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GeoSemOLAP: Geospatial OLAP on the Semantic Web
Made Easy

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ABSTRACT
The proliferation of spatial data and the publication of mul-
tidimensional (MD) data on the Semantic Web (SW) has
led to new opportunities for On-Line Analytical Processing
(SOLAP) over spatial data using SPARQL. However, for-
mulating such queries results in verbose statements and can
easily become very difficult for inexperienced users. Hence,
we have developed GeoSemOLAP to enable users without
detailed knowledge of RDF and SPARQL to query the SW
with SOLAP. GeoSemOLAP generates SPARQL queries
based on high-level SOLAP operators and allows the user
to interactively formulate queries using a graphical interface
with interactive maps.

Keywords
Multidimensional RDF Data; Spatial OLAP; SPARQL

1. INTRODUCTION
The data that is currently available on the Semantic Web
(SW) has evolved from being simple, mostly alphanumeric,
to also include more complex data such as spatial data [6].
Although spatial data is common on the SW, it remains dif-
ficult to utilize and analyze because spatial data requires
special techniques for encoding it in RDF and evaluating
spatial functions, which are often not supported by standard
triple stores. On the other hand, the support of spatial data
is more common in the area of relational databases, where
spatial data warehouses are typically based on a multidimen-
sional (MD) relational model involving spatial dimensions.
Eﬃciently processing spatial data in this context is typically
realized by Online Analytical Processing (OLAP) extended
to support spatial analyses (SOLAP) [2].

However, with the growing popularity of the Linked Open
Data (LOD) movement in the public sector, more and more
spatial datasets from governmental domains [1] are becom-
ing available on the SW. The availability of such datasets
has led to novel opportunities for decision makers to ana-
lyze the growing public data with analytical data warehouse
queries on SW data [4]. However, these potential users are
only in very rare cases suﬃciently familiar with the underly-
ing technologies that are necessary to actually perform the
desired analyses.

Let us consider an example scenario: Fig. 1 shows a map
highlighting the amount of sales between customers (c1, c2,
..., c5) and suppliers (s1, s2, s3) in three Danish cities
(Sorø, Holbæk, Ringsted). Let us assume that an analyst
wants to obtain the total sales of customers grouped by cities
of their closest supplier – Query 1 shows the corresponding
example query formulated in SPARQL. This means that,
ﬁrst, for each customer we need to determine the closest
supplier and the city in which the supplier is located. Then,
we create one group for each of these cities and compute the
total sales per city.

For each sales event, the dataset contains information
about the involved customer and supplier; and for each cus-
tomer and supplier the dataset contains the city they are
located in. As the dataset does not contain any informa-
tion about the distances between customers and suppliers,
we have to use a spatial function (distance in this example)
and evaluate it during runtime.

Based on the obtained information, we can aggregate the
results as described above. Technically, this corresponds to
a SOLAP operator: s-roll-up [2, 5].

As we can see in Query 1, formulating a roll-up to a
higher level, e.g., from sales by supplier to sales by city, in a
SPARQL query involves several triple patterns. Extending
such a query with spatial aspects (as necessary for s-roll-
up) requires even more triple patterns and spatial functions
(such as distance), which can easily become overwhelming
for inexperienced users.

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2. QUERIES FOR SPATIAL SEMANTIC DATA WAREHOUSES

To formulate SPARQL queries automatically, GeoSemOLAP needs some information about what data is contained in the spatial data warehouse. Our current implementation uses metadata using the QB4SOLAP vocabulary\(^1\) [4, 5] for this purpose. In addition to MD data elements, QB4SOLAP also describes spatial concepts and builds upon existing vocabularies: QB\(^2\) and QB4OLAP\(^3\).

A QB4SOLAP data cube contains a set of observations. Its structure is defined through a data structure definition (DSD) describing standard concepts, such as dimensions, measures, hierarchies, hierarchy steps, levels, and level attributes, as well as spatial concepts, such as spatial aggregate functions, topological relations, spatial attributes, and spatial measures.

Let us consider an example of a company (Northwind) that exports a number of goods. The company records its sales data in a spatial data warehouse, which is based on an MD model enabling analyses of sales according to their geographical distribution. The company decides to share the data warehouse on the Semantic Web for further analysis of its sales (e.g., involving economic and demographic data published as Open Data on the Web) to provide access to all branches as well as customers and suppliers. Fig. 2 illustrates an example schema of the company’s spatial data warehouse.

The example query from Section 1 (Query 1: “Total sales to customers grouped by city of their closest supplier”) can be represented as: S-Roll-Up (Sales, [DISTANCE(Customer, Supplier)] \rightarrow ClosestCity, SUM(SalesAmount)). The query’s s-roll-up operator takes the sales observations as input. Each sale observation has a set of associated measures representing quantitative descriptions, e.g., Sales Amount and Sales Location – the latter corresponds to a spatial measure. Measures have aggregation functions (e.g., SUM for Sales Amount and Convex Hull for Sales Location) that can be used to combine several measure values when rolling-up to a higher level, such as from City level to Country level. In Fig. 2 both Customer and Supplier are spatial dimensions.

The graph pattern in Lines 2–11 of Query 1 describes the roll-up path as a path-shaped join of triple patterns connecting observations to target levels but also to the corresponding measures and attributes.

Line 1 in Query 1 selects all sales observations (\(?obs\)) and the spatial level (\(?supCity\)) as output. It also specifies to use aggregation function SUM on the measure (\(?sales\)). Lines 2–5 describe a star-shaped join of triple patterns connecting sales observations (\(?obs\)) to the Sales Amount measure (\(?sales\)) as well as to the base level members of two spatial dimensions: Customer (\(?cust\)) and Supplier (\(?sup\)).

City \rightarrow Country \rightarrow All \rightarrow Fig. 2 depicts spatial hierarchies for the Customer and Supplier dimensions. In Query 1, Lines 6, 8, and 11 query intermediate spatial levels of these hierarchies. For each spatial level we query the spatial attributes (Lines 7 and 9), e.g., Customer and Supplier have points. Line 10 describes the roll-up from the lowest level in dimension Supplier to a higher level City. Each roll-up between levels is defined as a hierarchy step. Spatial hierarchy steps have a topological relation between the levels (e.g., Customer \rightarrow Within \rightarrow City or State \rightarrow Intersects \rightarrow Country).

Figure 2: Northwind spatial data cube members (symbols next to level names represent spatial characteristics of level members, e.g., point, polygon, and multi-polygon.)

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\(^1\)QB4SOLAP: https://w3id.org/qb4solarp#  
Vocabulary Structure: https://estbi.cs.uan.uio.dk/QB4SOLAP  
\(^2\)RDF Data Cube: https://w3.org/TR/vocab-data-cube/  
\(^3\)QB4OLAP: https://lorenae.github.io/qb4olap/  
\(^4\)http://northwinddatabase.codeplex.com/
3. SYSTEM OVERVIEW

3.1 GeoSemOLAP Workflow

The workflow of querying spatial semantic data warehouses with GeoSemOLAP consists of six main steps, as illustrated in Fig. 3. First, the user selects a SOLAP operator. In dependence on which SOLAP operator was selected, the user can choose several items from a drop-down menu to complete the definition of the operator, e.g., schema elements (spatial levels, attributes, etc.) and spatial operations (distance, within, etc.).

As some operators (e.g., s-slice, Fig. 5b) require spatial coordinates as input, GeoSemOLAP displays snippets of geographic maps so that the user can click on a position to indicate spatial coordinates that the query should operate on.

Afterwards, the user can decide to select another SOLAP operator that shall be applied on the results of the previous operator (nesting) and set its parameters.

Then, the SPARQL query is automatically generated by GeoSemOLAP. The query can optionally be edited by the user before GeoSemOLAP sends the query to a SPARQL endpoint (local or remote) for execution.

Finally, the result of the query is displayed to the user. The user may aggregate the results or decide to continue editing the query by, for example, adding additional SOLAP operators and repeating the steps above mentioned.

3.2 GeoSemOLAP Architecture

GeoSemOLAP consists of five architectural components: GUI, Metadata Manager, Query Generator, Data Processor, and SPARQL Endpoint. The system architecture is illustrated in Fig. 4. GeoSemOLAP is implemented in Javascript, HTML, and CSS. It uses Leaflet for visualizing maps and Virtuoso Open Source Edition (7.2) for running the endpoint. The GeoFarmHerdState [4] is a spatial data cube about livestock holdings in Denmark. To enable interesting analyses, we have integrated data about livestock holdings with environmental and geographical data.

4. DEMONSTRATION SCENARIO

We will demonstrate GeoSemOLAP using two datasets (GeoFarmHerdState [4] and Geo-Northwind), which are both also available at our public endpoint. The GeoNorthwind data cube has already been explained in Sect. 2. GeoFarmHerdState [4] is a spatial data cube about livestock holdings in Denmark. To enable interesting analyses, we have integrated data about livestock holdings with environmental and geographical data.

At the conference, we will demonstrate GeoSemOLAP by allowing attendees to interact with the system and formulate queries. To make it easier for the audience to understand the data and the cube structure, the graphical interface displays a high-level graphical representation at the top of the page – as illustrated in Fig. 5a.

Hence, conference attendees will be able to directly interact with the system, which during the demonstration will run on a laptop connected to an external screen. Although GeoSemOLAP can use a remote endpoint to execute the formulated queries, the demonstration will use a local endpoint (running on the same laptop as the graphical interface) to avoid problems with an unstable Internet connection.

Fig. 5 shows a compact screenshot of GeoSemOLAP. At the top, we see a graphical representation of the used data cube. As mentioned above, it shows the most important concepts that are necessary to formulate a SOLAP query, e.g., dimensions, hierarchies, measures, spatial levels, and level attributes.

In this example (Fig. 5), the user has first selected the operator s-slice. The menu on the left-hand side (Fig. 5b) allows the user to set the parameters so that the s-slice operator selects geometries from a map or spatial levels from the schema. S-slice requires two spatial parameters; the first one to define a spatial location and the second one to define the slice level with respect to the given location. Hence, to help the user better select coordinates to define a location, a map is displayed so that the user can simply click on a point, which is then automatically extracted. In Fig. 5b, we can see that the user clicked on a point in Germany and then selected Country from the spatial levels to make a projection on the observations in this country.

In addition, to an s-slice operator, the user has added an s-roll-up operator to aggregate measures and discover new perspectives on sales with respect to their spatial location – the s-roll-up operator with its parameters is displayed under s-slice in Fig. 5b. The obtained result (from s-roll-up) is similar to our running example introduced in Sect. 1 (Query 1).

Based on the provided operators and parameters, GeoSemOLAP will automatically create and display the corresponding SPARQL query (Fig. 5c). The user can then de-
Figure 5: Screenshot of GeoSemOLAP
5. PERSPECTIVES AND FUTURE WORK

Fig. 6 sketches our vision of a tool-oriented future for SOLAP on the SW based on the models and algorithms proposed in [5].

![Diagram of SOLAP on the Semantic Web]

Figure 6: Vision of SOLAP on the Semantic Web [5]

As mentioned in Sect. 1, there is a growing popularity of spatial LOD datasets from various governmental domains. These datasets contain observations and measures that are well-suited for analytical queries (e.g., water/air quality measurements, immigration rates, EU subsidies in agriculture, crop revenue, etc.). However, as observed in [5] such datasets are typically not modeled with spatial dimension levels and hierarchies. Thus, they cannot directly be queried with SOLAP on the SW.

With currently available SW technologies, a user, who would like to query available spatial RDF data with SOLAP, needs to download the datasets, map them to a relational data model, and then import the result into a traditional spatial data warehouse. Obviously, this workflow is not only slow but it is also time-consuming and requires storing the data in a non-open format on a local system.

GeoSemOLAP considerably lowers the entry barrier for advanced spatial analysis on the SW by providing a user-friendly interface to formulate SOLAP queries in SPARQL. Our future work strives at lowering the entry barrier even further by developing (semi-)automatic techniques for annotating existing spatial RDF data on the SW with QB4SOLAP and defining spatial levels and hierarchies using available datasets, such as GeoNames. Furthermore, it would be interesting to extend the model proposed in [5] and GeoSemOLAP to handle highly dynamic spatio-temporal data and queries as, for instance, found in large-scale transport analytics [3].

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8. BIOGRAPHIES

Nurefşan Gür is a Ph.D. student at the department of Computer Science at Aalborg University, Denmark. Her research focuses on spatial OLAP and data warehouses on the Semantic Web. She is working on integrating Linked Open Governmental Datasets from spatial domains to enable business intelligence.

Jacob Nielsen is a student programmer at the department of Computer Science at Aalborg University, Denmark, where he currently studies Computer Science. His work currently focuses on providing a user-friendly way to formulate SOLAP queries in SPARQL in consideration of spatial levels and coordinates.

Katja Hose is an associate professor at the department of Computer Science at Aalborg University, Denmark. Her research interests include Linked Open Data, knowledge representation, query processing and optimization in distributed systems, rank-aware query operators, and energy data management.

Torben Bach Pedersen is a professor of Computer Science at Aalborg University, Denmark. His research concerns business intelligence and big data, especially “Big Multidimensional Data” – the integration and analysis of large amounts of complex and highly dynamic multidimensional data.