for the modelling of nonlinear systems with dead-zone input, Appl. Soft Comput. 14 (2014) 289–304.
[39] P. Jiang, X.S. Liu, Big data mining yields novel insights on cancer, Nat. Genet. 47 (2) (2015) 103–104.
[40] Y. Jiang, Y. Tang, Q. Chen, J. Wang, Reasoning and change management in modular fuzzy ontologies, Expert Syst. Appl. 38 (11) (2011) 13975–13986.
[41] A. Khattak, Z. Pervez, W. Khan, A. Khan, K. Latif, S. Lee, Mapping evolution of dynamic web ontologies, Inf. Sci. 303 (2015) 101–119.
[42] C. Kidd, H. Palmeri, R.N. Aslin, Rational snacking: Young children's decision-making on the marshmallow task is moderated by beliefs about environmental reliability, Cognition 126 (1) (2013) 109–114.
[43] C. Lange, Ontologies and languages for representing mathematical knowledge on the semantic web, Semant. Web 4 (2) (2013) 119–158.
[44] T. Lukasiewicz, U. Straccia, Managing uncertainty and vagueness in description logics for the semantic web, Web Semant.: Sci., Serv. Agents World Wide Web 6 (4) (2008) 291–308.Semantic Web Challenge 2006/2007
[45] Z. Ma, F. Zhang, L. Yan, J. Cheng, Fuzzy Knowledge Management for the Semantic Web, in: Fuzzy ontology knowledge bases storage in fuzzy databases, Springer, 2014, pp. 233–242.
[46] S. Madden, From databases to big data, IEEE Internet Comput. 16 (3) (2012) 0004–6.
[47] A. Maedche, S. Staab, Ontology learning for the semantic web, IEEE Intell. Syst. 16 (2) (2001) 72–79.
[48] C. Martinez-Cruz, C. Porcel, J. Bernabé-Moreno, E. Herrera-Viedma, A model to represent users trust in recommender systems using ontologies and fuzzy linguistic modeling, Inf. Sci. 311 (2015) 102–118.
[49] N. Marz, J. Warren, Big Data: Principles and Best Practices of Scalable Realtime Data Systems, Manning Publications Co., 2015.
[50] S. Massanet, J.V. Riera, J. Torrens, E. Herrera-Viedma, A new linguistic computational model based on discrete fuzzy numbers for computing with words, Inf. Sci. 258 (2014) 277–290.
[51] V. Mayer-Schönberger, K. Cukier, Big Data: A Revolution that will Transform How We Live, Work, and Think, Houghton Mifflin Harcourt, 2013.
[52] J. Morente-Molinera, I. Pérez, M. Ureña, E. Herrera-Viedma, On multi-granular fuzzy linguistic modeling in group decision making problems: a systematic review and future trends, Knowl.-Based Syst. 74 (2015) 49–60.
[53] T. O'reilly, What is web 2.0, "O'Reilly Media, Inc.", 2009.
[54] W. Pedrycz, Granular Computing: Analysis and Design of Intelligent Systems, CRC Press, 2013.
[55] D.-H. Peng, T.-D. Wang, C.-Y. Gao, H. Wang, Multigranular uncertain linguistic prioritized aggregation operators and their application to multiple criteria group decision making, J. Appl. Math. 2013 (2013) 1–13.
[56] I. Pérez, R. Wikström, J. Mezei, C. Carlsson, E. Herrera-Viedma, A new consensus model for group decision making using fuzzy ontology, Soft Comput. 17 (9) (2013) 1617–1627.

[57] I.J. Pérez, F.J. Cabrerizo, S. Alonso, E. Herrera-Viedma, A new consensus model for group decision making problems with non-homogeneous experts, IEEE Trans. Syst., Man, Cybern.: Syst. 44 (4) (2014) 494–498.
[58] I.J. Pérez, F.J. Cabrerizo, E. Herrera-Viedma, A mobile decision support system for dynamic group decision-making problems, IEEE Trans. Syst., Man Cybern., Part A: Syst. Humans 40 (6) (2010) 1244–1256.
[59] I.J. Pérez, F.J. Cabrerizo, E. Herrera-Viedma, A mobile group decision making model for heterogeneous information and changeable decision contexts, Int. J. Uncertain., Fuzziness Knowl.-Based Syst. 19 (2011) 33–52.
[60] C. Porcel, E. Herrera-Viedma, Dealing with incomplete information in a fuzzy linguistic recommender system to disseminate information in university digital libraries, Knowl.-Based Syst.s 23 (1) (2010) 32–39.
[61] A. Rahimi, S.-T. Liaw, J. Taggart, P. Ray, H. Yu, Validating an ontology-based algorithm to identify patients with type 2 diabetes mellitus in electronic health records, Int. J. Med. Inf. 83 (10) (2014) 768–778.
[62] C. Reh, A. Héritier, E. Bressanelli, C. Koop, The informal politics of legislation explaining secluded decision making in the european union, Com. Political Stud. 46 (9) (2013) 1112–1142.
[63] M. Samwald, K.-P. Adlassnig, The bio-zen plus ontology, Appl. Ontol. 3 (4) (2008) 213–217.
[64] M. Samwald, J.A.M. Giménez, R.D. Boyce, R.R. Freimuth, K.-P. Adlassnig, M. Dumontier, Pharmacogenomic knowledge representation, reasoning and genome-based clinical decision support based on OWL 2 DL ontologies, BMC Med. Inf. Decis. Mak. 15 (1) (2015) 12.
[65] D. Sánchez, M. Batet, D. Isern, Ontology-based information content computation, Knowl.-Based Syst. 24 (2) (2011) 297–303.
[66] Á. Tejeda-Lorente, C. Porcel, E. Peis, R. Sanz, E. Herrera-Viedma, A quality based recommender system to disseminate information in a university digital library, Inf. Sci. 261 (2014) 52–69.
[67] J. Trant, Studying social tagging and folksonomy: a review and framework, J.Digit. Inf. 10 (1) (2009) 1–42.
[68] R. Ureña, F. Chiclana, J. Morente, E. Herrera-Viedma, Managing incomplete preference relations in decision making: a review and future trends, Inf. Sci. 302 (2015) 14–32.
[69] J. Wu, F. Chiclana, A social network analysis trust–consensus based approach to group decision-making problems with interval-valued fuzzy reciprocal preference relations, Knowl.-Based Syst. 59 (2014) 97–107.
[70] Y. Xing, L. Li, Z. Bi, M. Wilamowska-Korsak, L. Zhang, Operations research (or) in service industries: a comprehensive review, Syst. Res. Behav. Sci. 30 (3) (2013) 300–353.
[71] R.R. Yager, On ordered weighted averaging aggregation operators in multicriteria decisionmaking, IEEE Trans. Syst., Man Cybern. 18 (1) (1988) 183–190.
[72] R.R. Yager, Connectives and quantifiers in fuzzy sets, Fuzzy Sets Syst. 40 (1) (1991) 39–75.
[73] R.R. Yager, An approach to ordinal decision making, Int. J. Approx. Reason. 12 (3) (1995) 237–261.
[74] R.R. Yager, Quantifier guided aggregation using OWA operators, Int. J. Intell. Syst. 11 (1) (1996) 49–73.
[75] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (3) (1965) 338–353.
[76] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning-I, Inf. Sci. 8 (3) (1975) 199–249.
[77] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning-II, Inf. Sci. 8 (4) (1975) 301–357.
[78] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning-III, Inf. Sci. 9 (1) (1975) 43–80.
[79] A.H. Zai, S. Kim, A. Kamis, K. Hung, J.G. Ronquillo, H.C. Chueh, S.J. Atlas, Applying operations research to optimize a novel population management system for cancer screening, J. Am. Med. Inf. Assoc. 21 (e1) (2014) e129–e135.
[80] F. Zhang, Z. Ma, G. Fan, X. Wang, Automatic fuzzy semantic web ontology learning from fuzzy object-oriented database model, in: Database and Expert Systems Applications, Springer, 2010, pp. 16–30.