Semantic Granularity for the Semantic Web

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Abstract. In this paper we describe a framework for the application of semantic granularities to the Semantic Web. Given a data *source* and an ontology formalizing *qualities* which describe the source, we define a dynamic granularity system for the navigation of the repository according to different levels of detail, i.e., granularities. Semantic granularities summarize the degree of informativeness of the qualities, taking into account both the individuals populating the repository, which concur in the definition of the implicit semantics, and the ontology schema, which gives the formal semantics. The method adapts and extends to ontologies existing natural language processing techniques for topics generalization.

1. Introduction

Semantic Web is rising as an extension of the current Web to provide sophisticated and powerful inferences improving the accessibility to web content. In the traditional web, the huge amount of results returned by a search completely overwhelms the user's capability to exploit the represented information. The difficulties pertaining to information access are mainly due to a poor overlap between the information model employed by the user (i.e., the Cognitive Space) and the model defined by the information provider the information (i.e., the Information Space) [1]. Techniques of semantic searching as those proposed in [2] can be useful to improve the retrieval mechanism. However, in order to increase the aforementioned overlapping, every search activity has to be characterized by a highly interactive process [3]: the seeker refines the selection criteria according to the results he/she obtains alternating querying and browsing activities.

To reduce the consequences of information overload and the effects of the zero-hit problem, granularities may provide a valid help. Granularities allow exploring data according to different levels of detail, enhancing the flexibility in the information representation and retrieval. In the area of Information Systems, granularities have been already studied for both the temporal and the spatial domains [4,5,6]. However, in this field, granularities are static and embedded in the data model or in the database schema. The recent research has focused mainly on cognitive issues pertaining to the perception of vagueness, indeterminacy, imperfection, roughness, etc. [7]. Moreover,

some attempts to define semantic granularities have been made with respect to terminologies by Fonseca et al. [8]. They introduced the term semantic granularity exploiting the casting mechanism employed in the object-oriented paradigm to represent ontology instances at different levels of detail.

In this work we inspect how ontologies can be adopted to define *semantic granularities* aiming at browsing. Ontologies are fated to play a central role in the Semantic Web. However, to build them is a costly and time consuming activity. Thus we consider a complete exploitation of such a precious artifact as a primary research issue. This work is conceived as a step in this direction: ontologies representing *qualities* which describe information *sources* and the relations among them provide the starting point from which to build the granularity system. The user is expected to access the repository by using increasing granularities, which correspond to increasing detailed qualities. The resources are grouped according to the granularity chosen.

Automatic techniques such as clustering and classification can be employed to organize repositories and to ease their browsing. The clustering only relies on the model emerging from the Information Space, whereas the classification relies on a set of classes which are expected to be meaningful as belonging to the user's Cognitive Space. On the contrary, the semantic granularity takes into account both the spaces. It considers part of the Cognitive Space represented in the ontology as well as the Information Space by balancing the sources at a given granularity according to their occurrence. In this work semantic granularities are defined dynamically, according to the data model (represented by an ontology schema) as well as to data (represented as ontology instances).

The method proposed follows a two-phase process. In the first phase, namely *quality filtering*, each quality is evaluated with respect to its capability of abstracting sources. This evaluation is given taking into account both the relations in which the quality is involved, and the sources defined for it. Then, the qualities which provide a satisfactory facility to abstract sources become *granules* of some granularity. The second phase, namely *granularity building*, distributes the granules returned by the filtering phase among different granularities. This phase returns the set of granularities to employ for the repository navigation.

The contribution of the paper is twofold. First, we propose semantic granularities as a mean to browse the Semantic Web content at different levels of detail. Secondly, we provide an approach to automatically define semantic granularities extending to ontologies and repository navigation previous research results presented for topics identification [9] and automatic discourse structuring [10].

In the following, we consider the browsing of a repository of papers to exemplify the proposed methodology and its objectives. Scientific papers are considered as the sources to be navigated, whereas their topics are the quality of interest.

The paper is organized as follows. In Section 2 we formalize semantic granularities. In Section 3 and 4 we discuss how semantic granules and granularities are built, describing quality filtering and granularity building phases. In Section 5 we provide an example of repository navigation. Finally, Section 6 concludes the paper, outlining future research directions.

2. Semantic Granularities

Semantic granularities aim at structuring a repository at different levels of detail taking into account both its conceptual structure and its content. Assuming the following entities are available:

> **S**, the set of sources subject of the user exploration;
> **Q**, a quality represented as set of nominal values according to which the sources are organized;
> **O**, an ontology providing a data schema, where the sources and the quality are represented in terms of ontology entities;

the framework generates a *sequence* of granularities $G = <G_1, G_2, ..., G_n>$, such that each granularity G_i groups the sources the repository contains at increasing levels of detail, i.e., G_{i+1} gives a finer view on the sources in **S** than G_i (G_{i+1} is said to be *finer than* G_i). A granularity G_i is defined as a set of granules which provide a discrete view of the quality. A generic granule in G_i is denoted by g^{Gi}_j, and is described by a unique textual label $l^{Gi}_j \in$ **Q**. The granule labels are expected to be semantically meaningful for the user.

Let g^{Gi}_j be a granule at granularity G_i, the sources in **S** defined for g^{Gi}_j are denoted with s^{Gi}_j, whereas the sources defined for all the granules of granularity G_i are denoted with s^{Gi}. Let's consider for example a granularity G_i identifying scientific fields, such that the labels of its granules are $l^{Gi}_1 =$ *"Computer Science"*, $l^{Gi}_2 =$ *"Mathematics"*, $l^{Gi}_3 =$ *"Philosophy"*, etc., and a repository **S** of scientific papers classified with respect to their topics. Then, s^{Gi}_1 denotes the set of papers on Computer Science, s^{Gi}_2 the set of papers on Mathematics, and so on. Given two granules of the same granularity G_i we do not require that the corresponding sets of sources are disjoint. For instance, $s^{Gi}_1 \cap s^{Gi}_2$ gives the set of papers on topics shared by Mathematics and Computer Science.

The approach we propose assumes the repository is organized according to an ontology which recalls the pattern depicted in Fig. 1. In Fig. 1, IO is the relation Instance-Of; Is-A and Part-Whole are partial order relations; entities with capital initials are classes; $s_1, s_2, s_3, q_1, q_2, .., q_n$ are instances; F_1, F_2, A_1, A_2 are other class properties, which might be employed to further characterize the sources and the qualities. In particular, we assume the existence of a class grouping all the sources **S** the user is going to browse (**Source** in Fig. 1); a class representing the quality **Q** with respect to structuring the repository (**Quality** in Fig. 1); and a relation, which joins the sources s_1, s_2, s_3, etc. to the instances $q_1, q_2, .., q_n$ representing the quality values (rel in Fig. 1). Given for instance the granularity G_i representing scientific fields we defined above, and the set **S** of scientific papers on those fields, the papers in **S** are sources to browse, which will be reorganized according to a quality *topics* (i.e., the granules in G_i). The **Quality** *Topic* is defined for the **Source** *Paper* through the relation *hasTopic*.

Futhermore, we assume a hierarchy H^Q is induced by the relations Is-A and Part-Whole relating the qualities $Q_1, Q_2, …, Q_n$ in Fig. 1.
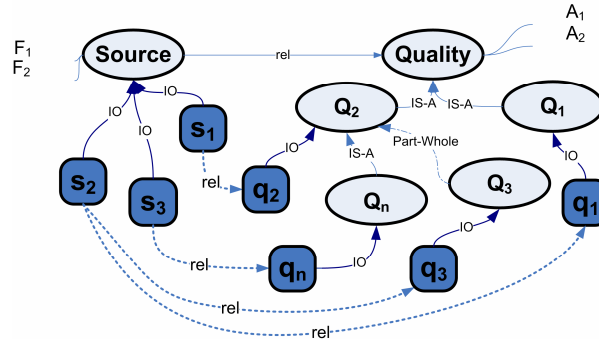
Fig. 1. The Ontology reference schema

Part-Whole and similar relations among parts and wholes have been widely investigated by the scientific literatures (e.g., [11,12,13]). The literature demonstrates that distinct parthood relations can be identified depending on how the parts differently contribute to the structure of the whole. A complete treatment of the issues concerning parts and wholes is beyond the scope of this work, thus we restrict the possible interpretations of the relation Part-Whole assuming the parthood among the qualities in **Q** adheres to the following properties defined in [11]:

- *transitivity*, i.e., parts of parts are parts of the whole;
- *reflexivity*, i.e., every part is part of itself;
- *antisymmetricy*, i.e., nothing is a part of its parts;
- *homeomericity*, i.e., parts are of the same kind of things as their wholes.

The first three properties induce the partial order needed to preserve the hierarchical structure of the qualities. The fourth property instead ensures the parts in the hierarchy are still a quality as their whole (e.g., a topic can be part of another topic).

We observe that the entities in Fig. 1 can be represented differently according to the ontology design choices. The solution adopted mainly depends on the expressiveness of the ontology language employed and the needs pertaining to the reasoning. For simplicity, the paper assumes classes in the hierarchy can not be used as relation values, i.e., the relations have only instance values. Similar assumptions have been made also by OWL-DL[1], one of the ontology language most adopted. As consequence of the latter assumption, the qualities are represented both as classes and instances, and each class Q_n has exactly one instance q_n. We introduce these restrictions to simplify the presentation of our method, but the approach could be easily adapted to different ontology designs.

Given the ontology schema in Fig. 1, the qualities in **Q** are related by a partial order $\leq_Q$ induced by H^Q according to both Is-A and Part-Whole. Since the granule labels correspond to qualities in **Q**, $\leq_Q$ is defined also on labels. Note that not all the values in **Q** become granule labels for some G_i in **G**, but only those resulting from the phase of quality filtering described in Section 3. Given a quality Q in **Q**, the set of sources s^Q are the instances of **S** associated via rel to Q, while the set of sources s^{Q*} are the instances of **S** associated via rel to Q and to each quality Q' such that $Q' \leq_Q Q$. For

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example, considering the quality Q_2 in Fig. 1, s^{Q2} corresponds to $\{s_1\}$, whereas s^{Q2*} corresponds to the set of instances $\{s_1, s_2, s_3\}$.

Given the granule g^{Gi}_j at granularity G_i, such that $Q = l^{Gi}_j$, note that s^{Gi}_j is equivalent to s^{Q*}. Let G_1 and G_2 be two granularities belonging to $\mathbf{G}$, such that G_2 is finer than G_1. Given g^{G1}_j a valid granule of G_1, we denote with $G_2(g^{G1}_j)$ the set of granules of G_2 which labels are related to l^{G1}_j through $\leq_Q$, i.e., $\{g^{G2}_k \mid l^{G2}_k \leq_Q l^{G1}_j\}$. Analogously, given g^{G2}_k a valid granule of G_2, we denote with $G_1(g^{G2}_k)$ the set of granules of G_1 $\{g^{G1}_j \mid l^{G2}_k \leq_Q l^{G1}_j\}$. Through this notation, we can move from a granularity to a different one. For instance, let's consider G_i the granularity for scientific fields defined above, g^{Gi}_1 the granule for Computer Science, and G_{i+1} a granularity finer than G_i; $G_{i+1}(g^{Gi}_1)$ results in all the granules representing the sub-fields in which Computer Science can be expanded into (e.g., Database, Artificial Intelligence, Computer Graphics, etc.)

In the following sections, we will detail how granularities to browse the sources are built starting from information sources defined with respect to a set of qualities. Firstly, the phase *quality filtering* (described in Section 3) evaluates which qualities can be employed as granule labels. Then, in the phase *granularity building* (described in Section 4)*,* granules representing qualities are assigned to different granularities.

3. Quality Filtering: Selection of Semantic Granules

The filtering selects the quality values to be adopted as granule labels. In the proposed approach, a quality value is considered as a granule label whenever it ensures a good level of abstraction or it is involved in Part-Whole.

The idea we adopt to evaluate the abstraction capability of qualities is borrowed from existing techniques applied in the area of Natural Language Processing for topic identification and generalization [9,10]. Lin [9] introduced the notion of degree of informativeness and summarization of a concept C in a lexical taxonomy as a measure of the capability of C to generalize its specializations, i.e., the children in the taxonomy, according to the terms occurrence in a corpus. According to Lin, the more the children of C have a similar number of occurrences, the more the concept C is a good generalization. The Lin algorithm is based on the assumption that the occurrences of the corpus are associated only to the leaves in the noun taxonomy.

Pike and Gahegan [10] extend the Lin's approach to identify and to abstract arguments of a discourse allowing the intermediate concepts of the taxonomy to have their own occurrences associated. Both works consider only the relation Is-A for structuring concepts, and ignore the occurrence of the concept C in the corpus for the evaluation of its degree of informativeness.

Given the schema of Fig. 1, to evaluate the degree of informativeness of a quality Q aiming at the definition of *semantic granularities*, we consider each source related through rel to Q as an occurrence of Q. We extend the method proposed by Pike and Gahegan to Part-Whole structures, taking into account also the influence of the occurrences of each quality under evaluation. Consider for instance the situation in Fig. 2, where we report a portion of a possible classification of the topics pertaining to

the Data Mining research field. The values reported have been retrieved by querying the ACM digital library[2] and considering qualities as paper keywords.
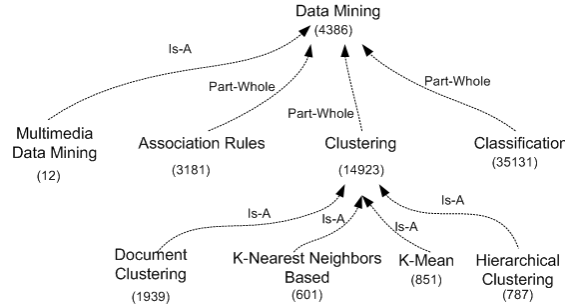

Fig. 2. Data Mining topics classification

In Fig. 2, Clustering has four unbalanced sub-topics, i.e., Document Clustering, K-Nearest Neighbors Based, K-Mean, and Hierarchical Clustering. According to both Lin-Pike's approach, Clustering does not provide a high level of generalization of its sub-topics. However, we observe that for Clustering a considerable amount of instances has been retrieved (14923), and this value is much bigger than the values reported for its sub-topics. In this situation, we would expect that this concept is eligible to be included among the most meaningful topics the repository refers to.

Given the aforementioned observations, we say that a quality Q is a *good abstraction* for its direct sub-qualities (including, as we specify above, both the qualities reachable through Is-A and Part-Whole) if the ratio R_Q between the maximum numbers of occurrences in the repository defined for its sub-qualities and the recursive number of occurrences defined for Q in the repository (i.e., including both its own occurrences and the recursive occurrence of its immediate sub-qualities) is less then a given a threshold R_t. R_Q is defined in (1) and its value ranges in [0,1]. Leafs in the hierarchy have R_Q equal to 0. We denote with $\prec_Q$ the non-reflexive and non-transitive relation induced by H^Q (e.g., referring to Fig. 2, Multimedia Data Mining $\prec_Q$ Data Mining, Association Rules $\prec_Q$ Data Mining, K-mean $\prec_Q$ Clustering). R_Q is defined as follows:

$$R_Q = \frac{\max_{\{Q'|Q'\prec_Q Q\}} |s^{Q'*}|}{\sum_{\{Q'|Q'\prec_Q Q\}} |s^{Q'*}| + s^Q} \tag{1}$$

Let us consider in Fig 2 the topics Association Rule, Classification and Clustering, which are related to Data Mining through the relation Part-Whole. Conversely to Is-A, we consider Part-Whole as a landmark for granule identification, because it intrinsically discriminates two separate levels of abstraction. Thus whenever two qualities are directly related by Part-Whole they are considered as granules of distinct granularities.

In the next section, we adopt the predicate *isGranule(Q,Rt)* to determine if the quality Q is promoted to be a granule according to the quality filtering phase. The predicate

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[2] http://portal.acm.org/ (accessed in March 2006).

isGranule(Q,R_t) is true whenever Q is involved in a Part-Whole, or it is a good abstraction, i.e. $R_Q \leq R_t$ where R_Q is defined according to (1).

4. Granularity Building: Distribution of Granules in Granularities

The granularity building phase aims at determining the distribution of the granules resulting from quality among the semantic granularities in *G*.

The partial order $\leq_Q$ induced by the relations Is-A and Part-Whole leads such a distribution. In particular, considering two distinct granule labels *a* and *b,* the principles we follow are:

    (1) if *b* $\leq_Q$ *a,* then the two granules have to belong to distinct granularities,

    (2) if *b* $\leq_Q$ *a, b* Part-Whole *a* holds and the whole granule with label *a* belongs to the granularity G_i, then the part granule with label *b* has to belong to the granularity G_{i+1}, such that G_{i+1} is finer than G_i.

Given for instance the hierarchy of Fig. 2, if Data Mining, Clustering and Document Clustering satisfy the predicate *isGranule* for a given value of R_t, and Data Mining belongs to granularity G_i, Clustering must belong to granularity G_{i+1}, while Document Clustering must belong to a granularity G_j, with $j > i+1$.

The granularity building phase is performed according to the algorithm in Fig. 3. The algorithm returns the sequences of granularities *G.* It performs a breath first visit of H^Q, inserting the granules in distinct granularities according to the principles stated in (1) (2). It terminates whenever the visit has reached all the H^Q leaves.

In Fig. 3, *ds* is the starting level (from the root) in H^Q; R_t is the ratio threshold for the evaluation of the degree of informativeness of qualities; `next(Q)` returns the child of Q in H^Q; `node(l)` returns the qualities laying at the level `l` in the hierarchy; `+` and `−` are the set operators for union and difference.

```
i = 0; Gᵢ = {};
NodeToConsider = Node(ds);
While (! empty(NodeToConsider)){
  For each Q belonging to NodeToConsider {
    If  isGranule(Q, Rₜ) Gᵢ  += { Q };
    else If Q is not leaf NodeToConsider += next(Q);
    NodeToConsider -= { Q };
  }
  i++; Gᵢ = {};
  For each Q belonging to Gᵢ₋₁ {
    For j=1 to i-1 {  // check for multi-inheritance
      For each Q₁ belonging to Gⱼ
        If ((Q₁ part-whole Q) or (Q₁ is-a Q)){
          Gⱼ -= { Q₁ }; Gᵢ += { Q₁ };
        }
      If Q is not leaf
        NodeToConsider += next(Q);
    }
  }
}
```

Fig. 3. Granularity building algorithm

5. Example: Semantic Granularity Extraction for Scientific Papers

In this section we refer to the repository of scientific papers provided by the ACM Digital Library, considering papers as the information sources to be browsed and the associated keywords as sources qualities. In the ACM Digital Library each paper is classified according to the ACM Computing Classification System[3], which is a taxonomy depicting the broadest research fields in the computer science. To provide an example of semantic granularities extracted through its application, we extend the ACM taxonomy deepening the fields we are familiar with. A portion of this taxonomy has been already shown in Fig. 2. The classes in the resulting taxonomy are mainly related through the relation Is-A. Moreover, the relation Part-Whole has been adopted whenever a research field is classified with respect to its important sub-parts, like techniques applied in the field (e.g., Clustering and Data Mining in Fig. 2).

In Table 1 a meaningful portion of the quality hierarchy we consider and the results we obtained are shown. The first column of the table reports the quality values (the indentation resembles the H_Q structure); the second gives the number of papers referring to each quality in the ACM repository; the third column reports the degree of informativeness obtained by applying an approach based on what proposed in [9,10], while the fourth reports the values we obtain according to the evaluation we presented in Section 3; finally, the last column gives the granules distribution according to the phase granularity building we described in Section 4.

The threshold R_t we apply in this example is 0.50. With this evaluation of R_t the qualities Database Management, General, Logical Design, Transaction processing, Database application, Multimedia Data Mining and Spatio-Temporal Data Mining are not considered as granules because their degree of informativeness is greater than the threshold. Note that the granularities preserve the partial order given by the hierarchy among qualities related by Is-A and Part-Whole, but not the general order as stated by the hierarchy. In particular, qualities at the same level in the hierarchy can be labels for granules that belong to different granularities.

Let's suppose a user wants to navigate the sources in the repository. At the first step, the labels of the granules at granularity G_1 give him/her a broad idea of the most meaningful arguments represented in the repository (l^{G1}_1 is the label for the quality "Security, Integrity and Protection", l^{G1}_2 is the label for "Data Models", etc). Let's suppose the user chooses to navigate the resources related to Data Mining. The labels of granules at granularity G_2 such that $G_2(g^{G1}_{12})$, where g^{G1}_{12} is the granule with label "Data Mining", are retrieved. As we formally defined in Section 2, the conversion is based on the partial order induced by the hierarchy H^Q. Thus, the set of labels $l^{G2}_5=$ "Sound Analysis", $l^{G2}_6 =$ "Video Analysis", $l^{G2}_7 =$ "Temporal Data Mining", $l^{G2}_8 =$ "Spatial Data Mining", $l^{G2}_9 =$ "Text Mining", $l^{G2}_{10} =$ "Association Rules", $l^{G2}_{11} =$ "Classification", $l^{G2}_{12} =$ "Clustering", and $l^{G2}_{13} =$ "Visual Data Exploration" is retrieved. The same happens for all the levels for which a granularity has been built, according to the algorithm we described in Section 4. Once the user chooses the set of instances is interested in by the browsing of labels, the corresponding set of sources is retrieved. Let the user be interested in Document Clustering, represented by the granule g^{G3}_1. Then, the set of sources s^{G3}_1 is returned to be processed by applying, for instance, existing navigation

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[3] http://www.acm.org/class/1998/

techniques (e.g., see the information visualization tools surveyed in [14]).

Table 1. Method evaluation with $R_t = 0.50$

Qualities-Research Topics	# Occurences	LPG-Based	Rq	Gi (Rt=0.50)
Database Management	6320	0,7869	0,7572	
General	1162	1,0000	0,5888	
Security, Integrity, and Protection	1664	0,0000	0,0000	G1
Logical Design	1859	0,7355	0,5238	
Data models	3382	0,0000	0,0000	G1
Normal forms	197	0,0000	0,0000	G1
Schema and subschema	1019	0,0000	0,0000	G1
Physical Design	499	0,6918	0,4879	G1
Access methods	826	0,0000	0,0000	G2
Deadlock avoidance	158	0,0000	0,0000	G2
Recovery and restart	210	0,0000	0,0000	G2
Languages	1438	0,6887	0,4027	G1
Transaction processing	1194	0,0000	0,0000	
Heterogeneous Databases	163	0,6838	0,2857	G1
Database Administration	745	0,5736	0,4557	G1
Database Applications	2689	0,5407	0,5292	
Image databases	660	0,0000	0,0000	G1
Scientific databases	556	0,0000	0,0000	G1
Statistical databases	229	0,0000	0,0000	G1
Data mining	4386	0,5612	0,5244	G1
Multimedia data mining	12	0,8922	0,8697	
Sound Analysis	50	0,0000	0,0000	G2
Video Analysis	414	0,0000	0,0000	G2
Spatio-Temporal Data Mining	27	0,8922	0,8432	
Temporal Data Mining	47	0,0000	0,0000	G2
Spatial Data Mining	138	0,0000	0,0000	G2
Text Mining	409	0,0000	0,0000	G2
Association Rules **(Part-Whole)**	3181	0,0000	0,0000	G2
Classification **(Part-Whole)**	35131	0,0000	0,0000	G2
Clustering **(Part-Whole)**	14923	0,5718	0,1012	G2
Document Clustering	1939	0,0000	0,0000	G3
k-Nearest Neighbors Based	601	0,0000	0,0000	G3
k-Mean	851	0,0000	0,0000	G3
Hierarchical Clustering	787	0,5000	0,0025	G3
Visual Data Exploration	3066	0,5909	0,1075	G2
Information Visualization	403	0,0000	0,0000	G3
Visual Reasoning	279	0,0000	0,0000	G3
Spatial databases, GIS	1459	0,2531	0,2466	G1

6. Conclusions

In this paper we present a framework for the dynamic definition of semantic granularities aiming at the effective representation of a huge semantic web repository at different levels of detail. The method is inspired by existing work on topic identification for discourse structuring. With respect to existing methods in the literature, we extend them to the browsing of any kind of information sources described with respect to a set of qualities represented in ontologies. We encompass the generalization performed according to a taxonomy, dealing also with qualities related by Part-Whole, towards a full ontology support. Furthermore, we provide a definition of semantic granularity which is dynamic, providing a bridge among the conceptual model of the user (i.e., the Cognitive Space) and the model structuring the repository (i.e., the Information Space).

Semantic granularities provide a way of supporting the user in the Semantic Web browsing at different levels of detail. For each granularity only the meaningful

granule labels for the specific repository are represented. Thus, the sources having qualities the user is not interested in can be discarded since the very first steps of the browsing. Semantic granularity is defined with respect to ontologies, aiming at fully exploiting the information this formal conceptualization can provide. A crucial extension is related to the inclusion of properties of ontology classes and their values in the evaluation of the degree of informativeness of qualities. We are also planning an experimental evaluation performed on multimedia sources (text, shape, etc.). Finally, we are going to integrate the method with traditional techniques of resource browsing (e.g., information visualization).

Acknowledgement

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