MGsP: Extending the GsP to Support Semantic Interoperability of Geospatial Datacubes

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Abstract. Data warehouses are being considered as substantial elements for decision support systems. They are usually structured according to the multidimensional paradigm, i.e. datacubes. Geospatial datacubes contain geospatial components that allow geospatial visualization and aggregation. However, the simultaneous use of multiple geospatial datacubes, which may be heterogeneous in design or content, drives to consider interoperability between them. Overcoming the heterogeneity problems has been the principal aim of several research works for the last fifteen years. Among these works, the geosemantic proximity notion (GsP) represents a qualitative approach to measure the semantic similarity between geospatial concepts. The GsP, which has been defined in the transactional context, and can be used to a certain extent in the multidimensional paradigm, needs to be revisited to be more suitable for this paradigm. This paper proposes an extension to the GSP notion in order to support the semantic interoperability between multidimensional geospatial datacubes. The extension, called MGsP, aims to give the possibility to dig into and resolve semantic heterogeneity related to key notions of the multidimensional paradigm.

Keywords: Geospatial datacubes, interoperability, semantic heterogeneity, ontology.

1 Introduction

Over the last decades, there has been an exponential increase in the amount of data being stored electronically and available from multiple sources. Furthermore, there have been significant innovations in information technology, especially in database technologies, decision support systems (DSS), knowledge discovery, and automatic communication between information systems. Data warehouses are being considered as efficient components of decision support systems [6] and [2]. Data warehouses are databases which are designed to supply DSS with data at different levels of aggregation. They are often structured according to the multidimensional paradigm, which facilitates a rapid navigation within the different levels of data granularity (from a coarser level to a finer level and vice versa). As such, users can rapidly get a global picture of a phenomenon, get more insight into that phenomenon information,

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compare with other phenomena, or analyse its evolution over time [2]. Thus, using the multidimensional paradigm, data warehouses provide the basis for decision making and problem solving in organizations. Multidimensional databases, hereafter called datacubes, allow users to navigate aggregated data according to a set of dimensions with different levels of hierarchy [6], [2], and [12]. Geospatial datacubes contain geospatial components that allow geospatial visualization and aggregation. Geospatial datacubes are becoming more widely used in the geographic field [2] and [12].

One may need to use several scattered geospatial datacubes at the same time. For example, users may need to simultaneously navigate through different geospatial datacubes, to create a new geospatial datacube from existing scattered ones, or to insert information in one geospatial datacube from the content of another one. For example, in order to analyze the risk of the West Nile virus on the population of Canada and USA, we may need to use two datacubes containing the location of dead birds in south-east of Canada, and in north-east of USA, respectively.

Interoperability has been widely recognized as an efficient paradigm for simultaneously (re)using heterogeneous systems by facilitating an efficient exchange of information [3], [4], and [8]. It deals with the heterogeneity of different kinds (e.g., technical, organizational, and semantic heterogeneities). An example of semantic heterogeneity is the fact that the concept *forest* may be represented, with different geometries, as vegetations, as trees, or as wooded areas. Resolution of semantic heterogeneity is considered as a significant challenge for interoperability [8] and [4]. Such a resolution consists basically of comparing different concepts and measuring the semantic similarity between them. Many researchers have been interested in measuring the semantic similarity between geospatial concepts, and different solutions have been proposed [3], [13], [4], [11], and [10]. Among these solutions, the Geosemantic proximity notion (GsP), proposed by [4], allows to qualitatively evaluate the semantic similarity of geospatial concepts.

While the GsP notion can be used to a certain extent to support the interoperability between geospatial datacubes, the efficiency of such interoperability can be improved by extending this notion. This paper revisits the GsP notion, and proposes an extension to this notion in order to offer a more suitable support for the interoperability between geospatial datacubes.

In the next section, we review the interoperability between geospatial datacubes. In section 3, we review the GsP notion. The, in section 4, we propose an extension of the GsP notion. We conclude and present further works in section 5.

2 Semantic Interoperability between Geospatial Datacubes

2.1 Geospatial Datacubes

Data warehouses are being considered an integral part of modern decision support systems [6], [2], and [12]. They are designed to supply these systems with data at different levels of aggregation. Data warehouses may be structured as datacubes, i.e. according to the multidimensional paradigm. A datacube is composed of a set of measures aggregated according to a set of dimensions with different levels of granularity.

Geospatial datacubes integrate geospatial data with the datacube structure. Both dimensions and measures of a geospatial datacube may contain geospatial data [2]. Geospatial datacubes support the user's mental model of the data and help him/her to make strategic decisions [1] and [2]. In fact, they allow decision makers to interactively navigate through different levels of granularity so; they can get a global picture of a phenomenon, and can get more insight into that phenomenon detailed information. Moreover, geospatial datacubes contains geospatial data (e.g. geographic coordinates, map coordinates) which allow the visualization of phenomena and, hence, help to extract insights that can be helpful to understand these phenomena [1].

2.2 Interoperating Geospatial Datacubes

Interoperability has been generally defined as the ability of heterogeneous systems to communicate and exchange information and applications in an accurate and effective manner [3], [4], and [9].

Geospatial interoperability is considered here as the ability of information systems to a) communicate all kinds of spatial information about the Earth and about the objects and phenomena on, above, and below its surface, and b) cooperatively run applications capable of manipulating such information [14]. Semantic interoperability aims to provide a mutual understanding of different data representations. For geospatial information systems, we include the consideration about object's geometry in the semantic level since geometry is not inherent to objects but defined according to the needs of a given application.

In previous work we discussed the need for interoperating geospatial datacubes, we proposed a definition of the semantic interoperability between geospatial datacubes, and we proposed a categorization of semantic heterogeneity that may occur during such interoperability [16]. The categorization includes Cube-to-Cube heterogeneity, Fact-to-Fact heterogeneity, Measure-to- Measure heterogeneity, and Dimension-to-Dimension heterogeneity which involves hierarchy heterogeneity and level heterogeneity. At each one of the previous categories, semantic heterogeneity may be due to the difference in the description of concepts (e.g., the concept forest may be represented, with different geometries, as vegetations, as trees, or as wooded areas) and datacube schemas.

Normally, resolving the semantic heterogeneity of different concepts is done through a comparison of theirs semantics. This is usually done by reconciling two or more heterogeneous ontologies which can be carried out by mapping, aligning or merging these ontologies [7]. In the context of geographic databases, many researchers have been interested in measuring the semantic similarity between geospatial concepts to support the interoperability process. Examples of research works are: the Semantic Formal Data Structure model [3], the Matching Distance model [13], the semantic matchmaking for geographic information retrieval [11], the geosemantic proximity notion (GsP) [4], and the similarity-based information retrieval approach [10]. In order to support the semantic interoperability between geospatial datacubes, and after reviewing these works, we chose the GsP notion, which allows to qualitatively evaluate the semantic similarity between geospatial concepts (i.e., similarities between their intrinsic and extrinsic properties).

The choice of this notion is explained by the fact that 1) the GsP was successfully tested for supporting the interoperability process between software agents in geospatial context, 2) the GsP is based on human-like communication which we believe it is the ideal paradigm for the interoperability process, and 3) the availability of the source code from previous work conducted in our research team [5], and the possibility to adapt it to the interoperability of geospatial datacubes.

3 Revisiting the GsP Notion

GsP evaluates qualitatively the semantic similarity between geospatial concepts. It compares the inherent properties of one concept with another. These properties are classified in two types: intrinsic and extrinsic. Intrinsic properties provide the literal meaning of a concept. They consist of the identification, the attributes, the attribute values, the geometries, the temporalities, and the domain of the concept. Extrinsic properties are properties that are subject to external factors (e.g., behaviours and relationships). The semantic of a geospatial concept is defined by the union of intrinsic and extrinsic properties. Then, the GsP of two concepts can be defined by the intersection of their respective properties. It results in a four-intersection matrix when consolidated with intrinsic and extrinsic properties [4]. Each component of the matrix can be evaluated empty (denoted by f or false) or not empty (denoted by t or true). Accordingly, 16 predicates were derived. The predicates are:

> GsP_ ffff (or disjoint), GsP_ffft, GsP_fftt (or contains), GsP_tfft (or equal), GsP_ftft (or inside), GsP_tftt (or covers), GsP_ttft (or coveredBy), GsP_fttt (or overlap), GsP_tttt, GsP_tfff (or meet), GsP_tftf, GsP_tttf, GsP_ttff, GsP_fttf, GsP_fftf, GsP_ftff [4].

In order to experiment GsP notion, Brodeur et al. developed the GsP tool which imitate human communication to support geospatial interoperability [5]. It depicts a communication process, which takes place between two software agents interacting through a communication channel.

In GsP, software agents (a source and destination) exchange concept representations between them. In order to resolve the semantic heterogeneity between a source concept and a destination concept, the intrinsic and extrinsic properties of the respective representations are compared. The comparison is proceeded until there are two equal concepts (‘‘GsP_tfft’’) is found or all concepts are visited. When the comparison is completed, the concepts having a GsP different from ‘‘GsP_ffff’’ (or disjoint relationship) are then sorted from the highest to the lowest GsP [4].

4 Extending the GsP to Support Semantic Interoperability between Geospatial Datacubes

The hierarchical structure of dimensions and the dependencies between dimensions and measures induce several semantic conflicts specific to the multidimensional datacube. Notably, the semantic heterogeneity of aggregation of dimension levels, semantic heterogeneity of measure function, and the semantic heterogeneity of hyper-cells[1] [15] present a particular obstacle when interoperating different geospatial datacubes. Thus, we intend to enable agents (software agent or human stakeholder) to focus on resolving semantic heterogeneities related to those particular concepts.

For that, we propose an extension of the GsP notion to include the comparisons of basic multidimensional concepts such as the semantic of aggregation and the semantic of hyper-cell. The objective of this extension (called Multidimensional Geosemantic Proximity: MGsP) is to give agents the possibility to focus on the heterogeneity of multidimensional data by digging into more details about the semantic aspects of important notions of the multidimensional paradigm (e.g., aggregation, measure function, and hyper-cell). As such, agents can concentrate on the multidimensional characteristics and make appropriate decisions with regards to their semantic similarity. Accordingly, we define three attributes to specialize the GsP: dimension aggregation, measure function, and hyper-cell. We should note that we chose these attributes as examples to illustrate the usefulness of the GsP extension for the interoperability between geospatial datacubes. This choice is motivated by the wide use of these attributes in the multidimensional paradigm. One can add other attributes if needed.

As in GsP, our methodology for qualitatively evaluating the semantic similarity consists of identifying the relations between the semantics of multidimensional elements of geospatial datacubes (e.g., dimension or measure). The semantics of each multi-dimensional element is evaluated as the union of the properties related to the measure function (or dimension aggregation) and the properties related to the hyper-cell.

Let:

M: a measure

D: a dimension

MInP: a set of intrinsic multidimensional properties (for measure: $MInP = MInP_M$, whereas for dimension: $MInP = MInP_D$).

Where $MInP_M$ is the set of properties related to the measure function. The function is considered as intrinsic property since it refers to the meaning of the measure, and $MInP_D$ is the set of properties related to the aggregation. The aggregation is considered as intrinsic property since it refers to the meaning of the dimension.

MExP: a set of properties related to the hyper-cell. The hyper-cell refers to the dependencies of measures with dimensions. Thus, it is considered as extrinsic property for both dimensions and measures.

MS_M: Multidimensional semantics of measure.

MS_D: Multidimensional semantics of dimension.

Then:

$$MS_M = MInP_M \cup MExP$$
$$MS_D = MInP_D \cup MExP$$

[1] A hyper-cell is a combination of a set of levels and measures of a datacube.

Then, the multidimensional geosemantic proximity (MGsP) is determined according to the intersection between the semantic of two elements (E1 and E2) of heterogeneous datacubes.

Let:

MS_{E1}: Multidimensional semantics of E1.

MS_{E2}: Multidimensional semantics of E2.

MGsP (E1, E2): Multidimensional Geosemantic proximity between E1 and E2.

Then:

$$MGsP\ (E1,E2) = MS_{E1} \cap MS_{E2}$$

Accordingly, we define a 4-Intersection matrix containing the following four topological sub-relations. In this matrix:

$MInP_E \in InP_E$ (the properties related to the measure function (or to the aggregation) belong to the intrinsic properties defined in GsP);

$MExP_E \in ExP_E$ (the properties related to the hyper-cell belong to the extrinsic properties defined in GsP).

Thus, MGsP's matrix is a specialization of the one defined in the GsP, allowing agents to dig into more details of the multidimensional characteristics of geospatial datacubes (see Figure 1).

$$\underline{\textbf{GsP}}\quad \begin{pmatrix} ExP_{E1} \cap GExP_{E2} & ExP_{E1} \cap InP_{E2} \\ InP_{E1} \cap ExP_{E2} & InP_{E1} \cap InP_{E2} \end{pmatrix} \Rightarrow \underline{\textbf{MGsP}}\quad \begin{array}{c|cc} & MExP_{E2} & MInP_{E2} \\ \hline MExP_{E1} & MExP_{E1} \cap MExP_{E2} & MExP_{E1} \cap MInP_{E2} \\ MInP_{E1} & MInP_{E1} \cap MExP_{E2} & MInP_{E1} \cap MInP_{E2} \end{array}$$

Fig. 1. 4-intersection multidimensional matrix as a specialization of the GsP

Since we consider the measure function as an attribute of the measure's intrinsic properties, whereas the hyper-cell as an attribute of the measure's extrinsic properties, we define a 4-Intersection matrix for measure as follows:

$$\begin{array}{c|cc} & hyper\_cell_{M2} & measure\_function_{M2} \\ \hline hyper\_cell_{M1} & hyper\_cell_{M1} \cap hyper\_cell_{M2} & hyper\_cell_{M1} \cap measure\_function_{M2} \\ measure\_function_{M1} & measure\_function_{M1} \cap hyper\_cell_{M2} & measure\_function_{M1} \cap measure\_function_{M2} \end{array}$$

Since we consider the aggregation as an attribute of the dimension's intrinsic properties, whereas the hyper-cell as an attribute of the dimension's extrinsic properties, we define the following 4-Intersection matrix for dimension:

$$\begin{array}{c c} & \begin{array}{cc} hyper\_cell_{D2} & aggregation_{D2} \end{array} \\ \begin{array}{c} hyper\_cell_{D1} \\ \\ aggregation_{D1} \end{array} & \begin{pmatrix} hyper\_cell_{D1} \cap & hyper\_cell_{D1} \cap \\ hyper\_cell_{D2} & aggregation_{D2} \\ aggregation_{D1} \cap & aggregation_{D1} \cap \\ hyper\_cell_{D2} & aggregation_{D2} \end{pmatrix} \end{array}$$

As in GsP, the comparison of properties of two elements (measures or dimensions) of heterogeneous datacubes could be evaluated empty (Ø or *f*) and non-empty (¬Ø or *t*) expressing respectively that none or some properties are common. This leads to 16 (i.e., 2^4) possible MGsP predicates for each matrix (see Figure 2).

If, for example, $hyper\_cell_{M1} \cap measure\_function_{M2}$ is ¬Ø (Ø), it indicates that the measure function of M2 fits (respectively does not fit) the hyper-cell of M1. In other words, it indicates that the measure function of M2 can be applied (respectively cannot be applied) to the set of measures to which M1 belongs. For example, the function *geometric union* of the measure *fire buffer* can be applied to the hyper-cell {fire zone}, {region, time, forest stand} of the measure *fire zone*.

If, for example, $hyper\_cell_{D1} \cap hyper\_cell_{D2}$ is ¬Ø (Ø), it indicates that the aggregation of D2 fits (respectively does not fit) the hyper-cell of D1. In other words, it indicates that both sets of levels and measures (i.e., hyper-cells) have (respectively does not have) common elements. For example, the hyper-cells {fire zone}, {region, time, fire class} and {fire zone}, {region, time, forest stand} have three common elements: {fire zone, region, time}.

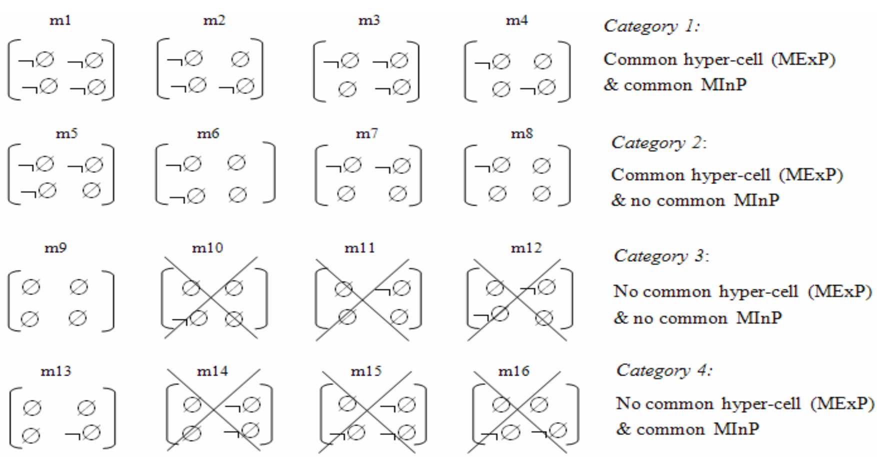

Fig. 2. 16 possible MGsP predicates of the GsP

In Figure 2, MGsP predicates are organized in four distinct categories according to four characteristics: common MExP and common MInP, common MExP and no common MInP, no common MExP and no common MInP, and no common MExP and common MInP.

1) The predicates of *category 1* refer to the case where both the functions and the hyper-cells of the heterogeneous measures are common. This category includes four possible matrixes:
   a. MGsP_tttt (E1, E2): $\begin{bmatrix} \neg\varnothing & \neg\varnothing \\ \neg\varnothing & \neg\varnothing \end{bmatrix}$
      In this particular case the function of M1 (respectively M2) fits the hyper-cell of M2 (respectively M1).
   b. MGsP_tftt (E1, E2): $\begin{bmatrix} \neg\varnothing & \varnothing \\ \neg\varnothing & \neg\varnothing \end{bmatrix}$
      In this case the function of M1 fits the hyper-cell of M2. However, the function of M2 does not fit the hyper-cell of M1.
   c. MGsP_ttft (E1, E2) : $\begin{bmatrix} \neg\varnothing & \neg\varnothing \\ \varnothing & \neg\varnothing \end{bmatrix}$
      In this particular case the function of M1 does not fit the hyper-cell of M2. However, function of M2 fits the hyper-cell of M1.
   d. MGsP_tfft (E1, E2): $\begin{bmatrix} \neg\varnothing & \varnothing \\ \varnothing & \neg\varnothing \end{bmatrix}$
      In this case the function of M1 (respectively M2) does not fit the hyper-cell of M2 (respectively M1).
2) The predicate of *category 2* refer to the case where the hyper-cells of the heterogeneous measures are common, whereas the functions are dissimilar. This category includes four possible matrixes:
   a. MGsP_tttf (E1, E2) : $\begin{bmatrix} \neg\varnothing & \neg\varnothing \\ \neg\varnothing & \varnothing \end{bmatrix}$
      In this particular case the function of M1 (respectively M2) fits the hyper-cell of M2 (respectively M1).
   b. MGsP_tftf (E1, E2) : $\begin{bmatrix} \neg\varnothing & \varnothing \\ \neg\varnothing & \varnothing \end{bmatrix}$
      In this case the function of M1 fits the hyper-cell of M2. However, function of M2 does not fit the hyper-cell of M1.
   c. MGsP_ttff (E1, E2) : $\begin{bmatrix} \neg\varnothing & \neg\varnothing \\ \varnothing & \varnothing \end{bmatrix}$
      In this particular case the function of M1 does not fit the hyper-cell of M2. However, function of M2 fits the hyper-cell of M1.
   d. MGsP_tfff (E1, E2): $\begin{bmatrix} \neg\varnothing & \varnothing \\ \varnothing & \varnothing \end{bmatrix}$
      In this case the function of M1 (respectively M2) does not fit the hyper-cell of M2 (respectively M1).

3) The predicates of *category 3* refer to the case where both the functions and the hyper-cell of the heterogeneous measures are dissimilar. We should note that in this case the function of M1 (respectively M2) should not fit the hyper-cell of M2 (respectively M1). Accordingly, we do not consider the matrix m10, m11 and m12 (see Figure 2):

   MGsP_ffff (E1, E2): $\begin{bmatrix} \varnothing & \varnothing \\ \varnothing & \varnothing \end{bmatrix}$

4) The predicates of *category 4* refer to the case where the hyper-cells of the heterogeneous measures are dissimilar, whereas the functions are similar. We should note that, in this case, since there is no intersection between the hyper-cells, the function of M1 (respectively M2) should not fit the hyper-cell of M2 (respectively M1). Accordingly, we do not consider the matrix m14, m15 and m16 (see Figure 2).

   MGsP_ffft (E1, E2): $\begin{bmatrix} \varnothing & \varnothing \\ \varnothing & \neg\varnothing \end{bmatrix}$

Ten resulting predicates are then defined for the MGsP of measures, which are: MGsP_tttt, MGsP_tftt, MGsP_ttft, MGsP_tfft, MGsP_tttf, MGsP_tftf, MGsP_ttff, MGsP_tfff, MGsP_ffff, and MGsP_ffft.

Similarly, we define the predicates for the MGsP of dimensions. The resulting predicates are the same ones as those for the measure element.

Using such attributes (e.g., hyper-cell, dimension aggregation, and measure function) agents can have a better idea about the semantic similarity of multidimensional concepts, and can make appropriate decisions about resolving the semantic heterogeneity that may occur between the elements of different geospatial datacubes. For example, if the functions of two semantically heterogeneous measures (e.g., *density* in a datacube C1 and *concentration* in a datacube C2) are completely different, agents may consider these measures are dissimilar even if they have other common characteristics (e.g., used for the same subject of analysis, represented with the same precision and having the same scale).

5 Conclusion

Resolution of semantic heterogeneity is considered as a significant challenge for interoperability. In order to resolve the semantic heterogeneity that may occur when interoperating geospatial datacubes, we extend the geosemantic proximity approach (GsP) which evaluates the semantic similarity of geospatial concepts. The GsP extension, called Multidimensional Geosemantic Proximity (MGsP), gives the possibility to focus on the heterogeneity of multidimensional data by digging into details about semantic characteristics of important notions of the multidimensional paradigm. The MGsP includes the semantics of basic multidimensional concepts such as the semantic of aggregation, the semantic of measure function and the semantic of hyper-cellability.

The MGsP extension was defined within a general research project, which was implemented to manage the risks of data misinterpretation during the semantic interoperability between geospatial datacube.

Further work is required to enhance the MGsP by defining more refined attributes. For example, for the aggregation attribute we can define the aggregation domain and aggregation constraint.

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