

Semantic High Level Querying in Sensor Networks

Ilaria Giordani¹, Daniele Toscani¹, Francesco Archetti^{1,2} and Mauro Cislighi²

¹Consorzio Milano Ricerche, via Cozzi 53, 20125 Milan, Italy

²University of Milano-Bicocca, Viale Sarca 336, 20125 Milan, Italy

Abstract. The quick development and deployment of sensor technology within the general frame of the Internet of Things poses relevant opportunity and challenges. The sensor is not a pure data source, but an entity (Semantic Sensor Web) with associated metadata and it is a building block of a “worldwide distributed” real time database, to be processed through real-time queries. Important challenges are to achieve interoperability in connectivity and processing capabilities (queries) and to apply “intelligence” and processing capabilities as close as possible to the source of data. This paper presents the extension of a general architecture for data integration in which we add capabilities for processing of complex queries and discuss how they can be adapted to, and used by, an application in the Semantic Sensor Web, presenting a pilot study in environment and health domains.

1 Background and Motivation

The rapid development and deployment of sensor technology involves many different types of sensors, both remote and in situ, with such diverse capabilities as range, modality, and manoeuvrability. It is possible today to utilize networks with multiple sensors to detect and identify objects of interest up close or from a great distance. Connected Objects – or the Internet of Things – is expected to be a significant new market and encompass a large variety of technologies and services in different domains. Transport, environmental management, health, agriculture, domestic appliances, building automation, energy efficiency will benefit of real-time reality mining, personal decision support capabilities provided by the growing information shadow (i.e. data traces) of people, goods and objects supplied by the huge data available from the emerging sensor Web [1].

Vertical applications can be developed to connect to and communicate with objects tailored for specific sub domains, service enablement to face fragmented connectivity, device standards, application information protocols etc. and device management. Building extending connectivity, connectivity tailored for object communication – with regards to business model, service level, billing etc, are possible exploitation areas of the Internet Connected Objects. Important challenges are to achieve interoperability in connectivity and processing capabilities (queries, etc.), to distribute “intelligence” and processing capabilities as close as possible to the source of data (the

sensor or mobile device), in order to avoid massive data flows and bottlenecks on the connectivity side.

The sensor is not a pure data source, but an entity (Semantic Sensor Web) with associated domain metadata, capable of autonomous processing and it is a building block of a “worldwide distributed” real time database, to be processed through real-time queries.

The vision of the Semantic Sensor Web promises to unify the real and the virtual world by integrating sensor technologies and Semantic Web technologies. Sensors and their data will be formally described and annotated in order to facilitate the common integration, discovery and querying of information. Since this semantic information ultimately needs to be communicated by the sensors themselves, one may wonder whether existing techniques for processing, querying and modeling sensor data are still applicable under this increased load of transmitted data.

In the following of this paper we introduce the state of the art in data querying over network of data providers. In Sect. 2 we present the software architecture of a data integration system in which we added complex query processing features. Sect. 3 introduces the case study in which we deployed our system: the study of short term effect of air pollution on health. Sect. 4 presents the detailed implementation of the querying features together with results on real data sets. Finally, Sect 5 presents the conclusions and future work.

1.1 State of the Art

This paper stems from the work presented in [12], in which is presented a software system aimed at forecasting the demand of patient admissions on health care structures due to environmental pollution. The target users of this decision support tool are health care managers and public administrators, which need help in resource allocation and policies implementation. The key feature of that system was the algorithmic kernel, to perform time series analysis through Autoregressive Hidden Markov Models (AHMM) [7]. The scenario in which the system has been deployed is the research project LENVIS¹, which is aimed to create a network of services for data and information sharing based on heterogeneous and distributed data sources and modeling. One of the innovations brought by LENVIS is the “service oriented business intelligence”, i.e. an approach to Business Intelligence in which the information presented to the user comes from data processing that is performed online, i.e. data are extracted under request of the applications, and on the basis of data availability, i.e. data are exchanged through web services, which does not guarantee response time neither availability.

Such a complex environment, in which data sources are distributed over the internet, is common to several problems and has been faced by different approaches. One of them is that of [13], in which “monitoring queries” continuously collect data about spatially-related physical phenomena. An algorithm, called Adaptive Pocket Driven Trajectories, is used to select data collection paths based on the spatial layout of sen-

¹ LENVIS - Localised environmental and health information services for all. FP7-ICT-2007-2. Project number 223925. www.lenvis.eu

sors nodes. This is not the case of our project, in which the geo-graphical location of the data providers is unknown; however, this approach can be extended in order to consider not only the geographical organization of sensors, but also any contextualization of thematic information in different spaces - be they conceptual or physical (e.g. considering as generalized concept of space any type of organization deriving from cooperation of data sources in an environmental monitoring network). The concept of modelling generalized spaces, locations and mapping between locations belonging to different spaces is introduced in [2]; this model has been implemented in a prototype system for space-aware communication [3] [4].

A different approach for continuous queries [11] is based on C-SPARQL, an extension of SPARQL, the standard language for querying Resource Description Framework (RDF) graphs. RDF graphs are data models, which in this case encode metadata using the Semantic Sensor Web ontology (http://knoesis.wright.edu/research/sensci/application_domain/sem_sensor/ont/sensor-observation.owl). C-SPARQL adds to SPARQL the possibility to perform continuous queries over data streams and supports simple forms of reasoning in terms of incremental view maintenance. The main drawback of RDF is the performance: the representation of data model based on XML requires executing inference and exploration of graphs; in case of several queries executed in very short time, this overhead can greatly increase the response time. The same problem in performance can affect systems based on ontology reasoning; an example is SEMbySEM [5], an European research project with the objective of creating a framework for the management of semantics in sensor networks. Sensor data are mapped in OWL ontologies and a rule based engine is applied for reasoning.

The explicit management of sensors semantics is addressed also in [8], which presents a framework for query processing. Distributed end users can request streams of interest with efficient energy management, based on the principle of pushing the query down to the network nodes as much as possible, to maximize lifetime and utility of the sensor network. Also in this case, the modelling of semantics is performed through ontology. The object oriented meta-model that is at the basis of our architecture allows explicit management of data types, taking benefits of the time and resource efficiency of Java objects manipulation (see Sect. 2).

LarKC [10] is an ongoing European research project with the objective of mixing logic reasoning with information retrieval. The attempt to fuse data retrieval and elaboration in sensor networks is not new; in [6], for instance, is presented FA, a system where users and applications can pose declarative forecasting queries and continuous queries to get forecasts in real-time along with accuracy estimates. A feature that is missing in this system is the automatic discovery of the data sources, which instead is addressed by systems based on ontologies, RDF and our meta-model: in FA the user must state explicitly from which source the data should be extracted; this is not always possible and easy in dynamically changing environment, like our application case (Sect 3), in which sensors and services may not be always available. Furthermore, the Analysis Layer of our architecture introduces at query execution level the possibility to obtain data from analysis and forecast models; the platform autonomously manages these models, without the need that the user explicitly deals with them.

2 System Architecture

The work presented in this paper is based on the architecture for data integration already developed for querying environmental and health data [12]. Data providers in the scenario in which our software is deployed are distributed over the web: in order to meet the requirements of data accessibility and increase the availability of information we extended the basic components of the software architecture by implementing in the *Analysis Layer* a set of complex queries for time series analysis. As described in Sect. 4, we applied these queries to extract indicators of critical situations in environmental monitoring.

The system architecture which we are developing has been designed to be used as basic infrastructure by other applications, like for instance Business Intelligence tools, to retrieve heterogeneous data of different nature and data series, like sensor measurements (e.g. environmental samples of different quantities), non-sequential (more “DB-like”) data; e.g. people lists, clinical records, etc. The idea is to access uniformly heterogeneous data sources (the containers of such data), integrating them logically without modifying their content or structure.

The data types that are manipulated correspond to domain entities, which are specific for each application. An example of data is “PM10”, which represent a sensor measurement of concentration of particulate matter; each type has a set of properties (i.e. attributes); for instance PM10 has a date and a concentration value. This is strongly different for a simple representation of sensor measurements as numeric values: it is not possible, for instance, to execute mathematical operation on values of types that are not compatible following the application specific model defined by the programmer. The requests of data items are performed by queries with SQL-like expressivity. Specific wrappers for each type of data source (e.g. DB, text file, software interface, ...) are configured to access the data.

The system architecture is implemented in Java SE 6; it is deployed on a centralized server, connected over the Internet to data providers, and it composed by four layers: 1) *Data*; 2) *Integration*; 3) *Analysis* and 4) *Application* layers (**Fig. 1**).

By *Data Layer* we identify the set of supported data sources: relational databases and structured text files, which store mostly static data, and web services, through which flow the data from sensors and services connected through the web.

The *Integration Layer* is kernel of our system; it provides the facilities to process queries extract the data and compose them to produce outputs. A key feature is the meta-model, which allows referring explicitly to the types of data in selection criteria and configuration of wrappers. Our meta-model is an object-oriented representation of domain entities, which is implemented in the DAC (Data Access Component). The querying mechanism defined by the DAC is an object oriented representation of query types and their elements, including constraints, expressions and operators. The main components of the DAC are: *Query Processor*, *Data Aggregator* and *Wrapper*. The *Query Processor* analyzes queries formulated by the user and processes them to produce the results. The *Data aggregator* merges the output of the different wrappers involved in the query evaluation, joining types when required. A *Wrapper* is a general component that links the *Query Processor* with a data source (DB, web service, text file...).

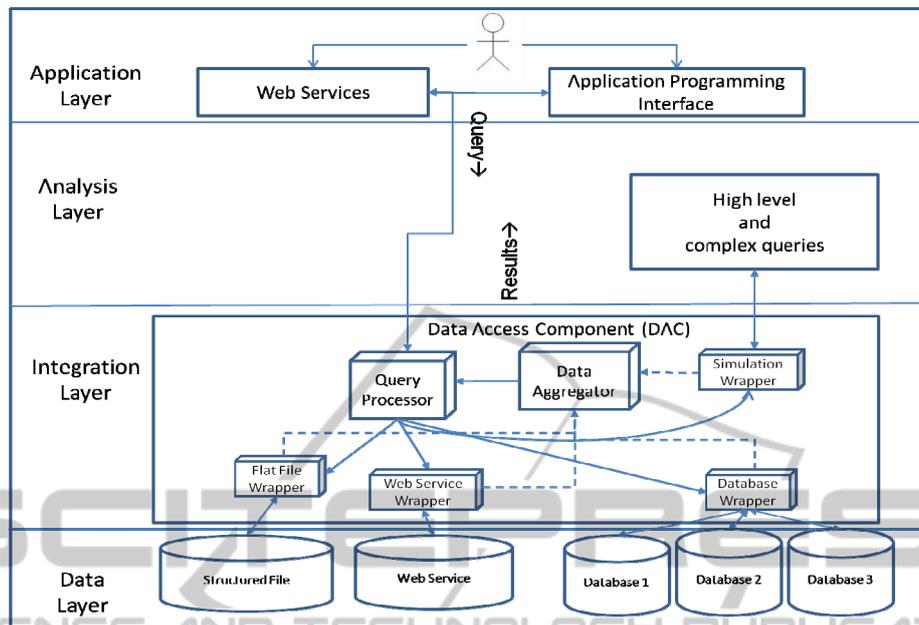


Fig. 1. System architecture.

In the *Analysis Layer* is implemented a set of built in queries (see Sect. 5), which combine the query operators of the DAC and computational components. These queries are not possible to perform through the standard querying mechanisms like SQL, since they involve data processing, for instance forecast produced by machine learning algorithms. One of the greatest innovations of our work is that each component in the *Analysis Layer* is connected to a *Wrapper* as a data source; it can then reply to queries and the data that it produces are part of the query output together with historical and streaming data from sensors.

In the *Application Layer* are defined web services and the Java API (Application Programming Interfaces) for the interaction with external applications and users' interfaces. These two technologies have been chosen in order to offer the widest, platform-independent support to the integration of our system. The possibility to formulate queries as object-oriented system calls and the features offered by our framework, in particular the masking of the data sources and automatic discovery of the data providers, make it easy to develop data analysis, visualization and business intelligence applications. Furthermore a set of pre-defined complex queries, some of which are presented in Sect. 4, is still under development to offer a continuously increasing library of embedded data analysis components, to be used by external applications. The data produced as output are presented by the framework as objects in the types defined by the user, with fields and attributes that can be configured for any specific application, delegating to the framework the responsibility to convert the data from the original formats in the sources.

3 The Case Study

The aim of this paper is to show how our system can simplify the access to information in network of distributed data sources. The LENVIS project is a test bed with a specific application: the querying of air pollution data and health indicators. As environmental data we consider the concentrations of air pollutants in the city of Milan.

The network of air pollution monitoring has 9 stations, each of which is equipped with a variable number of sensors, for a total of 37 sensors in the whole network. Each sensor measures the concentration (in $\mu\text{g}/\text{m}^3$) of one among: benzene, nitrogen dioxide, sulphur dioxide, carbon monoxide, nitrogen oxide, total nitrogen oxide, ozone, PM10 (Particulate Matter), PM2.5, TSP (Total Suspended Particulate). The station calculates every hour the mean of pollutant concentration and sends it to a control centre, where the data are manually validated to filter outliers and further aggregated to obtain a daily measure.

The health indicators that we collected are the daily number of hospitalizations in the town of Milan for respiratory and cardio-vascular diseases, whose acute occurrence can be related to air pollution. The number of hospitalizations for each pathology are collected by the local government of the Lombardy region and stored in a database.

4 High Level and Complex Queries

In this section we present the queries implemented for the case study introduced in Sect. 3 and the results of their execution. As introduced in Sect. 2, the querying mechanism defines an object-oriented abstraction of the *types* of objects and the constraints on which to perform selections; this requires that before the execution of all the queries we define types (in our case *pollutant* and *admission*) and their properties.

In the box below, we define two properties for each type: *date* represents the timestamp in which the pollutant concentration or the admission has been recorded; *value* is the numeric value of the pollutant concentration or, respectively, the number of hospital admissions.

```
//Definition of the new set of 2 properties for pollutant type: date and
value (pollutant concentration)
Property()pollutant_p = new Property(2);
pollutant_p (0) = new Property("date",SimpleType.DATE);
pollutant_p (1) = new Property("value",SimpleType.DOUBLE);
//Creation of the new data type: pollutant with the properties pollutant_p
createType("pollutant", pollutant_p);

//Definition of the new set of 2 properties for admission type: date and
value (number of admission)
Property()admission_p = new Property(2);
admission_p (0) = new Property("date",SimpleType.DATE);
admission_p (1) = new Property("value",SimpleType.INT);
//Creation of the new data type: admission, with the properties admission_p
createType("admission", admission_p);
```

As a general approach, in our system a query is defined with three steps: 1) definition of *symbolic expressions*, which create a reference to the attribute of a property; 2)

definition of *selection expressions*, which complete *symbolic expressions* by adding a *compound expression*, which defines operations and constants; 3) definition of the *query* that combines all the *selection expressions* previously defined.

4.1 Query 1

The objective of *Query 1* is, given a time period (e.g. a year, a month or a week), to find the number of days in which the pollution concentration exceeds a critical threshold. This is useful since risk thresholds are defined by the law and local administrations, for instance, need to have warnings to know when pollution reduction policies have to be actuated.

Query structure: The query structure follows the three steps described above. First, the *symbolic expressions* *poll_date* and *poll_val* create respectively a reference to the properties *date* and *value* of the pollutant of interest. In the second step it is defined the selection criteria, called *poll_Over_Thr*, through a *CompoundExpression* that extracts all the pollutant concentration values above the defined threshold. Since the user might be interested only to a particular time period, a *CompoundExpression* is defined to apply the *Poll_Over_Thr* selection criteria with the *dateRangeCriterion*. Finally, the query *q1* combines all the criteria previously defined to select the pollutant concentration values over the threshold in the time period. The number of days in which threshold is exceeded (*dayOverThr*) is given by the count of elements in the result set obtained after query execution.

```
Expression poll_date = new Symbolic(pollutant.getPropertyByName ("date"));

Expression poll_val = new Symbolic(pollutant.getPropertyByName ("value"));

DataObject pollThrObj = t_double.createDataObject();
pollThrObj.setDouble(threshold);
Expression poll_over_thr = new CompoundExpression(GTE,poll_val,new Constant(pollThrObj));

Expression dateFrom = new CompoundExpression(CmpOperator.GREATER_EQUAL,
poll_date,new Constant(dateF));
Expression dateTo = new CompoundExpression(CmpOperator.LESS, poll_date,new
Constant(dateT));
Expression dateRange = new CompoundExpression(AND,dateFrom,dateTo);

Expression dateRangeCriterion = new CompoundExpression(AND,dateFrom,
dateTo);
Expression compoundCriterion = new CompoundExpression(AND,poll_over_thres,
dateRangeCriterion);

Query q1 = new SelectQuery("pollutant", compoundCriterion);

int dayOverThr = count(q1.getResults());
```

Results: The query is executed with the following parameters: as pollutant we chose the Particulate Matter with a diameter less than 10 microns (PM10) and as temporal period we select the data in the month of February in all the years, from 1998 to 2008. The PM10 threshold is 50 $\mu\text{g}/\text{m}^3$.

The query identifies that the threshold has been exceeded in 211 days. A representation of the results is depicted in **Fig. 2**. Here, for each day of the month under study, a different colour represents the different concentration of pollutant PM10: darker

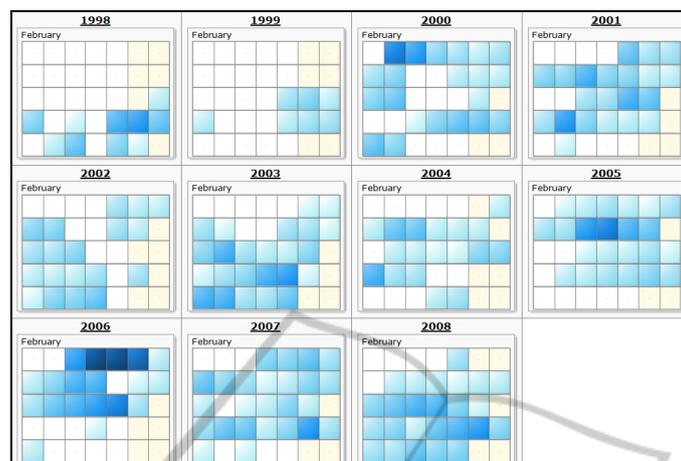


Fig. 2. Query 1 results.

cells correspond to days with higher pollution. Analyzing the results, we see immediately that the month with higher pollutant concentration is February 2006.

4.2 Query 2

The problem addressed by *Query 2* is to know the variations of pollution concentrations during the weekends (Saturday and Sunday) by comparing the results in different months or different years. *Query q2* extracts the number of Saturdays and Sundays in which the pollution concentration exceeds a specific threshold.

Query structure: The structure of *q2* is similar to *q1*. Also in this case we must define, through a *symbolic expression*, a reference to the *date* and *value* property of the pollutant of interest and then select all the episodes of pollutant concentration over the threshold during the time period of interest. Unlike the first query, here we introduce the selection of the weekend days by applying a post-processing phase in which, through the *Java GregorianCalendar* methods, we select only the Saturdays and Sundays in the time period under study.

Results: The pollutant selected is PM10 and as a time period we chose the years from 1998 to 2008. The threshold defined is $50 \mu\text{g}/\text{m}^3$.

The number of Saturdays and Sundays over PM10 threshold returned by the query is 380. In Fig. 3 are depicted the results of the query *q2* with a calendar view. In the figure is visualized only the year 2007. A peculiarity that is clearly visible from the image is that in December and January there are high pollutants concentrations during the weekends, probably due to general climatic conditions and higher vehicular traffic.

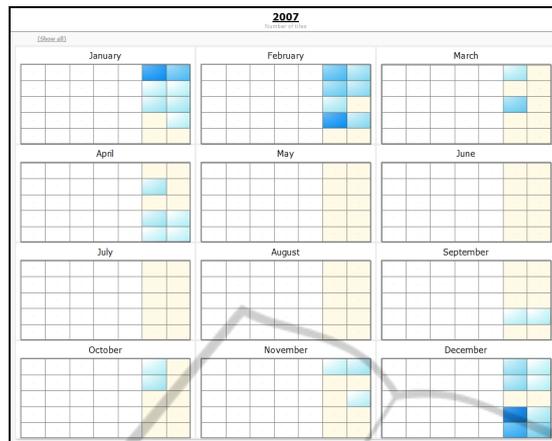


Fig. 3. Query 2 results.

4.3 Query 3

Both queries $q1$ and $q2$ have been executed on data collected by single sensors. In the next queries we want to elaborate data recorded by different sensors located in the network of air pollution monitoring stations. In this case the objective is the extraction of the number of days in which the pollution concentration exceeds the threshold (different for each pollutant) in four different sensors.

Query structure: The structure of this query is simpler than the previous ones. In fact, as visible in the box below, we must merge the results ($q3_s1$, $q3_s2$, $q3_s3$ and $q3_s4$ as reported in the pseudo-code) obtained with each simple query applied to each sensor.

```
//Definition of references to pollutant concentration attribute of each
sensor
Expression symbRefSens_1_Value = new Symbolic(sens1.getPropertyByName
("value"));
DataObject sens1ThrObj = t_double.createDataObject();
sens1ThrObj.setDouble(threshold_s1);

Expression sensor1_over_thr = new CompoundExpres-
sion(GT,symbRefSens_1_Value, new Constant(sens1ThrObj));
//similar selection criteria for sensors 2, 3 and 4
.....
Query q3_s1 = new SelectQuery("pollutant", sens1_over_thr);
Query q3_s2 = new SelectQuery("pollutant", sens2_over_thr);
Query q3_s3 = new SelectQuery("pollutant", sens3_over_thr);
Query q3_s4 = new SelectQuery("pollutant", sens4_over_thr);

List results = union
(q3_s1.getResults(),q3_s2.getResults(),q3_s3.getResults(),q3_s4.getResults(
));
```

Results: We use data recorded by two monitoring stations (called respectively *Juvara* and *Pascal*) situated in Milan. For each station we have two kinds of sensors: PM10 and the Sulphur dioxide (SO₂). The pollutant concentration thresholds are 50 µg/m³ for PM10 and 150 µg/m³ for SO₂.

Table 1. Query 3 results.

Sensor Name	Number of Days over the threshold
PM10_Juvara	1309
PM10_Pascal	172
SO2_Juvara	2
SO2_Pascal	0

Query results are reported in Table 1. The sensors for PM10 registered the higher number of days over threshold in all the period under study. This confirms what has been found by scientific studies: that the number of days over threshold for SO₂ decreased significantly over the years compared to PM10 [9].

4.4 Query 4

The fourth query is similar to *q3*; the only difference is that *q4* extracts the number of days in which the pollution concentration exceeds the threshold *at the same time* in three different sensors.

Query structure: This query is a combination of the previous ones. In fact, after the definition of a reference to each sensor pollutant concentration attribute and after the selection of all the measurements over the threshold *thr*, the query combines with the logical operator *and* the obtained results.

```
//Definition of references to pollutant concentration attribute of each
sensor (sensor1, sensor2, sensor3)
Expression symbRefsens1 = new Symbolic(sensor1.getPropertyByName("value"));
Expression symbRefsens2 = new Symbolic(sensor2.getPropertyByName("value"));
Expression symbRefsens3 = new Symbolic(sensor3.getPropertyByName("value"));
DataObject sensorThrObj = t_double.createDataObject();
sensorThrObj.setDouble(thr);
Expression sens1OverThr = new CompoundExpression(GT,symbRefsens1,new Constant(sensorThrObj));
Expression sens2OverThr = new CompoundExpression(GT,symbRefsens2,new Constant(sensorThrObj));
Expression sens3OverThr = new CompoundExpression(GT,symbRefsens3,new Constant(sensorThrObj));
Expression pollOverThr1 = new CompoundExpression(AND,sens1OverThr,sens2OverThr);
Expression pollOverThrTotal = new CompoundExpression(AND,pollOverThr1,sens3OverThr);

Query q_4 = new SelectQuery("pollutant", pollOverThrTotal);
```

Results: The query is applied on the network of PM10 sensors and in particular, the three sensors under study are *Verziere*, *Juvara* and *Pascal*. The query returns only three days in which the sensors exceed the threshold at the same time. The pollutant concentration values of these days are visible in Table 2.

4.5 Query 5

The last query that we propose is the more complex. The objective is to know the average lag between the local maxima of pollutant concentration and the local

Table 2. Query 4 results.

Date	PM10_Verziere ($\mu\text{g}/\text{m}^3$)	PM10_Juvara ($\mu\text{g}/\text{m}^3$)	PM10_Pascal ($\mu\text{g}/\text{m}^3$)
21/04/2007	71.0	61.0	80.0
22/05/2007	62.0	55.0	72.0
23/06/2007	71.0	60.0	76.0

maxima of hospital admission in a time period chosen by the user. This query represents the typical analysis that is applied to discover short-term variations on air pollutant data, to find how pollutant concentration and hospital admissions are correlated.

Query structure: This query is a three stages query, where the second and third stages are post processing steps. In the first step, through *q5_p* and *q5_a*, are extracted all the measurements for both pollutants and admissions in the period of interest. The extraction is made using a query similar to *q1*, with the only difference that here we take out a time series of all measurements. The pseudo-code is reported in the box below.

```

Expression poll_date = new Symbolic(pollutant.getPropertyByName ("date"));
Expression poll_val = new Symbolic(pollutant.getPropertyByName ("value"));
Expression adm_date = new Symbolic(admission.getPropertyByName ("date"));
Expression adm_val = new Symbolic(admission.getPropertyByName ("value"));

Expression dateFrom_p=new CompoundExpression (CmpOperator.GREATER_EQUAL,
poll_date,new Constant (dateF));
Expression dateTo_p = new CompoundExpression (CmpOperator.LESS,
poll_date,new Constant (dateT));
Expression dateRange_p = new CompoundExpression (AND,dateFrom_p, dateTo_p);
Expression dateRangeCrit_p = new CompoundExpression (AND,poll_val, dateRange_p);

//similar selection criteria for admissions
.....
Query q5_p = new SelectQuery ("pollutant", dateRangeCrit_p);
Query q5_a = new SelectQuery ("admission", dateRangeCrit_a);
//find local maxima
List localMax_p = findLocalMaxima (q5_p.getResults());
List localMax_a = findLocalMaxima (q5_a.getResults());
//compute average lag
Double avgLag = computeAvgLag (localMax_p, localMax_a);

```

The second step (method *findLocalMaxima*) is focalized on the analysis of each time series obtained in the previous step with the subsequent individuation of local maxima, generally defined as the maximal value in some segment of the series. In this way a local maximum is found by comparing each point in the time series with the previous and the next one: if in a given point the value is greater than the previous and the next, this point is defined as a local maximum. Local maximum extraction is applied on both pollutant concentration and hospital admission time series.

Finally, in the third step (method *computeAvgLag*), is computed the average lag between each local maximum of pollutant concentration series and the correspondent local maximum of hospital admissions.

Results: The query described above is applied on data recorded in the months of February and March. We analyze jointly PM10 and admissions for respiratory diseases, which are the health problems major related to particulate since, because of the size of the particle, it can penetrate the deepest part of the lungs. Larger particles are

Table 3. Query 5 results.

Max Admission	Max pollutant	Number of days
Thu Apr 09 1998	Fri Apr 03 1998	6
Mon Apr 13 1998	Wed Apr 08 1998	5
Thu Apr 16 1998	Wed Apr 15 1998	1
Tue Apr 21 1998	Fri Apr 17 1998	4
Thu Apr 23 1998	Wed Apr 22 1998	1

generally filtered in the nose and throat and do not cause problems, but particulate matter smaller than about 10 micrometers (PM₁₀) can settle in the bronchi and lungs and cause health problems.

Analyzing, for example, the month of April 1998, it's possible to obtain the results reported in Table 3. The average lag between max pollutant and hospital admission for respiratory diseases is 3.4 days

5 Conclusions and Future Work

The data integration and querying system with reasoning capabilities presented in this paper represents a further step in integrated processing of heterogeneous data sources without the need to replicate heavy and costly databases or data warehouses. It makes ETL dynamic, more suitable for analysing real-time data streams such as the ones coming from sensor networks, enriched with semantic information, jointly with data coming from more static databases.

Our query engine provides integration from heterogeneous data sources and does not need any database duplication. This feature makes it particularly efficient in analysing real-time data from sensors and down-scalable to a micro-engine suitable to be directly embedded into the sensor network themselves. In perspective the sensor network can become not only a data source, but also a data consumer, capable to run autonomous services by collecting the needed information elsewhere on the web.

“Smart cities”, urban computing, the environmental footprint of urban development, emergencies, precision agriculture are potential target domains.

Ongoing activities include further development of the architecture, including further data processing capabilities, and the study of configurable situation-aware agents (or query micro-engines) to be deployed in sensor networks, with the objective to enhance local processing and to reduce significantly the related communication overload, the reaction time and the power consumption. In order to better support the ease of query formulation, a future improvement will include the implementation of a high level querying language, which will allow to describe queries XML (through XSTREAM, <http://xstream.codehaus.org/>) or semi structured natural language, possibly integrating parsing libraries like JFLEX (an extension of JLEX, <http://jflex.de>) or CUP (<http://www.cs.princeton.edu/~appel/modern/java/CUP/>).

Upcoming research activities in 7th Framework Program by the European Commission will target the distribution of intelligence, data wrapping and processing capabilities as close as possible to the source of data, in particular in sensor networks and mobile devices in an interoperable frame. Our work, with its capabilities to query

data sources and web services, will be implemented having as key property its scalability, in order to meet the requirements and challenges posed by the growing theme of Internet Connected Objects.

References

1. Accenture, Information 2015: Reforming the paradigm, (2010)
2. Bernini, D., Micucci, D., Tisato, F.: A Space-Based Interoperability Model. In: Int. Workshop on Ontology, Conceptualization and Epistemology for Information Systems, Software Engineering and Service Science (ONTOSE 2010) - In conjunction with 22nd Int. Conf. On Advanced Information Systems Engineering (CAiSE'10) - June 7-11, Hammamet, Tunisia, (2010).
3. Bernini, D., Micucci, D., Tisato, F.: Space Integration Services: a platform for space-aware communication. In: Int. Workshop on Emergency Management: Communication and Computing Platforms) - In conjunction with IWCMC 2010 - 6th International Wireless Communications & Mobile Computing Conference (IWCMC 2010), Caen, France, (2010).
4. Bernini, D., Micucci, D., Tisato, F.: A Platform for Interoperability via Multiple Spatial Views in Open Smart Spaces, In: First Int. Workshop on Semantic Interoperability for Smart Spaces (SISS 2010) - In conjunction with IEEE Symposium on Computers and Communications (ISCC'10), Riccione, Italy, (2010).
5. Brunner, J.S., Goudou, J.-F., Gatellier, P., Beck, J., Laporte, C. E.: SEMbySEM: a framework for sensor management. In: Proc. of the 1st Int. Workshop on the Semantic Sensor Web (SemSensWeb) , collocated with ESWC, (2009).
6. Duan, S. and Babu, S.: Processing forecasting queries. In: VLDB '07: Proceedings of the 33rd international conference on Very large data bases, (2007), 711-722.
7. Messina, E., Toscani, D.:Hidden Markov Models for Scenario Generation. IMA Journal of Management Mathematics, Vol. 19 (4), pp. 379-401. October 2008
8. Li, L., Taylor, K.: A Framework for Semantic Sensor Network Services. Lecture Notes In Computer Science; Vol.5364 Proceedings of the 6th International Conference on Service-Oriented Computing table of contents, Sydney, Australia, (2008), 347 – 361.
9. Mitis F, Iavarone I, Martuzzi M. Health impact of ozone in 13 Italian cities, *Epidemiol Prev.*, Vol. 31, 323-32, (2007).
10. Simperl, E., Keller, U., Fischer, F., Oren, E., Bishop, B., Huang, Z., Tagni, G., Quesada, J., Fortuna, B., Hu, J., Qin, Y.: Deliverable D1.1.1 An Overview of Relevant Work in Other Areas. LarKC. The Large Knowledge Collider a platform for large scale integrated reasoning and Web-search. European Research Project FP7- 215535, (2009).
11. Stuckenschmidt, H., Ceri, S., Della Valle, E. and van Harmelen, F.: Towards Expressive Stream Reasoning. In: Proceedings of the Dagstuhl Seminar on Semantic Aspects of Sensor Networks, (2010).
12. Toscani, D., Bargna, F., Quarenghi, L., Archetti, F., Giordani, I.: A software system for data integration and decision support for evaluation of air pollution health impact. In: ICEIS conference, 8 - 12 June, Madeira - Portugal (2010).
13. Umer, M., Kulik, L. and Tanin, E.: Optimizing query processing using selectivity-awareness in Wireless Sensor Networks, Elsevier Computers, Environment and Urban Systems Vol. 33 79-8, (2009).